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Block-level dependency syntax based model for end-to-end aspect-based sentiment analysis

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ABSTRACT

End-to-End aspect-based sentiment analysis (E2E-ABSA) aims to jointly extract aspect terms and identify their sentiment polarities. Although previous research has demonstrated that syntax knowledge can be beneficial for E2E-ABSA, standard syntax dependency parsing struggles to capture the block-level relation between aspect and opinion terms, which hinders the role of syntax in E2E-ABSA. To address this issue, this paper proposes a block-level dependency syntax parsing (BDEP) based model to enhance the performance of E2E-ABSA. BDEP is constructed by incorporating routine dependency syntax parsing and part-of-speech tagging, which enables the capture of block-level relations. Subsequently. the BDEP-guided interactive attention module (BDEP-IAM) is used to obtain the aspect-aware representation of each word. Finally the adaptive fusion module is leveraged to combine the semantic-syntactic representation to simultaneously extract the aspect term and identify aspect-orient sentiment polarity. The model is evaluated on five benchmark datasets, including Laptop14, Rest _ALL, Restaurant14, Restaurant15, and TWITTER, with F1 scores of 62.67%, 76.53%, 75.42%, 62.21%, and 58.03%, respectively. The results show that our model outperforms the other compared state-of-the-art (SOTA) methods on all datasets. Additionally, ablation experiments confirm the efficacy of BDEP and IAM in improving aspect-level sentiment analysis.

1. Introduction

With the increasing prevalence of social media and e-commerce platforms, people often express their opinions about specific aspects of products, services, or events. It is of great application value to analyze these comments and extract opinions for different aspects (Ali et al., 2019). As a fundamental task of sentiment analysis, aspect-based sentiment analysis (ABSA) has received growing research attentions over the past few years, which aims to simultaneously extract aspect terms and identity their sentiment polarities. Most previous studies prefer to cast ABSA as a pipeline-based problem with two independent sub-tasks: aspect term extraction (ATE) and sentiment polarity classification (ASC). Unfortunately, the pipeline-based methods always suffer from the error propagation problem. End-to-End (E2E) is one of the most effective ways to alleviate the error accumulation problem for ABSA, which attempts to deal with both ATE task and ASC task at the same time. E2E-ABSA approaches are divided into two strategies, i.e. the joint ABSA and the unified ABSA. The joint ABSA (Mitchell, Aguilar, Wilson, & Durme, 2013) attempts to simultaneously predict aspect term boundary and sentiment tags within a multi-task learning framework by exploring the relations between ATE and ASC (Chen & Qian, 2020; He, Lee, Ng, & Dahlmeier, 2019; Liang, Meng, Zhang, Chen et al., 2021; Liang, Wei, Mao, Wang, & He, 2022; Luo, Ji, Li, Jiang, & Duan, 2020), while the unified ABSA (Zhang, Zhang, & Vo, 2015) tends to link two sub-tasks together within a unified tagging scheme (Li, Bing, Zhang, & Lam, 2019; Mao, Shen, Yu, & Cai, 2021; Wang, Lan, & Wang, 2018) by concatenating both BIO tags and sentiment tags.

For E2E-ABSA, opinion term extraction is often treated as an auxiliary task because opinion terms are important indicative clues in sentences, and can be leveraged to directly reflect sentiment polarities (Li, Bing, Zhang, & Lam, 2019; Mao et al., 2021; Zheng, Li, & Zhang, 2021). Moreover, modeling the relations between aspect terms and opinion terms also plays an important role for aspect-oriented sentiment analysis. As one of the most widely used word-level relations, dependency syntax parsing (DEP) can be employed to reveal the relations between words. Some recent studies attempt to incorporate the dependency syntactic relations to enhance sentiment classification performance through dependency-based word representations (Yin, Wang, & Zhang, 2020; Yin et al., 2016) or graph neural networks (Li et al., 2021; Sun, Zhang, Mensah, Mao, & Liu, 2019; Zhou, Cui et al., 2021; Zhou, Liao et al., 2021).

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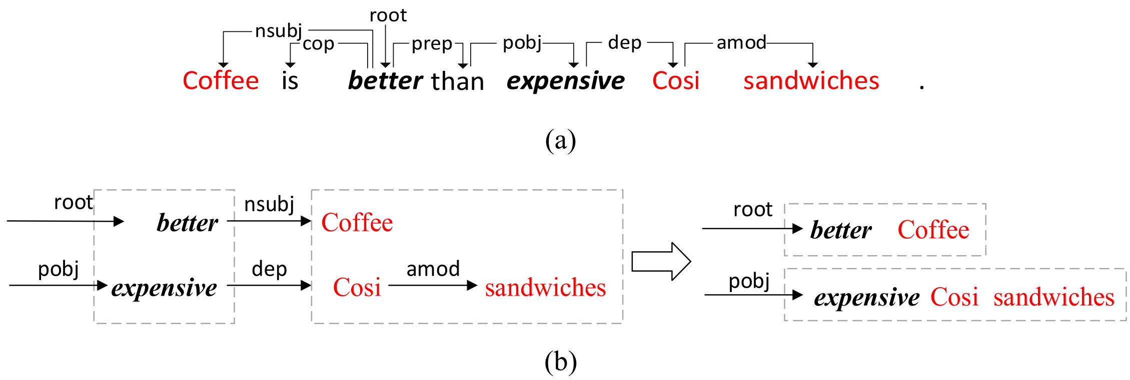

Fig. 1. An example of syntax tags for aspect terms and opinion terms. Aspect terms are marked in red, opinion words are marked in bold italics, and syntax tags are marked in black font. (a) Routine word-level syntactic dependency tree; (b) The left represents two aspect-opinion phrases labeled by routine syntactic dependency tree, and the right represents aspect-opinion phrases with the same syntax tags.

According the statistics[1] on the benchmark dataset, a number of aspect terms are blocks containing two or more words. Aspect terms or/and opinion terms may actually be noun or/and adjective/adverb phrases (Ali, El-Sappagh et al., 2021; Hu & B. Liu, 2004; Xu, Liu, Lai, Chen, & J. Zhao, 2013). Therefore, token-blocks should be considered when recognizing aspect terms and their sentiment polarities. However, the tags generated by routine dependency parsing are dispersed. For example, in Fig. 1. (a), given sentence "Coffee is better than expensive Cosi sandwiches", the aspect term "Cosi sandwiches" contains two words. The syntactic tags of these two words as tail nodes are "dep" and "amod", respectively. Meantime, the corresponding opinion word "expensive" also has a different tag. That is to say, these syntactic tags could not instruct block-level relations directly. To indicate relations of aspect terms and opinion terms, we need to update the dependency syntactic to bundle the aspect and the corresponding opinion tokens into one combination marked with the same syntactic tag, illustrated in Fig. 1. (b).

