------ Linear Regression ------

Connecting with Drive

from google.colab import drive
drive.mount('/content/drive')

→ Mounted at /content/drive

Import necessary libraries

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.feature_selection import chi2
from sklearn.preprocessing import StandardScaler, LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns

dataset = pd.read_csv('_content/drive/MyDrive/ML Project/Bengaluru_House_Data.csv')
dataset.head()

| ₹ | | area_type | availability | location | size | society | total_sqft | bath | balcony | price | |
|---|---|---------------------|---------------|--------------------------|-----------|---------|------------|------|---------|--------|-----|
| | 0 | Super built-up Area | 19-Dec | Electronic City Phase II | 2 BHK | Coomee | 1056 | 2.0 | 1.0 | 39.07 | ılı |
| | 1 | Plot Area | Ready To Move | Chikka Tirupathi | 4 Bedroom | Theanmp | 2600 | 5.0 | 3.0 | 120.00 | |
| | 2 | Built-up Area | Ready To Move | Uttarahalli | 3 BHK | NaN | 1440 | 2.0 | 3.0 | 62.00 | |
| | 3 | Super built-up Area | Ready To Move | Lingadheeranahalli | 3 BHK | Soiewre | 1521 | 3.0 | 1.0 | 95.00 | |
| | 4 | Super built-up Area | Ready To Move | Kothanur | 2 BHK | NaN | 1200 | 2.0 | 1.0 | 51.00 | |
| | | | | | | | | | | | |

Next steps:

Generate code with dataset



New interactive sheet

Data Cleaning

dataset.drop_duplicates(inplace=True)
dataset.dropna(subset=['total_sqft', 'size', 'price'], inplace=True)

dataset.head()

| _ | | area_type | availability | location | size | society | total_sqft | bath | balcony | price | |
|--------------|---|---------------------|---------------|--------------------------|-----------|---------|------------|------|---------|--------|-----|
| | 0 | Super built-up Area | 19-Dec | Electronic City Phase II | 2 BHK | Coomee | 1056 | 2.0 | 1.0 | 39.07 | ıl. |
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Next steps:

Generate code with dataset



New interactive sheet

Convert 'size' to number of bedrooms

Convert 'total_sqft' to a numeric value

```
def convert_sqft_to_num(x):
    if '-' in str(x):
        tokens = x.split('-')
        return (float(tokens[0]) + float(tokens[1])) / 2
    try:
        return float(x)
    except:
        return None

dataset['total_sqft'] = dataset['total_sqft'].apply(convert_sqft_to_num)
dataset.dropna(inplace=True)
```

Log-transform the 'price' column to reduce range

dataset['price'] = np.log1p(dataset['price'])
dataset.head()

| ₹ | area_t | ype | availability | location | size | society | total_sqft | bath | balcony | price | |
|---------|------------------|----------------------------|---------------|--------------------------|------|---------|-----------------------|------|---------|----------|-----|
| 0 | Super built-up A | Area | 19-Dec | Electronic City Phase II | 2 | Coomee | 1056.0 | 2.0 | 1.0 | 3.690628 | ıl. |
| 1 | Plot A | Area | Ready To Move | Chikka Tirupathi | 4 | Theanmp | 2600.0 | 5.0 | 3.0 | 4.795791 | |
| 3 | Super built-up A | Area | Ready To Move | Lingadheeranahalli | 3 | Soiewre | 1521.0 | 3.0 | 1.0 | 4.564348 | |
| 5 | Super built-up A | Area | Ready To Move | Whitefield | 2 | DuenaTa | 1170.0 | 2.0 | 1.0 | 3.663562 | |
| 11 | Plot A | Area | Ready To Move | Whitefield | 4 | Prrry M | 2785.0 | 5.0 | 3.0 | 5.690359 | |
| | | | | | | | | | | | |
| Next st | eps: Generate | Generate code with dataset | | View recommended plots | | New | New interactive sheet | | | | |

Handle categorical variable 'location'

```
location\_counts = dataset['location'].value\_counts() \\ dataset['location'] = dataset['location'].apply(lambda x: x if location\_counts[x] > 10 else 'Other')
```

Check if 'location' exists, then encode it

```
label_encoder = LabelEncoder()
if 'location' in dataset.columns:
    dataset['location_encoded'] = label_encoder.fit_transform(dataset['location'])
```

dataset.head()



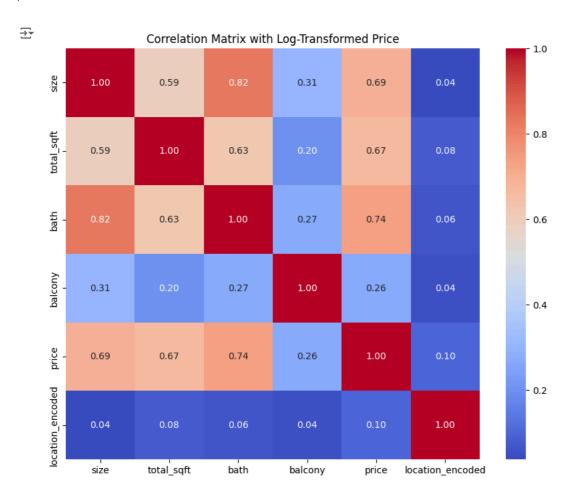
Double-click (or enter) to edit

Ensure only numeric columns are included for the correlation matrix

numeric_data = dataset.select_dtypes(include=[np.number])

Correlation Matrix for Numerical Features

```
plt.figure(figsize=(10, 8))
sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix with Log-Transformed Price")
plt.show()
```



Drop columns with low correlation to 'price' in the main dataset

correlation_matrix = numeric_data.corr()
low_correlation_features = correlation_matrix.index[abs(correlation_matrix['price']) < 0.1]
dataset = dataset.drop(columns=low_correlation_features)</pre>

dataset.head()



One-hot encode remaining categorical variables

dataset = pd.get_dummies(dataset, columns=['location', 'area_type', 'availability', 'society'], drop_first=True)

Define features and target variable

```
X = dataset.drop(['price'], axis=1)
y = dataset['price']
```

Standardize features

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Split data into training and testing sets

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

Model Training with Linear Regression

Predict on test set and convert predictions back to original scale

```
y_pred = model.predict(X_test)
y_test_exp = np.expm1(y_test)  # Convert log-transformed prices back to original scale
y_pred_exp = np.exp(y_pred)
```

Evaluate the model on the original scale

```
mae = mean_absolute_error(y_test_exp, y_pred_exp)
rmse = np.sqrt(mean_squared_error(y_test_exp, y_pred_exp))
print(f"Mean Absolute Error (MAE): {mae}")
print(f"Root Mean Squared Error (RMSE): {rmse}")

Mean Absolute Error (MAE): 18.2681967684906
Root Mean Squared Error (RMSE): 55.51325389232715
```

Plot Actual vs Predicted values on original scale

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test_exp, y_pred_exp, alpha=0.7)
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual vs Predicted Prices")
plt.show()
```



Actual vs Predicted Prices

