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Ara218 / HomeWork / HW_2.ipynb

ara218 fixing homework 2 History

1 contributor

1272 lines (1272 sloc) | 407 KB

HW 2

This assignment covers several aspects of Linear Regresstion. **DO NOT ERASE MARKDOWN CELLS AND INSTRUCTIONS IN YOUR HW submission**

- **Q** - QUESTION
- **A** - Where to input your answer

Instructions

Keep the following in mind for all notebooks you develop:

- Structure your notebook.
- Use headings with meaningful levels in Markdown cells, and explain the questions each piece of code is to answer or the reason it is there.
- Make sure your notebook can always be rerun from top to bottom.
- Please start working on this assignment as soon as possible. If you are a beginner in Python this might take a long time. One of the objectives of this assignment is to help you learn python and scikit-learn package.
- Follow README.md for homework submission instructions

Tutorials

- scikit-learn linear model
- train-test-split
- least squares fitting
- Linear Regression
- Seaborn

REGRESSION TASK USING SKLEARN

In jupyter notebook environment, commands starting with the symbol % are magic commands or magic functions. `%%timeit` is one of such function. It basically gives you the speed of execution of certain statement or blocks of codes.

In [18]:
```
import pandas as pd
import numpy as np
import seaborn as sns
```

Data Get the exploratory data and the folowwing files:

https://archive.ics.uci.edu/ml/machine-learning-databases/auto-mpg/auto-mpg.data

https://archive.ics.uci.edu/ml/machine-learning-databases/auto-mpg/auto-mpg.data
https://archive.ics.uci.edu/ml/machine-learning-databases/auto-mpg/auto-mpg.names

or Use from our 2024Spring/data repository folder

- Link should automatically download the data
- copy them in your HW folder
- If you are using command line:

```
>> wget https://archive.ics.uci.edu/ml/machine-learning-databases/auto-mpg/auto-mpg.data
```

- If wget is not working
  - dowload it from link
  - follow steps

Q1 Read the data using pandas, and replace the ??? in the code cell below to accomplish this taks. Note that auto-mpg.data does not have the column headers. use auto-mpg.names file to provide column names to the dataframe.

A1

In [19]:
```
# Replace ??? with code in the code cell below
column_names = [ "mpg","cylinders","displacement","horsepower","weight","acc
df = pd.read_csv("C:\\Users\\alsae\\Desktop\\ML\\Ara218\\data\\auto-mpg.data
```

In [20]:
```
# View head of the data to confirm the correctness of your answer
df.head()
```

Out[20]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin
0	18.0	8	307.0	130.0	3504.0	12.0	70	1
1	15.0	8	350.0	165.0	3693.0	11.5	70	1
2	18.0	8	318.0	150.0	3436.0	11.0	70	1
3	16.0	8	304.0	150.0	3433.0	12.0	70	1
4	17.0	8	302.0	140.0	3449.0	10.5	70	1

Data cleaning and manipulation

Use

Q2 Data cleaning and manipulation:

1. use `pandas.info()` method to find columns with large number of NaN values
2. remove the column with NaN values
3. Check if there are still NaN values in the dataframe using `isna()` method

A2 Replace ??? with code in the code cell below

In [21]:

```
#1. use pandas.info() method to find columns with large number of NaN values
df.info()

#2. remove the column with NaN values - replace ??? with code
df.dropna(axis=1)
# Print head
print(df.head())

#3. Check if there are still NaN values in the dataframe using ```isna()``` 
print(df.isna().sum())

# drop if any left or replace Nan values
df.dropna()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64  
 2   displacement  398 non-null    float64
 3   horsepower    392 non-null    float64
 4   weight        398 non-null    float64
 5   acceleration  398 non-null    float64
 6   model year    398 non-null    int64  
 7   origin        398 non-null    int64  
 8   car name      398 non-null    object 
dtypes: float64(5), int64(3), object(1)
memory usage: 28.1+ KB
    mpg  cylinders  displacement  horsepower  weight  acceleration  \
0  18.0          8         307.0       130.0  3504.0          12.0   
1  15.0          8         350.0       165.0  3693.0          11.5   
2  18.0          8         318.0       150.0  3436.0          11.0   
3  16.0          8         304.0       150.0  3433.0          12.0   
4  17.0          8         302.0       140.0  3449.0          10.5   

   model year  origin                   car name  
0          70       1  chevrolet chevelle malibu  
1          70       1          buick skylark 320  
2          70       1         plymouth satellite  
3          70       1              amc rebel sst  
4          70       1                ford torino  
```

```
mpg             0
cylinders       0
displacement    0
horsepower      6
weight          0
acceleration    0
model year      0
origin          0
car name        0
dtype: int64
```

