Experiment No. 1
Analyze the Boston Housing dataset and apply appropriate Regression Technique
Date of Performance: 24-7-23
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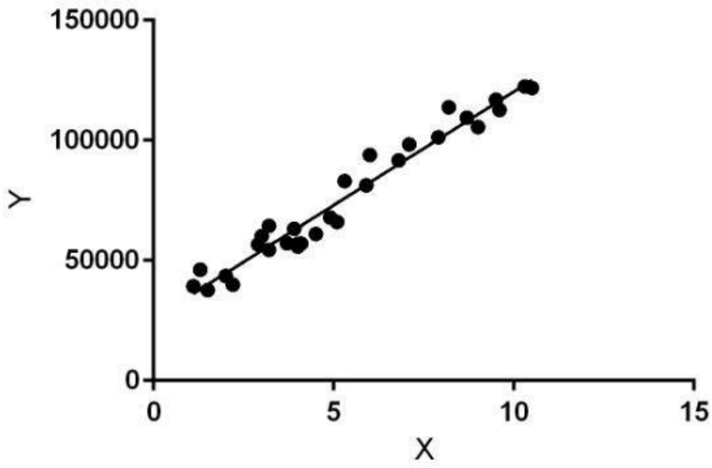
Aim: Analyze the Boston Housing dataset and apply appropriate Regression Technique.

Objective: Ablility to perform various feature engineering tasks, apply linear regression on the given dataset and minimise the error.

Theory:

Linear Regression is a machine learning algorithm based on supervised learning. It performs a regression task. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables and forecasting. Different regression models differ based on – the kind of relationship between dependent and independent variables they are considering, and the number of independent variables getting used.



Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a linear relationship between x (input) and y(output). Hence, the name is Linear Regression.
In the figure above, X (input) is the work experience and Y (output) is the salary of a person. The regression line is the best fit line for our model.

Dataset:
The Boston Housing Dataset
The Boston Housing Dataset is a derived from information collected by the U.S. Census Service concerning housing in the area of Boston MA. The following describes the dataset columns:

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

Code:

Conclusion:

A number of characteristics that capture different facets of the towns and may have an impact on the median home value are included in the features that were chosen for the purpose of predicting house prices. CRIM, ZN, INDUS, CHAS, NOX, RM, AGE, DIS, RAD, TAX, PTRATIO, B, and LSTAT are some of their characteristics. Average number of rooms, nitric oxide content, percentage of residential land, and crime rate. The proximity to highways, the rate of property taxes, and other variables affect the value of homes in various neighbourhoods. Our prediction model's primary focus is the target variable, MEDV (Median Home Value), which may be predicted using these features.

The average squared difference between the model's projected and actual house values is represented by the Mean Squared Error, which stands at 0.03112933398095344. The model's predictions are evaluated to see if they are sufficiently accurate by comparing this number to the range of real property prices.

```
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
for filename in filenames:
print(os.path.join(dirname, filename))
```

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression,SGDRegressor
from sklearn.metrics import mean_squared_error
import matplotlib
import matplotlib.pyplot as plt
```

```
data = pd.read_csv("/content/HousingData.csv")
```

```
data.head()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	NaN	36.2

```
data.keys()
```

```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'MEDV'],
      dtype='object')
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     486 non-null    float64
 1   ZN       486 non-null    float64
 2   INDUS    486 non-null    float64
 3   CHAS     486 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      486 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    486 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

```
data.describe()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO
count	486.000000	486.000000	486.000000	486.000000	506.000000	506.000000	486.000000	506.000000	506.000000	506.000000	506.000000
mean	3.611874	11.211934	11.083992	0.069959	0.554695	6.284634	68.518519	3.795043	9.549407	408.237154	18.455534
std	8.720192	23.388876	6.835896	0.255340	0.115878	0.702617	27.999513	2.105710	8.707259	168.537116	2.164946
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000
25%	0.081900	0.000000	5.190000	0.000000	0.449000	5.885500	45.175000	2.100175	4.000000	279.000000	17.400000
50%	0.253715	0.000000	9.690000	0.000000	0.538000	6.208500	76.800000	3.207450	5.000000	330.000000	19.050000
75%	3.560263	12.500000	18.100000	0.000000	0.624000	6.623500	93.975000	5.188425	24.000000	666.000000	20.200000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000

```
data.isnull().sum()
```

```
CRIM       20
ZN         20
INDUS      20
CHAS       20
NOX         0
RM          0
AGE        20
DIS         0
RAD         0
TAX         0
PTRATIO     0
B           0
LSTAT      20
MEDV        0
dtype: int64
```

```
dataset=data.dropna()
```

```
dataset.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
dtype: int64
```

```
import seaborn as sns

correlation_matrix = dataset.corr()

# Generate a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation')
plt.show()
```

```
x=dataset.drop('MEDV',axis=1)
y=dataset.MEDV
```

```
x.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	296	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94
5	0.02985	0.0	2.18	0.0	0.458	6.430	58.7	6.0622	3	222	18.7	394.12	5.21

