Simple Linear Regression

Estimated time needed: **15** 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
```

```
<ipython-input-2-76706e26cc54>:2: DeprecationWarning:
Pyarrow will become a required dependency of pandas in the next major release of pandas
(pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and better interope
rability with other libraries)
but was not found to be installed on your system.
If this would cause problems for you,
please provide us feedback at https://github.com/pandas-dev/pandas/issues/54466

  import pandas as pd
```

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/IBMDeveloperS
```

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 [ ]:

```

```

In [5]:

```
await download(path, "FuelConsumption.csv")
path="FuelConsumption.csv"
```

In [9]:

```
df = pd.read_csv("FuelConsumption.csv")

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

Out[9]:

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINESIZE	CYLINDERS	TRANSMISSION	FUELTYP
0	2014	ACURA	ILX	COMPACT	2.0	4	AS5	
1	2014	ACURA	ILX	COMPACT	2.4	4	M6	
2	2014	ACURA	ILX HYBRID	COMPACT	1.5	4	AV7	

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINESIZE	CYLINDERS	TRANSMISSION	FUELTYP
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5	6	AS6	
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5	6	AS6	
...	...	...	...	...	...	...	...	
1062	2014	VOLVO	XC60 AWD	SUV - SMALL	3.0	6	AS6	
1063	2014	VOLVO	XC60 AWD	SUV - SMALL	3.2	6	AS6	
1064	2014	VOLVO	XC70 AWD	SUV - SMALL	3.0	6	AS6	
1065	2014	VOLVO	XC70 AWD	SUV - SMALL	3.2	6	AS6	
1066	2014	VOLVO	XC90 AWD	SUV - STANDARD	3.2	6	AS6	

1067 rows × 13 columns

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	FUELCONSUMPTION_HWY	FUE
count	1067.0	1067.000000	1067.000000	1067.000000	1067.000000	
mean	2014.0	3.346298	5.794752	13.296532	9.474602	
std	0.0	1.415895	1.797447	4.101253	2.794510	
min	2014.0	1.000000	3.000000	4.600000	4.900000	
25%	2014.0	2.000000	4.000000	10.250000	7.500000	
50%	2014.0	3.400000	6.000000	12.600000	8.800000	
75%	2014.0	4.300000	8.000000	15.550000	10.850000	
max	2014.0	8.400000	12.000000	30.200000	20.500000	

Let's select some features to explore more.

In [8]:

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

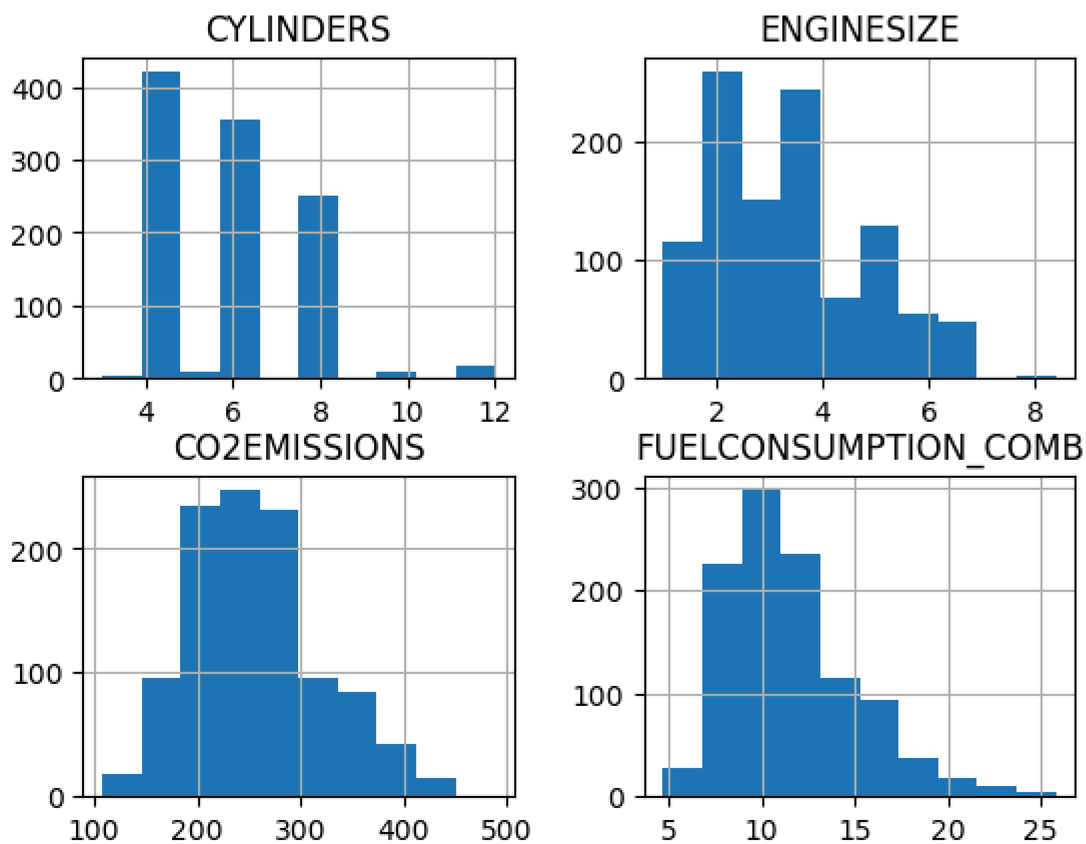
Out[8]:

	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 [10]:

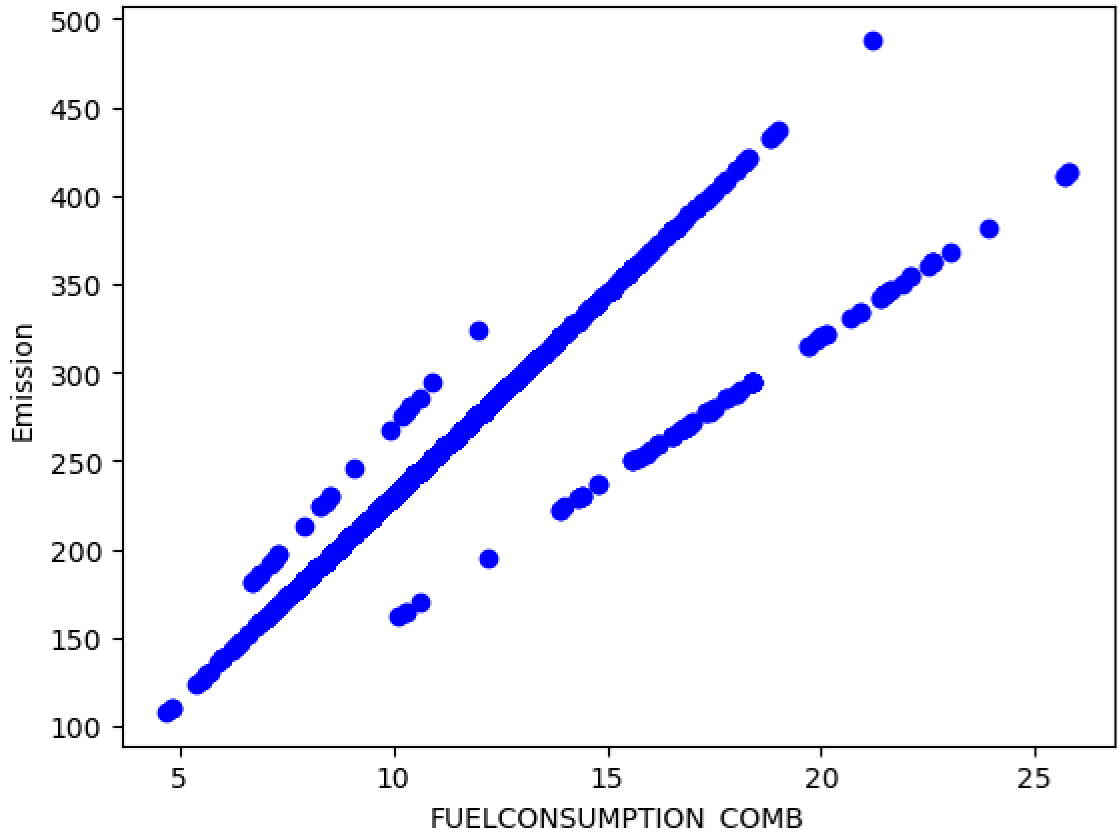
```
viz = cdf[['CYLINDERS','ENGINESIZE','CO2EMISSIONS','FUELCONSUMPTION_COMB']]
viz.hist()
plt.show()
```



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

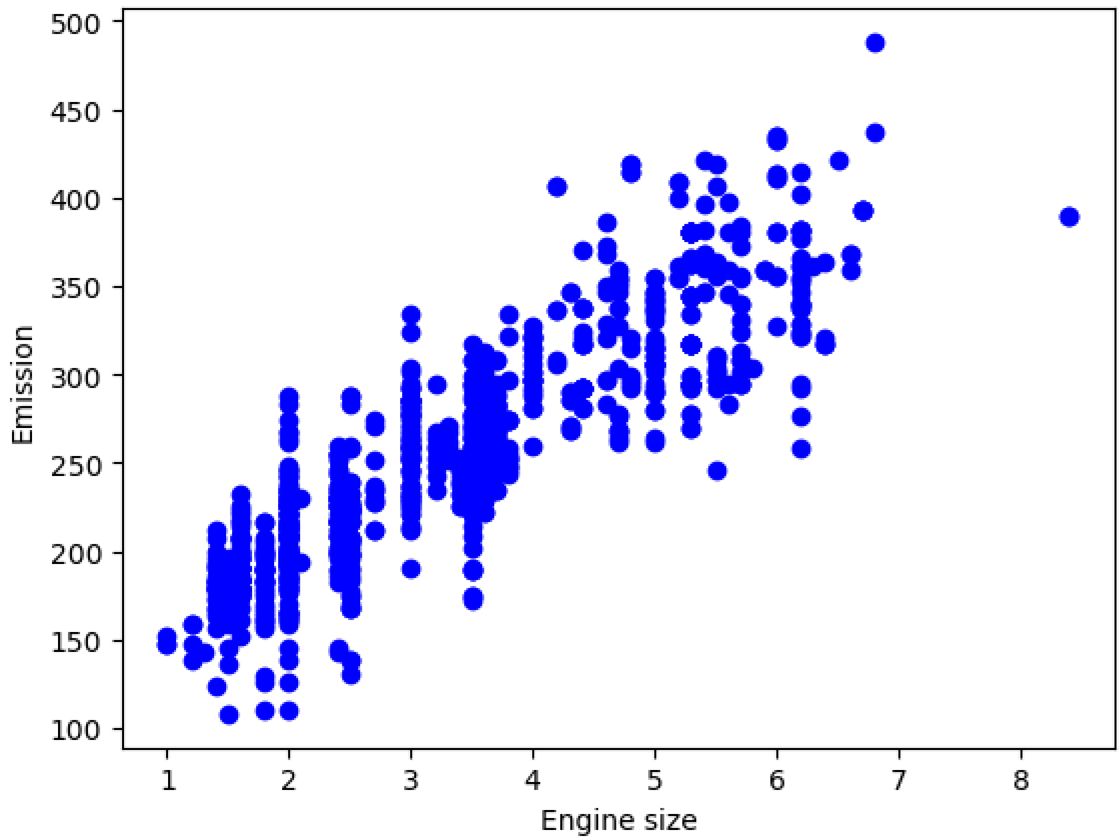
In [11]:

```
plt.scatter(cdf.FUELCONSUMPTION_COMB, cdf.CO2EMISSIONS,  color='blue')
plt.xlabel("FUELCONSUMPTION_COMB")
plt.ylabel("Emission")
plt.show()
```



In [12]:

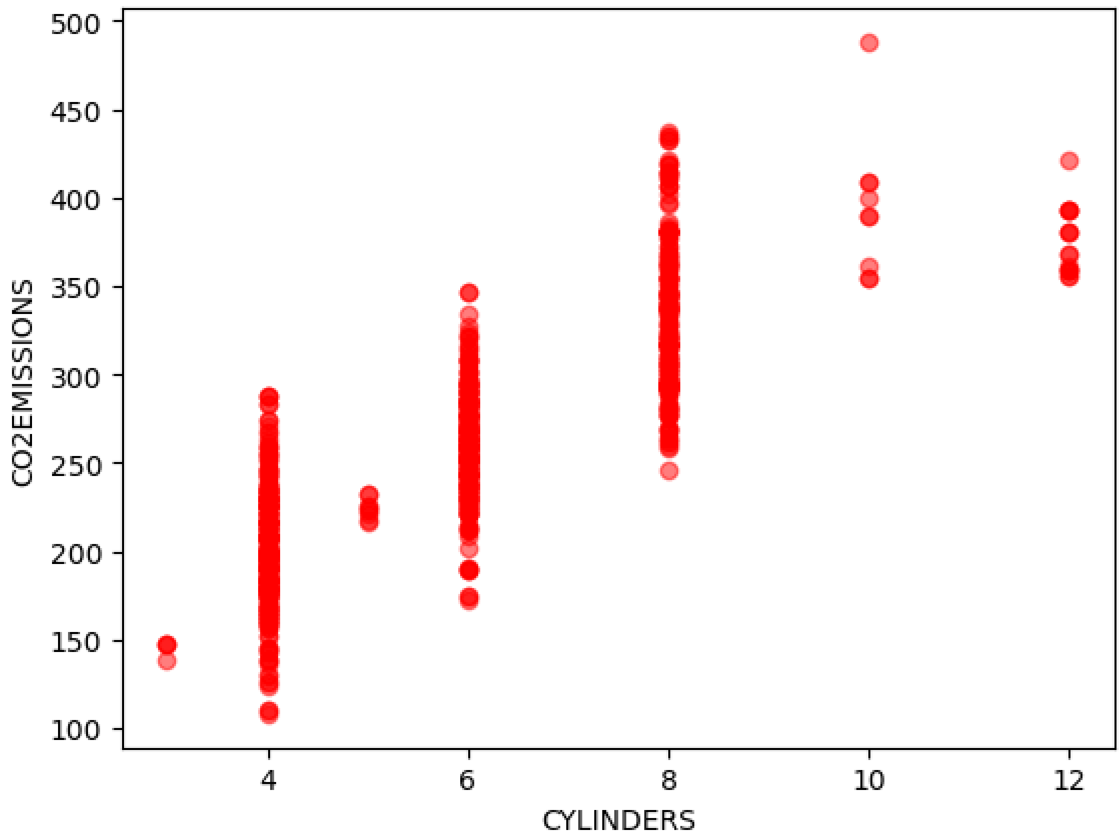
```
plt.scatter(cdf.ENGINESIZE, cdf.CO2EMISSIONS,  color='blue')
plt.xlabel("Engine size")
plt.ylabel("Emission")
plt.show()
```



Practice

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

In [14]:
```
# write your code here
plt.scatter(cdf.CYLINDERS, cdf.CO2EMISSIONS, color = "red", alpha=0.5)
plt.xlabel("CYLINDERS")
plt.ylabel("CO2EMISSIONS")
plt.show()
```



▶ 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 [15]:

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

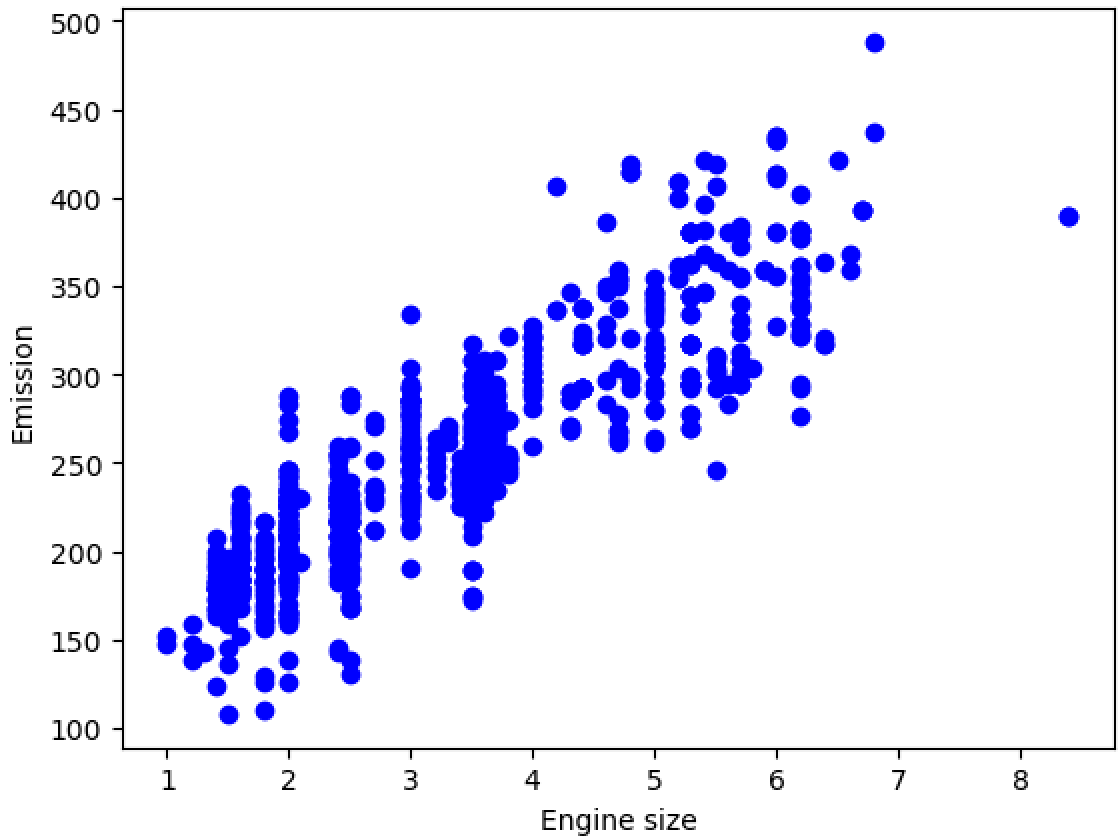
Simple Regression Model

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 [16]:

```
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 [17]:

```
from sklearn import linear_model
regr = linear_model.LinearRegression()
train_x = np.asanyarray(train[['ENGINESIZE']])
train_y = np.asanyarray(train[['CO2EMISSIONS']])
regr.fit(train_x, train_y)
# The coefficients
print ('Coefficients: ', regr.coef_)
print ('Intercept: ',regr.intercept_)
```

```
Coefficients:  [[38.87413113]]
Intercept:  [125.47166362]
```

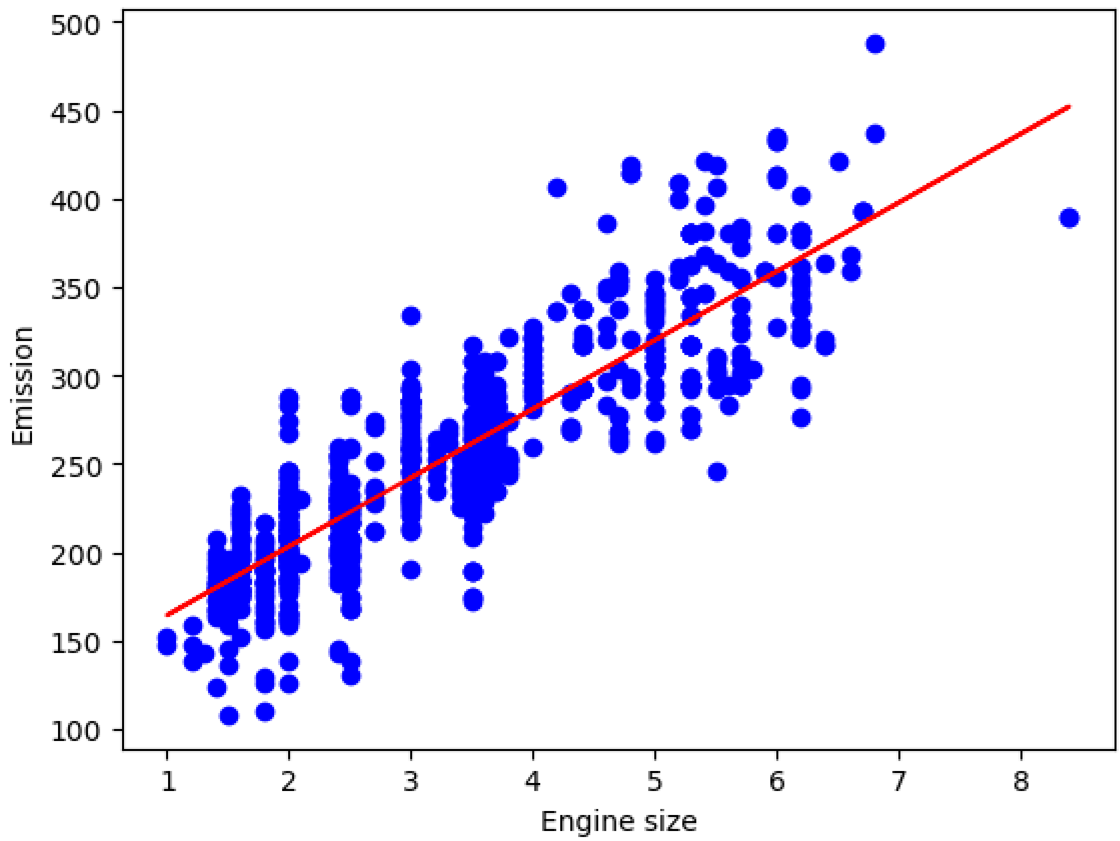
As mentioned before, **Coefficient** and **Intercept** in the simple linear regression, are the parameters of the fit line. Given that it is a simple linear regression, with only 2 parameters, and knowing that the parameters are the intercept and slope of the line, sklearn can estimate them directly 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 [24]:
```
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")
```

Out[24]:
```
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).

In [56]:

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

```
Mean absolute error: 136.307993
Residual sum of squares (MSE): 20764
R2-score: -3.77
```

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 [57]:

```
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 [61]:

```
regr = linear_model.LinearRegression()
regr.fit(train_x, train_y)
```

Out[61]:

```
▾ LinearRegression ⓘ ?
LinearRegression()
```

▶ Click here for the solution

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

In [62]:

```
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 [60]:
```
#ADD CODE
print("Mean Absolute Error: %.2f" % np.mean(np.absolute(predictions - test_y)))
```

```
Mean Absolute Error: 21.85
```

▶ Click here for the solution

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

Thank you for completing this lab!

Author

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Change Log

Date (YYYY-MM-DD)	Version	Changed By	Change Description
2020-11-03	2.1	Lakshmi Holla	Changed URL of the csv
2020-08-27	2.0	Lavanya	Moved lab to course repo in GitLab

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