HW6_Part2_Henry_Romero

April 27, 2025

[237]:
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# Sentiment Analysis: Airline Tweets Dataset
# In this notebook, we analyze the sentiment/emotions of user responses from␣
 ↪tweets.
# The goal is to use sentiment analysis on airline tweets and gather user␣
 ↪emotions toward them.

# Importing the libraries
import pandas as pd
import numpy as np
import re
import string
from textblob import TextBlob
from nltk.sentiment import SentimentIntensityAnalyzer
import nltk
from wordcloud import WordCloud
from nrclex import NRCLex
import matplotlib.pyplot as plt
import text2emotion as te
import seaborn as sns


#Load the dataset
df = pd.read_csv('~/Downloads/archive-2/Tweets.csv')
print(df.columns)
df.head()
```

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Index(['tweet_id', 'airline_sentiment', 'airline_sentiment_confidence',
       'negativereason', 'negativereason_confidence', 'airline',
       'airline_sentiment_gold', 'name', 'negativereason_gold',
       'retweet_count', 'text', 'tweet_coord', 'tweet_created',
       'tweet_location', 'user_timezone'],
      dtype='object')
```

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             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
```

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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)
```

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# Cleaning tweets function for a simpler analysis of the data, will be removing␣
↪@, # and URLs.
def clean_text(text):
    text = re.sub(r'@\w+', '', text)  # remove @
    text = re.sub(r'http\S+', '', text)  # remove URLs
    text = re.sub(r'www.\S+', '', text)  # remove URLs
    text = re.sub(r'#\w+', '', text)  # remove hashtags
    text = re.sub(r'\d+', '', text)  # remove numbers
    text = text.translate(str.maketrans('', '', string.punctuation))  # remove␣
↪punctuation
    text = re.sub(r'\s+', ' ', text).strip()  # remove extra spaces
    text = text.lower()  # lowercase
    return text

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

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

                                          clean_text
0                                          what said
1  plus youve added commercials to the experience…
2  i didnt today must mean i need to take another…
3  its really aggressive to blast obnoxious enter…
4            and its a really big bad thing about it
```

[239]:
```python
# Initializing VADER with SentimentIntensityAnalyzer to get scores
sia = SentimentIntensityAnalyzer()

# Apply VADER to get sentiment scores
df['scores'] = df['clean_text'].apply(lambda x: sia.polarity_scores(x))
df['compound'] = df['scores'].apply(lambda x: x['compound'])

# Classify based on compound score
def classify_sentiment(score):
    if score >= 0.05:
        return 'positive'
    elif score <= -0.05:
        return 'negative'
    else:
        return 'neutral'

# Defined my sentiment_nlk for data and plots
df['sentiment_nltk'] = df['compound'].apply(classify_sentiment)
df[['clean_text', 'compound', 'sentiment_nltk']].head()
```

[239]:
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                                          clean_text  compound sentiment_nltk
0                                          what said    0.0000        neutral
1  plus youve added commercials to the experience…    0.0000        neutral
2  i didnt today must mean i need to take another…    0.0000        neutral
3  its really aggressive to blast obnoxious enter…   -0.2716       negative
4            and its a really big bad thing about it   -0.5829       negative
```

[240]:
```python
# Join all clean tweets into one big string
text_all = " ".join(tweet for tweet in df['clean_text'])

# Generate the word cloud
# Top words are 'flight', 'thank', 'hour, and 'now'
# Lower words are 'stuck', 'love', 'service', and 'staff'
```

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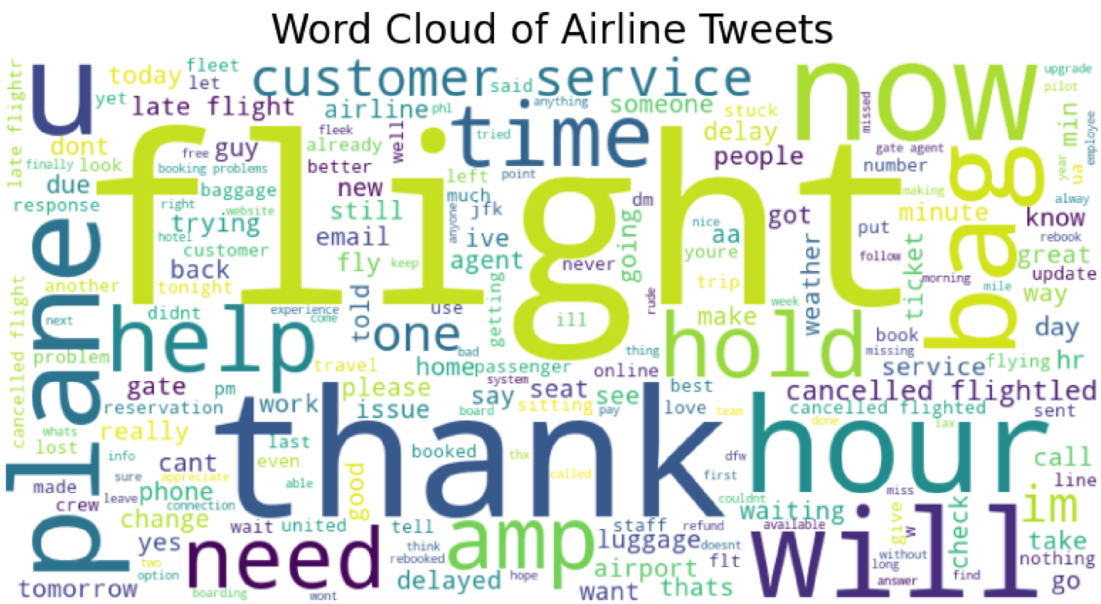
wordcloud = WordCloud(width=800, height=400, background_color='white').
↪generate(text_all)

# Plotting the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud of Airline Tweets', fontsize=20)
plt.show()
```



[241]:
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# Sentiment counts with NLTK VADER and converting to perentage
sentiment_counts = df['sentiment_nltk'].value_counts(normalize=True)*100

print(f'\n Sentiment Count')
print(df['sentiment_nltk'].value_counts())
print(f'\n Sentiment Percentages')
print(sentiment_counts)

# Plotting the sentiment distribution bar chart
sns.barplot(x=sentiment_counts.index, y=sentiment_counts.values,␣
↪color='skyblue')
plt.title('Sentiment Distribution (NLTK VADER)', fontsize=20)
plt.ylabel('Percentage (%)')
plt.xlabel('Sentiment')
plt.ylim(0, 100)
plt.grid(axis='y')
```

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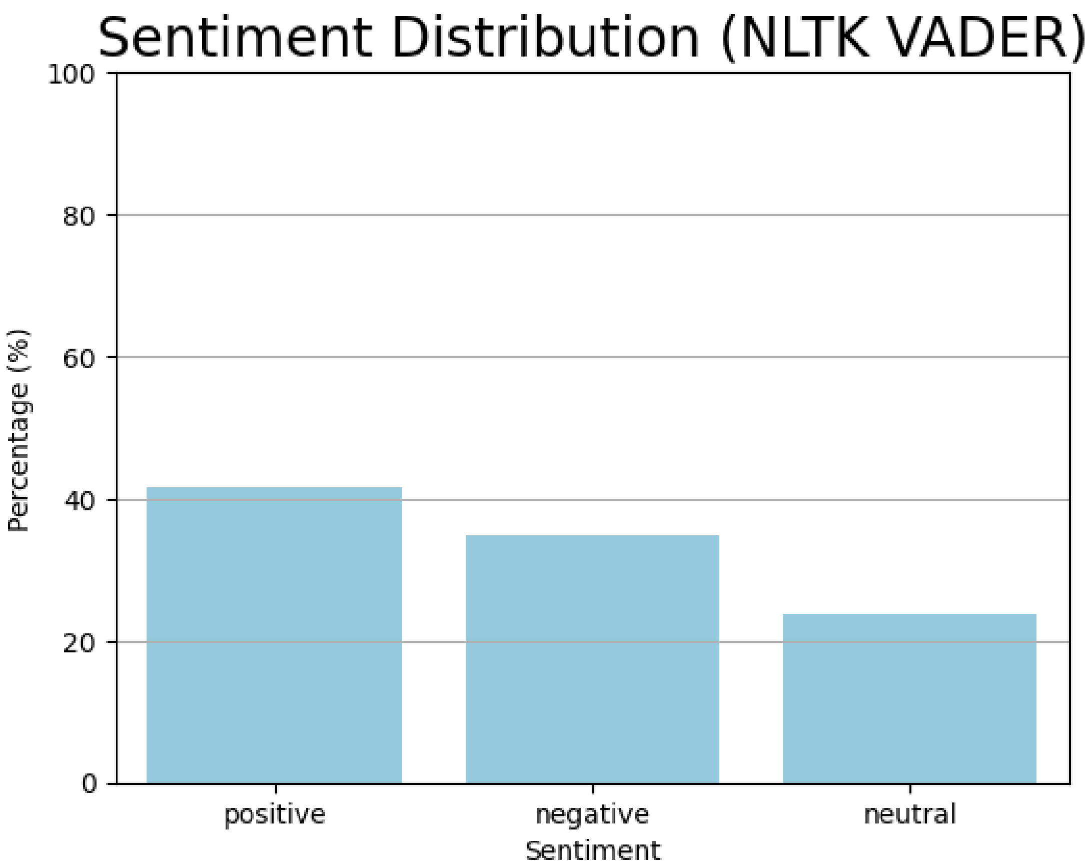
plt.show()
```

```
 Sentiment Count
sentiment_nltk
positive    6077
negative    5086
neutral     3477
Name: count, dtype: int64

