Car-CO2-Emission-Prediction

February 11, 2019

Car CO2 Emission Prediction (Regression)

About this notebook

In this notebook, I will use data about cars and regression models to predict CO2 emission. This data provides model-specific fuel consumption ratings and estimated carbon dioxide emissions for new light-duty vehicles for retail sale in Canada.

Note: This is a part of IBM Data Scientist course projects.

Table of contents

```
<ol>
    1. Variable Descriptions</ol>
    <ol>2. Understand Data</ol>
    <ol>3. Linear Regression</ol>
    <ol>4. Non-linear Regression</ol>
        <ol>4.1 Polynomial Regression</ol>
        <ol>4.2 Ridge Regression</ol>
</ol>
```

```
In [15]: #import packages
         import matplotlib.pyplot as plt
         import pandas as pd
         import pylab as pl
         import numpy as np
         %matplotlib inline
         import seaborn as sns
```

```
In [9]: #get data
        df=pd.read_csv(r'https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/Cogn
```

This dataset has 1,067 observations and 13 columns.

Variable Descriptions

We have downloaded a fuel consumption dataset, **FuelConsumption.csv**, which contains model-specific fuel consumption ratings and estimated carbon dioxide emissions for new light-duty vehicles for retail sale in Canada. Dataset source

- **MODELYEAR** e.g. 2014
- **MAKE** e.g. Acura
- **MODEL** e.g. ILX
- **VEHICLE CLASS** e.g. SUV

- **ENGINE SIZE** e.g. 4.7
- **CYLINDERS** e.g 6
- **TRANSMISSION** e.g. A6
- **FUEL CONSUMPTION in CITY(L/100 km)** e.g. 9.9
- **FUEL CONSUMPTION in HWY (L/100 km)** e.g. 8.9
- **FUEL CONSUMPTION COMB (L/100 km)** e.g. 9.2
- **CO2 EMISSIONS (g/km)** e.g. 182

Understand Data

In [12]:
```
#shape of the data
df.shape
```

Out[12]: (1067, 13)

In [10]:
```
#the head of data
df.head()
```

Out[10]:
```
   MODELYEAR   MAKE       MODEL VEHICLECLASS  ENGINESIZE  CYLINDERS  \
0       2014  ACURA         ILX      COMPACT         2.0          4
1       2014  ACURA         ILX      COMPACT         2.4          4
2       2014  ACURA  ILX HYBRID      COMPACT         1.5          4
3       2014  ACURA     MDX 4WD  SUV - SMALL         3.5          6
4       2014  ACURA     RDX AWD  SUV - SMALL         3.5          6

  TRANSMISSION FUELTYPE  FUELCONSUMPTION_CITY  FUELCONSUMPTION_HWY  \
0          AS5        Z                   9.9                  6.7
1           M6        Z                  11.2                  7.7
2          AV7        Z                   6.0                  5.8
3          AS6        Z                  12.7                  9.1
4          AS6        Z                  12.1                  8.7

   FUELCONSUMPTION_COMB  FUELCONSUMPTION_COMB_MPG  CO2EMISSIONS
0                   8.5                        33           196
1                   9.6                        29           221
2                   5.9                        48           136
3                  11.1                        25           255
4                  10.6                        27           244
```

In [103]:
```
df.dtypes
```

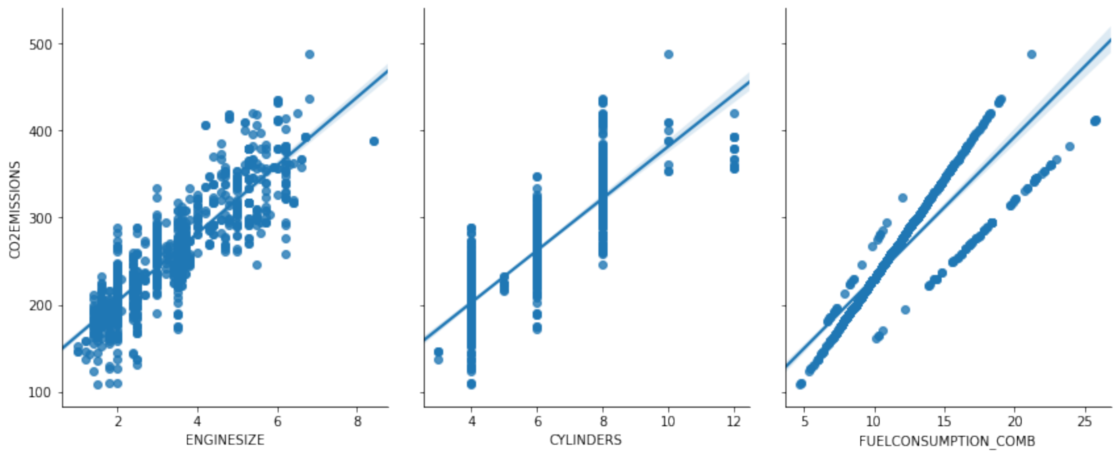
Out[103]:
```
MODELYEAR                     int64
MAKE                         object
MODEL                        object
VEHICLECLASS                 object
ENGINESIZE                  float64
CYLINDERS                     int64
TRANSMISSION                 object
FUELTYPE                     object
```

```
FUELCONSUMPTION_CITY        float64
FUELCONSUMPTION_HWY         float64
FUELCONSUMPTION_COMB        float64
FUELCONSUMPTION_COMB_MPG      int64
CO2EMISSIONS                  int64
dtype: object
```

