10_Flights_Challenge

September 4, 2021

Flights Chalenge

1 Flights Data Exploration Challenge

[2]:
```python
import pandas as pd

df_flights = pd.read_csv('flights.csv')
df_flights.head()
```

[2]:
```
   Year  Month  DayofMonth  DayOfWeek Carrier  OriginAirportID  \
0  2013      9          16          1      DL            15304
1  2013      9          23          1      WN            14122
2  2013      9           7          6      AS            14747
3  2013      7          22          1      OO            13930
4  2013      5          16          4      DL            13931

                OriginAirportName  OriginCity OriginState  DestAirportID  \
0             Tampa International       Tampa          FL          12478
1        Pittsburgh International  Pittsburgh          PA          13232
2    Seattle/Tacoma International     Seattle          WA          11278
3    Chicago O'Hare International     Chicago          IL          11042
4           Norfolk International     Norfolk          VA          10397

                       DestAirportName    DestCity DestState  CRSDepTime  \
0           John F. Kennedy International    New York        NY        1539
1            Chicago Midway International     Chicago        IL         710
2        Ronald Reagan Washington National  Washington        DC         810
3           Cleveland-Hopkins International   Cleveland        OH         804
4  Hartsfield-Jackson Atlanta International     Atlanta        GA         545

   DepDelay  DepDel15  CRSArrTime  ArrDelay  ArrDel15  Cancelled
0         4       0.0        1824        13         0          0
1         3       0.0         740        22         1          0
2        -3       0.0        1614        -7         0          0
3        35       1.0        1027        33         1          0
4        -1       0.0         728        -9         0          0
```

[4]:
```
len(df_flights.columns)
df_flights.shape
```

[4]:
```
(271940, 20)
```

1.1 Finding Missing Data

1. Start by cleaning the data.
    - Identify any null or missing data, and impute appropriate replacement values.
    - Identify and eliminate any outliers in the **DepDelay** and **ArrDelay** columns.

[5]:
```
missing_data = df_flights.isnull().sum()
missing_data
```

[5]:
```
Year                     0
Month                    0
DayofMonth               0
DayOfWeek                0
Carrier                  0
OriginAirportID          0
OriginAirportName        0
OriginCity               0
OriginState              0
DestAirportID            0
DestAirportName          0
DestCity                 0
DestState                0
CRSDepTime               0
DepDelay                 0
DepDel15              2761
CRSArrTime               0
ArrDelay                 0
ArrDel15                 0
Cancelled                0
dtype: int64
```

2761 data points are missing from the DepDel15 feature which indicates if departure is delayed by more than 15 minutes

[7]:
```
missing_data=missing_data.to_frame()
missing_data=missing_data.rename(columns={0:'Empty Cells'})
print(missing_data)
```

```
                   Empty Cells
Year                         0
Month                        0
DayofMonth                   0
DayOfWeek                    0
Carrier                      0
```

```
OriginAirportID            0
OriginAirportName          0
OriginCity                 0
OriginState                0
DestAirportID              0
DestAirportName            0
DestCity                   0
DestState                  0
CRSDepTime                 0
DepDelay                   0
DepDel15                2761
CRSArrTime                 0
ArrDelay                   0
ArrDel15                   0
Cancelled                  0
```

1.2 checking for zeros

[18]:
```
df_flights.isnull().any(axis=1)
```

[18]:
```
0         False
1         False
2         False
3         False
4         False
          …
271935    False
271936    False
271937    False
271938    False
271939    False
Length: 271940, dtype: bool
```

since only DepDel15 has missing value, lets describe the subset of dataset that has missing value, thus we are picking 2761 rows with NaN seen in DepDel15

[21]:
```
df_flights[df_flights.isnull().any(axis=1)].describe()
```

[21]:

	Year	Month	DayofMonth	DayOfWeek	OriginAirportID	\
count	2761.0	2761.000000	2761.000000	2761.000000	2761.000000	
mean	2013.0	6.455632	15.572619	3.604853	12757.763129	
std	0.0	1.759942	8.092708	1.748487	1426.462196	
min	2013.0	4.000000	1.000000	1.000000	10140.000000	
25%	2013.0	5.000000	10.000000	2.000000	11298.000000	
50%	2013.0	6.000000	16.000000	4.000000	12892.000000	
75%	2013.0	8.000000	22.000000	5.000000	13930.000000	
max	2013.0	10.000000	31.000000	7.000000	15376.000000	

```
       DestAirportID   CRSDepTime  DepDelay  DepDel15   CRSArrTime  ArrDelay  \
count    2761.000000  2761.000000    2761.0       0.0  2761.000000    2761.0
mean    12708.952553  1431.354944       0.0       NaN  1587.419051       0.0
std      1408.166022   457.450773       0.0       NaN   485.236232       0.0
min     10140.000000     5.000000       0.0       NaN     5.000000       0.0
25%     11298.000000  1050.000000       0.0       NaN  1229.000000       0.0
50%     12892.000000  1500.000000       0.0       NaN  1645.000000       0.0
75%     13930.000000  1815.000000       0.0       NaN  2003.000000       0.0
max     15376.000000  2359.000000       0.0       NaN  2359.000000       0.0

       ArrDel15  Cancelled
count    2761.0     2761.0
mean        1.0        1.0
std         0.0        0.0
min         1.0        1.0
25%         1.0        1.0
50%         1.0        1.0
75%         1.0        1.0
max         1.0        1.0
```

Appart from DepDel15, notice DepDelay has 0 as min, max and mode, but DepDel15 is same but has NaN instead. > **DepDelay** is the number of minutes depature was delayed > > **DepDel15** feature which indicates if departure is delayed by more than 15 minutes > > Since Since there is no delay showing 0 in DepDelay, there is no 15 minutes delay. > > Replay all NaN in DepDel15 with 0.

[22]:
```
df_flights.DepDel15 = df_flights.DepDel15.fillna(0)
df_flights.isnull().sum()
```

[22]:
```
Year                 0
Month                0
DayofMonth           0
DayOfWeek            0
Carrier              0
OriginAirportID      0
OriginAirportName    0
OriginCity           0
OriginState          0
DestAirportID        0
DestAirportName      0
DestCity             0
DestState            0
CRSDepTime           0
DepDelay             0
DepDel15             0
CRSArrTime           0
ArrDelay             0
ArrDel15             0
```

```
Cancelled          0
dtype: int64
```

[23]:
```
df_flights['DepDelay'].name # shows the name of the column
```

[23]:
```
'DepDelay'
```

- dentify and eliminate any outliers in the **DepDelay** and **ArrDelay** columns.

1.3 Clean outliers

View the distribution and summary for the DepDelay and ArrDelay columns.

[24]:
```
def show_distribution(var_data):
    from matplotlib import pyplot as plt

    # Get statistics
    min_val = var_data.min()
    max_val = var_data.max()
    mean_val = var_data.mean()
    med_val = var_data.median()
    mod_val = var_data.mode()[0]

    print(var_data.name,'\nMinimum:{:.2f}\nMean:{:.2f}\nMedian:{:.2f}\nMode:{:.
↪2f}\nMaximum:{:.2f}\n'.format(min_val,
                                                                               ␣
↪            mean_val,
                                                                               ␣
↪            med_val,
                                                                               ␣
↪            mod_val,
                                                                               ␣
↪            max_val))

    # Create a figure for 2 subplots (2 rows, 1 column)
    fig, ax = plt.subplots(2, 1, figsize = (10, 4))

    # Plot the histogram
    ax[0].hist(var_data)
    ax[0].set_ylabel('Frequency')

    # Add lines for mean, median, and mode
    ax[0].axvline(x=min_val, color = 'gray', linestyle='dashed', linewidth= 2)
    ax[0].axvline(x=mean_val, color = 'cyan', linestyle='dashed', linewidth = 2)
    ax[0].axvline(x=med_val, color = 'red', linestyle='dashed', linewidth = 2)
    ax[0].axvline(x=mod_val, color = 'yellow', linestyle='dashed', linewidth =␣
↪2)
    ax[0].axvline(x=max_val, color = 'gray', linestyle='dashed', linewidth = 2)
```

```python
    # Plot the boxplot
    ax[1].boxplot(var_data, vert=False)
    ax[1].set_xlabel('Value')

    # Add a title to the Figure
    fig.suptitle(var_data.name)

    # Show the figure
    fig.show()
```

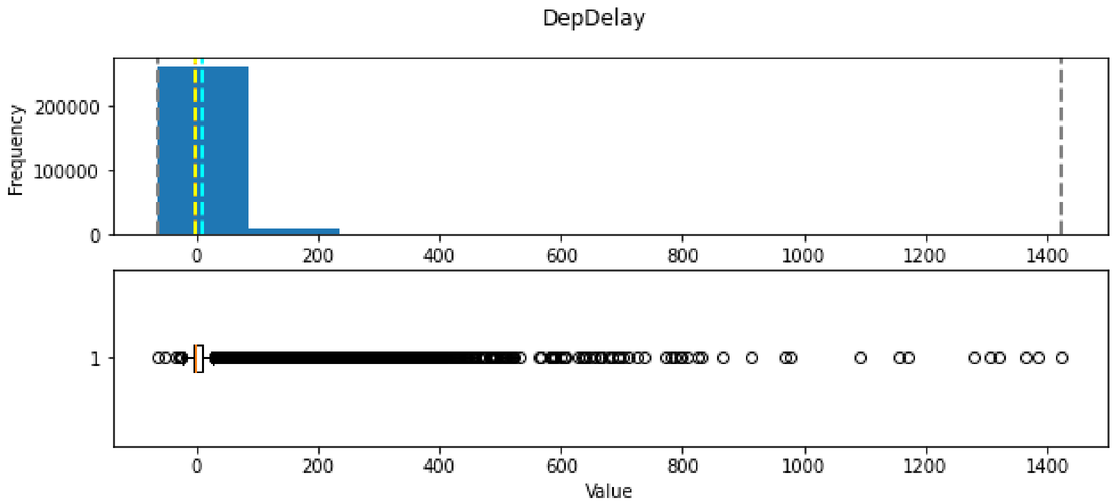
[25]:
```python
# Call the function for each delay field
delayFields = ['DepDelay', 'ArrDelay']
for col in delayFields:
    show_distribution(df_flights[col])
```

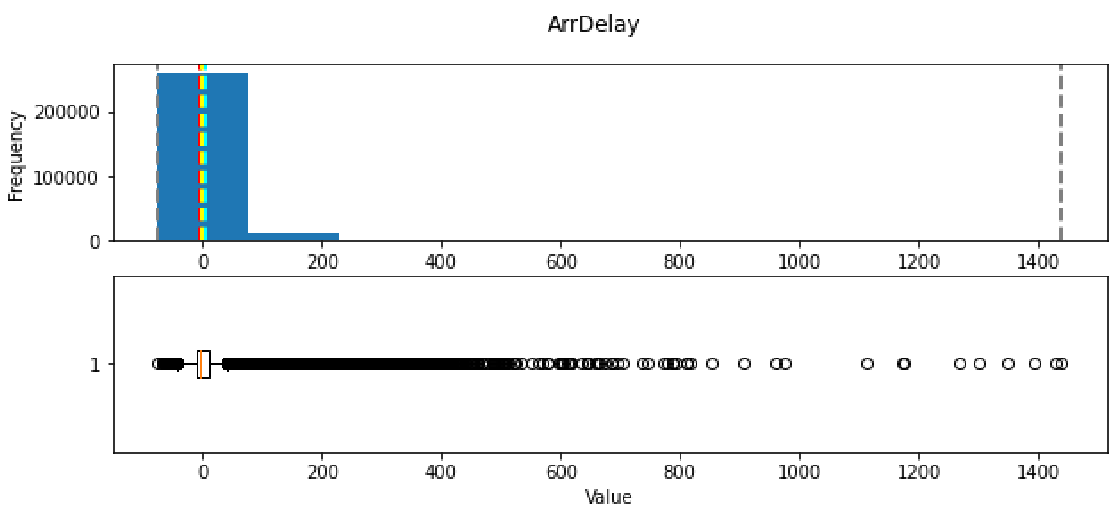
```
DepDelay
Minimum:-63.00
Mean:10.35
Median:-1.00
Mode:-3.00
Maximum:1425.00


C:\Users\aduzo\Anaconda3\lib\site-packages\ipykernel_launcher.py:39:
UserWarning: Matplotlib is currently using
module://ipykernel.pylab.backend_inline, which is a non-GUI backend, so cannot
show the figure.

ArrDelay
Minimum:-75.00
Mean:6.50
Median:-3.00
Mode:0.00
Maximum:1440.00


C:\Users\aduzo\Anaconda3\lib\site-packages\ipykernel_launcher.py:39:
UserWarning: Matplotlib is currently using
module://ipykernel.pylab.backend_inline, which is a non-GUI backend, so cannot
show the figure.
```





There are a outliers at the lower and upper ends of both variables - particularly at the upper end.

Let's trim the data so that we include only rows where the values for these fields are within the 1st and 90th percentile.

[26]:
```
# Trim outliers for ArrDelay based on 1% and 90% percentiles
ArrDelay_01pcntile = df_flights.ArrDelay.quantile(0.01)
ArrDelay_90pcntile = df_flights.ArrDelay.quantile(0.90)
print(f'1% percentile is  {ArrDelay_01pcntile} \n90% percentile is␣
 ↪{ArrDelay_90pcntile}')
```

```
1% percentile is  -33.0
90% percentile is 38.0
```

-33 is at 1% while 38 is at 90% of the data

[27]:
```
df_flights.shape
```

[27]: (271940, 20)

[28]:
```
df_flights = df_flights[df_flights.ArrDelay < ArrDelay_90pcntile]
df_flights = df_flights[df_flights.ArrDelay > ArrDelay_01pcntile]
```

[29]:
```
df_flights.shape
```

[29]: (241916, 20)

[30]:
```
# Trim outliers for DepDelay based on 1% and 90% percentiles
DepDelay_01pcntile = df_flights.DepDelay.quantile(0.01)
DepDelay_90pcntile = df_flights.DepDelay.quantile(0.90)
df_flights = df_flights[df_flights.DepDelay < DepDelay_90pcntile]
df_flights = df_flights[df_flights.DepDelay > DepDelay_01pcntile]
```

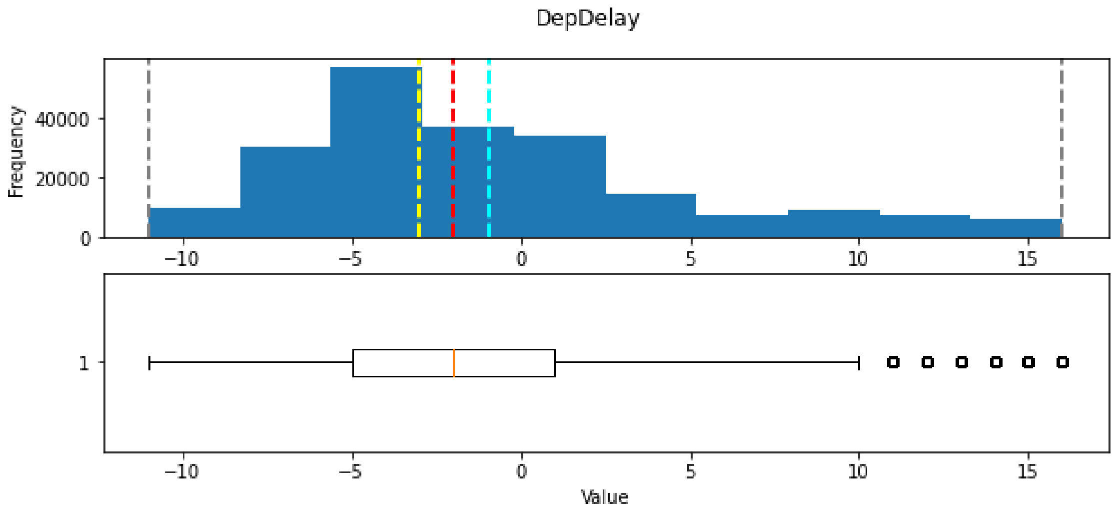
[31]:
```
# View the revised distributions
for col in delayFields:
    show_distribution(df_flights[col])
```

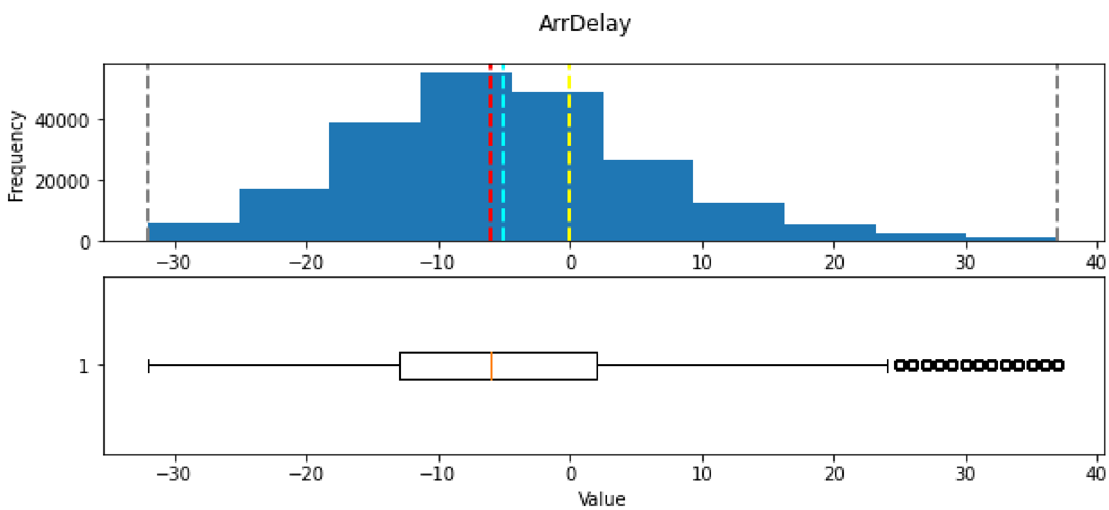
```
DepDelay
Minimum:-11.00
Mean:-0.92
Median:-2.00
Mode:-3.00
Maximum:16.00


C:\Users\aduzo\Anaconda3\lib\site-packages\ipykernel_launcher.py:39:
UserWarning: Matplotlib is currently using
module://ipykernel.pylab.backend_inline, which is a non-GUI backend, so cannot
show the figure.
```

```
ArrDelay
Minimum:-32.00
Mean:-5.03
Median:-6.00
Mode:0.00
Maximum:37.00


C:\Users\aduzo\Anaconda3\lib\site-packages\ipykernel_launcher.py:39:
UserWarning: Matplotlib is currently using
module://ipykernel.pylab.backend_inline, which is a non-GUI backend, so cannot
show the figure.
```





[32]:
```
df_flights.shape
```

[32]: `(214397, 20)`

That looks a bit better

2. Explore the cleaned data.
   - View summary statistics for the numeric fields in the dataset.
   - Determine the distribution of the **DepDelay** and **ArrDelay** columns.
   - Use statistics, aggregate functions, and visualizations to answer the following questions:
     - *What are the average (mean) departure and arrival delays?*
     - *How do the carriers compare in terms of arrival delay performance?*
     - *Are some days of the week more prone to arrival days than others?*

- *Which departure airport has the highest average departure delay?*
- *Do **late** departures tend to result in longer arrival delays than on-time departures?*
- *Which route (from origin airport to destination airport) has the most **late** arrivals?*
- *Which route has the highest average arrival delay?*

1.3.1 Explore the data

Let's start with an overall view of the summary statistics for the numeric columns.

[33]:
```
df_flights.describe()
```

[33]:
```
           Year          Month     DayofMonth      DayOfWeek  OriginAirportID  \
count  214397.0  214397.000000  214397.000000  214397.000000    214397.000000
mean     2013.0       7.018368      15.794703       3.902737     12757.827661
std         0.0       2.006398       8.859118       1.997744      1510.058629
min      2013.0       4.000000       1.000000       1.000000     10140.000000
25%      2013.0       5.000000       8.000000       2.000000     11292.000000
50%      2013.0       7.000000      16.000000       4.000000     12892.000000
75%      2013.0       9.000000      23.000000       6.000000     14100.000000
max      2013.0      10.000000      31.000000       7.000000     15376.000000

       DestAirportID     CRSDepTime       DepDelay       DepDel15  \
count  214397.000000  214397.000000  214397.000000  214397.000000
mean    12726.276147    1278.223879      -0.921692       0.018116
std      1506.251757     469.440262       5.708594       0.133371
min     10140.000000       1.000000     -11.000000       0.000000
25%     11292.000000     850.000000      -5.000000       0.000000
50%     12892.000000    1235.000000      -2.000000       0.000000
75%     14057.000000    1655.000000       1.000000       0.000000
max     15376.000000    2359.000000      16.000000       1.000000

          CRSArrTime       ArrDelay       ArrDel15      Cancelled
count  214397.000000  214397.000000  214397.000000  214397.000000
mean     1461.406596      -5.030276       0.068602       0.013228
std       485.676457      11.424280       0.252776       0.114249
min         1.000000     -32.000000       0.000000       0.000000
25%      1054.000000     -13.000000       0.000000       0.000000
50%      1445.000000      -6.000000       0.000000       0.000000
75%      1845.000000       2.000000       0.000000       0.000000
max      2359.000000      37.000000       1.000000       1.000000
```

[34]:
```
delayFields
```

[34]:
```
['DepDelay', 'ArrDelay']
```

What are the mean departure and arrival delays?

[35]:
```
df_flights[delayFields].mean()
```

[35]:
```
DepDelay   -0.921692
ArrDelay   -5.030276
dtype: float64
```

How do the carriers compare in terms of arrival delay performance?

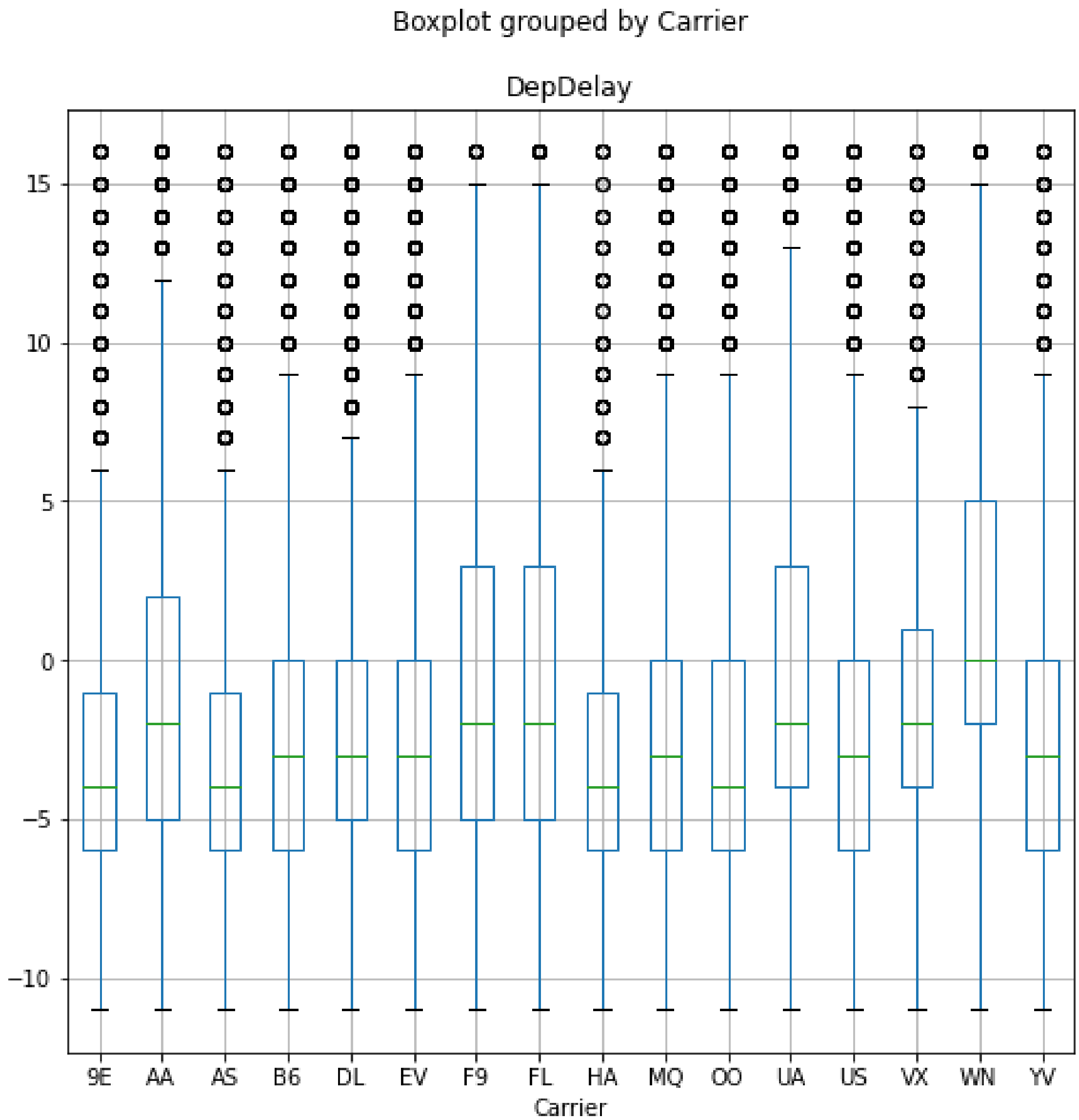
[36]:
```python
df_flights.Carrier.unique()
```

