Mulitple-Linear-Regression

October 13, 2025

1 Multiple Linear Regression

Estimated time needed: **15** minutes

1.1 Objectives

After completing this lab, you will be able to:

- Use scikit-learn to implement multiple linear regression
- Create, train, and test a multiple linear regression model on real data

1.1.1 Import needed packages

For this lab, you will need to have the following packages: - NumPy - Matplotlib - Pandas - Scikit-learn

To avoid issues importing these libraries, you may execute the following cell to ensure they are available.

[1]:
```
!pip install numpy==2.2.0
!pip install pandas==2.2.3
!pip install scikit-learn==1.6.0
!pip install matplotlib==3.9.3
```

```
Collecting numpy==2.2.0
  Downloading
numpy-2.2.0-cp312-cp312-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata
(62 kB)
Downloading
numpy-2.2.0-cp312-cp312-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (16.1 MB)
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152.8 MB/s eta 0:00:00
Installing collected packages: numpy
Successfully installed numpy-2.2.0
Collecting pandas==2.2.3
  Downloading
pandas-2.2.3-cp312-cp312-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata
(89 kB)
Requirement already satisfied: numpy>=1.26.0 in /opt/conda/lib/python3.12/site-
packages (from pandas==2.2.3) (2.2.0)
```

```
Requirement already satisfied: python-dateutil>=2.8.2 in
/opt/conda/lib/python3.12/site-packages (from pandas==2.2.3) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/python3.12/site-
packages (from pandas==2.2.3) (2024.2)
Collecting tzdata>=2022.7 (from pandas==2.2.3)
  Downloading tzdata-2025.2-py2.py3-none-any.whl.metadata (1.4 kB)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.12/site-
packages (from python-dateutil>=2.8.2->pandas==2.2.3) (1.17.0)
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pandas-2.2.3-cp312-cp312-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (12.7
MB)
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Downloading tzdata-2025.2-py2.py3-none-any.whl (347 kB)
Installing collected packages: tzdata, pandas
Successfully installed pandas-2.2.3 tzdata-2025.2
Collecting scikit-learn==1.6.0
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manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (18 kB)
Requirement already satisfied: numpy>=1.19.5 in /opt/conda/lib/python3.12/site-
packages (from scikit-learn==1.6.0) (2.2.0)
Collecting scipy>=1.6.0 (from scikit-learn==1.6.0)
  Downloading
scipy-1.16.2-cp312-cp312-manylinux2014_x86_64.manylinux_2_17_x86_64.whl.metadata
(62 kB)
Collecting joblib>=1.2.0 (from scikit-learn==1.6.0)
  Downloading joblib-1.5.2-py3-none-any.whl.metadata (5.6 kB)
Collecting threadpoolctl>=3.1.0 (from scikit-learn==1.6.0)
  Downloading threadpoolctl-3.6.0-py3-none-any.whl.metadata (13 kB)
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scikit_learn-1.6.0-cp312-cp312-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
(13.1 MB)
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Downloading joblib-1.5.2-py3-none-any.whl (308 kB)
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scipy-1.16.2-cp312-cp312-manylinux2014_x86_64.manylinux_2_17_x86_64.whl (35.7
MB)
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124.7 MB/s eta 0:00:0000:01
Downloading threadpoolctl-3.6.0-py3-none-any.whl (18 kB)
Installing collected packages: threadpoolctl, scipy, joblib, scikit-learn
Successfully installed joblib-1.5.2 scikit-learn-1.6.0 scipy-1.16.2
threadpoolctl-3.6.0
Collecting matplotlib==3.9.3
  Downloading matplotlib-3.9.3-cp312-cp312-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (11 kB)
Collecting contourpy>=1.0.1 (from matplotlib==3.9.3)
```

```
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Collecting cycler>=0.10 (from matplotlib==3.9.3)
  Downloading cycler-0.12.1-py3-none-any.whl.metadata (3.8 kB)
Collecting fonttools>=4.22.0 (from matplotlib==3.9.3)
  Downloading fonttools-4.60.0-cp312-cp312-
manylinux1_x86_64.manylinux2014_x86_64.manylinux_2_17_x86_64.manylinux_2_5_x86_6
4.whl.metadata (111 kB)
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  Downloading kiwisolver-1.4.9-cp312-cp312-
manylinux2014_x86_64.manylinux_2_17_x86_64.whl.metadata (6.3 kB)
Requirement already satisfied: numpy>=1.23 in /opt/conda/lib/python3.12/site-
packages (from matplotlib==3.9.3) (2.2.0)
Requirement already satisfied: packaging>=20.0 in
/opt/conda/lib/python3.12/site-packages (from matplotlib==3.9.3) (24.2)
Collecting pillow>=8 (from matplotlib==3.9.3)
  Downloading pillow-11.3.0-cp312-cp312-
manylinux_2_27_x86_64.manylinux_2_28_x86_64.whl.metadata (9.0 kB)
Collecting pyparsing>=2.3.1 (from matplotlib==3.9.3)
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Requirement already satisfied: python-dateutil>=2.7 in
/opt/conda/lib/python3.12/site-packages (from matplotlib==3.9.3) (2.9.0.post0)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.12/site-
packages (from python-dateutil>=2.7->matplotlib==3.9.3) (1.17.0)
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contourpy-1.3.3-cp312-cp312-manylinux_2_27_x86_64.manylinux_2_28_x86_64.whl (362
kB)
Downloading cycler-0.12.1-py3-none-any.whl (8.3 kB)
Downloading fonttools-4.60.0-cp312-cp312-
manylinux1_x86_64.manylinux2014_x86_64.manylinux_2_17_x86_64.manylinux_2_5_x86_6
4.whl (4.9 MB)
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```

```
Downloading pyparsing-3.2.4-py3-none-any.whl (113 kB)
Installing collected packages: pyparsing, pillow, kiwisolver, fonttools, cycler,
contourpy, matplotlib
Successfully installed contourpy-1.3.3 cycler-0.12.1 fonttools-4.60.0
kiwisolver-1.4.9 matplotlib-3.9.3 pillow-11.3.0 pyparsing-3.2.4
```

Now, you can import these libraries for making the code.

[8]:
```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
%matplotlib inline
```

1.2 Load the data

The dataset you will use resides at the following URL. You can use the URL directly with the Pandas library to load the dataset.

[9]:
```python
url= "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/
↪IBMDeveloperSkillsNetwork-ML0101EN-SkillsNetwork/labs/Module%202/data/
↪FuelConsumptionCo2.csv"
```

1.3 Understand the data

1.3.1 `FuelConsumption.csv`:

You will download and use 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

- **MODEL YEAR** e.g. 2014
- **MAKE** e.g. VOLVO
- **MODEL** e.g. S60 AWD
- **VEHICLE CLASS** e.g. COMPACT
- **ENGINE SIZE** e.g. 3.0
- **CYLINDERS** e.g 6
- **TRANSMISSION** e.g. AS6
- **FUEL TYPE** e.g. Z
- **FUEL CONSUMPTION in CITY(L/100 km)** e.g. 13.2
- **FUEL CONSUMPTION in HWY (L/100 km)** e.g. 9.5
- **FUEL CONSUMPTION COMBINED (L/100 km)** e.g. 11.5
- **FUEL CONSUMPTION COMBINED MPG (MPG)** e.g. 25
- **CO2 EMISSIONS (g/km)** e.g. 182

Your task will be to create a multiple linear regression model using some of these features to predict CO2 emissions of unobserved cars based on the selected features.

Load the data

[10]:
```python
df = pd.read_csv(url)

# verify successful load with some randomly selected records
df.sample(5)
```

[10]:
```
     MODELYEAR          MAKE                     MODEL     VEHICLECLASS  \
700       2014         MAZDA                  CX-9 4WD      SUV - SMALL
219       2014     CHEVROLET  EXPRESS 1500 PASSENGER  VAN - PASSENGER
959       2014        SUBARU               OUTBACK AWD      SUV - SMALL
798       2014          MINI            COOPER S COUPE       TWO-SEATER
18        2014  ASTON MARTIN                  VANQUISH      MINICOMPACT

     ENGINESIZE  CYLINDERS TRANSMISSION FUELTYPE  FUELCONSUMPTION_CITY  \
700         3.7          6          AS6        X                  14.3
219         5.3          8           A4        X                  18.6
959         2.5          4           M6        X                  10.8
798         1.6          4           A6        Z                   9.3
18          5.9         12           A6        Z                  18.0

     FUELCONSUMPTION_HWY  FUELCONSUMPTION_COMB  FUELCONSUMPTION_COMB_MPG  \
700                 10.6                  12.6                        22
219                 13.9                  16.5                        17
959                  8.5                   9.8                        29
798                  7.0                   8.3                        34
18                  12.6                  15.6                        18

     CO2EMISSIONS
700           290
219           380
959           225
798           191
18            359
```

1.3.2 Explore and select features

Let's select a few features to work with that might be predictive of CO2 emissions.

[11]:
```python
df.describe()
```

[11]:
```
       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
```

Notice that some of the variables are not included in the description. This is because they aren't numerical. In practice, you would analyze these features if required to improve the accuracy of your model. In the interest of time, you can omit this step here.
Notice also that MODELYEAR is the same for all cars, so you can drop these variables for this modeling illustration.

[12]:
```
# Drop categoricals and any unseless columns
df = df.drop(['MODELYEAR', 'MAKE', 'MODEL', 'VEHICLECLASS', 'TRANSMISSION',␣
↪'FUELTYPE',],axis=1)
```

Now that you have eliminated some features, take a look at the relationships among the remaining features.

Analyzing a correlation matrix that displays the pairwise correlations between all features indicates the level of independence between them.

It also indicates how predictive each feature is of the target.

You want to eliminate any strong dependencies or correlations between features by selecting the best one from each correlated group.

[13]:
```
df.corr()
```

[13]:
```
                      ENGINESIZE  CYLINDERS  FUELCONSUMPTION_CITY  \
ENGINESIZE              1.000000   0.934011              0.832225
CYLINDERS               0.934011   1.000000              0.796473
FUELCONSUMPTION_CITY    0.832225   0.796473              1.000000
FUELCONSUMPTION_HWY     0.778746   0.724594              0.965718
FUELCONSUMPTION_COMB    0.819482   0.776788              0.995542
```

```
FUELCONSUMPTION_COMB_MPG   -0.808554  -0.770430              -0.935613
CO2EMISSIONS                0.874154   0.849685               0.898039

                          FUELCONSUMPTION_HWY  FUELCONSUMPTION_COMB  \
ENGINESIZE                           0.778746              0.819482
CYLINDERS                            0.724594              0.776788
FUELCONSUMPTION_CITY                 0.965718              0.995542
FUELCONSUMPTION_HWY                  1.000000              0.985804
FUELCONSUMPTION_COMB                 0.985804              1.000000
FUELCONSUMPTION_COMB_MPG            -0.893809             -0.927965
CO2EMISSIONS                         0.861748              0.892129

                          FUELCONSUMPTION_COMB_MPG  CO2EMISSIONS
ENGINESIZE                               -0.808554      0.874154
CYLINDERS                                -0.770430      0.849685
FUELCONSUMPTION_CITY                     -0.935613      0.898039
FUELCONSUMPTION_HWY                      -0.893809      0.861748
FUELCONSUMPTION_COMB                     -0.927965      0.892129
FUELCONSUMPTION_COMB_MPG                  1.000000     -0.906394
CO2EMISSIONS                             -0.906394      1.000000
```

Look at the bottom row, which shows the correlation between each variable and the target, 'CO2EMISSIONS'. Each of these shows a fairly high level of correlation, each exceeding 85% in magnitude. Thus all of these features are good candidates.

Next, examine the correlations of the distinct pairs. 'ENGINESIZE' and 'CYLINDERS' are highly correlated, but 'ENGINESIZE' is more correlated with the target, so we can drop 'CYLINDERS'.

Similarly, each of the four fuel economy variables is highly correlated with each other. Since FUELCONSUMPTION_COMB_MPG is the most correlated with the target, you can drop the others: 'FUELCONSUMPTION_CITY,' 'FUELCONSUMPTION_HWY,' 'FUELCONSUMPTION_COMB.'

Notice that FUELCONSUMPTION_COMB and FUELCONSUMPTION_COMB_MPG are not perfectly correlated. They should be, though, because they measure the same property in different units. In practice, you would investigate why this is the case. You might find out that some or all of the data is not useable as is.

[14]:
```python
df = df.drop(['CYLINDERS', 'FUELCONSUMPTION_CITY',␣
↪'FUELCONSUMPTION_HWY','FUELCONSUMPTION_COMB',],axis=1)
```

[15]:
```python
df.head(9)
```

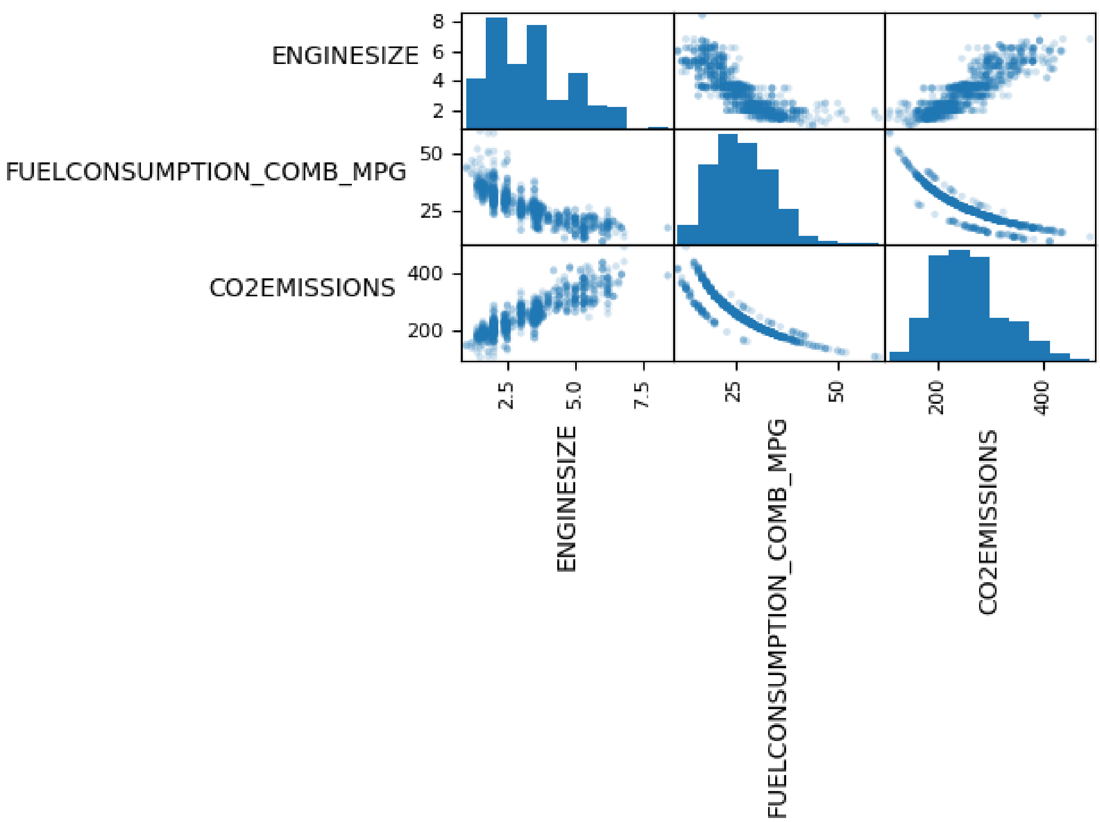
[15]:

	ENGINESIZE	FUELCONSUMPTION_COMB_MPG	CO2EMISSIONS
0	2.0	33	196
1	2.4	29	221
2	1.5	48	136
3	3.5	25	255
4	3.5	27	244

```
5          3.5                        28            230
6          3.5                        28            232
7          3.7                        25            255
8          3.7                        24            267
```

To help with selecting predictive features that are not redundant, consider the following scatter matrix, which shows the scatter plots for each pair of input features. The diagonal of the matrix shows each feature's histogram.

[16]:
```
axes = pd.plotting.scatter_matrix(df, alpha=0.2)
# need to rotate axis labels so we can read them
for ax in axes.flatten():
    ax.xaxis.label.set_rotation(90)
    ax.yaxis.label.set_rotation(0)
    ax.yaxis.label.set_ha('right')

plt.tight_layout()
plt.gcf().subplots_adjust(wspace=0, hspace=0)
plt.show()
```



As you can see, the relationship between 'FUELCONSUMPTION_COMB_MPG' and

'CO2EMISSIONS' is non-linear. In addition, you can clearly see three different curves. This suggests exploring the categorical variables to see if they are able to explain these differences. Let's leave this as an exercise for you to explore deeper. Regarding the non-linearity, you will handle this in the next lab. For now, let's just consider through modeling whether fuel economy explains some of the variances in the target as is.

1.3.3 Extract the input features and labels from the data set

Extract the required columns and convert the resulting dataframes to NumPy arrays.

[17]:
```
X = df.iloc[:,[0,1]].to_numpy()
y = df.iloc[:,[2]].to_numpy()
```

1.3.4 Preprocess selected features

You should standardize your input features so the model doesn't inadvertently favor any feature due to its magnitude. The typical way to do this is to subtract the mean and divide by the standard deviation. Scikit-learn can do this for you.

[18]:
```
from sklearn import preprocessing

std_scaler = preprocessing.StandardScaler()
X_std = std_scaler.fit_transform(X)
```

In practice, if you want to properly evaluate your model, you should definitely not apply such operations to the entire dataset but to the train and test data separately. There's more to it than that. You'll dive deeper into this and other advanced evaluation pitfalls later in the course.

[19]:
```
pd.DataFrame(X_std).describe().round(2)
```

[19]:

	0	1
count	1067.00	1067.00
mean	0.00	-0.00
std	1.00	1.00
min	-1.66	-2.07
25%	-0.95	-0.73
50%	0.04	-0.06
75%	0.67	0.61
max	3.57	4.50

As you can see, a standardized variable has zero mean and a standard deviation of one.

1.3.5 Create train and test datasets

Randomly split your data into train and test sets, using 80% of the dataset for training and reserving the remaining 20% for testing.

[22]:
```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X_std,y,test_size=0.
 ↪2,random_state=42)
```

1.3.6 Build a multiple linear regression model

Multiple and simple linear regression models can be implemented with exactly the same scikit-learn tools.

[23]:
```
from sklearn import linear_model

# create a model object
regressor = linear_model.LinearRegression()

# train the model in the training data
regressor.fit(X_train, y_train)

# Print the coefficients
coef_ =  regressor.coef_
intercept_ = regressor.intercept_

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

```
Coefficients:  [[ 25.27339614 -37.4381472 ]]
Intercept:  [256.29072488]
```

The Coefficients and Intercept parameters define the best-fit hyperplane to the data. Since there are only two variables, hence two parameters, the hyperplane is a plane. But this best-fit plane will look different in the original, unstandardized feature space.

You can transform your model's parameters back to the original space prior to standardization as follows. This gives you a proper sense of what they mean in terms of your original input features. Without these adjustments, the model's outputs would be tied to an abstract, transformed space that doesn't align with the actual independent variables and the real-world problem you're solving.

[24]:
```
# Get the standard scaler's mean and standard deviation parameters
means_ = std_scaler.mean_
std_devs_ = np.sqrt(std_scaler.var_)

# The least squares parameters can be calculated relative to the original,␣
 ↪unstandardized feature space as:
coef_original = coef_ / std_devs_
intercept_original = intercept_ - np.sum((means_ * coef_) / std_devs_)

print ('Coefficients: ', coef_original)
print ('Intercept: ', intercept_original)
```

```
Coefficients:  [[17.8581369  -5.01502179]]
Intercept:  [329.1363967]
```

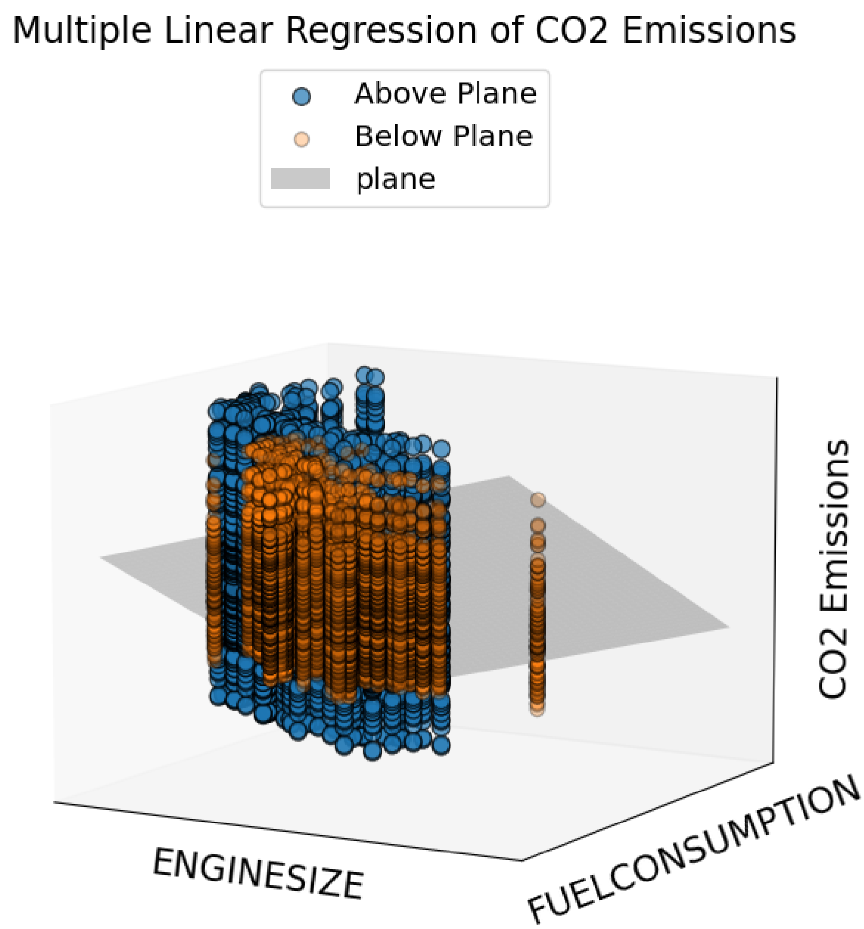
You would expect that for the limiting case of zero ENGINESIZE and zero FUELCONSUMPTION_COMB_MPG, the resulting CO2 emissions should also be zero. This is inconsistent with the 'best fit' hyperplane, which has a non-zero intercept of 329 g/km. The answer must be that the target variable does not have a very strong linear relationship to the dependent variables, and/or the data has outliers that are biasing the result. Outliers can be handled in preprocessing, or as you will learn about later in the course, by using regularization techniques. One or more of the variables might have a nonlinear relationship to the target. Or there may still be some colinearity amongst the input variables.

1.3.7 Visualize model outputs

You can visualize the goodness-of-fit of the model to the training data by plotting the fitted plane over the data.

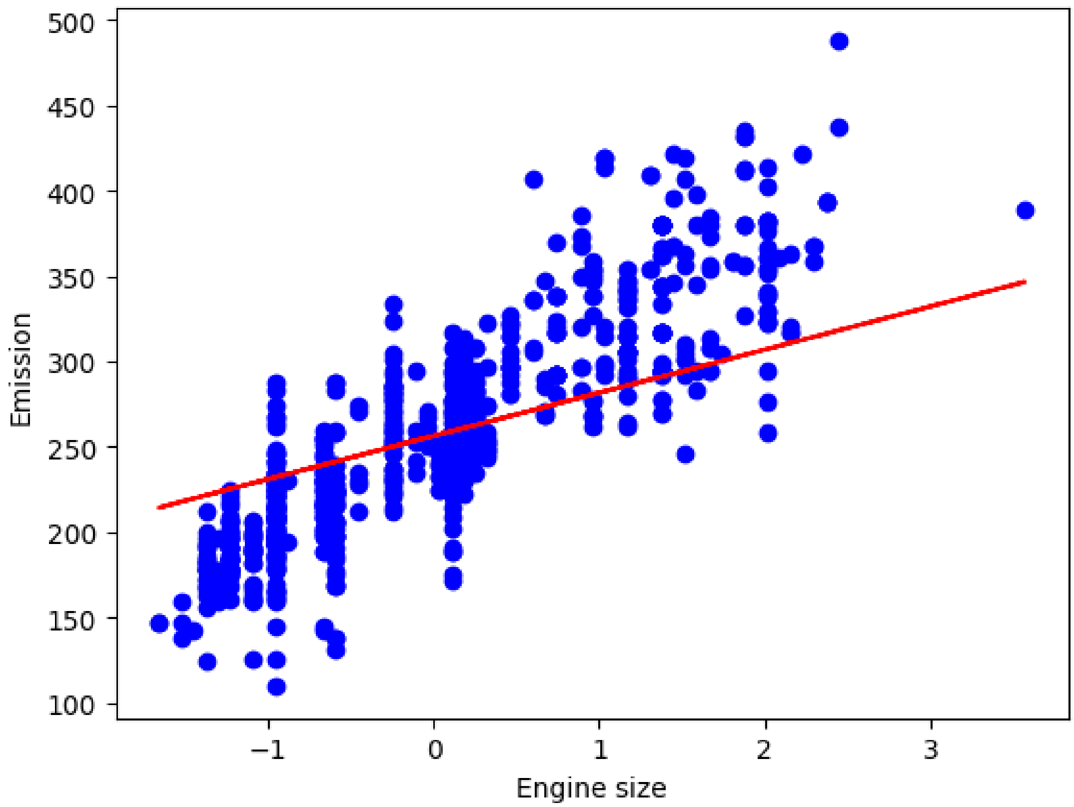
[25]:
```python
#from mpl_toolkits.mplot3d import Axes3D
import numpy as np
import matplotlib.pyplot as plt

# Ensure X1, X2, and y_test have compatible shapes for 3D plotting
X1 = X_test[:, 0] if X_test.ndim > 1 else X_test
X2 = X_test[:, 1] if X_test.ndim > 1 else np.zeros_like(X1)

# Create a mesh grid for plotting the regression plane
x1_surf, x2_surf = np.meshgrid(np.linspace(X1.min(), X1.max(), 100),
                               np.linspace(X2.min(), X2.max(), 100))

y_surf = intercept_ +  coef_[0,0] * x1_surf  +  coef_[0,1] * x2_surf

# Predict y values using trained regression model to compare with actual y_test␣
↪for above/below plane colors
y_pred = regressor.predict(X_test.reshape(-1, 1)) if X_test.ndim == 1 else␣
↪regressor.predict(X_test)
above_plane = y_test >= y_pred
below_plane = y_test < y_pred
above_plane = above_plane[:,0]
below_plane = below_plane[:,0]

# Plotting
fig = plt.figure(figsize=(20, 8))
ax = fig.add_subplot(111, projection='3d')

# Plot the data points above and below the plane in different colors
ax.scatter(X1[above_plane], X2[above_plane], y_test[above_plane],  label="Above␣
↪Plane",s=70,alpha=.7,ec='k')
ax.scatter(X1[below_plane], X2[below_plane], y_test[below_plane],  label="Below␣
↪Plane",s=50,alpha=.3,ec='k')
```

```python
# Plot the regression plane
ax.plot_surface(x1_surf, x2_surf, y_surf, color='k', alpha=0.21,label='plane')

# Set view and labels
ax.view_init(elev=10)

ax.legend(fontsize='x-large',loc='upper center')
ax.set_xticks([])
ax.set_yticks([])
ax.set_zticks([])
ax.set_box_aspect(None, zoom=0.75)
ax.set_xlabel('ENGINESIZE', fontsize='xx-large')
ax.set_ylabel('FUELCONSUMPTION', fontsize='xx-large')
ax.set_zlabel('CO2 Emissions', fontsize='xx-large')
ax.set_title('Multiple Linear Regression of CO2 Emissions', fontsize='xx-large')
plt.tight_layout()
plt.show()
```

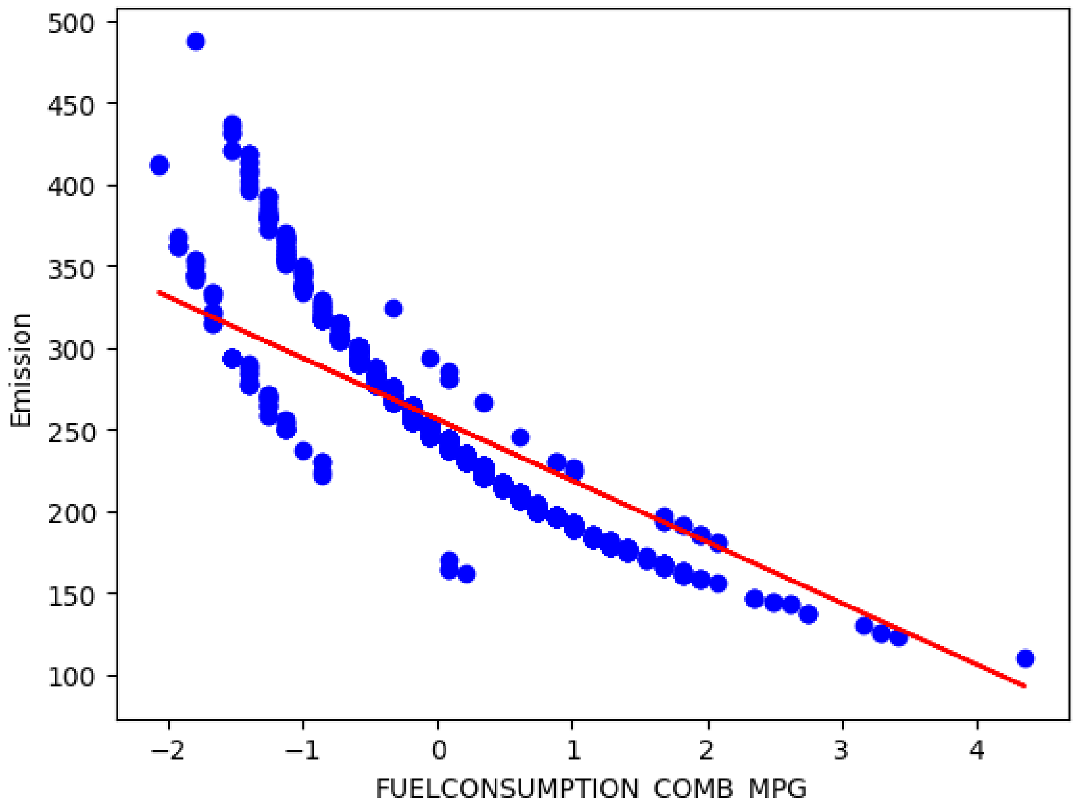


Instead of making a 3D plot, which is difficult to interpret, you can look at vertical slices of the 3D plot by plotting each variable separately as a best-fit line using the corresponding regression parameters.

[28]:
```
plt.scatter(X_train[:,0], y_train,  color='blue')
plt.plot(X_train[:,0], coef_[0,0] * X_train[:,0] + intercept_[0], '-r')
plt.xlabel("Engine size")
plt.ylabel("Emission")
plt.show()
```



[29]:
```
plt.scatter(X_train[:,1], y_train,  color='blue')
plt.plot(X_train[:,1], coef_[0,1] * X_train[:,1] + intercept_[0], '-r')
plt.xlabel("FUELCONSUMPTION_COMB_MPG")
plt.ylabel("Emission")
plt.show()
```



Evidently, the solution is incredibly poor because the model is trying to fit a plane to a non-planar surface.

1.3.8 Exercise 1

Determine and print the parameters for the best-fit linear regression line for CO2 emission with respect to engine size.

[30]:
```
X_train_1 = # ADD CODE

regressor_1 = linear_model.LinearRegression()
regressor_1.# ADD CODE
coef_1 =  # ADD CODE
intercept_1 = # ADD CODE

print ('Coefficients: ',coef_1)
print ('Intercept: ',intercept_1)
```

```
  Cell In[30], line 1
    X_train_1 = # ADD CODE
                ^
```

```
SyntaxError: invalid syntax
```

Click here for the solution

```
X_train_1 = X_train[:,0]
regressor_1 = linear_model.LinearRegression()
regressor_1.fit(X_train_1.reshape(-1, 1), y_train)
coef_1 =  regressor_1.coef_
intercept_1 = regressor_1.intercept_
print ('Coefficients: ',coef_1)
print ('Intercept: ',intercept_1)
```

1.3.9 Exercise 2

Produce a scatterplot of CO2 emission against ENGINESIZE and include the best-fit regression line to the training data.

[ ]:
```
# Enter your code here
plt.scatter(# ADD CODE, y_train,  color='blue')
plt.plot(# ADD CODE, coef_1[0] * X_train_1 + intercept_1, '-r')
plt.xlabel("Engine size")
plt.ylabel("Emission")
```

Click here for the solution

```
plt.scatter(X_train_1, y_train,  color='blue')
plt.plot(X_train_1, coef_1[0] * X_train_1 + intercept_1, '-r')
plt.xlabel("Engine size")
plt.ylabel("Emission")
```

Evidently, this simple linear regression model provides a much better fit of CO2 emissions on the training data than the multiple regression model did. Let's see what its performance is on the test data.

1.3.10 Exercise 3

Generate the same scatterplot and best-fit regression line, but now base the result on the test data set. Consider how the test result compares to the training result.

[ ]:
```
# Enter your code here
X_test_1 =# ADD CODE[:,0]
plt.scatter(#ADD CODE, y_test,  color='blue')
plt.plot(# ADD CODE, coef_1[0] * # ADD CODE + intercept_1, '-r')
plt.xlabel("Engine size")
plt.ylabel("CO2 Emission")
```

Click here for the solution

```
X_test_1 = X_test[:,0]
plt.scatter(X_test_1, y_test,  color='blue')
plt.plot(X_test_1, coef_1[0] * X_test_1 + intercept_1, '-r')
plt.xlabel("Engine size")
plt.ylabel("CO2 Emission")
```

1.3.11 Exercise 4

Repeat the same modeling but use FUELCONSUMPTION_COMB_MPG as the independent variable instead. Display the model coefficients including the intercept.

[ ]:
```
X_train_2 = # ADD CODE
```

Click here for the solution

```
X_train_2 = X_train[:,1]
regressor_2 = linear_model.LinearRegression()
regressor_2.fit(X_train_2.reshape(-1, 1), y_train)
coef_2 =  regressor_2.coef_
intercept_2 = regressor_2.intercept_
print ('Coefficients: ',coef_2)
print ('Intercept: ',intercept_2)
```

1.3.12 Exercise 5

Generate a scatter plot showing the results as before on the test data. Consider well the model fits, and what you might be able to do to improve it. We'll revisit this later in the course.

[ ]:
```
# write your code here
X_test_2 = X_test[:,# ADD CODE]
plt.scatter(X_test_2, # ADD CODE,  color='blue')
plt.plot(X_test_2, # ADD CODE, '-r')
plt.xlabel("# ADD CODE")
plt.ylabel("CO2 Emission")
```

Click here for the solution

```
X_test_2 = X_test[:,1]
plt.scatter(X_test_2, y_test,  color='blue')
plt.plot(X_test_2, coef_2[0] * X_test_2 + intercept_2, '-r')
plt.xlabel("combined Fuel Consumption (MPG)")
plt.ylabel("CO2 Emission")
```

1.3.13 Congratulations! You're ready to move on to your next lesson!

1.4 Author

Jeff Grossman

1.4.1 Other Contributor(s)

Abhishek Gagneja

<!– ## Change Log

Date (YYYY-MM-DD)	Version	Changed By	Change Description
2024-10-31	3.0	Jeff Grossman	Rewrite
2020-11-03	2.1	Lakshmi	Made changes in URL
2020-11-03	2.1	Lakshmi	Made changes in URL
2020-08-27	2.0	Lavanya	Moved lab to course repo in GitLab