King County, Data Analysis

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- Student pace: self paced / part time / full time: Flex Program
- Scheduled project review date/time:
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- Blog post URL: https://medium.com/@nataliagoncharov/data-analysis-real-estate-in-king-county-washington-6c74cadc2e79

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Data Description

- `id` - Unique identifier for a house
- `date` - Date house was sold
- `price` - Sale price (prediction target)
- `bedrooms` - Number of bedrooms
- `bathrooms` - Number of bathrooms
- `sqft_living` - Square footage of living space in the home
- `sqft_lot` - Square footage of the lot
- `floors` - Number of floors (levels) in house
- `waterfront` - Whether the house is on a waterfront
  - Includes Duwamish, Elliott Bay, Puget Sound, Lake Union, Ship Canal, Lake Washington, Lake Sammamish, other lake, and river/slough waterfronts
- `view` - Quality of view from house
  - Includes views of Mt. Rainier, Olympics, Cascades, Territorial, Seattle Skyline, Puget Sound, Lake Washington, Lake Sammamish, small lake / river / creek, and other
- `condition` - How good the overall condition of the house is. Related to maintenance of house.
  - See the King County Assessor Website for further explanation of each condition code
- `grade` - Overall grade of the house. Related to the construction and design of the house.
  - See the King County Assessor Website for further explanation of each building grade code
- `sqft_above` - Square footage of house apart from basement
- `sqft_basement` - Square footage of the basement
- `yr_built` - Year when house was built
- `yr_renovated` - Year when house was renovated
- `zipcode` - ZIP Code used by the United States Postal Service
- `lat` - Latitude coordinate
- `long` - Longitude coordinate

- `sqft_living15` - The square footage of interior housing living space for the nearest 15 neighbors
- `sqft_lot15` - The square footage of the land lots of the nearest 15 neighbors

Project's Purpose

The purpose of this project is to advise Edegon and Company, a real estate investment firm in King County, Washington. The following Data and Analysis will help the firm predict the market value of a given house, while the conclusions offer recommendations for future investments.

Importing Libraries

In [1]:
```
# Importing the neccessary libraries
import pandas as pd
# Import the neccessary libraries
import pandas as pd
import statsmodels as sm

from   statsmodels.api import formula
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statsmodels.formula.api as smf
import statsmodels.stats.api as sms
import statsmodels.api as sm
from statsmodels.formula.api import ols
from sklearn import datasets, linear_model
import seaborn as sns
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn import metrics
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error, make_scorer
from sklearn.model_selection import cross_val_score
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error,r2_score
from matplotlib.gridspec import GridSpec
import warnings
warnings.filterwarnings("ignore")

import seaborn_image as isns
isns.set_context(fontfamily="times") # Setting up global font type
# Uploading the data
kc_data = pd.read_csv("kc_house_data.csv", parse_dates = ['date'])

# Looking that the data has been uploaded properly and have a first glance
kc_data.head()
```

Out[1]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	

5 rows × 21 columns

Clean the data: *remove, replace, and/or fill missing values/errors/outliers*

In [2]:
```
# Converting price unites to $ millions so that the data appears
# cleaner in graphs later on.

kc_data['price'] = kc_data['price']
```

In [3]:
```
# Checking the size of the data.

kc_data.shape
```

Out[3]:
```
(21597, 21)
```

In [4]:
```
kc_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21597 non-null  int64
 1   date           21597 non-null  datetime64[ns]
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64
 6   sqft_lot       21597 non-null  int64
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  object
 9   view           21534 non-null  object
 10  condition      21597 non-null  object
 11  grade          21597 non-null  object
 12  sqft_above     21597 non-null  int64
 13  sqft_basement  21597 non-null  object
 14  yr_built       21597 non-null  int64
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64
 20  sqft_lot15     21597 non-null  int64
dtypes: datetime64[ns](1), float64(6), int64(9), object(5)
memory usage: 3.5+ MB
```

In [5]:
```
# Checking the columns that exist in the data.

columns = list(kc_data.columns)
print(columns)
```

```
['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']
```

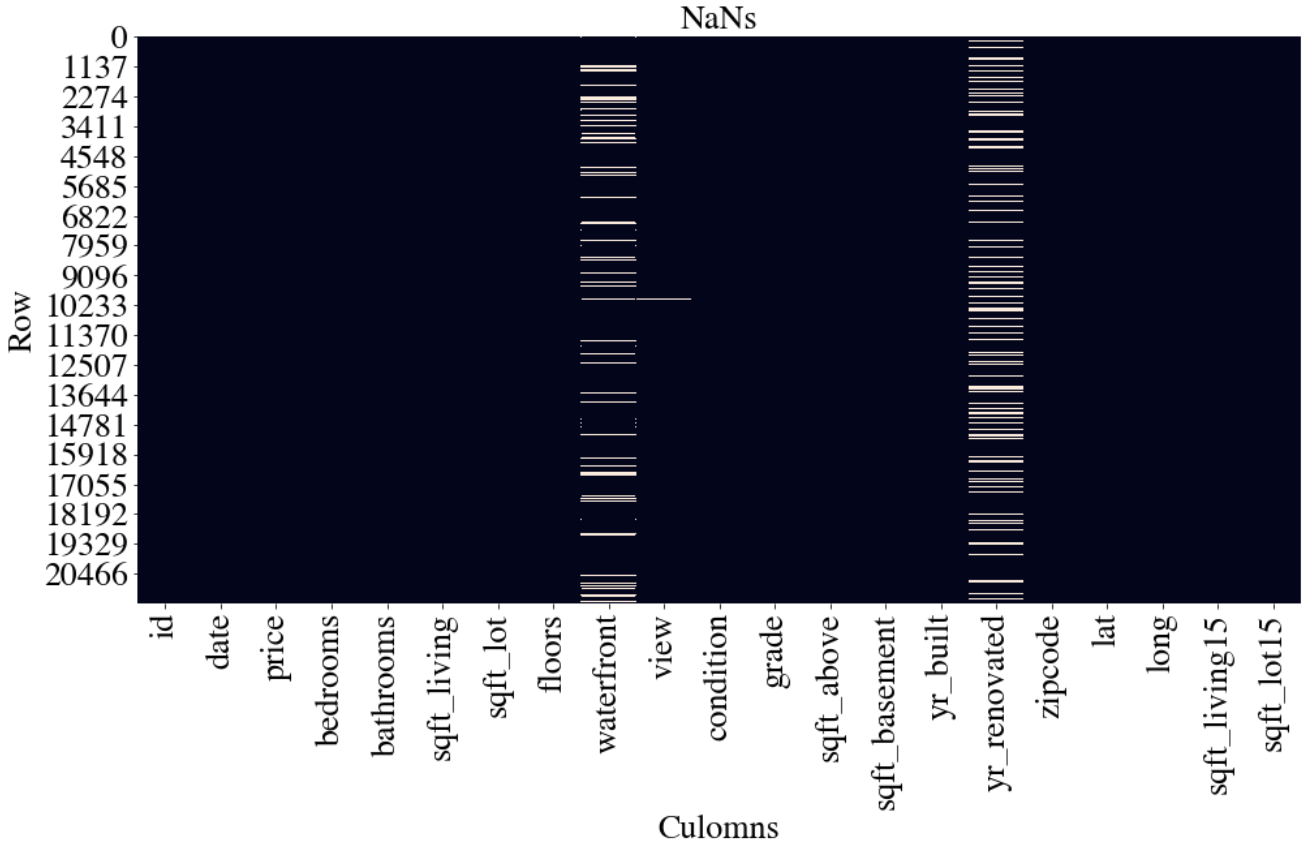
In [6]:
```
kc_data.isnull().sum()
```

Out[6]:
```
id                0
date              0
price             0
bedrooms          0
bathrooms         0
sqft_living       0
sqft_lot          0
```

```
floors              0
waterfront       2376
view               63
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated     3842
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

In [7]:

```
'''Visualizing the null values using heatmap. This allows me to see
the big picture of the data more clearly.'''

fig, ax = plt.subplots(figsize=(16,8))

plt.tick_params(labelsize=22)

sns.heatmap(kc_data.isnull(), cbar=False)


plt.title("NaNs",fontsize=26)
plt.xlabel('Culomns',fontsize=26)
plt.ylabel('Row',fontsize=26)
plt.tick_params(axis='both', which='major', labelsize=26)

plt.show()
```



Checking the percentage of null values to determined whether I can delete raws of the respective NaN values and not loose a significant amount of data.

In [8]:

```
percent_null = kc_data.isnull().sum() * 100 / len(kc_data)

missing_value_kc_data = pd.DataFrame({'column_name': kc_data.columns,
                                      'percent_missing': percent_null})
```

```
percent_null
```

Out[8]:
```
id               0.000000
date             0.000000
price            0.000000
bedrooms         0.000000
bathrooms        0.000000
sqft_living      0.000000
sqft_lot         0.000000
floors           0.000000
waterfront      11.001528
view             0.291707
condition        0.000000
grade            0.000000
sqft_above       0.000000
sqft_basement    0.000000
yr_built         0.000000
yr_renovated    17.789508
zipcode          0.000000
lat              0.000000
long             0.000000
sqft_living15    0.000000
sqft_lot15       0.000000
dtype: float64
```

View column has a small number of null values, therefore we can remove the rows in which the view column appears as NaN.

In [9]:
```
# Let's drop all the rows in which there is NaNs in the view column.
kc_data = kc_data.dropna(subset=['view'])
```

Year renovated and waterfront show a larger number of null values. I will replace the null with zero for the years renovated and then I will change it to the integer type of data.

In [10]:
```
kc_data['yr_renovated'] = kc_data['yr_renovated'].fillna(0)
```

In [11]:
```
kc_data['yr_renovated'] = kc_data['yr_renovated'].astype(int)
```

In [12]:
```
kc_data['yr_renovated'].value_counts()
```

Out[12]:
```
0       20791
2014       73
2003       31
2013       31
2007       30
          ...
1946        1
1951        1
1948        1
1953        1
1976        1
Name: yr_renovated, Length: 70, dtype: int64
```

Examining waterfront, the percentage of the missing data is 11% and we will be left with 19,164 eateries. Therefore, I decided to clean it by removing the respective rows. There is a '?' in the data.

In [13]:
```
kc_data.dropna(subset=['waterfront'], inplace=True)
```

In [14]:
```
# We will run the is sum of null code again to see what's left.
kc_data.isnull().sum()
```

Out[14]:
```
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 [15]:
```
kc_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19164 entries, 1 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             19164 non-null  int64
 1   date           19164 non-null  datetime64[ns]
 2   price          19164 non-null  float64
 3   bedrooms       19164 non-null  int64
 4   bathrooms      19164 non-null  float64
 5   sqft_living    19164 non-null  int64
 6   sqft_lot       19164 non-null  int64
 7   floors         19164 non-null  float64
 8   waterfront     19164 non-null  object
 9   view           19164 non-null  object
 10  condition      19164 non-null  object
 11  grade          19164 non-null  object
 12  sqft_above     19164 non-null  int64
 13  sqft_basement  19164 non-null  object
 14  yr_built       19164 non-null  int64
 15  yr_renovated   19164 non-null  int64
 16  zipcode        19164 non-null  int64
 17  lat            19164 non-null  float64
 18  long           19164 non-null  float64
 19  sqft_living15  19164 non-null  int64
 20  sqft_lot15     19164 non-null  int64
dtypes: datetime64[ns](1), float64(5), int64(10), object(5)
memory usage: 3.2+ MB
```

The data type for sqft_basement is shown to be 'object' and is supposed to be an integer or float. Scanning the sqft basement values to understand what values appear as objects.

In [16]:
```
# sqft_basement  21534 non-null  object should be a number
kc_data['sqft_basement'].unique()
```

Out[16]:
```
array(['400.0', '0.0', '910.0', '1530.0', '?', '730.0', '300.0', '970.0',
       '760.0', '720.0', '700.0', '820.0', '780.0', '790.0', '330.0',
       '1620.0', '360.0', '588.0', '1510.0', '410.0', '990.0', '600.0',
       '550.0', '1000.0', '1600.0', '1700.0', '500.0', '1040.0', '880.0',
       '1010.0', '240.0', '265.0', '290.0', '800.0', '540.0', '560.0',
       '840.0', '770.0', '570.0', '1490.0', '620.0', '1250.0', '1270.0',
       '120.0', '650.0', '180.0', '1130.0', '450.0', '1640.0', '1460.0',
       '1020.0', '1030.0', '750.0', '640.0', '1070.0', '490.0', '1310.0',
       '630.0', '2000.0', '390.0', '430.0', '210.0', '1950.0', '440.0',
       '220.0', '1160.0', '860.0', '580.0', '2060.0', '1820.0', '1180.0',
       '380.0', '200.0', '1150.0', '1200.0', '680.0', '1450.0', '1170.0',
       '1080.0', '960.0', '280.0', '870.0', '1100.0', '1400.0', '530.0',
       '660.0', '1220.0', '900.0', '420.0', '1580.0', '1380.0', '475.0',
       '690.0', '270.0', '350.0', '935.0', '710.0', '1370.0', '980.0',
       '850.0', '1470.0', '160.0', '950.0', '460.0', '50.0', '1900.0',
       '340.0', '470.0', '370.0', '140.0', '480.0', '1760.0', '130.0',
       '520.0', '890.0', '1110.0', '150.0', '1720.0', '810.0', '190.0',
       '1290.0', '670.0', '1800.0', '1120.0', '60.0', '1050.0', '940.0',
       '310.0', '930.0', '1390.0', '610.0', '1830.0', '1300.0', '510.0',
       '1590.0', '920.0', '1320.0', '1420.0', '1240.0', '1960.0',
       '1560.0', '2020.0', '1190.0', '2110.0', '1280.0', '250.0',
       '1230.0', '170.0', '1780.0', '830.0', '1330.0', '1410.0', '590.0',
       '1500.0', '1140.0', '260.0', '100.0', '320.0', '1480.0', '1260.0',
```

```
       '1284.0', '1670.0', '1350.0', '740.0', '2570.0', '1060.0',
       '1090.0', '110.0', '2500.0', '90.0', '1940.0', '1550.0', '2350.0',
       '2490.0', '1340.0', '1481.0', '1360.0', '1135.0', '1520.0',
       '1850.0', '1660.0', '2130.0', '2600.0', '243.0', '1210.0',
       '1024.0', '1798.0', '1610.0', '1440.0', '1690.0', '1570.0',
       '1650.0', '1910.0', '1630.0', '2360.0', '1852.0', '2400.0',
       '1790.0', '2150.0', '230.0', '70.0', '1430.0', '1680.0', '2100.0',
       '3000.0', '1870.0', '1710.0', '2030.0', '875.0', '1540.0',
       '2850.0', '2170.0', '506.0', '906.0', '145.0', '2040.0', '784.0',
       '1750.0', '374.0', '518.0', '2720.0', '2730.0', '1840.0', '3480.0',
       '1920.0', '2330.0', '1860.0', '2050.0', '4820.0', '1913.0', '80.0',
       '2010.0', '3260.0', '2200.0', '415.0', '1730.0', '652.0', '2196.0',
       '1930.0', '1810.0', '40.0', '2080.0', '2580.0', '1548.0', '1740.0',
       '235.0', '861.0', '1890.0', '2220.0', '792.0', '2070.0', '4130.0',
       '2090.0', '2250.0', '2240.0', '2160.0', '1990.0', '768.0', '515.0',
       '2550.0', '435.0', '1008.0', '2300.0', '2610.0', '666.0', '3500.0',
       '172.0', '2190.0', '1245.0', '1525.0', '1880.0', '862.0', '946.0',
       '1281.0', '414.0', '276.0', '1248.0', '602.0', '516.0', '176.0',
       '225.0', '266.0', '283.0', '2310.0', '10.0', '1770.0', '2120.0',
       '295.0', '207.0', '915.0', '556.0', '417.0', '143.0', '508.0',
       '2810.0', '20.0', '274.0', '248.0'], dtype=object)
```

I will replace it and 0 with a NaN and then drop the respective rows to remove it from the data.

In [17]:
```
kc_data.sqft_basement.replace('?' and '0', np.nan ,inplace = True)
```

In [18]:
```
kc_data.sqft_basement.replace('0.0', np.nan, inplace = True)
```

In [19]:
```
kc_data.sqft_basement.replace('?', np.nan, inplace = True)
```

In [20]:
```
# Dropping NaNs from sqft_basement
kc_data.dropna(subset=['sqft_basement'],inplace =True)
```

In [21]:
```
kc_data['sqft_basement'].unique()
```

Out[21]:
```
array(['400.0', '910.0', '1530.0', '730.0', '300.0', '970.0', '760.0',
       '720.0', '700.0', '820.0', '780.0', '790.0', '330.0', '1620.0',
       '360.0', '588.0', '1510.0', '410.0', '990.0', '600.0', '550.0',
       '1000.0', '1600.0', '1700.0', '500.0', '1040.0', '880.0', '1010.0',
       '240.0', '265.0', '290.0', '800.0', '540.0', '560.0', '840.0',
       '770.0', '570.0', '1490.0', '620.0', '1250.0', '1270.0', '120.0',
       '650.0', '180.0', '1130.0', '450.0', '1640.0', '1460.0', '1020.0',
       '1030.0', '750.0', '640.0', '1070.0', '490.0', '1310.0', '630.0',
       '2000.0', '390.0', '430.0', '210.0', '1950.0', '440.0', '220.0',
       '1160.0', '860.0', '580.0', '2060.0', '1820.0', '1180.0', '380.0',
       '200.0', '1150.0', '1200.0', '680.0', '1450.0', '1170.0', '1080.0',
       '960.0', '280.0', '870.0', '1100.0', '1400.0', '530.0', '660.0',
       '1220.0', '900.0', '420.0', '1580.0', '1380.0', '475.0', '690.0',
       '270.0', '350.0', '935.0', '710.0', '1370.0', '980.0', '850.0',
       '1470.0', '160.0', '950.0', '460.0', '50.0', '1900.0', '340.0',
       '470.0', '370.0', '140.0', '480.0', '1760.0', '130.0', '520.0',
       '890.0', '1110.0', '150.0', '1720.0', '810.0', '190.0', '1290.0',
       '670.0', '1800.0', '1120.0', '60.0', '1050.0', '940.0', '310.0',
       '930.0', '1390.0', '610.0', '1830.0', '1300.0', '510.0', '1590.0',
       '920.0', '1320.0', '1420.0', '1240.0', '1960.0', '1560.0',
       '2020.0', '1190.0', '2110.0', '1280.0', '250.0', '1230.0', '170.0',
       '1780.0', '830.0', '1330.0', '1410.0', '590.0', '1500.0', '1140.0',
       '260.0', '100.0', '320.0', '1480.0', '1260.0', '1284.0', '1670.0',
       '1350.0', '740.0', '2570.0', '1060.0', '1090.0', '110.0', '2500.0',
       '90.0', '1940.0', '1550.0', '2350.0', '2490.0', '1340.0', '1481.0',
       '1360.0', '1135.0', '1520.0', '1850.0', '1660.0', '2130.0',
       '2600.0', '243.0', '1210.0', '1024.0', '1798.0', '1610.0',
       '1440.0', '1690.0', '1570.0', '1650.0', '1910.0', '1630.0',
       '2360.0', '1852.0', '2400.0', '1790.0', '2150.0', '230.0', '70.0',
       '1430.0', '1680.0', '2100.0', '3000.0', '1870.0', '1710.0',
       '2030.0', '875.0', '1540.0', '2850.0', '2170.0', '506.0', '906.0',
       '145.0', '2040.0', '784.0', '1750.0', '374.0', '518.0', '2720.0',
       '2730.0', '1840.0', '3480.0', '1920.0', '2330.0', '1860.0',
       '2050.0', '4820.0', '1913.0', '80.0', '2010.0', '3260.0', '2200.0',
       '415.0', '1730.0', '652.0', '2196.0', '1930.0', '1810.0', '40.0',
       '2080.0', '2580.0', '1548.0', '1740.0', '235.0', '861.0', '1890.0',
```

```
       '2220.0', '792.0', '2070.0', '4130.0', '2090.0', '2250.0',
       '2240.0', '2160.0', '1990.0', '768.0', '515.0', '2550.0', '435.0',
       '1008.0', '2300.0', '2610.0', '666.0', '3500.0', '172.0', '2190.0',
       '1245.0', '1525.0', '1880.0', '862.0', '946.0', '1281.0', '414.0',
       '276.0', '1248.0', '602.0', '516.0', '176.0', '225.0', '266.0',
       '283.0', '2310.0', '10.0', '1770.0', '2120.0', '295.0', '207.0',
       '915.0', '556.0', '417.0', '143.0', '508.0', '2810.0', '20.0',
       '274.0', '248.0'], dtype=object)
```

In [22]:
```
kc_data['sqft_basement'] = kc_data['sqft_basement'].str.split \
('.',n=1, expand = True)
```

In [23]:
```
kc_data['sqft_basement'] = kc_data['sqft_basement'].astype(int)
```

In [24]:
```
kc_data['grade']= kc_data['grade'].astype(str)
```

In [25]:
```
kc_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7370 entries, 1 to 21591
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype         
---  ------         --------------  -----         
 0   id             7370 non-null   int64         
 1   date           7370 non-null   datetime64[ns]
 2   price          7370 non-null   float64       
 3   bedrooms       7370 non-null   int64         
 4   bathrooms      7370 non-null   float64       
 5   sqft_living    7370 non-null   int64         
 6   sqft_lot       7370 non-null   int64         
 7   floors         7370 non-null   float64       
 8   waterfront     7370 non-null   object        
 9   view           7370 non-null   object        
 10  condition      7370 non-null   object        
 11  grade          7370 non-null   object        
 12  sqft_above     7370 non-null   int64         
 13  sqft_basement  7370 non-null   int64         
 14  yr_built       7370 non-null   int64         
 15  yr_renovated   7370 non-null   int64         
 16  zipcode        7370 non-null   int64         
 17  lat            7370 non-null   float64       
 18  long           7370 non-null   float64       
 19  sqft_living15  7370 non-null   int64         
 20  sqft_lot15     7370 non-null   int64         
dtypes: datetime64[ns](1), float64(5), int64(11), object(4)
memory usage: 1.2+ MB
```

In [26]:
```
kc_data.dropna(subset=['sqft_basement'], inplace = True)
```

In [27]:
```
# Double checking that the '?' was removed.

kc_data.sqft_basement.unique()
```

Out[27]:
```
array([ 400,  910, 1530,  730,  300,  970,  760,  720,  700,  820,  780,
        790,  330, 1620,  360,  588, 1510,  410,  990,  600,  550, 1000,
       1600, 1700,  500, 1040,  880, 1010,  240,  265,  290,  800,  540,
        560,  840,  770,  570, 1490,  620, 1250, 1270,  120,  650,  180,
       1130,  450, 1640, 1460, 1020, 1030,  750,  640, 1070,  490, 1310,
        630, 2000,  390,  430,  210, 1950,  440,  220, 1160,  860,  580,
       2060, 1820, 1180,  380,  200, 1150, 1200,  680, 1450, 1170, 1080,
        960,  280,  870, 1100, 1400,  530,  660, 1220,  900,  420, 1580,
       1380,  475,  690,  270,  350,  935,  710, 1370,  980,  850, 1470,
        160,  950,  460,   50, 1900,  340,  470,  370,  140,  480, 1760,
        130,  520,  890, 1110,  150, 1720,  810,  190, 1290,  670, 1800,
       1120,   60, 1050,  940,  310,  930, 1390,  610, 1830, 1300,  510,
       1590,  920, 1320, 1420, 1240, 1960, 1560, 2020, 1190, 2110, 1280,
        250, 1230,  170, 1780,  830, 1330, 1410,  590, 1500, 1140,  260,
        100,  320, 1480, 1260, 1284, 1670, 1350,  740, 2570, 1060, 1090,
        110, 2500,   90, 1940, 1550, 2350, 2490, 1340, 1481, 1360, 1135,
       1520, 1850, 1660, 2130, 2600,  243, 1210, 1024, 1798, 1610, 1440,
```

```
1690, 1570, 1650, 1910, 1630, 2360, 1852, 2400, 1790, 2150,  230,
  70, 1430, 1680, 2100, 3000, 1870, 1710, 2030,  875, 1540, 2850,
2170,  506,  906,  145, 2040,  784, 1750,  374,  518, 2720, 2730,
1840, 3480, 1920, 2330, 1860, 2050, 4820, 1913,   80, 2010, 3260,
2200,  415, 1730,  652, 2196, 1930, 1810,   40, 2080, 2580, 1548,
1740,  235,  861, 1890, 2220,  792, 2070, 4130, 2090, 2250, 2240,
2160, 1990,  768,  515, 2550,  435, 1008, 2300, 2610,  666, 3500,
 172, 2190, 1245, 1525, 1880,  862,  946, 1281,  414,  276, 1248,
 602,  516,  176,  225,  266,  283, 2310,   10, 1770, 2120,  295,
 207,  915,  556,  417,  143,  508, 2810,   20,  274,  248])
```

In [28]:
```
'''Creating two new columns, 'month' and 'year' by extracting them
from the date column. This will help me detect any seasonality trends.'''

def extract_date(df,column):
    kc_data[column+"year"] = kc_data[column].apply(lambda x: x.year)
    kc_data[column+"_month"] = kc_data[column].apply(lambda x: x.month)
```

In [29]:
```
extract_date(kc_data,'date')
```

In [30]:
```
kc_data.head()
```

Out[30]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	sqft_baseme
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	4
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	9
5	7237550310	2014-05-12	1230000.0	4	4.50	5420	101930	1.0	NO	NONE	...	15
8	2414600126	2015-04-15	229500.0	3	1.00	1780	7470	1.0	NO	NONE	...	7
11	9212900260	2014-05-27	468000.0	2	1.00	1160	6000	1.0	NO	NONE	...	3

5 rows × 23 columns

In [31]:
```
# dropping 'data' column since we do not need it anymore
kc_data.drop(['date'], axis=1, inplace=True)
```

In [32]:
```
# Using describe method to check for outliers.

kc_data.describe()
```

Out[32]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above
count	7.370000e+03	7.370000e+03	7370.000000	7370.000000	7370.000000	7370.000000	7370.000000	7370.000000
mean	4.608717e+09	6.236722e+05	3.558480	2.272693	2313.011805	13188.630665	1.324830	1573.544912
std	2.870696e+09	4.497373e+05	1.014971	0.777863	959.555858	30776.711805	0.479015	726.383103
min	2.800031e+06	1.000000e+05	1.000000	0.500000	680.000000	572.000000	1.000000	480.000000
25%	2.145425e+09	3.750000e+05	3.000000	1.750000	1680.000000	5000.000000	1.000000	1117.000000
50%	3.971701e+09	5.130000e+05	3.000000	2.250000	2100.000000	7520.000000	1.000000	1370.000000
75%	7.338402e+09	7.110000e+05	4.000000	2.750000	2700.000000	10660.750000	2.000000	1780.000000
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	871200.000000	3.500000	9410.000000

Continuing Scrubbing

- There are some categorical variables such as: waterfront, view, condition, grade, yr_built and zip code. I will handle these later on.
- The maximum square feet is 13,450 and the minimum is 680 which suggests widely distributed data.
- In the bedroom column the maximum number is 33 and this seems to be an outlier or perhaps even a place holder, so I will remove that data point below.

In [33]:
```
# kc_data['bedrooms'].idxmax()
```

In [34]:
```
# I will remove 33 in the bedrooms column given that it is an outlier
# and I will use the idxmax() method.

kc_data['bedrooms'] = kc_data['bedrooms'].drop(kc_data['bedrooms'].idxmax())
kc_data.describe()
```

Out[34]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above
count	7.370000e+03	7.370000e+03	7369.000000	7370.000000	7370.000000	7370.000000	7370.000000	7370.000000
mean	4.608717e+09	6.236722e+05	3.554485	2.272693	2313.011805	13188.630665	1.324830	1573.544912
std	2.870696e+09	4.497373e+05	0.955325	0.777863	959.555858	30776.711805	0.479015	726.383103
min	2.800031e+06	1.000000e+05	1.000000	0.500000	680.000000	572.000000	1.000000	480.000000
25%	2.145425e+09	3.750000e+05	3.000000	1.750000	1680.000000	5000.000000	1.000000	1117.000000
50%	3.971701e+09	5.130000e+05	3.000000	2.250000	2100.000000	7520.000000	1.000000	1370.000000
75%	7.338402e+09	7.110000e+05	4.000000	2.750000	2700.000000	10660.750000	2.000000	1780.000000
max	9.900000e+09	7.700000e+06	11.000000	8.000000	13540.000000	871200.000000	3.500000	9410.000000

In [35]:
```
# Confirming that there are no missing values.

missing_value_kc_data
```

Out[35]:

	column_name	percent_missing
id	id	0.000000
date	date	0.000000
price	price	0.000000
bedrooms	bedrooms	0.000000
bathrooms	bathrooms	0.000000
sqft_living	sqft_living	0.000000
sqft_lot	sqft_lot	0.000000
floors	floors	0.000000
waterfront	waterfront	11.001528
view	view	0.291707
condition	condition	0.000000
grade	grade	0.000000
sqft_above	sqft_above	0.000000
sqft_basement	sqft_basement	0.000000
yr_built	yr_built	0.000000
yr_renovated	yr_renovated	17.789508
zipcode	zipcode	0.000000
lat	lat	0.000000
long	long	0.000000

	column_name	percent_missing
sqft_living15	sqft_living15	0.000000
sqft_lot15	sqft_lot15	0.000000

The data in both condition and view columns contain numbers and words in them. I will convert the data type to integer by replacing it with numbers, keeping the range of ranking.

In [36]:
```
kc_data['grade'].unique()
```

Out[36]:
```
array(['7 Average', '11 Excellent', '9 Better', '8 Good', '5 Fair',
       '6 Low Average', '10 Very Good', '12 Luxury', '13 Mansion',
       '4 Low'], dtype=object)
```

In [37]:
```
kc_data['grade'] = kc_data['grade'].str.extract(r'(\d+)', expand = True)
kc_data['grade'].unique()
```

Out[37]:
```
array(['7', '11', '9', '8', '5', '6', '10', '12', '13', '4'], dtype=object)
```

In [38]:
```
kc_data['grade'] = kc_data['grade'].astype(int)
```

In [39]:
```
# Setting up encoding by assigning an integer value for each unique category
dic_cond = {'Poor' : 1, 'Fair' : 2, 'Average': 3, 'Good' : 4, 'Very Good': 5}
dic_view = {'NONE':1,'FAIR':2, 'AVERAGE':3,'GOOD':4 , 'EXCELLENT':5}
#dic_waterfront ={'NO':0, 'YES':1}
kc_data['condition'] = kc_data['condition'].map(dic_cond)
kc_data['view'] = kc_data['view'].map(dic_view)
#kc_data['waterfront'] = kc_data['waterfront'].map(dic_waterfront)
kc_data.head()
```

Out[39]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_base
1	6414100192	538000.0	3.0	2.25	2570	7242	2.0	NO	1	3	...	
3	2487200875	604000.0	4.0	3.00	1960	5000	1.0	NO	1	5	...	
5	7237550310	1230000.0	4.0	4.50	5420	101930	1.0	NO	1	3	...	
8	2414600126	229500.0	3.0	1.00	1780	7470	1.0	NO	1	3	...	
11	9212900260	468000.0	2.0	1.00	1160	6000	1.0	NO	1	4	...	

5 rows × 22 columns

In [40]:
```
kc_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7370 entries, 1 to 21591
Data columns (total 22 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             7370 non-null   int64  
 1   price          7370 non-null   float64
 2   bedrooms       7369 non-null   float64
 3   bathrooms      7370 non-null   float64
 4   sqft_living    7370 non-null   int64  
 5   sqft_lot       7370 non-null   int64  
 6   floors         7370 non-null   float64
 7   waterfront     7370 non-null   object 
 8   view           7370 non-null   int64  
 9   condition      7370 non-null   int64  
 10  grade          7370 non-null   int64  
 11  sqft_above     7370 non-null   int64  
 12  sqft_basement  7370 non-null   int64  
 13  yr_built       7370 non-null   int64  
 14  yr_renovated   7370 non-null   int64  
 15  zipcode        7370 non-null   int64  
 16  lat            7370 non-null   float64
```

```
 17  long           7370 non-null   float64
 18  sqft_living15  7370 non-null   int64
 19  sqft_lot15     7370 non-null   int64
 20  dateyear       7370 non-null   int64
 21  date_month     7370 non-null   int64
dtypes: float64(6), int64(15), object(1)
memory usage: 1.5+ MB
```

In [41]:
```
kc_data.head()
```

Out[41]:

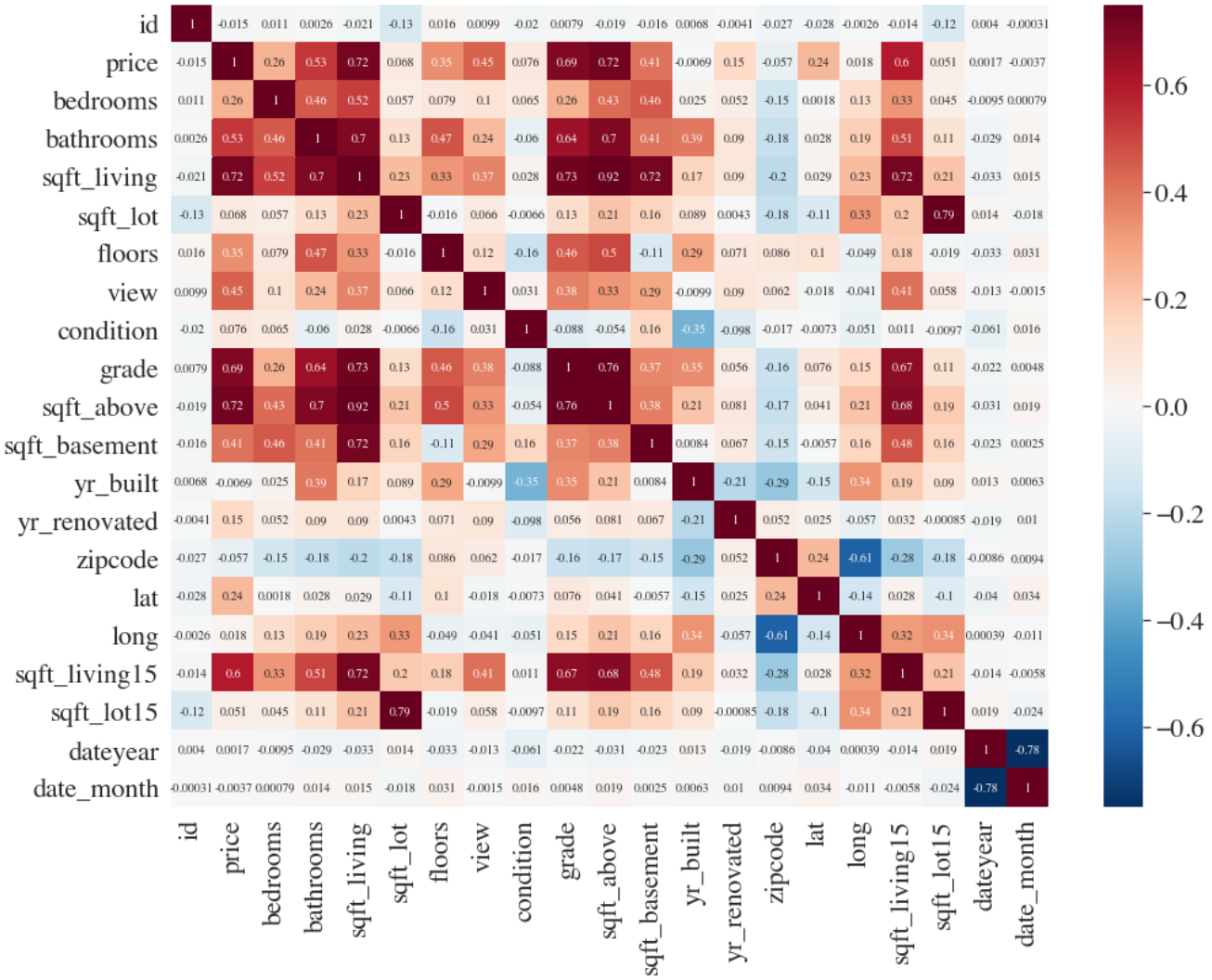
	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_base
1	6414100192	538000.0	3.0	2.25	2570	7242	2.0	NO	1	3	...	
3	2487200875	604000.0	4.0	3.00	1960	5000	1.0	NO	1	5	...	
5	7237550310	1230000.0	4.0	4.50	5420	101930	1.0	NO	1	3	...	
8	2414600126	229500.0	3.0	1.00	1780	7470	1.0	NO	1	3	...	
11	9212900260	468000.0	2.0	1.00	1160	6000	1.0	NO	1	4	...	

5 rows × 22 columns

Exploratory Data Analysis

Correlation

In [42]:
```
corr  = kc_data.corr()
plt.figure(figsize=(16, 12))
sns.set(font_scale=2)
isns.set_context(fontfamily="times")
heatmap = sns.heatmap(corr, annot=True, linewidths=0, vmin=-0.75,
                      vmax=0.75, cmap="RdBu_r")
```



In our data, I encountered 45 houses that were resold in 2014 and 2015. The majority of these were resold for a higher price. The grade or condition of the houses did not change, but the resale took place in a different time of the year.

In [43]:
```
#  Creating a new database for the duplicate (resale) data
kc_data_dublicate = kc_data[kc_data.duplicated(subset=['id'],keep= False)]
kc_data_dublicate.head()
```

Out[43]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_b
93	6021501535	430000.0	3.0	1.50	1580	5000	1.0	NO	1	3	...	
94	6021501535	700000.0	3.0	1.50	1580	5000	1.0	NO	1	3	...	
313	4139480200	1380000.0	4.0	3.25	4290	12103	1.0	NO	4	3	...	
314	4139480200	1400000.0	4.0	3.25	4290	12103	1.0	NO	4	3	...	
1084	9834200885	360000.0	4.0	2.50	2080	4080	1.0	NO	1	5	...	

5 rows × 22 columns

In [44]:
```
# Extracting only the necessary columns
kc_data_dublicate = kc_data_dublicate[['id', 'date_month', 'price',
                                       'grade','condition']]
kc_data_dublicate
```

Out[44]:

	id	date_month	price	grade	condition
93	6021501535	7	430000.0	8	3
94	6021501535	12	700000.0	8	3

	id	date_month	price	grade	condition
313	4139480200	6	1380000.0	11	3
314	4139480200	12	1400000.0	11	3
1084	9834200885	7	360000.0	7	5
...	...	...	...	...	...
18689	3558900590	3	692500.0	7	3
18976	7856400300	7	1410000.0	10	5
18977	7856400300	3	1510000.0	10	5
19536	643300040	11	481000.0	7	4
19537	643300040	3	719521.0	7	4

90 rows × 5 columns

In [45]:
```
'''Creating a new data frame in which I only include the duplicate data.
Consolidating it using  group by 'id' where one raw represents one house
that was sold and then re-sold at a later point.'''

kc_group_id = kc_data_dublicate.set_index(['id', kc_data_dublicate.groupby('id')
.cumcount()])[['price','date_month','grade','condition']].unstack().add_prefix('price').reset_index()
```

In [46]:
```
kc_group_id.head()
```

Out[46]:

	id	priceprice		pricedate_month		pricegrade		pricecondition	
		price0	price1	price0	price1	price0	price1	price0	price1
0	526059224	260000.0	470000.0	9	2	7	7	3	3
1	641900050	335000.0	499950.0	8	2	7	7	3	3
2	643300040	481000.0	719521.0	11	3	7	7	4	4
3	1139600270	300000.0	310000.0	7	3	8	8	3	3
4	1217000340	185000.0	340000.0	6	2	7	7	4	4

In [47]:
```
kc_group_id.columns
```

Out[47]:
```
MultiIndex([(             'id',       ''),
            (     'priceprice', 'price0'),
            (     'priceprice', 'price1'),
            ('pricedate_month', 'price0'),
            ('pricedate_month', 'price1'),
            (     'pricegrade', 'price0'),
            (     'pricegrade', 'price1'),
            ( 'pricecondition', 'price0'),
            ( 'pricecondition', 'price1')],
           )
```

In [48]:
```
# It turns into ta multi-inex dataframe -
# I will remove the layer by using droplevel()
kc_group_id.columns = kc_group_id.columns.droplevel(level=0)
```

In [49]:
```
# Generating a list of numerizing the houses.
myList = list(range(1, 46))
```

In [50]:
```
kc_group_id['home_no.'] = myList
kc_group_id.head()
```

Out[50]:

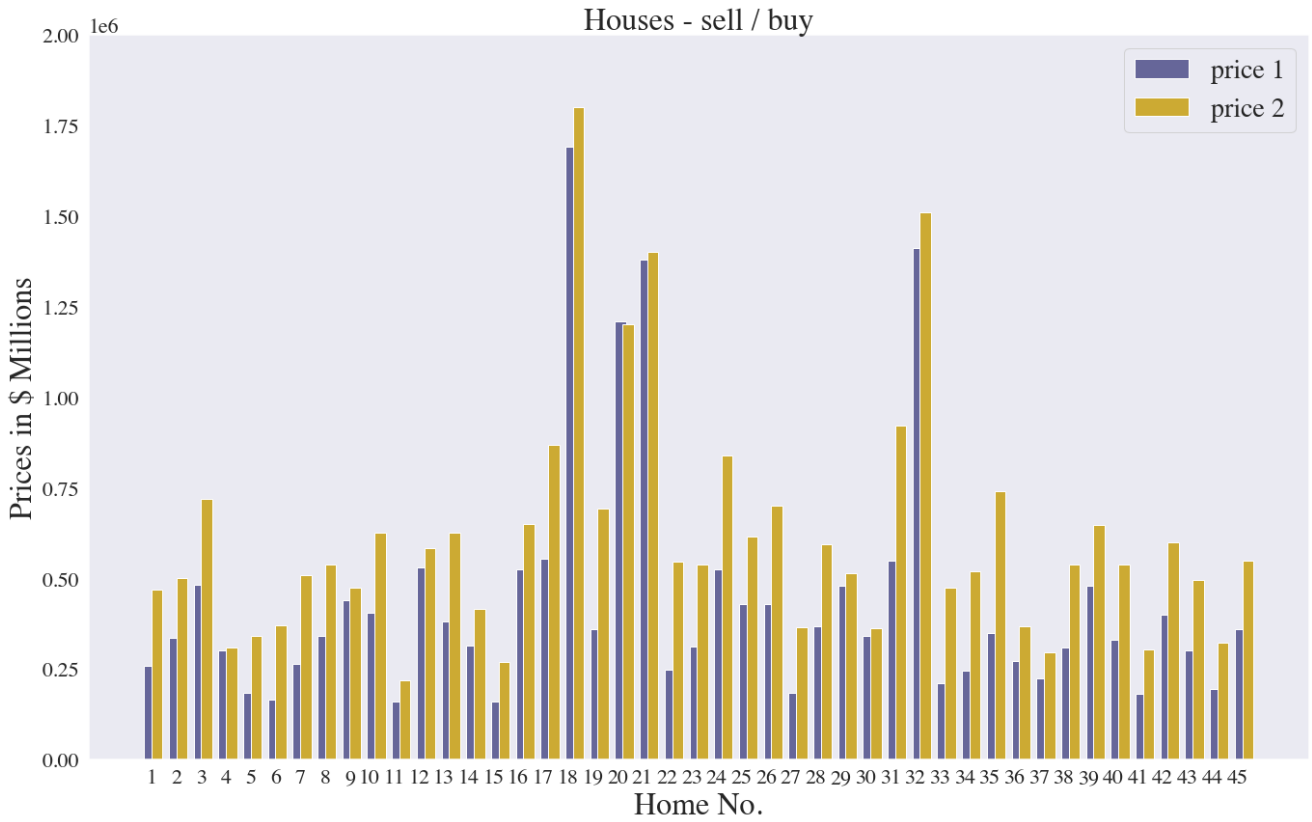
	price0	price1	price0	price1	price0	price1	price0	price1	home_no.

		price0	price1	price0	price1	price0	price1	price0	price1	home_no.
0	526059224	260000.0	470000.0	9	2	7	7	3	3	1
1	641900050	335000.0	499950.0	8	2	7	7	3	3	2
2	643300040	481000.0	719521.0	11	3	7	7	4	4	3
3	1139600270	300000.0	310000.0	7	3	8	8	3	3	4
4	1217000340	185000.0	340000.0	6	2	7	7	4	4	5

In [51]:
```
# Changing column names to clarify.

kc_group_id.columns.values[0] = 'id'
kc_group_id.columns.values[1] = 'price_1'
kc_group_id.columns.values[2] = 'price_2'
kc_group_id.columns.values[3] = 'month_1'
kc_group_id.columns.values[4] = 'month_2'
kc_group_id.columns.values[5] = 'grade_1'
kc_group_id.columns.values[6] = 'grade_2'
kc_group_id.columns.values[5] = 'cond_1'
kc_group_id.columns.values[6] = 'cond_2'
```

In [52]:
```
# Creating a new data frame where hume_no. is the index.
buy_sell = pd.DataFrame(kc_group_id['home_no.'].index)
```

In [53]:
```
marks = buy_sell # setting x-ticks

x = np.arange(len(marks))  # the label locations

# set the plot, format, and labels


fig, ax = plt.subplots(figsize=(19,12))
bar_width = 0.3
ax1 = ax.bar(x - bar_width / 2,
             kc_group_id['price_1'].values,
             width = 0.45,
             color = '#666699',
             label='price 1')
ax2 = ax.bar(x + bar_width / 2,
             kc_group_id['price_2'].values,
             width = 0.45,
             color = '#CCAA33',
             label='price 2')
#ax.yaxis.set_major_formatter(currency) #CCAA33
plt.ylim(0,2000000)

plt.tick_params(labelsize=22)

ax.set_xticks(x + bar_width / 2)
ax.set_xticklabels(kc_group_id['home_no.'].unique())


plt.setp(ax.get_xticklabels(), rotation=0, ha='right')
# cite: https://pythonguides.com/matplotlib-x-axis-label/


ax.grid(color='#AF3150', linestyle='-', linewidth=0.1)
ax.set_xlabel('Home No.',fontsize = 32)
ax.set_ylabel('Prices in $ Millions', fontsize = 32)
# Add title and legends

ax.set_title('Houses - sell / buy', fontsize = 32)
ax.legend(loc="upper right", frameon=True, fontsize=28)
# format the layout and display the visualization
fig.tight_layout()
plt.show()
```



