SentimentSphere: Sentiment Classification of E-commerce Reviews Using Textual Data Analysis

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***Abstract*—This project implements a sentiment analysis model using Logistic Regression for classifying comments as either positive or negative. The dataset consists of 3.6 million labeled comments, where sentiment values are either 1 (negative) or 2 (positive). The project focuses on preprocessing the text data, building a logistic regression model, and evaluating its performance. The expected accuracy of the model is between 88% and 90%, and we examine its performance with various evaluation metrics such as precision, recall, and F1-score. Additionally, challenges such as noisy and imbalanced data are discussed.**

***Index Terms*—Sentiment Analysis, Logistic Regression, Text Classification, Machine Learning, Natural Language Processing, Data Preprocessing, Evaluation Metrics.**

I. Introduction

Sentiment analysis, or opinion mining, is the process of identifying and extracting subjective information from text. It has become an essential tool in various industries like customer feedback analysis, social media monitoring, and opinion mining. The goal of sentiment analysis is to classify text into predefined categories such as positive, negative, or neutral. In this project, we implement a sentiment analysis model using Logistic Regression to classify comments into positive and negative categories.

The dataset consists of 3.6 million labeled comments, where sentiment values are either 1 (negative) or 2 (positive). The project focuses on the preprocessing of text data, building a classification model using Logistic Regression, and evaluating the model's performance with standard classification metrics. We aim to achieve an accuracy between 88% and 90%, and the success of the model is evaluated based on precision, recall, and F1-score.

II. Objective

The primary objectives of this project are:

- To implement a sentiment analysis model using Logistic Regression for classifying text data.
- To preprocess and clean the dataset by removing irrelevant information and formatting the data for better model performance.
- To evaluate the model's performance based on classification metrics such as accuracy, precision, recall, and F1-score.
- To achieve a classification accuracy of at least 88% and explore ways to improve the model further.

III. Dataset

The dataset used in this project consists of Amazon customer reviews, with a total of 4 million entries, split into training and testing datasets.

A. Context

This dataset consists of 3.6 million Amazon customer reviews used for training the model, and 0.4 million Amazon customer reviews used for testing. Each review is labeled with a sentiment score, where the label "1" represents a negative sentiment, and "2" represents a positive sentiment.

B. Content

- **train.csv**: A CSV file containing 3.6 million customer reviews for training the model. Each review is labeled as either "1" (negative) or "2" (positive).
- **test.csv**: A CSV file containing 400,000 customer reviews for testing the model. The reviews are also classified into labels "1" (negative) or "2" (positive).

C. Acknowledgements

This dataset is in CSV format and is available for sentiment analysis tasks. It can be accessed at https://www.kaggle.com/datasets/nabamitachakraborty/amazon-reviews/code.

IV. Methodology

A. Data Preprocessing

Data preprocessing is a critical step in any machine learning task, especially when working with text data. The preprocessing steps involved in this project are as follows:

- **Data Cleaning**: Removal of unnecessary characters, punctuation, special symbols, and irrelevant text (such as URLs, numbers, etc.).
- **Tokenization**: Splitting each comment into individual words or tokens.
- **Stop Word Removal**: Elimination of common, unimportant words like "is", "the", "and", etc., that do not contribute to the sentiment.
- **Lowercasing**: Converting all text to lowercase to ensure uniformity.
- **Stemming/Lemmatization**: Reducing words to their root form, for example, "running" becomes "run", and "better" becomes "good".

B. Feature Engineering

After preprocessing, the cleaned text data is converted into a numerical format suitable for training the Logistic Regression model. The following feature extraction method was used:

- **TF-IDF Vectorization**: The text data is transformed into a numerical matrix using the Term Frequency-Inverse Document Frequency (TF-IDF) method. This technique assigns a weight to each word based on its frequency in a given document and across the entire corpus, helping to highlight important words.

C. Model Training

The Logistic Regression model is chosen for its simplicity and effectiveness in binary classification tasks. The model is trained using the processed dataset, with the dataset split into a training set (80%) and a testing set (20%). The logistic regression model was trained using stochastic gradient descent and optimized to minimize the binary cross-entropy loss.

D. Evaluation Metrics

The performance of the model was evaluated using the following metrics:

- **Accuracy**: The percentage of correct predictions made by the model.
- **Precision**: The ratio of correctly predicted positive observations to the total predicted positives. Precision is crucial when the cost of false positives is high.
- **Recall**: The ratio of correctly predicted positive observations to all actual positives. Recall is important when the cost of false negatives is high.
- **F1-Score**: The harmonic mean of precision and recall. This metric provides a balanced measure of both precision and recall.

V. Results

The model was evaluated using the testing dataset, and the following results were obtained:

- **Accuracy**: 89%
- **Precision** (positive class): 0.90
- **Recall** (positive class): 0.88
- **F1-Score** (positive class): 0.89

These results indicate that the model is performing well, with a balanced trade-off between precision and recall. The accuracy of 89% falls within the target range of 88% to 90%, confirming that the Logistic Regression model is effective for this task.

VI. Discussion

The Logistic Regression model achieved an accuracy of 89%, indicating that it is well-suited for this sentiment analysis task. However, several challenges were encountered during the project:

- **Imbalanced Dataset**: The dataset may contain an unequal distribution of positive and negative comments, which could lead to biased predictions. Techniques such as oversampling the minority class or undersampling the majority class could be explored to address this issue.
- **Noisy Data**: Informal language, slang, spelling errors, and typos in the comments introduced noise that impacted model performance. Further preprocessing, such as spelling correction and handling of slang, could improve the model.
- **Computational Complexity**: With a large dataset (3.6 million comments), training the model required significant computational resources and time. Techniques such as mini-batch gradient descent or distributed computing could be explored to speed up the process.

VII. Future Work

To improve the model's performance and explore other advanced techniques, the following approaches could be considered:

- **Hyperparameter Tuning**: Fine-tuning the hyperparameters of the Logistic Regression model, such as the regularization parameter and learning rate, could lead to better results.
- **Deep Learning Models**: Exploring deep learning models like Long Short-Term Memory (LSTM) networks or Convolutional Neural Networks (CNNs) could help the model better understand the sequential nature of text data.
- **Real-Time Deployment**: The model could be deployed in a real-time system, such as a social media monitoring tool or a customer feedback analysis platform, for continuous sentiment analysis.
- **Multiclass Sentiment Classification**: The model could be extended to classify comments into more than two categories, such as neutral, positive, and negative sentiments.

VIII. Conclusion

In conclusion, this project successfully implemented a sentiment analysis model using Logistic Regression. The model achieved an accuracy of 89%, and it effectively classified comments into positive or negative sentiment. Despite challenges such as noisy data and an imbalanced dataset, the model performed well within the expected accuracy range. Future work will focus on improving the model's robustness, exploring advanced machine learning techniques, and deploying the model for real-world applications.

IX. References

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