

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

```
In [2]: df = pd.read_csv("Housing.csv")
df.head()
```

Out[2]:

|   | price    | area | bedrooms | bathrooms | stories | mainroad | guestroom | basement | hotw |
|---|----------|------|----------|-----------|---------|----------|-----------|----------|------|
| 0 | 13300000 | 7420 | 4        | 2         | 3       | yes      | no        | no       | no   |
| 1 | 12250000 | 8960 | 4        | 4         | 4       | yes      | no        | no       | no   |
| 2 | 12250000 | 9960 | 3        | 2         | 2       | yes      | no        | yes      | yes  |
| 3 | 12215000 | 7500 | 4        | 2         | 2       | yes      | no        | yes      | yes  |
| 4 | 11410000 | 7420 | 4        | 1         | 2       | yes      | yes       | yes      | yes  |



```
In [21]: binary_cols = ['mainroad', 'guestroom', 'basement', 'hotwaterheating', 'airconditioning']
for col in binary_cols:
    df[col] = df[col].map({'yes': 1, 'no': 0})
    df[col] = df[col].fillna(0)

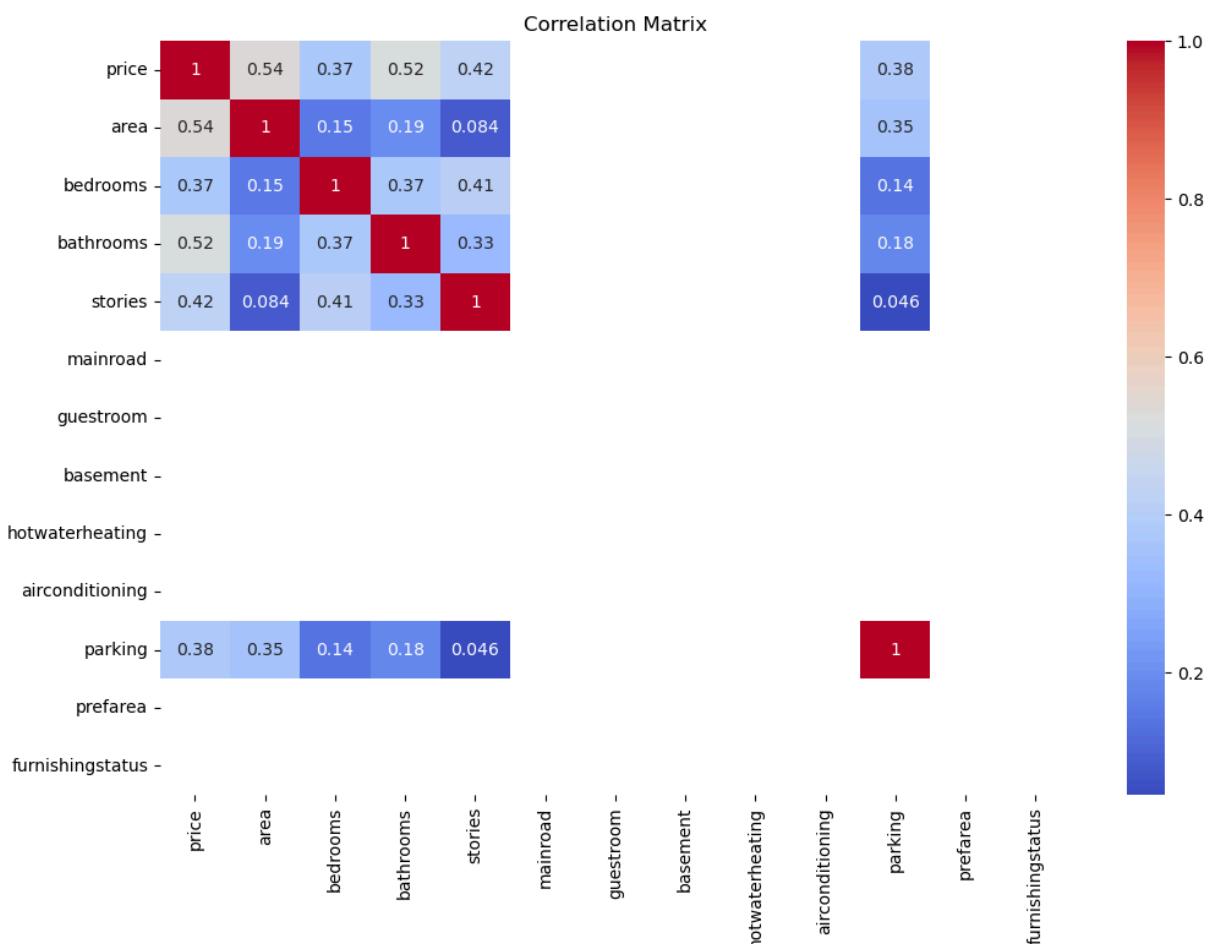
df['furnishingstatus'] = df['furnishingstatus'].map({'unfurnished': 0, 'semi-furnished': 1, 'furnished': 2})
df['furnishingstatus'] = df['furnishingstatus'].fillna(0)
```

```
In [22]: df.isnull().sum()
```

Out[22]:

|                  |   |
|------------------|---|
| price            | 0 |
| area             | 0 |
| bedrooms         | 0 |
| bathrooms        | 0 |
| stories          | 0 |
| mainroad         | 0 |
| guestroom        | 0 |
| basement         | 0 |
| hotwaterheating  | 0 |
| airconditioning  | 0 |
| parking          | 0 |
| prefarea         | 0 |
| furnishingstatus | 0 |
| dtype: int64     |   |

```
In [23]: plt.figure(figsize=(12,8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Matrix")
plt.show()
```



```
In [24]: X = df.drop('price', axis=1)
y = df['price']
```

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In [25]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

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In [26]: model = LinearRegression()
model.fit(X_train, y_train)
```

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Out[26]: ▾ LinearRegression ⓘ ?
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LinearRegression()
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In [27]: from sklearn.metrics import mean_absolute_error

y_pred = model.predict(X_test)

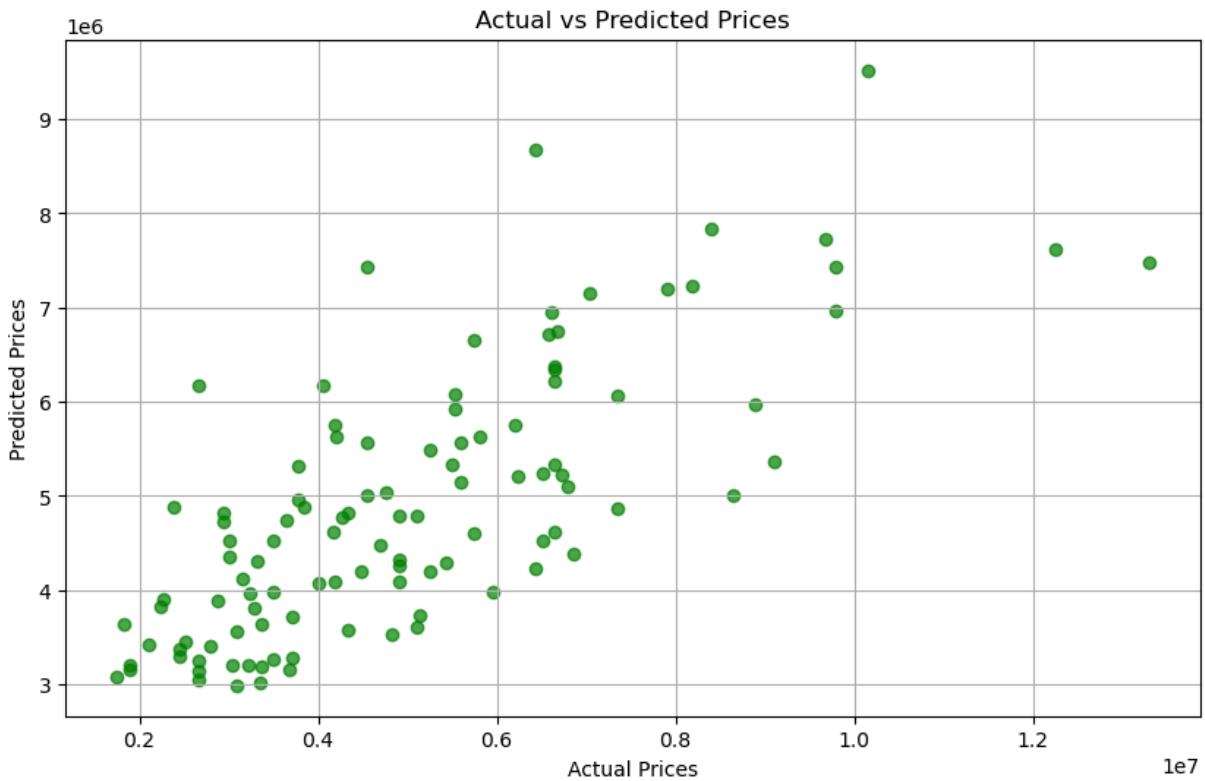
print("R² Score:", r2_score(y_test, y_pred))
print("Mean Squared Error:", mean_squared_error(y_test, y_pred))
print("Mean Absolute Error:", mean_absolute_error(y_test, y_pred))
```

R<sup>2</sup> Score: 0.5464062355495873

Mean Squared Error: 2292721545725.3613

Mean Absolute Error: 1127483.3523235186

```
In [28]: plt.figure(figsize=(10,6))
plt.scatter(y_test, y_pred, alpha=0.7, color='green')
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual vs Predicted Prices")
plt.grid(True)
plt.show()
```



```
In [29]: # Final Recommendations & Insights
"""
- Area and number of stories show strong positive correlation with house price.
- Features like air conditioning, guestroom, and hot water heating significantly increase property value.
- The model explains approximately 54.6% of the variance in price ( $R^2 = 0.546$ ).
- The average absolute error is around 1.12 million, which is reasonable given the scale of real estate prices.
- Model performance can be improved using more advanced algorithms such as Random Forest.
"""
```

```
Out[29]: '\n- Area and number of stories show strong positive correlation with house price.\n- Features like air conditioning, guestroom, and hot water heating significantly increase property value.\n- The model explains approximately 54.6% of the variance in price ( $R^2 = 0.546$ ).\n- The average absolute error is around 1.12 million, which is reasonable given the scale of real estate prices.\n- Model performance can be improved using more advanced algorithms such as Random Forest or Gradient Boosting.\n'
```

```
In [ ]: # Project Summary: House Price Prediction
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This project uses Linear Regression to predict house prices based on various features. Further improvements could include using more advanced models like Random Forest or Gradient Boosting.