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Neighborhood Network for Aspect-based Sentiment Analysis

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Abstract. Different aspects of a sentence may contain different sentiments, and sentiment descriptors for a given aspect exist in different places in the sentence, making it difficult to determine its sentiment polarity. Aiming at the above problems, a neighborhood network (Nenet) for aspect-based sentiment analysis is proposed. Firstly, the context information of the text is encoded, and the neighborhood information of the target aspect at the grammar level is extracted by using a graph convolutional neural network. At the same time, the convolutional neural network is used to extract the neighborhood information at the physical level, and the two extracted features are combined to improve the text expression ability. Finally, an attention mechanism is used to express the key information in sentences for judging sentiment polarity, and the final text representation is input to the sentiment analysis layer to predict sentiment polarity. Experiments are carried out on three standard datasets, and the experimental results show that the neighborhood network outperforms other baseline models in both index accuracy and F1 value.

Keywords: Aspect-based Sentiment Analysis, Sentiment Polarity, Neighborhood Network, Convolutional Neural Network, Attention Mechanism.

1 Introduction

With the development of society and the advancement of technology, social networks have become increasingly prosperous. How to mine the emotions expressed by users from massive text information has become a research hotspot in the field of Natural Language Processing (NLP). Sentiment analysis can be divided into three categories according to the granularity of research objects: document level, sentence level and aspect level. Document-level and sentence-level sentiment analysis take the entire document or specific sentences in the document as the analysis object, and are often used in scenarios such as product evaluation[1] or movie reviews. Aspect-based sentiment analysis (ABSA), also known as fine-grained sentiment analysis, uses the specified words or phrases in the sentence as the analysis object and judges their sentimental polarity in a specific context[2]. For example, in the sentence "The AMD Turin processor seems to always perform so much better than Intel." In terms of goals, the sentiment polarities of "AMD Turin processor" and "Intel" are positive and negative respectively.

In the past research, many scholars used traditional machine learning methods to solve the problem of text classification. This method manually marks part of the data as a training set, then extracts and learns the characteristics of the data on the training set to build a text classification model, and finally uses the model to predict the unlabeled data, so as to automatically realize text classification[3]. The method based on machine learning has made many achievements in the past research. This method usually depends on complex artificial rules, so the evaluation of model performance depends on the quality of text feature selection.

With the development of deep learning, aspect-based sentiment analysis based on deep neural networks has become the mainstream of research. At present, the commonly used methods are usually based on Long Short-Term Memory Networks(LSTM)[4] and Gated Recursive Unit (GRU)[5] etc. to transfer the information processed in front of the model and use it for subsequent processing. For aspect-based sentiment analysis, the key information that determines its sentiment polarity is often closer to the aspect word, but this type of model cannot effectively capture the neighborhood information of the aspect word.

This paper proposes an aspect-based sentiment analysis neighborhood network (Nenet), which adds an Aspect Neighborhood Information Representation (ANIR) layer after encoding the context of the sentence. The ANIR layer extracts the neighborhood information of the aspect word by adding the relative positional relationship between each word in the sentence and the target aspect word, and constructs a dependency syntax tree to capture the syntactic information between the words in the comment sentence. After the two parts of information being fused, the attention mechanism is used to focus on the key information in the sentence to improve the discriminative performance of the sentiment analysis model. The experimental results are significantly improved on three datasets, among which, on the 14Lap dataset, the accuracy and F1 value of the method are 76.15% and 72.52%, respectively, which are 1.54% and 2.38% higher than the previous model TNet-LF.

2 Related Work

Sentiment analysis is one of the most challenging tasks in the field of natural language processing, which makes it a current hot issue. There are some representative work in the early researches. Vo et al.[6] used sentiment word embeddings and sentiment dictionaries to obtain rich artificial features, and achieved good sentiment classification results on the dataset twitter. Yang et al.[7] used topic models to acquire new words and extended sentiment lexicons based on existing sentiment lexicons, achieving good results on multiple test datasets for sentiment analysis tasks. reference[8] proposed a new domain-specific sentiment dictionary generation method, and proposed a sentiment analysis framework based on the generated domain-specific sentiment dictionary. The experimental results show that the sentiment analysis framework based on the new dictionary achieves better performance. Most of the early methods were based on emotional dictionaries. However, due to the complex context structure of natural language, it is not easy to build a relatively complete emotion dictionary. At the same time, the

emotion dictionary built on one domain data can not be applied to other domains, which restricts the application of these methods in reality.

In recent years, deep learning has been widely used in the field of natural language processing and achieved good results in aspect-based sentiment analysis tasks. Representative work includes: reference[9] proposed a Recurrent Neural Network (RNN) model, which can process sequence data and learn long-term dependencies. RNN considered the relationship between the current output and the previous sequence output, which enabled it to fully learn the information between contextual texts, thereby got better sentence representations and complete sentiment analysis tasks. Therefore, many excellent methods for solving aspect-based sentiment analysis tasks are based on RNNs. Tang et al[10] proposed Target-Dependent Long Short-Term Memory neural network (TD-LSTM) and Target-Connection Long Short-Term Memory neural network (TC-LSTM). This method associates target aspects with contextual features for aspect-based sentiment analysis, and obtains promising experimental results. Ruder et al.[11] used a Hierarchical Bidirectional Long Short-Term Memory (H-LSTM) network model to model the relationship between words in comment sentences, and proved that the hierarchical model can obtain better results compared with the other two non hierarchical baseline models. This type of model can effectively express the sequence information between words in a sentence, but the sentence is not a simple word stacking, and the key information that affects the sentimental polarity of an aspect is not necessarily the sequence information of all contexts.

In the sentiment analysis task, the attention mechanism is used to extract the key information affecting the sentiment polarity of words in the judgment aspect in the sentence to enhance the expressive ability of the sentence. Ma et al.[12] proposed Interactive Attention Network (IAN), in which two attention networks are used to obtain important features to correctly judge aspect-based sentiment polarity. Reference[13] proposes a Dyadic Memory Networks (DyMemNN) that synthesizes or integrates parameterized neural tensors into memory selection operations to achieve rich binary interactions between aspect words and word embeddings. Experimental results show that the model achieves better performance than other neural architectures on six standard datasets. Lin et al.[14] proposed a Multi-Head Self-Attention Transformation (MSAT) network to solve the target-sensitive sentiment analysis problem, which applies target-specific multi-head self-attention to capture global features and adds target-sensitive transfer to solve the problem. Secondly, part of speech (POS) is added to the model to obtain the part of speech features of words. The experimental results show that compared with other excellent models, the MSAT model obtains good sentiment analysis results. This kind of model can focus on the characteristic information of a given target, so as to improve the classification results. However, because this kind of model based on attention mechanism pays high attention to the target's own information, it can not accurately distinguish the emotional tendency containing implicit emotional information.

In view of the above defects based on the attention mechanism model, Huang et al.[15] used the parametric filter and gate mechanism to incorporate aspect information into the convolution neural network to effectively capture aspect specific features, and

proposed a novel parametric convolution neural network model, which achieved excellent results on the data set semeval 2014. Literature[16] proposed a Convolution-based Memory Network (CMN) combined with attention mechanism to capture the word and multi word features in the evaluation sentence, so as to improve the classification results of aspect level emotion analysis model. To solve the problem of context dependence in sentences, Cheng Yan et al.[17] proposed a multi-channel CNN and BiGRU network model based on attention mechanism, which extracted local text information through CNN and fused the semantic features of long text captured by BiGRU to improve the information acquisition ability of the model. The network model based on CNN can effectively extract local features, which is conducive to identifying the emotional features related to the target aspect, but it often ignores the syntactic structure of the sentence.

Based on the inspiration and problems raised above, this paper proposes a neighborhood network for aspect-based sentiment analysis, and its aspect neighborhood information representation layer includes two modules: a physical-level representation module and a syntactic-level representation module. The physical-level features of aspect words are extracted through convolutional neural networks, and the grammatical-level feature representations of aspect words are captured using graph convolutional networks. After fusing the feature information of the two modules, the attention mechanism is used to obtain important information of sentences, and predict the final sentiment analysis result of the sentence. Experimental results showed that the network model improved the ability of sentiment analysis task.

3 Nenet Model

3.1 Neighborhood Network Model Architecture

Let $S = s_1 s_2 \dots s_n$ represent an arbitrary natural sentence composed of n words, where $s_i, i = 1, 2, \dots, n$ is the i -th word in S , and $T = s_{asp} \dots s_{asp+m}, m \geq 0$ is the word substring in the sentence S , which is continuous and has a single specific semantics is called Aspect. Let $y \in \{negative, positive, neutral\}$ be the emotional polarity of the predicted target. The low-dimensional embedding of S is denoted as $\mathbf{E} = [\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_{asp}, \dots, \mathbf{e}_{asp+m}, \dots, \mathbf{e}_{n-1}, \mathbf{e}_n]$, $\mathbf{e}_i \in \mathbb{R}^{dim}$, $\mathbf{E} \in \mathbb{R}^{n \times dim}$, where dim is the embedding dimension of the word vector.

As shown from Fig 1, Nenet is divided into four layers. The first layer is contextual information representation. Because the Bidirectional Gated Recurrent Unit (GRU) model can obtain the contextual dependency information in the sentence as a whole, this layer uses the BiGRU model to represent the contextual information, which is $\mathbf{H} = [\mathbf{h}_1^r, \mathbf{h}_2^r, \dots, \mathbf{h}_n^r] = \text{BiGRU}([\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n])$.

The second layer is Aspect Neighborhood Information Representation (ANIR) layer. Through the ANIR layer, you can obtain the neighborhood representation $\mathbf{q} = [q_1, q_2, \dots, q_{n-p+1}]$ at the aspect physical level and its neighborhood representation

$\mathbf{H}^K = [\mathbf{h}_1^K, \mathbf{h}_2^K, \dots, \mathbf{h}_{asp}^K, \dots, \mathbf{h}_{asp+m}^K, \dots, \mathbf{h}_{n-1}^K, \mathbf{h}_n^K]$ at the syntactic level, and perform dot product operation on the two output representations. The calculation method is shown in (1).

$$\lambda_t = \sum_{i=1}^n \mathbf{h}_i^K \mathbf{q}_t \quad (1)$$

The third layer is important information extraction layer, which uses the attention mechanism to extract the important features related to the meaning of aspect words from the hidden state vector, and set the corresponding weight score for each context word accordingly, e.g. equation (2) is the calculation method of attention weight, and equation (3) is the final prediction expression.

$$\lambda'_i = \frac{\exp(\lambda_i)}{\sum_{i=1}^n \exp(\lambda_i)} \quad (2)$$

$$\mathbf{f} = \sum_{i=1}^n \lambda'_i \mathbf{h}_i^r \quad (3)$$

where, λ'_i is the attention weight in formula (2), and \mathbf{h}_i^r represents the encoding output of the first layer of serialized information in formula (3), \mathbf{f} is the final representation of Nenet.

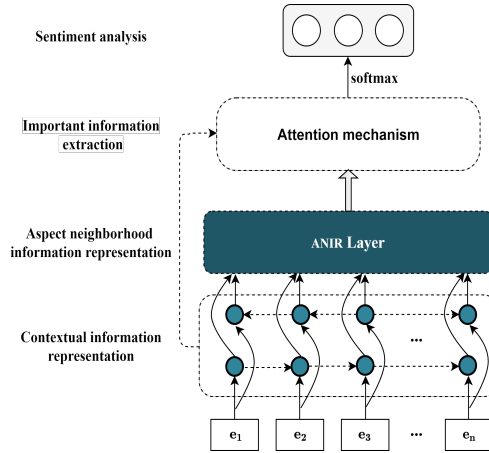


Fig. 1. The overall architecture of the Nenet model.

The fourth layer is sentiment analysis layer. The final text representation is input into the softmax function, as shown in equation(4), and the output of the sentiment polarity of the corresponding target in the comment sentence can be obtained.

$$\mathbf{z} = \text{softmax}(\mathbf{W}_z \mathbf{f} + \mathbf{b}_z) \quad (4)$$

where, \mathbf{W}_z represents the weight that can be learned, and \mathbf{b}_z represents the bias.

The above is the overall description of the Nenet structure, the following is a detailed introduction to the aspect neighborhood information representation (ANIR) layer.

3.2 Aspect Neighborhood Information Representation Layer

The distance between the aspect word and the descriptive word in the comment sentence is different. The key information for judging the emotional polarity is the neighborhood information of the aspect word at different levels. In order to solve this problem, this paper designs an aspect neighborhood information representation layer, and the specific structure is shown in Figure 2.

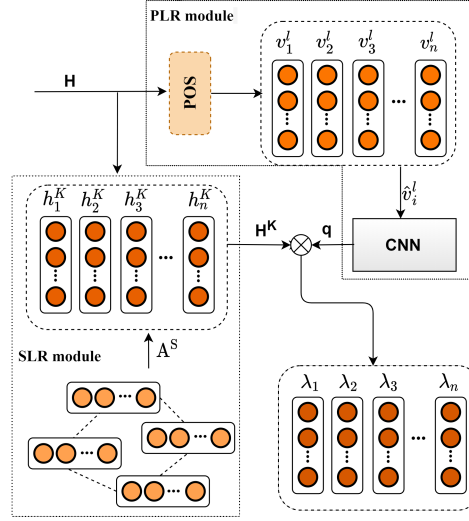


Fig. 2. ANIR Layer.

The following is a detailed discussion of the aspect neighborhood information presentation layer, which can be obtained from Fig 2. The ANIR layer includes a Physical Level Representation (PLR) module and a Syntax Level Representation (SLR) module.

The PLR module of this article first adds the position information of other words in the sentence relative to the aspect word, and then use the CNN module to extract the feature information at the physical level of the aspect word, as shown in equations (5) and (6). Among them, \mathbf{h}_i^k is the output representation after encoding of the BiGRU model, and \mathbf{v}_i^l is the feature vector representation after adding position information.

$$u_i = \begin{cases} \frac{n - asp + i}{n} & 1 \leq i < asp \\ 0 & asp \leq i \leq asp + m \\ \frac{n - i + asp + m}{n} & asp + m < i \leq n \end{cases} \quad (5)$$

$$\mathbf{v}_i^l = u_i * \mathbf{h}_i^k, \quad i \in [1, n] \quad (6)$$

After obtaining the relative position coding of aspect word and context word, the article uses CNN to further extract feature information, as shown in equation (7):

$$q_i = \delta(\mathbf{w}^T \hat{\mathbf{v}}_{i+i-p-1}^l + \mathbf{b}) \quad (7)$$

In equation (7), $\hat{\mathbf{v}}_{i+i-p-1}^l \in \mathbb{R}^{p \cdot \text{dim}_h}$ is the connection matrix of $\mathbf{v}_i^l, \dots, \mathbf{v}_{i+p-1}^l$, p is the size of the kernel, $\delta(\cdot)$ is a nonlinear function, $\mathbf{w}^T \in \mathbb{R}^{p \cdot \text{dim}_h}$ and $\mathbf{b} \in \mathbb{R}$ are the learnable weights of the convolution kernel.

Although the PLR module can obtain the contextual information of the aspect word, it cannot solve the situation when the aspect word is far away from the relative description word. The SLR module can extract the feature information of the aspect words at the grammatical level to solve this problem.

The SLR module uses the natural language processing library Spacy to obtain the grammatical analysis tree of the sentence S . In the syntax tree, the number d_i of connected edges of corresponding nodes is the degree of node s_i . By the tree, it is easy to obtain the adjacency matrix $\mathbf{A}^S = (a_{i,j}^S)_{n \times n}$ of statement S . For any element $a_{i,j}^S$ in \mathbf{A} , if node i is connected to node j , then $a_{i,j}^S = 1$, otherwise $a_{i,j}^S = 0$. Use the dependent syntax tree to generate the corresponding adjacency matrix for the sentence as the input of SLR, and use the L-layer Graph Convolutional Network (GCN) to represent non-Euclidean data.

GCN is represented by the adjacency matrix \mathbf{A}^S of S and the output of BiGRU encoding as the network input, the output of the i -th neuron in the $k+1$ layer is determined by equation (8):

$$\mathbf{h}_i^{k+1} = \varphi \left(\frac{1}{d_i + 1} \sum_{j=1}^n \mathbf{A}^S \mathbf{W}^k \mathbf{h}_j^k + \mathbf{b}^k \right) \quad (8)$$

Where \mathbf{W}^k is the parameter matrix, \mathbf{h}_j^k is the output representation of the j -th neuron in the k -th layer, and \mathbf{b}^k is the corresponding bias. $\varphi(\cdot)$ is a nonlinear activation function. \mathbf{h}_i^0 represents the initial state of the i -th node, which is the output of the first context presentation layer. For layer K GCN, $k \in [1, 2, 3, \dots, K]$, \mathbf{h}_i^k is the final state of the i -th node.

As mentioned above, ANIR can extract the neighborhood information of a given aspect word in the text at different levels, aiming to improve the performance of the aspect-based sentiment analysis model.

4 Experiment Analysis

4.1 Dataset

Nenet was tested on three public datasets, where 14Lap and 14Rest were from SemEv-

al 2014 task 4[18], and the third is Twitter dataset[19]. These datasets are mainly used for fine-grained sentiment analysis, and can be roughly divided into three types of user comment data, as shown in Table 1, showing the statistics of these three datasets.

Table 1. The distribution of samples on the benchmark dataset by category labels.

Dataset	Positive		Neutral		Negative	
	Train	Test	Train	Test	Train	Test
14Rest	2163	725	637	195	805	196
14Lap	993	340	462	169	868	127
Twitter	1560	173	3122	343	1559	170

4.2 Parameter Setting and Evaluation Index

In this paper, the 300d GloVe[20] pretraining model is used to initialize the word embedding, and the experimental parameter settings are shown in Table 2.

Table 2. Parameter setting.

Parameter	value
embed-dim	300
num-epoch	50
batch-size	32
d	0.6
lr	0.001

It can be seen from Table 2 that the dimension of the hidden state vector is set to 300. The batch size is set to 32. In this paper, the dropout layer loss rate is set to 0.6, Adam is used to optimizing the model, and the learning rate is 0.001. Set the epoch to 50, and perform the same experiment 5 times under random initialization. According to the results of the experiment report on the testset all indexes of average maximum.

Dropout Parameter Selection and Analysis. In this paper, the influence of dropout loss rate $d \in \{0.1, 0.2, \dots, 0.9\}$ on accuracy and F1 value is studied, and experiments are carried out on dataset 14Rest. The experimental results are shown in Fig.3. when the value of d is 0.6, the accuracy and F1 value obtain the optimal value, because when the value of d is 0.6, the dropout can randomly generate the most network structures.

GCN Layer Number Setting Analysis. GCN layer parameter setting is important which affects the performance of the model. To study the impact of GCN layers on sentiment analysis tasks, the accuracy and F1 value are used as evaluation indicators to determine the reasonable number of layers in the Nenet of GCN in the article. The experimental results are shown in Fig 4. The number of layers of GCN in the experimental setting ranges from 1 to 8. When k is 3, the two kinds of datasets reach the maximum in index accuracy and F1 value, and Nenet obtains the best performance.

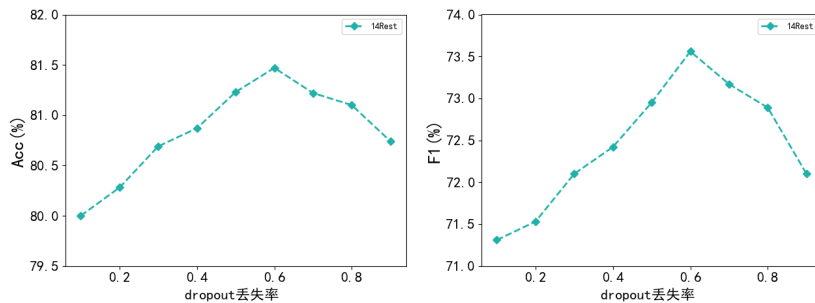


Fig. 3. The effect of dropout loss rate on the accuracy and F1 value on the dataset 14Rest.

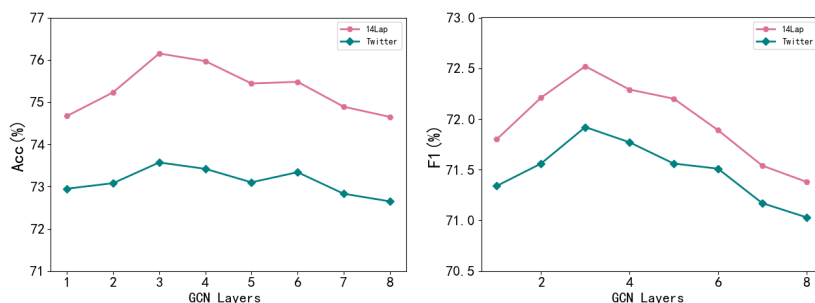


Fig. 4. The number of GCN layers has an impact on the accuracy and F1 value on the dataset 14Lap and Twitter.

4.3 Experimental Results and Analysis

This paper uses cross-entropy as the loss function of Nenet training. The ablation on three datasets and comparative experiments and analysis are carried out to verify the effectiveness of the proposed method, the results as stated below.

Ablation Experiment and Analysis. In order to verify the effectiveness of each component in Nenet for sentiment analysis tasks, this paper conducts corresponding ablation experiments on three datasets, and the results are shown in Table 3.

It can be seen from Table 3 that in the absence of any part, the Acc and F1 values of Nenet will decrease significantly on these three datasets. For the model being removed of the ANIR layer, the Acc and F1 values on the dataset 14Lap are 71.83% and 67.16% respectively, which is 4.32% and 5.36% lower than the Acc and F1 values of the Nenet model, respectively. It shows that adding the ANIR layer can better encode sentences and improve the experimental results of the emotion analysis task in the accuracy of the evaluation index and F1 value. For the model being removed of the PLR module and the model with the SLR module deleted, the accuracy and F1 value decreased to a certain extent compared with the Nenet model, which shows that the two modules in this method can enhance the text expression ability and improve the classification ability of the model.

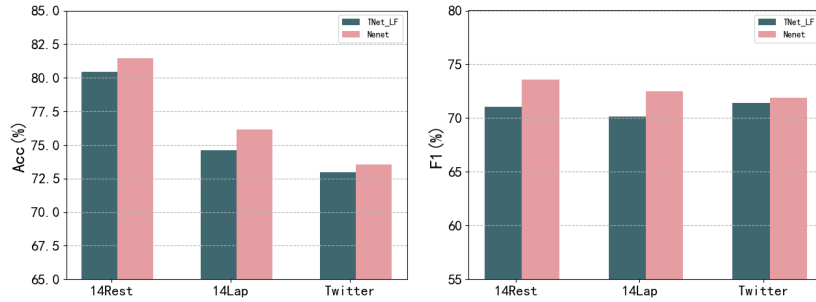
Table 3. Comparison of ablation model accuracy and F1 value on three datasets.

Model	(Unit:%)					
	14Rest		14Lap		Twitter	
	Acc	F1	Acc	F1	Acc	F1
Nenet	81.47	73.56	76.15	72.52	73.57	71.92
ANIR	80.45	70.50	71.83	67.16	71.76	70.47
-PLR	81.06	72.13	76.03	72.11	73.12	71.32
-SLR	81.13	72.21	75.11	70.89	72.63	71.01

Comparative Experiment and Analysis. In the experiments of sentiment analysis tasks on three different datasets, the baseline model listed below is compared with the Nenet proposed in this paper, and the accuracy and F1 value are used as evaluation indicators. The experimental results are shown in Table 4.

Table 4. Comparison results of different models on three datasets.

Model	(Unit:%)					
	14Rest		14Lap		Twitter	
	Acc	F1	Acc	F1	Acc	F1
ATAE-LSTM	77.20	-	68.70	-	-	-
MemNet	79.61	69.64	70.64	65.17	71.48	69.90
IAN	79.26	70.09	72.05	67.38	72.50	70.81
TNet-LF	80.42	71.03	74.61	70.14	72.98	71.43
TransCap	78.84	69.70	72.65	68.77	-	-
Nenet	81.47	73.56	76.15	72.52	73.57	71.92

**Fig. 5.** On the different datasets, the accuracy and F1 value of the Nenet model are higher than that of the TNet-LF model.

The baseline model is as follows: (1)ATAE-LSTM[21] model is an attention-based LSTM for aspect-level sentiment analysis, where the attention mechanism can focus on different parts of the sentence when aspect words are used as input. (2)MemNet[22] introduces a deep memory network to implement an attention mechanism to learn the correlation between context words and aspects. (3)IAN[12] uses LSTM to represent aspects and contexts and uses attention mechanisms for aspects and contexts to capture important feature information. (4)TNet-LF[23] implements a Context-Preserving

Transformation(CPT) mechanism to obtain the word representation of a specific aspect. (5)TransCap[24] network model encapsulates the semantic information in the sentence into a semantic capsule, and uses the semantic capsule to couple with the class capsule to implement aspect-based sentiment analysis.

It can be seen from Table 4 and Fig 5 that the accuracy and F1 value of the Nenet model proposed in this paper on the three datasets are significantly higher than those of other models, and the accuracy and F1 value on the dataset 14Rest are 1.05 and 2.53 percentage points higher than that of the TNet-LF model. The above shows that the aspect neighborhood information extracted by Nenet and the grammatical dependence of sentences can improve the results of aspect sentiment analysis.

5 Conclusion and Further Work

In the sentiment analysis tasks, ignoring the neighborhood features of aspect words at different levels can lead to misjudgment of sentiment polarity. To solve the above problems, this paper proposes a neighborhood network for aspect-based sentiment analysis, and designs an aspect neighborhood feature representation layer to extract aspect neighborhood information from both physical and syntactic levels to improve the overall performance of the model. Experiments on three public datasets show that the Nenet model can effectively improve the results of sentiment analysis tasks. In future work, sentiment analysis in specific fields can be studied to meet the needs of sentiment analysis in different scenarios.

References

1. Hu, Z., Hu, J., Ding, W., & Zheng, X.: Review sentiment analysis based on deep learning. In 2015 IEEE 12th International Conference on e-Business Engineering, pp. 87-94(2015).
2. Liu, B.: Sentiment analysis and opinion mining. Synthesis lectures on human language technologies, 5(1), 1-167(2012).
3. Giachanou, A., & Crestani, F.: Like it or not: A survey of twitter sentiment analysis methods. ACM Computing Surveys (CSUR), 49(2), 1-41(2016).
4. Hochreiter, S., & Schmidhuber, J.: Long short-term memory. Neural computation, 9(8), 1735-1780 (1997).
5. Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y.: Learning phrase representations using RNN encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078(2014).
6. Vo, D., & Zhang, Y.: Target-dependent twitter sentiment classification with rich automatic features. AAAI Press(2015).
7. Chen, L., & Yang, Y.: Emotional speaker recognition based on i-vector through Atom Aligned Sparse Representation. In 2013 IEEE International Conference on Acoustics, Speech and Signal Processing, pp. 7760-7764. IEEE(2013).
8. Han, H., Zhang, J., Yang, J., Shen, Y., & Zhang, Y.: Generate domain-specific sentiment lexicon for review sentiment analysis. Multimedia Tools and Applications, 77(16), 21265-21280(2018).
9. Mikolov, T., Karafiát, M., Burget, L., Cernocký, J., & Khudanpur, S.: Recurrent neural network-based language model. In Interspeech, pp. 1045-1048 (2010).

10. Tang, D., Qin, B., Feng, X., & Liu, T.: Effective LSTMs for target-dependent sentiment classification. In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers, pp. 3298–3307(2016).
11. Ruder, S., Ghaffari, P., & Breslin, J. G.: A hierarchical model of reviews for aspect-based sentiment analysis. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pp. 999–1005(2016).
12. Ma, D., Li, S., Zhang, X., & Wang, H.: Interactive attention networks for aspect-level sentiment classification. In IJCAI'17 Proceedings of the 26th International Joint Conference on Artificial Intelligence, pp. 4068–4074 (2017).
13. Tay, Y., Tuan, L. A., & Hui, S. C.: Dyadic memory networks for aspect-based sentiment analysis. In Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, pp. 107-116(2017).
14. Lin, Y., Wang, C., Song, H., et al.: Multi-head self-attention transformation networks for aspect-based sentiment analysis. IEEE Access, 9, 8762-8770(2021).
15. Huang, B. , & Carley, K.: Parameterized convolutional neural networks for aspect level sentiment classification. Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing.Brussels:Association for Computational Linguistics, 1091-1096(2018).
16. Fan, C., Gao, Q., Du, J, et al.: Convolution-based memory network for aspect-based sentiment analysis. In The 41st International ACM SIGIR conference on research & development in information retrieval.New York:ACM,1161-1164(2018).
17. Yan, C., Leibo, Y., Guanghe, Z., et al.: Text sentiment orientation analysis of multi-channels CNN and BIGRU based on attention mechanism. Journal of Computer Research and Development, 57(12), 2583-2595(2020).
18. Pontiki, M., Galanis, D., Pavlopoulos, J., et al.: SemEval-2014 Task 4: aspect based sentiment analysis. In Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014), pp. 27–35(2014).
19. Dong, L., Wei, F., Tan, C., et al.: Adaptive recursive neural network for target-dependent twitter sentiment classification. In Proceedings of the 52nd annual meeting of the association for computational linguistics, pp. 49-54 (2014).
20. Pennington, J., Socher, R., & Manning, C. D.: Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pp. 1532-1543 (2014).
21. Wang, Y., Huang, M., Zhu, X., & Zhao, L.: Attention-based LSTM for aspect-level sentiment classification. In Proceedings of the 2016 conference on empirical methods in natural language processing, pp. 606-615(2016).
22. Tang, D., Qin, B., & Liu, T.: Aspect level sentiment classification with deep memory network. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pp. 214–224(2016).
23. Li, X., Bing, L., Lam, W., & Shi, B.: Transformation networks for target-oriented sentiment classification. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, 946-956(2018).
24. Chen, Z., & Qian, T.: Transfer capsule network for aspect level sentiment classification. In Proceedings of the 57th annual meeting of the association for computational linguistics, pp. 547-556(2019).