WEEK-6
MODEL EVALUATION AND TESTING
Session-7

Implement Python Program to Build and Evaluate Regression model

Let us consider Boston housing price dataset to Build and Evaluate regression model**.** We can access this data from the scikit-learn library. There are 506 samples and 13 feature variables in this dataset. The objective is to predict the value of prices of the house using the given features.

We followed the general machine learning workflow step-by-step:

1. Import the Required Libraries

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
%matplotlib inline
```

2. Import Dataset and Understand It

```
from sklearn.datasets import load_boston
boston_dataset = load_boston()
```

Print the value of the boston_dataset to understand what it contains.

```
print(boston_dataset.keys())
```

Gives

```
dict_keys(['data', 'target', 'feature_names', 'DESCR'])
```

- *data*: contains the information for various houses
- *target*: prices of the house
- *feature_names*: names of the features

- *DESCR*: describes the dataset

To know more about the features use boston_dataset.DESCR The description of all the features is given below

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 oxide 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 centers
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 [people of African American descent] by town
LSTAT: Percentage of lower status of the population
MEDV: Median value of owner-occupied homes in $1000s

The prices of the house indicated by the variable MEDV is our ***target variable*** and the remaining are the ***feature variables*** based on which we will predict the value of a house.

We will now load the data into a pandas dataframe using pd.DataFrame. and then print the first 5 rows of the data using head()

```
boston = pd.DataFrame(boston_dataset.data, columns=boston_dataset.feature_names)
boston.head()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

3. Data Pre-processing

After loading the data, it's a good practice to see if there are any missing values in the data. We count the number of missing values for each feature using isnull()

```
boston.isnull().sum()
```

there are no missing values in this dataset as shown below.

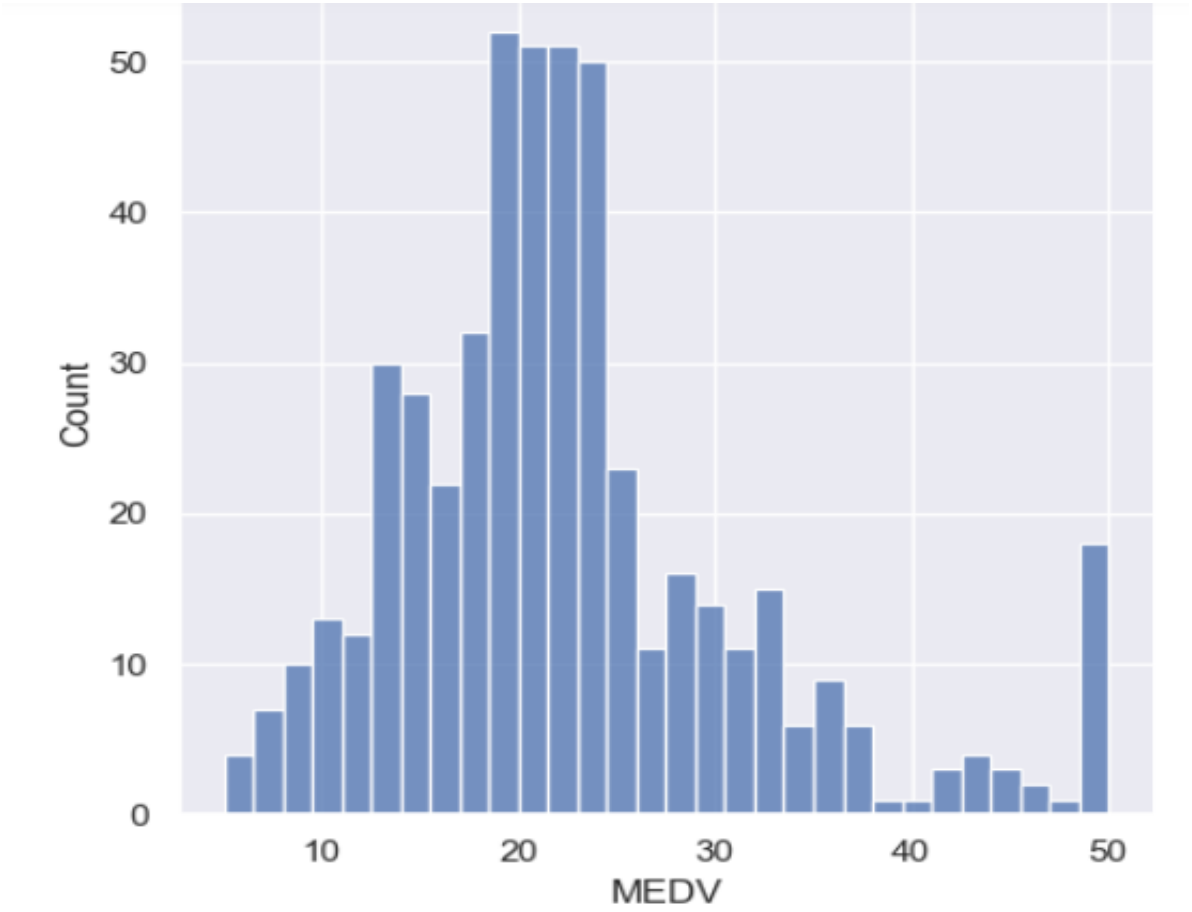
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
MEDV       0
dtype: int64
```

4. Exploratory Data Analysis

Exploratory Data Analysis is a very important step before training the model. In this section, we will use some visualizations to understand the relationship of the target variable with other features.

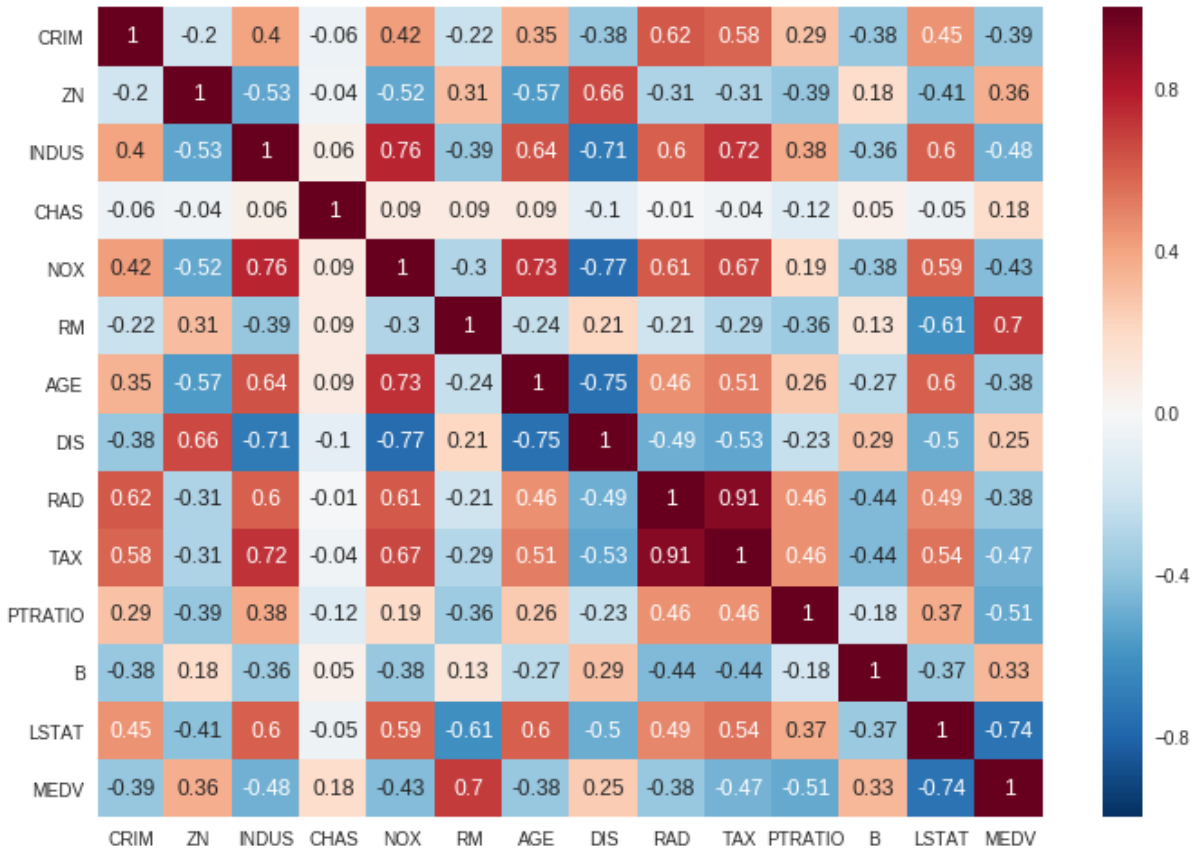
Let's first plot the distribution of the target variable MEDV. We will use the distplot function from the seaborn library.

```
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.distplot(boston['MEDV'], bins=30)
plt.show()
```



we create a correlation matrix that measures the linear relationships between the variables. The correlation matrix can be formed by using the corr function from the pandas dataframe library. We will use the heatmap function from the seaborn library to plot the correlation matrix.

```
correlation_matrix = boston.corr().round(2)
# annot = True to print the values inside the square
sns.heatmap(data=correlation_matrix, annot=True)
```



The correlation coefficient ranges from -1 to 1. If the value is close to 1, it means that there is a strong positive correlation between the two variables. When it is close to -1, the variables have a strong negative correlation.

Observations:

- To fit a linear regression model, we select those features which have a high correlation with our target variable MEDV. By looking at the correlation matrix we can see that RM has a strong positive correlation with MEDV (0.7) where as LSTAT has a high negative correlation with MEDV (-0.74).

- An important point in selecting features for a linear regression model is to check for multi-co-linearity. The features RAD, TAX have a correlation of 0.91. These feature

- pairs are strongly correlated to each other. We should not select both these features together for training the model. Same goes for the features DIS and AGE which have a correlation of -0.75.

Based on the above observations we will understand RM and LSTAT as our features. Using a scatter plot let’s see how these features vary with MEDV.

```
plt.figure(figsize=(20, 5))
features = ['LSTAT', 'RM']
target = boston['MEDV']
for i, col in enumerate(features):
    plt.subplot(1, len(features) , i+1)
    x = boston[col]
    y = target
    plt.scatter(x, y, marker='o')
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel('MEDV')
```

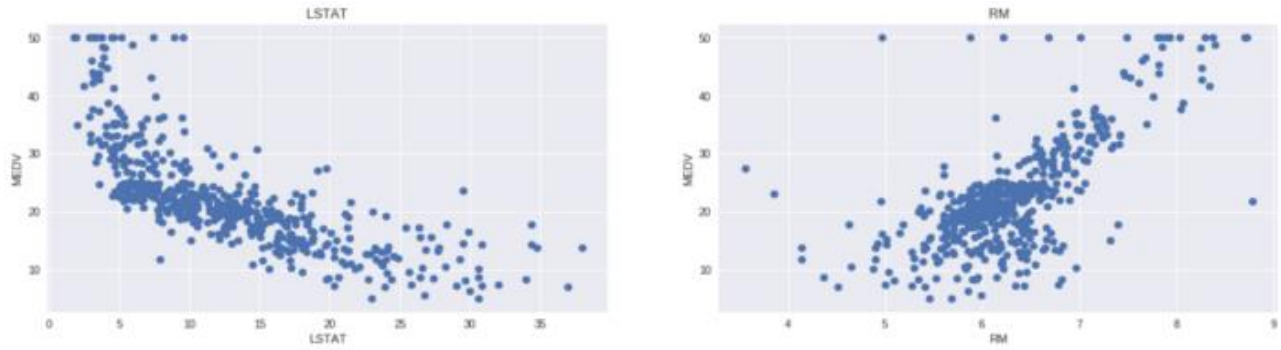


Fig: Comparing Features of RM and LSTAT

Observations:

- The prices increase as the value of RM increases linearly. There are few outliers and the data seems to be capped at 50.
- The prices tend to decrease with an increase in LSTAT. Though it doesn't look to be following exactly a linear line.

5. Preparing the Data for Training the Model

We concatenate the LSTAT and RM columns using np.c_ provided by the numpy library.

```
X = pd.DataFrame(np.c_[boston['LSTAT'], boston['RM']], columns = ['LSTAT','RM'])
Y = boston['MEDV']
```

6. Splitting the Data into Training and Testing Sets

Next, we split the data into training and testing sets. We train the model with 80% of the samples and test with the remaining 20%. We do this to assess the model's performance on unseen data. To split the data, we use train_test_split function provided by scikit-learn library. We finally print the sizes of our training and test set to verify if the splitting has occurred properly.

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2, random_state=5)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
```

```
(404, 2)
(102, 2)
(404,)
(102,)
```

7. Training and Testing the Model

We use scikit-learn's Linear Regression to train our model on both the training and test sets.

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

lin_model = LinearRegression()
lin_model.fit(X_train, Y_train)
```

8. Model Evaluation

We will evaluate our model using RMSE and R2-score.

```
# model evaluation for training set
y_train_predict = lin_model.predict(X_train)
rmse = (np.sqrt(mean_squared_error(Y_train, y_train_predict)))
r2 = r2_score(Y_train, y_train_predict)

print("The model performance for training set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse))
print('R2 score is {}'.format(r2))
print("\n")

# model evaluation for testing set
y_test_predict = lin_model.predict(X_test)
rmse = (np.sqrt(mean_squared_error(Y_test, y_test_predict)))
r2 = r2_score(Y_test, y_test_predict)

print("The model performance for testing set")
print("--------------------------------------")
print('RMSE is {}'.format(rmse))
print('R2 score is {}'.format(r2))
```

The model performance for training set

RMSE is 5.6371293350711955

R2 score is 0.6300745149331701

The model performance for testing set

RMSE is 5.137400784702911

R2 score is 0.6628996975186952

This concludes machine is able to predict the value of prices of the house based on the given features.