Phase 4: Development Part 2

In Phase 4 of the "Sentiment Analysis" project, you will continue building the sentiment analysis solution by employing various Natural Language Processing (NLP) techniques and generating valuable insights from the processed data. This phase is crucial for understanding customer feedback, extracting sentiments, and providing actionable insights to improve products and make informed business decisions. Here's a detailed outline of Phase 4:

1. NLP Techniques and Sentiment Analysis:

NLP techniques play a crucial role in sentiment analysis by enabling the automatic understanding and interpretation of human language to determine sentiment and emotions expressed in text data.

How NLP is applied to sentiment analysis:

- **Text Preprocessing:** NLP techniques are used to preprocess the text data.

- **Feature Extraction:** NLP methods are used to extract features from the text data

- **Machine Learning Models:** NLP is employed to build machine learning models, such as Naive Bayes, Support Vector Machines

- **Sentiment Classification:** NLP models are used to classify the sentiment of the text as positive, negative, neutral, or on a scale

- **Sentiment Analysis Applications:** Sentiment analysis is used in various applications, such as social media monitoring, product reviews, customer feedback analysis, and market research

2. Feature Extraction:

- feature extraction is like finding the most important clues or characteristics in data and ignoring the less important stuff.

- It helps simplify the data and makes it easier for computers to understand and make sense of it.

3. Visualization:

Visualization is the process of representing data or information graphically to help people understand and interpret it more easily. It can take the form of charts, graphs, diagrams, or any other visual representation that conveys information effectively

4. Insights Generation:

- **Text Classification:** Sentiment analysis categorizes text into positive, negative, or neutral sentiments**.**

- **Data Preprocessing:** Cleaning and preparing text data is crucial for accurate analysis.

- **Feature Extraction:** Techniques like word frequency and word embeddings help convert text into numerical data.

- **Lexicon-Based Analysis:** Some methods use sentiment dictionaries to assess word sentiment

- **Machine Learning Models:** Algorithms like Naive Bayes, SVM, and deep learning are commonly used.

- **Aspect-Based Analysis:** Identifying sentiment toward specific aspects or entities is important

- **Applications**: Sentiment analysis is used in social media monitoring, reviews, and more.

- **Challenges:** Dealing with idiomatic expressions and evolving language is an ongoing challenge.

5. Model Evaluation:

Model Evaluation in Sentiment Analysis: In sentiment analysis, model evaluation is like checking how accurately your program can understand and categorize whether a piece of text (like a customer review) is positive, negative, or neutral. Fine-Tuning in Sentiment Analysis: Fine-tuning in sentiment analysis involves making adjustments to your program so it can better understand the nuances of language and improve its accuracy in determining the sentiment of text, such as improving its ability to recognize sarcasm or context. It's like training your program to better understand people's feelings in their words.

6. Documention:

- Documentation is a way of writing down and explaining information, processes, and details about something, like a project or a system, so that others can understand, use, and maintain it. It helps with communication, learning, and making sure things work correctly.

- Documentation is essential for reproducibility and sharing insights from sentiment analysis projects. It helps others understand your methodology and findings.

Program:

[1]:
```
# Data Analysis
import pandas as pd
import numpy as np

#  Data  Visualization
from matplotlib import pyplot as plt
import seaborn as sns

# Machine  Learning
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score

from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier from
sklearn.ensemble import RandomForestClassifier from
xgboost import XGBClassifier

# NLP
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from wordcloud import WordCloud, STOPWORDS
import re

#  Warning
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
train_df = pd.read_csv("Tweets.csv")
print(f"Train data shape: {train_df.shape}")
train_df.head()
```

```
Train data shape: (14640, 15)
```

[2]:
```
            tweet_id airline_sentiment  airline_sentiment_confidence  \
0  570306133677760513           neutral                        1.0000
1  570301130888122368          positive                        0.3486
2  570301083672813571           neutral                        0.6837
3  570301031407624196          negative                        1.0000
4  570300817074462722          negative                        1.0000

  negativereason  negativereason_confidence         airline  \
0            NaN                        NaN  Virgin America
1            NaN                     0.0000  Virgin America
2            NaN                        NaN  Virgin America
3     Bad Flight                     0.7033  Virgin America
4     Can't Tell                     1.0000  Virgin America

  airline_sentiment_gold        name negativereason_gold  retweet_count  \
0                    NaN     cairdin                 NaN              0
1                    NaN    jnardino                 NaN              0
2                    NaN  yvonnalynn                 NaN              0
3                    NaN    jnardino                 NaN              0
4                    NaN    jnardino                 NaN              0

                                                text tweet_coord  \
0                @VirginAmerica What @dhepburn said.         NaN
1  @VirginAmerica plus you've added commercials t...         NaN
2  @VirginAmerica I didn't today... Must mean I n...         NaN
3  @VirginAmerica it's really aggressive to blast...         NaN
4  @VirginAmerica and it's a really big bad thing...         NaN

               tweet_created tweet_location               user_timezone
0  2015-02-24 11:35:52 -0800            NaN  Eastern Time (US & Canada)
1  2015-02-24 11:15:59 -0800            NaN  Pacific Time (US & Canada)
2  2015-02-24 11:15:48 -0800      Lets Play  Central Time (US & Canada)
3  2015-02-24 11:15:36 -0800            NaN  Pacific Time (US & Canada)
4  2015-02-24 11:14:45 -0800            NaN  Pacific Time (US & Canada)
```

[3]:
```python
test_df = pd.read_csv("Tweets.csv")
print(f"Test data shape: {test_df.shape}")
test_df.head()
```

```
Test data shape: (14640, 15)
```

[3]:
```
            tweet_id airline_sentiment  airline_sentiment_confidence  \
0  570306133677760513           neutral                        1.0000
1  570301130888122368          positive                        0.3486
2  570301083672813571           neutral                        0.6837
3  570301031407624196          negative                        1.0000
4  570300817074462722          negative                        1.0000
```

```
  negativereason  negativereason_confidence         airline  \
0            NaN                        NaN  Virgin America
1            NaN                     0.0000  Virgin America
2            NaN                        NaN  Virgin America
3     Bad Flight                     0.7033  Virgin America
4     Can't Tell                     1.0000  Virgin America

  airline_sentiment_gold        name negativereason_gold  retweet_count  \
0                    NaN     cairdin                 NaN              0
1                    NaN    jnardino                 NaN              0
2                    NaN  yvonnalynn                 NaN              0
3                    NaN    jnardino                 NaN              0
4                    NaN    jnardino                 NaN              0

                                                text tweet_coord  \
0                @VirginAmerica What @dhepburn said.         NaN
1  @VirginAmerica plus you've added commercials t...         NaN
2  @VirginAmerica I didn't today... Must mean I n...         NaN
3  @VirginAmerica it's really aggressive to blast...         NaN
4  @VirginAmerica and it's a really big bad thing...         NaN

               tweet_created tweet_location               user_timezone
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1  2015-02-24 11:15:59 -0800            NaN  Pacific Time (US & Canada)
2  2015-02-24 11:15:48 -0800      Lets Play  Central Time (US & Canada)
3  2015-02-24 11:15:36 -0800            NaN  Pacific Time (US & Canada)
4  2015-02-24 11:14:45 -0800            NaN  Pacific Time (US & Canada)
```

[4]:
```
train_df.duplicated().sum()
```

[4]: 36

[5]:
```
train_df.dtypes
```

[5]:
```
tweet_id                          int64
airline_sentiment                object
airline_sentiment_confidence    float64
negativereason                   object
negativereason_confidence       float64
airline                          object
airline_sentiment_gold           object
name                             object
negativereason_gold              object
retweet_count                     int64
text                             object
tweet_coord                      object
```

```
tweet_created                    object
tweet_location                   object
user_timezone                    object
dtype: object
```

[6]:
```python
# Missing values check
print(f"Missing values in train data:\n{train_df.isnull().sum()}")
print("-"*40)
```

```
Missing values in train data:
tweet_id                            0
airline_sentiment                   0
airline_sentiment_confidence        0
negativereason                   5462
negativereason_confidence        4118
airline                             0
airline_sentiment_gold          14600
name                                0
negativereason_gold             14608
retweet_count                       0
text                                0
tweet_coord                     13621
tweet_created                       0
tweet_location                   4733
user_timezone                    4820
dtype: int64
----------------------------------------
```

[7]:
```python
stopwords = set(STOPWORDS)

# Removing 'user' word as it does not hold any importance in our context
stopwords.add("user")

negative_tweets = train_df['text'][train_df['airline']==1].to_string()
wordcloud_negative = WordCloud(width = 800, height = 800,
                               background_color ="white", stopwords = stopwords,
                               min_font_size = 10).generate(negative_tweets)

positive_tweets = train_df['text'][train_df['airline']==0].to_string()
wordcloud_positive = WordCloud(width = 800, height = 800,
                               background_color ="white", stopwords = stopwords,
                               min_font_size = 10).generate(positive_tweets)

# Plotting the WordCloud images
plt.figure(figsize=(14, 6), facecolor=None)

plt.subplot(1, 2, 1)
```

```python
plt.imshow(wordcloud_negative)
plt.axis("off")
plt.title("Negative Tweets", fontdict={"fontsize": 20})

plt.subplot(1, 2, 2)
plt.imshow(wordcloud_positive)
plt.axis("off")
plt.title("Positive Tweets", fontdict={"fontsize": 20})

plt.tight_layout()
plt.show()

plt.show()
```

[8]:
```python
# Feature Engineering
train_df_fe = train_df.copy()
train_df_fe["tweet_length"] = train_df_fe["text"].str.len()
train_df_fe["num_hashtags"] = train_df_fe["text"].str.count("#")
train_df_fe["num_exclamation_marks"] = train_df_fe["text"].str.count("\!")
train_df_fe["num_question_marks"] = train_df_fe["text"].str.count("\?")
train_df_fe["total_tags"] = train_df_fe["text"].str.count("@")
train_df_fe["num_punctuations"] = train_df_fe["text"].str.count("[.,:;]")
train_df_fe["num_question_marks"] = train_df_fe["text"].str.count("[*&$%]")
train_df_fe["num_words"] = train_df_fe["text"].apply(lambda x: len(x.split()))
train_df_fe.head()
```

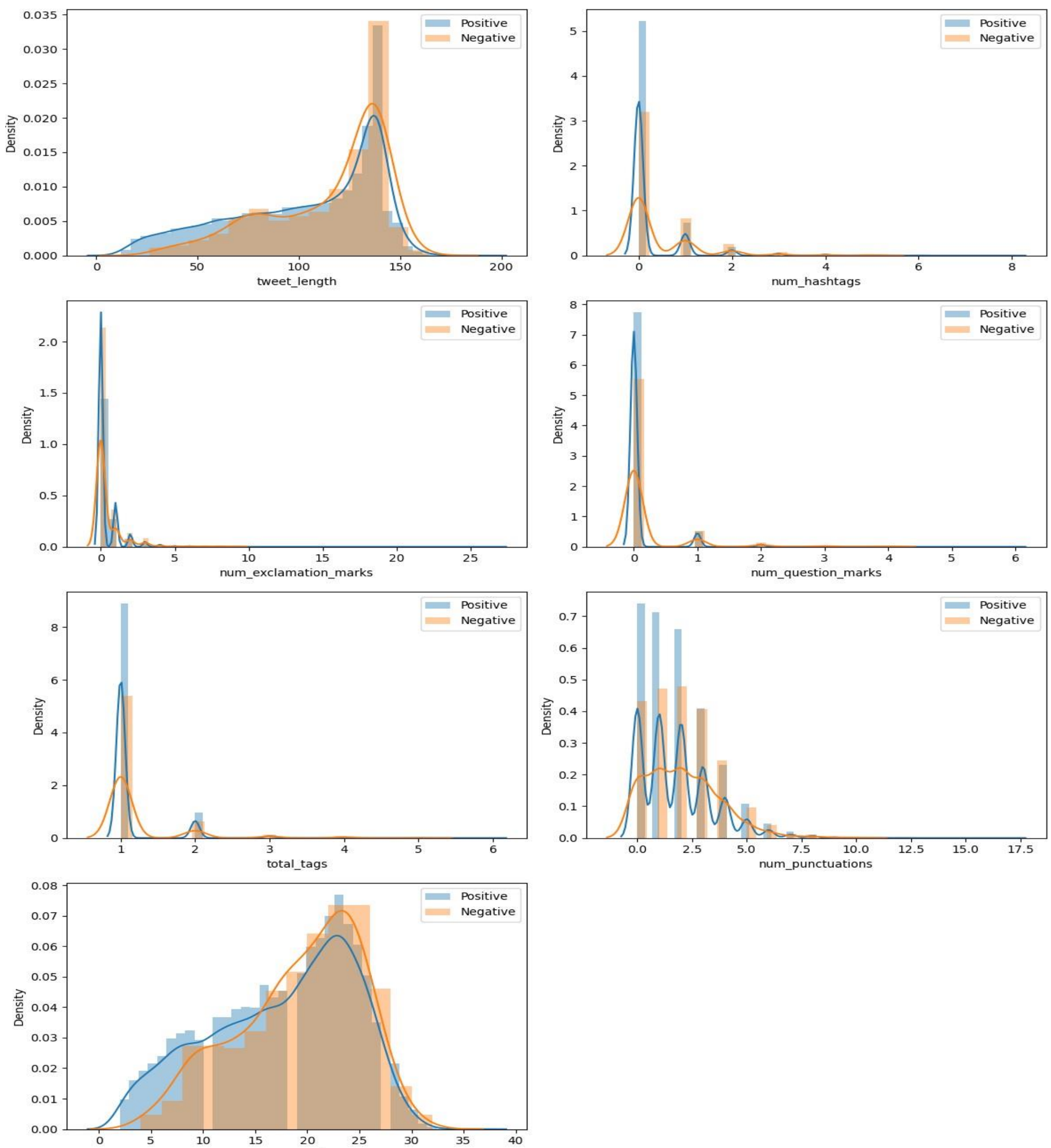
[8]:

	tweet_id	airline_sentiment	airline_sentiment_confidence	\
0	570306133677760513	neutral	1.0000	
1	570301130888122368	positive	0.3486	

```
2  570301083672813571           neutral                          0.6837
3  570301031407624196          negative                          1.0000
4  570300817074462722          negative                          1.0000

  negativereason  negativereason_confidence         airline   \
0            NaN                        NaN  Virgin America
1            NaN                     0.0000  Virgin America
2            NaN                        NaN  Virgin America
3     Bad Flight                     0.7033  Virgin America
4     Can't Tell                     1.0000  Virgin America

  airline_sentiment_gold         name  negativereason_gold  retweet_count  ... \
0                    NaN      cairdin                  NaN              0  ...
1                    NaN     jnardino                  NaN              0  ...
2                    NaN   yvonnalynn                  NaN              0  ...
3                    NaN     jnardino                  NaN              0  ...
4                    NaN     jnardino                  NaN              0  ...

               tweet_created  tweet_location               user_timezone  \
0  2015-02-24 11:35:52 -0800             NaN  Eastern Time (US & Canada)
1  2015-02-24 11:15:59 -0800             NaN   Pacific Time (US & Canada)
2  2015-02-24 11:15:48 -0800       Lets Play   Central Time (US & Canada)
3  2015-02-24 11:15:36 -0800             NaN  Pacific Time (US & Canada)
4  2015-02-24 11:14:45 -0800             NaN   Pacific Time (US & Canada)

  tweet_length  num_hashtags  num_exclamation_marks  num_question_marks  \
0           35             0                      0                   0
1           72             0                      0                   0
2           71             0                      1                   0
3          126             0                      0                   1
4           55             0                      0                   0

   total_tags  num_punctuations  num_words
0           2                 1          4
1           1                 4          9
2           1                 3         12
3           1                 1         17
4           1                 0         10

[5 rows x 22 columns]
```

[9]:
```python
# Visualizing relationship of newly created features with the tweet sentiments
plt.figure(figsize=(12, 16))
features = ['tweet_length', 'num_hashtags', 'num_exclamation_marks',␣
↪'num_question_marks',
            'total_tags', 'num_punctuations', 'num_words']
for i in range(len(features)):
```

```
    plt.subplot(4, 2, i+1)
    sns.distplot(train_df_fe[train_df_fe.retweet_count ==0][features[i]], label= 'Positive')
    sns.distplot(train_df_fe[train_df_fe.retweet_count ==1][features[i]], label= 'Negative')
    plt.legend()
plt.tight_layout()
plt.show()
```



[10]:

```python
test = test_df
#Data Preprocessing
# Train-Test Splitting
X = train_df.drop(columns=['tweet_id'])
y = train_df['tweet_id']

print(X.shape, test.shape, y.shape)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=8)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(14640, 14) (14640, 15) (14640,)
(11712, 14) (2928, 14) (11712,) (2928,)
```

[11]

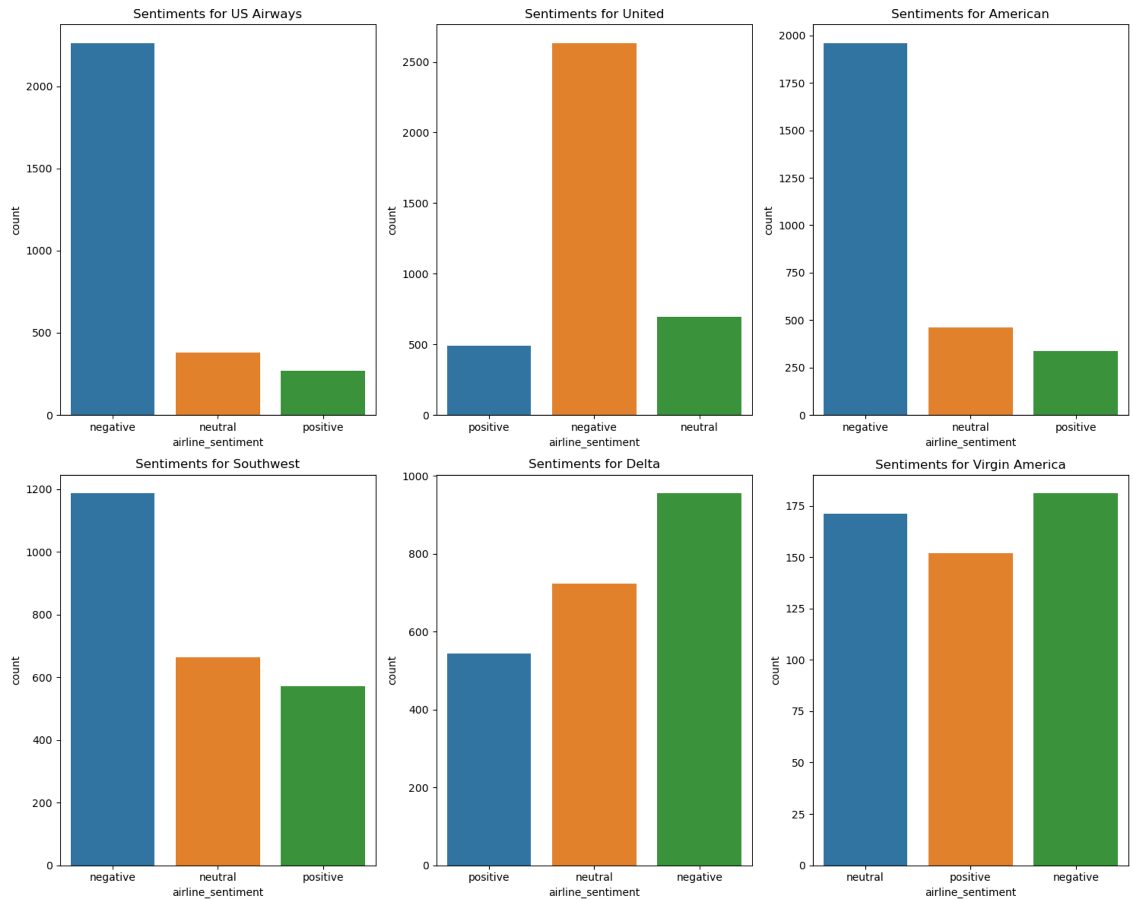
```python
# Function to tokenize and clean the text
def tokenize_and_clean(text):
    # Changing case of the text to lower case
    lowered = text.lower()

    # Cleaning the text
    cleaned = re.sub('@user', '', lowered)

    # Tokenization
    tokens = word_tokenize(cleaned)
    filtered_tokens = [token for token in tokens if re.match(r'\w{1,}', token)]

    # Stemming
    stemmer = PorterStemmer()
    stems = [stemmer.stem(token) for token in filtered_tokens]
    return stems
```

[12]:
```python
import nltk
nltk.download("punkt")


# BOW Vectorization
# bow_vectorizer = CountVectorizer(tokenizer=tokenize_and_clean,␣
    ↪stop_words='english')
# X_train_tweets_bow = bow_vectorizer.fit_transform(X_train['tweet'])
# X_test_tweets_bow = bow_vectorizer.transform(X_test['tweet'])
# print(X_train_tweets_bow.shape, X_test_tweets_bow.shape)

# TF-IDF Vectorization
tfidf_vectorizer = TfidfVectorizer(tokenizer=tokenize_and_clean,␣
    ↪stop_words="english")
X_train_tweets_tfidf = tfidf_vectorizer.fit_transform(X_train["name"])
X_test_tweets_tfidf = tfidf_vectorizer.transform(X_test["name"])
print(X_train_tweets_tfidf.shape, X_test_tweets_tfidf.shape)

# TF-IDF Vectorization on full training data
tfidf_vectorizer = TfidfVectorizer(tokenizer=tokenize_and_clean,␣
    ↪stop_words="english")
X_tweets_tfidf = tfidf_vectorizer.fit_transform(X["name"])
test_tweets_tfidf = tfidf_vectorizer.transform(test["name"])
print(X_tweets_tfidf.shape, test_tweets_tfidf.shape)
```

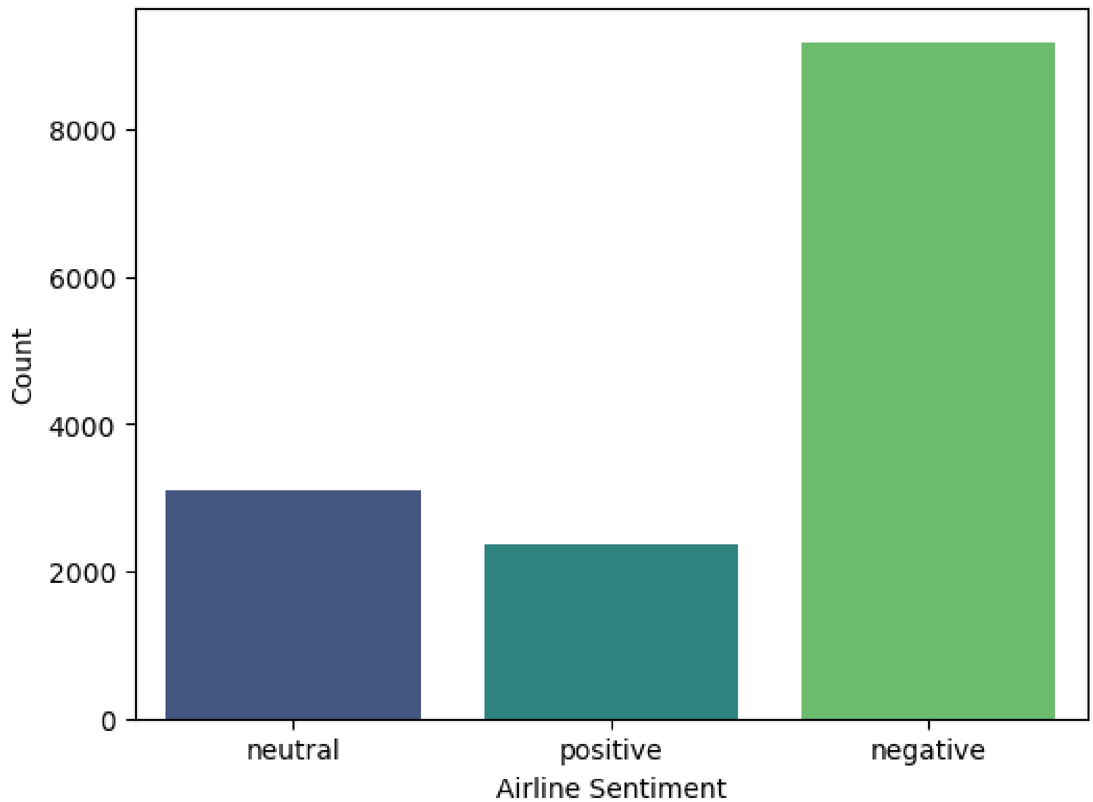
```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\Ragu\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
(11712, 6730) (2928, 6730)
(14640, 7704) (14640, 7704)
```

[13]:
```
plt.figure(1, figsize=(15, 12))  # Adjust the figsize as needed
airlines = ["US Airways", "United", "American", "Southwest", "Delta", "Virgin␣
↪America"]

for i, airline in enumerate(airlines, 1):
    plt.subplot(2, 3, i)
    new_value = train_df[train_df['airline'] == airline]

    print(new_value["airline_sentiment"].value_counts(), airline)

    sns.countplot(data=new_value, x="airline_sentiment")
    plt.title(f"Sentiments for {airline}")

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

```
negative    2263
neutral      381
positive     269
Name: airline_sentiment, dtype: int64 US Airways
negative    2633
neutral      697
positive     492
Name: airline_sentiment, dtype: int64 United
negative    1960
neutral      463
positive     336
Name: airline_sentiment, dtype: int64 American
negative    1186
neutral      664
positive     570
Name: airline_sentiment, dtype: int64 Southwes
negative     955
neutral      723
positive     544
Name: airline_sentiment, dtype: int64 Delta

Negative     181
neutral      171
positive     152
Name: airline_sentiment, dtype: int64 Virgin America
```



[14]:
```
sns.countplot(train_df, x = 'airline_sentiment', palette= 'viridis');
plt.xlabel("Airline Sentiment")
plt.ylabel("Count")
plt.show()
```



[15]:
```python
from transformers import pipeline
classifier = pipeline("sentiment-analysis")
texts = train_df['text'].tolist()
predictions = classifier(texts)
predictions[:5]
```

No model was supplied, defaulted to distilbert-base-uncased-finetuned-sst-2-english and revision af0f99b (https://huggingface.co/distilbert-base-uncased-finetuned-sst-2-english).
Using a pipeline without specifying a model name and revision in production is not recommended.

```
Downloading (…)lve/main/config.json:    0%|          | 0.00/629 [00:00<?, ?B/s]

Downloading  model.safetensors:    0%|          | 0.00/268M [00:00<?, ?B/s]

Downloading (…)okenizer_config.json:    0%|          | 0.00/48.0 [00:00<?, ?B/s]

Downloading  (…)solve/main/vocab.txt:    0%|          | 0.00/232k [00:00<?, ?B/s]
```

[15]:
```
[{'label': 'POSITIVE', 'score': 0.8633624911308289},
 {'label': 'POSITIVE', 'score': 0.6070874333381653},
 {'label': 'NEGATIVE', 'score': 0.9973426461219788},
```

```
{'label': 'NEGATIVE', 'score': 0.9973449110984802},
{'label': 'NEGATIVE', 'score': 0.9995823502540588}]
```

[19]:
```python
submission = pd.DataFrame({"tweet_id":test_df.tweet_id, "label":predictions})
submission.head()

submission.to_csv("Submission.csv", index=False)
print("Submission is successful!")
```

```
Submission is successful!
```