Sentiment Analysis for Amazon Reviews

**BIA5401** BUSINESS INTELLIGENCE

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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. A graph of a distribution of sentiment labels

  AI-generated content may be incorrect.
* Time-Based Sentiment Trends: Negative reviews show a notable increase during holiday seasons. A graph of different colored lines

  AI-generated content may be incorrect.
* Review Length Analysis: The number of words in reviews follows a normal distribution, with longer reviews often expressing stronger sentiment.A graph of a number of words

  AI-generated content may be incorrect.

# 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.

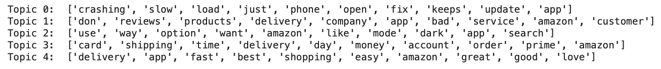
A graph of a graph showing different colored bars

AI-generated content may be incorrect.

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

**3.** **Topic** **Modeling**:

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



## Key Word Patterns

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

A graph of a number of words

AI-generated content may be incorrect.

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

A graph of a number of words

AI-generated content may be incorrect.

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

A word cloud of words

AI-generated content may be incorrect.

A close up of words

AI-generated content may be incorrect.

## 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.

A graph of negative and negative

AI-generated content may be incorrect.

A screenshot of a computer screen

AI-generated content may be incorrect.

* **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