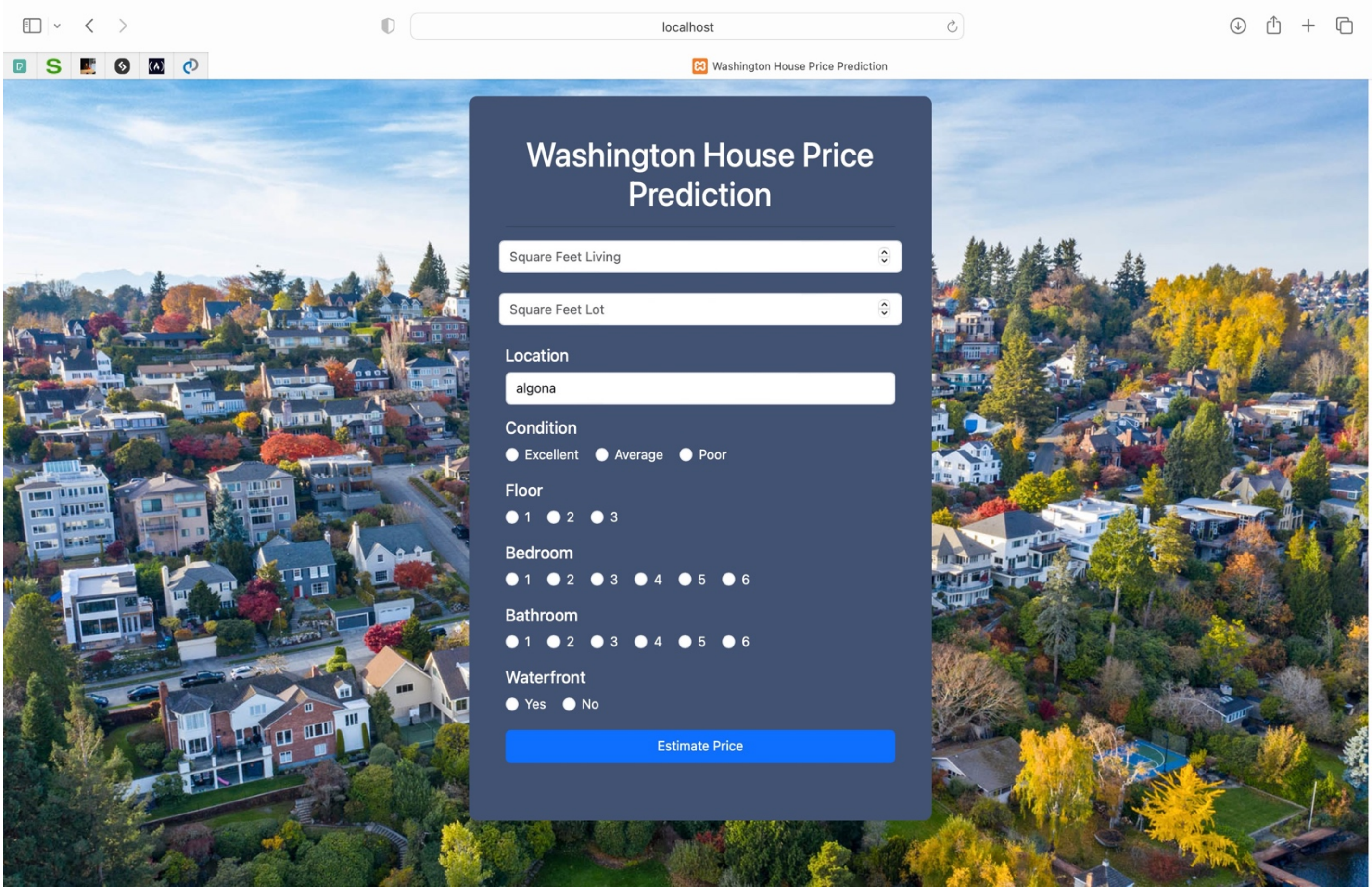


Milestones 🏆

- ◉ Problem Definition
- ◉ Data Collection and Preprocessing
- ◉ Data Exploration and Visualization
- ◉ Feature Engineering
- ◉ Model Development
- ◉ Model Evaluation
- ◉ Deployment and Integration

Problem Definition

I have obtained a dataset from Kaggle that contains information about real estate properties of USA. The aim of this project is to build a robust predictive model for real estate price prediction based on the given dataset. The model should be capable of accurately estimating the sale price of a property given its characteristics, such as the number of bedrooms, bathrooms, et cetera . The outcome of this project will provide valuable insights to potential buyers, sellers, and real estate professionals by enabling them to make informed decisions regarding property investments.

Data Dictionary

- Price: price at which house was sold.
- Date: This shows date on which house was sold.
- Bedrooms: The number of bedrooms.
- Bathrooms: The number of bathrooms.
- Sqft_living: living area of the house in square feet.
- Sqft_lot: total area of the lot in square feet.
- Floors: number of floors in the house.
- Waterfront: binary variable indicating the house is on a waterfront or not.
- View: How good the view of the property is between 0 and 4.
- Condition: The condition of the house between 0 and 5.
- Sqft_above: Apart from the basement The square footage of the house.
- Sqft_basement: Square footage of the basement.
- Yr_built: The year in which the house was built.
- Yr_renovated: The year in which the house was renovated.
- Street: street address of the house.
- City: The city of the house
- Statezip: The state and zipcode of the house where is located.
- Country: The country of houses (USA).

Importing Libraries

In [1]:

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

import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sn
import scipy.stats as stats

from sklearn.preprocessing import StandardScaler

from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import GridSearchCV

from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LogisticRegression

from sklearn.metrics import confusion_matrix
```

In [2]:

```
# Loading the dataset
```

In [3]:

```
df0 = pd.read_csv("data.csv")
```

Data Overview

In [4]:

```
df0.head()
```

Out[4]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	2014-05-02 00:00:00	313000.0	3.0	1.50	1340	7912	1.5	0
1	2014-05-02 00:00:00	2384000.0	5.0	2.50	3650	9050	2.0	0
2	2014-05-02 00:00:00	342000.0	3.0	2.00	1930	11947	1.0	0
3	2014-05-02 00:00:00	420000.0	3.0	2.25	2000	8030	1.0	0
4	2014-05-02 00:00:00	550000.0	4.0	2.50	1940	10500	1.0	0

In [5]:
```
df0.shape
```
Out[5]:
```
(4600, 18)
```

checking the data types of columns

In [6]:
```
df0.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4600 entries, 0 to 4599
Data columns (total 18 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   date           4600 non-null   object 
 1   price          4600 non-null   float64
 2   bedrooms       4600 non-null   float64
 3   bathrooms      4600 non-null   float64
 4   sqft_living    4600 non-null   int64  
 5   sqft_lot       4600 non-null   int64  
 6   floors         4600 non-null   float64
 7   waterfront     4600 non-null   int64  
 8   view           4600 non-null   int64  
 9   condition      4600 non-null   int64  
 10  sqft_above     4600 non-null   int64  
 11  sqft_basement  4600 non-null   int64  
 12  yr_built       4600 non-null   int64  
 13  yr_renovated   4600 non-null   int64  
 14  street         4600 non-null   object 
 15  city           4600 non-null   object 
 16  statezip       4600 non-null   object 
 17  country        4600 non-null   object 
dtypes: float64(4), int64(9), object(5)
memory usage: 647.0+ KB
```

Data Preprocessing

Checking the Statistical Summary

In [7]:
```
df0.describe()
```

Out[7]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	fl
count	4.600000e+03	4600.000000	4600.000000	4600.000000	4.600000e+03	4600.00
mean	5.519630e+05	3.400870	2.160815	2139.346957	1.485252e+04	1.51
std	5.638347e+05	0.908848	0.783781	963.206916	3.588444e+04	0.53
min	0.000000e+00	0.000000	0.000000	370.000000	6.380000e+02	1.00
25%	3.228750e+05	3.000000	1.750000	1460.000000	5.000750e+03	1.00
50%	4.609435e+05	3.000000	2.250000	1980.000000	7.683000e+03	1.50
75%	6.549625e+05	4.000000	2.500000	2620.000000	1.100125e+04	2.00
max	2.659000e+07	9.000000	8.000000	13540.000000	1.074218e+06	3.50

checking the unique values in each column

In [8]:
```
df0.nunique()
```

Out[8]:
```
date               70
price            1741
bedrooms           10
bathrooms          26
sqft_living       566
sqft_lot         3113
floors              6
waterfront          2
view                5
condition           5
sqft_above        511
sqft_basement     207
yr_built          115
yr_renovated       60
street           4525
city               44
statezip           77
country             1
dtype: int64
```

Making a list of all categorical variables

In [9]:
```
cat_col = ['city','bathrooms', 'bedrooms', 'sqft_living','condition','yr_

#print number of count of each unique value in each columns
for column in cat_col:
    print(df0[column].value_counts())
    print("-" * 45)
```

```
city
Seattle                1573
Renton                  293
Bellevue                286
Redmond                 235
Issaquah                187
Kirkland                187
Kent                    185
Auburn                  176
Sammamish               175
Federal Way             148
Shoreline               123
Woodinville             115
Maple Valley             96
Mercer Island            86
Burien                   74
Snoqualmie               71
Kenmore                  66
Des Moines               58
North Bend               50
Covington                43
Duvall                   42
Lake Forest Park         36
Bothell                  33
Newcastle                33
SeaTac                   29
Tukwila                  29
Vashon                   29
Enumclaw                 28
Carnation                22
Normandy Park            18
Clyde Hill               11
Medina                   11
Fall City                11
Black Diamond             9
Ravensdale                7
Pacific                   6
Algona                    5
Yarrow Point              4
Skykomish                 3
Preston                   2
Milton                    2
Inglewood-Finn Hill       1
Snoqualmie Pass           1
Beaux Arts Village        1
Name: count, dtype: int64
---------------------------------------------
bathrooms
2.50    1189
```

```
1.00     743
1.75     629
2.00     427
2.25     419
1.50     291
2.75     276
3.00     167
3.50     162
3.25     136
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
---------------------------------------------
bedrooms
3.0    2032
4.0    1531
2.0     566
5.0     353
6.0      61
1.0      38
7.0      14
8.0       2
0.0       2
9.0       1
Name: count, dtype: int64
---------------------------------------------
sqft_living
1940     32
1720     32
1660     31
1840     31
2000     30
         ..
2732      1
2009      1
1295      1
10040     1
2538      1
Name: count, Length: 566, dtype: int64
---------------------------------------------
condition
3    2875
4    1252
```

```
5     435
2      32
1       6
Name: count, dtype: int64
----------------------------------------
yr_built
2006    111
2005    104
2007     93
2004     92
1978     90
       ...
1915      6
1935      6
1933      5
1934      4
1936      3
Name: count, Length: 115, dtype: int64
----------------------------------------
yr_renovated
0       2735
2000     170
2003     151
2009     109
2001     109
2005      95
2004      77
2014      72
2006      68
2013      61
1923      57
1994      57
1989      55
2011      54
2012      45
2008      45
1988      43
1999      41
2002      41
1983      41
1998      40
1993      39
1912      33
1979      32
1992      32
2010      30
1985      29
1997      28
1996      22
1982      22
1972      17
1990      16
1956      15
1963      12
1969      11
1984      10
1970       9
```

```
1968       9
1954       8
1945       7
2007       7
1974       6
1934       6
1971       5
1958       5
1986       5
1978       3
1980       2
1995       2
1955       2
1977       1
1913       1
1991       1
1948       1
1966       1
1960       1
1987       1
1953       1
1981       1
1975       1
Name: count, dtype: int64
----------------------------------------
floors
1.0    2174
2.0    1811
1.5     444
3.0     128
2.5      41
3.5       2
Name: count, dtype: int64
----------------------------------------
sqft_above
1200    47
1010    47
1300    45
1140    44
1320    43
        ..
2481     1
560      1
2437     1
3590     1
2538     1
Name: count, Length: 511, dtype: int64
----------------------------------------
waterfront
0    4567
1      33
Name: count, dtype: int64
----------------------------------------
street
2520 Mulberry Walk NE     4
2500 Mulberry Walk NE     3
9413 34th Ave SW          2
```

```
6008 8th Ave NE            2
11034 NE 26th Pl           2
                          ..
1404 Broadmoor Dr E        1
3249 E Ames Lake Dr NE     1
6032 35th Ave NE           1
1006 NE Ravenna Blvd       1
18717 SE 258th St          1
Name: count, Length: 4525, dtype: int64
----------------------------------------------
statezip
WA 98103    148
WA 98052    135
WA 98117    132
WA 98115    130
WA 98006    110
           ...
WA 98047      6
WA 98288      3
WA 98050      2
WA 98354      2
WA 98068      1
Name: count, Length: 77, dtype: int64
----------------------------------------------
```

Rounding the Float values of bedrooms, bathrooms, floors

In [10]:

```
df1 = df0.copy()
df1['bedrooms'] = df1['bedrooms'].apply(lambda x: round(x))
df1['bathrooms'] = df1['bathrooms'].apply(lambda x: round(x))
df1['floors'] = df1['floors'].apply(lambda x: round(x))
```

Dropping the rows

Dropping the rows of condiion column having values 1 and 2, assigning 1, 2, and 3 to the rows having 3, 4 and 5

1 -> Excellent

2 -> Average

3 -> Poor

In [11]:

```
df1 = df1[df1['condition'].isin([5,4,3])]  # Drop rows with condition val

df1['condition'] = df1['condition'].replace({5: 1, 4: 2, 3: 3})  # Assign
```

In [12]:

```
df1['condition'].value_counts()
```

Out[12]:
```
condition
3    2875
2    1252
1     435
Name: count, dtype: int64
```

Dropping the rows having 3 and 4 floors

In [13]:
```
df1 = df1[df1['floors'].isin([1,2])]
```

In [14]:
```
df1['floors'].value_counts()
```

Out[14]:
```
floors
2    2288
1    2144
Name: count, dtype: int64
```

Dropping the rows having more than 6 bedrooms

In [15]:
```
df1 = df1[df1['bedrooms'].isin([1,2,3,4,5,6])]
```

In [16]:
```
df1['bedrooms'].value_counts()
```

Out[16]:
```
bedrooms
3    1930
4    1512
2     534
5     349
6      57
1      33
Name: count, dtype: int64
```

Dropping the rows having more than 6 bedrooms

In [17]:
```
df1 = df1[df1['bathrooms'].isin([1,2,3,4,5,6])]
```

In [18]:
```
df1['bathrooms'].value_counts()
```

Out[18]:
```
bathrooms
2    2842
1     739
3     555
4     255
5      17
6       6
Name: count, dtype: int64
```

Dropping unnecessary columns

In [19]:
```
df2 = df1.drop(['yr_built','yr_renovated','street','statezip','sqft_basem
```

In [20]:
```
df2.head()
```

Out[20]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition
0	313000.0	3	2	1340	7912	2	0	3
1	2384000.0	5	2	3650	9050	2	0	1
2	342000.0	3	2	1930	11947	1	0	2
3	420000.0	3	2	2000	8030	1	0	2
4	550000.0	4	2	1940	10500	1	0	2

checking the missing values

In [21]:
```
df2.isna().sum()
```

Out[21]:
```
price          0
bedrooms       0
bathrooms      0
sqft_living    0
sqft_lot       0
floors         0
waterfront     0
condition      0
city           0
dtype: int64
```

Removing Duplicates

In [22]:
```
df2.drop_duplicates()
```

Out[22]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	co
0	3.130000e+05	3	2	1340	7912	2	0	
1	2.384000e+06	5	2	3650	9050	2	0	
2	3.420000e+05	3	2	1930	11947	1	0	
3	4.200000e+05	3	2	2000	8030	1	0	
4	5.500000e+05	4	2	1940	10500	1	0	
...	...	...	...	...	...	...	...	
4595	3.081667e+05	3	2	1510	6360	1	0	
4596	5.343333e+05	3	2	1460	7573	2	0	
4597	4.169042e+05	3	2	3010	7014	2	0	
4598	2.034000e+05	4	2	2090	6630	1	0	
4599	2.206000e+05	3	2	1490	8102	2	0	

4414 rows × 9 columns

Removing Rows Having Price = 0

In [23]:
```
(df2.price == 0).sum()
```

Out[23]:
```
47
```

Price of 47 houses is 0, price can not be zero, we consider them missing values

In [24]:
```
df3 = df2[df2['price']!=0]
```

In [25]:
```
df3.shape
```

Out[25]:
```
(4367, 9)
```

Changing the Data Types of Columns

In [26]:
```
df4 = df3.copy()
df4["floors"] = df4["floors"].astype("int64")
df4["bedrooms"] = df4["bedrooms"].astype("int64")
df4['bathrooms'] = df4['bathrooms'].astype("int64")
df4['city']       = df4['city'].astype('string')
```

In [27]:
```
df4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 4367 entries, 0 to 4599
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  ------
 0   price         4367 non-null   float64
 1   bedrooms      4367 non-null   int64
 2   bathrooms     4367 non-null   int64
 3   sqft_living   4367 non-null   int64
 4   sqft_lot      4367 non-null   int64
 5   floors        4367 non-null   int64
 6   waterfront    4367 non-null   int64
 7   condition     4367 non-null   int64
 8   city          4367 non-null   string
dtypes: float64(1), int64(7), string(1)
memory usage: 341.2 KB
```

Adding new columns in dataset

In [28]:
```
df4['total_square_feet'] = df4['sqft_living'] + df4['sqft_lot']
df4['price_per_square_feet'] = df4['price'] / df4['total_square_feet']
```

In [29]:
```
df4.head(3)
```

Out[29]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition
0	313000.0	3	2	1340	7912	2	0	3
1	2384000.0	5	2	3650	9050	2	0	1
2	342000.0	3	2	1930	11947	1	0	2

Handling Outliers

In [30]:

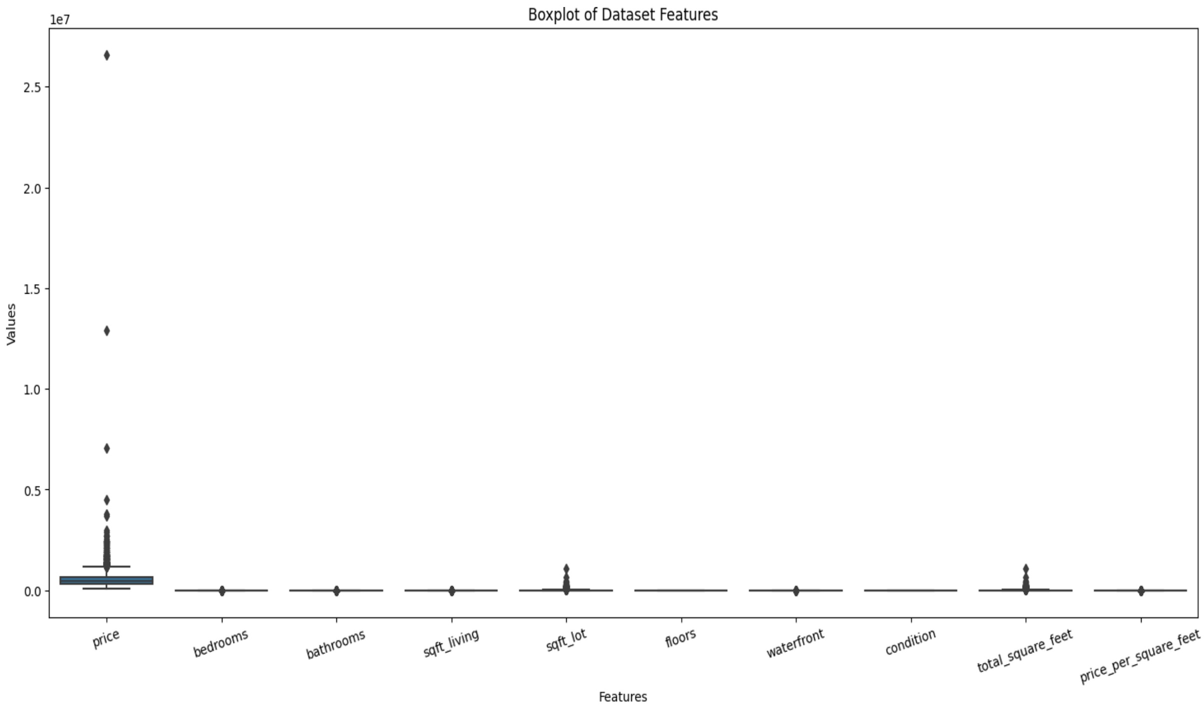
```
df5 = df4.copy()

# Select the features for boxplot
features = ['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',

# Create a DataFrame containing the selected features
data = df5[features]

# Create the boxplot
plt.figure(figsize=(18,8))
sn.boxplot(data=data)
plt.xticks(rotation=18)
plt.title('Boxplot of Dataset Features')
plt.xlabel('Features')
plt.ylabel('Values')

plt.show()
```



Removing outliers using IQR

1. Calculate Q1(25%) and Q2 (75%)
2. IQR (Q3 - Q1)
3. Find the Lower Fence => Q1-1.5(IQR)
4. Find the Higher Fence => Q3 + 1.5 (IQR)

In [31]:
```
df5.shape
```
Out[31]:
```
(4367, 11)
```

Outliers in Price Column

In [32]:
```
q1,q3 = np.percentile(df5.price,[25,75])
print(q1,q3)
```
```
325000.0 660000.0
```

In [33]:
```
iqr = q3 - q1
```

In [34]:
```
#Finding lower fence and upper fence

lower_fence = q1-(1.5*iqr)
upper_fence = q3+(1.5*iqr)
print(lower_fence,upper_fence)
```
```
-177500.0 1162500.0
```

In [35]:
```
outliers = df5[(df5.price>upper_fence) | (df5.price<lower_fence)]
len(outliers)
```
Out[35]:
```
223
```

Dataframe without outliers

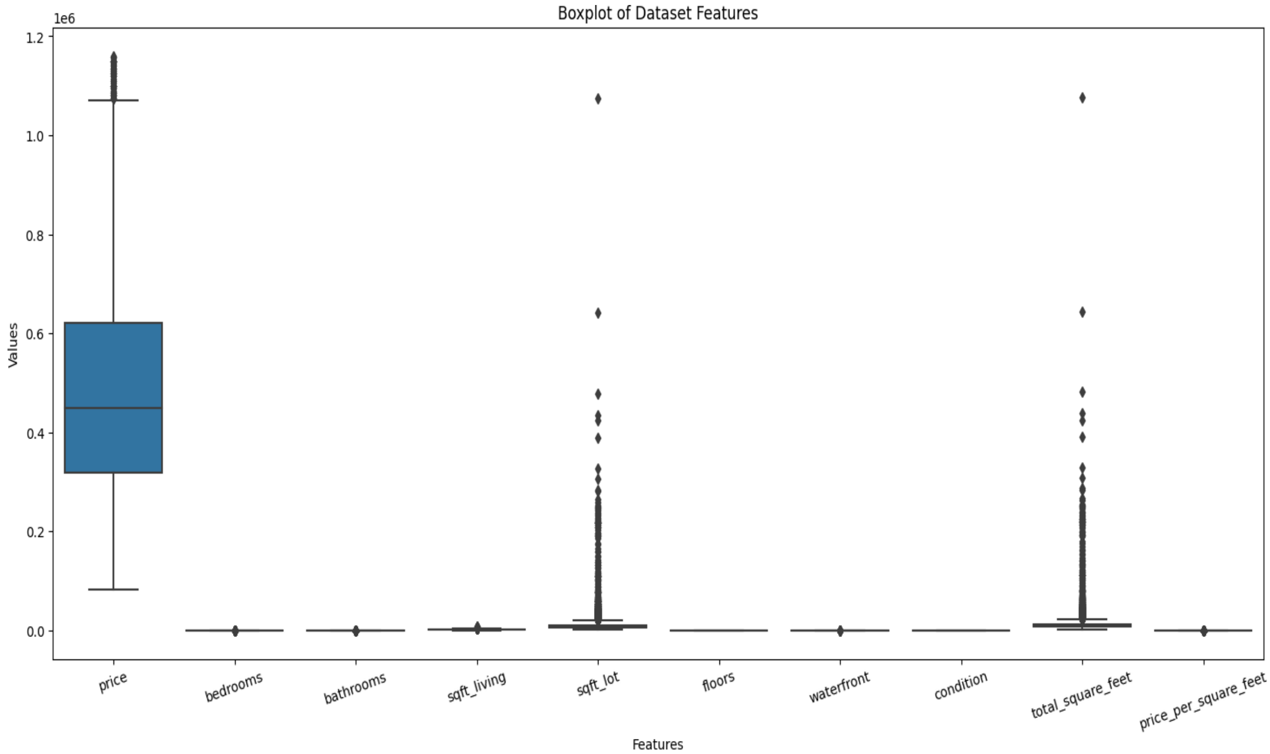
In [36]:
```
df6 = df5[(df5.price<upper_fence) & (df5.price>lower_fence)]
df6.shape
```
Out[36]:
```
(4144, 11)
```

In [37]:
```
# Select the features for boxplot
features = ['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',

# Create a DataFrame containing the selected features
data = df6[features]

# Create the boxplot
plt.figure(figsize=(18, 8))
sn.boxplot(data=data)
plt.xticks(rotation=18)
plt.title('Boxplot of Dataset Features')
plt.xlabel('Features')
plt.ylabel('Values')

plt.show()
```

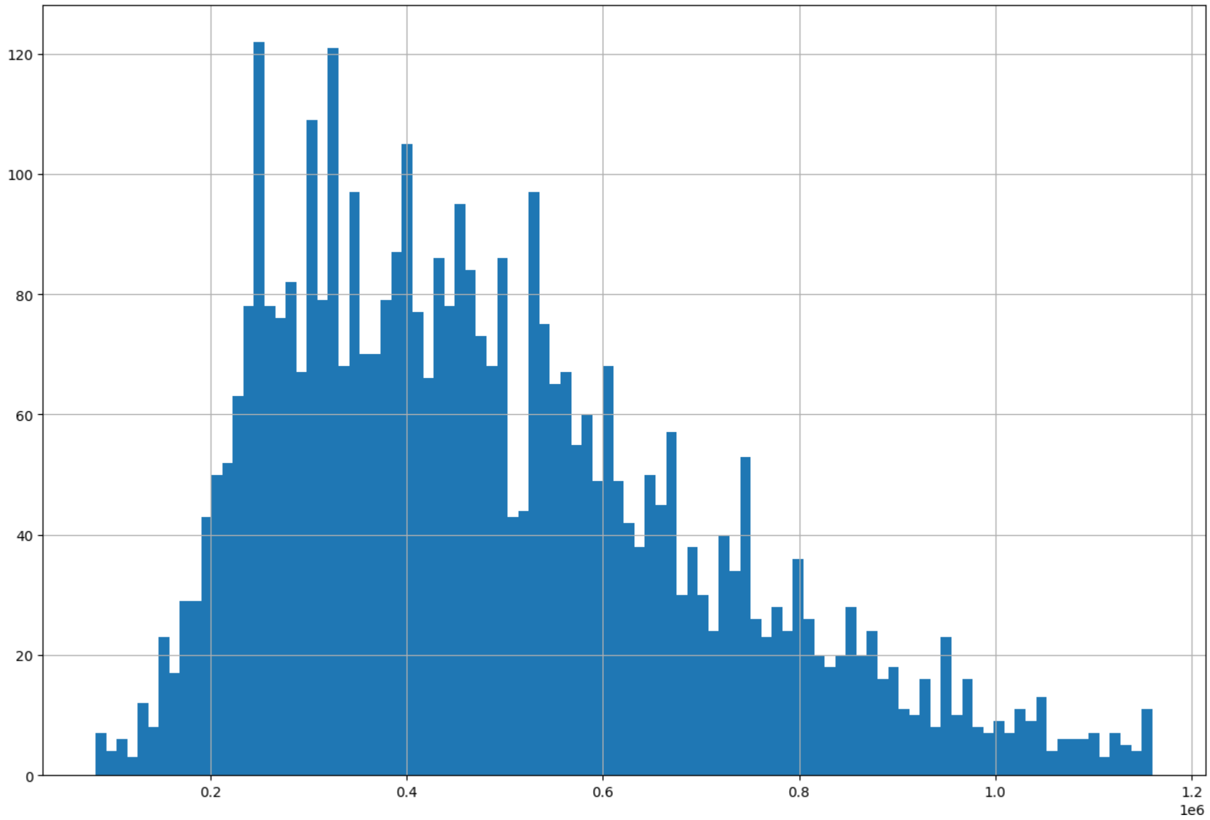


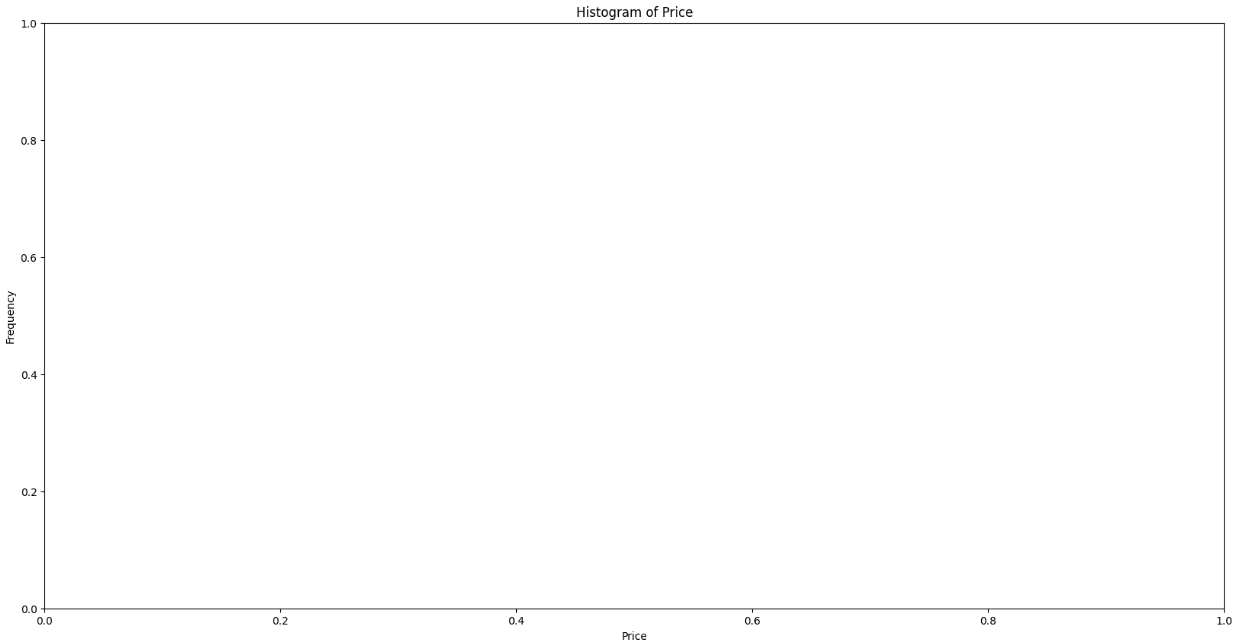
In [38]:
```
df6.price
```

Out[38]:
```
0       313000.000000
2       342000.000000
3       420000.000000
4       550000.000000
5       490000.000000
            ...
4595    308166.666667
4596    534333.333333
4597    416904.166667
4598    203400.000000
4599    220600.000000
Name: price, Length: 4144, dtype: float64
```

Exploratory Data Analysis (EDA)

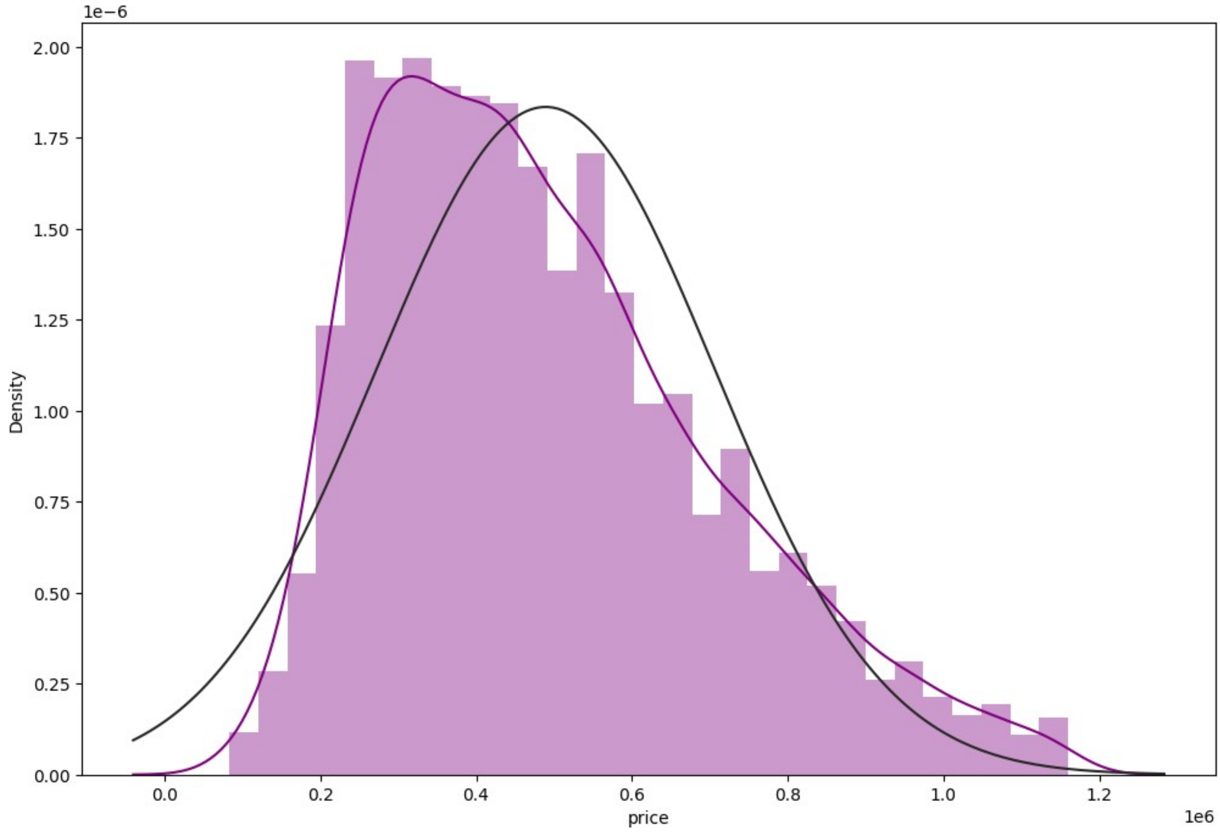
In [80]:
```
df6['price'].hist(bins=100)
plt.figure(figsize=(20, 10))
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.title('Histogram of Price')
plt.show()
```



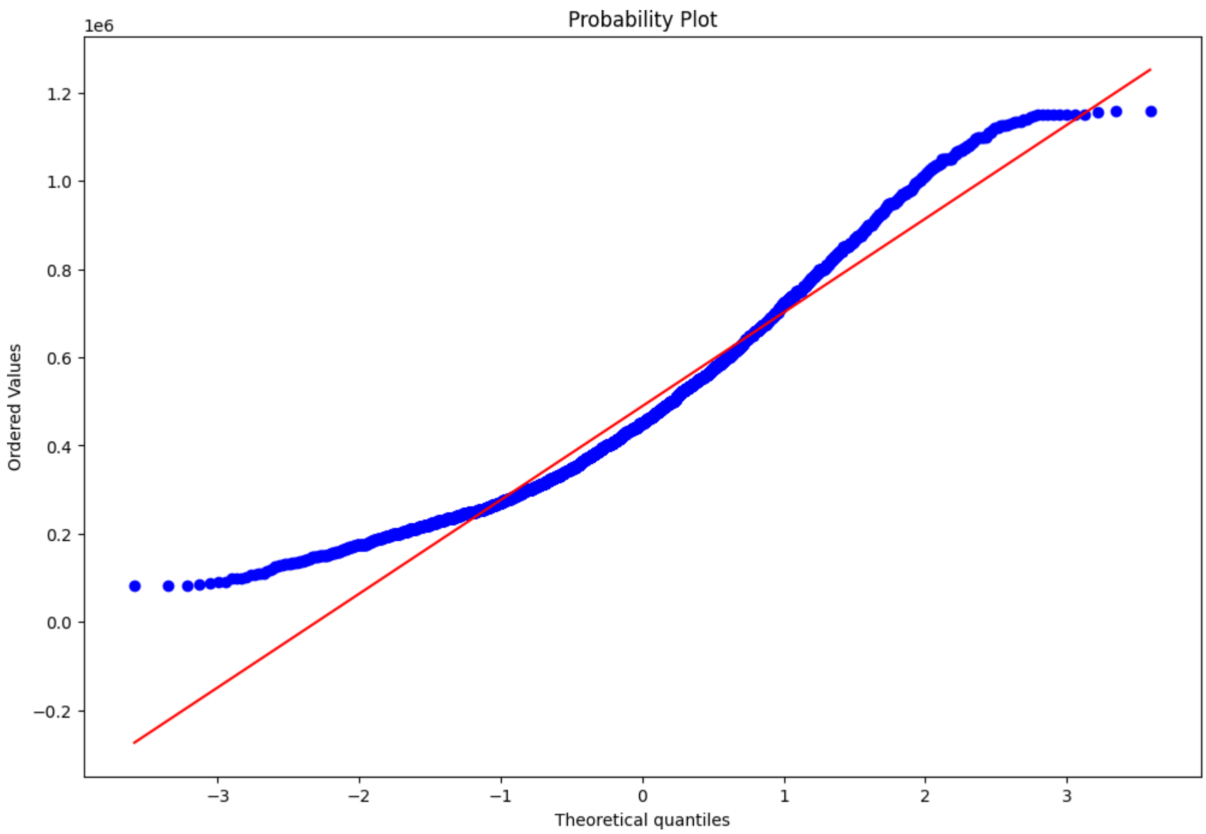


In [40]:
```
plt.figure(figsize=(12, 8))
sn.distplot(df6['price'],color="purple",kde=True , fit=stats.norm)
```

Out[40]: <Axes: xlabel='price', ylabel='Density'>



In [41]:
```
plt.figure(figsize=(12, 8))
res = stats.probplot(df6['price'], plot=plt)
plt.show()
```



Correlation between different features

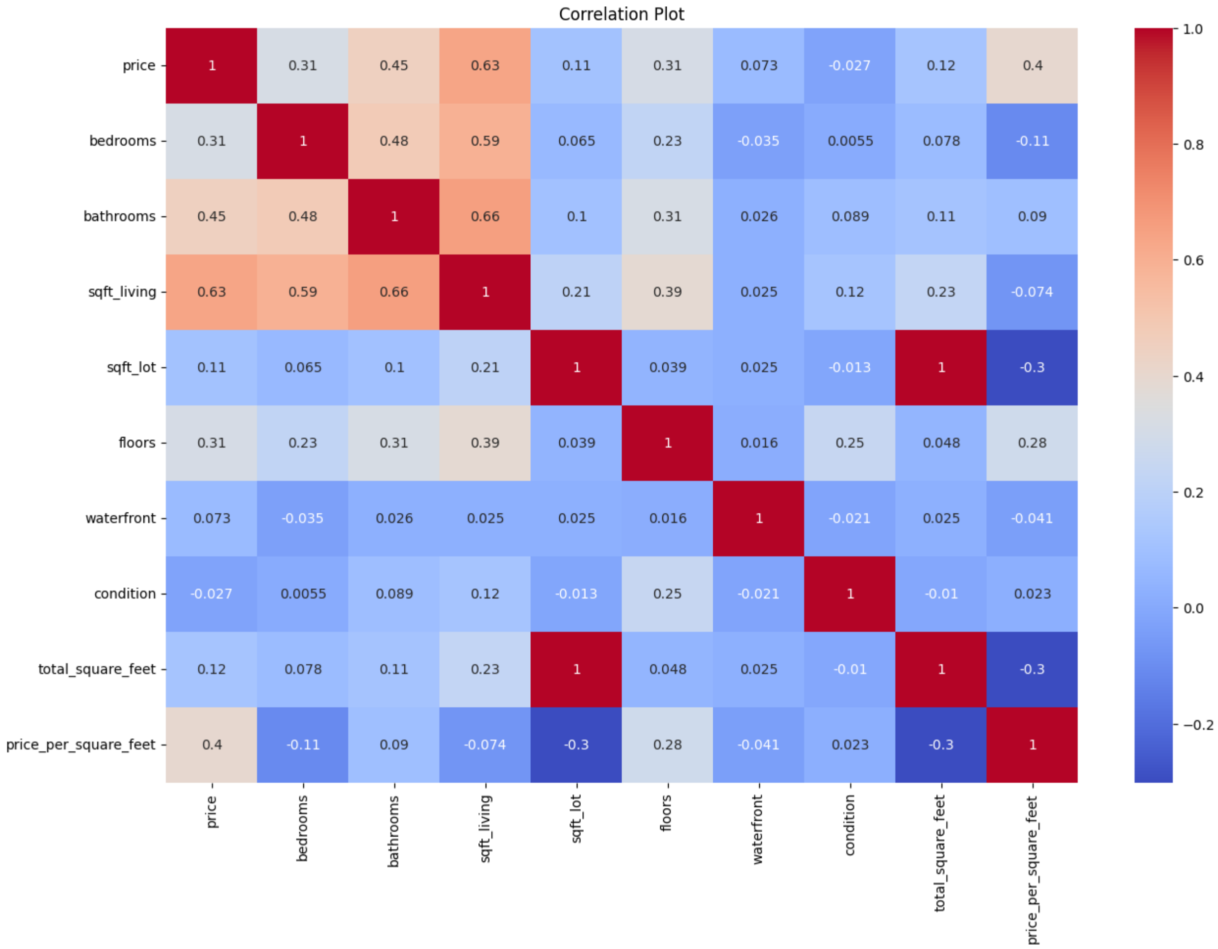
In [42]:
```
numeric_columns = df6.select_dtypes(include=['int64', 'float64']).columns
correlation_matrix = df6[numeric_columns].corr()
```

In [43]:
```
correlation_matrix
```

Out[43]:

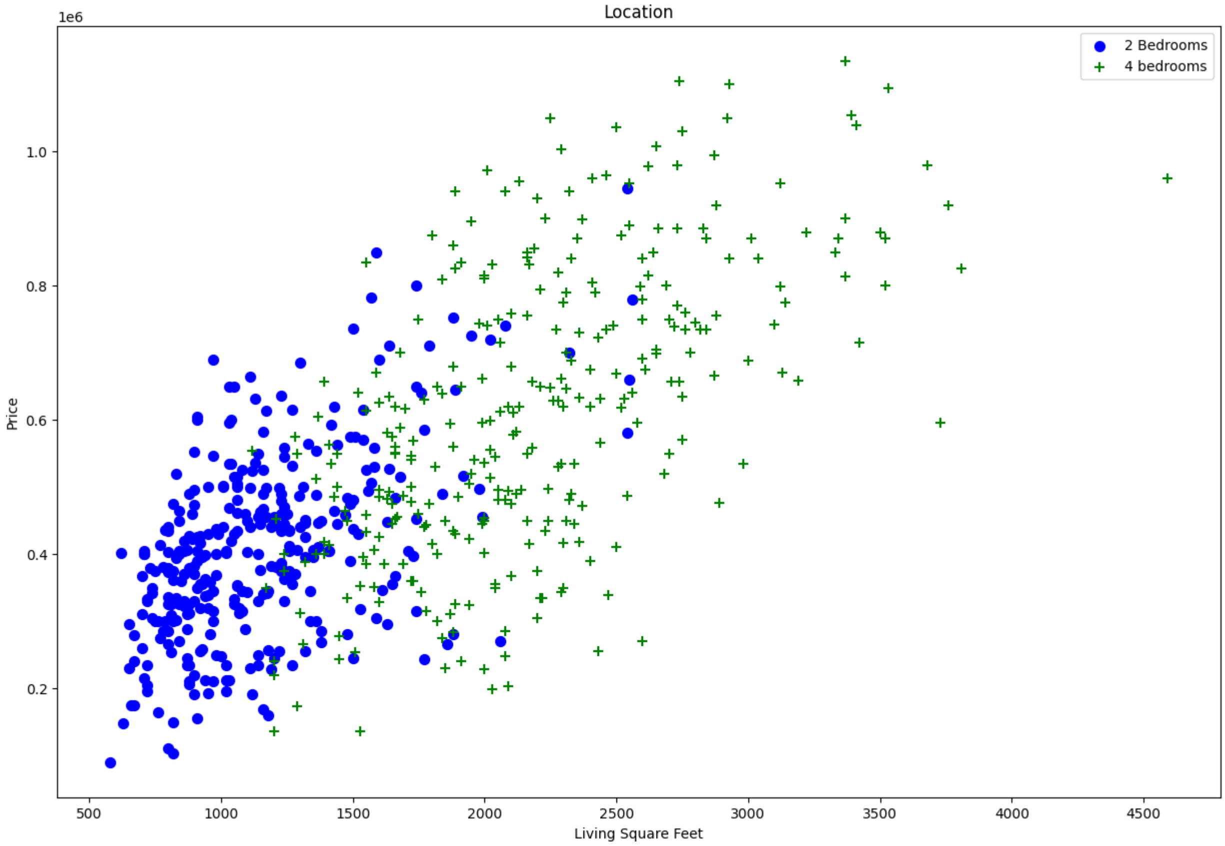
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floor
price	1.000000	0.314606	0.448596	0.634593	0.105904	0.31142
bedrooms	0.314606	1.000000	0.476301	0.593112	0.064975	0.22577
bathrooms	0.448596	0.476301	1.000000	0.658899	0.100297	0.31472
sqft_living	0.634593	0.593112	0.658899	1.000000	0.206999	0.38945
sqft_lot	0.105904	0.064975	0.100297	0.206999	1.000000	0.03947
floors	0.311421	0.225772	0.314721	0.389458	0.039476	1.00000
waterfront	0.072724	-0.035250	0.025864	0.025389	0.024576	0.01553
condition	-0.026665	0.005547	0.088564	0.115320	-0.012618	0.24664
total_square_feet	0.119625	0.077966	0.114591	0.228425	0.999759	0.04802
price_per_square_feet	0.399170	-0.111925	0.090166	-0.073543	-0.301483	0.28042

In [44]:
```
plt.figure(figsize=(15,  10))
sn.heatmap(correlation_matrix, annot=True,cmap='coolwarm')
plt.title("Correlation Plot")
plt.show()
```



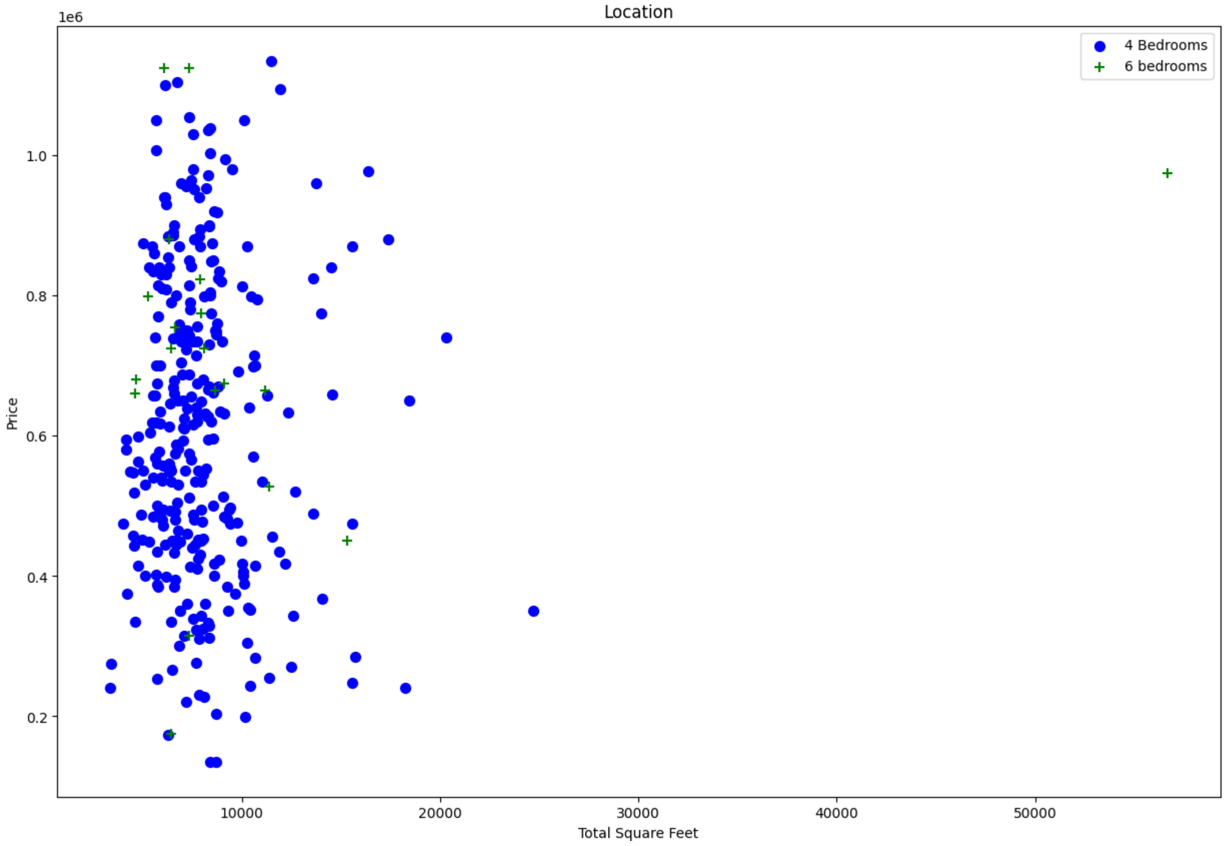
In [45]:
```
def plot_scatter_chart(df,city):
    br2 = df[(df6.city==city) & (df6.bedrooms==2)]
    br4 = df[(df6.city==city) & (df6.bedrooms==4)]
    plt.rcParams['figure.figsize'] = (15,10)
    plt.scatter(br2.sqft_living,br2.price, color='Blue', label='2 Bedroom
    plt.scatter(br4.sqft_living,br4.price, marker='+', color='green', lab
    plt.xlabel('Living Square Feet')
    plt.ylabel('Price')
    plt.title('Location')
    plt.legend()

plot_scatter_chart(df6, 'Seattle')
```



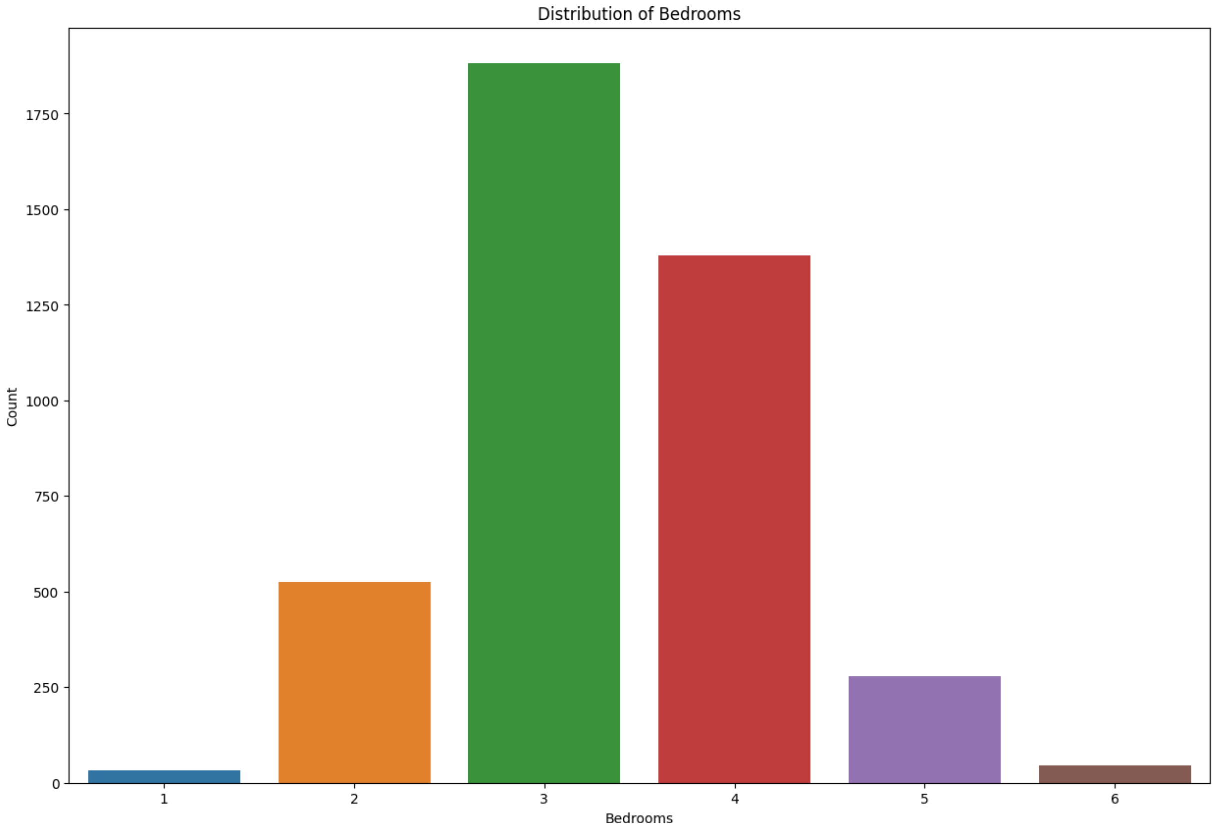
In [46]:
```
def plot_scatter_chart(df,city):
    br4 = df[(df6.city==city) & (df6.bedrooms==4)]
    br6 = df[(df6.city==city) & (df6.bedrooms==6)]
    plt.rcParams['figure.figsize'] = (15,10)
    plt.scatter(br4.total_square_feet,br4.price, color='Blue', label='4 B
    plt.scatter(br6.total_square_feet,br6.price, marker='+', color='green
    plt.xlabel('Total Square Feet')
    plt.ylabel('Price')
    plt.title('Location')
    plt.legend()

plot_scatter_chart(df6, 'Seattle')
```



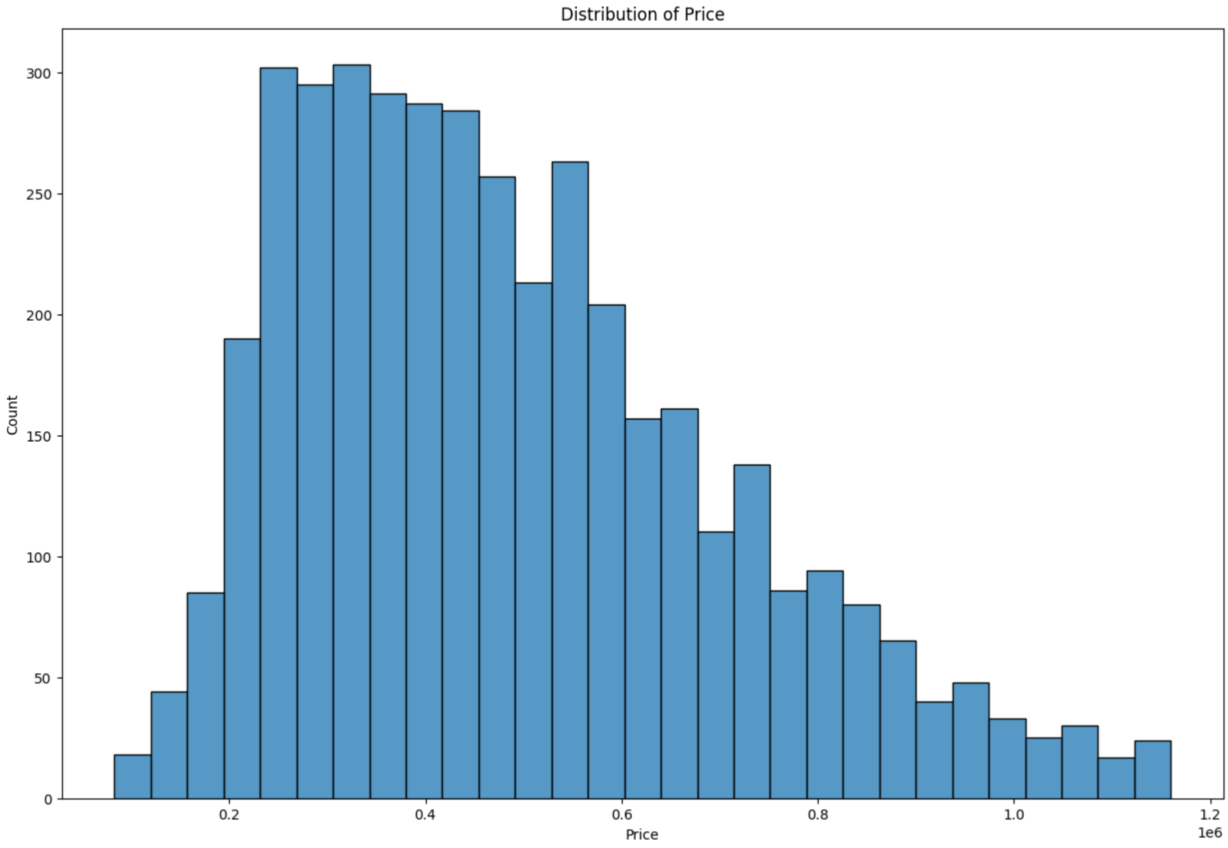
Bar Plot: Count of Bedrooms

In [47]:
```
sn.countplot(x='bedrooms', data=df6)
plt.xlabel('Bedrooms')
plt.ylabel('Count')
plt.title('Distribution of Bedrooms')
plt.show()
```



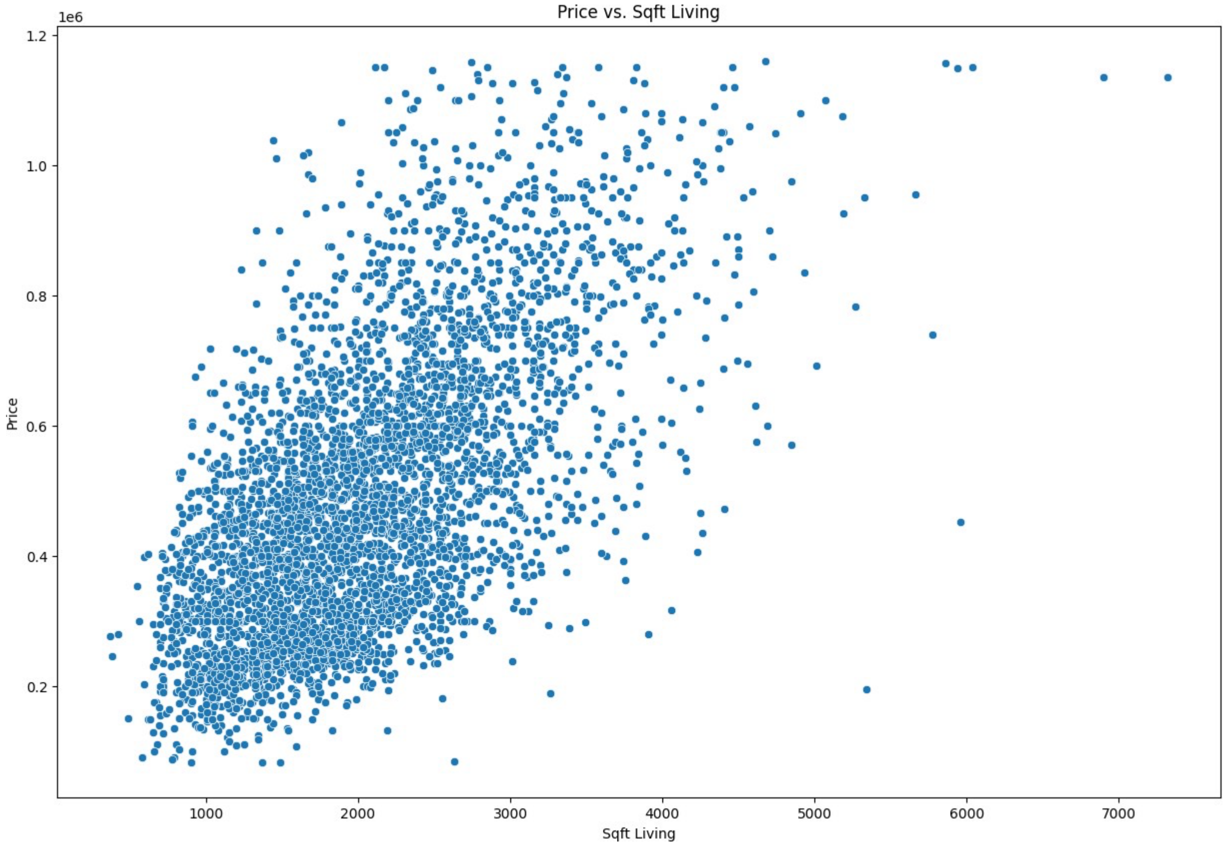
Histogram: Distribution of Price

In [48]:
```
sn.histplot(df6['price'])
plt.xlabel('Price')
plt.ylabel('Count')
plt.title('Distribution of Price')
plt.show()
```



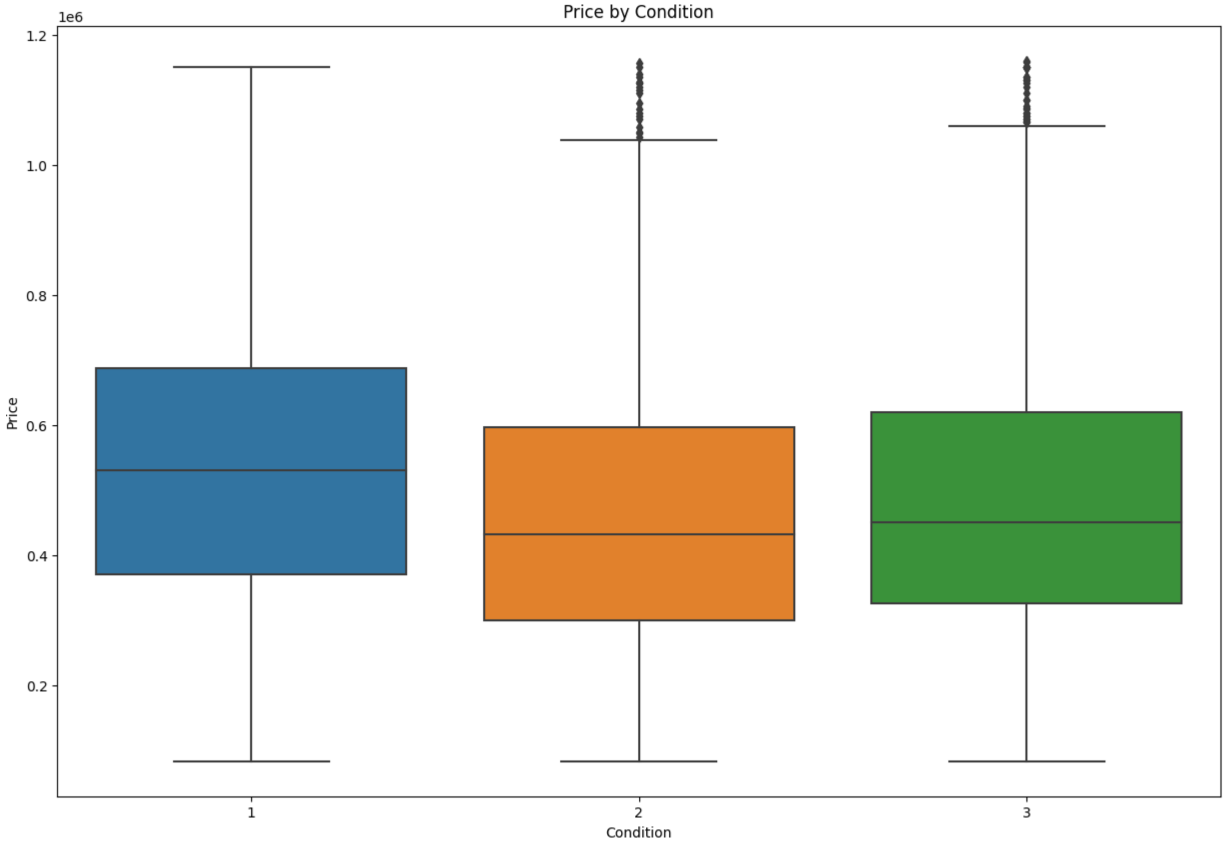
Scatter Plot: Price vs. Sqft Living

In [49]:
```
sn.scatterplot(x='sqft_living', y='price', data=df6)
plt.xlabel('Sqft Living')
plt.ylabel('Price')
plt.title('Price vs. Sqft Living')
plt.show()
```



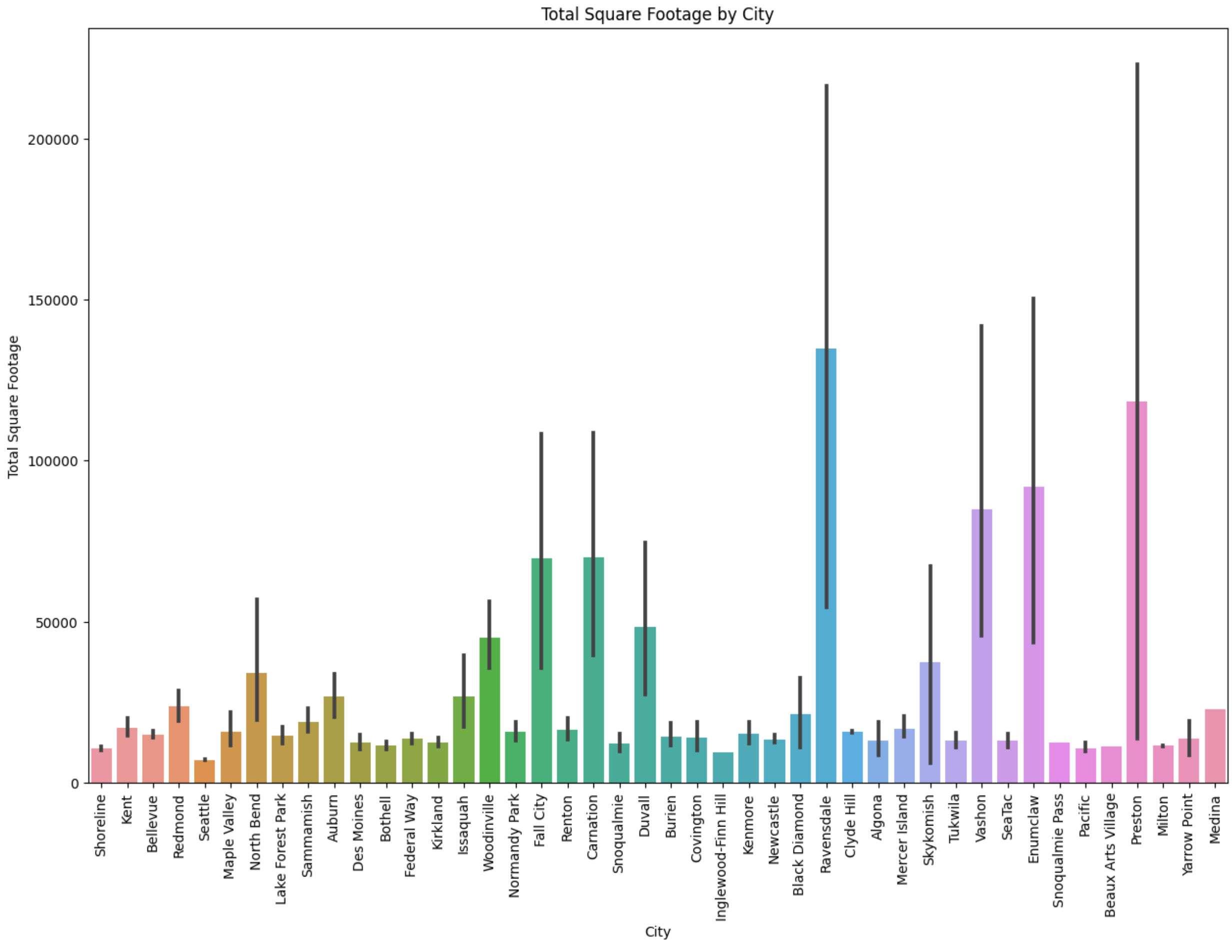
Box Plot: Price by Condition

In [50]:
```
sn.boxplot(x='condition', y='price', data=df6)
plt.xlabel('Condition')
plt.ylabel('Price')
plt.title('Price by Condition')
plt.show()
```



Bar Plot: Total Square Footage by City

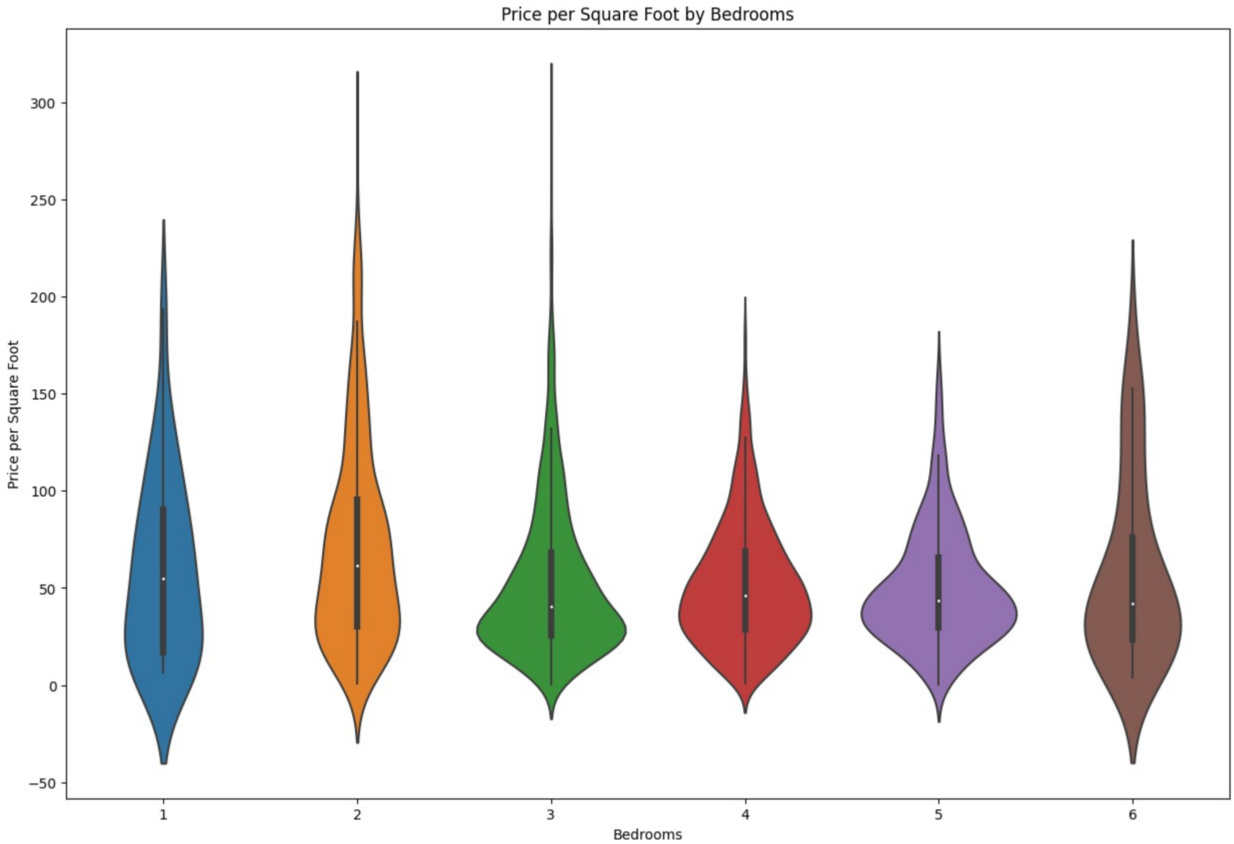
In [51]:
```
sn.barplot(x='city', y='total_square_feet', data=df6)
plt.xlabel('City')
plt.ylabel('Total Square Footage')
plt.title('Total Square Footage by City')
plt.xticks(rotation=90)
plt.show()
```



Violin Plot: Price per Square Foot by Bedrooms

In [52]:

```
sn.violinplot(x='bedrooms', y='price_per_square_feet', data=df6)
plt.xlabel('Bedrooms')
plt.ylabel('Price per Square Foot')
plt.title('Price per Square Foot by Bedrooms')
plt.show()
```



Using One Hot Encoding For Location(Cities)

In [53]:
```
dummies = pd.get_dummies(df6.city, dtype=int)
dummies.head(2)
```

Out[53]:

	Algona	Auburn	Beaux Arts Village	Bellevue	Black Diamond	Bothell	Burien	Carnation	Clyde Hill	Covin
0	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	

2 rows × 44 columns

In [54]:
```
df7 = pd.concat([df6,dummies],axis='columns')
```

In [55]:
```
df7.shape
```

Out[55]:
```
(4144, 55)
```

In [56]:
```
df7.head(2)
```

Out[56]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition
0	313000.0	3	2	1340	7912	2	0	3
2	342000.0	3	2	1930	11947	1	0	2

2 rows × 55 columns

In [57]:
```
df8 = df7.drop(['city','price_per_square_feet','total_square_feet'],axis=
```

In [58]:
```
df8.head()
```

Out[58]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition
0	313000.0	3	2	1340	7912	2	0	3
2	342000.0	3	2	1930	11947	1	0	2
3	420000.0	3	2	2000	8030	1	0	2
4	550000.0	4	2	1940	10500	1	0	2
5	490000.0	2	1	880	6380	1	0	3

5 rows × 52 columns

Building Model and Hyper Parameter Tunning

In [59]:
```
X = df8.drop(['price'],axis='columns')
X.head()
```

Out[59]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	Algona	Au
0	3	2	1340	7912	2	0	3	0	
2	3	2	1930	11947	1	0	2	0	
3	3	2	2000	8030	1	0	2	0	
4	4	2	1940	10500	1	0	2	0	
5	2	1	880	6380	1	0	3	0	

5 rows × 51 columns

In [60]:
```
y = df8.price
```

In [61]:

Out[61]:

Train Test Split

In [62]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.25,
y
```

```
0       313000.000000
2       342000.000000
3       420000.000000
4       550000.000000
5       490000.000000
            ...
4595    308166.666667
4596    534333.333333
4597    416904.166667
4598    203400.000000
4599    220600.000000
Name: price, Length: 4144, dtype: float64
```

In [63]:
```
len(X_train)
```

Out[63]:
```
3108
```

In [64]:
```
len(X_test)
```

Out[64]:
```
1036
```

Applying Linear Regression Model

In [65]:
```
lr  =  LinearRegression()
lr.fit(X_train, y_train)
lr.score(X_test,y_test)
```

Out[65]:
```
0.6711240116072386
```

In [66]:
```
y_pred = lr.predict(X_test)
y_pred
```

Out[66]:
```
array([765810.05375056, 733232.02473775, 502343.57552749, ...,
       275524.39807709, 452593.02598649, 555349.8709406 ])
```

Using K Fold cross validation to measure accuracy of our LinearRegression model

In [67]:
```
cv = ShuffleSplit(n_splits=5, test_size=0.20, random_state=0)

cv_score = cross_val_score(LinearRegression(), X , y , cv=cv)

cv_score
```

Out[67]:
```
array([0.66225479, 0.64979383, 0.65210312, 0.7081972 , 0.66447811])
```

In [68]:
```
np.average(cv_score)
```

Out[68]:
```
0.6673654100802061
```

We can see that in 5 iterations we get a score above 67% all the time. No such difference, but we want to test few other algorithms for regression to see if we can get even better score. We will use GridSearchCV for this purpose

Finding best model using GridSearchCV

In [69]:
```
def find_best_model_using_gridsearchcv(X, y):
    algos = {
        'linear_regression': {
            'model': LinearRegression(),
            'params': {
                'normalize': [True, False]
            }
        },
        'lasso': {
            'model': Lasso(),
            'params': {
                'alpha': [1, 2],
                'selection': ['random', 'cyclic']
            }
        },
        'decision_tree': {
            'model': DecisionTreeRegressor(),
            'params': {
                'criterion': ['mse', 'friedman_mse'],
                'splitter': ['best', 'random']
            }
        },
        'svr': {
            'model': SVR(gamma='auto'),
            'params': {
                'C': [1, 10, 20]
            }
        }
    }

    scores = []
    cv = ShuffleSplit(n_splits=5, test_size=0.25, random_state=0)
    for algo_name, config in algos.items():
        gs = GridSearchCV(config['model'], config['params'], cv=cv, retur
        gs.fit(X, y)
        scores.append({
            'model': algo_name,
            'best_score': gs.best_score_,
            'best_params': gs.best_params_
        })

    return pd.DataFrame(scores, columns=['model', 'best_score', 'best_par

find_best_model_using_gridsearchcv(X, y)
```

Out[69]:

	model	best_score	best_params
0	linear_regression	0.664422	{'normalize': False}
1	lasso	0.665312	{'alpha': 2, 'selection': 'random'}
2	decision_tree	0.412272	{'criterion': 'mse', 'splitter': 'random'}
3	svr	-0.028248	{'C': 20}

Based on the results obtained from applying various regression models and using GridSearchCV for hyperparameter tuning, the following conclusions can be drawn:

The Lasso and linear regression model achieved the same highest best_score of 66.5% and 66.4%, indicating a better overall fit to the data compared to other models. No such difference between these two algorithms.

Testing the model for few properties

In [70]:
```
def predict_price(bedrooms,bathrooms,sqft_living,sqft_lot,floors,waterfro
    loc_index = np.where(X.columns==location)[0][0]

    x = np.zeros(len(X.columns))
    x[0] = bedrooms
    x[1] = bathrooms
    x[2] = sqft_living
    x[3] = sqft_lot
    x[4] = floors
    x[5] = waterfront
    x[6] = condition


    if loc_index >= 0:
        x[loc_index] = 1

    return lr.predict([x])[0]
```

In [71]:
```
predicted_price = predict_price(3,2,1340,7912,2,0,3,'Shoreline')
predicted_price
```

Out[71]:
```
353053.52946618234
```

In [72]:
```
predicted_price = predict_price(3,2,1340,7912,2,0,3,'Seattle')
predicted_price
```

Out[72]:
```
460330.8431063853
```

Exporting the tested model to a pickle file

In [73]:
```
import pickle
with open('washington_home_prices_model.pickle','wb') as f:
    pickle.dump(lr,f)
```

Exporting location and column information to a file that will be useful later on in our prediction application

In [74]:
```
import json
columns = {
    'data_columns' : [col.lower() for col in X.columns]
}
with open("columns.json","w") as f:
    f.write(json.dumps(columns))
```

Deployment and Integration

👉 Used FastAPI server as a web backend

👉 Built website using HTML, CSS, Bootstrap and JavaScript

👉 Deployment to AWS (Pending)

Kamlish@outlook.com

In [ ]:
```
```