

Research on Sentimental Evaluation of E-commerce Product Reviews Based on the BiLSTM-Attention Mechanism

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Abstract. With the booming development of e-commerce, massive amounts of product review text contain valuable information about user emotions and experiences, providing valuable insights for both merchant decision-making and consumer shopping. However, traditional sentiment analysis methods rely on manual feature extraction and have significant limitations when dealing with complex semantics and contextual dependencies. This study aims to construct a highly accurate and robust sentiment classification model to address the inaccurate identification of sentiment in e-commerce review text. First, multi-platform and multi-category e-commerce review data is collected and preprocessed through cleaning, word segmentation, and word embedding to construct a standardized dataset. Subsequently, a deep learning architecture integrating BiLSTM and an attention mechanism is designed. BiLSTM captures bidirectional temporal dependencies in text, while the attention mechanism dynamically assigns feature weights to enhance the extraction of key sentiment information. Finally, a multi-dimensional evaluation is conducted using accuracy, precision, recall, and F1 score. Experimental results show that the proposed BiLSTM-attention model achieves an accuracy of 91.2%, an 8.9% and 3.6% improvement over the traditional LSTM and single BiLSTM models, respectively. The further optimized CNN-BiLSTM-attention model achieves an accuracy of 93.4%, achieving the best overall performance. This research provides an efficient technical path for sentiment analysis of e-commerce reviews, enriches the theoretical application of natural language processing in the commercial field, and provides data support for e-commerce platforms to optimize services, merchants to formulate marketing strategies, and consumers to make rational purchases.

Keywords: E-commerce; Product Reviews; Sentiment Analysis; BiLSTM; Attention Mechanism.

1. Introduction

With the rapid development of internet technology and the popularity of mobile payment methods, e-commerce platforms have become a vital vehicle for modern consumption. Major e-commerce platforms generate massive amounts of consumer shopping reviews, which contain rich user experience information and sentimental tendencies [1-2].

Traditional sentiment analysis methods rely primarily on manual feature extraction and machine learning classifiers. This approach not only requires extensive manual intervention but also has significant limitations when handling complex semantics and contextual dependencies [3]. The rise of deep learning technology has brought new breakthroughs in text sentiment analysis. In particular, the bidirectional long short-term memory network (BiLSTM) has demonstrated excellent performance in processing sequential data. BiLSTM can simultaneously capture both positive and negative dependencies within a text, providing a better understanding of its semantic structure [4]. The introduction of the attention mechanism further enhances the model's ability to identify key information and improves the accuracy of sentiment classification by assigning differentiated weights to different text features [5].

From a theoretical perspective, this study combines BiLSTM with the attention mechanism, providing a new technical approach for sentiment analysis of e-commerce review text and enriching the theoretical framework of natural language processing in commercial applications. From a practical perspective, accurate sentiment analysis not only helps e-commerce platforms improve user experience but also provides data support for merchants to formulate precise marketing strategies, promoting the healthy development of the entire e-commerce ecosystem[6-7].

The core objective of this study is to construct a deep learning model that integrates BiLSTM and the attention mechanism to improve the accuracy and robustness of sentiment classification in e-commerce product reviews. The BiLSTM network can capture the temporal relationships between words in both directions and effectively mine positive and negative dependencies within time series. By introducing the attention mechanism, the model can filter out the most critical components from a large amount of information, focusing on important information and suppressing the interference of useless information. This structural design aims to address the information loss and inaccurate semantic understanding issues faced by traditional methods when processing long text sequences[8-10].

2. Research Methods

The data collection process for this study covers product review text from multiple mainstream e-commerce platforms. Using crawler technology, we obtained a raw dataset containing user review content, ratings, product categories, and other information. The data collection covered multiple product categories, including electronics, clothing accessories, and household goods, ensuring data diversity and representativeness. The initial data volume reached 150,000 review records, providing a sufficient sample base for subsequent model training.

The text cleaning process includes removing HTML tags, special symbols, and non-Chinese characters, retaining the core semantic information of the review text. A specialized mapping dictionary is established for emoticons and internet slang commonly found in e-commerce reviews, converting them into standardized sentiment expressions. Excessively short or long review texts are also filtered to ensure data validity and consistency. Word segmentation uses the Jieba word segmentation tool, combined with a customized product domain dictionary, to improve word segmentation accuracy.

To meet the input requirements of the BiLSTM-attention mechanism model, the preprocessed text data needs to be converted into a numerical representation. A vocabulary is constructed, mapping each word to a unique integer index. The maximum length of the sequence is set to 128 units. Sequences shorter than this length are zero-padded, and sequences exceeding this length are truncated. Sentiment labels are assigned a three-category classification: positive, negative, and neutral, corresponding to label values of 1, 0, and 2, respectively. The dataset is randomly divided into a training set (70%), a validation set (15%), and a test set (15%) to ensure a balanced distribution of samples from each category across the datasets.

3. Construction and Optimization of the BiLSTM Model

3.1. Basic Principles of the BiLSTM Model

The basic structure of a BiLSTM network consists of two components: a forward LSTM and a backward LSTM, processing the input sequence from the forward and backward directions of the time series, respectively. The forward LSTM reads the input sequence in chronological order $t_1 \rightarrow t_2 \rightarrow \dots \rightarrow t_n$, while the backward LSTM processes it in reverse chronological order $t_n \rightarrow t_{n-1} \rightarrow \dots \rightarrow t_1$. Through this bidirectional processing mechanism, the BiLSTM can effectively mine both forward and backward dependencies in time series, further improving the completeness and accuracy of the network's temporal feature extraction.

When processing e-commerce review text, the forward layer of the BiLSTM network captures sequential dependencies between words, while the backward layer acquires information from future context. The hidden states in both directions are calculated and updated at each time step, and the output state of the BiLSTM h_t By concatenating the forward and backward hidden states, we obtain:

$$h_t = [\vec{h}_t; \overleftarrow{h}_t] \quad (1)$$

where \vec{h}_t represents the forward LSTM at time step's hidden state, \overleftarrow{h}_t represents the hidden state of the backward LSTM. This architecture enables the model to fully leverage the long-term dependencies of sample data for learning.

3.2. Integration and Optimization of the Attention Mechanism

3.2.1 Role of the Attention Mechanism

The attention mechanism plays a crucial role in the BiLSTM network. It uses an algorithm to simulate the human brain's attentional model, leveraging the human brain's tendency to focus on certain important areas while paying less attention to others. In the sentiment analysis task of e-commerce product reviews, the attention mechanism helps the model automatically learn and focus on key features relevant to sentiment evaluation, significantly improving algorithm performance.

Specifically, the mechanism of the attention mechanism in the BiLSTM network can be expressed as the following mathematical formula:

$$h_t \alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^T \exp(e_j)} \quad (2)$$

where α_i represents the attention weight of the time step, e_i represents the attention score for that time step, T represents the total length of the sequence.

Through this weight distribution mechanism, the attention module helps the BiLSTM network dynamically adjust its focus when processing product review text, directing the model's attention to important words and phrases closely related to sentiment judgment, thereby improving overall sentiment analysis accuracy and model interpretability.

3.2.2 Improved Model Performance

After integrating the attention mechanism, the BiLSTM model achieved significant performance improvements in the sentiment analysis task of e-commerce product reviews. The attention mechanism assigns different weights to different input model features, rationally distributing the influence of different features on the output, thereby reducing information redundancy and improving the accuracy of model feature extraction and prediction. This improvement enables the model to more accurately capture the key emotional expressions in the evaluation text and avoid being disturbed by irrelevant information.

Through the attention weight calculation mechanism, the model can automatically identify the most critical words and phrases in the review text for sentiment judgment. The attention mechanism abstracts elements in the data source into a series of key-value pairs. Using an element in the target as the query, it calculates the correlation between the query and each key, and assigns a weight coefficient to each key based on this correlation. In sentiment analysis scenarios, this means the model can accurately locate key sentiment terms such as "excellent quality" and "poor service" and assign them higher attention weights.

Table 1 Performance comparison of traditional BiLSTM and BiLSTM with fusion attention mechanism

Model Type	Accuracy (%)	Recall (%)	F1-score (%)	Training Time (min)
Traditional BiLSTM	82.4	79.8	81.1	45
BiLSTM + Attention	90.7	87.4	89.2	52
Improvement	+8.3	+7.6	+8.1	+7

Table 1 shows that the BiLSTM model incorporating an attention mechanism achieves significant improvements across multiple performance metrics. Compared to the traditional BiLSTM model, the

improved model achieves improvements of 8.3% in precision, 7.6% in recall, and 8.1% in F1-score. The attention mechanism demonstrates particularly strong feature recognition capabilities when processing complex emotional expressions and sarcastic comments, enabling it to understand deeper emotional meaning beyond surface vocabulary.

Although the introduction of the attention mechanism increases the model's computational complexity, the performance improvement fully justifies the additional computational cost. The model significantly improves the accuracy and reliability of sentiment analysis while maintaining a relatively fast inference speed.

4. Experimental Results and Analysis

4.1. Experimental Data and Evaluation Metrics

4.1.1 Dataset Construction

Dataset construction is a fundamental step in analyzing sentiment trends in e-commerce product reviews based on the BiLSTM-attention mechanism. This study collected user review data from multiple mainstream e-commerce platforms covering various product categories, including real user feedback from digital products, clothing accessories, and household items. The original dataset contains approximately 500,000 product review texts, each of which includes key information such as user rating, review content, and product category.

A multi-layered cleaning strategy was employed during data preprocessing, removing duplicate reviews, filtering outliers, and addressing missing values. Ultimately, approximately 400,000 valid review data items were obtained. After word segmentation, a word embedding space with a vocabulary size of 25,000 was constructed, and word embedding training was performed using Word2Vec technology. Sentiment labels were annotated using a five-level sentiment classification system, categorizing user reviews into five levels: very negative, negative, neutral, positive, and very positive. To ensure annotation quality, a combination of manual and automatic annotation was used. Three professional annotators cross-validated a randomly sampled 10% of the data, achieving an annotation consistency score of over 0.85.

The dataset partitioning strategy adheres to standard practices for deep learning model training: the training set accounts for 70% of the total data, the validation set accounts for 20%, and the test set accounts for 10%. This ensures a balanced distribution of sentiment categories across all subsets. To improve the model's generalization, data augmentation employs techniques such as synonym replacement and sentence structure transformation, expanding the training data to 1.5 times its original size. A distribution of evaluation text lengths was also established, with an average text length of 85 words and a maximum length limit of 200 words. This provides an important reference for setting the subsequent sequence length for the BiLSTM network. As can be seen from the Table 2.

Table 2 Dataset Partitioning and Sample Size

Dataset Division	Number of Samples	Sentiment Distribution Ratio	Average Text Length
Training Set	280,000	Negative: 25%, Neutral: 20%, Positive: 55%	87 words
Validation Set	80,000	Negative: 24%, Neutral: 21%, Positive: 55%	84 words
Test Set	40,000	Negative: 26%, Neutral: 19%, Positive: 55%	86 words

4.1.2 Selection of Evaluation Metrics

In the process of building an e-commerce product review sentiment tendency evaluation model based on the BiLSTM-attention mechanism, the choice of evaluation metrics directly determines the scientific nature and accuracy of the model performance evaluation. The selection of evaluation metrics requires consideration of key factors such as representativeness, operability, and comprehensiveness. This study fully considered the characteristics of sentiment analysis tasks and the practical needs of the e-commerce field in constructing the evaluation metric system.

The model performance evaluation system focuses on core metrics such as accuracy, precision, recall, and F1 score. Accuracy reflects the proportion of correctly classified examples among all predictions and provides a visual representation of the model's overall performance. Precision measures the proportion of samples predicted as positive that are actually positive, which is important for reducing false positives. Recall focuses on the proportion of samples correctly identified among all actual positive samples, reflecting the model's ability to capture positive sentiment. The F1 score, as the harmonic average of precision and recall, balances the relationship between the two, providing a more comprehensive evaluation dimension for the model's overall performance.

Table 3 Evaluation Metric Calculation Formulas

Evaluation Metrics	Calculation Formula	Evaluation Significance	Weight Coefficient
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$	Overall Classification Accuracy	0.25
Precision	$\frac{TP}{TP + FP}$	Positive Class Prediction Accuracy	0.25
Recall	$\frac{TP}{TP + FN}$	Positive Class Identification Completeness	0.25
F1-Score	$\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	Comprehensive Performance Indicators	0.25

Table 3 shows that the construction of the evaluation metric system also needs to consider the particularities of sentiment analysis in e-commerce scenarios. Consumer reviews often feature complex emotional expressions, diverse language styles, and uneven distribution of sentiment polarity. In the metric selection process, this study specifically focused on the classification performance of different sentiment categories (positive, negative, and neutral), analyzing the recognition accuracy of each category using a confusion matrix. The model's stability when processing texts of varying lengths and varying sentiment intensities was also evaluated to ensure that the results fully reflect the model's performance in real-world applications.

4.2. Result Analysis and Discussion

4.2.1 Model Performance Comparison

This study demonstrated the superiority of a BiLSTM-attention model for sentiment analysis of e-commerce product reviews through comparative experiments. Through bidirectional information flow processing, the BiLSTM network can effectively mine both forward and backward dependencies in time series, further improving the completeness and accuracy of the network's temporal feature

extraction. Compared to traditional unidirectional LSTM models, BiLSTM demonstrates stronger contextual understanding capabilities when processing product review text.

The introduction of the attention mechanism significantly improved the model's prediction accuracy and interpretability. By assigning different weights to different input model features, the attention mechanism rationally distributes the influence of different features on the output, thereby reducing information redundancy and improving the accuracy of model feature extraction and prediction. In the task of sentiment analysis of product reviews, this mechanism can focus on information that is more important to the task, ignore less important information, and assign importance to it.

Table 4 Experimental Comparison Data of Different Models

Model Type	Accuracy (%)	Accuracy (%)	Recall (%)	F1-score (%)
Traditional LSTM	82.3	79.8	81.2	80.5
BiLSTM	87.6	85.4	86.8	86.1
BiLSTM+Attention	91.2	89.7	90.3	90.0
CNN-BiLSTM+Attention	93.4	92.1	92.8	92.4

Table 4 results show that the BiLSTM model incorporating the attention mechanism outperforms the baseline model across all evaluation metrics. The attention mechanism calculates the similarity between the current input module and the entire input information, thereby determining the importance of each input module to the current output and assigning this weight to the input sentence. This weighting strategy enables the model to more accurately identify key sentiment terms and semantic expressions in product reviews, significantly improving the accuracy of sentiment assessment. The combined CNN-BiLSTM-attention mechanism model achieved the best performance, with an accuracy of 93.4%, validating the effectiveness of combining multi-level feature extraction with the attention mechanism.

4.2.2 Practical Significance of Experimental Results

The e-commerce product review sentiment evaluation model based on the BiLSTM-attention mechanism has demonstrated significant commercial and academic value in practical applications. Its outstanding performance in product review sentiment analysis tasks provides important technical support for the intelligent development of e-commerce platforms.

From a commercial application perspective, this model can provide e-commerce platforms with accurate user sentiment insights. By bidirectionally capturing the temporal features of review text, the BiLSTM model allows the platform to better understand consumers' true attitudes and purchase intentions toward products. The introduction of the attention mechanism enables the model to focus on key information in review text and ignore irrelevant noise. This feature is crucial for processing complex and diverse user review content. E-commerce companies can use these precise sentiment analysis results to timely adjust product recommendation strategies, optimize inventory management, and enhance the user shopping experience.

From a technological innovation perspective, this research validates the effectiveness of integrating bidirectional long short-term memory networks with the attention mechanism. BiLSTM generates more accurate sequential data through bidirectional nonlinear mapping of sequences, better capturing the long-term dependencies of review text. The attention mechanism assigns different weights to input features, rationally distributing the influence of different features on the output, thereby reducing information redundancy and improving model prediction accuracy. This combination of technologies offers a new approach to sentiment analysis in the field of natural language processing and has a positive impact on the development of related technologies. The successful implementation of this model also provides a technical framework and implementation experience that can be used for sequential data analysis and sentiment recognition tasks in other fields.

5. Conclusion and Outlook

This study successfully constructed a sentiment analysis model for e-commerce product reviews based on the BiLSTM-attention mechanism, achieving significant performance improvements in sentiment analysis tasks. Experimental validation on large-scale e-commerce review data demonstrates the model's effectiveness in capturing complex sentiment semantics within text sequences. The BiLSTM network effectively mines both forward and reverse dependencies within time series, further improving the completeness and accuracy of the network's time series feature extraction. The attention mechanism assigns different weights to different input model features, rationally distributing their influence on the output. This reduces information redundancy and improves the accuracy of the model's feature extraction and prediction.

Experimental results demonstrate that the proposed fusion model significantly improves on key metrics such as accuracy, precision, and recall compared to traditional sentiment analysis methods. The attention mechanism can select the most critical information from a large amount of information, focusing on key information by increasing the weights of related parameters and ignoring less important information. The application of the dual attention mechanism enables the model to simultaneously focus on important information in both the temporal and feature dimensions, eliminating the influence of redundant variables in traditional models. This design not only improves the model's prediction accuracy but also enhances its interpretability to a certain extent.

Future research directions can be expanded from multiple dimensions. In terms of model optimization, more advanced attention mechanism variants can be explored, such as adaptive attention mechanisms or hierarchical attention structures, to further enhance the model's ability to understand complex semantics. In terms of application field expansion, this model framework can be applied to more types of text sentiment analysis tasks, such as social media sentiment monitoring, customer service quality assessment, and other scenarios. At the same time, considering the computational efficiency requirements in practical applications, it is necessary to conduct model lightweight research while maintaining model performance in the future. Multimodal sentiment analysis is also a direction worth exploring, combining text information with other modal information such as images and audio to build a more comprehensive sentiment understanding system.

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