PROBLEM STATEMENT:

Analyze and visualize sentiment patterns in social media data to understand public opinion and attitudes towards specific topics or brands.

[1]:
```
from google.colab import files
```

[2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[3]:
```
#Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
```

[5]:
```
data = files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving twitter_validation.csv to twitter_validation.csv
Saving twitter_training.csv to twitter_training.csv
```

[6]:
```
twitter_training = pd.read_csv('twitter_training.csv')
twitter_validation = pd.read_csv('twitter_validation.csv')

twitter_training.head()

twitter_validation.head()
```

[6]:
```
   3364   Facebook Irrelevant  \
0   352     Amazon    Neutral
1  8312  Microsoft   Negative
2  4371      CS-GO   Negative
3  4433     Google    Neutral
4  6273       FIFA   Negative

  I mentioned on Facebook that I was struggling for motivation to go for a run
the other day, which has been translated by Tom’s great auntie as ‘Hayley can’t
get out of bed’ and told to his grandma, who now thinks I’m a lazy, terrible
person
0  BBC News - Amazon boss Jeff Bezos rejects clai…
1  @Microsoft Why do I pay for WORD when it funct…
2  CSGO matchmaking is so full of closet hacking,…
3  Now the President is slapping Americans in the…
4  Hi @EAHelp I’ve had Madeleine McCann in my cel…
```

[8]:
```
columns=['TweetID','entity','sentiment','Tweet content']
twitter_training = pd.read_csv('twitter_training.csv', header=␣
 ↪None,names=columns)
twitter_validation = pd.read_csv('twitter_validation.csv', header = None␣
 ↪,names=columns)
```

[9]:
```
twitter_training.head()
```

[9]:
```
   TweetID       entity sentiment  \
0     2401  Borderlands  Positive
1     2401  Borderlands  Positive
2     2401  Borderlands  Positive
3     2401  Borderlands  Positive
4     2401  Borderlands  Positive

                                        Tweet content
0  im getting on borderlands and i will murder yo…
1  I am coming to the borders and I will kill you…
2  im getting on borderlands and i will kill you …
3  im coming on borderlands and i will murder you…
4  im getting on borderlands 2 and i will murder …
```

[10]:
```
twitter_validation.head()
```

[10]:
```
   TweetID     entity   sentiment  \
0     3364   Facebook  Irrelevant
1      352     Amazon     Neutral
2     8312  Microsoft    Negative
3     4371      CS-GO    Negative
4     4433     Google     Neutral
```

```
                                                Tweet content
0  I mentioned on Facebook that I was struggling …
1  BBC News - Amazon boss Jeff Bezos rejects clai…
2  @Microsoft Why do I pay for WORD when it funct…
3  CSGO matchmaking is so full of closet hacking,…
4  Now the President is slapping Americans in the…
```

[11]:
```
twitter_training.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74682 entries, 0 to 74681
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   TweetID        74682 non-null  int64 
 1   entity         74682 non-null  object
 2   sentiment      74682 non-null  object
 3   Tweet content  73996 non-null  object
dtypes: int64(1), object(3)
memory usage: 2.3+ MB
```

[12]:
```
twitter_training.isna().sum()
```

[12]:
```
TweetID            0
entity             0
sentiment          0
Tweet content    686
dtype: int64
```

[13]:
```
twitter_validation.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   TweetID        1000 non-null   int64 
 1   entity         1000 non-null   object
 2   sentiment      1000 non-null   object
 3   Tweet content  1000 non-null   object
dtypes: int64(1), object(3)
memory usage: 31.4+ KB
```

[14]:
```
twitter_training.duplicated().sum()
```

[14]:
```
2700
```

[15]:
```
twitter_validation.duplicated().sum()
```

[15]:
```
0
```

[16]:
```
twitter_training = twitter_training.drop_duplicates()
```

[18]:
```
twitter_training = twitter_training.dropna()
```

[19]:
```
twitter_training.iloc[:, 2].value_counts()
```

[19]:
```
Negative      21698
Positive      19713
Neutral       17708
Irrelevant    12537
Name: sentiment, dtype: int64
```

