HOUSE PRICE PREDICTION ANALYSIS USING MACHINE LEARNING

PHASE 4: DEVELOPMENT PART 2

Creating a house price prediction model for a dataset of USA housing prices is a valuable task for both real estate professionals and individuals looking to buy or sell homes. Here's an introduction to building a house price prediction model for a USA housing dataset:

Project Title: Predicting House Prices: A Machine Learning Approach

Google colab link:
https://colab.research.google.com/drive/1piK4JcVIl0DN8yPCjxJ1Cgc5IRyknG4l#scrollTo=PHiG8zdRLfmm

INTRODUCTION:

For many individuals and families, buying a house is one of the biggest investments they will make in their lifetime. Therefore, it is essential to accurately predict the prices of houses so that buyers and sellers can make informed decisions. In this project, we aim to develop a robust machine learning model that predicts house prices in the USA based on various attributes.In this phase we are going to see how to load, preprocess, model selection and evaluation for the given dataset.

PROGRAM:

Loading the dataset:

Loading data is a crucial step in any data analysis or machine learning task. It involves bringing external datasets into your programming environment so that you can manipulate, analyze, and draw insights from the data.

❖ Importing Libraries:

- **Pandas:** Pandas, the abbreviation for **Pan**el-**Da**ta, is a library for representing data on a data-frame.
- **Numpy:** Numpy is a math library that supports many operations on arrays, from simple to complex.

- **Seaborn:** Seaborn is a python library for data visualization. It is built on top of matplotlib.
- **Matplotlib:** Matplotlib supports most of the basic plots that we need when starting with data science.
- **Scikit learn:** It is a simple and very fast tool for predictive data analysis and statistically modeling.
- **XG Boost:** XGBoost, short for "Extreme Gradient Boosting," is a powerful and popular machine learning algorithm, is widely used for both classification and regression tasks.
- **Warnings:** The warnings package in Python is part of the Python Standard Library and is used to issue warning messages in your code.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score, mean_absolute_error,mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
import xgboost as xg

%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

❖ Loading the dataset:

Use Pandas to load the dataset into a DataFrame.

```
[ ]  dataset = pd.read_csv('USA_Housing.csv')
```

Data Exploration:

Check out the first few rows using dataset.head().

```
dataset.head()
```

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
0	79545.45857	5.682861	7.009188	4.09	23086.80050	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1	79248.64245	6.002900	6.730821	3.09	40173.07217	1.505891e+06	188 Johnson Views Suite 079\nLake Kathleen, CA...
2	61287.06718	5.865890	8.512727	5.13	36882.15940	1.058988e+06	9127 Elizabeth Stravenue\nDanieltown, WI 06482...
3	63345.24005	7.188236	5.586729	3.26	34310.24283	1.260617e+06	USS Barnett\nFPO AP 44820
4	59982.19723	5.040555	7.839388	4.23	26354.10947	6.309435e+05	USNS Raymond\nFPO AE 09386

Data Preprocessing techniques:

Data preprocessing involves cleaning, transforming, and organizing raw data into a format that can be effectively used for modeling and analysis. Here are some common data preprocessing techniques:

❖ **Data cleaning:**

- **Handling missing data**: You can remove or impute missing values using techniques like mean, median, mode imputation, or more advanced methods like regression imputation.

```
round((dataset.isnull().sum()/dataset.shape[0])*100,2)
```

```
Avg. Area Income                0.0
Avg. Area House Age             0.0
Avg. Area Number of Rooms       0.0
Avg. Area Number of Bedrooms    0.0
Area Population                 0.0
Price                           0.0
Address                         0.0
dtype: float64
```

For our dataset, since there is no missing values ,no need to use the data handling techniques like mean, median, mode.

- **Outlier detection and treatment:** To identify the outliers, we use techniques like describe(), info(), duplicated() and to handle the outliers, we use techniques like percentiles, z-score using statistical methods or domain knowledge.

To find if there is any duplicates in the dataset, we use duplicated().

```
dataset.duplicated()
```

```
0       False
1       False
2       False
3       False
4       False
        ...
4995    False
4996    False
4997    False
4998    False
4999    False
Length: 5000, dtype: bool
```

To get an overview of data types and missing values, we use info().

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 7 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Avg. Area Income              5000 non-null   float64
 1   Avg. Area House Age           5000 non-null   float64
 2   Avg. Area Number of Rooms     5000 non-null   float64
 3   Avg. Area Number of Bedrooms  5000 non-null   float64
 4   Area Population               5000 non-null   float64
 5   Price                         5000 non-null   float64
 6   Address                       5000 non-null   object
dtypes: float64(6), object(1)
memory usage: 273.6+ KB
```

We use describe(), to get statistical summaries.

```
dataset.describe()
```

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000	5.000000e+03
mean	68583.108984	5.977222	6.987792	3.981330	36163.516039	1.232073e+06
std	10657.991214	0.991456	1.005833	1.234137	9925.650114	3.531176e+05
min	17796.631190	2.644304	3.236194	2.000000	172.610686	1.593866e+04
25%	61480.562390	5.322283	6.299250	3.140000	29403.928700	9.975771e+05
50%	68804.286405	5.970429	7.002902	4.050000	36199.406690	1.232669e+06
75%	75783.338665	6.650808	7.665871	4.490000	42861.290770	1.471210e+06
max	107701.748400	9.519088	10.759588	6.500000	69621.713380	2.469066e+06

```
# Categorical columns
cat_col = [col for col in dataset.columns if dataset[col].dtype == 'object']
print('Categorical columns :',cat_col)
# Numerical columns
num_col = [col for col in dataset.columns if dataset[col].dtype != 'object']
print('Numerical columns :',num_col)
```

```
Categorical columns : ['Address']
Numerical columns : ['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms', 'Avg. Area Number of Bedrooms', 'Area Population', 'Price']
```

This nunique() function in pandas is used to count the number of unique values in a dataframe.

```
[ ] dataset[cat_col].nunique()

    Address    5000
    dtype: int64
```

Some statistical techniques to handle the missing values and the outliers.

- Mean
- Variance
- Percentile

Standard deviation
Median
Mode

The **mean** is a measure of central tendency that represents the average value of a set of numbers.

```
[ ] def mean(df):
        return sum(dataset.Price)/len(dataset)
    print(mean(dataset))

    1232072.6541452995
```

The **median** is a measure of central tendency in a dataset, representing the middle value when the data is sorted in ascending or descending order.

```
median_value = np.median(dataset['Price'])
print(median_value)
```

```
1232669.378
```

The **"mode"** is a measure of central tendency, similar to mean (average) and median. (appears most frequently in a particular column or variable).

```
import statistics
mode_result = statistics.mode(dataset['Price'])

print(f'Mode: {mode_result}')
```

```
Mode: 1059033.558
```

Standard deviation is a measure of the amount of variation or dispersion in a set of values.

```
std_deviation = np.std(dataset['Price'])
print(f"Standard Deviation: {std_deviation}")
```

```
Standard Deviation: 353082.3130552725
```

Percentiles are a statistical concept used to describe the relative standing of a particular value within a dataset.

Quartiles:

- Q1 (25th percentile): The value below which 25% of the data falls.
- Q2 (50th percentile, median): The value below which 50% of the data falls.
- Q3 (75th percentile): The value below which 75% of the data falls.

Percentile Ranks:

- The nth percentile is the value below which n% of the data falls.

```
percentiles = np.percentile(dataset['Price'], [25, 50, 75])
print(f"25th Percentile (Q1): {percentiles[0]}")
print(f"50th Percentile (Q2 or Median): {percentiles[1]}")
print(f"75th Percentile (Q3): {percentiles[2]}")
```

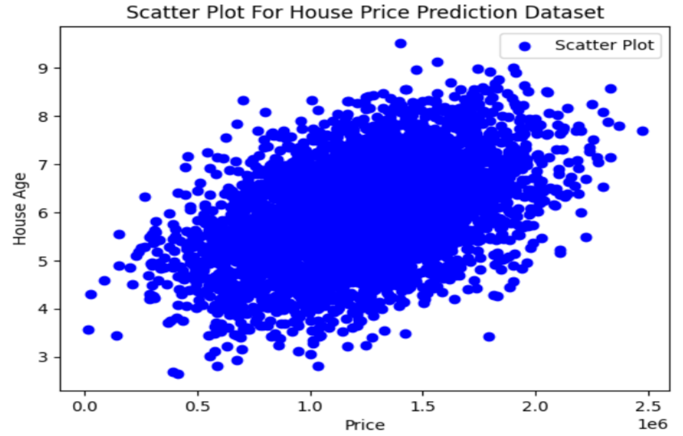
```
25th Percentile (Q1): 997577.135075
50th Percentile (Q2 or Median): 1232669.378
75th Percentile (Q3): 1471210.2045
```

Data Visualization Techniques:

Data visualization helps you to understand the data, identify trends, outliers, and relationships between different variables. Here are some commonly used data visualization techniques :

- **Scatter Plot:** Create scatter plots to explore the relationship between variables like square footage, number of bedrooms, or location and house prices. This can help identify patterns and outliers.

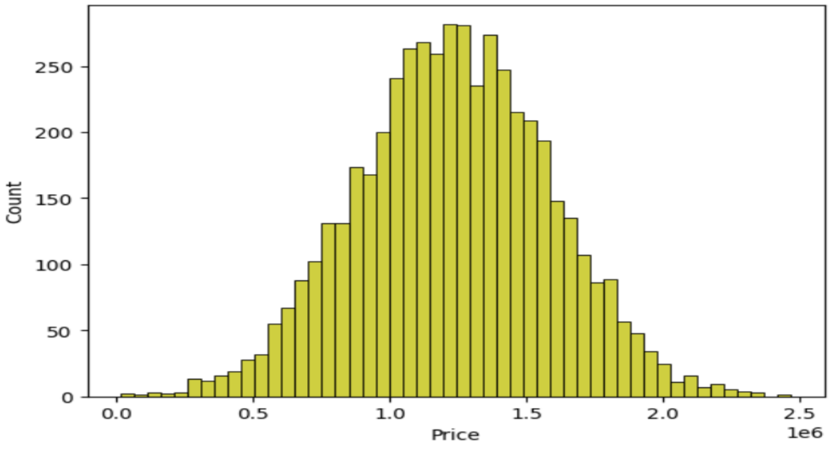
```
x_values = dataset['Price']
y_values = dataset['Avg. Area House Age']

plt.scatter(x_values, y_values, c='blue', label='Scatter Plot')
plt.title('Scatter Plot For House Price Prediction Dataset')
plt.xlabel('Price')
plt.ylabel('House Age')
plt.legend()
plt.show()
```



- **Histograms:** Use histograms to visualize the distribution of house prices.It helps you understand the central tendency and spread of the prices.

```
sns.histplot(dataset, x='Price', bins=50, color='y')
```

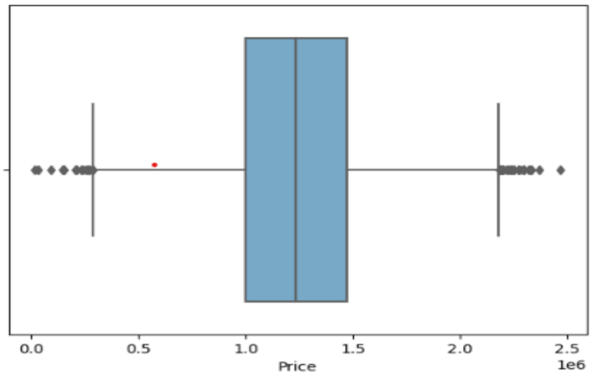
```
<Axes: xlabel='Price', ylabel='Count'>
```



- **Box Plot:** Box plots are useful for visualizing the distribution of house prices by different categories, such as the number of bedrooms or the neighbourhood.

```
sns.boxplot(dataset, x='Price',  palette='Blues')
```

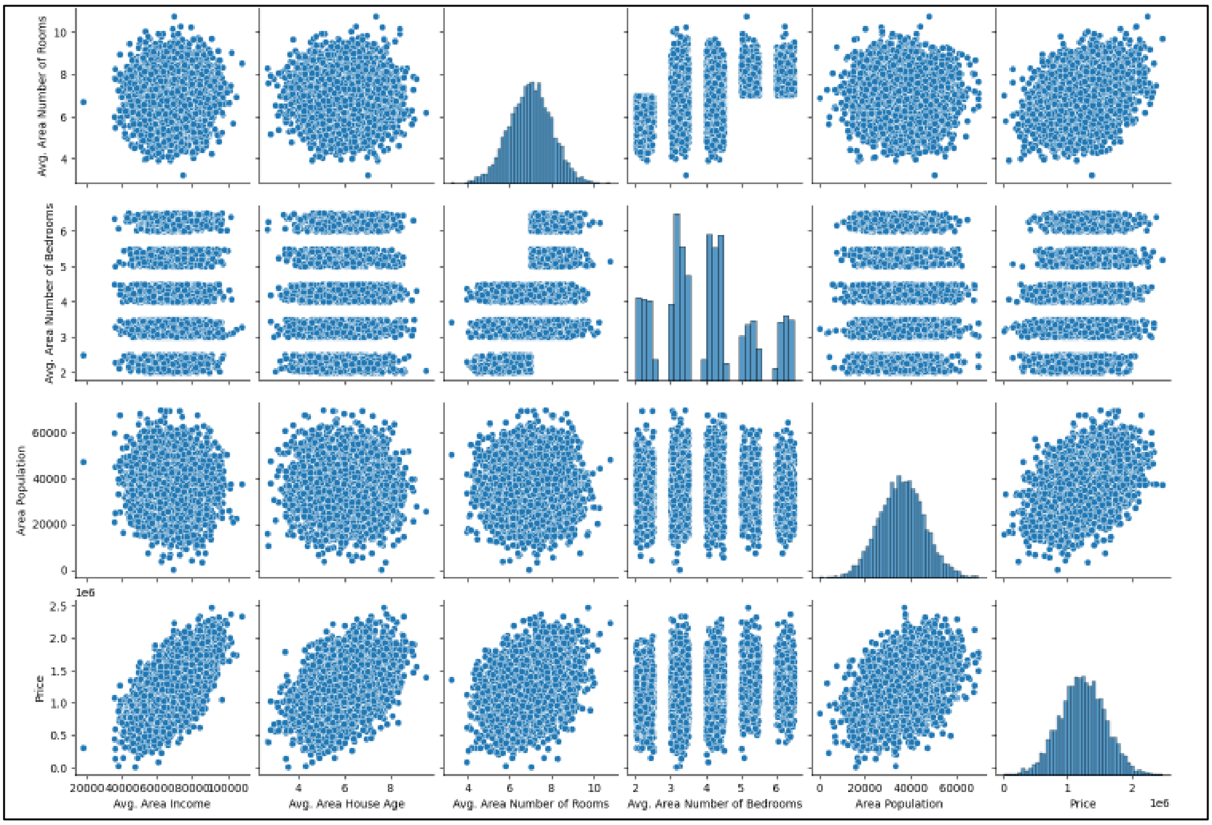
```
<Axes: xlabel='Price'>
```



- **Pairplot**: A pair plot displays scatter plots for multiple variables in your dataset. It's useful for identifying relationships and correlations among multiple features.

```
plt.figure(figsize=(12,8))
sns.pairplot(dataset)
```

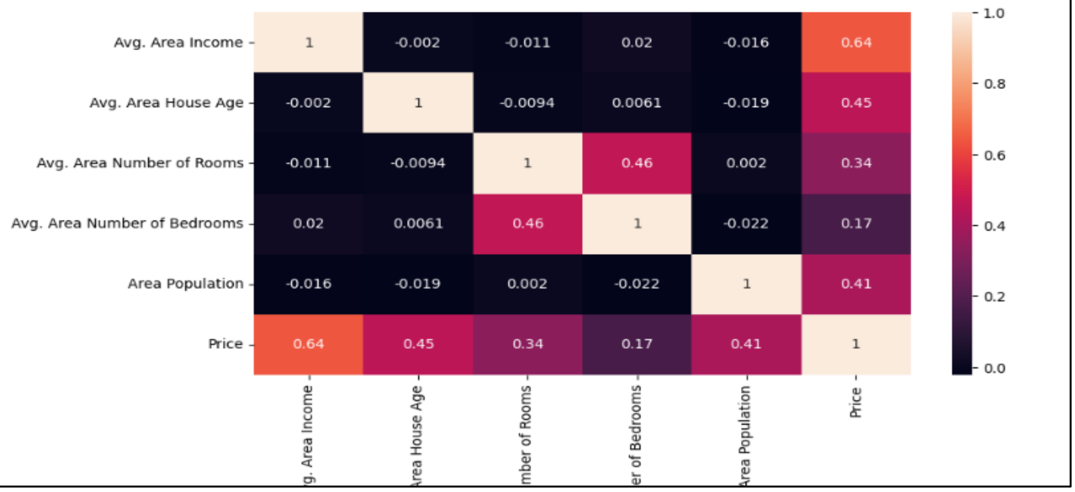
```
<seaborn.axisgrid.PairGrid at 0x7bf3882696c0>
<Figure size 1200x800 with 0 Axes>
```



- **Heatmap:** Heatmaps help to visualize the relationships and patterns in the data, which can be useful for understanding the factors that influence house prices.

```
plt.figure(figsize=(10,5))
sns.heatmap(dataset.corr(numeric_only = True), annot=True)
```

```
<Axes: >
```



Using LabelEncoder:

Label encoder is often used to convert the categorical values like address to the respective numerical values. These label encoder is available on the sklearn.preprocessing package.

```
from sklearn.preprocessing import LabelEncoder
labelencoder=LabelEncoder()
for column in dataset.columns:
    dataset[column] = labelencoder.fit_transform(dataset[column])
```

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 7 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Avg. Area Income              5000 non-null   int64
 1   Avg. Area House Age           5000 non-null   int64
 2   Avg. Area Number of Rooms     5000 non-null   int64
 3   Avg. Area Number of Bedrooms  5000 non-null   int64
 4   Area Population               5000 non-null   int64
 5   Price                         5000 non-null   int64
 6   Address                       5000 non-null   int64
dtypes: int64(7)
memory usage: 273.6 KB
```

Splitting the data:

To do this, you split your dataset into two main parts: a training set and a testing set.

```
[ ] X = dataset[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms',
           'Avg. Area Number of Bedrooms', 'Area Population']]
    Y = dataset['Price']
```

1.Training Set:

- This is the portion of your data used to train your model. The model learns patterns, relationships, and features from this set.
- The idea is that by exposing your model to a sufficient amount of data, it should be able to learn and understand the underlying patterns in the information.

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=101)
)
```

```
[ ] Y_train.head()

    3413    1.305210e+06
    1610    1.400961e+06
    3459    1.048640e+06
    4293    1.231157e+06
    1039    1.391233e+06
    Name: Price, dtype: float64
```

```
[ ] Y_train.shape

    (4000,)
```

2.Testing Set:

- This set is reserved to evaluate how well your model performs on unseen data.
- Once your model is trained, you use the testing set to see how accurately it can make predictions or classifications.
- The testing set serves as a simulation of real-world scenarios where your model encounters new, previously unseen examples.

```
Y_test.head()

1718    1.251689e+06
2511    8.730483e+05
345     1.696978e+06
2521    1.063964e+06
54      9.487883e+05
Name: Price, dtype: float64
```

```
[ ] Y_test.shape

    (1000,)
```

Standard Scalar:

Standard Scalar, or standardization, is a technique used in machine learning to scale and center the attributes or features of a dataset. The goal is to ensure that the features have the same scale or distribution.

```
[ ] sc = StandardScaler()
    X_train_scal = sc.fit_transform(X_train)
    X_test_scal = sc.fit_transform(X_test)
```

Linear regression:

Linear regression is like fitting a straight line through a cloud of points. It's a simple yet powerful method in statistics and machine learning used for predicting a continuous outcome variable (dependent variable) based on one or more predictor variables (independent variables).

The objective is to find the best-fitting line that minimizes the sum of squared differences between the observed and predicted values.

