A New Approach to Compute Customers' Influential Power in Review Network for Improved Recommendation

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Abstract. This study investigates how consumer behavior in the e-book market is influenced by electronic word-of-mouth (eWOM) and online customer reviews (OCRs). Addressing the limitations of traditional sales forecasting methods, we propose a novel framework leveraging network-based metrics and Ordered Weighted Averaging (OWA) scores. By integrating helpfulness scores, review quality, spelling error checks, clustering, clustering coefficients, and PageRank, our model offers comprehensive insights into customer sentiments. This research contributes to e-commerce analytics by providing a more accurate methodology for predicting sales performance and enhancing decision-making processes. The proposed model is validated with empirical data, demonstrating its effectiveness in capturing the complex dynamics of online consumer behavior. We can also recommend suitable items with more exclusive offer to the particular users who gain high Network Promoter Score (NePS) value with positive sign, because they are a reliable and positive reviewer. They will purchase those items and influence others to buy those items with ratings and reviews. The company should also give the same focus to the users, who gain high $NePS$ value with negative sign, because they are also reliable users. They may give negative ratings due to some dissatisfaction about the quality of the items. A company should recommend good quality items to those users based on their preferred areas. Rating based recommendation systems ignore these negative users. Ignoring detracted users is not at all good for a company's financial health.

Keywords: Electronic word-of-mouth · OWA · Clustering coefficients · PageRank · Helpfulness scores

1 Introduction

Consumer behavior is experiencing significant change as an outcome of the digital revolution, particularly when it concerns online shopping. The e-book market continues to grow quickly, giving consumers an enormous number of options. Decision-support tools like rating systems, suggestion engines, and online review sites have become essential for navigating this complexity. Making informed choices before a purchase requires an understanding of the dynamics of eWOM in digital markets. Despite the proliferation of decision-support technologies, existing works have notable limitations. Traditional analytical tools like price analysis, sales volume tracking, and emotion analysis of reviews often fail to correlate effectively with future sales data.

Numerous recent studies have shown the significance of customer behavior and satisfaction, as well as the impact of online reviews. Integrating Ordered Weighted Averaging operators with dynamic customer behavioral vectors has been found to enhance churn prediction models in the banking industry[1]. Hierarchical clustering using OWA uncovers user lifestyle patterns for personalized services and targeted marketing[16]. Key logistics service attributes affecting customer satisfaction include reliability, timeliness, and communication[19]. Review-specific and reviewer-specific features can effectively predict the helpfulness of online consumer reviews[18]. Personalized ranking of online reviews based on individual consumer preferences enhances their relevance and usefulness, leading to improved decision-making and satisfaction[2]. These findings emphasize the importance of understanding and leveraging customer behavior and preferences for business strategies and customer engagement.[3] [4]

The research aims to address limitations in existing literature by introducing a comprehensive framework to understand customer behavior in the digital marketplace. A new method is introduced to calculate customers' influential power in review networks, enhancing recommendation systems. The paper follows a standard format starting with an abstract, introduction, review of related works, problem formulation, proposed model, experimental settings, results, discussions, and conclusion. The approach aims to bridge the gap between traditional recommendation systems and evolving consumer needs in the digital marketplace

2 Related Works

The Measuring Business Performance review (2000-2012) analyzed organizational productivity and effectiveness measurement methods, highlighting diverse standards and potential selection bias concerns. Future research directions were suggested[15, 13]. Assessing company performance with financial and non-financial metrics, such as customer satisfaction and employee contributions, helps identify strengths and weaknesses[20]. Recent studies have shown that online product reviews significantly influence sales forecasts in the film industry. Further research is needed to understand how different reviews affect sales and whether these findings apply to other industries. The papers explore how revealing reviewer identities affects consumer behavior and purchases in online markets. Trust is a key factor, with disclosure potentially enhancing trustworthiness and influencing buying decisions[5, 12]. A new study explores how review positivity and score inconsistency affect customer behavior and purchase decisions, considering different levels of product involvement. Challenges remain in generalizing results and quantifying review attributes across various products[8][6]. Recent studies examine how consumers perceive the helpfulness of online service reviews and their impact on purchase intentions. Factors influencing behavior and the link between perceived helpfulness and purchasing desires were identified[7]. Recent research investigates the influence of information cascades, word of mouth, and recommendation systems on online reading behavior, offering insights for digital platforms and marketers to enhance content recommendations and user experiences [11]. Introduction of business management systems helps identify challenges and improve organizational coordination, emphasizing the importance of BPM for organizational effectiveness[10]. A method is proposed for assessing performance management systems, focusing on alignment and real-world application, highlighting the importance of empirical validation and the use of technology for data analysis[17]. Research develops methods to rank product reviews based on their anticipated impact on consumer choices and sales, revealing a strong link between review ratings and product sales, aiding consumer decisions and business promotion strategies[9].

Table 1. Summary of Studies on Business Performance and Review Analysis

Sno	**Year**	**Application**
1	2019	Better understanding of business performance
2	2012	Assessing company performance
3	2007	Better understanding of business performance
4	2008	Assess the Impact of Reviewer Identity Disclosure on Review Credibility
5	2018	Assess the impact of Review Positiveness on sales across different products.
6	2018	Assess consumer perceptions of review helpfulness
7	2019	Provides insights to understands drivers of engagement
8	2022	Assess the effectiveness of BPM systems.
9	2019	Implement and test performance evaluation methodology in real world settings.
10	2012	Identify key factors that incfluence the usefulness of reviews.

3 Problem Formulation

Online merchants are continually working on enhancing their ability to predict future product sales, but traditional analytical tools like price, sales volume, and emotion analysis of reviews often fail to correlate with future sales data. This is due to the challenge of assessing the complex and variable effects of individual customer reviews and ratings. Accurate forecasting is crucial for e-commerce success, and current methods may not fully capture the complexity of consumer feedback, highlighting the need for a more sophisticated approach.

E-commerce businesses struggle to predict future sales accurately because existing methodologies don't consider the intricate link between user reviews and sales results. To address this, a new framework leveraging the network structure of customer-product interactions is proposed. This framework includes the concept of the Review Network and the Network Promoter Score (NePS) to provide a more comprehensive understanding of customer behavior and improve forecast accuracy. E-commerce organizations can benefit from utilizing these tools to optimize their sales forecasting techniques and make informed decisions. This research contributes to the field of e-commerce analytics by introducing a more precise methodology for predicting sales performance.

4 Proposed model

The proposed model for analyzing customer reviews and predicting sales performance in the e-commerce sector uses Ordered Weighted Averaging (OWA) scores and various additional metrics. Traditional sentiment analysis methods are limited by oversimplified sentiment assessment, lack of context, and scalability issues, while star ratings and text mining techniques provide inconsistent and surface-level insights. The model leverages OWA scores and multiple metrics for a more comprehensive analysis.

Net Promoter Score (NPS) is insufficient for this model due to its oversimplification of customer sentiment with a single question, lack of contextual insights, and exclusion of detailed textual feedback. NPS can also be biased by recent experiences and doesn't incorporate critical performance metrics or advanced analysis techniques like OWA scores, Clustering Coefficients, or the PageRank Algorithm.

Key concepts of OWA involve ordering values, assigning weights based on importance, and summing the weighted values for a final score. The framework also includes network-based metrics like Clustering Coefficients to quantify group formation and the PageRank Algorithm to assign importance scores. One-mode Projection is used to simplify the network and identify key relationships and patterns.

5 Experimental Settings

Data Statistics: We perform our experiments on Amazon.com online review dataset collected by [14] with two categories electronics and books. The statistics of the dataset are shown in Table 2.

Table 2. Statistics of the dataset

Dataset	# users	# items	# reviews/ ratings
Electronics	811,034	82,067	1,241,778
Books	2,588,991	929,264	12,886,488

Our dataset contains "reviewerID", asin, reviewerName, helpful, reviewText, overall, summary, unixReviewTime, and reviewTime attributes. The data was sourced from a prominent e-commerce platform to ensure a diverse range of product reviews representing various customer sentiments and behaviors. Only reviews from the past year were considered based on recency and relevance to reflect current customer opinions and market trends.

The dataset underwent several preprocessing steps to enhance data quality before analysis. These steps included tokenization to split the review text into individual words, removal of stop words to focus on informative parts, exclusion of incomplete entries to ensure reliable data, spell-checking to identify misspellings, normalization to convert text to lowercase for uniformity, and date conversion for temporal trend analysis.

Several key metrics were calculated for each review: The Helpfulness Score, which indicates the perceived usefulness of the review by the community based on the ratio of helpful votes to total votes. The Spelling Error Score, which is the count of misspellings identified by the spell-checking algorithm, and the Readability Score, derived from the Flesch-Kincaid readability test, assessing the ease of understanding the review text.

Network-based metrics were calculated from a custom network graph of the reviews, including the One-Node Projection, simplifying the network to consider only direct connections between customers and products. The Clustering Coefficient, measuring the degree of interconnectedness within the network, and PageRank, which calculates the influence of each review based on its position within the network, similar to how web pages are ranked in search engines The experiments were conducted using Python 3.10, with libraries such as pandas, scikit-learn, and NetworkX. The hardware setup included a machine with an Intel Core i7 processor and 16GB of RAM. Statistical measures like mean, median, and standard deviation of the OWA scores were used to assess performance, along with visualizations (histograms and box plots) and correlation analyses to explore relationships between OWA scores and individual review metrics.

6 Results and Discussions

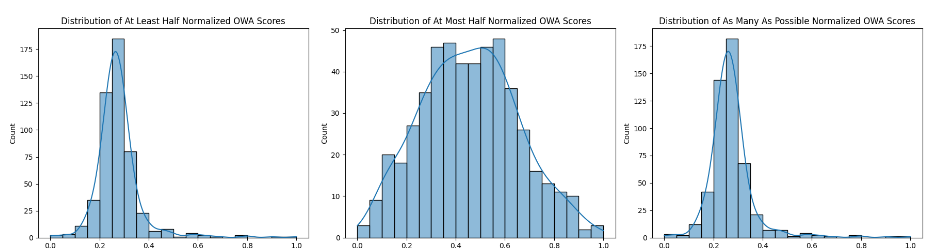

Fig. 1. Distribution of normalized OWA scores for three scenarios

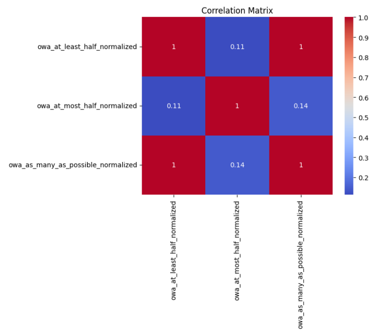

Fig. 2. Correlation Matrix: This figure displays the correlation matrix of the features used in our analysis. The matrix visually represents the strength and direction of linear relationships between pairs of features. Each cell in the matrix shows the correlation coefficient, which ranges from -1 to 1. A value closer to 1 indicates a strong positive correlation, while a value closer to -1 indicates a strong negative correlation. Values near 0 suggest no linear correlation. The diagonal of the matrix, where each feature is correlated with itself, contains all 1s. The color intensity and shading help to quickly identify strong correlations, which can be useful for feature selection and understanding the relationships within the data.

In the analysis of the three different distributions of normalized scores, it is evident that the majority of reviews have relatively low scores. The distribution of "at least half normalized" and "as many as possible normalized" shows a strong concentration of scores between 0.1 and 0.3, indicating a significant portion of reviews having low normalized scores. On the other hand, "at most half normalized" displays a more uniform distribution, suggesting a more even spread of scores, albeit still skewed towards lower values. The correlation between "at least half normalized" and "as many as possible normalized norm" is also highlighted, as both distributions exhibit similar concentration patterns.

In this research paper, the analysis of normalized OWA scores reveals valuable insights into review sentiments. The central tendency analysis shows that at least half normalized and as many as possible normalized have a clear mode around 0.2, indicating lower normalized scores for the majority of reviews. Conversely, at most half normalized captures a broader range of sentiments without a pronounced mode. When considering variability, at least half normalized and as many as possible normalized exhibits less variability, with scores concentrated in a narrow range, while at most half normalized shows greater variability, reflecting a wider range of sentiments. The study suggests redundancy between at least half normalized and as many as possible normalized due to their near-perfect correlation, indicating that one of these metrics could potentially be excluded without significant loss of information. Additionally, at most half normalized is highlighted for providing a more balanced view of review sentiments. However, the analysis acknowledges limitations such as the assumption that normalized

OWA scores represent review sentiments accurately and the potential biases in the review data or normalization process that could affect the results.

7 Conclusion

The analysis of normalized OWA scores shows that two metrics, owa at least half normalized and owa as many as possible normalized, are very similar and mostly reflect lower review scores, suggesting we might only need one of them. The third metric, owa at most half normalized, provides a broader view of customer opinions and captures a wider range of review sentiments. This means that while two of the scores give us similar information about customer reviews, the third one offers unique insights and should be included for a more balanced understanding. However, we should be aware that these findings might be affected by biases in the review data or how the scores were calculated. The proposed method for analyzing e-commerce reviews has some limitations that should be addressed. First, integrating multiple metrics and network analysis increases complexity and requires significant computational resources and data science expertise. Second, the method's accuracy heavily relies on the quality of input data, making it vulnerable to poor quality or biased reviews. Additionally, its applicability to other domains and review types requires further validation. Lastly, the assumption of metric independence may not always hold true, potentially affecting the overall analysis

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