PHASE 2: INNOVATION OF PREDICTING THE HOUSE PRICES USING MACHINE LEARNING

INTRODUCTION:

- Predicting house prices using machine learning involves using algorithms and data to estimate the market value of a property based on its features, such as location, size, and amenities.

- Key steps include data preprocessing, feature engineering, model selection, and rigorous evaluation using metrics like Mean Absolute Error (MAE) or Mean Squared Error (MSE).

- Ensuring model interpretability and addressing ethical considerations, such as bias, are essential. Deployment in a user-friendly interface and continuous monitoring for updates and market trends are crucial for maintaining accuracy in real-world applications.

House Price Prediction

Importing Dependencies

INPUT:

```
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.linear_model import Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
import xgboost as xg

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

```
/opt/conda/lib/python3.10/site-packages/scipy/__init__.py:146: UserWarning
: A NumPy version >=1.16.5 and <1.23.0 is required for this version of Sci
Py (detected version 1.23.5
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

Loading Dataset

INPUT :

```
dataset = pd.read_csv('/kaggle/input/usa-housing/USA_Housing.csv')
```

Data Exploration

Dataset

OUTPUT:

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
0	79545.458574	5.682861	7.009188	4.09	23086.800503	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1	79248.642455	6.002900	6.730821	3.09	40173.072174	1.505891e+06	188 Johnson Views Suite 079\nLake Kathleen, CA...
2	61287.067179	5.865890	8.512727	5.13	36882.159400	1.058988e+06	9127 Elizabeth Stravenue\nDanieltown, WI 06482...
3	63345.240046	7.188236	5.586729	3.26	34310.242831	1.260617e+06	USS Barnett\nFPO AP 44820
4	59982.197226	5.040555	7.839388	4.23	26354.109472	6.309435e+05	USNS Raymond\nFPO AE 09386
...	...	...	...	...	...	...	...
4995	60567.944140	7.830362	6.137356	3.46	22837.361035	1.060194e+06	USNS Williams\nFPO AP 30153-7653
4996	78491.275435	6.999135	6.576763	4.02	25616.115489	1.482618e+06	PSC 9258, Box 8489\nAPO AA 42991-3352

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
4997	63390.686886	7.250591	4.805081	2.13	33266.145490	1.030730e+06	4215 Tracy Garden Suite 076\nJoshualand, VA 01...
4998	68001.331235	5.534388	7.130144	5.44	42625.620156	1.198657e+06	USS Wallace\nFPO AE 73316
4999	65510.581804	5.992305	6.792336	4.07	46501.283803	1.298950e+06	37778 George Ridges Apt. 509\nEast Holly, NV 2...

5000 rows × 7 columns

INPUT:

```
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
```

INPUT :

```
dataset.describe()
```

OUTPUT:

	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%	61480.562388	5.322283	6.299250	3.140000	29403.928702	9.975771e+05
50%	68804.286404	5.970429	7.002902	4.050000	36199.406689	1.232669e+06
75%	75783.338666	6.650808	7.665871	4.490000	42861.290769	1.471210e+06
max	107701.748378	9.519088	10.759588	6.500000	69621.713378	2.469066e+06

INPUT :

```
dataset.columns
```

OUTPUT :

```
Index(['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Roo
ms',
       'Avg. Area Number of Bedrooms', 'Area Population', 'Price', 'Addres
s'],
      dtype='object')
```

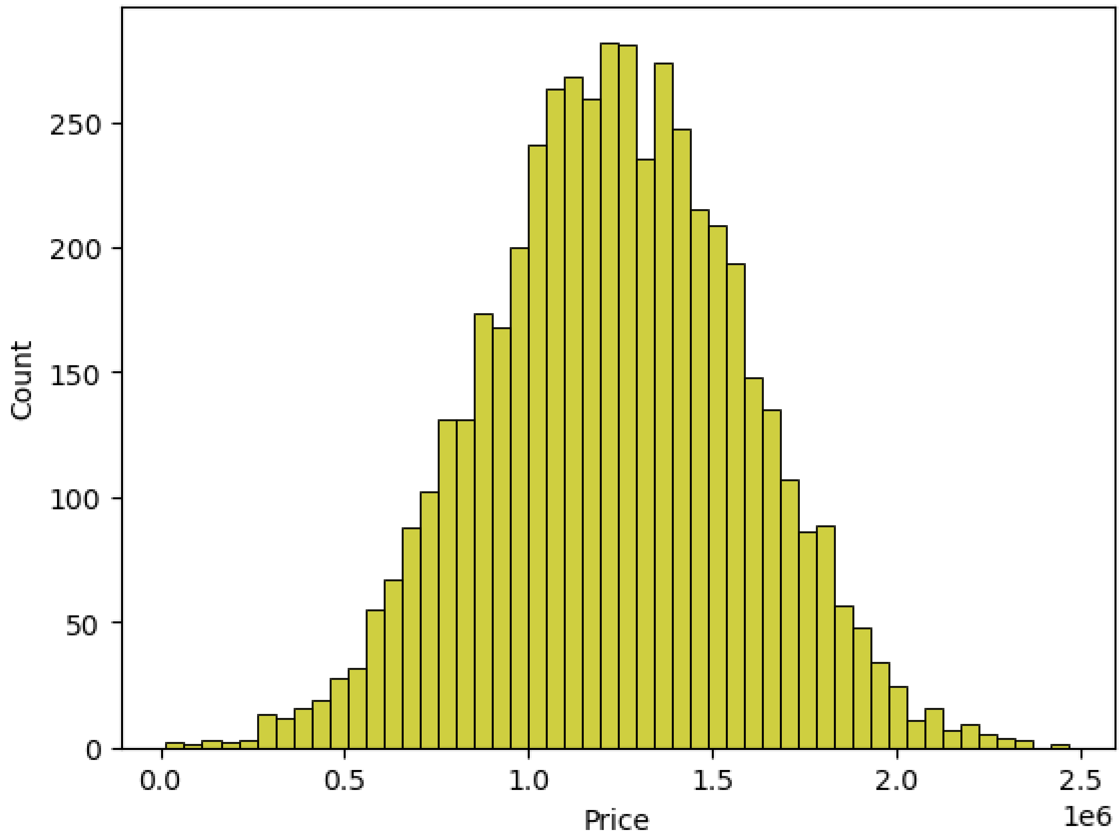
Visualisation and Pre-Processing of Data

INPUT :

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

OUTPUT :

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

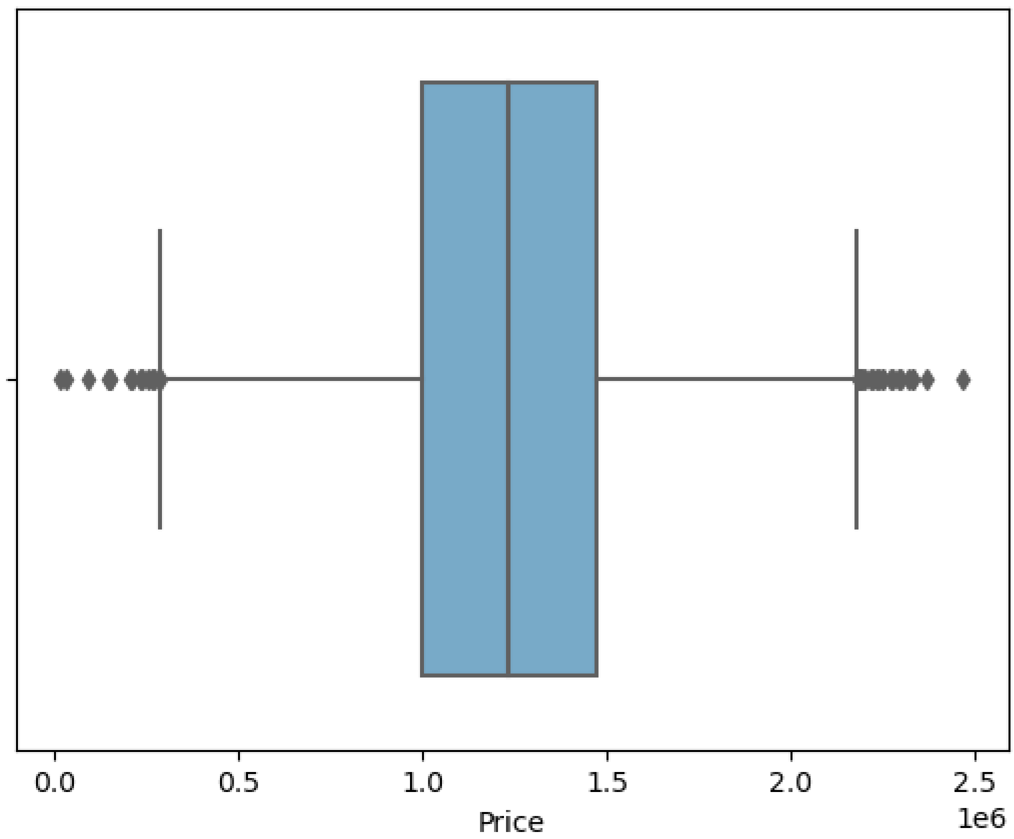


INPUT :

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

OUTPUT :

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

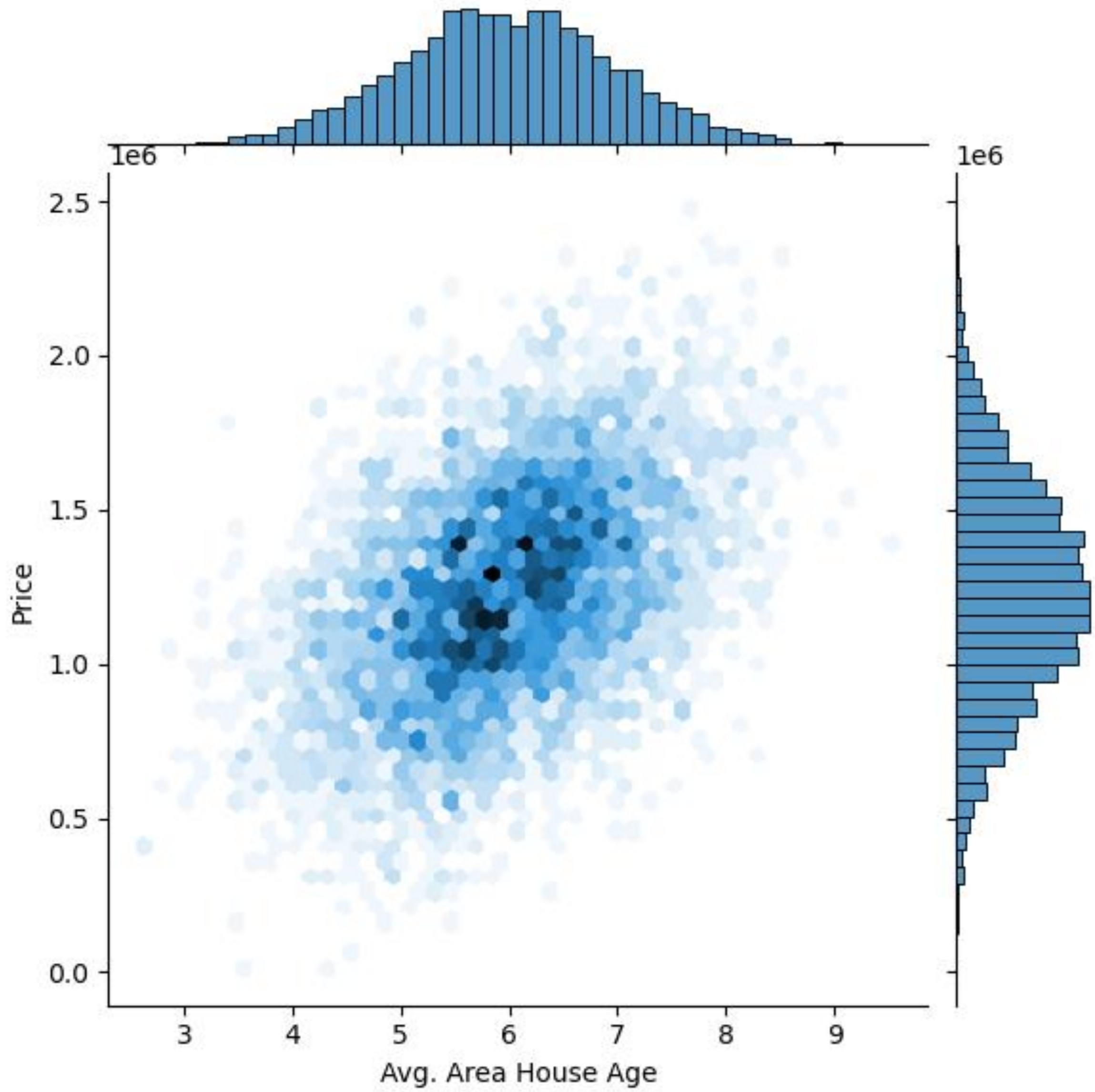


INPUT :

```
sns.jointplot(dataset, x='Avg. Area House Age', y='Price', kind='hex')
```

OUTPUT :

```
<seaborn.axisgrid.JointGrid at 0x7dbe246100a0>
```

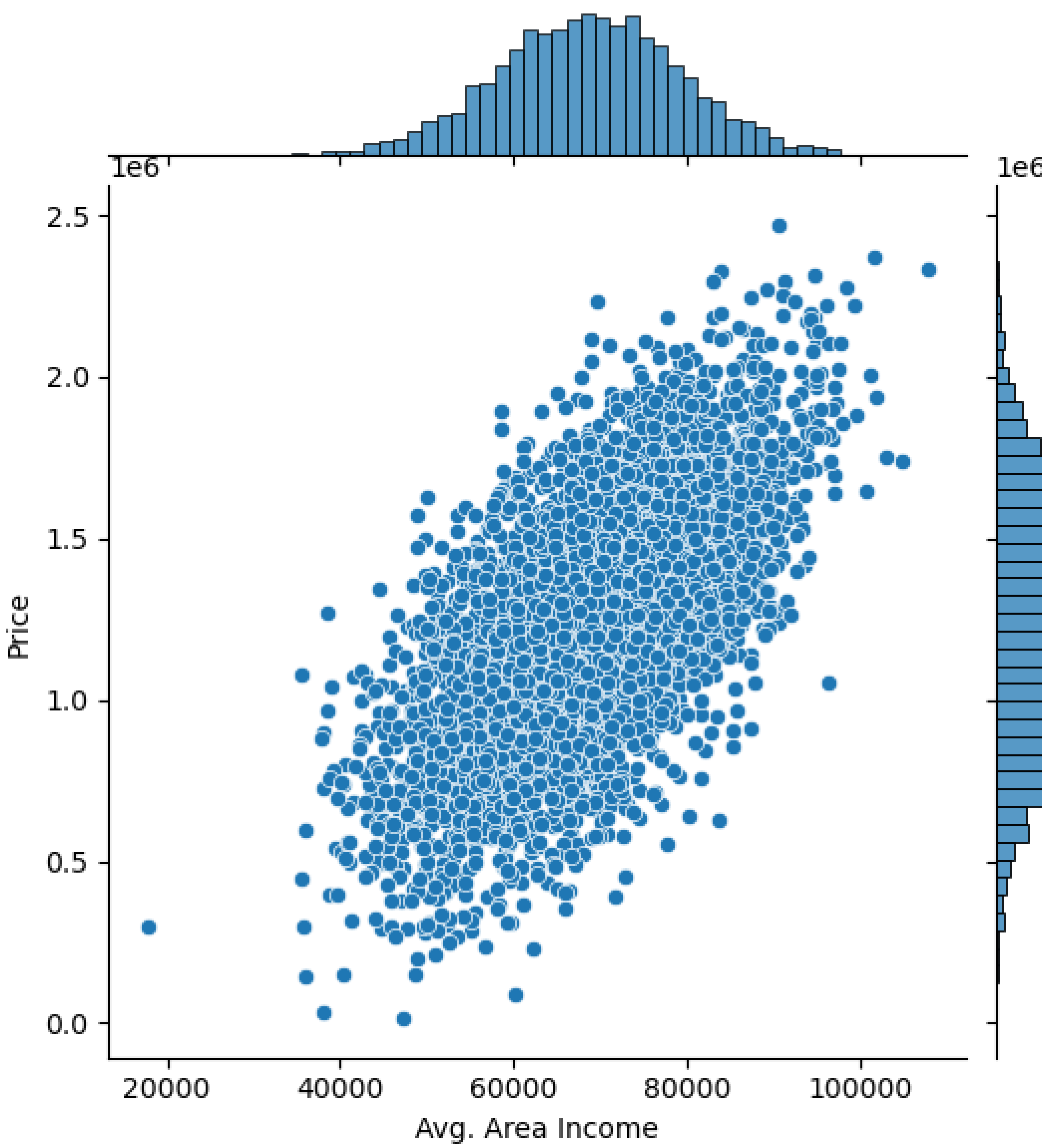


INPUT :

```
sns.jointplot(dataset, x='Avg. Area Income', y='Price')
```

OUTPUT:

<seaborn.axisgrid.JointGrid at 0x7dbe1333c250>

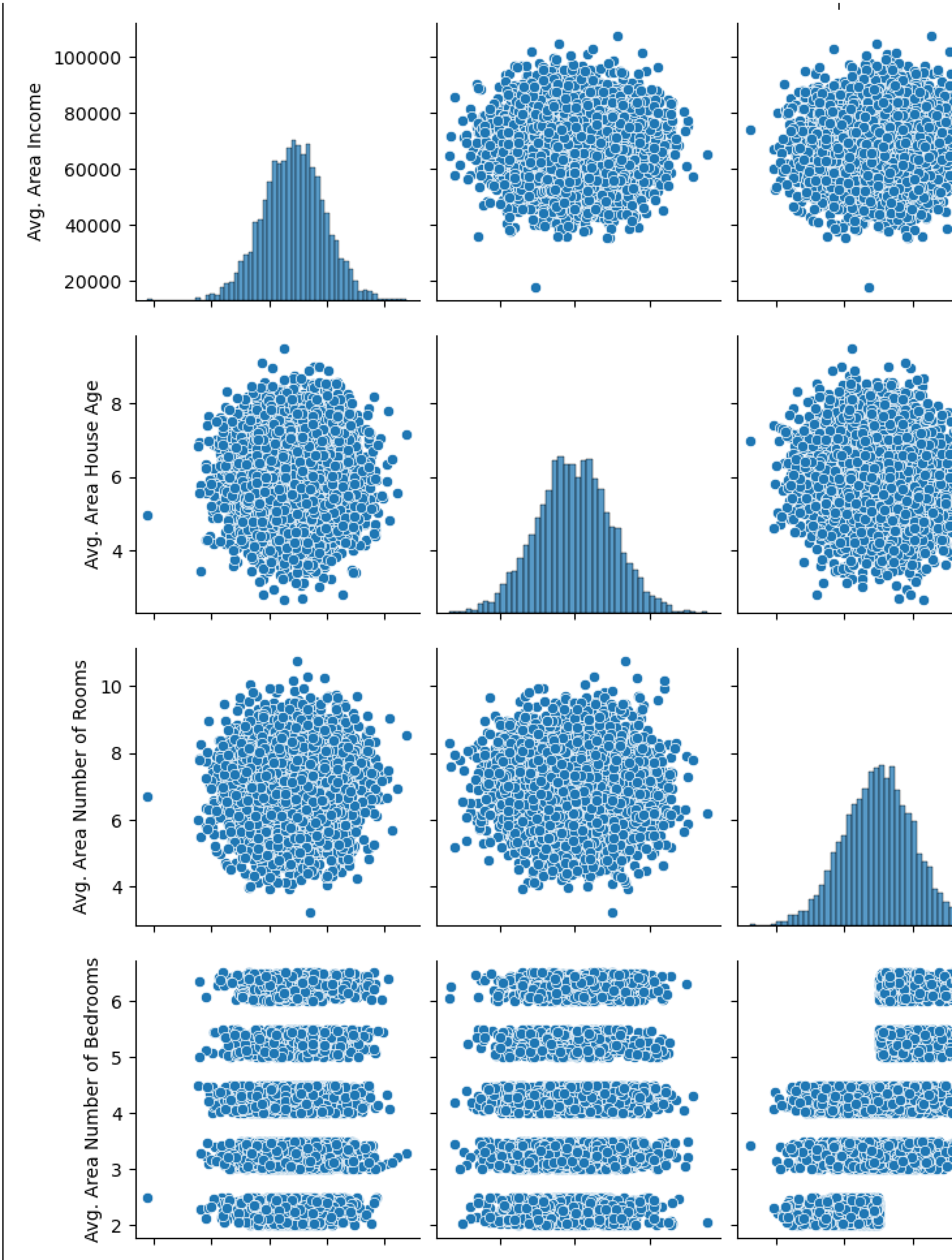


INPUT :

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

OUTPUT :

```
<seaborn.axisgrid.PairGrid at 0x7dbe1333c340>
<Figure size 1200x800 with 0 Axes>
```

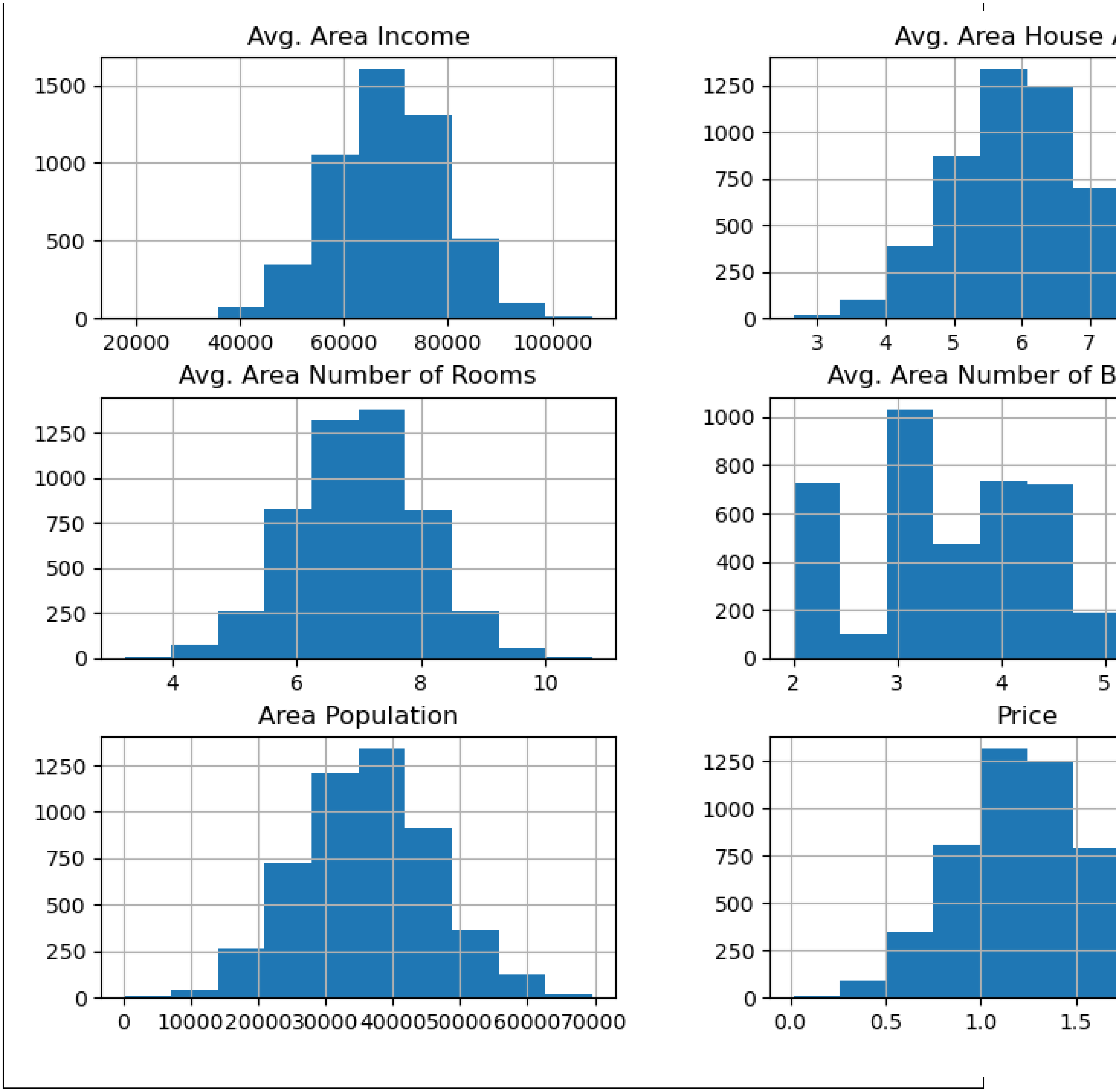

Avg. Area Income
100000
80000
60000
40000
20000
Avg. Area House Age
8
6
4
Avg. Area Number of Rooms
10
8
6
4
Avg. Area Number of Bedrooms
6
5
4
3
2

INPUT :

```
dataset.hist(figsize=(10,8)
```

OUTPUT :

```
array([[<Axes: title={'center': 'Avg. Area Income'}>,
        <Axes: title={'center': 'Avg. Area House Age'}>],
       [<Axes: title={'center': 'Avg. Area Number of Rooms'}>,
        <Axes: title={'center': 'Avg. Area Number of Bedrooms'}>],
       [<Axes: title={'center': 'Area Population'}>,
        <Axes: title={'center': 'Price'}>]], dtype=object)
```



Visualising Correlation

INPUT :

```
dataset.corr(numeric_only=True)
```

OUTPUT :

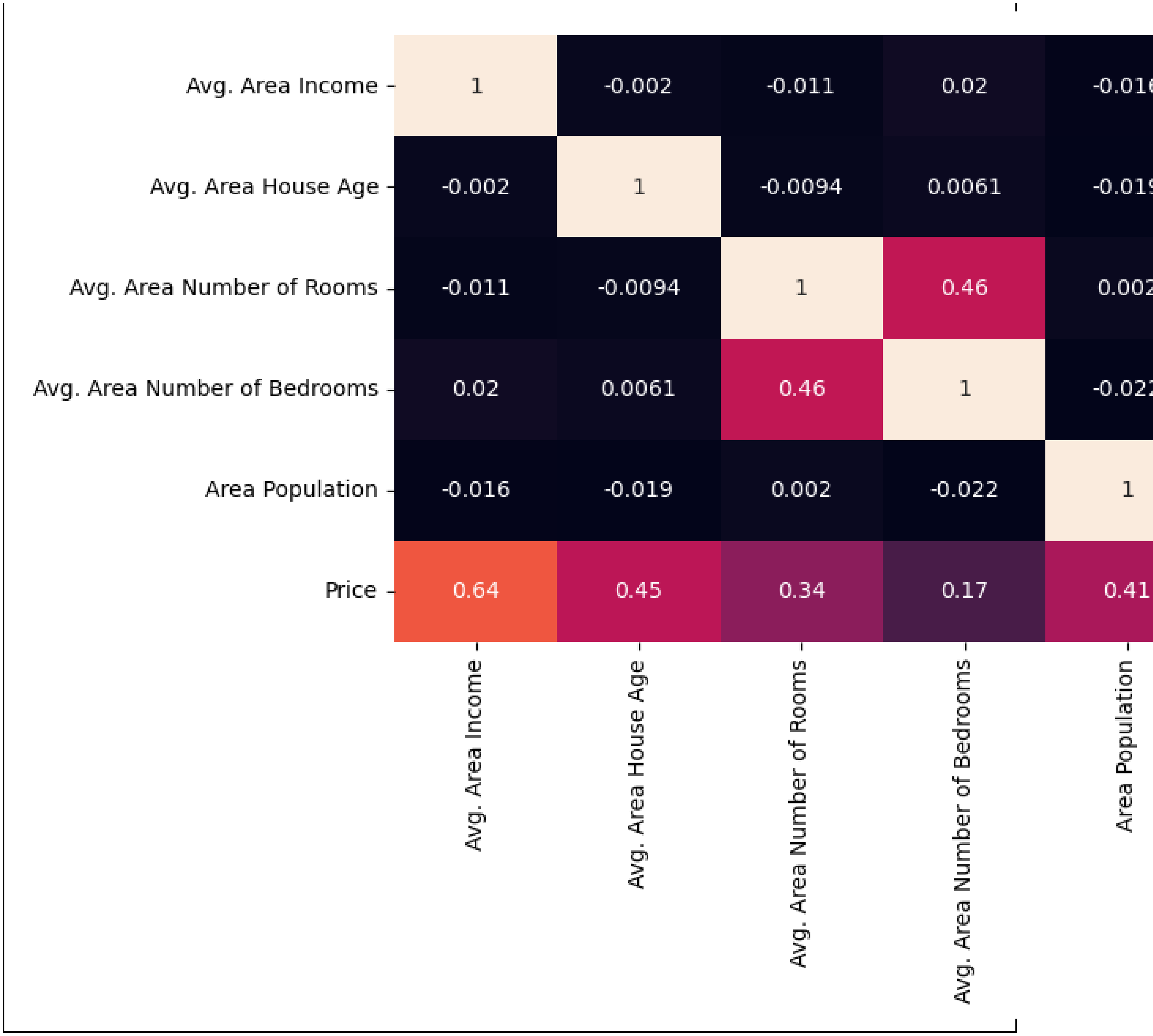
	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price
Avg. Area Income	1.000000	-0.002007	-0.011032	0.019788	-0.016234	0.639734
Avg. Area House Age	-0.002007	1.000000	-0.009428	0.006149	-0.018743	0.452543
Avg. Area Number of Rooms	-0.011032	-0.009428	1.000000	0.462695	0.002040	0.335664
Avg. Area Number of Bedrooms	0.019788	0.006149	0.462695	1.000000	-0.022168	0.171071
Area Population	-0.016234	-0.018743	0.002040	-0.022168	1.000000	0.408556
Price	0.639734	0.452543	0.335664	0.171071	0.408556	1.000000

INPUT :

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

OUTPUT :

```
<Axes: >
```



Dividing Dataset in to features and target variable

INPUT :

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

Using Train Test Split

INPUT :

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

INPUT :

```
Y_train.head()
```

OUTPUT :

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

INPUT :

```
Y_train.shape
```

OUTPUT :

```
(4000,)
```

INPUT :

```
Y_test.head()
```

OUTPUT :

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

INPUT :

```
Y_test.shape
```

OUTPUT :

```
(1000,)
```

Standardizing the data

INPUT :

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

Model Building and Evaluation

Model 1 - Linear Regression

INPUT :

```
model_lr=LinearRegression()
```

INPUT :

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

OUTPUT :

```
LinearRegression

LinearRegression()
```

Predicting Prices

INPUT :

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

Evaluation of Predicted Data

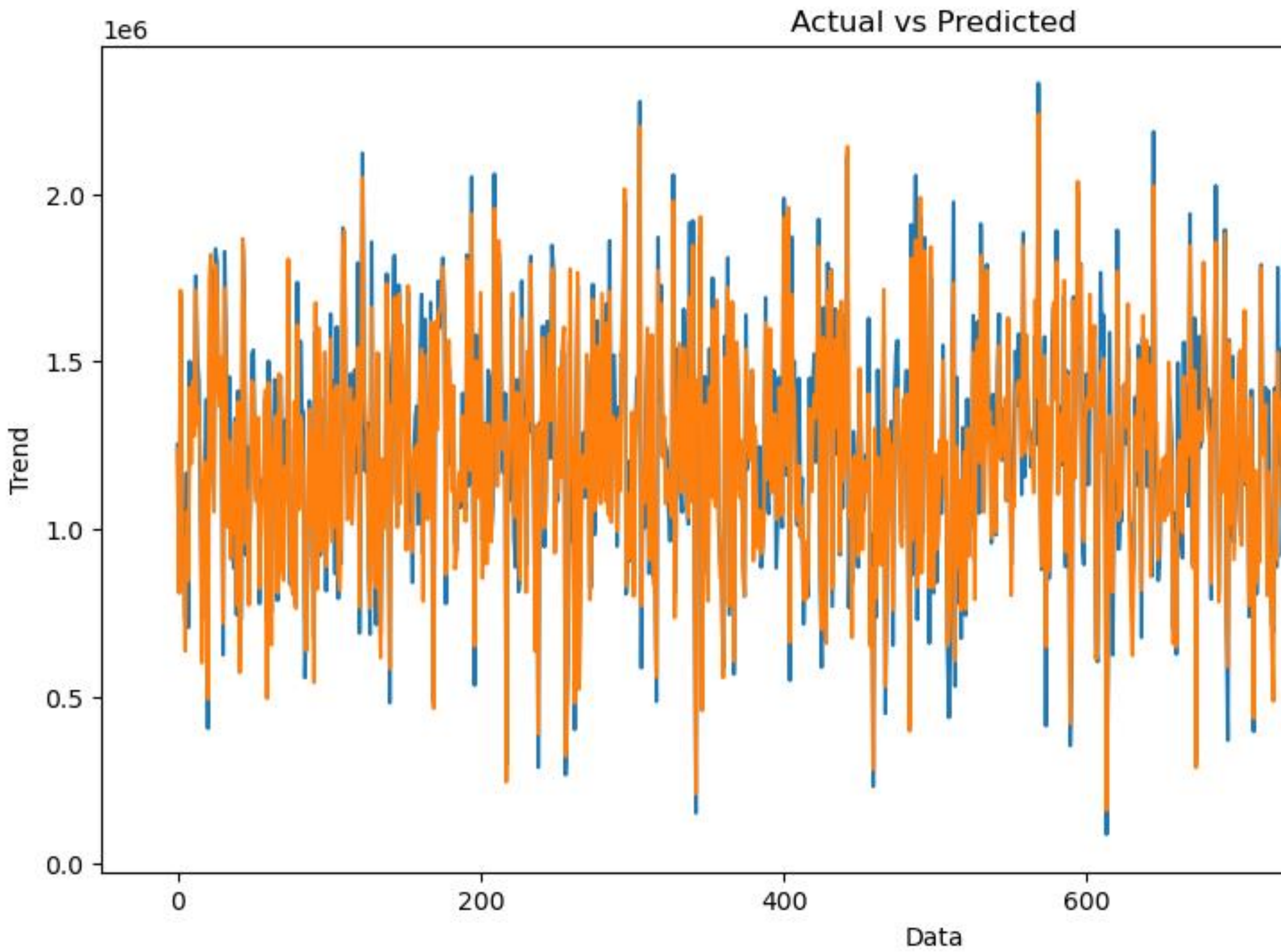
INPUT :

```
    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')
```

OUTPUT :

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

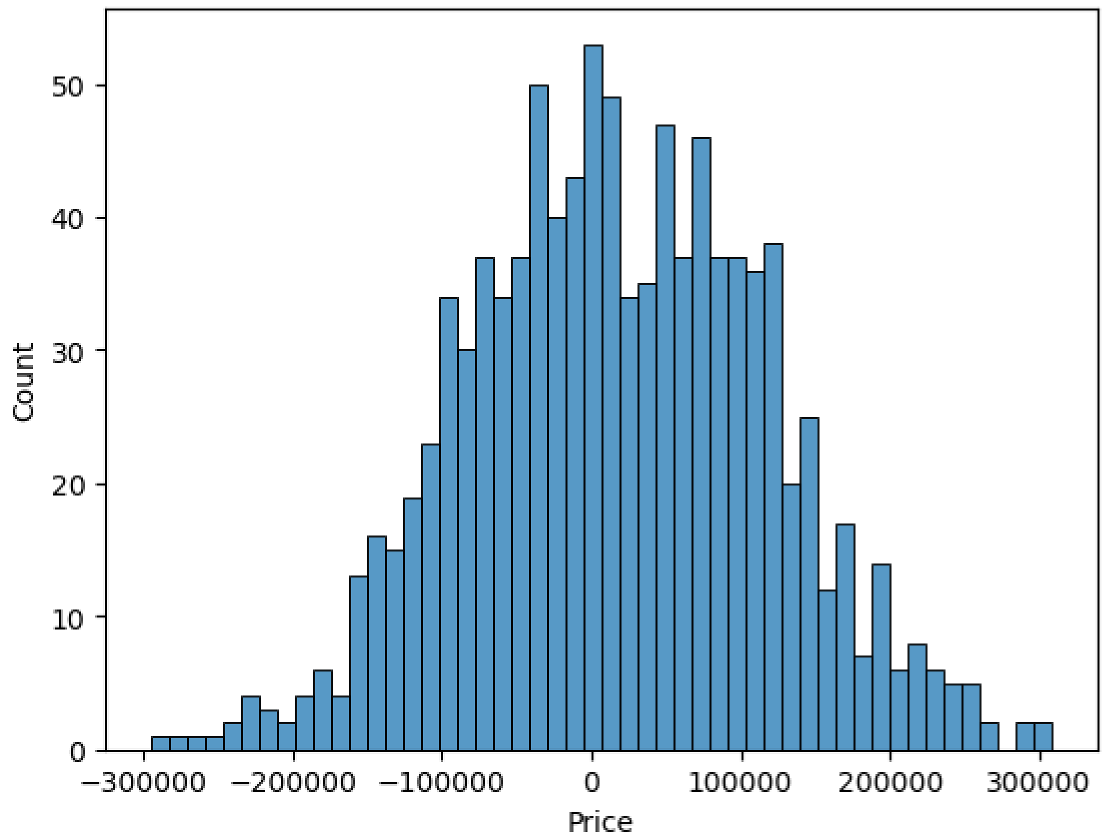


INPUT :

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

OUTPUT :

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



INPUT :

```
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
```

Model 2 - Support Vector Regressor

INPUT :

```
model_svr = SVR()
```

INPUT :

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

OUTPUT :

```
SVR

SVR()
```

Predicting Prices

INPUT :

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

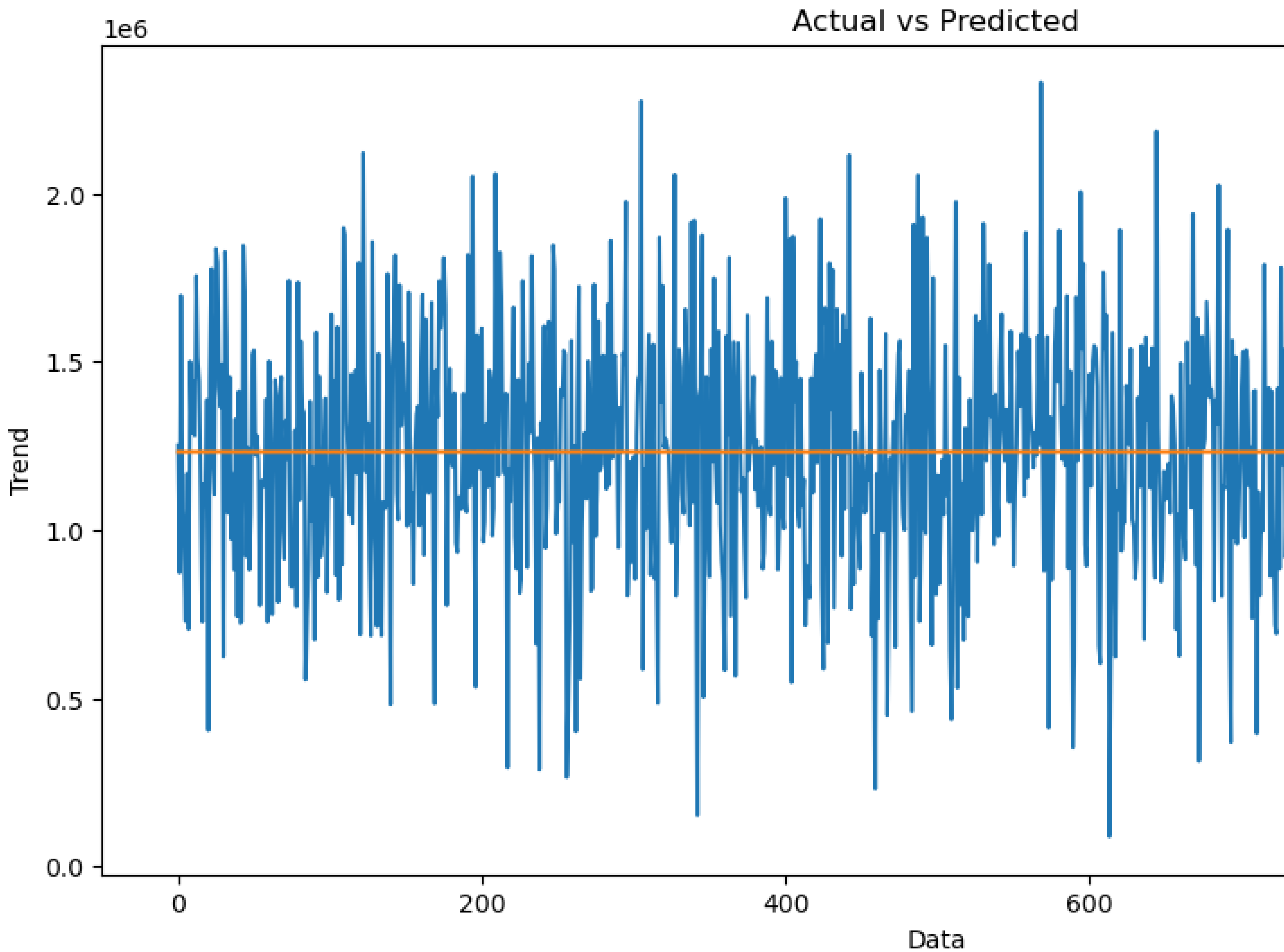
Evaluation of Predicted Data

INPUT :

```
    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')
```

OUTPUT :

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

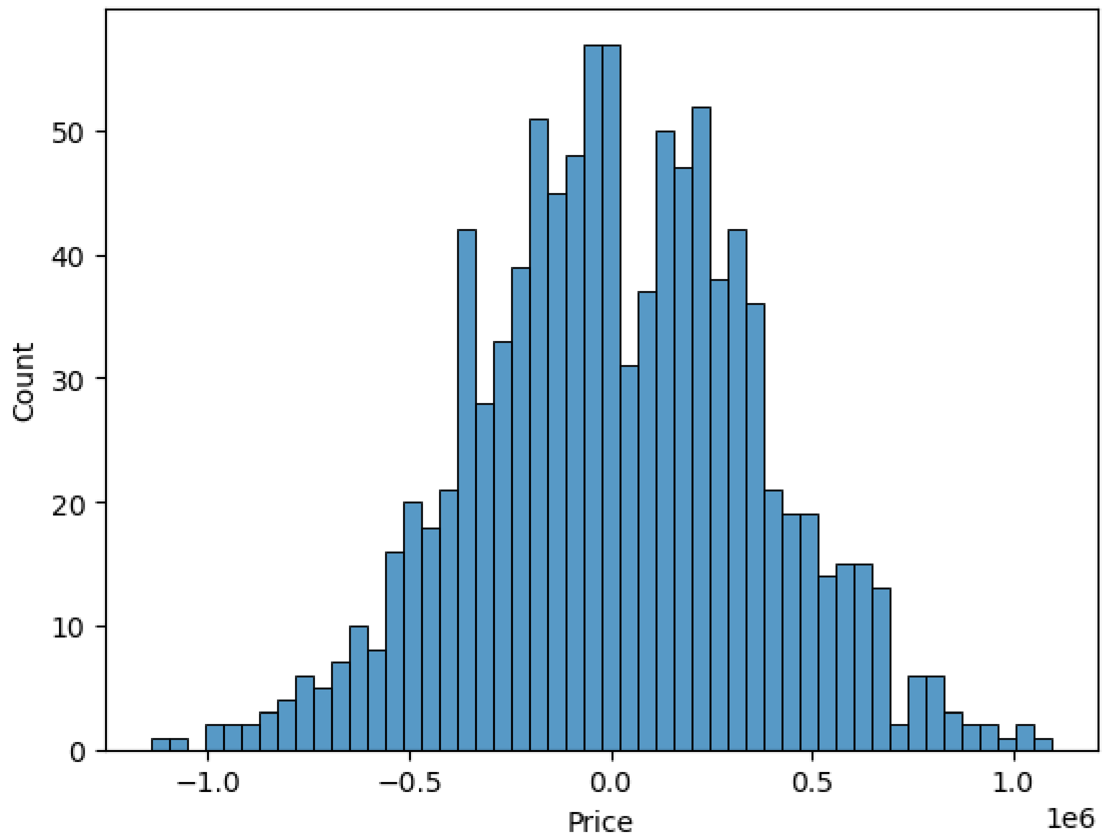


INPUT :

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

OUTPUT :

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



INPUT :

```
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
```

Model 3 - Lasso Regression

INPUT :

```
model_lar = Lasso(alpha=1)
```

INPUT :

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

OUTPUT :

```
Lasso

Lasso(alpha=1)
```

Predicting Prices

INPUT :

```
Prediction3 = model_lar.predict(X_test_scal)
```

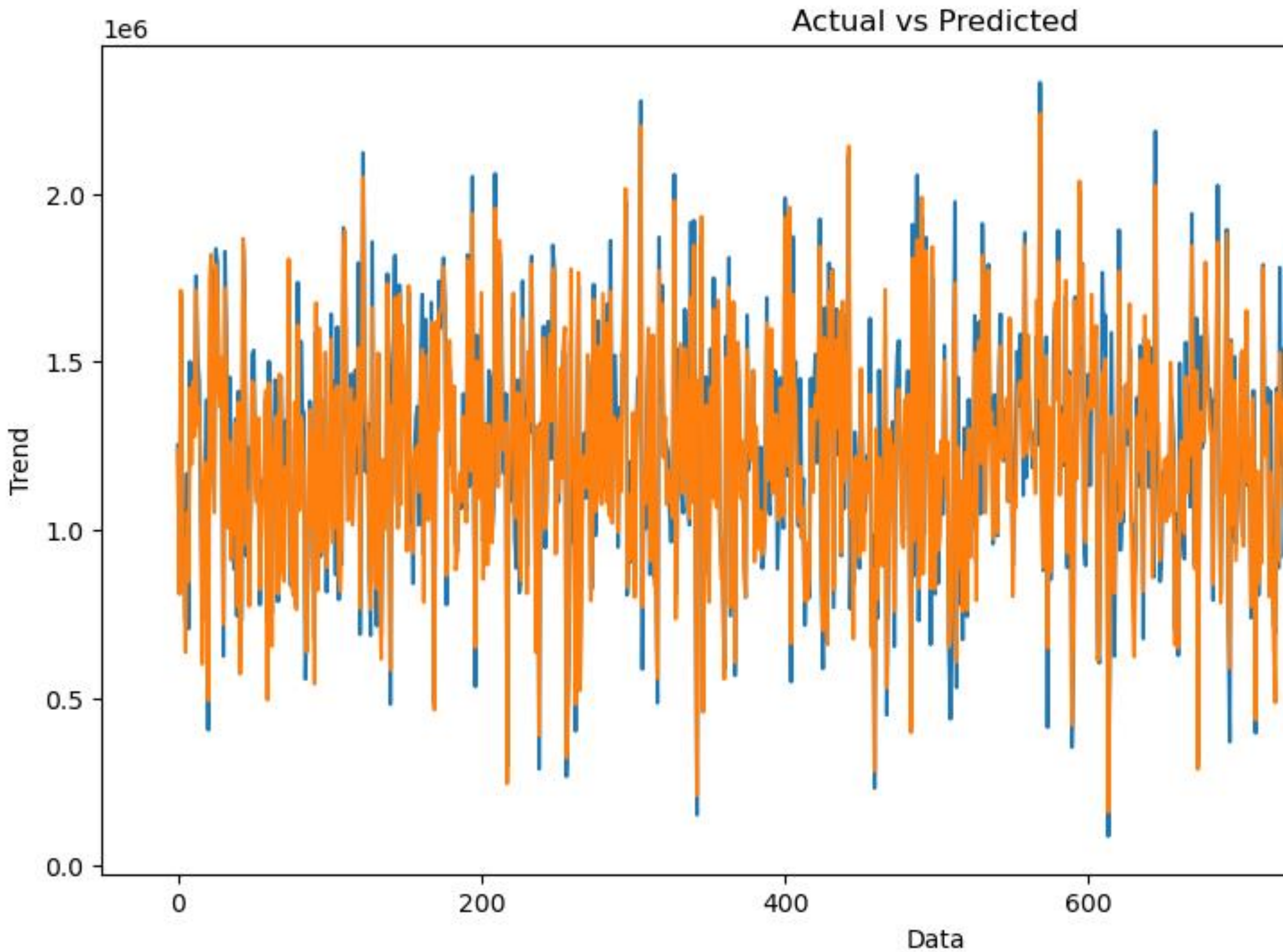
Evaluation of Predicted Data

INPUT :

```
    plt.figure(figsize=(12,6))
    plt.plot(np.arange(len(Y_test)), Y_test, label='Actual Trend')
    plt.plot(np.arange(len(Y_test)), Prediction3, label='Predicted Trend')
    plt.xlabel('Data')
    plt.ylabel('Trend')
    plt.legend()
    plt.title('Actual vs Predicted')
```

OUTPUT :

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

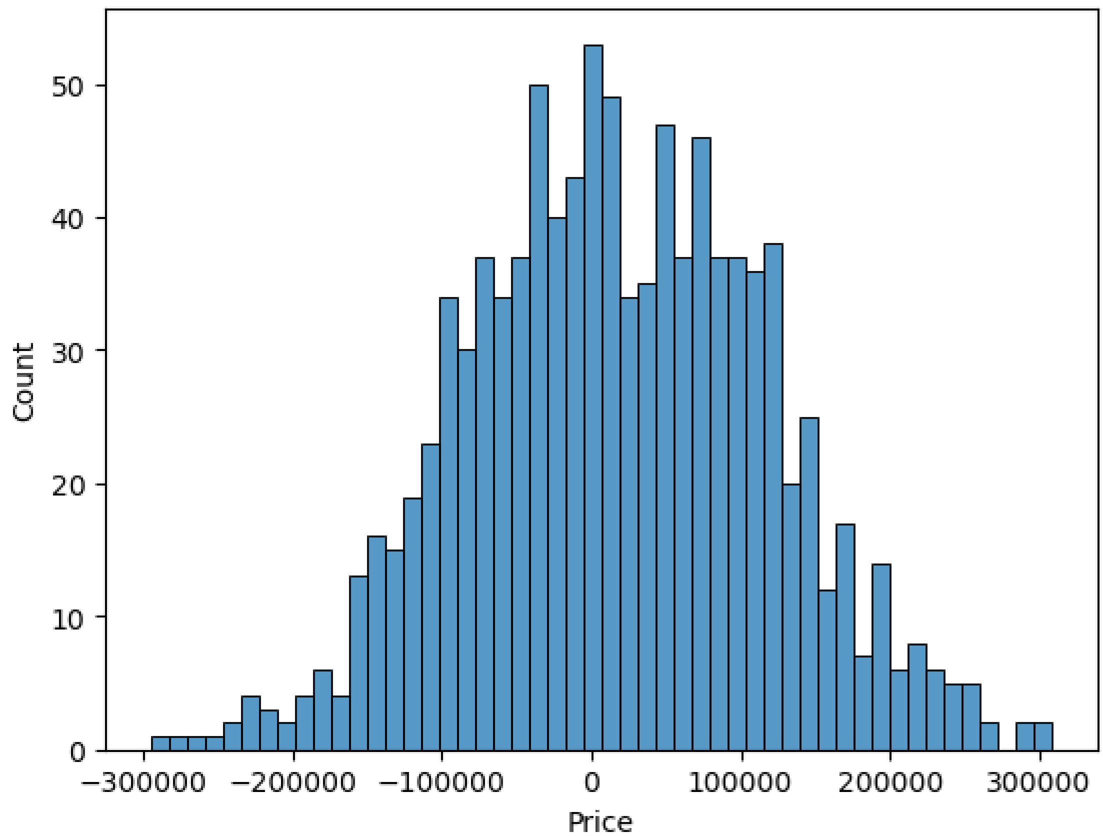


INPUT :

```
sns.histplot((Y_test-Prediction3), bins=50)
```

OUTPUT :

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



INPUT :

```
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
```

Model 4 - Random Forest Regressor

INPUT :

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

INPUT :

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

OUTPUT :

```
RandomForestRegressor

RandomForestRegressor(n_estimators=50)
```

Predicting Prices

INPUT :

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

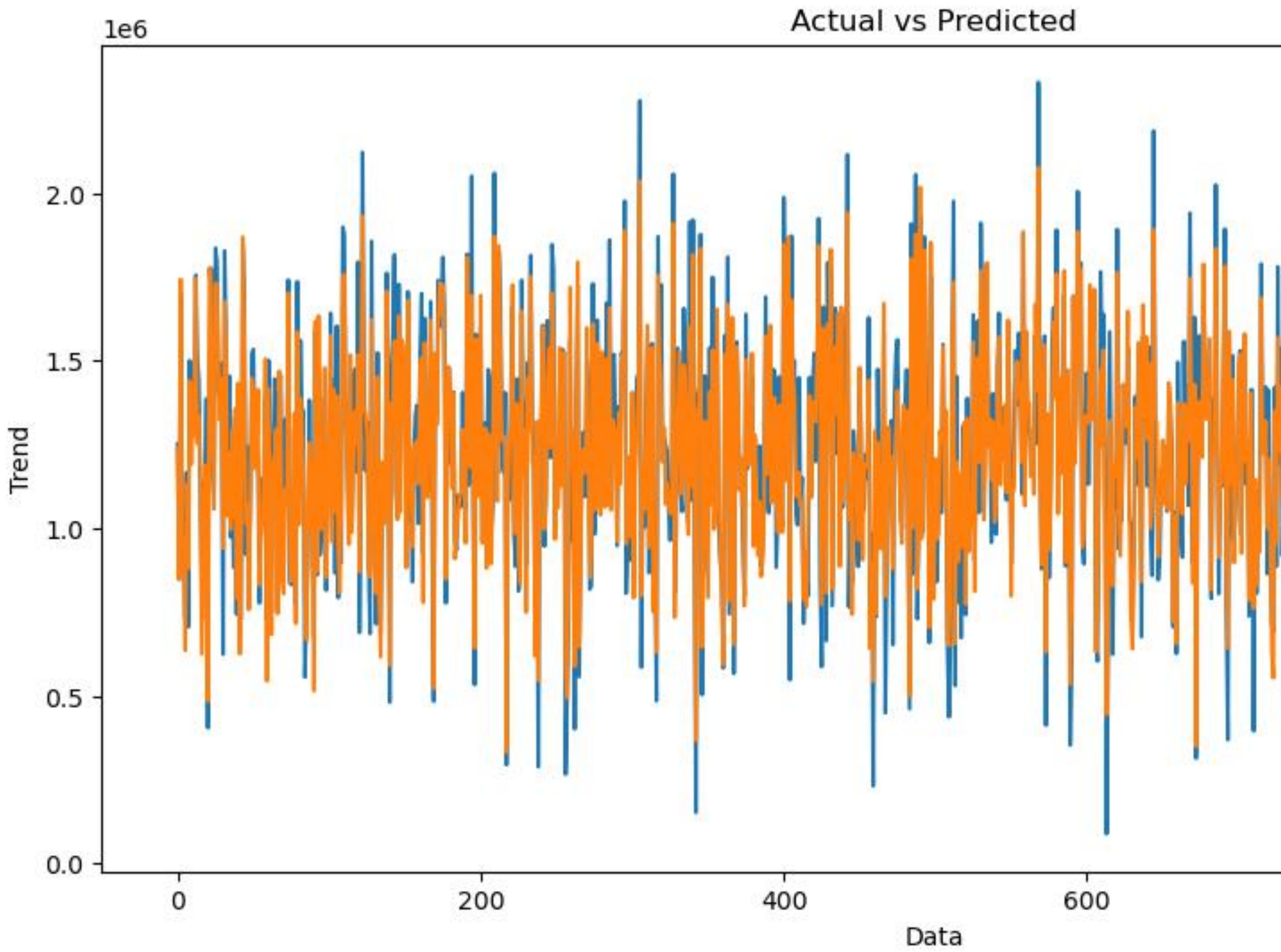
Evaluation of Predicted Data

INPUT :

```
    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')
```

OUTPUT :

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

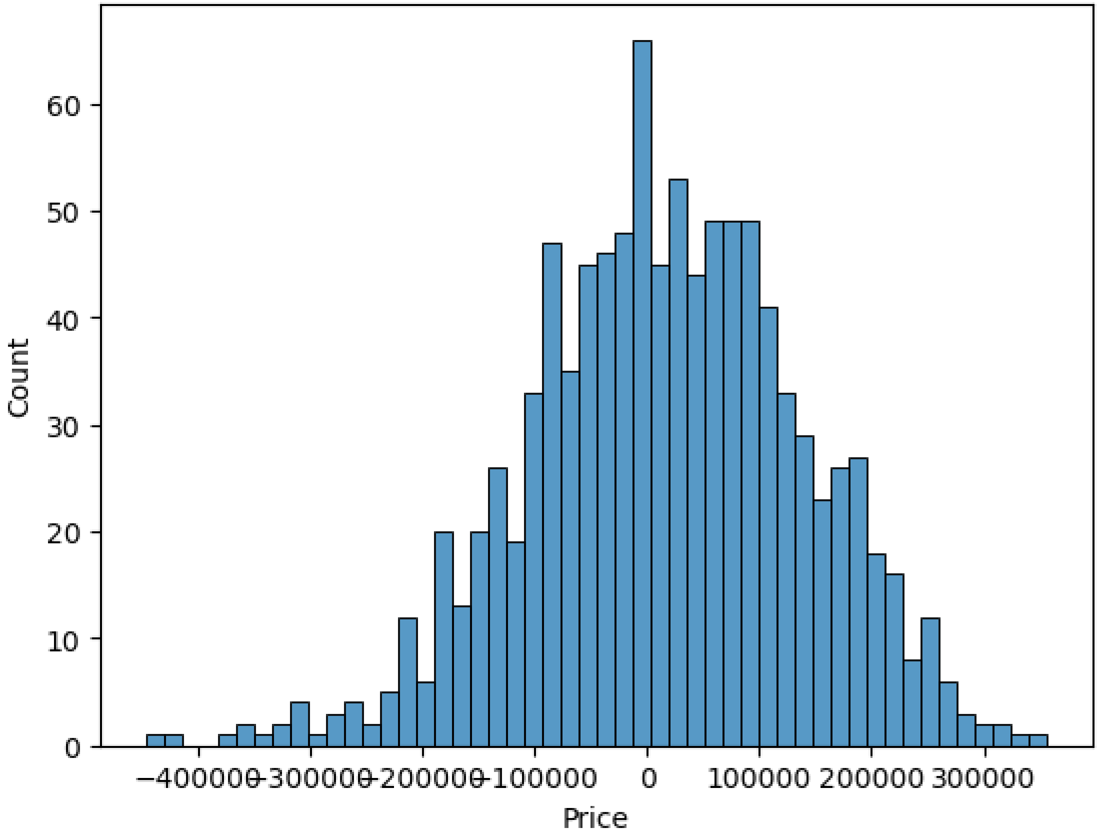


INPUT :

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

OUTPUT :

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



INPUT :

```
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
```

Model 5 - XGboost Regressor

INPUT :

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

INPUT :

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

OUTPUT :

```
XGBRegressor

XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=No
ne,
             gamma=None, gpu_id=None, grow_policy=None, importance_type=N
one,
             interaction_constraints=None, learning_rate=None, max_bin=No
ne,
             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=Non
e,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, ...)
```

Predicting Prices

INPUT :

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

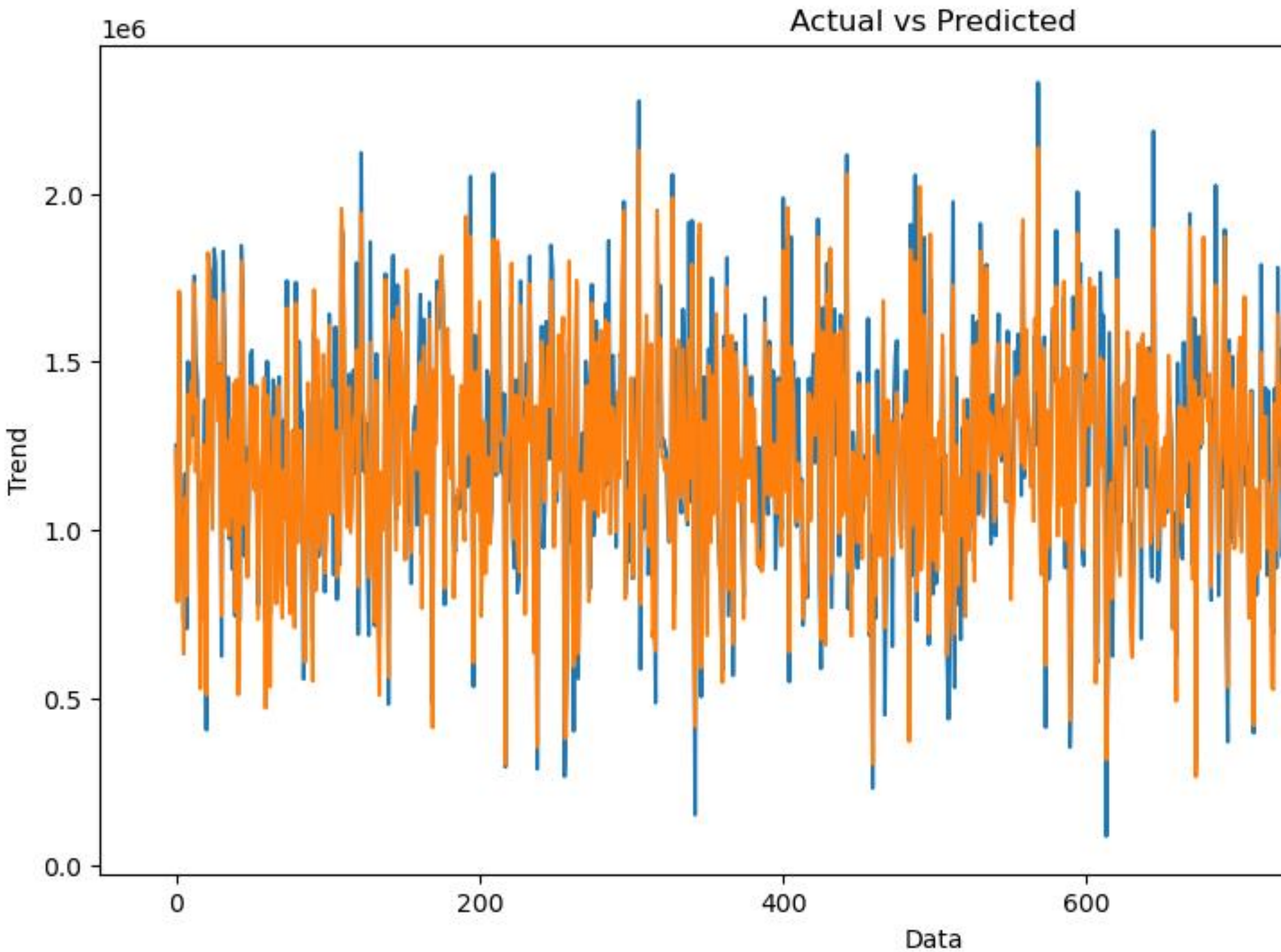
Evaluation of Predicted Data

INPUT :

```
    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')
```

OUTPUT :

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

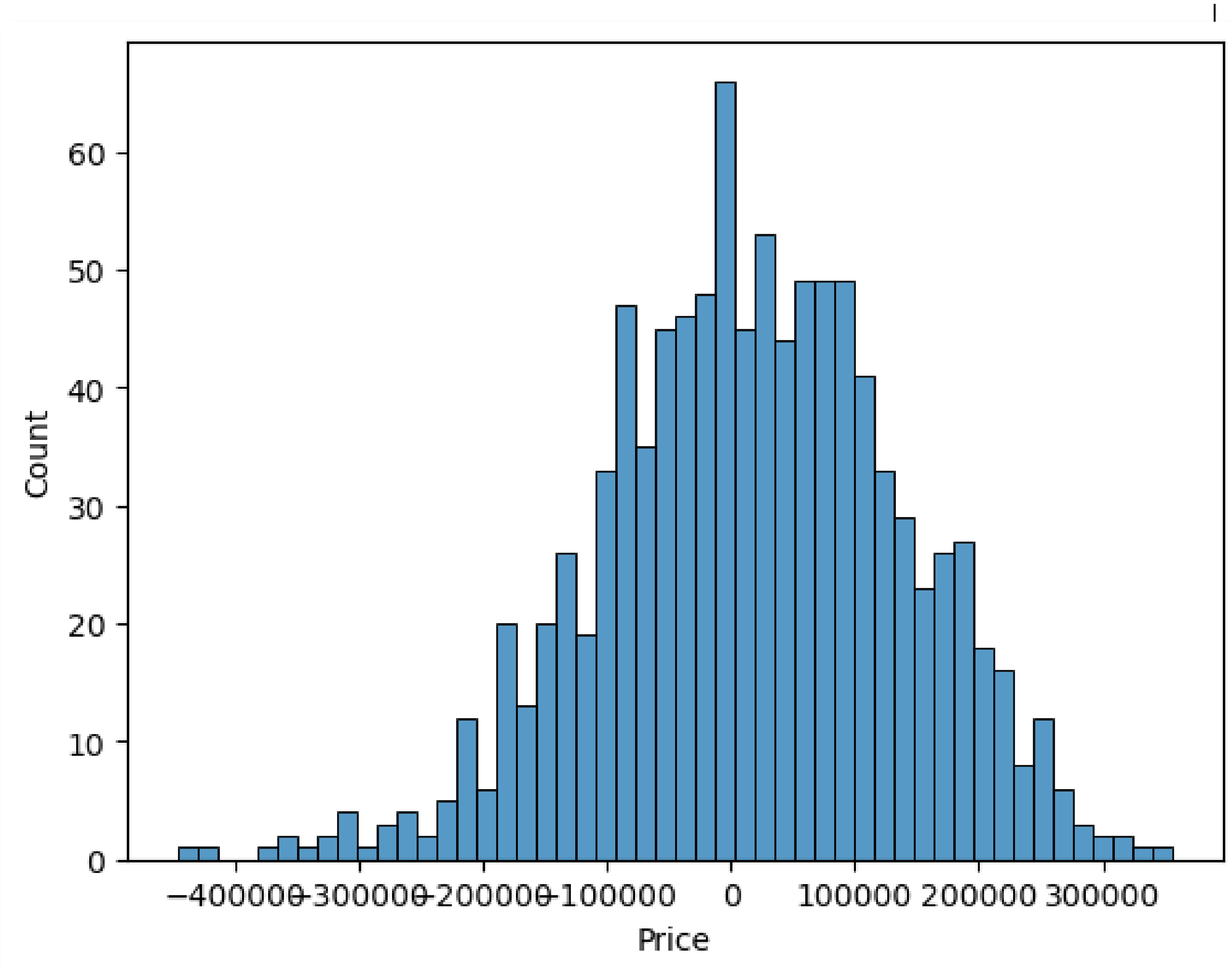


INPUT :

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

OUTPUT :

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



INPUT :

```
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
```

Conclusion :

Thus the prediction of house prices using machine learning has been explained clearly with the techniques and related example of code with output are explained with the given dataset as the model for the prediction of house prices using machine learning.