AIRLINE SENTIMENT ANALYSIS

BUSINESS OVERVIEW

INTRODUCTION

The airline industry is highly competitive, and customer satisfaction plays a crucial role in determining the success and reputation of airlines. In today's digital age, social media platforms have become a significant avenue for customers to express their opinions and experiences with airlines. This project aims to develop a comprehensive solution for monitoring, analyzing, and understanding customer sentiment expressed on Twitter regarding various airlines. The project focuses on leveraging natural language processing (NLP) and machine learning techniques to classify tweets into positive, negative, or neutral sentiment categories. By analyzing sentiment, airlines can gain actionable insights to enhance customer satisfaction, identify operational improvements, and effectively manage their brand reputation on Twitter.

METHODOLOGY

The project will follow a structured methodology encompassing the following steps:

- Data Collection: The data was sourced from here (https://data.world/socialmediadata/twitter-us-airline-sentiment). It was scraped from February 2015 and contains tweet reviews of different US airline companies.
- Data Preprocessing: Clean and preprocess the tweet data by removing noise, irrelevant information, and performing tasks such as tokenization, stemming, and removing stopwords.
- Sentiment Classification Model: Train a machine learning model (such as a supervised classifier or deep learning model) using the preprocessed dataset to classify tweets into positive, negative, or neutral sentiments. Evaluate the model's performance using appropriate evaluation metrics.
- Real-time Monitoring System: Implement a system that retrieves live tweets related to airlines and applies the sentiment classification model to categorize them in real time. Handle high volume and velocity of incoming tweets efficiently and ensure scalability.
- Insights and Recommendations: Analyze sentiment analysis results to generate actionable insights and recommendations for improving customer satisfaction, addressing pain points, and managing brand reputation effectively.
- Response and Engagement Strategy: Develop a strategy for airlines to respond to negative sentiment and engage with customers in a timely and personalized manner. Implement systems and processes to manage customer feedback, complaints, and turnaround negative experiences into positive ones.

CHALLENGES

1. Operational Efficiency: Maintaining operational efficiency while dealing with complex logistics, diverse destinations, and a large number of flights is a significant challenge. Ensuring smooth coordination between various departments, minimizing delays, optimizing aircraft utilization, and managing crew schedules are crucial for profitability.
2. Reputation Management in the Digital Age: With the rise of social media, airlines face the challenge of managing their brand reputation effectively. Negative experiences and customer complaints can spread

quickly on platforms like Twitter, impacting brand perception. Monitoring, addressing, and managing online sentiment and customer feedback is crucial.

3. Customer Expectations and Satisfaction: Meeting and exceeding customer expectations is a constant challenge in the airline industry. Customers demand personalized experiences, seamless travel

PROPOSED SOLUTIONS

1. Operational Efficiency:

- Utilize advanced analytics and predictive modeling to optimize scheduling, crew management, and aircraft utilization.
- Implement automated processes and digital solutions to streamline operations and reduce delays.
- Employ real-time data monitoring and analytics to proactively identify and address operational inefficiencie

2. Reputation Management in the Digital Age:

- Implement social media listening and sentiment analysis tools to monitor and manage online sentiment.
- Establish dedicated teams to address customer complaints and engage with customers on social media platforms.
- Actively manage brand reputation by promptly addressing negative sentiment and leveraging positive feedback for advocacy.

3. Customer Expectations and Satisfaction:

- Implement personalized customer experiences through data-driven insights and targeted marketing campaigns.
- Enhance customer service training for staff to deliver exceptional service.
- Leverage sentiment analysis to identify customer pain points and address them promptly.

PROBLEM STATEMENT

The airline industry is currently facing a notable decrease in customer satisfaction, leading to unfavorable brand perception and diminished customer loyalty. This decline in satisfaction can be attributed to several factors, including flight delays, inadequate customer service, mishandling of luggage, and other operational inefficiencies. As a result, addressing these customer concerns and enhancing the overall brand perception has become a crucial focus for airlines.

OBJECTIVES

1. Determine the overall sentiment expressed in tweets related to US airlines. This involves classifying tweets as positive, negative, or neutral to understand the general sentiment of customers towards different airlines.
2. Implement a real-time monitoring system to continuously capture and process tweets related to airlines from Twitter.
3. Generate actionable insights and recommendations based on sentiment analysis to improve customer satisfaction, address pain points, and enhance overall brand reputation.
4. Establish an effective response and engagement strategy to manage negative sentiment, address customer complaints, and foster positive customer experiences.

SUCCESS METRICS

After modeling, the success metrics for the sentiment analysis on this project includes:

- Accuracy: Measure the accuracy of the sentiment classification model in correctly categorizing tweets into positive, negative, or neutral sentiments. This metric indicates the model's ability to make accurate predictions.
- Precision, Recall, and F1 Score: Calculate precision, recall, and F1 score to assess the model's performance in correctly identifying positive, negative, and neutral sentiments. These metrics provide insights into the model's ability to balance precision (correctly identifying positive/negative sentiments) and recall (identifying all positive/negative sentiments).

DATA UNDERSTANDING

The data was sourced from [here (https://data.world/socialmediadata/twitter-us-airline-sentiment)](https://data.world/socialmediadata/twitter-us-airline-sentiment). It was scraped from February 2015 and contains tweet reviews of different US airline companies.

In [1]:

```
# importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use("fivethirtyeight")
import seaborn as sns
import plotly.express as px
import re
import string
import joblib

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

from sklearn.metrics import precision_score, accuracy_score, recall_score, f1_sco
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_sco
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.feature_extraction.text import TfidfVectorizer
from wordcloud import WordCloud
from sklearn.metrics import roc_curve, auc

#downloading dependencies
import nltk
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')
nltk.download('wordnet')
nltk.download('vader_lexicon')

from nltk.corpus import stopwords
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from nltk.stem import SnowballStemmer
from nltk.stem import WordNetLemmatizer
from nltk import pos_tag
from nltk.corpus import wordnet
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\User\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\User\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     C:\Users\User\AppData\Roaming\nltk_data...
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\User\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\User\AppData\Roaming\nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

In [2]:

```
# loading the dataset
df = pd.read_csv('Airline-Sentiment-2-w-AA.csv', encoding='latin1')
df.head()
```

Out[2]:

	_unit_id	_golden	_unit_state	_trusted_judgments	_last_judgment_at	airline_sentiment
0	681448150	False	finalized	3	2/25/15 5:24	neutral
1	681448153	False	finalized	3	2/25/15 1:53	positive
2	681448156	False	finalized	3	2/25/15 10:01	neutral
3	681448158	False	finalized	3	2/25/15 3:05	negative
4	681448159	False	finalized	3	2/25/15 5:50	negative

In [3]:

```
def describe_columns(df):
    # Print column names
    print("Column Names:")
    print(df.columns)

    # Print data types
    print("\nData Types:")
    print(df.dtypes)

    # Print number of rows and columns
    print("\nShape:")
    print(df.shape)

    # Print df information
    print("\nInfo:")
    print(df.info())

    # Print descriptive statistics for numerical columns
    print("\nDescriptive Statistics:")
    print(df.describe())

    # Print missing values count per column
    print("\nMissing Values in percentages:")
    print((df.isna().sum()/len(df)) * 100)

describe_columns(df)
```

```
Column Names:
Index(['_unit_id', '_golden', '_unit_state', '_trusted_judgments',
       '_last_judgment_at', 'airline_sentiment',
       'airline_sentiment:confidence', 'negativereason',
       'negativereason:confidence', 'airline', 'airline_sentiment_
gold',
       'name', 'negativereason_gold', 'retweet_count', 'text', 'tw
eet_coord',
       'tweet_created', 'tweet_id', 'tweet_location', 'user_timezo
ne'],
      dtype='object')

Data Types:
_unit_id                          int64
_golden                            bool
_unit_state                      object
_trusted_judgments                int64
_last_judgment_at                object
airline_sentiment                object
```

The dataset has 14640 rows and 20 columns. It also has missing values, with some columns registering aproximately 90%. This will be dealt with at the preprocessing stage. From our data overview, the text column needs preprocessing since it contains raw tweets with underscores and nametags.

In [4]:

```
# Checking for duplicates
print('Duplicates:')
print(df.duplicated().sum())
print('\n' )
print('Duplicates in Unit id column:')
print(df.duplicated(subset='_unit_id').sum())
```

