Title: A Machine Learning Approach to SMS Spam Detection

Currently, the use of cell phones has surged in the last decade, leading, among other things, to a problem regarding text messages with promotions from unscrupulous marketing agents, and with fraudulent messages that can lead us to have a bad day. To solve this problem, in this project we will focus building a m achine learning model that accurately allows us to predict and identify when a received text message is spam or not (ham), with the help of the text body of SMS, while using a SMS Spam Collection Dataset from kaggle.com with a total of 5,169 unique and legitimate text messages downloaded fro m the Kaggle website.

Objectives:

- Analyze the provided SMS dataset to understand the characteristics of spam and

legitimate (ham) messages.

- Explore the content of messages, examining factors like message length, common words,

and phrases.

- Develop and train a spam detection model using a machine learning algorithm.
- Assess the performance of the model through testing and validation.
- Implement the trained model to classify new messages and measure its accuracy in

In [ ]:
```
# Importing the libraries
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

In [ ]:
```
# Importing the dataset
df = pd.read_csv('spam.csv', encoding='latin1')
df.head()
```

Out[ ]:

	v1	v2	Unnamed: 2	Unnamed: 3	Unnamed: 4
0	ham	Go until jurong point, crazy.. Available only ...	NaN	NaN	NaN
1	ham	Ok lar... Joking wif u oni...	NaN	NaN	NaN
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	NaN	NaN	NaN
3	ham	U dun say so early hor... U c already then say...	NaN	NaN	NaN
4	ham	Nah I don't think he goes to usf, he lives aro...	NaN	NaN	NaN

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5572 entries, 0 to 5571
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   v1          5572 non-null   object
 1   v2          5572 non-null   object
 2   Unnamed: 2  50 non-null     object
 3   Unnamed: 3  12 non-null     object
 4   Unnamed: 4  6 non-null      object
dtypes: object(5)
memory usage: 217.8+ KB
```

> Notice that there are three columns almost empty: `Unnamed: 2`, `Unnamed: 3`, and `Unnamed: 4`. Let's check unique values for these columns and be sure what we have here.

In [ ]:
```
df['Unnamed: 2'].unique()
```

Out[ ]:
```
array([nan, ' PO Box 5249',
       ' the person is definitely special for u..... But if the person is so special',
       ' HOWU DOIN? FOUNDURSELF A JOBYET SAUSAGE?LOVE JEN XXX\\""',
       ' wanted to say hi. HI!!!\\" Stop? Send STOP to 62468"',
       'this wont even start........ Datz confidence.."', 'GN',
       '.;-):-D"',
       'just been in bedbut mite go 2 thepub l8tr if uwana mt up?loads a luv Jenxxx.\\""',
       ' bt not his girlfrnd... G o o d n i g h t . . .@"',
       ' I\'ll come up"',
       ' don\'t miss ur best life for anything... Gud nyt..."',
       ' just as a shop has to give a guarantee on what they sell. B. G."',
       ' But at d end my love compromised me for everything:-(\\".. Gud mornin:-)"',
       ' the toughest is acting Happy with all unspoken pain inside..\\""',
       ' smoke hella weed\\""', '\\" not \\"what i need to do.\\""',
       'JUST GOT PAYED2DAY & I HAVBEEN GIVEN Aå£50 PAY RISE 4MY WORK & HAVEBEEN MADE PRESCHOOLCO
-ORDINATOR 2I AM FEELINGOOD LUV\\""',
       ' justthought iåÕd sayhey! how u doin?nearly the endof me wk offdam nevamind!We will have
2Hook up sn if uwant m8? loveJen x.\\""',
       'JUST REALLYNEED 2DOCD.PLEASE DONTPLEASE DONTIGNORE MYCALLS',
       'u hav2hear it!c u sn xxxx\\""', " I don't mind",
       ' Dont Come Near My Body..!! Bcoz My Hands May Not Come 2 Wipe Ur Tears Off That Time..!G
ud ni8"',
       "Well there's still a bit left if you guys want to tonight",
       ' but dont try to prove\\" ..... Gud mrng..."',
       ' SHE SHUDVETOLD U. DID URGRAN KNOW?NEWAY',
       ' but watever u shared should be true\\"...."',
       ' like you are the KING\\"...! OR \\"Walk like you Dont care',
       ' HAD A COOL NYTHO', ' PO Box 1146 MK45 2WT (2/3)"',
       ' \\"It is d wonderful fruit that a tree gives when it is being hurt by a stone.. Good ni
ght....."',
       ' we made you hold all the weed\\""',
       ' but dont try to prove it..\\" .Gud noon...."',
       ' its a miracle to Love a person who can\'t Love anyone except U...\\" Gud nyt..."',
       ' Gud night...."',
       ' that\'s the tiny street where the parking lot is"',
       'PROBPOP IN & CU SATTHEN HUNNY 4BREKKIE! LOVE JEN XXX. PSXTRA LRG PORTIONS 4 ME PLEASE
\\""',
       ' hopeSo hunny. i amnow feelin ill & ithink i may have tonsolitusaswell! damn iam layin i
n bedreal bored. lotsof luv me xxxx\\""',
       ' GOD said',
       ' always give response 2 who cares 4 U\\"... Gud night..swt dreams..take care"',
       ' HOPE UR OK... WILL GIVE U A BUZ WEDLUNCH. GO OUTSOMEWHERE 4 ADRINK IN TOWN..CUD GO 2WAT
ERSHD 4 A BIT? PPL FROMWRK WILL BTHERE. LOVE PETEXXX.\\""',
       ' b\'coz nobody will fight for u. Only u &amp;amp; u have to fight for ur self &amp;amp; win the
battle. -VIVEKANAND- G 9t.. SD.."',
       'DEVIOUSBITCH.ANYWAY',
       ' ENJOYIN INDIANS AT THE MO..yeP. SaLL gOoD HehE ;> hows bout u shexy? Pete Xx\\""'],
      dtype=object)
```

In [ ]:
```
df['Unnamed: 3'].unique()
```

Out[ ]:
```
array([nan, ' MK17 92H. 450Ppw 16"', ' why to miss them', 'GE',
       'U NO THECD ISV.IMPORTANT TOME 4 2MORO\\""',
       'i wil tolerat.bcs ur my someone..... But',
       ' ILLSPEAK 2 U2MORO WEN IM NOT ASLEEP...\\""',
       'whoever is the KING\\"!... Gud nyt"', ' TX 4 FONIN HON',
       ' \\"OH No! COMPETITION\\". Who knew', 'IåÕL CALL U\\""'],
      dtype=object)
```

In [ ]:
```
df['Unnamed: 4'].unique()
```

Out[ ]:
```
array([nan, ' just Keep-in-touch\\" gdeve.."', 'GNT:-)"',
       ' Never comfort me with a lie\\" gud ni8 and sweet dreams"',
       ' CALL 2MWEN IM BK FRMCLOUD 9! J X\\""',
       ' one day these two will become FREINDS FOREVER!"'], dtype=object)
```

> As we saw here, these are reply messages for the initial one. So there is no relevant information here and we can drop these three columns.

1. Data Preprocessing

In [ ]:
```
# removing unnecessary columns
df = df.drop(["Unnamed: 2", "Unnamed: 3", "Unnamed: 4"], axis=1)
```

In [ ]:
```
df.head()
```

Out[ ]:

	v1	v2
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

In [ ]:
```
# changing v1 column to spam and text column to text
df = df.rename(columns={"v1": "spam", "v2": "text"})
df.head()
```

Out[ ]:

	spam	text
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

In [ ]:
```
# Count of duplicated rows
df.duplicated().sum()
```

Out[ ]:
```
403
```

> There are 403 duplicated rows to drop.

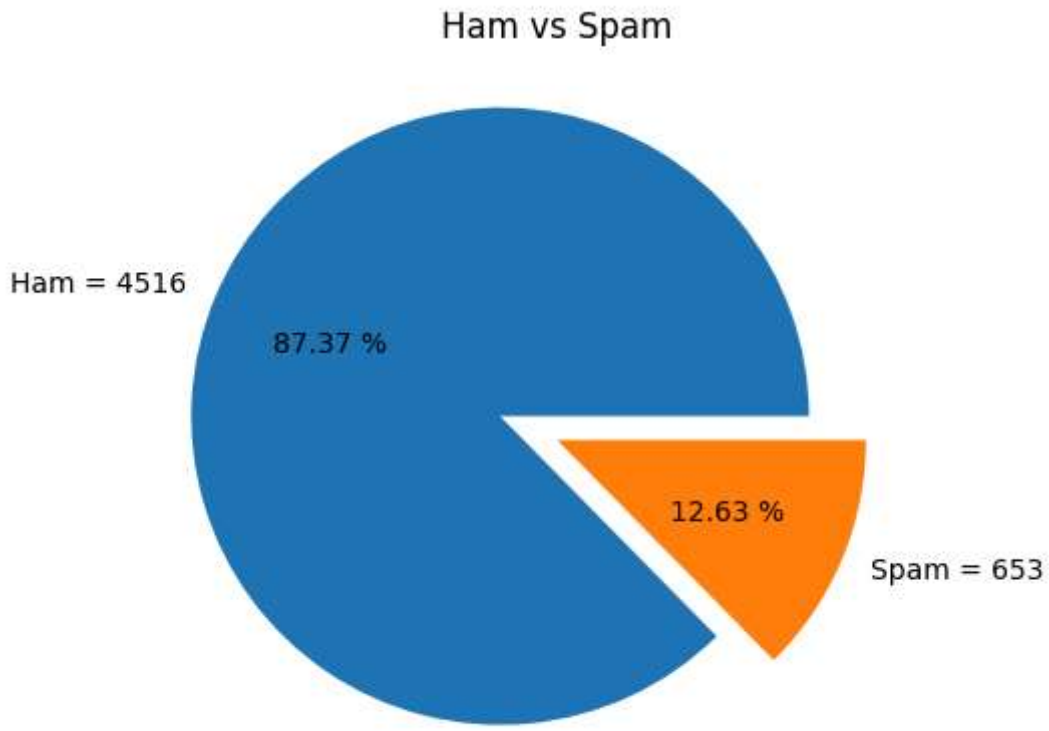
In [ ]:
```
#removing duplicates
df = df.drop_duplicates()
df.shape
```

Out[ ]:
```
(5169, 2)
```

> At this point I would like to understand better the features and the dataset in overall by plotting a few Graphs.

I woul like to start by checking whether the dataset is balanced or not in terms of the outcome variable `spam`.

In [ ]:
```
# Creating a Pie chart for spam and ham

number_of_spam = df[df['spam'] == 'spam'].shape[0]
number_of_ham = df[df['spam'] == 'ham'].shape[0]

plt.figure(figsize=(6,5))

mail_categories = [number_of_ham, number_of_spam]
labels = [f"Ham = {number_of_ham}", f"Spam = {number_of_spam}"]
explode = [.2, 0]

plt.pie(mail_categories, labels=labels, explode=explode, autopct="%.2f %%")
plt.title("Ham vs Spam")

plt.show()
```



In [ ]:
```
# Removing punctuation
import string
string.punctuation

def remove_punctuation(text):
    return text.translate(str.maketrans('', '', string.punctuation))

df['text'] = df['text'].apply(remove_punctuation)
df.head()
```

Out[ ]:

	spam	text
0	ham	Go until jurong point crazy Available only in ...
1	ham	Ok lar Joking wif u oni
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor U c already then say
4	ham	Nah I dont think he goes to usf he lives aroun...