In [13]:
```
#see the descriptive statistics of the numeric variables
df.describe()
```

Out[13]:
```
       MODELYEAR   ENGINESIZE    CYLINDERS  FUELCONSUMPTION_CITY  \
count     1067.0  1067.000000  1067.000000           1067.000000
mean      2014.0     3.346298     5.794752             13.296532
std          0.0     1.415895     1.797447              4.101253
min       2014.0     1.000000     3.000000              4.600000
25%       2014.0     2.000000     4.000000             10.250000
50%       2014.0     3.400000     6.000000             12.600000
75%       2014.0     4.300000     8.000000             15.550000
max       2014.0     8.400000    12.000000             30.200000

       FUELCONSUMPTION_HWY  FUELCONSUMPTION_COMB  FUELCONSUMPTION_COMB_MPG  \
count          1067.000000           1067.000000               1067.000000
mean              9.474602             11.580881                 26.441425
std               2.794510              3.485595                  7.468702
min               4.900000              4.700000                 11.000000
25%               7.500000              9.000000                 21.000000
50%               8.800000             10.900000                 26.000000
75%              10.850000             13.350000                 31.000000
max              20.500000             25.800000                 60.000000

       CO2EMISSIONS
count   1067.000000
mean     256.228679
std       63.372304
min      108.000000
25%      207.000000
50%      251.000000
75%      294.000000
max      488.000000
```

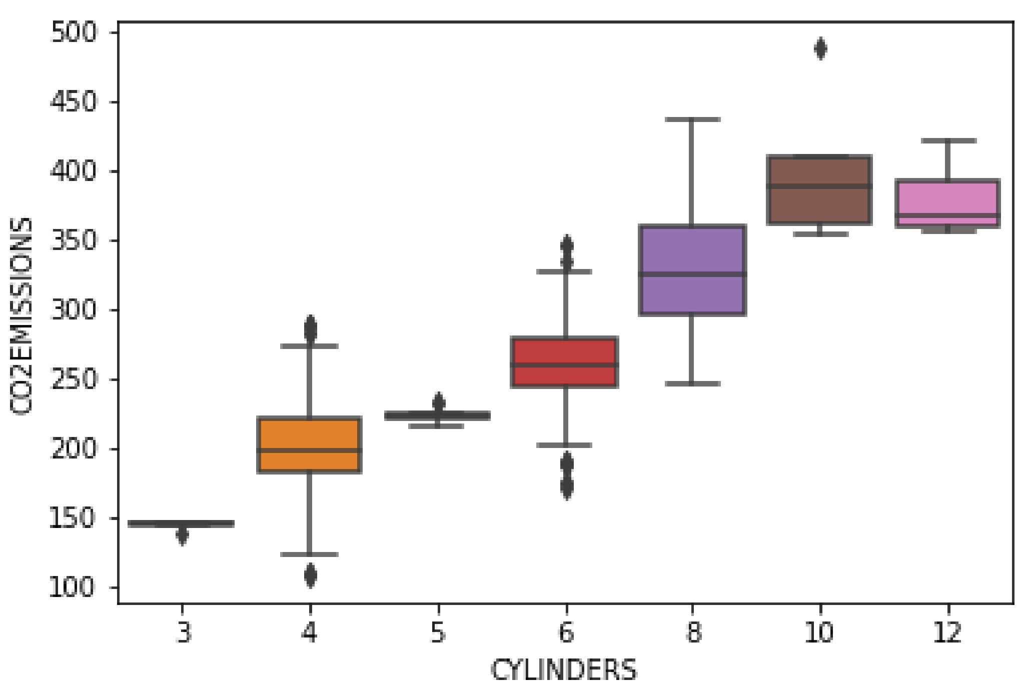
In [19]:
```
#Generate scatter plots for numeric variables VS CO2EMISSIONS to see if correlations
sns.pairplot(df, x_vars=["ENGINESIZE", "CYLINDERS", 'FUELCONSUMPTION_COMB'], y_vars=['
             height=5, aspect=.8, kind="reg");
```



CYLINDERS are categorical. There are 5 distinct values in the dataset. We want to see if there are any difference in the mean of each type of cylinder numbers realting to CO2EMISSIONS.

```
In [25]: #box plot for CYLINERS
         sns.boxplot(x="CYLINDERS", y="CO2EMISSIONS", data=df)
```

```
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x20c70bbf630>
```



So, the number of cylinders has some influence in CO2EMISSIONS.

There are four columns about fuel consumptions: FUELCONSUMPTION_CITY, FUELCONSUMPTION_HWY, FUELCONSUMPTION_COMB, and FUELCONSUMPTION_COMB_MPG. If they are highly correlated, we can eliminate some of them to make the model lighter. We will run a correlation.

In [29]:
```
df.corr()
```

Out[29]:
```
                          MODELYEAR  ENGINESIZE  CYLINDERS  \
MODELYEAR                       NaN         NaN        NaN
ENGINESIZE                      NaN    1.000000   0.934011
CYLINDERS                       NaN    0.934011   1.000000
FUELCONSUMPTION_CITY            NaN    0.832225   0.796473
FUELCONSUMPTION_HWY             NaN    0.778746   0.724594
FUELCONSUMPTION_COMB            NaN    0.819482   0.776788
FUELCONSUMPTION_COMB_MPG        NaN   -0.808554  -0.770430
CO2EMISSIONS                    NaN    0.874154   0.849685

                          FUELCONSUMPTION_CITY  FUELCONSUMPTION_HWY  \
MODELYEAR                                  NaN                  NaN
ENGINESIZE                            0.832225             0.778746
CYLINDERS                             0.796473             0.724594
FUELCONSUMPTION_CITY                  1.000000             0.965718
FUELCONSUMPTION_HWY                   0.965718             1.000000
FUELCONSUMPTION_COMB                  0.995542             0.985804
FUELCONSUMPTION_COMB_MPG             -0.935613            -0.893809
CO2EMISSIONS                          0.898039             0.861748

                          FUELCONSUMPTION_COMB  FUELCONSUMPTION_COMB_MPG  \
MODELYEAR                                  NaN                       NaN
ENGINESIZE                            0.819482                 -0.808554
CYLINDERS                             0.776788                 -0.770430
FUELCONSUMPTION_CITY                  0.995542                 -0.935613
FUELCONSUMPTION_HWY                   0.985804                 -0.893809
FUELCONSUMPTION_COMB                  1.000000                 -0.927965
FUELCONSUMPTION_COMB_MPG             -0.927965                  1.000000
CO2EMISSIONS                          0.892129                 -0.906394

                          CO2EMISSIONS
MODELYEAR                          NaN
ENGINESIZE                    0.874154
CYLINDERS                     0.849685
FUELCONSUMPTION_CITY          0.898039
FUELCONSUMPTION_HWY           0.861748
FUELCONSUMPTION_COMB          0.892129
FUELCONSUMPTION_COMB_MPG     -0.906394
CO2EMISSIONS                  1.000000
```

So, we can use one of the columns about fuel consumption without lossing too much information.Now we know ENGINESIZE, CYLINERS, and FUELCOMSUMPTION_COMB are useful for

building the regression model.
Linear Regression

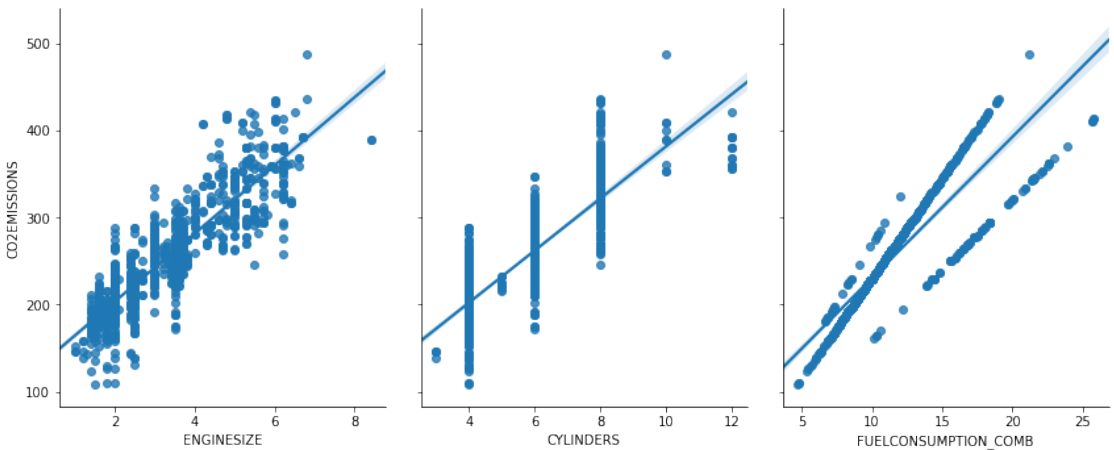
```
In [34]: #create a new dataframe for model building
         lrdf = df[['ENGINESIZE','CYLINDERS','FUELCONSUMPTION_COMB','CO2EMISSIONS']]
         lrdf.shape
```

```
Out[34]: (1067, 4)
```

```
In [35]: #spilt train and test data
         msk = np.random.rand(len(df)) < 0.8
         train = lrdf[msk]
         test = lrdf[~msk]
```

```
In [37]: #train data distribution
         sns.pairplot(lrdf, x_vars=['ENGINESIZE', 'CYLINDERS', 'FUELCONSUMPTION_COMB'], y_vars=
                      height=5, aspect=.8, kind="reg")
```

```
Out[37]: <seaborn.axisgrid.PairGrid at 0x20c70c95f60>
```




```
In [46]: #build the model
         #step 1, import packages
         from sklearn.linear_model import LinearRegression
         lm=LinearRegression()

         #step 2, create independent variables
         X=train[['ENGINESIZE', 'CYLINDERS', 'FUELCONSUMPTION_COMB']]
         Y=train[['CO2EMISSIONS']]
```

```
In [47]: #step 3, fit the linear regression model
         lm.fit(X,Y)
         # The coefficients
         print ('Coefficients: ', lm.coef_)
         print ('Intercept: ',lm.intercept_)
```

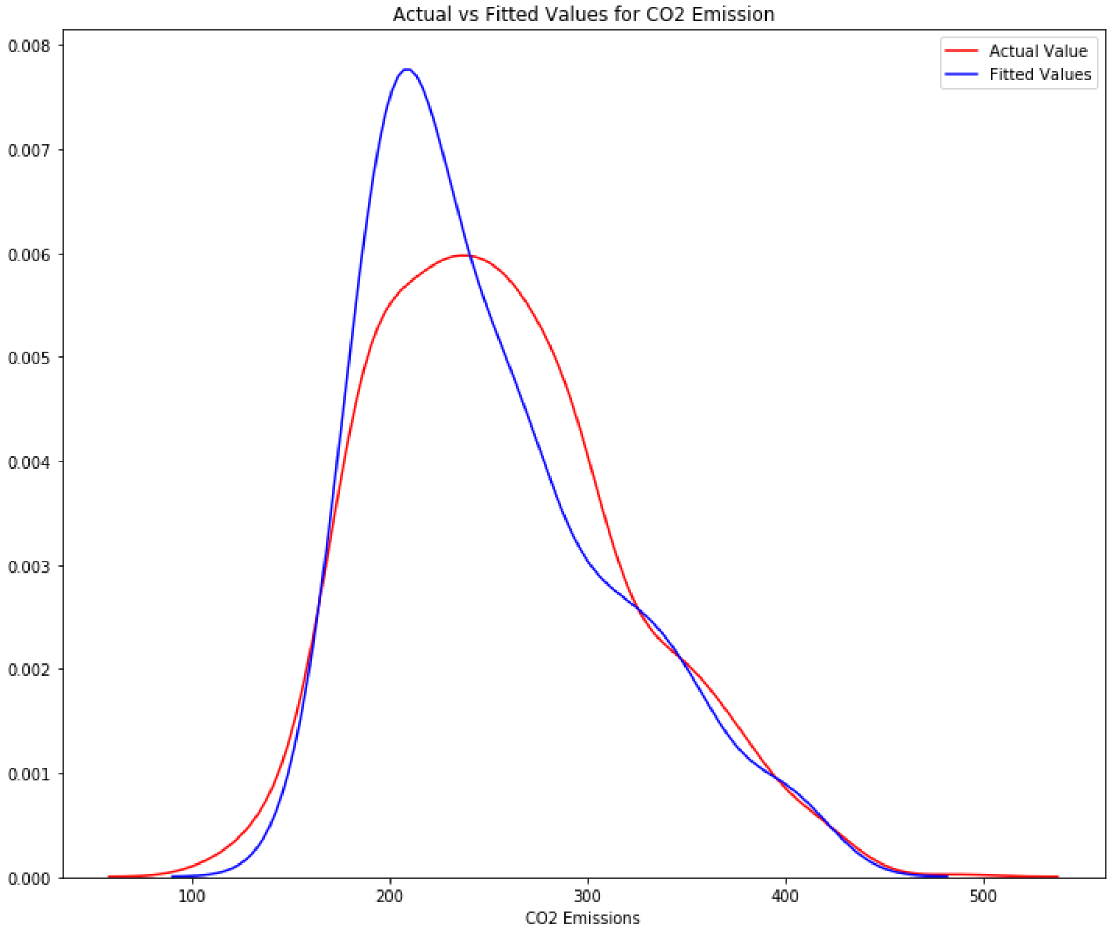
```
Coefficients:  [[ 9.92107897  7.75011521 10.0252928 ]]
Intercept:  [61.92097822]
```

Now the model equation is: Y = 61.92097822 + 9.92107897*ENGINESIZE + 7.75011521*CYLINDERS + 10.0252928*FUELCONSUMPTION_COMB + Error

```
In [48]: #model evaluation
         from sklearn.metrics import r2_score

         test_x = test[['ENGINESIZE', 'CYLINDERS', 'FUELCONSUMPTION_COMB']]
         test_y = test[['CO2EMISSIONS']]
         test_y_hat = lm.predict(test_x)

         print("Mean absolute error: %.2f" % np.mean(np.absolute(test_y_hat - test_y)))
         print("Residual sum of squares (MSE): %.2f" % np.mean((test_y_hat - test_y) ** 2))
         print("R2-score: %.2f" % r2_score(test_y_hat , test_y) )
```

```
Mean absolute error: 16.67
Residual sum of squares (MSE): 527.73
R2-score: 0.85
```

```
In [51]: #Distribution Plot
         width = 12
         height = 10
         plt.figure(figsize=(width, height))

         ax1 = sns.distplot(lrdf['CO2EMISSIONS'], hist=False, color="r", label="Actual Value")
         sns.distplot(test_y_hat, hist=False, color="b", label="Fitted Values" , ax=ax1)

         plt.title('Actual vs Fitted Values for CO2 Emission')
         plt.xlabel('CO2 Emissions')
         plt.ylabel('')

         plt.show()
         plt.close()
```



Non Linear Regression

Although the above linear model fits well (R^2 is 0.85), as seen from the distribution plot, it fails to explain some data points. This time we try non-linear regression models.

Polynomial Model

```
In [53]: #import packages
         from sklearn.preprocessing import PolynomialFeatures
         from sklearn import linear_model

In [55]: #first, try ENGINESIZE as the only independent variable
         train_x=train[['ENGINESIZE']]
         train_y=train[['CO2EMISSIONS']]
         poly = PolynomialFeatures(degree=2)
         train_x_poly = poly.fit_transform(train_x)
         train_x_poly

Out[55]: array([[ 1.  ,  2.  ,  4.  ],
                [ 1.  ,  2.4 ,  5.76],
                [ 1.  ,  1.5 ,  2.25],
```

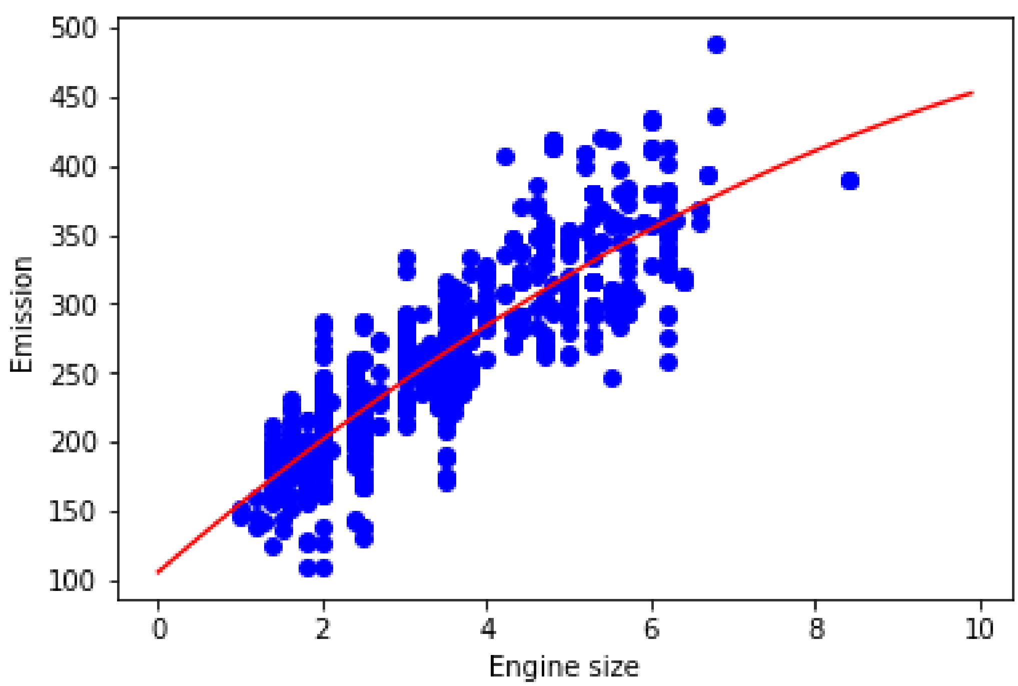
```
            ...,
            [ 1.   ,  3.   ,  9.  ],
            [ 1.   ,  3.2 , 10.24],
            [ 1.   ,  3.2 , 10.24]])
```

In [59]:
```
train_y_ = lm.fit(train_x_poly, train_y)
# The coefficients
print ('Coefficients: ', lm.coef_)
print ('Intercept: ',lm.intercept_)
```

```
Coefficients:  [[ 0.         51.17136746 -1.63000129]]
Intercept:  [105.69276866]
```

In [60]:
```
plt.scatter(train.ENGINESIZE, train.CO2EMISSIONS,  color='blue')
XX = np.arange(0.0, 10.0, 0.1)
yy = lm.intercept_[0]+ lm.coef_[0][1]*XX+ lm.coef_[0][2]*np.power(XX, 2)
plt.plot(XX, yy, '-r' )
plt.xlabel("Engine size")
plt.ylabel("Emission")
```

Out[60]: Text(0, 0.5, 'Emission')



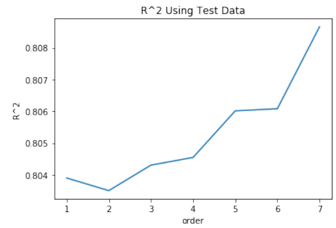
In [62]:
```
#Evaluation
test_x = test[['ENGINESIZE']]
```

```
test_y = test[['CO2EMISSIONS']]
test_x_poly = poly.fit_transform(test_x)
test_y_ = lm.predict(test_x_poly)

print("Mean absolute error: %.2f" % np.mean(np.absolute(test_y_ - test_y)))
print("Residual sum of squares (MSE): %.2f" % np.mean((test_y_ - test_y) ** 2))
print("R2-score: %.2f" % r2_score(test_y_ , test_y) )
```

```
Mean absolute error: 20.65
Residual sum of squares (MSE): 737.28
R2-score: 0.74
```

In [73]:
```
#Optimize the polynomial degrees
Rsqu_test = []

order = [1, 2, 3, 4, 5, 6, 7]
for n in order:
    poly = PolynomialFeatures(degree=n)
    train_x=train[['ENGINESIZE']]
    train_y=train[['CO2EMISSIONS']]
    train_x_poly = poly.fit_transform(train_x)
    test_x = test[['ENGINESIZE']]
    test_y = test[['CO2EMISSIONS']]
    test_x_poly = poly.fit_transform(test_x)
 #lr=LinearRegression()
    lm.fit(train_x_poly, train_y)
    Rsqu_test.append(lm.score(test_x_poly, test_y))

plt.plot(order, Rsqu_test)
plt.xlabel('order')
plt.ylabel('R^2')
plt.title('R^2 Using Test Data')
plt.text(3, 0.75, 'Maximum R^2 ')
```

Out[73]: Text(3, 0.75, 'Maximum R^2 ')

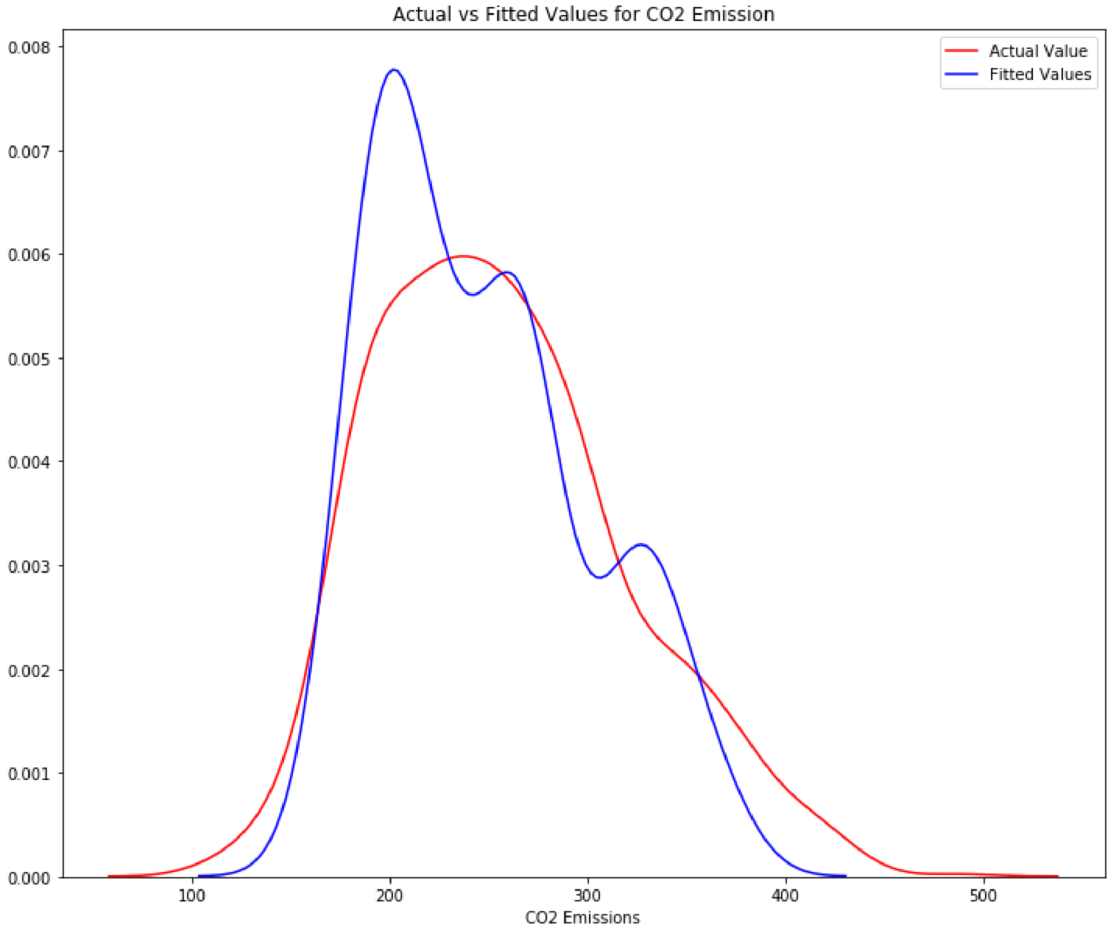


Maximum R^2

When the polynomial degree for ENGINESIZE is 4, we have a good R^2. Although it the R^2 increases when the degree increases, we use degreee=4 because it's not necessary to let the degree equal to 7 or even higer. The model may fit the noise too well. Let's have a look of the distribution plot.

```
In [81]: #degree equals to 4
         poly = PolynomialFeatures(degree=4)
         train_x=train[['ENGINESIZE']]
         train_y=train[['CO2EMISSIONS']]
         train_x_poly = poly.fit_transform(train_x)
         test_x = test[['ENGINESIZE']]
         test_y = test[['CO2EMISSIONS']]
         test_x_poly = poly.fit_transform(test_x)
         lm.fit(train_x_poly, train_y)
         test_y_hat=lm.predict(test_x_poly)

         width = 12
         height = 10

         plt.figure(figsize=(width, height))

         ax1 = sns.distplot(lrdf['CO2EMISSIONS'], hist=False, color="r", label="Actual Value")
         sns.distplot(test_y_hat, hist=False, color="b", label="Fitted Values" , ax=ax1)

         plt.title('Actual vs Fitted Values for CO2 Emission')
         plt.xlabel('CO2 Emissions')
         plt.ylabel('')

         plt.show()
         plt.close()
```

```
D:\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple seq
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Ridge Regression

We will use Ridge Regression to improve the model. Ridge Regression controls the degree of polynomial regression by the parameter Alpha. Ridge Regression has the following benefits: -reduce the multicollinearity of endogenous variables in models -reduce model complexity and prevent over-fitting which may result from simple linear regression.

In [123]:
```
#prepare data
x_data = lrdf[['ENGINESIZE', 'CYLINDERS', 'FUELCONSUMPTION_COMB']]
y_data= lrdf[['CO2EMISSIONS']]
train_x, test_x, train_y, test_y = train_test_split(x_data, y_data, test_size=0.2, ra
poly=PolynomialFeatures(degree=2)
lm=LinearRegression()
```

In [117]:
```
#import packages
from sklearn.linear_model import Ridge
```

Let's create a Ridge regression object, setting the regularization parameter to 0.1

In [118]:
```
RigeModel=Ridge(alpha=0.1)
```

```
In [124]: train_x_poly= poly.fit_transform(train_x)
          test_x_poly = poly.fit_transform(test_x)
```

```
In [125]: RigeModel.fit(train_x_poly, train_y)
          yhat = RigeModel.predict(test_x_poly)
```

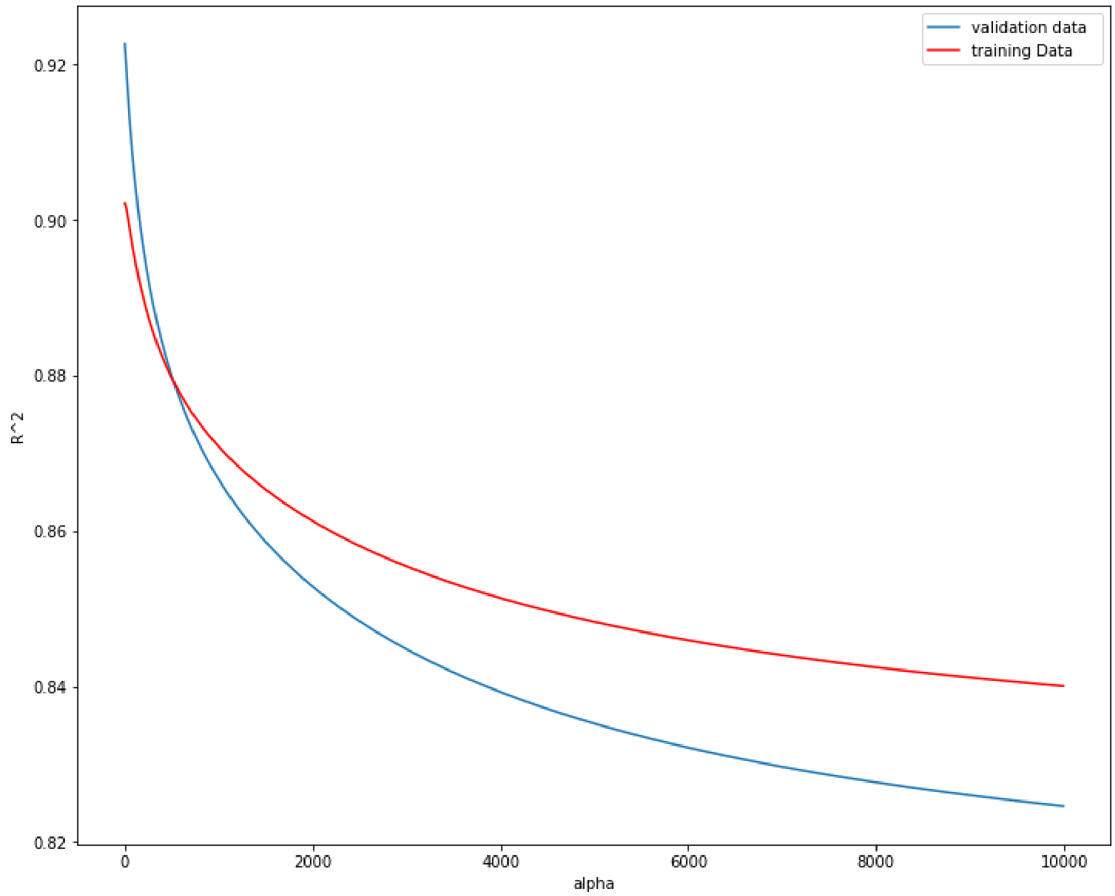
```
In [127]: print('predicted:', yhat[0:4])
          print('test set :', test_y[0:4].values)
```

```
predicted: [[346.34060871]
 [211.77465377]
 [224.66033349]
 [221.681592  ]]
test set : [[356]
 [209]
 [230]
 [212]]
```

```
In [128]: Rsqu_test = []
          Rsqu_train = []
          dummy1 = []
          ALFA = 10 * np.array(range(0,1000))
          for alfa in ALFA:
              RigeModel = Ridge(alpha=alfa)
              RigeModel.fit(train_x_poly, train_y)
              Rsqu_test.append(RigeModel.score(test_x_poly, test_y))
              Rsqu_train.append(RigeModel.score(train_x_poly, train_y))
```

```
In [129]: #plot for different alfa
          width = 12
          height = 10
          plt.figure(figsize=(width, height))

          plt.plot(ALFA,Rsqu_test, label='validation data  ')
          plt.plot(ALFA,Rsqu_train, 'r', label='training Data ')
          plt.xlabel('alpha')
          plt.ylabel('R^2')
          plt.legend()
```

```
Out[129]: <matplotlib.legend.Legend at 0x20c72115c18>
```



The blue line represents the R^2 of the test data, and the red line represents the R^2 of the training data. The x-axis represents the different values of Alpha. The red line in represents the R^2 of the test data, as Alpha increases the R^2 decreases; therefore as Alpha increases the model performs worse on the test data. The blue line represents the R^2 on the validation data, as the value for Alpha increases the R^2 decreases.

Lower alpha value (lower polynomial degree) will yield better R^2. Let's find the exact alpha value and then determine the model.

In [189]:
```
x_data = lrdf[['ENGINESIZE','CYLINDERS','FUELCONSUMPTION_COMB']]
y_data= lrdf[['CO2EMISSIONS']]
train_x, test_x, train_y, test_y = train_test_split(x_data, y_data, test_size=0.2, ra
```

In [ ]:
```
alphas = 10**np.linspace(10,-2,100)*0.5
alphas
```

In [190]:
```
ridge = Ridge(normalize = True)
coefs = []

for a in alphas:
    ridge.set_params(alpha = a)
```

```
        ridge.fit(train_x, train_y)
        coefs.append(ridge.coef_)

    np.shape(coefs)
```

```
Out[190]: (100, 1, 3)
```

```
In [181]: from sklearn.preprocessing import scale
          from sklearn.model_selection import train_test_split
          from sklearn.linear_model import Ridge, RidgeCV, Lasso, LassoCV
          from sklearn.metrics import mean_squared_error
```

```
In [191]: #obtian the best alpha by cross-vaildation
          ridgecv = RidgeCV(alphas = alphas, scoring = 'neg_mean_squared_error', normalize = T
          ridgecv.fit(train_x, train_y)
          ridgecv.alpha_
```

```
Out[191]: 0.01155064850041579
```

Therefore, we see that the value of alpha that results in the smallest cross-validation error is 0.012.

```
In [192]: #obtain the RMSE
          ridge = Ridge(alpha = ridgecv.alpha_, normalize = True)
          ridge.fit(train_x, train_y)
          mean_squared_error(test_y, ridge.predict(test_x))
```

```
Out[192]: 593.7935827354731
```

```
In [195]: #Use the optimized alpha for the new ridge regression model using all data
          ridge_final = Ridge(alpha=0.012)
          ridge_final.fit(x_data, y_data)
          ridge_final.coef_
```

```
Out[195]: array([[10.85494779,  7.51636562,  9.5956638 ]])
```

Is it necessary to use Ridge Regression than Linear Regression? We compare the MSE. The MSE obtained from the linear regression model is 737.28, however MSE from Ridge Regression is much better: 593.79. So in this case, we use the Ridge Regression model.