Part I - (USA Trips)

localhost:8888/notebooks/DATA/UDACITY/flight/Part_I_exploration_template.ipynb

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Introduction

> In this project I'm going to analyze a data set with information about flights in the United States.

Preliminary Wrangling

Entrée [1]:

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

import glob

import requests as re

import os

import warnings

warnings.filterwarnings('ignore')

%matplotlib inline
```

Entrée [2]:

```
data = pd.read_csv('data/2007.csv')

df = data.copy()
```

Entrée [3]:

```
df.sample(5)
```

Out[3]:

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime	UniqueCarrier	FlightN
2288123	2007	4	9	1	1826.0	1831	1925.0	1934	9E	2844
368072	2007	1	14	7	612.0	620	757.0	816	FL	989
5999199	2007	10	19	5	1045.0	1045	1147.0	1148	MQ	3045
578813	2007	1	19	5	1223.0	1225	1618.0	1617	CO	554
2459447	2007	5	7	1	1204.0	1210	1457.0	1450	WN	949

5 rows × 29 columns

Entrée [4]:

```
df.shape
```

Out[4]:

```
(7453215, 29)
```

Entrée [5]:

```
df.columns
```

Out[5]:

```
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')
```

Entrée [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7453215 entries, 0 to 7453214
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             int64  
 20  TaxiOut            int64  
 21  Cancelled          int64  
 22  CancellationCode   object 
 23  Diverted           int64  
 24  CarrierDelay       int64  
 25  WeatherDelay       int64  
 26  NASDelay           int64  
 27  SecurityDelay      int64  
 28  LateAircraftDelay  int64  
dtypes: float64(7), int64(17), object(5)
memory usage: 1.6+ GB
```

Entrée [7]:

```
(df.isnull().sum()/len(df)).sort_values(ascending=False)
```

Out[7]:

```
CancellationCode     0.978432
ArrTime              0.023873
AirTime              0.023873
ActualElapsedTime    0.023873
ArrDelay             0.023873
DepTime              0.021568
DepDelay             0.021568
CRSElapsedTime       0.000133
TailNum              0.000003
WeatherDelay         0.000000
CarrierDelay         0.000000
Diverted             0.000000
Distance             0.000000
NASDelay             0.000000
SecurityDelay        0.000000
Cancelled            0.000000
TaxiOut              0.000000
TaxiIn               0.000000
Year                 0.000000
Dest                 0.000000
Origin               0.000000
Month                0.000000
FlightNum            0.000000
UniqueCarrier        0.000000
CRSArrTime           0.000000
CRSDepTime           0.000000
DayOfWeek            0.000000
DayofMonth           0.000000
LateAircraftDelay    0.000000
dtype: float64
```

Entrée [8]:

```
df.describe()
```

Out[8]:

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime
count	7453215.0	7.453215e+06	7.453215e+06	7.453215e+06	7.292467e+06	7.453215e+06	7.275288e+06	7.453215e+06

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime
mean	2007.0	6.514876e+00	1.572589e+01	3.933804e+00	1.339221e+03	1.330596e+03	1.482105e+03	1.495392e+03
std	0.0	3.425117e+00	8.781154e+00	1.992267e+00	4.798528e+02	4.647080e+02	5.072241e+02	4.815902e+02
min	2007.0	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	0.000000e+00	1.000000e+00	0.000000e+00
25%	2007.0	4.000000e+00	8.000000e+00	2.000000e+00	9.300000e+02	9.300000e+02	1.107000e+03	1.115000e+03
50%	2007.0	7.000000e+00	1.600000e+01	4.000000e+00	1.329000e+03	1.322000e+03	1.513000e+03	1.520000e+03
75%	2007.0	9.000000e+00	2.300000e+01	6.000000e+00	1.733000e+03	1.720000e+03	1.911000e+03	1.906000e+03
max	2007.0	1.200000e+01	3.100000e+01	7.000000e+00	2.400000e+03	2.359000e+03	2.400000e+03	2.400000e+03

8 rows × 24 columns

Entrée [9]:

```
df.describe(include='object')
```

Out[9]:

	UniqueCarrier	TailNum	Origin	Dest	CancellationCode
count	7453215	7453193	7453215	7453215	160749
unique	20	5505	304	310	4
top	WN	0	ATL	ATL	A
freq	1168871	105239	413851	413805	66779

What is the structure of your dataset?

> The Dataset has 7453215 rows and 29 columns. With a large number of missing values

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

> The essential variables are those relating to delays, airport name, air company and distance

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

> All the variables are usable. Everyone has information to give

Univariate Exploration

Entrée [10]:

```
df.columns
```

Out[10]:

```
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')
```

Entrée [11]:

```
# Year

df.Year.unique()
```

Out[11]:

```
array([2007], dtype=int64)
```

> The dataset only contains data from 2007. We can proceed with the analysis then

Entrée [12]:

```
# Month

df.Month.unique()
```

Out[12]:

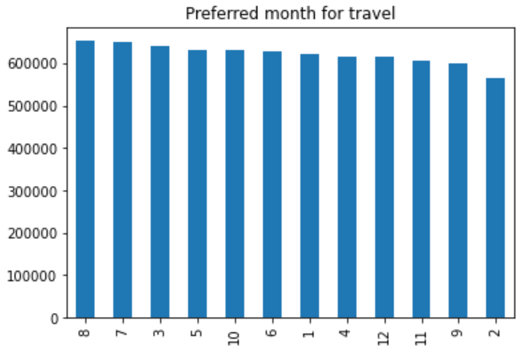
```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12], dtype=int64)
```

Entrée [13]:

```
plt.figure()

df.Month.value_counts().head(12).plot(kind='bar')

plt.title('Preferred month for travel')
```

Out[13]:

```
Text(0.5, 1.0, 'Preferred month for travel')
```



> We see that people tend to travel between July and August, which is normal because it is the holiday period.

Entrée [14]:

```
#DayofMonth

df.DayofMonth.unique()
```

Out[14]:

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31],
      dtype=int64)
```

Entrée [15]:

```
df_day = df.copy()
```

Entrée [16]:

```
print('Number of travel in 1st week: ' , df_day.query('DayofMonth < 9 ').shape[0]);

print('Number of travel in 2nd week: ' , df_day.query('DayofMonth >= 9 & DayofMonth < 17 ').shape[0])

print('Number of travel in 3rd week: ' , df_day.query('DayofMonth >= 17 & DayofMonth < 26 ').shape[0])

print('Number of travel in 4th week: ' , df_day.query('DayofMonth >= 26 ').shape[0])
```

```
Number of travel in 1st week:  1951552
Number of travel in 2nd week:  1971506
Number of travel in 3rd week:  2201918
Number of travel in 4th week:  1328239
```

> We see that there is much less travel at the end of the month from the 26th to the 31st.

Entrée [17]:

```
#DayofWeek

df.DayOfWeek.unique()
```

Out[17]:

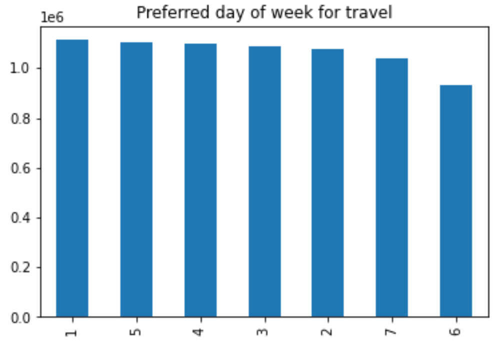
```
array([1, 2, 3, 4, 5, 6, 7], dtype=int64)
```

Entrée [18]:

```
plt.figure()

df.DayOfWeek.value_counts().head(7).plot(kind='bar')

plt.title('Preferred day of week for travel')
```

Out[18]:

```
Text(0.5, 1.0, 'Preferred day of week for travel')
```



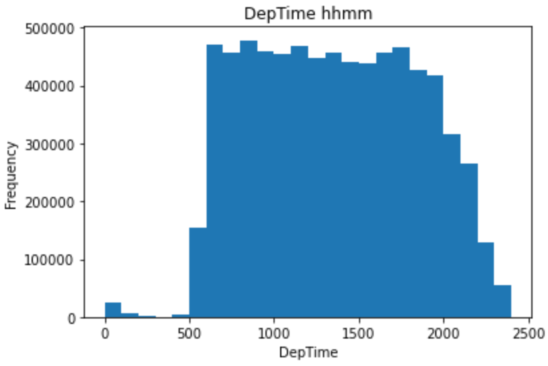
> Monday and Friday are the days when we record a lot more travel

Entrée [19]:

```
#Deptime

df.DepTime.plot(kind='hist', bins = 24)

plt.title('DepTime hhmm')

plt.xlabel('DepTime')
```

Out[19]:

```
Text(0.5, 0, 'DepTime')
```



Entrée [20]:

```
df.query('DepTime >2400')['DepTime']
```

Out[20]:

```
Series([], Name: DepTime, dtype: float64)
```

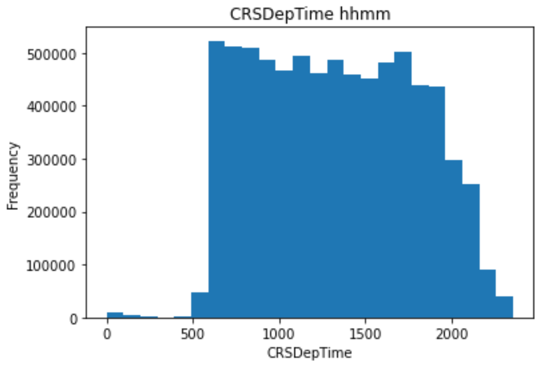
> Effective departures from the airport are generally between 6 a.m. and 8 p.m.

Entrée [21]:

```
#CRSDepTime

df.CRSDepTime.plot(kind='hist', bins=24)

plt.title('CRSDepTime hhmm')

plt.xlabel('CRSDepTime')
```

Out[21]:

```
Text(0.5, 0, 'CRSDepTime')
```



Entrée [22]:

```
df.query('CRSDepTime >2400')['CRSDepTime']
```

Out[22]:

```
Series([], Name: CRSDepTime, dtype: int64)
```

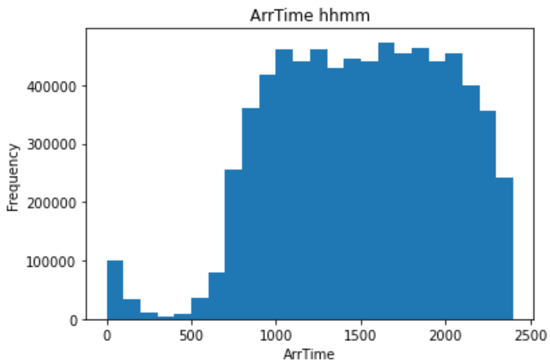
> Flights are mostly scheduled between 6 a.m. and 7 p.m.

Entrée [23]:

```
#ArrTime

df.ArrTime.plot(kind='hist', bins=24)

plt.title('ArrTime hhmm')

plt.xlabel('ArrTime')
```

Out[23]:

```
Text(0.5, 0, 'ArrTime')
```



Entrée [24]:

```
df.query('ArrTime >2400')['ArrTime']
```

Out[24]:

```
Series([], Name: ArrTime, dtype: float64)
```

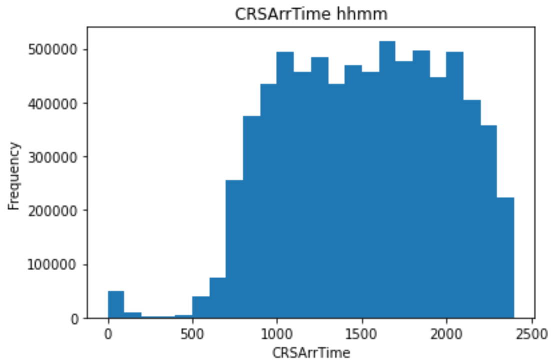
> Planes land at their destination between 10 a.m. and 9 p.m.

Entrée [25]:

```
#CRSArrTime

df.CRSArrTime.plot(kind='hist', bins=24)

plt.title('CRSArrTime hhmm')

plt.xlabel('CRSArrTime')
```

Out[25]:

```
Text(0.5, 0, 'CRSArrTime')
```



Entrée [26]:

```
df.query('CRSArrTime >2400')['CRSArrTime']
```

Out[26]:

```
Series([], Name: CRSArrTime, dtype: int64)
```

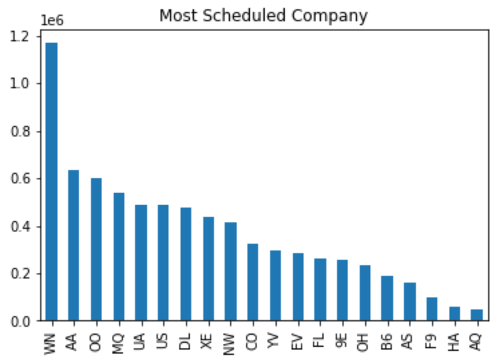
> Most landings are scheduled between 11 a.m. and 9 p.m.

Entrée [27]:

```
#UniqueCarrier

plt.figure()

df.UniqueCarrier.value_counts().plot(kind='bar')

plt.title('Most Scheduled Company')
```

Out[27]:

```
Text(0.5, 1.0, 'Most Scheduled Company')
```



> WN, AA, OO, MQ, UA are the airlines that made the most trips

Entrée [28]:

```
#FlightNum

df.FlightNum.nunique()
```

Out[28]:

```
7596
```

Entrée [29]:

```
#TailNum

df.TailNum.nunique()
```

Out[29]:

```
5505
```

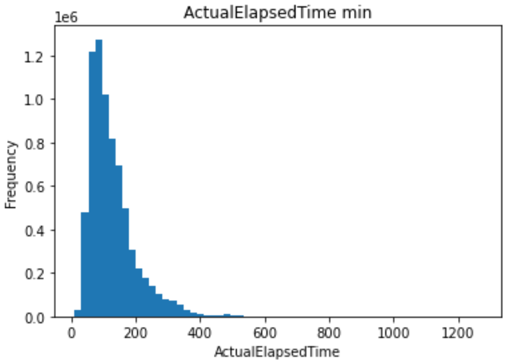
Entrée [30]:

```
#ActualElapsedTime

df.ActualElapsedTime.plot(kind='hist', bins=60)

plt.title('ActualElapsedTime min')
```

```
plt.xlabel('ActualElapsedTime')
```

Out[30]:

```
Text(0.5, 0, 'ActualElapsedTime')
```



Entrée [31]:

```
df_time = df.query('ActualElapsedTime>420')[['Origin','Dest','ActualElapsedTime']].sort_values(by
='ActualElapsedTime',ascending=False)

df_time
```

Out[31]:

	Origin	Dest	ActualElapsedTime
172666	CVG	LAN	1270.0
3867296	CVG	JAN	1260.0
2205995	HNL	SEA	1095.0
6608082	SFO	HNL	1090.0
2828314	LAX	HNL	989.0
...	...	...	...
7112586	BOS	PHX	421.0
1510130	JFK	SEA	421.0
7090808	DEN	KOA	421.0
7090807	DEN	KOA	421.0
12228	PHL	LAX	421.0

33177 rows × 3 columns

Entrée [32]:

```
df_time.quantile(q=0.95)
```

Out[32]:

```
ActualElapsedTime    559.0
Name: 0.95, dtype: float64
```

Entrée [33]:

```
df_time = df.query('ActualElapsedTime>638')[['Origin','Dest','ActualElapsedTime']].sort_values(by
='ActualElapsedTime',ascending=False)

df_time
```

Out[33]:

	Origin	Dest	ActualElapsedTime
172666	CVG	LAN	1270.0
3867296	CVG	JAN	1260.0
2205995	HNL	SEA	1095.0

	Origin	Dest	ActualElapsedTime
6608082	SFO	HNL	1090.0
2828314	LAX	HNL	989.0
...	...	...	...
4596408	IAD	SMF	639.0
6795233	EWR	HNL	639.0
1169119	ATL	HNL	639.0
3024201	EWR	HNL	639.0
6809148	EWR	HNL	639.0

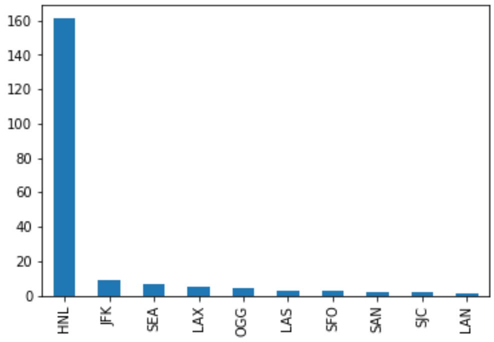
200 rows × 3 columns

Entrée [34]:

```
df_time.Dest.value_counts().head(10).plot(kind='bar')
```

Out[34]:

```
<AxesSubplot:>
```



Entrée [35]:

```
df_time.query('Dest == "HNL"').sort_values(by ='ActualElapsedTime',ascending=False)
```

Out[35]:

	Origin	Dest	ActualElapsedTime
6608082	SFO	HNL	1090.0
2828314	LAX	HNL	989.0
7434434	EWR	HNL	836.0
1162131	EWR	HNL	725.0
7432009	EWR	HNL	711.0
...	...	...	...
2396229	EWR	HNL	639.0
6795233	EWR	HNL	639.0
1169119	ATL	HNL	639.0
3024201	EWR	HNL	639.0
6809148	EWR	HNL	639.0

161 rows × 3 columns

> Trips generally last less than 420 minutes. It would seem that the farthest place to reach in general is HNL airport. 95% of the time, when the destination is this one, the trip is harder than the others

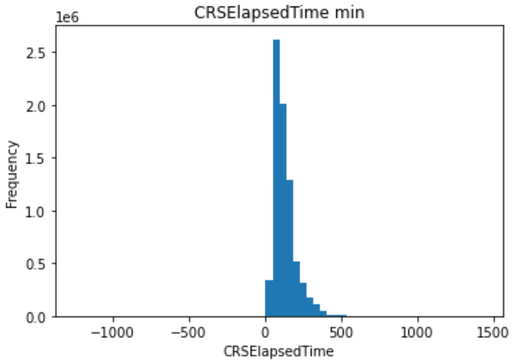
Entrée [36]:

```
#CRSElapsedTime
```

```
df.CRSElapsedTime.plot(kind='hist', bins=60)

plt.title('CRSElapsedTime min')

plt.xlabel('CRSElapsedTime')
```

Out[36]:

```
Text(0.5, 0, 'CRSElapsedTime')
```



Entrée [37]:

```
df_time.groupby(['Dest'])
```

Out[37]:

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x0000013822C34520>
```

Entrée [38]:

```
df.query('CRSElapsedTime<0')['CRSElapsedTime'].sort_values(ascending=False)
```

Out[38]:

```
1538199     -46.0
566619    -1240.0
Name: CRSElapsedTime, dtype: float64
```

Entrée [39]:

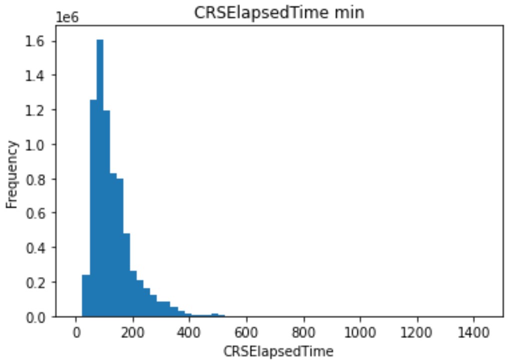
```
df.drop(df.query('CRSElapsedTime<0').index , inplace=True)
```

Entrée [40]:

```
df.CRSElapsedTime.plot(kind='hist', bins=60)

plt.title('CRSElapsedTime min')

plt.xlabel('CRSElapsedTime')
```

Out[40]:

```
Text(0.5, 0, 'CRSElapsedTime')
```



Entrée [41]:

```
df.query('CRSElapsedTime>420')['CRSElapsedTime'].sort_values(ascending=False)
```

Out[41]:

```
6026104    1430.0
7252332    1430.0
1781003     660.0
6809486     660.0
6812831     660.0
            ...
4683231     421.0
4691074     421.0
4695105     421.0
4687222     421.0
4692380     421.0
Name: CRSElapsedTime, Length: 30669, dtype: float64
```

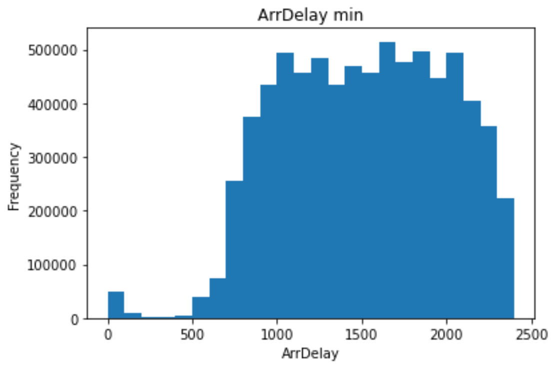
> Estimates on the duration of a flight in the air seem good. The predicted time histogram closely approximates the actual histogram.

Entrée [42]:

```
#ArrDelay

df.CRSArrTime.plot(kind='hist', bins=24)

plt.title('ArrDelay min')

plt.xlabel('ArrDelay')
```

Out[42]:

```
Text(0.5, 0, 'ArrDelay')
```



Entrée [43]:

```
df.query('ArrDelay >2400')['ArrDelay']
```

Out[43]:

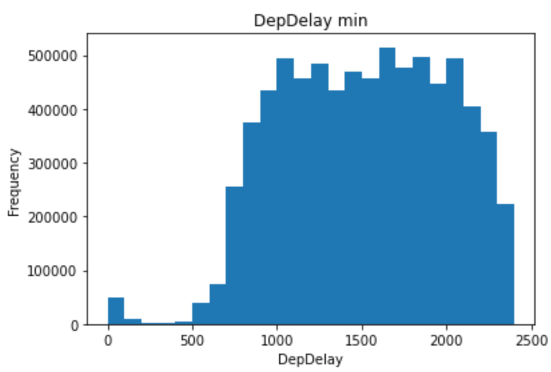
```
6061662    2598.0
Name: ArrDelay, dtype: float64
```

Entrée [44]:

```
#DepDelay

df.CRSArrTime.plot(kind='hist', bins=24)

plt.title('DepDelay min')

plt.xlabel('DepDelay')
```

Out[44]:

```
Text(0.5, 0, 'DepDelay')
```



Entrée [45]:

```
df.query('DepDelay >2400')['DepDelay']
```

Out[45]:

```
6061662    2601.0
Name: DepDelay, dtype: float64
```

Entrée [46]:

```
len(df.query('DepDelay<0')['DepDelay'])*100/len(df)
```

Out[46]:

```
47.246925587662666
```

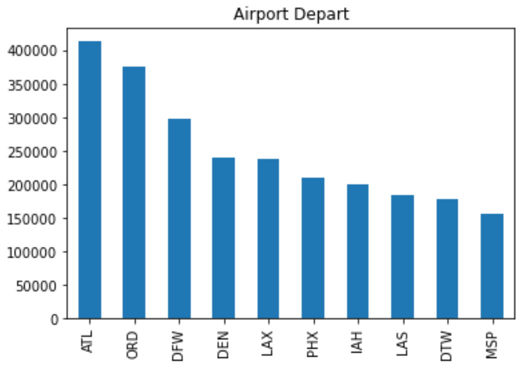
> Delayed flights often land 1000 minutes (4:00 p.m.) later. It has even happened that a scheduled flight has reached 2500 minutes (41h) later. However, note that 47% of flights land before the scheduled time

Entrée [47]:

```
#Origin

plt.figure()

df.Origin.value_counts().head(10).plot(kind='bar')

plt.title('Airport Depart')
```

Out[47]:

```
Text(0.5, 1.0, 'Airport Depart')
```

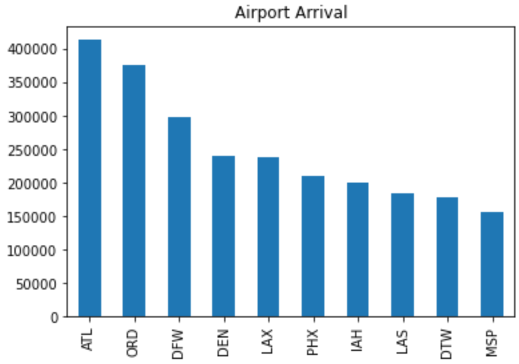


Entrée [48]:

```
#Dest

plt.figure()

df.Dest.value_counts().head(10).plot(kind='bar')

plt.title('Airport Arrival')
```

Out[48]:

```
Text(0.5, 1.0, 'Airport Arrival')
```



> The airports recording the most travel are in order, ATL, ORD, DFW, DEN, LAX, PHX, IAH, LAS, DTW, MSP

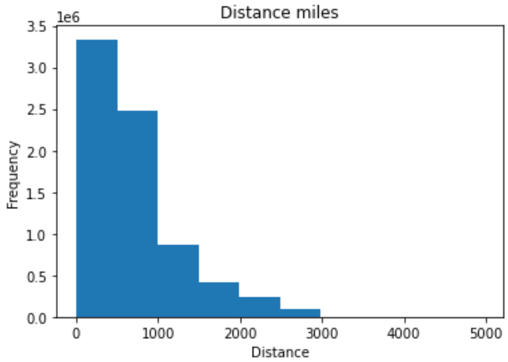
Entrée [49]:

```
#Distance
```

```
df.Distance.plot(kind='hist')

plt.title('Distance miles')

plt.xlabel('Distance')
```

Out[49]:

```
Text(0.5, 0, 'Distance')
```



Entrée [50]:

```
df_dist = df.query('Distance>3000')[['Origin','Dest','Distance']].sort_values(by ='Distance',ascending=False)

df_dist
```

Out[50]:

	Origin	Dest	Distance
1166010	HNL	EWR	4962
1154566	EWR	HNL	4962
1152195	EWR	HNL	4962
1152030	EWR	HNL	4962
1151770	EWR	HNL	4962
...	...	...	...
2938724	DFW	ANC	3043
2938725	DFW	ANC	3043
2938726	DFW	ANC	3043
2938727	DFW	ANC	3043
4866132	DFW	ANC	3043

11229 rows × 3 columns

Entrée [51]:

```
df_dist.quantile(q=0.85)
```

Out[51]:

```
Distance    4502.0
Name: 0.85, dtype: float64
```

Entrée [52]:

```
df_dist = df.query('Distance>4502')[['Origin','Dest','Distance']].sort_values(by ='Distance',ascending=False)

df_dist
```

Out[52]:

	Origin	Dest	Distance
574557	EWR	HNL	4962
4979003	EWR	HNL	4962

	Origin	Dest	Distance
4979281	HNL	EWR	4962
4979705	HNL	EWR	4962
4979775	HNL	EWR	4962
...	...	...	...
3025408	HNL	EWR	4962
3026180	EWR	HNL	4962
3026456	EWR	HNL	4962
3026946	EWR	HNL	4962
7434799	HNL	EWR	4962

730 rows × 3 columns

Entrée [53]:

```
df_dist.query('Dest == "HNL"').sort_values(by ='Distance',ascending=False)
```

Out[53]:

	Origin	Dest	Distance
574557	EWR	HNL	4962
582703	EWR	HNL	4962
578673	EWR	HNL	4962
578590	EWR	HNL	4962
578026	EWR	HNL	4962
...	...	...	...
7433923	EWR	HNL	4962
7433807	EWR	HNL	4962
7433342	EWR	HNL	4962
7433278	EWR	HNL	4962
3026946	EWR	HNL	4962

365 rows × 3 columns

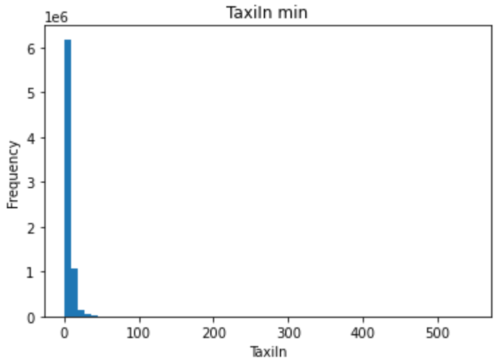
> Trips are generally a maximum of 3000 miles. It would seem that the farthest place to reach in general is HNL airport. 85% of the time, when the destination is this one, the trip is longer than the others

Entrée [54]:

```
#TaxiIn

df.TaxiIn.plot(kind='hist', bins=60)

plt.title('TaxiIn min')

plt.xlabel('TaxiIn')
```

Out[54]:

```
Text(0.5, 0, 'TaxiIn')
```



Entrée [55]:

```
df.query('TaxiIn>40')['TaxiIn'].sort_values(ascending=False)
```

Out[55]:

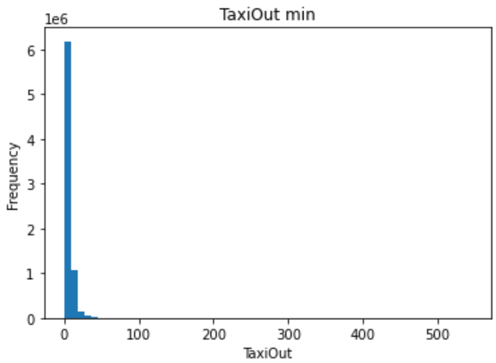
```
1137098    545
1136659    486
1136778    459
775498     353
1136654    353
          ...
2905448     41
5361918     41
5363269     41
2866917     41
4302812     41
Name: TaxiIn, Length: 17202, dtype: int64
```

Entrée [56]:

```
#TaxiOut

df.TaxiIn.plot(kind='hist', bins=60)

plt.title('TaxiOut min')

plt.xlabel('TaxiOut')
```

Out[56]:

```
Text(0.5, 0, 'TaxiOut')
```



Entrée [57]:

```
df.query('TaxiOut>40')['TaxiOut'].sort_values(ascending=False)
```

Out[57]:

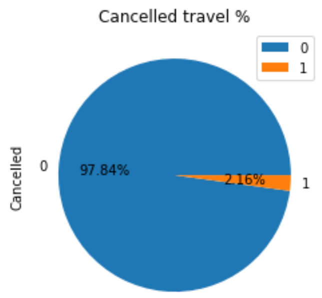
```
7025465    530
1136857    435
1185812    403
7025468    400
2553986    392
          ...
6546684     41
5320451     41
7155573     41
6546810     41
5981679     41
Name: TaxiOut, Length: 251130, dtype: int64
```

Entrée [58]:

```
#Cancelled

df.Cancelled.value_counts().plot(kind='pie',autopct='%1.2f%%')

plt.legend()

plt.title('Cancelled travel %')
```

Out[58]:

```
Text(0.5, 1.0, 'Cancelled travel %')
```

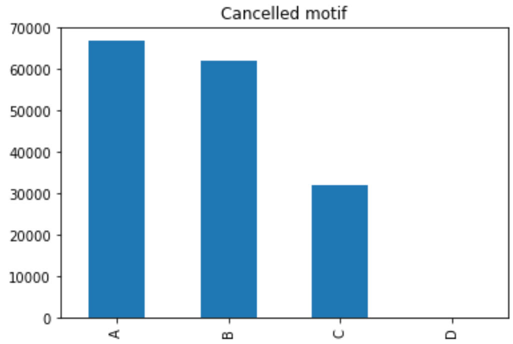


Entrée [59]:

```
#CancellationCode

df.CancellationCode.value_counts().plot(kind='bar')

plt.title('Cancelled motif')
```

Out[59]:

```
Text(0.5, 1.0, 'Cancelled motif')
```



> Only 2% of flights are cancelled. The two main reasons are: carrier and weather

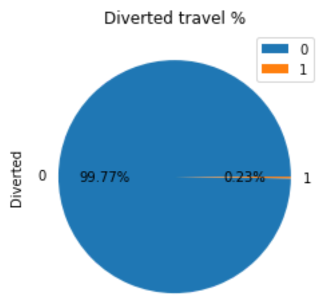
Entrée [60]:

```
#Diverted

df.Diverted.value_counts().plot(kind='pie',autopct='%1.2f%%')

plt.legend()

plt.title('Diverted travel %')
```

Out[60]:

```
Text(0.5, 1.0, 'Diverted travel %')
```

> A tiny part of the flights was hijacked, 0.23%

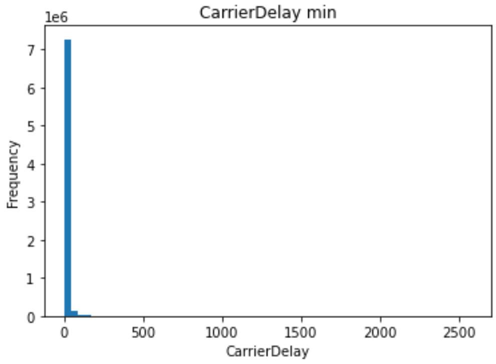


Entrée [61]:

```
#CarrierDelay

df.CarrierDelay.plot(kind='hist', bins=60)

plt.title('CarrierDelay min')

plt.xlabel('CarrierDelay')
```

Out[61]:

```
Text(0.5, 0, 'CarrierDelay')
```



Entrée [62]:

```
df.query('CarrierDelay>120')['CarrierDelay'].sort_values(ascending=False)
```

Out[62]:

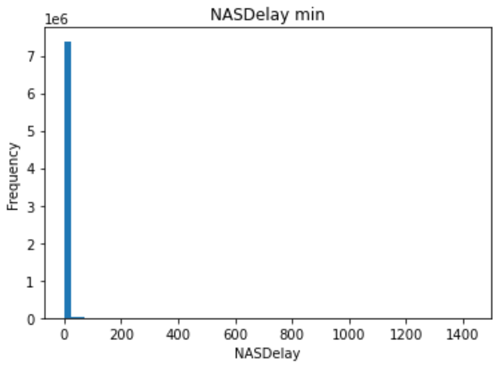
```
6061662    2580
7299451    1942
6060526    1831
6082457    1715
5439037    1665
           ...
1780801     121
7077974     121
1489458     121
4041225     121
5933593     121
Name: CarrierDelay, Length: 39564, dtype: int64
```

Entrée [63]:

```
#NASDelay

df.WeatherDelay.plot(kind='hist', bins=60)

plt.title('NASDelay min')

plt.xlabel('NASDelay')
```

Out[63]:

```
Text(0.5, 0, 'NASDelay')
```



Entrée [64]:

```
df.query('NASDelay>120')['NASDelay'].sort_values(ascending=False)
```

Out[64]:

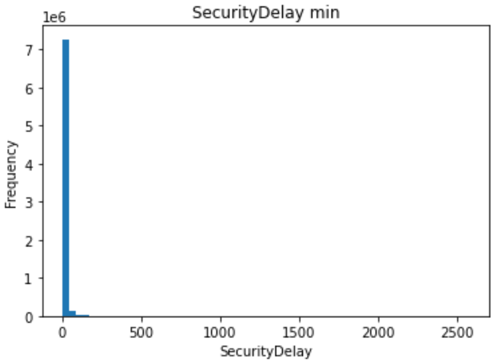
```
4230378    1386
2857190    1352
1643023    1324
7242415    1321
4157828    1270
           ...
6026605     121
3381791     121
6039144     121
6040612     121
7060803     121
Name: NASDelay, Length: 29961, dtype: int64
```

Entrée [65]:

```
#SecurityDelay

df.CarrierDelay.plot(kind='hist', bins=60)

plt.title('SecurityDelay min')

plt.xlabel('SecurityDelay')
```

Out[65]:

```
Text(0.5, 0, 'SecurityDelay')
```



Entrée [66]:

```
df.query('SecurityDelay>120')['SecurityDelay'].sort_values(ascending=False)
```

Out[66]:

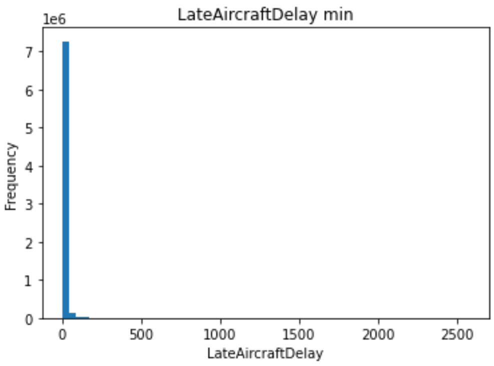
```
1701614    382
5019603    366
739315     357
6985047    299
6336981    297
          ...
418388     126
5624121    124
2780709    123
789322     121
4511620    121
Name: SecurityDelay, Length: 113, dtype: int64
```

Entrée [67]:

```
#LateAircraftDelay

df.CarrierDelay.plot(kind='hist', bins=60)

plt.title('LateAircraftDelay min')

plt.xlabel('LateAircraftDelay')
```

Out[67]:

```
Text(0.5, 0, 'LateAircraftDelay')
```



Entrée [68]:

```
df.query('LateAircraftDelay>120')['LateAircraftDelay'].sort_values(ascending=False)
```

Out[68]:

```
6669348    1031
3304430    1014
1019198    1011
1486680    1003
2357337     996
           ...
824053      121
3799974     121
3005914     121
4272151     121
4855003     121
Name: LateAircraftDelay, Length: 58705, dtype: int64
```

> Regardless of the reasons for a flight delay, the flight generally takes off within 2 hours. But in case of carrier it can take much longer than usual

Discuss the distribution(s) of your variable(s) of interest. Were there any unusual points? Did you need to perform any transformations?

> For the CRSElapsedTime variable, an inappropriate value had to be deleted. As for the others, the valuers can be considered good.

Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

> In the distance, we noticed that the values related to flights on Hawaii are very far from the others, which is quite normal. So we didn't touch that.

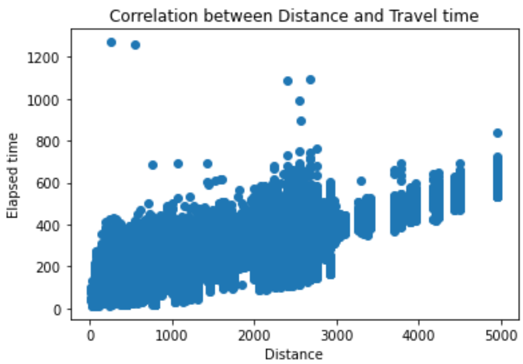
Bivariate Exploration

Entrée [69]:

```
#Distance and ActualElapsedTime

plt.scatter(data=df,x='Distance',y='ActualElapsedTime')

plt.ylabel('Elapsed time')

plt.xlabel('Distance')

plt.title('Correlation between Distance and Travel time')
```

Out[69]:

```
Text(0.5, 1.0, 'Correlation between Distance and Travel time')
```



Entrée [70]:

```
df.drop(df.query('ActualElapsedTime>800').index , inplace=True)
```

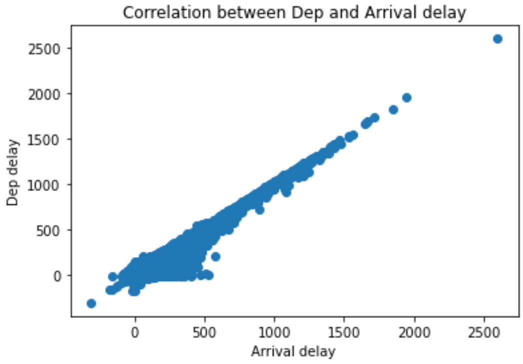
> It can be seen that there is a correlation between the two variables. Indeed, the greater the distance, the longer the trip takes. However, outliers are observed. We decided to delete them for a better analysis

Entrée [71]:

```
# ArrDelay and DepDelay

plt.scatter(data=df,x='ArrDelay',y='DepDelay')

plt.xlabel('Arrival delay')

plt.ylabel('Dep delay')

plt.title('Correlation between Dep and Arrival delay')
```

Out[71]:

```
Text(0.5, 1.0, 'Correlation between Dep and Arrival delay')
```



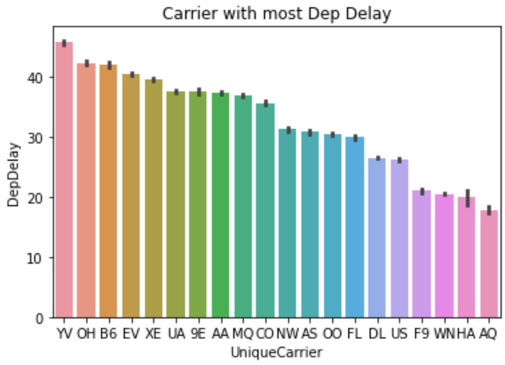
> It can be seen that there is a correlation between the two variables. Indeed, the more the departure time is delayed, the more the arrival time is too. Which is completely normal.

Entrée [72]:

```
# UniqueCarrier and DepDelay

df_late=df[df.DepDelay > 0]

order2 = df_late.groupby(['UniqueCarrier']).DepDelay.mean().sort_values(ascending=False).index

sns.barplot(data=df_late, x='UniqueCarrier',y='DepDelay',order=order2)

plt.title('Carrier with most Dep Delay')
```

Out[72]:

```
Text(0.5, 1.0, 'Carrier with most Dep Delay')
```



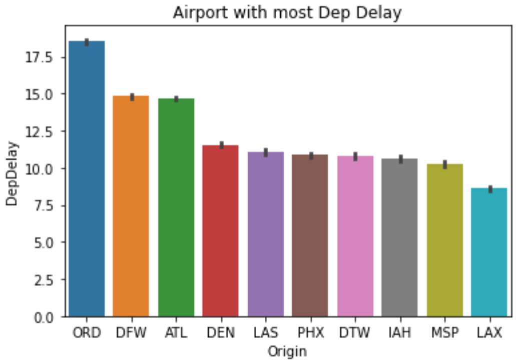
> In the event of inconvenience causing a delay, companies YV, CH and B6 take a long time before taking off. AQ is the most responsive.

Entrée [73]:

```
# Origin and DepDelay

plt.figure()

airport = df.Origin.value_counts().head(10).index.tolist()

df_airport = df[df.Origin.isin(airport)]

order3 = df_airport.groupby(['Origin']).DepDelay.mean().sort_values(ascending=False).index

sns.barplot(data=df_airport, x='Origin',y='DepDelay',order=order3)

plt.title('Airport with most Dep Delay')
```

Out[73]:

```
Text(0.5, 1.0, 'Airport with most Dep Delay')
```



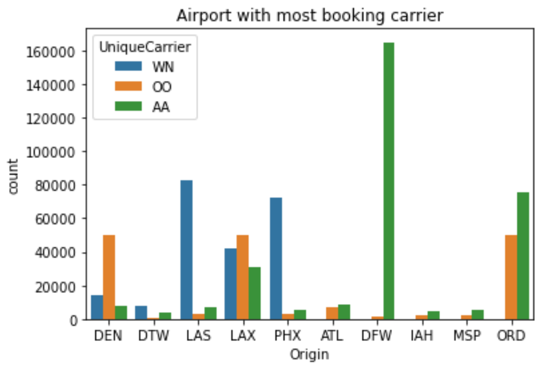
> The airport where the most delays are recorded is ORD airport. It is followed successively by DFW, ATL, DEN and LAS.

Entrée [74]:

```
#Origin and UniqueCarrier

plt.figure()

airport = df.Origin.value_counts().head(10).index.tolist()

aircomp= df.UniqueCarrier.value_counts().head(3).index.tolist()

df_airport = df[df.Origin.isin(airport)]

df_airport_aircomp = df_airport[df_airport.UniqueCarrier.isin(aircomp)]

sns.countplot(data=df_airport_aircomp, x='Origin',hue='UniqueCarrier')

plt.title('Airport with most booking carrier')
```

Out[74]:

```
Text(0.5, 1.0, 'Airport with most booking carrier')
```



> We note that companies are privileged in certain airports. At DFW, AA manages a large majority of trips

Entrée [75]:

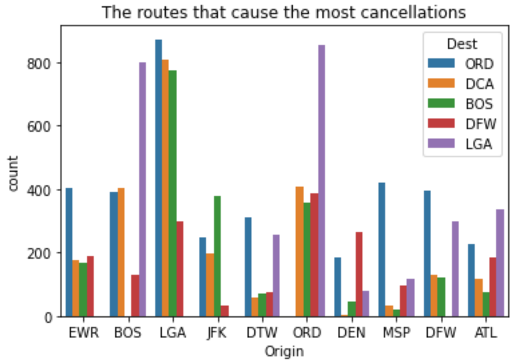
```
cancelled = df.query('Cancelled == 1')
```

Entrée [76]:

```
#Origin and Dest

plt.figure()

can_ori = cancelled.Origin.value_counts().head(10).index.tolist()

cancelled_airport = cancelled[cancelled.Origin.isin(can_ori)]

can_dest = cancelled_airport.Dest.value_counts().head(5).index.tolist()

can_routes = cancelled_airport[cancelled_airport.Dest.isin(can_dest)]

sns.countplot(data=can_routes, x='Origin',hue='Dest')

plt.title('The routes that cause the most cancellations')
```

Out[76]:

```
Text(0.5, 1.0, 'The routes that cause the most cancellations')
```



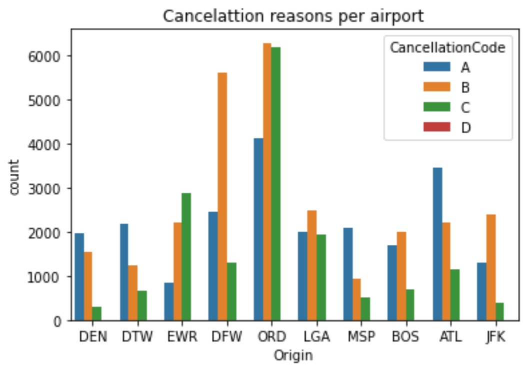
> This graph allows us to have an overview of the routes with the most canceled flights

Entrée [77]:

```
#Origin and CancellationCode

sns.countplot(data=cancelled_airport, x='Origin',hue='CancellationCode')

plt.title('Cancelattion reasons per airport')
```

Out[77]:

```
Text(0.5, 1.0, 'Cancelattion reasons per airport')
```



> This graph allows us to have an overview of the reasons for cancellation of trips in each city

Talk about some of the relationships you observed in this part of the investigation. How did the feature(s) of interest vary with other features in the dataset?

> During the investigation, it was noticed that there is a correlation between the distance and the duration of the flights. In addition, we note that on the whole each company has operated in its own way. each presents unique and unique data

Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

> The other variables have no common characteristics

Multivariate Exploration

Entrée [78]:

```
df2= df.query('Diverted==1')
```

Entrée [79]:

```
df2.columns
```

Out[79]:

```
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')
```

Entrée [80]:

```
df2 = df2[['Month', 'DayofMonth', 'DayOfWeek', 'UniqueCarrier', 'CRSDepTime', 'DepTime','Origin','Dest', 'Distance']]
```

```
df2.sample(3)
```

Out[80]:

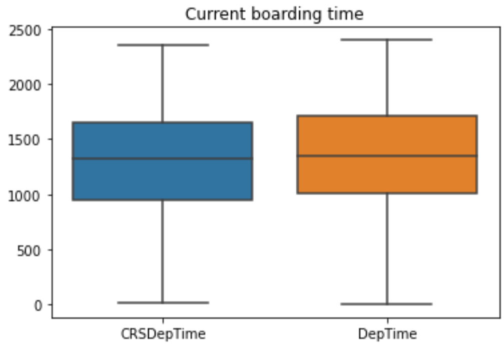
	Month	DayofMonth	DayOfWeek	UniqueCarrier	CRSDepTime	DepTime	Origin	Dest	Distance
165355	1	16	2	OH	1150	1310.0	SRQ	CVG	812
4362379	8	5	7	WN	1255	1248.0	SAN	MDW	1728
5975760	10	7	7	FL	1221	1221.0	ATL	BUF	712

Entrée [81]:

```
vars = ["CRSDepTime","DepTime"]

sns.boxplot(data = df2[vars].sample(10000))

plt.title('Current boarding time')
```

Out[81]:

```
Text(0.5, 1.0, 'Current boarding time')
```



Entrée [82]:

```
df2.describe(include='all')
```

Out[82]:

	Month	DayofMonth	DayOfWeek	UniqueCarrier	CRSDepTime	DepTime	Origin	Dest	Distance
count	17179.00000	17179.000000	17179.000000	17179	17179.000000	17179.000000	17179	17179	17179.000
unique	NaN	NaN	NaN	20	NaN	NaN	272	271	NaN
top	NaN	NaN	NaN	AA	NaN	NaN	ATL	DFW	NaN
freq	NaN	NaN	NaN	2097	NaN	NaN	920	1948	NaN
mean	6.46778	16.239304	3.889574	NaN	1319.734327	1347.600035	NaN	NaN	936.07613
std	3.19982	8.742754	1.942525	NaN	438.986813	466.295527	NaN	NaN	631.11641
min	1.00000	1.000000	1.000000	NaN	10.000000	3.000000	NaN	NaN	30.000000
25%	4.00000	9.000000	2.000000	NaN	950.000000	1004.000000	NaN	NaN	483.00000
50%	7.00000	16.000000	4.000000	NaN	1325.000000	1348.000000	NaN	NaN	802.00000
75%	9.00000	24.000000	5.000000	NaN	1650.000000	1715.000000	NaN	NaN	1188.5000
max	12.00000	31.000000	7.000000	NaN	2359.000000	2400.000000	NaN	NaN	4962.0000

> By studying the cases of hijacked planes, we notice that almost no company or city is spared. The kidnappers are probably acting randomly. However, we can say that daytime flights are a relevant selection criterion for them to operate.

Conclusions

> During this analysis, I came across a lot of information that I personally did not know. here is the strength of data analysis, bringing a surplus of information to decision-makers. however I am a little surprised that the air sector is so diversified from one city to another but also of the many cases of flight delays. For a country like the United States it can be surprising

Entrée [ ]: