Spam Email Detection

4AI3 Final Report

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ABSTRACT

In today's digital landscape, the constant flood of spam emails poses a significant threat to both user experience and online security. This report delves into the development of a spam email detection model utilizing the Multinomial Naive Bayes classifier. By focusing on the intricacies of the algorithmic framework, data acquisition, preprocessing, and model training, this project aims to provide a comprehensive solution to mitigate the impact of unwanted and potentially harmful emails. The report emphasizes the practicality and real-world applicability of the developed model, showcasing its potential to enhance user security and overall email experience.

I. INTRODUCTION

Spam emails have become a pervasive issue in the digital age, posing challenges to user convenience and online safety. This report outlines the creation of a spam email detection model leveraging the Multinomial Naive Bayes classifier. The algorithm's effectiveness stems from its ability to discern between spam and ham emails through a meticulous process. This includes data acquisition and preprocessing, text vectorization, model training, and real-world testing. By understanding the nuances of each step, we can appreciate the model's capability to accurately classify emails, thereby improving user security and experience.

II. HOW THE ALGORITHM WORKS

Our spam detection system relies on the Multinomial Naive Bayes classifier, known for its efficiency in text classification. The algorithm distinguishes between spam and ham emails through a sequence of calculated steps: *Figure a.1* shows these steps.

A. Algorithmic Framework

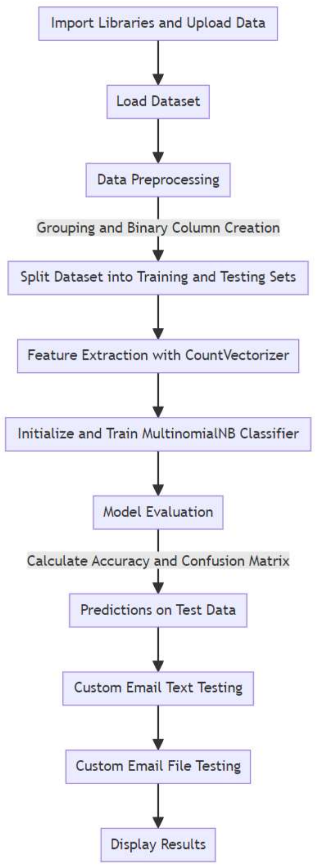
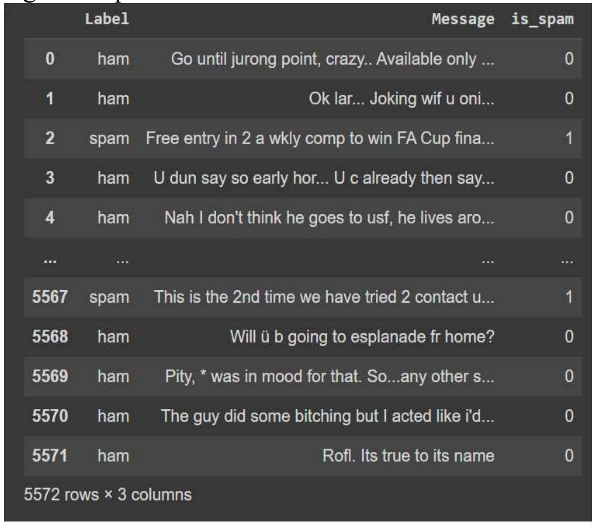

Import Libraries and Upload Data
Load Dataset
Data Preprocessing
Grouping and Binary Column Creation
Split Dataset into Training and Testing Sets
Feature Extraction with CountVectorizer
Initialize and Train MultinomialNB Classifier
Model Evaluation
Calculate Accuracy and Confusion Matrix
Predictions on Test Data
Custom Email Text Testing
Custom Email File Testing
Display Results

Figure a.1 shows the framework for spam detection model

B. Data Acquisition and Preprocessing

The process starts by acquiring a dataset labeled "spam.csv," containing emails categorized as 'spam' or 'ham' (non-spam). This dataset serves as the foundation for the algorithm's learning phase. After loading the data into a Pandas Data Frame, a binary column 'is_spam' is created as seen in *figure b.1*to indicate whether emails are spam (1) or ham (0). This simplifies subsequent processing steps for optimal algorithm performance.



	Label	Message	is_spam
0	ham	Go until jurong point, crazy.. Available only ...	0
1	ham	Ok lar... Joking wif u oni...	0
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	1
3	ham	U dun say so early hor... U c already then say...	0
4	ham	Nah I don't think he goes to usf, he lives aro...	0
...	...	...	...
5567	spam	This is the 2nd time we have tried 2 contact u...	1
5568	ham	Will ü b going to esplanade fr home?	0
5569	ham	Pity, * was in mood for that. So...any other s...	0
5570	ham	The guy did some bitching but I acted like i'd...	0
5571	ham	Rofl. Its true to its name	0

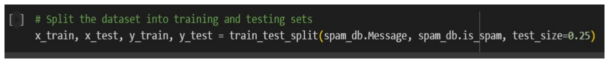
5572 rows × 3 columns

Figure b.1 shows the data frame contents with newly added 'is_spam' binary column.

C. Text Vectorization

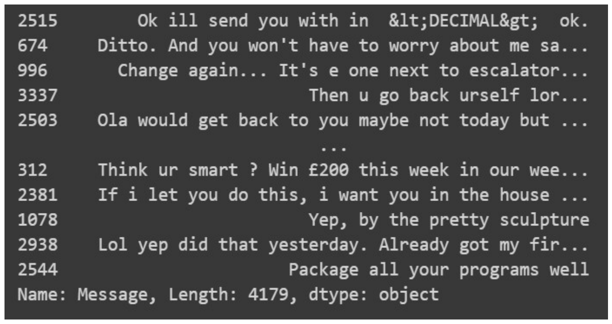
Data Splitting and Text Vectorization:

The dataset is divided into a 75% training set and a 25% testing set for robust model validation. By employing the Count Vectorizer, email texts are converted into a numerical format, producing a sparse matrix of token counts (*as seen in figure c.4*). Each email is transformed into a vector, capturing the frequency of individual words. This process serves as the foundation for our model's interpretation.



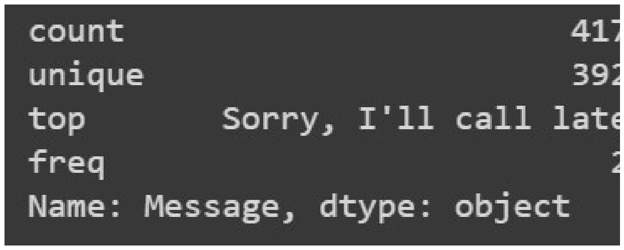
```
[ ] # Split the dataset into training and testing sets
    x_train, x_test, y_train, y_test = train_test_split(spam_db.Message, spam_db.is_spam, test_size=0.25)
```

Figure c.1 shows implementation of train and test data and setting up test size.



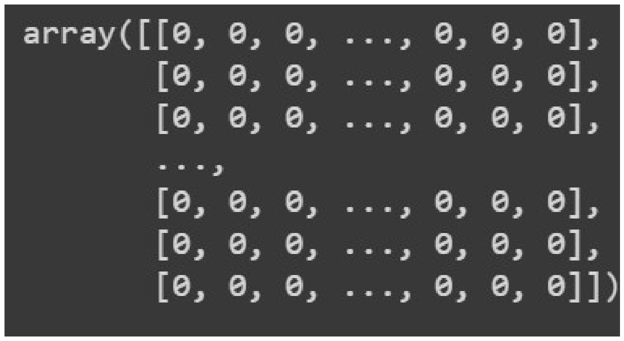
```
2515         Ok ill send you with in  &lt;DECIMAL&gt;  ok.
674      Ditto. And you won't have to worry about me sa...
996        Change again... It's e one next to escalator...
3337                         Then u go back urself lor...
2503     Ola would get back to you maybe not today but ...
                                ...
312      Think ur smart ? Win £200 this week in our wee...
2381     If i let you do this, i want you in the house ...
1078                         Yep, by the pretty sculpture
2938     Lol yep did that yesterday. Already got my fir...
2544                         Package all your programs well
Name: Message, Length: 4179, dtype: object
```

Figure c.2 shows the trained data



```
count                                 417
unique                                392
top        Sorry, I'll call late
freq                                    2
Name: Message, dtype: object
```

Figure c.3 shows statistical information about trained data

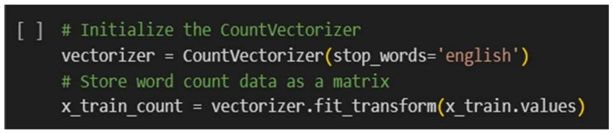


```
array([[0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       ...,
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]])
```

Figure c.4 shows how training data looks after being transformed and converted to matrix by count vectorization.

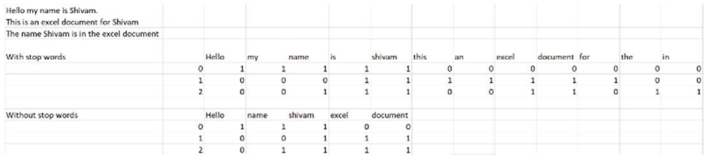
Enhanced Feature Extraction through Stop Word Exclusion:

To refine feature extraction, common English stop words are intentionally excluded during vectorization (*as seen in figure c.5*). This deliberate removal of commonplace language elements allows the model to concentrate on more meaningful patterns within the text. This strategy significantly contributes to the overall efficacy of the model, enabling it to discern valuable information from the dataset. *Figure c.6* showcases how count vectorization process works with and without stop words.



```
[ ] # Initialize the CountVectorizer
    vectorizer = CountVectorizer(stop_words='english')
    # Store word count data as a matrix
    x_train_count = vectorizer.fit_transform(x_train.values)
```

Figure c.5 shows how count vectorizer is initialized with stop words filter.



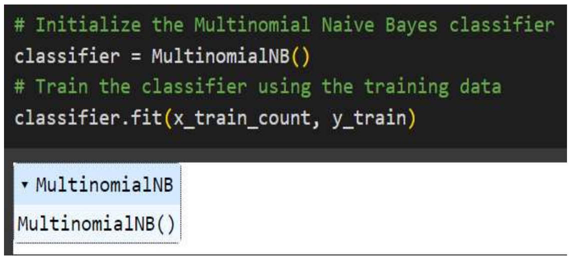
Hello my name is Shivam.
This is an excel document for Shivam
The name Shivam is in the excel document

With stop words	Hello	my	name	is	shivam	this	an	excel	document	for	the	in
0	1	1	1	1	1	0	0	0	0	0	0	0
1	0	0	0	1	1	1	1	1	1	1	0	0
2	0	0	1	1	1	0	0	1	1	0	1	1
Without stop words	Hello	name	shivam	excel	document							
0	1	1	1	0	0							
1	0	0	1	1	1							
2	0	1	1	1	1							

Figure c.6 shows how text vectorization works

D. Model Training

At the core of our spam email detection system is the Multinomial Naive Bayes classifier, a probabilistic algorithm rooted in Bayes' Theorem. This framework calculates probabilities to discern whether an email is spam or ham based on the presence of specific words.



```
# Initialize the Multinomial Naive Bayes classifier
classifier = MultinomialNB()
# Train the classifier using the training data
classifier.fit(x_train_count, y_train)

▾ MultinomialNB
MultinomialNB()
```

Figure d.1 shows how Multinomial Naive Bayes is implemented

Probabilistic Components:

P(spam|words): is the probability that an email is spam given the words in the email.
P(ham|words): is the probability that an email is ham given the words in the email.
P(words|spam) and P(words|ham) are the likelihoods of observing the words in the given class (spam or ham).

Multinomial Naive Bayes Framework:

1. **Prior Probability Calculation:**
   Calculate the prior probabilities P(spam) and P(ham) based on the proportions of spam and ham emails in the training dataset.

2. **Likelihood Calculation:**
   For each word in the vocabulary, calculate the likelihood of observing that word in the given class (spam or ham).

3. **Posterior Probability Calculation:**
In this step, we use Bayes' Theorem to calculate the probability that an email belongs to a specific class (spam or ham) given the observed words in the email. This is done for both spam and ham classes as seen in formulas shown *in figure d.3 and d.4.*

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

Figure d.2 shows formula for general bayes theorem

$$P(\text{spam}|\text{words}) = \frac{P(\text{words}|\text{spam}) \cdot P(\text{spam})}{P(\text{words})}$$

Figure d.3 shows formula used to calculate the probability of the word being spam.

$$P(\text{ham}|\text{words}) = \frac{P(\text{words}|\text{ham}) \cdot P(\text{ham})}{P(\text{words})}$$

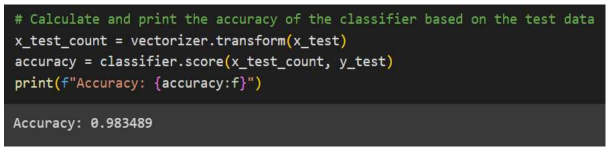
Figure d.4 shows formula used to calculate the probability of the word being ham.

4. **Class Assignment:**
Assign the class label (spam or ham) based on the higher posterior probability.

If P(spam|words)>P(ham|words), the email is classified as spam.
If P(spam|words)<P(ham|words), the email is classified as ham.

E. Prediction and Evaluation

Following the training phase, the model uses the testing set to make predictions, and its performance is evaluated using the **classifier.score()** method (*Shown in figure e.1).* This method takes the transformed test data, represented as 'x_test_count,' predicts labels using the trained classifier, and compares these predictions with the true labels ('y_test'). The resulting accuracy score reflects the proportion of correctly predicted instances among the total number of instances in the test set. This evaluation approach provides a quantitative measure of the model's proficiency in correctly classifying previously unseen data, contributing to a holistic assessment of its predictive capabilities.



```
# Calculate and print the accuracy of the classifier based on the test data
x_test_count = vectorizer.transform(x_test)
accuracy = classifier.score(x_test_count, y_test)
print(f"Accuracy: {accuracy:f}")

Accuracy: 0.983489
```

Figure e.1 shows how accuracy is assed for the model

F. Confusion Matrix Visualization

To gain insights into the model's performance, a confusion matrix is generated and visualized (*as seen in figure f.1 below*) using seaborn and matplotlib. It makes predictions on the test data, calculates the confusion matrix by comparing predictions with actual labels, and creates a heatmap for a clear representation. This resulting visualization provides insights into the model's accuracy in classifying spam and non-spam instances by detailing true positives, false positives, true negatives, and false negatives. The detailed breakdown of these components in the confusion matrix allows for a nuanced evaluation of the classifier's ability to discern between spam and non-spam instances, offering a comprehensive view of its strengths and weaknesses.

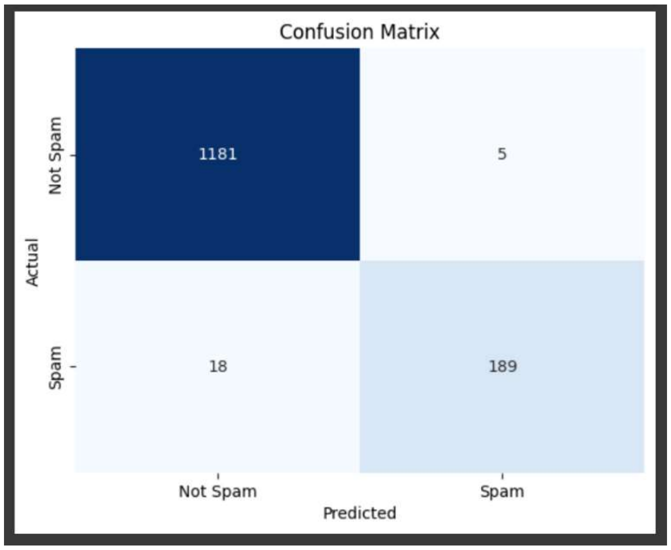
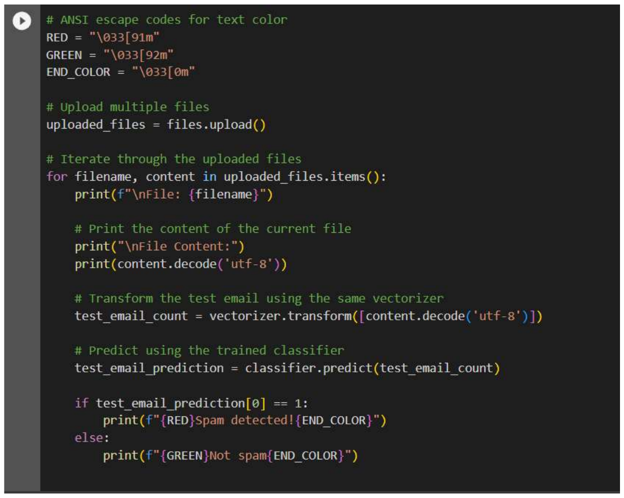


Figure f.1 Shows confusion matrix of the model. It provides insight into the model's accuracy in classifying spam and non-spam.

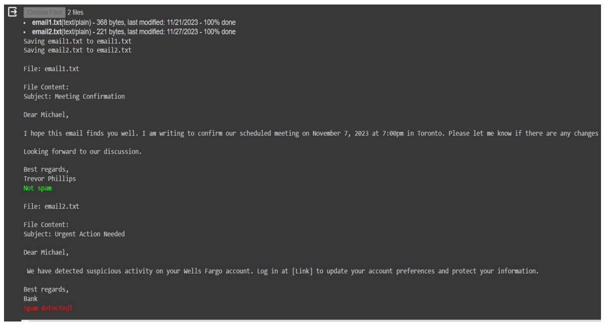
G. Real-world Testing

The code shown in *figure g.1* and output in *figure g.2* presents an interactive real-world demonstration of the spam classifier's performance. Users have the option to upload multiple files for evaluation. The implementation utilizes ANSI escape codes to colorize the output, making it visually clear with red indicating spam and green indicating non-spam predictions. For each uploaded file, the code displays the file's name and content, transforming the content using the vectorizer applied during training. The trained classifier then predicts whether the content is spam or not, providing a practical showcase of the model's effectiveness in handling diverse input sources.



```
# ANSI escape codes for text color
RED = "\033[91m"
GREEN = "\033[92m"
END_COLOR = "\033[0m"

# Upload multiple files
uploaded_files = files.upload()

# Iterate through the uploaded files
for filename, content in uploaded_files.items():
    print(f"\nFile: {filename}")

    # Print the content of the current file
    print("\nFile Content:")
    print(content.decode('utf-8'))

    # Transform the test email using the same vectorizer
    test_email_count = vectorizer.transform([content.decode('utf-8')])

    # Predict using the trained classifier
    test_email_prediction = classifier.predict(test_email_count)

    if test_email_prediction[0] == 1:
        print(f"{RED}Spam detected!{END_COLOR}")
    else:
        print(f"{GREEN}Not spam{END_COLOR}")
```

Figure g.1 shows the code used to test the model using email text files.



```
Choose Files 2 files
• email1.txt(text/plain) - 368 bytes, last modified: 11/21/2023 - 100% done
• email2.txt(text/plain) - 221 bytes, last modified: 11/27/2023 - 100% done
Saving email1.txt to email1.txt
Saving email2.txt to email2.txt

File: email1.txt

File Content:
Subject: Meeting Confirmation

Dear Michael,

I hope this email finds you well. I am writing to confirm our scheduled meeting on November 7, 2023 at 7:00pm in Toronto. Please let me know if there are any changes

Looking forward to our discussion.

Best regards,
Trevor Phillips
Not spam

File: email2.txt

File Content:
Subject: Urgent Action Needed

Dear Michael,

 We have detected suspicious activity on your Wells Fargo account. Log in at [Link] to update your account preferences and protect your information.

Best regards,
Bank
Spam detected!
```

Figure g.2 shows output of testing multiple email text files.

III. Conclusion

In conclusion, the developed spam detection model showcases a pragmatic approach to categorizing emails as spam or ham, demonstrating its potential for real-world applications. By systematically addressing each phase, from data acquisition to model training, the model offers an efficient solution for filtering unwanted emails in users' inboxes. The project underscores the importance of robust algorithms in enhancing cybersecurity and user experience in the face of evolving digital threats.

IV. References

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