Journal of Internet Technology Vol. 26 No. 2, March 2025 199

A Span-based Enhanced Bidirectional Extraction Framework for Multi-word Aspect Sentiment Triplets

Geng Liu[1], Yingsi Zhao[2], Bo Shen[1,3]*

[1] School of Electronic and Information Engineering, Beijing Jiaotong University, China
[2] School of Economics and Management, Beijing Jiaotong University, China
[3] Key Laboratory of Communication and Information Systems, Beijing Municipal Commission of Education, China
geng-liu@foxmail.com, yszhao@bjtu.edu.cn, bshen@bjtu.edu.cn

Abstract

Aspect Sentiment Triplet Extraction (ASTE), aiming to jointly identify all the aspect terms, opinion terms and their corresponding sentiment polarities simultaneously, is a most recent fine-grained sentiment analysis subtask. There are two main categories of ASTE methods, named pipeline approaches and tagging-based joint extraction approaches. The former suffers from error propagation and the latter fail to handle one-to-many and many-to-one problems in triples. In order to address these issues, we propose a span-based enhanced bidirectional extraction framework. The framework utilizes all possible candidate spans as input and adopts syntactic dependency tree to fully explore sentence features. The proposed model extracts triples bilaterally from two directions, to handle multi-word triples and complex correspondence problems between aspects and opinions. In our framework, dual-channel pruning strategy is introduced to choose the correct spans. Meanwhile, bidirectional transformer-based decoders are proposed to model the association among spans and then to extract corresponding triplets. Experiments on four benchmark datasets indicate that our framework reveals significant performance improvement compared to the current state-of-the-art model, especially in predicting triplets with multi-word targets or opinions.

Keywords: Aspect-based sentiment analysis, Span-based model, Syntactic dependency tree, Bidirectional extraction, Multi-word

1 Introduction

Sentiment analysis aims to automatically identify and analyze the emotional tendencies contained in the text, which is one of the important tasks in NLP. And aspect-based sentiment analysis (ABSA) consists of several different subtasks [1-4], which aims to identify more detailed and comprehensive emotional information in the review sentences. For instance, "*It feels cheap, the keyboard is not very sensitive.*". The subtask aspect term extraction (ATE) [5-7] pays attention to recognize aspect terms "keyboard", opinion term extraction (OTE) [8-10] focus on extracting the opinion terms "cheap" and "not very sensitive", and aspect sentiment classification (ASC) [11-14, 47] aims to forecast the sentiment polarity of the provided aspect term: "keyboard (Negative)".

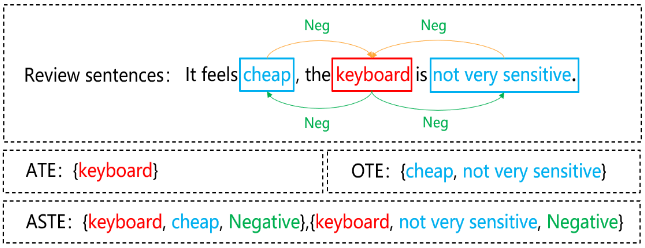

Figure 1. The example of the different ABSA subtasks (Aspects, opinions and sentiment polarities are marked with blue, red and green respectively.)

Many research efforts have been made on ABSA, which generally focus on the prediction of a single element or co-extract them together such as aspect polarity coextraction (APCE) [15] and aspect-opinion pair extraction (AOPE) [16-17]. These methods neglect the association of sentiment elements and fail to provide more comprehensive insights into the review sentences. To tackle this problem, more recent works propose the target-oriented opinion word extraction (TOWE) [18-19] and ASTE [20-25] which aim to extract multiple associated sentiment elements to provide a more detailed sentiment information. As shown in Figure 1, there are two sentiment triplets: ("keyboard", "cheap", Negative) and ("keyboard", "not very sensitive", Negative).

Some initial researches formulated the ASTE task as the two-stage method [26-27]. The first stage not only identifies aspect terms and corresponding sentiments polarity, but also opinion terms. And in the second stage, aspects and opinions are coupled to determine the corresponding sentiment. However, the pipeline method neglects the interaction within the triplets and fails to deal with the error propagation problem. The previous approaches to ASTE were the sequence tagging problem [28-29], but they fail to handle one-to-many and many-to-one problems in triples. Although the recent researches in an end-to-end manner [20, 22, 30-32] can jointly extract sentiment elements as a triplet, they heavily depend on the interactions between aspects and opinions, and fail

*Corresponding Author: Yingsi Zhao; E-mail: yszhao@bjtu.edu.cn
DOI: https://doi.org/10.70003/160792642025032602005

to deal with aspects and opinions containing multi-word. In addition, they neglect the syntactic information in the sentence.

In order to tackle the above issues, we propose a span-based enhanced bidirectional extraction network to generate triplets in the sentences. First, the proposed framework generates all possible spans on the sentence as the candidates. Meanwhile, we utilize syntactic dependency trees to fully mine syntactic features in sentences, and then transmits these features to the follow-up subtasks. To remove the incorrect spans, we utilize dual-channel pruning strategy to distinguish the candidate aspect and opinion terms. Subsequently, the dual transformer-based decoders take in two candidate spans and their corresponding local context to efficiently extract sentiment triplets. According to the combination of syntactic and semantic information, the one-to-many and many-to-one problem can be better processed. Moreover, negative sampling method is adopted to improve the robustness of the model during the training process.

In summary, the following are the main contributions of the paper:

• We propose a span-based enhanced bidirectional extraction network to explicitly harvest triplets in the sentences. This framework effectively mitigates the issue of error propagation in the recent research. Additionally, we carry out extensive analysis to reveal its effectiveness not only on multi-word entities but also on one-to-many and many-to-one problem in sentiment triples.

• We leverage syntactic dependency trees to integrate syntactic information into contextualized language models and adopt dual-channel pruning strategy to distinguish the candidate terms. Meanwhile, by the bidirectional extraction framework consist of multi-head attention mechanisms, our model can fully take advantage of semantic information in the sentences, and bidirectionally establishes associations among potential triplets. Moreover, the proposed model can exactly extract triples through the combination of syntactic and semantic information.

• We carry out extensive experiments on multiple ABSA benchmark datasets to indicate the effectiveness of our model. Compared to the current state-of-the-art model, our method can achieve better performances for ASTE task.

2 Related Works

ABSA can extract core sentiment triplets in sentences and provide more fine-grained sentiment analysis. We introduce the related work from the following three parts in this section.

2.1 Pipeline Approaches

The most recent ABSA researches only focus on the single element or the combination of them. As the name suggests, the pipeline approaches, following a straightforward two-stage method, involves initially extracting aspects and subsequently identifying the corresponding opinions for each aspect. To provide more sentiment information, Peng et al. [27] extended Wang et al. [33] and Dai et al. [34], first proposed ASTE task aiming to extract aspect, opinion terms and the corresponding sentiments in the two-stage pipeline. Gao et al. [35] first employ an MRC model to extract all aspect terms, and then construct the other MRC model to predict opinion term for each extracted aspect term. Although Chen et al. [36] Mao et al. [37] all achieve good performance, the pipeline-style method fails to address the error propagation problem.

2.2 Tagging-based Joint Extraction Approaches

To tackle the error propagation problem, many scholars have proposed the tagging based joint extraction method in end-to-end manners. Compared with Peng [27], Xu et al. [28] introduce the JET model, which incorporates position and sentiment polarity tags to consider word interactions. However, this model falls short in leveraging the mutual correspondence between aspects and opinions. To enhance the model's performance, Wu et al. [29] propose a grid tagging scheme (GTS), which generates triplets in the end-to-end manner with the unified TokenClass problem. GTS limited by the model, only depends on the interaction between each words and fails to handle multi-word situations. Li et al. [38] achieve promising results by only using a simple neural model with the unified tagging scheme.

2.3 Span-based Approaches

Although the tagging-based method effectively mitigates error propagation, it overlooks the internal correlations between aspect and opinion terms, can't deal with complex triplets with multi-word targets. More recent works focus on span-based approaches [23, 39] to ASTE which fully consider the relationships between them and fuse semantic information. To address these limitations, Zhao et al. [17] treat the problem as a multi-task learning task based on the supervision of span boundaries and utilize the span representations to jointly extract the sentiment target pair. Similarly, Xu et al. [22] introduce a span-level interaction model that explicitly takes into account the internal interaction between aspect and opinion spans during the prediction of the corresponding sentiment polarity. This approach enhances the model's ability to capture the nuanced correspondence between aspects and opinions, resulting in improved sentiment polarity prediction. Compared with the previous complex models, it achieves good results with only a simple model. To simultaneously extract multiple over-lap or multi-word triplets, we design a span-based enhanced bidirectional extraction network to jointly generate triplets. The detailed description is presented in Section 3.

3 Methodology

In this section, we begin by providing the task definition of the ASTE. Subsequently, we elaborate on the proposed framework, outlining its components and methodology.

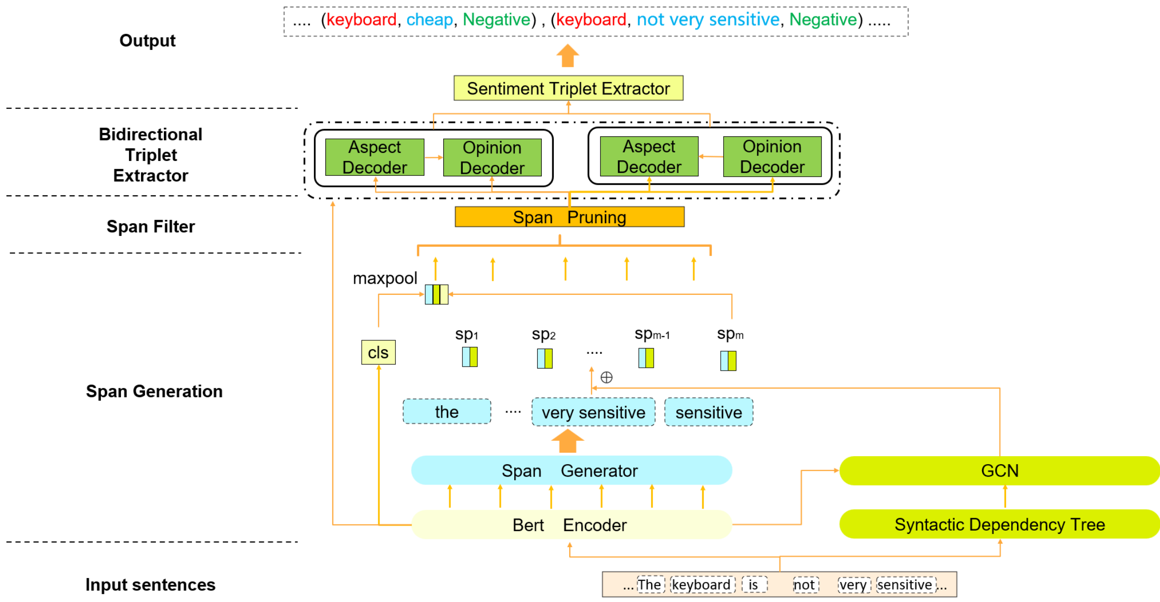

Figure 2. Overview of our span-based enhanced bidirectional extraction framework
(The blue, green and yellow squares represent the span features, the contextual syntactic features and the global context respectively. Then they are fed into span filter through the max pooled layer to extract candidate sentiment triplets.)

3.1 Task Definition

We denote a review sentence with n tokens as $S = \{x_1, x_2, \ldots, x_n\}$, we aim to extract all expected triplets $T = \{(a, o, s)_i\}_{i=1}^{|T|}$, where a, o and s denote aspects, opinions, the sentiment and $|T|$ indicates the total number of triplets respectively. Meanwhile, sentiment polarity $sc \in \{Positive, Negative, Neutral, O\}$.

3.2 Model Architecture

Overview of the span-based enhanced bidirectional extraction framework is shown in Figure 2. The framework contains the following five modules: the encoding module, the syntactic dependency module, the span generator, the span filter, and the bidirectional triplet extractor. It leverages the BERT encoder to get the contextual semantic representation from an input sentence and acquire syntactic dependency information from the syntactic dependency tree. Subsequently, we incorporate syntactic information into contextual representation to augment semantic features. Meanwhile, the span generator generates all spans and the span filter reduce the candidate spans without aspect or opinion terms. Finally, the candidate spans and the hidden representations sequence H are fed into the bidirectional triplet extractor. The bidirectional triplet extractor consists of two decoder module which each module contains an aspect and opinion decoder. Dual-decoders output the different sentiment triplets for the given specific terms respectively to implement ASTE task.

3.3 Encoding

3.3.1 Sentence Encoding

To leverage the semantic context representation, we employ the BERT encoder [40] on the sentence S with n tokens to generate the hidden representations $H = \{h_1, h_2, \ldots, h_n\}$. There are m possible spans, and each span $s_i = \{x_{start(i)}, \ldots, x_{end(i)}\}$ can be the single word or the multiple words from start(i) to end(i).

$$1 \le start(i) \le end(i) \le n \qquad \textbf{(1)}$$

$$0 \le end(i) \le start(i) \le L_s \qquad \textbf{(2)}$$

where L_s is the max length of span s_i. We can reduce the number of spans by modifying the value of L_s, and different values lead to different experimental results. Detailed results are presented in Section 4.

3.3.2 Syntactic Constituents

The interaction between different words in a sentence is an important clue for us to extract sentiment triples. However, their complex relationship can pose a major challenge [41]. The recent researches adopt attention mechanism [30] to reduce the interference between different words, but can fail to deal with complex triples. As shown in Figure 1, the opinion term “not very sensitive” is a holistic expression of negative emotions. However, more attentions are paid to “very sensitive” and the important turning word “not” which leads to an incorrect sentiment prediction are ignored. Meanwhile, it is possible that the attention mechanism allocates more attention to incorrect opinion terms due to their proximity, rather than focusing on the correct opinion terms.

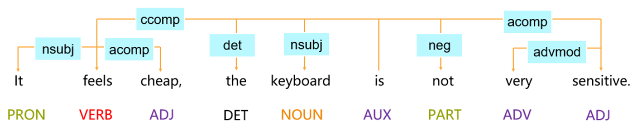

Figure 3. An example of the syntax dependency tree

As shown in Figure 3, a syntax dependency tree can offer the dependency relation between aspect–opinion pairs. To address the above issues, we utilize the syntax dependency tree to extract contextual syntactic features of sentences and introduce graph convolutional networks (GCN) [42] to learn syntactic information between words. For the directional graph $G = (V, E)$, where V is the set of N nodes and E is the set of edges, the graph serves as a representation of words and their dependency relations. Each node in the graph represents a word from the sentence, and the edges between different nodes represent their respective dependency relationships. We build the adjacency matrix $A \in R^{n\times n}$ over the syntax dependency tree. The element a_{ij} in A indicates whether the i-th node is connected to the j-th node. Specifically, $a_{ij} = 1$ if $i = j$ or the i-th node and the j-th node is connected, otherwise $a_{ij} = 0$.

$$a_{ij} = \begin{cases} 1\ if\ \ i = j\ or\ i - jth\ node\ is\ connected \\ 0 \qquad\qquad otherwise \end{cases} \tag{3}$$

The hidden state representation, denotes as g_i^l, for the i-th node at the l-th layer is updated as follows:

$$g_i^l = RELU(\sum\nolimits_{j=1}^{j\in N} a_{ij} W^l g_j^{l-1} + b^l) \tag{4}$$

where W^l represents the trainable weight matrix specific to the l-th layer, b^l represents a bias term and g_j^0 refers to the word embedding for the j-th node.

3.4 Span Generation and Pruning

3.4.1 Span Generation

To address the intricate relationships between aspects and opinions, we enumerate all spans, considering an appropriate length constraint. These spans can consist of the single word or multiple phrases. The multiple consecutive spans can be repeatedly selected as the candidate aspects or opinions which leads to address the challenge of multi-word terms. In addition, we concatenate the BERT representation h_i^l with the GCN representation g_i^l to fuse contextual semantic and syntactic information into new representations hg.

In order to acquire the span vector representation, we employ the maxpool to generate the hidden representation with token.

$$s_i = \max pool(hg_{start(i)}, ..., hg_{end(i)}) \tag{5}$$

The complete span representation is expressed as $S_p = S_1, S_2, \ldots, S_m$.

3.4.2 Dual-channel Span Pruning

We enumerate all spans as input to utilize semantic information in the review sentence for the potential triples extraction, but the increasing input size of the model inevitably results in the huge computational cost. The previous researches [43-44] only filter all spans into the same pool which can lead to the insufficient use of the semantic information between aspects and opinions. In contrast, we utilize the dual-channel pruning strategy to filter aspects and opinions into two separate pools which reduce computational costs significantly. Specifically, the pruning process can be converted to the binary classification problem, and all candidate spans are respectively filtered into two candidate pool by ATE and OTE according to the calculated probability.

$$\Phi_{aspect}(s_i) = soft\max(W_a[s_i; C_{cls}] + b_a) \tag{6}$$

$$\Phi_{opinion}(s_i) = soft\max(W_o[s_i; C_{cls}] + b_o) \tag{7}$$

where W_a, W_o represent weight parameters, and b_a and b_o represent bias terms. C_{cls} is the hidden state of the token "[CLS]" of the entire sentence context, and it combines with span s_i as input.

Meanwhile, we can formulate the cross-entropy loss function as loss function for the span filter:

$$J_{SP} = -\sum\nolimits_i^m P(y_i^* | s_i) \cdot \log(P(y_i | s_i)) \tag{8}$$

where $P(y_i|s_i)$, $P(y^*_i|s_i)$ are the predicted distribution and gold distribution respectively.

3.5 Bidirectional Triplet Extractor

To use the semantic and syntactic information in the sentence, we design a bidirectional triplet extractor to bidirectionally extract triples. Compared with the previous extraction in one direction, the bidirectional triplet extractor can obtain more complete triples. In the subsequent sections, we delve into the specifics of the two decoders.

The Opinion-to-Aspect Decoder. The O-A decoder is composed of opinion decoder and aspect decoder, aspect decoder extracts the aspect term, opinion decoder extracts all opinions terms of the given aspect and corresponding sentiments. The aspect decoder is responsible for predicting all the possible aspects. Firstly, it employs multi-head self-attention mechanism to capture the relationships among the potential aspects. Subsequently, it utilizes the multi-head inner attention mechanism to integrate the semantic information into candidate spans. The representation of the result obtained from the multi-head self-attention mechanism is shown as follow:

$$\alpha_i^{OA,as,self} = \frac{\exp(s_i)}{\Sigma_{s_j \in s_p^a} \exp(s_j)} \tag{9}$$

$$s_i^{OA,as,self} = \Sigma_{s_j \in s_p^a} \alpha_i^{OA,as,self} \cdot s_j \tag{10}$$

where S_p^a represents the aspect spans through span filter.

To further use the semantic information, the hidden representations sequence H is also fed into multi-head inner attention mechanism with the $s_i^{OA,as,self}$. The result is shown as follow:

$$u_i^{OA,as,inner} = FFNN^{OA,as,inner}(s_i^{OA,as,self}, \theta^{OA,as,inner}) \quad (11)$$

$$\alpha_i^{OA,as,inner} = \frac{\exp(u_i^{OA,as,inner})}{\Sigma_{h_j \in H} \exp(h_j)} \quad (12)$$

$$s_i^{OA,as,inner} = u_i^{OA,as,inner} + \Sigma_{h_j \in H} \alpha_i^{OA,as,inner} \cdot h_j \quad (13)$$

where $\theta^{OA,as,inner}$ indicates the parameter for FFNN in the multi-head inner attention mechanism.

Similarly, the opinion decoder also comprises a multi-head self-attention mechanism and a multi-head inner attention mechanism. However, the opinion decoder incorporates an additional attention mechanism to establish the interactions between the given aspect and the candidate opinion spans. The multi-head aspect attention mechanism aims to generate all candidate opinions for the potential aspect. In short, the whole calculation process is as follows:

$$s_i^{OA,op,self} = \Sigma_{s_j \in s_p^o} \alpha_i^{OA,op,self} \cdot s_j \quad (14)$$

$$s_i^{OA,op,inner} = u_i^{OA,op,inner} + \Sigma_{h_j \in H} \alpha_i^{OA,op,inner} \cdot h_j \quad (15)$$

where $s_i^{OA,op,self}$ and $s_i^{OA,op,inner}$ represent the results of the multi-head self-attention mechanism and multi-head inner attention mechanism respectively. And S_p^o represents the opinion spans through the span filter.

$$u_i^{OA,as,res} = FFNN^{OA,as,res}(s_i^{OA,op,inner}, \theta^{OA,op,res}) \quad (16)$$

$$\alpha_i^{OA,op,res} = \frac{\exp(u_i^{OA,op,inner})}{\exp(s^{as})} \quad (17)$$

$$s_i^{OA,op,res} = u_i^{OA,op,res} + \alpha_i^{OA,op,res} \cdot s^{as} \quad (18)$$

where $\theta^{OA,op,res}$ denotes the parameter in the multi-head inner attention mechanism. And s^{as} is the given specific aspect term.

The Aspect-to-Opinion Decoder. The O-A decoder shares similarities with the A-O decoder, it's also composed of an aspect and opinion decoder. The opinion decoder is responsible for extracting the opinion term, while the aspect decoder is designed to generate all aspects associated with the given opinion, along with their corresponding sentiments. This decoder allows the model to capture the relationships between opinion and aspect terms bidirectionally, enhancing its understanding of the target sentiment expressed towards different aspects. The difference is that the aspect decoder has an additional multi-head attention mechanism than the opinion decoder, and we adopt the multi-head opinion attention mechanism to extract all candidate aspects for a given opinion term. The results are as follows:

$$s_i^{AO,op,self} = \Sigma_{s_j \in S_p^o} \alpha_i^{AO,op,self} \cdot s_j \quad (19)$$

$$s_i^{AO,op,inner} = u_i^{AO,op,inner} = \Sigma_{h_j \in H} \alpha_i^{AO,op,inner} \cdot h_j \quad (20)$$

$$s_i^{AO,as,self} = \Sigma_{s_j \in S_p^a} \alpha_i^{AO,as,self} \cdot s_j \quad (21)$$

$$s_i^{AO,as,inner} = u_i^{AO,as,inner} = \Sigma_{h_j \in H} \alpha_i^{AO,as,inner} \cdot h_j \quad (22)$$

$$s_i^{AO,as,res} = u_i^{AO,as,res} = \alpha_i^{AO,as,res} \cdot s^{op} \quad (23)$$

where s^{op} and $s_i^{AO,as,res}$ represent the given specific opinion term and the result of the multi-head opinion attention mechanism, respectively.

In order to extract the final triplets, the outputs of two decoder are fed into the sentiment triplet extractor respectively. Each decoder's output is normalized using the softmax function, which assigns probabilities to the labels of the triplets. The triplets with the highest probabilities are then extracted as the final results.

$$q_i = FFNN(s_i^{res}, \theta) \quad (24)$$

$$p(sc|s_i) = soft\max(q_i) \quad (25)$$

where s_i^{res} indicates the two final results of the decoders respectively, θ is the parameter of the FFNN.

3.6 Inference

The two designed decoders can output the different triplets for the given specific terms, so we propose an inference strategy to deal with it, which remove the conflicting sentiment triplets according to the probability of the term label.

Meanwhile, we also adopt negative sampling method [45-46] to improve the robustness of the model. In the real-world scenarios, triplets usually contain more complex expressions. Compared to the previous approaches which fail to handle the complex correspondence between aspects and opinions, the proposed model learns the difference between positive and negative samples so that it can handle triplets with multi-word targets or opinions in real-life scenarios.

In the span filter, the positive samples are the spans labeled as aspects or opinions. On the other hand, the negative samples, denoted as N_{ns}, are randomly selected from the spans without the labeled. These negative samples represent spans that are not associated with the target entities and serve as contrast examples to help the model learn to distinguish between positive and negative instances. In the sentiment triplet extractor, the correct predicted triplets are labeled as the positive samples, and the remaining unmatched are used as the negative samples. It is worth noting that although negative samples are randomly selected, we averagely select multi-word samples and single-word samples to form negative samples together which make the model to learn multi-word information in sentences. If any part of the sample is not enough, fill it up from the other part. In the training process, we generate the different samples and train the model to identify the difference between them to optimize the performance of model.

3.7 Training Procedure

The proposed model is trained using an end-to-end framework, and the loss function for the training is defined as the sum of the span filter loss and the sentiment triplet extractor loss.

For the O-A decoder, the loss function is defined as cross-entropy cost function:

$$J_{OA} = -\sum_{i}^{m} P_{as}^{OA}(sc^{*}|s^{i})\log(P_{as}^{OA}(sc|s^{i})) - \sum_{i}^{m}\sum_{j}^{s_p^{a*}} P_{op}^{OA}(sc^{*}|s^{i},s_j^{a})\cdot P_{op}^{OA}(sc|s^{i},s_j^{a}) \tag{26}$$

In the same way, for the A-O decoder, the loss function is also defined as follow:

$$J_{AO} = -\sum_{i}^{m} P_{op}^{AO}(sc^{*}|s^{i})\log(P_{op}^{AO}(sc|s^{i})) - \sum_{i}^{m}\sum_{j}^{s_p^{o*}} P_{as}^{AO}(sc^{*}|s^{i},s_j^{o})\cdot P_{as}^{AO}(sc|s^{i},s_j^{o}) \tag{27}$$

where $P_{as}(sc^{*}|si)$ and $P_{op}(sc^{*}|si)$ are the gold distribution, and $P_{as}(sc|si)$ and $P_{op}(sc|si)$ represent the predicted distribution. Moreover, S_p^{a*} and S_p^{o*} indicate the gold truth of the aspects and opinions.

Eventually, the loss function of entire framework has the following form:

$$J = J_{SP} + J_{OA} + J_{AO} \tag{28}$$

Table 1. Statistics on ASTE-Data-V2 dataset

(#S and #T denotes the number of sentences and triplets. #+, #0 and #- denote the numbers of positive, neutral and negative samples. #SW denotes the numbers of triplets which aspects and opinions are all single word. #MW denotes the numbers of triplets with the aspects or opinions are multi-word.)

Datasets		#S	#T	#+	#0	#-	#SW	#MW
14LAP	Train	906	1460	817	126	517	824	636
	Dev	219	346	169	36	141	190	156
	Test	328	843	364	63	116	291	252
14RES	Train	1266	2338	1692	166	480	1586	752
	Dev	310	577	404	54	119	388	189
	Test	492	994	773	66	155	657	337
15RES	Train	605	1013	783	25	205	678	335
	Dev	148	249	158	11	53	165	84
	Test	322	485	317	25	143	297	188
16RES	Train	857	1394	1015	50	329	918	476
	Dev	210	339	252	11	76	216	123
	Test	326	514	407	29	78	344	170

4 Experiments

4.1 Datasets

We carry out extensive experiments on four benchmark datasets [28] derived from the SemEval Challenges [2-4] and another research [8]. Compared to the ASTE-Data-V1 [27], ASTE-Data-V2 transforms the triplets without annotation into the missing, removes the conflicting triplets and contains more complex expressions which are more common. Detailed information is shown in Table 1.

4.2 Experiment Settings

In the experiments, the encoder used in the model is the uncased base version of BERT. According to multiple comparative experiments, we set the batch size and the dropout rate to 16 and 0.1, respectively. To determine the optimal combination of parameters, a grid search is performed. The parameters that are varied during the grid search include the maximum length of spans L_S, the pruning threshold z, the number of negative samples N_{ns}. Moreover, we employ AdamW [48] with a fixed learning rate of 1e-5 to update the model parameters during optimization.

4.3 Baselines

We conduct extensive experiments to compare our models with the following baselines:

• Peng-two-stage [27]: Peng proposed a two-stage framework to generate triplets in the sentences. In the first stage, Peng extracts both aspect terms, sentiment polarity and opinion terms. In the second stage, each aspect sentiment pairs are combined with the corresponding opinion terms.

• JET [28]: Xu utilizes unified location-aware labeling scheme which adds location and sentiment information to address the ASTE as a structured prediction task. There are two variants of JET: JET_t and JET_o .

• GTS [29]: GTS is a tagging-based method which deal with ASTE as a grid tagging task in the end-to-end way. It first gets the initial prediction probabilities of each word pair, and then assigns the specific sentiment dependency for them to perform the final prediction.

• Span-ASTE [22]: Xu proposed the Span-ASTE framework which considers all spans in the sentence to learn the interactions between aspects and opinions. Meanwhile, to reduce the high computational cost, they proposed a dual-channel pruning strategy which improves computational efficiency significantly.

• BMRC [36]: Chen performs the ASTE as the multi-turn machine reading comprehension task which design two extraction queries and the classification queries to extract triplets.

4.4 Main Results

4.4.1 Effect of ASTE

The results of our framework and the baseline models are presented in Table 2, showcasing the Precision (P.), Recall (R.), and F1 scores for each dataset. From the table, our framework demonstrates state-of-the-art performance across all datasets.

As shown in the Table 2, the joint extraction models usually achieve better performance than the pipeline models. This improvement in performance can be attributed to the end-to-end manner which mitigates the error propagation problem arised in pipeline models. Compared to GTS fail to handle multi-word triples and one-to-many and many-to-one problems between aspects and opinions for its semantical annotation, our model can address the entity overlap problem by fully considering the interaction between them. BMRC and Ro-BMRC implement the ASTE as a multi-turn machine reading task and extract sentiment triplets via multiple queries. However, the error propagation within subtasks may decrease final performance. Unlike those approaches, our method fuses syntactic and semantic information, and utilizes the span-level interactions to address ASTE task from bidirectional directions, which can solve entity overlap problem and avoid the cascading errors.

Specifically, our framework outperforms the previous best baselines on ASTE. Although some of the precise scores are slightly lower than BMRC, the significant increasement in other scores demonstrates the superior performance of our framework in the ASTE task.

Table 2. The overall experimental performance (%) on the different set (The best scores are in bold.)

Model	14LAP			14RES			15RES			16RES		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Peng-two-stage	40.41	47.25	43.51	44.19	63.00	51.90	40.98	54.69	46.80	47.77	62.98	53.63
JET_t	53.54	43.29	47.87	63.45	54.13	58.42	**68.21**	42.90	52.67	65.29	51.96	57.86
JET_o	55.40	47.34	51.05	70.57	55.95	62.41	64.46	51.97	57.52	**70.42**	58.38	63.82
GTS	57.31	50.87	54.52	69.88	69.85	70.11	59.36	58.32	57.99	67.56	67.02	68.13
Span-ASTE	63.33	54.87	60.03	72.54	70.26	71.95	62.38	**64.25**	63.17	69.77	71.09	70.44
BMRC	**67.92**	51.36	59.47	71.89	66.21	69.85	66.56	56.36	58.62	68.43	66.71	67.19
Ours	66.81	**56.98**	**61.51**	**74.88**	**70.64**	**72.70**	65.93	63.07	**64.47**	70.36	**72.29**	**71.31**

Table 3. Analysis on triplets with multi-word aspects or opinions in the ASTE

Model	14LAP			14RES			15RES			16RES		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
GTS	52.27	41.26	46.13	56.86	49.26	52.78	50.28	47.34	48.77	56.63	55.28	55.96
Span-ASTE	54.63	44.44	49.02	61.64	55.79	58.57	50.70	57.45	53.87	62.43	63.53	62.97
BMRC	54.43	43.11	45.32	61.24	56.33	59.12	51.48	57.26	53.92	**67.32**	64.76	58.61
Ours	**55.81**	**44.74**	**49.67**	**62.47**	**57.34**	**60.34**	**52.76**	**58.24**	**55.37**	65.78	**65.95**	**65.86**

Table 4. Experimental results of ablation study

(The symbol ↓ (↑) are employed to indicate the change over the effect of our model. The n-s method denotes the negative sampling method.)

Model	14LAP	14RES	15RES	16RES
	F1	F1	F1	F1
Full model	61.51	72.70	64.47	71.31
w/o O-A decoder	58.37(↓3.14)	69.28(↓3.42)	60.18(↓4.29)	67.22(↓4.09)
w/o A-O decoder	59.41(↓2.10)	70.43(↓2.27)	61.67(↓2.80)	68.47(↓2.84)
w/o n-s method	59.62(↓1.89)	70.49 (↓2.21)	61.86(↓2.61)	68.58(↓2.73)

4.4.2 Effect of Multi-word Triplets

We conduct experiments on the multi-word sentiment triplet which contains at least one multi-word aspects or opinions for the ASTE task. As shown in Table 3, multi-word triplets pose a great challenge to all models. It is obvious that there is a significant decreasement in the model's performance compared to the above. However, our model still achieves the better performance on almost all datasets. The main reason is that we address the complex correspondence between aspects and opinions, and fully consider the interrelationship between word span and multi-word spans. Meanwhile, to solve the challenge of traditional labeling tasks, we enumerate all possible spans, not only focusing on the relationship between each word, which is beneficial to the extraction of multi-word spans. In addition, we also adopt the negative sample method, which fully considers the syntactic information of multi-word spans.

4.5 Ablation Analysis

We conduct ablation analysis on 14LAP datasets to validate the origination of our designed modules. From the Table 4, our enhanced bidirectional model outperforms unidirectional models, which clearly indicates the superiority of the collaboration in both A-O and O-A directions. No matter which direction the decoder is removed, the performance of our model will drop significantly. The average F1 score on four sub datasets decreases by 3.74% when the O-A decoder is removed. Similarly, the average F1 score decreases by 2.50% when the A-O decoder is removed. This could be caused by the more sentiment information in aspect spans than in opinion spans. Meanwhile, the average F1 score decreases by 2. 36% when the negative sampling method is removed. Experiments show that the negative sampling method can effectively extract sentiment information in the sentence.

4.6 Parameter Sensitivity

In this section, we utilize grid parameter adjustment to analyze the effects of the three hyperparameters on our proposed model. Specially, to ensure the effect of the certain hyperparameters, we fix the others, just adjust one for the experiments.

The maximum span length L_S. To investigate the performance with different entity lengths, we modify L_S in the range of [2, 9] with a step of 1. In Figure 4, we observe that the proposed model is gradually improved with the gradual increase in the maximum span length. Furthermore, the performance of the extraction task tends to plateau and even fall when the L_S reaches 6. Therefore, taking into account the training time and performance, it suggests that setting L_S to 6 can be the optimal choice.

The Dual-channel Pruning Threshold z. For the sentence with n tokens, the number of aspect and opinion candidate spans are both limited to n_z , so that the computational cost varies with the change of the threshold z obviously. As illustrated in the Figure 5, the average performance of model increases with z and stabilizes at 0.5, so we select z = 0.5.

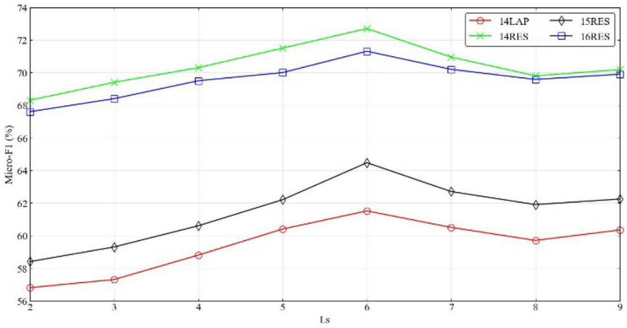

Figure 4. Study on the maximum span length L_S

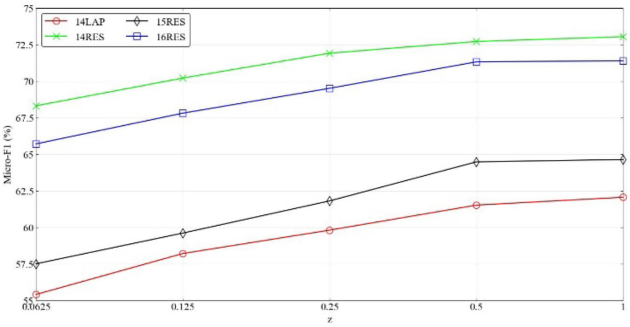

Figure 5. Study on the confidence threshold z

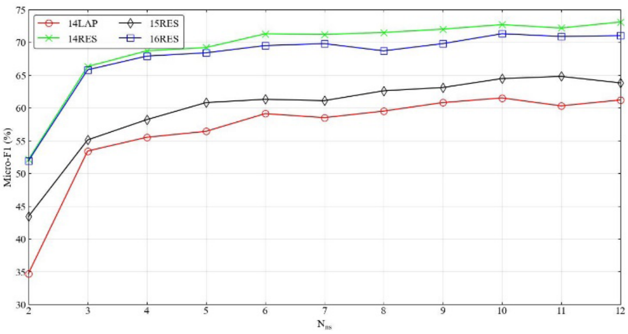

Figure 6. Study on the negative sample number N_{ns}

The negative sample number N_{ns}. We design the negative sampling method to optimize our model. From the Figure 6, the F1 scores are small at the beginning, but when N_{ns} increases to 10, the F1 scores continue to increase with the number of negative samples, and then tend to be stable. Considering the computational pressure of the model, we set N_{ns} to 10.

4.7 Case Study

In order to express the superiority of our model, we show four sentences from ASTE-Data-V2 dataset with the ground truth. Meanwhile, our model is compared with the current state-of-the-art model. The final results are shown in Table 5.

In the first and the second sentence, there is a one-to-many correspondence between the aspects and opinions. In this case, GTS and BMRC fail to extract all sentiment triplets. However, our model exactly extracts all triplets in the S2 and S3 and successfully handle the one-to-many correspondence between the aspects and opinions. In addition, for the many-to-one correspondence between the aspects and opinions in the third and fourth sentences, our model also achieves the better performance. GTS detects “the shrimp fritters” by mistake, and both GTS and BMRC fail to extract all sentiment triplets. The results of our model indicate it takes account in syntactic information and semantic information and overcome the complex correspondence between the aspects and opinions. Meanwhile, it also achieves great performance in multi-word triples.

Table 5. Case study of ABSA task (Correct and Wrong results are labeled with ✓ and × respectively.)

Sentences	Ground truth	GTS	BMRC	Ours
1. It feels cheap, the keyboard is not very sensitive.	(keyboard, cheap, NEG), (keyboard, not very sensitive, NEG)	(keyboard, cheap, NEG)✓, (keyboard, sensitive, POS)×	(keyboard, cheap, NEG)✓, ×	(keyboard, cheap, NEG)✓, (keyboard, not very sensitive, NEG)✓
2. The salads are delicious, both refreshing and very spicy.	(salads, delicious, POS), (salads, refreshing, POS), (salads, spicy, POS)	(salads, delicious, POS)✓, (salads, refreshing, POS)✓, ×	(salads, delicious, POS)✓, ×, ×	(salads, delicious, POS)✓, (salads, refreshing, POS)✓, (salads, spicy, POS)✓
3. For appetizers, I recommend the shrimp fritters and dumplings.	(shrimp fritters, recommend, POS), (dumplings, recommend, POS)	(the shrimp fritters, recommend, POS)×, (dumplings, recommend, POS)✓	×, (dumplings, recommend, POS)✓	(shrimp fritters, recommend, POS)✓, (dumplings, recommend, POS)✓
4. We have been to this place many times, and always have great food, wine, and service.	(food, great, POS), (wine, great, POS), (service, great, POS)	(food, great, POS)✓, ×, (service, great, POS)✓	(food, great, POS)✓, ×, ×	(food, great, POS)✓, (wine, great, POS)✓, (service, great, POS)✓

5 Conclusion

In this paper, we propose a span-based enhanced bidirectional extraction network to harvest triplets from review sentences. The proposed model can handle the issue of the recent researches which only rely on the interaction of each word and address the challenge of handling multi-word terms to a certain extent.

The proposed framework generates all possible spans on the sentence as the candidates, and takes an end-to-end manner to extract aspect sentiment triplets which not only address the error propagation, but also effectively deal with the situation of multiword. Meanwhile, the dual-channel pruning strategy is introduced to choose the correct spans and reduce the computational cost. Moreover, we deploy two decoder module which each module contains an aspect and opinion decoder. These decoder modules are capable of modeling the span relationships and performing bidirectional decoding for both A-O and O-A directions. Experiments on four benchmark datasets reveal the better performance of our framework compared to the baselines.

However, our method still exists certain limitations, such as the poor generalization of triplets containing implicit information and insufficient diversity by negative sampling method. In the future, we plan to plan to employ a multi-task learning network to enhance our model by leveraging the interaction between subtasks. Currently, there exists a noticeable performance gap between common triples and triples involving implicit information, which presents a promising avenue for future research and improvement. In addition, how to empower the model to deal with complex triplet cases in common real-world scenarios is also the focus of our future research.

Acknowledgments

This work was supported by Fundamental Research Funds for the Central Universities (Grant No. 2022JBZY002). It was also supported by the National Natural Science Foundation of China (Grant No. 62376018).

References

[1] W. Zhang, X. Li, Y. Deng, L. Bing, W. Lam, A survey on aspect-based sentiment analysis: tasks, methods, and challenges, *IEEE Transactions on Knowledge and Data Engineering*, Vol. 35, No. 11, pp. 11019–11038, November, 2023.

[2] M. Pontiki, D. Galanis, J. Pavlopoulos, H. Papageorgiou, I. Androutsopoulos, S. Manandhar, SemEval-2014 task 4: Aspect based sentiment analysis, *2014 8th International Workshop on Semantic Evaluation (SemEval 2014)*, Dublin, Ireland, 2014, pp. 27–35.

[3] M. Pontiki, D. Galanis, H. Papageorgiou, S. Manandhar, I. Androutsopoulos, Semeval-2015 task 12: Aspect based sentiment analysis, *2015 9th international workshop on semantic evaluation (SemEval 2015)*, Denver, CO, 2015, pp. 486–495.

[4] M. Pontiki, D. Galanis, H. Papageorgiou, I. Androutsopoulos, S. Manandhar, M. AL-Smadi, M. Al-Ayyoub, Y. Zhao, B. Qin, O. De Clercq, V. Hoste, M. Apidianaki, X. Tannier, N. Loukachevitch, E. Kotelnikov, N. Bel, S. M. Jiménez-Zafra, G. Eryiğit, Semeval-2016 task 5: Aspect based sentiment analysis, *2016 10th International Workshop on Semantic Evaluation (SemEval-2016)*, San Diego, CA, United States, 2016, pp. 19–30.

[5] Y. Yin, F. Wei, L. Dong, K. Xu, M. Zhang, M. Zhou, Unsupervised word and dependency path embeddings

for aspect term extraction, *IJCAI International Joint Conference on Artificial Intelligence*, New York, United States, 2016, pp. 2979–2985.

[6] X. Li, L. Bing, P. Li, W. Lam, Z. Yang, Aspect term extraction with history attention and selective transformation, *IJCAI International Joint Conference on Artificial Intelligence*, Stockholm, Sweden, 2018, pp. 4194–4200.

[7] D. Ma, S. Li, F. Wu, X. Xie, H. Wang, Exploring sequence-to-sequence learning in aspect term extraction, *2019 57th annual meeting of the association for computational linguistics*, Florence, Italy, 2019, pp. 3538–3547.

[8] Z. Fan, Z. Wu, X. Dai, S. Huang, J. Chen, Target-oriented opinion words extraction with target-fused neural sequence labeling, *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, Minneapolis, Minnesota, 2019, pp. 2509–2518.

[9] Z. Wu, F. Zhao, X.-Y. Dai, S. Huang, J. Chen, Latent opinions transfer network for target-oriented opinion words extraction, *Proceedings of the AAAI Conference on Artificial Intelligence*, New York, United States, 2020, pp. 9298–9305.

[10] M. Wu, W. Wang, S. J. Pan, Deep weighted maxsat for aspect-based opinion extraction, *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Punta Cana, Dominican Republic, 2020, pp. 5618–5628.

[11] L. Dong, F. Wei, C. Tan, D. Tang, M. Zhou, K. Xu, Adaptive recursive neural network for target-dependent twitter sentiment classification, *In Proceedings of the 52nd annual meeting of the association for computational linguistics*, Baltimore, Maryland, United States, 2014, pp. 49–54.

[12] D.-T. Vo, Y, Zhang, Target-dependent twitter sentiment classification with rich automatic features, *Twenty-fourth international joint conference on artificial intelligence*, Buenos Aires, Argentina, 2015, pp. 1347–1353.

[13] Y. Tay, L. A. Tuan, S. C. Hui, Learning to attend via word-aspect associative fusion for aspect-based sentiment analysis, *Proceedings of the AAAI conference on artificial intelligence*, New Orleans, Louisiana, United States, 2018, pp. 5956–5963.

[14] B. Xing, L. Liao, D. Song, J. Wang, F. Zhang, Z. Wang, H. Huang, Earlier attention? Aspect-aware lstm for aspect-based sentiment analysis, *IJCAI International Joint Conference on Artificial Intelligence*, Macao, P.R. China, 2019, pp. 5313–5319.

[15] R. He, W. S. Lee, H. T. Ng, D. Dahlmeier, An interactive multi-task learning network for end-to-end aspect-based sentiment analysis, *2019 57th Annual Meeting of the Association for Computational Linguistics*, Florence, Italy, 2019, pp. 504–515.

[16] S. Chen, J. Liu, Y. Wang, W. Zhang, Z. Chi, Synchronous double-channel recurrent network for aspect-opinion pair extraction, *2020 58th annual meeting of the association for computational linguistics*, Seattle, Washington, United States, 2020, pp. 6515–6524.

[17] H. Zhao, L. Huang, R. Zhang, Q. Lu, H. Xue, Spanmlt: A span-based multi-task learning framework for pair-wise aspect and opinion terms extraction, *2020 58th annual meeting of the association for computational linguistics*, Seattle, Washington, United States, 2020, pp. 3239–3248.

[18] A. P. B. Veyseh, N. Nouri, F. Dernoncourt, D. Dou, T. H. Nguyen, Introducing syntactic structures into target opinion word extraction with deep learning, *EMNLP 2020 - 2020 Conference on Empirical Methods in Natural Language Processing*, Punta Cana, Dominican Republic, 2020, pp. 8947–8956.

[19] S. Mensah, K. Sun, N. Aletras, An empirical study on leveraging position embeddings for target-oriented opinion words extraction, *EMNLP 2021 - 2021 Conference on Empirical Methods in Natural Language Processing*, Punta Cana, Dominican Republic, 2021, pp. 9174–9179.

[20] H. Yan, J. Dai, T. Ji, X. Qiu, Z. Zhang, A unified generative framework for aspect-based sentiment analysis, *2021 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing*, Bangkok, Thailand, 2021, pp. 2416–2429.

[21] H. Chen, Z. Zhai, F. Feng, R. Li, X. Wang, Enhanced multi-channel graph convolutional network for aspect sentiment triplet extraction, *2022 60th Annual Meeting of the Association for Computational Linguistics*, Dublin, Ireland, 2022, pp. 2974–2985.

[22] L. Xu, Y. K. Chia, L. Bing, Learning span-level interactions for aspect sentiment triplet extraction, *2021 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing*, Bangkok, Thailand, 2021, pp. 4755–4766.

[23] Y. Chen, C. Keming, X. Sun, Z. Zhang, A span-level bidirectional network for aspect sentiment triplet extraction, *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, Abu Dhabi, United Arab Emirates, 2022, pp. 4300–4309.

[24] S. Liu, K. Li, Z. Li, A robustly optimized bmrc for aspect sentiment triplet extraction, *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, Dublin, Ireland, 2022, pp. 272–278.

[25] S. Zhao, W. Chen, T. Wang, Learning cooperative interactions for multi-overlap aspect sentiment triplet extraction, *Findings of the Association for Computational Linguistics: EMNLP 2022*, Abu Dhabi, United Arab Emirates, 2022, pp. 3337–3347.

[26] X. Li, L. Bing, P. Li, W. Lam, A unified model for opinion target extraction and target sentiment prediction, *Proceedings of the AAAI conference on artificial intelligence*, Hawaii, United States, 2019, pp. 6714–6721.

[27] H. Peng, L. Xu, L. Bing, F. Huang, W. Lu, and Luo Si, Knowing what, how and why: A near complete solution for aspect-based sentiment analysis, *In Proceedings of the AAAI Conference on Artificial Intelligence*, New York, United States, 2020, pp. 8600– 8607.

[28] L. Xu, H. Li, W. Lu, L. Bing, Position-aware tagging for aspect sentiment triplet extraction, *EMNLP 2020 - 2020 Conference on Empirical Methods in Natural Language Processing*, Punta Cana, Dominican Republic, 2020, pp. 2339–2349.

[29] Z. Wu, C. Ying, F. Zhao, Z. Fan, X. Dai, R. Xia, Grid tagging scheme for aspect-oriented fine-grained opinion extraction, *Findings of the Association for Computational Linguistics Findings of ACL: EMNLP 2020*, Punta Cana, Dominican Republic, 2020, pp. 2576–2585.

[30] Z. Li, X. Li, Y. Wei, L. Bing, Y. Zhang, Q. Yang, Transferable end-to-end aspect-based sentiment analysis with selective adversarial learning, *EMNLP-IJCNLP 2019 - 2019 Conference on Empirical Methods in Natural Language Processing and 9th International Joint Conference on Natural Language Processing*, Hong Kong,

P.R. China, 2019, pp. 4590–4600.
[31] M. Schmitt, S. Steinheber, K. Schreiber, B. Roth, Joint aspect and polarity classification for aspect-based sentiment analysis with end-to-end neural networks, *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, Brussels, Belgium, 2018, pp. 1109–1114.
[32] H. Fei, Y. Ren, Y. Zhang, D. Ji, Nonautoregressive encoder-decoder neural framework for end-to-end aspect-based sentiment triplet extraction, *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 34, No. 9, pp. 5544–5556, September, 2023.
[33] W. Wang, S. J. Pan, D. Dahlmeier, X. Xiao, Coupled multi-layer attentions for co-extraction of aspect and opinion terms, *Proceedings of the AAAI conference on artificial intelligence*, San Francisco, CA, United States, 2017, pp. 3316–3322.
[34] H. Dai, Y, Song, Neural aspect and opinion term extraction with mined rules as weak supervision, *2019 57th Annual Meeting of the Association for Computational Linguistics*, Florence, Italy, 2019, pp. 5268–5277.
[35] L. Gao, Y. Wang, T. Liu, J. Wang, L. Zhang, J. Liao, Question-driven span labeling model for aspect–opinion pair extraction, *Proceedings of the AAAI conference on artificial intelligence*, Vancouver, Canada, 2021, pp. 12875–12883.
[36] S. Chen, Y. Wang, J. Liu, Y. Wang, Bidirectional machine reading comprehension for aspect sentiment triplet extraction, *Proceedings of the AAAI conference on artificial intelligence*, volume 35, Vancouver, Canada, 2021, pp. 12666–12674.
[37] Y. Mao, Y. Shen, C. Yu, L. Cai, A joint training dual-mrc framework for aspect based sentiment analysis, *In Proceedings of the AAAI conference on artificial intelligence*, Vancouver, Canada, 2021, pp. 13543–13551.
[38] X. Li, L. Bing, W. Zhang, W. Lam, Exploiting bert for end-to-end aspect-based sentiment analysis, *W-NUT@EMNLP 2019 - 5th Workshop on Noisy User-Generated Text*, Hong Kong, P.R. China, 2019, pp. 34–41.
[39] W. Chen, J. Du, Z. Zhang, F. Zhuang, Z. He, A hierarchical interactive network for joint span-based aspect-sentiment analysis, *Proceedings - International Conference on Computational Linguistics*, Gyeongju, Republic of Korea, 2022, pp. 7013–7019.
[40] J. Devlin, M.-W. Chang, K. Lee, K. Toutanova, Bert: Pre-training of deep bidirectional transformers for language understanding, *NAACL HLT 2019 - 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies - Proceedings of the Conference*, Minneapolis, MN, USA, 2019, pp. 4171–4186.
[41] Z. Chen, T. Qian, Relation-aware collaborative learning for unified aspect-based sentiment analysis, *2020 58th annual meeting of the association for computational linguistics*, Seattle, Washington, United States, 2020, pp. 3685–3694.
[42] T. N. Kipf, M. Welling, Semi-supervised classification with graph convolutional networks, *International Conference on Learning Representations*, Toulon, France, 2017, pp. 1–14.
[43] Y. Luan, D. Wadden, L. He, A. Shah, M. Ostendorf, H. Hajishirzi, A general framework for information extraction using dynamic span graphs, *NAACL HLT 2019 - 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, Minneapolis, Minnesota, 2019, pp. 3036–3046.
[44] D. Wadden, U. Wennberg, Y. Luan, H. Hajishirzi, Entity, relation, and event extraction with contextualized span representations, *EMNLP-IJCNLP 2019 - 2019 Conference on Empirical Methods in Natural Language Processing and 9th International Joint Conference on Natural Language Processing*, Hong Kong, P.R. China, 2019, pp. 5784–5789.
[45] T.-Y. Lin, P. Goyal, R. Girshick, K. He, P. Doll´ar, Focal loss for dense object detection, *Proceedings of the IEEE international conference on computer vision*, Venice, Italy, 2017, pp. 2980–2988.
[46] Q. Xia, B. Zhang, R. Wang, Z. Li, Y. Zhang, F. Huang, L. Si, M. Zhang, A unified span-based approach for opinion mining with syntactic constituents, *In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, Online, 2021, pp. 1795–1804.
[47] Y.-J. Su, C.-H. Chen, T.-Y. Chen, C.-C. Cheng, Chinese Microblog Sentiment Analysis by Adding Emoticons to Attention-Based CNN, *Journal of Internet Technology*, Vol. 21, No. 3, pp. 821–829, May, 2020.
[48] I. Loshchilov, F. Hutter, Fixing weight decay regularization in adam, *International Conference on Learning Representations*, Vancouver, BC, Canada, 2018, pp. 1–14.

Biographies

Geng Liu is currently a graduate student at the School of Electronic and Information Engineering, Beijing Jiaotong University, Beijing, China. His research interests include sentiment analysis, opinion evolution and network security.

Yingsi Zhao received the Master's degree in Engineering in 2009 and the doctoral degree in Management in 2014 from Beijing Jiaotong University respectively. She currently works as a teacher in Beijing Jiaotong University from 2014. Her research interests include Human Resources, Complex network, Innovation performance and Blockchain Technology.

Bo Shen received Ph.D. degree in Communication and Information Systems from Beijing Jiaotong University in 2006, and after he engaged in post-doctoral research in Institute of System Science, Beijing Jiaotong University. Now, he is a professor at Beijing Jiaotong University. His research interests include opinion evolution, data mining and NLP.