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Aspect sentiment analysis with heterogeneous graph neural networks

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ABSTRACT

Aspect-based sentiment analysis technologies may be a very practical methodology for securities trading, commodity sales, movie rating websites, etc. Most recent studies adopt the recurrent neural network or attention-based neural network methods to infer aspect sentiment using opinion context terms and sentence dependency trees. However, due to a sentence often having multiple aspects sentiment representation, these models are hard to achieve satisfactory classification results. In this paper, we discuss these problems by encoding sentence syntax tree, words relations and opinion dictionary information in a unified framework. We called this method heterogeneous graph neural networks (Hete_GNNs). Firstly, we adopt the interactive aspect words and contexts to encode the sentence sequence information for parameter sharing. Then, we utilized a novel heterogeneous graph neural network for encoding these sentences' syntax dependency tree, prior sentiment dictionary, and some part-of-speech tagging information for sentiment prediction. We perform the Hete_GNNs sentiment judgment and report the experiments on five domain datasets, and the results confirm that the heterogeneous context information can be better captured with heterogeneous graph neural networks. The improvement of the proposed method is demonstrated by aspect sentiment classification task comparison.

1. Introduction

The aspect-based sentiment analysis (ABSA) task aims to distinguish the aspect sentiment tendency judgment among the context syntactic and semantic information. It is a scorching research field for text processing. For example, for the sentence "The atmosphere is noisy, and the waiters are literally walking around doing things as fast as they can"., the aspect "atmosphere" is expressed as "negative" sentiments, while the aspects of the "waiters" is described as "positive" sentiment polarities. The tendentiousness of sentiment polarities is implied with the opinion adjective word "noisy" and the phrase "walking around doing things as fast as they can". Since the two aspects have opposite tendentiousness of sentiment polarities, designating only a sentence-level sentiment is unsuitable. For this matter, ABSA is more appropriate to describe sentiment polarities task than the level of sentence emotion judgment.

In order to accomplish the aspect level sentiment analysis tasks, some advanced methods have been raised. For example, the literature (Mubarok, Adiwijaya, & Aldhi, 2017; Pérez-Rosas, 2012) employed the sentiment tendency dictionary, the position information of sentiment words and other parts of speech of words, and bag-of-words features to construct a classification model.

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Since these methods cost enormous human resources to form feature engineering, researchers are paying less and less attention to them.

Researchers have paid more attention to the deep neural network in the recent ten years and tried to employ these technologies to deal with sentiment classification problems. They utilized the dense vector representation to describe the contexts and the target aspect words captured by a large-scale corpus. Hence, sentiment similarly can be calculated by the vectorial angle cosine. These methods using deep neural networks do not depend on feature engineering, and it is a significant improvement in reducing human labour for sentiment classification.

The heart of ABSA tasks is to find the connecting relations among their respective opinion words. Most recent efforts (Fan, Feng, & Zhao, 2018; Ma, Li, Zhang, & Wang, 2017; Wang, Huang, Zhu, & Zhao, 2016a) used the attention mechanisms to achieve the model construction and have obtained excellent results. The sequence representation learning can capture most of the sentiment words' position features, so many researchers appreciate it. However, sometimes the grammar and syntax are very complex to the sequence representation learning failed work. For instance, the text content in the Lap14 dataset "Everything is so easy to use, Mac software is just so much simpler than Microsoft software". has sentiment term "simpler" is closer to the aspect "Microsoft software" than the aspect of "Mac software", so the tendency of sentiment "so easy to use for Mac software", but they are also could be used simpler "Microsoft software" appearing in these kinds of sentences. The attention models used in previous works give equal importance to all context words (He, Lee, Ng, & Dahlmeier, 2018); however, they are insufficient to capture syntactic dependencies between context words and aspects within a sentence.

When studying the ABSA task, we observe two facts. (1) The current attention the mechanism may cause the given aspect to pay attention to syntactically irrelevant context words as descriptors erroneously (Zhang, Li, & Song, 2019). (2) Many opposite aspect sentiments often appear in one sentence simultaneously. For instance, the review content "The food itself was just ok – nothing spectacular – but the service was awful", the opinion words "nothing spectacular" indicate the neutral sentiment of "food", the word "but" indicates the other aspect "service" is different from the aspect of "food" and indicates the negative sentiment.

To address this problem, some researchers used the syntactic structure to construct the connections relations among words. Liu, Xu, Liu, and Zhao (2013) and Qiu, Liu, Bu, and Chen (2011) have attempted to utilize syntactic rules for their tasks by extracting the syntactic relations that link opinion words and aspect words. They adopt the dependency parser to form the relation information among the aspect words and sentiment words. And the dependency parse graph/tree provides more coarse-grained understandable information. To leverage the dependency parse graph/tree information, they encode it by the recursive neural networks (RNNs) (Nguyen & Shirai, 2015; Wang, Pan, Dahlmeier and Xiao, 2016) or by calculating the words in the graph/tree distance for attention weight (Nguyen & Le Nguyen, 2018).

Recently, graph neural networks (GNNs) are also applied to establish a context syntax tree for capturing these kinds of representation (Huang & Carley, 2019; Sun, Zhang, Mensah, Mao, & Liu, 2019; Zhang et al., 2019). Peng et al. (2022), Yuan, Zhong, Lei, Zhu, and Hu (2021) and Zhu et al. (2017) designed graph methods for similarity search and subspace learning tasks. However, Zhang et al. (2019) exploits the parse tree or parse graph to encode the word relations while the aspects and opinion words are ignored in their methods. The other problem is that the method is a batch operation and do not optimized. Ma et al. (2017) proposed a method with interactive learning between aspect words and contexts. Lu and Huang (2021) designed a graph neural network framework using the prior sentiment dictionary information based on the concurrence-words relation graph, and with the help of a multi-head attention mechanism to obtain many rich emotion features. However, previous work is still challenging to capture complex relationships for aspect sentiment analysis, which has excellent potential for improvement.

To effectively improve the above problems, in this paper, we employ the syntax tree information in the sentence sequences and attempt to bring the adverb words, the adjective words, and the sentiment dictionary to establish heterogeneous graph relations to form a preferable representation for our tasks. Firstly, we employ the syntax tree to construct an initialized graph. Secondly, we append some parts of speech and the sentiment dictionary. Lastly, we obtain these dependency relations among them. Furthermore, this graph structure enables us to focus on the sentiment word relations and utilize the sentence structure information. Then we encode this different information together and construct a heterogeneous relation graph that is fed into the graph attention network (GAT) model. Extensive evaluations are conducted on the Twitter, Lap14, Rest14, Rest15, and Rest16 datasets. Through experiments on emotion judgment tasks, we demonstrate the GAT model can be boosted.

We highlight the contributions of Hete_GNNs as follows:

- The work presents a heterogeneous graph neural networks(Hete_GNNs) framework, which adopts the interactive aspect of words and contexts for the sentence encoder. To preserve the aspect words and contexts interactive properties, we used the interactive attention networks to encode the sentence sequence representation in order to conduct parameters sharing.
- We design the heterogeneous graph with syntactic sentence relations, the prior sentiment dictionary information and some part-of-speech tagging information to capture the multiple different ties.
- We do experiments to verify Hete_GNNs framework can be obtained promotion with the aspect sentiment classification tasks significantly. Besides, we analyze the Hete_GNNs on five different datasets and demonstrate the benefits of employing the heterogeneous graph information.

2. Related work

Many researchers pay much attention to aspect-based sentiment analysis (ABSA). Many recent works take the text as the sequence processing problem, so the long-short terms memories (LSTMs), Bidirectional LSTMs model and other extended attention-based neural models are to be proposed. Such methods have accomplished great progress. Tang, Qin and Liu (2016) proposed a neural network similar to the memory mechanism to read the importance of word context representation and infer the aspect sentiment polarity simultaneously. The literature (Hu et al., 2021; Xiao et al., 2021; Zhu, Hao, Hu, Wang, & Zhang, 2018; Zhu, Ma, Yuan, & Zhu, 2022) studied the dynamic graph learning method, which is applied to disease analysis. Ma et al. (2017) introduced the interactive module to share parameters to capture attention representation in target aspects and contexts, then establish the suitable target and context vector representations separately.

Huang, Ou, and Carley (2018) learned the aspect and context representations by employing an attention-over-attention module jointly. The attentional encoder network (Youwei, Jiahai, Tao, Zhiyue, & Yanghui, 2019) has success in utilizing attention-based encoders between context and targets. Biqing, Heng, Ruyang, Wu, and Xuli (2019) designed a method to obtain the local and global context with long-term internal dependencies. Chen, Sun, Bing, and Yang (2017) capture sentiment representations respectively using the long-distance for distinguishing the irrelevant information by multi-attention mechanism. Liu, Zhang, Zeng, Huang, and Wu (2018) considered the vocabulary relations among the aspect in their context, then modelled the complex context syntax structure and multi-aspect sentiments by two attention enhancing mechanisms.

He et al. (2018) employed the attention model for capturing the semantic meaning of the opinion target. The pre-trained model BERT (Devlin, Chang, Lee, & Toutanova, 2019) with large scale corpus is designed for different text analysis processing assignments, for instance, Li, Bing, Zhang, and Lam (2019) build multiple frameworks based on neural networks methods for ABSA, Chi, Luyao, and Xipeng (2019) have modelled the aspect with an auxiliary sentence representation, and consider the ABSA problem as the context-pair classification task.

Many works try to model and preserve the sentence sequence syntax and semantics information in ABSA, because aspect sentiments are represented as words or phrases. Consequently, it is essential to capture the aspect of target word connections and the sentiment words. Ganapathibhotla and Liu (2008) employed the tendency of sentiment which came from the website by user comment and constructed a method to mine the trend of opinion with the comparative contexts. Su et al. (2008) studied an approach that preserves the product features and sentiment tendency terms by fusing the emotion syntax connection with the content information.

Many previous works have realized that aspect words and their context relation are essential for sentiment classification tasks. However, they either consider these tasks as text sequence processing problems or do not take care of the high-level semantics of words. Recently, graph neural networks have been used for modelling the syntax tree information from each sentence in ABSA. Lu and Huang (2021) designed a method to construct a concurrence words graph as a part of sentiment classification tasks. Sun et al. (2019) and Zhang et al. (2019) designed a method using a graph convolutional network to obtain word dependencies relations by the tree representations of the sentences, then fed these representations to the sentiment classifier. However, the above-mentioned the method does not consider the relation graph quality; further, the emotion terms and aspect phrase relations are often ignored.

3. The architecture of heterogeneous graph neural network

First of all, we introduce some notations and give the ABSA task definition. Secondly, we describe the heterogeneous graph construction. Next, we show our heterogeneous graph neural network architecture. Lastly, we show how to train the proposed model.

3.1. Problem definition

For the purpose to solve the aspect sentiment classification problem, we suppose that a context sentence $\mathbf{w}^c = \{w_1^c, w_2^c, \ldots, w_n^c\}$ which come from the corpus consisting of n words and the ith aspect[1] subsequence $\mathbf{w}^{a,i} = \{w_1^{a,i}, w_2^{a,i}, \ldots, w_m^{a,i}\}$, and the corresponding word embedding are represented as $\mathbf{e}^c = \{e_1^c, e_2^c, \ldots, e_n^c\}$ and $\mathbf{e}^{a,i} = \{e_1^{a,i}, e_2^{a,i}, \ldots, e_m^{a,i}\}$, respectively. The issue that the tendency of emotion analysis aims to judge the tendency of opinion $y \in \{positive, neural, negative\}$ of the context representations $\mathbf{w}^c$ via the target aspect vectors $\mathbf{w}^{a,i}$.

3.2. Heterogeneous graph neural networks model

The framework of Hete_GNNs is composed of two parts. One module is captured by the aspect sentiment sequence and context terms dependence, and the other is the relations module that is captured by the aspect term, context term, and sentiment dictionary. The architecture of Hete_GNNs model is described in Fig. 1.

The part of the left side is the word embedding layer, which consists of target aspect embedding representation and context representation. We use the GloVe (Pennington, Socher, & Manning, 2014) word embedding to speed up the model pre-trained. Then the pre-trained embedding representations are fed into the GRU (Chung, Gulcehre, Cho, & Bengio, 2014) layers to obtain the hidden state's features (including the vectors learned by target aspect and contexts terms). We consider the influence of the target on the context and the impact of the relative context, take the pooling representation of the context and the target as input, and adopt the attention mechanism to select important information that helps to judge the sentiment polarity. Furthermore, to utilize the heterogeneous graph capturing relations information, we assume the graph attention network (Velickovic et al., 2017; Wang, Shen, Yunyi, Quan, & Wang, 2020) to encode the syntax dependency relations of sentences by words. Finally, we combine the target aspect representation, context representation, and output representation with the graph attention network layers as the final output layer, which are fed to the loss function to achieve the tendency of opinion judgment.

[1] A sentence sequence might be contain multi-aspects expression with different sentiments.

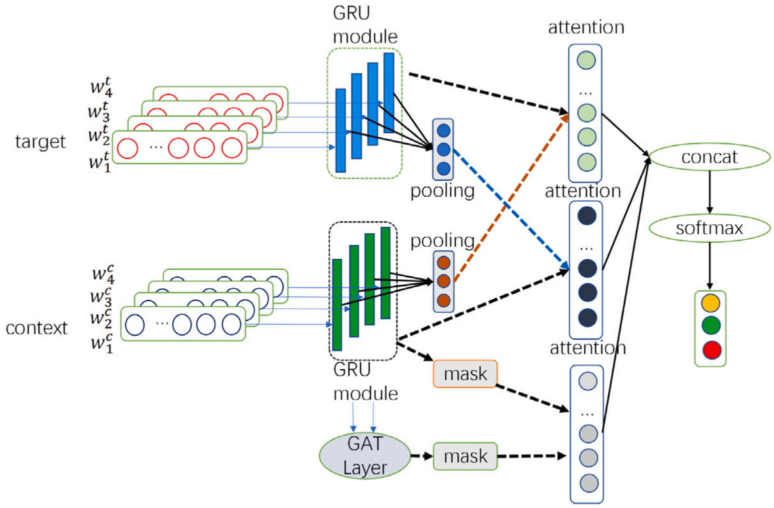

Fig. 1. The framework of Hete_GNNs model. The context of sentences and the target aspect words are encoded as word embedding. Then they are fed into the GRU module for encoding as hidden features, and the pooling operations are utilized to fetch the target aspect and the context interactive messages. The graph attention layer is utilized for preserving heterogeneous graph relation features. At last, the output layers are constructed as the attention layers with the concatenation operation, so these representations are connected with the softmax function to perform the tendency of sentiment judgment together.

3.3. Sentence sequence and target aspect representations

Generally, the pre-trained GloVe (Pennington et al., 2014) embeddings are used for extracting each context in the training set or each of the target aspect vocabulary. Suppose $L \in R^{d_e \times \|V\|}$ as the pre-trained embedding matrix by large corpus, and the dimension of vector denoted as d_e, $\|V\|$ is denoted as the vocabulary size. The term vocabulary embeddings can be regarded as parameters obtained by pre-training from corpus via language model (Pennington et al., 2014). We loop up each vector embedding, including the context vectors e^c and aspect-based word sequence vectors e^a, and the context and target aspect feature representation is constructed.

With the word embeddings of sentences and target aspect words, the recurrent neural networks (RNNs) are suitable for time-series classification, and they can handle variable length text sequences naturally. Moreover, RNNs share some parameters, which dramatically reduce what we need to learn. Among many variants of the RNNs, we used the gated recurrent units (GRUs) (Chung et al., 2014) to obtain annotation of words from forwarding directions for words, and produced hidden state vectors $\hat{\mathbf{h}}$.

Given the length of sentence L, we denote x_{ij} as the sentence words embedding vectors and $\mathbf{E}$ represents the pre-trained word embedding matrix, $x_{ij} = Ew_{ij}$, $j \in [0, L]$. Without loss of generality, the forward direction GRU effectively $\overrightarrow{f}$ read the input context symbol representation from x_{i1} to x_{iL}. So the forward direction hidden states can be written as follow:

$$\vec{\mathbf{h}}_{ij} = \overrightarrow{GRU}(x_{ij}), j \in [1, L], \tag{1}$$

By the forward direction GRU, we can capture the interpretation for each word, $h_{ij} = \overrightarrow{h_{ij}}$, the interpretation h_{ij} includes the forward direction dense representation of current word. Inspired by Ma et al. (2017), we preserve the pooling module of sentence context and target aspect word representations in our model to influence the representations interactively. Specifically, we compute the importance of words and inject the words representation into the attention mechanism by performing as follow

$$u_{ij} = \tanh(h_{ij} W_w p_{avg}^T + b_w) \tag{2}$$

$$\alpha_{ij} = \frac{\exp(u_{ij}^T u_w)}{\sum_j \exp(u_{ij}^T u_w)} \tag{3}$$

$$s_i = \sum_{j=1}^{L} \alpha_{ij} h_{ij} \tag{4}$$

$$p_{avg} = \sum_{i=1}^{t} \frac{h_{ij}}{t}, t \in [1, L]. \tag{5}$$

where p_{avg} is the pooling representation of the context or target (pooling in Fig. 1), which we can get by averaging the hidden states. u_{ij} is represented as output by feeding the hidden representation of h_{ij} to the $\tanh(.)$ function. Therefore a normalized importance weight α_{ij} which states the significance of each word context is calculated. The attention weight α_{ij} is assigned greater, the context

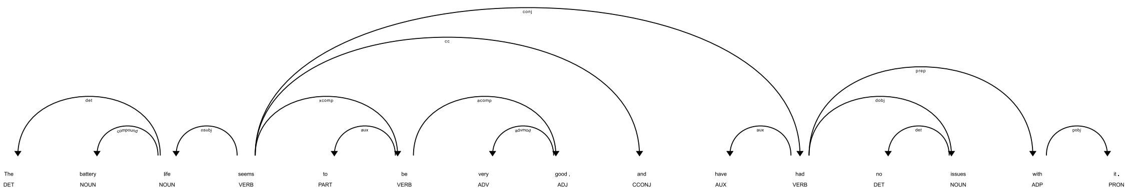

Fig. 2. An instance of a dependency parsing tree extracted by the syntactic dependencies. The word "very good" as a adjective phrase and it implies a positive tendency of opinion description of the aspect phrase "battery life" .

self-representation and each word local representation are more likely to be highly similar. And the context vector self-representation s_i is acquired by a linear sum among each representation in context sequence.

3.4. Heterogeneous graph based syntax dependency tree

The structure of sentences can be represented as a syntactic dependency parsing tree. The syntax dependency parsing tree reflects the grammatical of sentences. The words and their relations can be denoted as nodes and directed edges. Here is an example to explain the syntax dependency parsing tree in Fig. 2. The word "very good" is an adjective phrase, and it implies a positive tendency of opinion description of the aspect phrase "battery life". In order to obtain the sentence structure information, we construct a matrix of relation called $A' \in R^{n \times n}$ according to the contexts representation, their part of speech and sentiment toward in context, where n represents the number of terms in contexts. In addition, we assume that the adjective and adverb are significant to the sentence's sentiment. The positive, negative or neural descriptions for embellishing aspect targets are also equally important. Motivated by the above observations, we reshaped them and obtain an argument matrix $A \in R^{(n+q) \times (n+q)}$ from the syntax dependency tree structure A', where q represents the length of $\{adjective, adverb, positive, negative, neural\}$, so in this paper, $q = 5$. And the argument matrix A includes the syntax dependency relations, the pos of speech relation and the sentiment toward relations. In other words, it includes heterogeneous information, so we call it the heterogeneous graph. There are two advantages to the heterogeneous graph. Firstly, each sentence has a special syntax dependency structure. These kinds of information are preserved in the relation graph. Secondly, additional information, the pos of speech or the sentiment dictionary, is captured by the algorithm and fed into the model training.

Algorithm 1 Heterogeneous Graph Generation.

Require: sentence $\mathbf{s} = \{w_1^s, w_2^s, \cdots, w_n^s\}$, n, sentiment dictionary $\mathbf{D}_p$, $\mathbf{D}_{neg}$, $\mathbf{D}_{neu}$, adjective, adverb.
Ensure: Heterogeneous graph matrix $\mathbf{W}^{(n+5)\times(n+5)}$;
Initialize heterogeneous graph **W**;
for all $word_i, word_j \in sentence$ **do**
  if $word_i \xrightarrow{r_{ij}} word_j$ **then**
    $w_{ij} \xleftarrow{r_{ij}} R, w_{ji} \xleftarrow{r_{ij}} R$
  end if
  if $word_i$ is an adjective word **then**
    $w_{i,adj} \xleftarrow{r_{i,adj}} R, w_{adj,i} \xleftarrow{r_{adj,i}} R$
  end if
  if $word_i$ is an adverb word **then**
    $w_{i,adv} \xleftarrow{r_{i,adv}} R, w_{adv,i} \xleftarrow{r_{adv,i}} R$
  end if
  if $word_i \in \mathbf{D}_p$ **then**
    $w_{i,p} \xleftarrow{r_{i,p}} R, w_{p,i} \xleftarrow{r_{p,i}} R$
  end if
  if $word_i \in \mathbf{D}_{neg}$ **then**
    $w_{i,neg} \xleftarrow{r_{i,neg}} R, w_{neg,i} \xleftarrow{r_{neg,i}} R$
  end if
  if $word_i \in \mathbf{D}_{neu}$ **then**
    $w_{i,neu} \xleftarrow{r_{i,neu}} R, w_{neu,i} \xleftarrow{r_{neu,i}} R$
  end if
end for

In order to realize our image, algorithm 1 illustrates the establishment process of a heterogeneous graph. For each input context, the dependency parser tree[2] are obtained. Then we obtain the adjacency matrix A'. Where r_{ij} is represented as the dependency relation from $word_i$ to $word_j$. Then we add the pos of speech relations and the sentiment toward relations. We assume the adjective terms and the adverb terms have a great impact on sentiment analysis. Therefore, we treat the adjective and the adverb as entities to construct these relations. And the sentiment dictionary often occurs in traditional machine learning. This paper also brings this information to enrich our model representation capacity.

The heterogeneous graph generation described is partially inspired by previous studies (Lu & Huang, 2021; Zhang et al., 2019) that leverage a graph to capture the dependency trees of sentences and utilize the sentiment dictionary to strengthen the representation capacity. Our approach provides a novel view to model the sentence of context information. Such a heterogeneous graph not only does it allows our method to focus on the syntax dependency tree among the word relations but also employs the pos of speech and the sentiment dictionary during training. We consider this heterogeneous graph is superior to other relative methods and evaluate the heterogeneous graph module in the experiment and validate our guess.

3.5. Graph attention networks

In order to utilize the heterogeneous graph capturing relations information, we adopt the graph attention network (Velickovic et al., 2017; Wang et al., 2020) to encode the syntax dependency relations of sentence by the words. The relations are represented as the edges of G. N_i is represented as the first-order neighborhood nodes of node i. The multi-head attention is beneficial to the learning processing and it is introduced for neighborhood node aggregating representation. So resulting in the following output feature representation of the attention of ith head node at $(l+1)th$ layer:

$$\vec{h}^{l+1}_{gat_i} = \|_{k=1}^{K} \sum_{j \in N_i} \alpha_{ij}^{lk} W^{lk} \vec{h}_j^l \tag{6}$$

$\|_{k=1}^{K} z_i$ represents the concatenation operation from z_1 to z_k. α_{ij}^{lk} is a normalized attention weight coefficient of the kth attention at layer l, W^{lk} represents the transformations weight matrix. The α_{ij}^{lk} coefficient is used to compute the linear combination of features corresponding to nodes. We employ the dot-product operation to calculate neighbour nodes attention weights in our work.

To expand the representation ability of network, we also add the multi-head attention on the last fully-connected layer of network, by the averaging operation, so the aggregation process of multi-head graph attentional layer $\vec{h}^{l+1}_{aggregation}$ is defined as follow:

$$\vec{h}^{l+1}_{aggregation} = \frac{1}{K} \sum_{k=1}^{K} \sum_{j \in N_i} \alpha_{ij}^{lk} W^{lk} \vec{h}_j^l. \tag{7}$$

Because researchers have realized that context representation is significant for target aspect sentiments, people design some interactive attention network (Ma et al., 2017) for this task. Inspired by this, we preserve the pooling module of sentence context and target aspect word representations in our model to influence the representations interactively. At last, the graph attention representation, target aspect word and context representation are formed with the output representation, then it is fed to an activation function for model training.

3.6. Model training

The Heterogeneous graph neural network of representation h_o is fed into a full connected layer by σ function (e.g. tanh) whose is a probability distribution with different sentiment opinions polarity. Finally, the model is trained through the backpropagation technology, where the cross entropy loss is minimized as the objective function:

$$\mathbf{L}(\theta) = -\sum_{(S,A) \in D} \sum_{a \in A} \log p(a) + \lambda \sum_{\theta \in \Theta} \theta^2, \tag{8}$$

where Θ denotes the trainable parameters of Hete_GNNs model. $p(a)$ denotes the sentiment judgment tendency output distribution element calculated by the last fully connected layer, and D denotes the whole context and aspects relation pairs, A represents the aspects appearing in text sequence S, and λ is denoted as an adjustment parameter, and it multiplies L_2 regularization term.

4. Empirical evaluation

We evaluate the Hete_GNNs model on the benchmark datasets by aspect sentiment classification task in this section. To distinguish Hete_GNNs and validate it can work well, we compare Hete_GNNs with several well-established models, showing that Hete_GNNs outperforms the recent models in the sentiment classification task. We further analyze and show how the Hete_GNNs method is improved in emotion tendency judgment tasks by the ablation study.

[2] We employ the spaCy toolkit to get the dependency parser tree, https://spacy.io/.

Table 1
Five datasets are utilized in our experiments.

Dataset	Pos		Neu		Neg	
	Train	Test	Train	Test	Train	Test
Twitter	1561	173	3127	346	1560	173
Rest14	2164	728	637	196	807	196
Rest15	912	326	36	34	256	182
Rest16	1240	469	69	30	439	117
Lap14	994	341	464	169	870	128

4.1. Datasets

Five public datasets are shown in Table 1, which are employed in the experimental comparison, they are all the review datasets, and Twitter is also used by Li, Wei, Tan, Tang, and Ke (2014), others are come from the sentiment task evaluation, for instance, SemEval 2014 (Pontiki et al., 2014), includes the laptop reviews and restaurant reviews, SemEval 2015 (Pontiki, Galanis, Papageorgiou, Manandhar, & Androutsopoulos, 2015) and SemEval 2016 (Pontiki et al., 2016) are all the restaurant reviews.

4.2. Parameters setting and implementation details

Hete_GNNs model used the embedding vectors, which are learned by GloVe (Pennington et al., 2014) to emotion tendency judgment. The size of vectors (e.g. be set to 300 in our experiments) is pre-trained on a large-scale textual corpus of about 840 billion. We used the weight parameters , which range to $\mathcal{U}(-0.01, 0.01)$ gaussian distribution. For different datasets, the parameter settings are kept consistent in each experiment. We adopt 1×10^{-3} as the learning rate parameter, and use parameter 0.1 as the dropout rate. And the training process will early terminate after the value of the loss function does not decline for three epochs.

4.3. Methods analysis

So as to illustrate our method is effective, the comparison mainstream approaches are listed as follows:

- LSTM (Tang, Qin, Feng and Liu, 2016) is a special recurrent neural network that can learn the long dependence of sequences. They used the hidden state representation to judge the emotion tendency.
- TD-LSTM (Tang, Qin, Feng et al., 2016) is a method based LSTM which captures the target-dependent, and in view of target words which surround on the left and right, and both the forward and background directions context are captured for feature representation for the tendency of aspect sentiment judgment.
- ATAE-LSTM (Wang, Huang, Zhu, & Zhao, 2016b) construct a method on account of the simple LSTM, which is for a weight hidden representation by the popular attention method. They take into aspect embedding term to each word embedding in context to construct representation.
- MGAN (Fan et al., 2018) utilized different thickness perspective attention mechanism together to establish interactive information by the context and aspect target, then fed that into the softmax function for classification.
- AOA (Huang et al., 2018) modeled the aspect words and contexts interactively, and the form of construction is similar to the manner of machine translation, which employs the attention-over-attention.
- MemNet (Tang, Qin, Liu, 2016) used multiple different layers and each layer owning themself attention and linear layers, and designed a memory network for emotion tendency judgment.
- IAN (Ma et al., 2017) construct a classification model interactively with contexts and target aspect representation, and they also employ an attention layer to capture the hidden representation parameters were shared for sentiment analysis.
- ASGCN-DG (Zhang et al., 2019) model build a GCN module by loop dependency graph in context, and try to find the context syntactical and word dependencies relations.

The comparison approaches are shown in Table 2, where the bold and underlined values represent the highest scores in all methods and all baselines, respectively. We can conclude that the Hete_GNNs method performs well in sentiment classification accuracy. Table 2 reports the comparison results, and we find:

Hete_GNNs model using the interactive aspect words and contexts sequence representation and graph information usually achieves better performance than other comparison methods, for instance, shown in Rest14, Rest15, and Twitter datasets, while in Lap14, Hete_GNNs obtained the second-best result. Moreover, its macro-F1 on Rest16 exhibits an improvement of approximately 1.4% compared with ASGCN-DG. The investigation demonstrates that multi-representation fusing contributes to the Hete_GNNs model from different sides. That is because the heterogeneous graph not only does it allows our method to focus on the syntax dependency tree among the word relations but also employs the pos of speech and the sentiment dictionary during training. Overall, the Hete_GNNs model shows strong evidence advocating our proposed framework. To capture the proposed method mechanics in detail, we give further analysis.

Table 2
Main comparison results (%). Experiments are done in five epochs, the overall performance on average emotion tendency judgment accuracy and macro-F1 score. We mark experimental best results and the second results in bold font and underline, respectively.

Method	Lap14		Rest14		Rest15		Rest16		Twitter	
	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
LSTM	71.49	65.96	78.74	67.92	78.15	57.45	86.61	65.60	69.05	67.42
TD-LSTM	68.75	62.07	79.04	68.25	76.49	55.32	86.79	67.33	71.01	69.34
ATAE-LSTM	63.61	55.96	73.88	60.49	72.21	48.87	83.02	53.89	64.77	61.93
AOA	73.42	68.77	80.54	71.66	79.15	60.92	87.89	68.51	71.10	69.41
MemNet	70.85	65.83	78.48	69.05	78.82	60.68	85.62	67.36	70.64	68.89
IAN	72.73	67.92	79.86	70.31	76.71	57.98	85.23	63.89	70.03	68.26
MGAN	72.45	67.25	80.79	71.63	79.82	62.07	87.82	68.13	72.08	70.96
ASGCN-DG	**75.55**	**71.42**	81.79	73.67	79.54	60.71	**88.20**	68.78	71.76	70.01
Hete_GNNs	74.08	69.45	**81.91**	**73.74**	**80.37**	**63.21**	87.92	**70.18**	**72.80**	**71.36**

Table 3
Ablation study on different dataset (%). Experiments are done in five epochs, the overall performance on average accuracy and macro-F1 score.

Method	Lap14		Rest14		Rest15		Rest16		Twitter	
	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
LSTM	71.49	65.96	78.74	67.92	78.15	57.45	86.61	65.60	69.05	67.42
Hete_GNNs	**74.08**	69.45	**81.91**	**73.74**	**80.37**	**63.21**	87.92	**70.18**	72.80	71.36
Hete_GNNs w/o GAT	73.48	68.48	80.32	70.96	79.37	62.95	87.21	68.63	72.23	70.81
Hete_GNNs w/o mask	73.26	68.29	79.68	69.84	79.34	59.97	87.18	68.24	71.97	70.57
Hete_GNNs w/o pos mask	74.01	**69.49**	81.55	73.23	79.41	62.21	88.12	68.73	72.11	70.35
Hete_GNNs w/o heterogeneous	73.89	69.28	80.82	71.99	79.59	60.73	87.24	68.22	**72.95**	**71.38**

To evaluate the impact of each module design, such as graph attention network and mask. We conduct the ablation study on Hete_GNNs. Table 3 reports the effect of each module with the indicator of emotion tendency judgment accuracy and macro-F1. Our findings are listed below:

We take the simple LSTM as a baseline, which learns the representation, and model one LSTM for context and each word by hidden states. The experimental results of the Hete_GNNs model obtained better results than LSTM. On account of the Hete_GNNs model, add the heterogeneous graph for relation representations, graph attention network, mask, and pos mask component simultaneously. In other words, we only keep the state of aspect words in the mask component (mask after GAT layer). In the pos mask component (mask after GRU), we keep the state of aspect words, the adjective words, the adverb words, and the sentiment dictionary.

(1) Removal of graph attention network(GAT) and masking (i.e. Hete_GNNs w/o GAT) gives rise to (73.48%, 68.48%), (80.32%, 70.96%), (79.37%, 62.95%), (87.21%, 68.63%), (72.23%, 70.81%) on all five datasets, respectively, in other words, the accuracy and F1 measure results are come worse, which show that the GAT module provides some valuable information to prediction. Further, the heterogeneous graph includes syntax dependency relations, and it is helpful for sentiment aspect prediction. Consequently, it demonstrates that the relation graph utilized is an essential component.

(2) Get rid of mask (i.e. Hete_GNNs w/o mask). We observed that the results declined consistently on five datasets. This test noticed that the mask part of our model is helpful for context representation learning.

(3) Compared with Hete_GNNs, Hete_GNNs w/o pos mask(i.e. preserving graph attention network module and the aspect mask, and removing pos mask). The results decline on five datasets except for ACC on the Rest16 dataset and Macro-F1 on the Lap14 dataset. The pos mask to some performance in Hete_GNNs, which states the effectiveness.

(4) To verify the effectiveness of heterogeneous graphs, we replace heterogeneous graphs with dependency graphs. The results show that the heterogeneous graph helps promote the aspect sentiment classification tasks. In the Twitter dataset, Hete_GNNs w/o heterogeneous outperform Hete_GNNs because of the incomplete syntactic information of tweets. However, our Hete_GNNs framework is also able to achieve effective improvements compared to other methods.

To intuitively show the different heads' attention, we visualize the head number on the final performance of Hete_GNNs in 2D space. We set the number of head attentions range in {1,4,8,16,24,32,40} and validate the impact of Hete_GNNs on the Rest16 dataset. We obtain the results in Fig. 3. The visualization shows that Hete_GNNs achieve the best performance when the number of head attention is 24.

5. Conclusion

We introduced a novel emotion tendency judgment approach to encode heterogeneous relations information, which can learn each term around their context and relative representations together and demonstrated its effectiveness in experiments. We first utilized the GRU module to capture the text sequence features and the interactive module to obtain the target aspect and context information. Also, we construct the heterogeneous graph to preserve syntax tree dependence and some important word relations.

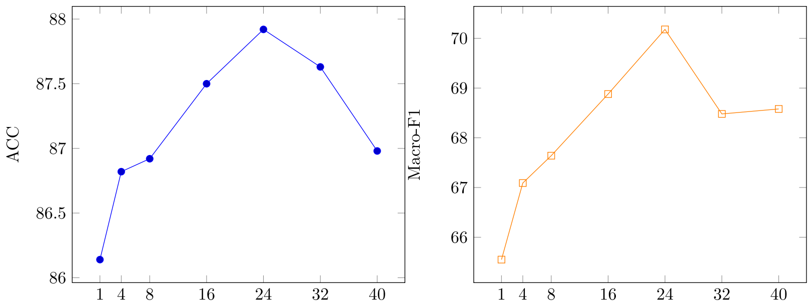

Fig. 3. The impact of number of heads attention on Rest16. Experiment are done in five epochs.

At last, the output representations by the graph attention network and the GRU output features are fed into the attention layer for sentiment classification. To empirically show the advantage of Hete_GNNs, we conduct experiments to compare with other relative models. As desired, the ablation studies' results validate the role of each module structure and confirm the framework for sentiment analysis experimental benefit that we described. However, GRU still cannot fully solve the vanishing gradient problem. To further improve the ABSA task, we will utilize the powerful contextual features of the BERT model in our future work.

CRediT authorship contribution statement

Guangquan Lu: Conceived of the presented idea, Developed the theory and performed the method analysis, Supervised the findings of the work, Discussed the results and contributed to the final manuscript. **Jiecheng Li:** Conceived of the presented idea, Verified the analytical methods, Discussed the results and contributed to the final manuscript. **Jian Wei:** Verified the analytical methods, Discussed the results and contributed to the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Code available at https://github.com/mr-independent/Hete_GNNs

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