Sentiment Analysis of Amazon Product Reviews

A Machine Learning Approach

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1. Introduction

The rapid growth of e-commerce has led to an explosion of user-generated content, particularly product reviews. Analyzing these reviews can provide businesses with actionable insights into customer satisfaction, product performance, and emerging trends. However, manually processing vast amounts of textual data is impractical.

This project aims to develop an automated sentiment analysis model that classifies Amazon product reviews as positive or negative using machine learning (ML) techniques. The model leverages Natural Language Processing (NLP) for preprocessing and Logistic Regression for classification, ensuring efficient and scalable sentiment analysis.

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2. Problem Statement

In the digital age, the volume of online reviews grows rapidly with each transaction and product interaction. Manual analysis of this data is not only inefficient but also prone to subjective interpretation and inconsistency. Businesses need an automated system that can reliably analyze customer sentiments to enhance product recommendations, improve customer service, and adapt marketing strategies. The challenge lies in processing natural language data which involves complexities such as sarcasm, context understanding, spelling variations, and noise in data. The

objective of this project is to develop a sentiment classification model that addresses these challenges and provides high accuracy and reliability.

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3. Objectives

This project is guided by the following objectives:

- To develop a supervised machine learning model that accurately classifies Amazon product reviews as either positive or negative.

- To apply standard NLP preprocessing techniques to clean and normalize raw textual data.
- To use TF-IDF (Term Frequency-Inverse Document Frequency) for effective feature extraction from text.

- To evaluate the model using robust performance metrics including accuracy, precision, recall, and F1-score.

- To serialize and store the trained model and vectorizer, enabling reuse in applications such as web-based review analysis or customer feedback dashboards.

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4. Dataset Description

The dataset used in this project consists of a large collection of Amazon product reviews, which include the text of the review and an associated sentiment label. These labels are binary-either positive or negative. The dataset is balanced, meaning it has a roughly equal number of positive and negative reviews, which is critical for preventing model bias during training. The reviews span various product categories such as electronics, apparel, home essentials, and books, thus offering diverse language patterns and contexts. The dataset is pre-split into training and testing subsets to ensure consistent evaluation.

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5. Data Preprocessing and Feature Engineering

Raw text data must be preprocessed to convert it into a structured form suitable for machine learning algorithms. The following steps were conducted:

- Lowercasing: All review text was converted to lowercase to eliminate case sensitivity issues.

- Punctuation Removal: Punctuation marks were removed as they typically do not add value in sentiment classification.

- Stopword Removal: Common English stopwords were removed using the NLTK library to reduce dimensionality and focus on sentiment-bearing words.

- Tokenization: Sentences were broken down into individual tokens (words) for easier processing.

- Stemming/Lemmatization: Words were reduced to their base forms to standardize variations (e.g., "running" to "run").

- Vectorization: TF-IDF was used to transform the cleaned text into numerical vectors, emphasizing words that are important in individual documents but rare across the entire dataset.

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6. Model Development

For classification, Logistic Regression was selected due to its effectiveness in binary classification tasks and its interpretability.

The steps included:

- Model Training: The model was trained on the TF-IDF feature vectors derived from the training dataset.

- Hyperparameter Tuning: Grid Search with Cross-Validation was employed to identify the optimal regularization parameter (C value) and improve performance.

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7. Model Evaluation

The model was evaluated using standard classification metrics:

Metric	Formula	Description
Accuracy	(TP + TN) / (TP + TN + FP + FN)	Overall correctness
Precision	TP / (TP + FP)	How many predicted positives are correct?
Recall	TP / (TP + FN)	How many actual positives were detected?
F1-Score	2*(Precision*Recall)/(Precision+Recall)	Balance between precision & recall

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8. Model Serialization

To deploy the model, we save it using Python's `pickle` module.

Files Generated:

1. `amazon_review_predictor.pkl` – Trained Logistic Regression model.
2. `tfidf_vectorizer.pkl` – Fitted TF-IDF vectorizer.

Saving the Model:

```
import pickle
pickle.dump(model, open('amazon_review_predictor.pkl', 'wb'))
pickle.dump(tfidf, open('tfidf_vectorizer.pkl', 'wb'))
```

```
model = pickle.load(open('amazon_review_predictor.pkl', 'rb'))
vectorizer = pickle.load(open('tfidf_vectorizer.pkl', 'rb'))
```

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9. Repository

(GitHub Link: https://github.com/Nivedita-svg/Final-Year-Project.git)

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10. Conclusion

- The model successfully classifies Amazon reviews with ~69% accuracy.
- TF-IDF + Logistic Regression proved effective for sentiment analysis.
- The serialized model allows easy deployment in real-world applications.

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11. Future Work

- Integrate deep learning models like LSTM, GRU, or Transformer-based BERT for improved context understanding.

- Expand the dataset to include multilingual and neutral reviews.

- Build an interactive web application using Flask or Streamlit to allow users to input reviews and get real-time sentiment analysis.

- Use SHAP or LIME for interpretability of model predictions.

Final Thoughts

This project demonstrates the power of NLP and ML in automating sentiment analysis, providing businesses with a scalable solution for customer feedback analysis. Future enhancements can further improve accuracy and applicability across industries.