Import Liebrary

```
import pandas as pd
import numpy as np
from datetime import datetime
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from scipy.stats import ttest_ind
```

Import File

```
df = pd.read_excel("housing.xlsx")

df.shape

(4600, 18)

df.head()

        date     price  bedrooms  bathrooms  sqft_living  sqft_lot
floors  \
0 2014-05-03  310000.0         3        1.0       1010.0    9945.0
1
1 2014-05-04  775000.0         2        2.5       2680.0    7392.0
1
2 2014-05-04  365000.0         3        2.5       2200.0    7350.0
1
3 2014-05-04  331950.0         4        2.5       2530.0    9933.0
2
4 2014-05-04  783500.0         3        2.5       2850.0    7130.0
2

  waterfront       view  condition  ...  yr_built  yr_renovated  \
0         No    No View      Great  ...      1973             0
1         No    No View       Good  ...      2004          2003
2         No    No View  Excellent  ...      1988             0
3         No  Good View       Good  ...      1990          2009
4         No    No View       Good  ...      1980             0

             street        city  statezip country  year month  day  \
0  7528 N Fork Rd SE  Snoqualmie  WA 98065     USA  2014     5    3
1  13134 234th Ct NE     Redmond  WA 98053     USA  2014     5    4
2  13420 SE 182nd St      Renton  WA 98058     USA  2014     5    4
3        925 48th Ct      Auburn  WA 98092     USA  2014     5    4
4     151 Euclid Ave     Seattle  WA 98122     USA  2014     5    4
```

```
   state_name
0  Washington
1  Washington
2  Washington
3  Washington
4  Washington

[5 rows x 22 columns]
```

```
df.describe()
```

```
                                date         price     bedrooms
bathrooms  \
count                           4600  4.600000e+03  4600.000000
4600.000000
mean   2014-06-07 03:14:42.782608640  5.539483e+05     3.400870
2.160815
min              2014-05-02 00:00:00  0.000000e+00     0.000000
0.000000
25%              2014-05-21 00:00:00  3.225000e+05     3.000000
1.750000
50%              2014-06-09 00:00:00  4.610000e+05     3.000000
2.250000
75%              2014-06-24 00:00:00  6.550000e+05     4.000000
2.500000
max              2014-07-10 00:00:00  2.659000e+07     9.000000
8.000000
std                              NaN  5.808371e+05     0.908848
0.783781

        sqft_living      sqft_lot       floors   waterfront
view  \
count   4560.000000  4.586000e+03  4600.000000  4600.000000
4600.000000
mean    2138.935526  1.485981e+04     1.512065     0.007174
0.240652
min      370.000000  6.380000e+02     1.000000     0.000000
0.000000
25%     1460.000000  5.000000e+03     1.000000     0.000000
0.000000
50%     1980.000000  7.683500e+03     1.500000     0.000000
0.000000
75%     2620.000000  1.101850e+04     2.000000     0.000000
0.000000
max    13540.000000  1.074218e+06     3.500000     1.000000
4.000000
std      965.011449  3.592050e+04     0.538288     0.084404
0.778405

         condition    sqft_above  sqft_basement     yr_built
```

```
yr_renovated
count  4600.000000   4600.000000    4600.000000  4577.000000
4600.000000
mean      3.451739   1840.825435     312.081522  1970.808827
808.608261
min       1.000000    350.000000       0.000000  1900.000000
0.000000
25%       3.000000   1190.000000       0.000000  1951.000000
0.000000
50%       3.000000   1590.000000       0.000000  1976.000000
0.000000
75%       4.000000   2300.000000     610.000000  1997.000000
1999.000000
max       5.000000  20450.000000    4820.000000  2014.000000
2014.000000
std       0.677230    970.705795     464.137228    29.724793
979.414536
```

INTRODUCTION

Objective

The goal of this project is to analyze housing data to understand what factors influence house prices, identify patterns and trends

and provide actionable insights for buyers, sellers, and investors

Dataset Summary

Location: City, State ZIP Code

Property Characteristics: Bedrooms, Bathrooms, Square Footage, Floors

Quality & Condition: House Condition, Grade, Renovation Year

Special Features: View, Waterfront

Financial Info: Price, Date of Sale

Process

Clean and Prepare the Data

Explore the Data (EDA)

Feature Engineering

Visualization

Final Recommendations & Insights

Data Cleaning

```
df.isnull().sum()
```

```
date            0
price           0
bedrooms        0
bathrooms       0
sqft_living    40
sqft_lot       14
floors          0
waterfront      0
view            0
condition       0
```

```
sqft_above        0
sqft_basement     0
yr_built         23
yr_renovated      0
street            0
city             57
statezip          0
country           0
dtype: int64
```

```
df.dropna(inplace=True)
```

```
df.shape
```

```
(4510, 18)
```

Null Values Removed

```
df.isnull().sum()
```

```
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
street           0
city             0
statezip         0
country          0
dtype: int64
```

```
df.duplicated().sum()
```

```
0
```

```
df.dtypes
```

```
date             datetime64[ns]
price                   float64
bedrooms                  int64
```

```
bathrooms                   float64
sqft_living                 float64
sqft_lot                    float64
floors                      float64
waterfront                    int64
view                          int64
condition                     int64
sqft_above                    int64
sqft_basement                 int64
yr_built                    float64
yr_renovated                  int64
street                       object
city                         object
statezip                     object
country                      object
dtype: object
```

```
print(df['bedrooms'].value_counts())
print(df['bathrooms'].value_counts())
```

```
bedrooms
3    1986
4    1503
2     555
5     348
6      61
1      38
7      14
8       2
0       2
9       1
Name: count, dtype: int64
bathrooms
2.50    1158
1.00     729
1.75     615
2.00     418
2.25     411
1.50     285
2.75     273
3.00     165
3.50     162
3.25     133
3.75      37
4.50      29
4.25      23
4.00      23
0.75      17
4.75       7
```

```
5.00        6
5.25        4
5.50        4
1.25        3
6.25        2
0.00        2
8.00        1
5.75        1
6.50        1
6.75        1
Name: count, dtype: int64
```

Remove Invalid Rows

```
invalid_rows = df[(df['bedrooms'] <= 0) | (df['bathrooms'] <= 0) |
(df['yr_built'] >= pd.Timestamp.now().year)|
(df['price'] <= 0)]

df = df.drop(invalid_rows.index)

df.shape

(4460, 18)
```

Data type Changed

```
df['floors'] = df['floors'].round().astype(int)
df['yr_built'] = df['yr_built'].astype(int)

df.dtypes

date             datetime64[ns]
price                   float64
bedrooms                  int64
bathrooms               float64
sqft_living             float64
sqft_lot                float64
floors                    int32
waterfront                int64
view                      int64
condition                 int64
sqft_above                int64
sqft_basement             int64
yr_built                  int32
yr_renovated              int64
```

```
street                        object
city                          object
statezip                      object
country                       object
dtype: object
```

Convert to DateTime

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

df['year'] = df['date'].dt.year
df['month'] = df['date'].dt.month
df['day'] = df['date'].dt.day
```

Convert Numerical Data to Categorical Data

```
df['waterfront'].value_counts()

waterfront
0    4430
1      30
Name: count, dtype: int64

df['waterfront'] = df['waterfront'].apply(lambda x: 'Yes' if x == 1
else 'No')

df['waterfront'].value_counts()

waterfront
No     4430
Yes      30
Name: count, dtype: int64

df['condition'].value_counts()

condition
3    2800
4    1205
5     419
2      30
1       6
Name: count, dtype: int64
```

```
df['condition'] = df['condition'].map({
    1: 'Poor',2: 'Average',3: 'Good',
    4: 'Great',5: 'Excellent'})

df['condition'].value_counts()

condition
Good         2800
Great        1205
Excellent     419
Average        30
Poor            6
Name: count, dtype: int64

df['view'].value_counts()

view
0    4020
2     195
3     115
1      68
4      62
Name: count, dtype: int64

df['view'] = df['view'].map({
    0: 'No View',1: 'Fair View',2: 'Good View',
    3: 'Great View', 4: 'Excellent View'})

df['view'].value_counts()

view
No View           4020
Good View          195
Great View         115
Fair View           68
Excellent View      62
Name: count, dtype: int64
```

State convert to seperate column

```
df['state'] = df['statezip'].str.split(' ').str[0]
state_map = {'WA': 'Washington'}
df['state_name'] = df['state'].map(state_map)


df.head()

         date     price  bedrooms  bathrooms  sqft_living  sqft_lot
floors  \
67 2014-05-03  310000.0         3        1.0       1010.0    9945.0
1
```

```
68 2014-05-04  775000.0         2        2.5       2680.0    7392.0
1
69 2014-05-04  365000.0         3        2.5       2200.0    7350.0
1
70 2014-05-04  331950.0         4        2.5       2530.0    9933.0
2
71 2014-05-04  783500.0         3        2.5       2850.0    7130.0
2

   waterfront       view  condition  ...  yr_renovated
street  \
67         No    No View      Great  ...             0  7528 N Fork Rd
SE
68         No    No View       Good  ...          2003  13134 234th Ct
NE
69         No    No View  Excellent  ...             0  13420 SE 182nd
St
70         No  Good View       Good  ...          2009        925 48th
Ct
71         No    No View       Good  ...             0     151 Euclid
Ave

          city  statezip country  year month day  state  state_name
67  Snoqualmie  WA 98065     USA  2014     5   3     WA  Washington
68     Redmond  WA 98053     USA  2014     5   4     WA  Washington
69      Renton  WA 98058     USA  2014     5   4     WA  Washington
70      Auburn  WA 98092     USA  2014     5   4     WA  Washington
71     Seattle  WA 98122     USA  2014     5   4     WA  Washington

[5 rows x 23 columns]
```

```
df.dtypes
```

```
date             datetime64[ns]
price                   float64
bedrooms                  int64
bathrooms               float64
sqft_living             float64
sqft_lot                float64
floors                    int32
waterfront               object
view                     object
condition                object
sqft_above                int64
sqft_basement             int64
yr_built                  int32
yr_renovated              int64
street                   object
city                     object
statezip                 object
```

```
country                      object
year                          int32
month                         int32
day                           int32
state                        object
state_name                   object
dtype: object
```

```python
df.drop('state',axis=1,inplace=True)
```

```python
df = df.reset_index(drop=True)
```

```python
df.shape
```

```
(4460, 22)
```

```python
df.head()
```

```
        date     price  bedrooms  bathrooms  sqft_living  sqft_lot
floors  \
0 2014-05-03  310000.0         3        1.0       1010.0    9945.0
1
1 2014-05-04  775000.0         2        2.5       2680.0    7392.0
1
2 2014-05-04  365000.0         3        2.5       2200.0    7350.0
1
3 2014-05-04  331950.0         4        2.5       2530.0    9933.0
2
4 2014-05-04  783500.0         3        2.5       2850.0    7130.0
2

  waterfront       view  condition  ...  yr_built  yr_renovated  \
0         No    No View      Great  ...      1973             0
1         No    No View       Good  ...      2004          2003
2         No    No View  Excellent  ...      1988             0
3         No  Good View       Good  ...      1990          2009
4         No    No View       Good  ...      1980             0

              street        city  statezip country  year month  day  \
0  7528 N Fork Rd SE  Snoqualmie  WA 98065     USA  2014     5    3
1  13134 234th Ct NE     Redmond  WA 98053     USA  2014     5    4
2  13420 SE 182nd St      Renton  WA 98058     USA  2014     5    4
3        925 48th Ct      Auburn  WA 98092     USA  2014     5    4
4     151 Euclid Ave     Seattle  WA 98122     USA  2014     5    4

   state_name
0  Washington
1  Washington
2  Washington
3  Washington
4  Washington
```

```
[5 rows x 22 columns]
```

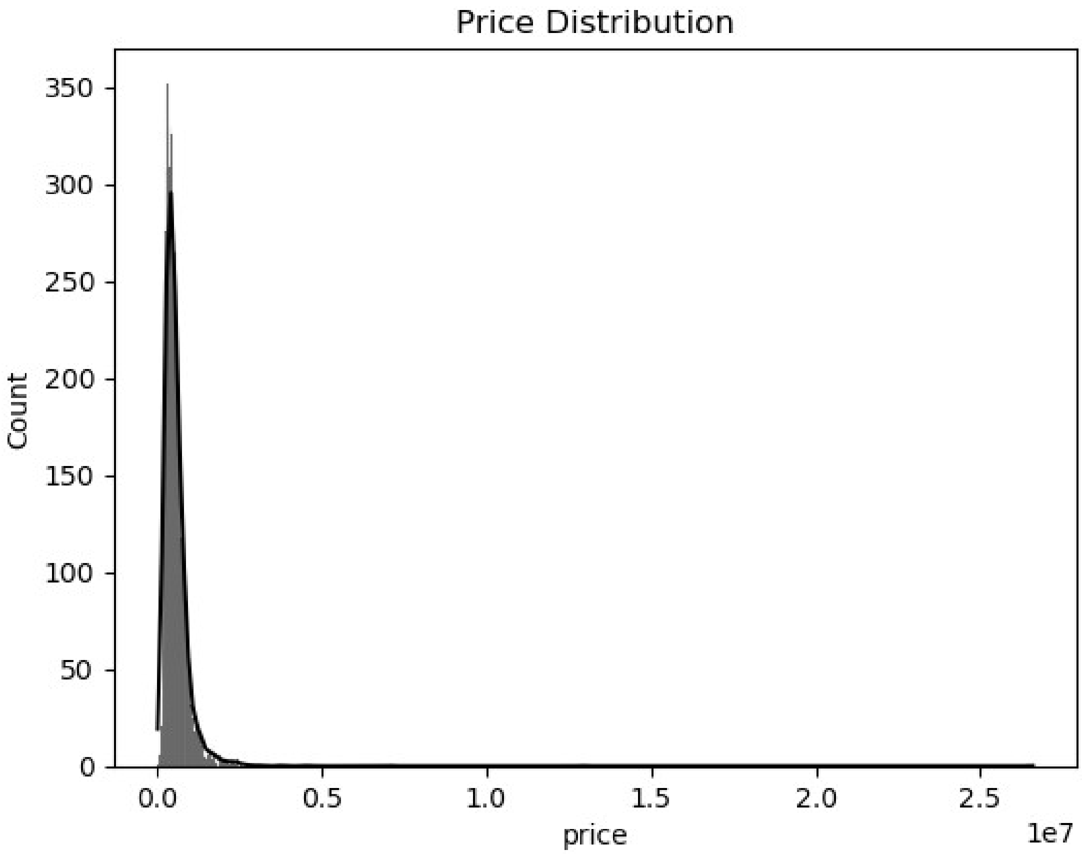
Exploratory Data Analysis (EDA)

```
df[['price', 'sqft_living', 'bedrooms', 'bathrooms']].describe()
```

```
              price   sqft_living     bedrooms    bathrooms
count  4.460000e+03   4460.000000  4460.000000  4460.000000
mean   5.589898e+05   2133.884305     3.398206     2.158016
std    5.679830e+05    959.342290     0.904598     0.778071
min    7.800000e+03    370.000000     1.000000     0.750000
25%    3.264821e+05   1460.000000     3.000000     1.750000
50%    4.650000e+05   1970.000000     3.000000     2.250000
75%    6.599625e+05   2610.000000     4.000000     2.500000
max    2.659000e+07  13540.000000     9.000000     8.000000
```

Univariate Analysis: Explore distributions and summary statistics of individual variables such as price, square footage, and number of bedrooms and bathrooms

```
sns.histplot(df['price'],kde=True,color='black')
plt.title('Price Distribution')
plt.show()
```



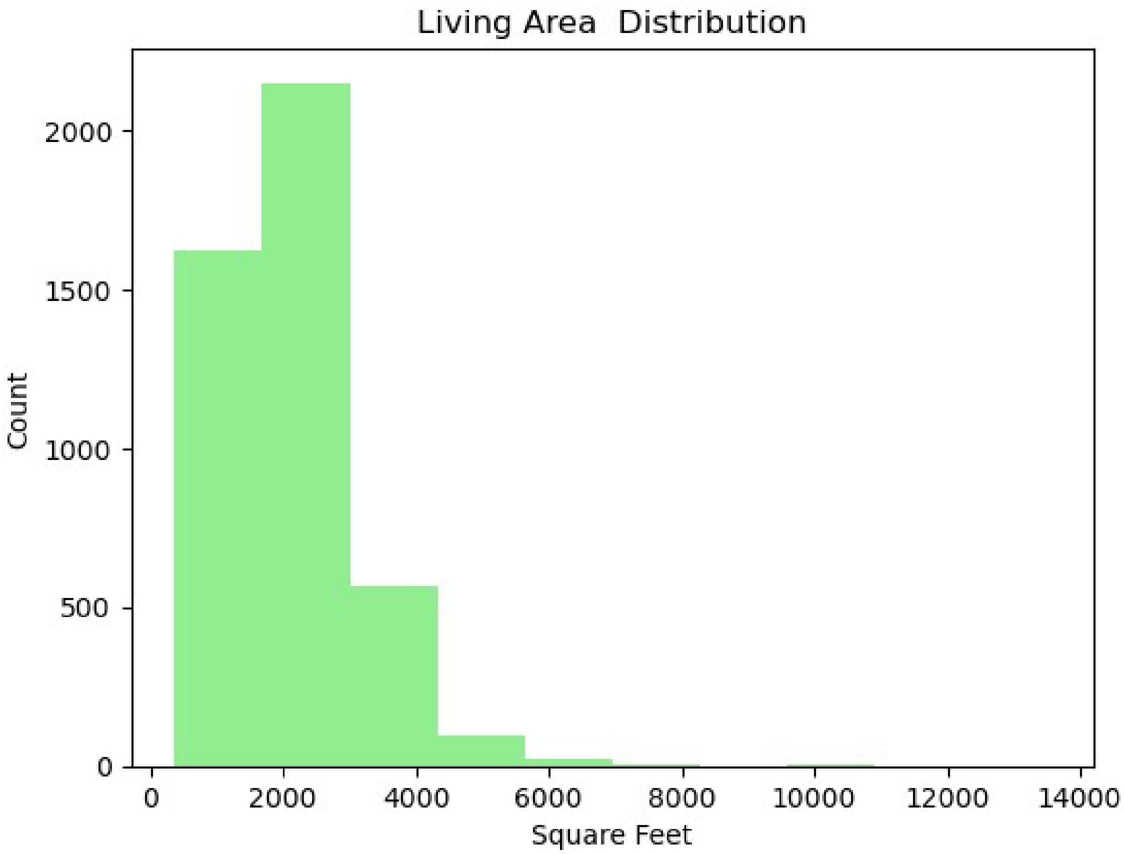
Highly Skewed Distribution:

Most houses are priced on the lower end left side

Very few houses are priced at very high levels right tail

This is called right-skewed or positively skewed data

```
plt.hist(df['sqft_living'], color='lightgreen')
plt.title('Living Area  Distribution')
plt.xlabel('Square Feet')
plt.ylabel('Count')
plt.show()
```



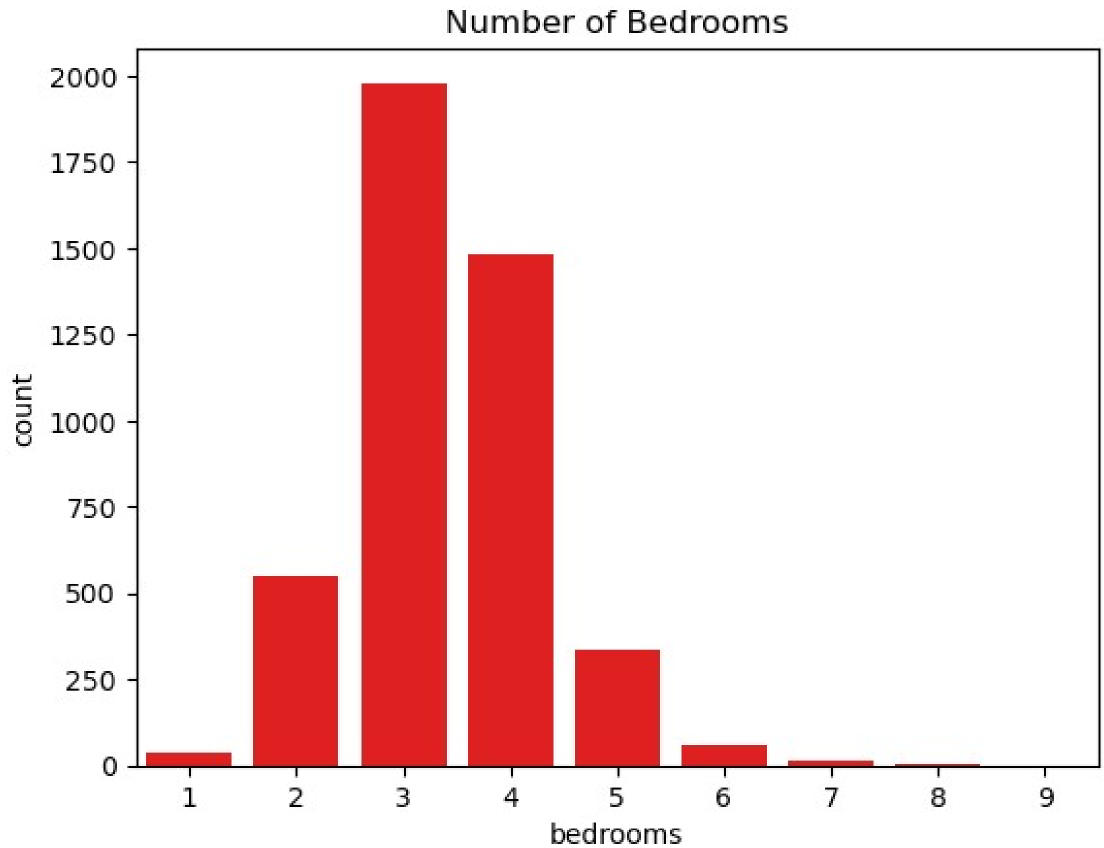
Most Common Living Area Range:

Majority of homes have a living area between 500 and 3000 square feet This is the most popular size for homes

Right-Skewed Distribution:

There are few houses with very large living spaces above 4000+ sqft These are less common and could be luxury or custom homes

```
sns.countplot(x=df['bedrooms'],color='red')
plt.title('Number of Bedrooms')
plt.show()
```



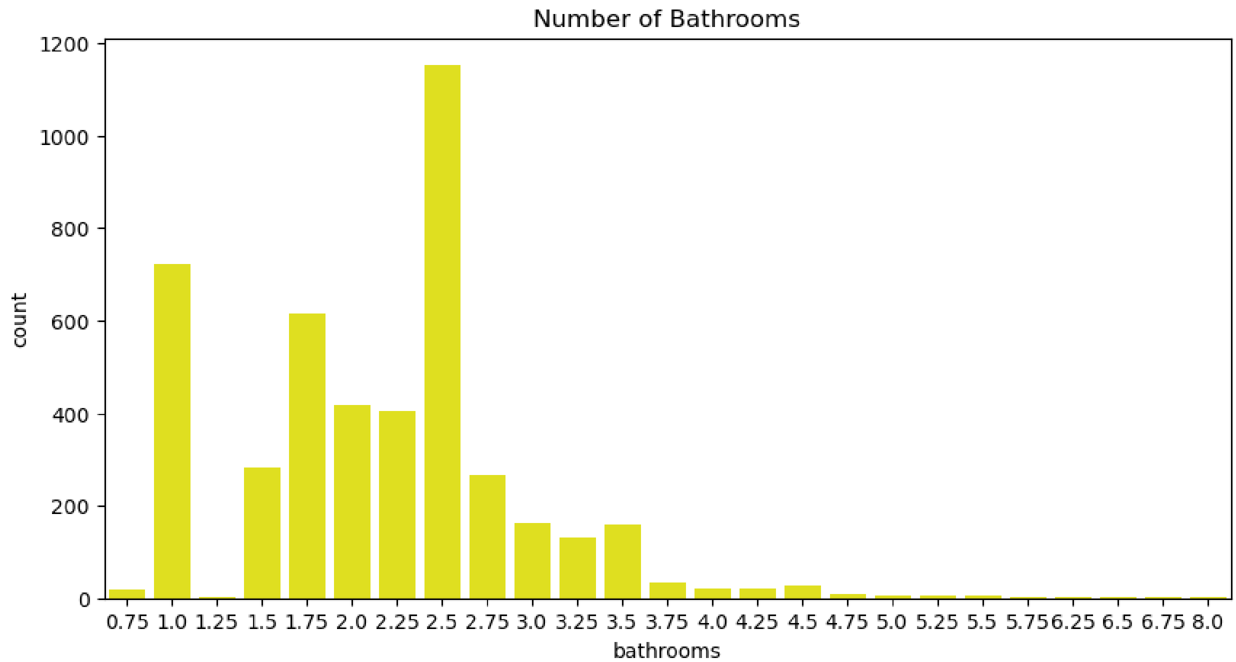
Most Common Bedroom Counts:

The majority of homes have 3 bedrooms, followed by 4 bedrooms. These are standard family house sizes.

Rare Cases:

Houses with 1 or more than 6 bedrooms are rare, possibly outliers or luxury/special-purpose homes.

```
plt.figure(figsize=(10,5))
sns.countplot(x='bathrooms', data=df,color='yellow')
plt.title('Number of Bathrooms')
plt.show()
```



Most Common:

Houses with 2 bathrooms are the most common, followed by those with 1 bathroom. This aligns with typical residential layouts

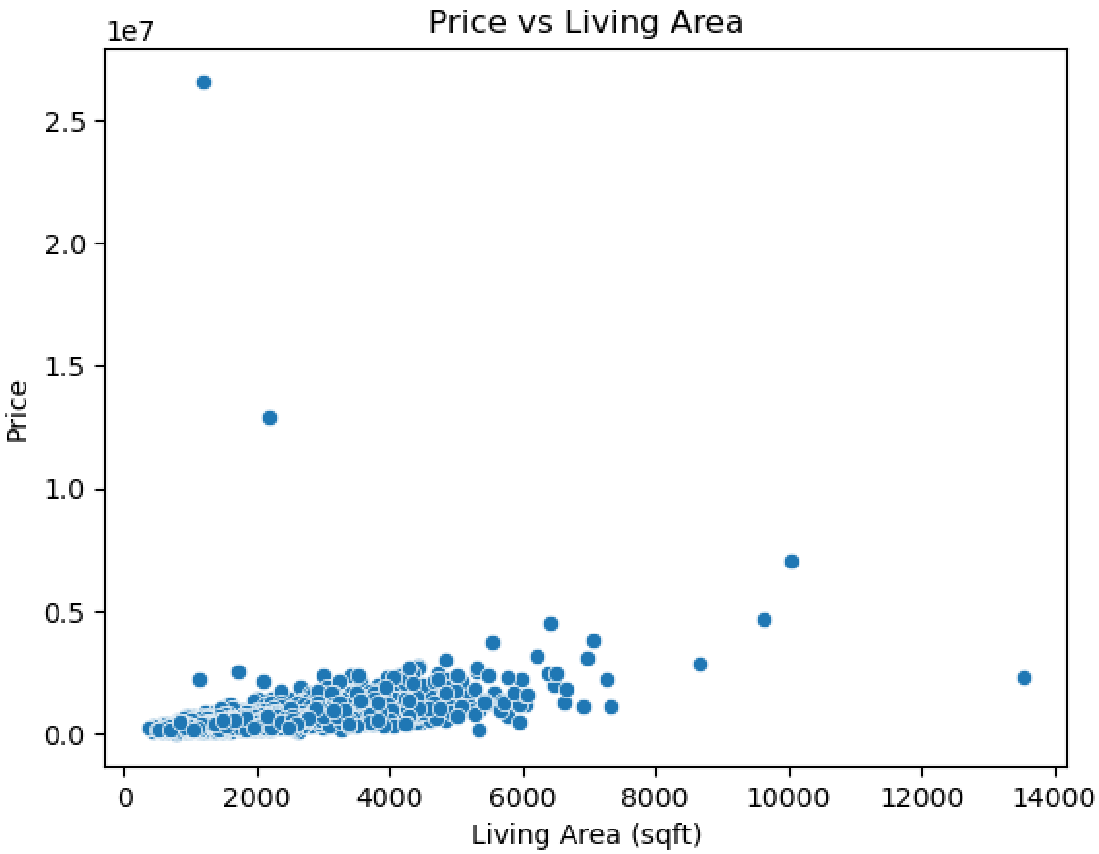
Less Common:

Properties with 3 or more bathrooms are less frequent. These are likely larger homes or luxury listings. Very few homes have more than 4 bathrooms

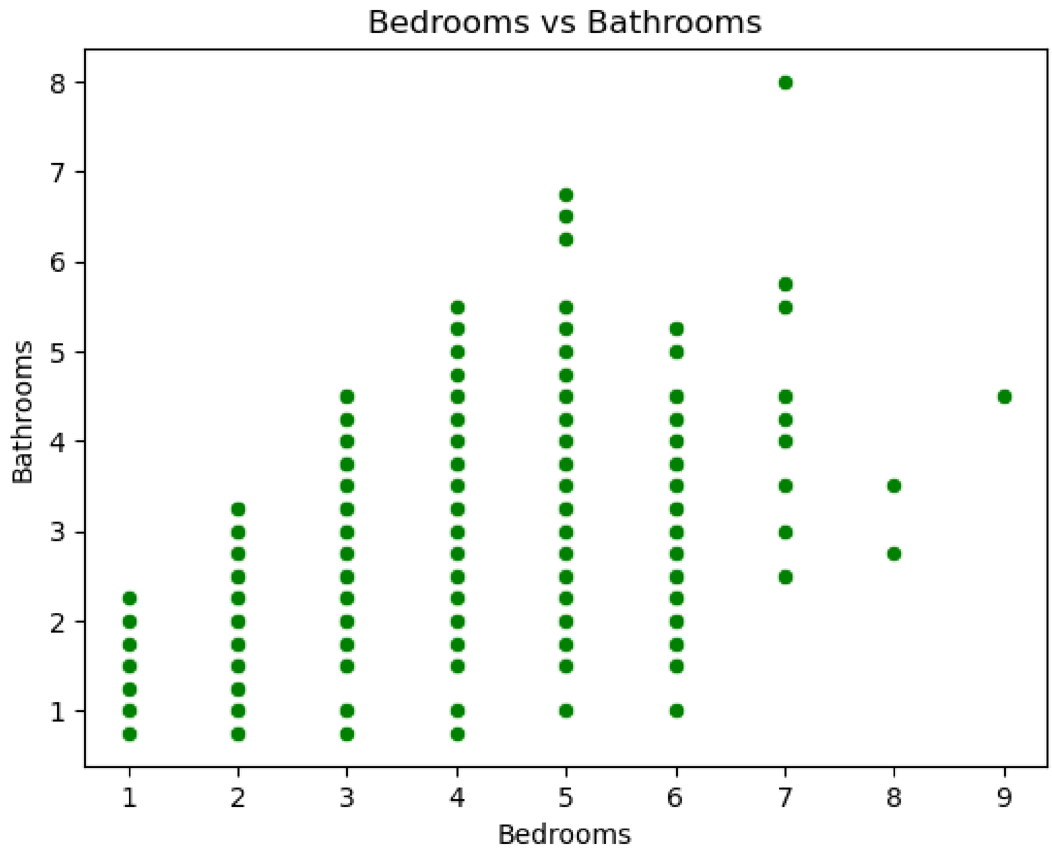
Bivariate Analysis: Investigate relationships between pairs of variables, such as price vs. square footage, bedrooms vs.

bathrooms, etc., using visualizations and statistical methods

```
sns.scatterplot(x='sqft_living', y='price', data=df)
plt.title('Price vs Living Area')
plt.xlabel('Living Area (sqft)')
plt.ylabel('Price')
plt.show()
```



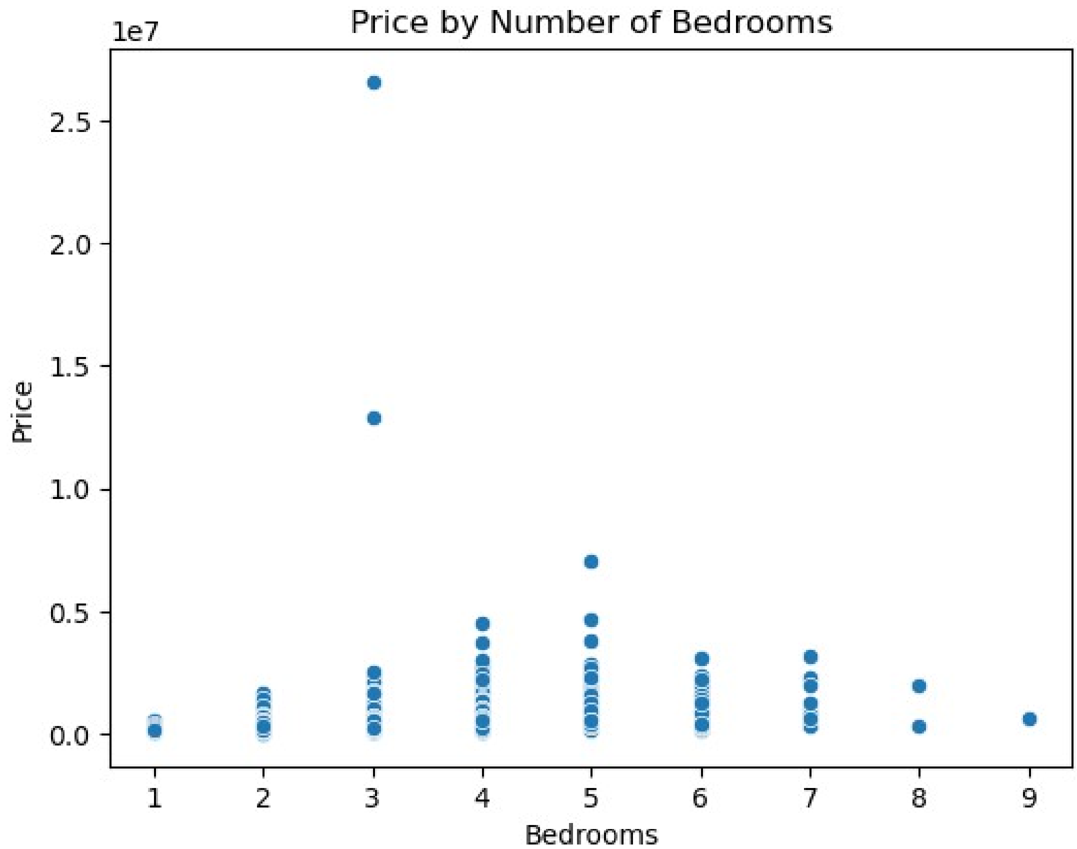

```python
sns.scatterplot(x='bedrooms', y='bathrooms', data=df,color='green')
plt.title('Bedrooms vs Bathrooms')
plt.xlabel('Bedrooms')
plt.ylabel('Bathrooms')
plt.show()
```



Bedrooms vs Bathrooms

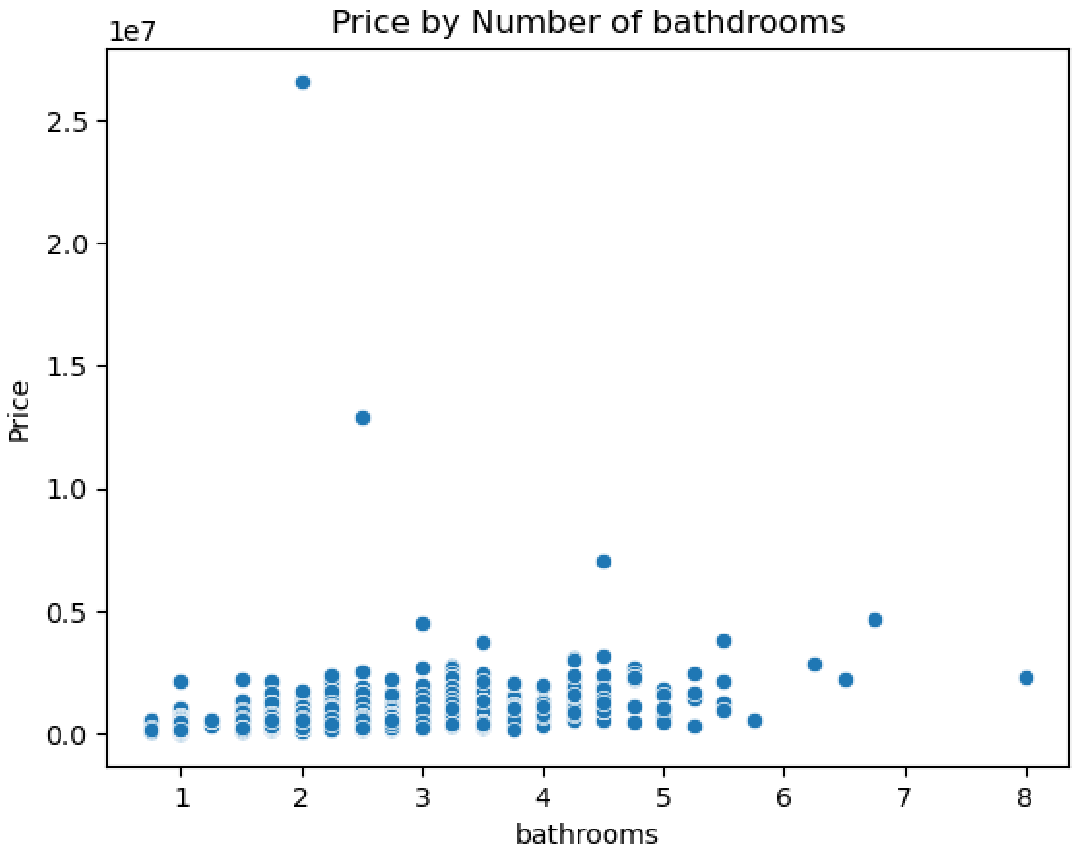
here's a positive relationship — houses with more bedrooms tend to have more bathrooms Most data points are concentrated in the 3 to 5 bedroom and 1 to 3 bathroom range. These are likely the most common residential layouts A few unusual combinations like houses with 1 bedroom and 3 bathrooms, or 8 bedrooms with few bathrooms, which may indicate data anomalies or rare property types

```
sns.scatterplot(x='bedrooms', y='price', data=df)
plt.title('Price by Number of Bedrooms')
plt.xlabel('Bedrooms')
plt.ylabel('Price')
plt.show()
```



There is no clear linear relationship between the number of bedrooms and house price. Houses with 3–5 bedrooms span a wide price range

```
sns.scatterplot(x='bathrooms', y='price', data=df)
plt.title('Price by Number of bathrooms')
plt.xlabel('bathrooms')
plt.ylabel('Price')
plt.show()
```



here is no clear trend indicating that more bathrooms lead to higher prices. Prices are spread widely even for houses with 2–4 bathrooms

Multivariate Analysis: Examine interactions and dependencies among multiple variables

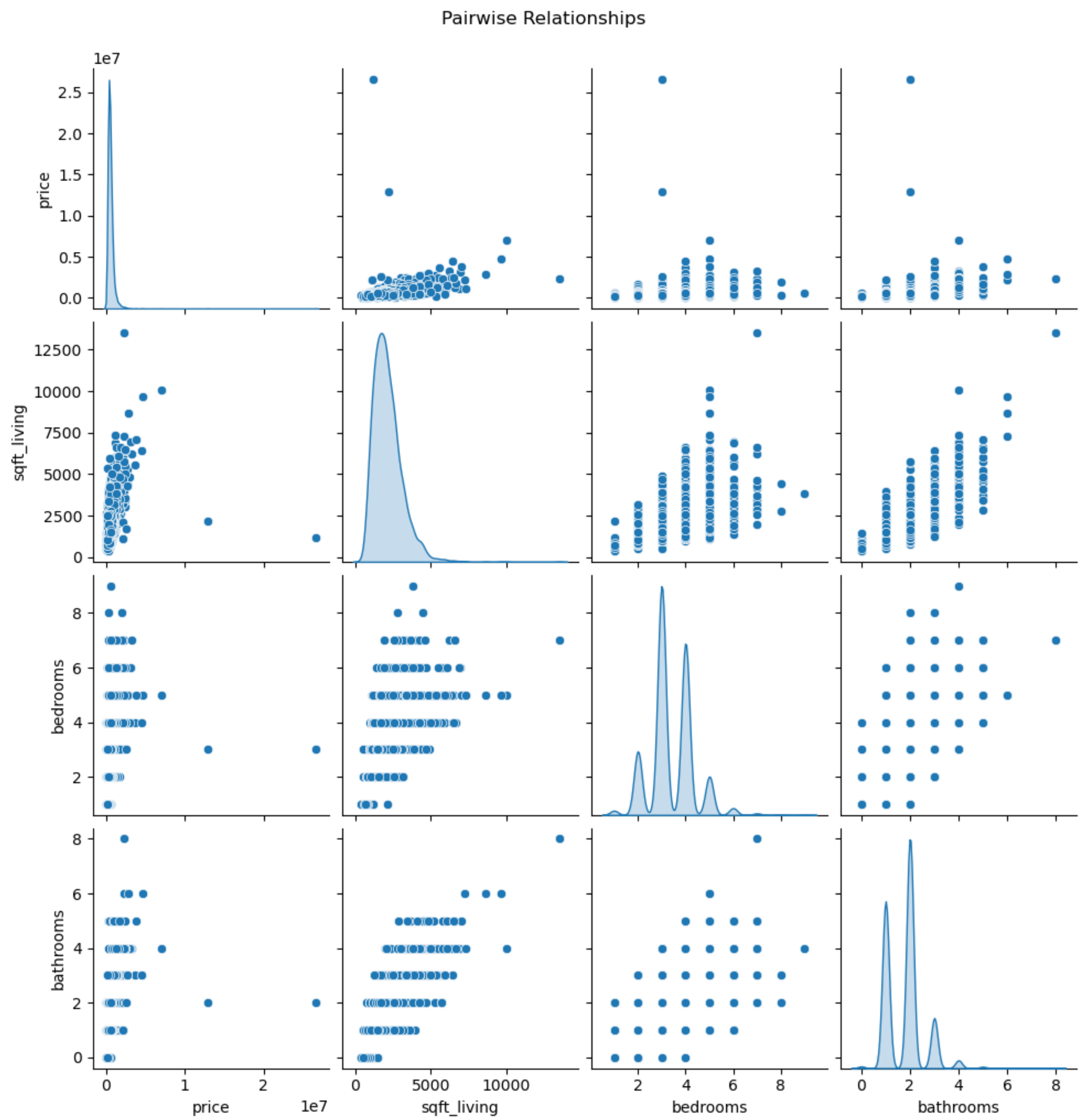
identifying correlations and patterns that may influence housing prices

```
corr = df[['price', 'sqft_living', 'bedrooms', 'bathrooms']].corr()
corr
```

	price	sqft_living	bedrooms	bathrooms
price	1.000000	0.444453	0.210773	0.334649
sqft_living	0.444453	1.000000	0.601190	0.711951
bedrooms	0.210773	0.601190	1.000000	0.498619
bathrooms	0.334649	0.711951	0.498619	1.000000

sqft_living is the most correlated with price (0.444), supporting what we see in the scatter plot. bedrooms have the lowest correlation with price, suggesting quantity of rooms is not as useful as size (sqft_living) High correlation between sqft_living and bathrooms (0.712) may cause multicollinearity in regression models — worth watchi

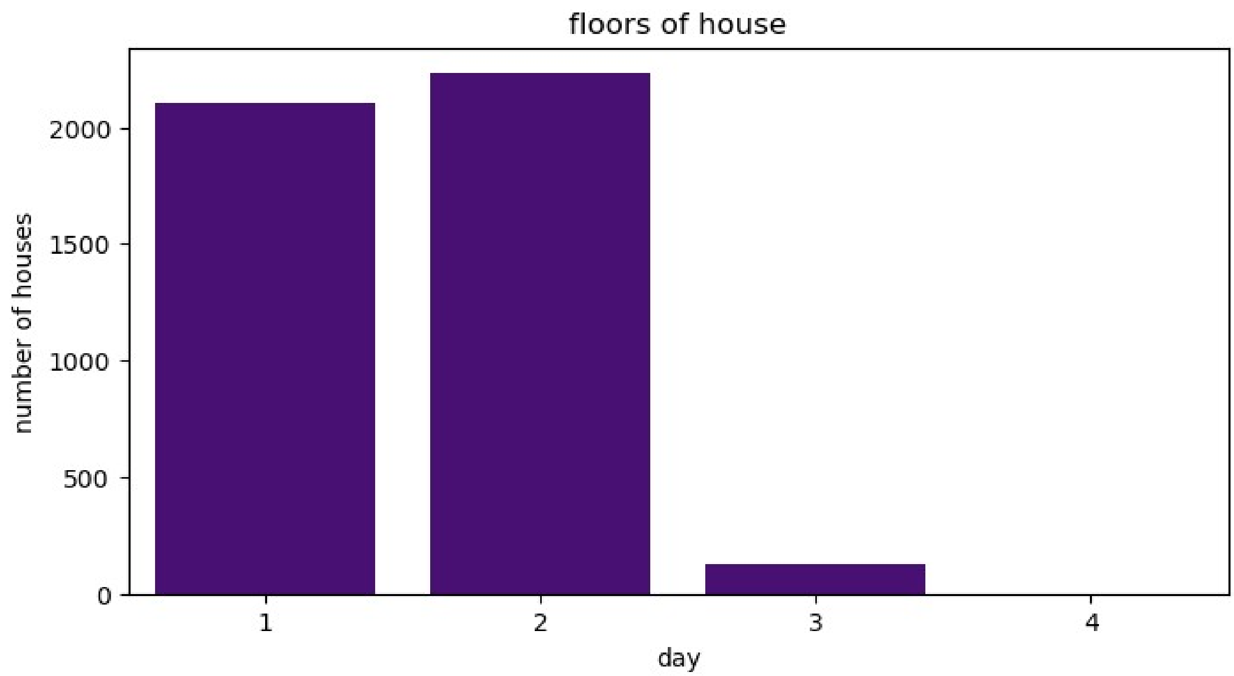
```python
sns.pairplot(df[['price', 'sqft_living', 'bedrooms', 'bathrooms']],
diag_kind='kde')
plt.suptitle('Pairwise Relationships', y=1.02)
plt.show()
```



Visualization

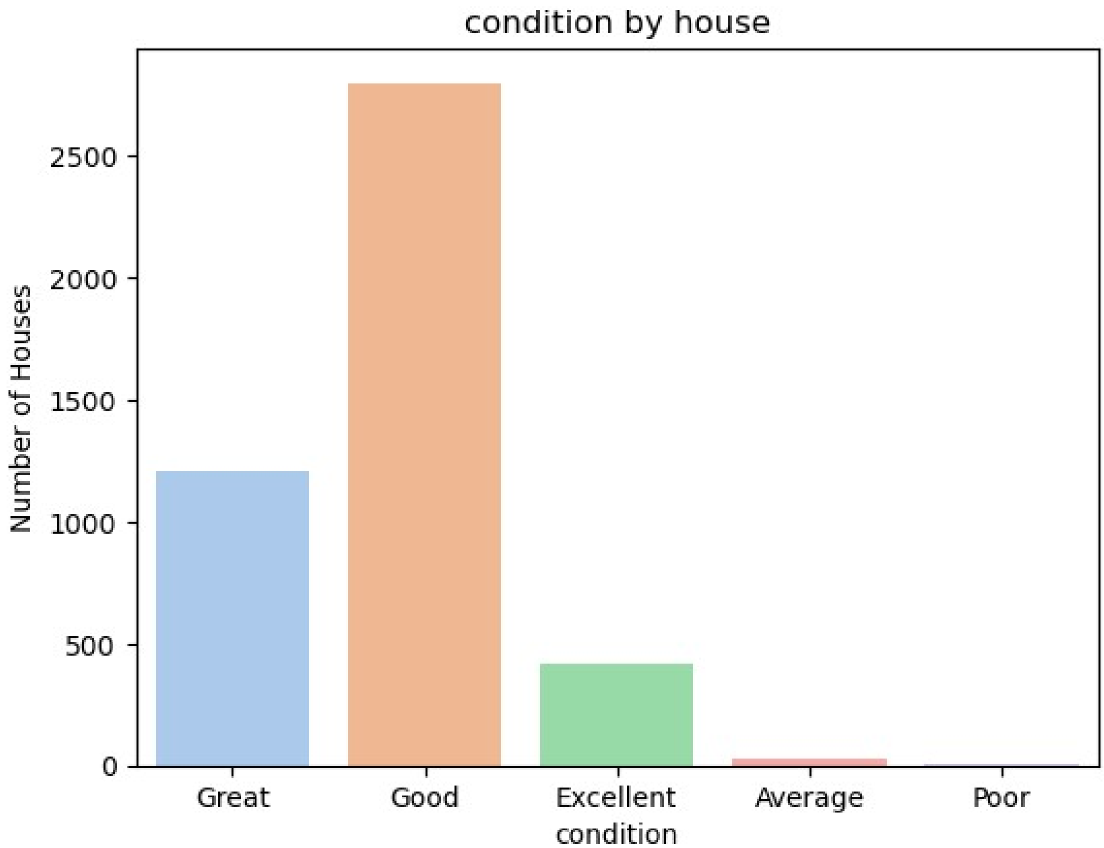
```python
plt.figure(figsize=(8,4))
sns.countplot(x='floors', data=df,color='Indigo')
```

```
plt.title('floors of house')
plt.xlabel('day')
plt.ylabel('number of houses')
plt.show()
```

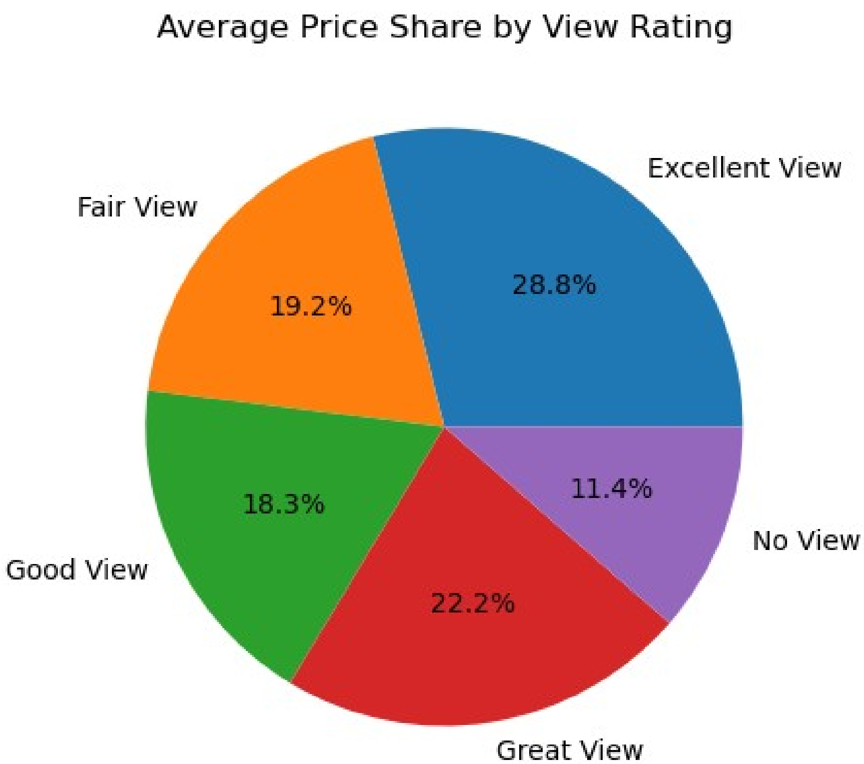



```
sns.countplot(x='condition',data=df,palette='pastel')
plt.title('condition by house')
plt.xlabel('condition')
plt.ylabel('Number of Houses')
plt.show()
```

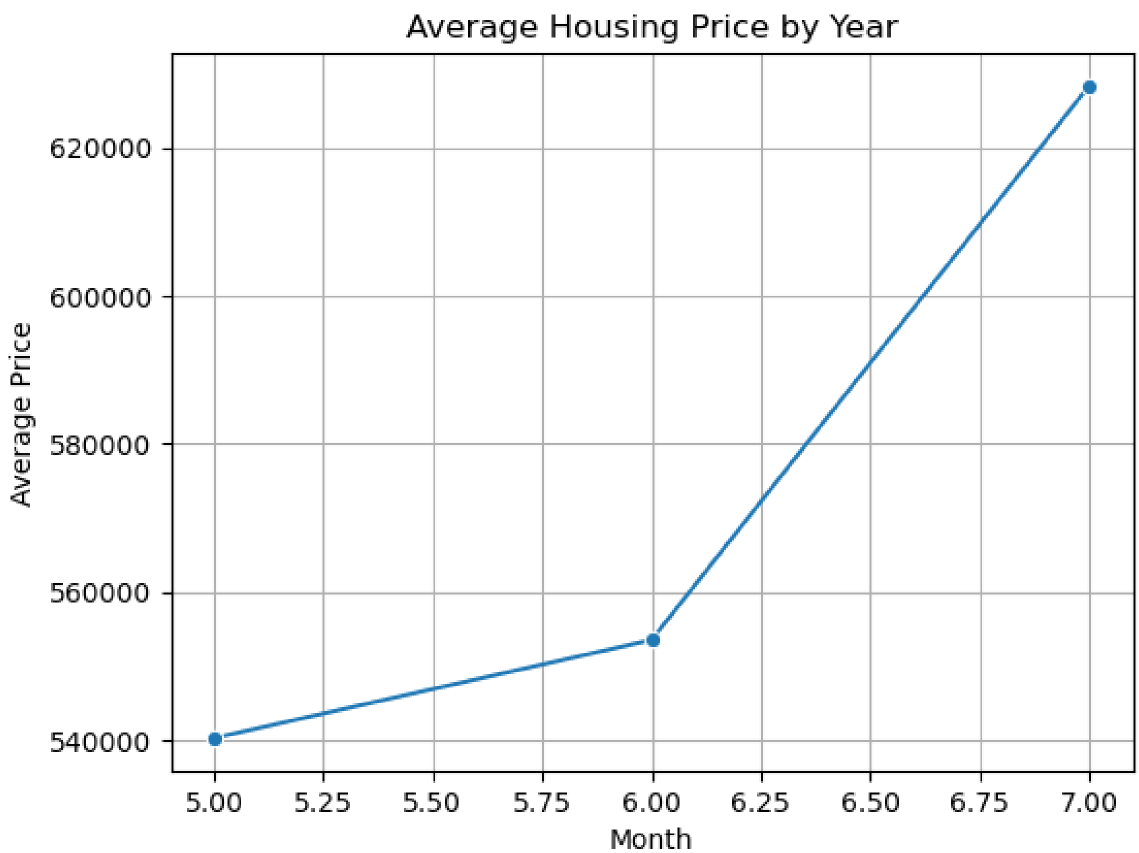
```
C:\Users\jackl\AppData\Local\Temp\ipykernel_20764\3786289910.py:1:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(x='condition',data=df,palette='pastel')
```




```
avg_price_by_view = df.groupby('view')['price'].mean()

plt.figure(figsize=(6,5))
plt.pie(avg_price_by_view,labels=avg_price_by_view.index,autopct='%2.1f%%')
plt.title('Average Price Share by View Rating')
plt.show()
```

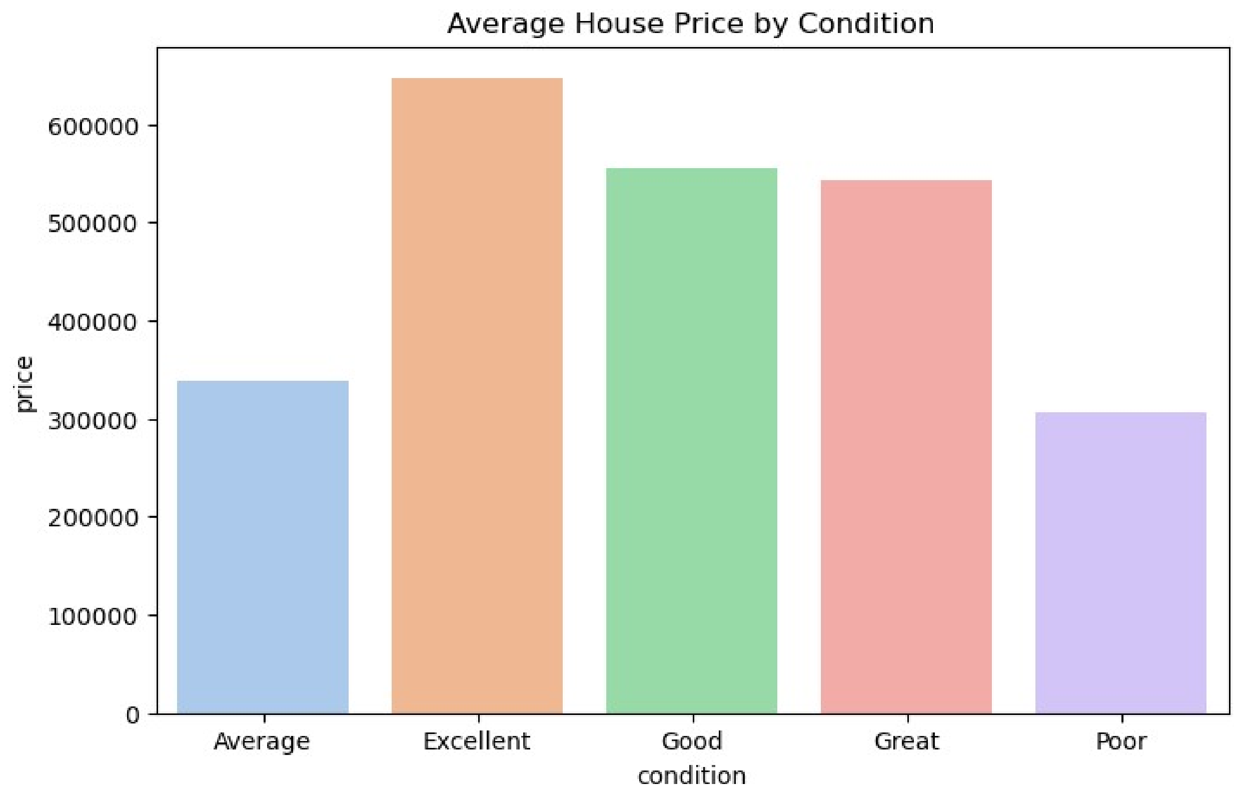



```
avg_price_by_year = df.groupby('month')['price'].mean().reset_index()

df.columns

Index(['date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
'sqft_lot',
       'floors', 'waterfront', 'view', 'condition', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'street', 'city',
       'statezip', 'country', 'year', 'month', 'day', 'state_name'],
      dtype='object')

sns.lineplot(x='month', y='price', data=avg_price_by_year, marker='o')
plt.title('Average Housing Price by Year')
plt.xlabel('Month')
plt.ylabel('Average Price')
plt.grid(True)
plt.show()
```



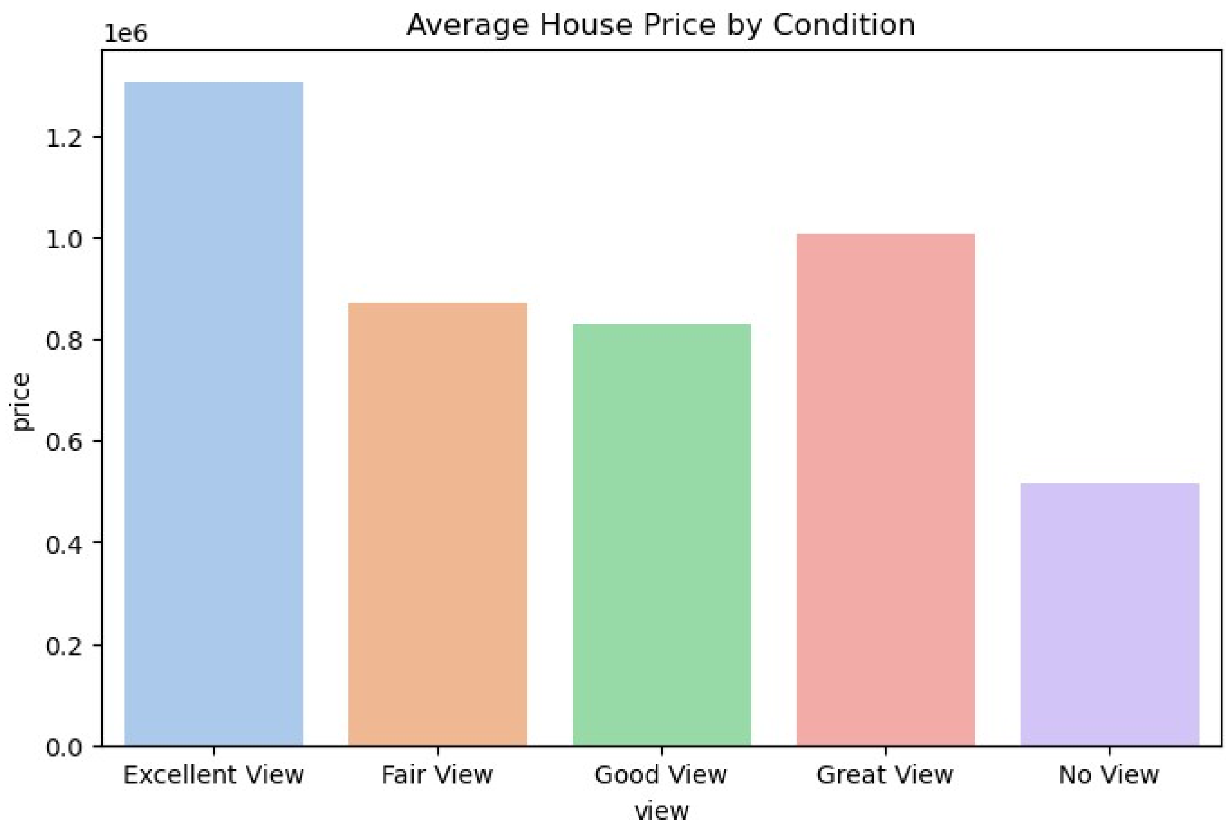

```
avg_price_by_condition = df.groupby('condition')
['price'].mean().reset_index()


plt.figure(figsize=(8,5))
sns.barplot(x='condition', y='price',
data=avg_price_by_condition,palette='pastel')
plt.title('Average House Price by Condition')
```

```
C:\Users\jackl\AppData\Local\Temp\ipykernel_20764\1434616118.py:5:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='condition', y='price',
data=avg_price_by_condition,palette='pastel')

Text(0.5, 1.0, 'Average House Price by Condition')
```

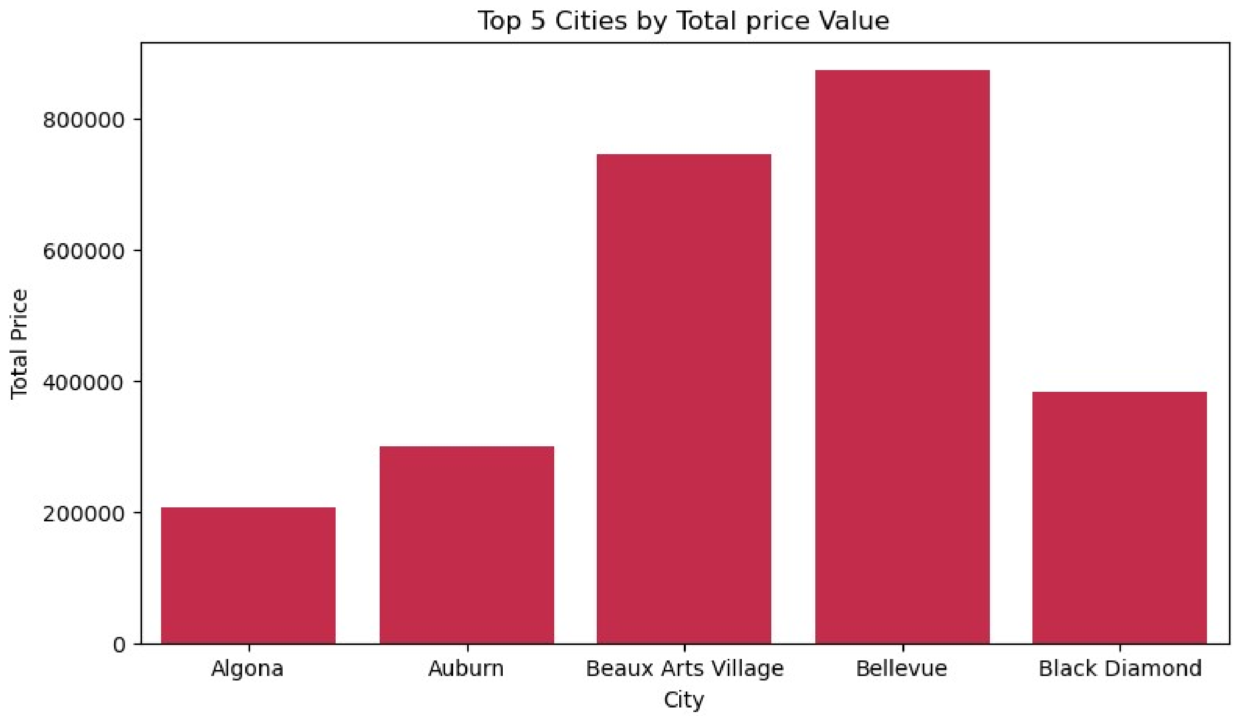



```
avg_price_by_condition = df.groupby('view')
['price'].mean().reset_index()


plt.figure(figsize=(8,5))
sns.barplot(x='view', y='price',
data=avg_price_by_condition,palette='pastel')
plt.title('Average House Price by Condition')
```

```
C:\Users\jackl\AppData\Local\Temp\ipykernel_20764\3223630538.py:5:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='view', y='price',
data=avg_price_by_condition,palette='pastel')

Text(0.5, 1.0, 'Average House Price by Condition')
```




```
top_price_cities = df.groupby('city')['price'].mean().head(5)

plt.figure(figsize=(9,5))
sns.barplot(x=top_price_cities.index,
y=top_price_cities.values,color='Crimson')
plt.title('Top 5 Cities by Total price Value')
plt.xlabel('City')
plt.ylabel('Total Price')
plt.show()
```



Create insightful visualizations to illustrate trends, outliers, and geographical patterns in housing prices and attributes

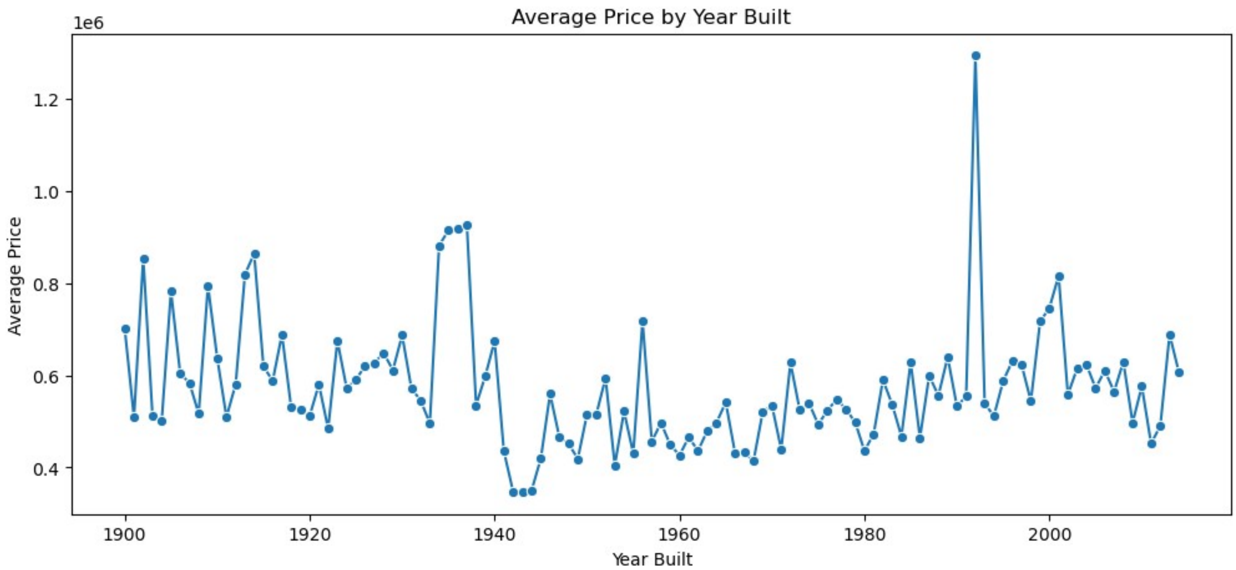
Trends Over Time

```
df['yr_built'].value_counts()
```

```
yr_built
2006    107
2005    102
2004     91
2007     91
1978     89
       ...
1915      6
1935      6
1933      5
1934      4
1936      3
Name: count, Length: 115, dtype: int64
```

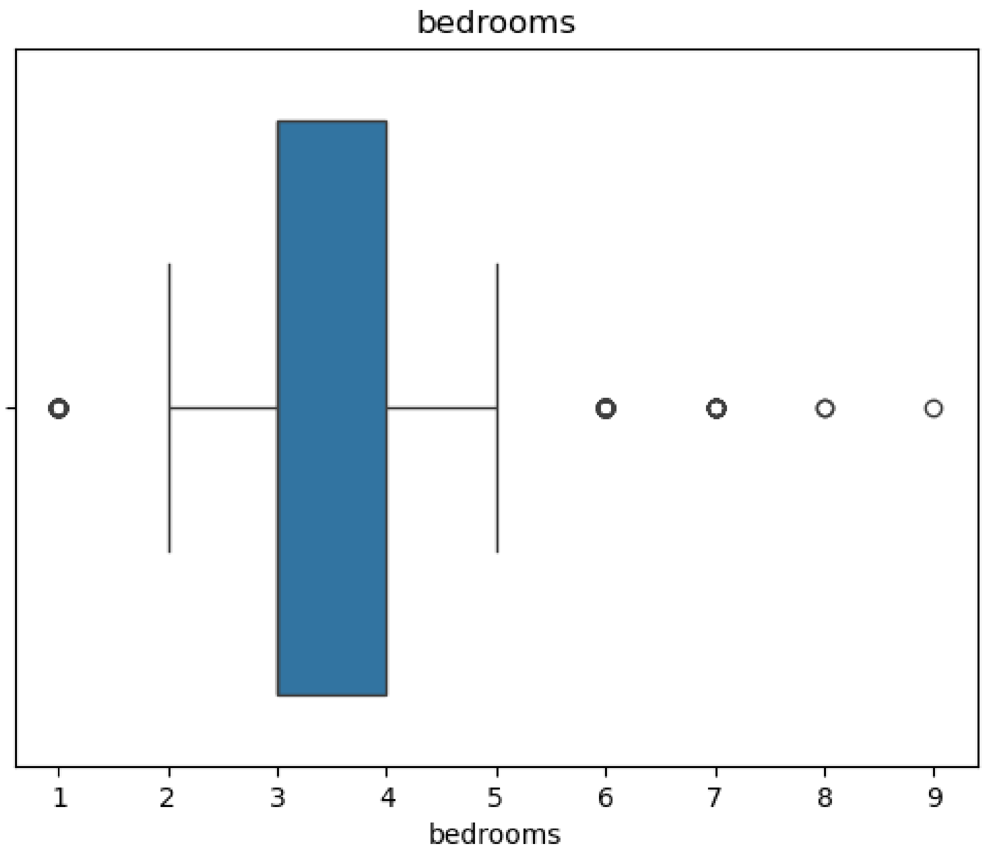
```
avg_price = df.groupby('yr_built')['price'].mean().reset_index()
```

```
avg_price = df.groupby('yr_built')['price'].mean().reset_index()
plt.figure(figsize=(12,5))
sns.lineplot(x='yr_built', y='price', data=avg_price,marker='o')
plt.title('Average Price by Year Built')
plt.xlabel('Year Built')
plt.ylabel('Average Price')
plt.show()
```

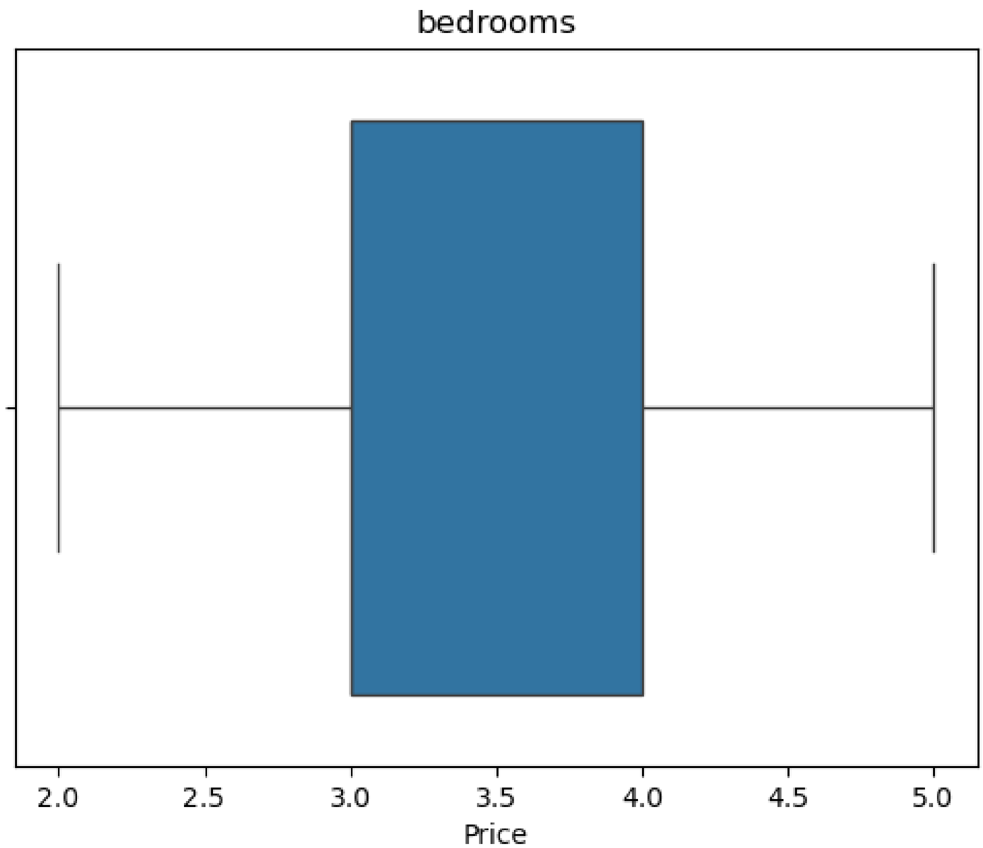


Outliers

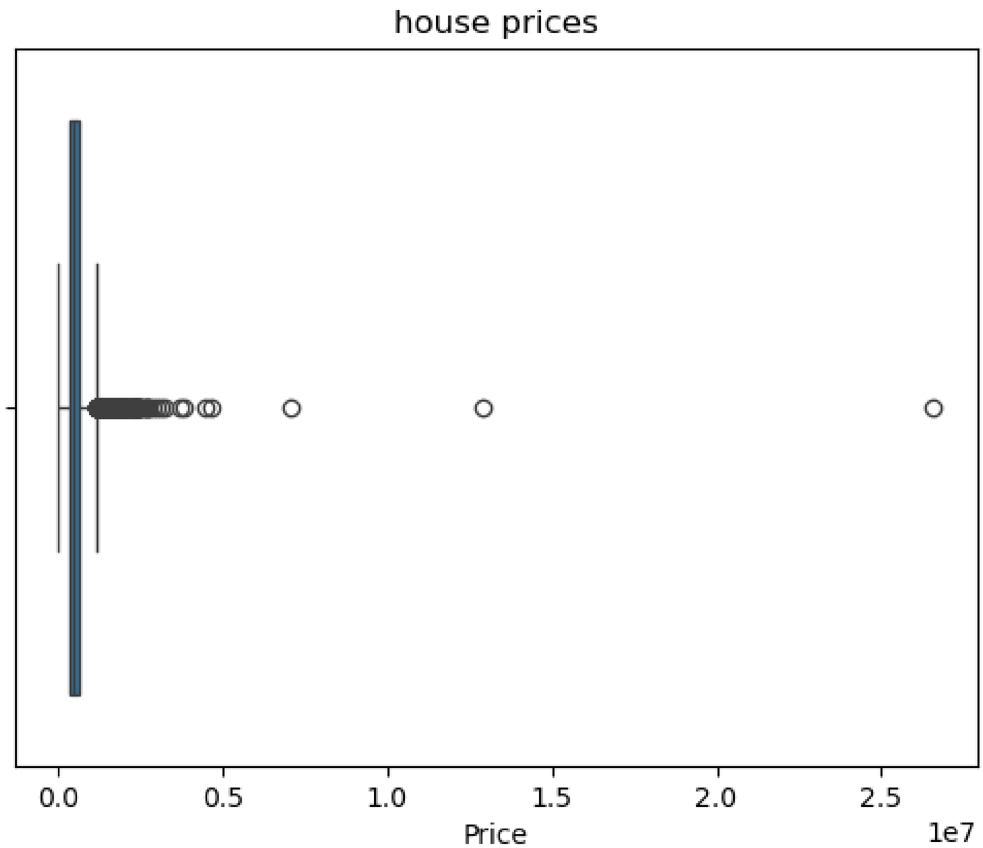
```
sns.boxplot(x=df['bedrooms'])
plt.title('bedrooms')
plt.xlabel('bedrooms')
plt.show()
```



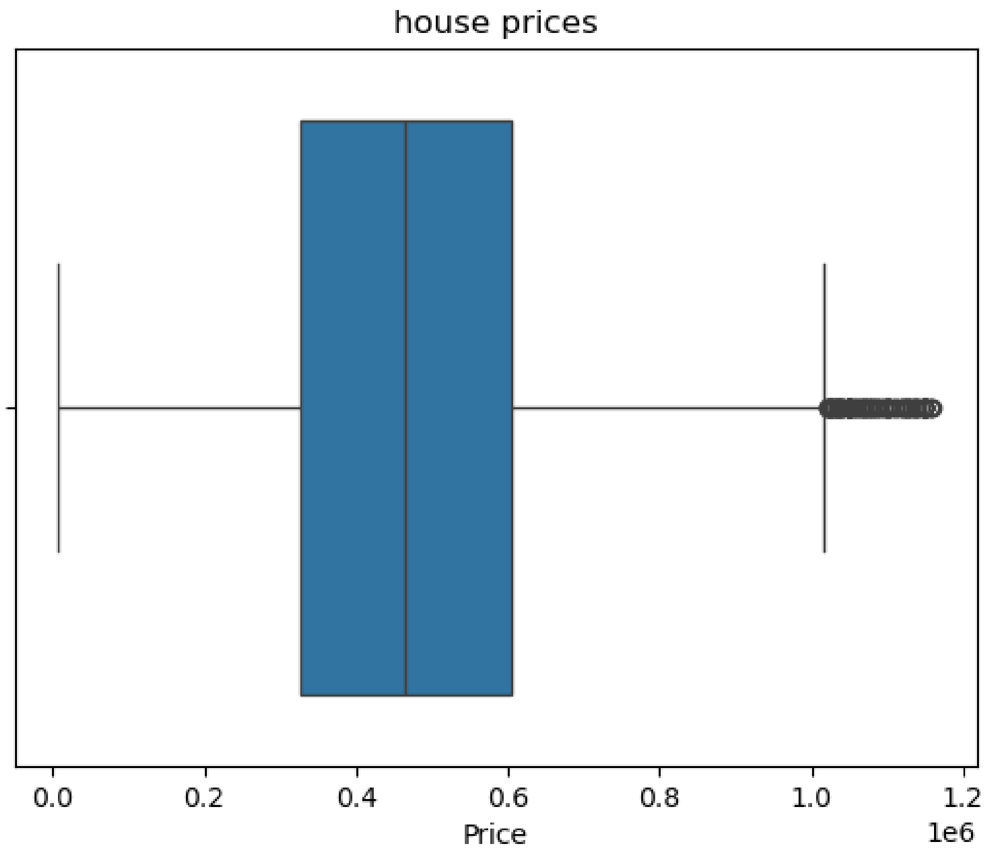

```
Q1 = df['bedrooms'].quantile(0.25)
Q3 = df['bedrooms'].quantile(0.75)
IQR = Q3 - Q1


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


outliers = df[(df['bedrooms'] < lower_bound) | (df['bedrooms'] >
upper_bound)]['bedrooms']

mean=df['bedrooms'].mean()


df['bedrooms'] = df['bedrooms'].replace(outliers.tolist(), mean)

sns.boxplot(x=df['bedrooms'])
plt.title('bedrooms')
plt.xlabel('Price')
plt.show()
```



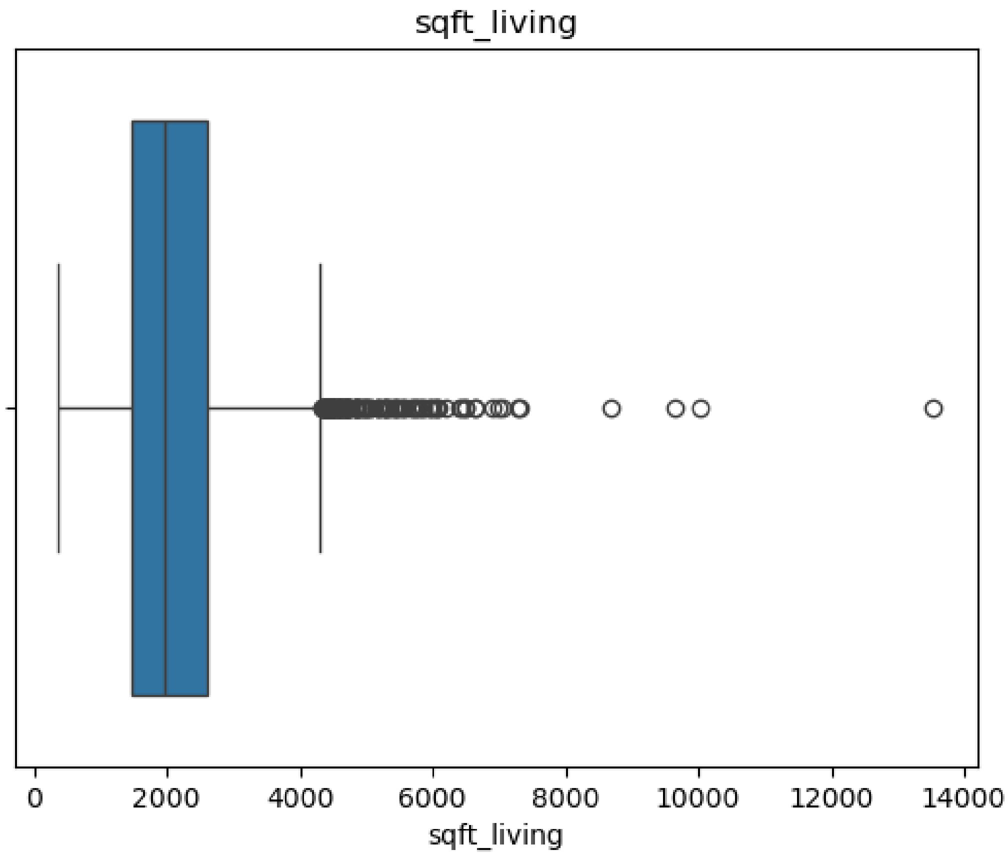

```
sns.boxplot(x=df['price'])
plt.title('house prices')
plt.xlabel('Price')
plt.show()
```



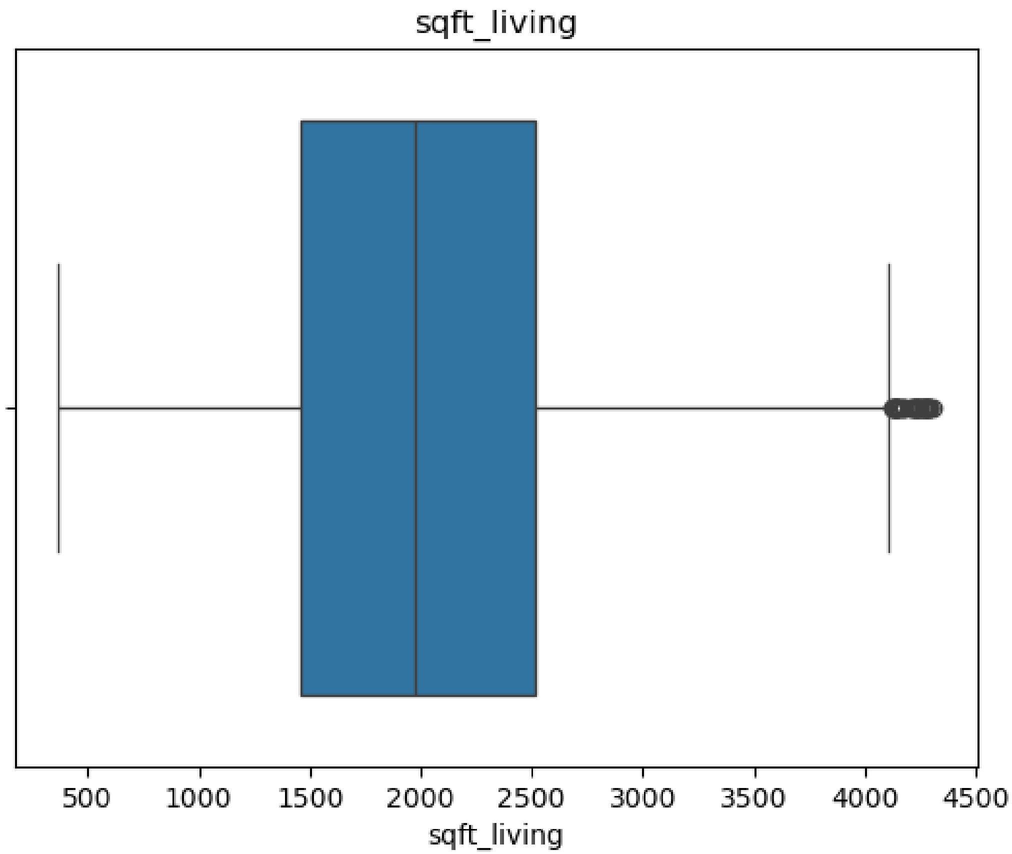

```
Q1 = df['price'].quantile(0.25)
Q3 = df['price'].quantile(0.75)
IQR = Q3 - Q1


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


outliers = df[(df['price'] < lower_bound) | (df['price'] >
upper_bound)]['price']

mean=df['price'].mean()

df['price'] = df['price'].replace(outliers.tolist(), mean)

sns.boxplot(x=df['price'])
plt.title('house prices')
plt.xlabel('Price')
plt.show()
```




```
sns.boxplot(x=df['sqft_living'])
plt.title('sqft_living')
plt.show()
```



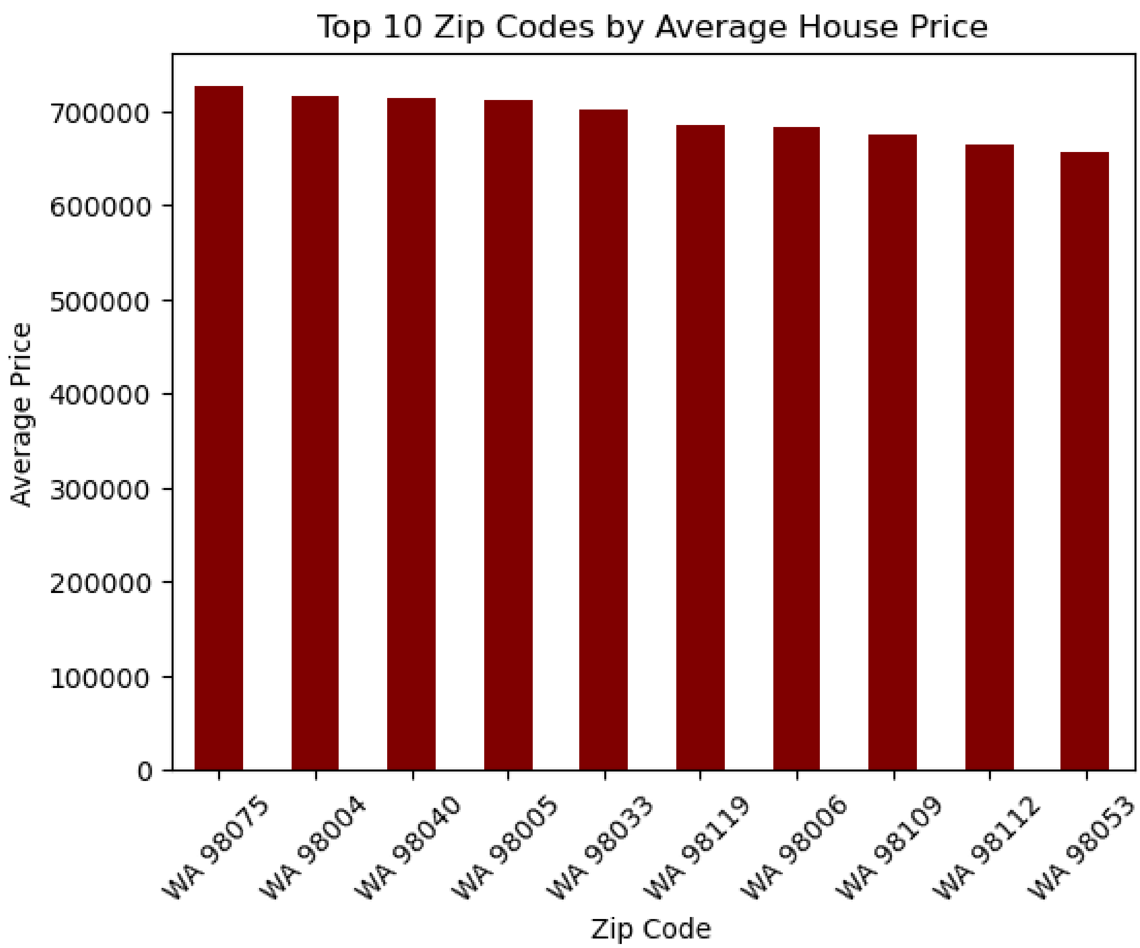

```
Q1 = df['sqft_living'].quantile(0.25)
Q3 = df['sqft_living'].quantile(0.75)
IQR = Q3 - Q1


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


outliers = df[(df['sqft_living'] < lower_bound) | (df['sqft_living'] >
upper_bound)]['sqft_living']

mean=df['sqft_living'].mean()

df['sqft_living']=df['sqft_living'].replace(outliers.tolist(),mean)

sns.boxplot(x=df['sqft_living'])
plt.title('sqft_living')
plt.show()
```




```
sns.boxplot(x=df['yr_built'])
plt.title('yr_built')
plt.show()
```

geographical

```
avg_price_zip = df.groupby('statezip')
['price'].mean().sort_values(ascending=False).head(10)

avg_price_zip.plot(kind='bar', color='Maroon')
plt.title('Top 10 Zip Codes by Average House Price')
plt.xlabel('Zip Code')
plt.ylabel('Average Price')
plt.xticks(rotation=45)
plt.show()
```



Feature Engineering

```
df['House_renovated'] = df['yr_renovated'].apply(lambda x: 'Renovated'
if x > 0 else 'Not Renovated')
```

price category

```
df['price_category'] = pd.qcut(df['price'], q=3, labels=['Low',
'Medium', 'High'])
```

House Age

```
df['house_age'] = datetime.now().year - df['yr_built']
```

price per sqft

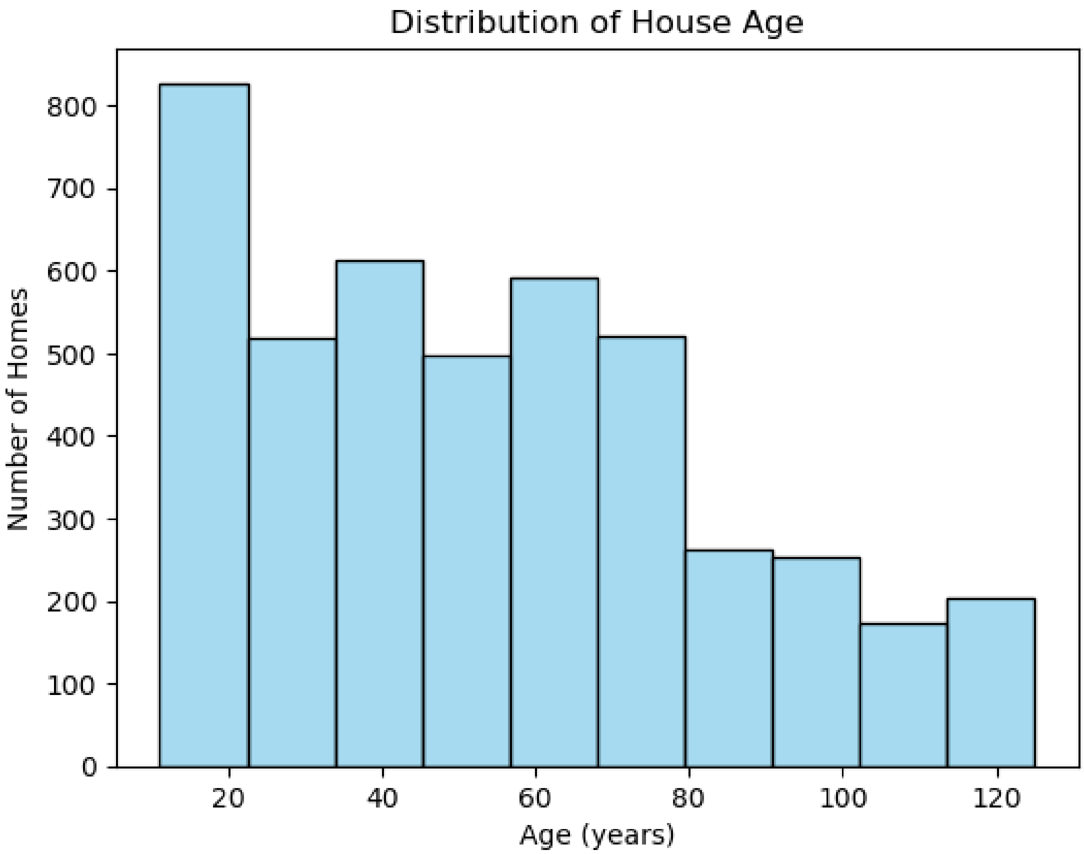
```
df['price_per_sqft'] = df['price'] / df['sqft_living']
```

```
df.head()
```

```
        date     price  bedrooms  bathrooms  sqft_living  sqft_lot  
floors  \
0 2014-05-03  310000.0       3.0          1       1010.0    9945.0     
1   
1 2014-05-04  775000.0       2.0          2       2680.0    7392.0     
1   
2 2014-05-04  365000.0       3.0          2       2200.0    7350.0     
1   
3 2014-05-04  331950.0       4.0          2       2530.0    9933.0     
2   
4 2014-05-04  783500.0       3.0          2       2850.0    7130.0     
2   

  waterfront       view  condition  ...  statezip  country  year  
month day  \
0         No    No View      Great  ...  WA 98065      USA  2014      
5   3   
1         No    No View       Good  ...  WA 98053      USA  2014      
5   4   
2         No    No View  Excellent  ...  WA 98058      USA  2014      
5   4   
3         No  Good View       Good  ...  WA 98092      USA  2014      
5   4   
4         No    No View       Good  ...  WA 98122      USA  2014      
5   4   

   state_name House_renovated price_category  house_age  
price_per_sqft  
0  Washington   Not Renovated            Low         52      
306.930693  
1  Washington       Renovated           High         21      
289.179104  
2  Washington   Not Renovated            Low         37      
165.909091  
3  Washington       Renovated            Low         35      
131.205534  
4  Washington   Not Renovated           High         45      
274.912281  

[5 rows x 26 columns]
```

Feature Engineering Analysis

```
sns.histplot(df['house_age'], bins=10,color='skyblue')
plt.title("Distribution of House Age")
plt.xlabel("Age (years)")
plt.ylabel("Number of Homes")
plt.show()
```

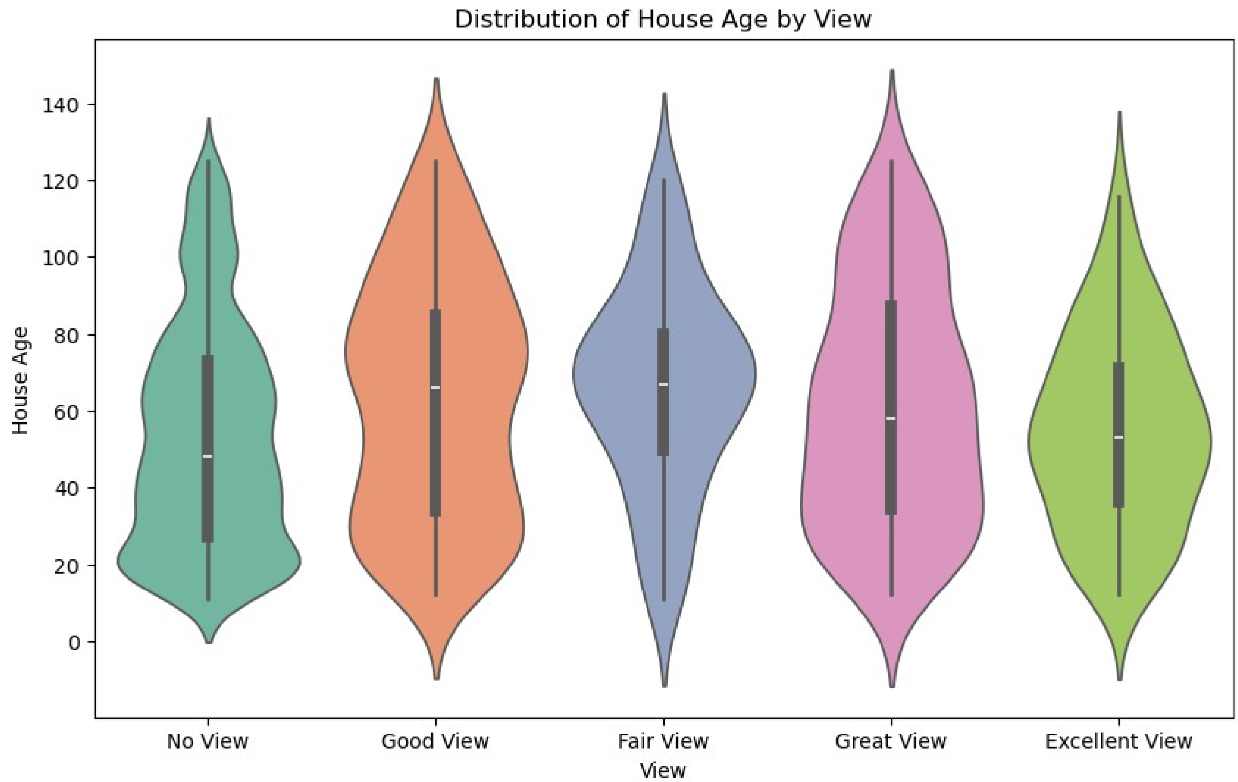



```
avg_pps = df.groupby('city')
['price_per_sqft'].mean().sort_values(ascending=False).tail(10)
sns.barplot(x=avg_pps.index, y=avg_pps.values,color='yellow')
plt.title("Top 10 Cities by Avg Price per Sqft")
plt.xticks(rotation=80)
plt.ylabel("Price per Sqft")
plt.show()

----------------------------------------------------------------------
-----
KeyError                                  Traceback (most recent call
last)
Cell In[147], line 1
----> 1 avg_pps = df.groupby('city')
['price_per_sqft'].mean().sort_values(ascending=False).tail(10)
      2 sns.barplot(x=avg_pps.index, y=avg_pps.values,color='yellow')
      3 plt.title("Top 10 Cities by Avg Price per Sqft")

File ~\anaconda3\Lib\site-packages\pandas\core\groupby\
generic.py:1951, in DataFrameGroupBy.__getitem__(self, key)
   1944 if isinstance(key, tuple) and len(key) > 1:
   1945     # if len == 1, then it becomes a SeriesGroupBy and this is
actually
```

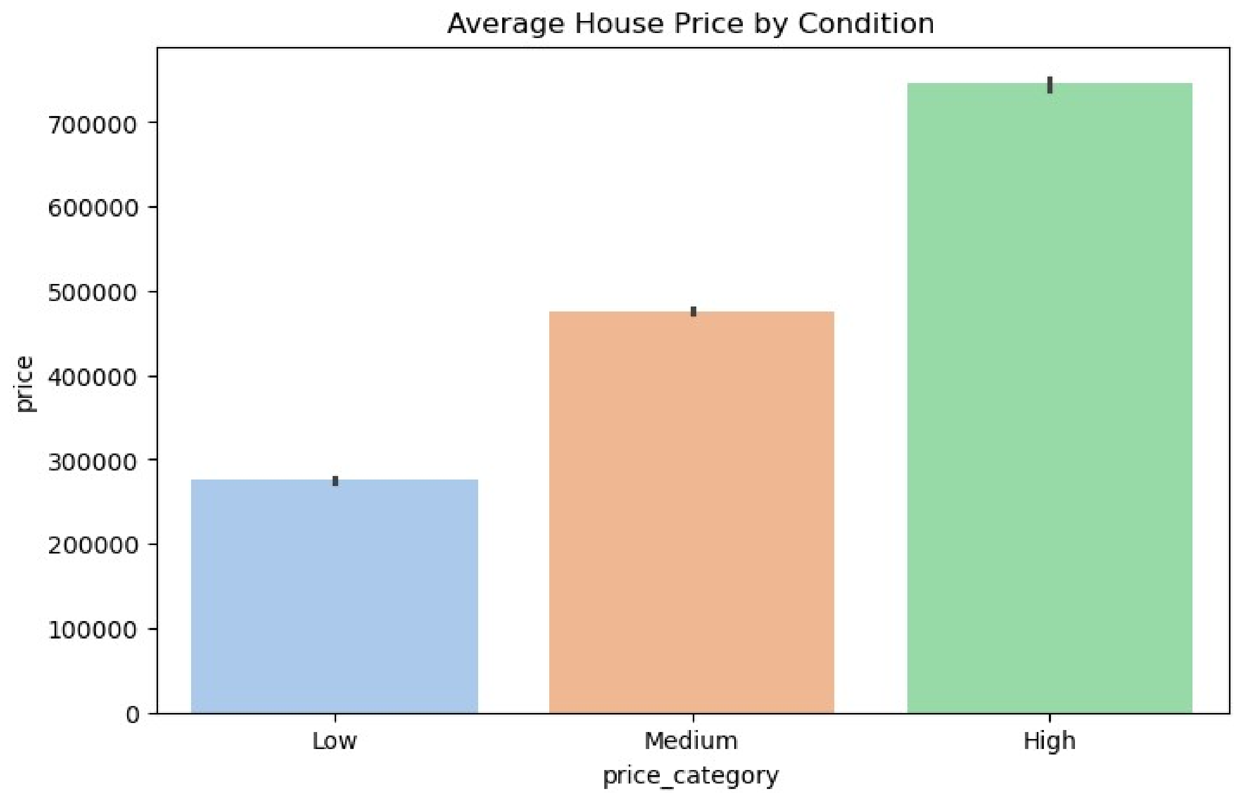
```
   1946     # valid syntax, so don't raise
   1947     raise ValueError(
   1948         "Cannot subset columns with a tuple with more than one
element. "
   1949         "Use a list instead."
   1950     )
-> 1951 return super().__getitem__(key)

File ~\anaconda3\Lib\site-packages\pandas\core\base.py:244, in
SelectionMixin.__getitem__(self, key)
    242 else:
    243     if key not in self.obj:
--> 244         raise KeyError(f"Column not found: {key}")
    245     ndim = self.obj[key].ndim
    246     return self._gotitem(key, ndim=ndim)

KeyError: 'Column not found: price_per_sqft'
```

```
plt.figure(figsize=(10, 6))
sns.violinplot(x='view', y='house_age', data=df, palette='Set2')
plt.title('Distribution of House Age by View')
plt.xlabel('View')
plt.ylabel('House Age')
plt.show()
```

```
C:\Users\jackl\AppData\Local\Temp\ipykernel_20764\3350196163.py:2:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.violinplot(x='view', y='house_age', data=df, palette='Set2')
```




```
avg_price_by_condition = df.groupby('price_category')
['price'].mean().reset_index()


plt.figure(figsize=(8,5))
sns.barplot(x='price_category', y='price', data=df,palette='pastel')
plt.title('Average House Price by Condition')

C:\Users\jackl\AppData\Local\Temp\ipykernel_20764\3661168591.py:1:
FutureWarning: The default of observed=False is deprecated and will be
changed to True in a future version of pandas. Pass observed=False to
retain current behavior or observed=True to adopt the future default
and silence this warning.
  avg_price_by_condition = df.groupby('price_category')
['price'].mean().reset_index()
C:\Users\jackl\AppData\Local\Temp\ipykernel_20764\3661168591.py:5:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='price_category', y='price', data=df,palette='pastel')

Text(0.5, 1.0, 'Average House Price by Condition')
```




```
water_yes = df[df['waterfront'] == 'Yes']['price']
water_no = df[df['waterfront'] == 'No']['price']

alpha = 0.05

_, p_value = ttest_ind(water_yes, water_no, equal_var=False)


if p_value > alpha:
    print("Fail to reject the null huypothesis: There is  Price no difference by waterfront.")
else:
    print("Reject the null huypothesis: There is Price difference by waterfront.")
```

```
Reject the null huypothesis: There is Price difference by waterfront.
```

Analysis and Interpretation

*Bedrooms vs Bathrooms Most homes have 2–4 bedrooms and 1–3 bathrooms big homes usually have higher prices

*priced under a certain amount 500000 A few luxury homes are priced much higher

*Price Distribution Highly skewed —most houses are in a low to medium price with a very few excellent ones

*Better condition like Good or excellent tends to higher prices

*Waterfront Property Waterfront homes are much more costly on average

*View Rating Houses with better views 3–4 tend to have higher prices

*Year Built New homes usually sell at higher prices than older ones

*Renovation Renovated homes are sell for more

*City and ZipCode Location some zip codes or cities have consistently higher prices than others

*Older homes may be cheaper or renovated. Newer homes may cost more

*Most homes may be in average or good condition

*Very few are in poor or excellent condition

*housing prices are increasing or decreasing over the years

*Most homes have no view 0. Better views 3-4 are rare but likely increase value

*sqft_living has the highest correlation with price

*Price increases most with square living and house

*More bathrooms usually mean higher price, even with the same size

*Bedrooms don't affect price as much when controlling for size

*Most homes are affordable, but a few luxury houses raise the average price

*price_per_sqft helps compare value across cities and neighborhoods

*Removed outliers in price, bathrooms, sqft_living to improve analysis

*Cleaned columns like view, condition, and waterfront to be more interpretable Yes/No, Good/Average

*Converted date column to proper datetime like year

Recommendations

For Sellers:

Improve condition: Simple renovations (e.g., paint, flooring, kitchen updates) can significantly increase price.

Highlight location advantages: Mention nearby parks, schools, or waterfronts.

Stage the view: Homes with views should be emphasized in listings.

For Buyers/Investors:

Look for undervalued areas: Use price-per-sqft analysis to find areas with potential.

Consider renovation projects: Older homes with low price but good structure may yield high ROI.

Avoid overpaying for size: After a point, increasing sqft doesn’t add as much to price.

For Developers:

Focus on high-demand zip codes.

Waterfront or scenic view areas offer premium opportunities.

Smaller high-quality homes might give better returns than larger low-grade constructions.

CONCLUSTION

analysis demonstrated how to clean, visualize, and extract meaningful insights from housing data using Python.

It included univariate, bivariate, and multivariate analysis, along with feature engineering and insightful visualizations.

These findings can assist in data-driven decision-making for real estate pricing, investment, or development planning.