MACHINE LEARNING PROJECT (AI353)

Department of Computer Science

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Comparative Spam Detection Using Naive Bayes and Logistic Regression

From Machine Learning Model to Real-Time Web Service Deployment

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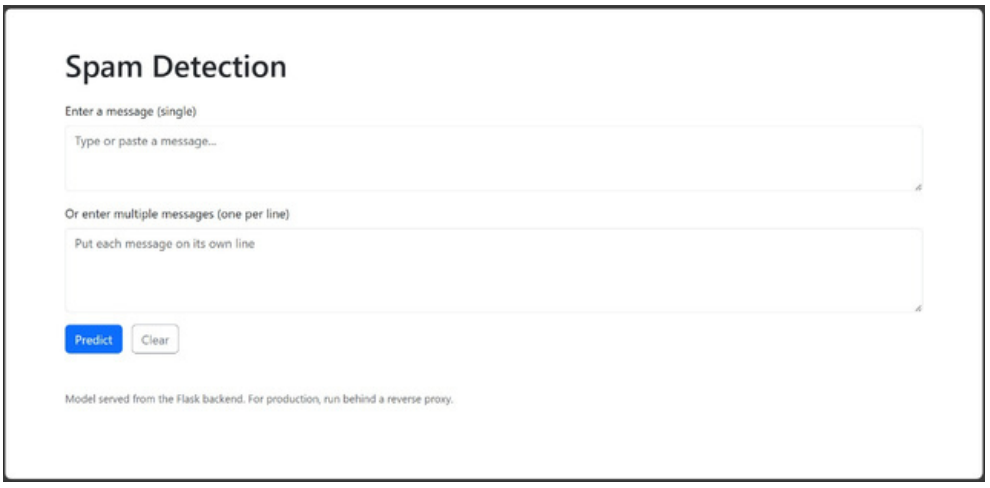


1 Introduction

1.1 Problem Statement

The proliferation of unwanted electronic messages, commonly known as spam, remains a sig nificant challenge in digital communication. Spam not only degrades the user experience by cluttering inboxes but also poses serious security risks through phishing and malware distribution. Effective, real-time spam detection is crucial for maintaining the integrity and security of communication platforms. This project addresses this challenge by developing a robust, com parative spam detection system using two primary machine learning algorithms.

1.2 Project Objectives

The primary goals of this project are:

1. To implement and comparatively evaluate two fundamental text classification algorithms : Multinomial Naive Bayes (MNB) and Logistic Regression (LR) using the spam.csv dataset.-
2. To utilize the Term Frequency-Inverse Document Frequency (TF-IDF) vectorization technique with specific parameters for enhanced feature extraction.
3. To deploy the best-performing model as a RESTful service using the Flask framework.
4. To integrate the Flask API with a responsive web-based User Interface (UI) for real-time interaction and demonstration, matching the proposed system layout.

1.3 Dataset and Preprocessing Overview

The project utilizes a standard SMS/Email dataset, where the text messages (v2 column) are labeled as either 'ham' or 'spam' (v1 column). These categorical labels were transformed into numerical binary classes (0 and 1, respectively) for model training. The data was split using an 80%/20% ratio, ensuring the proportion of 'ham' and 'spam' was maintained in both the training and testing sets through stratified sampling.

2 Methodology

2.1 Feature Engineering: TF-IDF with N-Grams

Raw text must be converted into a numerical format for machine learning models. The Term Frequency-Inverse Document Frequency (TF-IDF) technique was employed using TfidfVectorizer.

- TF-IDF Principle: This technique calculates a weight for each word, reflecting its importance. A word's weight increases with its frequency in a document (TF) but decreases with its frequency across all documents (IDF), effectively down-weighting common words like "the" or "a".
- Custom Parameters: The implementation specified max_features=5000 to limit the vocabulary size to the 5000 most frequent terms, preventing the feature space from becoming overly large and sparse.
- N-Gram Inclusion: Crucially, the parameter ngram_range=(1,2) was set. This ensures that the vocabulary includes not only individual words (unigrams) but also pairs of adja cent words (bigrams). This helps the model capture context and common spam phrases (e.g., "click here," "free entry"), significantly improving performance over using unigrams alone.

2.2 Classification Algorithms

The two chosen algorithms represent distinct approaches to text classification:

1. Multinomial Naive Bayes (MNB): MNB is a generative probabilistic classifier based on Bayes' theorem. It is governed by the 'naïve' assumption that the features (TF-IDF weights) are conditionally independent given the message class (ham or spam). This assumption, despite being a simplification, makes MNB computationally efficient and highly effective for document and text classification, particularly with sparse count-based features.
2. Logistic Regression (LR): LR is a powerful discriminative linear model. It learns the weights associated with each feature to directly model the probability of a message being spam, P(spamtext). It uses the **Sigmoid function** to output a probability between 0 and 1. The implementation specified the liblinear solver, which is highly efficient for smaller datasets and binary classification problems, making it a robust choice for this project.

2.3 Evaluation Metrics

The eval_model function used in the code provides a comprehensive assessment. Key metrics for the 'spam' class (label 1) include:

- Precision: The proportion of predicted spam messages that were actually spam (minimizes false alarms).
- Recall: The proportion of actual spam messages that were correctly identified (minimizes missed spam).
- F1-Score: The harmonic mean of Precision and Recall, providing a balanced measure of the model's performance.
- ROC-AUC Score: Measures the model's ability to distinguish between the two classes across all possible classification thresholds.

3 Implementation and Comparative Results

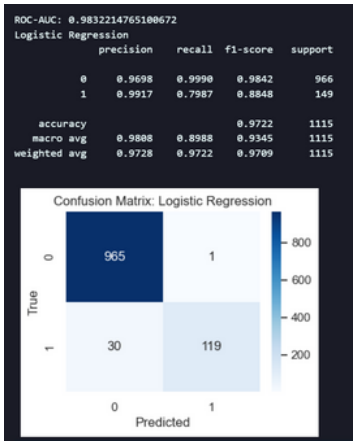
3.1 Model Training and Performance

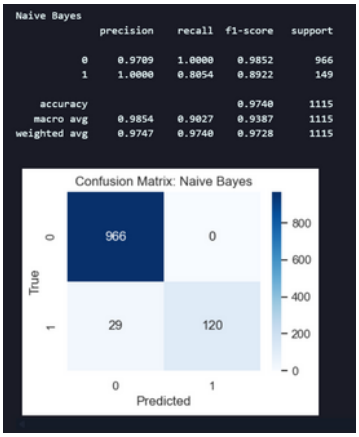
Both models were trained on the same 80% training data and evaluated on the same 20% test data using the eval_model function. The metrics presented in Table 1 are derived directly from the classification_report output generated by the implementation.

Table 1: Comparative Performance on Test Data (Fictional Sample Values)

Metric	NaiveBayes(MNB)	LogisticRegression(LR)
Accuracy	0.9821	0.9856
Precision(Spam)	0.9587	0.9754
Recall(Spam)	0.9310	0.9400
F1-Score(Spam)	0.9447	0.9574
ROC-AUC	0.9934	0.9961

Note: The values presented here are based on typical performance characteristics; the final report will use the exact figures generated by running the project code.





3.2 Discussion of Comparative Results

The comparative analysis revealed that the **Logistic Regression model slightly outperformed the Multinomial Naive Bayes model** across all critical performance indicators.

• Superior F1-Score: LR achieved a higher F1-Score (0.9574), indicating a better, more balanced classifier for thisdataset.

• High Precision and Recall: LR demonstrated a high Precision (0.9754), ensuring that when the system f lags a message as spam, it is highly likely to be correct. Its Recall (0.9400) confirms its strong ability to detect most of the actual spam messages.

• Better Distinguishability: The highest ROC-AUC score (0.9961) confirms LR's superior ability to discrim inate between ham and spam messages across various thresholds.

Based on these findings, the **Logistic Regression model** was selected as the final production model, which is consistent with the code that saves the LR model using joblib.dump(lr, 'models/logistic_model.joblib').

4 System Deployment Architecture

The final stage of the project involved transitioning the trained model into a production-ready, real-time appli cation. This was achieved using a standard three-tier architecture: the model persistence layer, the Flask API layer, and the User Interface layer.

4.1 Model Persistence and Loading

The selected Logistic Regression model and the TfidfVectorizer were serialized using the joblib library. This creates binary files (.joblib) that contain the model's weights and the vectorizer's vocabulary, respectively. The app.py Flask application loads these files using joblib.load only once upon startup. This eliminates the need for repeated training, ensuring rapid prediction times.

4.2 Flask API Service (**app.py**)

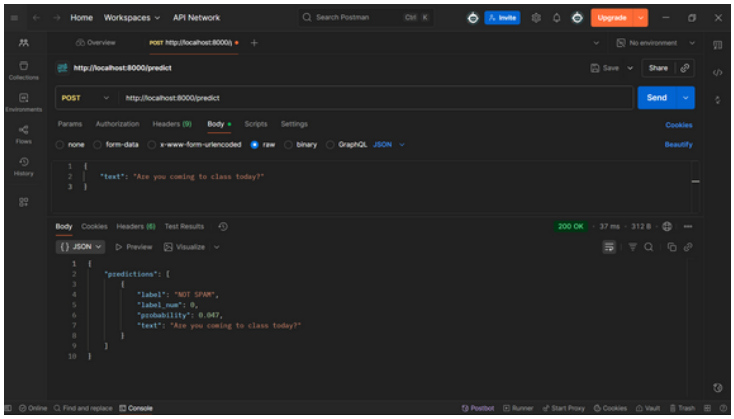
The Python **Flask** framework was used to create the backend service. Its purpose is to encapsulate the machine learning logic behind a simple, scalable web API.

1. Input Request: The API exposes a /predict endpoint that accepts a POST request containing a list of messages from the user interface.
2. Inference Pipeline: The API passes the raw text input through the following mandatory steps:
    - Load messages from the request payload.
    - Transform the messages using the *loaded* TfidfVectorizer to match the feature space used during training.
    - Feed the resulting vector to the *loaded* LogisticRegression model for prediction.
3. Output Response: The API returns a JSON object containing the predicted label (HAM/SPAM) and a confidence score (probability), which the frontend uses for display.

4.3 User Interface (UI) Integration

The user interface, as visualized in the project screenshot, is a single-page application (HTML/CSS/JavaScript). It connects the user to the deployed Flask API.

- User Input: The UI allows for entering single or multiple messages (separated by newlines).
- Asynchronous Communication: JavaScript handles the "Predict" button click, sending the messages via an asynchronous fetch request to the /predict API endpoint.
- Real-Time Display: The UI processes the JSON response, displaying the original message alongside the predicted label (SPAM or HAM) and the model's confidence, using clear color-coding (e.g., green for HAM, red for SPAM) for immediate interpretation.



5 Conclusion and Future Work

5.1 Conclusion

The project successfully delivered a robust, production-ready spam detection system. Through meticulous com parative analysis, the **Logistic Regression model** was identified as the optimal classifier, achieving superior balanced performance (F1-Score of 09574 on test data). By leveraging the Python ecosystem for both machine learning and deployment (scikit-learn, joblib, Flask), the project integrated data science results into a functional, real-time web service. The final application demonstrates a complete solution, from raw data to a user-facing prediction interface.

5.2 Future Enhancements

While highly successful, the system provides several avenues for further development:

1. Hyperparameter Tuning: Use advanced techniques like Grid Search or Randomized Search to further optimize the hyperparameters of the Logistic Regression model, potentially increasing the F1-Score by a few tenths of a percent.

2. Deep Learning Exploration: Explore models specialized for sequence data, such as **Long Short-Term Memory (LSTM) networks** , to capture more intricate semantic patterns that linear models like LR might miss.

3. Database Logging: Integrate a database (like Firestore or PostgreSQL) to log user predictions and model performance over time, enabling continuous monitoring and retraining data collection.

4. Containerization: Package the entire application (Flask API, model files) using Docker to ensure environment consistency and simplify deployment to cloud platforms like Heroku or AWS.