```
# Dataset link: https://huggingface.co/datasets/osanseviero/twitter-airline-sentiment
pip install nltk
Requirement already satisfied: nltk in /usr/local/lib/python3.10/dist-packages (3.9.1)
     Requirement already satisfied: click in /usr/local/lib/python3.10/dist-packages (from nltk) (8.1.7)
     Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-packages (from nltk) (1.4.2)
     Requirement already satisfied: regex>=2021.8.3 in /usr/local/lib/python3.10/dist-packages (from nltk) (2024.9.11)
     Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from nltk) (4.66.6)
import pandas as pd
df = pd.read csv("hf://datasets/osanseviero/twitter-airline-sentiment/Tweets.csv")
df.shape

→ (14640, 15)
df.info()
</pre
     RangeIndex: 14640 entries, 0 to 14639
     Data columns (total 15 columns):
         Column
                                          Non-Null Count Dtype
      0
          tweet_id
                                          14640 non-null
          airline_sentiment
                                          14640 non-null
                                                          object
          \verb"airline_sentiment_confidence"
                                          14640 non-null
                                                           float64
          negativereason
                                          9178 non-null
                                                           object
          negativereason_confidence
                                          10522 non-null float64
                                          14640 non-null object
          airline
          airline_sentiment_gold
                                          40 non-null
                                                           object
                                          14640 non-null object
          negativereason_gold
                                          32 non-null
                                                           object
          retweet_count
                                          14640 non-null
      10
          text
                                          14640 non-null object
      11
          tweet_coord
                                          1019 non-null
      12 tweet_created
                                          14640 non-null object
                                          9907 non-null
      13 tweet_location
                                                           object
                                          9820 non-null object
      14 user_timezone
     dtypes: float64(2), int64(2), object(11)
     memory usage: 1.7+ MB
df.head()
\overline{\Rightarrow}
                                                                                                                                                                       name negativereason_gold retweet_count
                   tweet_id airline_sentiment airline_sentiment_confidence negativereason negativereason_confidence airline airline_sentiment_gold
                                                                                                                                  Virgin
      0 570306133677760513
                                                                          1.0000
                                                                                             NaN
                                                                                                                                                                                             NaN
                                                                                                                                                                                                                0
                                          neutral
                                                                                                                         NaN
                                                                                                                                                           NaN
                                                                                                                                                                     cairdin
                                                                                                                               America
                                                                                                                                 Virgin
      1 570301130888122368
                                                                          0.3486
                                                                                                                       0.0000
                                                                                                                                                                                             NaN
                                          positive
                                                                                             NaN
                                                                                                                                                            NaN
                                                                                                                                                                    jnardino
                                                                                                                               America
                                                                                                                                 Virgin
      2 570301083672813571
                                           neutral
                                                                          0.6837
                                                                                             NaN
                                                                                                                                                                                             NaN
                                                                                                                               America
                                                                                                                                 Virgin
      3 570301031407624196
                                                                          1.0000
                                                                                        Bad Flight
                                                                                                                       0.7033
                                         negative
                                                                                                                                                            NaN
                                                                                                                                                                                             NaN
                                                                                                                                                                    inardino
                                                                                                                               America
                                                                                                                                 Virgin
      4 570300817074462722
                                         negative
                                                                          1.0000
                                                                                         Can't Tell
                                                                                                                       1.0000
                                                                                                                                                            NaN
                                                                                                                                                                    jnardino
                                                                                                                                                                                             NaN
                                                                                                                               America
print(df['airline_sentiment'].value_counts())
    airline_sentiment
     negative
                 9178
     neutral
                  3099
                 2363
     positive
     Name: count, dtype: int64
# Import necessary libraries
import pandas as pd
import re
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from imblearn.over_sampling import SMOTE
from sklearn.ensemble import RandomForestClassifier
                                                     confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import classification_report,
# Download necessary NLTK resources
nltk.download('stopwords')
nltk.download('wordnet')
# Define text cleaning function
def clean_text(text):
    {\sf text = re.sub(r'@\backslash w+|\#\backslash w+|http\backslash S+|www\backslash S+', '', text)} \quad \# \; {\sf Remove \; mentions, \; hashtags, \; and \; URLs \; }
    text = re.sub(r'[^a-zA-Z\s]', '', text) # Remove special characters and numbers
    text = text.lower() # Convert to lowercase
    tokens = text.split() # Tokenize
    {\sf tokens} = [{\sf word} \ {\sf for} \ {\sf word} \ {\sf in} \ {\sf tokens} \ {\sf if} \ {\sf word} \ {\sf not} \ {\sf in} \ {\sf stopwords}. {\sf words}({\sf 'english'})] \quad \# \ {\sf Remove} \ {\sf stopwords}.
    lemmatizer = WordNetLemmatizer() # Initialize lemmatizer
    tokens = [lemmatizer.lemmatize(word) for word in tokens] # Lemmatize tokens
    return ' '.join(tokens)
# Apply cleaning function to the text column
df['cleaned_text'] = df['text'].apply(clean_text)
# Split the dataset
X = df['cleaned_text']
y = df['airline_sentiment']
 \textbf{X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, stratify=y, random\_state=42) } 
\# Vectorize the text data using TF-IDF
vectorizer = TfidfVectorizer(max_features=5000)
```

X_train_vec = vectorizer.fit_transform(X_train)

```
X_test_vec = vectorizer.transform(X_test)
# Handle class imbalance with SMOTE
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_vec, y_train)
# Train a Random Forest model
clf = RandomForestClassifier(class_weight='balanced', random_state=42)
clf.fit(X_train_resampled, y_train_resampled)
# Make predictions
y_pred = clf.predict(X_test_vec)
# Evaluate the model
print(classification_report(y_test, y_pred))
# Display the confusion matrix
cm = confusion_matrix(y_test, y_pred, labels=['negative', 'neutral', 'positive'])
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['negative', 'neutral', 'positive'])
disp.plot(cmap='viridis')
     [nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data] Package stopwords is already up-to-date!
      [nltk_data] Downloading package wordnet to /root/nltk_data...
                  Package wordnet is already up-to-date!
     [nltk_data]
                   precision
                                 recall f1-score support
         negative
                         0.84
                                   0.85
                                             0.84
                                                        1835
          neutral
                         0.58
                                   0.58
                                             0.58
                                                         620
         positive
                         0.67
                                   0.62
                                             0.64
                                                         473
         accuracy
                                             0.76
                                                        2928
                         0.69
                                   0.68
                                             0.69
                                                        2928
        macro avg
     weighted avg
                         0.75
                                   0.76
                                             0.76
                                                        2928
     <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7eef215d6650>
```

1400 negative 1562 1200 1000 True label neutral 800 600 400 109 positive -200 negative positive neutral Predicted label

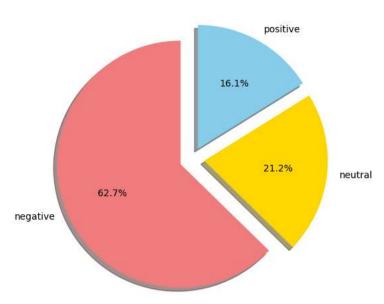
import matplotlib.pyplot as plt

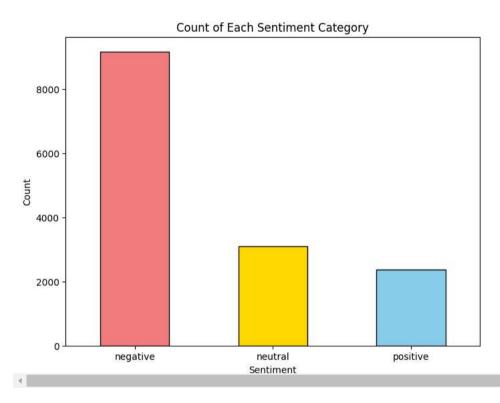
4

```
# Count the number of tweets in each sentiment category
sentiment_counts = df['airline_sentiment'].value_counts()
# Plot pie chart
plt.figure(figsize=(8, 6))
sentiment_counts.plot.pie(
    autopct='%1.1f%%',
    startangle=90,
    colors=['lightcoral', 'gold', 'skyblue'],
    explode=(0.1, 0.1, 0.1),
    shadow=True
plt.title('Distribution of Sentiments in Tweets')
plt.ylabel('') # Remove the y-label
plt.show()
# Plot bar chart
plt.figure(figsize=(8, 6))
sentiment_counts.plot.bar(
    color=['lightcoral', 'gold', 'skyblue'],
    edgecolor='black'
plt.title('Count of Each Sentiment Category')
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()
```

 $\overline{\Rightarrow}$

Distribution of Sentiments in Tweets





```
from sklearn.metrics import classification_report, accuracy_score
import numpy as np
nltk.download('vader_lexicon') # Download VADER lexicon if not already present
from \ nltk.sentiment.vader \ import \ SentimentIntensityAnalyzer
# Initialize the VADER sentiment analyzer
analyzer = SentimentIntensityAnalyzer()
\# Assuming y_test and y_pred are already defined (test labels and predicted labels)
# Compare predictions with actual labels
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of the model: {accuracy:.2f}")
# Detailed classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
# Find the most negative and most positive sentiment tweets
\label{eq:dfseq} $$ df['sentiment\_polarity'] = df['cleaned\_text'].apply(lambda x: analyzer.polarity\_scores(x)['compound']) $$ $$ df['sentiment\_polarity\_scores(x)['compound']) $$ $$ df['sentiment\_polarity\_scores(x)['compound']) $$ $$ df['sentiment\_polarity\_scores(x)['compound']) $$ df['sentiment\_polarity\_scores(x)['compound']) $$ $$ df['sentiment\_polarity\_scores(x)['compound']) $$ df['sentiment\_polarity\_scores(x)['comp
# Most negative sentiment tweet
most_negative_tweet = df[df['sentiment_polarity'] == df['sentiment_polarity'].min()]
print("\nMost Negative Tweet:")
print(most_negative_tweet[['text', 'sentiment_polarity']])
# Most positive sentiment tweet
most_positive_tweet = df[df['sentiment_polarity'] == df['sentiment_polarity'].max()]
print("\nMost Positive Tweet:")
print(most_positive_tweet[['text', 'sentiment_polarity']])
          [nltk_data] Downloading package vader_lexicon to /root/nltk_data...
           [nltk_data] Package vader_lexicon is already up-to-date!
            Accuracy of the model: 0.76
          Classification Report:
                                     precision recall f1-score support
                  negative
                                                 0.84
                                                                   0.85
                                                                                                              1835
                                                                                         0.84
                                                               0.58
                   neutral
                                              0.58
                                                                                         0.58
                                                                                                               620
                  positive
                                               0.67
                                                                   0.62
                                                                                         0.64
                  accuracy
                                                                                                              2928
                                          0.69 0.68
0.75 0.76
                macro avg
                                                                                         0.69
                                                                                                              2928
          weighted avg
                                              0.75
                                                                   0.76
                                                                                         0.76
                                                                                                              2928
          Most Negative Tweet:
                                                                                                                   text sentiment_polarity
          1214 @united is the worst. Worst reservation polici...
          4511 @SouthwestAir I love this airline so much! Tha...
          8922 @JetBlue huge fan of great brands and people d...
```

pip install wordcloud

Requirement already satisfied: wordcloud in /usr/local/lib/python3.10/dist-packages (1.9.4)
Requirement already satisfied: numppy>=1.6.1 in /usr/local/lib/python3.10/dist-packages (from wordcloud) (1.26.4)
Requirement already satisfied: pillow in /usr/local/lib/python3.10/dist-packages (from wordcloud) (11.0.0)

```
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from wordcloud) (3.8.0)
     Requirement \ already \ satisfied: \ contourpy >= 1.0.1 \ in \ /usr/local/lib/python 3.10/dist-packages \ (from \ matplotlib->wordcloud) \ (1.3.1)
     Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python 3.10/dist-packages (from matplotlib->wordcloud) (0.12.1)
     Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (4.54.1)
     Requirement \ already \ satisfied: \ kiwisolver>=1.0.1 \ in \ /usr/local/lib/python3.10/dist-packages \ (from \ matplotlib->wordcloud) \ (1.4.7)
     Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (24.2)
     Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (3.2.0)
     Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib->wordcloud) (2.8.2)
     Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib->wordcloud) (1.16.0)
# prompt: create word cloud for positive and negative sentiment
from wordcloud import WordCloud
import matplotlib.pyplot as plt
# Assuming 'df' is your DataFrame with 'cleaned_text' and 'airline_sentiment' columns
# Separate positive and negative tweets
positive_tweets = df[df['airline_sentiment'] == 'positive']['cleaned_text']
negative_tweets = df[df['airline_sentiment'] == 'negative']['cleaned_text']
# Create word clouds
positive_wordcloud = WordCloud(width=800, height=400, background_color='white').generate(" ".join(positive_tweets))
negative_wordcloud = WordCloud(width=800, height=400, background_color='white').generate(" ".join(negative_tweets))
# Plot the word clouds
plt.figure(figsize=(20, 10))
plt.subplot(1, 2, 1)
plt.imshow(positive_wordcloud, interpolation='bilinear')
plt.axis("off")
plt.title("Positive Sentiment Word Cloud")
plt.subplot(1, 2, 2)
plt.imshow(negative_wordcloud, interpolation='bilinear')
plt.axis("off")
plt.title("Negative Sentiment Word Cloud")
plt.show()
 \overline{\Rightarrow}
```