Out[21]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origi
0	18.0	8	307.0	130.0	3504.0	12.0	70	
1	15.0	8	350.0	165.0	3693.0	11.5	70	
2	18.0	8	318.0	150.0	3436.0	11.0	70	
3	16.0	8	304.0	150.0	3433.0	12.0	70	
4	17.0	8	302.0	140.0	3449.0	10.5	70	
...	...	...	...	...	...	...	...	..
393	27.0	4	140.0	86.0	2790.0	15.6	82	
394	44.0	4	97.0	52.0	2130.0	24.6	82	
395	32.0	4	135.0	84.0	2295.0	11.6	82	
396	28.0	4	120.0	79.0	2625.0	18.6	82	
397	31.0	4	119.0	82.0	2720.0	19.4	82	

392 rows × 9 columns

In [22]:

```
#Print Tail
df.tail()
```

Out[22]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origi

393	27.0	4	140.0	86.0	2790.0	15.6	82
394	44.0	4	97.0	52.0	2130.0	24.6	82
395	32.0	4	135.0	84.0	2295.0	11.6	82
396	28.0	4	120.0	79.0	2625.0	18.6	82
397	31.0	4	119.0	82.0	2720.0	19.4	82

Q3:

1. Convert following columns 'cylinders', 'year', 'origin' to dummy variable using pandas get_dummies() function
2. Do data normalization on real value/continous columns
   - The formula for normalization is: (Col_value- Mean of the col)/ Standard Deviation of the col

A3 Replace ??? with code in the code cell below

In [23]:

```
# 1. Convert following columns 'cylinders', 'year', 'origin'  to dummy varia
cols = ['cylinders', 'model year', 'origin']
df_dummies = pd.get_dummies(df,columns=cols)

#show the head
print(df_dummies.head())

# 2. Do data normalization on real value/continous columns
realcols = ['mpg', 'displacement', 'horsepower', 'weight', 'acceleration']

for col in realcols:
  mean = df[col].mean()
  std = df[col].std()
  df[col] = (df[col] - mean) / std
```

```
    mpg  displacement  horsepower  weight  acceleration  \
0  18.0         307.0       130.0  3504.0          12.0
1  15.0         350.0       165.0  3693.0          11.5
2  18.0         318.0       150.0  3436.0          11.0
3  16.0         304.0       150.0  3433.0          12.0
4  17.0         302.0       140.0  3449.0          10.5

                    car name  cylinders_3  cylinders_4  cylinders_5  \
0  chevrolet chevelle malibu            0            0            0
1          buick skylark 320            0            0            0
2         plymouth satellite            0            0            0
3              amc rebel sst            0            0            0
4                ford torino            0            0            0

   cylinders_6  ...  model year_76  model year_77  model year_78  \
```

```
0           0  ...           0           0           0
1           0  ...           0           0           0
2           0  ...           0           0           0
3           0  ...           0           0           0
4           0  ...           0           0           0

   model year_79  model year_80  model year_81  model year_82  origin_1  \
0              0              0              0              0         1
1              0              0              0              0         1
2              0              0              0              0         1
3              0              0              0              0         1
4              0              0              0              0         1

   origin_2  origin_3
0         0         0
1         0         0
2         0         0
3         0         0
4         0         0

[5 rows x 27 columns]
```

Regression Task

Given all the information we will try to predict mpg - miles per gallon. The First step toward predicting the mpg from the dataset is to find the correlation between the columns/features of the dataset.

