Example 1-Multiple_Linear_Regression

```
import numpy as np
from sklearn.linear_model import LinearRegression

x = [[0, 1], [5, 1], [15, 2], [25, 5], [35, 11],[45, 15], [55, 34], [60, 35]]
y = [4, 5, 20, 14, 32, 22, 38, 43]
x, y = np.array(x), np.array(y)
print(x)
print(y)
x.shape
y.shape
```

```
[[ 0  1]
 [ 5  1]
 [15  2]
 [25  5]
 [35 11]
 [45 15]
 [55 34]
 [60 35]]
[ 4  5 20 14 32 22 38 43]
(8,)
```

```
model = LinearRegression().fit(x, y)
```

```
r_sq = model.score(x, y)
print(f"coefficient of determination: {r_sq}")
print(f"intercept: {model.intercept_}")
print(f"coefficients: {model.coef_}")
```

```
coefficient of determination: 0.8615939258756776
intercept: 5.52257927519819
coefficients: [0.44706965 0.25502548]
```

```
y_pred = model.predict(x)
print(f"predicted response:\n{y_pred}")
```

```
predicted response:
[ 5.77760476  8.012953   12.73867497 17.9744479  23.97529728 29.4660957
 38.78227633 41.27265006]
```

```
# Verification of predict expression
y_pred = model.intercept_ + np.sum(model.coef_ * x, axis=1)
print(f"predicted response:\n{y_pred}")
```

```
predicted response:
[ 5.77760476  8.012953   12.73867497 17.9744479  23.97529728 29.4660957
 38.78227633 41.27265006]
```

Example 2-Multiple_Linear_Regression using boston data

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
boston_data_frame= pd.read_csv("/content/drive/MyDrive/AI Tools Lab/boston_house_prices.csv")
boston_data_frame.head()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LST.
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.

```
"""CRIM - per capita crime rate by town
ZN - proportion of residential land zoned for lots over 25,000 sq.ft.
INDUS - proportion of non-retail business acres per town.
CHAS - Charles River dummy variable (1 if tract bounds river; 0 otherwise)
NOX - nitric oxides concentration (parts per 10 million)
RM - average number of rooms per dwelling
AGE - proportion of owner-occupied units built prior to 1940
DIS - weighted distances to five Boston employment centres
RAD - index of accessibility to radial highways
TAX - full-value property-tax rate per $10,000
PTRATIO - pupil-teacher ratio by town
B - 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
LSTAT - % lower status of the population
MEDV - Median value of owner-occupied homes in $1000's
Price-Price"""
```

```
#First, check for missing information.
boston_data_frame.isnull().sum()
```

```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
MEDV       0
PRICE      0
dtype: int64
```

```
boston_data_frame.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 15 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    int64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    int64
 9   TAX      506 non-null    int64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    506 non-null    float64
 13  MEDV     506 non-null    float64
 14  PRICE    506 non-null    float64
dtypes: float64(12), int64(3)
memory usage: 59.4 KB
```

```
#We can separate dependent and independent variables
boston_data_X = boston_data_frame[boston_data_frame.columns[0:13]]
boston_data_Y = boston_data_frame[boston_data_frame.columns[13:14]]
```

```
print(boston_data_X)
print(boston_data_Y)
```

```
        CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD  TAX  \
0    0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296
1    0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242
2    0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242
3    0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222
4    0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222
..       ...   ...    ...   ...    ...    ...   ...     ...  ...  ...
501  0.06263   0.0  11.93     0  0.573  6.593  69.1  2.4786    1  273
502  0.04527   0.0  11.93     0  0.573  6.120  76.7  2.2875    1  273
503  0.06076   0.0  11.93     0  0.573  6.976  91.0  2.1675    1  273
504  0.10959   0.0  11.93     0  0.573  6.794  89.3  2.3889    1  273
505  0.04741   0.0  11.93     0  0.573  6.030  80.8  2.5050    1  273

     PTRATIO       B  LSTAT
0       15.3  396.90   4.98
1       17.8  396.90   9.14
```

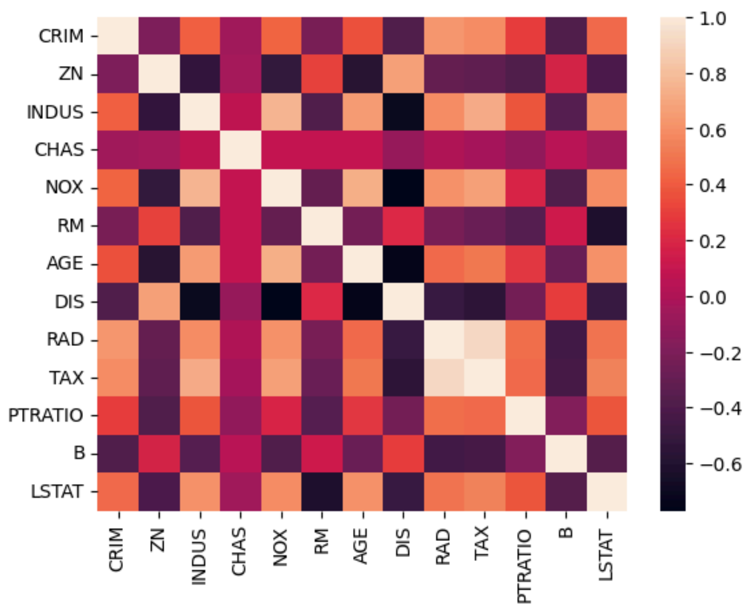
```
2       17.8  392.83   4.03
3       18.7  394.63   2.94
4       18.7  396.90   5.33
..       ...     ...    ...
501     21.0  391.99   9.67
502     21.0  396.90   9.08
503     21.0  396.90   5.64
504     21.0  393.45   6.48
505     21.0  396.90   7.88

[506 rows x 13 columns]
     MEDV
0    24.0
1    21.6
2    34.7
3    33.4
4    36.2
..    ...
501  22.4
502  20.6
503  23.9
504  22.0
505  11.9

[506 rows x 1 columns]
```

```
#Check the correlation
boston_data_X.corr()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.37
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.66
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.70
CHAS	-0.055892	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518	-0.09
NOX	0.420972	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470	-0.76
RM	-0.219247	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265	0.20
AGE	0.352734	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000	-0.74
DIS	-0.379670	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	1.00
RAD	0.625505	-0.311948	0.595129	-0.007368	0.611441	-0.209847	0.456022	-0.49
TAX	0.582764	-0.314563	0.720760	-0.035587	0.668023	-0.292048	0.506456	-0.53
PTRATIO	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.23
B	-0.385064	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534	0.29
LSTAT	0.455621	-0.412995	0.603800	-0.053929	0.590879	-0.613808	0.602339	-0.49

```
#Visualize correlation between attributes by using heatmap
sns.heatmap(boston_data_X.corr())
```

```
<Axes: >
```



```
#Feature contains high correlation. We need to remove them first before applying regression techniques. Create correlation matrix
abs_corr_matrix = boston_data_X.corr().abs()
#print(abs_corr_matrix)
#Select upper triangle of matrix
up_tri=abs_corr_matrix.where(np.triu(np.ones(abs_corr_matrix.shape),k=1).astype(np.bool_))
print(up_tri)
# Find all the features which is having correlation > 0.75 with other features.
correlated_features = [column for column in up_tri.columns if any(up_tri[column] > 0.75)]
#Print correlated_features
print(correlated_features)
```

```
             CRIM        ZN     INDUS      CHAS       NOX        RM       AGE  \
CRIM          NaN  0.200469  0.406583  0.055892  0.420972  0.219247  0.352734
ZN            NaN       NaN  0.533828  0.042697  0.516604  0.311991  0.569537
INDUS         NaN       NaN       NaN  0.062938  0.763651  0.391676  0.644779
CHAS          NaN       NaN       NaN       NaN  0.091203  0.091251  0.086518
NOX           NaN       NaN       NaN       NaN       NaN  0.302188  0.731470
RM            NaN       NaN       NaN       NaN       NaN       NaN  0.240265
AGE           NaN       NaN       NaN       NaN       NaN       NaN       NaN
DIS           NaN       NaN       NaN       NaN       NaN       NaN       NaN
RAD           NaN       NaN       NaN       NaN       NaN       NaN       NaN
TAX           NaN       NaN       NaN       NaN       NaN       NaN       NaN
PTRATIO       NaN       NaN       NaN       NaN       NaN       NaN       NaN
B             NaN       NaN       NaN       NaN       NaN       NaN       NaN
LSTAT         NaN       NaN       NaN       NaN       NaN       NaN       NaN

              DIS       RAD       TAX   PTRATIO         B     LSTAT
CRIM     0.379670  0.625505  0.582764  0.289946  0.385064  0.455621
ZN       0.664408  0.311948  0.314563  0.391679  0.175520  0.412995
INDUS    0.708027  0.595129  0.720760  0.383248  0.356977  0.603800
CHAS     0.099176  0.007368  0.035587  0.121515  0.048788  0.053929
NOX      0.769230  0.611441  0.668023  0.188933  0.380051  0.590879
RM       0.205246  0.209847  0.292048  0.355501  0.128069  0.613808
AGE      0.747881  0.456022  0.506456  0.261515  0.273534  0.602339
DIS           NaN  0.494588  0.534432  0.232471  0.291512  0.496996
RAD           NaN       NaN  0.910228  0.464741  0.444413  0.488676
TAX           NaN       NaN       NaN  0.460853  0.441808  0.543993
PTRATIO       NaN       NaN       NaN       NaN  0.177383  0.374044
B             NaN       NaN       NaN       NaN       NaN  0.366087
LSTAT         NaN       NaN       NaN       NaN       NaN       NaN
['NOX', 'DIS', 'TAX']
```

```
#Drop correlated features to avoid redundancy
boston_data_X = boston_data_X.drop(correlated_features,
axis=1)
```

```
#Divide the data into training and test set. Train set contains 80% of the data. Testset contains 20% of the data.
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(boston_data_X, boston_data_Y, test_size=0.20)
```

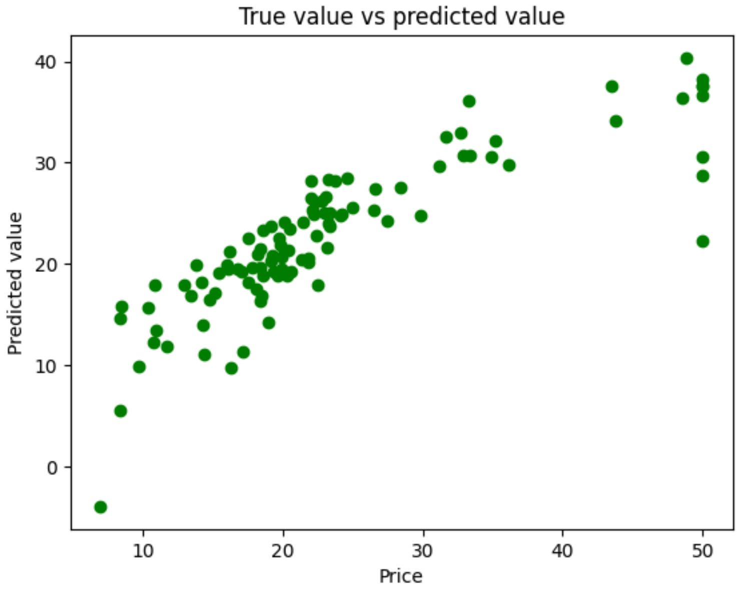
```
from sklearn.linear_model import LinearRegression
linear_regression = LinearRegression()
```

```
linear_regression.fit(X_train,Y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
Y_pred = linear_regression.predict(X_test)
```

```
plt.scatter(Y_test, Y_pred, c = 'green')
plt.xlabel("Price")
plt.ylabel("Predicted value")
plt.title("True value vs predicted value")
plt.show()
```




```
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
mse = mean_squared_error(Y_test, Y_pred)
mae = mean_absolute_error(Y_test, Y_pred)
r2=r2_score(Y_test, Y_pred)
print("Mean Square Error : ", mse)
print("Mean Absolute Error : ", mae)
#MSE is more sensitive to outliers than MAE because the errors are squared, which means that larger errors have a disproportionately lar
print("R2score : ", r2)
```

```
Mean Square Error :  35.936830198059006
Mean Absolute Error :  4.005302201237243
R2score :  0.6844594894233893
```

Start coding or generate with AI.