Decoding Customer Reviews: Unraveling the Linguistic Dynamics of 5-Star and 1-Star Ratings in Online Commerce

Stefan Groen
S4502132

Abstract

This report studies language distinctions in 1-star and 5-star online reviews. Anticipating a positive tone in 5-star reviews and more negative language in 1-star reviews, sentiment analysis using the AFINN Lexicon is applied to a dataset extracted from Amazon.com The study highlights the significance of higher-rated reviews, suggesting retailers actively seek positive feedback from satisfied customers. Analyzing 1-star reviews offers insights for improvement. Despite limitation, this study provides insights into the dynamics of online commerce and customer decision-making.

1 Introduction

In the current landscape of online commerce, user-generated reviews have emerged as pivotal instruments influencing consumer purchasing decisions and at the same time serving as an important tool for retailers in cultivating trust and reputation within the digital marketplace Lackermair et al. (2013).

Acknowledging the paramount significance of online word-of-mouth activity, characterized by its influential nature (Duan et al., 2005), many businesses have jumped on the bandwagon of offering review systems. Although Lackermair et al. (2013) show that different rating systems have different impacts, and understanding why is key, it is generally agreed that higher scores mean happier customers and more effective reviews. What is not so clear is what exactly distinguishes these high-rated reviews from the lower-rated ones.

This study focusses on the following question: How does the language used in 5-star reviews differ from that in 1-star reviews. Our hypothesis posits that 5-star reviews employ a lexicon characterized by positivity, whereas 1-star reviews are characterized by a prevalence of negative language.

2 Related Work

The realm of online reviews has been extensively explored, recognizing opinions as pivotal elements influencing human behavior (Cardie 2014). Our perceptions and decision-making processes are, to a considerable extent, shaped by how others perceive and evaluate the world around them. This interplay between opinions and behavior became particularly pronounced with the surge in internet users, leading to an unprecedented volume of user-generated content, including the birth on online reviews (Turetken and Olfman 2013).

Wu et al. (2017) delved into the impact of language style in online reviews on consumers' attitudes toward hotel reservations. Their study investigated whether the user of figurative language, as opposed to literal language, influenced the intention to reserve a hotel room. Despite previous research that suggested that figurative language enhances reservations, Wu et al. (2017) found that, particularly when reviews were contributed low-expertise-level reviewers, figurative language did not significantly enhance persuasive power.

Lak and Turetken (2014) addressed a common consumer dilemma related to purchase decisions, exploring the trade-off between the cost of information acquisition and the potential decline in decision quality due to insufficient information. They focused on the role of online product/service reviews in this decision-making process, highlighting star rating as convenient indicators of overall sentiment. However, situations where star rating were unavailable or lacked detail led to the exploration of sentiment analysis as a complementary tool for more nuanced analysis. Their study aimed to compare these sentiment analysis results with the star ratings to see any similarities.

Liu, Bi, and Fan (2017) introduced a method based on sentiment analysis techniques to rank products through online reviews. They developed an algorithm employing different sentiment dictionaries to identify the positive, neutral or negative sentiment orientation of products.

3 Data

In order to investigate the distinct linguistic patterns between 1-star and 5-star reviews, the research will employ a dataset comprising a substantial number of both low-rated 1-star and high-rated 5-star reviews. The data will be sourced from amazon.com. This will ensure a broad representation of consumer opinions.

The number of stars of a review will be considered as independent variable. The language used in the reviews will be analyzed as the dependent variable. A coding system will be developed to categorize linguistic elements within the reviews. This system aims to capture sentiments or expressions of satisfaction or dissatisfaction. The AFINN Lexicon, a widely recognized sentiment analysis tool will be used for this.

To work with the AFINN Lexicon, the reviews will be tokenized to break down the text into individual words. Then the AFINN Lexicon will be applied to conduct the sentiment analysis on these words. This involves assigning a numerical value to each word based on its sentiment. This allows for quantitative assessment of the overall sentiment of a review, in which a higher score means a more positive review.

4 Predicted Results

The anticipated results of this study align with existing literature. It is expected that 5-star reviews will predominantly exhibit a positive lexicon, characterized by expressions of satisfaction towards the product. At the same time, 1 -star reviews are anticipated to show a prevalence of more negative language and dissatisfaction.

The application of the AFINN Lexicon will thus be expected to yield higher sentiment scores for 5-star reviews, further supporting the hypothesis that positive language is more prevalent in higher-rated reviews. Meanwhile, 1-star review are anticipated to have lower sentiment scores.

Utilizing a dataset of reviews from Amazon.com is expected to offer a diverse range of products and reviews, contributing to findings that are generalizable. It is however acknowledged that the specific characteristics of the dataset, such as chosen products, categories of products, and customer demographics may introduce some degree of bias.

The study's implications suggest a strategic approach for retailers based on the anticipated results. If positive language is associated with higher-rated reviews, retailers are encouraged to actively engage satisfied customers to share positive experiences. This aligns with Lackermair et al.'s (2013) emphasis on the influence of higher-rated reviews and word-of-mouth in shaping consumer decisions.

Analyzing 1-star reviews provides an opportunity for retailers to identify recurring issues and areas for improvement. Engaging positively with customers who provide negative feedback can contribute to reputation repair and heightened customer satisfaction.

Recognizing negative reviews as avenues for growth, retailers can implement adaptive strategies. Regular monitoring and addressing concerns highlighted in 1-star reviews contribute to continuous improvement, demonstrating responsiveness to customer feedback. Encouraging customers to update their reviews after experiencing positive changes showcases a commitment to ongoing improvement, providing an evolving narrative that reflects dedication to customer satisfaction.

5 Conclusion

This study aimed to explore the linguistic patterns in 1-star and 5-star online reviews, focusing on the language's impact on consumer perceptions. The hypothesis posited that 5-star reviews would exhibit a positive lexicon, while 1-star reviews would lean towards negative language.

The anticipated results align with established literature, expecting higher sentiment scores for 5-star reviews and lower scores for 1-star reviews when employing the AFINN Lexicon. An Amazon.com dataset was chosen to ensure diversity in products and reviews, albeit with acknowledgment of potential dataset biases.

The implications for retailers are significant. Encouraging satisfied customers to share positive experiences can enhance higher-rated reviews, aligning with Lackermair et al. (2013) emphasis on their influential role in consumer decision-making. Analyzing 1-star reviews offers opportunities for improvement and engagement. Addressing concerns and actively participating in constructive conversations can contribute to reputation repair and heightened customer satisfaction.

Limitations include potential dataset biases and the simplicity of sentiment analysis tools. Future research could explore more nuanced linguistic analyses.Overall, this study contributes insights to the evolving landscape of online commerce and consumer decision-making.

6 Github

https://github.com/Stefan-Groen/language-in-review-rating

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