

flight_delay_exploration

May 16, 2020

1 Airlines Delay and Cancellation Analysis

In 2008 more than 10 million flights were made in the United States, not all of these flights depart on time, what happens to these flights? Are they diverted or canceled? What are the causes main cancellation of these flights? We have information on 1,936,757 flights that present delays and 30 variables that describe the delay time in departure, arrival or during the flight, the causes of the flight and the day of the year when the delay occurred. We'll start by reading in and lightly cleaning the data. Then we'll do some data exploration that gives us a clearer idea of what is in this dataset. Once we feel more comfortable with the dataset.

1. **Year** 2008
2. **Month** 1-12
3. **DayofMonth** 1-31
4. **DayOfWeek** 1 (Monday) - 7 (Sunday)
5. **DepTime** actual departure time (local, hhmm)
6. **CRSDepTime** scheduled departure time (local, hhmm)
7. **ArrTime** actual arrival time (local, hhmm)
8. **CRSArrTime** scheduled arrival time (local, hhmm)
9. **UniqueCarrier** unique carrier code
10. **FlightNum** flight number
11. **TailNum** plane tail number: aircraft registration, unique aircraft identifier
12. **ActualElapsedTime** in minutes
13. **CRSElapsedTime** in minutes
14. **AirTime** in minutes
15. **ArrDelay** arrival delay, in minutes
16. **DepDelay** departure delay, in minutes
17. **Origin** origin IATA airport code
18. **Dest** destination IATA airport code
19. **Distance** in miles
20. **TaxiIn** taxi in time, in minutes
21. **TaxiOut** taxi out time in minutes
22. **Cancelled** *was the flight cancelled
23. **CancellationCode** reason for cancellation (A = carrier, B = weather, C = NAS, D = security)
24. **Diverted** 1 = yes, 0 = no
25. **CarrierDelay** in minutes: Carrier delay is within the control of the air carrier.
26. **WeatherDelay** in minutes: Weather delay is caused by extreme or hazardous weather conditions.

27. **NASDelay** in minutes: Delay that is within the control of the National Airspace System (NAS).
28. **SecurityDelay** in minutes: Security delay is caused by evacuation of a terminal or concourse, re-boarding of aircraft because of security breach.
29. **LateAircraftDelay** in minutes: Arrival delay at an airport due to the late arrival of the same aircraft at a previous airport.

1.1 Understanding and reading the the data

```
[52]: #import needed libraries & float format definition
```

```
import unicodedata
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
from scipy import stats
from scipy.stats import norm

pd.options.display.float_format = '{:.0f}'.format
```

```
[53]: # Reading and showing head data
flights = pd.read_csv("DelayedFlights.csv")
flights.head()
```

	Unnamed: 0	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	\
0	0	2008	1	3	4	2003	1955	
1	1	2008	1	3	4	754	735	
2	2	2008	1	3	4	628	620	
3	4	2008	1	3	4	1829	1755	
4	5	2008	1	3	4	1940	1915	

	ArrTime	CRSArrTime	UniqueCarrier	\	TaxiIn	TaxiOut	Cancelled	\
0	2211	2225	WN	\	4	8	0	
1	1002	1000	WN	\	5	10	0	
2	804	750	WN	\	3	17	0	
3	1959	1925	WN	\	3	10	0	
4	2121	2110	WN	\	4	10	0	

	CancellationCode	Diverted	CarrierDelay	WeatherDelay	NASDelay	\
0	N	0	nan	nan	nan	
1	N	0	nan	nan	nan	
2	N	0	nan	nan	nan	
3	N	0	2	0	0	
4	N	0	nan	nan	nan	

```

SecurityDelay  LateAircraftDelay
0             nan                 nan
1             nan                 nan
2             nan                 nan
3              0                  32
4             nan                 nan

```

[5 rows x 30 columns]

1.1.1 We can see how some of the 29 variables in the dataset present multicollinearity, in other words, can be linearly predicted from the others. In order to have a better analysis and work with a lighter dataset, we are going to delete some of those unwanted variables and create new ones.

1.1.2 We can also make the following observations:

1. Only when Arrival Delay is longer than 15 minutes there's data about what caused the delay. Arrival Delay is the sum of CarrierDelay, WeatherDelay, NASDelay and LateAircraftDelay. In cases of cancelation or diversion there's no data related to delay causes.
2. More often than not, airports and carriers allocate a CRSElapsedTime higher than the actual time spent in the Taxi In + Taxi out + Airtime operations (Actual Elapsed Time). This is the reason why, when planes take off on time, landing usually takes place before the expected time! It also allows to absorb delay by late aircraft down the lane of chained flights.

```
[68]: # creating new variables and renaming
flights['DepDate'] = pd.to_datetime(flights.Year*10000+flights.
                                     Month*100+flights.DayofMonth,format='%Y%m%d')

#Status represents whether the flight was on time (0), slightly delayed (1), or
#highly delayed (2), diverted (3), or cancelled (4)
for dataset in flights:
    flights.loc[flights['ArrDelay'] <= 15, 'Status'] = 0
    flights.loc[flights['ArrDelay'] >= 15, 'Status'] = 1
    flights.loc[flights['ArrDelay'] >= 60, 'Status'] = 2
    flights.loc[flights['Diverted'] == 1, 'Status'] = 3
    flights.loc[flights['Cancelled'] == 1, 'Status'] = 4

#Cancellation cause
flights.loc[flights["CancellationCode"] == "A", 'CancellationCode'] = "0"
flights.loc[flights["CancellationCode"] == "B", 'CancellationCode'] = "1"
flights.loc[flights["CancellationCode"] == "C", 'CancellationCode'] = "2"
```

1.2 Exploratory Data analysis

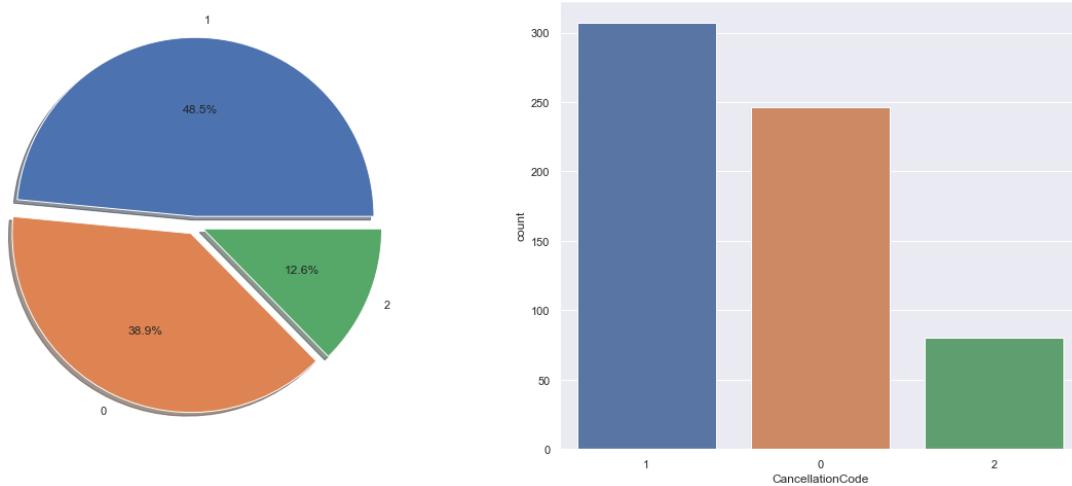
1.2.1 In 2008, a whooping 64,4% of domestic flights in the US were delayed by more than 15 minutes. 35,8% of them (or 23,1% of total flights) had delays of more than one hour! Another different interpretation is that 76,5% of flights have delay of one hour or less.

1.2.2 On the other hand, just a 0,03% of flights were cancelled and 0,4% were diverted.

1.3 Cancelled flights

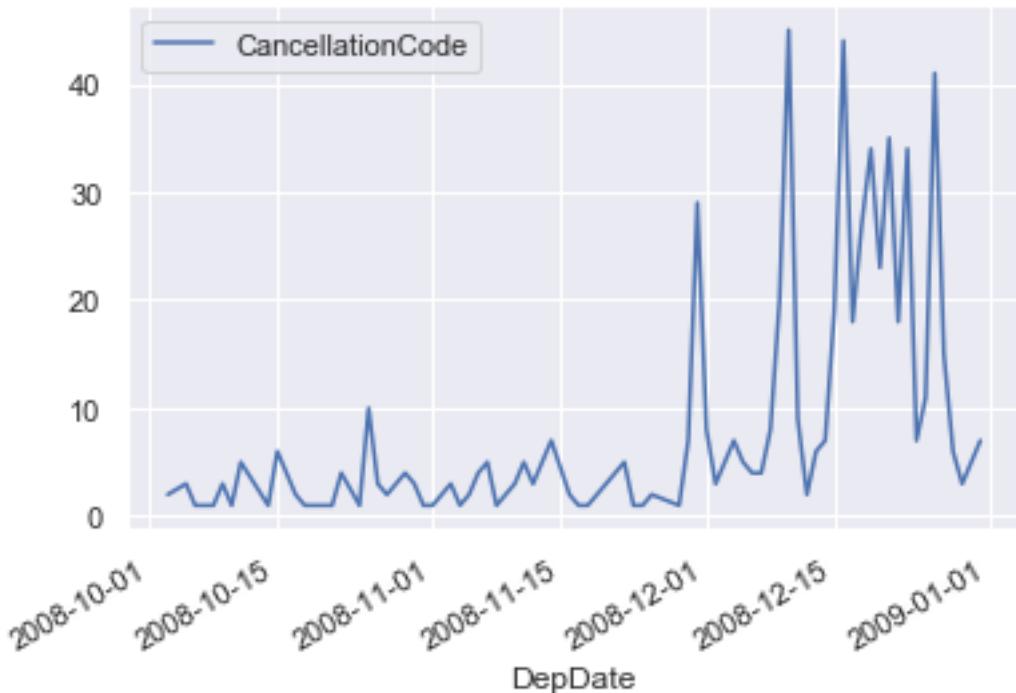
```
[56]: CancFlights = flights[(flights.Status == 4)]
colors = ['#ffff99','#6693ff','#99ff99','#fccc99']
f,ax=plt.subplots(1,2,figsize=(20,8))
CancFlights['CancellationCode'].value_counts().plot.pie(explode=[0.05,0.05,0.
    ↪05,], autopct='%.1f%%',ax=ax[0],shadow=True)
ax[0].set_ylabel('')
sns.countplot('CancellationCode', order = CancFlights['CancellationCode'].
    ↪value_counts().index, data=CancFlights, ax=ax[1])
plt.show()

print('0 = carrier, 1 = weather, 2 = NAS')
```



0 = carrier, 1 = weather, 2 = NAS

```
[57]: CancFlights[['DepDate','CancellationCode']].groupby(['DepDate']).count().plot()
plt.show()
```



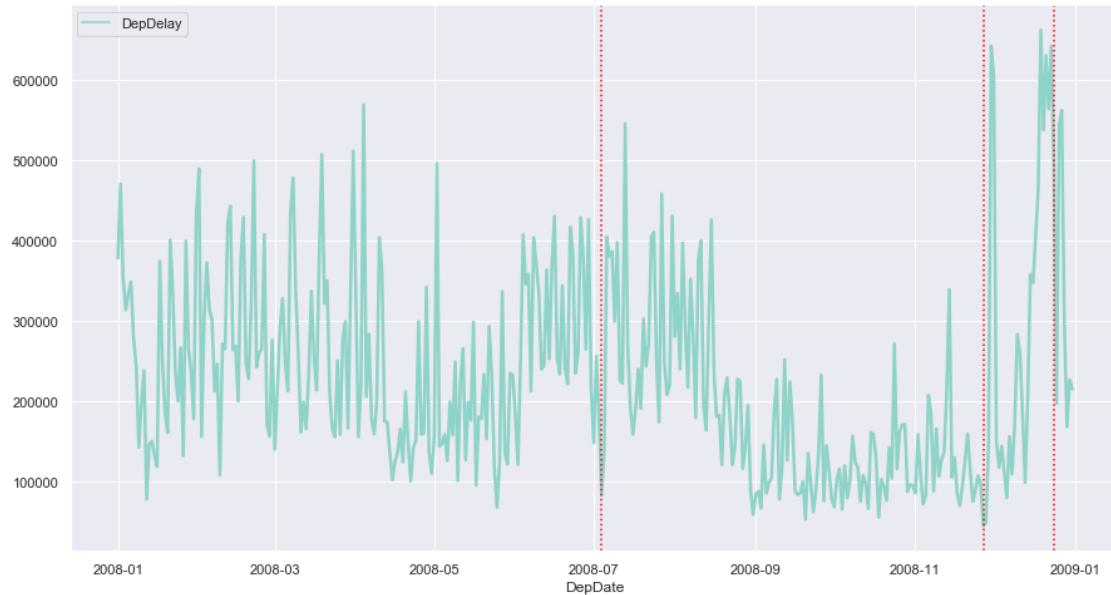
- 1.3.1 During 2008, there were only cancellations in the last three months of the year (from October to December). Doing a bit of research we find that 2008 winter was unusual, especially in December, with coast-to-coast severe winter weather, including one low pressure system from December 9-12 that brought snow to Houston and New Orleans, severe storms and flooding to other parts of the South, and an ice storm that left more than 1.27 million homes and business without power in the Northeast.
- 1.3.2 The bad weather might actually be the reason behind all the cancellations, since for rest of the year there are no registered cancellations at all. The compounded effect of the flights cancelled affect other programmed flights down the lane.

1.4 Delayed flights

1.4.1 Delay during Holidays

```
[58]: date_delay = flights[['DepDate', 'DepDelay']]
date_delay = date_delay.groupby(by='DepDate').sum()
date_delay.head()
plt.figure(figsize=(15,8))
sns.lineplot(data=date_delay, palette="Set3", linewidth=2.5)
plt.axvline(dt.datetime(2008, 7,4), color='red', linestyle=':') #Year, month, ↵day
plt.axvline(dt.datetime(2008, 12,24), color='red', linestyle=':')
plt.axvline(dt.datetime(2008, 11,27), color='red', linestyle=':')
```

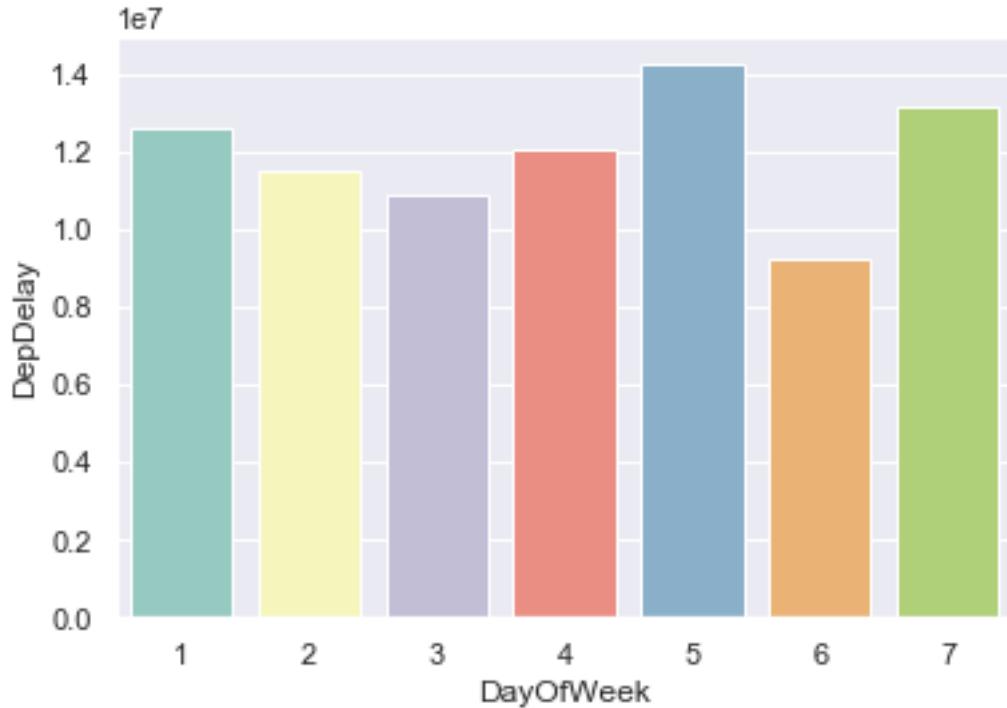
```
plt.show()
```



The days of the main festivities: July 4, Thanksgiving and Christmas present the lowest levels of flight delay time, due to the low demand for them, but the following or previous days present the highest levels of delay. of flights due to the increase in operations generated by people trying to fly home

1.4.2 Delays during the week

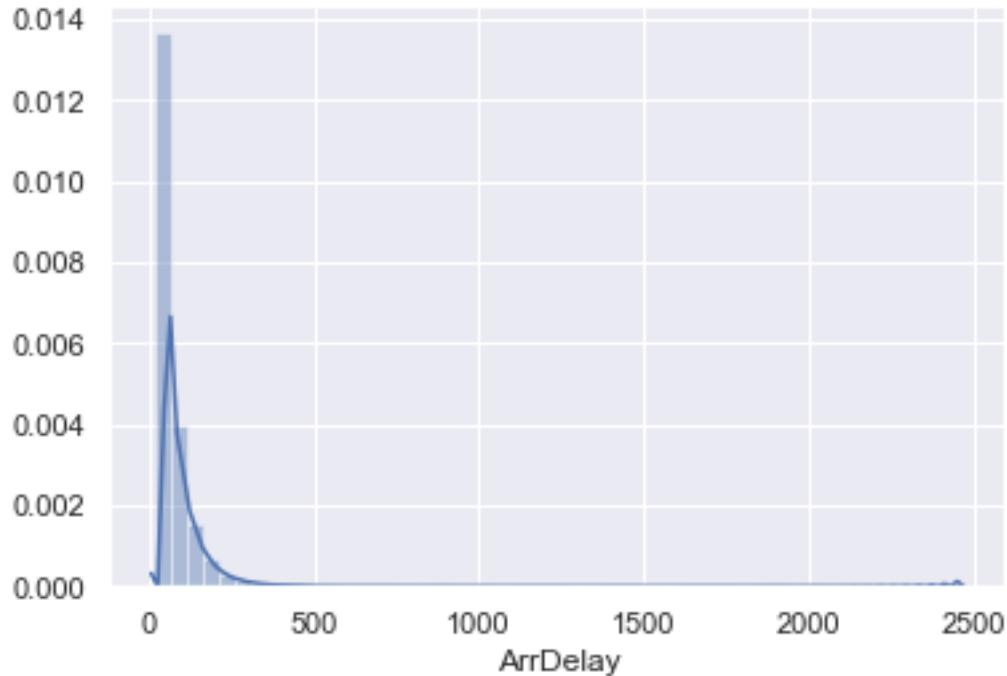
```
[59]: day_delay = flights[['DayOfWeek', 'DepDelay']]  
#type(date_delay)  
day_delay = day_delay.groupby(by='DayOfWeek').sum()  
day_delay=day_delay.reset_index(drop=False)  
day_delay.head(7)  
sns.barplot(x="DayOfWeek", y="DepDelay", data=day_delay, palette="Set3")  
plt.show()
```



Friday is the day of the week with the longest delay time and Saturday is the day with the least delay.

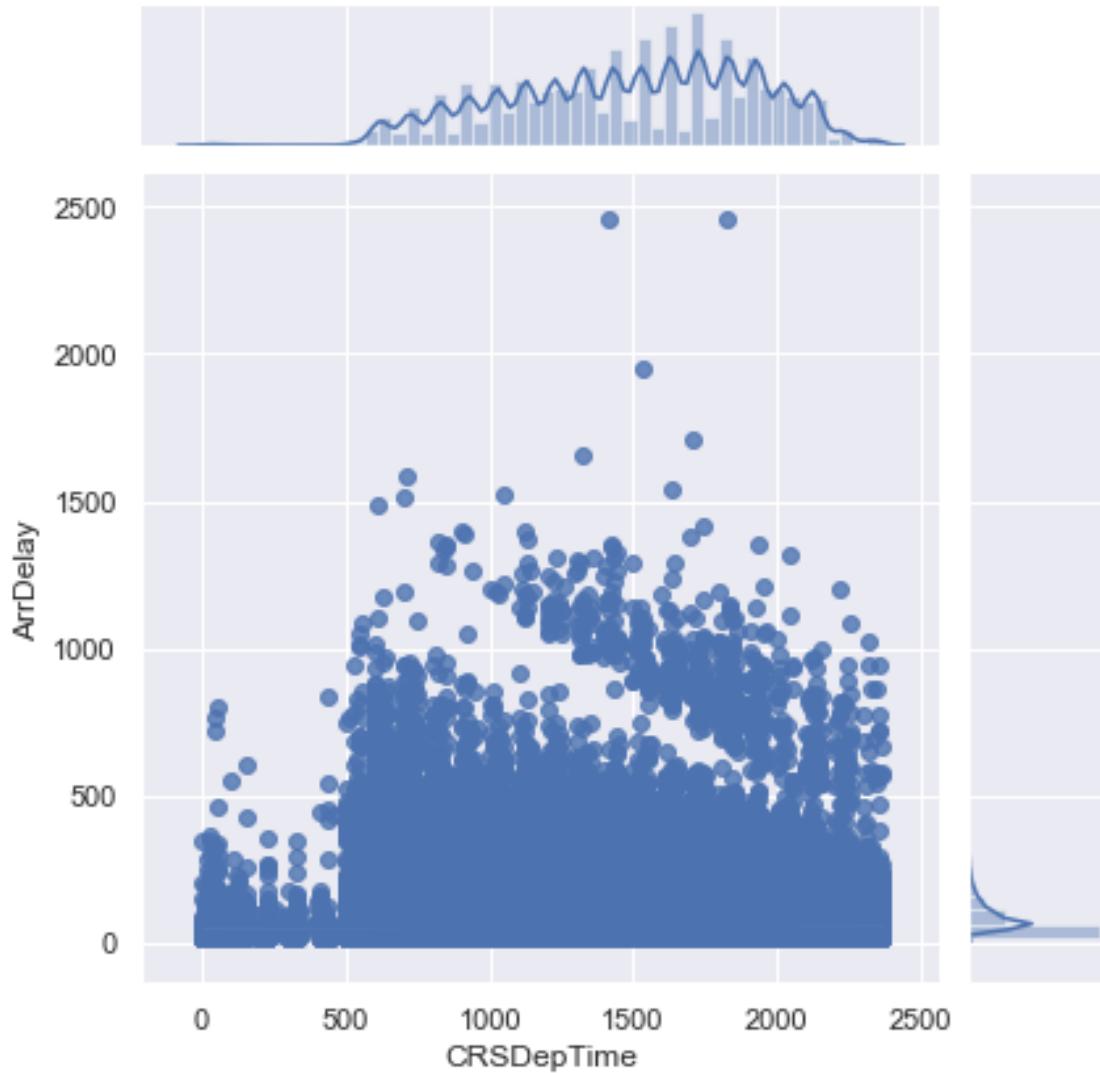
```
[60]: Delayedflights = flights[(flights.Status >= 1) &(flights.Status < 3)]
```

```
[61]: #histogram  
sns.distplot(Delayedflights['ArrDelay'])  
plt.show()
```



1.4.3 It can be seen on the histogram and by the skewness and kurtosis indexes, that delays are mostly located on the left side of the graph, with a long tail to the right. The majority of delays are short, and the longer delays, while unusual, are more heavily loaded in time.

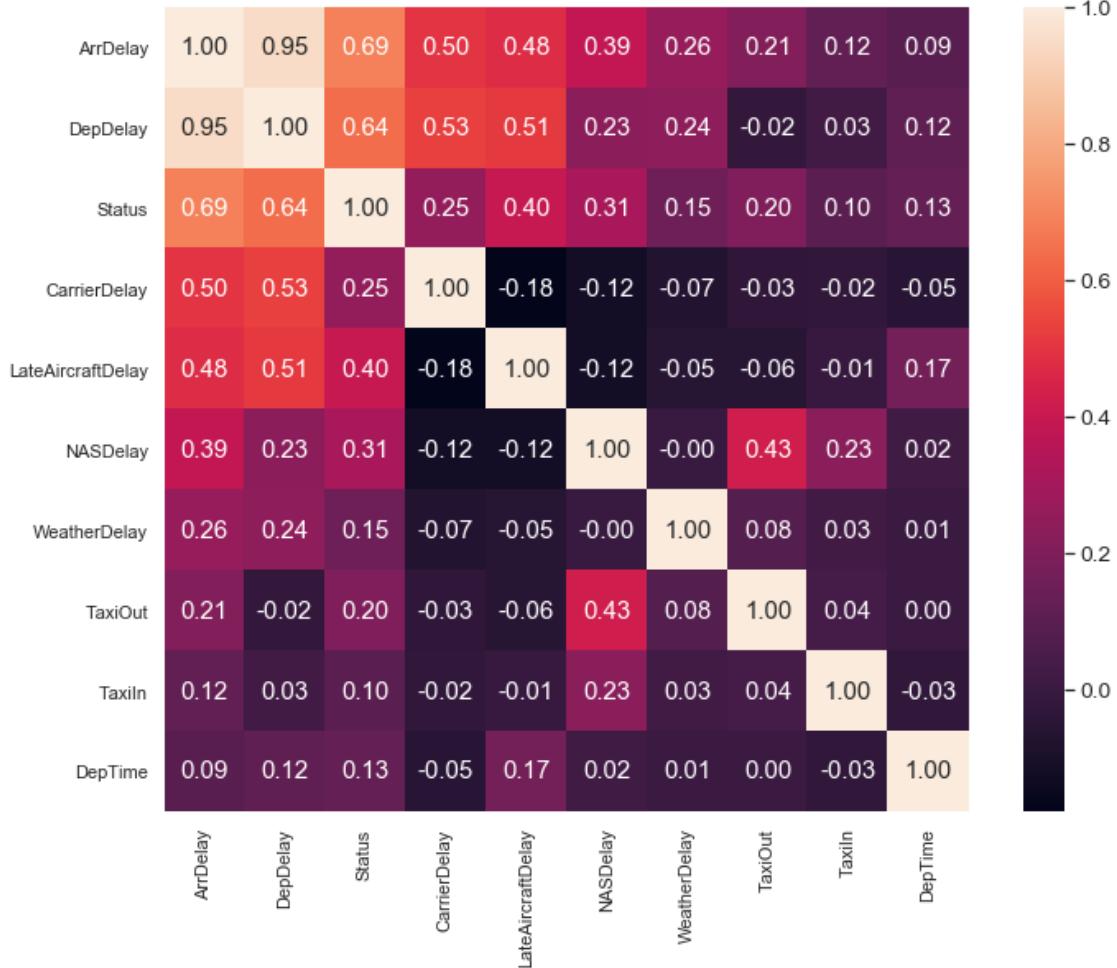
```
[62]: sns.jointplot(x='CRSDepTime',y='ArrDelay',data=Delayedflights,kind='reg',  
                   color='b',fit_reg = True)  
plt.show()
```



- 1.4.4 Delays focused on February, June and December, with a peak on average delays on July 2008.
- 1.4.5 Regarding the time of the day the take off was programmed, it can be seen in the higher part of the scatterplot how the delays are concentrated in an hourly manner, focused on the hour. As the day goes on, there are more and more delays, but as it's shown in the center of the scatterplot, the delayed flights get divided into two groups: one with longer delays and other with shorter. One likely interpretation is that the delays generated by previous flights either increase or decrease in each following trip.

```
[63]: delcorrmat = Delayedflights.corr()

k = 10 #number of variables for heatmap
f, ax = plt.subplots(figsize=(12, 9))
cols = delcorrmat.nlargest(k, 'ArrDelay')['ArrDelay'].index
cm = np.corrcoef(Delayedflights[cols].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', ▾
    ↪annot_kws={'size': 15}, yticklabels=cols.values, xticklabels=cols.values)
plt.show()
```

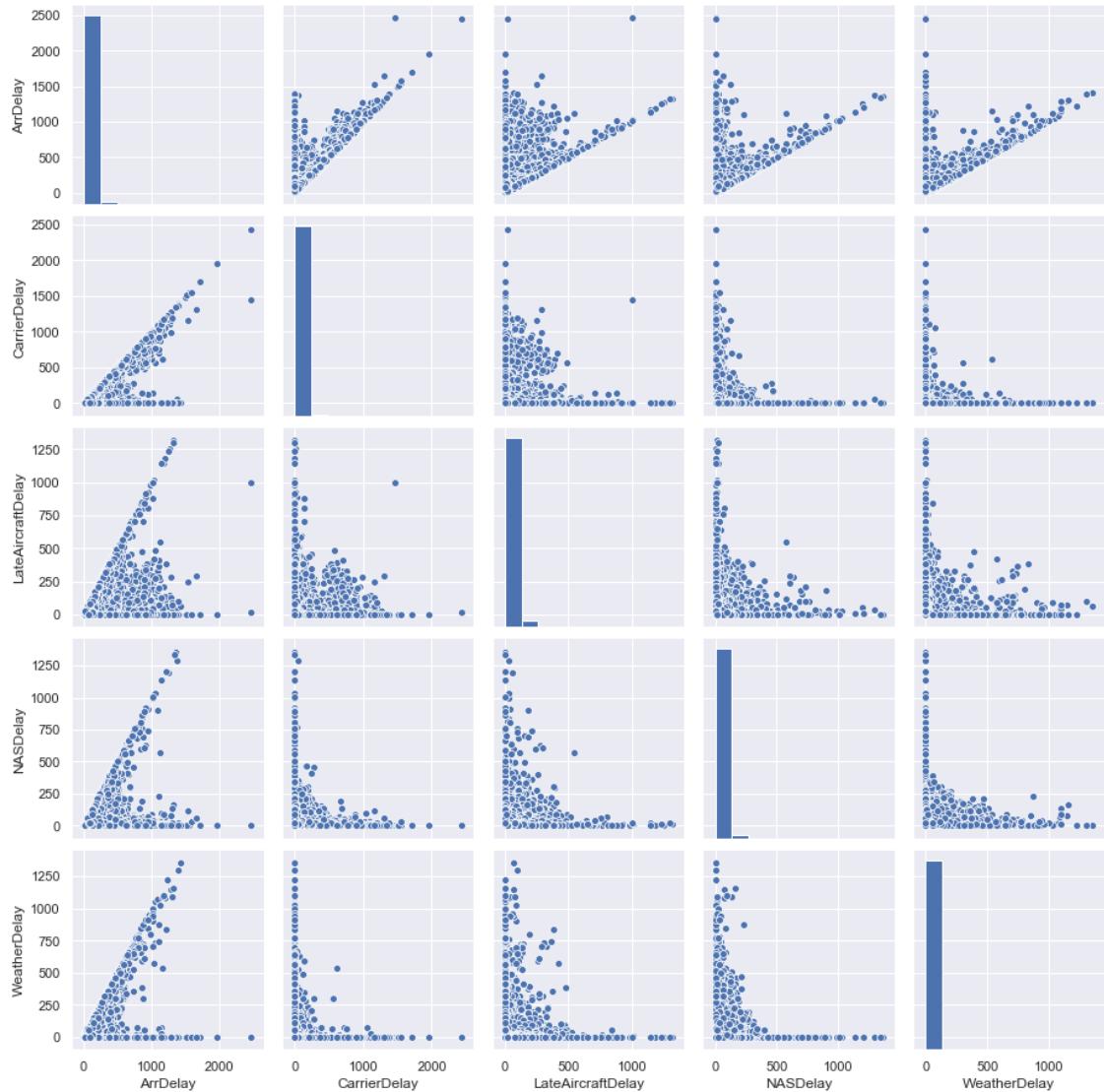


1.4.6 The correlation matrix identifies three main variables for delays: Late Aircraft Delay, Carrier Delay and NAS Delay. The graph corroborates this assumption, showing how those three variables create most of delays during the year. The variable Status can't be taken into account since it has been created 'ad hoc' and by its own definition has a high correlation.

```
[64]: #scatterplot
sns.set()
cols = ['ArrDelay', 'CarrierDelay', 'LateAircraftDelay', 'NASDelay', ↴
        'WeatherDelay']
sns.pairplot(Delayedflights[cols], size = 2.5)
plt.show()
```

```
C:\Users\Pranav\anaconda3\lib\site-packages\seaborn\axisgrid.py:2079:
UserWarning: The `size` parameter has been renamed to `height`; please update
your code.

warnings.warn(msg, UserWarning)
```



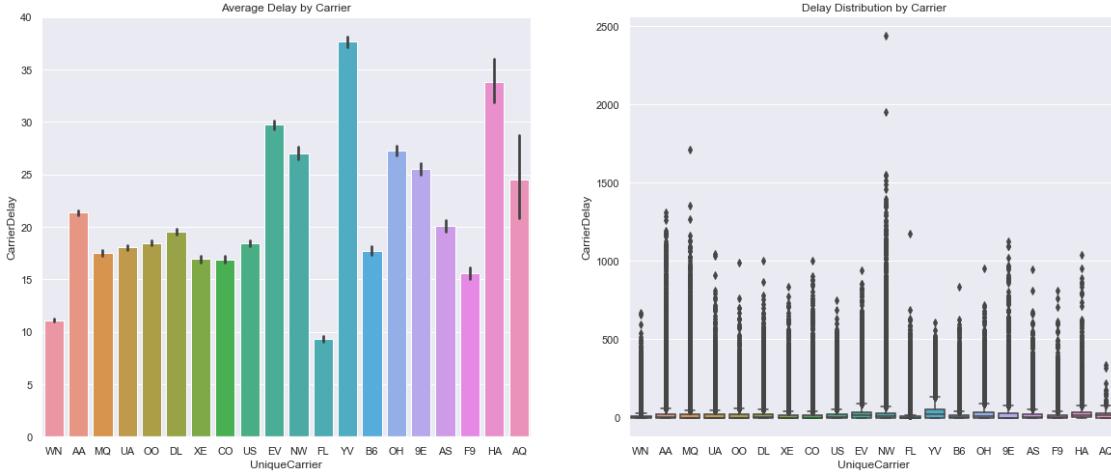
1.5 Late Aircraft Delay

- 1.5.1 Late Aircraft Delay seems to be the most important variable, not only due to its longer wait periods, but it's affected by the others due to the ripple effect and delay propagation. Its distribution is almost parallel to NAS Delay, and seems to be the compounded effect of the other delays minus the delay reduction from the allotted Elapsed time > Actual Elapsed Time in the flight operations.
- 1.5.2 However, analyzing the scatterplot, it doesn't seem to be a significant correlation between the types of delay themselves. A more in depth analysis, following the exact routes of the aircrafts and their connections and subsequent flights could help identifying the exact root cause to each delay, but that is not within the scope of this analysis.

1.6 Carrier Delays

```
[65]: f,ax=plt.subplots(1,2,figsize=(20,8))
sns.barplot('UniqueCarrier','CarrierDelay', data=Delayedflights,ax=ax[0],order=['WN', 'AA', 'MQ', 'UA', 'OO', 'DL', 'XE', 'CO',
→'US', 'EV', 'NW', 'FL', 'YV', 'B6', 'OH', '9E',
→ 'AS', 'F9', 'HA', 'AQ'])
ax[0].set_title('Average Delay by Carrier')
sns.boxplot('UniqueCarrier','CarrierDelay', data=Delayedflights,ax=ax[1],order=['WN', 'AA', 'MQ', 'UA', 'OO', 'DL', 'XE', 'CO',
→'US', 'EV', 'NW', 'FL', 'YV', 'B6', 'OH', '9E',
→ 'AS', 'F9', 'HA', 'AQ'])
ax[1].set_title('Delay Distribution by Carrier')
plt.close(2)
plt.show()

print(['WN: Southwest Airlines', 'AA: American Airlines', 'MQ: American Eagle',
→Airlines', 'UA: United Airlines',
'OO: Skywest Airlines', 'DL: Delta Airlines', 'XE: ExpressJet', 'CO:',
→Continental Airlines', 'US: US Airways',
'EV: Atlantic Southeast Airlines', 'NW: Northwest Airlines', 'FL: AirTran',
→Airways', 'YV: Mesa Airlines',
'B6: JetBlue Airways', 'OH: Comair', '9E: Pinnacle Airlines', 'AS: Alaska',
→Airlines', 'F9: Frontier Airlines',
'HA: Hawaiian Airlines', 'AQ: Aloha Airlines'])
```



[`'WN': Southwest Airlines', 'AA': American Airlines', 'MQ': American Eagle Airlines', 'UA': United Airlines', 'OO': Skywest Airlines', 'DL': Delta Airlines', 'XE': ExpressJet', 'CO': Continental Airlines', 'US': US Airways', 'EV': Atlantic Southeast Airlines', 'NW': Northwest Airlines', 'FL': AirTran Airways', 'YV': Mesa Airlines', 'B6': JetBlue Airways', 'OH': Comair', '9E': Pinnacle Airlines', 'AS': Alaska Airlines', 'F9': Frontier Airlines', 'HA': Hawaiian Airlines', 'AQ': Aloha Airlines'`]

- 1.6.1 4 from the top 5 companies in the domestic market (Southwest Airlines (WN), American Eagle Airlines (MQ), United Airlines (UA) and Skywest Airlines (OO) create an average delay below the mean (19 minutes). Southwest Airlines, with an outstanding 11.7 minutes per flight, the second lowest of all the carriers.
- 1.6.2 Carriers with higher average delay generation are Mesa Airlines (YV) with 37.63 minutes per flight, Hawaiian Airlines (HA) with 33.76 minutes per flight and ExpressJet (EV) with 29.70. As we go from left to right in the barplot, it can be seen how airlines with lower volume of flights tend to have a higher Carrier Delay (with the exception of AirTrans, integrated into Southwest in 2014); so it seems like size matters.
- 1.6.3 On the other hand, taking responsibility of a higher number of flights results in a higher chance of having an extreme waiting situation. Northwest, American Eagle and American Airlines registered the maximum Carrier Delay for 2008.

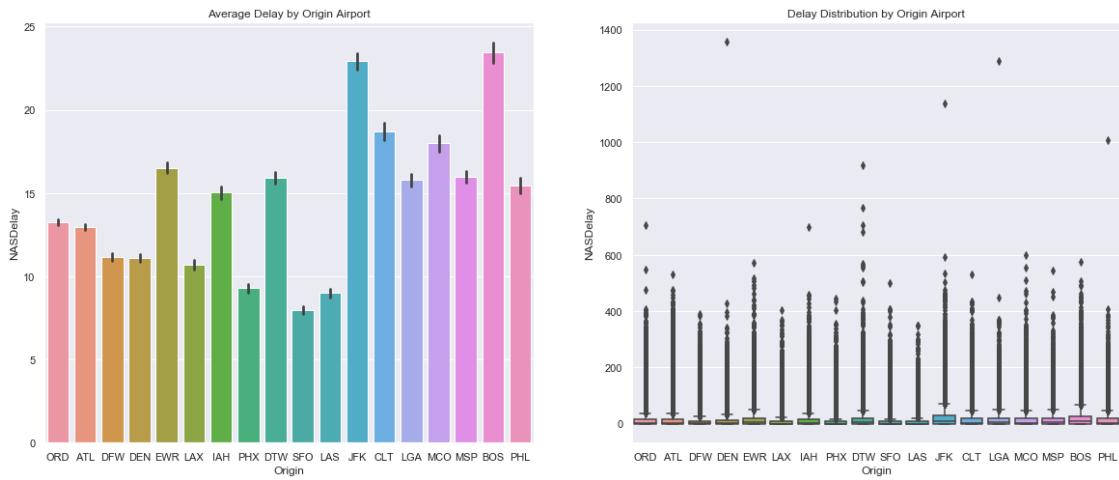
1.7 NAS Delay

```
[67]: f,ax=plt.subplots(1,2,figsize=(20,8))
sns.barplot('Origin','NASDelay', data=Top20airports,ax=ax[0], order=['ORD', 'ATL', 'DFW', 'DEN', 'EWR', 'LAX', 'IAH', 'PHX', 'DTW', 'SFO', 'LAS', 'JFK', 'CLT', 'LGA', 'MCO', 'MSP', 'BOS', 'PHL'])
ax[0].set_title('Average Delay by Origin Airport')
```

```

sns.boxplot('Origin', 'NASDelay', data=Top20airports, ax=ax[1], order=['ORD', 'ATL', 'DFW', 'DEN', 'EWR', 'LAX', 'IAH', 'PHX', 'DTW', 'SFO', 'LAS', 'JFK', 'CLT', 'LGA', 'MCO', 'MSP', 'BOS', 'PHL'])
ax[1].set_title('Delay Distribution by Origin Airport')
plt.close(2)
plt.show()

```



['ORD: Chicago', 'ATL: Atlanta', 'DFW: Dallas Fortworth', 'DEN: Denver', 'EWR: Newark', 'LAX: Los Angeles', 'IAH: Houston', 'PHX: Phoenix', 'DTW: Detroit', 'SFO: San Francisco', 'LAS: Las Vegas', 'JFK: New York', 'CLT: Charlotte', 'LGA: La Guardia (NY)', 'MCO: Orlando', 'MSP: Minneapolis', 'BOS Boston', 'PHL Philadelphia']

- 1.7.1 There seems to be a correlation between the number of flights operated and NASDelay, with the exceptions of Newark (EWR), Houston (IAH) and Detroit (DTW). From Chicago Airport (ORD) to Las Vegas (LAS) a descending average NASDelay per flight can be seen. In less busy airports (less than 30.000 flights per year), delays increase once again. This seems to entail that there are two sizes of airport, and that the size, the number of flights are correlated with the delays.
- 1.7.2 While this tendency might be true in some cases, this reasoning is flawed. The dataset is limited to domestic flights, but airports like LAX, JFK and Atlanta have a higher operations volume due to being notorious international airports, so we advise taking the conclusions with a pinch of salt.

2 The situation today

- 2.0.1 So far, we have seen causes for flight delay in 2008, but has the situation changed since then? 8 years later, in 2016, the ratio of domestic flights in the US data offers a much brighter present.
- 2.1 Making a comparison between then and now, we can see how the numbers have improved (*):
 - 2.1.1 On time: 35,2% in 2008 vs 81,42% in 2016.
 - 2.1.2 Delayed: 64,4% in 2008 vs 17,17% in 2016.
 - 2.1.3 Cancelled: 0,03% in 2008 vs 1,17% in 2016.
 - 2.1.4 Diverted: 0,4% in 2008 vs 0,24% in 2016.

(*) After searching for the reason behind this significant improvement in the last 8 years, we have compared the data offered on the BTS website for 2008 and 2016 and our dataset. The BTS ratios are based on datasets containing the averages by air carrier and origin airport, and they don't compare individual flights. Their sample consider nearly 20.000 flights. Our dataset, in comparison, contains around 2 million individual flights. #### The BTS data for 2008 is 76,04% flights on time, 21,75% delayed, 1,96% cancelled and 0,25% diverted. Taking into account these ratios, in the period between 2008 and 2016, there has been a 7% increase in the number of flights on time, an average of 0.875% each year. However, there's still a lot of room for improvement.

3 A glimpse into the future

3.0.1 While the dataset itself doesn't offer a solution to the delay issue, it's clear that delay reduction has many intertwined variables. A solution applicable to one type of delay will heavily affect the others, resulting in a compounded effect that will allow more efficient operations; benefiting passengers, airports, carriers and even the world as a whole.

3.0.2 Here are some of the solutions to be seen on the near future:

3.0.3 5.1 LateAircraft and NAS Delay

Some experts, like Michael Baiada (retired pilot and President of ATH Group), argues that the solution to NAS Delay lies within the carriers. If carriers allowed aircrafts a higher speed and fuel consumption on planes that departed late, the effect wouldn't spread along the flight chain. This would decrease the NAS Delay itself and the Late Aircraft Delay, decreasing significantly the number of planes delayed.

3.0.4 5.2 Better information efficiency

Amadeus, top GDS (Global Distribution Systems) and IT solutions provider to the travel industry identifies the approaches that Airlines, IT solutions and Big Data are taking in order to solve this issue.