

Kaggle_Flight_Data_Analysis_Notebook

October 24, 2021

1 Mount dataset resources

Mounted at /content/drive

/content/drive/MyDrive/github/eda_examples/Kaggle_Flight_Data_Analysis

[3]: '/content/drive/MyDrive/github/eda_examples/Kaggle_Flight_Data_Analysis'

2 Kaggle 2015 Flight Delay Data Analysis

[5]:

	YEAR	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	\
0	2015	1	1	4	EV	4160	N11150	
1	2015	1	1	4	AA	1635	N025AA	
2	2015	1	1	4	WN	119	N271LV	
3	2015	1	1	4	EV	4936	N738EV	
4	2015	1	1	4	DL	2319	N960DL	

	ORIGIN_AIRPORT	DESTINATION_AIRPORT	SCHEDULED_DEPARTURE	DEPARTURE_TIME	\
0	JAX	EWB	540	531.0	
1	ATL	DFW	625	NaN	
2	RSW	ATL	800	754.0	
3	MSP	IAD	900	901.0	
4	LGA	MSP	1010	1010.0	

	DEPARTURE_DELAY	TAXI_OUT	WHEELS_OFF	SCHEDULED_TIME	ELAPSED_TIME	\
0	-9.0	9.0	540.0	137	132.0	
1	NaN	NaN	NaN	150	NaN	
2	-6.0	11.0	805.0	105	100.0	
3	1.0	56.0	957.0	148	159.0	
4	0.0	22.0	1032.0	200	195.0	

	AIR_TIME	DISTANCE	WHEELS_ON	TAXI_IN	SCHEDULED_ARRIVAL	ARRIVAL_TIME	\
0	109.0	820	729.0	14.0	757	743.0	
1	NaN	731	NaN	NaN	755	NaN	
2	84.0	515	929.0	5.0	945	934.0	
3	100.0	908	1237.0	3.0	1228	1240.0	

4	171.0	1020	1223.0	2.0	1230	1225.0
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	ARRIVAL_DELAY	DIVERTED	CANCELLED	CANCELLATION_REASON	AIR_SYSTEM_DELAY	\
0	-14.0	0	0	NaN	NaN	
1	NaN	0	1	B	NaN	
2	-11.0	0	0	NaN	NaN	
3	12.0	0	0	NaN	NaN	
4	-5.0	0	0	NaN	NaN	

	SECURITY_DELAY	AIRLINE_DELAY	LATE_AIRCRAFT_DELAY	WEATHER_DELAY
0	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN

2.0.1 Part 1: Exploratory Analysis

1. How many observations are there? How many features are there?

5821 - Total number of observations
 31 - Total number of features

The column names in the flights dataset are:

```
['YEAR' 'MONTH' 'DAY' 'DAY_OF_WEEK' 'AIRLINE' 'FLIGHT_NUMBER'
'TAIL_NUMBER' 'ORIGIN_AIRPORT' 'DESTINATION_AIRPORT'
'SCHEDULED_DEPARTURE' 'DEPARTURE_TIME' 'DEPARTURE_DELAY' 'TAXI_OUT'
'WHEELS_OFF' 'SCHEDULED_TIME' 'ELAPSED_TIME' 'AIR_TIME' 'DISTANCE'
'WHEELS_ON' 'TAXI_IN' 'SCHEDULED_ARRIVAL' 'ARRIVAL_TIME' 'ARRIVAL_DELAY'
'DIVERTED' 'CANCELLED' 'CANCELLATION_REASON' 'AIR_SYSTEM_DELAY'
'SECURITY_DELAY' 'AIRLINE_DELAY' 'LATE_AIRCRAFT_DELAY' 'WEATHER_DELAY']
```

2. How many different airlines are there? What are their counts?

14 - total num of different airlines in the dataset

The count for the airlines in the dataset in the descending order are:

```
[23]: AIRLINE
WN    1285
DL     922
AA     722
OO     593
EV     563
UA     512
MQ     288
B6     263
US     212
```

```

AS      145
NK      119
F9       74
VX       66
HA       57
Name: AIRLINE, dtype: int64

```

3. How many missing values are there in the departure delays? How about arrival delays? Do they match? Why or why not? Remove these observations afterwards.

```

91 - total number of missing values in departure delays
108 - total number of missing values in arrival delays

```

The number of missing values for departure delays and arrival delays DO NOT match. We have more missing values for arrival delays.

```

[25]:
DEPARTURE_TIME  DEPARTURE_DELAY  ARRIVAL_TIME  ARRIVAL_DELAY
1              NaN              NaN           NaN           NaN
10             NaN              NaN           NaN           NaN
47             NaN              NaN           NaN           NaN
115            NaN              NaN           NaN           NaN
116            NaN              NaN           NaN           NaN
172            NaN              NaN           NaN           NaN
174            NaN              NaN           NaN           NaN
190            NaN              NaN           NaN           NaN
350            1221.0           31.0           NaN           NaN
359            NaN              NaN           NaN           NaN
362            NaN              NaN           NaN           NaN
363            NaN              NaN           NaN           NaN
365            NaN              NaN           NaN           NaN
367            NaN              NaN           NaN           NaN
371            NaN              NaN           NaN           NaN
372            NaN              NaN           NaN           NaN
431            NaN              NaN           NaN           NaN
432            NaN              NaN           NaN           NaN
434            NaN              NaN           NaN           NaN
437            NaN              NaN           NaN           NaN
446            NaN              NaN           NaN           NaN
447            NaN              NaN           NaN           NaN
449            NaN              NaN           NaN           NaN
453            NaN              NaN           NaN           NaN
465            NaN              NaN           NaN           NaN
467            NaN              NaN           NaN           NaN
478            NaN              NaN           NaN           NaN
498            NaN              NaN           NaN           NaN
513            NaN              NaN           NaN           NaN
545            NaN              NaN           NaN           NaN
551            NaN              NaN           NaN           NaN
638            NaN              NaN           NaN           NaN

```

683	NaN	NaN	NaN	NaN
689	NaN	NaN	NaN	NaN
740	NaN	NaN	NaN	NaN
741	NaN	NaN	NaN	NaN
760	NaN	NaN	NaN	NaN
778	NaN	NaN	NaN	NaN
782	NaN	NaN	NaN	NaN
786	NaN	NaN	NaN	NaN
801	NaN	NaN	NaN	NaN
826	NaN	NaN	NaN	NaN
830	NaN	NaN	NaN	NaN
856	1302.0	21.0	2008.0	NaN
860	NaN	NaN	NaN	NaN
861	NaN	NaN	NaN	NaN
869	NaN	NaN	NaN	NaN
899	NaN	NaN	NaN	NaN
934	NaN	NaN	NaN	NaN
1015	NaN	NaN	NaN	NaN
1217	NaN	NaN	NaN	NaN
1372	1936.0	-4.0	143.0	NaN
1521	NaN	NaN	NaN	NaN
1605	NaN	NaN	NaN	NaN
1799	1317.0	2.0	1735.0	NaN
1804	NaN	NaN	NaN	NaN
1901	NaN	NaN	NaN	NaN
2029	NaN	NaN	NaN	NaN
2038	NaN	NaN	NaN	NaN
2055	NaN	NaN	NaN	NaN
2089	1316.0	1.0	2225.0	NaN
2110	NaN	NaN	NaN	NaN
2152	1609.0	22.0	NaN	NaN
2153	NaN	NaN	NaN	NaN
2196	NaN	NaN	NaN	NaN
2263	NaN	NaN	NaN	NaN
2277	NaN	NaN	NaN	NaN
2291	NaN	NaN	NaN	NaN
2368	NaN	NaN	NaN	NaN
2478	1821.0	46.0	2322.0	NaN
2533	NaN	NaN	NaN	NaN
2560	NaN	NaN	NaN	NaN
2577	1911.0	-9.0	2241.0	NaN
2716	NaN	NaN	NaN	NaN
2842	NaN	NaN	NaN	NaN
2899	NaN	NaN	NaN	NaN
2926	1733.0	8.0	2311.0	NaN
3011	NaN	NaN	NaN	NaN
3050	NaN	NaN	NaN	NaN

3128	NaN	NaN	NaN	NaN
3194	NaN	NaN	NaN	NaN
3208	1255.0	4.0	1807.0	NaN
3251	NaN	NaN	NaN	NaN
3426	NaN	NaN	NaN	NaN
3445	NaN	NaN	NaN	NaN
3522	1831.0	101.0	2313.0	NaN
3568	NaN	NaN	NaN	NaN
3578	NaN	NaN	NaN	NaN
3661	NaN	NaN	NaN	NaN
3699	1613.0	48.0	2159.0	NaN
3766	643.0	-2.0	NaN	NaN
4171	NaN	NaN	NaN	NaN
4295	1442.0	-3.0	2143.0	NaN
4771	1741.0	1.0	246.0	NaN
4809	NaN	NaN	NaN	NaN
5097	NaN	NaN	NaN	NaN
5183	NaN	NaN	NaN	NaN
5232	1316.0	-2.0	1808.0	NaN
5247	NaN	NaN	NaN	NaN
5250	NaN	NaN	NaN	NaN
5567	NaN	NaN	NaN	NaN
5576	NaN	NaN	NaN	NaN
5587	NaN	NaN	NaN	NaN
5595	NaN	NaN	NaN	NaN
5641	2001.0	29.0	230.0	NaN
5716	NaN	NaN	NaN	NaN
5755	NaN	NaN	NaN	NaN
5764	NaN	NaN	NaN	NaN

From the above subset of data we can see that there are flights with departure time but are missing arrival delay values.

[26]:

	DEPARTURE_TIME	DEPARTURE_DELAY	ARRIVAL_TIME	ARRIVAL_DELAY	DIVERTED	\
1	NaN	NaN	NaN	NaN	0	
10	NaN	NaN	NaN	NaN	0	
47	NaN	NaN	NaN	NaN	0	
115	NaN	NaN	NaN	NaN	0	
116	NaN	NaN	NaN	NaN	0	
172	NaN	NaN	NaN	NaN	0	
174	NaN	NaN	NaN	NaN	0	
190	NaN	NaN	NaN	NaN	0	
350	1221.0	31.0	NaN	NaN	1	
359	NaN	NaN	NaN	NaN	0	
362	NaN	NaN	NaN	NaN	0	
363	NaN	NaN	NaN	NaN	0	
365	NaN	NaN	NaN	NaN	0	
367	NaN	NaN	NaN	NaN	0	

371	NaN	NaN	NaN	NaN	0
372	NaN	NaN	NaN	NaN	0
431	NaN	NaN	NaN	NaN	0
432	NaN	NaN	NaN	NaN	0
434	NaN	NaN	NaN	NaN	0
437	NaN	NaN	NaN	NaN	0
446	NaN	NaN	NaN	NaN	0
447	NaN	NaN	NaN	NaN	0
449	NaN	NaN	NaN	NaN	0
453	NaN	NaN	NaN	NaN	0
465	NaN	NaN	NaN	NaN	0
467	NaN	NaN	NaN	NaN	0
478	NaN	NaN	NaN	NaN	0
498	NaN	NaN	NaN	NaN	0
513	NaN	NaN	NaN	NaN	0
545	NaN	NaN	NaN	NaN	0
551	NaN	NaN	NaN	NaN	0
638	NaN	NaN	NaN	NaN	0
683	NaN	NaN	NaN	NaN	0
689	NaN	NaN	NaN	NaN	0
740	NaN	NaN	NaN	NaN	0
741	NaN	NaN	NaN	NaN	0
760	NaN	NaN	NaN	NaN	0
778	NaN	NaN	NaN	NaN	0
782	NaN	NaN	NaN	NaN	0
786	NaN	NaN	NaN	NaN	0
801	NaN	NaN	NaN	NaN	0
826	NaN	NaN	NaN	NaN	0
830	NaN	NaN	NaN	NaN	0
856	1302.0	21.0	2008.0	NaN	1
860	NaN	NaN	NaN	NaN	0
861	NaN	NaN	NaN	NaN	0
869	NaN	NaN	NaN	NaN	0
899	NaN	NaN	NaN	NaN	0
934	NaN	NaN	NaN	NaN	0
1015	NaN	NaN	NaN	NaN	0
1217	NaN	NaN	NaN	NaN	0
1372	1936.0	-4.0	143.0	NaN	1
1521	NaN	NaN	NaN	NaN	0
1605	NaN	NaN	NaN	NaN	0
1799	1317.0	2.0	1735.0	NaN	1
1804	NaN	NaN	NaN	NaN	0
1901	NaN	NaN	NaN	NaN	0
2029	NaN	NaN	NaN	NaN	0
2038	NaN	NaN	NaN	NaN	0
2055	NaN	NaN	NaN	NaN	0
2089	1316.0	1.0	2225.0	NaN	1

2110	NaN	NaN	NaN	NaN	0
2152	1609.0	22.0	NaN	NaN	0
2153	NaN	NaN	NaN	NaN	0
2196	NaN	NaN	NaN	NaN	0
2263	NaN	NaN	NaN	NaN	0
2277	NaN	NaN	NaN	NaN	0
2291	NaN	NaN	NaN	NaN	0
2368	NaN	NaN	NaN	NaN	0
2478	1821.0	46.0	2322.0	NaN	1
2533	NaN	NaN	NaN	NaN	0
2560	NaN	NaN	NaN	NaN	0
2577	1911.0	-9.0	2241.0	NaN	1
2716	NaN	NaN	NaN	NaN	0
2842	NaN	NaN	NaN	NaN	0
2899	NaN	NaN	NaN	NaN	0
2926	1733.0	8.0	2311.0	NaN	1
3011	NaN	NaN	NaN	NaN	0
3050	NaN	NaN	NaN	NaN	0
3128	NaN	NaN	NaN	NaN	0
3194	NaN	NaN	NaN	NaN	0
3208	1255.0	4.0	1807.0	NaN	1
3251	NaN	NaN	NaN	NaN	0
3426	NaN	NaN	NaN	NaN	0
3445	NaN	NaN	NaN	NaN	0
3522	1831.0	101.0	2313.0	NaN	1
3568	NaN	NaN	NaN	NaN	0
3578	NaN	NaN	NaN	NaN	0
3661	NaN	NaN	NaN	NaN	0
3699	1613.0	48.0	2159.0	NaN	1
3766	643.0	-2.0	NaN	NaN	0
4171	NaN	NaN	NaN	NaN	0
4295	1442.0	-3.0	2143.0	NaN	1
4771	1741.0	1.0	246.0	NaN	1
4809	NaN	NaN	NaN	NaN	0
5097	NaN	NaN	NaN	NaN	0
5183	NaN	NaN	NaN	NaN	0
5232	1316.0	-2.0	1808.0	NaN	1
5247	NaN	NaN	NaN	NaN	0
5250	NaN	NaN	NaN	NaN	0
5567	NaN	NaN	NaN	NaN	0
5576	NaN	NaN	NaN	NaN	0
5587	NaN	NaN	NaN	NaN	0
5595	NaN	NaN	NaN	NaN	0
5641	2001.0	29.0	230.0	NaN	1
5716	NaN	NaN	NaN	NaN	0
5755	NaN	NaN	NaN	NaN	0
5764	NaN	NaN	NaN	NaN	0

CANCELLED

1	1
10	1
47	1
115	1
116	1
172	1
174	1
190	1
350	0
359	1
362	1
363	1
365	1
367	1
371	1
372	1
431	1
432	1
434	1
437	1
446	1
447	1
449	1
453	1
465	1
467	1
478	1
498	1
513	1
545	1
551	1
638	1
683	1
689	1
740	1
741	1
760	1
778	1
782	1
786	1
801	1
826	1
830	1
856	0
860	1

861	1
869	1
899	1
934	1
1015	1
1217	1
1372	0
1521	1
1605	1
1799	0
1804	1
1901	1
2029	1
2038	1
2055	1
2089	0
2110	1
2152	1
2153	1
2196	1
2263	1
2277	1
2291	1
2368	1
2478	0
2533	1
2560	1
2577	0
2716	1
2842	1
2899	1
2926	0
3011	1
3050	1
3128	1
3194	1
3208	0
3251	1
3426	1
3445	1
3522	0
3568	1
3578	1
3661	1
3699	0
3766	1
4171	1

4295	0
4771	0
4809	1
5097	1
5183	1
5232	0
5247	1
5250	1
5567	1
5576	1
5587	1
5595	1
5641	0
5716	1
5755	1
5764	1

From the above subset of data we can conclude that this mismatch in the missing values is due to the flight diversion.

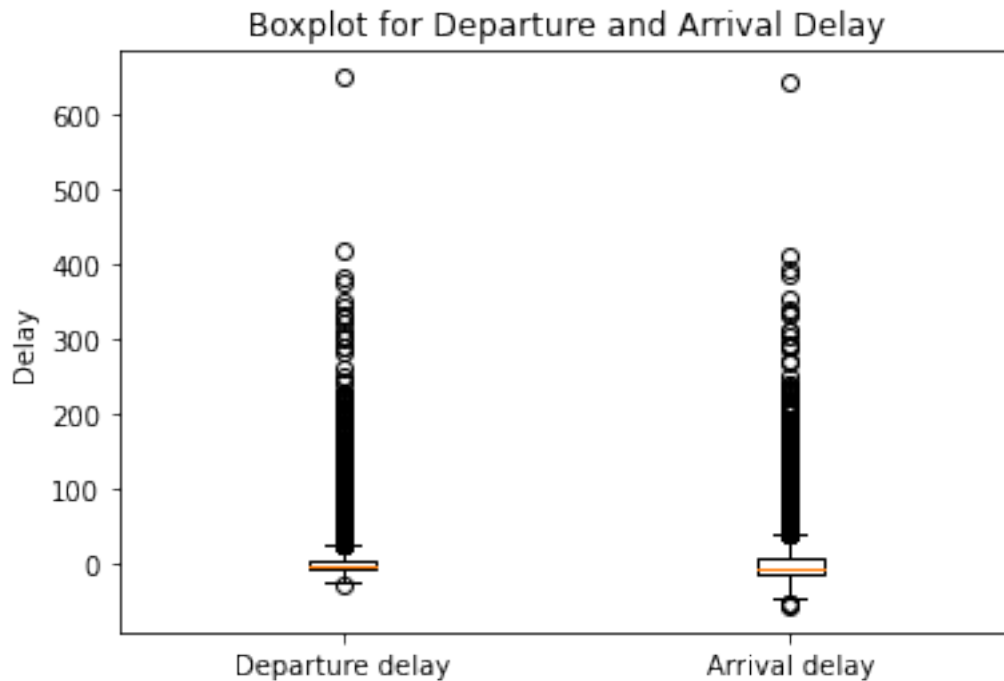
0 - total number of missing values in departure delays
 0 - total number of missing values in arrival delays

4. What is the average and median departure and arrival delay? What do you observe?

8.887 - Average departure delay
 3.988 - Average arrival delay
 -2.000 - Median departure delay
 -5.000 - Median arrival delay

Based on the values above we find that the mean is greater than median for both departure and arrival delay

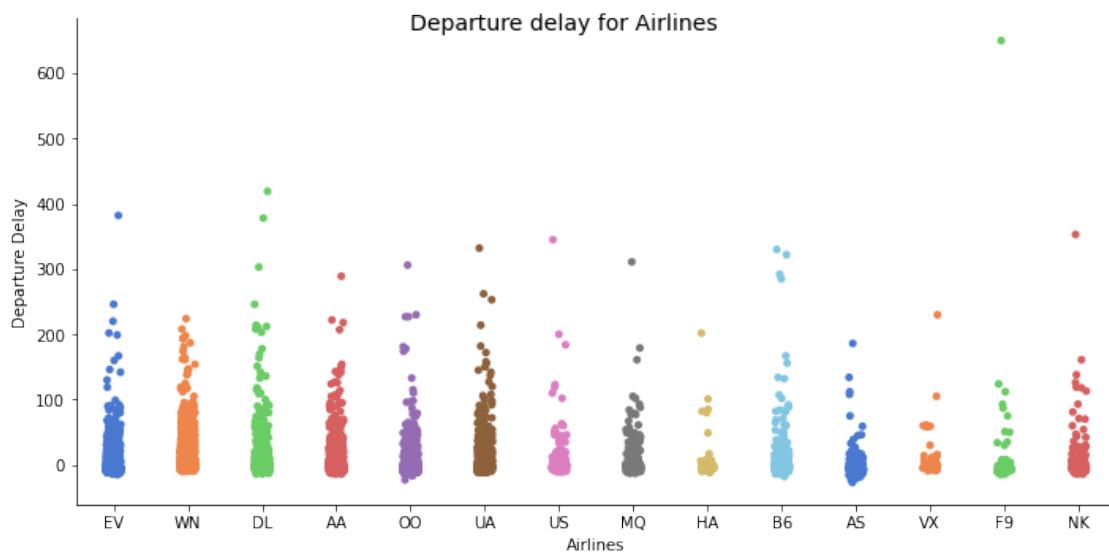
Skew DEPARTURE_DELAY: 5.667
 Skew ARRIVAL_DELAY: 4.798

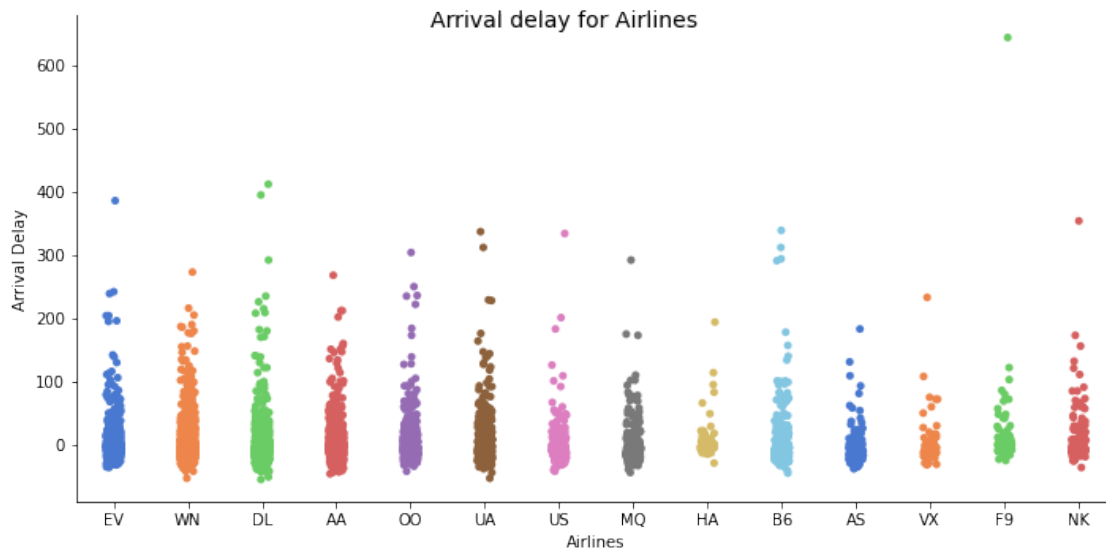


Observations:

- * From the above box plot we can see that there are a lot of outliers and extreme values in the dataset.
- * The coefficient of skewness is also significantly higher than zero.
- * The distribution is skewed to the right and extremely high values have a significant impact on the mean.

5. Display graphically the departure delays and arrival delays for each airline. What do you notice? Explain





Correlation Matrix

[38]:

	DISTANCE	DEPARTURE_DELAY	ARRIVAL_DELAY
DISTANCE	1.000000	0.023095	-0.027935
DEPARTURE_DELAY	0.023095	1.000000	0.936069
ARRIVAL_DELAY	-0.027935	0.936069	1.000000

Observations:

- We can see that the arrival and departure delay follow the same trend.
- This trend indicate that there might be a strong correlation between the arrival and departure delay.
- From the above correlation matrix we can see that there is no correlation between the distance and delays (0.02 & -0.02).
- However there is a strong positive correlation between the departure and arrival delays (0.93). Hence, delayed flights arrive late.

6. Now calculate the 5 number summary (min, Q1, median, Q3, max) of departure delay for each airline. Arrange it by median delay (descending order). Do the same for arrival delay.

Departure delay 5 number summary

[39]:

	Min	Q1	Q3	Max	Median
AIRLINE					
UA	-12.0	-3.0	14.00	332.0	1.5
WN	-10.0	-3.0	10.00	224.0	0.0
B6	-18.0	-5.0	11.00	330.0	-1.0

VX	-9.0	-4.0	3.25	230.0	-1.5
AA	-14.0	-5.0	7.00	289.0	-2.0
DL	-14.0	-4.0	3.00	419.0	-2.0
NK	-14.0	-6.0	20.00	353.0	-2.0
EV	-15.0	-6.0	4.00	382.0	-3.0
HA	-12.0	-6.0	1.00	202.0	-3.0
MQ	-13.0	-5.0	6.00	311.0	-3.0
OO	-23.0	-7.0	2.00	306.0	-3.0
US	-11.0	-5.0	2.75	345.0	-3.0
AS	-27.0	-8.0	2.00	186.0	-4.0
F9	-15.0	-7.0	4.00	650.0	-4.0

Arrival delay 5 number summary

```
[40]:
```

	Min	Q1	Q3	Max	Median
AIRLINE					
F9	-25.0	-9.00	15.00	644.0	1.0
HA	-29.0	-5.00	10.00	194.0	-1.0
NK	-36.0	-10.75	23.00	354.0	-2.0
OO	-42.0	-12.00	8.00	304.0	-3.0
EV	-36.0	-12.00	8.00	386.0	-4.0
US	-42.0	-13.00	11.00	334.0	-4.0
WN	-53.0	-12.00	8.00	273.0	-4.0
B6	-45.0	-15.00	14.00	339.0	-5.0
UA	-53.0	-15.00	10.00	337.0	-5.5
AA	-46.0	-15.00	7.75	268.0	-6.0
AS	-38.0	-14.00	2.00	183.0	-6.0
VX	-32.0	-15.00	5.25	233.0	-6.0
MQ	-44.0	-14.00	8.00	292.0	-7.0
DL	-55.0	-15.00	3.00	412.0	-8.0

7. Which airport has the most averaged departure delay? Give me the top 10 airports. Why do you think the number 1 airport has that much delay?

The airport with the most averaged departure delay is

```
[41]:
```

	mean
ORIGIN_AIRPORT	
FAR	161.0

```
[42]:
```

	mean
ORIGIN_AIRPORT	
FAR	161.000000
12898	119.000000
BMI	101.333333
ERI	92.000000
MYR	88.000000
14576	88.000000
14696	88.000000

```

10157      87.500000
12992      80.000000
12206      67.500000

```

```

[43]:      YEAR  MONTH  DAY  DAY_OF_WEEK  AIRLINE  FLIGHT_NUMBER  TAIL_NUMBER  \
2991  2015      7    6              1      MQ             3195      N658MQ

      ORIGIN_AIRPORT  DESTINATION_AIRPORT  SCHEDULED_DEPARTURE  DEPARTURE_TIME  \
2991              FAR                  ORD              1214          1455.0

      DEPARTURE_DELAY  TAXI_OUT  WHEELS_OFF  SCHEDULED_TIME  ELAPSED_TIME  \
2991              161.0      21.0      1516.0              116          130.0

      AIR_TIME  DISTANCE  WHEELS_ON  TAXI_IN  SCHEDULED_ARRIVAL  ARRIVAL_TIME  \
2991       88.0       557      1644.0      21.0              1410          1705.0

      ARRIVAL_DELAY  DIVERTED  CANCELLED  CANCELLATION_REASON  \
2991              175.0        0        0                  NaN

      AIR_SYSTEM_DELAY  SECURITY_DELAY  AIRLINE_DELAY  LATE_AIRCRAFT_DELAY  \
2991              100.0              0.0              0.0              75.0

      WEATHER_DELAY
2991              0.0

```

Observation:

- Here, we can see that the airport FAR has only one observation in the dataset. Hence, the reason for it being the airport with the maximum average delay.

8. Do you expect the departure delay has anything to do with distance of trip? What about arrival delay and distance? Prove your claims.

```

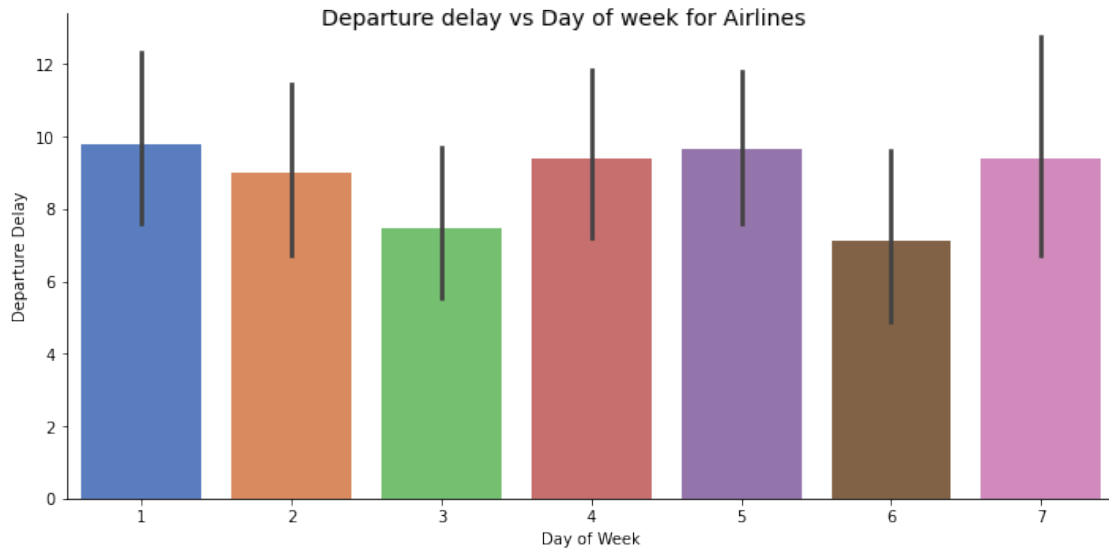
[44]:      DISTANCE  DEPARTURE_DELAY  ARRIVAL_DELAY
DISTANCE      1.000000      0.023095     -0.027935
DEPARTURE_DELAY  0.023095      1.000000      0.936069
ARRIVAL_DELAY   -0.027935      0.936069      1.000000

```

Observations:

- The above correlation matrix proves that the distance has nothing to do with the departure and arrival delays.
- There is no correlation between the distance and the departure and arrival delays.

9. What about day of week vs departure delay?



[46]:

	DAY_OF_WEEK	DEPARTURE_DELAY
DAY_OF_WEEK	1.000000	-0.004786
DEPARTURE_DELAY	-0.004786	1.000000

Observations:

- From the above graph we can see that the average departure delay for each day of the week is nearly same.
- The correlation matrix also proves that there is no correlation between the departure delay and day of the week.

10. If there is a departure delay (i.e. positive values for departure delay), does distance have anything to do with arrival delay? Explain. (My experience has been that longer distance flights can make up more time.)

[47]:

	YEAR	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	\
3	2015	1	1	4	EV	4936	N738EV	
7	2015	1	1	4	OO	5354	N472CA	
12	2015	1	1	4	US	705	N567UW	
14	2015	1	1	4	UA	1468	N68807	
15	2015	1	1	4	WN	688	N242WN	

	ORIGIN_AIRPORT	DESTINATION_AIRPORT	SCHEDULED_DEPARTURE	DEPARTURE_TIME	\
3	MSP	IAD	900	901.0	
7	ORD	MBS	1317	1349.0	
12	CLT	LAS	1800	1813.0	
14	IAH	SEA	1912	1924.0	
15	MKE	STL	1945	1951.0	

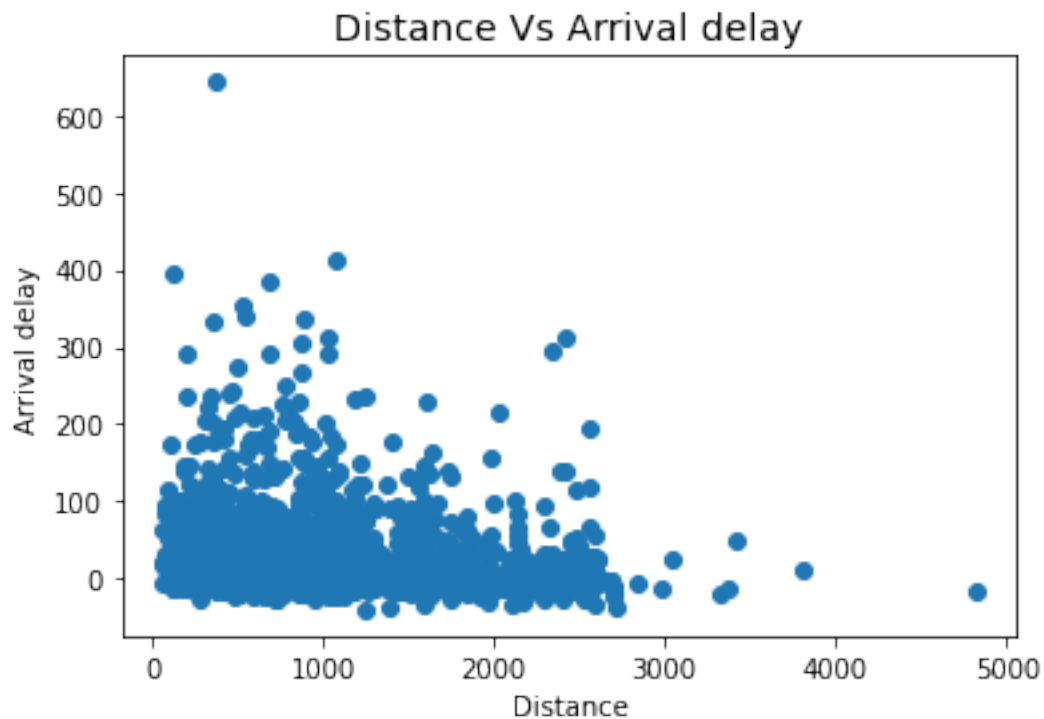
	DEPARTURE_DELAY	TAXI_OUT	WHEELS_OFF	SCHEDULED_TIME	ELAPSED_TIME	\
--	-----------------	----------	------------	----------------	--------------	---

3	1.0	56.0	957.0	148	159.0
7	32.0	27.0	1416.0	66	70.0
12	13.0	15.0	1828.0	295	289.0
14	12.0	9.0	1933.0	289	259.0
15	6.0	9.0	2000.0	75	69.0

	AIR_TIME	DISTANCE	WHEELS_ON	TAXI_IN	SCHEDULED_ARRIVAL	ARRIVAL_TIME \
3	100.0	908	1237.0	3.0	1228	1240.0
7	39.0	222	1555.0	4.0	1523	1559.0
12	266.0	1916	1954.0	8.0	1955	2002.0
14	245.0	1874	2138.0	5.0	2201	2143.0
15	55.0	317	2055.0	5.0	2100	2100.0

	ARRIVAL_DELAY	DIVERTED	CANCELLED	CANCELLATION_REASON	AIR_SYSTEM_DELAY \
3	12.0	0	0	NaN	NaN
7	36.0	0	0	NaN	4.0
12	7.0	0	0	NaN	NaN
14	-18.0	0	0	NaN	NaN
15	0.0	0	0	NaN	NaN

	SECURITY_DELAY	AIRLINE_DELAY	LATE_AIRCRAFT_DELAY	WEATHER_DELAY
3	NaN	NaN	NaN	NaN
7	0.0	11.0	21.0	0.0
12	NaN	NaN	NaN	NaN
14	NaN	NaN	NaN	NaN
15	NaN	NaN	NaN	NaN



[49]:

	DISTANCE	ARRIVAL_DELAY
DISTANCE	1.000000	-0.094924
ARRIVAL_DELAY	-0.094924	1.000000

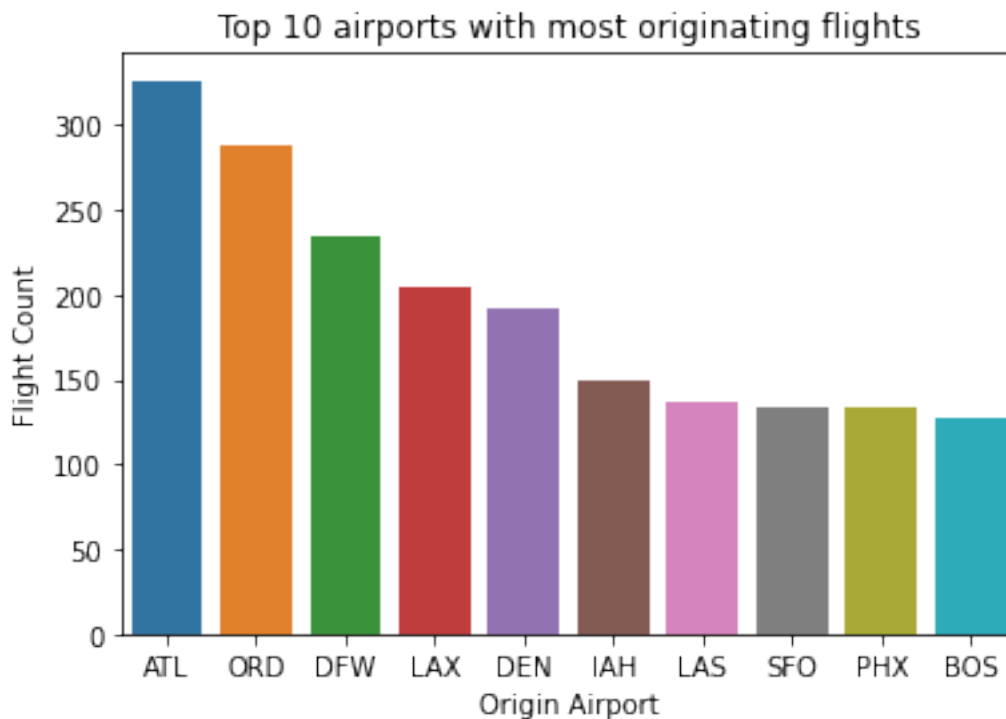
Observations:

- Distance has nothing to do with arrival delay.
- The scatter plot and the correlation matrix suggests the same. All the long distance flight may or may not be able to makeup the lost time.

11. Come up with two interesting questions that you want to answer, then explore it in using this data set. Use any numerical or graphical methods to support your answers. (preferably both). Q1. From which airport does most flights originate?

[50]:

	ORIGIN_AIRPORT	AIRLINE
127	ATL	326
292	ORD	287
180	DFW	235
249	LAX	205
179	DEN	191

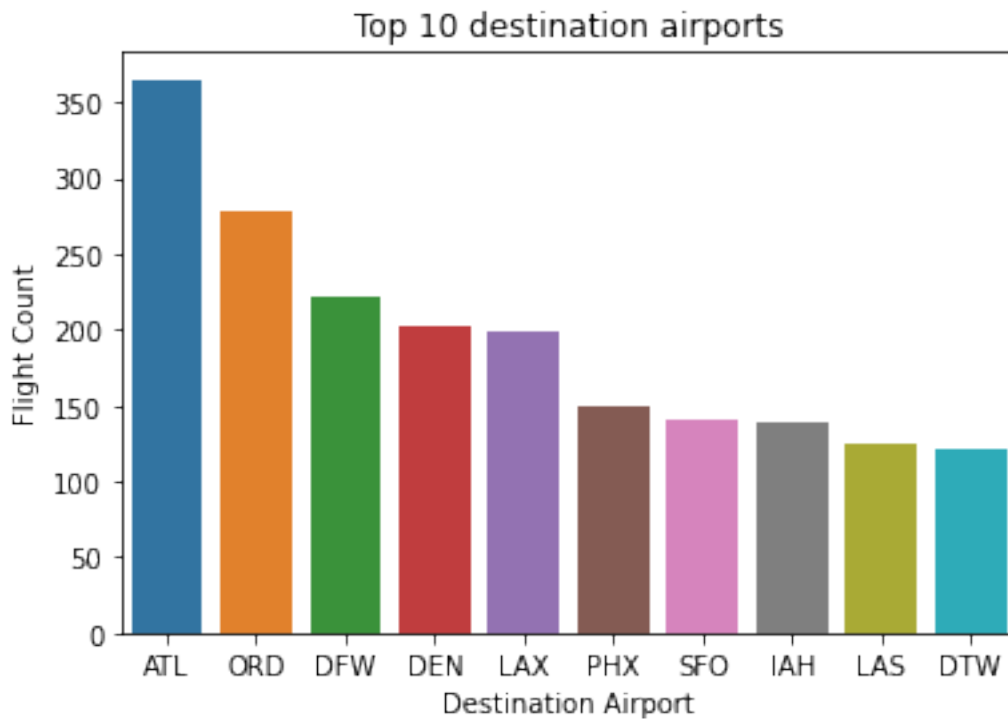


Answer: From the analysis above, we can see that the most flights originate from ATL airport

Q2. Which is the most visited city?

[52]:

	DESTINATION_AIRPORT	AIRLINE
122	ATL	365
297	ORD	278
177	DFW	221
176	DEN	203
248	LAX	199

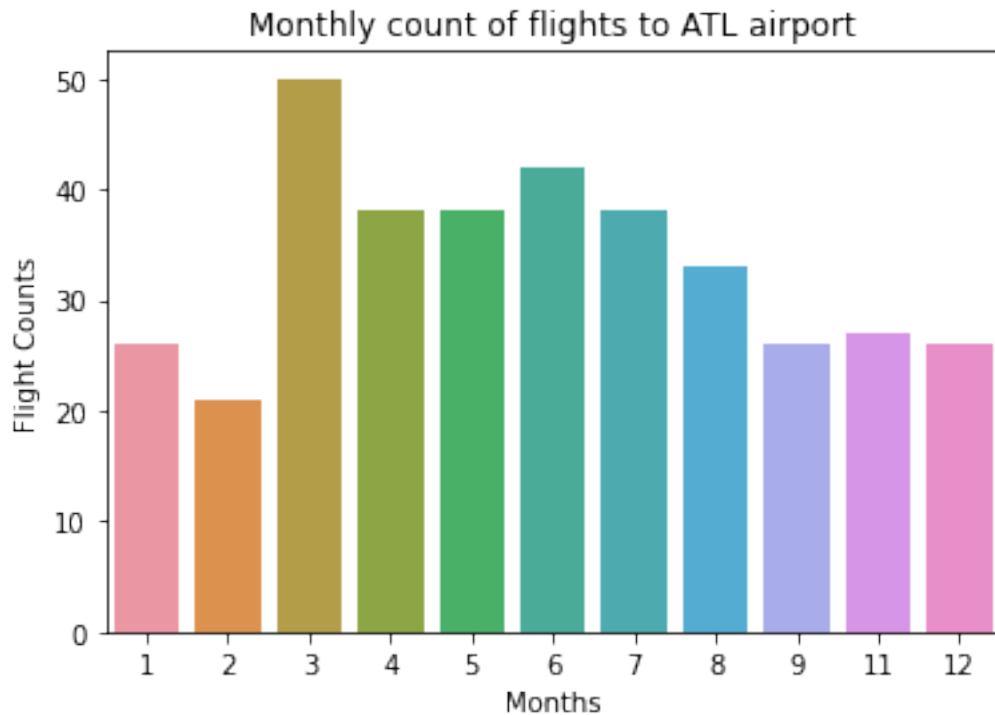


Answer: From the above analysis, we can deduce that ATL is the most visited city. If we combine the results of both Q1 and Q2 we can say ATL is the busiest airport.

Q3. Since ATL is the most visited destination. In which part of the year do people visit it most?

[54]:

	MONTH	AIRLINE
0	1	26
1	2	21
2	3	50
3	4	38
4	5	38
5	6	42
6	7	38
7	8	33
8	9	26
9	11	27
10	12	26



Answer: There are maximum flights in the month of March and in the summer months the count of flights is more. Hence people visit ATL mostly during Spring and Summer.

```
[56]:  YEAR  MONTH  DAY  DAY_OF_WEEK  AIRLINE  FLIGHT_NUMBER  TAIL_NUMBER  \
0   2015     1     1           4         EV           4160       N11150
2   2015     1     1           4         WN            119       N271LV
3   2015     1     1           4         EV           4936       N738EV
4   2015     1     1           4         DL           2319       N960DL
5   2015     1     1           4         DL           1806       N594NW

  ORIGIN_AIRPORT  DESTINATION_AIRPORT  SCHEDULED_DEPARTURE  DEPARTURE_TIME  \
0             JAX                   EWR                   540             531.0
2             RSW                   ATL                   800             754.0
3             MSP                   IAD                   900             901.0
4             LGA                   MSP                  1010            1010.0
5             LAX                   DTW                  1115            1113.0

  DEPARTURE_DELAY  TAXI_OUT  WHEELS_OFF  SCHEDULED_TIME  ELAPSED_TIME  \
0             -9.0        9.0       540.0           137           132.0
2             -6.0       11.0       805.0           105           100.0
3              1.0       56.0       957.0           148           159.0
4              0.0       22.0      1032.0           200           195.0
5             -2.0       15.0      1128.0           266           248.0

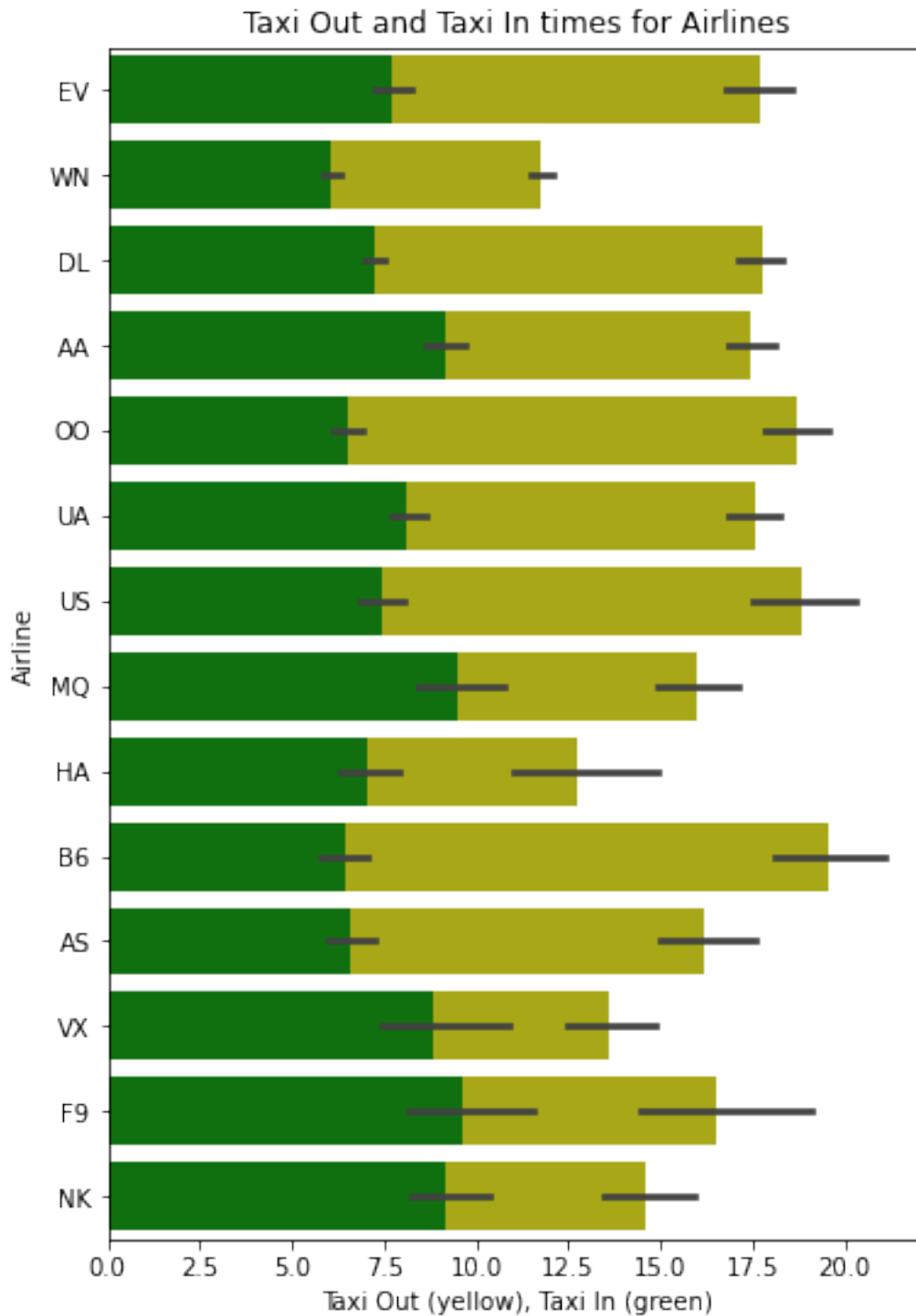
  AIR_TIME  DISTANCE  WHEELS_ON  TAXI_IN  SCHEDULED_ARRIVAL  ARRIVAL_TIME  \
```

0	109.0	820	729.0	14.0	757	743.0
2	84.0	515	929.0	5.0	945	934.0
3	100.0	908	1237.0	3.0	1228	1240.0
4	171.0	1020	1223.0	2.0	1230	1225.0
5	226.0	1979	1814.0	7.0	1841	1821.0

	ARRIVAL_DELAY	DIVERTED	CANCELLED	CANCELLATION_REASON	AIR_SYSTEM_DELAY	\
0	-14.0	0	0	NaN	NaN	
2	-11.0	0	0	NaN	NaN	
3	12.0	0	0	NaN	NaN	
4	-5.0	0	0	NaN	NaN	
5	-20.0	0	0	NaN	NaN	

	SECURITY_DELAY	AIRLINE_DELAY	LATE_AIRCRAFT_DELAY	WEATHER_DELAY
0	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN
5	NaN	NaN	NaN	NaN

Q4. Does all airlines have same taxi in and taxi out times?



Answer: Taxi out and Taxi in times for all the airlines is different. However, for all the airlines taxi in times is significantly less than taxi out.

