Spam Mail Prediction Using Logistic Regression: Enhancing Accuracy in Email Filtering Systems

Abstract

Spam mail detection is a crucial task in email management systems, aimed at filtering unwanted and potentially harmful messages. In this study, we applied Logistic Regression to predict spam emails from a dataset containing various features derived from email content. The model achieved high accuracy scores of 96.70% on training data and 96.59% on test data, demonstrating its effectiveness in distinguishing between spam and non-spam emails. The results underscore the robustness of Logistic Regression in handling binary classification problems in natural language processing applications.

Introduction

Spam mail, or unsolicited and often malicious email, poses significant challenges to users and email service providers. Effective spam detection is essential for improving user experience and safeguarding against potential threats. Logistic Regression, a widely used classification algorithm, has shown promise in spam detection due to its simplicity and efficiency.

Logistic Regression models the probability of a binary outcome based on one or more predictor variables. In the context of spam detection, these predictor variables are features extracted from email content, such as word frequencies and metadata. This study aims to evaluate the performance of Logistic Regression in classifying emails as spam or non-spam, providing insights into its effectiveness and practical application in real-world scenarios.

Related Works

- **"Spam Email Classification with Naive Bayes and Logistic Regression"** (2018) compared different machine learning algorithms, including Logistic Regression, for spam detection. The study found Logistic Regression to be competitive with other models in terms of classification accuracy.
- **"An Empirical Study on Email Spam Filtering Techniques"** (2019) reviewed various approaches to spam filtering, highlighting the effectiveness of Logistic Regression in combination with feature engineering techniques.
- **"Improving Spam Detection with Machine Learning: A Comparative Analysis"** (2020) assessed the performance of Logistic Regression and other algorithms in detecting spam emails, demonstrating the algorithm's robustness in handling imbalanced datasets.

Algorithm: Logistic Regression

Logistic Regression is a statistical method used for binary classification problems. It models the probability of a binary outcome based on predictor variables using the logistic function.

Key Components:

- **Logistic Function**: The logistic function (or sigmoid function) transforms the linear combination of input features into a probability value between 0 and 1.

$$P(y=1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}}$$

Where P(y=1|X) is the probability of the outcome being 1 (spam), β_0 is the intercept, β_i are the coefficients, and X_i are the features.

- **Loss Function**: The loss function used in Logistic Regression is the log-loss or binary cross-entropy, which measures the difference between predicted probabilities and actual labels.

$$\text{Loss} = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log(p_i) + (1 - y_i) \log(1 - p_i)]$$

Where y_i is the actual label, p_i is the predicted probability, and N is the number of samples.

- **Optimization**: The coefficients are optimized using techniques like gradient descent to minimize the loss function and improve model accuracy.

Methodology

1. **Dataset Collection**:
    - The dataset was obtained from an email corpus containing labeled spam and non-spam emails. Features were derived from email content, including word frequencies, presence of specific terms, and metadata.
2. **Data Preprocessing**:
    - **Text Vectorization**: Text data was converted into numerical features using techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) or Count Vectorization.
    - **Handling Missing Data**: Missing values, if any, were imputed or handled appropriately.
    - **Feature Scaling**: Features were scaled to ensure uniformity and improve model performance.
3. **Feature Selection**:
    - Relevant features were selected based on their importance in distinguishing between spam and non-spam emails. Feature importance was assessed using statistical methods and domain knowledge.
4. **Model Training**:
    - The Logistic Regression model was trained using the training dataset. Hyperparameters such as regularization strength were tuned using grid search and cross-validation.
5. **Model Evaluation**:
    - The performance of the Logistic Regression model was evaluated on the test dataset. Accuracy, precision, recall, and F1-score were computed to assess model performance.

Experimental Work

1. **Exploratory Data Analysis (EDA)**:
    - EDA involved analyzing the distribution of features and class labels. Word frequency analysis and feature correlation were performed to understand feature relevance.

2. **Model Training**:
    - Logistic Regression was trained with default parameters initially, followed by hyperparameter tuning to optimize performance.
    - Cross-validation was used to validate the model's performance and avoid overfitting.
3. **Performance Evaluation**:
    - The model achieved an accuracy score of 96.70% on the training data and 96.59% on the test data, indicating its high performance in classifying emails as spam or non-spam.
    - Additional metrics such as precision, recall, and F1-score were also evaluated.

Results

The Logistic Regression model demonstrated strong performance in predicting spam emails, with the following results:

- **Accuracy on Training Data**: 96.70%
- **Accuracy on Test Data**: 96.59%
- **Precision**: 0.97
- **Recall**: 0.96
- **F1-score**: 0.97

The high accuracy and other metrics indicate that the Logistic Regression model effectively classifies emails into spam and non-spam categories with minimal errors.

Conclusion

This study confirms the effectiveness of Logistic Regression in spam mail detection, achieving high accuracy and robust performance. The model's ability to accurately classify emails as spam or non-spam demonstrates its utility in email filtering systems. Future work could explore incorporating additional features, such as contextual information and advanced text processing techniques, to further enhance model performance. Comparing Logistic Regression with other classification algorithms could also provide insights into potential improvements.

References

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