S09 T02: Aprenentatge Supervisat - Regressions part 2

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
pd.set_option('display.max_columns', None)
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.float_format', '{:.10f}'.format)
```

I will load again the dataset from the previous exercise called data and I will apply again dummy transformation here because it takes less memory space if I do it this way (because of dtypes of the dummy columns). I could also change dtypes from here but it takes a lot of time so it is faster doing it this way.

In [2]:
```
# open dataset from the previous exercise
data = pd.read_csv('data.csv')
data.head()
```

Out[2]:

	ArrDelay	ActualElapsedTime	CRSElapsedTime	AirTime	DepDelay	Distance	Speed	TaxiIn	TaxiOut
0	-14.0000000000	128.0000000000	150.0000000000	116.0000000000	8.0000000000	810	418.9700000000	4.0000000000	8.0000000000
1	2.0000000000	128.0000000000	145.0000000000	113.0000000000	19.0000000000	810	430.0900000000	5.0000000000	10.0000000000
2	14.0000000000	96.0000000000	90.0000000000	76.0000000000	8.0000000000	515	406.5800000000	3.0000000000	17.0000000000
3	34.0000000000	90.0000000000	90.0000000000	77.0000000000	34.0000000000	515	401.3000000000	3.0000000000	10.0000000000
4	11.0000000000	101.0000000000	115.0000000000	87.0000000000	25.0000000000	688	474.4800000000	4.0000000000	10.0000000000

In [3]:
```
# do the sample explained in previous exercise
data_sample = data.groupby('UniqueCarrier', group_keys= False).apply(lambda x : x.sample(frac=0.1, random_state
```

In [4]:
```
# now i will generate the dummy columns that are already explained in the previous exercise
# create a column to categorize ArrDelay, explained in previous exercise
def delay_interval(x):
    if x < 15:
        return "Less than 15"
    elif x < 30:
        return "Between 15 and 30"
    elif x < 60:
        return "Between 30 and 60"
    else:
        return "More than 60"

