PREDICTINGHOUSEPRICEUSINGMACHINELEARNING

TEAM

MEMBERNAME: RAM

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Phase2SubmissionDocument

Project:HousePricePrediction

Introduction:

✓ Therealestatemarketisoneofthemostdynamicandlucrativesectors,with house prices constantly fluctuating based on various factors such aslocation, size, amenities, and economic conditions. Accurately predictinghouse prices is crucial for both buyers and sellers, as it can help makeinformeddecisionsregardingbuying,selling,orinvestinginproperties.

✓ Traditional linear regression models are often employed for house priceprediction.However, they may not capture complex relationships betweenpredictorsandthetargetvariable,leadingtosuboptimalpredictions.Int hisproject, we will explore advanced regression techniques to enhance theaccuracyandrobustnessofhouseprice prediction models.

✓ Brieflyintroducetherealestatemarketandtheimportanceofaccuratehouse priceprediction. Highlight the limitations of traditional linearregressionmodelsin capturingcomplex relationships.

✓ EmphasizetheneedforadvancedregressiontechniqueslikeGradientBoo stingandXGBoostto enhancepredictionaccuracy.

ContentforProjectPhase2:

ConsiderexploringadvancedregressiontechniqueslikeGradientBoostingorXGBoostforimprovedPredictionaccuracy.

DataSource:

A good data source for house price prediction using machine learning should beAccurate,Complete, Coveringthegeographic areaofinterest,Accessible.

DatasetLink:(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

DataCollectionandPreprocessing:

✓ Importing the dataset: Obtain a comprehensive dataset containing relevantfeaturessuchassquarefootage,numberofbedrooms,location,amenities,etc.

✓ Datapreprocessing:Cleanthedatabyhandlingmissingvalues,outliers,andcategoricalvariables.Standardize ornormalize numericalfeatures.

Exploratory DataAnalysis (EDA):

✓ Visualizeandanalyzethedatasettogaininsightsintotherelationshipsbetweenvariables.

✓ Identifycorrelationsandpatternsthatcaninformfeatureselectionandengineering.

✓ Presentvariousdatavisualizationstogaininsightsintothedataset.

✓ Explorecorrelationsbetweenfeaturesandthetargetvariable(houseprices).

✓ DiscussanysignificantfindingsfromtheEDAphasethatinformfeatureselection.

FeatureEngineering:

✓ Createnewfeaturesortransformexistingonestocapturevaluableinformation.

✓ Utilizedomainknowledgetoengineerfeaturesthatmayimpacthouseprices,suchasproximity toschools, transportation,orcrimerates.

✓ Explaintheprocessofcreatingnewfeaturesortransformingexistingones.

✓ Showcasedomain-specificfeatureengineering,suchasproximityscoresorcomposite indicators.

✓ Emphasizetheimpactofengineeredfeaturesonmodelperformance.

AdvancedRegressionTechniques:

- RidgeRegression:IntroduceL2regularizationtomitigatemulticollinearityandover fitting.

- LassoRegression:EmployL1regularizationtoperformfeatureselectionandsimpl ifythemodel.

- ElasticNetRegression: CombinebothL1andL2regularizationtobenefitfromtheirrespectiveadvantages.

- RandomForestRegression: Implementanensembletechniquetohandlenonlinearityandcapture complexrelationships inthe data.

- GradientBoostingRegressors(e.g.,XGBoost,LightGBM):Utilizegradientboo stingalgorithmsforimprovedaccuracy.

ModelEvaluationandSelection:

- Splitthedatasetintotrainingandtestingsets.
- Evaluatemodelsusingappropriatemetrics(e.g.,MeanAbsoluteError,MeanSquaredError,R-squared) toassess theirperformance.
- Usecross-validationtechniquestotunehyperparametersandensuremodelstability.
- Comparetheresultswithtraditionallinearregressionmodelstohighlightimpro vements.
- Selectthebest-performingmodelforfurtheranalysis.

ModelInterpretability:

- Explainhowtointerpret featureimportancefromGradientBoostingandXGBoostmodels.
- Discusstheinsightsgainedfromfeatureimportanceanalysisandtheirrelevancetohouseprice prediction.
- InterpretfeatureimportancefromensemblemodelslikeRandomForestandGradientBoosting to understand the factors influencinghouseprices.

DeploymentandPrediction:

- Deploythechosenregressionmodeltopredicthouseprices.
- Developauser-friendlyinterfaceforuserstoinputpropertyfeaturesandreceivepricepredictions.

Program:

HousePricePrediction

ImportingDependencies
import pandas as
pdimport numpy as
npimportseabornassns
importmatplotlib.pyplotasplt
fromsklearn.model_selectionimporttrain_test_splitfr
omsklearn.preprocessingimportStandardScaler
fromsklearn.metricsimportr2_score,mean_absolute_error,mean_squared_errorfroms
klearn.linear_modelimportLinearRegression
fromsklearn.linear_modelimportLasso
fromsklearn.ensembleimportRandomForestRegressorfr
omsklearn.svmimportSVR
importxgboostasxg

%matplotlibinlinei

mportwarnings

warnings.filterwarnings("ignore")
/opt/conda/lib/python3.10/site-packages/scipy/_init_.py:146: UserWarning:
ANumPy version >=1.16.5 and <1.23.0 is required for this version of
SciPy(detectedversion1.23.5
warnings.warn(f"ANumPyversion>={np_minversion}and<{np_maxversion}"

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

<u>Model1- LinearRegression</u>

In[1]:
model_lr=LinearRegression()

In[2]:

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

Out[2]:

```
▾ LinearRegression
LinearRegression()
```

PredictingPrices

In[3]:

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

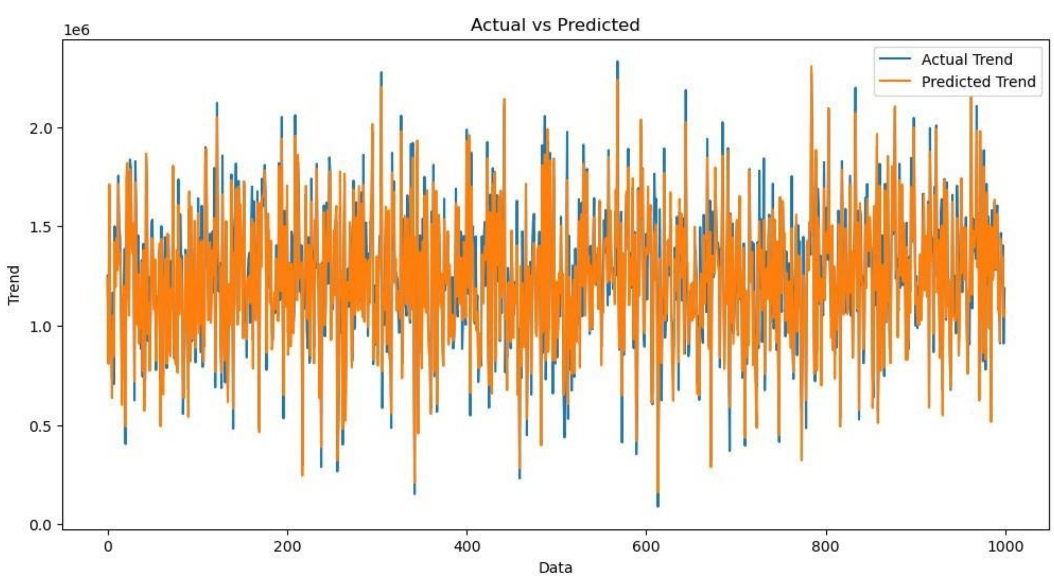
EvaluationofPredictedData

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='PredictedTrend')plt.xlabel('
Data')
plt.ylabel('Trend')
plt.legend()
plt.title('ActualvsPredicted')
```

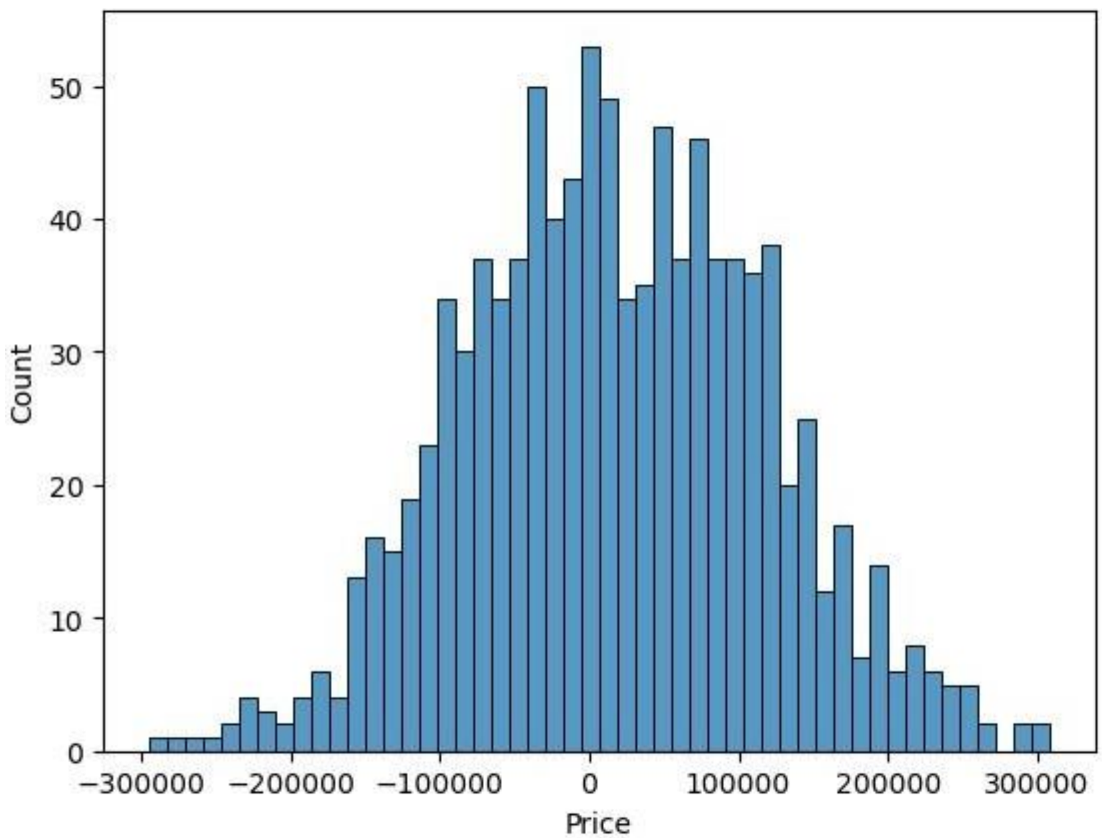
Out[4]:

Text(0.5,1.0,'ActualvsPredicted')



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]:0.9182928179

392918
82295.49779231755
10469084772.975954

Model2-SupportVectorRegressor

In[7]:
```
model_svr=SVR()
```

In[8]:
```
model_svr.fit(X_train_scal,Y_train)
```
Out[8]:

PredictingPrices

In[9]:

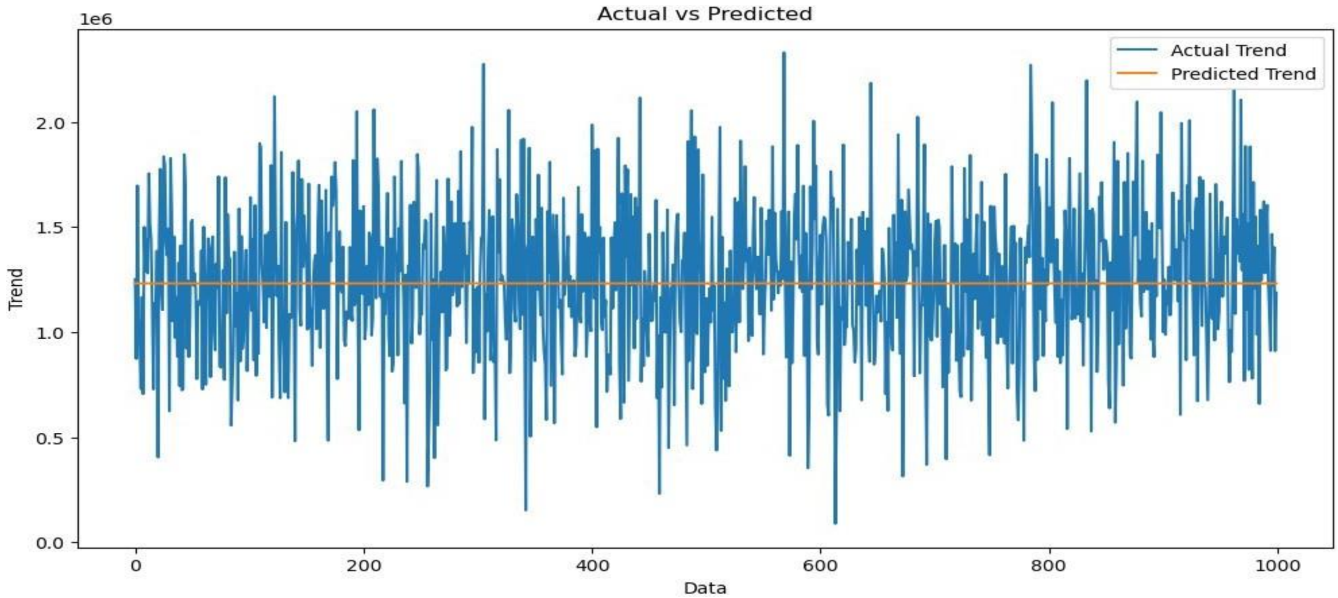
```
Prediction2=model_svr.predict(X_test_scal)
```

EvaluationofPredictedData

In[10]:

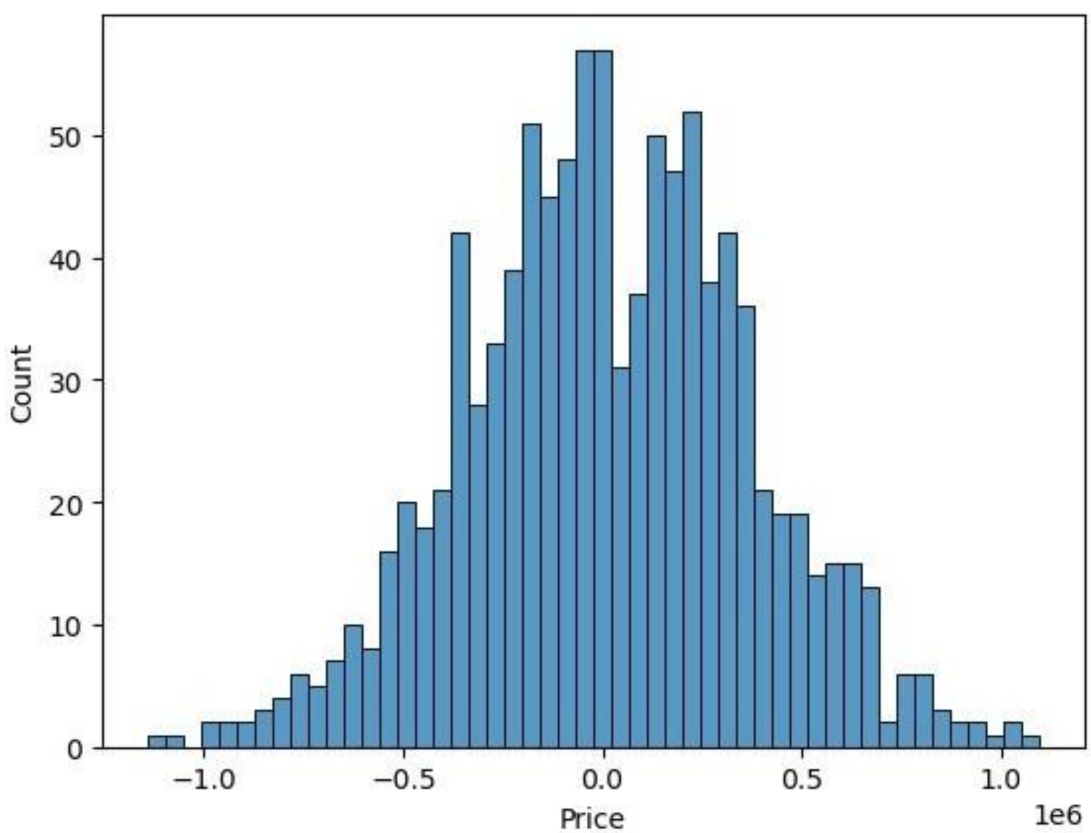
```
plt.figure(figsize=(12,6))
plt.plot(np.arange(len(Y_test)), Y_test, label='Actual
Trend')plt.plot(np.arange(len(Y_test)),Prediction2,label='PredictedTrend')plt.xl
abel('Data')
plt.ylabel('Trend')
plt.legend()
plt.title('ActualvsPredicted')
```

Out[10]:
```
Text(0.5,1.0,'ActualvsPredicted')
```



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
```

