BUSINESS UNDERSTANDING

The objective of this assessment is to predict the prices of housing in a simulated market based on the Linear Regression model. The goal of this assessment is to evaluate the price of a house based on its size, number of bedrooms, how old the house is, and the distance to the city center. Using the data set provided, the outcome of this assessment is to understand the relationship between these factors and housing prices, and to make informed predictions about the value of properties in the simulated market.

DATA UNDERSTANDING:

Features:

House_Size: Size of the house in square meters.

Num_Bedrooms: Number of bedrooms in the house.

House_Age: Age of the house in years.

Distance_to_City: Distance to the city center in kilometers.

Target:

Price: Predicted price of the house in a simulated market.

```
#Import necessary libraries import pandas as pd import
matplotlib.pyplot as plt from sklearn.linear_model
import LinearRegression from sklearn.preprocessing
import StandardScaler from sklearn.metrics import
mean_squared_error, r2_score

# Load data from CSV train_data =
pd.read_csv("/content/real_estate_training_data.csv") score_data =
pd.read_csv("/content/real_estate_scoring_data.csv")
train_data.head()
```

	House_Size	Num_Bedrooms	House_Age	Distance_to_City	Price
0	61.612603	3	21.214844	23.659116	5.065851e+05
1	286.191432	3	36.493015	3.765776	1.552872e+06
2	202.655011	2	2.887053	28.652518	1.192197e+06
3	57.1956692		45.016063	25.724964	2.908226e+05
4	278.711475	4	28.590458	29.667128	1.731602e+06

Next steps: Generate code with train_data View recommended plots New interactive sheet

```
train_data.info()
train_data.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800 entries, 0 to 799
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
0   House_Size        800 non-null    float64
1   Num_Bedrooms      800 non-null    int64
2   House_Age         800 non-null    float64
3   Distance_to_City  800 non-null    float64
    4   Price             800 non-null
    float64 dtypes: float64(4), int64(1)
    memory usage: 31.4 KB
```

	House_Size	Num_Bedrooms	House_Age	Distance_to_City	Price
count	800.000000	800.000000	800.000000	800.000000	8.000000e+02
mean	173.829065	3.055000	25.563417	15.827001	1.067202e+06
std	73.195773	1.430746	14.514750	8.141743	3.975056e+05
min	51.158006	1.000000	0.009420	1.012841	1.951062e+05
25%	109.999922	2.000000	12.826628	9.148973	7.503198e+05
50%	175.664515	3.000000	26.518222	15.939974	1.071068e+06

75%	237.171221	4.000000	37.751604	22.833444	1.373069e+06
max	299.929418	5.000000	49.985690	29.986774	1.970344e+06

```
score_data.head()
```

	House_Size	Num_Bedrooms	House_Age	Distance_to_City
0	145.222714	2	13.891104	3.030102
1	254.149860	2	26.361309	14.773578
2	165.669946	5	40.989890	3.169815
3	139.024181	5	41.927461	13.848722
4	287.515492	4	19.487969	11.832085

Next steps: Generate code with score_data | View recommended plots | New interactive sheet

```
score_data.info()
score_data.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
0   House_Size        200 non-null    float64
1   Num_Bedrooms      200 non-null    int64
2   House_Age         200 non-null    float64
    3   Distance_to_City  200 non-null
    float64 dtypes: float64(3), int64(1)
    memory usage: 6.4 KB
```

	House_Size	Num_Bedrooms	House_Age	Distance_to_City
count	200.000000	200.00000	200.000000	200.000000
mean	167.504432	2.97000	23.772490	16.271103
std	72.345535	1.43506	15.044703	8.553506
min	51.265396	1.00000	0.093994	1.186621
25%	105.053554	2.00000	9.503693	9.365798
50%	167.207506	3.00000	22.538745	16.989464
75%	227.269489	4.00000	36.870737	23.779201
max	297.513463	5.00000	49.806147	29.895551

DATA PREPARATION

When using linear regression as a predictive model, it is extremely important to remember that the ranges for all attributes in the scoring data must be within the ranges for the corresponding attributes in the training data. This is because a training data set cannot be relied upon to predict a target attrtibute for observations whose values fall outside the training data set's values.

```
# Check for missing values print("Missing values in training data:\n",
train_data.isnull().sum())
# Normalize the features (optional, if needed)
scaler = StandardScaler()
X_train = scaler.fit_transform(train_data.drop(columns=["Price"]))
y_train = train_data["Price"]
X_score = scaler.transform(score_data)
```

```
Missing values in training data:
 House_Size          0
Num_Bedrooms        0
House_Age           0
Distance_to_City    0
Price               0
dtype: int64
```

MODELING

Linear regression modeling is all about determing how close a given observation is to an imaginary line representing the average, or center of all points in the data set. That imaginary line gives us the rst part of the term “linear regression”. The formula for calculating a prediction using linear regression is y=mx+b. You may recognize this from a former algebra class as the formula for calculating the slope of a line. In this formula, the variable y, is the target, the label, the thing we want to predict. So in this example, y is the amount of Heating_Oil we expect each home to consume. But how will we predict y? We need to know what m, x, and b are. The variable m is the value for a given predictor attribute, or what is sometimes referred to as an independent variable. The variable x is that attribute's coe cient. The variable b is a constant that is added to all linear regression calculations. It is represented by the Intercept.

```
# Train the model model =
LinearRegression()
model.fit(X_train, y_train)
# Predict on training data to evaluate the model
train_predictions = model.predict(X_train)
# Evaluate the model mse =
mean_squared_error(y_train, train_predictions) r2 =
r2_score(y_train, train_predictions)
print(f"Model Performance on Training Data:\nMSE: {mse:.2f}\nR^2: {r2:.2f}")
```

```
Model Performance on Training Data:
MSE: 2414820194.45
R^2: 0.98
```

```
# Predict on the scoring dataset
score_predictions = model.predict(X_score)
# Save the predictions score_data["Predicted_Price"]
= score_predictions
score_data.to_csv("scoring_results.csv", index=False)
print("Predictions saved to scoring_results.csv")
```

```
Predictions saved to scoring_results.csv
```

```
scoring_results = pd.read_csv("/content/scoring_results.csv")
```

```
scoring_results.describe()
```

1 to 8 of 8 entries Filter

index	House_Size	Num_Bedrooms	House_Age	Distance_to_City	Predicted_Price
count	200.0	200.0	200.0	200.0	200.0
mean	167.5044318017525	2.97	23.77248998205692	16.27110342033981	1031820.1620299238
std	72.34553529503616	1.435059923809673	15.044702992965899	8.553505649097838	390998.9578547579
min	51.265395961554674	1.0	0.093994176245532	1.1866211334070758	203767.8012867599
25%	105.05355402435032	2.0	9.503692502092607	9.365797525367494	721498.5514394378
50%	167.2075056503568	3.0	22.53874471071435	16.989464084927242	1039679.1284677077
75%	227.26948910251616	4.0	36.87073722722393	23.779201400642663	1322834.7044843948
max	297.51346252606584	5.0	49.80614748197205	29.89555051669261	1859654.4816482223

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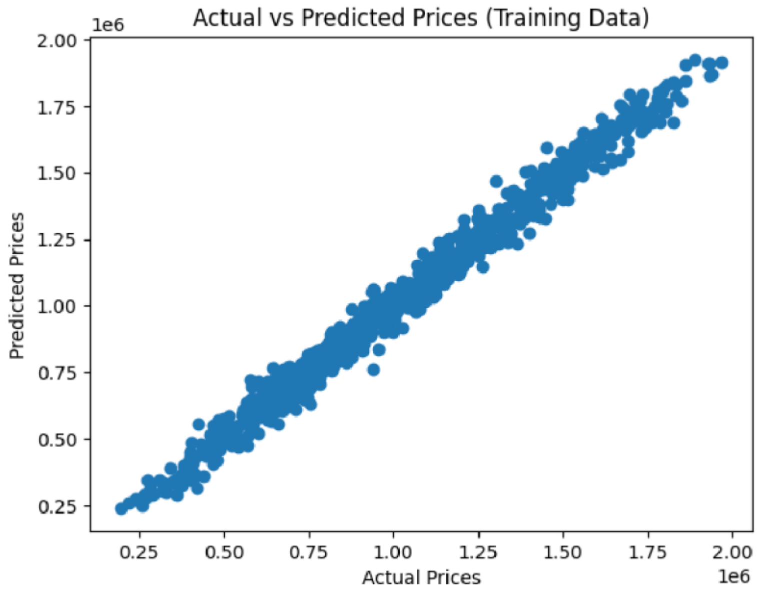
Like what you see? Visit the data table notebook to learn more about interactive tables.

```
# Scatter plot of actual vs predicted prices
plt.scatter(y_train, train_predictions)
plt.xlabel("Actual Prices") plt.ylabel("Predicted
Prices") plt.title("Actual vs Predicted Prices
(Training Data)")
```

```
plt.show()
```




```
**FINDINGS**

The predicted housing prices in the dataset show significant variability,
ranging from 203,768 to 1,859,654, with an average predicted price of
approximately 1,031,820. Larger houses, newer constructions, and those closer
to the city center generally have higher predicted prices, while smaller,
older, and more remote properties tend to have lower values. The significant
standard deviation in predicted prices suggests that these factors collectively
contribute to a complex price determination process.
```

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