data_sample['DelayInterval'] = data_sample['ArrDelay'].apply(delay_interval)
data_sample.head()
```

Out[4]:

	ArrDelay	ActualElapsedTime	CRSElapsedTime	AirTime	DepDelay	Distance	Speed	TaxiIn	Ta
143019	21.0000000000	95.0000000000	88.0000000000	63.0000000000	14.0000000000	364	346.6700000000	11.0000000000	21.00000
1886001	24.0000000000	139.0000000000	126.0000000000	105.0000000000	11.0000000000	813	464.5700000000	18.0000000000	16.00000
1881989	2.0000000000	86.0000000000	102.0000000000	65.0000000000	18.0000000000	490	452.3100000000	9.0000000000	12.00000
1030789	37.0000000000	114.0000000000	90.0000000000	87.0000000000	13.0000000000	442	304.8300000000	4.0000000000	23.00000
687997	10.0000000000	90.0000000000	88.0000000000	61.0000000000	8.0000000000	382	375.7400000000	7.0000000000	22.00000

In [5]:
```
# creating the dummy columns
# we´ll use the param drop first = True so we don t have duplicated information
data_sample= pd.get_dummies(data = data_sample, columns = ['UniqueCarrier','Origin', 'Dest'],
                            drop_first= True)
# map dummies for DelayInterval
data_sample['DelayInterval'] = data_sample['DelayInterval'].map({"Less than 15": 0, "Between 15 and 30": 1,
                        "Between 30 and 60" : 2, "More than 60": 3})
data_sample.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 192825 entries, 143019 to 1544585
Columns: 637 entries, ArrDelay to Dest_YUM
dtypes: float64(15), int64(7), uint8(615)
memory usage: 146.9 MB
```

Now I will delete the columns that show multicollinearity (explained in the previous Notebook on the VIF process)

In [6]:
```
data_cleaned = data_sample.copy()
```

In [7]:
```
data_cleaned.drop(['ActualElapsedTime', 'CRSElapsedTime', 'TaxiIn', 'LateAircraftDelay', 'AirTime',
                   'CRSDepTime', 'Speed', 'CRSArrTime', 'DepTime'], axis = 1, inplace = True)
data_cleaned.shape
```

Out[7]:
```
(192825, 628)
```

Now we have the same dataset that we had at the end of our previous Notebook.

Exercici 5

Realitza algun procés d'enginyeria de variables per millorar-ne la predicció

To improve our predictions, we could scale our data, let´s check the data:

In [8]:
```
data_scaled = data_cleaned.copy()
```

In [9]:
```
data_scaled.head()
```

Out[9]:

	ArrDelay	DepDelay	Distance	TaxiOut	CarrierDelay	WeatherDelay	NASDelay	SecurityDelay	ArrTime
143019	21.0000000000	14.0000000000	364	21.0000000000	14.0000000000	0.0000000000	7.0000000000	0.0000000000	1746.0000000000
1886001	24.0000000000	11.0000000000	813	16.0000000000	0.0000000000	0.0000000000	13.0000000000	0.0000000000	1419.0000000000
1881989	2.0000000000	18.0000000000	490	12.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	1209.0000000000
1030789	37.0000000000	13.0000000000	442	23.0000000000	13.0000000000	0.0000000000	24.0000000000	0.0000000000	2102.0000000000
687997	10.0000000000	8.0000000000	382	22.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	1208.0000000000

In [10]:
```
data_scaled.columns[:16]
```

Out[10]:
```
Index(['ArrDelay', 'DepDelay', 'Distance', 'TaxiOut', 'CarrierDelay',
       'WeatherDelay', 'NASDelay', 'SecurityDelay', 'ArrTime', 'Month',
       'DayofMonth', 'DayOfWeek', 'DelayInterval', 'UniqueCarrier_AA',
       'UniqueCarrier_AQ', 'UniqueCarrier_AS'],
      dtype='object')
```

We can scale the data in different ways:

- We can use RobustScaler on those features that refer to delay and have heavy outliers: 'ArrDelay', 'DepDelay', 'Distance', 'TaxiOut', 'CarrierDelay','WeatherDelay', 'NASDelay', 'SecurityDelay'
- We can use MinMaxScaler with those features that refer to the time of the flight, these features don't have outliers: 'ArrTime', 'Month','DayofMonth', 'DayOfWeek', they refer to the dates and hours of the flights.

We won' t scale dummy columns.

Robust Scaler

In [11]:
```
cols_robust = ['ArrDelay', 'DepDelay', 'Distance', 'TaxiOut', 'CarrierDelay',
       'WeatherDelay', 'NASDelay', 'SecurityDelay']
```

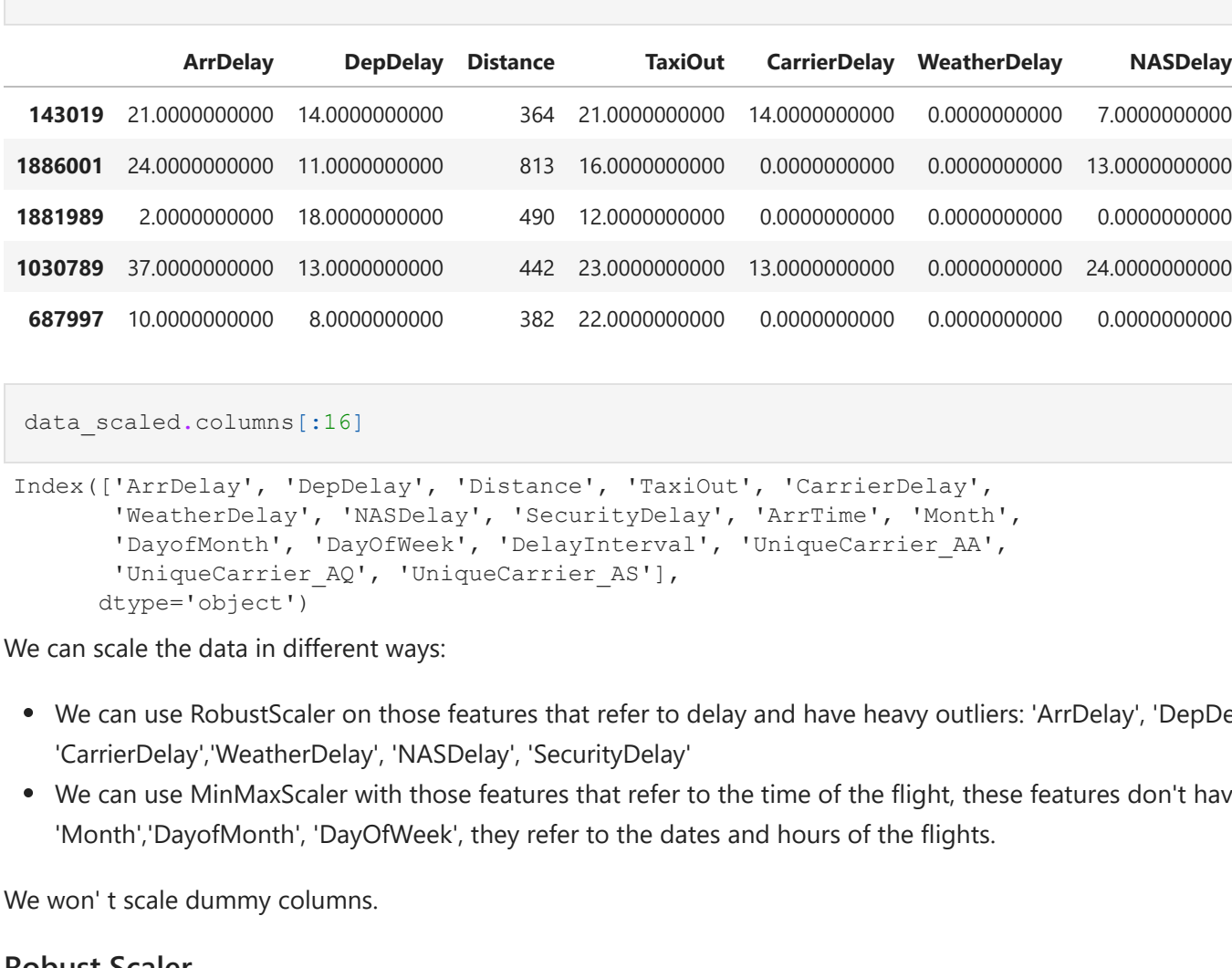
In [12]:
```
data_scaled[cols_robust].describe().round(2)
```

Out[12]:

	ArrDelay	DepDelay	Distance	TaxiOut	CarrierDelay	WeatherDelay	NASDelay
count	192825.0000000000	192825.0000000000	192825.0000000000	192825.0000000000	192825.0000000000	192825.0000000000	192825.0000000000
mean	42.2200000000	43.1300000000	765.2800000000	18.2300000000	12.2900000000	2.3900000000	9.7100000000
std	56.9200000000	53.5600000000	573.9400000000	14.2300000000	35.8100000000	17.9000000000	28.2100000000
min	-59.0000000000	6.0000000000	31.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
25%	9.0000000000	12.0000000000	338.0000000000	10.0000000000	0.0000000000	0.0000000000	0.0000000000
50%	24.0000000000	24.0000000000	606.0000000000	14.0000000000	0.0000000000	0.0000000000	0.0000000000
75%	56.0000000000	53.0000000000	998.0000000000	21.0000000000	10.0000000000	0.0000000000	6.0000000000
max	1655.0000000000	1597.0000000000	4962.0000000000	356.0000000000	1312.0000000000	1148.0000000000	1289.0000000000

Comparing max values and quartiles we can see we have outliers in this columns, let´s draw some boxplots to confirm this.

In [13]:
```
plt.figure(figsize=(12,9))
sns.boxplot(data = data_scaled[cols_robust]);
```



Some features have more outliers than others, but let´s try this approach and see how it works:

In [14]:
```
#import libraries
from sklearn import preprocessing

robust_scaler = preprocessing.RobustScaler()
#apply robust scaler on selected columns
data_scaled[cols_robust] = robust_scaler.fit_transform(data_scaled[cols_robust])
```

In [15]:
```
data_scaled.head()
```

Out[15]:

	ArrDelay	DepDelay	Distance	TaxiOut	CarrierDelay	WeatherDelay	NASDelay	SecurityDelay	ArrTime
143019	-0.0638297872	-0.2439024390	-0.3666666667	0.6363636364	1.4000000000	0.0000000000	1.1666666667	0.0000000000	1746.000000000
1886001	0.0000000000	-0.3170731707	0.3136363636	0.1818181818	0.0000000000	0.0000000000	2.1666666667	0.0000000000	1419.000000000
1881989	-0.4680851064	-0.1463414634	-0.1757575758	-0.1818181818	0.0000000000	0.0000000000	0.0000000000	0.0000000000	1209.000000000
1030789	0.2765957447	-0.2682926829	-0.2484848485	0.8181818182	1.3000000000	0.0000000000	4.0000000000	0.0000000000	2102.000000000
687997	-0.2978723404	-0.3902439024	-0.3393939394	0.7272727273	0.0000000000	0.0000000000	0.0000000000	0.0000000000	1208.000000000

In [16]:
```
data_scaled[cols_robust].describe().round(2)
```

Out[16]:

	ArrDelay	DepDelay	Distance	TaxiOut	CarrierDelay	WeatherDelay	NASDelay
count	192825.0000000000	192825.0000000000	192825.0000000000	192825.0000000000	192825.0000000000	192825.0000000000	192825.0000000000
mean	0.3900000000	0.4700000000	0.2400000000	0.3800000000	1.2300000000	2.3900000000	1.6200000000
std	1.2100000000	1.3100000000	0.8700000000	1.2900000000	3.5800000000	17.9000000000	4.7000000000
min	-1.7700000000	-0.4400000000	-0.8700000000	-1.2700000000	0.0000000000	0.0000000000	0.0000000000
25%	-0.3200000000	-0.2900000000	-0.4100000000	-0.3600000000	0.0000000000	0.0000000000	0.0000000000
50%	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
75%	0.6800000000	0.7100000000	0.5900000000	0.6400000000	1.0000000000	0.0000000000	1.0000000000
max	34.7000000000	38.3700000000	6.6000000000	31.0900000000	131.2000000000	1148.0000000000	214.8300000000

We see the data has been scaled in a way that preserves the information about outliers.

MinMax Scaler

For the columns that refer to the time of the flight ('ArrTime', 'Month', 'DayofMonth','DayOfWeek',) I will use MinMaxScaler.

In [17]:
```
from sklearn.preprocessing import MinMaxScaler

cols_minmax = ['ArrTime', 'Month', 'DayofMonth','DayOfWeek', 'DelayInterval']

mms = MinMaxScaler()
# apply scaler on selected features
data_scaled[cols_minmax] = mms.fit_transform(data_scaled[cols_minmax])
```

In [18]:
```
data_scaled[cols_minmax].describe().round(2)
```

Out[18]:

	ArrTime	Month	DayofMonth	DayOfWeek	DelayInterval
count	192825.0000000000	192825.0000000000	192825.0000000000	192825.0000000000	192825.0000000000
mean	0.6700000000	0.4700000000	0.4900000000	0.5000000000	0.4400000000
std	0.2300000000	0.3200000000	0.2900000000	0.3300000000	0.3900000000
min	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000
25%	0.5500000000	0.1800000000	0.2300000000	0.1700000000	0.0000000000
50%	0.7100000000	0.4500000000	0.5000000000	0.5000000000	0.3300000000
75%	0.8500000000	0.7300000000	0.7300000000	0.8300000000	0.6700000000
max	1.0000000000	1.0000000000	1.0000000000	1.0000000000	1.0000000000

Now these features have all a min value of 0 and max value of 1.

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

Out[19]:

	ArrDelay	DepDelay	Distance	TaxiOut	CarrierDelay	WeatherDelay	NASDelay	SecurityDelay	ArrTime
143019	-0.0638297872	-0.2439024390	-0.3666666667	0.6363636364	1.4000000000	0.0000000000	1.1666666667	0.0000000000	0.7273864110
1886001	0.0000000000	-0.3170731707	0.3136363636	0.1818181818	0.0000000000	0.0000000000	2.1666666667	0.0000000000	0.5910796165
1881989	-0.4680851064	-0.1463414634	-0.1757575758	-0.1818181818	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.5035431430
1030789	0.2765957447	-0.2682926829	-0.2484848485	0.8181818182	1.3000000000	0.0000000000	4.0000000000	0.0000000000	0.8757815757
687997	-0.2978723404	-0.3902439024	-0.3393939394	0.7272727273	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.5031263026

Now let´s test our models with the scaled data.

Model 1 : Simple Linear Regression

First we will apply scaled features on our Simple Linear Regression model where we are using only 2 variables:

In [20]:
```
# declare dependent variable
y_simple_scaled = data_scaled['ArrDelay']
# independent variable
x_simple_scaled = data_scaled['DepDelay']
```

In [21]:
```
# since the input has only 1 dimension, (1 feature), we reshape first
x_simple_scaled = x_simple_scaled.values.reshape(-1, 1)
x_simple_scaled.shape
```

Out[21]:
```
(192825, 1)
```

In [22]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
# we´ll use a test size of 30%
# use the same random_state as before
x_simple_train_scaled, x_simple_test_scaled, y_simple_train_scaled, y_simple_test_scaled = train_test_split(x_s
                                        y_simple_scaled, test_size= 0.3, random_state= 10)
```

In [23]:
```
# regression
scaled_regression = LinearRegression()
scaled_regression.fit(x_simple_train_scaled, y_simple_train_scaled)
```

Out[23]:
```
LinearRegression()
```

In [24]:
```
# import modules for the metrics
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
import sklearn.metrics as metrics
```

In [25]:
```
# functions to show the results
def print_results_test(true, predicted):

    r2_square = metrics.r2_score(true, predicted)
    mse = metrics.mean_squared_error(true, predicted)

    print('R2 for test set : ', r2_square)
    print('MSE (mean squared error) for test set: ', mse)
    print('-----------------------------------------')

def print_results_train(true, predicted):

    r2_square = metrics.r2_score(true, predicted)
    mse = metrics.mean_squared_error(true, predicted)

    print('R2 for train set : ', r2_square)
    print('MSE (mean squared error) for train set: ', mse)
```

In [26]:
```
#predictions for test sets
scaled_reg_test_pred = scaled_regression.predict(x_simple_test_scaled)
# predcitions for train
scaled_reg_train_pred = scaled_regression.predict(x_simple_train_scaled)
```

In [27]:
```
print_results_test(y_simple_test_scaled, scaled_reg_test_pred)
print_results_train(y_simple_train_scaled, scaled_reg_train_pred)
```

```
R2 for test set :  0.9095964548101837
MSE (mean squared error) for test set:  0.13149831985240448
-----------------------------------------
R2 for train set :  0.9098436088946703
MSE (mean squared error) for train set:  0.13269306321908042
```

In [28]:
```
# define a function to get the results to a dataframe:
def get_results(true, predicted):
    r2_square = metrics.r2_score(true, predicted)
    mse = metrics.mean_squared_error(true, predicted)

    return r2_square, mse
```

In [29]:
```
# we will save the results in a dataframe
scaled_results = pd.DataFrame(data =[['Simple Linear Regression',
                                     get_results(y_simple_test_scaled, scaled_reg_test_pred)[0],
                                     get_results(y_simple_test_scaled, scaled_reg_test_pred)[1],
                                     get_results(y_simple_train_scaled, scaled_reg_train_pred)[0],
                                     get_results(y_simple_train_scaled, scaled_reg_train_pred)[1]]],
                                     columns = ['Model', 'R2_test', 'MSE_test', 'R2_train', 'MSE_train'])
scaled_results
```

Out[29]:

	Model	R2_test	MSE_test	R2_train	MSE_train
0	Simple Linear Regression	0.9095964548	0.1314983199	0.9098436089	0.1326930632

If we compare this with our previous model:

In [30]:
```
# compare with previous model:
# open results_df with previous results
results_df = pd.read_csv('results_df.csv')
results_df[0:1]
```

Out[30]:

	Model	R2_test	MSE_test	R2_train	MSE_train
0	Simple Linear Regression	0.9095964548	290.4797885540	0.9098436089	293.1189766509

- The results we got in R2 are exactly the same!!! This is logical because both ArrDelay and DepDelay are in the same scale and we have scaled them equally, since in this model we only got these two features the result is the same.
- MSE cannot be compared because the scale is different

Model 2 : Ridge Regression

In this model again we will use all the features that were kept after VIF analyisis.

In [31]:
```
# dependent variable
y_scaled = data_scaled['ArrDelay']
# independent features
X_scaled = data_scaled.drop(['ArrDelay'], axis = 1)
```

In [32]:
```
print('data_scaled.shape: ', data_scaled.shape)
print('X_scaled.shape: ', X_scaled.shape)
print('y_scaled.shape: ', y_scaled.shape)
```

```
data_scaled.shape:  (192825, 628)
X_scaled.shape:  (192825, 627)
y_scaled.shape:  (192825,)
```

In [33]:
```
# use test size of 0.3
X_train_scaled, X_test_scaled, y_train_scaled, y_test_scaled = train_test_split(X_scaled, y_scaled,
                                                               test_size= 0.3, random_state= 0)
```

In [34]:
```
print('X_train_scaled.shape: ' , X_train_scaled.shape)
print('X_test_scaled.shape: ', X_test_scaled.shape)
print('y_train_scaled.shape: ', y_train_scaled.shape)
print('y_test_scaled.shape: ', y_test_scaled.shape)
```

```
X_train_scaled.shape:  (134977, 627)
X_test_scaled.shape:  (57848, 627)
y_train_scaled.shape:  (134977,)
y_test_scaled.shape:  (57848,)
```

In [35]:
```
from sklearn.linear_model import Ridge

scaled_ridge = Ridge()
scaled_ridge.fit(X_train_scaled, y_train_scaled)
```

Out[35]:
```
Ridge()
```

In [36]:
```
scaled_ridge_test_prediction = scaled_ridge.predict(X_test_scaled)
scaled_ridge_train_prediction = scaled_ridge.predict(X_train_scaled)

print_results_test(y_test_scaled, scaled_ridge_test_prediction)
print_results_train(y_train_scaled, scaled_ridge_train_prediction)
```

```
R2 for test set :  0.9728951593612505
MSE (mean squared error) for test set:  0.039633283165410385
-----------------------------------------
R2 for train set :  0.9729783614904497
MSE (mean squared error) for train set:  0.03968255427364781
```

In [37]:
```
# recall results from the first model
results_df[1:2]
```

Out[37]:

	Model	R2_test	MSE_test	R2_train	MSE_train
1	Ridge Regression	0.9728951602	87.5499197516	0.9729783617	87.6587618537

For ridge model the results are the same, scaling the features has no effect on R2 (MSE is not comparable)

In [38]:
```
# store the results
scaled_ridge = pd.DataFrame(data = [['Ridge Regression',
                                    get_results(y_test_scaled, scaled_ridge_test_prediction)[0],
                                    get_results(y_test_scaled, scaled_ridge_test_prediction)[1],
                                    get_results(y_train_scaled, scaled_ridge_train_prediction)[0],
                                    get_results(y_train_scaled, scaled_ridge_train_prediction)[1]]],
                                    columns = ['Model', 'R2_test', 'MSE_test', 'R2_train', 'MSE_train'])
scaled_results = pd.concat([scaled_results, scaled_ridge])
scaled_results
```

Out[38]:

	Model	R2_test	MSE_test	R2_train	MSE_train
0	Simple Linear Regression	0.9095964548	0.1314983199	0.9098436089	0.1326930632
0	Ridge Regression	0.9728951594	0.0396332832	0.9729783615	0.0396825543

Model 3 : Random Forest Regression

In [39]:
```
from sklearn.ensemble import RandomForestRegressor
# choose n_estimators to 50
scaled_regressor = RandomForestRegressor(n_estimators= 50, random_state= 0)
scaled_regressor.fit(X_train_scaled, y_train_scaled)
```

Out[39]:
```
RandomForestRegressor(n_estimators=50, random_state=0)
```

In [40]:
```
scaled_forest_test_prediction = scaled_regressor.predict(X_test_scaled)
scaled_forest_train_prediction = scaled_regressor.predict(X_train_scaled)

print_results_test(y_test_scaled, scaled_forest_test_prediction)
print_results_train(y_train_scaled, scaled_forest_train_prediction)
```

```
R2 for test set :  0.9881189928626017
MSE (mean squared error) for test set:  0.017372665142830097
-----------------------------------------
R2 for train set :  0.9982919395442333
MSE (mean squared error) for train set:  0.002508367570481544
```

In [41]:
```
# comparing with previous results:
results_df[2:3]
```

Out[41]:

	Model	R2_test	MSE_test	R2_train	MSE_train
2	Random Forest Regression	0.9881187248	38.3770832457	0.9982827110	5.5709214014

We can see that our results improve but very litle!! we have to look up to the 7th decimal to notice the improvement. We have to take into account our R2 is actually really high and may be difficult to increase it much more.

In [42]:
```
#df.round(decimals=number of decimal places needed)
# save results
scaled_forest = pd.DataFrame( data = [['Random Forest Regression',
                                      get_results(y_test_scaled, scaled_forest_test_prediction)[0],
                                      get_results(y_test_scaled, scaled_forest_test_prediction)[1],
                                      get_results(y_train_scaled, scaled_forest_train_prediction)[0],
                                      get_results(y_train_scaled, scaled_forest_train_prediction)[1]]],
                                      columns = ['Model', 'R2_test', 'MSE_test', 'R2_train', 'MSE_train'])
scaled_results = pd.concat([scaled_results, scaled_forest])
scaled_results
```

Out[42]:

	Model	R2_test	MSE_test	R2_train	MSE_train
0	Simple Linear Regression	0.9095964548	0.1314983199	0.9098436089	0.1326930632
0	Ridge Regression	0.9728951594	0.0396332832	0.9729783615	0.0396825543
0	Random Forest Regression	0.9881189929	0.0173726651	0.9982919395	0.0025083676

Model 4: XGBoost Regressor

In [43]:
```
from xgboost import XGBRegressor

xgb_scaled_regressor = XGBRegressor()

xgb_scaled_regressor.fit(X_train_scaled, y_train_scaled)
```

Out[43]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.300000012,
             max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=100, n_jobs=8,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,
             reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

In [44]:
```
scaled_xgb_test_prediction = xgb_scaled_regressor.predict(X_test_scaled)
scaled_xgb_train_prediction = xgb_scaled_regressor.predict(X_train_scaled)

print_results_test(y_test_scaled, scaled_xgb_test_prediction)
print_results_train(y_train_scaled, scaled_xgb_train_prediction)
```

```
R2 for test set :  0.988296972800585
MSE (mean squared error) for test set:  0.0171124190349901
-----------------------------------------
R2 for train set :  0.9913340014958506
MSE (mean squared error) for train set:  0.012726428704710743
```

In [45]:
```
# look at previous result:
results_df[3:4]
```

Out[45]:

	Model	R2_test	MSE_test	R2_train	MSE_train
3	XGBoost Regression	0.9882029254	38.1051112017	0.9913355160	28.1077679962

We see a little improvement in R2 in test set but not in train set.

In [46]:
```
# store the results
scaled_xgb = pd.DataFrame(data = [['XGBoost Regression',
                                  get_results(y_test_scaled, scaled_xgb_test_prediction)[0],
                                  get_results(y_test_scaled, scaled_xgb_test_prediction)[1],
                                  get_results(y_train_scaled, scaled_xgb_train_prediction)[0],
                                  get_results(y_train_scaled, scaled_xgb_train_prediction)[1]]],
                                  columns = ['Model', 'R2_test', 'MSE_test', 'R2_train', 'MSE_train'])
scaled_results = pd.concat([scaled_results, scaled_xgb])
scaled_results
```

Out[46]:

	Model	R2_test	MSE_test	R2_train	MSE_train
0	Simple Linear Regression	0.9095964548	0.1314983199	0.9098436089	0.1326930632
0	Ridge Regression	0.9728951594	0.0396332832	0.9729783615	0.0396825543
0	Random Forest Regression	0.9881189929	0.0173726651	0.9982919395	0.0025083676
0	XGBoost Regression	0.9882969728	0.0171124190	0.9913340015	0.0127264287

Let´s put together the scaled results with the results from the first models to compare them:

In [47]:
```
# put together the 2 dataframes row by row
compared_df = results_df[0:4].stack().to_frame('results_df')
compared_df.loc[:, 'scaled_results'] = scaled_results.stack().values
compared_df = compared_df.stack().unstack(1)
compared_df
```

Out[47]:

		Model	R2_test	MSE_test	R2_train	MSE_train
0	results_df	Simple Linear Regression	0.9095964548	290.4797885540	0.9098436089	293.1189766509
	scaled_results	Simple Linear Regression	0.9095964548	0.1314983199	0.9098436089	0.1326930632
1	results_df	Ridge Regression	0.9728951602	87.5499197516	0.9729783617	87.6587618537
	scaled_results	Ridge Regression	0.9728951594	0.0396332832	0.9729783615	0.0396825543
2	results_df	Random Forest Regression	0.9881187248	38.3770832457	0.9982827110	5.5709214014
	scaled_results	Random Forest Regression	0.9881189929	0.0173726651	0.9982919395	0.0025083676
3	results_df	XGBoost Regression	0.9882029254	38.1051112017	0.9913355160	28.1077679962
	scaled_results	XGBoost Regression	0.9882969728	0.0171124190	0.9913340015	0.0127264287

- In Simple Linear Regression and Ridge Regression results are the same (a little lower in the case of Ridge but we have to look at the 8th decimal to notice)
- In Random Forest and XGBoost the results are a little better with scaled features (but we have to look from the 5th decimal)

Maybe in our models these improvements don' t matter too much because R2 is already quite high, but this is a tool that maybe can improve the prediction of a model when the features are in different scales.

- Exercici 6

No utilitzis la variable DepDelay a l'hora de fer prediccions

We have seen in our Simple Linear Regression model that 'DepDelay' alone has a R2 of 0.9, so if we remove it we are losing an important feature to predict 'ArrDelay'.

We will use the dataset data_sample that has all the features, if we remove 'ArrDelay' we will have to make VIF analysis again to evaluate multicollinearity.

First we will drop the feature 'DepDelay'.

In [48]:
```
data_sample.head()
```

Out[48]:

	ArrDelay	ActualElapsedTime	CRSElapsedTime	AirTime	DepDelay	Distance	Speed	TaxiIn	Ta
143019	21.0000000000	95.0000000000	88.0000000000	63.0000000000	14.0000000000	364	346.6700000000	11.0000000000	21.00000
1886001	24.0000000000	139.0000000000	126.0000000000	105.0000000000	11.0000000000	813	464.5700000000	18.0000000000	16.00000
1881989	2.0000000000	86.0000000000	102.0000000000	65.0000000000	18.0000000000	490	452.3100000000	9.0000000000	12.00000
1030789	37.0000000000	114.0000000000	90.0000000000	87.0000000000	13.0000000000	442	304.8300000000	4.0000000000	23.00000
687997	10.0000000000	90.0000000000	88.0000000000	61.0000000000	8.0000000000	382	375.7400000000	7.0000000000	22.00000

In [49]:
```
data_sample.shape
```

Out[49]:
```
(192825, 637)
```

In [50]:
```
data_final = data_sample.copy()
```

In addition to 'DepDelay' we will also delete 'DelayInterval' since contains info about 'ArrDelay' but categorized (this column I created it in the first exercise)

In [51]:
```
# drop 'DepDelay' and 'DelayInterval'
data_final.drop(['DepDelay', 'DelayInterval'], axis = 1, inplace= True)
```

In [52]:
```
data_final.shape
```

Out[52]:
```
(192825, 635)
```

In [53]:
```
data_final.columns[1:22]
```

Out[53]:
```
Index(['ActualElapsedTime', 'CRSElapsedTime', 'AirTime', 'Distance', 'Speed',
       'TaxiIn', 'TaxiOut', 'CarrierDelay', 'WeatherDelay', 'NASDelay',
       'SecurityDelay', 'LateAircraftDelay', 'DepTime', 'CRSDepTime',
       'ArrTime', 'CRSArrTime', 'Month', 'DayofMonth', 'DayOfWeek',
       'UniqueCarrier_AA', 'UniqueCarrier_AQ'],
      dtype='object')
```

In [54]:
```
# features to evaluate multicollinearity:
cols = ['ActualElapsedTime', 'CRSElapsedTime', 'AirTime', 'Distance', 'Speed',
        'TaxiIn', 'TaxiOut', 'CarrierDelay', 'WeatherDelay', 'NASDelay',
        'SecurityDelay', 'LateAircraftDelay', 'DepTime', 'CRSDepTime',
        'ArrTime', 'CRSArrTime', 'Month', 'DayofMonth', 'DayOfWeek']
```

In [55]:
```
# import module to evaluate multicollinearity
from statsmodels.stats.outliers_influence import variance_inflation_factor

# we ´ll define a function that loops across al features and show their multicollinearity
def calculate_vif(df, cols):
    variables = df[cols]
    vif = pd.DataFrame()

    vif['VIF'] = [variance_inflation_factor(variables.values, i) for i in range(variables.shape[1])]
    vif['features'] = variables.columns
    return vif
```

In [56]:
```
calculate_vif(data_final, cols)
```

Out[56]:

	VIF	features
0	inf	ActualElapsedTime
1	245.7363588775	CRSElapsedTime
2	inf	AirTime
3	94.9029457809	Distance
4	31.1451418154	Speed
5	inf	TaxiIn
6	inf	TaxiOut
7	1.1618265398	CarrierDelay
8	1.0397106665	WeatherDelay
9	1.6318301006	NASDelay
10	1.0015683896	SecurityDelay
11	1.2914013093	LateAircraftDelay
12	64.2920918451	DepTime
13	65.4647007095	CRSDepTime
14	16.3433849154	ArrTime
15	39.6348959234	CRSArrTime
16	4.0187522360	Month
17	4.1477520497	DayofMonth
18	4.8481698255	DayOfWeek

- delete 'ActualElapsedTime'. 'TaxiIn', 'CRSDepTime' (we can delete them together because they are not correlated between each other)

In [57]:
```
data_final.drop([ 'ActualElapsedTime','TaxiIn', 'CRSDepTime'], axis = 1, inplace = True)
data_final.shape
```

Out[57]:
```
(192825, 632)
```

In [58]:
```
# evaluate vif again with remaining columns
cols =  ['CRSElapsedTime', 'AirTime', 'Distance', 'Speed', 'TaxiOut', 'CarrierDelay', 'WeatherDelay', 'NASDelay
        'SecurityDelay', 'LateAircraftDelay', 'DepTime',  'ArrTime', 'CRSArrTime', 'Month', 'DayofMonth', 'DayOf
calculate_vif(data_final, cols)
```

Out[58]:

	VIF	features
0	236.7007283891	CRSElapsedTime
1	198.4662078866	AirTime
2	92.9733222219	Distance
3	30.4784076721	Speed
4	3.7614264099	TaxiOut
5	1.1431276021	CarrierDelay
6	1.0359750747	WeatherDelay
7	1.5077971384	NASDelay
8	1.0014669259	SecurityDelay
9	1.2842450547	LateAircraftDelay
10	25.5332727704	DepTime
11	15.9337731632	ArrTime
12	36.2018100655	CRSArrTime
13	4.0148325042	Month
14	4.1449507572	DayofMonth
15	4.8352286234	DayOfWeek

- drop 'CRSElapsedTime', 'CRSArrTime'

In [59]:
```
data_final.drop([ 'CRSElapsedTime', 'CRSArrTime'], axis = 1, inplace = True)
data_final.shape
```

Out[59]:
```
(192825, 630)
```

In [60]:
```
cols =  [ 'AirTime', 'Distance', 'Speed', 'TaxiOut', 'CarrierDelay', 'WeatherDelay', 'NASDelay',
        'SecurityDelay', 'LateAircraftDelay', 'DepTime',  'ArrTime', 'Month', 'DayofMonth', 'DayOfWeek']
calculate_vif(data_final, cols)
```

Out[60]:

	VIF	features
0	96.2884375751	AirTime
1	86.0591888458	Distance
2	25.7105627114	Speed
3	3.3276291404	TaxiOut
4	1.1398150462	CarrierDelay
5	1.0353867745	WeatherDelay
6	1.4666311527	NASDelay
7	1.0012801849	SecurityDelay
8	1.2788338071	LateAircraftDelay
9	15.9393363281	DepTime
10	12.4470471196	ArrTime
11	4.0029270008	Month
12	4.1429779295	DayofMonth
13	4.8335642362	DayOfWeek

- drop 'AirTime' and 'DepTime'

In [61]:
```
data_final.drop(['AirTime','DepTime'], axis = 1, inplace= True)
data_final.shape
```

Out[61]:
```
(192825, 628)
```

In [62]:
```
cols =  ['Distance', 'Speed', 'TaxiOut', 'CarrierDelay', 'WeatherDelay', 'NASDelay',
        'SecurityDelay', 'LateAircraftDelay', 'ArrTime', 'Month', 'DayofMonth', 'DayOfWeek']
calculate_vif(data_final, cols)
```

Out[62]:

	VIF	features
0	4.3572211651	Distance
1	21.3171591452	Speed
2	3.2864654499	TaxiOut
3	1.1300343585	CarrierDelay
4	1.0325927511	WeatherDelay
5	1.4300775947	NASDelay
6	1.0011940839	SecurityDelay
7	1.2142223966	LateAircraftDelay
8	8.3143713897	ArrTime
9	3.9409143736	Month
10	4.0530068788	DayofMonth
11	4.7030819318	DayOfWeek

- Lastly, we will drop 'Speed'.

In [63]:
```
data_final.drop(['Speed'], axis = 1, inplace= True)
data_final.shape
```

Out[63]:
```
(192825, 627)
```

In [64]:
```
cols =  ['Distance', 'TaxiOut', 'CarrierDelay', 'WeatherDelay', 'NASDelay',
      'SecurityDelay', 'LateAircraftDelay', 'ArrTime', 'Month', 'DayofMonth', 'DayOfWeek']

calculate_vif(data_final, cols)
```

Out[64]:

	VIF	features
0	2.5976295963	Distance
1	3.1706768437	TaxiOut
2	1.1263764712	CarrierDelay
3	1.0325659941	WeatherDelay
4	1.3993505497	NASDelay
5	1.0011875757	SecurityDelay
6	1.2062993968	LateAircraftDelay
7	5.9749557045	ArrTime
8	3.6347775313	Month
9	3.7528621858	DayofMonth
10	4.1945767366	DayOfWeek

Now all of the features have a VIF under 10.

- Random Forest and XGBoost have been the models with better performance.
- I will choose for this exercise XGBoost because its prediction power is as good as Random Forest but it recquires much less computational power (aprox 5 times faster than Random Forest).

In [65]:
```
data_final.head()
```

Out[65]:

	ArrDelay	Distance	TaxiOut	CarrierDelay	WeatherDelay	NASDelay	SecurityDelay	LateAircraftDelay	ArrTi
143019	21.0000000000	364	21.0000000000	14.0000000000	0.0000000000	7.0000000000	0.0000000000	0.0000000000	1746.00000000
1886001	24.0000000000	813	16.0000000000	0.0000000000	0.0000000000	13.0000000000	0.0000000000	11.0000000000	1419.00000000
1881989	2.0000000000	490	12.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	1209.00000000
1030789	37.0000000000	442	23.0000000000	13.0000000000	0.0000000000	24.0000000000	0.0000000000	0.0000000000	2102.00000000
687997	10.0000000000	382	22.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	0.0000000000	1208.00000000

In [66]:
```
y = data_final['ArrDelay']
X = data_final.drop(['ArrDelay'], axis = 1)
```

In [67]:
```
print('data_final.shape: ' , data_final.shape)
print('X.shape: ', X.shape)
print('y.shape: ', y.shape)
```

```
data_final.shape:  (192825, 627)
X.shape:  (192825, 626)
y.shape:  (192825,)
```

In [68]:
```
# use test size of 0.3
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size= 0.3, random_state= 0)
```

In [69]:
```
print('X_train.shape: ', X_train.shape)
print('X_test.shape: ', X_test.shape)
print('y_train.shape: ', y_train.shape)
print('y_test.shape: ', y_test.shape)
```

```
X_train.shape:  (134977, 626)
X_test.shape:  (57848, 626)
y_train.shape:  (134977,)
y_test.shape:  (57848,)
```

XGBoost Regression model

Let´s see how well it performs our model without 'DepDelay' feature.

In [70]:
```
import xgboost as xgb

regressor = XGBRegressor()
regressor.fit(X_train, y_train)
```

Out[70]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.300000012,
             max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=100, n_jobs=8,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,
             reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

In [71]:
```
xgb_test_prediction = regressor.predict(X_test)
xgb_train_prediction = regressor.predict(X_train)

print_results_test(y_test, xgb_test_prediction)
print_results_train(y_train, xgb_train_prediction)
```

```
R2 for test set :  0.987861778128612
MSE (mean squared error) for test set:  39.20703310680892
------------------------------------------
R2 for train set :  0.9936557755501771
MSE (mean squared error) for train set:  20.5807972526312
```

This model shows quite good results in R2, let´s compare with our previous results:

In [72]:
```
# comparing this results with the results we got the first time we applied XGBRegressor
results_df[3:4]
```

Out[72]:

	Model	R2_test	MSE_test	R2_train	MSE_train
3	XGBoost Regression	0.9882029254	38.1051112017	0.9913355160	28.1077679962

- Deleting 'DepDelay' has caused the R2 to increase a little in train set but dicrease in test set
- MSE is lower in train without 'DepDelay' but higher in test set.

Let´s draw actual vs predicted values both in test and train set:

In [73]:
```
# df actual vs predicted in test and train
XGB_test_df = pd.DataFrame({'y_test': y_test, 'test_predictions' : xgb_test_prediction})
XGB_train_df = pd.DataFrame({'y_train' : y_train, 'train_predictions' : xgb_train_prediction})
```

In [74]:
```
# plot actual vs predicted
plt.figure(figsize = (18,9))
plt.suptitle('Actual vs Predicted in XGBoost Regression(without DepDelay) in test and train sets', fontsize = 1

plt.subplot(121)
plt.scatter(x= XGB_test_df['y_test'], y = XGB_test_df['test_predictions'] , alpha = 0.7)
plt.plot([0, 1750], [0, 1750], color = 'green', linewidth = 1.5, linestyle = 'dashed')
plt.xlabel('Actual values', fontsize= 13)
plt.ylabel('Predicted values', fontsize = 13)
plt.title('Actual vs Predicted values in test set', fontsize = 16)

plt.subplot(122)
plt.scatter(x=XGB_train_df['y_train'], y = XGB_train_df['train_predictions'], alpha = 0.7, c = 'magenta')
plt.plot([0, 1750], [0, 1750], color = 'green', linewidth = 1.5, linestyle = 'dashed')
plt.xlabel('Actual values', fontsize = 13)
plt.ylabel('Predicted values', fontsize = 13)
plt.title('Actual vs Predicted values in train set', fontsize = 16)
plt.tight_layout();
```

- We observe here the dispersion in test set is much more noticeable compared with the results we got in our models where we used DepDelay.
- The errors are more visisble compared with the train set too: the plot is much thinner around the 45° degree line in the train set than in test set.

Let´s see the distribution of errors in test set:

In [75]:
```
# create df of errors in test set
XGBoost_errors_df = pd.DataFrame({'Error Values' : (y_test -xgb_test_prediction)})
```

In [76]:
```
# now we plot it
plt.figure(figsize=(10, 7))
plt.title('Distribution of errors in test set with XGBoost Regression', fontsize = 16)
sns.kdeplot(data = XGBoost_errors_df, fill = True);
```

In [77]:
```
XGBoost_errors_df.describe().round(2)
```

Out[77]:

	Error Values
count	57848.0000000000
mean	0.0600000000
std	6.2600000000
min	-179.5500000000
25%	-1.5100000000
50%	0.0200000000
75%	1.8000000000
max	708.8200000000

- The max value of error here is the double of the model when we used DepDelay
- On the other hand, errors seem concentrated around values around zero.

Cross Validation

Since this model shows more differences between test and train than the model we used when we used 'depDelay' we will do cross validation now to compare the results.

In [78]:
```
from sklearn.model_selection import cross_val_score
# use cv=5, same as before
xgb_reg = XGBRegressor()
xgb_r2_scores = cross_val_score(xgb_reg, X, y, cv = 5)
xgb_r2_scores
```

Out[78]:
```
array([0.97235609, 0.99097991, 0.98266899, 0.98815041, 0.99189471])
```

In [79]:
```
# compute the mean of cv R2
r2_cv_xgb = np.mean(xgb_r2_scores)
r2_cv_xgb
```

Out[79]:
```
0.9852100210588507
```

In [81]:
```
xgb_mse_scores = cross_val_score(xgb_reg, X, y, cv = 5, scoring = 'neg_mean_squared_error')
xgb_mse_scores
```

Out[81]:
```
array([-108.3043837 ,  -28.13787229,  -64.6892613 ,  -31.22398048,
        -22.1609237 ])
```

In [82]:
```
# calculate the mean of mse in cv
mse_cv_xgb = abs(np.mean(xgb_mse_scores))
mse_cv_xgb
```

Out[82]:
```
50.90328429413569
```

Now, let´s compare these results with our previous Cross Validation results:

In [83]:
```
print('R2 cv without DepDelay: ',  r2_cv_xgb)
print('MSE cv withou DepDelay: ', mse_cv_xgb)
# open the dataframe with cross validation results :
cv_results = pd.read_csv('cv_results')
# add results from model without 'DepDelay' to our dataframe of cross validation results
cv_no_depdelay = pd.DataFrame(data= [['XGBoost Regression without DepDelay', r2_cv_xgb, mse_cv_xgb]],
                              columns = ['Model', 'R2', 'MSE'])
cv_results = pd.concat([cv_results, cv_no_depdelay])
cv_results[3:5]
```

```
R2 cv without DepDelay:  0.9852100210588507
MSE cv withou DepDelay:  50.90328429413569
```

Out[83]:

	Model	R2	MSE
3	XGBoost Regression	0.9874545799	40.1445838049
0	XGBoost Regression without DepDelay	0.9852100211	50.9032842941

- We observe that our R2 now is lower (0.985) and MSE is higher (50.90) than before.
- The model loses predcitive power when we delete DepDelay but it still has high predictive power.
- This may be explained from the fact that we have a lot of feratures that are hihgly correlated with 'ArrDelay'.

To show which features are important to predict 'ArrDelay' we can do a feature importance analyisis, that shows the importance of each feature. We will order these featutes from more to less important and select the 5 most important features (we will excelude dummy columns) :

Feature importance

In [89]:
```
X.columns[:11] # select the columns used in last model(we have droped DepDelay), we will exclude dummies
```

Out[89]:
```
Index(['Distance', 'TaxiOut', 'CarrierDelay', 'WeatherDelay', 'NASDelay',
       'SecurityDelay', 'LateAircraftDelay', 'ArrTime', 'Month', 'DayofMonth',
       'DayOfWeek'],
      dtype='object')
```

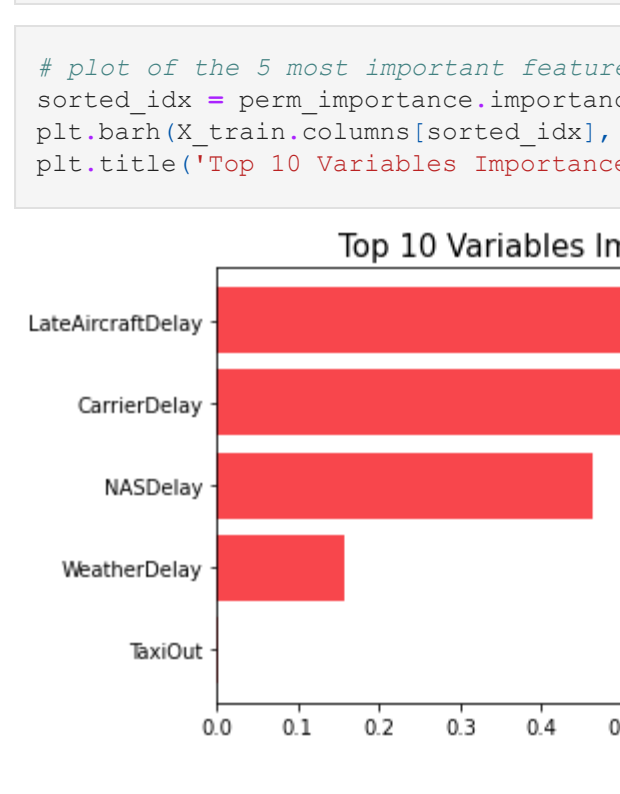
In [90]:
```
# let's do a feature importance analysis
regressor.feature_importances_[:11]
```

Out[90]:
```
array([0.00108322, 0.00068382, 0.2974295 , 0.14345698, 0.20989503,
       0.01257295, 0.27630112, 0.00107032, 0.00073453, 0.00086872,
       0.00030355], dtype=float32)
```

In [91]:
```
from sklearn.inspection import permutation_importance
# let´s do a plot with the  5 most important features of our model:

perm_importance = permutation_importance(regressor, X_test, y_test)
```

In [92]:
```
# plot of the 5 most important features in our last model (without DepDelay)
sorted_idx = perm_importance.importances_mean.argsort()[-5:]
plt.barh(X_train.columns[sorted_idx], perm_importance.importances_mean[sorted_idx], color = '#f8464c')
plt.title('Top 10 Variables Importance', fontsize = 15);
```



- Out of all the features (if we exclude 'DepDelay'), the most important ones in our last model are : LateAircraftDelay, CarrierDelay, NASDelay and WeatherDelay. This makes sense because in the cases where ArrDelay is bigger than 15, the delay is disaggregated between these features (these features are 0 in the cases where ArrDelay is less than 15 minutes).
- Actually, DepDelay is the sum of these features in the case where ArrDelay is less than 15.

What would happen if we do our model using only these 4 features?

We will do now our model using only these 4 features and see how it performs.

In [93]:
```
# choose dependent variable
y4 = data_sample['ArrDelay']
# we choose our 4 indeoendent features
X4 = data_sample[['WeatherDelay', 'NASDelay','LateAircraftDelay','CarrierDelay']]
```

In [95]:
```
print('X4.shape: ', X4.shape)
print('yshape:', y.shape)
```

```
X4.shape:  (192825, 4)
yshape: (192825,)
```

In [96]:
```
# use test size of 0.3 and same random state
X4_train, X4_test, y4_train, y4_test = train_test_split(X4, y4, test_size= 0.3, random_state= 0)
```

In [97]:
```
xgb_4regressor = XGBRegressor()
xgb_4regressor.fit(X4_train, y4_train)
```

Out[97]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.300000012,
             max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=100, n_jobs=8,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,
             reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

In [98]:
```
xgb4_test_prediction = xgb_4regressor.predict(X4_test)
xgb4_train_prediction = xgb_4regressor.predict(X4_train)

print_results_test(y4_test, xgb4_test_prediction)
print_results_train(y4_train, xgb4_train_prediction)
```

```
R2 for test set :  0.9876581318162035
MSE (mean squared error) for test set:  39.86482036735483
------------------------------------------
R2 for train set :  0.9916961446486076
MSE (mean squared error) for train set:  26.93788102136856
```

Seeing these results, we are able to predict 'ArrDelay' quite well using only 4 features!!

CONCLUSIONS

- We have performed models using all features available and compared the results with models using only some of the features
- 'DepDelay' alone can explain 90 % of the variability of the dependent variable 'ArrDelay'.
- 'DepDelay' is the sum of 'WeatherDelay', 'NASDelay','LateAircraftDelay','CarrierDelay' when ArrDelay > 15, so using a model with only these 4 features can return pretty good results.
- Removing 'DepDelay' does not decrease predictive power considerably because we have other features that measure delay too. In our exploratory exercise we saw that average delay varies depending on other features like Month or Carriers, it could also be interesting to build a model studying these other causes in a deeper way and exclude all the features that refer to delays (idea for another exercise).
- Although we have some outliers, the outliers in the important predictors are also outliers in the dependent variable, so the results are not so much affected by outliers (if some of the causes of delay has a big outlier, 'ArrDelay' will be an outlier too in that observation)
- Scaling the features doesn' t change our model so much since the most important predictors are in the same scale as our dependent variable (scaling improves the best performing models but very little). Besides R2 without scaling is already very high, so there's actually little room for improvement.
- Regarding to the models we used, the ones with better results have been Random Forest and XGboost Regressor, but XGBoost is much more efficient with respect to the computational time (5 times faster than Random Forest).

In [ ]: