King County, Data Analysis

Please fill out:

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

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,mean_squared_error,r2_score
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
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	NaN
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	NO

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	NO
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	NO
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	NO

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 graph

kc_data['price'] = kc_data['price']/1000000
```

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)
```

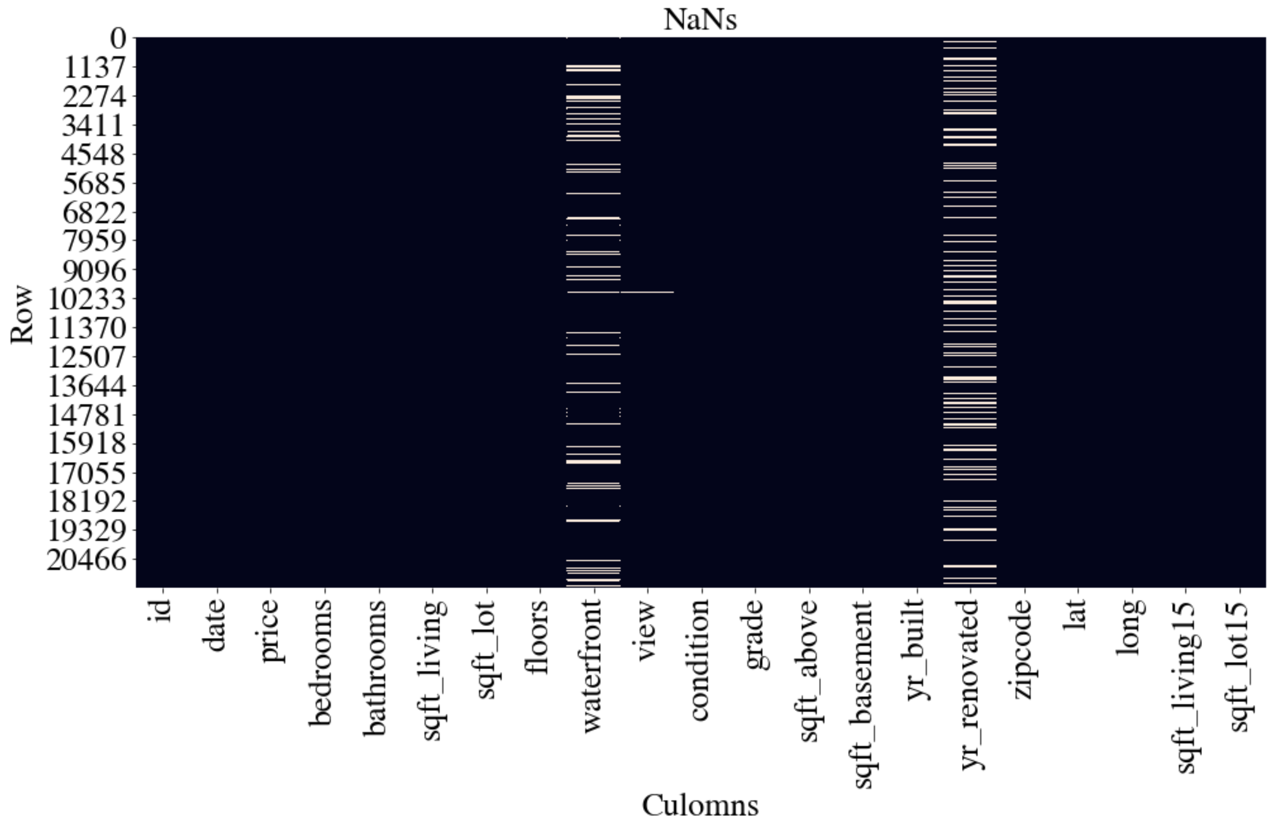
```
['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floo
rs', 'waterfront', 'view', 'condition', 'grade', 'sqft_above', 'sqft_basement',
'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot1
5']
```

In [6]:
```
#kc_data = kc_data.drop(not_needed_columns,axis=1)
```

In [7]:
```
kc_data.isnull().sum()
```

Out[7]:
```
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 [8]:
```
'''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 [9]:
```
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[9]:
```
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 [10]:
```
# 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 [11]:
```
kc_data['yr_renovated'] = kc_data['yr_renovated'].fillna(0)
```

In [12]:
```
kc_data['yr_renovated'] = kc_data['yr_renovated'].astype(int)
```

In [13]:
```
kc_data['yr_renovated'].value_counts()
```

Out[13]:
```
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 [14]:
```
# Checking the percentage of the missing vlues.
2376/21597
```

Out[14]:
```
0.11001527989998611
```

In [15]:
```
kc_data.dropna(subset=['waterfront'], inplace=True)
```

In [16]:
```
# We will run the is sum of null code again to see what's left.
kc_data.isnull().sum()
```

Out[16]:
```
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 [17]:

```
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 [18]:

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

Out[18]:

```
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 [19]:
```
kc_data.sqft_basement.replace('?' and '0', np.nan ,inplace = True)
```

In [20]:
```
kc_data.sqft_basement.replace('0.0', np.nan, inplace = True)
```

In [21]:
```
kc_data.sqft_basement.replace('?', np.nan, inplace = True)
```

In [22]:
```
# Dropping NaNs from sqft_basement
kc_data.dropna(subset=['sqft_basement'],inplace =True)
```

In [23]:
```
kc_data['sqft_basement'].unique()
```

Out[23]:
```
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 [24]:
```
kc_data['sqft_basement'] = kc_data['sqft_basement'].str.split('.',n=1, expand = T
```

In [25]:
```
kc_data['sqft_basement'] = kc_data['sqft_basement'].astype(int)
```

In [26]:
```
kc_data['grade']= kc_data['grade'].astype(str)
```

In [27]:
```
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 [28]:

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

In [29]:

```
# Double checking that the '?' was removed.

kc_data.sqft_basement.unique()
```

Out[29]:

```
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 [30]:

```
# Creating two new columns, 'month' and 'year' by extracting them from the date c
# 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 [31]:

```
extract_date(kc_data,'date')
```

In [32]:

```
kc_data['year'] = pd.DatetimeIndex(kc_data['date']).year
```

In [33]:

```
kc_data['month'] = pd.DatetimeIndex(kc_data['date']).month
```

In [34]:
```
# Using describe method to check for outliers.