```
Duplicates:
0


Duplicates in Unit id column:
0
```

The dataset has no duplicates.

EDA

In [5]:

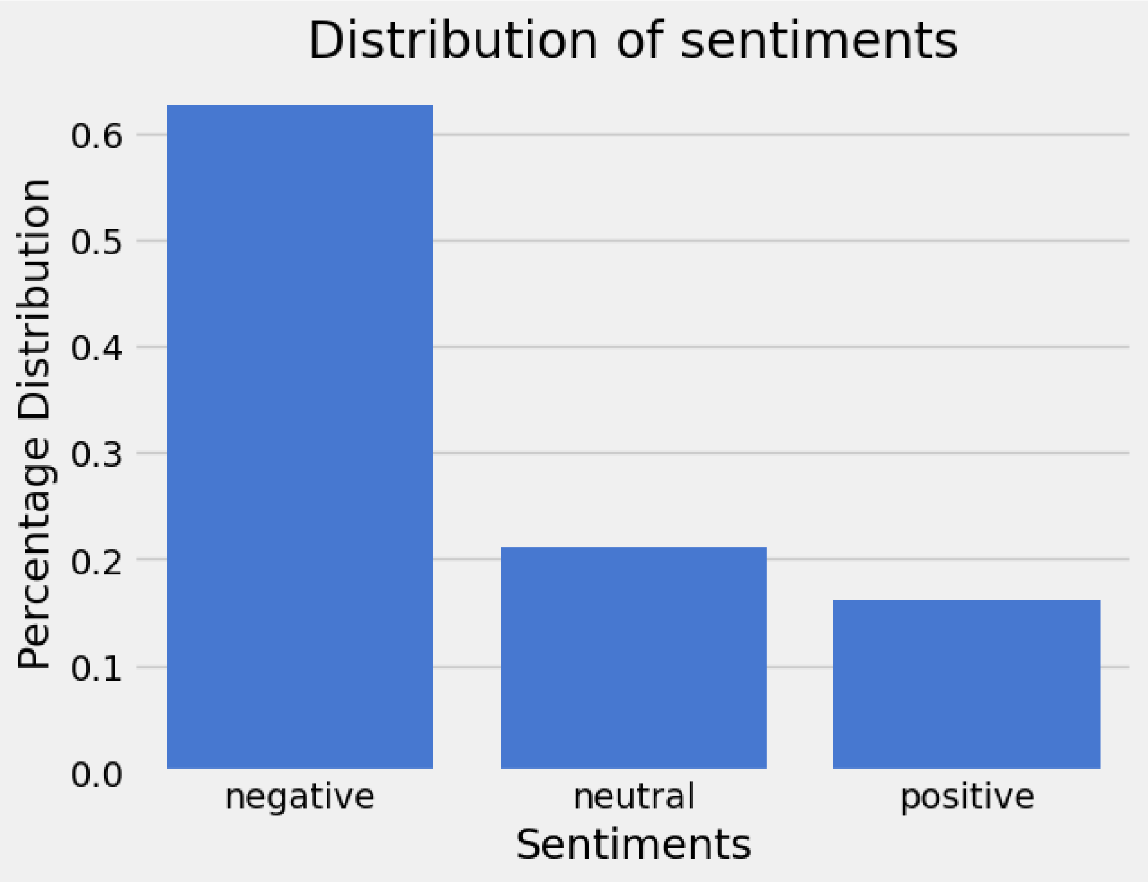
```
# distribution of airline sentiments

sentiments = df['airline_sentiment'].value_counts(normalize=True)
sentiments
```

Out[5]:

```
negative    0.626913
neutral     0.211680
positive    0.161407
Name: airline_sentiment, dtype: float64
```

In [6]:

```
# plot the distribution of sentiments

sns.barplot(x=sentiments.index, y=sentiments.values, color='#3071E7')
plt.xlabel('Sentiments')
plt.ylabel('Percentage Distribution')
plt.title('Distribution of sentiments');
```



Majority (63%) of all sentiments are negative. Positive sentiments account for only 16% of the dataset.

In [7]:

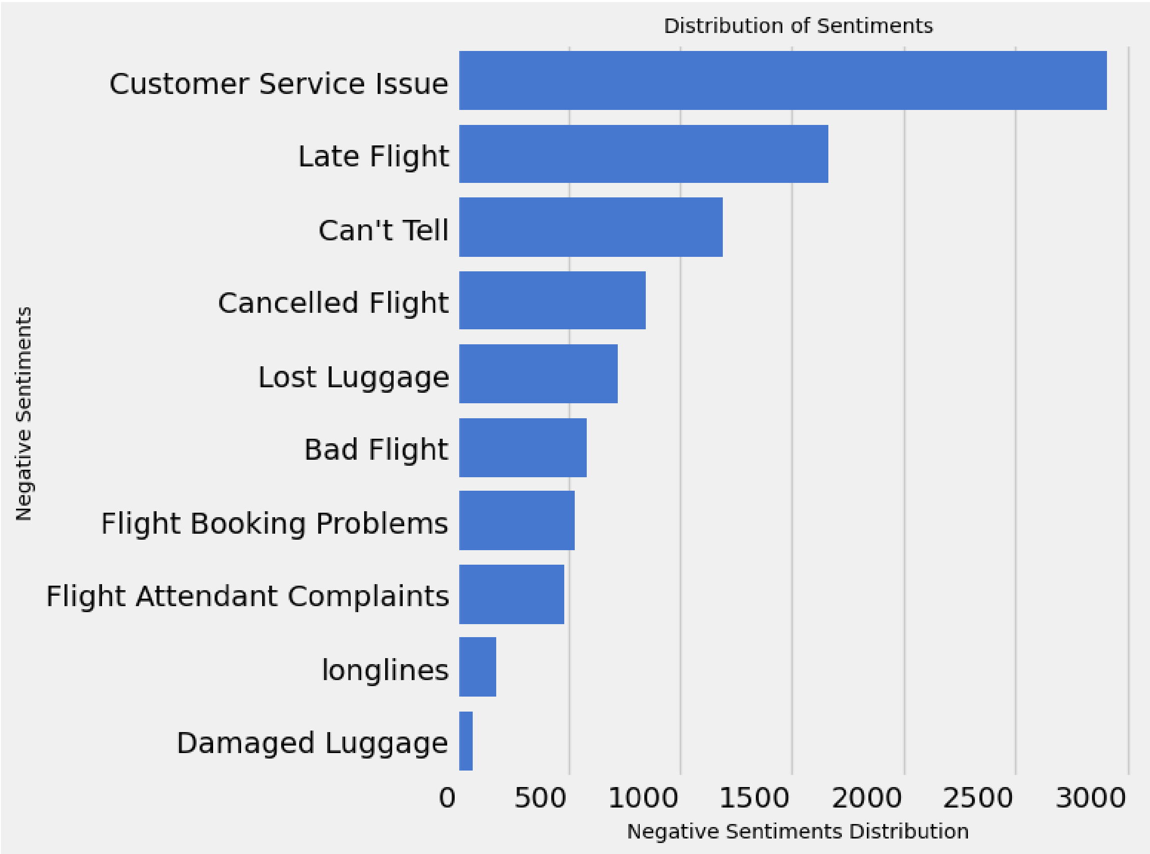
```
neg_reason = df['negativereason'].value_counts()
neg_reason
```

Out[7]:

```
Customer Service Issue        2910
Late Flight                   1665
Can't Tell                    1190
Cancelled Flight               847
Lost Luggage                   724
Bad Flight                     580
Flight Booking Problems        529
Flight Attendant Complaints    481
longlines                      178
Damaged Luggage                 74
Name: negativereason, dtype: int64
```

In [8]:

```
plt.figure(figsize=(8, 6))  # Adjust the figure size if needed


ax = sns.barplot(y=neg_reason.index, x=neg_reason.values, color='#3071E7', orient
plt.ylabel('Negative Sentiments'). set_size(10)
plt.xlabel('Negative Sentiments Distribution'). set_size(10)
plt.title('Distribution of Sentiments'). set_size(10)

# Organize the x-labels
ax.set_xticklabels(ax.get_xticklabels(), ha='right')

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



From the reasons given in the data, there are 10 reasons resulting to complains. The top being customer satisfaction issues followed by late flight and cancelled flight. A significant number of the reviews could not be classified to the exact issues.

In [9]:

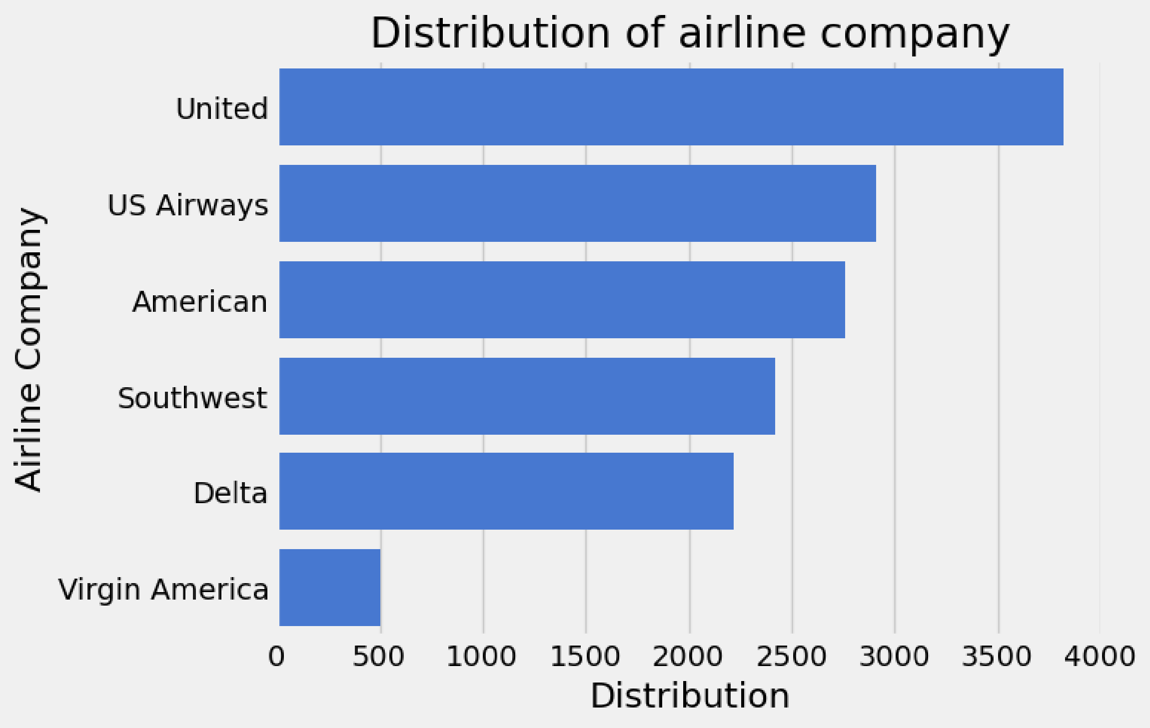
```
# distribution of airlines

airlines = df['airline'].value_counts()
airlines
```

Out[9]:

```
United            3822
US Airways        2913
American          2759
Southwest         2420
Delta             2222
Virgin America     504
Name: airline, dtype: int64
```

In [10]:

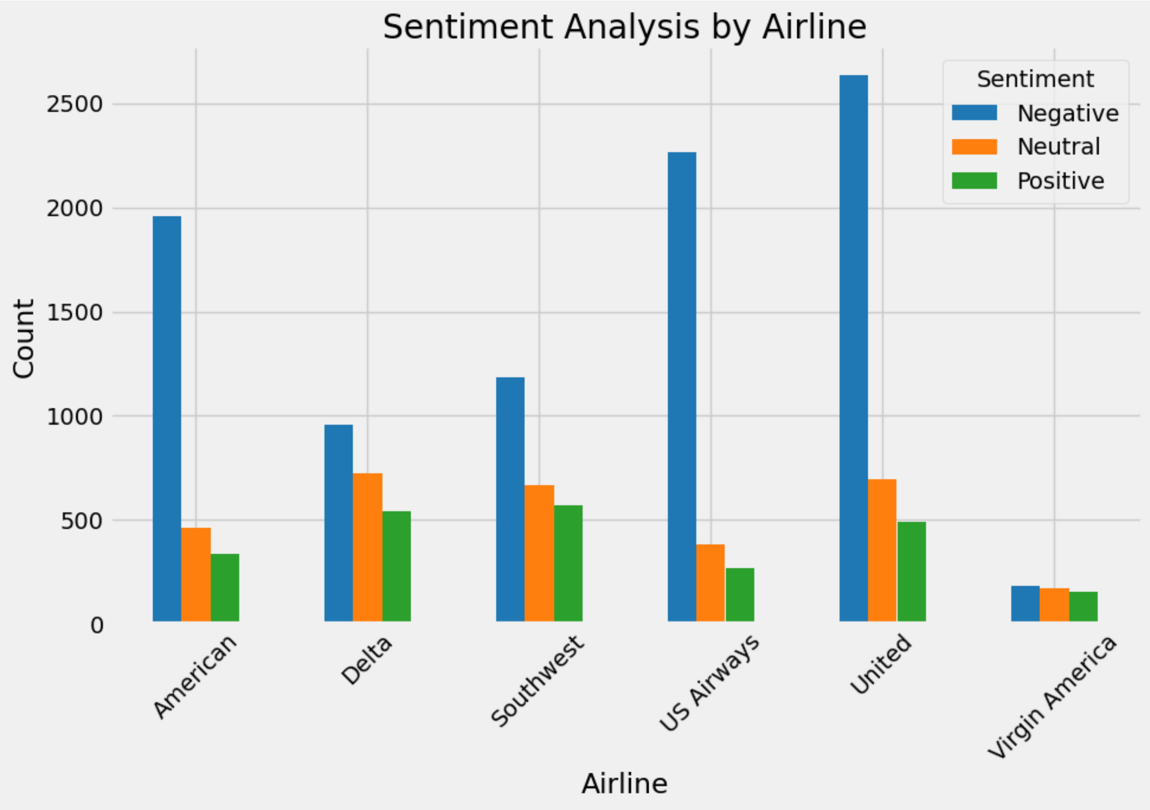
```
# plot the distribution of airlines

sns.barplot(y=airlines.index, x=airlines.values, color='#3071E7', orient='h')
plt.ylabel('Airline Company')
plt.xlabel('Distribution')
plt.title('Distribution of airline company');
```



From the graph above we see that the United Airlines has the highest number of reviews followed by US Airways and American airways.

In [11]:

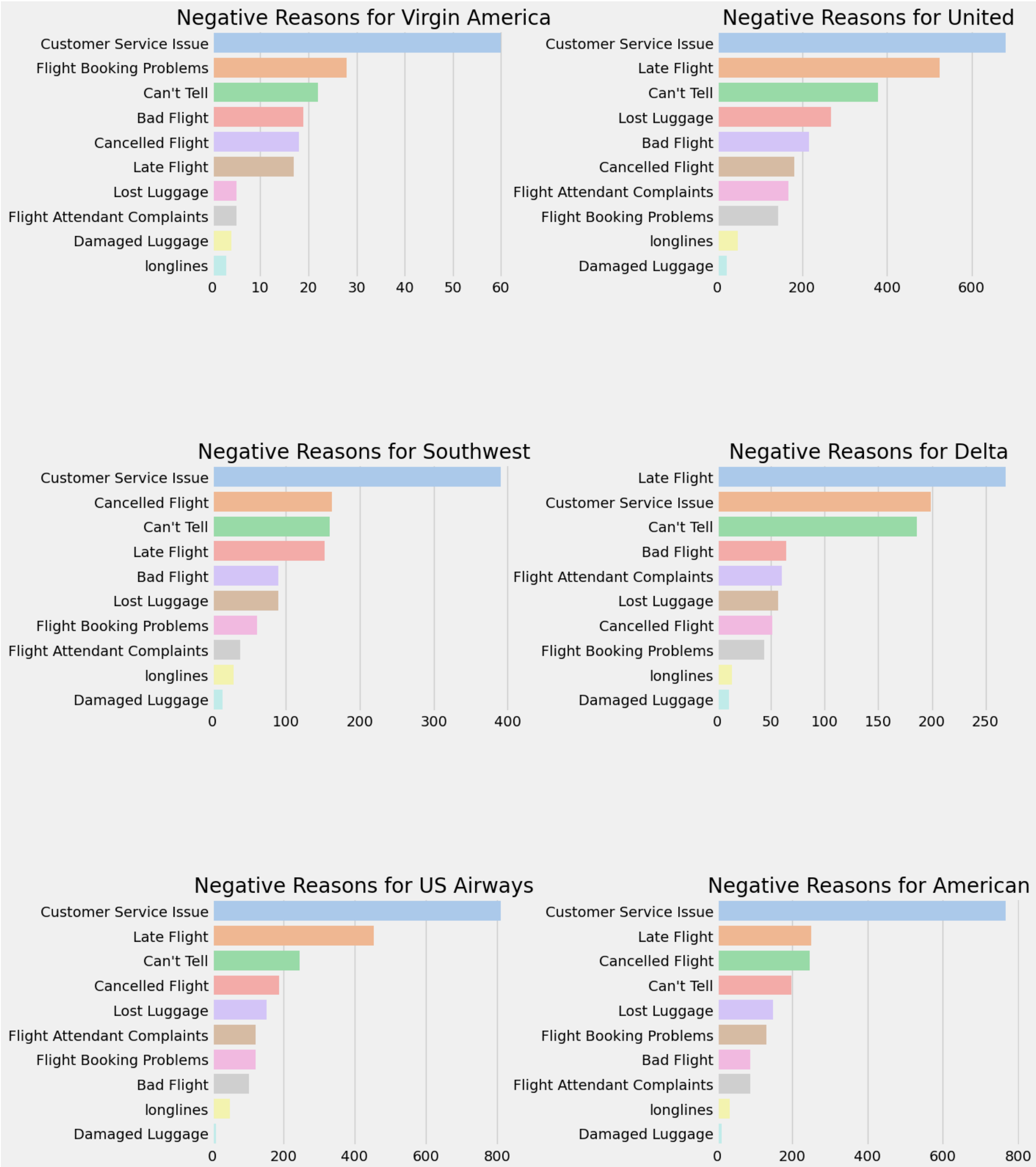
```
# Group the sentiment by airline
sentiment_by_airline = df.groupby(['airline', 'airline_sentiment']).size().unstac

# Set the colors for each sentiment category
colors = ['#1f77b4', '#ff7f0e', '#2ca02c']

# Plot the grouped data
ax = sentiment_by_airline.plot(kind='bar', stacked=False, figsize=(10, 6), color=

# Set labels and title
plt.xlabel('Airline')
plt.ylabel('Count')
plt.title('Sentiment Analysis by Airline')
plt.xticks(rotation=45)

# Set legend
legend_labels = ['Negative', 'Neutral', 'Positive']
plt.legend(title='Sentiment', labels=legend_labels, loc='upper right')

# Remove the top and right spines
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

# Show the plot
plt.show()
```



From the plot above, United, US Airways and American Airways have skyrocketing number of negative sentiments. Virgin America has an almost even distribution of negative, positive and neutral sentiments.

In [12]:

```
def plot_reason(airline, ax):
    airline_data = df[df['airline'] == airline]
    reason_count = airline_data['negativereason'].value_counts()
    sns.barplot(y=reason_count.index, x=reason_count.values, palette='pastel', ax
    ax.set_title('Negative Reasons for ' + airline)

# Get unique airlines
airlines = df['airline'].unique()

# Calculate number of rows and columns for subplots
num_rows = 3
num_cols = (len(airlines) + 1) // 3  # Round up to the nearest integer

# Create subplots
fig, axes = plt.subplots(num_rows, num_cols, figsize=(16, 20))
fig.tight_layout(pad=11.5) # Increase spacing between subplots

# Iterate over airlines and plot reasons
for i, airline in enumerate(airlines):
    row = i // num_cols
    col = i % num_cols
    plot_reason(airline, axes[row][col])

# Remove empty subplots if the number of airlines is odd
if len(airlines) % 2 != 0:
    fig.delaxes(axes[num_rows-1][num_cols-1])

# Show the subplots
plt.show()
```



There is a general trend in customers' negative setiments across all airlines. The top three being customer service issues for all airlines except Delta airlines which had late flight as the leading challenge. Late flight comes second and cancelled flight comes third.

DATA PREPROCESSING

A. Airline data preprocessing

Feature Selection

In [13]:

```
df.columns
```

Out[13]:

```
Index(['_unit_id', '_golden', '_unit_state', '_trusted_judgments',
       '_last_judgment_at', 'airline_sentiment',
       'airline_sentiment:confidence', 'negativereason',
       'negativereason:confidence', 'airline', 'airline_sentiment_go
ld',
       'name', 'negativereason_gold', 'retweet_count', 'text', 'twee
t_coord',
       'tweet_created', 'tweet_id', 'tweet_location', 'user_timezon
e'],
      dtype='object')
```

In [14]:

```
tweet_df = df[['airline_sentiment', 'text']]
tweet_df.head()
```

Out[14]:

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

From our data overview, the text column contains raw tweets with underscores and nametags which will need to be parsed.

In [15]:

```
def remove_nametags(sentence):
    """A simple function to remove name tags"""
    clean_words = []
    for word in sentence.split():
        if "@" not in word:
            clean_words.append(word)
    return " ".join(clean_words)

tweet_df["text"] = tweet_df["text"].apply(remove_nametags)
tweet_df.head()
```

Out[15]:

	airline_sentiment	text
0	neutral	What said.
1	positive	plus you've added commercials to the experienc...
2	neutral	I didn't today... Must mean I need to take ano...
3	negative	it's really aggressive to blast obnoxious "ent...
4	negative	and it's a really big bad thing about it

In [16]:

```
# remove numbers
num_pattern = r'[0-9]'
tweet_df['text'] = tweet_df['text'].replace(to_replace=num_pattern, value='', reg
tweet_df.head(10)
```

Out[16]:

	airline_sentiment	text
0	neutral	What said.
1	positive	plus you've added commercials to the experienc...
2	neutral	I didn't today... Must mean I need to take ano...
3	negative	it's really aggressive to blast obnoxious "ent...
4	negative	and it's a really big bad thing about it
5	negative	seriously would pay $ a flight for seats that ...
6	positive	yes, nearly every time I fly VX this ❱ÛÏear wo...
7	neutral	Really missed a prime opportunity for Men With...
8	positive	Well, I didn't❱Û_but NOW I DO! :-D
9	positive	it was amazing, and arrived an hour early. You...

In [17]:

```
# remove punctuations
tweet_df['text'] = tweet_df['text'].apply(lambda x: x.translate(str.maketrans('',
# change to lowercase
tweet_df['text'] = tweet_df['text'].apply(lambda x: x.lower())
tweet_df.head(10)
```

Out[17]:

	airline_sentiment	text
0	neutral	what said
1	positive	plus youve added commercials to the experience...
2	neutral	i didnt today must mean i need to take another...
3	negative	its really aggressive to blast obnoxious enter...
4	negative	and its a really big bad thing about it
5	negative	seriously would pay a flight for seats that d...
6	positive	yes nearly every time i fly vx this ❥ûïear wor...
7	neutral	really missed a prime opportunity for men with...
8	positive	well i didnt❥ûbut now i do d
9	positive	it was amazing and arrived an hour early youre...

In [18]:

```
#remove emoticons
def remove_emojis(data):
    """A simple function to remove all emojis"""
    emoji_pattern = re.compile("["
                           u"\U0001F600-\U0001F64F"
                           u"\U0001F300-\U0001F5FF"
                           u"\U0001F680-\U0001F6FF"
                           u"\U0001F1E0-\U0001F1FF"
                           u"\U00002500-\U00002BEF"
                           u"\U00002702-\U000027B0"
                           u"\U00002702-\U000027B0"
                           u"\U000024C2-\U0001F251"
                           u"\U0001f926-\U0001f937"
                           u"\U00010000-\U0010ffff"
                           u"\u2640-\u2642"
                           u"\u2600-\u2B55"
                           u"\u200d"
                           u"\u23cf"
                           u"\u23e9"
                           u"\u231a"
                           u"\ufe0f"
                           u"\u3030"
                           "]+", re.UNICODE)
    return re.sub(emoji_pattern, "", data)

tweet_df["text"] = tweet_df["text"].apply(remove_emojis)
```

In [19]:

```
def remove_non_standard_char(review):
    """A simple function to remove characters outside the ASCII range"""
    pattern = re.compile(r"[^\x00-\x7F]+")
    clean_string = re.sub(pattern, "", review)
    return clean_string

tweet_df["text"] = tweet_df["text"].apply(remove_non_standard_char)

tweet_df.head(10)
```

Out[19]:

	airline_sentiment	text
0	neutral	what said
1	positive	plus youve added commercials to the experience...
2	neutral	i didnt today must mean i need to take another...
3	negative	its really aggressive to blast obnoxious enter...
4	negative	and its a really big bad thing about it
5	negative	seriously would pay a flight for seats that d...
6	positive	yes nearly every time i fly vx this ear worm w...
7	neutral	really missed a prime opportunity for men with...
8	positive	well i didntbut now i do d
9	positive	it was amazing and arrived an hour early youre...

In [20]:

```
# remove http tags
urlpattern = r'(?:http)s?\S+'
tweet_df['text'] = tweet_df['text'].str.replace(urlpattern, '')
tweet_df.head()
```

Out[20]:

	airline_sentiment	text
0	neutral	what said
1	positive	plus youve added commercials to the experience...
2	neutral	i didnt today must mean i need to take another...
3	negative	its really aggressive to blast obnoxious enter...
4	negative	and its a really big bad thing about it

In [21]:

```
# list stopwords
stop_words = set(stopwords.words("english"))
include_stopwords = ["wouldn", "won", "weren", "wasn", "shouldn", "shan", "needn"
                     "mightn", "isn", "haven", "hasn", "hadn", "doesn", "didn", "
                     "aren", "ain", "don", "not"]
stop_words = list(stop_words - set(include_stopwords)) + ['would','youve']
```

In [22]:

```
def remove_stopwords(words):
    """A simple function to remove stopwords from a string"""
    clean_words = []
    for word in words.split():
        if word not in stop_words:
            clean_words.append(word)
    return " ".join(clean_words)

tweet_df['text'] = tweet_df['text'].apply(remove_stopwords)
# Print the first 5 rows of the new column
tweet_df.head()
```

Out[22]:

	airline_sentiment	text
0	neutral	said
1	positive	plus added commercials experience tacky
2	neutral	didnt today must mean need take another trip
3	negative	really aggressive blast obnoxious entertainmen...
4	negative	really big bad thing

Stopwords occur frequently in texts but provide little semantic value. By removing them, we eliminate unnecessary noise and focus on the more important words, thus improving the efficiency and effectiveness of our models. We customized our stopword list to include stopwords which we felt negates the sentiments.

Stemming

In [23]:

```
stemmer = SnowballStemmer("english")
#lemmatizer = WordNetLemmatizer()
def stem_words(review):
    """A function to stem words in a review text"""
    stem_words = []
    for word in review.split():
        stem_word = stemmer.stem(word)
        stem_words.append(stem_word)
    return " ".join(stem_words)

tweet_df["text"] = tweet_df["text"].apply(stem_words)
tweet_df.head(10)
```

Out[23]:

	airline_sentiment	text
0	neutral	said
1	positive	plus ad commerci experi tacki
2	neutral	didnt today must mean need take anoth trip
3	negative	realli aggress blast obnoxi entertain guest fa...
4	negative	realli big bad thing
5	negative	serious pay flight seat didnt play realli bad ...
6	positive	yes near everi time fli vx ear worm wont go away
7	neutral	realli miss prime opportun men without hat parodi
8	positive	well didntbut
9	positive	amaz arriv hour earli your good

In [24]:

```
def impactful_words_positive(review, num_words=2):
    """Function that gets the most impactful words in positive reviews"""
    tokens = nltk.word_tokenize(review)
    sia = SentimentIntensityAnalyzer()
    scores = {token: sia.polarity_scores(token)["compound"] for token in tokens}
    sorted_words =  sorted(scores.items(), key=lambda x: x[1], reverse=True)
    impactful_words = [word for word, score in sorted_words][:num_words]
    return list(impactful_words)
```

In [25]:

```
def impactful_words_negative(review, num_words=2):
    """Function that gets the most impactful words in negative reviews"""
    tokens = nltk.word_tokenize(review)
    sia = SentimentIntensityAnalyzer()
    scores = {token: sia.polarity_scores(token)["compound"] for token in tokens}
    impactful_words = [(word, score) for word, score in scores.items() if score <
    sorted_words =  sorted(impactful_words, key=lambda x: np.abs(x[1]), reverse=T
    impactful_words = [word for word, score in sorted_words][:num_words]
    return list(impactful_words)
```

In [26]:

```
# Subsetting the sentiments into positive, negative and neutral.
neg_df = tweet_df[tweet_df['airline_sentiment']=='negative']
pos_df = tweet_df[tweet_df['airline_sentiment']=='positive']
neu_df = tweet_df[tweet_df['airline_sentiment']=='neutral']
```

In [27]:

```
pos_df['impactful_words'] = pos_df['text'].apply(impactful_words_positive)
neg_df['impactful_words'] = neg_df['text'].apply(impactful_words_negative)
```

In [28]:

```
pos_df.head()
```

Out[28]:

	airline_sentiment	text	impactful_words
1	positive	plus ad commerci experi tacki	[plus, ad]
6	positive	yes near everi time fli vx ear worm wont go away	[yes, near]
8	positive	well didntbut	[well, didntbut]
9	positive	amaz arriv hour earli your good	[good, amaz]
11	positive	lt pretti graphic much better minim iconographi	[better, lt]

In [29]:

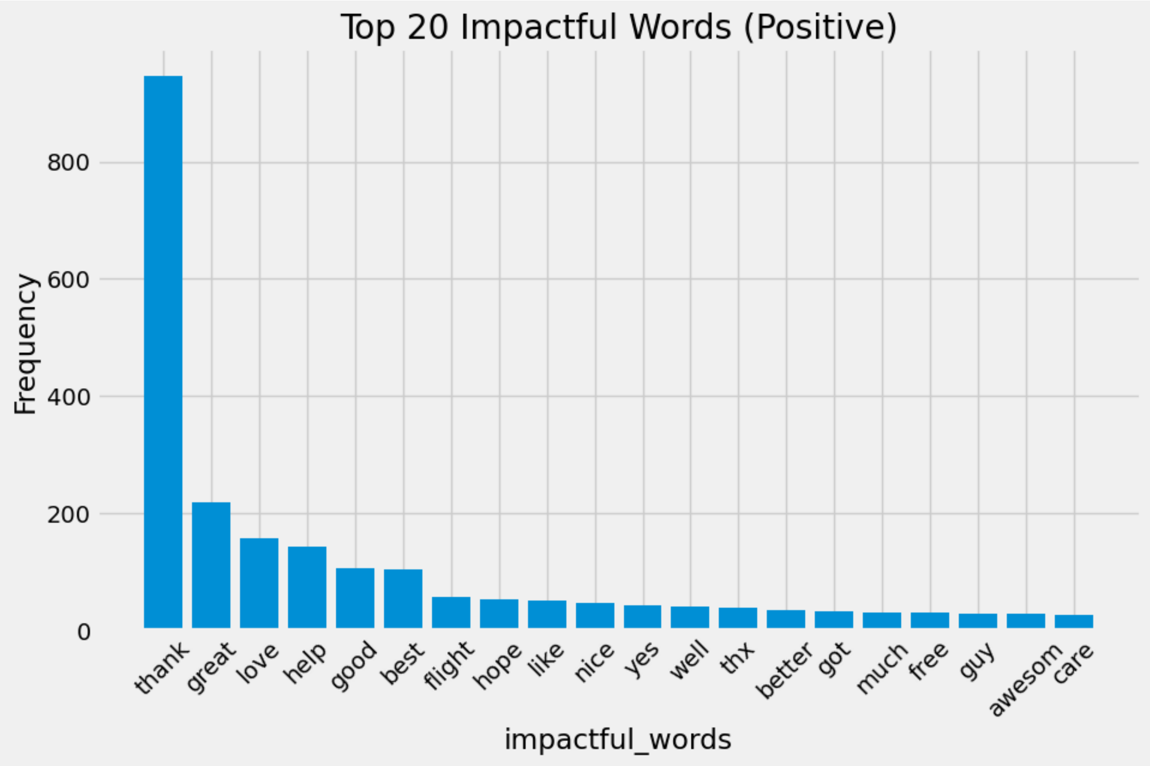
```
neg_df.head()
```

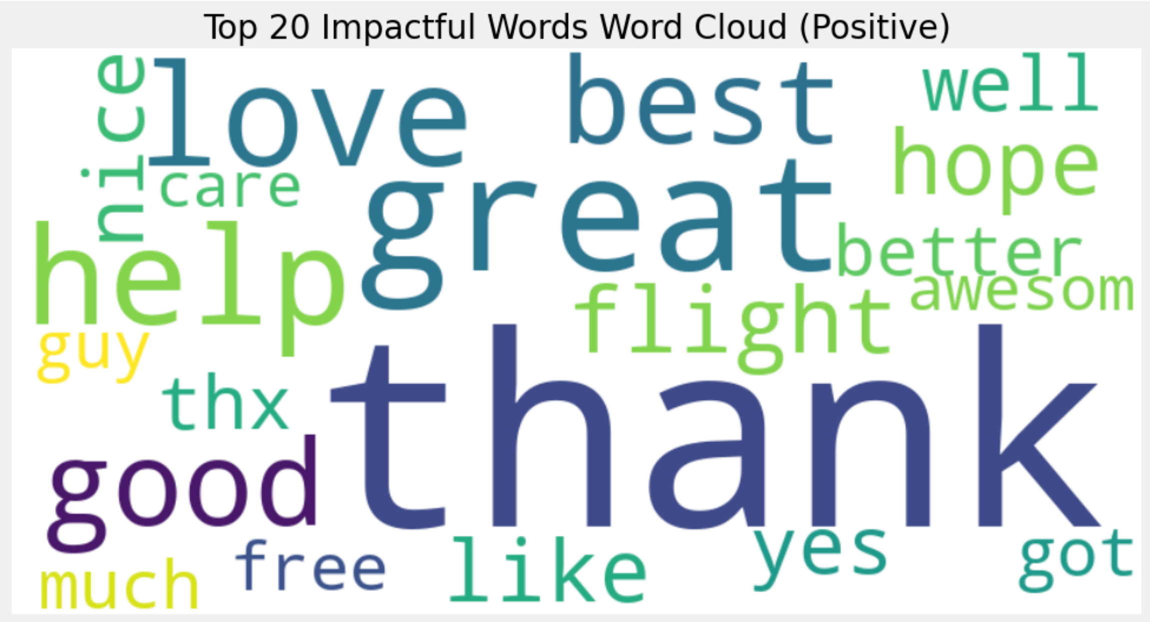
Out[29]:

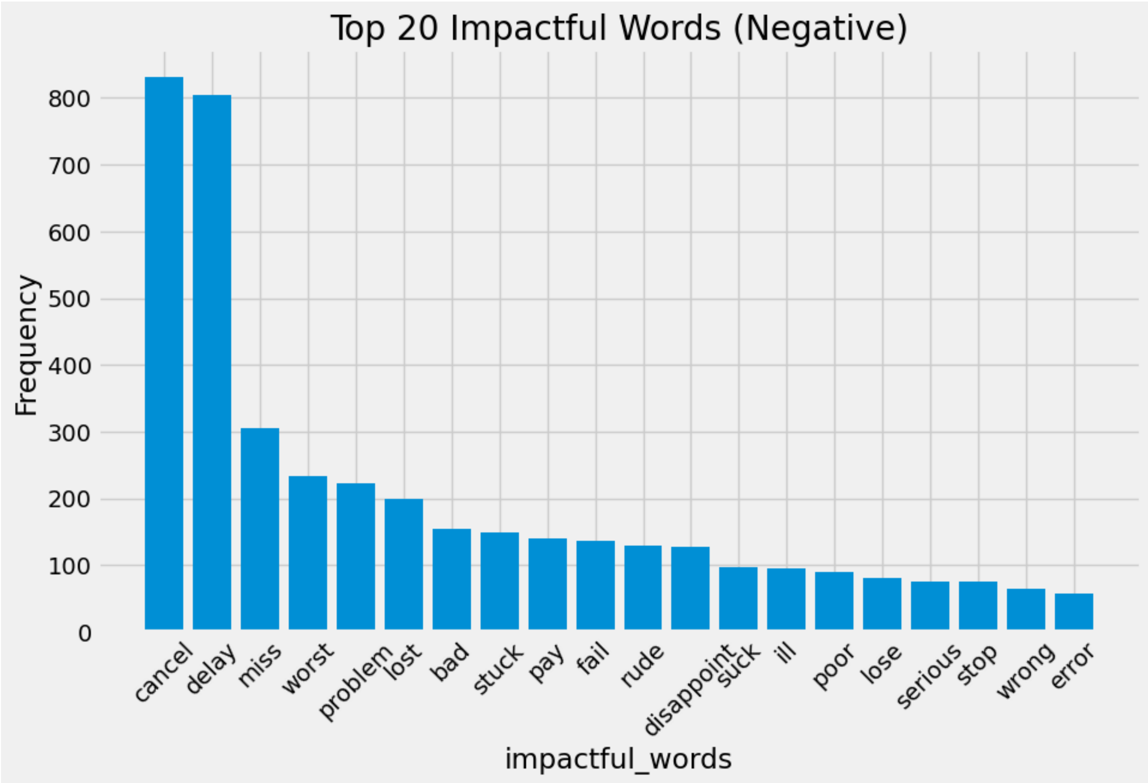
	airline_sentiment	text	impactful_words
3	negative	realli aggress blast obnoxi entertain guest fa...	[aggress]
4	negative	realli big bad thing	[bad]
5	negative	serious pay flight seat didnt play realli bad ...	[bad, pay]
15	negative	sfopdx schedul still mia	[mia]
17	negative	flew nyc sfo last week couldnt fulli sit seat ...	[]

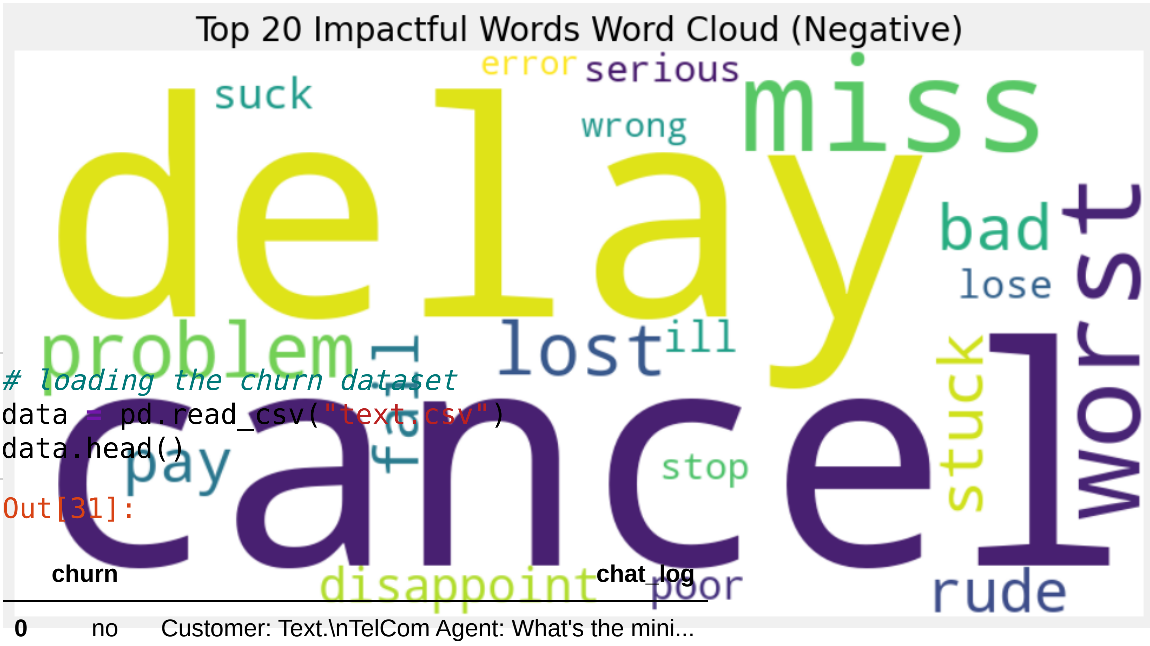
In [30]:

```
def plot_top_words(df, category, num_words=20, column='impactful_words'):
    # Flatten the list of impactful words
    words_flat = np.concatenate(df[column].values)

    # Calculate the word frequencies
    word_counts = np.unique(words_flat, return_counts=True)

    # Sort the words and counts in descending order
    sorted_indices = np.argsort(word_counts[1])[::-1]
    sorted_words = word_counts[0][sorted_indices]
    sorted_counts = word_counts[1][sorted_indices]

    # Select the top N words
    top_words = sorted_words[:num_words]
    top_counts = sorted_counts[:num_words]

    # Create the bar plot
    plt.figure(figsize=(10, 6))
    plt.bar(top_words, top_counts)

    # Set labels and title
    plt.xlabel(column)
    plt.ylabel('Frequency')
    plt.title(f'Top {num_words} Impactful Words ({category})')

    # Rotate x-axis labels if needed
    plt.xticks(rotation=45)

    # Generate word cloud
    wordcloud = WordCloud(width=800, height=400, background_color='white').genera

    # Plot the word cloud
    plt.figure(figsize=(10, 6))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
    plt.title(f'Top {num_words} Impactful Words Word Cloud ({category})')

    # Display the plots
    plt.tight_layout()
    plt.show()

# Plot top impactful words and word cloud for positive reviews
plot_top_words(pos_df, 'Positive')

# Plot top impactful words and word cloud for negative reviews
plot_top_words(neg_df, 'Negative')
```


Top 20 Impactful Words (Positive)
Frequency
0
200
400
600
800
thank
great
love
help
good
best
flight
hope
like
nice
yes
well
thx
better
got
much
free
guy
awesom
care
impactful_words


Top 20 Impactful Words Word Cloud (Positive)
love
best
well
nice
hope
care
great
help
better
awesom
flight
guy
thx
thank
good
much
free
like
yes
got





l words to our
flights are the

```
# loading the churn dataset
data = pd.read_csv("text.csv")
data.head()
```

Out[31]:

	churn	chat_log
0	no	Customer: Text.\nTelCom Agent: What's the mini...
1	no	Customer: Just voice.\nTelCom Agent: And how m...
2	no	NaN
3	no	Customer: I can't upgrade my voice package I'm...
4	no	Customer: I'm looking to upgrade my contract t...

In [32]:

```
#Dropping null values
data.dropna(inplace=True)
```

In [33]:

```
# transforming our labels to numeric values
data["churn"] = data["churn"].map({"no": 0, "yes": 1})
data.head()
```

Out[33]:

	churn	chat_log
0	0	Customer: Text.\nTelCom Agent: What's the mini...
1	0	Customer: Just voice.\nTelCom Agent: And how m...
3	0	Customer: I can't upgrade my voice package I'm...
4	0	Customer: I'm looking to upgrade my contract t...
6	0	Customer: I would like to upgrade my voice and...

In [34]:

```
def remove_nametags_(sentence):
    """A simple function to remove name tags"""
    clean_words = []
    for word in sentence.split():
        if ":" not in word:
            clean_words.append(word)
    return " ".join(clean_words)
data["chat_log"] = data["chat_log"].apply(remove_nametags_)
```

In [35]:

```
# removing numbers from chat logs
num_pattern = r'[0-9]'
data['chat_log'] = data['chat_log'].replace(to_replace=num_pattern, value='', reg
```

In [36]:

```
# removing punctuations, non standard characters and converting to lower case
data['chat_log'] = data['chat_log'].apply(lambda x: x.translate(str.maketrans('',
data['chat_log'] = data['chat_log'].apply(lambda x: x.lower())
data["chat_log"] = data["chat_log"].apply(remove_non_standard_char)
```

In [37]:

```
# removing stopwords from a sentence
stop_words = stop_words + ["telcom", "per", "text", "texts", "call", "calls", 'se
                           'okay', 'upgrade', 'contract', 'phone', 'phone', 'serv
                           'number, upgrading', 'upgraded', 'services', 'upgrades
data['chat_log'] = data['chat_log'].apply(remove_stopwords)
```

In [38]:

```
# removing two letter words from chat log
def remove_two_letter_words(text):
    """removes two letter words from chat log
    """
    pattern = r'\b\w{1,2}\b'
    matches = re.findall(pattern, text)
    filtered_text = re.sub(pattern, '', text)
    return filtered_text

data['chat_log'] = data['chat_log'].apply(remove_two_letter_words)
```

In [39]:

```
# stemming
data["chat_log"] = data["chat_log"].apply(stem_words)
data.head()
```

Out[39]:

	churn	chat_log
0	0	what minimum new month month that expens yes s...
1	0	voic much ill pay month next month thank belin...
3	0	cant voic packag verizon explain unabl voic pa...
4	0	look singtel standard plan think benefici new ...
6	0	like voic data packag one like voic one want p...

In [40]:

```
# Subsetting our chat log into churned and not churned
# churn_df = data[data['churn']== 1]
# nochurn_df = data[data['churn']== 0]
```

In [41]:

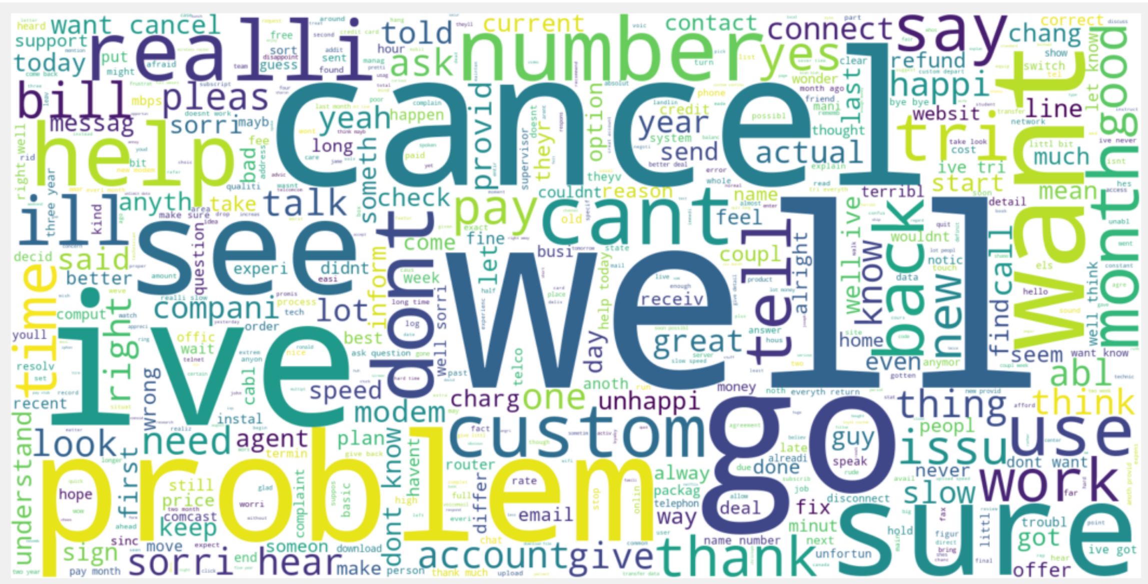
```
def generate_word_cloud(data, label):
    """A function to generate a word cloud for a given label in the dataset."""
    review = " ".join(data[data["churn"] == label].chat_log)
    word_cloud = WordCloud(background_color='white', width=1600,\
                           height=800, max_words=2000, min_font_size=5).generate(
    plt.figure(figsize=(12,8))
    plt.imshow(word_cloud, interpolation='bilinear')
    plt.axis('off')
    plt.show()
```

In [42]:

```
#generate wordcloud for those who did not churn
generate_word_cloud(data, 0)
```

In [43]:

```
#generate wordcloud for those who churned
generate_word_cloud(data, 1)
```



MODELLING

We will use 3 classifiers and tuned the best fitting model to get optimal parameters.

- Gaussian Naive Bayes
- Decision Classifier
- Random Forest Classifier

In [44]:

```
def train_test(data, random_state=42):
    # Function to split the data into train and test set (0.75, 0.25) split.
    train, test = train_test_split(data, random_state=random_state)
    return train, test
```

In [45]:

```
# split the data into train and test sets
neg_train, neg_test = train_test(neg_df)
pos_train, pos_test = train_test(pos_df)
neu_train, neu_test = train_test(neu_df)
```

In [46]:

```
# joining impactful_words in train and test data to a single string
neg_train["impactful_words"] = neg_train["impactful_words"].apply(lambda x: " ".j
neg_test["impactful_words"] = neg_test["impactful_words"].apply(lambda x: " ".joi
pos_train["impactful_words"] = pos_train["impactful_words"].apply(lambda x: " ".j
pos_test["impactful_words"] = pos_test["impactful_words"].apply(lambda x: " ".joi
```

In [47]:

```
# concatenate the three dataframess into two dataframes, train and test
train = pd.concat([neg_train, pos_train, neu_train])
test = pd.concat([neg_test, pos_test, neu_test])
```

In [48]:

```
def replace(text):
    """Replaces empty strings with np.NaN where we did not have impactful words""
    if text == "":
        return np.NaN
    else:
        return text

train["impactful_words"] = train["impactful_words"].apply(replace)
test["impactful_words"] = test["impactful_words"].apply(replace)
train.head()
```

Out[48]:

	airline_sentiment	text	impactful_words
10160	negative	one come line hold hour u help provid conf code	NaN
4846	negative	custom servic rather inconsist inform	NaN
3423	negative	flight delay minut ord plane didnt food fix fu...	dumb delay
237	negative	today flight palm spring ca jfk ny cancel flightl	cancel
10707	negative	year naval servic run travel depart command	NaN

In [49]:

```
# filling the missing values with the cant tell string
train.fillna("cant tell", inplace=True)
test.fillna("cant tell", inplace=True)
```

In [50]:

```
# vectorizing our data with TFIDF
# vectorizing sentiments
vectorizer_sents = TfidfVectorizer(max_features=2000)
X_train_sents = vectorizer_sents.fit_transform(train["text"])
X_test_sents = vectorizer_sents.transform(test["text"])

# vectorizing impactful words
vectorizer_impacts = TfidfVectorizer()
X_train_impacts = vectorizer_impacts.fit_transform(train["impactful_words"])
X_test_impacts = vectorizer_impacts.transform(test["impactful_words"])

# putting the matrices into  dataframes, X_train and X_test
X_train_sents = pd.DataFrame(X_train_sents.todense())
X_train_impacts = pd.DataFrame(X_train_impacts.todense())

X_test_sents = pd.DataFrame(X_test_sents.todense())
X_test_impacts = pd.DataFrame(X_test_impacts.todense())

X_train = pd.concat([X_train_sents, X_train_impacts], axis=1)
X_test = pd.concat([X_test_sents, X_test_impacts], axis=1)

# splitting our data into training and testing set labels
y_train = train["airline_sentiment"]
y_test = test["airline_sentiment"]
```

In [51]:

```
def evaluation(y_true, y_pred):
    """A simple function to print evaluation metrics of a model"""
    print(f"The model has an accuracy score of {accuracy_score(y_true, y_pred):.2
    print("------------------------------------------------")
    print(f"The model's recall rate is {recall_score(y_true, y_pred, average='wei
    print("------------------------------------------------")
    print(f"The model's precision is {precision_score(y_true, y_pred, average='we
    print("------------------------------------------------")
    print(f"The model's f1_score is {f1_score(y_true, y_pred,average='weighted'):
    print("------------------------------------------------")
```

Naive Bayes Classifier

In [52]:

```
# Instanciating a GaussianNB classifier
naive_clf = GaussianNB()

# fit the model
naive_clf.fit(X_train, y_train)

# predict
test_preds_naive = naive_clf.predict(X_test)
```

In [53]:

```
# crossvalidating
scores = cross_val_score(naive_clf, X_train, y_train, cv=5)
scores.mean()
```

Out[53]:

```
0.7411414001850538
```

In [54]:

```
# Evaluate the performance of the naive model on the test set
evaluation(y_test, test_preds_naive)
```

```
The model has an accuracy score of 73.94%
-----------------------------------------------
The model's recall rate is 73.94%
-----------------------------------------------
The model's precision is 84.29%
-----------------------------------------------
The model's f1_score is 75.54%
-----------------------------------------------
```

Decision Tree Classifier

In [55]:

```
clf = DecisionTreeClassifier(random_state=42)
clf.fit(X_train, y_train)

test_preds = clf.predict(X_test)
train_preds = clf.predict(X_train)
```

In [56]:

```
# crossvalidate the training set
scores = cross_val_score(clf, X_train, y_train, cv=5)
scores.mean()
```

Out[56]:

```
0.8247562974304078
```

In [57]:

```
# evaluate the model on the test dataset
evaluation(y_test, test_preds)
```

```
The model has an accuracy score of 82.93%
-----------------------------------------------
The model's recall rate is 82.93%
-----------------------------------------------
The model's precision is 82.85%
-----------------------------------------------
The model's f1_score is 82.86%
-----------------------------------------------
```

Random Forest Classifier

In [58]:

```
# create the model
rf_model = RandomForestClassifier(random_state=42)

# fit model
rf_model.fit(X_train, y_train)

# predict on test data
test_predictions_rf = rf_model.predict(X_test)

#predict on train data
train_predictions_rf = rf_model.predict(X_train)
```

In [59]:

```
# cross validation for random forest
scores = cross_val_score(rf_model, X_train, y_train, cv=5)
scores.mean()
```

Out[59]:

```
0.8627378418412437
```

In [60]:

```
# evaluate random forest algorithm on test set
evaluation(y_test, test_predictions_rf)
```

```
The model has an accuracy score of 86.51%
-----------------------------------------------
The model's recall rate is 86.51%
-----------------------------------------------
The model's precision is 86.46%
-----------------------------------------------
The model's f1_score is 86.17%
-----------------------------------------------
```

Tuned random forest

In [62]:

```
# tuned_rf = RandomForestClassifier()

# param_grid = {
#     'n_estimators': [10, 50, 100, 200],
#     'max_depth': [5, 10, 15, 20, None],
#     'min_samples_split': [2, 5, 10],
#     'min_samples_leaf': [1, 2, 5],
#     'criterion': ['gini', 'entropy']

# }
# rf_tree = GridSearchCV(tuned_rf, param_grid, cv=5)

# rf_tree.fit(X_train, y_train)

# rf_tree.best_params_

# opening our pickle model
with open('random_forest.pkl', 'rb') as f:
    tuned_rf = joblib.load(f)

# making predictions on our test data
tuned_preds = tuned_rf.predict(X_test)
```

In [63]:

```
evaluation(y_test, tuned_preds)
```

```
The model has an accuracy score of 85.96%
-----------------------------------------------
The model's recall rate is 85.96%
-----------------------------------------------
The model's precision is 85.71%
-----------------------------------------------
The model's f1_score is 85.60%
-----------------------------------------------
```

Final sentiment classifier model

In [64]:

```
# evaluate random forest algorithm on test set
evaluation(y_test, test_predictions_rf)
```

```
The model has an accuracy score of 86.51%
-----------------------------------------------
The model's recall rate is 86.51%
-----------------------------------------------
The model's precision is 86.46%
-----------------------------------------------
The model's f1_score is 86.17%
-----------------------------------------------
```

Our final and preferred model is the untuned random forest classifier which performed better compared to other models with an accuracy of 86.51 percent. This is a remarkable improvement from the baseline model by approximately 13%.

Churn modelling

In [65]:

```
# splitting the data into train and test sets
X_tr, X_te, y_tr, y_te = train_test_split(data["chat_log"], data["churn"], random
```

In [66]:

```
# vectorizing our data
vect = TfidfVectorizer(max_features=500)
X_tr_1 = vect.fit_transform(X_tr)
X_te_1 = vect.transform(X_te)
```

In [67]:

```
# instanciating our model and fitting it to our training data.
rf = RandomForestClassifier(random_state=42)
rf.fit(X_tr_1, y_tr)
rf_prds = rf.predict(X_te_1)
```

In [68]:

```
# evaluating our churn model on our test set
evaluation(y_te, rf_prds)
```

```
The model has an accuracy score of 94.69%
-----------------------------------------------
The model's recall rate is 94.69%
-----------------------------------------------
The model's precision is 95.00%
-----------------------------------------------
The model's f1_score is 94.18%
-----------------------------------------------
```

The churn model accuracy score in test data is 96 percent which shows that it is a good model that can be used to predict if a customer(commuter) churned or not in our airline dataset.

In [69]:

```
airline_data = pd.concat([train, test])
airline_churn = vect.transform(airline_data["text"])
churn_preds = rf.predict(airline_churn)
churn_series = pd.Series(churn_preds, index=airline_data.index, name="churn")
```

In [70]:

```
nw_airline_data = pd.concat([airline_data, churn_series], axis=1)
nw_airline_data
```

Out[70]:

	airline_sentiment	text	impactful_words	churn
10160	negative	one come line hold hour u help provid conf code	cant tell	0
4846	negative	custom servic rather inconsist inform	cant tell	0
3423	negative	flight delay minut ord plane didnt food fix fu...	dumb delay	0
237	negative	today flight palm spring ca jfk ny cancel flightl	cancel	1
10707	negative	year naval servic run travel depart command	cant tell	0
...	...	...	...	...
11954	neutral	love dm twitter app say your not follow cant	cant tell	0
12629	neutral	travel auh iad via etihad iad dfw via aa abl r...	cant tell	0
9977	neutral	got transf dividend milesne chang flight grand...	cant tell	0
2216	neutral	request upgrad ewr bom flight end may mile cop...	cant tell	0
2234	neutral	u serv peanutsnut yr flight yr polici r confus...	cant tell	0

14640 rows × 4 columns

In [71]:

```
nw_airline_data['churn'].value_counts(normalize=True)
```

Out[71]:

```
0    0.930601
1    0.069399
Name: churn, dtype: float64
```

In [72]:

```
# subset the customers that churned
nw_airline_data[(nw_airline_data['churn'] == 1) & (nw_airline_data['airline_senti
```

Out[72]:

	airline_sentiment	text	impactful_words	churn
14502	neutral	flight columbus ohio dalla texa cancel flight	cant tell	1
11307	neutral	differ cancel flight reflight book problem hel...	cant tell	1
4990	neutral	updat flight get cancel flight dal connect fli...	cant tell	1
12059	neutral	flight got cancel flightl grk dfw lex tomorrow...	cant tell	1
13833	neutral	group cancel flight close thousand flight monday	cant tell	1

CONCLUSIONS

- Sentiments expressed by customers play a significant role in their decision to continue or discontinue their relationship with an airline as we've seen through the prediction of churn rates in our dataset.
- From the dataset, we are able to predict that 7% of the customers are likely to churn.
- From our sentiment analysis in the tweets, we find that most customer pain points are about canceled, delayed and missed flights.
- We settled on the final model, which is the Random Forest Model which had the highest accuracy score as compared to other models.
- The model has proven to have an accuracy of 86% in classifying whether a tweet is postive, negative or neutral and it can be used to continuosly monitor the sentiments coming from the social media platforms.

MODEL LIMITATIONS

- The model incorrectly identifies one out of seven reviews
- We had a class imbalanced and so the model maybe biased towards the majority class

RECOMMENDATIONS

- Airlines with a higher count of negative sentiments should pay attention to the feedback provided by customers. Negative sentiments can indicate areas where improvements are needed, such as customer service, flight punctuality and baggage handling.
- Airlines should provide comprehensive training to airline staff, including customer-facing employees such as flight attendants, ground staff, and customer service representatives in order to ensure customers are proper handled to curb on the churning rates.
- Following many complaints coming from the tweet sentiments revolving around cancaled, delayed and missed flights, the airlines should provide effective schedules and effeciency in operations on their flight depatures and incase of any challenge like bad weather, there should be proper communication to the customers in due time to avoid inconveniences.
- Personalized Marketing and Offers could help mitigate negative reviews.
- Identifying influential individuals or social media accounts within the customers through collaborative promotional campaigns.