ARTIFICIAL INTELLIGENCE

SUDHARSHAN EDUCATIONAL TRUST

Creating Pathways to Wisdom

SUDHARSAN ENGINEERING COLLEGE

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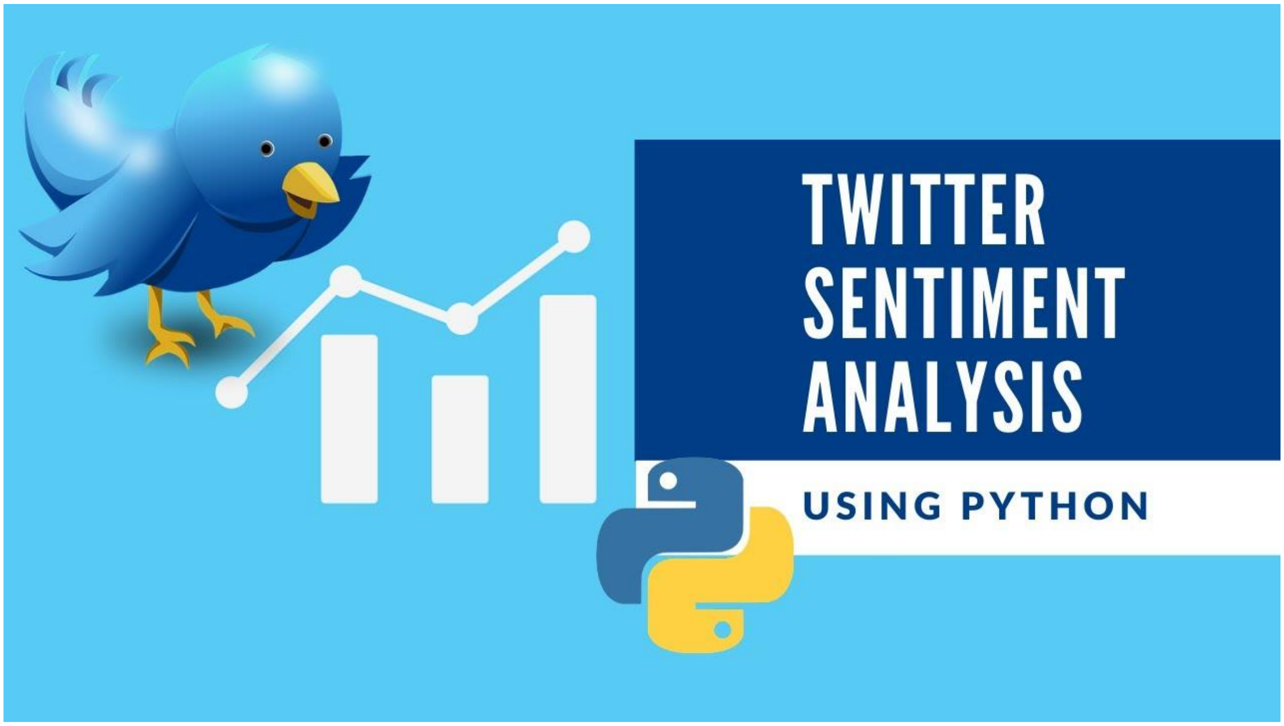
Dept : Computer Science and Engineering

Title : Sentimental Analysis for Marketing



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1. Executive Summary:

The Executive Summary provides a concise yet comprehensive overview of the entire project. It should include:

- This phase involves summarizing the project's journey, methodologies, and results, ensuring that no important detail is missed.
- It represents the closure of the analysis process and the beginning of the implementation of valuable insights in real-world business decisions.
- The project documentation serves as a lasting record, offering reference material for future work and presentations to stakeholders.

2. Introduction:

- The project focuses on sentiment analysis and its significance in understanding customer perceptions of competitor products.
- Understanding customer sentiments is vital for improving products and enhancing marketing strategies.
- This project utilizes various NLP methods to extract insights from customer feedback.
- It encompasses problem definition, data collection, preprocessing, advanced sentiment analysis, and visualization.
- The project aims to enhance sentiment analysis accuracy by exploring advanced techniques.
- The ultimate goal is to generate actionable business insights.

3. Problem Statement Revisited:

- The problem is to perform sentiment analysis on customer feedback to gain insights into competitor products."

4. Data Collection and Preprocessing:

- This section should provide detailed information on data collection and preprocessing, including:

Data Collection:

- The project begins with the essential step of data collection. A dataset containing customer reviews and sentiments about competitor products is identified for analysis.
- The provided dataset comes from a reputable source, such as Kaggle, and contains relevant data for sentiment analysis.

Data Preprocessing:

- Data preprocessing is a critical phase in the project, involving cleaning and transforming the textual data for analysis.
- Textual data is carefully cleaned to remove noise and irrelevant information, ensuring that the dataset is suitable for analysis.

5. Sentiment Analysis Techniques:

- The project utilizes various Natural Language Processing (NLP) methods, including Bag of Words (BoW), Word Embeddings, and Transformer models like BERT and RoBERTa.

- These techniques enable the analysis of customer sentiments and opinions expressed in the textual data.
- Specific NLP libraries and tools, such as NLTK, spaCy, and Hugging Face Transformers, are employed to implement these techniques effectively.

6. Feature Extraction:

- Feature extraction is a critical step in your project, where textual data is transformed into numerical representations suitable for sentiment analysis.
- This phase is responsible for converting raw text into structured features that can be analyzed effectively, facilitating the understanding of customer sentiments.
- The chosen techniques and algorithms for feature extraction play a pivotal role in revealing the underlying patterns and nuances within the data.

7. Sentiment Analysis Results:

- Sentiment analysis results form a core part of the project, presenting insights into customer feedback and opinions.
- These results showcase the distribution of sentiments, trends in customer responses, and key findings that shed light on the strengths and weaknesses of competitor products.
- The use of visualizations, such as charts and graphs, aids in presenting the sentiment analysis findings in a clear and accessible manner.
- The analysis results help in drawing actionable business insights, guiding marketing strategies, product improvements, and competition analysis.

8. Advanced Techniques:

- Advanced techniques represent a pivotal phase in your project, where fine-tuning pre-trained sentiment analysis models, such as BERT and RoBERTa, are investigated for improving prediction accuracy.
- These state-of-the-art models are leveraged to capture nuanced sentiments and contextual understanding within customer feedback.
- The application of advanced techniques signifies the project's commitment to enhancing the quality of sentiment predictions.

9. Business Insights:

Summarize the valuable insights generated from the sentiment analysis results:

- Business insights are the heart of the project, offering actionable guidance to shape marketing strategies and product development.
- These insights are distilled from the sentiment analysis results and highlight areas of improvement, customer preferences, and competitive strengths and weaknesses.
- They are a valuable asset for making data-driven decisions in the ever-evolving business landscape.

10. Conclusion:

- The conclusion marks the culmination of the project, summarizing the key findings and their implications for marketing and product development.
- It highlights the significance of sentiment analysis in the modern business landscape, emphasizing the value of understanding customer feedback.

- The insights obtained from the sentiment analysis results contribute to data-driven decision-making, providing a roadmap for improvement and competition analysis.
- The project underlines the power of NLP techniques in transforming raw textual data into actionable insights.
- The journey from problem definition to insight generation is a testament to the project's ability to enhance marketing strategies and guide businesses toward success in a competitive market.

11. Acknowledgments:

- Acknowledge individuals or organizations that provided support, data, or resources during the project:

- Express gratitude for their contributions or assistance.

Program:

[1]:

```
import pandas as pd
import numpy as np
# %load_ext nb_black

# library to suppress warnings or deprecation notes
import warnings

warnings.filterwarnings("ignore")


# import Regex, string and unicodedata.
import re, string, unicodedata

import contractions

# import BeautifulSoup.
from bs4 import BeautifulSoup

# import Natural Language Tool-Kit.
import nltk

# download Stopwords.
nltk.download("stopwords")
nltk.download("punkt")
nltk.download("wordnet")

# import stopwords.
from nltk.corpus import stopwords

# import Tokenizer.
from nltk.tokenize import word_tokenize, sent_tokenize

# library to split data
from sklearn.model_selection import train_test_split, StratifiedKFold

# libaries to help with data visualization
import matplotlib.pyplot as plt
```

```
import seaborn as sns
import missingno as msno

# import wordcloud
import wordcloud
from wordcloud import STOPWORDS
from wordcloud import WordCloud

# remove the limit for the number of displayed columns
pd.set_option("display.max_columns", None)

# set the limit for the number of displayed rows
pd.set_option("display.max_rows", 200)

# to get diferent metric scores
from sklearn.metrics import (
    recall_score,
    accuracy_score,
    confusion_matrix,classification_report,
    f1_score,
    precision_score,
    precision_recall_fscore_support
)

# import vectorizers
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

# import rfc and cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score

# import word prepocessors
from nltk.tokenize import word_tokenize
from nltk.stem import LancasterStemmer, WordNetLemmatizer
```

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

[2]:
```
df = pd.read_csv("Tweets.csv")
df.head()
```

[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
texts = [[word.lower() for word in text.split()] for text in df]
df.head()
```

[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
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)
```

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14640 entries, 0 to 14639
Data columns (total 15 columns):
 #   Column                        Non-Null Count  Dtype
--------                           --------------  ------
 0   tweet_id                      14640 non-null  int64
 1   airline_sentiment             14640 non-null  object
 2   airline_sentiment_confidence  14640 non-null  float64
 3   negativereason                9178 non-null   object
 4   negativereason_confidence     10522 non-null  float64
 5   airline                       14640 non-null  object
 6   airline_sentiment_gold        40 non-null     object
 7   name                          14640 non-null  object
 8   negativereason_gold           32 non-null     object
 9   retweet_count                 14640 non-null  int64
 10  text                          14640 non-null  object
 11  tweet_coord                   1019 non-null   object
 12  tweet_created                 14640 non-null  object
 13  tweet_location                9907 non-null   object
```

```
 14  user_timezone                   9820 non-null   object
dtypes: float64(2), int64(2), object(11)
memory usage: 1.7+ MB
```

[5]:
```python
df.isnull().sum()
```

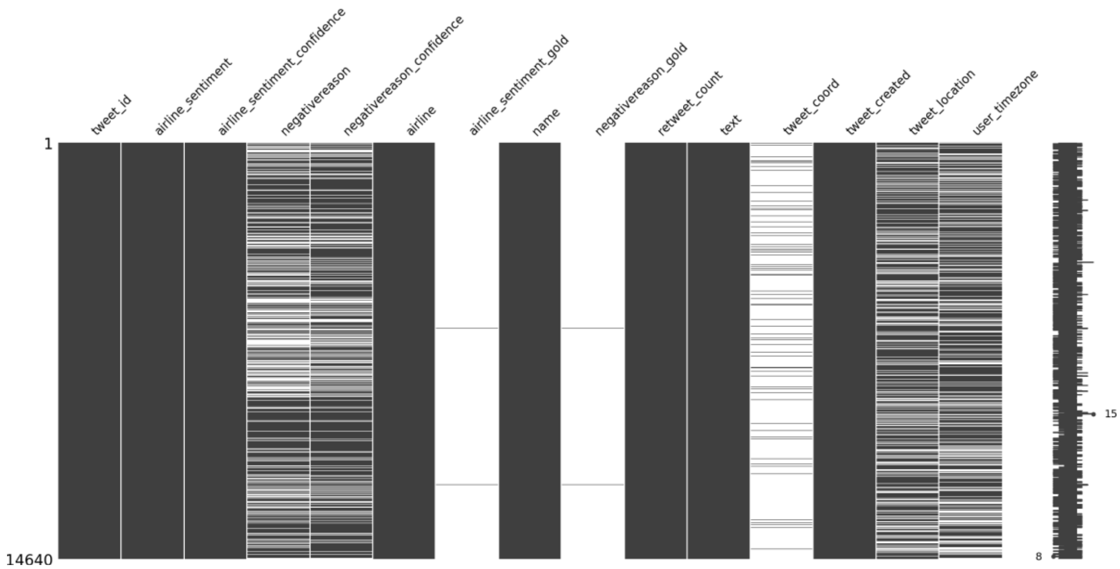
[5]:
```
tweet_id                            0
airline_sentiment                   0
airline_sentiment_confidence        0
negativereason                   5462
negativereason_confidence        4118
airline                             0
airline_sentiment_gold          14600
name                                0
negativereason_gold             14608
retweet_count                       0
text                                0
tweet_coord                     13621
tweet_created                       0
tweet_location                   4733
user_timezone                    4820
dtype: int64
```

[6]:
```python
df.isnull().sum() / len(df) * 100
```

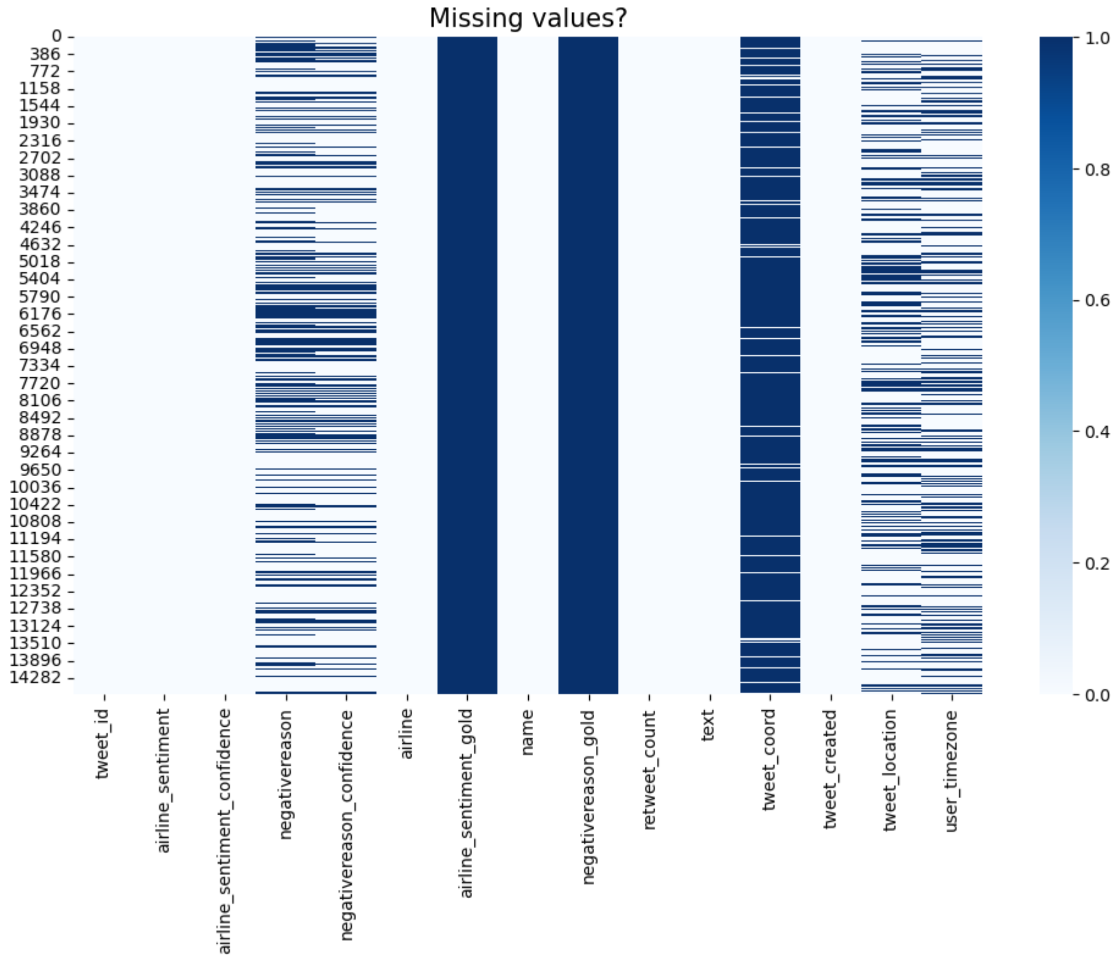
[6]:
```
tweet_id                         0.000000
airline_sentiment                0.000000
airline_sentiment_confidence     0.000000
negativereason                  37.308743
negativereason_confidence       28.128415
airline                          0.000000
airline_sentiment_gold          99.726776
name                             0.000000
negativereason_gold             99.781421
retweet_count                    0.000000
text                             0.000000
tweet_coord                     93.039617
tweet_created                    0.000000
tweet_location                  32.329235
user_timezone                   32.923497
dtype: float64
```

[7]:
```python
msno.matrix(df)
```

[7]: <AxesSubplot:>



[8]:
```
plt.figure(figsize=(12,7))
sns.heatmap(df.isnull(), cmap = "Blues")                  #Visualization␣
 ↪of missing value using heatmap
plt.title("Missing values?", fontsize = 15)
plt.show()
```



[9]:
```
print("Percentage null or na values in df")
((df.isnull() | df.isna()).sum() * 100 / df.index.size).round(2)
```

Percentage null or na values in df

[9]:
```
tweet_id                         0.00
airline_sentiment                0.00
airline_sentiment_confidence     0.00
negativereason                  37.31
negativereason_confidence       28.13
airline                          0.00
airline_sentiment_gold          99.73
name                             0.00
negativereason_gold             99.78
retweet_count                    0.00
text                             0.00
tweet_coord                     93.04
```

```
tweet_created                      0.00
tweet_location                    32.33
user_timezone                     32.92
dtype: float64
```

[10]:
```
del df["tweet_coord"]
del df["airline_sentiment_gold"]
del df["negativereason_gold"]
```

[11]:
```
df.head()
```

[11]:
```
             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        name  \
0            NaN                        NaN  Virgin America     cairdin
1            NaN                     0.0000  Virgin America    jnardino
2            NaN                        NaN  Virgin America  yvonnalynn
3     Bad Flight                     0.7033  Virgin America    jnardino
4     Can't Tell                     1.0000  Virgin America    jnardino

