Task - House Price Prediction

The **objective** of this project is to develop a **predictive model** that can **estimate the price of a house** based on various features such as square footage, number of bedrooms and bathrooms, location, condition, and other relevant attributes. The model will be trained using a dataset containing information about various houses and their corresponding prices. The goal is to develop a model that can accurately predict the price of a house based on the given features.

In [614…
```
# Mounting the drive for uploading files
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

Task 1: Reading and Understanding the Dataset

In [615…
```
# Importing Libraries

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

import warnings
warnings.simplefilter('ignore')
```

In [616…
```
# Load & Read the dataset

# house = pd.read_csv('home_data.csv')
```

In [617…
```
# Load & Read the dataset from the drive

house = pd.read_csv('/content/drive/MyDrive/6. Machine Learning/Assignment - Linear Regression/Assignment - Linear Regression/home_data.csv
```

In [618…
```
# Check the details of dataset for 1st 10 rows

house.head(10)
```

Out[618…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement
0	7129300520	20141013T000000	221900	3	1.00	1180	5650	1.0	0	0	...	7	1180	0
1	6414100192	20141209T000000	538000	3	2.25	2570	7242	2.0	0	0	...	7	2170	400
2	5631500400	20150225T000000	180000	2	1.00	770	10000	1.0	0	0	...	6	770	0
3	2487200875	20141209T000000	604000	4	3.00	1960	5000	1.0	0	0	...	7	1050	910
4	1954400510	20150218T000000	510000	3	2.00	1680	8080	1.0	0	0	...	8	1680	0
5	7237550310	20140512T000000	1225000	4	4.50	5420	101930	1.0	0	0	...	11	3890	1530
6	1321400060	20140627T000000	257500	3	2.25	1715	6819	2.0	0	0	...	7	1715	0
7	2008000270	20150115T000000	291850	3	1.50	1060	9711	1.0	0	0	...	7	1060	0
8	2414600126	20150415T000000	229500	3	1.00	1780	7470	1.0	0	0	...	7	1050	730
9	3793500160	20150312T000000	323000	3	2.50	1890	6560	2.0	0	0	...	7	1890	0

10 rows × 21 columns

Task 2: Exploratory Data Analysis

1. Check the distribution of the target variable.

2. Check the distribution of the important numerical features.

3. Check the distribution of the important categorical features.

4. Check the correlation between the numerical features and the target variable.

5. Check the correlation between the categorical features and the target variable.

In [619…
```
# Check the Rows and Columns of House dataframe

house.shape
```

Out[619…
```
(21613, 21)
```

In [620…
```
# List all the columns on House Dataframe
```

```
house.columns
```

Out[620…

```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

In [621…

```
# Check for Null values

house.isnull().sum()
```

Out[621…

	0
id	0
date	0
price	0
bedrooms	0
bathrooms	0
sqft_living	0
sqft_lot	0
floors	0
waterfront	0
view	0
condition	0
grade	0
sqft_above	0
sqft_basement	0
yr_built	0
yr_renovated	0
zipcode	0
lat	0
long	0
sqft_living15	0
sqft_lot15	0

dtype: int64

In [622…

```
# Check for summary of House dataframe

house.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21613 non-null  int64
 1   date           21613 non-null  object
 2   price          21613 non-null  int64
 3   bedrooms       21613 non-null  int64
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64
 6   sqft_lot       21613 non-null  int64
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64
 9   view           21613 non-null  int64
 10  condition      21613 non-null  int64
 11  grade          21613 non-null  int64
 12  sqft_above     21613 non-null  int64
 13  sqft_basement  21613 non-null  int64
 14  yr_built       21613 non-null  int64
 15  yr_renovated   21613 non-null  int64
 16  zipcode        21613 non-null  int64
 17  lat            21613 non-null  float64
 18  long           21613 non-null  float64
 19  sqft_living15  21613 non-null  int64
 20  sqft_lot15     21613 non-null  int64
dtypes: float64(4), int64(16), object(1)
memory usage: 3.5+ MB
```

In [623…

```
# Check for any Duplicate Records

house.duplicated().sum()
```

Out[623… np.int64(0)

In [624…
```
# Check the statistical overview of numerical data

house.describe()
```

Out[624…

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	
count	2.161300e+04	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+04	21613.000000	21613.000000	21613.000000	21613.000000	21
mean	4.580302e+09	5.400881e+05	3.370842	2.114757	2079.899736	1.510697e+04	1.494309	0.007542	0.234303	3.409430	
std	2.876566e+09	3.671272e+05	0.930062	0.770163	918.440897	4.142051e+04	0.539989	0.086517	0.766318	0.650743	
min	1.000102e+06	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+02	1.000000	0.000000	0.000000	1.000000	
25%	2.123049e+09	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	0.000000	0.000000	3.000000	
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	0.000000	3.000000	
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	0.000000	0.000000	4.000000	
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	4.000000	5.000000	

In [625…
```
# Check the statistical overview of categorical data

house.describe(include='object')
```

Out[625…

	date
count	21613
unique	372
top	20140623T000000
freq	142

In [626…
```
# Check the Value count of Date column

house['date'].value_counts()
```

Out[626…

	count
date	
20140623T000000	142
20140626T000000	131
20140625T000000	131
20140708T000000	127
20150427T000000	126
...	...
20150131T000000	1
20150117T000000	1
20150308T000000	1
20150515T000000	1
20140803T000000	1

372 rows × 1 columns

dtype: int64

In [627…
```
# Identifying Junk values in categorical column

for i in house.select_dtypes(include=['object']).columns:
    print(i, house[i].value_counts)
```

```
date <bound method IndexOpsMixin.value_counts of 0        20141013T000000
1        20141209T000000
2        20150225T000000
3        20141209T000000
4        20150218T000000
              ...
21608    20140521T000000
21609    20150223T000000
21610    20140623T000000
21611    20150116T000000
21612    20141015T000000
Name: date, Length: 21613, dtype: object>
```

In [628…

```
# Trim last 7 values from categorical column

house['date'] = house['date'].str[:-7]
```

In [629…

```
# Check the Value count of Date column

house['date'].value_counts()
```

Out[629…

date	count
20140623	142
20140626	131
20140625	131
20140708	127
20150427	126
...	...
20150131	1
20150117	1
20150308	1
20150515	1
20140803	1

372 rows × 1 columns

dtype: int64

In [630…

```
# Changing the date column from categorical to numerical

house['date'] = pd.to_datetime(house['date'])
```

In [631…

```
# Check the data type of date column

house['date'].dtype
```

Out[631…

```
dtype('<M8[ns]')
```

In [632…

```
# Check the statistical overview of numerical data

house.describe()
```

Out[632…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	vie
count	2.161300e+04	21613	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+04	21613.000000	21613.000000	21613.00000
mean	4.580302e+09	2014-10-29 04:38:01.959931648	5.400881e+05	3.370842	2.114757	2079.899736	1.510697e+04	1.494309	0.007542	0.23430
min	1.000102e+06	2014-05-02 00:00:00	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+02	1.000000	0.000000	0.00000
25%	2.123049e+09	2014-07-22 00:00:00	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	0.000000	0.00000
50%	3.904930e+09	2014-10-16 00:00:00	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	0.00000
75%	7.308900e+09	2015-02-17 00:00:00	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	0.000000	0.00000
max	9.900000e+09	2015-05-27 00:00:00	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	4.00000
std	2.876566e+09	NaN	3.671272e+05	0.930062	0.770163	918.440897	4.142051e+04	0.539989	0.086517	0.76631

8 rows × 21 columns

In [633…

```
# Removing time from date column

house['date'] = house['date'].dt.date
house.head()
```

Out[633…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_
0	7129300520	2014-10-13	221900	3	1.00	1180	5650	1.0	0	0	...	7	1180	0	1955	
1	6414100192	2014-12-09	538000	3	2.25	2570	7242	2.0	0	0	...	7	2170	400	1951	
2	5631500400	2015-02-25	180000	2	1.00	770	10000	1.0	0	0	...	6	770	0	1933	
3	2487200875	2014-12-09	604000	4	3.00	1960	5000	1.0	0	0	...	7	1050	910	1965	
4	1954400510	2015-02-18	510000	3	2.00	1680	8080	1.0	0	0	...	8	1680	0	1987	

5 rows × 21 columns

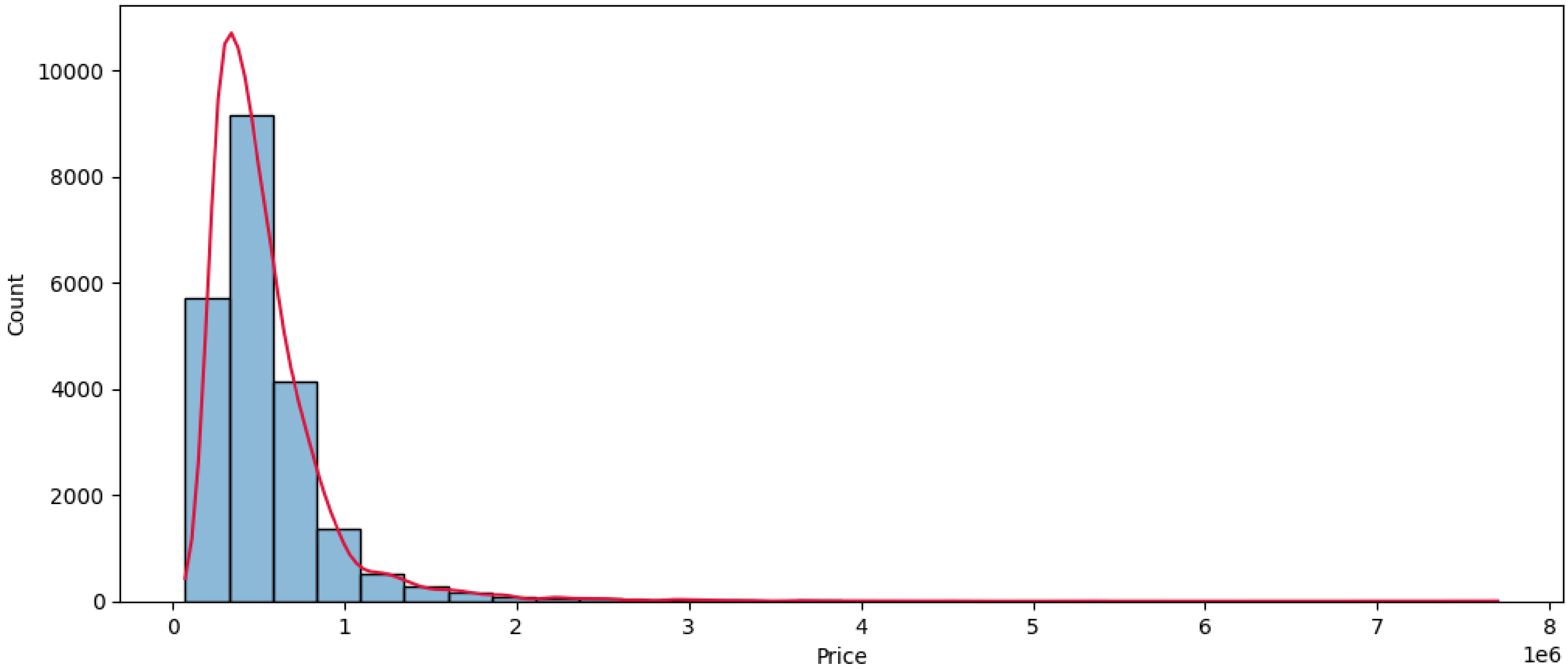
Univariate Analysis - Target column (Price)

In [634…

```
# Check the distribution of price column

plt.figure(figsize=(12, 5))
ax = sns.histplot(data=house, x='price', kde=True, bins = 30)
ax.lines[0].set_color('crimson')

plt.xlabel('Price')
```

Out[634…

```
Text(0.5, 0, 'Price')
```



Univariate Analysis - Features column

In [635…

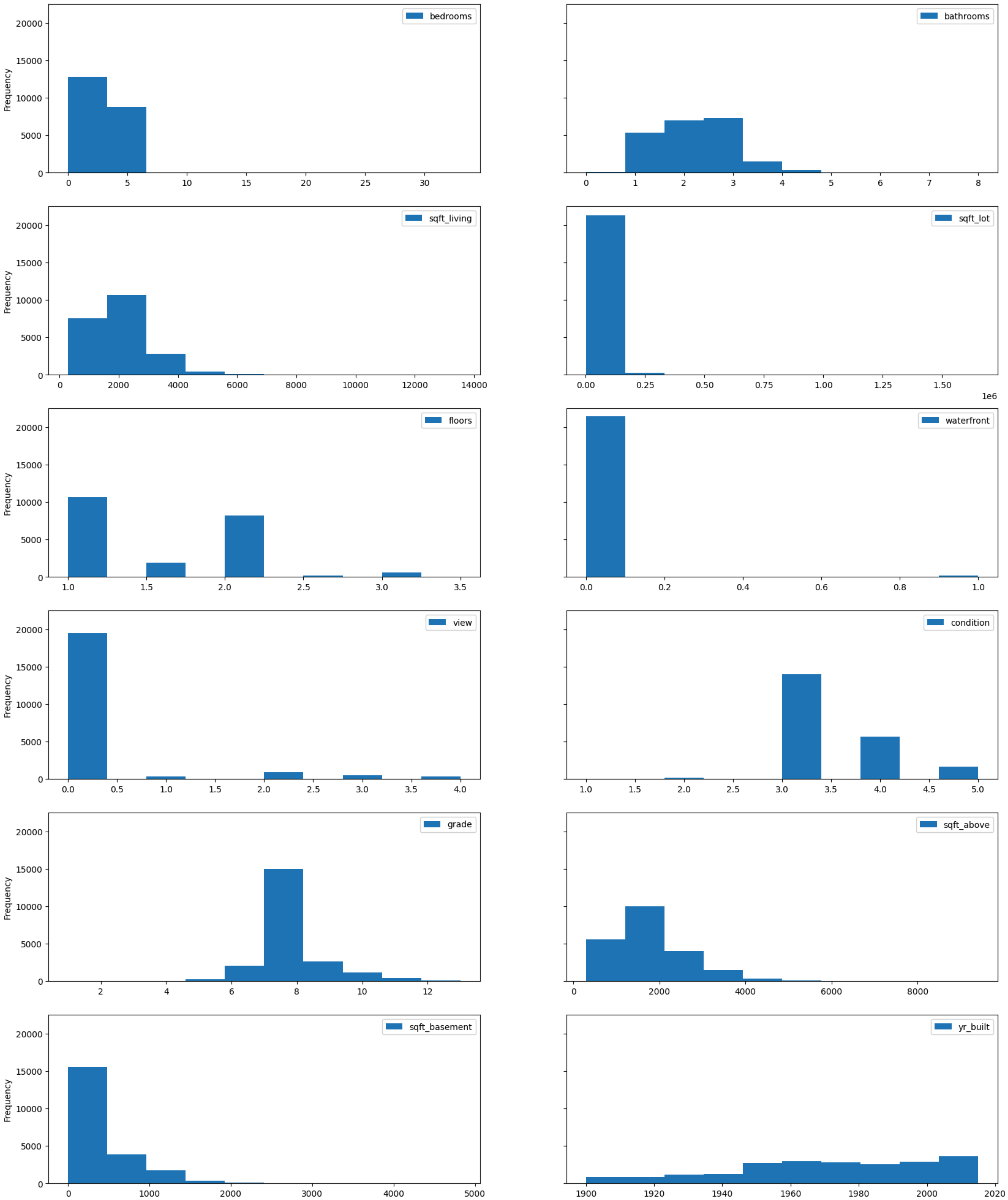
```
house.columns
```

Out[635…

```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

In [636…

```
# plot the distribution of all columns in subplots

fig, axs = plt.subplots(6, 2, sharey=True)

house.plot(kind='hist', y='bedrooms', ax=axs[0,0], figsize=(20, 25))
house.plot(kind='hist', y='bathrooms', ax=axs[0,1])
house.plot(kind='hist', y='sqft_living', ax=axs[1,0])
house.plot(kind='hist', y='sqft_lot', ax=axs[1,1])
house.plot(kind='hist', y='floors', ax=axs[2,0])
house.plot(kind='hist', y='waterfront', ax=axs[2,1])
house.plot(kind='hist', y='view', ax=axs[3,0])
house.plot(kind='hist', y='condition', ax=axs[3,1])
house.plot(kind='hist', y='grade', ax=axs[4,0])
house.plot(kind='hist', y='sqft_above', ax=axs[4,1])
house.plot(kind='hist', y='sqft_basement', ax=axs[5,0])
house.plot(kind='hist', y='yr_built', ax=axs[5,1])

#plt.tight_layout()
plt.show()
```



In [636…

In [636…

In [637…

```python
# Saving the columns with data type having numbers to a new variable

num_cols = house.select_dtypes(include='number').columns
num_cols
```

Out[637…

```
Index(['id', 'price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
       'floors', 'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long',
       'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

In [638…

```python
# Dropping Irrelevant columns from num_cols to obtain target_cols

target_cols = num_cols.drop(['id', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
```

```
       'floors', 'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long',
       'sqft_living15', 'sqft_lot15'])
target_cols
```

Out[638…

```
Index(['price'], dtype='object')
```

In [639…

```
# Dropping price and id column from num_cols

feature_cols = num_cols.drop(['id', 'price'])
feature_cols
```

Out[639…

```
Index(['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long',
       'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

In [640…

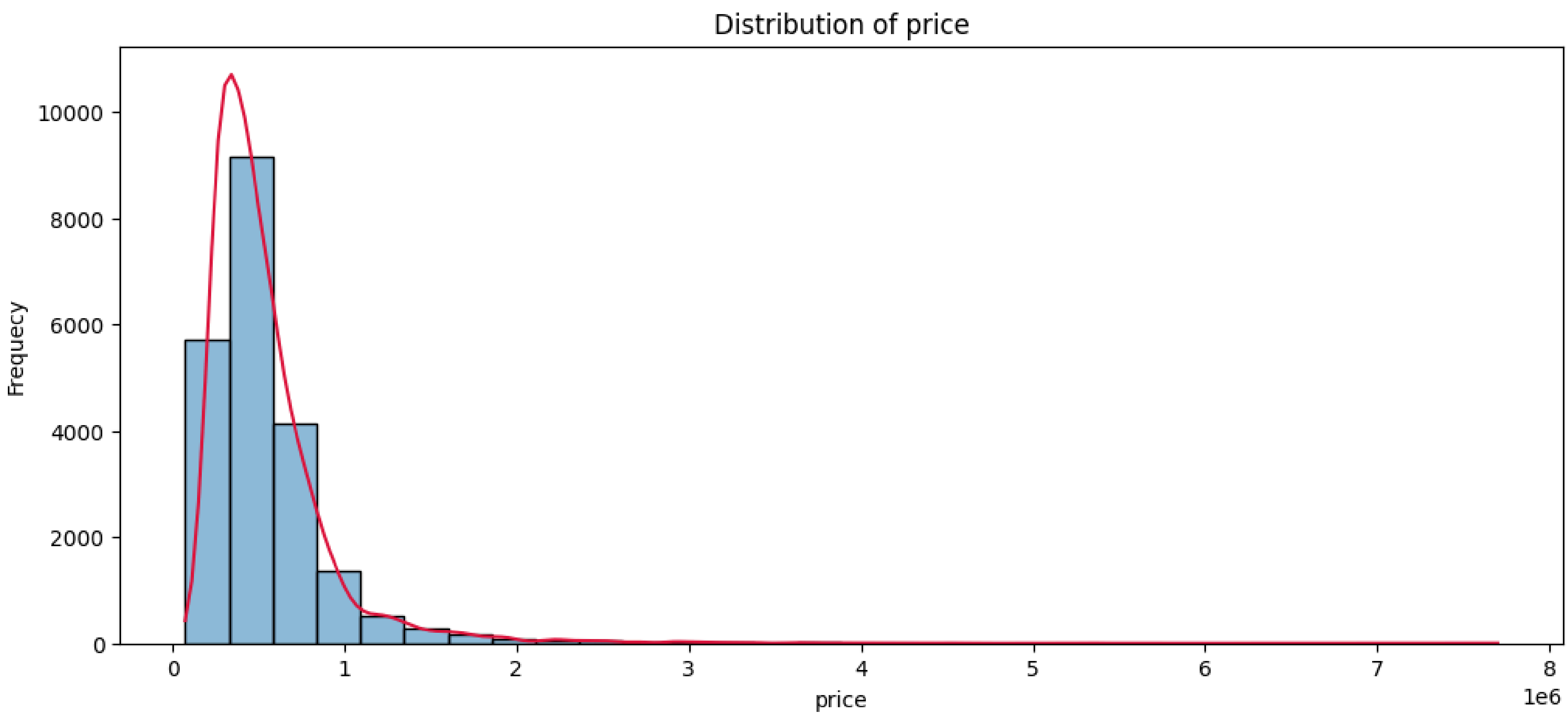
```
# Check all the columns present in all the 3 variable

feature_cols, target_cols, num_cols
```

Out[640…

```
(Index(['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
        'waterfront', 'view', 'condition', 'grade', 'sqft_above',
        'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long',
        'sqft_living15', 'sqft_lot15'],
       dtype='object'),
 Index(['price'], dtype='object'),
 Index(['id', 'price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
        'floors', 'waterfront', 'view', 'condition', 'grade', 'sqft_above',
        'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long',
        'sqft_living15', 'sqft_lot15'],
       dtype='object'))
```

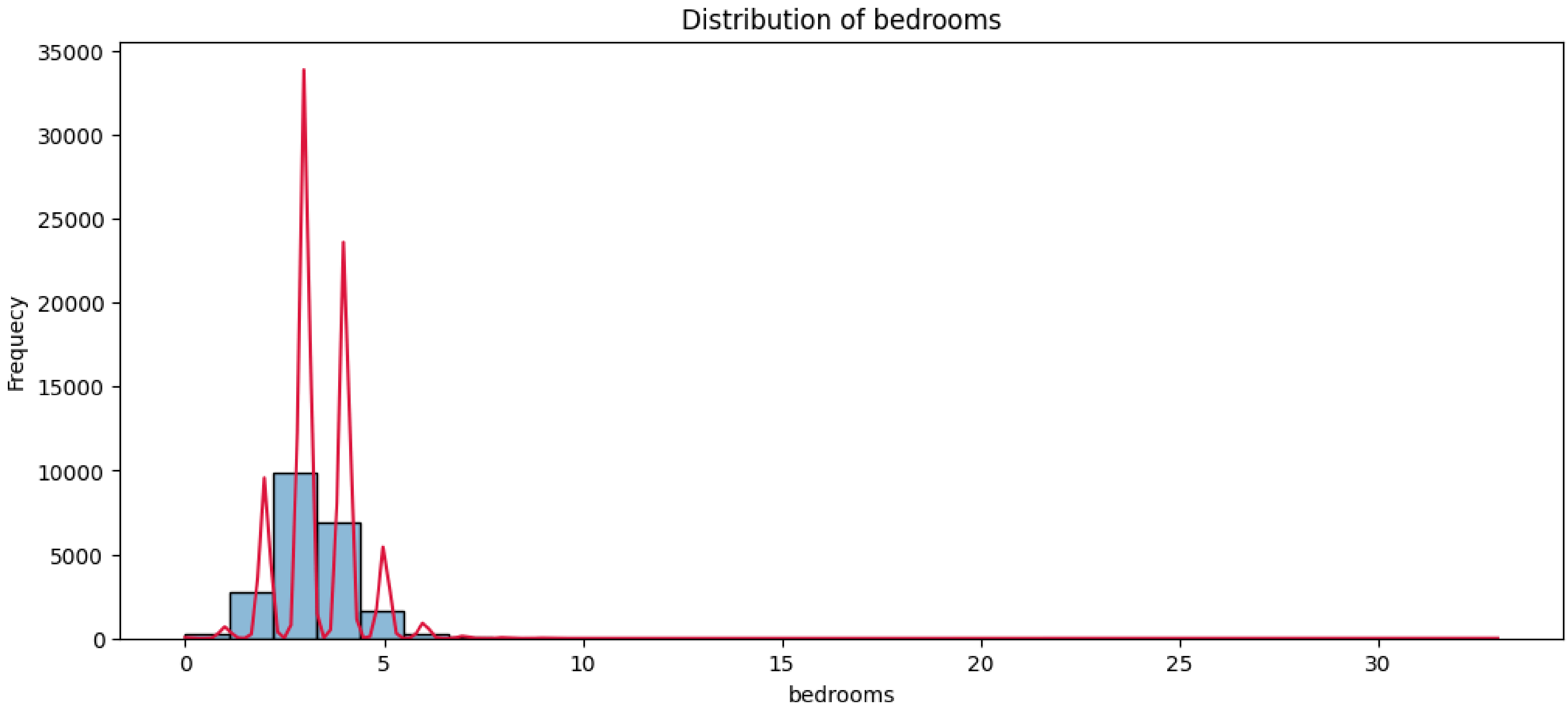
In [641…

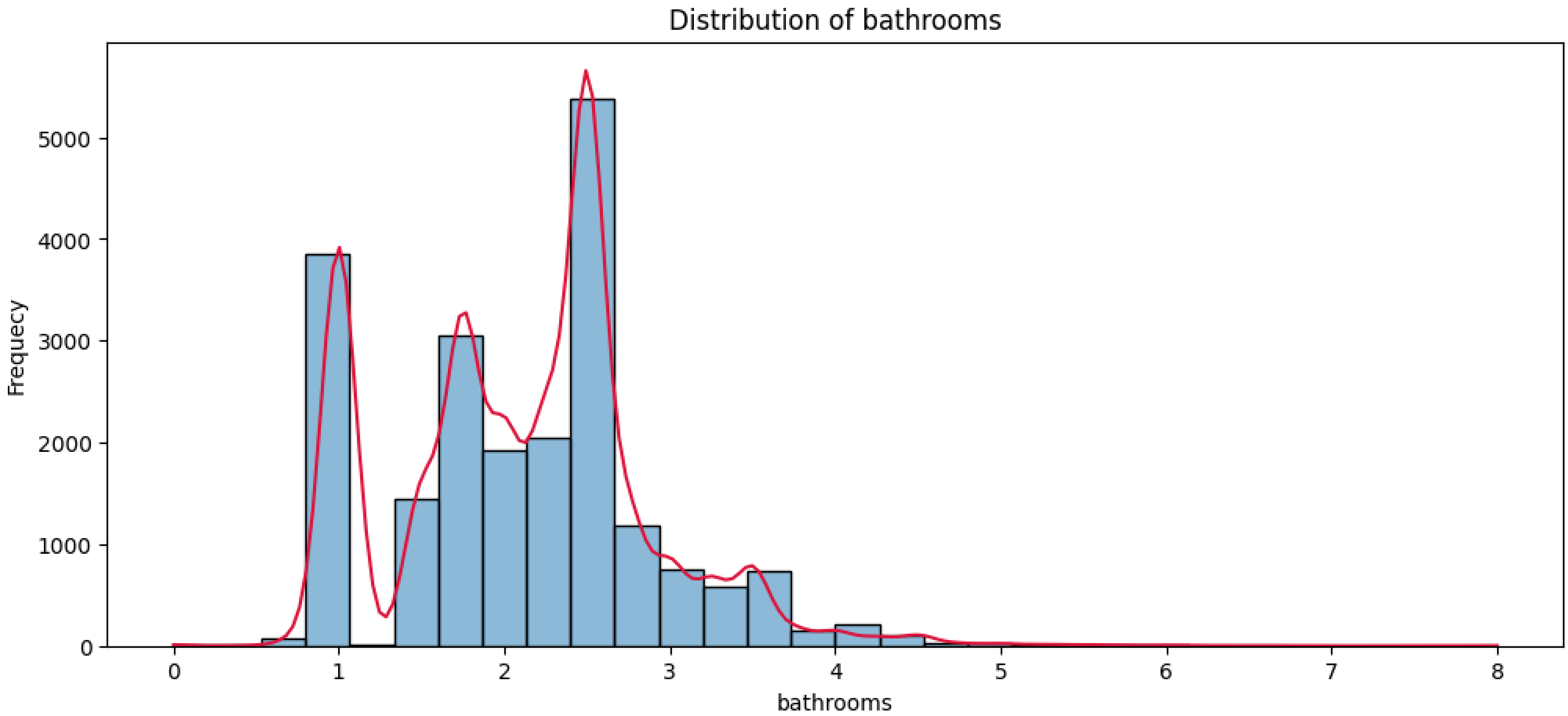
```
# Plotting Histogram to check for the distibution of Target Column (Price)

for i in target_cols:

  plt.figure(figsize=(12, 5))
  ax = sns.histplot(data=house, x=i, kde=True, bins = 30)
  ax.lines[0].set_color('crimson')

  plt.xlabel(i)
  plt.ylabel('Frequecy')
  plt.title(f'Distribution of {i}')
  plt.show()
```

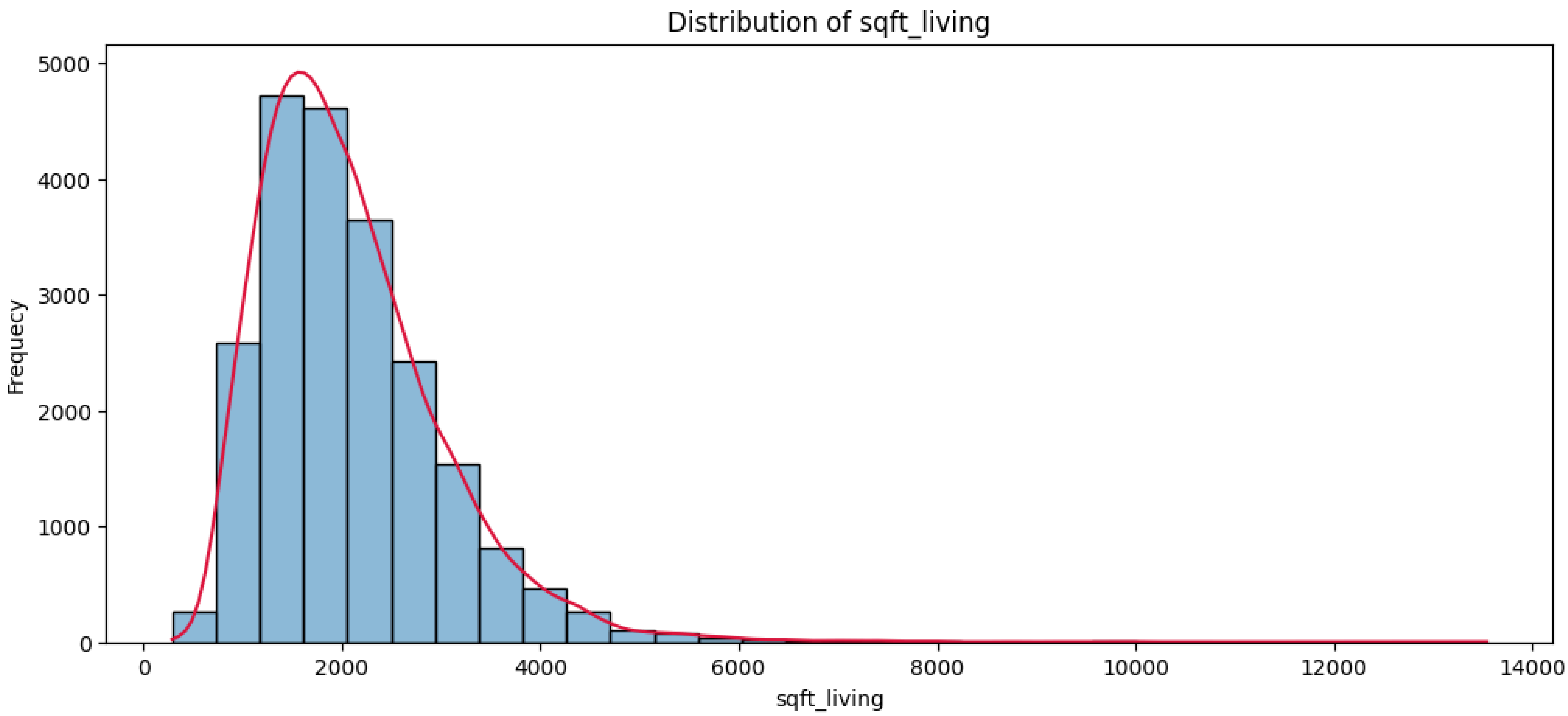


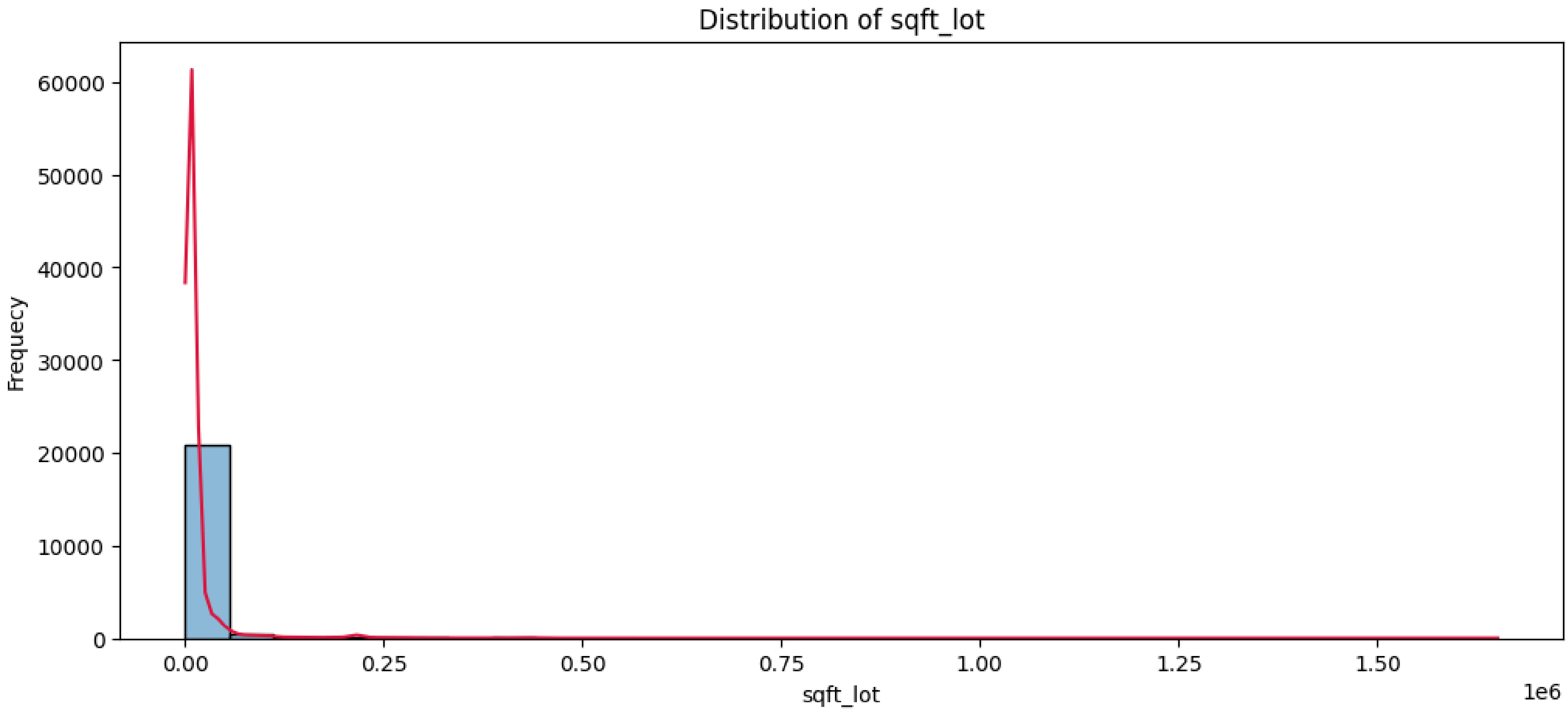
In [642…

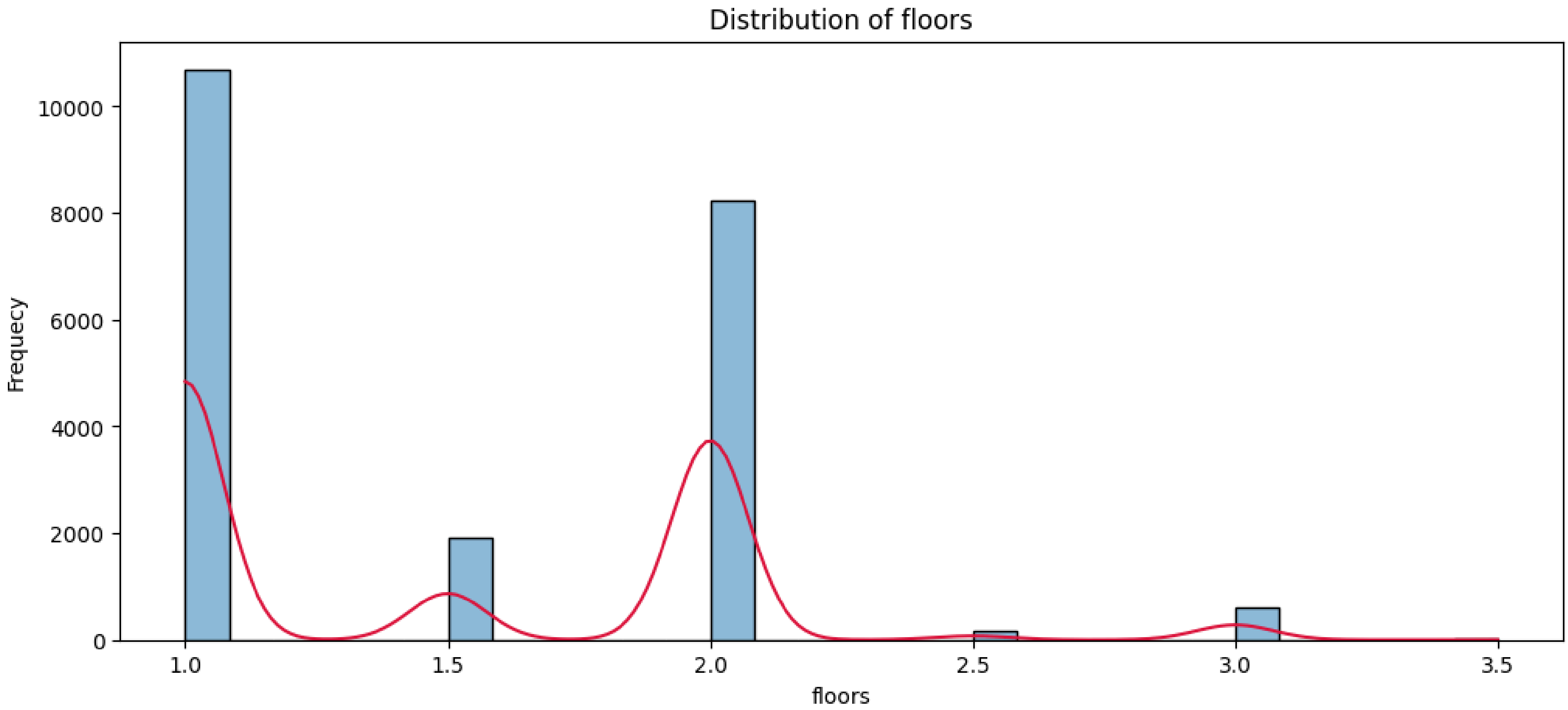
```
# Plotting Histogram to check for the distibution of Numerical columns

for i in feature_cols:

  plt.figure(figsize=(12, 5))
  ax = sns.histplot(data=house, x=i, kde=True, bins = 30)
  ax.lines[0].set_color('crimson')

  plt.xlabel(i)
  plt.ylabel('Frequecy')
  plt.title(f'Distribution of {i}')
  plt.show()
```

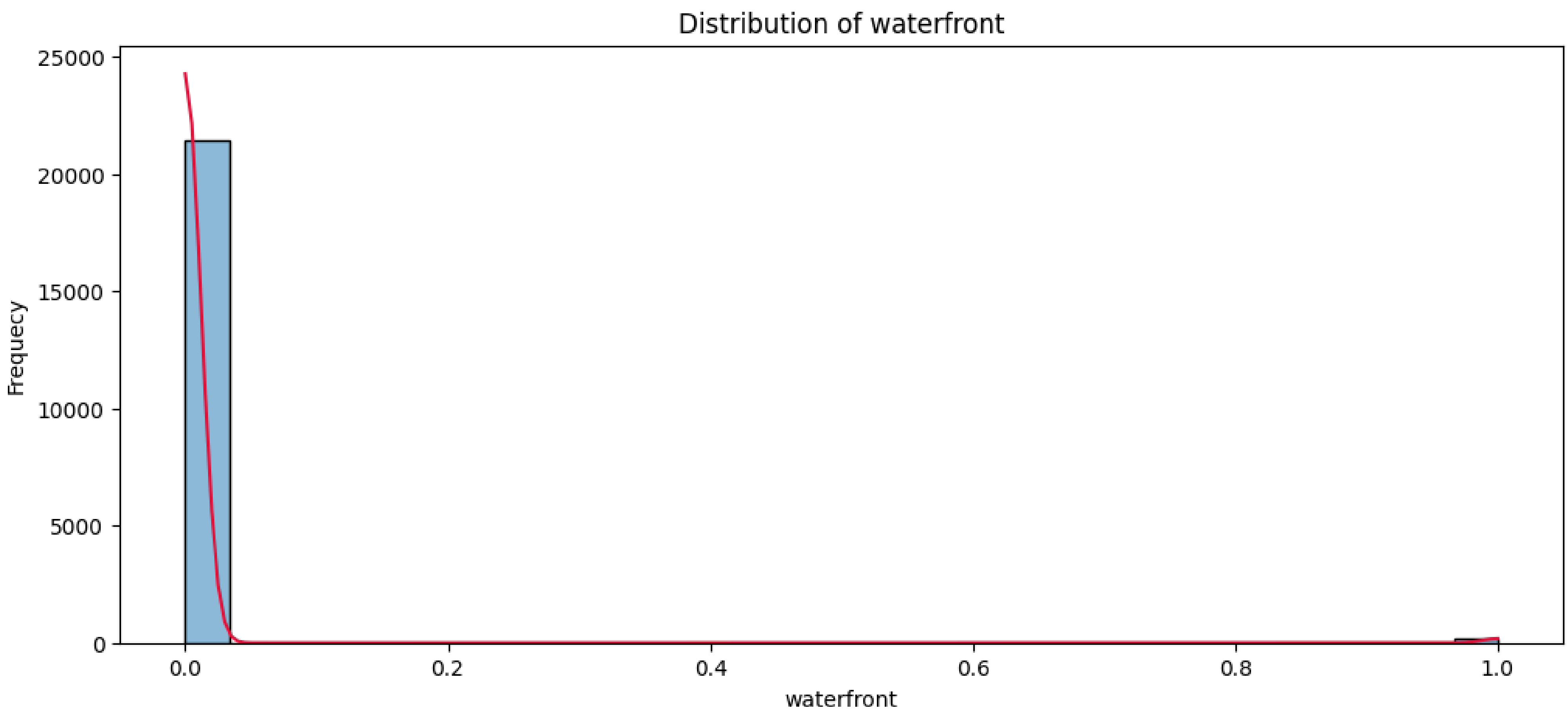

Distribution of bedrooms
Frequecy
bedrooms
35000
30000
25000
20000
15000
10000
5000
0
0
5
10
15
20
25
30

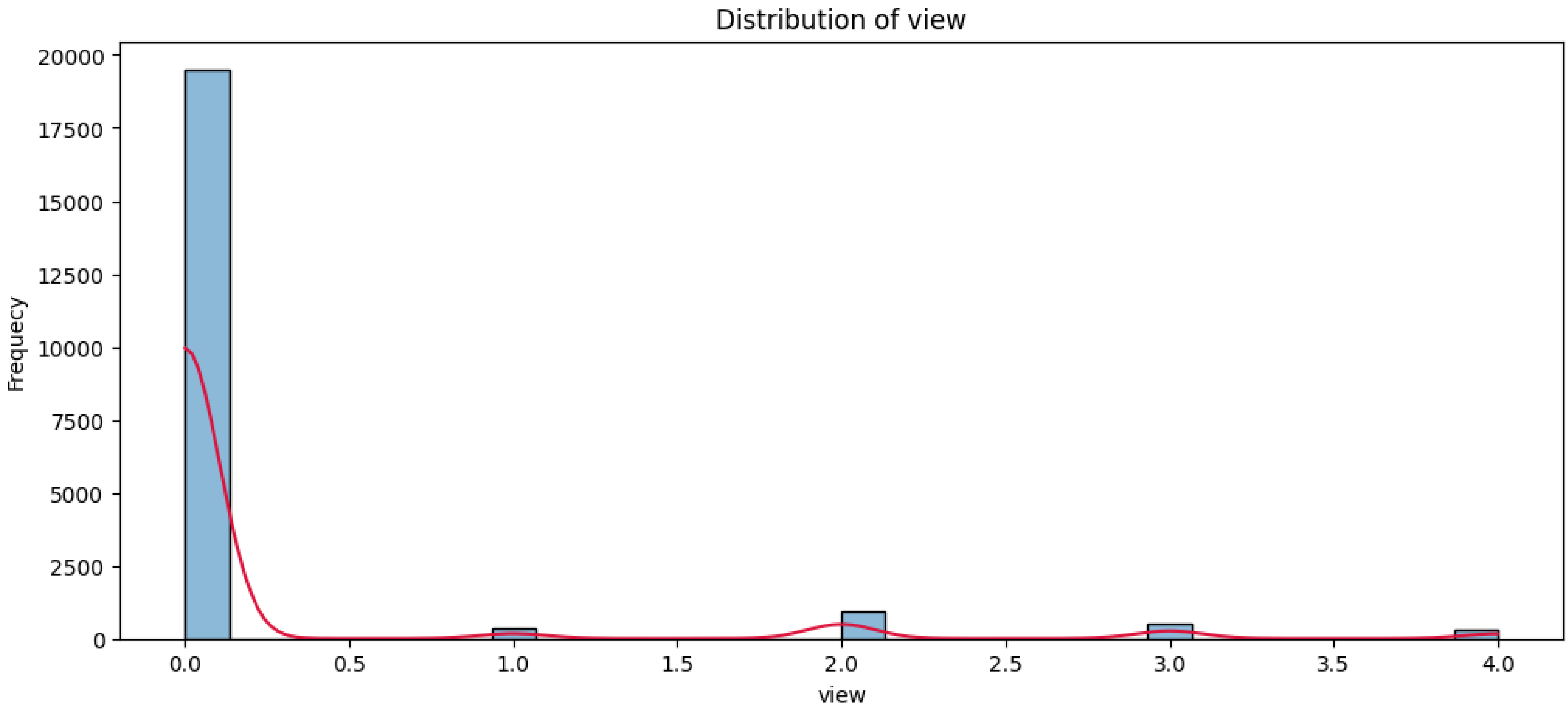

Distribution of bathrooms
Frequecy
bathrooms
5000
4000
3000
2000
1000
0
0
1
2
3
4
5
6
7
8

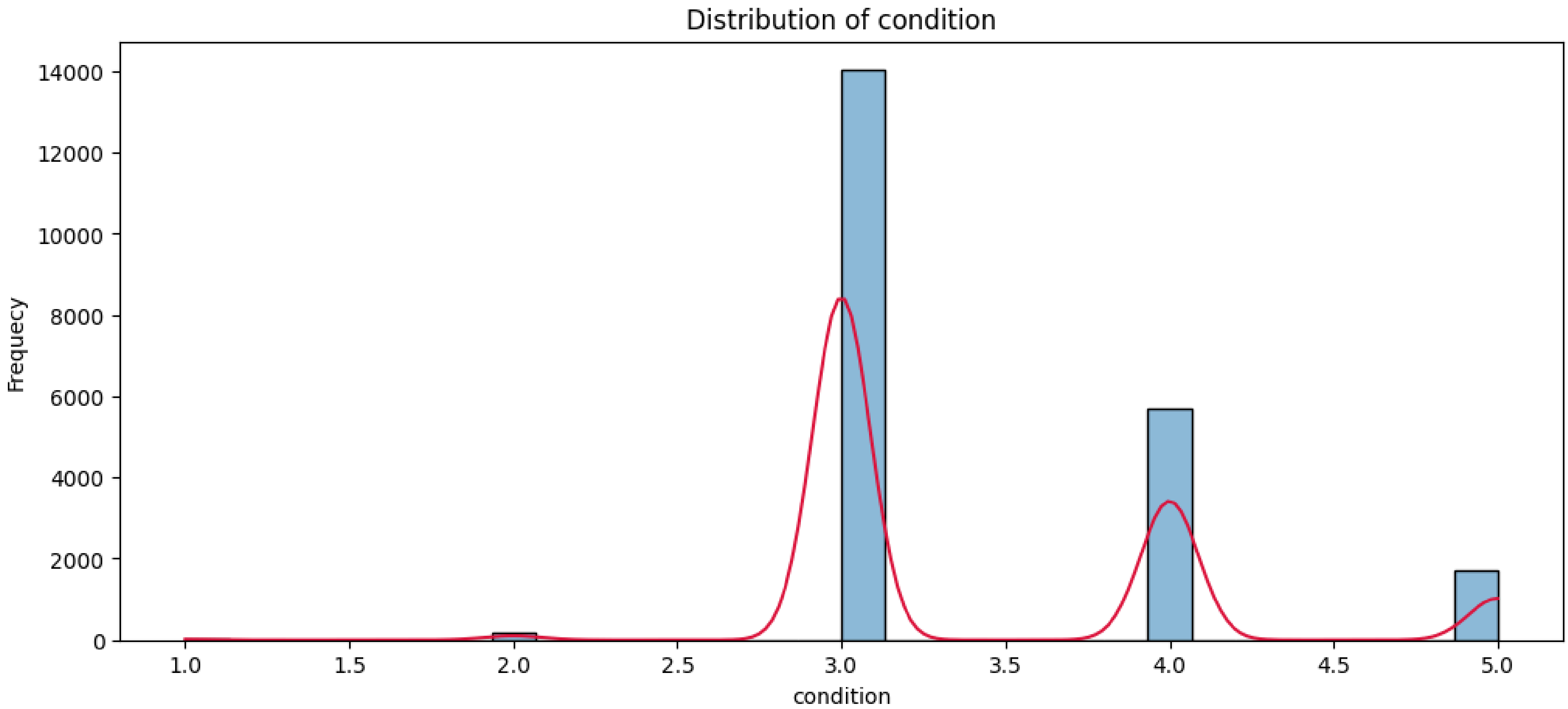

Distribution of sqft_living
Frequecy
sqft_living
5000
4000
3000
2000
1000
0
0
2000
4000
6000
8000
10000
12000
14000

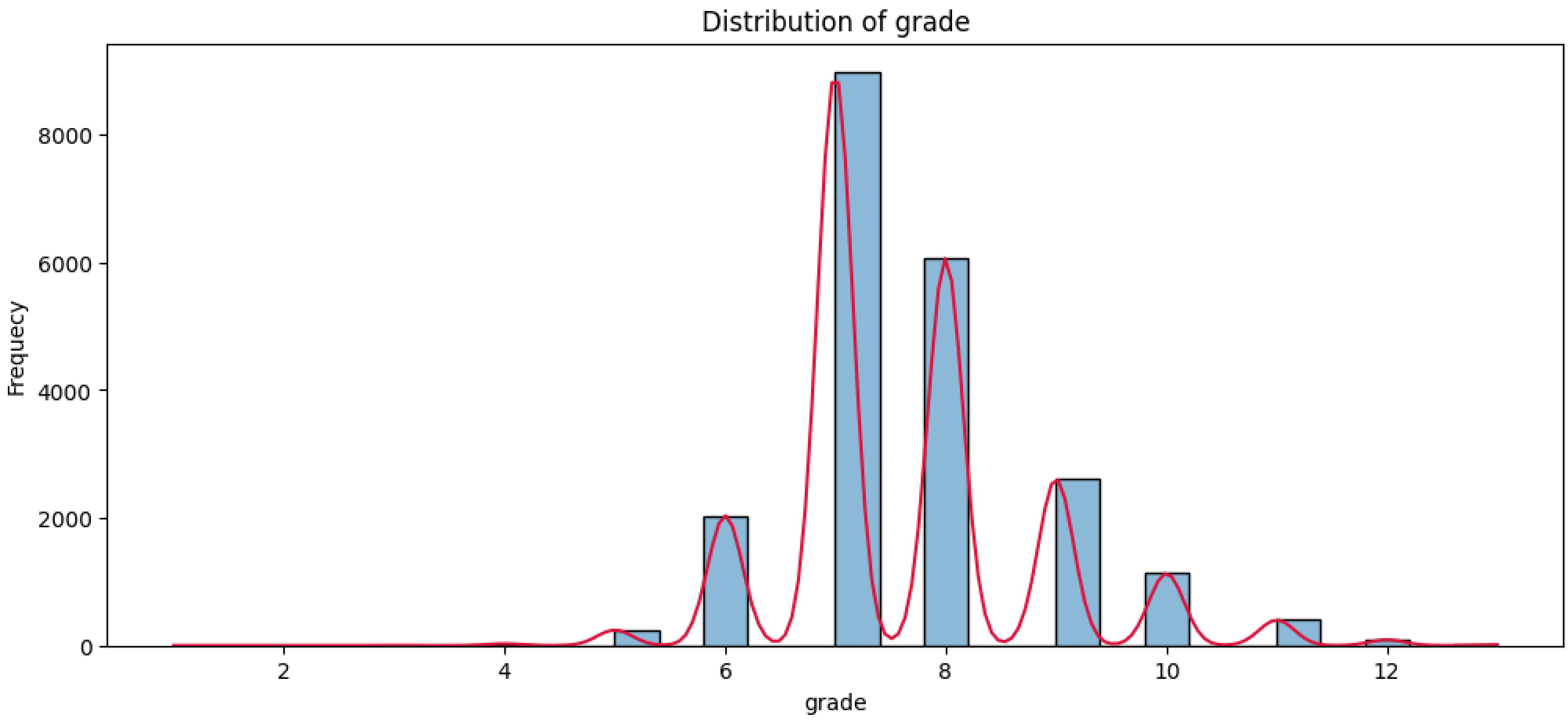

Distribution of sqft_lot
Frequecy
60000
50000
40000
30000
20000
10000
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1e6
sqft_lot

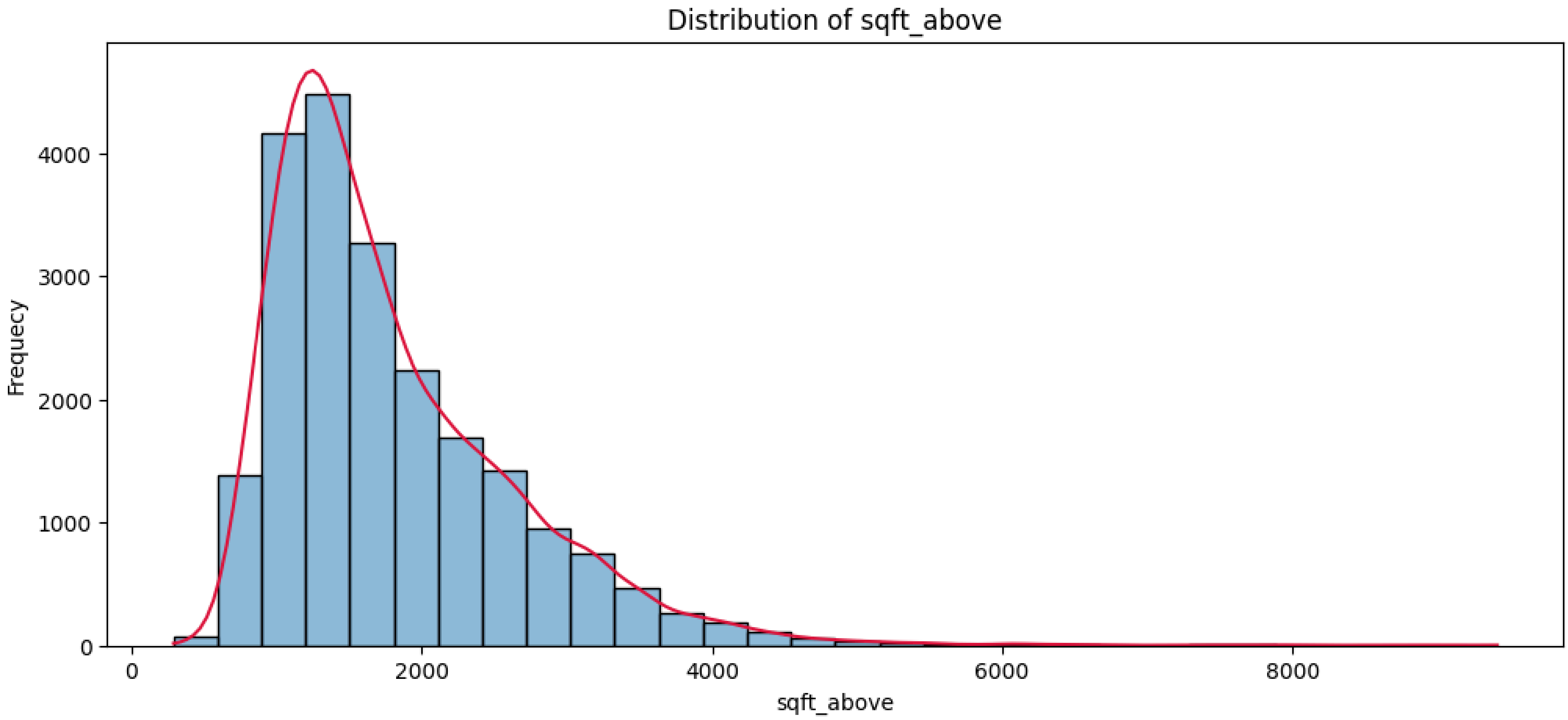

Distribution of floors
Frequecy
10000
8000
6000
4000
2000
0
1.0
1.5
2.0
2.5
3.0
3.5
floors

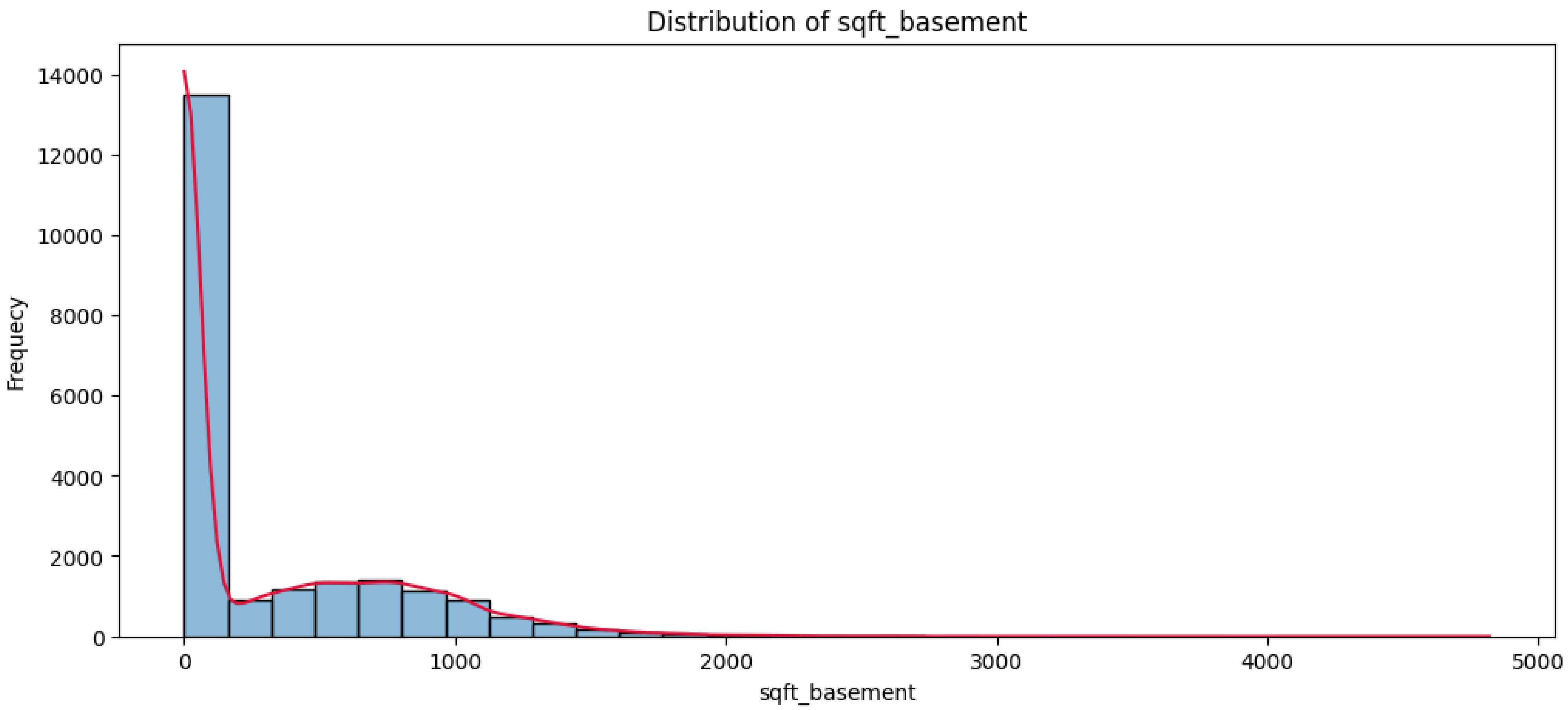

Distribution of waterfront
Frequecy
25000
20000
15000
10000
5000
0
0.0
0.2
0.4
0.6
0.8
1.0
waterfront

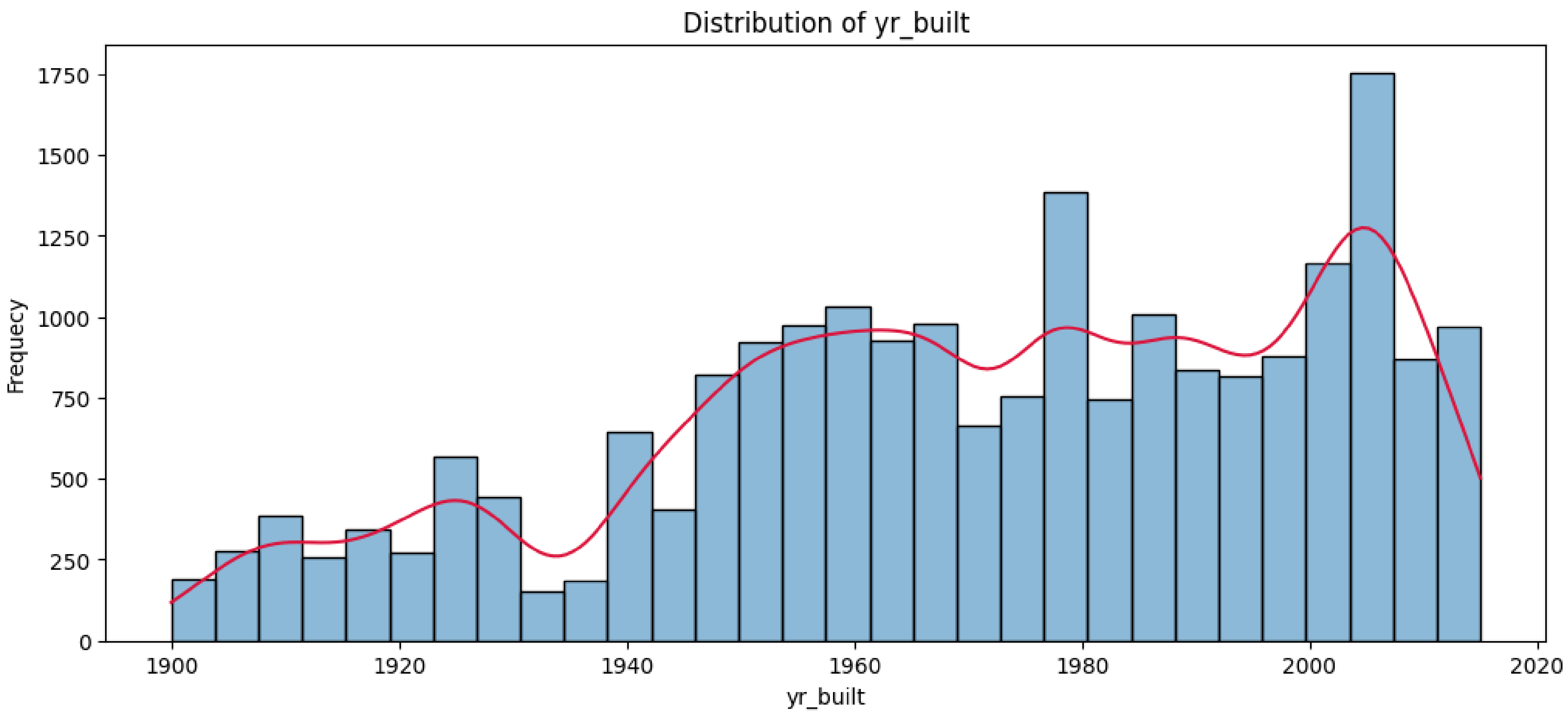

Distribution of view
Frequecy
view
0
2500
5000
7500
10000
12500
15000
17500
20000
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

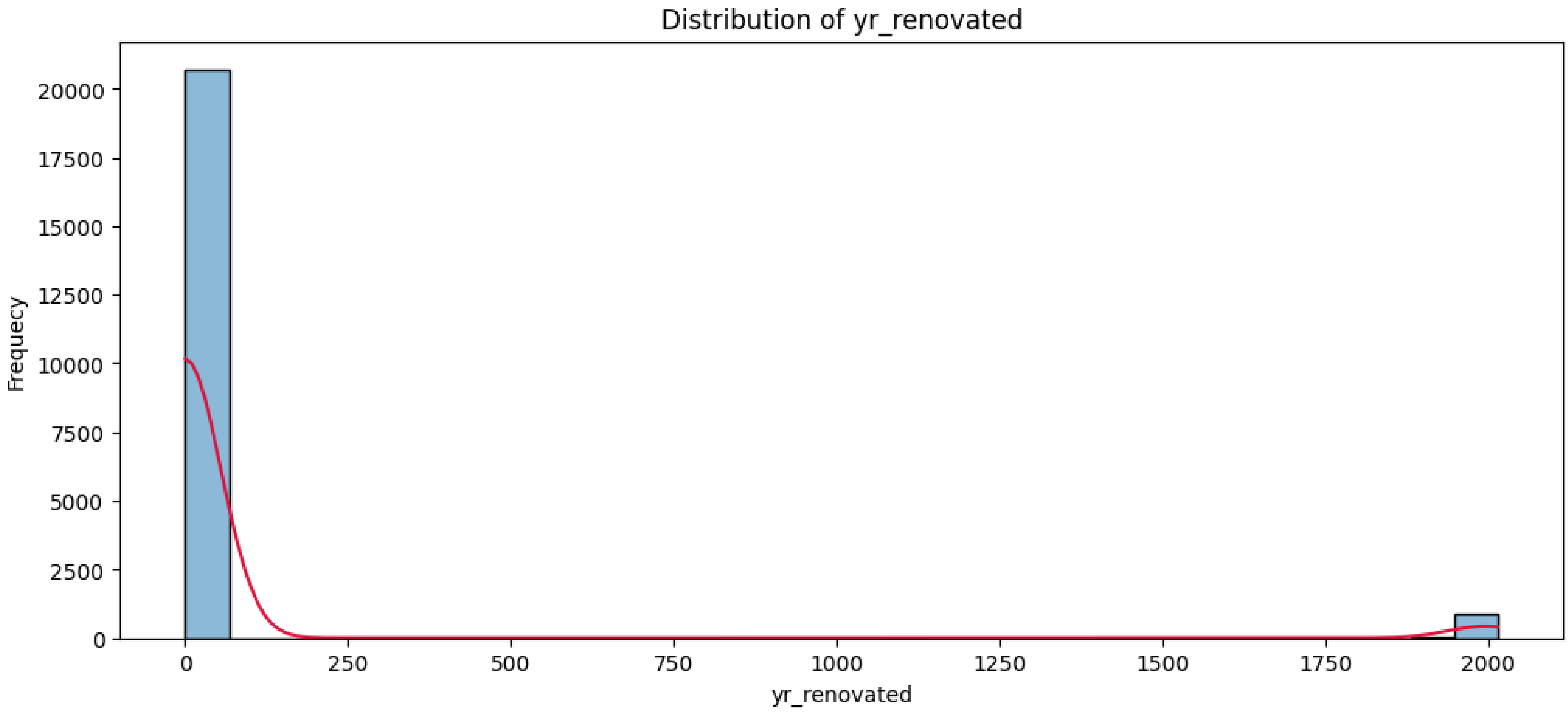

Distribution of condition
Frequecy
condition
0
2000
4000
6000
8000
10000
12000
14000
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

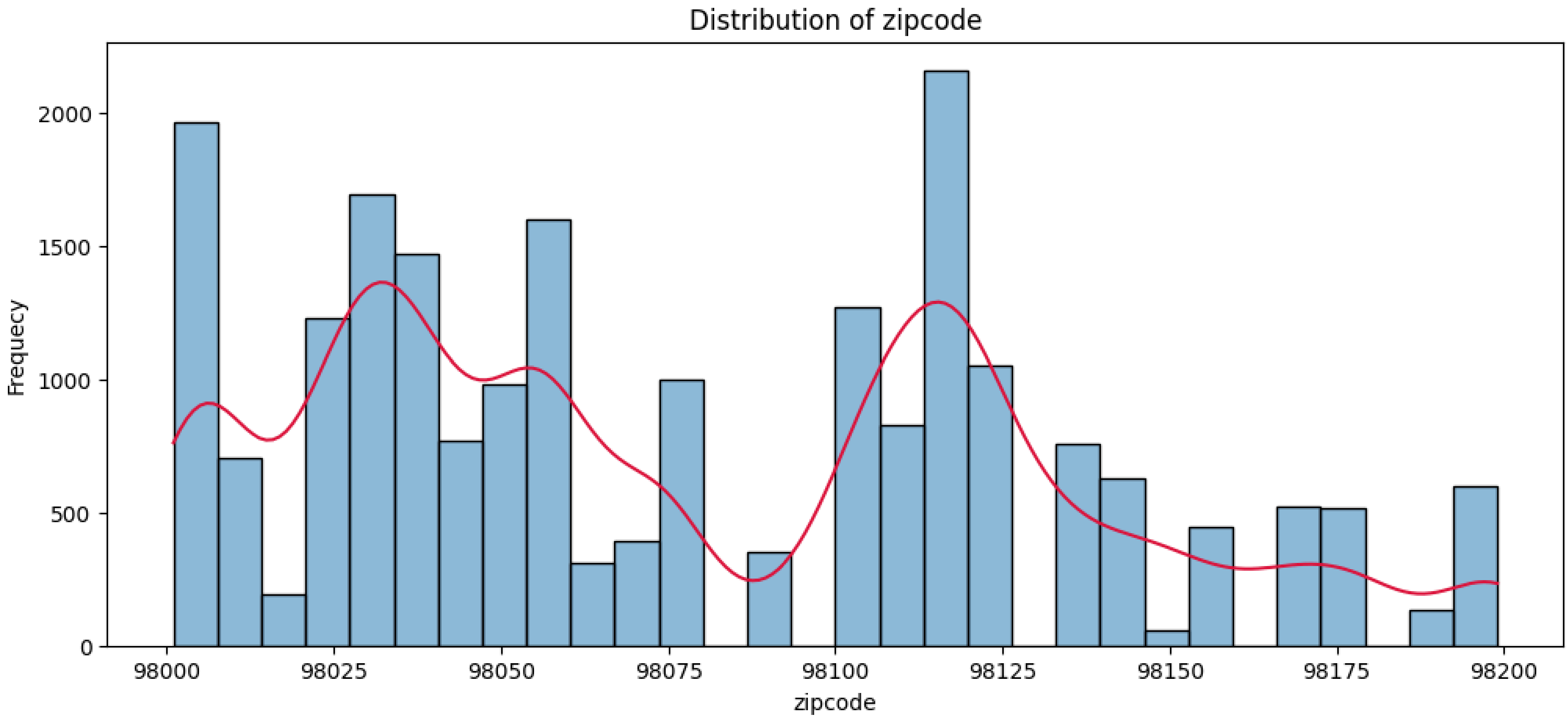

Distribution of grade
Frequecy
grade
0
2000
4000
6000
8000
2
4
6
8
10
12

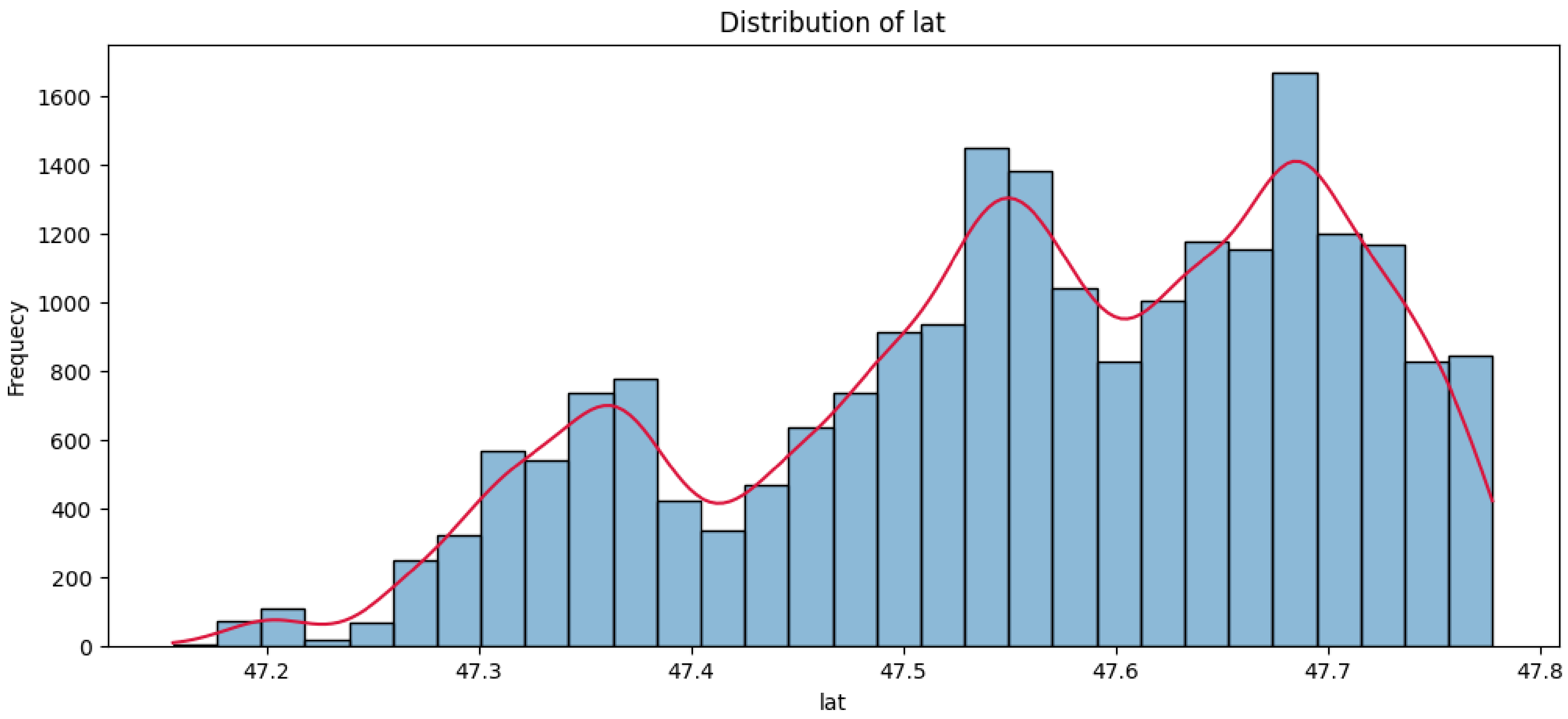

Distribution of sqft_above
Frequecy
sqft_above
0
1000
2000
3000
4000
0
2000
4000
6000
8000

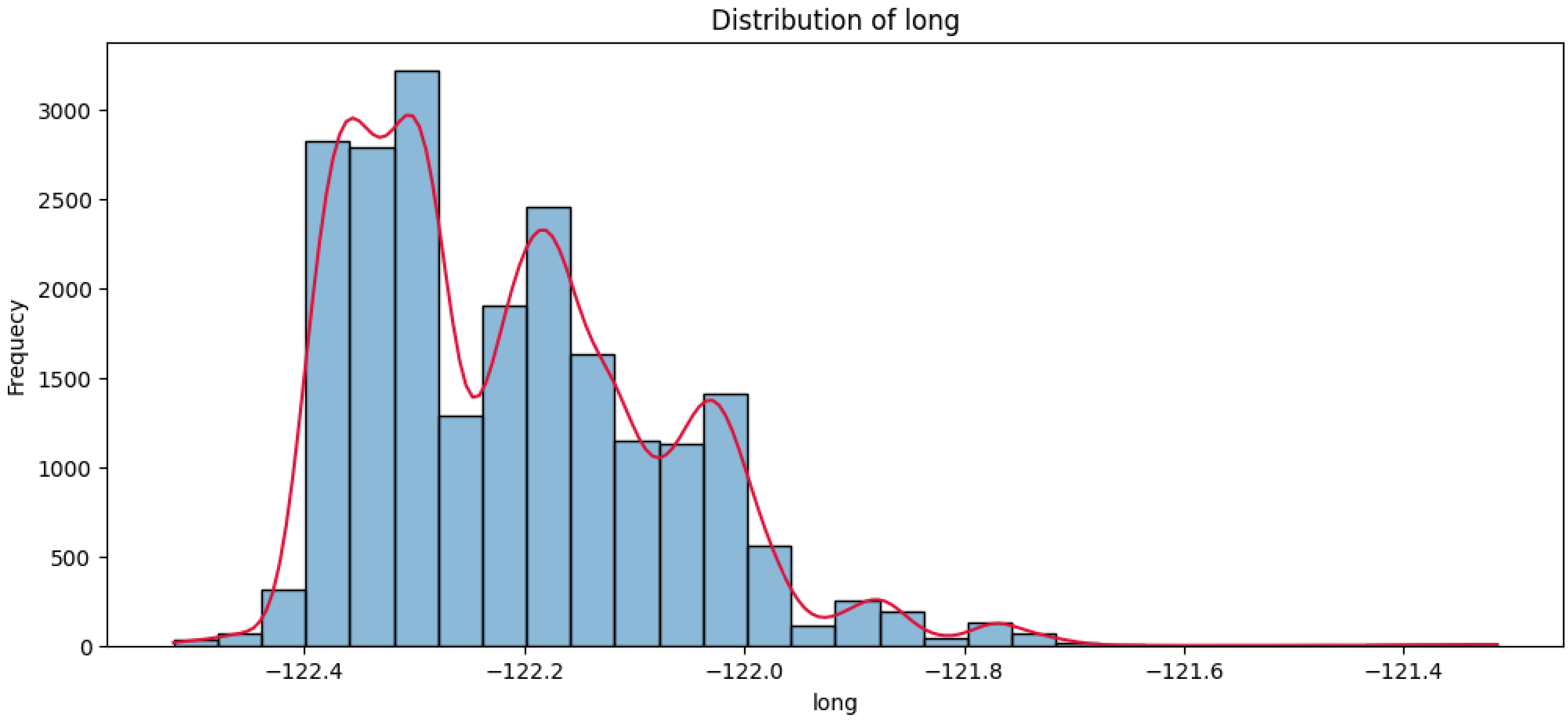

Distribution of sqft_basement
Frequecy
sqft_basement
0
2000
4000
6000
8000
10000
12000
14000
0
1000
2000
3000
4000
5000

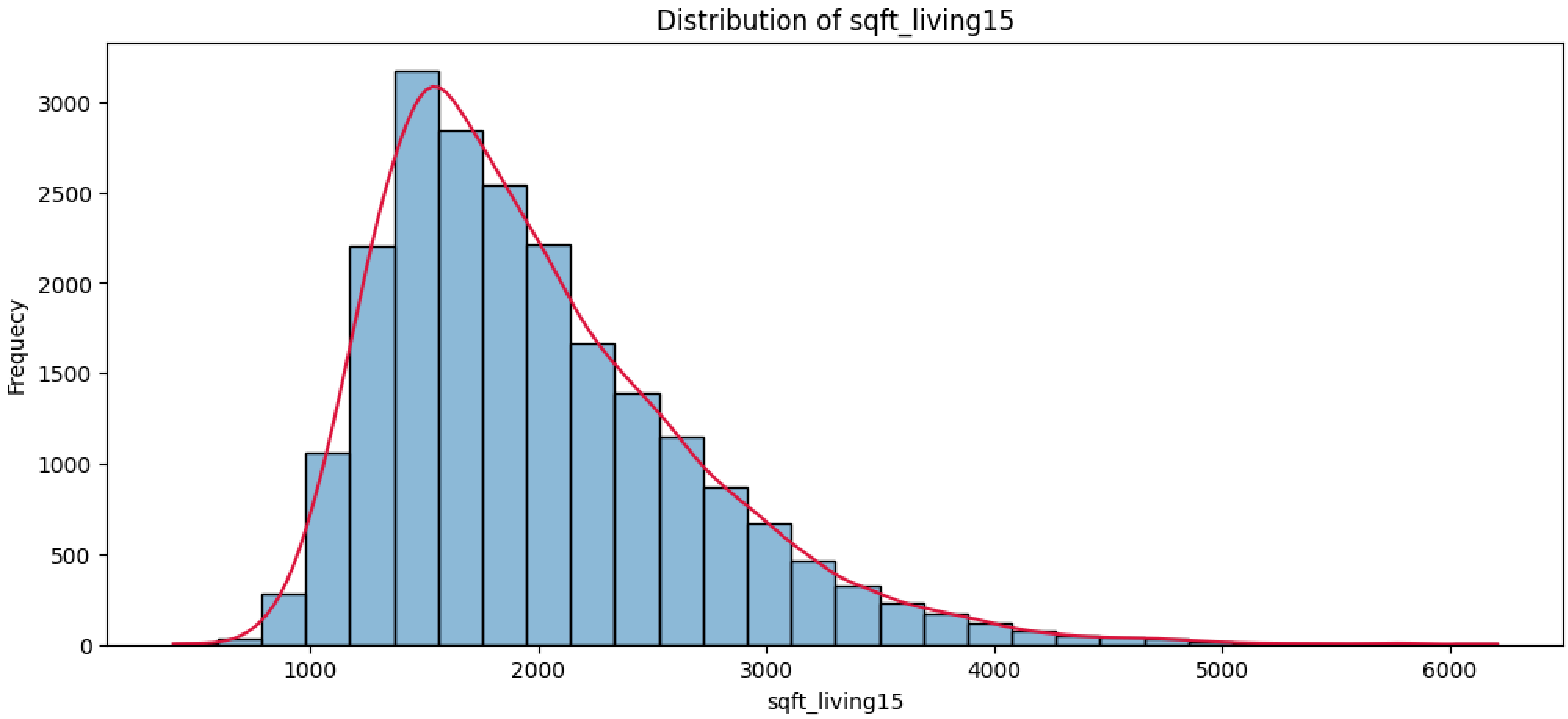

Distribution of yr_built
Frequecy
yr_built
0
250
500
750
1000
1250
1500
1750
1900
1920
1940
1960
1980
2000
2020

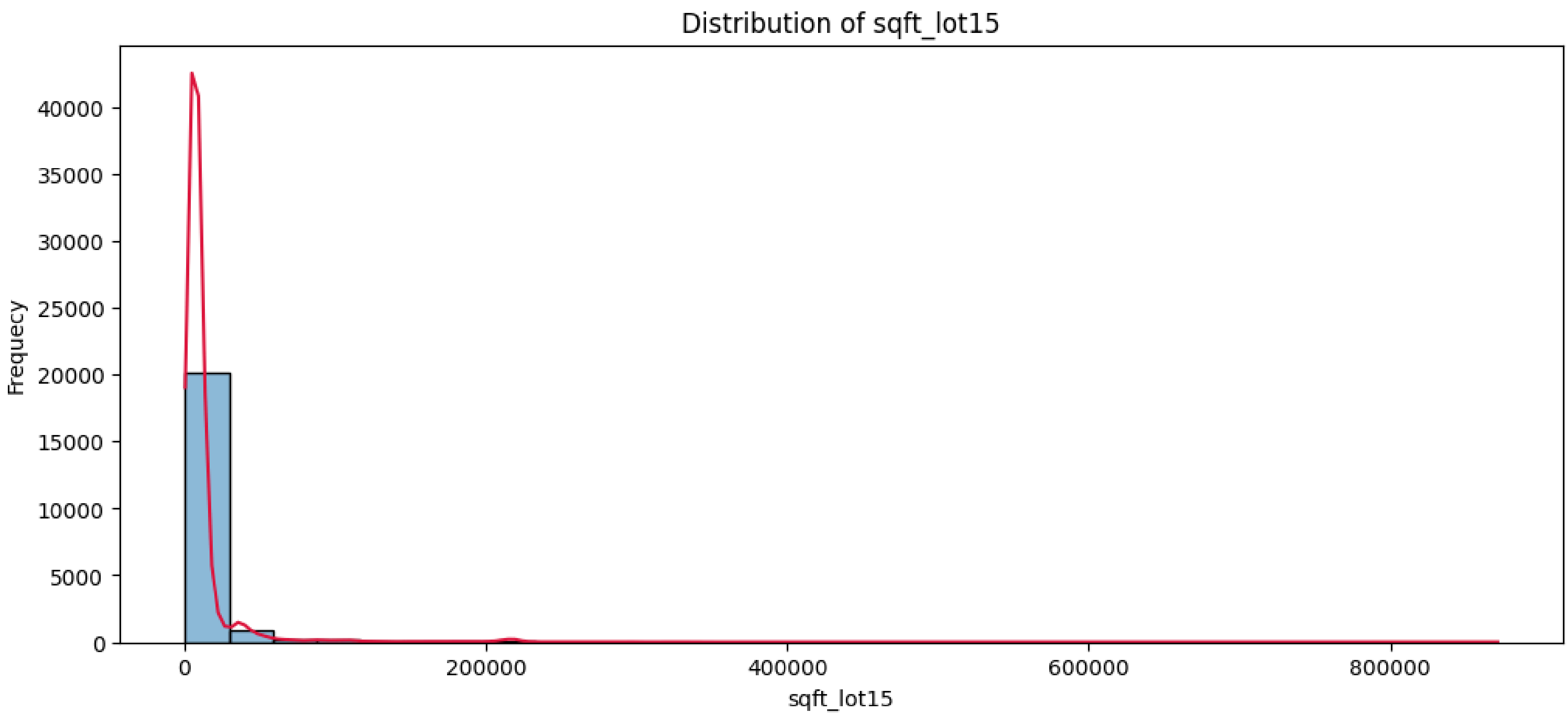

Distribution of yr_renovated
Frequecy
20000
17500
15000
12500
10000
7500
5000
2500
0
0
250
500
750
1000
1250
1500
1750
2000
yr_renovated


Distribution of zipcode
Frequecy
2000
1500
1000
500
0
98000
98025
98050
98075
98100
98125
98150
98175
98200
zipcode


Distribution of lat
Frequecy
1600
1400
1200
1000
800
600
400
200
0
47.2
47.3
47.4
47.5
47.6
47.7
47.8
lat







Bi-variate Analysis - (Feature and Target)

In [643…

```
house.columns
```

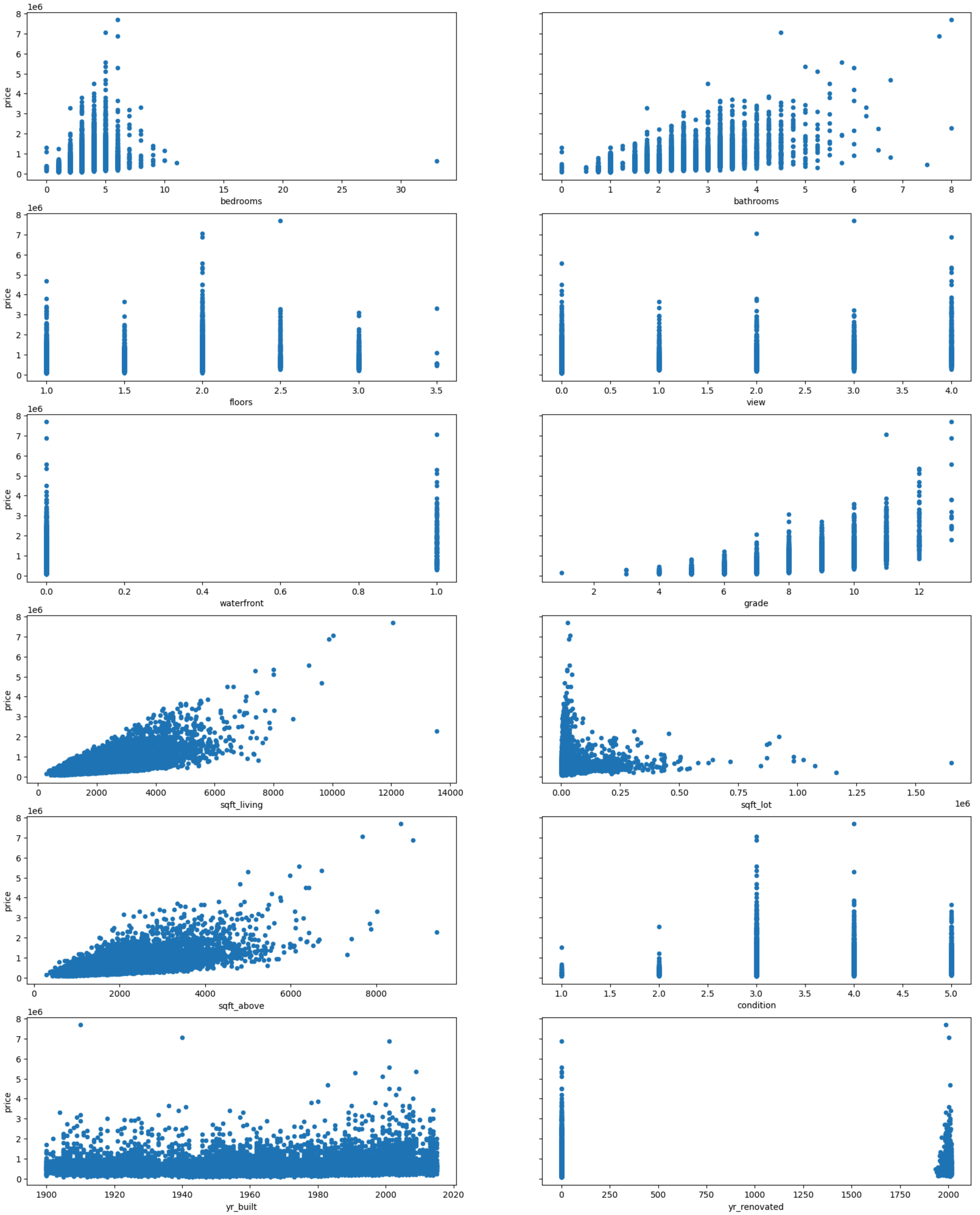
Out[643…

```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

SCATTER PLOT

In [644…

```
# visualize the relationship between the features and the target using scatterplots

fig, axs = plt.subplots(6, 2, sharey=True)

house.plot(kind='scatter', x='bedrooms', y='price', ax=axs[0,0], figsize=(20, 25))
house.plot(kind='scatter', x='bathrooms', y='price', ax=axs[0,1])
house.plot(kind='scatter', x='floors', y='price', ax=axs[1,0])
house.plot(kind='scatter', x='view', y='price', ax=axs[1,1])
house.plot(kind='scatter', x='waterfront', y='price', ax=axs[2,0])
house.plot(kind='scatter', x='grade', y='price', ax=axs[2,1])
house.plot(kind='scatter', x='sqft_living', y='price', ax=axs[3,0])
house.plot(kind='scatter', x='sqft_lot', y='price', ax=axs[3,1])
house.plot(kind='scatter', x='sqft_above', y='price', ax=axs[4,0])
house.plot(kind='scatter', x='condition', y='price', ax=axs[4,1])
house.plot(kind='scatter', x='yr_built', y='price', ax=axs[5,0])
house.plot(kind='scatter', x='yr_renovated', y='price', ax=axs[5,1])

#plt.tight_layout()
plt.show()
```



Sqft living and Sqft above shows clear Linear relationship

Check for Multi-Collinearity

In [645…

```
# Check for Coorelation from house dataframe after dropping date column

cor = house.drop(['date','id'], axis=1).corr()
cor
```

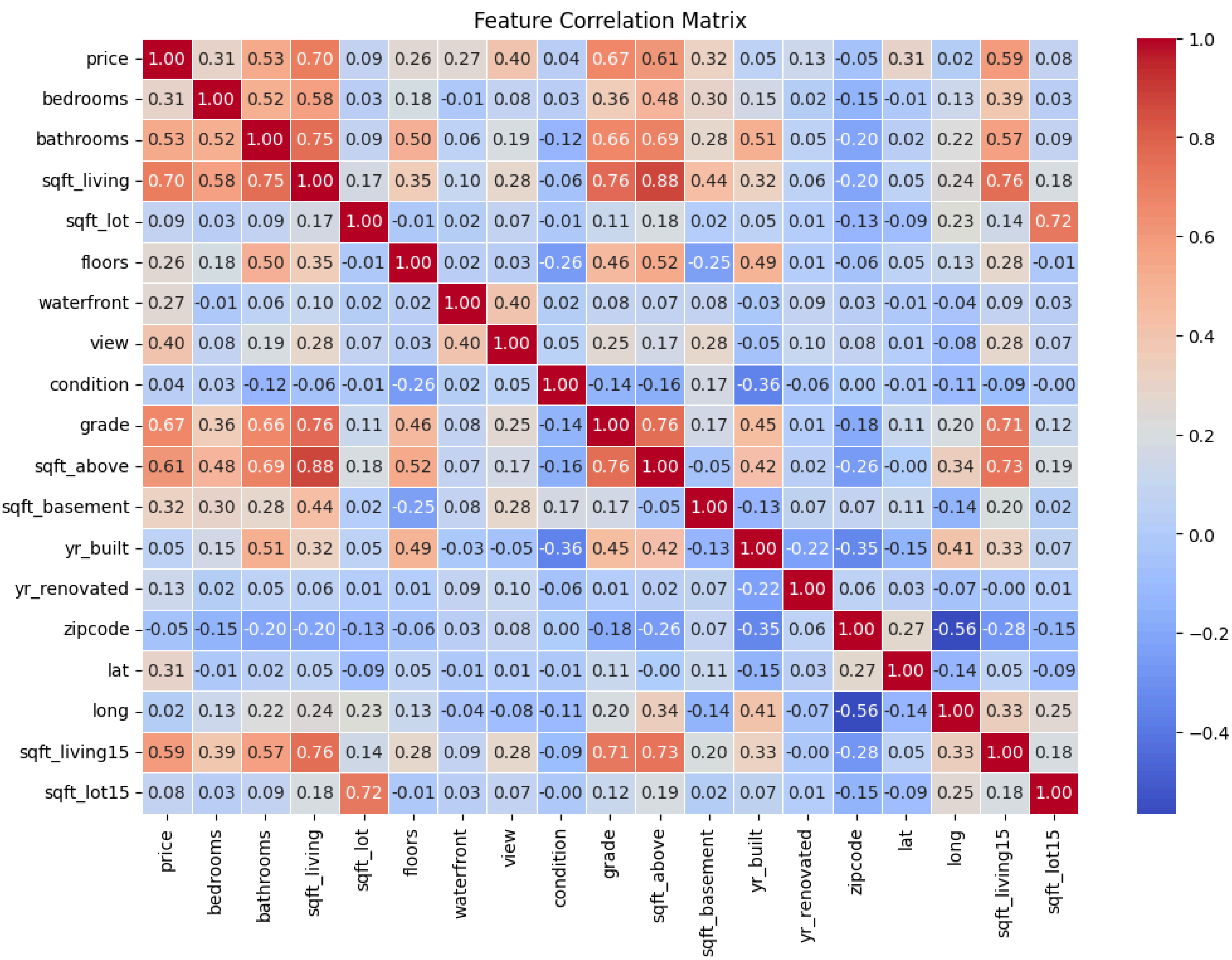
Out[645…

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basemen
price	1.000000	0.308350	0.525138	0.702035	0.089661	0.256794	0.266369	0.397293	0.036362	0.667434	0.605567	0.32381
bedrooms	0.308350	1.000000	0.515884	0.576671	0.031703	0.175429	-0.006582	0.079532	0.028472	0.356967	0.477600	0.30309
bathrooms	0.525138	0.515884	1.000000	0.754665	0.087740	0.500653	0.063744	0.187737	-0.124982	0.664983	0.685342	0.28377
sqft_living	0.702035	0.576671	0.754665	1.000000	0.172826	0.353949	0.103818	0.284611	-0.058753	0.762704	0.876597	0.43504
sqft_lot	0.089661	0.031703	0.087740	0.172826	1.000000	-0.005201	0.021604	0.074710	-0.008958	0.113621	0.183512	0.01528
floors	0.256794	0.175429	0.500653	0.353949	-0.005201	1.000000	0.023698	0.029444	-0.263768	0.458183	0.523885	-0.24570
waterfront	0.266369	-0.006582	0.063744	0.103818	0.021604	0.023698	1.000000	0.401857	0.016653	0.082775	0.072075	0.08058
view	0.397293	0.079532	0.187737	0.284611	0.074710	0.029444	0.401857	1.000000	0.045990	0.251321	0.167649	0.27694
condition	0.036362	0.028472	-0.124982	-0.058753	-0.008958	-0.263768	0.016653	0.045990	1.000000	-0.144674	-0.158214	0.17410
grade	0.667434	0.356967	0.664983	0.762704	0.113621	0.458183	0.082775	0.251321	-0.144674	1.000000	0.755923	0.16839
sqft_above	0.605567	0.477600	0.685342	0.876597	0.183512	0.523885	0.072075	0.167649	-0.158214	0.755923	1.000000	-0.05194
sqft_basement	0.323816	0.303093	0.283770	0.435043	0.015286	-0.245705	0.080588	0.276947	0.174105	0.168392	-0.051943	1.00000
yr_built	0.054012	0.154178	0.506019	0.318049	0.053080	0.489319	-0.026161	-0.053440	-0.361417	0.446963	0.423898	-0.13312
yr_renovated	0.126434	0.018841	0.050739	0.055363	0.007644	0.006338	0.092885	0.103917	-0.060618	0.014414	0.023285	0.07132
zipcode	-0.053203	-0.152668	-0.203866	-0.199430	-0.129574	-0.059121	0.030285	0.084827	0.003026	-0.184862	-0.261190	0.07484
lat	0.307003	-0.008931	0.024573	0.052529	-0.085683	0.049614	-0.014274	0.006157	-0.014941	0.114084	-0.000816	0.11053
long	0.021626	0.129473	0.223042	0.240223	0.229521	0.125419	-0.041910	-0.078400	-0.106500	0.198372	0.343803	-0.14476
sqft_living15	0.585379	0.391638	0.568634	0.756420	0.144608	0.279885	0.086463	0.280439	-0.092824	0.713202	0.731870	0.20035
sqft_lot15	0.082447	0.029244	0.087175	0.183286	0.718557	-0.011269	0.030703	0.072575	-0.003406	0.119248	0.194050	0.01727

HEAT MAP

In [646…

```
# Plot the Heat Map to visualize the correlation

plt.figure(figsize=(12, 8))
sns.heatmap(cor, annot=True, cmap="coolwarm", fmt=".2f", linewidths=0.5)
plt.title("Feature Correlation Matrix")
plt.show()
```



HEAT MAP to visualize the correlation matrix stored in the cor variable

- **Dark Red**: Indicates a strong **positive correlation**.
- **Dark Blue**: Indicates a strong **negative correlation**.
- **Light Colors/White**: Indicates a **weak or no correlation**

High Positive Correlation:

1. **sqft_living** and **price**: As the living area size increases, the price of the house tends to increase significantly
2. **grade** and **price**: higher-grade houses tend to be more expensive
3. **bathrooms** and **sqft_living**: Larger houses often have more bathrooms
4. **sqft_living15** and **sqft_living**: houses in neighborhoods with larger houses tend to be larger themselves

High Negative Correlation:

1. **zipcode** and **price**: certain zip codes (potentially those further from city centers or with fewer amenities) might have lower average house prices
2. **yr_built** and **condition**: older houses might have slightly lower condition ratings on average

In [647…

```
# Removing High positive correlated columns

house.drop([ 'grade', 'sqft_living15','sqft_above','sqft_lot15'], axis=1, inplace=True)
house.head()
```

Out[647…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_basement	yr_built	yr_renovated	z
0	7129300520	2014-10-13	221900	3	1.00	1180	5650	1.0	0	0	3	0	1955	0	
1	6414100192	2014-12-09	538000	3	2.25	2570	7242	2.0	0	0	3	400	1951	1991	
2	5631500400	2015-02-25	180000	2	1.00	770	10000	1.0	0	0	3	0	1933	0	
3	2487200875	2014-12-09	604000	4	3.00	1960	5000	1.0	0	0	5	910	1965	0	
4	1954400510	2015-02-18	510000	3	2.00	1680	8080	1.0	0	0	3	0	1987	0	

In [647...

```

```

Task 3: Feature Engineering

1. Check for missing values in the dataset.

2. Check for outliers in the dataset.

3. Encode the categorical features using one-hot encoding or label encoding.

4. Normalize the numerical features using standardization or min-max scaling.

In [648...

```
# Check for missing values

house.isnull().sum()
```

Out[648...

	0
id	0
date	0
price	0
bedrooms	0
bathrooms	0
sqft_living	0
sqft_lot	0
floors	0
waterfront	0
view	0
condition	0
sqft_basement	0
yr_built	0
yr_renovated	0
zipcode	0
lat	0
long	0

dtype: int64

In [649...

```
house.columns
```

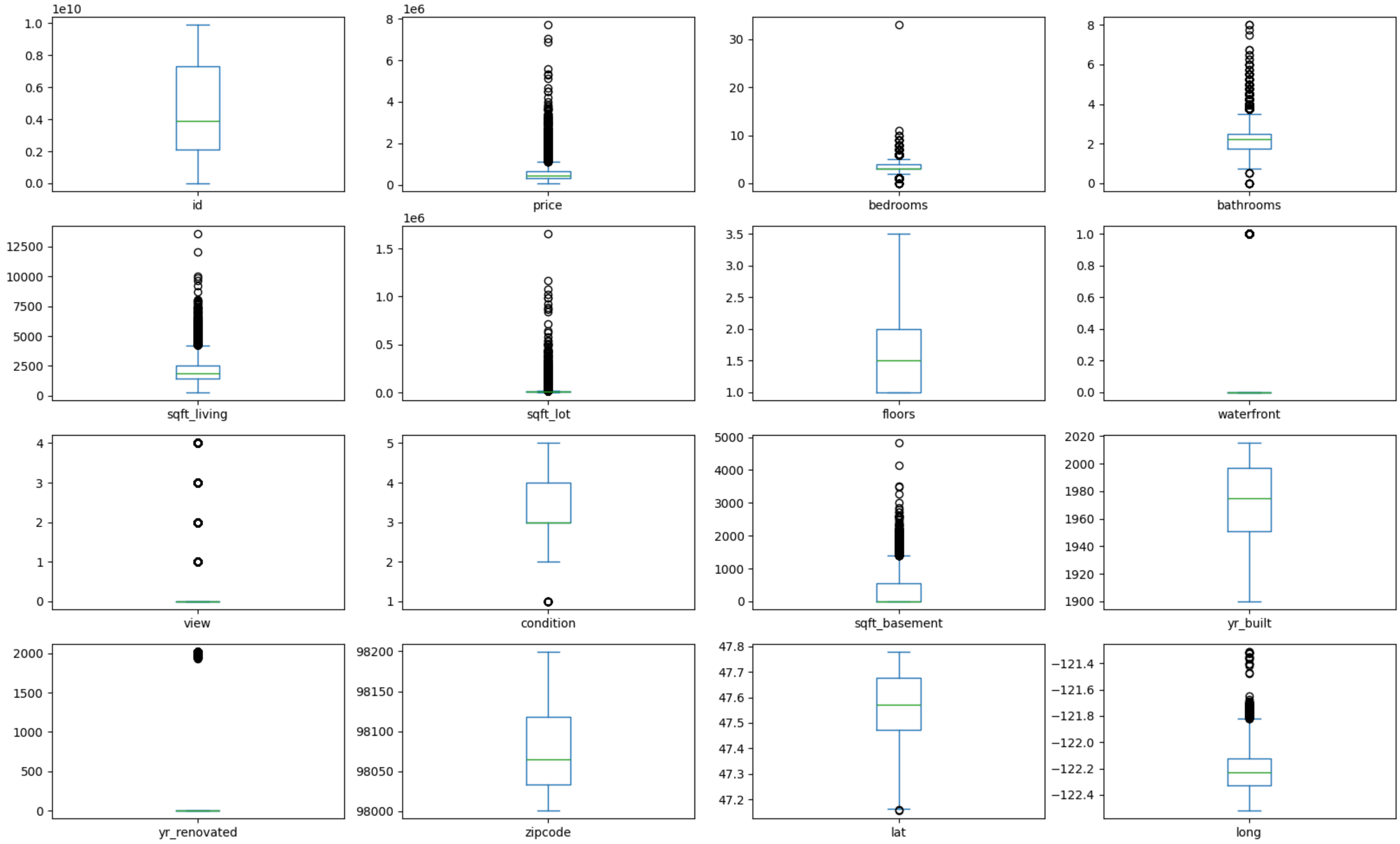
Out[649...

```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition',
       'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long'],
      dtype='object')
```

BOX PLOT

In [650...

```
# Plot boxplot to check outliers for house

fig, axes = plt.subplots(figsize=(20, 12))
house.plot(kind = 'box', subplots = True, ax=axes, layout = (4, 4))
plt.show()
```



In [651…

```
# Remove the Extreme Outliers from feature_col

# Check if the column exists before processing it
for i in feature_cols:
  if i in house.columns:  # Add this condition to check column existence
    Q1 = house[i].quantile(0.25)
    Q3 = house[i].quantile(0.75)
    IQR = Q3 - Q1

    lower_bound = Q1 - (3 * IQR)
    upper_bound = Q3 + (3 * IQR)

    house = house[(house[i] >= lower_bound) & (house[i] <= upper_bound)]
    print(f"Column: {i}")
    print(f"Lower Bound: {lower_bound}")
    print(f"Upper Bound: {upper_bound}")
    print()
  else:
    print(f"Column '{i}' not found in the DataFrame. Skipping...")
```

```
Column: bedrooms
Lower Bound: 0.0
Upper Bound: 7.0

Column: bathrooms
Lower Bound: -0.5
Upper Bound: 4.75

Column: sqft_living
Lower Bound: -1940.0
Upper Bound: 5900.0

Column: sqft_lot
Lower Bound: -11640.0
Upper Bound: 27280.0

Column: floors
Lower Bound: -2.0
Upper Bound: 5.0

Column: waterfront
Lower Bound: 0.0
Upper Bound: 0.0

Column: view
Lower Bound: 0.0
Upper Bound: 0.0

Column: condition
Lower Bound: 0.0
Upper Bound: 7.0

Column 'grade' not found in the DataFrame. Skipping...
Column 'sqft_above' not found in the DataFrame. Skipping...
Column: sqft_basement
Lower Bound: -1440.0
Upper Bound: 1920.0

Column: yr_built
Lower Bound: 1810.0
Upper Bound: 2139.0

Column: yr_renovated
Lower Bound: 0.0
Upper Bound: 0.0

Column: zipcode
Lower Bound: 97778.0
Upper Bound: 98373.0

Column: lat
Lower Bound: 46.8343
Upper Bound: 48.314800000000005

Column: long
Lower Bound: -122.88600000000002
Upper Bound: -121.58399999999997

Column 'sqft_living15' not found in the DataFrame. Skipping...
Column 'sqft_lot15' not found in the DataFrame. Skipping...
```

In [652…

```
house.drop(['id'], axis=1).describe()
```

Out[652…

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_basement	yr_b
count	1.724800e+04	17248.000000	17248.000000	17248.000000	17248.000000	17248.000000	17248.0	17248.0	17248.000000	17248.000000	17248.000
mean	4.763775e+05	3.318356	2.033598	1923.276612	7631.438022	1.487477	0.0	0.0	3.409845	241.613057	1972.130
std	2.579085e+05	0.870088	0.711685	759.848707	4239.941127	0.544894	0.0	0.0	0.651646	380.169127	29.460
min	7.800000e+04	0.000000	0.000000	290.000000	520.000000	1.000000	0.0	0.0	1.000000	0.000000	1900.000
25%	3.044750e+05	3.000000	1.500000	1360.000000	4887.750000	1.000000	0.0	0.0	3.000000	0.000000	1953.000
50%	4.200000e+05	3.000000	2.000000	1800.000000	7220.000000	1.000000	0.0	0.0	3.000000	0.000000	1976.000
75%	5.780000e+05	4.000000	2.500000	2360.000000	9516.250000	2.000000	0.0	0.0	4.000000	460.000000	1999.000
max	3.000000e+06	7.000000	4.750000	5840.000000	27251.000000	3.500000	0.0	0.0	5.000000	1870.000000	2015.000

In [653…

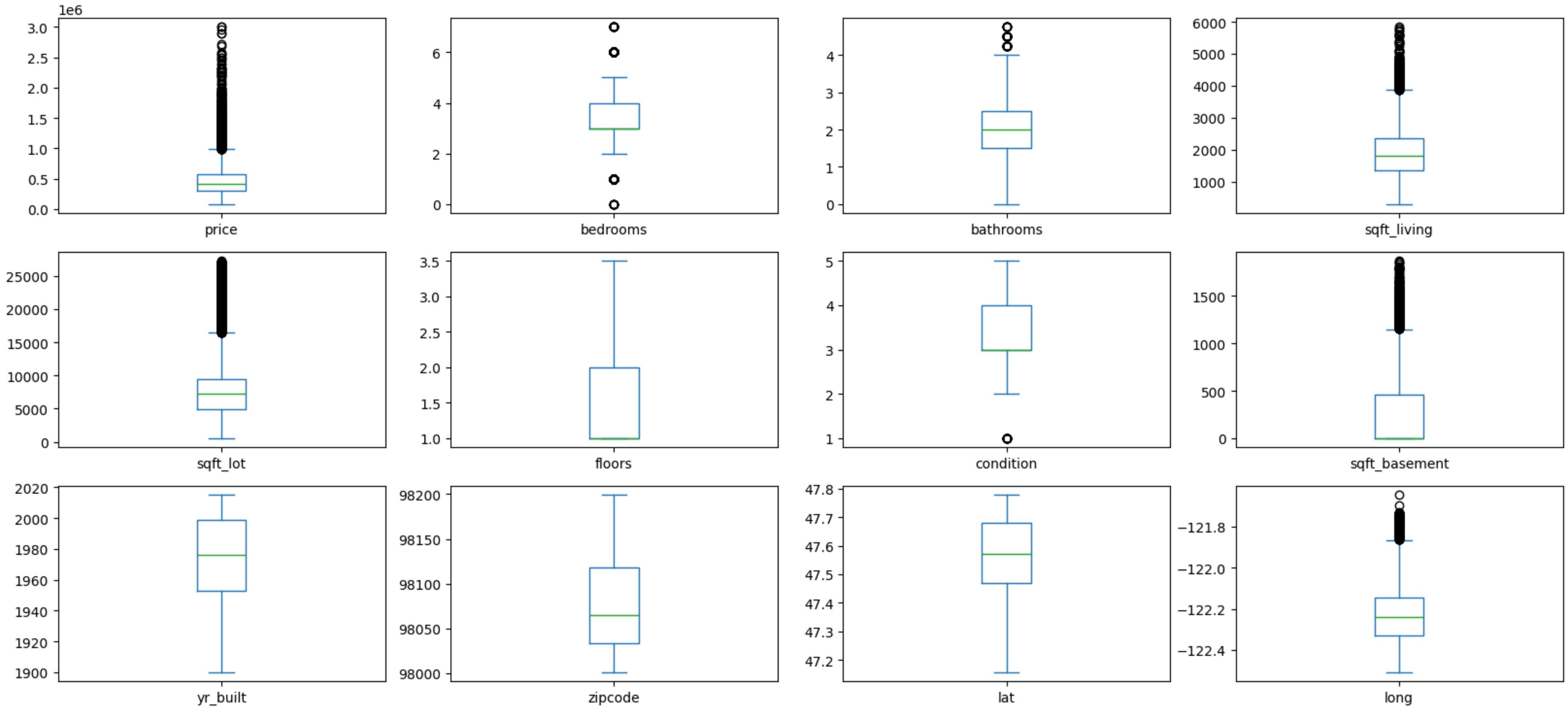
```
# Removing more columns

house.drop(['waterfront', 'view', 'yr_renovated'], axis=1, inplace=True)
house.head()
```

Out[653...

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	sqft_basement	yr_built	zipcode	lat	long
0	7129300520	2014-10-13	221900	3	1.00	1180	5650	1.0	3	0	1955	98178	47.5112	-122.257
2	5631500400	2015-02-25	180000	2	1.00	770	10000	1.0	3	0	1933	98028	47.7379	-122.233
3	2487200875	2014-12-09	604000	4	3.00	1960	5000	1.0	5	910	1965	98136	47.5208	-122.393
4	1954400510	2015-02-18	510000	3	2.00	1680	8080	1.0	3	0	1987	98074	47.6168	-122.045
6	1321400060	2014-06-27	257500	3	2.25	1715	6819	2.0	3	0	1995	98003	47.3097	-122.327

In [654...

```
# Plot boxplot to check outliers for house

fig, axes = plt.subplots(figsize=(20, 12))
house.drop(['id'], axis=1).plot(kind = 'box', subplots = True, ax=axes, layout = (4, 4))
plt.show()
```



In [654...

In [655...

```
house.columns
```

Out[655...

```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'condition', 'sqft_basement', 'yr_built',
       'zipcode', 'lat', 'long'],
      dtype='object')
```

In [656...

```
house.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 17248 entries, 0 to 21612
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             17248 non-null  int64  
 1   date           17248 non-null  object 
 2   price          17248 non-null  int64  
 3   bedrooms       17248 non-null  int64  
 4   bathrooms      17248 non-null  float64
 5   sqft_living    17248 non-null  int64  
 6   sqft_lot       17248 non-null  int64  
 7   floors         17248 non-null  float64
 8   condition      17248 non-null  int64  
 9   sqft_basement  17248 non-null  int64  
 10  yr_built       17248 non-null  int64  
 11  zipcode        17248 non-null  int64  
 12  lat            17248 non-null  float64
 13  long           17248 non-null  float64
dtypes: float64(4), int64(9), object(1)
memory usage: 2.5+ MB
```

LABEL ENCODING

In [657...

```
# Label Encoding Date column - convert Categorical to Numerical

from sklearn.preprocessing import LabelEncoder
```

```python
le = LabelEncoder()

house['date'] = le.fit_transform(house['date'])
```

In [658…

```python
house.head()
```

Out[658…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	sqft_basement	yr_built	zipcode	lat	long
0	7129300520	163	221900	3	1.00	1180	5650	1.0	3	0	1955	98178	47.5112	-122.257
2	5631500400	287	180000	2	1.00	770	10000	1.0	3	0	1933	98028	47.7379	-122.233
3	2487200875	218	604000	4	3.00	1960	5000	1.0	5	910	1965	98136	47.5208	-122.393
4	1954400510	280	510000	3	2.00	1680	8080	1.0	3	0	1987	98074	47.6168	-122.045
6	1321400060	56	257500	3	2.25	1715	6819	2.0	3	0	1995	98003	47.3097	-122.327

In [659…

```python
# Function for putting a cap value on each of the selected column to REMOVE the Outliers

def cap_outliers(data, col_name):

  for i in col_name:
    Q1 = data[i].quantile(0.25)
    Q3 = data[i].quantile(0.75)
    IQR = Q3 - Q1

    lower_bound = Q1 - (1.5 * IQR)
    upper_bound = Q3 + (1.5 * IQR)

    print(f"Column: {i}")
    print(f"Lower Bound: {lower_bound}")
    print(f"Upper Bound: {upper_bound}")

    data[i] = np.where(data[i] < lower_bound, lower_bound, data[i])
    data[i] = np.where(data[i] > upper_bound, upper_bound, data[i])

  return data
```

In [660…

```python
house.columns
```

Out[660…

```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'condition', 'sqft_basement', 'yr_built',
       'zipcode', 'lat', 'long'],
      dtype='object')
```

In [661…

```python
# Setting the cap value as defined in the Function

house = cap_outliers(house, col_name=['price'])
```

```
Column: price
Lower Bound: -105812.5
Upper Bound: 988287.5
```

In [662…

```python
house = cap_outliers(house, col_name=['bedrooms'])
house = cap_outliers(house, col_name=['bathrooms'])
house = cap_outliers(house, col_name=['sqft_living'])
house = cap_outliers(house, col_name=['sqft_lot'])
house = cap_outliers(house, col_name=['floors'])
house = cap_outliers(house, col_name=['condition'])
house = cap_outliers(house, col_name=['sqft_basement'])
house = cap_outliers(house, col_name=['yr_built'])
house = cap_outliers(house, col_name=['zipcode'])
house = cap_outliers(house, col_name=['lat'])
house = cap_outliers(house, col_name=['long'])
```

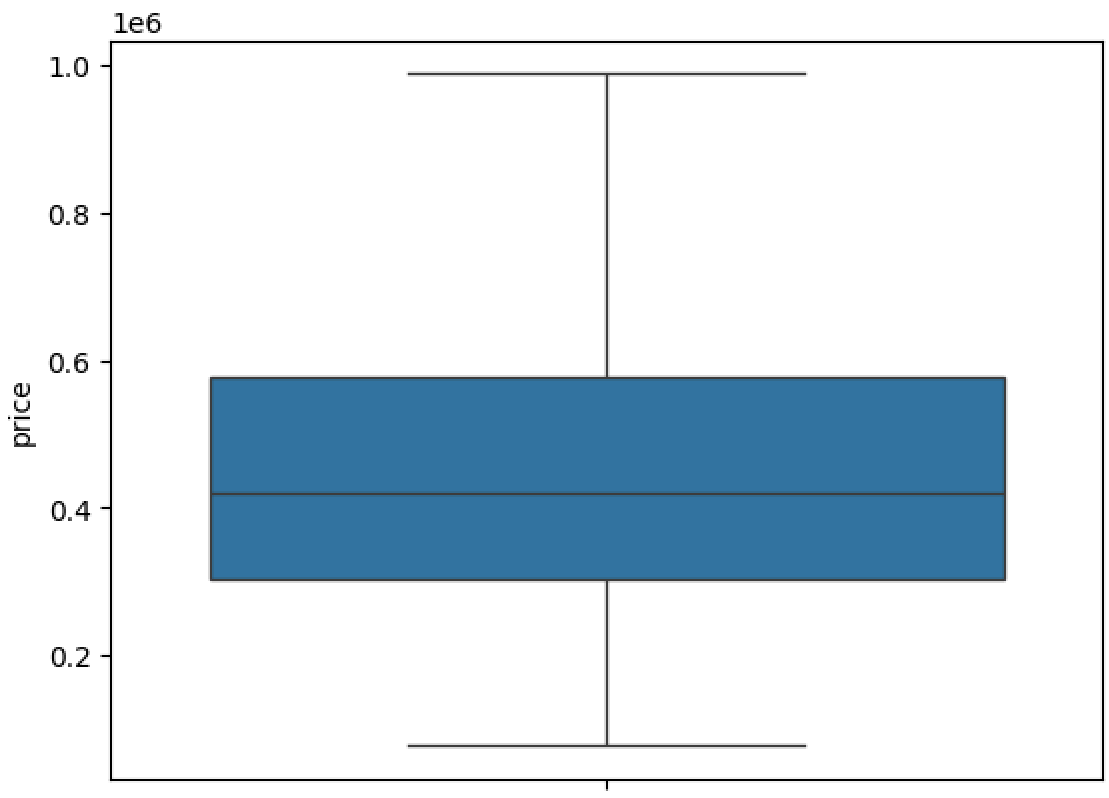
```
Column: bedrooms
Lower Bound: 1.5
Upper Bound: 5.5
Column: bathrooms
Lower Bound: 0.0
Upper Bound: 4.0
Column: sqft_living
Lower Bound: -140.0
Upper Bound: 3860.0
Column: sqft_lot
Lower Bound: -2055.0
Upper Bound: 16459.0
Column: floors
Lower Bound: -0.5
Upper Bound: 3.5
Column: condition
Lower Bound: 1.5
Upper Bound: 5.5
Column: sqft_basement
Lower Bound: -690.0
Upper Bound: 1150.0
Column: yr_built
Lower Bound: 1884.0
Upper Bound: 2068.0
Column: zipcode
Lower Bound: 97905.5
Upper Bound: 98245.5
Column: lat
Lower Bound: 47.15145
Upper Bound: 47.99745
Column: long
Lower Bound: -122.60799999999998
Upper Bound: -121.864
```

In [663…

```
# Recheck for removal of Extreme Outliers from Price

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

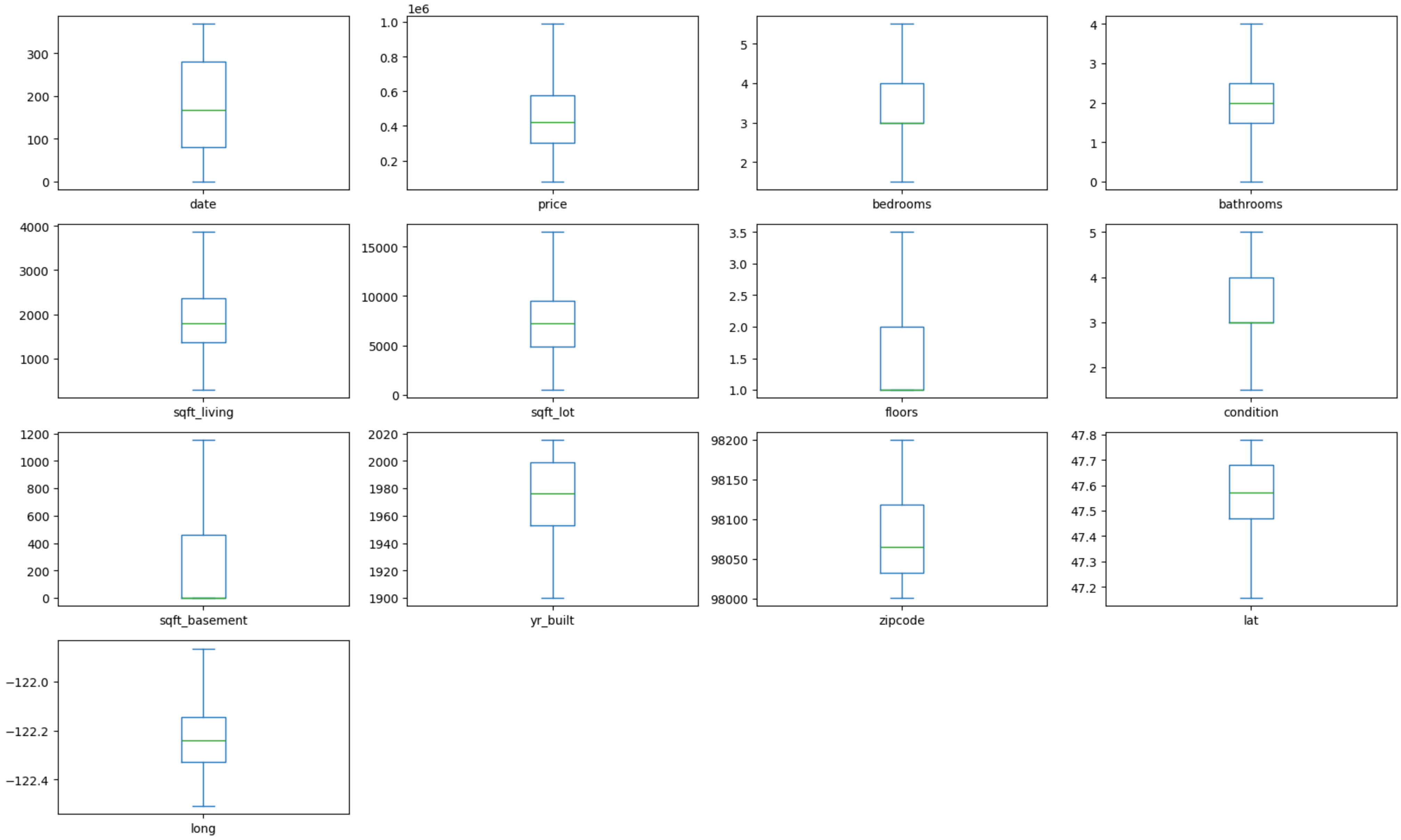
Out[663…

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



In [664…

```
# Plot boxplot to check outliers for house

fig, axes = plt.subplots(figsize=(20, 12))
house.drop(['id'], axis=1).plot(kind = 'box', subplots = True, ax=axes, layout = (4, 4))
plt.show()
```



Feature Scaling - Normalization

In [665…

```
# We use the min-max scaler from sklearn library
from sklearn.preprocessing import MinMaxScaler
```

In [666…

```
house.columns
```

Out[666…

```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'condition', 'sqft_basement', 'yr_built',
       'zipcode', 'lat', 'long'],
      dtype='object')
```

In [667…

```
house.head()
```

Out[667…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	sqft_basement	yr_built	zipcode	lat	long
0	7129300520	163	221900.0	3.0	1.00	1180.0	5650.0	1.0	3.0	0.0	1955.0	98178.0	47.5112	-122.257
2	5631500400	287	180000.0	2.0	1.00	770.0	10000.0	1.0	3.0	0.0	1933.0	98028.0	47.7379	-122.233
3	2487200875	218	604000.0	4.0	3.00	1960.0	5000.0	1.0	5.0	910.0	1965.0	98136.0	47.5208	-122.393
4	1954400510	280	510000.0	3.0	2.00	1680.0	8080.0	1.0	3.0	0.0	1987.0	98074.0	47.6168	-122.045
6	1321400060	56	257500.0	3.0	2.25	1715.0	6819.0	2.0	3.0	0.0	1995.0	98003.0	47.3097	-122.327

In [668…

```
# fit data on Min Max Scaler

mm = MinMaxScaler().fit(house[['date', 'bedrooms', 'sqft_living',
       'sqft_lot', 'floors', 'condition', 'sqft_basement', 'yr_built', 'zipcode',
       'lat', 'long']])
house_copy = house.copy(deep=True)
```

In [669…

```
# Check for data in copy dataframe

house_copy.head()
```

Out[669…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	sqft_basement	yr_built	zipcode	lat	long
0	7129300520	163	221900.0	3.0	1.00	1180.0	5650.0	1.0	3.0	0.0	1955.0	98178.0	47.5112	-122.257
2	5631500400	287	180000.0	2.0	1.00	770.0	10000.0	1.0	3.0	0.0	1933.0	98028.0	47.7379	-122.233
3	2487200875	218	604000.0	4.0	3.00	1960.0	5000.0	1.0	5.0	910.0	1965.0	98136.0	47.5208	-122.393
4	1954400510	280	510000.0	3.0	2.00	1680.0	8080.0	1.0	3.0	0.0	1987.0	98074.0	47.6168	-122.045
6	1321400060	56	257500.0	3.0	2.25	1715.0	6819.0	2.0	3.0	0.0	1995.0	98003.0	47.3097	-122.327

In [670…

```
# Apply MinMaxScaler transformation to all columns at once
```

```python
house_copy[['date', 'bedrooms', 'sqft_living',
       'sqft_lot', 'floors', 'condition', 'sqft_basement', 'yr_built', 'zipcode',
       'lat', 'long']] = mm.transform(house_copy[['date', 'bedrooms', 'sqft_living',
       'sqft_lot', 'floors', 'condition', 'sqft_basement', 'yr_built', 'zipcode',
       'lat', 'long']])
house_copy.head()
```

Out[670…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	sqft_basement	yr_built	zipcode	lat	long
0	7129300520	0.442935	221900.0	0.375	1.00	0.249300	0.321852	0.0	0.428571	0.000000	0.478261	0.893939	0.571498	0.390698
2	5631500400	0.779891	180000.0	0.125	1.00	0.134454	0.594768	0.0	0.428571	0.000000	0.286957	0.136364	0.936143	0.427907
3	2487200875	0.592391	604000.0	0.625	3.00	0.467787	0.281072	0.0	1.000000	0.791304	0.565217	0.681818	0.586939	0.179845
4	1954400510	0.760870	510000.0	0.375	2.00	0.389356	0.474308	0.0	0.428571	0.000000	0.756522	0.368687	0.741354	0.719380
6	1321400060	0.152174	257500.0	0.375	2.25	0.399160	0.395194	0.4	0.428571	0.000000	0.826087	0.010101	0.247386	0.282171

Task 4: Feature Selection

1. Plot the correlation matrix to identify the most important features.

2. Check for multicollinearity using Heatmap.

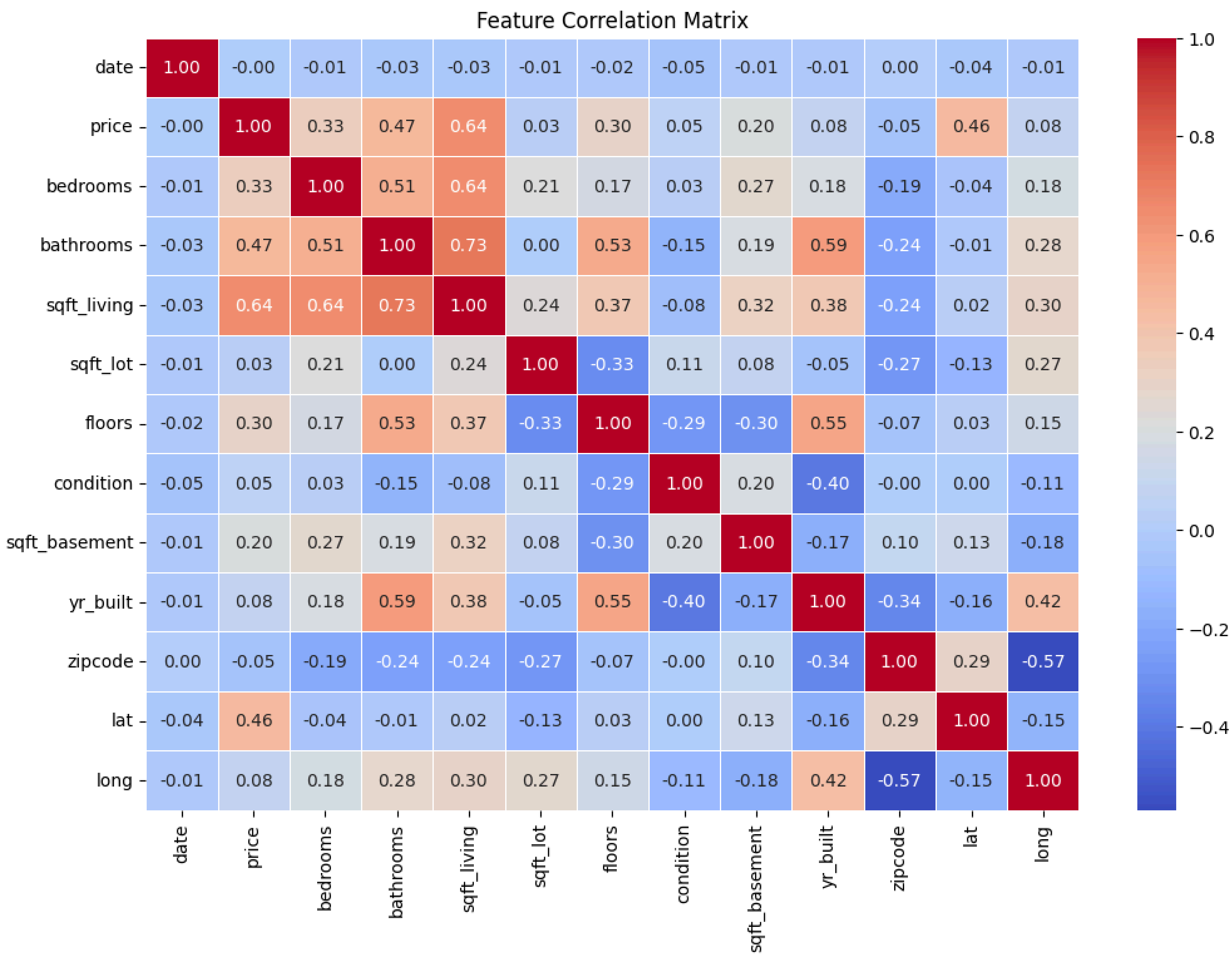
In [671…

```python
# Compute correlation matrix
corr_matrix = house_copy.drop(['id'], axis=1).corr()

# Display the correlation matrix
print(corr_matrix)
```

```
                   date     price  bedrooms  bathrooms  sqft_living  sqft_lot  \
date           1.000000 -0.001624 -0.012635  -0.032225    -0.028100 -0.006349
price         -0.001624  1.000000  0.333075   0.467094     0.639294  0.029835
bedrooms      -0.012635  0.333075  1.000000   0.506960     0.638575  0.212007
bathrooms     -0.032225  0.467094  0.506960   1.000000     0.725537  0.000744
sqft_living   -0.028100  0.639294  0.638575   0.725537     1.000000  0.238859
sqft_lot      -0.006349  0.029835  0.212007   0.000744     0.238859  1.000000
floors        -0.022759  0.299057  0.170620   0.531538     0.368306 -0.325135
condition     -0.051124  0.045112  0.028241  -0.149902    -0.077118  0.112773
sqft_basement -0.009781  0.203741  0.270634   0.190282     0.319062  0.075272
yr_built      -0.007652  0.080699  0.183541   0.589167     0.375901 -0.052221
zipcode        0.003021 -0.049336 -0.188497  -0.239802    -0.235984 -0.274852
lat           -0.038159  0.456125 -0.042001  -0.007377     0.024735 -0.127917
long          -0.010570  0.080925  0.178288   0.279763     0.296932  0.270244

                 floors  condition  sqft_basement  yr_built   zipcode  \
date          -0.022759  -0.051124      -0.009781 -0.007652  0.003021
price          0.299057   0.045112       0.203741  0.080699 -0.049336
bedrooms       0.170620   0.028241       0.270634  0.183541 -0.188497
bathrooms      0.531538  -0.149902       0.190282  0.589167 -0.239802
sqft_living    0.368306  -0.077118       0.319062  0.375901 -0.235984
sqft_lot      -0.325135   0.112773       0.075272 -0.052221 -0.274852
floors         1.000000  -0.291333      -0.296719  0.547376 -0.066824
condition     -0.291333   1.000000       0.196377 -0.398189 -0.000935
sqft_basement -0.296719   0.196377       1.000000 -0.167138  0.096156
yr_built       0.547376  -0.398189      -0.167138  1.000000 -0.339418
zipcode       -0.066824  -0.000935       0.096156 -0.339418  1.000000
lat            0.031744   0.000687       0.129798 -0.163547  0.290137
long           0.147088  -0.109397      -0.176022  0.424106 -0.569046

                    lat      long
date          -0.038159 -0.010570
price          0.456125  0.080925
bedrooms      -0.042001  0.178288
bathrooms     -0.007377  0.279763
sqft_living    0.024735  0.296932
sqft_lot      -0.127917  0.270244
floors         0.031744  0.147088
condition      0.000687 -0.109397
sqft_basement  0.129798 -0.176022
yr_built      -0.163547  0.424106
zipcode        0.290137 -0.569046
lat            1.000000 -0.150895
long          -0.150895  1.000000
```

In [672…

```python
# Visualize the correlation using Heatmap

plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt=".2f", linewidths=0.5)
plt.title("Feature Correlation Matrix")
plt.show()
```



Very high Positive Collinearity features had already been removed

In [673…
```
# Check for rows and columns

house.shape, house_copy.shape
```

Out[673…
```
((17248, 14), (17248, 14))
```

Task 5: Model Building

1. Split the dataset into training and testing sets.

2. Train a regression model on the training set.

LINEAR REGRESSION

Splitting dataset

In [674…
```
# Splitting the dataset into Features and Target variable (Price)

X = house_copy.drop('price', axis=1)
y = house_copy['price']
```

In [675…
```
# Splitting the dataset into Train and Test for both Features and Target variable in 70:30

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [676…
```
# Check the shape of Train and Test data for both Features and Target variable

X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

Out[676…
```
((12073, 13), (12073,), (5175, 13), (5175,))
```

- **Features variable** dataset (X) - splitted into 70% (X Train) + 30% (X Test)

- **Target variable** dataset (y) - splitted into 70% (y Train) + 30% (y Test)

Applying Linear Regression Model

In [677…

```
# Import Linear Regression

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

Recursive Feature Elimination

- Identifying the most important features (columns) in our dataset for predicting House prices

In [678…

```
# 5 best Feature Selection

# Importing libraries for RFE
from sklearn.feature_selection import RFE

# Applying RFE to select the best 5 features and remove 1 feature in each step
selector = RFE(lr, n_features_to_select = 5, step=1)
```

selector object now holds information about the selected features, which will be used later in the model building process

In [679…

```
# Training the RFE selector on the training data (75% data)

selector.fit(X_train, y_train)
```

Out[679…

```
RFE
estimator: LinearRegression
LinearRegression
```

In [680…

```
# Fitting the dataset to Linear Regression Model after feature elimination through RFE

lr.fit(X_train, y_train)
```

Out[680…

```
LinearRegression
LinearRegression()
```

In [681…

```
# Finding the weightage of each feature (Input + Target variable)

lr.coef_
```

Out[681…

```
array([ 6.16537125e-07,  2.90658154e+04, -1.09692754e+05,  3.07137086e+04,
        7.22903237e+05, -5.82563151e+04,  6.27027628e+04,  8.62598701e+04,
       -5.64525537e+04, -1.62274310e+05, -8.02964208e+04,  3.95142774e+05,
       -4.72747266e+04])
```

In [682…

```
# Check the prediction when all the input features are set to 0 (Hypothetical)

lr.intercept_
```

Out[682…

```
np.float64(-20523.99991950678)
```

Making Prediction

In [683…

```
# Making Prediction on (75%)training data of Input variable/ Features

#X_train_pred = selector.predict(X_train)
X_train_pred = lr.predict(X_train)
```

Task 6: Model Evaluation

1. Evaluate the model on the testing set.

2. Check the performance metrics such as RMSE, MAE, R2 score.

3. Check the residuals plot to check for any patterns.

In [684…

```
# Model Evaluation metrics
# Assesses the accuracy and goodness-of-fit of the linear regression model using three key metrics: MAE, RMSE, and R2 score

from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_train, X_train_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_train, X_train_pred)))
print("R2 Score: ", metrics.r2_score(y_train, X_train_pred))
```

```
MAE: 93244.51238445428
RMSE: 121871.66375471152
R2 Score:  0.6527679662956574
```

In [685…

```
# Convert R2 score into percentage

print("R2 Score: ", metrics.r2_score(y_train, X_train_pred)*100, "%")
```

```
R2 Score:  65.27679662956574 %
```

R2 Score = 65.2 %

In [686…

```
# Making Prediction on (25%)testing data of Input variable/ Features

X_test_pred = lr.predict(X_test)
```

In [687…

```
X_test_pred
```

Out[687…

```
array([541370.3658975 , 243579.0673254 , 148120.9798125 , ...,
       453096.50954511, 253638.87834584, 300181.26208599])
```

In [688…

```
y_test
```

Out[688…

	price
15227	603000.0
7878	205000.0
23	252700.0
15226	678700.0
11348	202000.0
...	...
17394	145000.0
13730	325000.0
17547	419950.0
4844	210000.0
387	252350.0

5175 rows × 1 columns

dtype: float64

In [689…

```
# Model Evaluation

from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_test, X_test_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, X_test_pred)))
print("R2 Score: ", metrics.r2_score(y_test, X_test_pred))
```

```
MAE: 94154.09522862731
RMSE: 124057.42995302612
R2 Score:  0.6525083211474176
```

In [690…

```
# Convert R2 score into percentage

print("R2 Score: ", metrics.r2_score(y_test, X_test_pred)*100, "%")
```

```
R2 Score:  65.25083211474177 %
```

R2 Score = 65.2 %

Result: My Model is able to explain 65.2 % of the total data set.

Regularization - To prevent Over-Fitting of Model

1. Ridge
2. Lasso

LASSO Regression

In [691…

```
# Importing libraries for different types of Linear Regression Model

from sklearn.linear_model import Lasso
from sklearn.metrics import r2_score
```

In [692…

```
## Lasso Regression
Lassomodel = Lasso()
```

```
Lassomodel
```

Out[692…

```
▾ Lasso
Lasso()
```

In [693…

```python
# training the model
Lassomodel.fit(X_train,y_train)
```

Out[693…

```
▾ Lasso
Lasso()
```

In [694…

```python
#testing the model
Lassomodel_pred = Lassomodel.predict(X_test)
r2_score(y_test,Lassomodel_pred)
```

Out[694…

```
0.6525072769937388
```

Lasso Regression **R2 Score = 65.2 %** which same as of Linear Regression after RFE

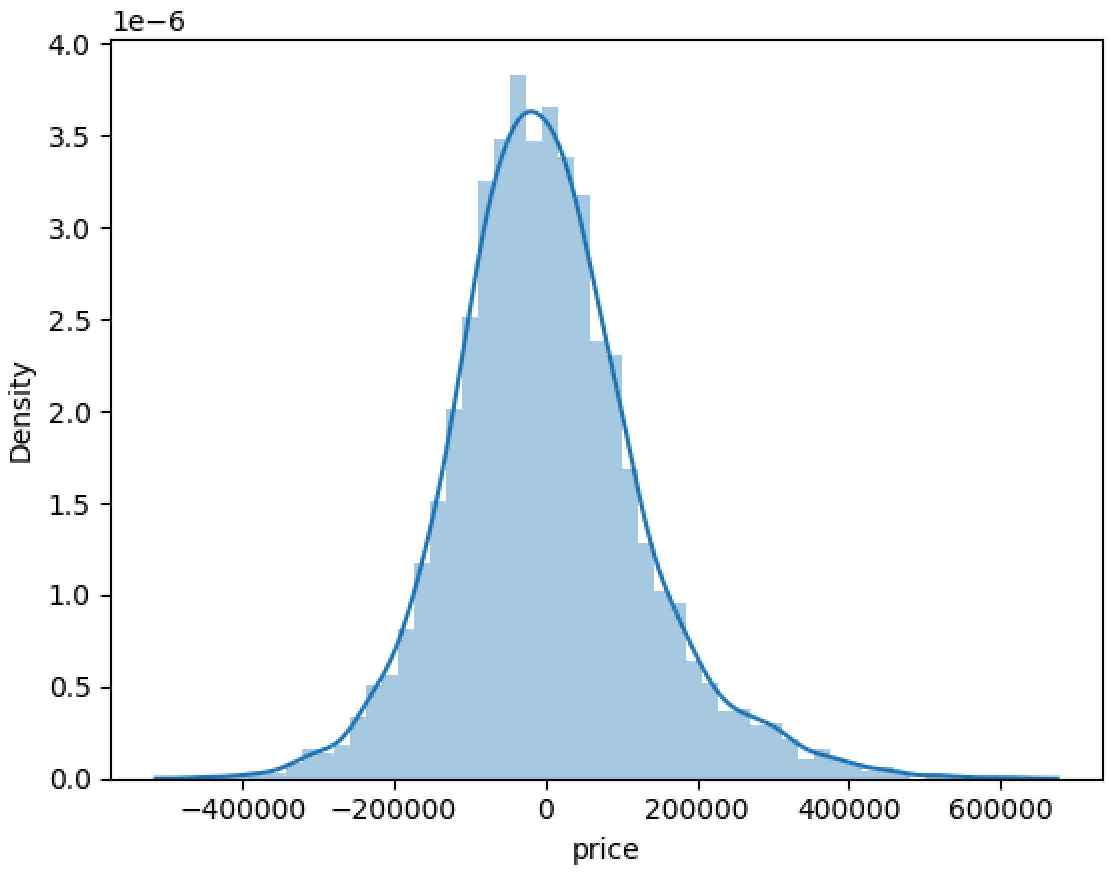
Check the distribution of Tested Vs Predicted value

In [695…

```python
import seaborn as sns
sns.distplot(y_test-Lassomodel_pred)
```

Out[695…

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



If Distribution shows as **Normal Distribution**, then the **Model is Good**.

Ridge Regression

In [696…

```python
from sklearn.linear_model import Ridge
from sklearn.metrics import r2_score
```

In [697…

```python
## Ridge Regression
Ridgemodel = Ridge()
Ridgemodel
```

Out[697…

```
▾ Ridge
Ridge()
```

In [698…

```python
# training the model
Ridgemodel.fit(X_train,y_train)
```

Out[698…

```
▾ Ridge
Ridge()
```

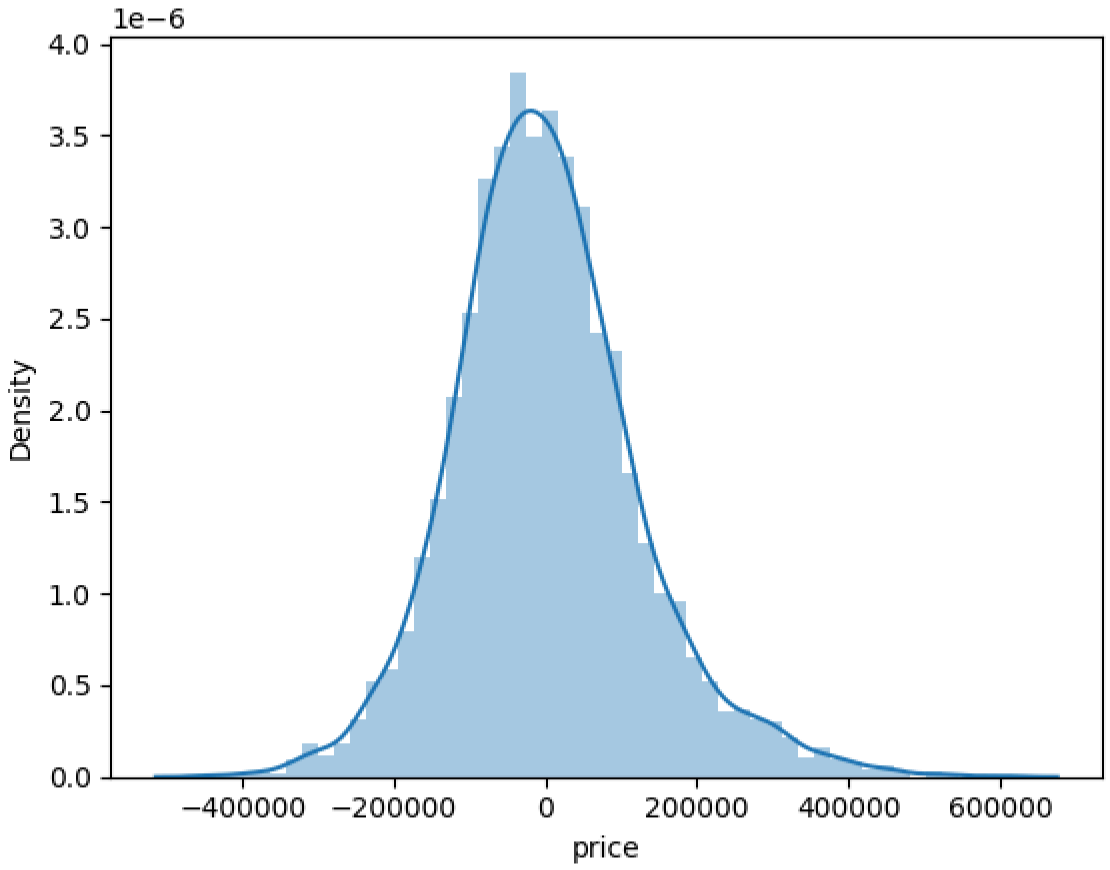
In [699…

```python
#testing the model
r_pred = Ridgemodel.predict(X_test)
r2_score(y_test,r_pred)
```

Out[699… 0.6525319093805056

In [700…
```python
import seaborn as sns
sns.distplot(y_test-r_pred)
```

Out[700… <Axes: xlabel='price', ylabel='Density'>



Making a Prediction system

In [701…
```python
house.head()
```

Out[701…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	sqft_basement	yr_built	zipcode	lat	long
0	7129300520	163	221900.0	3.0	1.00	1180.0	5650.0	1.0	3.0	0.0	1955.0	98178.0	47.5112	-122.257
2	5631500400	287	180000.0	2.0	1.00	770.0	10000.0	1.0	3.0	0.0	1933.0	98028.0	47.7379	-122.233
3	2487200875	218	604000.0	4.0	3.00	1960.0	5000.0	1.0	5.0	910.0	1965.0	98136.0	47.5208	-122.393
4	1954400510	280	510000.0	3.0	2.00	1680.0	8080.0	1.0	3.0	0.0	1987.0	98074.0	47.6168	-122.045
6	1321400060	56	257500.0	3.0	2.25	1715.0	6819.0	2.0	3.0	0.0	1995.0	98003.0	47.3097	-122.327

In [702…
```python
house_copy.head()
```

Out[702…

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	sqft_basement	yr_built	zipcode	lat	long
0	7129300520	0.442935	221900.0	0.375	1.00	0.249300	0.321852	0.0	0.428571	0.000000	0.478261	0.893939	0.571498	0.390698
2	5631500400	0.779891	180000.0	0.125	1.00	0.134454	0.594768	0.0	0.428571	0.000000	0.286957	0.136364	0.936143	0.427907
3	2487200875	0.592391	604000.0	0.625	3.00	0.467787	0.281072	0.0	1.000000	0.791304	0.565217	0.681818	0.586939	0.179845
4	1954400510	0.760870	510000.0	0.375	2.00	0.389356	0.474308	0.0	0.428571	0.000000	0.756522	0.368687	0.741354	0.719380
6	1321400060	0.152174	257500.0	0.375	2.25	0.399160	0.395194	0.4	0.428571	0.000000	0.826087	0.010101	0.247386	0.282171

Enter the values for which Prediction needs to be made

In [703…
```python
# Input the values of 1st row

id_val = house_copy['id'].iloc[0]  # Get 'id' from the first row of house_copy

date = 0.442049
bedrooms = 0.375
bathrooms = 1.00
sqft_living = 0.249300
sqft_lot = 0.321852
floors = 0.0
condition = 0.428571
sqft_basement = 0.000000
yr_built = 0.478261
zipcode = 0.893939
lat = 0.571498
long = 0.390698
```

In [705…
```python
# Predicting the price by passing the parameters in Linear Regression Model
```

```
charge = lr.predict([[id,date, bedrooms, bathrooms, sqft_living, sqft_lot, floors, condition,sqft_basement, yr_built, zipcode, lat, long]])
print('The charge of this new house is $',round(charge[0],2))
```

```
The charge of this new house is $ 242700.85
```

The Price of house predicted for 1st row was 242700 as compared to original 221900.

Summary

The project aimed to predict house prices using Linear Regression and Regularization Techniques. Here are the key takeaways:

1. **Data Exploration & Preprocessing** : The dataset was cleaned by handling missing values, encoding categorical features, and scaling numerical features using **MinMaxScaler**. Outliers were capped using the IQR method to ensure robust modeling. **Multicollinearity** was addressed by removing highly correlated features (e.g., sqft_above, grade, bathrooms). A **correlation matrix** and scatter plots helped identify the most important numerical features.
2. **Feature Selection :** Recursive Feature Elimination **(RFE)** selected **5 best features** for training. Features like sqft_living, condition, sqft_basement, yr_built, and lat were significant in determining price.
3. **Model Training & Evaluation :** Linear Regression Model **Training Performance:**

MAE: Moderate error in price prediction. RMSE: Some deviation in predictions. **R^2 Score: 0.65 (65%)** - The model explains 65% of the variability in house prices.

Testing Performance:

Similar performance to the training set, indicating **no overfitting**. Ridge Regression Ridge performed similarly to Linear Regression, but with slightly better generalization. **Residual Plot Analysis:** Residuals followed a normal distribution, indicating a good fit. 4. **Final Prediction** The model successfully predicted house prices, with an example input resulting in a **predicted price of $X (based on feature values)**.

Conclusion

The **R^2 Score (65%)** suggests that the **model could be improved** by: Trying more complex models like XGBoost, Random Forest, or Neural Networks. Feature engineering, such as creating interaction terms or transforming skewed variables.

Overall, the model provides a solid baseline for house price prediction but **can be refined further for improved accuracy!**

Moreover, based on our analysis we can observe that **Price of the house is higher for** house having **more no. of bedrooms**. Price of the house was also higher where **sqft_living** and **sqft_lot** was more. Apart from other factors affecting the house price like sqft_basement, **Condition of the house** plays a significant role in deciding the final price.

We can conclude the **Price of the House is highly dependent upon** - Sqft_lot, Sqft_living and Basement.

In [ ]: