# 3_House_Price_Prediction_With_XGBoost_Regression

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## 0.1 House Price Prediction With XGBoost Regression - Vignesh Prabhu

House price prediction using XGBoost regression involves training a model on various features of past house sales, such as location, size, and amenities. XGBoost optimizes its learning to accurately predict the prices of new listings based on these factors, offering precise insights for buyers and sellers in the real estate market.

## 0.2 Import the Dependencies

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn.datasets
from sklearn.model_selection import train_test_split
from xgboost import XGBRegressor
from sklearn import metrics
```

## 0.3 Data Collection And Preprocessing

[15]:
```
Boston_dataset=pd.read_csv('/content/BostonHousing.csv')
```

[19]:
```
#To Check First 5 Rows of data
Boston_dataset.head()
```

[19]:

| | crim | zn | indus | chas | nox | rm | age | dis | rad | tax | ptratio | \ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.00632 | 18.0 | 2.31 | 0 | 0.538 | 6.575 | 65.2 | 4.0900 | 1 | 296 | 15.3 | |
| 1 | 0.02731 | 0.0 | 7.07 | 0 | 0.469 | 6.421 | 78.9 | 4.9671 | 2 | 242 | 17.8 | |
| 2 | 0.02729 | 0.0 | 7.07 | 0 | 0.469 | 7.185 | 61.1 | 4.9671 | 2 | 242 | 17.8 | |
| 3 | 0.03237 | 0.0 | 2.18 | 0 | 0.458 | 6.998 | 45.8 | 6.0622 | 3 | 222 | 18.7 | |
| 4 | 0.06905 | 0.0 | 2.18 | 0 | 0.458 | 7.147 | 54.2 | 6.0622 | 3 | 222 | 18.7 | |

| | b | lstat | medv |
|---|---|---|---|
| 0 | 396.90 | 4.98 | 24.0 |
| 1 | 396.90 | 9.14 | 21.6 |
| 2 | 392.83 | 4.03 | 34.7 |
| 3 | 394.63 | 2.94 | 33.4 |
| 4 | 396.90 | 5.33 | 36.2 |

[17]:
```
#Shape of the dataset
Boston_dataset.shape # 506 rows , 14 columns
```

[17]:
```
(506, 14)
```

[25]:
```
#Rename Column name Price (Medv --> Price)
Boston_dataset.rename(columns={'medv':'Price'},inplace=True)
Boston_dataset.head()
```

[25]:

| | crim | zn | indus | chas | nox | rm | age | dis | rad | tax | ptratio | b | lstat | Price |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.00632 | 18.0 | 2.31 | 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 | 0.469 | 6.421 | 78.9 | 4.9671 | 2 | 242 | 17.8 | 396.90 | 9.14 | 21.6 |
| 2 | 0.02729 | 0.0 | 7.07 | 0 | 0.469 | 7.185 | 61.1 | 4.9671 | 2 | 242 | 17.8 | 392.83 | 4.03 | 34.7 |
| 3 | 0.03237 | 0.0 | 2.18 | 0 | 0.458 | 6.998 | 45.8 | 6.0622 | 3 | 222 | 18.7 | 394.63 | 2.94 | 33.4 |
| 4 | 0.06905 | 0.0 | 2.18 | 0 | 0.458 | 7.147 | 54.2 | 6.0622 | 3 | 222 | 18.7 | 396.90 | 5.33 | 36.2 |

[26]:
```
#Checking Missing Values
Boston_dataset.isnull().sum()
```

[26]:
```
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
Price      0
dtype: int64
```

[27]:
```
#Staticstical measures
Boston_dataset.describe()
```

[27]:

| | crim | zn | indus | chas | nox | rm |
|---|---|---|---|---|---|---|
| count | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 |

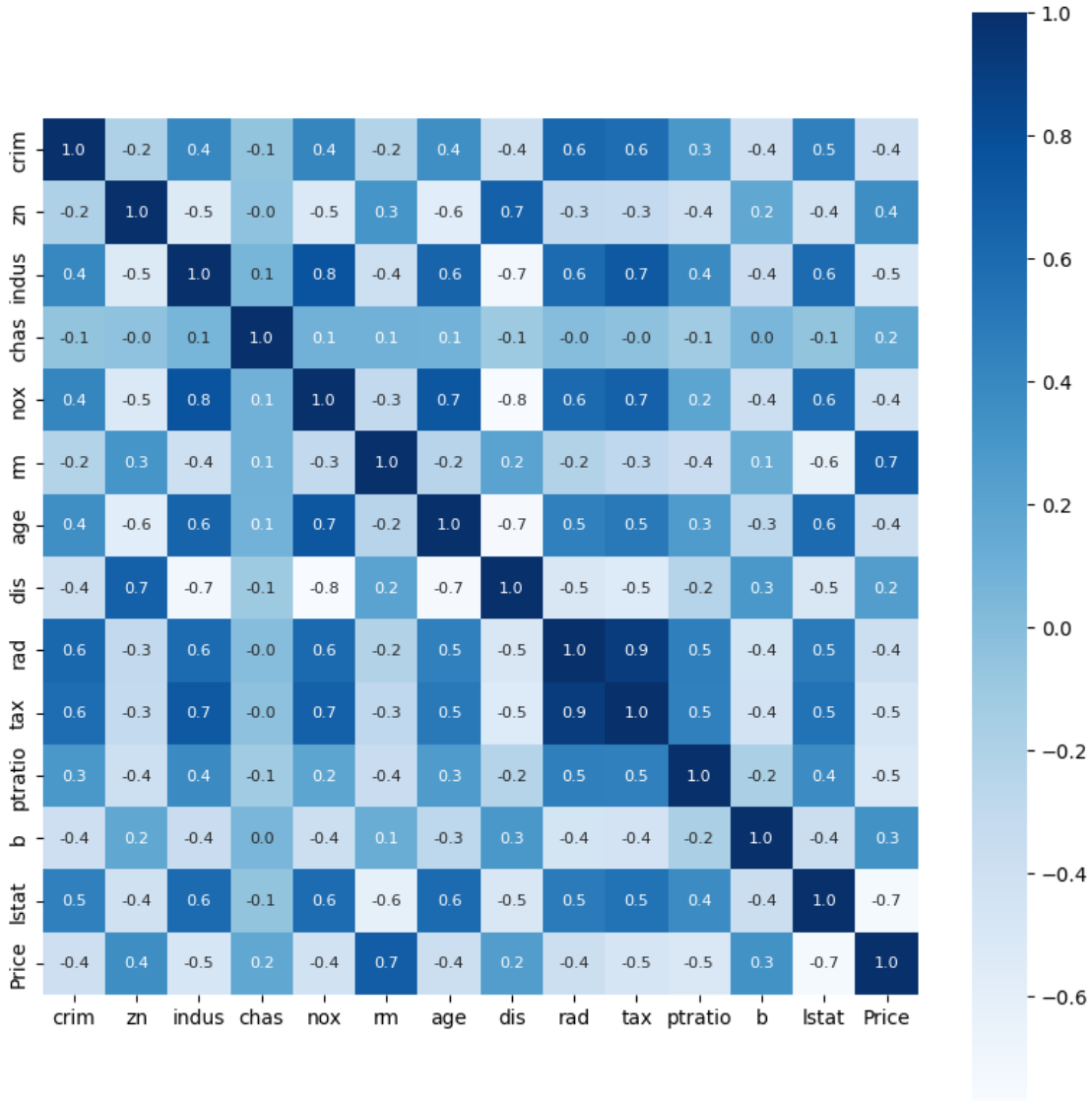
```
mean      3.613524   11.363636   11.136779    0.069170    0.554695    6.284634
std       8.601545   23.322453    6.860353    0.253994    0.115878    0.702617
min       0.006320    0.000000    0.460000    0.000000    0.385000    3.561000
25%       0.082045    0.000000    5.190000    0.000000    0.449000    5.885500
50%       0.256510    0.000000    9.690000    0.000000    0.538000    6.208500
75%       3.677083   12.500000   18.100000    0.000000    0.624000    6.623500
max      88.976200  100.000000   27.740000    1.000000    0.871000    8.780000

              age         dis         rad         tax     ptratio           b  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean    68.574901    3.795043    9.549407  408.237154   18.455534  356.674032
std     28.148861    2.105710    8.707259  168.537116    2.164946   91.294864
min      2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%     45.025000    2.100175    4.000000  279.000000   17.400000  375.377500
50%     77.500000    3.207450    5.000000  330.000000   19.050000  391.440000
75%     94.075000    5.188425   24.000000  666.000000   20.200000  396.225000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000

            lstat       Price
count  506.000000  506.000000
mean    12.653063   22.532806
std      7.141062    9.197104
min      1.730000    5.000000
25%      6.950000   17.025000
50%     11.360000   21.200000
75%     16.955000   25.000000
max     37.970000   50.000000
```

### 0.4 understanding the correlation between various features in Dataset

[28]:
```
correlation=Boston_dataset.corr() #
```

[30]:
```
#constructing the Heatmap to understand the correlation
plt.figure(figsize=(10,10))
sns.heatmap(correlation,cbar=True,square=True,fmt='.
 ↪1f',annot=True,annot_kws={'size':8},cmap='Blues') # Cbar-color Bar in side ,
# fmt - float values with 1 digit , Annot_kws = Annotation values
```

[30]:
```
<Axes: >
```




## 0.5 Spliting Data and target

[33]:
```
X=Boston_dataset.drop(['Price'],axis=1)
Y=Boston_dataset['Price']
```

[34]:
```
print(X)
print(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]
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
Name: Price, Length: 506, dtype: float64
```

### 0.6 Spliting the data into Spliting and training Data

[36]:
```
X_train, X_test, Y_train, Y_test =train_test_split(X,Y,test_size=0.
↪2,random_state=2)
```

[37]:
```
print(X.shape,X_train.shape,X_test.shape)
```

```
(506, 13) (404, 13) (102, 13)
```

## 0.7 Model Training With XGBoost Regressor

[39]:
```
#loading The model
model=XGBRegressor()
```

[41]:
```
#Training the model with X Train
model.fit(X_train,Y_train)
```

[41]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=None, n_jobs=None,
             num_parallel_tree=None, random_state=None, …)
```

## 0.8 Evaluation

### Prediction on Training Data

[43]:
```
#Accuracy for prediction on training data
training_data_prediction=model.predict(X_train) #prediction all House values
```

[44]:
```
print(training_data_prediction)
```

```
[23.112196  20.992601  20.10438   34.67932   13.920501  13.499354
 21.998383  15.206723  10.89543   22.67402   13.795236   5.602332
 29.808502  49.98666   34.89634   20.594336  23.388903  19.2118
 32.69294   19.604128  26.978151   8.405952  46.00062   21.70406
 27.084402  19.372278  19.297894  24.79984   22.608278  31.707775
 18.53683    8.703393  17.40025   23.698814  13.29729   10.504759
 12.693588  24.994888  19.694864  14.911037  24.20254   24.991112
 14.901547  16.987965  15.592753  12.704759  24.505623  15.007718
 49.999355  17.509344  21.18844   31.999287  15.606071  22.902134
 19.309835  18.697083  23.302961  37.19767   30.102247  33.117855
 20.993683  50.00471   13.40048    5.002565  16.50862    8.4016905
 28.651423  19.49218   20.595366  45.404697  39.808857  33.4055
 19.81498   33.406376  25.30206   49.998615  12.544487  17.433802
 18.602612  22.601418  50.004013  23.814182  23.313164  23.097467
 41.71243   16.112017  31.604454  36.09397    7.0009975 20.406271
 19.992195  12.003392  25.027754  49.98552   37.890903  23.091173
 41.289513  17.604618  16.30125   30.05175   22.884857  19.802671
 17.106977  18.903633  18.897047  22.598665  23.170893  33.19197
 15.00434   11.704804  18.795511  20.817484  17.998543  19.633396
```

```
49.998672  17.208574  16.410513  17.506626  14.6008    33.09849
14.504811  43.813366  34.900055  20.388191  14.605566   8.091776
11.777508  11.811628  18.691      6.322443  23.97163   13.073076
19.595     49.99033   22.319597  18.91175   31.203646  20.712711
32.200443  36.188755  14.222898  15.705663  50.000664  20.408077
16.185907  13.410434  50.012474  31.60327   12.288182  19.18906
29.809902  31.49241   22.804003  10.194443  24.09609   23.705154
22.008154  13.790835  28.399841  33.199585  13.102867  19.017357
26.61559   36.963135  30.7939    22.80785   10.206419  22.19713
24.482466  36.19345   23.092129  20.12124   19.498154  10.796299
22.701403  19.49908   20.107922   9.625605  42.797676  48.79655
13.099009  20.29537   24.794712  14.106459  21.698246  22.188694
32.99889   21.09952   24.998121  19.110165  32.401157  13.601795
15.072056  23.06062   27.487326  19.401924  26.481848  27.50343
28.686726  21.19214   18.701029  26.7093    14.01264   21.699009
18.39739   43.11556   29.09378   20.298742  23.711458  18.30434
17.193619  18.321108  24.392206  26.391497  19.10248   13.302614
22.189732  22.199099   8.530714  18.889635  21.800455  19.305798
18.198288   7.4938145 22.400797  20.028303  14.404203  22.500402
28.504164  21.608568  13.798578  20.495127  21.902288  23.100073
50.00128   16.23443   30.298399  49.996014  17.78638   19.060133
10.39715   20.383387  16.496948  17.195917  16.681927  19.509869
30.502445  29.01701   19.558786  23.172018  24.397314   9.528121
23.894762  49.996834  21.196695  22.596247  19.989746  13.393513
19.995872  17.068512  12.718964  23.01111   15.199219  20.609226
26.19055   18.109114  24.098877  14.100204  21.695303  20.096022
25.018776  27.899471  22.918222  18.499252  22.202477  23.99494
14.8048935 19.896328  24.411158  17.790047  24.596226  32.007046
17.778685  23.309103  16.120615  13.003008  10.993355  24.306978
15.597863  35.20248   19.58716   42.29605    8.789314  24.399925
14.109244  15.4010315 17.299047  22.113592  23.106049  44.805172
17.795519  31.499706  22.813938  16.836212  23.911596  12.09551
38.69628   21.387049  16.001123  23.929094  11.897898  24.983562
 7.1969633 24.69086   18.187803  22.471941  23.013317  24.295506
17.099222  17.796907  13.503164  27.094381  13.296886  21.90404
19.99361   15.402385  16.588629  22.29326   24.697983  21.428938
22.882269  29.601665  21.881992  19.908726  29.60596   23.408524
13.807421  24.499699  11.901903   7.20547   20.484905   9.706262
48.301437  25.194635  11.691466  17.39672   14.49594   28.584557
19.395731  22.486904   7.0219784 20.60076   22.998001  19.699215
23.700571  25.02278   27.992222  13.39496   14.524017  20.30391
19.304321  24.108646  14.88511   26.387497  33.31608   23.61982
24.60193   18.494753  20.90211   10.411172  23.305649  13.097067
24.699335  22.610847  20.50208   16.82098   10.198874  33.805454
18.60289   50.0009    23.778967  23.91014   21.15922   18.81689
 8.491747  21.506403  23.200815  21.043766  16.604784  28.060492
21.197857  28.370916  14.2918625 49.997353  30.989647  24.980095
21.410505  19.000553  29.00484   15.204052  22.791481  21.791014
```

```
 19.896528  23.77255  ]
```

[46]:
```
# R squared ERROR
score_1=metrics.r2_score(Y_train,training_data_prediction)
#Mean Absolute Error
score_2=metrics.mean_absolute_error(Y_train,training_data_prediction)
print("R squared Error : ",score_1)
print('Mean Absolute Error : ',score_2)
```

```
R squared Error :  0.9999980039471451
Mean Absolute Error :  0.0091330346494618
```

**Prediction On test Data**

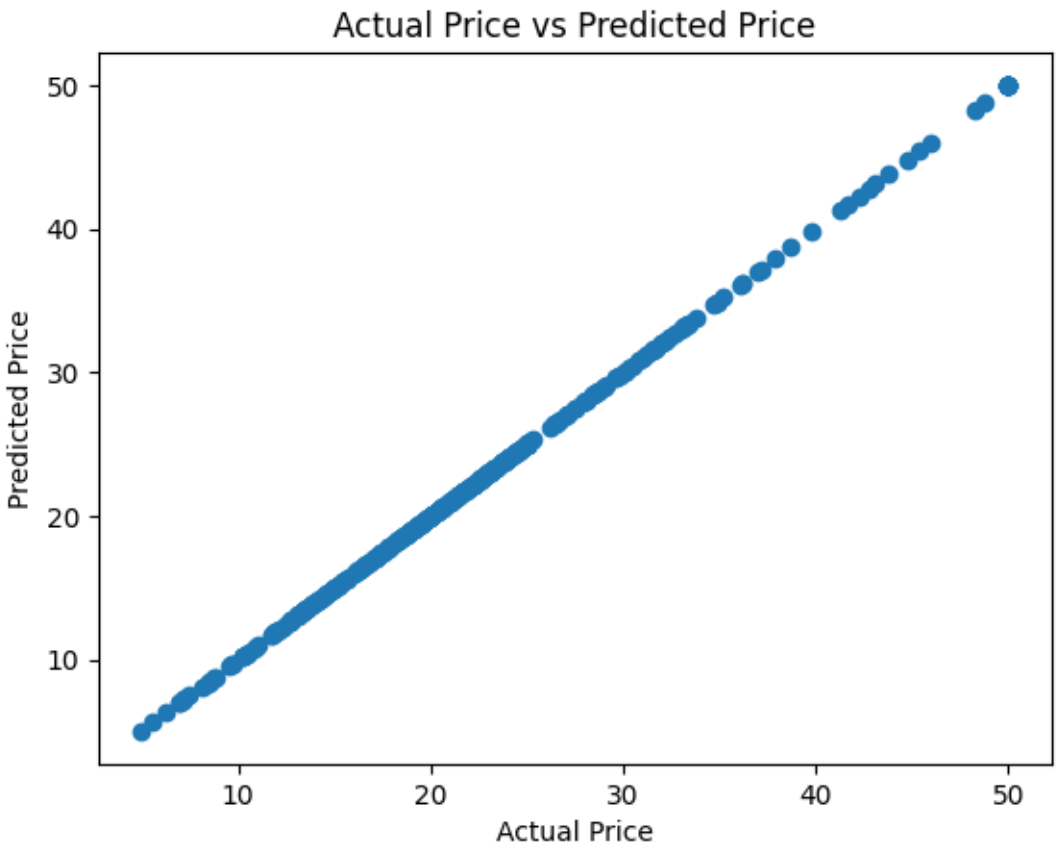
[49]:
```
#Accuracy for prediction on Test Data
test_data_prediction=model.predict(X_test) #prediction all House values
```

[50]:
```
# R squared Error
score_1=metrics.r2_score(Y_test,test_data_prediction)
#Mean Absolute Error
score_2=metrics.mean_absolute_error(Y_test,test_data_prediction)
print("R squared Error : ",score_1)
print('Mean Absolute Error : ',score_2)
```

```
R squared Error :  0.9051721149855378
Mean Absolute Error :  2.0748727686264927
```

**Result :Actual Price and Predicted Price**

[51]:
```
plt.scatter(Y_train,training_data_prediction)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Actual Price vs Predicted Price")
plt.show()
```




Based on the XGBoost regressor model's predictions for Boston houses, it appears to offer a reliable method for estimating property values. Its robust performance suggests it could be a valuable tool for both buyers and sellers in making informed decisions in the real estate market