

A Majority Voting System For Reliable Sentiment Analysis Of Product Reviews

M. Suyunova

A basic doctoral student at the Alisher Navoi, Tashkent State University of Uzbek Language and Literature, Uzbekistan

M. Amirqulov

A basic doctoral student at the Alisher Navoi, Tashkent State University of Uzbek Language and Literature, Uzbekistan

Received: 16 October 2025 **Accepted:** 08 November 2025 **Published:** 14 December 2025

ABSTRACT

This article examines the majority voting approach to enhance the reliability of product reviews submitted by users on online platforms and improve the accuracy of sentiment analysis results. The majority voting system determines the final sentiment label by aggregating the results produced by multiple annotators or different models. The advantages of this approach and its application areas (in the annotation process and in combining model outputs) are also examined. The article further details the working principles of the system, the process of evaluating and selecting reviews, and the impact of user votes on reliability. The majority voting approach not only enhances sentiment analysis outcomes but also helps filter out fake or biased reviews. This method is particularly noteworthy as an important methodological tool for improving dataset quality and ensuring trustworthy model outputs in developing ABSA and other linguistics-based models for the Uzbek language.

Keywords: Product reviews, sentiment analysis, majority voting, reliability, annotation, ensemble models, ABSA, BERT, RoBERTa, Naive Bayes.

INTRODUCTION

In today's digital era, online shopping platforms are becoming an integral part of people's daily lives. On internet stores, social networks, mobile applications, and service websites, users not only purchase products or services but also have the opportunity to share their opinions and experiences about them. These user reviews are now regarded as one of the most important sources of information in consumers' decision-making processes. Through reviews, customers gain a clear understanding of product or service quality, value for money, delivery performance, and customer service. Therefore, even a single positive or negative comment can significantly influence product sales. For example, if negative reviews appear about a product that has been heavily promoted through a high-quality advertising campaign, this may

create distrust among consumers and lead to a decrease in sales volume. Conversely, lesser-known products that attract attention through positive user feedback may quickly gain popularity in a short period.

Consumers also tend to pay close attention to the overall rating of reviews. However, in some cases, products with perfect scores (for example, five-star ratings) may create doubt or distrust among customers. This is because users often perceive such ratings as overly ideal and fear that they may not reflect real user experience. Therefore, some buyers prefer products with slightly lower but seemingly more credible ratings. Announcing discounts on low-rated products does not always yield the expected results either. In many cases, customers associate such discounts with poor product quality, and as a result, this marketing

strategy can have the opposite effect, leading to a decrease in sales volume [1]. However, not all user reviews are reliable or objective. The number of fake, biased, or manipulative reviews on the internet is steadily increasing. In some cases, competing companies post false or spam reviews to protect their interests or damage the reputation of other brands. Such situations not only reduce consumer trust but also significantly affect the accuracy of AI-based sentiment analysis systems.

Therefore, determining the reliability of online reviews, distinguishing genuine user opinions from fake ones, and identifying useful versus non-useful reviews have become pressing scientific and practical issues in the automatic analysis of online feedback. Such analyses play an important role for companies in improving their products, enhancing customer service, and gaining a competitive advantage.

LITERATURE REVIEW

In recent years, the issue of determining the reliability of user-generated reviews has gained significant importance in scientific research. Many scholars have conducted studies based on various approaches and models in this area. Hu and Liu (2004), in their research, empirically examined the direct influence of user reviews on consumers' purchasing decisions. By analysing reviews of various products on the Amazon platform, they demonstrated that positive comments increase sales volume, whereas negative feedback leads to a decline. The study also proposed the use of word frequency and sentiment lexicons for the automatic analysis of user opinions [2].

In the study conducted by Chevalier and Mayzlin (2006), the impact of online ratings on sales volume was examined using book reviews as an example. The authors found that an increase in positive ratings boosts product sales, while

negative ratings have the opposite effect. They also highlighted the relationship between the quantity and quality of user reviews [3].

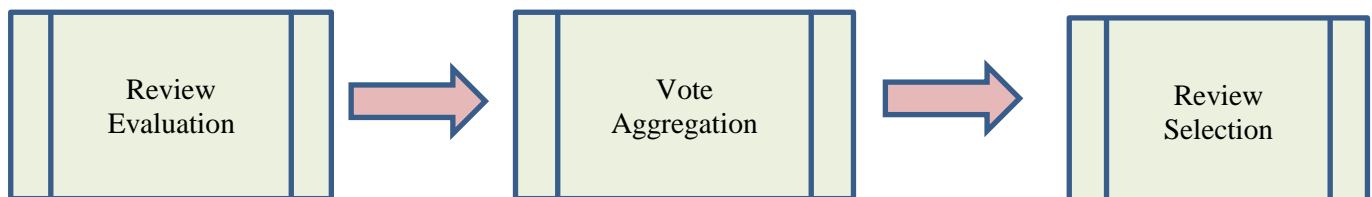
Jindal and Liu (2008) were the first to scientifically analyse the problem of “spam” or “fake” content in online user reviews. They identified that some reviews were written by competitors or biased users who excessively praised the product. The study emphasised that fake reviews can be detected through linguistic features such as text structure, vocabulary richness, and writing style [4].

Mukherjee et al. (2013) proposed detecting fake reviews by analysing user activity. They developed a spam detection model using features such as a user's review posting frequency, time intervals between reviews, and overall rating patterns. This approach allows for assessing reliability not only based on the text but also on the user's online behaviour [5].

In recent years, the emergence of deep learning-based models has marked a significant turning point in the field of sentiment analysis. Zhang et al. (2018) used convolutional neural networks (CNN) to accurately identify positive and negative expressions in texts. Later, the BERT (Bidirectional Encoder Representations from Transformers) model, developed by Devlin et al. (2019), enabled deep contextual analysis, which has also proven effective in detecting fake reviews [6].

Majority Voting System (Crowdsourced Voting System)

The majority voting system is an approach that takes into account users' collective opinions to increase the reliability of reviews and improve the accuracy of sentiment analysis results. This system serves to determine the significance of reviews based on user ratings and comments. It operates as follows:



Review Evaluation: Each review is read by users and can be marked as “useful” or “reliable.” The purpose of this

evaluation is to ensure that only trustworthy information is used in the sentiment analysis process. Users leave comments on products based on their previous purchases

and personal experiences shared on social networks.

Vote Aggregation: In this step, ratings from multiple users are combined to form a reliability score for each review. The reliability score indicates how trustworthy a review is for sentiment analysis and depends on both the number and quality of user votes. For example, if a review is marked as useful by many users (👍), the system considers it with higher weight. Conversely, if only a few users vote on a review, its influence is reduced.

Review Selection: The selection of reviews is carried out based on the collected votes and the calculated reliability score. The system automatically ranks the reviews and includes only those with high reliability scores in the sentiment analysis process. Reviews with low reliability scores are disregarded, as they may be incorrect or suspicious. This ensures that sentiment analysis results are based solely on genuine and reliable information. For instance, a review marked as useful by only a few users has minimal impact on sentiment analysis, whereas a review highly rated by many users significantly influences the sentiment results.

Application of the Majority Voting Approach in the ABSA Process

The majority voting approach is effectively applied in ABSA systems in two main contexts:

1. **During the Annotation Process (Dataset Creation Stage):** When a dataset is labeled with the help of human annotators, each annotator's judgment may be subjective. In such cases, the majority voting approach increases reliability and ensures that the final label is objective. For example, if two out of three annotators mark an aspect as "service – poor," the final aspect–polarity label will reflect the same. This approach balances the judgments of different annotators during the annotation process, thereby improving dataset quality.
2. **In Combining Model Outputs (Ensemble Learning):** During the process of aggregating outputs from multiple ABSA models (e.g., LSTM, BERT, RoBERTa), majority voting stabilizes the final result and enhances its reliability. The final aspect–polarity label is determined based on the outputs of all models, reducing errors from individual models and improving the overall accuracy of the ensemble result.

The reliability of majority voting is particularly important when multiple annotators are involved or when comparing outputs from several models. If the models produce varying results, the label supported by the majority of positive votes will be selected, ensuring a final output that reflects consensus. This approach provides higher accuracy. Conversely, when working with a single model, majority voting is not necessary, as the model generates only one output and determines the label on its own.

Benefits of Reliable Sentiment Analysis

- **Improved Customer Decision-Making:** Conducting sentiment analysis based only on reliable reviews provides consumers with accurate information.
- **Marketing Strategy for Companies:** Reliable data allows for the improvement of products or services and the optimization of advertising campaigns.
- **Detection of Spam and Biased Reviews:** The majority voting system separates fake or biased reviews from the analysis.
- **Increased Accuracy:** Combining automatic NLP models with user votes significantly enhances the accuracy of sentiment analysis.

CONCLUSION

Sentiment analysis of product reviews is an important tool for both businesses and consumers. However, the quality and reliability of reviews directly affect the accuracy of sentiment analysis. Therefore, determining the reliability of reviews using a majority voting system is a crucial solution. This approach filters out trustworthy reviews based on user votes and includes only them in the sentiment analysis process. As a result, companies and consumers can make decisions based on genuine and reliable information.

B. Elov et al. tested the Naïve Bayes method for sentiment analysis of texts in the Uzbek language. They found that this model is a reliable and effective approach for those performing sentiment analysis at an initial level, but it faces limitations in handling complex syntax and context-dependent sentiments [7]. In such cases, applying a majority voting system proves to be an effective solution. In the future, combining automatic NLP models with crowdsourcing systems could make sentiment analysis

even more accurate and efficient, playing a significant role in digital marketing, product development, and enhancing customer satisfaction.

REFERENCES

1. Maslowska E, Malthouse EC, Bernritter SF. 2017. Too good to be true: the role of online reviews' features in probability to buy. *International Journal of Advertising* 36(1):142–163 DOI 10.1080/02650487.2016.1195622.
2. Hu, M., & Liu, B. (2004, August). Mining and summarizing customer reviews. In *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 168-177).
3. Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of marketing research*, 43(3), 345-354.
4. Jindal, N., & Liu, B. (2008, February). Opinion spam and analysis. In *Proceedings of the 2008 international conference on web search and data mining* (pp. 219-230).
5. Beutel, A., Xu, W., Guruswami, V., Palow, C., & Faloutsos, C. (2013, May). Copycatch: stopping group attacks by spotting lockstep behavior in social networks. In *Proceedings of the 22nd international conference on World Wide Web* (pp. 119-130).
6. Zhang, Y., & Wallace, B. (2015). A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification. *arXiv preprint arXiv:1510.03820*.
7. Elov, B., Abdullayev, A., & Xudayberganov, N. (2025). O 'ZBEK TILI MATNLARINI NAIVE BAYES USULI ASOSIDA SENTIMENT TAHLIL QILISH. *DIGITAL TRANSFORMATION AND ARTIFICIAL INTELLIGENCE*, 3(2), 153-159.