[36]:
```
array(['DL', 'WN', 'AS', 'EV', 'AA', 'OO', 'US', 'UA', 'FL', 'B6', 'VX',
       'MQ', '9E', 'YV', 'F9', 'HA'], dtype=object)
```

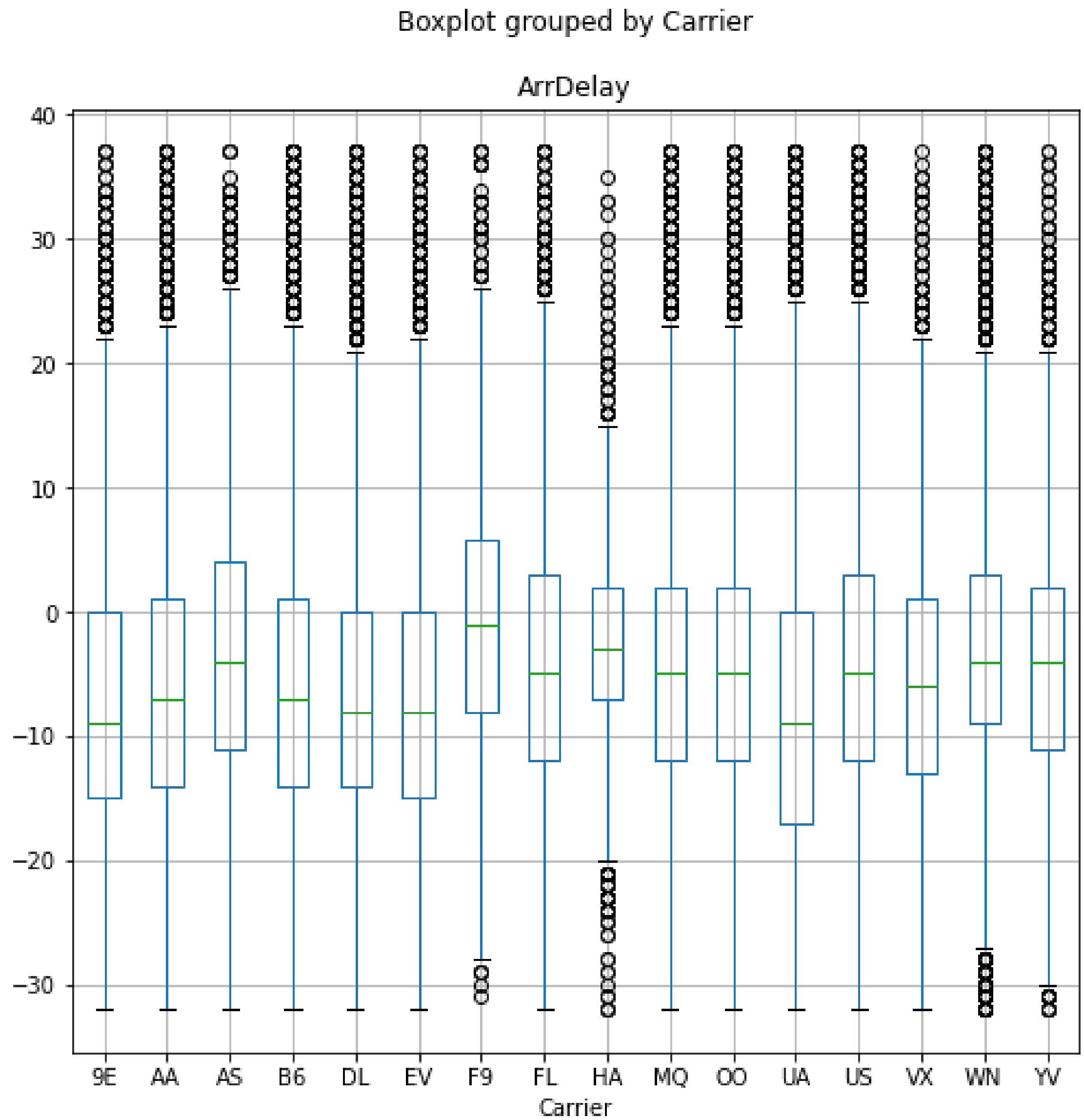
[39]:
```python
print(f'{len(df_flights.Carrier.unique())} unique Carriers')
```

[39]:
```
16
```

[40]:
```python
for col in delayFields:
    df_flights.boxplot(column=col, by='Carrier', figsize=(8,8))
```



Boxplot grouped by Carrier
DepDelay
15
10
5
0
−5
−10
9E
AA
AS
B6
DL
EV
F9
FL
HA
MQ
OO
UA
US
VX
WN
YV
Carrier



As seen above,for DepDelay most carriers has mean with no delay or departs earlier on average thus no delay, but delays occurs, but in some instances, departure was delayed by more than 5 minutes. Carriers such as 9E,AS,HA 75% of their times departs earlier than slated time.

For ArrDelay All carriers Arrive on time on the average.

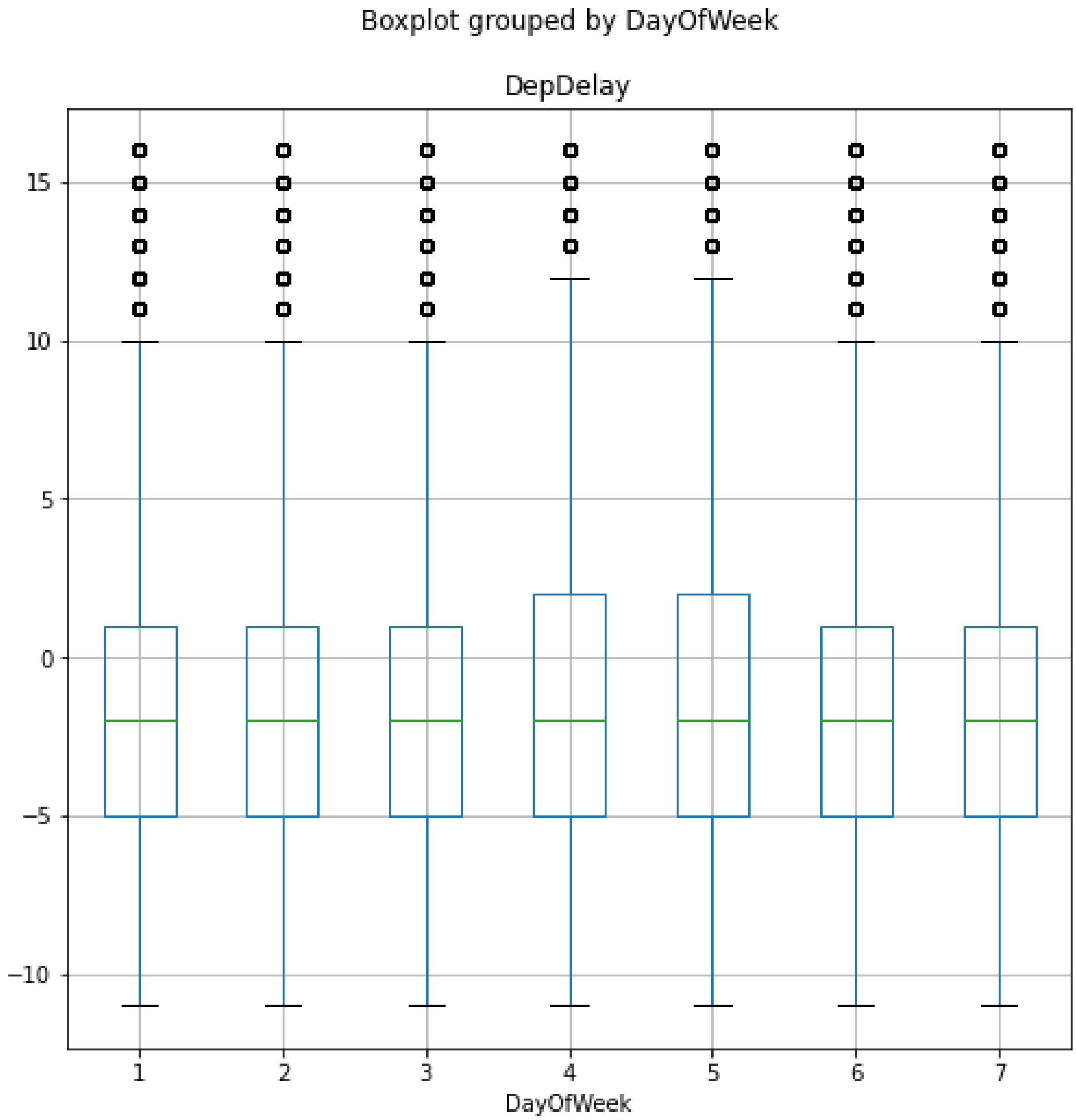
Are some days of the week more prone to arrival days than others?

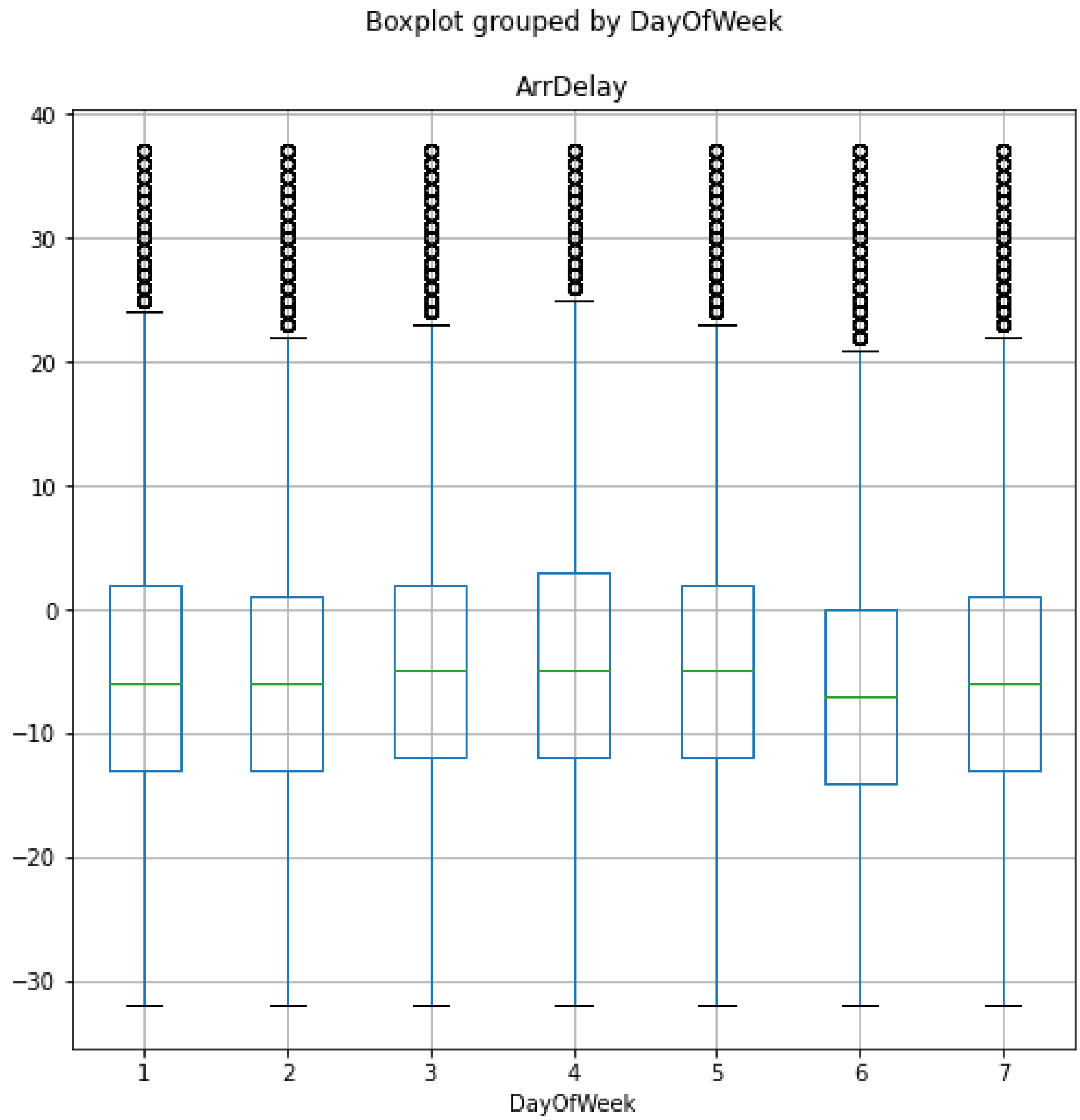
[42]:
```
df_flights.DayOfWeek.unique()
```

[42]:
```
array([1, 6, 4, 7, 2, 5, 3], dtype=int64)
```

DayOfWeek: The day of the week on which the flight departed - from 1 (Monday) to 7 (Sunday)

[41]:
```python
for col in delayFields:
    df_flights.boxplot(column=col, by='DayOfWeek', figsize=(8,8))
```





All days of the week has on average same arrival time. But Thursday is slighly more prone, but this is negligible.

