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Aspect-Level Sentiment Analysis of Customer Reviews Based on Neural Multi-task Learning

Yadong Shi [1,*], Lianwei Li [2], Huixiang Li[3], Ang Li[4], Yiyu Lin[5]

[1]Computer Science, Fudan University, ShangHai, China
[2]Computer Science, The University of Texas at Arlington, Arlington, USA
[3]Information Studies, Trine University, AZ, USA
[4]Business Analytics, University College Dublin, Dublin,Ireland
[5]Computer Science and Engineering, Santa Clara University, CA, USA
**Corresponding author: lizenyi.zy@bytedance.com*

Abstract: ***In the era of big data, major e-commerce platforms are facing the challenge of an exponential growth in the number of user comments. Effectively utilizing these comments has become an urgent issue. Traditional manual statistical methods are no longer able to meet the demands for accuracy and real-time analysis. The rise of artificial intelligence-based text mining techniques provides a new approach to address this problem. By building deep learning analysis models, it is possible to uncover user preferences and product characteristics, helping businesses proactively adjust sales strategies, improve product and service quality, and achieve precise marketing. Text sentiment analysis is one of the important research directions in the field of text mining. Its basic idea is to transform subjective texts with emotional color into structured data, and then use machine learning, deep learning, and other artificial intelligence technologies to extract emotional features and discover knowledge patterns. This article proposes a deep learning-based sentiment analysis model, which includes a shared sentiment prediction layer used to transfer emotional knowledge between different aspect categories and alleviate the problem of insufficient data. The model consists of two parts: the Aspect Category Detection (ACD) classifier based on attention mechanism and the Aspect Category Sentiment Analysis (ACSA) classifier. The ACD part generates word weights using attention mechanism, while the ACSA part predicts the sentiment of words and combines weights to determine the sentiment of aspect categories within sentences.***

Keywords: Deep learning; Sentiment Analysis; Aspect Based Sentiment Analysis; Machine learning.

1. INTRODUCTION

In the era of big data, the number of user comments on products on major e-commerce platforms is growing exponentially. Effectively utilizing these comments has become an urgent issue for e-commerce platforms [1]-[3]. Most user comment data is unstructured and contains a large amount of redundant information, making it difficult to directly utilize. Relying solely on traditional manual statistical methods to extract information no longer meets the demand for accuracy and real-time updates. The emergence of artificial intelligence-based text mining technology provides a solution for evaluating and utilizing massive amounts of online user comment data [4]. By constructing deep learning analysis models, preferences of users and characteristics of products can be mined, aiding enterprises in adjusting sales strategies proactively, improving product and service quality, and achieving precision marketing. Sentiment analysis of comment texts is an important research direction in the field of text mining [5]. Conducting sentiment analysis on online product review data is currently a hot research topic in the industry. The basic idea is to use text segmentation techniques to extract text features, transform text data into structured data that describes the content of the text, and use machine learning, deep learning, and other artificial intelligence data mining technologies to extract textual description features and discover knowledge patterns, thus understanding the sentiments expressed by users [6]-[8].

In this paper, we propose a novel model for sentiment prediction by fine-grained mining of aspect information within sentences. This deep learning model is built upon an intuitive assumption that the representation of overall aspect sentiment is a combination of representations of multiple aspect words. Specifically, the first module is a aspect category detection module which extracts key entities indicating aspect categories in sentences using attention mechanism, and then identifies aspect categories. This module consists of several parts: converting inputs into vectors through word embedding layer, generating embeddings for each word, encoding sentences via LSTM [20] to extract important features. The generated features are passed through an attention layer to generate specific importance parameters for each embedding. The final vector obtained by element-wise multiplication of importance weights and vectors is used for aspect category detection. The second module is the ACSA module, which generates embeddings through different embedding layers, encodes embeddings through multi-layer Bi-LSTM, concatenates the resulting vectors with those generated in the aspect category detection module, and then feeds them into the sentiment attention layer [11] to extract features for sentiment polarity prediction. Through multiple experiments on three sentiment datasets, the effectiveness of the proposed model is validated.

2. RELATED WORK

In comment texts, users often evaluate multiple aspects and express their sentiments towards each aspect, as shown in Figure 1. Analyzing the sentiment polarity of these aspects is known as aspect-category sentiment analysis. To identify the sentiment of specific aspect categories within sentences, most methods first generate representations of sentences tailored to those aspect categories, and then recognize sentiment polarity based on these embedded representations. However, these methods overlook the fact that the learned representations of models are not robust enough, and different models excel at capturing different aspects of the data, leading to suboptimal performance. In response to this challenge, several multi-task models have been proposed for this task. These models, when given comment texts, can detect various aspect words involved in the comment text and simultaneously estimate the sentiment tendency of these aspect categories.

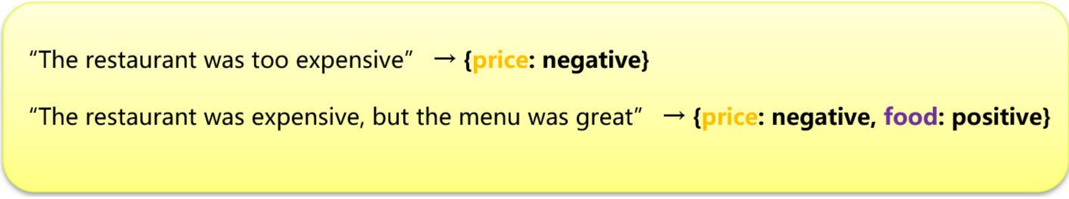

Figure 1: Aspect-category polarity

Hier-GCN [12] restructures the aspect-category sentiment analysis task into a hierarchical analysis problem from category to sentiment, ultimately outputting a hierarchical structure. Initially, BERT is used as a feature extractor, and then the processed sentence representations and representations of each aspect category are fed into the first layer of GCN [9] network to simulate relationships between internal aspect categories. Subsequent GCN layers identify the sentiment of each aspect category.

MNN [14] simultaneously models aspect term extraction and aspect sentiment analysis as a multi-task model. Previous works segmented ABSA into multiple tasks, leading to error propagation between tasks and wasting computational resources on designing models for each subtask. The MNN model designs an algorithm framework for automatically matching aspect categories and sentiment, enabling simultaneous learning of multiple subtasks and achieving end-to-end aspect sentiment analysis.

E2E-ABSA [15] is an end-to-end sentiment analysis model that simultaneously models opinion target extraction and aspect sentiment analysis. The model framework is a stacked recursive neural network, where the upper layers predict sentiment polarity, and the lower layers constrain aspect word boundaries to predict target boundaries, thus improving the prediction accuracy of the upper layers. It also ensures sentiment consistency within the target word domain through gating mechanisms.

IMN [16] jointly models four tasks, including document classification, document sentiment analysis, aspect term detection, and aspect sentiment analysis. These tasks not only learn through shared features but also have message passing mechanisms between different tasks, jointly optimizing the four tasks through information propagation to achieve better results. The bottom layer of IMN is a shared CNN [10] network that generates hidden layer features and then passes them into different upper-layer tasks. Information interaction between different tasks is iterative, allowing information to propagate along the links.

Although these joint models have achieved significant effectiveness, the imbalance in data distribution among different aspect categories, with some having fewer training samples, can lead to models biased towards specific aspect categories, resulting in performance degradation. To address this challenge, we propose a novel deep learning joint model. This model predicts the overall aspect sentiment by stacking multiple aspect word representations and sentence representations. The attention-based stacking layer can extract sentiment information from different aspect categories, thereby mitigating the impact of sparse samples.

3. METHODOLOGY

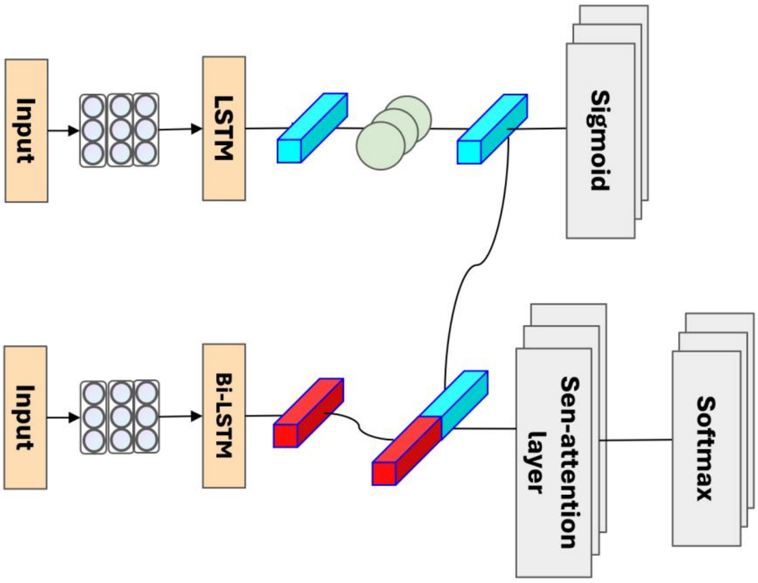

Figure 2: The architecture diagram of the model proposed in this paper

Specifically, the model we propose consists of two parts, as shown in Figure 2. The first part is the Aspect Category Detection (ACD) module, which detects aspect categories by extracting key words indicating aspect categories from sentences. The second part is the Aspect Category Sentiment Analysis (ACSA) module, which identifies aspect category sentiments based on the detected key words' sentiments and the overall sentiment of the sentence. In the ACD part, all aspect categories share embedding layers and $LSTM$ layers, but they have different attention layers and aspect category detection layers.

The embedding layer converts the sentence into a vector $X = \{x^1, x^2, ..., x^n\}$ using an embedding matrix W, where W is a $d \times v$ matrix, d represents the dimension of word embeddings, and v is the size of the lookup table. Then, it enters the $LSTM$ layer, where the vectors are encoded, and the encoded hidden layer vectors $T = \{t_1, t_2, ..., t_n\}$ are outputted. In each propagation calculation process, the formula for calculating hidden layer vectors is as follows:

$$t_i = LSTM(t_{i-1}, x_i^D) \tag{1}$$

The attention layer of ACD calculates attention by processing the encoded hidden layer vectors, assigning corresponding weights to each word that can indicate an aspect category. Different aspect category indicator words have different weight parameters based on their importance:

$$\alpha_j = softmax\left(u_j^T tanh\big(W_j T + b_j\big)\right), \ j = 1,2, ..., N \tag{2}$$

Where $W_j \in R^{d\times d}$, $b_j \in R^d$, $u_j \in R^d$ are the trainable model parameters, and $\alpha_j \in R^n$ is the weight parameter vector. Finally, the aspect category detection layer uses the element-wise multiplication of the hidden layer vectors and the weight parameters as the aspect representation for ACD. For the $j - th$ class:

$$y_{ACD}^j = sigmoid(W_j T \alpha_j^T + b_j), \ j = 1,2, ..., N \tag{3}$$

Where $W_j \in R^{d\times 1}$, b_j is a scalar.

The ACSA classifier first generates the embedding representation of the sentence, then obtains the sentiment for each aspect category by combining and concatenating the sentence embedding with the sentiment of the words. In the ACSA part, all aspect categories share embedding representation layers, multi-layer $Bi - LSTM$, and have different aspect sentiment attention layers. The embedding layer converts the sentence into a vector $X = \{x^1, x^2, ..., x^n\}$ using an embedding matrix W, where W is a $d \times v$ matrix, d represents the dimension of word embeddings, and v is the size of the lookup table. The output of the embedding layer is fed into multi-layer $Bi-LSTM$ [20]. The hidden states of the $i-th$ layer $Bi-LSTM$ output are $T^l = \{t_1^l, t_2^l, ..., t_n^l\}$. In each propagation calculation process, the formula for calculating the hidden state t_i^l is:

$$t_i^l = [\overrightarrow{LSTM}(\overrightarrow{t_{i-1}^l}, t_i^{l-1}); \overleftarrow{LSTM}(\overleftarrow{t_{i+1}^l}, t_i^{l-1})] \tag{4}$$

The sentiment attention layer extracts important features based on the concatenated aspect embedding and sentence embedding vectors to generate specific text representations. For the $j-th$ aspect category, the specific text representation can be calculated as follows:

$$V_j^H = g(T, K, V), j = 1,2, ..., N \tag{5}$$

T represents the text representation of the $j-th$ aspect category outputted by the $Bi-LSTM$ layer. $g(\cdot)$ denotes an attention mechanism. Afterwards, the concatenated text representation of the $j-th$ aspect for the ACSA task is fed into a feedforward network with $ReLU$ activation [25], and then the output is passed to another feedforward network with $softmax$ activation to generate the sentiment polarity distribution. For the sentiment of the $j-th$ aspect:

$$y_{ACSA}^j = \frac{\exp\left(ReLU\left(W_s v_j + b_s\right)\right)}{\sum_{k=1}^{M} \exp\left(ReLU\left(W_s v_k + b_s\right)\right)} \tag{6}$$

Where W_s and b_s are shared parameters.
For the ACD task, each prediction is a binary classification problem. For the ACSA task, the loss is computed for all aspect categories. The joint modeling loss function for these two tasks is formulated as follows:

$$L(\theta) = L_{ACD}(\theta_{ACD}) + \beta L_{ACSA}(\theta_{ACSA}) + \lambda||\theta||_2^2 \tag{7}$$

Where β is the hyperparameter for the ACSA loss, λ is the $L2$ regularization hyperparameter, and θ represents the model's trainable parameters.

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Datasets

Experiments were conducted on three datasets (Table 1), details of which are as follows:

- SE-2014 [22]: Unlike previous sentiment analysis datasets, this dataset considers sentiment at a finer granularity level rather than just the overall sentiment of sentences or document-level sentiment. It consists of e-commerce reviews containing mentions of multiple entities and the corresponding sentiment expressions towards these entities. The objective is to determine the sentiment polarity of users towards the mentioned entities.
- SE-2015 [23]: This dataset is a continuation of the SE-2014 dataset, aiming to identify the sentiment expressed by users towards each mentioned entity in user comments. It also pertains to the same domains (restaurant reviews and laptop purchase reviews), but unlike before, each data instance in SE-2015 consists of complete comments rather than isolated samples.
- SE-2016 [24]: This dataset encompasses online reviews from various domains (laptop purchase reviews, restaurant reviews, hotel reviews). Compared to the previous datasets, this dataset offers more diverse data. Additionally, the organization of samples has been expanded, introducing an additional layer of attributes

(such as usability, quality, price) under existing aspect categories (e.g., laptops), thereby refining users' sentiment evaluations further.

Table 1: Datasets description

Dataset		Pos.	Neu.	Neg.
SE-2014	Train	9732	8310	6209
	Dev	4323	2144	4912
	Test	5246	2523	4982
SE-2015	Train	8225	3084	9721
	Dev	5837	3461	7248
	Test	4193	2748	6820
SE-2016	Train	11851	8361	9184
	Dev	4629	3532	3934
	Test	11413	8217	9372

4.2 Competitors

To evaluate the constructed models, they were compared with several aspect-category sentiment analysis methods:

- E2E LSTM [17]: This model employs an end-to-end trainable Long Short-Term Memory (LSTM) model to jointly model aspect-category detection and sentiment polarity classification for the first time. Considering differences in data distribution from the original paper, we adjusted the model's hyperparameters to achieve better results.
- E2E CNN [18]: In this approach, an end-to-end convolutional neural network (CNN) replaces the bidirectional gated recurrent units (Bi-LSTM). Similarly, the model's hyperparameters were adjusted to fit our data, resulting in improved performance.
- Bi-GRU [19]: This is a basic bidirectional gated recurrent unit neural network with two hidden layers.
- TextCNN [13]: The core idea of Convolutional Neural Networks (CNNs) is to capture local features, which for text are sliding windows composed of several words. CNNs excel in automatically combining and filtering features to obtain semantic information at different abstraction levels.
- TextCNN+Bi-GRU (pipeline): This is a pipeline method. Firstly, a TextCNN neural network is trained to obtain node representations of comments for a graph convolutional neural network. Then, these representations are combined with comment embeddings trained by bidirectional gated recurrent units (Bi-GRU) [19]. Finally, the combined vector is passed through a classifier. This experiment aims to validate the effectiveness of joint training.
- Hier-GCN: This method restructures the aspect-category sentiment analysis task into a hierarchical analysis problem from category to sentiment. It outputs a hierarchical structure, initially using BERT as a feature extractor. The processed sentence representations and representations of each aspect category are then input into the first layer of Graph Convolutional Network (GCN) to simulate relationships between internal aspect categories. Subsequent GCNs identify the sentiment of each aspect category.
- ACSA-joint-Affine: This approach replaces the LSTM in the model with an affine hidden layer to evaluate the effectiveness of attention in ACSA-joint.

4.3 Training Protocol

Implement the model in $PyTorch$, using $GloVe$ pre-trained 300-dimensional word vectors to initialize the word embedding vectors. Set the batch size to 32. All models are optimized using the Adam optimizer [21] with a learning rate of 0.001. We set $\lambda = 0.0001$ and $\beta = 1$. For the ACSA task, apply dropout with a probability of $p = 0.5$ after the embedding and Bi-LSTM layers, while utilizing early stopping. Initially, train ACD, then train ACD and ACSA together, where ACD and ACSA are jointly trained. All models were run five times, and the best results of all models were reported on the test dataset.

4.4 Evaluation Strategy

The text uses accuracy and $Macro - F1$ value as evaluation metrics for sentiment polarity classification. $Macro - F1$ calculates the $F1$ score for each individual class and then averages them, thus $Macro - F1$ treats each class equally.

$$F1 = 2 \times \frac{precision \times recall}{precision + recall} \tag{8}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

$$precision = \frac{TP}{TP+FP} \tag{10}$$

$$recall = \frac{TP}{TP+TN} \tag{11}$$

4.5 Results Analysis

Table 2: Experimental Result

Model	SE-2014		SE-2015		SE-2016	
	ACC.	**Macro-F1**	**ACC.**	**Macro-F1**	**ACC.**	**Macro-F1**
E2E LSTM	81.33%	82.14%	71.54%	75.41%	77.09%	76.14%
E2E CNN	82.17%	81.39	73.24%	74.24	77.21%	76.39
Bi-GRU	80.56%	80.03%	69.93%	70.13%	71.74%	70.13%
TextCNN	81.37%	82.21%	74.29%	77.84%	78.32%	77.39%
TextCNN+Bi-GRU	82.29%	82.24%	74.38%	74.91%	78.71%	77.81%
Hier-GCN	83.16%	83.37%	75.82%	73.03%	79.49%	78.27%
ACSA-joint-Affine	83.46%	83.58%	76.21%	75.22%	79.91%	78.94%
Our Model	**84.39%**	**84.13%**	**77.03%**	**78.98%**	**80.16%**	**79.51%**

Based on the experimental results, as shown in Table 2, we can draw the following conclusions. Firstly, Our Model outperforms all comparison models on three datasets, indicating that our model can extract relationships between different aspects from sentences and identify the sentiment polarity of different aspects. Secondly, it can be observed that all models perform better on SE-2014 compared to other datasets. This is because the complexity of samples in the SE-2014 dataset is relatively lower, with fewer hard samples. Additionally, Our Model achieves higher accuracy compared to ACSA-joint-Affine, which includes an additional affine layer. One possible reason is that the attention layer can better capture key information in sentences compared to the affine layer, thereby improving sentiment polarity identification. Another possible reason is that the affine layer has fewer model parameters compared to the attention layer, which may weaken the model's fitting ability. The TextCNN+Bi-GRU model performs better than using TextCNN or Bi-GRU separately for modeling because joint modeling can capture more fine-grained information. By learning the commonalities and differences in information extraction methods through multiple models, the TextCNN+Bi-GRU model becomes more sensitive to samples in small datasets, leading to better performance. Our Model is also a multitask model, jointly modeling the ACD and ACSA tasks, and achieving better performance by utilizing cross-task information.

5. CONCLUSION

In the era of big data, effectively harnessing review data has become a pressing issue for e-commerce platforms. The emergence of artificial intelligence-based text mining technology provides a fresh perspective on addressing this challenge. By constructing deep learning analytical models, it becomes feasible to uncover user preferences and product features, thereby assisting businesses in refining their sales strategies, enhancing product and service quality, and achieving precision marketing.

Aspect-category sentiment analysis aims to predict the sentiment polarity of sentences for given aspect categories. To discern the sentiment of specific aspect categories within sentences, most approaches initially generate representations of sentences tailored to those aspect categories, and subsequently predict sentiment polarity based on these representations. To tackle the issue of insufficiently robust representations learned by models for aspect-category sentiment analysis, several joint models have been proposed to bolster the effectiveness of sentiment polarity prediction through auxiliary tasks. This paper introduces a joint training model for aspect-category sentiment analysis, which predicts the sentiment of aspect categories mentioned in sentences by aggregating the sentiment representations of multiple aspect words. Experiments conducted on three sentiment analysis datasets, SE-2014, SE-2015, and SE-2016, validate the effectiveness of the proposed model.

REFERENCES

[1] Zhang W, Li X, Deng Y, et al. A survey on aspect-based sentiment analysis: Tasks, methods, and challenges[J]. IEEE Transactions on Knowledge and Data Engineering, 2022.

[2] Brauwers G, Frasincar F. A survey on aspect-based sentiment classification[J]. ACM Computing Surveys, 2022, 55(4): 1-37.

[3] Nazir A, Rao Y, Wu L, et al. Issues and challenges of aspect-based sentiment analysis: A comprehensive survey[J]. IEEE Transactions on Affective Computing, 2020, 13(2): 845-863.

[4] Liu H, Chatterjee I, Zhou M C, et al. Aspect-based sentiment analysis: A survey of deep learning methods[J]. IEEE Transactions on Computational Social Systems, 2020, 7(6): 1358-1375.

[5] Soni P K, Rambola R. A survey on implicit aspect detection for sentiment analysis: terminology, issues, and scope[J]. IEEE Access, 2022, 10: 63932-63957.

[6] Sabeeh A, Dewang R K. Comparison, classification and survey of aspect based sentiment analysis[C]//Advanced Informatics for Computing Research: Second International Conference, ICAICR 2018, Shimla, India, July 14–15, 2018, Revised Selected Papers, Part I 2. Springer Singapore, 2019: 612-629.

[7] Do H H, Prasad P W C, Maag A, et al. Deep learning for aspect-based sentiment analysis: a comparative review[J]. Expert systems with applications, 2019, 118: 272-299.

[8] Laskari N K, Sanampudi S K. Aspect based sentiment analysis survey[J]. IOSR Journal of Computer Engineering (IOSR-JCE), 2016, 18(2): 24-28.

[9] Kipf T N, Welling M. Semi-supervised classification with graph convolutional networks[J]. arXiv preprint arXiv:1609.02907, 2016.

[10] Li Z, Liu F, Yang W, et al. A survey of convolutional neural networks: analysis, applications, and prospects[J]. IEEE transactions on neural networks and learning systems, 2021, 33(12): 6999-7019.

[11] Vaswani A, Shazeer N, Parmar N, et al. Attention is all you need[J]. Advances in neural information processing systems, 2017, 30.

[12] Cai H, Tu Y, Zhou X, et al. Aspect-category based sentiment analysis with hierarchical graph convolutional network[C]//Proceedings of the 28th international conference on computational linguistics. 2020: 833-843.

[13] Zhang Y, Wallace B. A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification[J]. arXiv preprint arXiv:1510.03820, 2015.

[14] Wang F, Lan M, Wang W. Towards a one-stop solution to both aspect extraction and sentiment analysis tasks with neural multi-task learning[C]//2018 International joint conference on neural networks (IJCNN). IEEE, 2018: 1-8.

[15] Li X, Bing L, Li P, et al. A unified model for opinion target extraction and target sentiment prediction[C]//Proceedings of the AAAI conference on artificial intelligence. 2019, 33(01): 6714-6721.

[16] He R, Lee W S, Ng H T, et al. An interactive multi-task learning network for end-to-end aspect-based sentiment analysis[J]. arXiv preprint arXiv:1906.06906, 2019.

[17] Schmitt M, Steinheber S, Schreiber K, et al. Joint aspect and polarity classification for aspect-based sentiment analysis with end-to-end neural networks[J]. arXiv preprint arXiv:1808.09238, 2018.

[18] Chen Y. Convolutional neural network for sentence classification[D]. University of Waterloo, 2015.

[19] Chung J, Gulcehre C, Cho K H, et al. Empirical evaluation of gated recurrent neural networks on sequence modeling[J]. arXiv preprint arXiv:1412.3555, 2014.

[20] Hochreiter S, Schmidhuber J. Long short-term memory[J]. Neural computation, 1997, 9(8): 1735-1780.

[21] Kingma D P, Ba J. Adam: A method for stochastic optimization[J]. arXiv preprint arXiv:1412.6980, 2014.

[22] Kirange D, Deshmukh R R, Kirange M. Aspect based sentiment analysis semeval-2014 task 4[J]. Asian Journal of Computer Science and Information Technology (AJCSIT) Vol, 2014, 4.
[23] Maria Pontiki, Dimitris Galanis, Haris Papageorgiou, Suresh Manandhar, and Ion Androutsopoulos. 2015. SemEval-2015 Task 12: Aspect Based Sentiment Analysis. In Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015), pages 486–495, Denver, Colorado. Association for Computational Linguistics.
[24] Pontiki M, Galanis D, Papageorgiou H, et al. Semeval-2016 task 5: Aspect based sentiment analysis[C]//ProWorkshop on Semantic Evaluation (SemEval-2016). Association for Computational Linguistics, 2016: 19-30.
[25] Glorot X, Bordes A, Bengio Y. Deep sparse rectifier neural networks[C]//Proceedings of the fourteenth international conference on artificial intelligence and statistics. JMLR Workshop and Conference Proceedings, 2011: 315-323.
[26] Xu, J., Wu, B., Huang, J., Gong, Y., Zhang, Y., & Liu, B. (2024). Practical Applications of Advanced Cloud Services and Generative AI Systems in Medical Image Analysis. arXiv preprint arXiv:2403.17549.
[27] Zhang, Y., Liu, B., Gong, Y., Huang, J., Xu, J., & Wan, W. (2024). Application of Machine Learning Optimization in Cloud Computing Resource Scheduling and Management. arXiv preprint arXiv:2402.17216.
[28] Gong, Y., Huang, J., Liu, B., Xu, J., Wu, B., & Zhang, Y. (2024). Dynamic Resource Allocation for Virtual Machine Migration Optimization using Machine Learning. arXiv preprint arXiv:2403.13619.
[29] Liu, B. (2023). Based on intelligent advertising recommendation and abnormal advertising monitoring system in the field of machine learning. International Journal of Computer Science and Information Technology, 1(1), 17-23.
[30] Che, C., Zheng, H., Huang, Z., Jiang, W., & Liu, B. (2024). Intelligent Robotic Control System Based on Computer Vision Technology. arXiv preprint arXiv:2404.01116.