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TS-GCN: Aspect-level Sentiment Classification Model for Consumer Reviews

Shunxiang Zhang[1,2], Tong Zhao[1,2], Houyue Wu[1,2], Guangli Zhu[1,2], and KuanChing Li[3]

[1] School of Computer Science and Engineering,
Anhui University of Science & Technology, 232001 Huainan, China
[2] Institute of Artificial Intelligence, Hefei Comprehensive National Science Center,
WangJiang Road 5089, Hefei, 230088, Anhui, China
sxzhang@aust.edu.cn
zhaotongmail2022@163.com
why3664@163.com
glzhu@aust.edu.cn
[3] Department of Computer Science and Information Engineering (CSIE),
Providence University, 43301 Taichung, Taiwan
kuancli@pu.edu.tw

Abstract. The goal of aspect-level sentiment classification (ASC) task is to obtain the sentiment polarity of aspect words in the text. Most existing methods ignore the implicit aspects, resulting in low classification accuracy. To improve the accuracy, this paper proposes a classification model for consumer reviews, abbreviated as TS-GCN (Truncated history attention and Selective transformation network-Graph Convolutional Networks). TS-GCN can classify sentiment from both explicit and implicit aspects. Firstly, we process the text by the BERT model and the BiLSTM model to obtain the text features. Secondly, the GCN model completes explicit sentiment classification by training text features. Due to the lack of implicit words, the GCN model cannot classify implicit sentiments. Finally, we predict implicit words based on the TS model, which makes up for the deficiency of the GCN model and completes the sentiment classification of implicit words. TS-GCN is proved on several datasets in the consumer reviews field. The results of experiments show that the TS-GCN can improve the accuracy and F1 of ASC.

Keywords: consumer reviews; aspect-level sentiment classification (ASC); implicit aspect; GCN.

1. Introduction

ASC is one of the important research directions of natural language processing (NLP) [1]. The purpose of the classification is to get the sentiment tendency of the aspect words in the text [2-3]. The results of the classification can provide support for both customers' purchasing decisions and merchants' sales strategies. Due to these positive effects, ASC has become one of the popular research topics.

The earliest ASC methods were based on rules. In 2004, a rule-based ASC model was first proposed by Hu et al. [4]. Later, Nigam et al. [5] improved it by adding a topic classifier to identify topic-specific sentiment expressions. Although rule-based methods are easier to interpret, the quality of classification is limited by whether the rules are well formulated or not. To address these problems, machine learning-based methods have started to receive widespread attention. Pang et al. [6] first used traditional machine learning algorithms to classify the sentiment polarity of movie reviews. The combination of naive bayesian classifier with support vector machine was proposed by Wang et al [7], which led to a better result for classification. Traditional machine learning methods rely on the selection of features. In contrast, neural network model can automatically generate features from texts. Ruidan et al. [8] proposed an interactive multitask learning network to improve the accuracy of classification by sharing information. A model framework for multi-task learning was demonstrated by Akhtar et al. [9] to accomplish the recognition of aspect words and prediction of sentiment polarity.

Although these advances have been made in ASC, there are still some problems to be studied. Aspect words include both explicit aspect words and implicit aspect words [10-11]. An example shown in Figure 1, "environment" is an explicit aspect word and "price" is an implicit aspect word. The implicit aspect word is the smallest object described by the opinion word but omitted in the sentence. There are a large number of implicit aspect words in the oral consumer reviews. Most of the existing ASC studies have only considered explicit aspects and ignored the implicit aspects. Different from previous work, our work classifies the sentiment in both explicit and implicit aspects. Adding sentiment classification of implicit aspects can improve the accuracy of ASC.

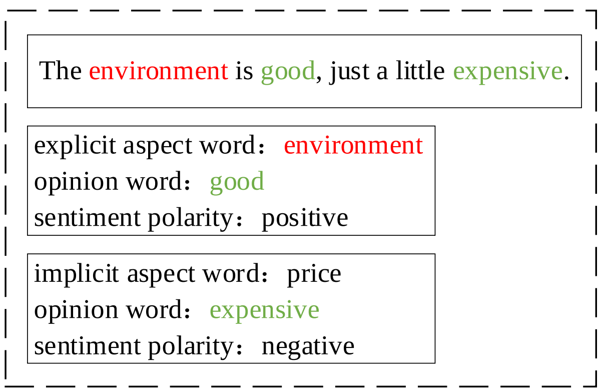


Fig. 1. An example of explicit and implicit aspect words

In the field of consumer reviews, an accurate ASC model needs to consider two aspects. Firstly, the model should accurately classify explicit aspects sentiment; Secondly, the model can classify implicit aspects sentiment when there are implicit aspect words in reviews. Based on the above two considerations, we propose a sentiment classification model named TS-GCN. The TS-GCN consists of the following three main parts, as shown in Figure 2.

(1) The extraction of text features. We use the BERT [12] model to code the semantics and location of consumer reviews and aspect words. After that, we input the encoded information into the BiLSTM model to extract text features.

(2) Explicit aspect sentiment classification. We construct the graph of text features in the form of points and edges. Then, we input text features into the GCN model training to complete explicit sentiment classification. Due to the lack of implicit aspect words, the GCN model cannot complete implicit aspect sentiment classification.

(3) Implicit aspect sentiment classification. Firstly, we input text features into the THA module in the TS [13] model to establish the mapping relationship between aspect words and opinion words. Secondly, we combine the mapping relationship with the results of explicit aspect sentiment classification and then input it into the STN module in the TS model. Finally, we use the TS model to predict the implicit aspect words and then complete the implicit aspect sentiment classification.

The advantage of TS-GCN is to consider the implicit aspect words in consumer reviews and propose a sentiment classification method from both explicit and implicit aspects.

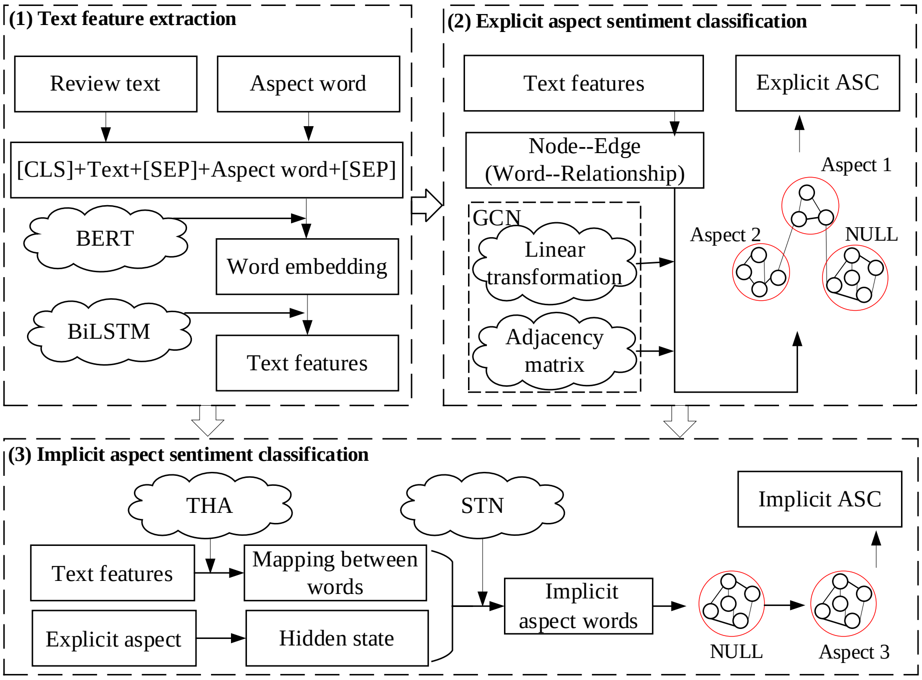


Fig. 2. TS-GCN frame diagram

This paper is organized according to the following sections. In Section 2, we present the related work of this paper. In Section 3, the content of TS-GCN is described in detail. In Section 4, we discuss the results of the experiments. Finally, in Section 5, we give the conclusions of this paper.

2. Related Work

In recent years, there are two main approaches for ASC. One is the classical neural network [14-17] and the other is the graph convolutional neural network (GCN) [18-19].

2.1. Classical Neural Networks

Among the classical neural network models, recurrent neural networks (RNN) [20] and convolutional neural networks (CNN) [21] are widely used for sentiment classification tasks. The powerful text feature extraction ability of RNN and CNN improves the accuracy of sentiment classification [22-23].

In the ASC task, Wang et al. [24] first combined RNN models with attention mechanisms and achieved good training results. However, this model is not good at handling complex text because it does not capture contextual features. Chen et al. [25] remedied this deficiency by proposing a memory recursive attention network called RAM. RAM uses a weighted attention mechanism to filter irrelevant encoded information and captures contextual features more accurately. Huang et al. [26] proposed an attention overload model called AOA. The AOA model was able to focus on the important sections of the text and improved the effect of complex text sentiment classification. After the good results achieved by RNN, researchers also further tried to use CNN to achieve sentiment classification. Xue et al. [27] used a gating mechanism to improve CNNs. This approach is simpler and more independent than models with attention mechanisms and LSTM while weakening the dependence of the model on time. Song et al. [28] used an attention encoder network to fill the gap that RNN models cannot handle the task in parallel. This approach achieves better extraction of aspect words and sentiment polarity in sentences. Fang et al. [29] proposed a target fusion sequence labeling neural network model called IO-LSTM, which can match aspect words and opinion words in sentences more accurately. Unlike the IO-LSTM, Huang et al. [30] used parametric filters to extract aspect features and achieved similarly good results on sentiment classification.

2.2. Graph Convolutional Neural Networks

Compared with classical neural networks, GCN [31] is more adept at dealing with the problem of relationships between entities. In recent years, many studies have shown that the sentiment classification results based on GCN are better than traditional neural networks.

Based on the GCN model, Wang et al. [32] proposed a sentiment prediction model with an encoded tree structure called R-GAT. R-GAT solved the confusion of opinion words and aspect words in connection to a large extent. To avoid the problem of confusion on connections, Sun et al. [33] performed joint inference between entity types and relation types. Zhang et al. [34] improved the accuracy of relation extraction by pruning the relational dependency tree of GCN with a path-centric approach. Li et al. [35] designed a multi-granularity alignment network named MGAN. MGAN addressed the problem of inconsistent granularity in cross-domain text analysis. Sun et al. [36] tried to extract the text directly on the dependency tree, and this method is easier to extract the syntactic information of the text. Guo et al. [37] showed an attention-guided graph convolution model abbreviated AGGCN. The GCN model in AGGCN prunes the dependency tree by an attention mechanism to ensure that the dependency tree focuses only on useful information. Zhang et al. [38] constructed an affective classification model called ASGCN. ASGCN uses syntactic rules to guide attentional mechanisms to better focus on the occurrence of important words. Zhao et al. [39] considered that aspect words are not independent and proposed the SDGCN model to verify the feasibility of their idea. In their experiments, they demonstrated that there is a connection between aspect words and that this connection can influence the classification results. Xiao et al. [40] demonstrated an improved classification accuracy by enhancing the interaction information between sentences.

We conclude from reviewing related research works that GCN models have more advantages over ASC. Therefore, a classification model named TS-GCN is proposed, which can perform sentiment classification of consumer reviews from both explicit and implicit aspects, which improves the classification accuracy.

3. Methods

We use an aspect unit $U = (A, O, P)$ to denote the result of this aspect sentiment classification. Where 'A' represents aspect words, 'O' represents opinion words, and 'P' represents sentiment polarity. The TS-GCN model is divided into three parts, which are text feature extraction, explicit aspect sentiment classification and implicit aspect sentiment classification. In this section, we will describe the specific working process of each part and the relationship between the parts. A training example of the model is given at the end of this section.

3.1. The Extraction of Text Features.

The word embedding serves to encode the text, where the encoding contains the content and location of the text. We choose the BERT model as the encoder for the TS-GCN model due to its excellent achievement in the field of NLP. In the text $\{w_1^c, w_2^c, ..., w_T^c, w_{T+1}^c ..., w_{T+M}^c, ..., w_N^c\}$ which contains N words, there are M words $\{w_T^c, w_{T+1}^c, ..., w_{T+M}^c\}$ corresponding to K aspect words $\{w_1^a, w_2^a, ..., w_K^a\}$. We construct the text and aspect words as "[CLS] + text + [SEP] + aspect words + [SEP]" structure, and then input them into the BERT model for training. This input structure allows the text encoding to contain both semantic information and the corresponding aspects of word information. After aggregating the codes, we obtain the text content coding sequence $E_c = \{e_1^c, e_2^c, ..., e_N^c\}$ and the aspect word coding sequence $E_a = \{e_1^a, e_2^a, ..., e_K^a\}$. After completing the encoding, we established a mapping relationship between the text content encoding and the sentiment polarity of the words.

The role of the BiLSTM model is to get the text features of consumer reviews. In the BiLSTM model, the forward and backward layers form a bidirectional transfer mechanism and then connect to the same output layer. This type of transmission allows the model to obtain the degree of association between words. We input the text content encoding sequence into the BiLSTM model to get the hidden state h_t. Each word corresponds to a hidden state. The hidden states of the text is $H_c = \{h_1^c, h_2^c, ..., h_N^c\}$.

3.2. Explicit Aspect Sentiment Classification

This section is based on the GCN model to accomplish the explicit aspect of sentiment classification. Since the GCN model is good at processing graphs, we make the text features and feature relations form the nodes and edges of the graph for the GCN model to process.

We form the text hidden states $H_c = \{h_1^c, h_2^c, ..., h_N^c\}$ into an *N*N* adjacency matrix A_{ij}, and then input it into the GCN model. A_{ij} is shown in formula (1), where r_{ij} represents the relationship coefficient between each text hidden state h_i^c.

$$A_{ij} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1N} \\ r_{21} & r_{22} & \cdots & r_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ r_{N1} & r_{N2} & \cdots & r_{NN} \end{bmatrix} \tag{1}$$

The GCN model updates the state of the nodes in each iteration, and the nodes gain information in this process. The update of the node state is calculated as shown in formula (2).

$$x_i^l = \sigma\left(\sum_{j=1}^{N} A_{ij} W^l x_i^{l-1} + b^l\right) \tag{2}$$

Where each word corresponds to a node, and *N* is the number of nodes, x_i^l represents the current node state, x_i^{l-1} represents the previous state of the node, σ is the nonlinear function, W^l is the linear transformation weight matrix, and b^l is the offset vector. The GCN model performs a linear transformation of the last node state x_i^{l-1}, then updates the node information using the adjacency matrix A_{ij} as the state matrix, and finally obtains the current node state x_i^l.

Each node is influenced by other nodes during iterative computation until it reaches an equilibrium state. When the iteration parameters reach a steady state, the GCN model aggregates the nodes associated with the same aspect word. We set a threshold for the number of nodes aggregated to determine the existence of an aspect unit. After the training of the GCN model, the initial and equilibrium states of the nodes in the graph are shown in a simplified two-dimensional diagram in Figure 3.

After determining the existence of aspect units, we need to find the corresponding aspect words. Our method is to calculate the similarity between the aspect unit and the aspect word encoding sequence $E_a = \{e_1^a, e_2^a, ..., e_K^a\}$ by probabilistic prediction. The probabilistic prediction is shown in formula (3).

$$y_i = \frac{\exp(x_i)}{\sum_{j=1}^{K} \exp(x_{ij})} \tag{3}$$

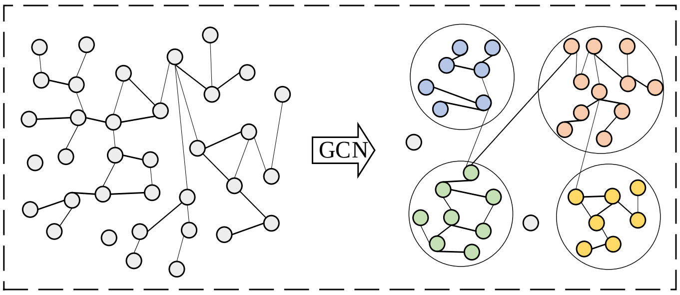


Fig. 3. The nodes before and after the GCN model training. We use different colors to indicate that the nodes are aggregated into different parts after training, and each part corresponds to an aspect word

The working process of the GCN model is shown in the following algorithm:

```
1.     For h in Hc:
2.       Row_stack(A,h)
3.     end for
4.     for each epoch until Δw<threshold:
5.       for each x do
6.         for j in Dimension(x)
7.           temp=LinearMap(x)
8.         end for
9.         x=ReLU(temp)
10.      end for
11.      xl=ReLU(LinearMap(xl))+x
12.    end for
```

In the algorithm above, we complete the explicit aspect of ASC. The adjustment matrix A is constructed in lines 1-3. The working process of multilayer GCN is in lines 4-12. Where line 11 describes the adjustment of the node values. The time complexity of the algorithm is related to three variables, the number of nodes *N*, the number of connections between nodes *N* (including self-connections) and the embedding dimension of each node *d*. The time complexity of the algorithm is $O(N) = O(N^2d)$.

We combine the matched aspect word a_i, the opinion word o_i in the text and the sentiment polarity p_i of the opinion word to form the aspect unit $u_i = (a_i, o_i, p_i)$. The result of the processing of each sentence in the text is presented in the form of one or more aspect units $U = \{u_1, u_2, ..., u_L\}$, L is the number of aspect units. If there is no match for the corresponding aspect word, the opinion word o_i and the sentiment polarity p_i will be constructed into an implicit aspect unit $u_i = (NULL, o_i, p_i)$. The implicit aspect unit will be processed in the TS model in the next section.

3.3. Implicit Aspect Sentiment Classification

After the training of the GCN model, we have been able to extract the aspect units containing the explicit aspect words. However, we are unable to extract implicit aspect units that do not contain aspect words. For example, for the sentence "The environment is good, just a little expensive.", the GCN model can only extract explicit aspect units <environment, good, positive> and incomplete implicit aspect units <NULL, expensive, negative>. In this section, the TS model will be used to predict the implicit aspect words and fill in the incomplete implicit aspect unit $u_i = (NULL, o_i, p_i)$, thus completing the sentiment classification of implicit aspects.

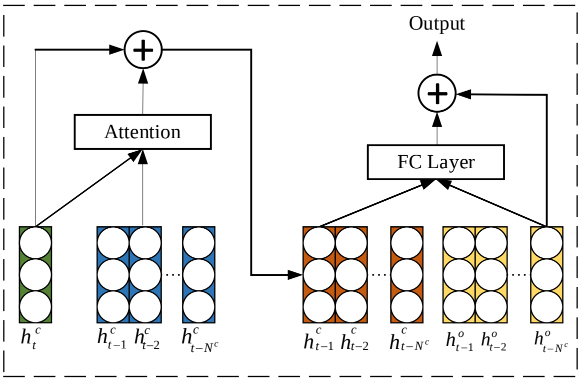


Fig. 4. The TS model

The TS model consists of the truncated history-attention (THA) module and the selective transformation network (STN) module. The structure of the TS model is shown in Figure 4. The input of the THA module comes from the text hidden states $H_c = \{h_1^c, h_2^c, ..., h_N^c\}$ output by the BiLSTM model. The THA module scores each hidden state and obtains the standard score s_i^t after normalization by softmax, as shown in formula (4).

$$s_i^t = \mathrm{Softmax}(v^{\mathrm{T}} \tanh(W_1 h_i^c + W_2 h_t^c + W_3 \tilde{h}_i)) \tag{4}$$

Where t denotes the processing step at this moment, N^c is the number of hidden states processed by the THA module per unit time, $i \in [t - N^c, t-1]$ is the parameter used for model training. h_i^c is the feature representation of the previous step, h_t^c is the feature representation of the current step, and then h_i^c and h_t^c are used to obtain the historical aware feature representation $\tilde{h}_i$ through the THA module. W_1, W_2 and W_3 are the parameters for h_i^c, h_t^c and $\tilde{h}_i$.

By calculating the historical aware feature representation $\tilde{h}_i$ and the standard score s_i^t, we obtained the historical feature $\hat{h}_t^c$. The calculation process of $\hat{h}_t^c$ is shown in formula (5).

$$\hat{h}_t^c = \sum_{i=t-N^c}^{t-1} s_i^t \times \tilde{h}_i \tag{5}$$

We use the nonlinear function ReLU to activate the historical feature $\hat{h}_t^c$. Then, we combine the activated historical feature $\hat{h}_t^c$ with the feature representation of the current step h_t^c to obtain the historical aware feature representation of the current step $\tilde{h}_t$. The calculation process of $\tilde{h}_t$ is shown in formula (6).

$$\tilde{h}_t = h_t^c + \mathrm{ReLU}(\hat{h}_t^c) \tag{6}$$

The STN module builds a fully connected layer using the historical aware feature representation $\tilde{h}_t$ output by the THA module and the aspect unit feature h_i^o output by the GCN model. And then the STN module uses the set of historical aware feature representations in the fully connected layer as a vocabulary to build an index of candidate aspect words. We obtain the corresponding implicit aspect words by computing the historical aware feature representations of the implicit aspect units. The calculation process of implicit aspect words is shown in formula (7).

$$y_i = \mathrm{ReLU}(W_4 \tilde{h}_t + W_5 h_i^o) \tag{7}$$

Where W_4 is the parameter of the current historical aware feature representation $\tilde{h}_t$ and W_5 is the parameter of the aspect unit feature h_i^o.

The loss function is calculated as shown in formula (8).

$$Loss = -\sum_{i=1}^{K} \sum_{j=1}^{c} y_{ij} \log \hat{y}_{ij} + \lambda \|\theta\|^2 \tag{8}$$

The working process of the TS model is shown in the following algorithm:

```
1.      Codes=BERT(Hc)
2.      HStates=LSTM(Codes)
3.      for i=1:Hc.Count:
4.          s= HStates [i]
5.          f=Attention.Feature(s)
6.          Attention.Insert(f)
7.          abstract=FCLayer.Deal(s,f)
8.          FullConn.Insert(abstract)
9.      end for
10.     Initialize out to an empty list
11.     For i=1:U.Count:
12.         u=U[i]
13.         f=Feature(u)
14.         abstract=FCLayer.Deal(f)
15.         a=FCLayer.Deal(FullConn,abstract)
16.         u.A=a
17.         out.Insert(u)
18.     end for
19.     End
```

The algorithm is divided into two parts. The first part is in lines 1-9 of the algorithm. The THA module in the TS model trains the prediction model and calculates the association of all words in the text with aspect words. The second part is in lines 10-19 of the algorithm. The time complexity of the algorithm is related to three variables, the number of hidden states of words *N*, the number of aspect unit *L* and the dimensionality of word embedding *d*. In the TS module, the attention mechanism and the fully connected layer occupy the majority runtime of the model, and the time complexity is $O(N^2d)$ and $O(N^2)$ respectively. The global time complexity is $O(N,L,d)=O(N^3d+L^2d)$.

The STN module in the TS model predicts the implicit aspect words. In the model training step, the TS model takes as input the hidden states of the text processed by the BERT model and the BiLSTM model. The TS model constructs complete connections between words through the positional and semantic relationships between words. Since the source of the corpus for building the model is the review text itself, it is extremely relevant to product reviews and does not suffer from severe overfitting or poor adaptation of the model to the task. The TS model completes the implicit aspect units by predicting the implicit aspect words to complete the implicit aspect sentiment classification.

3.4. A model training example

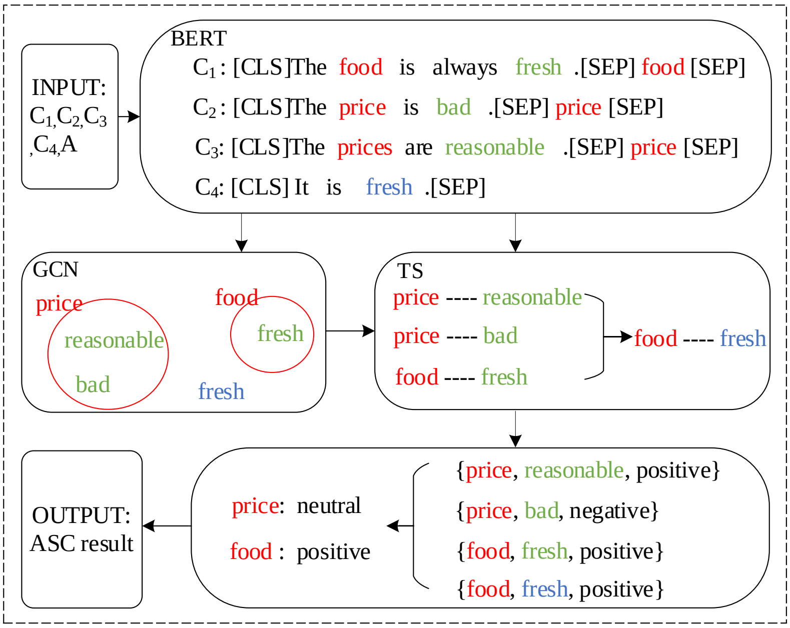


Fig. 5. Example of the training process

We demonstrate the training process of our model TS-GCN with a brief example, as shown in Figure 5. Input sentences C_1, C_2, C_3, C_4 and the marked aspect word A in the sentence. C_1="The food is always fresh.", C_2="The price is bad.", C_3="The prices are reasonable." and C_4="It is fresh.", A="food", "price". We enter the sentences into BERT in the form "[CLS] sentence [SEP] aspect word [SEP]". After BERT encoding, the sentences are input to BiLSTM to mine text features H_c. The GCN aggregates opinion words with the same aspect word, such as "bad" and "reasonable", by adjusting the relationship of H_c. The clustered opinion words are computed to an aspect code. The aspect words, opinion words, and sentiment polarity form the explicit aspect unit $u_i = (a_i, o_i, p_i)$. The GCN module cannot classify the opinion word "fresh" in C_4 because it is not encoded with the corresponding explicit aspect word. The TS module uses text features and aspect units to build a fully connected layer and establish a correspondence system between aspect words and opinion words, such as "food--fresh" and "price--reasonable". Then, the TS module uses the fully connected layer to predict the implicit aspect words and then form the implicit aspect units. Finally, we count all the aspect units and obtain the results of ASC.

4. Experiments

4.1. Dataset and Experimental Setup

To validate the sentiment classification ability of the TS-GCN model in the consumer review field, we performed experiments on four consumer review datasets. The four review datasets are Laptop 14[1], Restaurant 14[1], Restaurant 15[2], and Restaurant 16[3]. The above experimental dataset contains consumer reviews of laptops and restaurants, and all aspects of sentiment polarity contained in the reviews are annotated. The details of the four datasets are shown in Table 1.

Table 1. Experimental dataset

Data	Laptop 14		Restaurant 14		Restaurant 15		Restaurant 16	
	Train	Text	Train	Text	Train	Text	Train	Text
Positive	992	339	2125	725	910	321	1018	460
Neutral	460	165	626	193	32	32	62	28
Negative	866	123	800	190	244	178	430	110

In this experiment, we use the GloVe model and the BERT model as pre-training models. The experimental setup of the two models is shown in Table 2.

Table 2. Experimental setup for the GloVe and BERT models

Data	GloVe	BERT
Embedding dimension	300	768
Batch-size	32	16
Dropout	0.5	0.1
Learning rate	0.001	0.001

4.2. Comparing models

To validate the performance of the TS-GCN model proposed in this paper, the following seven models were selected for experimental comparison.

RAM[25]: This model uses a weighted attention mechanism to filter irrelevant coded information and captures contextual features more accurately. The model outperformed the ordinary attention model in processing complex text.

AOA[26]: This model processes the known aspect words and sentences to be analyzed through the AOA (attention-over-attention) model. The AOA model makes it easier to focus attention on important parts of the text.

1 https://alt.qcri.org/semeval2014/task4/index.php?id=important-dates
2 https://alt.qcri.org/semeval2015/task12/index.php?id=important-dates
3 https://alt.qcri.org/semeval2016/task5/index.php?id=important-dates

TNet-LF[17]: This model abandons the attention model and uses CNNs and Bidirectional RNNs, which have achieved good performance in classification tasks, to extract aspect and sentiment features and perform classification.

AEN[28]: This model improves on the shortcomings of the RNN model that cannot process the task in parallel by using the attention encoder network (AEN) to accomplish the extraction and classification of aspectual and sentiment polarity in sentences.

ASGCN[38]: The syntactic rules in this model help the attention mechanism to better focus on where important words appear.

AEGCN[40]: This model combines the attention mechanism with GCN to enhance the interaction information between sentences. The model compares the effect of sentiment classification under different word embedding models, which provides a reference for us to choose the pre-training model.

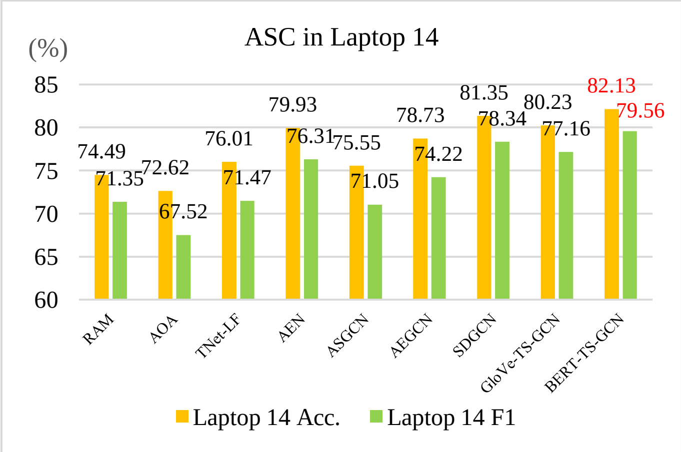
SDGCN[39]: This model proposes that different aspect terms are interrelated. The model captures the relationship between aspect words in sentences through GCN, which improves the accuracy of sentiment classification.

4.3. Experimental results and discussion

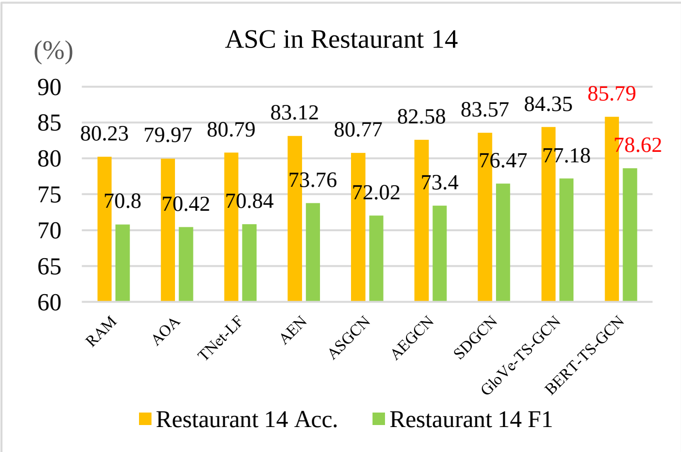
The experimental results of TS-GCN and the seven comparison models are shown in Table 3. We evaluate the model performance using accuracy and F1 as the criteria. Since some comparison models use the GloVe model as a pre-training model, to control the variables, TS-GCN experimented with both the GloVe model and the BERT model as pre-training models. From the experimental results, it can be seen that our proposed TS-GCN model works best among the models that also use the GloVe pre-trained model. And the TS-GCN model under BERT pre-training is better than the TS-GCN model under GloVe pre-training.

Table 3. Comparison results with other ASC models. The experimental results of our proposed model are shown in bold. The experimental results of the comparison model in the table are from the paper that proposed the model. Comparison models that were not experimented on the datasets of Restaurant 15 and Restaurant 16 are indicated by "-"

Model	Laptop14		Restaurant14		Restaurant15		Restaurant16	
	Acc.(%)	F1(%)	Acc.(%)	F1(%)	Acc.(%)	F1(%)	Acc.(%)	F1(%)
RAM	74.49	71.35	80.23	70.80	-	-	-	-
AOA	72.62	67.52	79.97	70.42	78.17	57.02	87.50	66.21
TNet-LF	76.01	71.47	80.79	70.84	78.47	59.47	89.07	70.43
AEN	79.93	76.31	83.12	73.76	-	-	-	-
ASGCN	75.55	71.05	80.77	72.02	79.89	61.89	88.99	67.48
AEGCN	78.73	74.22	82.58	73.40	82.71	69.00	89.61	73.93
SDGCN	81.35	78.34	83.57	76.47	-	-	-	-
GloVe-TS-GCN	80.23	77.16	84.35	77.18	83.95	71.43	90.07	75.14
BERT-TS-GCN	**82.13**	**79.56**	**85.79**	**78.62**	**85.23**	**73.65**	**92.45**	**78.75**



(a)



(b)

Fig. 5. Comparison results of the models on Laptop 14 and Restaurant 14. The experimental results on Laptop 14 are shown in Figure 5(a), and the experimental results on Restaurant 14 are shown in Figure 5(b)

We compared the experimental results of the seven models with those of the TS-GCN under the same criteria. Because the experimental data of dataset Laptop 14 and dataset Restaurant 14 are more complete, the experimental results under these two datasets were chosen to plot the bar chart as shown in Figure 5.

(1) The accuracy and F1 of ASC for models using GCN are mostly higher than those not. We analyzed the possible reasons for such experimental results according to the methods used by the models. Comparing the experimental results of all models, the AOA model performed the worst. AOA combines aspects with sentences in a joint process capturing the interaction between aspects and context. However, the AOA only uses existing information as the full information space at training time and is unable to analyze new data. The RAM model, on the other hand, makes sentiment features the focus of the model construction, using a multi-attention mechanism to extract multifaceted features. TNet-LF does not use an attention-based approach but treats sentences as bags of words and analyses them using a classification task-based approach. The AEN model was the best result achieved before the addition of classification to the graph neural network.

(2) The TS-GCN under BERT pre-training achieved the best results among all the compared models. Among all the ASC models based on GCN, the ASGCN model introduces syntactic trees, which store the relationships between sentences through syntactic trees. The ASGCN uses a targeted graph convolutional network to process The ASGCN model does not incorporate word location information in the word encoding part, while the AEGCN model compensates for this deficiency. The AEGCN model uses the nodes in the syntactic tree as the individual words of the original utterance, while the SDGCN uses the aspectual words as the nodes of the syntactic tree to better classify the aspectual sentiment through the relationships between the aspectual words in the original text. TS-GCN classifies sentiment from both explicit and implicit aspects, so it improves the accuracy of ASC.

TS-GCN can get the best results in the comparison model because it classifies sentiment from both explicit and implicit aspects. All of the above methods for extracting aspect words are based on the aspect words that appear in the text. However, in consumer reviews, colloquial expressions make it common to omit aspect words from reviews. Therefore, the existing ASC methods are challenged in the consumer review field. TS-GCN constructs a global network of aspectual relations by mining the relationship between aspect words and text words. The model achieves prediction of implicit aspect words through this network, and then further achieves ASC for implicit aspects.

4.4. Case study

To better demonstrate our model, we conducted a case study with several test examples. We visualized the attention scores of words using annotation methods. The words with darker colors have higher scores. We compared the attention scores and prediction results of the four models, as shown in Table 4. These four models are represented by "AEN", "ASGCN", "Ours w/o TS" and "Ours ". "AEN" and "ASGCN" are from two of the comparison models in Section 4.2, "Ours w/o TS" is our model without the TS module, and "Ours" is our model TS-GCN.

The first test example "Great food but the service was dreadful!" is labeled with two explicit aspect words "food" and "service", and two opinion words "good" and "dreadful". The AEN model relies on the attention mechanism to give equal weight to both the word "good" and "dreadful". Therefore, AEN is unable to classify the sentiment of each aspect when multiple aspects are included in the sentence, however, the ASGCN model solves this problem. The ASGCN model correctly identifies multiple pairs of aspect words and opinion words by building dependency trees on the GCN. Our model achieves sentiment classification of multiple explicit aspect words in a sentence by computing aspect words through opinion words. Since this part is implemented in the GCN module, the prediction results of both our model and Ours w/o TS are correct.

Table 4. Case study. The test examples are selected from the dataset used in Section 4.1. When the predicted sentiment polarity is the same as the labeled , the result is ✓, otherwise it is ×

Model	Test	Aspect	Label	Prediction	Result
AEN [28]	Great food but the service was dreadful!	food	Positive	Neutral	×
		service	Negative	Neutral	×
	I found the food to be just as good as its owner, Da Silvano, just much less expensive.	food	Positive	Neutral	×
		price	Negative	-	×
ASGCN [38]	Great food but the service was dreadful!	food	Positive	Positive	✓
		service	Negative	Negative	✓
	I found the food to be just as good as its owner, Da Silvano, just much less expensive.	food	Positive	Neutral	×
		price	Negative	-	×
Ours w/o TS	Great food but the service was dreadful!	food	Positive	Positive	✓
		service	Negative	Negative	✓
	I found the food to be just as good as its owner, Da Silvano, just much less expensive.	food	Positive	Positive	✓
		price	Negative	-	×
Ours	Great food but the service was dreadful!	food	Positive	Positive	✓
		service	Negative	Negative	✓
	I found the food to be just as good as its owner, Da Silvano, just much less expensive.	food	Positive	Positive	✓
		price	Negative	Negative	✓

The second test example "I found the food to be just as good as its owner, Da Silvano, just much less expensive." is marked with an explicit aspect word "food", an implicit aspect word "price", and two opinion words of opposite emotional polarity "good", "expensive". The inability of AEN and ASGCN to recognize the implicit aspect words leads to matching the opinion words of the implicit aspect words to the explicit aspect words. In the example, attention is assigned to the word "good" and "expensive" with the same weight, resulting in the incorrect prediction of the explicit aspect word "food". While Ours w/o TS does not recognize implicit aspect words, it does not match opinion words of implicit aspect words to explicit aspect words incorrectly. Therefore, the sentiment prediction of the explicit aspect words in the sentence is correct. AEN, ASGCN and Ours w/o TS cannot recognize the implicit aspectual word "price" resulting in no prediction results. Our model TS-GCN can predict the implicit aspect words and correctly predicts the sentiment polarity of the aspect word "price".

After the comparison of several models mentioned above, our model has the highest accuracy of ASC in different categories of sentences.

4.5. Ablation study

We performed ablation experiments on TS-GCN to verify the important contribution of each module to the model performance. We have verified the positive effect of the BERT pre-training model. In the ablation experiments in this section, we compared the two models. One is to abandon the TS model directly; The other is to replace the GCN model with the LSTM-CRF model. The results of the ablation experiments are shown in Table 5.

From the results of the ablation experiments, it can be seen that each module plays a crucial role in TS-GCN.

Table 5. Results of ablation experiments. "Ours w/o TS" means our model without TS module, "Ours w/o GCN" means our model without GCN module, and "Ours" means our model TS-GCN

Model	Laptop 14		Restaurant 14		Restaurant 15		Restaurant 16	
	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1
Ours w/o TS	73.74	70.03	66.35	70.14	77.59	65.92	86.18	71.24
Ours w/o GCN	79.52	77.27	82.18	74.58	82.67	69.49	88.53	75.05
Ours	82.13	79.56	85.79	78.62	85.23	73.65	92.45	78.75

4.6. GCN layers study

For purpose of verifying the effect of the number of layers of the GCN on the classification effect, we classified four categories of text with the different numbers of layers of the GCN. We performed the classification operation on the text with the GCN of layers 1 to 8. We simplified the GCN classification results into a 2D diagram by PCA. On the 2D diagram, the four categories of text data are represented in yellow, red, green and blue. The simplified diagrams of the classification results for different layers of GCN are shown in Figure 6.

We can see that the 2-layer GCN has the best classification result, so the final TS-GCN model uses a 2-layer GCN.

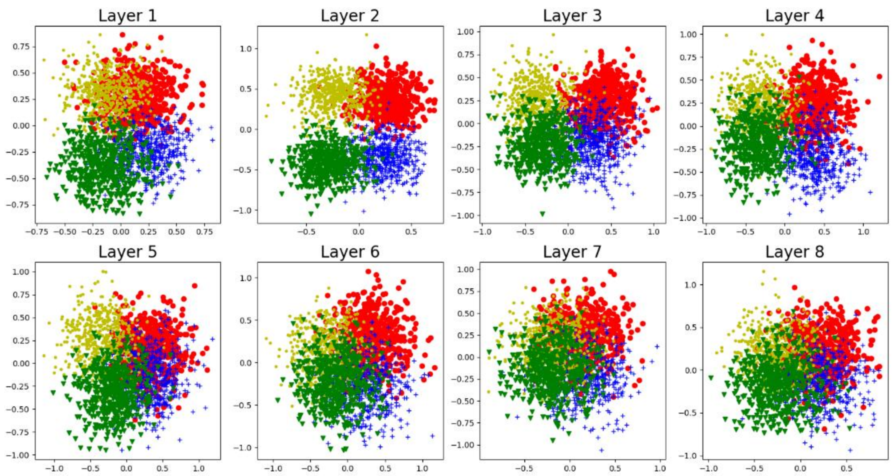


Figure 6. Simplified diagram of the classification results of the GCN with different layers. The coordinates of the data points are constrained to be between -1 and 1

5. Conclusions

To improve the accuracy of ASC in the field of consumer reviews, a model that can accomplish ASC in both explicit and implicit aspects is proposed, which is called TS-GCN. TS-GCN has the following two achievements.

(1) TS-GCN improves the accuracy of explicit aspect sentiment classification by training a GCN model. We use the BERT model and the BiLSTM model to extract text features and then input them into the GCN model for training. The GCN model obtains explicit aspects of ASC by processing the text features.

(2) TS-GCN achieves the implicit aspect of sentiment classification by introducing and training the TS model. The TS model predicts implicit aspect words by establishing correspondences between explicit aspect words and other words. The successful prediction of implicit aspect words compensates for the inability of the GCN model to classify sentiment for implicit aspects.

Through experiments on four datasets, we demonstrate that adding sentiment classification for implicit aspects can improve the accuracy of ASC. In the future, we will further study the ASC combined with multimodal features such as image and audio.

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Shunxiang Zhang, born in 1970. PhD, professor, PhD supervisor. He is an professor at Anhui University of Science and Technology, China. His current research interests include Web Mining, Semantic Search, and Complex network.

Tong Zhao, born in 1997. Master candidate at Anhui University of Science and Technology. Her main research interests are Named Entity Recognition and Relation Extraction.

Houyue Wu, born in 1996. Master candidate at Anhui University of Science and Technology. His main research interests are Adversarial Sample Generation and Relation Extraction.

Guangli Zhu, born in 1969. Master, Associate professor, Master supervisor. Her current research interests include Web Mining, Semantic Search, and Calculation theory.

KuanChing Li, born in 1967, professor, PhD supervisor. He is a University Distinguished Professor at Providence University, Taiwan. His current research interests include Paraallel and Distributed Computing, Big Data and Emerging Technologies.

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