UM-SJTU JOINT INSTITUTE

Advanced Technical Communication

Proposal DRAFT

Product satisfaction and buyback intention prediction based on review analysis

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Contents

1 Introduction

Sentiment analysis is crucial for interpreting customer feedback on e-commerce platforms. This report explores machine learning techniques to predict numerical customer ratings from textual reviews using the "Amazon Product Review Dataset" from UC San Diego. Previous research has highlighted the adaptability of sentiment analysis techniques and their utility in deciphering customer sentiments from textual data (Alibasic and Popovic, 2021). Traditional methods often use binary classification, which misses nuances in numerical ratings. The project aims to bridge this gap by enhancing sentiment analysis tailored for e-commerce, improving the predictive accuracy of customer ratings to provide businesses with actionable insights into consumer preferences and satisfaction drivers. We compare the performance of Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Transformer models, focusing on preprocessing and performance metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). LSTM models demonstrated superior accuracy in sentiment assessment (Ni et al., 2019).

2 Problem Description and Proposed Solution

Traditional sentiment analysis fails to capture the nuances in numerical ratings, leading to a loss of valuable information. Our solution involves developing CNN, LSTM, and Transformer models to accurately predict numerical ratings from reviews, offering a more detailed understanding of customer feedback. By analyzing specific words and features that significantly influence customer ratings, my project provides actionable insights that can help businesses enhance customer satisfaction and loyalty. This approach has the potential to revolutionize sentiment analysis in the e-commerce sector.

3 Methods and Procedures

To develop my solution, I utilized the "Amazon Product Review Dataset" from the University of California, San Diego (Ni et al., 2019). This dataset is a comprehensive collection of customer reviews for products sold on Amazon, encompassing several key features:

- **Overall Rating**: Numeric customer rating, ranging from 1 to 5.

- **Verified Purchase**: Indicates if the review is from a verified purchase.
- **Reviewer Information**: Includes reviewerID, asin (Amazon Standard Identification Number), and reviewerName.
- **Review Content**: Contains reviewText for the full review and summary for a brief overview.
- **Review Timing**: reviewTime and unixReviewTime for the date and UNIX timestamp of the review, respectively.

Key steps involved in my methodology:

- **Data Preprocessing**: Clean text to remove non-textual elements, handle missing values, focus on specific product categories to manage dataset size. Includes tokenization, stemming, and removing stopwords to prepare text data for model training.
- **Model Development**:
  - **Convolutional Neural Network (CNN)**: Utilize Word2Vec embeddings to transform text into vectors, followed by convolutional layers, global max pooling, and dropout regularization to capture local patterns in text [1].
  - **Long Short-Term Memory (LSTM)**: Implement LSTM layers to sequentially process text, preserving valuable information over extended sequences, followed by dropout and dense layers to predict sentiment [2].
  - **Transformer Model**: Employ multi-head attention mechanisms and positional encodings to capture global context and interpret sentiment flows in text [3].
- **Analysis of Word Influence**: Map attention weights to words commonly found in reviews and correlate these weights with average scores. This analysis helps in understanding the impact of specific words on customer ratings.

[1] https://keras.io
[2] https://tensorflow.org
[3] https://pytorch.org

- **Baseline Comparison**: Establish baselines using a random classifier and a frequency-based classifier to assess model performance. These baselines provide a reference point to evaluate the effectiveness of the developed models.

This methodology ensures a thorough evaluation of each model's capabilities and provides a robust framework for sentiment analysis in e-commerce.

4 Outcome and Feasibility Assessment

The success of my proposed solution was evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These metrics provide a quantitative measure of the models' predictive accuracy and help compare their performance. The LSTM model demonstrated superior performance with an MAE of 1.20 and an RMSE of 1.61, followed by the CNN model with an MAE of 1.50 and an RMSE of 1.97. The Transformer model, while effective in certain respects, showed an MAE of 1.60 and an RMSE of 2.00, indicating the need for further tuning.

My analysis revealed the significant impact of specific words like "comfort" and "price" on review scores. Words with higher attention weights, such as "comfort," are associated with higher review scores, indicating a positive sentiment. Conversely, words like "material" had a lower average score, suggesting potential dissatisfaction among customers. These insights are critical for enhancing the interpretability and accuracy of sentiment analysis models.

The feasibility of my approach is demonstrated through consistent improvement in predictive accuracy over baseline models. The LSTM and CNN models significantly outperformed the random and frequency-based classifiers, highlighting their robustness and effectiveness in capturing complex sentiments from textual data. This evaluation underscores the potential of advanced machine learning models in providing accurate and actionable insights into consumer sentiments.

5 Implications

My research offers significant implications for e-commerce businesses by providing a deeper understanding of customer feedback and satisfaction levels. The ability to accurately predict numerical ratings from textual reviews can help businesses identify key areas for improvement and tailor their products and services to better meet customer needs. For instance, understanding that "comfort" significantly impacts positive ratings can guide product development and marketing strategies.

Additionally, my findings contribute to the academic field by advancing the state-of-the-art in sentiment analysis. By demonstrating the effectiveness of advanced machine learning models in predicting numerical ratings, my research provides valuable insights for future studies in natural language processing and machine learning. The integration of CNN, LSTM, and Transformer models offers a comprehensive framework that can be adapted for various applications beyond e-commerce, such as healthcare, finance, and social media analysis.

The intellectual merit of my work lies in its contribution to the development of more nuanced and interpretable sentiment analysis models. By highlighting the specific words and features that influence customer ratings, my research paves the way for more targeted and effective sentiment analysis tools. These tools can empower businesses and researchers to gain deeper insights into customer sentiments, ultimately leading to better decision-making and enhanced customer satisfaction.

6 Closing Remarks

In summary, my project has successfully developed advanced machine learning models for predicting numerical customer ratings from e-commerce reviews. The superior performance of the LSTM model, along with valuable insights gained from word influence analysis, underscores the potential of my approach in enhancing sentiment analysis. My work not only demonstrates my capability in handling complex NLP tasks but also sets the stage for future research and innovation in this field.

Looking ahead, I plan to further refine my models and explore new methodologies to continue advancing the understanding of customer sentiments. This includes experimenting with bidirectional LSTMs, fine-tuning Transformer models, and incorporating unsupervised learning techniques to capture more subtle nuances in consumer feedback. I am excited about the potential of my research to contribute to the ongoing development of more accurate and actionable sentiment analysis tools that can benefit businesses and researchers alike.

References

Alibasic, A. and Popovic, T. (2021). Applying natural language processing to analyze customer satisfaction. pages 1–4.

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