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
```

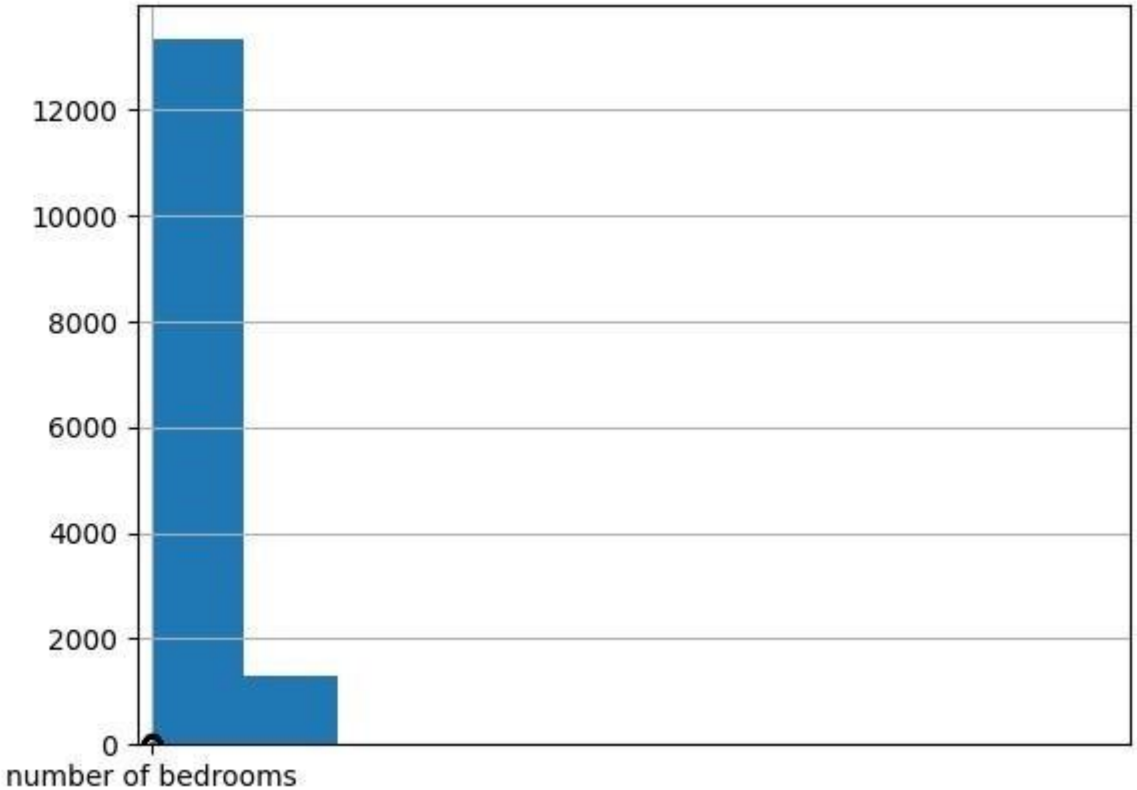
```
3600                 0       122023    52.5491   -114.367               1710
4207                 0       122038    52.9865   -114.521               1760
4486                 0       122044    52.8325   -114.484               2280
4658                 0       122048    52.8640   -114.411               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 nonnull  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
```

```
# replace outliers
```

```
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
```

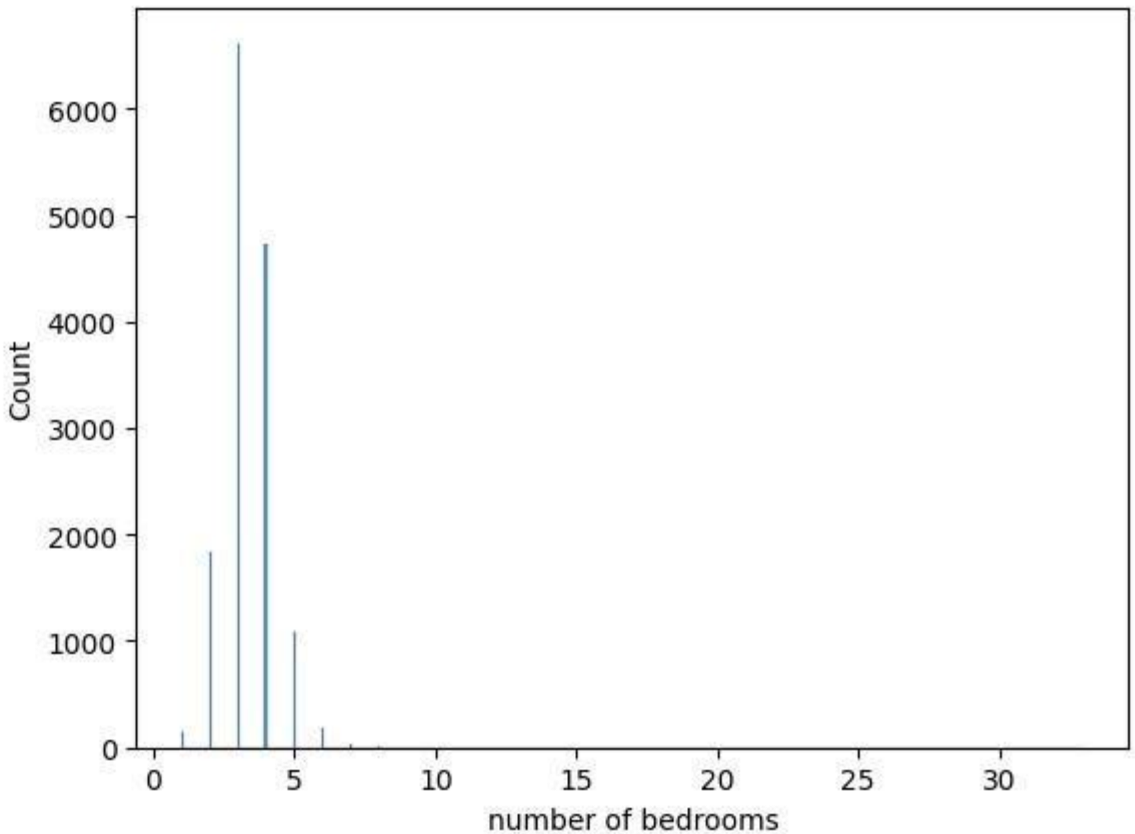
```
In [ ]: # Identify outliers outliers = df[np.abs(df['number of bedrooms'] - df['number of bedrooms'].mean()) > 3 * df['number
        of bedrooms'].std()]
```

```
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')
```

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

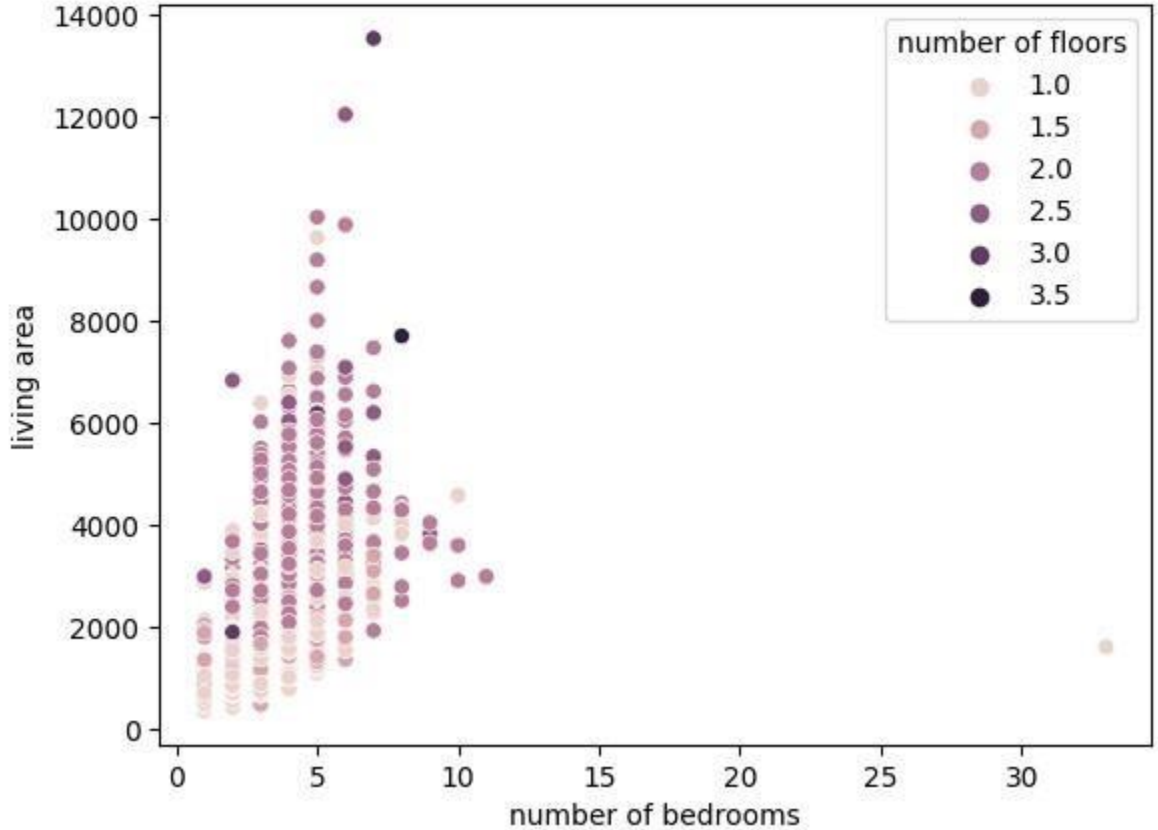
Out[ ]:



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

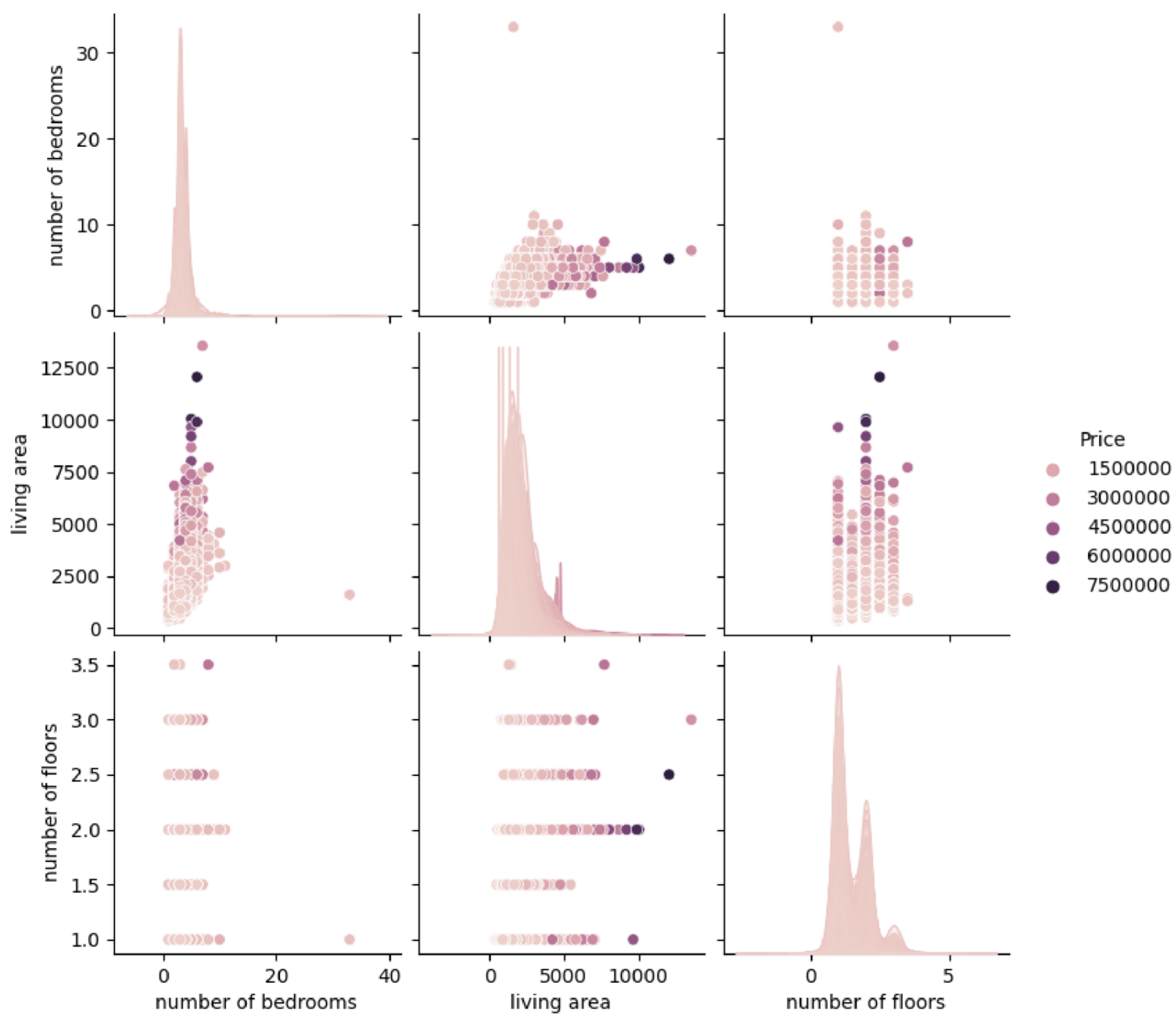
```
<Axes: xlabel='number of bedrooms', ylabel='living area'>
```

Out[ ]:




```
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

```
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 nonnull  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 [ ]:

```
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 [ ]:

Out[ ]:

```
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)
```

▾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
```