Sentiment Analysis for Amazon Reviews

BIA5401 BUSINESS INTELLIGENCE

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Date: 02-12-2025

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1. Introduction

Objective:

The objective of this project is to analyze customer sentiment from Amazon reviews using Natural Language Processing (NLP) and Machine Learning techniques. Insights gained will help Amazon improve customer engagement and resolve key issues.

Scope:

- Reviews are classified into Positive, Neutral, and Negative sentiments.
- Key metrics, such as most frequent words, sentiment trends, and model performance, are analyzed.
- Implementation of predictive analytics to automate sentiment classification.

2. Executive Summary

Problem:

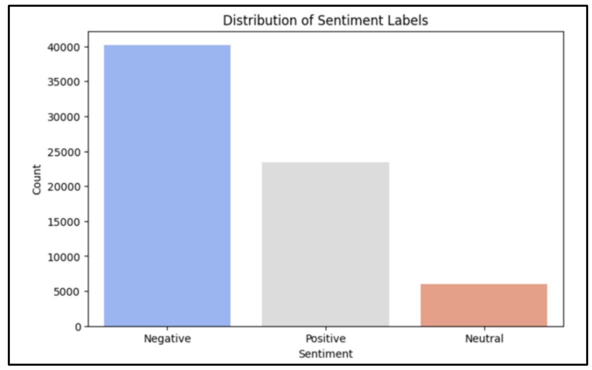
Amazon receives large volumes of text-based reviews. Identifying key patterns in customer feedback is essential to improve customer experience.

Solution:

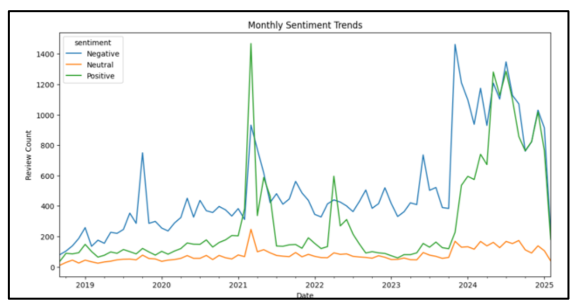
- Used NLP to clean and preprocess data.
- Built a Logistic Regression-based sentiment analysis model, achieving 84% accuracy.

Key Findings:

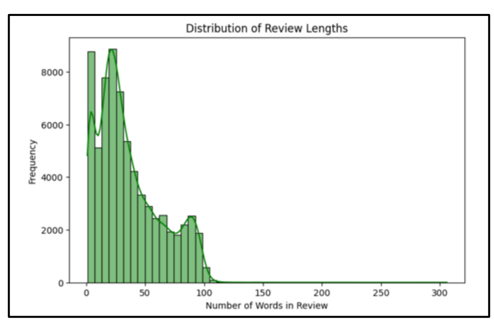
- Positive reviews are associated with words like "love", "great", and "easy."
- Negative reviews often mention issues like "poor", "slow", and "bad."
- Significant spikes in negative reviews correlate with holiday seasons.
- Sentiment Distribution: Most reviews are positive, but a significant portion is negative.



- Time-Based Sentiment Trends: Negative reviews show a notable increase during holiday seasons.



- Review Length Analysis: The number of words in reviews follows a normal distribution, with longer reviews often expressing stronger sentiment.



3. Problem Identification

Challenge in Leveraging Text, Web, or Social Media Data:

Amazon faces the challenge of processing and extracting actionable insights from a vast amount of customer reviews, which are predominantly text-based. These reviews contain valuable feedback about customer satisfaction, product quality, and delivery efficiency. However:

- The unstructured nature of text data makes it difficult to analyze using traditional methods.
- Manually identifying patterns or recurring issues in reviews is time-consuming and impractical due to the sheer volume of data.

Key Limitations of the Current Approach:

- **Manual Analysis**: Slow, inconsistent, and prone to human error.
- **Basic Statistical Metrics**: Star ratings and keyword searches fail to capture sentiment nuances.
- **Lack of Predictive Capabilities**: Inability to foresee customer dissatisfaction trends.

