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Aspect Sentiment Triplet Extraction Based on Deep Relationship Enhancement Networks

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Abstract: The task of aspect-based sentiment analysis (ASBA) is to identify all the sentiment analyses expressed by specific aspect words in the text. How to identify specific objects (i.e., aspect words), describe the modifiers of the specific objects (i.e., opinion words), and judge the sentiment analysis expressed by opinion words (sentimental classification) in one step has become a focus of research in ASBA. ASTE (Aspect Sentiment Triplet Extraction) based on DREN (Deep Relationship Enhancement Networks) has been proposed in this paper. It aims to extract the aspect words and opinion words in the review text in one-step. They can judge the sentiment analysis expressed by the opinion words. Therefore, the study defines ten kinds of word relations; then, the study uses the parts of the speech feature, syntactic feature, relative position feature and tree distance relative feature to enhance the word representation relationship, which enriches the table of information in the relational matrix. Secondly, based on the word representation of BERT and GCN, the structural information of the texts are extracted; then, further extraction of higher-level word semantic information and word relationship information through SWDA (Sliding Window Dilated Attention) occurs, as SWDA can capture the multi-granularity relationship in words. Finally, the experimental results show that the proposed method is effective.

Keywords: triplet extraction; Graph Neural Networks; attention mechanism

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1. Introduction

In recent years, the advancements in deep learning have led to the widespread application of sentiment analysis technology across various fields and platforms. Public opinion platforms enable governments to influence the course of events by monitoring netizens' opinions on specific matters. Similarly, on consumer platforms, businesses can enhance their products by conducting targeted improvement based on the analysis of consumer reviews, considering sentiment analysis [1]. Sentiment analysis can be conducted at different levels, including sentence, paragraph, and fine-grained sentiment analyses [1,2]. Sentence-based sentiment analysis aims to identify the overall sentiment conveyed within a single sentence, while paragraph-based sentiment analysis determines the overall sentiment expressed in a paragraph by comprehensively analyzing each sentence [3]. In contrast to sentence-based and paragraph-based sentiment analyses, aspect-based sentiment analysis falls under the category of fine-grained sentiment analysis. This approach seeks to identify the sentiment associated with different aspect words in text, offering greater research opportunities and application value. For example, in e-commerce scenarios, users often provide mixed reviews regarding multiple aspects of a product. Similarly, in movie reviews, users may express diverse opinions on aspects such as dubbing, plot, and casting. In such common yet slightly complex scenarios, sentence- and paragraph-based sentiment analyses prove insufficient. Hence, aspect-based sentiment analysis becomes particularly important.

Attribute-based sentiment analysis, also known as ABSA (aspect-based sentiment analysis), focuses on analyzing the sentiment orientation expressed towards multiple

aspects or aspects of a thing in a comment. For example, in the statement "The mobile operating system is very smooth, but the battery performance is not good", the user assesses both the operating system and the phone's battery, each with different sentiment orientations. Such evaluations of multiple aspects with diverse sentiment orientations are common in e-commerce scenarios and public opinion analyses, making aspect-based sentiment analysis a topic of considerable interest in academia and the business community.

In recent years, with the progress in deep learning, aspect-based sentiment analysis has witnessed significant advancement. Some studies have proposed the use of attention mechanisms and related variants to process ABSA tasks. Tang et al. [4] and Wang et al. [5] proposed using attention mechanism networks to determine the sentiment polarity associated with a given aspect term in the text. Ma et al. [6] suggested that there is a mutual relationship between aspect words and their context, introducing an interactive attention mechanism to give weights to the words in the context and aspect text. Li et al. [7] suggested using collaborative attention mechanism to associate aspect words with their context while concatenating the term, embedding the context of the term with the aspect words, enhancing the interaction between aspect words and their contexts.

The advent of models like BERT (Bidirectional Encoder Representations from Transformers) and GCN (Graph Neural Networks) has further fueled the emergence of a large number of models based on BERT and GCN that are widely used in ABSA. BERT was presented in [8], which used mask tasks and predict next sentence task to learn the semantic information connecting words and sentences. So, Pang et al. [9] used BERT to extract more auxiliary information about aspect words from the context of comments, while Zhou et al. [10] used the syntactic relationship in sentences to construct a graph, and then they used GCN to determine sentiment polarity expressed by aspect words in context. GCN [11] realized the convolution operation on the topological graph with the help of graph theory, and semantic information was extracted via graph instruction and convolution.

