import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore")

In [2]: data=pd.read\_csv(r"C:\Users\reshma\_koduri\Downloads\Tweets airline.csv")

In [3]: data

data

	negative reason_confidence	negative reason	airline_sentiment_confidence	airline_sentiment	tweet_id		Out[3]:
1	NaN	NaN	1.0000	neutral	5.700000e+17	0	
,	0.0000	NaN	0.3486	positive	5.700000e+17	1	
ļ	NaN	NaN	0.6837	neutral	5.700000e+17	2	
,	0.7033	Bad Flight	1.0000	negative	5.700000e+17	3	
ļ	1.0000	Can't Tell	1.0000	negative	5.700000e+17	4	
						•••	
Aı	0.0000	NaN	0.3487	positive	5.700000e+17	14635	
Aı	1.0000	Customer Service Issue	1.0000	negative	5.700000e+17	14636	
Aı	NaN	NaN	1.0000	neutral	5.700000e+17	14637	
Aı	0.6659	Customer Service Issue	1.0000	negative	5.700000e+17	14638	
Αı	0.0000	NaN	0.6771	neutral	5.700000e+17	14639	

14640 rows × 12 columns

In [4]:	data.head(10)					
Out[4]:	tweet_id	airline_sentiment	airline_sentiment_confidence	negative reason	negative reason_confidence	airline
	<b>0</b> 5.700000e+17	neutral	1.0000	NaN	NaN	Virgir America
	<b>1</b> 5.700000e+17	positive	0.3486	NaN	0.0000	Virgir America
	<b>2</b> 5.700000e+17	neutral	0.6837	NaN	NaN	Virgir America
	<b>3</b> 5.700000e+17	negative	1.0000	Bad Flight	0.7033	Virgir America
	<b>4</b> 5.700000e+17	negative	1.0000	Can't Tell	1.0000	Virgir America
	<b>5</b> 5.700000e+17	negative	1.0000	Can't Tell	0.6842	Virgir America
	<b>6</b> 5.700000e+17	positive	0.6745	NaN	0.0000	Virgir America
	<b>7</b> 5.700000e+17	neutral	0.6340	NaN	NaN	Virgir America
	<b>8</b> 5.700000e+17	positive	0.6559	NaN	NaN	Virgir America
	<b>9</b> 5.700000e+17	positive	1.0000	NaN	NaN	Virgir America
	4					•
In [5]:	data.tail(10)					
Out[5]:	twee	t_id airline_sentim	ent airline_sentiment_confide	negat ence rea	tive neg son reason_confid	ative ence
	<b>14630</b> 5.700000e	+17 posi	tive 1.0	N 0000	laN	NaN Aı

	tweet_id	airline_sentiment	airline_sentiment_confidence	negative reason	negative reason_confidence	
14631	5.700000e+17	negative	1.0000	Bad Flight	1.0000	Aı
14632	5.700000e+17	neutral	0.6760	NaN	0.0000	Aı
14633	5.700000e+17	negative	1.0000	Cancelled Flight	1.0000	Aı
14634	5.700000e+17	negative	0.6684	Late Flight	0.6684	Aı
14635	5.700000e+17	positive	0.3487	NaN	0.0000	Aı
14636	5.700000e+17	negative	1.0000	Customer Service Issue	1.0000	Aı
14637	5.700000e+17	neutral	1.0000	NaN	NaN	Aı
14638	5.700000e+17	negative	1.0000	Customer Service Issue	0.6659	Aı
14639	5.700000e+17	neutral	0.6771	NaN	0.0000	Aı

In [6]:

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14640 entries, 0 to 14639
Data columns (total 12 columns):

- 0. 0 0.			
#	Column	Non-Null Count	Dtype
0	tweet_id	14640 non-null	float64
1	airline_sentiment	14640 non-null	object
2	<pre>airline_sentiment_confidence</pre>	14640 non-null	float64
3	negative reason	9178 non-null	object
4	negative reason_confidence	10522 non-null	float64
5	airline	14640 non-null	object
6	name	14640 non-null	object
7	retweet_count	14640 non-null	int64
8	text	14640 non-null	object

9 tweet\_created 14640 non-null object 10 tweet\_location 9907 non-null object 11 user\_timezone 9820 non-null object

dtypes: float64(3), int64(1), object(8)

memory usage: 1.3+ MB

In [7]: data.describe()

[7]:		tweet_id	airline_sentiment_confidence	e negative reason_confidence	retweet_count
	count	1.464000e+04	14640.00000	10522.000000	14640.000000
	mean	5.692605e+17	0.90016	0.638298	0.082650
	std	8.098842e+14	0.16283	0.330440	0.745778
	min	5.680000e+17	0.33500	0.000000	0.000000
	25%	5.690000e+17	0.69230	0.360600	0.000000
	50%	5.690000e+17	1.00000	0.670600	0.000000
	75%	5.700000e+17	1.00000	1.000000	0.000000
	max	5.700000e+17	1.00000	1.000000	44.000000
]:	data	shape			
:	(1464)	0, 12)			
:	data	.isna().sum()			
]:	tweet_		0		
		ne_sentiment	0		
		ne_sentiment_	_		
		ive reason ive reason_co	5462 onfidence 4118		
	airli		0 dilitaence 4118		
	name		0		
		et_count	0		
	text		0		
	tweet	_created	0		
		_ _location	4733		
	user_	timezone	4820		
	1.0				

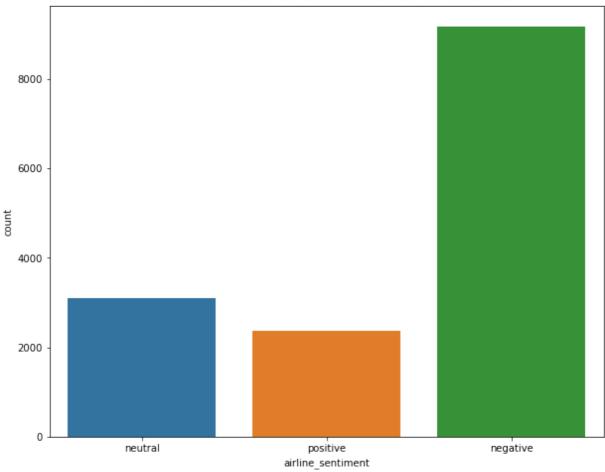
In [10]: data.groupby(['airline\_sentiment']).count()

Out[10]: negative negative tweet\_id airline\_sentiment\_confidence airline name reason reason\_confidence airline\_sentiment 9178 9178 9178 negative 9178 9178 9178 3099 3099 0 1014 3099 3099 neutral positive 2363 0 330 2363 2363 2363

dtype: int64

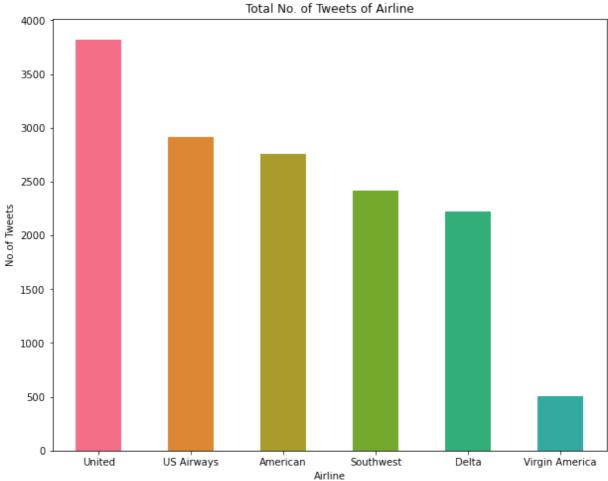
```
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize = (10, 8))
ax = sns.countplot(x = 'airline_sentiment', data = data)
ax.set_title(label = 'Total number of sentiments of tweets', fontsize = 20)
plt.show()
```

## Total number of sentiments of tweets

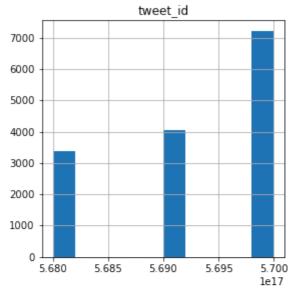


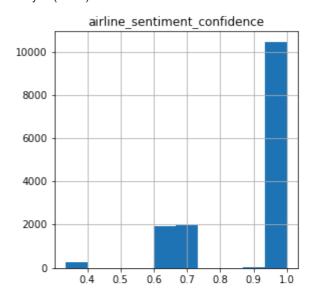
```
colors=sns.color_palette('husl',10)
pd.Series(data['airline']).value_counts().plot(kind="bar",color=colors,figsize=(10,8
plt.xlabel('Airline',fontsize=10)
plt.ylabel('No.of Tweets',fontsize=10)
```

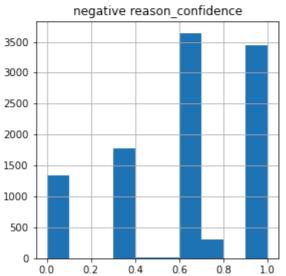
Out[12]: Text(0, 0.5, 'No.of Tweets')

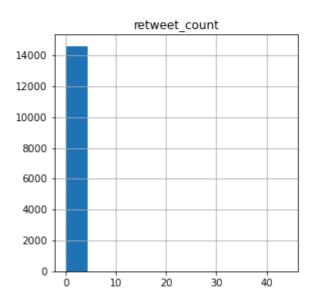


```
In [13]:
          data.hist(figsize=(10,10))
         array([[<AxesSubplot:title={'center':'tweet_id'}>,
Out[13]:
                  <AxesSubplot:title={'center':'airline_sentiment_confidence'}>],
                 [<AxesSubplot:title={'center':'negative reason_confidence'}>,
                 <AxesSubplot:title={'center':'retweet_count'}>]], dtype=object)
```



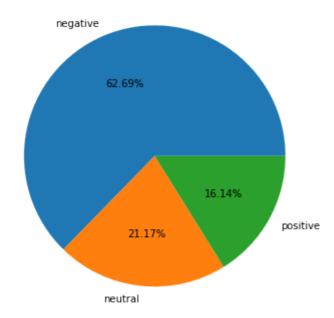






```
plt.figure(figsize=(8, 6))
    data['airline_sentiment'].value_counts().plot.pie(autopct='%2.2f%%')
    plt.title('sentiment analysis')
    plt.ylabel('')
    plt.show()
```

## sentiment analysis



In [15]:	<pre>data['final_text'] = data['negative reason'].fillna('') + ' ' + data['text']</pre>
In [16]:	<pre>#import nltk #nltk.download('stopwords')</pre>
In [17]:	<pre>data['airline_sentiment']=data['airline_sentiment'].map({'neutral':0,'positive':1,'n data</pre>

Out[17]:		tweet_id	airline_sentiment	airline_sentiment_confidence	negative reason	negative reason_confidence	
	0	5.700000e+17	0	1.0000	NaN	NaN	,
	1	5.700000e+17	1	0.3486	NaN	0.0000	,
	2	5.700000e+17	0	0.6837	NaN	NaN	,
	3	5.700000e+17	-1	1.0000	Bad Flight	0.7033	,
	4	5.700000e+17	-1	1.0000	Can't Tell	1.0000	,
	•••						
	14635	5.700000e+17	1	0.3487	NaN	0.0000	Αı

 $tweet\_id \quad airline\_sentiment \quad airline\_sentiment\_confidence$ 

negative

negative

reason\_confidence

1463 1463 1463	36 5.700000e+17 37 5.700000e+17 38 5.700000e+17 39 5.700000e+17	-1 0 -1		1.0000 1.0000	Customer Service Issue NaN Customer Service	1.0000 NaN	
1463 1463	<b>38</b> 5.700000e+17	-1			Customer		Þ
1463				1.0000			
	<b>39</b> 5.700000e+17	0			Issue	0.6659	A
1.46.4				0.6771	NaN	0.0000	A
1464	0 rows × 13 columns						
]: dat	ca['final_text']						
0 1 2 3 4	@VirginAmeric @VirginAmeric Bad Flight @Vi Can't Tell @Vi	a plus you'v a I didn't t rginAmerica	oday Must r it's really ag	rcials mean I ggressi			
1463 1463 1463 1463 Name	36 Customer Servi 37 @AmericanAir 38 Customer Servi	ce Issue @Am Please bring ce Issue @Am we have 8 pp	ericanAir leav American Air ericanAir you l so we need 2	ving ov lines t have m			
cor	r=data.corr()						
]:		tweet_id ai	rline_sentiment	airline_sent	iment_confidence	nereason_conf	ega fid
	tweet_id	1.000000	-0.087910		0.037667	0.	.03
	airline_sentiment	-0.087910	1.000000		-0.205936	-0.	.69
airli	ne_sentiment_confidence	0.037667	-0.205936		1.000000	0.	.68
ne	gative reason_confidence	0.034864	-0.693294		0.685879	1.	.00
	waterway against	-0.006689	-0.015717				

```
In [20]:
            import seaborn as sb
            sb.heatmap(cor,vmax=0,vmin=-2,annot=True,linewidth=-5,cmap="rocket")
           <AxesSubplot:>
Out[20]:
                                                                                        0.00
                             tweet id
                                                 -0.088
                                                          0.038
                                                                   0.035
                                                                           -0.0067
                                                                                         -0.25
                                                                                        -0.50
                                                  1
                                                          -0.21
                                                                            -0.016
                      airline sentiment -
                                                                                        -0.75
            airline sentiment confidence -
                                                           1
                                       0.038
                                                 -0.21
                                                                   0.69
                                                                            0.013
                                                                                        -1.00
                                                                                         -1.25
                                       0.035
                                                          0.69
                                                                    1
                                                                            0.022
            negative reason confidence -
                                                                                        -1.50
                                                                                         -1.75
                        retweet_count - -0.0067
                                                 -0.016
                                                          0.013
                                                                   0.022
                                                                              1
                                                                                         -2.00
                                                                    negative reason confidence
                                         bweet id
                                                           airline sentiment confidence
                                                  airline sentiment
                                                                             retweet count
In [21]:
            x=data['final_text']
            y=data['airline_sentiment']
In [22]:
                                       @VirginAmerica What @dhepburn said.
Out[22]:
                       @VirginAmerica plus you've added commercials ...
           2
                       @VirginAmerica I didn't today... Must mean I ...
           3
                      Bad Flight @VirginAmerica it's really aggressi...
           4
                      Can't Tell @VirginAmerica and it's a really bi...
           14635
                       @AmericanAir thank you we got on a different ...
           14636
                      Customer Service Issue @AmericanAir leaving ov...
           14637
                       @AmericanAir Please bring American Airlines t...
           14638
                      Customer Service Issue @AmericanAir you have m...
           14639
                       @AmericanAir we have 8 ppl so we need 2 know ...
           Name: final_text, Length: 14640, dtype: object
In [23]:
                      0
Out[23]:
                      1
           2
                      0
           3
                     -1
           4
                     -1
           14635
                      1
           14636
                     -1
                      0
           14637
           14638
                     -1
```

```
14639
         Name: airline_sentiment, Length: 14640, dtype: int64
In [24]:
          from sklearn.feature_extraction.text import TfidfVectorizer
          tfid = TfidfVectorizer()
In [25]:
          x_final=tfid.fit_transform(x)
In [26]:
          x_final
          <14640x15052 sparse matrix of type '<class 'numpy.float64'>'
Out[26]:
                 with 252187 stored elements in Compressed Sparse Row format>
In [27]:
          from imblearn.over_sampling import SMOTE
          smote = SMOTE()
          x_sm,y_sm = smote.fit_resample(x_final,y)
In [28]:
          from sklearn.model_selection import train_test_split
In [29]:
          x_train,x_test,y_train,y_test=train_test_split(x_sm,y_sm,test_size=0.33,random_state
In [30]:
          from sklearn.ensemble import RandomForestClassifier
In [31]:
          cls=RandomForestClassifier()
In [32]:
          cls.fit(x_train,y_train)
Out[32]:
         ▼ RandomForestClassifier
         RandomForestClassifier()
In [33]:
          ypred=cls.predict(x_test)
          ypred
         array([-1, -1, 1, ..., 1, 1], dtype=int64)
Out[33]:
In [34]:
          from sklearn.metrics import accuracy score,confusion matrix
In [35]:
          confusion_matrix(ypred,y_test)
         array([[3028,
                          84,
                                60],
Out[35]:
                 [ 23, 2774, 133],
                    3, 106, 2876]], dtype=int64)
In [36]:
          from sklearn.metrics import ConfusionMatrixDisplay
          cm1=confusion matrix(ypred,y test)
          ConfusionMatrixDisplay(cm1).plot(cmap='Oranges')
          plt.title('Confusion Matrix')
```

```
Out[36]: Text(0.5, 1.0, 'Confusion Matrix')
```

```
Confusion Matrix
                                                        3000
          3028
                          84
                                         60
   0
                                                        2500
                                                        2000
True label
           23
                         2774
                                        133
                                                        1500
                                                        1000
                         106
                                       2876
   2
            3
                                                        500
                                         ż
            Ó
                    Predicted label
```

```
In [37]: accuracy_score(ypred,y_test)
```

Out[37]: 0.9549906459777704

In [38]:

from sklearn.metrics import classification\_report
report1=classification\_report(ypred,y\_test)
print("Classification Report:\n", report1)

Classification Report:

	precision	recall	f1-score	support
-1 0 1	0.99 0.94 0.94	0.95 0.95 0.96	0.97 0.94 0.95	3172 2930 2985
accuracy macro avg weighted avg	0.95 0.96	0.95 0.95	0.95 0.95 0.96	9087 9087 9087

```
In [39]: from sklearn.tree import DecisionTreeClassifier
```

In [40]: tree=DecisionTreeClassifier()

In [41]: tree.fit(x\_train,y\_train)

Out[41]: • DecisionTreeClassifier

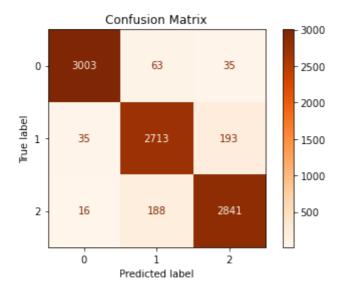
DecisionTreeClassifier()

Out[42]: array([-1, -1, 1, ..., 1, 1], dtype=int64)

```
In [43]:
          confusion_matrix(ypred1,y_test)
          array([[3000,
                          43,
                                25],
Out[43]:
                    36, 2663, 269],
                 [
                         258, 2775]], dtype=int64)
                 18,
In [44]:
          cm2=confusion_matrix(ypred1,y_test)
          #ConfusionMatrixDisplay(cm2).plot(cmap='Oranges')
          #plt.title('Confusion Matrix')
In [45]:
          accuracy_score(ypred1,y_test)
          0.9285792890943105
Out[45]:
In [46]:
          from sklearn.metrics import classification report
          report2=classification_report(ypred1,y_test)
          print("Classification Report:\n", report2)
         Classification Report:
                         precision
                                      recall f1-score
                                                          support
                    -1
                             0.98
                                       0.98
                                                  0.98
                                                            3068
                             0.90
                                       0.90
                                                  0.90
                                                            2968
                     0
                             0.90
                                       0.91
                                                  0.91
                                                            3051
                     1
                                                 0.93
                                                            9087
             accuracy
             macro avg
                             0.93
                                       0.93
                                                 0.93
                                                            9087
         weighted avg
                             0.93
                                       0.93
                                                 0.93
                                                            9087
In [47]:
          from sklearn.linear_model import LogisticRegression
In [48]:
          reg=LogisticRegression()
In [49]:
          reg.fit(x_train,y_train)
Out[49]:
          ▼ LogisticRegression
         LogisticRegression()
In [50]:
          ypred2=reg.predict(x_test)
          ypred2
          array([-1, -1, 1, ..., 1, 1], dtype=int64)
Out[50]:
In [51]:
          confusion matrix(ypred2,y test)
                          63,
         array([[3003,
                                35],
Out[51]:
                 [
                   35, 2713, 193],
                   16, 188, 2841]], dtype=int64)
```

```
In [52]:
    cm3=confusion_matrix(ypred2,y_test)
    ConfusionMatrixDisplay(cm3).plot(cmap='Oranges')
    plt.title('Confusion Matrix')
```

Out[52]: Text(0.5, 1.0, 'Confusion Matrix')



```
In [53]: accuracy_score(ypred2,y_test)
```

Out[53]: 0.9416749202156928

```
In [54]: from sklearn.metrics import classification_report
     report3=classification_report(ypred2,y_test)
```

print("Classification Report:\n", report3)

Classification Report:

```
precision
                              recall f1-score
                                                  support
          -1
                    0.98
                               0.97
                                         0.98
                                                    3101
           0
                    0.92
                               0.92
                                         0.92
                                                    2941
                    0.93
                                         0.93
                                                    3045
           1
                               0.93
                                         0.94
                                                    9087
    accuracy
                    0.94
                               0.94
                                         0.94
   macro avg
                                                    9087
                    0.94
                               0.94
                                         0.94
weighted avg
                                                    9087
```

```
import tkinter as tk
from tkinter import ttk
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

# Function to analyze sentiment
def analyze_sentiment():
    text = text_entry.get("1.0", "end-1c") # Get text from the Text widget
    if text:
        analyzer = SentimentIntensityAnalyzer()
        sentiment_scores = analyzer.polarity_scores(text)
        sentiment = sentiment_scores['compound']
    if sentiment >= 0.05:
        result_label.config(text="Positive")
    elif sentiment <= -0.05:
        result_label.config(text="Negative")
    else:</pre>
```

```
result_label.config(text="Neutral")
    else:
        result_label.config(text="Please enter text!")
# Create the main window
window = tk.Tk()
window.title('Sentiment Analysis')
# Create and place widgets
text_label = ttk.Label(window, text='Enter text:')
text_label.pack()
text_entry = tk.Text(window, height=5, width=50)
text_entry.pack()
analyze_button = ttk.Button(window, text='Analyze Sentiment', command=analyze_sentiment')
analyze_button.pack()
result_label = ttk.Label(window, text='')
result_label.pack()
# Start the GUI event loop
window.mainloop()
```

In [ ]: