Data Science amb Python

Sprint 12

S12 T01 : Supervised Learning - Regressions

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Dataset Description

Airline2008Nov Dataset Variable definition

Name	Description
1.Year	2008
2.Month	11
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	CRS Elapsed Time of Flight (estimated elapse time), in minutes
14.AirTime	Flight Time, in Minutes, in minutes
15.ArrDelay	Difference in minutes between scheduled and actual arrival time. Early arrivals show negative numbers, in minutes
16.DepDelay	Difference in minutes between scheduled and actual departure time. Early departures show negative numbers, in minutes
17.Origin	origin IATA airport code
18.Dest	destination IATA airport code
19.Distance	Distance between airports (miles)
20.TaxiIn	Wheels down and arrival at the destination airport gate, in minutes

21.TaxiOut	The time elapsed between departure from the origin airport gate and wheels off, in minutes
22.Cancelled	was the flight cancelled?
23.CancellationCode	reason for cancellation (A = carrier, B = weather, C = NAS, D = security)
24.Diverted	1 = yes, 0 = no
25.CarrierDelay	minutes. Carrier delay is within the control of the air carrier. Examples:: aircraft cleaning, aircraft damage, etc
26.WeatherDelay	munutes. Weather delay is caused by extreme or hazardous weather conditions
27.NASDelay	minutes. Delay that is within the control of the National Airspace System (NAS) Ex:airport operations,heavy traffic volume,etc
28.SecurityDelay	minutes. caused by evacuation of a terminal or concourse, re-boarding of aircraft because of security breach,etc
29.LateAircraftDelay	minutes. Arrival delay at an airport due to the late arrival of the same aircraft at a previous airport.

More information about flights delay can be seen in Federal Aviation Administration site.

Exercise 1

Create at least three different regression models to try to best predict DelayedFlights.csv flight delay (ArrDelay).

1. Load the dataset

I'll import the dataset cleaned from the previous sprint 11.

In [1]:
```
# import the needed libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Load the dataframe

df_flights = pd.read_csv('DelayedFlights_clean.csv')
df_flights.head()
```

Out[2]:

	Month	DayofMonth	DayOfWeek	DepTime	ArrTime	UniqueCarrier	ActualElapsedTime
0	1	3	4	2003.0	2211.0	WN	128.0
1	1	3	4	754.0	1002.0	WN	128.0
2	1	3	4	628.0	804.0	WN	96.0
3	1	3	4	1829.0	1959.0	WN	90.0
4	1	3	4	1940.0	2121.0	WN	101.0

In [3]:
```
df_flights.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1928371 entries, 0 to 1928370
Data columns (total 14 columns):
 #   Column             Dtype  
---  ------             -----  
 0   Month              int64  
 1   DayofMonth         int64  
 2   DayOfWeek          int64  
 3   DepTime            float64
 4   ArrTime            float64
 5   UniqueCarrier      object 
 6   ActualElapsedTime  float64
 7   CRSElapsedTime     float64
 8   AirTime            float64
 9   ArrDelay           float64
 10  DepDelay           float64
 11  Origin             object 
 12  Dest               object 
 13  Distance           int64  
dtypes: float64(7), int64(4), object(3)
memory usage: 206.0+ MB
```

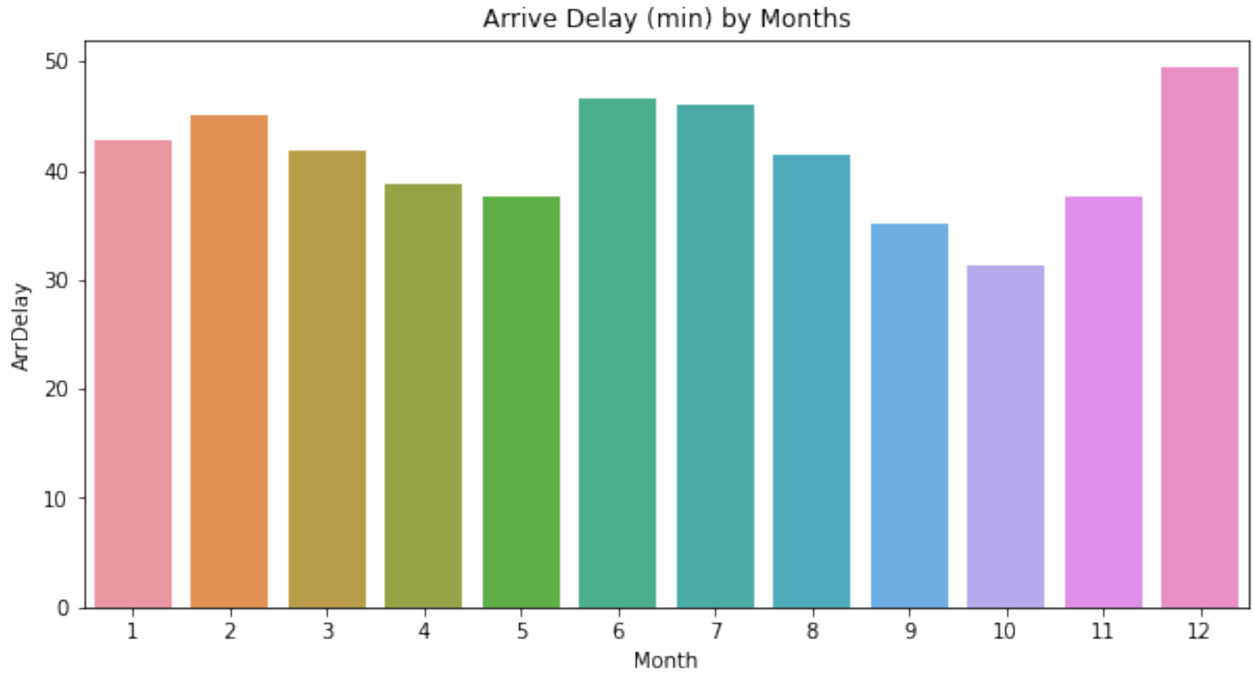
Exploratory Data Analysis

In [4]:
```
# average of arrive delay by month
month_mean = pd.DataFrame(df_flights.groupby('Month')['ArrDelay'].mean()).r
month_mean
```

Out[4]:

	Month	ArrDelay
0	1	42.801492
1	2	45.006123
2	3	41.914769
3	4	38.835305
4	5	37.593572
5	6	46.532728
6	7	45.995136
7	8	41.434409
8	9	35.168126
9	10	31.385769
10	11	37.705510
11	12	49.481435

In [5]:
```
# Month
plt.figure(figsize=(10,5))
sns.barplot( x='Month', y='ArrDelay',data=month_mean)
plt.title('Arrive Delay (min) by Months');
```



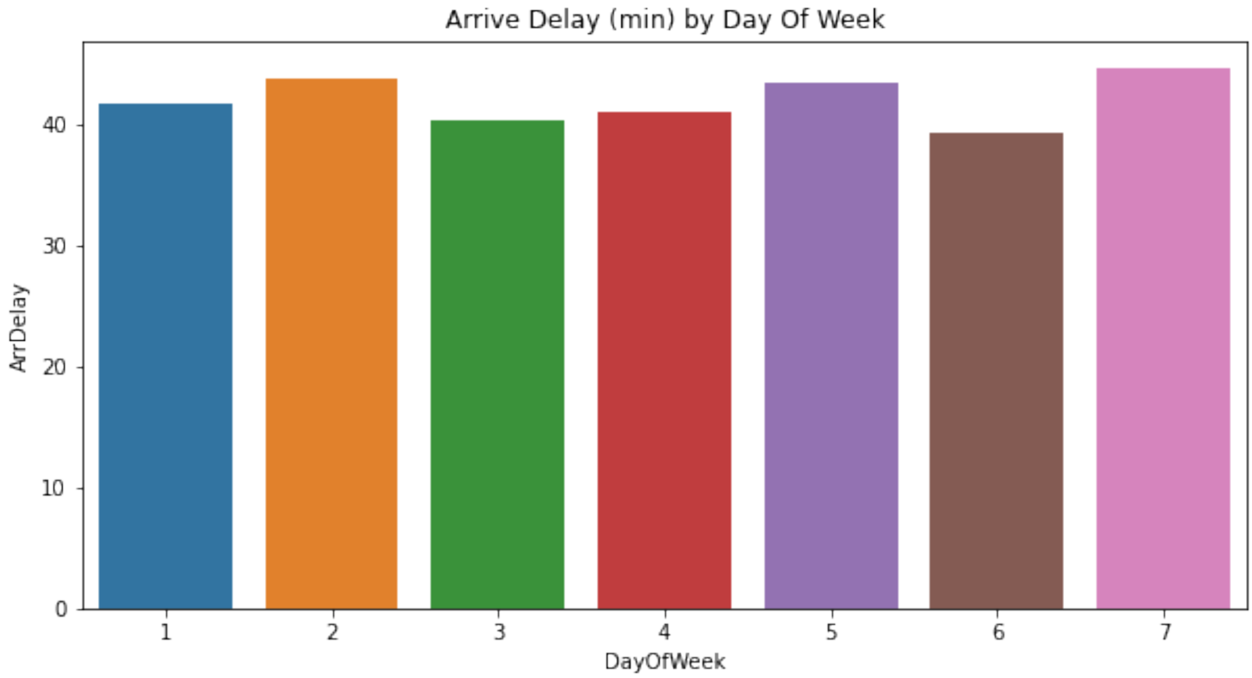
The month where the average delay is higher is December whereas the lower mean is Octobre

In [6]:
```
day_mean = pd.DataFrame(df_flights.groupby('DayOfWeek')['ArrDelay'].mean()
day_mean
```

Out[6]:

	DayOfWeek	ArrDelay
0	1	41.731356
1	2	43.806679
2	3	40.438229
3	4	41.071599
4	5	43.493618
5	6	39.393828
6	7	44.697413

In [7]:
```
# Day
plt.figure(figsize=(10,5))
sns.barplot( x='DayOfWeek', y='ArrDelay',data=day_mean)
plt.title('Arrive Delay (min) by Day Of Week');
```



In [8]:

```
#Data Transforming

from sklearn import preprocessing
le = preprocessing.LabelEncoder()

df_cat = df_flights[['UniqueCarrier','Origin', 'Dest' ]]
df_cat.head()
```

Out[8]:

	UniqueCarrier	Origin	Dest
0	WN	IAD	TPA
1	WN	IAD	TPA
2	WN	IND	BWI
3	WN	IND	BWI
4	WN	IND	JAX

In [9]:

```
df_transform = df_flights.copy()

for col in df_cat:
    df_transform[col] = le.fit_transform(df_cat[col])


df_transform.head()
```

Out[9]:

	Month	DayofMonth	DayOfWeek	DepTime	ArrTime	UniqueCarrier	ActualElapsedTime
0	1	3	4	2003.0	2211.0	17	128.0
1	1	3	4	754.0	1002.0	17	128.0
2	1	3	4	628.0	804.0	17	96.0
3	1	3	4	1829.0	1959.0	17	90.0
4	1	3	4	1940.0	2121.0	17	101.0

In [ ]:

```
```

Correlation

Let's check the features that better met with the target.

For this case, let' use the correlation (Pearson's) between the **ArrDelay** target and the other attributes.

In [10]:

```
# using the corr() method

corr_matrix = df_transform.corr()

# How much each attribute correlates with the Arrival Delay
corr_matrix['ArrDelay'].sort_values(ascending=False)
```

Out[10]:

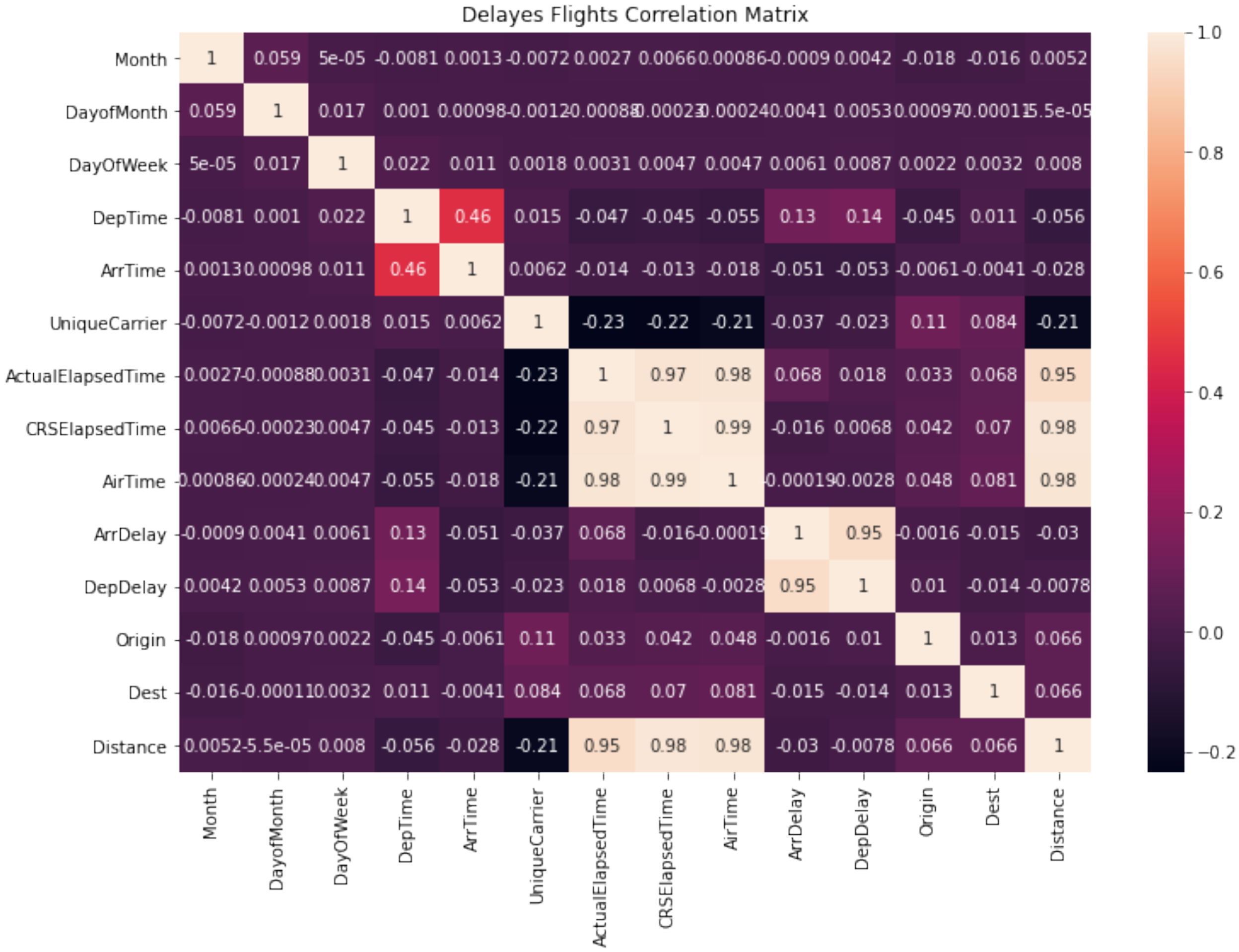
```
ArrDelay             1.000000
DepDelay             0.952927
DepTime              0.127017
ActualElapsedTime    0.068130
DayOfWeek            0.006123
DayofMonth           0.004129
AirTime             -0.000189
Month               -0.000897
Origin              -0.001597
Dest                -0.014805
CRSElapsedTime      -0.015676
Distance            -0.029853
UniqueCarrier       -0.037337
ArrTime             -0.050948
Name: ArrDelay, dtype: float64
```

In [11]:

```
# Matrix correlation

plt.figure(figsize=(12,8))

sns.heatmap(corr_matrix, annot=True)
plt.title('Delayes Flights Correlation Matrix')
plt.show()
```



3. Model Development

Training and Test

In [12]:

```
from sklearn.model_selection import train_test_split

y = df_transform['ArrDelay']

X = df_transform.drop('ArrDelay',axis=1)
```

In [13]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, 

print("number of test samples :", X_test.shape[0])
print("number of training samples:",X_train.shape[0])
```

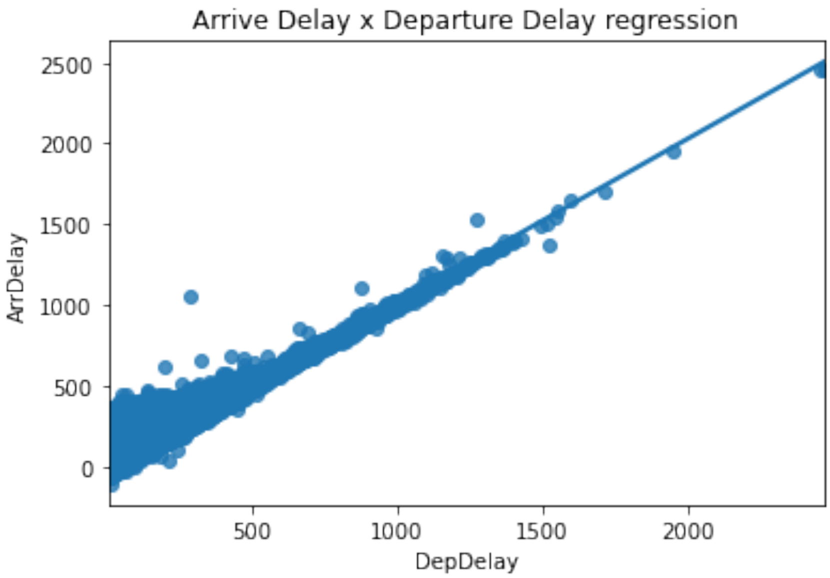
```
number of test samples : 578512
number of training samples: 1349859
```

Linear Regression

Fit a linear regression model using the DepDelay feature, which have the biggest correlation coefficient

In [14]:

```
sns.regplot(x="DepDelay", y="ArrDelay", data=df_transform)
plt.title('Arrive Delay x Departure Delay regression');
```



In [15]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler,PolynomialFeatures
from sklearn.linear_model import LinearRegression
```

In [16]:
```
lr=LinearRegression()
lr.fit(X_train[['DepDelay']], y_train)
```

Out[16]: LinearRegression()

In [17]:
```
#Calculate the R^2 on the test data:

r2_lr = lr.score(X_test[['DepDelay']], y_test)
r2_lr
```

Out[17]: 0.9089131986650585

In [18]:
```
yhat_test_lr = lr.predict(X_test[['DepDelay']])
yhat_test_lr
```

Out[18]:
```
array([38.04535139,  7.56674327,  7.56674327, ..., 37.02939779,
        6.55078967,  9.59865048])
```

In [19]:
```
MSE_lr = np.square(np.subtract(yhat_test_lr,y_test)).mean()
MSE_lr
```

Out[19]: 296.24644740741746

Multiple linear regression

I choose the features most correlated with the ArrDelay

In [20]:
```
lrm=LinearRegression()
lrm.fit(X_train[['DepDelay', 'DepTime', 'ActualElapsedTime', 'DayOfWeek',

#Prediction using test data:
yhat_test_lrm = lrm.predict(X_test[['DepDelay', 'DepTime', 'ActualElapsedTi
yhat_test_lrm[0:5]
```

Out[20]:
```
array([36.63418163,  4.76897249,  6.55394339, 27.57827137,  9.94032713])
```

In [21]:
```
#Calculate the R^2 on the test data:

r2_lrm = lrm.score(X_test[['DepDelay', 'DepTime', 'ActualElapsedTime', 'Day
r2_lrm
```

Out[21]:
```
0.9114066193226147
```

In [22]:
```
MSE_lrm = np.square(np.subtract(yhat_test_lrm,y_test)).mean()
MSE_lrm
```

Out[22]:
```
288.13696281838975
```

Polynomial Regression

In [23]:
```
from sklearn.preprocessing import PolynomialFeatures

pr1=PolynomialFeatures(degree=2)

X_train_pr1=pr1.fit_transform(X_train)
```

X_pr1 now contains the original feature of X plus the square of this feature.

In [24]:
```
X_train_pr1.shape
```

Out[24]:
```
(1349859, 105)
```

In [25]:
```
lr_poly = LinearRegression()

train_y_ = lr_poly.fit(X_train_pr1, y_train)
```

In [26]:
```
from sklearn.metrics import r2_score

X_test_pr1 = pr1.fit_transform(X_test)
test_y_ = lr_poly.predict(X_test_pr1)
```

In [27]:
```
MSE_poly =  np.mean((test_y_ - y_test) ** 2)
r2_poly = r2_score(y_test,test_y_ )
```

In [28]:
```
MSE_poly
```

Out[28]:
```
5.183904349632293e-06
```

In [29]:
```
r2_poly
```
Out[29]:
```
0.9999999984061065
```
In [30]:
```
yhat_test_poly=lr_poly.predict(X_test_pr1)
yhat_test_poly
```
Out[30]:
```
array([43.00001036,  0.99999422, -0.9999964 , ..., 39.9999916 ,
       10.99998558, 31.00000917])
```
In [31]:
```
r2_poly = lr_poly.score(X_test_pr1, y_test)
r2_poly
```
Out[31]:
```
0.9999999984061065
```
In [32]:
```
MSE_poly = np.square(np.subtract(yhat_test_poly,y_test)).mean()
MSE_poly
```
Out[32]:
```
5.183904349632293e-06
```
Ridge regression

In [33]:
```
from sklearn.linear_model import Ridge

RidgeModel = Ridge(alpha=0.1)
RidgeModel.fit(X_train, y_train)

r2_rdg = RidgeModel.score(X_test, y_test)
r2_rdg
```
Out[33]:
```
0.9999999984056435
```
In [34]:
```
yhat_test_rdg=RidgeModel.predict(X_test)
```
In [35]:
```
MSE_rdg = np.square(np.subtract(yhat_test_rdg,y_test)).mean()
MSE_rdg
```
Out[35]:
```
5.185410412183048e-06
```
Decision Tree Regression

In [36]:
```
from sklearn.tree import DecisionTreeRegressor

regressor = DecisionTreeRegressor(random_state=0)
regressor.fit(X_train, y_train)
```
Out[36]:
```
DecisionTreeRegressor(random_state=0)
```
In [37]:
```
yhat_tree = regressor.predict(X_test)
r2_tree = regressor.score(X_test, y_test)
r2_tree
```

Out[37]: 0.9957803518058488

In [38]:
```
MSE_tre = np.square(np.subtract(yhat_tree,y_test)).mean()
MSE_tre
```

Out[38]: 13.723786196310535

Exercises 2

Compare them based on MSE and R2.

In [39]:
```
measure_eval = pd.DataFrame({'Measure': ['R2', 'MSE'],
                             'Lin_Reg': [r2_lr, MSE_lr],
                             'Mult_Lin_Reg':[r2_lrm,MSE_lrm],
                             'Poly_Reg': [r2_poly, MSE_poly],
                             'Ridge_Reg': [r2_rdg,MSE_rdg],
                             'Decision_Tree': [r2_tree,MSE_tre]
                            })
measure_eval
```

Out[39]:

	Measure	Lin_Reg	Mult_Lin_Reg	Poly_Reg	Ridge_Reg	Decision_Tree
0	R2	0.908913	0.911407	1.000000	1.000000	0.995780
1	MSE	296.246447	288.136963	0.000005	0.000005	13.723786

Exercises 3

Train them using the different parameters they support.

The term Alfa is a hyperparameter Let's import GridSearchCV from the module model_selection.

In [40]:
```
from sklearn.model_selection import GridSearchCV

#create a dictionary of parameters values

parameters= [{'alpha': [0.001,0.1,1, 10, 100, 1000, 10000, 100000, 100000]}
parameters
```

Out[40]: [{'alpha': [0.001, 0.1, 1, 10, 100, 1000, 10000, 100000, 100000]}]

In [41]:
```
# Create a Ridge  region object
RR=Ridge()

#Create a ridge grid search object
Grid = GridSearchCV(RR, parameters,cv=4)
```

In [42]:
```
#Fit the model
Grid.fit(X_train, y_train)
```

Out[42]:
```
GridSearchCV(cv=4, estimator=Ridge(),
             param_grid=[{'alpha': [0.001, 0.1, 1, 10, 100, 1000, 10000, 10
0000,
                                    100000]}])
```

In [43]:
```
#Obtain the estimator with the best parameters
BestRR=Grid.best_estimator_
BestRR
```

Out[43]:
```
Ridge(alpha=0.001)
```

In [44]:
```
#test our model on the test data
BestRR.score(X_test, y_test)
```

Out[44]:
```
0.9999999984056435
```

Exercises 4

Compare your performance using the traint / test approach or using all data (internal validation)

I'll use the Multiple Linear Regression as a example , using all the X and y data instead of split them in train and test ones.

Multiple Linear Regression- Using all data

In [45]:
```
lrm.fit(X, y)
```

Out[45]:
```
LinearRegression()
```

In [46]:
```
yhat_lrmall=lrm.predict(X)
yhat_lrmall[0:5]
```

Out[46]:
```
array([-13.99999103,   1.99999961,  13.99999238,  33.99999969,
        11.00000232])
```

In [47]:
```
r2_rlmall = lrm.score(X,y)
r2_rlmall
```

Out[47]:
```
0.9999999980702016
```

With all data used, the r-squared in Multiple Linear Regression was 0.999. This value is less that 0.911, when there was the splitted of the original dataset (X and y).

The r2 increased because I evaluated the predictived performance of the model with the same data I used for training. Although the r2 is higher, that doesn't mean it's better, after all, it was a biased evaluation.

Exercises 5

Perform some variable engineering process to improve prediction.

Let's create a attribute to see if the weekend influences the flight delay.

In [48]:
```
# Create 'weekend' attribute
df_new = df_transform.copy()

df_new['weekend'] = np.where(df_new['DayOfWeek']>=6, 1, 0)
df_new.head()
```

Out[48]:

	Month	DayofMonth	DayOfWeek	DepTime	ArrTime	UniqueCarrier	ActualElapsedTime
0	1	3	4	2003.0	2211.0	17	128.0
1	1	3	4	754.0	1002.0	17	128.0
2	1	3	4	628.0	804.0	17	96.0
3	1	3	4	1829.0	1959.0	17	90.0
4	1	3	4	1940.0	2121.0	17	101.0

In [49]:
```
df_new['weekend'].value_counts()
```

Out[49]:
```
0    1421230
1     507141
Name: weekend, dtype: int64
```

New Correlation

New correlation considering the new attribute ' weekend'

In [50]:
```
corr_matrix = df_new.corr()

# How much each attribute correlates with the Arrival Delay
corr_matrix['ArrDelay'].sort_values(ascending=False)
```

Out[50]:
```
ArrDelay             1.000000
DepDelay             0.952927
DepTime              0.127017
ActualElapsedTime    0.068130
DayOfWeek            0.006123
DayofMonth           0.004129
weekend              0.001828
AirTime             -0.000189
Month               -0.000897
Origin              -0.001597
Dest                -0.014805
CRSElapsedTime      -0.015676
Distance            -0.029853
UniqueCarrier       -0.037337
ArrTime             -0.050948
Name: ArrDelay, dtype: float64
```

The attribute 'weekend' has a small and positive correlation with the target 'ArrDelay'.

That's confirm that on weekends the arrive delays are a little bigger.

Exercises 6

Do not use the DepDelay variable when making predictions

New Train and Test

In [51]:
```
# Create new dataset for attributes and target

y_new = df_new['ArrDelay']

X_new = df_new.drop(['ArrDelay', 'DepDelay'],axis=1)
```

In [52]:
```
# New split
X_train_new, X_test_new, y_train_new, y_test_new = train_test_split(X_new,

print("number of test samples :", X_test_new.shape[0])
print("number of training samples:",X_train_new.shape[0])
```

```
number of test samples : 674930
number of training samples: 1253441
```

Multiple Linear Regression - No 'DepDelay'

Now, I'll consider all attributes but 'DepDelay'

In [53]:
```
lrm2=LinearRegression()
lrm2.fit(X_train_new, y_train_new)

#Prediction using test data:
yhat_test_new = lrm2.predict(X_test_new)
yhat_test_new[0:5]
```

Out[53]:
```
array([ 3.78296201, 39.92019647, 40.8348433 , 26.46675383, 36.65337127])
```

In [54]:
```
#Calculate the R^2 on the test data:

r2_lrm_new = lrm2.score(X_test_new, y_test_new)
r2_lrm_new
```

Out[54]:
```
0.1634381956858456
```

In [55]:
```
MSE_lrm_new = np.square(np.subtract(yhat_test_new, y_test_new)).mean()
MSE_lrm_new
```

Out[55]:
```
2707.245460974804
```

Polynomial Regression - No 'DepDelay'

In [56]:
```
pr2=PolynomialFeatures(degree=2)

X_train_pr2=pr2.fit_transform(X_train_new)
```

In [57]:
```
lr_poly2 = LinearRegression()

new_train_y_ = lr_poly2.fit(X_train_pr2, y_train_new)
```

In [58]:
```
X_test_pr2 = pr1.fit_transform(X_test_new)
new_test_y_ = lr_poly2.predict(X_test_pr2)
```

In [59]:
```
MSE_poly2 =  np.mean((new_test_y_ - y_test_new) ** 2)
r2_poly2 = r2_score(y_test_new,new_test_y_ )
```

In [60]:
```
MSE_poly2
```

Out[60]:
```
2574.0157370475217
```

In [61]:
```
r2_poly2
```

Out[61]:
```
0.20460731013944933
```

Ridge regression - No 'DepDelay'

In [62]:
```
from sklearn.linear_model import Ridge

RidgeModel2 = Ridge(alpha=0.1)
RidgeModel2.fit(X_train_new, y_train_new)
r2_rdg_new = RidgeModel2.score(X_test_new, y_test_new)
r2_rdg_new
```

Out[62]:
```
0.16343819571681495
```

In [63]:
```
yhat_test_rdg2=RidgeModel.predict(X_test_new)
MSE_rdg2 = np.square(np.subtract(yhat_test_rdg2, y_test_new)).mean()
MSE_rdg2
```

Out[63]:
```
19866.179321959396
```

Decision Tree - No 'DepDelay'

In [64]:
```
regressor_new = DecisionTreeRegressor(random_state=5)
regressor_new.fit(X_train_new, y_train_new)
```

Out[64]:
```
DecisionTreeRegressor(random_state=5)
```

In [65]:
```
yhat_tree_new = regressor_new.predict(X_test_new)
r2_tree_new = regressor_new.score(X_test_new, y_test_new)
r2_tree_new
```

Out[65]:
```
-0.18697835393844664
```

The r2 score is **negative** because the model is arbitrarily worse without the attribute 'DepDelay'.

In [66]:
```
MSE_tre_new = np.square(np.subtract(yhat_tree_new, y_test_new)).mean()
MSE_tre_new
```

Out[66]: 3841.248482064807

In [67]:
```
measure_eval_new = pd.DataFrame({'Measure_new': ['R2', 'MSE'],
                                 'Mult_Lin_Reg':[r2_lrm_new, MSE_lrm_new],
                                 'Poly_Reg': [r2_poly2, MSE_poly2],
                                 'Ridge_Reg': [r2_rdg_new,MSE_rdg2],
                                 'Decision_Tree': [r2_tree_new, MSE_tre_new]
                                })
measure_eval_new
```

Out[67]:

	Measure_new	Mult_Lin_Reg	Poly_Reg	Ridge_Reg	Decision_Tree
0	R2	0.163438	0.204607	0.163438	-0.186978
1	MSE	2707.245461	2574.015737	19866.179322	3841.248482