Based on the analysis above, incorporating block-level inner- and inter-relations of aspect terms and opinion terms could improve the performance of sentiment analysis, which has been overlooked by most previous syntax-based ABSA models. This paper aims to investigate the use of block-level syntax knowledge to enhance the accuracy of fine-grained sentiment analysis. In comparison to prior research, this paper makes three main contributions:

- We propose a block-level dependency syntax-based model to jointly extract aspect terms and identify their corresponding sentiment polarities. To the best of our knowledge, it is the first attempt to employ block-level dependency syntax to capture aspect terms and their latent sentiment representations to improve the performance of ABSA.
- In the proposed model, the block-level dependency syntax parsing (BDEP) is set to build the internal and mutual connection of aspect terms and opinion terms. Additionally, BDEP-guided interactive attention (BDEP-IAM) and adaptive semantic-syntactic fusion modules are employed to significantly enhance the ability of identifying aspect terms and their sentiment.
- Extensive experiments on benchmark datasets show that our proposed method significantly outperforms the other competitive methods, and the in-depth analysis shows the effectiveness of BDEP and BDEP-IAM.

[1] Statistical results of aspect terms on Rest_ALL dataset. The details are summarized in Appendix.

2. Related work

ATE and ASC are two fundamental tasks of ABSA, and there are two kinds of main approaches: the pipeline method and the End-to-End method.

2.1. The pipeline method

ATE and ASC are generally regarded as two independent tasks, and pipeline-based ABSA is accomplished by connecting these two tasks sequentially. Incorporating the dependency syntactic knowledge into the model (Ali, El-Sappagh et al., 2021) is one of the most effective ways for ATE and ASC. Yin et al. (2016)utilized the dependency relations to study the dependency-related word representations for aspect term extraction. Yin et al. (2020) designed a positional dependency-based word embedding (POD) module to extract aspect term by incorporating both dependency relations and contextual semantic information. Luo, Li, Liu, Wang and Unger (2019)proposed a novel bidirectional dependency tree network to represent dependency-related token features to improve aspect term extraction performance. Sun et al. (2019) and Zhang, Li, and D. Song (2019) employed the graph neural network (GNN) to construct the dependency tree for aspect-oriented sentiment analysis by exploiting both the syntactic information and long-range word dependencies. Moreover, other structural information has also been employed for ABSA. For example, Chen et al. (2020) proposed a two-step ABSA approach by exploring the sentence-level relations for ATE and ASC. In Addition to syntactic knowledge, text topics are also a useful knowledge for sentiment analysis. To this end, Ali et al. (2019) proposed an ontology and latentDirichletallocation (OLDA)-based method for topic modeling, which can extract the most appropriate features to improve the performance of sentiment analysis. Additionally, the authors proposed a method of combining OLDA and Bi-directional Long Short-Term Memory (Bi-LSTM), which integrated ontology information into word2vec and adopted a Bi-LSTM to improve the classification accuracy (Ali, Ali et al., 2021).

2.2. The end-to-end method

E2E-ABSA methods are divided into the joint ABSA and the unified ABSA.

The joint ABSA usually adopts a multi-task learning framework to combine ATE and ASC. Luo, Li, Liu, and Zhang (2019) proposed a dual cross-shared RNN architecture with attention mechanism by considering the relations between ATE and ASC for ABSA. He et al. (2019) presented an interactive multi-task learning network (IMN) by leveraging both word-level and document-level

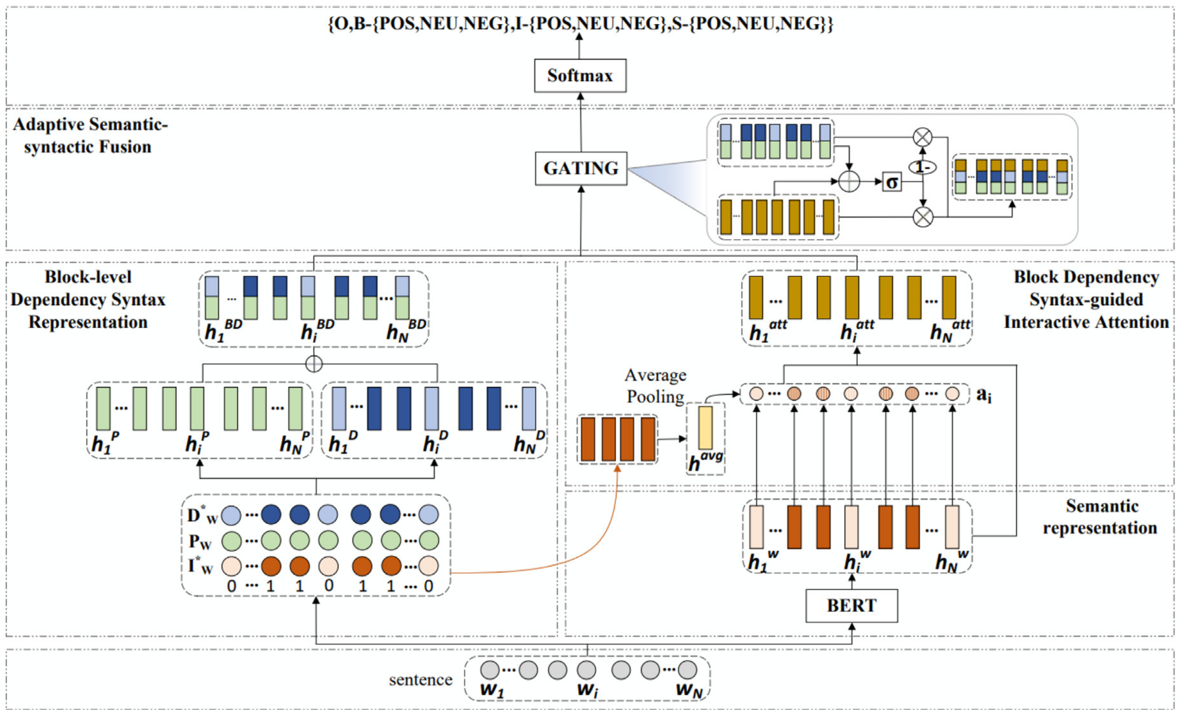

Fig. 2. The overall framework of the block-level dependency syntax parsing (BDEP) based model. The model consists of the block-level dependency syntax representation, the block dependency syntax-guided interactive attention and the adaptive semantic-syntactic fusion.

information for ABSA. Liang, Meng, Zhang, Xu et al. (2021) proposed a novel dependency syntax-aware interactive framework to improve both aspect extraction and sentiment classification performance.

The unified approaches attempt to build a unified tagging scheme to accomplish ATE and ASC within a unified tag space. Schmitt, Steinheber, Schreiber, and B. Roth (2018) proposed a CNN-LSTM-based ABSA framework to select the potential aspect terms word by word, and then identify their corresponding sentiment polarity. Li, Bing, Li and Lam (2019) designed a unified framework with two stacked RNNs to ensure the consistency of the sentiment polarity for all words in aspect terms.

In addition, the pre-trained model and graph model have also been employed for E2E-ABSA. Li, Bing, Zhang, and Lam (2019)employed BERT to couple the context word embedding layer with the downstream neural network layer for ABSA. Liu, Li, Wu, Su, and Sun (2020) proposed a dynamic heterogeneous graph approach to explore the interaction between aspect and sentiment polarity for sentiment analysis. Chen and Qian (2020) proposed the relation-aware collaborative learning (RACL) framework to simulate the interaction between ATE, ASC and opinion term extraction (OTE) for aspect-based sentiment classification.

Aspect terms may be the token-block that contains two or more words. Mining and exploration the block-level relations always play an important role in ABSA task. Unfortunately, the block-level relations are often be neglected in most above approaches.

3. Our model

In this section, we will introduce our proposed approach. We attempt to exploit the block-level relations to enhance the performance of fine-grained sentiment analysis by capturing the association of aspect terms and opinion terms. The overall framework of our model is illustrated in Fig. 2, which mainly consists of the following four modules, (1) Semantic representation, (2) Block-level dependency syntax representation, (3) Block dependency syntax-guided interactive attention and (4) adaptive semantic-syntactic fusion.

3.1. Semantic representation

Given a sentence with N tokens $W = [w_1, \ldots, w_N]$. We sent the sentence into the pre-trained BERT model[2] to obtain the semantic representation:

$$\mathbf{H^w} = \mathrm{BERT}\,(\mathrm{w}) \tag{1}$$

where $\mathbf{H^w} = \left[h_1^w, \ldots, h_N^w\right] \in \mathbb{R}^{N\times d}$, d is the dimension of each token-level semantic vector h_i^w, which is a combination of the corresponding token embedding, positional embedding, and segment embedding.

3.2. Block-level dependency syntactic representation

3.2.1. Block-level dependency syntax construction

In order to effectively capture the block-level relations, a dependency syntax simplification strategy is adopted to obtain block-level dependency syntactic representations by reassigning dependent tags of each word. Specifically, we first exploit the traditional parsing tool (Dozat & Manning, 2017) (e.g., HanLP [3]) to get the word-level dependency syntactic tree T_W and part-of-speech (POS) tags sequence P_W of the sentence W:

$$T_W = \mathrm{DEP\_Parsing}\,(W) \tag{2}$$

$$P_W = \mathrm{POS\_Parsing}\,(W) \tag{3}$$

where DEP_Parsing(.) and POS_Parsing(.) denote dependency syntactic parsing and POS parsing operations, respectively.

[2] https://github.com/ huggingface/pytorch-transformers
[3] https://www.hanlp.com

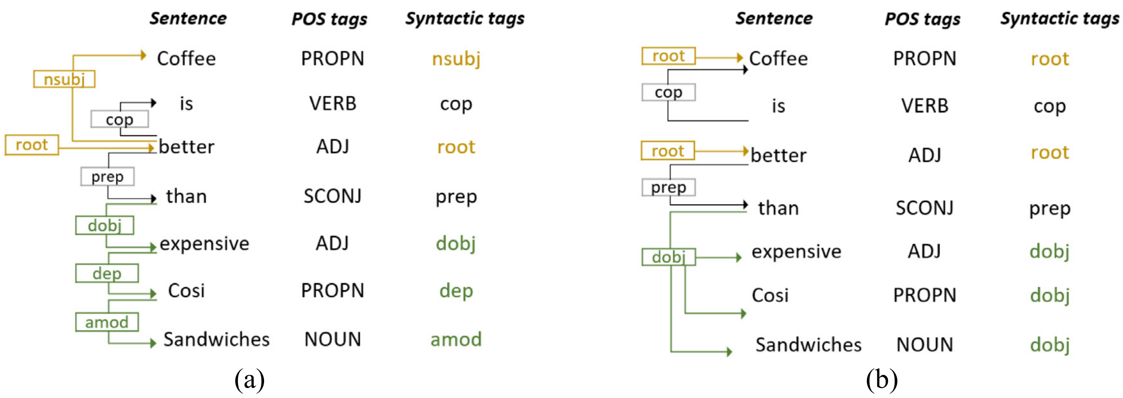

Fig. 3. An example of reconstructing block-level syntax tags. The various colored fonts represent different aspect-opinion combinations. (a) The original word-level syntax tags for the example in Table 1.; (b) The updated block-level syntax tags.

Table 1
An example of sub-sequences and dependency syntactic tags.

s_1^w	better → is
$D_{s_1^w}$	root cop
s_2^w	better → Coffee
$D_{s_2^w}$	root nsubj
s_3^w	better → than → expensive → Cosi → sandwiches
$D_{s_3^w}$	root prep dobj dep amod

We assign the dependent arc tag between two words to the tail node word according to T_W, and get the original dependency syntactic tag sequence $D_W = \{d_1^w, \ldots, d_N^w\}$.

Then we traverse the dependency syntactic tree T_W from the root node to each leaf node according to the dependency syntactic arcs, and obtain the sub-sequence set:

$$S_w = \mathrm{Travs}\,(D_W) \tag{4}$$

where Travs denotes the traversing operation from the root node, $S_w = \{s_k^w \,|\, k = 1, \ldots, m\}$, s_k^w is the $k'th$ sub-sequence starting from the root node, and m is the number of sub-sequences.

For example, the sub-sequences and their corresponding dependency syntactic tags of the sentence "Coffee is better than expensive Cosi sandwiches" are listed in the following Table 1, in which $\mathrm{D}_{s_k^w}$ denotes the original syntactic tags of the sub-sequence s_k^w.

For the $k'th$ sub-sequence s_k^w, if two words w_i, w_j have dependency relation and their POS tags accord with one of rules $\mathcal{R}$ enumerated in Appendix, we assign the original syntactic tag of the head node word to the tail node word, and keep their original POS tags unchanged. We traverse all sub-sequences and obtain the block-level dependency syntax parsing (BDEP) D_w^* and the corresponding indicative tags I_w^*. The detailed block-level dependency syntax construction algorithm is shown in Algorithm I, and the original dependency syntax and its corresponding block-level dependency syntax of the example in Table 1 are illustrated in Fig. 3. It can be seen that after reconstruction, the aspect and its corresponding opinion tokens are bundled into a single combination marked with the same syntactic tag.

3.2.2. Block-level dependency syntactic representation

We denote the embedding vectors of the BDEP D_w^* and POS P_w as $\mathbf{H^D} = [h_1^D, \ldots, h_N^D]$ and $\mathbf{H^P} = [h_1^P, \ldots, h_N^P]$, respectively. Both $\mathbf{H^D}$ and $\mathbf{H^P}$ are initialized as random vectors, and $\mathbf{H^D}, \mathbf{H^P} \in \mathbb{R}^{N\times d/2}$. It should be noted that all sub-words would share the same POS and DEP tags when a word is split into two or more sub-words with BERT tokenizer.

Then $\mathbf{H^D}$ and $\mathbf{H^P}$ are concatenated to obtain the overall block-level dependency syntactic representation $\mathbf{H^{BD}}$,

$$\mathbf{H^{BD}} = \mathrm{concat}\left(\mathbf{H^D}, \mathbf{H^P}\right) \tag{5}$$

where concat(·) represents the concatenation operation in the last dimension, and $\mathbf{H^{BD}} \in \mathbb{R}^{N\times d}$.

3.3. Block dependency syntax-guided interactive attention

In the attention module, the BDEP-guided interactive attention (BDEP-IAM) is employed to capture the aspect-aware sentiment representation of each word. We first extract and represent the potential aspect block with the indicative tags I_W^*, which can be formulated as,

$$\mathbf{H^{AO}} = \mathrm{concat}\left(\left[h_i^w \middle| I_W^*(i) = 1\right], i = 1, 2, \ldots, N\right) \tag{6}$$

where concat(·) denotes the concatenation operation in the length dimension, i is the word index of the sentence W. $\mathbf{H^{AO}} \in \mathbb{R}^{l\times d}$, l is the number of words in the potential aspect block.

And the global representation of the potential aspect block $h^{\mathrm{avg}} \in \mathbb{R}^d$ is obtained by average $\mathbf{H^{AO}}$ in the length dimension, which can be shown that:

$$h^{\mathrm{avg}} = \sum_{i=1}^{l} \frac{h_i^w}{l} \tag{7}$$

Then the interactive attention mechanism is carried out to obtain aspect-sentiment attention distribution α_i based on the semantic representation $\mathbf{H^w}$ and the global representation h^{avg}:

$$\alpha_i = \frac{\exp\left(\gamma\left(h_i^w, h^{\mathrm{avg}}\right)\right)}{\sum_{j=1}^{N}\exp\left(\gamma\left(h_j^w, h^{\mathrm{avg}}\right)\right)} \# (8) \tag{8}$$

where γ is the attention score, which is defined as:

$$\gamma\left(h_i^r, h^{\mathrm{avg}}\right) = \tanh\left(h_i^r.\mathbf{W_a}.h^{\mathrm{avg}\,\mathrm{T}} + b_a\right) \tag{9}$$

where tanh(.) is a nonlinear function, and $\mathbf{W_a} \in \mathbb{R}^{d\times d}$ and b_a are trainable parameters.

Then we can obtain the attentive representation $\mathbf{H^{ATT}}$ by,

$$\mathbf{H^{ATT}} = \mathrm{concat}([\alpha_i h_i^r], i = 1, 2, \ldots, N) \tag{10}$$

where $\mathbf{H^{ATT}} \in \mathbb{R}^{N\times d}$.

3.4. Adaptive semantic-syntactic fusion

We introduce the gating strategy to adaptively integrate the attentive representation $\mathbf{H^{ATT}}$ and the block-level dependency

Algorithm 1: Block-level Dependency Syntax Construction Algorithm

Input: sentence W; the statistical rules $\mathcal{R}$ listed in Appendix I
Output: block-level dependency syntactic tags D_W^*; the indicative tags I_W^*

obtain the original dependency syntactic tags D_W and POS tags P_W of the sentence W through Eq. (2) and Eq. (3)
get all sub-sequences $S = \{s_k | k = 1, \cdots, m\}$ using Eq. (4)
initialize the block-level dependency syntactic tags $D_W^* = D_W$, the indicative tags $I_W^* = \{i_j = 0 | j = 1,2, \cdots N\}$
for $k = 1, \cdots, m$ do
    initial the dependency syntactic tags, POS tags, and indicative tags of s_k by mapping operations: $D_{s_k} = \mathcal{M}_{w \to s}(D_W),\ P_{s_k} = \mathcal{M}_{w \to s}(P_W),\ I_{s_k} = \mathcal{M}_{w \to s}(I_W^*)$
    for $j = 1, \cdots, len(s_k)$ do
        if $P_{s_k}(j) \to P_{s_k}(j+1) \subseteq \mathcal{R}$ then
        update $D_{s_k}(j+1) = D_{s_k}(j),\ I_{s_k}(j) = I_{s_k}(j+1) = 1$
        end if
    end for
    update the block-level dependency syntactic tags and POS tags of W: $D_W^* = \mathcal{M}_{s \to w}(D_{s_k})$, $I_W^* = \mathcal{M}_{s \to w}(I_{s_k})$
end for
Return $D_W^*,\ I_W^*$

Note : $\mathcal{M}_{w \to s}$ and $\mathcal{M}_{s \to w}$ are two mapping operations. The former is to align words in the sentence and the sub-sequence, and to assign the tags of words in the sentence to the same words in the sequence; the latter is to assign the tags of the word in the sequence to the same words in the sentence.

syntactic representation $\mathbf{H^{BD}}$, and get the final representation $\mathbf{H_f}$ as follow:

$$\mathbf{H_f} = g^{\circ}\mathbf{H^{BD}} + (1-g)^{\circ}\,\mathbf{H^{ATT}} \tag{11}$$

where $\circ$ is element-wise product operation, and the gate g is computed by:

$$g = \sigma\left(\mathbf{W_g}\left[\mathbf{H^{BD}}; \mathbf{H^{ATT}}\right] + b_g\right) \tag{12}$$

where $\mathbf{W_g}$ and b_g are trainable parameters.

The final representation $\mathbf{H_f}$ is then leveraged to predict the label probability of each word:

$$p\left(y_w | W\right) = \text{softmax}\left(\mathbf{W_o}\mathbf{H_f} + b_o\right) \tag{13}$$

where $\mathbf{W_o}$ and b_o are trainable parameters. According to the probability, each word would be assigned a label among B-{POS, NEG, NEU}, I-{POS, NEG, NEU}, E-{POS, NEG, NEU}, S-{POS, NEG, NEU}, O.

4. Experimental settings

4.1. Datasets

We conduct experiments on five datasets originated from the SemEval challenges (Pontiki et al., 2016; Pontiki, Galanis, Papageorgiou, Manandhar, & Androutsopoulos, 2015; Pontiki et al., 2014) and TWITTER (Mitchell et al., 2013). Both aspect terms and their corresponding sentiment polarities are labeled. The statistics of these datasets are presented in Table 2.

Table 2
The basic statistics of four datasets.

Dataset	Positive			Negative			Neutral		
	Train	Dev	Test	Train	Dev	Test	Train	Dev	Test
Laptop14	817	169	364	517	141	116	126	36	63
Rest _ ALL	3490	841	1497	1014	248	376	241	76	120
Restaurant 14	1692	404	773	404	119	54	166	54	66
Restaurant 15	783	185	317	205	53	143	25	11	25
TWITTER		703			274			2266	

4.2. Parameter setting

We set the dimension of both DEP and POS representation vectors as 384. The sentence is presented through the pre-trained Bert-base-uncased model with 12 transformer layers, and the dimension of hidden layer is 768. For Laptop 14, Restaurant 14 and Restaurant 15 dataset, the batch size is set to 32; for Rest_ALL and TWITTER dataset, the batch size is set to 16. The parameter optimization is Adam and the learning rate is 2e-5. We train the model up to 1500 steps. After training 1000 steps, we conduct model selection on the development set for every 100 steps according to the averaged F1 score. Following these settings, we train 5 models with different random seeds and report the average results.

4.3. Baseline models

To verify the performance of our model on ABSA tasks, we compare our proposed model with the following pipeline, joint and unified approaches on five datasets:

Pipeline approaches

{CMLA, DECNN} - {ATAELSTM, dTrans} (Liang, Meng, Zhang, Chen et al., 2021): CMLA and DECNN are employed for ATE. CMLA is leveraged to model the inter dependencies for aspect term extraction, and DECNN utilizes a multi-layer CNN module with double embedding to extract the aspect term. ATAELSTM and dTrans are used for ASC. ATAELSTM is an attention-based LSTM structure, and dTrans introduces a large document-level corpus to improve the ASC performance. We construct the following four pipeline-based baselines: CMLA-ATAELSTM, CMLA-dTrans, DECNN-ATAELSTM and DECNN-dTrans.

HAST-TNET (Mao et al., 2021): HAST employs historical information to extract aspect terms, and TNET is composed of the

Table 3
F1 scores of different models on five datasets.

Models			Laptop 14	Rest _ ALL	Restaurant 14	Restaurant 15	TWITTER
Pipeline methods	CMLA-ATAELSTM		53.68	–	63.87	54.79	–
	CMLA-dTrans		55.56	–	65.34	56.09	–
	DECNN-ATAELSTM		55.05	–	65.26	55.10	–
	DECNN-dTrans		56.60	–	67.25	56.28	–
	HAST-TNet		55.29	67.36	–	–	–
	IMN-PIPELINE		56.02	–	66.53	55.96	–
Joint methods	CRF-joint		44.06	53.68	–	–	31.35
	NN-CRF- joint		45.49	55.18	–	–	39.67
	DOER		60.35	72.78	–	–	51.37
	IMN		58.37	69.54	–	59.18	–
	RACL		58.28	–	69.59	59.85	–
	DREGCN		*61.51*	*–*	*70.21*	*61.06*	*–*
Unified methods	without BERT	CRF-unified	49.06	60.43	–	–	27.86
		NN-CRF-unified	51.56	61.56	–	–	38.36
		LSTM-unified	51.40	63.14	–	–	43.41
		BG-SC-OE	57.90	69.8	–	–	48.01
	BERT-based	IMN-BERT	*61.73*	–	70.72	60.22	–
		GRU-BERT	61.12	–	73.17	59.60	*56.52*
		SAN-BERT	60.49	–	73.68	59.90	55.94
		TFM-BERT	*60.80*	*–*	*73.98*	*60.24*	55.62
		Our model	**62.67**	**76.53**	**75.42**	**62.21**	**58.03**

Bi-LSTM layer, the Transformer attention layer and the CNN layer to obtain aspect-aware representation for ASC.

IMN-pipeline (Luo, Li, Liu, & Zhang, 2019): An interactive multitask learning network (IMN) is employed for ATE and ASC independently.

Joint approaches

CRF-joint (Mitchell et al., 2013): Conditional Random Fields (CRF) based sequence tagger with the word position tag {B,I,O,E} and the sentiment polarity tag {POS, NEU,NEG} for the joint-ABSA.

CRF-NN-joint (Zhang et al., 2015): The enhanced CRF and structural neural models are applied to jointly extract aspect terms and identify their sentiment polarities.

DOER (Zhang et al., 2019): A dual cross-shared RNN framework utilizes the interaction between ATE and ASC, and outputs all aspect terms with their sentiment polarities.

IMN-joint (He et al., 2019): An interactive multitask learning network that can be used to learn the multiple related tasks with a message passing architecture in both word-level and document-level.

RACL (Chen & Qian, 2020): This model presents a relation-aware collaborative learning (RACL) framework to model the interactive relations among three subtasks (ATE, OTE, ASC).

DREGCN (Liang, Meng, Zhang, Xu et al., 2021): The model designs a dependency syntactic knowledge augmented interactive architecture with multi-task learning for end-to-end ABSA.

Unified approaches

CRF-unified (Mitchell et al., 2013): The model combines sentiment (SENT) and named entity (TARG) into one label sequence (e.g., O, B+SENT-TARG, I+SENT-TARG).

NN-CRF-unified (Zhang et al., 2015): The enhanced CRF and structural neural models are applied to identify sentiment polarities of all aspect terms based on a unified tagging scheme (B- {+, -, 0}, I- {+, -, 0}, E- {+, -, 0}, Φ).

LSTM-unified (Mao et al., 2021): The standard LSTM is employed for ABSA by adopting the unified tagging scheme.

BG-SC-OE (Mao et al., 2021): Two stacked recursive neural networks are used for ABSA, in which the lower-level neural network is used for auxiliary aspect terms boundary recognition, and the upper-level neural network is for joint tag prediction.

IMN-BERT (Chen & Qian, 2020):A unified method based on BERT-large is proposed for ATE and ASC with separate labels, and OTE task is fused into ATE to explicitly model relations between ASC and OTE, ASC and ATE.

{GRU, SAN, TFM}-BERT (Li, Bing, Zhang, & Lam, 2019): The recurrent neural network (GRU), self-attention network (SAN), transformer layer (TFM) are leveraged based on BERT for ABSA, respectively.

5. Result analysis

5.1. Overall results

We compare the proposed model with the existing ABSA methods on five datasets to verify the superiority of the proposed method, as shown in Table 3. We can see that: (1) Our proposed model obviously outperforms all the other methods on five datasets; (2) Due to the error propagation problem, the pipeline-based approaches perform worse than the joint-based approaches and the unified-based approaches. Additionally, the overall performance of the unified methods is better than that of the joint methods because the former adopts "unified tagging scheme", which eliminates the boundary between ATE and ASC and strengthens the correlation of them; (3) Compared with the dependency syntax-based model DERGCN, our model achieves 1.16%, 5.21% and 1.15% improvement on Laptop14, Restaurant14 and Restaurant15 datasets, respectively. This demonstrates that constructing the block-level syntax relations, rather than the ordinary syntax relations, can effectively improve the performance of sentiment analysis; (4) The models {CMLA, DECNN}-{dTrans} are better than the models {CMLA, DECNN}-{ATAELSTM}, thanks to learning additional sentiment knowledge by introducing document-level tasks for joint training; (5) Utilizing pre-trained language models can significantly enhance the performance of different ABSA models due to the semantic embeddings learned from large corpora. Although models such as {GRU, SAN, TFM}-BERT have achieved good results by leveraging global context information, our model improves more than 1.44% on F1 score comparing to them. This suggests that explicit guidance of aspect-opinion relationships is more important than global context information for ABSA task. What is more, compare with the interactive model IMN-BERT, our model also achieves much improvement on F1 score. Due to neglect the triple relations of ATE, OTE and ASC, IMN-BERT may lead to the underlying false associations between aspect and opinion, and then suffer from the degradation of F1 scores.

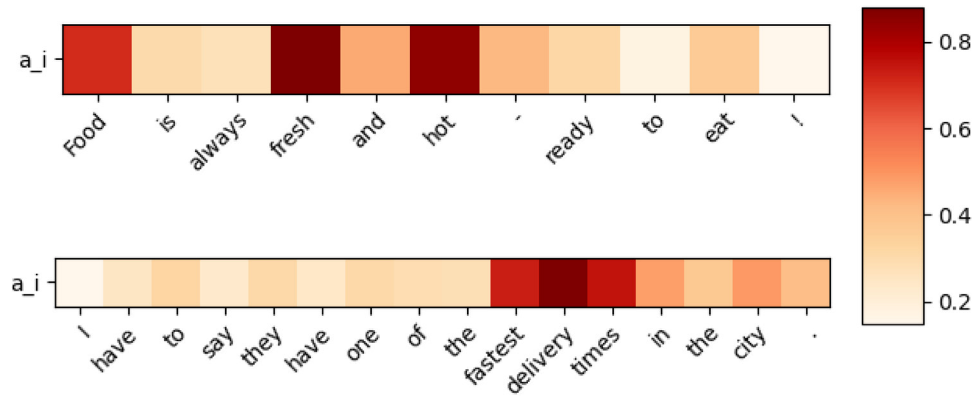

Fig. 4. Visualization of the distribution of aspect-sentiment attention weight α_i, where darker colors indicate higher attention weights.

Table 4
Ablation study on POS and DEP representation(F1 score %).

Model	Rest_ALL	Laptop14
w/o POS & Dep	74.22	61.43
w/o Dep	75.04	61.76
w/o POS	75.16	61.93
Full model	76.53	62.97

5.2. Ablation study

5.2.1. Ablation study on dep and pos representation

In order to show the effectiveness of DEP and POS representations for ABSA, we compare our model with the following three ablation models. The detailed experiment results are shown in Table 4.

w/o DEP: remove the DEP representations from the full model.
w/o POS: remove the POS representations from the full model.
w/o POS&DEP: remove both the POS and DEP representations from the full model.

The experiment results confirm the effectiveness of both POS and DEP representations for ABSA. (1) removing POS representations from our full model resulted in a drop in F1 scores, which may indicate that these representations could provide assistance for aspect and opinion words recognition; (2) The F1 scores drop significantly when we remove the DEP representations, which shows that the DEP representations are more important than the POS representations for ABSA; (3) removing both POS and DEP representations led to a significant performance degradation in both datasets, confirming the effectiveness of these representations in our ABSA model.

5.2.2. Ablation study on block-level dependency syntax

To verify the effectiveness and rationality of block-level dependency syntax, we compare our full model with the following models:

Dep_org: Replace the block-level dependency syntax tags with the original dependency syntax tags.
Dep_A: Modify the dependency syntactic tags by traversing the original sentence sequence instead of sub-sequences, according to the aspect-rule R1.
Dep_O: Modify the dependency syntactic tags by traversing the original sentence sequence instead of sub-sequences, according to the opinion-rule R2.
Dep_AO: Modify the dependency syntactic by traversing the original sentence sequence instead of sub-sequences, according to all rules enumerated in Appendix.

The comparison results on Rest_ALL and Laptop14 datasets are shown in Table 5, and we can make the following observations: (1) Due to the limits of original dependency syntax for recognizing relations of aspect and opinion terms, the F1 scores of Dep_org drop significantly; (2) Comparing Dep_A or Dep_O with Dep_AO, discarding aspect term or opinion term dependency relations will lead to a significant drop on F1 scores; (3) Full model achieves the best performance among all ablation models. Our conjecture is that the proposed block-level dependency syntax comprehensively reflects the internal and mutual relationships of aspect terms and opinion terms, so as to enhance the performance of E2E- ABSA.

Table 5
Ablation study on block dependency syntax(F1 score %).

Model	Rest_ ALL	Laptop14
Dep_org	73.98	61.03
Dep _A	74.56	61.34
Dep _O	74.18	61.10
Dep _A&O	75.29	61.75
Full model	76.53	62.67

Table 6
Ablation study on the interactive attention (F1 score %).

Model	Rest_ALL	Laptop14
w/o IAM	75.44	61.69
w/o IAM _ A	75.56	61.73
w/o IAM _O	76.09	62.14
Full model	76.53	62.67

5.2.3. Ablation study on the interactive attention module

To verify the effectiveness of the interactive attention module, we compare our model with the following three different approaches:

w/o IAM: remove the interactive module from our model.
w/o IAM_A: only employ opinion representations to obtain aspect-sentiment attention distribution for ABSA.
w/o IAM_O: only employ aspect representations to obtain aspect-sentiment attention distribution for ABSA.

The experiment results are shown in Table 6. We can make the following observations: (1) Removing the interactive module leads to a huge drop of F1 score, which suggests that the IAM module is essential in obtaining more accurate sentiment representations, which in turn leads to improved performance in ABSA; (2) comparing w/o IAM_A with w/o IAM_O, the experiment results show that aspect representations play an more important role than opinion representations. Aspect-guided interactive attention is more effective to obtain the aspect-based sentiment representations, and then achieve the higher F1 scores.

In order to show the effect of the BDEP-IAM module, the visualization of the attention weights are illustrated in the following Fig. 4. In these two examples, "food" and "delivery times" are

Table 7
Effective analysis of gating mechanism (F1 score %).

Model	Rest_ALL	Laptop14
Concatenation	76.17	62.43
Gating	76.53	62.67

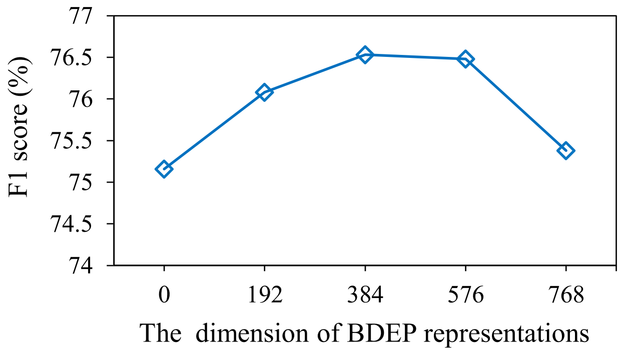

Fig. 5. The F1 scores of different BDEP representation dimension.

the aspect terms respectively; "hot" and "fastest" are the opinion words of "food", and "fastest" is the corresponding opinion word of "delivery times". We can see that: (1) the proposed approach could recognize the aspect and opinion words, e.g., "food", "fresh" and "hot", even when two or more opinion words are given in the first example; and (2) the block-level aspect-opinion words "delivery times" and "fastest" are captured in the second example. The results verify that the BDEP-IAM module has the ability of capturing aspect-opinion relations for ABSA.

5.3. Effectiveness of gating mechanism

In order to verify the effectiveness of gating fusion mechanism in fusing semantic-syntactic representations, two kinds of fusion strategies are adopted.
Concatenation: semantic representations and block dependency syntactic representations are concatenated for final label prediction.
Gating: semantic representations and block dependency syntactic representations are adaptively fused through gating mechanism.
The detailed experiment results are shown in Table 7, which shows that the adaptive gating fusion strategy is more effective than the feature concatenation strategy.

5.4. Effect of the syntactic representation dimension

The dimension of BDEP representations $\mathbf{H}^{\mathbf{D}}$ is an important hyper-parameter in our model. In order to show the effect of BDEP representation dimension for ABSA, we set the dimension as {0, 192,384,576,768}, and the corresponding dimension of POS as {768,576,384,192,0} (see Figs. 5 and 6).
The experiment results show that the performance of our model achieves the highest F1 score when the BDEP representation dimension is 384. Therefore, we choose the dimension of BDEP representation and the corresponding POS representation to be 384 in our model.

5.5. Case study

Table 8 displays the results of two examples in test set. Comparing with the other ABSA methods, our proposed approach could correctly extract the aspect terms and identify their corresponding sentiment polarities. The aspect terms in the two examples are composed of more than one words. Due to the limits of capturing the block-level relations, Dep_org fails to extract the aspect terms. Our model and w/o IAM approaches are able to extract "hot dogs" and "back garden area" correctly, demonstrating that BDEP is helpful to capture the entire aspect terms.

Although both the w/o IAM model and our full model can extract the aspect terms in the second example, the w/o IAM model fails to identify the aspect-oriented sentiment polarity. This may be because the corresponding opinion term "not really nice" of the aspect term "back garden area" is complex, and the model w/o IAM cannot capture it completely, resulting in a mis-prediction of its sentiment polarity as "positive". It indicates that IAM can strengthen the sentiment representation for the overall aspect term, therefore enhance the accuracy of polarity prediction.

6. Conclusion

This paper presented a block-level syntax knowledge guided model to address the fine-grained sentiment analysis problem. The block-level dependency syntax is constructed to capture the potential connection inside and between aspect terms and opinion terms. We successfully deploy the BDEP-guided method to jointly extract aspect terms and identify their corresponding sentiment polarities. The experiment results on four benchmark datasets show that our model can significantly outperforms the state-of-the-art methods. In the further, we plan to explore the application of the BDEP-based approach to other ABSA tasks such as opinion term extraction, aspect-sentiment-opinion triplet extraction, and more. Additionally, we aim to investigate the application of block-level syntax to processing long text, such as internet news.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yan Xiang reports financial support was provided by National Natural Science Foundation of China. Yan Xiang reports financial support was provided by General projects of basic research in Yunnan Province Grant.

Data availability

Data will be made available on request.

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Appendix. Rules settings

Part I: Statistics

We make the following statistics on Rest_ALL dataset: (1) The proportion of multi-word form in aspect terms and opinion terms; (2) The proportion of different POS relations in multi-word aspect terms and opinion terms, and (3) The proportion of different POS relations between aspect and opinion.

Table 8
Case analysis.

Examples	Dep_org		w/o IAM		Full model	
	Aspect	Sentiment	Aspect	Sentiment	Aspect	Sentiment
The [hot dogs] $_{pos}$ were good but the buns were stale.	dogs (✗)	[dogs] $_{neg}$ (✗)	hot dogs	[hot dogs] $_{pos}$	hot dogs	[hot dogs] $_{pos}$
In the summer months, the [back garden area] $_{neg}$ is not really nice.	back garden(✗)	[back garden] $_{pos}$(✗)	back garden area	[back garden area] $_{pos}$(✗)	back garden area	[back garden area] $_{neg}$

Note: "[ ]" indicates the boundary of an aspect term. The marker ✗ denotes the incorrect prediction.

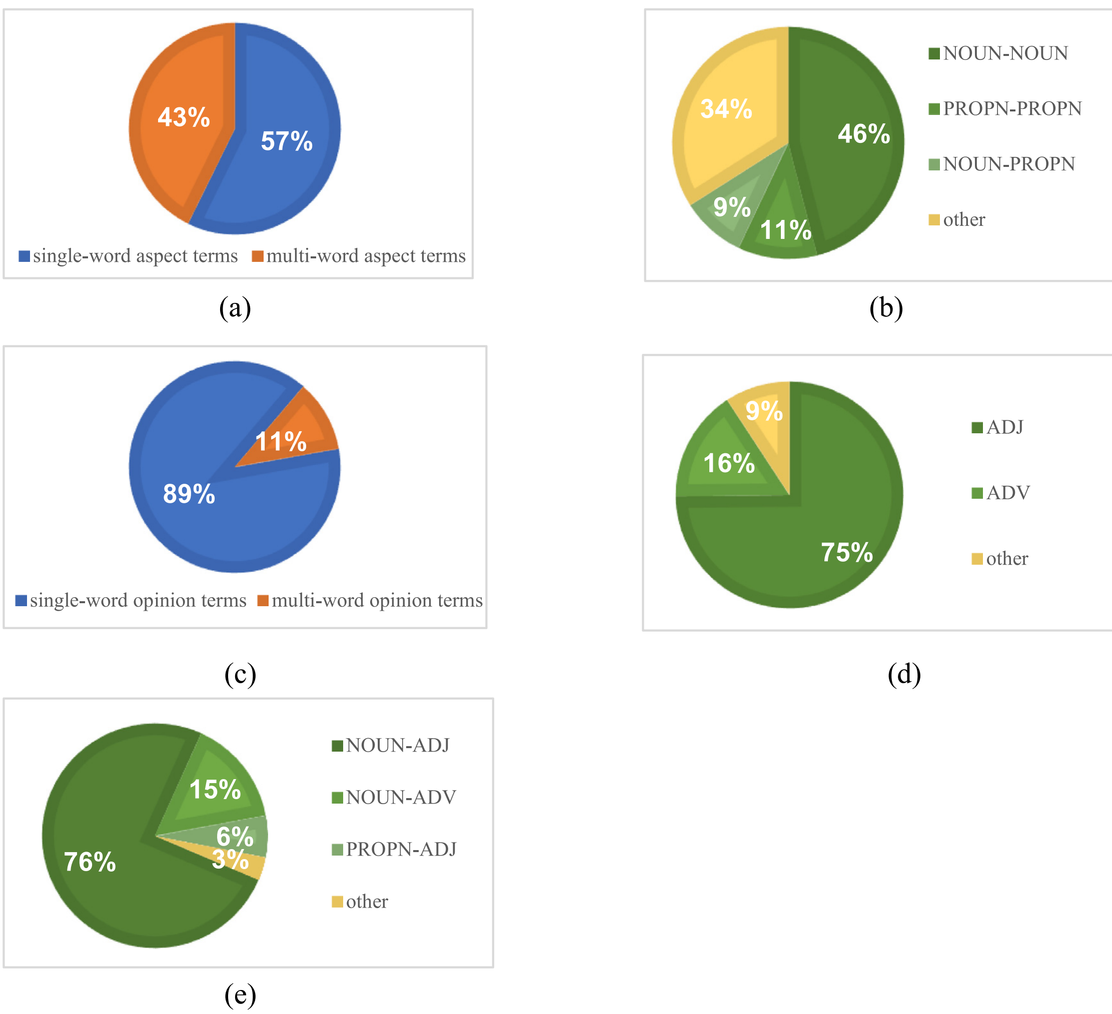

Fig. 6. Statistics on Rest_ALL dataset. (a) The proportion of single-word and multi-word aspect terms; (b) The proportion of different POS relations in multi-word aspect terms; (c) The proportion of single-word and multi-word opinion terms; (d) The proportion of different POS relations in multi-word opinion terms; (e) The proportion of different POS relations between aspect and opinion.

Part II: Rules

According to the above statistics, we design a set of rules $\mathcal{R}$={R1, R2, R3}, where an arrow indicates a syntactic dependency arc from a head node to a tail node. R1 and R2 are used to recognize multi-word aspect terms and opinion terms respectively; R3 is used to recognize aspect-opinion connection (see Table 9).

Table 9
Rule summary.

RuleID	Rules	Example
R1	NOUN → NOUN	The **wine list** is interesting. (list → wine)
	PROPN → PROPN	I like how the **Mac OS** is so simple and easy to use. (OS → Mac)
	PROPN → NOUN	The **Internet Explorer** was very slow from the very beginning. (Explorer → Internet)
	NOUN → PROPN	The **Thai food** is good. (food → Thai)
R2	ADJ → ADJ	Every pie is **ultra fresh**. (ultra → fresh)
	ADV → ADV	The dessert was **so so**. (so → so)
	ADJ → ADV	The prices are **wonderfully low**. (low → wonderfully)
	ADV → ADJ	All the bagels are **unbelievably good**. (unbelievably → good)
	NOUN → ADJ	The rice was **poor quality**. (quality → poor)
	ADJ → PART	The food was **not fresh**. (fresh → not)
R3	ADJ → NOUN	The **ceiling** is **amazing**! (amazing → ceiling)
	NOUN → ADJ	They have **nice dessert**. (dessert → nice)
	NOUN → ADV	Within a few hours I was using the **gestures unconsciously**. (gestures → unconsciously)
	ADJ → PROPN	The **MacBook** is **outstanding**. (outstanding → MacBook)
	PROPN → ADJ	**Best Pastrami** I ever had and great portion without being ridiculous. (Pastrami → Best)

Note: In column "Example", the red bold font denotes aspect, and the black bold fond denotes opinion.

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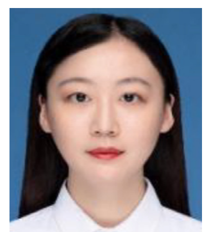

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