Part I - (Flight Data Exploratory Data Analysis)

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Introduction

> It is bad enough to miss your date or an important appointment because your flight was delayed or, worse, cancelled. It is even worse if you had no idea that this could happen, or if this happens on a regular basis. Wouldn't it be nice to have some fair knowledge about the flight activities of carriers so that you could plan your flights well? Well, we could try and get some insights into the carriers' flight activities for 2008 from the exploratory analysis of the flight dataset below. From the analysis, we aim to get some insights into the leading factors that cause flight delays and/or cancellations.

Preliminary Wrangling

In [13]:
```
# import all packages and set plots to be embedded inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

In [14]:
```
# import data set and view the first few rows
df = pd.read_csv('2008.csv')
df.head()
```

Out[14]:

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime	UniqueCarrier	F
0	2008	1	3	4	1343.0	1325	1451.0	1435	WN	
1	2008	1	3	4	1125.0	1120	1247.0	1245	WN	
2	2008	1	3	4	2009.0	2015	2136.0	2140	WN	
3	2008	1	3	4	903.0	855	1203.0	1205	WN	
4	2008	1	3	4	1423.0	1400	1726.0	1710	WN	

5 rows × 29 columns

In [10]:
```
# dmension of the data
df.shape
```

Out[10]:
```
(2389217, 29)
```

In [12]:
```
#Get the columns of the data
df.columns
```

Out[12]:
```
Index(['Year', 'Month', 'DayofMonth', 'DayOfWeek', 'DepTime', 'CRSDepTime',
       'ArrTime', 'CRSArrTime', 'UniqueCarrier', 'FlightNum', 'TailNum',
       'ActualElapsedTime', 'CRSElapsedTime', 'AirTime', 'ArrDelay',
       'DepDelay', 'Origin', 'Dest', 'Distance', 'TaxiIn', 'TaxiOut',
```

```
 'Cancelled', 'CancellationCode', 'Diverted', 'CarrierDelay',
 'WeatherDelay', 'NASDelay', 'SecurityDelay', 'LateAircraftDelay'],
dtype='object')
```

Structure of the Dataset

> The dataset is fairly large with almost 7.5 million rows and 29 features (columns).

- `Year` : The year for which the data about flights was collected. This data recorded in 2008
- `Month` : The month in the year in which the flight was recorded. 1 represents January, 2 represents February in that order
- `DayofMonth` : The day of the month in which the flight was recorded
- `DayOfWeek` : Day of the week in which the flight was recorded. 1 represents Monday, and 7 represents Sunday
- `DepTime` : The departure time of the flight
- `CRSDepTime` : 'The scheduled departure time of the flight
- `ArrTime` : The actual arrival time of the flight
- `CRSArrTime` : The scheduled arrival time time of the flight
- `UniqueCarrier` : The unique code of the carrier
- `FlightNum` : The flight number
- `TailNum` : The tail number of the aircraft
- `ActualElapsedTime` : The actual elapsed time of the flight
- `CRSElapsedTime` : The scheduled elapsed time of the flight
- `AirTime` : The recorded airtime of the flight
- `ArrDelay` : The recorded arrival delay of the flight
- `DepDelay` : The flight delay time
- `Origin` : The IATA code of the flight orgin
- `Dest` : The IATA code of the flight destination
- `Distance` : Flight distance, measured in miles
- `TaxiIn` : The recorded time for the flight to taxi into the runway
- `TaxiOut` : The recorded time for the flight to taxi out of the runway
- `Cancelled` : Whether the flight was cancelled (0 = No, 1 = Yes)
- `CancellationCode` : Flight cancellation reason (A = carrier, B = weather, C = NAS, D = security)
- `Diverted` : Whether the flight was diverted (0 = No, 1 = Yes)
- `CarrierDelay` : Flight delay caused by carrier
- `WeatherDelay` : Flight delay caused by weather conditions
- `NASDelay` : Flight delay caused by NAS
- `SecurityDelay` : Flight delay caused by security concerns
- `LateAircraftDelay` : Flight delays caused by late arrival of the aircraft

Features of interest in the dataset

> The `UniqueCarrier` variable is a major feature of interest for this exploration.

What features in the dataset do you think will help support your investigation into your feature(s) of interest?

> The variables Month, DayOfMonth, DayOfWeek, Cancelled, CancellationCode, Diverted, CarrierDelay, WeatherDelay, NASDelay, SecurityDelay and LateAircraftDelay will be the

features of the dataset that will support our investigations into the main feature of interest of the dataset

Visual Assessment

Programmatic Assessment

In [13]:

```
# a look at data types
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2389217 entries, 0 to 2389216
Data columns (total 29 columns):
 #   Column             Dtype  
---  ------             -----  
 0   Year               int64  
 1   Month              int64  
 2   DayofMonth         int64  
 3   DayOfWeek          int64  
 4   DepTime            float64
 5   CRSDepTime         int64  
 6   ArrTime            float64
 7   CRSArrTime         int64  
 8   UniqueCarrier      object 
 9   FlightNum          int64  
 10  TailNum            object 
 11  ActualElapsedTime  float64
 12  CRSElapsedTime     float64
 13  AirTime            float64
 14  ArrDelay           float64
 15  DepDelay           float64
 16  Origin             object 
 17  Dest               object 
 18  Distance           int64  
 19  TaxiIn             float64
 20  TaxiOut            float64
 21  Cancelled          int64  
 22  CancellationCode   object 
 23  Diverted           int64  
 24  CarrierDelay       float64
 25  WeatherDelay       float64
 26  NASDelay           float64
 27  SecurityDelay      float64
 28  LateAircraftDelay  float64
dtypes: float64(14), int64(10), object(5)
memory usage: 528.6+ MB
```

In [14]:

```
#Descriptive statistics
df.describe()
```

Out[14]:

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTim
count	2389217.0	2.389217e+06	2.389217e+06	2.389217e+06	2.324775e+06	2.389217e+06	2.319121e+0
mean	2008.0	2.505009e+00	1.566386e+01	3.909625e+00	1.340018e+03	1.329992e+03	1.485835e+0
std	0.0	1.121493e+00	8.750405e+00	1.980431e+00	4.802717e+02	4.657833e+02	5.081295e+0
min	2008.0	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	0.000000e+00	1.000000e+0
25%	2008.0	1.000000e+00	8.000000e+00	2.000000e+00	9.300000e+02	9.270000e+02	1.110000e+0
50%	2008.0	3.000000e+00	1.600000e+01	4.000000e+00	1.330000e+03	1.325000e+03	1.516000e+0
75%	2008.0	4.000000e+00	2.300000e+01	6.000000e+00	1.733000e+03	1.720000e+03	1.914000e+0

max	2008.0	4.000000e+00	3.100000e+01	7.000000e+00	2.400000e+03	2.359000e+03	2.400000e+0

8 rows × 24 columns

1. Drop duplicated values

2. Convert Month, DayofMonth, DayOfWeek, Diverted datatypes to strings (Object) datatype

In [15]:
```
# make a copy of dataset to begin data wrangle
df_copy = df.copy()
df_copy.head(20)
```

Out[15]:

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime	UniqueCarrier
0	2008	1	3	4	1343.0	1325	1451.0	1435	WN
1	2008	1	3	4	1125.0	1120	1247.0	1245	WN
2	2008	1	3	4	2009.0	2015	2136.0	2140	WN
3	2008	1	3	4	903.0	855	1203.0	1205	WN
4	2008	1	3	4	1423.0	1400	1726.0	1710	WN
5	2008	1	3	4	2024.0	2020	2325.0	2325	WN
6	2008	1	3	4	1753.0	1745	2053.0	2050	WN
7	2008	1	3	4	622.0	620	935.0	930	WN
8	2008	1	3	4	1944.0	1945	2210.0	2215	WN
9	2008	1	3	4	1453.0	1425	1716.0	1650	WN
10	2008	1	3	4	2030.0	2015	2251.0	2245	WN
11	2008	1	3	4	708.0	615	936.0	840	WN
12	2008	1	3	4	1749.0	1730	2039.0	2000	WN
13	2008	1	3	4	1217.0	1215	1431.0	1440	WN
14	2008	1	3	4	954.0	940	1206.0	1205	WN
15	2008	1	3	4	1758.0	1800	1854.0	1900	WN
16	2008	1	3	4	2210.0	2120	2305.0	2215	WN
17	2008	1	3	4	740.0	740	836.0	840	WN
18	2008	1	3	4	1011.0	1005	1116.0	1105	WN
19	2008	1	3	4	1612.0	1520	1707.0	1620	WN

20 rows × 29 columns

Define : Drop duplicates

Code

In [16]:
```
#  drop duplicates from dataset
df_copy = df.drop_duplicates()
```

Test

In [17]:
```
# check to confirm there are no duplicate
df_copy.duplicated().sum()
```

Out[17]:
```
0
```

Define: ConvertMonth, DayofMonth, DayOfWeek, Diverted datatypes to strings (Object) datatype

Code

In [18]:
```
# convert to Month, DayofMonth, DayOfWeek, Diverted datatypes to object datatype
df_copy.Month= df_copy.Month.astype('object')
df_copy.DayofMonth= df_copy.DayofMonth.astype('object')
df_copy.DayOfWeek= df_copy.DayOfWeek.astype('object')
df_copy.Diverted= df_copy.Diverted.astype('object')
```

```
/var/folders/9z/j18d1hs552g8rpcpybsp0jj80000gp/T/ipykernel_51247/1912092760.py:2: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  df_copy.Month= df_copy.Month.astype('object')
/var/folders/9z/j18d1hs552g8rpcpybsp0jj80000gp/T/ipykernel_51247/1912092760.py:3: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  df_copy.DayofMonth= df_copy.DayofMonth.astype('object')
/var/folders/9z/j18d1hs552g8rpcpybsp0jj80000gp/T/ipykernel_51247/1912092760.py:4: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  df_copy.DayOfWeek= df_copy.DayOfWeek.astype('object')
/var/folders/9z/j18d1hs552g8rpcpybsp0jj80000gp/T/ipykernel_51247/1912092760.py:5: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  df_copy.Diverted= df_copy.Diverted.astype('object')
```

Test

In [19]:
```
df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2389213 entries, 0 to 2389216
Data columns (total 29 columns):
 #   Column             Dtype
---  ------             -----
 0   Year               int64
 1   Month              object
 2   DayofMonth         object
 3   DayOfWeek          object
 4   DepTime            float64
 5   CRSDepTime         int64
 6   ArrTime            float64
```

```
 7   CRSArrTime          int64
 8   UniqueCarrier       object
 9   FlightNum           int64
 10  TailNum             object
 11  ActualElapsedTime   float64
 12  CRSElapsedTime      float64
 13  AirTime             float64
 14  ArrDelay            float64
 15  DepDelay            float64
 16  Origin              object
 17  Dest                object
 18  Distance            int64
 19  TaxiIn              float64
 20  TaxiOut             float64
 21  Cancelled           int64
 22  CancellationCode    object
 23  Diverted            object
 24  CarrierDelay        float64
 25  WeatherDelay        float64
 26  NASDelay            float64
 27  SecurityDelay       float64
 28  LateAircraftDelay   float64
dtypes: float64(14), int64(6), object(9)
memory usage: 546.8+ MB
```

In [20]:
```
# save wrangled dataset
df_copy.to_csv('df_clean.csv', index = False)
```

In [22]:
```
# get a visual view of the few rows of the dataset
df_clean = pd.read_csv('df_clean.csv')
df_clean.sample(20)
```

Out[22]:

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime	UniqueCa
2059497	2008	4	13	7	1502.0	1503	1947.0	1939	
1494672	2008	3	27	4	1652.0	1650	1908.0	1837	
1956458	2008	4	3	4	1632.0	1609	1804.0	1733	
1917859	2008	4	3	4	1512.0	1505	1648.0	1629	
445866	2008	1	2	3	2133.0	2118	2201.0	2131	
878058	2008	2	25	1	708.0	703	1040.0	1022	
2178674	2008	4	17	4	701.0	655	817.0	815	
1440237	2008	3	4	2	2225.0	2220	2253.0	2248	
725329	2008	2	4	1	2122.0	2125	2239.0	2237	
1595672	2008	3	24	1	1340.0	1345	1523.0	1530	
500339	2008	1	17	4	1830.0	1835	2047.0	2040	
570214	2008	1	28	1	1607.0	1607	1718.0	1710	
1982092	2008	4	30	3	720.0	730	929.0	934	
203754	2008	1	22	2	NaN	1310	NaN	1526	
2127450	2008	4	6	7	1923.0	1925	2051.0	2053	
545696	2008	1	30	3	602.0	615	805.0	827	
131528	2008	1	4	5	1009.0	1018	1118.0	1135	
2286099	2008	4	5	6	1739.0	1740	2015.0	2015	
1800848	2008	4	6	7	2351.0	2130	147.0	2340	

22336	2008	1	10	4	1549.0	1545	1634.0	1640

20 rows × 29 columns

Univariate Exploration

> In the exploration and analysis of the data that follows, we will answer the following questions:
>
> 1. Which month(s) of the year had more flights?
> 2. Which day(s) of the month had more flights?
> 3. Which days of the week had more flights?
> 4. Which carriers recorded the most flights?
> 5. Which is the most frequent cause of delay?

Question: Which month(s) of the year had more flights?

Visualization

In [23]:

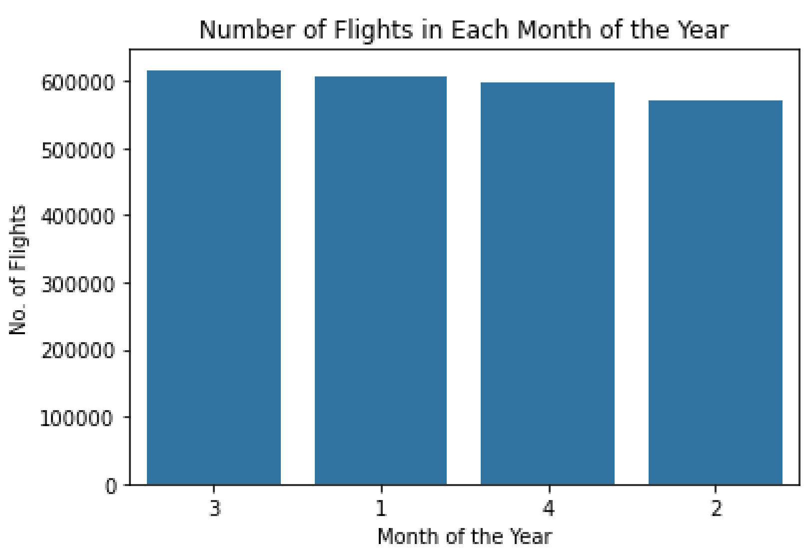
```
# choose a base color for all  visuals
base_color = sns.color_palette()[0]

# get the order of months with highest no. of flights
order_month = df_clean.Month.value_counts().index
```

In [24]:

```
# create a plotting function
def plot(data, feature, order):
    sns.countplot(data = data, x =  feature, color = base_color, order = order);
```

In [27]:

```
#plot flights of months
plot(df_clean, df_copy.Month, order_month)
plt.title('Number of Flights in Each Month of the Year')
plt.xlabel('Month of the Year')
plt.ylabel('No. of Flights');
```

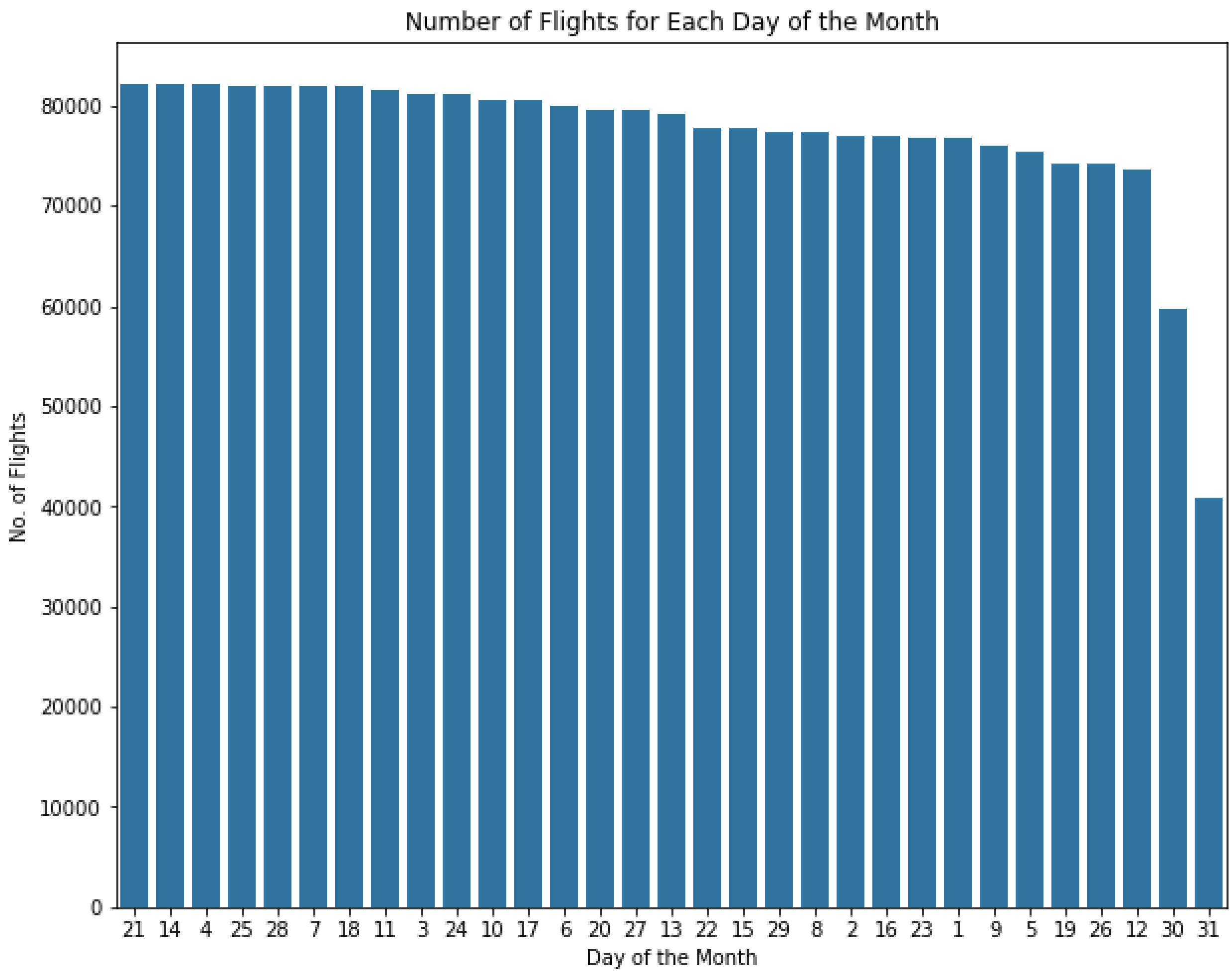


Observation

From the visualization above, it is observed that in the year 2008, the month of March had the highest number of flights while February had the least number of flights.

Question: Which day(s) of the month had more flights?

In [29]:
```
# plot flights of days in a months
order_day = df_clean.DayofMonth.value_counts().index
plt.figure(figsize=[10,8])
plot(df_clean, df_clean.DayofMonth, order_day)
plt.title('Number of Flights for Each Day of the Month')
plt.xlabel('Day of the Month')
plt.ylabel('No. of Flights');
```



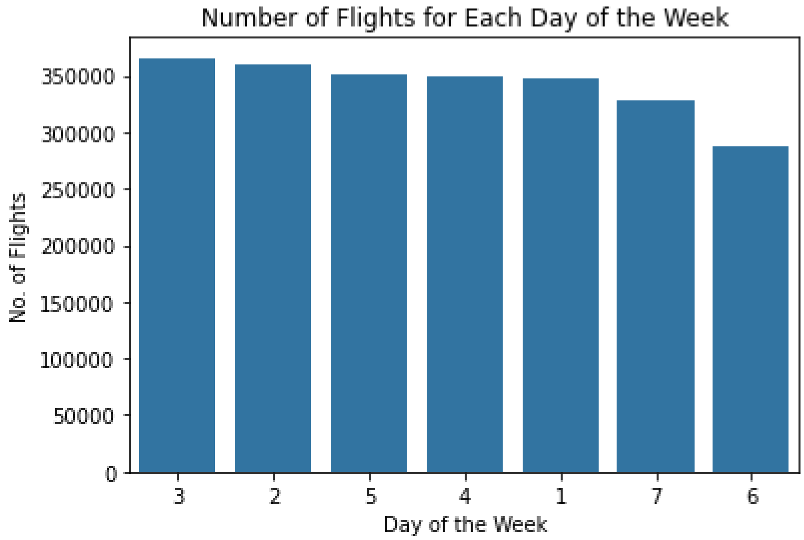
Observation

From the visualization above, it is observed that the most flights take place on the 21 of the month whereas less fligths are recorded on the last days of the month (30 and 31)

Question: Which day(s) of the week had more flights?

Visualization

In [30]:
```
#plot for days of the week
order_week = df_clean.DayOfWeek.value_counts().index
plot(df_clean, df_clean.DayOfWeek,order_week)
plt.title('Number of Flights for Each Day of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('No. of Flights');
```



Observation

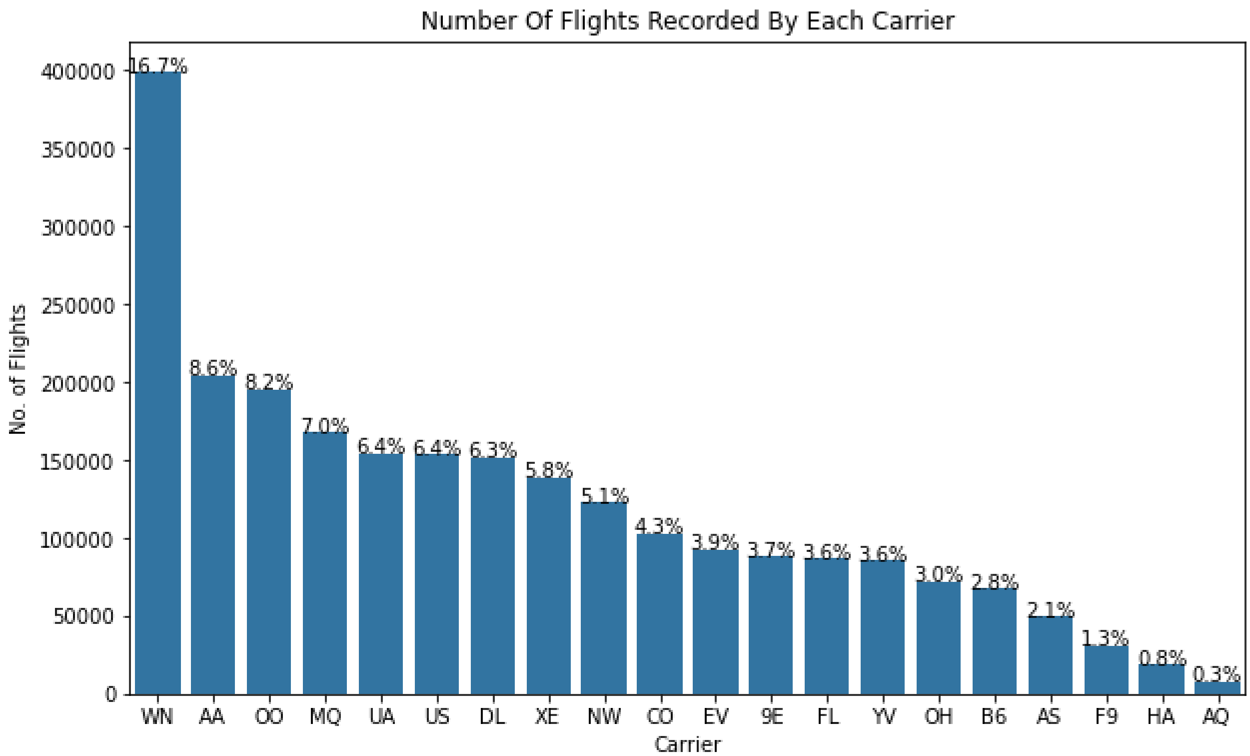
From the visualization, it be be observed that weekends have fewer flights than weekdays. Wednesdays had the most flights, followed by Teusdays.

Question: Which carriers recorded the most flights?

Visualization

In [31]:

```
# plot flights recorded by carriers
plt.figure(figsize=[10,6])
carrier_counts= df_clean.UniqueCarrier.value_counts()
order_carrier = carrier_counts.index
sum_unique_carrier = df_clean.UniqueCarrier.value_counts().sum()
plot(df_clean, df_clean.UniqueCarrier, order_carrier)
plt.title('Number Of Flights Recorded By Each Carrier')
plt.xlabel('Carrier')
plt.ylabel('No. of Flights');


# get the current tick locations and labels
locs, labels = plt.xticks()

# loop through each pair of locations and labels
for loc, label in zip(locs, labels):

    # get the text property for the label to get the correct count
    count = carrier_counts[label.get_text()]
    pct_string = '{:0.1f}%'.format(100*count/sum_unique_carrier)

    # print the annotation just below the top of the bar
    plt.text(loc, count+2, pct_string, ha = 'center', color = 'black')
```



Observation

WN Airlines recorded the most number of flights for the year 2008 (Almost 400,000 flights). AQ had the least number of recorded flights

In percentage terms, WN undertook a whooping 16% of all recorded flights in 2008 whereas HA and AQ each had less than 1%

Question: Which is the most frequent cause of delay?

Visualization

In [32]:

```
# get unique cancellation codes
df_clean.CancellationCode.value_counts()
```

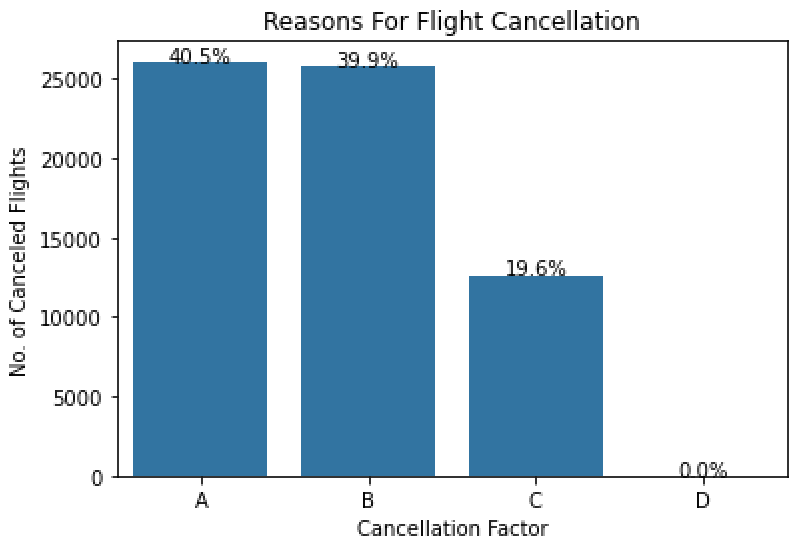
Out[32]:

```
A    26075
B    25744
C    12617
D        6
Name: CancellationCode, dtype: int64
```

In [33]:

```
# plot reasons for flight cancellation
sum_cancel = df_clean.CancellationCode.value_counts().sum()
cancel_counts = df_clean.CancellationCode.value_counts()
order_cancel = df_clean.CancellationCode.value_counts().index
plot(df_clean, df_clean.CancellationCode, order_cancel)
plt.title('Reasons For Flight Cancellation')
plt.xlabel('Cancellation Factor')
plt.ylabel('No. of Canceled Flights')


# get the current tick locations and labels
locs, labels = plt.xticks()

# loop through each pair of locations and labels
for loc, label in zip(locs, labels):

    # get the text property for the label to get the correct count
```

```
    count = cancel_counts[label.get_text()]
    pct_string = '{:0.1f}%'.format(100*count/sum_cancel)

    # print the annotation just below the top of the bar
    plt.text(loc, count+2, pct_string, ha = 'center', color = 'black');
```



Observation

From the above visualization, it can be observed that about 40.5% of all canceled flights were as a result of delays from the carriers. Also, 39.9% of flights that were canceled were as a result of bad weather. Lastly,about 19.6% of all flights canceled were caused by NAS. There were no flights that were canceled due to security reasons.

Summary of Univariate Exploration

> Some variables of the dataset were chosen as features of interest for the analysis. These variables are `Month, DayofMonth, DayOfWeek, UniqueCarriers` and `CancellationCode`. These were used to answer the following questions
>
> - Which month(s) of the year had more flights?
> - Which day(s) of the month had more flights?
> - Which day(s) of the week had more flights?
> - Which carriers recorded the most flights?
> - Which is the most frequent cause of delay?
>
> From the analysis done above, the following observations were made
>
> 1. February had the least number of flights in 2008, whereas March had the most.
> 2. The last days of the month saw significantly less number of flights recorded.
> 3. Most flights took place mid-week than on weekends.
> 4. WN Airlines recorded the most number of flights with 16.7% of the total number of recorded flights.
> 5. Of the factors that contribute to cancellation of flights, carrier delays account for 41%. No flights were canceled due to security reasons.

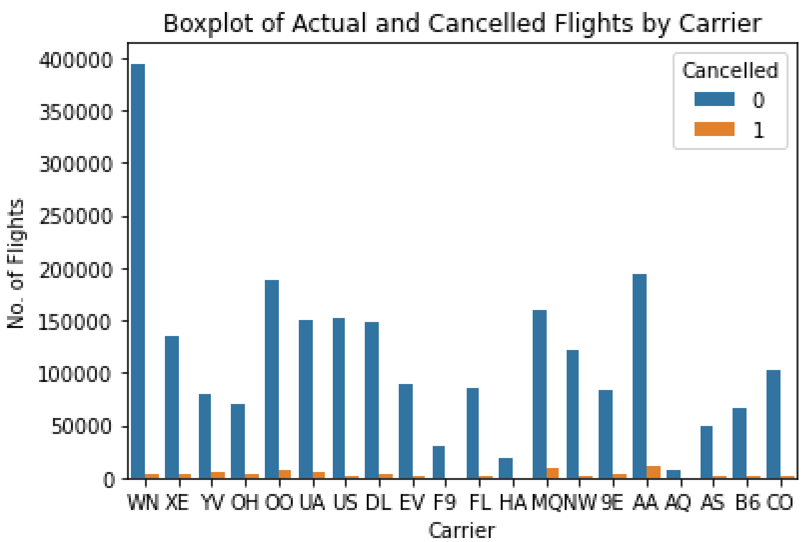
Unusual Distributions

> The features considered in the univariate exploration above were seen to be normal. There were no unusual features that needed further investigations. As such, there was no need to make any transformations or feature engineerign to the data.

Bivariate Exploration

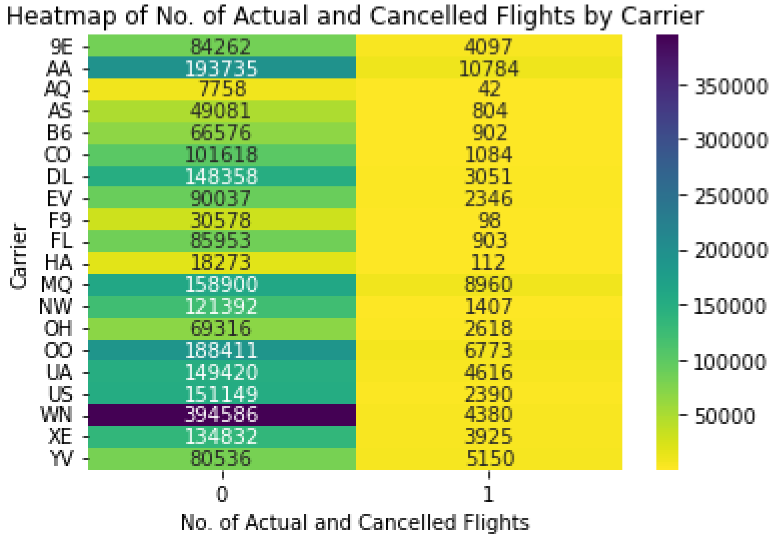
Question: Which carrier(s) had the most number of cancelled flights?

In [66]:
```
# plotting a clusterd barchart of actual and cancelled flights by carrier
sns.countplot(data=df_clean, x='UniqueCarrier', hue='Cancelled')
plt.title('Barchart of Actual and Cancelled Flights by Carrier')
plt.xlabel('Carrier')
plt.ylabel('No. of Flights');
```



In [53]:
```
# grouping UniqueCarrier using the Cancelled flags
cancelled_counts = df_clean.groupby(['UniqueCarrier', 'Cancelled']).size()
cancelled_counts = cancelled_counts.reset_index(name='count')

# Use DataFrame.pivot() to rearrange the data for plotting
cancelled_counts = cancelled_counts.pivot(index = 'UniqueCarrier', columns = 'Cancelled'
```

In [67]:
```
# plotting a heatmap of actual and cancelled flights by carrier
sns.heatmap(cancelled_counts, annot = True, fmt = 'd', cmap='viridis_r')
plt.title('Heatmap of No. of Actual and Cancelled Flights by Carrier')
plt.xlabel('No. of Actual and Cancelled Flights')
plt.ylabel('Carrier');
```



Observation

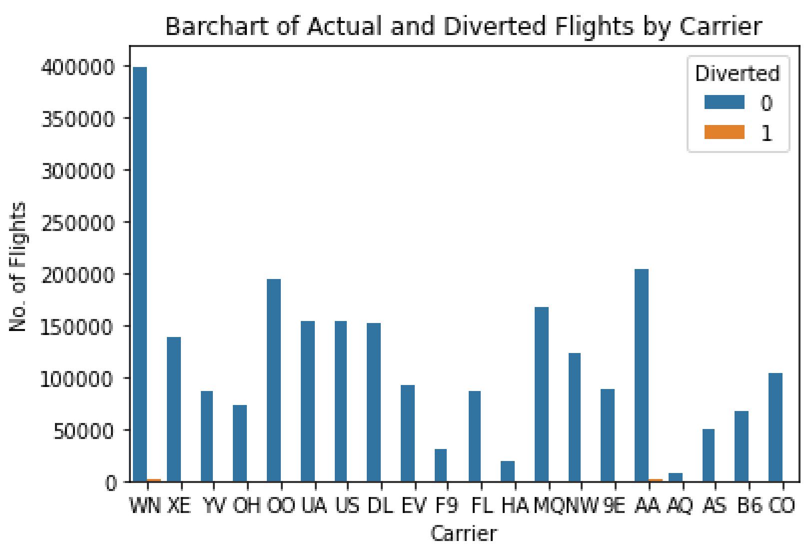
From the two graphs above, it can be obsereved that although WN had the most number of flights in 2008, they recorded very low flight cancellations. Carrier AA had by far the most number of flight cancellations.

Question: Which carriers have the most diverted flights?

Visualization

In [133…

```
# barplot of diverted flights
sns.countplot(data=df_clean, x='UniqueCarrier', hue='Diverted')
plt.title('Barchart of Actual and Diverted Flights by Carrier')
plt.xlabel('Carrier')
plt.ylabel('No. of Flights');
```



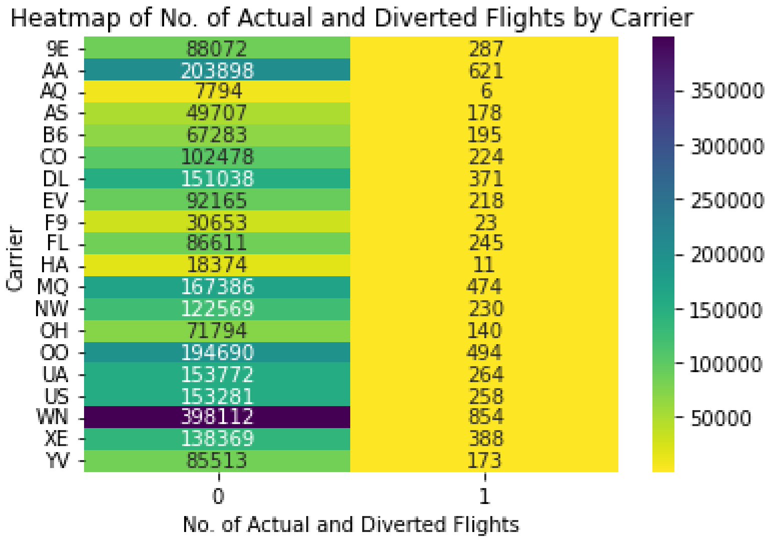
In [70]:

```
diverted_counts = df_clean.groupby(['UniqueCarrier', 'Diverted']).size()
diverted_counts = diverted_counts.reset_index(name='count')

# Use DataFrame.pivot() to rearrange the data for plotting
diverted_counts = diverted_counts.pivot(index = 'UniqueCarrier', columns = 'Diverted', v
```

In [71]:

```
# plotting a heatmap of actual and cancelled flights by carrier
sns.heatmap(diverted_counts, annot = True, fmt = 'd', cmap='viridis_r')
plt.title('Heatmap of No. of Actual and Diverted Flights by Carrier')
```

```
plt.xlabel('No. of Actual and Diverted Flights')
plt.ylabel('Carrier');
```



Observation

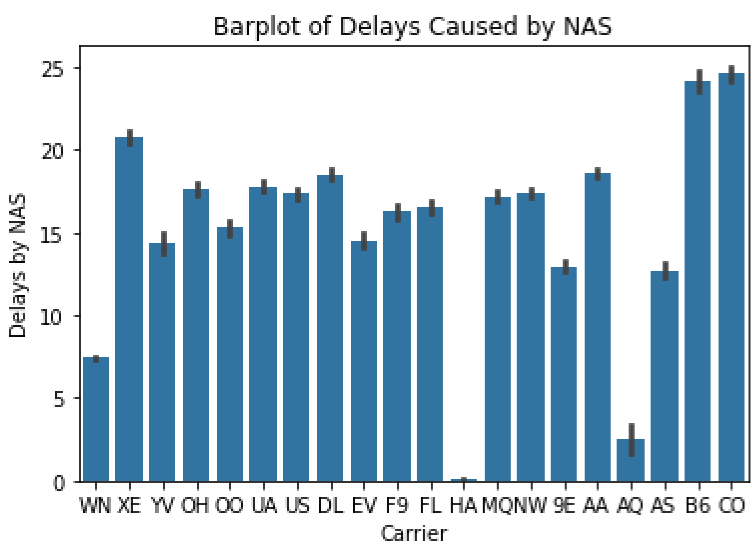
From the observation above, WN had the most diverted flights in 2008 with 854 flight diversions

Question: Which carrier(s) expereinced more delays? And of which delay reasons?

Visualization

In [98]:

```
#barplot
sns.barplot(data=df_clean, x='UniqueCarrier', y='NASDelay', color = base_color)
plt.title('Barplot of Delays Caused by NAS')
plt.xlabel('Carrier')
plt.ylabel('Delays by NAS');
```

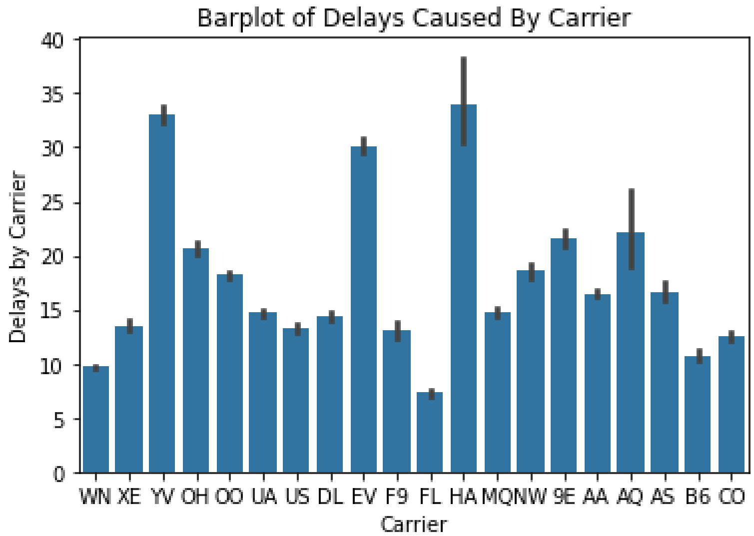


Observation

From the graph above, it can be observed that B6 and CO had the most flight delays by NAS

In [93]:

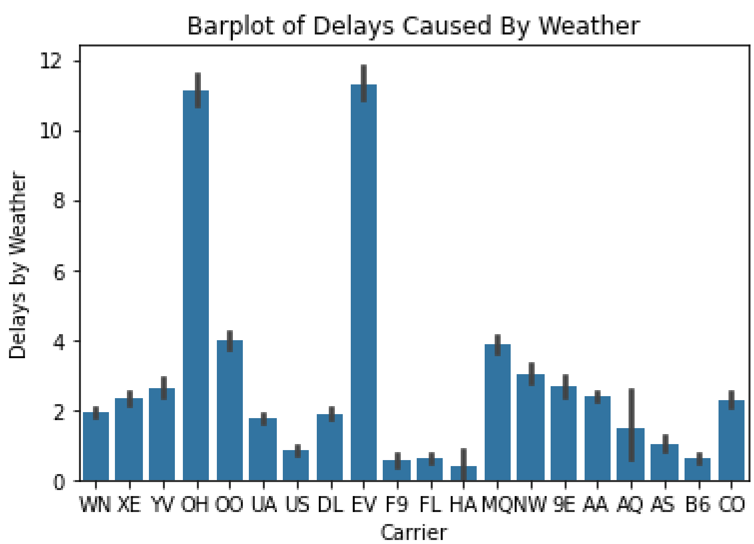
```
#barplot
sns.barplot(data=df_clean, x='UniqueCarrier', y='CarrierDelay', color = base_color)
plt.title('Barplot of Delays Caused By Carrier')
plt.xlabel('Carrier')
plt.ylabel('Delays by Carrier');
```



Observation

From the graph above, it can be observed that HA had the most flight delays occasioned by carrier delays

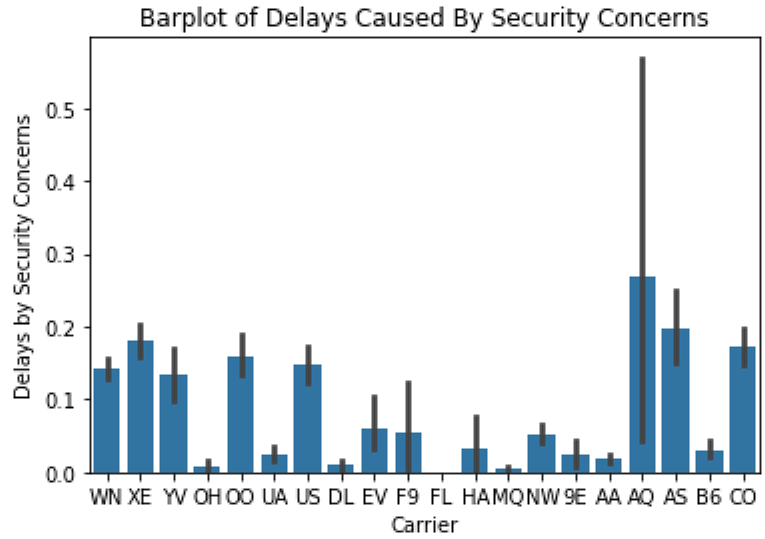
In [95]:
```
#barplot
sns.barplot(data=df_clean, x='UniqueCarrier', y='WeatherDelay', color = base_color)
plt.title('Barplot of Delays Caused By Weather')
plt.xlabel('Carrier')
plt.ylabel('Delays by Weather');
```



Observation

From the graph above, it can be observed that OH and EV carriers had the most flight delays by occasioned by (poor) weather conditions

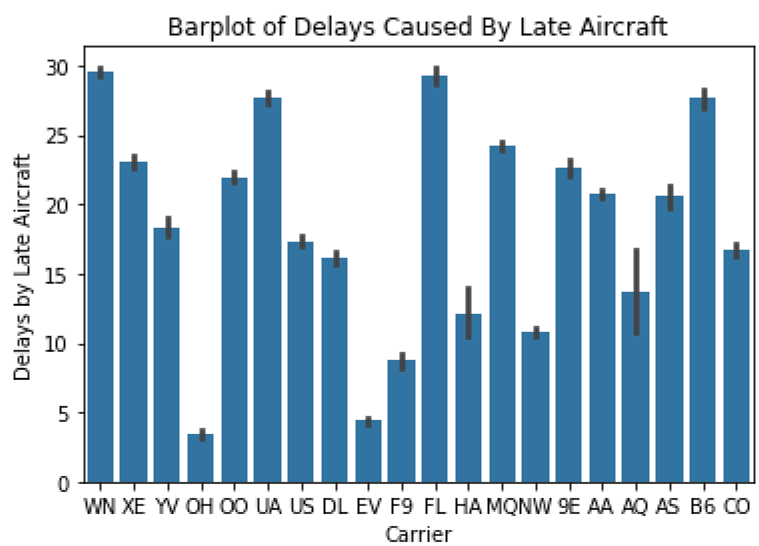
In [96]:
```
#barplot
sns.barplot(data=df_clean, x='UniqueCarrier', y='SecurityDelay', color = base_color)
plt.title('Barplot of Delays Caused By Security Concerns')
plt.xlabel('Carrier')
plt.ylabel('Delays by Security Concerns');
```



Observation

From the graph above, it can be observed that AQ had the most flight delays by security reasons

In [97]:
```
#barplot
sns.barplot(data=df_clean, x='UniqueCarrier', y='LateAircraftDelay', color = base_color)
plt.title('Barplot of Delays Caused By Late Aircraft')
plt.xlabel('Carrier')
plt.ylabel('Delays by Late Aircraft');
```



Observation

From the graph above, it can be observerd that quite a number of carriers had a lot of aircraft delays. Particularly, WN, UA, FL and AS had some high occurences of flight delays.

Summary of Bivariate Exploration

> **Questions**
>
> 1. Which carrier(s) had the most number of cancelled flights?
> 2. Which carrier(s) have the most diverted flights?
> 3. Which carrier(s) expereinced more delays? And of which delay reasons?
>
> **Observations**

- Although WN had the most number of flights in 2008, they recorded very low flight cancellations. Carrier AA had by far the most number of flight cancellations.
- WN had the most diverted flights in 2008 with 854 flight diversions
- B6 and CO had the most flight delays by NAS
- HA had the most flight delays occasioned by carrier delays
- OH and EV carriers had the most flight delays by occasioned by (poor) weather conditions
- Quite a number of carriers had a lot of aircraft delays but WN, UA, FL and AS had the highest of delays as a result of aircraft delay.

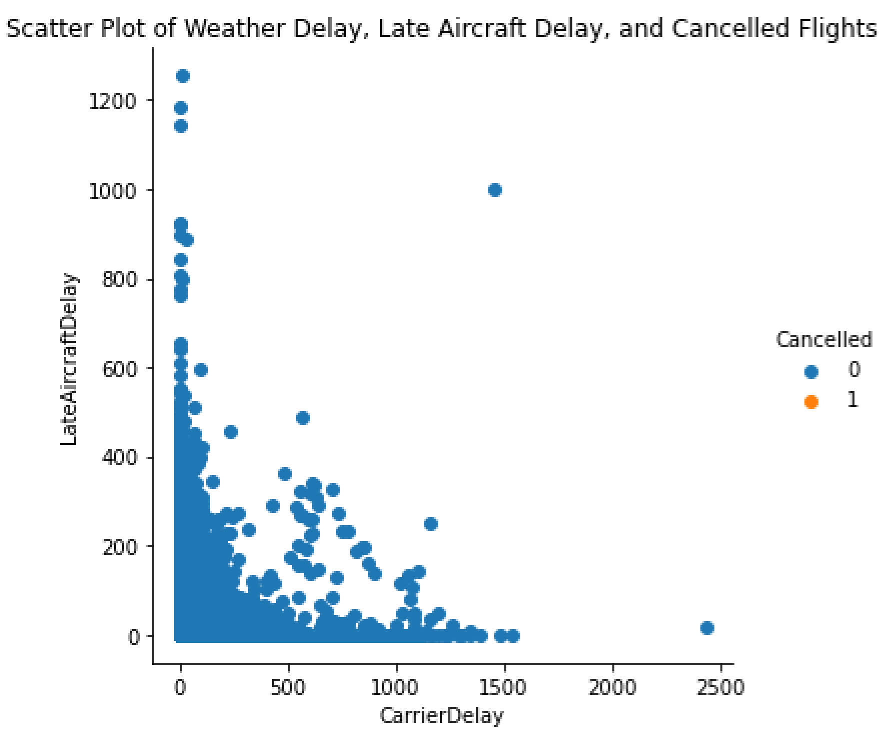
Interesting feature of interest

- Even though WN airlines had the highest number of recorded flights in 2008, they recorded the lowest number of cancelled flights. Wihtout making any concrete inference, it could be argued that travelers may have prefereed WN to the other carriers because booked flights with WN were less likely to be cancelled. Further investigations into the correlation between number of cancelled flights and number of recorded flights could give better insights into the relationship between number of recorded flights by a carrier and the number of cancelled flights by that carrier.

Multivariate Exploration

In [132…

```
#plot a scatter for correlation between delays and cancelled flights
g = sns.FacetGrid(data = df_clean, hue = 'Cancelled',  height = 5)
g.map(plt.scatter, 'CarrierDelay','LateAircraftDelay')
g.add_legend()

plt.title('Scatter Plot of Weather Delay, Late Aircraft Delay, and Cancelled Flights');
```



Talk about some of the relationships you observed in this part of the investigation. Were there features that strengthened each other in terms of looking at your feature(s) of interest?

> From the multivariate visualization above, there is a strong positive correlation between between Carrier Delay and Late Aircraft Delay. However, there was no observed correlation between these two variables and cancelled flights. This means that neither of these delay factors resulted in flight cancellations

Interesting Observation

> No flights were cacelled due to Carrier Delays or Late Aircraft Delay.

Conclusions

1. February had the least number of flights in 2008, whereas March had the most.
2. The last days of the month saw significantly less number of flights recorded.
3. Most flights took place mid-week than on weekends.
4. WN Airlines recorded the most number of flights with 16.7% of the total number of recorded flights.
5. Of the factors that contribute to cancellation of flights, carrier delays account for 41%. No flights were canceled due to security reasons.
6. Although WN had the most number of flights in 2008, they recorded very low flight cancellations. Carrier AA had by far the most number of flight cancellations.
7. WN had the most diverted flights in 2008 with 854 flight diversions
8. B6 and CO had the most flight delays by NAS
9. HA had the most flight delays occasioned by carrier delays
10. OH and EV carriers had the most flight delays by occasioned by (poor) weather conditions
11. Quite a number of carriers had a lot of aircraft delays but WN, UA, FL and AS had the highest of delays as a result of aircraft delay.
12. Even though WN airlines had the highest number of recorded flights in 2008, they recorded the lowest number of cancelled flights. Wihtout making any concrete inference, it could be argued that travelers may have prefereed WN to the other carriers because booked flights with WN were less likely to be cancelled. Further investigations into the correlation between number of cancelled flights and number of recorded flights could give better insights into the relationship between number of recorded flights by a carrier and the number of cancelled flights by that carrier.
13. No flights were cacelled due to Carrier Delays or Late Aircraft Delay.

In [ ]: