ML For Business II Final Project

Predicting YouTube Spam Comments

Group Members:
Elie LAFORGE
Yunan WANG

Introduction

- Objective: Predict whether a YouTube comment is spam (`1`) or not (`0`).
- Dataset sourced from Kaggle, labeled in the `CLASS` column.

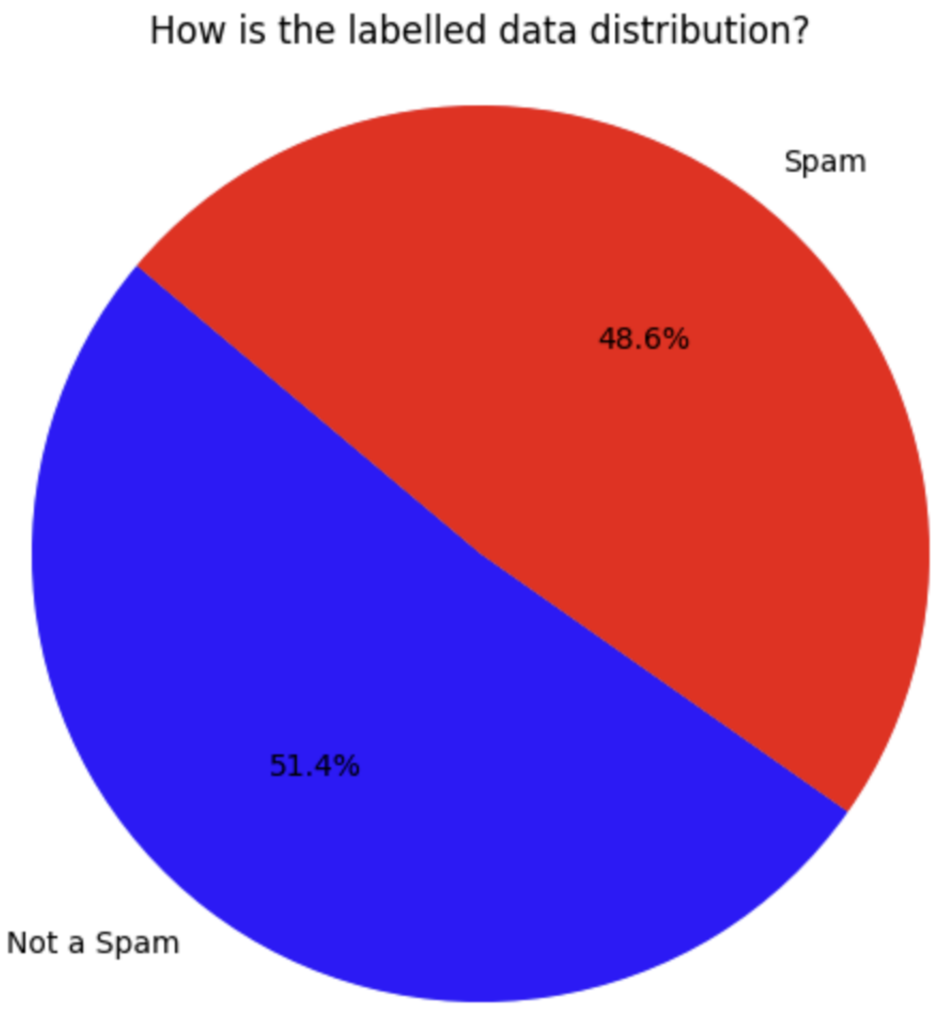
Dataset Overview

- Dataset contains labeled comments from YouTube.
- Key features include comment_id, author, date, content and video name.
- Target column: `CLASS` (1 = spam, 0 = not spam).

Exploratory Data Analysis (EDA)

Label Distribution

- Analyze distribution of spam vs. non-spam comments.



Exploratory Data Analysis (EDA)

Word Cloud

- Visualizing common words in spam comments

Data Preprocessing

- Data cleaning steps:
    - Handling missing values.
    - Removing duplicates.
    - Text vectorization using TF-IDF.

Model Selection

- Tried different models:
  - Logistic Regression (tested with both TF-IDF and Count Vectorizer)
  - Bernoulli Naive Bayes
  - XGBoost

Model Evaluation

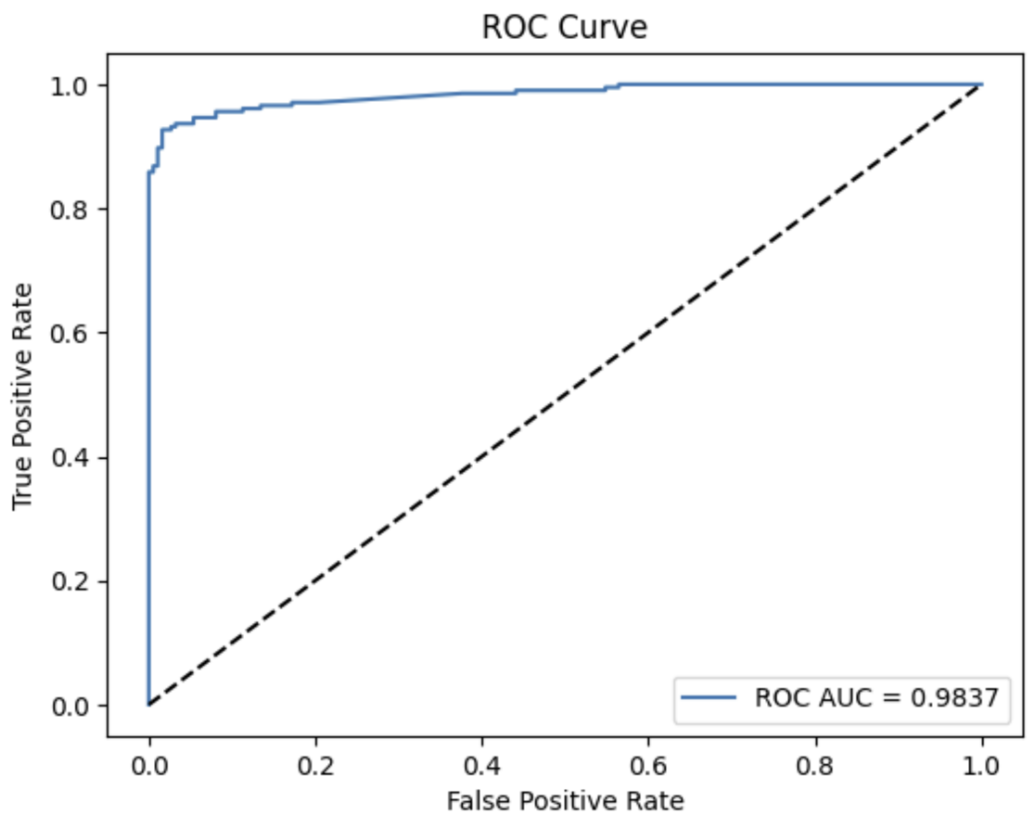
- Metrics used:
  - Accuracy
  - Precision
  - Recall
  - F1 Score
  - ROC-AUC (Receiver Operating Characteristic Area Under the Curve)
- Compared performance across models.

Models tried

Metrics	Log Reg	Naive Bayes	XGBoost
Accuracy	0.90	0.78	0.90
F1-Score	0.89	0.73	0.89
ROC-AUC	0.95	0.90	0.96

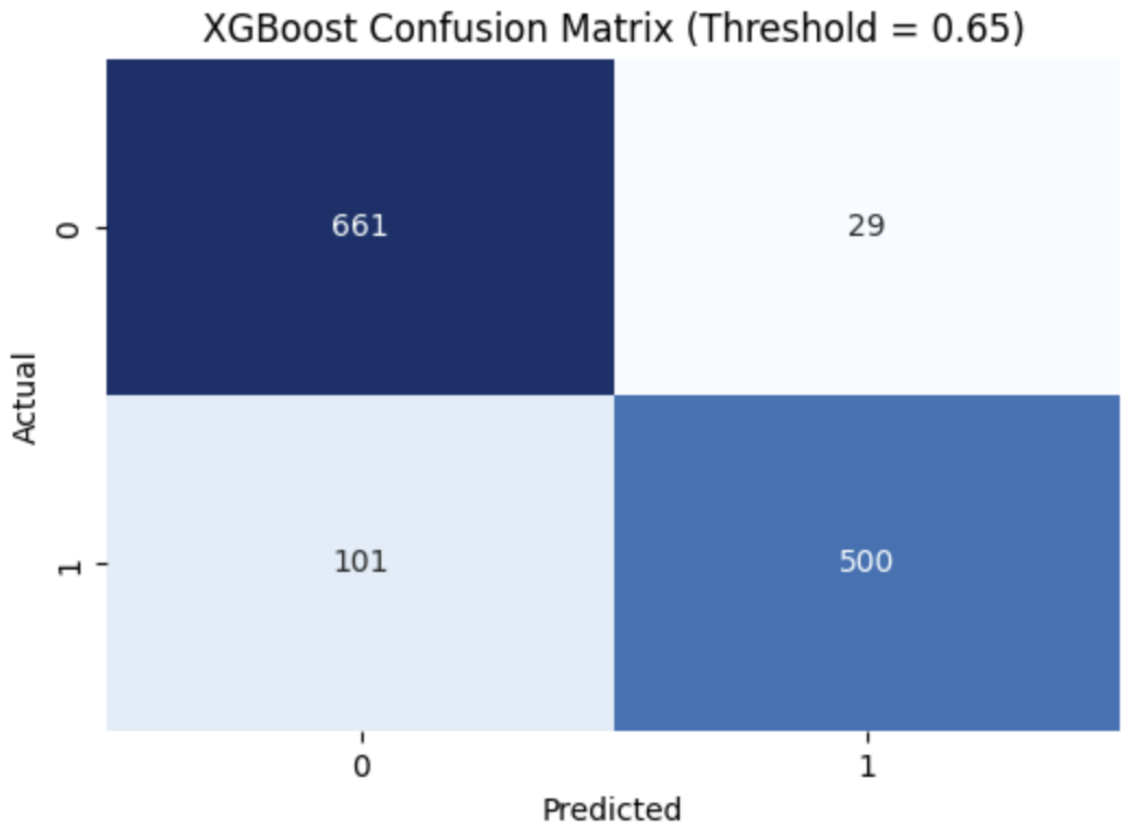
Best Model : XGBoost

- Best performance observed with XGBoost.
- TF-IDF vectorization + hyperparameter tuning.
- Performance metrics:
    - Accuracy on test: 0.95
    - F1 Score: 0.95
    - ROC-AUC : 0.98



Results Visualization

- Confusion matrix of the best model.
- Hyperparameters tuned:
    - learning rate = 0.2
    - max depth = 6
    - n estimators = 150



Recap

- XGBoost + TF-IDF gave the best performance.
- Spam detection accuracy: 90%.

DevOps Structure: Chrome Extension

Frontend PoC with Chrome Extension

- Connect to backend API server deployed on Heroku.
- Dynamically insert a pill into the comment section to indicate the spam probability.

DevOps Structure: Testing

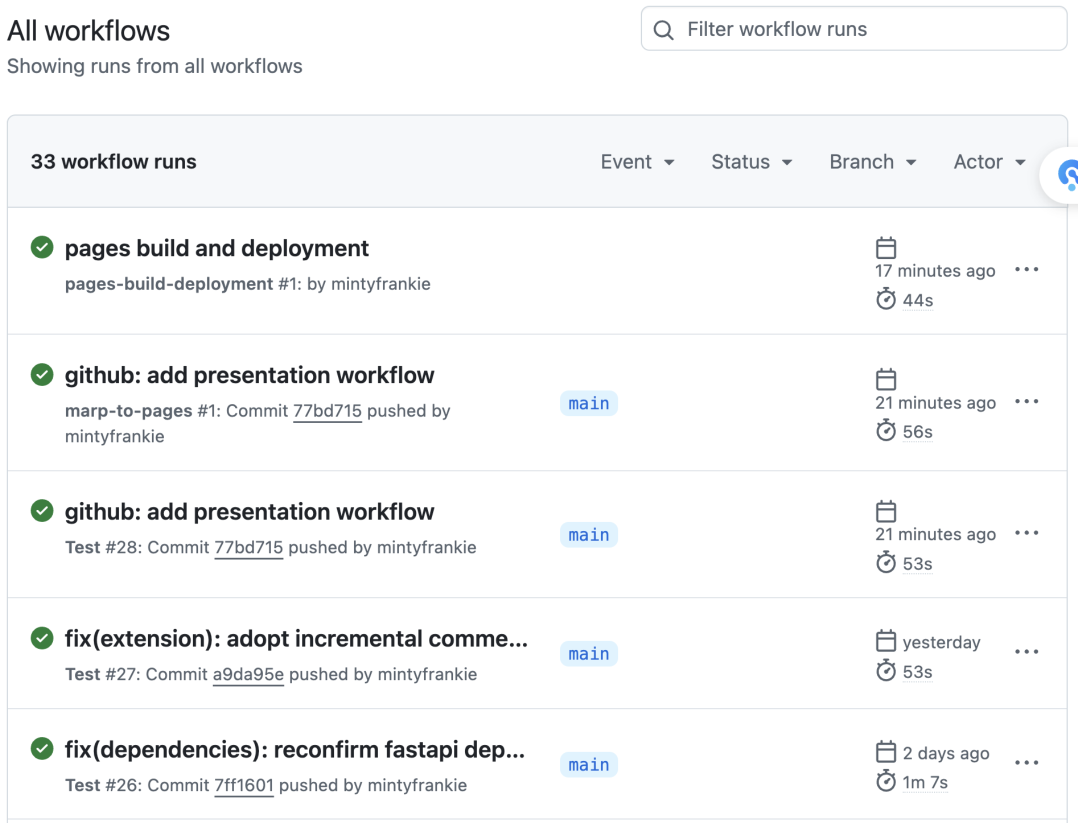
Unit testing with pytest on API server, covering all the endpoints and edge cases; For example:

- requests with empty content;
- malformed requests;
- internal server errors (model loading failure, etc.)

DevOps Structure: CI/CD

Main tool: GitHub Actions

- Code quality check on commits & PRs (format, linting, unit testing)
- Build Docker image and push to GitHub Container Registry
- Deploy to Heroku worker
- Compile this Marp deck and publish to GitHub Pages



DevOps Structure: Experiment Tracking

- MLFlow for experiment tracking on Databricks
  - Two environments: staging and production
  - Log parameters, metrics, and model artifacts.
- Leverage `mlflow.autolog()` to automatically log parameters, metrics, and model artifacts.

Live demo time!

Next Steps

- Potential improvements:
  - Use deep learning models (e.g., LSTM, BERT).
  - Experiment with more feature engineering.
  - Use an even larger dataset to have an even more general model

- Sell it to Youtube and live off the profits!