Model3-LassoRegression

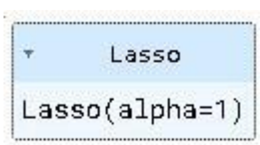
In[13]:

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

In[14]:

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

Out[14]:



PredictingPrices

In[15]:

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

EvaluationofPredictedData

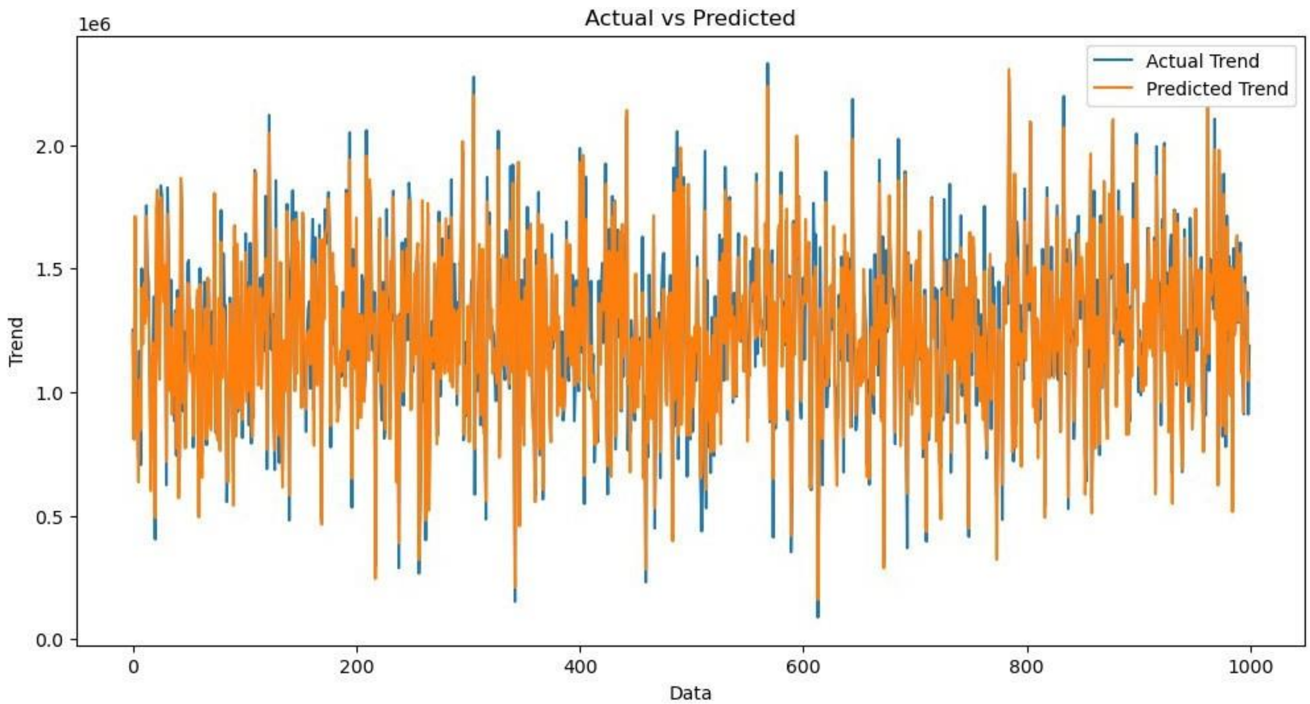
In[16]:

```
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='PredictedTrend')
```

```
plt.xlabel('Data')p
lt.ylabel('Trend')p
lt.legend()
plt.title('ActualvsPredicted')
```

Out[16]:

```
Text(0.5,1.0,'ActualvsPredicted')
```

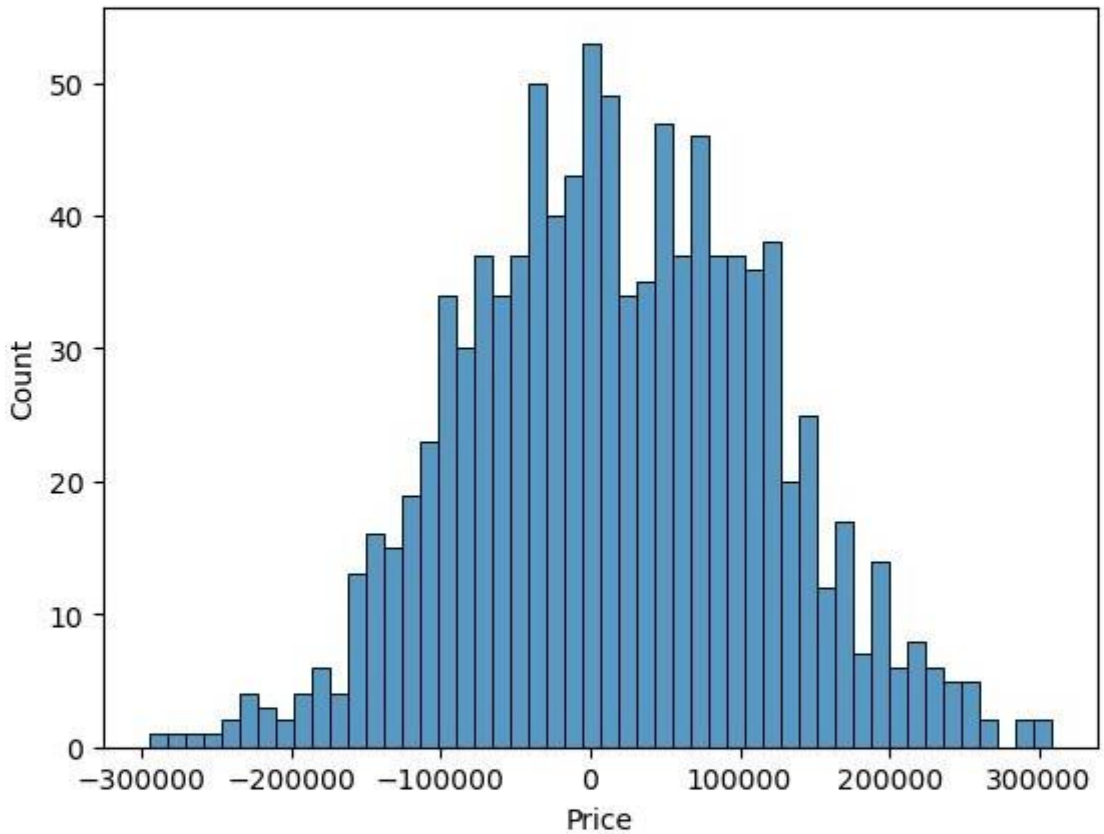


In[17]:

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

Out[17]:

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



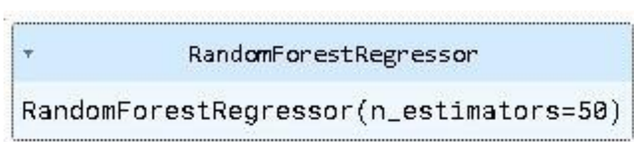
In[18]:
print(r2_score(Y_test, Prediction2))print(mean_absolute_error(Y_test, Prediction2))print(mean_squared_error(Y_test, Prediction2))
-0.0006222175925689744
286137.81086908665
128209033251.4034

Model4-RandomForestRegressor

In[19]:
model_rf=RandomForestRegressor(n_estimators=50)

In[20]:
model_rf.fit(X_train_scal,Y_train)

Out[20]:



PredictingPrices

In[21]:

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

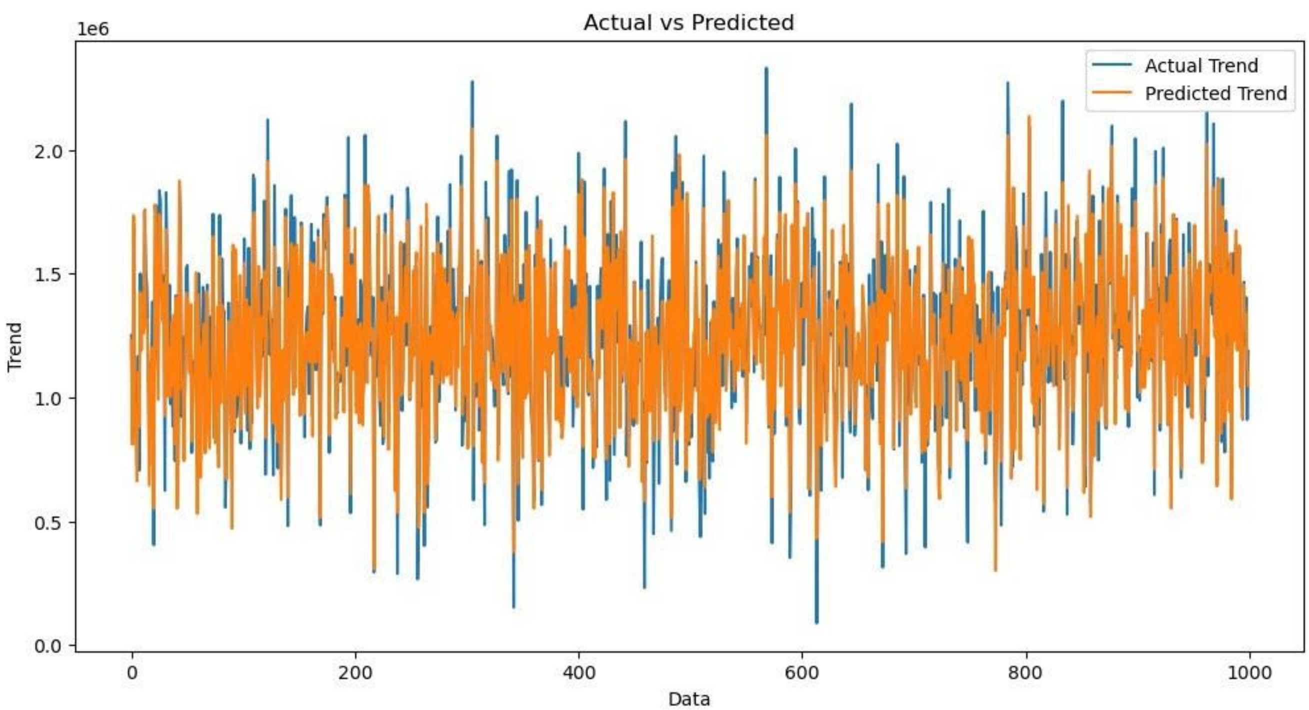
EvaluationofPredictedData

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='PredictedTrend')plt.xl
abel('Data')
plt.ylabel('Trend')
plt.legend()
plt.title('ActualvsPredicted')
```

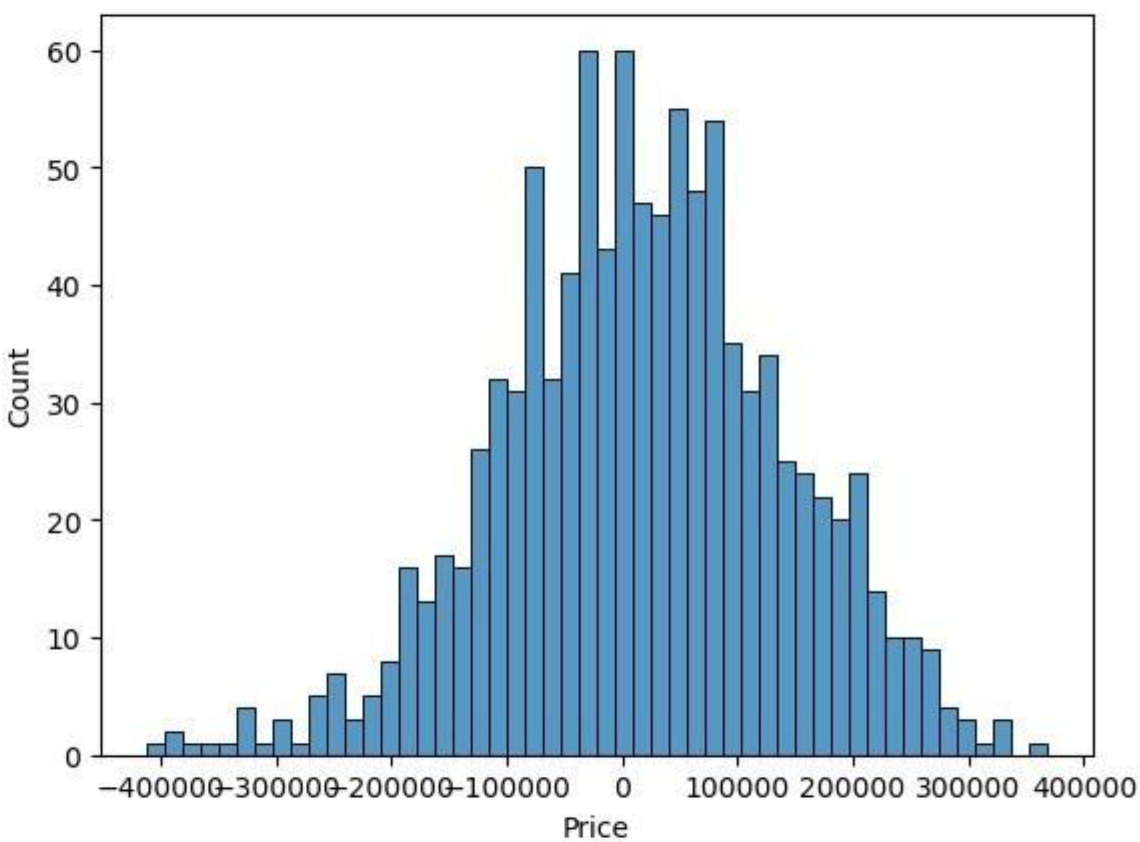
Out[22]:

```
Text(0.5,1.0,'ActualvsPredicted')
```



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

Model5-XGboostRegressor

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,impo

rtance_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_const

raints=None,

n_estimators=100,n_jobs=None,num_parallel_tree=None,

predictor=None, random_state=None,…)

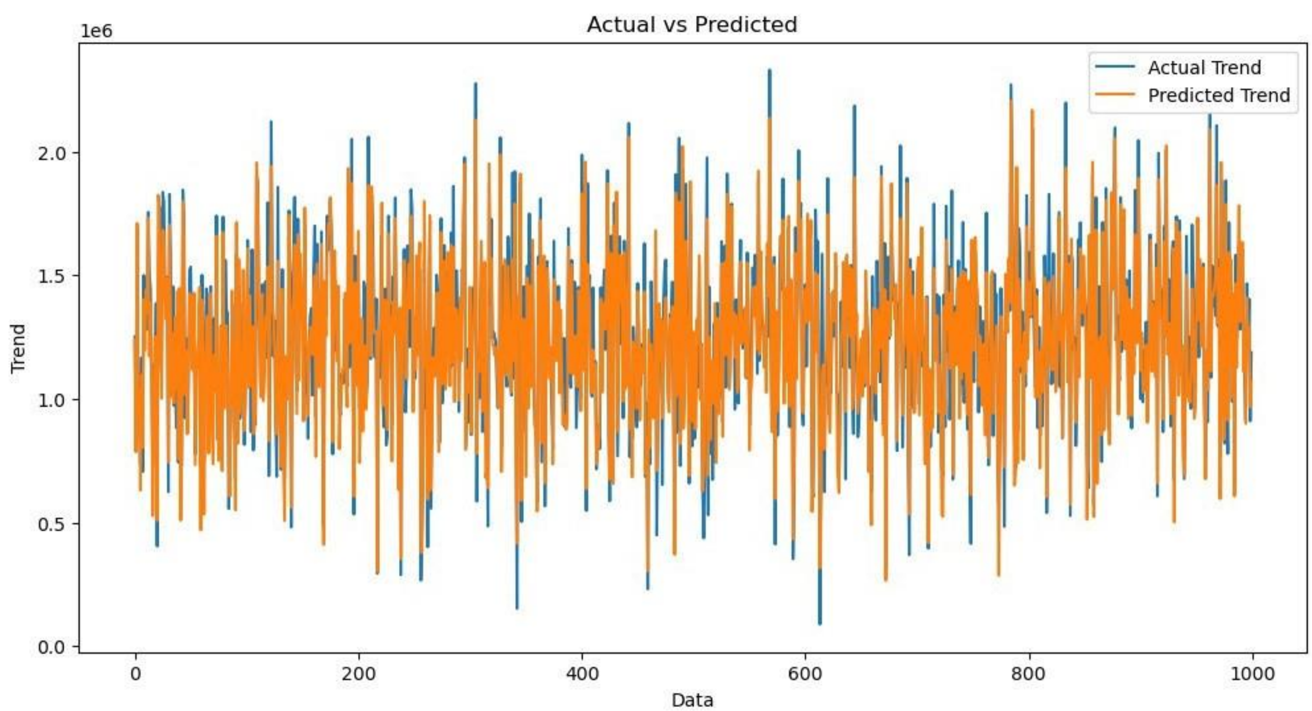
PredictingPrices

In[27]:
```
Prediction5=model_xg.predict(X_test_scal)
```

EvaluationofPredictedData

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='PredictedTrend')plt.xl
abel('Data')
plt.ylabel('Trend')
plt.legend()
plt.title('ActualvsPredicted')
```

Out[28]:
Text(0.5,1.0,'ActualvsPredicted')

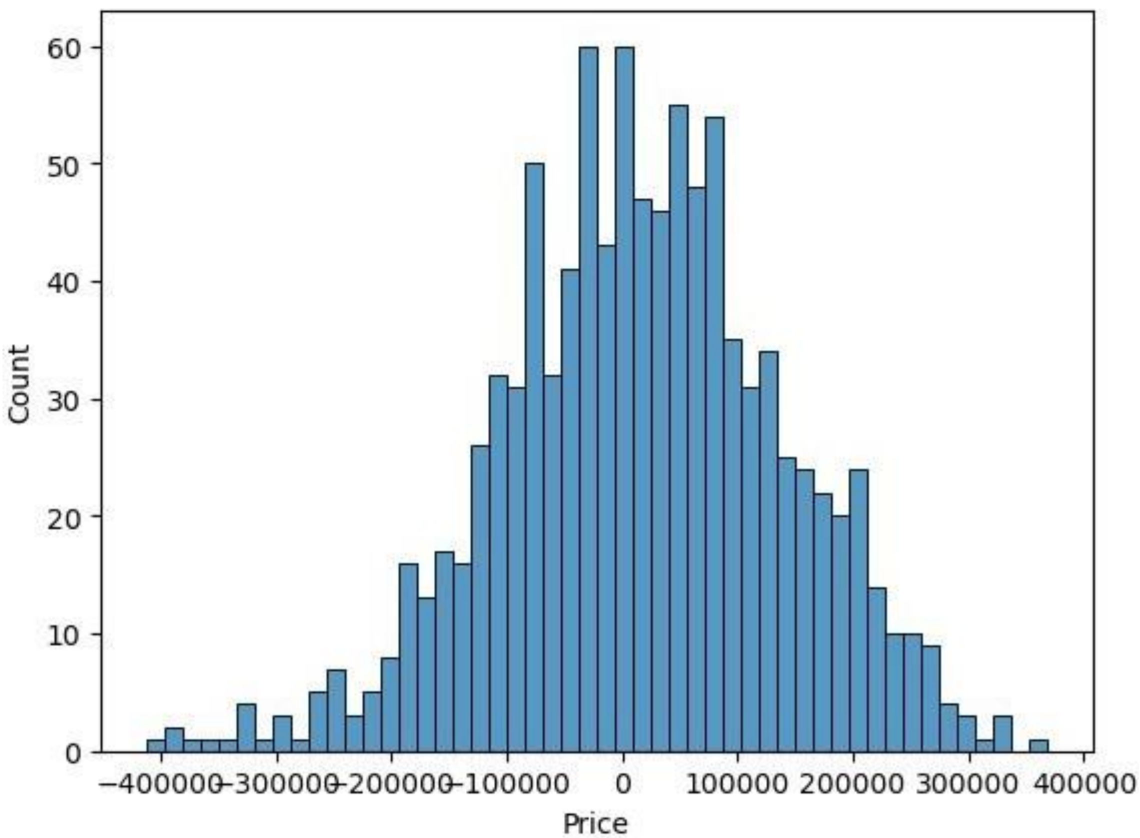


In[29]:

```
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

ConclusionandFutureWork(Phase2):

ProjectConclusion:

◌ InthePhase2conclusion, wewillsummarizethekeyfindingsand insightsfromtheadvanced regression techniques. We will reiterate the impact of these techniques onimprovingthe accuracy androbustnessof housepricepredictions.

◌ FutureWork:Wewilldiscusspotentialavenuesforfuturework,suchasincorporatingadditional data sources (e.g., real-time economic indicators), exploring deep learningmodels for prediction, or expanding the project into a web application with morefeaturesandinteractivity.