Importing Necessary Libariries

In [100…
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

Reading the data

In [101…
```
flights_df = pd.read_csv("FlightDelays.csv")
print(flights_df)
```

```
      CRS_DEP_TIME CARRIER  DEP_TIME DEST  DISTANCE     FL_DATE  FL_NUM  \
0             1455      OH      1455  JFK       184  01/01/2004    5935
1             1640      DH      1640  JFK       213  01/01/2004    6155
2             1245      DH      1245  LGA       229  01/01/2004    7208
3             1715      DH      1709  LGA       229  01/01/2004    7215
4             1039      DH      1035  LGA       229  01/01/2004    7792
...            ...     ...       ...  ...       ...         ...     ...
2196           645      RU       644  EWR       199   1/31/2004    2761
2197          1700      RU      1653  EWR       213   1/31/2004    2497
2198          1600      RU      1558  EWR       199   1/31/2004    2361
2199          1359      RU      1403  EWR       199   1/31/2004    2216
2200          1730      RU      1736  EWR       199   1/31/2004    2097

     ORIGIN  Weather  DAY_WEEK  DAY_OF_MONTH TAIL_NUM Flight Status
0       BWI        0         4             1   N940CA        ontime
1       DCA        0         4             1   N405FJ        ontime
2       IAD        0         4             1   N695BR        ontime
3       IAD        0         4             1   N662BR        ontime
4       IAD        0         4             1   N698BR        ontime
...     ...      ...       ...           ...      ...           ...
2196    DCA        0         6            31   N15555        ontime
2197    IAD        0         6            31   N16976        ontime
2198    DCA        0         6            31   N14902        ontime
2199    DCA        0         6            31   N16961        ontime
2200    DCA        0         6            31   N13994        ontime

[2201 rows x 13 columns]
```

In [102…
```
flights_df.shape
```

Out[102…
```
(2201, 13)
```

Renaming the columns

In [103…
```
flights_df.columns = [s.strip().replace(' ', '_').upper() for s in flights_df.colum
flights_df.columns
```

Out[103…
```
Index(['CRS_DEP_TIME', 'CARRIER', 'DEP_TIME', 'DEST', 'DISTANCE', 'FL_DATE',
       'FL_NUM', 'ORIGIN', 'WEATHER', 'DAY_WEEK', 'DAY_OF_MONTH', 'TAIL_NUM',
       'FLIGHT_STATUS'],
      dtype='object')
```

In [104…
```
## checking the null values
```

In [105…
```
flights_df.isnull().sum()
```

Out[105…
```
CRS_DEP_TIME     0
CARRIER          0
DEP_TIME         0
DEST             0
DISTANCE         0
FL_DATE          0
FL_NUM           0
ORIGIN           0
WEATHER          0
DAY_WEEK         0
DAY_OF_MONTH     0
TAIL_NUM         0
FLIGHT_STATUS    0
dtype: int64
```

Understanding of data

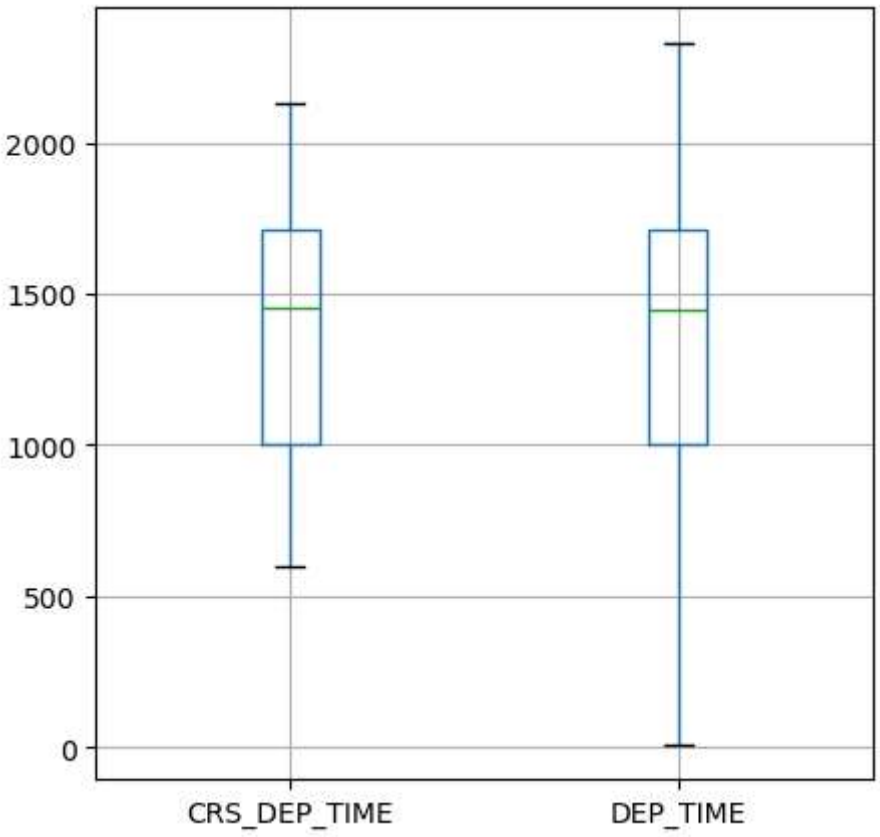
In [106…
```
flights_df.describe()
```

Out[106…

	CRS_DEP_TIME	DEP_TIME	DISTANCE	FL_NUM	WEATHER	DAY_WEEK	D
count	2201.000000	2201.000000	2201.000000	2201.000000	2201.000000	2201.000000	
mean	1371.938664	1369.298955	211.871422	3815.086324	0.014539	3.905498	
std	432.697149	442.462754	13.316815	2409.750224	0.119725	1.903149	
min	600.000000	10.000000	169.000000	746.000000	0.000000	1.000000	
25%	1000.000000	1004.000000	213.000000	2156.000000	0.000000	2.000000	
50%	1455.000000	1450.000000	214.000000	2385.000000	0.000000	4.000000	
75%	1710.000000	1709.000000	214.000000	6155.000000	0.000000	5.000000	
max	2130.000000	2330.000000	229.000000	7924.000000	1.000000	7.000000	

Now looking at the summary statistics, we will drop the row which has minimum value for 10 according to our analysis of being an incorrect value

In [107…
```
#Distributed of scheduled departure time and actual departure time
plt.figure(figsize=(5,5))
flights_df.boxplot(column=["CRS_DEP_TIME","DEP_TIME"])
plt.show()
```



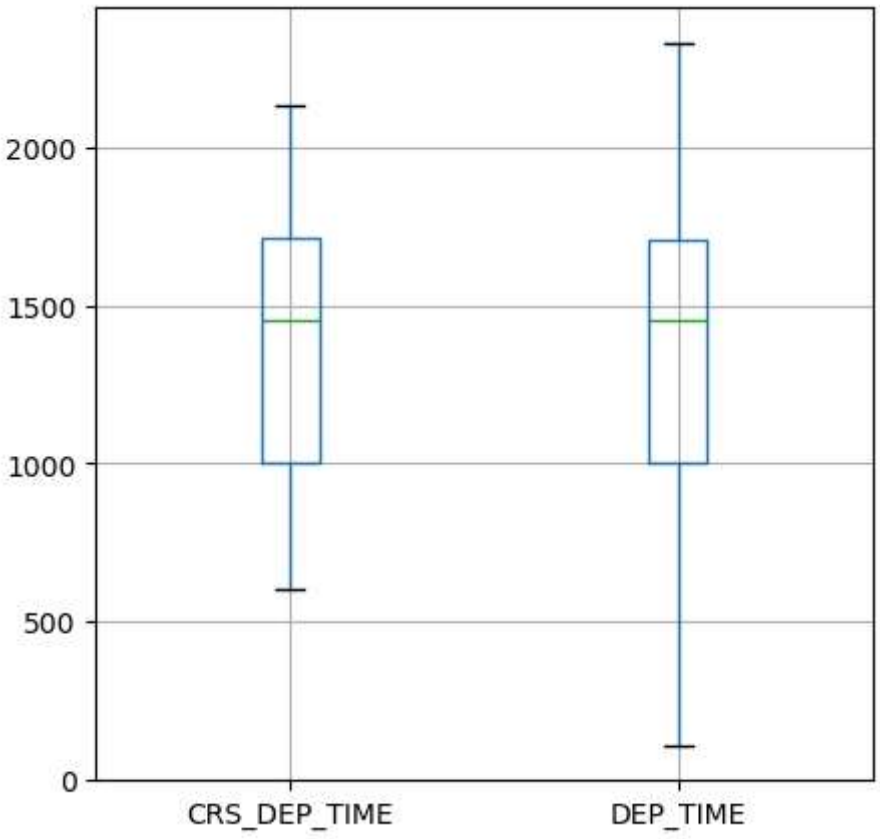
In [108…
```
# Drop rows where DEP_TIME is 10
flights_df = flights_df[flights_df['DEP_TIME'] != 10]
flights_df.describe()
```

Out[108…

	CRS_DEP_TIME	DEP_TIME	DISTANCE	FL_NUM	WEATHER	DAY_WEEK	D
count	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	
mean	1371.598636	1369.916818	211.863636	3813.327727	0.014545	3.906818	
std	432.501297	441.612605	13.314831	2408.884969	0.119751	1.902572	
min	600.000000	109.000000	169.000000	746.000000	0.000000	1.000000	
25%	1000.000000	1004.750000	213.000000	2156.000000	0.000000	2.000000	
50%	1455.000000	1450.000000	214.000000	2385.000000	0.000000	4.000000	
75%	1710.000000	1709.000000	214.000000	5990.000000	0.000000	5.000000	
max	2130.000000	2330.000000	229.000000	7924.000000	1.000000	7.000000	

In [109…

```
#After dropping the row
#Distributed of scheduled departure time and actual departure time
plt.figure(figsize=(5,5))
flights_df.boxplot(column=["CRS_DEP_TIME","DEP_TIME"])
plt.show()
```



In [110…

```
flights_df.dtypes
```

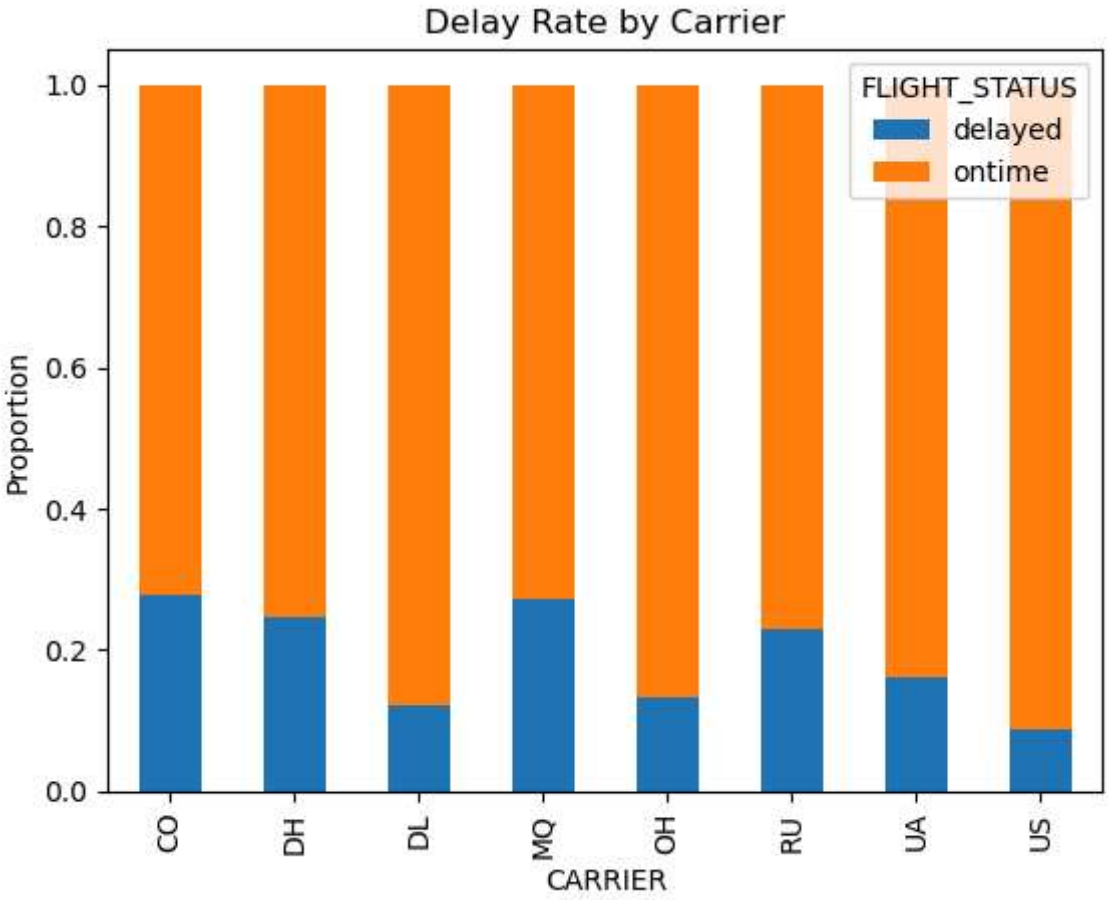
Out[110…

```
CRS_DEP_TIME      int64
CARRIER          object
DEP_TIME          int64
DEST             object
DISTANCE          int64
FL_DATE          object
FL_NUM            int64
ORIGIN           object
WEATHER           int64
DAY_WEEK          int64
DAY_OF_MONTH      int64
TAIL_NUM         object
FLIGHT_STATUS    object
dtype: object
```

Analysis of the data

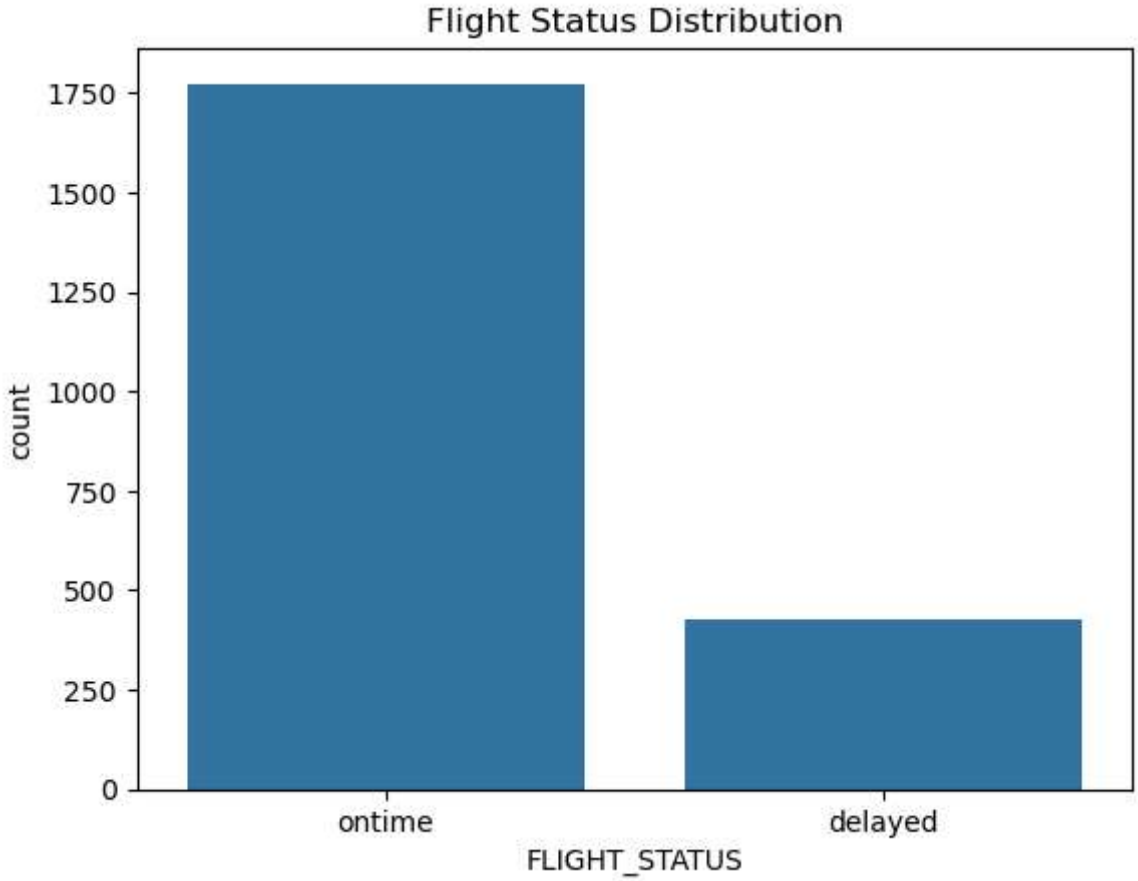
In [111…

```
# Delay rate by carrier
carrier_delay_rate = flights_df.groupby('CARRIER')['FLIGHT_STATUS'].value_counts(no
carrier_delay_rate.plot(kind='bar', stacked=True)
plt.title('Delay Rate by Carrier')
plt.ylabel('Proportion')
plt.show()
```



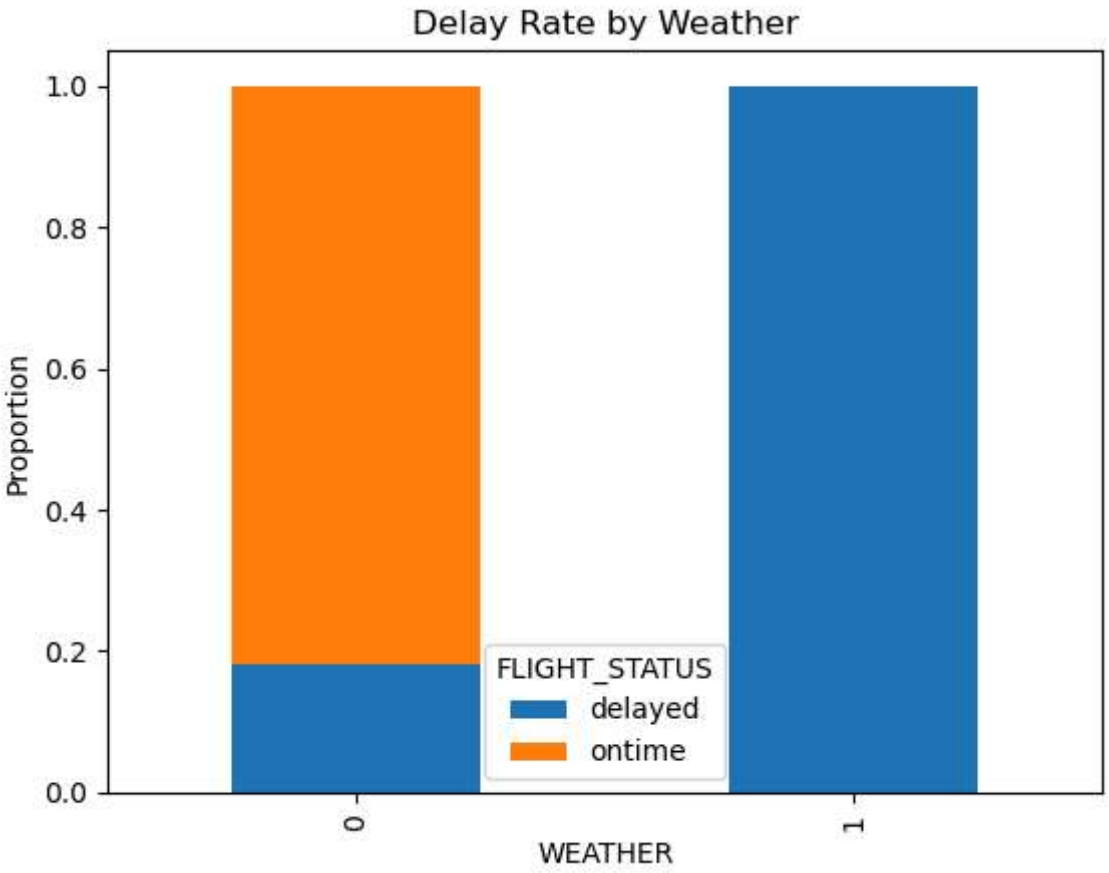
1. The carriers MQ (likely American Eagle) and RU show the highest proportion of delayed flights among the carriers listed.
2. DL (Delta Air Lines) has the lowest proportion of delayed flights
3. There is a noticeable variation in delay proportions among carriers. Some carriers like MQ and RU have higher delays, while others like DL, UA and US have lower delays.

In [112…
```
# Bar plot for Flight Status
sns.countplot(x='FLIGHT_STATUS', data=flights_df)
plt.title('Flight Status Distribution')
plt.show()
```



In our dataset, there are more ontime flights as compared to the delayed flights

In [113…
```
# Delay Rate by weather
carrier_delay_rate = flights_df.groupby('WEATHER')['FLIGHT_STATUS'].value_counts(no
carrier_delay_rate.plot(kind='bar', stacked=True)
plt.title('Delay Rate by Weather')
plt.ylabel('Proportion')
plt.show()
```



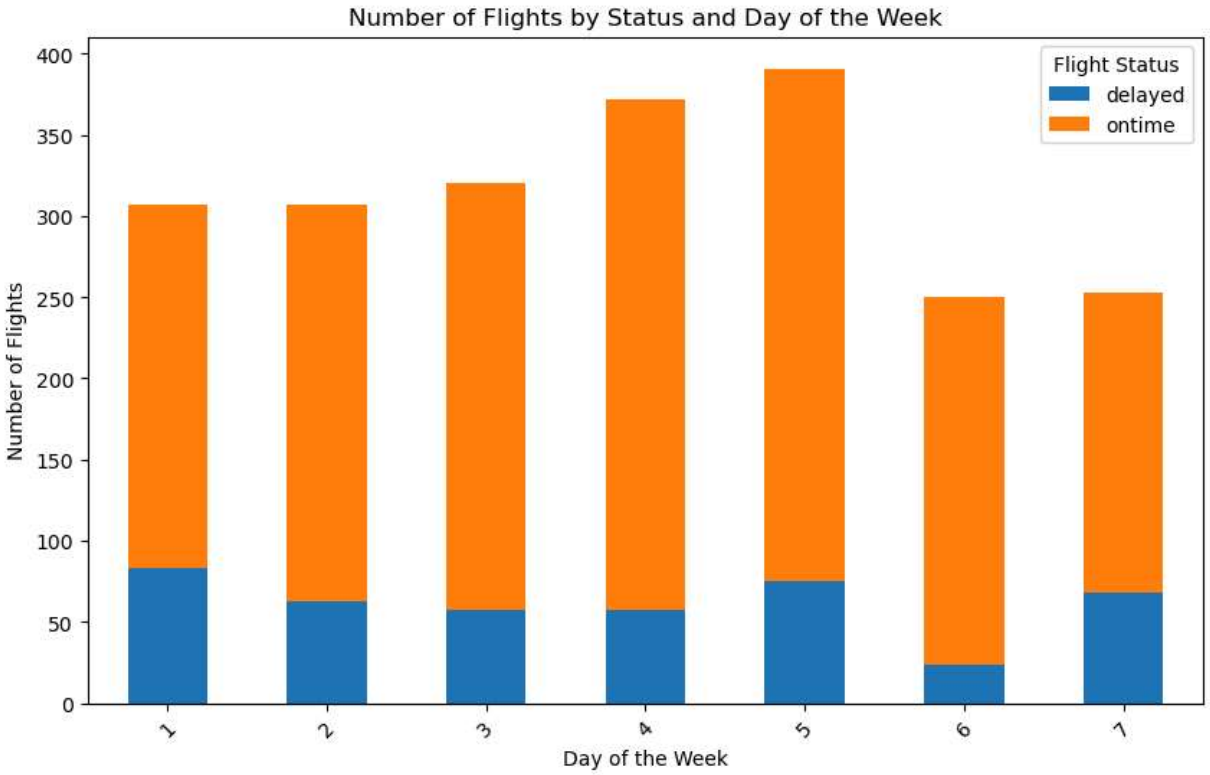
1. Most flights are on time when the weather is clear. There is still a portion of flights that are delayed (about 80%) , but it is relatively small compared to the on-time flights.
2. All flights are delayed when the weather is adverse.

In [114…
```
#number of flights from each airport
flights_df['ORIGIN'].value_counts()
```

Out[114…
```
ORIGIN
DCA    1370
IAD     685
BWI     145
Name: count, dtype: int64
```

Most of the flights are taking off from DCA terminal

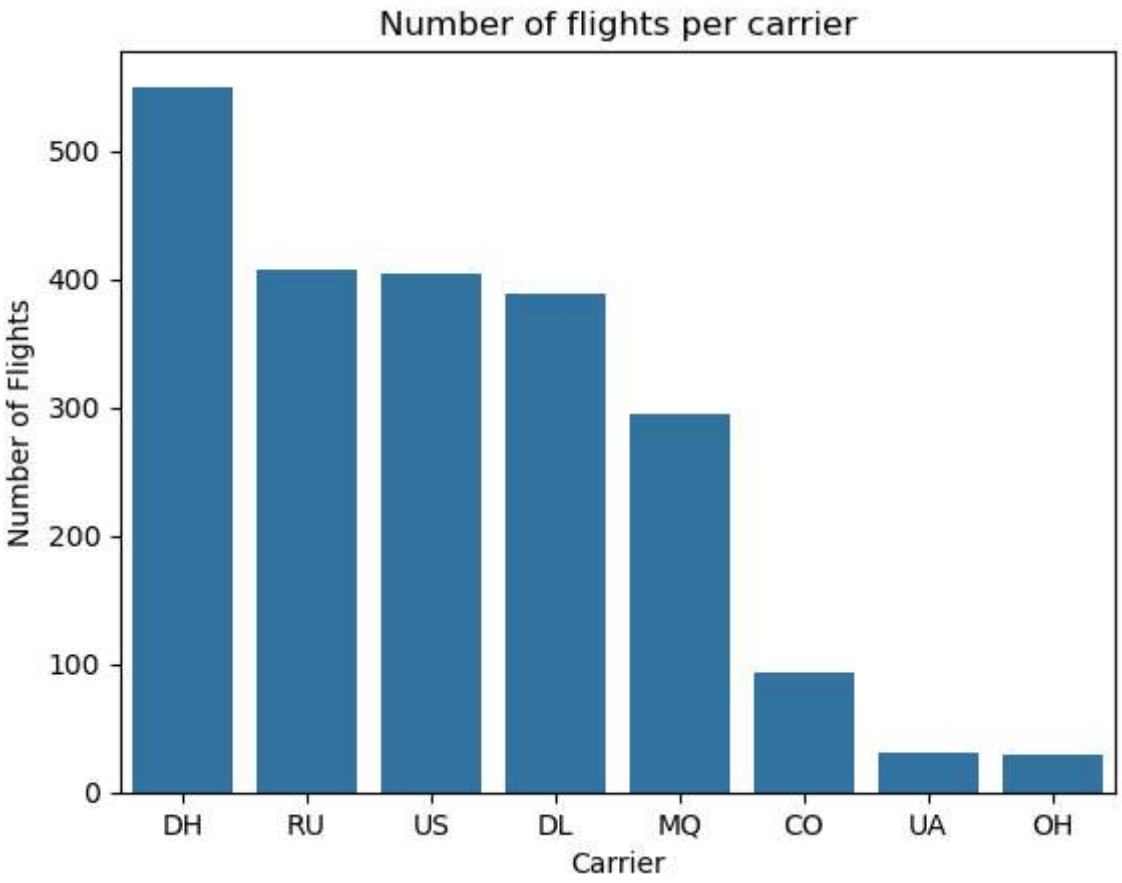
In [115…
```
#to check the distribution of the flight status by the days of the week
grouped_data = flights_df.groupby(['DAY_WEEK', 'FLIGHT_STATUS']).size().unstack(fil
grouped_data.plot(kind='bar', stacked=True, figsize=(10, 6))
plt.title('Number of Flights by Status and Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Number of Flights')
plt.legend(title='Flight Status')
plt.xticks(rotation=45)
plt.show()
```



1. Day 5 (likely Friday) has the highest total number of flights, both on-time and delayed, compared to other days.
2. Day 7 (likely Sunday) has the lowest total number of flights.
3. In absolute numbers, Day 5 (Friday) also has the highest number of delayed flights due to its high total flight volume.
4. Day 6 (Saturday) has the lowest absolute number of delays, consistent with its lower total flight volume.

In [116…

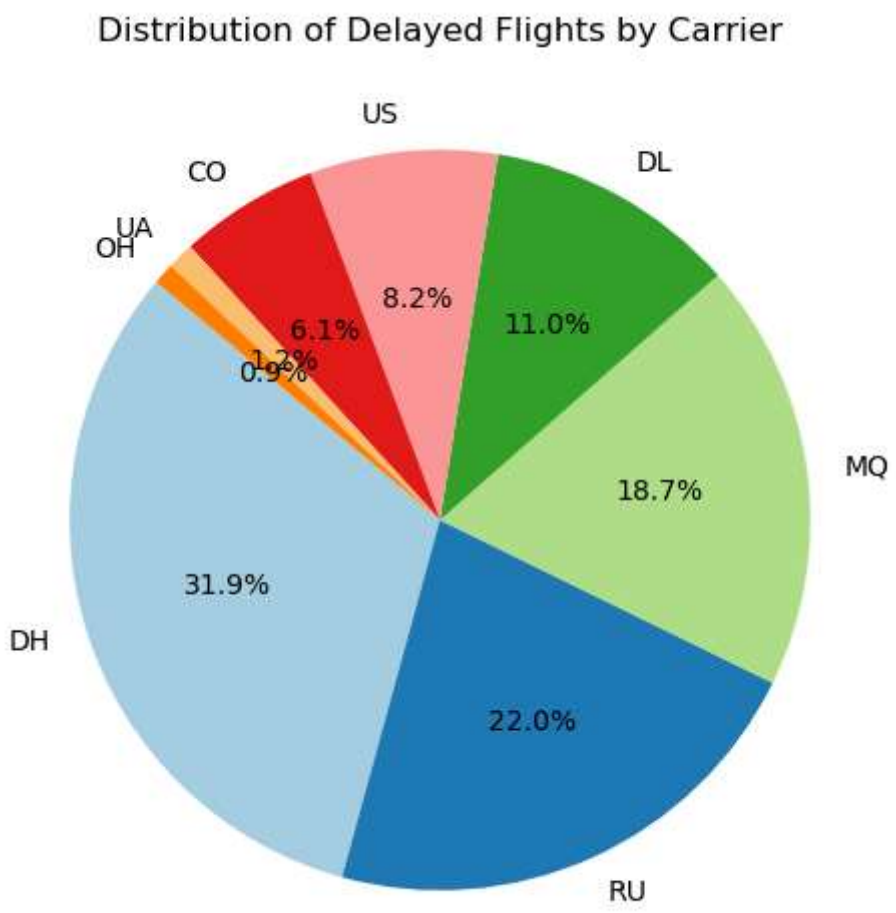
```
#distrubution of flights across carrier
carrier_counts = flights_df['CARRIER'].value_counts()
sns.barplot(x=carrier_counts.index, y=carrier_counts.values)
plt.title('Number of flights per carrier')
plt.xlabel('Carrier')
plt.ylabel('Number of Flights')
plt.show()
```



DH carrier has the highest number of flights taking off and OH and UA has the lowest number of flights taking off

In [117…

```
#delayed flights by carrier
delayed_flights = flights_df[flights_df['FLIGHT_STATUS'] == 'delayed']
carrier_delays = delayed_flights['CARRIER'].value_counts()
plt.figure(figsize=(6, 6))
plt.pie(carrier_delays, labels=carrier_delays.index, autopct='%1.1f%%', startangle=
plt.title('Distribution of Delayed Flights by Carrier')
plt.show()
```



1. The majority of delayed flights are concentrated among a few carriers, specifically DH, RU, and MQ, which together account for more than 70% of all delays.
2. The carriers with the smallest proportions of delayed flights (UA and OH) contribute less than 2% combined.

Manipulation of data for the ease in analysis

In [118…

```
# changing the outcome variable column
flights_df['FLIGHT_STATUS']=np.where(flights_df['FLIGHT_STATUS'].str.contains('dela
flights_df.head(5)
```

Out[118…

	CRS_DEP_TIME	CARRIER	DEP_TIME	DEST	DISTANCE	FL_DATE	FL_NUM	ORIGIN	V
0	1455	OH	1455	JFK	184	01/01/2004	5935	BWI	
1	1640	DH	1640	JFK	213	01/01/2004	6155	DCA	
2	1245	DH	1245	LGA	229	01/01/2004	7208	IAD	
3	1715	DH	1709	LGA	229	01/01/2004	7215	IAD	
4	1039	DH	1035	LGA	229	01/01/2004	7792	IAD	

Specificying the predictors and Outcomes, scaling the data

In [119…

```
predictors=['DISTANCE','WEATHER','DAY_WEEK','DAY_OF_MONTH','CARRIER','DEST','ORIGIN
X=pd.get_dummies(flights_df[predictors],drop_first=True)
X.head(5)
```

Out[119…

	DISTANCE	WEATHER	DAY_WEEK	DAY_OF_MONTH	CARRIER_DH	CARRIER_DL	CARRIE
0	184	0	4	1	False	False	
1	213	0	4	1	True	False	
2	229	0	4	1	True	False	
3	229	0	4	1	True	False	
4	229	0	4	1	True	False	

In [120…

```
Y = flights_df['FLIGHT_STATUS']
Y.head(5)
```

Out[120…

```
0    0
1    0
2    0
3    0
4    0
Name: FLIGHT_STATUS, dtype: int32
```

In [121…

```
scaler=StandardScaler()
scaled_fd=pd.DataFrame(scaler.fit_transform(X),index=X.index,columns=X.columns)
print(scaled_fd)
```

```
      DISTANCE   WEATHER  DAY_WEEK  DAY_OF_MONTH  CARRIER_DH  CARRIER_DL  \
0    -2.093153 -0.121491  0.048988     -1.731400   -0.577350    -0.46274
1     0.085365 -0.121491  0.048988     -1.731400    1.732051    -0.46274
2     1.287306 -0.121491  0.048988     -1.731400    1.732051    -0.46274
3     1.287306 -0.121491  0.048988     -1.731400    1.732051    -0.46274
4     1.287306 -0.121491  0.048988     -1.731400    1.732051    -0.46274
...        ...       ...       ...           ...         ...         ...
2196 -0.966333 -0.121491  1.100435      1.725953   -0.577350    -0.46274
2197  0.085365 -0.121491  1.100435      1.725953   -0.577350    -0.46274
2198 -0.966333 -0.121491  1.100435      1.725953   -0.577350    -0.46274
2199 -0.966333 -0.121491  1.100435      1.725953   -0.577350    -0.46274
2200 -0.966333 -0.121491  1.100435      1.725953   -0.577350    -0.46274

      CARRIER_MQ  CARRIER_OH  CARRIER_RU  CARRIER_UA  CARRIER_US  DEST_JFK  \
0      -0.393517    8.504901   -0.477157    -0.11955   -0.474283  2.167829
1      -0.393517   -0.117579   -0.477157    -0.11955   -0.474283  2.167829
2      -0.393517   -0.117579   -0.477157    -0.11955   -0.474283 -0.461291
3      -0.393517   -0.117579   -0.477157    -0.11955   -0.474283 -0.461291
4      -0.393517   -0.117579   -0.477157    -0.11955   -0.474283 -0.461291
...          ...         ...         ...         ...         ...       ...
2196   -0.393517   -0.117579    2.095747    -0.11955   -0.474283 -0.461291
2197   -0.393517   -0.117579    2.095747    -0.11955   -0.474283 -0.461291
2198   -0.393517   -0.117579    2.095747    -0.11955   -0.474283 -0.461291
2199   -0.393517   -0.117579    2.095747    -0.11955   -0.474283 -0.461291
2200   -0.393517   -0.117579    2.095747    -0.11955   -0.474283 -0.461291

      DEST_LGA  ORIGIN_DCA  ORIGIN_IAD
0    -1.045583   -1.284758   -0.672417
1    -1.045583    0.778357   -0.672417
2     0.956404   -1.284758    1.487171
3     0.956404   -1.284758    1.487171
4     0.956404   -1.284758    1.487171
...        ...         ...         ...
2196 -1.045583    0.778357   -0.672417
2197 -1.045583   -1.284758    1.487171
2198 -1.045583    0.778357   -0.672417
2199 -1.045583    0.778357   -0.672417
2200 -1.045583    0.778357   -0.672417

[2200 rows x 15 columns]
```

Checking Skewness and correlation

In [122…

```
skewness=print(X.skew())
```

```
DISTANCE       -1.628363
WEATHER         8.115082
DAY_WEEK        0.025375
DAY_OF_MONTH    0.034621
CARRIER_DH      1.155489
CARRIER_DL      1.699461
CARRIER_MQ      2.149135
CARRIER_OH      8.393045
CARRIER_RU      1.619695
CARRIER_UA      8.250748
CARRIER_US      1.635278
DEST_JFK        1.707702
DEST_LGA       -0.089240
ORIGIN_DCA     -0.506746
ORIGIN_IAD      0.815310
dtype: float64
```

1. WEATHER, CARRIER_OH, and CARRIER_UA have very high positive skewness, indicating that adverse weather and certain carriers have many lower values and few higher values.
2. DAY_WEEK and DAY_OF_MONTH are nearly symmetrical.
3. Most CARRIER and DEST variables exhibit positive skewness, suggesting these variables are not evenly distributed and have more frequent lower values with some higher values.

In [123…

```
scaled_fd.corr(). round(2)
```

Out[123…

	DISTANCE	WEATHER	DAY_WEEK	DAY_OF_MONTH	CARRIER_DH	CARRI
DISTANCE	1.00	0.03	-0.02	0.01	0.49	
WEATHER	0.03	1.00	-0.12	0.14	0.03	
DAY_WEEK	-0.02	-0.12	1.00	0.02	0.03	
DAY_OF_MONTH	0.01	0.14	0.02	1.00	-0.00	
CARRIER_DH	0.49	0.03	0.03	-0.00	1.00	
CARRIER_DL	0.07	-0.03	-0.01	0.02	-0.27	
CARRIER_MQ	0.05	0.06	-0.02	-0.01	-0.23	
CARRIER_OH	-0.25	-0.01	0.01	0.01	-0.07	
CARRIER_RU	-0.60	-0.03	0.03	-0.02	-0.28	
CARRIER_UA	0.15	0.05	0.01	-0.00	-0.07	
CARRIER_US	0.08	-0.05	-0.02	0.02	-0.27	
DEST_JFK	0.24	0.02	0.06	-0.00	0.38	
DEST_LGA	0.36	-0.01	-0.06	0.02	-0.28	
ORIGIN_DCA	-0.07	-0.02	-0.04	0.01	-0.68	
ORIGIN_IAD	0.50	0.03	0.02	-0.01	0.80	

In [124…

```
#combining the dataframe
combined_fd=pd.concat([scaled_fd,Y],axis=1)
corr=combined_fd.corr().round(3)
print(corr)
```

	DISTANCE	WEATHER	DAY_WEEK	DAY_OF_MONTH	CARRIER_DH	\
DISTANCE	1.000	0.033	-0.020	0.010	0.487	
WEATHER	0.033	1.000	-0.124	0.144	0.026	
DAY_WEEK	-0.020	-0.124	1.000	0.016	0.027	
DAY_OF_MONTH	0.010	0.144	0.016	1.000	-0.002	
CARRIER_DH	0.487	0.026	0.027	-0.002	1.000	
CARRIER_DL	0.071	-0.026	-0.011	0.017	-0.267	
CARRIER_MQ	0.054	0.064	-0.024	-0.013	-0.227	
CARRIER_OH	-0.246	-0.014	0.008	0.006	-0.068	
CARRIER_RU	-0.603	-0.029	0.029	-0.023	-0.275	
CARRIER_UA	0.154	0.050	0.012	-0.000	-0.069	
CARRIER_US	0.076	-0.048	-0.023	0.017	-0.274	
DEST_JFK	0.240	0.024	0.060	-0.005	0.379	
DEST_LGA	0.356	-0.005	-0.062	0.018	-0.282	
ORIGIN_DCA	-0.075	-0.023	-0.042	0.012	-0.683	
ORIGIN_IAD	0.503	0.033	0.023	-0.008	0.797	
FLIGHT_STATUS	-0.020	0.248	-0.039	0.066	0.078	

	CARRIER_DL	CARRIER_MQ	CARRIER_OH	CARRIER_RU	CARRIER_UA	\
DISTANCE	0.071	0.054	-0.246	-0.603	0.154	
WEATHER	-0.026	0.064	-0.014	-0.029	0.050	
DAY_WEEK	-0.011	-0.024	0.008	0.029	0.012	
DAY_OF_MONTH	0.017	-0.013	0.006	-0.023	-0.000	
CARRIER_DH	-0.267	-0.227	-0.068	-0.275	-0.069	
CARRIER_DL	1.000	-0.182	-0.054	-0.221	-0.055	
CARRIER_MQ	-0.182	1.000	-0.046	-0.188	-0.047	
CARRIER_OH	-0.054	-0.046	1.000	-0.056	-0.014	
CARRIER_RU	-0.221	-0.188	-0.056	1.000	-0.057	
CARRIER_UA	-0.055	-0.047	-0.014	-0.057	1.000	
CARRIER_US	-0.219	-0.187	-0.056	-0.226	-0.057	
DEST_JFK	-0.116	0.138	0.255	-0.220	-0.055	
DEST_LGA	0.369	0.133	-0.123	-0.499	0.114	
ORIGIN_DCA	0.360	0.306	-0.151	-0.222	-0.154	
ORIGIN_IAD	-0.311	-0.265	-0.079	0.010	0.178	
FLIGHT_STATUS	-0.085	0.077	-0.018	0.044	-0.010	

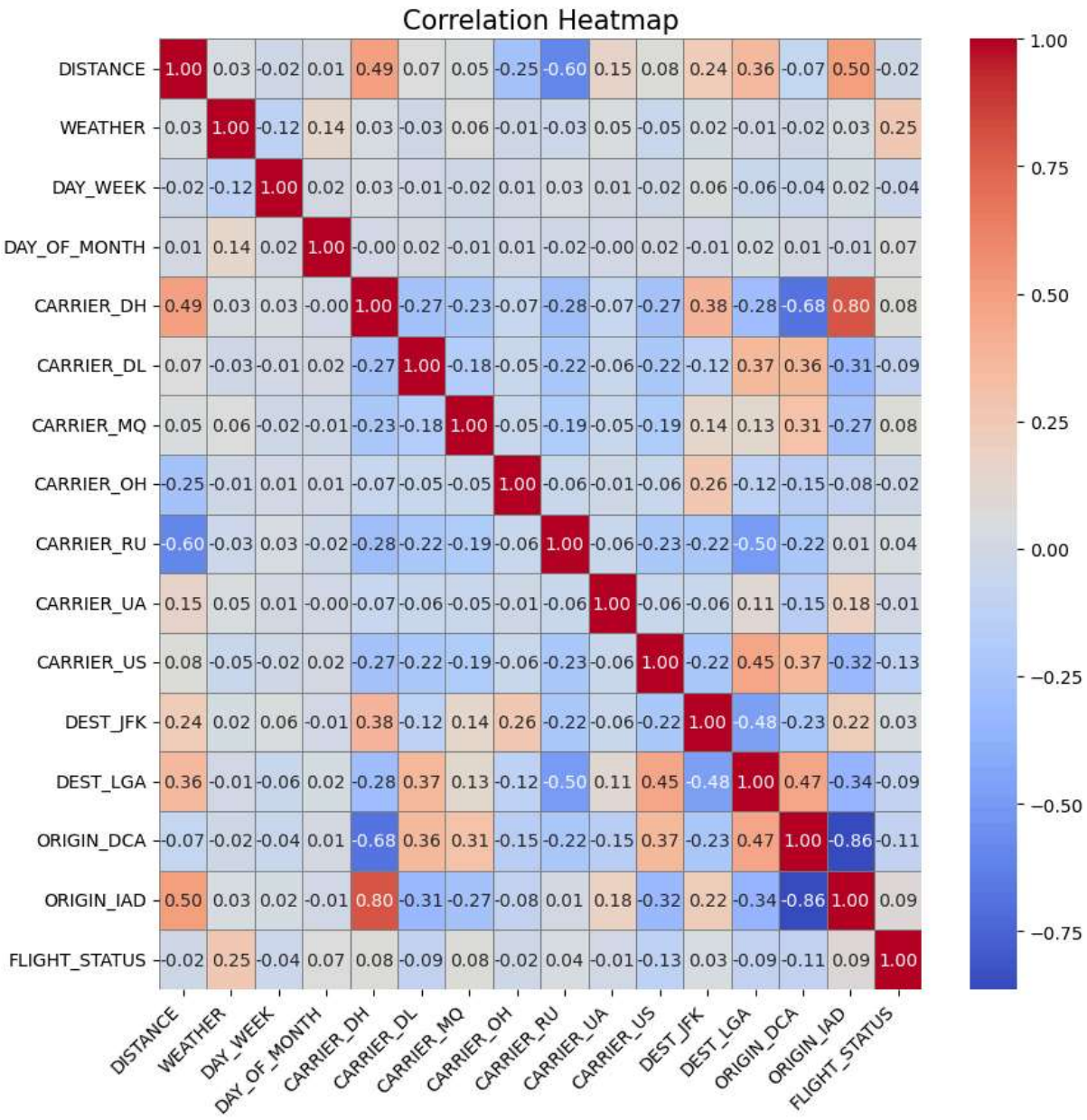
	CARRIER_US	DEST_JFK	DEST_LGA	ORIGIN_DCA	ORIGIN_IAD	\
DISTANCE	0.076	0.240	0.356	-0.075	0.503	
WEATHER	-0.048	0.024	-0.005	-0.023	0.033	
DAY_WEEK	-0.023	0.060	-0.062	-0.042	0.023	
DAY_OF_MONTH	0.017	-0.005	0.018	0.012	-0.008	
CARRIER_DH	-0.274	0.379	-0.282	-0.683	0.797	
CARRIER_DL	-0.219	-0.116	0.369	0.360	-0.311	
CARRIER_MQ	-0.187	0.138	0.133	0.306	-0.265	
CARRIER_OH	-0.056	0.255	-0.123	-0.151	-0.079	
CARRIER_RU	-0.226	-0.220	-0.499	-0.222	0.010	
CARRIER_UA	-0.057	-0.055	0.114	-0.154	0.178	
CARRIER_US	1.000	-0.219	0.454	0.369	-0.319	
DEST_JFK	-0.219	1.000	-0.482	-0.225	0.224	
DEST_LGA	0.454	-0.482	1.000	0.468	-0.341	
ORIGIN_DCA	0.369	-0.225	0.468	1.000	-0.864	
ORIGIN_IAD	-0.319	0.224	-0.341	-0.864	1.000	
FLIGHT_STATUS	-0.129	0.027	-0.094	-0.106	0.089	

	FLIGHT_STATUS
DISTANCE	-0.020

```
WEATHER              0.248
DAY_WEEK            -0.039
DAY_OF_MONTH         0.066
CARRIER_DH           0.078
CARRIER_DL          -0.085
CARRIER_MQ           0.077
CARRIER_OH          -0.018
CARRIER_RU           0.044
CARRIER_UA          -0.010
CARRIER_US          -0.129
DEST_JFK             0.027
DEST_LGA            -0.094
ORIGIN_DCA          -0.106
ORIGIN_IAD           0.089
FLIGHT_STATUS        1.000
```

In [125…

```
#Plotting the heatmap to show the correlation
plt.figure(figsize=(9, 9))
sns.heatmap(corr, annot=True, fmt=".2f", cmap="coolwarm", cbar=True, annot_kws={"si
            linewidths=0.5, linecolor='gray')
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.yticks(rotation=0, fontsize=10)
plt.title("Correlation Heatmap", fontsize=15)
plt.tight_layout()
plt.show()
```



1. Specific carriers, such as Carrier US (CARRIER_US) (-0.24) and Carrier DH (CARRIER_DH) (-0.18), show a notable negative correlation with delay minutes, suggesting flights operated by these carriers tend to experience fewer delays.
2. There is a strong positive correlation between flights originating from DCA (ORIGIN_DCA) and IAD (ORIGIN_IAD) (0.86), as well as between flights destined for JFK (DEST_JFK) and LGA (DEST_LGA) (0.47), indicating similar flight patterns or operational conditions between these pairs of airports.

In [126…

```
correlation_Target=corr['FLIGHT_STATUS'].drop('FLIGHT_STATUS').round(3)
print(correlation_Target)
```

```
DISTANCE       -0.020
WEATHER         0.248
DAY_WEEK       -0.039
DAY_OF_MONTH    0.066
CARRIER_DH      0.078
CARRIER_DL     -0.085
CARRIER_MQ      0.077
CARRIER_OH     -0.018
CARRIER_RU      0.044
CARRIER_UA     -0.010
CARRIER_US     -0.129
DEST_JFK        0.027
DEST_LGA       -0.094
ORIGIN_DCA     -0.106
ORIGIN_IAD      0.089
Name: FLIGHT_STATUS, dtype: float64
```

Variables selected: "WEATHER","CARRIER_US","CARRIER_DL"

1. Fitting KNN MODEL

In [127…
```
#splitting the dataset
train_data,valid_data=train_test_split(combined_fd,test_size=0.4,random_state=1)
print(train_data.shape,valid_data.shape)
```

```
(1320, 16) (880, 16)
```

In [128…
```
train_data.head(5)
```

Out[128…

	DISTANCE	WEATHER	DAY_WEEK	DAY_OF_MONTH	CARRIER_DH	CARRIER_DL	CAR
1247	0.160486	-0.121491	1.626159	0.227766	-0.577350	-0.46274	
1215	1.287306	-0.121491	1.626159	0.227766	1.732051	-0.46274	
1477	0.160486	-0.121491	-0.476736	0.573502	-0.577350	-0.46274	
1898	0.160486	-0.121491	-1.002460	1.264972	-0.577350	-0.46274	
83	0.160486	-0.121491	0.574712	-1.616155	-0.577350	-0.46274	

In [129…
```
knn=KNeighborsClassifier(n_neighbors=3)
knn.fit(train_data[["WEATHER","CARRIER_US","CARRIER_DL"]],np.ravel(train_data[["FLI
```

Out[129…
```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

In [130…
```
classification=knn.predict(valid_data[["WEATHER","CARRIER_US","CARRIER_DL"]])
```

In [131…
```
#checking the accuracy score
accuracy=accuracy_score(valid_data[["FLIGHT_STATUS"]],classification)
```

```
print(f'accuracy:{accuracy}')
```

```
accuracy:0.8272727272727273
```

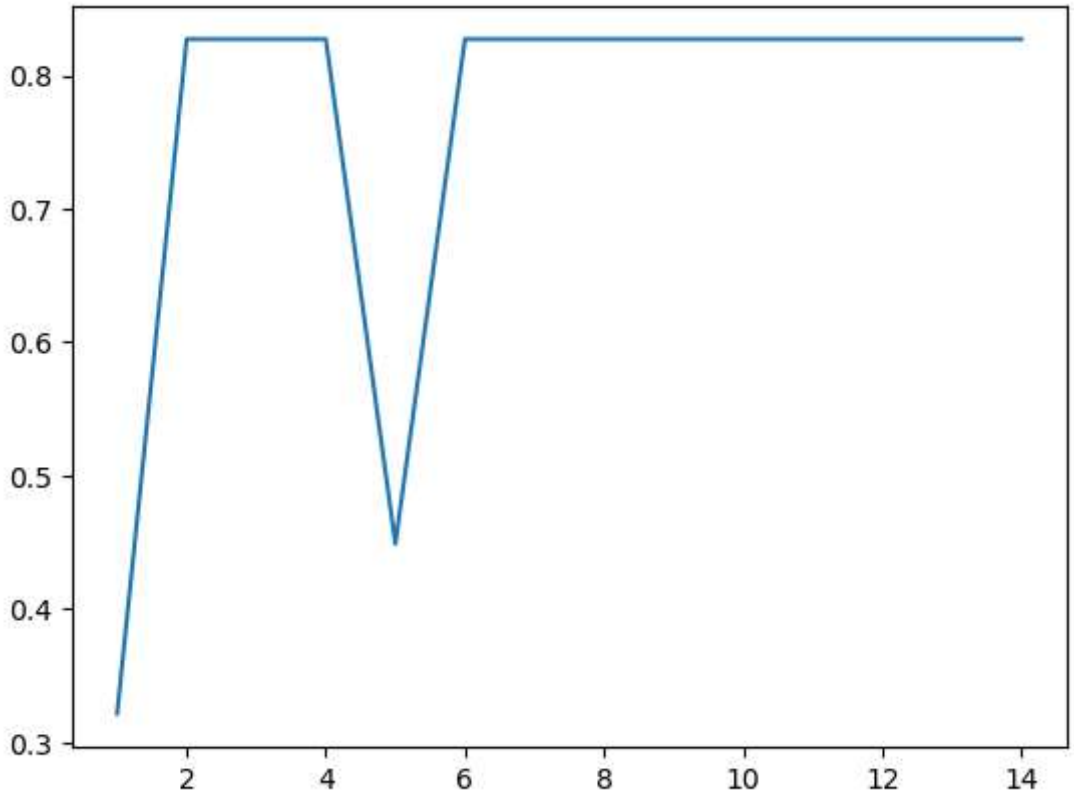
In [132…
```
# Train a classifier for different values of k
results = []
for k in range(1, 15):
     knn = KNeighborsClassifier(n_neighbors=k).fit(train_data[["WEATHER","CARRIER_U
     results.append({
    'k': k,
     'accuracy': accuracy_score(valid_data["FLIGHT_STATUS"], knn.predict(valid_data
})
```

In [133…
```
# Convert results to a pandas data frame
results = pd.DataFrame(results)
print(results)
```

```
    k  accuracy
0   1  0.321591
1   2  0.827273
2   3  0.827273
3   4  0.827273
4   5  0.448864
5   6  0.827273
6   7  0.827273
7   8  0.827273
8   9  0.827273
9  10  0.827273
10 11  0.827273
11 12  0.827273
12 13  0.827273
13 14  0.827273
```

In [134…
```
plt.plot(results["k"],results["accuracy"])
```

Out[134…
```
[<matplotlib.lines.Line2D at 0x1f6533fca10>]
```



Given the highest accuracy and stable performance around that region k=2, k=2 is the optimal choice as it provides the best accuracy without significant fluctuation.

In [135…
```
# predicting a new data point with  neighbours
new_data = pd.DataFrame([{"WEATHER":0,"CARRIER_US":True,"CARRIER_DL":False}])
print(new_data)
```

```
   WEATHER  CARRIER_US  CARRIER_DL
0        0        True       False
```

In [136…
```
#Train the KNN model on the training data.
knn = KNeighborsClassifier(n_neighbors=7)
knn.fit(combined_fd[["WEATHER","CARRIER_US","CARRIER_DL"]],combined_fd["FLIGHT_STAT
distances, indices = knn.kneighbors(new_data)
print(knn.predict(new_data))
print('Distances',distances)
print('Indices', indices)
print(combined_fd.iloc[indices[0], :])
```

```
[0]
Distances [[1.20728651 1.20728651 1.20728651 1.20728651 1.20728651 1.20728651
  1.20728651]]
Indices [[2180 2182 2178 2179 2177 2181 2176]]
      DISTANCE   WEATHER  DAY_WEEK  DAY_OF_MONTH  CARRIER_DH  CARRIER_DL  \
2181  0.160486 -0.121491  1.100435      1.725953    -0.57735    -0.46274
2183  0.160486 -0.121491  1.100435      1.725953    -0.57735    -0.46274
2179  0.160486 -0.121491  1.100435      1.725953    -0.57735    -0.46274
2180  0.160486 -0.121491  1.100435      1.725953    -0.57735    -0.46274
2178  0.160486 -0.121491  1.100435      1.725953    -0.57735    -0.46274
2182  0.160486 -0.121491  1.100435      1.725953    -0.57735    -0.46274
2177  0.160486 -0.121491  1.100435      1.725953    -0.57735    -0.46274

      CARRIER_MQ  CARRIER_OH  CARRIER_RU  CARRIER_UA  CARRIER_US  DEST_JFK  \
2181   -0.393517   -0.117579   -0.477157    -0.11955    2.108446 -0.461291
2183   -0.393517   -0.117579   -0.477157    -0.11955    2.108446 -0.461291
2179   -0.393517   -0.117579   -0.477157    -0.11955    2.108446 -0.461291
2180   -0.393517   -0.117579   -0.477157    -0.11955    2.108446 -0.461291
2178   -0.393517   -0.117579   -0.477157    -0.11955    2.108446 -0.461291
2182   -0.393517   -0.117579   -0.477157    -0.11955    2.108446 -0.461291
2177   -0.393517   -0.117579   -0.477157    -0.11955    2.108446 -0.461291

      DEST_LGA  ORIGIN_DCA  ORIGIN_IAD  FLIGHT_STATUS
2181  0.956404    0.778357   -0.672417              0
2183  0.956404    0.778357   -0.672417              0
2179  0.956404    0.778357   -0.672417              0
2180  0.956404    0.778357   -0.672417              0
2178  0.956404    0.778357   -0.672417              0
2182  0.956404    0.778357   -0.672417              0
2177  0.956404    0.778357   -0.672417              0
```

In [137…
```
print("Accuracy of the KNN Model where k=2 is: ",round(results["accuracy"].max()*10
```

```
Accuracy of the KNN Model where k=2 is:  82.73 %
```

2. Fitting the Random Forest Model

In [138…
```
le = LabelEncoder()
categorical_features = ['CARRIER', 'DEST', 'ORIGIN', 'TAIL_NUM', 'FL_NUM']
for feature in categorical_features:
    flights_df[feature] = le.fit_transform(flights_df[feature])
```

In [139…
```
# Defining feature set (X) and target variable (y)
X = flights_df.drop(columns=['FLIGHT_STATUS','FL_DATE','CRS_DEP_TIME', 'DEP_TIME'])
y = flights_df['FLIGHT_STATUS']
```

In [140…
```
# Encoding the target variable
y = le.fit_transform(y)
```

In [141…
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Initialize the Random Forest Classifier
clf = RandomForestClassifier(n_estimators=100, random_state=42)
```

```
# Train the classifier
clf.fit(X_train, y_train)
```

Out[141…

RandomForestClassifier

RandomForestClassifier(random_state=42)

In [142…

```
# Make predictions on the test set
y_pred = clf.predict(X_test)
```

In [143…

```
# Evaluate the model
accuracy_1 = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy_1:.2f}')
```

```
Accuracy: 0.79
```

In [144…

```
# Print detailed classification report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.93      0.87       342
           1       0.56      0.30      0.39        98

    accuracy                           0.79       440
   macro avg       0.69      0.61      0.63       440
weighted avg       0.76      0.79      0.77       440
```

In [145…

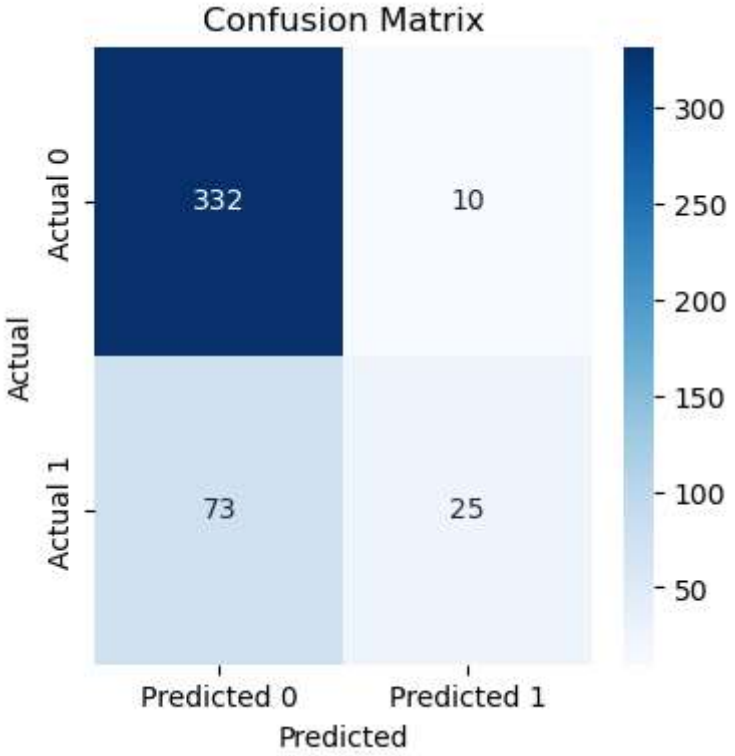
```
#Trying Ensemble Methods to improve the performance
from sklearn.ensemble import GradientBoostingClassifier, VotingClassifier

# Example of stacking multiple models
stacked_model = VotingClassifier(estimators=[
    ('rf', RandomForestClassifier(class_weight='balanced', random_state=42)),
    ('gb', GradientBoostingClassifier(random_state=42))
], voting='soft')

stacked_model.fit(X_train, y_train)
y_pred_stack = stacked_model.predict(X_test)
print(classification_report(y_test, y_pred_stack))
```

```
              precision    recall  f1-score   support

           0       0.82      0.97      0.89       342
           1       0.71      0.26      0.38        98

    accuracy                           0.81       440
   macro avg       0.77      0.61      0.63       440
weighted avg       0.80      0.81      0.77       440
```

In [146…

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, roc_curve, auc
```

```
# Compute and plot confusion matrix
cm = confusion_matrix(y_test, y_pred_stack)
plt.figure(figsize=(4, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Predicted 0', 'Pre
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



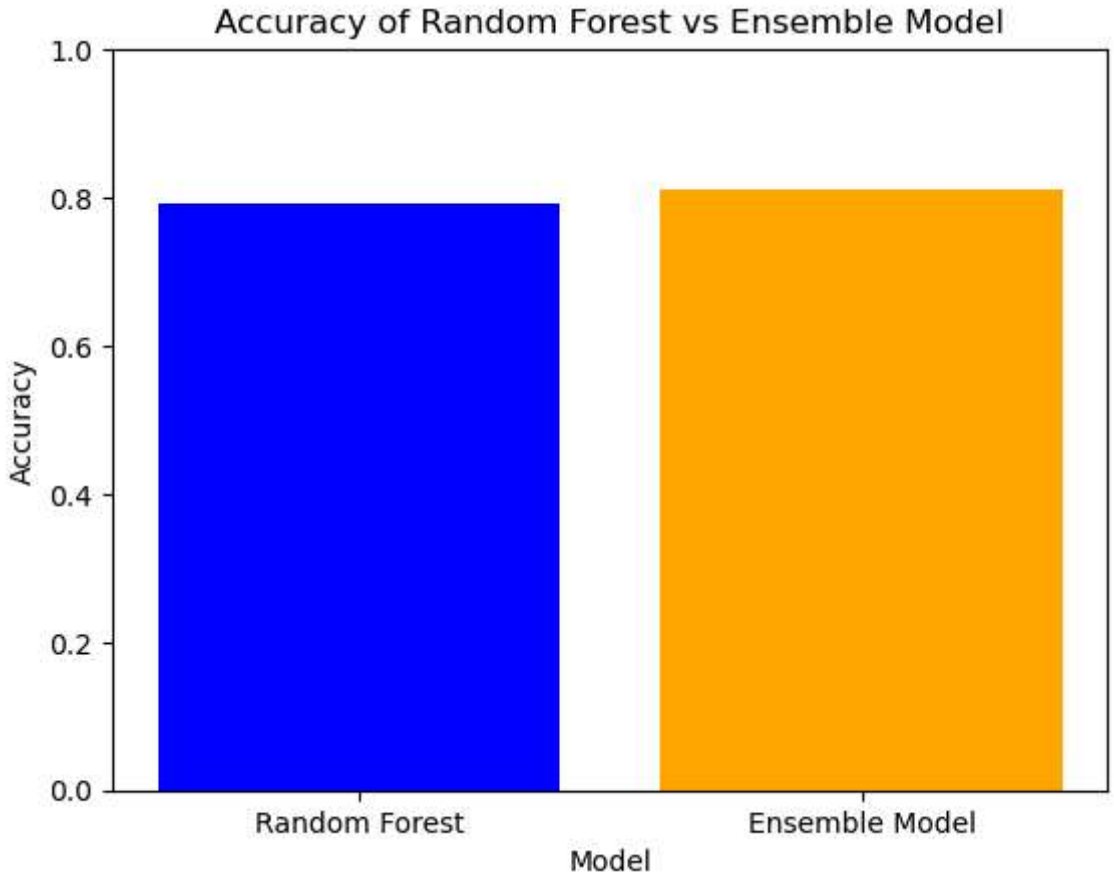
In [147…

```
# Evaluate the model
accuracy_2 = accuracy_score(y_test, y_pred_stack)
print(f'Accuracy: {accuracy_2:.2f}')
```

```
Accuracy: 0.81
```

In [148…

```
models = ['Random Forest', 'Ensemble Model']
accuracies = [accuracy_1, accuracy_2]

plt.figure()
plt.bar(models, accuracies, color=['blue', 'orange'])
plt.ylim([0, 1])
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.title('Accuracy of Random Forest vs Ensemble Model')
plt.show()
```


Accuracy of Random Forest vs Ensemble Model
1.0
0.8
0.6
0.4
0.2
0.0
Accuracy
Random Forest
Ensemble Model
Model

In [ ]: