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RESEARCH ARTICLE

Knowledge Graph-Driven Approach in Aspect-Based Sentiment Analysis: Exploring the Impact of Embedding Techniques

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ABSTRACT Despite the high performance of the existing embedding approaches for Aspect-Based Sentiment Analysis (ABSA), such as Word2Vec and GloVe, they still have several limitations, mainly in contextual understanding and relational insights of natural language, especially in complex and long sentences. This paper presents a novel approach that enhances ABSA by integrating knowledge graphs into a transformer model, where the graphs are automatically built from raw text without requiring external resources, making the system adaptable and fully data-driven. Our approach allows a better understanding of context and relationships between entities, by combining of the contextual understanding of BERT with the relational insights provided by Node2Vec, a graph-based embedding technique. In this paper, we benchmark our hybrid embedding technique with the existing state-of-the-art embedding techniques. Specifically, we compare traditional embeddings, such as Word2Vec and GloVe, against BERT for textual input, while also exploring Word2Vec and Node2Vec for graph-based embeddings. Our experiments demonstrate that combining BERT's deep contextual embeddings with the structural insights of Node2Vec leads to promising improvements in sentiment classification performance. Our model achieved 98% accuracy on SemEval2015 Restaurant dataset. These results demonstrate that integrating both contextual and relational information significantly enhances the performance of ABSA models, thereby making them more effective at capturing nuanced sentiment relationships. The proposed model's modular design also allows flexible integration of alternative embeddings or graph configurations, making it suitable for broader sentiment analysis applications beyond the benchmark datasets.

INDEX TERMS Sentiment analysis, ABSA, transformers, knowledge graph, NLP.

I. INTRODUCTION

Human societies are integrating increasingly digital objects, building a narrower link between humans and machines. This has created a significant opportunity for the advancement of language technology, which has today reached a major milestone. Vocal recognition, machine translation, chatbots, or sentiment analysis are applications integrated into most

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digital objects, and in turn, have enhanced human society's development in an international context of sharing knowledge and informative content. In this context, natural language processing is among the most promising technologies for machines to understand, interpret, and generate human language naturally. Among these applications, Sentiment Analysis is one of the NLP tasks that specifically identifies the sentiment towards an entity in a text, expressed as positive, neutral, or negative [34]. A recent approach, known as Aspect-Based Sentiment Analysis (ABSA), provides a

more nuanced analysis by determining the sentiment towards a specific aspect of the entity, for example, by breaking down the review of a restaurant into positive sentiment for the taste of the food and negative sentiment for the service. Traditional sentiment analysis would struggle to capture this nuance, often providing a single, overall sentiment score for the entire review, which makes ABSA models more complicated, especially for complex sentences [22]. It is important to note that NLP is fully compatible with AI techniques such as deep learning, particularly with language-specialized models known as Large Language Models (LLMs). However, the complex sentence structures or multiple aspects in the same text make it challenging to accurately determine the sentiment about each aspect, especially in traditional neural networks, which often struggle with long-range dependencies [9].

To better understand this limitation, it is worth to note that attention-based approaches have improved sentiment detection by focusing on relevant words, but they overlook deeper syntactic relationships within sentences [35]. On the other side, graph-based methods, particularly dependency trees, have improved understanding of these relationships by incorporating contextual information and relationships between entities [2]. The *contra* is that noise and complexity can lead to misinterpretation of sentiment for aspects [11]. Therefore, models that integrate external information through knowledge graphs can enhance text comprehension [5], but may not fully capture all relevant features [38]. If we focus on the transformer, traditional embeddings, such as Word2Vec and GloVe, often lack contextual understanding, leading to misinterpretations in sentiment classification [33]. For instance, BERT captures context by considering the full sentence in both directions but can be sensitive to adversarial attacks [30] while Knowledge Graph Embeddings (KGE) preserve original graph structure, simplify manipulation, and improve classification accuracy [7]. In the literature, only a few works relate to Node2Vec, a graph-based embedding method, which remains underexplored in ABSA despite demonstrating accuracy in sentiment analysis [27], [29]. This leaves room for exploring this approach with more detail.

In light of these developments, we propose a novel approach based on Transformers that combines contextual embedding from BERT with the integration of KGE using Node2Vec.

The objectives of our research are as follows:

- Propose a hybrid ABSA framework that fuses contextual embeddings from BERT with structural embeddings from Node2Vec, integrated over dynamically constructed knowledge graphs.
- Explore the performance of Node2Vec embeddings in ABSA models and evaluate them against traditional embeddings like Word2Vec and GloVe.
- Investigate the impact of integrating different knowledge graph configurations, including polarity-annotated graphs, on the performance of ABSA models.

- Conduct comprehensive experiments on three SemEval benchmark datasets to systematically evaluate combinations of embedding techniques and graph configurations.
- Demonstrate that the integration of BERT with Node2Vec over polarity-aware graphs (KG3) consistently improves ABSA performance, achieving up to 98% accuracy, and offering a flexible architecture for real-world sentiment analysis tasks.

Indeed, we expect that the model's performance, when integrated with Node2Vec, will be enhanced since it captures the complex relationships between aspect terms and facilitates understanding of semantic connections in the text [28]. With this novel approach we achieve a 98% accuracy on one of the benchmark datasets, SemEval2015, and prove the effectiveness of this contribution for future development in ABSA state-of-the-art.

In addition to the proposed model, we compared traditional embeddings with BERT contextual embedding on the input level. We evaluated how these embeddings perform when concatenated with graph-based embedding, applying Word2Vec and Node2Vec. This comparison shows the importance of choosing the right embeddings for ABSA and provides insights into how various embedding strategies can be effectively combined to optimize sentiment classification accuracy. A precise comparison of four methods for combining information in the graph will be carried out.

To make our model easier to adapt and more effective for different types of sentiment tasks, we focused on three main improvements that go beyond just combining BERT with Node2Vec:

1. **A Flexible and Modular Design** We designed our model to allow its components to be replaced or removed. For example, the BERT encoder or the graph embeddings from Node2Vec can be modified without requiring a complete system rebuild. This makes the model highly flexible and easy to use for other tasks, such as relation extraction or domain-specific sentiment analysis. It also supports future updates without changing the core architecture.

2. **Automatic Graph Building from the Text Itself** Instead of using ready-made knowledge graphs from external resources (such as ConceptNet or DBpedia), our model creates its own graph based on the text it's working with. We built four types of graphs (KG1 to KG4) that each capture a different kind of relationship:

KG1 adds a basic link between aspect terms (without weights, only presence).

KG2 adds the same links but also tracks how often the terms appear together across the dataset by assigning a frequency-based weight to each connection.

KG3 adds sentiment (positive, negative) to these links.

KG4 focuses only on structure without sentiment labels.

This approach enables the model to better align with the text's domain, making it easier to apply to new datasets that lack predefined ontologies or graph data.

3. Ablation Testing and Flexible Fusion Methods We conducted several experiments to determine the contribution of each component to the model's overall performance. We tested various types of word embeddings, including Word2Vec, GloVe, and Node2Vec, as well as different graph types (KG1-KG4), and evaluated the model both with and without graph features. We also explored various methods for combining the graph embeddings with BERT, including simple concatenation, attention-based fusion, and transformer block-based integration. Among these, the concatenation method followed by a linear projection layer and multi-head attention achieved the best overall performance across all datasets, offering a balanced trade-off between accuracy and model complexity.

This setup makes the model more adaptable, easier to extend, and better at handling real-world sentiment data where both structure and context are important.

The rest of the paper is organized as follows. In the next section, a comprehensive literature review is presented to compare existing ABSA models with their advantages and disadvantages. It then details a hybrid model that integrates BERT, Word2Vec, and Node2Vec, followed by the experimental setup, the results, and a comparative analysis with existing ABSA models. Finally, we discuss the findings, implications for future research, and potential applications in the fields.

II. MODELS AND TECHNIQUES IN ABSA

ABSA has evolved significantly through advances in various methods and the integration of multiple technologies. This section reviews the significant recent contributions in this field, focusing on three main areas: (1) graph neural networks (GNNs) in ABSA, (2) transformer models and their limitations, and (3) integration of knowledge graphs in ABSA.

A. GRAPH NEURAL NETWORKS

Graph neural networks (GNNs) are widely used in ABSA because they capture complex relationships between entities and process heterogeneous data [14]. Especially when exploiting syntactic structures such as dependency trees, GNNs provide insights into syntactic dependencies, enabling a deeper understanding of sentence structure [23]. A recent study [33] provides a comprehensive review of GNNs, with a focus on enhancing performance in sentiment analysis tasks. Enhancements have been proposed based on GNNs to manage long texts. In a specific implementation of GNNs, the GCN applies the concept of convolution (from CNNs) to graphs [8]. Additionally, models proposed an innovation in GNN-based ABSA that includes the use of attention mechanisms in Graph Convolutional Networks (GCNs) [10]. The MHAKE-GCN model [24] also integrates dependency trees and affective knowledge for ABSA, utilizing GCNs to improve aspect-level sentiment detection. An alternative approach was to propose a model combining

a Transformer-like BERT with a SenticNet-enhanced GCNs for ABSA [12]. Additionally, an improvement is achieved by utilizing the model KMGCN, which enables better interaction between aspect terms and opinion words [13]. Finally, the model PRoGCN, which combines RoBERTa and GCN, demonstrated high performance by enabling interaction between semantic and syntactic features [17]. These advancements demonstrate the evolution of GNNs toward more robust and precise ABSA solutions.

B. TRANSFORMER MODELS IN ABSA

Transformer models, particularly BERT, have revolutionized ABSA models due to their robust contextual understanding and flexibility. The ability to consider both directions of a sentence allows for nuanced interpretations of sentiments, making them more effective than traditional embeddings [19], [25]. The TSPKT model addresses cross-domain ABSA using a transformer-based semantic-primary knowledge transferring network [5]. Models that incorporate transformers, such as PyABSA, represent a framework that consolidates various architectures [3], including transformers and graph-based methods, for robust ABSA performance across different datasets. In contrast, the model of [34] enhanced the contextual BERT with syntax representation encoding for better sentiment analysis in complex sentence structures with SRE-BERT model. Knowledge graphs have been integrated into the models to improve transformers further. Further enhanced models introduced a knowledge-enabled BERT model that embeds sentiment knowledge graphs, improving sentiment classification accuracy [22]. Similarly, [38] incorporated commonsense knowledge through a knowledge graph for more precise sentiment triplet extraction. The model in [17] combines transformers with GNNs and proposes PRoGCN, which integrates RoBERTa with GCN to enhance semantic and syntactic synergy.

C. KNOWLEDGE GRAPH

Knowledge graphs have been integrated into ABSA and have become an integral component of ABSA models, bridging the structural and contextual gaps. GCN-EGTS, a recent contribution, incorporates commonsense knowledge from ConceptNet into the sentiment triplet extraction process, thereby enhancing the model's ability to accurately identify and classify sentiments [38]. Another enhancement involves using knowledge graphs for cross-domain aspect extraction in transformer-based models [4]. The model KDGN in [18] introduces a knowledge-aware dependency graph to ABSA tasks. Another type of graph is Graph Attention Networks (GATs) that extend the attention mechanism to graphs. These models assign different weights to various parts of the graph, enabling the network to focus on each part with specific values [26].

Additionally, [36] evaluated GATs as an alternative to transformers, particularly in low-resource languages. The

contribution in [31] proposes SSK-GAT, which combines syntactic, semantic, and knowledge information using GAT for more effective sentiment classification. Additionally, recent models, such as Graph Transformer Structures (GTS), have combined syntactic trees with attention mechanisms [6]. However, they do not offer the same level of flexibility in combining different embeddings or supporting polarity-aware graph structures as proposed in our approach. While RGAT incorporates relational graphs and adversarial training within a BERT framework to enhance ABSA performance, particularly in complex and nuanced sentiment classification scenarios [30].

Additionally, recent studies included dependency graphs. The model in [25] utilizes heterogeneous graphs, incorporating external knowledge and syntactic information to enhance ABSA. For knowledge graph embedding, approaches [20], [21], [37] propose novel embedding techniques for knowledge graphs that are based on modular arithmetic. These developments underscore knowledge graph's critical role in capturing nuanced relationships and improving ABSA performance.

While models like PProGCN and SenticGAT have combined graph-based methods with transformers for ABSA, they often depend on external resources such as syntactic parsers or sentiment-specific knowledge bases like SenticNet. In our work, we take a different approach: we build knowledge graphs directly from the data itself, without relying on predefined rules or external ontologies. This makes our method easier to apply across domains, especially when labeled linguistic resources are limited or unavailable.

We also use Node2Vec to embed these graphs, capturing structural patterns around aspect terms in a way that complements BERT's contextual understanding. The architecture is designed to be modular, allowing flexible combinations of embeddings and graph types. This not only simplifies adaptation to new datasets but also offers a practical setup for real-world applications where data can be noisy, diverse, or domain-specific.

III. METHODOLOGY

In this section, we outline the methodology of our approach to explore the impact of different embedding techniques—GloVe, Word2Vec, BERT, and Node2Vec ABSA. The proposed approach aims to integrate these embeddings into a transformer-based model, with the incorporation of knowledge graph, and to evaluate their effectiveness in sentiment classification tasks. We detail the overall pipeline, including data preprocessing, embedding generation, and model architecture below, represented in Figure 1.

The preprocessing step follows a series of operations. First, all text is converted to lowercase to ensure uniformity, and then special characters, such as punctuation and other non-alphanumeric elements, are removed to exclude them from contributing to the sentiment analysis task. Finally, a tokenization is performed to break down the text into individual words or tokens.

A. KNOWLEDGE GRAPH CONSTRUCTION

As mentioned earlier, we aim to develop a specific LLM for the ABSA application in NLP. More specifically, the proposed approach relies on the construction of knowledge graphs, which serve as a foundational element in the model architecture. In deep learning applications, particularly within NLP, integrating structured knowledge into LLMs enables the development of more accurate and interpretable models [38]. It is worth reminding that knowledge graphs are structured representations that capture the relationships between words, aspects, and sentiments in the text. In this research, we built four distinct types of knowledge graphs to assess their impact on the ABSA model's performance:

KG1: This graph is constructed by treating aspect terms as nodes and adding edges based on the co-occurrence of these terms within the same sentence. This basic structure provides a straightforward way to represent the relationships between different aspects in the text.

KG2: Building on KG1, this graph incorporates weighted edges where the weights represent the frequency of co-occurrences between aspect terms. Adding weights enables the model to prioritize stronger relationships, thereby enhancing its ability to distinguish between aspects that are more closely related.

KG3: The sentiment of each aspect term (positive, negative, or neutral) is taken directly from the dataset. For every sentence, a connection (edge) is made between each aspect term and all other words in that sentence. The sentiment label is attached to these edges based on the aspect's polarity. For example, if "service" and "staff" co-occur in a sentence with a positive sentiment, the edge between these terms will carry a "positive" label. This lets the graph reflect how different words relate to the sentiment of each aspect.

KG4: Similar to KG3, but without polarity annotations. This means KG4 connects words in the same way as KG3 and keeps the same structure between terms, but without adding any positive or negative sentiment information. It helps us see how the model performs using just the links between words, without knowing the tone of those links.

The purpose of these graphs is to capture the complex and nuanced relationships between words and aspects. By embedding these graphs using Node2Vec, we generate relational representations that are combined with BERT's contextual embeddings. This combination is designed to enhance the model's ability to understand and classify sentiment at the aspect level, especially in sentences with intricate syntactic structures and multiple sentiments.

B. EMBEDDING TECHNIQUES

The model incorporates multiple embedding techniques, including GloVe, Word2Vec, BERT, and Node2Vec, each offering distinct advantages for representing both textual and structural information.

To do so, we investigate how different embedding techniques perform when used together within the same model,

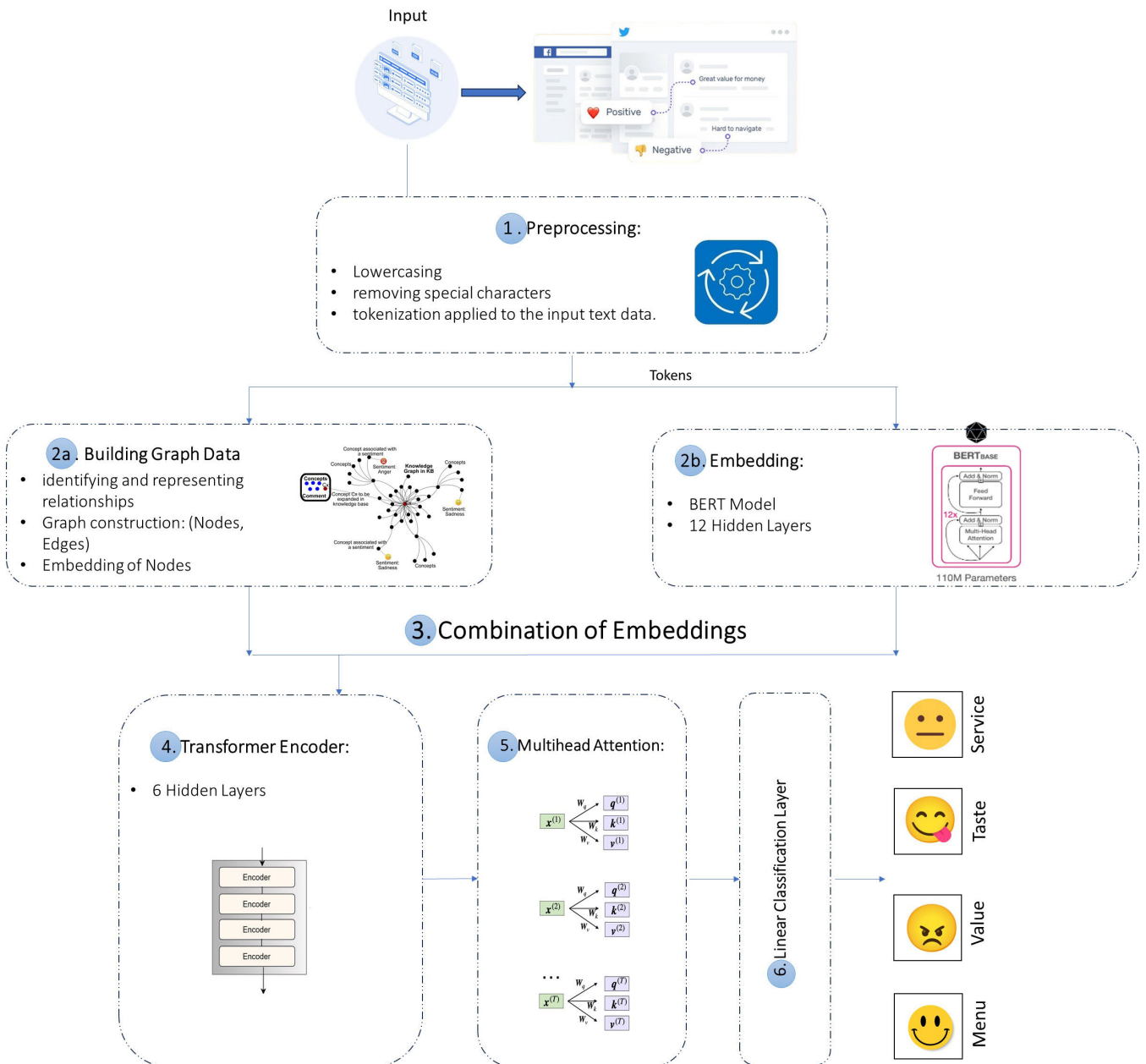


FIGURE 1. Architecture of the proposed aspect-based sentiment analysis (ABSA) model.

comparing their impact on the model’s accuracy and ability to classify sentiment correctly. The model was designed with modularity in mind. Each component can be replaced with alternative embedding methods without altering the core structure. The fusion mechanism automatically adapts to the size of the embeddings, making the model easy to customize or extend to other tasks. By systematically evaluating embeddings and knowledge graphs using various construction methods, we aim to identify the most effective strategies for enhancing ABSA performance, particularly in challenging scenarios where traditional sentiment analysis

methods, such as Word2vec and GloVe, may fall short. In the following, we are reviewing the mathematical formalism of the different embeddings we aim to use.

1) GloVe EMBEDDINGS

GloVe [15] is an embedding technique that captures the global statistical information of a corpus by using co-occurrence matrices to find how frequently words appear together within a specific window in the text. The co-occurrence matrix X is used to compute word vectors w and context vectors c by minimizing the following weighted

least squares objective:

$$J = \sum_{i,j=1}^V f(X_{ij}) \left(w_i^T c_j + b_i + \tilde{b}_j - \log X_{ij} \right)^2 \quad (1)$$

Here J is the objective function (or loss function) that the GloVe algorithm minimizes during training, where $f(X_{ij})$ is a weighting function b_i and \tilde{b}_j are bias terms for words and contexts, respectively, and V is the vocabulary size. For the proposed model, GloVe embeddings convert each word in the dataset into a fixed-dimensional vector, which serves as input vectors to the transformer model, capturing the statistical relationships within the corpus.

2) Word2Vec EMBEDDINGS

Word2Vec [40] is an embedding technique that learns word representations by predicting surrounding words in a text (skip-gram) or by predicting the current word based on its surrounding context (CBOW). The skip-gram model maximizes the following objective:

$$\frac{1}{T} \sum_{t=1}^T \sum_{-m \leq j \leq m, j \neq 0} \log p(w_{t+j} | w_t) \quad (2)$$

This formula calculates the likelihood of context words appearing near a given target word in the corpus and optimizes the embeddings to maximize this likelihood, where T is the total number of words in the training corpus, w_t is the current word, and w_{t+j} are the context words within a window of size m , and T is the total word count, allowing Word2Vec embeddings to capture short-range context relationships effectively.

In the present study, we use the skip-gram model of Word2Vec to generate embeddings, which capture the contextual meaning of words in shorter text windows. The generated Word2Vec embeddings are fed into the transformer model, allowing it to utilize context-based word relationships in the sentiment analysis task.

3) BERT EMBEDDINGS

BERT provides dynamic embeddings by considering the entire context of a sentence, processing it in both directions. Unlike GloVe and Word2Vec, BERT embeddings are contextual and can capture the nuanced meanings of words based on their surroundings.

BERT embeddings are generated by fine-tuning a pre-trained BERT model on our ABSA-specific datasets. We used the ‘bert-base-uncased’ model from Hugging Face Transformers and fine-tuned it on the respective ABSA datasets. The objective function for BERT includes the Masked Language Model (MLM) and Next Sentence Prediction (NSP) tasks:

$$L = L_{MLM} + L_{NSP} \quad (3)$$

L the total loss function optimized during BERT training, which combines L_{MLM} , the cross-entropy loss for predicting

masked tokens and L_{NSP} , the cross-entropy loss for predicting whether a sentence follows another in the context.

Each word or token in the text is transformed into a vector that reflects its meaning within the full context of the sentence. This process creates BERT embeddings that are contextualized within the sentence, capturing the complex meanings of words. These BERT embeddings are then incorporated into the transformer architecture, enhancing the model’s ability to understand complex sentences and accurately classify sentiments.

4) Node2Vec EMBEDDINGS

Although advanced knowledge graph embedding models such as RotatE, CompGCN, and ConvE are effective in structured settings with labeled relational triplets, they are less suited for graphs derived directly from raw text, which often lack predefined relations or ontologies. These models assume predefined, labeled relations between entities and often require supervised triples to learn meaningful embeddings [32], [39].

In contrast, ABSA graphs, such as those we construct, are built directly from the dataset without any fixed schema. They represent unlabeled co-occurrence, contextual proximity, or sentiment polarity, which do not follow standard RDF-like structures. In these cases, embedding methods like Node2Vec [16] are more appropriate. Node2Vec learns from graph topology using biased random walks, capturing both local neighborhoods and structural roles without needing relation labels. This makes Node2Vec well-suited for unsupervised graph construction, focusing on lightweight embeddings that adapt well to real-world, domain-specific data.

The objective of Node2Vec is to maximize the log-probability of observing a network neighborhood $N_S(u)$ for a node u :

$$N_S(u) = \max_{\Phi} \sum_{u \in V} \log \Pr(N_S(u) | \Phi(u)) \quad (4)$$

$N_S(u)$ represents the neighborhood of a node u , and the objective function seeks to maximize the probability of observing these neighborhoods given the node’s embedding, $\Phi(u)$, and V is the set of nodes. Node2Vec creates vectors that capture both local and global graph structures, ensuring that nodes with similar structural or semantic relationships are mapped to nearby points in the embedding space.

In this study, we construct knowledge graphs where nodes represent words or aspects, and edges represent their relationships, such as co-occurrence or syntactic dependencies. Node2Vec embeddings are generated by simulating random walks through each graph, exploring neighborhoods with different traversal parameters. Each node is embedded as a high-dimensional vector, encoding structural relationships and semantic proximity. High co-occurrence weights or polarity-based connections with other words result in nodes with higher relational importance being closer in the vector space.

The embeddings generated by Node2Vec are combined with BERT's contextual embeddings. By bringing together Node2Vec's focus on relationships within the graph and BERT's deep understanding of word context, we create a rich representation of each sentence. This approach enables the model to recognize structural connections between words and their specific meanings within a given context, particularly to sentiment. This enhances the model's ability to accurately identify sentiments, even in complex sentences with multiple aspects carrying different sentiments.

C. MODEL ARCHITECTURE

The transformer-based model we use integrates the embeddings generated by the techniques described above. The model is structured as follows:

- 1) **Preprocessing:** (Figure 1, step 1) This step involves preparing the input text data by lowercasing, removing special characters, and applying tokenization to create a sequence of tokens.
- 2) **Building Graph Data:** (Figure 1, step 2a) Relationships between entities are identified, and a graph is constructed with nodes representing words or concepts and edges representing their relationships. Node embeddings are generated for these graphs.
- 3) **Input Layer:** (Figure 1, step 2b) This layer receives the word embeddings, whether they are from GloVe, Word2Vec, or BERT.
- 4) **Embedding Fusion:** (Figure 1, step 3) In cases where the embeddings are combined (e.g., BERT and Node2Vec), a concatenation layer merges these embeddings before they are passed to the transformer layers (BERT in this case).
- 5) **Transformer Layers:** (Figure 1, step 4) These layers process the input embeddings, applying multi-head attention and feed-forward neural networks to capture the relationships between words in the context of the entire sentence.
- 6) **Multi-head Attention:** (Figure 1, step 5) This mechanism allows the model to focus on different parts of the input sentence simultaneously, capturing dependencies between words across the sentence.
- 7) **Output Layer:** (Figure 1, step 6) Finally, the processed embeddings are passed through a fully connected layer with a softmax activation function to classify the sentiment of each aspect in the text.

The model is trained on ABSA benchmark datasets, with cross-entropy loss used as the loss function. We use the Adam optimizer to adjust the model weights during training. To evaluate the performance of each embedding technique, we assess the model using accuracy, precision, recall, and F1-score metrics on a separate test set.

This methodology allows us to systematically compare the impact of different embedding techniques on the performance of ABSA models, providing insights into which methods offer the best balance of contextual understanding and structural representation for accurate sentiment analysis.

IV. EXPERIMENTS

In this work, various ABSA embedding techniques are compared, and we also conducted a set of experiments using a transformer model integrated with knowledge graph structures. The present experiments focused on comparing the performance of four different types of embeddings: GloVe, Word2Vec, BERT, and Node2Vec, providing a brief background and highlighting the main similarities and differences between these four techniques. Hence, for a fair comparison, each embedding type was fine-tuned within the end-to-end ABSA model. For BERT, we updated all its layers during training so it could learn directly from the sentiment data. For Word2Vec and GloVe, we began with pre-trained word vectors and allowed them to be updated during training, enabling the model to adapt them to the ABSA task. Node2Vec embeddings were first learned from the knowledge graph in an unsupervised way, then included in the model and also updated as training progressed. When we combined embeddings (such as BERT and Node2Vec), we merged their representations and trained the full model together. This allowed us to see how each embedding, alone or combined, affects the model's ability to classify sentiment for different aspects in the datasets.

A. DATASETS

To experiment, SemEval challenge datasets have been chosen based on three criteria: (1) accessibility, (2) the use case context, and (3) the compatibility for ABSA applications. More specifically, they provide a diverse set of aspects and sentiments, making them ideal for evaluating the robustness of various embedding techniques.

These datasets are widely used benchmarks for ABSA and include multiple annotated aspects and corresponding sentiment labels. The three publicly available benchmark datasets from the SemEval challenges are represented in Table 1:

- **SemEval 2014 (Restaurants):** This dataset contains customer reviews of restaurants, with each sentence annotated for aspects such as food, service, and ambiance, along with their corresponding sentiment polarities.
- **SemEval 2014 (Laptops):** This dataset consists of customer reviews of laptops, annotated with aspects related to product features like battery life, screen quality, and performance, along with sentiment labels.
- **SemEval 2015 (Restaurants):** Similar to the 2014 dataset, this dataset also focuses on restaurant reviews but offers different data points for evaluating the model.

B. EXPERIMENTAL SETUP

Each experiment follows the setup described below:

- **Model Architecture:** The model is based on a transformer backbone. BERT was used for contextual embeddings, while graph embeddings were generated using Word2Vec, GloVe, or Node2Vec, depending on

TABLE 1. Dataset statistics for the SemEval 2014 (Restaurants, Laptops) and SemEval 2015 (Restaurants) ABSA benchmarks.

Dataset	Split	Positive	Neutral	Negative
Restaurant14	Train	2164	637	807
	Test	728	196	196
Laptop14	Train	996	464	870
	Test	341	169	128
Restaurant15	Train	1178	50	382
	Test	439	35	328

the experiment. The architecture is modular: different embeddings were tested individually and in combination (e.g., BERT + Node2Vec), across various knowledge graph configurations (KG1-KG4). Embedding fusion was performed via concatenation, followed by a linear projection and multi-head attention.

- **Embedding Fusion Strategy** To combine contextual and structural information, BERT embeddings (768D) and Node2Vec (300D) parameters, as listed in Table 2, are concatenated and passed through a linear projection layer to 1024 dimensions. This is followed by a multi-head attention mechanism and a transformer encoder block. The final classification is performed through a fully connected layer with softmax activation.

TABLE 2. Hyperparameter settings for Node2Vec used in knowledge graph embedding.

Hyperparameter	Value
Dimensions	300
Walk length	30
Number of walks per node	200
Context window size	10
Return parameter p	1.0
In-out parameter q	1.0
Embedding model	Skip-Gram

- **Training Parameters:** All models were trained for 25 epochs using the AdamW optimizer. The learning rate was set to 2×10^{-5} with a batch size of 32. A dropout rate of 0.1 was applied after the BERT pooled output. When Node2Vec was used, it was configured with 300 dimensions, walk length of 30, 200 walks per node, window size of 10, and parameters $p = 1.0$, $q = 1.0$.
- **Evaluation Metrics:** The model performance was evaluated using standard classification metrics: accuracy, precision, recall, and F1-score, computed on the test sets of each SemEval dataset.

V. RESULTS AND DISCUSSION

All experiments are based on standard transformer architecture, the difference between the models lies in the type of embedding and the method of knowledge graph construction, as described in the previous section. The models are summarized in Table 3. All reported results are based on a fixed random seed. In future work, we aim to evaluate performance stability across multiple training runs.

TABLE 3. Overview of models with different input embeddings and knowledge graph configurations.

Model	Input Embedding	Graph Embedding	KG
Trans	BERT	None	None
TransWv	Word2Vec	None	None
TransGc	GloVe	None	None
TWvKG1	BERT	Word2Vec	KG1
TWvKG2	BERT	Word2Vec	KG2
TWvKG3	BERT	Word2Vec	KG3
TWvKG4	BERT	Word2Vec	KG4
TNvKG1	BERT	Node2Vec	KG1
TNvKG2	BERT	Node2Vec	KG2
TNvKG3	BERT	Node2Vec	KG3
TNvKG4	BERT	Node2Vec	KG4
TGlovKG1	BERT	GloVe	KG1
TGlovKG2	BERT	GloVe	KG2
TGlovKG3	BERT	GloVe	KG3
TGlovKG4	BERT	GloVe	KG4

The results of the conducted experiments are summarized in Table 4. The key findings are discussed as follows.

The baseline transformer model (Trans) performed the worst across all datasets, with F1-scores ranging between 0.18 and 0.50. This was expected, as the model had no access to additional relational information from embeddings or knowledge graphs, which limited its ability to understand complex sentence structures and aspect-sentiment relationships. Interestingly, when the Word2Vec embeddings are examined, the model's performance is slightly improved. Indeed, the TWvKG1 model achieved an F1-score of 0.55 on the SemEval 2014 Restaurant dataset, 0.57 on the SemEval 2014 Twitter Sentiment dataset, and 0.62 on the SemEval 2014 Emotion dataset, i.e., significantly outperforming the baseline transformer model. Additionally, the most significant gains were noted when knowledge graphs were integrated with Word2Vec embeddings. In this case, the TWvKG3, which, as previously stated, incorporates polarity annotations in the KG, showed significantly better performance: F1-scores are found to be around 0.92 across most datasets. This demonstrates that the model benefited from the additional sentiment information provided by polarity annotations. Note that the difference between TWvKG3 and TWvKG4 (with and without polarity, respectively) suggests that sentiment-specific information can boost model performance, but the standalone relational structure is still more powerful.

GloVe models generally underperformed when compared to Word2Vec and Node2Vec models, especially when no additional graph structures are involved. For example, TGvKG1 achieved an F1-score of 0.65 on the SemEval 2014 Restaurant dataset. Though the results for GloVe models improved significantly when combined with KGs such as TGvKG3 and TGvKG4. Indeed, the inclusion of polarity annotations in TGvKG3 led to better sentiment classification: F1-scores up to 0.98 (larger than TWvKG3). These enhancements indicate that with static embeddings like GloVe, the relational structure of knowledge graphs,

TABLE 4. Performance measures comparison of different models on the SemEval datasets.

Dataset	SemEval 2014 (restaurants)				SemEval 2014 (laptops)				SemEval 2015			
	Acc	Prec.	Recall	F1	Acc	Prec.	Recall	F1	Acc	Prec.	Recall	F1
Trans	0.53	0.18	0.19	0.19	0.48	0.31	0.29	0.29	0.73	0.49	0.50	0.49
TransWV	0.61	0.64	0.48	0.55	0.74	0.72	0.68	0.71	0.58	0.33	0.34	0.32
TransGv	0.41	0.18	0.22	0.19	0.66	0.45	0.45	0.43	0.74	0.52	0.52	0.51
TWvKG1	0.93	0.92	0.92	0.92	0.78	0.76	0.75	0.75	0.95	0.94	0.95	0.94
TWvKG2	0.93	0.92	0.92	0.92	0.78	0.75	0.74	0.75	0.96	0.96	0.95	0.95
TWvKG3	0.93	0.91	0.92	0.91	0.82	0.80	0.79	0.81	0.95	0.95	0.95	0.95
TWvKG4	0.93	0.91	0.92	0.91	0.81	0.79	0.78	0.81	0.95	0.95	0.93	0.94
TNvKG1	0.93	0.91	0.93	0.92	0.80	0.79	0.77	0.78	0.96	0.96	0.94	0.95
TNvKG2	0.92	0.92	0.88	0.90	0.79	0.76	0.77	0.75	0.95	0.94	0.96	0.94
TNvKG3	0.96	0.94	0.95	0.95	0.83	0.83	0.79	0.78	0.95	0.94	0.96	0.95
TNvKG4	0.94	0.93	0.93	0.93	0.84	0.79	0.75	0.80	0.98	0.98	0.98	0.98
TGlovKG1	0.71	0.65	0.65	0.65	0.80	0.75	0.79	0.77	0.97	0.96	0.97	0.97
TGlovKG2	0.71	0.65	0.64	0.64	0.78	0.73	0.78	0.75	0.98	0.98	0.97	0.98
TGlovKG3	0.69	0.66	0.64	0.59	0.79	0.73	0.77	0.75	0.97	0.97	0.98	0.97
TGlovKG4	0.71	0.67	0.67	0.67	0.80	0.75	0.78	0.76	0.96	0.95	0.96	0.96

especially when enhanced with sentiment information, can significantly improve ABSA.

An overall analysis of the previous results led to the conclusion that models employing Node2Vec embedding outperformed those using Word2Vec and GloVe embeddings. It is worth reminding that TNvKG3 achieved an F1-score of 0.95 on the SemEval 2014 Restaurant dataset and 0.98 on the SemEval 2015 Restaurant dataset. This represents a significant improvement over Word2Vec models, indicating that graph-based embeddings have the advantage of capturing word relations and aspects more effectively. Comparing the results between models where graph data is embedded with Word2Vec and Node2Vec, the comparison showed that Node2Vec demonstrated an average increase in F1-score and accuracy of approximately 2% across all datasets. Node2Vec paid attention to both the local and global structures of the graph, providing more informative and powerful feature representations, which in turn enhanced the classification performance of sentiments in given complex sentences.

In comparison to traditional embeddings, such as Word2Vec and GloVe, BERT consistently achieves better performance, particularly when combined with Node2Vec. This confirms the strength of combining contextual and structural embeddings in ABSA tasks. BERT's dynamic embeddings can capture the full context of words within a sentence, which is particularly beneficial in ABSA tasks. In addition, combining BERT with Node2Vec further improved results, suggesting that contextual and relational embeddings complementarity offer a new perspective for ABSA applications. In fact, the best results were achieved when BERT and Node2Vec were used together with a knowledge graph structure, especially when polarity annotations provided sentiment-specific information.

Ultimately, these results demonstrate that the choice of embedding technique and knowledge graph structure can have a significant impact on the performance of ABSA

models. While traditional embeddings, such as Word2Vec and GloVe, provide a solid foundation, they fall short in capturing the full complexity of sentence structure and aspect relationships [31]. BERT and Node2Vec, particularly when combined with knowledge graphs, provide a more comprehensive representation of text, leading to significant improvements in sentiment classification accuracy.

VI. CONCLUSION

This work presented a novel approach to Aspect-Based Sentiment Analysis (ABSA) by integrating contextual embeddings from BERT with graph-based embeddings generated by Node2Vec. Integrating Knowledge graph into the approach enhanced the model's capability to capture complicated relationships between words, aspects, and sentiments. We consecutively performed experiments in which we contrasted different embeddings, including GloVe, Word2Vec, BERT, and Node2Vec, both individually and in combination with various basic knowledge graph structures.

The experimental results presented in this paper show that combining BERT with Node2Vec outperforms models that rely solely on traditional embeddings such as Word2Vec and GloVe. The results highlight the benefits of combining graph-based and contextual embeddings, showing notable improvements in sentiment classification accuracy. When combined with BERT's context-aware embeddings, Node2Vec's ability to model the structure of relationships between words and aspects resulted in significant improvements in sentiment classification performance.

Despite the strong results, there are some limits. Although the four knowledge graphs (KG1-KG4) are built to avoid reliance on external resources, this data-driven approach also introduces certain risks. All graph versions, particularly KG3, which uses sentiment polarity annotations, are affected by the quality and balance of the training data. For instance, if the sentiment labels or co-occurrence patterns

in the data are biased or noisy, the resulting graph may reflect incorrect or misleading relationships. This can affect sentiment classification. Also, building graphs and generating embeddings takes time and memory. With large datasets, the model becomes slower and needs more resources. This makes real-time use more difficult. We have not yet tested the model in other domains or languages. It may behave differently with new types of data. In the future, we plan to explore faster graph methods, test domain changes, and apply the model in multilingual settings.

Cross-domain sentiment analysis remains a challenging task, as it requires models to generalize to unseen domains with different vocabularies or writing styles. Future research could investigate how various types of knowledge graphs and embedding strategies perform in these settings, particularly when combined with external knowledge sources. In addition, future work could explore how modular embedding affect cross-domain transfer and performance across datasets.

Furthermore, exploring low-resource languages and graph-based models can also be beneficial, as most of the available literature on sentiment analysis is conducted on high-resource languages, such as English [1]. Applying these techniques to other languages may create new opportunities for the development of multilingual and cross-linguistic sentiment analysis. Based on our findings, we suggest that combining Transformers with Knowledge Graphs could be particularly effective for sentiment analysis in languages with complex grammar or rich morphology, as this approach could better capture the intricate relationships within the text. Finally, we also aim to study lighter, faster graph construction methods and more efficient embedding strategies to reduce training time and memory usage, especially for large datasets and real-time applications.

REFERENCES

- [1] S. Al Katat, C. Zaki, H. Hazimeh, I. El Bitar, R. Angarita, and L. Trojman, "Natural language processing for Arabic sentiment analysis: A systematic literature review," *IEEE Trans. Big Data*, vol. 10, no. 5, pp. 576–594, Oct. 2024.
- [2] S. Feng, B. Wang, Z. Yang, and J. Ouyang, "Aspect-based sentiment analysis with attention-assisted graph and variational sentence representation," *Knowl.-Based Syst.*, vol. 258, Dec. 2022, Art. no. 109975.
- [3] H. Yang, C. Zhang, and K. Li, "PyABSA: A modularized framework for reproducible aspect-based sentiment analysis," 2022, *arXiv:2208.01368*.
- [4] P. Howard, A. Ma, V. Lal, A. P. Simoes, D. Korat, O. Pereg, M. Wasserblat, and G. Singer, "Cross-domain aspect extraction using transformers augmented with knowledge graphs," in *Proc. 31st ACM Int. Conf. Inf. Knowl. Manage.*, Oct. 2022, pp. 780–790.
- [5] B. Zhang, X. Fu, C. Luo, Y. Ye, X. Li, and L. Jing, "Cross-domain aspect-based sentiment classification by exploiting domain-invariant semantic-primary feature," *IEEE Trans. Affect. Comput.*, vol. 14, no. 4, pp. 3106–3119, Oct. 2023.
- [6] S. Yin and G. Zhong, "TextGT: A double-view graph transformer on text for aspect-based sentiment analysis," in *Proc. AAAI Conf. Artif. Intell.*, vol. 38, Mar. 2024, pp. 19404–19412.
- [7] A. Teo, Z. Wang, H. Pen, B. Subagdja, S.-B. Ho, and B. K. Quek, "Knowledge graph enhanced aspect-based sentiment analysis incorporating external knowledge," in *Proc. IEEE Int. Conf. Data Mining Workshops (ICDMW)*, Shanghai, China, Dec. 2023, pp. 791–798.
- [8] X. Shi, M. Hu, F. Ren, P. Shi, and S. Nakagawa, "Aspect based sentiment analysis with instruction tuning and external knowledge enhanced dependency graph," *Appl. Intell.*, vol. 54, no. 8, pp. 6415–6432, May 2024.
- [9] H. Wu, Z. Zhang, S. Shi, Q. Wu, and H. Song, "Phrase dependency relational graph attention network for aspect-based sentiment analysis," *Knowl.-Based Syst.*, vol. 236, Jan. 2022, Art. no. 107736.
- [10] J. Leng and X. Tang, "Graph attention networks for multiple pairs of entities and aspects sentiment analysis in long texts," *J. Syst. Sci. Inf.*, vol. 10, no. 3, pp. 203–215, Jan. 2022.
- [11] Z. Zhang, Z. Zhou, and Y. Wang, "SSEGCN: Syntactic and semantic enhanced graph convolutional network for aspect-based sentiment analysis," in *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics, Human Language Technol.*, Jan. 2022, pp. 4916–4925.
- [12] B. Liang, H. Su, L. Gui, E. Cambria, and R. Xu, "Aspect-based sentiment analysis via affective knowledge enhanced graph convolutional networks," *Knowl.-Based Syst.*, vol. 235, Jan. 2022, Art. no. 107643.
- [13] Z. Zhu, D. Zhang, L. Li, K. Li, J. Qi, W.-L. Wang, G. Zhang, and P. Liu, "Knowledge-guided multi-granularity GCN for ABSA," *Inf. Process. Manag.*, vol. 60, no. 2, Dec. 2022, Art. no. 103223.
- [14] Z. Dai, Y. Liu, S. Di, and Q. Fan, "Aspect-level sentiment analysis merged with knowledge graph and graph convolutional neural network," *J. Phys., Conf. Ser.*, vol. 2083, no. 4, Nov. 2021, Art. no. 042044.
- [15] J. Pennington, R. Socher, and C. Manning, "Glove: Global vectors for word representation," in *Proc. Conf. Empirical Methods Natural Language Process. (EMNLP)*, Oct. 2014, pp. 1532–1543.
- [16] A. Grover and J. Leskovec, "Node2vec: Scalable feature learning for networks," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Aug. 2016, pp. 855–864.
- [17] X. Shi, M. Hu, F. Ren, P. Shi, J. Deng, and Y. Tang, "Prompted and integrated textual information enhancing aspect-based sentiment analysis," *J. Intell. Inf. Syst.*, vol. 62, no. 1, pp. 91–115, Aug. 2023.
- [18] H. Wu, C. Huang, and S. Deng, "Improving aspect-based sentiment analysis with knowledge-aware dependency graph network," *Inf. Fusion*, vol. 92, pp. 289–299, Apr. 2023.
- [19] Z. Zhang, Z. Ma, S. Cai, J. Chen, and Y. Xue, "Knowledge-enhanced dual-channel GCN for aspect-based sentiment analysis," *Mathematics*, vol. 10, no. 22, p. 4273, Nov. 2022.
- [20] H. Baalbaki, H. Hazimeh, H. Harb, and R. Angarita, "KEMA: Knowledge-graph embedding using modular arithmetic," in *Proc. Int. Conf. Softw. Eng. Knowl. Eng.*, vol. 2022, Jul. 2022, pp. 263–268.
- [21] H. Baalbaki, H. Hazimeh, H. Harb, and R. Angarita, "KEMA++: A full representative knowledge-graph embedding model (036)," *Int. J. Softw. Eng. Knowl. Eng.*, vol. 32, no. 11n12, pp. 1619–1641, Nov. 2022.
- [22] A. Zhao and Y. Yu, "Knowledge-enabled BERT for aspect-based sentiment analysis," *Knowl.-Based Syst.*, vol. 227, Jun. 2021, Art. no. 107220.
- [23] B. Yang, H. Li, and Y. Xing, "SenticGAT: Sentiment knowledge enhanced graph attention network for multi-view feature representation in aspect-based sentiment analysis," *Int. J. Comput. Commun. Control*, vol. 18, no. 5, p. 5089, Aug. 2023.
- [24] X. Cui, W. Tao, and X. Cui, "Affective-Knowledge-Enhanced graph convolutional networks for aspect-based sentiment analysis with multi-head attention," *Appl. Sci.*, vol. 13, no. 7, p. 4458, Mar. 2023.
- [25] X. Song, G. Ling, W. Tu, and Y. Chen, "Knowledge-guided heterogeneous graph convolutional network for aspect-based sentiment analysis," *Electronics*, vol. 13, no. 3, p. 517, Jan. 2024.
- [26] Z. Li, Y. Qin, Z. Liu, and W. Wang, "Powering comparative classification with sentiment analysis via domain adaptive knowledge transfer," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, Jan. 2021, pp. 6818–6830.
- [27] Z. Jin, X. Zhao, and Y. Liu, "Heterogeneous graph network embedding for sentiment analysis on social media," *Cognit. Comput.*, vol. 13, no. 1, pp. 81–95, Jan. 2021.
- [28] Y. Wang, L. Dong, X. Jiang, X. Ma, Y. Li, and H. Zhang, "KG2Vec: A node2vec-based vectorization model for knowledge graph," *Plos One*, vol. 16, no. 3, Mar. 2021, Art. no. e0248552.
- [29] V. S. Anoop, C. S. Krishna, and U. H. Govindarajan, "Graph embedding approaches for social media sentiment analysis with model explanation," *Int. J. Inf. Manage. Data Insights*, vol. 4, no. 1, Apr. 2024, Art. no. 100221.
- [30] M. Chen, W. Wu, Y. Zhang, and Z. Zhou, "Combining adversarial training and relational graph attention network for aspect-based sentiment analysis with BERT," in *Proc. 14th Int. Congr. Image Signal Process., Biomed. Eng. Informat. (CISP-BMEI)*, Oct. 2021, pp. 1–6, doi: [10.1109/CISP-BMEI53629.2021.9624384](https://doi.org/10.1109/CISP-BMEI53629.2021.9624384).
- [31] S. Zhang, H. Gong, and L. She, "An aspect sentiment classification model for graph attention networks incorporating syntactic, semantic, and knowledge," *Knowl.-Based Syst.*, vol. 275, Sep. 2023, Art. no. 110662.

- [32] X. Zhou, Y. Yi, and G. Jia, "Path-RotatE: Knowledge graph embedding by relational rotation of path in complex space," in *Proc. IEEE/CIC Int. Conf. Commun. China (ICCC)*, Jul. 2021, pp. 905–910.
- [33] A. K. Zarandi and S. Mirzaei, "A survey of aspect-based sentiment analysis classification with a focus on graph neural network methods," *Multimedia Tools Appl.*, vol. 83, no. 19, pp. 56619–56695, Dec. 2023.
- [34] X. Huang, J. Li, J. Wu, J. Chang, D. Liu, and K. Zhu, "Flexibly utilizing syntactic knowledge in aspect-based sentiment analysis," *Inf. Process. Manage.*, vol. 61, no. 3, May 2024, Art. no. 103630.
- [35] Y. Wen, W. Li, Q. Zeng, H. Duan, F. Zhang, and S. Kang, "Syntactic knowledge embedding network for aspect-based sentiment classification," *Mobile Inf. Syst.*, vol. 2022, pp. 1–8, Apr. 2022.
- [36] G. Gomes, A. T. Bender, A. Cerveira, L. A. Freitas, and U. B. Corrêa, "Evaluating graph attention networks as an alternative to transformers for ABSA task in low-resource languages," in *Proc. Int. FLAIRS Conf.*, vol. 37, May 2024, p. 135630.
- [37] H. Baalbaki, H. Hazimeh, H. Harb, and R. Angarita, "TransModE: Translational knowledge graph embedding using modular arithmetic," *Proc. Comput. Sci.*, vol. 207, pp. 1154–1163, Jan. 2022.
- [38] Z. Hu, Z. Wang, Y. Wang, and A.-H. Tan, "Aspect sentiment triplet extraction incorporating syntactic constituency parsing tree and common-sense knowledge graph," *Cognit. Comput.*, vol. 15, no. 1, pp. 337–347, Dec. 2022.
- [39] S. Vashishth, S. Sanyal, V. Nitin, and P. Talukdar, "Composition-based multi-relational graph convolutional networks," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, Jan. 2019, pp. 1–15.
- [40] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," 2013, *arXiv:1301.3781*.



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