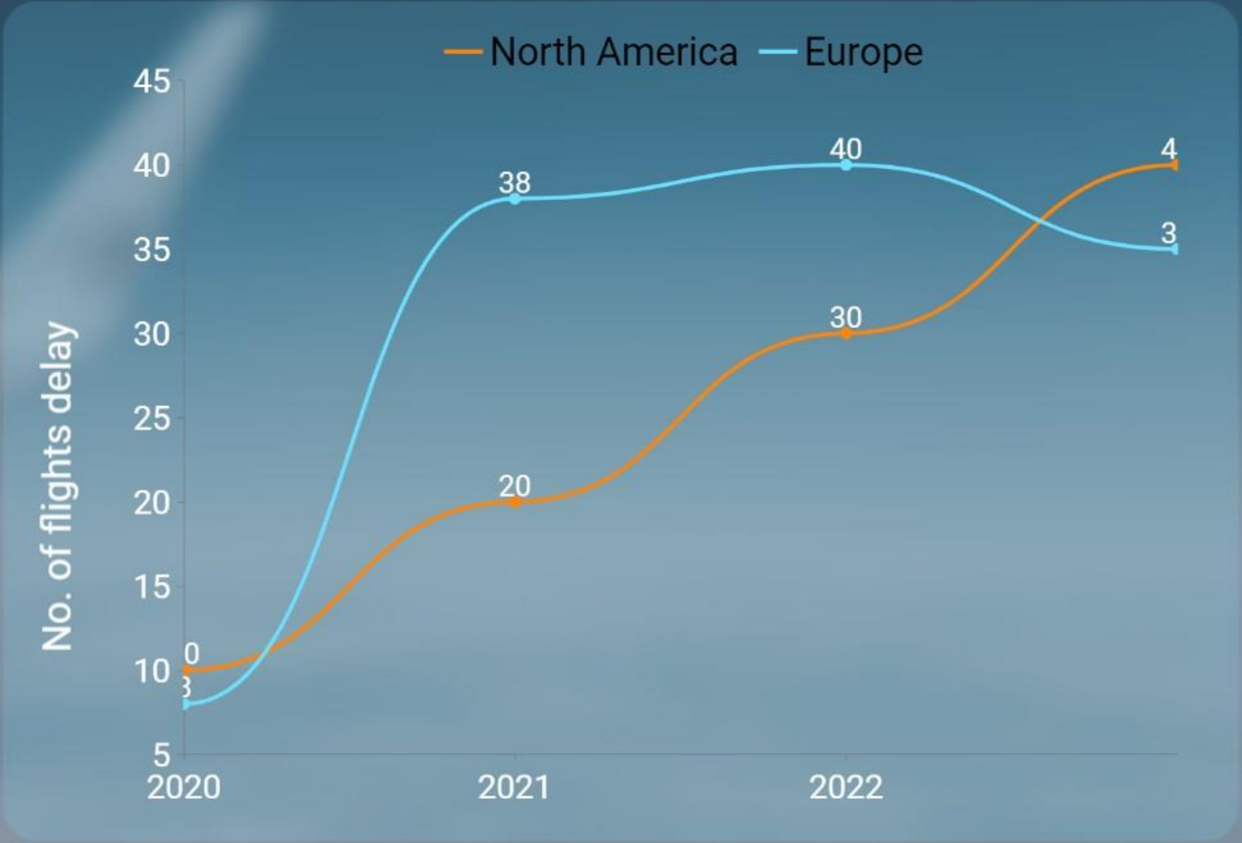
Tata Prashikshan: A Tata Steel Internship Program

Flight Delay Prediction using Machine Learning



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Objective

Flight delays could always be annoying, especially in the case when the period of delay was so long that there was even a danger to miss the next flight. Flight delay is a prevailing problem in this world. It's very tough to explain the reason for a delay.

A few factors responsible for the flight delays like runway construction to excessive traffic are rare, but bad weather seems to be a common cause. Some flights are delayed because of the reactionary delays, due to the late arrival of the previous flight.It hurts airports, airlines, and affects a company's marketing strategies as companies rely on customer loyalty to support their frequent flying programs.

However, if there was a way to predict whether there would be a delay or even better – how long the delay could be, then people could make earlier preparation to reschedule following flights in an earlier manner.

Data Set

TERMS	DESCRIPTION
Year	Year of the flight
Month	Months of the year
DayOfMonth	Day of the month
DayOfWeek	Day of week starting Sunday
Carrier	Unique airlines
OriginAirportID	Origin airport ID
DestinationAirportID	Destination airport ID
CRSDepTime	Scheduled departure time
DepDelay	Difference in minutes between scheduled and actual departure time.
DepDel15	Departure delay indicator, 15 mins or more (1= Yes, 0 = No)
CRSArrTime	Scheduled arrival time
ArrDel	Difference in minutes between scheduled and actual arrival time.
ArrDel15	Arrival delay indicator, 15 mins or more (1= Yes, 0 = No)
Cancelled	Cancelled flight indicator

Data Set

We chose the “Airlines Delay” data from www.kaggle.com/datasets, which was actually provided by Bureau of Transportation Statistics (BTS), that tracks the on time performance of domestic flights of USA. Summary information on the number of on-time, delayed, cancelled and diverted flights appears in the data. In the dataset, around 850k rows included, and 14 variables involved.

For data cleaning, we firstly replace "null’ values with certain values, to make the data suitable for machine learning. Afterwards, used pandas, seaborn and matplotlib to make initial exploration in order to find some intuitive relationship between variables.

Finally, we deploy machine learning method to dig out factors and their correlation with flight delays – we used logistic regression to predict whether a flight might or might not be delayed.

Data Collection

Flight Delay Prediction

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, classification_report, precision_recall_fscore_support
```

In [2]:

```
df = pd.read_csv('flightDelayData1.csv')
df.head()
```

Out[2]:

	Year	Month	DayOfMonth	DayOfWeek	Carrier	OriginAirportID	DestinationAirportID	CRSDepTime	DepDelay	DepDel15	CRSArrTime	ArrDel	ArrDel15	Car
0	2013	4	19	5	DL	14057	14869	600	-4.0	0.0	851	-15.0	0	
1	2013	4	19	5	DL	15016	11433	1630	28.0	1.0	1903	24.0	1	
2	2013	4	19	5	DL	11193	12892	1615	-6.0	0.0	1805	-11.0	0	
3	2013	4	19	5	DL	10397	15016	1726	-1.0	0.0	1818	-19.0	0	
4	2013	4	19	5	DL	15016	10397	1900	0.0	0.0	2133	-1.0	0	

Data Collection

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

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 849041 entries, 0 to 849040
Data columns (total 14 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   Year                  849041 non-null  int64  
 1   Month                 849041 non-null  int64  
 2   DayOfMonth            849041 non-null  int64  
 3   DayOfWeek             849041 non-null  int64  
 4   Carrier               849041 non-null  object 
 5   OriginAirportID       849041 non-null  int64  
 6   DestinationAirportID  849041 non-null  int64  
 7   CRSDepTime            849041 non-null  int64  
 8   DepDelay              838935 non-null  float64
 9   DepDel15              838935 non-null  float64
 10  CRSArrTime            849041 non-null  int64  
 11  ArrDel                838436 non-null  float64
 12  ArrDel15              849041 non-null  int64  
 13  Cancelled             849041 non-null  int64  
dtypes: float64(3), int64(10), object(1)
memory usage: 90.7+ MB
```

Data Cleaning

```
In [14]: df.columns
```

```
Out[14]: Index(['Year', 'Month', 'DayOfMonth', 'DayOfWeek', 'Carrier',
               'OriginAirportID', 'DestinationAirportID', 'CRSDepTime', 'DepDelay',
               'DepDel15', 'CRSArrTime', 'ArrDel', 'ArrDel15', 'Cancelled'],
              dtype='object')
```

Dropping unnecessary columns

```
In [15]: df = df[['Month', 'DayOfMonth', 'DayOfWeek', 'DepDel15', 'CRSArrTime', 'ArrDel15','OriginAirportID', 'DestinationAirportID']]
```

```
In [16]: df
```

Out[16]:

	Month	DayOfMonth	DayOfWeek	DepDel15	CRSArrTime	ArrDel15	OriginAirportID	DestinationAirportID
0	4	19	5	0.0	851	0	14057	14869
1	4	19	5	1.0	1903	1	15016	11433
2	4	19	5	0.0	1805	0	11193	12892
3	4	19	5	0.0	1818	0	10397	15016
4	4	19	5	0.0	2133	0	15016	10397
...	...	...	...	...	...	...	...	...
849036	6	5	3	0.0	1410	1	11618	12892
849037	6	5	3	0.0	2000	0	12892	12173
849038	6	5	3	0.0	1505	0	12892	13930
849039	6	5	3	0.0	1849	0	13930	11278
849040	6	5	3	0.0	1738	0	14771	11697

849041 rows × 8 columns

Data Cleaning

Handling Missing values

Checking for null values

In [17]:
```
df.isnull().any()
```

Out[17]:
```
Month                   False
DayOfMonth              False
DayOfWeek               False
DepDel15                 True
CRSArrTime              False
ArrDel15                False
OriginAirportID         False
DestinationAirportID    False
dtype: bool
```

In [18]:
```
df.fillna(df['DepDel15'].mode()[0], inplace=True)
```

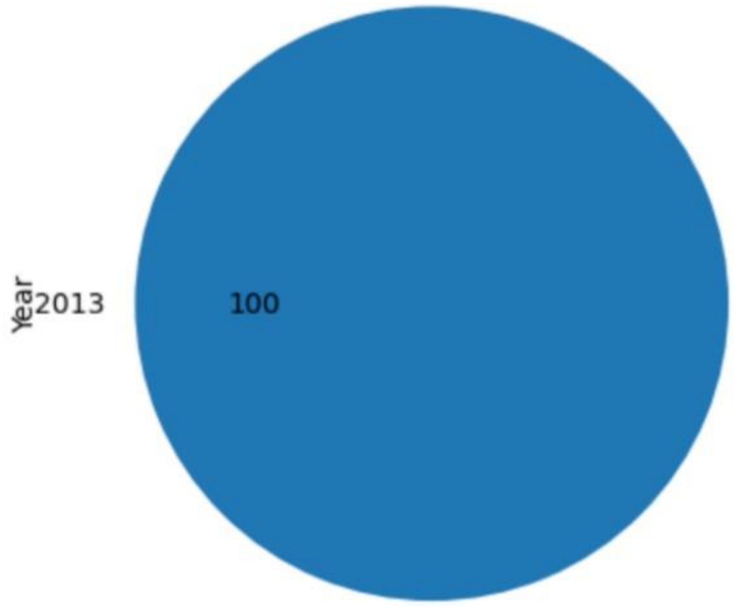
In [19]:
```
df.isnull().any()
```

Out[19]:
```
Month                   False
DayOfMonth              False
DayOfWeek               False
DepDel15                False
CRSArrTime              False
ArrDel15                False
OriginAirportID         False
DestinationAirportID    False
dtype: bool
```

