Simple Linear Regression

Estimated time needed: **60 minutes**

Objectives

After completing this lab you will be able to:

- **Use scikit-learn to implement simple Linear Regression**
- **Create a model, train it, test it and use the model**

Importing Needed packages

In [1]:
```
import piplite
await piplite.install(['pandas'])
await piplite.install(['matplotlib'])
await piplite.install(['numpy'])
await piplite.install(['scikit-learn'])
```

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

Downloading Data

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

In [3]:
```
path= "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDevelo
```

In [4]:
```
from pyodide.http import pyfetch

async def download(url, filename):
    response = await pyfetch(url)
    if response.status == 200:
        with open(filename, "wb") as f:
            f.write(await response.bytes())
```

Understanding the Data

`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**

Reading the data in

In [5]:
```
await download(path, "FuelConsumption.csv")
path="FuelConsumption.csv"
```

In [6]:
```
df = pd.read_csv("FuelConsumption.csv")

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

Out[6]:

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINESIZE	CYLINDERS	TRANSMISSIO
0	2014	ACURA	ILX	COMPACT	2.0	4	AS
1	2014	ACURA	ILX	COMPACT	2.4	4	M
2	2014	ACURA	ILX HYBRID	COMPACT	1.5	4	AV
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5	6	AS
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5	6	AS

Data Exploration

Let's first have a descriptive exploration on our data.

In [7]:
```
# summarize the data
df.describe()
```

Out[7]:

	MODELYEAR	ENGINESIZE	CYLINDERS	FUELCONSUMPTION_CITY	FUELCONSUMPT
count	1067.0	1067.000000	1067.000000	1067.000000	10
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	

Let's select some features to explore more.

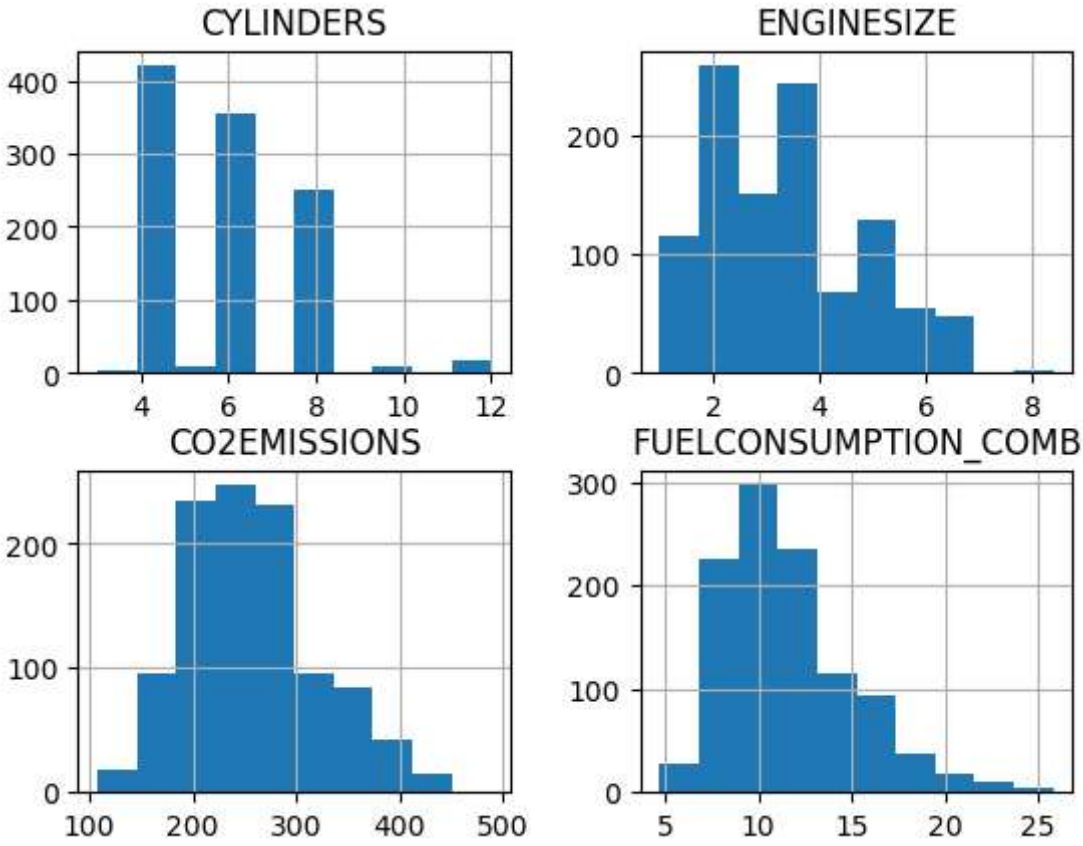
In [23]:
```
cdf = df[['ENGINESIZE','CYLINDERS','FUELCONSUMPTION_COMB','CO2EMISSIONS']]
cdf.head(9)
```

Out[23]:

