House Price Prediction using Linear Regression

Introduction:

In this project, we are tasked with analyzing a dataset that contains housing-related information for a fictional town. The dataset consists of various numerical features such as average income, house age, number of rooms, and population, along with the corresponding house prices. Additionally, there is a categorical feature representing the addresses of the houses.

Problem Statement:

The goal is to develop a predictive model using Linear Regression that can accurately estimate house prices based on the given features. This involves several key steps in data preprocessing, model selection, and evaluation:

1. **Data Preprocessing**:
    - Handling categorical data: Convert the categorical 'Address' feature into a numerical format suitable for machine learning models.
    - Feature scaling: Normalize or standardize numerical features to ensure all features contribute equally to model training.
    - Optional feature engineering: Create new features or transform existing ones to potentially enhance model performance.
2. **Model Selection and Training**:
    - Choose an appropriate regression model: Given the nature of the problem (predicting house prices), linear regression is a common starting point due to its interpretability and ease of implementation.
    - Train the selected model on a training dataset prepared from the preprocessed data.
3. **Model Evaluation**:
    - Evaluate the trained model's performance using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R2). These metrics provide insights into how well the model predicts house prices on both training and test datasets.

Procedure:

- **Data Loading**: Load the dataset containing housing information into a pandas DataFrame.
- **Data Engineering**: Preprocess the data by encoding categorical variables, scaling numerical features, and optionally performing feature engineering.
- **Model Training**: Select a linear regression model, split the data into training and testing sets, and train the model using the training set.
- **Model Evaluation**: Evaluate the model's performance using appropriate metrics on the test set to assess its accuracy and generalization capability.

Summary:

In summary, this project involves preparing and analyzing a housing dataset, building a predictive model using linear regression, and evaluating its performance. By following a systematic approach to data preprocessing, model selection, and evaluation, we aim to develop a robust model that accurately predicts house prices based on the provided features.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

# Applying style settings for seaborn and matplotlib
sns.set_theme(style="whitegrid")
plt.style.use("ggplot")
```

```
df = pd.read_csv('/content/USA_Housing.csv')
# Displaying data
df.head()
```

	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

Next steps: Generate code with df View recommended plots

```
#Displaying information about like dat type, Not- Null counts
df.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
```

```
#Summarize the distribution and central tendencies
df.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%	61480.562388	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

```
#Displaying columns
df.columns
```

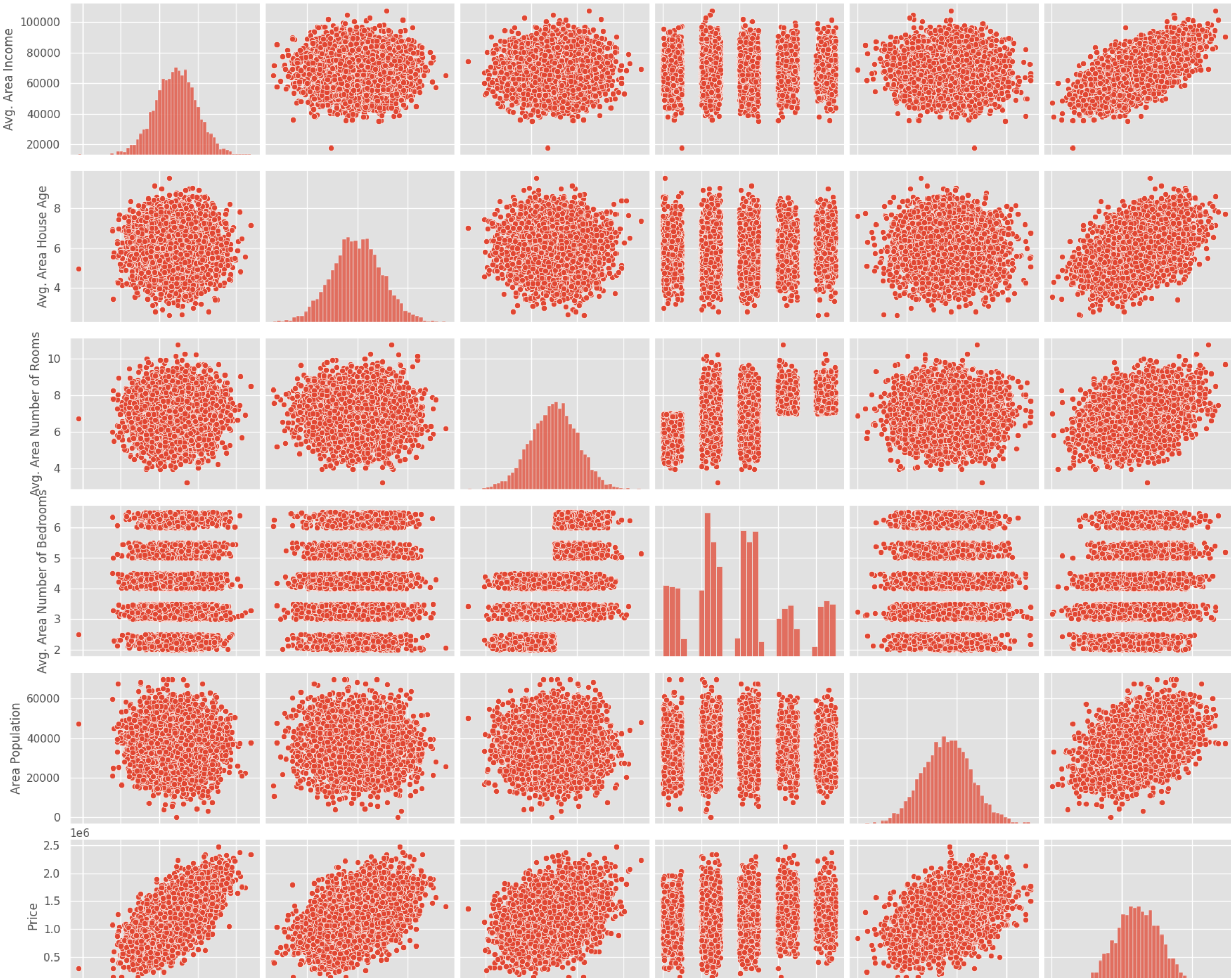
```
Index(['Avg. Area Income', 'Avg. Area House Age', 'Avg. Area Number of Rooms',
       'Avg. Area Number of Bedrooms', 'Area Population', 'Price', 'Address'],
      dtype='object')
```

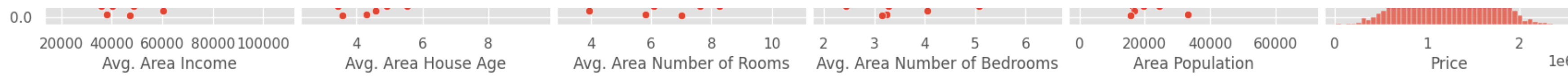
Exploratory Data Analysis (EDA)

Let's create some simple plots to check out the data!

```
# Plotting pairplot
sns.pairplot(df, height=2.5, aspect=1.2)
```

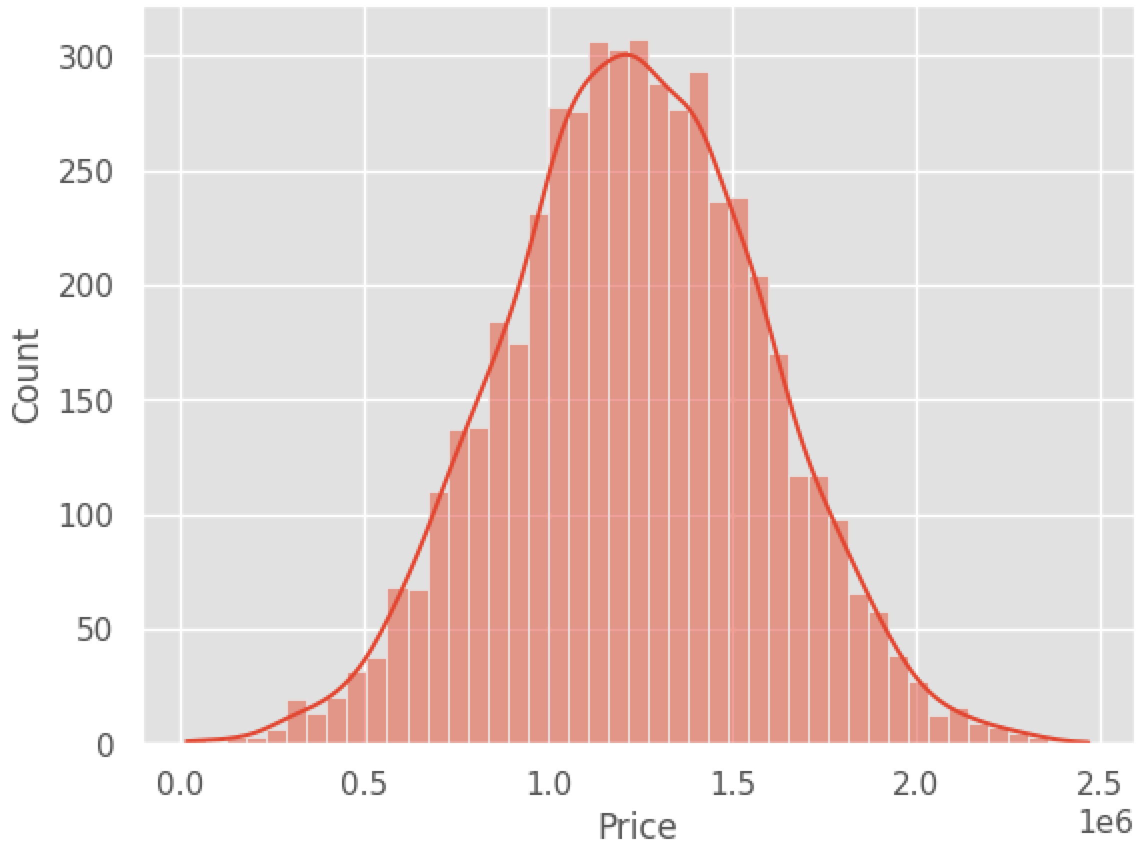
<seaborn.axisgrid.PairGrid at 0x7bfff9936fe0>






```
sns.histplot(df['Price'], kde=True)
```

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




```
# Convert relevant columns to numeric, handling errors
for col in df.columns:
    if df[col].dtype == 'object':  # Check if column is of object (string) type
        try:
            df[col] = pd.to_numeric(df[col], errors='coerce')  # Convert to numeric, replacing non-convertible values with
        except:
            pass  # Skip columns that cannot be converted

sns.heatmap(df.corr(), annot=True)
```

```
<Axes: >
```

Start coding or generate with AI.

```
#Displaying the data after converstion
df.head()
```

	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	NaN
1	79248.642455	6.002900	6.730821	3.09	40173.072174	1.505891e+06	NaN
2	61287.067179	5.865890	8.512727	5.13	36882.159400	1.058988e+06	NaN
3	63345.240046	7.188236	5.586729	3.26	34310.242831	1.260617e+06	NaN
4	59982.197226	5.040555	7.839388	4.23	26354.109472	6.309435e+05	NaN

Next steps: Generate code with df View recommended plots

Training a Linear Regression Model

> Let's now begin to train out regression model! We will need to first split up our data into an X array that contains the features to train on, and a y array with the target variable,

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

Train Test Split

Now let's split the data into a training set and a testing set. We will train out model on the training set and then use the test set to evaluate the model.

```
from sklearn.model_selection import train_test_split

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

```
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score


# Define a function to calculate MAPE (Mean Absolute Percentage Error)
def mape_score(y_true, y_pred):
    return np.mean(np.abs((y_pred - y_true) / y_true)) * 100

# Function to print and return evaluation metrics
def evaluate(true, predicted):
    mae = mean_absolute_error(true, predicted)
    mse = mean_squared_error(true, predicted)
    rmse = np.sqrt(mse)
    mape = mape_score(true, predicted)
    r2_square = r2_score(true, predicted)
    print('MAE:', mae)
    print('MSE:', mse)
    print('RMSE:', rmse)
    print('MAPE:', mape)
    print('R2 Square:', r2_square)
    print('__________________________________')
    return mae, mse, rmse, mape, r2_square

# Function to perform cross-validation and return mean score
def cross_val(model, X, y, cv=10):
    scores = cross_val_score(model, X, y, scoring='neg_mean_squared_error', cv=cv)
    return np.sqrt(-scores.mean())
```

Preparing Data For Linear Regression

```
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

pipeline = Pipeline([
    ('std_scalar', StandardScaler())
])
# use piplines to scale data (Whenever our data is not normally distributed, we use it to get normal distribution. You mus
X_train = pipeline.fit_transform(X_train)
X_test = pipeline.transform(X_test)
```

```
#
X_train
```

```
array([[-0.19049241, -0.12817719, -0.13160635,  0.12038585, -0.82761782],
       [-1.38876401,  0.43080443,  0.80028487, -0.55648895,  1.15829878],
       [-0.35012392,  0.46680752,  1.70375078,  0.03067955, -0.31904298],
       ...,
       [-0.22335061,  0.53809182, -0.36489661, -0.68697084,  0.11908894],
       [-0.92417067,  1.43077434,  2.26846315,  0.2753331 ,  1.39018355],
       [-0.69357335, -0.07762332,  0.89219611,  1.67801341, -0.00681852]])
```

```
X_test
```

```
array([[-0.62396497,  1.05134233, -0.53493732, -0.59726454,  0.77509854],
       [-1.06752524,  0.92593776, -0.05804915, -0.69512596,  0.73880748],
       [ 0.14995479,  0.77674776, -0.31465336, -1.60849918, -0.69076777],
       ...,
       [ 1.16115701,  1.18417775,  0.25662849,  1.18870632,  0.93991305],
       [ 1.69832503,  0.56046124, -1.85607396, -1.54325824,  1.16585758],
       [-0.14145775, -1.04516314,  0.64633545,  0.8625016 , -0.40292631]])
```

Linear Regression

```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(X_train,y_train)
```

```
▾ LinearRegression
LinearRegression()
```

Model Evaluation

Let's evaluate the model by checking out it's coefficients and how we can interpret them.

```
# print the intercept
print(lin_reg.intercept_)
```

```
1229576.9925600903
```

```
coeff_df = pd.DataFrame(lin_reg.coef_, X.columns, columns=['Coefficient'])
coeff_df
```

	Coefficient
Avg. Area Income	231741.876652
Avg. Area House Age	163580.776566
Avg. Area Number of Rooms	120724.771387
Avg. Area Number of Bedrooms	2992.449135
Area Population	152235.900097

Next steps: Generate code with `coeff_df` View recommended plots

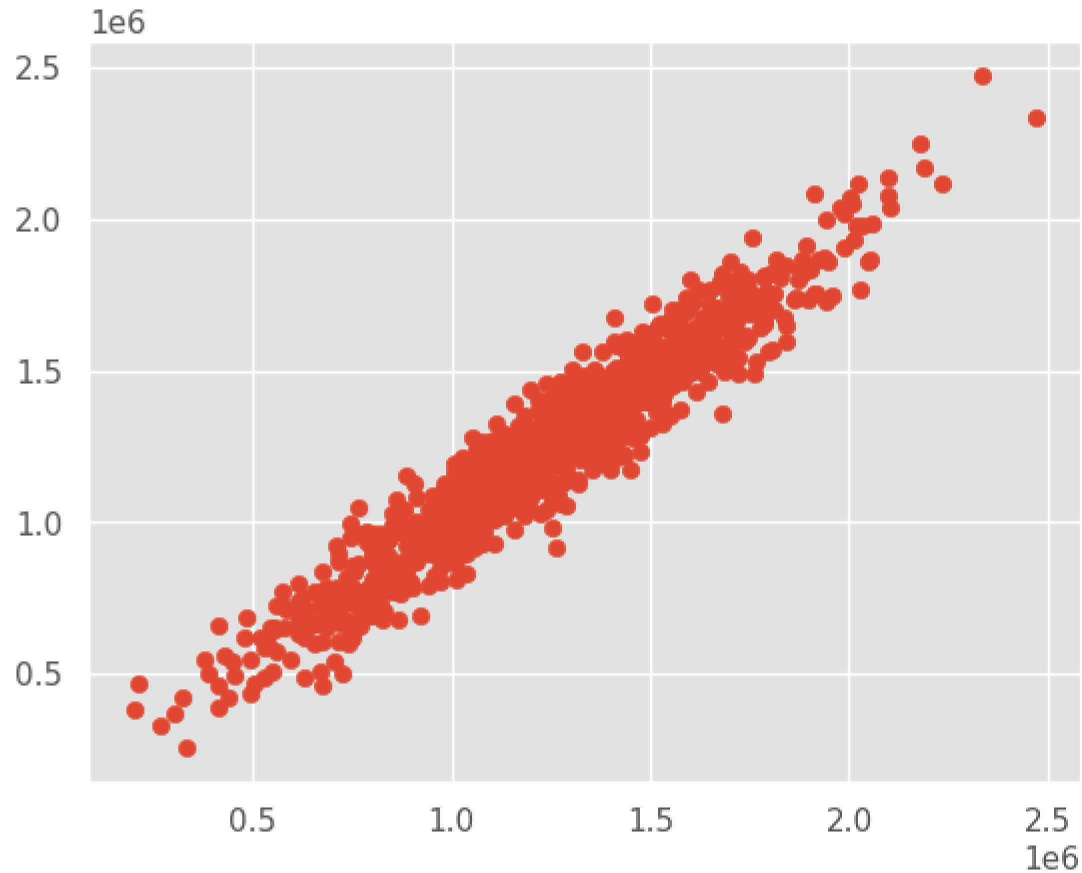
Predictions from our Model

Let's grab predictions off our test set and see how well it did!

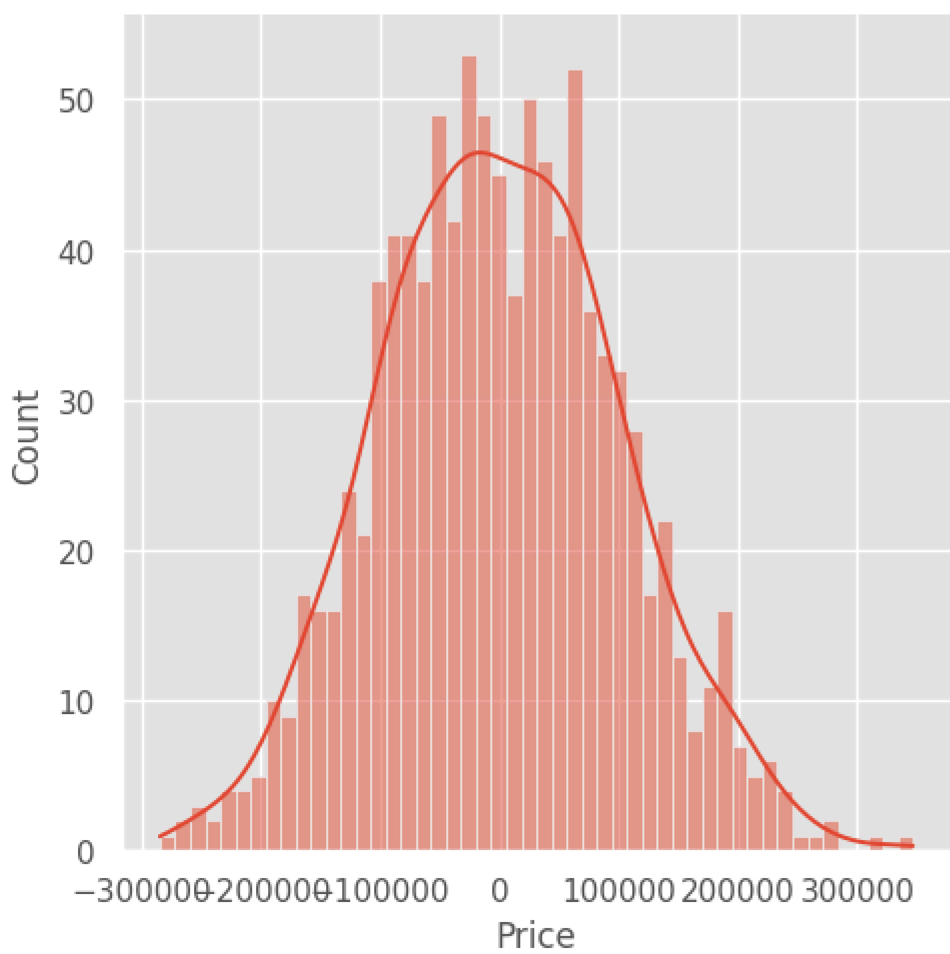
```
pred = lin_reg.predict(X_test)
```

```
plt.scatter(y_test, pred)
```

```
<matplotlib.collections.PathCollection at 0x7bfff7ad5b40>
```



```
sns.displot((y_test - pred), bins=50, kde=True)  # Replace with your data and parameters
plt.show()  # Display the plot
```




```
#Displaying Evaluation of Model
test_pred = lin_reg.predict(X_test)
train_pred = lin_reg.predict(X_train)

print('Test set evaluation:\n_____________________________________')
evaluate(y_test, test_pred)
print('Train set evaluation:\n_____________________________________')
evaluate(y_train, train_pred)
```

```
Test set evaluation:
_____________________________________
MAE: 80879.09723489445
MSE: 10089009300.89399
RMSE: 100444.06055558482
MAPE: 7.387838859754366
R2 Square: 0.9179971706834331
__________________________________
Train set evaluation:
_____________________________________
MAE: 81509.3933124445
MSE: 10256318867.482723
RMSE: 101273.48551068401
MAPE: 7.682929604751326
R2 Square: 0.9179787435623722
__________________________________
(81509.3933124445,
 10256318867.482723,
 101273.48551068401,
 7.682929604751326,
 0.9179787435623722)
```

```
results_df = pd.DataFrame(data=[["Linear Regression", *evaluate(y_test, test_pred), cross_val(LinearRegression(), X_train, y
                          columns=['Model', 'MAE', 'MSE', 'RMSE', 'MAPE', 'R2 Square', 'Cross Validation'])

# Display the results_df
results_df
```

```
MAE: 80879.09723489445
MSE: 10089009300.89399
RMSE: 100444.06055558482
MAPE: 7.387838859754366
R2 Square: 0.9179971706834331
```