Experiment No. 1
Analyze the Boston Housing dataset and apply appropriate Regression Technique
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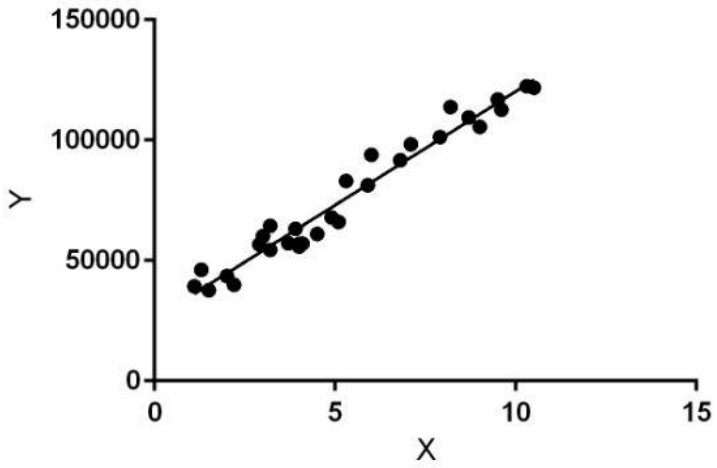
Aim: Analyze the Boston Housing dataset and apply appropriate Regression Technique.

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:

```
import numpy as np
import pandas as pd
from sklearn.datasets import load_boston
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

boston = load_boston()
data=pd.DataFrame(data=np.c_[boston.data,boston.target],
columns=np.append(boston.feature_names, 'PRICE'))
X = data.drop('PRICE', axis=1)
y = data['PRICE']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

```
print(f"Mean Squared Error: {mse:.2f}")
print(f"R-squared (R2) Score: {r2:.2f}")
print("Coefficients:", model.coef_)
print("Intercept:", model.intercept_)
```

Output:

Mean Squared Error: 24.29

R-squared (R2) Score: 0.67

Conclusion:

In conclusion, selecting the right features for a house price prediction model is crucial for its accuracy and effectiveness. By choosing relevant features such as the number of bedrooms, bathrooms, square footage, location, and other significant factors, we can build a model that provides meaningful and accurate estimates of housing prices. The success of the model hinges on the careful selection of features that best represent the dynamics of the real estate market, allowing for valuable insights and predictions in the housing industry.