```
y.head()
```

```
0    24.0
1    21.6
2    34.7
3    33.4
5    28.7
Name: MEDV, dtype: float64
```

```
# Train Test split
from sklearn.model_selection import train_test_split
```

```
x_train,x_test,y_train,y_test= train_test_split(x,y,test_size=0.30,random_state=42)
```

```
x_train
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	L
21	0.85204	0.0	8.14	0.0	0.538	5.965	89.2	4.0123	4	307	21.0	392.53	
456	4.66883	0.0	18.10	0.0	0.713	5.976	87.9	2.5806	24	666	20.2	10.48	
28	0.77299	0.0	8.14	0.0	0.538	6.495	94.4	4.4547	4	307	21.0	387.94	
156	2.44668	0.0	19.58	0.0	0.871	5.272	94.0	1.7364	5	403	14.7	88.63	
445	10.67180	0.0	18.10	0.0	0.740	6.459	94.8	1.9879	24	666	20.2	43.06	2
...	...	...	...	...	...	...	...	...	...	...	...	...	
84	0.05059	0.0	4.49	0.0	0.449	6.389	48.0	4.7794	3	247	18.5	396.90	
128	0.32543	0.0	21.89	0.0	0.624	6.431	98.8	1.8125	4	437	21.2	396.90	
345	0.03113	0.0	4.39	0.0	0.442	6.014	48.5	8.0136	3	352	18.8	385.64	
448	9.32909	0.0	18.10	0.0	0.713	6.185	98.7	2.2616	24	666	20.2	396.90	
122	0.09299	0.0	25.65	0.0	0.581	5.961	92.9	2.0869	2	188	19.1	378.09	

275 rows × 13 columns

```
x_test
```

```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
```

352 0.07244 60.0 1.69 0.0 0.411 5.884 18.5 10.7103 4 411 18.3 392.33

```
x_train=scaler.fit_transform(x_train)
```

```
x_test=scaler.transform(x_test)
```

```
from sklearn.linear_model import LinearRegression
```

```
regression=LinearRegression(fit_intercept=True, copy_X=True, n_jobs=None, positive=False)
```

```
regression.fit(x_train,y_train)
```

```
▾ LinearRegression
LinearRegression()
```

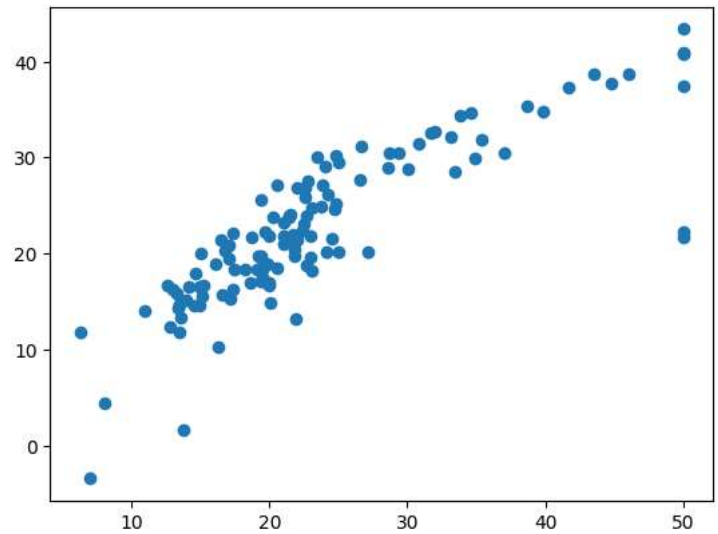
```
reg_pred=regression.predict(x_test)
```

```
reg_pred
```

```
array([29.48758967, 16.89843072, 21.88395113, 30.03140416, 18.33998157,
       34.41717332, 22.29567579, 30.18541478, 32.68800811, 15.15148614,
       22.00937236, 40.89756783, 21.39760824, 16.631487  , 18.56021823,
       20.16135634, 17.03230083, 15.23458095, 22.21007405, 14.03864948,
       18.38308584, 20.31978106, 16.70540425, 29.04732153, 25.84896274,
       16.21750987, 26.91521769, 31.48625718, 23.80195772, 26.88649048,
       40.79205858, 17.93939578, 21.74000234, 17.0218407 , 17.45215081,
       20.87478891, 22.15708989, 21.38558618, 23.05850448, 21.06608939,
       27.72449001, 34.81400202, 21.78651421, 30.44288708, 34.59722541,
       19.75813031, 24.68728038, 10.22457273, 19.81849411, 25.15817576,
       21.82205121, 25.58520471, 14.76531893, 18.31754995, 18.17045495,
       23.96198129, 43.37418034, 22.39050206, 15.68056608, 23.22677962,
       20.98939499, 21.55059106, 14.59407927, 28.87042011, -3.45096729,
       32.51557282, 16.5500498 , 31.10947226, 24.8731608 , 20.17179858,
       31.82632689, 32.10353069, 18.89283602, 19.60454126, 18.94484527,
       35.33878188, 19.45363796, 28.50358261, 16.74216045, 16.49518606,
       37.34165479, 24.06073859, 23.94385418, 12.41794664, 28.97896464,
       20.48236223, 14.85215853, 11.78000225, 38.66722878, 37.41206574,
       20.17277203, 18.30950838, 27.59233841, 15.8175198 , 27.11758465,
       38.63671197, 30.48942947, 23.78547261, 21.67667179, 13.39747245,
       21.61336573, 29.8835334 , 20.00344429, 14.5877518 , 15.61540198,
       16.32430674, 19.69636054, 14.37075878, 37.73041983, 13.2498713 ,
        4.48800447,  1.60372156, 26.11850957, 27.16021033, 18.77002216,
       11.85383586, 24.73833354, 30.44494752, 19.10867414])
```

```
plt.scatter(y_test,reg_pred)
```

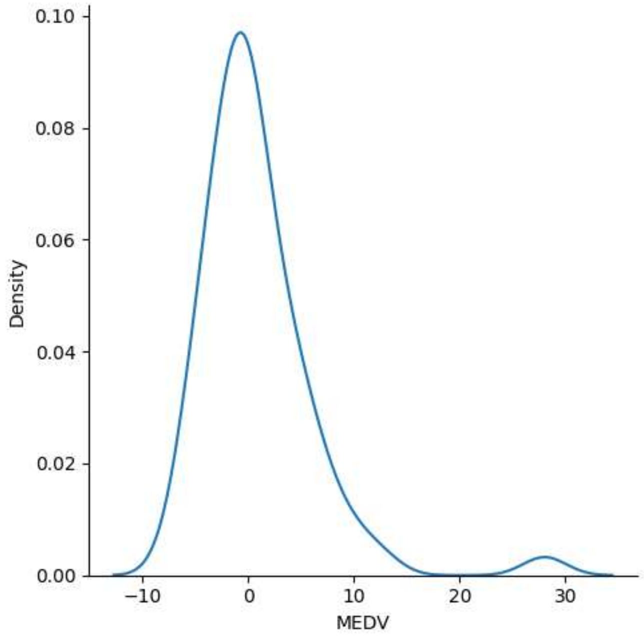
<matplotlib.collections.PathCollection at 0x7aa2ddff8430>




```
residual=y_test-reg_pred
```

```
sns.displot(residual,kind='kde')
```

```
<seaborn.axisgrid.FacetGrid at 0x7aa2e0b7d120>
```




```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
```

```
print(mean_squared_error(y_test,reg_pred))
print(mean_absolute_error(y_test,reg_pred))
```

```
28.870771928253443
3.4558210072479936
```

```
from sklearn.metrics import r2_score
score=r2_score(y_test,reg_pred)
```

```
print(score)
```

```
0.6905175764205996
```

```
data=dataset.drop("MEDV",axis=1)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-1-418df5c1ee81> in <cell line: 1>()
----> 1 data=dataset.drop("MEDV",axis=1)

NameError: name 'dataset' is not defined
```

SEARCH STACK OVERFLOW

```
data.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	296	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94
5	0.02985	0.0	2.18	0.0	0.458	6.430	58.7	6.0622	3	222	18.7	394.12	5.21

```
data=scaler.transform(data)
```

```
data
```

```
array([[-0.40933976,  0.27402606, -1.27968808, ..., -1.52711029,
         0.44817157, -1.07231454],
       [-0.40730263, -0.48865541, -0.57792953, ..., -0.36108594,
         0.44817157, -0.51376907],
       [-0.40730457, -0.48865541, -0.57792953, ..., -0.36108594,
```

```
         0.40599731, -1.19986699],
        ...,
       [-0.40555957, -0.48865541,  0.13857185, ...,  1.13142523,
         0.44817157, -0.52182501],
       [-0.40405623, -0.48865541,  0.13857185, ...,  1.13142523,
         0.44817157, -0.98369915],
       [-0.39931715, -0.48865541,  0.13857185, ...,  1.13142523,
         0.41242189, -0.87091593]])
```

```
new=data[0]
```

```
new=new.reshape(1,-1)
```

```
new.shape
```

```
(1, 13)
```

```
regression.predict(new)
```

```
array([29.04732153])
```