LAB 1

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Problem Statement

A data science team is working on an important project related to airports and optimization. You are a new team member and was hired as junior data scientist. Each team member has received a task and your task is to check if you can say that Delta Airlines (DL) flights are delayed more than United Airlines (UA) flights ? The file (data source) is already available to start your analysis. To solve this problem you will need to use statistical concepts and python programming language that are the foundation of modern machine learning development.

Installing and Importing required Libraries

In [1]:

```
#installing researchpy for t test and sweetviz for EDA
!pip install researchpy
!pip install sweetviz
import sweetviz as sv
import numpy as np
import pandas as pd
import statistics
import scipy.stats as sp
from scipy.stats import sem
import seaborn as sns
import matplotlib.pyplot as plt
import researchpy as rp
import scipy.stats as stats
from matplotlib.lines import Line2D
%matplotlib inline
```

```
Requirement already satisfied: researchpy in d:\anaconda\lib\site-packages
(0.3.5)
Requirement already satisfied: statsmodels in d:\anaconda\lib\site-packages
(from researchpy) (0.12.2)
Requirement already satisfied: scipy in d:\anaconda\lib\site-packages (from
researchpy) (1.7.1)
Requirement already satisfied: pandas in d:\anaconda\lib\site-packages (from
researchpy) (1.3.4)
Requirement already satisfied: patsy in d:\anaconda\lib\site-packages (from
researchpy) (0.5.2)
Requirement already satisfied: numpy in d:\anaconda\lib\site-packages (from
researchpy) (1.20.3)
Requirement already satisfied: python-dateutil>=2.7.3 in d:\anaconda\lib\sit
e-packages (from pandas->researchpy) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in d:\anaconda\lib\site-packages
(from pandas->researchpy) (2021.3)
Requirement already satisfied: six>=1.5 in d:\anaconda\lib\site-packages (fr
om python-dateutil>=2.7.3->pandas->researchpy) (1.16.0)
Requirement already satisfied: sweetviz in d:\anaconda\lib\site-packages (2.
1.4)
Requirement already satisfied: numpy>=1.16.0 in d:\anaconda\lib\site-package
s (from sweetviz) (1.20.3)
Requirement already satisfied: tqdm>=4.43.0 in d:\anaconda\lib\site-packages
(from sweetviz) (4.62.3)
Requirement already satisfied: pandas!=1.0.0,!=1.0.1,!=1.0.2,>=0.25.3 in
d:\anaconda\lib\site-packages (from sweetviz) (1.3.4)
Requirement already satisfied: jinja2>=2.11.1 in d:\anaconda\lib\site-packag
es (from sweetviz) (2.11.3)
Requirement already satisfied: importlib-resources>=1.2.0 in d:\anaconda\lib
\site-packages (from sweetviz) (5.9.0)
Requirement already satisfied: matplotlib>=3.1.3 in d:\anaconda\lib\site-pac
kages (from sweetviz) (3.4.3)
Requirement already satisfied: scipy>=1.3.2 in d:\anaconda\lib\site-packages
(from sweetviz) (1.7.1)
Requirement already satisfied: zipp>=3.1.0 in d:\anaconda\lib\site-packages
(from importlib-resources>=1.2.0->sweetviz) (3.6.0)
Requirement already satisfied: MarkupSafe>=0.23 in d:\anaconda\lib\site-pack
ages (from jinja2>=2.11.1->sweetviz) (1.1.1)
Requirement already satisfied: pillow>=6.2.0 in d:\anaconda\lib\site-package
s (from matplotlib>=3.1.3->sweetviz) (8.4.0)
Requirement already satisfied: pyparsing>=2.2.1 in d:\anaconda\lib\site-pack
ages (from matplotlib>=3.1.3->sweetviz) (3.0.4)
Requirement already satisfied: cycler>=0.10 in d:\anaconda\lib\site-packages
(from matplotlib>=3.1.3->sweetviz) (0.10.0)
Requirement already satisfied: python-dateutil>=2.7 in d:\anaconda\lib\site-
packages (from matplotlib>=3.1.3->sweetviz) (2.8.2)
Requirement already satisfied: kiwisolver>=1.0.1 in d:\anaconda\lib\site-pac
kages (from matplotlib>=3.1.3->sweetviz) (1.3.1)
Requirement already satisfied: six in d:\anaconda\lib\site-packages (from cy
cler>=0.10->matplotlib>=3.1.3->sweetviz) (1.16.0)
Requirement already satisfied: pytz>=2017.3 in d:\anaconda\lib\site-packages
(from pandas!=1.0.0,!=1.0.1,!=1.0.2,>=0.25.3->sweetviz) (2021.3)
Requirement already satisfied: colorama in d:\anaconda\lib\site-packages (fr
om tqdm>=4.43.0->sweetviz) (0.4.4)
```

In [2]:
```python
# Read the data set of flights
data= pd.read_csv("D:/AIDI Course/AI Algo/LAB1/flights.csv")

# Printing the data
data
```

Out[2]:

	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_
0	2013	1	1	517.0	515	2.0	830.0	819	
1	2013	1	1	533.0	529	4.0	850.0	830	
2	2013	1	1	542.0	540	2.0	923.0	850	
3	2013	1	1	544.0	545	-1.0	1004.0	1022	
4	2013	1	1	554.0	600	-6.0	812.0	837	
...	...	...	...	...	...	...	...	...	
336771	2013	9	30	NaN	1455	NaN	NaN	1634	
336772	2013	9	30	NaN	2200	NaN	NaN	2312	
336773	2013	9	30	NaN	1210	NaN	NaN	1330	
336774	2013	9	30	NaN	1159	NaN	NaN	1344	
336775	2013	9	30	NaN	840	NaN	NaN	1020	

336776 rows × 19 columns

Task 1: Create a Jupyter Notebook to present your analysis and perform an exploratory data analysis (EDA) on flights.csv file.

1.1 Using sweetviz module to generate html report

The analyze module will be used to generate report

In [3]:
```
flights_report = sv.analyze(data)
flights_report.show_html()
```

```
                                             |          | [  0%]   00:00 ->
(? left)

Report SWEETVIZ_REPORT.html was generated! NOTEBOOK/COLAB USERS: the web bro
wser MAY not pop up, regardless, the report IS saved in your notebook/colab
files.
```

1.2 Displaying concise summary for variables

Pandas dataframe.info() function is used to get a concise summary of the dataframe. It comes really handy when doing exploratory analysis of the data. It shows the data type of variables and count of non null values for the variables

In [4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 336776 entries, 0 to 336775
Data columns (total 19 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   year            336776 non-null  int64  
 1   month           336776 non-null  int64  
 2   day             336776 non-null  int64  
 3   dep_time        328521 non-null  float64
 4   sched_dep_time  336776 non-null  int64  
 5   dep_delay       328521 non-null  float64
 6   arr_time        328063 non-null  float64
 7   sched_arr_time  336776 non-null  int64  
 8   arr_delay       327346 non-null  float64
 9   carrier         336776 non-null  object 
 10  flight          336776 non-null  int64  
 11  tailnum         334264 non-null  object 
 12  origin          336776 non-null  object 
 13  dest            336776 non-null  object 
 14  air_time        327346 non-null  float64
 15  distance        336776 non-null  int64  
 16  hour            336776 non-null  int64  
 17  minute          336776 non-null  int64  
 18  time_hour       336776 non-null  object 
dtypes: float64(5), int64(9), object(5)
memory usage: 48.8+ MB
```

1.3 Displaying Descriptive statistics

Dataframe.describe() method is used for Descriptive statistics including those that summarize the central tendency, dispersion and shape of a dataset’s distribution, excluding NaN values

In [5]:
```
data.describe()
```

Out[5]:

	year	month	day	dep_time	sched_dep_time	dep_delay
count	336776.0	336776.000000	336776.000000	328521.000000	336776.000000	328521.000000
mean	2013.0	6.548510	15.710787	1349.109947	1344.254840	12.639070
std	0.0	3.414457	8.768607	488.281791	467.335756	40.210061
min	2013.0	1.000000	1.000000	1.000000	106.000000	-43.000000
25%	2013.0	4.000000	8.000000	907.000000	906.000000	-5.000000
50%	2013.0	7.000000	16.000000	1401.000000	1359.000000	-2.000000
75%	2013.0	10.000000	23.000000	1744.000000	1729.000000	11.000000
max	2013.0	12.000000	31.000000	2400.000000	2359.000000	1301.000000

1.4 Displaying number of null values for each column

Dataframe.isnull().sum() method is used to display number of null values for each column. The following result shows that arr_delay has null values. This information is useful in subsequent tasks

In [6]:
```
data.isnull().sum()
```

Out[6]:
```
year                 0
month                0
day                  0
dep_time          8255
sched_dep_time       0
dep_delay         8255
arr_time          8713
sched_arr_time       0
arr_delay         9430
carrier              0
flight               0
tailnum           2512
origin               0
dest                 0
air_time          9430
distance             0
hour                 0
minute               0
time_hour            0
dtype: int64
```

1.5 Displaying correlation of arr_delay wih other variables

From the below result it can be noted tht arrival delay depends largely on departure delay as there is a srong positive correlation between arr_delay and dep_delay

In [7]:
```
data.corr()['arr_delay']
```

Out[7]:
```
year                   NaN
month            -0.017382
day              -0.000319
dep_time          0.232306
sched_dep_time    0.173896
dep_delay         0.914803
arr_time          0.024482
sched_arr_time    0.133261
arr_delay         1.000000
flight            0.072862
air_time         -0.035297
distance         -0.061868
hour              0.173456
minute            0.021522
Name: arr_delay, dtype: float64
```

1.6 Displaying total carriers

unique() method will be used to display the unique values for carrier

In [8]:
```
data['carrier'].unique()
```

Out[8]:
```
array(['UA', 'AA', 'B6', 'DL', 'EV', 'MQ', 'US', 'WN', 'VX', 'FL', 'AS',
       '9E', 'F9', 'HA', 'YV', 'OO'], dtype=object)
```

1.7 Displaying dataframe with records having zero arrival delays

From the output below, it can be seen 5409 records have zero arrival delays

```
In [9]: no_arr_delay = data.query("arr_delay == 0")
display(no_arr_delay)
```

	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr
35	2013	1	1	627.0	630	-3.0	1018.0	1018	
114	2013	1	1	807.0	810	-3.0	1043.0	1043	
217	2013	1	1	956.0	1000	-4.0	1241.0	1241	
273	2013	1	1	1124.0	1125	-1.0	1445.0	1445	
317	2013	1	1	1219.0	1220	-1.0	1415.0	1415	
...	...	...	...	...	...	...	...	...	
336296	2013	9	30	1409.0	1415	-6.0	1550.0	1550	
336383	2013	9	30	1530.0	1530	0.0	1845.0	1845	
336438	2013	9	30	1615.0	1620	-5.0	1828.0	1828	
336491	2013	9	30	1703.0	1645	18.0	1915.0	1915	
336595	2013	9	30	1843.0	1830	13.0	1950.0	1950	

5409 rows × 19 columns

Task 2: Create at least 5 different views (reports) to the team using the imported dataset. The reports should be composed of a description, charts and tables based on some selected columns. These reports can give some insights to the team about the airport operation and potential optimizations.

Report 1: Creatng a Vizualization to display top 5 Carriers with most arrival delays in 2013

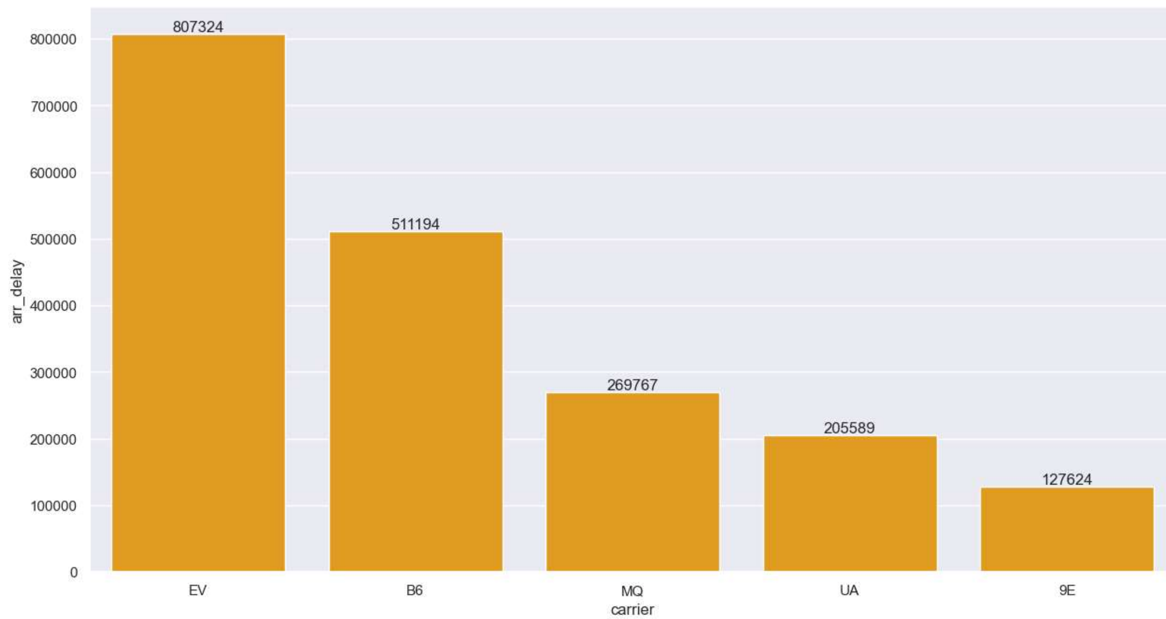
Step 1: Creating a dataframe report1 to contain top 5 carrier with most arrival delays

Step 2: Using Seaborn library to create barplot

Step 3: adding data labels

In [10]:
```
sns.set(rc = {'figure.figsize':(15,8)})
#step 1
report1 = data.groupby('carrier')['arr_delay'].sum().to_frame().nlargest(5, 'a
report1.reset_index(inplace=True)
#step 2
ax1 = sns.barplot(x='carrier', y='arr_delay', data=report1, color = 'orange')
#step 3
ax1.bar_label(ax1.containers[0])
```

Out[10]:
```
[Text(0, 0, '807324'),
 Text(0, 0, '511194'),
 Text(0, 0, '269767'),
 Text(0, 0, '205589'),
 Text(0, 0, '127624')]
```



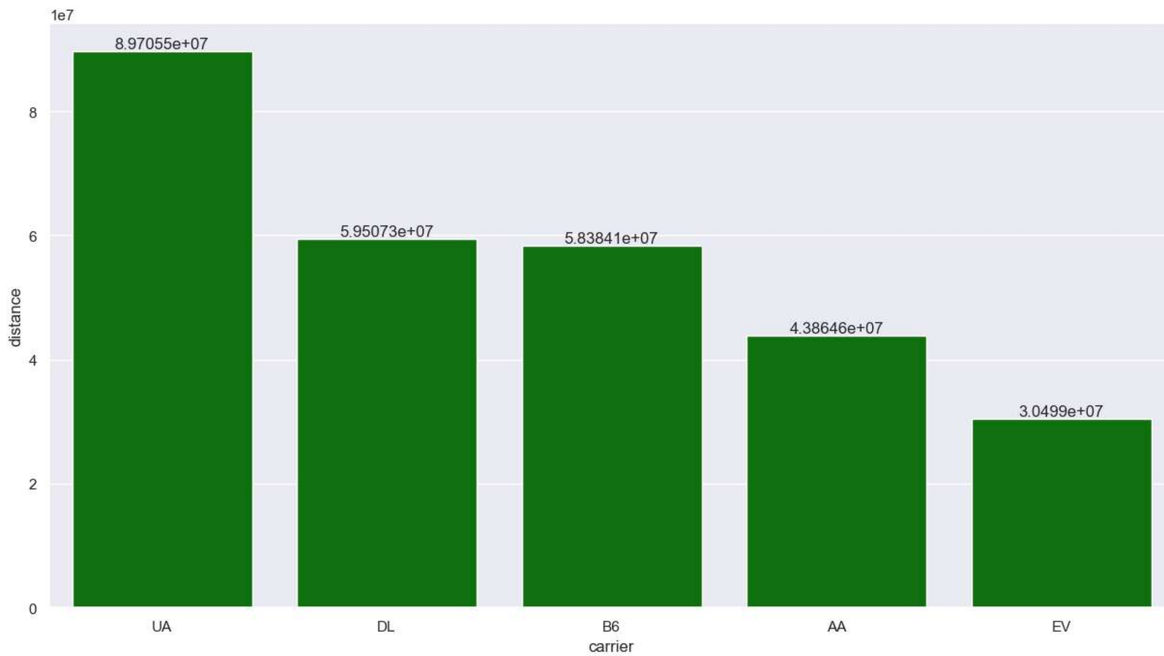
From the above graph, it can be seen that EV carrier experienced the most arrival delays in 2013 followed by B6 and MQ. UA follows next in experiencing the arrival delays.

Report 2: Creatng a Vizualization to display top 5 Carriers with most distance covered through flights in 2013

Step 1: Creating a dataframe report2 to contain top 5 carrier with most distance covered through flights in 2013
Step 2: Using Seaborn library to create barplot
Step 3: adding data labels

In [11]:
```
#step 1
report2 = data.groupby('carrier')['distance'].sum().to_frame().nlargest(5, 'di
report2.reset_index(inplace=True)
#step 2
ax2 = sns.barplot(x='carrier', y='distance', data=report2, color = 'green')
#step 3
ax2.bar_label(ax2.containers[0])
```

Out[11]:
```
[Text(0, 0, '8.97055e+07'),
 Text(0, 0, '5.95073e+07'),
 Text(0, 0, '5.83841e+07'),
 Text(0, 0, '4.38646e+07'),
 Text(0, 0, '3.0499e+07')]
```



From the above graph, it can be concluded that UA carrier covered most disance in 2013 followed by DL carrier. UA and DL carriers are thus most widely used carriers in 2013

Report 3: Creatng a Vizualization to display top 5 Months with most arrival delays in 2013

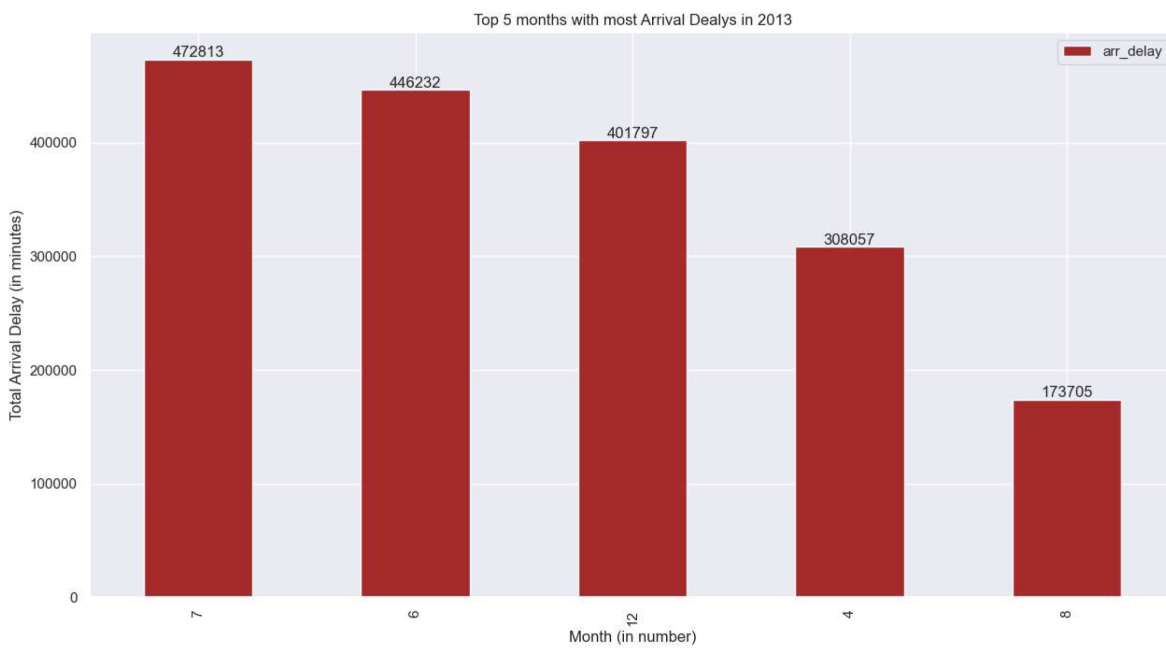
Step 1: Creating a dataframe report3 to contain top 5 months with most arrival delays

Step 2: Using plot method on dataframe to generate bar plot

Step 3: adding data labels

In [12]:
```
#step 1
report3 = data.groupby('month')['arr_delay'].sum().to_frame().nlargest(5, 'arr
#step 2
ax3 = report3.plot(kind='bar', title='Top 5 months with most Arrival Dealys ir
         xlabel='Month (in number)', figsize=(15, 8))
#step 3
ax3.bar_label(ax3.containers[0])
```

Out[12]:
```
[Text(0, 0, '472813'),
 Text(0, 0, '446232'),
 Text(0, 0, '401797'),
 Text(0, 0, '308057'),
 Text(0, 0, '173705')]
```



From the above graph, it can be ssen that 7th month i.e., July experienced most arrival delays in 2013 followed by 6th month i.e., June

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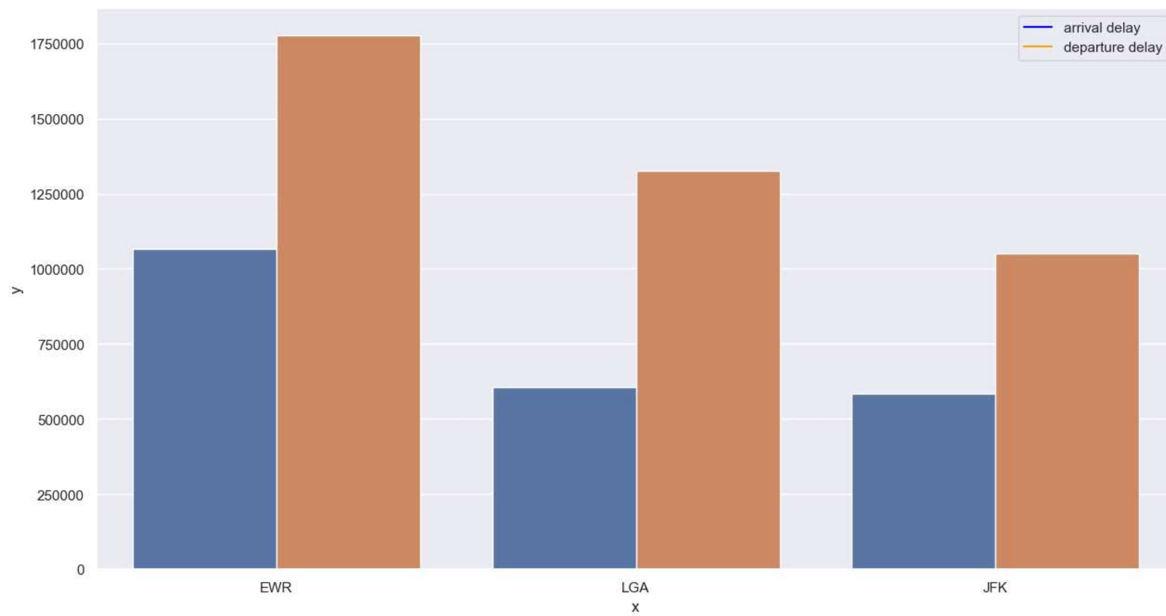
Report 4: Creatng a Vizualization to display arrival delays and departure delays for all three origins

Step 1: Creating a two sub dataframes: one to store arrival delays for all origins and other to store departure delay for all origins
Step 2: Creating unified dataframe from two created in step 1
Step 3: Using Seaborn library to create barplot
Step 4: Creating Legends
Step 5: Displaying plot

In [13]:

```
#step 1
report41 = pd.DataFrame({'x':['EWR', 'LGA', 'JFK'],'y':data.groupby('origin')|
report42 = pd.DataFrame({'x':['EWR', 'LGA', 'JFK'],'y':data.groupby('origin')|
report41['hue'] = 'blue'
report42['hue'] = 'orange'
#step 2
report4 = pd.concat([report41,report42])
#step 3
sns.barplot(x='x',y='y',data = report4, hue ='hue')
#step 4
a = Line2D([], [], color='blue', label='arrival delay')
b = Line2D([], [], color='orange', label='departure delay')
plt.legend(handles=[a, b])
#step 5
plt.show()
```



From the above graph, it can be seen that among three places, flights originating from EWR experienced most arrival delays as well as departure delays in 2013

Report 5: Creating a vizualisaion to display top 5 carriers that experienced no arrival delays in 2013 and also displaying which carrier experienced zero delays the most

Step 1: Creating a dataframe with zero arrival delays

Step 2: Modifying the dataframe to contain top 5 carriers with zero arrival delays

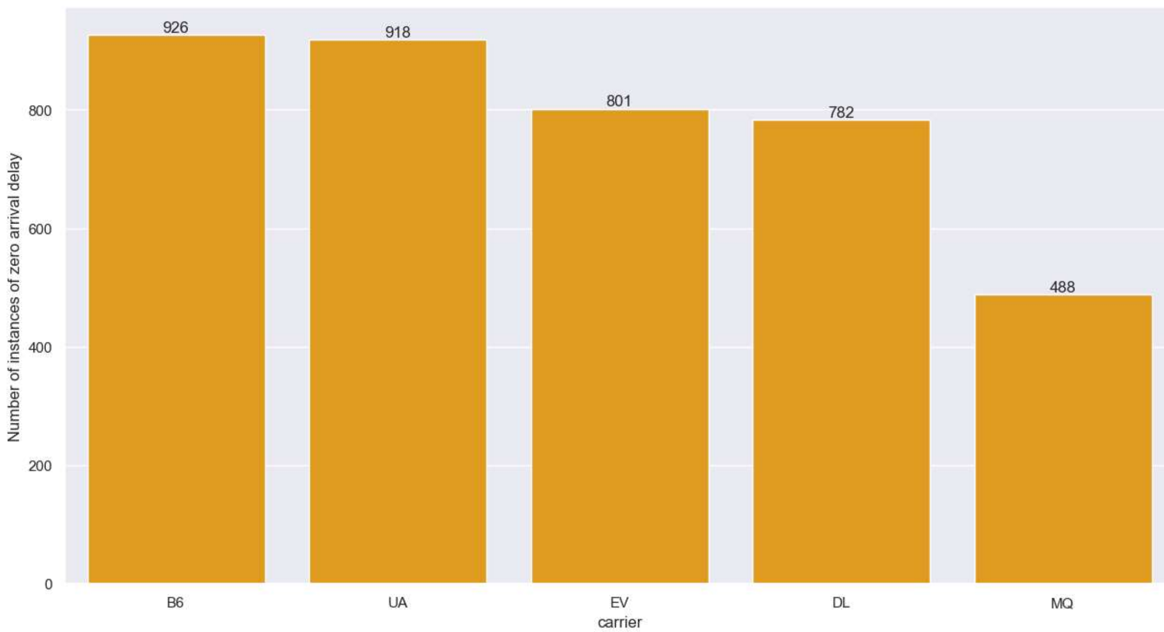
Step 3: Using Seaborn library to create barplot

Step 4: Adding labels to plot

Step 5: Adding data label

In [14]:
```python
#step 1
report5 = data.query("arr_delay == 0")
#step 2
report5 = report5.groupby(['carrier']).count().nlargest(5, 'arr_delay')
report5.reset_index(inplace=True)
#step 3
ax5 = sns.barplot(x='carrier', y='arr_delay', data=report5, color = 'orange')
#step 4
plt.xlabel('carrier')
plt.ylabel('Number of instances of zero arrival delay')
#step 5
ax5.bar_label(ax5.containers[0])
```

Out[14]:
```
[Text(0, 0, '926'),
 Text(0, 0, '918'),
 Text(0, 0, '801'),
 Text(0, 0, '782'),
 Text(0, 0, '488')]
```



The visual shows the top 5 carriers having zero arrival delays in 2013. The x axis shows the carrier name and y axis shows the number of times carrier experienced zero arrival delays. According to the graph, B6 carrier was on time the most number of time with highest number of zero arrival delays

Task 3: Create a new dataset named (pop_data) with flight data from airlines UA (United Airlines) and DL (Delta Airlines). The data set must contain only two columns, company name and delayed arrival flights. The data must be extracted from dataset flights.csv to build the pop_data dataset. The dataset should be limited to no more than 20,000 rows per airlines.

Creating intermediate dataframe

Step 1: Creating a dataset df1 that contains only two columns 'carrier' and 'arr_delay'
Step 2: Removing null values from the dataset by modifying datafarme df1 to contain not null values. (This is achieved by using negation operator '~' on dataframe obtained by 'isnull()' function.
Step 3: printing the intermediate dataframe

In [15]:
```
#step 1
df1 = data[['carrier', 'arr_delay']]
#step 2
df1 = df1[~df1['arr_delay'].isnull()]
#step 3
display(df1)
```

	carrier	arr_delay
0	UA	11.0
1	UA	20.0
2	AA	33.0
3	B6	-18.0
4	DL	-25.0
...	...	...
336765	B6	-17.0
336766	B6	-20.0
336767	B6	-16.0
336768	B6	1.0
336769	B6	-25.0

327346 rows × 2 columns

Creating first filtered dataframe containing 20000 records for UA carrier

step 1: Creating filtered dataframe df_UA where carrier is 'UA'
step 2: Creating sample dataset of 20000 records using sample function (replace = false to select distinct records. Also sample method allows to select different set of unique rows each time it is run)
step 3: Display the dataframe

In [16]:
```
#step 1
df_UA = df1[df1.carrier.isin(["UA"])]
#step 2
df_UA = df_UA.sample(n = 20000, replace = False)
#step 3
display(df_UA)
```

	carrier	arr_delay
77580	UA	-8.0
46850	UA	-6.0
243325	UA	-6.0
277998	UA	14.0
130078	UA	-3.0
...	...	...
300354	UA	124.0
221317	UA	-2.0
100018	UA	-21.0
57796	UA	-9.0
325638	UA	-10.0

20000 rows × 2 columns

Creating second filtered dataframe containing 20000 records for UA carrier

step 1: Creating filtered dataframe df_DL where carrier is 'DL'
step 2: Creating sample dataset of 20000 records using sample function (replace = false to select distinct records. Also sample method allows to select different set of unique rows each time it is run)
step 3: Display the dataframe

In [17]:
```
#step 1
df_DL = df1[df1.carrier.isin(["DL"])]
#step 2
df_DL = df_DL.sample(n = 20000, replace = False)
#step 3
display(df_DL)
```

	carrier	arr_delay
138140	DL	-24.0
227636	DL	17.0
278673	DL	-23.0
69969	DL	-12.0
210594	DL	46.0
...	...	...
27674	DL	-14.0
229808	DL	-9.0
209759	DL	-16.0
55843	DL	-5.0
89823	DL	-19.0

20000 rows × 2 columns

Creating pop_data dataframe

Step 1: Appending df_DL at end of df_UA
Step 2: Displaying the Dataframe

In [18]:
```
#step 1
pop_data = df_UA.append(df_DL)
#step 2
display(pop_data)
```

	carrier	arr_delay
77580	UA	-8.0
46850	UA	-6.0
243325	UA	-6.0
277998	UA	14.0
130078	UA	-3.0
...	...	...
27674	DL	-14.0
229808	DL	-9.0
209759	DL	-16.0
55843	DL	-5.0
89823	DL	-19.0

40000 rows × 2 columns

Task 4: Create two new datasets (“dl” and “ua”) of 1000 observations each from the “pop_data” dataset only with data from the DL (Delta Airlines) for “dl” and only data from UA (United Airlines) for “ua” . Tip: Include a column called sample_id populated with number 1 for the first sample and 2 for the second sample

Creating sample_id column

Step 1: Creating sample_id column with its value = 1 for UA carrier and its value = 2 for DL carrier
Step 2: Displaying pop_data with new added coumn

In [19]:
```
pop_data['sample_id'] = [1 if x =='UA' else 2 for x in pop_data['carrier']]
pop_data
```

Out[19]:

	carrier	arr_delay	sample_id
77580	UA	-8.0	1
46850	UA	-6.0	1
243325	UA	-6.0	1
277998	UA	14.0	1
130078	UA	-3.0	1
...	...	...	...
27674	DL	-14.0	2
229808	DL	-9.0	2
209759	DL	-16.0	2
55843	DL	-5.0	2
89823	DL	-19.0	2

40000 rows × 3 columns

Creating ua dataframe

Step 1: Creating ua dataframe by selecting records with sample_id = 1
Step 2: Selecting 1000 distinct records randomly for ua dataframe using sample function
Step 3: Displaying ua dataframe

In [20]:
```python
#step 1
ua = pop_data.loc[pop_data['sample_id'] == 1]
#step 2
ua = ua.sample(n = 1000, replace = False)
#step 3
display(ua)
```

	carrier	arr_delay	sample_id
6428	UA	1.0	1
14229	UA	20.0	1
132633	UA	-22.0	1
275015	UA	0.0	1
297101	UA	-25.0	1
...	...	...	...
287010	UA	-15.0	1
92619	UA	9.0	1
264359	UA	12.0	1
108585	UA	42.0	1
193858	UA	-19.0	1

1000 rows × 3 columns

Creating dl dataframe

Step 1: Creating dl dataframe by selecting records with sample_id = 2
Step 2: Selecting 1000 distinct records randomly for dl dataframe using sample function
Step 3: Displaying dl dataframe

In [21]:
```
#step 1
dl = pop_data.loc[pop_data['sample_id'] == 2]
#step 2
dl = dl.sample(n = 1000, replace = False)
#step 3
display(dl)
```

	carrier	arr_delay	sample_id
111370	DL	-22.0	2
272696	DL	-3.0	2
55133	DL	-14.0	2
158995	DL	-1.0	2
288964	DL	-9.0	2
...	...	...	...
15006	DL	-1.0	2
313573	DL	-15.0	2
234827	DL	-7.0	2
181885	DL	24.0	2
150109	DL	9.0	2

1000 rows × 3 columns

Task 5: Create a new dataset (samples) containing the data of the 2 samples created in the previous item to be used in future analysis.

Creating samples dataframe

Step 1: Appending dl at end of ua
Step 2: Displaying the Dataframe

In [22]:
```
#step 1
samples = ua.append(dl)
#step 2
display(samples)
```

	carrier	arr_delay	sample_id
6428	UA	1.0	1
14229	UA	20.0	1
132633	UA	-22.0	1
275015	UA	0.0	1
297101	UA	-25.0	1
...	...	...	...
15006	DL	-1.0	2
313573	DL	-15.0	2
234827	DL	-7.0	2
181885	DL	24.0	2
150109	DL	9.0	2

2000 rows × 3 columns

Task 6: For each sample (“dl” and “ua”) calculate the standard error and the mean.

Calculating mean value of arrival dealys for ua and dl dataframe and displaying mean value

In [23]:
```
#calculating mean
mean_ua = statistics.mean(ua['arr_delay'])
mean_dl = statistics.mean(dl['arr_delay'])

#displaying mean
print("The mean arrival delays for UA Carrier is : ",mean_ua)
print("The mean arrival delays for DL Carrier is : ",mean_dl)
```

```
The mean arrival delays for UA Carrier is :  4.694
The mean arrival delays for DL Carrier is :  1.138
```

Calculating standard error of arrival dealys for ua and dl dataframe and displaying the same

In [24]:
```
#calculating Standard error
sem_ua = sem(ua['arr_delay'])
sem_dl = sem(dl['arr_delay'])

#displaying standard error
print("The standard error at mean for arrival delays for UA Carrier is : ",ser
print("The standard error at mean for arrival delays for DL Carrier is : ",ser
```

```
The standard error at mean for arrival delays for UA Carrier is :  1.4531855
050584948
The standard error at mean for arrival delays for DL Carrier is :  1.2433112
15576687
```

Task 7: For each mean calculated before we need to define the "confidence intervals" in this case 95% confidence interval. It means calculate lower and upper values.

Calculating confidence interval

t.interval method from scipy.stats will be used to define confidence intervals

In [25]:
```
sp.t.interval(alpha = 0.95, df = len(ua['arr_delay'])-1, loc = mean_ua, scale
```

Out[25]:
```
(1.8423538327055646, 7.545646167294436)
```

In [26]:
```
sp.t.interval(alpha = 0.95, df = len(dl['arr_delay'])-1, loc = mean_dl, scale
```

Out[26]:
```
(-1.3018011474183604, 3.57780114741836)
```

Displaying Confidence intervals for UA and DL

The following format will be used to display the values:
Lower value Mean value Upper value

In [27]:
```
print("UA Carrier : ")
print("Lower value   Mean Value  Upper Value ")
print("3.594         6.228       8.862  ")
print("DL Carrier : ")
print("Lower value   Mean Value  Upper Value ")
print("-0.593        2.543       5.679  ")
```

```
UA Carrier :
Lower value   Mean Value  Upper Value
3.594         6.228       8.862
DL Carrier :
Lower value   Mean Value  Upper Value
-0.593        2.543       5.679
```

Task 8: After these set of previous calculations, it was requested that you take the T-TEST concept and apply in both datasets (“dl” and “ul”) to answer this question: Is it possible to say that Delta Airlines (DL) flights are delayed more than United Airlines (UA) flights ?

To test whether Delta Airlines (DL) flights are delayed more than United Airlines (UA) flights, two sample one tailed t test would be used:
The hypothesis is:
H0 (null hypothesis): DL flights are more delayed than UA
H1 (alternate hypothesis): UA flights are more delayed than DL
The hypothesis can be written as follows:
H0: DL - UA > 0 (DL: mean arrival delays with DL carrier, UA: mean arrival delays with UA carrier)
H1: DL - UA < 0
ttest method of reseachpy woud be used for interpretation

In [28]:
```
summary, results_ttest = rp.ttest(group1= dl['arr_delay'], group1_name= "DL",
print(summary)
```

```
   Variable       N   Mean         SD        SE  95% Conf.  Interval
0        DL  1000.0  1.138  39.316953  1.243311 -1.301801  3.577801
1        UA  1000.0  4.694  45.953761  1.453186  1.842354  7.545646
2  combined  2000.0  2.916  42.790577  0.956826  1.039519  4.792481
```

In [29]:
```
print(results_ttest)
```

```
          Independent t-test    results
0    Difference (DL - UA) =     -3.5560
1      Degrees of freedom =   1998.0000
2                       t =     -1.8594
3   Two side test p value =      0.0631
4  Difference < 0 p value =      0.0316
5  Difference > 0 p value =      0.9684
6               Cohen's d =     -0.0832
7               Hedge's g =     -0.0831
8          Glass's delta1 =     -0.0904
9        Point-Biserial r =     -0.0416
```

The p value assocíaed with Difference (DL-UA) > 0 is greater than 0.05 (significance level). Hence, we cannot reject null hypothesis (DL - UA > 0) and say that DL flights are more delayed than UA carrier flights.
Therefore, The mean arrival delay for DL carrier is more than mean arrival delay for UA carrier according to T test

Checking whether T Test is suitable to draw above conclusion

The indepentent T-test is a parametric test used to test for a statistically significant difference in the means between 2 groups. As with all parametric tests, there are certain conditions that need to be met in order for the test results to be considered reliable. The following assumptions should be met before performing T test: -Population distributions are normal -Samples have equal variances -The two samples are independent Although both samples are independent. The other two conditions need to be checked

Checking whether Population distributions are normal

One of the assumptions is that the sampling distribution is normally distributed. This test of normality applies to the difference in values between the groups. One method for testing this assumption is the Shapiro-Wilk test. This can be completed using the shapiro() method from Scipy.stats.

In [30]:
```
sampling_difference = ua['arr_delay'].values - dl['arr_delay'].values
stats.shapiro(sampling_difference)
```

Out[30]:
```
ShapiroResult(statistic=0.8355467319488525, pvalue=7.009003086410712e-31)
```

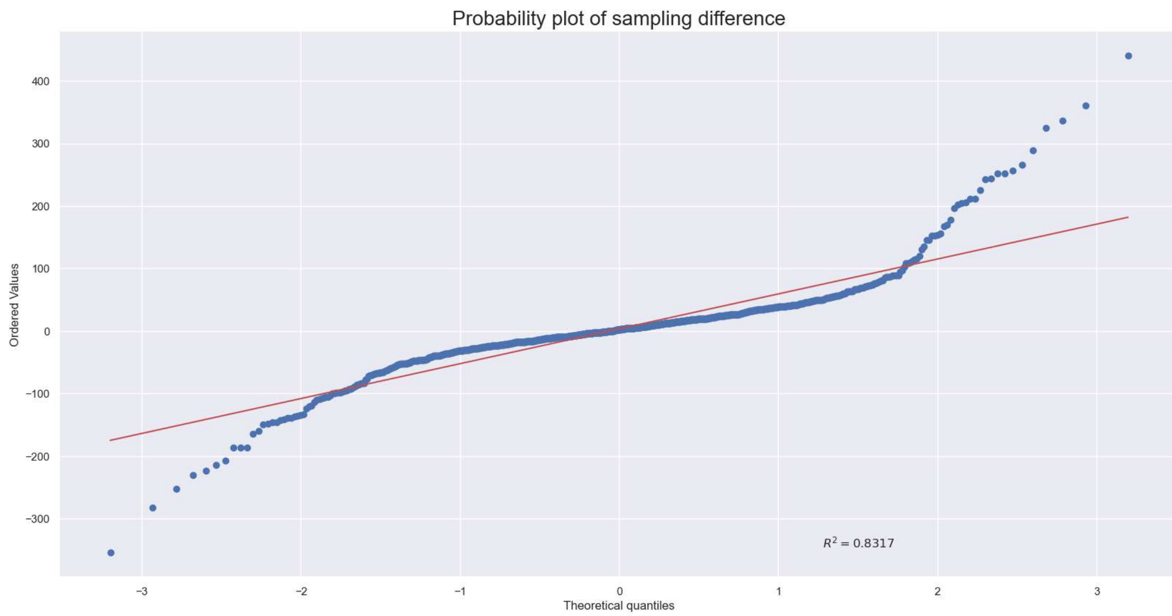
The above presents the results from well-known test of normality, the Shapiro-Wilk Test. The Shapiro-Wilk Test is more appropriate for small sample sizes (< 50 samples), but can also handle sample sizes as large as 2000. For this reason, we will use the Shapiro-Wilk test as our numerical means of assessing normality.

If the Sig. value of the Shapiro-Wilk Test is greater than 0.05, the data is normal. If it is below 0.05, the data significantly deviate from a normal distribution. Since p value is below 0.05, the sampling distribution is not normally distributed. This can be seen from following plot also:

In [31]:
```
fig = plt.figure(figsize= (20, 10))
ax = fig.add_subplot(111)

normality_plot, stat = stats.probplot(sampling_difference, plot= plt, rvalue=
ax.set_title("Probability plot of sampling difference", fontsize= 20)
ax.set

plt.show()
```



The graph above shows data points stray from the line in an obvious non-linear fashion, the data are not normally distributed. Therefore, t-test may not be the best statistical method to be used.

Checking whether Samples have equal variances

One of the assumptions is that both groups have equal variances. One method for testing this assumption is the Levene's test of homogeneity of variances. This can be completed using the levene() method from Scipy.stats.

In [32]:
```
stats.levene(ua['arr_delay'], dl['arr_delay'], center = 'mean')
```

Out[32]:
```
LeveneResult(statistic=2.113276339858747, pvalue=0.14618343424608268)
```

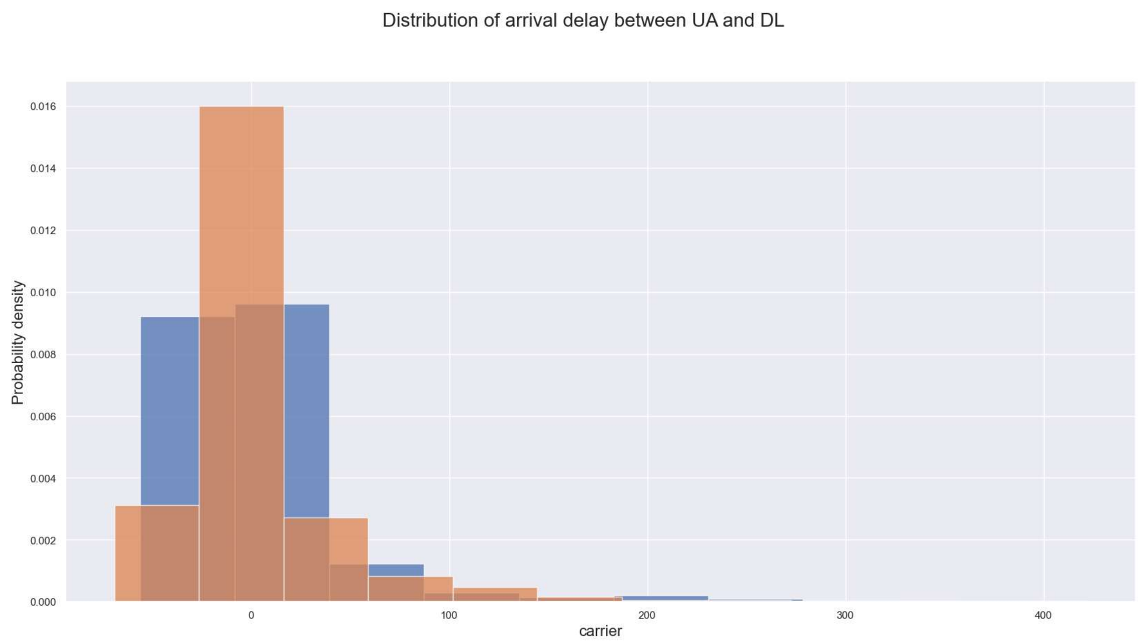
The test is significant which indicates the groups have a different amount of variation and that the t-test may not be the best statistical method to be used. Again, it may be worthwhile to check this assumption visually as well.

In [33]:
```
fig = plt.figure(figsize= (20, 10))
ax = fig.add_subplot(111)


p_ua = plt.hist(ua['arr_delay'], label= "UA", density= True, alpha=0.75)
p_dl = plt.hist(dl['arr_delay'], label= "DL", density= True, alpha=0.75)


plt.suptitle("Distribution of arrival delay between UA and DL", fontsize= 20)
plt.xlabel("carrier", fontsize= 16)
plt.ylabel("Probability density", fontsize= 16)

plt.show()
```



The graph indicates the groups have a different amount of variation and that the t-test may not be the best statistical method to be used.

Therefore, T test cannot be used to say that Delta Airlines (DL) flights are delayed more than United Airlines (UA) flights as all assumptions of T test are not met

In [ ]: