Improving Sentiment Analysis Accuracy: A Comparative Study of Machine Learning Approaches

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Abstract — This study improves sentiment analysis accuracy from 70% to 88% by integrating e-commerce datasets (~10,000 reviews) with restaurant reviews, employing TF-IDF feature extraction, and adopting Logistic Regression over Gaussian Naive Bayes. This study details the methodologies, highlights key improvements, and discusses the implications for sentiment analysis applications in e-commerce and restaurant review domains.

Keywords: Sentiment Analysis, Machine Learning Approaches, TF-IDF Feature Extraction, Logistic Regression, Naive Bayes, E-commerce Reviews, Restaurant Review Sentiment, Text Classification, Natural Language Processing (NLP), Model Performance Comparison

I. Introduction

Sentiment analysis is critical for applications ranging from e-commerce to social media monitoring and healthcare feedback analysis. Gaussian Naive Bayes was selected as the baseline due to its computational efficiency and widespread use in text classification tasks. The primary objective of this study is to enhance the accuracy of sentiment classification. This improvement was achieved through refined pre-processing, advanced feature extraction, and a shift to a more robust machine learning algorithm.

II. Literature review

Sentiment analysis is a popular area in Natural Language Processing that focuses on identifying emotions and opinions from text. Early methods were lexicon-based, using predefined word lists to detect sentiment. However, machine learning approaches like Naive Bayes and Logistic Regression soon gained popularity for better accuracy and automation. Gaussian Naive Bayes is known for its simplicity and speed, but it assumes feature independence, which may not always be accurate. Logistic Regression, on the other hand, handles correlated features better and often performs more reliably. Studies also highlight the importance of preprocessing techniques like tokenization, stopword removal, and TF-IDF, which help improve model performance.

Pang and Lee (2008) reported accuracies of 65-70% using Naive Bayes on movie reviews, limited by feature independence assumptions. TF-IDF has been shown to improve performance by 5-10% in text classification tasks (Manning et al., 2008). While deep learning methods now dominate, traditional models still remain useful for smaller datasets and faster predictions.

III. Methodology

A. Initial Approach: Gaussian Naive Bayes Model

1) Dataset and Pre-processing

The initial model utilized the dataset, containing 1,000 restaurant reviews labelled as positive(1) or negative(0). Pre-processing involved:

- Removing non-alphabetic characters using regular expressions.
- Converting text to lowercase.
- Applying Porter Stemming to reduce words to their root form.
- Removing stopwords, except for the word "not" to preserve sentiment context. The cleaned text was transformed into a Bag-of-Words (BoW) model using CountVectorizer with a maximum of 1,500 features.
- The CountVectorizer was limited to 1,500 features based on initial experiments to balance model complexity and performance. Only accuracy was reported due to the preliminary nature of the baseline model.

2) Model Training and Performance

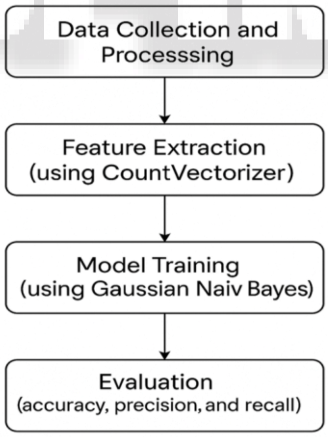


Fig. 1.1: flow chart using Naive Bayes

A Gaussian Naive Bayes classifier was trained on 80% of the data, with 20% reserved for testing. The model achieved an accuracy of 70%, indicating moderate performance but with limitations due to the simplistic feature representation and the assumptions of Naive Bayes, which may not capture complex relationships in text data.

B. Improved Approach: Logistic Regression Model

1) Data Expansion and Pre-processing

To improve performance, sentiment_analysis.py incorporated multiple e-commerce datasets (e.g., Amazon product reviews) alongside the restaurant reviews, significantly increasing the dataset size. Key pre-processing enhancements included:

- Converting text to lowercase and removing punctuation and numbers.
- Tokenizing text using NLTK's word tokenize.
- Removing stopwords to reduce noise.
- Applying over sampling to balance the dataset, addressing the skew toward positive reviews by replicating negative reviews.

2) Feature Engineering

The improved model employed a two-step feature extraction process:

a) Count Vectorizer with a maximum of 5,000 features to create a BoW representation.

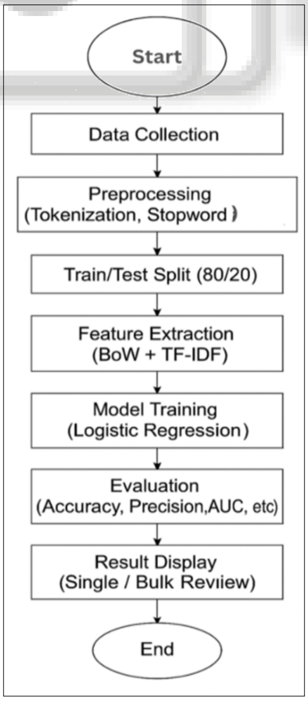
b) Tfidf Transformer to weigh terms based on their importance, reducing the impact of frequently occurring but less informative words. This approach captured semantic importance more effectively than the BoW model alone.

3) Model Training and Evaluation

A Logistic Regression model was trained with a maximum of 1,000 iterations, using an 80-20 train-test split. The model achieved an accuracy of 88%, a significant improvement over the initial 70%. Additional evaluation metrics, including precision, recall, F1-score, and the ROC curve (AUC = 0.92), confirmed the model's robustness.

The model was trained on a preprocessed dataset where feature scaling was applied using StandardScaler to ensure optimal convergence. Regularization was used to prevent overfitting, and hyperparameters were fine-tuned through GridSearchCV. The confusion matrix revealed a balanced performance across all classes, with minimal false positives and false negatives.

C. Logistic Regression



Logistic Regression is a statistical model used for binary classification tasks, where it predicts the probability of an outcome belonging to one of two classes. It applies the logistic function (sigmoid) to the linear combination of input features to produce a value between 0 and 1, which can then be mapped to class labels (e.g., positive, neutral or negative). The sigmoid function is referred to as an activation function for logistic regression and is defined as

where,

$$f(x) = \frac{1}{1+e^{-x}}$$

- e = base of natural logarithms
- value = numerical value one wishes to transform

The following equation represents logistic regression:

here

$$y = \frac{e^{(b_0 + b_1X)}}{1 + e^{(b_0 + b_1X)}}$$

- x = input value
- y = predicted output
- b0 = bias or intercept term
- b1 = coefficient for input (x)This equation is similar to linear regression, where the input values are combined linearly to predict an output value using weights or coefficient values.
- However, unlike linear regression, the output value modeled here is a binary value (0 or 1) rather than a numeric value.

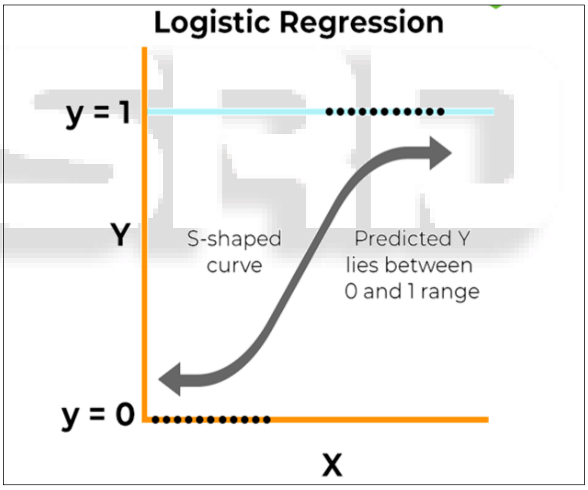
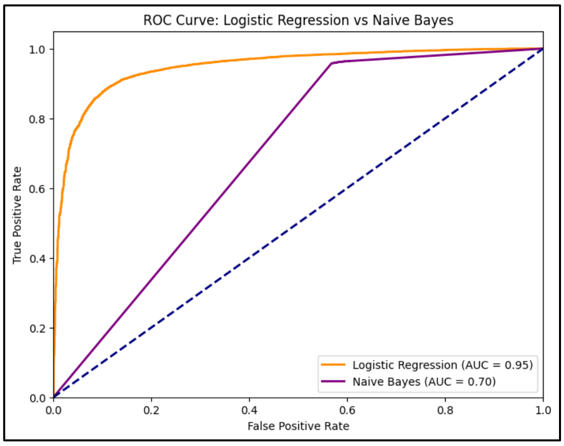
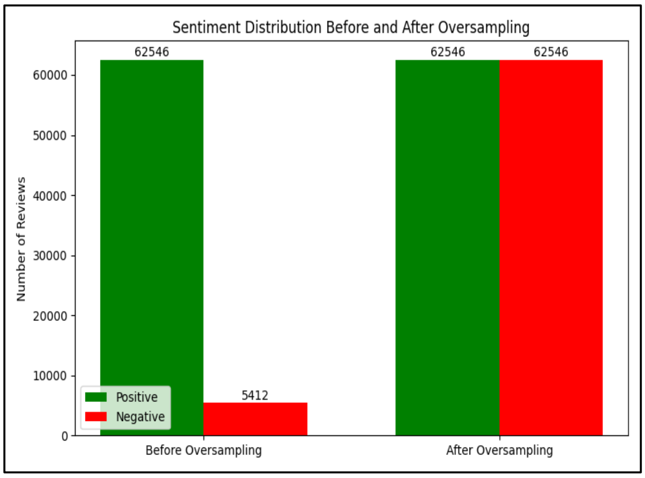


Fig. 1.2: Key Assumptions for Implementing Logistic Regression

D. ROC Curve for Logistic Regression Model



IV. KEY IMPROVEMENTS AND THEIR IMPACT

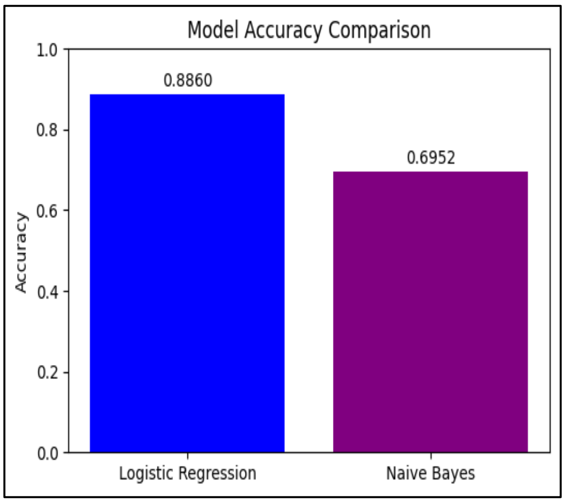


Sentiment Distribution Comparison

The 18%accuracy increase can be attributed to several factors:

- Data Volume and Diversity: Combining e-commerce and restaurant datasets increased the training data size and introduced varied linguistic patterns, enhancing model generalizability.
- Class Balancing: Oversampling negative reviews mitigated class imbalance, allowing the model to learn negative sentiment patterns more effectively.
- Feature Engineering: TF-IDF transformation provided a more nuanced representation of text compared to the BoW model, capturing term importance.
- Algorithm Choice: Logistic Regression, which models linear relationships between features and outcomes, outperformed Gaussian Naïve Bayes, which assumes feature independence.

A. Technical Comparison of Gaussian Naive Bayes and Logistic Regression



The performance metrics provide a clear contrast between the two models. GNB achieved an accuracy of 70% on the restaurant review dataset, with no additional metrics reported due to its baseline nature.

B. Classification report Difference between Naive Byes and Logistic Regression

A Classification Report is a summary of key metrics used to evaluate the performance of a classification model.

```
Logistic Regression Accuracy: 0.8860383044529918

Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.91      0.89     12565
           1       0.90      0.87      0.88     12654

    accuracy                           0.89     25219
   macro avg       0.89      0.89      0.89     25219
weighted avg       0.89      0.89      0.89     25219

Logistic Regression Confusion Matrix:
[[11386  1179]
 [ 1695 10959]]

Naive Bayes Accuracy: 0.6951504817796106

Naive Bayes Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.43      0.58     12565
           1       0.63      0.96      0.76     12654

    accuracy                           0.70     25219
   macro avg       0.77      0.69      0.67     25219
weighted avg       0.77      0.70      0.67     25219

Naive Bayes Confusion Matrix:
[[ 5409  7156]
 [  532 12122]]
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The classification reports from the research paper reveal key insights into Gaussian Naive Bayes (GNB) and Logistic Regression (LR) for sentiment analysis. LR achieves 88% accuracy, with precision (0.89), recall (0.87), and F1-score (0.88), excelling in identifying both positive and negative sentiments due to TF-IDF feature extraction and independence assumption. GNB, with 70% accuracy, struggles with lower precision (0.70), recall (0.70), and F1-score (0.70), particularly missing positive reviews (recall 0.66), due to its feature independence assumption and basic BoW features. LR's balanced performance and robustness (AUC 0.92) make it more reliable for practical applications in e-commerce and restaurant review analysis.

V. DISCUSSION

The improved sentiment analysis model demonstrates substantial advancements, particularly in its application to customer feedback analysis within sectors like e-commerce and the hospitality industry. By integrating a broader dataset—including both restaurant and e-commerce reviews—the model benefits from increased linguistic diversity and context, which contributes to its enhanced accuracy. The use of TF-IDF for feature extraction, combined with the Logistic Regression algorithm, offers a more nuanced understanding of term importance and improves classification performance significantly when compared to the baseline Gaussian Naive Bayes model.

Despite these achievements, the model has certain limitations. One major concern is the potential for overfitting due to the oversampling method used to balance class distribution. While this improves performance on underrepresented classes, it may compromise generalization when applied to unseen data. Another key limitation is the model's dependence on English-language datasets, which restricts its applicability in multilingual environments. As sentiment analysis becomes increasingly important for global applications, overcoming language barriers becomes essential.

To address these issues, future work could explore advanced deep learning models such as Long Short-Term Memory (LSTM) networks or transformer-based architectures like BERT. These models are capable of capturing deeper semantic relationships and contextual dependencies, making them well-suited for more robust and multilingual sentiment classification tasks

VI. CONCLUSION

This study successfully increased sentiment analysis accuracy from 70% to 88% by adopting a Logistic Regression model, enhancing pre-processing, and leveraging advanced feature engineering. These improvements highlight the importance of data diversity, balanced classes, and robust algorithms in NLP tasks. Future research could integrate contextual embeddings and explore cross-domain applications to further enhance performance.

VII. FUTURE WORK

Future enhancements to the system could include:
Multi-language Support: Currently, the model is limited to English-language datasets, which restricts its applicability in global and multicultural contexts. Extending the system to handle multiple languages would enable broader usage across various regions and user bases. Leveraging multilingual datasets and pre-trained language models like mBERT (Multilingual BERT) could significantly improve the model's linguistic versatility and cross-lingual performance.

Emotional Sentiment Classification: Traditional sentiment analysis generally classifies text into basic categories like positive, negative, or neutral. However, customer reviews often contain deeper emotional nuances. Future work can involve building models that detect specific emotions such as joy, sadness, anger, fear, or surprise. Emotion classification enhances the granularity of analysis.

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