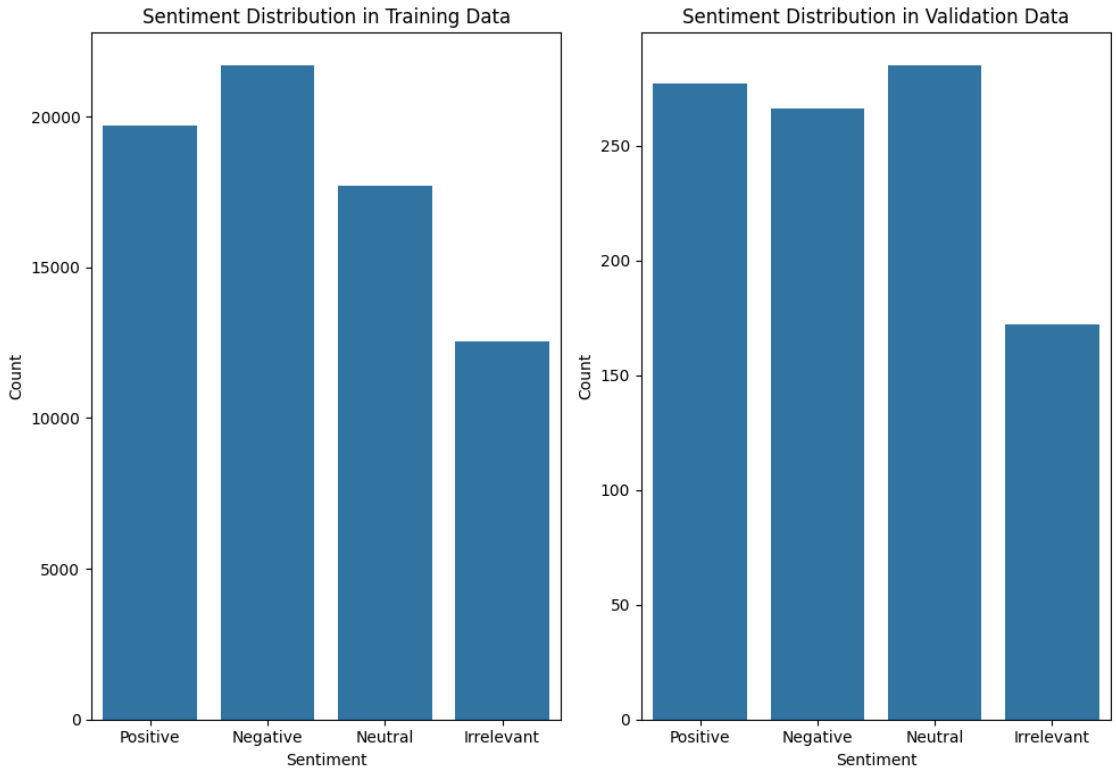
[20]:
```
twitter_validation.iloc[:, 2].value_counts()
```

[20]:
```
Neutral       285
Positive      277
Negative      266
Irrelevant    172
Name: sentiment, dtype: int64
```

[21]:
```
twitter_training['sentiment'].unique()
```

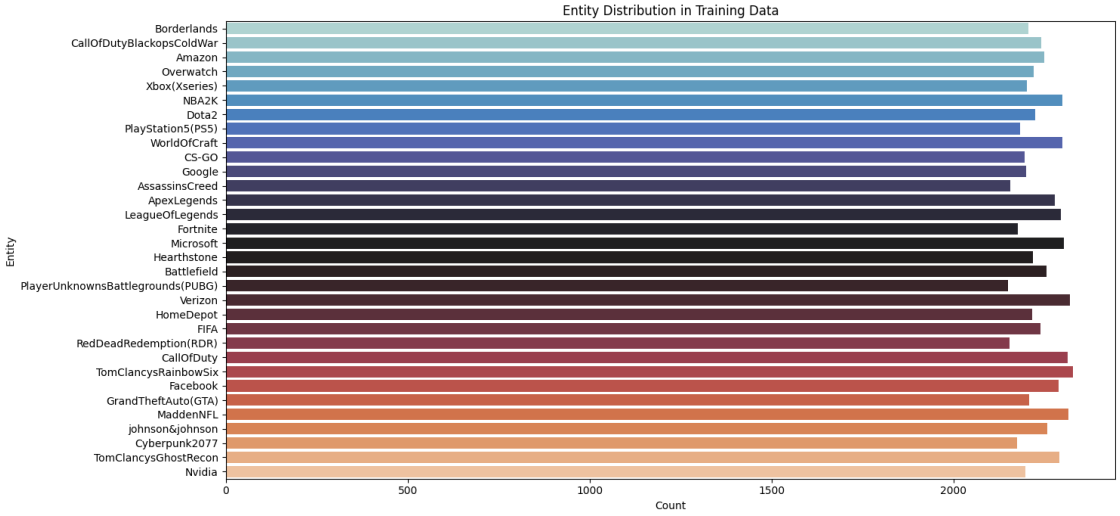
[21]:
```
array(['Positive', 'Neutral', 'Negative', 'Irrelevant'], dtype=object)
```

[22]:
```
#Setting up the plots
fig, ax = plt.subplots(1, 2, figsize=(10, 7))

#Plotting sentiment distribution for training data
sns.countplot(data=twitter_training, x=twitter_training.columns[2],␣
 ↪order=['Positive', 'Negative', 'Neutral', 'Irrelevant'], ax=ax[0])
ax[0].set_title('Sentiment Distribution in Training Data')
ax[0].set_ylabel('Count')
ax[0].set_xlabel('Sentiment')

#Plotting sentiment distribution for validation data
sns.countplot(data=twitter_validation, x=twitter_validation.columns[2],␣
 ↪order=['Positive', 'Negative', 'Neutral', 'Irrelevant'], ax=ax[1])
ax[1].set_title('Sentiment Distribution in Validation Data')
ax[1].set_ylabel('Count')
ax[1].set_xlabel('Sentiment')

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



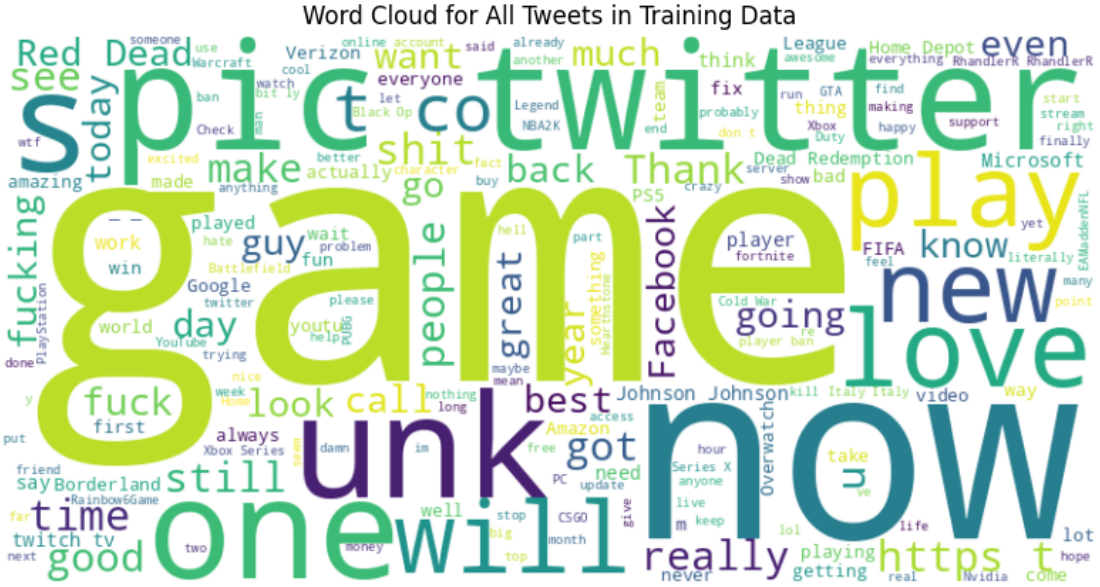
[23]:
```
#Setting up the plot
plt.figure(figsize=(15, 7))

#Plotting entity distribution for training data
sns.countplot(data=twitter_training, y=twitter_training.columns[1], ␣
 ↪palette='icefire')
plt.title('Entity Distribution in Training Data')
plt.xlabel('Count')
plt.ylabel('Entity')
plt.tight_layout()
plt.show()
```

```
<ipython-input-23-486dd81633c5>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(data=twitter_training, y=twitter_training.columns[1],
palette='icefire')
```



[24]:
```
#Generating the word cloud for the entire training dataset
all_text = " ".join(tweet for tweet in twitter_training[twitter_training.
 ↪columns[3]])
wordcloud_all = WordCloud(background_color='white', width=800, height=400).
 ↪generate(all_text)
```

[25]:
```
#Plotting the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud_all, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for All Tweets in Training Data')
plt.show()
```



[26]:
```
#Initializing sentiment categories
sentiments = ['Positive', 'Negative', 'Neutral', 'Irrelevant']

#Setting up the plots
fig, axs = plt.subplots(2, 2, figsize=(15, 10))

#Generating and plotting word clouds for each sentiment
for sentiment, ax in zip(sentiments, axs.ravel()):
    sentiment_text = " ".join(tweet for tweet in␣
 ↪twitter_training[twitter_training[twitter_training.columns[2]] ==␣
 ↪sentiment][twitter_training.columns[3]])
    wordcloud_sentiment = WordCloud(background_color='white', width=400,␣
 ↪height=200).generate(sentiment_text)

    ax.imshow(wordcloud_sentiment, interpolation='bilinear')
    ax.axis('off')
    ax.set_title(f'Word Cloud for {sentiment} Sentiment',y=1.05)

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

[27]:
```
#Alternative function to preprocess text without lemmatization or NLTK stopwords
def preprocess_text_simplified(text):
```

```
    #Converting to lowercase
    text = text.lower()
    #Simple tokenization using split (without relying on NLTK)
    tokens = text.split()
    #Removing special characters and numbers
    tokens = [token for token in tokens if token.isalpha()]
    return " ".join(tokens)

#Applying simplified preprocessing to training data
twitter_training['processed_message_simplified'] =␣
 ↪twitter_training[twitter_training.columns[3]].
 ↪apply(preprocess_text_simplified)

#Extracting most frequent terms using CountVectorizer with simplified␣
 ↪preprocessing
vectorizer_simplified = CountVectorizer(max_features=20)
X_simplified = vectorizer_simplified.
 ↪fit_transform(twitter_training['processed_message_simplified'])
frequent_terms_simplified = vectorizer_simplified.get_feature_names_out()

frequent_terms_simplified
```

[27]:
```
array(['and', 'but', 'for', 'game', 'have', 'in', 'is', 'it', 'just',
       'my', 'not', 'of', 'on', 'so', 'that', 'the', 'this', 'to', 'with',
       'you'], dtype=object)
```

[28]:
```
#Applying simplified preprocessing to the validation data
twitter_validation['processed_message_simplified'] =␣
 ↪twitter_validation[twitter_validation.columns[3]].
 ↪apply(preprocess_text_simplified)
```

[29]:
```
#Adjusting the labels: Convert "Irrelevant" labels to "Neutral"
twitter_training[twitter_training.columns[2]] =␣
 ↪twitter_training[twitter_training.columns[2]].replace('Irrelevant',␣
 ↪'Neutral')
twitter_validation[twitter_validation.columns[2]] =␣
 ↪twitter_validation[twitter_validation.columns[2]].replace('Irrelevant',␣
 ↪'Neutral')
```

[30]:
```
twitter_training['sentiment'].value_counts()
```

[30]:
```
Neutral     30245
Negative    21698
Positive    19713
Name: sentiment, dtype: int64
```

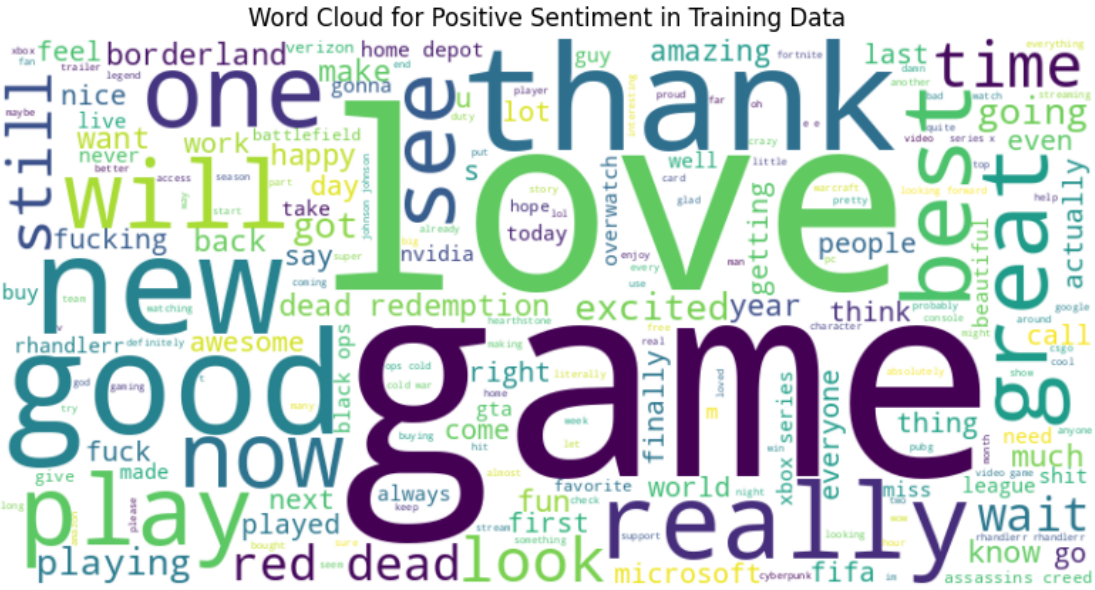
[31]:
```
twitter_validation['sentiment'].value_counts()
```

[31]:
```
Neutral     457
Positive    277
Negative    266
Name: sentiment, dtype: int64
```

[32]:
```
#Initializing the TF-IDF vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=5000)  # Limiting to 5000␣
 ↪features for computational efficiency

#Fitting and transforming the preprocessed text from the training data
X_train_tfidf = tfidf_vectorizer.
 ↪fit_transform(twitter_training['processed_message_simplified'])

#Transforming the preprocessed text from the validation data
X_validation_tfidf = tfidf_vectorizer.
 ↪transform(twitter_validation['processed_message_simplified'])

#Extracting target labels for training and validation
y_train = twitter_training[twitter_training.columns[2]]
y_validation = twitter_validation[twitter_validation.columns[2]]

X_train_tfidf.shape, X_validation_tfidf.shape
```

[32]:
```
((71656, 5000), (1000, 5000))
```

[33]:
```
#Extracting text for Positive sentiment from the training dataset
positive_text = " ".join(tweet for tweet in␣
 ↪twitter_training[twitter_training[twitter_training.columns[2]] ==␣
 ↪'Positive']['processed_message_simplified'])

#Generating word cloud for Positive sentiment
wordcloud_positive = WordCloud(background_color='white', width=800, height=400).
 ↪generate(positive_text)

#Plotting the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud_positive, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Positive Sentiment in Training Data')
plt.show()
```



[36]:
```
#The target variable for training and validation again
y_train = twitter_training[twitter_training.columns[2]]
y_validation = twitter_validation[twitter_validation.columns[2]]

#Creating the ML pipeline with TF-IDF vectorization and Logistic Regression
pipeline = Pipeline([
    ('tfidf', TfidfVectorizer(max_features=5000)),
    ('classifier', LogisticRegression(solver='sag', multi_class='auto',␣
  ↪max_iter=10000))  # using 'sag' solver for faster convergence
])

#Training the pipeline model using the training data
pipeline.fit(twitter_training['processed_message_simplified'], y_train)
```

[36]:
```
Pipeline(steps=[('tfidf', TfidfVectorizer(max_features=5000)),
                ('classifier',
                 LogisticRegression(max_iter=10000, solver='sag'))])
```

[35]:
```
#Validating the model's performance on the training dataset
training_accuracy = pipeline.
  ↪score(twitter_training['processed_message_simplified'], y_train)
training_accuracy
```

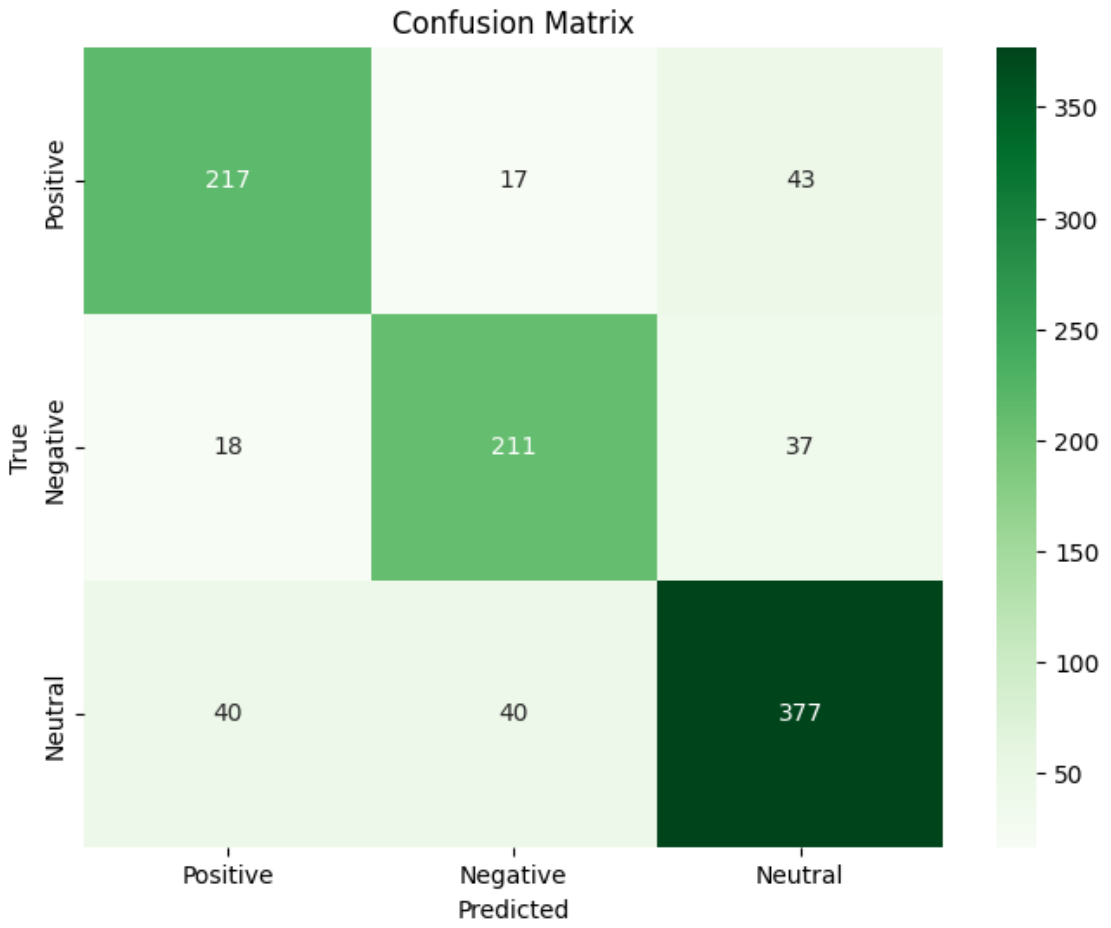
[35]:
```
0.7466506642849168
```

[37]:
```
#Validating the model's performance on the validation dataset
```

```
validation_accuracy = pipeline.
 ↪score(twitter_validation['processed_message_simplified'], y_validation)
validation_accuracy
```

[37]: 0.805

[38]:
```
#Generating predictions on the validation data
y_validation_pred = pipeline.
 ↪predict(twitter_validation['processed_message_simplified'])

#Creating a confusion matrix
conf_matrix = confusion_matrix(y_validation, y_validation_pred,␣
 ↪labels=['Positive', 'Negative', 'Neutral'])

#Plotting the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Greens',␣
 ↪xticklabels=['Positive', 'Negative', 'Neutral'], yticklabels=['Positive',␣
 ↪'Negative', 'Neutral'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



[39]:
```
#Generating predictions on the training data
y_train_pred = pipeline.
 ↪predict(twitter_training['processed_message_simplified'])

#Creating a confusion matrix
conf_matrix_train = confusion_matrix(y_train, y_train_pred, labels=['Positive',␣
 ↪'Negative', 'Neutral'])

#Plotting the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_train, annot=True, fmt='d', cmap='Blues',␣
 ↪xticklabels=['Positive', 'Negative', 'Neutral'], yticklabels=['Positive',␣
 ↪'Negative', 'Neutral'])
plt.title('Confusion Matrix - Training Data')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```