	ENGINESIZE	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

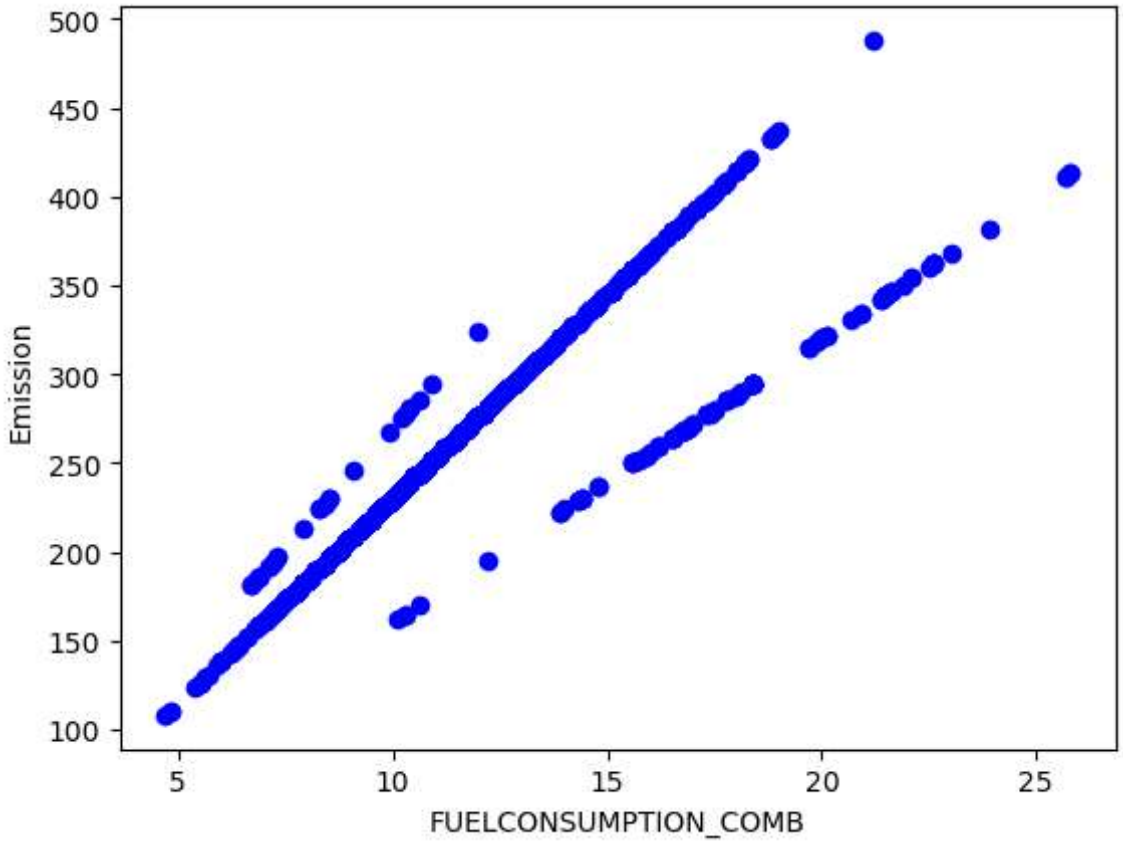
We can plot each of these features:

In [25]:
```
viz.hist()
plt.show()
```

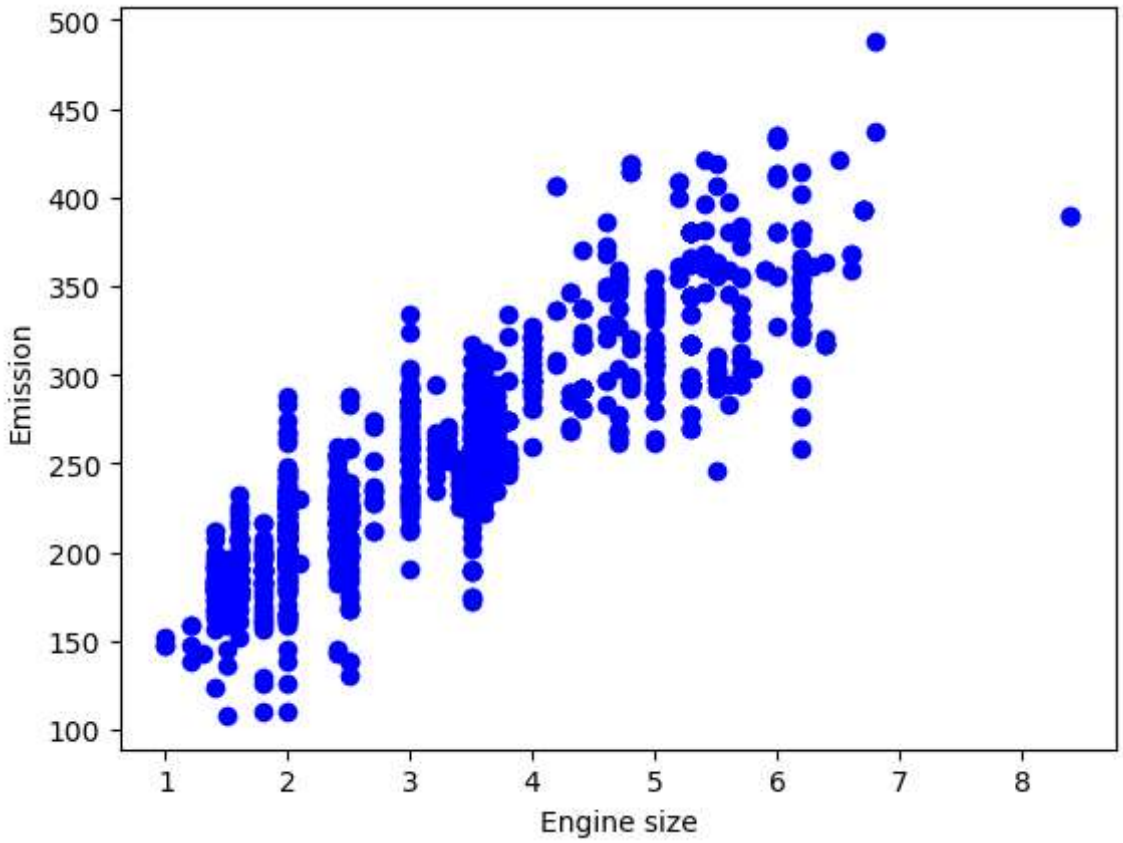


Now, let's plot each of these features against the Emission, to see how linear their relationship is:

In [10]:
```
plt.scatter(cdf.FUELCONSUMPTION_COMB, cdf.CO2EMISSIONS,  color='blue')
plt.xlabel("FUELCONSUMPTION_COMB")
plt.ylabel("Emission")
plt.show()
```



In [11]:
```
plt.scatter(cdf.ENGINESIZE, cdf.CO2EMISSIONS,  color='blue')
plt.xlabel("Engine size")
plt.ylabel("Emission")
plt.show()
```

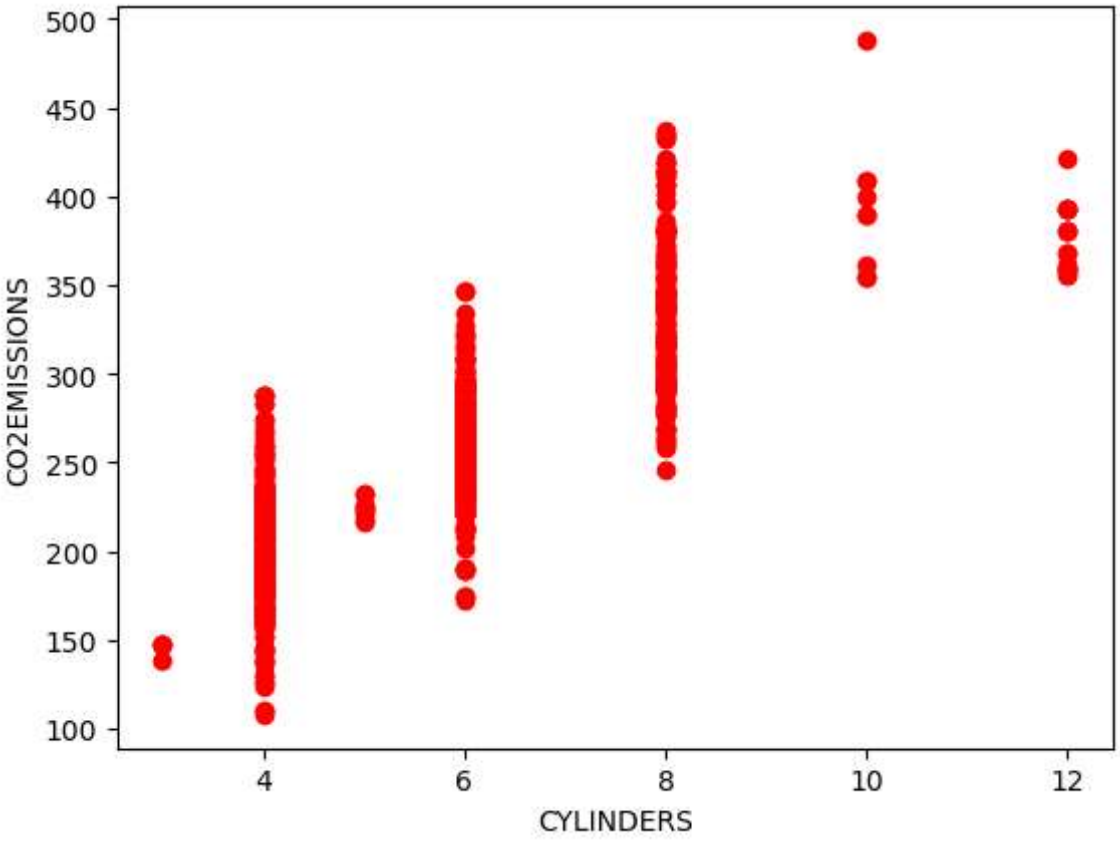


Practice

Plot CYLINDER vs the Emission, to see how linear is their relationship is:

In [31]:
```
# write your code here
plt.scatter(cdf.CYLINDERS, cdf.CO2EMISSIONS, color='red')
plt.xlabel('CYLINDERS')
plt.ylabel('CO2EMISSIONS')
```

Out[31]:
```
Text(0, 0.5, 'CO2EMISSIONS')
```



▶ **Click here for the solution**

Creating train and test dataset

Train/Test Split involves splitting the dataset into training and testing sets that 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 model. Therefore, it gives us a better understanding of how well our model generalizes on new data.

This means that we know the outcome of each data point in the testing dataset, making it great to test with! 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.

Let's split our dataset into train and test sets. 80% of the entire dataset will be used for training and 20% for testing. We create a mask to select random rows using np.random.rand() function:

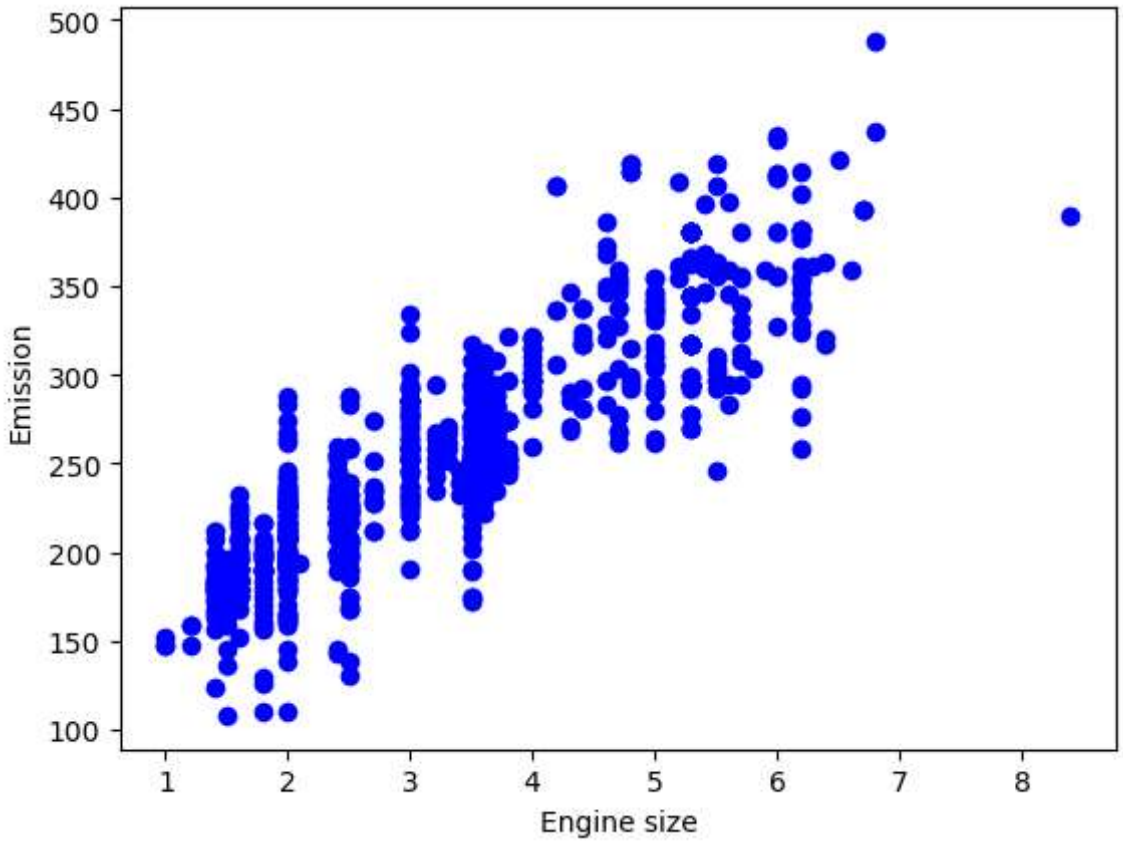
In [33]:
```
msk = np.random.rand(len(df)) < 0.8
train = cdf[msk]
test = cdf[~msk]
```

Simple Regression Model

Linear Regression fits a linear model with coefficients B = (B1, ..., Bn) to minimize the 'residual sum of squares' between the actual value y in the dataset, and the predicted value yhat using linear approximation.

Train data distribution

In [14]:
```
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 [34]:
```
from sklearn import linear_model
#This line creates an instance of the LinearRegression class, which will be used to
regr = linear_model.LinearRegression()
"""Extracting the 'ENGINESIZE' column from the training dataset (train)
and converting it to a NumPy array (train_x). Similarly,
extracting the 'CO2EMISSIONS' column and converting it to another NumPy array (trai
These arrays will be used as input features (independent variable)
and target values (dependent variable) for training the linear regression model."""
train_x = np.asanyarray(train[['ENGINESIZE']])
```

```
train_y = np.asanyarray(train[['CO2EMISSIONS']])
"""This line trains the linear regression model using the training data. The model
#learns the relationship between the engine size ('ENGINESIZE') and CO2 emissions (
regr.fit(train_x, train_y)
# The coefficients
print ('Coefficients: ', regr.coef_)
print ('Intercept: ',regr.intercept_)
```

```
Coefficients:  [[38.84847505]]
Intercept:  [126.50294311]
```

In [38]:
```
from sklearn import linear_model
regr2 = linear_model.LinearRegression()
train2_x = np.asanyarray(train[['FUELCONSUMPTION_COMB']])
train2_y = np.asanyarray(train[['CO2EMISSIONS']])
regr2.fit(train2_x, train2_y)
print ('Coefficients: ', regr2.coef_)
print ('Intercept: ',regr2.intercept_)
```

```
Coefficients:  [[15.9774728]]
Intercept:  [71.44763819]
```

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.

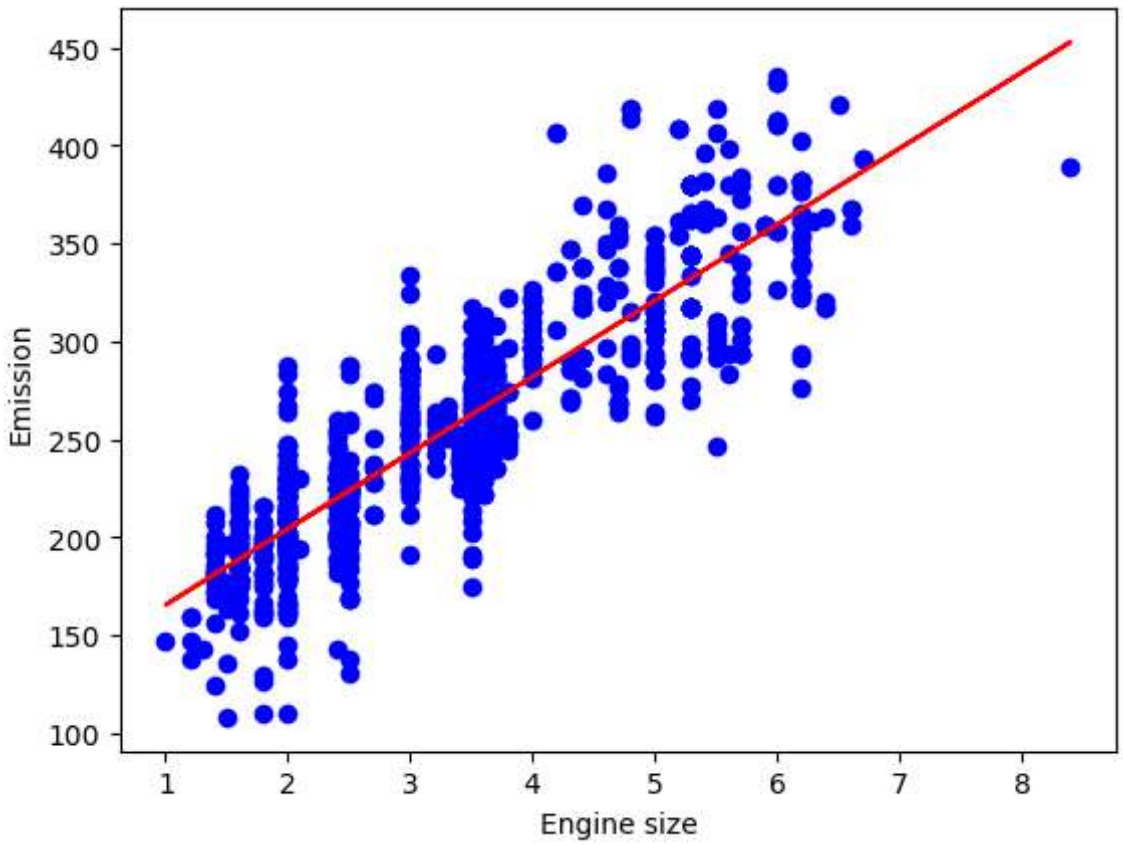
Plot outputs

We can plot the fit line over the data:

For Enginesize and Emissions

In [39]:
```
plt.scatter(train.ENGINESIZE, train.CO2EMISSIONS,  color='blue')
"""
plt.plot(): This function is used to create a plot in matplotlib.

train_x: This is the independent variable (engine size) from the training data.

regr.coef_[0][0]: This part retrieves the coefficient (slope) of the linear regress
regr.coef_ is a 2D array, and [0][0] accesses the actual coefficient value.

regr.intercept_[0]: This part retrieves the intercept of the linear regression mode

'-r': This argument specifies the style of the plot. -r means a solid red line.
"""
plt.plot(train_x, regr.coef_[0][0]*train_x + regr.intercept_[0], '-r')
plt.xlabel("Engine size")
plt.ylabel("Emission")
```

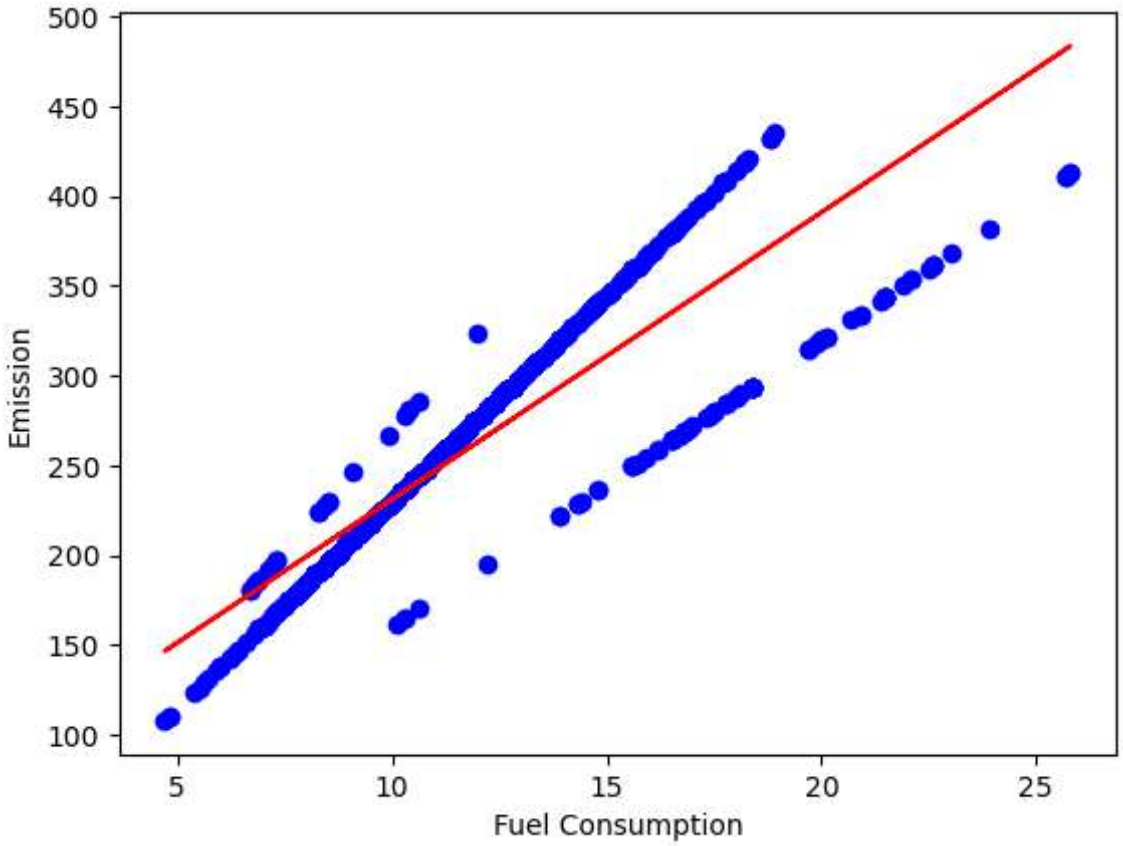
Out[39]:
```
Text(0, 0.5, 'Emission')
```



For Fuel Consumption and Emissions

In [41]:
```
plt.scatter(train.FUELCONSUMPTION_COMB, train.CO2EMISSIONS,  color='blue')
plt.plot(train2_x, regr2.coef_[0][0]*train2_x + regr2.intercept_[0], '-r')
plt.xlabel("Fuel Consumption")
plt.ylabel("Emission")
```

Out[41]:
```
Text(0, 0.5, 'Emission')
```



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, lets 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 an error, but rather a popular metric to measure the performance of your regression model. It represents how close the data points are to the fitted regression line. The higher the R-squared value, the better the model fits your data. The best possible score is 1.0 and it can be negative (because the model can be arbitrarily worse).**

For Enginesize and Emissions

In [17]:
```
from sklearn.metrics import r2_score

test_x = np.asanyarray(test[['ENGINESIZE']])
test_y = np.asanyarray(test[['CO2EMISSIONS']])
test_y_ = regr.predict(test_x)

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: 24.43
Residual sum of squares (MSE): 957.40
R2-score: 0.78
```

For Fuel Consumption and Emissions

In [42]:
```
test2_x = np.asanyarray(test[['FUELCONSUMPTION_COMB']])
test2_y = np.asanyarray(test[['CO2EMISSIONS']])
# using our trained linear regression model (regr2) to make predictions on the test
test2_y_ = regr2.predict(test2_x)
# This line calculates the Mean Absolute Error (MAE), which measures the average ab
print("Mean absolute error: %.2f" % np.mean(np.absolute(test2_y_ - test2_y)))
# This line calculates the Residual Sum of Squares (MSE), which measures the averag
print("Residual sum of squares (MSE): %.2f" % np.mean((test2_y_ - test2_y) ** 2))
# This line calculates the R-squared (R2) score, which measures the proportion of t
print("R2-score: %.2f" % r2_score(test2_y , test2_y_) )
```

```
Mean absolute error: 20.64
Residual sum of squares (MSE): 822.79
R2-score: 0.81
```

Exercise

Lets see what the evaluation metrics are if we trained a regression model using the `FUELCONSUMPTION_COMB` feature.

Start by selecting `FUELCONSUMPTION_COMB` as the train_x data from the `train` dataframe, then select `FUELCONSUMPTION_COMB` as the test_x data from the `test` dataframe

In [62]:
```
train_x = train[["FUELCONSUMPTION_COMB"]]

test_x = test[["FUELCONSUMPTION_COMB"]]
```

▶ **Click here for the solution**

Now train a Linear Regression Model using the `train_x` you created and the `train_y` created previously

In [47]:
```
regr = linear_model.LinearRegression()

regr.fit(train_x, train_y)
```

Out[47]:
```
▾ LinearRegression

LinearRegression()
```

▶ **Click here for the solution**

Find the predictions using the model's `predict` function and the `test_x` data

In [48]:
```
predictions = regr.predict(test_x)
```

▶ **Click here for the solution**

Finally use the `predictions` and the `test_y` data and find the Mean Absolute Error value using the `np.absolute` and `np.mean` function like done previously

In [59]:
```
#ADD CODE
print("Mean Absolute Error: %.2f" % np.mean(np.absolute(predictions - test2_y)))
```

```
Mean Absolute Error: 20.64
```

▶ **Click here for the solution**

We can see that the MAE is much worse when we train using `ENGINESIZE` than `FUELCONSUMPTION_COMB`.