PREDICTING HOUSE PRICE USING MACHINE LEARNING

TEAM MEMBER

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Phase 2 Submission Document

Project: House Price Prediction

Introduction:

√ The real estate market is one of the most dynamic and lucrative sectors, with house prices constantly fluctuating based on various factors such as location, size, amenities, and economic conditions. Accurately predicting house prices is crucial for both buyers and sellers, as it can help make informed decisions regarding buying, selling, or investing in properties.

√ Traditional linear regression models are often employed for house price prediction. However, they may not capture complex relationships between predictors and the target variable, leading to suboptimal predictions. In this project, we will explore advanced regression techniques to enhance the accuracy and robustness of house price prediction models.

√ Briefly introduce the real estate market and the importance of accurate house price prediction.
Highlight the limitations of traditional linear regression models in capturing complex relationships.

√ Emphasize the need for advanced regression techniques like Gradient Boosting and XGBoost to enhance prediction accuracy.

Content for Project Phase 2 :

Consider exploring advanced regression techniques like Gradient Boosting or XGBoost for improved Prediction accuracy.

Data Source

A good data source for house price prediction using machine learning should be Accurate, Complete, Covering the geographic area of interest, Accessible.

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

Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
79545.45857	5.682861322	7.009188143	4.09	23086.8005	1059033.56	208
79248.64245	6.002899808	6.730821019	3.09	40173.07217	1505890.91	188
61287.06718	5.86588984	8.51272743	5.13	36882.1594	1058987.99	9127
63345.24005	7.188236095	5.586728665	3.26	34310.24283	1260616.81	USS
59982.19723	5.040554523	7.839387785	4.23	26354.10947	630943.489	USNS
80175.75416	4.988407758	6.104512439	4.04	26748.42842	1068138.07	06039
64698.46343	6.025335907	8.147759585	3.41	60828.24909	1502055.82	4759
78394.33928	6.989779748	6.620477995	2.42	36516.35897	1573936.56	972 Joyce
59927.66081	5.36212557	6.393120981	2.3	29387.396	798869.533	USS
81885.92718	4.42367179	8.167688003	6.1	40149.96575	1545154.81	Unit 9446
80527.47208	8.093512681	5.0427468	4.1	47224.35984	1707045.72	6368
50593.6955	4.496512793	7.467627404	4.49	34343.99189	663732.397	911
39033.80924	7.671755373	7.250029317	3.1	39220.36147	1042814.1	209
73163.66344	6.919534825	5.993187901	2.27	32326.12314	1291331.52	829
69391.38018	5.344776177	8.406417715	4.37	35521.29403	1402818.21	PSC 5330,
73091.86675	5.443156467	8.517512711	4.01	23929.52405	1306674.66	2278
79706.96306	5.067889591	8.219771123	3.12	39717.81358	1556786.6	064
61929.07702	4.788550242	5.097009554	4.3	24595.9015	528485.247	5498
63508.1943	5.94716514	7.187773835	5.12	35719.65305	1019425.94	Unit 7424
62085.2764	5.739410844	7.091808104	5.49	44922.1067	1030591.43	19696
86294.99909	6.62745694	8.011897853	4.07	47560.77534	2146925.34	030 Larry
60835.08998	5.551221592	6.517175038	2.1	45574.74166	929247.6	USNS
64490.65027	4.21032287	5.478087731	4.31	40358.96011	718887.232	95198
60697.35154	6.170484091	7.150536572	6.34	28140.96709	743999.819	9003 Jay
59748.85549	5.339339881	7.748681606	4.23	27809.98654	895737.133	24282

Data Collection and Preprocessing:

- √ Importing the dataset: Obtain a comprehensive dataset containing relevant features such as square footage, number of bedrooms, location, amenities, etc.
- √ Data preprocessing: Clean the data by handling missing values, outliers, and categorical variables. Standardize or normalize numerical features.

Exploratory Data Analysis (EDA):

- √ Visualize and analyze the dataset to gain insights into the relationships between variables.
- √ Identify correlations and patterns that can inform feature selection and engineering.
- √ Present various data visualizations to gain insights into the dataset.
- √ Explore correlations between features and the target variable (house prices).
- √ Discuss any significant findings from the EDA phase that inform feature selection.

