Project 9: Predicting House Prices using Machine Learning

Project Title: House Price Predictor

Problem Statement:

The housing market is an important and complex sector that impacts people's lives in many ways. 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. This project aims to use machine learning techniques to predict house prices based on various features such as location, square footage, number of bedrooms and bathrooms, and other relevant factors.

Dataset Link: https://www.kaggle.com/datasets/vedavyasv/usa-housing

Project Steps:

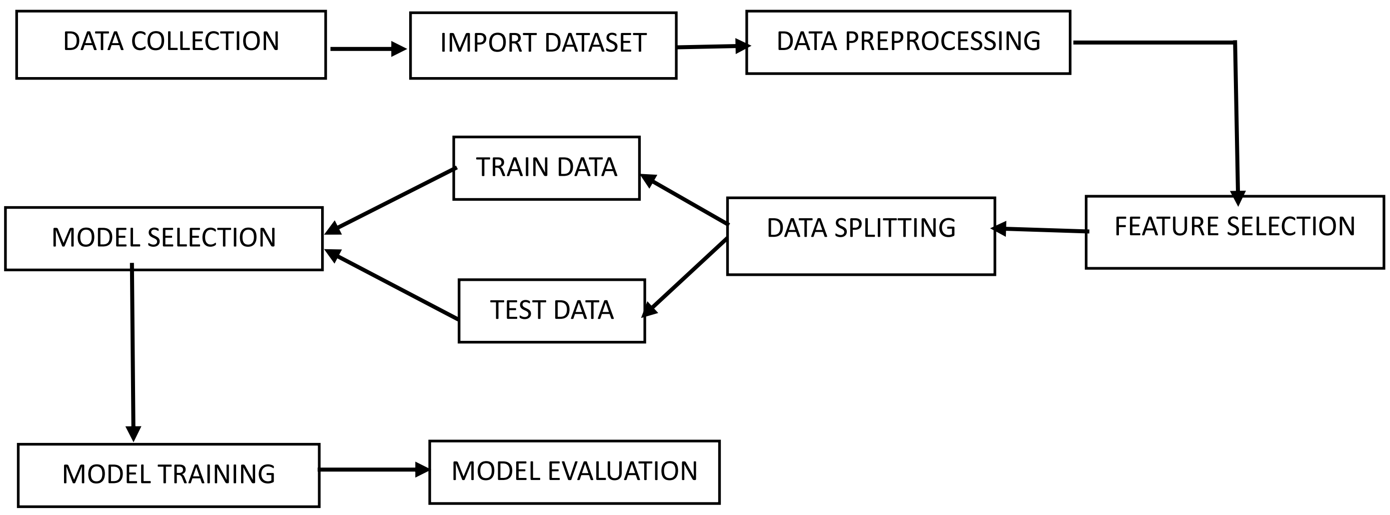
Phase 1: Problem Definition and Design Thinking

Problem Definition:

The problem is to predict house prices using machine learning techniques. The objective is to develop a model that accurately predicts the prices of houses based on a set of features such as location, square footage, number of bedrooms and bathrooms, and other relevant factors. This project involves data preprocessing, feature engineering, model selection, training, and evaluation.

Design Thinking:

FLOW DIAGRAM:



1.Data Source:

Choose a dataset containing information about houses, including features like Income, House Age, Number of Rooms, Number of Bedrooms, Population, Price and Address.

Features/Attributes: These are variables or characteristics of a property that are believed to have an impact on its price. Common features includes

- Number of Rooms and Bedrooms: The count of rooms and bedrooms in the house, which can affect its price due to the increased area and size.
- Address: The geographical location of the property, which can include factors like neighbourhood, city, and proximity to amenities or landmarks.
- House Age: The age of the house or building can also influence its price.
- Income: The income earned by the people living in those areas can also influence its price.
- Population: The number of people who are currently living in those areas can also influence the price of the houses.
- Price: The total cost of the house can be displayed here based on certain factors like area, number of rooms, age etc..

Target Variable: This is the variable you're trying to predict, which is the price of the house or property. It is typically rep resented as the dependent variable in a regression analysis.

Dataset Size: The number of records or data points in the dataset, which can range from a few hundred to thousands or more.

Data Sources: Information about where the data was collected from, such as real estate listings, government records, or surveys.

2.Data preprocessing :

It is a crucial step in preparing a house price prediction dataset for analysis or machine learning. Here's a short overview of the key steps involved:

Data Cleaning:

Handle missing values by filling them with appropriate values (e.g., mean, median, or mode).Remove duplicates if they exist in the dataset.Correct any inconsistent or erroneous data entries.

Feature Selection:

Choose relevant features that are likely to impact house prices.Remove irrelevant or redundant features to simplify the dataset. Consider using domain knowledge and feature importance techniques.

Feature Encoding:

Convert categorical variables into numerical representations through techniques like one-hot encoding or label encoding. Standardize or normalize numerical features to have a consistent scale (e.g., using Min-Max scaling or z-score normalization).

Outlier Detection and Handling:

Identify and handle outliers in the data, either by removing them or transforming them. Use visualization and statistical methods (e.g., Z-scores or IQR) to detect outliers.

Data Splitting:

Split the dataset into training, validation, and test sets to assess model performance effectively.A common split ratio is 70% training, 15% validation, and 15% testing.

Handling Skewed Data:

If the target variable (house prices) or some features are highly skewed, consider applying transformations like log transformations to make the data more symmetric.

Scaling and Normalization:

Ensure that numerical features are scaled or normalized to have similar scales, preventing some features from dominating others during modeling.

Data Transformation (if needed):

For some modeling algorithms, you might need to transform the data to meet their assumptions (e.g., transforming the target variable for linear regression).

Data preprocessing ensures that the dataset is clean, well-structured, and ready for analysis or modeling. The specific steps may vary depending on the dataset and the machine learning algorithm you plan to use, but these general steps provide a solid foundation for preparing data for house price prediction tasks.

3.Feature selection:

Feature selection for a house price prediction dataset involves choosing the most relevant and informative features while excluding irrelevant ones to improve the accuracy of your prediction model. Here's a concise guide to feature selection:

Correlation Analysis: Identify features that have a strong correlation with the target variable (house price) using techniques like Pearson correlation. Keep features with high correlations and eliminate those with low or negative correlations.

Feature Importance: If you're using tree-based models (e.g., Random Forest, XGBoost), use their feature importance scores to rank and select the most important features.

Cross-Validation: Use cross-validation to evaluate different feature subsets' performance and select the one that yields the best model performance metrics.

Regularization Hyperparameters: When using models like Ridge or Elastic Net, tune their regularization hyperparameters to encourage feature selection during training.

4.Model Selection:

Choose a suitable regression algorithm (e.g., Linear Regression, Random Forest Regressor) for predicting house prices.

Linear Regression: Start with a basic linear regression model, which is simple and interpretable. It's a good baseline.

Decision Trees: Try decision tree-based models like Random Forest and Gradient Boosting. They often perform well and handle non-linear relationships.

Neural Networks: Experiment with deep learning models, such as neural networks, if you have a large dataset and complex features.

5. Model Training:

- Train the selected model using the preprocessed data.
- Train the selected model on the training data using the features to predict house prices.
- The model will learn the relationships between the features and target variable.

6. Evaluation:

Evaluate the model's performance using metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared.

- **MAE:** It represents the average absolute error in house price predictions. Lower MAE values indicate better model accuracy. It's easy to understand and suitable for comparing models.

- **RMSE:** RMSE penalizes larger errors more than MAE because of the squaring. It's also sensitive to outliers. Lower RMSE values indicate better model accuracy.

- **R-squared**: R-squared measures the goodness of fit. It tells you the proportion of variance in the target variable that is explained by the model. Higher R-squared values (closer to 1) indicate a better fit.

These steps provide a simplified overview of the model training process for house price prediction. The specific implementation details and choice of algorithms may vary depending on the dataset and the goals of the project.

Phase:2 Innovation

GRADIENT BOOSTING:

Gradient Boosting is an ensemble learning technique used for both classification and regression tasks. It builds a predictive model in a stage-wise fashion, where each stage corrects the errors of the previous one. The general idea is to combine the predictions of multiple weak learners (often decision trees) to create a strong, accurate model.

Here's a high-level overview of how Gradient Boosting works:

Initialization: A simple model is created, often the mean or median of the target variable for regression tasks.

Iteration: Sequential trees (weak learners) are built, and each subsequent tree corrects the errors of the combined predictions of the existing trees.

Learning Rate: A hyperparameter called the learning rate controls the contribution of each tree to the final prediction. A lower learning rate requires more trees but may result in better generalization.

Handles Non-Linearity: Gradient Boosting is well-suited for capturing non-linear relationships between input features and the target variable. It can automatically adapt to complex patterns in the data.

Stopping Criteria: The process continues until a specified number of trees are built or until a certain level of performance is reached.

SAMPLE CODE:

```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Gradient Boosting Model
gb_model = GradientBoostingRegressor(learning_rate=0.1, n_estimators=100, max_depth=3)
# Model Evaluation
y_pred_gb = gb_model.predict(X_test)
mse_gb = mean_squared_error(y_test, y_pred_gb)
print(f'Mean Squared Error (Gradient Boosting): {mse_gb}')
```

XGBOOST:

XGBoost (Extreme Gradient Boosting) is a specific implementation of gradient boosting that is highly efficient and scalable. It was developed by Tianqi Chen and is widely used in machine learning competitions and real-world applications.

Key features of XGBoost include:

Regularization: XGBoost incorporates L1 (Lasso) and L2 (Ridge) regularization terms in its objective function to control overfitting.

Parallelization: It is designed for parallel and distributed computing, making it faster than traditional gradient boosting implementations.

Missing Value Handling: XGBoost can handle missing values in the dataset, eliminating the need for imputation.

Tree Pruning: Trees are pruned during the building process to prevent overfitting and improve computational efficiency.

Cross-Validation: XGBoost has built-in cross-validation capabilities to help with hyperparameter tuning.

Optimized Implementation: The algorithm is optimized for performance and memory usage.

SAMPLE CODE:

```
from xgboost import XGBRegressor

# XGBoost Model

xgb_model = XGBRegressor(learning_rate=0.1, n_estimators=100, max_depth=3)

xgb_model.fit(X_train, y_train)

# Model Evaluation

y_pred_xgb = xgb_model.predict(X_test)

mse_xgb = mean_squared_error(y_test, y_pred_xgb)

print(f'Mean Squared Error (XGBoost): {mse_xgb}')
```

PURPOSE OF USING THESE TECHNIQUES:

High Predictive Accuracy: Both Gradient Boosting and XGBoost often outperform traditional linear models in terms of predictive accuracy, especially when dealing with complex relationships and non-linear patterns.

Versatility: These techniques are versatile and can be applied to a wide range of regression problems, from predicting house prices to financial forecasting.

Robustness: The regularization techniques employed by these methods contribute to building more robust models, reducing the risk of overfitting.

When applying these techniques, it's essential to fine-tune hyperparameters, handle feature engineering thoughtfully, and ensure proper validation to achieve the best performance on your specific dataset.

COLAB LINK:
https://colab.research.google.com/drive/1bE0cFUY6tFo317FFmzpjncu8Mxi1TkC-?usp=sharing

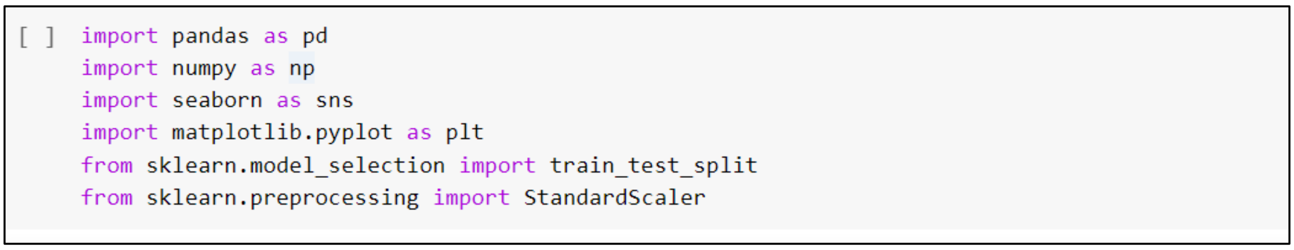
PROGRAM:

Importing 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:

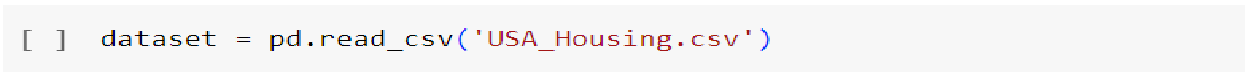
- import pandas as pd: For handling your dataset.
- import numpy as np: Useful for numerical operations.
- from sklearn.model_selection import train_test_split: Split your data into training and testing sets.
- import seaborn as sns: for data visualization in python.
- import matplotlib.pyplot as plt: another powerful library for creating visualizations.



```
[ ] 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
```

Load Your Dataset:

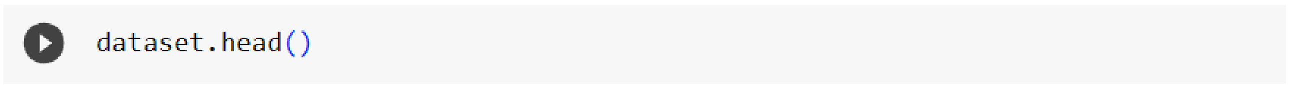
Use pd.read_csv() if your dataset is in a CSV file.



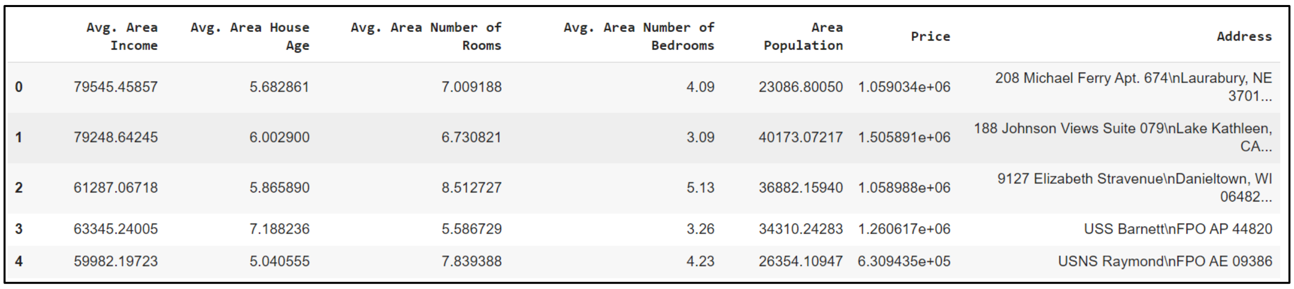
```
[ ]  dataset = pd.read_csv('USA_Housing.csv')
```

Explore Your Data:

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



```
dataset.head()
```



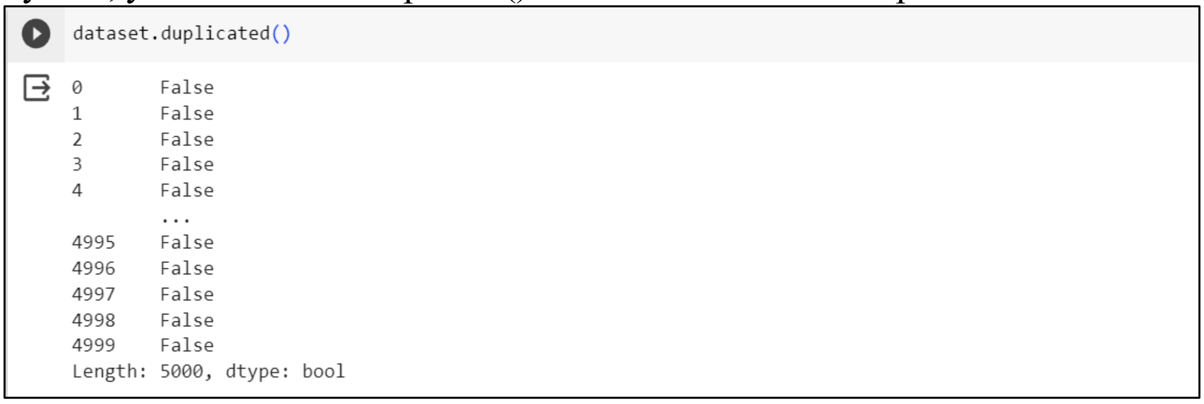
	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
0	79545.45857	5.682861	7.009188	4.09	23086.80050	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1	79248.64245	6.002900	6.730821	3.09	40173.07217	1.505891e+06	188 Johnson 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 cleaning techniques:

Data cleaning is the process of identifying and correcting errors, inconsistencies, and inaccuracies in datasets. It's a crucial step in the data analysis pipeline, as the quality of your analysis depends heavily on the quality of your data.

- Handling missing values
- Dealing with duplicates
- Handling Outliers
- Data type Conversion

If we want to identify and handle duplicate rows in a Pandas,DataFrame in Python, you can use the duplicate() function to check for duplicates.

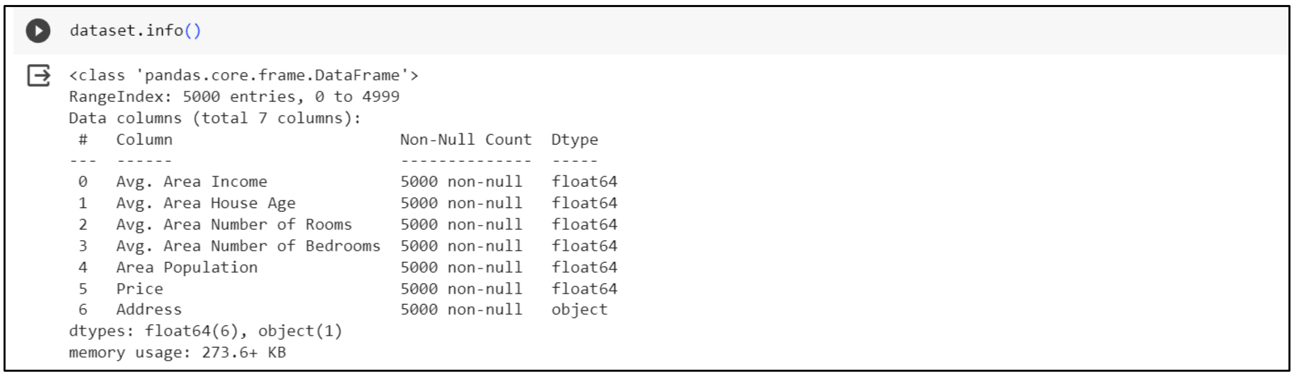


```
dataset.duplicated()
```

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

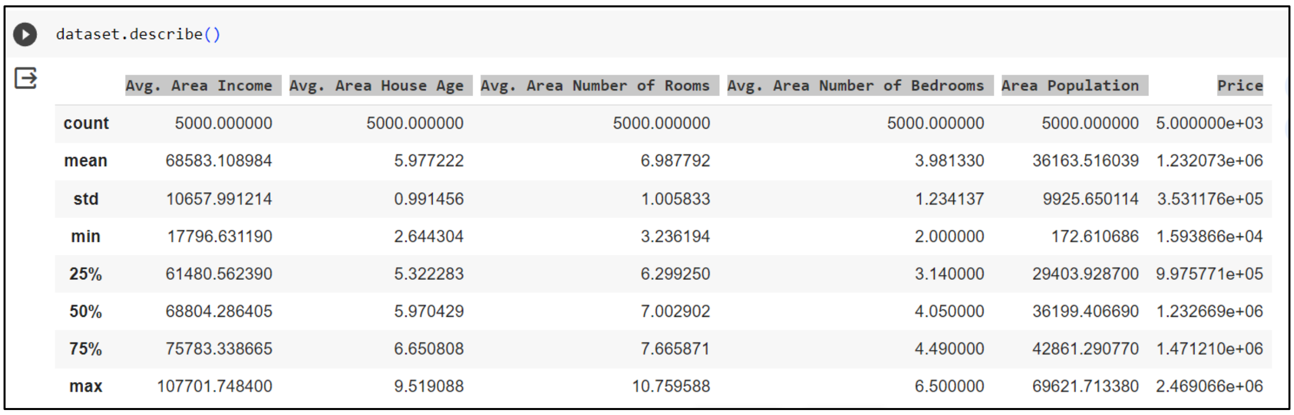
Use dataset.info() to get an overview of data types and missing values.

dataset.describe() gives you statistical summaries



```
dataset.info()
```

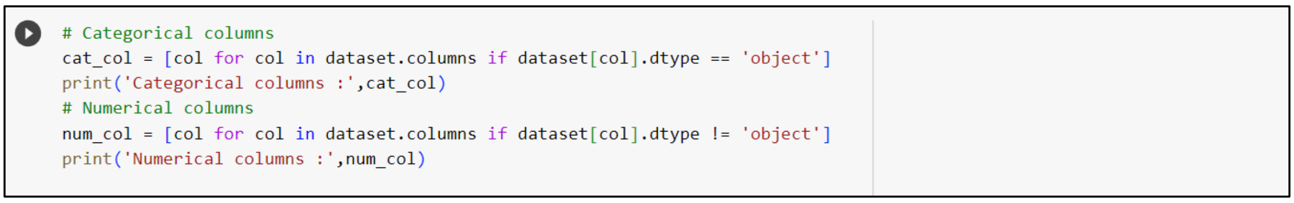
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 7 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Avg. Area Income              5000 non-null   float64
 1   Avg. Area 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
```



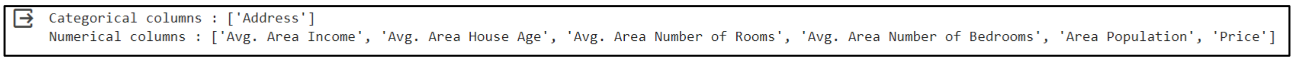
```
dataset.describe()
```

	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

If we want to split a DataFrame into two separate DataFrames based on whether a column is of type "object" or not, we can use a for loop to iterate through the columns and check their data types.Then we can split the Dataframe into numerical column and categorical columns.

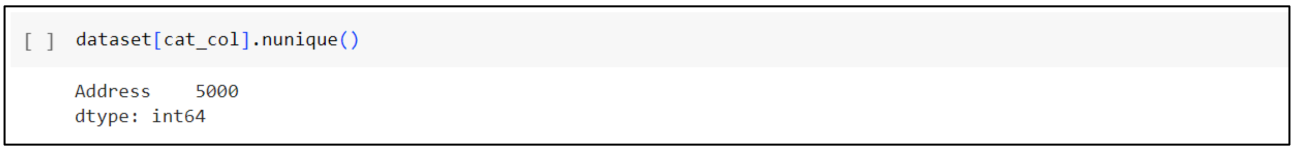


```
# Categorical columns
cat_col = [col for col in dataset.columns if dataset[col].dtype == 'object']
print('Categorical columns :',cat_col)
# Numerical columns
num_col = [col for col in dataset.columns if dataset[col].dtype != 'object']
print('Numerical columns :',num_col)
```



```
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']
```

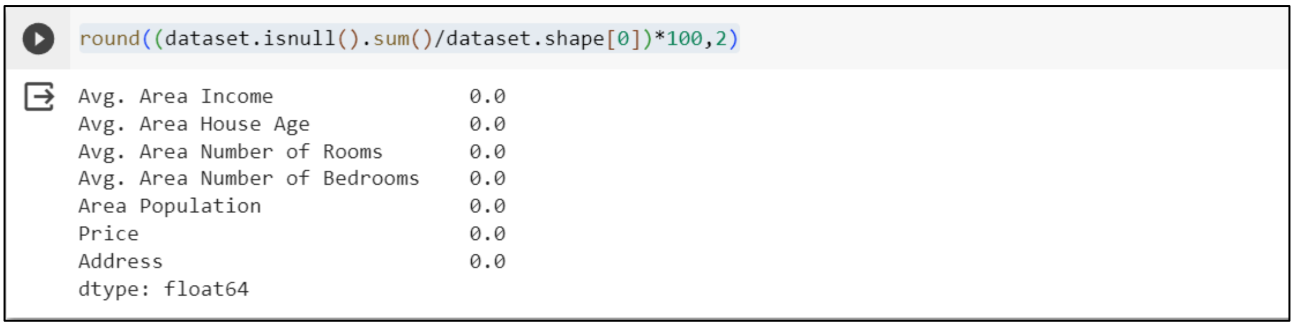
The nunique() function in pandas is used to count the number of unique values in a dataframe.



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

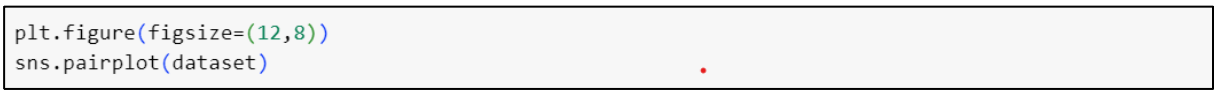
```
Address    5000
dtype: int64
```

Check for missing values and decide on a strategy for handling them.

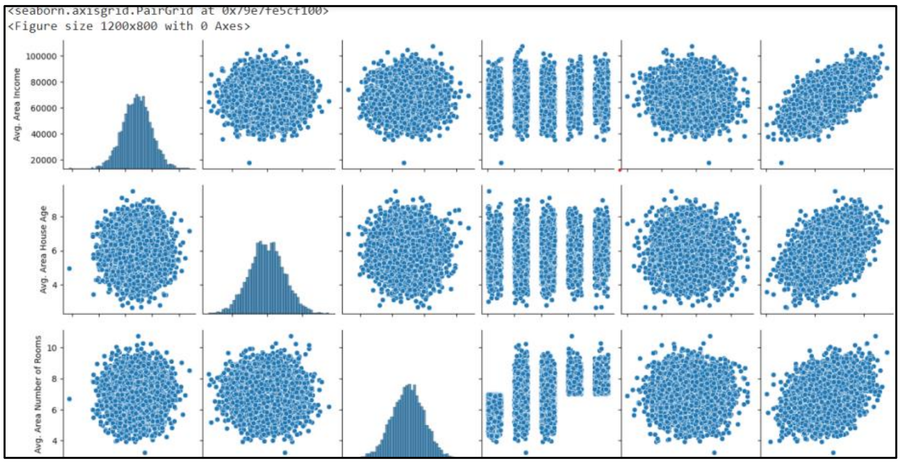


```
round((dataset.isnull().sum()/dataset.shape[0])*100,2)
```

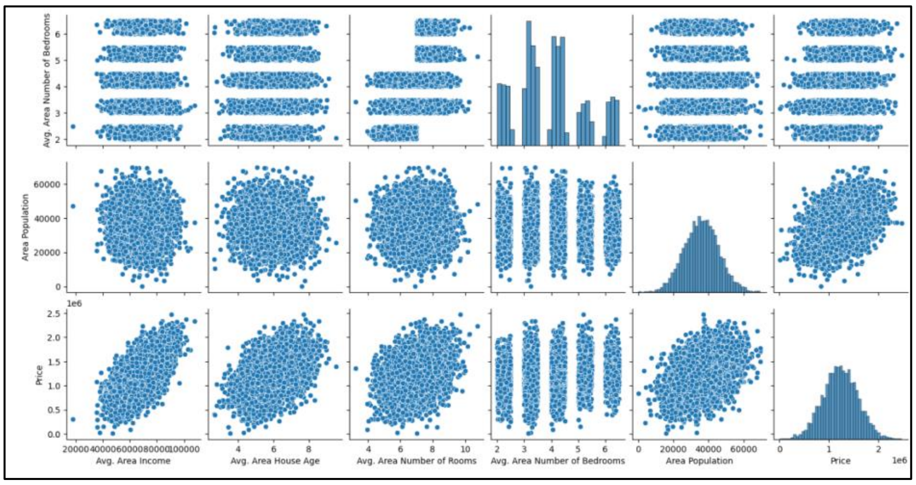
```
Avg. Area Income                0.0
Avg. Area House Age             0.0
Avg. Area Number of Rooms       0.0
Avg. Area Number of Bedrooms    0.0
Area Population                 0.0
Price                           0.0
Address                         0.0
dtype: float64
```



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



```
<seaborn.axisgrid.PairGrid at 0x79e7fe5cf100>
<Figure size 1200x800 with 0 Axes>
```



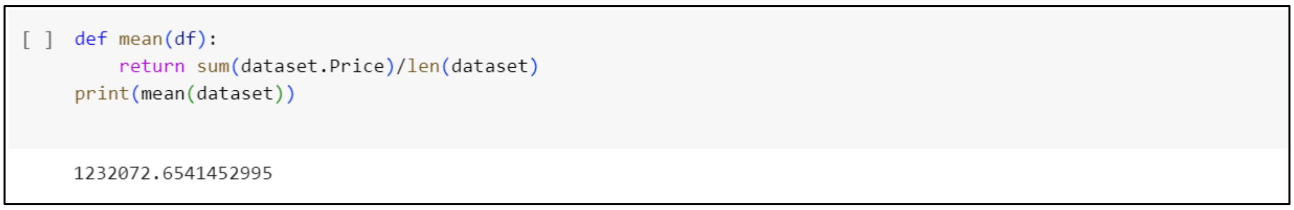
Phase 3:Development part 1

Data Analysis:

Data analysis is the process of inspecting, cleaning, transforming, and modeling data to uncover useful information, draw conclusions, and support decision-making.

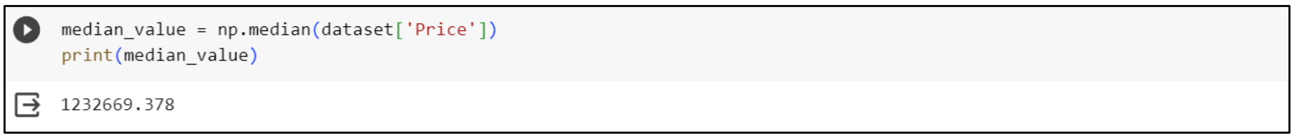
- Data visualization
- Exploratory Data Analysis

The mean is a measure of central tendency that represents the average value of a set of numbers. In the context of a dataset, it is often used to describe the central or typical value of a numerical variable.However, it's essential to be cautious with the mean, especially if the dataset contains outliers, as they can significantly impact its value.



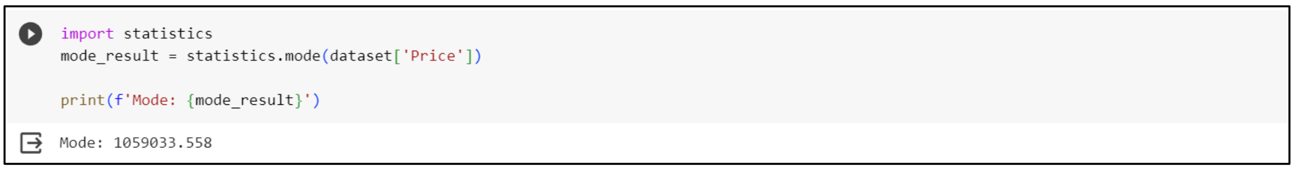
```
[ ] def mean(df):
        return sum(dataset.Price)/len(dataset)
    print(mean(dataset))

    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. Unlike the mean (average), which is sensitive to extreme values, the median is resistant to outliers.



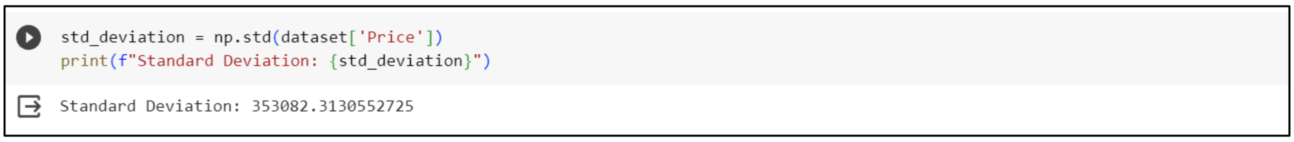
```
median_value = np.median(dataset['Price'])
print(median_value)

1232669.378
```

In the context of a dataset, the "mode" refers to the value that appears most frequently in a particular column or variable. It's a measure of central tendency, similar to mean (average) and median. It's particularly handy when dealing with categorical variables or when you want to identify the most common value in a dataset.



```
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. In the context of a dataset, it provides a quantifiable measure of how much individual data points differ from the mean (average) of the dataset.The formula for calculating the standard deviation involves taking the square root of the variance. While it provides valuable information about the spread of data, it should be used in conjunction with other descriptive statistics for a comprehensive analysis of a dataset.



```
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. The nth percentile of a dataset is the value below which n percent of the data falls. It's a way to understand the distribution of values and identify specific points in the data.

Median (50th percentile):

The value below which 50% of the data falls.

It divides the dataset into two equal halves.

Quartiles:

Q1 (25th percentile): The value below which 25% of the data falls.

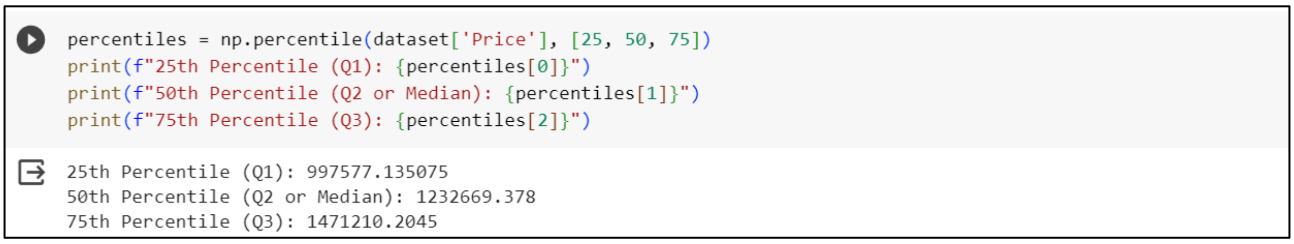
Q2 (50th percentile, median): The value below which 50% of the data falls.

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.

For example, the 90th percentile is the value below which 90% 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
```

A scatter plot is a type of data visualization that displays individual data points on a two-dimensional graph. Each point on the graph represents the values of two variables. Scatter plots are useful for visually identifying relationships or patterns between the two variables.

Key components of a scatter plot:

Data Points: Each point represents a pair of values from the two variables.

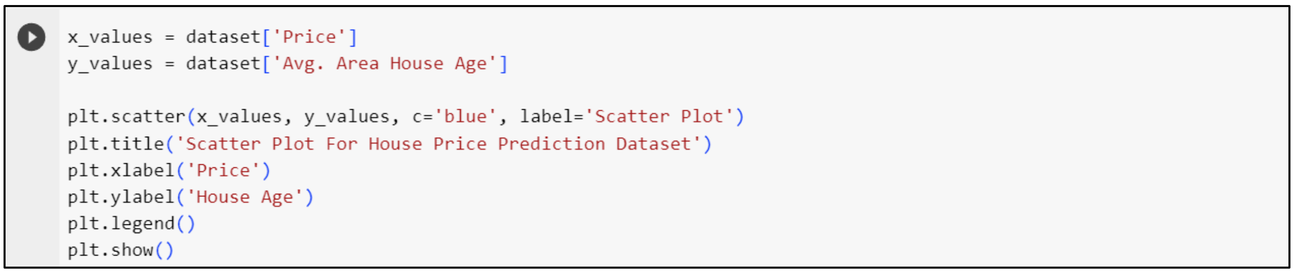
X-axis and Y-axis: The horizontal and vertical axes represent the values of the two variables.

Labels: Axes are labeled to indicate which variable they represent.

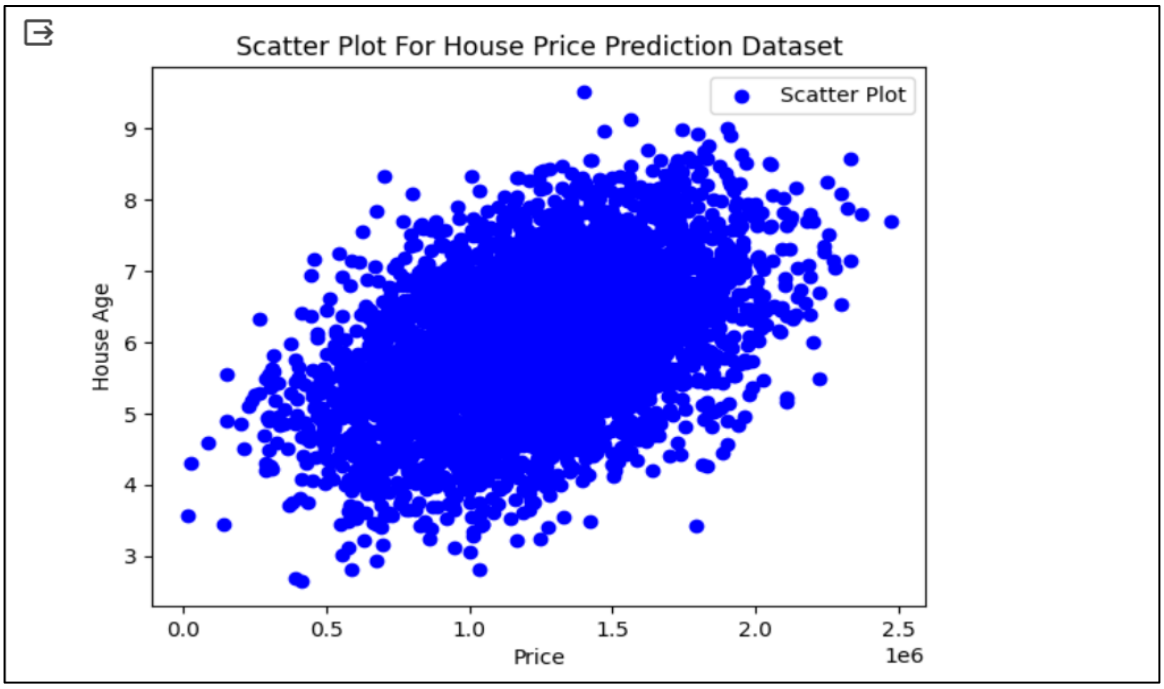
Title: Describes the purpose or context of the scatter plot.

Legend: If multiple datasets are plotted, a legend helps identify them.

Scatter plots are especially useful when you want to explore the relationship between two continuous variables, identify trends, clusters, or 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()
```



A histogram is a graphical representation of the distribution of a dataset. It displays the frequency of data points in different bins or ranges. In Python, you can create a histogram using the matplotlib library.

- data is an array of random values drawn from a normal distribution using NumPy.
- plt.hist() creates the histogram. The bins parameter determines the number of bins or ranges for the data, and alpha controls the transparency of the bars.
- Labels and a title are added for clarity.
- Finally, plt.show() displays the histogram.

Key components of a histogram:

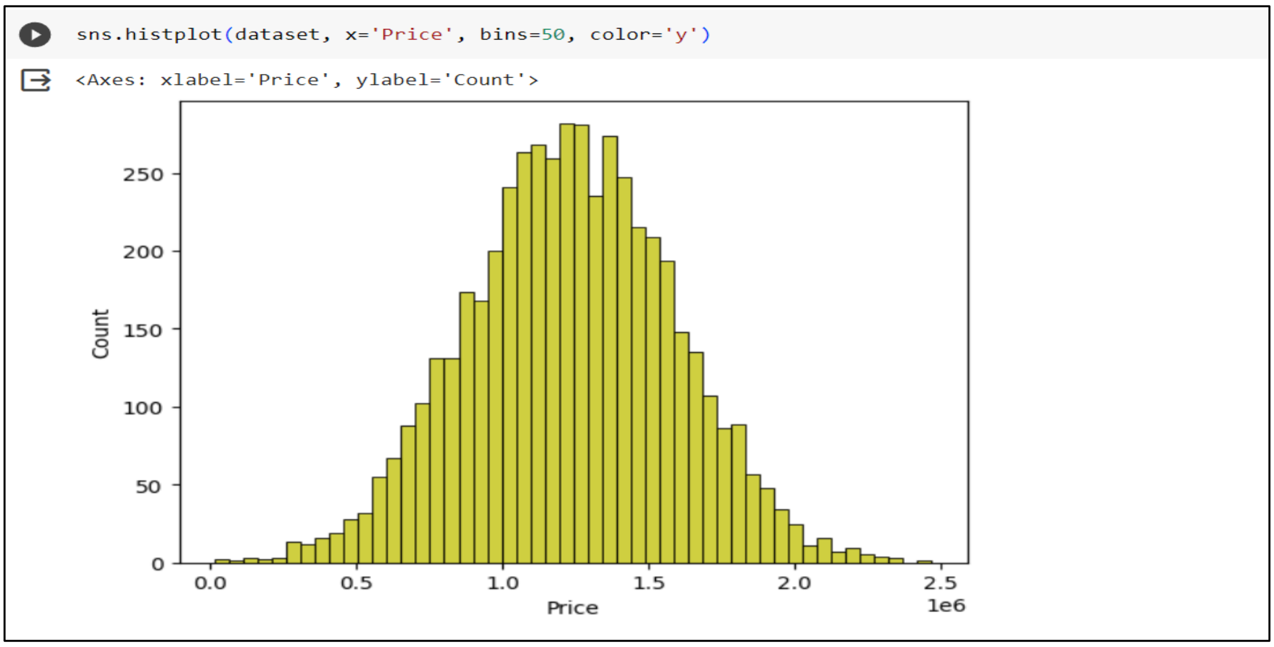
Bins: Intervals along the x-axis representing ranges of values.

Frequency: Height of the bars indicates the number of data points in each bin.

X-axis: Represents the values or ranges of the variable.

Y-axis: Represents the frequency or count of data points.

Histograms are useful for visualizing the distribution of a dataset, including information about central tendency, spread, and potential outliers.



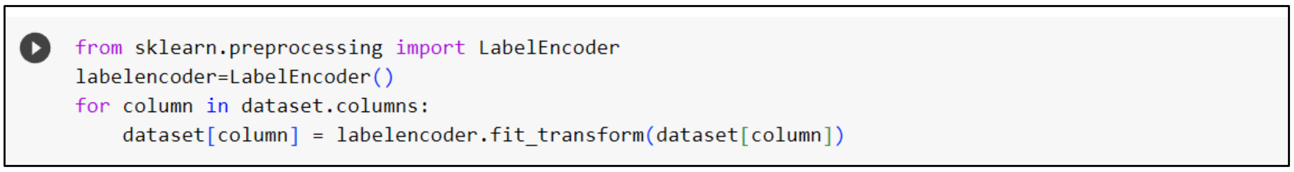
```
sns.histplot(dataset, x='Price', bins=50, color='y')
```

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

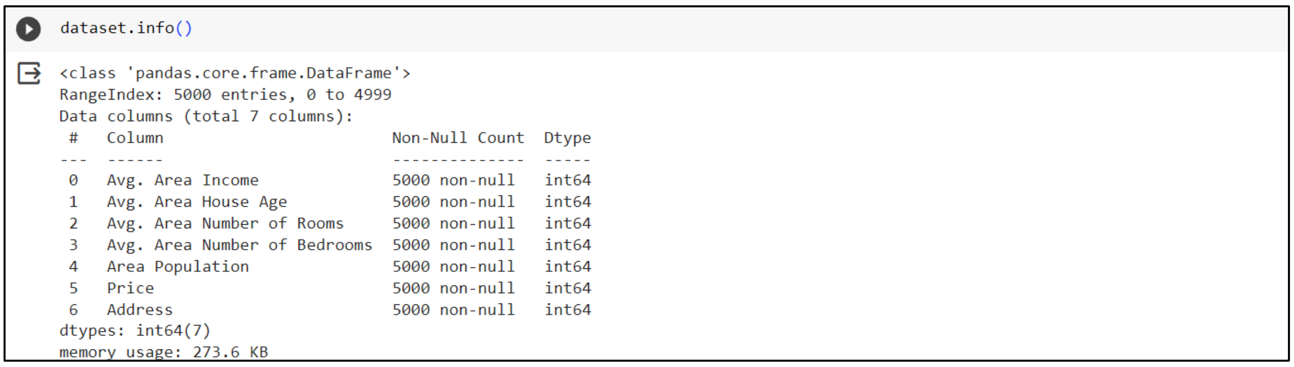
Data Preprocessing techniques:

Data preprocessing is a crucial step in the data analysis and machine learning pipeline. It involves cleaning and transforming raw data into a format suitable for analysis or model training. The goal is to enhance the quality of the data, address issues like missing values and outliers, and prepare it for effective exploration and modeling.

Label encoding is a technique to convert categorical data into numerical form, which is required for many machine learning algorithms. In Python, you can use the LabelEncoder class from the sklearn.preprocessing module to perform label encoding.



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



```python
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
```

FEATURE SELECTION:

A). Feature Importance-based Selection (using Random Forest Regressor):

1.Random Forest Regressor: A Random Forest Regressor is an ensemble machine learning model that uses multiple decision trees to make predictions.

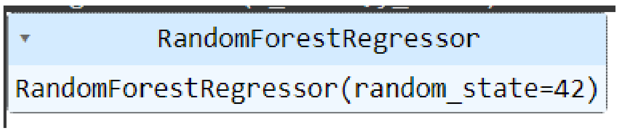
Training the Random Forest Regressor:

CODE:

regressor = RandomForestRegressor(n_estimators=100, random_state=42)

regressor.fit(X_train, y_train)

In this code, a Random Forest Regressor is created with 100 trees (n_estimators=100) for the ensemble, and a random seed (random_state=42) is set for reproducibility.It's trained using the training data X_train (features) and y_train (target).



```
▾ RandomForestRegressor
RandomForestRegressor(random_state=42)
```

2. Getting Feature Importances:

CODE:

```
feature_importances = regressor.feature_importances_
```

After training, we access the feature importances using the feature_importances_ attribute of the regressor.

3. Creating a DataFrame for Visualization:

CODE:

```
feature_importance_df = pd.DataFrame({'Feature': X_train.columns, 'Importance':

feature_importances})

feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)
```

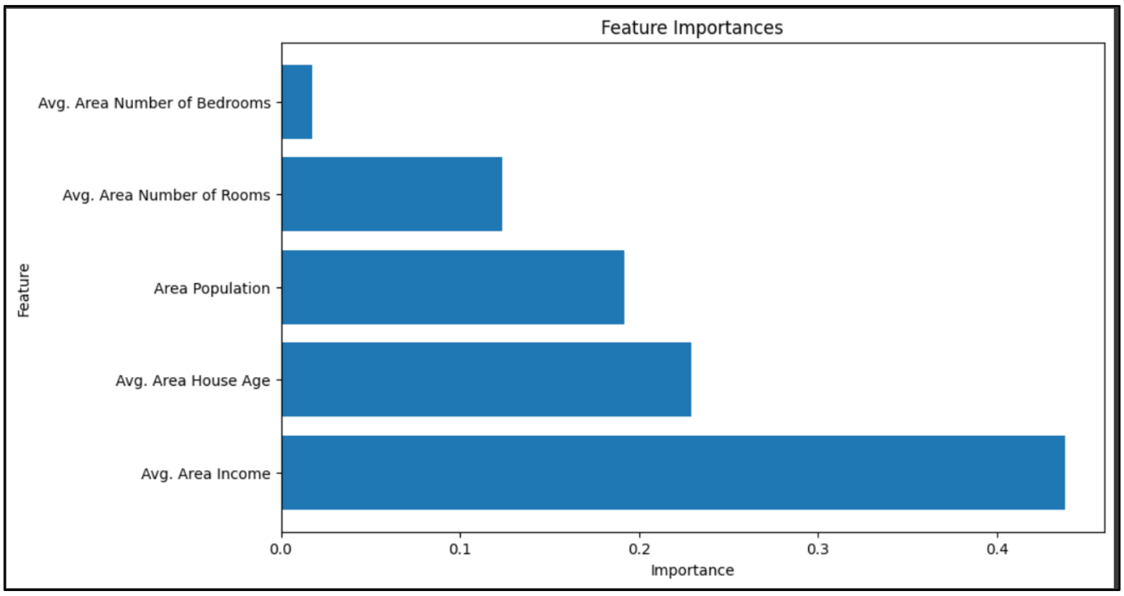
A DataFrame feature_importance_df is created to organize the feature names and their respective importances. It's sorted in descending order based on feature importances.

4. Visualizing Feature Importances:

CODE:

```
plt.figure(figsize=(10, 6))

plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance'])

plt.title('Feature Importances')

plt.xlabel('Importance')

plt.ylabel('Feature')

plt.show()
```

A horizontal bar plot is generated to visualize the feature importances. This shows which features have the most significant impact on the regression model's predictions.



B). Correlation-based Selection:

1.Calculating the Correlation Matrix:

CODE:

```
corr_matrix = X_train.corr()
```

The code calculates a correlation matrix corr_matrix for the features in your training data (X_train).

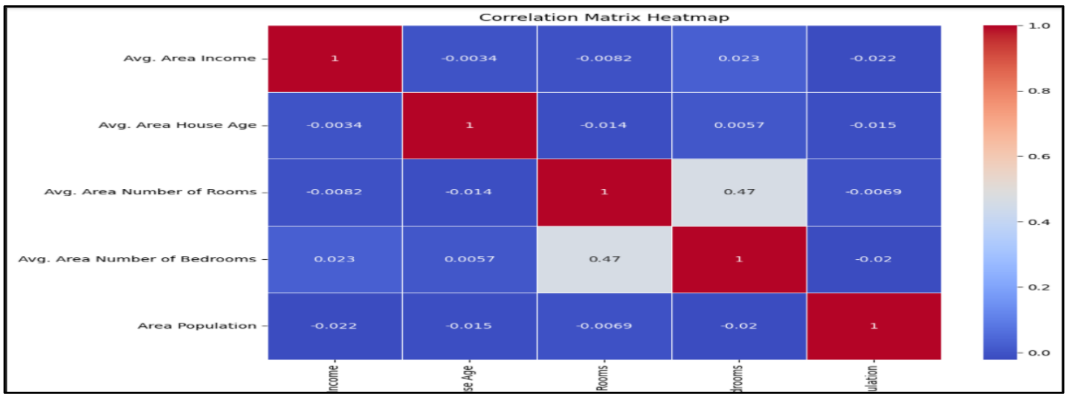
2. Creating a Heatmap for Visualization Correlation Matrix:

CODE:

```
plt.figure(figsize=(10, 8))

sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', linewidths=0.5)

plt.title('Correlation Matrix Heatmap')

plt.show()
```

A heatmap is generated to visualize the correlations between features. This heatmap uses color coding to represent the strength and direction of the correlations. It can help to identify relationships between features.

OUTPUT:



3. Selecting the top k features based on mutual information:

CODE:

```
selector = SelectKBest(score_func=mutual_info_regression, k=3)

X_train_selected = selector.fit_transform(X_train, y_train)
```

The code shows the performance of feature selection using SelectKBest. In this case, it selects the top 5 features based on mutual information with the target variable. The selected features are stored in X_train_selected, and can access them using X_train.columns[selector.get_support()].

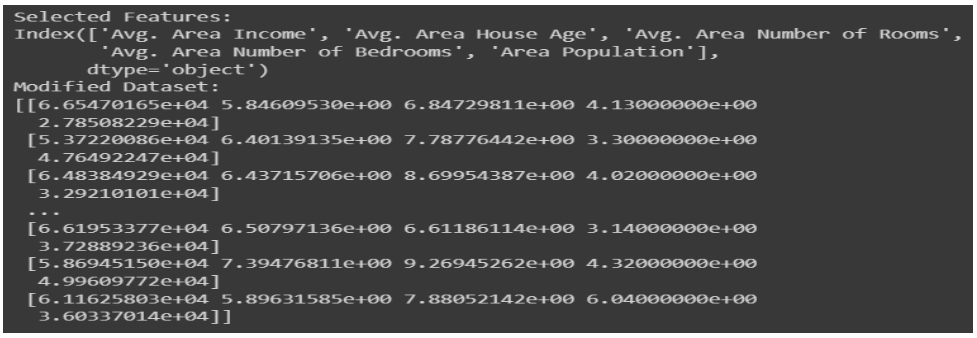
Feature Selection using SelectKBest:

CODE:

```
from sklearn.feature_selection import SelectKBest, f_regression

from sklearn.model_selection import train_test_split

import pandas as pd

data = pd.read_csv('/content/dataset.csv.csv')

X = data[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms', 'Avg. Area

Number of Bedrooms', 'Area Population']]
```

```
y = data[['Price']]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

k = 5

selector = SelectKBest(score_func=f_regression, k=k)

X_train_selected = selector.fit_transform(X_train, y_train)

selected_feature_indices = selector.get_support(indices=True)

selected_features = X_train.columns[selected_feature_indices]

X_train.columns[selector.get_support()]

selected_feature_indices = selector.get_support()

selected_features = X_train.columns[selected_feature_indices]

print("Selected Features:")

print(selected_features)

print("Modified Dataset:")

print(X_train_selected)
```

OUTPUT:



```
Selected Features:
Index(['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms',
       'Avg. Area Number of Bedrooms', 'Area Population'],
      dtype='object')
Modified Dataset:
[[6.65470165e+04 5.84609530e+00 6.84729811e+00 4.13000000e+00
  2.78508229e+04]
 [5.37220086e+04 6.40139135e+00 7.78776442e+00 3.30000000e+00
  4.76492247e+04]
 [6.48384929e+04 6.43715706e+00 8.69954387e+00 4.02000000e+00
  3.29210101e+04]
 ...
 [6.61953377e+04 6.50797136e+00 6.61186114e+00 3.14000000e+00
  3.72889236e+04]
 [5.86945150e+04 7.39476811e+00 9.26945262e+00 4.32000000e+00
  4.99609772e+04]
 [6.11625803e+04 5.89631585e+00 7.88052142e+00 6.04000000e+00
  3.60337014e+04]]
```

Phase 4:Development part 2

Splitting the data:

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

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.

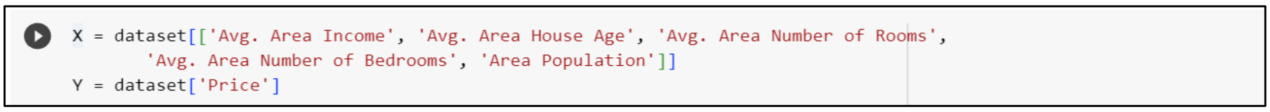
•The idea is that by exposing your model to a sufficient amount of data, it should be able to learn and understand the underlying patterns in the information.

2.Testing Set:

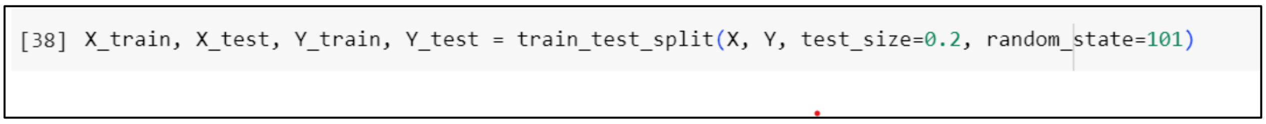
•This set is reserved to evaluate how well your model performs on unseen data.

•Once your model is trained, you use the testing set to see how accurately it can make predictions or classifications.

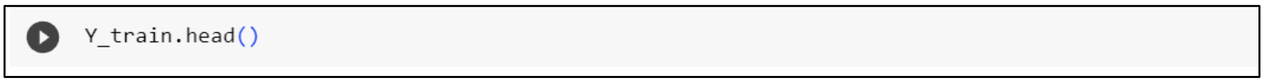
•The testing set serves as a simulation of real-world scenarios where your model encounters new, previously unseen examples.



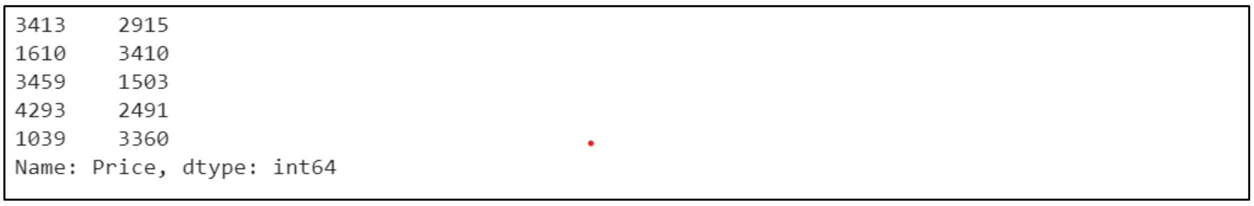
```
X = dataset[['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms',
       'Avg. Area Number of Bedrooms', 'Area Population']]
Y = dataset['Price']
```



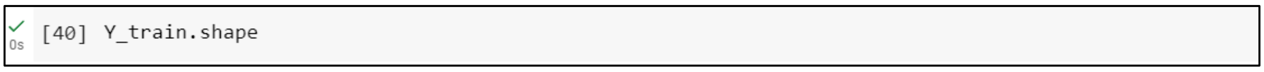
```
[38] X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=101)
```



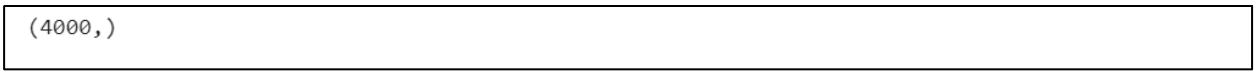
```
Y_train.head()
```



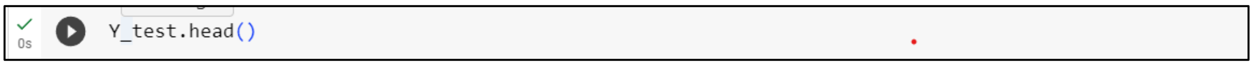
```
3413    2915
1610    3410
3459    1503
4293    2491
1039    3360
Name: Price, dtype: int64
```



```
[40] Y_train.shape
```



```
(4000,)
```



```
Y_test.head()
```

```
1718    2628
2511     786
345     4524
2521    1596
54      1049
Name: Price, dtype: int64
```

```
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).

```
[45] from sklearn.metrics import r2_score, mean_absolute_error,mean_squared_error
     from sklearn.linear_model import LinearRegression
```

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

```
[46] model_lr=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.

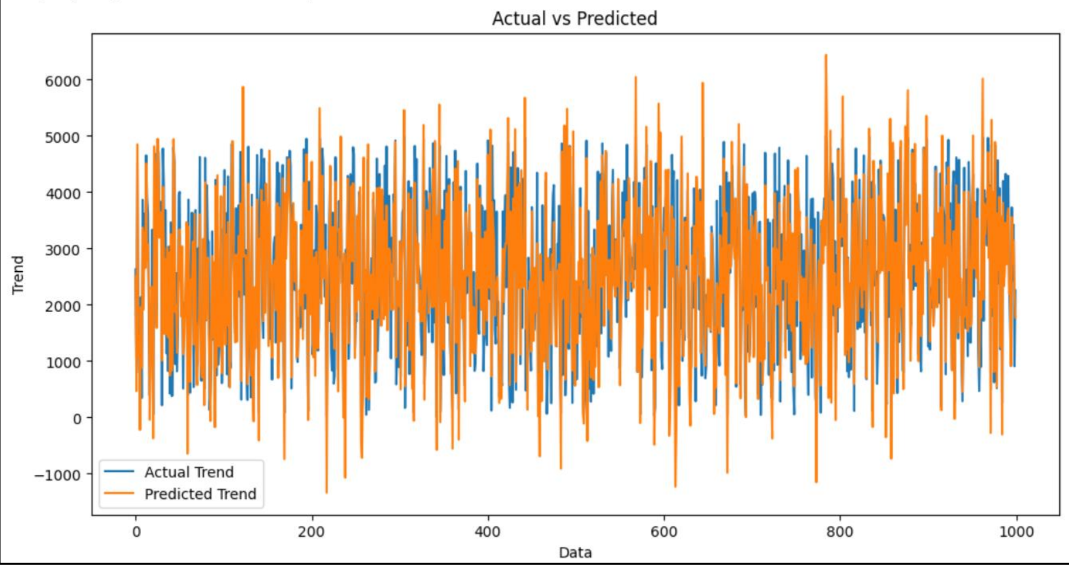
```
model_lr.fit(X_train_scal, Y_train)
```

```
▾ LinearRegression
LinearRegression()
```

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

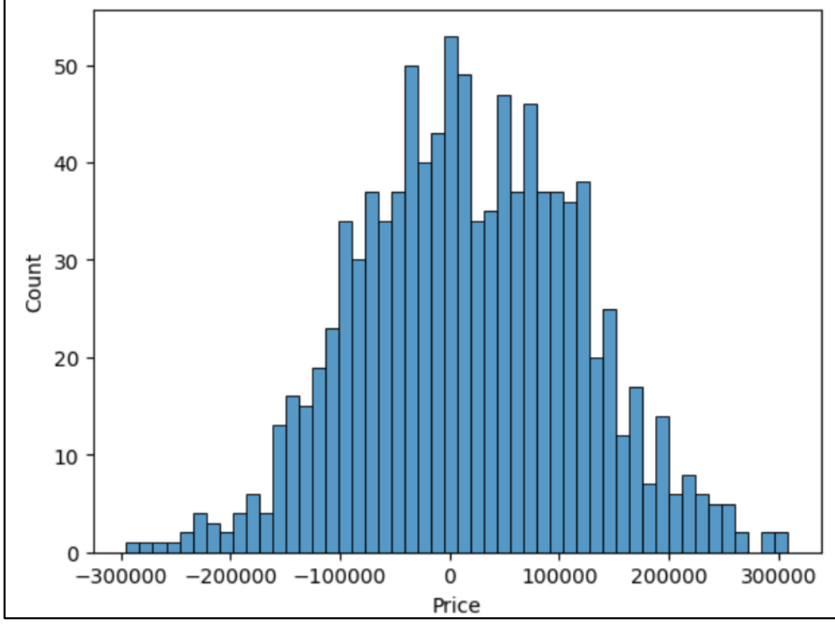
```
[50] plt.figure(figsize=(12,6))
     plt.plot(np.arange(len(Y_test)), Y_test, label='Actual Trend')
     plt.plot(np.arange(len(Y_test)), Prediction1, label='Predicted Trend')
     plt.xlabel('Data')
     plt.ylabel('Trend')
     plt.legend()
     plt.title('Actual vs Predicted')
```

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



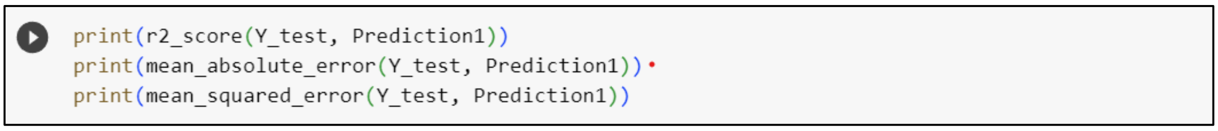
```
sns.histplot((Y_test-Prediction1), bins=50)
```

```
<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.



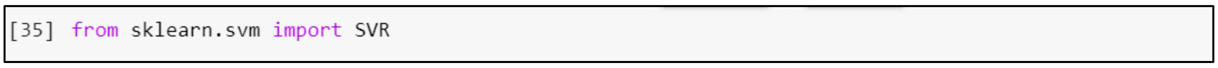
```
print(r2_score(Y_test, Prediction1))
print(mean_absolute_error(Y_test, Prediction1))
print(mean_squared_error(Y_test, Prediction1))
```

```
0.9182928179527469
82295.49777553751
10469084771.329184
```

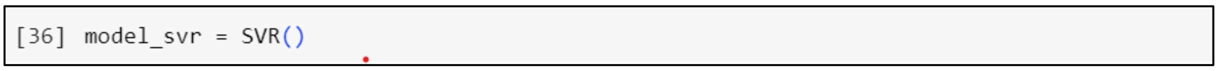
Linear regression is a great starting point for many predictive modeling tasks, and it forms the foundation for more complex models. It's widely used in various fields due to its simplicity and interpretability.

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.

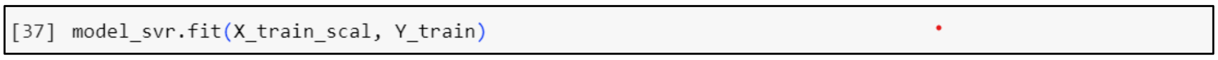


```
[35] from sklearn.svm import SVR
```

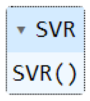


```
[36] model_svr = SVR()
```

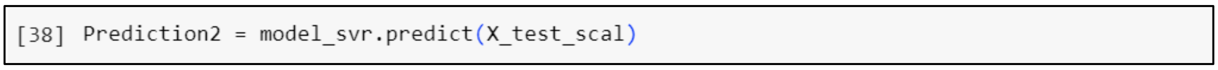
The primary goal of SVR is to find a hyperplane that best represents the trend in the data, while allowing for a margin of error.



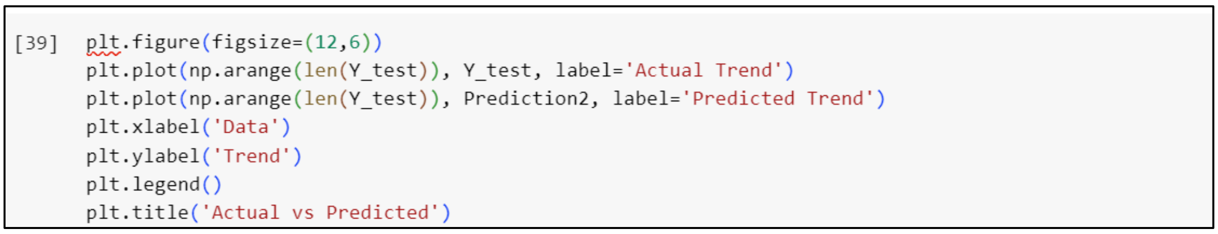
```
[37] model_svr.fit(X_train_scal, Y_train)
```



```
▾ SVR
SVR()
```

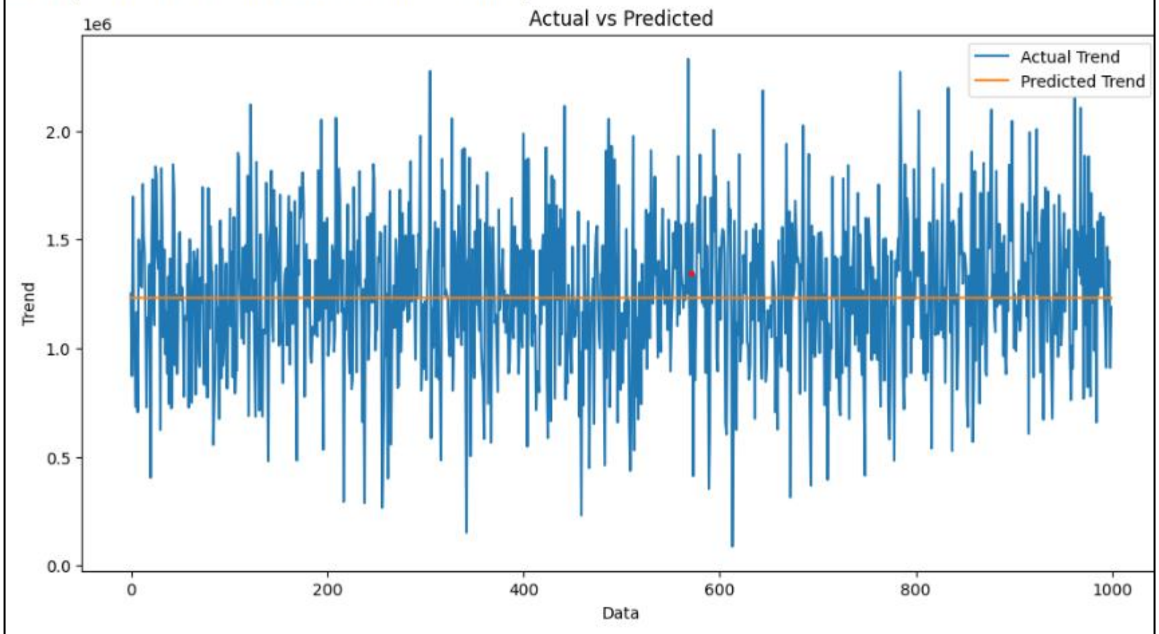


```
[38] Prediction2 = model_svr.predict(X_test_scal)
```



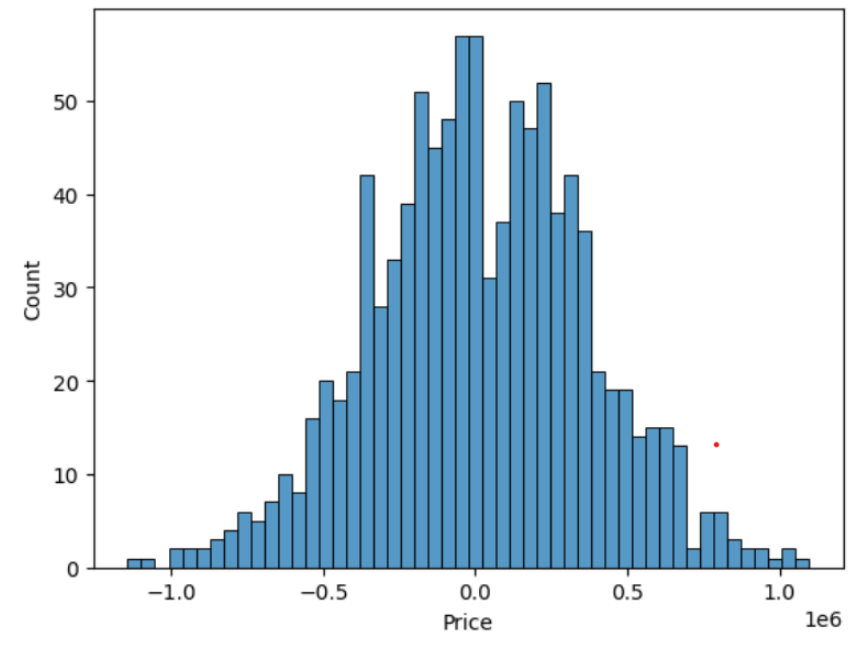
```
[39] plt.figure(figsize=(12,6))
     plt.plot(np.arange(len(Y_test)), Y_test, label='Actual Trend')
     plt.plot(np.arange(len(Y_test)), Prediction2, label='Predicted Trend')
     plt.xlabel('Data')
     plt.ylabel('Trend')
     plt.legend()
     plt.title('Actual vs Predicted')
```

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

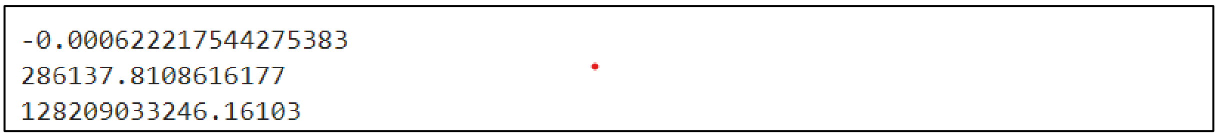


```
sns.histplot((Y_test-Prediction2), bins=50)
```

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



```
[41] print(r2_score(Y_test, Prediction2))
     print(mean_absolute_error(Y_test, Prediction2))
     print(mean_squared_error(Y_test, Prediction2))
```

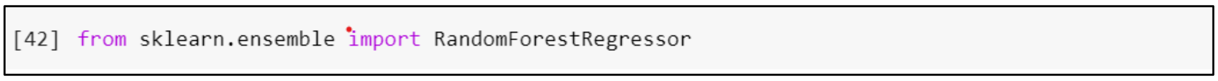


```
-0.000622217544275383
286137.8108616177
128209033246.16103
```

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:

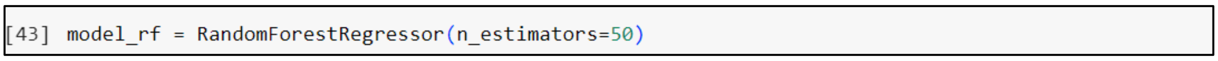
Random Forest Regression is like the wisdom of the crowd applied to predicting numbers. It's an ensemble learning method that combines the predictions of multiple decision trees to improve accuracy and robustness in regression tasks.



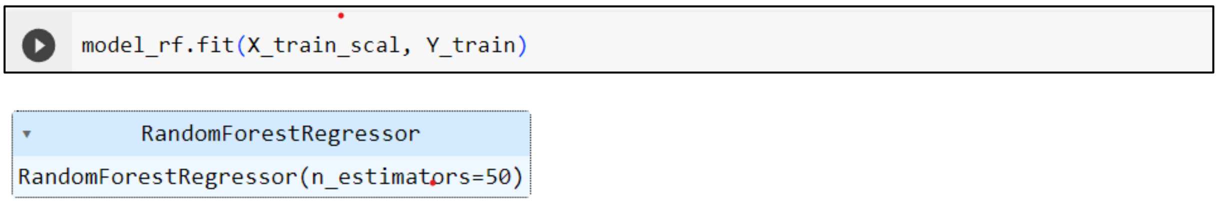
```
[42] from sklearn.ensemble import RandomForestRegressor
```

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.

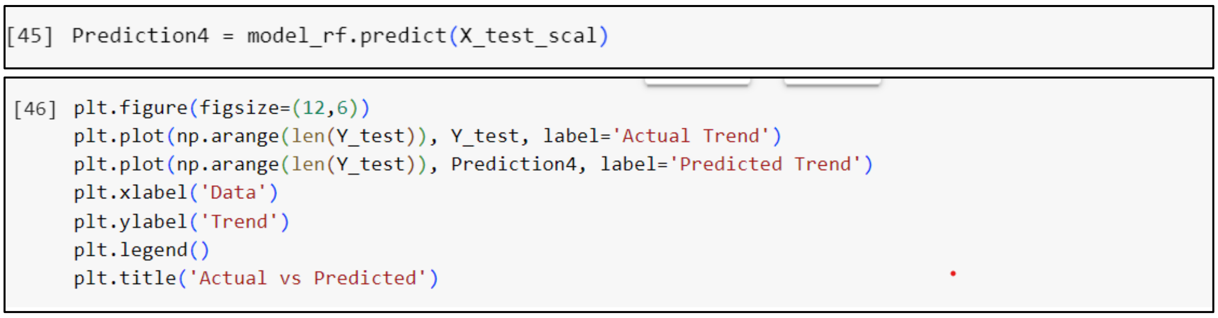


```
[43] model_rf = RandomForestRegressor(n_estimators=50)
```



```
model_rf.fit(X_train_scal, Y_train)
```

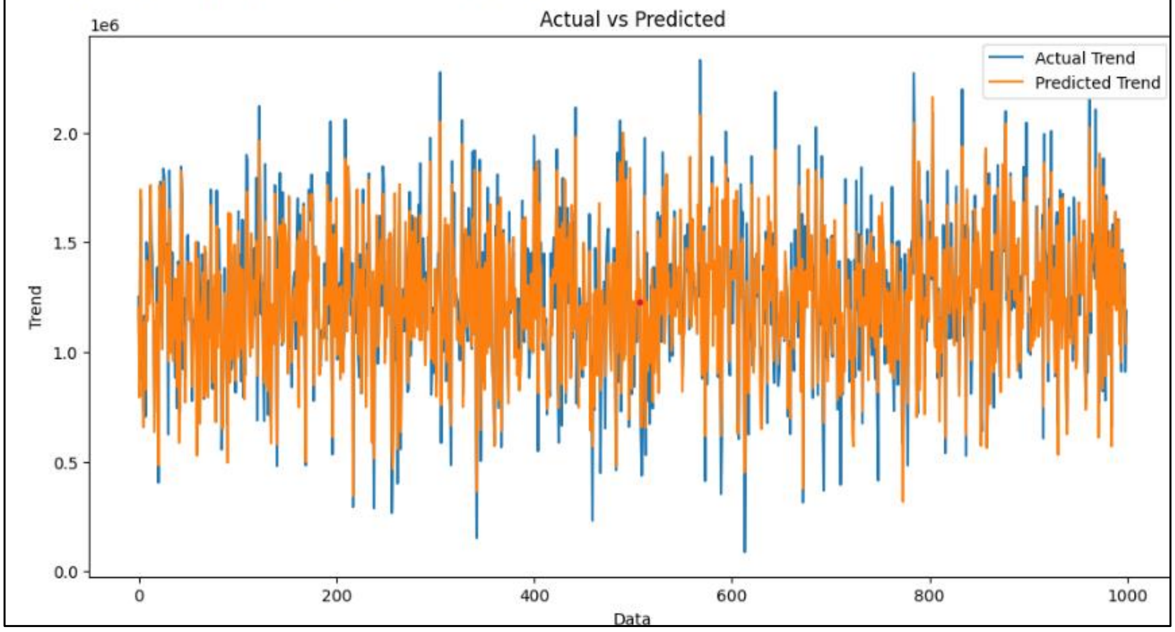
```
▾          RandomForestRegressor
RandomForestRegressor(n_estimators=50)
```



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

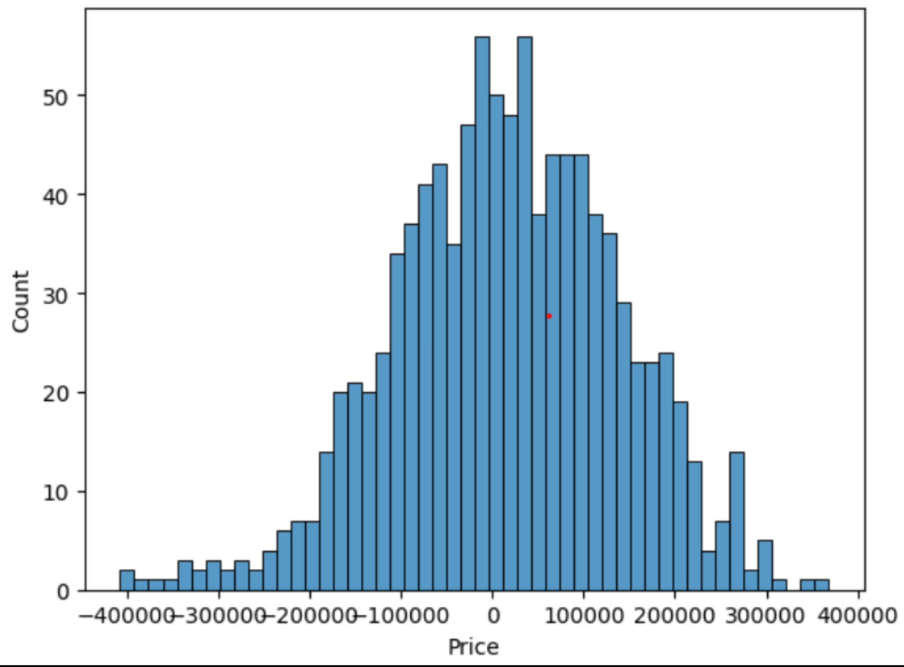
```
[46] plt.figure(figsize=(12,6))
     plt.plot(np.arange(len(Y_test)), Y_test, label='Actual Trend')
     plt.plot(np.arange(len(Y_test)), Prediction4, label='Predicted Trend')
     plt.xlabel('Data')
     plt.ylabel('Trend')
     plt.legend()
     plt.title('Actual vs Predicted')
```

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



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

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



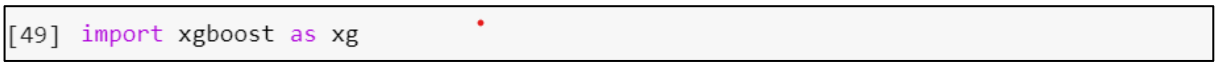
```
[48] print(r2_score(Y_test, Prediction4))
     print(mean_absolute_error(Y_test, Prediction4))
     print(mean_squared_error(Y_test, Prediction4))
```

```
0.8785992367029718
99585.8014007088
15554995906.303984
```

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

XGBoost:

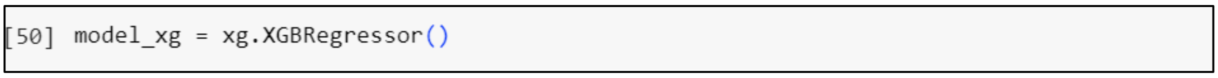
XGBoost is the gradient boosting algorithms—it's powerful, versatile, and can tackle a wide range of machine learning tasks



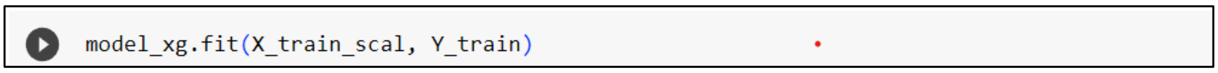
```
[49] import xgboost as xg
```

Objective:

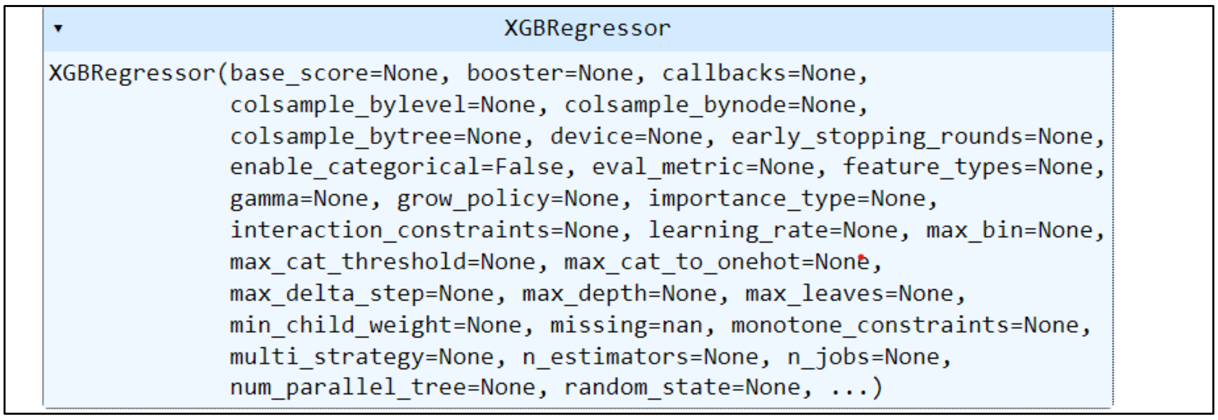
The fundamental objective of gradient boosting is to create a strong predictive model by combining the outputs of multiple weak models (typically decision trees) in an additive manner.



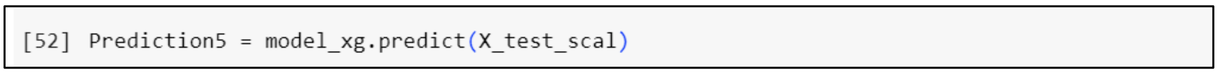
```
[50] model_xg = xg.XGBRegressor()
```



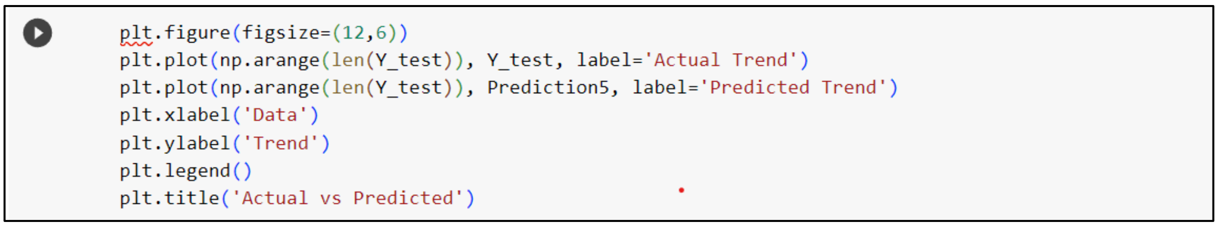
```
model_xg.fit(X_train_scal, Y_train)
```



```
▾                        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, ...)
```

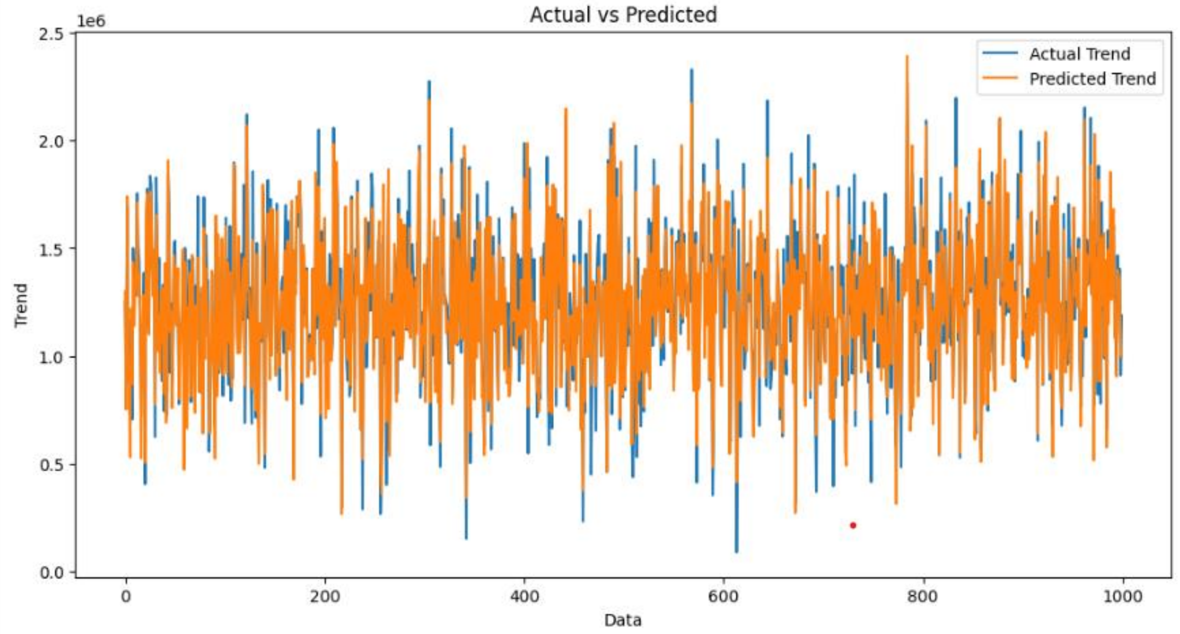


```
[52] Prediction5 = model_xg.predict(X_test_scal)
```



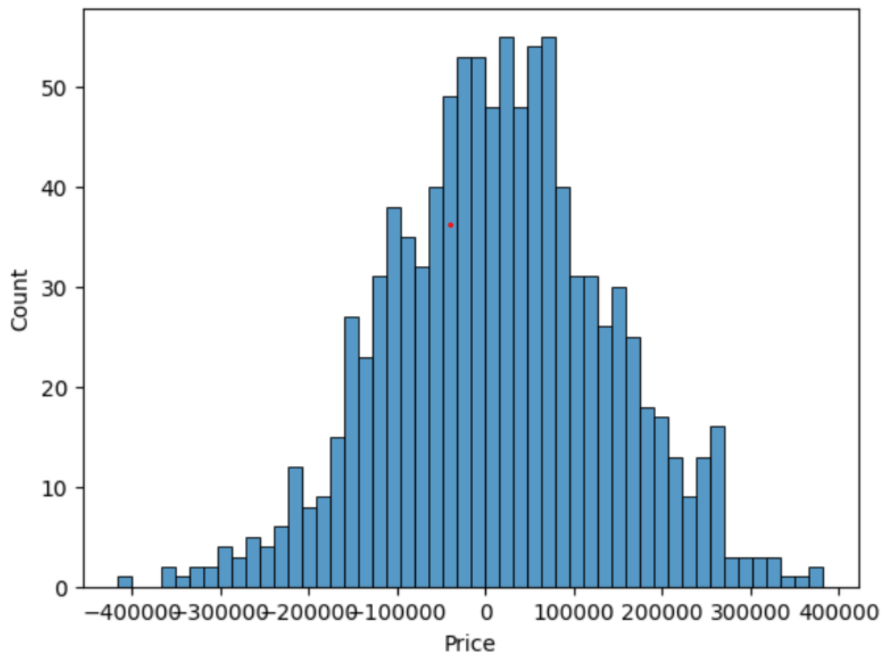
```
plt.figure(figsize=(12,6))
plt.plot(np.arange(len(Y_test)), Y_test, label='Actual Trend')
plt.plot(np.arange(len(Y_test)), Prediction5, label='Predicted Trend')
plt.xlabel('Data')
plt.ylabel('Trend')
plt.legend()
plt.title('Actual vs Predicted')
```

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

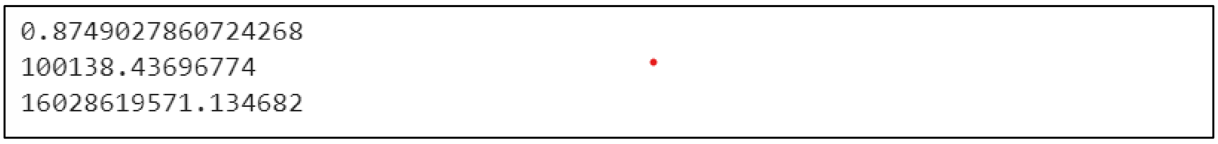


```
54] sns.histplot((Y_test-Prediction5), bins=50)
```

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



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



```
0.8749027860724268
100138.43696774
16028619571.134682
```

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.

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

Including an attribute to check accuracy:

Here,we included the Address attribute while training and testing the dataset to check the accuracy.

```
print(r2_score(y_test,y_pred))

0.8571890180399251
```

While the address attribute is get included we get lesser accuracy when compared when it is not get included.Thus while excluding the address attribute we get more accuracy.

CONCLUSION:

Here, we performed prediction analysis of housing dataset by importing the necessary libraries, loading the dataset, cleaning the dataset, preprocessing the dataset, training the model, evaluating the model and predicted the value of accuracy using Linear regression algorithm.