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Problem Statement: House Price Prediction

Description:

House price prediction is a common problem in the real estate industry and involves predicting the selling price of a house based on various features and attributes. The problem is typically approached as a regression problem, where the target variable is the price of the house, and the features are various attributes of the house.

The features used in house price prediction can include both quantitative and categorical variables, such as the number of bedrooms, house area, bedrooms, furnished, nearness to main road, and various amenities such as a garage and other factors that may influence the value of the property.

Accurate predictions can help agents and appraisers price homes correctly, while homeowners can use the predictions to set a reasonable asking price for their properties. Accurate house price prediction can also be useful for buyers who are looking to make informed decisions about purchasing a property and obtaining a fair price for their investment.

Attribute Information:

Name - Description

1- Price-Prices of the houses

2- Area- Area of the houses

3- Bedrooms- No of house bedrooms

4- Bathrooms- No of bathrooms

5- Stories- No of house stories

6- Main Road- Weather connected to Main road

7- Guestroom-Weather has a guest room

8- Basement-Weather has a basement

9- Hot water heating- Weather has a hot water heater

10-Airconditioning-Weather has a air conditioner

11-Parking- No of house parking

12-Furnishing Status-Furnishing status of house

Building a Regression Model

1. Download the dataset: Dataset
2. Load the dataset into the tool.
3. Perform Below Visualizations.
   - Univariate Analysis
   - Bi-Variate Analysis
   - Multi-Variate Analysis
4. Perform descriptive statistics on the dataset.
5. Check for Missing values and deal with them.
6. Find the outliers and replace them outliers
7. Check for Categorical columns and perform encoding.
8. Split the data into dependent and independent variables.
9. Scale the independent variables
10. Split the data into training and testing
11. Build the Model
12. Train the Model
13. Test the Model
14. Measure the performance using Metrics.

Importing necessary libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

1. Download the dataset: Dataset

Housing.csv downloaded.

2. Load the dataset into the tool

```
data = pd.read_csv('Housing.csv')
data.head(5)
```

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

```
data.isnull().any()
```

```
price               False
area                False
bedrooms            False
bathrooms           False
stories             False
mainroad            False
guestroom           False
basement            False
hotwaterheating     False
airconditioning     False
parking             False
furnishingstatus    False
dtype: bool
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 545 entries, 0 to 544
Data columns (total 12 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  furnishingstatus  545 non-null    object
dtypes: int64(6), object(6)
memory usage: 51.2+ KB
```

3. Perform Below Visualizations.

- Univariate Analysis
- Bi-Variate Analysis
- Multi-Variate Analysis

Univariate Analysis

Distribution plot

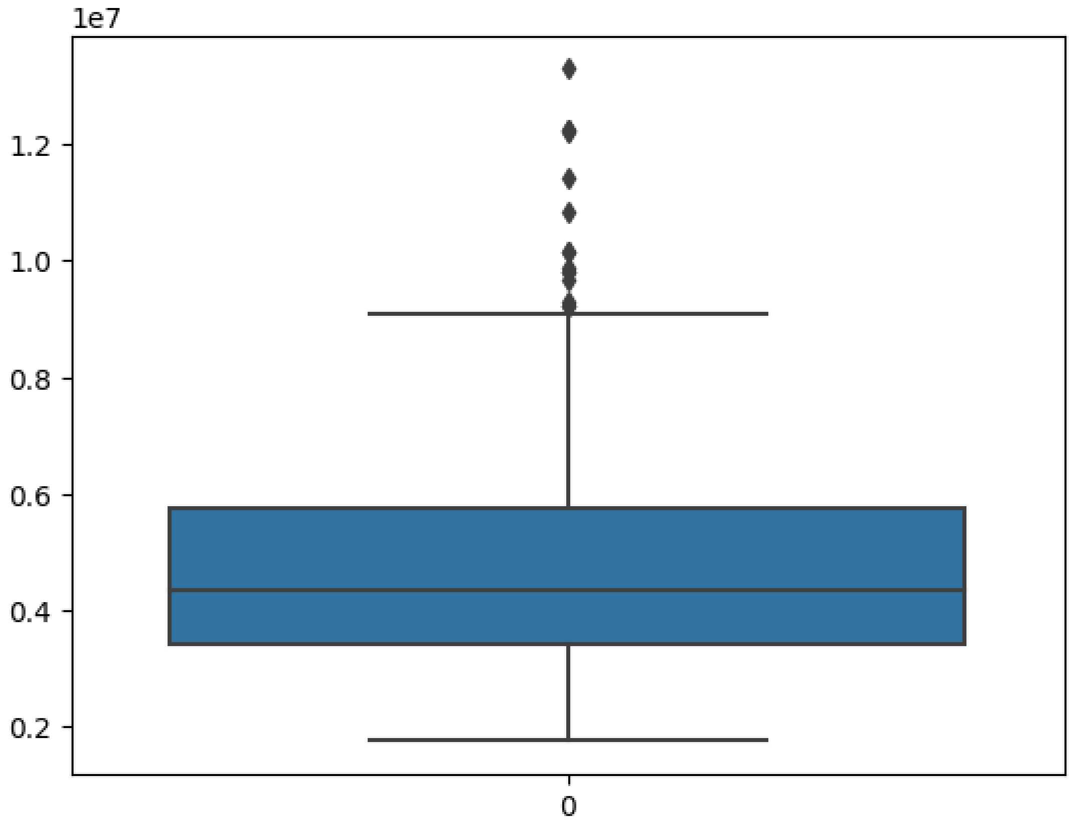
```
sns.distplot(data['price'], color = 'b')
```

Box plot

```
distplot` is a deprecated function and will be removed in seaborn v0.14.0.
```

```
sns.boxplot(data['price'])
```

```
<Axes: >
```



Scatter plot

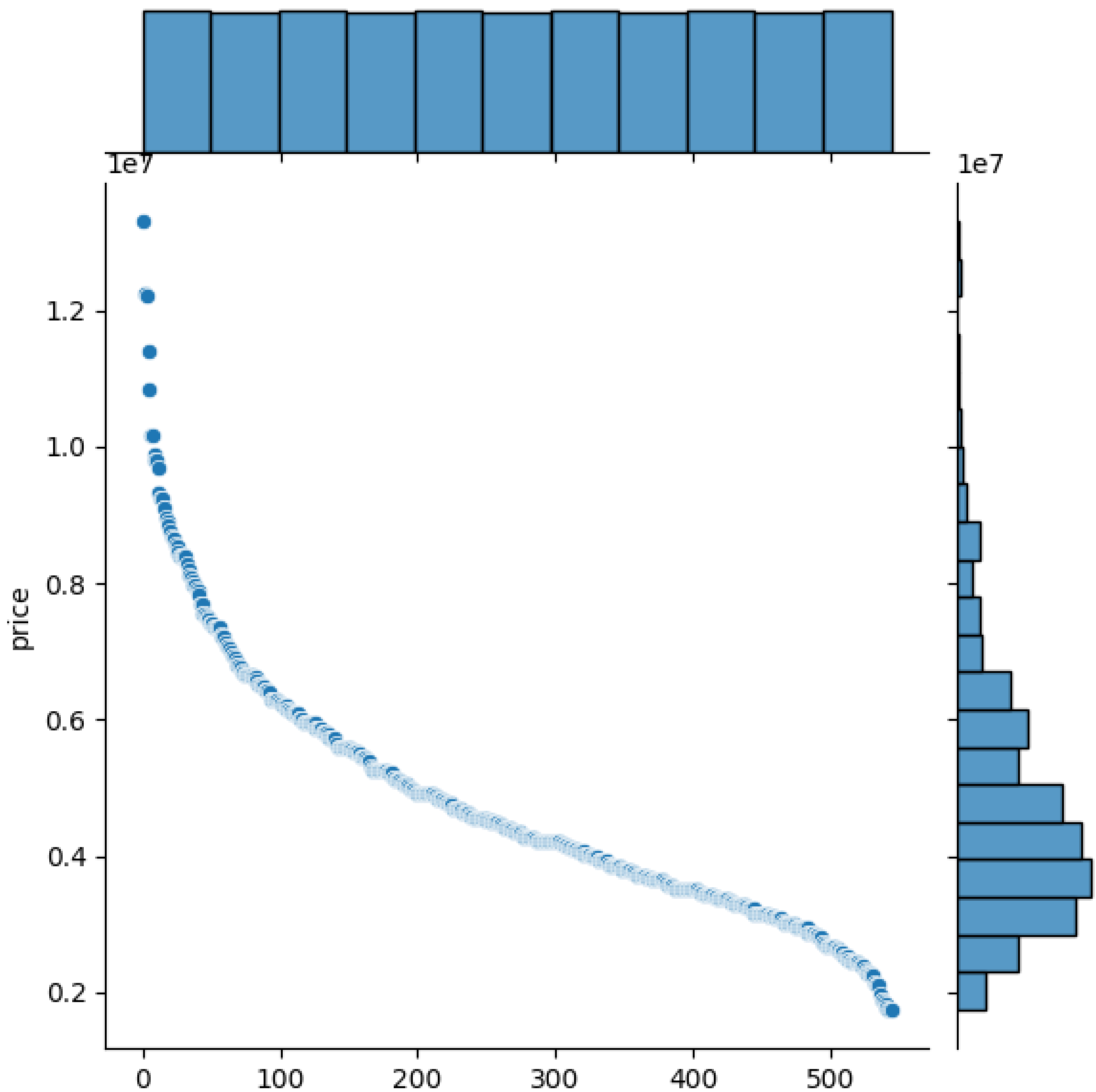

```
sns.scatterplot(data['price'])
```

```
<Axes: ylabel='price'>
```

Joint plot

```
sns.jointplot(data['price'])
```

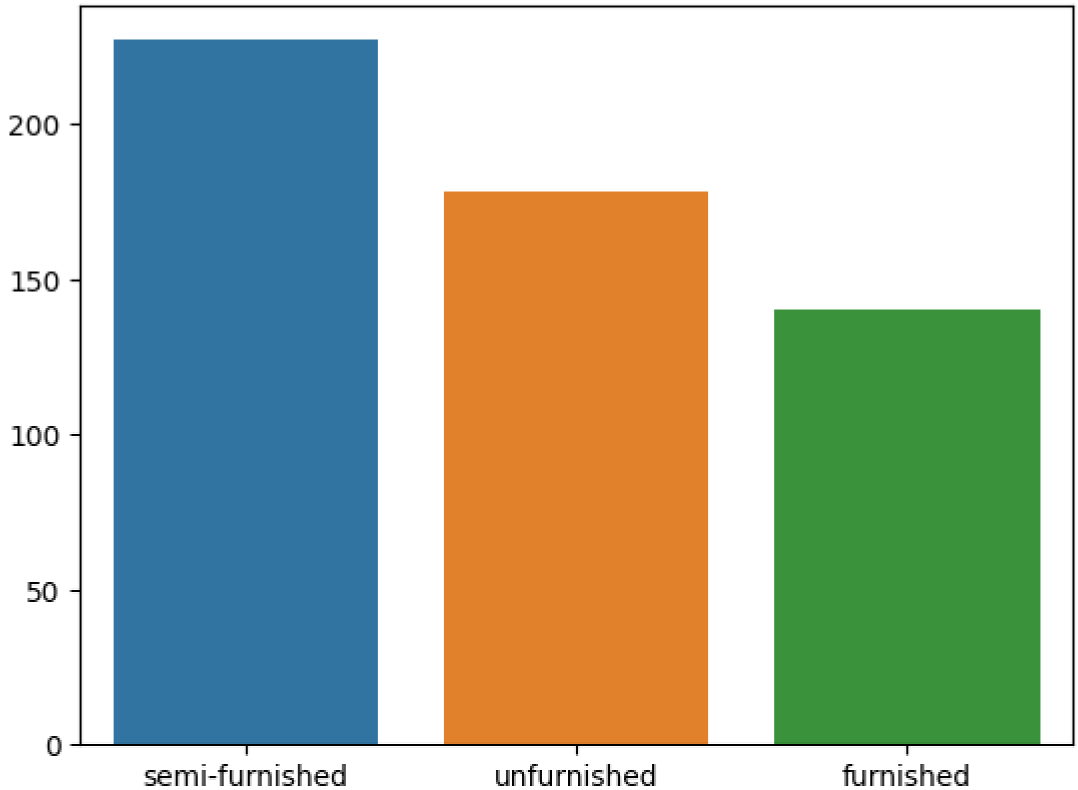
```
<seaborn.axisgrid.JointGrid at 0x7fe58d228d60>
```



Bar plot

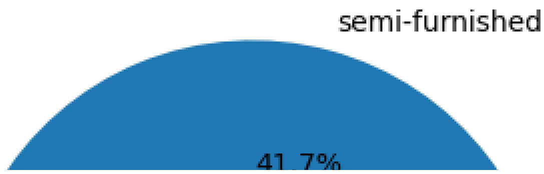
```
x = data.furnishingstatus.value_counts()
sns.barplot(x=x.index, y=x.values)
```

```
<Axes: >
```



Pie plot

```
x = data['furnishingstatus'].value_counts()
plt.pie(x.values,
        labels=x.index,
        autopct='%1.1f%%')
plt.show()
```

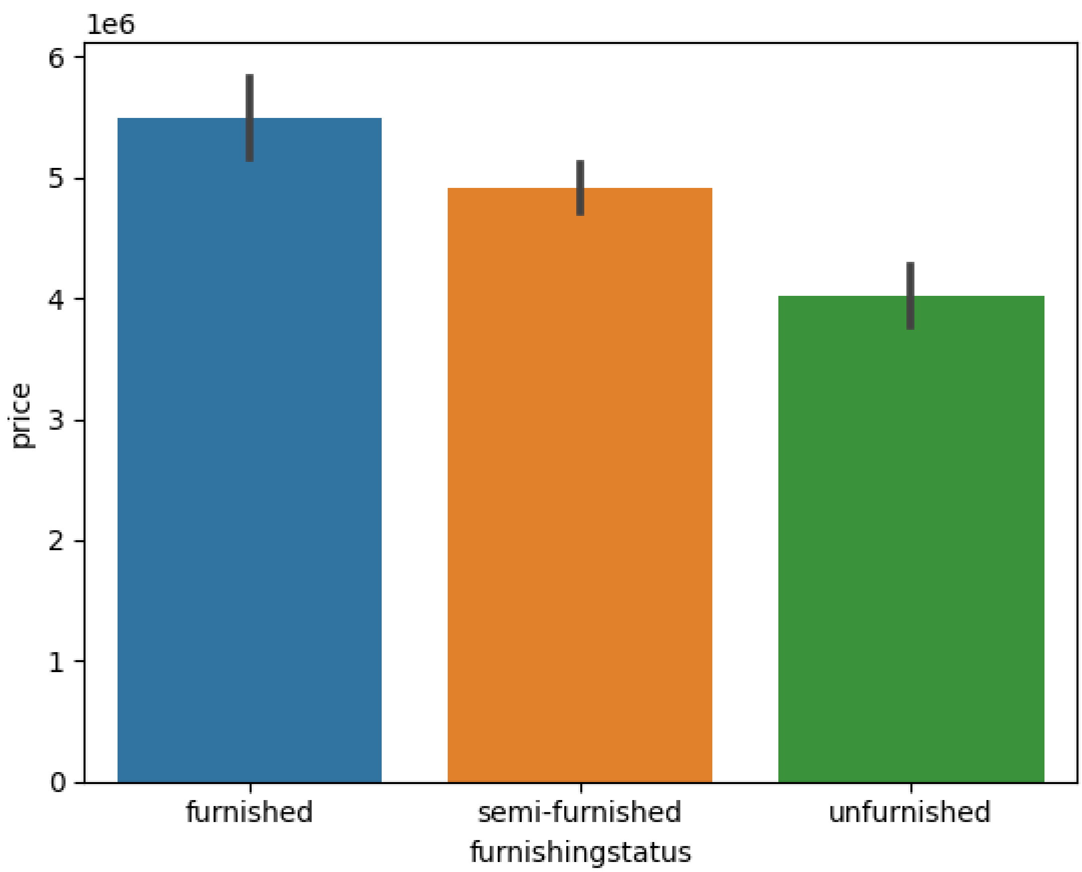


Bivariate analysis

Bar plot

```
sns.barplot(x=data.furnishingstatus, y=data.price)
```

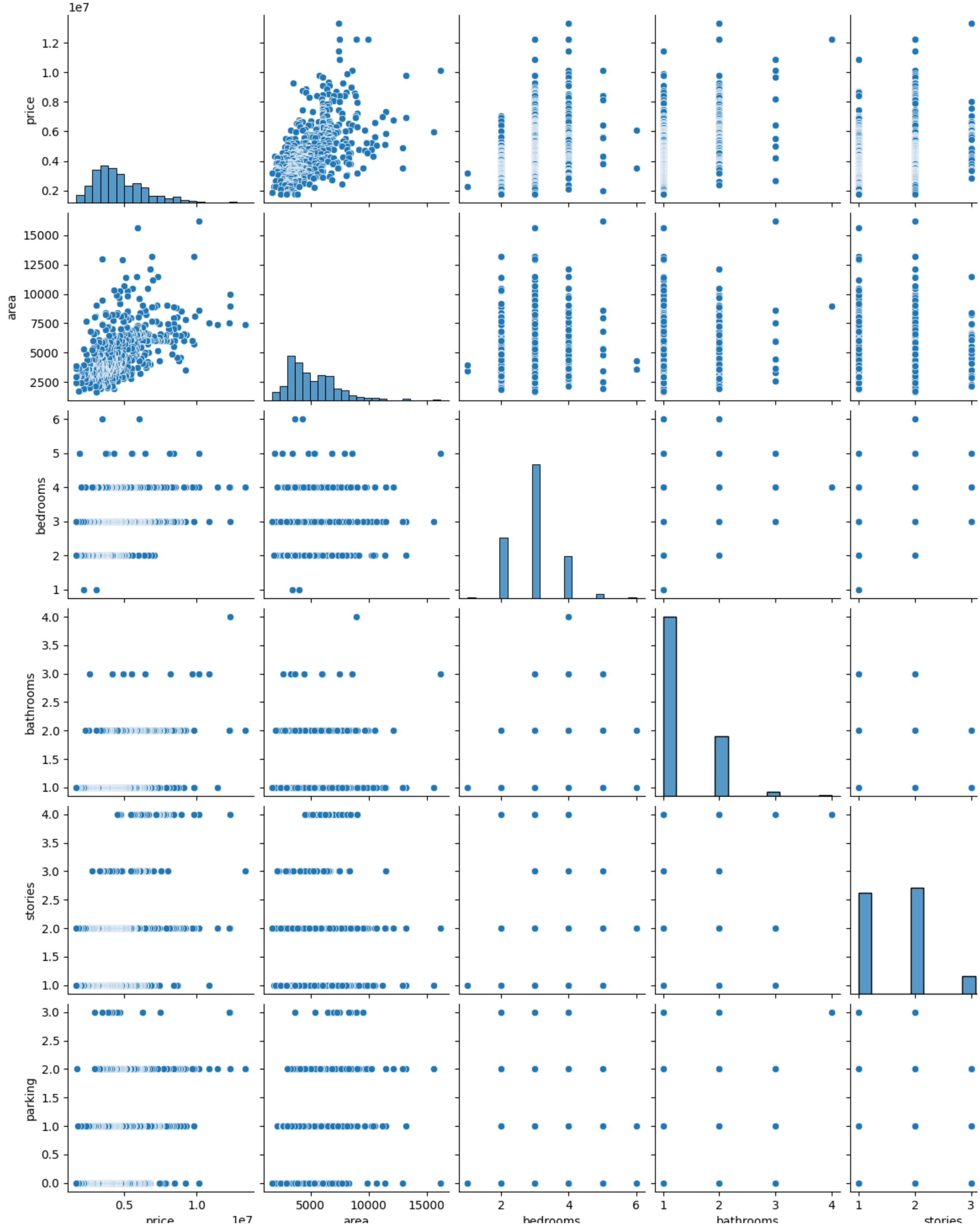
```
<Axes: xlabel='furnishingstatus', ylabel='price'>
```



Pair plot

```
sns.pairplot(data)
```

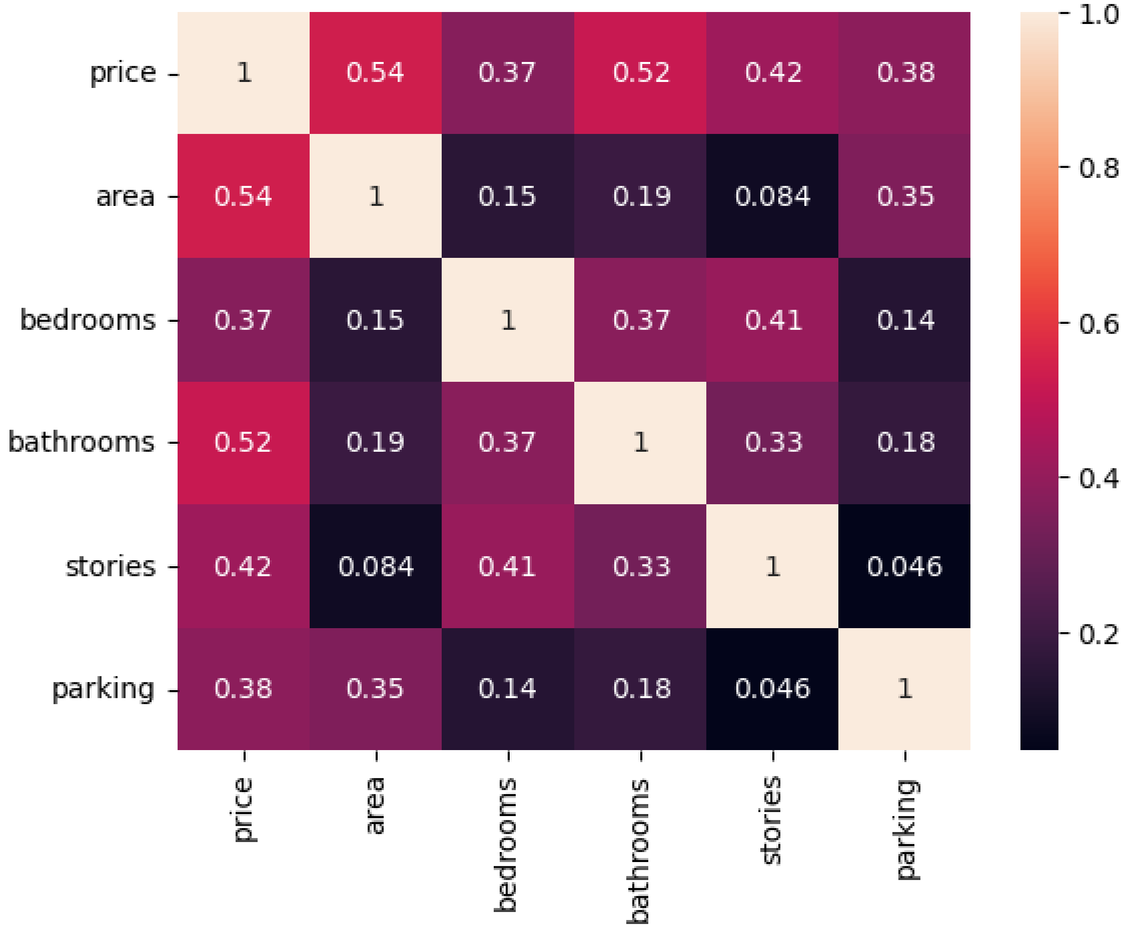
```
<seaborn.axisgrid.PairGrid at 0x7fe58cd9ff70>
```



Multivariate Analysis

```
sns.heatmap(data.corr(), annot=True)
```

```
<ipython-input-14-b699050ce883>:1: FutureWarning: The default value of numeric_only in [
  sns.heatmap(data.corr(), annot=True)
<Axes: >
```



4. Perform descriptive statistics on the dataset.

Measure of central tendency - Mean, Median and Mode

```
data.mean()
```

```
<ipython-input-15-abc01cf6c622>:1: FutureWarning: The default value of numeric_only in [
  data.mean()
price        4.766729e+06
area         5.150541e+03
bedrooms     2.965138e+00
bathrooms    1.286239e+00
stories      1.805505e+00
parking      6.935780e-01
dtype: float64
```

```
data.median()
```

```
<ipython-input-16-135339ac59ce>:1: FutureWarning: The default value of numeric_only in D
  data.median()
price        4340000.0
area            4600.0
bedrooms           3.0
bathrooms          1.0
stories            2.0
parking            0.0
dtype: float64
```

```
data.mode()
```

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwater
0	3500000	6000.0	3.0	1.0	2.0	yes	no	no	
1	4200000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

Measure of variability:

Kurtosis

```
data.kurt()
```

```
<ipython-input-18-de7992f92dad>:1: FutureWarning: The default value of numeric_only in D
  data.kurt()
price        1.960130
area         2.751480
bedrooms     0.728323
bathrooms    2.164856
stories      0.679404
parking     -0.573063
dtype: float64
```

Range

```
data.max()
```

```
price                 13300000
area                     16200
bedrooms                     6
bathrooms                    4
```

```
stories                     4
mainroad                  yes
guestroom                 yes
basement                  yes
hotwaterheating           yes
airconditioning           yes
parking                     3
furnishingstatus  unfurnished
dtype: object
```

```
data.min()
```

```
price               1750000
area                   1650
bedrooms                  1
bathrooms                 1
stories                   1
mainroad                 no
guestroom                no
basement                 no
hotwaterheating          no
airconditioning          no
parking                   0
furnishingstatus  furnished
dtype: object
```

```
Range = data.max()['price'] - data.min()['price']
print(Range)
```

```
11550000
```

Skewness

```
data.skew()
```

```
<ipython-input-22-b3b431164adb>:1: FutureWarning: The default value of numeric_only in D
  data.skew()
price        1.212239
area         1.321188
bedrooms     0.495684
bathrooms    1.589264
stories      1.082088
parking      0.842062
dtype: float64
```

Interquartile range - for price

```
quantiles = data['price'].quantile(q=[0.75, 0.25])
quantiles
```

```
0.75    5740000.0
0.25    3430000.0
Name: price, dtype: float64
```

```
#Q3
quantiles.iloc[0]
```

```
5740000.0
```

```
#Q1
quantiles.iloc[1]
```

```
3430000.0
```

```
IQR = quantiles.iloc[0]-quantiles.iloc[1]
IQR
```

```
2310000.0
```

Upper extreme Q3 + 1.5*IQR

```
quantiles.iloc[0] + (1.5*IQR)
```

```
9205000.0
```

Lower extreme Q1 - 1.5*IQR

```
quantiles.iloc[1] - (1.5*IQR)
```

```
-35000.0
```

Standard deviation

```
data.std()
```

```
<ipython-input-29-a47ac8255c06>:1: FutureWarning: The default value of numeric_only in D
  data.std()
price        1.870440e+06
area         2.170141e+03
bedrooms     7.380639e-01
bathrooms    5.024696e-01
stories      8.674925e-01
```

```
parking      8.615858e-01
dtype: float64
```

Variance

```
data.var()
```

```
<ipython-input-30-6bf595b3cfe5>:1: FutureWarning: The default value of numeric_only in D
  data.var()
price        3.498544e+12
area         4.709512e+06
bedrooms     5.447383e-01
bathrooms    2.524757e-01
stories      7.525432e-01
parking      7.423300e-01
dtype: float64
```

```
data.describe()
```

	price	area	bedrooms	bathrooms	stories	parking
count	5.450000e+02	545.000000	545.000000	545.000000	545.000000	545.000000
mean	4.766729e+06	5150.541284	2.965138	1.286239	1.805505	0.693578
std	1.870440e+06	2170.141023	0.738064	0.502470	0.867492	0.861586
min	1.750000e+06	1650.000000	1.000000	1.000000	1.000000	0.000000
25%	3.430000e+06	3600.000000	2.000000	1.000000	1.000000	0.000000
50%	4.340000e+06	4600.000000	3.000000	1.000000	2.000000	0.000000
75%	5.740000e+06	6360.000000	3.000000	2.000000	2.000000	1.000000
max	1.330000e+07	16200.000000	6.000000	4.000000	4.000000	3.000000

5. Check for Missing values and deal with them.

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

```
price               0
area                0
bedrooms            0
bathrooms           0
stories             0
mainroad            0
guestroom           0
```

```
basement            0
hotwaterheating     0
airconditioning     0
parking             0
furnishingstatus    0
dtype: int64
```

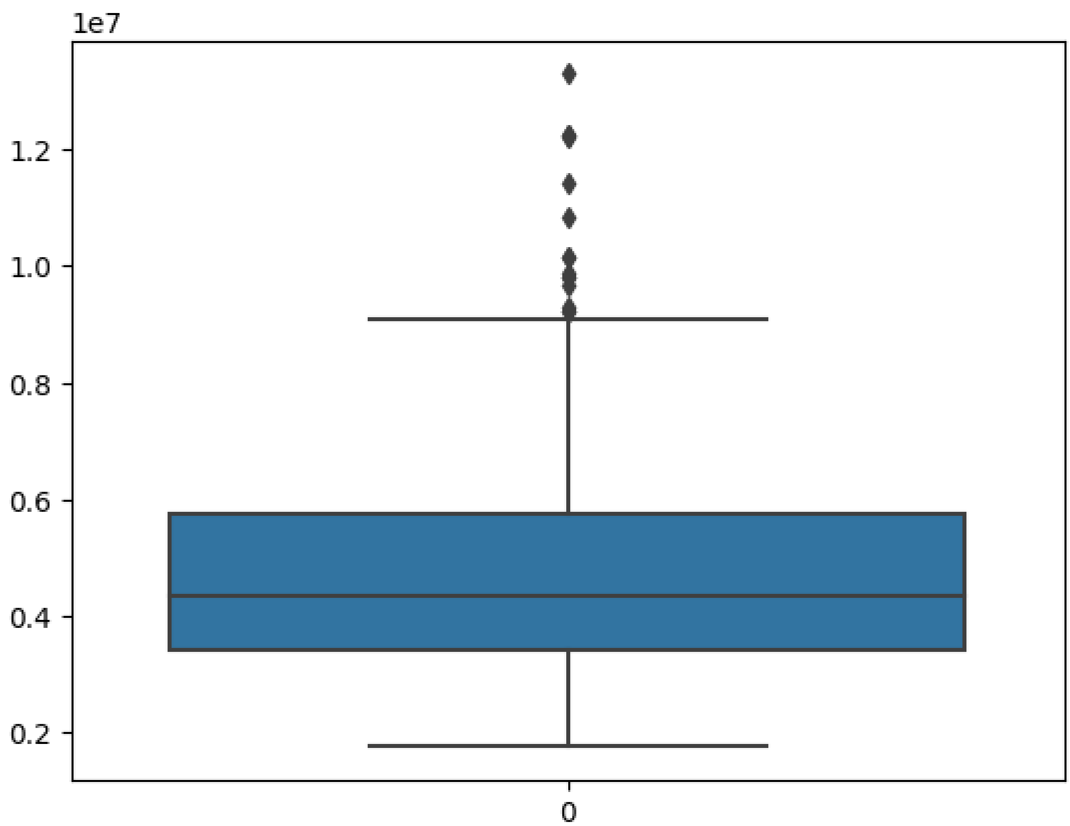
No missing values

6. Find the outliers and replace the outliers

Removing outliers

```
sns.boxplot(data.price)
```

```
<Axes: >
```




```
quant99 = data.price.quantile(0.99)
upper_array = np.where(data.price>quant99)[0]

data.drop(index=upper_array, inplace=True)
```

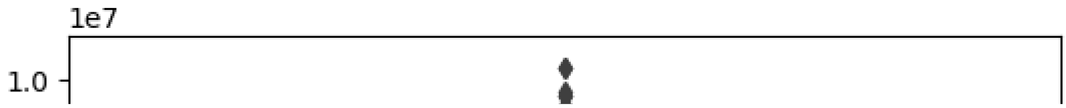
```
data.reset_index(drop = True, inplace=True)
data
```

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwa
0	10150000	8580	4	3	4	yes	no	no	
1	10150000	16200	5	3	2	yes	no	no	
2	9870000	8100	4	1	2	yes	yes	yes	
3	9800000	5750	3	2	4	yes	yes	no	
4	9800000	13200	3	1	2	yes	no	yes	
...	...	...	...	...	...	...	...	...	
534	1820000	3000	2	1	1	yes	no	yes	
535	1767150	2400	3	1	1	no	no	no	
536	1750000	3620	2	1	1	yes	no	no	
537	1750000	2910	3	1	1	no	no	no	
538	1750000	3850	3	1	2	yes	no	no	

539 rows × 12 columns

```
sns.boxplot(data['price'])
```

```
<Axes: >
```




```
data['price']
```

```
0      10150000
1      10150000
2       9870000
3       9800000
4       9800000
         ...
534     1820000
535     1767150
536     1750000
537     1750000
538     1750000
Name: price, Length: 539, dtype: int64
```

7. Check for Categorical columns and perform encoding

Encoding techniques

Label encoding

```
from sklearn.preprocessing import LabelEncoder
```

```
le = LabelEncoder()
```

```
data.head()
```

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwate
0	10150000	8580	4	3	4	yes	no	no	
1	10150000	16200	5	3	2	yes	no	no	
2	9870000	8100	4	1	2	yes	yes	yes	
3	9800000	5750	3	2	4	yes	yes	no	
4	9800000	13200	3	1	2	yes	no	yes	

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 539 entries, 0 to 538
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   price             539 non-null    int64
 1   area              539 non-null    int64
 2   bedrooms          539 non-null    int64
 3   bathrooms         539 non-null    int64
 4   stories           539 non-null    int64
 5   mainroad          539 non-null    object
 6   guestroom         539 non-null    object
 7   basement          539 non-null    object
 8   hotwaterheating   539 non-null    object
 9   airconditioning   539 non-null    object
 10  parking           539 non-null    int64
 11  furnishingstatus  539 non-null    object
dtypes: int64(6), object(6)
memory usage: 50.7+ KB
```

```
columns = ['mainroad', 'guestroom', 'basement', 'hotwaterheating', 'airconditioning']
for col in columns:
 data[col] = le.fit_transform(data[col])
```

```
data.head()
```

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwate
0	10150000	8580	4	3	4	1	0	0	
1	10150000	16200	5	3	2	1	0	0	
2	9870000	8100	4	1	2	1	1	1	
3	9800000	5750	3	2	4	1	1	0	
4	9800000	13200	3	1	2	1	0	1	

One Hot Encoding

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

```
data
```

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwa
0	10150000	8580	4	3	4	1	0	0	
1	10150000	16200	5	3	2	1	0	0	
2	9870000	8100	4	1	2	1	1	1	
3	9800000	5750	3	2	4	1	1	0	
4	9800000	13200	3	1	2	1	0	1	
...	...	...	...	...	...	...	...	...	
534	1820000	3000	2	1	1	1	0	1	
535	1767150	2400	3	1	1	0	0	0	
536	1750000	3620	2	1	1	1	0	0	
537	1750000	2910	3	1	1	0	0	0	
538	1750000	3850	3	1	2	1	0	0	

539 rows × 14 columns

8. Split the data into dependent and independent variables.

Dependent variable

```
y = data.loc[:, 'price':'price']
y
```

	price
0	10150000
1	10150000
2	9870000

Independent variable

```
X = data.drop(columns=['price'], axis=1)
X
```

	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating
0	8580	4	3	4	1	0	0	0
1	16200	5	3	2	1	0	0	0
2	8100	4	1	2	1	1	1	0
3	5750	3	2	4	1	1	0	0
4	13200	3	1	2	1	0	1	0
...	...	...	...	...	...	...	...	...
534	3000	2	1	1	1	0	1	0
535	2400	3	1	1	0	0	0	0
536	3620	2	1	1	1	0	0	0
537	2910	3	1	1	0	0	0	0
538	3850	3	1	2	1	0	0	0

539 rows × 13 columns

9. Scale the independent variables

Scaling

StandardScaler --> mean=0 std=1

MinMaxScaler --> scale between 0 to 1

```
from sklearn.preprocessing import MinMaxScaler
scale = MinMaxScaler()


name = X.columns
X_scaled = scale.fit_transform(X)


X_scaled
```

```
array([[0.47628866, 0.6       , 1.        , ..., 0.        , 1.        ,
        0.        ],
       [1.        , 0.8       , 1.        , ..., 0.        , 0.        ,
        1.        ],
       [0.44329897, 0.6       , 0.        , ..., 1.        , 0.        ,
        0.        ],
       ...,
       [0.13539519, 0.2       , 0.        , ..., 0.        , 0.        ,
        1.        ],
       [0.08659794, 0.4       , 0.        , ..., 1.        , 0.        ,
        0.        ],
       [0.15120275, 0.4       , 0.        , ..., 0.        , 0.        ,
        1.        ]])
```

```
X = pd.DataFrame(X_scaled, columns=name)
X
```

	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheat
0	0.476289	0.6	1.0	1.000000	1.0	0.0	0.0	
1	1.000000	0.8	1.0	0.333333	1.0	0.0	0.0	
2	0.443299	0.6	0.0	0.333333	1.0	1.0	1.0	
3	0.281787	0.4	0.5	1.000000	1.0	1.0	0.0	
4	0.793814	0.4	0.0	0.333333	1.0	0.0	1.0	
...	...	...	...	...	...	...	...	
534	0.092784	0.2	0.0	0.000000	1.0	0.0	1.0	
535	0.051546	0.4	0.0	0.000000	0.0	0.0	0.0	
536	0.135395	0.2	0.0	0.000000	1.0	0.0	0.0	
537	0.086598	0.4	0.0	0.000000	0.0	0.0	0.0	
538	0.151203	0.4	0.0	0.333333	1.0	0.0	0.0	

539 rows × 13 columns

10. Split the data into training and testing

Train-Test Split

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

```
X_train
```

	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheat
470	0.288660	0.4	0.0	0.333333	1.0	0.0	1.0	
208	0.185567	0.2	0.0	0.000000	1.0	0.0	1.0	
250	0.161512	0.4	0.0	0.333333	1.0	0.0	0.0	
157	0.355670	0.4	0.0	0.000000	1.0	1.0	1.0	
118	0.335052	0.4	0.5	1.000000	1.0	0.0	0.0	
...	...	...	...	...	...	...	...	
70	0.327835	0.4	0.5	0.666667	1.0	0.0	0.0	
277	0.186254	0.6	0.0	0.333333	1.0	0.0	0.0	
9	0.298969	0.6	0.0	0.333333	1.0	0.0	1.0	
359	0.261168	0.2	0.0	0.000000	1.0	0.0	0.0	
192	0.295395	0.4	0.0	0.333333	1.0	0.0	0.0	

431 rows × 13 columns

```
y_train
```

	price
470	2940000
208	4865000
250	4480000
157	5425000
118	5950000
...	...
70	6650000
277	4270000

```
X_test
```

	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheat
172	0.373540	0.4	0.0	0.000000	1.0	1.0	1.0	
469	0.092784	0.2	0.0	0.333333	1.0	0.0	0.0	
196	0.169759	0.2	0.0	0.000000	1.0	0.0	1.0	
417	0.144330	0.4	0.0	0.000000	1.0	0.0	0.0	
535	0.051546	0.4	0.0	0.000000	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	
494	0.079038	0.4	0.0	0.000000	1.0	0.0	0.0	
225	0.183505	0.4	0.0	0.000000	1.0	0.0	0.0	
337	0.167010	0.2	0.0	0.000000	1.0	0.0	0.0	
318	0.195876	0.4	0.0	0.333333	0.0	0.0	1.0	
10	0.340206	0.6	0.5	0.333333	1.0	1.0	1.0	

108 rows × 13 columns

```
y_test
```

	price
172	5229000
469	2961000
196	4900000
417	3360000
535	1767150
...	...
494	2660000
225	4690000
337	3850000
318	4007500

11. Build the Model

```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
```

12. Train the Model

```
#train the model
lr.fit(X_train,y_train)
```

```
▾ LinearRegression
LinearRegression()
```

13. Test the Model

```
#test the model
y_pred=lr.predict(X_test)
```

```
y_pred #prediction
```

```
array([[5292032.],
       [3473408.],
       [3915776.],
       [2867200.],
       [2359296.],
```

```
       [4194304.],
       [2834432.],
       [4620288.],
       [4734976.],
       [5341184.],
       [4702208.],
       [6619136.],
       [2277376.],
       [3719168.],
       [5062656.],
       [4046848.],
       [2801664.],
       [2818048.],
       [3260416.],
       [5259264.],
       [5013504.],
       [3915776.],
       [6553600.],
       [2818048.],
       [5767168.],
       [3244032.],
       [3555328.],
       [3866624.],
       [6062080.],
       [6651904.],
       [6012928.],
       [5668864.],
       [5718016.],
       [3194880.],
       [6668288.],
       [4407296.],
       [2719744.],
       [4882432.],
       [4341760.],
       [4358144.],
       [6307840.],
       [3637248.],
       [4767744.],
       [5062656.],
       [6373376.],
       [2621440.],
       [6045696.],
       [5505024.],
       [3801088.],
       [6111232.],
       [3424256.],
       [5537792.],
       [7618560.],
       [3784704.],
       [4177920.],
       [7454720.],
       [6553600.],
       [4718592.],
```

```
y_test # Actual outcome
```

	price
172	5229000
469	2961000
196	4900000
417	3360000
535	1767150
...	...
494	2660000
225	4690000
337	3850000
318	4007500
10	9100000

108 rows × 1 columns

14. Measure the performance using Metrics.

```
from sklearn.metrics import mean_squared_error,r2_score, mean_absolute_error
```

Error

```
error=y_test-y_pred
```

```
error
```

	price
172	-63032.0
469	-512408.0
196	984224.0
417	492800.0

Square error

```
se=error*error
```

494 22176.0

```
se
```

	price
172	3.973033e+09
469	2.625620e+11
196	9.686969e+11
417	2.428518e+11
535	3.506369e+11
...	...
494	4.917750e+08
225	1.602108e+12
337	3.476093e+11
318	5.533277e+11
10	4.778386e+12

108 rows × 1 columns

Mean square error

```
mse=np.mean(se)
```

```
/usr/local/lib/python3.10/dist-packages/numpy/core/fromnumeric.py:3472: FutureWarning: I
  return mean(axis=axis, dtype=dtype, out=out, **kwargs)
```

```
mse
```

```
price    9.902522e+11
dtype: float64
```

```
mse2=mean_squared_error(y_test,y_pred)
```

```
mse2
```

```
990252212649.3704
```

Mean absolute eroor

```
mae=mean_absolute_error(y_test,y_pred)
```

```
mae
```

```
778780.9444444445
```

```
rmse=np.sqrt(mse2)
```

```
rmse
```

```
995114.1706605179
```

R2 Score

```
acc=r2_score(y_pred,y_test)
acc
```

```
0.49589197394008533
```