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
```

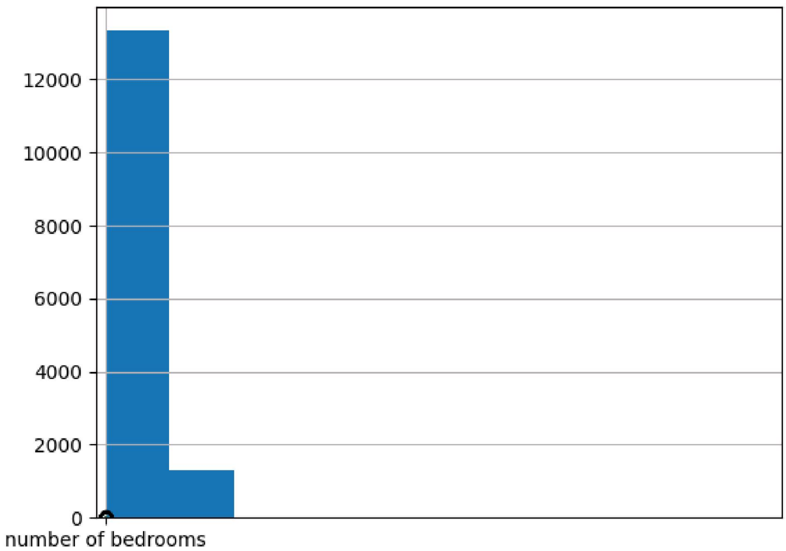
4680	0	122007	52.9075	-114.580	1340
6591	0	122048	52.8521	-114.398	2920
6596	2010	122004	52.8904	-114.479	2510
6730	0	122054	52.8223	-114.491	1448
6982	0	122048	52.8161	-114.303	2730
6998	0	122007	52.9081	-114.566	1360
7003	0	122047	52.8541	-114.495	1540
7454	1999	122034	52.7860	-114.553	1420
8559	0	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()
```

```
<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 [ ]:

```
# replace outliers
```

In [ ]:

```
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 [ ]:

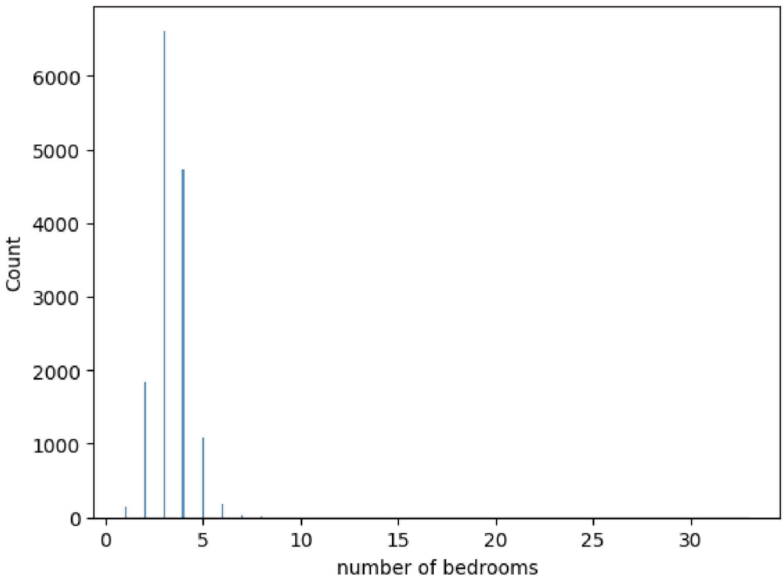
```
# we get null, hence we sucessfully repplaced the outliers.
```