In [54]:
```
# Creating a column that captures the difference of the price
# differences(gross profit).

kc_group_id['price_diff'] = kc_group_id['price_2'] - kc_group_id['price_1']
```

In [55]:
```
# Looking tinto the new dataset
kc_group_id.head()
```

Out[55]:

	id	price_1	price_2	month_1	month_2	cond_1	cond_2	price0	price1	home_no.	price_diff
0	526059224	260000.0	470000.0	9	2	7	7	3	3	1	210000.0
1	641900050	335000.0	499950.0	8	2	7	7	3	3	2	164950.0
2	643300040	481000.0	719521.0	11	3	7	7	4	4	3	238521.0
3	1139600270	300000.0	310000.0	7	3	8	8	3	3	4	10000.0
4	1217000340	185000.0	340000.0	6	2	7	7	4	4	5	155000.0

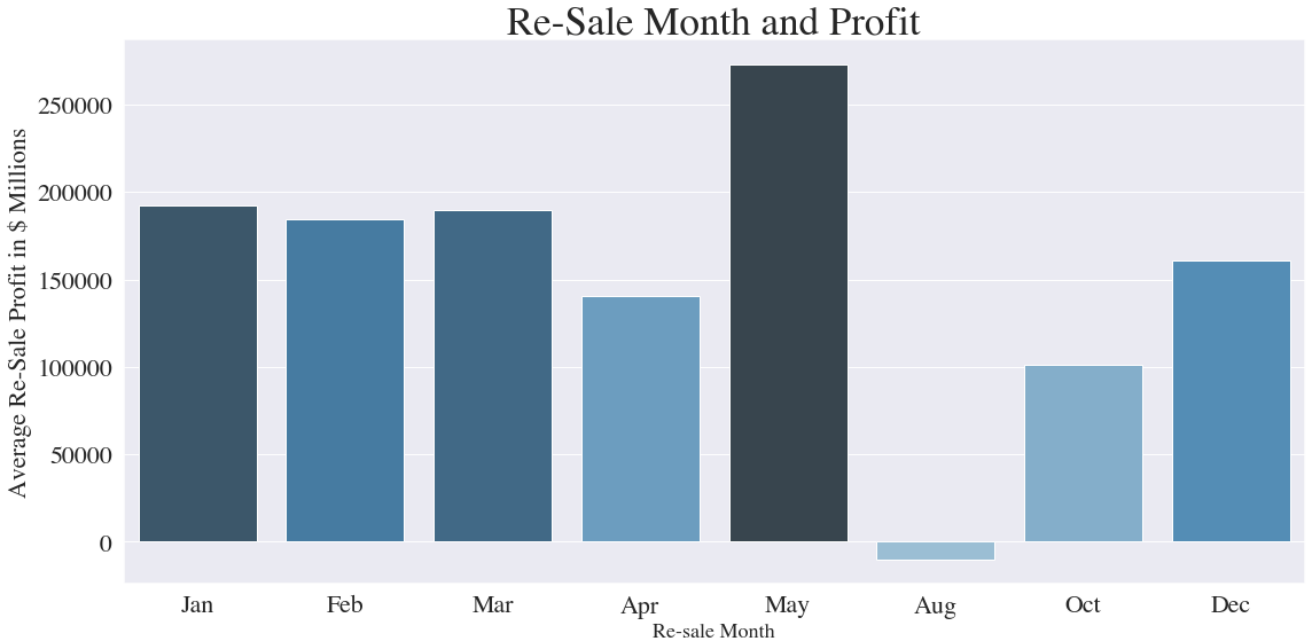
In [56]:
```
# Creating a new data set using groupby of the month when
# the home was sold
group_month = kc_group_id.groupby(['month_2']).mean()
group_month = pd.DataFrame.reset_index(group_month)

group_month.head()
```

Out[56]:

	month_2	id	price_1	price_2	month_1	cond_1	cond_2	price0	price1	home_nc
0	1	5.286512e+09	361483.000000	553625.000000	6.250000	7.000000	7.000000	3.500000	3.500000	25.00000
1	2	4.510416e+09	299475.363636	483804.545455	8.181818	7.272727	7.272727	3.272727	3.272727	20.90909
2	3	4.853603e+09	494596.666667	684534.733333	7.866667	7.400000	7.400000	3.333333	3.333333	21.46666
3	4	6.686515e+09	391100.000000	531714.285714	9.285714	7.428571	7.428571	3.285714	3.285714	31.28571
4	5	2.766601e+09	255500.000000	528470.000000	9.000000	6.500000	6.500000	3.000000	3.000000	14.50000

In [57]:
```
# Creating a function that has bars with range of colores - darker from
# tightest and lighter to the lowset.
def colors_from_values(values: pd.Series, palette_name:str, ascending=True):
    values = values.sort_values(ascending=ascending).reset_index()
    indices = values.sort_values(by=values.columns[0]).index
    palette = sns.color_palette(palette_name, len(values))
    return np.array(palette).take(indices, axis=0)

s = group_month ["price_diff"]
#s2 = total_group_month ["price"]
```

In [58]:
```
# Plot bar displaying the months of the release day and
#making the darkest color to be the highest.

fig, ax = plt.subplots(figsize=(16, 8))

# Create plot here with sns.

sns.barplot(x="month_2", y="price_diff", data=group_month,
            palette=colors_from_values(s, "Blues_d"))

# Lable and define fontsize for main and axis titles.

plt.xlabel('Re-sale Month', fontsize=18)
plt.ylabel('Average Re-Sale Profit in $ Millions', fontsize=22)
plt.title('Re-Sale Month and Profit', fontsize=35)
plt.tick_params(axis='both', which='major', labelsize=22)

# Set x-axis tick labels.

ax.set_xticklabels(['Jan', 'Feb', 'Mar', 'Apr', 'May','Aug','Oct','Dec'])


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



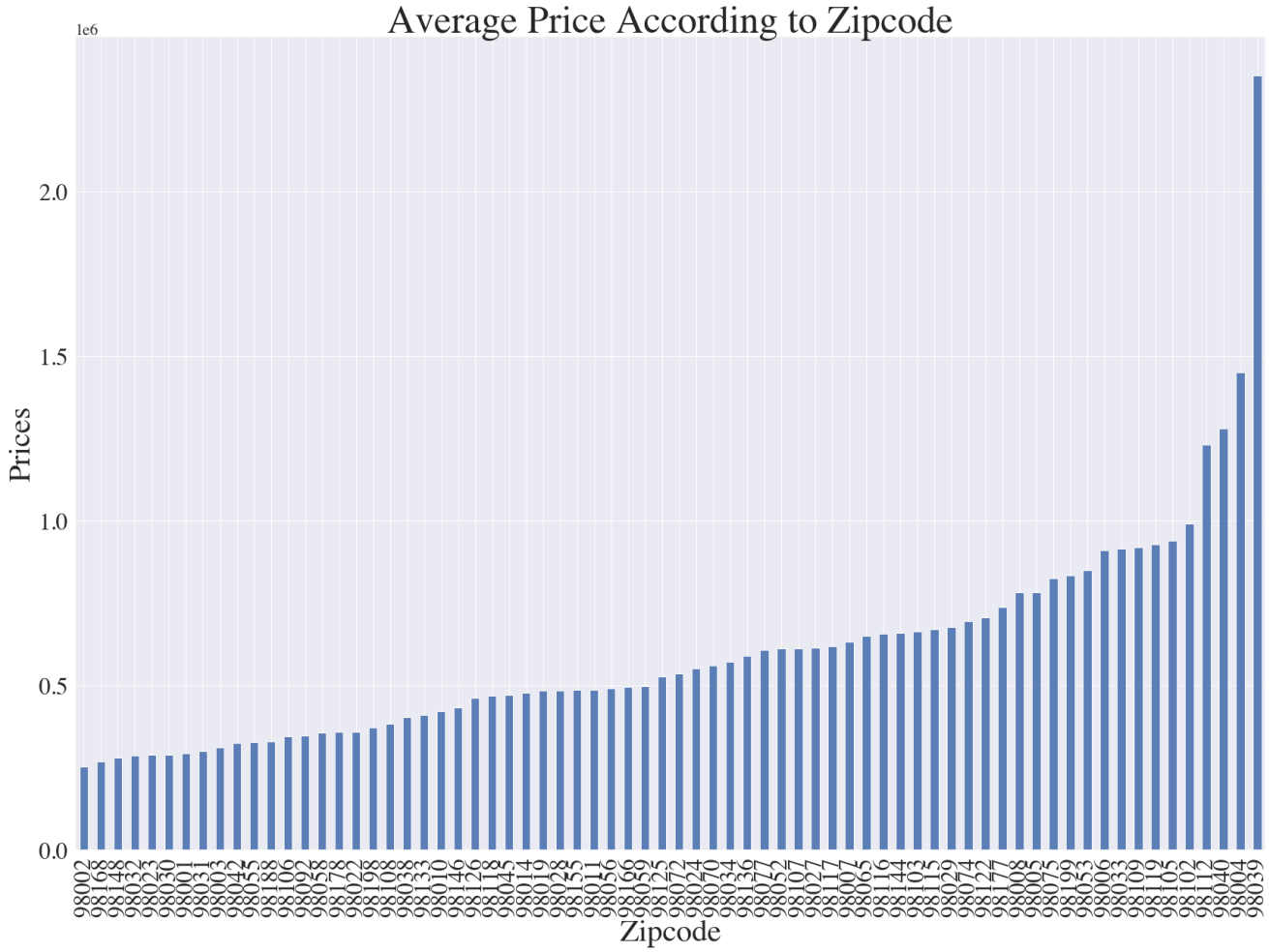
The resale price was highest during the month of May, followed by January and March. In the summer, there were no resales, and those that did take place (August) lost money. This suggests that the timing of the sale makes a difference.

Where houses hold most value?

Zipcode

In [59]:
```
''' will group the zipcodes by price and check their mean
so that I could see if there is any pattern of the prices '''
group_zipcode = kc_data.groupby(['zipcode'])['price'].mean()
```

In [60]:
```
# Let's view the data with a sorted value

plt.figure(figsize=(8, 8))
isns.set_context(fontfamily="times")
group_zipcode = group_zipcode.sort_values()
group_zipcode.plot(kind='bar',x='zipcode',y='price',align='center',
                   alpha=0.9,figsize=(24,18))
# the plot gets saved to 'output.png'

plt.title('Average Price According to Zipcode', fontsize=52)
plt.xticks(rotation = 90,fontsize=32)
plt.yticks(rotation = 0,fontsize=32)
plt.xlabel('Zipcode',fontsize=42)
plt.ylabel('Prices',fontsize=42)
plt.tight_layout()

plt.show()
plt.savefig('output.png')
```



<Figure size 432x288 with 0 Axes>

In [61]:
```
# Creating a new dataset for the top 5% zipcodes
top5p = kc_data.sort_values(by= 'zipcode', ascending = False).head(368)
top5p.head()
```

Out[61]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_l
3153	6821100195	830000.0	4.0	3.00	2020	6000	1.0	NO	1	3	...	

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_l
8678	6822100750	700000.0	3.0	1.75	1500	6000	1.0	NO	1	5	...	
19452	3271800870	1230000.0	4.0	2.25	2020	5800	1.0	NO	4	4	...	
3110	5035300750	850000.0	3.0	1.75	2450	8603	1.0	NO	1	5	...	
3119	3271800850	765000.0	3.0	1.75	2440	5800	1.0	NO	4	4	...	

5 rows × 22 columns

In [62]:
```
# Creating a new dataset for the top 20% zipcodes
top20p = kc_data.sort_values(by= 'price', ascending = False).head(1474)
top20p.head()
```

Out[62]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_b
7245	6762700020	7700000.0	6.0	8.00	12050	27600	2.5	NO	4	4	...	
3910	9808700762	7060000.0	5.0	4.50	10040	37325	2.0	YES	3	3	...	
9245	9208900037	6890000.0	6.0	7.75	9890	31374	2.0	NO	5	3	...	
4407	2470100110	5570000.0	5.0	5.75	9200	35069	2.0	NO	1	3	...	
1446	8907500070	5350000.0	5.0	5.00	8000	23985	2.0	NO	5	3	...	

5 rows × 22 columns

Looking into any 20 % of the most expensive houses with their respective latitude, longitude. Houses seem to be scattered around with high prices being less frequent while the majority of the houses are below $2 million.

In [63]:
```
# Creating a new dataset for the top 20% and mapping out latitude and longitude
top20p_long_lat = top20p[['lat', 'long']]
top20p_long_lat
```

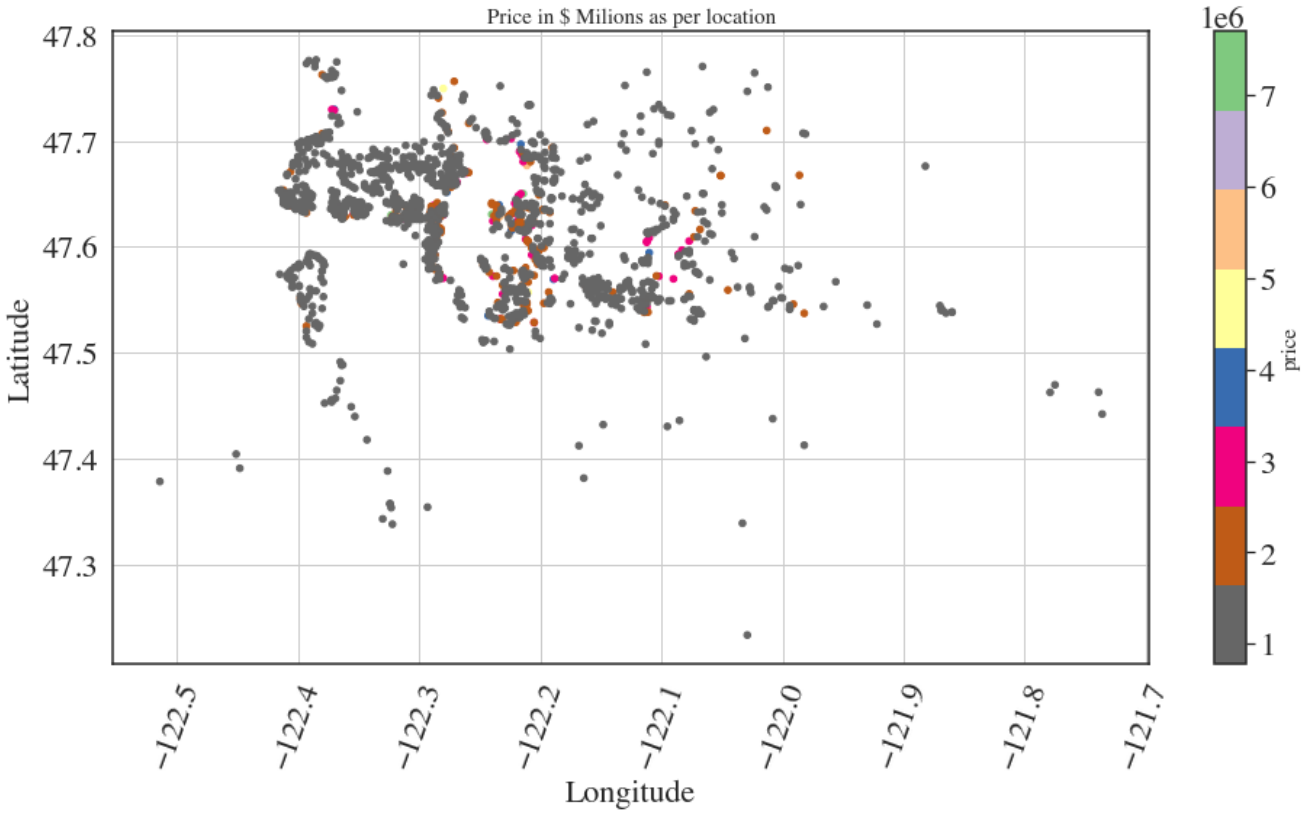
Out[63]:

	lat	long
7245	47.6298	-122.323
3910	47.6500	-122.214
9245	47.6305	-122.240
4407	47.6289	-122.233
1446	47.6232	-122.220
...	...	...
13392	47.6853	-122.305
16371	47.6296	-122.205
3145	47.7027	-122.282
19693	47.6214	-122.062
1604	47.4961	-122.063

1474 rows × 2 columns

In [64]:
```
plt.style.use("seaborn-ticks")
isns.set_context(fontfamily="times")
top20p.plot(kind="scatter", x="long", y="lat", figsize=(16, 8), c="price",
            cmap="Accent_r", colorbar=True, sharex=False)


plt.xticks(rotation = 70)
plt.grid(which='both')
plt.title('Price in $ Milions as per location')
```

```
plt.xlabel('Longitude', fontsize=22)
plt.ylabel('Latitude', fontsize=22)
plt.savefig('output.png')
plt.show()
```



In [65]:
```
# I will group the zipcodes and check their mean so that
# I could see if there is any pattern of the prices
group_zipcode = top20p.groupby(['zipcode'])['price'].mean()
group_zipcode.head()
```

Out[65]:
```
zipcode
98001    8.500000e+05
98003    8.100000e+05
98004    1.606250e+06
98005    9.391482e+05
98006    1.216673e+06
Name: price, dtype: float64
```

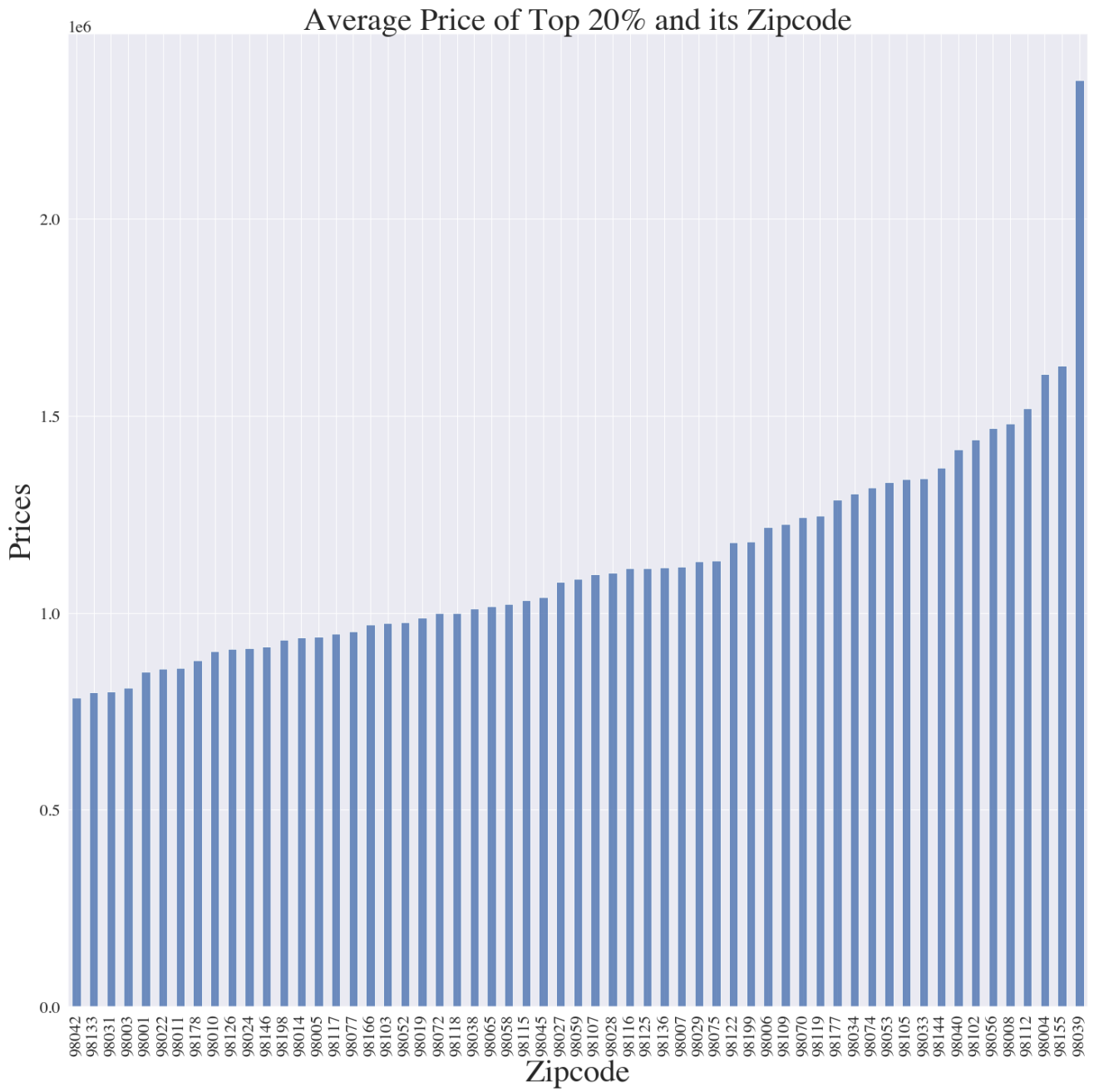
Extracting top and bottom 20 % of the most expensive houses with their respective latitude, longitude, and zip codes.

In [66]:
```
zipcode = top20p.groupby('zipcode', as_index = False)
zipcode
```

Out[66]:
```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x7fc838533610>
```

In [67]:
```
# Let's view the data with a sorted value
plt.figure(figsize=(12, 8))
sns.set(font_scale=2)
isns.set_context(fontfamily="times")

group_zipcode = group_zipcode.sort_values()
group_zipcode.plot(kind='bar',x='zipcode',y='price',align='center',
                   alpha=0.8,figsize=(20,20))
# the plot gets saved to 'output.png'

plt.title('Average Price of Top 20% and its Zipcode',fontsize=42 )
```

```
plt.xticks(rotation = 90)
plt.xlabel('Zipcode', fontsize=42)
plt.ylabel('Prices', fontsize=42)
plt.tight_layout()

plt.show()
plt.savefig('output.png')
```




```
<Figure size 432x288 with 0 Axes>
```

In [68]:

```
# Creating a new dataset for the bottom 20%
bottom20p = kc_data.sort_values(by= 'price', ascending = False).tail(368)
bottom20p
```

Out[68]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_b
9430	4302201085	248000.0	3.0	1.00	1470	7680	1.0	NO	1	3	...	
1619	1310500550	248000.0	4.0	2.25	2320	8760	1.0	NO	1	4	...	
8412	2172000846	248000.0	4.0	2.00	2080	13510	1.0	NO	1	3	...	
4834	5151600480	248000.0	3.0	1.75	1840	19501	1.0	NO	1	4	...	

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_b
4295	2122059160	248000.0	5.0	1.75	2190	16788	1.0	NO	3	3	...	
...	...	...	...	...	...	...	...	...	...	...	...	
12729	5560000650	135000.0	3.0	1.00	1520	8450	1.0	NO	1	2	...	
10376	3361402041	134000.0	3.0	1.00	1270	8508	1.0	NO	1	4	...	
3686	6303401050	132500.0	3.0	0.75	850	8573	1.0	NO	1	3	...	
3481	3352402250	119900.0	2.0	1.00	700	3180	1.0	NO	1	3	...	
5634	7224000980	100000.0	4.0	1.00	1120	2685	1.0	NO	1	3	...	

368 rows × 22 columns

In [69]:
```
# Grouping the bottom 20 % by zipcode
group_zipcode_b = bottom20p.groupby(['zipcode'])['price'].mean()
group_zipcode_b.head()
```

Out[69]:
```
zipcode
98001    213632.521739
98002    218162.500000
98003    223143.518519
98006    247500.000000
98010    200000.000000
Name: price, dtype: float64
```

In [70]:
```
# Grouping the bottom 20 % by zipcode
zipcode_b = bottom20p.groupby('zipcode', as_index = False)
zipcode_b.head()
```

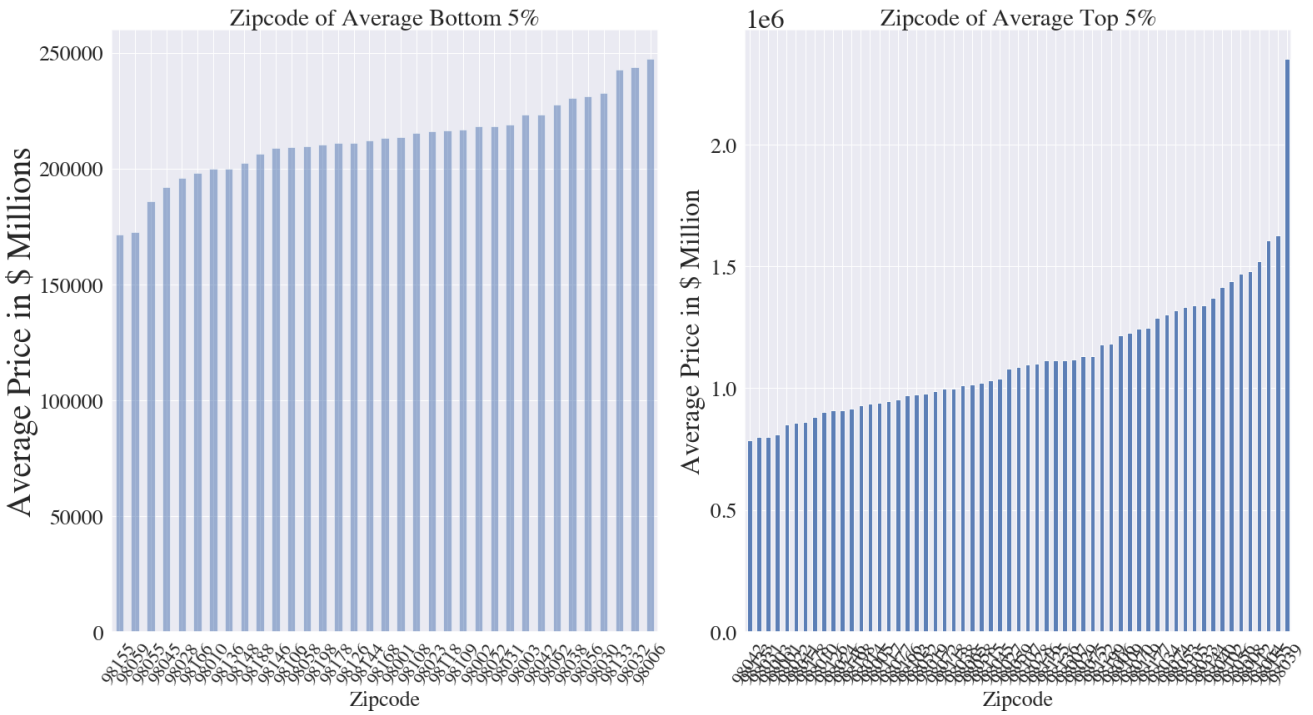
Out[70]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_b
9430	4302201085	248000.0	3.0	1.00	1470	7680	1.0	NO	1	3	...	
1619	1310500550	248000.0	4.0	2.25	2320	8760	1.0	NO	1	4	...	
8412	2172000846	248000.0	4.0	2.00	2080	13510	1.0	NO	1	3	...	
4834	5151600480	248000.0	3.0	1.75	1840	19501	1.0	NO	1	4	...	
4295	2122059160	248000.0	5.0	1.75	2190	16788	1.0	NO	3	3	...	
...	...	...	...	...	...	...	...	...	...	...	...	
2350	7229700105	172500.0	2.0	2.00	1510	20685	1.0	NO	1	2	...	
19547	42000245	171000.0	4.0	2.00	1520	19672	1.0	NO	1	3	...	
9865	1219000473	164950.0	3.0	1.75	1570	15330	1.0	NO	1	3	...	
8716	7883603425	155000.0	3.0	1.00	1250	6250	1.0	NO	1	2	...	
5811	7568700480	153000.0	2.0	1.00	1140	10152	1.0	NO	1	3	...	

135 rows × 22 columns

In [71]:
```
# Comparing the data of the two top and bottom 20%

sns.set(font_scale=3)
plt.figure(2, figsize=(8,8))

#plt.figure(figsize=(18, 12))
isns.set_context(fontfamily="times")
plt.subplot(1,2,1) # two subplots
#sns.histplot(data=waterfront_non, kde=True)
group_zipcode_b = group_zipcode_b.sort_values()
group_zipcode_b.plot(kind='bar',x='zipcode',y='price',
                     alpha=0.5,figsize=(22,12))
# the plot gets saved to 'output.png'
```

```
#sns.set(font="Garamond")
#plt.axvline(np.median(waterfront_non),color='b', linestyle='--')

#m = np.mean(waterfront_non)
#m = round(m,2)

plt.title('Zipcode of Average Bottom 5%', fontsize=29)
plt.xticks(rotation =55, fontsize=22)
plt.yticks(rotation =0, fontsize=26)
plt.xlabel('Zipcode',fontsize=26)
plt.ylabel('Average Price in $ Millions',labelpad=0.3, fontsize=40)


plt.subplot(1,2,2)
group_zipcode = group_zipcode.sort_values()
group_zipcode.plot(kind='bar',x='zipcode',y='price',
                   alpha=0.9,figsize=(22,12))

plt.title('Zipcode of Average Top 5%',fontsize=29);
plt.xticks(rotation =55, fontsize=22)
plt.yticks(rotation =0, fontsize=26)
plt.xlabel('Zipcode',fontsize=26)
plt.ylabel('Average Price in $ Million',labelpad=5,fontsize=32)

plt.tight_layout()

plt.show()
```



Does the view or waterfront play a big role in house prices?

View

Looking into the price distribution in respect to the ranking of view using a box plot.

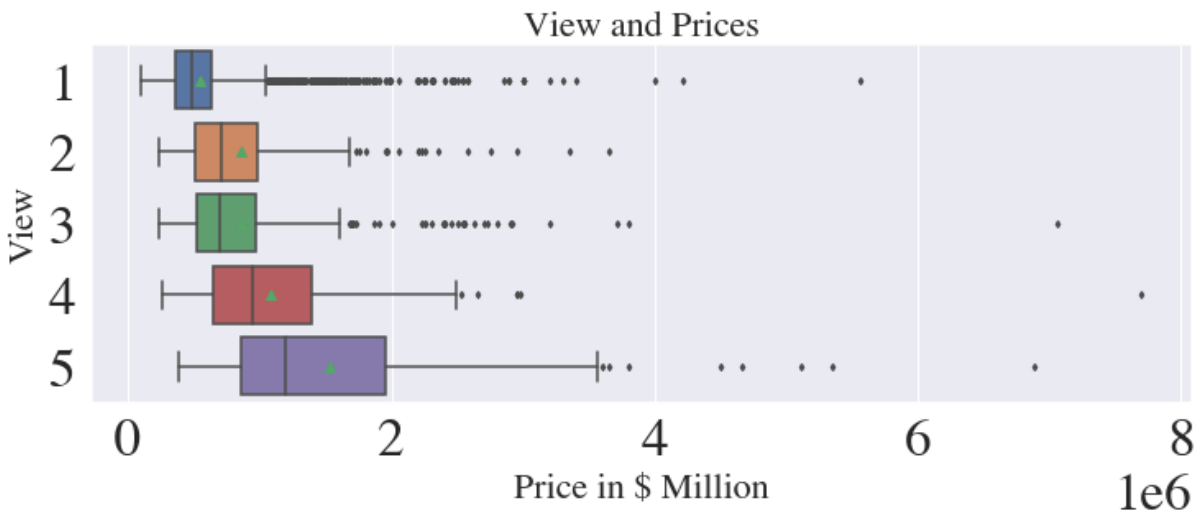
The majority of houses are shown to have a low grade view.

Only 7% of houses have what is considered a "good" or "excellent" view, and these range from 800K dollars to 2 million dollars in value. By comparison, 83% of houses do not have a view, and these range from 350K-500K dollars in value.

In [72]:
```
fig, ax = plt.subplots(figsize=(12,4))
```

```
isns.set_context(fontfamily="times")
sns.boxplot(y = kc_data['view'], x = kc_data['price'],
            width = 0.8,orient = 'h', showmeans = True,
            fliersize = 3, ax = ax)
plt.title('View and Prices', fontsize=22)
plt.xlabel('Price in $ Million',fontsize=22)
plt.ylabel('View',fontsize=22)
```

Out[72]: Text(0, 0.5, 'View')



In [73]:
```
kc_data['view'].value_counts()
```

Out[73]:
```
1    6147
3     501
4     305
2     212
5     205
Name: view, dtype: int64
```

Waterfront

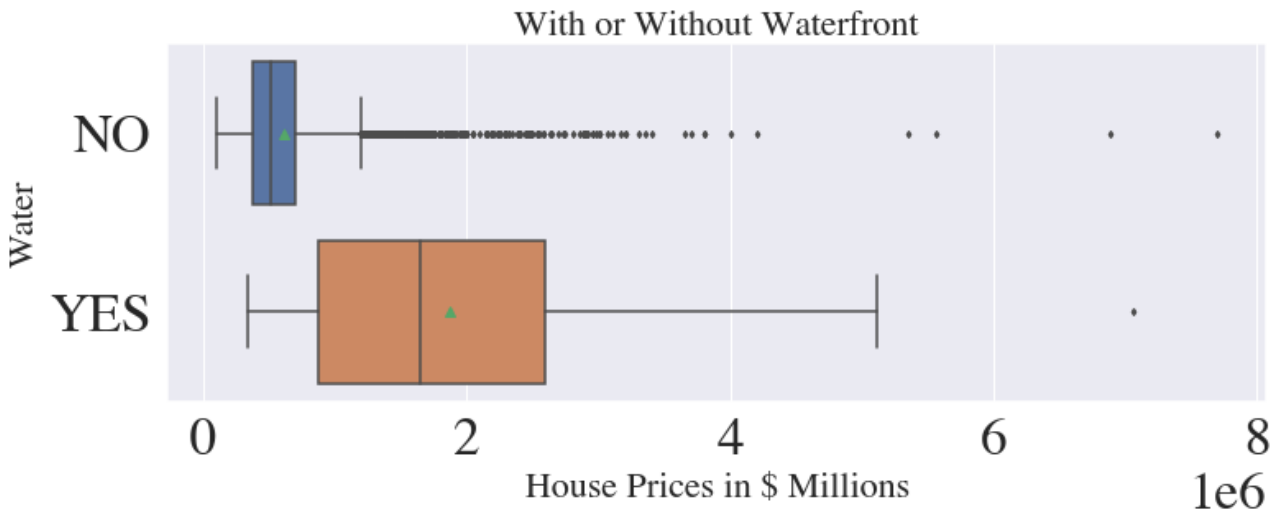
Examining the distribution of waterfront using a box plot.

Zeroing into the distribution of the houses with waterfront and houses without waterfront.

In particular, waterfront homes are significantly more valuable than those without. Homes without a waterfront typically range from 300K-600K dollars, while waterfront homes typically cost more than three times that amount, from 900K-2.6M dollars.

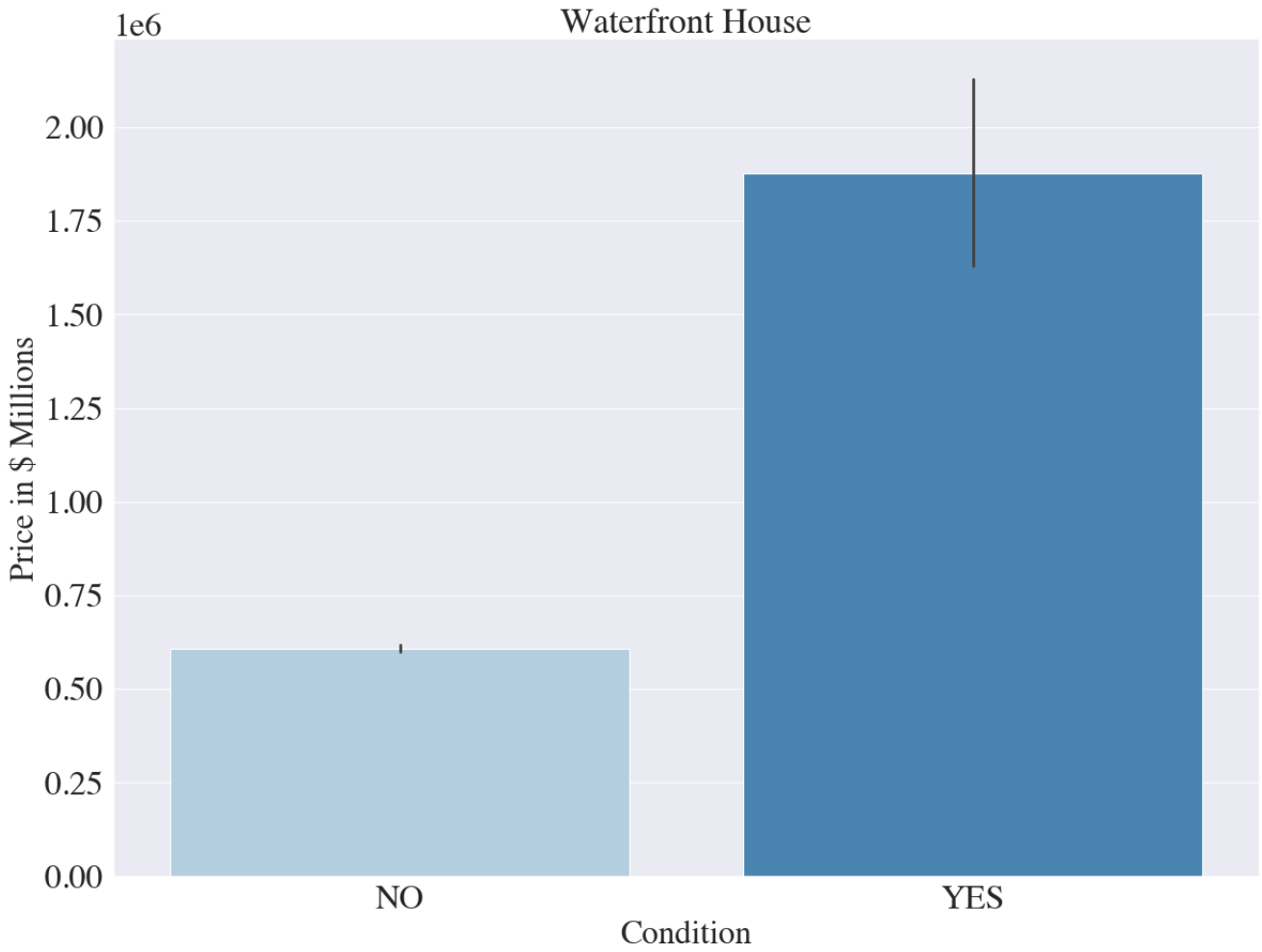
In [74]:
```
# We would need to visualize the data to clearly see where the data rests.
# Let's use boxplot to visualize waterfront:

from scipy import stats, linalg

fig, ax = plt.subplots(figsize=(12,4))

sns.boxplot(y = kc_data['waterfront'], x = kc_data['price'],
            width = 0.8,orient = 'h', showmeans = True,
            fliersize = 3, ax = ax)
plt.title('With or Without Waterfront', fontsize=22)
plt.xlabel('House Prices in $ Millions',fontsize=22)
plt.ylabel('Water',fontsize=22)



# Calculate the correlation coefficient
#r, p = stats.pointbiserialr(kc_data['waterfront'], kc_data['price'])
#print ('point biserial correlation r is %s with p = %s' %(r,p))
```

```
plt.show()
```



In [75]:
```
# Plotting a bar chart to see the comparison in a a simpler
# way to add to presentation
sns.set(font_scale=3)
isns.set_context(fontfamily="times")
plt.figure(1, figsize=(20,15))


sns.barplot(x='waterfront', y='price', data=kc_data,  palette='Blues')
plt.title('Waterfront House' , fontsize=34)
plt.xlabel('Condition', fontsize=32)
plt.ylabel('Price in $ Millions', fontsize=32)
```

Out[75]:
```
Text(0, 0.5, 'Price in $ Millions')
```



In [76]:
```
# Dividing the data into water front and not water front to check the
# distribution for each.
waterfront_non = kc_data.loc[kc_data['waterfront']=='NO','price']
```

In [77]:
```
# Glance at non waterfront houses
waterfront_non.head()
```

Out[77]:
```
1      538000.0
3      604000.0
5     1230000.0
8      229500.0
11     468000.0
Name: price, dtype: float64
```

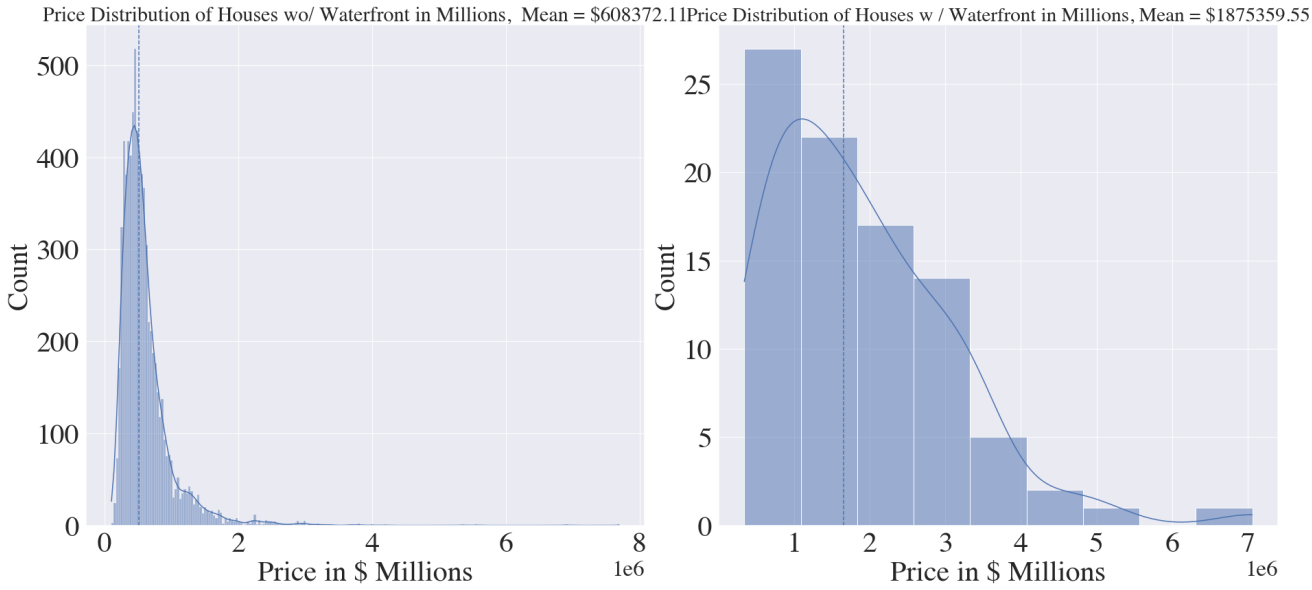
In [78]:
```
# The portion of the data with waterfront
waterfront = kc_data.loc[kc_data['waterfront']=='YES','price']
waterfront.head()
```

Out[78]:
```
49     1350000.0
230     655000.0
246    2400000.0
300    3080000.0
457     705000.0
Name: price, dtype: float64
```

In [79]:
```
# The portion of the data with waterfront
#kc_water=kc_data['waterfront']=0
```

In [80]:
```
# We will look closely at the distributions of water front and non
# waterfront side by side.
```

```
plt.figure(figsize=(26, 12))
sns.set(font_scale=3)
isns.set_context(fontfamily="times")
plt.subplot(1,2,1) # two subplots
sns.histplot(data=waterfront_non, kde=True)

#sns.set(font="Garamond")
plt.axvline(np.median(waterfront_non),color='b', linestyle='--')

m = np.mean(waterfront_non)
m = round(m,2)

plt.title('Price Distribution of Houses wo/ Waterfront in Millions,  Mean = $' +str(m),
          fontsize=30);
plt.xticks(rotation =0, fontsize=42)
plt.yticks(rotation =0, fontsize=42)
plt.xlabel('Price in $ Millions',fontsize=42)
plt.ylabel('Count',fontsize=40)


plt.subplot(1,2,2)
sns.histplot(data=waterfront, kde=True)
plt.axvline(np.median(waterfront),color='b', linestyle='--')

m = np.mean(waterfront)
m = round(m,2)

plt.title('Price Distribution of Houses w / Waterfront in Millions, Mean = $' +str(m),
            fontsize=29);
plt.xticks(rotation =0, fontsize=42)
plt.yticks(rotation =0, fontsize=42)
plt.xlabel('Price in $ Millions',fontsize=42)
plt.ylabel('Count',fontsize=40)

plt.tight_layout()

plt.show()
```



In [81]:

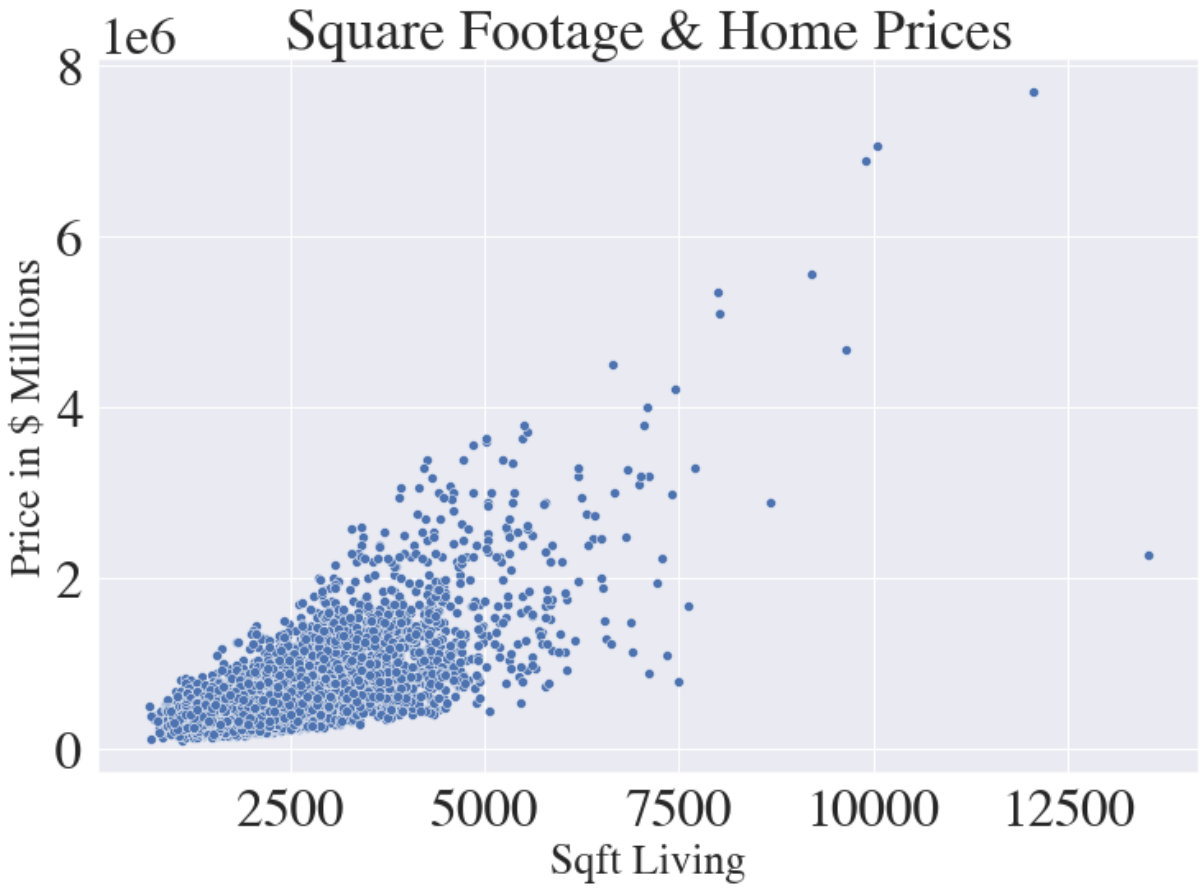
```
kc_data['waterfront'] = kc_data['waterfront'].replace(['NO', 'YES'],[0,1])
```

How many square feet should the house/lot be to hold its value?

I plotted a scatter plot to show the strong correlation to price and soft living. I also included additional information about the year built to check if any pattern could be captured. But unexpectedly, the year a house was built did not show a relationship to price.

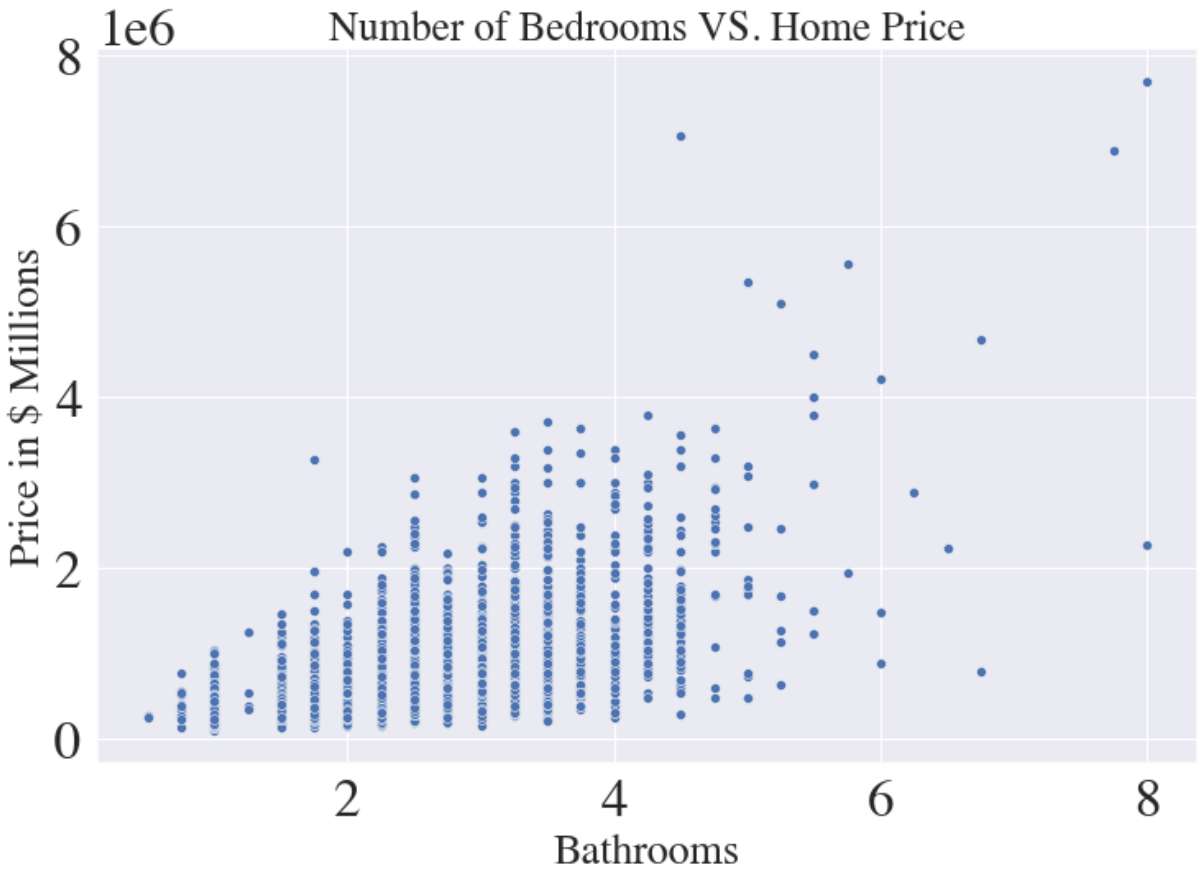
In [82]:
```
plt.subplots(figsize=(12,8))

isns.set_context(fontfamily="times")
cmap = sns.cubehelix_palette(rot=-.2, as_cmap=True)
ax = sns.scatterplot(x="sqft_living", y="price",
                     palette=cmap, sizes=(900, 900),
                     data=kc_data)


plt.title('Square Footage & Home Prices', fontsize=35)
plt.xlabel('Sqft Living', fontsize=26)
plt.ylabel('Price in $ Millions', fontsize=26)
```

Out[82]: Text(0, 0.5, 'Price in $ Millions')



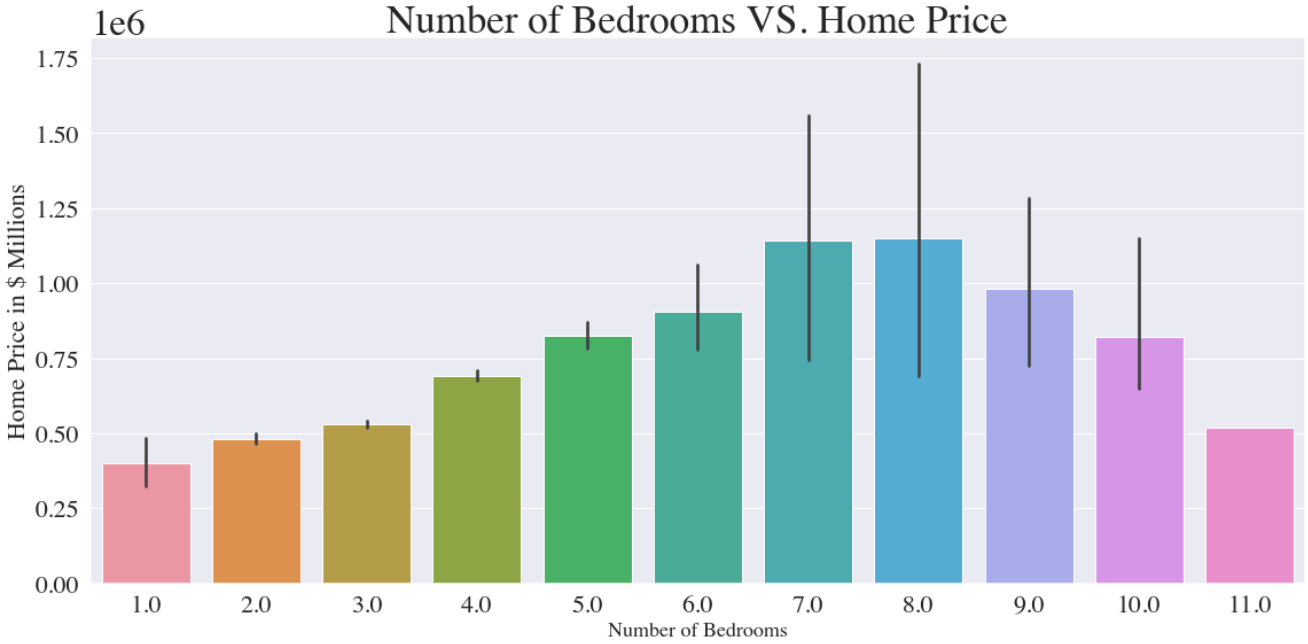
In [83]:
```
# Plotting number of bathrooms vs home price.
plt.subplots(figsize=(12,8))

isns.set_context(fontfamily="times")
cmap = sns.cubehelix_palette(rot=-.2, as_cmap=True)
ax = sns.scatterplot(x="bathrooms", y="price",
                     palette=cmap, sizes=(900, 900),
                     data=kc_data)


plt.title('Number of Bedrooms VS. Home Price', fontsize=25)
plt.xlabel('Bathrooms', fontsize=26)
plt.ylabel('Price in $ Millions', fontsize=26)
```

Out[83]: Text(0, 0.5, 'Price in $ Millions')



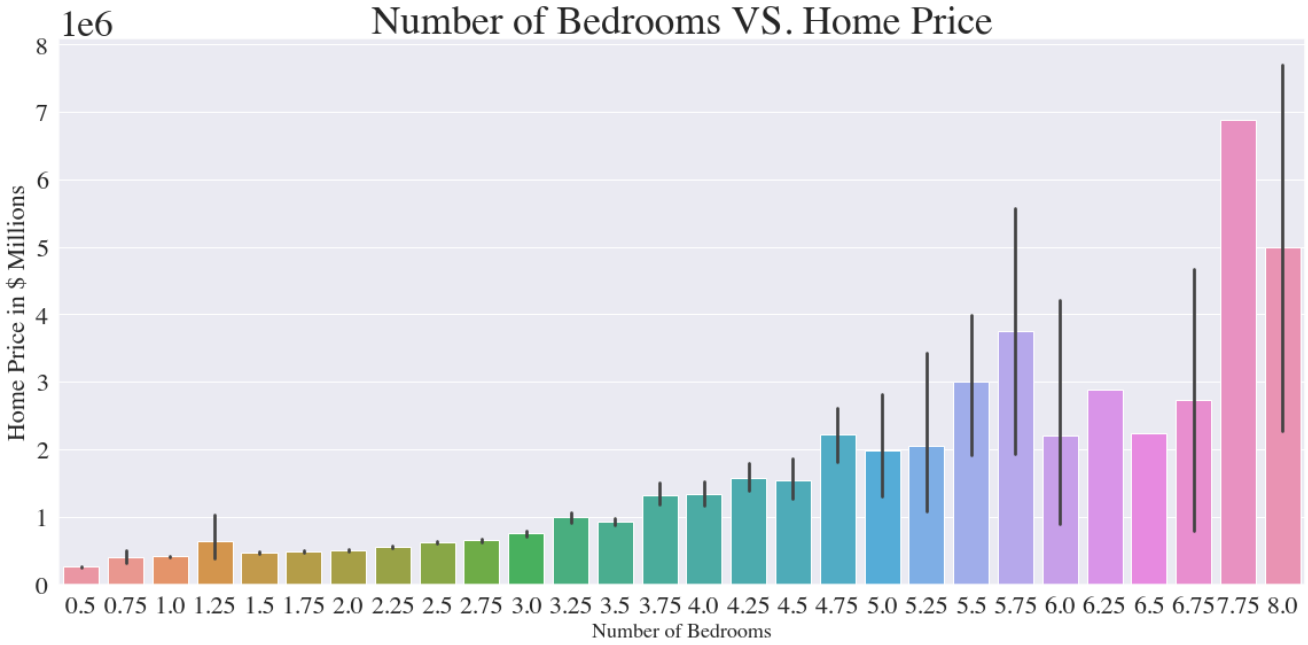
In [84]:

```
# Plotting number of bedrooms versus home price.
fig, ax = plt.subplots(figsize=(16, 8))

sns.barplot(x="bedrooms", y="price", data=kc_data)

# Lable and define fontsize for main and axis titles.

plt.xlabel('Number of Bedrooms', fontsize=18)
plt.ylabel('Home Price in $ Millions', fontsize=22)
plt.title('Number of Bedrooms VS. Home Price', fontsize=35)
plt.tick_params(axis='both', which='major', labelsize=22)

# Set x-axis tick labels.

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



In [85]:

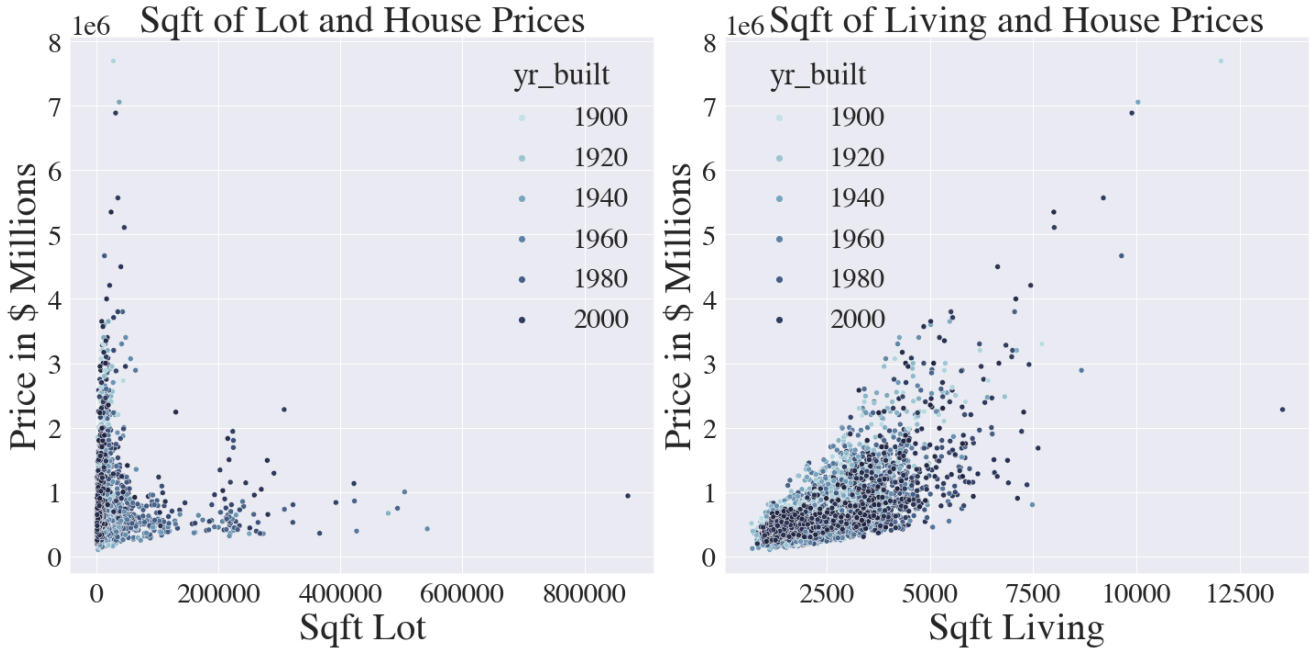
```
# Plotting number of bathrooms versus home price.

fig, ax = plt.subplots(figsize=(16, 8))

sns.barplot(x="bathrooms", y="price", data=kc_data)
sns.set_color_codes("pastel")

# Lable and define fontsize for main and axis titles.

plt.xlabel('Number of Bedrooms', fontsize=18)
plt.ylabel('Home Price in $ Millions', fontsize=22)
plt.title('Number of Bedrooms VS. Home Price', fontsize=35)
plt.tick_params(axis='both', which='major', labelsize=22)

# Set x-axis tick labels.


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



In [86]:

```
# Comparing the lot versus square living.
```

```
plt.figure(figsize=(20, 10))


sns.set(font_scale=2.8)

isns.set_context(fontfamily="times")
plt.subplot(1,2,1) # two subplots



cmap = sns.cubehelix_palette(rot=-.2, as_cmap=True)


ax = sns.scatterplot(x="sqft_lot", y="price",
                     hue="yr_built",
                     palette=cmap,
                     data=kc_data)


plt.title('Sqft of Lot and House Prices' , fontsize=42)
plt.xlabel('Sqft Lot', fontsize=42)
plt.ylabel('Price in $ Millions', fontsize=42)

plt.subplot(1,2,2)

cmap = sns.cubehelix_palette(rot=-.2, as_cmap=True)


isns.set_context(fontfamily="times")
ax = sns.scatterplot(x="sqft_living", y="price", hue="yr_built",
                     palette=cmap,
                     data=kc_data)


plt.title('Sqft of Living and House Prices',fontsize=42)
plt.xlabel('Sqft Living', fontsize=42)
plt.ylabel('Price in $ Millions', fontsize=42)

plt.tight_layout()
```



In [87]:

```
# Correlation table gives us a precise number which supports the heatmap.

corrTable = kc_data.corr()
corrTable=round(corrTable,2)
corrTable
```

Out[87]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	sqft_bas
id	1.00	-0.02	0.01	0.00	-0.02	-0.13	0.02	-0.00	0.01	-0.02	...	
price	-0.02	1.00	0.26	0.53	0.72	0.07	0.35	0.31	0.45	0.08	...	
bedrooms	0.01	0.26	1.00	0.46	0.52	0.06	0.08	-0.00	0.10	0.07	...	
bathrooms	0.00	0.53	0.46	1.00	0.70	0.13	0.47	0.09	0.24	-0.06	...	
sqft_living	-0.02	0.72	0.52	0.70	1.00	0.23	0.33	0.15	0.37	0.03	...	
sqft_lot	-0.13	0.07	0.06	0.13	0.23	1.00	-0.02	0.05	0.07	-0.01	...	
floors	0.02	0.35	0.08	0.47	0.33	-0.02	1.00	0.05	0.12	-0.16	...	
waterfront	-0.00	0.31	-0.00	0.09	0.15	0.05	0.05	1.00	0.38	0.01	...	
view	0.01	0.45	0.10	0.24	0.37	0.07	0.12	0.38	1.00	0.03	...	
condition	-0.02	0.08	0.07	-0.06	0.03	-0.01	-0.16	0.01	0.03	1.00	...	
grade	0.01	0.69	0.26	0.64	0.73	0.13	0.46	0.13	0.38	-0.09	...	
sqft_above	-0.02	0.72	0.43	0.70	0.92	0.21	0.50	0.13	0.33	-0.05	...	
sqft_basement	-0.02	0.41	0.46	0.41	0.72	0.16	-0.11	0.12	0.29	0.16	...	
yr_built	0.01	-0.01	0.03	0.39	0.17	0.09	0.29	-0.01	-0.01	-0.35	...	
yr_renovated	-0.00	0.15	0.05	0.09	0.09	0.00	0.07	0.08	0.09	-0.10	...	
zipcode	-0.03	-0.06	-0.15	-0.18	-0.20	-0.18	0.09	0.01	0.06	-0.02	...	
lat	-0.03	0.24	0.00	0.03	0.03	-0.11	0.10	-0.03	-0.02	-0.01	...	
long	-0.00	0.02	0.13	0.19	0.23	0.33	-0.05	-0.01	-0.04	-0.05	...	
sqft_living15	-0.01	0.60	0.33	0.51	0.72	0.20	0.18	0.13	0.41	0.01	...	
sqft_lot15	-0.12	0.05	0.04	0.11	0.21	0.79	-0.02	0.05	0.06	-0.01	...	
dateyear	0.00	0.00	-0.01	-0.03	-0.03	0.01	-0.03	-0.01	-0.01	-0.06	...	
date_month	-0.00	-0.00	0.00	0.01	0.02	-0.02	0.03	0.01	-0.00	0.02	...	

22 rows × 22 columns

It's evident that, unlike living space, lot size does not show a correlation to price.

Grade and Condition

In [88]:
```
# Checking unique values for condition
kc_data['condition'].unique()
```

Out[88]:
```
array([3, 5, 4, 1, 2])
```

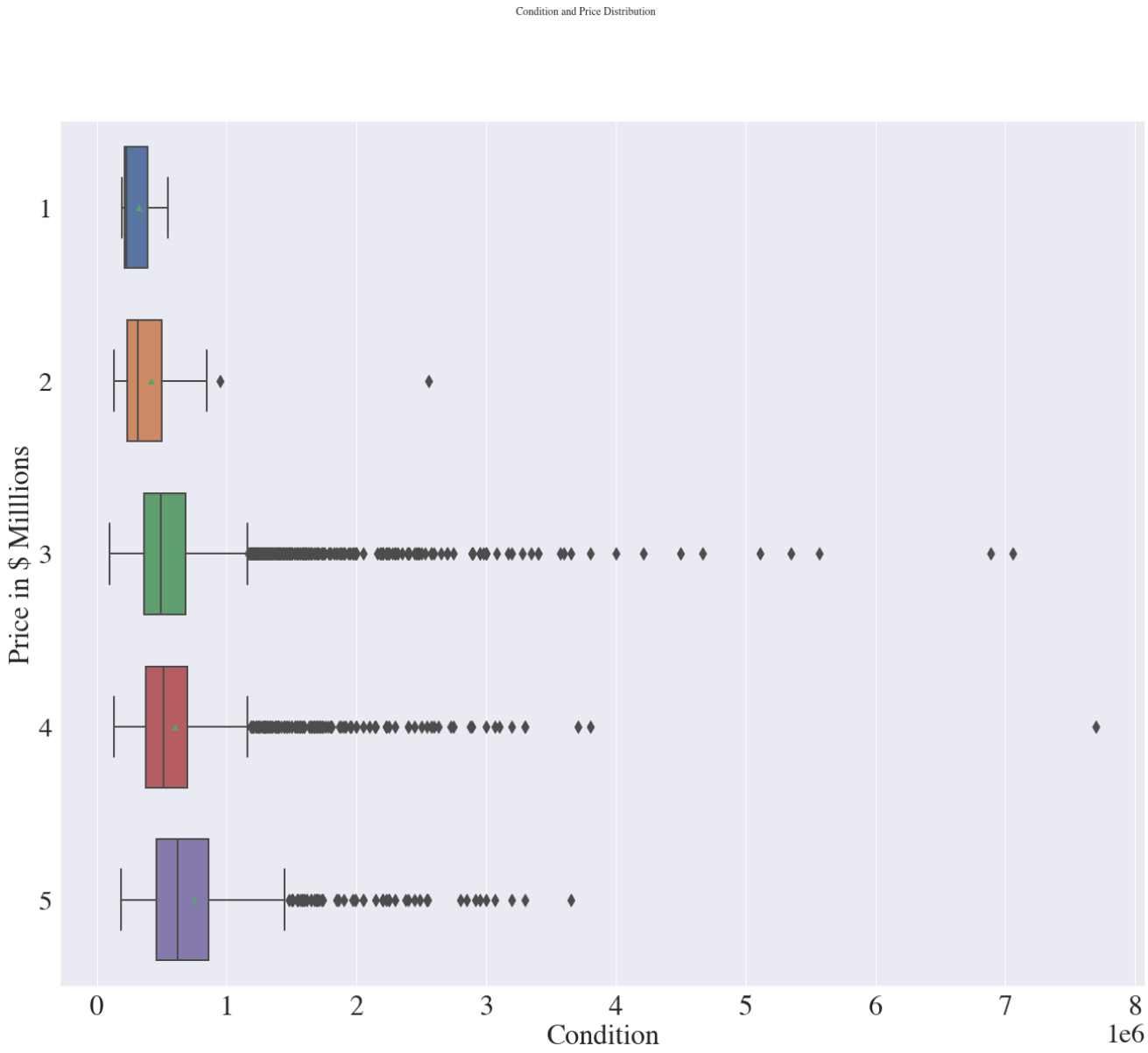
In [89]:
```
# Grouping condition
group_condition = kc_data.groupby(['condition']).mean()
group_condition = pd.DataFrame.reset_index(group_condition)
group_condition
```

Out[89]:

	condition	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	
0	1	5.337300e+09	324333.333333	3.333333	1.666667	1850.000000	19043.000000	1.000000	0.000000	1.0
1	2	5.097944e+09	417773.460000	3.200000	1.800000	1861.400000	26088.940000	1.050000	0.020000	1.1
2	3	4.642844e+09	612184.257477	3.514252	2.350058	2313.367290	12714.375000	1.415421	0.011215	1.3
3	4	4.575608e+09	603975.530814	3.590193	2.118534	2281.827260	14584.501125	1.173639	0.011696	1.4
4	5	4.486960e+09	751617.242015	3.691267	2.318182	2425.753071	11056.217445	1.279484	0.017199	1.4

5 rows × 22 columns

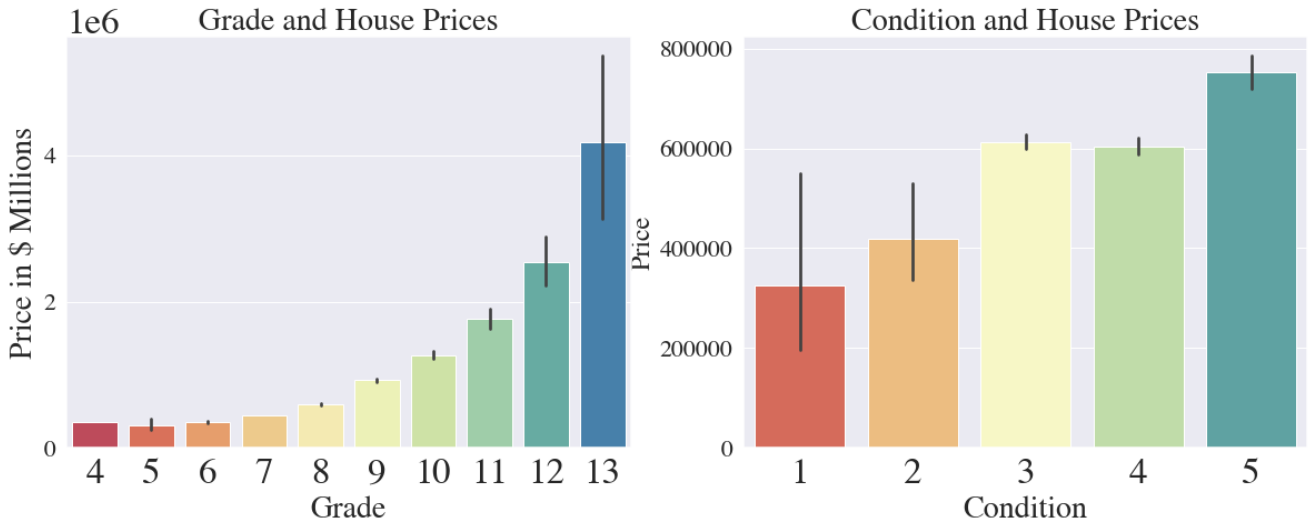
In [90]:
```
# Checking distribution of condition

fig, axes = plt.subplots(1, 1, figsize=(22,18))

isns.set_context(fontfamily="times")

fig.suptitle('Condition and Price Distribution')
sns.boxplot(y = kc_data['condition'], x=kc_data['price'],
            width = 0.7, orient ='h', showmeans = True,
            linewidth = 2, fliersize =10)

plt.xlabel('Condition', fontsize=32)
plt.ylabel('Price in $ Milllions', fontsize=32)
plt.xticks(fontsize=32,rotation = 0);
```



Condition and Grade

In [91]:
```
sns.set(font_scale=3)
isns.set_context(fontfamily="times")
plt.figure(2, figsize=(20,15))
the_grid = GridSpec(2, 2)
```

```
plt.subplot(the_grid[0, 1],  title='Condition')

sns.barplot(x='condition', y='price', data=kc_data,
            palette='Spectral')
plt.title('Condition and House Prices' , fontsize=28)
plt.xlabel('Condition', fontsize=28)
plt.ylabel('Price', fontsize=24)
plt.yticks(fontsize=22,rotation = 0);

plt.subplot(the_grid[0, 0], title='Grade')

sns.barplot(x='grade',y='price', data=kc_data, palette='Spectral')


plt.title('Grade and House Prices' , fontsize=28)
plt.xlabel('Grade', fontsize=28)
plt.ylabel('Price in $ Millions', fontsize=28)
plt.yticks(fontsize=22,rotation = 0);
fig.tight_layout()
plt.show()
```



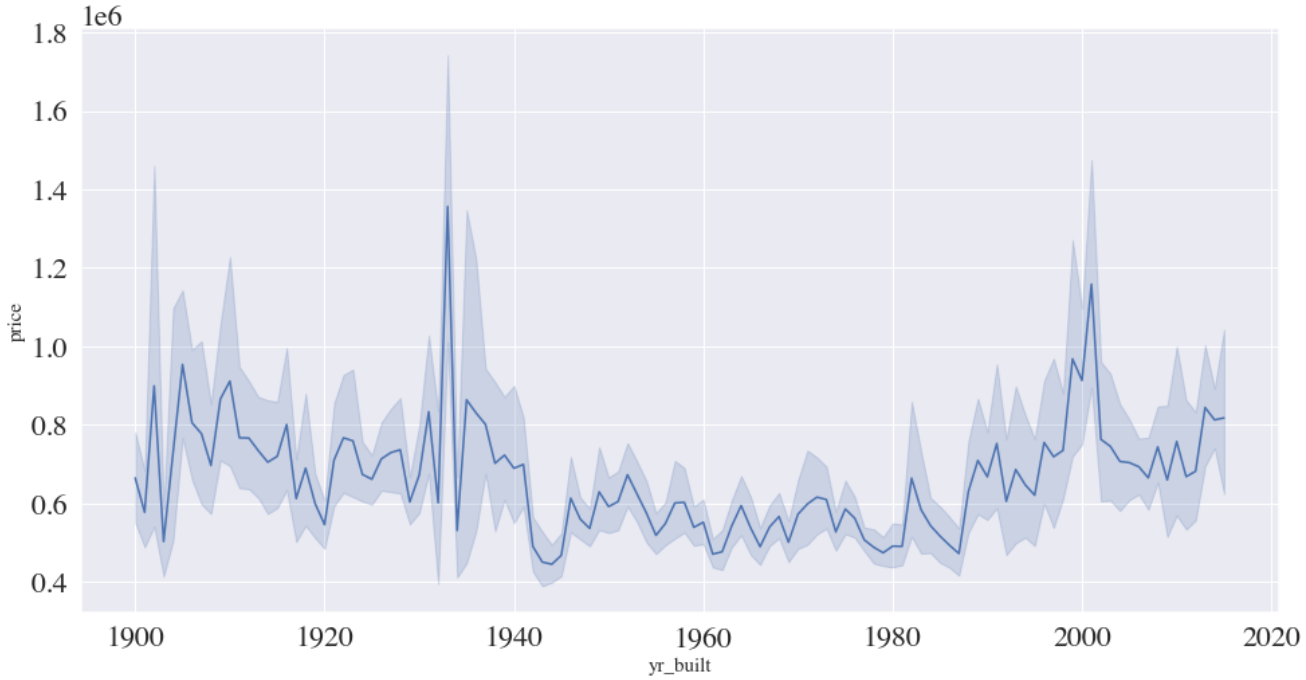
The higher the grade and condition the higher the price. However the price increases significantly with the increase of the house's grade.

Year Built/Renovated

Looking closely, I build a line plot to access wether here was any trend with year build but as the graph shows there was not. Newer home did not necessarily suggest that prices increases. From 1980 to 2000 house prices rise from 700K to $1.1 million.

In [92]:
```
# Plotting line plot
sns.set_style('whitegrid')
sns.set_color_codes("pastel")
sns.set(font_scale=2)
isns.set_context(fontfamily="times")

fig, ax = plt.subplots(1,1, figsize=(16,8))

sns.lineplot(data=kc_data, x="yr_built", y="price")
```

Out[92]:
```
<AxesSubplot:xlabel='yr_built', ylabel='price'>
```



Year Renovated

In [93]:
```
# Checking years
kc_data.yr_renovated.unique()
```

Out[93]:
```
array([1991,    0, 2002, 1992, 1994, 1978, 2005, 2003, 1984, 2011, 2014,
       2013, 1988, 1995, 1977, 1998, 1970, 1989, 1990, 2004, 1986, 2007,
       1987, 2006, 2000, 1979, 1997, 1983, 2015, 2012, 2008, 1962, 1999,
       2001, 1985, 1980, 1993, 1955, 1996, 2010, 2009, 1969, 1940, 1975,
       1957, 1956, 1973, 1968, 1982, 1934, 1965, 1964])
```

In [94]:
```
kc_data['yr_renovated'].value_counts()
```

Out[94]:
```
0       7052
2014      41
2013      17
2000      14
2008      13
2003      12
2005      12
2006      12
2004      11
2007      10
1990       9
1996       9
2010       9
2015       8
1987       8
1999       8
1991       8
1998       7
1984       7
2001       7
1970       6
2009       6
2002       6
1993       6
1986       6
2011       5
1992       5
1983       5
1989       4
1985       4
1995       4
1988       4
1994       3
1975       3
```

```
1982       3
1977       3
1980       3
1979       2
1969       2
1965       2
2012       2
1997       2
1964       1
1955       1
1956       1
1978       1
1962       1
1968       1
1940       1
1973       1
1957       1
1934       1
Name: yr_renovated, dtype: int64
```

Since the majority of the data shows 0 for the houses, I assume that these houses were not renovated.

In [95]:
```
year_price = kc_data[['yr_renovated','price']]
year_price.head()
```

Out[95]:

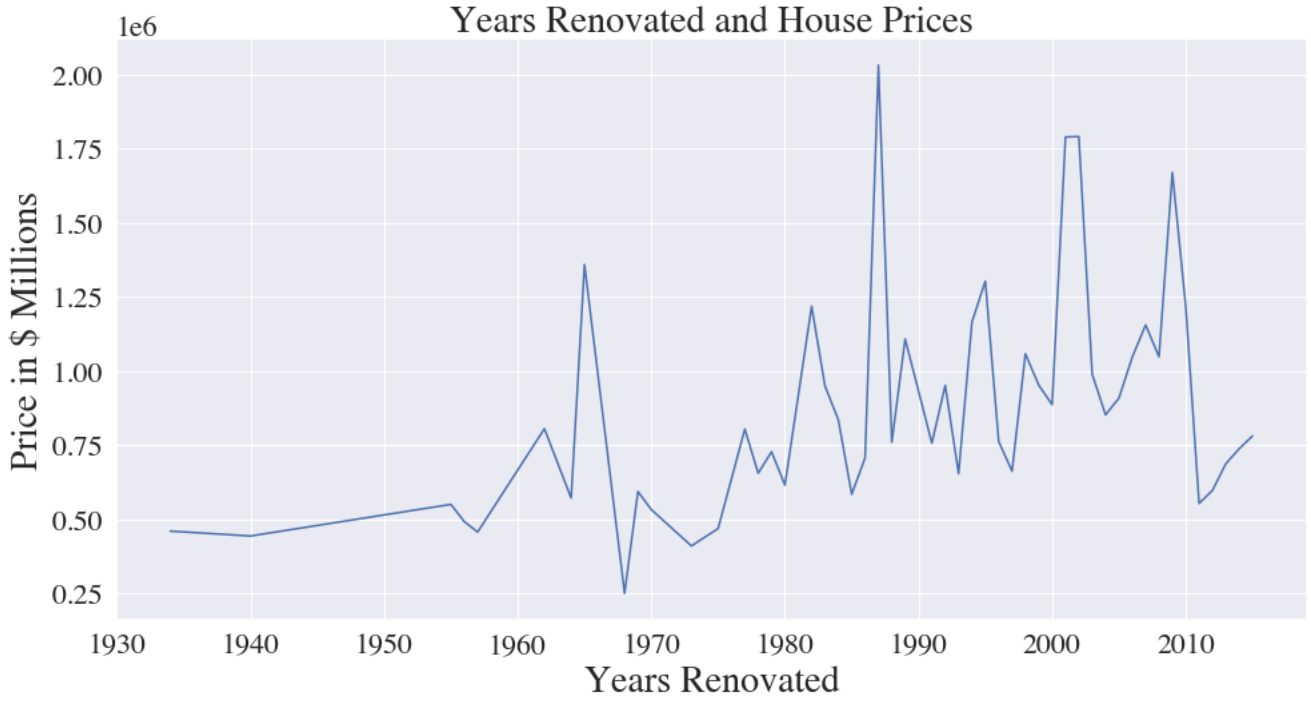
	yr_renovated	price
1	1991	538000.0
3	0	604000.0
5	0	1230000.0
8	0	229500.0
11	0	468000.0

In [96]:
```
# Removing the renovation years that are zero - these houses were
# not renovated
reno_years  = year_price.replace(0, pd.np.nan).dropna(axis=0,
                                 how='any').fillna(0).astype(int)
```

In [97]:
```
'''Creating a new data frame - extracting year renovated and price.
Grouping by year renovated and plotting a bar graph into the avert
price for a given year.'''
group_yr_reno= reno_years.groupby(['yr_renovated']).mean()
group_yr_reno = pd.DataFrame.reset_index(group_yr_reno)
```

In [98]:
```
'''I build a line plot to access wether here was any trend with year
renovated but as the graph shows there was not.'''

sns.set_style('whitegrid')
sns.set_color_codes("pastel")
sns.set(font_scale=2)
isns.set_context(fontfamily="times")

fig, ax = plt.subplots(1,1, figsize=(16,8))

plt.title('Years Renovated and House Prices' , fontsize=28)
plt.xlabel('Years Renovated', fontsize=28)
plt.ylabel('Price in $ Millions', fontsize=28)

sns.lineplot(data=group_yr_reno, x="yr_renovated", y="price")
```

Out[98]:
```
<AxesSubplot:title={'center':'Years Renovated and House Prices'}, xlabel='Years Renovated', ylabel='P
rice in $ Millions'>
```

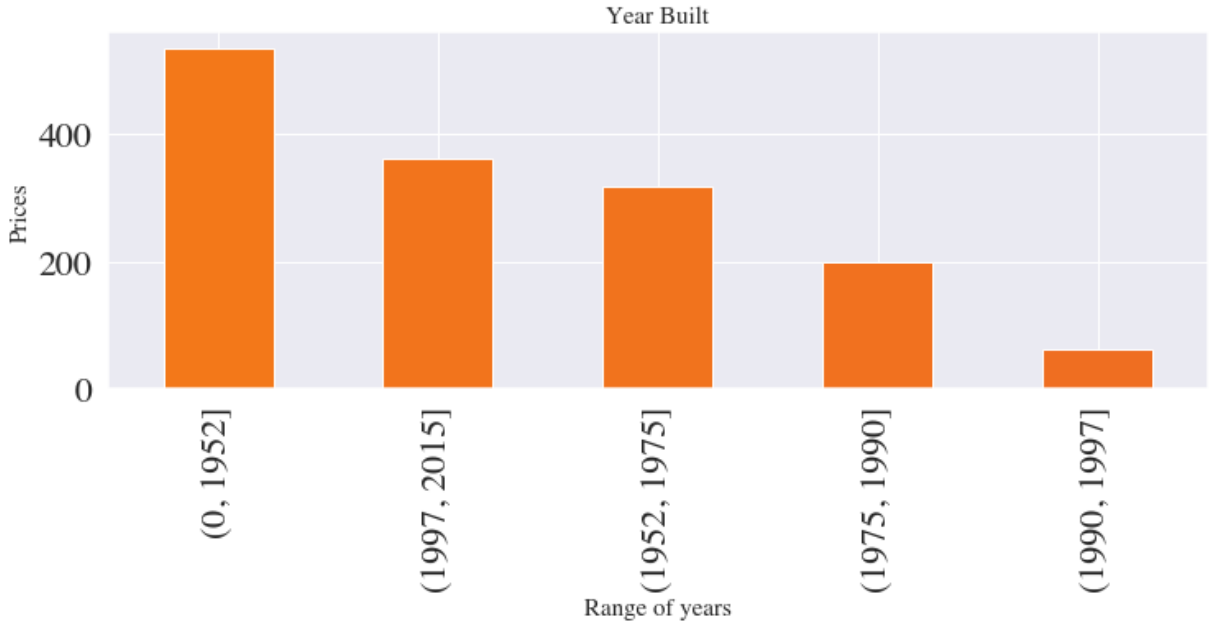


In [99]:
```
# Let's check yr_built stats and asses the virable.
top20p.yr_built.describe()
```

Out[99]:
```
count    1474.000000
mean     1965.005427
std        33.081355
min      1900.000000
25%      1937.000000
50%      1967.000000
75%      1996.000000
max      2015.000000
Name: yr_built, dtype: float64
```

In [100…
```
# Here are the  bins  based on the values observed above.
# 5 values will result in 4 bins

bins = [0, 1952, 1975, 1990, 1997, 2015]

#We'll pd.cut method to separate data into bins.
bins_yr_built = pd.cut(top20p['yr_built'], bins)

#We'll use .cat.as_unordered() method transforming the data to
# ordered categories.
bins_yr_built = bins_yr_built.cat.as_unordered()
#bins_yr_built.head()
```

In [101…
```
#Let's visualize the bins
fig, ax = plt.subplots(figsize=(15,6))
from matplotlib import cm

color = cm.inferno_r(np.linspace(.3, .5, 40))
isns.set_context(fontfamily="times")
bins_yr_built.value_counts().plot(kind='bar',stacked=True, color=color,
                                  legend=False, figsize=(12, 4))
plt.xlabel('Range of years')
plt.ylabel('Prices')
plt.title('Year Built')
#plt.legend()
plt.show()
```



Mid-low-range house prices investment opportunities

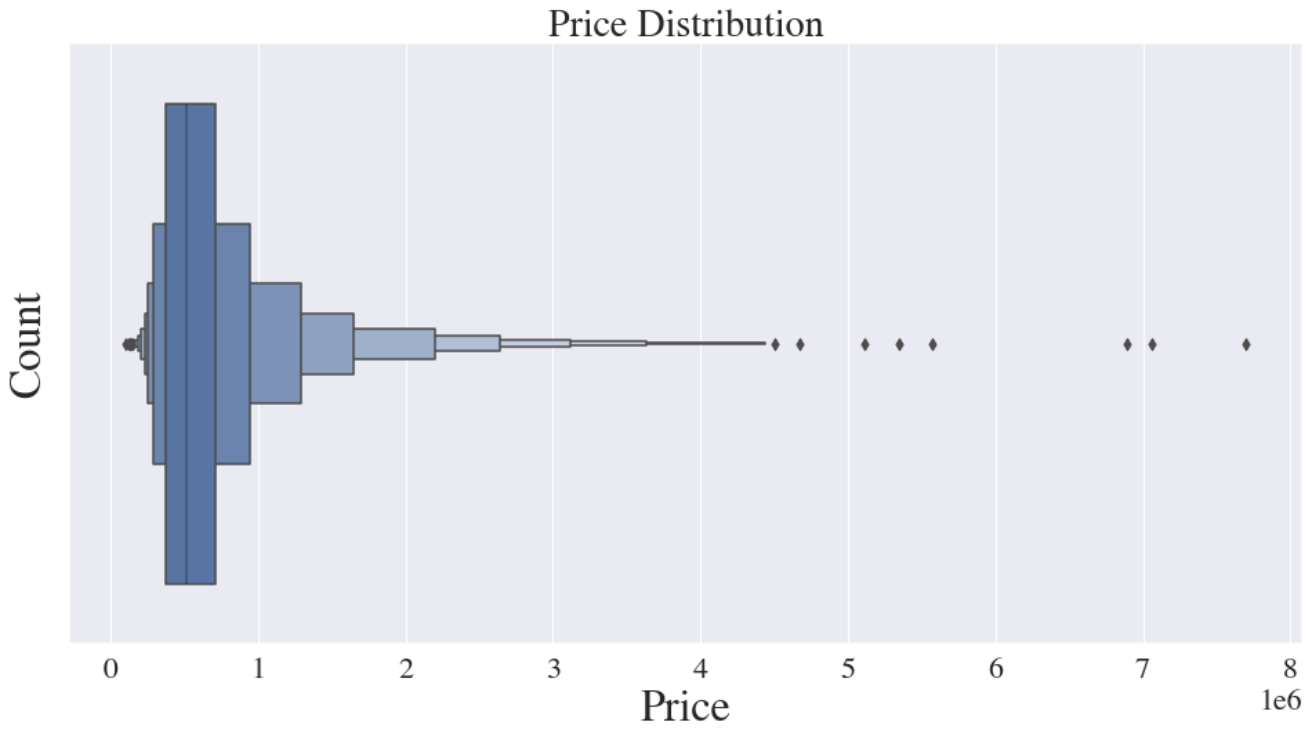
In [102…

```
# Checking the distribution for house prices.

fig, ax = plt.subplots(figsize=(16, 8))
sns.histplot(kc_data["price"],alpha=.5)
plt.title('Price Distribution',  fontsize=28)
plt.xlabel('Price', fontsize =32)
plt.ylabel('Count', fontsize =32)
plt.show()
```

In [103…

```
# Checking the distribution for house prices.

fig, ax = plt.subplots(figsize=(16, 8))
sns.boxenplot(x=kc_data["price"])
plt.title('Price Distribution',  fontsize=28)
plt.xlabel('Price', fontsize =32)
```

```
plt.ylabel('Count', fontsize =32)
plt.show()
```



In [104…
```
kc_data['price'].unique()
```

Out[104…
```
array([ 538000.,  604000., 1230000., ...,  747450.,  608500., 3570000.])
```

The majority of the houses fall between 250K to 1 million dollars.

In [105…
```
# Filter the dataset to get mid range prices
mid_price = kc_data[(kc_data['price'] < np.quantile(kc_data['price'], 0.9))
                    & (kc_data['bathrooms'].isin(range(3, 6)))
                    & (kc_data['view'].isin(range(3,5)))
                    & (kc_data['sqft_living'].isin(range(2000,5700)))]

# View summary statistics
mid_price.describe()
```

Out[105…

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
count	3.400000e+01	34.000	34.000000	34.000000	34.000000	34.000000	34.000000	34.0	34.000000
mean	4.810090e+09	718650.000	4.323529	3.176471	3282.235294	17310.029412	1.602941	0.0	3.352941
std	2.865201e+09	192865.463	1.036328	0.386953	672.085089	18885.111257	0.519023	0.0	0.485071
min	2.690010e+08	315000.000	3.000000	3.000000	2350.000000	3900.000000	1.000000	0.0	3.000000
25%	2.358001e+09	565250.000	4.000000	3.000000	2792.500000	6250.000000	1.000000	0.0	3.000000
50%	4.058801e+09	749500.000	4.000000	3.000000	3140.000000	9734.500000	1.750000	0.0	3.000000
75%	7.380576e+09	867000.000	5.000000	3.000000	3687.500000	18136.500000	2.000000	0.0	4.000000
max	9.523104e+09	1030000.000	7.000000	4.000000	4660.000000	80471.000000	3.000000	0.0	4.000000

8 rows × 22 columns

In [106…
```
mid_price= mid_price[['price','sqft_living','zipcode']]
```

In [107…
```
group_mid_zip = mid_price.groupby(['zipcode'])['price'].mean()
```

In [108…
```
group_mid_zip = mid_price.sort_values(by= 'price', ascending = False)
group_mid_zip.head()
```

Out[108…

	price	sqft_living	zipcode
20056	1030000.0	3880	98034
7069	990000.0	2550	98199
1034	980000.0	3680	98199
17480	959750.0	3060	98008
10581	951250.0	2710	98199

Preparing for Modeling

In order to prepare for the model prediction, I will be dealing with the following elements:

```
    * Split the data- dependent(X) and independent(y)
    * Handle categorical valuables by using dummy encoding.
    * Ensure that there is no  multicollinearity that none of the independent variables
  are correlated.
    * Scale the data.
```

In [109…
```
kc_data.isnull().sum()
```

Out[109…
```
id               0
price            0
bedrooms         1
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
dateyear         0
date_month       0
dtype: int64
```

In [110…
```
kc_data.dropna(subset=['bedrooms'], inplace=True)
```

In [111…
```
kc_data.isnull().sum()
```

Out[111…
```
id               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
dateyear         0
date_month       0
dtype: int64
```

Split the data: dependent(X) and independent(y)

I will split the data into dependent and independent variable X and y. I will make sure there are no new NaNs values.

In [172…
```
# Split features X and target y
X = kc_data.drop('price', axis = 1)
y = kc_data['price']
```

In [173…
```
# Creating a copy of X
X_copy = X.copy()
```

Adding New Columns

I am adding new columns where the model can understand better the values. Year built and renovated would be hard to the model to understand therefore, I will subtract the year renovated from the year the house was sold. I will do the same for the year the house was built. The new column will have the number of years as opposed to just four digit year.

In [174…
```
# Adding a column of number of years house has been built
X['houselife'] = X['dateyear']- X['yr_built']
```

In [176…
```
# Creating a new column called 'renovated'. Subtracting date year from
# year renovated.
X['renovated'] = X['yr_renovated'] - X['dateyear']
```

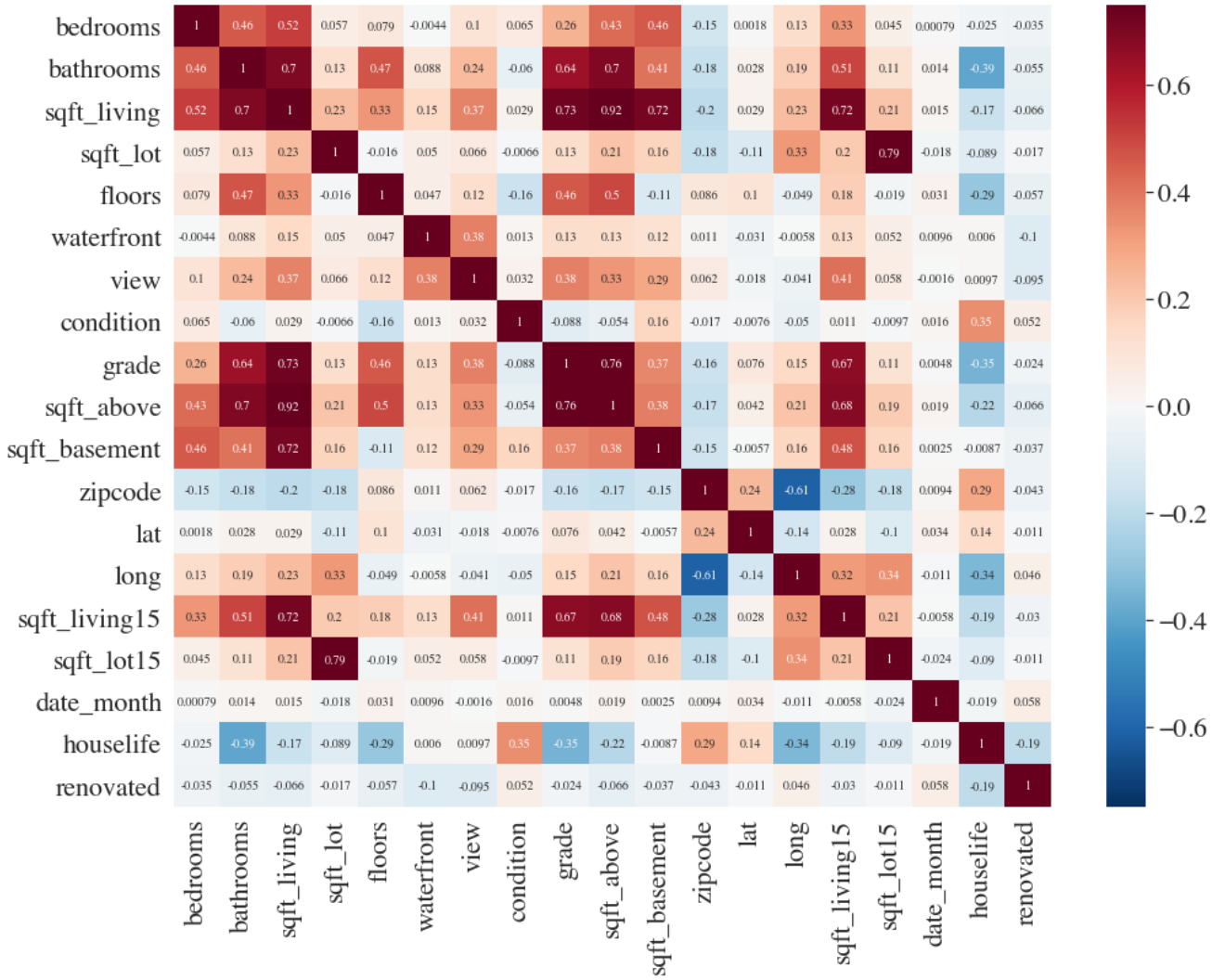
In [177…
```
# There a lot of 0s in the year renovated which we will replace with
# the year the house was sold because we assume that the respective
# house was not renovated.

for indx, row in X.iterrows():
    if row['yr_renovated']==0:
        X['yr_renovated'].loc[indx] = row['dateyear']
```

In [178…
```
X.drop(['yr_built','yr_renovated','dateyear'],axis=1,inplace=True)
```

In [179…
```
# Dropping 'id' -since it has so meaningful value.
X.drop(['id'],axis=1,inplace=True)
```

Checking for Multicollinearity

In [180…
```
corr  = X.corr()
plt.figure(figsize=(16, 12))
sns.set(font_scale=2)
isns.set_context(fontfamily="times")
heatmap = sns.heatmap(corr, annot=True, linewidths=0, vmin=-0.75,
                      vmax=0.75, cmap="RdBu_r")
```



Check VIF Score

Creating a function that generates a list of two variables and the respective correlation to check for multicoliniartiy. I will not include a correlation higher than 0.6.

In [181…

```
# We will extract all the variables beside the target variable.
kc_pred = X
kc_pred.head()
```

Out[181…

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	sqft_basement	zip
1	3.0	2.25	2570	7242	2.0	0	1	3	7	2170	400	9
3	4.0	3.00	1960	5000	1.0	0	1	5	7	1050	910	9
5	4.0	4.50	5420	101930	1.0	0	1	3	11	3890	1530	9
8	3.0	1.00	1780	7470	1.0	0	1	3	7	1050	730	9
11	2.0	1.00	1160	6000	1.0	0	1	4	7	860	300	

In [182…

```
# Double checking null values
kc_pred.isnull().sum()
```

Out[182…

```
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
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
date_month       0
houselife        0
renovated        0
dtype: int64
```

In [183…

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
def vif_scores(kc_pred):

    kc_pred_temp = kc_pred.copy()

    VIF_Scores = pd.DataFrame()
    VIF_Scores["Independent Features"] = kc_pred_temp.columns
    VIF_Scores["VIF_Scores"] = [variance_inflation_factor(kc_pred_temp.values,i)
                                for i in range(kc_pred_temp.shape[1])]
    return VIF_Scores

vif_scores(kc_pred)
```

Out[183…

	Independent Features	VIF_Scores
0	bedrooms	2.330536e+01
1	bathrooms	2.649350e+01
2	sqft_living	inf
3	sqft_lot	3.294432e+00
4	floors	1.648491e+01
5	waterfront	1.197943e+00
6	view	4.507693e+00
7	condition	3.206290e+01
8	grade	1.654118e+02
9	sqft_above	inf
10	sqft_basement	inf
11	zipcode	2.256854e+06
12	lat	1.706998e+05
13	long	2.022170e+06
14	sqft_living15	2.700967e+01
15	sqft_lot15	3.428056e+00
16	date_month	5.582151e+00
17	houselife	7.031338e+00
18	renovated	2.705799e+00

In [184…

```
# Dropping high VIF
X.drop(['sqft_living15', 'sqft_lot15', 'houselife','sqft_above','sqft_basement'], axis = 1,inplace =T
```

In [185…

```
# Running vif score one more time
vif_scores(X)
```

Out[185…

	Independent Features	VIF_Scores
0	bedrooms	2.303511e+01

	Independent Features	VIF_Scores
1	bathrooms	2.357956e+01
2	sqft_living	2.400372e+01
3	sqft_lot	1.377627e+00
4	floors	1.263046e+01
5	waterfront	1.194717e+00
6	view	4.239099e+00
7	condition	2.807544e+01
8	grade	1.355188e+02
9	zipcode	2.070907e+06
10	lat	1.649436e+05
11	long	1.871179e+06
12	date_month	5.577196e+00
13	renovated	2.526631e+00

Categorical Values

Using get_dummies method in order to create a column for waterfront and not waterfront homes. Also, each zipcode will have their own column. This way the model can work better with such data.

Here are all the categorical features which we will convert to dummy variables by using get_dummies method.

- Zipcode
- Waterfront

In [186…
```
# Creating a column of yes_waterfront and no_waterfront
X = pd.get_dummies(X, columns=['waterfront'])
```

In [187…
```
# Creating a column for each zipcode
X = pd.get_dummies(X, columns=['zipcode'])
```

In [188…
```
X.head()
```

Out[188…

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	view	condition	grade	lat	long	…	zipcode_98146	zipc
1	3.0	2.25	2570	7242	2.0	1	3	7	47.7210	-122.319	…	0	
3	4.0	3.00	1960	5000	1.0	1	5	7	47.5208	-122.393	…	0	
5	4.0	4.50	5420	101930	1.0	1	3	11	47.6561	-122.005	…	0	
8	3.0	1.00	1780	7470	1.0	1	3	7	47.5123	-122.337	…	1	
11	2.0	1.00	1160	6000	1.0	1	4	7	47.6900	-122.292	…	0	

5 rows × 84 columns

Implementing VIF Score function using statsmodels.

VIF starts at 1 and has no upper limit VIF = 1, no correlation between the independent variable and the other variables VIF exceeding 5 or 10 indicates high multicollinearity between this independent variable and the others.

In [189…
```
# Dropping more variables that have large VIF
```

In [190…

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7369 entries, 1 to 21591
Data columns (total 84 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   bedrooms       7369 non-null   float64
 1   bathrooms      7369 non-null   float64
 2   sqft_living    7369 non-null   int64  
 3   sqft_lot       7369 non-null   int64  
 4   floors         7369 non-null   float64
 5   view           7369 non-null   int64  
 6   condition      7369 non-null   int64  
 7   grade          7369 non-null   int64  
 8   lat            7369 non-null   float64
 9   long           7369 non-null   float64
 10  date_month     7369 non-null   int64  
 11  renovated      7369 non-null   int64  
 12  waterfront_0   7369 non-null   uint8  
 13  waterfront_1   7369 non-null   uint8  
 14  zipcode_98001  7369 non-null   uint8  
 15  zipcode_98002  7369 non-null   uint8  
 16  zipcode_98003  7369 non-null   uint8  
 17  zipcode_98004  7369 non-null   uint8  
 18  zipcode_98005  7369 non-null   uint8  
 19  zipcode_98006  7369 non-null   uint8  
 20  zipcode_98007  7369 non-null   uint8  
 21  zipcode_98008  7369 non-null   uint8  
 22  zipcode_98010  7369 non-null   uint8  
 23  zipcode_98011  7369 non-null   uint8  
 24  zipcode_98014  7369 non-null   uint8  
 25  zipcode_98019  7369 non-null   uint8  
 26  zipcode_98022  7369 non-null   uint8  
 27  zipcode_98023  7369 non-null   uint8  
 28  zipcode_98024  7369 non-null   uint8  
 29  zipcode_98027  7369 non-null   uint8  
 30  zipcode_98028  7369 non-null   uint8  
 31  zipcode_98029  7369 non-null   uint8  
 32  zipcode_98030  7369 non-null   uint8  
 33  zipcode_98031  7369 non-null   uint8  
 34  zipcode_98032  7369 non-null   uint8  
 35  zipcode_98033  7369 non-null   uint8  
 36  zipcode_98034  7369 non-null   uint8  
 37  zipcode_98038  7369 non-null   uint8  
 38  zipcode_98039  7369 non-null   uint8  
 39  zipcode_98040  7369 non-null   uint8  
 40  zipcode_98042  7369 non-null   uint8  
 41  zipcode_98045  7369 non-null   uint8  
 42  zipcode_98052  7369 non-null   uint8  
 43  zipcode_98053  7369 non-null   uint8  
 44  zipcode_98055  7369 non-null   uint8  
 45  zipcode_98056  7369 non-null   uint8  
 46  zipcode_98058  7369 non-null   uint8  
 47  zipcode_98059  7369 non-null   uint8  
 48  zipcode_98065  7369 non-null   uint8  
 49  zipcode_98070  7369 non-null   uint8  
 50  zipcode_98072  7369 non-null   uint8  
 51  zipcode_98074  7369 non-null   uint8  
 52  zipcode_98075  7369 non-null   uint8  
 53  zipcode_98077  7369 non-null   uint8  
 54  zipcode_98092  7369 non-null   uint8  
 55  zipcode_98102  7369 non-null   uint8  
 56  zipcode_98103  7369 non-null   uint8  
 57  zipcode_98105  7369 non-null   uint8  
 58  zipcode_98106  7369 non-null   uint8  
 59  zipcode_98107  7369 non-null   uint8  
 60  zipcode_98108  7369 non-null   uint8  
 61  zipcode_98109  7369 non-null   uint8  
 62  zipcode_98112  7369 non-null   uint8  
 63  zipcode_98115  7369 non-null   uint8  
 64  zipcode_98116  7369 non-null   uint8  
 65  zipcode_98117  7369 non-null   uint8  
 66  zipcode_98118  7369 non-null   uint8  
 67  zipcode_98119  7369 non-null   uint8  
 68  zipcode_98122  7369 non-null   uint8  
 69  zipcode_98125  7369 non-null   uint8  
 70  zipcode_98126  7369 non-null   uint8  
 71  zipcode_98133  7369 non-null   uint8
```

```
 72  zipcode_98136  7369 non-null   uint8
 73  zipcode_98144  7369 non-null   uint8
 74  zipcode_98146  7369 non-null   uint8
 75  zipcode_98148  7369 non-null   uint8
 76  zipcode_98155  7369 non-null   uint8
 77  zipcode_98166  7369 non-null   uint8
 78  zipcode_98168  7369 non-null   uint8
 79  zipcode_98177  7369 non-null   uint8
 80  zipcode_98178  7369 non-null   uint8
 81  zipcode_98188  7369 non-null   uint8
 82  zipcode_98198  7369 non-null   uint8
 83  zipcode_98199  7369 non-null   uint8
dtypes: float64(5), int64(7), uint8(72)
memory usage: 1.2 MB
```

In [196…
```
print(X.shape, y.shape)
```

```
(7369, 84) (7369,)
```

Scaling the data

In [197…
```
colname = list(X)
```

In [198…
```
sc_X = StandardScaler()
sc_X = sc_X.fit_transform(X)
```

Model and Interpretation

Baseline model (Most correlated features)

In [199…
```
# y_train = pd.DataFrame(y_train)
```

In [200…
```
# X.dropna(inplace=True)
```

In [201…
```
y.shape
```

Out[201… (7369,)

In [202…
```
y = pd.DataFrame(y)
X = pd.DataFrame(X) # columns
```

In [203…
```
X.reset_index(drop=True,inplace=True)
y.reset_index(drop=True,inplace=True)
```

In [204…
```
# Run OLS Regression - using the most correlated features for the model
# X_train_base = X_train[best_features_base]
#Fitting the training data

X_ols = sm.add_constant(sc_X)
model_base = sm.OLS(y, X_ols).fit()
model_base.summary()
```

Out[204…

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.796
Model:	OLS	**Adj. R-squared:**	0.794
Method:	Least Squares	**F-statistic:**	347.1
Date:	Thu, 13 Oct 2022	**Prob (F-statistic):**	0.00

Time:	14:56:21	**Log-Likelihood:**	-1.0051e+05
No. Observations:	7369	**AIC:**	2.012e+05
Df Residuals:	7286	**BIC:**	2.018e+05
Df Model:	82		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	6.245e+05	3348.994	186.465	0.000	6.18e+05	6.31e+05
x1	-3.023e+04	3075.215	-9.832	0.000	-3.63e+04	-2.42e+04
x2	9048.8361	3801.683	2.380	0.017	1596.436	1.65e+04
x3	2.191e+05	4587.146	47.768	0.000	2.1e+05	2.28e+05
x4	-5403.1022	2812.628	-1.921	0.055	-1.09e+04	110.464
x5	-1.764e+04	3219.273	-5.478	0.000	-2.39e+04	-1.13e+04
x6	4.958e+04	2953.452	16.788	0.000	4.38e+04	5.54e+04
x7	2.288e+04	2531.545	9.037	0.000	1.79e+04	2.78e+04
x8	8.996e+04	4189.616	21.472	0.000	8.17e+04	9.82e+04
x9	3.139e+04	1.86e+04	1.687	0.092	-5084.551	6.79e+04
x10	5798.8329	1.53e+04	0.380	0.704	-2.41e+04	3.57e+04
x11	-9239.7977	2401.931	-3.847	0.000	-1.39e+04	-4531.317
x12	-9968.4999	2439.858	-4.086	0.000	-1.48e+04	-5185.673
x13	1.116e+16	3.29e+16	0.339	0.734	-5.34e+16	7.57e+16
x14	1.116e+16	3.29e+16	0.339	0.734	-5.34e+16	7.57e+16
x15	-2.309e+16	6.81e+16	-0.339	0.734	-1.57e+17	1.1e+17
x16	-1.379e+16	4.07e+16	-0.339	0.734	-9.35e+16	6.59e+16
x17	-2.422e+16	7.14e+16	-0.339	0.734	-1.64e+17	1.16e+17
x18	-2.963e+16	8.73e+16	-0.339	0.734	-2.01e+17	1.42e+17
x19	-2.309e+16	6.81e+16	-0.339	0.734	-1.57e+17	1.1e+17
x20	-3.931e+16	1.16e+17	-0.339	0.734	-2.67e+17	1.88e+17
x21	-1.563e+16	4.61e+16	-0.339	0.734	-1.06e+17	7.47e+16
x22	-2.826e+16	8.33e+16	-0.339	0.734	-1.92e+17	1.35e+17
x23	-1.044e+16	3.08e+16	-0.339	0.734	-7.08e+16	4.99e+16
x24	-2.144e+16	6.32e+16	-0.339	0.734	-1.45e+17	1.02e+17
x25	-1.076e+16	3.17e+16	-0.339	0.734	-7.29e+16	5.14e+16
x26	-1.428e+16	4.21e+16	-0.339	0.734	-9.68e+16	6.82e+16
x27	-1.474e+16	4.35e+16	-0.339	0.734	-9.99e+16	7.05e+16
x28	-3.47e+16	1.02e+17	-0.339	0.734	-2.35e+17	1.66e+17
x29	-1.044e+16	3.08e+16	-0.339	0.734	-7.08e+16	4.99e+16
x30	-3.489e+16	1.03e+17	-0.339	0.734	-2.37e+17	1.67e+17
x31	-2.568e+16	7.57e+16	-0.339	0.734	-1.74e+17	1.23e+17
x32	-1.727e+16	5.09e+16	-0.339	0.734	-1.17e+17	8.26e+16
x33	-1.93e+16	5.69e+16	-0.339	0.734	-1.31e+17	9.22e+16
x34	-2.175e+16	6.41e+16	-0.339	0.734	-1.47e+17	1.04e+17
x35	-1.766e+16	5.21e+16	-0.339	0.734	-1.2e+17	8.44e+16
x36	-3.018e+16	8.9e+16	-0.339	0.734	-2.05e+17	1.44e+17
x37	-3.722e+16	1.1e+17	-0.339	0.734	-2.52e+17	1.78e+17

x38	-1.964e+16	5.79e+16	-0.339	0.734	-1.33e+17	9.39e+16
x39	-1.166e+16	3.44e+16	-0.339	0.734	-7.91e+16	5.58e+16
x40	-2.985e+16	8.8e+16	-0.339	0.734	-2.02e+17	1.43e+17
x41	-2.542e+16	7.5e+16	-0.339	0.734	-1.72e+17	1.22e+17
x42	-1.542e+16	4.54e+16	-0.339	0.734	-1.05e+17	7.37e+16
x43	-3.376e+16	9.95e+16	-0.339	0.734	-2.29e+17	1.61e+17
x44	-1.379e+16	4.07e+16	-0.339	0.734	-9.35e+16	6.59e+16
x45	-2.22e+16	6.55e+16	-0.339	0.734	-1.51e+17	1.06e+17
x46	-2.503e+16	7.38e+16	-0.339	0.734	-1.7e+17	1.2e+17
x47	-2.907e+16	8.57e+16	-0.339	0.734	-1.97e+17	1.39e+17
x48	-2.112e+16	6.23e+16	-0.339	0.734	-1.43e+17	1.01e+17
x49	-1.606e+16	4.73e+16	-0.339	0.734	-1.09e+17	7.68e+16
x50	-1.379e+16	4.07e+16	-0.339	0.734	-9.35e+16	6.59e+16
x51	-2.476e+16	7.3e+16	-0.339	0.734	-1.68e+17	1.18e+17
x52	-2.449e+16	7.22e+16	-0.339	0.734	-1.66e+17	1.17e+17
x53	-1.998e+16	5.89e+16	-0.339	0.734	-1.35e+17	9.55e+16
x54	-1.519e+16	4.48e+16	-0.339	0.734	-1.03e+17	7.26e+16
x55	-1.895e+16	5.59e+16	-0.339	0.734	-1.28e+17	9.06e+16
x56	-2.031e+16	5.99e+16	-0.339	0.734	-1.38e+17	9.71e+16
x57	-3.756e+16	1.11e+17	-0.339	0.734	-2.55e+17	1.8e+17
x58	-3.114e+16	9.18e+16	-0.339	0.734	-2.11e+17	1.49e+17
x59	-3.207e+16	9.46e+16	-0.339	0.734	-2.17e+17	1.53e+17
x60	-2.755e+16	8.12e+16	-0.339	0.734	-1.87e+17	1.32e+17
x61	-2.555e+16	7.53e+16	-0.339	0.734	-1.73e+17	1.22e+17
x62	-1.981e+16	5.84e+16	-0.339	0.734	-1.34e+17	9.47e+16
x63	-3.238e+16	9.55e+16	-0.339	0.734	-2.19e+17	1.55e+17
x64	-4.494e+16	1.32e+17	-0.339	0.734	-3.05e+17	2.15e+17
x65	-3.535e+16	1.04e+17	-0.339	0.734	-2.4e+17	1.69e+17
x66	-4.227e+16	1.25e+17	-0.339	0.734	-2.87e+17	2.02e+17
x67	-3.866e+16	1.14e+17	-0.339	0.734	-2.62e+17	1.85e+17
x68	-2.755e+16	8.12e+16	-0.339	0.734	-1.87e+17	1.32e+17
x69	-3.018e+16	8.9e+16	-0.339	0.734	-2.05e+17	1.44e+17
x70	-3.217e+16	9.49e+16	-0.339	0.734	-2.18e+17	1.54e+17
x71	-3.176e+16	9.36e+16	-0.339	0.734	-2.15e+17	1.52e+17
x72	-3.356e+16	9.89e+16	-0.339	0.734	-2.28e+17	1.6e+17
x73	-3.072e+16	9.06e+16	-0.339	0.734	-2.08e+17	1.47e+17
x74	-3.581e+16	1.06e+17	-0.339	0.734	-2.43e+17	1.71e+17
x75	-2.422e+16	7.14e+16	-0.339	0.734	-1.64e+17	1.16e+17
x76	-8.254e+15	2.43e+16	-0.339	0.734	-5.6e+16	3.94e+16
x77	-3.227e+16	9.52e+16	-0.339	0.734	-2.19e+17	1.54e+17
x78	-2.657e+16	7.83e+16	-0.339	0.734	-1.8e+17	1.27e+17
x79	-2.422e+16	7.14e+16	-0.339	0.734	-1.64e+17	1.16e+17
x80	-2.963e+16	8.73e+16	-0.339	0.734	-2.01e+17	1.42e+17
x81	-2.767e+16	8.16e+16	-0.339	0.734	-1.88e+17	1.32e+17

x82	-1.708e+16	5.03e+16	-0.339	0.734	-1.16e+17	8.16e+16
x83	-2.422e+16	7.14e+16	-0.339	0.734	-1.64e+17	1.16e+17
x84	-3.765e+16	1.11e+17	-0.339	0.734	-2.55e+17	1.8e+17

Omnibus:	6178.878	**Durbin-Watson:**	1.993
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	682302.263
Skew:	3.425	**Prob(JB):**	0.00
Kurtosis:	49.640	**Cond. No.**	4.78e+15

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.16e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [205…
```
# predict on X
y_pred = model_base.predict(X_ols)
print(y_pred)
```

```
[ 585285.  524425. 1390829. ...  545853.  979721.  460183.]
```

RMSE/MSE

In [206…
```
rms_1 = mean_squared_error(y, y_pred)
print('MSE',rms_1)
```

```
MSE 41221262647.66047
```

In [207…
```
rmse_1 = np.sqrt(rms_1)
print('RMSE',rmse_1)
```

```
RMSE 203030.201319066
```

R Squared is only 81% - let's try to use the stepwise_selection function to see if the R Squared increases.

Model 2, using stepwise_selection function

Using statsmodels stepwise selection in order to select features based on its p-values.

In [208…
```
import statsmodels.api as sm

def stepwise_selection(X, y,
                       initial_list=[],
                       threshold_in=0.01,
                       threshold_out = 0.05,
                       verbose=True):
    """ Perform a forward-backward feature selection
    based on p-value from statsmodels.api.OLS
    Arguments:
        X - pandas.DataFrame with candidate features
        y - list-like with the target
        initial_list - list of features to start with (column names of X)
        threshold_in - include a feature if its p-value < threshold_in
        threshold_out - exclude a feature if its p-value > threshold_out
        verbose - whether to print the sequence of inclusions and exclusions
    Returns: list of selected features
    Always set threshold_in < threshold_out to avoid infinite looping.
    See https://en.wikipedia.org/wiki/Stepwise_regression for the details
    """
    included = list(initial_list)
    while True:
        changed=False
```

```
        # forward step
        excluded = list(set(X.columns)-set(included))
        new_pval = pd.Series(index=excluded)
        for new_column in excluded:
            model = sm.OLS(y, sm.add_constant(pd.DataFrame(X[included+[new_column]]))).fit()
            new_pval[new_column] = model.pvalues[new_column]
        best_pval = new_pval.min()
        if best_pval < threshold_in:
            best_feature = new_pval.idxmin()
            included.append(best_feature)
            changed=True
            if verbose:
                print('Add  {:30} with p-value {:.6}'.format(best_feature, best_pval))

        # backward step
        model = sm.OLS(y, sm.add_constant(pd.DataFrame(X[included]))).fit()
        # use all coefs except intercept
        pvalues = model.pvalues.iloc[1:]
        #worst_pval = pvalues.max() # null if pvalues is empty
        #if worst_pval > threshold_out:
         #   changed=True
          #  worst_feature = pvalues.argmax()
           # included.remove(worst_feature)
           # if verbose:
            #    print('Drop {:30} with p-value {:.6}'.format(worst_feature, worst_pval))
        if not changed:
            break
    return included
```

In [209…

```
result = stepwise_selection(X, y, verbose = True)
print('resulting features:')
print(result)
```

```
Add  grade                          with p-value 0.0
Add  sqft_living                    with p-value 0.0
Add  lat                            with p-value 2.42007e-164
Add  waterfront_1                   with p-value 1.67653e-180
Add  waterfront_0                   with p-value 6.81662e-213
Add  zipcode_98004                  with p-value 1.29421e-88
Add  zipcode_98039                  with p-value 6.18844e-86
Add  zipcode_98112                  with p-value 1.69006e-87
Add  view                           with p-value 3.43324e-82
Add  long                           with p-value 1.7e-45
Add  zipcode_98040                  with p-value 1.42666e-39
Add  zipcode_98105                  with p-value 2.04925e-35
Add  condition                      with p-value 8.71856e-31
Add  zipcode_98119                  with p-value 1.38336e-26
Add  bedrooms                       with p-value 9.45259e-26
Add  zipcode_98155                  with p-value 8.63517e-23
Add  zipcode_98133                  with p-value 9.14686e-24
Add  zipcode_98028                  with p-value 6.24159e-22
Add  zipcode_98102                  with p-value 2.69847e-19
Add  zipcode_98177                  with p-value 2.0398e-16
Add  zipcode_98011                  with p-value 3.06666e-14
Add  zipcode_98072                  with p-value 2.03528e-15
Add  zipcode_98125                  with p-value 6.34316e-16
Add  zipcode_98034                  with p-value 2.02094e-18
Add  zipcode_98077                  with p-value 1.17851e-15
Add  zipcode_98019                  with p-value 3.44484e-13
Add  zipcode_98109                  with p-value 2.19304e-11
Add  zipcode_98178                  with p-value 1.43299e-09
Add  zipcode_98070                  with p-value 7.78935e-10
Add  zipcode_98122                  with p-value 1.25999e-07
Add  zipcode_98166                  with p-value 2.16511e-07
Add  renovated                      with p-value 1.02948e-06
Add  zipcode_98053                  with p-value 1.92387e-06
Add  zipcode_98014                  with p-value 1.46544e-06
Add  zipcode_98065                  with p-value 2.03e-06
Add  zipcode_98199                  with p-value 8.71529e-07
Add  zipcode_98052                  with p-value 8.8402e-06
Add  zipcode_98056                  with p-value 2.82845e-05
```

```
Add  zipcode_98116                  with p-value 0.000122841
Add  date_month                     with p-value 0.000159867
Add  zipcode_98022                  with p-value 0.000253374
Add  floors                         with p-value 0.000126604
Add  zipcode_98144                  with p-value 0.00012259
Add  zipcode_98136                  with p-value 0.000130705
Add  zipcode_98074                  with p-value 0.000185135
Add  zipcode_98103                  with p-value 0.00138966
Add  zipcode_98033                  with p-value 0.0022897
Add  zipcode_98115                  with p-value 0.0029891
Add  zipcode_98198                  with p-value 0.00260878
Add  zipcode_98107                  with p-value 0.0030569
Add  zipcode_98010                  with p-value 0.00826678
resulting features:
['grade', 'sqft_living', 'lat', 'waterfront_1', 'waterfront_0', 'zipcode_98004', 'zipcode_98039', 'zi
pcode_98112', 'view', 'long', 'zipcode_98040', 'zipcode_98105', 'condition', 'zipcode_98119', 'bedroo
ms', 'zipcode_98155', 'zipcode_98133', 'zipcode_98028', 'zipcode_98102', 'zipcode_98177', 'zipcode_98
011', 'zipcode_98072', 'zipcode_98125', 'zipcode_98034', 'zipcode_98077', 'zipcode_98019', 'zipcode_9
8109', 'zipcode_98178', 'zipcode_98070', 'zipcode_98122', 'zipcode_98166', 'renovated', 'zipcode_9805
3', 'zipcode_98014', 'zipcode_98065', 'zipcode_98199', 'zipcode_98052', 'zipcode_98056', 'zipcode_981
16', 'date_month', 'zipcode_98022', 'floors', 'zipcode_98144', 'zipcode_98136', 'zipcode_98074', 'zip
code_98103', 'zipcode_98033', 'zipcode_98115', 'zipcode_98198', 'zipcode_98107', 'zipcode_98010']
```

The function has chosen the following features:

In [229…
```
best_features = result
```

In [230…
```
X_2= X[best_features]
```

In [231…
```
X_2.shape
```

Out[231…
```
(7369, 51)
```

Model 2, using stepwise_selection function

In [232…
```
X_2  = sm.add_constant(X_2)
model_2 = sm.OLS(y, X_2).fit()
model_2.summary()
```

Out[232…

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.794
Model:	OLS	**Adj. R-squared:**	0.792
Method:	Least Squares	**F-statistic:**	563.3
Date:	Thu, 13 Oct 2022	**Prob (F-statistic):**	0.00
Time:	15:03:14	**Log-Likelihood:**	-1.0056e+05
No. Observations:	7369	**AIC:**	2.012e+05
Df Residuals:	7318	**BIC:**	2.016e+05
Df Model:	50		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-3.666e+07	2.56e+06	-14.309	0.000	-4.17e+07	-3.16e+07
grade	8.339e+04	3596.733	23.186	0.000	7.63e+04	9.04e+04
sqft_living	229.6969	4.486	51.204	0.000	220.903	238.491
lat	9.747e+05	3.41e+04	28.612	0.000	9.08e+05	1.04e+06
waterfront_1	-1.796e+07	1.28e+06	-14.018	0.000	-2.05e+07	-1.54e+07
waterfront_0	-1.87e+07	1.28e+06	-14.599	0.000	-2.12e+07	-1.62e+07
zipcode_98004	4.988e+05	1.91e+04	26.154	0.000	4.61e+05	5.36e+05

zipcode_98039	1.115e+06	4.67e+04	23.881	0.000	1.02e+06	1.21e+06
zipcode_98112	4.184e+05	1.78e+04	23.498	0.000	3.83e+05	4.53e+05
view	5.18e+04	2973.261	17.423	0.000	4.6e+04	5.76e+04
long	-6.863e+04	2.94e+04	-2.334	0.020	-1.26e+05	-1.1e+04
zipcode_98040	2.619e+05	1.87e+04	13.997	0.000	2.25e+05	2.99e+05
zipcode_98105	2.141e+05	1.84e+04	11.614	0.000	1.78e+05	2.5e+05
condition	3.47e+04	3602.975	9.630	0.000	2.76e+04	4.18e+04
zipcode_98119	2.405e+05	2.08e+04	11.573	0.000	2e+05	2.81e+05
bedrooms	-2.957e+04	3041.877	-9.721	0.000	-3.55e+04	-2.36e+04
zipcode_98155	-2.435e+05	1.92e+04	-12.710	0.000	-2.81e+05	-2.06e+05
zipcode_98133	-2.055e+05	1.84e+04	-11.164	0.000	-2.42e+05	-1.69e+05
zipcode_98028	-2.678e+05	2.29e+04	-11.702	0.000	-3.13e+05	-2.23e+05
zipcode_98102	2.804e+05	2.74e+04	10.246	0.000	2.27e+05	3.34e+05
zipcode_98177	-1.636e+05	2.06e+04	-7.954	0.000	-2.04e+05	-1.23e+05
zipcode_98011	-2.457e+05	2.67e+04	-9.202	0.000	-2.98e+05	-1.93e+05
zipcode_98072	-2.328e+05	2.37e+04	-9.806	0.000	-2.79e+05	-1.86e+05
zipcode_98125	-1.403e+05	1.86e+04	-7.561	0.000	-1.77e+05	-1.04e+05
zipcode_98034	-1.36e+05	1.66e+04	-8.205	0.000	-1.69e+05	-1.04e+05
zipcode_98077	-3.134e+05	3.68e+04	-8.511	0.000	-3.86e+05	-2.41e+05
zipcode_98019	-3.028e+05	3.95e+04	-7.675	0.000	-3.8e+05	-2.25e+05
zipcode_98109	2.346e+05	2.78e+04	8.424	0.000	1.8e+05	2.89e+05
zipcode_98178	-1.177e+05	1.97e+04	-5.964	0.000	-1.56e+05	-7.9e+04
zipcode_98070	-2.056e+05	4.02e+04	-5.110	0.000	-2.84e+05	-1.27e+05
zipcode_98122	1.34e+05	1.87e+04	7.155	0.000	9.73e+04	1.71e+05
zipcode_98166	-8.452e+04	2.09e+04	-4.050	0.000	-1.25e+05	-4.36e+04
renovated	-1820.4906	440.589	-4.132	0.000	-2684.171	-956.810
zipcode_98053	-2.17e+05	4.01e+04	-5.409	0.000	-2.96e+05	-1.38e+05
zipcode_98014	-2.777e+05	5.14e+04	-5.404	0.000	-3.78e+05	-1.77e+05
zipcode_98065	-1.873e+05	3.53e+04	-5.301	0.000	-2.57e+05	-1.18e+05
zipcode_98199	1.102e+05	1.62e+04	6.825	0.000	7.86e+04	1.42e+05
zipcode_98052	-6.204e+04	1.76e+04	-3.533	0.000	-9.65e+04	-2.76e+04
zipcode_98056	-7.919e+04	2.17e+04	-3.656	0.000	-1.22e+05	-3.67e+04
zipcode_98116	9.345e+04	1.64e+04	5.687	0.000	6.12e+04	1.26e+05
date_month	-2829.6283	773.793	-3.657	0.000	-4346.485	-1312.772
zipcode_98022	1.135e+05	3.83e+04	2.966	0.003	3.85e+04	1.89e+05
floors	-3.085e+04	6239.912	-4.943	0.000	-4.31e+04	-1.86e+04
zipcode_98144	8.091e+04	1.58e+04	5.131	0.000	5e+04	1.12e+05
zipcode_98136	8.423e+04	1.84e+04	4.583	0.000	4.82e+04	1.2e+05
zipcode_98074	-6.538e+04	2.32e+04	-2.821	0.005	-1.11e+05	-2e+04
zipcode_98103	7.104e+04	1.6e+04	4.431	0.000	3.96e+04	1.02e+05
zipcode_98033	7.359e+04	1.91e+04	3.858	0.000	3.62e+04	1.11e+05
zipcode_98115	4.748e+04	1.39e+04	3.422	0.001	2.03e+04	7.47e+04
zipcode_98198	-6.76e+04	2.29e+04	-2.954	0.003	-1.12e+05	-2.27e+04
zipcode_98107	5.99e+04	2.09e+04	2.871	0.004	1.9e+04	1.01e+05

zipcode_98010	1.379e+05	5.22e+04	2.642	0.008	3.56e+04	2.4e+05

Omnibus:	6120.856	**Durbin-Watson:**	1.990
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	661979.758
Skew:	3.377	**Prob(JB):**	0.00
Kurtosis:	48.939	**Cond. No.**	8.07e+16

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 7.11e-24. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [233…
```
## predict on X
y_pred_2 = model_2.predict(X_2)
print(y_pred_2)
```

```
0       5.912843e+05
1       4.998293e+05
2       1.382598e+06
3       3.467582e+05
4       4.815624e+05
           ...
7364    4.381029e+05
7365    1.400076e+06
7366    5.309018e+05
7367    9.821098e+05
7368    4.587546e+05
Length: 7369, dtype: float64
```

MSE/RMSE

In [234…
```
rms_2 = mean_squared_error(y, y_pred_2)
print('MSE',rms_2)
```

```
MSE 41716383255.777504
```

In [235…
```
rmse_2 = np.sqrt(rms_2)
print('RMSE',rmse_2)
```

```
RMSE 204245.88920166178
```

Evaluating and Interpreting the Regression Model 1

Using LinearRegression() to fit the final model.

In [236…
```
linreg = LinearRegression()

# Fit the model on X  and y final
linreg.fit(X_2, y)
```

Out[236… `LinearRegression()`

In [237…
```
# calcualte y_hat
y_hat = linreg.predict(X_2)
y_hat
```

Out[237…
```
array([[ 591284.26274724],
       [ 499829.25000514],
       [1382598.09775002],
       ...,
       [ 530901.77924874],
```

```
       [ 982109.81156497],
       [ 458754.64043183]])
```

In [238…
```
# Calculate intercept
print('\nModel Intercept:', linreg.intercept_)
```

```
Model Intercept: [-54993452.91998314]
```

In [239…
```
# We will use sklearn.metrics to calculate the test
# data Mean Square Error

residuals = y -y_hat
```

Root Mean Squared Error - the average deviation between the predicted house and the actual house price is roughly $200K.

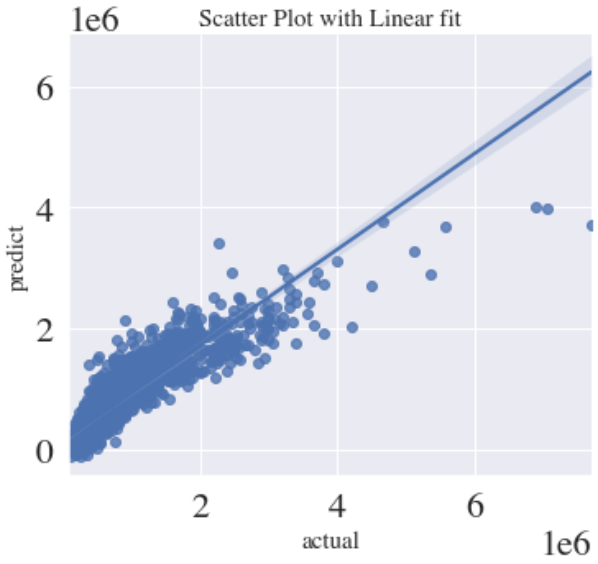
R squared - 79% of the variability observed in the house prices is explained by the independent variables 9 (i.e sqft_living, view, grade, waterfront...etc.) in a regression model.

Homoscedasticity

In [246…
```
# Creating a new data frame to store the predicted and the actual values
y['actual']= pd.DataFrame(y)

y_hat['predict'] = pd.DataFrame(y_hat)
```

In [248…
```
# Merging the data frames

resid = pd.concat([y['actual'], y_hat['predict']], axis=1,)
```

In [249…
```
# Plotting the error terms with predicted and actual values.

sns.lmplot(x='actual', y='predict', data=resid)
plt.title("Scatter Plot with Linear fit");
```

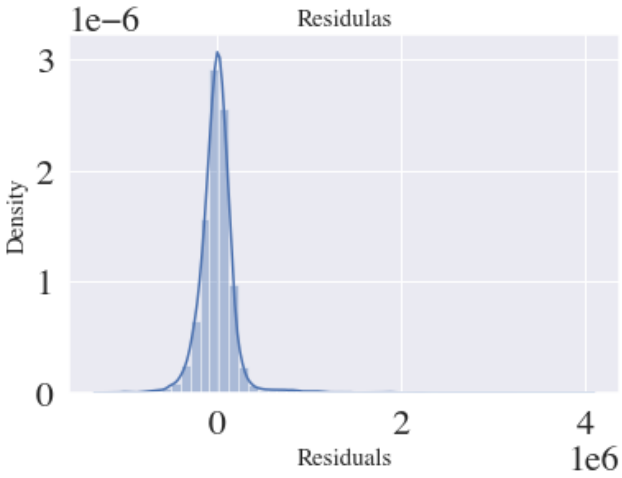


The assumptions validated since the graph shows similar variances for actual and predicted. They follow a linear direction.

Plotting a histogram of the residuals. Ensuring that the residuals are distributed normally.

In [250…
```
sns.distplot(residuals)
plt.title('Residulas' )
plt.xlabel('Residuals')
```

```
plt.ylabel('Density')
plt.show()
```



For the most part the the residuals do follow normal distribution.

Conclusions:

I have determined that the most valuable assets of a house in King County are zip code, view, grade and condition, square footage, and seasonality. Below are investment recommendations for Edegon and Company:

LOCATION: Invest in the zip codes where the value of the house is higher than average in order to increase the chances of maintaining the house value. Consider investing in zip codes 98118, 98116, 98109, 98122, whose market value is currently mid-range but also include some of the most profitable housing features.

VIEW: Prioritize a house with a great view, particularly if it has a waterfront.

SEASONALITY: Sell during the spring season when prices are at their peak. On average, During the months of March and April, the average price of a house increases by 34,000- 38,000 dollars.

GRADE Very important, more than house age. Keeping high end finishes and choosing high quality materials will lead to a profitable outcome.

SIZE: Look for large living area rather than a lot size! Houses ranging from 2,500 sqft to 5,000 sqft have a high correlation to house prices.