Q4

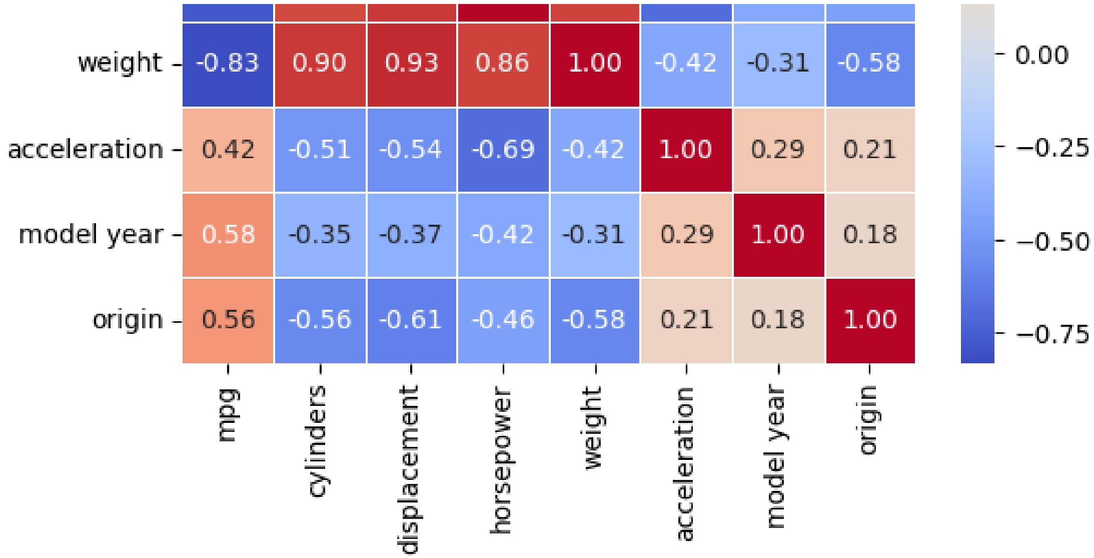
1. Use heatmap chart from seaborn library to findout the correlation between the columns.
2. Which of the columns is mostly related to mpg column and why?

In [24]:

```python
# A4 code goes below
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.
```

```
C:\Users\alsae\AppData\Local\Temp\ipykernel_16020\3874445986.py:2: FutureWarni
ng: The default value of numeric_only in DataFrame.corr is deprecated. In a fu
ture version, it will default to False. Select only valid columns or specify t
he value of numeric_only to silence this warning.
  sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.
5)
```

Out[24]: <Axes: >

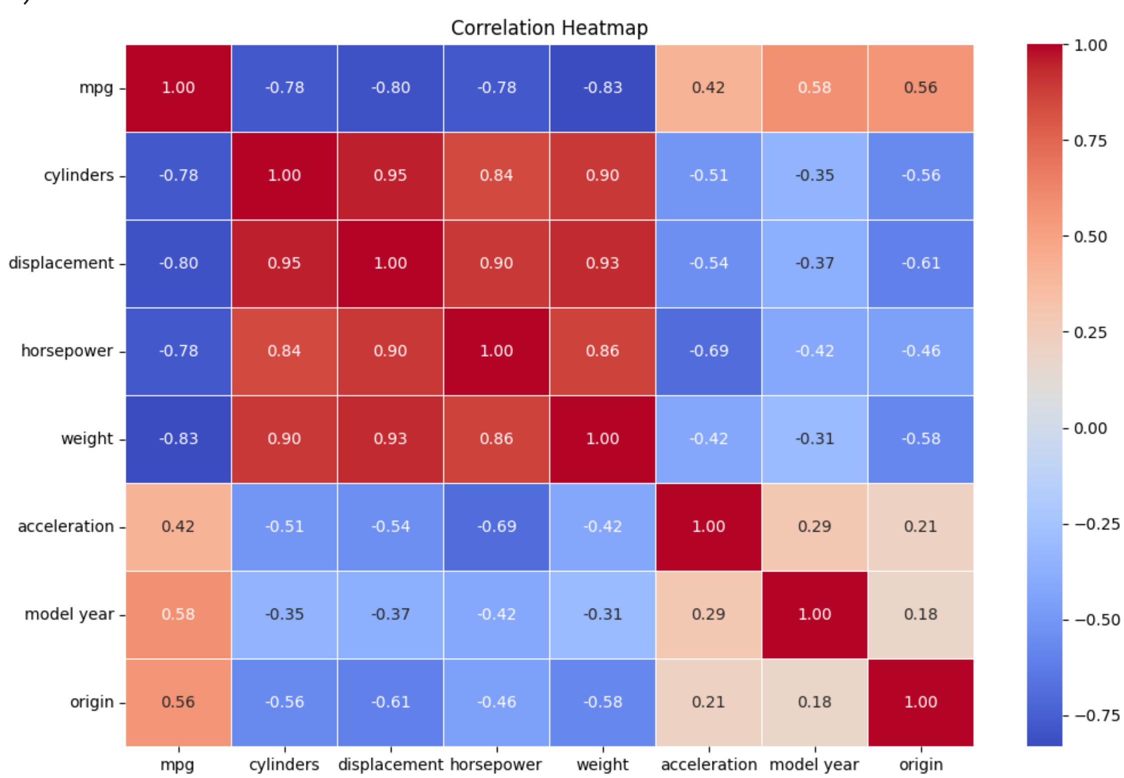


In [25]:

```
import matplotlib.pyplot as plt

# A4 code goes below
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.
plt.title('Correlation Heatmap')
plt.show()
```

```
C:\Users\alsae\AppData\Local\Temp\ipykernel_16020\1981092764.py:5: FutureWarni
ng: The default value of numeric_only in DataFrame.corr is deprecated. In a fu
ture version, it will default to False. Select only valid columns or specify t
he value of numeric_only to silence this warning.
  sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.
5)
```



A4

the coulmns most related to horse power are displacement horsepower and weight, the bigger the car and the stronger the car the more of an effect that will have on the mpg for example if a car weighs more it will have a lower mpg they have a negtive corrlation ot one another so mpg is dependent on those 3 columns

Q5

1. Draw a lineplot or scattered plot between mpg and your answer from the above cell.
2. Use pairplot from sns to plot our data frame df for better understanding of your selection
   - NOTE: 2. should inform 3.
3. Choose a set of columns/ features based on pairplot and heatmap for the mpg prediction.

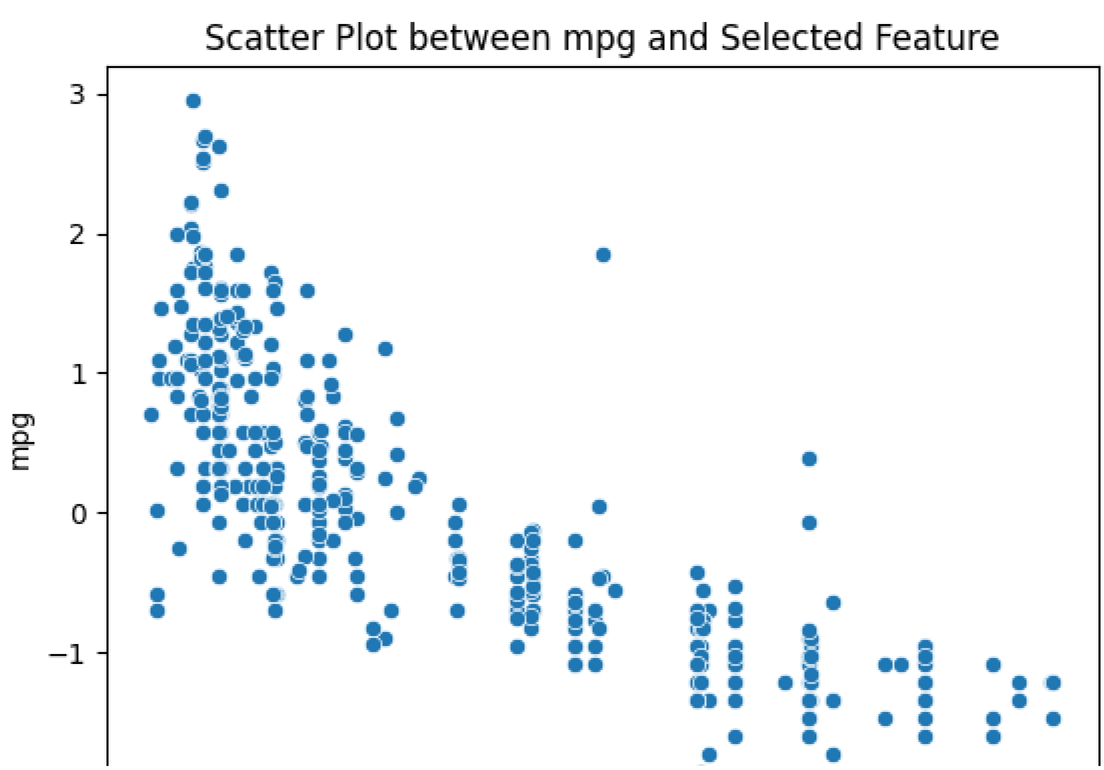
- Justify your answer using some explanation from the heatmap and pairplot graph formulated from the dataset.

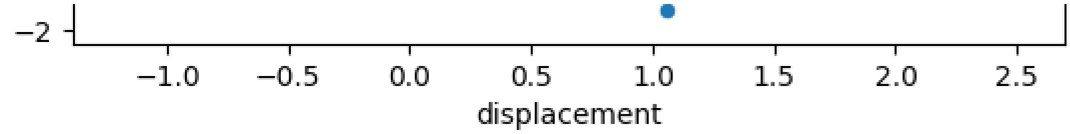
A5 For 1. and 2. replace ??? with code in the code cell below.

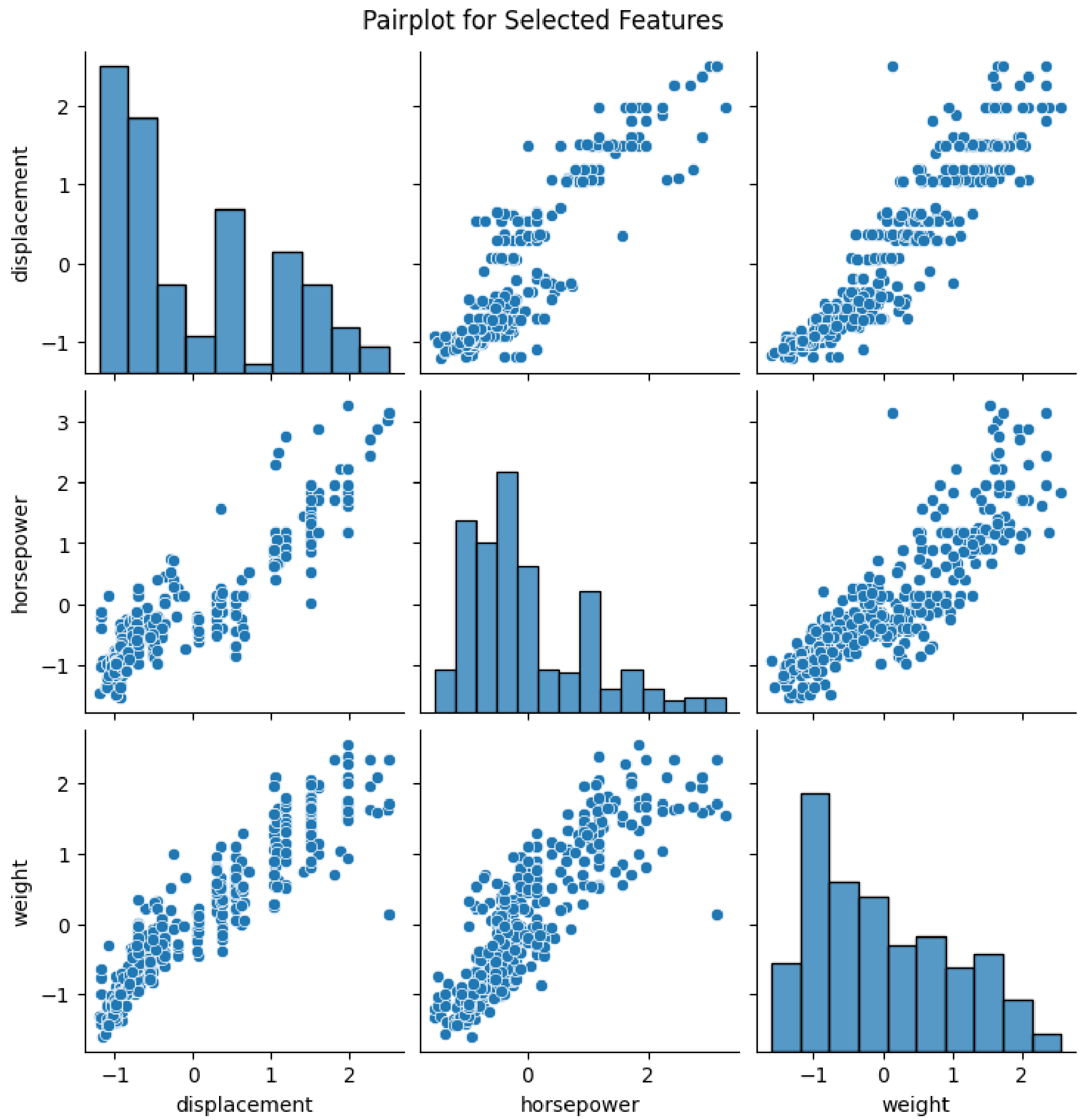
In [26]:

```
# Draw a lineplot or scattered plot between mpg and your answer from the abo
sns.scatterplot(x='displacement', y='mpg', data=df)
plt.title('Scatter Plot between mpg and Selected Feature')
plt.show()

# Use pairplot from sns to plot our data frame df for better understanding o
selected_columns = ["displacement","horsepower","weight"]  # Replace with th
sns.pairplot(df[selected_columns])
plt.suptitle('Pairplot for Selected Features', y=1.02)
plt.show()
```







A5

For 3., write down your explanation here replacing this line

Data Preparation

Q7 Assign mpg column value to y and rest columns to x, remember x shouldn't have mpg

A7 Replace ??? with code in the code cell below

In [27]:

```
df = df.drop('car name', axis=1)
df.dropna(inplace=True)
```

In [28]:
```
y = df['mpg']
x = df.drop('mpg', axis=1)
```

Q8 Use train_test_split to split the data set as train:test=(80%:20%) ratio.

