

Knowledge Graph Augmented Network Towards Multiview Representation Learning for Aspect-based Sentiment Analysis

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Abstract—Aspect-based sentiment analysis (ABSA) is a fine-grained task of sentiment analysis. To better comprehend long complicated sentences and obtain accurate aspect-specific information, linguistic and commonsense knowledge are generally required in this task. However, most methods employ complicated and inefficient approaches to incorporate external knowledge, *e.g.*, directly searching the graph nodes. Additionally, the complementarity between external knowledge and linguistic information has not been thoroughly studied. To this end, we propose a knowledge graph augmented network (KGAN), which aims to effectively incorporate external knowledge with explicitly syntactic and contextual information. In particular, KGAN captures the sentiment feature representations from multiple different perspectives, *i.e.*, context-, syntax- and knowledge-based. First, KGAN learns the contextual and syntactic representations in parallel to fully extract the semantic features. Then, KGAN integrates the knowledge graphs into the embedding space, based on which the aspect-specific knowledge representations are further obtained via an attention mechanism. Last, we propose a hierarchical fusion module to complement these multiview representations in a *local-to-global* manner. Extensive experiments on three popular ABSA benchmarks demonstrate the effectiveness and robustness of our KGAN. Notably, with the help of the pretrained model of RoBERTa, KGAN achieves a new record of state-of-the-art performance.

Index Terms—Knowledge Graph, Multiview Learning, Feature Fusion, Aspect-Based Sentiment Analysis

1 INTRODUCTION

As a fine-grained task of sentiment analysis, aspect-based sentiment analysis (ABSA) has grown to be an active research task in the community of natural language understanding (NLU) [1], [2], [3]. In particular, ABSA refers to judging the sentiment polarities (*e.g.* positive, neutral, and negative) towards the given aspects, which are usually the target entities appearing in the sentence [4]. Taking the sentence “The *food* was good, but the *service* was poor.” as an example, as shown in Fig. 1(a), the goal of ABSA is to predict the polarities “positive” and “negative” for the aspects *food* and *service*, respectively.

Recent ABSA modeling approaches are mainly based on deep neural networks (DNNs) owing to the capability of automatically extracting semantic features [5]. More specifically, based on the type of learned feature representations, existing DNNs for ABSA can be classified into two groups: context-based methods [6],

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Our source code and final models are publicly available at <https://github.com/WHU-ZQH/KGAN>

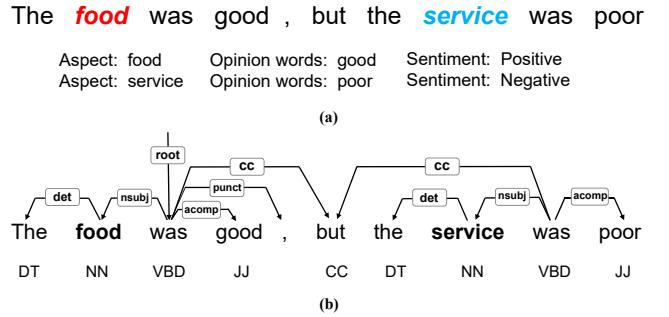


Fig. 1. (a) An example sentence of the ABSA task from the restaurant reviews. There are two aspects with opposite sentiment polarities in this sentence. (b) Illustration of the dependency parsing result.

[7], [8] and syntax-based methods [9], [10], [11]. Context-based methods first employ convolutional neural networks (CNNs) or long short-term memory networks (LSTMs) to extract the features of aspects and context words and then use the attention mechanism to capture the aspect-specific contextual representations. In addition to context-based methods, syntax-based methods attempt to model the nonlocal dependency trees (a case in point is shown in Fig. 1(b)) of sentences with graph neural networks, *e.g.* graph convolutional networks (GCNs) to encode the syntactic information and syntactically connect the aspects with related opinion words [12].

More recently, given effective knowledge, *e.g.* linguistic and commonsense, for representation approaches in NLU tasks [13], [14], [15], researchers employ external knowledge to augment the semantic features in ABSA models [16], [17], [18], [19].

However, they make extensive modifications to model structures or objectives to encode the different kinds of knowledge, limiting the applicability of their methods to a broader range of tasks and knowledge types. For example, [17] directly utilized the words in knowledge graphs as the seed nodes and selected the related nodes to construct the subgraphs, making it trivial to balance the number of selected graph nodes.

In this paper, we propose a novel knowledge graph augmented network, namely, KGAN, to address the aforementioned problems. In general, KGAN employs three parallel branches to learn the feature representations from multiple perspectives (*i.e.* context-, syntax- and knowledge-based). The contextual and syntactic branches are used to extract the explicit context and syntax information from the labeled ABSA data, respectively, as most existing ABSA models do. More specifically, in the knowledge branch, unlike the above previous methods that usually employ complicated approaches to encode the knowledge, we recast them with a simpler and more efficient strategy to incorporate the external knowledge. In practice, instead of directly operating on graph-structure data, we first integrate external knowledge graphs into low-dimensional continuous embeddings, which can be simply and efficiently used to represent sentences and aspects. Then, based on the knowledge embeddings, a soft attention mechanism is utilized to capture the aspect-specific knowledge representations. As a result, we can obtain multiple representations that establish the relations between aspects and opinion words from different views. To take full advantage of the complementarity of these multiview representations, we introduce a novel hierarchical fusion module to effectively fuse them.

We conduct a comprehensive evaluation of KGAN on SemEval2014 (*i.e.* Laptop14 and Restaurant14) and Twitter benchmarks, and experimental results show that KGAN achieves comparable performance compared to the prior SOTA model with the GloVe-based setting. Moreover, we also investigate and demonstrate the effectiveness and robustness of our KGAN in BERT- and RoBERTa-based settings. In particular, our model achieves accuracies of 78.91% and 84.46% on Laptop14 and Restaurant14, respectively, using GloVe embedding and outperforms the previous best results on the Twitter dataset in all settings. Finally, we compare KGAN with the other models in terms of latency and model size and prove that KGAN can achieve a good trade-off between efficiency and performance.

The main contributions of this paper can be summarized as follows:

- 1) We propose a novel knowledge graph augmented network (KGAN), where different types of information are encoded as multiview representations to augment the semantic features, thus boosting the performance of ABSA.
- 2) To achieve better complementarity between multiview features, we design a novel hierarchical fusion module to effectively fuse them.
- 3) Experiments on several commonly used ABSA benchmarks show the effectiveness and universality of our proposed KGAN. In combination with pretrained models, *i.e.* RoBERTa, we achieve new state-of-the-art performance on these benchmarks.

The rest of this paper is organized as follows. In Sec. 2, we briefly review the related works. In Sec. 3, we introduce our proposed method in detail. Sec. 4 reports and discusses our experimental results. Lastly, we conclude our study in Sec. 5.

2 RELATED WORKS

2.1 Aspect-based Sentiment Analysis

Benefiting from the representation learned from the training data, DNN-based ABSA models have shown promising performance compared to handcrafted feature-based models. We categorize them into two classes, *e.g.* context- and syntax-based methods.

First, considering the easily obtained contextual information, using CNNs [6], [20], [21], [22], [23] and LSTMs [7], [16], [24], [25], [26] to extract the aspect-specific feature representations from context has become the mainstream approach for ABSA. In particular, owing to the ability to learn sequential patterns, the target-dependent LSTM (TD-LSTM) was proposed by Tang *et al.* [24] to capture the aspect information. TD-LSTM simplifies connecting the aspect with all context words, neglecting the effect of relative opinion words. Therefore, Wang *et al.* [25] improved upon the TD-LSTM by introducing an attention mechanism to explore the potential correlations between aspects and opinion words. In the study of [26], two separate LSTMs were used to encode the context and aspect terms, and then an interactive attention mechanism was further proposed to extract the more relevant information between the context and aspect features.

On the other hand, considering the complexity and inefficiency of LSTM-like sequential models, many studies have attempted to employ more efficient CNNs to capture the compositional structure and n-gram features. Xue and Li [20] proposed a gated convolution network to extract the contextual features and employed the gate mechanism to selectively output the final sentiment features. Huang and Carley [22] introduced two neural units, *i.e.* the parameterized filter and parameterized gate, to incorporate aspect information into CNN. Notably, in CNN-based methods, it is common to employ the average of aspect embeddings as the aspect representation, which would cause the loss of sequence information. To address this issue, Li *et al.* [6] introduced a target-specific transformation component based on CNNs to better learn the target-specific representation.

However, due to the challenge of multiple aspects with different polarities in a sentence, context-based models usually confuse the connections between aspects and related opinion words. To this end, most recent efforts focus on leveraging the syntactic structure of the sentence to effectively establish the connection [9], [10], [11], [12], [27], [28], [29]. In practice, syntactic dependency trees are introduced to represent the sentence, and then GNNs are used to model the dependency trees and encode the syntactic information. Zhang *et al.* [9] first utilized dependency trees to represent sentences and then proposed graph convolution networks (GCNs) to exploit syntactical information from dependency trees. Additionally, to better connect the aspect and opinion words syntactically, Wang *et al.* [12] presented a novel aspect-oriented dependency tree structure and employed a relational graph attention network to encode the tree structure. In addition, regarding sentences that have no remarkable syntactic structure, Pang *et al.* [28] introduced a multichannel GCN to optimally fuse syntactic and semantic information and their combinations simultaneously. Similarly, in the study of [11], a dual GCN model that consists of SemGCN and SynGCN modules was used to take advantage of the complementarity of syntax structure and semantic correlations.

2.2 Incorporating External Knowledge

Since linguistic and commonsense knowledge can be beneficial to understanding natural language, incorporating this knowledge into

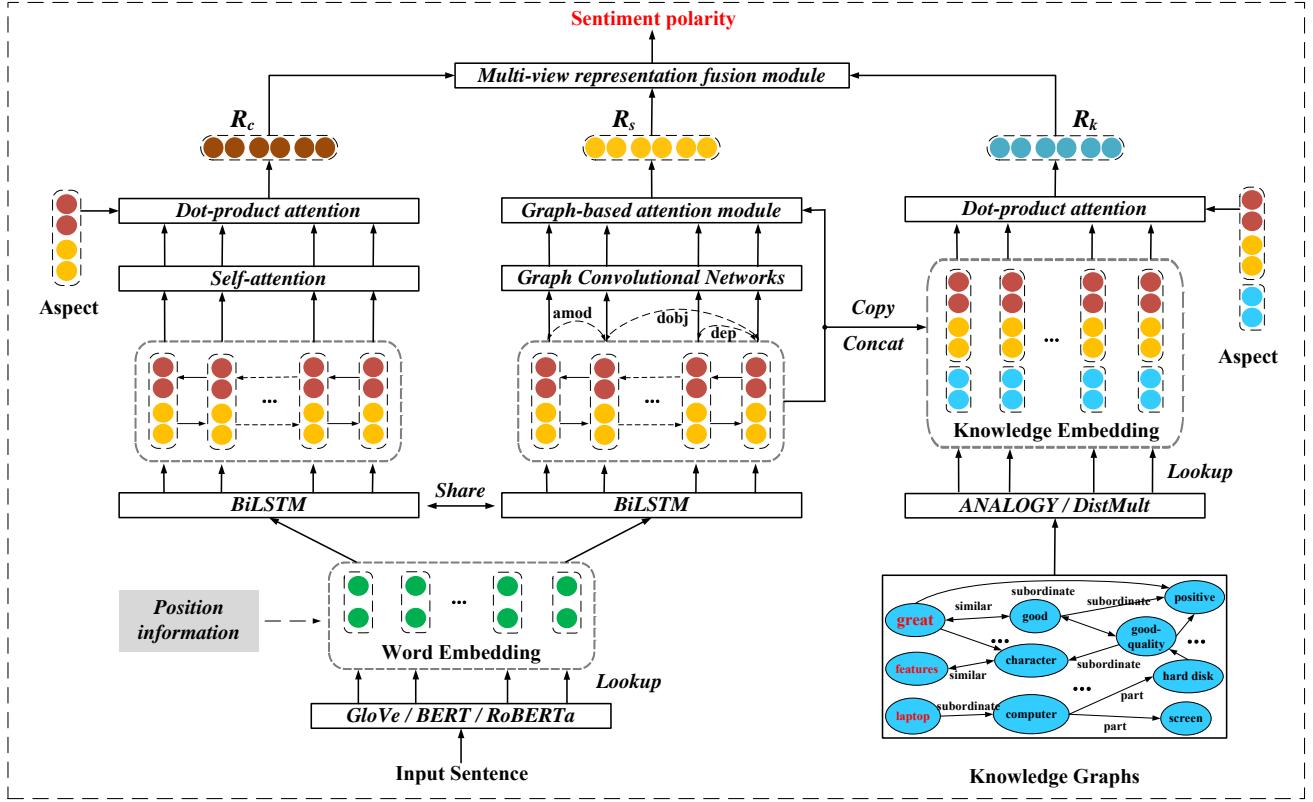


Fig. 2. The architecture of our proposed knowledge graph augmented network (KGAN), which leverages external knowledge graphs to augment contextual and syntactic information. The R_c , R_s and R_k denote the context- (left), syntax- (middle) and knowledge-based (right) representations, respectively. In the knowledge branch, ANALOGY and DistMult refer to the approaches of knowledge graph embeddings.

deep learning models has become an active topic in many fields [13], [14], [30], [31], [32]. A case in point is the ERNIE [30], which employed the large-scale corpora and knowledge graphs to train a knowledge-enhanced pretraining language model. ERNIE experimentally achieves great performance on various knowledge-driven downstream tasks.

However, in the task of ABSA, the existing methods fall short in exploring the knowledge to augment the sentiment analysis. One main reason for this is that the above knowledge is not explicitly expressed in the ABSA datasets. Therefore, some recent studies attempt to incorporate external knowledge to alleviate this issue [16], [17], [18], [33], [34], [35]. Wu *et al.* [33] proposed a unified model to integrate sentiment and structure knowledge with contextual representations for better performance. Zhou *et al.* [17] proposed jointly encoding syntactic information and external commonsense knowledge, where the knowledge was sampled via the individual nodes. Moreover, in the study of [32], a knowledge-enhanced BERT was introduced to obtain representations enhanced with sentiment domain knowledge to improve ABSA performance.

Following this line of research, we introduce knowledge graphs to explicitly provide external knowledge for ABSA. In contrast, we start from the multiview learning perspective and employ a simpler and more efficient strategy to model knowledge graphs. Additionally, instead of only integrating external knowledge with contextual or syntactic information, we synergistically combine the knowledge with both contextual and syntactic information to obtain richer feature representations and effectively boost the performance of sentiment analysis.

3 KNOWLEDGE GRAPH AUGMENTED NETWORK

3.1 Problem Formulation

In this section, we first define the task of ABSA mathematically. Suppose we have a sentence-aspect pair $\{S, T\}$, where $S = \{w_1, w_2, \dots, w_{start}, \dots, w_m\}$ denotes the m -words sentence, and $T = \{w_{start}, w_{start+1}, \dots, w_{start+n-1}\}$ denotes the n -words aspect that is usually the subsequence of the sentence S . Note that $start$ is the starting index of T in S . The goal of ABSA is to predict the sentiment polarity $y \in \{0, 1, 2\}$ of the sentence S towards the aspect T , where 0, 1, and 2 denote the *positive*, *neutral* and *negative* sentiment polarities, respectively.

3.2 Overview of the KGAN model

The architecture of our proposed KGAN model is shown in Fig. 2, where KGAN contains three branches, *i.e.*, context-, syntactic- and knowledge-based branches, which learn the feature representations from multiple views. Specifically, the contextual and syntactic branches extract the contextual and syntactic features from the sentence represented by the pretrained word embeddings and explicitly establish the relevance between aspects and opinion words in the sentence. We then present the knowledge branch to model the introduced knowledge graphs and incorporate the external knowledge into the learned semantic features. In practice, knowledge graphs are first embedded into distributed representations, and a soft attention mechanism is then utilized to learn aspect-specific knowledge representations. Last, we synergistically fuse the learned multiview representations with a hierarchical fusion module.

3.3 Multi-View Representation Learning

3.3.1 Context-based Representations

Recent works [36], [37] have shown that context-aware representation could successfully improve the language understanding ability, thus achieving better performance. Given the sentence-aspect pair $\{S, T\}$, we employ the popular pretrained word embedding model to represent each word of S and T , respectively. In particular, we embed each word w_i into a low-dimensional vector space with embedding matrix $E \in \mathbb{R}^{|V| \times d_w}$, where $|V|$ and d_w are the size of the vocabulary and the dimension of word embeddings, respectively. Notably, the embedding matrix is usually initialized with the embeddings of pretrained models, *e.g.* the static word embedding model GloVe and the language model BERT. Moreover, considering the benefit of positional information between context words and aspects, we follow [38] and encode the relative position features into the word embeddings of S . Thus, the sentence S and aspect T are converted to the corresponding word embeddings $X^s = \{x_1^s, x_2^s, \dots, x_m^s\}$ and $X^t = \{x_1^t, x_2^t, \dots, x_n^t\}$ in the end.

Based on the word embeddings, two separate bidirectional LSTMs (BiLSTMs) are used to capture the statistical dependencies in the sentence and aspect. In particular, we denote the forward operation of the LSTM as \overrightarrow{LSTM} and the backward operation as \overleftarrow{LSTM} . The hidden state vectors h_i^s and h_i^t can be obtained with:

$$h_i^s = [\overrightarrow{LSTM}(x_i^s), \overleftarrow{LSTM}(x_i^s)], \quad i \in \{1, m\} \quad (1)$$

$$h_j^t = [\overrightarrow{LSTM}(x_j^t), \overleftarrow{LSTM}(x_j^t)], \quad j \in \{1, n\} \quad (2)$$

As a result, we obtain the hidden output of BiLSTM for the sentence as $H_c^s = \{h_1^s, h_2^s, \dots, h_i^s, \dots, h_m^s\}$, which preserves the contextual information, and the target representation as $H_c^t = \{h_1^t, h_2^t, \dots, h_n^t\}$. In addition to H_c^s , two attention mechanisms are introduced to capture the aspect-specific contextual features. Specifically, a self-attention mechanism is first used to fully learn the long-range dependencies of context. Then, we make the other soft attention mechanism assign the weight for each word of S towards the T and obtain the weighted aggregation as the aspect-specific contextual representation, namely, R_c .

3.3.2 Syntax-based Representations

In the syntactic branch, we aim to leverage the explicit syntactic information to encourage the model to learn the syntax-aware representations, denoted as R_s , which has been shown to be helpful for many NLP tasks, *e.g.* machine translation [39], [40]. In practice, the same pretrained word embedding model and BiLSTM are also sequentially used to obtain the hidden state vectors H_s . Note that we share the parameters of word embeddings and BiLSTM in both contextual and syntactic branches to reduce the computation and lighten the model size, *i.e.*, $H_s = H_c^s$. Following the representative work in [9], we then employ a two-layer GCN module to extract the syntactic features of the sentence. To enable a close look at this, we show an illustration of the syntactic branch in Fig. 3.

First, we construct the syntactic dependency tree of the S with the spaCy toolkit¹ and obtain the adjacency matrix, namely, A , according to the words in the sentences. In practice, we make each word adjacent to its children's nodes and itself and set the values of adjacency nodes to ones.

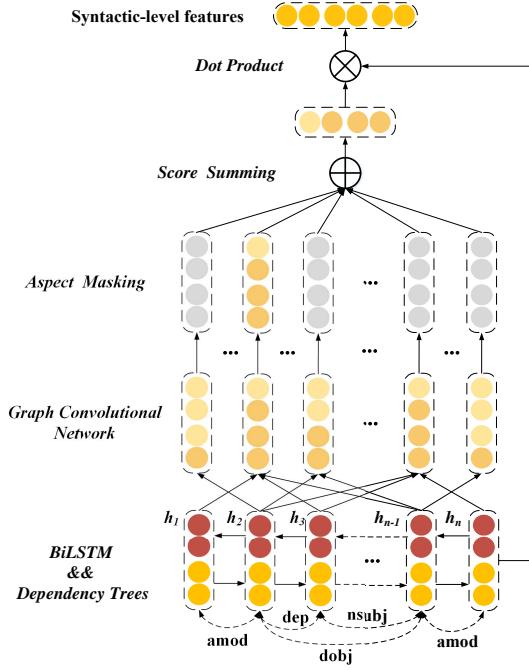


Fig. 3. Detailed illustration of the syntactic branch.

The GCN is further used to encode the syntactic information of G into H_s . In our preliminary experiments, we found that a two-layer GCN performs better than a one-layer GCN, while more layers did not improve the performance, which is consistent with results reported by previous works [41] and [42]. We claim that a one-layer GCN hardly captures the larger neighboring information, while multiple layers lead to high complexity. Therefore, the two-layer GCN is used last in our work. Specifically, with the operation of GCNs, the update of hidden state vectors H_s can be formulated as follows:

$$H_s^{(l+1)} = \text{ReLU}\left(\frac{AH_s^{(l)}W^{(l)}}{(D+1)} + B^{(l)}\right), \quad l \in \{0, 1\} \quad (3)$$

where A is the adjacency matrix over the dependency tree, D is the degree matrix of A (*i.e.*, $D_{ii} = \sum_j A_{ij}$), and $W^{(l)}$ and $B^{(l)}$ are the weight and bias matrices for the $(l+1)$ -th GCN layer. $H_s^{(0)}$ is the initial hidden state vector H_s , and $H_s^{(2)}$ is the final output of the GCNs.

Additionally, we further introduce a graph-based attention module to learn the aspect-specific R_s . More specifically, the attention module first performs aspect masking on the top of $H_s^{(2)}$ to mask the nonaspect words with zero. Since the above GCNs perceived the important information in the hidden aspect state, masking the other states could alleviate the effect of noise. A dot-product attention mechanism is utilized to transition the related aspect-specific features from the initial H_s towards the refined aspect features $H_s^{(2)}$ and thus syntactically build the connections of aspects and related opinion words.

3.3.3 Knowledge-based Representations

To incorporate external knowledge and enrich the semantic features, we introduce the knowledge graphs of WordNet² [43] as the external knowledge base, which contains more than 166,000 word

1. <https://spacy.io/>

2. <https://wordnet.princeton.edu/>

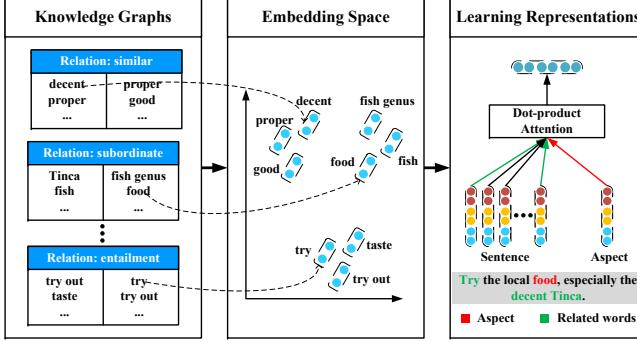


Fig. 4. The detailed illustration of the knowledge branch. In the right box, the words in red denote the aspect, while those in green are the related opinion words.

form and sense pairs, and employs sets of synonyms to represent the concepts. There are several semantic relations between different concepts, *e.g.* similar, opposite, part, subordinate and entailment. As with human language acquisition, we first learn the basic (simple) concepts and progressively learn the abstract (difficult) concepts. For rare difficult words, we could comprehend their meanings via their relevant normal words. Inspired by this phenomenon, we employ WordNet as prior knowledge for sentence understanding. For example, the “Tinca” is the subordinate of the “fish genus”, which can be directly related to aspects such as “fish” or “food”, thus alleviating the difficulty of comprehending the sentence.

Different from [17], which directly employs the graph-structure data of the knowledge base, we introduce a simple and efficient strategy to process the knowledge graphs. In practice, semantic matching approaches (see the analysis of different approaches in Sec. 4.3.3) for the task of knowledge graph embedding (KGE) [44] are used to model the semantic relations of knowledge graphs into distributed representations, *i.e.* learned knowledge embeddings. Subsequently, we represent the words of S and T with the knowledge embeddings and concatenate them with the hidden state vectors H_s to alleviate the negative effect of noise in knowledge embeddings. To establish the connection of S and T in knowledge embedding space, we further employ a soft attention mechanism to calculate the semantic relatedness of each word in S and T and capture the most important semantic features as aspect-specific knowledge representations, denoted as R_k . For better understanding, taking the sentence “Try the local *food*, especially the decent *Tinca*.” and the aspect word “*food*” as an example, the process of the knowledge branch is illustrated in Fig. 4. Notably, since the context word “*Tinca*” is the subordinate of the aspect “*food*” and they are also adjacent to each other in the knowledge embedding space, KGAN could easily capture their relatedness and make the correct prediction.

3.4 Hierarchical Fusion Module

Since the above representations $\{R_c, R_s, R_k\}$ are obtained from different views, directly fusing them may scarcely take advantage of their complementarity. To this end, we adopt a hierarchical fusion module to synergistically fuse these representations in a local-to-global manner, which could effectively boost the performance. An illustration of this fusion module is shown in Fig. 5. For ease of illustration, we employ the “input” to represent the procedures of multiple branches.

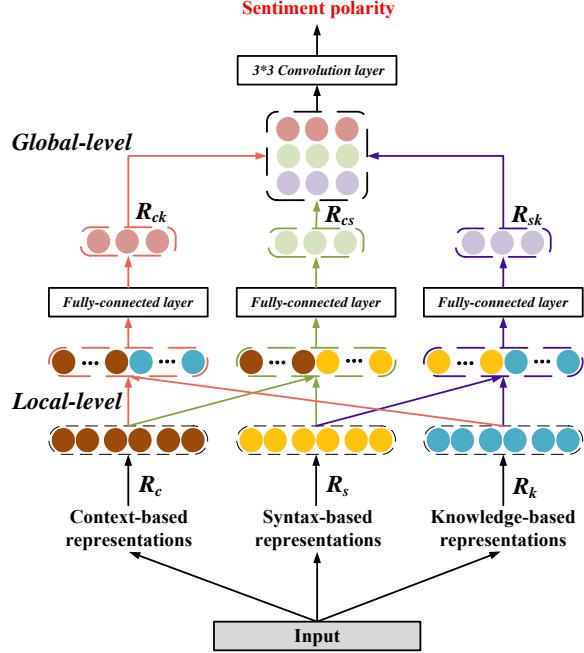


Fig. 5. Illustration of the hierarchical fusion module.

TABLE 1
Statistics of evaluated aspect-level datasets.

Datasets	Division	#Positive	#Negative	#Neutral
Laptop14	Train	980	858	454
	Test	340	128	171
Restaurant14	Train	2159	800	632
	Test	730	195	196
Twitter	Train	1567	1563	3127
	Test	174	174	346

In the local fusion procedure, we first concatenate two of the three feature representations in rows, *i.e.*, $[R_c; R_s]$, $[R_c; R_k]$ and $[R_s; R_k]$. The fused representations are fed into three separate fully connected layers to obtain the predicted sentiment features, denoted as R_{cs} , R_{ck} and R_{sk} . It is noteworthy that we do not share the parameters of these fully connected layers. Subsequently, to make full use of the complementarity between multiple sentiment features, we further fuse them at the global level. Specifically, the obtained sentiment features are concatenated in columns, *i.e.* $[R_{cs}, R_{ck}, R_{sk}]^T$, and we feed them into a 3×3 convolution layer to selectively incorporate these features.

Through the above local and global fusion procedures, we can make the feature representations benefit from each other step by step. In this way, external knowledge could be better integrated with contextual and syntactic information, thus achieving more promising performance.

Last, we cast the output of the convolution layer as the final sentiment prediction, namely, p , and employ the following cross-entropy loss function to guide the optimization and training of KGAN.

$$\mathcal{L} = - \sum_i \sum_j y_i^j \log(p_i^j) \quad (4)$$

where i indexes the instance of the ABSA dataset, and j indexes the sentiment polarity.

4 EXPERIMENTS

4.1 Datasets and Experimental Settings

Experiments are conducted on three public standard aspect-level datasets, *i.e.* Laptop14, Restaurant14 and Twitter. The Laptop14 and Restaurant14 datasets are from the SemEval2014 ABSA challenge [4], while the Twitter dataset is a collection of tweets [45]. Following [46], we remove a few instances with conflict sentiment polarity and list the final statistics of these datasets in Tab. 2. Note that we evaluate the performance with respect to Accuracy (“Acc”) and Macro-F1 (“F1”).

In our implementation, we carefully validate the effectiveness of our KGAN on three pretrained models, including GloVe [47], BERT [48] and RoBERTa [49]. In particular, we employ them to initialize the word embeddings. The learning rates are empirically set as 1e-3 for GloVe-based KGAN, 5e-5 for KGAN-BERT and 3e-5 for KGAN-RoBERTa³. The batch sizes are {64, 32, 32} for Laptop14, Restaurant14 and Twitter, respectively. To avoid overfitting, we apply dropout on the word embeddings with a drop rate of 0.5. Adam [50] is employed to fulfill the optimization and training.

For comparison, we report other competitive approaches on different pretrained embeddings. Specifically, the GloVe-based methods can be roughly divided into three categories:

1) Context-based methods:

- **ATAE-LSTM** [25]: The aspect embedding and attention mechanism are utilized in the LSTM for aspect-level sentiment classification.
- **RAM** [51]: This method employs multiple attention and memory networks to capture the aspect-specific sentence representation.
- **TNet-AS** [6]: Using the CNN as the feature extractor, TNet-AS introduces a target-specific transformation component to better incorporate the target information into the representation.
- **MGAN** [52]: This network proposes to employ the coarse-grained aspect category classification task to enhance the fine-grained aspect term classification task and introduces a novel attention mechanism to align the features between different tasks.

2) Syntax-based methods:

- **R-GAT** [12]: To better model syntax information, R-GAT proposes a novel aspect-oriented dependency tree structure to reshape and prune ordinary dependency parse trees.
- **DGEDT** [29]: The transformer is introduced into the network to diminish the error induced by incorrect dependency trees, thus boosting the performance.
- **RGAT** [53]: A relational graph attention network is proposed to make full use of the dependency label information, which is intuitively useful for the ABSA task.
- **DM-GCN** [28]: Considering the lack of syntactic information in some bad cases, a dynamic and multichannel GCN is used to jointly model the syntactic and semantic structures for richer feature representations.
- **DualGCN** [11]: To tackle the inaccuracy problem of dependency parsing results, Dual-GCN leverages the additional semantic information to complement the syntactic structure.

³ In preliminary experiments, we performed a grid search for the learning rate with {1e-3, 1e-4, 5e-5, 3e-5, 1e-5}

3) External knowledge-based methods:

- **Sentic-LSTM** [54]: To explicitly leverage commonsense knowledge, this method proposes an extension of LSTM, which could utilize the knowledge to control the information.
- **MTKEN** [33]: Multiple sources of knowledge, *i.e.* structure and sentiment knowledge, are fused in a unified model to boost the performance.
- **SK-GCN** [17]: A syntax- and knowledge-based GCN model is proposed to effectively incorporate syntactic information and commonsense knowledge by jointly modeling the dependency tree and knowledge graph.

Additionally, we compare KGAN to some powerful BERT- and RoBERTa-based methods to investigate the complementarity of our KGAN with powerful pretrained language models.

4.2 Main Results and Analysis

Tab. 2 lists the results of previous competitive models. First, we find that our KGAN model outperforms the other cutting-edge methods on most evaluated datasets. Specifically, KGAN performs better than Sentic-LSTM and SK-GCN, which only combine external knowledge with single contextual or syntactic information, indicating the superiority of multiview representation learning. Additionally, in the Laptop14 dataset, compared to the current SOTA model DualGCN (Acc: 78.48%; F1: 74.74%), KGAN (Acc: 78.91%; F1: 75.21%) achieves performance improvements of 0.43% and 0.47% in terms of accuracy and macro-F1 score, respectively. Although the performance of KGAN (Acc: 84.46%; F1: 77.47%) for Restaurant14 is suboptimal, it also outperforms all models by at least 0.19% with respect to the accuracy metric and outperforms most models by over 1.39% in terms of macro-F1 score. These results demonstrate the effectiveness and superiority of KGAN.

Interestingly, we can find that the averaged performance of context-based models is worse than their syntax-based counterparts, especially on the Restaurant14 benchmark. One possible reason for this is that the ratio of multiaspect instances in Restaurant14 (26.58%) is higher than that of Laptop14 (20.05%) [57], where the nonlocal modeling ability provided by the syntactic dependent trees could effectively address such a multiaspect problem. More specifically, in the group of context-based methods, the CNN-based models, *e.g.* TNet-AS, significantly outperform the LSTM-based models, *e.g.* ATAE-LSTM and RAM, on the Twitter dataset. This is because instances of the Twitter dataset are almost ungrammatical and noisy [6], which greatly hinders the effectiveness of the LSTM.

Last, we see that the performance of our KGAN on pretrained language models, *i.e.* BERT and RoBERTa, could achieve significant and consistent improvements compared with the results for GloVe, showing the complementarity between our approach and powerful pretrained language models. Encouragingly, our KGAN on RoBERTa achieves the new SOTA on two benchmarks, while the KGAN on BERT also outperforms most cutting-edge models in the same setting.

4.3 Ablation Study

In this section, we conduct extensive ablation studies to investigate the effects of multiple representations and the proposed fusion module in KGAN. Additionally, we analyze the influences of different knowledge graph embedding approaches. Unless otherwise

TABLE 2

Comparison with previous work on Laptop14, Restaurant14 and Twitter. Most results are retrieved from corresponding papers, and results marked with “ \natural ” are from [17]. Notably, we report the averaged performance of KGAN with 5 random seeds to avoid stochasticity. The best results for each pretrained model are in bold, while the second-best results are underlined.

Embedding	Category	Method	Laptop14		Restaurant14		Twitter	
			Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
GloVe	Syntax	ATAE-LSTM [25]	68.88 \natural	63.93 \natural	78.60 \natural	67.02 \natural	68.64 \natural	66.60 \natural
		RAM [51]	74.49	71.35	80.23	70.80	69.36	67.30
		TNet-AS [6]	76.54	71.75	80.69	71.27	74.90	73.60
		MGAN [55]	76.21	71.42	81.49	71.48	74.62	73.53
GloVe	External	R-GAT [12]	77.42	73.76	83.30	76.08	75.57	73.82
		DGEDT [29]	76.80	72.30	83.90	75.10	74.80	73.40
		RGAT [53]	78.02	74.00	83.55	75.99	75.36	74.15
		DM-GCN [28]	78.48	74.90	83.98	75.59	76.93	75.90
BERT	External	DualGCN [11]	78.48	74.74	84.27	78.08	75.92	74.29
		Sentic-LSTM [54]	70.88 \natural	67.19 \natural	79.43 \natural	70.32 \natural	70.66	67.87
		MTKEN [33]	73.43	69.12	79.47	68.08	69.80	67.54
		SK-GCN [17]	77.62	73.84	81.53	72.90	71.97	70.22
Ours			KGAN	78.91	75.21	84.46	77.47	77.27
RoBERTa	-	R-GAT-BERT [12]	78.21	74.07	86.60	81.35	76.15	74.88
		DGEDT-BERT [29]	79.80	75.60	86.30	80.00	77.90	75.40
		DM-GCN-BERT [28]	80.22	77.28	87.66	82.79	78.06	77.36
		DualGCN-BERT [11]	81.80	78.10	87.13	81.16	77.40	76.02
RoBERTa	-	KGAN-BERT (Ours)	82.66	78.98	87.15	82.05	79.12	78.14
		MLP-RoBERTa [56]	83.78	80.73	87.37	80.96	77.17	76.20
		RGAT-RoBERTa [56]	83.33	79.95	87.52	81.29	75.81	74.91
		KGAN-RoBERTa (Ours)	83.91	81.07	88.45	84.05	79.97	79.01

TABLE 3

Experimental results (%) of different combinations of multi-view representations (R_c , R_s and R_k mean context, syntax, and knowledge, respectively) on Restaurant14 and Twitter datasets.

R_c	R_s	R_k	Restaurant14		Twitter	
			Acc. (%)	F1 (%)	Acc. (%)	F1 (%)
✓			81.94	73.92	75.43	74.31
	✓		81.42	72.85	73.30	71.49
		✓	66.84	36.75	57.67	52.33
✓	✓		82.81	75.00	75.99	74.92
✓		✓	82.81	74.71	76.14	74.53
✓	✓	✓	83.25	75.15	75.99	74.17
✓	✓	✓	83.25	75.31	76.70	75.80

stated, all mentioned KGAN models below are based on GloVe, and we believe that KGAN-BERT and KGAN-RoBERTa show similar trends.

4.3.1 Effects of Different Multiview Representation Combinations.

Tab. 3 lists the results of different representation combinations, i.e. $\{R_c, R_s, R_k\}$. For fair comparison, we concatenate different representations and feed them into a one-layer MLP classifier to achieve multiview fusion. Note that we do not employ the proposed hierarchical fusion module to fuse the entire representation combination “[R_c, R_s, R_k]”; thus, the performances of the last row in Tab. 3 are slightly worse than the relative ones in Tab. 2.

Clearly, all representations from different views are of benefit to our KGAN, except merely using knowledge (“ R_k ”) representation. We attribute this relatively worse performance to the poor knowledge embeddings, which learned the linguistic knowledge from knowledge graphs from scratch. Notably, with the help of R_k , the representation without knowledge “[R_c, R_s]” can achieve an averaged +0.38% improvement, showing the effectiveness of introducing knowledge to ABSA models. Recall that the combi-

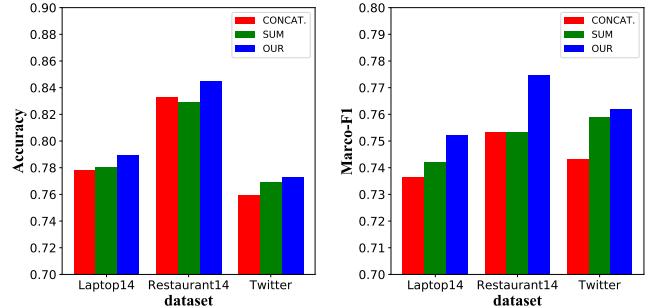


Fig. 6. The performance in terms of accuracy (left) and macro-F1 (right) for different fusion approaches. “CONCAT.” and “SUM” denote the concatenation strategy and the elementwise summation strategy, respectively.

nation of multiview representations “[R_c, R_s, R_k]” performs best among all combinations, and thus remains as the default setting.

4.3.2 Effects of Different Fusion Modules.

To validate the effectiveness of our proposed hierarchical fusion module (see Fig. 5), we compare it with two typical information fusion approaches: 1) “CONCAT”: the multiview representations are directly concatenated in rows and fused by a fully connected layer; 2) “SUM”: the representations are fed into three separate fully connected layers and fused via elementwise summation; 3) “OURS”: the representations are fused by our proposed hierarchical fusion module.

As shown in Fig. 6, compared to the other fusion strategies, our hierarchical fusion module significantly and consistently outperforms them with respect to both accuracy and macro-F1 metrics. More specifically, the improvement of the macro-F1 score on Restaurant14 is 2.16%, and the relative increase in accuracy is at least 0.94% on Laptop14. These results provide evidence that directly fusing multiview representations with CONCAT. and SUM is sub-optimal. In contrast, our proposed fusion module proposes

TABLE 4
Analysis of different approaches for knowledge graph embedding. Best results are in bold.

Approach	Laptop14		Restaurant14	
	Acc. (%)	F1 (%)	Acc. (%)	F1 (%)
TransE	77.80	73.69	82.55	74.67
ComplEx	78.13	74.09	83.51	76.01
ANALOGY	78.91	75.21	83.33	75.19
DistMult	77.81	73.96	84.46	77.47

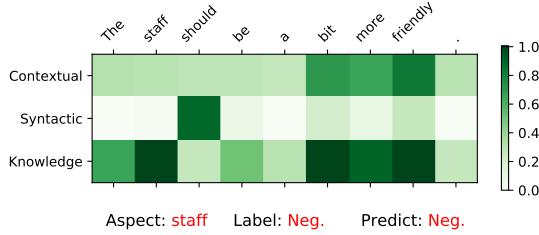


Fig. 7. Attention scores of different branches, where the aspect is **staff**, and the label and prediction are the same **negative**.

to fuse these multiview representations in a *local-to-global* manner, which could take full advantage of their complementarity.

4.3.3 Effects of Different Knowledge Graph Embeddings.

As mentioned above, we employ several simple approaches in knowledge graph embeddings (KGE) to model the knowledge graphs. To further analyze the influences of different KGE approaches, we conduct contrastive experiments on four typical approaches: a translated-based method **TransE** [58] and three semantic matching methods, *i.e.*, **ComplEx** [59], **ANALOGY** [60] and **DistMult** [61]. Tab. 4 reports the experimental results.

The translated-based method TransE performs worse than the other semantic matching methods. Since TransE only focuses on encoding the relation information of entities, instead of semantic information, the knowledge embeddings learned by TransE fall short in enriching the semantic features of KGAN. Correspondingly, the models that could capture relational semantics are able to achieve better performance, especially ANALOGY (Acc: 78.91%; F1: 75.21%) on Laptop14. More interestingly, we find that the performance of DistMult is unstable. For Laptop14, the competitive DistMult method cannot achieve the optimal performance as it does for Restaurant14. One possible reason for this is that the Distmult falls short in modeling the semantic relation of the laptop domain. More potential reasons will be explored in future works.

4.4 Case Study

For a closer look, we select cases from several evaluated datasets for extensive case studies. We first present some instances in Tab. 5 to show the effectiveness of our proposed KGAN. In practice, the aspects are enclosed in [], where the subscripts *p*, *n*, and *o* denote the true polarities “positive”, “negative”, and “neutral”, respectively. Based on the table, we can obviously find that the context-based models (*e.g.*, RAM and TNet-AS) perform worse than the syntax-based method (R-GAT), which shows that the syntax-based methods could effectively encode the syntactic information, thus better establishing the connections between aspects and related opinion words.

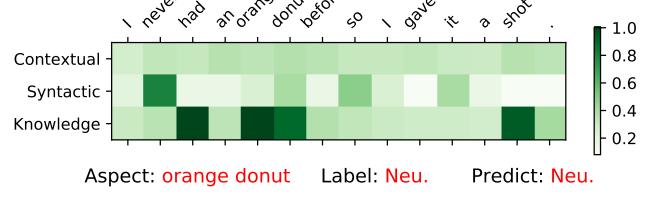


Fig. 8. In this case, the aspect is **orange donut**, and the label and prediction are the same **neural**.

Moreover, our KGAN makes the correct predictions in most cases, indicating its effectiveness and superiority. In particular, the second sentence demonstrates that our KGAN model can effectively address complicated and informal sentences with the help of multiview representation learning. However, it should also be noted that all models predict erroneously in the last case, since the models are likely to focus on the opinion word “thick”, which misleads the comprehension of this sentence. Such a phenomenon indicates that KGAN requires further improvement to understand complicated sentences.

Additionally, we select two cases to show exactly how the multiview representations affect the KGAN. For both cases, we visualize the final attention weights of multiple branches and show the results in Fig. 7 and Fig. 8, respectively. The sentences are as follows:

- 1) The [*staff*]_{*n*} should be a bit more friendly.
- 2) I never had an [*orange donut*]_{*o*} before so I gave it a shot.

In the first case, for the aspect “staff”, both representations from contextual and knowledge views focus on the opinion words “bit more friendly”, which facilitates the KGAN to understand the sentence and make the correct prediction. Moreover, we find that the representation from the syntactic view pays more attention to the other word “should”, which is also important for comprehension. These attention results demonstrate the complementarity of multiview representations.

On the other hand, in the second instance, the representation from the contextual view hardly captures the aspect-specific contextual information, while the representation from the syntactic view also fails to focus on the closely-related opinion words. However, the representation from the knowledge view can effectively extract the important related words “had” and “shot”. One possible reason for this is that the opinion words are not syntactically adjacent to the aspect, thus leading to the difficulty of capturing important semantic information. Instead, the “orange donut” is much closer to “had” in the introduced knowledge graph, which allows the knowledge branch to easily capture the relatedness. This case shows the significance of incorporating external knowledge and confirms our contribution.

4.5 Discussion

4.5.1 Latency and Model Size.

Introducing external knowledge will admittedly increase the latency and model size [6], [12], [28]. We therefore perform a contrastive investigation on whether we achieve a good trade-off between efficiency and performance. For a fair comparison, all experiments are trained and tested on an Nvidia GTX-1660 SUPER. Tab. 6 shows the details of KGAN and previous models, including ATAE-LSTM, R-GAT, and DM-GCN. Their

TABLE 5
The words enclosed in [] are aspect terms, and p , n , and o denote the true polarities. P, N, and O respectively denote the positive, negative and neutral predictions. The symbol \times indicates the wrong prediction.

Sentences	RAM	TNet-AS	MGAN	R-GAT	KGAN
1. Great [food] _P but the [service] _n is dreadful.	(P, N)	(P, N)	(P, N)	(P, N)	(P, N)
2. In mi burrito, here was nothing but dark [chicken] _n that had that cooked last week and just warmed up in a microwave [taste] _n .	(N, P \times)	(N, N)	(N, P \times)	(N, O \times)	(N, N)
3. [Startuptimes] _n are incredibly long: over two minutes.	P \times	N	N	N	N
4. The [folding chair] _n I was seated at was uncomfortable.	N	O \times	N	N	N
5. The [staff] _n should be a bit more friendly.	P \times	P \times	P \times	P \times	N
6. It is really thick around the [battery] _o .	N \times	N \times	N \times	N \times	N \times

TABLE 6

Comparison of latency and model size with previous works on Restaurant14. “#Params.(M)”: number of parameters in millions. “Train(s)” and “Test(s)” indicate the averaged training time (seconds) of each epoch, and the inference time of all testing samples, respectively.

Model	Latency		#Params. (M)
	Train (s)	Test (s)	
ATAE-LSTM	1.98	0.71	2.53
R-GAT	4.61	0.88	3.72
DM-GCN	7.04	2.25	8.80
KGAN (Ours)	4.41	1.31	3.62

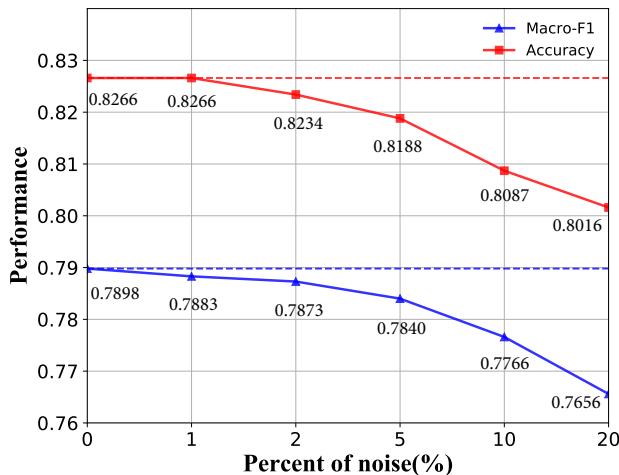


Fig. 9. Experiments with noise attacks on the KGAN-BERT model, where the results are evaluated on the Laptop14 dataset. The ratio of noisy knowledge ranges from 1% to 20%.

corresponding performances can be found in Tab. 2. Clearly, although our proposed KGAN model is more complicated than the previous context-based ATAE-LSTM, we can achieve significantly better performance (averaged +10.87% F1 scores). Compared to more recent models, *i.e.* R-GAT and DM-GCN, our KGAN could achieve better performance while preserving comparable or better latency. The main reason for this is that these models introduced the sophisticated module to capture the semantic features, leading to larger model sizes, while we only employ the original BiLSTM as the feature extractor and share its parameters between three branches, greatly decreasing the model parameters. **Takeaway:** *our KGAN establishes a good trade-off between efficiency and performance due to our parameter-sharing mechanism.*

4.5.2 Robustness of our KGAN.

Some researchers may doubt that the incorporated external knowledge may function as the regularizer [62]. To dispel such doubt, we investigate whether our model is robust to noisy knowledge by introducing different percentages of noise to the knowledge embeddings on the Laptop14 dataset. Notably, noise attacks are widely used in the NLP community to investigate the robustness of models, such as neural machine translation [63], [64]. In particular, we randomly initialize some of the knowledge embeddings as noise. As shown in Fig. 9, our proposed multiview representation learning method can tolerate slight noise, *e.g.*, 1%, 2% and 5%, and maintain performance to some extent. However, as noise increases, *e.g.* to 20%, the performance deteriorates, indicating that noisy knowledge does not function as regularization. **Takeaway:** 1) *our multiview knowledge representation approach is robust to slight noise; 2) KGAN does not benefit from noise as much as it benefits from incorporated knowledge.*

5 CONCLUSION

We present a novel knowledge graph augmented network for ABSA that incorporates external knowledge to augment semantic information. Specifically, KGAN captures the sentiment features from three different views: context, syntax and knowledge. These multiview feature representations are fused via a hierarchical fusion module. Extensive experiments demonstrate the effectiveness and robustness of our proposed KGAN. Ablation experiments and case studies show the complementarity between contextual, syntactic and external knowledge, confirming our claim. Extensive analyses illustrate that our KGAN can achieve a better trade-off between latency and performance and is robust to slight noise attacks.

Future work includes validating the proposed KGAN multiview representation approach in other challenging language understanding tasks, *e.g.* reading comprehension [65], intent identification and slot filling [66], and end-to-end language generation tasks [67], *e.g.* translation, summarization and grammatical error correction tasks.

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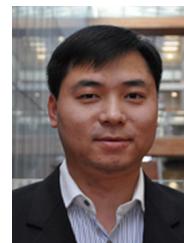
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