Research on Cultural Film and Television Criticism and User Behavior Communication Model Based on Sentiment Analysis

Yiran Li*

School of Humanities and Communication, Xinyang Agriculture and Forestry University, Xinyang, Henan, 464000, China

*Email: Lyr20230522@163.com

Abstract. To enhance the interpretative efficiency of cultural film and television reviews and the accuracy of user behavior prediction, sentiment analysis technology is applied to assess the polarity and intensity of film and television reviews. This approach aims to identify users' emotional attitudes toward films and predict their interactive behaviors. By collecting 2,000 data entries from social media and film review platforms, a deep learning model based on Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks achieved an overall accuracy rate of 88% in sentiment classification. Additionally, experimental results indicate that reviews with high emotional intensity significantly increase the probability of dissemination behaviors such as likes and shares, highlighting the critical role of emotional information in driving user behavior.

Keywords: sentiment analysis; film reviews; user behavior prediction

1 Introduction

Sentiment analysis, a core technique in natural language processing, is widely used in interpreting cultural film reviews and predicting user behaviors, with continuous improvements in accuracy and depth. With the rapid growth of social media and online review platforms, sentiment analysis not only identifies audiences' emotional attitudes toward films but also provides insights into predicting users' dissemination behaviors. Exploration of sentiment-driven communication models reveals how emotional information influences user interactions, sharing behaviors, and the spread process, offering valuable reference points for optimizing film content and marketing strategies.

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2 Application of Sentiment Analysis in Cultural Film and Television Reviews

As a natural language processing technique, sentiment analysis has made significant strides in its application to cultural film and television reviews in recent years. With the rise of social media and online review platforms, the volume and influence of film and television reviews have grown, enabling researchers and industry practitioners to more effectively understand audience reactions to cultural works. The primary applications of sentiment analysis in film reviews focus on two areas: (1) Sentiment polarity analysis, which identifies the emotional polarity in review text (such as positive, negative, or neutral sentiment), and (2) Sentiment intensity assessment, which further explores the strength of emotional responses. These analyses not only assist film companies in gauging market feedback on movies or TV series but also inform content creation and marketing strategies. Additionally, sentiment analysis is widely used in automated public opinion monitoring, user preference analysis, and social media sentiment tracking [1]. However, challenges remain in handling complex emotional expressions, such as sarcasm, puns, and ambiguous language. Improving the accuracy and diversity of these analyses continues to be a key direction for future development.

3 Design and Implementation of a Film Review Dissemination System Based on Sentiment Analysis

3.1 Data Collection Phase

The core task during the data collection phase is to gather comments related to film and television works from multiple platforms for subsequent sentiment analysis and dissemination path research [2]. As shown in Figure 1, the data sources include social media platforms (e.g., Weibo, Twitter, Douban), film review websites (e.g., Maoyan, Mtime), and professional online rating platforms. During the data collection process, strict adherence to privacy protection and legal compliance requirements is ensured, with all activities conducted in accordance with relevant laws and regulations. Only public data is collected, avoiding unauthorized access to private user information. The purpose of data collection is clearly defined, and anonymization measures are implemented to prevent potential personal information leakage. Moreover, when using web scraping techniques, the terms of service of target platforms are strictly followed to avoid conflicts with platform rules or violations. To further enhance compliance, the data collection process is subject to ethical review to ensure adherence to data ethics principles. These measures not only ensure data quality but also support the credibility and legitimacy of the research.

The data collected through these methods typically includes multidimensional information such as review content, user sentiment orientation, ratings, and discussion topics, which provides robust support for subsequent sentiment analysis. However, it is crucial to strictly adhere to platform usage guidelines during data collection to prevent violations of user privacy or platform rules, ensuring the legality and compliance of the data [3].

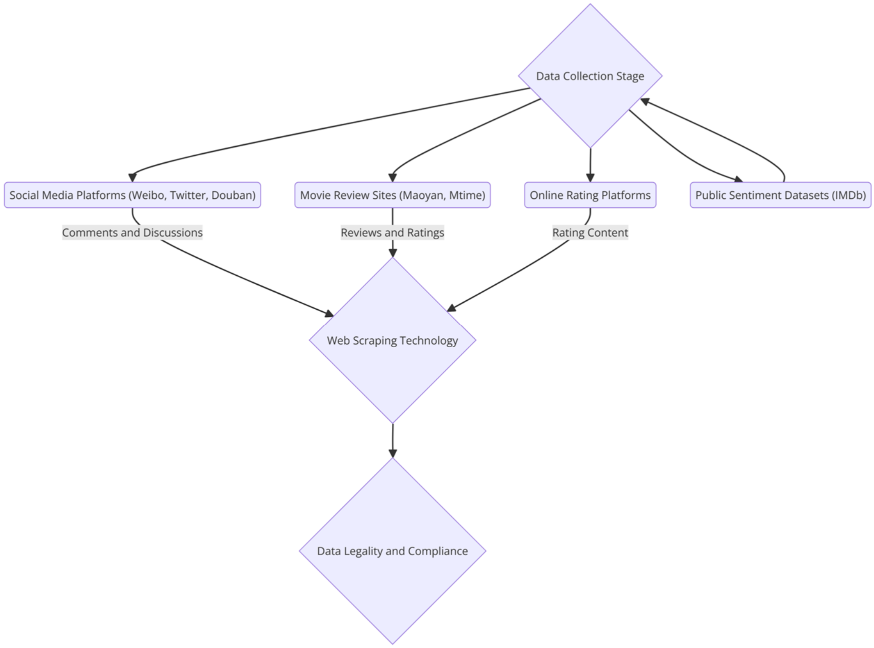

Fig. 1. Workflow of Film Review Data Collection

3.2 Sentiment Analysis Module

The implementation of the sentiment analysis module in the film review dissemination system integrates both traditional and modern technical methods. Basic approaches, such as the sentiment lexicon method, rely on predefined sentiment vocabulary databases (e.g., SentiWordNet) to label comments. However, this method is limited in handling complex emotional expressions like sarcasm, irony, and puns, often constrained by the lexicon's scale and semantic adaptability. To overcome these limitations, recent years have seen increased adoption of deep learning techniques, particularly the combination of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), which has significantly improved the accuracy of sentiment classification [4]. Nevertheless, these deep learning methods also have limitations, such as lower adaptability to sarcastic language, ambiguous expressions, and unstructured text. Additionally, sentiment analysis shows significant variation in performance across cultures, which may stem from linguistic and contextual factors. This study attempts to mitigate these issues partially through adjustments in sentiment intensity weighting and contextual semantic association modeling. However, further optimization is needed for implicit emotional features in unstructured text. The formula for sentiment orientation analysis typically takes the following form:

$$S = \sum_{i=1}^{n} (w_i \cdot f(t_i)) \tag{1}$$

In this formula, S represents emotional polarity, w_i is the weight of the emotional word, and $f(t_i)$ is the emotional scoring function for the word t_i. n refers to the number of emotional words in the text. The emotional scoring function $f(t_i)$ can be determined based on the dictionary value of emotional words (e.g., the score for "good" is +1, and for "bad" is -1) or dynamically generated through machine learning models. The weight w_i is adjusted according to the contextual importance of the emotional word, with higher weights assigned in emphatic sentence structures. This formula is suitable for classifying the overall emotional tendency of reviews. Moreover, emotional intensity evaluation can be calculated using the emotional intensity weighted summation formula.

$$I = \frac{\sum_{i=1}^{n} (f(t_i) \cdot \alpha_i)}{\sum_{i=1}^{n} \alpha_i} \tag{2}$$

In this context, I represents emotional intensity, and α_i denotes the intensity coefficient of the emotional word. For instance, "excellent" may have a higher emotional value than "good." t_i indicates the contextual influence weight of the emotional word, such as the amplifying effect of the contextual word "very" on the emotional word "good," identified through text analysis models. The emotional intensity formula calculates the significance of sentiment in reviews more accurately by multiplying the intensity of each emotional word by its contextual influence weight and summing the results [5]. For clarity, consider a simple text: "This movie is very good." If the base emotional value of "good" is +1, and the amplifying weight of "very" is 1.5, the final emotional intensity would be $1 \times 1.5 = 1.5$. Such explicit term definitions and examples enhance the practical applicability of the formula.

3.3 User Behavior Dissemination Prediction

User behavior dissemination prediction based on sentiment analysis involves further application of sentiment polarity and intensity analysis results. The levels of sentiment polarity and intensity directly influence user interactive behaviors, such as sharing, commenting, and liking. By quantifying emotional responses, predicting users' dissemination intentions can be modeled, with the following formula used to estimate the likelihood of user dissemination:

$$P(u_i) = \frac{S_i \cdot W_{social} + I_i \cdot W_{impact}}{T} \tag{3}$$

In this formula, $P(u_i)$ represents the probability of user u_i engaging in interactive behavior, S_i denotes the sentiment polarity of the user's comment, I_i is the sentiment intensity, and W_{social} and W_{impact} are the weights for social dissemination and emotional influence, respectively. T is a time decay factor used to adjust the timeliness of dissemination behaviors. By continuously training and optimizing this model, accurate predictions of user behaviors such as sharing, commenting, and liking can be achieved. Additionally, by integrating dissemination paths within social networks, prediction accuracy can be further enhanced. The following formula is used to estimate user dissemination influence:

$$R(u_i) = \sum_{j=1}^{n} f\left(P\left(u_j\right), W_{ij}\right) \tag{4}$$

In this formula, $R(u_i)$ represents the dissemination influence of user u_i, $f\left(P\left(u_j\right), W_{ij}\right)$ denotes the impact of user u_j's dissemination behavior on u_i, W_{ij} is the weight of the connection between users, and n is the range of influence. By evaluating the dynamics of the dissemination network, this formula enables further prediction of the chain reactions in user behavior [6].

4 Experimental Results and Analysis

4.1 System Function Demonstration

In the experiment for this system, 2,000 movie review data entries were collected from various social media platforms (e.g., Weibo, Twitter) and film review websites (e.g., Maoyan, Mtime) to form the foundational dataset for sentiment analysis and dissemination prediction. Through the sentiment analysis module, the system extracts sentiment information from review texts and evaluates both sentiment polarity and sentiment intensity. Sentiment polarity identification employs a deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, effectively distinguishing positive, negative, and neutral sentiments. Sentiment intensity is calculated using a weighted summation formula that fully considers contextual information within the text. Following data analysis, a user behavior dissemination prediction model, based on sentiment polarity and intensity, was used to further quantify user dissemination intentions from social media interactions (such as likes, comments, and shares) [7]. In the experiment, a dissemination prediction model was constructed with social dissemination and emotional influence weights incorporated to evaluate user behavior probabilities across different dissemination paths on social networks. For reviews with high sentiment intensity and positive polarity, the system can predict that the review will likely receive more likes and shares in a short period, as shown in Table 1.

Table 1. Experimental Parameter Settings

Parameter Name	Value
Data Collection Volume	2,000 reviews
Sentiment Classification Model	CNN + LSTM
Sentiment Polarity Categories	Positive, Negative, Neutral
Sentiment Intensity Coefficient Range	0-1
Social Dissemination Weight	0.5
Sentiment Influence Weight	0.7
Time Decay Factor	0.1

4.2 Model Performance Evaluation

In the experiments, a systematic evaluation of the accuracy of the sentiment analysis model and the effectiveness of propagation prediction was conducted to ensure its practicality and reliability. The sentiment classification model, combining CNN and LSTM, achieved high accuracy through comprehensive training and validation. However, to further enhance the model's performance, optimizations in sentiment intensity evaluation were explored [8]. Specific measures include: (1) Introducing the Multi-Head Attention mechanism to capture key emotional words in review texts and dynamically assign weights, enhancing the flexibility of sentiment intensity computation; (2) Incorporating Contrastive Learning techniques by designing positive and negative sample pairs to optimize the model's ability to distinguish between sentiment polarity and intensity; (3) Expanding the training dataset through Data Augmentation, particularly addressing the issue of limited samples for negative sentiments and ambiguous expressions. This was achieved using synonym replacement with semantic preservation and contextual expansion strategies to improve the model's generalization capability. Details of the data are shown in Table 2.

Table 2. Sentiment Classification Model Accuracy

Sentiment Category	Precision	Recall	F1 Score
Positive	91%	90%	90.50%
Negative	84%	82%	83.50%
Neutral	85%	87%	86%
Overall	88%	86.50%	87.20%

Table 2 presents the accuracy, recall, and F1 score of the sentiment classification model across different sentiment categories. The classification performance for positive sentiment is the highest, achieving a precision of 91%, indicating that the system effectively captures emotional features in positive evaluations. The precision for negative sentiment is comparatively lower, as the diversity of emotions within negative comments introduces ambiguity that leads to occasional classification deviations. Neutral sentiment classification is stable, with balanced recall and precision, demonstrating the model's adaptability to neutral sentiment. To further test the model’s effectiveness in predicting user dissemination, particularly the impact of sentiment intensity on predicting user interactions, an experiment on graded sentiment intensity prediction was conducted, as shown in Figure 2.

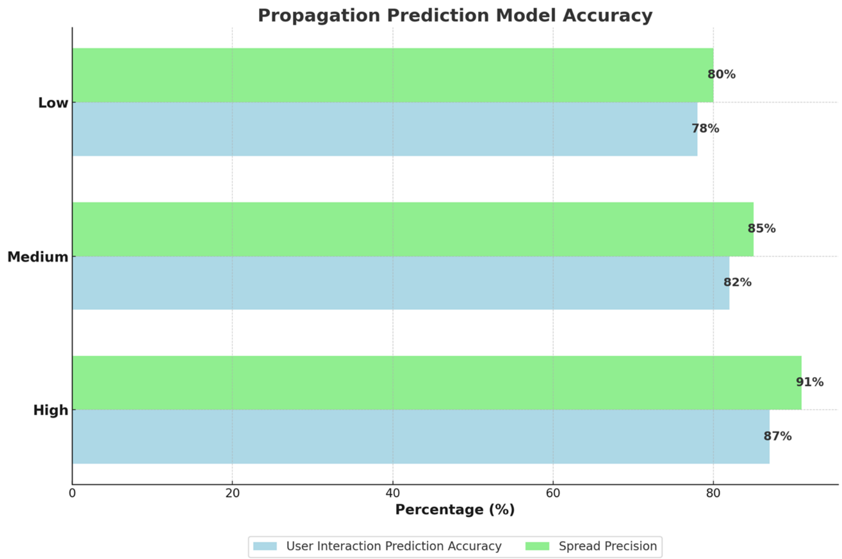

Fig. 2. Dissemination Prediction Model Accuracy (Classified by Sentiment Intensity)

The data in Figure 2 indicates that sentiment intensity significantly impacts the prediction of user interactions. High-intensity sentiment comments, especially those with clear polarity, more accurately predict behaviors such as sharing, liking, and commenting. In contrast, comments with low sentiment intensity, while possessing some dissemination potential, exhibit slightly lower prediction accuracy due to their weaker emotional response [9]. Predictions for medium-intensity sentiment are relatively balanced, showing the model's good adaptability to moderate-intensity comments. Subsequently, the dissemination model's performance across different social platforms was analyzed to explore how platform characteristics affect prediction outcomes. Table 3 presents the dissemination influence prediction results on each platform, further analyzing the system's applicability and dissemination differences across platforms.

Table 3 presents the analysis of propagation influence across different social platforms. The results indicate that Weibo achieved the highest propagation prediction accuracy (84%) and the largest user interaction volume (3,500 interactions), primarily due to the high activity level of its user base and the platform's real-time nature. In comparison, Twitter and Douban showed prediction accuracies of 80% and 82%, respectively, performing slightly lower. However, their propagation behaviors were significantly influenced by platform-specific factors. Further analysis revealed that Twitter users primarily focus on discussions and information dissemination, with an interaction style more suited to spreading negative sentiment content, reflecting the platform's tendency toward public discourse. Douban users, on the other hand, prefer in-depth content and emotional resonance, leading to a higher focus on comments with greater emotional intensity. These differences highlight that the user base, content type, and interaction style of different platforms significantly impact the performance of sentiment analysis models in predicting user propagation behavior. This provides valuable insights for subsequent platform-specific optimization efforts [10].

Table 3. Social Platform Dissemination Influence Analysis

Platform	Dissemination Influence Prediction Accuracy	Average Dissemination Time	User Interaction Volume
Weibo	84%	1.2 hours	3,500 interactions
Twitter	80%	2.5 hours	2,200 interactions
Douban	82%	3.0 hours	1,500 interactions

4.3 Analysis of the Impact of Different Sentiment Information on Dissemination Effectiveness

Different sentiment polarities and intensities significantly impact the dissemination effectiveness and interaction rate of user behaviors. Positive or negative sentiment polarity not only affects the breadth of comment dissemination but also influences interaction rates. Positive sentiment comments are more likely to receive likes and shares, while negative sentiment tends to drive higher comment rates, as shown in Figure 3.

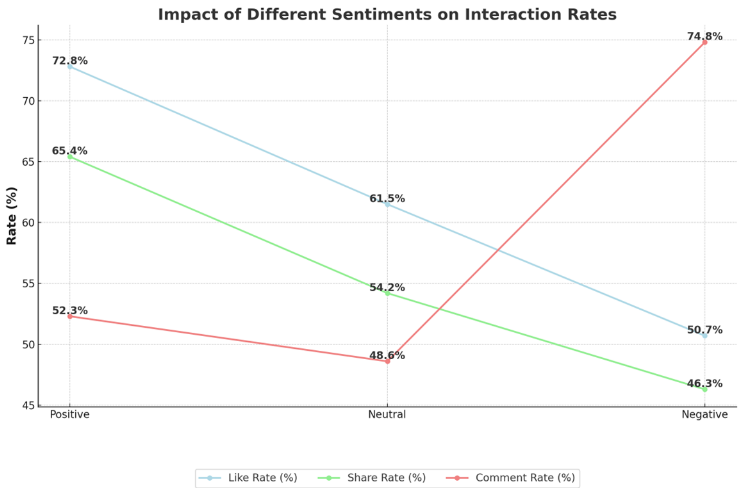

Fig. 3. Impact of Different Sentiment Polarities on Interaction Rate

Figure 3 illustrates the interaction rate differences across positive, negative, and neutral sentiments. The like and share rates for positive sentiments are relatively high, reaching 72.8% and 65.4%, respectively, indicating that positive emotions more readily stimulate user recognition and dissemination willingness. In contrast, negative sentiments have a much higher comment rate of 74.8%, far exceeding like and share rates, suggesting that negative comments are more likely to provoke user discussion and feedback. Neutral sentiments show a relatively balanced interaction rate, though slightly lower across all categories. Further analysis was conducted on the impact of sentiment intensity on dissemination effectiveness, with statistical results for different sentiment intensities shown in Figure 4.

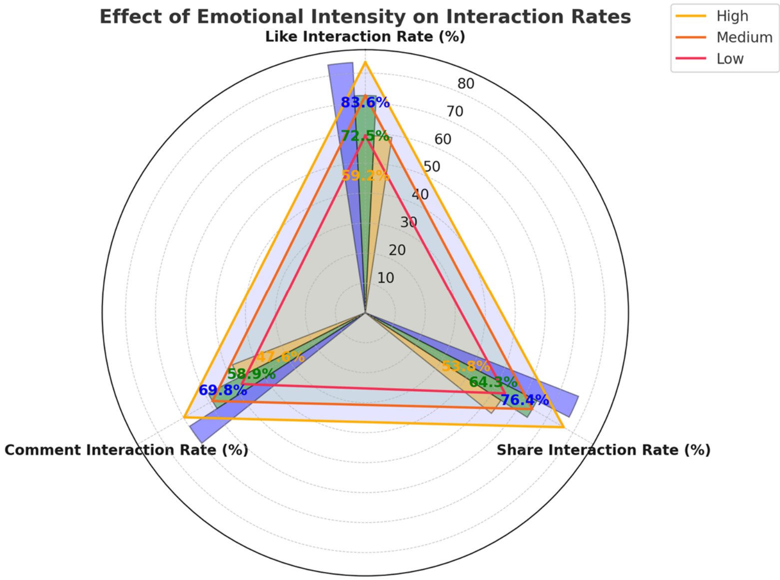

Fig. 4. Impact of Sentiment Intensity on Dissemination Effectiveness

The data in Figure 4 shows that high-intensity sentiment content has a significantly higher interaction rate compared to low-intensity sentiment. High-intensity sentiment content achieved a like interaction rate of 83.6% and a share interaction rate of 76.4%, indicating a strong dissemination potential for highly emotional content. Moderate sentiment intensity shows a balanced interaction rate, while low-intensity sentiment content has a notably lower interaction rate, underscoring the significant influence of sentiment intensity on dissemination effectiveness. To further evaluate the relationship between sentiment information and dissemination depth, an analysis of the dissemination depth for different sentiment information across various social platforms is provided in Figure 5.

Figure 5 reveals the impact of sentiment type on dissemination depth across platforms. Positive sentiment achieves the highest level of dissemination on Weibo, with an average depth of 4.2, indicating that positive emotions tend to spread widely among users. Negative sentiment follows, particularly on Twitter, where it reaches a dissemination depth of 3.7, correlating with the platform's user-driven discussion dynamics.

Neutral sentiment has the lowest dissemination depth, suggesting that neutral content is less effective in sustaining user interaction.

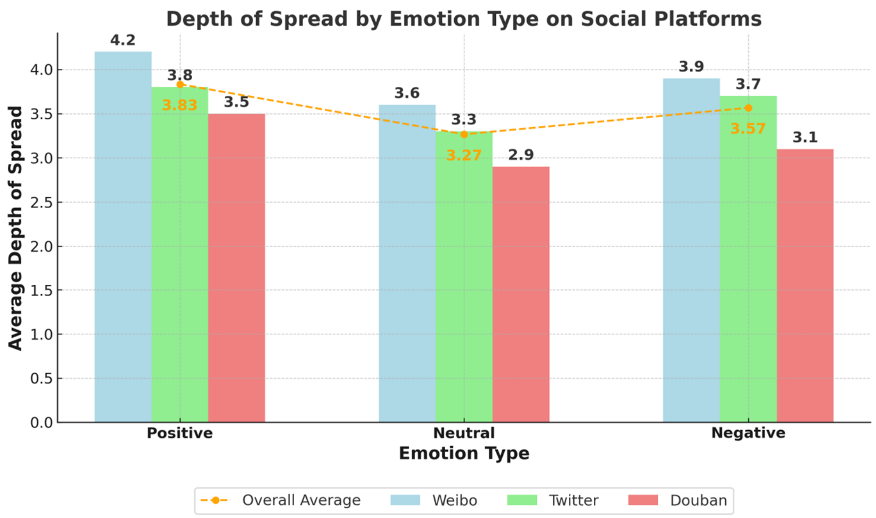

Fig. 5. Dissemination Depth of Different Sentiment Information

5 Conclusion

The application of sentiment analysis in film reviews not only reveals audience emotional reactions to works but also effectively predicts user interaction behaviors and dissemination trends, demonstrating significant practical value. By integrating multi-platform data collection and deep learning models, the system achieves precise user behavior predictions, providing scientific support for content optimization and market strategies in the film industry. Future efforts should focus on improving the accuracy of sentiment analysis for complex emotional expressions and optimizing the adaptability of dissemination prediction models across different platforms, further advancing the intelligent and precise development of film review dissemination systems.

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