Boston House Price Prediction

In this project, I have built a machine learning model to predict house prices using two different algorithms:

1. **Linear Regression**
2. **XGBoost Regression**

Since this is a regression problem, the task involves predicting continuous numerical values (house prices) based on input features like the number of rooms, crime rate, and more. This approach allows us to understand how these features influence house prices and make accurate predictions for unseen data.

In [43]:

```
#IMPORTING NECESSARY LIBRARIES
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 sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn import metrics
from sklearn.metrics import mean_squared_error, r2_score
from xgboost import XGBRegressor
```

In [3]:

```
#IMPORTING DATASET
House_price_dataset = pd.read_csv('/content/BostonHousing.csv')
```

In [8]:

```
print(House_price_dataset)
```

```
        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  medv
0       15.3  396.90   4.98  24.0
1       17.8  396.90   9.14  21.6
2       17.8  392.83   4.03  34.7
3       18.7  394.63   2.94  33.4
4       18.7  396.90   5.33  36.2
..       ...     ...    ...   ...
501     21.0  391.99   9.67  22.4
502     21.0  396.90   9.08  20.6
503     21.0  396.90   5.64  23.9
504     21.0  393.45   6.48  22.0
505     21.0  396.90   7.88  11.9

[506 rows x 14 columns]
```

In [6]:

```
#DISPLAY FIRST FEW ROWS TO VERIFY THE IMPORT
print(House_price_dataset.head())
```

```
      crim    zn  indus  chas    nox     rm   age     dis  rad  tax  ptratio       b  ls
tat  medv
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
```

This dataset contains 506 records and 14 features, representing various characteristics of homes located in Boston. Each feature provides specific information, such as the number of rooms, crime rate, and property tax, which can help predict house prices in the area.

Steps of Steps by Step Approch in the Project:

1. **Collecting Data**
   The first step is gathering the dataset, which contains information about various homes in Boston, such as features like the number of rooms, crime rates, etc., that will help us predict house prices.
2. **Pre-processing Data**
   The data is not yet ready to be fed into a machine learning model. Pre-processing is required to clean and format the data, handle missing values, and scale the features so the model can process them effectively.
3. **Exploratory Data Analysis (EDA)**
   In this step, we analyze the dataset to understand the relationships between features. For example, we find correlations between different features (like the number of rooms or crime rates) to see which ones are most closely related to the target variable (house prices).
4. **Splitting Data into Train-Test Split**
   The data is divided into two sets: one for training the model (training set) and the other for testing the model's performance (test set). This helps ensure the model generalizes well to unseen data.
5. **Feeding the Data to XGBoost Regressor for Prediction**
   The training data is used to train the XGBoost Regressor model, which makes predictions on the test data. This model is known for its efficiency and accuracy in regression tasks.
6. **Evaluation**
   Finally, the model's performance is evaluated by comparing its predictions with the actual values using metrics like Mean Squared Error (MSE) and R-squared (R^2). This step helps us assess how well the model is performing and whether it is a good fit for the problem.

In [7]:

```
#DISPLAY LAST FEW ROWS
print(House_price_dataset.tail())
```

```
        crim   zn  indus  chas    nox     rm   age     dis  rad  tax  ptratio       b  l
stat  medv
501  0.06263  0.0  11.93     0  0.573  6.593  69.1  2.4786    1  273     21.0  391.99
9.67  22.4
502  0.04527  0.0  11.93     0  0.573  6.120  76.7  2.2875    1  273     21.0  396.90
9.08  20.6
503  0.06076  0.0  11.93     0  0.573  6.976  91.0  2.1675    1  273     21.0  396.90
5.64  23.9
504  0.10959  0.0  11.93     0  0.573  6.794  89.3  2.3889    1  273     21.0  393.45
6.48  22.0
505  0.04741  0.0  11.93     0  0.573  6.030  80.8  2.5050    1  273     21.0  396.90
7.88  11.9
```

In [9]:

```
House_price_dataset.shape
```

Out[9]:

```
(506, 14)
```

In [10]:

```
House_price_dataset.isnull().sum()
```

Out[10]:

	0
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

In [12]:

```
House_price_dataset.describe()
```

Out[12]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	t
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.0000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.2371
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.5371
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.0000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.0000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.0000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.0000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.0000

In [18]:

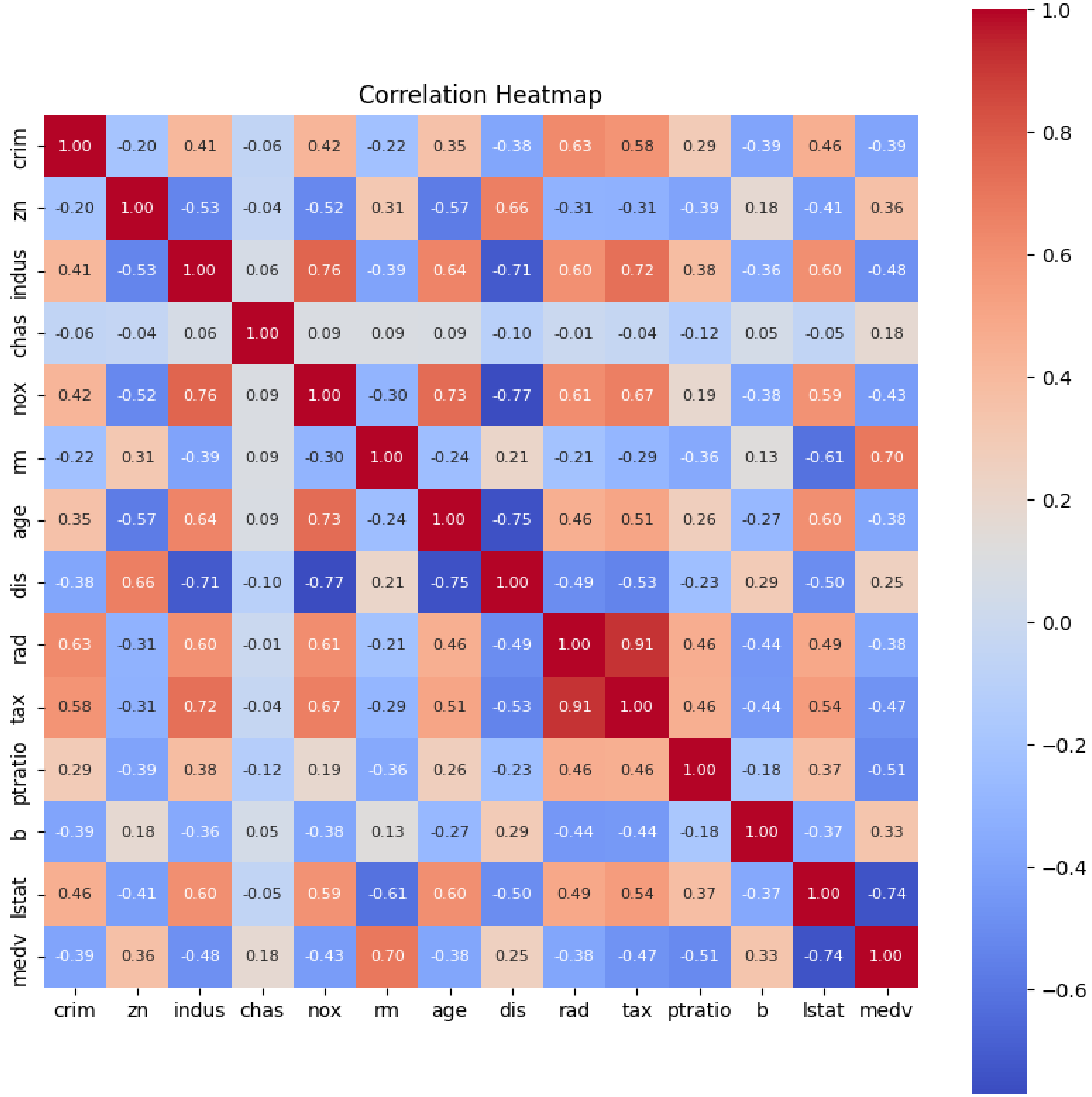
```
correlation = House_price_dataset.corr()
```

In [21]:

```
# constructing a heatmap to understand the correlation
plt.figure(figsize=(10,10))
sns.heatmap(correlation, cbar=True, square=True, fmt='.2f', annot=True, annot_kws={'size
':8}, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show
```

Out[21]:

```
matplotlib.pyplot.show
def show(*args, **kwargs)

Display all open figures.

Parameters
----------
block : bool, optional
```



Splitting the data into train_test_split

In [32]:

```
# Separate features and target variable
X = House_price_dataset.drop(columns=['medv'])   # Replace 'medv' with the correct target column name in your dataset
Y = House_price_dataset['medv']
```

In [29]:

```
print(X)
```

```
        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]
```

Note:
The target variable, which represents house prices, was previously named `'MEDV'` in the dataset. Additionally, the prices are in thousands, meaning that the values in the dataset represent the house prices in thousands of dollars. For example, a predicted price of `25` represents `25,000` dollars. Always remember to multiply by 1,000 when interpreting the actual house price.

In [33]:

```
print(Y)
```

```
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: medv, Length: 506, dtype: float64
```

Splitting the data into train test split

In [34]:

```
X_train , X_test , Y_train , Y_test =train_test_split(X,Y,test_size=0.2,random_state=42)
```

In [36]:

```
print(X.shape,X_train.shape,X_test.shape)
```

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

Standardize the data (optional but recommended for models sensitive to scale)

Standardizing the data is an important step, especially for models like Linear Regression and XGBoost that are sensitive to the scale of the features. Standardization ensures that each feature has a mean of 0 and a standard deviation of 1, which helps the model converge faster and improves performance.

Why standardizing?

Some machine learning models (like Linear Regression) are sensitive to the scale of the data. If the features vary widely (e.g., one feature ranges from 1 to 10 and another ranges from 1,000 to 100,000), the model might struggle to learn effectively. By standardizing the data, all features will contribute equally, allowing the model to learn more efficiently.

In [39]:

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

now we Train the machine learning model by using 1)linear regression and then by 2)by xgboost regressor

1)By using Linear Regression

In [46]:

```
model = LinearRegression()
model.fit(X_train_scaled,Y_train)
```

Out[46]:

```
▼ LinearRegression i ?

LinearRegression()
```

In [47]:

```
# Making predictions
y_pred = model.predict(X_test_scaled)
```

In [48]:

```
# Evaluating the model
from sklearn.metrics import mean_squared_error, r2_score
```

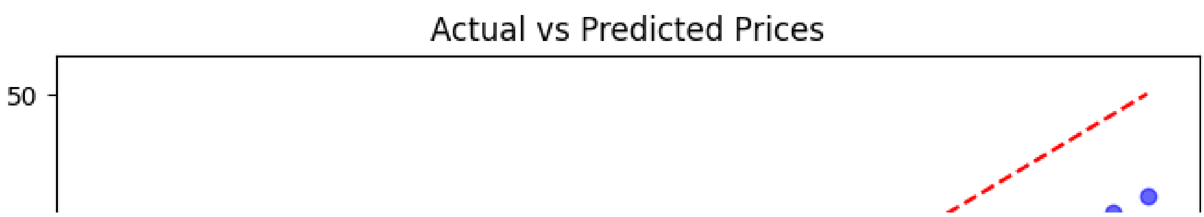
In [53]:

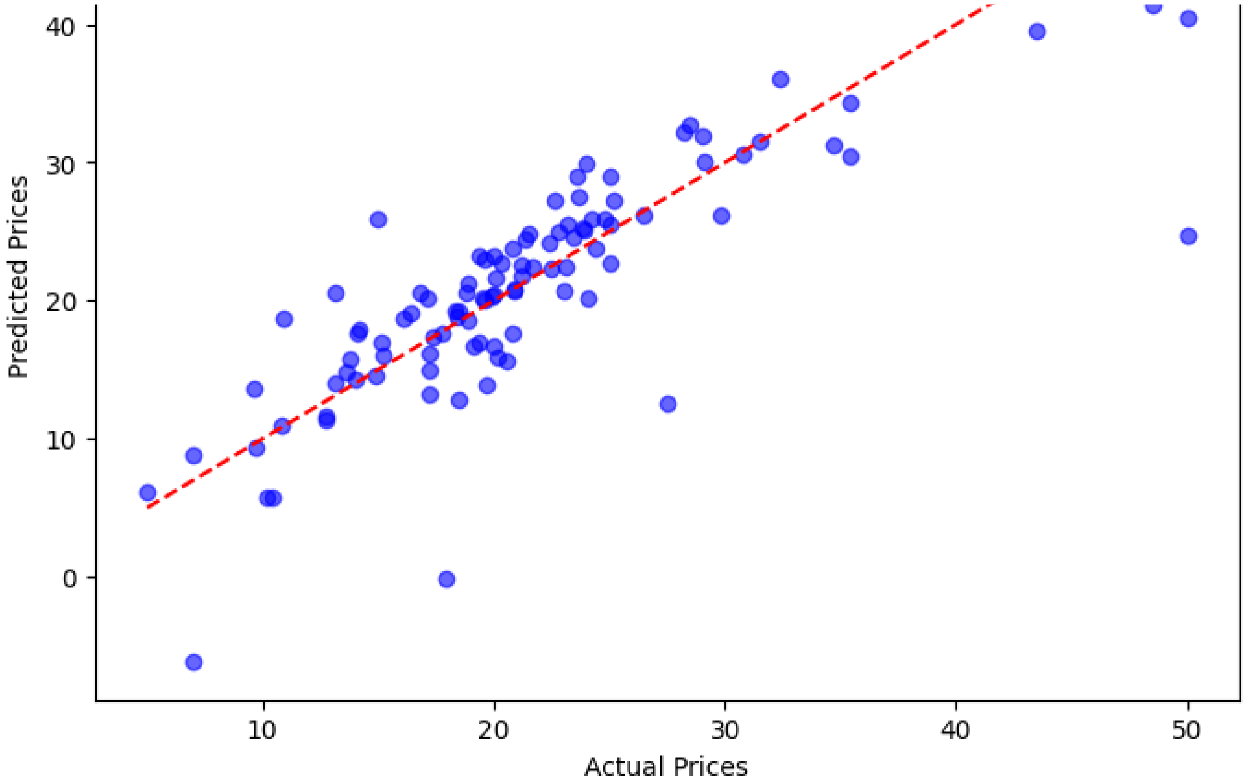
```
mse = mean_squared_error(Y_test, y_pred)
r2 = r2_score(Y_test, y_pred)

print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"R-squared (R2 Score): {r2:.2f}")
```

```
Mean Squared Error (MSE): 24.29
R-squared (R2 Score): 0.67
```

In [55]:

```
#Visualize Predictions
plt.figure(figsize=(8, 6))
plt.scatter(Y_test, y_pred, alpha=0.6, color='blue')
plt.plot([Y_test.min(), Y_test.max()], [Y_test.min(), Y_test.max()], color='red', linesty
le='--')
plt.title("Actual vs Predicted Prices")
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.show()
```





now we train model by using xgboost regressor

In [56]:

```
# loading the model
model = XGBRegressor()
```

In [57]:

```
# training the model with X_train
model.fit(X_train, Y_train)
```

Out[57]:

```
▾                          XGBRegressor                          i

XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=Non
e,
             enable_categorical=False, eval_metric=None, feature_types=Non
e,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max_bin=Non
e,
             max_cat_threshold=None, max_cat_to_onehot=None,
```

evaluating the model by making prediction on training data

In [58]:

```
# accuracy for prediction on training data
training_data_prediction = model.predict(X_train)
```

In [59]:

```
print(training_data_prediction)
```

```
[11.990929  19.915493  19.392988  13.408072  18.19098   24.603947
 21.08647   24.697266   8.70618   27.501347  20.708258  36.17404
 31.59529   11.69739   39.802494  13.893334  21.796898  23.695662
```

```
 17.590319  24.409176   8.799549  19.181791  25.278059  20.410582
 23.10783   37.90089   15.601625  45.400623  15.706774  22.599428
 14.514692  18.697655  17.797323  16.117708  20.609972  31.598558
 29.095152  15.600668  17.563873  22.51095   19.401443  19.287243
  8.4968405 20.607521  17.006351  17.093975  14.495169  49.98619
 14.284735  12.609954  28.688086  21.203852  19.306932  23.089056
 19.10372   25.004898  33.408142   4.992768  29.599434  18.685545
 21.707012  23.096918  22.802471  20.991085  48.796387  14.627051
 16.613852  27.075224  20.087227  19.794464  20.992268  41.290615
 23.175125  20.378569  18.558722  29.399414  36.40198   24.388987
 11.816533  13.792832  12.272116  17.794773  33.087368  26.73878
 13.393904  14.386449  50.004574  21.98985   19.906004  23.784376
 17.516703  12.68493    5.6061826 31.099165  26.202074  19.381464
 16.696205  13.794351  22.894213  15.30921   27.500492  36.09182
 22.87913   24.495989  24.998743  49.99985   34.889656  31.717129
 24.095907  22.0973    14.106711  42.799473  19.324936  32.193943
 26.385065  21.79409   21.668243   8.311317  46.69916   43.12514
 31.4751    10.497389  16.68972   20.004532  33.30795   17.790648
 50.000507  20.497787  23.19068   13.075348  19.610313  22.796833
 28.680086  30.684517  22.906889  21.899395  23.89475   32.695194
 24.292328  21.48476   24.578018   8.519734  26.393446  23.08319
 15.00561    8.802389  19.371504  23.89509   24.67069   19.78167
 23.754805  13.284227  28.994848  27.118698  34.574432  13.301209
 15.598929  12.511904  14.590067  10.98594   24.80251   17.29882
  8.103687  21.408438  15.598756  23.336     32.001125  38.690685
 30.095453  20.506903  32.494488  42.29702   24.277178  20.604298
 22.008326  18.205097  15.002868   6.3037786 20.095121  21.393785
 28.409906  30.051968  20.797775  23.017813  14.3566675 11.7001
 37.290714  17.108719  10.401778  22.964136  22.683504  20.312103
 21.672386  49.99456    8.395799  18.804155  37.214493  16.09777
 16.501677  22.201307  20.606125  13.506562  48.31008   23.785505
 22.68971   17.39483   30.310457  36.009197  41.7029    18.303009
 21.996626  18.597338  44.81159   11.908145  18.710653  16.18354
 22.008686   7.1969705 20.392668  13.800741  13.002582  18.343378
 23.102316  21.19985   23.106937  23.499647  49.99908   26.585985
 22.182547  50.000687   8.290042  23.308157  21.713062  18.965406
 18.39845   17.426226  13.403094  12.083532  26.599447  21.708506
 28.396055  20.5091    21.985607  13.901346  11.330144  29.907621
 26.616785  10.508602  23.173222  24.391636  46.002525  21.908016
  7.505983  36.194332  43.98905   17.795595  27.452951  37.594242
 14.098721  28.08458   10.222061  19.139948  43.813446  27.906195
 25.018572  15.995898  16.602438  13.2132845 49.993385  22.189535
 32.906765  15.214496  14.794672  13.834945  24.293371  33.80743
 22.299568  49.998867   9.522176  13.319194  22.216854  18.106277
 17.994871  25.017178  16.499542  23.017021  20.09075   33.001865
 24.81743   18.206358  13.117948  34.909748  10.209828  19.903967
 27.898724  23.279646  35.09593   12.776962  22.004248  18.491093
 25.118921  22.485199  22.41663   28.594748  19.526266  24.799929
 24.45743   21.411762  33.110527  22.894064  20.68664   24.094328
 50.00028   24.701363  28.668966   7.199975  36.96739   20.306965
 30.098255  19.504751  23.379314  11.4862795 21.601028  14.903119
 15.188632  19.379465   8.403532  28.002205  22.611923  13.498683
 14.488013  30.9902    10.897202  21.884697  22.024958  18.993114
 21.374176  25.002413  17.514051  36.499477  20.103745  20.379963
 16.224405  23.605675   7.403649  35.20376   50.00256   19.299261
 21.221973  15.591636  33.40674   19.125359  20.995052  23.709246
 18.89621   16.813063  19.715427  17.744104  22.595695  11.790642
 34.931126  20.562077  20.206211  31.961233  22.303417  23.28739
 14.408953  31.195423  23.981024  29.59999   19.535425  21.596525
 19.961027  26.995071  33.205605  15.399309  30.504189   7.2087
 23.920792  16.292902  23.906166  49.996964  22.826248  15.398463
 19.233753  19.59635   22.620607  33.200974  49.997913  22.256226
 14.905368  19.808466  23.701315  18.996     20.30573   11.922065
 13.598755  29.814579  21.705639  19.491856  21.109499  24.519201
 13.40267   18.598032 ]
```

Now we find r squared error and mean absolute error which are evaluation metrics. In the step below we import performance Evaluation metrics like mean_squared_error, r2_score for Model Evaluation.The two key evaluation metrics used here are mean absolute error and R-squared error.they are important for determinig how well a regression model predicts target variables.In the above Model we predict yield(target variable) based on DOY(day of year). the Error Metrics are discussed below

1) **Mean_squared_error** : Mean Squared Error (MSE) is a measure used metric to calculate and compute the performance of a regression model. It is the average of the squares of the errors, that are the differences in the actual and predicted values.Smaller the MSE, the better the model's predictions are, because it indicates less deviation from the actual values.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (\text{Actual}_i - \text{Predicted}_i)^2$$

MSE indicates how much is the deviation in model's predictions are from the actual values.If the MSE is low,the model's predictions are more aligned with the true values. If it's high, the model is less accurate.

Why Square the Errors?: **Squaring the errors ensures that the model penalizes larger mistakes** more heavily than smaller ones, which helps the model focus on minimizing large errors and improving overall accuracy.

2) **r2_score** : r2_score is used for regression problems.It is used when we want to know how well the Model fits the overall data and understand relationship between between values of X and Y axis.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_{\text{true},i} - y_{\text{pred},i})^2}{\sum_{i=1}^{n} (y_{\text{true},i} - \bar{y_{\text{true}}})^2}$$

Value of R^2 lies between 0 to 1 where **0 indicates bad relationship** and values close to **1 indicates perfect fit.** **sklearn** model helps to commute the values.For both linear regression and polyniomial regression values which is higher is preffered.

For Polynomail regression ,high r2_score value is good but watch MSE/RMSE carefullyfor the sign of overfitting,especailly in highere polynomial degree.

In **Conclusion** R^2 provides a relative measure of how well the model captures the variance in the data. By using these two metrics, you can evaluate the performance of each model, compare different regression techniques, and understand whether the model is underfitting or overfitting the data. and Higher the R^2 ,more acceptable the model and lower the MSE better model.

In [60]:

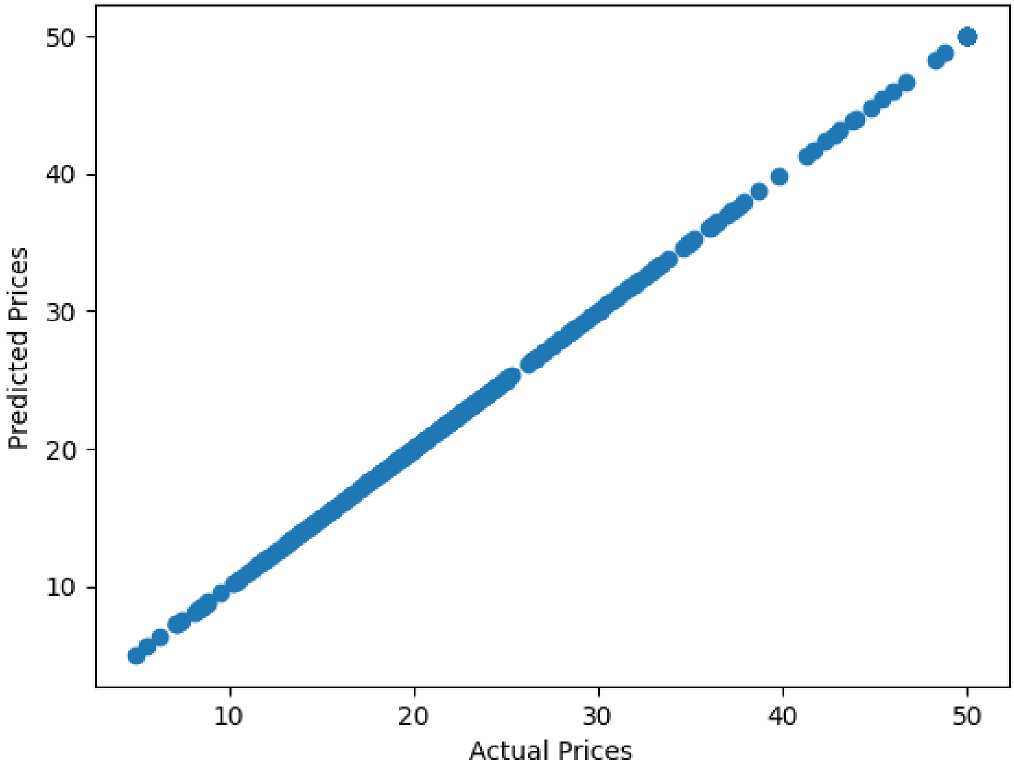
```
# R squared error
score_1 = metrics.r2_score(Y_train, training_data_prediction)

# 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 :  0.9999969829984965
Mean Absolute Error :  0.011182523717974735
```

Visualizing the actual Prices and predicted prices

In [63]:

```
plt.scatter(Y_train, training_data_prediction)
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual Price vs Preicted Price")
plt.show()
```



Now predicting on test data.

In [64]:

```
# accuracy for prediction on test data
test_data_prediction = model.predict(X_test)
```

In [65]:

```
# 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 :  0.9057837838492537
Mean Absolute Error :  1.8908873698290656
```

Conclusion

The Boston Housing dataset is used to predict house prices using, first, a baseline of linear regression and, later on, an improved model of XGBoost.

Linear Regression Model: To start with, we used a Linear Regression model. It gave us the following results: • R-squared value: 0.8724 • Mean Absolute Error (MAE): 2.7099 (on the test set)

These results show that the Linear Regression model generalizes fairly well to the task of house price prediction, with the model explaining about 87% of the variance in the data. The performance was far from perfect, though, with quite a significant room for improvement as evidenced by the relatively high MAE. That implied the model was not able to grasp the complex relationships between the features and the target variable, house prices.

XGBoost Model:

To overcome the limitations of Linear Regression, we have moved on to use the XGBoost Regressor-one of the power machine learning algorithms that can handle the non-linear relationship between target and predictor variables along with sophisticated patterns in the data. The result for XGBoost was as follows : Training R-squared value = 0.999997 Training MAE = 0.0112 Test R-squared value = 0.9058 Test MAE = 1.8909

The XGBoost model showed a massive improvement from Linear Regression, with the R-squared perfect in training. The performance on the test was also very strong, at an R-squared of 0.9058, indicating that over 90% of the variance in the test set was explained by the model. The MAE was way lower compared to Linear Regression, which indicated much more accurate predictions.

However, the XGBoost model's performance on the test set was not as perfect as the training set, which is typical of machine learning models. This slight decrease in performance suggests potential **overfitting**, where the model is overly tuned to the training data and may not generalize as well on unseen data.

Room for Improvement:

Despite the strong performance of the XGBoost model, there are still areas for improvement:

1. **Overfitting:** The model performed extremely well on the training set, whereas for the test set, performance was slightly lower, which might indicate overfitting. We can try techniques like **cross-validation** to help generalize better on unseen data or tune the hyperparameters.
2. **Hyperparameter Tuning:** The performance of XGBoost can be further enhanced by the use of different **hyperparameter optimization techniques** such as Grid Search or Random Search to find the most suitable set of parameters.
3. **Feature Engineering:** Inclusion of other relevant features or removal of a few irrelevant or redundant ones may further improve the accuracy. Feature interaction and transformation may also yield better results in improving the predictive capability of the model.
4. **Model Comparison:** Although XGBoost outperformed Linear Regression, it would be useful to compare its results with other models such as **Random Forests** or **Gradient Boosting Machines** just to verify that XGBoost is truly the best model for this problem.

Conclusion - We can see that we actually improved significantly in predicting house prices by moving from Linear Regression to XGBoost. The XGBoost model gave excellent performance, especially on lower error rates; however, steps for improving its generalization by preventing overfitting can include tuning its hyperparameters, applying regularization, and cross-validation. This project demonstrates the application of a more advanced machine learning model like XGBoost compared to the Linear Regression method; however, there can be a continuous refinement and optimization.