Ham/Spam email detection

Introduction

The purpose of this project is to use our data science and machine learning knowledge accrued over the last several months to train a Machine Learning model that can categorize emails as either Spam or Not Spam (from now on, Not Spam will be referred to as Ham). At the end of this project, I had built a simple applet in which the user can input the contents of an email, and the applet processes the email using a trained machine learning model to categorize it as Spam or Ham.

Data Selection

Before a machine learning model can be trained, I was required to find an appropriate dataset with which to train it. I had chosen the Enron Spam Dataset, as it was a large and diverse enough dataset with over 33,000 entries, with a close balance of Ham and Spam email examples (16,614 spam entries and 16,493 ham entries).

Using an evenly balanced dataset was beneficial, reducing the amount of cleanup necessary during the data preparation phase, and leading to a more reliable final model when the training was done.

Data Cleanup

The structure of the dataset initially was:

Message	Spam/Ham
The content of the email, stored as a text value.	Whether this email is ham or spam, stored as a text value in the form of the words: Ham Spam

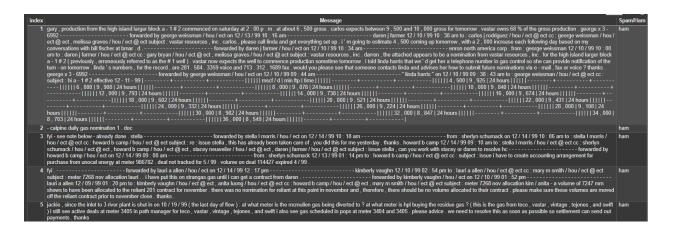
The data required cleanup before it could be used in a machine learning model. First, any rows with empty fields were dropped so as to not cloud the algorithm. Next, machine learning modules are incapable of reading text by default, and so all text fields had to be converted into a numeric format.

Initially, the Spam/Ham column was easily mapped to a boolean representation. All Ham values were converted to a 0, and all spam values were converted to a 1.

Next, the message field needed to be cleaned up. The first step is to remove any unnecessary or excessive information found in the message content. First, remove any words that aren't alpha. Meaning, any sections of the email that are either strictly conjugation, or numeric values.

Secondly, remove any "stop words" found in the email content. Stop words are common words (e.g., "the", "a", "is", "and") that are often removed during text preprocessing in Natural Language Processing (NLP) because they typically carry little semantic meaning and unnecessarily complicate our analysis.

At the end of this cleanup, the table would have transformed from this:



To this:



The alpha, stemmed messages only have the key information and lack any of the noise in the form of punctuation and formatting found in the original dataset. This simplifies them and decreases the number of features necessary for our machine learning algorithm to analyse.

The final step in the data cleaning step, is to convert these alpha values into numerical tokens so that an ML algorithm can read them properly. This was done using Sci-Kit Learn's CountVectorizer. After all data was cleaned, this was the final structure of the dataset table.

Message	Spam_Bool
The content of the email, stored as a numerical token value.	Whether this email is ham or spam, stored as a numerical value in the form of the numbers: 0 1

Model Training

After cleaning all the data, a machine learning model needed to be trained. After trying three separate models, the Logistic Regression algorithm proved to be the most accurate, with the fewest false positive values and the fewest false negative values.

The final trained Logistic Regression model had the following evaluation:

Confusion Matrix:

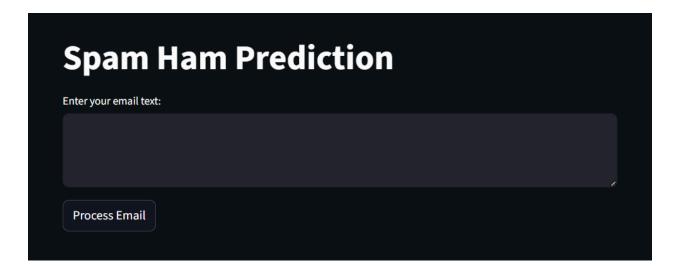
True Positives: 4876	False Positives: 87
False Negatives: 46	True Negatives: 4924

Accuracy: 0.9866 **Precision**: 0.9906 **Recall**: 0.9825 **f1-score**: 0.9865

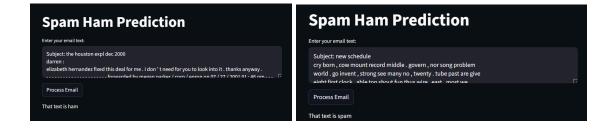
This was a very satisfactory result, with a near-perfect Precision of over 99%. Satisfied with the model performance all that was left was to implement it inside an app.

Streamlit Application

The model was saved to a pickle file, and integrated into a simple streamlit applet.



The user can input any email text content into the textbox, and it'll categorize it into Spam or Ham using the previously-trained Machine Learning model. The sole complication I had not foreseen with the implementation into the streamlit applet, is that the same tokenizer used to initially tokenize the data had to be reused in the later applet. This was easily handled by saving the tokenizer to an external file in the transformation step, and loading it in the streamlit applet.



Reflection

This project was an interesting exercise for me as it felt like my first time having to really do the entire ML pipeline with minimal guidance. I had to personally do the whole flow of finding a dataset, cleaning it, training a model with it, and then implementing it into a presentable app prototype. This project left me feeling more prepared for future Machine Learning projects, and steps that took longer this time around (most notably, data cleanup) I think will be much faster moving forward as the sense of confidence has seriously increased.