Exploratory Data Analysis

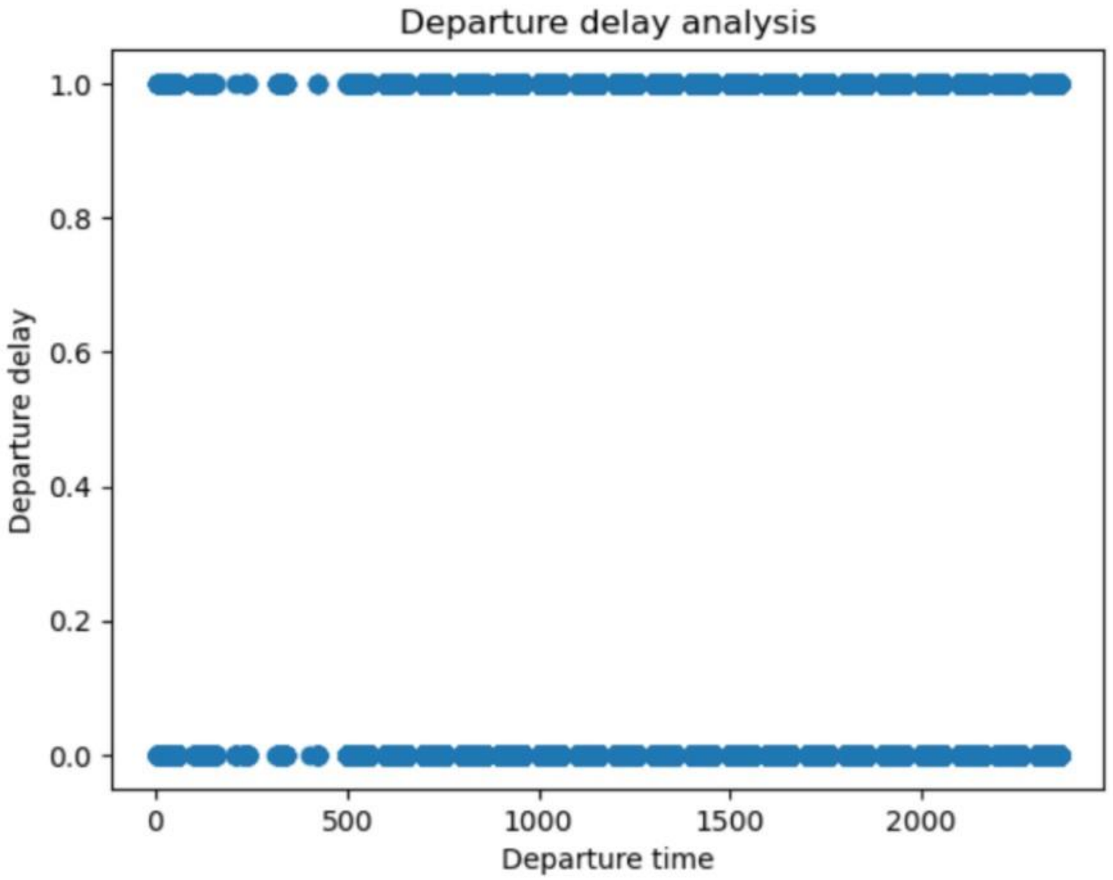
Exploratory Data Analysis

In [7]:
```
df['Year'].value_counts().plot(kind='pie', autopct='%.0f')
plt.show()
```



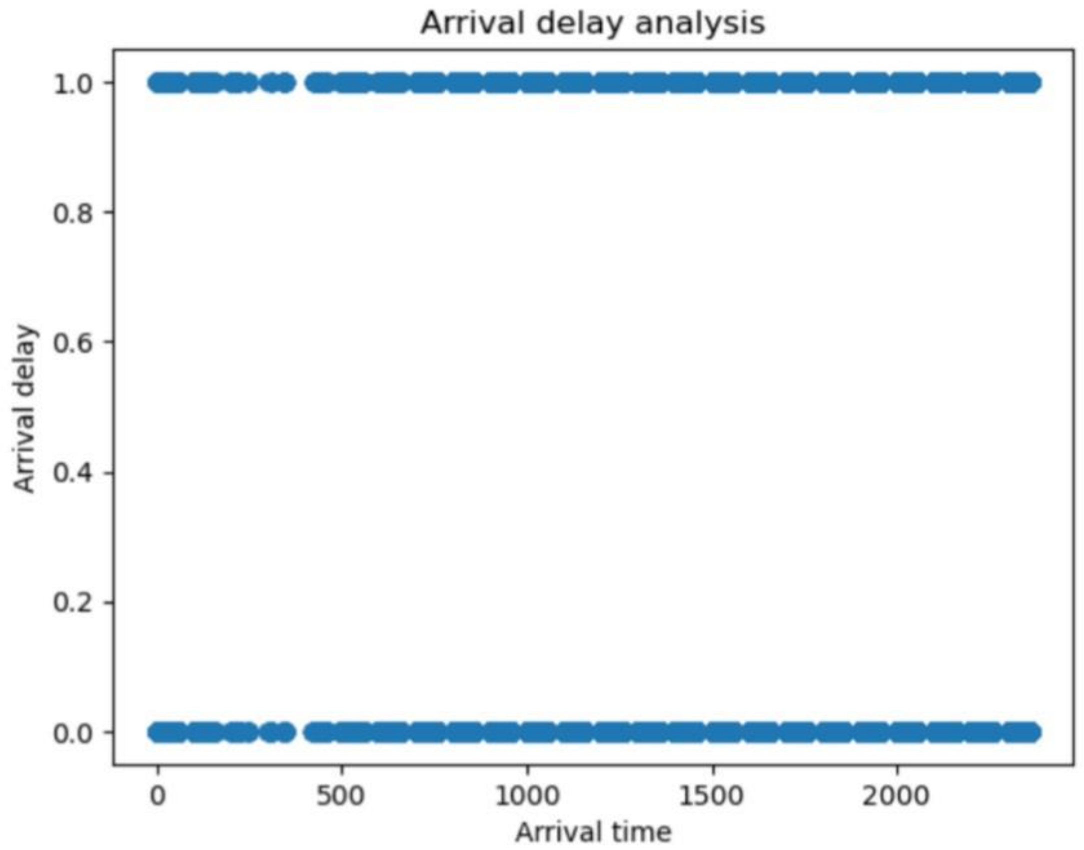
Exploratory Data Analysis

```
In [8]: plt.scatter(df.CRSDepTime, df.DepDel15)
        plt.title('Departure delay analysis')
        plt.xlabel('Departure time')
        plt.ylabel('Departure delay')
        plt.show()
```



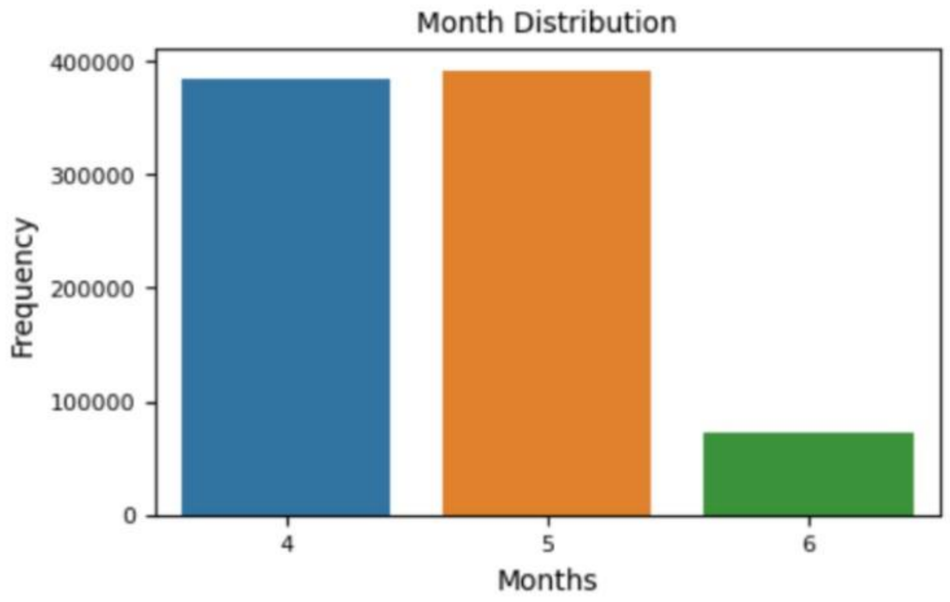
Exploratory Data Analysis

```
In [9]: plt.scatter(df.CRSArrTime, df.ArrDel15)
        plt.title('Arrival delay analysis')
        plt.xlabel('Arrival time')
        plt.ylabel('Arrival delay')
        plt.show()
```



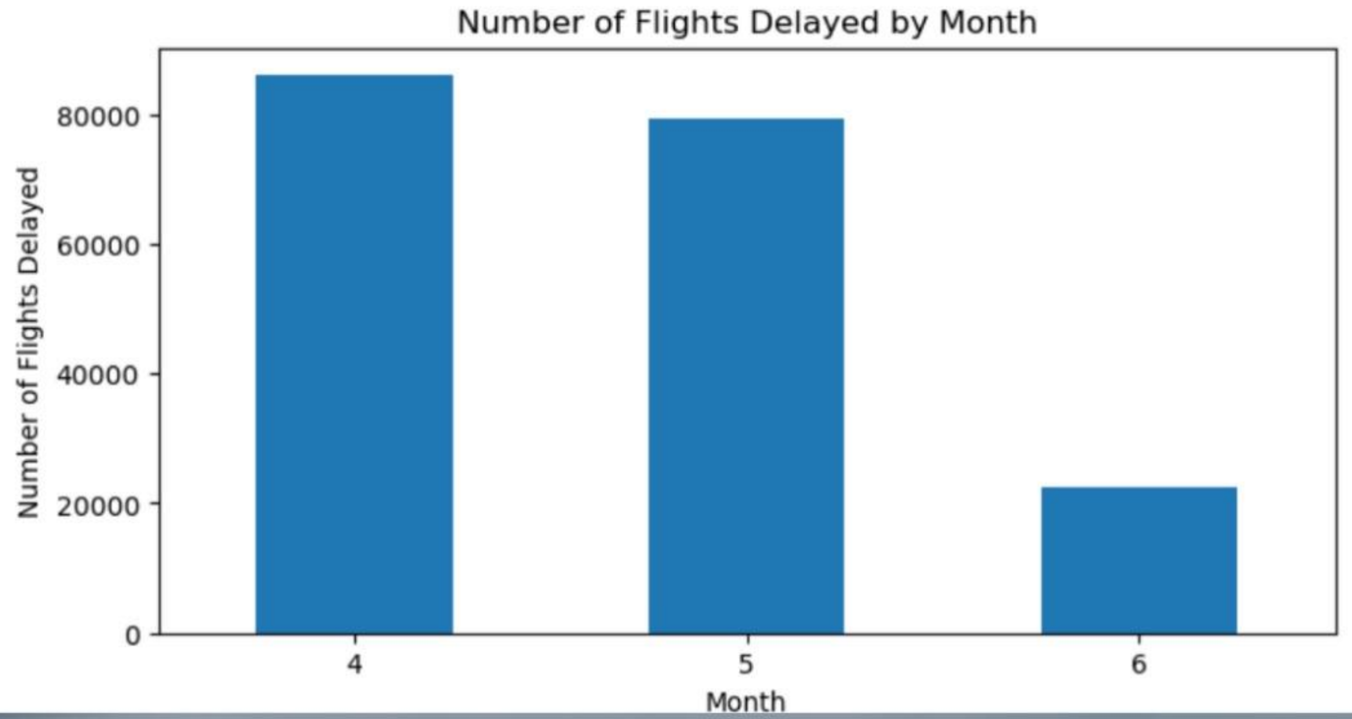
Exploratory Data Analysis

```
plt.figure(figsize = (5,3))
sns.countplot(data=df, x='Month')
plt.title('Month Distribution', size=10)
plt.xticks(size=8)
plt.yticks(size=8)
plt.xlabel("Months", size=10)
plt.ylabel("Frequency", size=10)
plt.show()
```



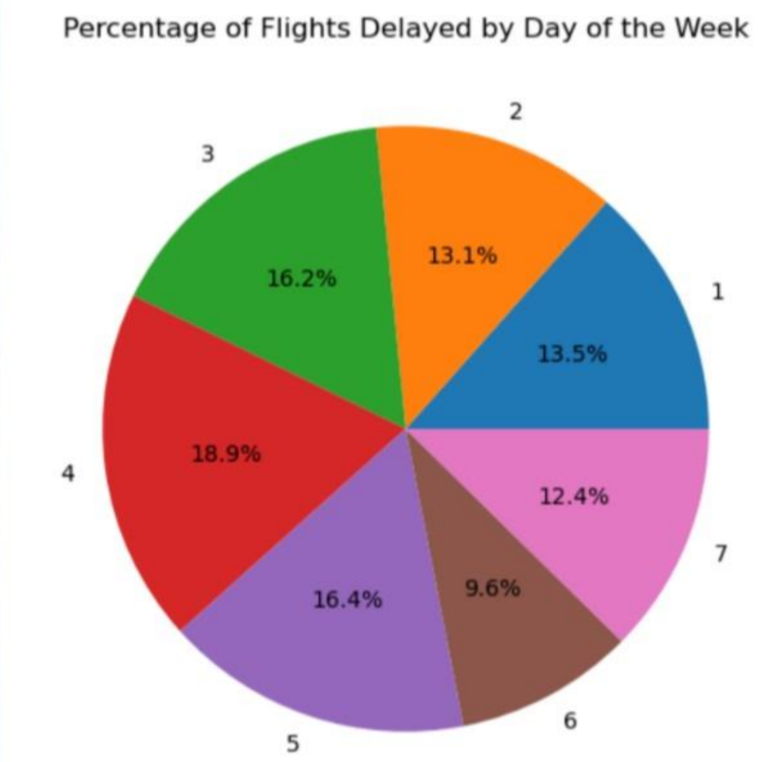
Exploratory Data Analysis

```python
# Group the data by month and calculate the total number of flights delayed
grouped_data = df.groupby('Month')['ArrDel15'].sum()

# Create a bar chart
plt.figure(figsize=(8, 4))
grouped_data.plot(kind='bar')
plt.title('Number of Flights Delayed by Month')
plt.xlabel('Month')
plt.ylabel('Number of Flights Delayed')
plt.xticks(rotation=0)
plt.show()
```



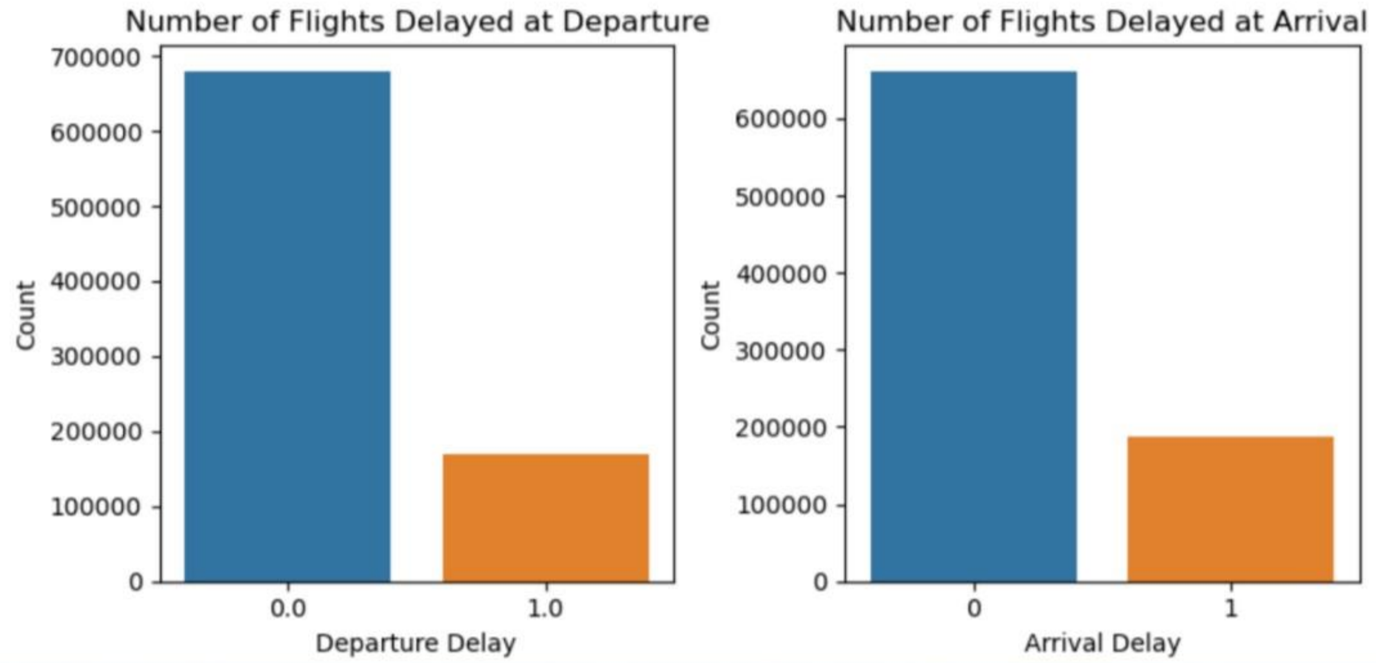
Exploratory Data Analysis

```
# Group the data by day of the week and calculate the total number of flights and the number of delayed flights
grouped_data = df.groupby('DayOfWeek')['ArrDel15'].agg(['count', 'sum'])

# Calculate the percentage of flights delayed for each day
grouped_data['Percentage Delayed'] = (grouped_data['sum'] / grouped_data['count']) * 100

# Create a pie chart
plt.figure(figsize=(8, 6))
plt.pie(grouped_data['Percentage Delayed'], labels=grouped_data.index, autopct='%1.1f%%')
plt.title('Percentage of Flights Delayed by Day of the Week')
plt.show()
```



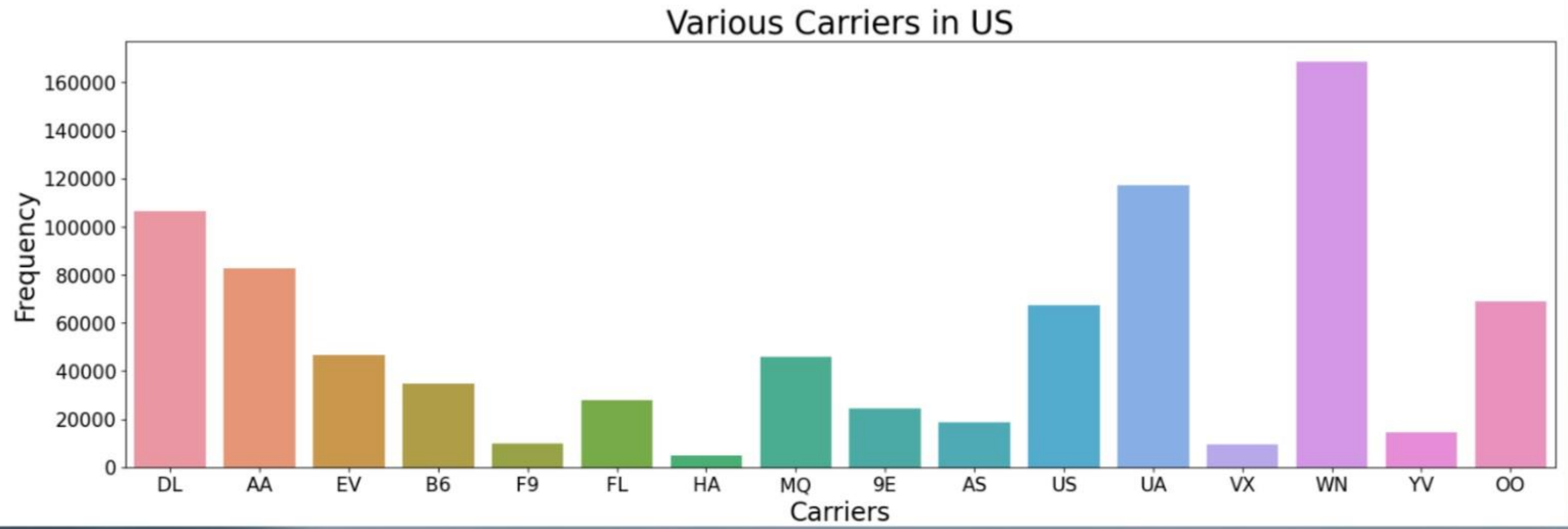
Exploratory Data Analysis

```python
# Create a figure with two subplots
fig, axes = plt.subplots(1, 2, figsize=(8, 4))
# Plot the count of flights delayed at departure
sns.countplot(data=df, x='DepDel15', ax=axes[0])
axes[0].set_title('Number of Flights Delayed at Departure')
axes[0].set_xlabel('Departure Delay')
axes[0].set_ylabel('Count')
# Plot the count of flights delayed at arrival
sns.countplot(data=df, x='ArrDel15', ax=axes[1])
axes[1].set_title('Number of Flights Delayed at Arrival')
axes[1].set_xlabel('Arrival Delay')
axes[1].set_ylabel('Count')
plt.tight_layout()
plt.show()
```



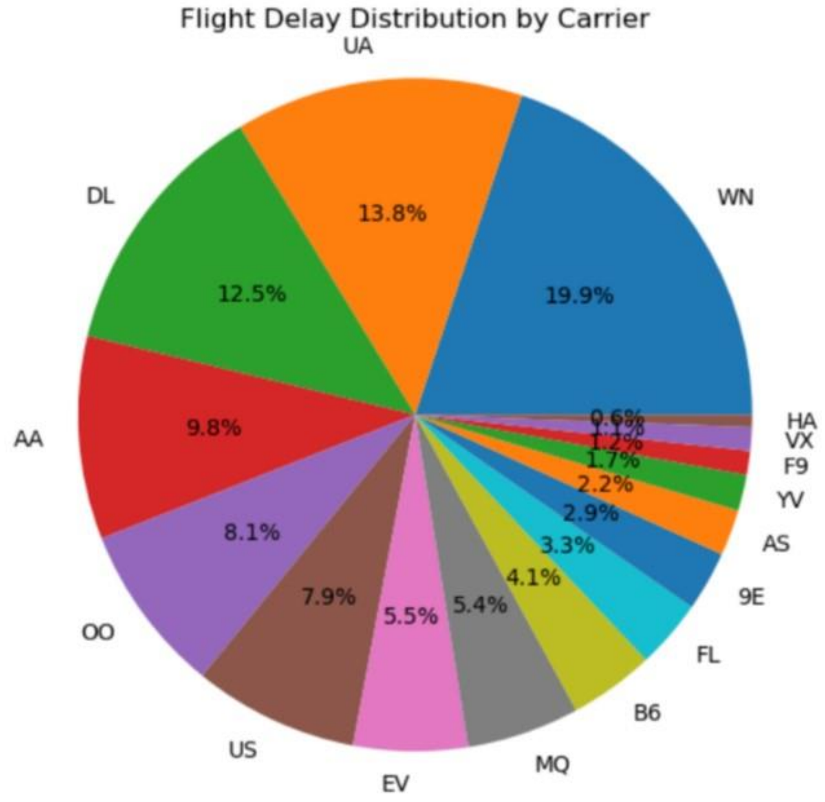
Exploratory Data Analysis

```
plt.figure(figsize=(20, 6))
sns.countplot(x='Carrier', data=df)
plt.title('Various Carriers in US', size=25)
plt.xticks(size=15)
plt.yticks(size=15)
plt.xlabel("Carriers", size=20)
plt.ylabel("Frequency", size=20)
plt.show()
```



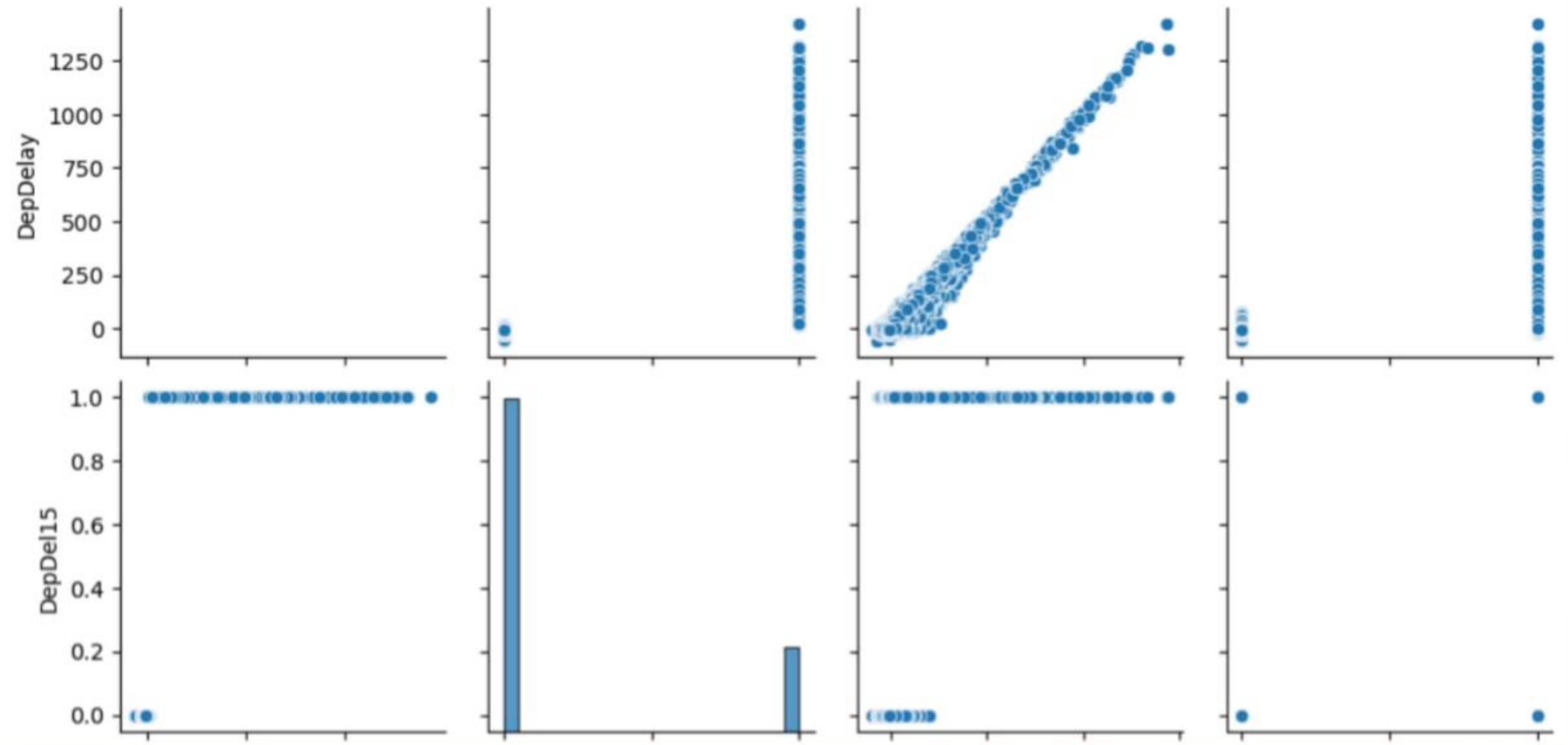
Exploratory Data Analysis

```
In [12]: # Calculate the frequency of each carrier
         carrier_counts = df['Carrier'].value_counts()

         # Plot the pie chart
         plt.figure(figsize=(7, 6))
         plt.pie(carrier_counts, labels=carrier_counts.index, autopct='%1.1f%%')
         plt.title('Flight Delay Distribution by Carrier')
         plt.axis('equal')
         plt.show()
```

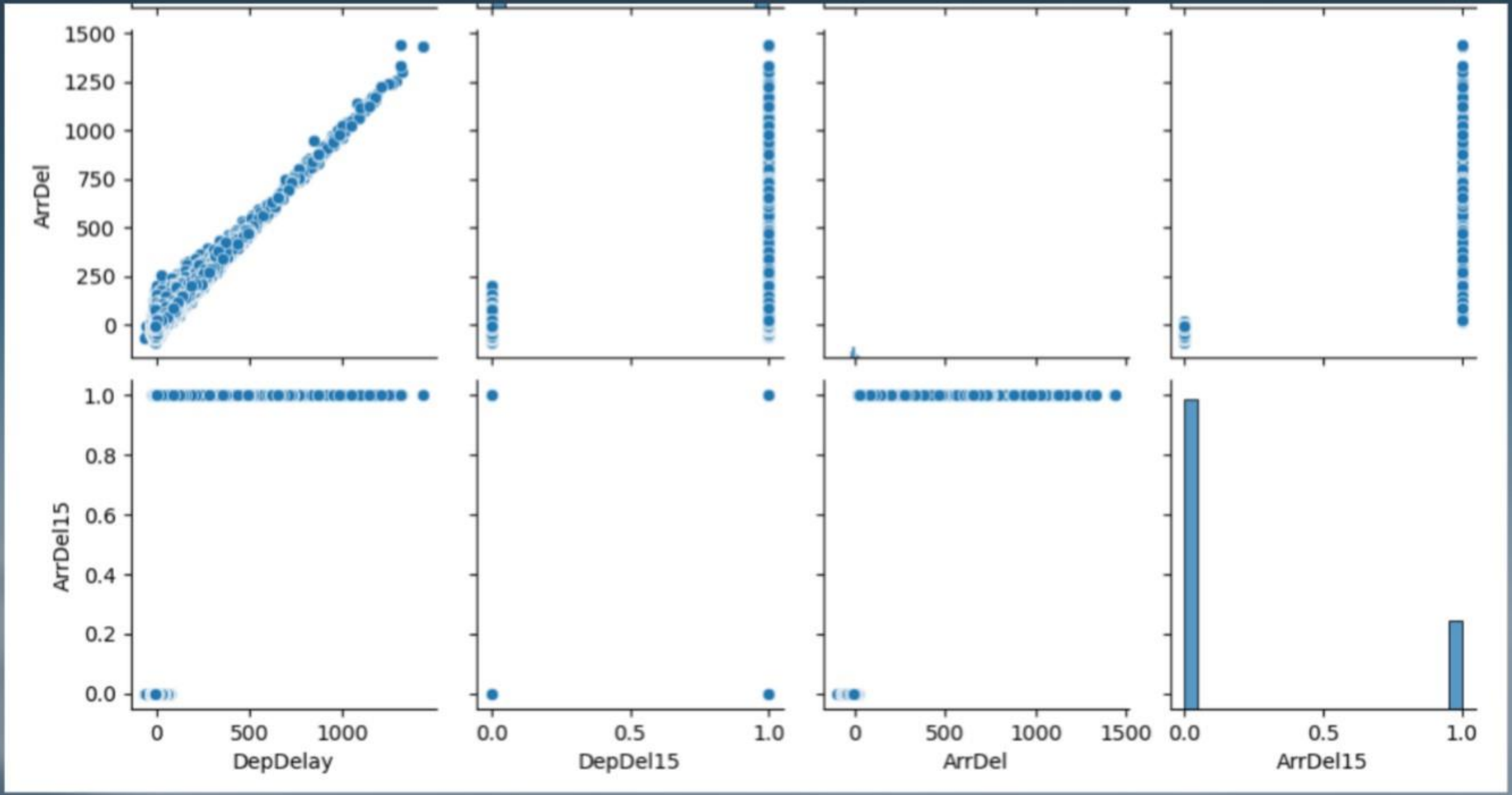


Exploratory Data Analysis

In [13]:
```
# Select the columns to include in the pairplot
columns = ['DepDelay','DepDel15', 'ArrDel', 'ArrDel15']

# Create a pairplot
sns.pairplot(df[columns])

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



Exploratory Data Analysis

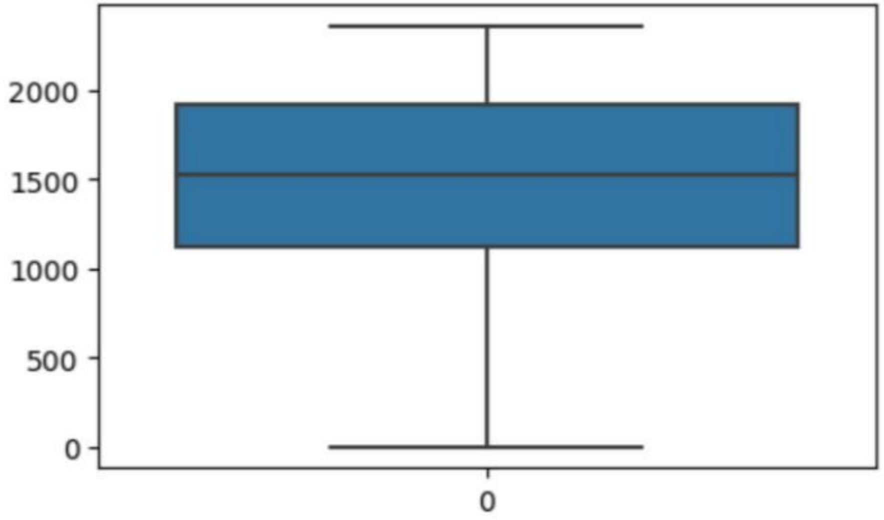


```
In [15]: fig, ax = plt.subplots(figsize=(10, 8))
         corr_matrix= df.iloc[:, 7:14].corr()
         sns.heatmap(corr_matrix, annot=True, ax= ax)
         plt.show()
```

Exploratory Data Analysis

Handling outliers

In [21]:
```
fig, ax= plt.subplots(figsize= (5,3))
sns.boxplot(data = df['CRSArrTime'])
plt.show()
```



theres no outliers

Descriptive Analysis

Performancing Describe Analysis

In [24]:
```
df.describe()
```

Out[24]:

	Month	DayOfMonth	DayOfWeek	DepDel15	CRSArrTime	ArrDel15	OriginAirportID	DestinationAirportID
count	849041.000000	849041.000000	849041.000000	849041.000000	849041.000000	849041.000000	849041.000000	849041.000000
mean	4.634214	15.759071	3.860750	0.199533	1504.150161	0.221068	12765.887084	12765.573081
std	0.636225	8.783494	1.962858	0.399650	500.688376	0.414967	1493.212890	1493.429950
min	4.000000	1.000000	1.000000	0.000000	1.000000	0.000000	10140.000000	10140.000000
25%	4.000000	8.000000	2.000000	0.000000	1117.000000	0.000000	11292.000000	11292.000000
50%	5.000000	16.000000	4.000000	0.000000	1527.000000	0.000000	12892.000000	12892.000000
75%	5.000000	23.000000	5.000000	0.000000	1920.000000	0.000000	14057.000000	14057.000000
max	6.000000	31.000000	7.000000	1.000000	2359.000000	1.000000	15376.000000	15376.000000

Modelling

Splitting data sets into independent and dependent variables

In [23]:
```
X= df.drop(columns = ['ArrDel15'])
y = df[['ArrDel15']]
```

In [24]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

In [25]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[25]:
```
((679232, 7), (169809, 7), (679232, 1), (169809, 1))
```

Building Machine Learning model

using Logistic regression

In [26]:
```
from sklearn.linear_model import LogisticRegression
log_reg = LogisticRegression(max_iter =800)
log_reg.fit(X_train, y_train.values.ravel())
```

Out[26]:
```
LogisticRegression(max_iter=800)
```

In [27]:
```
log_reg.score(X_test, y_test)
```

Out[27]:
```
0.9012419836404431
```

Modelling

```
In [28]: y_pred_log_train = log_reg.predict(X_train)
         y_pred_log_test = log_reg.predict(X_test)

In [29]: pd.DataFrame(y_pred_log_train).value_counts()

Out[29]: 0    543839
         1    135393
         dtype: int64

In [30]: pd.DataFrame(y_pred_log_test).value_counts()

Out[30]: 0    135790
         1     34019
         dtype: int64

In [31]: from sklearn.metrics import confusion_matrix
         confusion_matrix(y_test, y_pred_log_test)

Out[31]: array([[125606,   6586],
                [ 10184,  27433]], dtype=int64)
```

Modelling

Model building using Decision Tree Classifier

In [32]:
```
from sklearn.tree import DecisionTreeClassifier
clf = DecisionTreeClassifier()
clf.fit(X_train, y_train.values.ravel())
```
Out[32]:
```
DecisionTreeClassifier()
```

In [33]:
```
clf.score(X_test, y_test)
```
Out[33]:
```
0.8460387847522804
```

In [34]:
```
y_pred_clf_train = clf.predict(X_train)
y_pred_clf_test = clf.predict(X_test)
```

In [35]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test, y_pred_clf_test)
```
Out[35]:
```
array([[118947,  13245],
       [ 12899,  24718]], dtype=int64)
```

In [36]:
```
pd.DataFrame(y_pred_clf_train).value_counts()
```
Out[36]:
```
0    529275
1    149957
dtype: int64
```

In [37]:
```
pd.DataFrame(y_pred_clf_test).value_counts()
```
Out[37]:
```
0    131846
1     37963
dtype: int64
```

Evaluation of the ML Model using metrics

Logistic Regression Model Evaluation ¶

Classification Report

```
In [38]: print(classification_report(y_test, y_pred_log_test))

              precision    recall  f1-score   support

           0       0.93      0.95      0.94    132192
           1       0.81      0.73      0.77     37617

    accuracy                           0.90    169809
   macro avg       0.87      0.84      0.85    169809
weighted avg       0.90      0.90      0.90    169809
```

```
In [39]: acc_log = accuracy_score(y_test, y_pred_log_test)
```

```
In [40]: prec_log, recall_log, f1_log, sup_log = precision_recall_fscore_support(y_test, y_pred_log_test)
print("Accuracy score = ", acc_log)
print("Recall score = ", recall_log)
print("F1 score = ", f1_log)
print("Support score = ", sup_log)

Accuracy score =  0.9012419836404431
Recall score =  [0.95017853 0.72927134]
F1 score =  [0.93742117 0.76589983]
Support score =  [132192  37617]
```

Evaluation of the ML Model using metrics

Decision Tree Model Evaluation

In [42]:
```
print(classification_report(y_test, y_pred_clf_test))
```

```
              precision    recall  f1-score   support

           0       0.90      0.90      0.90    132192
           1       0.65      0.66      0.65     37617

    accuracy                           0.85    169809
   macro avg       0.78      0.78      0.78    169809
weighted avg       0.85      0.85      0.85    169809
```

In [43]:
```
acc_clf = accuracy_score(y_test, y_pred_clf_test)
prec_clf, recall_clf, f1_clf, sup_clf = precision_recall_fscore_support(y_test, y_pred_clf_test)
print("Accuracy score = ", acc_clf)
print("Recall score = ", recall_clf)
print("F1 score = ", f1_clf)
print("Support score = ", sup_clf)
```

```
Accuracy score =  0.8460387847522804
Recall score =  [0.89980483 0.65709653]
F1 score =  [0.90098395 0.65408838]
Support score =  [132192  37617]
```

Analysis Of the Evaluated Result

On analysis of the evaluated result of the two machine learning model, we observe that the accuracy score, precision score, recall score, F1 score and support score of Logistic Regression is higher than that of decision tree.

Hence we conclude that Logistic Regression model gives better result with higher accuracy.

Testing the Prediction Model

Predict using function applying logistic regression

```
In [46]:
def predict_delay(Month, DayOfMonth, DayOfWeek,OriginAirportID, DestinationAirportID, DepDel15, CRSArrTime):
    input_data = {

        'Month': [Month],
        'DayOfMonth': [DayOfMonth],
        'DayOfWeek': [DayOfWeek],
        'OriginAirportID': [OriginAirportID],
        'DestinationAirportID': [DestinationAirportID],
        'DepDel15': [DepDel15],
        'CRSArrTime': [CRSArrTime],
    }

    input_df = pd.DataFrame(input_data)
    return log_reg.predict(input_df)
```

```
In [47]: print(predict_delay(7,15,1,14843,14100,0,1831))
[1]
```

It returns 1 showing flight was not delayed

Conclusion

In this project, we use flight data to predict flight departure delay. Our result shows that the Logistic Regression method yields the best performance compared to the Decision Tree model. Somehow the Decision Tree model is very time consuming and does not necessarily produce better results. In the end, our model correctly predicts 90% of the flights delay.

Hence we conclude that, there can be additional features related to the causes of flight delay that are not yet discovered using our existing data sources.