2. Feature Engineering

> Following data cleaning, we proceed to feature engineering. The initial step entails encoding the 'spam' feature using scikit-learn's LabelEncoder class.

In [ ]:
```
# Using sci-kit learn to label encode the spam column

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['spam'] = le.fit_transform(df['spam'])
df.head()
```

Out[ ]:

	spam	text
0	0	Go until jurong point crazy Available only in ...
1	0	Ok lar Joking wif u oni
2	1	Free entry in 2 a wkly comp to win FA Cup fina...
3	0	U dun say so early hor U c already then say
4	0	Nah I dont think he goes to usf he lives aroun...

> To enrich the model's feature set, we can introduce two additional numerical features: word count and message length

In [ ]:
```
# Column to represent the length of the text
df['length'] = df['text'].apply(len)
df.head()
```

Out[ ]:

	spam	text	length
0	0	Go until jurong point crazy Available only in ...	102
1	0	Ok lar Joking wif u oni	23
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	149
3	0	U dun say so early hor U c already then say	43
4	0	Nah I dont think he goes to usf he lives aroun...	59

In [ ]:
```
# Column with the number of words

def count_words(text):
    return len(text.split())
```

```
df['words'] = df['text'].apply(count_words)
df.head()
```

Out[ ]:

	spam	text	length	words
0	0	Go until jurong point crazy Available only in ...	102	20
1	0	Ok lar Joking wif u oni	23	6
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	149	28
3	0	U dun say so early hor U c already then say	43	11
4	0	Nah I dont think he goes to usf he lives aroun...	59	13

Word tokenization:

> Word tokenization, in the context of Natural Language Processing (NLP), is the process of splitting a piece of text into smaller units called tokens. The tokenizer splits the text based on predefined rules or delimiters. The most common delimiter is a whitespace character (space, tab, newline, etc.), resulting in individual words as tokens.

In [ ]:
```
import nltk
from nltk.tokenize import word_tokenize

# Download necessary NLTK resources (do this only once)
nltk.download('punkt')

def tokenize_text_nltk(text):
  # Lowercase the text
  text = text.lower()
  # Tokenize using NLTK word_tokenize
  tokens = word_tokenize(text)
  return tokens

df['tokens_nltk'] = df['text'].apply(tokenize_text_nltk)

df.head()
```

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

Out[ ]:

	spam	text	length	words	tokens_nltk
0	0	Go until jurong point crazy Available only in ...	102	20	[go, until, jurong, point, crazy, available, o...
1	0	Ok lar Joking wif u oni	23	6	[ok, lar, joking, wif, u, oni]
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	149	28	[free, entry, in, 2, a, wkly, comp, to, win, f...
3	0	U dun say so early hor U c already then say	43	11	[u, dun, say, so, early, hor, u, c, already, t...
4	0	Nah I dont think he goes to usf he lives aroun...	59	13	[nah, i, dont, think, he, goes, to, usf, he, l...

Removing Stop Words:

> In Natural Language Processing (NLP), removing stop words is a technique where you eliminate frequently occurring, generic words from your text data. These stop words typically

> don't contribute much to the core meaning of a sentence and can even add noise to your analysis.

In [ ]:
```
# removing stopwords

from nltk.corpus import stopwords

# Download necessary NLTK resources
nltk.download('stopwords')

stop_words = set(stopwords.words('english'))

def remove_stopwords(tokens):
    return [t for t in tokens if t not in stop_words]

df['tokens_nltk'] = df['tokens_nltk'].apply(remove_stopwords)

df.head()
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\carlo\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[ ]:

	spam	text	length	words	tokens_nltk
0	0	Go until jurong point crazy Available only in ...	102	20	[go, jurong, point, crazy, available, bugis, n...
1	0	Ok lar Joking wif u oni	23	6	[ok, lar, joking, wif, u, oni]
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	149	28	[free, entry, 2, wkly, comp, win, fa, cup, fin...
3	0	U dun say so early hor U c already then say	43	11	[u, dun, say, early, hor, u, c, already, say]
4	0	Nah I dont think he goes to usf he lives aroun...	59	13	[nah, dont, think, goes, usf, lives, around, t...

> Now let's add a new column to count the number of words after having removed the stop words.

In [ ]:
```
# Column with the number of words for nltk tokens

def count_words_nltk(tokens):
    return len(tokens)

df['words_nltk'] = df['tokens_nltk'].apply(count_words_nltk)
df.head()
```

Out[ ]:

	spam	text	length	words	tokens_nltk	words_nltk
0	0	Go until jurong point crazy Available only in ...	102	20	[go, jurong, point, crazy, available, bugis, n...	16
1	0	Ok lar Joking wif u oni	23	6	[ok, lar, joking, wif, u, oni]	6
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	149	28	[free, entry, 2, wkly, comp, win, fa, cup, fin...	23
3	0	U dun say so early hor U c already then say	43	11	[u, dun, say, early, hor, u, c, already, say]	9
4	0	Nah I dont think he goes to usf he lives aroun...	59	13	[nah, dont, think, goes, usf, lives, around, t...	8

> Note that the number of words decreased so we now have a cleaner text message.

Lemmatization:

> In this step, Lemmatization uses a dictionary and morphological analysis to map a word to its base form, called a lemma. It considers the part of speech of the word and aims to identify the canonical form used in the dictionary. Lemmatization goes a step further, considering the part of speech (e.g., "better" becomes "good").

In [ ]:
```
# Stemming/Lemmatization: using NLTK
from nltk.stem import WordNetLemmatizer

# Download necessary NLTK resources
nltk.download('wordnet')

lemmatizer = WordNetLemmatizer()

def lemmatize_text(tokens):
    return [lemmatizer.lemmatize(t) for t in tokens]

df['lemmatized'] = df['tokens_nltk'].apply(lemmatize_text)

df.head()
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\carlo\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Out[ ]:

	spam	text	length	words	tokens_nltk	words_nltk	lemmatized
0	0	Go until jurong point crazy Available only in ...	102	20	[go, jurong, point, crazy, available, bugis, n...	16	[go, jurong, point, crazy, available, bugis, n...
1	0	Ok lar Joking wif u oni	23	6	[ok, lar, joking, wif, u, oni]	6	[ok, lar, joking, wif, u, oni]
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	149	28	[free, entry, 2, wkly, comp, win, fa, cup, fin...	23	[free, entry, 2, wkly, comp, win, fa, cup, fin...
3	0	U dun say so early hor U c already then say	43	11	[u, dun, say, early, hor, u, c, already, say]	9	[u, dun, say, early, hor, u, c, already, say]
4	0	Nah I dont think he goes to usf he lives aroun...	59	13	[nah, dont, think, goes, usf, lives, around, t...	8	[nah, dont, think, go, usf, life, around, though]

In [ ]:
```
# Convert lemmatized tokens back to text

def tokens_to_text(tokens):
    return ' '.join(tokens)

df['lemmatized_text'] = df['lemmatized'].apply(tokens_to_text)
df.head()
```

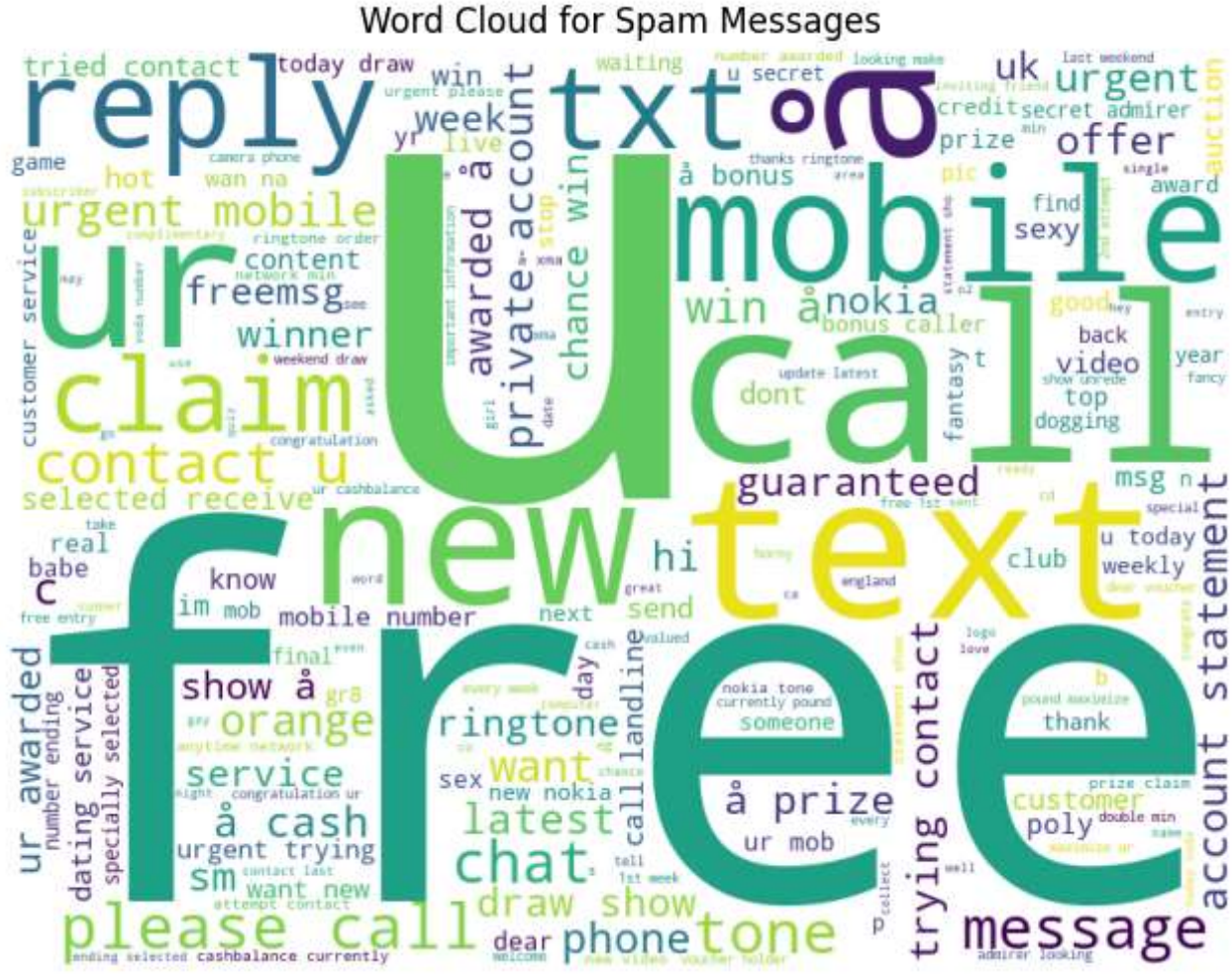
Out[ ]:

	spam	text	length	words	tokens_nltk	words_nltk	lemmatized	lemmatized_text
0	0	Go until jurong point crazy Available only in ...	102	20	[go, jurong, point, crazy, available, bugis, n...	16	[go, jurong, point, crazy, available, bugis, n...	go jurong point crazy available bugis n great ...
1	0	Ok lar Joking wif u oni	23	6	[ok, lar, joking, wif, u, oni]	6	[ok, lar, joking, wif, u, oni]	ok lar joking wif u oni
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	149	28	[free, entry, 2, wkly, comp, win, fa, cup, fin...	23	[free, entry, 2, wkly, comp, win, fa, cup, fin...	free entry 2 wkly comp win fa cup final tkts 2...
3	0	U dun say so early hor U c already then say	43	11	[u, dun, say, early, hor, u, c, already, say]	9	[u, dun, say, early, hor, u, c, already, say]	u dun say early hor u c already say
4	0	Nah I dont think he goes to usf he lives aroun...	59	13	[nah, dont, think, goes, usf, lives, around, t...	8	[nah, dont, think, go, usf, life, around, though]	nah dont think go usf life around though

3. Data vizualization

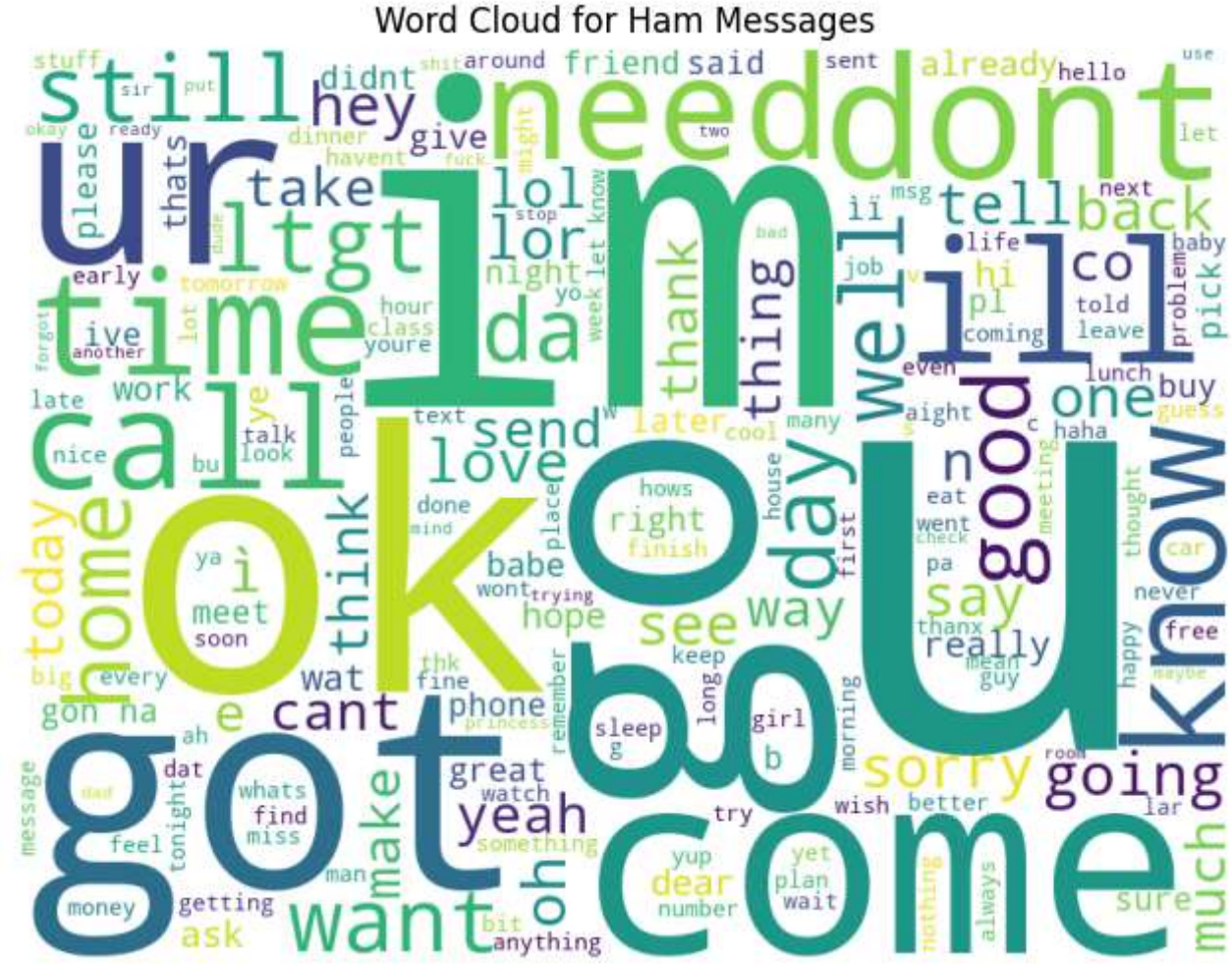
In [ ]:

```
from wordcloud import WordCloud
import matplotlib.pyplot as plt

df_spam = df[df['spam'] == 1]

# Create a WordCloud object
wordcloud = WordCloud(width=800, height=600, background_color="white")

# Generate the word cloud
wordcloud.generate(df_spam['lemmatized_text'].to_string())

# Create a figure and display the word cloud
plt.figure(figsize=(8, 6))
plt.imshow(wordcloud)
plt.axis("off")
plt.title("Word Cloud for Spam Messages")
plt.show()
```



In [ ]:

```
df_ham = df[df['spam'] == 0]

# Create a WordCloud object
wordcloud = WordCloud(width=800, height=600, background_color="white")

# Generate the word cloud
wordcloud.generate(df_ham['lemmatized_text'].to_string())

# Create a figure and display the word cloud
plt.figure(figsize=(8, 6))
plt.imshow(wordcloud)
plt.axis("off")
plt.title("Word Cloud for Ham Messages")
plt.show()
```



> **N-grams:**
> Creating sequences of n words. Bigrams (2 words) and trigrams (3 words). N-grams can capture word relationships that single words might miss.

> Single Words vs. Sequences: Individual words might not always convey the full meaning on their own. Bigrams (two-word sequences) and trigrams (three-word sequences) can capture the relationships between words, which can be crucial for tasks like:
>
> - Sentiment Analysis: "not good" vs. "very good" expresses a clear difference in sentiment.
> - Topic Modeling: Identifying bigrams like "machine learning" or trigrams like "natural language processing" can help identify topics within text data.
> - Machine Translation: Capturing word order and phrasal meaning is essential for accurate translation.

In [ ]:
```python
# N-grams

from nltk.util import ngrams

def extract_ngrams(tokens, n):
    return list(ngrams(tokens, n))

df['bigrams'] = df['lemmatized'].apply(lambda x: extract_ngrams(x, 2))
df['trigrams'] = df['lemmatized'].apply(lambda x: extract_ngrams(x, 3))

df.head()
```

Out[ ]:

	spam	text	length	words	tokens_nltk	words_nltk	lemmatized	lemmatized_text	bigrams	trigrams
0	0	Go until jurong point crazy Available only in ...	102	20	[go, jurong, point, crazy, available, bugis, n...	16	[go, jurong, point, crazy, available, bugis, n...	go jurong point crazy available bugis n great ...	[(go, jurong), (jurong, point), (point, crazy)...	[(go, jurong, point), (jurong, point, crazy), ...
1	0	Ok lar Joking wif u oni	23	6	[ok, lar, joking, wif, u, oni]	6	[ok, lar, joking, wif, u, oni]	ok lar joking wif u oni	[(ok, lar), (lar, joking), (joking, wif), (wif...	[(ok, lar, joking), (lar, joking, wif), (jokin...
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	149	28	[free, entry, 2, wkly, comp, win, fa, cup, fin...	23	[free, entry, 2, wkly, comp, win, fa, cup, fin...	free entry 2 wkly comp win fa cup final tkts 2...	[(free, entry), (entry, 2), (2, wkly), (wkly, ...	[(free, entry, 2), (entry, 2, wkly), (2, wkly,...
3	0	U dun say so early hor U c already then say	43	11	[u, dun, say, early, hor, u, c, already, say]	9	[u, dun, say, early, hor, u, c, already, say]	u dun say early hor u c already say	[(u, dun), (dun, say), (say, early), (early, h...	[(u, dun, say), (dun, say, early), (say, early...
4	0	Nah I dont think he goes to usf he lives aroun...	59	13	[nah, dont, think, goes, usf, lives, around, t...	8	[nah, dont, think, go, usf, life, around, though]	nah dont think go usf life around though	[(nah, dont), (dont, think), (think, go), (go,...	[(nah, dont, think), (dont, think, go), (think...

> Now we need to convert our text message into a numerical representation suitable for machine learning algorithms, an we have to options:
>
> - TF-IDF: If you want to emphasize the importance of words that are frequent within a document but rare across the corpus (potentially good indicators of spam), TF-IDF might be a better choice.
> - BoW: If a simple word count representation is sufficient for your task, BoW might be a more efficient option.

To potentially improve the accuracy of our spam/ham classification model, we can now incorporate TF-IDF **(Term Frequency-Inverse Document Frequency)**. This technique assigns weights to words based on their frequency within a document and rarity across the entire corpus, potentially highlighting terms that are more indicative of spam emails.

In [ ]:

```
# TF-IDF

from sklearn.feature_extraction.text import TfidfVectorizer

# Create a TfidfVectorizer object
vectorizer = TfidfVectorizer()
```

```
# Fit the vectorizer
vectorizer.fit(df['lemmatized_text'])

# Transform the text to a TF-IDF vector
X_tfidf = vectorizer.transform(df['lemmatized_text'])
```

> **Convert bigrams/trigrams** lists into numerical representations:
> Use CountVectorizer to create a sparse matrix where each row is a message and columns represent unique bigrams/trigrams with their counts.

Alternatively, apply feature hashing to bigrams/trigrams for a fixed-size vector representation.

In [ ]:
```
from sklearn.feature_extraction.text import CountVectorizer

def custom_preprocessor(text):
    # Customize preprocessing for lists (e.g., join with a special character)
    return ' '.join(['_'.join(bigram) for bigram in text])

vectorizer_bigrams = CountVectorizer(preprocessor=custom_preprocessor)
vectorizer_bigrams.fit_transform(df['bigrams'])
X_bigrams = vectorizer_bigrams.transform(df['bigrams'])


vectorizer_trigrams = CountVectorizer(preprocessor=custom_preprocessor)
vectorizer_trigrams.fit_transform(df['trigrams'])
X_trigrams = vectorizer_trigrams.transform(df['trigrams'])
```

> Concatenate these features into a single DataFrame or NumPy array for training your mode

In [ ]:
```
from scipy.sparse import hstack

# Combine the sparse matrices
X_combined = hstack((X_tfidf, X_bigrams, X_trigrams))

y = df['spam']
```

4. Modeling

Splitting the data

Now I will split the data into features/target variable and training and test sets.

In [ ]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_combined, y, test_size=0.2, random_state=4
```

Random forest

I will start by using `GridSearchCV` to tune a random forest model using parameter as follows:

- estimator= `rf`
- param_grid= `cv_params`
- scoring= `scoring`
- cv: define the number of cross-validation folds you want (`cv=_`)

- refit: indicate which evaluation metric you want to use to select the model (`refit=_`)

For this case I will set `refit` to `'f1'` given that:

In this case:

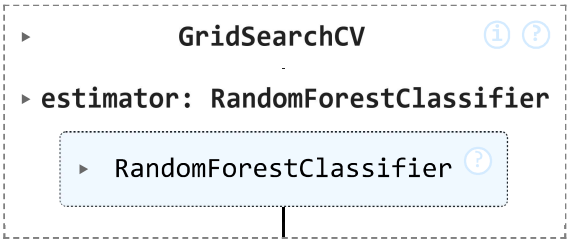
- Accuracy might be high if the model mostly predicts non-churn (majority class), even if it misses many actual churners (minority class).
- Precision is valuable to ensure customers flagged as likely to churn actually do churn, minimizing unnecessary interventions.
- Recall is crucial to identify as many churners as possible, even if it means some false positives (non-churners predicted as churn).
- F1-score provides a balance between precision and recall, giving a more holistic view of churn prediction performance.

In [ ]:
```
# 1. Instantiate the random forest classifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

rf = RandomForestClassifier(random_state=42)

# 2. Create a dictionary of hyperparameters to tune
cv_params = {'max_depth': [None],
             'max_features': [1.0],
             'max_samples': [1.0],
             'min_samples_leaf': [2],
             'min_samples_split': [2],
             'n_estimators': [300],
             }

# 3. Define a dictionary of scoring metrics to capture
scoring = ['accuracy', 'precision', 'recall', 'f1']

# 4. Instantiate the GridSearchCV object
rf_cv = GridSearchCV(rf, cv_params, scoring=scoring, cv=4, refit='f1')
```

In [ ]:
```
%%time
rf_cv.fit(X_train, y_train)
```

```
CPU times: total: 15min 25s
Wall time: 31min 4s
```

Out[ ]:



In [ ]:
```
# Examine best score
rf_cv.best_score_
```

Out[ ]:
```
0.833854339698875
```

> Examine the best combination of hyperparameters.

In [ ]:
```
# Examine best hyperparameter combo
rf_cv.best_params_
```

Out[ ]:
```
{'max_depth': None,
 'max_features': 1.0,
 'max_samples': 1.0,
 'min_samples_leaf': 2,
 'min_samples_split': 2,
 'n_estimators': 300}
```

Use the `make_results()` function to output all of the scores of your model. Note that the function accepts three arguments.

In [ ]:
```
def make_results(model_name:str, model_object, metric:str):
    '''
    Arguments:
        model_name (string): what you want the model to be called in the output table
        model_object: a fit GridSearchCV object
        metric (string): precision, recall, f1, or accuracy

    Returns a pandas df with the F1, recall, precision, and accuracy scores
    for the model with the best mean 'metric' score across all validation folds.
    '''

    # Create dictionary that maps input metric to actual metric name in GridSearchCV
    metric_dict = {'precision': 'mean_test_precision',
                   'recall': 'mean_test_recall',
                   'f1': 'mean_test_f1',
                   'accuracy': 'mean_test_accuracy',
                   }

    # Get all the results from the CV and put them in a df
    cv_results = pd.DataFrame(model_object.cv_results_)

    # Isolate the row of the df with the max(metric) score
    best_estimator_results = cv_results.iloc[cv_results[metric_dict[metric]].idxmax(), :]

    # Extract accuracy, precision, recall, and f1 score from that row
    f1 = best_estimator_results.mean_test_f1
    recall = best_estimator_results.mean_test_recall
    precision = best_estimator_results.mean_test_precision
    accuracy = best_estimator_results.mean_test_accuracy

    # Create table of results
    table = pd.DataFrame({'model': [model_name],
                          'precision': [precision],
                          'recall': [recall],
                          'F1': [f1],
                          'accuracy': [accuracy],
                          },
                         )

    return table
```

Pass the `GridSearch` object to the `make_results()` function.

In [ ]:
```
results = make_results('RF cv', rf_cv, 'recall')
results
```

Out[ ]:

	model	precision	recall	F1	accuracy
0	RF cv	0.91542	0.765748	0.833854	0.962515

XGBoost

As in Desicion Treen I will be using `GridSearchCV` to tune a random forest model using parameter as follows:

- estimator= `xgb`
- param_grid= `cv_params`
- scoring= `scoring`
- cv: define the number of cross-validation folds you want (`cv=_`)
- refit: indicate which evaluation metric you want to use to select the model (`refit=_`)

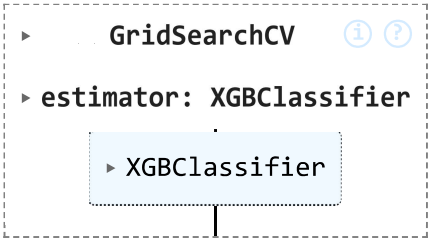
For this case I will also set `refit` to `'f1'` because of the resons I mentioned before.

In [ ]:
```
# 1. Instantiate the XGBoost classifier
from xgboost import XGBClassifier

xgb = XGBClassifier(objective='binary:logistic', random_state=42)

# 2. Create a dictionary of hyperparameters to tune
cv_params = {'max_depth': [6, 12],
             'min_child_weight': [3, 5],
             'learning_rate': [0.01, 0.1],
             'n_estimators': [300]
             }

# 3. Define a dictionary of scoring metrics to capture
scoring = ['accuracy', 'precision', 'recall', 'f1']

# 4. Instantiate the GridSearchCV object
xgb_cv = GridSearchCV(xgb, cv_params, scoring=scoring, cv=4, refit='f1')
```

In [ ]:
```
%%time
xgb_cv.fit(X_train, y_train)
```

```
CPU times: total: 44min 27s
Wall time: 6min 48s
```

Out[ ]:



In [ ]:
```
# Examine best score
xgb_cv.best_score_
```

Out[ ]:
```
0.82160085717805
```

In [ ]:
```
# Examine best parameters
xgb_cv.best_params_
```

Out[ ]:
```
{'learning_rate': 0.1,
 'max_depth': 6,
 'min_child_weight': 3,
 'n_estimators': 300}
```

In [ ]:
```
# Call 'make_results()' on the GridSearch object
xgb_cv_results = make_results('XGB cv', xgb_cv, 'f1')
results = pd.concat([results, xgb_cv_results], axis=0)
results
```

Out[ ]:

	model	precision	recall	F1	accuracy
0	RF cv	0.91542	0.765748	0.833854	0.962515
0	XGB cv	0.88976	0.763780	0.821601	0.959369

5. Model Selection

Now, I will use the best random forest model and the best XGBoost model to predict on the test data. Whichever performs better will be selected as the champion model.

Random Forest

In [ ]:
```
# Use random forest model to predict on test data
rf_test_preds = rf_cv.best_estimator_.predict(X_test)
```

> The next function will help to generate a table with the scores from the predictions made

In [ ]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score,f1_score

def get_test_scores(model_name:str, preds, y_test_data):
    '''
    Generate a table of test scores.

    In:
        model_name (string): Your choice: how the model will be named in the output table
        preds: numpy array of test predictions
        y_test_data: numpy array of y_test data

    Out:
        table: a pandas df of precision, recall, f1, and accuracy scores for your model
    '''
    accuracy = accuracy_score(y_test_data, preds)
    precision = precision_score(y_test_data, preds)
    recall = recall_score(y_test_data, preds)
    f1 = f1_score(y_test_data, preds)

    table = pd.DataFrame({'model': [model_name],
                          'precision': [precision],
                          'recall': [recall],
                          'F1': [f1],
                          'accuracy': [accuracy]
                          })

    return table
```

In [ ]:
```
# Get validation scores for RF model
rf_val_scores = get_test_scores('RF Test', rf_test_preds, y_test)
```

```
# Append to the results table
results = pd.concat([results, rf_val_scores], axis=0)
results
```

Out[ ]:

	model	precision	recall	F1	accuracy
0	RF cv	0.915420	0.765748	0.833854	0.962515
0	XGB cv	0.889760	0.763780	0.821601	0.959369
0	RF Test	0.899225	0.800000	0.846715	0.959381

XGBoost Classifier

In [ ]:
```
# Use XGBoost model to predict on test data
xgb_test_preds = xgb_cv.best_estimator_.predict(X_test)

# Get test scores for XGBoost model
xgb_test_scores = get_test_scores('XGB test', xgb_test_preds, y_test)

# Append to the results table
results = pd.concat([results, xgb_test_scores], axis=0)
results
```

Out[ ]:

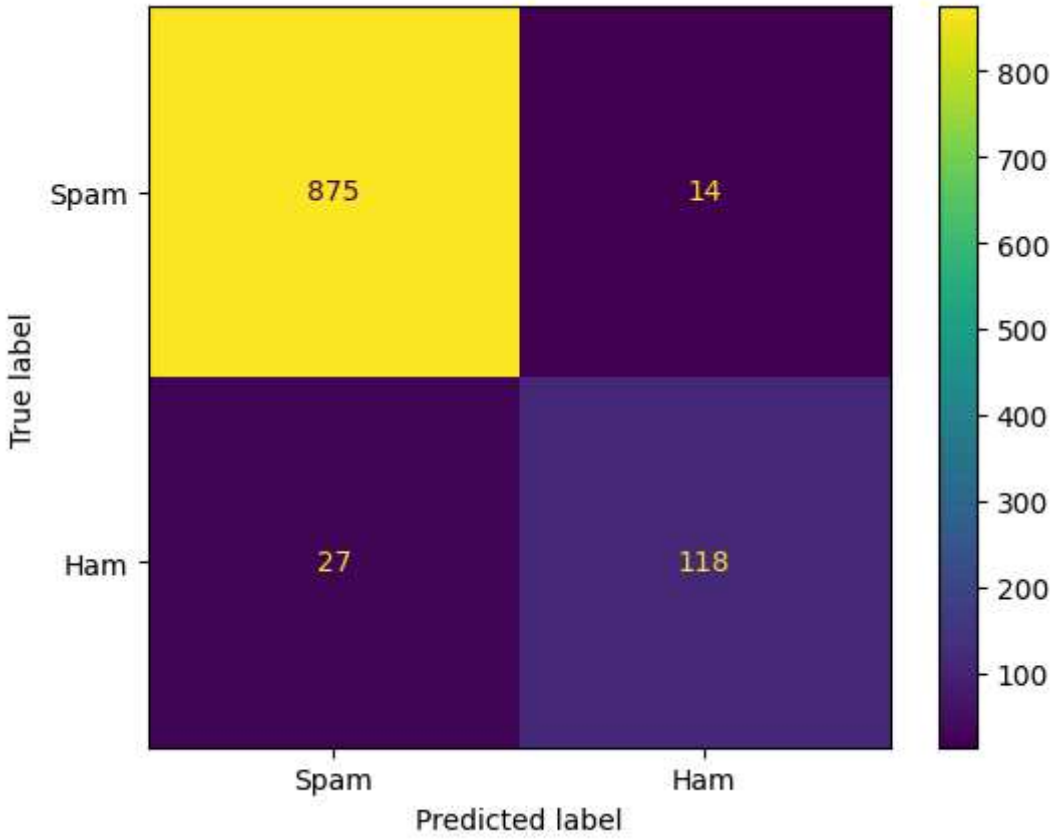
	model	precision	recall	F1	accuracy
0	RF cv	0.915420	0.765748	0.833854	0.962515
0	XGB cv	0.889760	0.763780	0.821601	0.959369
0	RF Test	0.899225	0.800000	0.846715	0.959381
0	XGB test	0.893939	0.813793	0.851986	0.960348

> Noticed that the Champion Model here is the `XGBoost Regressor` given that all scores indicate that performed better

6. Use champion model to predict on test data

In [ ]:
```
# Use XGBoost model to predict on test data
xgb_test_preds = xgb_cv.best_estimator_.predict(X_test)
```

In [ ]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Generate array of values for confusion matrix
cm = confusion_matrix(y_test, xgb_test_preds, labels=xgb_cv.classes_)

# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=['Spam', 'Ham'])
disp.plot();
```



Conclusion:

- High TP and Low FP: The model effectively identifies **875** spam emails with minimal **27** false positives (correctly classifying most actual spam).
- High TN and Low FN: The model accurately classifies **118** ham emails, avoiding false **14** negatives (missing very little actual spam).

There is a discrepancy between the predicted spam emails (875) and the initial number of spam rows in your dataset (653). Here's how the precision and recall values shed light on this:

- The high precision (0.89) suggests a significant portion of the predicted spam (875) are likely true positives (actual spam).
- The lower recall (0.81) indicates the model might still be missing some spam emails (false negatives), contributing to the difference between predicted and actual spam counts.