Housing Price Prediction Using Linear Regression

In [ ]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [ ]:
```python
data= pd.read_csv('Housingprice.csv')
```

In [ ]:
```python
data.head(5)
```

Out[ ]:

	Unnamed: 0	price	lotsize	bedrooms	bathrms	stories	driveway	recroom	fullb
0	1	42000.0	5850	3	1	2	yes	no	
1	2	38500.0	4000	2	1	1	yes	no	
2	3	49500.0	3060	3	1	1	yes	no	
3	4	60500.0	6650	3	1	2	yes	yes	
4	5	61000.0	6360	2	1	1	yes	no	

In [ ]:
```python
# Dropping the 'Unnamed: 0' column as it's just identifier
data.drop('Unnamed: 0', axis=1, inplace=True)
data.head(5)
```

Out[ ]:

	price	lotsize	bedrooms	bathrms	stories	driveway	recroom	fullbase	gashw
0	42000.0	5850	3	1	2	yes	no	yes	no
1	38500.0	4000	2	1	1	yes	no	no	no
2	49500.0	3060	3	1	1	yes	no	no	no
3	60500.0	6650	3	1	2	yes	yes	no	no
4	61000.0	6360	2	1	1	yes	no	no	no

In [ ]:
```python
print('Shape of DataFrame: ',data.shape,'\n')
```

```
Shape of DataFrame:  (546, 12)
```

About Dataset There are 546 rows and 12 columns in the dataset, each are:

- price: The price of the property.
- lotsize: The size of the lot in square feet.
- bedrooms: The number of bedrooms in the property.
- bathrms: The number of bathrooms in the property.
- stories: The number of stories in the property.

- driveway: Whether the property has a driveway (yes/no).
- recroom: Whether the property has a recreational room (yes/no).
- fullbase: Whether the property has a full basement (yes/no). gashw: Whether the property has gas hot water heating (yes/no).
- airco: Whether the property has central air conditioning (yes/no).
- garagepl: The number of garage places.
- prefarea: Whether the property is in a preferred location (yes/no).

In [ ]:
```
data.isnull().sum()
```

Out[ ]:
```
price       0
lotsize     0
bedrooms    0
bathrms     0
stories     0
driveway    0
recroom     0
fullbase    0
gashw       0
airco       0
garagepl    0
prefarea    0
dtype: int64
```

In [ ]:
```
data.duplicated().sum()
```

Out[ ]:
```
1
```

In [ ]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 546 entries, 0 to 545
Data columns (total 12 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   price     546 non-null    float64
 1   lotsize   546 non-null    int64  
 2   bedrooms  546 non-null    int64  
 3   bathrms   546 non-null    int64  
 4   stories   546 non-null    int64  
 5   driveway  546 non-null    object 
 6   recroom   546 non-null    object 
 7   fullbase  546 non-null    object 
 8   gashw     546 non-null    object 
 9   airco     546 non-null    object 
 10  garagepl  546 non-null    int64  
 11  prefarea  546 non-null    object 
dtypes: float64(1), int64(5), object(6)
memory usage: 51.3+ KB
```

In [ ]:
```
data.describe()
```

Out[ ]:

	price	lotsize	bedrooms	bathrms	stories	garage
count	546.000000	546.000000	546.000000	546.000000	546.000000	546.0000
mean	68121.597070	5150.265568	2.965201	1.285714	1.807692	0.6923
std	26702.670926	2168.158725	0.737388	0.502158	0.868203	0.8613
min	25000.000000	1650.000000	1.000000	1.000000	1.000000	0.0000
25%	49125.000000	3600.000000	2.000000	1.000000	1.000000	0.0000
50%	62000.000000	4600.000000	3.000000	1.000000	2.000000	0.0000
75%	82000.000000	6360.000000	3.000000	2.000000	2.000000	1.0000
max	190000.000000	16200.000000	6.000000	4.000000	4.000000	3.0000

The dataset presents various features related to housing attributes:

- Price: Mean price stands at approximately $68, 121, rangingfrom$25,000 to $190,000.
- Lotsize: The average lot size is about 5150 square feet, with values ranging from 1650 to 16,200 square feet.
- Bedrooms: On average, houses feature around 3 bedrooms, varying from 1 to 6.
- Bathrooms: The dataset records an average of 1.29 bathrooms per house, with a range of 1 to 4.
- Stories: The average number of stories per house is approximately 1.81, with a minimum of 1 and a maximum of 4.
- Garagepl: Houses typically offer around 0.69 garage places on average, ranging from 0 to 3.

In [ ]:

```
# Converting categorical columns to numerical
categorical_columns = ['driveway', 'recroom', 'fullbase', 'gashw', 'airco',
data[categorical_columns] = (data[categorical_columns] == 'yes').astype(int)
data
```

Out[ ]:

	price	lotsize	bedrooms	bathrms	stories	driveway	recroom	fullbase	gas
0	42000.0	5850	3	1	2	1	0	1	
1	38500.0	4000	2	1	1	1	0	0	
2	49500.0	3060	3	1	1	1	0	0	
3	60500.0	6650	3	1	2	1	1	0	
4	61000.0	6360	2	1	1	1	0	0	
...	...	...	...	...	...	...	...	...	
541	91500.0	4800	3	2	4	1	1	0	
542	94000.0	6000	3	2	4	1	0	0	
543	103000.0	6000	3	2	4	1	1	0	
544	105000.0	6000	3	2	2	1	1	0	
545	105000.0	6000	3	1	2	1	0	0	

546 rows × 12 columns

In [ ]:

```
# Let's see the top 5 houses with the highest prices
highest_prices = pd.DataFrame(data.nlargest(5, ['price']))
highest_prices
```

Out[ ]:

	price	lotsize	bedrooms	bathrms	stories	driveway	recroom	fullbase	gas
161	130000.0	6000	4	1	2	1	0	1	
360	130000.0	6600	4	2	2	1	1	1	
93	128000.0	8500	3	2	4	1	0	0	
129	127000.0	4600	3	2	2	1	1	0	
374	126500.0	6420	3	2	2	1	0	0	

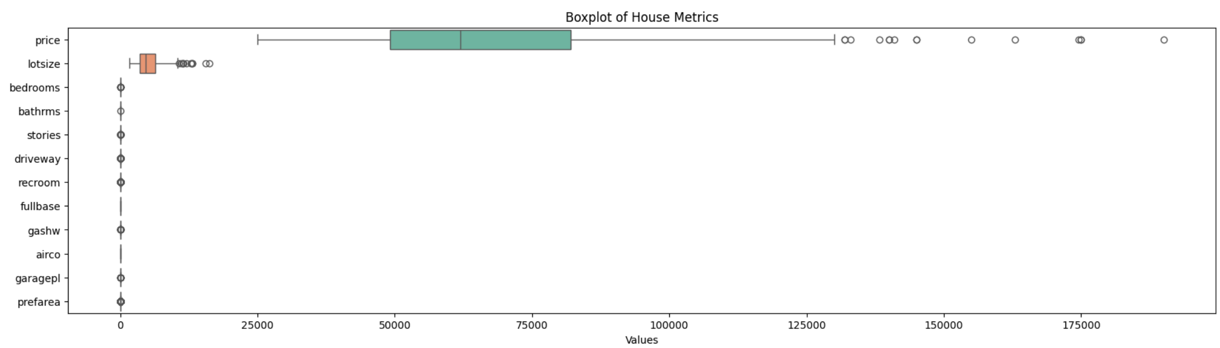
In [ ]:

```
# Also, the top 5 houses with the lowest prices

lowest_sales = pd.DataFrame(data.nsmallest(5, ['price']))
lowest_sales
```

Out[ ]:

	price	lotsize	bedrooms	bathrms	stories	driveway	recroom	fullbase	gasl
55	25000.0	3620	2	1	1	1	0	0	
162	25000.0	2910	3	1	1	0	0	0	
232	25000.0	3850	3	1	2	1	0	0	
56	25245.0	2400	3	1	1	0	0	0	
238	26000.0	3000	2	1	1	1	0	1	

In [ ]:
```
# Ploting the boxplot
plt.figure(figsize=(20, 5))
sns.boxplot(data=data, orient='h', palette='Set2')
plt.title('Boxplot of House Metrics')
plt.xlabel('Values')
plt.show()
```

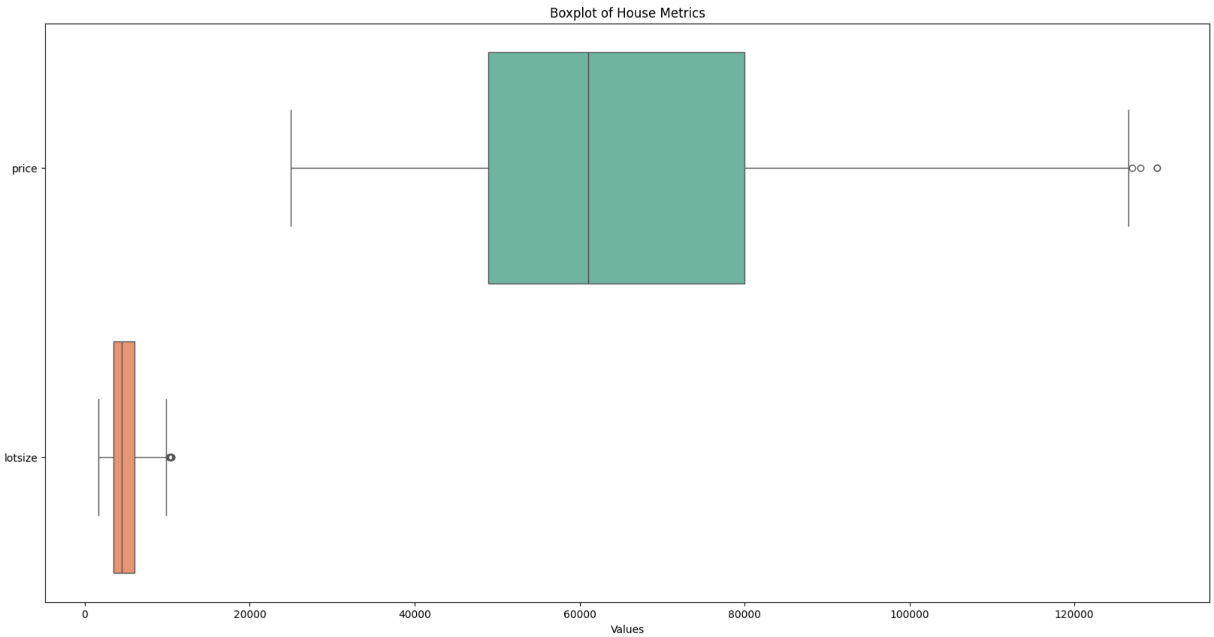


In [ ]:
```
# Calculate outlier bounds for 'price' and 'lotsize'
outlier_bounds_price = outlier_bounds(data['price'])
outlier_bounds_lotsize = outlier_bounds(data['lotsize'])

# Check if the outlier bounds are not None before unpacking
if outlier_bounds_price is not None and outlier_bounds_lotsize is not None:
    price_lower, price_upper = outlier_bounds_price
    lotsize_lower, lotsize_upper = outlier_bounds_lotsize

    # Create a mask for rows without outliers
    mask_no_outliers = ((data['price'] >= price_lower) & (data['price'] <= p
                        (data['lotsize'] >= lotsize_lower) & (data['lotsize'

    # Apply the mask to the DataFrame
    data = data[mask_no_outliers]

else:
    print("No outliers detected.")
```

In [ ]:
```
# Defining the features and target variable
X = data[['lotsize', 'bedrooms', 'bathrms', 'stories', 'driveway', 'recroom'
y = data['price']
```

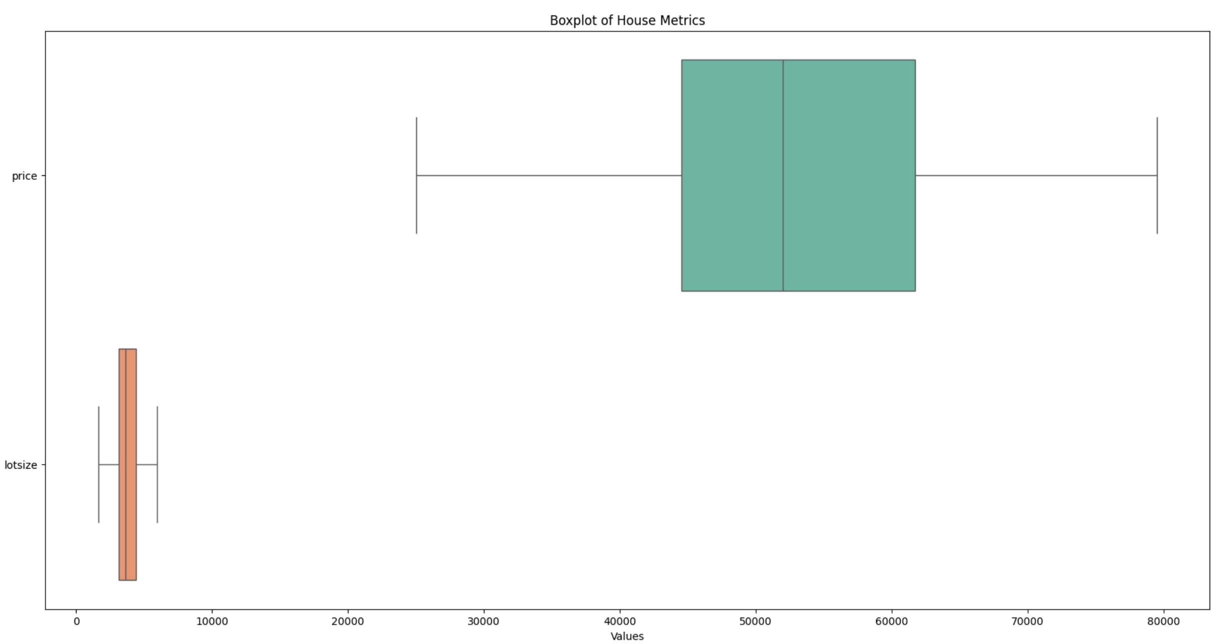
In [ ]:
```
# Plot the boxplot
plt.figure(figsize=(20, 10))
```

```
sns.boxplot(data=data[['price', 'lotsize']], orient='h', palette='Set2')
plt.title('Boxplot of House Metrics')
plt.xlabel('Values')
plt.show()
```



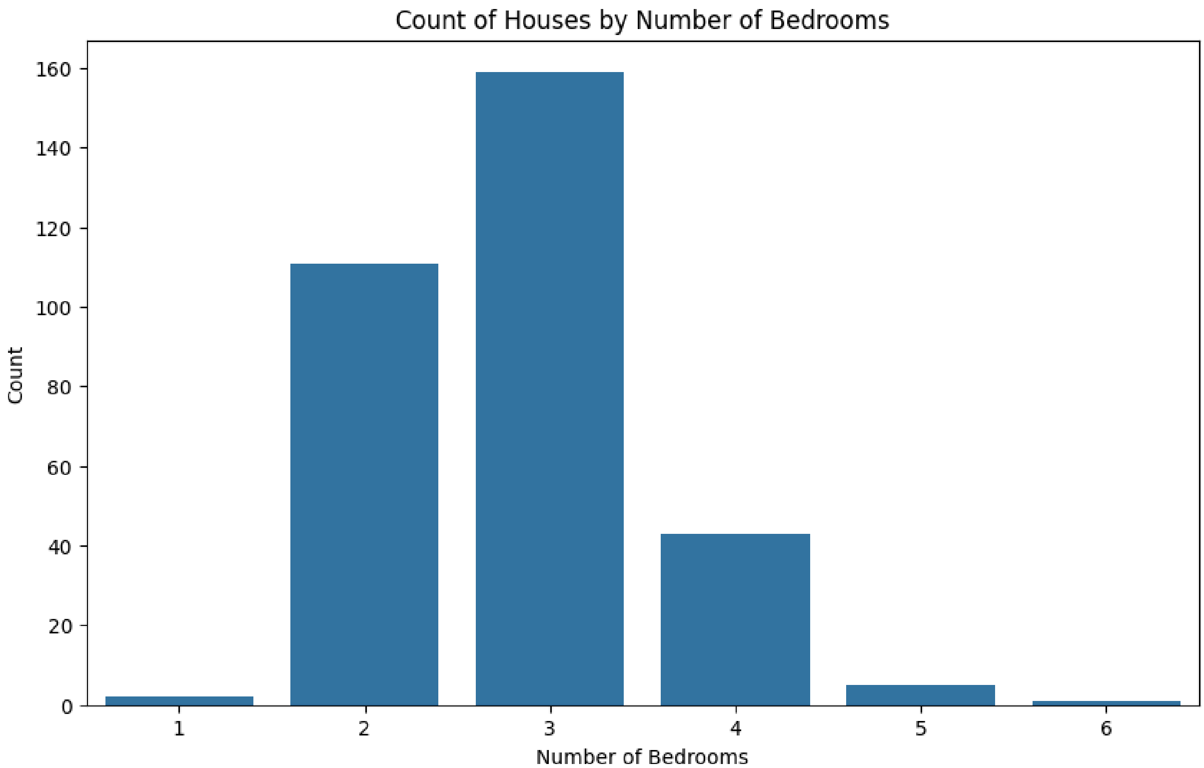

```
In [ ]: # Removing Outliers further
        data = data[(data['price'] < 80000) &
                    (data['lotsize'] < 6000)]
```

```
In [ ]: # Let's see outliers are removed or not
        plt.figure(figsize=(20, 10))
        sns.boxplot(data=data[['price', 'lotsize']], orient='h', palette='Set2')
        plt.title('Boxplot of House Metrics')
        plt.xlabel('Values')
        plt.show()
```



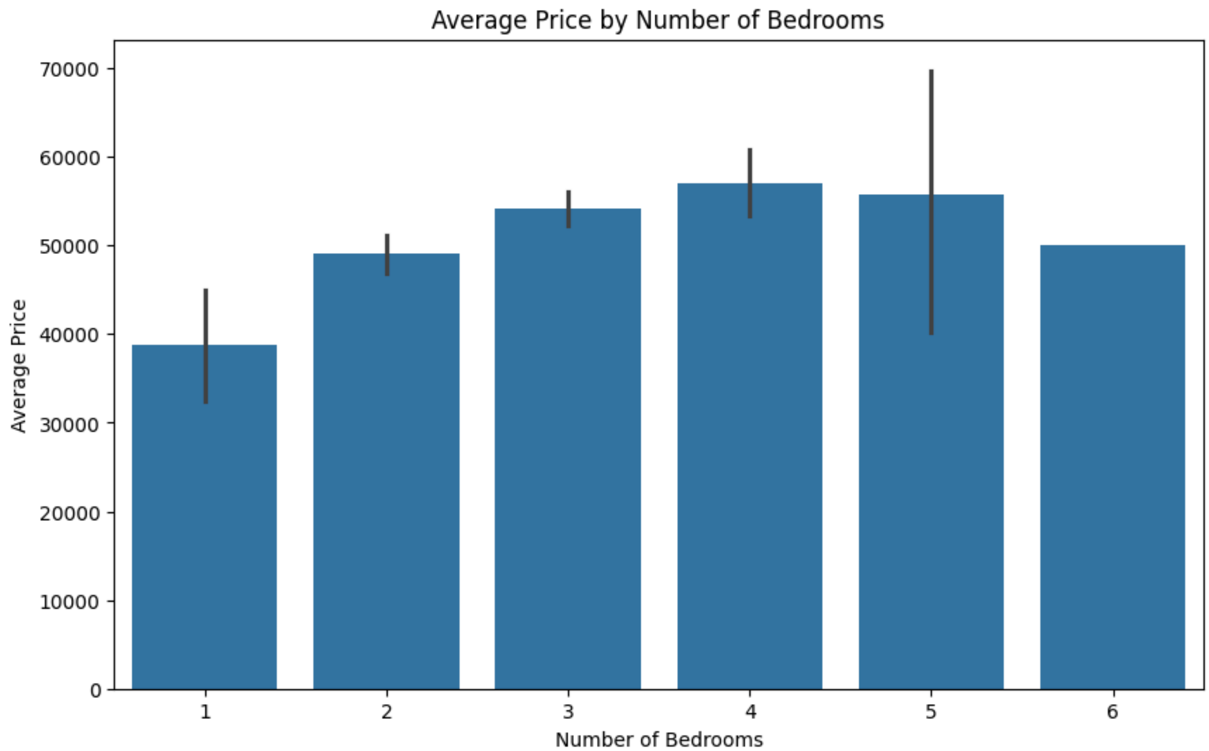
In [ ]:

```
# Barplot to visualize the distribution of houses by number of bedrooms
plt.figure(figsize=(10, 6))
sns.countplot(x='bedrooms', data=data)
plt.title('Count of Houses by Number of Bedrooms')
plt.xlabel('Number of Bedrooms')
plt.ylabel('Count')
plt.show()
```



In [ ]:

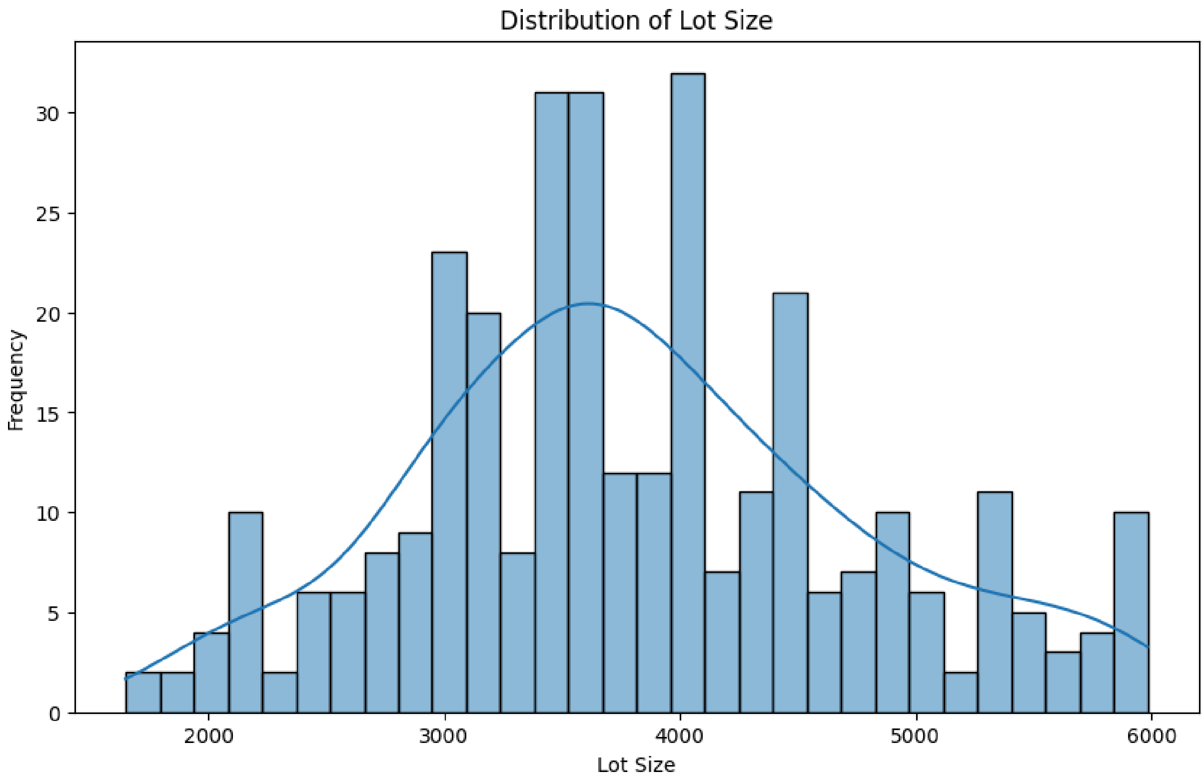
```
#Barplot to visualize Average prices by Number of Bedrooms
plt.figure(figsize=(10, 6))
sns.barplot(x='bedrooms', y='price', data=data)
plt.title('Average Price by Number of Bedrooms')
plt.xlabel('Number of Bedrooms')
plt.ylabel('Average Price')
plt.show()
```



In [ ]:
```
#Scatterplot to visualize relationship between Lot Size and Price
plt.figure(figsize=(10, 6))
sns.scatterplot(x='lotsize', y='price', data=data)
plt.title('Lot Size vs Price')
plt.xlabel('Lot Size')
plt.ylabel('Price')
plt.show()
```

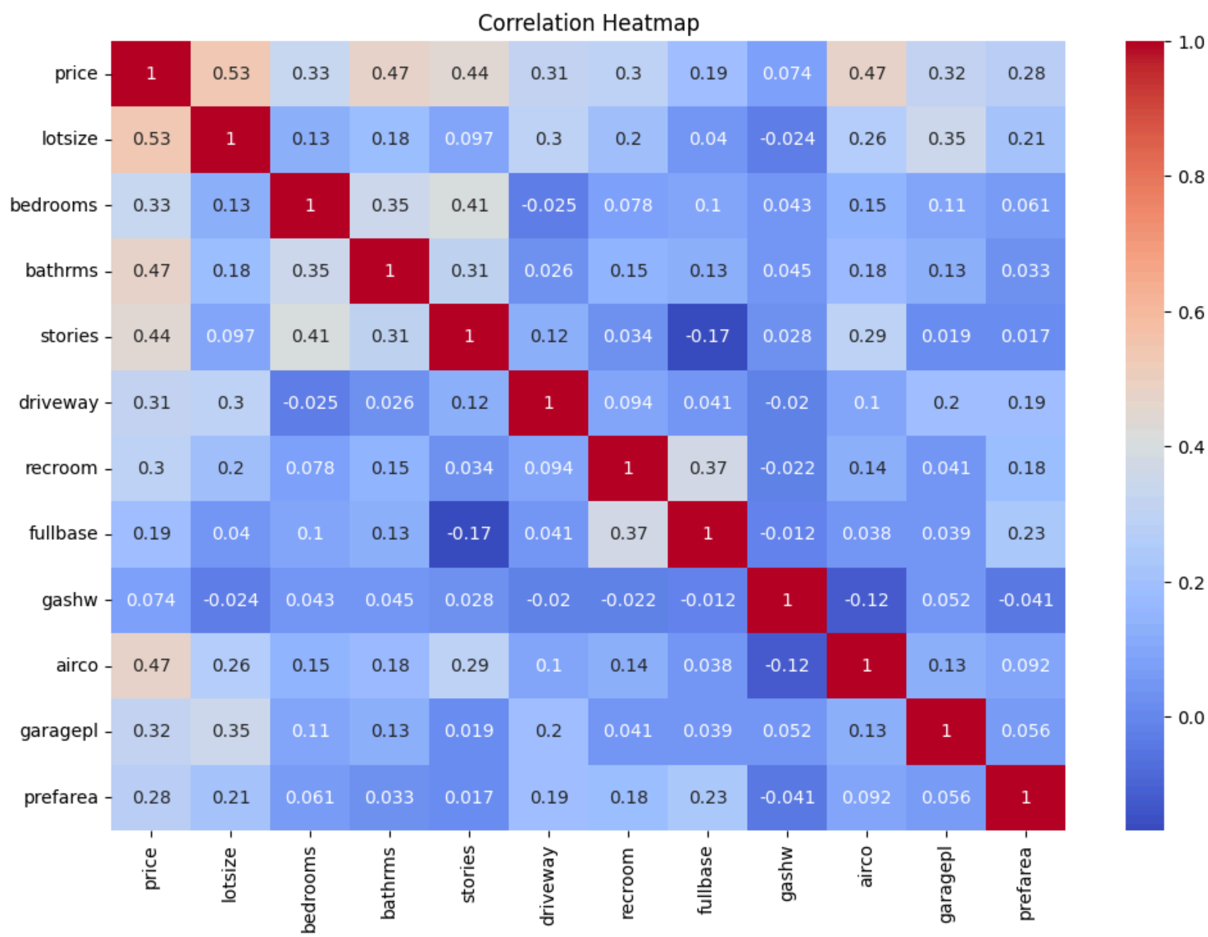
In [ ]:

```python
#Histogram to visualize the distribution of lot size
plt.figure(figsize=(10, 6))
sns.histplot(data['lotsize'], bins=30, kde=True)
plt.title('Distribution of Lot Size')
plt.xlabel('Lot Size')
plt.ylabel('Frequency')
plt.show()
```



In [ ]:

```python
# Heatmap to visualize the correlation between variables
correlation_matrix = data.corr()
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



Model Building

In [ ]:
```
#importing necessary libraries
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_erro
from sklearn.preprocessing import StandardScaler
```

In [ ]:
```
# Spliting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

In [ ]:
```
# Standardizing the features using Standard Scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [ ]:
```
# Modeling
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

In [ ]:
```
# Evaluating the model
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)
```

```python
print("Root Mean Squared Error (RMSE):", rmse)
print("R-squared (R^2) Score:", r2)
```

```
Root Mean Squared Error (RMSE): 11391.130147172003
R-squared (R^2) Score: 0.7471154326157805
```

In [ ]:

```python
accuracy_score = r2_score(y_test, y_pred)
print("Accuracy Score:", accuracy_score)
```

```
Accuracy Score: 0.7471154326157805
```