 Sentiment Percentages
sentiment_nltk
positive    41.509563
negative    34.740437
neutral     23.750000
Name: proportion, dtype: float64
```



[242]:
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# Creating a function to get emotion scores set with 10 emotions
```
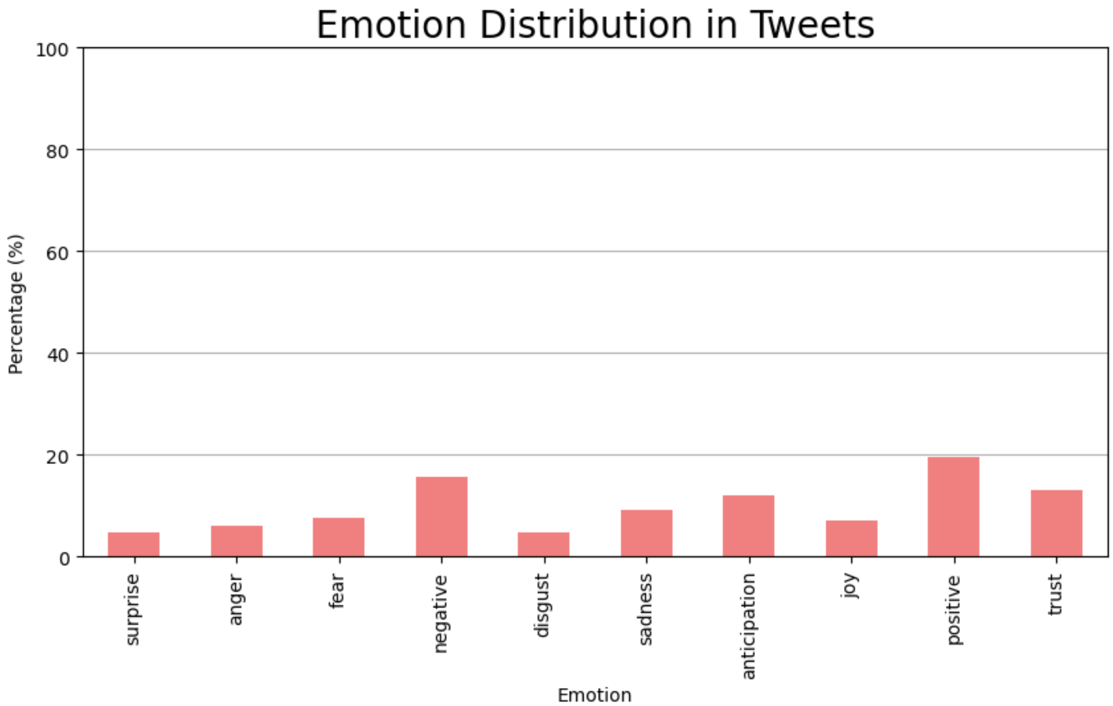

```python
# Used nrc emotions from the library to simplify this task with these set of␣
↪emotions:
# Surprise, anger, fear, negative, disgust, sadness, anticipation, joy,␣
↪positive and trust
def get_nrc_emotions(text):
    emotion = NRCLex(text)
    return emotion.raw_emotion_scores

# Apply to the cleaned tweets
emotion_scores = df['clean_text'].apply(get_nrc_emotions)

# Turn into a DataFrame
emotion_list = []
for item in emotion_scores:
    emotion_list.append(item)

emotion_df = pd.DataFrame(emotion_list).fillna(0)

# Sum across all tweets and normalize final results
emotion_totals = emotion_df.sum()
emotion_percentages = (emotion_totals / emotion_totals.sum()) * 100

print(f'\n Emotion Totals')
print(emotion_totals)
print(f'\n Emotion Percntages')
print(emotion_percentages)

# Plotting the emotional bar chart
emotion_percentages.plot(kind='bar', figsize=(10,5), color='lightcoral')
plt.title('Emotion Distribution in Tweets', fontsize=20)
plt.ylabel('Percentage (%)')
plt.xlabel('Emotion')
plt.ylim(0, 100)
plt.grid(axis='y')
plt.show()


# In this analysis, I performed sentiment and emotion analysis on airline␣
↪tweets.
# Sentiment analysis was conducted using the NLTK VADER model, categorizing the␣
↪tweets into
# positive, neutral, and negative sentiments. A word cloud was generated to␣
↪visualize the
# most frequent words appearing in the tweets, highlighting important topics␣
↪such as flights,
# delays, and service.
```

```
#
# For emotion analysis, I utilized the NRCLex library, which assigns a set of␣
↪emotional labels
# such as joy, sadness, anger, and fear to the text. The analysis revealed the␣
↪distribution
# of emotions across the dataset like anticipation and trust.
# This shows how customers express frustration or favorability with the airline.
#
# Overall, the project demonstrates the ability to apply sentiment models, pull
# emotional context, and visualize results on a real world dataset.
```

```
 Emotion Totals
surprise        2231.0
anger           2772.0
fear            3458.0
negative        7189.0
disgust         2203.0
sadness         4236.0
anticipation    5510.0
joy             3291.0
positive        8927.0
trust           5940.0
dtype: float64

 Emotion Percntages
surprise         4.875757
anger            6.058089
fear             7.557314
negative        15.711257
disgust          4.814564
sadness          9.257600
anticipation    12.041873
joy              7.192342
positive        19.509583
trust           12.981620
dtype: float64
```


Emotion Distribution in Tweets
Percentage (%)
100
80
60
40
20
0
surprise
anger
fear
negative
disgust
sadness
anticipation
joy
positive
trust
Emotion