The above studies were all based on the given attributive words and the contextual information to judge the sentiment polarity expressed by the attributive words in the text. At present, great progress is being made in ASTE for given aspect words. However, a pressing and challenging issue that requires urgent attention is how to determine the polarity of aspect words and sentiment words in one step without specifying pre-existing aspect words. In this scenario, where aspect words are not specified in advance, it is necessary to first identify aspect words and opinion words and then combine aspect words and opinion words to obtain aspect words and their corresponding sentiment polarity (The aspect words, opinion words and sentiment polarity were referred to as triplets in this paper). For example, consider the sentence "The taste is good but the service could be better". In this case, the aspect words are "taste" and "the service", while the opinion words are "good" and "could be better". Consequently, the triplets derived from the above sentence are ("taste", "good", "positive") and ("the service", "could be better", "negative"). It is worth noting that obtaining all these triplets from a comment sentence in a single step poses a more intricate challenge compared with determining the sentiment polarity of aspect words when the aspects are specified.

Therefore, the research questions considered in this study are as follows:

Research Question 1: What method can be used to obtain the polarity (triplet) of aspect and sentiment in one step without giving the aspect?

Research Question 2: How can we solve the problem of possible discontinuity between aspect and opinion in ASBA?

Research Question 3: What is the effect of the method derived from research question 1?

To solve the problem of extracting triplets from comments, Chen et al. [12] introduces a methodology involving the construction of a term relationship matrix from all the words present in the comments. Triplets are then extracted based on the assessment of these term relationships. Based on Chen et al. [12], this paper introduces DREN designed to evaluate term relationships.

To address the above three issues, we proposed DREN. Our contribution is as follows: first, we will transform the problem of extracting triplets into a word relationship classification problem and define ten's word relationships, which obtain the polarity (triplet) of aspect and sentiment in one step. In words with more details, this paper employs BERT to extract term information from the text to identify term relationships comprehensive, solves the problem of nested entity term embedding, and obtains the relationship information between words through the LBAM (Linear Biaffine Attention Mechanism) and GCN. Secondly, since aspect words and opinion words may appear non-sequentially in the sentence, SWDA is employed to effectively capture the relationships between words situated at varying distances from each other. Thirdly, this paper also uses the part-of-speech features, syntactic features, relative position features, and tree distance relative features in the comment to fully utilize the information in the comment text and integrates these features with the text representation. The experimental results on a large number of publicly available ASTE-related datasets demonstrate the effectiveness of the proposed model.

2. Review of Literature

ABSA (aspect-based sentiment analysis) is a fine-grained sentiment analysis that involves three sequential tasks: aspect extraction, opinion extraction, and sentiment polarity determination for aspect–opinion pairs. While existing works often focus on individual tasks such as sentiment polarity with aspect words specified, there are also some works on AOTE (Aspect and Opinion Term Co-Extraction). However, the identification of aspect words, corresponding opinion words, and sentiment expressed by those opinion words proposed in this paper belongs to a sequential task of aspect words, opinion sub-term, and sentiment polarity judgement, and ASTE needs to be accomplished at once; therefore, this section will provide a detailed description of these three inter-related tasks.

Since the introduction of deep neural networks for ABSA [4], numerous studies have explored the application of deep neural networks to determine the sentiment orientation of aspect words in text. Wang et al. [5] proposed using LSTM (Long Short-Term Memory) combined with attention mechanism to address this task, and Ma et al. [6] proposed an interactive attention mechanism to assess the importance of words expressing aspect words in comments, while Li et al. [7] employed a collaborative attention mechanism to deepen the interaction between aspect words and their contexts. Fan et al. [13] argued that when both aspect words and contexts are long, the simplicity of the weighted sum attention mechanism would introduce some noise; thus, they proposed a multi-granularity attention mechanism to reduce irrelevant information. Since the application of BERT and GCN in the field of NLP, a large number of works based on BERT and GCN have also studied ABSA, such as Zhou et al. [10] and Zhang et al. [14].

In the AOTE task, Wang et al. [15] used the high-level semantic representation of each term in its context through dependency syntax and recursive neural network to extract aspect words and opinion words, the aspect words were associated with the opinion words, and, finally, the aspect words and opinion words in the sentence were identified through CRF (Conditional Random Fields). Dai and Song [16] proposed using BiLSTM-CRF (Bi-Directional Long Short-Term Memory Conditional Random Fields) to extract aspect words and opinion words. Wang et al. [17] argued that syntax-based methods exhibit low accuracy when applied to unstructured text, and methods relying on the HMM (Hidden Markov Model) and CRF require a large number of manual labels. Therefore, a coupled attention mechanism is proposed to extract opinion words and aspect words. This mechanism necessitates the use of two separate attention mechanisms for each sentence to capture the direct and indirect relationships between aspect and opinion words. In addressing the challenge of extracting aspect words and opinion words across domains, Wang and Pan [18] proposed an Interaction Memory Network featuring local and global memory units, which enabled aspect words and opinion words within the same domain to interact with each other, as well as facilitating interaction between aspect words and opinion words across different domains. Consequently, this approach achieved higher experimental results in

the extraction of aspect words and opinion words across domains, eliminating the need for additional resources. Chen et al. [19] stated that there are certain difficulties in extracting aspect words and opinion words, such as the fact that the relationships between aspect words and opinion words can be one-to-many, many-to-one, or even overlapping, while the extraction of aspect words and opinion words is interdependent rather than independent; therefore, when extracting these two types of entities, it is necessary to synchronously determine the relationship between entities. Therefore, a new SDRN (Synchronous Double-Channel Recurrent Network) model is proposed, which consists of an entity extraction unit, a relationship detection unit, and a synchronization unit, enabling the simultaneous extraction of entities and their relationships. Wu et al. [20] stated that it is unreasonable to divide the AOTE task into multiple sub-tasks and extract them through multiple channels and proposed a unified grid-labeling task to solve the AOTE task in an End-to-End manner. In ASPE, the problems of small data and insufficient training are compensated by jointly extracting aspect words and determining the sentiment classification task corresponding to aspect words, as well as by training on other data and transferring some parameters to the current network [21].

With the enormous prospects of social media cosmetic electronic word of mouth (eWOM), it is imperative to examine the influence of cosmetic eWOM on social media and for cosmetic marketers to understand the antecedents that result in cosmetic consumers making a purchase [22]. Previous research shows that electronic word-of-mouth spread through social media has a strong influence on customers' purchase decisions [23]. In recent years, the business community has delved into aspect words and their corresponding opinion words in comments and made judgments on sentiment polarity in one step (i.e., ABSA triplet judgment). Since Li et al. [24] proposed this task, ASTE has received a lot of attention from scholars. In words of triplet extraction, previous work divided it into several parts, namely AOTE and AFOE. ASTE integrates these two tasks, with Xu et al. [25] discovering a strong correlation between the three elements of a triplet and designing a sequence labeling joint model that can capture the relationship between the three elements to extract triplets. Mao et al. [26] transformed the triplet extraction task into two Machine Reading Comprehension (MRC) problems. Firstly, the task of triplet extraction was decomposed into tasks of AE, AOE, and SC; then, left MRC and right MRC were used to process AE, AOE, and SC separately. Faced with the various ABSA sub-tasks, Yan et al. [27] converted ABSA into a unified generative task. Based on the unified formula, the model solved all ABSA sub-tasks using the End-to-End framework of the pre-trained sequence-to-sequence model BERT and achieved good experimental results on ASTE. Chen et al. [12] dealt with the triplet extraction task as a term relationship classification task and defined ten categories of term relations. They used a multichannel network to extract features such as vocabulary, grammar, syntax, and position. Experimental results on a large dataset proved the effectiveness of this model.

In these works, the task of extracting aspect words, opinion words, and the sentiment expressed by opinion words in a cascading way has a wider application scenario, and cascading methods can also reduce losses and have higher accuracy.

Inspired by Chen et al. [12], we still define 10 word relationships to facilitate the extraction of triplets and process DREN. And the following research hypotheses were made:

Research Hypothesis 1: *DREN can obtain the polarity (triplet) of aspect and sentiment in one step without giving the aspect.*

Research Hypothesis 2: *SWDA can solve the possible discontinuity problem between aspect words and opinion words.*

Research Hypothesis 3: *DREN can achieve higher F1 values than GTS-BiLSTM and GTS-BERT.*

3. Model Building

3.1. Research Methodology

Inspired by Chen et al. and Jiao et al. [12,28], we proposed DREN to process the ASTE, as shown in Figure 1, which is divided into encoding layer, information extraction and fusion layer, and prediction layer. The three layers are introduced in detail in the following text. As we described before, BERT have good presentation in semantics, and GCN is good at extracting instruction information. So, in the encoding layer, we used BERT, the Biaffine Attention Mechanism, and GCN to extract information, which included semantic information, structural information, and syntactic information. We combined other information, including part-of-speech information, dependency syntax information, relative position information, and tree distance information, in the information extraction and fusion layer to obtain a good representation. After that, SWDA was used to mitigate redundancy in global attention and discontinuity between aspect words and opinion words. Finally, triplets were extracted by predicting the relationships between words in the prediction layer.

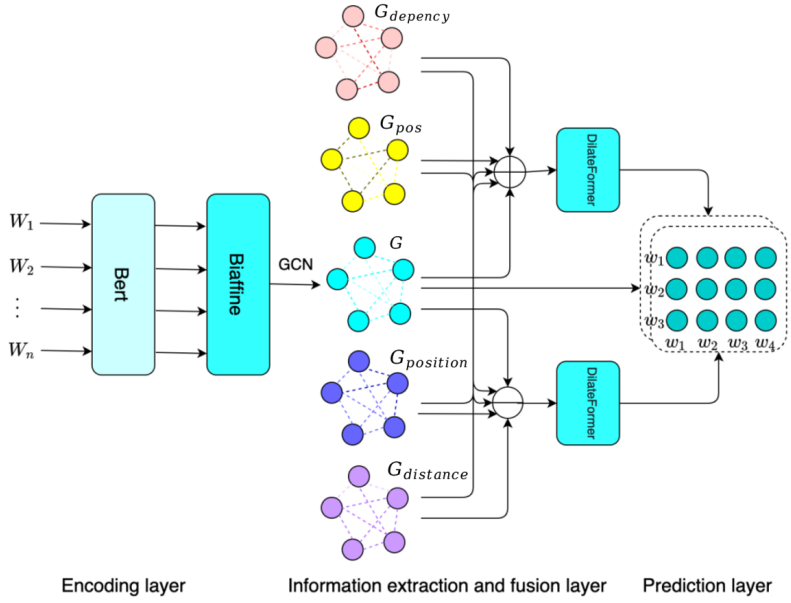


Figure 1. The Model of ASTE based on DREN.

When given a comment with n words, the task of the ATST was to extract the m aspect words a, opinion words o, and s pairs of sentiment polarities from the comment, i.e., $T = \{[a, o, s]_m\}$. According to the definition in Chen et al. [12], the triplet extraction task was transformed into a term relationship judgment task, and ten types of term relationships were defined (where o represents aspect words, while B_o,I_o,o represent the beginning, end, and opinion words, respectively; where a represents aspect words, while B_a,I_a,a represent the beginning, end, and opinion words, respectively; and POS, NEG, and NEU represent positive, negative, and neutral sentiment polarity, respectively; the sign * represents words that are not part of a triplet). Thus, the aspect term extraction, opinion term extraction, and the sentiment orientation expressed by aspect words in the comment were solved in one step. This paper uses the definitions of Chen et al.'s [12] pairs of triplet relationships and further improved the accuracy of relationship categories by using DREN. And this paper will continue to provide a detailed introduction to the model.

3.2. Encoding Layer

After obtaining the text $X = [W_1, W_2, \cdots W_n]$ containing m pairs of aspect words a, opinion words o, and sentiment polarity s, the semantic information of long dependency and structure was fully captured. Then, the model input X into BERT, which is the

encoder part of the Transformer [11]. A large number of studies have shown that BERT has better semantic feature extraction ability in natural language processing tasks compared with traditional LSTM and CNN. Afterward, through the last encoding layer of BERT, $H = [h_1, h_2, \cdots h_n] \in \mathbb{R}^{n \times d_h}$ is obtained, where d_h is the dimension of the vectors in BERT.

While this paper eventually transforms the triplet recognition task into a term relationship discrimination task, it fundamentally involves the initial steps of entity identification, followed by relationship determination between entities and subsequently sentiment polarity assignment. The recognition of entities heavily depends on other information, such as the syntactic structure, semantic structure, and part-of-speech structure within a sentence. Hence, how to identify entities becomes one of the challenges that this paper needs to address. To address this challenge, the obtained H, H is first input into LBAM. This mechanism serves to facilitate the model in solving the nesting problem between entities. As a classic neural network in entity recognition, the LBAM interacts through the boundaries of entity heads and tails, thereby better identifying the boundary problems between entities. The LBAM is shown in Formulas (1)–(5).

$$h_i^a = MLP_a(h_i) \tag{1}$$

$$h_j^o = MLP_o(h_j) \tag{2}$$

$$g_{i,j} = h_i^{aT} U_1 h_j^o + U_2\left(h_i^a \bigoplus h_j^o\right) + b \tag{3}$$

$$r_{i,j,k} = \frac{exp\left(g_{i,j,k}\right)}{\sum_{l=1}^{d_b} exp\left(g_{i,j,l}\right)} \tag{4}$$

$$B = Biaffine(MLP_a(H), MLP_o(H)) \tag{5}$$

In Formulas (1)–(4), U_1 and U_2 are parameter matrices, and b is the bias vector, where $\bigoplus$ represents a splice and MLP is a fully connected layer. Formulas (1)–(4) are used to measure the K relationships between the words W_i and W_j in the same sentence through the operations of full concatenation, planning etc. We used Formula (4) to normalize the kth relationships between word i and word j. So, the d_b relationships of the comment sentence with n words, namely $B = [b_1, b_2, \cdots b_n] \in \mathbb{R}^{n \times n \times d_b}$, are determined. Afterward, we obtained H through the Biaffine Attention Mechanism Network, where d_b is the dimension of the vectors in the LBAM, in order to enhance the identification of entity and structure relationships. In this paper, B is used to further obtain the graph information features through GCN to solve the problem of insufficient information in entity recognition. GCN [25] is also widely used in natural language processing, such as BERT. So, GCN is a variant of CNN (Convolutional Neural Networks). It is different from CNN and GCN regarding the use of text as the structure of graph. Then, we obtained $G = [g_1, g_2, \cdots g_n] \in \mathbb{R}^{n \times n \times d_g}$ after convoluting the information of graph, in which d_g is the dimension of the vector in GCN.

3.3. Information Extraction and Fusion Layer

Secondly, to fully exploit other information beyond semantics, this paper incorporated part-of-speech information, dependency syntactic information, relative position information, and tree distance information to broaden the expression of the semantic vector space and enrich vector representation. So, it could improve the accuracy of entity recognition, contributing to the improved judgment of relationships between words. The part-of-speech information, dependency syntactic information, relative position information, and tree distance information used in this paper are all provided in the dataset and are represented, respectively, as $G_{pos} = [g_1, g_2, \cdots g_n] \in \mathbb{R}^{n \times n \times d_g}$, $G_{depency} = [g_1, g_2, \cdots g_n] \in \mathbb{R}^{n \times n \times d_g}$, $G_{position} = [g_1, g_2, \cdots g_n] \in \mathbb{R}^{n \times n \times d_g}$, and $G_{distance} = [g_1, g_2, \cdots g_n] \in \mathbb{R}^{n \times n \times d_g}$ through random initialization. After obtaining G, G_{pos},$G_{depency}$, $G_{position}$, and $G_{distance}$, this paper first adds and subtracts matrices and normalizes them through $SoftMax$ to integrate matrix rep-

resentations and find differences between matrices, and it fully integrates this information and strengthens the relationships between words, as shown in Formulas (6) and (7).

$$G_{add} = softmax\Big(G + G_{pos} + G_{depency} + G_{position} + G_{distance} \Big) \tag{6}$$

$$G_{sub} = softmax\Big(G - G_{pos} - G_{depency} - G_{position} - G_{distance} \Big) \tag{7}$$

To address the issue of discontinuity between aspect words and opinion words in ABSA, this paper introduces a multiscale global network attention mechanism designed to link discontinuous words. The multiscale global network attention mechanism was initially introduced to mitigate redundancy in global attention modules in image processing [28]. Jiao et al. [28] asserts that attention mechanisms across different distances also prove effective at addressing different distance of pixels. We think that it could also process the discontinuity between the aspect words and opinion words. The structure of the SWDA is shown in Figure 2.

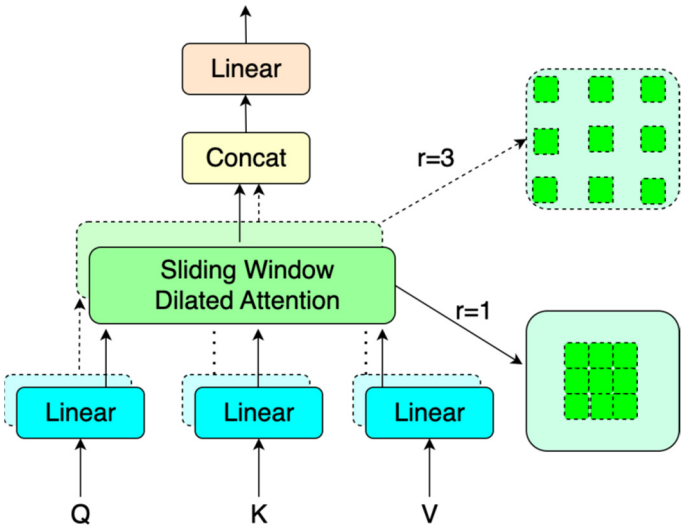


Figure 2. Structure of SWDA.

For G_{add}, when the scale $r = 1$, after the SWDA, Formula (8) is as follows.

$$X_1 = SWDA(Q, K, V, r = 1) \tag{8}$$

Among them, Q, K, and V are matrices of query, key, and value. They were the three feature matrices obtained by G_{add} through CNN, and each row of these three matrices represented a query/key/value feature vector. For the query at position (i, j), in the original feature mapping, the SWDA sparsely selected keys and values, with (i, j) as the center, to perform the attention mechanism in sliding windows of different sizes, as shown in Formula (9).

$$X_{i,j} = softmax(\frac{q_{i,j}K_r^T}{\sqrt{d_k}})V_r,\ 1 \le i \le W,\ 1 \le j \le H \tag{9}$$

W and H are the height and width of the feature map at position $X_{i,j}$. For position (i, j), the width and height have a certain limit range:

$$\{(i' + j') | i' = i + p \times r, j' = j + p \times r\} \quad -1 <= p.q <= 1 \tag{10}$$

Similarly, when $r = 3$, X_3 is obtained, X_1 and X_3 are then spliced after passing through the linear layer. And X_{add} is finally obtained. X_{sub} is similarly obtained. In order to better

capture the relationships between words, the loss calculation used in this paper for G, X_{add} and X_{sub} consists of two parts, namely L, L_{add} and L_{sub}, as shown in Formula (5).

$$L = L^{g} + \alpha L^{add} + \beta L^{sub} \tag{11}$$

4. Experimental Process

4.1. Parameter Settings

In this paper, the text length n is defined as 102 because the text length of 100 can fit the lengths of most sentences in the dataset, while the start and end characters of BERT are +2. Therefore, any text that exceeds this limit will be truncated by experimentally looking for hyperparameters. The BERT used is BERT-base-uncased, featuring default dimensions of 768 and default layers of 12. The dimension of GCN is set to 300, with one layer. The part-of-speech information, dependency parsing information, relative position information, and tree distance information are initialized randomly with a dimension of 10. The batch size is set to 16, the learning rate is set to 10^{-3}, the dropout is set to 0.5, and α and β are set to 0.1. The values r are set to 1 and 3.

In addition, this paper uses F_1 as the evaluation standard for the experiment, as shown in Formulas (12)–(14).

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

$$Recall = \frac{TP}{TP + FN} \tag{13}$$

$$F_1 = \frac{2 \times Precison \times Recall}{Precision + Recall} \tag{14}$$

where TP means that the true case is positive and the predicted value is positive, FP means that the true case is negative and the predicted value is positive, and FN means that the true case is positive and the predicted value is negative.

4.2. Dataset Description

This paper uses two ABSA datasets of D1 and D2 from SemEval. Each dataset contains information in the latter two domains, namely note reviews and restaurant data, in which the note data are derived from the SemEval of 2014, while the restaurant reviews are derived from the SemEval of 2014, 2015, and 2016. Each dataset is divided into training, validation, and testing sets. SemEval of 2014 is split into 14res and 14lap, and SemEval of 2015 and SemEval of 2016 are selected in the res domain. Table 1 provides specific details regarding the number of sentences in each dataset. Table 2 shows the numbers of aspect words in each dataset.

Table 1. Statistics regarding the number of sentences in each dataset.

Dataset	14lap	14res	15res	16res
D1_train	899	1259	603	863
D1_vaild	225	315	151	216
D1_test	332	493	325	328
D2_train	906	1266	605	857
D2_valid	219	310	148	210
D2_test	328	492	322	326

Table 2. Statistics regarding the number of aspect words in each dataset.

Dataset	14res	14lap	15res	16res
D1_train	1452	2356	1038	1421
D1_vaild	383	580	239	348
D1_test	547	1008	493	525
D2_train	1460	2338	1013	1394
D2_valid	346	577	249	339
D2_test	543	994	485	514

4.3. Comparison Experiment

To assess the effectiveness of the model of DREN in this paper, the Peng-two-stage-IOG [27], GTS-CNN/GTS-BiLSTM/GTS-BERT [28], S^3E^2 [20], CMLA+ [29], RINANTE [29], Li-unified-R [29], OTE-MTL [30], and JET-BERT [25] are chosen for comparison, in which CMLA+, RINANTE+, Li-unified-R, and Peng-two-stage are Pipeline methods, while GTS-CNN/GTS-BiLSTM/GTS-BERT, S^3E^2, OTE-MTL, and JET-BERT are End-to-End models. The following is a description of several baselines:

Peng-two-stage-IOG: It divides the triplet extraction task into two stages. In the first stage, BiLSTM and GCN are used to predict the possible descriptive aspect words and opinion words; then, in the second stage, the aspect words and opinion words predicted in the first stage are paired.

GTS-CNN/GTS-BiLSTM/GTS-BERT: It defines six kinds of word relationships, which are encoded via CNN/BilISTM/BERT and attention mechanism on the encoder. After pooling and some linear transformation operations, the SoftMax classifier is used to classify the word relationships.

S^3E^2: In order to solve the long tail problem in the extraction of aspect words and opinion words in review texts, the SoftProto framework makes samples related to each other, thus allowing rare words to be extracted.

CMLA: It considers that the extractions of aspect words and opinion words need to be correlated with each other and proposes using SWDA to correlate aspect words and opinion words. Each layer of attention mechanism is composed of a pair of attention mechanisms, one of which extracts aspect words and one of which extracts opinion words. Through interactive learning, the extraction performance is improved.

RINANTE: It proposes to use BiLSTM-CRF to train the data, which is composed of two parts: one is manually labeled data, and the other is automatically labeled based on dependency syntax and Part-of-Speech annotators.

Li-unified-R: It uses a two-layer recurrent neural network to process the extraction task. The first layer of the recurrent neural network is used to generate labeled results, and the second layer is used to label the target boundary.

OTE-MTL: It proposes a multi-task learning framework for joint extraction of attributive words and opinion words while using bilinear affine attention mechanism to record the sentiment dependency between words.

JET-BERT: It believes that attributive words, opinion words, and polarity judgments need to be extracted in End-to-End, rather than through multiple stages. The paper proposes using two kinds of location information to improve the extraction accuracy of recognition: one is to mark the distance between the sentiment words and attributive words, with attributive words as the center, and the other is to calculate the distance between attributive words and sentiment words, with sentiment words as the center.

There are comparative experimental baseline and DREN results for two datasets in Tables 3 and 4. Some baseline results can be found in [12,25,30,31].

Table 3. Experimental results of the value F1 for the Dataset D1.

Model	14res	14lap	15res	16res
Peng-two-stage-IOG	59.64	47.02	48.71	58.67
GTS-CNN	65.94	51.38	56.64	64.73
GTS-BiLSTM	64.49	51.30	56.29	65.56
S^3E^2	66.74	52.01	58.66	66.87
GTS-BERT	70.20	54.58	58.67	**67.58**
DREN	**72.27**	**56.75**	**61.41**	65.84

Table 4. Experimental results of the value F1 for the Dataset D2.

Model	14res	14lap	15res	16res
CMLA	42.79	33.16	37.01	41.72
RINANTE	34.95	20.07	29.97	23.87
Li-unified-R	51.00	42.34	47.82	44.31
Peng-two-stage-IOG	51.46	42.87	52.32	54.21
OTE-MTL	58.71	43.42	47.13	56.96
JET-BERT	62.40	51.04	57.53	63.83
GTS-BERT	68.81	55.42	58.60	**67.58**
DREN	**69.05**	**57.52**	**59.45**	67.20

4.4. Discussion

As shown in Tables 3 and 4, Peng-two-stage-IOG, GTS-CNN, GTS-BiLSTM, S^3E^2, GTS-BERT, and DREN are tested in D1, and CMLA, RINANTE, Li-unified-R, Peng-two-stage-IOG, OTE-MTL, JET-BERT, and GTS-BERT are tested in D2. It can be seen that the experiments on 14res, 14lap, and 15res in the DREN dataset all achieved the best results. Peng-two-stage demonstrated poor performance on D1 and D2. CMLA+, RINANTE+, and Li-unified-R had poor experimental results on D2, primarily attributed to the pipeline approach, which overlooked the correlation between aspect term extraction and opinion term extraction tasks, resulting in loss accumulation. Based on the performance of Peng-two-stage, CMLA+, RINANTE+, and Li-unified-R on the dataset, it can be inferred that the traditional two-step method of first identifying the attributed word and then identifying the sentiment of the attributed word in the context is defective. GTS-CNN/GTS-BiLSTM/GTS-BERT and S^3E^2 use End-to-End to identify relationships between words. GTS-BERT have a better result than GTS- BiLSTM in D1. The reason for this result is that BERT has been pre-trained on large-scale data and can provide a strong language understanding ability. However, this method will overlook the importance of other information in entity recognition, such as structural and syntactic information. OTE-MTL uses a bilinear affine attention mechanism to recognize the boundary relationship between words, and JET-BERT uses distance information. However, the information used by the above methods is limited, and the task features are not fully utilized for the attribute word extraction and sentiment orientation discrimination task. So, the DREN proposed in this paper not only considers various available information comprehensively, thus enriching the expression of semantics, and improves the accuracy of entity recognition, but it also further improves the accuracy of term relationship discrimination. In the 16res dataset, the DREN's performance is slightly less effective than that of GTS-BERT. While enhanced with deep relationships, DREN also introduces a small amount of noise, thus affecting the accuracy of the model.

This paper further illustrates the effectiveness of DREN through ablation experiments on D2, as shown in Table 5, where G_{other} represents the comprehensive information of $G_{pos}, G_{depency}, G_{position}$, and $G_{distance}$. It can be seen that in the absence of $G_{pos}, G_{depency}$,

$G_{position}$, and $G_{distance}$, the F1 values of the four datasets all decline to varying degrees. Compared with G_{pos}, $G_{depency}$, $G_{position}$, and $G_{distance}$, SWDA makes a larger contribution, thus further illustrating the effectiveness of SWDA on the model.

Table 5. Ablation experiment for Dataset D2.

Model	14res	14lap	15res	16res
DREN	69.05	57.52	59.45	67.20
(W/o) SWDA	67.45	55.05	58.89	65.85
(W/o) G_{other}	68.67	56.58	58.09	66.05

In order to validate the feasibility of the model, this section employs a case study for illustration. The triplets in this review, "The food is surprisingly good, and the decor is nice", from res14 in D1, are (food, good, positive) and (decor, nice, positive). DREN successfully identified the relationships between food and good and decor and nice. However, GTS-BiLSTM and GTS-BERT both mistakenly considered good and nice to be opinion words for the aspect term "food", leading to incorrect judgments, as shown in Figure 3.

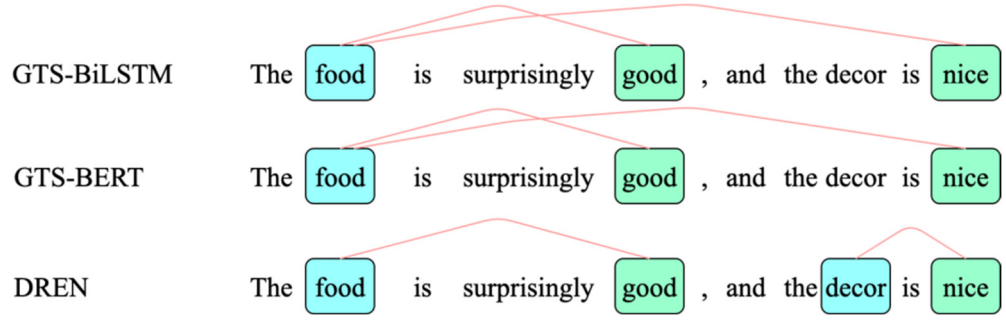


Figure 3. Case study.

The triplet extraction task is transformed into a term relationship judgment task, and ten types of term relationships are defined (where *o* represents aspect words, while *B_o*, *I_o*,*o* represent the beginning, end, and opinion words respectively; *a* represents aspect words, while *B_a*,*I_a*,*a* represent the beginning, end, and opinion words respectively; and POS, NEG, NEU represent positive, negative, and neutral sentiment polarity, respectively. Compared to the method of extracting aspect and opinion words first and then combining the two to judge sentiment. DREN can use the relationship between the words to extract the triplet in one step. As for Research Hypothesis 2, from Table 5 and the case study that we just discussed, we can see SWDA's importance to our results. It is also better for processing the difficulty of the main problem, which is how to associate aspect with opinion words. Compared with GTS BiLSTM and GTS BERT, the DREN proposed in this paper not only considers various available information comprehensively, thus enriching the expression of semantics, but also improves the accuracy of entity recognition, as shown in Tables 3 and 4.

5. Conclusions

This paper proposes a DREN for identifying extracting triplet problems in ABSA in one step. Firstly, the triplet extraction task is transformed into a relationship discrimination task between words. To improve the conversion rate of the discrimination task, the BERT and GCN methods are employed to enhance the semantic representation. Additionally, part-of-speech information, dependency syntax information, relative position information, and tree distance information are utilized to increase semantic richness and identify differences. Then, SWDA is used to mitigate redundancy in global attention and discontinuity between aspect words and opinion words. In capturing word relationships, the part-of-speech information, dependency syntactic information, relative position information, and tree

distance information enrich the representation. SWDA further improved the effect. Bert, GCN, and LBAM are also crucial. We have noticed that in ASTE, a large number of works are currently concentrated in the e-commerce field because there are already mature datasets in the e-commerce field, but there are serious deficiencies in the education field, especially in online courses and the reviews of online courses. Therefore, in the future, we will consider generating ASTE data in the online education field, before applying ABSA to the construction of the education field, and training the model by adding domain information through prompts and other methods.

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