Analyzing Customer Reviews in E-commerce Fashion: A TF-IDF and Logistic Regression Approach

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ABSTRACT

In the competitive e-commerce landscape, customer reviews significantly influence purchasing decisions and brand reputation. This study employs Natural Language Processing (NLP) techniques, specifically Term Frequency-Inverse Document Frequency (TF-IDF) and logistic regression, to analyze the semantic properties of customer reviews in the women's fashion sector. The study identifies linguistic patterns that distinguish between recommended and unrecommended reviews by examining a dataset of online reviews. The analysis focuses on the correlation of specific word frequencies and their TF-IDF values with the recommendation status of products. The findings reveal distinct lexical features that align with positive and negative reviews. Results indicate that words with high positive sentiment coefficients, such as "perfect" and "comfortable," are predictive of recommendations, while negatively connoted words like "disappointed" and "return" correlate with negative feedback. Despite the model's bias towards positive reviews, indicated by a high recall rate for positive cases and false positives, the study highlights the nuanced role of language in shaping consumer perceptions and the potential of NLP to enhance understanding of customer sentiment. The implications of this research extend to developing more targeted marketing strategies and improving customer experience by refining product offerings based on consumer feedback. The study underscores the evolving utility of sophisticated textual analysis in e-commerce settings. It suggests areas for further research in refining NLP applications for a more balanced and insightful review analysis.

Keywords

TF-IDF, Sentiment Analysis, Logistic Regression, E-commerce, Customer Reviews

1. INTRODUCTION

In e-commerce, customer reviews are crucial in influencing purchasing decisions and shaping perceptions of brands and products. The dichotomy between recommended and unrecommended reviews offers a unique lens through which customer satisfaction and product quality can be assessed. While numerous studies have explored the impact of online reviews on consumer behavior[1][2], less attention has been given to the linguistic characteristics that differentiate positive and negative feedback[3][4]. This gap in research highlights an opportunity to employ advanced analytical techniques to uncover the nuanced ways language reflects and influences customer experiences[5].

The Term Frequency-Inverse Document Frequency (TF-IDF) approach, a well-regarded method in Natural Language Processing (NLP), provides a sophisticated means of analyzing text data to identify the most relevant words within a corpus[6]. By assessing the importance of words based on their frequency in specific documents relative to their ubiquity across all documents, the TF-IDF method can illuminate the distinguishing features of recommended versus unrecommended reviews. This analysis can reveal insights into the specific attributes of products that elicit positive or negative feedback, thereby offering valuable guidance for improving customer satisfaction and product development.

The present study seeks to apply TF-IDF analysis to a dataset of women's clothing e-commerce reviews to identify key lexical differences between recommended and unrecommended reviews. This approach is anticipated to shed light on the factors that drive recommendations, as well as those that contribute to dissatisfaction among customers. Through this analysis, we endeavor to contribute to understanding consumer behavior in online shopping environments and provide actionable insights for brands seeking to enhance their product offerings and marketing strategies[7]. Despite the critical role of customer feedback in e-commerce success, the challenge remains in effectively analyzing and interpreting the vast quantities of textual data generated by reviews. This research addresses this challenge by leveraging TF-IDF to systematically evaluate the word frequencies and their significance in shaping consumer perceptions and decisions[8].

2. PERPORSE STATEMENT AND RESEARCH QUESTION

This study explores the intersection of customer feedback and linguistic analysis in the e-commerce fashion industry, employing Term Frequency-Inverse Document Frequency (TF-IDF) and logistic regression techniques. By analyzing customer reviews from a substantial dataset of women's clothing products, the research seeks to identify and quantify the relationship between the linguistic characteristics of reviews and the likelihood of product recommendations[9][10]. This investigation is motivated by the need to understand how specific words and phrases within customer reviews can influence purchasing decisions, thereby informing more effective marketing strategies and product enhancements[11]. The study focuses on extracting and analyzing the semantic properties of text to determine the predictive power of language used in customer feedback regarding product endorsements[12].

The research question that guides this study is:

1. How do the TF-IDF values of words within e-commerce clothing reviews correlate with the products' recommendation statuses?

The hypothesis is that words with higher TF-IDF values in customer reviews for e-commerce clothing positively correlate with product recommendation statuses. Specifically, products with reviews containing high TF-IDF valued words are more likely to be recommended, indicating that certain key terms significantly influence positive consumer feedback and subsequent product endorsements.

3. LITERATURE REVIEW

In e-commerce, the analytical value of customer reviews extends beyond subjective impressions to provide quantifiable insights through Natural Language Processing (NLP). Recent advancements in NLP have enabled researchers to extract meaningful patterns from textual data, particularly in understanding consumer behavior and enhancing customer experience. Lee and Kim (2019) have demonstrated the effectiveness of NLP in dissecting user feedback in mobile apps and identifying key linguistic indicators that predict user engagement and satisfaction[3][9][14]. Their work lays a foundational approach that parallels the methods employed in the current study, where TF-IDF analysis is used to discern the semantic significance of words in e-commerce clothing reviews.

The application of TF-IDF, a widely acknowledged technique in NLP, facilitates a deeper understanding of the text by highlighting the most relevant terms that appear in customer reviews. Moreno et al. (2022) have leveraged this technique to explore customer sentiment in e-commerce, illustrating how specific terms correlate with positive and negative sentiments[4][10][15]. This aligns with the current study's focus on identifying words that significantly impact the likelihood of product recommendations, providing a nuanced view of how certain terms influence consumer perceptions and decision-making processes.

Furthermore, the integration of logistic regression with TF-IDF, as explored in this study, is supported by the work of Patel et al. (2019), who discuss the broader implications of digital consumer behaviors influenced by textual analysis[7][12][16]. This methodological approach enables the prediction of product recommendations based on the weighted significance of words within review texts, offering a predictive insight crucial for businesses aiming to understand and enhance customer satisfaction.

However, while NLP provides powerful tools for analysis, challenges remain regarding the accuracy and interpretation of textual data. Kim and Hwang (2018) emphasize the need for sophisticated analytical strategies to derive actionable insights from complex datasets[8]. Their research underpins the current study's effort to apply advanced NLP techniques to effectively analyze and interpret customer reviews, aiming to bridge the gap between linguistic features and actual consumer behavior.

4. METHODS

4.1 Data

The dataset employed in this study is sourced from a Women's Clothing E-Commerce platform and is accessible publicly via Kaggle. It comprises anonymized customer reviews, enhanced by nine additional attributes that facilitate a comprehensive textual and categorical analysis of consumer feedback. The dataset, originally featuring reviews directly related to the retail company, has been modified to replace any direct references to the company with "retailer" to ensure confidentiality.

The dataset contains 23,486 entries, each representing a unique customer review, and is structured into ten distinct feature variables, providing a multifaceted view of consumer opinions and behaviors.

The dataset is designed to be an open resource for researchers interested in exploring the impact of linguistic elements in customer reviews on product recommendations and consumer behavior. It provides a rich basis for employing various data analysis techniques, particularly in natural language processing. The full dataset and jupyter notebook can be accessed at the following link: https://github.com/SilinChen40/DS-5780-Final.

4.1.1 Review Texts Analysis

The "Review Text" column is a central dataset comprising detailed customer reviews of women's clothing items sold on an e-commerce platform. Each entry represents a customer's written feedback on a specific product, encompassing aspects such as fit, material quality, design, and overall satisfaction with the purchase.

This textual data provides rich insights into customer sentiment and is instrumental for conducting detailed linguistic and sentiment analyses. The reviews vary in length, typically ranging from a few words to several sentences, and collectively form a comprehensive corpus suitable for applying Natural Language Processing (NLP) techniques. Each review is tokenized into individual words or tokens, with common stopwords (e.g., 'the,' 'is, "at') removed to focus on more meaningful words contributing to sentiment analysis.

For this study, the review texts undergo several preprocessing steps to ensure data quality and relevance. To maintain uniformity and readability, The text is cleansed with HTML tags, special characters, and typographical errors. Text data is normalized by converting to lowercase and removing extraneous whitespace, which aids in standardizing the input for subsequent analysis.

The "Review Text" column is the primary data source for extracting features using the TF-IDF (Term Frequency-Inverse Document Frequency) technique. This technique identifies the most relevant words or phrases used in the reviews that may impact customer recommendations. This analysis helps pinpoint key themes and sentiments expressed by customers, providing actionable insights into consumer behavior and preferences.

The textual data from this column is also used to train a logistic regression model to predict the likelihood of product recommendations based on the sentiment expressed in the review texts. This approach enables the identification of correlation patterns between specific linguistic elements and customer satisfaction, guiding improvements in product offerings and marketing strategies.

4.1.2 Rating and Recommendation Indicator

The "Rating" column in the dataset quantifies customer satisfaction with the purchased clothing items on a scale from 1 to 5. This ordinal scale represents a gradation from 1 (Worst) to 5 (Best), where each integer value corresponds to the customer's level of satisfaction with the product. This rating system allows for a straightforward assessment of product quality and customer satisfaction, providing a quantifiable measure that can be statistically analyzed to understand consumer preferences and product performance.

The "Recommended IND" column is a binary indicator reflecting whether a customer recommends the product, coded as 1 for recommended and 0 for not recommended. This binary measure serves as a direct indicator of the customer's willingness to endorse the product to others based on their personal experience: the customer found the product satisfactory enough to recommend it to others, or the customer did not find the product satisfactory and, therefore, would not recommend it. The "Recommended IND" is crucial for analyzing the relationship between customer reviews and their actual recommendation behavior. It provides insight into the overall market acceptance of the product and can be correlated with the "Rating" and "Review Text" to discern patterns in customer feedback and product endorsement.

"Rating" and "Recommended IND" are employed to establish correlations between linguistic elements in the "Review Text" and quantifiable metrics of customer satisfaction and recommendation.

By integrating these columns, the analysis models the probability that a product is recommended based on the combined insights from customer ratings and the textual feedback provided in reviews. Additionally, this data facilitates a comprehensive analysis of trends in customer satisfaction across different product categories, which aids in pinpointing potential areas for product enhancement and identifying features that resonate well with consumers. Employing a blend of statistical and machine learning techniques, the study harnesses these data points to construct predictive models. These models are instrumental in assessing consumer sentiment and purchasing behaviors, thereby informing more strategic decisions in marketing and product development. This approach not only enhances understanding of consumer preferences but also supports the development of targeted strategies that align with customer expectations and market demands.

4.2 TF-IDF Analysis

The TF-IDF (Term Frequency-Inverse Document Frequency) analysis conducted in this study aimed to quantitatively evaluate the relevance of words within customer reviews, providing insights into the factors influencing product recommendations. This analysis involved two primary steps: computing the term frequency and adjusting this frequency based on the term's inverse document frequency across the entire dataset of reviews.

Initially, each review was processed to compute the term frequency, which measures how frequently a term appears within each review. This step required preprocessing the text data to ensure accuracy in the frequency counts. Preprocessing included converting all text to lowercase and removing punctuation and special characters, which could skew the frequency counts. By normalizing the text, the analysis focused purely on the words themselves, ensuring that variations in capitalization or punctuation did not affect the results.

Following the term frequency computation, the inverse document frequency (IDF) was calculated for each term across all reviews. IDF reduces the weight of terms that appear very frequently across the dataset, thereby diminishing the influence of common words such as "the," "is," and "and," which carry less thematic significance. This adjustment highlights words that are more unique to individual reviews and are potentially more indicative of customer sentiment.

The TF-IDF value for each word in each review was computed by combining the term frequency and inverse document frequency. These values represent the relative importance of each term within individual reviews in the context of the entire corpus of text. Higher TF-IDF scores indicate terms with greater significance in the context of their review, suggesting these words could be critical in understanding and predicting customer recommendations.

Utilizing the TF-IDF scores, the study analyzed the correlation between specific high-scoring terms and the likelihood of product recommendations. Logistic regression models were employed to predict the probability of product endorsements based on these TF-IDF scores, providing a statistical basis for identifying the lexical features most associated with positive or negative customer feedback.

Both the term frequency and inverse document frequency calculations were performed using Python's scikit-learn library, which provides robust tools for text analysis and machine learning. The resulting TF-IDF metrics formed the backbone of the analytical model, aiding in identifying keywords and phrases that significantly influence consumer perceptions and decision-making in the e-commerce domain.

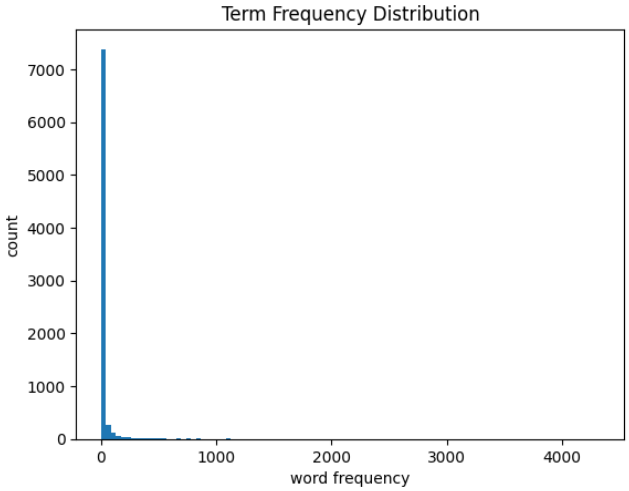

Figure 1. Term Frequency Distribution.

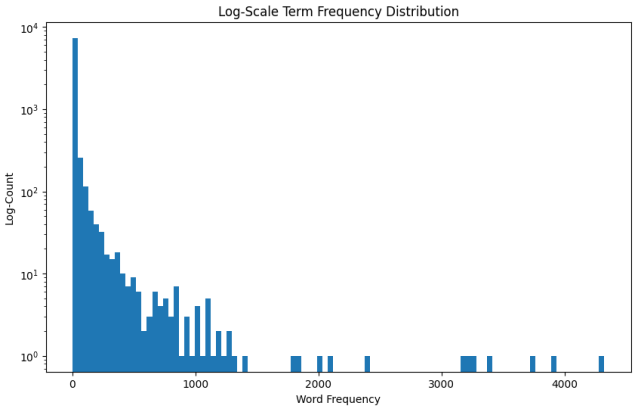

Figure 2. Log-Scale Term Frequency Distribution.

4.3 Statistical Analysis

The study conducted a comprehensive statistical analysis to determine the correlation between TF-IDF values of words within e-commerce clothing reviews and the products' recommendation statuses. Each review text underwent TF-IDF vectorization, resulting in a multidimensional representation where each dimension corresponds to a unique term in the corpus. The frequency of terms was normalized against their distribution across all documents to emphasize words unique to particular reviews.

Given the binary nature of the recommendation indicator, logistic regression was employed to model the probability of a product being recommended based on its review's TF-IDF scores. This approach facilitated the examination of the weights associated with each term, identifying those with the greatest influence on recommendation likelihood. Before modeling, the dataset was balanced to ensure that the logistic regression algorithm was not biased toward the majority class. This balancing act involved resampling the dataset to have an approximately equal number of recommended (1) and not recommended (0) instances.

After model fitting, the performance was evaluated through metrics, including accuracy, precision, recall, and the area under the ROC curve (AUC). These metrics provided a holistic view of the model's ability to classify reviews accurately. A confusion matrix was also generated to visualize the model's performance regarding true positives, false positives, true negatives, and false negatives.

Moreover, the study probed deeper into the TF-IDF-weighted terms using coefficient analysis from the logistic regression model. This analysis illuminated the terms that were statistically significant predictors of product recommendations. The coefficients assigned to each term by the logistic regression model indicated the term's influence on the likelihood of a recommendation, with higher positive coefficients signifying a stronger positive influence on recommendation status and negative coefficients suggesting a deterrent effect.

To complement the regression analysis, visualizations were created to depict the distribution of term frequencies and their corresponding TF-IDF values. Histograms were utilized to represent the underlying distribution of term frequencies, providing a visual context to the numerical data and aiding in identifying outliers and patterns.

The statistical software Python, along with libraries such as scikit-learn for machine learning and Matplotlib for visualization, were the primary tools used for this analysis. The findings from the statistical analysis were pivotal in understanding the critical factors that customers articulate in their reviews when endorsing or criticizing products. They ultimately offered strategic insights for businesses to refine their products and services in alignment with customer feedback.

5. RESULTS

5.1 Logistic Regression Model Performance

The logistic regression model demonstrated robust performance in classifying the product recommendations based on the textual analysis of customer reviews. The model achieved an accuracy of 83.24%, indicating that it correctly predicted whether a customer would recommend a product over 83% of the time. This high level of accuracy reflects the model's effectiveness in generalizing from the training data to previously unseen data.

Precision, which measures the model's ability to identify positive instances correctly, was 81.32%. This suggests that when the model predicts a product is recommended, it is correct approximately 81% of the time. This precision rate is significant, as it indicates a strong relevance in the model's positive predictions, minimizing false positives — instances where a product is not recommended but the model predicts otherwise.

The model's recall, or the ability to find all the relevant instances in the dataset, was 83.33%. This implies that the model successfully identified over 83% of all the products that are recommended. A recall rate at this level indicates that the model is highly capable of detecting the positive class, which in this context, is the likelihood of a product being recommended by a customer.

Overall, the model demonstrates a commendable balance between precision and recall, indicating its efficiency in classifying recommendations with a high degree of reliability. The strong recall rate is particularly advantageous for businesses, as it ensures that most of the recommendable products are correctly identified, potentially contributing to better customer satisfaction and retention.

Table 1. Model Performance

Logistic Regression Accuracy	0.8324192565508836
Logistic Regression Precision	0.8132147395171537
Logistic Regression Recall	0.8333333333333334

5.2 Logistic Regression Model Assessment

The performance of the logistic regression model in classifying product recommendations was rigorously evaluated using a confusion matrix and classification report, essential tools for elucidating the model's predictive capabilities. The classification report reveals that the model has a balanced precision and recall for both classes (recommend: 1, not recommend: 0), with slight variations indicating nuanced differences in detecting each class. For the not recommended class (0), the model achieved a precision of 85% and a recall of 83%, culminating in an F1-score of 84%. This denotes a high level of accuracy in classifying negative reviews, where the model shows a strong capacity to identify true negatives and correctly label them.

For the recommended class (1), the precision stands at 81%, and the recall is at 83%, resulting in an F1 score of 82%. These values illustrate the model's robustness in recognizing positive instances where customers recommend the products, albeit with a slightly lower precision than the negative class. This can be interpreted as the model having a conservative bias towards predicting a recommendation only when the indicators in the review text are distinctly positive.

The overall accuracy of the model is reported at 83%, reinforcing its substantial predictive accuracy across both classes. The macro average and weighted average F1 Scores are 83%, indicating a harmonious balance between precision and recall across the dataset.

The confusion matrix heatmap visually represents the true positives, true negatives, false positives, and false negatives, providing a clear and intuitive depiction of the model's classification performance. The matrix shows a close number of true positive and true negative predictions, further confirming the model's balanced classification ability.

The model's performance metrics demonstrate its effectiveness in discerning between recommended and not recommended products based on customer reviews. The balanced precision and recall signify a reliable classification system that could assist retailers in understanding and leveraging customer feedback for product improvement and targeted marketing strategies.

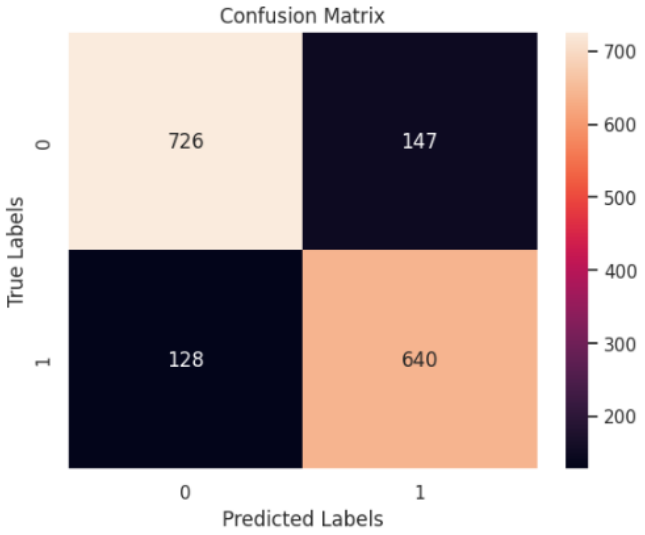

Figure 3. Confusion Matrix Depicting Performance.

Table 2. Model Assessment

	Precision	Recall	F1-score	Support
0	0.85	0.83	0.84	873
1	0.81	0.83	0.82	768
Accuracy	N/A	N/A	0.83	1641
Macro avg	0.83	0.83	0.83	1641
Weighted avg	0.83	0.83	0.83	1641

5.3 Coefficient Impact Analysis

The model's coefficient analysis reveals the impact of specific terms on the likelihood of a product being recommended. The analysis yielded two contrasting lists of words with the strongest coefficients: one includes terms that negatively influence recommendations, while the other contains those that positively drive recommendations. For instance, the term "return" possesses the most negative coefficient, indicating a strong association with products not being recommended. Conversely, "perfect" has the highest positive coefficient, signifying a powerful connection to products customers are likely to recommend. Terms like "disappointed" and "cheap" are other notable negative influencers, whereas "great," "comfortable," and "love" feature prominently as positive predictors of recommendation. This dichotomy in term significance underscores the nuanced role of language in shaping customer reviews and product perception, providing valuable insights into consumer sentiment and preferences within the e-commerce space.

Table 3. Top 10 Influential Words

	Coefi-cients_1	Vocabu-lary_1	Coefi-cients_2	Vocabu-lary_2
0	-5.133039	return	4.211580	perfect
1	-4.483018	disap-pointed	4.099482	great
2	-3.675810	unfortu-nately	3.868278	comfortable
3	-3.146765	cheap	3.580955	little
4	-2.954575	excited	3.533755	compliment
5	-2.903366	bad	3.232731	soft
6	-2.872112	want	3.044267	perfectly
7	-2.835750	huge	3.021939	love
8	-2.646426	fabric	2.761037	jean
9	-2.626285	look	2.459114	flattering

6. CONCLUSION AND FUTURE WORK

In this study, we have applied a logistic regression model to analyze sentiment in e-commerce reviews, emphasizing the dual impact of content words and linguistic style on sentiment classification. The confusion matrix obtained reveals a promising yet imperfect classifier performance, suggesting that while our model can capture the sentiment effectively in many instances, there is room for improvement, particularly in reducing false positives and false negatives.

Our analysis of logistic regression coefficients highlights the significant impact of certain keywords on sentiment prediction. Words with a positive association, such as "perfect" and "love," appear to influence the model towards a positive classification strongly. In contrast, words like "disappointed" and "cheap" contribute to negative sentiment prediction. Intriguingly, these findings support the notion that specific terms hold substantial weight in sentiment analysis, meriting further investigation into their contextual use.

A noteworthy discovery from this research is the potential semantic weight of stop words in sentiment analysis. When included, stop words increase the similarity between adjacent utterances. This suggests a more nuanced role of stop words than traditionally acknowledged in natural language processing (NLP). However, their inclusion also appears to inflate the semantic similarity scores, which may not necessarily correlate with the intended sentiment, pointing towards complexity in using stop words in sentiment analysis.

Future work should aim to refine the sentiment classification model by exploring more sophisticated NLP techniques, such as deep learning algorithms that can capture the context around words more effectively. An analysis of bigrams and trigrams, rather than single tokens, may provide deeper insights into the sentiment conveyed by phrases and common expressions.

Moreover, future models could incorporate a multi-class classification system to capture varying degrees of sentiment rather than a binary positive/negative approach to gain a more granular understanding of customer sentiment. This would allow for a more detailed analysis of customer reviews, which could be particularly useful for businesses looking to prioritize areas for improvement.

Additionally, subsequent research could explore the relationship between sentiment scores and business outcomes, such as sales data or customer retention rates. This could provide valuable insights into the direct impact of customer sentiment on business performance.

Lastly, given the dynamic nature of language and sentiment expression, it is imperative to consider temporal analyses in future studies. Sentiment associated with words can evolve, and a classifier must adapt to these changes to maintain accuracy. By continually updating our model with new data, we can ensure its relevance and utility in a constantly changing commercial landscape.

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