About the Dataset

This dataset is from Bureau of Transportation Statistics. It tracks the on time performance of domestic flights operated by large air carriers. The dataset is for each year and can be downloaded directly from their website. The description is posted on their website in detail.

For this data analysis, we will be using data for the years of 2007 and 2008.

Wrangling of Dataset

In [1]:

```
#importing all libraries needed
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import requests
import matplotlib.patches as mpatches
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures

%matplotlib inline
```

In [2]:

```
# Load in the dataset into a pandas dataframe
df_2008 = pd.read_csv('2008.csv')
df_2007 = pd.read_csv('2007.csv')
```

In [3]:

```
df_data=df_2007.append([df_2008])
```

In [4]:

```
print(df_data.shape)
```

```
(9842432, 29)
```

In [5]:

```
# df_data.to_csv('final.csv')
```

In [2]:

```
df = pd.read_csv('final.csv')
```

In [3]:

```
df.shape
```

Out[3]:

```
(9842432, 30)
```

In [4]:

```
df.head()
```

Out[4]:

	Unnamed: 0	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRS/
0	0	2007	1	1	1	1232.0	1225	1341.0	
1	1	2007	1	1	1	1918.0	1905	2043.0	
2	2	2007	1	1	1	2206.0	2130	2334.0	
3	3	2007	1	1	1	1230.0	1200	1356.0	
4	4	2007	1	1	1	831.0	830	957.0	

5 rows × 30 columns

In [5]:

```
df.drop(["Unnamed: 0"], axis='columns', inplace=True)
df.head()
```

Out[5]:

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime	Un
0	2007	1	1	1	1232.0	1225	1341.0	1340	
1	2007	1	1	1	1918.0	1905	2043.0	2035	
2	2007	1	1	1	2206.0	2130	2334.0	2300	
3	2007	1	1	1	1230.0	1200	1356.0	1330	
4	2007	1	1	1	831.0	830	957.0	1000	

5 rows × 29 columns

In [6]:

```
print(df.dtypes)
print(df.describe)
```

```
Year                   int64
Month                  int64
DayofMonth             int64
DayOfWeek              int64
DepTime              float64
CRSDepTime             int64
ArrTime              float64
CRSArrTime             int64
UniqueCarrier         object
FlightNum              int64
TailNum               object
ActualElapsedTime    float64
CRSElapsedTime       float64
AirTime              float64
ArrDelay             float64
DepDelay             float64
Origin                object
Dest                  object
Distance               int64
TaxiIn               float64
TaxiOut              float64
Cancelled              int64
CancellationCode      object
Diverted               int64
CarrierDelay         float64
WeatherDelay         float64
NASDelay             float64
SecurityDelay        float64
LateAircraftDelay    float64
dtype: object
<bound method NDFrame.describe of          Year  Month  DayofMonth  DayOfW
eek  DepTime  CRSDepTime  ArrTime  \
0        2007      1           1          1   1232.0        1225   1341.0
1        2007      1           1          1   1918.0        1905   2043.0
2        2007      1           1          1   2206.0        2130   2334.0
3        2007      1           1          1   1230.0        1200   1356.0
4        2007      1           1          1    831.0         830    957.0
...       ...    ...         ...        ...      ...         ...      ...
9842427  2008      4          17          4   1025.0        1025   1234.0
9842428  2008      4          17          4   1319.0        1320   1527.0
9842429  2008      4          17          4   1335.0        1335   1556.0
9842430  2008      4          17          4   1933.0        1935   2140.0
9842431  2008      4          17          4    621.0         615    752.0

         CRSArrTime UniqueCarrier  FlightNum  ... TaxiIn  TaxiOut  Cancell
ed  \
0              1340            WN       2891  ...    4.0     11.0
0
1              2035            WN        462  ...    5.0      6.0
0
2              2300            WN       1229  ...    6.0      9.0
0
3              1330            WN       1355  ...    3.0      8.0
0
4              1000            WN       2278  ...    3.0      9.0
0
...             ...           ...        ...  ...    ...      ...
...
9842427        1237            DL       1207  ...    5.0     16.0
0
9842428        1524            DL       1208  ...    9.0     12.0
```

```
0
9842429       1553          DL       1209  ...    7.0     31.0
0
9842430       2141          DL       1210  ...    9.0     12.0
0
9842431        754          DL       1211  ...   15.0     12.0
0

         CancellationCode  Diverted  CarrierDelay WeatherDelay NASDelay  \
0                     NaN         0           0.0          0.0      0.0
1                     NaN         0           0.0          0.0      0.0
2                     NaN         0           3.0          0.0      0.0
3                     NaN         0          23.0          0.0      0.0
4                     NaN         0           0.0          0.0      0.0
...                   ...       ...           ...          ...      ...
9842427               NaN         0           NaN          NaN      NaN
9842428               NaN         0           NaN          NaN      NaN
9842429               NaN         0           NaN          NaN      NaN
9842430               NaN         0           NaN          NaN      NaN
9842431               NaN         0           NaN          NaN      NaN

         SecurityDelay  LateAircraftDelay
0                  0.0                0.0
1                  0.0                0.0
2                  0.0               31.0
3                  0.0                3.0
4                  0.0                0.0
...                ...                ...
9842427            NaN                NaN
9842428            NaN                NaN
9842429            NaN                NaN
9842430            NaN                NaN
9842431            NaN                NaN

[9842432 rows x 29 columns]>
```

What's the structure of the dataset ?

The dataset has 29 columns and 9842432 rows.

What is/are the main feature(s) of interest in the dataset?

The main features are; the factors affecting the delays and cncellations of the flights. These factors will help us to determine the time performace and characteristics of flights of different destinations.

What features in the dataset will help to support the investigation into the feature(s) of interest?

The main features of interest of the dataset are the factors which are involved in delaying arrival and departure (in time, minutes), cancellation codes and reasons. Also an effort will be undergone for spotting any correlation between parameters.

Univariate Exploration

In [7]:

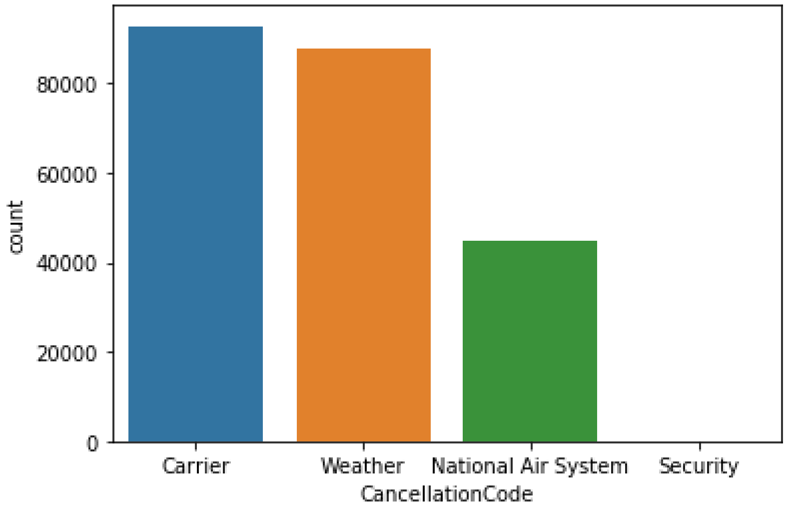
```
df['CancellationCode'].unique().tolist()
```

Out[7]:

```
[nan, 'A', 'B', 'C', 'D']
```

In [8]:

```
#Define plot (reference: http://alanpryorjr.com/visualizations/seaborn/countplot/countp
lot/)
plot = sb.countplot(x="CancellationCode", data=df)
plot.set_xticklabels(['Carrier','Weather','National Air System','Security']);
```



The avobe graph shows that "Carrier" and "Weather" are the staple reason for the flight cancellation.

Which Carrier had the most cancellations?

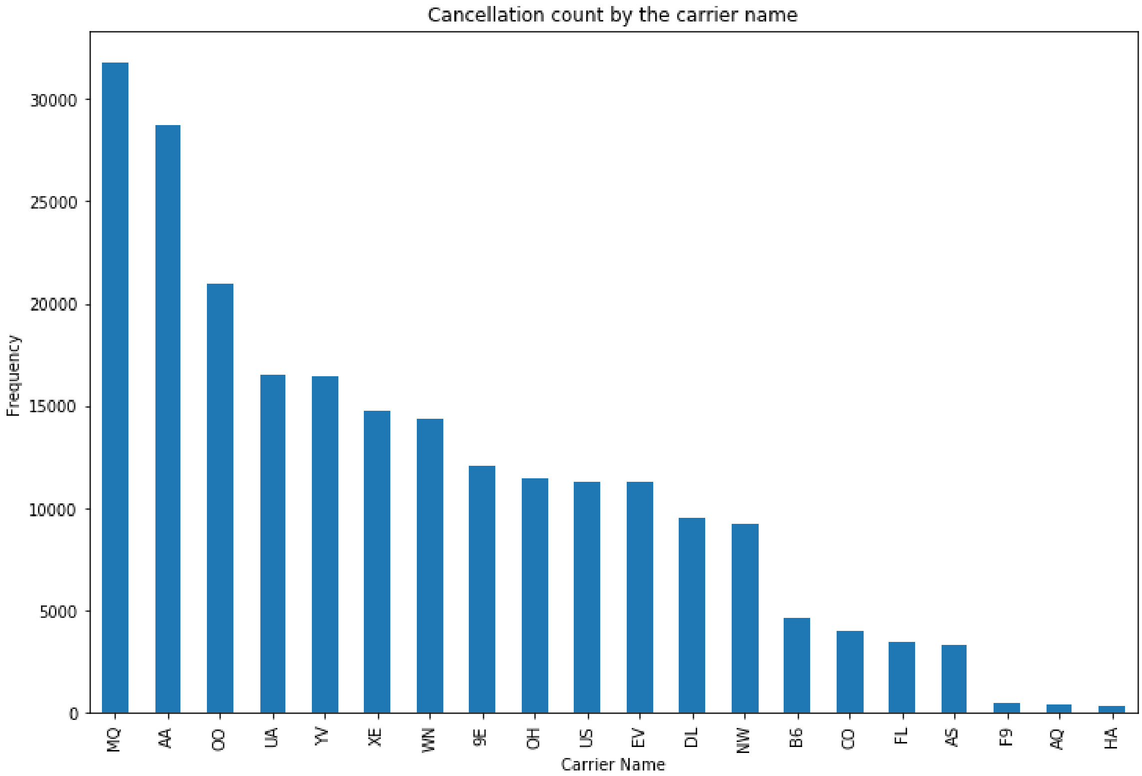
In [9]:

```
# creating a DataFrame with carrier and cancellation code
carrier = df.UniqueCarrier.tolist()
cancellation_code = df.CancellationCode.tolist()

most_cancellation = pd.DataFrame({'cancellation_code':cancellation_code, 'carrier': car
rier})
most_cancellation = most_cancellation.dropna()
#most_cancellation
```

In [10]:

```
#Define Plot
plt.figure(figsize=(12,8))
fig= most_cancellation['carrier'].value_counts().plot(kind ='bar')
fig.set_title('Cancellation count by the carrier name')
fig.set_xlabel('Carrier Name')
fig.set_ylabel('Frequency');
```



The above bar plot shows that the MQ, AA and OO are the top three carriers with highest cancellation whereas HA is the carrier with lowest cancellations. The cancellation has been considered for the four type of cancellation code A, B,C and D.

Which carriers had the highest delays ? (arrival and departure)

In [11]:

```
#To explore delays, we created new dataframes that excluded NaN (missing) values in del
ays to plot histogram.
arrival_delay = df[df.ArrDelay.notnull()]
departure_delay = df[df.DepDelay.notnull()]
```

In [12]:

```
# grouping the arrival and departure by Carrier
arrival_delay_carrier = arrival_delay.groupby('UniqueCarrier').ArrDelay.sum().sort_valu
es(ascending=False)
departure_delay_carrier = departure_delay.groupby('UniqueCarrier').DepDelay.sum().sort_
values(ascending=False)
delay=pd.merge(arrival_delay_carrier,departure_delay_carrier,on='UniqueCarrier')
# delay.head()
```

In [13]:

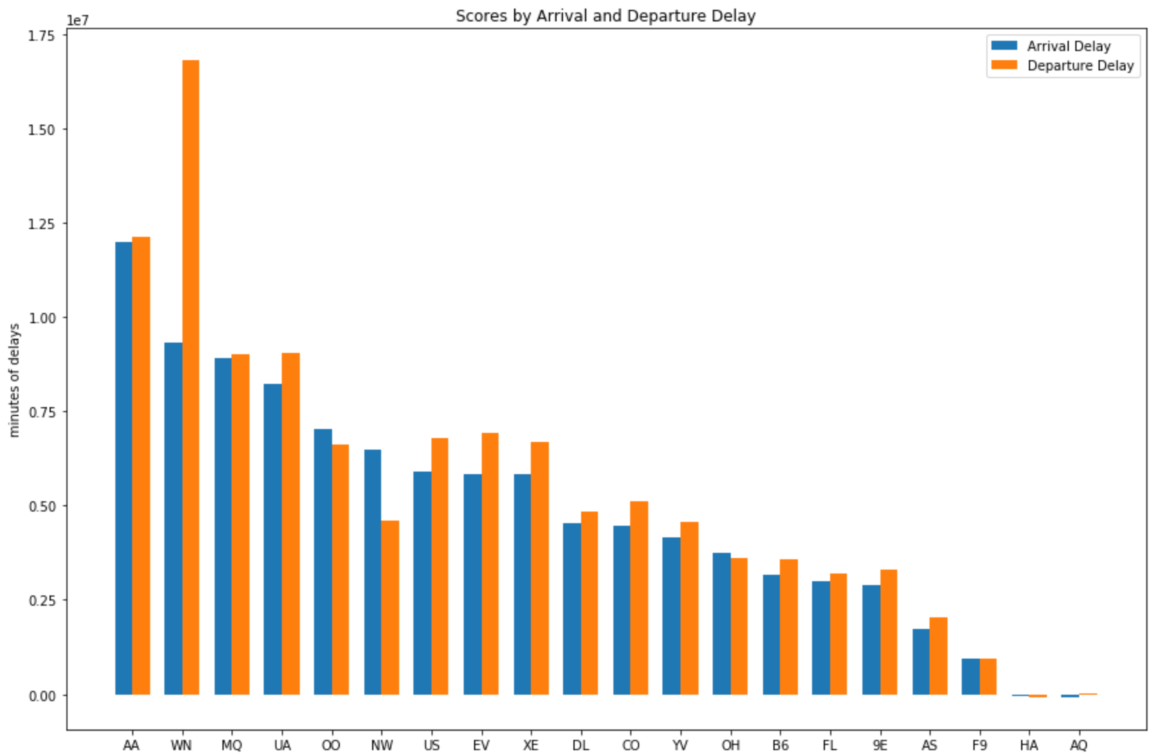
```
# delay.ArrDelay.tolist()
# delay.index.tolist()
```

In [14]:

```
#Define Plot
x = np.arange(len(delay.index))  # the carrier locations
width = 0.35  # the width of the bars

fig, ax = plt.subplots(figsize=(15, 10))
rects1 = ax.bar(x - width/2, delay.ArrDelay, width, label='Arrival Delay')
rects2 = ax.bar(x + width/2, delay.DepDelay, width, label='Departure Delay')

# Adding some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('minutes of delays')
ax.set_title('Scores by Arrival and Departure Delay')
ax.set_xticks(x)
ax.set_xticklabels(delay.index)
ax.legend()
plt.show();
```



From the plot it can be seen that (AA)American Airlines has the highest arrival delays. On the contrary 'WN' has the highest Departure Delay.

In which month of the vear the most cancellations occurred?

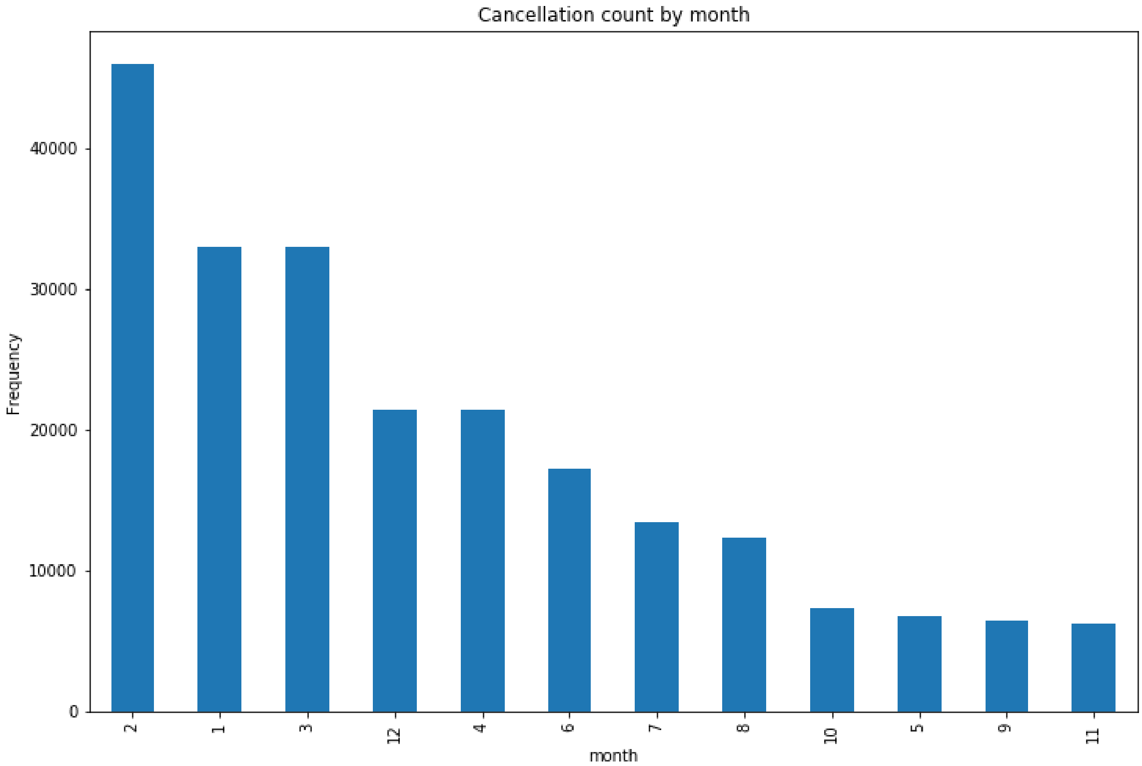
In [15]:

```
cancellation_code = df.CancellationCode.tolist()
month = df.Month.tolist()

cancellation_month = pd.DataFrame({'cancellation_code':cancellation_code, 'month': mont
h})
cancellation_month = cancellation_month.dropna()
# cancellation_month
```

In [16]:

```
#Define Plot
plt.figure(figsize=(12,8))
fig= cancellation_month['month'].value_counts().plot(kind ='bar')
fig.set_title('Cancellation count by month')
fig.set_xlabel('month')
fig.set_ylabel('Frequency');
```



It can be seen that the first three months see the major cancellations whereas 2nd month has the most. In January and March the cancellation were almost same.

What does the distribution of arrival delays and departure delays look like?

In [17]:

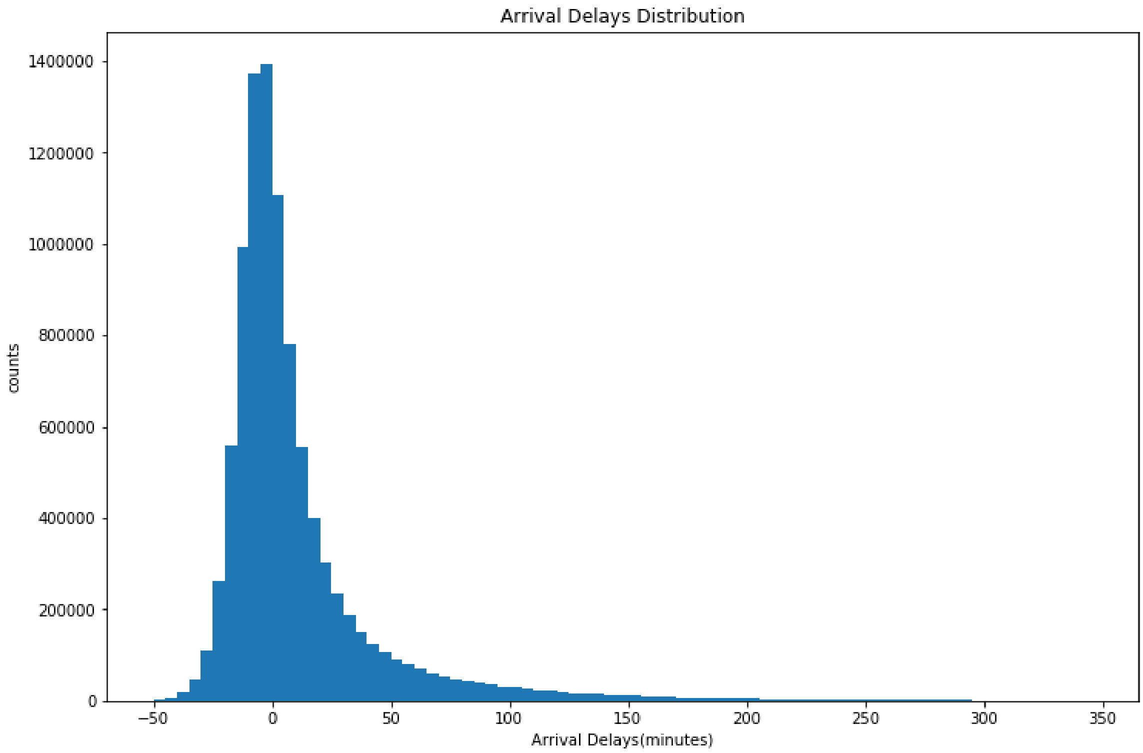
```
# recalling previously used dataFrame
arrival_delay = df[df.ArrDelay.notnull()]
adelay = arrival_delay.ArrDelay
adelay.head()
```

Out[17]:

```
0     1.0
1     8.0
2    34.0
3    26.0
4    -3.0
Name: ArrDelay, dtype: float64
```

In [18]:

```
#Define plot
plt.figure(figsize=(12,8))
plt.title('Arrival Delays Distribution')
plt.xlabel('Arrival Delays(minutes)')
plt.ylabel('counts')
plt.hist(adelay,bins=np.arange(-50,350,5));
```



From the histogram we can see that most of the delays are concentrated between 0 and 50 minutes. The distribution is skewed to the right.

In [19]:

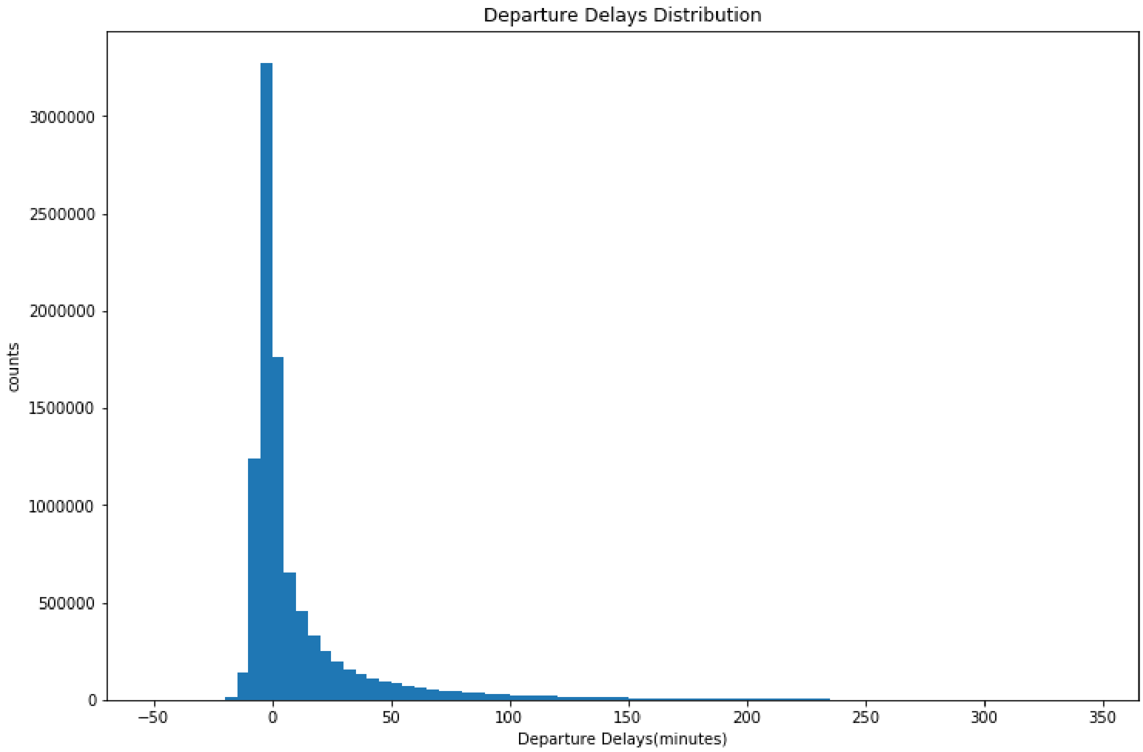
```
#Filtering only data with departure_delay information, excluding NaN
depart_delay=df[df.DepDelay.notnull()]
ddelay = depart_delay.DepDelay
ddelay.head()
```

Out[19]:

```
0     7.0
1    13.0
2    36.0
3    30.0
4     1.0
Name: DepDelay, dtype: float64
```

In [20]:

```
#Define plot
plt.figure(figsize=(12,8))
plt.title('Departure Delays Distribution')
plt.xlabel('Departure Delays(minutes)')
plt.ylabel('counts')
plt.hist(ddelay,bins=np.arange(-50,350,5));
```



The histogram above shows the distribution of departure delays. From the graph, it can be observed that most of the delays are between 0 and 50. The graph is skewed to the right

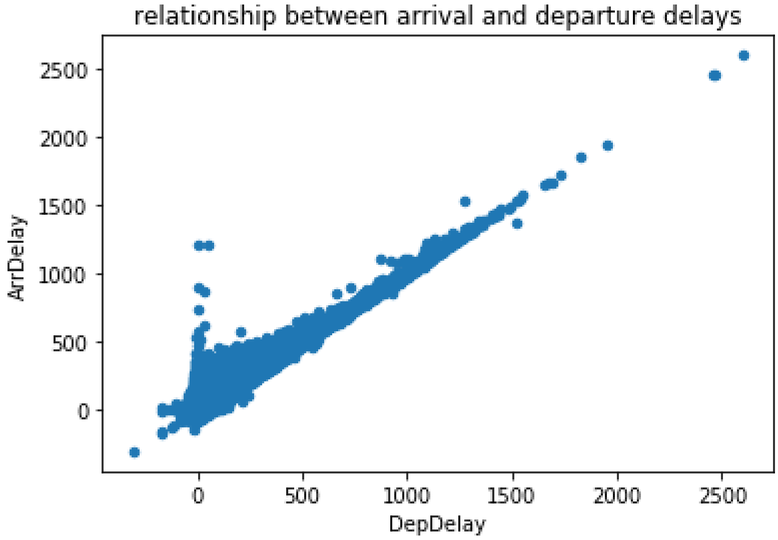
Bivariate Exploration

What is the relationship between arrival and departure delays?

In [21]:

```
#Define Plot
plt.figure(figsize=(14,8))
df.plot.scatter(x='DepDelay', y='ArrDelay')
plt.title('relationship between arrival and departure delays')
plt.show();
```

<Figure size 1008x576 with 0 Axes>

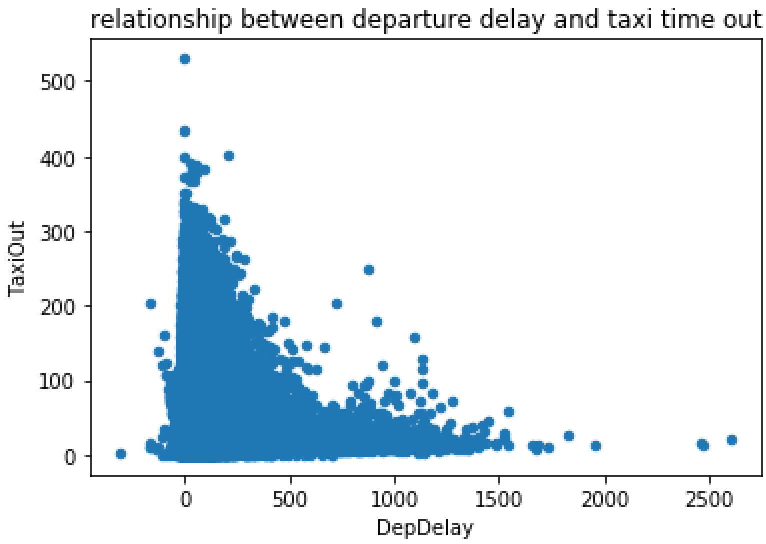


There is a linear realationship between departure and arrival delays. With the increase of Arrival delay, departure delay is also increasing.

Is there any relationship between departure delay and taxi out time?

In [22]:

```
#Define plot
df.plot.scatter(x='DepDelay', y='TaxiOut')
plt.title('relationship between departure delay and taxi time out')
plt.show();
```



There is no linear relationship between departure delay and taxi out time. The data at the left on the graph shows that, there is no effect on departure delay as the delay for Taxi Out increased.

What is the Fight performance of the carriers in terms of arrival delays?

In [23]:

```
#Getting a dataframe with number of flights that were delayed and not cancelled by each carrier
df_depart_delay=df[df.DepDelay.notnull()]
arrival_delayed=df_depart_delay.query('Cancelled==0 & ArrDelay>0').groupby('UniqueCarrier').size().reset_index(name='delayed_flights')

arrival_delayed.head()
```

Out[23]:

	UniqueCarrier	delayed_flights
0	9E	144283
1	AA	423359
2	AQ	14693
3	AS	97363
4	B6	116799

In [24]:

```
#Getting a dataframe with number of total flights that took off (not cancelled)
uncancelled_flights=df.query('Cancelled==0').groupby('UniqueCarrier').size().reset_index(name='total_flights')
uncancelled_flights.head()
```

Out[24]:

	UniqueCarrier	total_flights
0	9E	335174
1	AA	809668
2	AQ	53730
3	AS	206703
4	B6	254316

In [25]:

```
#Merging both dataframes on unique_carrier_code
df_merged=pd.merge(arrival_delayed,uncancelled_flights,on='UniqueCarrier')
df_merged = df_merged.sort_values(by =['delayed_flights', 'total_flights'], ascending =
False)
df_merged.head()
```

Out[25]:

	UniqueCarrier	delayed_flights	total_flights
17	WN	671617	1553464
1	AA	423359	809668
14	OO	361584	772107
11	MQ	328208	676602
16	US	317405	627654

In [26]:

```
# changing the index as carrier
carrier = df_merged.UniqueCarrier.tolist()
delay_flight = df_merged.delayed_flights.tolist()
total_flight = df_merged.total_flights.tolist()

df1 = pd.DataFrame({'delay_flight':delay_flight, 'total_flight':total_flight}, index =
carrier)
df1.head()
```

Out[26]:

	delay_flight	total_flight
WN	671617	1553464
AA	423359	809668
OO	361584	772107
MQ	328208	676602
US	317405	627654

In [27]:

```
df1['ratio']=df1.delay_flight/df1.total_flight
df1
```

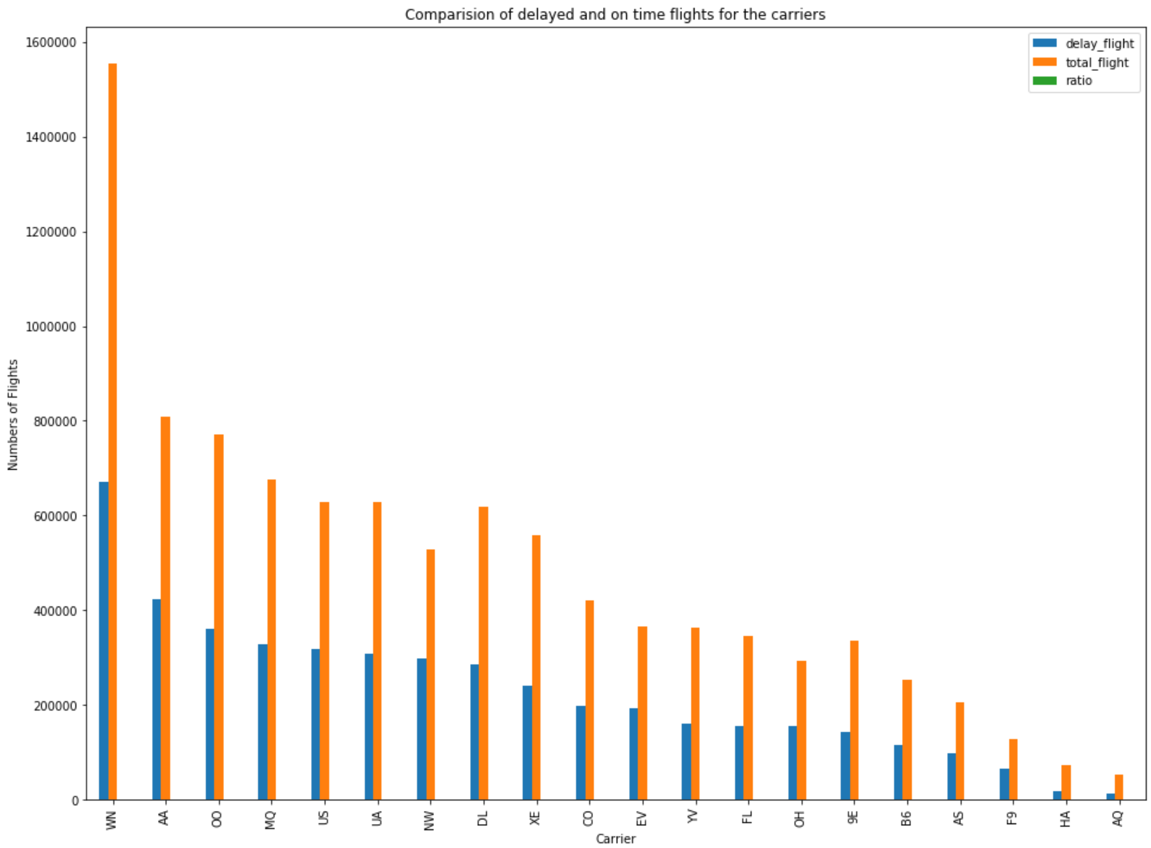
Out[27]:

	delay_flight	total_flight	ratio
WN	671617	1553464	0.432335
AA	423359	809668	0.522880
OO	361584	772107	0.468308
MQ	328208	676602	0.485083
US	317405	627654	0.505701
UA	309194	627493	0.492745
NW	299206	528104	0.566566
DL	286888	617726	0.464426
XE	241805	558805	0.432718
CO	198755	421818	0.471187
EV	193304	367351	0.526211
YV	160684	363611	0.441912
FL	157267	346510	0.453860
OH	155217	294252	0.527497
9E	144283	335174	0.430472
B6	116799	254316	0.459267
AS	97363	206703	0.471028
F9	65772	127944	0.514069
HA	19079	74210	0.257095
AQ	14693	53730	0.273460

In [28]:

```
# Define plot
ax = df1.plot.bar(figsize= [16,12], rot=90)
plt.xlabel('Carrier')
plt.ylabel('Numbers of Flights')
plt.title('Comparision of delayed and on time flights for the carriers')

plt.show()
```

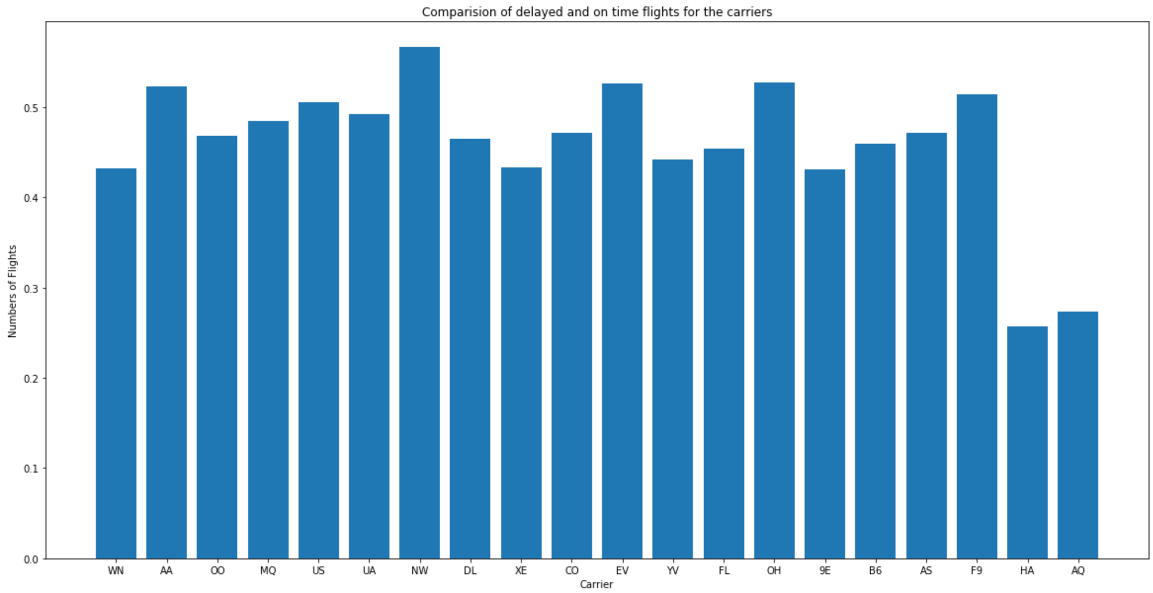


It is visible that the carrier 'WN' has conducted more flights and they have the highest number of delays as well, next plot the percentage will be showen.

In [29]:

```
# Define plot
plt.figure(figsize=(20,10))
plt.bar(list(df1.index), df1.ratio)
plt.xlabel('Carrier')
plt.ylabel('Numbers of Flights')
plt.title('Comparision of delayed and on time flights for the carriers')

plt.show()
```



So, it is now clear that the highest percentage of delays has been occured in the carrier named 'NW'.

Is there any relationship between the flight delays and destination ?

In [30]:

```
# getting information for destination based flights that has delayed but not cancelled
df_depart_delay=df[df.DepDelay.notnull()]
arrival_delayed_dest=df_depart_delay.query('Cancelled==0 & ArrDelay>0').groupby('Dest')
.size().reset_index(name='delayed_flights')

arrival_delayed_dest.head()
```

Out[30]:

	Dest	delayed_flights
0	ABE	3347
1	ABI	1743
2	ABQ	24599
3	ABY	901
4	ACK	164

In [31]:

```
#Getting a dataframe with number of total flights that took off (not cancelled) based o
n destination
uncancelled_flights_dest=df.query('Cancelled==0').groupby('Dest').size().reset_index(na
me='total_flights')
uncancelled_flights_dest.head()
```

Out[31]:

	Dest	total_flights
0	ABE	7054
1	ABI	3601
2	ABQ	54298
3	ABY	1693
4	ACK	282

In [32]:

```
#Merging both dataframes on Destination
df_merged_dest=pd.merge(arrival_delayed_dest,uncancelled_flights_dest,on='Dest')
df_merged_dest.head()
```

Out[32]:

	Dest	delayed_flights	total_flights
0	ABE	3347	7054
1	ABI	1743	3601
2	ABQ	24599	54298
3	ABY	901	1693
4	ACK	164	282

In [33]:

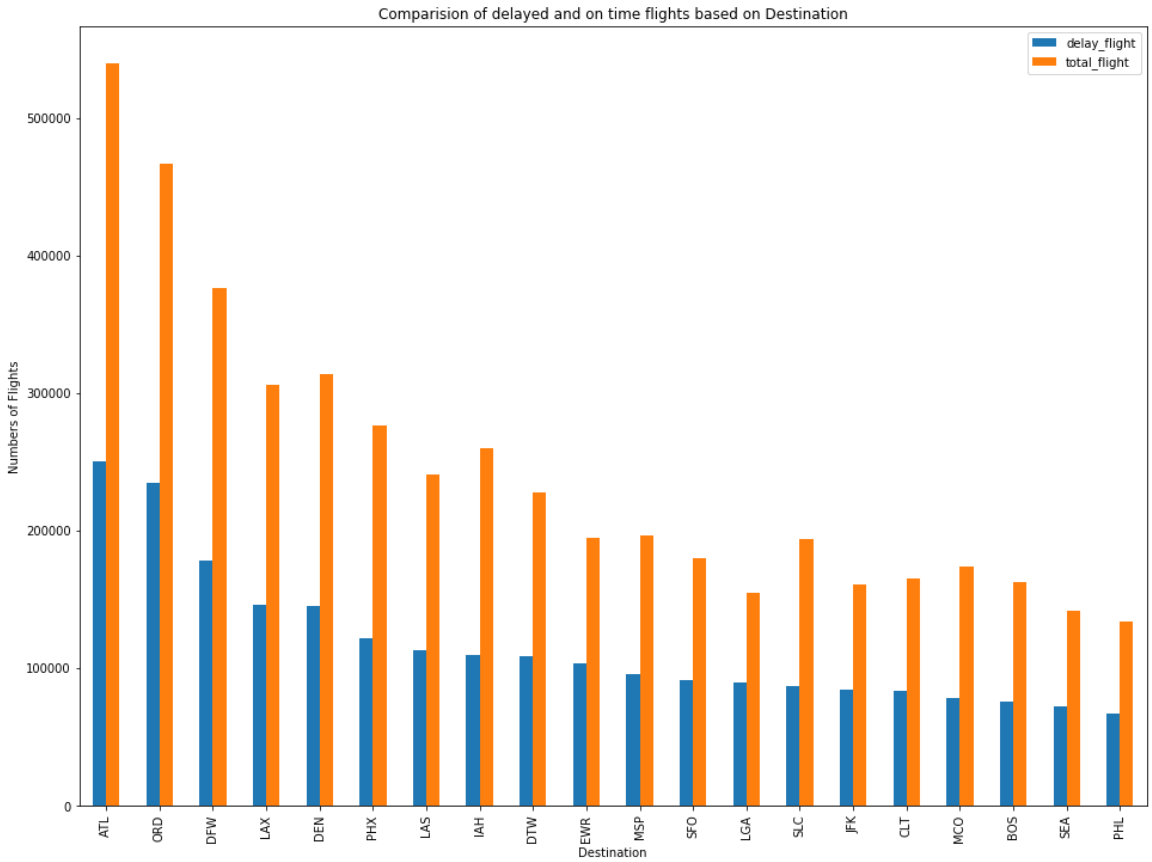
```
df_merged_dest_sort = df_merged_dest.sort_values(by =['delayed_flights', 'total_flight
s'], ascending = False)
top_20_destination = df_merged_dest_sort.head(20)
```

In [34]:

```
# changing the index as Destination
dest = top_20_destination.Dest.tolist()
delay_flight = top_20_destination.delayed_flights.tolist()
total_flight = top_20_destination.total_flights.tolist()

df2 = pd.DataFrame({'delay_flight':delay_flight, 'total_flight':total_flight}, index =
dest)
df2.head()
# Define Plot
ax = df2.plot.bar(figsize= [16,12], rot=90)
plt.xlabel('Destination')
plt.ylabel('Numbers of Flights')
plt.title('Comparision of delayed and on time flights based on Destination')

plt.show()
```



The figure above gives an overview of top 20 Desitinations where the flights has conducted on Time and delayed. The highest number of flight has been conducted in 'ATL'(Atlanta, GA: Hartsfield-Jackson Atlanta International) and the delayed number of flights is also higher in 'ATL'. It's pretty interesting all the destinations has a delayed number flights which is almost the half the number of total flights conducted for respective destinations.

Multivariate Exploration

Is there any relations between the AirTime and the flight delays? Are long distance flights prone delay more than that of small distance Flights while conducting Flights ? [long/small distance flights(in time)]

In [35]:

```
#creating arrays for the necessary columns
data = {'AirTime':df.AirTime,'CD':df.CarrierDelay,'WD':df.WeatherDelay, 'NASD':df.NASDe
lay, 'SD':df.SecurityDelay, 'LAD':df.LateAircraftDelay}
```

In [36]:

```
# creating dataframe with all the delays and AirTime
df3=pd.DataFrame(data)
```

In [37]:

```
#droping null values
df3 = df3.dropna()
```

In [38]:

```
#dropping flights having less airtime than 30, for generating good graph
df3 = df3.drop(df3[df3.AirTime < 30.0].index)
```

In [39]:

```
#sorting
df3 = df3.sort_values(by=['AirTime'])
```

In [40]:

```
df3['MeanDelay'] = df3.loc[:,'CD':].mean(axis=1)
```

In [41]:

```
df3 = df3.astype('float32')
df3
```

Out[41]:

	AirTime	CD	WD	NASD	SD	LAD	MeanDelay
799326	30.0	0.0	0.0	0.0	0.0	0.0	0.000000
2838763	30.0	0.0	0.0	0.0	0.0	0.0	0.000000
2838779	30.0	0.0	0.0	0.0	0.0	0.0	0.000000
2838781	30.0	0.0	0.0	18.0	0.0	0.0	3.600000
2838785	30.0	0.0	0.0	0.0	0.0	0.0	0.000000
...	...	...	...	...	...	...	...
2828314	966.0	853.0	0.0	0.0	0.0	18.0	174.199997
6608082	1068.0	894.0	0.0	0.0	0.0	0.0	178.800003
2205995	1071.0	620.0	0.0	0.0	0.0	0.0	124.000000
3867296	1248.0	49.0	0.0	1154.0	0.0	0.0	240.600006
172666	1257.0	0.0	0.0	1209.0	0.0	0.0	241.800003

7557391 rows × 7 columns

In [42]:

```
# defining a function for polynomial regression (for each delay)
def polyreg(data):
    poly = PolynomialFeatures(degree = 2)
    X_poly = poly.fit_transform(np.array(df3.AirTime).reshape(-1, 1))

    poly.fit(X_poly, np.array(data))
    lin2 = LinearRegression()
    lin2.fit(X_poly, np.array(data))

    reg = lin2.predict(poly.fit_transform(np.array(df3.AirTime).reshape(-1, 1)))
    scale = (reg*(min(data)-max(data))-max(reg)*min(data)+min(reg)*max(data))/(min(reg)
-max(reg))
    return scale
```

In [43]:

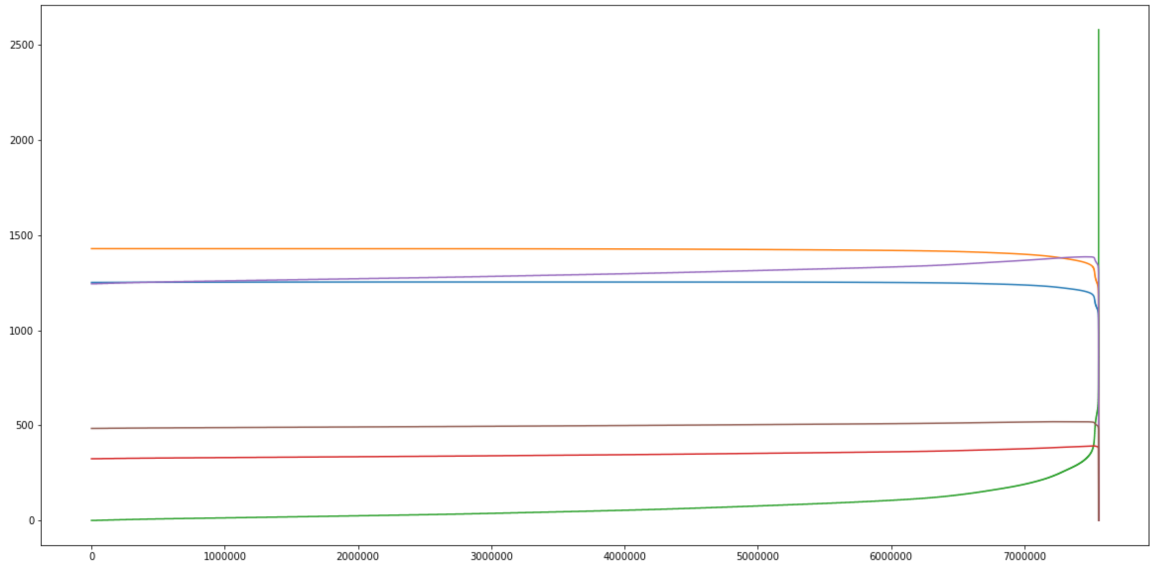
```
# inserting every delays in the function
lad= polyreg(df3.LAD)
wd= polyreg(df3.WD)
cd= polyreg(df3.CD)
sd= polyreg(df3.SD)
nasd= polyreg(df3.NASD)
md= polyreg(df3.MeanDelay)
```

In [44]:

```
#Define Plot (regression plot for the delays)
plt.figure(figsize=(20,10))
plt.plot(lad)
plt.plot(wd)
plt.plot(cd)
plt.plot(sd)
plt.plot(nasd)
plt.plot(md)
#plt.plot(df3.AirTime*(len(scaled)/max(exp)),exp)
```

Out[44]:

```
[<matplotlib.lines.Line2D at 0x22152d67248>]
```



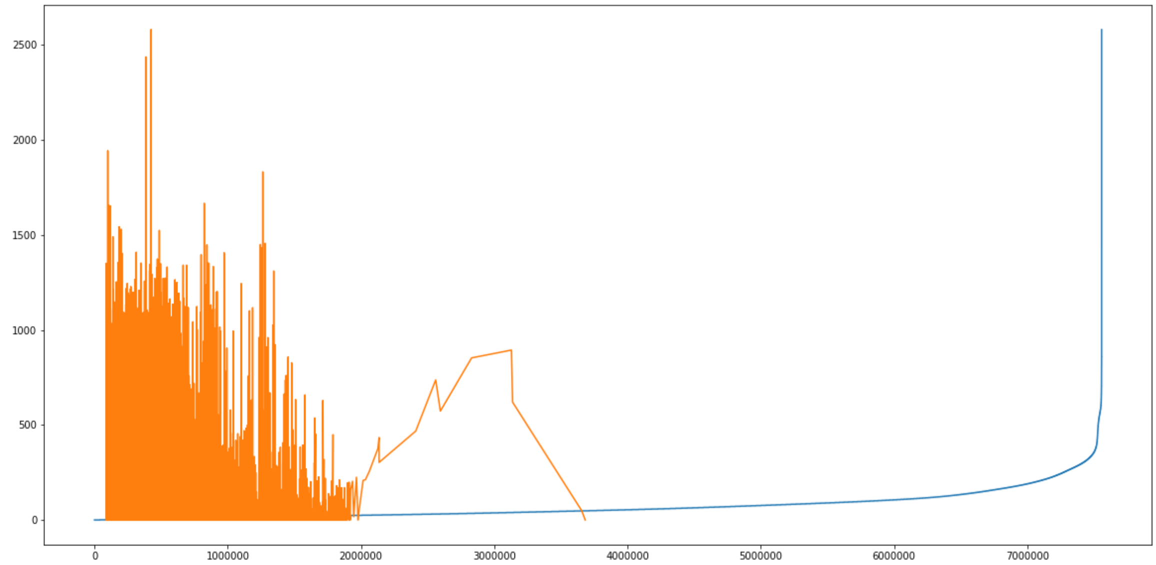
The figure above shows the regression line for each delays with resepect to Air Time. It can be observed that at the end of the dataset there are some outliers for which the regression line has gone up suddenly. It is also observable that the delays are in gerneral acute in those flights where the AirTime is less and delays are decreasing as the AirTime increases.

In [45]:

```
# Define Plot (original Carrier delay vs the regression line for Carrier Delay)
plt.figure(figsize=(20,10))
plt.plot(cd)
plt.plot(df3.AirTime*(len(cd)/max(df3.CD)),df3.CD)
```

Out[45]:

```
[<matplotlib.lines.Line2D at 0x22153104648>]
```



The figure shows the comparision between the regression line for carrier delay and carrier delay with respect to the AirTime. It is seen that delays are more acute in the flights where the AirTime is less. For example, the figure for the carrier delay has been shown, but other delays can be compared with regression line as well.

Reference

1. http://alanpryorjr.com/visualizations/seaborn/countplot/countplot/ (http://alanpryorjr.com/visualizations/seaborn/countplot/countplot/)
2. https://etav.github.io/python/count_basic_freq_plot.html (https://etav.github.io/python/count_basic_freq_plot.html)