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# INTEGRATED KNOWLEDGE GUIDANCE AND DEPENDENCY ENHANCEMENT FOR ASPECT SENTIMENT TRIPLET EXTRACTION

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Abstract. Aspect sentiment triplet extraction is a subtask of aspect-based sentiment analysis that involves identifying aspects, expressed opinions, and sentiment polarity from reviews. However, existing methods typically rely on either pipeline or sequence tagging, which do not consider contextual affective knowledge or syntactic dependencies among words. In this paper, we propose a novel solution to enrich the sentiment expression capability of sentences for aspect sentiment triplets. Specifically, the ordinary structure of dependency trees is extended by integrating knowledge guidance and dependency enhancement methodologies. The former method functions on the nodes of the dependency tree, while the latter method operates on the edges of the same. To verify the effectiveness of the proposed method, we performed comprehensive experiments across four benchmark datasets. The results from our experiments indicate that our proposed model outperforms existing methods.

## 1. Introduction

Sentiment analysis, also referred to as opinion mining, is a pivotal aspect of natural language processing (NLP) and stands out as a significant area of research. Within sentiment analysis, aspect-based sentiment analysis (ABSA) emerges as a specialized field that seeks to extract and evaluate opinions and sentiments expressed towards particular aspects or features of a product, service, or event. In contrast to traditional sentiment analysis, which gauges the overall sentiment of a document or sentence, ABSA focuses on discerning sentiment polarity (positive, negative, or neutral) associated with specific aspects. ABSA targets the identification of three fundamental entities within a sentence: aspect terms, opinion terms, and the sentiment polarity linked to each aspect. The aspect term signifies the subject of evaluation, the opinion term denotes the language used to describe the subject, and sentiment reflects the overall attitude towards the evaluated subject [22]. As illustrated in the sentence "The food is great, but its price is excessive," two distinct aspects are referenced: "food" and "price." It is apparent that the sentiment polarity toward "food" is positive, while it is negative toward "price". Due to its capacity to offer comprehensive and detailed solutions for sentiment assessment across various aspects, ABSA has garnered growing interest within both academic and industrial communities.

Most current methods for ABSA concentrate on extracting a single entity or combining two entities. These approaches encompass aspect term extraction (ATE)

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method [16, 19], opinion term extraction (OTE) method [10, 13, 27], aspect-opinion pair extraction (AOPE) method [2,9,24], and aspect sentiment classification (ASC) method [20,30,35]. Despite the notable advancements demonstrated by these methods, they often overlook the intricate interplay among aspect terms, opinion terms, and sentiment polarity. Therefore, they cannot extract these entities in unison, limiting their ability to solve this task entirely.

To tackle this issue, a recent addition to ABSA is the aspect sentiment triple extraction (ASTE) subtask. The goal of the ASTE task is to extract aspect terms, opinion terms, and their corresponding sentiment polarity from the provided text. In the above example, we can obtain two triples, i.e., <food, great, positive>and <price, excessive, negative>.Peng et al. [23] introduced the ASTE task and devised a two-stage framework to address it. In the initial stage, the model predicts aspect terms, their associated sentiment polarity, and opinion terms through a unified approach. Subsequently, in the second stage, the aspect and opinion terms predicted in the first stage are paired to generate the desired triples. However, this pipeline method causes errors to propagate between different stages, destroying the interactions within the triplet structure. Subsequent research has proposed span methods as a means to solve this issue. For instance, Xu et al. [32] introduced a span-based method that maximizes the matching of valid aspect and opinion candidates by incorporating a pruning strategy, effectively combining the aspect and the opinion item extraction. However, their approach neglected the intricacies of multiword entities and the complex relationship between aspect and opinion items. Addressing this, Li et al. [14] proposed a span-shared joint extraction framework. This framework simultaneously identified the aspect item, opinion item, and sentiment in final stage, thus mitigating the propagation of errors.

Although the approach mentioned above are proficient in extracting aspect sentiment triplets, they do not adequately consider the significance of dependency relations among spans and the interaction between multiword entities. Furthermore, the extraction performance of these methods may diminish when multiple words are present in aspect or opinion items. As such, it is crucial to consider the impact of dependency relations and multiword entities in aspect sentiment triplet extraction to enhance the accuracy and effectiveness of the process. To pursue this goal, we propose a knowledge guidance and dependency enhancement network, named KGDE, to extract aspect sentiment triples from review sentences. KGDE initially using the encoder to learn the word-level vector representation . Subsequently, sentiment knowledge is integrated into the ordinary dependency tree to enhance the sentiment representation ability of nodes. To further improve the performance, statistical data are used to enhance potential dependencies among aspect and opinion terms, creating a knowledge-syntax aware dependency tree. The resulting tree is input to a graph convolutional network (GCN) for capturing rich word node representation, which is integrated into span representation. Finally, a specific enumeration and filtering strategy is employed to extract all possible candidate spans containing candidate aspects and opinions. These are then jointly fed into the sentiment classifier to generate aspect sentiment triples.

In contrast to the pipeline method, the KGDE model simultaneously identifies aspect items, opinion items, and sentiment polarity in the final step. This method effectively avoids the error propagation problem often encountered with the pipeline method. Additionally, in contrast to the sequence tagging approach, the suggested span-based method utilizes the dependency relationships among spans, strengthens the interaction between multiword entities, and handles both one-to-many and many-to-one relationships between opinion and aspect items. To evaluate the efficacy of the proposed model, a series of experiments are conducted on various benchmark datasets concerning the Aspect-based Sentiment Analysis (ASTE) task. Results from these experiments indicate that the KGDE model surpasses the current baseline model by a considerable margin, showcasing superior performance. Furthermore, the knowledge guidance and dependency enhancement mechanism are shown to be beneficial in addressing the intricate relationships between aspect and opinion words in sentences, thereby achieving a more holistic understanding of the text, leading to improved accuracy in sentiment analysis.

The key contributions of this paper can be outlined as follows:

- A span-based triplet extraction method is leveraged to avoid error propagation in different subtasks and addresses complex one-to-many and many-to-one relationships between aspect and opinion terms.
- A framework based on knowledge guidance and dependency enhancement is proposed to utilize syntactic dependencies and aspect-specific sentiment knowledge information of sentences.
- The contributions are highlighted through comprehensive experiments conducted on various public datasets, demonstrating the superior performance of the proposed model compared to existing methods in the context of the ASTE task.

The structure of this paper is outlined as follows: Section 2 delves into related works. Section 3 formally presents the ASTE task and provides a comprehensive description of the proposed model. Detailed experimental results, comparing the effectiveness of the proposed model against existing models, are presented in Section 4. Finally, Section 5 offers a summary and discusses potential avenues for future research.

## 2. Related work

2.1. **Sequence tagging extraction methods.** In recent years, sequence labeling methods have gained significant attention, providing effective solutions to the problem of error propagation [18,37,40]. For instance, Wu et al. [29] introduced an end-to-end grid tagging scheme to tackle the ASTE task. This approach encodes all word pair relationships, transforming opinion pair extraction into a unified grid tagging task, and finally decoding all opinion pairs simultaneously using a decoding strategy. Still, the method treats each aspect and opinion terms as equal weight, which could be more conducive to extracting multiple-word aspects or opinions. To address this problem, Xu et al. [31] proposed a position-aware tagging scheme, augmenting the expressive power of tags for the joint extraction of aspect sentiment triplets. However, this approach overlooked the significance of syntactic dependencies. Chen et al. [8] proposed a graph neural network model to leverage both syntactic and semantic relationships between triples. This approach involves constructing a distinct text graph for each sentence, effectively capturing the inner relationships among triplet elements. On this basis, Chen et al. [6] proposed an augmented multi-channel GCN model that feeds word lexical combination, syntactic dependency, word distance, and attention score information into the GCN in a multi-channel manner to capture the relationships between words better. The above methods only use a single label sequence to extract all types of triples, which is limited to a certain extent. The previous methods are constrained by utilizing a single label sequence to extract all types of triples, imposing limitations. Thus, Chen et al. [5] introduced a decomposition of the ASTE task into three sequence labeling subtasks: target annotation, opinion annotation, and sentiment annotation. Target annotation identifies the boundaries of the opinion object, opinion annotation detects the opinion expression boundaries, while sentiment annotation determines their correspondence and sentiment polarity within a given sentence.

2.2. **Machine reading comprehension methods.** Machine reading comprehension (MRC) methods, which convert ASTE tasks into MRC tasks to further capture and exploit the associations between aspect sentiment triplets, have likewise received much research attention. Chen et al. [7] introduced a bidirectional machine reading integrated framework. This design involves three types of queries: restrictive extraction queries, nonrestrictive extraction queries, and sentiment classification queries. The framework sequentially identifies aspects, opinion expressions, and sentiment in one direction, and opinion expressions, aspects, and sentiment in the other direction. However, the framework uses a pipeline approach to handle different subtasks, which causes the problem of error propagation. Mao et al. [21] proposed a unified end-to-end framework, tackling the problem by formulating two MRC problems. They employed joint training with shared parameters for two BERT-MRC models to collectively address all subtasks. Yu et al. [34] proposed a role-flipped approach for MRC, where they considered the predicted results of aspect or opinion item extraction as queries. Matching opinion or aspect items were extracted as answers, and the queries and answers could be reversed for multi-hop detection. Ultimately, a sentiment classifier predicted each matching aspect-opinion pair. While these methods effectively handle the ASTE task, they neglect the robustness issue in MRC. Therefore, Liu et al. [17] proposed a robust optimization method that effectively dealt with the relationship between aspect, opinion, and sentiment by adding word segmentation, improving span matching, and probability generation.

2.3. **Generative extraction methods.** Additionally, researchers have successfully used text-generation methods on ASTE tasks. Yan et al. [33] introduced a unified framework that redefined each subtask target as a sequence comprising a combination of pointer indices and sentiment class indices. They transformed all Aspect-Based Sentiment Analysis (ABSA) subtasks into a unified generation formulation and employed the sequence-to-sequence model BART to address all ABSA subtasks. However, previous methods ignored label semantic information and required many task-specific designs. To mitigate this problem, Zhang et al. [38] proposed an annotation style and extraction style modeling approach using both modeling paradigms to formulate target sentences and solve multiple sentiment pairs or triplet extraction tasks using a unified generative model.

Among the various methods used for ABSA [1,25], tagging-based methods struggle with aspects and opinions that contain multiple words, while MRC-based methods have a high task complexity. Generation-based methods may suffer from memory limitations and a gradient disappearance problem when the sentence length is too long. Our proposed model is different from previous methods in two ways. First, we utilize a span-based approach to extract aspect sentiment triples in a single step. Second, we integrate an external sentiment knowledge base and enhance dependency information between words, which has been previously ignored in ASTE research.

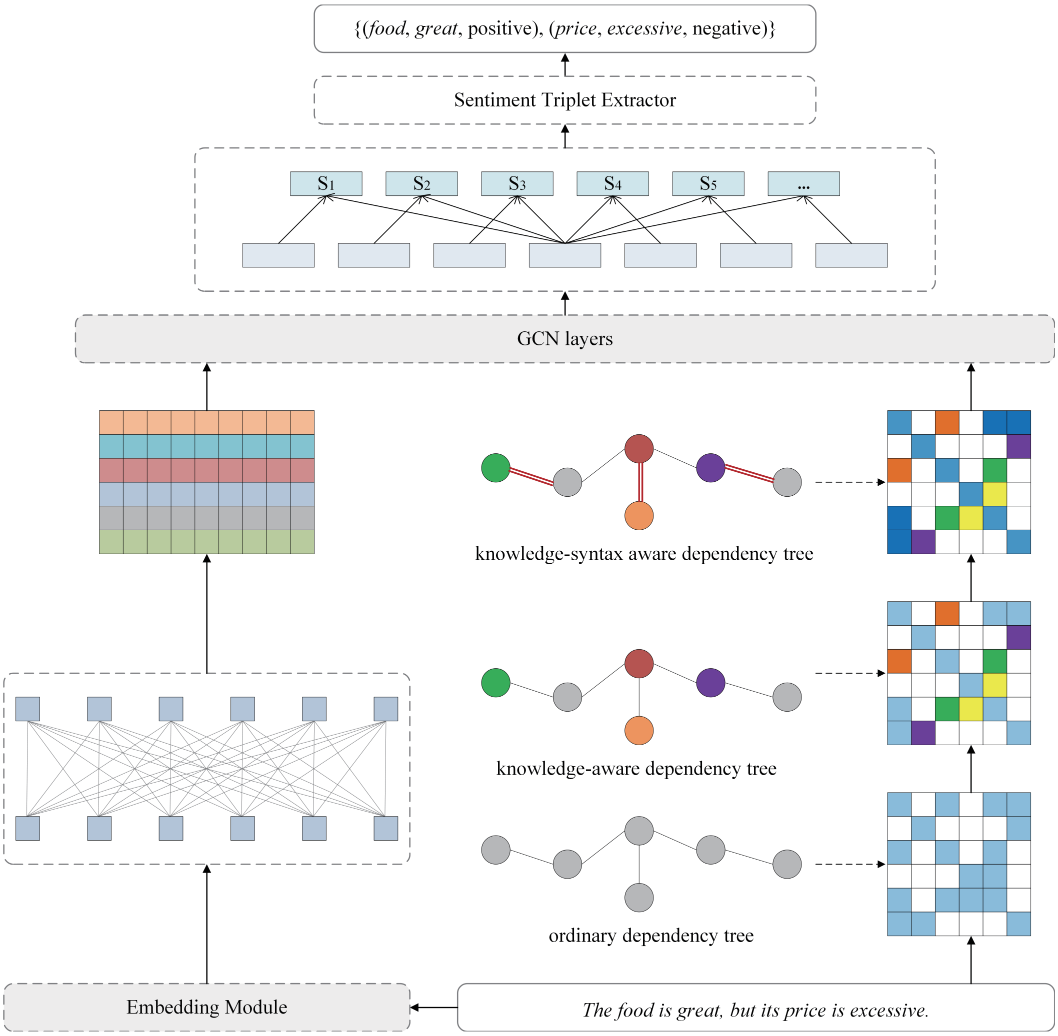


FIGURE 1. Overall framework of the KGDE model

## 3. Proposed model

3.1. **Task definition.** The ASTE task aims to extract a collection $T = \{(a, o, s)_m\}_{m=1}^{|T|}$ of triples from a sentence $X = \{w_1, w_2, ...w_n\}$, where $n$ is the number of words. In these triples, $a$ and $o$ represent aspect and opinion items, respectively. These items can consist of a single word or more consecutive words. $s$ indicates a specific sentiment polarity, with $S$ being the set of sentiment polarities. This paper focuses on three types of sentiment, positive, negative, and neutral, which are also commonly used in the ASTE task.

3.2. **Overview.** The diagram in Fig. 1 introduces the comprehensive structure of KGDE model, comprising five primary components: (1) Utilizing the pre-trained model BERT, we obtain contextual representations by feeding the embedding matrix of each sentence into the model and retrieving the resulting hidden contextual representations for those sentences. (2) Integrating sentiment knowledge from SenticNet into regular dependency trees of sentences, creating a knowledge-aware dependency tree. This tree, coupled with the hidden contextual representation of sentences and sentiment-enhanced graphs, serves as input to get potential sentiment dependencies among contextual words. (3) Enhancing the dependencies between aspect and opinion terms based on statistical data creates a knowledge-syntax dependency tree. This tree can identify the relationship between different aspects and opinions. (4) Deriving the dependency tree obtained in the previous step as an adjacency matrix, it is input into a GCN to learn the enhanced sentiment dependencies for a given aspect. (5) Creating all potential candidate spans to represent aspect and opinion terms. Subsequently, applying span filters to eliminate invalid spans. The extraction of aspect-sentiment triplets is achieved through a multiclassification task.

3.2.1. *Encoding.* We utilize BERT [11] to acquire the semantic contextual representation of a sentence, denoted as $X$. In this process, a sentence containing $n$ words is initially processed by adding $[CLS]$ and $[SEP]$ tokens at the beginning and end. Then, the modified sentence is inputted into BERT to obtain the word embedding representation of words. The process is as follows.

$$H = BERT([CLS] + X + [SEP]), \tag{3.1}$$

where $H = \{h_0, h_1, ...h_n, h_{n+1}\}$ indicates the feature representation of each word in the sentence. The output vector associated with the $[CLS]$ serves as the semantic representation of entire sentence, utilized for subsequent tasks.

3.2.2. *Integrating sentiment knowledge information.* In recent years, there has been a growing recognition of the importance of integrating external commonsense knowledge in the field of NLP. It is frequently utilized in ABSA tasks to improve sentiment feature representation, a topic that has garnered the interest of many scholars [3,12,15,28]. SenticNet [4], a publicly accessible resource for conducting opinion mining and sentiment analysis, is often used as a common knowledge database for enhanced sentiment representation, which provides sentiment polarity values ranging from -1 to 1 for each natural language concept value. Specifically, words with a more positive sentiment have a polarity value closer to 1, while those with a more negative sentiment have a value closer to -1. Some examples from SenticNet are provided in Table 1.

TABLE 1. Sentiment word examples from SenticNet

| Word | Polarity label | Polarity value |
|---|---|---|
| Love | Positive | 0.66 |
| Quick | Positive | 0.451 |
| Delicious | Positive | 0.985 |
| Slow | Negative | -0.468 |
| Broke | Negative | -0.391 |

Hence, integrating SenticNet into graph convolutional networks can contribute to the model better extracting the sentiment dependency of contextual words. To achieve this, we construct a knowledge-aware dependency tree over the ordinary dependency tree. Specifically, the sentiment values $S_{i,j}$ between nodes $w_i$ and $w_j$ are obtained from their corresponding average sentiment scores, which are used to construct the adjacency matrix to capture the sentiment relevance between the nodes. Denoting SenticNet as $SN$, it is calculated as follows.

$$S_{i,j} = \begin{cases} SN(w_i), & i = j, \\ avg(SN(w_i), SN(w_j)), & i \neq j, \end{cases} \tag{3.2}$$

where $SN(*) \in [-1, 1]$ indicates the sentiment score of words. If the word does not exist in SenticNet, the score is assigned to 0.

3.2.3. *Enhancing dependency information.* To leverage the dependency relations of words in sentences, we build the input graph for the GCN based on the dependency tree for each sentence, which can be formally regarded as an adjacency matrix $D_{i,j} = 0$ if the node $i$ is connected to the node $j$. Previous studies [18, 26, 39] have revealed an interaction between the dependencies of words, so we constructed an undirected dependency graph, that is, $D_{i,j} = D_{j,i}$ . However, the ordinary dependency tree treats each relationship equally. Specifically, it ignores the significance of dependencies between opinion terms and aspect and internal dependencies in multiple-word aspects or opinions for the ASTE task. As exhibit in Fig. 2, given a sentence "The mushroom soup is amazing here".

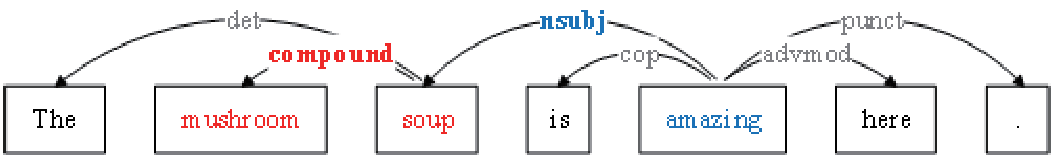


FIGURE 2. Syntactic dependency tree

The aspect item is "mushroom soup", and the opinion item is "amazing". According to the results of the syntactic analysis, the dependency between "mushroom" and "soup" is a compound expression in terms of aspect item, namely, compound, indicating a strong correlation. “Soup” is the noun subject of “amazing” in terms of aspect and opinion, namely, nsubj. Improving the syntactic relevance between aspects and opinions can further enhance the contextual relevance of specific aspects.

Hence, we conduct a suite of statistical analyses on ASTE-Data-V2 dataset [31], which is built on SemEval and annotated with triples. It contains 14lap, 14res, 15res, and 16res sub-datasets, where lap and res denote datasets from the laptop and restaurant domains, respectively. The statistical outcomes, depicted in Fig. 3, reveal that ”compound” constitutes the largest proportion for the internal dependency of multi-word aspect or opinion terms, while ”nsubj” holds the largest proportion for the dependency in aspect and opinion terms.

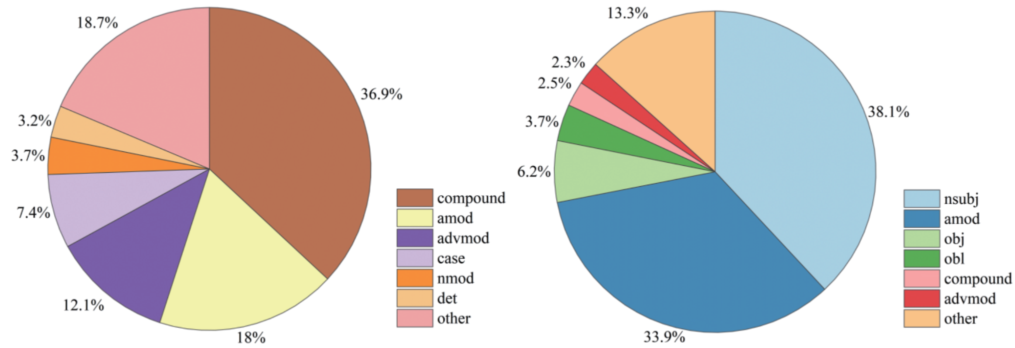


FIGURE 3. Co-occurrence ratio of multiple-word aspect/opinion internal dependencies (left) and aspect-opinion dependencies (right)

Based on the above statistical analysis, we use an enhancement strategy to strengthen the dependencies between words. Specifically, for the dependencies that occupy a larger proportion, we give them more weight in the syntactic dependency tree, which makes the syntactic dependency tree contain richer relationship information and is beneficial to further extraction by the GCN. The enhanced dependence $R_{i,j}$ can be counted formally by the below equation:

$$R_{i,j} = D_{i,j} * W_k^r, \tag{3.3}$$

where $D_{i,j}$ denotes the original dependency matrix, $W_k^r$ denotes the weight corresponding to the $k-th$ dependency $r$ to be enhanced. In this way, we can obtain a knowledge-syntax-aware dependency tree.

3.2.4. *Convolving over the derived graph.* Based on the fusion of sentiment knowledge and dependency syntax, the knowledge-syntax-aware dependency tree structure is derived as an adjacency matrix, which is input into the GCN to enhance the semantic and syntactic relationships. In the $l-th$ Graph Convolutional Network layer, the hidden representations of each node are refreshed according to its neighborhoods:

$$A_{i,j} = D_{i,j} \times (S_{i,j} + R_{i,j}), \tag{3.4}$$

$$g_i^l = \sigma(\sum_{j=1}^{N}(A_{ij} + h_0)W^l g_j^{l-1} + b^l), \tag{3.5}$$

where $A_{ij}$ represents the derived adjacency matrix, $h_0$ is the word embedding generated by BERT, the weight and bias of $l$-th layer are denoted by $W^l$ and $b^l$, respectively, and $\sigma$ denote activation function.

3.2.5. *Generating spans and extracting triplets.* In real-world scenarios, it is frequent for an aspect item to be associated with multiple opinions or for an opinion item be related to multiple aspects. Hence, we enumerate all possible spans as candidate aspects and opinion items following the method proposed by [14]. Each span comprises one or more consecutive words, and its length is constrained by 0 <end - start< $L$, where end and start represent the end and start word positions, respectively, and $L$ represents the max length of span. Then, we subject the vector representation of these words to a maximum pooling operation and train the embedding matrix by backpropagation, which can be expressed as:

$$S_i = f(h_0, h_1, ..., h_L). \tag{3.6}$$

Furthermore, considering the enormous search space generated by the enumeration approach and the problem of producing many invalid samples, we employ a binary classifier to ascertain if a span exhibits a sentiment relationship with another span, the result of which is resolved by the Softmax function.

$$P(y_i|S_i) = Softmax(W_s S_i + b_s). \tag{3.7}$$

Finally, the loss function, cross-entropy, is utilized to compute the loss in the predicted value $y_i$ and the true value $\bar{y}_i$:

$$L_s = -\sum_{i=1}^{k} P(\bar{y}_i|S_i)\ln(P(y_i|S_i)). \tag{3.8}$$

The enumerated and filtered spans can be used as candidate aspect items or opinion items, and any combination of them will be considered potential sentiment expressions. ASTE aims to classify aspect items $S_i$ and opinion items $S_j$ into specific sentiment $s_{i,j}$.

The model introduces local contextual semantic information between the aspect item and the opinion item, connecting it with the candidate span as input for the sentiment classifier.

$$C_{i,j} = f(C_i, C_{i+1}, ..., C_j), \tag{3.9}$$

$$I_{i,j} = S_i \oplus C_{i,j} \oplus S_j, \tag{3.10}$$

where $f$ denotes the maximum pooling function, while $C_i, C_{i+1}, ..., C_j$ represent semantic information between the aspect items and viewpoint items.

Then, the overall representation of the candidate span is input into the classifier, and the cross-entropy function calculates variance among predicted value $s_{i,j}$ and true value $\bar{s}_{i,j}$.

$$P(s_{i,j}|(S_i, S_j)) = \sigma(W_r I_{i,j} + b_r), \tag{3.11}$$

$$L_c = -\sum_{i=1}^{k}\sum_{j=1}^{k} P(\bar{s}_{i,j}|(S_i, S_j)) \ln(P(s_{i,j}|(S_i, S_j))). \tag{3.12}$$

3.3. **Training procedure.** During the training phase of the KGDE, a combined training loss function is devised for aspect-sentiment triplet extractor and span filter, represented as follows:

$$Loss = \alpha L_s + \beta L_c, \tag{3.13}$$

where $L_s$ and $L_c$ are cross-entropy loss functions for aspect sentiment triples extractor and span filter , respectively, while $\alpha$ and $\beta$ represent loss weight parameters. We believe that fine-tuning the hyperparameters $\alpha$ and $\beta$ will allow for better modulation of the interaction between aspect-sentiment triplet extractor and span filter, enabling them to collaboratively and consistently perform the ASTE task. Finally, the model maximizes its training effect by optimizing the loss.

## 4. Experiments

4.1. **Datasets and metrics.** To validate the efficacy of the KGDE, we performed a comprehensive set of experiments using the ASTE-Data-V2 dataset, as introduced by Xu et al. [31]. It solved the problem of missing opinion spans associated with multiple targets in the original ASTE datasets, enriched the training data. Compared to original dataset, ASTE-Data-V2 has more targets and opinion segments, making it more representative of real-world sentiment analysis problems.

Table 2 presents the dataset statistics, where #S repersnt the number of sentences and #T denote the number of aspect sentiment triples, respectively.

In the process of the experiment, accuracy ($P$), recall ($R$), and F1-score ($F1$) are employed as evaluation metrics to assess the model performance, and only when the forecast value aligns perfectly with the practical value are the extracted aspect-sentiment triplets considered to be correct:

$$P = \frac{TP}{TP + FP}, \tag{4.1}$$

$$R = \frac{TP}{TP + FN}, \tag{4.2}$$

Table 2. Statistics of each dataset

| **Dataset** | | **Positive** | **Negative** | **Neutral** | **#S** | **#T** |
|---|---|---|---|---|---|---|
| **14lap** | Train | 817 | 517 | 126 | 906 | 1460 |
| | Dev | 169 | 141 | 36 | 219 | 346 |
| | Test | 364 | 116 | 63 | 328 | 543 |
| **14res** | Train | 1692 | 480 | 166 | 1266 | 2338 |
| | Dev | 404 | 119 | 54 | 310 | 577 |
| | Test | 773 | 155 | 66 | 492 | 994 |
| **15res** | Train | 783 | 205 | 25 | 605 | 1013 |
| | Dev | 185 | 53 | 11 | 148 | 249 |
| | Test | 317 | 143 | 25 | 322 | 485 |
| **16res** | Train | 1015 | 329 | 50 | 857 | 1394 |
| | Dev | 252 | 76 | 11 | 210 | 339 |
| | Test | 407 | 78 | 29 | 326 | 514 |

$$F1 = \frac{2 * P * R}{P + R}, \tag{4.3}$$

where $TP$ denotes the count of samples with both positive forecast and true values, $FN$ signifies the count of samples where the forecast value is negative but the true value is positive, and $FP$ denotes the count of samples where the forecast value is positive while the true value is negative.

4.2. **Experimental settings.** The experimental environment in this paper includes an Intel Core i9-10900X CPU, DDR4 16 GB*2 memory, NVIDIA Quadro RTX6000 GPU, and Ubuntu 20.04 operating system.

The proposed model parameters are set as follows. For the GCN, the num-layers is configured to 2. Throughout model training process, AdamW optimizer is employed, setting the learning rate to 5e-5, weight decay to 0.1. The external sentiment knowledge base adopts the SenticNet English version. According to the statistical analysis results, the initial dependency relations are weighted according to their proportion.

4.3. **Baseline Models.** To evaluate the efficiency of KGDE in ASTE task, we conduct comparative experiments with the following baselines:

1) **RINANTE+** [9] proposes a method to improve neural aspects and opinion item extraction performance by using automatic mining rules and incorporating this rule into LSTM-CRF to capture word correlation in sentences.

2) **TwoStage** [23] introduces the ASTE task. The model first isolates aspect features and their sentiment implications, then associates each aspect with a sentiment type and an opinion item during a second stage.

3) **OTE-MTL** [36] perceives ABSA task as a challenge of opinion triplet extraction and introduces a multi-task learning platform to fuse extraction aspects and opinion items, while examining their sentiment correlation.

4) **JET** [31] introduces a new position-aware tagging method that specifies the connection between three elements to extract a triplet jointly more efficiently. It encompasses two tagging approaches: target-oriented joint extraction triples (JETt) and opinion-oriented joint extraction triples (JETo).

5) **GTS-BERT** [29] presents a grid tagging strategy. The model establishes connections between all word pairs and incorporates all opinion elements into a unified grid tagging task. It employs a specifically designed decoding algorithm to generate opinion pairs or opinion triples.

6) **Span-ASTE** [32] put forward the triplet extraction method at the span level, which can use the semantics of the whole span for prediction. The interaction between the whole span is considered when predicting the sentiment relations between opinions, ensuring better sentiment consistency.

7) **EMC-GCN** [6] presents an enhanced multi-channel GCN model in which type relations are embedded as word vectors through the attention module, and sentences are converted into multi-channel graphs to learn the node representation of relational awareness.

8) **SSJE** [14] introduces a span-shared joint extraction technique for extracting aspect-sentiment triples from sentence units within end-to-end computational framework.

4.4. **Results and analysis.** In the ASTE-Data-V2 dataset, the KGDE model is compared with different baseline models. The results are presented in Table 3 and the best and second-best performances are highlighted in bold and underlined text, respectively.

TABLE 3. Comparison of experimental results

| **Models** | **14lap** | | | **14res** | | | **15res** | | | **16res** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **P** | **R** | **F1** | **P** | **R** | **F1** | **P** | **R** | **F1** | **P** | **R** | **F1** |
| RINANTE+ | 21.71 | 18.66 | 20.07 | 31.42 | 39.38 | 34.95 | 29.88 | 30.06 | 29.97 | 25.68 | 22.3 | 23.87 |
| TwoStage | 37.38 | 50.38 | 42.87 | 43.24 | 63.66 | 51.46 | 48.07 | 57.51 | 52.32 | 46.94 | 64.24 | 54.21 |
| OTE-MTL | 49.37 | 43.09 | 46.02 | 66.42 | 55.13 | 60.25 | 64.8 | 40.62 | 49.94 | 57.66 | 59.34 | 58.48 |
| JETt | 53.53 | 43.28 | 47.86 | 63.44 | 54.12 | 58.41 | **68.2** | 42.89 | 52.66 | 65.28 | 51.95 | 57.86 |
| JETo | 55.39 | 47.33 | 51.04 | 70.56 | 55.94 | 62.4 | 64.45 | 51.94 | 57.53 | 70.42 | 58.37 | 63.83 |
| GTS-BERT | 57.12 | 53.42 | 55.21 | 71.76 | 59.09 | 64.81 | 54.71 | 55.05 | 54.88 | 65.89 | 66.27 | 66.08 |
| EMC-GCN | 61.7 | **56.26** | 58.81 | 71.21 | 72.39 | 71.78 | 61.54 | 62.47 | 61.93 | 65.62 | 71.3 | 68.33 |
| Span-ASTE | 63.44 | 55.84 | 59.38 | 72.89 | 70.89 | 71.85 | 62.18 | 64.45 | 63.27 | 69.45 | 71.17 | 70.26 |
| SSJE | 67.43 | 54.71 | 60.41 | 73.12 | 71.43 | 72.26 | 63.94 | 66.17 | 65.05 | 70.82 | 72 | 71.38 |
| KGDE | **67.82** | 56.13 | **61.42** | **74.71** | **72.48** | **73.58** | 64.85 | **67.24** | **66.03** | **72.11** | **72.57** | **72.34** |

The experimental outcomes strongly suggest that the KGDE model significantly surpasses the competing models on the benchmark datasets, effectively demonstrating the efficiency of the KGDE model for the ASTE task.

First, the results presented in the table demonstrate that the evaluation metrics for the end-to-end models (OTE-MTL, JET, GTS-BERT, EMC-GCN, Span-ASTE, SSJE) on all four datasets outperform those of the pipe-based models (RINANTE+, TwoStage). This finding suggests that the models based on the end-to-end methods are better equipped to simultaneously handle the challenge of different opinions expressed in the same aspect. Consequently, these models avoid the problem of error propagation often associated with pipeline-based methods, resulting in improved performance on the ASTE task.

Second, regarding end-to-end models, both Span-ASTE and SSJE exhibit superior performance compared to tagging-based methods (OTE-MTL, JET, GTS-BERT, EMC-GCN). While the tagging-based method employs semantic markers to determine the function of words, it overlooks the interconnectedness of words within a sentence. This method proves challenging to apply when a single relationship exists among opinion and aspect elements within a specific sentence. On the other hand, the span-based method effectively employs interaction information at the span level, playing a crucial role in accomplishing the ASTE task.

Finally, in terms of span-based models (Span-ASTE, SSJE), the proposed method displays higher evaluation metrics than other models across four datasets. Although some indicators on the 14lap and 15res datasets are marginally lower than other models, the method still achieves the second-best performance. Notably, the F1 outcomes of the KGDE are 2.04%, 1.73%, 2.76%, and 2.08% higher than that of the Span-ASTE model across the four datasets. Moreover, it outperforms the SSJE model by 1.01%, 1.32%, 0.98%, and 0.96% across the same datasets. These findings validate the efficiency of the KGDE model in tackling the ASTE assignment.

### 4.5. **Ablation studies.**

4.5.1. *The influence of sentiment knowledge and dependency relation.* To examine the effects of external sentiment knowledge and enhanced dependency of the KGDE performance, an ablation analysis was performed on these two factors using the original model as a base. The outcomes are tabulated in Table 4, "s" and "r" denote external sentiment knowledge and enhanced dependency, respectively.

TABLE 4. F1 comparison of the ablation experiment

| **Model** | **14lap** | **14res** | **15res** | **16res** |
|---|---|---|---|---|
| KGDE w/o s | 60.28 (↓ 1.14) | 71.61 (↓ 1.97) | 63.10 (↓ 2.93) | 70.93 (↓ 1.41) |
| KGDE w/o r | 61.04 (↓ 0.38) | 71.66 (↓ 1.92) | 64.61 (↓ 1.42) | 71.53 (↓ 0.81) |
| KGDE w/o s+r | 59.33 (↓ 2.09) | 70.76 (↓ 2.82) | 60.97 (↓ 5.06) | 69.91 (↓ 2.43) |
| KGDE | **61.42** | **73.58** | **66.03** | **72.34** |

It can be observed from Table 4 that after the removal of sentiment knowledge and enhanced dependency, the execution of the models is considerably influenced, with all of them demonstrating a varying extent of deterioration. Specifically, in the case of w/o s+r, the model's performance in the four datasets decreases more than that of w/o s and w/o r. These results indicate that incorporating external sentiment knowledge and enhancing dependencies is beneficial for KGDE to comprehensively forecast text feature representation and capture relationships between words. Meanwhile, compared with 14res and 15res datasets, 14lap and 16res have lower model performance degradation under w/o s or w/o r. The reason for this could be that the syntactic structure of these datasets is not prominent and contains more implicit sentiment expressions. The alteration in feature representation due to the introduction of external sentiment knowledge and enhanced dependency positively impacts the model's performance, resulting in the best achieved results.

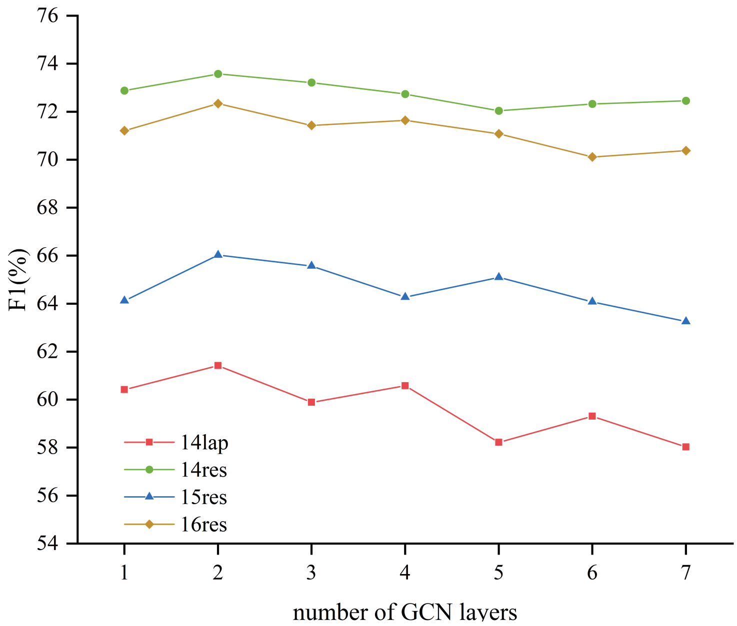


FIGURE 4. The effect of the number of graph convolution layers

4.5.2. *The influence of GCN layers.* To investigate how the layers number of GCN affects the KGDE performance, we limited the range of GCN layer values to [1, 7] and performed experiments on four datasets. The trend of F1 metrics for each layer is presented in Fig. 4.

Illustrating in Fig. 4, the F1 score of KGDE demonstrates a general fluctuation pattern with an upward and downward trend as the GCN layer number escalates. Specifically, for a single GCN layer, the F1 scores perform poorly on all four datasets, indicating that sigle layer of GCN is inadequate to exploit sentiment dependence of sentences in specific aspects. When the number of GCN layers is 2, the model performance is the best. Subsequently, by increasing of GCN layers, although the F1 score increased slightly, it always failed to reach the best performance. The trend reveals a downward shift, suggesting that merely elevating the GCN layer number might undermine the forecasting effectiveness of KGDE.

## 5. Conclusion

In this work, we introduce KGDE that relies on sentiment knowledge and dependency enhancement to obtain aspect sentiment triples from sentences by a seamless manner, effectively circumventing error propagation problem inherent of pipeline approach for distinct subtasks. We introduce a knowledge guidance and dependency enhancement model, which integrates the external sentiment knowledge into the word representation and further enhances the syntactic dependency of the multiple-word aspects and opinions. Then, through the GCN module, the relationship among the words is captured to strengthen the semantic representation of sentence. Finally, KGDE model enumerates and filters all invalid spans. It effectively deals with the complex dependencies between words. The outcomes of the experiment demonstrate that the KGDE surpasses other pertinent state-of-the-art models in performance.

Despite the excellent performance of ASTE task by the proposed model, there is still potential for further enhancement. First, due to language diversity, some sentences may contain irony, sarcasm, and other rhetorical methods that are hard to grasp by neural networks. Therefore, the external sentiment knowledge base will fail to correctly identify the sentiment extremum of words, leading to the model making opposite judgments on such sentences. Second, because of the complexity of language, there may be a lack of direct syntactic relationships between aspects and opinions. This will leads to model be unable to capture the relationship among words through full dependency parsing. In future, we will concentrate on the possible solutions to the above problems and further improve the research of fine-grained sentiment analysis.

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