STA141C: Email Spam Classification Model

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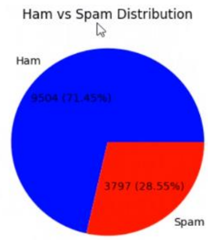
Introduction:

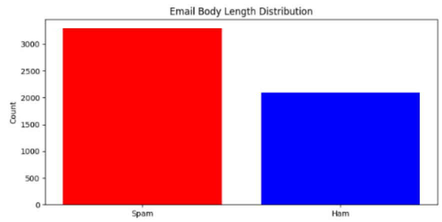
Most people know what spam emails are. If not, they are unsolicited messages sent via email that can range from advertisements to malware. More often than not, these types of emails are a nuisance and should not be in anyone's inbox. When people see the spam folder, do they ever stop and think about how it works? Or do they assume that it just works? Either way, there are many methods for separating spam emails from non-spam (ham) emails.

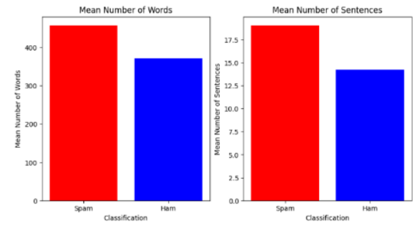
Our goal is to determine how to classify an email as spam or ham. We focused on a database from *spamassassin* which is verified and publicly available. The database was made specifically to test spam classification methods on. Each email is checked to ensure that no confidential or sensitive information is shared, along with swapping personal email addresses with dummy email addresses. The types of emails included in the *spamassassin* database consist of newsletters, email lists, work emails, advertisements, and scams. They are already separated into spam and ham categories which is extremely important for testing how accurate our classification methods are. There are thousands of emails, and it would be impossible to categorize each and every email on our own, hence the main reason we chose this database.

We chose ten classification models: logistic regression, linear discriminant analysis, quadratic discriminant analysis, decision tree, K-nearest neighbor, random forest, bagging classifier, extra trees, gradient boosting, XGBoost. Each of these models were selected for three reasons consisting of accuracy, computational complexity, and interpretability. We used these three reasons as a guideline to decide which model was the "best" model. Deciding which model is the "best" is subjective, though because the decision is based on which of the three reasons we prioritized the most. We wanted accuracy to be the top priority without sacrificing too much of the interpretability. Computational complexity was still very important, but we were willing to sacrifice that if need be for our case.

Exploratory Data Analysis:

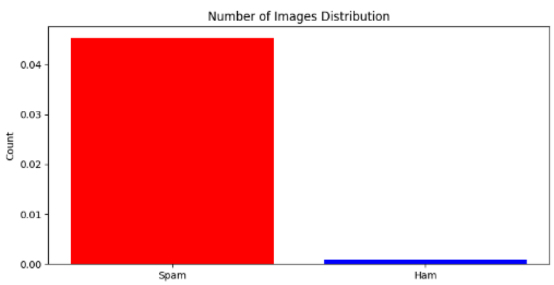


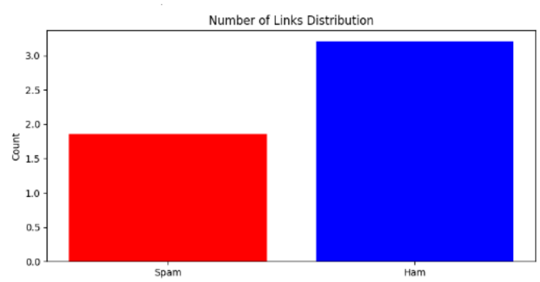




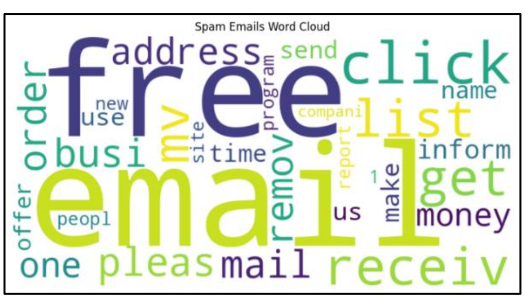
We explored our dataset by first visualizing the class distribution of “Ham” and “Spam,” and noticed that almost three-fourth of the emails were classified as “Ham”, while the remaining emails were classified as “Spam.” After then checking the mean number of characters, words, and sentences each class contained, we discovered “Spam” emails contained the most for all these characteristics, thereby revealing that the length of each “Spam” email was longer than that of each Ham email.

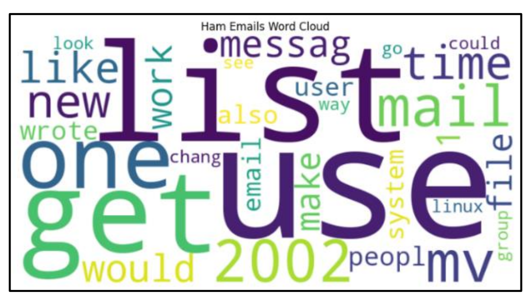
Furthermore, we gathered the mean number of links and images per email and observed that there were more links in the “Ham” emails, whereas there were more images in the “Spam” emails.



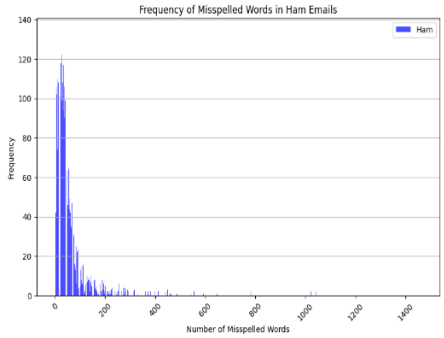


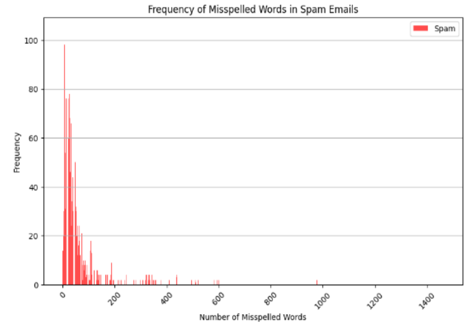
Additionally, we observed the word cloud for each class. In these word clouds, the larger a particular word appears, the more frequently it occurs in each class. While “Ham” showed seemingly mundane words, “Spam” showed words such as “click,” “free,” and “money”, which are expected to appear frequently in “Spam” emails as one is most likely being scammed.





Finally, we used a spell-checker in Python to gather the frequency of misspelled words in each class because we expected more misspelled words in the “Spam” class. However, we did not notice much of a difference between the classes. This was unexpected but considering the relatively smaller number of “Spam” emails in comparison to “Ham”, this frequency is not entirely negligible.





Methodology:

As far as methodology is concerned, we first performed the **acquisition and storage** of our unprocessed data. After downloading the pre-categorized subsets of our overall dataset, we placed them into two corresponding subfolders titled “Ham” and “Spam”. We then placed these subfolders into a main folder titled “Email” and looped through this folder structure in Python (programming language) while appending all files to a list (Python object) **to better manage the data**.

Next, we **processed our data** by first **standardizing** each email’s text through techniques such as lowercasing, tokenizing, and stemming. These techniques, which made different variations of a specific word equivalent in the context of text classification, resulted in a cleaner, more uniform dataset, thereby improving our models’ accuracy and efficiency. We further improved our models’ accuracy by **removing** English stopwords (“and,” “the”, etc.), punctuation, html tags, and other irrelevant text from each of the emails. Our last processing step was **extracting** the body of each email, as the email body generally contained the most contextually relevant information. This technique, along with all other processing techniques, **was chosen** because they significantly reduce noise and focus the model on the most discriminative features, streamlining the classification process and enhancing the overall predictive power.

After processing each email, we created a dictionary (Python object) for each cleaned email. For each dictionary, we stored two key-value pairs, with the values being each cleaned email’s classification, which was determined by a previously written function, along with the cleaned email itself. We then aggregated all dictionaries into a Dataframe (Python object), and within this Dataframe, we created a new column for our prepared texts, which served as our sole feature variable. We also set our sole label as Email Classification.

To understand the essence of each email better and help our models learn to differentiate between Ham and Spam effectively, we applied a technique called TF-IDF vectorization onto our prepared texts. This method transforms the prepared texts into a numerical format, emphasizing words that are most telling of an email's nature while considering the unique context of our entire dataset. Specifically, the prepared texts variable was transformed from a column vector to a matrix, with the matrix containing each cleaned email and the 3000 most important words for rows and columns, respectively. This serves as an example of **feature extraction,** as we transformed our single feature into a matrix with 3000 features, which is crucial for optimizing the performance of classifiers that rely on individual token importance. We also converted our classes “Ham” and “Spam” to numerical values “0” and “1”, respectively. This conversion was necessary because classifiers only accept numerical values for labels.

After performing a standard 80-20 percent split of our data into training and test sets, respectively, we initialized many different classifiers, ranging from Logistic Regression to XGBoost. **We chose many classifiers (prediction models) for the sake of comparison and contrast**, which could provide further insights into why certain models may perform better than others. However, the primary classifiers we were concerned with optimizing were Logistic Regression, QDA, and Decision Tree, as we covered these in lecture. We then performed 5-fold cross validation to assess the robustness of each classifier, before training and predicting with all the same classifiers to obtain our prediction performance results.

Main Results:

Based on the scores for cross-validation, we can see that most models passed the robustness check. We can see that K-nearest neighbor had the lowest score, and that extra trees had the highest score. Overall, each model achieved relatively high scores which is good and shows that our classifiers performed well. Next, we performed an accuracy test on each model.

```
Cross-Validation:
Logistic Regression: 0.9772
LDA: 0.9682
QDA: 0.9702
Decision Tree: 0.9629
K-Nearest Neighbors: 0.8932
Random Forest: 0.9783
Bagging Classifier: 0.9635
Extra Trees: 0.9838
Gradient Boosting: 0.9458
XGBoost: 0.9738
```

The Model Performance summary (depicted to the right) exhibits robust performance amongst all models except for K-Nearest Neighbors (KNN). KNN’s poor performance may be attributed to our feature existing in a 3000-dimensional space. In such a high-dimensional space, the difference in distance between the nearest and farthest data points tends to be less distinct, making it harder to identify which points are truly closest to each other. Since this phenomenon, known as the “curse of dimensionality”, complicates KNN’s ability to make distinctions for the distances between points, the effectiveness of the algorithm is reduced significantly.

```
Model performance summary:
Logistic Regression: 0.9835
LDA: 0.9872
QDA: 0.9718
Decision Tree: 0.9846
K-Nearest Neighbors: 0.6490
Random Forest: 0.9947
Bagging Classifier: 0.9853
Extra Trees: 0.9951
Gradient Boosting: 0.9714
XGBoost: 0.9936
```

Regarding classifiers covered (at least broadly) in lecture, some of the ensemble methods (Random forest and Extra Trees) exhibit **superior performance** compared to all other classifiers, with performance scores of .9947 and .9951, respectively. These scores can be attributed to these methods merging the judgements of numerous decision trees, each informed by a subset of the 3000 most important words, thereby utilizing their combined insight for better distinguishment between spam and non-spam emails. Although these ensemble methods performed well, their counterpart in the Decision Tree performed slightly worse (.9853), possibly because the Decision Tree overfitted (captured random fluctuations) in the training data, which essentially means the Decision Tree model was too complex for the given data. The other ensemble methods, namely XGBoost and Gradient Boosting, also performed well , with any differences in performance potentially arising from how these algorithms deal with the specific data.

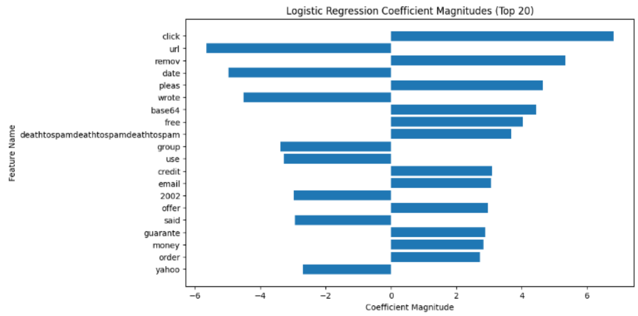
Logistic Regression and Linear Discriminant Analysis (LDA) also show strong performance, with scores above 0.98. These models are typically less complex than ensemble methods, which can make them faster to train and easier to interpret. The high accuracy of Logistic Regression and LDA suggests that the relationship between the features and the target variable can be effectively captured by linear boundaries. Interestingly, QDA (Quadratic Discriminant Analysis) performed worse than LDA, which indicates that it is not beneficial to assume a quadratic decision boundary over a linear one in this case. This further supports the idea that complexity, rather than leading to better performance, can sometimes result in an **overgeneralization of the patterns in the training data**.

In summary, the ensemble classifiers perform slightly better in our procedure, although the more simplistic models like Logistic Regression and LDA also perform well. These results suggest that the data has an inherent structure that ensemble methods can exploit very effectively, but the data is also well- captured by linear models, indicating a mix of complex and simple relationships within the features.

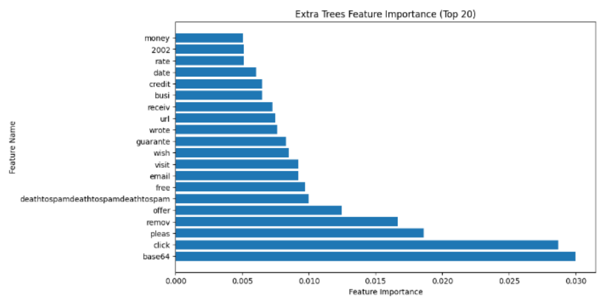
Discussion and Outlook:

From our results it might seem easy to choose which model is best for our classification, that being the extra trees method, which had the highest accuracy. As mentioned, we must also consider the interpretability and computational complexity of each model. The ensemble methods and Logistic Regression had some of the highest performance summaries. We omitted LDA because Logistic Regression had almost the same accuracy and has higher interpretability than LDA.

This graph plots the most common words found against the coefficient magnitude. Positive values contribute to emails classified as spam, and negative values contribute to emails classified as ham. “Click” was the word that contributed most to spam emails. URLs, surprisingly, contributed most to ham emails. That does not mean that there are not suspicious URLs out there. If a URL seems suspicious do not click on it.



On the right is the plot for extra trees. The plot gives us the importance of the most common words and phrases, but it cannot tell us how each of the words contributes to classification. “Base64” itself is not a word, but is an encoding commonly found in spam emails to spread malware. Logistic Regression has higher interpretability than extra trees and can be more useful in this case.



Conclusion:

Based on our findings, we are now equipped to make the appropriate choice for our final model. The classification accuracy is the most important factor for selecting a final model, and we have discovered that all models were very accurate, with” K-nearest neighbors” being the only exception. We also learned that “Extra Trees” had the highest accuracy, but “logistic regression” had the second highest accuracy. This is because “Extra Trees” utilizes the same method and possesses the same interpretability, whereas logistic regression has a different interpretability. Based on the accuracy and interpretability of these top two classifiers, it would be most reasonable to conclude that “**logistic regression” is the best classification method for spam versus non-spam emails.** This is because “logistic regression” has an extremely high accuracy and superior interpretability compared to “Extra Trees”.

Bibliography

Spamassasin, 2018, https://spamassassin.apache.org/old/publiccorpus/

STA141CFinalProjectCode

March 18, 2024

Code Appendix

[1]:
```
#Appropriate Folder Setup

#1. Create two new folders specifically named 'Ham' and 'Spam'. At the end,␣
↪these will be subfolders placed in the main 'Email' folder.

#2. Download each zipfile for each subset of the data from https://spamassassin.
↪apache.org/old/publiccorpus/

#3 Extract each zip file for each subset into the corresponding 'Ham' or 'Spam'␣
↪folder, while ignoring the detection difficulty aspect of the subsets

#4  Once all the data has been placed in the appropriate subfolder, create a␣
↪new folder specifically titled "Email",  and place the two
#subfolders into the 'Email' folder.

#5 You guys must also run the following two lines of code once
# nltk.download('punkt')
# nltk.download('stopwords')

#These download the Punkt tokenizer models, as well as a collection of␣
↪stopwords, and are both essential resources for NLTK (Natural Language␣
↪Toolkit)
```

[2]:
```
# Step 1: Importing Neccesary
import os #Importing os to navigate through the "Email" folder and get all␣
↪files
import pandas as pd
import nltk # Importing nltk, which is used a lot for preprocessing the data
from nltk.stem.porter import PorterStemmer #Importing PorterStemmer, used for␣
↪"stemming" or reducing words to their base
from nltk.corpus import stopwords
import string
from collections import Counter # Importing counter function for when we need␣
↪to get most common words from  both Ham and Spam emails
```

```
from bs4 import BeautifulSoup #Importing BeautifulSoup to extract HTML content␣
↪that we won't want to include in our "content" variable


# NEED to run these next 2 lines of code below ONCE to tokenize the text, and␣
↪remove stopwords (words like "and",or "the" that aren't meaningful)
nltk.download('punkt')
nltk.download('stopwords')


#STEP 1: (Preprocessing) Stemming the words to

#Initializing the PorterStemmer, used for "stemming" or reducing words to their␣
↪base. Enables matching between diff types of same word
#(ex: running, ran, runner all reduced to run). Once we have this, we can use␣
↪"ps.stem()" later on
ps = PorterStemmer()



#Function for preprocessing text, which standardizes text (LOWERCASING,␣
↪TOKENIZING, REMOVING USELESS TEXT). Standardization ALSO
#enables matching of different types of same word.
def transform_text(text):
    # Transforming all text to lowercase (so all variations of a given word are␣
↪considered the same)
    text = text.lower()

    # Tokenizing using nltk, which helps structure the text, specifically since
    text = nltk.word_tokenize(text)

    # Starting stopword removal process by by iterating through the token, and␣
↪appending to empty list all alphanumeric values
    #alphanumeric values include words we will want to keep, as well as␣
↪stopwords, which we don't want
    y = []
    for i in text:
        if i.isalnum(): #"isalnum() selects all words that alphanumeric
            y.append(i)

    # Creating a set of words to exclude ('http' and 'https' are highly␣
↪problematic and therefore undesired)
    exclude_words = set(['http', 'https'])

    #Copying all elements in y into a new object, "text"
    text = y[:]
```

```python
    #Clearing y for now, but it will later be filled again, only with the words␣
↪we want
    y.clear()

    for i in text:
        # Checking if the token is not in the list of stopwords for English␣
↪provided by NLTK,and that its not punctuation or from exclude_words set
        if i not in stopwords.words('english') and i not in string.punctuation␣
↪and i not in exclude_words:
            y.append(i) #Appending to y every token that passed the "if"␣
↪condition

    # Putting new list of desired words into 'text' object, clearing y again,␣
↪and then stemming each element in 'text' before placing back into y
    #Purpose of this is to stemming the list of cleaned words to root form
    text = y[:]
    y.clear()
    for i in text:
        #
        y.append(ps.stem(i))

    return " ".join(y)

# Cleaning HTML content within the emails, as the HTML content is widespread␣
↪but not useful in any way
def extract_text_from_html(content):
    soup = BeautifulSoup(content, 'html.parser')
    return soup.get_text()

# Specify the directory containing the files
folder_path = "C:/Users/Zohd/Desktop/Email"

# Initialize a list to keep track of files
all_files = []

# Going through the folder structure and appending to our list all files in the␣
↪folder
for dirpath, dirnames, filenames in os.walk(folder_path):
    for filename in filenames:
        # Construct the full file path
        file_path = os.path.join(dirpath, filename)
        # Append the file path to the list
        all_files.append(file_path)

        #if len(all_files) >= 1000:
            #break
```

```
    #if len(all_files) >= 1000:
        #break

# Writing function to classify. This function checks if words 'spam' and 'ham'␣
↪are in the folder path, and then returns either Spam text or Ham text in
#string format
def determine_classification(path):
    if 'spam' in path.lower():
        return 'Spam'
    elif 'ham' in path.lower():
        return 'Ham'
    else:
        return 'Unknown'


# This portion of the code is making use of the previously written functions,␣
↪and applying these functions to the actual data we have stored.
# Our specific goals here are to extract the email bodies, handle the HTML␣
↪emails, classify the emails, and storing the data into a dictionary

# Initialize a list to store email data
email_data = []
cnt = 0
# Loop over each file path in the collected files
for file_path in all_files:
    try:
        with open(file_path, 'r', encoding='utf-8', errors='ignore') as file:
            content = file.read()
            #cnt += 1
            #if cnt == 3000:
                #break
            # Find the start of the email body and extract it
            body_start_index = content.find("\n\n") + 2
            email_body = content[body_start_index:]

            # Check if the email is in HTML format and extract text
            if "<html" in email_body.lower():
                email_body = extract_text_from_html(email_body)

            #Applying "determine_classification" function from earlier to␣
↪classify each email
            classification = determine_classification(file_path)


            #After having processed and classified each email, we are appending␣
↪a dictionary to email_data list
```

```
            #This dictionary, which contains 'EmailBody' and 'Classification',␣
↪simplifies the process of storing
            #all our variables into Dataframe.
            email_data.append({'EmailBody': email_body, 'Classification':␣
↪classification})
    except Exception as e:
        print(f"Could not read {file_path}: {e}")

# Create the DataFrame from the list of dictionaries
emails_df = pd.DataFrame(email_data)

# Apply the transformation to each email body using "transform_text" function␣
↪written earlier
emails_df['trfm_text'] = emails_df['EmailBody'].apply(transform_text)

# Analyze the most common words in 'ham' and 'spam' emails
selected_words_ham = []
for sentence in emails_df[emails_df['Classification'] == 'Ham']['trfm_text'].
↪tolist(): #looping through all 'Ham' emails
    for word in sentence.split(): #for each word from the split of each␣
↪sentence, appending to list of most selected words
        selected_words_ham.append(word)

selected_words_spam = []
for sentence in emails_df[emails_df['Classification'] == 'Spam']['trfm_text'].
↪tolist(): # Repeating process from previous portion of code for "Spam"
    for word in sentence.split():
        selected_words_spam.append(word)

# Creating a DataFrame with the most common words and their counts for both␣
↪'ham' and 'spam'
swh_df = pd.DataFrame(Counter(selected_words_ham).most_common(30),␣
↪columns=['Word', 'Frequency'])
sws_df = pd.DataFrame(Counter(selected_words_spam).most_common(30),␣
↪columns=['Word', 'Frequency'])

#Printing the DataFrames to see the top words
print(swh_df)
print(sws_df)
```

```
      Word  Frequency
0      use       9480
1     list       6736
2      get       6320
3      one       6028
4     2002       5366
5     mail       5245
```

6	time	5015
7	like	5007
8	would	4843
9	new	4794
10	messag	4703
11	work	4430
12	mv	3908
13	1	3892
14	make	3867
15	file	3845
16	peopl	3652
17	wrote	3633
18	also	3284
19	email	3177
20	look	3057
21	date	3040
22	think	3028
23	system	3021
24	chang	3006
25	way	2995
26	could	2987
27	said	2970
28	group	2958
29	go	2956

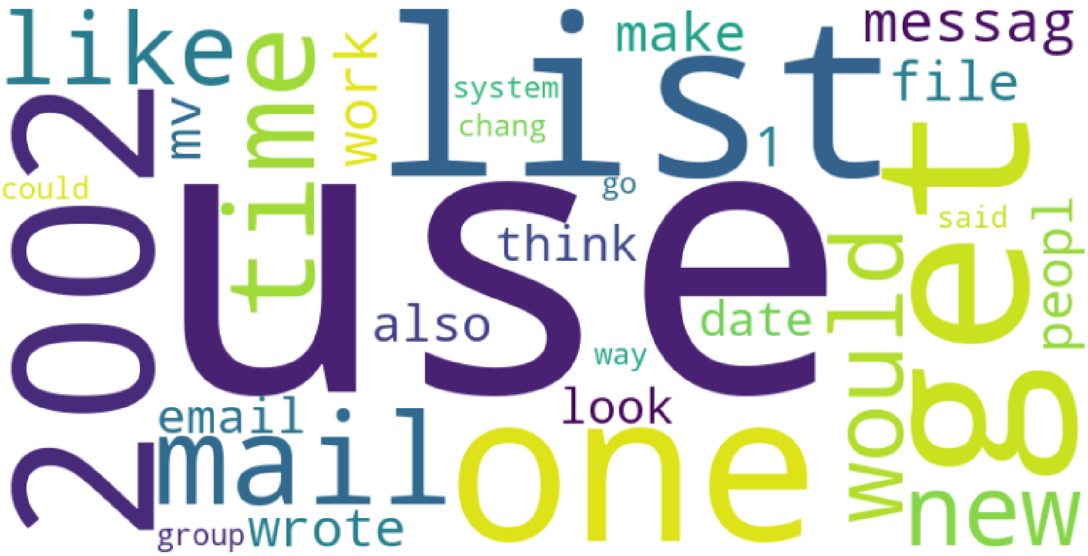
	Word	Frequency
0	email	6212
1	free	5180
2	click	4153
3	receiv	3986
4	list	3953
5	get	3841
6	mv	3797
7	pleas	3708
8	busi	3578
9	order	3517
10	mail	3469
11	remov	3352
12	address	3333
13	one	3080
14	money	3079
15	inform	3015
16	us	2797
17	make	2777
18	use	2760
19	send	2677
20	time	2623
21	name	2551
22	offer	2471

```
23    peopl      2422
24     site      2363
25        1      2312
26      new      2294
27   report      2274
28  program      2245
29  compani      2198
```

[3]:

```
#Importing neccesary packages for WordCloud code
import pandas as pd
from collections import Counter
from wordcloud import WordCloud
import matplotlib.pyplot as plt


# Writing Function to generate a word cloud from the swh_df and sws_df␣
↪Dataframes, respectively
def generate_wordcloud(dataframe, title):
    # Converting DataFrame to dictionary
    data_dict = dataframe.set_index('Word')['Frequency'].to_dict()

    # Initializing WordCloud object with appproprиate proportions
    wc = WordCloud(width=800, height=400, max_words=200,␣
↪background_color='white')

    # Generate WordClouds
    wc.generate_from_frequencies(data_dict)

    # Plotting with appropriate measurements
    plt.figure(figsize=(10, 5))
    plt.imshow(wc, interpolation='bilinear')
    plt.title(title)
    plt.axis('off')
    plt.show()

# Generating word cloud for 'ham' emails
generate_wordcloud(swh_df, 'Ham Emails Word Cloud')

# Generating word cloud for 'spam' emails
generate_wordcloud(sws_df, 'Spam Emails Word Cloud')
```

Ham Emails Word Cloud



Spam Emails Word Cloud

[4]:
```python
#Importing tokenizers
import nltk
from nltk.tokenize import word_tokenize, sent_tokenize

nltk.download('punkt')

# Writing Function to count total number of words in a text
```

```
def count_words(text):
    words = word_tokenize(text) #using function from nltk.tokenize to tokenize␣
 ↪each word
    return len(words) #returning the length of "words"

# Writing Function to count total number of sentences in a text
def count_sentences(text):
    sentences = sent_tokenize(text)
    return len(sentences)

# Applying the functions to each email body and create new columns for word␣
 ↪count and sentence count
emails_df['NumWords'] = emails_df['EmailBody'].apply(count_words)
emails_df['NumSentences'] = emails_df['EmailBody'].apply(count_sentences)

# Calculating total number of words for 'Spam' and 'Ham' emails separately
total_words_spam = emails_df[emails_df['Classification'] == 'Spam']['NumWords'].
 ↪mean()
total_words_ham = emails_df[emails_df['Classification'] == 'Ham']['NumWords'].
 ↪mean()
# Calculating total number of words for 'Spam' and 'Ham' emails separately
total_sentences_spam = emails_df[emails_df['Classification'] ==␣
 ↪'Spam']['NumSentences'].mean()
total_sentences_ham = emails_df[emails_df['Classification'] ==␣
 ↪'Ham']['NumSentences'].mean()
#Printing all of the results
print("Total Number of Words in Spam:", total_words_spam)
print("Total Number of Words in Ham:", total_words_ham)

print("Total Number of Sentences in Spam:", total_sentences_spam)
print("Total Number of Sentences in Ham:", total_sentences_ham)
```

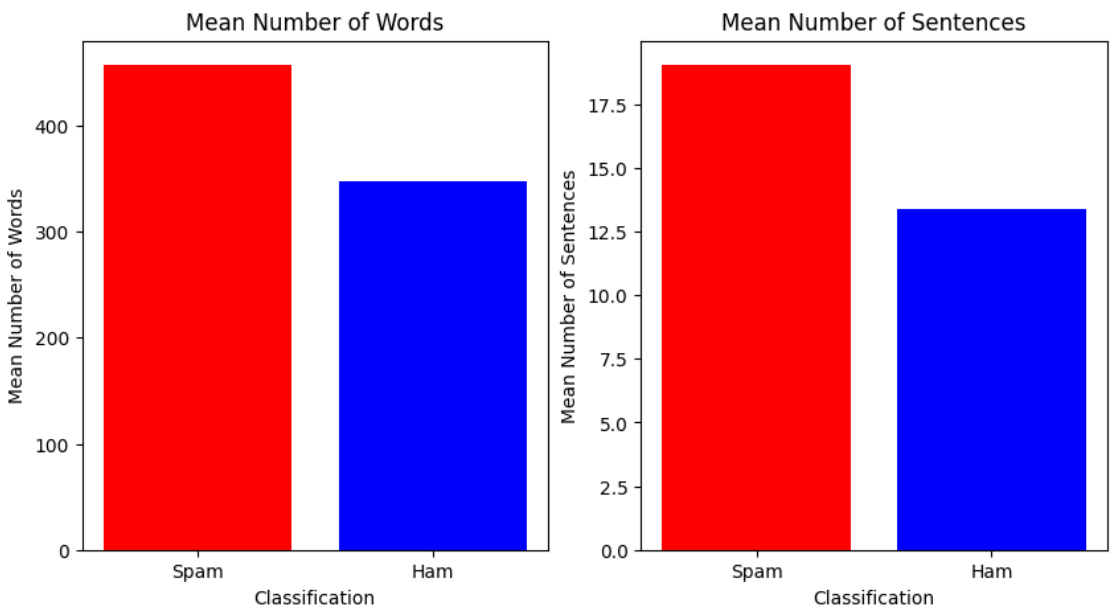
```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\Zohd\AppData\Roaming\nltk_data…
[nltk_data]   Package punkt is already up-to-date!
```

```
Total Number of Words in Spam: 457.2873321042929
Total Number of Words in Ham: 346.98674242424244
Total Number of Sentences in Spam: 19.043982091124573
Total Number of Sentences in Ham: 13.370791245791246
```

[5]:
```
# Creating bar plots
plt.figure(figsize=(10, 5))

# Plotting mean number of words
plt.subplot(1, 2, 1)
plt.bar(['Spam', 'Ham'], [total_words_spam, total_words_ham], color=['red',␣
 ↪'blue'])
```

```
plt.title('Mean Number of Words')
plt.xlabel('Classification')
plt.ylabel('Mean Number of Words')

# Plotting mean number of sentences
plt.subplot(1, 2, 2)
plt.bar(['Spam', 'Ham'], [total_sentences_spam, total_sentences_ham],␣
 ↪color=['red', 'blue'])
plt.title('Mean Number of Sentences')
plt.xlabel('Classification')
plt.ylabel('Mean Number of Sentences')
```

[5]: Text(0, 0.5, 'Mean Number of Sentences')



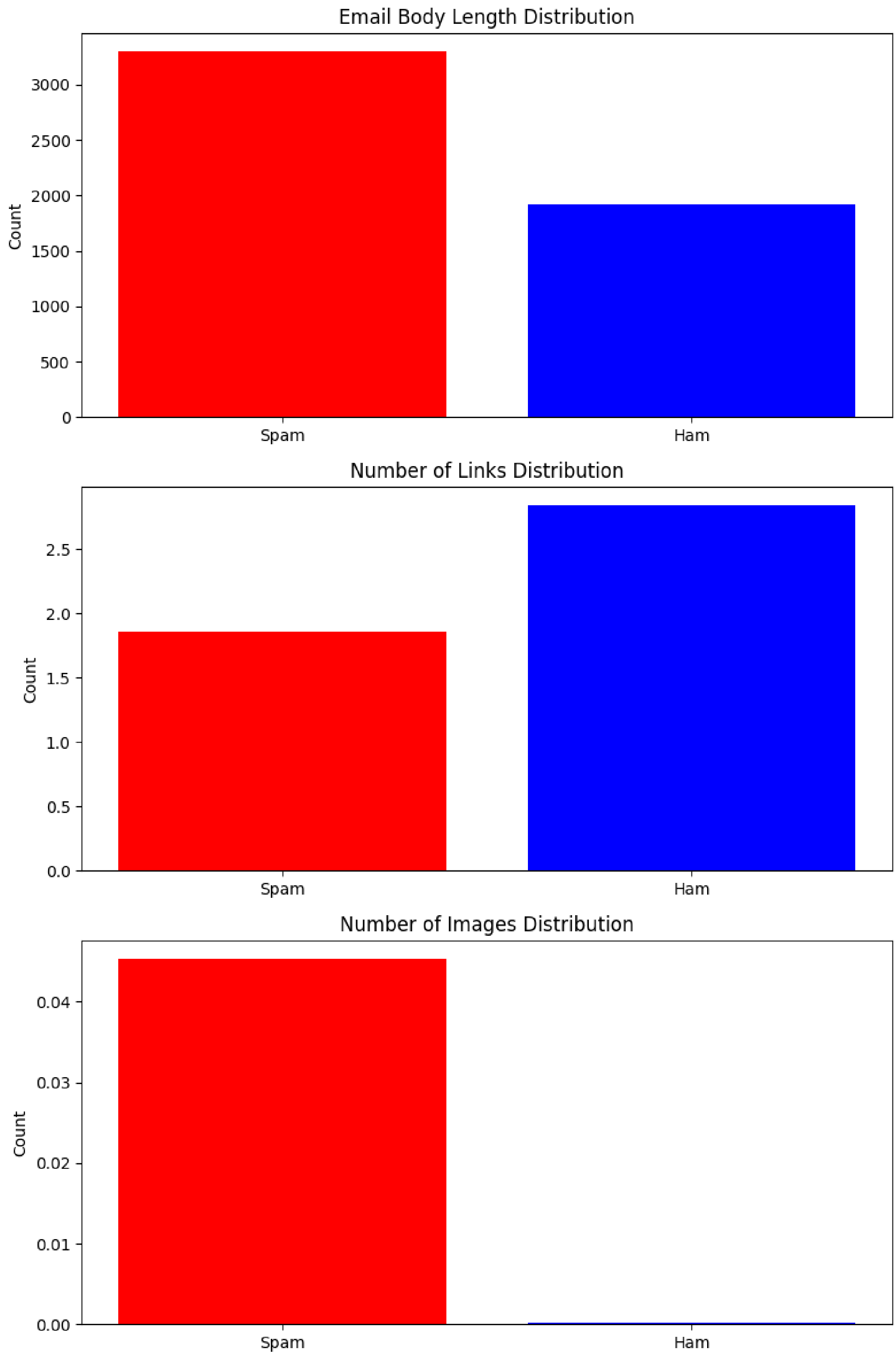
[6]:
```
#Importing modules for getting various summary/important statistics
import re

# Calculate email body length
emails_df['EmailBodyLength'] = emails_df['EmailBody'].apply(len)

# Calculate number of links using regex pattern matching
emails_df['NumLinks'] = emails_df['EmailBody'].apply(lambda x: len(re.
 ↪findall(r'http[s]?://(?:[a-zA-Z]|[0-9]|[$-_@.&+]|[!*\\(\\),]|(?:
 ↪%[0-9a-fA-F][0-9a-fA-F]))+', x)))

# Calculate number of images using regex pattern matching
```

```
emails_df['NumImages'] = emails_df['EmailBody'].apply(lambda x: len(re.
 ↪findall(r'<img [^>]*>', x)))

# Calculate mean email body length for 'Spam' and 'Ham' separately
total_email_body_length_spam = emails_df[emails_df['Classification'] ==␣
 ↪'Spam']['EmailBodyLength'].mean()
total_email_body_length_ham = emails_df[emails_df['Classification'] ==␣
 ↪'Ham']['EmailBodyLength'].mean()

# Calculate mean number of links using regex pattern matching for 'Spam' and␣
 ↪'Ham' separately
total_num_links_spam = emails_df[emails_df['Classification'] ==␣
 ↪'Spam']['NumLinks'].mean()
total_num_links_ham = emails_df[emails_df['Classification'] ==␣
 ↪'Ham']['NumLinks'].mean()

# Calculate mean number of images using regex pattern matching for 'Spam' and␣
 ↪'Ham' separately
total_num_images_spam = emails_df[emails_df['Classification'] ==␣
 ↪'Spam']['NumImages'].mean()
total_num_images_ham = emails_df[emails_df['Classification'] ==␣
 ↪'Ham']['NumImages'].mean()

# Print the total counts separately for 'Spam' and 'Ham'
print("Email Body Length for Spam:", total_email_body_length_spam)
print("Email Body Length for Ham:", total_email_body_length_ham)
print("Number of Links for Spam:", total_num_links_spam)
print("Number of Links for Ham:", total_num_links_ham)
print("Number of Images for Spam:", total_num_images_spam)
print("Number of Images for Ham:", total_num_images_ham)
```

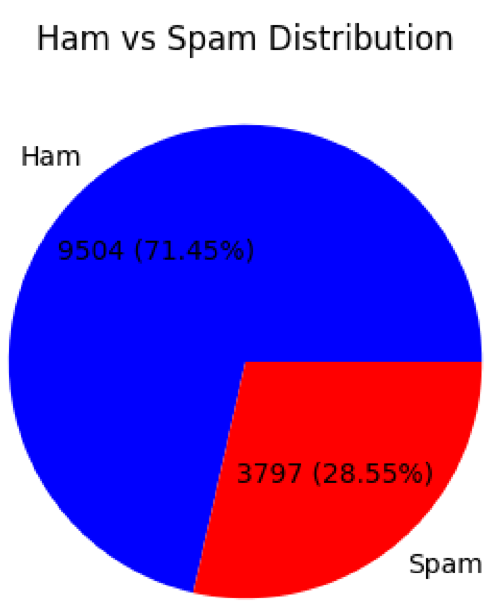
```
Email Body Length for Spam: 3297.755069791941
Email Body Length for Ham: 1922.503787878788
Number of Links for Spam: 1.8617329470634711
Number of Links for Ham: 2.836910774410774
Number of Images for Spam: 0.04529892020015802
Number of Images for Ham: 0.00021043771043771043
```

[18]:
```
import matplotlib.pyplot as plt

#  Creating a dictionary for the Total counts for 'Spam' and 'Ham'
totals = {
    'Email Body Length': [total_email_body_length_spam,␣
 ↪total_email_body_length_ham],
    'Number of Links': [total_num_links_spam, total_num_links_ham],
    'Number of Images': [total_num_images_spam, total_num_images_ham]
}
```

```python
fig, axes = plt.subplots(3, 1, figsize=(8, 12))

for i, (feature, counts) in enumerate(totals.items()):
    ax = axes[i]
    ax.bar(['Spam', 'Ham'], counts, color=['red', 'blue'])
    ax.set_title(feature + ' Distribution')
    ax.set_ylabel('Count')

plt.tight_layout()
plt.show()
```


Email Body Length Distribution
Count
0
500
1000
1500
2000
2500
3000
Spam
Ham
Number of Links Distribution
Count
0.0
0.5
1.0
1.5
2.0
2.5
Spam
Ham
Number of Images Distribution
Count
0.00
0.01
0.02
0.03
0.04
Spam
Ham

[25]:
```
import matplotlib.pyplot as plt
import numpy as np

# Custom function for autopct that includes both count and percentage
def make_autopct(values):
    def my_autopct(pct):
        total = sum(values)
        val = int(round(pct*total/100.0))
        return '{v:d} ({p:.2f}%)'.format(p=pct,v=val)
    return my_autopct

# Get the counts for each classification
classification_counts = emails_df['Classification'].value_counts()

plt.figure(figsize=(6, 4))
# Specify the colors: first for 'Ham', second for 'Spam'
colors = ['blue', 'red']
classification_counts.plot(kind='pie',␣
↪autopct=make_autopct(classification_counts), colors=colors)

plt.title('Ham vs Spam Distribution')
plt.xticks([])
plt.ylabel('')
plt.show()
```

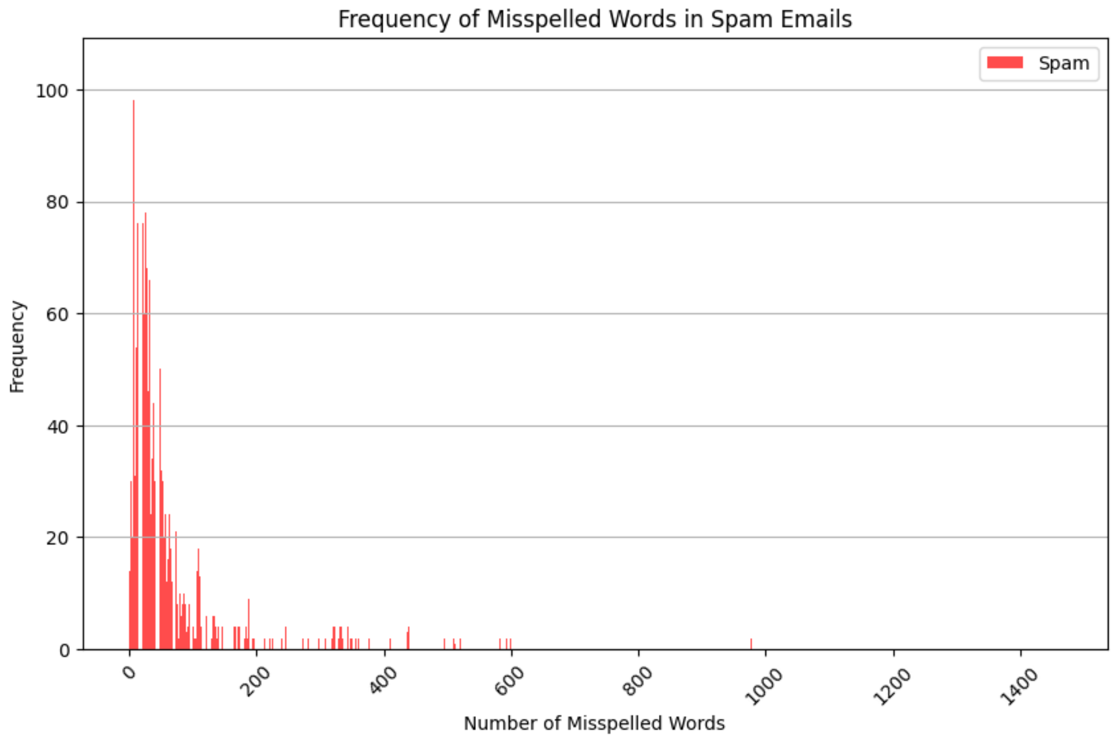


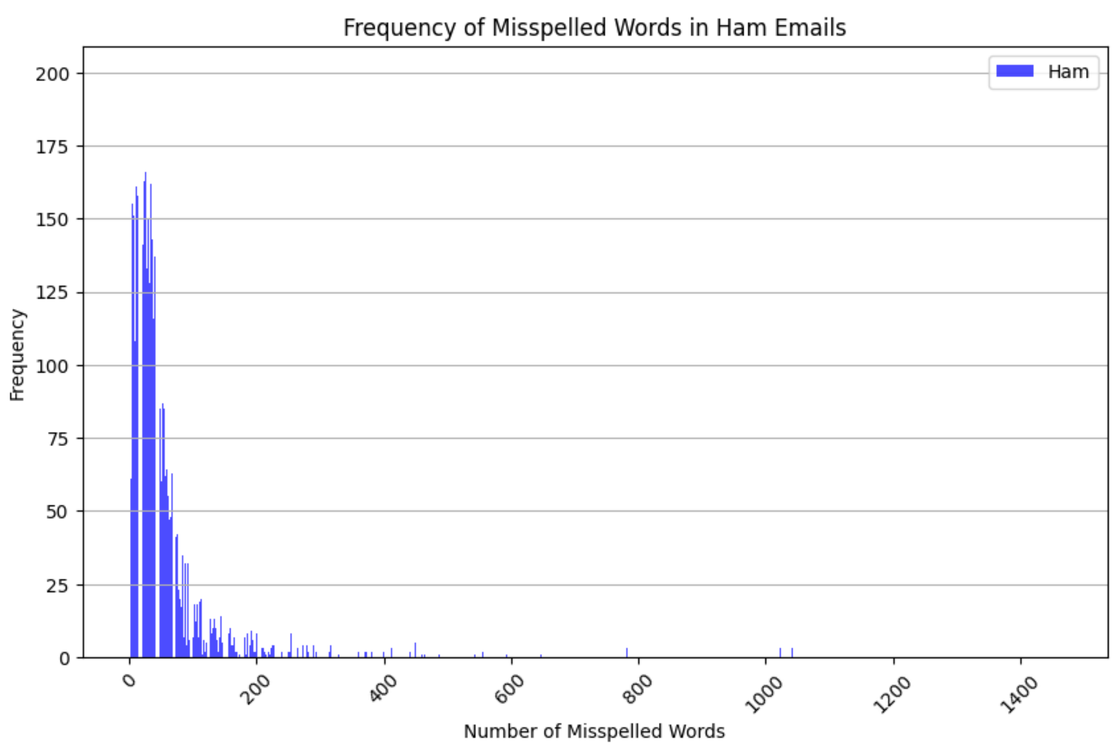
[13]:
```python
from spellchecker import SpellChecker

# Initialize SpellChecker
spell_checker = SpellChecker()

# Function to count misspelled words in a text
def count_misspelled_words(text):
    # Tokenize the text
    words = text.split()
    # Find misspelled words
    misspelled_words = spell_checker.unknown(words)
    # Return the count of misspelled words
    return len(misspelled_words)

# Applying the functions to each email body and create new columns for␣
 ↪misspelled words and grammar errors
emails_df['NumMisspelledWords'] = emails_df['EmailBody'].
 ↪apply(count_misspelled_words)

# Calculating the frequency of misspelled words for spam and ham emails
misspelled_words_spam_freq = emails_df[emails_df['Classification'] ==␣
 ↪'Spam']['NumMisspelledWords'].value_counts().sort_index()
misspelled_words_ham_freq = emails_df[emails_df['Classification'] ==␣
 ↪'Ham']['NumMisspelledWords'].value_counts().sort_index()

# Printing the frequency of misspelled words for spam emails
print("Frequency of Misspelled Words in Spam Emails:")
print(misspelled_words_spam_freq)

# Printing the frequency of misspelled words for ham emails
print("\nFrequency of Misspelled Words in Ham Emails:")
print(misspelled_words_ham_freq)
```

```
Frequency of Misspelled Words in Spam Emails:
0       36
1       14
2       32
3       30
4       14
        ..
632      2
659      2
977      2
987      2
1463     2
Name: NumMisspelledWords, Length: 228, dtype: int64
```

```
Frequency of Misspelled Words in Ham Emails:
0         3
2        33
3        61
4        93
5       155
       …
1042      3
1409      1
2098      1
4615      1
5349      2
Name: NumMisspelledWords, Length: 297, dtype: int64
```

[14]:
```
import matplotlib.pyplot as plt

# Determining the common range for the x-axis
common_range = range(min(misspelled_words_spam_freq.index.max(),
 ↪misspelled_words_ham_freq.index.max()) + 1)

# Plotting the frequency of misspelled words for spam emails with standardized
 ↪x-axis
plt.figure(figsize=(10, 6))
plt.bar(common_range, misspelled_words_spam_freq.reindex(common_range,
 ↪fill_value=0), color='red', alpha=0.7, label='Spam')
plt.xlabel('Number of Misspelled Words')
plt.ylabel('Frequency')
plt.title('Frequency of Misspelled Words in Spam Emails')
plt.xticks(rotation=45)
plt.legend()
plt.grid(axis='y')
plt.show()

# Plotting the frequency of misspelled words for ham emails with standardized
 ↪x-axis
plt.figure(figsize=(10, 6))
plt.bar(common_range, misspelled_words_ham_freq.reindex(common_range,
 ↪fill_value=0), color='blue', alpha=0.7, label='Ham')
plt.xlabel('Number of Misspelled Words')
plt.ylabel('Frequency')
plt.title('Frequency of Misspelled Words in Ham Emails')
plt.xticks(rotation=45)
plt.legend()
plt.grid(axis='y')
plt.show()
```


Frequency of Misspelled Words in Spam Emails
Spam
Frequency
Number of Misspelled Words
0
20
40
60
80
100
200
400
600
800
1000
1200
1400


Frequency of Misspelled Words in Ham Emails
Ham
Frequency
Number of Misspelled Words
0
25
50
75
100
125
150
175
200
400
600
800
1000
1200
1400

[15]:

```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
↪BaggingClassifier, ExtraTreesClassifier, GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.model_selection import cross_val_score
import numpy as np
import pandas as pd

#Initializes TF-IDF Vectorizer with a limit of 3000 features to transform text␣
↪data into a matrix of TF-IDF values.
# This process emphasizes words that are important and unique to documents,␣
↪making it crucial for analyzing and classifying email content effectively.
tfidf = TfidfVectorizer(max_features=3000)
#Setting feature variable as matrix of TF-IDF values derived from our␣
↪transformed text column
#Each row in X represents an email, and each column represents one of up to␣
↪3000 most important words across all emails based on TF-IDF scores
X = tfidf.fit_transform(emails_df['trfm_text']).toarray()
y = emails_df['Classification'].map({'Ham': 0, 'Spam': 1}).values
# Step 2: Splitting the data according to a standard 80-20 split into train and␣
↪test sets, respectively, with a seed for reproducibility
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Creating a dictionary of Models to train and this will be looped through␣
↪later to perform CV and Model Predictions
models = {
    "Logistic Regression": LogisticRegression(),
    "LDA": LinearDiscriminantAnalysis(),
    "QDA": QuadraticDiscriminantAnalysis(),
    "Decision Tree": DecisionTreeClassifier(),
    "K-Nearest Neighbors": KNeighborsClassifier(),
    "Random Forest": RandomForestClassifier(),
    "Bagging Classifier": BaggingClassifier(),
    "Extra Trees": ExtraTreesClassifier(),
    "Gradient Boosting": GradientBoostingClassifier(),
    "XGBoost": XGBClassifier(eval_metric='logloss')
```

```
}

# Step 3: Training with cross-validation, and we are doing 5 fold cross␣
↪validation for this
results = {}
for name, model in models.items():
    scores = cross_val_score(model, X, y, cv=5)  # 5-fold cross-validation
    accuracy = scores.mean()
    results[name] = accuracy

# Step 4: Displaying  the Results for cross-validation
print("\nCross-Validation:")
for name, accuracy in results.items():
    print(f"{name}: {accuracy:.4f}")

# Step 5: Training and evaluating models, by looping through respective key and␣
↪value of dict, and performing standard fit, pred, results, etc.
results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    results[name] = accuracy


# Step 6: Displaying Results for training model
print("\nModel performance summary:")
for name, accuracy in results.items():
    print(f"{name}: {accuracy:.4f}")
```

```
C:\Users\Zohd\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\discriminant_analysis.py:935: UserWarning: Variables are
collinear
  warnings.warn("Variables are collinear")
C:\Users\Zohd\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\discriminant_analysis.py:935: UserWarning: Variables are
collinear
  warnings.warn("Variables are collinear")
C:\Users\Zohd\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\discriminant_analysis.py:935: UserWarning: Variables are
collinear
  warnings.warn("Variables are collinear")
C:\Users\Zohd\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\discriminant_analysis.py:935: UserWarning: Variables are
collinear
  warnings.warn("Variables are collinear")
C:\Users\Zohd\AppData\Local\Programs\Python\Python310\lib\site-
```

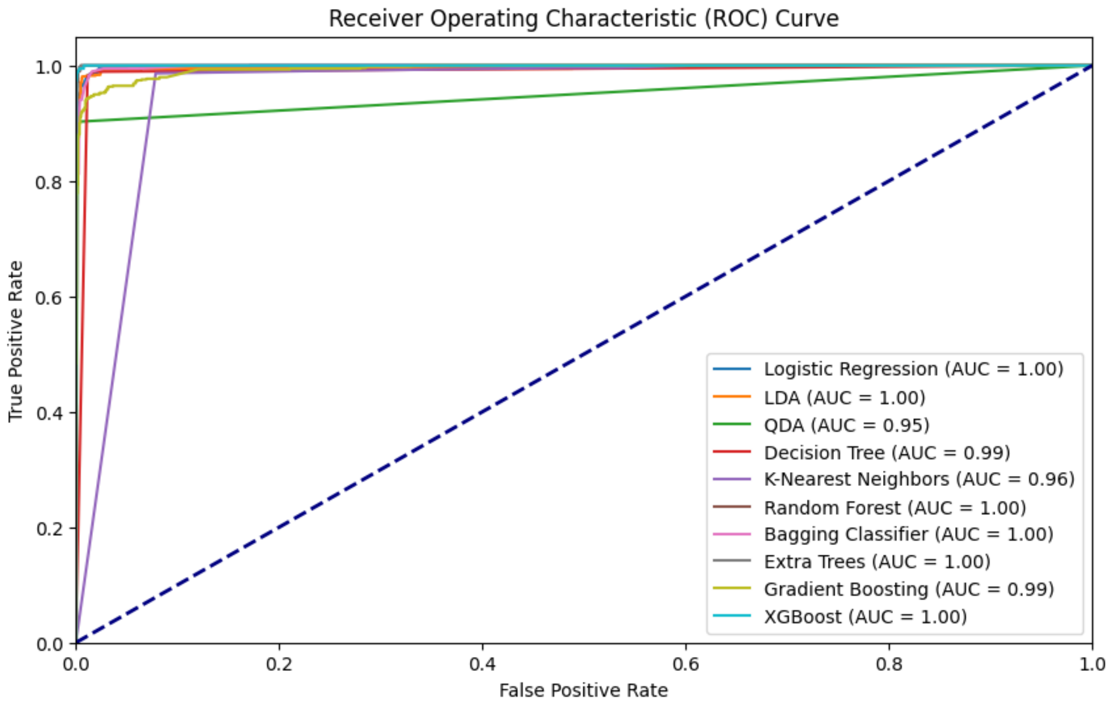
```
packages\sklearn\discriminant_analysis.py:935: UserWarning: Variables are
collinear
  warnings.warn("Variables are collinear")


Cross-Validation:
Logistic Regression: 0.9772
LDA: 0.9682
QDA: 0.9702
Decision Tree: 0.9623
K-Nearest Neighbors: 0.8932
Random Forest: 0.9814
Bagging Classifier: 0.9613
Extra Trees: 0.9862
Gradient Boosting: 0.9457
XGBoost: 0.9738
```

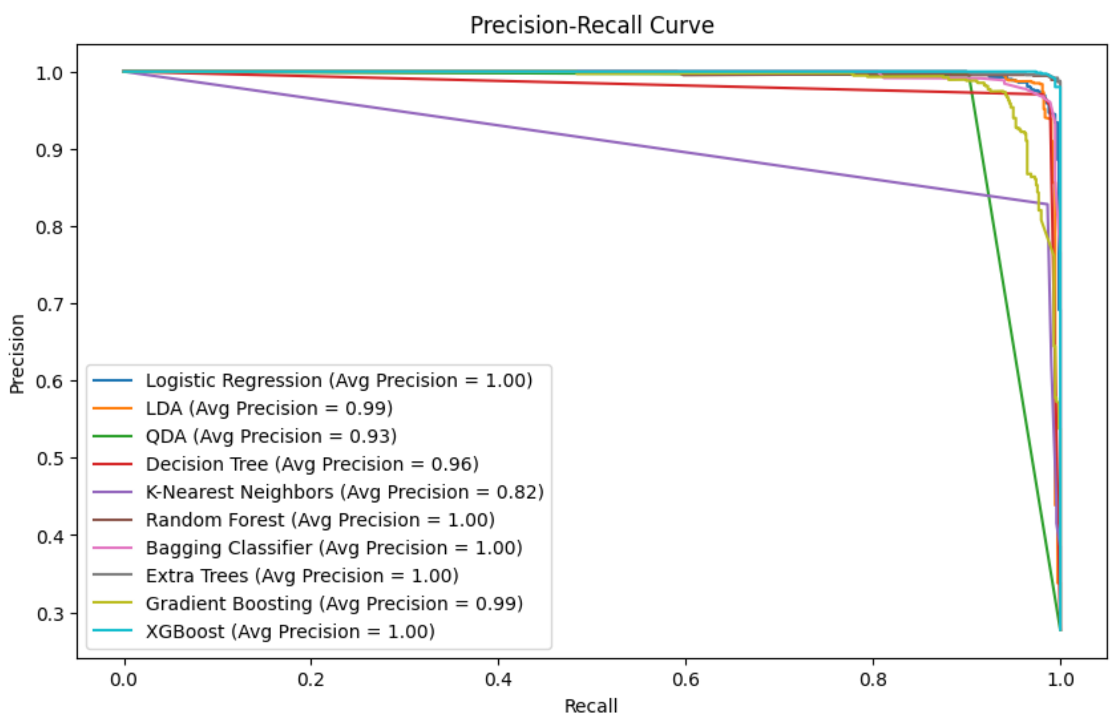
```
C:\Users\Zohd\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\discriminant_analysis.py:935: UserWarning: Variables are
collinear
  warnings.warn("Variables are collinear")


Model performance summary:
Logistic Regression: 0.9835
LDA: 0.9872
QDA: 0.9718
Decision Tree: 0.9846
K-Nearest Neighbors: 0.6490
Random Forest: 0.9947
Bagging Classifier: 0.9853
Extra Trees: 0.9951
Gradient Boosting: 0.9714
XGBoost: 0.9936
```

[16]:

```python
from sklearn.metrics import confusion_matrix, roc_curve, auc,␣
 ↪precision_recall_curve, average_precision_score

# Plotting ROC curve for each model
plt.figure(figsize=(10, 6))
for name, model in models.items(): #Looping through the different models and␣
 ↪performing the appropriate steps
    y_score = model.predict_proba(X_test)[:, 1] #Using predict_proba to get␣
 ↪class probabilities
    fpr, tpr, _ = roc_curve(y_test, y_score) #FItting the roc_curve with the␣
 ↪associateed y test and score variables
    roc_auc = auc(fpr, tpr) #fitting the auc function again with the␣
 ↪appropriate fpr and tpr
```

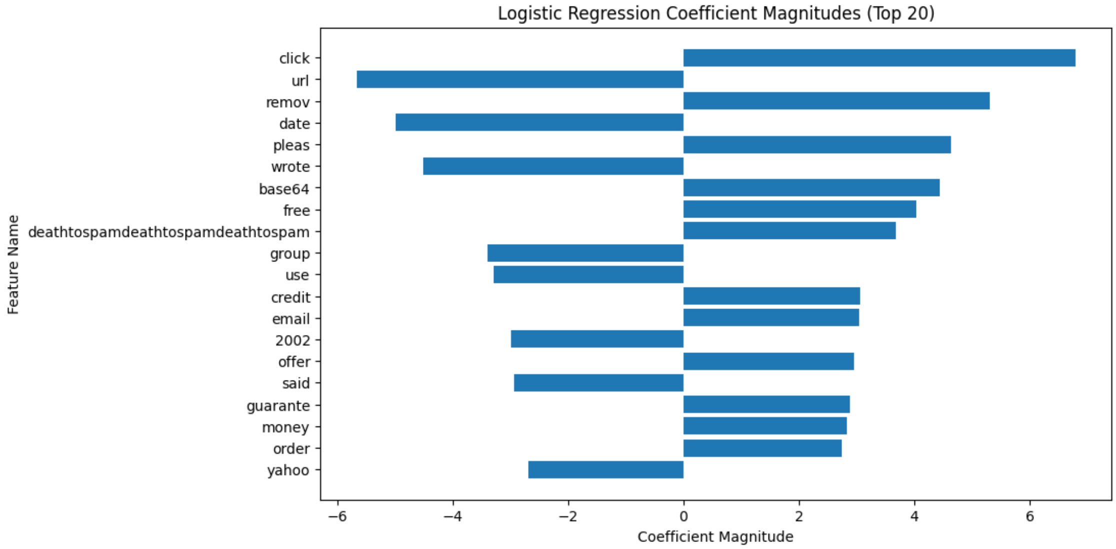
```
    plt.plot(fpr, tpr, label=f'{name} (AUC = {roc_auc:.2f})') #Plotting based␣
 ↪on the values of auc at two point precision
#Plotting everything based on the code we have thus far
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()

# Plotting Precision-Recall curve for each model by looping through everything␣
 ↪and including the avg-precision, y-score, etc.
plt.figure(figsize=(10, 6))
for name, model in models.items():
    y_score = model.predict_proba(X_test)[:, 1]
    precision, recall, _ = precision_recall_curve(y_test, y_score)
    avg_precision = average_precision_score(y_test, y_score)
    plt.plot(recall, precision, label=f'{name} (Avg Precision = {avg_precision:.
 ↪2f})')
#Setting appropriate labels and plotting
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc="lower left")
plt.show()
```

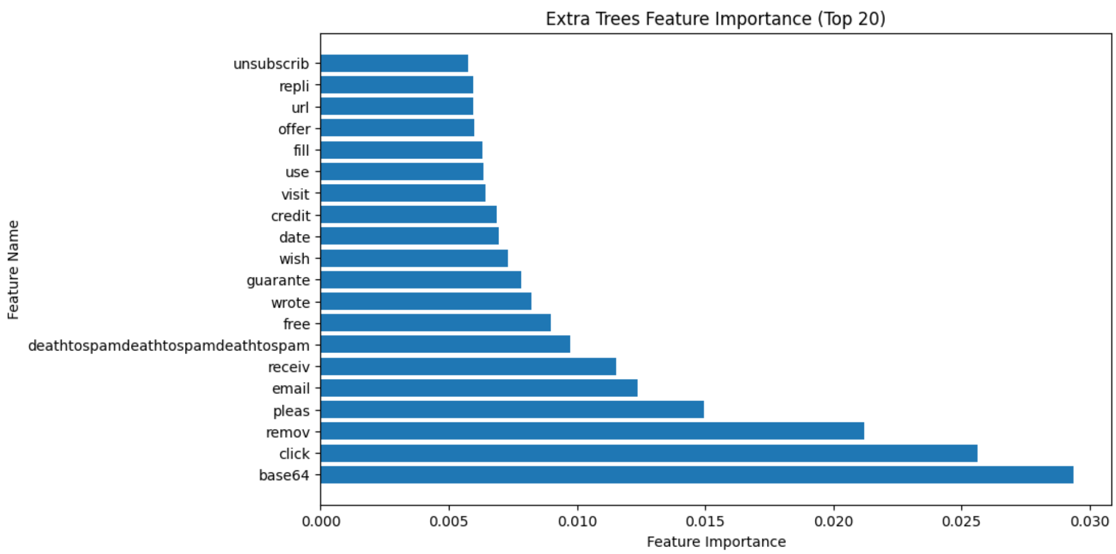

Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Logistic Regression (AUC = 1.00)
LDA (AUC = 1.00)
QDA (AUC = 0.95)
Decision Tree (AUC = 0.99)
K-Nearest Neighbors (AUC = 0.96)
Random Forest (AUC = 1.00)
Bagging Classifier (AUC = 1.00)
Extra Trees (AUC = 1.00)
Gradient Boosting (AUC = 0.99)
XGBoost (AUC = 1.00)


Precision-Recall Curve
Precision
Recall
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Logistic Regression (Avg Precision = 1.00)
LDA (Avg Precision = 0.99)
QDA (Avg Precision = 0.93)
Decision Tree (Avg Precision = 0.96)
K-Nearest Neighbors (Avg Precision = 0.82)
Random Forest (Avg Precision = 1.00)
Bagging Classifier (Avg Precision = 1.00)
Extra Trees (Avg Precision = 1.00)
Gradient Boosting (Avg Precision = 0.99)
XGBoost (Avg Precision = 1.00)

[26]:

```python
import matplotlib.pyplot as plt
import numpy as np

# Fit logistic regression model
logistic_regression_model = LogisticRegression()
logistic_regression_model.fit(X_train, y_train)

# Obtain coefficients and feature names
coefficients = logistic_regression_model.coef_[0]
feature_names = tfidf.get_feature_names_out()

# Get indices of top 20 features with highest coefficients
top_indices = np.argsort(np.abs(coefficients))[-20:]

# Plot coefficient magnitudes for top 20 features
plt.figure(figsize=(10, 6))
plt.barh(np.array(feature_names)[top_indices], coefficients[top_indices])
plt.xlabel('Coefficient Magnitude')
plt.ylabel('Feature Name')
plt.title('Logistic Regression Coefficient Magnitudes (Top 20)')
plt.show()

# For Extra Trees feature importance
extra_trees_model = models['Extra Trees']
extra_trees_model.fit(X_train, y_train)

# Plot feature importance for Extra Trees
plt.figure(figsize=(10, 6))
feature_importances = extra_trees_model.feature_importances_
sorted_indices = np.argsort(feature_importances)[::-1]
top_features = 20  # Change as needed
plt.barh(feature_names[sorted_indices[:top_features]],␣
 ↪feature_importances[sorted_indices][:top_features])
plt.xlabel('Feature Importance')
plt.ylabel('Feature Name')
plt.title('Extra Trees Feature Importance (Top 20)')
plt.show()
```


Logistic Regression Coefficient Magnitudes (Top 20)
Feature Name
click
url
remov
date
pleas
wrote
base64
free
deathtospamdeathtospamdeathtospam
group
use
credit
email
2002
offer
said
guarante
money
order
yahoo
−6
−4
−2
0
2
4
6
Coefficient Magnitude


Extra Trees Feature Importance (Top 20)
Feature Name
unsubscrib
repli
url
offer
fill
use
visit
credit
date
wish
guarante
wrote
free
deathtospamdeathtospamdeathtospam
receiv
email
pleas
remov
click
base64
0.000
0.005
0.010
0.015
0.020
0.025
0.030
Feature Importance