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

               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)
```

[12]:
```
freq = df.groupby("negativereason").size()
```

[13]:
```
# Checking duplicates
df.duplicated().sum()
```

[13]: 39

[14]:
```
df.drop_duplicates(inplace = True)
df.duplicated().sum()
```

[14]: 0

[15]:
```
df.sample(n = 10)
```

[15]:

	tweet_id	airline_sentiment	airline_sentiment_confidence
10589	569156425626329089	neutral	1.0000
6182	568149878095753216	neutral	0.6545
11336	568196165780578304	negative	1.0000
623	570245555064074240	negative	1.0000
1186	569902065247322112	negative	1.0000
2425	569213883371683840	positive	0.6679
13299	569893723091238912	negative	1.0000
7693	569343003476819969	neutral	0.6641
5148	569308552671707136	negative	1.0000
11135	568486436355346432	negative	1.0000

	negativereason	negativereason_confidence	airline
10589	NaN	NaN	US Airways
6182	NaN	0.0000	Southwest
11336	Can't Tell	0.3579	US Airways
623	Flight Booking Problems	0.6740	United
1186	Late Flight	1.0000	United
2425	NaN	NaN	United
13299	longlines	0.3512	American
7693	NaN	0.0000	Delta
5148	Lost Luggage	1.0000	Southwest
11135	Bad Flight	1.0000	US Airways

	name	retweet_count
10589	observepeople	0
6182	Brian_Fox	0
11336	thefisch26	0
623	fatwmnonthemtn	0
1186	LukeXuanLiu	1
2425	PierreSchmit	0
13299	elisakathleen	0
7693	dgruber1700	0
5148	scoobydoo9749	0
11135	kristenlc	0

	text
10589	@usairways Does anyone know the hold times for…
6182	@SouthwestAir I would but you need to follow m…
11336	@USAirways Secondary screenings, a piece of th…

```
623    @united What's going on with your website? I'm...
1186   @united and most frustratingly, all this delay...
2425   @united gave me a smile today, with a Zero Awa...
13299  @AmericanAir the most stressful morning and st...
7693                                  @JetBlue flite454
5148   @SouthwestAir 9 hrs in Baltimore, still not go...
11135  @USAirways we bought our tickets months ago. H...

                  tweet_created        tweet_location  \
10589  2015-02-21 07:27:20 -0800                  NaN
6182   2015-02-18 12:47:41 -0800   NH, United States
11336  2015-02-18 15:51:37 -0800      Washington, DC
623    2015-02-24 07:35:09 -0800          Summit, NJ
1186   2015-02-23 08:50:15 -0800                  NaN
2425   2015-02-21 11:15:39 -0800  Rixensart, Belgium
13299  2015-02-23 08:17:06 -0800          Boston, MA
7693   2015-02-21 19:48:44 -0800                  NaN
5148   2015-02-21 17:31:50 -0800     Tallahassee, FL
11135  2015-02-19 11:05:03 -0800                  NaN

                     user_timezone
10589  Eastern Time (US & Canada)
6182   Eastern Time (US & Canada)
11336  Central Time (US & Canada)
623    Central Time (US & Canada)
1186          Atlantic Time (Canada)
2425                      Brussels
13299                          NaN
7693                           NaN
5148                America/Chicago
11135  Eastern Time (US & Canada)
```

[16]:
```
df.describe().T
```

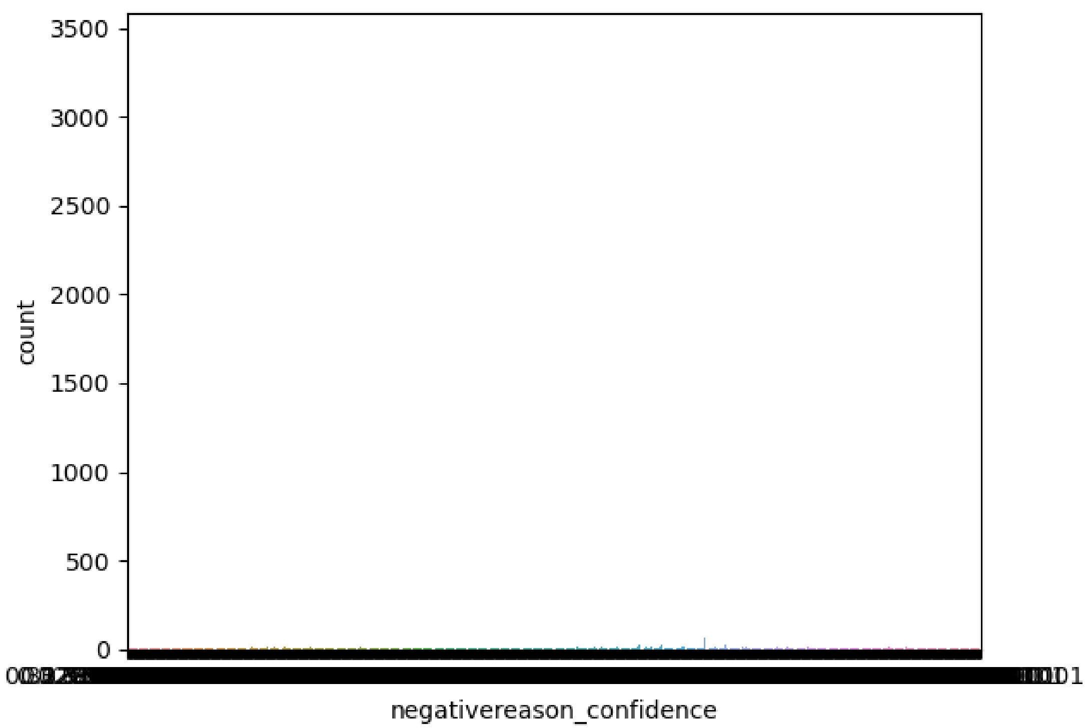
[16]:
```
                                count          mean           std  \
tweet_id                      14601.0  5.692156e+17  7.782706e+14
airline_sentiment_confidence  14601.0  8.999022e-01  1.629654e-01
negativereason_confidence     10501.0  6.375749e-01  3.303735e-01
retweet_count                 14601.0  8.280255e-02  7.467231e-01

                                       min           25%           50%  \
tweet_id                      5.675883e+17  5.685581e+17  5.694720e+17
airline_sentiment_confidence  3.350000e-01  6.923000e-01  1.000000e+00
negativereason_confidence     0.000000e+00  3.605000e-01  6.705000e-01
retweet_count                 0.000000e+00  0.000000e+00  0.000000e+00

                                       75%           max
```

```
tweet_id                        5.698884e+17   5.703106e+17
airline_sentiment_confidence    1.000000e+00   1.000000e+00
negativereason_confidence       1.000000e+00   1.000000e+00
retweet_count                   0.000000e+00   4.400000e+01
```

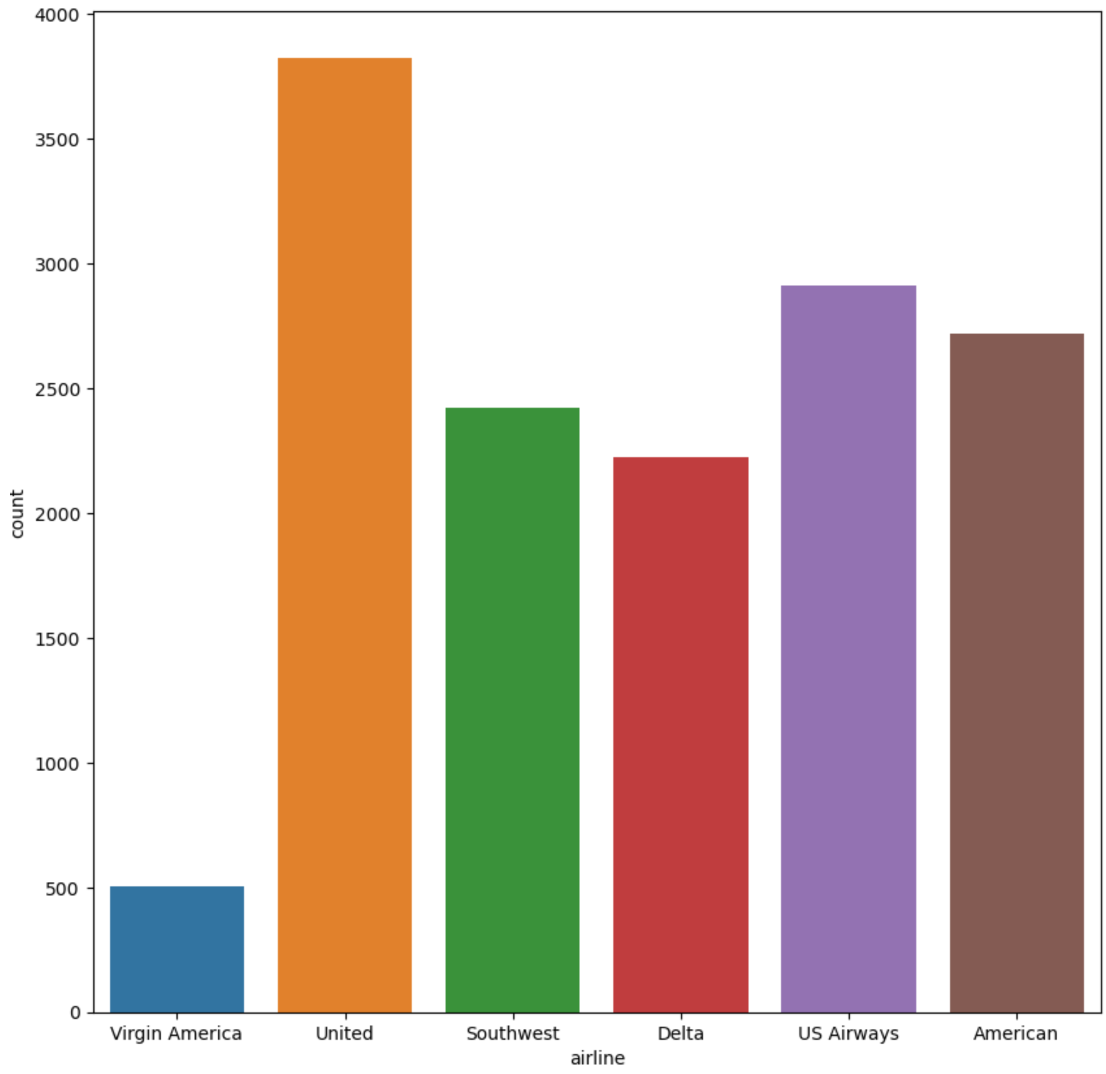
[17]:
```
df.nunique()
```

[17]:
```
tweet_id                        14485
airline_sentiment                   3
airline_sentiment_confidence     1023
negativereason                     10
negativereason_confidence        1410
airline                             6
name                             7701
retweet_count                      18
text                            14427
tweet_created                   14247
tweet_location                   3081
user_timezone                      85
dtype: int64
```

[18]:
```
ax = sns.countplot(x = "negativereason_confidence", data = df)
```



[19]:
```
plt.figure(figsize = (10, 10))
ax = sns.countplot(x = "airline", data = df)
```



[20]:
```
import plotly.graph_objects as go
crosstab_sentiments=pd.crosstab(df.airline, df.negativereason)
companies=list(crosstab_sentiments.index)

fig = go.Figure(data=[
    go.Bar(name=col_name, x=companies, y=list(crosstab_sentiments[col_name]))
for col_name in list(crosstab_sentiments.columns)])#
Change the bar mode
fig.update_layout(barmode='stack',
                  title='Sentiment distribution per company',
                  yaxis=dict(title='Sentiment distribution'),
```

```
                    xaxis=dict(title='Companies'))
fig.show()
```

[21]:
```
crosstab_neg_reasons = pd.crosstab(df["airline"], df["negativereason"])
companies = list(crosstab_neg_reasons.index)

fig = go.Figure(data = [
    go.Bar(name = col_name, x = companies, y =
 ↪list(crosstab_neg_reasons[col_name]))
for col_name in list(crosstab_neg_reasons.columns)])

fig.update_layout(barmode = "stack",
                    title = "Negative Reasons Distribution per Company",
                    yaxis = dict(title = "Negative reasons Distribution"),
                    xaxis = dict(title = "Companies"))
fig.show()
```

[22]:
```
labels = list(crosstab_neg_reasons.columns)
values = [crosstab_neg_reasons[col_name].sum() for col_name in labels]

# Use `hole` to create a donut-like pie chart
fig = go.Figure(data=[go.Pie(labels=labels, values=values, hole=.3)])
fig.update_layout(title='Overall distribution for negative reasons')
fig.show()
```

[23]:
```
df.drop(df.loc[df["airline_sentiment"] == "neutral"].index, inplace = True)
```

[24]:
```
data = df[["airline_sentiment", "text"]]
data.head()
```

[24] :

	airline_sentiment	text
1	positive	@VirginAmerica plus you've added commercials t...
3	negative	@VirginAmerica it's really aggressive to blast...
4	negative	@VirginAmerica and it's a really big bad thing...
5	negative	@VirginAmerica seriously would pay $30 a fligh...
6	positive	@VirginAmerica yes, nearly every time I fly VX...

[25]:
```
X = df["text"]
y = df["airline_sentiment"]
X
```

[25] :
```
1        @VirginAmerica plus you've added commercials t...
3        @VirginAmerica it's really aggressive to blast...
4        @VirginAmerica and it's a really big bad thing...
5        @VirginAmerica seriously would pay $30 a fligh...
6        @VirginAmerica yes, nearly every time I fly VX...
                              ...
```

```
14633    @AmericanAir my flight was Cancelled Flightled...
14634              @AmericanAir right on cue with the delays
14635    @AmericanAir thank you we got on a different f...
14636    @AmericanAir leaving over 20 minutes Late Flig...
14638    @AmericanAir you have my money, you change my ...
Name: text, Length: 11510, dtype: object
```

[26]:
```python
y
```

[26]:
```
1        positive
3        negative
4        negative
5        negative
6        positive
           ...
14633    negative
14634    negative
14635    positive
14636    negative
14638    negative
Name: airline_sentiment, Length: 11510, dtype: object
```

[27]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,␣
↪random_state = 42)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(9208,) (2302,) (9208,) (2302,)
```

[28]:
```python
tfidf = TfidfVectorizer(stop_words="english")
```

[29]:
```python
tfidf.fit(y_train)
```

[29]:
```
TfidfVectorizer(stop_words='english')
```

[30]:
```python
print(tfidf.get_feature_names_out())
```

```
['negative' 'positive']
```

[31]:
```python
print(tfidf.vocabulary_)
```

```
{'negative': 0, 'positive': 1}
```

[32]:
```python
print(df)
```

```
              tweet_id airline_sentiment  airline_sentiment_confidence  \
1      570301130888122368          positive                        0.3486
3      570301031407624196          negative                        1.0000
4      570300817074462722          negative                        1.0000
```

```
5      570300767074181121    negative          1.0000
6      570300616901320704    positive          0.6745
...          ...               ...               ...
14633  569587705937600512    negative          1.0000
14634  569587691626622976    negative          0.6684
14635  569587686496825344    positive          0.3487
14636  569587371693355008    negative          1.0000
14638  569587188687634433    negative          1.0000

               negativereason  negativereason_confidence         airline  \
1                         NaN                     0.0000  Virgin America
3                  Bad Flight                     0.7033  Virgin America
4                  Can't Tell                     1.0000  Virgin America
5                  Can't Tell                     0.6842  Virgin America
6                         NaN                     0.0000  Virgin America
...                       ...                        ...             ...
14633        Cancelled Flight                     1.0000        American
14634             Late Flight                     0.6684        American
14635                     NaN                     0.0000        American
14636  Customer Service Issue                     1.0000        American
14638  Customer Service Issue                     0.6659        American

                  name  retweet_count  \
1             jnardino              0
3             jnardino              0
4             jnardino              0
5             jnardino              0
6           cjmcginnis              0
...                ...            ...
14633  RussellsWriting              0
14634    GolfWithWoody              0
14635  KristenReenders              0
14636         itsropes              0
14638       SraJackson              0

                                                    text  \
1      @VirginAmerica plus you've added commercials t...
3      @VirginAmerica it's really aggressive to blast...
4      @VirginAmerica and it's a really big bad thing...
5      @VirginAmerica seriously would pay $30 a fligh...
6      @VirginAmerica yes, nearly every time I fly VX...
...                                                  ...
14633  @AmericanAir my flight was Cancelled Flightled...
14634         @AmericanAir right on cue with the delays
14635  @AmericanAir thank you we got on a different f...
14636  @AmericanAir leaving over 20 minutes Late Flig...
14638  @AmericanAir you have my money, you change my ...
```

```
                   tweet_created    tweet_location               user_timezone
1      2015-02-24 11:15:59 -0800               NaN  Pacific 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)
5      2015-02-24 11:14:33 -0800               NaN  Pacific Time (US & Canada)
6      2015-02-24 11:13:57 -0800  San Francisco CA  Pacific Time (US & Canada)
...                          ...               ...                         ...
14633  2015-02-22 12:01:06 -0800       Los Angeles                     Arizona
14634  2015-02-22 12:01:02 -0800               NaN                       Quito
14635  2015-02-22 12:01:01 -0800               NaN                         NaN
14636  2015-02-22 11:59:46 -0800             Texas                         NaN
14638  2015-02-22 11:59:02 -0800        New Jersey  Eastern Time (US & Canada)

[11510 rows x 12 columns]
```

[33]:
```python
data[data["airline_sentiment"] == "negative"]["text"]
```

[33]:
```
3        @VirginAmerica it's really aggressive to blast...
4        @VirginAmerica and it's a really big bad thing...
5        @VirginAmerica seriously would pay $30 a fligh...
15                @VirginAmerica SFO-PDX schedule is still MIA.
17       @VirginAmerica  I flew from NYC to SFO last we...
                               ...
14631    @AmericanAir thx for nothing on getting us out...
14633    @AmericanAir my flight was Cancelled Flightled...
14634           @AmericanAir right on cue with the delays
14636    @AmericanAir leaving over 20 minutes Late Flig...
14638    @AmericanAir you have my money, you change my ...
Name: text, Length: 9157, dtype: object
```

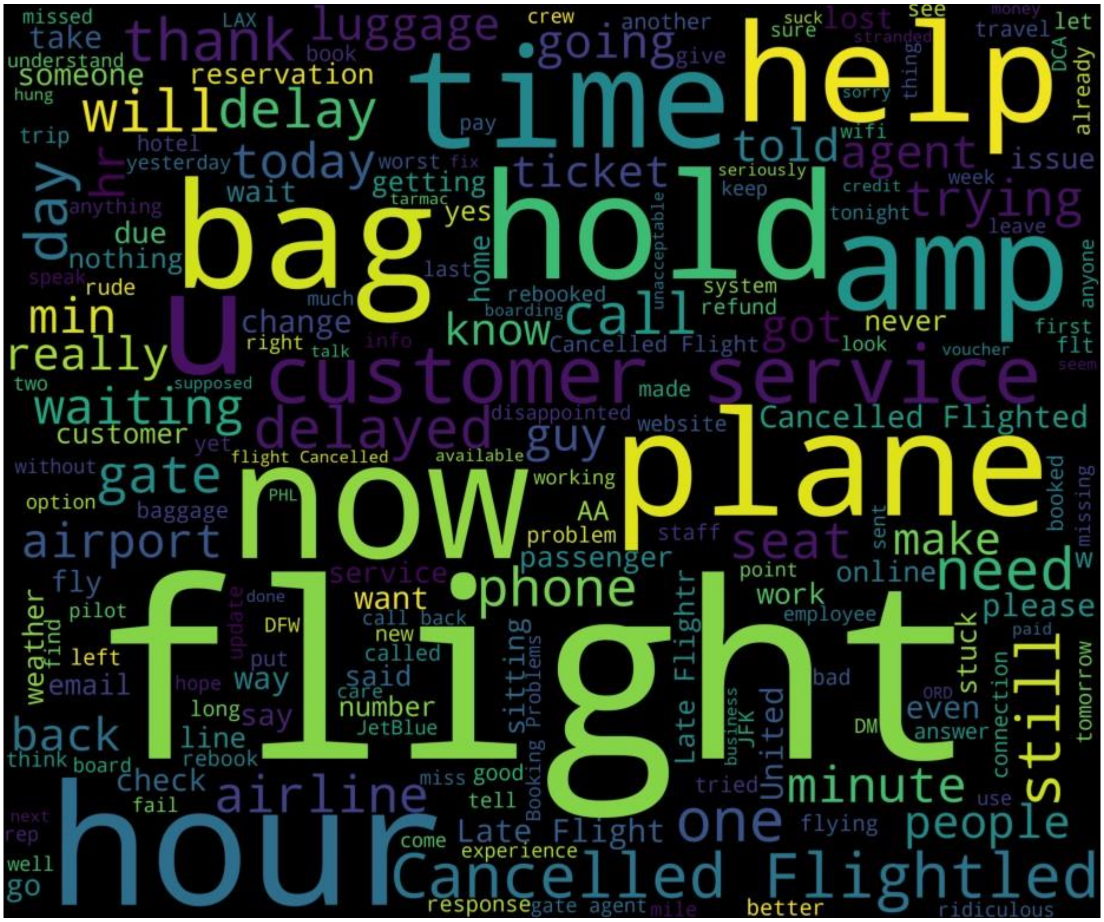
[34]:
```python
count_vect = CountVectorizer(stop_words="english")
neg_matrix = count_vect.
 ↪fit_transform(data[data["airline_sentiment"]=="negative"]["text"])
freqs = zip(count_vect.get_feature_names_out(), neg_matrix.sum(axis=0).
 ↪tolist()[0])
# Sort from largest to smallest
print(sorted(freqs, key=lambda x: -x[1])[:100])
```

```
[('flight', 2937), ('united', 2899), ('usairways', 2375), ('americanair', 2089),
('southwestair', 1214), ('jetblue', 1051), ('cancelled', 921), ('service', 746),
('hours', 646), ('just', 622), ('help', 618), ('hold', 611), ('customer', 609),
('time', 596), ('plane', 530), ('delayed', 505), ('amp', 503), ('hour', 452),
('flightled', 445), ('http', 436), ('flights', 419), ('bag', 415), ('gate',
410), ('ve', 398), ('don', 388), ('late', 377), ('need', 373), ('phone', 367),
('waiting', 341), ('thanks', 315), ('got', 298), ('airline', 294), ('like',
291), ('trying', 288), ('delay', 272), ('wait', 272), ('today', 269),
('minutes', 266), ('day', 251), ('going', 249), ('bags', 245), ('luggage', 245),
('told', 245), ('airport', 244), ('people', 242), ('worst', 241), ('fly', 237),
```

('really', 236), ('did', 227), ('guys', 224), ('weather', 224), ('lost', 221), ('agent', 218), ('hrs', 217), ('way', 212), ('make', 211), ('change', 210), ('seat', 208), ('flighted', 205), ('want', 205), ('check', 204), ('know', 201), ('days', 200), ('home', 194), ('virginamerica', 191), ('baggage', 190), ('getting', 181), ('sitting', 179), ('ticket', 176), ('tomorrow', 176), ('let', 174), ('min', 171), ('customers', 169), ('flying', 168), ('line', 164), ('email', 163), ('online', 163), ('experience', 162), ('didn', 161), ('stuck', 160), ('work', 159), ('bad', 157), ('number', 156), ('won', 156), ('said', 155), ('seats', 154), ('30', 153), ('10', 150), ('problems', 150), ('times', 150), ('crew', 149), ('flightr', 148), ('doesn', 146), ('good', 145), ('ll', 144), ('aa', 143), ('travel', 142), ('yes', 142), ('response', 139), ('miss', 137)]

[35]:
```
new_df = data[data["airline_sentiment"] == "positive"]
words = " ".join(new_df["text"])
cleaned_word = " ".join([word for word in words.split() if "http" not in word␣
  ↪and not word.startswith("@") and word != "RT"])
wordcloud = WordCloud(stopwords = STOPWORDS,
                      background_color = "black", width = 3000, height = 2500).
  ↪generate(cleaned_word)
plt.figure(figsize = (12, 12))
plt.imshow(wordcloud)
plt.axis("off")
plt.show()
```

[36]:
```
new_df = data[data["airline_sentiment"] == "negative"]
words = " ".join(new_df["text"])
cleaned_word = " ".join([word for word in words.split() if "http" not in word and not word.startswith("@") and word != "RT"])
wordcloud = WordCloud(stopwords = STOPWORDS,
                      background_color = "black", width = 3000, height = 2500).generate(cleaned_word)
plt.figure(figsize = (12, 12))
plt.imshow(wordcloud)
plt.axis("off")
plt.show()
```



[37]:
```
data.drop(data.loc[data["airline_sentiment"] == "neutral"].index, inplace =␣
↪True)
```

[38]:
```
from sklearn.preprocessing import LabelEncoderle
= LabelEncoder()

le.fit(data["airline_sentiment"])
data["airline_sentiment_encoded"] = le.transform(data["airline_sentiment"])
data.head()
```

[38]:
```
  airline_sentiment                                               text  \
1          positive  @VirginAmerica plus you've added commercials t...
3          negative  @VirginAmerica it's really aggressive to blast...
4          negative  @VirginAmerica and it's a really big bad thing...
5          negative  @VirginAmerica seriously would pay $30 a fligh...
6          positive  @VirginAmerica yes, nearly every time I fly VX...

   airline_sentiment_encoded
```

```
1    1
3    0
4    0
5    0
6    1
```

[39]:
```
def tweet_to_words(tweet):
    letters_only = re.sub("[^a-zA-Z]", " ", tweet)
    words = letters_only.lower().split()
    stops = set(stopwords.words("english"))
    meaningful_words = [w for w in words if not w in stops]
    return(" ".join( meaningful_words ))
```

[40]:
```
nltk.download("stopwords")
data["clean_tweet"] = data["text"].apply(lambda x: tweet_to_words(x))
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\Administrator\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

[41]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11510 entries, 1 to 14638
Data columns (total 4 columns):
 #   Column                     Non-Null Count  Dtype
---                             --------------  -----
 0   airline_sentiment          11510 non-null  object
 1   text                       11510 non-null  object
 2   airline_sentiment_encoded  11510 non-null  int32
 3   clean_tweet                11510 non-null  object
dtypes: int32(1), object(3)
memory usage: 404.6+ KB
```

[42]:
```
X = data["clean_tweet"]
y = data["airline_sentiment"]
```

[43]:
```
print(X.shape, y.shape)
```

```
(11510,) (11510,)
```

[44]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 42)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(8632,) (2878,) (8632,) (2878,)
```

[45]:
```
vect = CountVectorizer()
vect.fit(X_train)
```

[45]: CountVectorizer()

[46]:
```
X_train_dtm = vect.transform(X_train)
X_test_dtm = vect.transform(X_test)
```

[47]:
```
vect_tunned = CountVectorizer(stop_words = "english", ngram_range = (1, 2),
  min_df = 0.1, max_df = 0.7, max_features = 100)
vect_tunned
```

[47]:
```
CountVectorizer(max_df=0.7, max_features=100, min_df=0.1, ngram_range=(1, 2),
                stop_words='english')
```

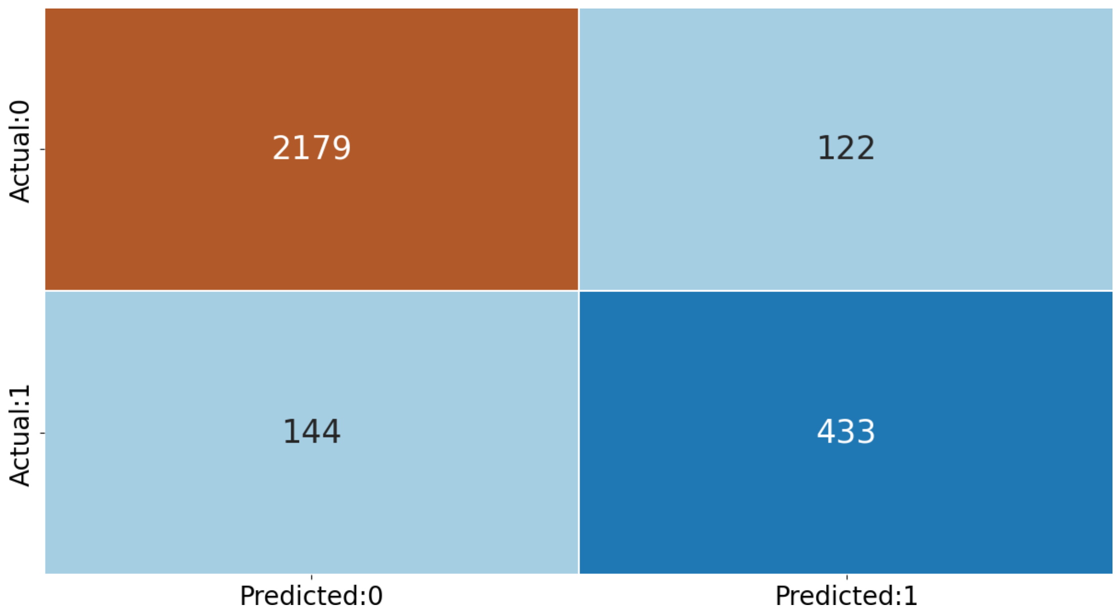
[48]:
```
from sklearn.svm import SVC
model = SVC(kernel = "linear", random_state = 10)
model.fit(X_train_dtm, y_train)
pred = model.predict(X_test_dtm)
print("Accuracy Score: ", accuracy_score(y_test, pred) * 100)
```

```
Accuracy Score:  90.7574704656011
```

[49]:
```
print("Confusion Matrix\n\n", confusion_matrix(y_test, pred))
```

```
Confusion Matrix

 [[2179  122]
 [ 144  433]]
```

[50]:
```
#defining the size of the canvas
plt.rcParams['figure.figsize'] = [15,8]
#confusion matrix to DataFrame
conf_matrix = pd.DataFrame(data = confusion_matrix(y_test, pred),columns =
  ['Predicted:0','Predicted:1',], index = ['Actual:0','Actual:1',])
#plotting the confusion matrix
sns.heatmap(conf_matrix, annot = True, fmt = 'd', cmap = 'Paired', cbar =
  False,linewidths = 0.1, annot_kws = {'size':25})
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.show()
```



[51]:
```
print(classification_report(y_test, pred))
```

```
              precision    recall  f1-score   support

    negative       0.94      0.95      0.94      2301
    positive       0.78      0.75      0.77       577

    accuracy                           0.91      2878
   macro avg       0.86      0.85      0.85      2878
weighted avg       0.91      0.91      0.91      2878
```

[ ]: