

ML0101EN-Reg-Simple-Linear-Regression-Co2-py-v1

April 1, 2019

```
#  
Simple Linear Regression
```

About this Notebook In this notebook, we learn how to use scikit-learn to implement simple linear regression. We download a dataset that is related to fuel consumption and Carbon dioxide emission of cars. Then, we split our data into training and test sets, create a model using training set, Evaluate your model using test set, and finally use model to predict unknown value

0.0.1 Importing Needed packages

```
In [2]: import matplotlib.pyplot as plt  
import pandas as pd  
import pylab as pl  
import numpy as np  
%matplotlib inline
```

0.0.2 Downloading Data

To download the data, we will use !wget to download it from IBM Object Storage.

```
In [3]: !wget -O FuelConsumption.csv https://s3-api.us-gio.objectstorage.softlayer.net/cf-course  
--2019-04-01 16:00:20-- https://s3-api.us-gio.objectstorage.softlayer.net/cf-courses-data/Cognit  
Resolving s3-api.us-gio.objectstorage.softlayer.net (s3-api.us-gio.objectstorage.softlayer.net).  
Connecting to s3-api.us-gio.objectstorage.softlayer.net (s3-api.us-gio.objectstorage.softlayer.n  
HTTP request sent, awaiting response... 200 OK  
Length: 72629 (71K) [text/csv]  
Saving to: FuelConsumption.csv  
  
FuelConsumption.csv 100%[=====>] 70.93K --.-KB/s in 0.04s  
  
2019-04-01 16:00:20 (1.65 MB/s) - FuelConsumption.csv saved [72629/72629]
```

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0.1 Understanding the Data

0.1.1 FuelConsumption.csv:

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 --> low --> 0

0.2 Reading the data in

```
In [4]: df = pd.read_csv("FuelConsumption.csv")
```

```
# take a look at the dataset  
df.head()
```

```
Out[4]:
```

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINE SIZE	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

0.2.1 Data Exploration

Lets first have a descriptive exploration on our data.

```
In [5]: # summarize the data
df.describe()
```

```
Out [5]:
```

	MODELYEAR	ENGINE SIZE	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

Lets select some features to explore more.

```
In [6]: cdf = df[['ENGINE SIZE', 'CYLINDERS', 'FUELCONSUMPTION_COMB', 'CO2EMISSIONS']]
cdf.head(9)
```

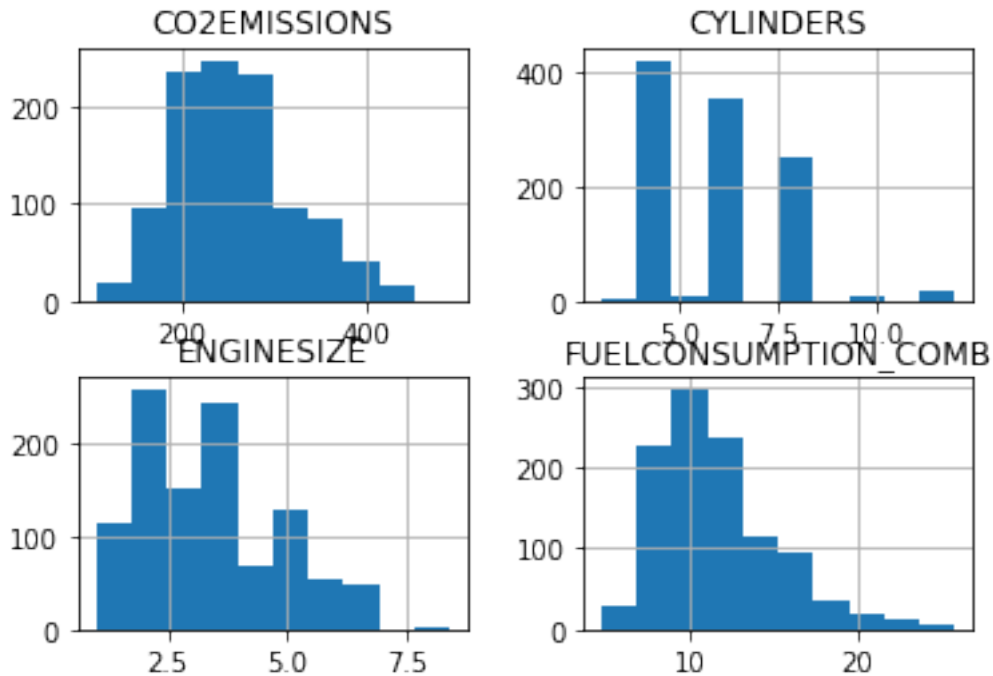
```
Out [6]:
```

	ENGINE SIZE	CYLINDERS	FUELCONSUMPTION_COMB	CO2EMISSIONS
0	2.0	4	8.5	196
1	2.4	4	9.6	221
2	1.5	4	5.9	136
3	3.5	6	11.1	255
4	3.5	6	10.6	244
5	3.5	6	10.0	230

6	3.5	6	10.1	232
7	3.7	6	11.1	255
8	3.7	6	11.6	267

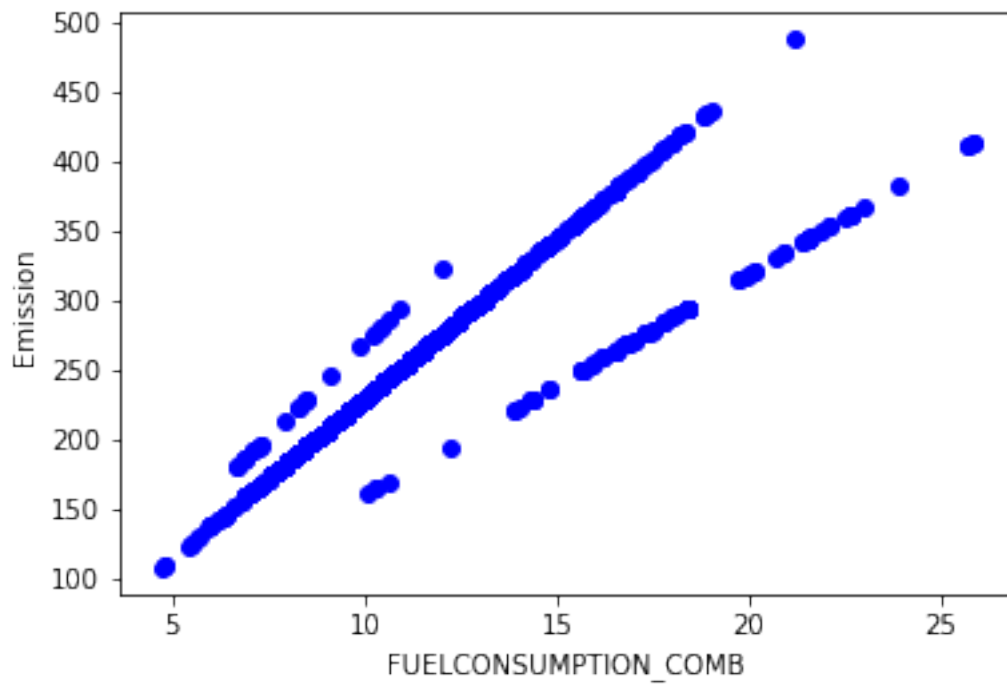
we can plot each of these features:

```
In [7]: viz = cdf[['CYLINDERS', 'ENGINE_SIZE', 'CO2EMISSIONS', 'FUELCONSUMPTION_COMB']]
viz.hist()
plt.show()
```

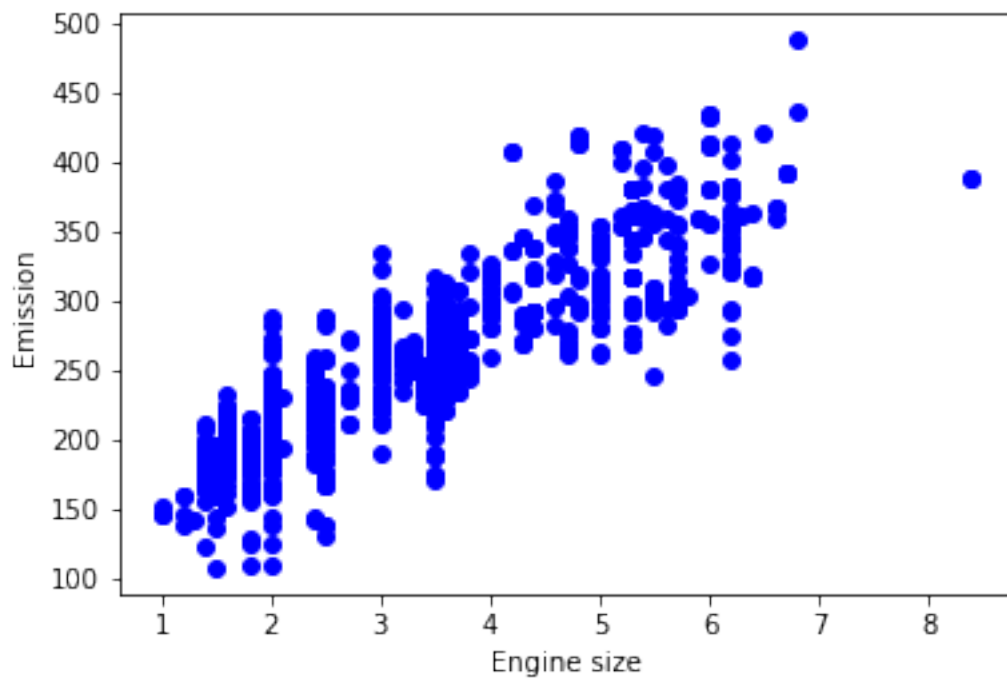


Now, let's plot each of these features vs the Emission, to see how linear is their relation:

```
In [8]: plt.scatter(cdf.FUELCONSUMPTION_COMB, cdf.CO2EMISSIONS, color='blue')
plt.xlabel("FUELCONSUMPTION_COMB")
plt.ylabel("Emission")
plt.show()
```



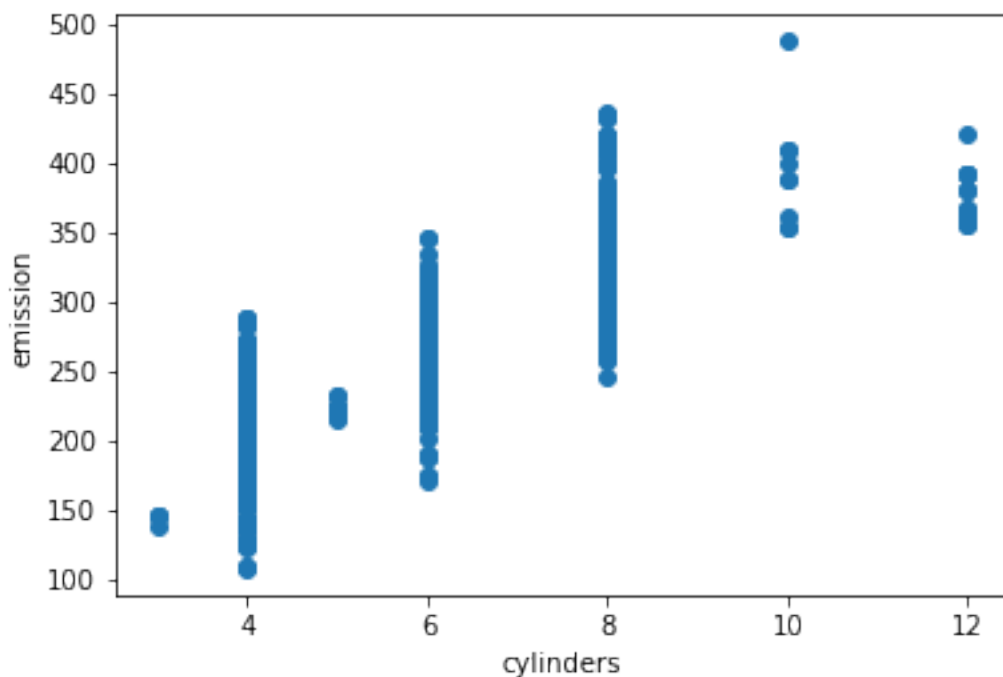
```
In [9]: plt.scatter(cdf.ENGINESIZE, cdf.CO2EMISSIONS, color='blue')
plt.xlabel("Engine size")
plt.ylabel("Emission")
plt.show()
```



0.3 Practice

plot **CYLINDER** vs the Emission, to see how linear is their relation:

```
In [10]: # write your code here
plt.scatter(cdf.CYLINDERS, cdf.CO2EMISSIONS)
plt.xlabel("cylinders")
plt.ylabel("emission")
plt.show()
```



Double-click [here](#) for the solution.

Creating train and test dataset Train/Test Split involves splitting the dataset into training and testing sets respectively, which are mutually exclusive. After which, you train with the training set and test with the testing set. This will provide a more accurate evaluation on out-of-sample accuracy because the testing dataset is not part of the dataset that have been used to train the data. It is more realistic for real world problems.

This means that we know the outcome of each data point in this dataset, making it great to test with! And since this data has not been used to train the model, the model has no knowledge of the outcome of these data points. So, in essence, it is truly an out-of-sample testing.

Lets split our dataset into train and test sets, 80% of the entire data for training, and the 20% for testing. We create a mask to select random rows using **np.random.rand()** function:

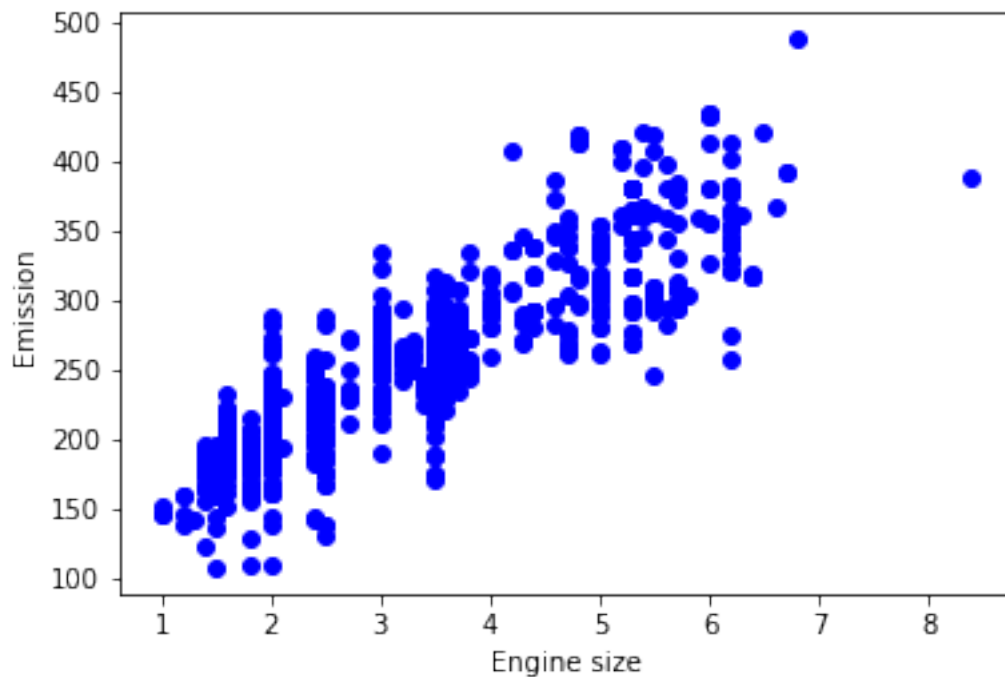
```
In [11]: msk = np.random.rand(len(df)) < 0.8
        train = cdf[msk]
        test = cdf[~msk]
```

0.3.1 Simple Regression Model

Linear Regression fits a linear model with coefficients $B = (B_1, \dots, B_n)$ to minimize the 'residual sum of squares' between the independent x in the dataset, and the dependent y by the linear approximation.

Train data distribution

```
In [12]: plt.scatter(train.ENGINESIZE, train.CO2EMISSIONS, color='blue')
        plt.xlabel("Engine size")
        plt.ylabel("Emission")
        plt.show()
```



Modeling Using sklearn package to model data.

```
In [18]: from sklearn import linear_model
        regr = linear_model.LinearRegression()
        train_x = train[['ENGINE SIZE']]
        train_y = train[['CO2 EMISSIONS']]
        regr.fit(train_x, train_y)
        # The coefficients
```

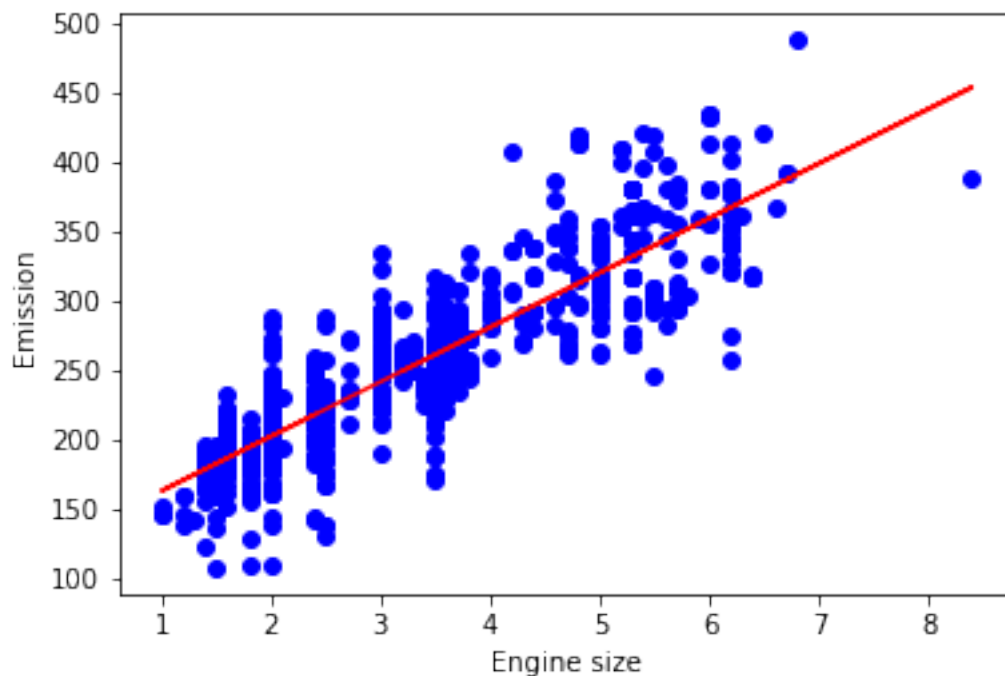
```
print ('Coefficients: ', regr.coef_)
print ('Intercept: ',regr.intercept_)
```

```
Coefficients:  [[39.2733887]]
Intercept:    [124.0456377]
```

As mentioned before, **Coefficient** and **Intercept** in the simple linear regression, are the parameters of the fit line. Given that it is a simple linear regression, with only 2 parameters, and knowing that the parameters are the intercept and slope of the line, sklearn can estimate them directly from our data. Notice that all of the data must be available to traverse and calculate the parameters.

Plot outputs we can plot the fit line over the data:

```
In [22]: plt.scatter(train.ENGINESIZE, train.CO2EMISSIONS, color='blue')
plt.plot(train_x, regr.coef_[0][0]*train_x + regr.intercept_[0], '-r')
plt.xlabel("Engine size")
plt.ylabel("Emission")
plt.show()
```



Evaluation we compare the actual values and predicted values to calculate the accuracy of a regression model. Evaluation metrics provide a key role in the development of a model, as it provides insight to areas that require improvement.

There are different model evaluation metrics, let's use MSE here to calculate the accuracy of our model based on the test set: - Mean absolute error: It is the mean of the absolute value of the errors.

This is the easiest of the metrics to understand since it's just average error. - Mean Squared Error (MSE): Mean Squared Error (MSE) is the mean of the squared error. It's more popular than Mean absolute error because the focus is geared more towards large errors. This is due to the squared term exponentially increasing larger errors in comparison to smaller ones. - Root Mean Squared Error (RMSE). - R-squared is not error, but is a popular metric for accuracy of your model. It represents how close the data are to the fitted regression line. The higher the R-squared, the better the model fits your data. Best possible score is 1.0 and it can be negative (because the model can be arbitrarily worse).

```
In [35]: from sklearn.metrics import r2_score
         from sklearn.metrics import mean_absolute_error
         from sklearn.metrics import mean_squared_error

         test_x = np.asanyarray(test[['ENGINE_SIZE']])
         test_y = np.asanyarray(test[['CO2_EMISSIONS']])
         test_y_ = regr.predict(test_x)

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

```
Mean absolute error: 22.21
22.20902138648825
Residual sum of squares (MSE): 837.67
837.674707095907
R2-score: 0.77
```

0.4 Want to learn more?

IBM SPSS Modeler is a comprehensive analytics platform that has many machine learning algorithms. It has been designed to bring predictive intelligence to decisions made by individuals, by groups, by systems – by your enterprise as a whole. A free trial is available through this course, available here: [SPSS Modeler](#).

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0.4.1 Thanks for completing this lesson!

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