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Graph Convolutional Networks for Aspect-Based Sentiment Analysis

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Abstract: Aspect-based sentiment analysis, as an important fine-grained sentiment analysis problem, aims to analyze and understand the emotions at the aspect level in sentences. However, existing models often overlook the syntactic relationship between words and fail to extract specific semantic information.We propose a graph convolutional network model to extract aspectual word features from local context. This paper also proposes a model to address the problem of under-use of explicit syntactic dependency in aspect category emotion analysis, based on a graph convolutional network and incorporating external knowledge to extract deep and surface structure information from the dependency graph, using the aspect item as a reference point. Both models are superior to existing models.

1. Introduction

Aspect Based Sentiment Analysis (ABSA) is a fine-grained sentiment analysis task that identifies the positive and negative aspects of sentences associated with particular aspects. ABSA has four important elements: entities, attributes (or aspect categories), viewpoints, and sentiment polarity[1]. These elements are crucial for understanding sentiment in text. ABSA identifies and extracts these elements through tasks corresponding to different aspects of sentiment analysis.

This paper presents models for text sentiment analysis from two different perspectives: aspect words and aspect categories. The main innovations are outlined below:

1) For aspectual sentiment analysis, we propose a model based on target-level fusion of BiLSTM and Graph Convolutional Network (TBGCN). The model addresses the problem of ignoring syntactic relationships. A graph convolutional network is used to generate aspectual word features focusing on local context while considering global context effects on target sentiment.

2) Analysing aspect category sentiment in the context of covert aspects is challenging. This paper achieves this by fusing multi-headed Attention Convolutional Neural Networks and Graph Convolutional Neural Networks (ACMAGCNN). The model extracts deeper information in the dependency graph and finds its aspect categories.

2. Related Work

Aspect Based Sentiment Analysis (ABSA) has become popular among researchers in recent years. To perform ABSA in different scenarios, tasks are introduced to analyse different sentiment elements and their relations. This paper analyses two tasks, aspect terms and aspect categories.

For aspect-based sentiment analysis, researchers often use deep learning graph convolutional neural networks (GCN). For instance, Dai Zuhua et al [2] used GCNs to construct semantically enhanced aspect-level text sentiment models. Chunxia Yang et al [3] proposed incorporating tight connections into GCN to capture local and global information. Thus, the paper employs the graph convolution network to address the issue of ineffective extraction of local contextual syntactic relationship feature information by the model.

Liang et al [12] used beta distributions to infer aspect-weighted values for each aspect-weighted word, and their aspect-weighted graph construction took into account entity effects on attribute sentiment, effectively improving accuracy in this task. To enhance the effectiveness of graph convolutional networks in extracting aspectual category emotions from sentence information, it is suggested to consider the impact of entities and incorporate a multi-head attention convolution fusion graph convolutional network for deeper feature extraction.

3. Aspect-based Sentiment Analysis

In aspect sentiment analysis, determining whether a context word belongs to the local context of an aspect is essential. This paper proposes a TBGCN model for target-level fusion based on BiLSTM and GCN. The model utilizes graph convolutional networks to generate aspect word features that focus on both local and global context information. Inputting word-specific feature information enhances the model's ability to capture textual target information.

3.1. Model Architecture

Figure 1 shows the overall architecture of the TBGCN. It includes a word vector input layer, a dynamic weighted layer, an aspect word feature extraction layer, an attention layer, and an output layer. The following sections will detail the principles and effects of each layer.

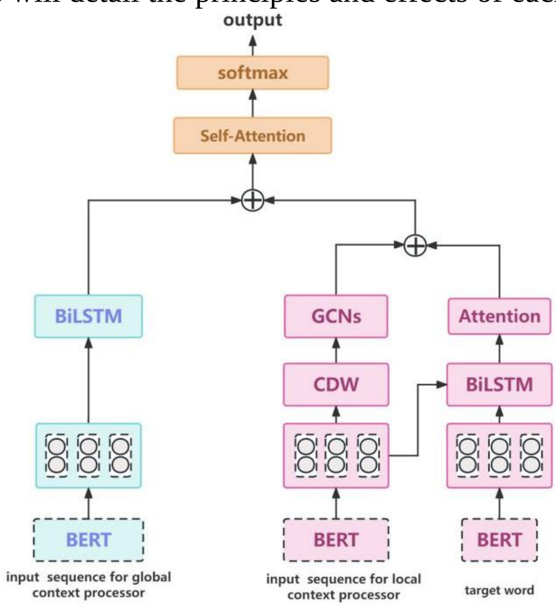

Figure 1: Shows the architecture of the TBGCN model.

3.1.1. Input Layer For Word Vectors

The input layer converts each word into a high-dimensional vectorspace. The BERT model extracts features and learns contextual links between words. A sentence S={w_1,w_2,...w_n} is entered into BERT, where the local context input format is "[CLS]+sentence+[SEP]" and the global context input format is "[CLS]+sentence+[SEP]+aspect word+[SEP]". Target words are also generated by BERT as word vectors.

3.1.2. Dynamic Weighted Layer

zeng et al. [4] found local aspect information more important than global context. Therefore, this layer does not process global context to fully preserve sentence information and semantics. The CDW (Dynamic Weighted for Context Features)[4] is a method used to assign weights between 0 and 1 to words based on the distance between attribute words. This allows for the weighted sum of features extracted by BERT output, enabling the model to capture local context information of the sentence. Notably, the distance between words in the CDW is no longer calculated by location, but rather by the distance between the two words in the syntax-dependent tree [14].

$$v_i^w = \begin{cases} (1 - \frac{SRD_i - \alpha}{N}) \cdot I & SRD_i > \alpha \\ I & SRD_i \leq \alpha \end{cases} \tag{1}$$

$$W = [v_1^w, v_2^w, \ldots, v_n^w] \tag{2}$$

$$V^{CDW} = V^l \odot W \tag{3}$$

The shortest distance between the corresponding nodes in the dependency resolution tree measures the SRD between words.

$$SRD_i = |i - P_a| - \left\lfloor \frac{m}{2} \right\rfloor \tag{4}$$

The vector information for the target word and the feature information for the local context are input into the hidden vector of the bidirectional LSTM.

3.1.3. Aspect Of The Word Feature Extraction Layer

The input to this layer is the combination of the local and global context features associated with the target word.

Based on the local context weighting, the graph structure data of the entity words in the local context are entered into the GCN.

$$E_i = \tilde{A} ReLU(\tilde{A} X W_0) W_1 \tag{5}$$

$$\tilde{A} = D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \tag{6}$$

Since graph convolution only encodes nearest neighbour information, applying it to the sentence tree provides syntactic constraints on sentence aspects. This can identify descriptive words based on syntactic distance and extract emotional information from complex text at a deeper level.

Next, the attention mechanism connects the hidden vector and aspect word vector to extract the vector of local context, which is then fused with the output results of GCN.

In the global context part, the BiLSTM network integrates the semantic information of the feature vector of the input sentence and the feature vector of the target words in the sentence.

3.1.4. Attention Layer

The model uses a self-attention mechanism to assemble the feature vectors obtained from both the local and global contexts to easily capture the internal hidden features of the complete sentence.

3.1.5. Output Layer

In the fully connected network classifier, the probability distribution of emotions was obtained using the attention mechanism output vector and then the softmax activation function.

3.2. Experiment and Analysis

3.2.1. Experimental Datasets

Table 1 displays the statistical information for the SemEval 2014 (Laptop and Restaurant) and ACL 14 Twitter datasets used in this paper.

Table 1: Experimental dataset.

dataset	positive		neutral		negative	
	train set	test set	train set	test set	train set	test set
Laptop	994	341	464	169	870	128
Restaurant	2164	728	637	196	807	196
Twitter	1561	173	3127	346	1560	173

3.2.2. Benchmark Model

To evaluate the performance of the TBGCN model, we compared it with the benchmark model.

ATAE-LSTM[5] and IAN [6] use Glove training word vectors combined with LSTM or attention mechanisms. The final feature vector is a splice of the output from the last layer of the LSTM.

TD-LSTM [7] model expands on the LSTM architecture by using two LSTM networks to combine a given target with context features in order to classify aspect emotions.

ASGCN [8] use GCN and Bi-LSTM to classify sentiment at the target level. The study shows that GCN improves performance by exploiting syntactic information and word dependencies.

AEN-BERT [9] proposes an Attentional Encoding Network (AEN) that utilises attention-based encoding to model the relationship between context and target, while avoiding repetition.

BERT-SPC [10] is a pre-trained BERT model designed for sentence pair classification tasks. The input sequence is constructed as follows: [CLS] + sentence + [SEP] + [asp] + [SEP].

CDT [11] proposes a dependency treebased GCN model using Bi-LSTM to learn sentence features. The model further improves the embeddings using GCN acting on the dependency syntax tree.

LCF-BERT[4] proposes a mechanism for local context focusing at the target level, based on multiple attention.

3.2.3. Analysis of Experimental Results

Table 2 displays the experiment results, with '-' indicating that the experiments were not conducted on the current dataset. The best results are highlighted in bold.

Based on the data presented in the table, it is evident that the TBGCN model outperforms the other models on the English dataset. The Laptop dataset also shows significant optimization.

While LSTMs and attentional models can extract richer semantic features, they ignore syntactic information associated with aspect words. On the other hand, the ASGCN model uses graph convolutional neural network to extract contextual syntactic information, but it does not emphasize aspect word semantic information. Finally, the LCF-BERT model is close to the effect of this paper. It can fuse the local context information around the aspect words. However, it does not effectively exploit the syntactic features present in each node of the context.

Table 2: Experimental results of the dataset.

model	Laptop		Restaurant		Twitter	
	Accuracy (%)	F1 (%)	Accuracy (%)	F1 (%)	Accuracy (%)	F1 (%)
ATAE-LSTM	68.70	-	77.20	-	-	-
IAN	72.10	-	78.60	-	-	-
TD-LSTM	68.13	63.71	75.63		70.80	69.00
ASGCN	74.14	69.24	80.86	72.19	71.53	69.68
AEN-BERT	79.62	76.22	81.43	72.47	74.28	71.59
BERT-SPC	78.21	74.65	83.39	73.80	76.73	75.22
CDT	77.19	72.99	82.30	74.02	74.66	73.66
LCF-BERT	78.84	74.88	86.52	81.01	74.86	73.26
TBGCN(ours)	**81.19**	**77.46**	**87.14**	**81.76**	**75.87**	**74.95**

In conclusion, the TBGCN model is verified by fusing semantic information from words in the local context and extracting semantic features in the global context using BiLSTM.

4. Aspect Category Sentiment Analysis

Since many aspectual categories in a sentence may not be explicit in the context of hidden aspects, this paper proposes a multi-head attentional and graph convolutional neural network (ACMAGCNN) model for aspectual category sentiment analysis (ACSA). It aims to capture contextual sentiment information, determine categories and output appropriate sentiment. This is achieved by explicitly considering words related to the aspect in the sentence.

4.1. Model Architecture

The model consists of three layers: an input layer, a MAGCNN layer, and an output layer. The role of each layer is described below. As shown in Figure 2.

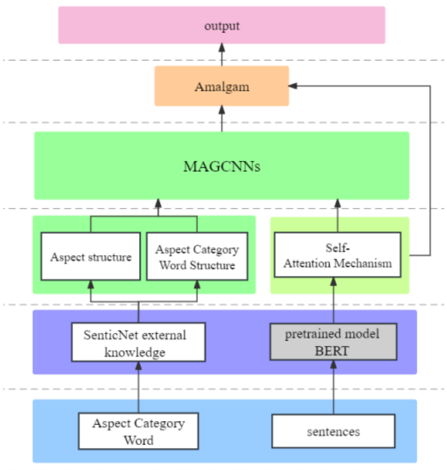

Figure 2: Architecture of the Aspect Category Sentiment Analysis Model

4.1.1. Input Layer

Once the raw data has been captured, SenticeNet is first used as external knowledge to enrich the data by generating graph matrices using the relevant entity and aspect categories of the pre-defined data set. The processed data set is also subjected to the BERT method.

Draw a context dependency diagram of aspect and calculate edge weights of each word pair:

$$A_{i,j} = p(w_i) + p(w_j) \tag{7}$$

If w_i and w_j contain dependencies in the sentence dependency tree, add the edge weight of $A_{i,j}$to 1 and then construct the undirected graph$A_{i,j} = \mathrm{A}_{\mathrm{j,i}}$ and set a self loop for each word: $A_{i,,i} = 1$.

To model the contextual sentiment information of aspect categories, the model inputs entities and aspect categories together, using explicit occurrences of aspect-related words. This approach learns contextual emotional dependencies on aspectual categories. Simultaneously, to obtain sentence feature information, the entire sentence is fed into the BERT pre-training model.

4.1.2. MAGCNN Layer

The main function of this layer is to process BERT-generated word vectors and aspect categories.

The design of this layer considers the possibility of merging graphs to supplement information and address sparsity in short text categorisation corpora. But there are limits to how flexible and scalable GCN can be. To process matrices and extract local text features, the use of convolutional layers and multiple attention mechanisms can complement GCN.

This layer uses unfolding convolution to increase the convolution kernel's range and process local text features without adding parameters or reducing speed. In this paper, the deep network is modelled using GLU, which reduces gradient dispersion and preserves nonlinearity. The processed information is then fed into a multiple attention mechanism for selective attention.

Based on this approach, we input the aspect-aware graph and contextual representation into the GCN to map emotional dependencies on aspects and capture potential interactions between entity and aspect categories. The hidden representation of each node in the lth GCN block is updated according to its neighbourhood in the entity/category adjacency matrix. The formula is:

$$\widetilde{h}^{l}_{i} = \sum_{j=1}^{n} A_{ij} W_e^l g_j^{l-1} \tag{8}$$

$$\widetilde{g}^{l}_{i} = \sum_{j=1}^{n} A_{ij} W_a^l g_j^{l-1} \tag{9}$$

$$h_i^j = ReLU(\widetilde{h}^{l}_{i}/(d_i^e + 1) + b_e^l) \tag{10}$$

$$g_i^j = ReLU(\widetilde{g}^{l}_{i}/(d_i^a + 1) + b_a^l) \tag{11}$$

Where h_i^l and g_i^l are hidden representations developed from the previous GCN block. $\mathrm{d_i^e}$ and $\mathrm{d_i^a}$ are the degrees of the ith symbol in the entity and attribute syntactic dependency trees.

Using graph convolution, these features sense the context around aspects in a way that takes into account both syntactic dependencies and long-range multi-word relationships.

4.1.3. Output Layer

This layer takes upper-layer output as input, gathers important internal relevance information, and merges it with input via a self-attention mechanism to output emotionality.

4.2. Experiment and Analysis

4.2.1. Experimental Datasets

The experiments employed the Semeval 2015 datasets (REST15 and LAP15) and the Semeval 2016 datasets (REST16 and LAP16). Table 3 presents the statistical information.

Table 3: Experimental data set of category emotion analysis.

datasets	positive		neutral		negative	
	train set	test set	train set	test set	train set	test set
Res15	1058	400	49	42	344	319
Lap15	1101	540	106	79	763	328
Res16	1460	506	188	46	661	187
Lap16	1634	479	500	94	1081	272

4.2.2. Benchmark Model

To evaluate the performance of the ACMAGCNN model, we compared it with the benchmark models listed below. The results are presented in Table 4.

TC-LSTM [7]: Based on TD-LSTM, the target word information is added to the input end, integrating the interrelated information of the target word and the context.

ATAE-LSTM [5]: Fine-grained emotion analysis with aspect word information, combining attention mechanism and LSTM to solve aspect-level emotion analysis.

BERT [10]: The input format is "[CLS]" + sentence + "[SEP]" + aspect word + "[SEP]".

ASGCN-BERT [8]: Aspect-level sentiment classification is performed using GCN and Bi-LSTM, using syntactic information and long-range word dependencies to improve overall performance.

Capsnet[13]: The model captures complex relationships between aspects and contexts, uses the marginal loss function to classify aspect-based emotions, and is randomly initialised.

Capsnet-BERT [13]: The depth representation of sentences and aspects is computed using the pre-trained BERT model. These representations are fed into the capsule layer.

AAGCN-BERT [12]: This paper explores the use of beta distributions to infer aspect weights for each aspect word in external knowledge-based guided aspect graph construction.

Table 4: Results of aspect emotion analysis.

model	Lap15		Lap16		Res15		Res16	
	Acc (%)	F1 (%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)	Acc (%)	F1 (%)
TC-LSTM	74.13	60.08	77.12	58.23	76.39	58.70	83.55	60.26
ATAE-LSTM	75.32	63.02	78.39	62.45	78.48	59.77	84.19	62.89
BERT	81.57	66.23	82.18	64.33	82.41	64.35	88.60	73.62
ASGCN-BERT	84.48	68.98	84.57	63.68	82.52	57.94	88.84	74.31
Capsnet	74.71	61.75	76.31	61.07	78.14	61.57	83.79	61.36
Capsnet-BERT	82.19	59.75	80.53	61.03	81.89	61.85	86.50	62.12
AAGCN-BERT	83.00	65.17	83.94	**69.42**	84.63	61.96	88.03	**75.15**
ACMAGCNN	**83.53**	**66.82**	**84.07**	68.21	**84.89**	**65.42**	**89.66**	75.12

From the experimental results, we can conclude that the ACMAPGCNN model is slightly lower than the AAGCN-BERT model, except for the lap16 dataset.

Clearly, using LSTM alone without pre-training the model with BERT limits the ability to acquire features effectively. The ASGCN-BERT model, which uses graph convolutional networks combined with relevant syntactic constraints and distant word dependencies, and the AAGCN-BERT model, which introduces an external knowledge base to identify highly relevant words, both improve the accuracy of the model.

However, experiments show that the model proposed in this paper works better. It uses MAGCNN to associate target words with external knowledge base categories to capture syntactic relationships, retain category information and analyse sentiment polarity.

5. Conclusions

The paper proposes two separate models for performing sentiment analysis based on the basic sentiment elements of ABSA, namely aspect words and aspect category words.The TBGCN model is proposed for aspectual sentiment analysis. It continuously extracts aspectual word features fused with local context through multilayer GCN, effectively combining local context semantics and global context semantics. ACMAGCNN model is proposed for aspect-category sentiment analysis. Aspect words are used to find implicit aspect-category words, and neighbourhood graph after weighting goes through MAGCNN module to further extract features. The two models were tested on the dataset separately, and the results show that both models perform well.

In the future, based on this paper's research, sentence feature information will be extracted from multiple aspects and angles by combining grammatical features. Further datasets from other domains will be included in migration learning experiments to improve model generalisation.

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