Importing the library

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
```

Importing DataSet

In [3]:

```
data = pd.read_csv("E:\Housing.csv")
```

Display first few rows of the dataframe :

In [4]:

```
data.head()
```

Out[4]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditio
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	no	
3	12215000	7500	4	2	2	yes	no	yes	no	
4	11410000	7420	4	1	2	yes	yes	yes	no	

Display last few row of dataframe :

In [5]:

```
data.tail()
```

Out[5]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditi
540	1820000	3000	2	1	1	yes	no	yes	no	
541	1767150	2400	3	1	1	no	no	no	no	
542	1750000	3620	2	1	1	yes	no	no	no	
543	1750000	2910	3	1	1	no	no	no	no	
544	1750000	3850	3	1	2	yes	no	no	no	

Shape of data:

In [6]:

```
data.shape
```

Out[6]:

```
(545, 13)
```

idenfying the information of dataframe :

In [7]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 545 entries, 0 to 544
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   price             545 non-null    int64 
 1   area              545 non-null    int64 
 2   bedrooms          545 non-null    int64 
 3   bathrooms         545 non-null    int64 
 4   stories           545 non-null    int64 
 5   mainroad          545 non-null    object
 6   guestroom         545 non-null    object
 7   basement          545 non-null    object
 8   hotwaterheating   545 non-null    object
 9   airconditioning   545 non-null    object
 10  parking           545 non-null    int64 
 11  prefarea          545 non-null    object
 12  furnishingstatus  545 non-null    object
dtypes: int64(6), object(7)
memory usage: 55.5+ KB
```

Display columns of data frame :

In [8]:

```
data.columns
```

Out[8]:

```
Index(['price', 'area', 'bedrooms', 'bathrooms', 'stories', 'mainroad',
       'guestroom', 'basement', 'hotwaterheating', 'airconditioning',
       'parking', 'prefarea', 'furnishingstatus'],
      dtype='object')
```

Show the statistical summary of the column of our data :

In [9]:

```
data.describe(include='all')
```

Out[9]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwa
count	5.450000e+02	545.000000	545.000000	545.000000	545.000000	545	545	545	
unique	NaN	NaN	NaN	NaN	NaN	2	2	2	
top	NaN	NaN	NaN	NaN	NaN	yes	no	no	
freq	NaN	NaN	NaN	NaN	NaN	468	448	354	
mean	4.766729e+06	5150.541284	2.965138	1.286239	1.805505	NaN	NaN	NaN	
std	1.870440e+06	2170.141023	0.738064	0.502470	0.867492	NaN	NaN	NaN	
min	1.750000e+06	1650.000000	1.000000	1.000000	1.000000	NaN	NaN	NaN	
25%	3.430000e+06	3600.000000	2.000000	1.000000	1.000000	NaN	NaN	NaN	
50%	4.340000e+06	4600.000000	3.000000	1.000000	2.000000	NaN	NaN	NaN	
75%	5.740000e+06	6360.000000	3.000000	2.000000	2.000000	NaN	NaN	NaN	
max	1.330000e+07	16200.000000	6.000000	4.000000	4.000000	NaN	NaN	NaN	

Checking the Null Values

In [10]:

```
data.isnull().sum()
```

Out[10]:

```
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
```

The inference we can make after checking for null values and finding that there are no null values in any of the columns is that the dataset is complete in term of missing values.

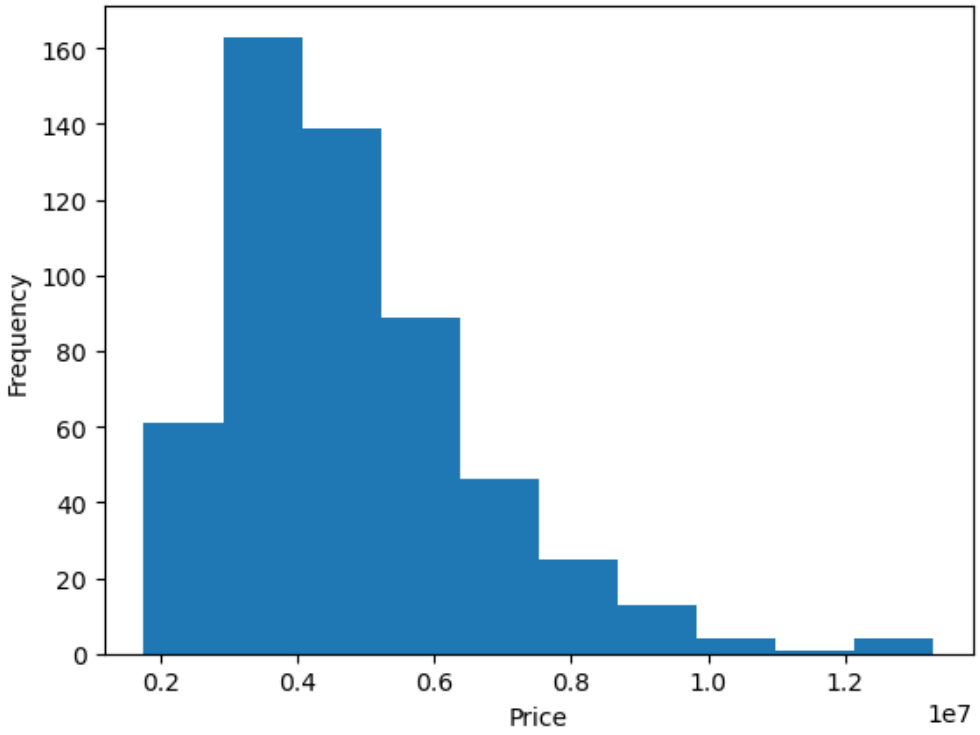
Having no null values is beneficial because it allows us to work with the entire dataset without the need for imputation or handling missing data. we can proceed with further data analysis, visualization, and modeling.

Performing EDA

Histogram of Price

In [12]:

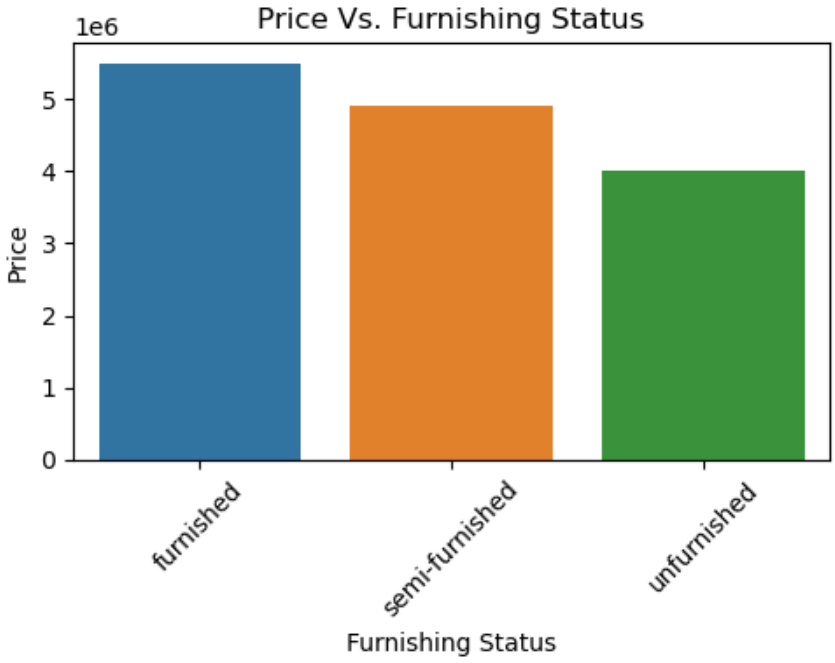
```
plt.hist(data['price'])
plt.xlabel('Price')
plt.ylabel('Frequency')

plt.show()
```



Price VS Furnishing Status

In [14]:

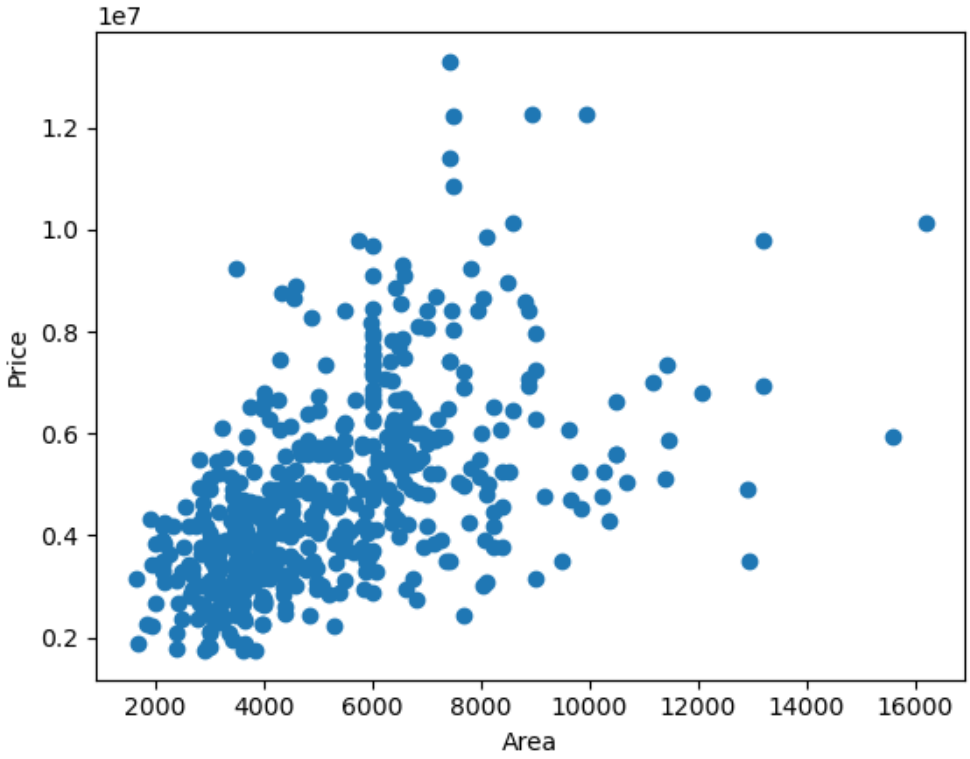
```
plt.figure(figsize=(5,4))
sns.barplot(data=data, x='furnishingstatus', y='price', errorbar=None)
plt.xlabel('Furnishing Status')
plt.ylabel('Price')
plt.title('Price Vs. Furnishing Status')
plt.xticks(rotation=45)  # Rotate x axis labels for better readability
plt.tight_layout()
plt.show()
```



Scatter plot of Area Vs Price

In [15]:

```
plt.scatter(data['area'], data['price'])
plt.xlabel('Area')
plt.ylabel('Price')
plt.show()
```

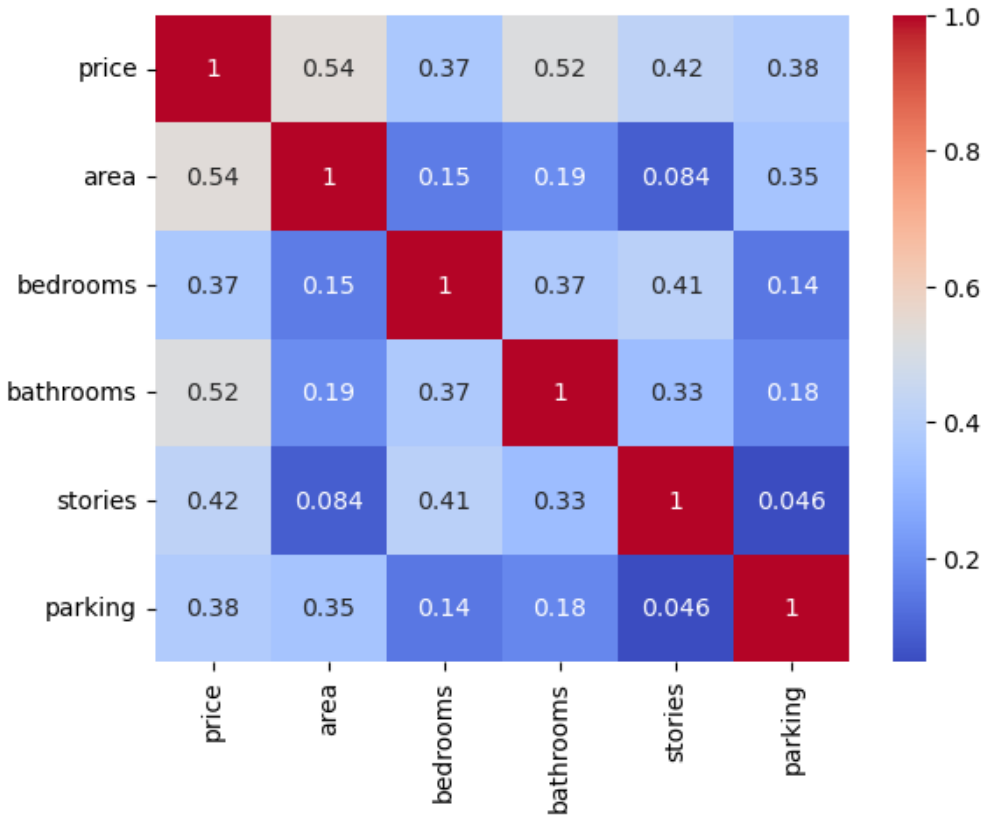


Heatmap of Correlation Matrix

In [16]:

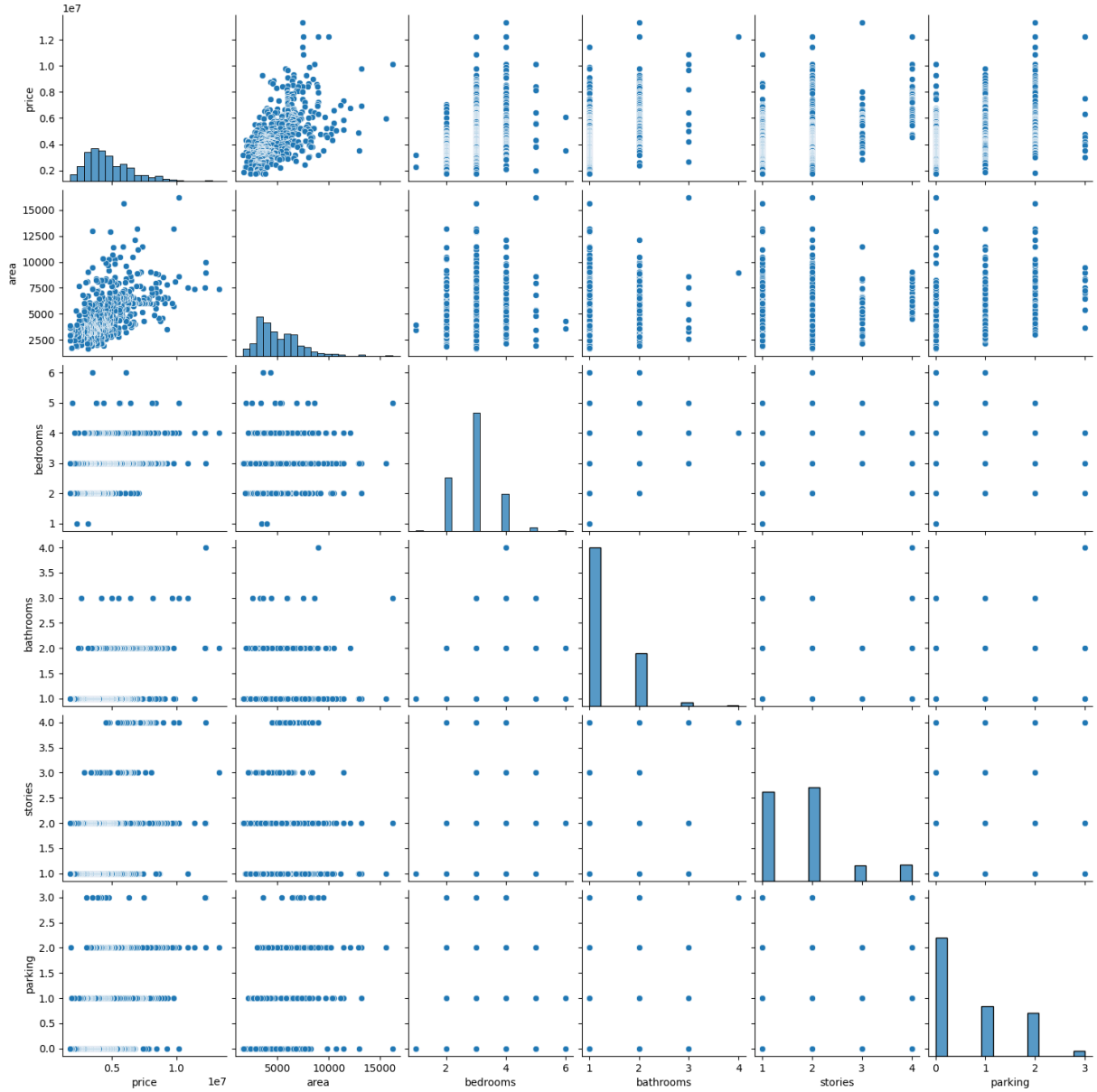
```
correlation_matrix = data.corr()
sns.heatmap(correlation_matrix, annot = True,cmap='coolwarm')
plt.show()
```

```
C:\Users\meanu\AppData\Local\Temp\ipykernel_9772\1471923354.py:1: FutureWarning: The defau
lt value of numeric_only in DataFrame.corr is deprecated. In a future version, it will def
ault to False. Select only valid columns or specify the value of numeric_only to silence t
his warning.
  correlation_matrix = data.corr()
```



In [17]:

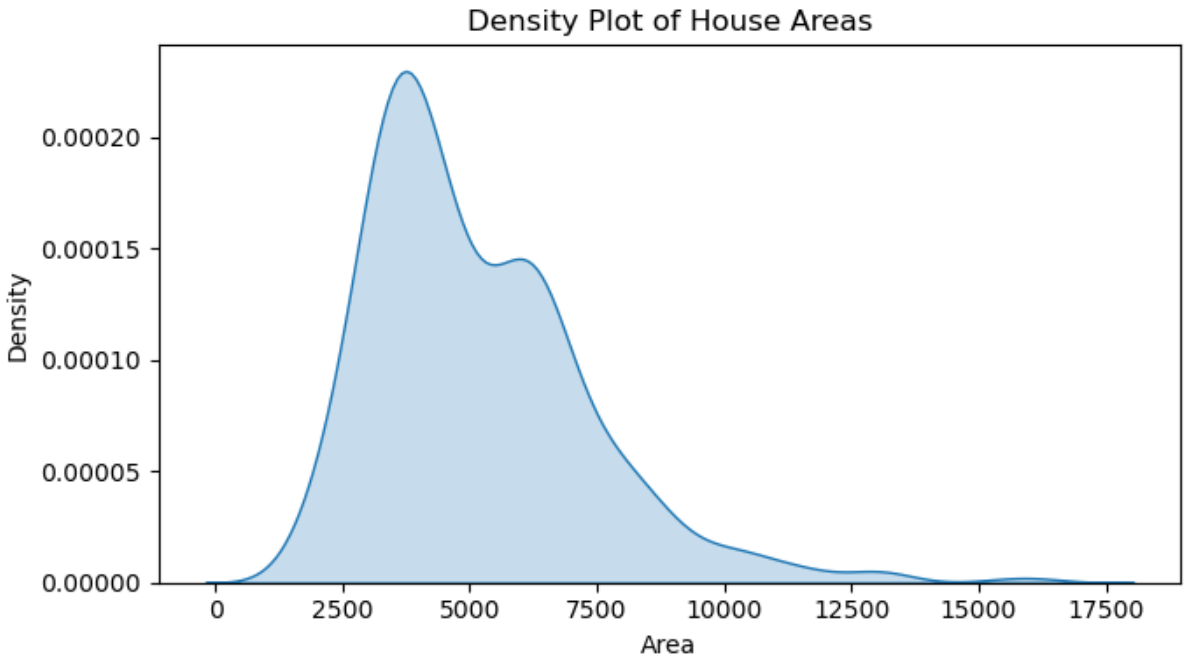
```
sns.pairplot(data)
plt.show()
```



Density Plot of House Areas

In [18]:

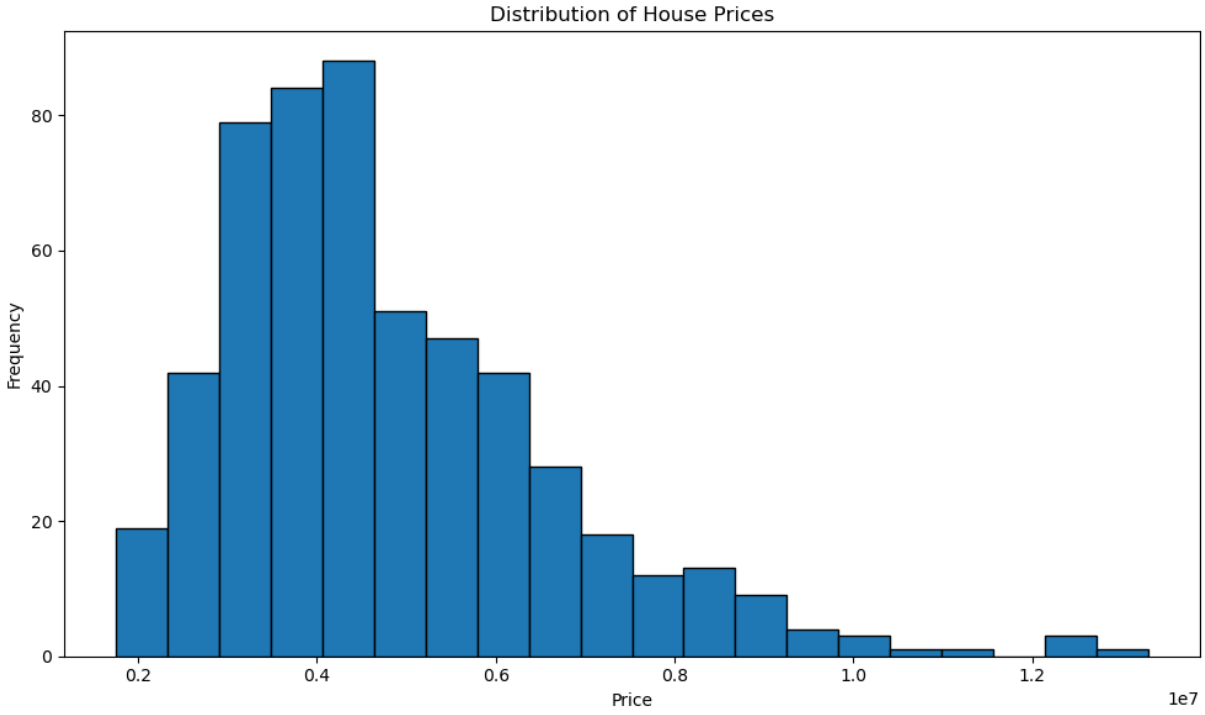
```
plt.figure(figsize=(7,4))
sns.kdeplot(data['area'], fill=True)
plt.title('Density Plot of House Areas')
plt.xlabel('Area')
plt.ylabel('Density')
plt.tight_layout()
plt.show()
```



Distribution of House Prices

In [19]:

```
plt.figure(figsize=(10,6))
plt.hist(data['price'], bins=20, edgecolor='black')
plt.title('Distribution of House Prices')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



Data Cleaning and Prepration

1. Handling Binary Category Variables :

Some column like 'mainroad', 'guestroom', 'basement', 'hotwaterheating', 'airconditioning',and 'prefarea' have "yes" and "no" values.

we'll convert these into numbers: "yes" becomes , and "no" becomes 0.

This change help us use them as binary variables for analysis and modeling.

2. Creating Dummy Variables :

The 'furnishingstatus' clumn shows how a house is furnished : "unfurnished", "semi-furnished" or "fully furnished".

To use this information in analysis and modeling, we'll create dummy variables.

Dummy variables are like switches : for each category , we'll have a new column where 1 means that category is present , and 0 means it's not.

This let us include furnishing status as valuable data for our analysis.

Handling Binary Categorical Variables (Yes/No) categories

In [21]:

```
# list of categorical columns containing 'yes' and 'no' values.

categorical_col = ['mainroad', 'guestroom', 'basement', 'hotwaterheating', 'airconditioning', 'prefarea']
```

In [22]:

```
data[categorical_col]
```

Out[22]:

	mainroad	guestroom	basement	hotwaterheating	airconditioning	prefarea
0	yes	no	no	no	yes	yes
1	yes	no	no	no	yes	no
2	yes	no	yes	no	no	yes
3	yes	no	yes	no	yes	yes
4	yes	yes	yes	no	yes	no
...	...	...	...	...	...	...
540	yes	no	yes	no	no	no
541	no	no	no	no	no	no
542	yes	no	no	no	no	no
543	no	no	no	no	no	no
544	yes	no	no	no	no	no

545 rows × 6 columns

In [25]:

```
def binary_map(x):
    """
    Function to map 'yes' or 'no' values to 1 and 0 , respectively.

    parameter:
    x(pandas series) : input series containing 'yes' and 'no' values.

    Returns:
    pandas series: Mapped series with 'yes' mapped to 1 and 'no' mapped to 0.
    """

    return x.map({'yes': 1, 'no': 0})
```

In [27]:

```
# Apply the binary_map functtion to mulptiple categorical column in the dataframe .

data[categorical_col] = data[categorical_col].apply(binary_map)

# Display the updated values of the categorical columns
data[categorical_col]
```

Out[27]:

	mainroad	guestroom	basement	hotwaterheating	airconditioning	prefarea
0	1	0	0	0	1	1
1	1	0	0	0	1	0
2	1	0	1	0	0	1
3	1	0	1	0	1	1
4	1	1	1	0	1	0
...	...	...	...	...	...	...
540	1	0	1	0	0	0
541	0	0	0	0	0	0
542	1	0	0	0	0	0
543	0	0	0	0	0	0
544	1	0	0	0	0	0

545 rows × 6 columns

Display the first five rows of the DataFrame after the conversions

In [28]:

```
data.head()
```

Out[28]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditioi
0	13300000	7420	4	2	3	1	0	0	0	
1	12250000	8960	4	4	4	1	0	0	0	
2	12250000	9960	3	2	2	1	0	1	0	
3	12215000	7500	4	2	2	1	0	1	0	
4	11410000	7420	4	1	2	1	1	1	0	

Handling Categorical data with dummy variables:

In [29]:

```
dummy_col = pd.get_dummies(data['furnishingstatus'])

#display the first five row of the dummy variables DataFrame
dummy_col.head()
```

Out[29]:

	furnished	semi-furnished	unfurnished
0	1	0	0
1	1	0	0
2	0	1	0
3	1	0	0
4	1	0	0

Furnished will be 00 and to avoid redundency we drop it. semi-furnihed will be 10 and unfurnished will be 01

In [30]:

```
# regarding dummy variables for the 'furnishingstatus' column dropping first category

dummy_col = pd.get_dummies(data['furnishingstatus'], drop_first=True)


# Display the first five rows of the dummy variables DataFrame
dummy_col.head()
```

Out[30]:

	semi-furnished	unfurnished
0	0	0
1	0	0
2	1	0
3	0	0
4	0	0

Why dropped first category among three? When creating dummy variables for these categories, dropping the first category ('furnished') among the three would be appropriate. This is because we want to avoid the dummy variable trap or multicollinearity in regression models.

By dropping the first category, 'furnished', we create two dummy variables: 'semi-furnished' and 'unfurnished'. These two variables will capture the presence or absence of 'semi-furnished' and 'unfurnished' categories relative to the baseline category, which is 'furnished'.

Consider the following example:

Original 'furnishingstatus' column:

```
Index furnishingstatus:
```

0 furnished

1 semi-furnished

2 unfurnished

3 furnished

4 semi-furnished

After creating dummy variables and dropping ‘furnished’:

```
    Index semi-furnished unfurnished
```

0 0 0

1 1 0

2 0 1

3 0 0

4 1 0

Here, the first row with ‘semi-furnished’ and ‘unfurnished’ as both 0 indicates that it corresponds to the dropped category ‘furnished’. The presence or absence of ‘semi-furnished’ and ‘unfurnished’ is captured by the values in the respective dummy variables.

By dropping the first category, we ensure linear independence among the dummy variables, which helps avoid multicollinearity and allows for proper interpretation of the coefficients associated with each category in the regression model.

In [31]:

```
#Concatenate the original 'data' DAtaFrame with the dummy_col DataFrame along columns

data= pd.concat([data, dummy_col], axis=1)

#Display the first few rows of the updated DataFrame
data.head()
```

Out[31]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditio
0	13300000	7420	4	2	3	1	0	0	0	
1	12250000	8960	4	4	4	1	0	0	0	
2	12250000	9960	3	2	2	1	0	1	0	
3	12215000	7500	4	2	2	1	0	1	0	
4	11410000	7420	4	1	2	1	1	1	0	

In [32]:

```
# Drop the 'furnushingstatus' column from the DataFrame
data.drop(['furnishingstatus'],axis=1, inplace=True)

# Display the fist few rows of the updated DataFrame
data.head()
```

Out[32]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditio
0	13300000	7420	4	2	3	1	0	0	0	
1	12250000	8960	4	4	4	1	0	0	0	
2	12250000	9960	3	2	2	1	0	1	0	
3	12215000	7500	4	2	2	1	0	1	0	
4	11410000	7420	4	1	2	1	1	1	0	

Splitting Data into Training and Testing Data

In [33]:

```
# To show the columns or features of our dataset

data.columns
```

Out[33]:

```
Index(['price', 'area', 'bedrooms', 'bathrooms', 'stories', 'mainroad',
       'guestroom', 'basement', 'hotwaterheating', 'airconditioning',
       'parking', 'prefarea', 'semi-furnished', 'unfurnished'],
      dtype='object')
```

In [35]:

```
np.random.seed(0)
```

In [36]:

```
# Split the data into training and testing subsets
df_train, df_test= train_test_split(data,train_size=0.7, test_size=0.3, random_state=100)
```

In [37]:

```
# Display the first few rows of the training subset
df_train.head()
```

Out[37]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditi
359	3710000	3600	3	1	1	1	0	0	0	
19	8855000	6420	3	2	2	1	0	0	0	
159	5460000	3150	3	2	1	1	1	1	0	
35	8080940	7000	3	2	4	1	0	0	0	
28	8400000	7950	5	2	2	1	0	1	1	

In [38]:

```
# Checking the shape of the training set
df_train.shape
```

Out[38]:

```
(381, 14)
```

In [39]:

```
# Display the first few rows of the testing subset
df_test.head()
```

Out[39]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	aircondit
265	4403000	2880	3	1	2	1	0	0	0	
54	7350000	6000	3	2	2	1	1	0	0	
171	5250000	10269	3	1	1	1	0	0	0	
244	4550000	5320	3	1	2	1	1	1	0	
268	4382000	4950	4	1	2	1	0	0	0	

In [40]:

```
# Checking the shape of training set
df_test.shape
```

Out[40]:

```
(164, 14)
```

Scaling Training Data: MinMaxScaler

Why to scale our data?

1. Equal Treatment of Features: Scaling ensures that all features are treated equally, no matter their size or units. This prevents one feature from overshadowing others just because it has larger values.
2. Avoid Biased Results: Without scaling, algorithms might wrongly emphasize features with larger values, leading to skewed or incorrect predictions.
3. Sensitive Algorithms: Some algorithms (like linear regression, logistic regression, and knearest neighbors) are sensitive to unscaled data. Scaling helps these algorithms work properly and make more accurate predictions.
4. Faster Optimization: Scaling speeds up the process of finding the best model parameters. With scaled data, optimization algorithms converge more quickly to the optimal solution.
5. Fair Distance Calculations: Algorithms that use distances, such as k-means clustering or k-nearest neighbors, can be biased if features have different scales. Scaling ensures all features contribute fairly to distance calculations.

In [43]:

```
#Creating an instance of the MinMaxScaler
scaler = MinMaxScaler()
```

In [45]:

```
#list  of columns to scale
col_to_scale = ['area', 'bedrooms','bathrooms','stories', 'parking', 'price']
```

In [46]:

```
# Scaing the specified columns in the training subset using the MinMaxScaler
df_train[col_to_scale] = scaler.fit_transform(df_train[col_to_scale])
```

In [47]:

```
# Displaying the training subset
df_train.head()
```

Out[47]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airc
359	0.169697	0.155227	0.4	0.0	0.000000	1	0	0	0	
19	0.615152	0.403379	0.4	0.5	0.333333	1	0	0	0	
159	0.321212	0.115628	0.4	0.5	0.000000	1	1	1	0	
35	0.548133	0.454417	0.4	0.5	1.000000	1	0	0	0	
28	0.575758	0.538015	0.8	0.5	0.333333	1	0	1	1	

Training The Model

In [48]:

```
# Separate the target variable from the training subset
y_train = df_train.pop('price')

# Extract the remaining feature as the training data
x_train= df_train
```

In [49]:

```
# to display the first few rows of the target variables in the training subset
y_train.head()
```

Out[49]:

```
359    0.169697
19     0.615152
159    0.321212
35     0.548133
28     0.575758
Name: price, dtype: float64
```

In [52]:

```
# Creating an instance if LinearRegression
linear_regression = LinearRegression()
```

In [53]:

```
# Fitting the linear Regression model to the training data
linear_regression.fit(x_train, y_train)
```

Out[53]:

```
LinearRegression
LinearRegression()
```

In [55]:

```
# Retrieve the coeffficients of the Linear Regresssion model
coefficients = linear_regression.coef_

# Print the coefficients
print(coefficients)
```

```
[ 0.23466354  0.04673453  0.19082319  0.10851563  0.05044144  0.03042826
  0.02159488  0.08486327  0.06688093  0.06073533  0.05942788  0.00092052
 -0.03100561]
```

In [56]:

```
# Calculate the coefficient of determination (Rsqaure) for the Linear Regression model on the training da

score = linear_regression.score(x_train,y_train)

# Print the coefficient of determination (R Square)

print(score)
```

```
0.6814893088451202
```

Scaling Test Data: MinMaxScaler

MinMaxScaler is a data transformation technique that scales numerical features to a specific range, usually between 0 and 1. It works by subtracting the minimum value of the feature from each data point and then dividing the result by the range (difference between the maximum and minimum values).

Why to scale our data?

1. Equal Treatment of Features: Scaling ensures that all features are treated equally, no matter their size or units. This prevents one feature from overshadowing others just because it has larger values.
2. Avoid Biased Results: Without scaling, algorithms might wrongly emphasize features with larger values, leading to skewed or incorrect predictions.
3. Sensitive Algorithms: Some algorithms (like linear regression, logistic regression, and knearest neighbors) are sensitive to unscaled data. Scaling helps these algorithms work properly and make more accurate predictions.
4. Faster Optimization: Scaling speeds up the process of finding the best model parameters. With scaled data, optimization algorithms converge more quickly to the optimal solution.
5. Fair Distance Calculations: Algorithms that use distances, such as k-means clustering or k-nearest neighbors, can be biased if features have different scales. Scaling ensures all features contribute fairly to distance calculations.

In [60]:

```
# List of coluns to scale

col_to_scale =[ 'area', 'bedrooms','bathrooms','stories', 'parking', 'price']
```

In [61]:

```
# Scaling the specified columns in the testing subset using the MinMaxScaler
df_test[col_to_scale] = scaler.fit_transform(df_test[col_to_scale])
```

Testing our Model

In [62]:

```
# Seprate the target variable from the testing subset
y_test = df_test.pop('price')

# Extract the remaining features as the testing data
x_test = df_test
```

In [63]:

```
# Make prediction on the testing data using the trained linear Regression model
prediction = linear_regression.predict(x_test)
```

Checking R Squared value

In [64]:

```
# calculate the coefficient of determination (R Square) for the predictions
r2 = r2_score(y_test, prediction)
```

Comparing the actual and predicted values

In [66]:

```
# Get the shape of y_test
y_test.shape

# Reshape y_test to a matrix with a single column
y_test_matrix = y_test.values.reshape(-1,1)
```

In [67]:

```
# Creating a DataFrame with actual and predicted values
data_frame = pd.DataFrame({'actual': y_test_matrix.flatten(), 'predicted': prediction.flatten()})
```

In [68]:

```
# Display the first 10 rows of the dataFrame :

data_frame.head(10)
```

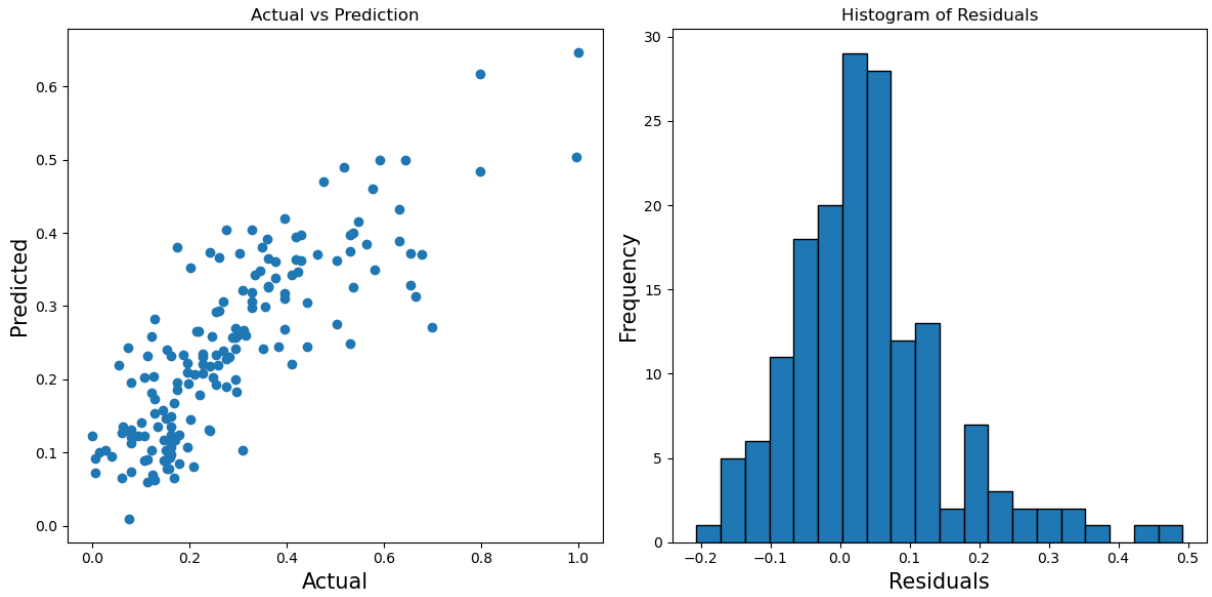
Out[68]:

	actual	predicted
0	0.247651	0.202410
1	0.530201	0.374464
2	0.328859	0.305654
3	0.261745	0.293786
4	0.245638	0.258827
5	0.275168	0.189463
6	0.644295	0.499099
7	0.328859	0.297637
8	0.087248	0.122528
9	0.395973	0.316860

Plotting the Graph

In [75]:

```
# Create a new figure with subplots
fig,(ax1, ax2) = plt.subplots(1,2, figsize=(12,6))

# Scatter plot of actual versus predicted values on the first subplot

ax1.scatter(y_test, prediction)
ax1.set_title('Actual vs Prediction')
ax1.set_xlabel('Actual', fontsize =15)
ax1.set_ylabel('Predicted', fontsize=15)

# Create another plot (e.g , histogram of residuals) on the second subplot

residuals = y_test - prediction
ax2.hist(residuals, bins=20, edgecolor = 'black')
ax2.set_title('Histogram of Residuals')
ax2.set_xlabel('Residuals', fontsize=15)
ax2.set_ylabel('Frequency', fontsize=15)


# Adjusted layout for better readability
plt.tight_layout()
plt.show()
```



Conclusion

we performed an in-depth Exploratory Data Analysis (EDA) on a house price dataset and built a linear regression model to predict house prices.

We loaded and preprocessed the data, explored correlations and relationships using visualizations, selected relevant features based on EDA insights, built and trained a linear regression model, and evaluated its performance.

The linear regression model showed promise in predicting house prices based on the selected features. However, there is still room for improvement.

Further steps could involve trying different regression algorithms, fine-tuning hyperparameters, and engineering new features for better performance.

EDA and feature selection played a crucial role in understanding the data and building an initial predictive model

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