Which departure airport has the highest average departure delay?

[44]:
```
print(f'There are {len(df_flights.OriginAirportName.unique())} departure␣
↪airports')
```

```
There are 70 departure airports
```

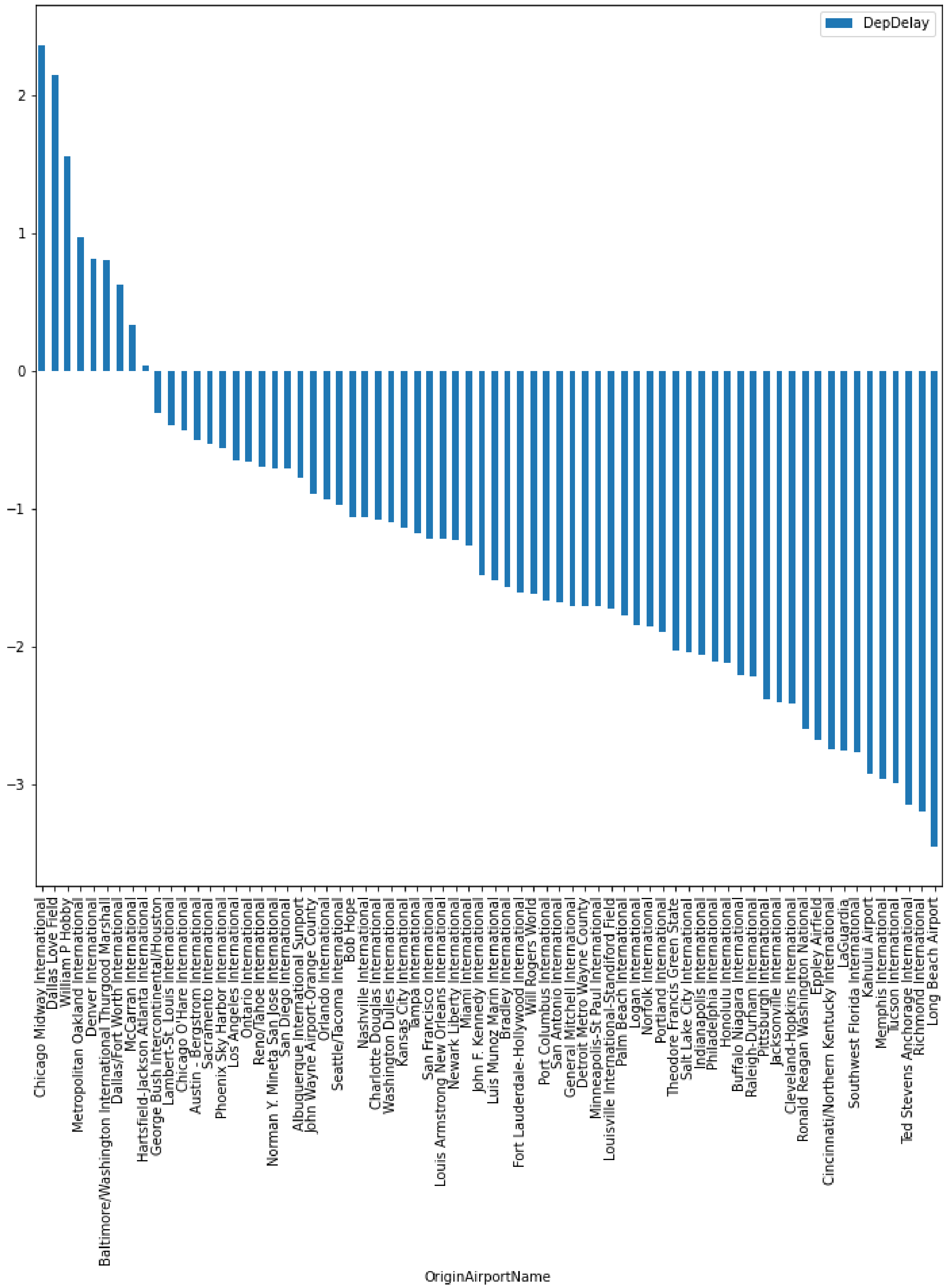
[45]:
```
departure_airport_group = df_flights.groupby(df_flights.OriginAirportName)
```

```python
mean_departure_delays =pd.DataFrame(departure_airport_group['DepDelay'].mean()).
 ↪sort_values('DepDelay', ascending=False)
mean_departure_delays.plot(kind = 'bar', figsize=(12,12))
mean_departure_delays
```

[45]:

```
                                     DepDelay
OriginAirportName
Chicago Midway International         2.365960
Dallas Love Field                    2.148798
William P Hobby                      1.561927
Metropolitan Oakland International   0.964853
Denver International                 0.807272
…                                        …
Memphis International               -2.962737
Tucson International                -2.989154
Ted Stevens Anchorage International -3.149758
Richmond International              -3.198073
Long Beach Airport                  -3.447844

[70 rows x 1 columns]
```



Do late departures tend to result in longer arrival delays than on-time departures?

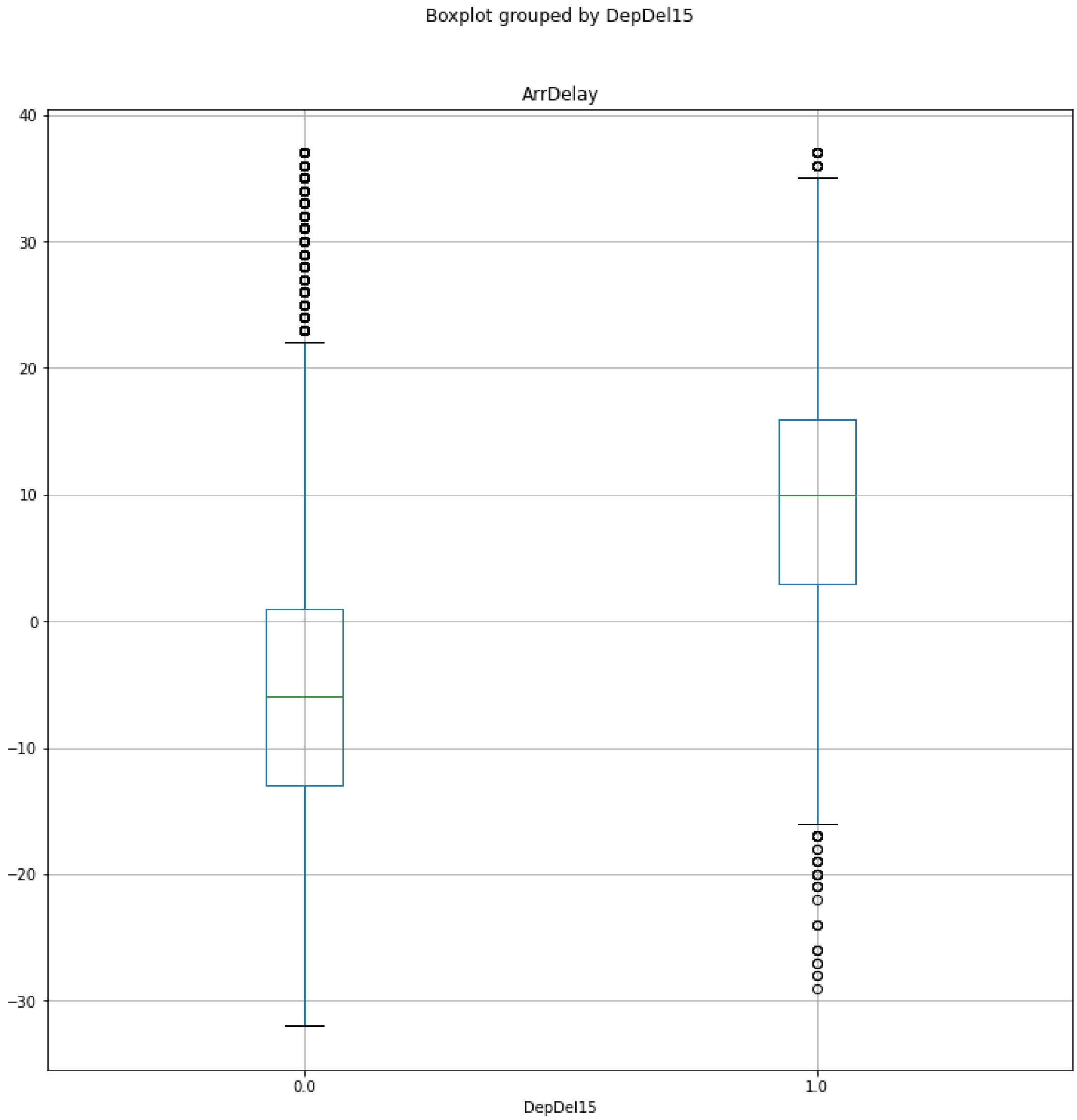
[47]:
```
df_flights.DepDel15.unique()
```

[47]:
```
array([0., 1.])
```

0 if no delay by 15 minutes or more, 1 if so

[50]:
```
df_flights.boxplot(column='ArrDelay', by='DepDel15', figsize=(12,12))
```

[50]:
```
<AxesSubplot:title={'center':'ArrDelay'}, xlabel='DepDel15'>
```



Yes as seen in the above box plot,

[51]:
```
df_flights.groupby(by='DepDel15').ArrDelay.mean()
```

[51]:

```
DepDel15
0.0   -5.299464
1.0    9.559732
Name: ArrDelay, dtype: float64
```

As seen from the above graph, late depareture influences arrival time as shown in there mean, early depature arrives 5 minutes earlier on average, while late departure arrives 10 minutes later than scheduled.

Which route (from origin airport to destination airport) has the most late arrivals?

> Note: no column named route, rather there is Origin and Destination columns, so route is by combining these two columns.

[52]:

```
df_flights.columns
```

[52]:

```
Index(['Year', 'Month', 'DayofMonth', 'DayOfWeek', 'Carrier',
       'OriginAirportID', 'OriginAirportName', 'OriginCity', 'OriginState',
       'DestAirportID', 'DestAirportName', 'DestCity', 'DestState',
       'CRSDepTime', 'DepDelay', 'DepDel15', 'CRSArrTime', 'ArrDelay',
       'ArrDel15', 'Cancelled'],
      dtype='object')
```

[53]:

```
# Add a routes column

routes = pd.Series(df_flights['OriginAirportName']+␣
 ↪'->'+df_flights['DestAirportName'])
df_flights = pd.concat([df_flights, routes.rename("Route")], axis=1)

# Group by routes
route_group = df_flights.groupby(df_flights.Route)
pd.DataFrame(route_group['ArrDel15'].sum()).
 ↪sort_values('ArrDel15',ascending=False)
```

[53]:

```
                                                    ArrDel15
Route
San Francisco International->Los Angeles Intern…        90
Los Angeles International->San Francisco Intern…        69
LaGuardia->Hartsfield-Jackson Atlanta Internati…        68
Los Angeles International->John F. Kennedy Inte…        52
LaGuardia->Charlotte Douglas International                51
…                                                      …
Logan International->Austin - Bergstrom Interna…         0
Logan International->Memphis International                 0
Logan International->Port Columbus International           0
San Diego International->Cincinnati/Northern Ke…         0
Louis Armstrong New Orleans International->San …         0

[2479 rows x 1 columns]
```

Which route has the highest average arrival delay?

[54]:
```
pd.DataFrame(route_group['ArrDelay'].mean()).sort_values('ArrDelay',␣
↪ascending=False)
```

[54]:
```
                                                      ArrDelay
Route
Louis Armstrong New Orleans International->Rona…  24.500000
Cleveland-Hopkins International->Palm Beach Int…  18.000000
John F. Kennedy International->Louisville Inter…  18.000000
Cleveland-Hopkins International->Philadelphia I…  12.800000
Memphis International->Denver International          9.758621
…                                                        …
Lambert-St. Louis International->Cleveland-Hopk… -20.000000
Eppley Airfield->LaGuardia                         -20.750000
Denver International->Kahului Airport              -22.666667
Jacksonville International->Chicago Midway Inte… -24.125000
Indianapolis International->Logan International    -26.000000

[2479 rows x 1 columns]
```