```
[ ] model_lr=LinearRegression()

[ ] model_lr.fit(X_train_scal, Y_train)

    ▾ LinearRegression
    LinearRegression()
```

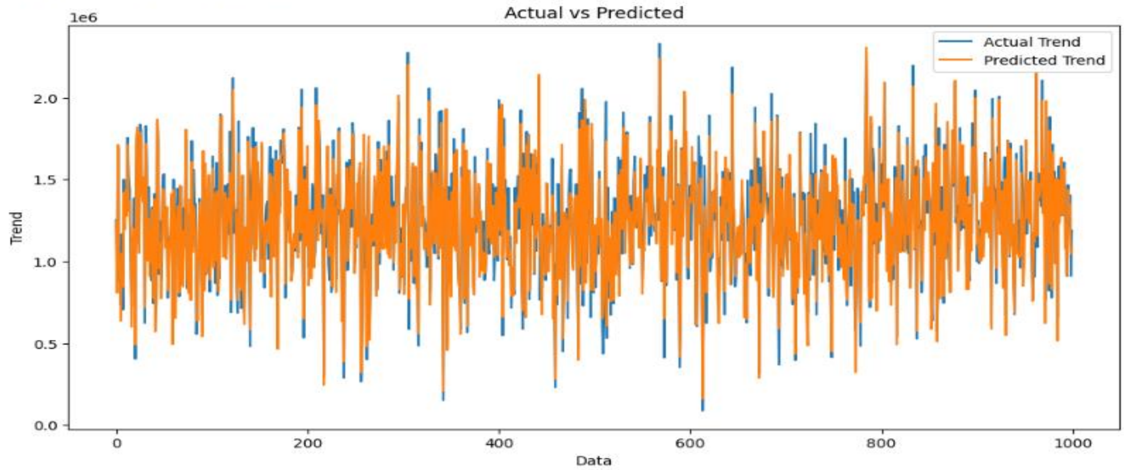
Predictions:

Once trained, the model can make predictions for new, unseen data. You input a value for x, and the model predicts the corresponding y.

```
[ ] Prediction1 = model_lr.predict(X_test_scal)
```

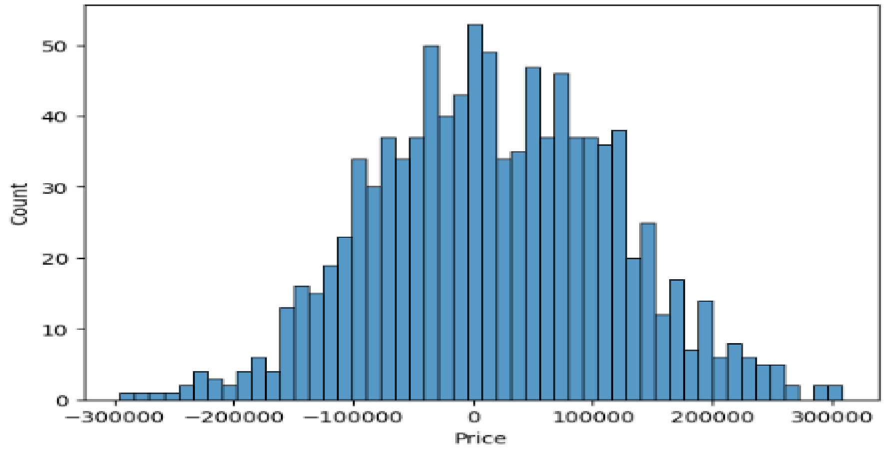
```
plt.figure(figsize=(12,6))
plt.plot(np.arange(len(Y_test)), Y_test, label='Actual Trend')
plt.plot(np.arange(len(Y_test)), Prediction1, label='Predicted Trend')
plt.xlabel('Data')
plt.ylabel('Trend')
plt.legend()
plt.title('Actual vs Predicted')
```

Text(0.5, 1.0, 'Actual vs Predicted')



```
sns.histplot((Y_test-Prediction1), bins=50)
```

```
<Axes: xlabel='Price', ylabel='Count'>
```



Evaluation:

Common metrics for evaluating linear regression models include Mean Squared Error (MSE) and R-squared. MSE measures the average squared difference between predicted and actual values, while R-squared represents the proportion of the variance in the dependent variable that is predictable from the independent variables.

```
print(r2_score(Y_test, Prediction1))
print(mean_absolute_error(Y_test, Prediction1))
print(mean_squared_error(Y_test, Prediction1))
```

```
0.9182928179392918
82295.49779231755
10469084772.975954
```

Linear regression is a great starting point for many predictive modeling tasks, and it forms the foundation for more complex models. It's widely used in various fields due to its simplicity and interpretability.

Support vector Regressor:

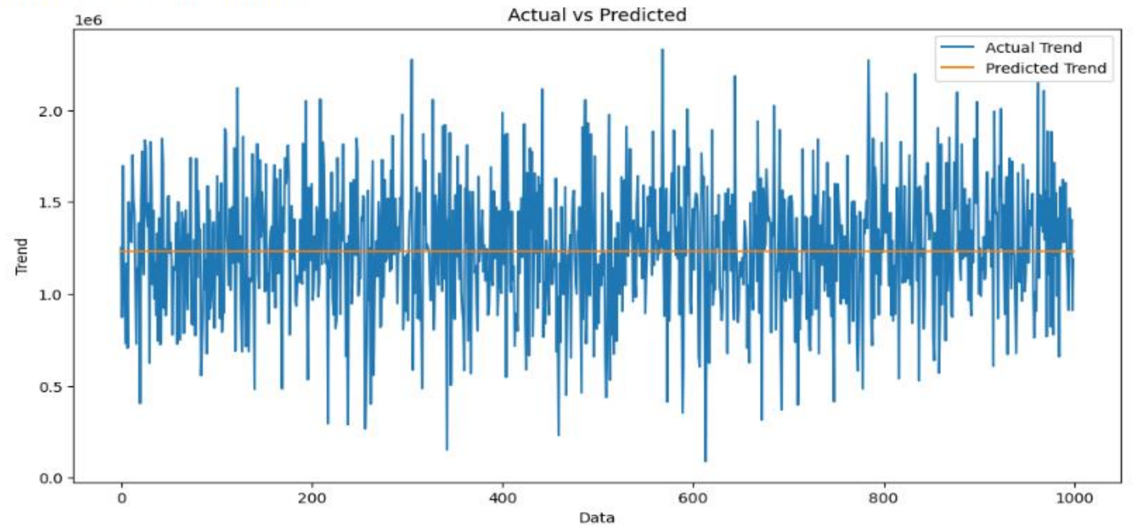
Support Vector Regression (SVR) is a type of machine learning model that utilizes support vector machines for regression tasks. Similar to Support Vector Machines (SVM) for classification, SVR aims to find a hyperplane that best fits the data while minimizing the error between the predicted and actual values.

The primary goal of SVR is to find a hyperplane that best represents the trend in the data, while allowing for a margin of error.

```
[ ]  model_svr = SVR()

[ ]  model_svr.fit(X_train_scal, Y_train)

     ▾ SVR
     SVR()

[ ]  Prediction2 = model_svr.predict(X_test_scal)
```

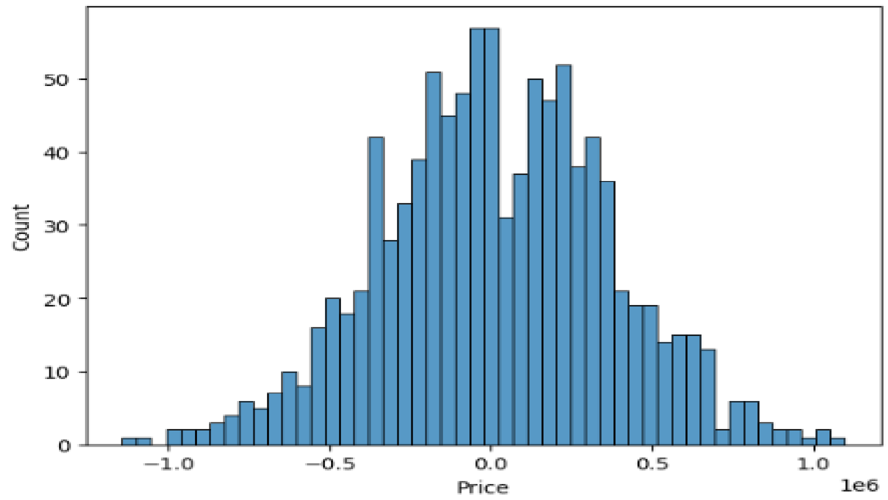
```
plt.figure(figsize=(12,6))
plt.plot(np.arange(len(Y_test)), Y_test, label='Actual Trend')
plt.plot(np.arange(len(Y_test)), Prediction2, label='Predicted Trend')
plt.xlabel('Data')
plt.ylabel('Trend')
plt.legend()
plt.title('Actual vs Predicted')
```

```
Text(0.5, 1.0, 'Actual vs Predicted')
```




```
sns.histplot((Y_test-Prediction2), bins=50)
```

```
<Axes: xlabel='Price', ylabel='Count'>
```



```
print(r2_score(Y_test, Prediction2))
print(mean_absolute_error(Y_test, Prediction2))
print(mean_squared_error(Y_test, Prediction2))
```

```
-0.0006222175925689744
286137.81086908665
128209033251.4034
```

SVR is particularly useful when dealing with datasets where the relationship between the features and the target variable is complex and nonlinear. It's a powerful regression technique, and the choice of the kernel function (linear, polynomial, radial basis function, etc.) can significantly impact its performance on different types of data.

Random Forest Regressor:

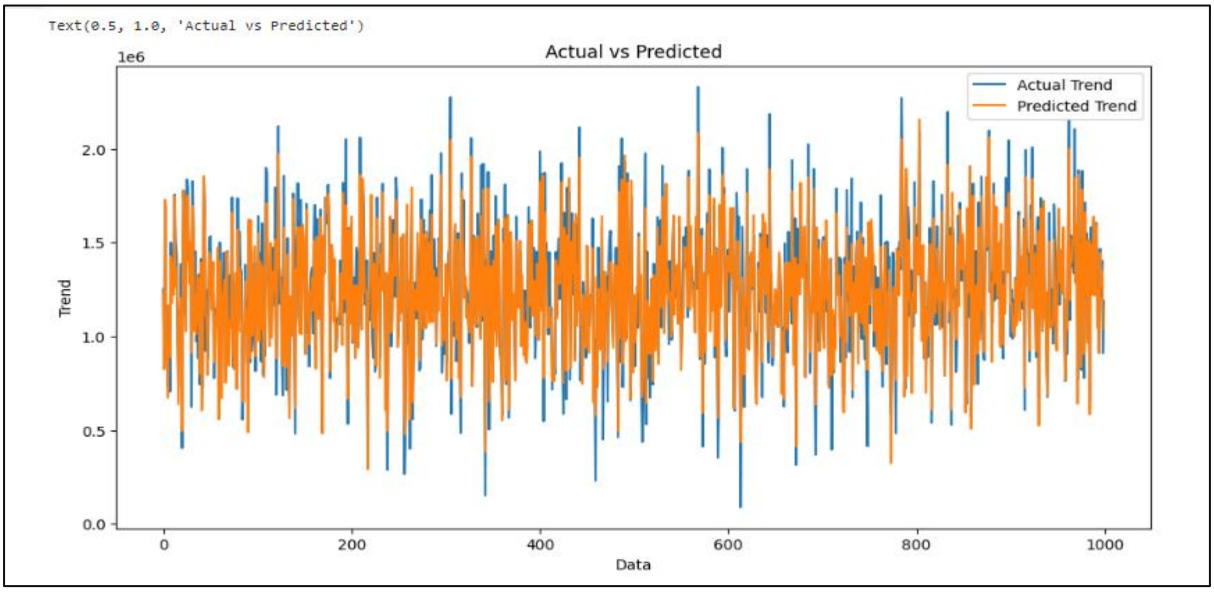
Random Forest Regression is like the wisdom of the crowd applied to predicting numbers. It's an ensemble learning method that combines the predictions of multiple decision trees to improve accuracy and robustness in regression tasks.

Objective:

The primary objective of a Random Forest Regressor is to build an ensemble of decision trees that collectively make accurate predictions for a regression task. Each decision tree is trained on a subset of the data and features, and the final prediction is an average or a weighted average of the predictions of individual trees.

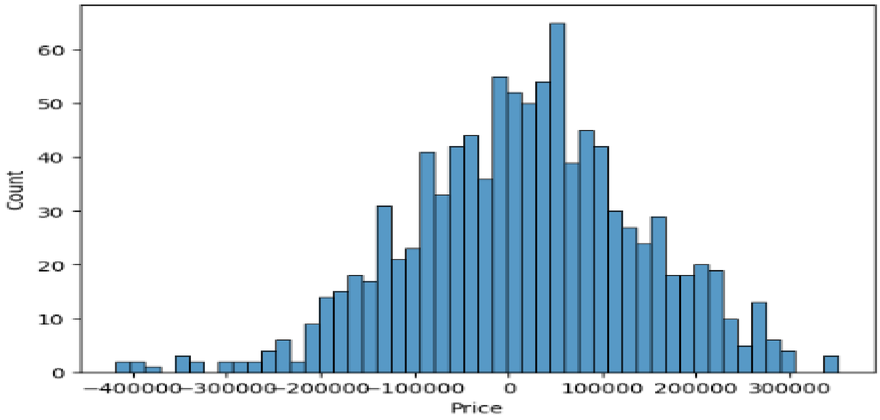
```
[ ] model_rf = RandomForestRegressor(n_estimators=50)

[ ] model_rf.fit(X_train_scal, Y_train)

    RandomForestRegressor
    RandomForestRegressor(n_estimators=50)

[ ] Prediction4 = model_rf.predict(X_test_scal)
```

```
plt.figure(figsize=(12,6))
plt.plot(np.arange(len(Y_test)), Y_test, label='Actual Trend')
plt.plot(np.arange(len(Y_test)), Prediction4, label='Predicted Trend')
plt.xlabel('Data')
plt.ylabel('Trend')
plt.legend()
plt.title('Actual vs Predicted')
```




```
sns.histplot((Y_test-Prediction4), bins=50)
```

<Axes: xlabel='Price', ylabel='Count'>




```
print(r2_score(Y_test, Prediction4))
print(mean_absolute_error(Y_test, Prediction2))
print(mean_squared_error(Y_test, Prediction2))
```

```
0.8762714539301639
286137.81086908665
128209033251.4034
```

The "random" in Random Forest is key to its success—it adds an element of diversity that prevents overfitting and improves generalization.

XGBoost:

XGBoost is the gradient boosting algorithms—it's powerful, versatile, and can tackle a wide range of machine learning tasks

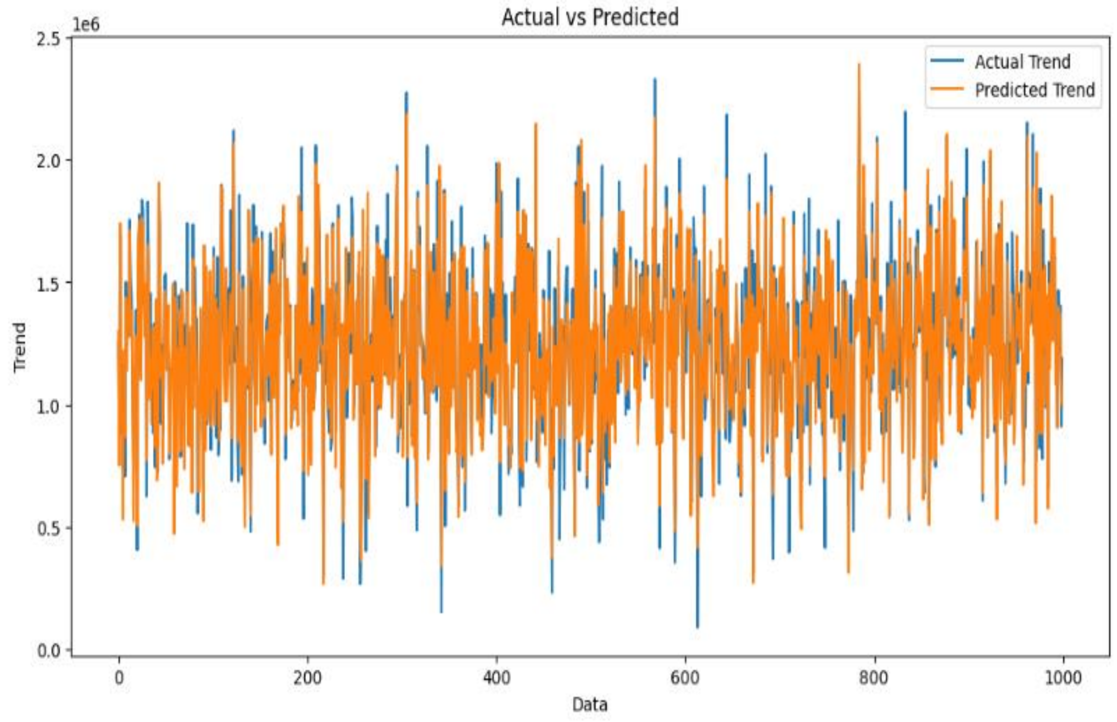
Objective:

The fundamental objective of gradient boosting is to create a strong predictive model by combining the outputs of multiple weak models (typically decision trees) in an additive manner.

```
[ ] model_xg = xg.XGBRegressor()

[ ] model_xg.fit(X_train_scal, Y_train)

                          XGBRegressor
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, ...)

[ ] Prediction5 = model_xg.predict(X_test_scal)
```

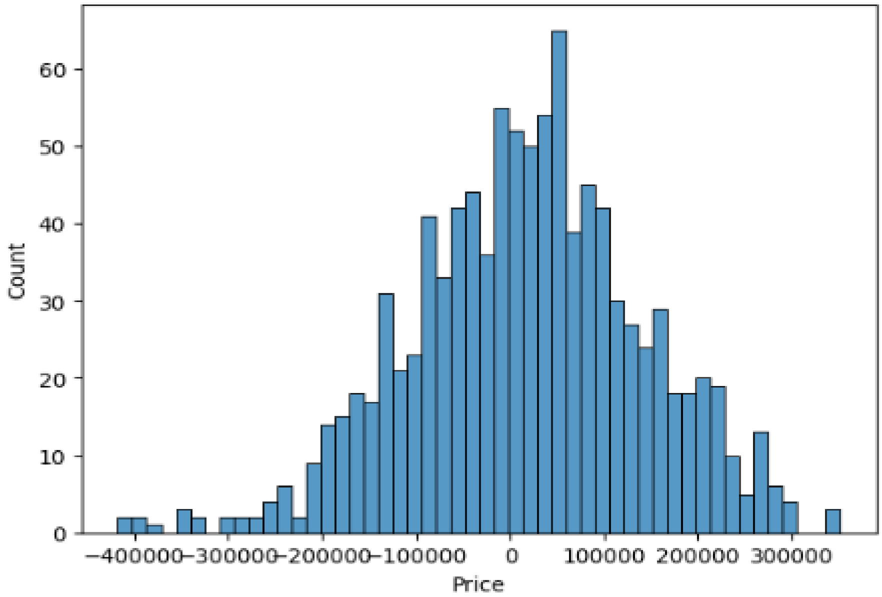
```
[ ] plt.figure(figsize=(12,6))
    plt.plot(np.arange(len(Y_test)), Y_test, label='Actual Trend')
    plt.plot(np.arange(len(Y_test)), Prediction5, label='Predicted Trend')
    plt.xlabel('Data')
    plt.ylabel('Trend')
    plt.legend()
    plt.title('Actual vs Predicted')
```

```
Text(0.5, 1.0, 'Actual vs Predicted')
```



```
sns.histplot((Y_test-Prediction4), bins=50)
```

```
<Axes: xlabel='Price', ylabel='Count'>
```




```
print(r2_score(Y_test, Prediction5))
print(mean_absolute_error(Y_test, Prediction2))
print(mean_squared_error(Y_test, Prediction2))
```

```
0.8749027861384089
286137.81086908665
128209033251.4034
```

XGBoost optimizes an objective function, which includes a loss function that measures the difference between predicted and actual values, regularization terms to control model complexity, and a component for each tree that corrects errors in the current ensemble. The iterative process of adding trees and optimizing the objective function results in a highly accurate and robust predictive model.

While comparing the machine learning algorithms like linear regression, random forest, support vector machine and XGBoost for the house price prediction analysis, the linear regression algorithm gives the best prediction score.

```
Linear Regression is giving us best Accuracy.
```

Thus the linear regression algorithm is a straightforward and interpretable model that works well in many scenarios, particularly when the relationship between the input features and the target variable is approximately linear.

CONCLUSION:

These steps provide a simplified overview of concepts like data cleaning, data preprocessing, data analysis, model selection and evaluation for the house price prediction analysis. The specific implementation details and choice of algorithms may vary depending on the dataset and the goals of the project that we work on.