Assignment 2 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.

In [ ]:
```
from google.colab import files
```

```
uploaded = files.upload()
```

Choose Files No file chosen    Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving House Price India.csv to House Price India.csv
```

In [ ]:
```
import pandas as pd
 import numpy as np
```

In [ ]:
```
# AUTHOR RESHMA FROM PRINCE DR K VASUDEVAN COLLEGE OF ENGINEERING AND TECHNOLOGY
```

In [ ]:
```
df = pd.read_csv('House Price India.csv')
```

In [ ]:
```
import pandas as pd
import numpy as np

# Load data into a pandas dataframe df
= pd.read_csv('House Price India.csv')

# Calculate measures of central tendency
mean = df['number of bedrooms'].mean()
median = df['number of bedrooms'].median()
mode = df['number of bedrooms'].mode()

# Calculate measures of dispersion
range = df['number of bedrooms'].max() - df['number of
bedrooms'].min() std_dev = df['number of bedrooms'].std() variance =
df['number of bedrooms'].var()

# Examine the distribution of the data histogram
= df['number of bedrooms'].hist() boxplot =
df.boxplot(column=['number of bedrooms'])

# Identify outliers
outliers = df[np.abs(df['number of bedrooms'] - df['number of bedrooms'].mean()) > 3 * df['number of
bedrooms'].std()]

# Print the results
print("Mean: ", mean)
print("Median: ", median)
print("Mode: ", mode)
print("Range: ", range)
```

```
print("Standard Deviation: ", std_dev)
print("Variance: ", variance)
print("Outliers: ", outliers)
```

Mean:  3.379343365253078
Median:  3.0
Mode:  0    3
Name: number of bedrooms, dtype: int64
Range:  32
Standard Deviation:  0.9387188525270168
Variance:  0.881193084089639
Outliers:

| | id | Date | number of bedrooms | number of bathrooms \ |
|---|---|---|---|---|
| 76 | 6762810164 | 42494 | 7 | 8.00 |
| 243 | 6762810052 | 42496 | 7 | 4.50 |
| 268 | 6762816384 | 42496 | 9 | 4.50 |
| 275 | 6762817937 | 42496 | 7 | 5.75 |
| 624 | 6762817573 | 42502 | 7 | 4.00 |
| 785 | 6762819926 | 42504 | 7 | 3.50 |
| 1512 | 6762810234 | 42517 | 8 | 3.50 |
| 1519 | 6762811513 | 42517 | 7 | 4.00 |
| 1553 | 6762817186 | 42517 | 7 | 4.50 |
| 1706 | 6762812569 | 42519 | 7 | 4.50 |
| 2814 | 6762812756 | 42537 | 7 | 4.25 |
| 3109 | 6762810241 | 42540 | 7 | 3.50 |
| 3114 | 6762810926 | 42540 | 7 | 5.50 |
| 3322 | 6762824851 | 42543 | 7 | 3.00 |
| 3532 | 6762815473 | 42545 | 33 | 1.75 |
| 3600 | 6762827935 | 42545 | 7 | 2.50 |
| 4207 | 6762825321 | 42553 | 8 | 2.75 |
| 4486 | 6762816413 | 42559 | 7 | 2.50 |
| 4658 | 6762810410 | 42561 | 8 | 2.75 |
| 4680 | 6762816797 | 42561 | 7 | 2.75 |
| 6591 | 6762810158 | 42589 | 7 | 4.75 |
| 6596 | 6762810849 | 42589 | 9 | 4.50 |
| 6730 | 6762820817 | 42592 | 9 | 7.50 |
| 6982 | 6762811117 | 42595 | 10 | 5.25 |
| 6998 | 6762813966 | 42595 | 7 | 3.75 |
| 7003 | 6762814707 | 42595 | 8 | 2.75 |
| 7454 | 6762818607 | 42602 | 11 | 3.00 |
| 8559 | 6762820832 | 42621 | 7 | 4.00 |
| 8650 | 6762822185 | 42622 | 7 | 3.25 |
| 9282 | 6762816452 | 42634 | 7 | 4.00 |
| 9629 | 6762810083 | 42638 | 7 | 3.00 |
| 9810 | 6762810131 | 42642 | 7 | 4.25 |
| 9955 | 6762813377 | 42644 | 7 | 2.25 |
| 10168 | 6762810199 | 42649 | 8 | 6.00 |
| 10177 | 6762812988 | 42649 | 7 | 6.75 |

| | | | | |
|---|---|---|---|---|
| 10676 | 6762813920 | 42657 | 7 | 2.75 |
| 10748 | 6762812073 | 42658 | 8 | 4.00 |
| 10916 | 6762810049 | 42662 | 8 | 4.00 |
| 10944 | 6762818039 | 42662 | 7 | 2.25 |
| 11247 | 6762811840 | 42666 | 7 | 3.75 |
| 11441 | 6762816963 | 42670 | 7 | 1.50 |
| 11547 | 6762815290 | 42671 | 10 | 2.00 |
| 11877 | 6762827515 | 42677 | 7 | 1.00 |
| 12273 | 6762813642 | 42685 | 7 | 2.75 |
| 13048 | 6762816970 | 42698 | 8 | 3.00 |
| 13444 | 6762819515 | 42707 | 8 | 5.00 |
| 13825 | 6762821692 | 42714 | 8 | 3.25 |
| 14220 | 6762812912 | 42722 | 8 | 3.75 |
| 14481 | 6762815079 | 42732 | 10 | 3.00 |

| | living area | lot area | number of floors | waterfront present \ |
|---|---|---|---|---|
| 76 | 13540 | 307752 | 3.0 | 0 |
| 243 | 6210 | 8856 | 2.5 | 0 |
| 268 | 3830 | 6988 | 2.5 | 0 |
| 275 | 3700 | 7647 | 2.0 | 0 |
| 624 | 3440 | 8100 | 2.0 | 0 |
| 785 | 2870 | 29699 | 1.0 | 0 |
| 1512 | 4440 | 6480 | 2.0 | 0 |
| 1519 | 3150 | 34830 | 1.0 | 0 |
| 1553 | 4140 | 9066 | 1.0 | 0 |
| 1706 | 4290 | 37607 | 1.5 | 0 |
| 2814 | 3670 | 4000 | 2.0 | 0 |
| 3109 | 4640 | 15235 | 2.0 | 0 |
| 3114 | 6630 | 13782 | 2.0 | 0 |
| 3322 | 2800 | 9569 | 1.0 | 0 |
| 3532 | 1620 | 6000 | 1.0 | 0 |
| 3600 | 1940 | 5458 | 2.0 | 0 |
| 4207 | 2790 | 6695 | 1.0 | 0 |
| 4486 | 2580 | 5750 | 1.0 | 0 |
| 4658 | 4040 | 20666 | 1.0 | 0 |
| 4680 | 2310 | 2400 | 1.5 | 0 |
| 6591 | 5310 | 8816 | 2.0 | 0 |
| 6596 | 3650 | 5000 | 2.0 | 0 |
| 6730 | 4050 | 6504 | 2.0 | 0 |
| 6982 | 4590 | 10920 | 1.0 | 0 |
| 6998 | 2310 | 5000 | 2.0 | 0 |
| 7003 | 2530 | 4800 | 2.0 | 0 |
| 7454 | 3000 | 4960 | 2.0 | 0 |

```
8559          3150      7800               2.0                 0
8650          4340      8521               2.0                 0
9282          2690     10880               1.0                 0
9629          5350     14400               2.5                 0   9810          4670     23115
2.0                 0
9955          3260      8145               2.0                 0
10168         4340      9415               2.0                 0
10177         7480     41664               2.0                 0
10676         3110      4400               1.5                 0
10748         4020      7500               1.0                 0
10916         7710     11750               3.5                 0
10944         2620      6890               2.0                 0
11247         5100     21802               2.0                 0
11441         2670     11250               1.5                 0
11547         3610     11914               2.0                 0
11877         2350      8636               1.0                 0
12273         3410      4056               1.5                 0
13048         3840     15990               1.0                 0
13444         2800      2580               2.0                 0
13825         4300     10441               2.0                 0
14220         3460      4600               2.0                 0
14481         2920      3745               2.0                 0

       number of views  condition of the house  ...  Built Year  \
76                   4                       3  ...        1999
243                  2                       5  ...        1910
268                  0                       3  ...        1938
275                  1                       3  ...        1948
624                  0                       3  ...        1970
785                  0                       3  ...        1961
1512                 3                       5  ...        1959
1519                 0                       3  ...        1957
1553                 0                       3  ...        1978
1706                 0                       5  ...        1982
2814                 1                       3  ...        1964
3109                 1                       3  ...        1965
3114                 0                       3  ...        2004
3322                 2                       3  ...        1963
3532                 0                       5  ...        1947
3600                 0                       3  ...        1994
4207                 0                       3  ...        1977
4486                 0                       4  ...        1901
4658                 0                       4  ...        1962
```

```
4680                  0                        3  ...        1915
6591                  0                        3  ...        2013
6596                  0                        3  ...        1915
6730                  0                        3  ...        1996
6982                  2                        3  ...        2008
6998                  0                        3  ...        1984   7003                  0
4  ...         1901
7454                  0                        3  ...        1918
8559                  0                        3  ...        2013
8650                  0                        3  ...        1986
9282                  0                        4  ...        1960
9629                  0                        4  ...        1910
9810                  2                        3  ...        1992
9955                  0                        5  ...        1967
10168                 0                        3  ...        1967
10177                 2                        3  ...        1953
10676                 0                        5  ...        1914
10748                 0                        3  ...        1968
10916                 0                        5  ...        1904
10944                 0                        4  ...        1961
11247                 0                        3  ...        2001
11441                 0                        4  ...        1948
11547                 0                        4  ...        1958
11877                 0                        3  ...        1962
12273                 0                        4  ...        1906
13048                 0                        3  ...        1961
13444                 0                        3  ...        1997
13825                 0                        4  ...        1979
14220                 0                        3  ...        1987
14481                 0                        4  ...        1913

       Renovation Year  Postal Code  Lattitude  Longitude  living_area_renov  \
76                   0       122045    52.8975   -114.176               4850
243                  0       122061    52.8607   -114.544               2940
268                  0       122028    52.9227   -114.528               1460
275               1984       122014    52.9693   -114.479               2510
624                  0       122028    52.9281   -114.539               1420
785                  0       122022    52.9453   -114.517               1380
1512                 0       122047    52.8610   -114.493               4440
1519              2005       122030    52.8329   -114.337               2390
1553                 0       122022    52.9602   -114.481               1440
1706                 0       122012    52.7112   -114.223               2810
2814                 0       122032    52.8675   -114.578               2010
```

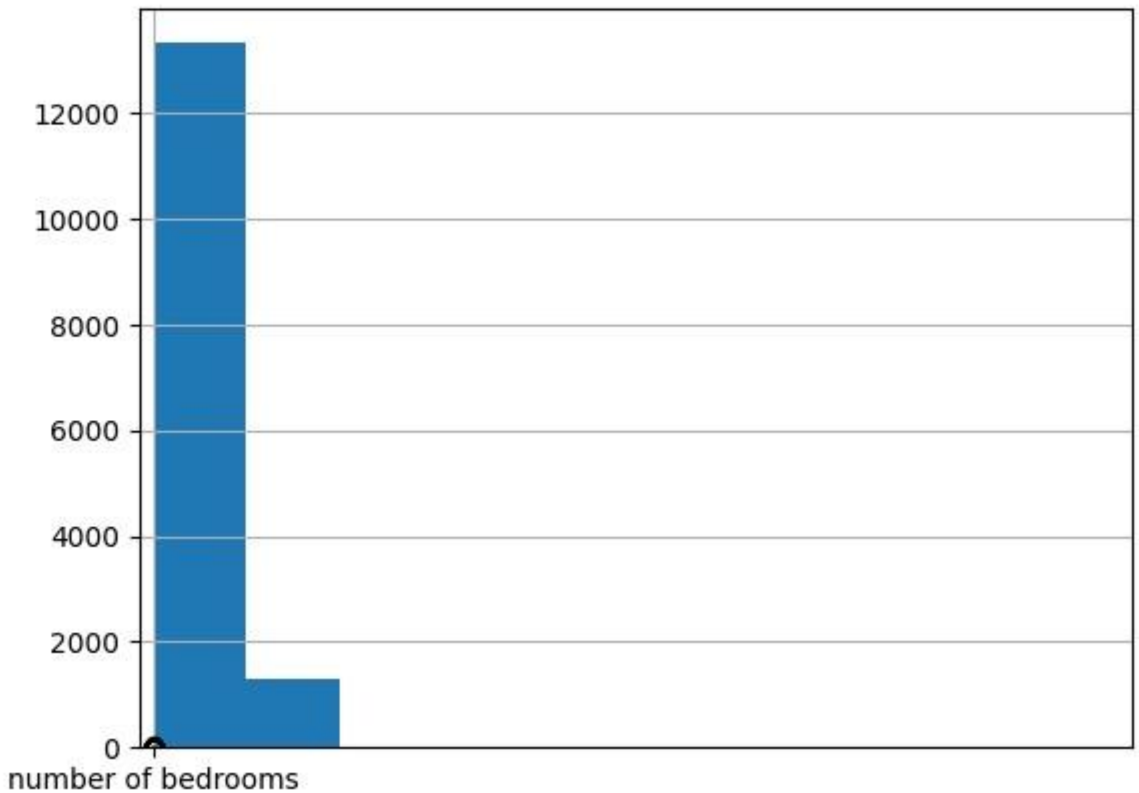
```
3109             2003     122057    52.7966   -114.421              3230
3114                0     122027    52.7699   -114.308              4470
3322                0     122053    52.7402   -114.373              2150
3532                0     122028    52.9178   -114.521              1330
3600                0     122023    52.5491   -114.367              1710
4207                0     122038    52.9865   -114.521              1760
4486                0     122044    52.8325   -114.484              2280
4658                0     122048    52.8640   -114.411              3670   4680                 0
122007    52.9075   -114.580                1340
6591                0     122048    52.8521   -114.398              2920
6596             2010     122004    52.8904   -114.479              2510
6730                0     122054    52.8223   -114.491              1448
6982                0     122048    52.8161   -114.303              2730
6998                0     122007    52.9081   -114.566              1360
7003                0     122047    52.8541   -114.495              1540
7454             1999     122034    52.7860   -114.553              1420
8559                0     122051    52.7559   -114.469              1880
8650                0     122034    52.7500   -114.528              1890
9282                0     122010    52.9087   -114.358              1840
9629                0     122047    52.8595   -114.475              3050
9810                0     122071    52.8483   -114.417              3240
9955                0     122029    52.8636   -114.305              2340
10168               0     122048    52.8616   -114.392              2050
10177               0     122031    52.6943   -114.558              2810
10676               0     122004    52.8984   -114.509              1240
10748               0     122026    52.9032   -114.553              1560
10916               0     122047    52.8563   -114.504              4210
10944               0     122030    52.8423   -114.324              2070
11247               0     122020    52.8250   -114.230              3350
11441               0     122038    52.9421   -114.522              2030
11547               0     122027    52.8005   -114.365              2040
11877               0     122051    52.7732   -114.467              1500
12273               0     122013    52.8754   -114.506              2510
13048               0     122033    52.9411   -114.401              1380
13444               0     122044    52.8386   -114.493              1800
13825               0     122015    52.7086   -114.321              1780
14220               0     122004    52.8917   -114.479              2170
14481               0     122004    52.8935   -114.510              1810

       lot_area_renov  Number of schools nearby  Distance from the airport  \
76             217800                         1                         55
243              5400                         1                         64
268              6291                         1                         62
```

| | | | | | |
|---|---|---|---|---|---|
| 275 | 7479 | 1 | 65 | | |
| 624 | 1560 | 1 | 62 | | |
| 785 | 7555 | 3 | 57 | | |
| 1512 | 8640 | 2 | 55 | | |
| 1519 | 12054 | 2 | 70 | | |
| 1553 | 1865 | 3 | 78 | | |
| 1706 | 40510 | 3 | 71 | | |
| 2814 | 4000 | 1 | 72 | | |
| 3109 | 20697 | 2 | 66 | | |
| 3114 | 8639 | 2 | 64 | 3322 | 7333 |
| 1 | 62 | | | | |
| 3532 | 4700 | 2 | 50 | | |
| 3600 | 5688 | 1 | 80 | | |
| 4207 | 7624 | 3 | 74 | | |
| 4486 | 5750 | 1 | 74 | | |
| 4658 | 20500 | 3 | 55 | | |
| 4680 | 3825 | 3 | 67 | | |
| 6591 | 10610 | 2 | 73 | | |
| 6596 | 5000 | 2 | 63 | | |
| 6730 | 3866 | 1 | 55 | | |
| 6982 | 10400 | 3 | 73 | | |
| 6998 | 1552 | 1 | 59 | | |
| 7003 | 4800 | 2 | 80 | | |
| 7454 | 4960 | 1 | 52 | | |
| 8559 | 6000 | 3 | 58 | | |
| 8650 | 8951 | 2 | 79 | | |
| 9282 | 10836 | 3 | 58 | | |
| 9629 | 7469 | 1 | 75 | | |
| 9810 | 13912 | 3 | 70 | | |
| 9955 | 8145 | 3 | 72 | | |
| 10168 | 9100 | 3 | 69 | | |
| 10177 | 33190 | 2 | 66 | | |
| 10676 | 4280 | 3 | 75 | | |
| 10748 | 3737 | 2 | 53 | | |
| 10916 | 8325 | 2 | 66 | | |
| 10944 | 7910 | 3 | 52 | | |
| 11247 | 10005 | 2 | 58 | | |
| 11441 | 9000 | 1 | 66 | | |
| 11547 | 11914 | 1 | 75 | | |
| 11877 | 7366 | 1 | 74 | | |
| 12273 | 4056 | 1 | 65 | | |
| 13048 | 8172 | 3 | 60 | | |
| 13444 | 2580 | 1 | 72 | | |

| | | | |
|---|---|---|---|
| 13825 | 10457 | 2 | 77 |
| 14220 | 3750 | 3 | 71 |
| 14481 | 3745 | 1 | 58 |

| | Price |
|---|---|
| 76 | 2280000 |
| 243 | 3200000 |
| 268 | 599999 |
| 275 | 540000 |
| 624 | 550000 |
| 785 | 475000 |
| 1512 | 1970000 |
| 1519 | 999000 |
| 1553 | 565000 |
| 1706 | 840000 |
| 2814 | 824000 |
| 3109 | 1950000 |
| 3114 | 1240000 |
| 3322 | 350000 |
| 3532 | 640000 |
| 3600 | 280000 |
| 4207 | 340000 |
| 4486 | 599000 |
| 4658 | 1650000 |
| 4680 | 580000 |
| 6591 | 2300000 |
| 6596 | 1280000 |
| 6730 | 450000 |
| 6982 | 1150000 |
| 6998 | 727160 |
| 7003 | 680000 |
| 7454 | 520000 |
| 8559 | 450000 |
| 8650 | 419000 |
| 9282 | 597157 |
| 9629 | 2890000 |
| 9810 | 2450000 |
| 9955 | 770000 |
| 10168 | 2150000 |
| 10177 | 800000 |
| 10676 | 730000 |
| 10748 | 900000 |
| 10916 | 3300000 |

```
10944   539000
11247   936000
11441   575000
11547   650000
11877   291000
12273   750000
13048   575000
13444   490000
13825   430000
14220   808000
14481   660000

[49 rows x 23 columns]
```




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

In [ ]: In [ ]:

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 14620 entries, 0 to 14619
Data columns (total 23 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                   --------------  ---
--    0   id                                          14620 non-null
int64    1   Date                                         14620 non-
null  int64
2   number of bedrooms                       14620 non-null  int64
3   number of bathrooms                      14620 non-null  float64
4   living area                              14620 non-null  int64   5   lot area
    14620 non-null  int64
6   number of floors                         14620 non-null  float64
7   waterfront present                       14620 non-null  int64
8   number of views                          14620 non-null  int64   9   condition of the house
    14620 non-null  int64
10  grade of the house                       14620 non-null  int64
11  Area of the house(excluding basement)   14620 non-null  int64
12  Area of the basement                     14620 non-null  int64   13  Built Year
    14620 non-null  int64
14  Renovation Year                          14620 non-null  int64
15  Postal Code                              14620 non-null  int64
16  Lattitude                                14620 non-null  float64  17  Longitude
    14620 non-null  float64
18  living_area_renov                        14620 non-null  int64
19  lot_area_renov                           14620 non-null  int64
20  Number of schools nearby                 14620 non-null  int64   21  Distance from the airport
    14620 non-null  int64    22  Price                                          14620 non-null  int64  dtypes:
    float64(4), int64(19) memory usage: 2.6 MB
```

```python
# replace outliers
```

```python
import pandas as pd
import numpy as np

# Load data into a pandas dataframe df
= pd.read_csv('House Price India.csv')


# Identify outliers using the Z-score method
outliers = df[np.abs(df['number of bedrooms'] - df['number of bedrooms'].mean()) > 3 * df['number of
bedrooms'].std()]

# Replace outliers with the median of the column
median = df['number of bedrooms'].median()
```

```
df['number of bedrooms'] = np.where(np.abs(df['number of bedrooms'] - df['number of bedrooms'].mean()) > 3 * df['number

# Print the updated dataframe
print(df)
```

```
              id   Date  number of bedrooms  number of bathrooms
\ 0      6762810145  42491                 5.0                2.50
1      6762810635  42491                 4.0                2.50
2      6762810998  42491                 5.0                2.75
3      6762812605  42491                 4.0                2.50
4      6762812919  42491                 3.0                2.00   ...           ...    ...
       ...                    ...
14615  6762830250  42734                 2.0                1.50
14616  6762830339  42734                 3.0                2.00
14617  6762830618  42734                 2.0                1.00   14618  6762830709  42734
       4.0                1.00   14619  6762831463  42734                 3.0                1.00

       living area  lot area  number of floors  waterfront present
\ 0            3650      9050               2.0                   0
1            2920      4000               1.5                   0
2            2910      9480               1.5                   0
3            3310     42998               2.0                   0   4             2710      4500
             1.5                  0   ...            ...       ...               ...
             ...
14615        1556     20000               1.0                   0
14616        1680      7000               1.5                   0   14617         1070
             6120               1.0                   0
14618         1030      6621               1.0                   0
14619          900      4770               1.0                   0

       number of views  condition of the house  ...  Built Year
\ 0                   4                       5  ...        1921
1                  0                       5  ...        1909
2                  0                       3  ...        1939   3
                   0                       3  ...        2001
4                  0                       4  ...        1929
...              ...                     ...  ...         ...
14615              0                       4  ...        1957
14616              0                       4  ...        1968
14617              0                       3  ...        1962
14618              0                       4  ...        1955
14619              0                       3  ...        1969

       Renovation Year  Postal Code  Lattitude  Longitude  living_area_renov
\ 0                   0       122003    52.8645   -114.557               2880
1                  0       122004    52.8878   -114.470               2470
2                  0       122004    52.8852   -114.468               2940
3                  0       122005    52.9532   -114.321               3350
```

```
4                    0       122006    52.9047   -114.485              2060   ...                 ...
                     ...        ...        ...                   ...
14615            0       122066    52.6191   -114.472              2250   14616               0
                 122072    52.5075   -114.393              1540
14617                0       122056    52.7289   -114.507              1130
14618                0       122042    52.7157   -114.411              1420   14619
                     2009       122018    52.5338   -114.552              900

       lot_area_renov  Number of schools nearby  Distance from the airport
\ 0            5400                        2                         58
1              4000                        2                         51
2              6600                        1                         53
3             42847                        3                         76
4             4500                        1                         51   ...
              ...                        ...                        ...   14615
              17286                        3                         76
14616          7480                        3                         59
14617          6120                        2                         64
14618          6631                        3                         54   14619            3480
                 2                          55

         Price
0      2380000
1      1400000
2       1200000
3       838000
4       805000  ...        ...
14615   221700
14616   219200
14617   209000  14618   205000
14619            146000

14620            rows x 23 columns]
```

```
In [ ]: # checking for any other outliers
```

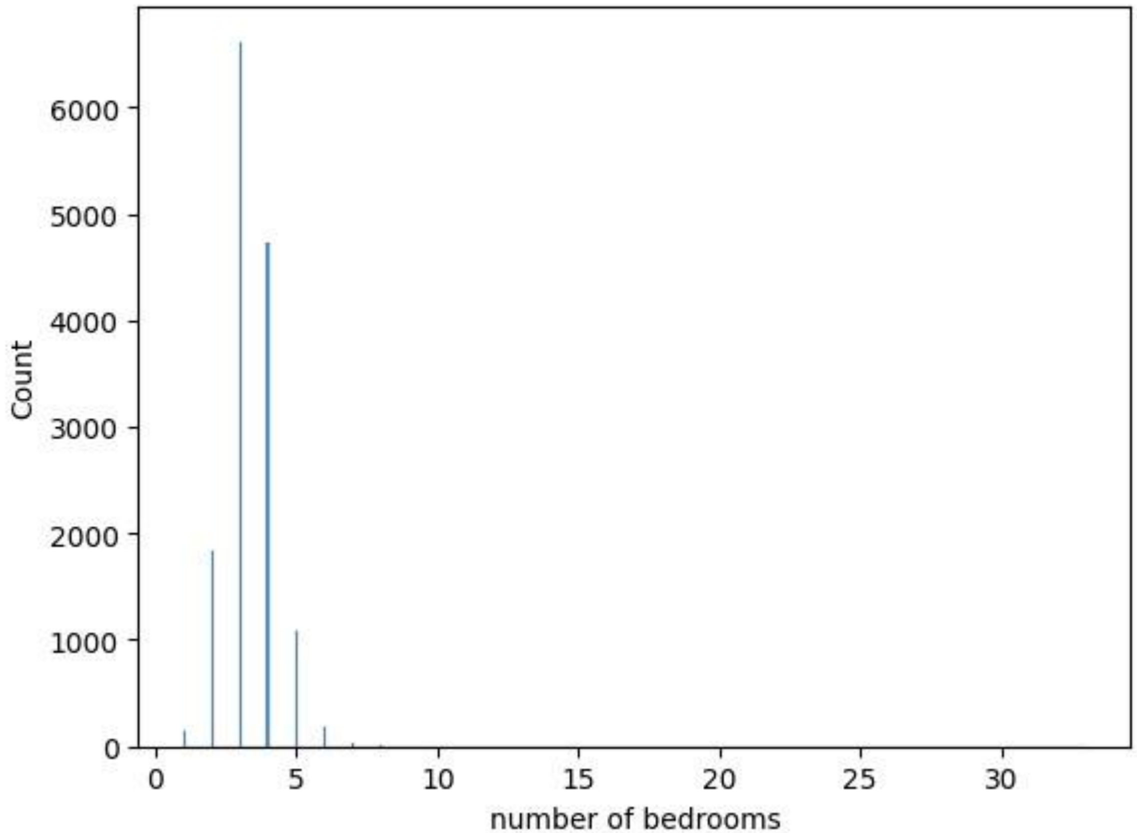
```
In [ ]: # Identify outliers outliers = df[np.abs(df['number of bedrooms'] - df['number of bedrooms'].mean()) > 3 *
        df['number of bedrooms'].std()]
```

```
In [ ]: # we get null, hence we sucessfully repplaced the outliers.
```

```
In [ ]: import pandas as pd
```

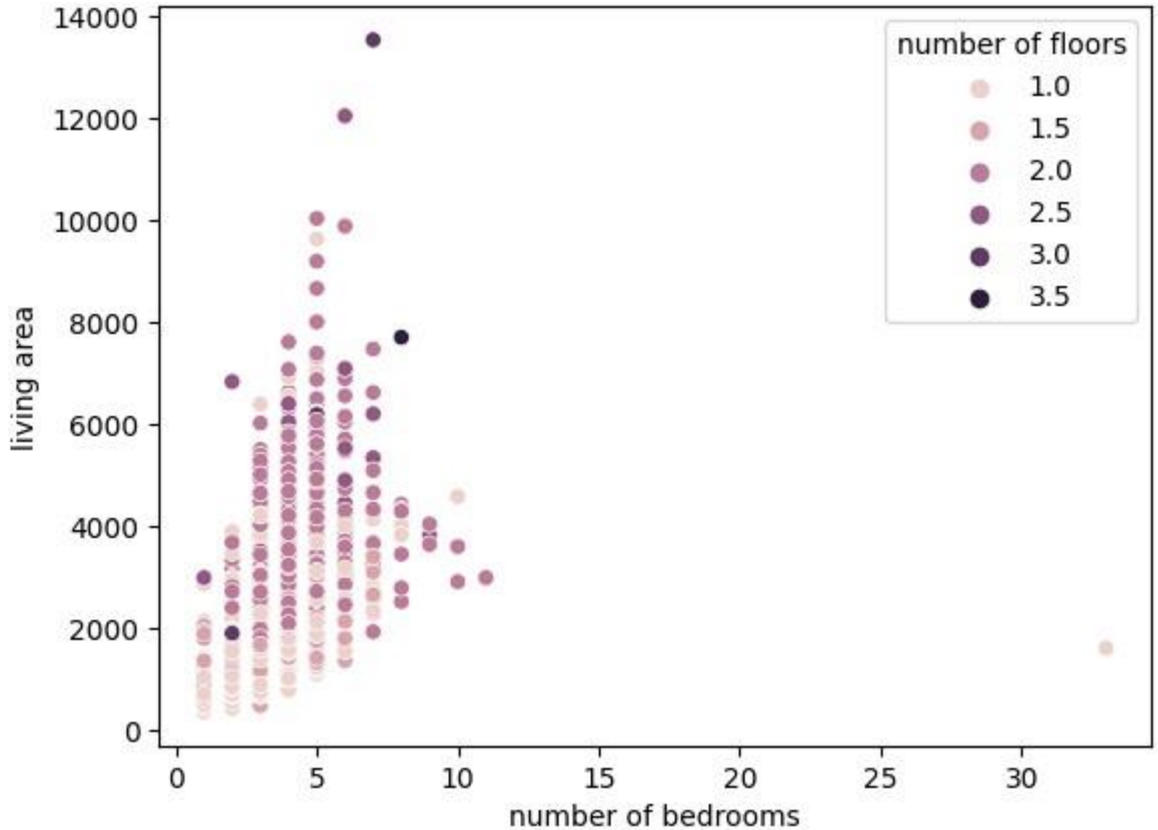
```
import seaborn as sns

# Load data into a pandas dataframe df
= pd.read_csv('House Price India.csv')

# Univariate analysis - histogram
sns.histplot(data=df, x='number of bedrooms')
```

```
Out[ ]: <Axes: xlabel='number of bedrooms', ylabel='Count'>
```



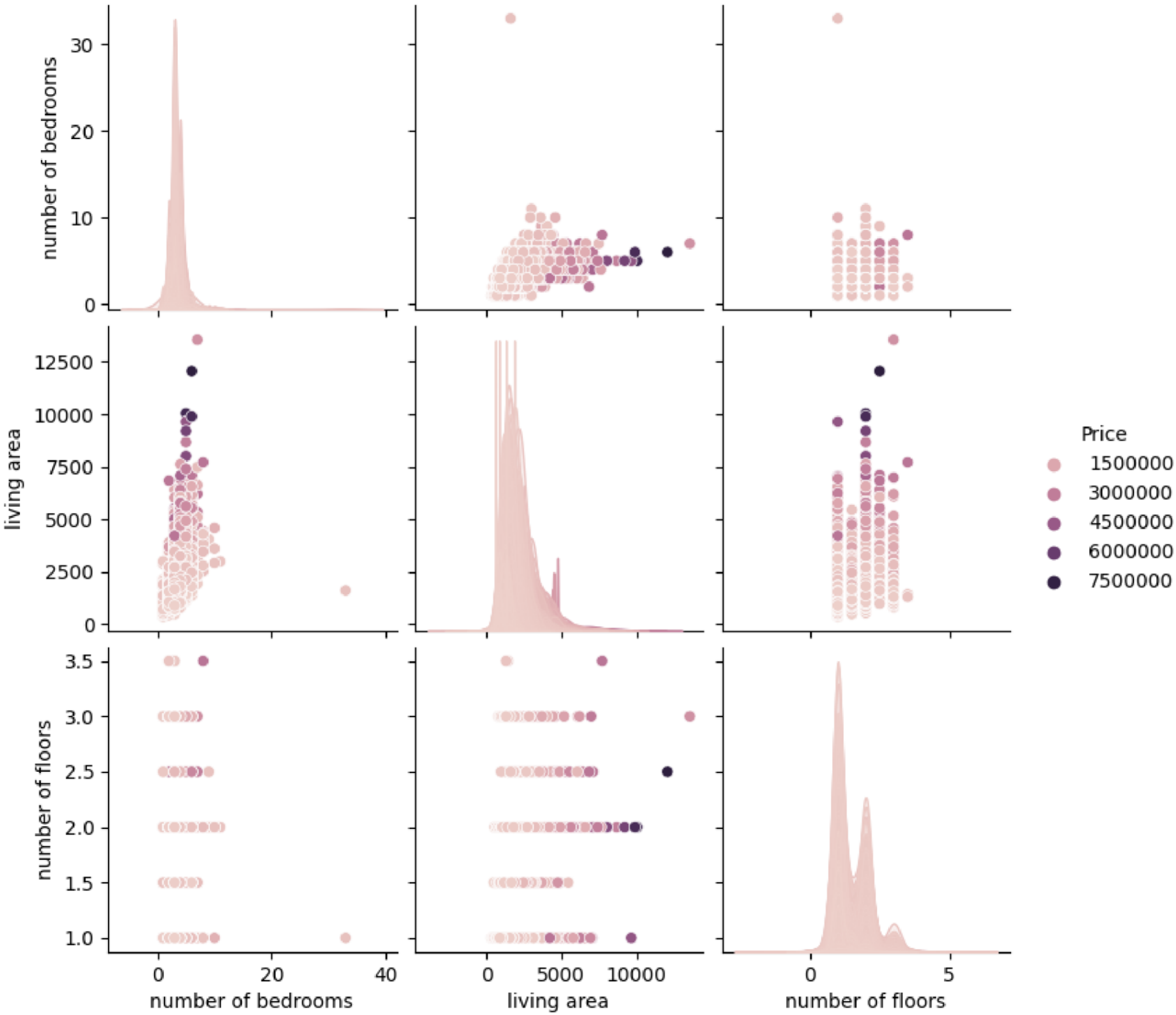

```
In [ ]: # Bi-variate analysis - scatter plot sns.scatterplot(data=df, x='number of bedrooms',
        y='living area', hue='number of floors')
```

```
Out[ ]: <Axes: xlabel='number of bedrooms', ylabel='living area'>
```




```
In [ ]: # Multi-variate analysis - pair plot sns.pairplot(data=df, vars=['number of bedrooms', 'living
        area', 'number of floors'], hue='Price')
```

```
        <seaborn.axisgrid.PairGrid at 0x7fe092701c60>
Out[ ]:
```


number of bedrooms
living area
number of floors
Price
1500000
3000000
4500000
6000000
7500000
0
10
20
30
0
2500
5000
7500
10000
12500
1.0
1.5
2.0
2.5
3.0
3.5
0
20
40
0
5000
10000
0
5

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

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14620 entries, 0 to 14619
Data columns (total 23 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                                --------------  ---
--   0   id                                     14620 non-null
int64   1   Date                                       14620 non-
null  int64
2   number of bedrooms                    14620 non-null  int64
3   number of bathrooms                   14620 non-null  float64
 4   living area                           14620 non-null  int64
 5   lot area                              14620 non-null  int64
6   number of floors                      14620 non-null  float64
7   waterfront present                    14620 non-null  int64
8   number of views                       14620 non-null  int64
    9   condition of the house                14620 non-null
    int64
10  grade of the house                    14620 non-null  int64
11  Area of the house(excluding basement) 14620 non-null  int64
12  Area of the basement                  14620 non-null  int64
    13  Built Year                            14620 non-null
    int64
14  Renovation Year                       14620 non-null  int64
15  Postal Code                           14620 non-null  int64
     16  Lattitude                            14620 non-null
float64  17  Longitude                               14620 non-null
                             float64
        18  living_area_renov                      14620 non-null
int64
        19  lot_area_renov                         14620 non-null
int64
        20  Number of schools nearby               14620 non-null
int64   21  Distance from the airport              14620 non-null
int64   22  Price                                  14620 non-null
int64  dtypes: float64(4), int64(19) memory usage: 2.6 MB In [ ]:
# we have no null values
```

In [ ]:

```
import pandas as pd

# Load data into a pandas dataframe df
= pd.read_csv('House Price India.csv')

# Identify categorical columns
cat_cols = df.select_dtypes(include=['object']).columns.tolist()

# Perform one-hot encoding for categorical columns
df = pd.get_dummies(df, columns=cat_cols)

# Print the updated dataframe
print(df)
```

```
               id   Date  number of bedrooms  number of bathrooms
\ 0      6762810145  42491                   5
2.50   1      6762810635  42491                   4
2.50
2      6762810998  42491                   5                 2.75
3      6762812605  42491                   4                 2.50
4      6762812919  42491                   3                 2.00
       ...           ...    ...                 ...
       ...
14615  6762830250  42734                   2                 1.50
14616  6762830339  42734                   3                 2.00
14617  6762830618  42734                   2                 1.00
       14618  6762830709  42734                   4
       1.00   14619  6762831463  42734                   3
       1.00

       living area  lot area  number of floors  waterfront present
\ 0            3650      9050               2.0                   0
1            2920      4000               1.5                   0
2            2910      9480               1.5                   0
3            3310     42998               2.0                   0
             4             2710      4500               1.5
             0   ...            ...       ...                 ...
             ...
14615        1556     20000               1.0                   0
14616        1680      7000               1.5                   0
             14617         1070      6120               1.0
             0
14618        1030      6621               1.0                   0
14619         900      4770               1.0                   0

       number of views  condition of the house  ...  Built Year
\ 0                  4                       5  ...        1921
1                  0                       5  ...        1909
2                  0                       3  ...        1939
                   3                    0
                   3  ...        2001
4                  0                       4  ...        1929
...              ...                     ...  ...         ...
14615              0                       4  ...        1957
14616              0                       4  ...        1968
14617              0                       3  ...        1962
14618              0                       4  ...        1955
```

```
14619               0                      3  ...        1969

       Renovation Year  Postal Code  Lattitude  Longitude  living_area_renov
\ 0                  0       122003    52.8645   -114.557               2880
1                  0       122004    52.8878   -114.470               2470
2                  0       122004    52.8852   -114.468               2940
3                  0       122005    52.9532   -114.321               3350
4                  0       122006    52.9047   -114.485               2060
                   ...                ...          ...        ...        ...
                   ...
14615              0       122066    52.6191   -114.472               2250
14616              0       122072    52.5075   -114.393               1540
14617              0       122056    52.7289   -114.507               1130
14618              0       122042    52.7157   -114.411               1420
14619           2009       122018    52.5338   -114.552                900

       lot_area_renov  Number of schools nearby  Distance from the airport
\ 0              5400                        2                         58
 1             4000                        2                         51
 2             6600                        1                         53
3             42847                        3                         76
4             4500                        1                         51
              ...                ...                      ...
              ...   14615           17286                        3
              76
14616          7480                        3                         59
14617          6120                        2                         64
14618          6631                        3                         54
14619          3480                        2                         55

         Price
0      2380000
1      1400000
2       1200000
3       838000
4       805000  ...        ...
14615   221700
14616   219200
14617   209000  14618   205000
14619   146000
```

```
[14620 rows x 23 columns]
```

In [ ]:

```
import pandas as pd

# Load data into a pandas dataframe df
= pd.read_csv('House Price India.csv')

# Split the data into dependent and independent variables
X = df.drop('number of bedrooms',
axis=1) y = df['Price']

# Print the shapes of the X and y variables
print('Independent_variable:',

X.shape)

print('dependent_variable:',

y.shape)
```

```
Independent_variable: (14620, 22)
dependent_variable: (14620,)
```

In [ ]:

```
import pandas as pd
from sklearn.preprocessing import StandardScaler

# Load data into a pandas dataframe df
= pd.read_csv('House Price India.csv')

# Split the data into dependent and independent
variables X = df.drop('number of bedrooms', axis=1)

# Scale the independent variables using StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Print the scaled data
print(X_scaled)
```

```
[[-1.71314837 -1.68590818  0.48111873 ... -0.01498123 -0.77788599
5.0094382 ]
 [-1.63458951 -1.68590818  0.48111873 ... -0.01498123 -1.56126035
2.34291528]
```

```
 [-1.57639183 -1.68590818  0.80583278 ... -1.23858786 -1.33743911
   1.79872693]
 ...
 [ 1.56916901  1.92234067 -1.46716559 ... -0.01498123 -0.10642226
  -0.89772635]
 [ 1.58375852  1.92234067 -1.46716559 ...  1.2086254  -1.22552848
  -0.90861012]
 [ 1.70464296  1.92234067 -1.46716559 ... -0.01498123 -1.11361786
  -1.06914568]]
```

In [ ]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
# Load data into a pandas dataframe df
= pd.read_csv('House Price India.csv')

# Split the data into dependent and independent variables
X = df.drop('number of bedrooms',
axis=1) y = df['Price']

# Split the 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)

# Print the shapes of the training and testing sets
print('Training set shape:', X_train.shape, y_train.shape)
print('Testing set shape:', X_test.shape, y_test.shape)
```

```
Training set shape: (11696, 22) (11696,)
```

```
Testing set shape: (2924, 22) (2924,)
```

In [ ]:

```python
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import
train_test_split from sklearn.preprocessing import
StandardScaler

# Load data into a pandas dataframe df
= pd.read_csv('House Price India.csv')

# Split the data into dependent and independent variables
X = df.drop('number of bedrooms',
axis=1) y = df['Price']

# Scale the independent variables using StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# Build a linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Print the coefficients of the model
print('Coefficients:', model.coef_)

# Predict the target variable for the test set
y_pred = model.predict(X_test)

# Print the mean squared error of the model
from sklearn.metrics import
mean_squared_error
print('Mean squared error:', mean_squared_error(y_test, y_pred))
```

```
Coefficients: [ 2.48053844e-10  0.00000000e+00 -2.19755645e-10 -1.69150617e-10
 -6.58161947e-11 -1.49083521e-10  1.02334038e-10 -5.80226402e-11
2.83806532e-10 -2.86978606e-10 -1.18451701e-10 -1.43294350e-10  -
2.44295998e-10  1.19270580e-10 -3.39268519e-11 -5.63918396e-11
8.62988441e-11 -7.27595761e-12 -2.03726813e-10  7.90123522e-11
 -2.00088834e-11  3.67519811e+05]
Mean squared error: 2.143431357174532e-18
```

In [ ]:

```
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import
train_test_split from sklearn.preprocessing import
StandardScaler

# Load data into a pandas dataframe df
= pd.read_csv('House Price India.csv')

# Split the data into dependent and independent variables
X = df.drop('number of bedrooms',
axis=1) y = df['Price']

# Scale the independent variables using StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# Build a linear regression model
model = LinearRegression()

# Train the model using the training data
model.fit(X_train, y_train)
```

Out[ ]:

▾LinearRegression

```
LinearRegression()
```

In [ ]:
```
from sklearn.metrics import mean_squared_error

# Use the trained model to make predictions on the testing data
y_pred = model.predict(X_test)

# Calculate the mean squared error between the predicted values and the actual values


mse = mean_squared_error(y_test, y_pred)
print('Mean squared error:', mse)
```

```
Mean squared error: 2.143431357174532e-18
```

In [ ]:
```
from sklearn.metrics import r2_score, mean_absolute_error

# Use the trained model to make predictions on the testing data
y_pred = model.predict(X_test)

# Calculate the R-squared value
r2 = r2_score(y_test, y_pred)
print('R-squared:', r2)

# Calculate the mean absolute error mae
= mean_absolute_error(y_test, y_pred)
print('Mean absolute error:', mae)
```

```
R-squared: 1.0
Mean absolute error: 1.1375178385490269e-09
```

In [ ]:
```
# AUTHOR RESHMA FROM PRINCE DR K VASUDEVAN COLLEGE OF ENGINEERING AND
TECHNOLOGY
```