Project-5-Communicate_Data_Findings

June 2, 2019

1 Flights in the United States

1.1 by Benoît Courty

1.2 Preliminary Wrangling

This dataset reports flights in the United States, including carriers, arrival and departure delays, and reasons for delays, from 1987 to 2008.

```
In [1]: # Put these at the top of every notebook, to get automatic reloading and inline plotti
        %reload_ext autoreload
        %autoreload 2
        %matplotlib inline
        from IPython.core.interactiveshell import InteractiveShell
        InteractiveShell.ast_node_interactivity = "all"
        def pv(variable):
            if(len(variable)>1): print(variable, ":", eval(variable))
```

```
In [2]: # import all packages
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
```

1.2.1 Downloading the datasets

The dataset consist of a file per year.
We will look over a list of availiable years and download the files.
Source : http://stat-computing.org/dataexpo/2009/1987.csv.bz2

```
In [3]: import os
        import requests
        folder_name = "./"

        def download_files(folder_name):
            years = []
            for year in range(1987, 2008+1):
                years.append(year)
```

```
            url = "http://stat-computing.org/dataexpo/2009/" + str(year) + ".csv.bz2"
            filename = url.split('/')[-1]
            response = requests.get(url)
            with open(os.path.join(folder_name, filename), mode='wb') as file:
                file.write(response.content)
        print("Files retreived !")
        return years

years = []
#years = download_files(folder_name)
```

Now, we have our dataset, let's load it.

1.2.2 Loading the dataset

I've writen the code to merge all the data, but it's too big for my computer. If needed later I could sample data, or compute some agregate.

I will begin by using only 2008 as it is the more recent datas.

```
In [4]: import pandas as pd

        years = ['2008']
        df = pd.DataFrame()
        for year in years:
            datafilename = folder_name + year + '.csv.bz2'
            print(datafilename)
            df_temp = pd.read_csv(datafilename)
            df = pd.concat([df, df_temp])
```

```
./2008.csv.bz2
```

Get a rapid overview of it.

```
In [5]: # df.head(3)
        # df.tail(3)
        # df.columns
        #df.dtypes
        # df.describe()
        # df.info()
```

It's a huge Dataset : 7 009 728 entries with 29 columns.
At first look it seems clean and tidy.
I have to change the type of FlightNum to String.

```
In [6]: df = df.astype({"FlightNum": str})
```

Let's explore categorical variable with less than 15 unique values.

```python
In [7]: def explore_value(df):
            to_be_removed = []
            columns = df.columns
            for column in columns:
                nb_unique_values = eval('df.' + column + '.nunique()')
                #print("Distinct values in", column, ":", nb_unique_values)
                if nb_unique_values > 15:
                    to_be_removed.append(column)
            columns_redux = [item for item in columns if item not in to_be_removed ]

            #print(columns_redux)
            for column in columns_redux:

                code = 'df.' + column + '.value_counts()'
                print("Distinct values in", column, ':', code)
                print(eval(code))

        explore_value(df)
```

```
Distinct values in Year : df.Year.value_counts()
2008    7009728
Name: Year, dtype: int64
Distinct values in Month : df.Month.value_counts()
7     627931
3     616090
8     612279
6     608665
5     606293
1     605765
4     598126
2     569236
10    556205
12    544958
9     540908
11    523272
Name: Month, dtype: int64
Distinct values in DayOfWeek : df.DayOfWeek.value_counts()
3    1039665
1    1036201
5    1035166
4    1032224
2    1032049
7     976887
6     857536
Name: DayOfWeek, dtype: int64
Distinct values in Cancelled : df.Cancelled.value_counts()
0    6872294
1     137434
```

```
Name: Cancelled, dtype: int64
Distinct values in CancellationCode : df.CancellationCode.value_counts()
B    54904
A    54330
C    28188
D       12
Name: CancellationCode, dtype: int64
Distinct values in Diverted : df.Diverted.value_counts()
0    6992463
1      17265
Name: Diverted, dtype: int64
```

Only 12 Security cancellation (D) in one year. We will have miss it if we have used a sample.

Check if it will be a good idea to merge CarrierDelay, WeatherDelay, NASDelay, SecurityDelay and LateAircraftDelay.

```
In [8]: df.query("CarrierDelay > 0 and WeatherDelay > 0")[['CarrierDelay', 'WeatherDelay']][:3
```

```
Out[8]:         CarrierDelay  WeatherDelay
        98551           12.0           8.0
        101614         224.0         120.0
        303687           2.0          61.0
```

The delay could exist for more than one category, so we will not merge them.

1.3 Dropping unnessary columns

I will drop some columns as I think I will not need them.

```
In [9]: # Drop unused columns
        df.drop(['Year', 'TaxiIn', 'TaxiOut', 'ActualElapsedTime', 'CRSElapsedTime', 'AirTime'
```

1.4 Adding external data

We saw that the dataset contain only codes for airports and carriers, as we will display it, we are going to retreive the label for them.

I get it from http://stat-computing.org/dataexpo/2009/supplemental-data.html : - For City / Airport : http://stat-computing.org/dataexpo/2009/airports.csv - For Carrier : http://stat-computing.org/dataexpo/2009/carriers.csv

```
In [10]: def download(url):
             filename = url.split('/')[-1]
             response = requests.get(url)
             with open(os.path.join(folder_name, filename), mode='wb') as file:
                 file.write(response.content)
             return filename
         # download("http://stat-computing.org/dataexpo/2009/airports.csv")
         # download("http://stat-computing.org/dataexpo/2009/carriers.csv")
```

In [11]:
```python
df_airports = pd.read_csv("airports.csv")
df_carriers = pd.read_csv("carriers.csv")
```

Now we have the data, let's merge it with our dataset.

In [12]:
```python
# Add Origin City name
df_tmp = df.merge(df_airports[['iata', 'city', 'state', 'lat', 'long']], how='left', l
df_tmp.drop('iata', axis=1, inplace=True)
df_tmp.rename(columns={'city':'OriginCity', 'state':'OriginState', 'lat':'OriginLat',

# Add Destination City name
df_tmp = df_tmp.merge(df_airports[['iata', 'city', 'state', 'lat', 'long']], how='lef
df_tmp.drop('iata', axis=1, inplace=True)
df_tmp.rename(columns={'city':'DestCity', 'state':'DestState', 'lat':'DestLat', 'long

# Add Carrier Name
df_tmp = df_tmp.merge(df_carriers[['Code', 'Description']], how='left', left_on='Uniq
df_tmp.drop('Code', axis=1, inplace=True)
df_tmp.rename(columns={'Description':'CarrierName'}, inplace=True)
```

We still have a problem with state code instead of state name, let's improve it :

In [13]:
```python
#filename = download("https://github.com/jasonong/List-of-US-States/raw/master/states
filename = "states.csv"
df_states = pd.read_csv(filename)

df_tmp = df_tmp.merge(df_states, how='left', left_on='OriginState', right_on='Abbrevia
df_tmp.drop('Abbreviation', axis=1, inplace=True)
df_tmp.rename(columns={'State':'OriginStateName'}, inplace=True)


df_tmp = df_tmp.merge(df_states, how='left', left_on='DestState', right_on='Abbreviati
df_tmp.drop('Abbreviation', axis=1, inplace=True)
df_tmp.rename(columns={'State':'DestStateName'}, inplace=True)
```

Check the data :

In [14]:
```python
df_tmp[['OriginCity',
        'OriginState', 'OriginLat', 'OriginLong', 'DestCity', 'DestState',
        'DestLat', 'DestLong', 'CarrierName', 'OriginStateName',
        'DestStateName']].head(3)
```

Out[14]:
```
     OriginCity OriginState  OriginLat  OriginLong   DestCity DestState  \
0     Chantilly          VA  38.944532  -77.455810      Tampa        FL
1     Chantilly          VA  38.944532  -77.455810      Tampa        FL
2  Indianapolis          IN  39.717329  -86.294384  Baltimore        MD

     DestLat   DestLong              CarrierName OriginStateName DestStateName
0  27.975472 -82.533250  Southwest Airlines Co.        Virginia       Florida
1  27.975472 -82.533250  Southwest Airlines Co.        Virginia       Florida
2  39.175402 -76.668198  Southwest Airlines Co.         Indiana      Maryland
```

Great, we know have label better to understand, so let's replace main dataframe with our new one.

```
In [15]: df = df_tmp;
```

We also have to rename a carrier that is too long :

```
In [16]: df.CarrierName.replace('US Airways Inc. (Merged with America West 9/05. Reporting for
```

1.4.1 What is the structure of your dataset?

As stated on http://stat-computing.org/dataexpo/2009/ : The data consists of flight arrival and departure details for all commercial flights within the USA, from October 1987 to April 2008. This is a large dataset: there are nearly 120 million records in total, and takes up 1.6 gigabytes of space compressed and 12 gigabytes when uncompressed.

The data come from the US Bureau of Transportation Statistics.

The dataset is a series of CSV containing one line per flight in the US. With 29 informations about the fligth : origin, destination, date, reason of delay, take off time... Mainly numerical. Some of them are continuous (delay) and others categorical (month).

It's only the internal US flights (domestic), not the international flight arriving/living the US.

It's already a huge file with seven millions of lines just for 2008 year.

The file are compressed in BZ2 and it was an happy surprise that Pandas could directly load it.

We are also provided with a description of every columns : https://www.transtats.bts.gov/Fields.asp?Table_ID=236

1.4.2 Information about the data

```
If Cancelled==1 it mean the flight has been canceled
If Diverted==1 it mean the flight has been delayed

Variable descriptions from http://stat-computing.org/dataexpo/2009/the-data.html
    Name    Description
1   Year    1987-2008
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
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 = securi
24  Diverted    1 = yes, 0 = no
25  CarrierDelay    in minutes
26  WeatherDelay    in minutes
27  NASDelay    in minutes
28  SecurityDelay   in minutes
29  LateAircraftDelay   in minutes
```

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

We could use this dataset for many things, but I will focus on exploring the flight delay.

So the main feature will be the ArrDelay columns that containt the difference in minutes between planed arrival time and actual arrival time.

Here is some questions I have : - Are there certain departure cities that are home to more delays ? - Is threre an influence on delay of month or day of week ? - Wich airport that are more subject to delay ?

I may also look at cancelled and diverted flight as it is an inconvenient for passengers.

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

Well, almost all column could have a corelation with delay. For exemple maybe night flight have more delay, or sunday flight, on february flight, or flights from a specific carrier or specific airport...

We even have the Tail Number (the ID of the plane) to check if a specific aircraft has more delay than others.

I will quickly look to them, before investigate the ones that seems more revelant.

We have many years so we could also look at changes between years, but I will focus on 2008.

1.5 Tidy

The dataset looks clean and tidy. Some datas are missing but not much.

I was thinking of merging CarrierDelay, WeatherDelay, NASDelay, SecurityDelay and LateAircraftDelay in one column, with another with the reason. But there could be many delay for the same flight, so I let them as is.

The main thing I made is merging with others datasets to get labels instead of code.

Time of day like CRSDepTime are in hhmm format. That's not good because we can't make reliable operation on it. For example, if we want to compute difference in time to get the delay :

1905 (19h05) - 1855 (15h55) = 50 but it's only 10 minutes.

To get it clean it will be best to convert it in minutes (hours * 60 + min).

But what I need for my study is only the hour string, to use it as categorical variable, so I will now convert the int "hhmm" format to hour string.

```
In [17]: def only_hour(row):
             # Fill with zero to always have 4 digits
             hour = str(row['CRSDepTime']).zfill(4)
             # Keep only the first two caracter
             hour = int(hour[:2])
             return hour

         df['CRSDepTimeHour'] = df.apply(only_hour, axis=1)
         # Check if it's ok
         df.loc[[6863908,686398]]
```

```
Out[17]:          Month  DayofMonth  DayOfWeek  DepTime  CRSDepTime  ArrTime  \
         6863908     12           1          1     48.0          50    619.0
         686398       2          27          3   1507.0        1450   1626.0

                  CRSArrTime UniqueCarrier FlightNum TailNum       ...        \
         6863908         553            NW       774  N584NW       ...
         686398         1615            WN      2011  N354SW       ...

                  OriginLat  OriginLong     DestCity DestState    DestLat   DestLong  \
         6863908  36.080361 -115.152333  Minneapolis        MN  44.880547 -93.216922
         686398   41.785983  -87.752424  Kansas City        MO  39.297605 -94.713906

                              CarrierName  OriginStateName  DestStateName  \
         6863908  Northwest Airlines Inc.           Nevada      Minnesota
         686398    Southwest Airlines Co.         Illinois       Missouri

                  CRSDepTimeHour
         6863908               0
         686398               14

         [2 rows x 35 columns]
```

It works fine.

1.6 Univariate Exploration

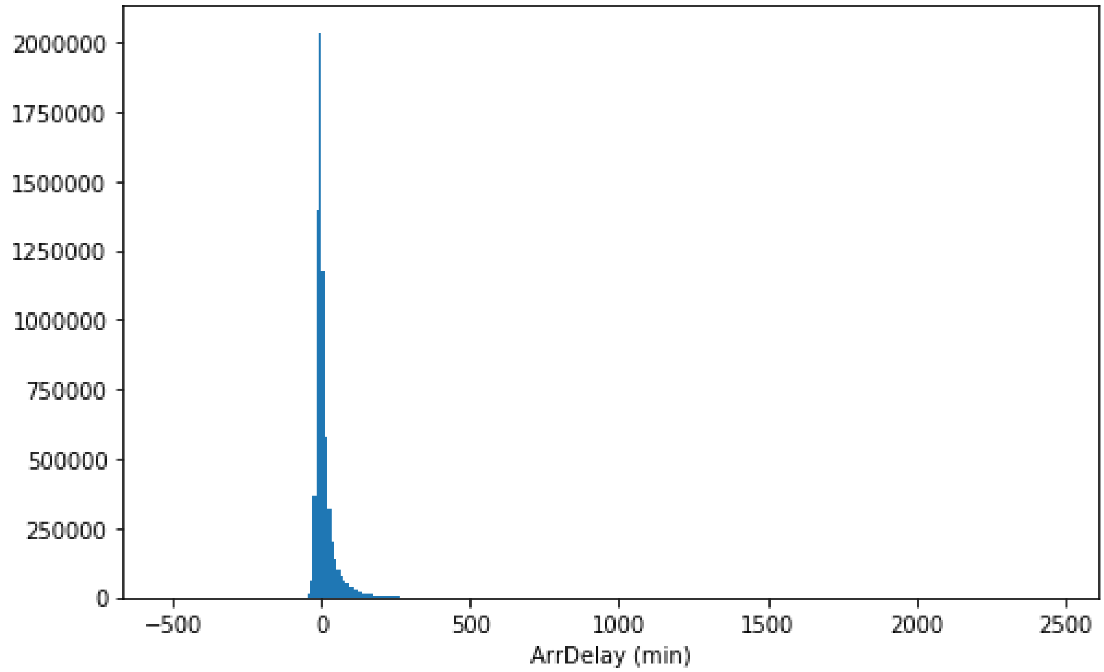
Let see how ArrDelay look like as it is our main feature.

```
In [18]: pv("df['ArrDelay'].max()/60")
         pv("df['ArrDelay'].min()/60")
```

```
df['ArrDelay'].max()/60 : 41.016666666666666
df['ArrDelay'].min()/60 : -8.65
```

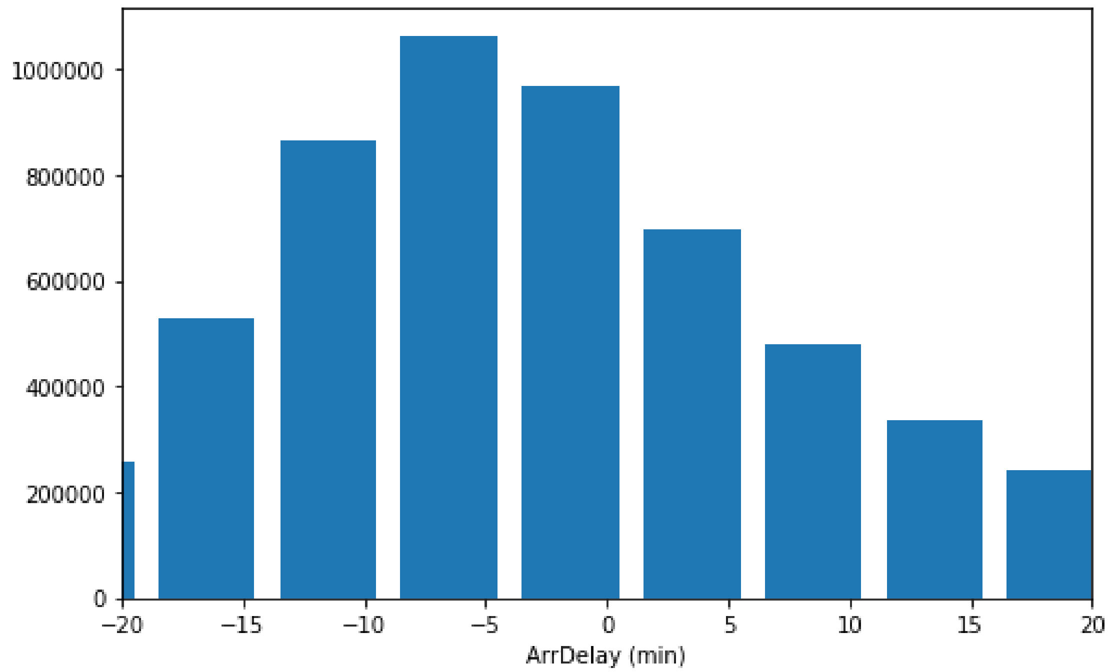
The range is huge. A plane has landed 8 hours earlier than expected, while another land 41 hours after !

In [19]:
```
binsize = 10
bins = np.arange(df['ArrDelay'].min(), df['ArrDelay'].max()+binsize, binsize);
#print(bins)
plt.figure(figsize=[8, 5]);
plt.hist(data = df[np.isfinite(df['ArrDelay'])], x = 'ArrDelay', bins = bins);

plt.xlabel('ArrDelay (min)');
plt.show();
```



As expected, huge spike aroud zero, so let's zoom around it.

In [20]:
```
# Histogram plot
binsize = 5
bins = np.arange(df['ArrDelay'].min(), df['ArrDelay'].max()+binsize, binsize);
#print(bins)
plt.figure(figsize=[8, 5]);
plt.hist(data = df[np.isfinite(df['ArrDelay'])], x = 'ArrDelay', bins = bins, rwidth=(
plt.xlabel('ArrDelay (min)');
plt.xticks(range(-30,30, binsize))
axes = plt.gca()
axes.set_xlim([-20,20])
plt.show();
```



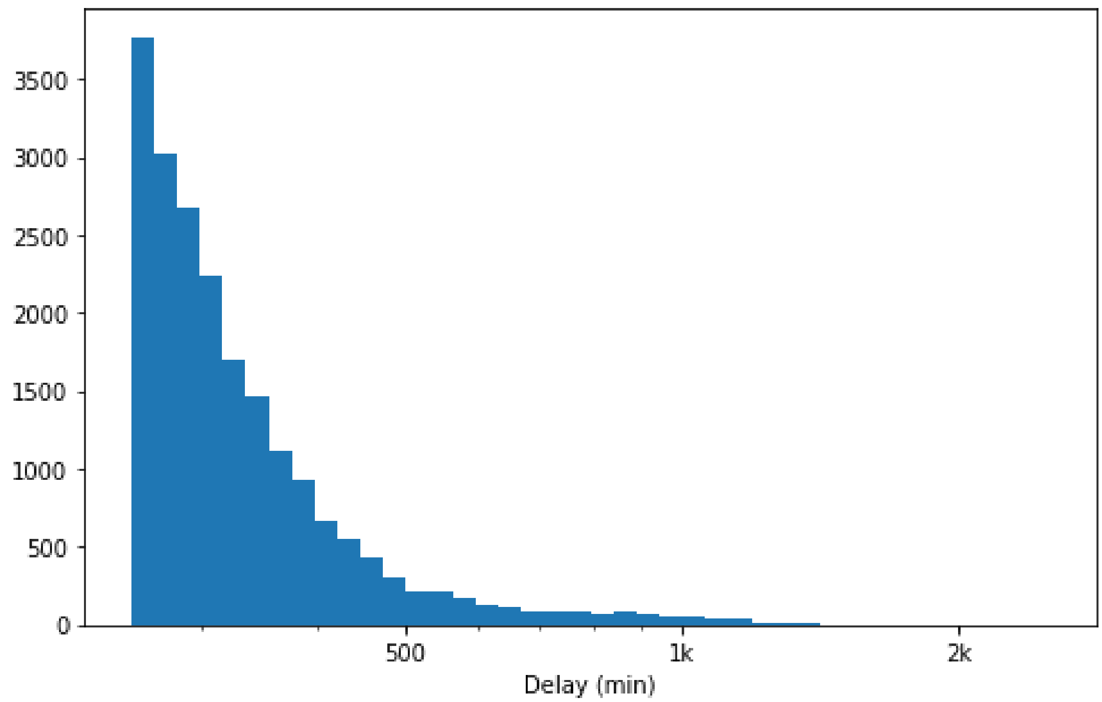
The majority of planes landed early than expected.

There probably is a good reason for that, it's an interresting question to ask to a professional.

We first saw that the ArrDelay is right skewed with a slope with long tail that's look like a Landau distribution. https://en.wikipedia.org/wiki/Landau_distribution

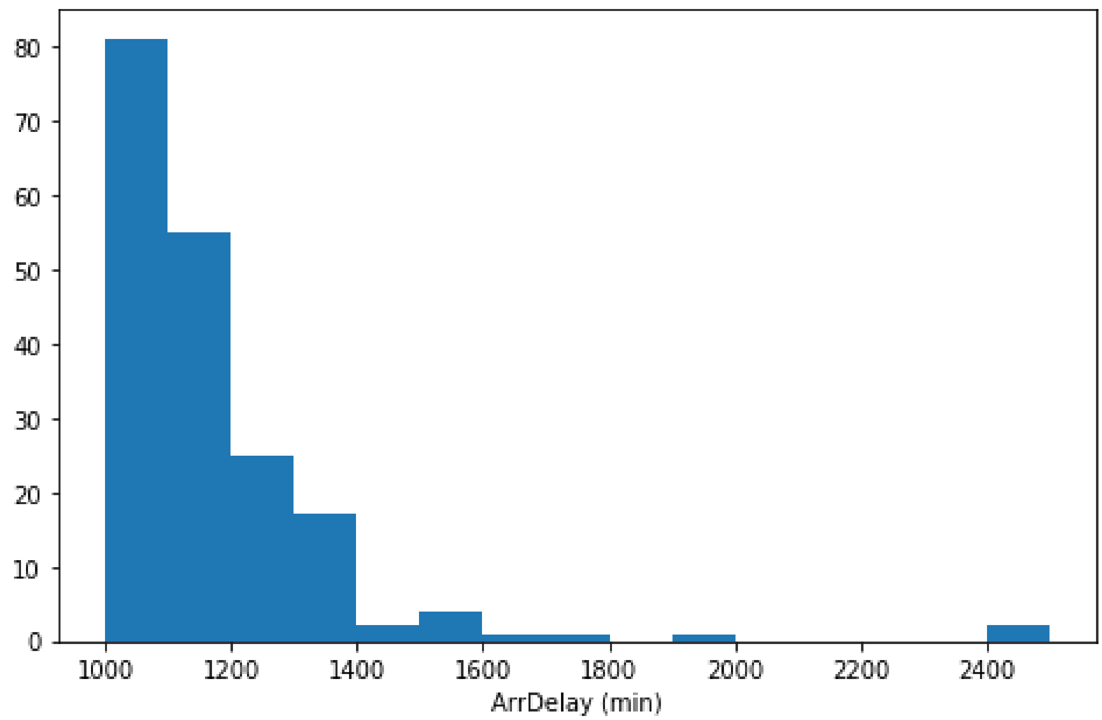
So let's have a look to the ArrDelay at log scale.

In [21]:
```
log_binsize = 0.025
bins = 10 ** np.arange(2.4, np.log10(df['ArrDelay'].max())+log_binsize, log_binsize)
# Use non-equal bin sizes, such that they look equal on log scale.
# Thanks to https://stackoverflow.com/questions/47850202/plotting-a-histogram-on-a-lo
# logbins = np.logspace(np.log10(bins[0]),np.log10(bins[-1]),len(bins))
plt.figure(figsize=[8, 5]);
plt.hist(data = df[np.isfinite(df['ArrDelay'])], x = 'ArrDelay', bins = bins);
plt.xscale('log');
plt.xticks([500, 1e3, 2e3], [500, '1k', '2k', '5k', '10k', '20k'])
plt.xlabel('Delay (min)');
plt.show();
```



Even at log scale, the delay time seems to derease rapidly.
The distribution still have the same shape. With many short delay and few long delay.
It's not surprising as it is what we could expect for such metrics.
So let's have a look at huge delay to saw what they look like :

In [22]:
```
min_delay = 1000
df_hight_delay = df[np.isfinite(df['ArrDelay'])].query("ArrDelay > @min_delay")

binsize = 100
bins = np.arange(min_delay, df_hight_delay['ArrDelay'].max()+binsize, binsize);
plt.figure(figsize=[8, 5]);
plt.hist(data = df_hight_delay, x = 'ArrDelay', bins = bins);
plt.xlabel('ArrDelay (min)');
plt.show();
```




```
In [23]: 24*60
         2400/60/24
```

```
Out[23]: 1440
```

```
Out[23]: 1.6666666666666667
```

The biggest outliers have a delay of more than a day and half.
But it coud have append, we will keep them.
Let's check closely, just in case.

```
In [24]: df[np.isfinite(df['ArrDelay'])].query("ArrDelay > 1200")[['Month', 'CRSDepTime', 'Dep
                'DepDelay',
                'CRSArrTime','ArrTime', 'ArrDelay', 'UniqueCarrier',
                 'Origin',
                ]].head(3)
```

```
Out[24]:         Month  CRSDepTime  DepTime  DepDelay  CRSArrTime  ArrTime  ArrDelay  \
         503727      1        1930   1805.0    1355.0        2215   2052.0    1357.0
         527950      1        1045    800.0    1275.0        1327   1452.0    1525.0
         996512      2        1420   1257.0    1357.0        1650   1527.0    1357.0

                UniqueCarrier Origin
         503727            AA    DEN
         527950            AA    EGE
         996512            MQ    VPS
```

The hight delay flight seems real. But some of them are strange like flight who take off with a small delay but arrived with a huge delay of many hours. For exemple, it's impossible for a plane to flight 10 hours when only 1 hour was expected at take off.

So we could supposed that the plane have landed on an another airport before going to the final airport.

Another strange behaviour at first look is when real departure time are before planed but with a huge positive delay. Well, it just means the plane has take off the day after it was expected.

I have found strange exemple but I think we could keep them because we have a huge dataset and the values are in an acceptable range.

1.7 Build a classification of delay

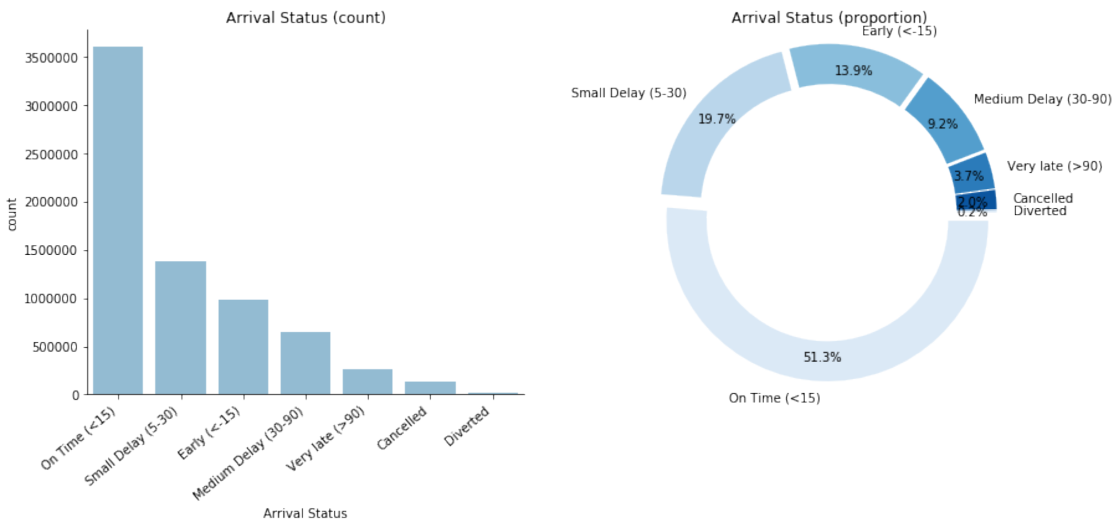
To better undertand the delay I will classify them in bins for : - Early (more than 15 minutes before expected) - On Time (between, -15 and 5 minutes after) - Small Delay (between 5 and 30) - Medium Delay (between 30 and 90) - Very late (above 90) - Diverted : A diverted flight is one that has been routed from its original arrival destination to a new, typically temporary, arrival destination. - Cancelled : Plane never takeof

```
In [25]: # Thanks to https://stackoverflow.com/questions/32633977/how-to-create-categorical-va
         # For building classification in Pandas.

         # Set the categorical variable values
         arr_status = ['Unknown', 'Early', 'On Time', 'Small Delay',
                       'Medium Delay' ,'Very late', 'Diverted', 'Cancelled']
         # Set default value
         df['ArrStatus'] = 'Unknown';
         _ = pd.Categorical(df.ArrStatus, categories=arr_status, ordered=True);
         # Cancelled Flight
         df.loc[(df['Cancelled'] == 1) , 'ArrStatus'] = 'Cancelled'
         # Cancelled Flight
         df.loc[(df['Diverted'] == 1) , 'ArrStatus'] = 'Diverted'
         # Delayed flights
         df.loc[(df['ArrDelay'] <= -15) , 'ArrStatus'] = 'Early (<-15)'
         df.loc[(df['ArrDelay'] > -15) , 'ArrStatus'] = 'On Time (<15)'
         df.loc[(df['ArrDelay'] > 5) , 'ArrStatus'] = 'Small Delay (5-30)'
         df.loc[(df['ArrDelay'] > 30) , 'ArrStatus'] = 'Medium Delay (30-90)'
         df.loc[(df['ArrDelay'] > 90) , 'ArrStatus'] = 'Very late (>90)'
```

Now, we can plot them.

```
In [26]: base_color = sns.color_palette("Blues")[2]
         f,ax=plt.subplots(1,2,figsize=(13,6));
         sns.countplot('ArrStatus',order = df['ArrStatus'].value_counts().index, data=df,ax=ax
                       color = base_color);
         sns.despine(ax=ax[0])
         #plt.xticks(rotation = 90)
         # Thanks to https://stackoverflow.com/questions/42528921/how-to-prevent-overlapping-x
         ax[0].set_xticklabels(ax[0].get_xticklabels(), rotation=40, ha="right")
```

```
ax[0].set_title('Arrival Status (count)');
ax[0].set_xlabel('Arrival Status');

# Thanks to https://medium.com/@kvnamipara/a-better-visualisation-of-pie-charts-by-ma
#explosion
explode = []
for i in range(len(df['ArrStatus'].value_counts())):
    explode.append(0.05)

df['ArrStatus'].value_counts().plot.pie(autopct='%1.1f%%',ax=ax[1],
                                        wedgeprops = {'width' : 0.25},
                                        startangle = 0,
                                        counterclock = False,
                                        colors = sns.color_palette("Blues"),
                                        pctdistance=0.85, explode = explode);


ax[1].set_title('Arrival Status (proportion)');
ax[1].set_ylabel('');
# Equal aspect ratio ensures that pie is drawn as a circle
ax[1].axis('equal')
plt.tight_layout()
plt.show();
```



We learn that pie chart is not suited for too much bin, so let's group it a bit more.

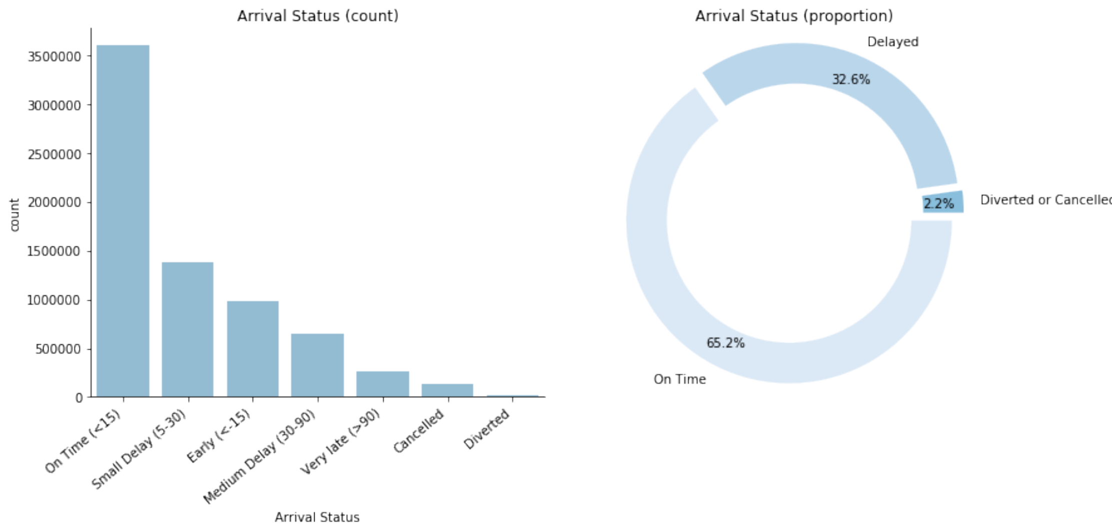
```
In [27]: df['ArrStatus_light'] = df['ArrStatus']

         # Thanks to https://stackoverflow.com/questions/48345415/how-to-group-categorical-val
         # For them replace method.
         mapping = {
```

```
    'On Time (<15)':'On Time',
    'Early (<-15)':'On Time',
    'Small Delay (5-30)':'Delayed',
    'Medium Delay (30-90)':'Delayed',
    'Very late (>90)':'Delayed',
    'Diverted':'Diverted or Cancelled',
    'Cancelled':'Diverted or Cancelled'
    }

df['ArrStatus_light'] = df['ArrStatus_light'].replace(mapping);
df.ArrStatus_light.value_counts()
```

Out[27]:
```
On Time                  4571981
Delayed                  2283048
Diverted or Cancelled     154699
Name: ArrStatus_light, dtype: int64
```

And re-draw.

In [28]:
```
base_color = sns.color_palette("Blues")[2]
#sns.palplot(sns.color_palette("Blues"))

f,ax=plt.subplots(1,2,figsize=(13,6));
sns.countplot('ArrStatus',order = df['ArrStatus'].value_counts().index, data=df,ax=ax
             color = base_color);
sns.despine(ax=ax[0])

# Thanks to https://stackoverflow.com/questions/42528921/how-to-prevent-overlapping-x
ax[0].set_xticklabels(ax[0].get_xticklabels(), rotation=40, ha="right")
ax[0].set_title('Arrival Status (count)');
ax[0].set_xlabel('Arrival Status');

# Thanks to https://medium.com/@kvnamipara/a-better-visualisation-of-pie-charts-by-ma
#explosion
explode = []
for i in range(len(df['ArrStatus_light'].value_counts())):
    explode.append(0.05)

df['ArrStatus_light'].value_counts().plot.pie(autopct='%1.1f%%',ax=ax[1],
                                              wedgeprops = {'width' : 0.25},
                                              startangle = 0,counterclock = False,
                                              colors = sns.color_palette("Blues"),
                                              pctdistance=0.85, explode = explode);
ax[1].set_title('Arrival Status (proportion)');
ax[1].set_ylabel('');
ax[1].axis('equal') # Equal aspect ratio ensures that pie is drawn as a circle
plt.tight_layout()
plt.show();
```



Only 2.2% of flights where Diverted or Cancelled.
But more than 30% get delayed by more than 5 minutes.
More than 15% are delayed by more than 30 minutes. I think it's too much.
But there is quite the same proportion of flight that land in advance.

1.8 Filter the dataset

Let's build a dataframe with only dealayed flights as we will focus on them.

```
In [29]: df_late = df[df.ArrStatus_light == 'Delayed']
```

1.9 Build methods to draw viz

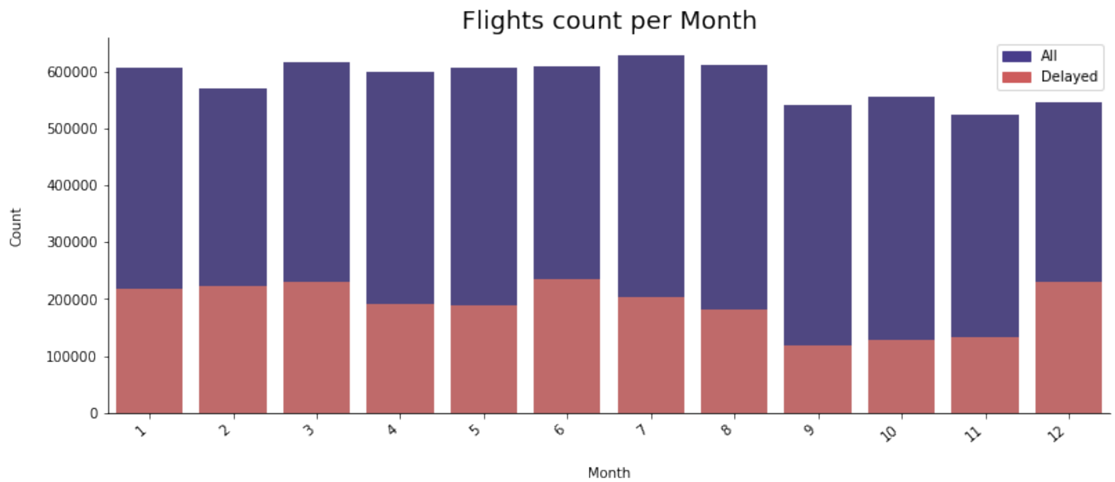
To be able to explore faster and change all graph in one time, I build method for frequent plot.
It also allows me to plot the late data over the whole dataset to get insight on correlation, while on univariate exploration.

```
In [30]: import matplotlib.patches as mpatches

         _ = sns.axes_style("whitegrid")

         def histogram_continuous_variable(column_name, binsize = 100, legend=''):
             bins = np.arange(df[column_name].min(), df[column_name].max()+binsize, binsize);
             #plt.figure(figsize=[8, 5]);
             plt.hist(data = df_late, x = column_name, bins = bins, label=legend);
             plt.title('Flights count per ' + column_name, fontsize=18);
             legend = column_name if legend == '' else legend
             plt.xlabel('Minutes');
             plt.ylabel('Count');
             plt.xlim([20,200]);
             plt.ylim([0,20000]);
```

```
    plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)

def comparative_histogram_continuous_variable(column_name, binsize = 100, xlabel=''):
    global df, df_late
    bins = np.arange(df[column_name].min(), df[column_name].max()+binsize, binsize);
    plt.figure(figsize=[13, 5]);
    plt.hist(data = df, x = column_name, bins = bins);
    ax = plt.hist(data = df_late, x = column_name, bins = bins);
    plt.title('Flights count per ' + column_name, fontsize=18);
    xlabel = column_name if xlabel == '' else xlabel
    plt.xlabel(xlabel);
    plt.ylabel('Count');
    blue_patch = mpatches.Patch(color='darkslateblue', label='All')
    red_patch = mpatches.Patch(color='indianred', label='Delayed')
    plt.legend(handles=[blue_patch, red_patch])

def comparative_barchart_categorical_variable(column_name, xlabel=''):
    global df, df_late
    plt.figure(figsize=[13, 5]);
    xlabel = column_name if xlabel == '' else xlabel
    ax1 = sns.countplot(x=column_name, color='darkslateblue', data=df);
    sns.despine(ax=ax1)
    ax2 = sns.countplot(x=column_name, color='indianred', data=df_late);
    sns.despine(ax=ax2)
    plt.title('Flights count per ' + column_name, fontsize=18);
    plt.xlabel(xlabel, labelpad=16);
    plt.ylabel('Count', labelpad=16);
    ax2.set_xticklabels(ax1.get_xticklabels(), rotation=40, ha='right')
    blue_patch = mpatches.Patch(color='darkslateblue', label='All')
    red_patch = mpatches.Patch(color='indianred', label='Delayed')
    plt.legend(handles=[blue_patch, red_patch])
```

1.10 Check Month

```
In [31]: comparative_barchart_categorical_variable('Month');
```

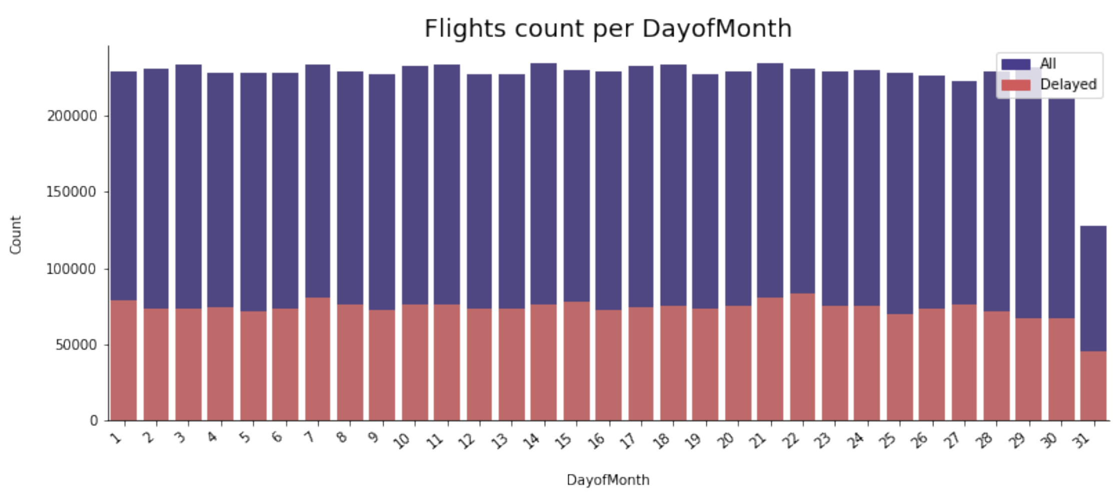


Flights vary a little bit between month.

It seems to have more delay in December. But it's a count of flights, we may look at it in bi-variate exploration.

1.11 Check Day of Month

```
In [32]: comparative_barchart_categorical_variable('DayofMonth');
```

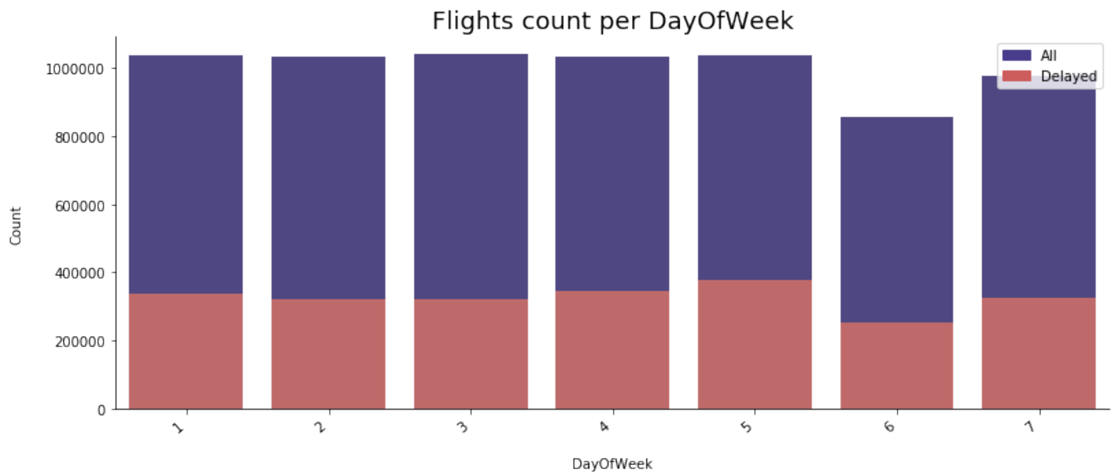


We have less count for the 31th day of month. It's normal because not all month has 31 days.

Don't seems to have correlation between Day Of Month and delay. But it's not surprising as day of month over the year don't mean much for human activity in our case.

1.12 Check Day of Week

```
In [33]: comparative_barchart_categorical_variable('DayOfWeek');
```

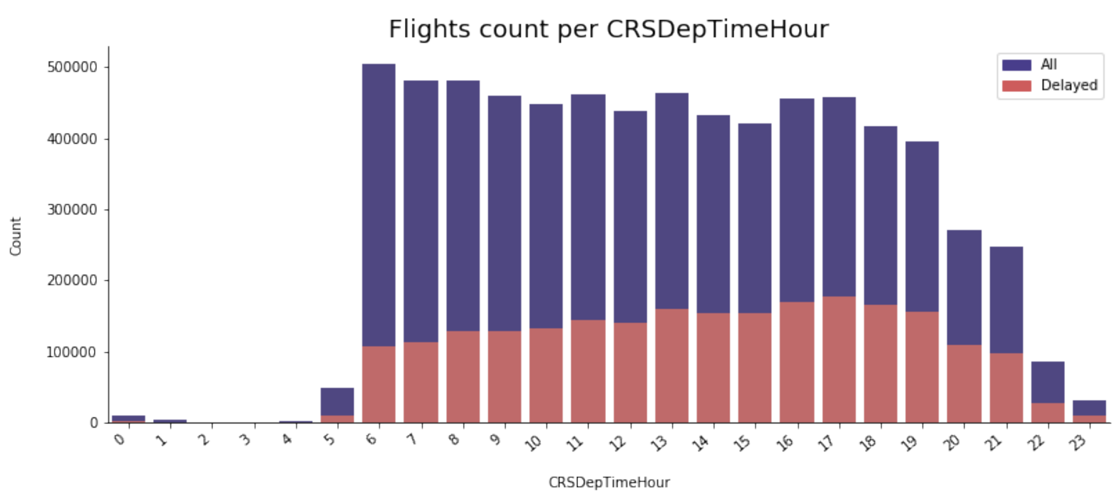


I have checked that in the datas, 1 is Monday and 7 Sunday.

We saw that there is less flights on Saterday. And it seems to have more delayed flights on Friday.

1.13 Check Departure Time

```
In [34]: comparative_barchart_categorical_variable('CRSDepTimeHour');
```

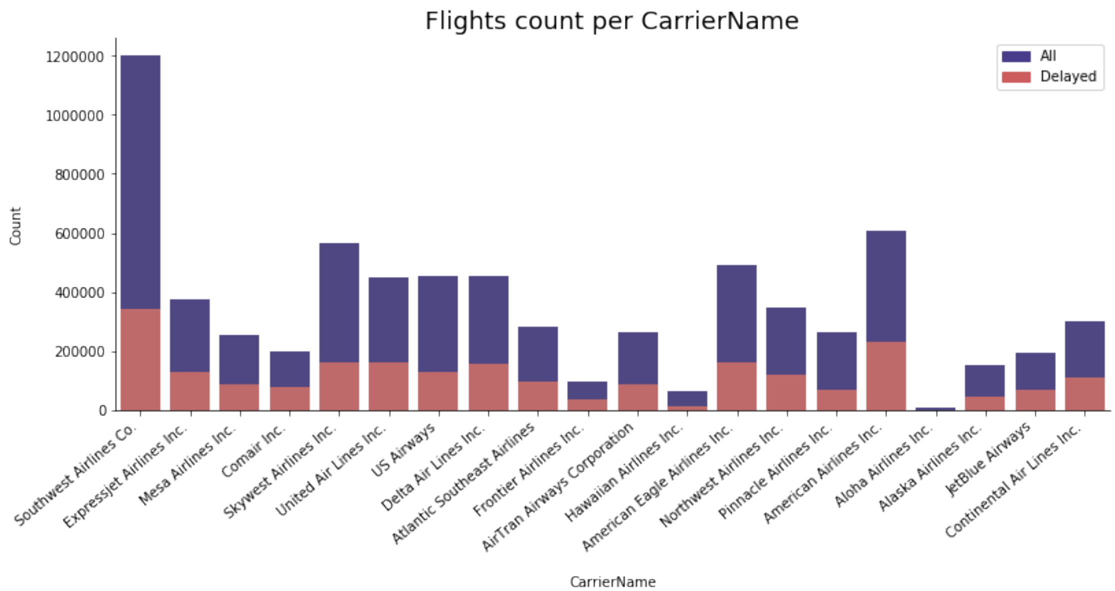


There is almost no takeoff in early night. Then it suddently grow up around 6 am.

There are more flights at 6 in the morning, but more delay in the evening. It will be interesting to look at this in bi-variate exploration.

1.14 Check Carrier

```
In [35]: comparative_barchart_categorical_variable('CarrierName')
```



Here we saw that Southwest airline is the carrier with most flights, far above the others.

And we saw a correlation between carrier and delay : American Airline, despite operating half of Southwest Airline, has almost the same delayed flights.

1.15 Reason of Cancellation

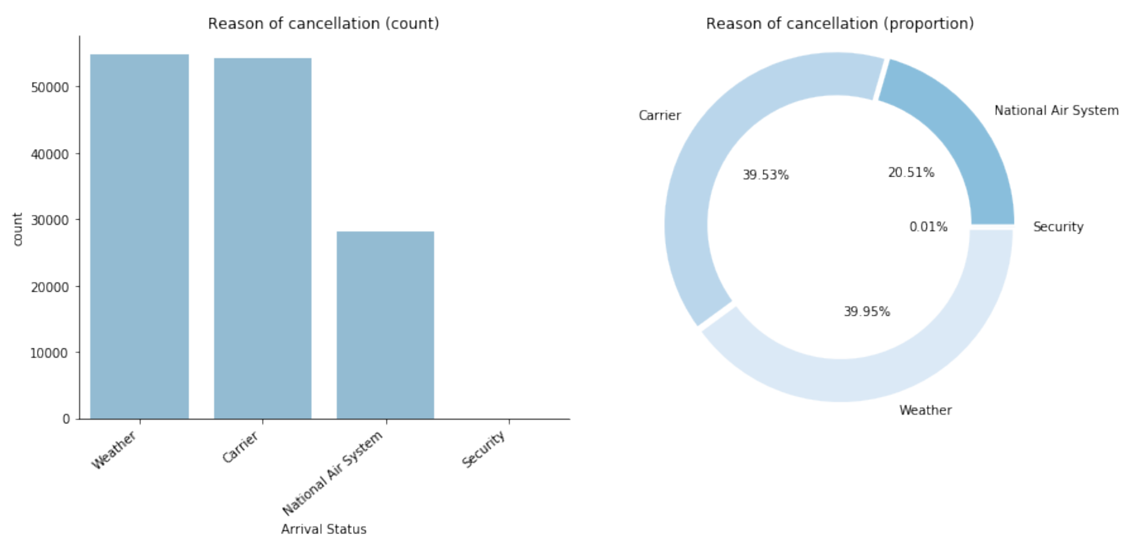
I will create a new column with the label of cancellation code.

```
In [36]: df['CancellationReason'] = df['CancellationCode']

         # Thanks to https://stackoverflow.com/questions/48345415/how-to-group-categorical-val
         mapping = {
             'A':'Carrier',
             'B':'Weather',
             'C':'National Air System',
             'D':'Security'
             }

         df['CancellationReason'] = df['CancellationReason'].replace(mapping);
```

Then, plot it.

```
In [37]: base_color = sns.color_palette("Blues")[2]

         f,ax=plt.subplots(1,2,figsize=(13,6));
         #with sns.axes_style("whitegrid"):
         axp = sns.countplot('CancellationReason', order = df['CancellationReason'].value_coun
                             data=df, ax=ax[0], color = base_color);
         sns.despine(ax=axp)
```

```
axp.set_title('Reason of cancellation (count)');
axp.set_xlabel('Arrival Status');
axp.set_xticklabels(ax[0].get_xticklabels(), rotation=40, ha="right");

# Thanks to https://medium.com/@kvnamipara/a-better-visualisation-of-pie-charts-by-ma
#explosion
explode = []
for i in range(len(df['CancellationReason'].value_counts())):
    explode.append(0.02)

df['CancellationReason'].value_counts().plot.pie(autopct='%1.2f%%',ax=ax[1],
                                                  wedgeprops = {'width' : 0.25},
                                                  startangle = 0, counterclock = False,
                                                  colors = sns.color_palette("Blues"),
                                                  pctdistance=0.50, explode = explode);

ax[1].set_title('Reason of cancellation (proportion)');
ax[1].set_ylabel('');
#ax[1].set_xticklabels(ax[1].get_xticklabels(), rotation=40, ha="right");
# Equal aspect ratio ensures that pie is drawn as a circle
ax[1].axis('equal')
plt.tight_layout()
plt.show();
```



I was expecting more cancellation for security reason. But it almost never append.

Weather and Carrier are equaly responsible of delay.

I was surprised by the amount of NAS cancellation. According to http://www.flightbucks.com/blog/9-biggest-causes-of-flight-delays-or-cancellations This might include non-severe weather events, heavy air traffic, air traffic control delays, and airport operations.

20% is huge but we have to remember that it's 20% of cancellation, wich occure only 2% of flights.

1.16 Mosts used plane (TailNum)

TailNum is the identification of a plane.

```
In [38]: import itertools
         vc = df.TailNum.value_counts()
         print('Number of plane :', len(vc))
         print('\n5 mosts used plane')
         # Thanks to https://stackoverflow.com/questions/36106712/how-can-i-limit-iterations-o
         for name, cnt in itertools.islice(vc.iteritems(),0,5):
               print(name, cnt)
```

```
Number of plane : 5373

5 mosts used plane
N476HA 4701
N477HA 4548
N484HA 4505
N475HA 4499
N480HA 4416
```

```
In [39]: 4701/365
```

```
Out[39]: 12.87945205479452
```

N476HA is the most often used plane : 4 701 times in 2008, it's 12 flights per day !

Having a look at https://www.flightradar24.com/data/aircraft/n476ha it is a plane that do rotation between Hawai islands. Not a bad place to fly !

I did not know that an airplane could fly so much in one day.

1.17 Mosts frequent flight (FlightNum)

TailNum is the identification of a plane.

```
In [40]: import itertools
         vc = df.FlightNum.value_counts()
         print('Number of flight in 2008:', len(vc))
         print('\n5 mosts frequent flight :')
         # Thanks to https://stackoverflow.com/questions/36106712/how-can-i-limit-iterations-o
         for name, cnt in itertools.islice(vc.iteritems(),0,5):
               print(name, cnt)
```

```
Number of flight in 2008: 7539

5 mosts frequent flight :
```

```
152 4883
12 4793
16 4717
511 4621
308 4449
```

Let's look at the most frequent :

```
In [41]: df.query("FlightNum == '152'").head(3)
```

```
Out[41]:       Month  DayofMonth  DayOfWeek  DepTime  CRSDepTime  ArrTime  CRSArrTime  \
         1180      1           3          4    625.0         625    741.0         735
         1983      1           3          4    805.0         755    952.0        1005
         4618      1           4          5    632.0         625    803.0         735

              UniqueCarrier FlightNum TailNum          ...          DestState  \
         1180            WN       152  N379SW          ...                 CA
         1983            WN       152  N379SW          ...                 WA
         4618            WN       152  N344SW          ...                 CA

                 DestLat    DestLong             CarrierName  OriginStateName  \
         1180  37.361862 -121.929009  Southwest Airlines Co.       California
         1983  47.448982 -122.309313  Southwest Airlines Co.       California
         4618  37.361862 -121.929009  Southwest Airlines Co.       California

               DestStateName CRSDepTimeHour            ArrStatus  ArrStatus_light  \
         1180     California              6  Small Delay (5-30)          Delayed
         1983     Washington              7       On Time (<15)          On Time
         4618     California              6  Small Delay (5-30)          Delayed

               CancellationReason
         1180                 NaN
         1983                 NaN
         4618                 NaN

         [3 rows x 38 columns]
```

"152" is the most frequent flight.

I thought that Flight Number represented a flight from an airport to another for a specific company at a specific time. But data show that it's not always the same destination, nor the same company.

1.18 10 mosts used origin City

```
In [42]: import itertools
         vc = df.OriginCity.value_counts()
         print('Number of Origin airport :', len(vc))
         print('\n10 mosts used origin airport')
```

```
    # Thanks to https://stackoverflow.com/questions/36106712/how-can-i-limit-iterations-o
    for name, cnt in itertools.islice(vc.iteritems(),0,10):
        print(name, cnt)
```

```
Number of Origin airport : 288

10 mosts used origin airport
Chicago 437999
Atlanta 414513
Dallas-Fort Worth 281281
Denver 241443
Houston 241105
New York 237939
Los Angeles 215608
Phoenix 199408
Las Vegas 172876
Detroit 161989
```

Chicago and Atlanta are the city with most departure.

1.19 Destination

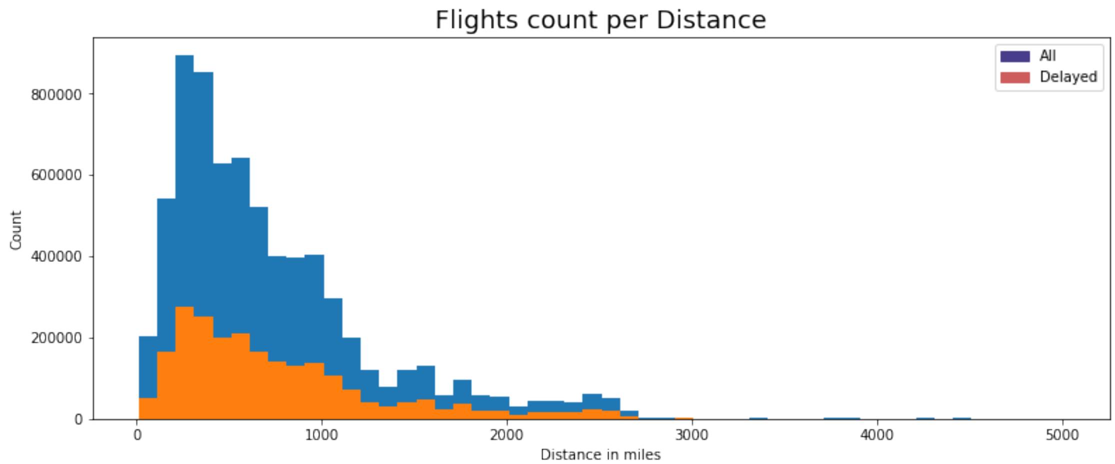
```
In [43]: import itertools
         vc = df.DestCity.value_counts()
         print('Number of Dest airport :', len(vc))
         print('\n10 mosts used Dest airport')
         # Thanks to https://stackoverflow.com/questions/36106712/how-can-i-limit-iterations-o
         for name, cnt in itertools.islice(vc.iteritems(),0,10):
             print(name, cnt)
```

```
Number of Dest airport : 289

10 mosts used Dest airport
Chicago 438052
Atlanta 414521
Dallas-Fort Worth 281401
Denver 241470
Houston 241094
New York 237919
Los Angeles 215685
Phoenix 199416
Las Vegas 172871
Detroit 162000
```

Not surprisingly, Chicago and Atlanta are the cities with most arrival.
We note that we have 288 departure cities but 289 destination city. That's a sort of outlier.

1.20 Distance

```
In [44]: comparative_histogram_continuous_variable('Distance', xlabel='Distance in miles')
```



Majority of flights are for less than 500 miles, around 1 000 km.
Delay count seams to follow the distance in the same proportion.
Having flight distance above 3 000 miles for domestics flights is strange, let's look at them :

```
In [45]: df.query("Distance > 4000").head(3)
```

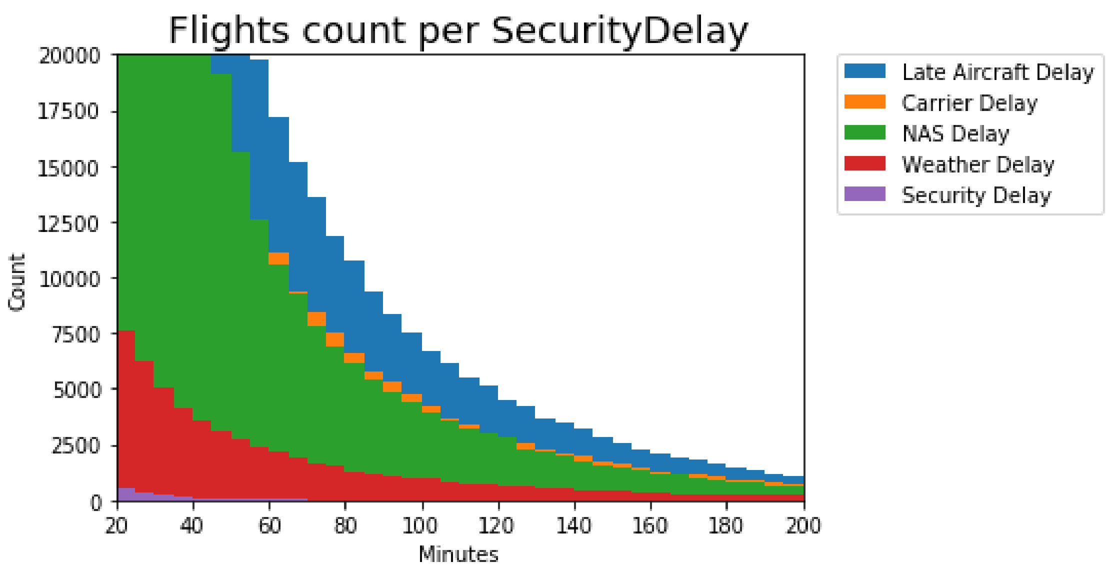
```
Out[45]:         Month  DayofMonth  DayOfWeek  DepTime  CRSDepTime  ArrTime  \
         218178      1           1          2   1030.0        1010   1541.0
         218179      1           2          3   1037.0        1010   1535.0
         218180      1           3          4   1028.0        1010   1515.0

                 CRSArrTime UniqueCarrier FlightNum TailNum         ...          \
         218178        1522            UA         1  N213UA         ...
         218179        1522            UA         1  N211UA         ...
         218180        1522            UA         1  N212UA         ...

                 DestState    DestLat     DestLong            CarrierName  \
         218178         HI  21.318691 -157.922407  United Air Lines Inc.
         218179         HI  21.318691 -157.922407  United Air Lines Inc.
         218180         HI  21.318691 -157.922407  United Air Lines Inc.

                 OriginStateName  DestStateName CRSDepTimeHour           ArrStatus  \
         218178         Illinois         Hawaii             10  Small Delay (5-30)
         218179         Illinois         Hawaii             10  Small Delay (5-30)
         218180         Illinois         Hawaii             10       On Time (<15)

                 ArrStatus_light  CancellationReason
         218178          Delayed                 NaN
         218179          Delayed                 NaN
```

```
218180           On Time                  NaN

[3 rows x 38 columns]
```

No error here : it's the flights from and to Hawai.

2 Reason of delay

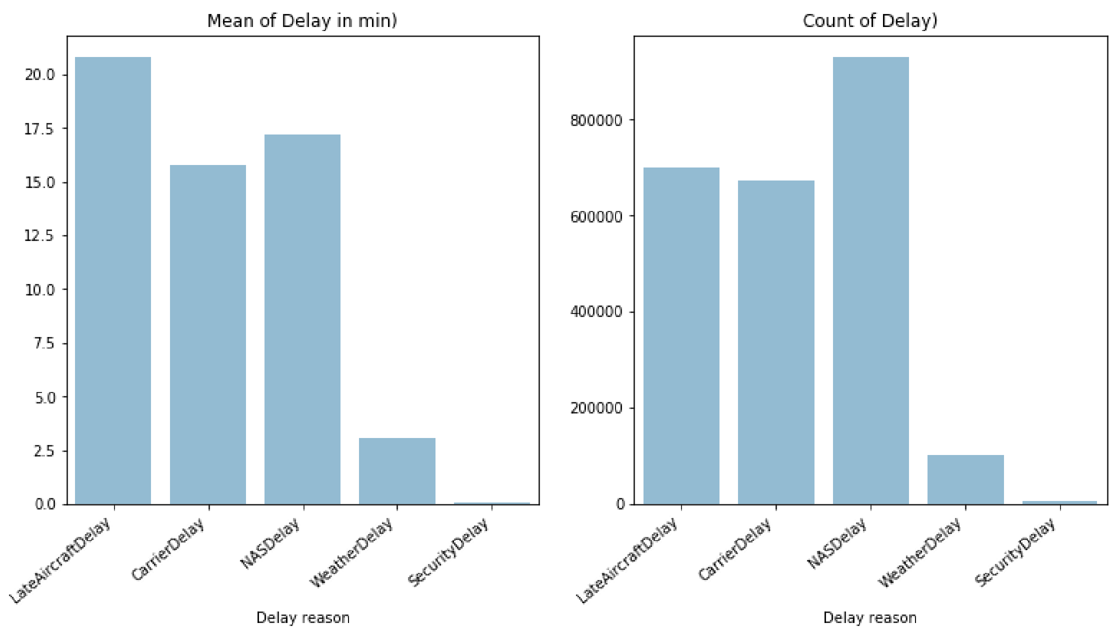
```
In [46]: histogram_continuous_variable('LateAircraftDelay', binsize=5, legend='Late Aircraft De
         histogram_continuous_variable('CarrierDelay', binsize=5, legend='Carrier Delay')
         histogram_continuous_variable('NASDelay', binsize=5, legend='NAS Delay')
         histogram_continuous_variable('WeatherDelay', binsize=5, legend='Weather Delay')
         histogram_continuous_variable('SecurityDelay', binsize=5, legend='Security Delay')
```



The distribution is quite the same for all delay.
Let's have a different look.

```
In [47]: reasons = ['LateAircraftDelay', 'CarrierDelay', 'NASDelay', 'WeatherDelay', 'Security

         name = []
         sum_delay = []
         num_delay = []
         for reason in reasons:
             name.append(reason)
             sum_delay.append(df_late[reason].mean())
             num_delay.append(
                 len( df_late.query(reason + " > 0") )
             )
```

```
fig,ax=plt.subplots(1,2,figsize=(13,6));
sns.barplot(x=name, y=sum_delay, ax=ax[0], color=sns.color_palette("Blues")[2]);
ax[0].set_xticklabels(ax[0].get_xticklabels(), rotation=40, ha="right")
ax[0].set_title('Mean of Delay in min)');
ax[0].set_xlabel('Delay reason');

sns.barplot(x=name, y=num_delay, ax=ax[1], color=sns.color_palette("Blues")[2]);
ax[1].set_xticklabels(ax[1].get_xticklabels(), rotation=40, ha="right")
ax[1].set_title('Count of Delay)');
ax[1].set_xlabel('Delay reason');
```



We must be careful about these data as we have many missing values for them. I don't know if it means that it was 0 or unregistered values.

Late Aircraft delay is the one causing the more delay, on average. But NAS Delay is the most frequent delay.

It's a real problem, we saw that delay are causing more delay. Maybe company need to be incentived to reduce delay by flying faster, even if it cost, to reduce them ?

There is almos no Security Delay. That's something I feel strange about it. I thing there is missing data about it.

Here is some information of the delay reason from https://aspmhelp.faa.gov/index.php/Types_of_Delay :

Carrier Delay is within the control of the air carrier. Examples of occurrences that may determine carrier delay are: aircraft cleaning, aircraft damage, baggage, bird strike, cargo loading, and so on...

Late Aircraft Delay at an airport due to the late arrival of the same aircraft at a previous airport. The ripple effect of an earlier delay at downstream airports is referred to as delay propagation.

NAS Delay is within the control of the National Airspace System (NAS) may include: non-extreme weather conditions, airport operations, heavy traffic volume, air traffic control, etc. Delays that occur after Actual Gate Out are usually attributed to the NAS and are also reported through OPSNET.

Security delay is caused by evacuation of a terminal or concourse, re-boarding of aircraft because of security breach, inoperative screening equipment and/or long lines in excess of 29 minutes at screening areas.

Weather delay is caused by extreme or hazardous weather conditions that are forecasted or manifest themselves on point of departure, enroute, or on point of arrival.

So maybe we could assume that if there is less than 29 min of delay due to security check, it's not took as "security delay" ?

2.0.1 Drop unnessary data.

```
In [48]: df_late.drop(['DepTime', 'ArrTime', 'CRSArrTime', 'DepDelay', ], axis=1, inplace=True
```

```
/media/data-nvme/dev/anaconda3/lib/python3.7/site-packages/pandas/core/frame.py:3697: SettingW
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.htm
  errors=errors)
```

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

The ArrDelay seems clean and tidy, I do not plan to remove points.

2.0.3 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?

I did not saw unusual distribution.

I saw data that seems strange but investigation give me me legit answers.

I will not investigate Flight Num as it not representing something usefull.

I have build categorical feature to help better understand the delay by putting flight in bins of different delay.

I will also build a categorical variable for season, based on month to study winter delay.

3 Bivariate Exploration

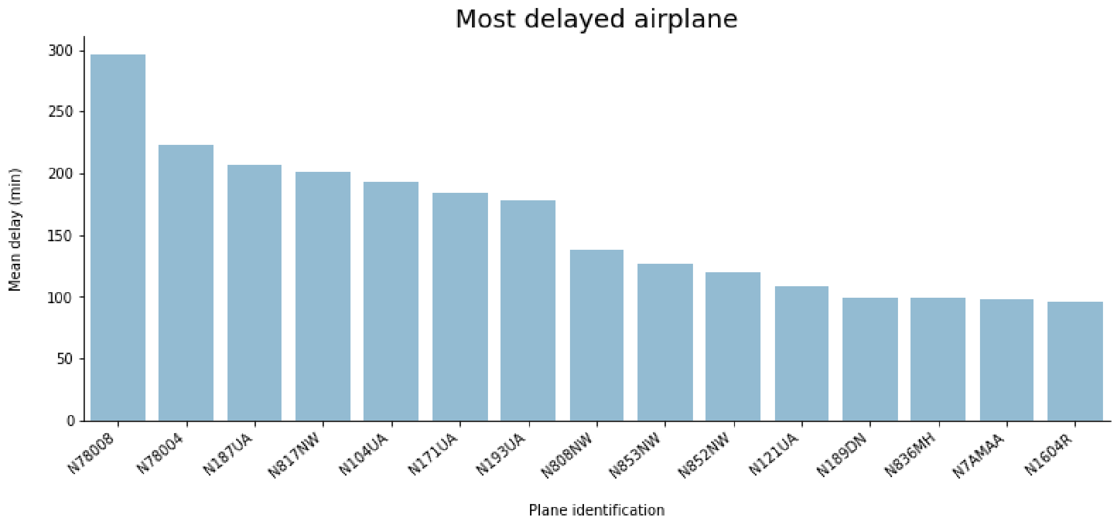
I will no study delay versus another variable.

Let's begin with specific plane to see if there is plane more subject to delay.

3.1 TailNum study

```
In [49]: def plot_categorical_variable(df_data, x_column_name, y_column_name, xlabel='', ylabel
             plt.figure(figsize=[13, 5]);
             xlabel = x_column_name if xlabel == '' else xlabel
             ylabel = y_column_name if ylabel == '' else ylabel
             ax1 = sns.barplot(x=x_column_name, y=y_column_name, color= sns.color_palette("Blue
             sns.despine(ax=ax1)
             plt.title(title, fontsize=18);
             plt.xlabel(xlabel, labelpad=16);
             plt.ylabel(ylabel, labelpad=16);
             ax1.set_xticklabels(ax1.get_xticklabels(), rotation=40, ha='right')
```

```
In [50]: df_late_plane = df_late.groupby(['TailNum'])['ArrDelay'].mean().sort_values(ascending

         plot_categorical_variable(df_late_plane[:15], 'TailNum', 'ArrDelay', 'Plane identifica
```



It seems you have to avoid flying with airplane N78008 as he land with a mean delay of 5 hours !

We could get info of the plane on https://www.planespotters.net/airframe/Boeing/777/N78008-United-Airlines/D7dbtJWO

It's a Boeing 777-200 build in 1999.

Let's check it in detail :

```
In [51]: df_late.query("TailNum == 'N78008'")
```

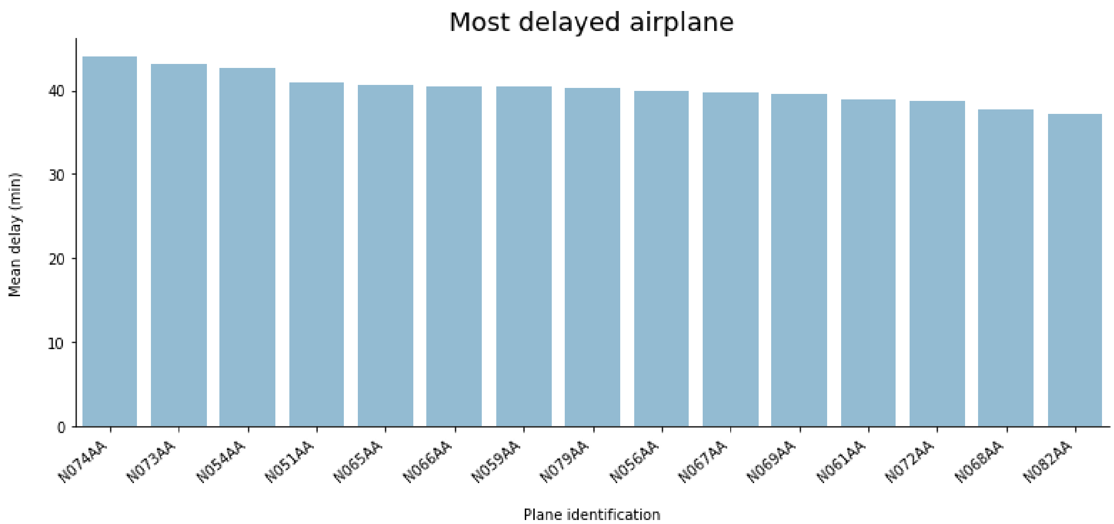
```
Out[51]:          Month  DayofMonth  DayOfWeek  CRSDepTime UniqueCarrier FlightNum  \
         6981780     12          17          3        1030            CO        40

                 TailNum  ArrDelay Origin Dest       ...       DestCity  DestState  \
         6981780  N78008     296.0    IAH  EWR       ...         Newark         NJ
```

```
            DestLat    DestLong                 CarrierName  OriginStateName  \
6981780   40.692497 -74.168661  Continental Air Lines Inc.            Texas

          DestStateName  CRSDepTimeHour        ArrStatus ArrStatus_light
6981780      New Jersey              10   Very late (>90)         Delayed

[1 rows x 33 columns]
```

And here we learn that our result was clearly not statisticaly significant : this plane only made one flight !

Let's take only plane with more than 200 flights.

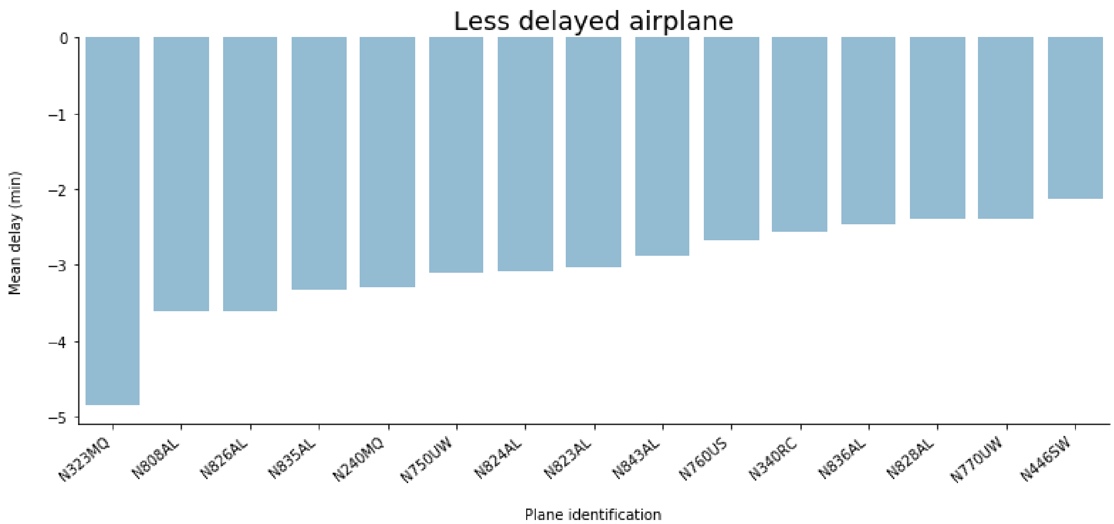
```
In [52]: # Get the plane with more than 200 flight in the main dataset
         df_most_flights = df.groupby(['TailNum'])['Month'].count().sort_values(ascending = Fal
         df_most_flights = df_most_flights.query("Month > 200")
         # Filter the df_late dataset for them
         df_late_plane = df[df['TailNum'].isin(df_most_flights['TailNum'])]
         # Compute the delay mean for them
         df_late_plane = df_late_plane.groupby(['TailNum'])['ArrDelay'].mean().sort_values(asce
         # Plot the top 15
         plot_categorical_variable(df_late_plane[:15], 'TailNum', 'ArrDelay', 'Plane identifica
```



Now we have a better list of plane to avoid. Still with a mean of almost one hour late.

Let's have a look to less delayed plane.

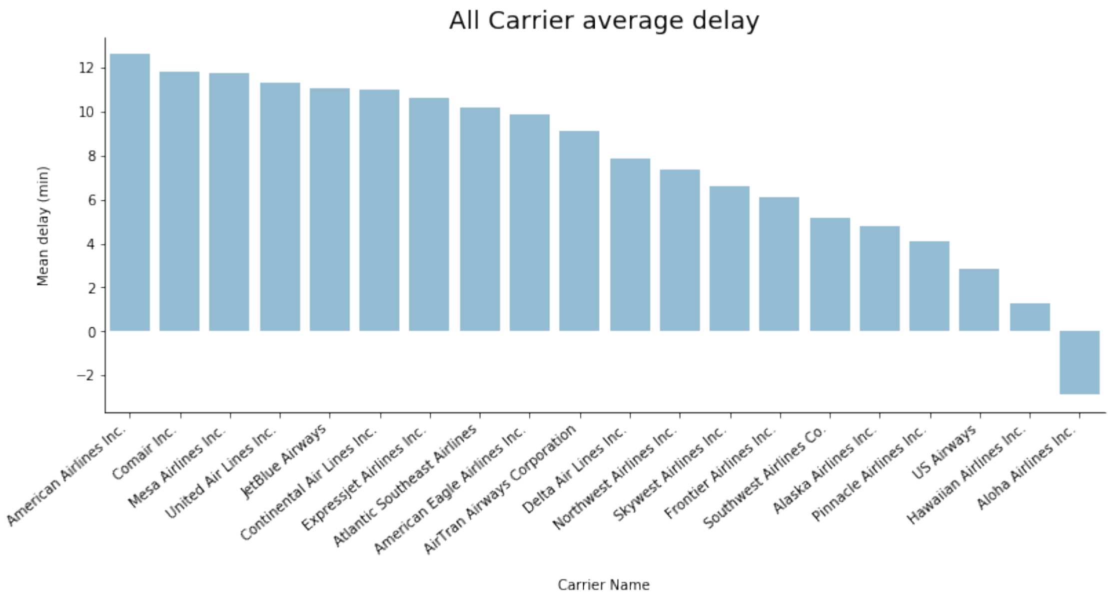
```
In [53]: df_late_plane = df_late_plane.groupby(['TailNum'])['ArrDelay'].mean().sort_values(asce
         # Plot the top 15
         plot_categorical_variable(df_late_plane[:15], 'TailNum', 'ArrDelay', 'Plane identifica
```



OK, at the other side of the graph we have always in advance plane in average.
Let's do the same for Carrier.

3.2 Carrier

```
In [54]: # Get the Carrier with more than 1000 flights in the main dataset
         df_most_flights = df.groupby(['CarrierName'])['Month'].count().sort_values(ascending =
         df_most_flights = df_most_flights.query("Month > 500")
         # Filter the df dataset for them
         df_late_plane = df[df['CarrierName'].isin(df_most_flights['CarrierName'])]
         # Compute the delay mean for them
         df_late_plane = df_late_plane.groupby(['CarrierName'])['ArrDelay'].mean().sort_values
         # Plot the top 15
         plot_categorical_variable(df_late_plane, 'CarrierName', 'ArrDelay', 'Carrier Name', 'I
```



JetBlue is the company with the more delay on average : more than 50 minutes.

While Aloha Airline are landind early on average !

If I look only at top 3 carriers, who operate more than 500 000 flights per year, we have : - American Airline are 13 minutes late on average - SkyWest 6 min - SouthWest 5 min

So, based on that, we could say that you have to avoid American Airline to be on time.

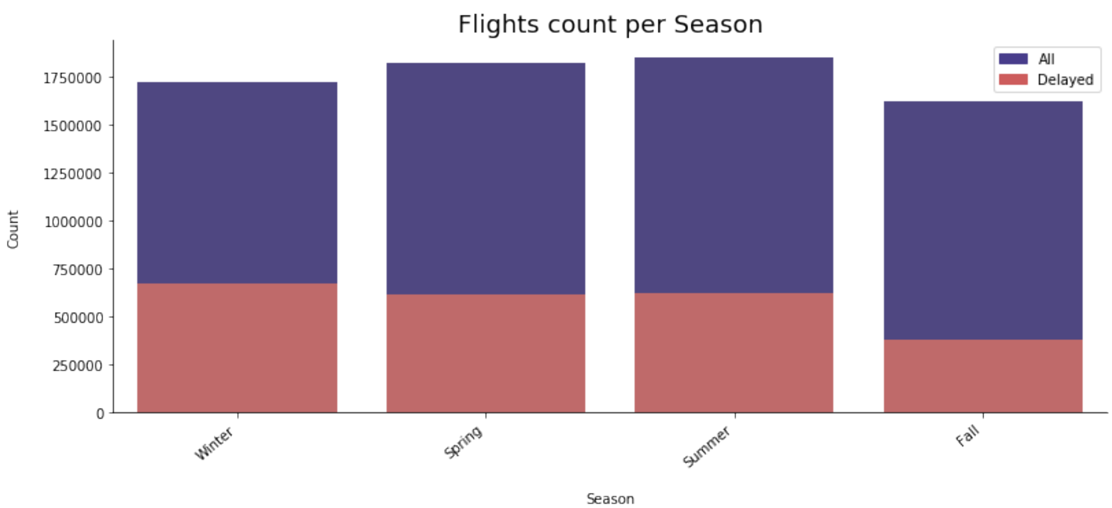
3.3 Season delay

```
In [55]: # Thanks to https://stackoverflow.com/questions/32633977/how-to-create-categorical-va

         def create_season(df):
             # Set the categorical variable values
             season = ['Spring', 'Summer', 'Fall', 'Winter', 'Unknown']
             # Set default value
             df['Season'] = 'Unknown';
             _ = pd.Categorical(df.Season, categories=season, ordered=True);

             df.loc[(df['Month'] == 3) , 'Season'] = 'Spring'
             df.loc[(df['Month'] == 4) , 'Season'] = 'Spring'
             df.loc[(df['Month'] == 5) , 'Season'] = 'Spring'

             df.loc[(df['Month'] == 6) , 'Season'] = 'Summer'
             df.loc[(df['Month'] == 7) , 'Season'] = 'Summer'
             df.loc[(df['Month'] == 8) , 'Season'] = 'Summer'

             df.loc[(df['Month'] == 9) , 'Season'] = 'Fall'
             df.loc[(df['Month'] == 10) , 'Season'] = 'Fall'
             df.loc[(df['Month'] == 11) , 'Season'] = 'Fall'
```

```
        df.loc[(df['Month'] == 12) , 'Season'] = 'Winter'
        df.loc[(df['Month'] == 1) , 'Season'] = 'Winter'
        df.loc[(df['Month'] == 2) , 'Season'] = 'Winter'

    create_season(df);
    create_season(df_late);
    df['Season'].value_counts();
    df_late['Season'].value_counts();
```

```
/media/data-nvme/dev/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:7: SettingWit
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: http://pandas.pydata.org/pandas-docs/stable/indexing.htm
  import sys
/media/data-nvme/dev/anaconda3/lib/python3.7/site-packages/pandas/core/indexing.py:543: Settin
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: http://pandas.pydata.org/pandas-docs/stable/indexing.htm
  self.obj[item] = s
```

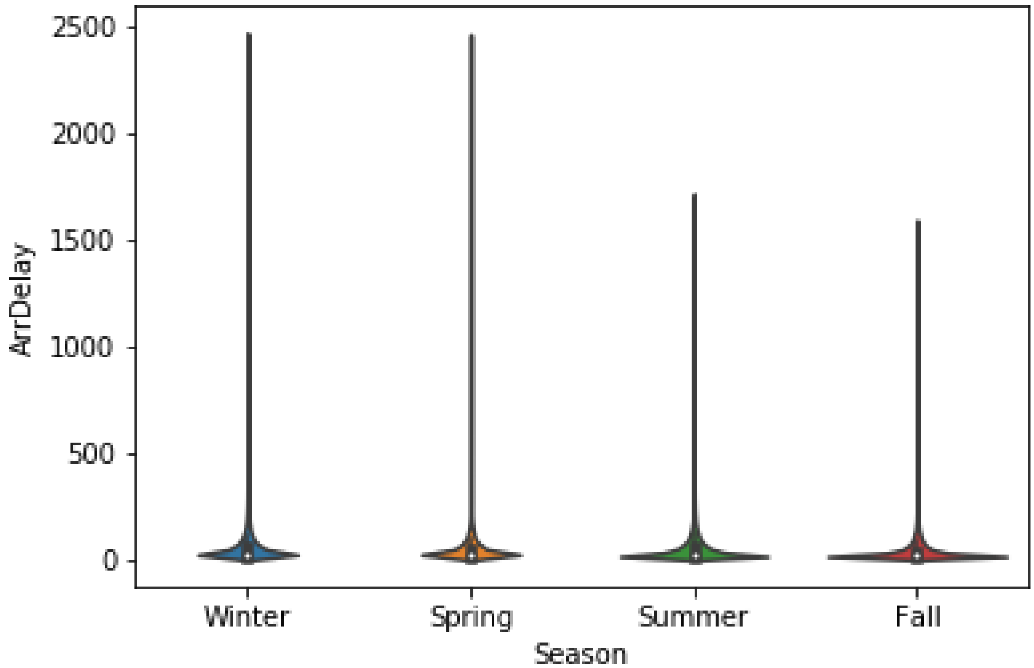
```
In [56]: comparative_barchart_categorical_variable('Season')
```



There is less flight in Spring than in winter, but more delay.
Let's look at Violin plot.

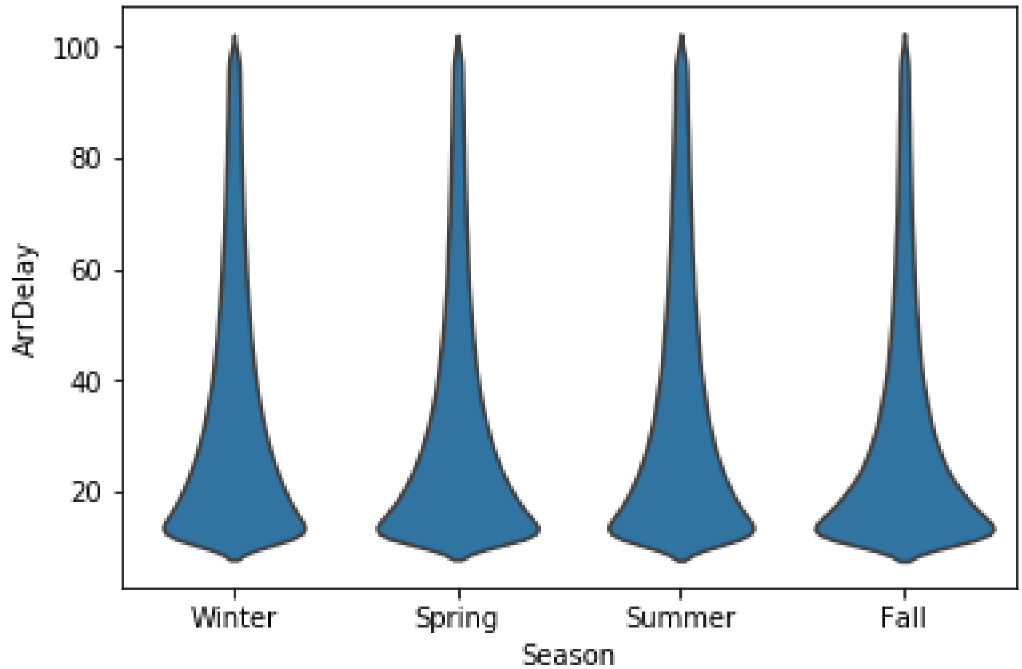
```
In [57]: sns.violinplot(data = df_late, x = 'Season', y = 'ArrDelay');
```

```
/media/data-nvme/dev/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWa
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



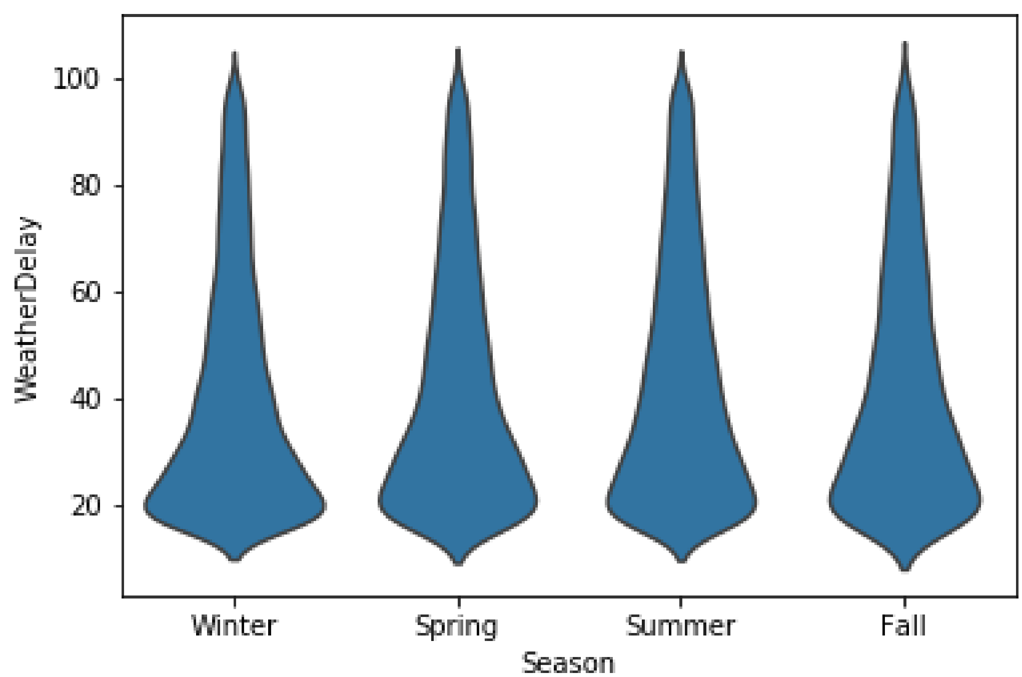
We can't see nothing with default parameters.
Let's keep only delay between 10 minutes and 100 minutes.

```
In [58]: base_color = sns.color_palette()[0]
         sns.violinplot(data = df_late.query("ArrDelay > 10 and ArrDelay < 100"), x = 'Season'
                        inner = None);
```



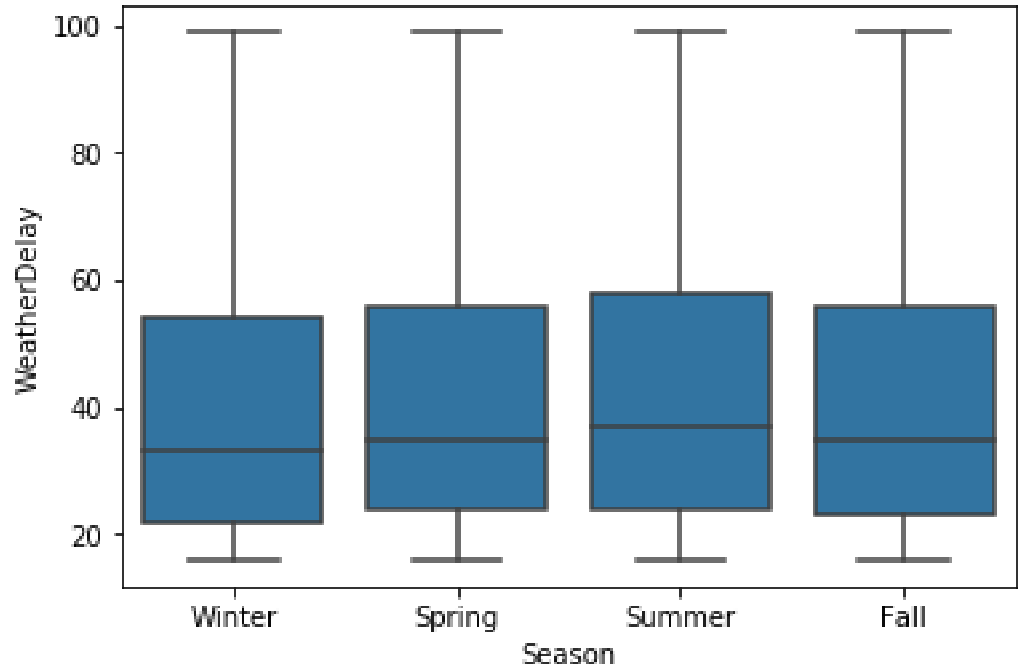
We don't see much more info, let's switch to WeatherDelay instead of ArrDelay.

```
In [59]: base_color = sns.color_palette()[0]

         sns.violinplot(data = df_late.query("WeatherDelay > 15 and WeatherDelay < 100"), x =
                        inner = None);
```



We don't see much more info, let's switch to a boxplot.

```
In [60]: base_color = sns.color_palette()[0]

         sns.boxplot(data = df_late.query("WeatherDelay > 15 and WeatherDelay < 100"), x = 'Sea
                     y = 'WeatherDelay', color = base_color, showfliers=False);
```



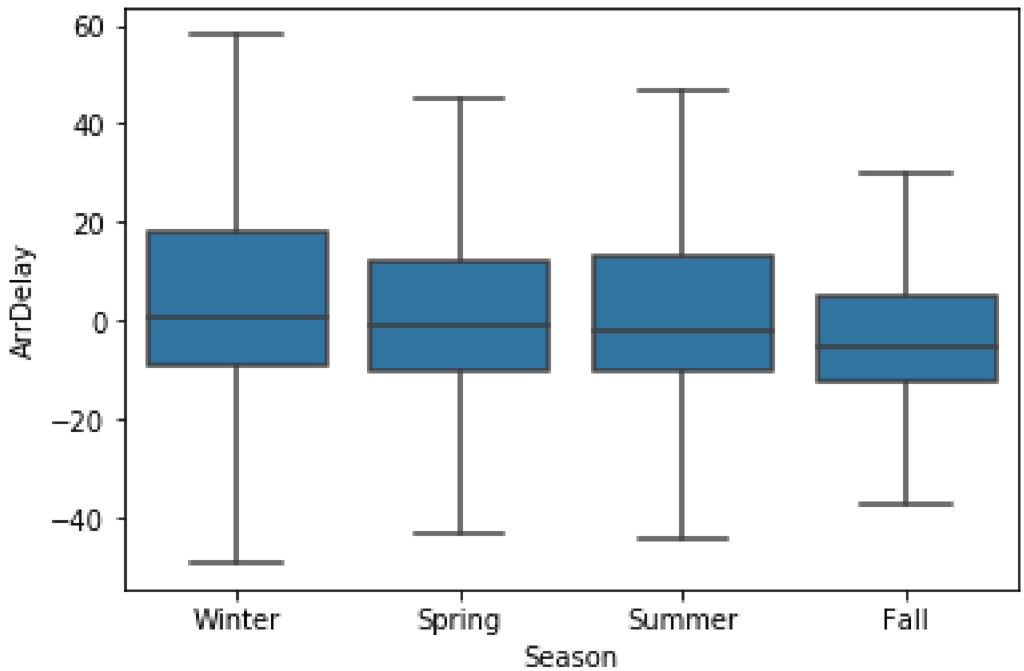
Here we see a correlation. Being french I was expected to have more delay in Winter, due to snow, but it's in Summer and Fall.

I have forgotten that there are hurricanes in US in theses season.

And airplane are very impacted by hurricane.

But I feel strange about it, let's look at ArrDelay in the whole dataset, not only WeatherDelay.

```
In [61]: base_color = sns.color_palette()[0]

         sns.boxplot(data = df, x = 'Season',
                     y = 'ArrDelay', color = base_color, showfliers=False);
```



OK, here we saw more delay in Winter, so we could expect that we are missing WeatherDelay data.

3.4 City

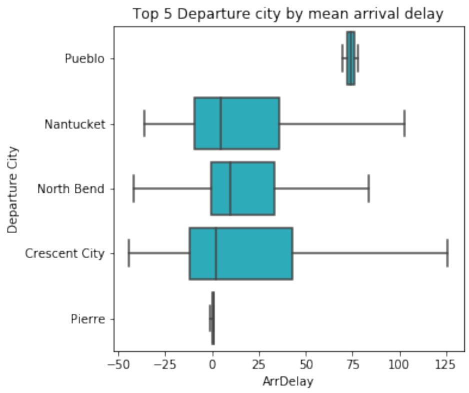
Let's explore delay by city.

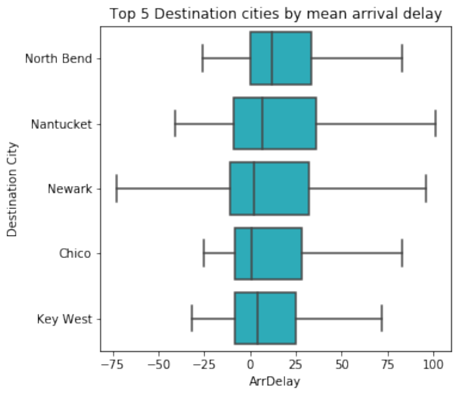
My goal is to plot a box plot of the top 10 city with most delay.

I will compute on order index based on delay mean, then use it to plot.

```
In [62]: # 1 Compute the order by delay mean
         delay_origin_city_order = df.groupby(['OriginCity'])['ArrDelay'].mean().sort_values(as
         delay_dest_city_order = df.groupby(['DestCity'])['ArrDelay'].mean().sort_values(ascend

         # Initiate a figure
         plt.figure(figsize = [15, 5])
         plt.subplots_adjust(wspace = 0.85) # adjust spacing between subplots, in order to show
         # Draw the first boxplot
         plt.subplot(1, 2, 1)
         ax1 = sns.boxplot(x = df['ArrDelay'], y = df['OriginCity'], order = delay_origin_city_
                     color = sns.color_palette()[9], showfliers=False);
         plt.ylabel('Departure City')
         plt.title('Top 5 Departure city by mean arrival delay');

         plt.subplot(1, 2, 2)
         ax2 = sns.boxplot(x = df['ArrDelay'], y = df['DestCity'], order = delay_dest_city_orde
```

```
                color = sns.color_palette()[9], showfliers=False);
plt.ylabel('Destination City')
plt.title('Top 5 Destination cities by mean arrival delay');
```





Pueblo is the origin city with most delay, but North Bend is the Destination with most delay, with 75% of late arrival.

Pueblo and Pierre look like outlier based on the shape of the box plot.

To avoid outliers of these small airport, I will only took the top 50 airports by flights count, then filter the dataset with it.

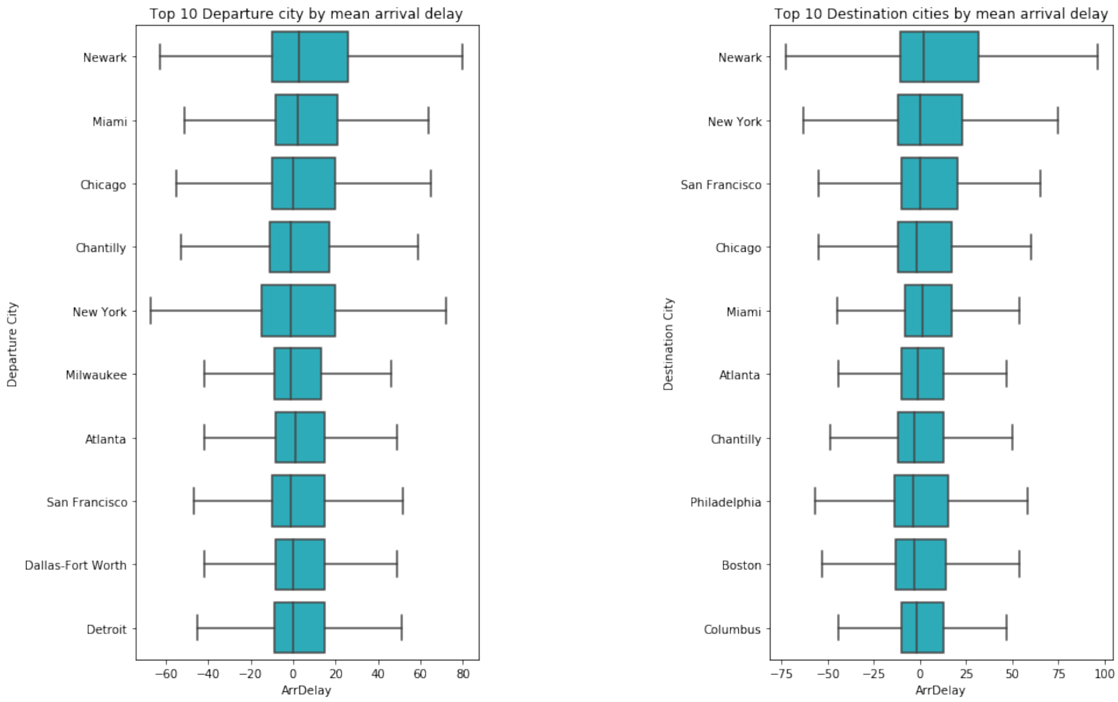
Then, I will compute an order based on mean delay.

And use it to display the plot.

So the order will not be by the biggest airport, but by the delay mean of the biggest airport.

In [63]:
```
## 1 Filter the city with most flights
# Get the 50 cities with with most flights
df_most_flights = df.groupby(['OriginCity'])['Month'].count().sort_values(ascending =
df_most_flights = df_most_flights[:50]
# Filter the dataset on them
df_late_ori_city = df[df['OriginCity'].isin(df_most_flights['OriginCity'])]
df_late_dest_city = df[df['DestCity'].isin(df_most_flights['OriginCity'])]

# 2 Compute the order by delay mean
delay_origin_city_order = df_late_ori_city.groupby(['OriginCity'])['ArrDelay'].mean()
delay_dest_city_order = df_late_dest_city.groupby(['DestCity'])['ArrDelay'].mean().so

# Initiate a figure
plt.figure(figsize = [15, 10])
plt.subplots_adjust(wspace = 0.85) # adjust spacing between subplots, in order to sho
# Draw the first boxplot
plt.subplot(1, 2, 1)
ax1 = sns.boxplot(x = df_late_ori_city['ArrDelay'], y = df_late_ori_city['OriginCity']
                color = sns.color_palette()[9], showfliers=False);
plt.ylabel('Departure City')
plt.title('Top 10 Departure city by mean arrival delay');
```

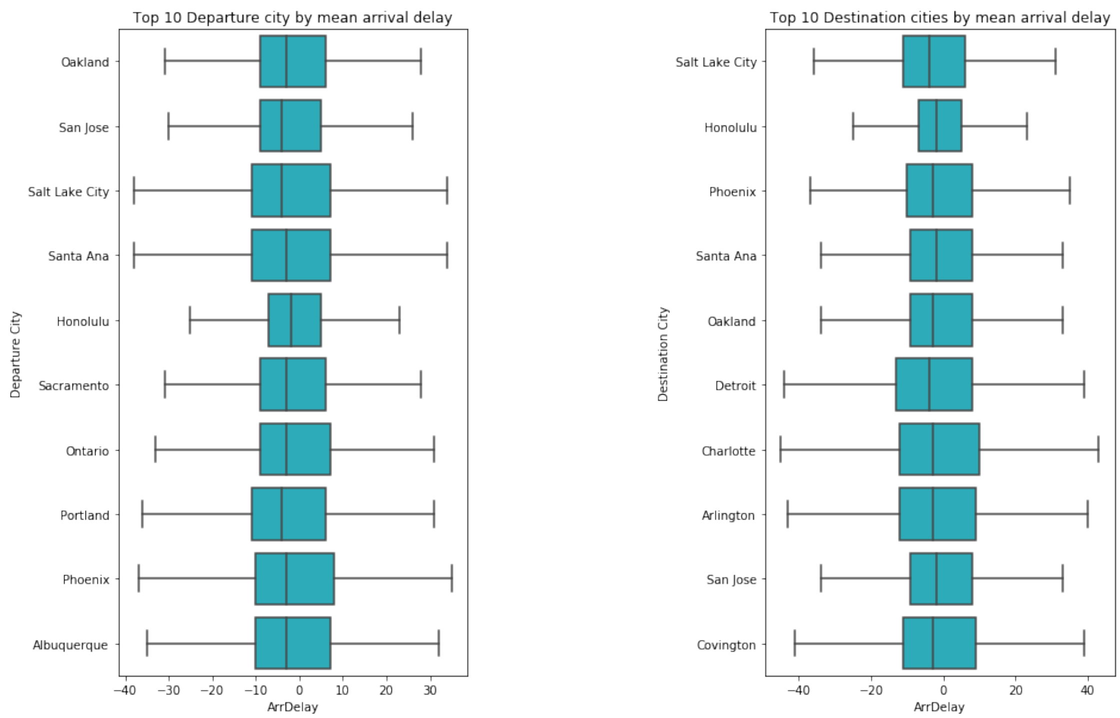
```
plt.subplot(1, 2, 2)
ax2 = sns.boxplot(x = df_late_dest_city['ArrDelay'], y = df_late_dest_city['DestCity']
            color = sns.color_palette()[9], showfliers=False);
plt.ylabel('Destination City')
plt.title('Top 10 Destination cities by mean arrival delay');
```



Newark is the departure city where, in average, you have to expect to be late.
But the distribution is large : you have more than 25% chance to arrive early.
If it's your destination, you also have to expect to be late, in more than 50% of the flights, in average.
What is interesting is some of top departure with hight mean delay are not in the Top 10 for destination, like Milwaukee.
Let's look to the other side, to major airport with lowest mean delay.

```
In [64]: # 2 Compute the order by delay mean
         delay_origin_city_order = df_late_ori_city.groupby(['OriginCity'])['ArrDelay'].mean()
         delay_dest_city_order = df_late_dest_city.groupby(['DestCity'])['ArrDelay'].mean().so

         # Initiate a figure
         plt.figure(figsize = [15, 10])
         plt.subplots_adjust(wspace = 0.85) # adjust spacing between subplots, in order to sho
         # Draw the first boxplot
         plt.subplot(1, 2, 1)
         ax1 = sns.boxplot(x = df_late_ori_city['ArrDelay'], y = df_late_ori_city['OriginCity']
                     color = sns.color_palette()[9], showfliers=False);
```

```
plt.ylabel('Departure City')
plt.title('Top 10 Departure city by mean arrival delay');

plt.subplot(1, 2, 2)
ax2 = sns.boxplot(x = df_late_dest_city['ArrDelay'], y = df_late_dest_city['DestCity']
            color = sns.color_palette()[9], showfliers=False);
plt.ylabel('Destination City')
plt.title('Top 10 Destination cities by mean arrival delay');
```



Honolulu is a good destination, with 99% chance to have less than 25 minutes delay.

3.4.1 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?

I found that the plane you take influence on delay. But it's only statistics, they probalbly doesn't do the same type of flight, nor be the same model operated by the same company... It's difficult to draw individual conclusion like this. We arrive in the domain of machine learning.

For major Carrier we could have a better confidence in our conclusion as American Airline is twice late in average than SkyWest or SouthWest.

Season have an influence on delay : you are more subject to delay in winter. But we are clearly missing WeatherDelay info to be sure.

Airport seems to have an influence on delay.

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

No, I have not tried to find them.

I could say there is strong correlation between ArrDelay and other delay columns but it's obvious.

4 Multivariate Exploration

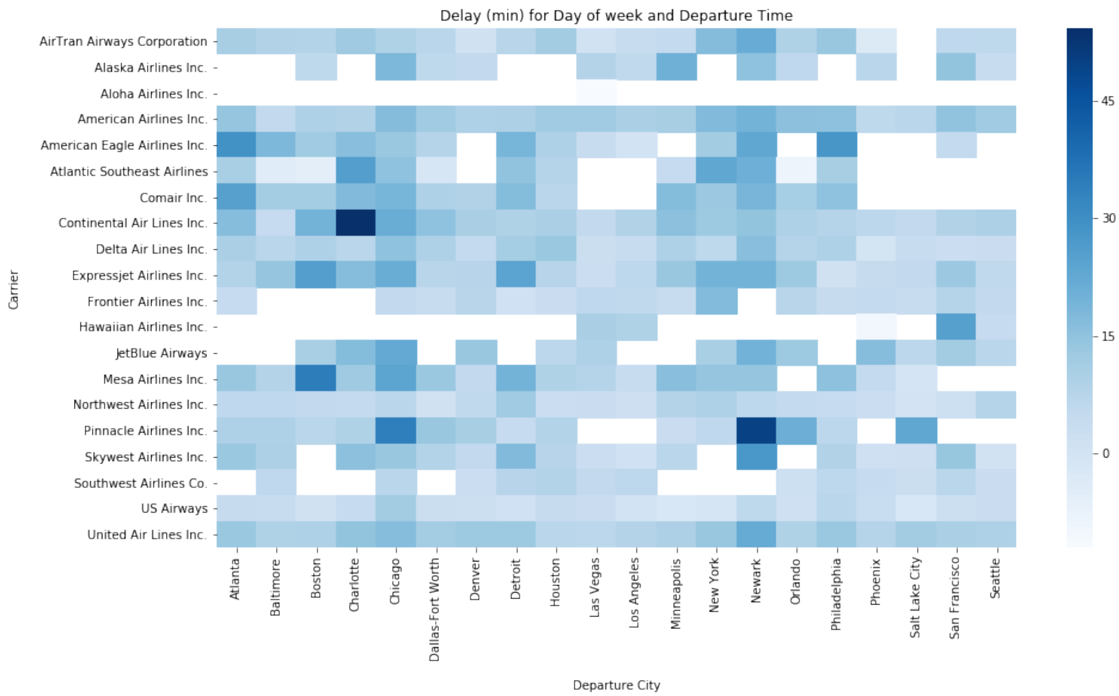
I will have a look to three variables at the same time to see if there is relationship between our previous observations.

4.1 Delay by Carrier by City

As we have previously build "df_most_flights" with the most used city, we will use it to draw a plot of the delay by city and carrier.

The Seaborn Heatmap is good for that.

In [65]:
```
plt.figure(figsize=(15,8))

df_most_flights = df_most_flights[:20]
# Filter the dataset on them
df_late_ori_city = df[df['OriginCity'].isin(df_most_flights['OriginCity'])]

df_group = df_late_ori_city.groupby(['CarrierName', 'OriginCity'])['ArrDelay'].mean()
df_pivot = df_group.pivot('CarrierName', 'OriginCity', 'ArrDelay');

heat_map = sns.heatmap(df_pivot, cmap = 'Blues');

plt.title('Delay (min) for Day of week and Departure Time');
plt.xlabel('Departure City', labelpad = 16);
plt.ylabel('Carrier',  labelpad = 16);
```



Continental Airlines is causing more delay in Charlotte.

We clearly see Newark in the top delayed city. Now we see that "Pinnacle Airline" is responsible of the majority of delay there. And also in other city like Chicago or Salt Lake City.

That's realy interresting because "Pinnacle Airline" was far from the top of delay by carrier.

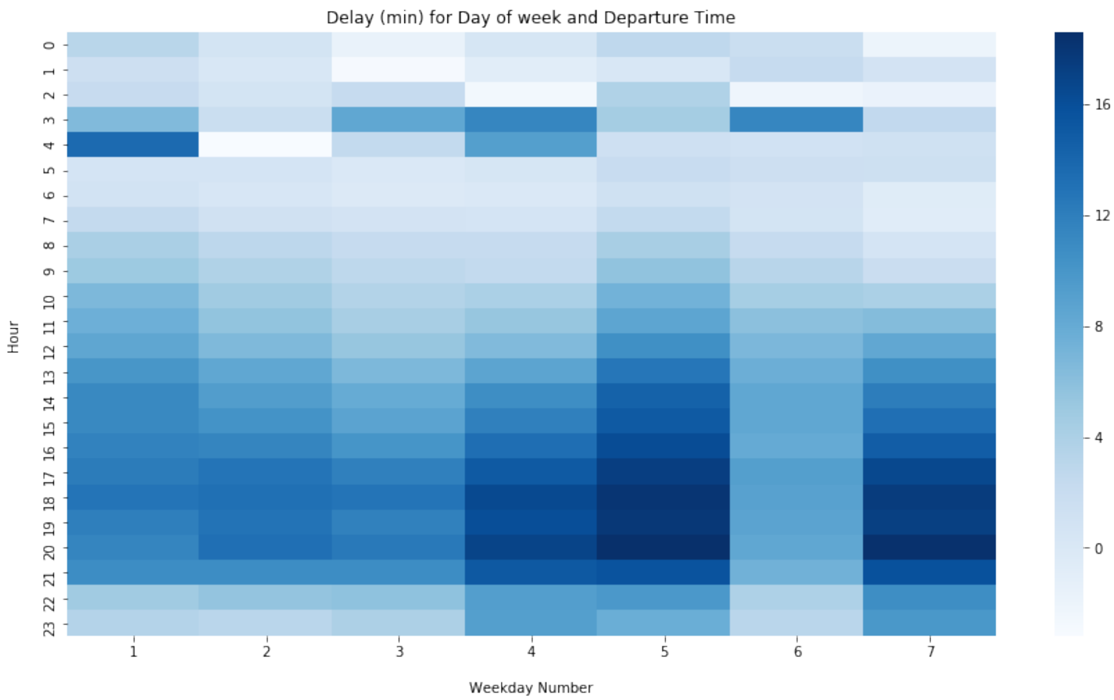
And American Airlines that sit on the top of delay by carrier don't show up here.

We have to remember that it's a plot only on the top 20 most frequently used city. So we could expect that American Airlines is causing more delay on small airport.

4.2 Day of week and DepTime and Delay

I will use the same technic to view the delay by day of week and hour of day.

```
In [66]: plt.figure(figsize=(15,8))
         df_group = df.groupby(['CRSDepTimeHour', 'DayOfWeek'])['ArrDelay'].mean().reset_index
         df_pivot = df_group.pivot('CRSDepTimeHour', 'DayOfWeek', 'ArrDelay');

         heat_map = sns.heatmap(df_pivot, cmap = 'Blues');

         plt.title('Delay (min) for Day of week and Departure Time');
         plt.xlabel('Weekday Number', labelpad = 16);
         plt.ylabel('Hour',  labelpad = 16);
```



Worst time to take a plane is friday and sunday evening, probably because of people going and returning of week-end trip.

And also realy early (3/4 am) in the morning, maybe because teams are not fully operational at that time ?

4.3 Map of delay

I think it will be interresting to draw a map of the delay.

For that we will need GeoPandas who provide geographic feature with pandas style. Perfect for what I want to do.

```
In [67]: #!pip install geopandas descartes
```

```
In [68]: import geopandas as gpd
         df_orig_season_delay_geo = df[['OriginState', 'OriginStateName', 'Season', 'ArrDelay']
         df_orig_season_delay_geo.dropna(inplace=True)
         df_orig_season_delay_geo = df_orig_season_delay_geo.groupby(['OriginStateName', 'Orig
         df_orig_season_delay_geo.head(3)
```

```
/media/data-nvme/dev/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:3: SettingWit
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.htm
  This is separate from the ipykernel package so we can avoid doing imports until
```

Out[68]:

```
  OriginStateName OriginState  Season  ArrDelay
0         Alabama          AL    Fall  2.528451
1         Alabama          AL  Spring  9.230210
2         Alabama          AL  Summer  8.766196
```

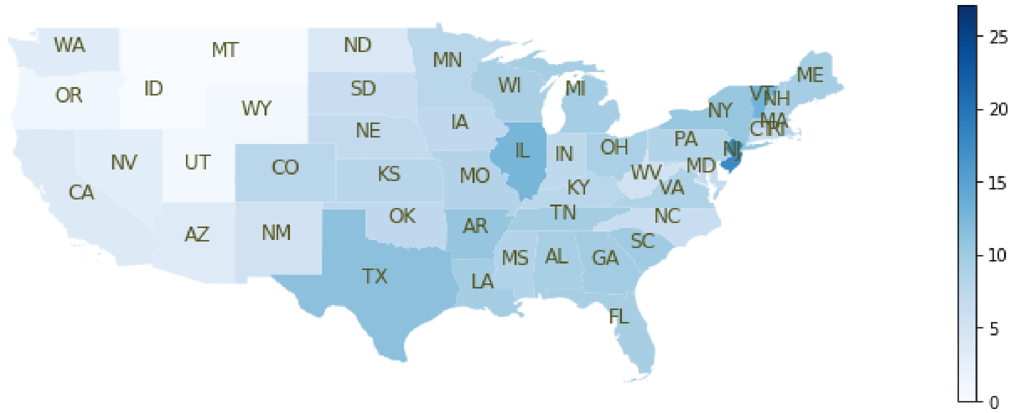
In [69]:

```
# You have to downlaod and unzip https://www2.census.gov/geo/tiger/GENZ2017/shp/cb_20
# To get the map background.
shape = "./cb_2017_us_state_20m/cb_2017_us_state_20m.shp"
usa_map = gpd.read_file(shape)
df_map = usa_map.merge(df_orig_season_delay_geo, how='left', left_on='NAME', right_on
```

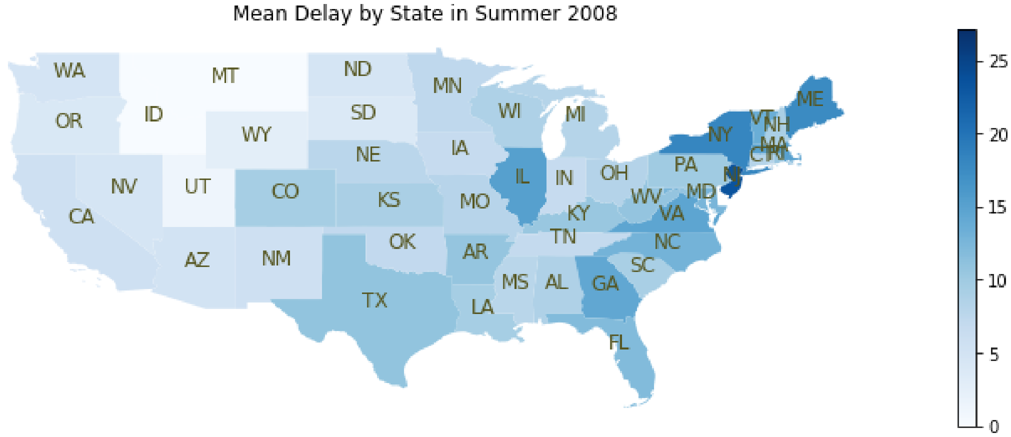
In [70]:

```
seasons = ['Spring', 'Summer', 'Fall', 'Winter']

# Zoom to US only, without Alaska and Hawai
df_non_alaska = df_map.cx[-120:-65, 20:80]

# Initiate a figure
plt.figure(figsize = [15, 5*4])
#f, ax = plt.subplots(2,2,figsize=(6,3));
i=0
vmax=df_non_alaska.ArrDelay.max()
for season in seasons:
    # Thanks to https://github.com/bendoesdata/make-a-map-geopandas
    figsize = (7, 3);
    ax = plt.subplot(4, 1, i+1);
    _ = ax.set_title('Mean Delay by State in ' + season + ' 2008');
    # Draw the map
    _ = df_non_alaska.query("Season == @season").plot(column='ArrDelay', ax=ax, cmap=
                                                    vmin=0, vmax=vmax);
    # thanks to https://stackoverflow.com/questions/38899190/geopandas-label-polygons
    _ = df_non_alaska.query("Season == @season").apply(lambda x: ax.annotate(s=x.Orig
               fontsize=12, ha='center', color='#555520'),axis=1);
    # remove the axis
    _ = ax.axis('off');
    i+=1
plt.show();
```

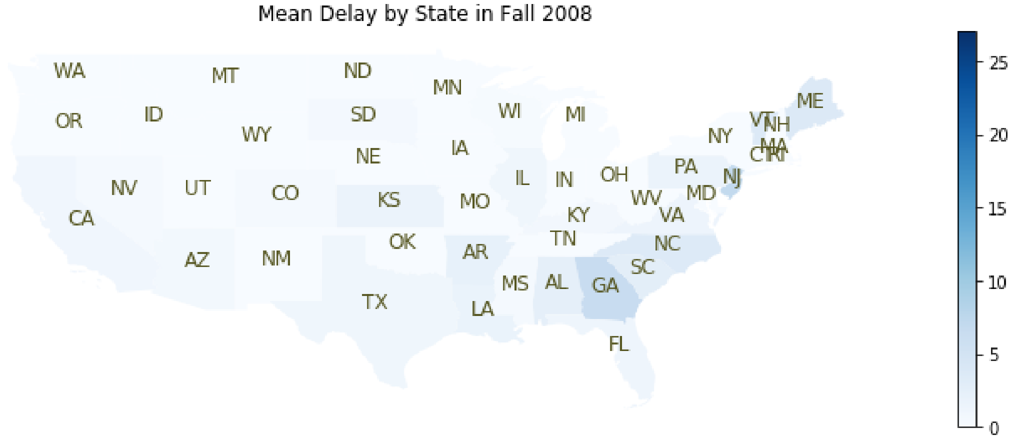
Mean Delay by State in Spring 2008



Mean Delay by State in Summer 2008



Mean Delay by State in Fall 2008



Mean Delay by State in Winter 2008