In [ ]:

```
import pandas as pd
import seaborn as sns
```

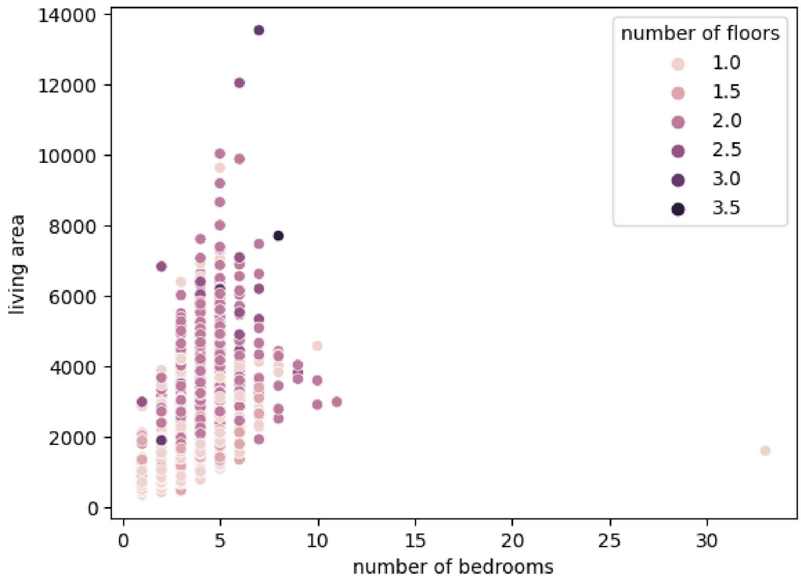
```python
# Load data into a pandas dataframe
df = pd.read_csv('House Price India.csv')

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

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



In [ ]:
```python
# 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'>
```

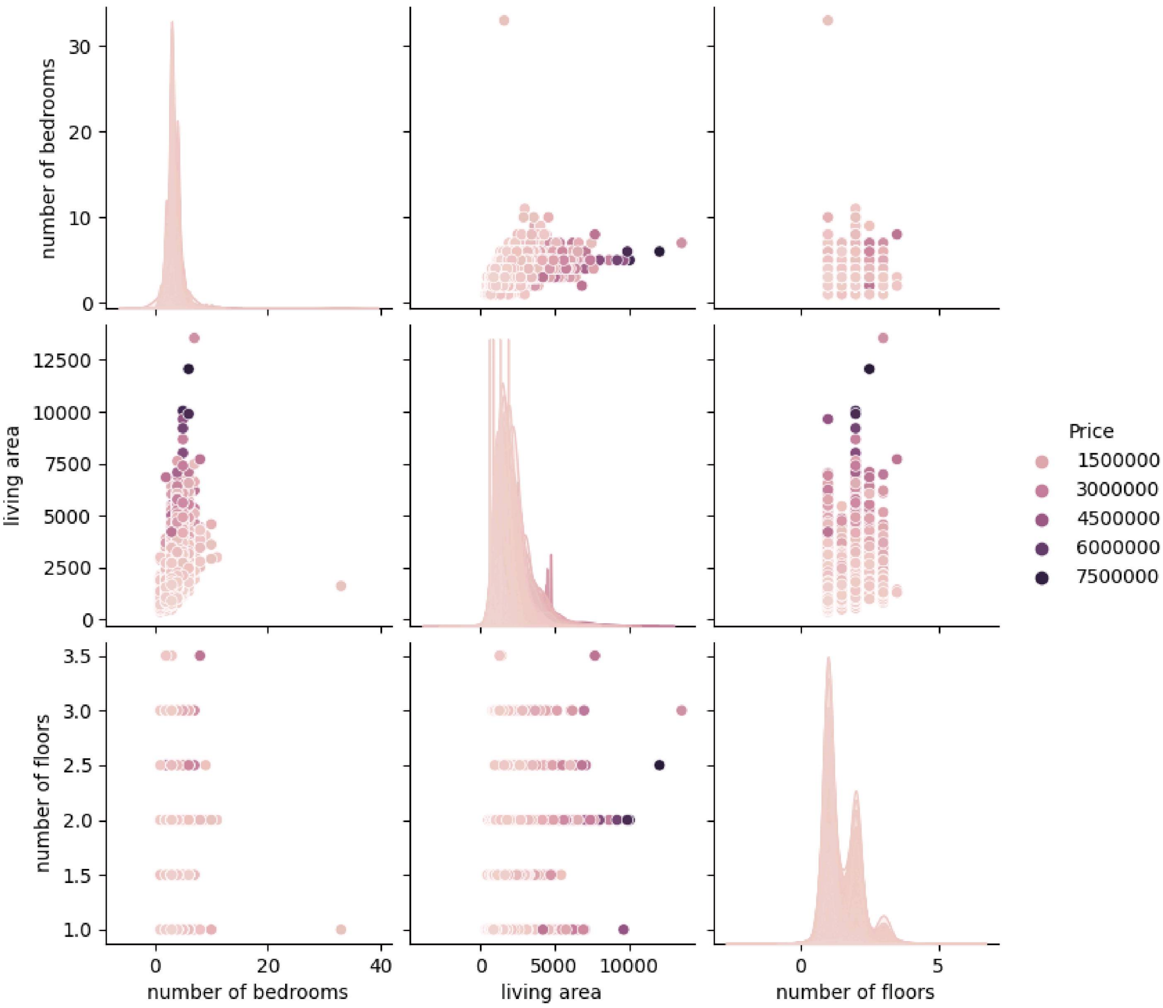


In [ ]:

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

Out[ ]:

```
<seaborn.axisgrid.PairGrid at 0x7fe092701c60>
```


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 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 [ ]:

```python
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 [ ]:

```
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
```

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

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

In [ ]:

```python
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 [ ]:

```python
# AUTHOR RESHMA FROM PRINCE DR K VASUDEVAN COLLEGE OF ENGINEERING AND TECHNOLOGY
```