Exploring US Flights Data

The dataset, used for this project, can be found in Airline On-Time Performance Data link.

Burcin Sarac
M.Sc. Business Analytics FT-18

In [1]:
```
import os
import pandas as pd
import matplotlib.pyplot as plt
```

In [11]:
```
os.chdir("E:/dersler/Practicum 1/assignment")
```

In [24]:
```
flights = pd.read_csv("flights.csv", parse_dates=['FL_DATE', 'DEP_TIME','ARR_TIME'])
```

In [14]:
```
flights.shape
```

Out[14]:
```
(5674621, 20)
```

In [19]:
```
flights.head()
```

Out[19]:

	FL_DATE	TAIL_NUM	CARRIER	ORIGIN	ORIGIN_CITY_NAME	DEST	DEST_CITY_NAME	DEP_TIME	DEP_DELAY	ARR_TIME	ARR_DELAY	CANCELLED	C
0	2017-01-01	N3CGAA	AA	DEN	Denver, CO	PHX	Phoenix, AZ	1135	-10.0	1328	-17.0	0.0	
1	2017-01-01	N3CGAA	AA	PHX	Phoenix, AZ	PDX	Portland, OR	1502	-8.0	1653	-8.0	0.0	
2	2017-01-01	N3EVAA	AA	DCA	Washington, DC	MIA	Miami, FL	0646	-13.0	0930	-14.0	0.0	
3	2017-01-01	N3NAAA	AA	MIA	Miami, FL	LGA	New York, NY	1402	-3.0	1646	-14.0	0.0	
4	2017-01-01	N3FCAA	AA	PHX	Phoenix, AZ	DEN	Denver, CO	2310	16.0	0107	28.0	0.0	

Question 1

Since the DEP_DELAY column shows the difference in minutes between scheduled and actual departure time and early departures shown with negative numbers, I calculate the probability of delay in a particular airport mentioned at "ORIGIN" column, by using DEP_DELAY column data. For calculating this probability, I first group by the data into Departure airports(ORIGIN) by using groupby() function and I count all positive values(occured delays) and divide it to the number of all delay data by airport. When I use DEP_DELAY, I saw that there were some Null values, it seems they were mostly caused by cancelled flights. I tried calculations both dropping and keeping this Null values and it causes slightly change in mean, median and probabity values, which may lead me to draw wrong conclusions. So I decided to drop all Null values before calculations with using notnull() at all questions.

After that, I dropped %1 of airports in terms of the lowest number of departures by using quantile function. 4 of total 320 locations dropped according to this criteria.

After all, I merged these two calculations by matching ORIGIN data using merge() function in pandas. I use left join at this merging stage to avoid to get back the outlier data, which was dropped at the previous step. In other words, I keep ORIGIN data from dropped dataset and match the values in this column with the probabilities. With this, unmatched ORIGIN values, which are still kept in probability dataset, will drop automatically.

At last, I again use groupby() function in ORIGIN to split the row data into groups and calculate mean and median of each airport(ORIGIN). And I merge these values with the previously created data frame to collect probability, mean and median of delays in every single airport.

In [428]:
```
delayprob = (flights.loc[(flights.DEP_DELAY>0) &(flights.DEP_DELAY.notnull())].groupby("ORIGIN").DEP_DELAY.count()/flights.loc[f
lights.DEP_DELAY.notnull()].groupby("ORIGIN").DEP_DELAY.count()).sort_values(ascending=False)
```

In [439]:
```
delayprob
```

Out[439]:
```
ORIGIN
SWO    1.000000
TKI    1.000000
GGG    0.833333
MVY    0.668085
UST    0.600000
ACK    0.562986
HYA    0.559140
BQN    0.548326
DAL    0.526197
HOU    0.501605
BPT    0.500000
OTH    0.484211
MDW    0.479777
OAK    0.479249
GUM    0.450549
WYS    0.449782
ADK    0.438776
SUX    0.428571
LAX    0.427414
MMH    0.426667
LAS    0.422838
STL    0.412243
FLL    0.410455
STS    0.410305
BUR    0.401379
SWF    0.398292
SFO    0.397707
BWI    0.397331
IAG    0.396040
APN    0.389439
         ...
COU    0.174267
GCC    0.173173
PIH    0.172979
CLL    0.172734
BET    0.172377
LAR    0.171334
FLG    0.170862
MFE    0.169838
RKS    0.169440
HYS    0.166392
DRO    0.165767
COD    0.163952
HIB    0.161631
RHI    0.160109
FSM    0.159449
GFK    0.155942
ROW    0.150655
BTM    0.143939
GTF    0.141777
TXK    0.138889
BIL    0.135160
INL    0.132901
GCK    0.132597
LCH    0.130471
HLN    0.125895
HOB    0.125612
CPR    0.123288
GJT    0.117829
BRO    0.112069
LWS    0.086551
Name: DEP_DELAY, Length: 320, dtype: float64
```

In [446]:
```
origin = flights['ORIGIN'].value_counts()
```

In [341]:
```
origincutted = origin.loc[origin>origin.quantile(0.01)]
```

In [342]:
```
origincutted.count()
```

Out[342]:
```
316
```

In [343]:
```
origincutted = origincutted.reset_index()
```

In [344]:
```
origincutted.columns = ['ORIGIN','TotalFlight']
```

In [429]:
```
delaysmerged = pd.merge(origincutted,delayprob.to_frame('probofdelay'),how='left', on='ORIGIN')
```

In [430]:
```
delaysmerged.head()
```

Out[430]:

	ORIGIN	TotalFlight	probofdelay
0	ATL	364655	0.359352
1	ORD	266460	0.334790
2	DEN	223165	0.366954
3	LAX	214297	0.427414
4	DFW	181208	0.360143

In [440]:
```
delaysmerged.shape
```

Out[440]:
```
(316, 3)
```

In [431]:
```
flights.loc[flights.DEP_DELAY.notnull()].groupby("ORIGIN").DEP_DELAY.mean().sort_values().head(3)
```

Out[431]:
```
ORIGIN
YAK   -6.954738
BET   -5.388651
DLG   -5.285714
Name: DEP_DELAY, dtype: float64
```

In [432]:
```
flights.loc[flights.DEP_DELAY.notnull()].groupby("ORIGIN").DEP_DELAY.median().sort_values().head(3)
```

Out[432]:
```
ORIGIN
YAK   -14.0
WRG   -12.0
CDV   -12.0
Name: DEP_DELAY, dtype: float64
```

In [434]:
```
groupmean = flights.loc[flights.DEP_DELAY.notnull()].groupby("ORIGIN").DEP_DELAY.mean()
```

In [435]:
```
delaysmerged2 = pd.merge(delaysmerged,groupmean.to_frame('meanofdelay'),how='left', on='ORIGIN')
```

In [436]:
```
groupmedian = flights.loc[flights.DEP_DELAY.notnull()].groupby("ORIGIN").DEP_DELAY.median()
```

In [437]:
```
delaysmerged2 = pd.merge(delaysmerged2,groupmedian.to_frame('medianofdelay'),how='left', on='ORIGIN').sort_values(by=['probofdel
ay'], ascending=False)
```

In [438]:
```
delaysmerged2.head()
```

Out[438]:

	ORIGIN	TotalFlight	probofdelay	meanofdelay	medianofdelay
293	MVY	241	0.668085	34.293617	11.0
310	UST	66	0.600000	59.369231	14.0
266	ACK	665	0.562986	30.203733	4.0
305	HYA	94	0.559140	17.182796	2.0
182	BQN	1710	0.548326	21.129501	3.0

It seems from results that, MVY airport has the highest probability with the ratio of 66% of flights delayed in departure. However it can be said from means of delay for example, the flight departures from UST airport has 60% probability of delay, however if it delays, the possible delay time is longer than MVY. On the other hand if HYA airport is taken into account, there is 55% posibility of departure delay occured, but the delay times were shorter.

Question 2

This time, I use same codes only changing groupby column into Carrier for checking probability that a flight operated by the airline has a delay.

In [293]:
```
delayprobbycr = (flights.loc[(flights.DEP_DELAY>0)&(flights.DEP_DELAY.notnull())].groupby("CARRIER").DEP_DELAY.count()/flights.g
roupby("CARRIER").DEP_DELAY.count()).sort_values(ascending=False)
```

In [294]:
```
delayprobbycr
```

Out[294]:
```
CARRIER
WN    0.468958
VX    0.413506
B6    0.410006
F9    0.363760
AA    0.319286
UA    0.318173
NK    0.312332
DL    0.307152
EV    0.286598
HA    0.285814
AS    0.270324
OO    0.266412
Name: DEP_DELAY, dtype: float64
```

In [311]:
```
delayprobbycr = delayprobbycr.reset_index()
```

In [315]:
```
delayprobbycr.columns = ['CARRIER','probofdelay']
```

In [316]:
```
delayprobbycr
```

Out[316]:

	CARRIER	probofdelay
0	WN	0.468958
1	VX	0.413506
2	B6	0.410006
3	F9	0.363760
4	AA	0.319286
5	UA	0.318173
6	NK	0.312332
7	DL	0.307152
8	EV	0.286598
9	HA	0.285814
10	AS	0.270324
11	OO	0.266412

In [305]:
```
crmean = flights.loc[flights.DEP_DELAY.notnull()].groupby("CARRIER").DEP_DELAY.mean().sort_values(ascending=False)
```

In [306]:
```
crmean.head(4)
```

Out[306]:
```
CARRIER
B6    16.582982
VX    13.219399
EV    12.689932
F9    12.127640
Name: DEP_DELAY, dtype: float64
```

In [307]:
```
crmedian = flights.loc[flights.DEP_DELAY.notnull()].groupby("CARRIER").DEP_DELAY.median().sort_values(ascending=False)
```

In [308]:
```
crmedian.head(3)
```

Out[308]:
```
CARRIER
WN    0.0
VX   -2.0
F9   -2.0
Name: DEP_DELAY, dtype: float64
```

In [323]:
```
delaysbycr = pd.merge(delayprobbycr,crmean.to_frame('meanofdelay'),how='left', on='CARRIER')
```

In [325]:
```
delaysbycr = pd.merge(delaysbycr,crmedian.to_frame('medianofdelay'),how='left', on='CARRIER')
```

In [327]:
```
airlines = pd.read_csv("L_UNIQUE_CARRIERS.csv")
```

In [330]:
```
airlines.head(2)
```

Out[330]:

	Code	Description
0	02Q	Titan Airways
1	04Q	Tradewind Aviation

In [331]:
```
delaysbycr = pd.merge(delaysbycr,airlines,how='left', left_on='CARRIER',right_on='Code')
```

In [335]:
```
delaysbycr
```

Out[335]:

	CARRIER	probofdelay	meanofdelay	medianofdelay	Code	Description
0	WN	0.468958	10.248374	0.0	WN	Southwest Airlines Co.
1	VX	0.413506	13.219399	-2.0	VX	Virgin America
2	B6	0.410006	16.582982	-2.0	B6	JetBlue Airways
3	F9	0.363760	12.127640	-2.0	F9	Frontier Airlines Inc.
4	AA	0.319286	8.180574	-3.0	AA	American Airlines Inc.
5	UA	0.318173	9.484484	-3.0	UA	United Air Lines Inc.
6	NK	0.312332	10.171258	-4.0	NK	Spirit Air Lines
7	DL	0.307152	8.497947	-2.0	DL	Delta Air Lines Inc.
8	EV	0.286598	12.689932	-4.0	EV	ExpressJet Airlines Inc.
9	HA	0.285814	1.401808	-3.0	HA	Hawaiian Airlines Inc.
10	AS	0.270324	2.456161	-5.0	AS	Alaska Airlines Inc.
11	OO	0.266412	10.325922	-4.0	OO	SkyWest Airlines Inc.

From the results it seems that Southwest Airlines has the highest delay probability in departure. Yet, according to the mean of departure delays with them shows that, delay times were shorter than the some of other airways, which have lower probability of delay. On the other hand, Alaska Airlines delayed in 27% of its departures and the average delay time was around 2.46, which was one of the best ratios.

Question 3

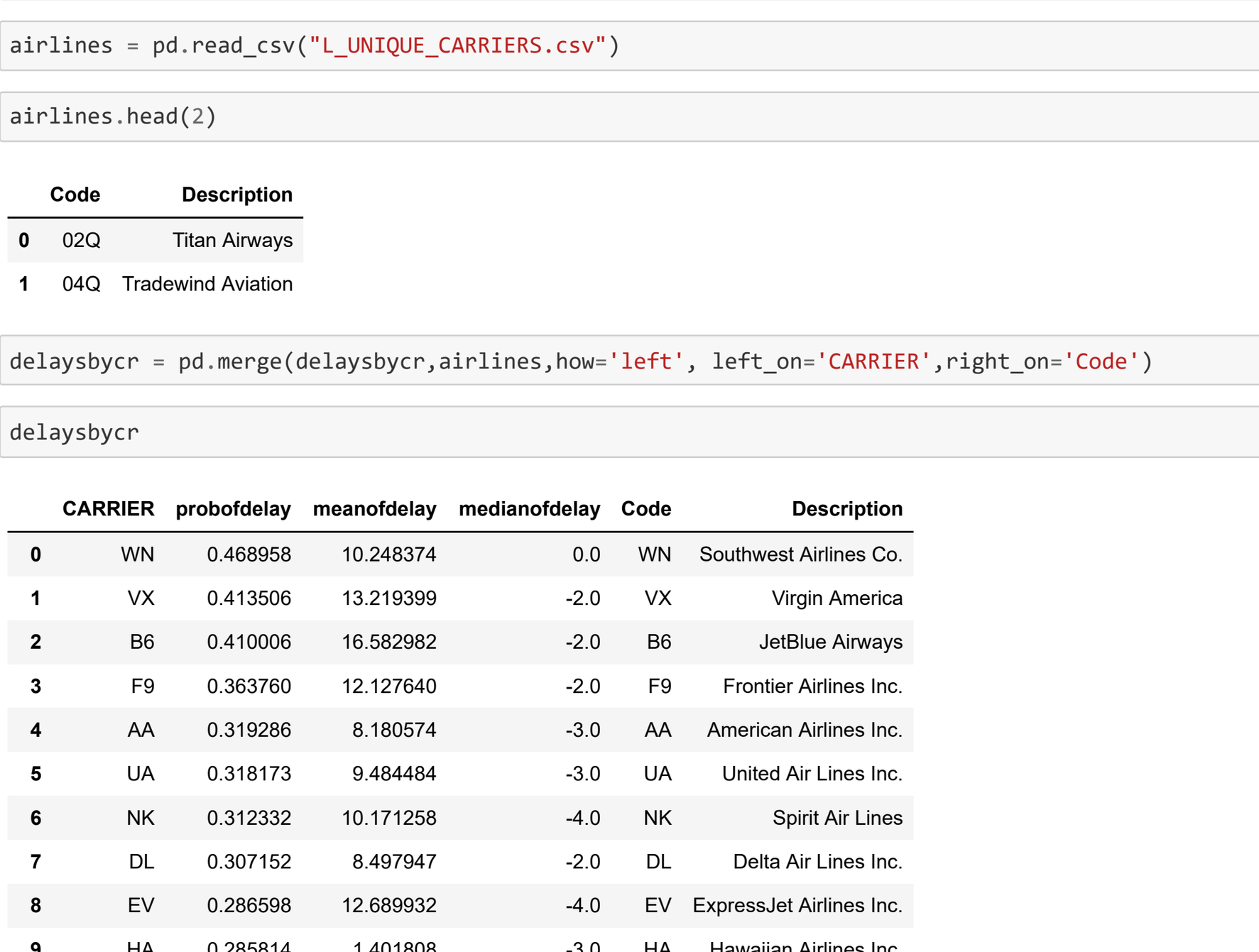
This histogram shows the distribution of departures for airports. That is, the x-axis is bins containing flights and the y-axis is the number of airports with departing flights in each particular bin.

I created "origin" data to draw a histogram with only filtering 'ORIGIN' column via value_counts() function. So I can see the the flight numbers in terms of departure airports. And then I used this dataset to create a histogram with .hist() function. And I also add labels and title for the graph.

In [377]:
```
origin = flights['ORIGIN'].value_counts()
```

In [452]:
```
origin.hist(color='blue', edgecolor='black',
            alpha=0.5, figsize=(12, 10))
plt.xlabel('Nr of Flights')
plt.ylabel('Nr of Airports')
plt.title(' Distribution of Departures for Airports')
```

Out[452]:
```
Text(0.5,1,' Distribution of Departures for Airports')
```



It can be seen from graph that, most of the airports, which is around 260, have less than 50 thousand departing flights in 2017, and there are a few outlier airports, which have more than 300 thousand departing flights only in 2017.

Question 4

This time, I will create a plot shows the number of flights and the number of delayed flights per month of year. With this I aim to check the distribution of delayed departures by month.

For drawing this plot, I decide to create a new column which includes only month data. Since I read my csv data with using parse_dates function for FL_DATE column inside read_csv() command, it allows me to shape the dates as Months, years and even days with only a single command. And this time I used dt.to_period('M') to create month column from that FL_DATE column.

After creating new column, I use groupby() again in the data by grouping "month" column for both delayed flights and all flights numbers. And then I concatenate them with again using merge() function. This command only works with dataframes, so I first reset indexes of that newly created datasets and rename their column names. After all I use to_frame() command to merge the datasets added into the merge command with a specific column name.

In [463]:
```
flights['month'] = pd.to_datetime(flights['FL_DATE']).dt.to_period('M')
```

In [464]:
```
flights.tail()
```

Out[464]:

	FL_DATE	TAIL_NUM	CARRIER	ORIGIN	ORIGIN_CITY_NAME	DEST	DEST_CITY_NAME	DEP_TIME	DEP_DELAY	ARR_TIME	...	CANCELLED	CAN
5674616	2017-12-31	N705SW	WN	TUS	Tucson, AZ	LAX	Los Angeles, CA	1616	26.0	1653	...	0.0	
5674617	2017-12-31	N463WN	WN	TUS	Tucson, AZ	MDW	Chicago, IL	0843	-7.0	1251	...	0.0	
5674618	2017-12-31	N956WN	WN	TUS	Tucson, AZ	SAN	San Diego, CA	1451	1.0	1459	...	0.0	
5674619	2017-12-31	N222WN	WN	TUS	Tucson, AZ	SAN	San Diego, CA	1038	13.0	1049	...	0.0	
5674620	2017-12-31	N488WN	WN	TUS	Tucson, AZ	SAN	San Diego, CA	0800	-5.0	0812	...	0.0	

5 rows × 21 columns

In [467]:
```
delayedbymonth = flights.loc[(flights2.DEP_DELAY>0)&(flights.DEP_DELAY.notnull())].groupby("month").DEP_DELAY.count()
```

In [489]:
```
delayedbymonth.reset_index()
```

Out[489]:

	month	DEP_DELAY
0	2017-01	168679
1	2017-02	123753
2	2017-03	167523
3	2017-04	163216
4	2017-05	177062
5	2017-06	197341
6	2017-07	196822
7	2017-08	188299
8	2017-09	124503
9	2017-10	145727
10	2017-11	125099
11	2017-12	168280

In [470]:
```
flightbymonth = flights.loc[(flights.DEP_DELAY.notnull())].groupby("month").DEP_DELAY.count()
```

In [485]:
```
flightbymonth.reset_index()
flightbymonth.columns =['month', 'NumberofFlights']
```

In [491]:
```
flights_delays = pd.merge(flightbymonth.to_frame('NumberofFlights'),delayedbymonth.to_frame('NumberofDelays') ,how='left', on='m
onth')
```

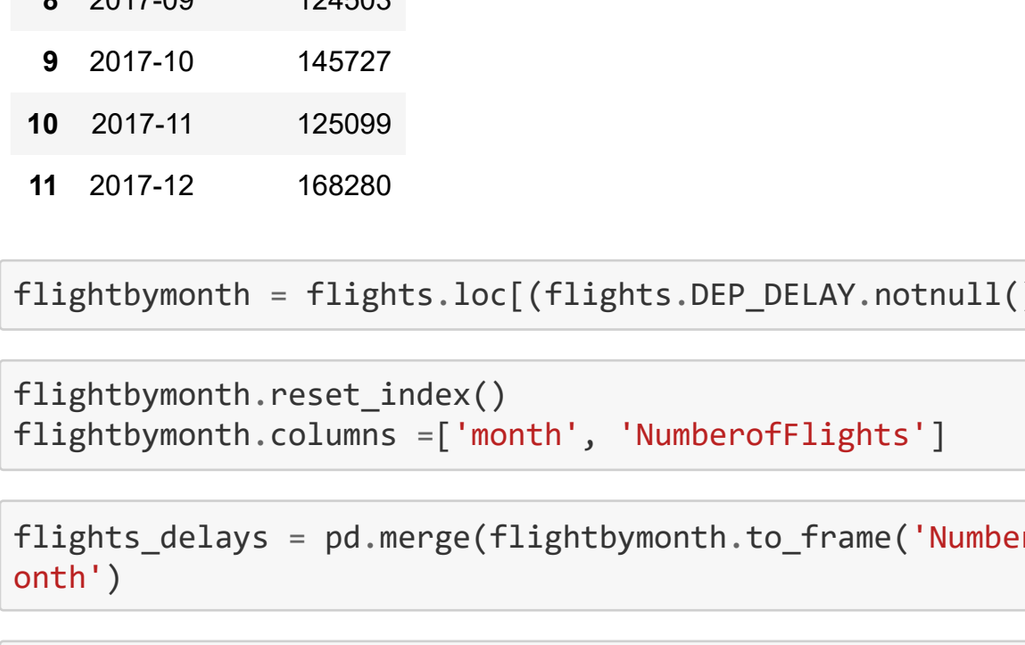
In [492]:
```
flights_delays
```

Out[492]:

month	NumberofFlights	NumberofDelays
2017-01	441131	168679
2017-02	404205	123753
2017-03	480070	167523
2017-04	460931	163216
2017-05	482444	177062
2017-06	488887	197341
2017-07	503313	196822
2017-08	499444	188299
2017-09	443384	124503
2017-10	476493	145727
2017-11	452744	125099
2017-12	458881	168280

In [524]:
```
flights_delays.plot()
plt.xlabel('Months')
plt.ylabel('Nr of Flights')
plt.title('All Flights & Delayed Flights by Month')
```

Out[524]:
```
Text(0.5,1,'All Flights & Delayed Flights by Month')
```



From the graph it can be said that, the departure delays only differentiates on December in a negative way, in other words departure delays don't affected from monthly changes except December. On December it seems that, the flights delayed more than general trend. And there is a slight change than regular trend on March and October, it means delays occured less than expected.

Question 5

Lastly, I try to show for each possible origin and destination, which airline has the best performance, in terms of mean departure delay. For creating this table, I used again groupby() function, but this time with three columns(ORIGIN,DEST,CARRIER) inside this command. This filter shows me best possible airlines in terms of average delay times in specific departure and arrival destinations.

In [534]:
```
flights.loc[(flights.DEP_DELAY.notnull())].groupby(["ORIGIN","DEST","CARRIER"]).DEP_DELAY.mean().sort_values()
```

Out[534]:
```
ORIGIN  DEST  CARRIER
RHI     IMT   OO          -33.676471
PDX     OKC   OO          -32.000000
HIB     INL   OO          -25.250000
PHL     ISP   F9          -16.000000
MSN     SFO   UA          -16.000000
SAT     MCO   F9          -14.000000
SIT     ANC   AS          -13.375000
BTV     IAD   EV          -13.000000
OMA     SFO   UA          -12.000000
MSN     IAD   UA          -11.500000
SDF     BOS   DL          -11.000000
IAH     BOS   AA          -11.000000
MOB     IAH   OO          -11.000000
PIA     DTW   EV          -11.000000
GJT     ATL   OO          -11.000000
STL     IAD   EV          -11.000000
MYR     LGA   EV          -10.000000
DCA     DTW   OO          -10.000000
CLE     MSN   EV          -10.000000
MKE     IAH   UA          -10.000000
        CLE   OO          -10.000000
LNK     MKE   EV          -10.000000
LGA     MHT   EV           -9.200000
DTW     DCA   OO           -9.000000
MSN     CLE   EV           -9.000000
IAH     MSN   UA           -9.000000
LGA     ORF   DL           -9.000000
SFO     OMA   UA           -9.000000
YAK     JNU   AS           -8.870056
OAK     PDX   AS           -8.779221
                              ...
AGS     ATL   UA          140.000000
JAC     MSP   OO          145.000000
PHX     LAS   F9          149.000000
MIA     BOS   DL          150.000000
SJC     MSP   OO          155.000000
EWR     LAS   WN          158.750000
MDT     IAD   EV          164.000000
PHX     OMA   OO          169.000000
DCA     BDL   AA          178.000000
RNO     ORD   OO          183.500000
MSO     BTM   OO          188.000000
PVD     ERI   EV          195.000000
ATL     SGF   OO          210.000000
SMF     SEA   DL          216.250000
STL     UIN   OO          219.000000
BTR     DCA   UA          227.000000
HSV     DTW   EV          228.000000
IND     ORD   AA          230.142857
PWM     DTW   OO          291.250000
LGA     LEX   DL          307.000000
IAD     MDT   EV          374.000000
SMF     RDM   OO          387.000000
EUG     OTH   OO          420.666667
OMA     EWR   UA          482.333333
PSP     BUR   OO          800.000000
CVG     JFK   EV          888.000000
JAX     IAD   EV          939.000000
TVC     IMT   OO         1470.000000
PIH     MSO   OO         1475.000000
TVC     MQT   OO         1480.000000
Name: DEP_DELAY, Length: 8445, dtype: float64
```

It is hard to tell something for all destinations but for example, for flights, which depart from RHI airport and arrive to IMT directly, best option seems Skywest Airlines(OO) if only the departure delay times taken into account. From this table best possible airline option for all destinations can be interpreted. And also it can be filtered by using .loc function again to check best possible option in a specific route.