Feature Engineering:

- √ Create new features or transform existing ones to capture valuable information.
- √ Utilize domain knowledge to engineer features that may impact house prices, such as proximity to schools, transportation, or crime rates.
- √ Explain the process of creating new features or transforming existing ones.
- √ Showcase domain-specific feature engineering, such as proximity scores or composite indicators.
- √ Emphasize the impact of engineered features on model performance.

<u>Advanced Regression Techniques:</u>

- ➢ **Ridge Regression:** Introduce L2 regularization to mitigate multicollinearity and overfitting.

- ➢ **Lasso Regression:** Employ L1 regularization to perform feature selection and simplify the model.

- ➢ **ElasticNet Regression:** Combine both L1 and L2 regularization to benefit from their respective advantages.

- ➢ **Random Forest Regression:** Implement an ensemble technique to handle non-linearity and capture complex relationships in the data.

- ➢ **Gradient Boosting Regressors (e.g., XGBoost, LightGBM):** Utilize gradient boosting algorithms for improved accuracy.

Model Evaluation and Selection:

- Split the dataset into training and testing sets.
- Evaluate models using appropriate metrics (e.g., Mean Absolute Error, Mean Squared Error, R-squared) to assess their performance.
- Use cross-validation techniques to tune hyperparameters and ensure model stability.
- Compare the results with traditional linear regression models to highlight improvements.
- Select the best-performing model for further analysis.

Model Interpretability:

- Explain how to interpret feature importance from Gradient Boosting and XGBoost models.
- Discuss the insights gained from feature importance analysis and their relevance to house price prediction.
- Interpret feature importance from ensemble models like Random Forest and Gradient Boosting to understand the factors influencing house prices.

Deployment and Prediction:

- Deploy the chosen regression model to predict house prices.
- Develop a user-friendly interface for users to input property features and receive price predictions.

Program:

House Price Prediction

Importing Dependencies

```
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 SciPy (detected version 1.23.5

  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

Loading Dataset

```
dataset = pd.read_csv('E:/USA_Housing.csv')
```

Model 1 - Linear Regression

In [1]:

```
model_lr=LinearRegression()
```

In [2]:

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

Out[2]:

```
LinearRegression
LinearRegression()
```

Predicting Prices

In [3]:

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

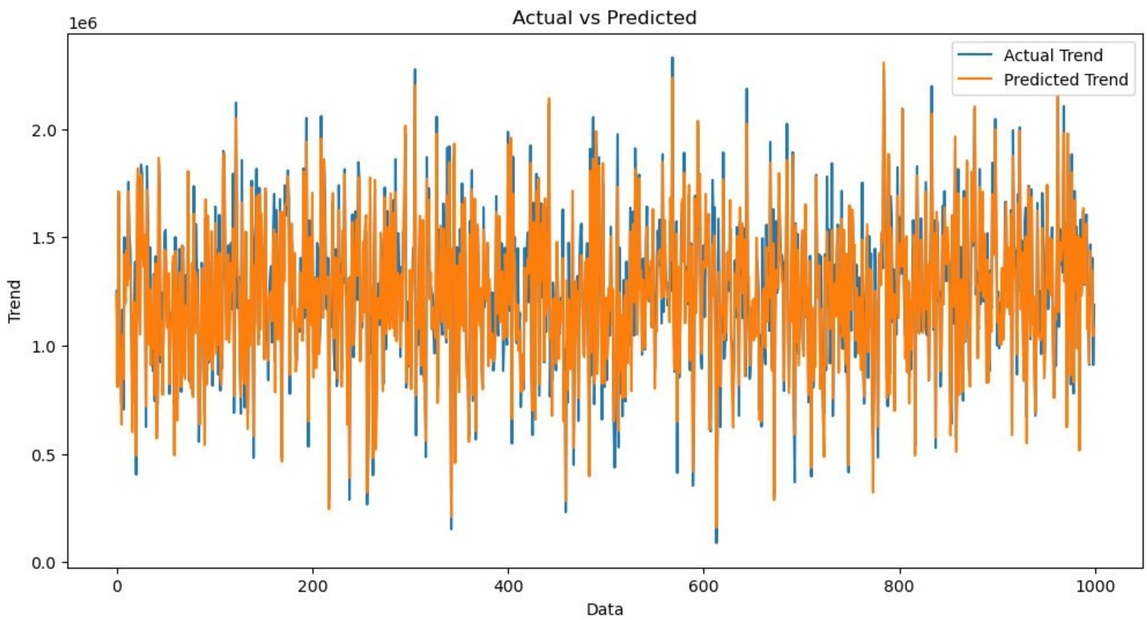
Evaluation of Predicted Data

In [4]:

```
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')
```

Out[4]:

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

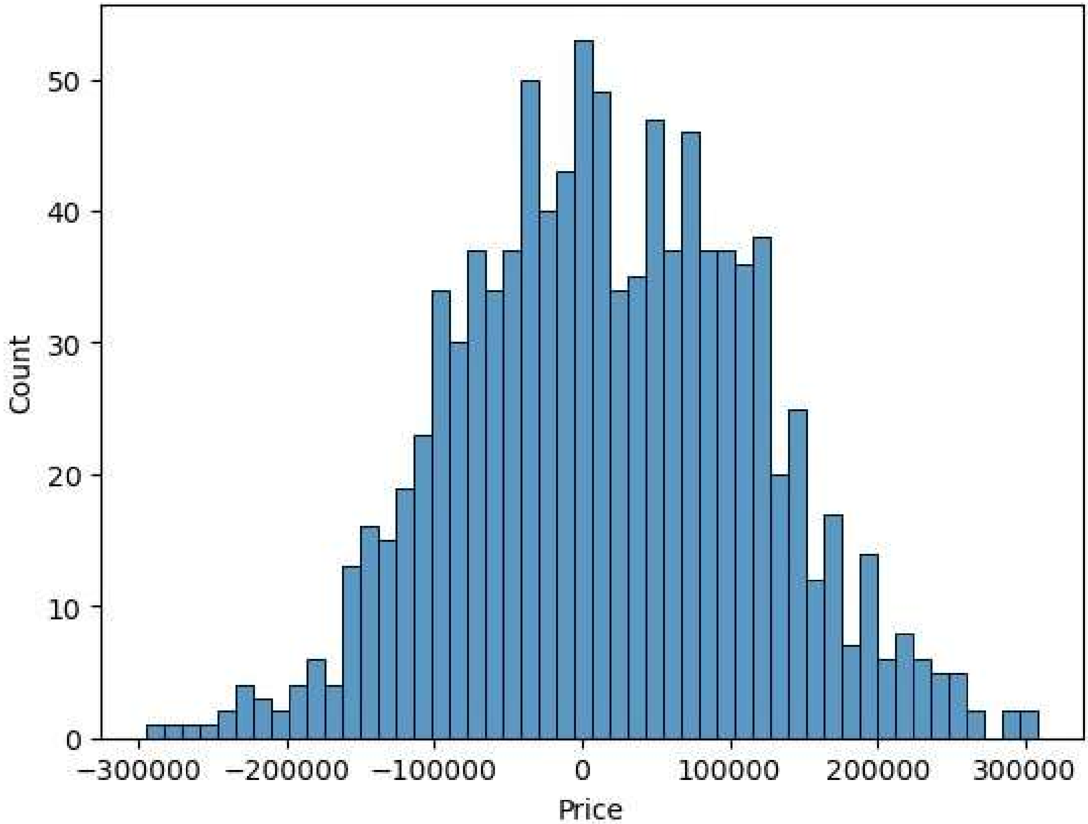


In [5]:

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

Out[5]:

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



In [6]:

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

Out[6]:

```
0.9182928179392918
82295.49779231755
10469084772.975954
```

Model 2 - Support Vector Regressor

In [7]:

```
model_svr = SVR()
```

In [8]:

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

Out[8]:

Predicting Prices

In [9]:

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

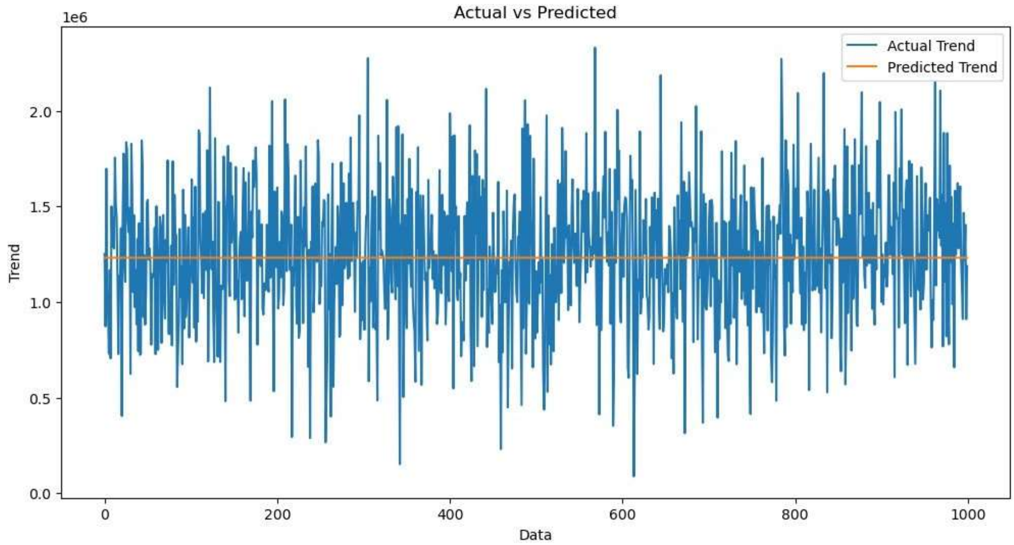
Evaluation of Predicted Data

In [10]:

```
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')
```

Out[10]:

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

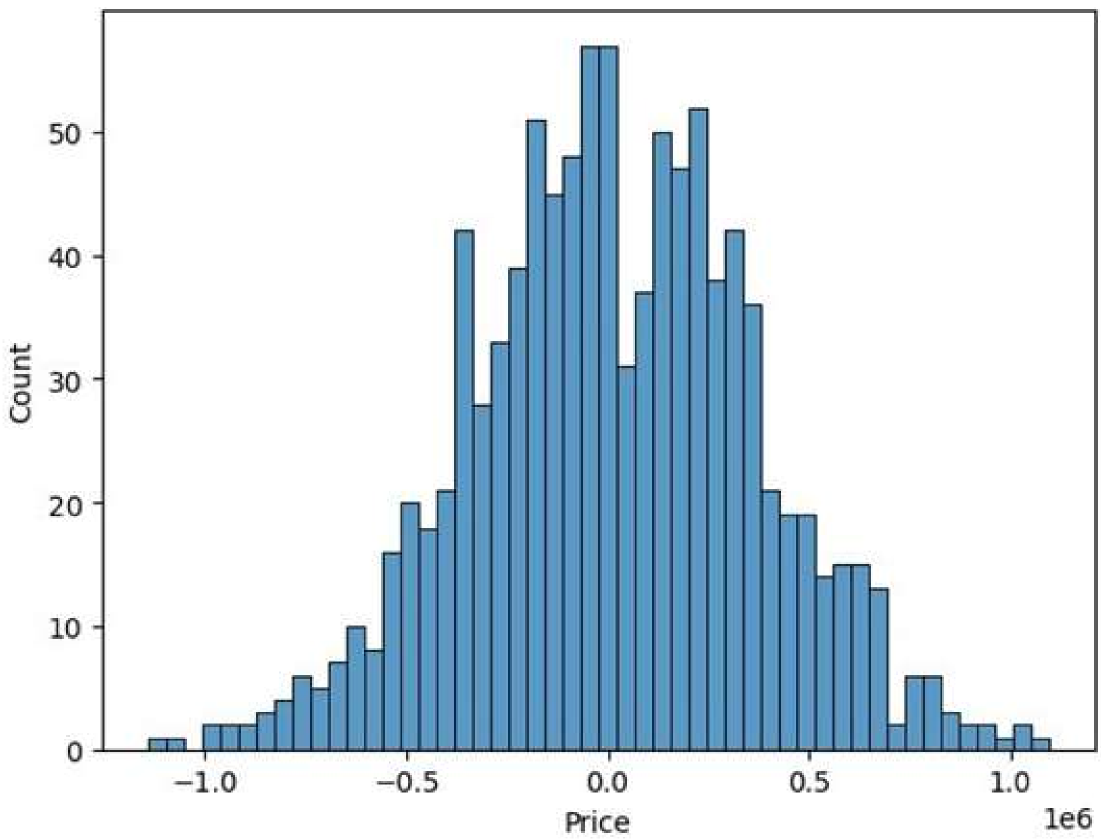


In [11]:

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

Out[12]:

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



In [12]:

```
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

In [13]:

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

In [14]:

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

Out[14]:

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

Predicting Prices

In [15]:

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

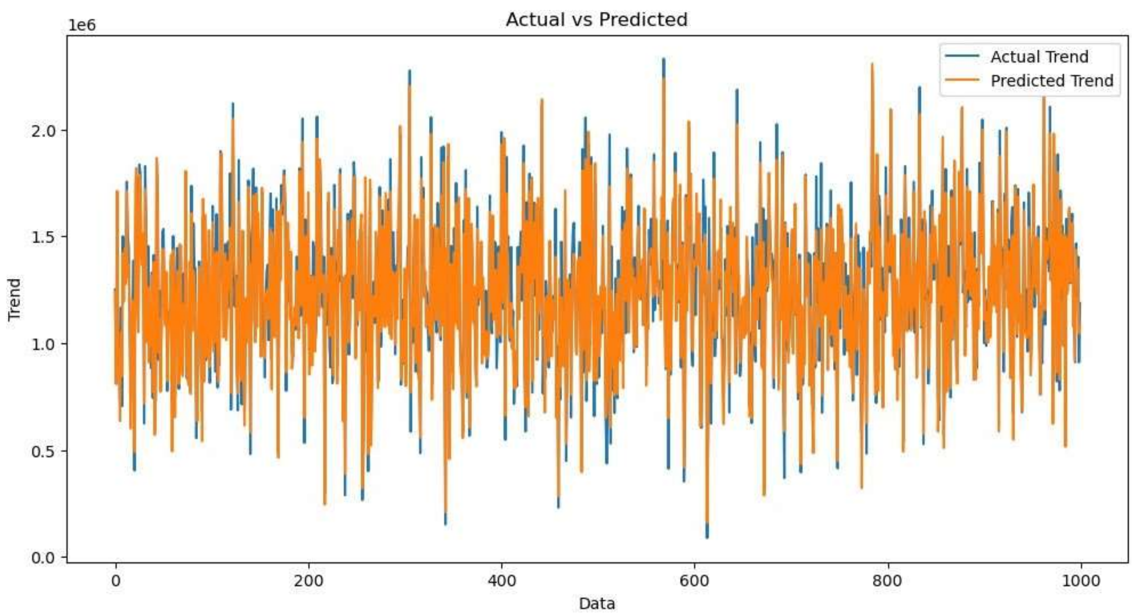
Evaluation of Predicted Data

In [16]:

```
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')
```

Out[16]:

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

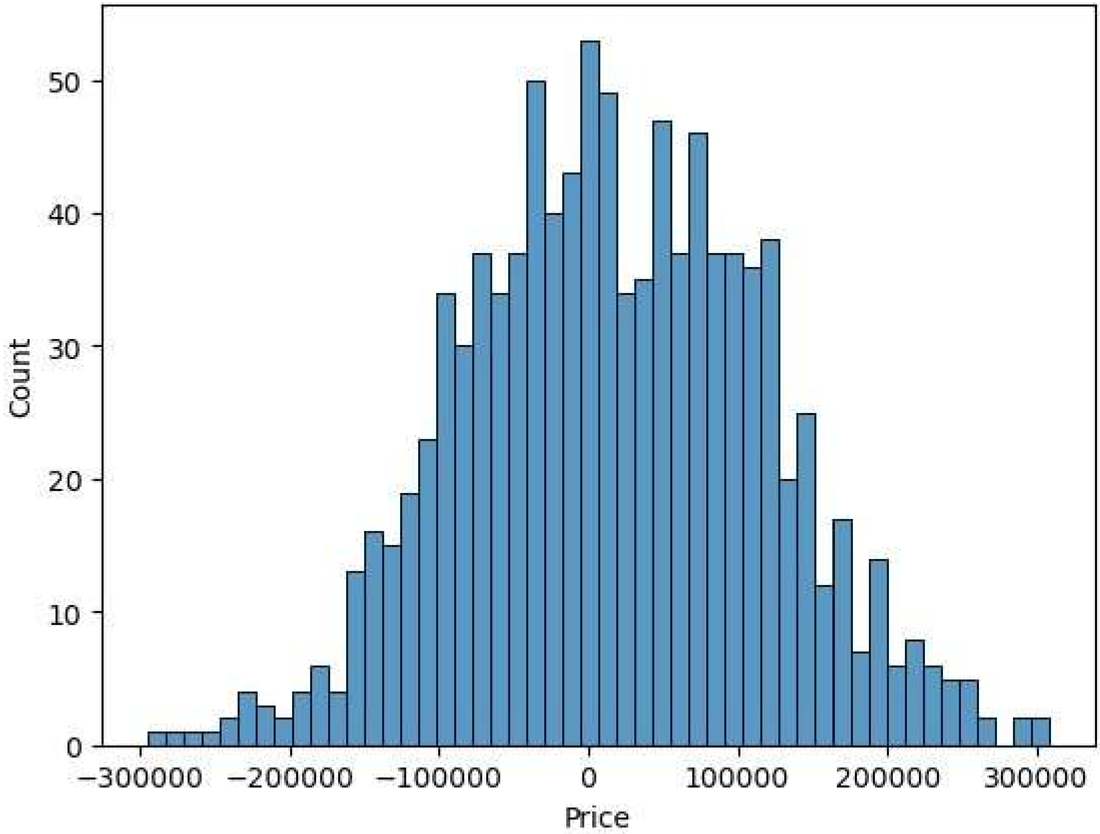


In [17]:

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

Out[17]:

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



In [18]:

```
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

In [19]:

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

In [20]:

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

Out[20]:

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

Predicting Prices

In [21]:

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

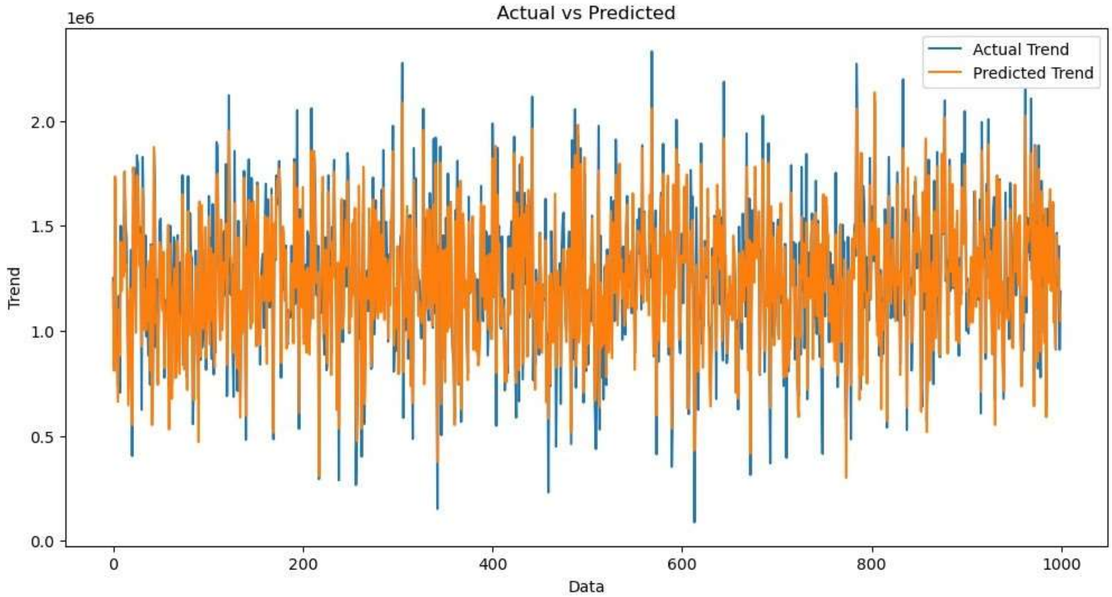
Evaluation of Predicted Data

In [22]:

```
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')
```

Out[22]:

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

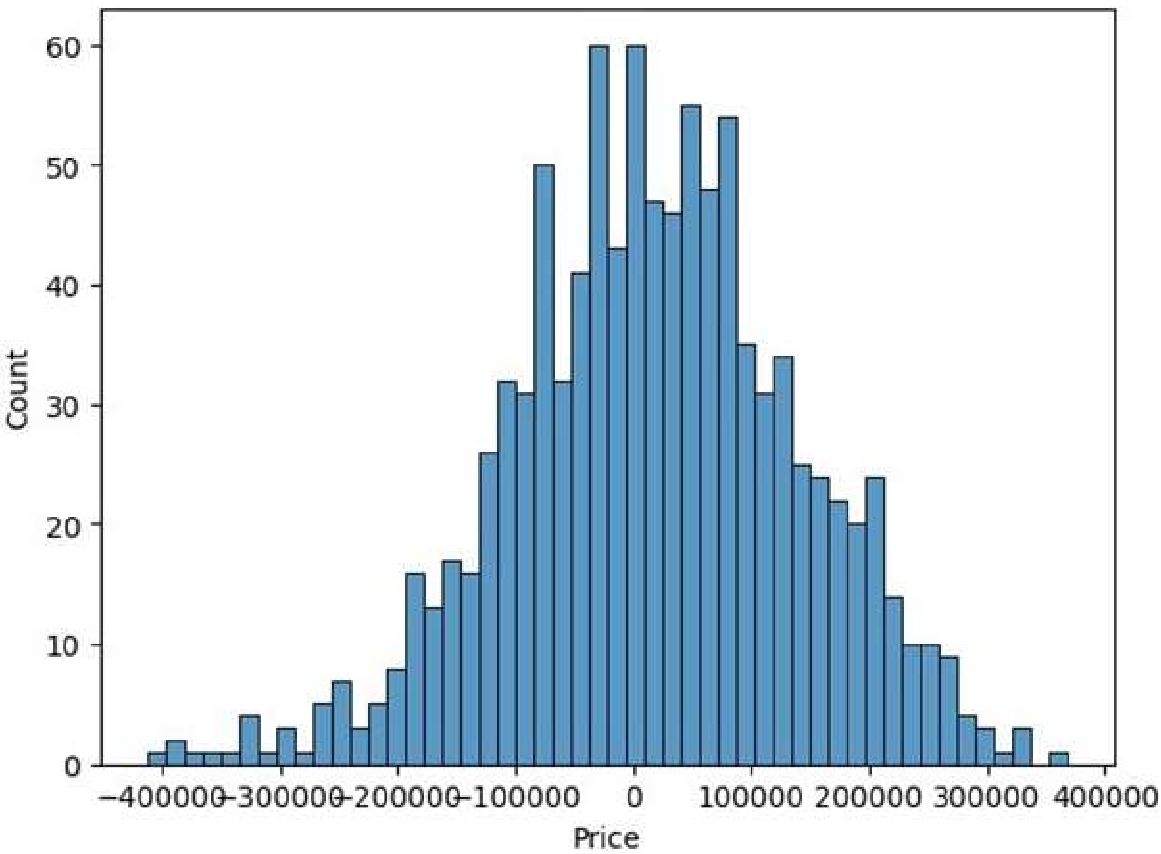


In [23]:

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

Out[23]:

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



In [24]:

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

Out [24] :

```
-0.0006222175925689744
286137.81086908665
128209033251.4034
```

Model 5 - XGboost Regressor

In [25]:

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

In [26]:

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

Out[26]:

```
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=None,
             gamma=None, gpu_id=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,
n_estimators=100, n_jobs=None, num_parallel_tree=None,
predictor=None, random_state=None, ...)
```

Predicting Prices

In [27]:

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

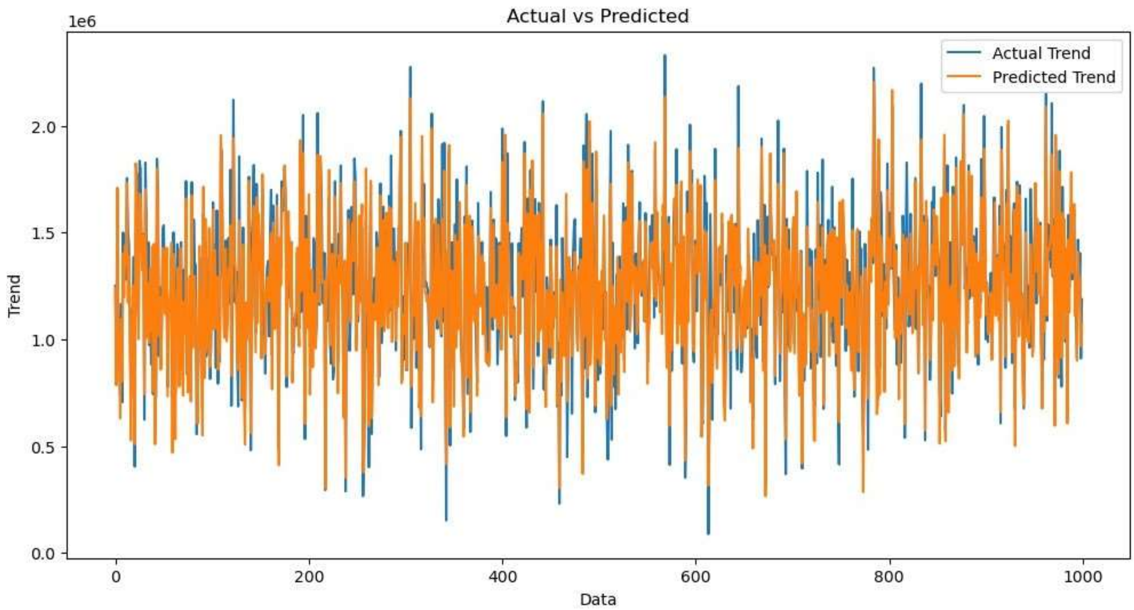
Evaluation of Predicted Data

In [28]:

```
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')
```

Out[28]:

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

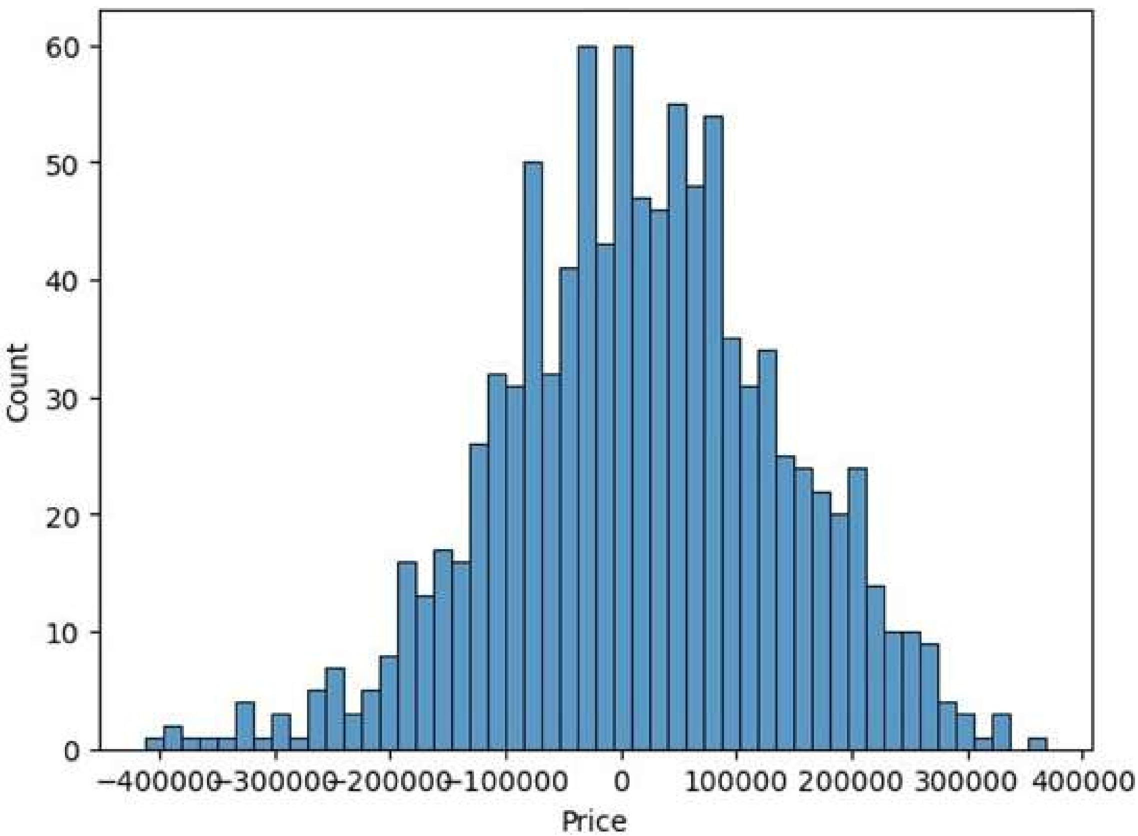


In [29]:

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

Out[29]:

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



In [30]:

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

print(mean_absolute_error(Y_test, Prediction2))

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

Out [30] :

```
-0.0006222175925689744

286137.81086908665

128209033251.4034
```

Conclusion and Future Work (Phase 2):

Project Conclusion:

- In the Phase 2 conclusion, we will summarize the key findings and insights from the advanced regression techniques. We will reiterate the impact of these techniques on improving the accuracy and robustness of house price predictions.

- Future Work: We will discuss potential avenues for future work, such as incorporating additional data sources (e.g., real-time economic indicators), exploring deep learning models for prediction, or expanding the project into a web application with more features and interactivity.