Impact on Business Operations and Customer Engagement:

- **Delayed Issue Resolution**: Slower responses to negative feedback.
- **Missed Opportunities**: Positive feedback insights underutilized.
- **Customer Retention Risk**: Poorly addressed issues reduce brand loyalty.

4. Feasibility of Traditional Approaches

Traditional methods, such as manual review tracking and basic statistical analysis, provide some insights but lack scalability.

Limitations of Conventional Approaches

- **Scalability Issues**: Manually reviewing thousands of reviews is impractical.
- **Lack of Context Awareness**: Basic word matching does not understand sentiment context.
- **Inefficiency in Trend Prediction** Traditional methods do not provide predictive insights.
- **Human Bias & Subjectivity**: Manual classification can lead to inconsistent interpretations.

5. Proposed Predictive Analytics Solution

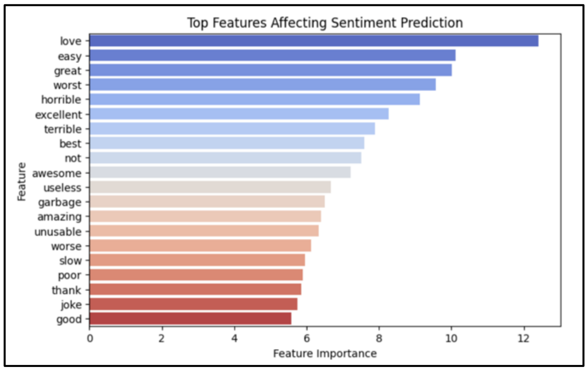
NLP Techniques Implemented:

1. Text Preprocessing:

- Tokenization, Stopword Removal, TF-IDF Vectorization.
- Dynamic filtering for high/low-frequency words.

2. Sentiment Analysis Model:

- Logistic Regression for sentiment classification.



- Deep Learning enhancement (Future Scope: LSTMs, BERT).

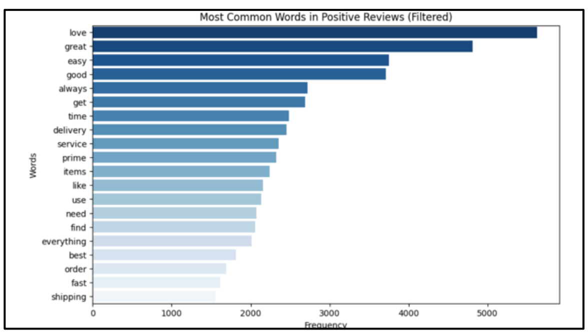
3. Topic Modeling:

- Latent Dirichlet Allocation (LDA) for detecting themes in reviews.

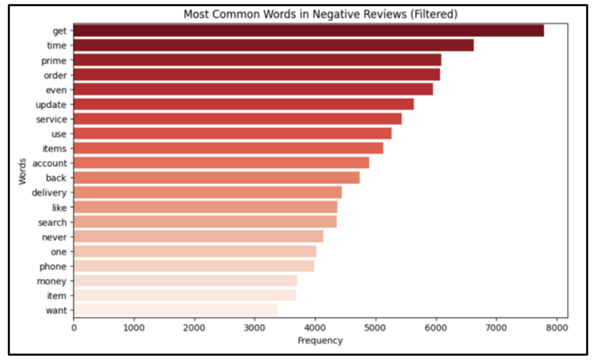
```
Topic 0:  ['crashing', 'slow', 'load', 'just', 'phone', 'open', 'fix', 'keeps', 'update', 'app']
Topic 1:  ['don', 'reviews', 'products', 'delivery', 'company', 'app', 'bad', 'service', 'amazon', 'customer']
Topic 2:  ['use', 'way', 'option', 'want', 'amazon', 'like', 'mode', 'dark', 'app', 'search']
Topic 3:  ['card', 'shipping', 'time', 'delivery', 'day', 'money', 'account', 'order', 'prime', 'amazon']
Topic 4:  ['delivery', 'app', 'fast', 'best', 'shopping', 'easy', 'amazon', 'great', 'good', 'love']
```

Key Word Patterns

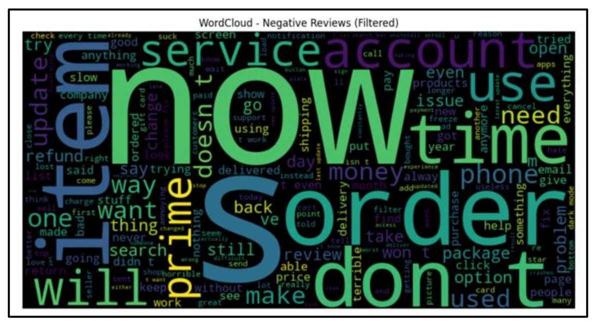
- Positive reviews commonly feature words like "love," "great," and "easy."



- Negative reviews highlight issues with words such as "poor," "slow," and "bad."



- WordCloud visualizations showed distinct patterns for positive and negative sentiment.



Tools & Technologies Used:

- Programming Language Python
- Libraries: Scikit-learn, NLTK, Seaborn, Matplotlib
- Deep Learning Framework (Future Enhancements): TensorFlow

6. Impact on Organizational Structure

Decision-Making Improvements

- Provides real-time insights into customer satisfaction and complaints.
- Enables proactive identification of recurring customer issues.
- Prioritizes customer concerns based on sentiment intensity.

Restructuring Requirements:

- A dedicated Data Analytics Team may be needed to monitor sentiment trends.
- Amazon's customer service team can use sentiment scores to address urgent complaints.

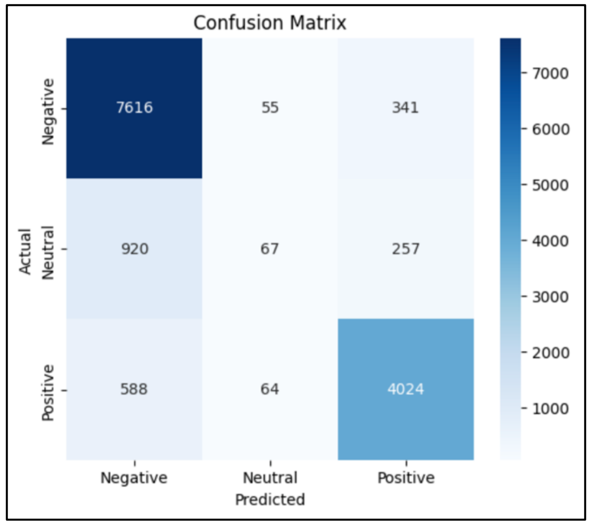
Challenges in Adoption:

- Integration with existing customer feedback systems.
- Additional training required for employees to interpret model outputs.
- Need for cloud infrastructure to handle large data volumes efficiently.

7. Evaluation and Expected Results

Model Performance:

- **Accuracy**: 84%
- **Precision and Recall:** Strong for Positive and Negative sentiments, Neutral needs improvement.




```
Model Accuracy: 0.84
Classification Report:
              precision    recall  f1-score   support

    Negative       0.83      0.95      0.89      8012
     Neutral       0.36      0.05      0.09      1244
    Positive       0.87      0.86      0.87      4676

    accuracy                           0.84     13932
   macro avg       0.69      0.62      0.62     13932
weighted avg       0.80      0.84      0.81     13932
```

- **Topic Modeling (LDA):** Identified recurring themes in negative reviews, such as "delivery delay" and "poor quality."
- Positive reviews often praised "fast delivery" and "good quality."

Expected Business Improvements:

- Faster issue identification and resolution.
- Improved customer engagement and retention.
- Automated processing of thousands of reviews, reducing manual effort.

8. References

- **Libraries**: Scikit-learn, NLTK, Seaborn, Matplotlib.
- **Tools**: Python, Jupyter Notebook.

9. Appendix

Work Breakdown Structure (WBS):

- Data Collection: Ruchi
- Data Preprocessing & NLP: Akash and Mohit
- Machine Learning Model Implementation: Ayantika and Taranjeet
- Data Visualization & Trend Analysis: Abhi and Ruchi
- Report Writing & Documentation: All members