2.0.2 Part 2: Regression Analysis

Subpart 1

1. Your response is `ARRIVAL_DELAY`. First, remove all the missing data in the `WEATHER_DELAY` column. Once you do this, there shouldn't be anymore missing values in the data set(except for the cancellation reason feature). Check that.

4641 - Total missing values

```
[59]: YEAR                0
      MONTH              0
      DAY                0
      DAY_OF_WEEK        0
      AIRLINE            0
      FLIGHT_NUMBER      0
      TAIL_NUMBER        0
      ORIGIN_AIRPORT     0
      DESTINATION_AIRPORT 0
      SCHEDULED_DEPARTURE 0
      DEPARTURE_TIME     0
      DEPARTURE_DELAY    0
      TAXI_OUT           0
      WHEELS_OFF         0
      SCHEDULED_TIME     0
      ELAPSED_TIME       0
      AIR_TIME           0
      DISTANCE           0
      WHEELS_ON          0
      TAXI_IN            0
      SCHEDULED_ARRIVAL  0
      ARRIVAL_TIME       0
      ARRIVAL_DELAY      0
      DIVERTED           0
      CANCELLED          0
      CANCELLATION_REASON 1072
      AIR_SYSTEM_DELAY   0
      SECURITY_DELAY     0
      AIRLINE_DELAY      0
      LATE_AIRCRAFT_DELAY 0
      WEATHER_DELAY      0
      dtype: int64
```

2. Build a regression model using all the observations, and the following predictors: `[LATE_AIRCRAFT_DELAY, AIRLINE_DELAY, AIR_SYSTEM_DELAY, WEATHER_DELAY, DAY_OF_WEEK, DEPARTURE_TIME, DEPARTURE_DELAY, DISTANCE, AIRLINE]` a total of 9 predictors. Notice the `AIRLINE` variable is a categorical variable.

[60]:

	YEAR	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	\			
7	2015	1	1	4	OO	5354	N472CA				
9	2015	1	1	4	UA	1062	N73291				
19	2015	1	2	5	US	2065	N534UW				
21	2015	1	2	5	OO	5211	N943SW				
22	2015	1	2	5	HA	335	N477HA				
	ORIGIN_AIRPORT		DESTINATION_AIRPORT		SCHEDULED_DEPARTURE		DEPARTURE_TIME		\		
7	ORD		MBS		1317		1349.0				
9	DCA		DEN		1603		1603.0				
19	CLT		IAH		1120		1128.0				
21	IDA		DEN		1338		1428.0				
22	OGG		HNL		1503		1644.0				
	DEPARTURE_DELAY		TAXI_OUT	WHEELS_OFF	SCHEDULED_TIME		ELAPSED_TIME		\		
7	32.0		27.0	1416.0	66		70.0				
9	0.0		12.0	1615.0	249		272.0				
19	8.0		11.0	1139.0	163		176.0				
21	50.0		31.0	1459.0	91		122.0				
22	101.0		10.0	1654.0	37		50.0				
	AIR_TIME	DISTANCE	WHEELS_ON	TAXI_IN	SCHEDULED_ARRIVAL		ARRIVAL_TIME		\		
7	39.0	222	1555.0	4.0	1523		1559.0				
9	248.0	1476	1823.0	12.0	1812		1835.0				
19	154.0	912	1313.0	11.0	1303		1324.0				
21	64.0	458	1603.0	27.0	1509		1630.0				
22	23.0	100	1717.0	17.0	1540		1734.0				
	ARRIVAL_DELAY		DIVERTED	CANCELLED	CANCELLATION_REASON		AIR_SYSTEM_DELAY		\		
7	36.0		0	0	NaN		4.0				
9	23.0		0	0	NaN		23.0				
19	21.0		0	0	NaN		13.0				
21	81.0		0	0	NaN		31.0				
22	114.0		0	0	NaN		0.0				
	SECURITY_DELAY		AIRLINE_DELAY		LATE_AIRCRAFT_DELAY		WEATHER_DELAY		AS	B6	\
7	0.0		11.0		21.0		0.0		0	0	
9	0.0		0.0		0.0		0.0		0	0	
19	0.0		8.0		0.0		0.0		0	0	
21	0.0		0.0		50.0		0.0		0	0	
22	0.0		25.0		89.0		0.0		0	0	
	DL	EV	F9	HA	MQ	NK	OO	UA	US	VX	WN
7	0	0	0	0	0	0	1	0	0	0	0
9	0	0	0	0	0	0	0	1	0	0	0
19	0	0	0	0	0	0	0	0	1	0	0
21	0	0	0	0	0	0	1	0	0	0	0

22 0 0 0 1 0 0 0 0 0 0 0

[61]:

	YEAR	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	\
7	2015	1	1	4	00	5354	N472CA	
9	2015	1	1	4	UA	1062	N73291	
19	2015	1	2	5	US	2065	N534UW	
21	2015	1	2	5	00	5211	N943SW	
22	2015	1	2	5	HA	335	N477HA	

	ORIGIN_AIRPORT	DESTINATION_AIRPORT	SCHEDULED_DEPARTURE	DEPARTURE_TIME	\
7	ORD	MBS	1317	1349.0	
9	DCA	DEN	1603	1603.0	
19	CLT	IAH	1120	1128.0	
21	IDA	DEN	1338	1428.0	
22	OGG	HNL	1503	1644.0	

	DEPARTURE_DELAY	TAXI_OUT	WHEELS_OFF	SCHEDULED_TIME	ELAPSED_TIME	\
7	32.0	27.0	1416.0	66	70.0	
9	0.0	12.0	1615.0	249	272.0	
19	8.0	11.0	1139.0	163	176.0	
21	50.0	31.0	1459.0	91	122.0	
22	101.0	10.0	1654.0	37	50.0	

	AIR_TIME	DISTANCE	WHEELS_ON	TAXI_IN	SCHEDULED_ARRIVAL	ARRIVAL_TIME	\
7	39.0	222	1555.0	4.0	1523	1559.0	
9	248.0	1476	1823.0	12.0	1812	1835.0	
19	154.0	912	1313.0	11.0	1303	1324.0	
21	64.0	458	1603.0	27.0	1509	1630.0	
22	23.0	100	1717.0	17.0	1540	1734.0	

	ARRIVAL_DELAY	DIVERTED	CANCELLED	CANCELLATION_REASON	AIR_SYSTEM_DELAY	\
7	36.0	0	0	NaN	4.0	
9	23.0	0	0	NaN	23.0	
19	21.0	0	0	NaN	13.0	
21	81.0	0	0	NaN	31.0	
22	114.0	0	0	NaN	0.0	

	SECURITY_DELAY	AIRLINE_DELAY	LATE_AIRCRAFT_DELAY	WEATHER_DELAY	AS	B6	\
7	0.0	11.0	21.0	0.0	0	0	
9	0.0	0.0	0.0	0.0	0	0	
19	0.0	8.0	0.0	0.0	0	0	
21	0.0	0.0	50.0	0.0	0	0	
22	0.0	25.0	89.0	0.0	0	0	

	DL	EV	F9	HA	MQ	NK	OO	UA	US	VX	WN	DAY_2	DAY_3	DAY_4	DAY_5	\
7	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	
9	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	

19	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
21	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
22	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1

	DAY_6	DAY_7
7	0	0
9	0	0
19	0	0
21	0	0
22	0	0

[62]: <class 'statsmodels.iolib.summary.Summary'>

```

"""
                                OLS Regression Results
=====
Dep. Variable:            ARRIVAL_DELAY    R-squared:                0.999
Model:                    OLS              Adj. R-squared:           0.999
Method:                   Least Squares    F-statistic:             4.273e+04
Date:                     Sun, 24 Oct 2021  Prob (F-statistic):       0.00
Time:                     15:53:33         Log-Likelihood:          -2140.7
No. Observations:         1072            AIC:                    4335.
Df Residuals:             1045            BIC:                    4470.
Df Model:                 26
Covariance Type:          nonrobust
=====
=====
                                coef      std err          t      P>|t|      [0.025
0.975]
-----
const                0.5743        0.300        1.916    0.056    -0.014
1.163
LATE_AIRCRAFT_DELAY  0.9814        0.004    251.351    0.000    0.974
0.989
AIRLINE_DELAY        0.9820        0.004    258.523    0.000    0.975
0.989
AIR_SYSTEM_DELAY     0.9853        0.003    311.685    0.000    0.979
0.992
WEATHER_DELAY        0.9846        0.004    239.180    0.000    0.977
0.993
DEPARTURE_TIME       -0.0001        0.000     -0.923    0.356    -0.000
0.000
DEPARTURE_DELAY      0.0158        0.003        4.647    0.000    0.009
0.023
DISTANCE              0.0001        0.000        1.106    0.269   -8.74e-05
0.000
AS                   1.8908        0.434        4.354    0.000    1.039

```

2.743					
B6	0.0009	0.277	0.003	0.997	-0.542
0.544					
DL	-0.2385	0.224	-1.062	0.288	-0.679
0.202					
EV	-0.1519	0.241	-0.629	0.529	-0.625
0.322					
F9	0.0010	0.445	0.002	0.998	-0.872
0.874					
HA	-0.1183	0.548	-0.216	0.829	-1.194
0.957					
MQ	-0.1080	0.295	-0.366	0.715	-0.687
0.471					
NK	0.4677	0.333	1.404	0.161	-0.186
1.122					
OO	-0.1077	0.241	-0.448	0.654	-0.580
0.364					
UA	-0.3509	0.233	-1.505	0.133	-0.808
0.107					
US	-0.1699	0.319	-0.533	0.594	-0.796
0.456					
VX	-0.1395	0.546	-0.256	0.798	-1.210
0.931					
WN	-0.1731	0.199	-0.870	0.384	-0.563
0.217					
DAY_2	-0.2517	0.207	-1.214	0.225	-0.659
0.155					
DAY_3	0.0896	0.208	0.431	0.667	-0.319
0.498					
DAY_4	-0.2768	0.197	-1.404	0.161	-0.664
0.110					
DAY_5	-0.2329	0.198	-1.175	0.240	-0.622
0.156					
DAY_6	-0.2907	0.238	-1.222	0.222	-0.757
0.176					
DAY_7	-0.1769	0.206	-0.859	0.390	-0.581
0.227					
=====					
Omnibus:	2216.606	Durbin-Watson:		2.019	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		4284200.685	
Skew:	16.511	Prob(JB):		0.00	
Kurtosis:	310.936	Cond. No.		2.21e+04	
=====					

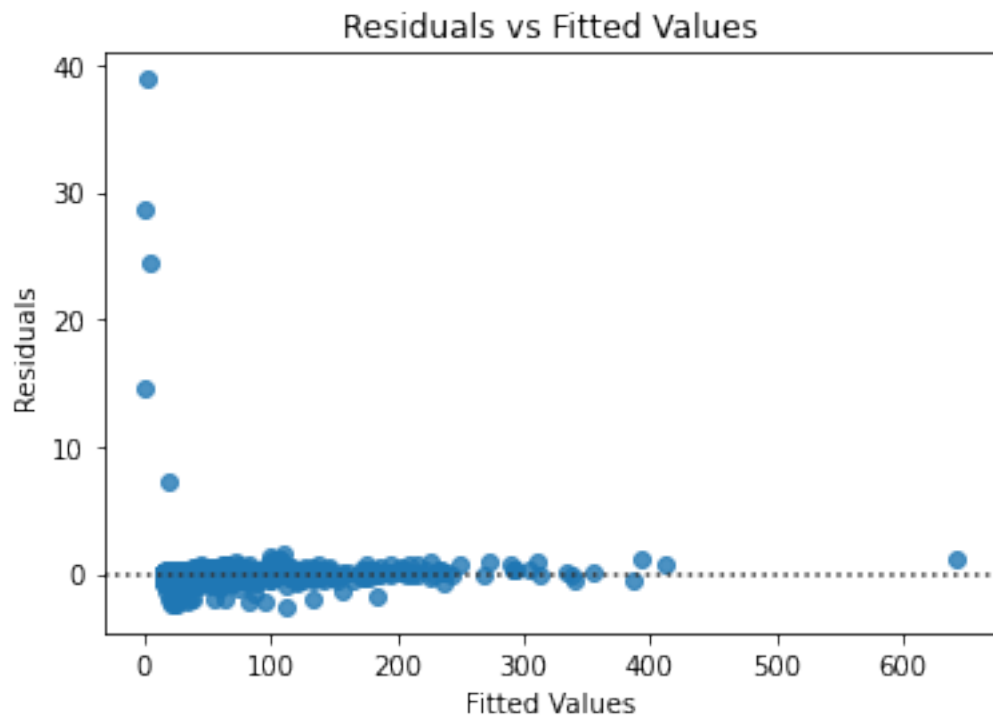
Warnings:

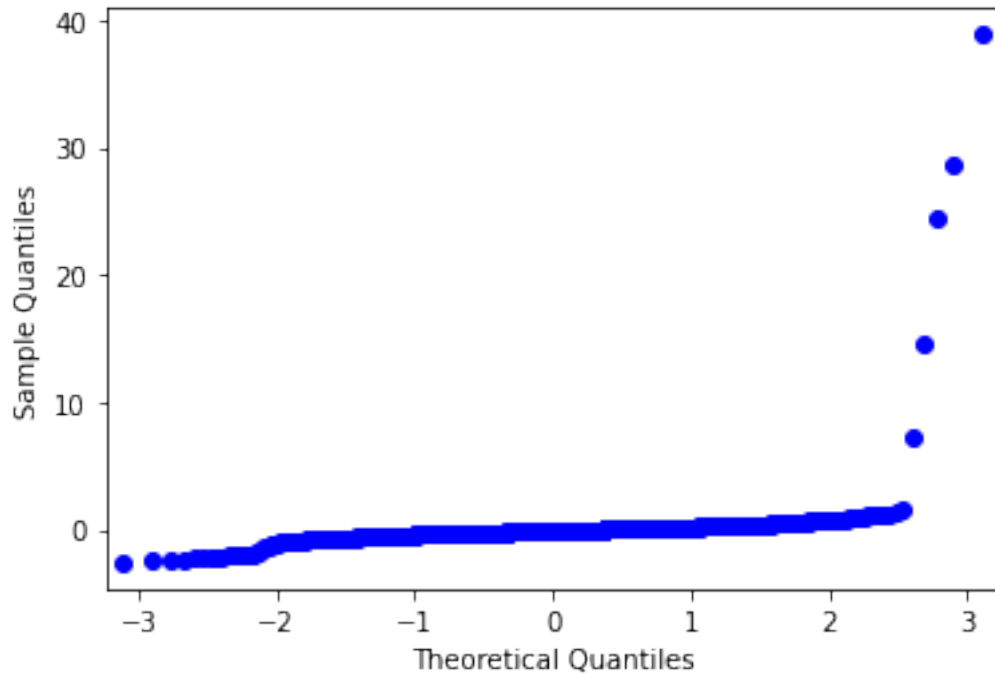
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, $2.21e+04$. This might indicate that there are strong multicollinearity or other numerical problems.

```
"""
```

3. Perform model diagnostics. What do you observe? Explain.





Observations:

- There are outliers.
- The model does not satisfy the linearity, constant variance and normality.

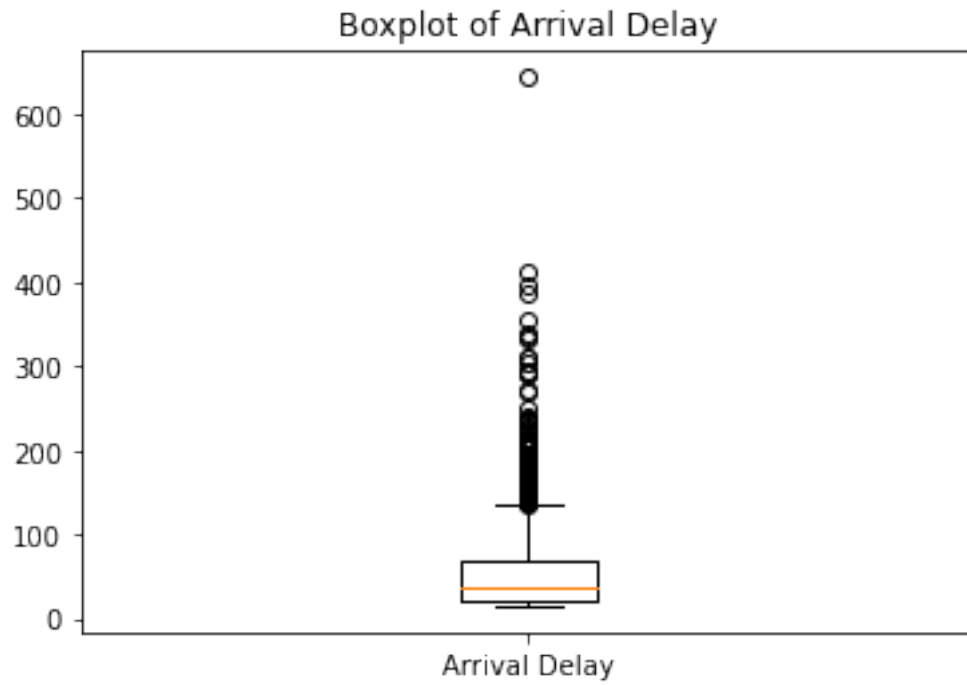
4. Provide interpretations for a few of the coefficients, and comment on whether they make sense.

Interpretations:

- Every one minute increase in airline delay, results in 0.98 minute increase in arrival (arrival delay).
- There is an impact of 'late aircraft delay', 'air system delay', 'weather delay' and 'departure delay' on aircraft arrivals (arrival delay).
- There is no effect of day of the week on arrivals. This is evident from the high p-values.
- For every one minute increase in departure delay, arrival delay increases by 0.018 minutes.

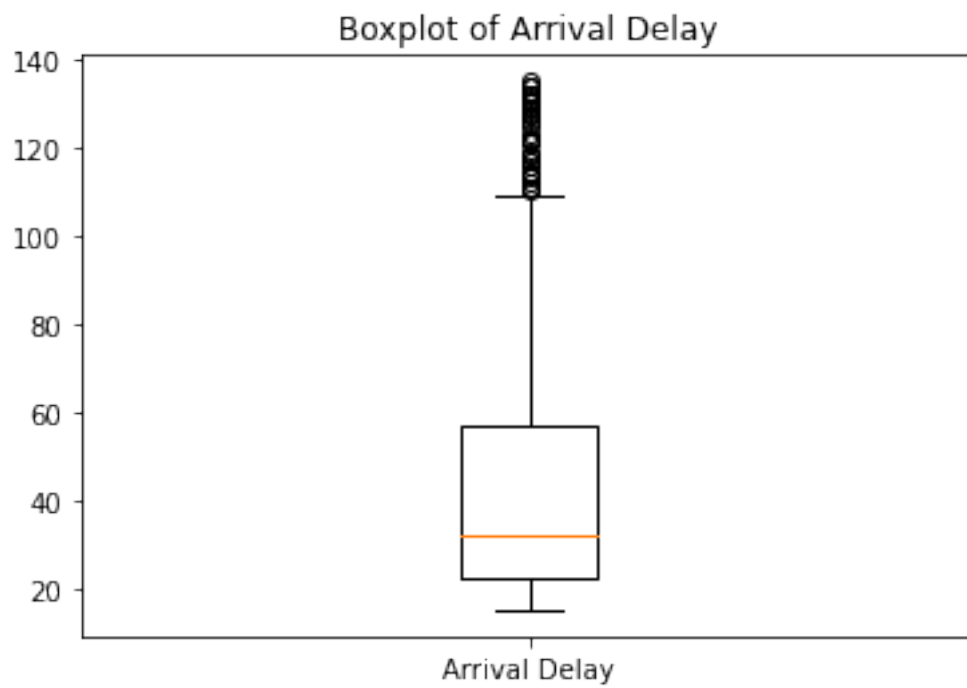
Subpart 2 If you have done the above steps correctly, you will notice a lot of things "doesn't seem right". We will try to fix a couple of these things here.

1. **Removing outliers:** first is to remove outliers. Using the boxplot method, remove the outliers in the ARRIVAL_DELAY variable.



45.25

[68]: 986



2. Refit the linear regression model, but now with $\log(\text{ARRIVAL_DELAY})$ as your response. Also, remove the nonsignificant predictors from the previous model (with p-values larger than 0.05) and the AIRLINE variable. (Remember that when removing nonsignificant predictors one can only eliminate one variable per step.)

[70]:

	YEAR	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	\
7	2015	1	1	4	OO	5354	N472CA	
9	2015	1	1	4	UA	1062	N73291	
19	2015	1	2	5	US	2065	N534UW	
21	2015	1	2	5	OO	5211	N943SW	
22	2015	1	2	5	HA	335	N477HA	

	ORIGIN_AIRPORT	DESTINATION_AIRPORT	SCHEDULED_DEPARTURE	DEPARTURE_TIME	\
7	ORD	MBS	1317	1349.0	
9	DCA	DEN	1603	1603.0	
19	CLT	IAH	1120	1128.0	
21	IDA	DEN	1338	1428.0	
22	OGG	HNL	1503	1644.0	

	DEPARTURE_DELAY	TAXI_OUT	WHEELS_OFF	SCHEDULED_TIME	ELAPSED_TIME	\
7	32.0	27.0	1416.0	66	70.0	
9	0.0	12.0	1615.0	249	272.0	
19	8.0	11.0	1139.0	163	176.0	
21	50.0	31.0	1459.0	91	122.0	
22	101.0	10.0	1654.0	37	50.0	

	AIR_TIME	DISTANCE	WHEELS_ON	TAXI_IN	SCHEDULED_ARRIVAL	ARRIVAL_TIME	\
7	39.0	222	1555.0	4.0	1523	1559.0	
9	248.0	1476	1823.0	12.0	1812	1835.0	
19	154.0	912	1313.0	11.0	1303	1324.0	
21	64.0	458	1603.0	27.0	1509	1630.0	
22	23.0	100	1717.0	17.0	1540	1734.0	

	ARRIVAL_DELAY	DIVERTED	CANCELLED	CANCELLATION_REASON	AIR_SYSTEM_DELAY	\
7	36.0	0	0	NaN	4.0	
9	23.0	0	0	NaN	23.0	
19	21.0	0	0	NaN	13.0	
21	81.0	0	0	NaN	31.0	
22	114.0	0	0	NaN	0.0	

	SECURITY_DELAY	AIRLINE_DELAY	LATE_AIRCRAFT_DELAY	WEATHER_DELAY	AS	B6	\
7	0.0	11.0	21.0	0.0	0	0	
9	0.0	0.0	0.0	0.0	0	0	
19	0.0	8.0	0.0	0.0	0	0	
21	0.0	0.0	50.0	0.0	0	0	

22 0.0 25.0 89.0 0.0 0 0

	DL	EV	F9	HA	MQ	NK	OO	UA	US	VX	WN	DAY_2	DAY_3	DAY_4	DAY_5	\
7	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	
9	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	
19	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	
21	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	
22	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	

	DAY_6	DAY_7	LOG_ARRIVAL_DELAY
7	0	0	3.610918
9	0	0	3.178054
19	0	0	3.091042
21	0	0	4.406719
22	0	0	4.744932

[71]: <class 'statsmodels.iolib.summary.Summary'>

"""

OLS Regression Results

```

=====
Dep. Variable:          LOG_ARRIVAL_DELAY    R-squared:                0.920
Model:                  OLS                  Adj. R-squared:           0.920
Method:                 Least Squares        F-statistic:              2269.
Date:                  Sun, 24 Oct 2021      Prob (F-statistic):       0.00
Time:                  15:54:58              Log-Likelihood:           391.96
No. Observations:      986                  AIC:                     -771.9
Df Residuals:          980                  BIC:                     -742.6
Df Model:              5
Covariance Type:       nonrobust
=====
=====
               coef      std err          t      P>|t|      [0.025
0.975]
-----
const              2.7613      0.010    287.307      0.000      2.742
2.780
LATE_AIRCRAFT_DELAY  0.0186      0.000    41.198      0.000      0.018
0.020
AIRLINE_DELAY       0.0188      0.000    40.344      0.000      0.018
0.020
AIR_SYSTEM_DELAY    0.0198      0.000    60.354      0.000      0.019
0.020
WEATHER_DELAY       0.0190      0.001    28.730      0.000      0.018
0.020
DEPARTURE_DELAY     0.0008      0.000     2.283      0.023      0.000
0.002

```

```

=====
Omnibus:                37.990    Durbin-Watson:                1.914
Prob(Omnibus):           0.000    Jarque-Bera (JB):            56.372
Skew:                   -0.344    Prob(JB):                    5.74e-13
Kurtosis:                3.948    Cond. No.                    108.
=====

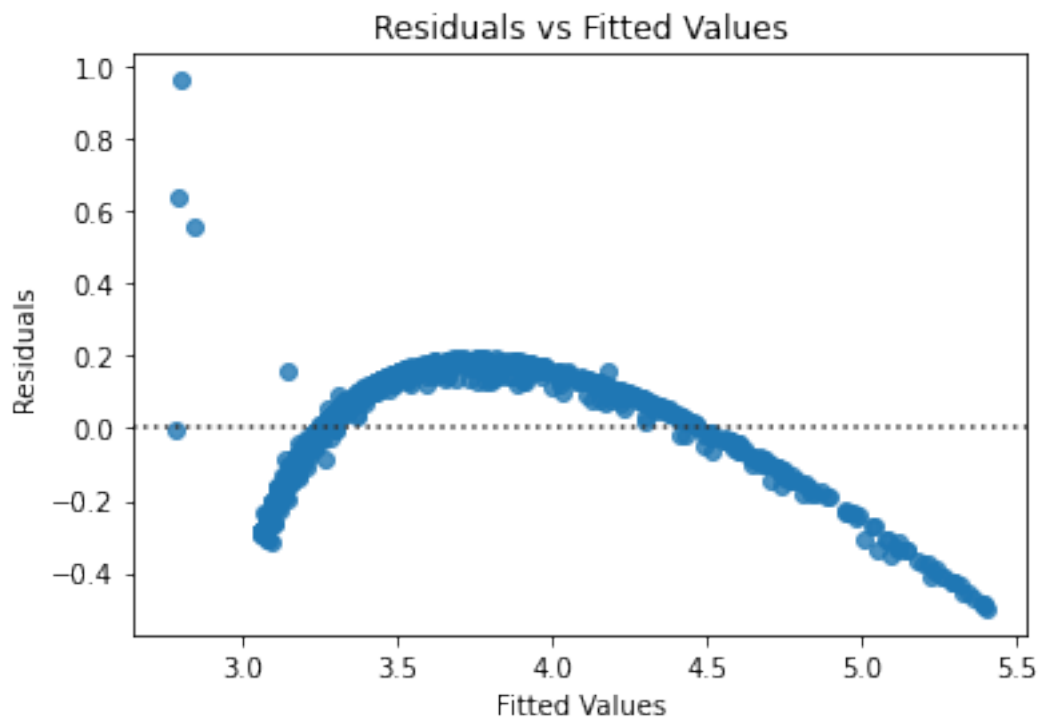
```

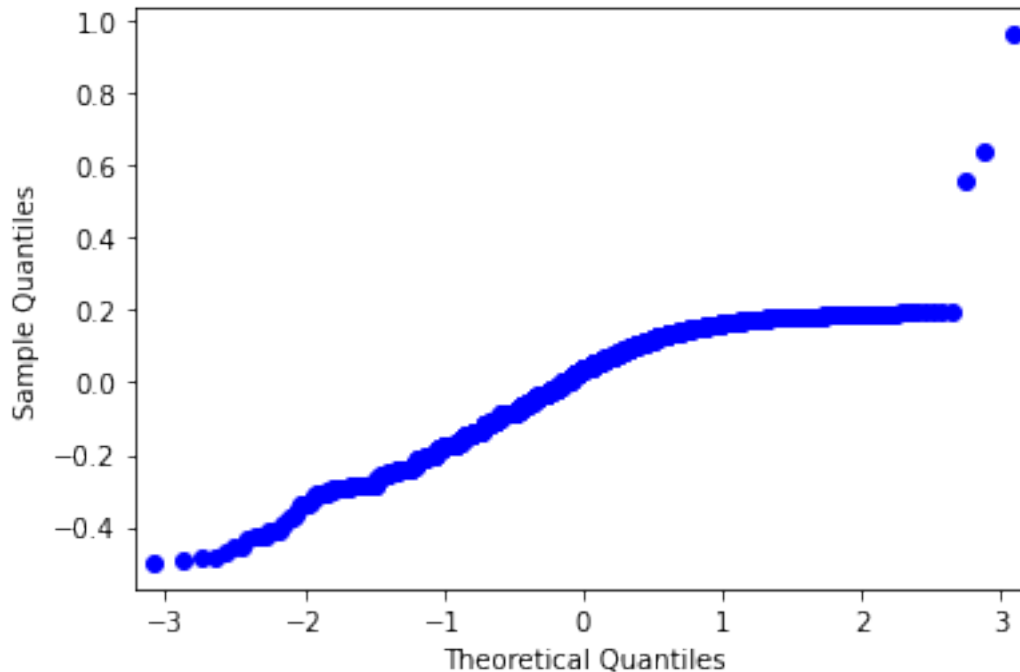
Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

""

3. Perform model diagnostics. Did anything improve?





Observations:

- The model needs improvement.
- The model does not satisfy the constraints of linearity, constant variance and normality.

4. Provide interpretations to a few of the coefficients. Do you think they make sense?

Interpretations:

- Weather delay has an impact on arrival delays. For every one minute increase in weather delay there is an increase of 0.0190 minutes in arrival delay.
- For every one minute increase in air system delay, there is an increase of 0.0198 minutes in arrival delay.

5. Obviously there's still a lot that needs to be done. Provide a few suggestions on how we can further improve the model fit (you don't need to implement them).

Suggestions:

- We can add interaction among the independent variables in the model.
- Using Tukey's ladder transformation, we may increase or decrease the power of independent variables and use them in the model.