Proceedings of CONF-MLA 2025 Symposium: Intelligent Systems and Automation: AI Models, IoT, and Robotic Algorithms
DOI: 10.54254/2755-2721/2025.LD26890

Research on the Application of Sentiment Analysis in the E-Commerce Field

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Abstract. With the vigorous development of e-commerce, user-generated content (UGC) has become a core resource for insight into consumer needs in the e-commerce ecosystem. Sentiment analysis technology, through natural language processing and machine learning methods, identifies of emotional tendencies in text data such as reviews and bullet screens, providing support for consumer decision-making, merchant operations, and platform optimization. This paper adopts the methods of literature review and case study to systematically sort out the technological evolution of sentiment analysis in the e-commerce field, including typical models in the stages of traditional methods, machine learning, and deep learning. Combined with segmented scenarios such as fresh produce, home appliances, and pre-prepared dishes, it analyzes its application practices in topic mining and sentiment classification. Finally, it discusses challenges such as data noise and multimodal fusion in technical applications. It looks forward to future trends such as large language model fine-tuning and cross-domain adaptation, providing a reference for sentiment analysis research and applications in the e-commerce field.

Keywords: Sentiment Analysis, E-commerce, Natural Language Processing, Machine Learning, User Reviews

1. Introduction

In recent years, global e-commerce transaction volume has grown at an average annual rate of 15%. In 2023, China's online retail sales of e-commerce reached 15.42 trillion yuan, accounting for 40% of total social consumer goods retail sales [1]. Against this background, user-generated content (UGC) data, such as user reviews and Q&A interactions, have grown explosively, and the emotional tendencies and demand preferences contained therein have become a key basis for competition among e-commerce platforms. As an important branch of (Natural Language Processing) NLP, sentiment analysis identifies positive, negative, or neutral emotions in text through automated technology, and has become a bridge connecting consumers and merchants.

Sentiment analysis is of great significance to multiple subjects in the e-commerce ecosystem. For consumers, sentiment analysis can quickly extract the advantages and disadvantages of products to assist rational decision-making. For merchants, it can capture user feedback in real time to guide product iteration and service optimization. For example, by analyzing reviews of household

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companion robots, users' privacy concerns about the "monitoring function" were discovered [2]. For platforms, sentiment analysis helps build a trust system and improve user retention.

Although the application of sentiment analysis in the e-commerce field has made some progress, current research still has two significant gaps. First, existing achievements mostly focus on a single text modality, and there is insufficient research on emotional fusion analysis of increasingly growing multimodal data, such as images and videos, in e-commerce scenarios. Second, the problem of cross-domain adaptability is prominent. The performance of models decays significantly when analyzing reviews from different categories such as home appliances to fresh produce, and there is a lack of universal solutions.

This paper systematically sorts out the technological evolution of sentiment analysis in the e-commerce field through literature review, and deeply analyzes its multi-domain applications combined with cases. It provides a reference framework with academic value and practical guiding significance for theoretical research and industrial applications of e-commerce sentiment analysis.

2. Literature review

2.1. Traditional methods stage

The development of sentiment analysis technology can be divided into three stages, and the methods of each stage have typical applications in e-commerce scenarios, with significant differences in their technical characteristics and adaptability.

This stage relies on preset dictionaries and grammatical rules to judge emotional tendencies, with the core being to adjust emotional polarity by matching emotional words such as "satisfied" and "bad" and negative words. For example, Chen and others used the Snow NLP library to segment words and calculate emotional values for JD's household robot reviews, defining words with emotional values greater than 0.9 as positive words and less than 0.5 as negative words, and achieved users' positive evaluations of the "companionship function" and negative feedback on "harsh sound quality" through word cloud maps [2]. Although the traditional stage has the advantages of low cost and high interpretability, it relies on the completeness of the dictionary and has weak adaptability to texts with complex contexts. Scholars such as Zhao pointed out that the phenomenon of polysemy in Chinese sentiment dictionaries further limits its accuracy in e-commerce review analysis [3].

2.2. Machine learning stage

With the expansion of data scale, machine learning models such as Support Vector Machine (SVM) and Naive Bayes have gradually replaced rule-based methods, realizing sentiment prediction through training classifiers with labeled data. Cheng used the LinearSVC model for sentiment analysis of electric water heater reviews, combined with TF-IDF vectorization technology. They achieved high accuracy in binary classification tasks, proving the effectiveness of linear classifiers in processing structured text [1]. The key of this stage is feature engineering, which requires manually designing features such as part-of-speech and word frequency. However, the generalization ability of the model is limited by the quality of training data, and its performance declines significantly in cross-domain applications [1].

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2.3. Deep learning stage

Deep learning has significantly advanced sentiment analysis by automatically extracting features, surpassing the limitations of traditional methods, and becoming the current mainstream technology. For instance, Liu et al. developed a CNN-LSTM hybrid model for catering reviews. This model extracts local features such as “taste” and “service”, and LSTM captures text sequence dependencies. It achieved an accuracy rate of 93.21% on the Jijihong hot pot review dataset, with a specificity of identifying negative reviews reaching 98.21% [4]. Wang and researchers proposed the BERT-CNN-BiLSTM-Attention model, which leverages BERT’s ability to capture contextual semantics and combines the attention mechanism to strengthen key information such as “glaze quality”, achieving an F1-score of 80.76% in ceramic e-commerce reviews [5].

Traditional methods , while suitable for rapid analysis in simple scenarios, often fall short in terms of accuracy. Machine learning models, on the other hands, rely on labeled data and perform stably in structured text. However, deep learning models have broken through the limitations of the first two by automatically extracting features and demonstrating stronger adaptability in complex contexts. This adaptability is a key factor in their widespread adoption as the mainstream technology of sentiment analysis in current e-commerce.

3. Application scenarios of sentiment analysis in the e-commerce field

The text characteristics of different e-commerce segmented scenarios are significantly different. Sentiment analysis technology, with the advantages of accurately locating problems, efficiently processing data, and adapting to complex scenarios, has become an important tool to solve domain pain points.

3.1. Fresh produce e-commerce: logistics and quality

In the fresh produce field, due to the strong timeliness of products, unstable product quality (such as deterioration caused by delayed delivery, taste defects of pre-prepared dishes), and user feedback scattered in massive reviews, manual screening is highly inefficient.

With the help of sentiment analysis, core words can be extracted from tens of thousands of reviews and quantitatively compared. Wang et al. extracted 6 core topics such as “logistics”, “taste”, and “after-sales” from JD fresh produce reviews based on the LDA model, and found that negative reviews on the “after-sales” topic accounted for 13.24%, mainly involving the problem of “delayed compensation for deterioration”. Based on this data, the platform was promoted to establish a “2-hour compensation response” mechanism [6]. Xia et al. used the BTM topic model to analyze pre-prepared dish reviews. They found that the proportion of negative emotions in instant heating products reached 16.24%, with negative keywords focusing on “greasy” and “small portion”, providing a basis for product formula optimization [7]. Based on the quantitative results of sentiment analysis, the platform can establish a targeted “2-hour compensation response” mechanism to solve the timeliness problem.

3.2. Home appliances and smart devices: functions and experience

In the field of home appliances and smart devices, products place greater emphasis on functionality and user experience. “Installation fees” and “slow after-sales response” are areas with concentrated negative emotions, prompting manufacturers to standardize service processes [1]. In the field of household companion robots, Chen and scholars found through emotional value calculation that

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85.55% of positive reviews focused on the "companionship function", but 7.70% of negative reviews pointed to "monitoring privacy risks". Based on this, manufacturers were promoted to add a "privacy mode" [2]. Through sentiment analysis, producers can more timely understand users' experience, accurately identify product problems and area for improvement, and improve production and innovation efficiency.

3.3. Social e-commerce live streaming: fragmentation and multimodality

UGC in social e-commerce is characterized by fragmentation and multimodality. Xieet al. designed a hierarchical structure model for Weibo reviews, combined with topic-related features, to improve the accuracy of sentiment analysis [1]. The live broadcast scenario requires sentiment analysis to integrate multimodal data such as bullet screen text and anchor expressions. For example, when the comment text is "average" but users frequently like it, the attention mechanism needs to be used to prioritize text emotions to reflect real experience [4]. With the help of sentiment analysis technology, fragmented user-generated content is integrated and adapted to different media characteristics to obtain more accurate analysis results.

4. Core challenges

4.1. Data noise and semantic lag

In the data collection process of e-commerce sentiment analysis, noise data, such as fake reviews and paid posters, have become prominent problems that interfere with the accurate judgment of models. For example, some merchants hire paid posters to publish homogeneous positive reviews in batches to create an illusion of "a flood of praise".

At the same time, the iteration speed of emotional semantics of emerging words is much faster than the update frequency of traditional tools. Taking the word "atmosphere" as an example, in reviews of clothing, home furnishing and other categories, it may express positive emotions such as "high-end design, suitable for scenarios", or imply negative semantics such as "flashy, lacking practicality". However, mainstream sentiment dictionaries take an average of 3-6 months to include such words, resulting in long-term lag in the model's recognition of new semantics, which cannot adapt to the rapidly updating e-commerce language ecosystem.

4.2. Multimodality and real-time challenges

There is no unified standard for handling emotional conflicts in multimodal data. In live broadcasts, consumers may post comment texts such as "the product is average, but the anchor is very interesting", along with pictures of perfunctorily placed products and video clips of enthusiastic interactions. Due to conflicting emotional tendencies among text, image, and video modalities, existing models lack effective fusion strategies and are prone to misjudging product quality as positive.

In addition, live broadcast e-commerce has strict requirements on the real-time performance of sentiment analysis, but the inference efficiency of existing models is difficult to match. For example, the BERT-Large model takes about 200ms to process a single review. If multimodal data processing is superimposed, the delay will exceed 500ms, which is far from meeting the operational needs of live broadcasts for "real-time capture of negative feedback and timely adjustment of marketing words".

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4.3. Privacy and fairness risks

There is a hidden danger of private information leakage in review data. Taking categories such as home robots and smart home appliances as examples, expressions in user reviews such as "the monitoring position covers the living room" and "the floor-sweeping robot scratched children's toys" may imply sensitive data such as family layout and children's activity areas.

Algorithmic bias can also lead to unfair services. The elderly group is accustomed to using vague expressions such as "not bad" and "so-so", which are quite different from the "clear positive and negative words" in the model training set. Data from an elderly care products platform shows that the accuracy of sentiment recognition for elderly users' reviews is 23% lower than that for young groups, resulting in the platform's customer service resources and product recommendation accuracy allocated to elderly users being lower than those for other groups [4].

5. Future directions

5.1. Lightweight models

In the future, large language models will gradually achieve lightweight, models by compressing parameters through technologies such as knowledge distillation and model pruning. Taking DistilBERT as an example, it distills knowledge from the BERT model, reducing the parameter scale by 53% while increasing inference speed by nearly 2 times. In the future, it can be further optimized for e-commerce scenarios, extracting exclusive knowledge in vertical fields such as "product evaluation and service feedback", and building a lightweight distillation framework, so that the delay of the model in processing single multimodal reviews in live broadcast e-commerce can be controlled within a specific range, ensuring real-time analysis needs and being compatible with low-computing-power devices such as mobile phones and mini-programs [5,8].

5.2. Cross-domain adaptation paths

Transfer learning and prompt engineering will become the core paths for cross-domain adaptation. On the one hand, using training data of mature categories such as home appliances and fresh produce, the sentiment model of new categories can be optimized through the "pre-training plus fine-tuning" mode of transfer learning. On the other hand, combined with prompt engineering, structured instructions such as "product quality, logistics service, after-sales experience" are designed to guide the model to focus on domain characteristics. For example, the outdoor tent category can reuse the sentiment analysis logic of "waterproofness and portability" of camping equipment, and guide the model to identify semantics such as "wind resistance level and setup difficulty" through customized prompts.

At the same time, future sentiment analysis should pay attention to multimodal fusion. A unified feature space for text, images, and audio should be constructed to solve the conflict between "beautiful pictures and negative reviews" [4,8]. For example, when the text mentions "shoddy packaging" but the image shows "the product itself is intact and functional", the model can use GNN to correlate the weights of "packaging" and "core value of the product" and prioritize emotions related to product quality. The speech rate and intonation features of the audio modality can assist in identifying the user's real emotional state, especially supplementing missing text information in after-sales negotiation scenarios.

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5.3. Construction of ethical guidelines

Finally, more attention should be paid to the construction of ethical norms. First, the government should strengthen supervision measures for data privacy protection, gradually promote the establishment of unified industry standards for privacy protection in data collection, and establish detection and correction mechanisms for algorithmic bias. Enterprises and e-commerce platforms should actively promote technological improvements, such as reducing the risk of privacy leakage through differential privacy (setting noise disturbance to prevent personal information from being restored).

6. Conclusion

This study explores the application of sentiment analysis technology in the e-commerce field, pointing out that it has developed from basic sentiment recognition to scenario-based decision support, and its technological evolution reflects the transformation from rule-driven to data-driven. Traditional methods, machine learning, and deep learning models have their advantages in low-cost, structured data, and complex semantic processing, respectively. The study further points out that large language model fine-tuning provides a new path for few-sample scenarios. Sentiment analysis has achieved remarkable results in fields, such as fresh produce and home appliances, but it also has problems such as ethical issues and data noise. Finally, this paper points out the future development directions of sentiment analysis in the e-commerce field, such as the realization of a lightweight model.

However, although this paper systematically sorts out the application logic of sentiment analysis in the e-commerce field, it has certain limitations in the research: it lacks empirical support with specific data, and the persuasiveness and refinement of the conclusions need to be improved. Future research can collect more reviews from typical fields based on empirical evidence, compare the performance of multiple models, and quantify the impact of noise.

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