A8 Replace ??? with code in the code cell below

In [29]:
```
from sklearn.model_selection import train_test_split

xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.2, random_

# View the shape of your data sets
print(xtrain.shape, xtest.shape, ytrain.shape, ytest.shape)
```

```
(313, 7) (79, 7) (313,) (79,)
```

Q9 Follow examples from references given in the top of this notebook

- Note:Use linear model to fit regression line and plot
- Our linear model will be of following type
- Y = b + coef0*x0* + *coef1*x1+coef2*x2+...........

A9: Replace ??? with code in the code cell below

In [30]:
```
from sklearn import linear_model

reg = linear_model.LinearRegression()
reg.fit(xtrain,ytrain)

#Now view the coefficient use .coef_ and shape of .coef_
print(reg.coef_)
print(reg.intercept_)
print(reg.coef_.shape[0])
```

```
[-0.04424124  0.2015591  -0.10490412 -0.66542926  0.01338978  0.09822724
  0.20643044]
-7.54470861207705
7
```

Q10 Relates to the code in the cell below. Why the printed values the same?

In [31]:
```
# Now if you view
print(f'{reg.coef_.shape[0]},{xtrain.shape[1]}, ', f'are equal? {reg.coef_.s
```

```
7,7,  are equal? True
```

A10 Since each feature corresponds to a coefficient in the linear regression model, the number of coefficients is equal to the number of features

Model Scoring

In [32]:

```
# Model Score
from sklearn import linear_model
reg = linear_model.LinearRegression()
reg.fit(xtrain, ytrain)
reg.score(xtest,ytest)

# Calculate the score on train and test sets
# Your code goes below
reg.score(xtrain,ytrain), reg.score(xtest,ytest)
```

Out[32]: (0.826001578671067, 0.7901500386760345)

Q11 Each of the sklearn models have different model evaluations core value.

- LinearRegression documentation
- More on model_evaluation

Explain what's the meaning of reg.score return value in this notebook.

A11 Write your answer replacing this line

In [33]:

```
# A custom function to calculate r2 score
# Details on the custom scorers: https://scikit-learn.org/stable/modules/mod

def r2score_(ytrue, ypred):
  rss = ((ytrue - ypred)**2).sum()
  tss = ((ytrue - ytrue.mean()) ** 2).sum()
  r2 = 1 - rss/tss
  return r2

# Now do prediction on xtrain and xtest and check your r2 score by printing
trainpredict = reg.predict(xtrain)
testpredict = reg.predict(xtest)

print(r2score_(ytrain, trainpredict), r2score_(ytest, testpredict))
```

0.826001578671067 0.7901500386760345

One way of achieving linear regression is by minimizing the error between actual y and predicted y. The method is known as least square method. We will make our custom least square optimize to calculate model parameters that minimizes output error.

Q12 Write a function which takes weights(or params), x and y and do following

- 1. calculate dot product between x and params , which is ypredicted
- 2. calculate difference between actual y and ypredicted
- 3. return the difference

A12 complete the code below

In [34]:

```
import scipy.optimize as optimization
from sklearn.metrics import r2_score
```

```
def constraint(params, x, y):
  ypred = x@params
  return y-ypred

# Our initial params is a vector of size equal to dimension of x, or you can
# You can create zeros vector using np.zeros(size)

# complete code
params = np.zeros(xtrain.shape[1])


# Now study the documentation and complete following code
params, _ = optimization.leastsq(constraint, params, args=(xtrain, ytrain))

# Now we have parameter or weight we can now create our model
model = lambda x:np.dot(x,params)

# Now predict ytrain using model and see first 5 predicted and actual values
ypred_train = model(xtrain)
# see first 5 predicted values
print("Predicted values (train):", ypred_train[:5])
# see first 5 actual values
print("Actual values (train):", ytrain[:5])

# Now predict ytest using model and see first 5 predicted and actual values
ypred_test = model(xtest)
```