kc_data.describe()
```

Out[34]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	7.370000e+03	7370.000000	7370.000000	7370.000000	7370.000000	7370.000000	737
mean	4.608717e+09	0.623672	3.558480	2.272693	2313.011805	13188.630665	[illegible]
std	2.870696e+09	0.449737	1.014971	0.777863	959.555858	30776.711805	[illegible]
min	2.800031e+06	0.100000	1.000000	0.500000	680.000000	572.000000	[illegible]
25%	2.145425e+09	0.375000	3.000000	1.750000	1680.000000	5000.000000	[illegible]
50%	3.971701e+09	0.513000	3.000000	2.250000	2100.000000	7520.000000	[illegible]
75%	7.338402e+09	0.711000	4.000000	2.750000	2700.000000	10660.750000	[illegible]
max	9.900000e+09	7.700000	33.000000	8.000000	13540.000000	871200.000000	[illegible]

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 [35]:
```
# 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[35]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	7.370000e+03	7370.000000	7369.000000	7370.000000	7370.000000	7370.000000	737
mean	4.608717e+09	0.623672	3.554485	2.272693	2313.011805	13188.630665	[illegible]
std	2.870696e+09	0.449737	0.955325	0.777863	959.555858	30776.711805	[illegible]
min	2.800031e+06	0.100000	1.000000	0.500000	680.000000	572.000000	[illegible]
25%	2.145425e+09	0.375000	3.000000	1.750000	1680.000000	5000.000000	[illegible]
50%	3.971701e+09	0.513000	3.000000	2.250000	2100.000000	7520.000000	[illegible]
75%	7.338402e+09	0.711000	4.000000	2.750000	2700.000000	10660.750000	[illegible]
max	9.900000e+09	7.700000	11.000000	8.000000	13540.000000	871200.000000	[illegible]

In [36]:
```
# Confirming that there are no missing values.
```

```
missing_value_kc_data
```

Out[36]:

	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
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 [37]:

```
kc_data['grade'].unique()
```

Out[37]:

```
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 [38]:

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

Out[38]:

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

In [39]:

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

In [40]:
```
# 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[40]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	vie
1	6414100192	2014-12-09	0.5380	3.0	2.25	2570	7242	2.0	NO	
3	2487200875	2014-12-09	0.6040	4.0	3.00	1960	5000	1.0	NO	
5	7237550310	2014-05-12	1.2300	4.0	4.50	5420	101930	1.0	NO	
8	2414600126	2015-04-15	0.2295	3.0	1.00	1780	7470	1.0	NO	
11	9212900260	2014-05-27	0.4680	2.0	1.00	1160	6000	1.0	NO	

5 rows × 25 columns

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7370 entries, 1 to 21591
Data columns (total 25 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       7369 non-null   float64
 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   int64
 10  condition      7370 non-null   int64
 11  grade          7370 non-null   int64
 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
 21  dateyear       7370 non-null   int64
 22  date_month     7370 non-null   int64
 23  year           7370 non-null   int64
 24  month          7370 non-null   int64
dtypes: datetime64[ns](1), float64(6), int64(17), object(1)
memory usage: 1.7+ MB
```

In [42]:
```
kc_data.head()
```

Out[42]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	vie
1	6414100192	2014-12-09	0.5380	3.0	2.25	2570	7242	2.0	NO	
3	2487200875	2014-12-09	0.6040	4.0	3.00	1960	5000	1.0	NO	
5	7237550310	2014-05-12	1.2300	4.0	4.50	5420	101930	1.0	NO	
8	2414600126	2015-04-15	0.2295	3.0	1.00	1780	7470	1.0	NO	
11	9212900260	2014-05-27	0.4680	2.0	1.00	1160	6000	1.0	NO	

5 rows × 25 columns

Exploratory Data Analysis

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]:
```
kc_data_dublicate = kc_data[kc_data.duplicated(subset=['id'],keep= False)]
kc_data_dublicate.head()
```

Out[43]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	v
93	6021501535	2014-07-25	0.43	3.0	1.50	1580	5000	1.0	NO	
94	6021501535	2014-12-23	0.70	3.0	1.50	1580	5000	1.0	NO	
313	4139480200	2014-06-18	1.38	4.0	3.25	4290	12103	1.0	NO	
314	4139480200	2014-12-09	1.40	4.0	3.25	4290	12103	1.0	NO	
1084	9834200885	2014-07-17	0.36	4.0	2.50	2080	4080	1.0	NO	

5 rows × 25 columns

In [44]:
```
kc_data_dublicate = kc_data_dublicate[['id', 'date_month', 'price','grade','condi
kc_data_dublicate
```

Out[44]:

	id	date_month	price	grade	condition

	id	date_month	price	grade	condition
93	6021501535	7	0.430000	8	3
94	6021501535	12	0.700000	8	3
313	4139480200	6	1.380000	11	3
314	4139480200	12	1.400000	11	3
1084	9834200885	7	0.360000	7	5
...	...	...	...	...	...
18689	3558900590	3	0.692500	7	3
18976	7856400300	7	1.410000	10	5
18977	7856400300	3	1.510000	10	5
19536	643300040	11	0.481000	7	4
19537	643300040	3	0.719521	7	4

90 rows × 5 columns

In [45]:

```
'''Creating a new data frame in which I only include the duplicate data. Consolid
    using  group by ‘id’ where one raw represents one house that was sold and the
    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('p
```

In [46]:

```
kc_group_id.head()
```

Out[46]:

	id	priceprice		pricedate_month		pricegrade		pricecondition	
		price0	price1	price0	price1	price0	price1	price0	price1
0	526059224	0.260	0.470000	9	2	7	7	3	3
1	641900050	0.335	0.499950	8	2	7	7	3	3
2	643300040	0.481	0.719521	11	3	7	7	4	4
3	1139600270	0.300	0.310000	7	3	8	8	3	3
4	1217000340	0.185	0.340000	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 drople
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.
0	526059224	0.260	0.470000	9	2	7	7	3	3	1
1	641900050	0.335	0.499950	8	2	7	7	3	3	2
2	643300040	0.481	0.719521	11	3	7	7	4	4	3
3	1139600270	0.300	0.310000	7	3	8	8	3	3	4
4	1217000340	0.185	0.340000	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'
```

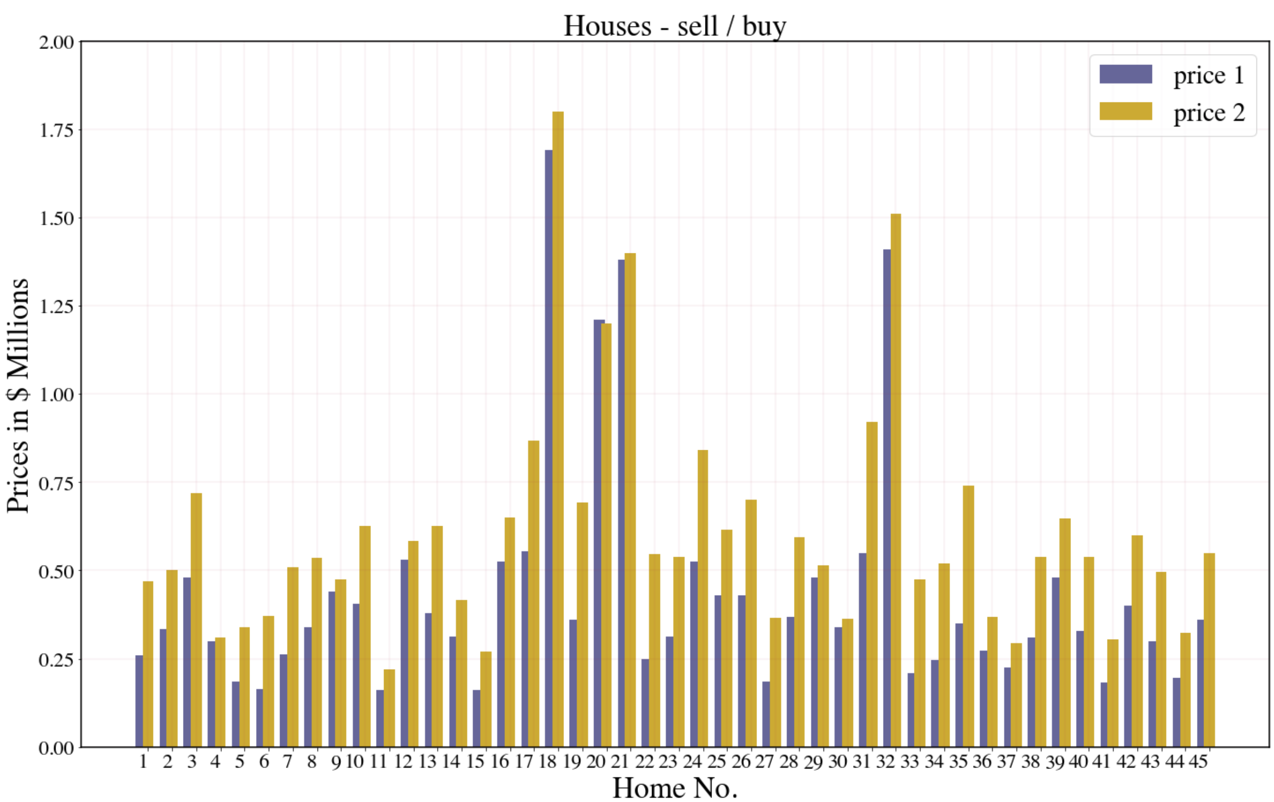
In [52]:

```
# 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(0,2.)

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 p

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

In [55]:

```
kc_group_id.head()
```

Out[55]:

id	price_1	price_2	month_1	month_2	cond_1	cond_2	price0	price1	home_no.

	id	price_1	price_2	month_1	month_2	cond_1	cond_2	price0	price1	home_no.
0	526059224	0.260	0.470000	9	2	7	7	3	3	1
1	641900050	0.335	0.499950	8	2	7	7	3	3	2
2	643300040	0.481	0.719521	11	3	7	7	4	4	3
3	1139600270	0.300	0.310000	7	3	8	8	3	3	4
4	1217000340	0.185	0.340000	6	2	7	7	4	4	5

In [56]:

```
group_month = kc_group_id.groupby(['price_diff']).mean()
group_month = pd.DataFrame.reset_index(group_month)

group_month.head()
```

Out[56]:

	price_diff	id	price_1	price_2	month_1	month_2	cond_1	cond_2	price0	price1	I
0	-0.0100	4139420590	1.210	1.2000	5	8	12	12	3	3	
1	0.0100	1139600270	0.300	0.3100	7	3	8	8	3	3	
2	0.0200	4139480200	1.380	1.4000	6	12	11	11	3	3	
3	0.0230	7387500235	0.340	0.3630	5	3	7	7	3	3	
4	0.0335	1250201165	0.441	0.4745	11	3	6	6	3	3	

In [57]:

```
# Creating a function that has bars with range of colores - darker from tightest
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"]
```

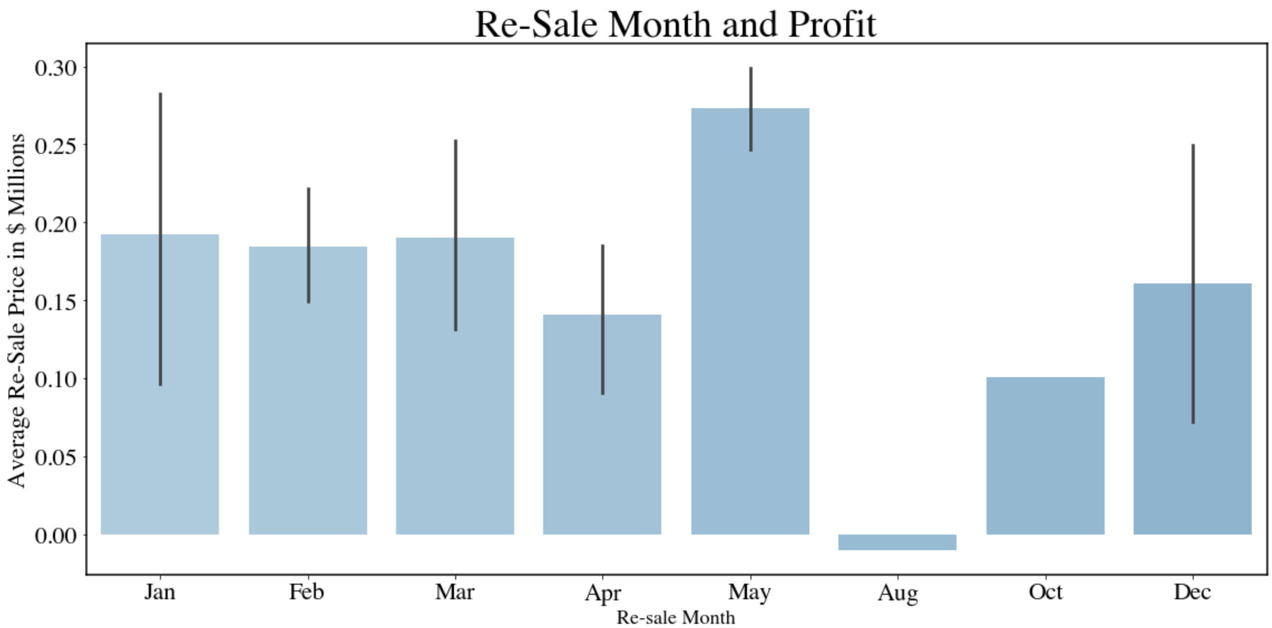
In [58]:

```
#sns.pairplot(kc_data, height=5.5, aspect=1)

#sns.set(font_scale=2)
```

In [59]:

```
# Plot bar displaying the months of the release day and making the darkest color

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 Price 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?

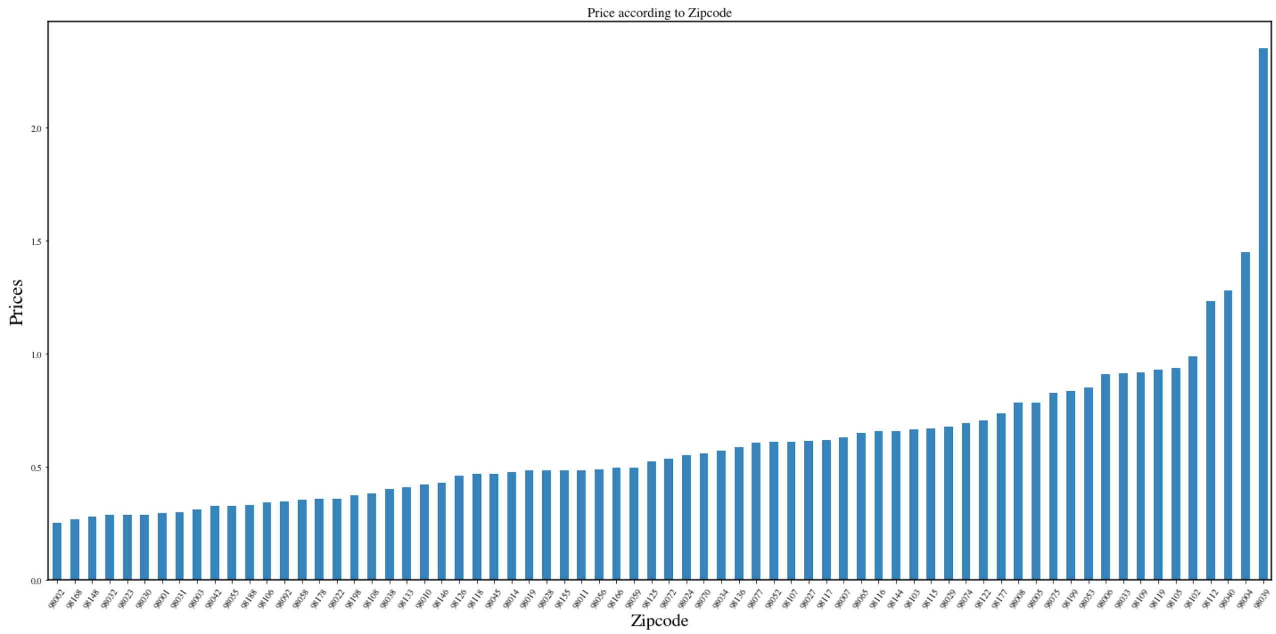
Zipcode

Grouping the zip codes by price and checking their mean so I can see if there is a pattern of prices.

In [60]:
```
''' will group the zipcodes by price and check their mean so that I could see if
pattern of the prices '''
group_zipcode = kc_data.groupby(['zipcode'])['price'].mean()
```

In [61]:
```
# Let's view the data with a sorted value

plt.figure(figsize=(20, 18))
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,fig
# the plot gets saved to 'output.png'

plt.title('Price according to Zipcode' )
```

```
plt.xticks(rotation = 55)
plt.xlabel('Zipcode',fontsize=20)
plt.ylabel('Prices',fontsize=22)
plt.tight_layout()

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




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

In [62]:

```
top20p = kc_data.sort_values(by= 'zipcode', ascending = False).head(368)
top20p.head()
```

Out[62]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
3153	6821100195	2015-03-31	0.830	4.0	3.00	2020	6000	1.0	NO
8678	6822100750	2015-05-08	0.700	3.0	1.75	1500	6000	1.0	NO
19452	3271800870	2014-08-07	1.230	4.0	2.25	2020	5800	1.0	NO
3110	5035300750	2014-07-31	0.850	3.0	1.75	2450	8603	1.0	NO
3119	3271800850	2014-08-06	0.765	3.0	1.75	2440	5800	1.0	NO

5 rows × 25 columns

In [63]:

```
top20p = kc_data.sort_values(by= 'price', ascending = False).head(1474)
top20p.head()
```

Out[63]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
7245	6762700020	2014-10-13	7.70	6.0	8.00	12050	27600	2.5	NO
3910	9808700762	2014-06-11	7.06	5.0	4.50	10040	37325	2.0	YES
9245	9208900037	2014-09-19	6.89	6.0	7.75	9890	31374	2.0	NO
4407	2470100110	2014-08-04	5.57	5.0	5.75	9200	35069	2.0	NO
1446	8907500070	2015-04-13	5.35	5.0	5.00	8000	23985	2.0	NO

5 rows × 25 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 [64]:

```
top20p_long_lat = top20p[['lat', 'long']]
top20p_long_lat
```

Out[64]:

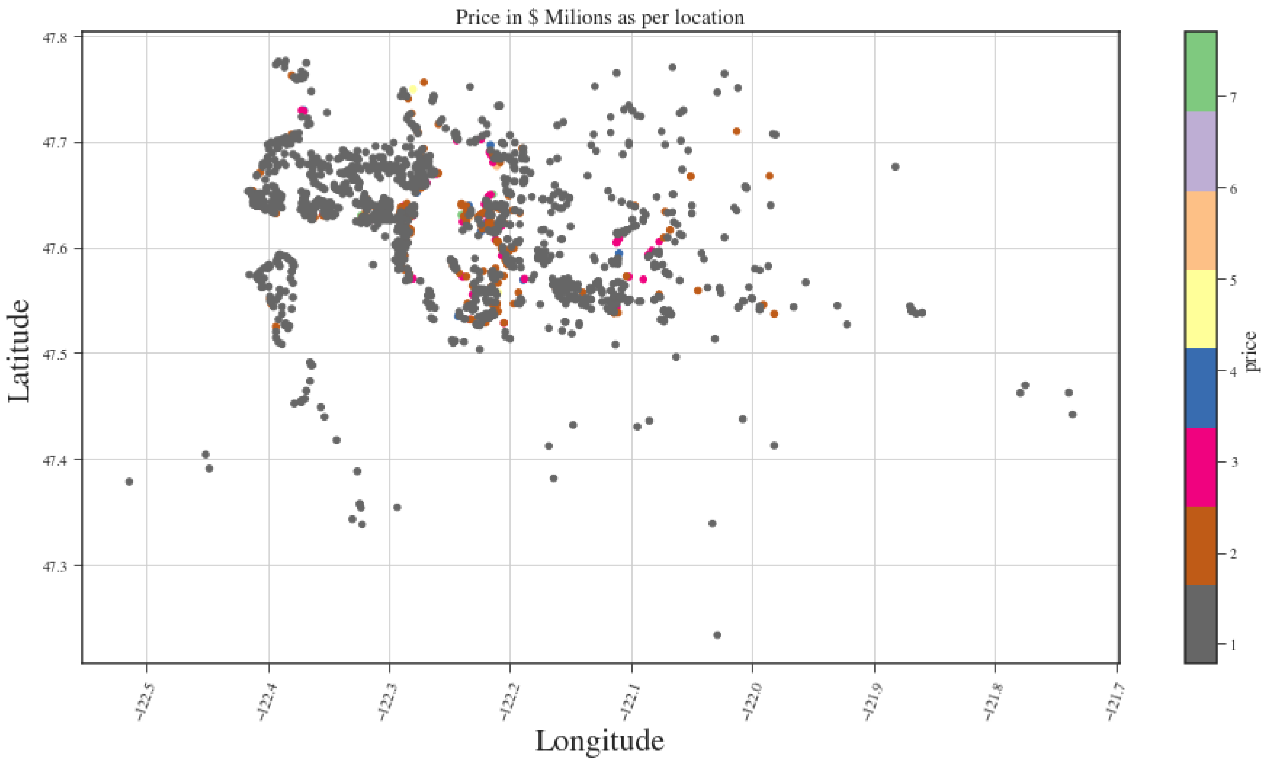
	lat	long
7245	47.6298	-122.323
3910	47.6500	-122.214
9245	47.6305	-122.240
4407	47.6289	-122.233
1446	47.6232	-122.220
...	...	...
13392	47.6853	-122.305
16371	47.6296	-122.205
3145	47.7027	-122.282
19693	47.6214	-122.062
1604	47.4961	-122.063

1474 rows × 2 columns

In [65]:

```
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 [66]:

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

Out[66]:

```
zipcode
98001    0.850000
98003    0.810000
98004    1.606250
98005    0.939148
98006    1.216673
Name: price, dtype: float64
```

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

In [67]:

```
zipcode = top20p.groupby('zipcode', as_index = False)
zipcode
```

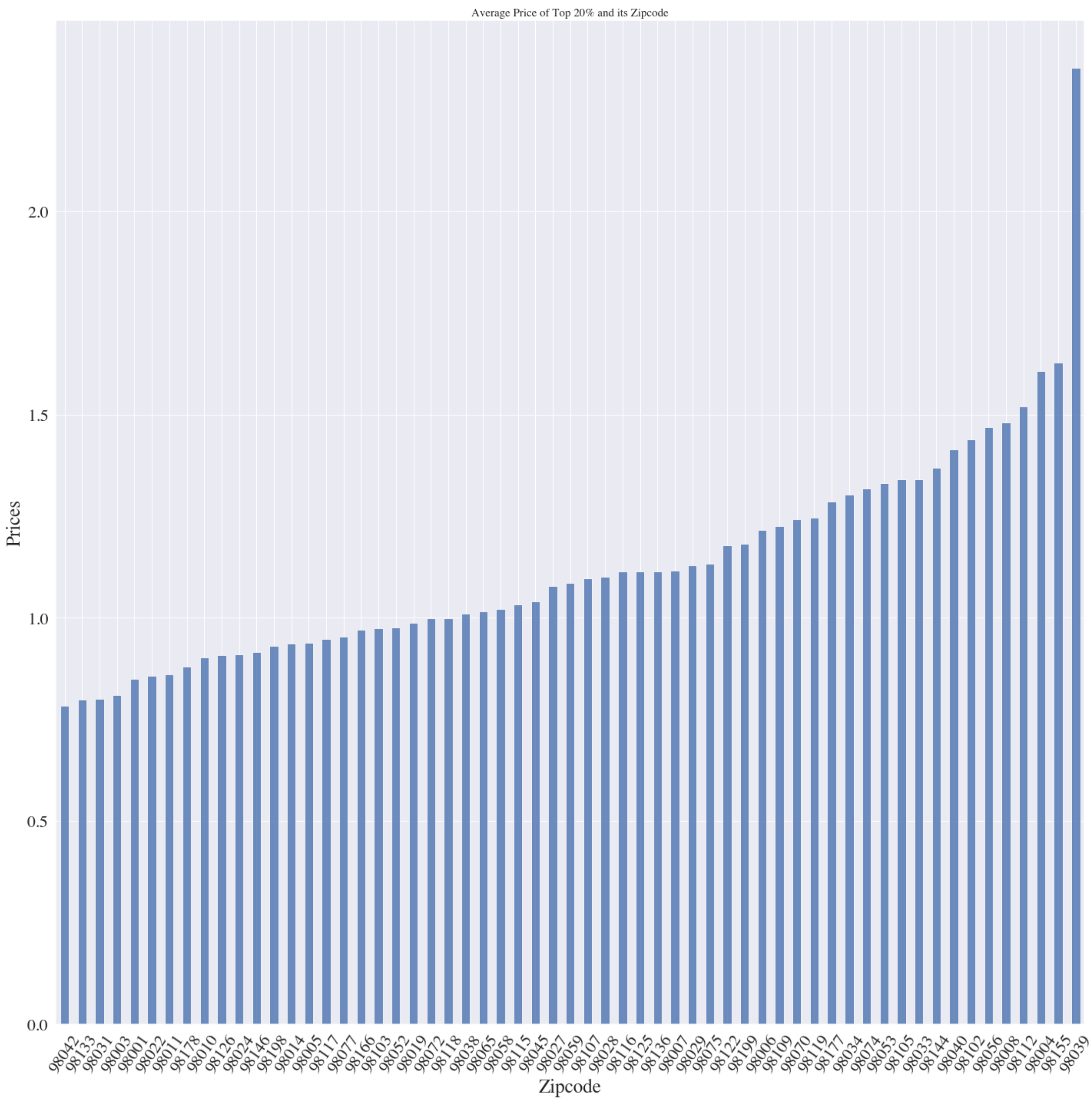
Out[67]:

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x7fb11d1b3940>
```

In [68]:

```
# 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,fig
# the plot gets saved to 'output.png'

plt.title('Average Price of Top 20% and its Zipcode' )

plt.xticks(rotation = 55)
plt.xlabel('Zipcode', fontsize=25)
plt.ylabel('Prices', fontsize=25)
plt.tight_layout()

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



<Figure size 432x288 with 0 Axes>

In [69]:

```
bottom20p = kc_data.sort_values(by= 'price', ascending = False).tail(368)
bottom20p
```

Out[69]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
9430	4302201085	2014-09-18	0.2480	3.0	1.00	1470	7680	1.0	NO
1619	1310500550	2014-12-20	0.2480	4.0	2.25	2320	8760	1.0	NO
8412	2172000846	2014-06-19	0.2480	4.0	2.00	2080	13510	1.0	NO
4834	5151600480	2015-04-02	0.2480	3.0	1.75	1840	19501	1.0	NO
4295	2122059160	2015-04-27	0.2480	5.0	1.75	2190	16788	1.0	NO
...	...	...	...	...	...	...	...	...	...
12729	5560000650	2014-12-02	0.1350	3.0	1.00	1520	8450	1.0	NO
10376	3361402041	2014-10-30	0.1340	3.0	1.00	1270	8508	1.0	NO
3686	6303401050	2015-02-20	0.1325	3.0	0.75	850	8573	1.0	NO
3481	3352402250	2014-10-21	0.1199	2.0	1.00	700	3180	1.0	NO
5634	7224000980	2014-06-10	0.1000	4.0	1.00	1120	2685	1.0	NO

368 rows × 25 columns

In [70]:

```
group_zipcode_b = bottom20p.groupby(['zipcode'])['price'].mean()
group_zipcode_b.head()
```

Out[70]:

```
zipcode
98001    0.213633
98002    0.218162
98003    0.223144
98006    0.247500
98010    0.200000
Name: price, dtype: float64
```

In [71]:

```
zipcode_b = bottom20p.groupby('zipcode', as_index = False)
zipcode_b.head()
```

Out[71]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfron
9430	4302201085	2014-09-18	0.24800	3.0	1.00	1470	7680	1.0	N(
1619	1310500550	2014-12-20	0.24800	4.0	2.25	2320	8760	1.0	N(

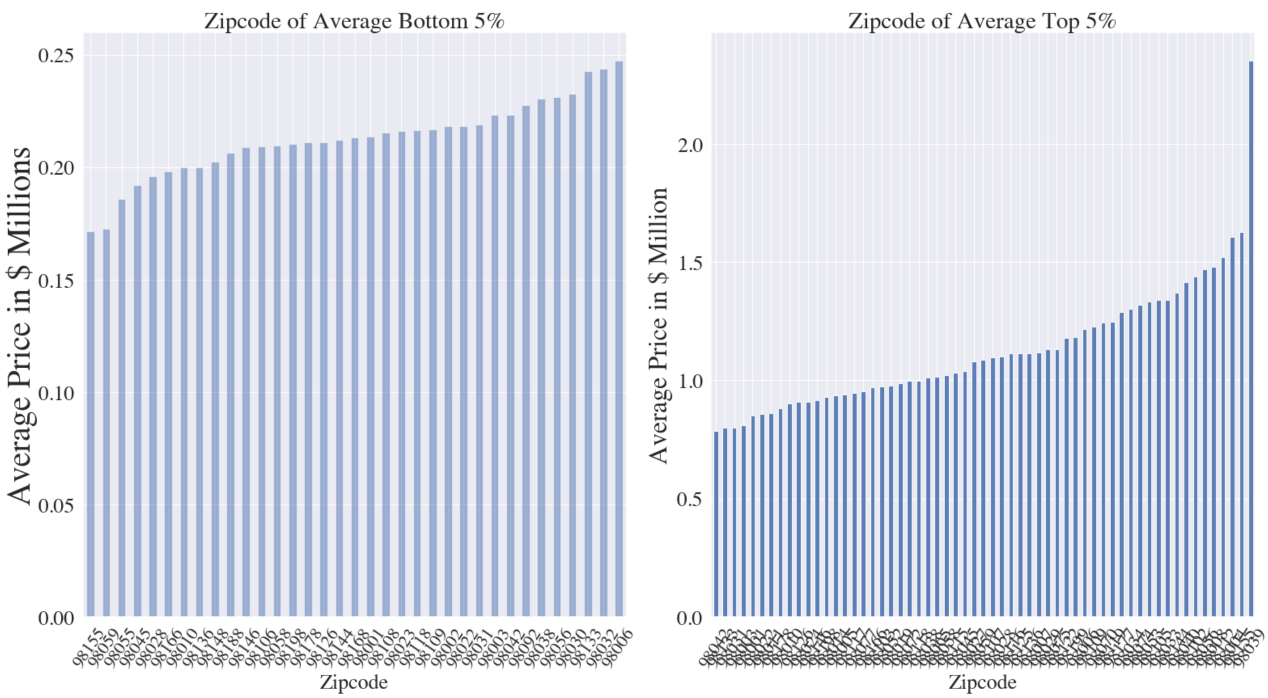
	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfron
8412	2172000846	2014-06-19	0.24800	4.0	2.00	2080	13510	1.0	N(
4834	5151600480	2015-04-02	0.24800	3.0	1.75	1840	19501	1.0	N(
4295	2122059160	2015-04-27	0.24800	5.0	1.75	2190	16788	1.0	N(
...	...	...	...	...	...	...	...	...	.
2350	7229700105	2015-04-24	0.17250	2.0	2.00	1510	20685	1.0	N(
19547	42000245	2014-06-13	0.17100	4.0	2.00	1520	19672	1.0	N(
9865	1219000473	2014-06-26	0.16495	3.0	1.75	1570	15330	1.0	N(
8716	7883603425	2014-05-29	0.15500	3.0	1.00	1250	6250	1.0	N(
5811	7568700480	2015-03-23	0.15300	2.0	1.00	1140	10152	1.0	N(

135 rows × 25 columns

In [72]:

```
sns.set(font_scale=3)
plt.figure(2, figsize=(20,15))

#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.

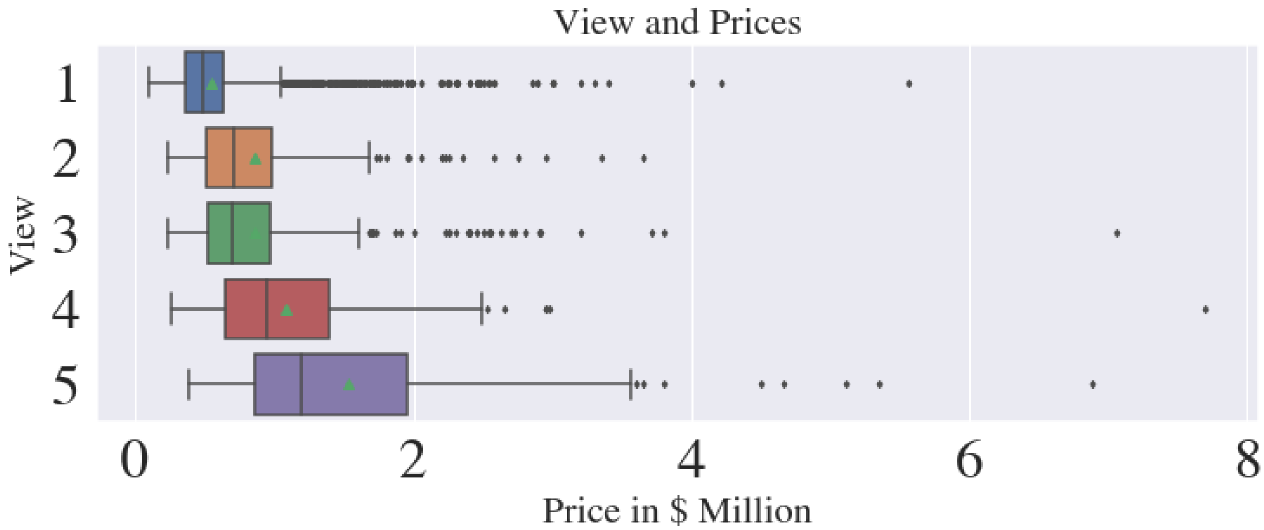
The majority of houses are shown to have a low grade view.

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

In [73]:

```
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',
            fliersize = 3, ax = ax)
plt.title('View and Prices', fontsize=22)
plt.xlabel('Price in $ Million',fontsize=22)
plt.ylabel('View',fontsize=22)
```

Out[73]: Text(0, 0.5, 'View')



In [74]:
```
kc_data['view'].value_counts()
```

Out[74]:
```
1    6147
3     501
4     305
2     212
5     205
Name: view, dtype: int64
```

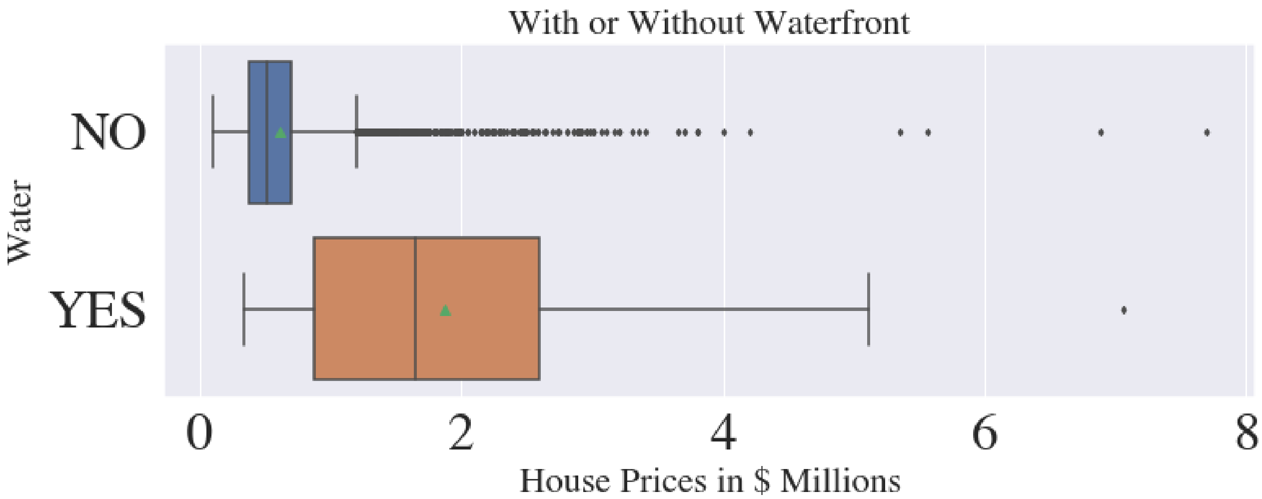
Waterfront

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, while waterfront homes typically cost more than three times that amount, from $900K-$2.6M.

In [75]:
```
#We would need to visualize the data to clearly see where the data rests. Let's u

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 =
            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 [76]:
```
waterfront_non = kc_data.loc[kc_data['waterfront']=='NO','price']
```

In [77]:
```
waterfront_non.head()
```

Out[77]:
```
1     0.5380
3     0.6040
5     1.2300
8     0.2295
11    0.4680
Name: price, dtype: float64
```

In [78]:
```
waterfront = kc_data.loc[kc_data['waterfront']=='YES','price']
waterfront.head()
```

Out[78]:
```
49     1.350
230    0.655
246    2.400
300    3.080
457    0.705
Name: price, dtype: float64
```

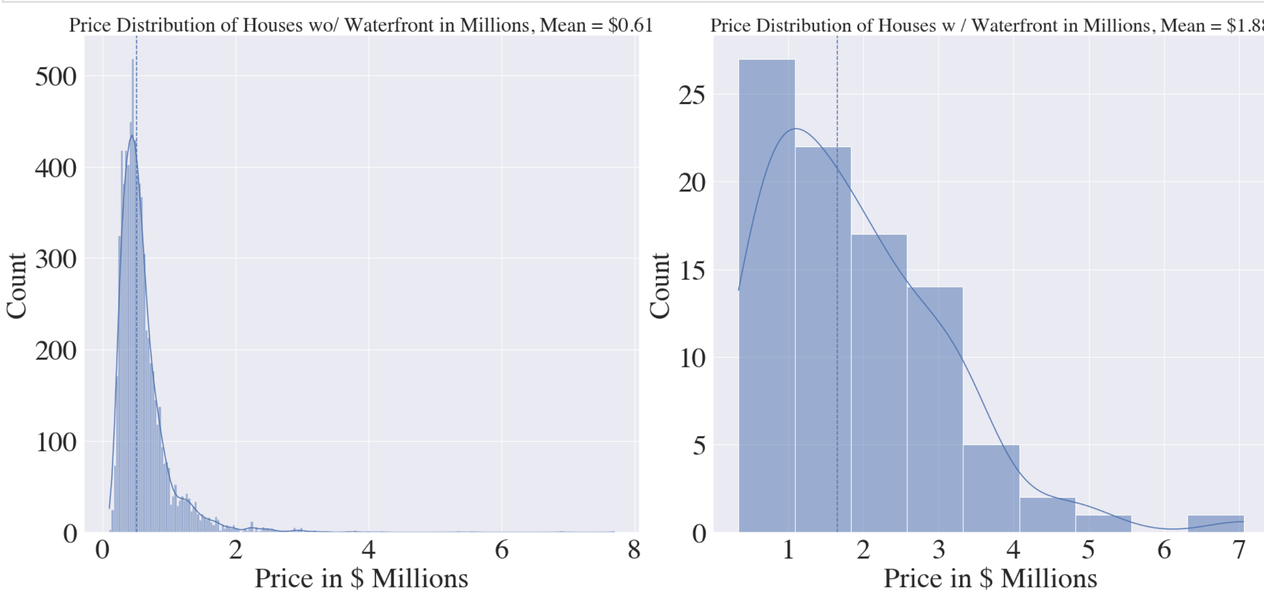
In [79]:
```
kc_water=kc_data['waterfront']=0
```

In [80]:
```
kc_data.shape
```

Out[80]:
```
(7370, 25)
```

In [81]:
```
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 = $' +st
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 = $' +st
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()
```



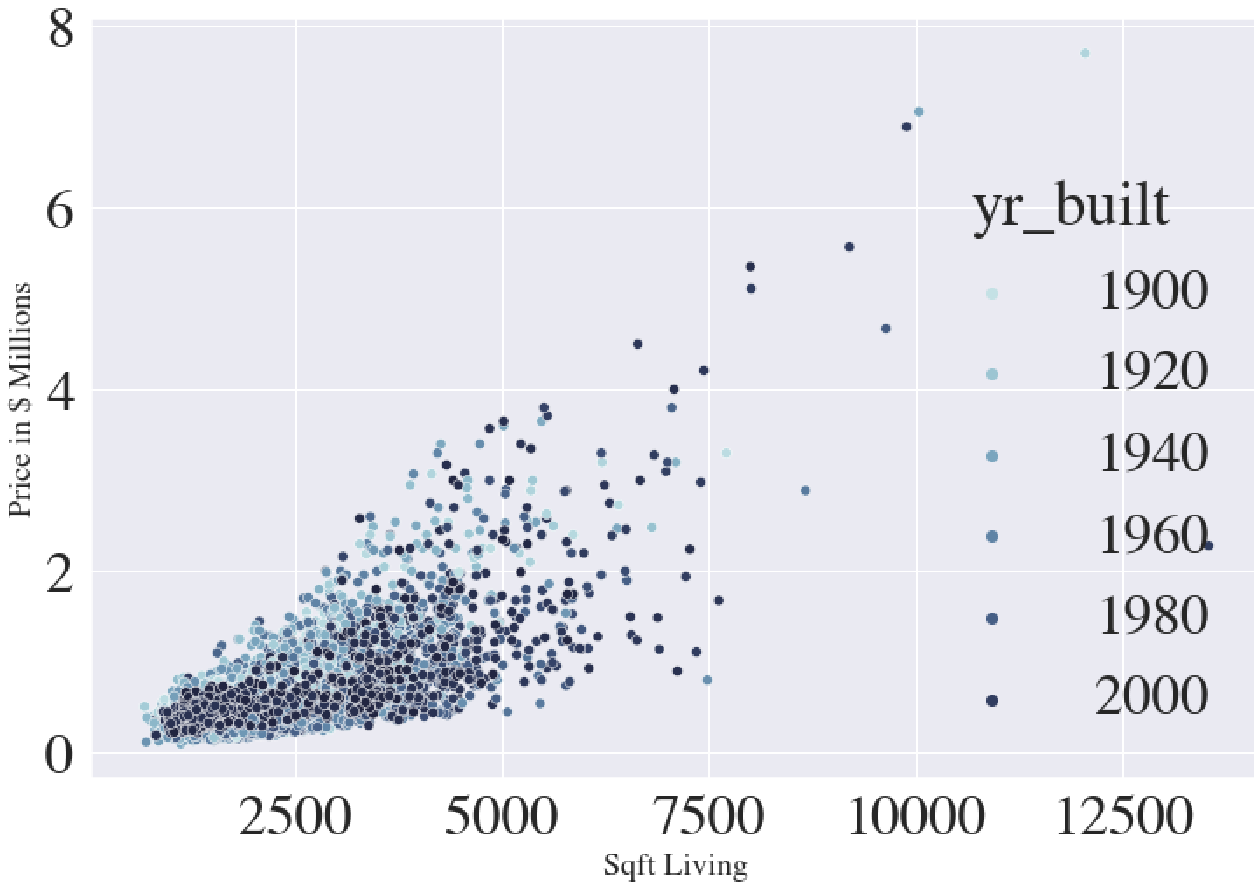
How many square feet should the house/lot be to hold its value?

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",
                     hue="yr_built",
                     palette=cmap, sizes=(500, 500),
                     data=kc_data)
```

```
fig.suptitle('Sqft of living and House prices ')
plt.xlabel('Sqft Living', fontsize=18)
plt.ylabel('Price in $ Millions', fontsize=18)
```

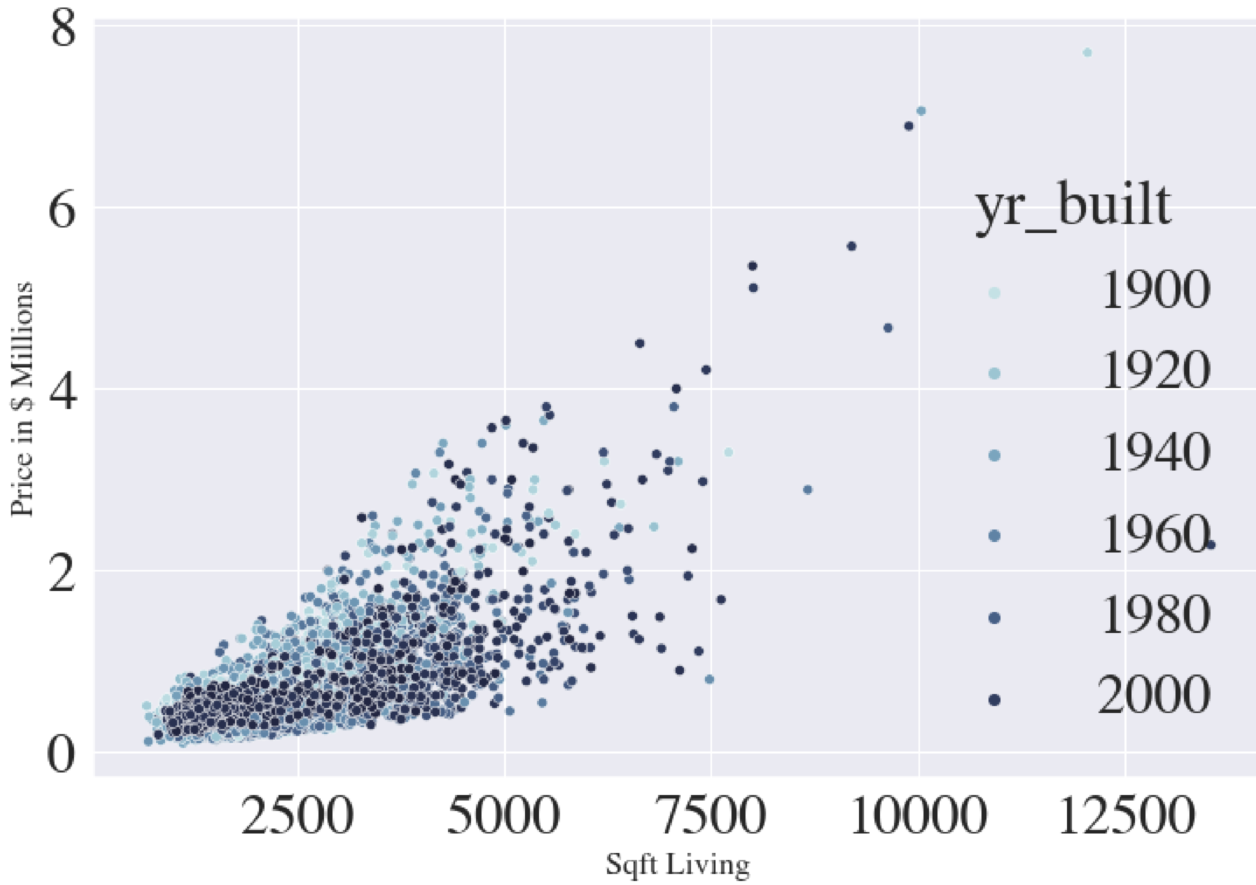
Out[82]: Text(0, 0.5, 'Price in $ Millions')



In [83]:

```
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",
                     hue="yr_built",
                     palette=cmap, sizes=(500, 500),
                     data=kc_data)


fig.suptitle('Sqft of living and House prices ')
plt.xlabel('Sqft Living', fontsize=18)
plt.ylabel('Price in $ Millions', fontsize=18)
```

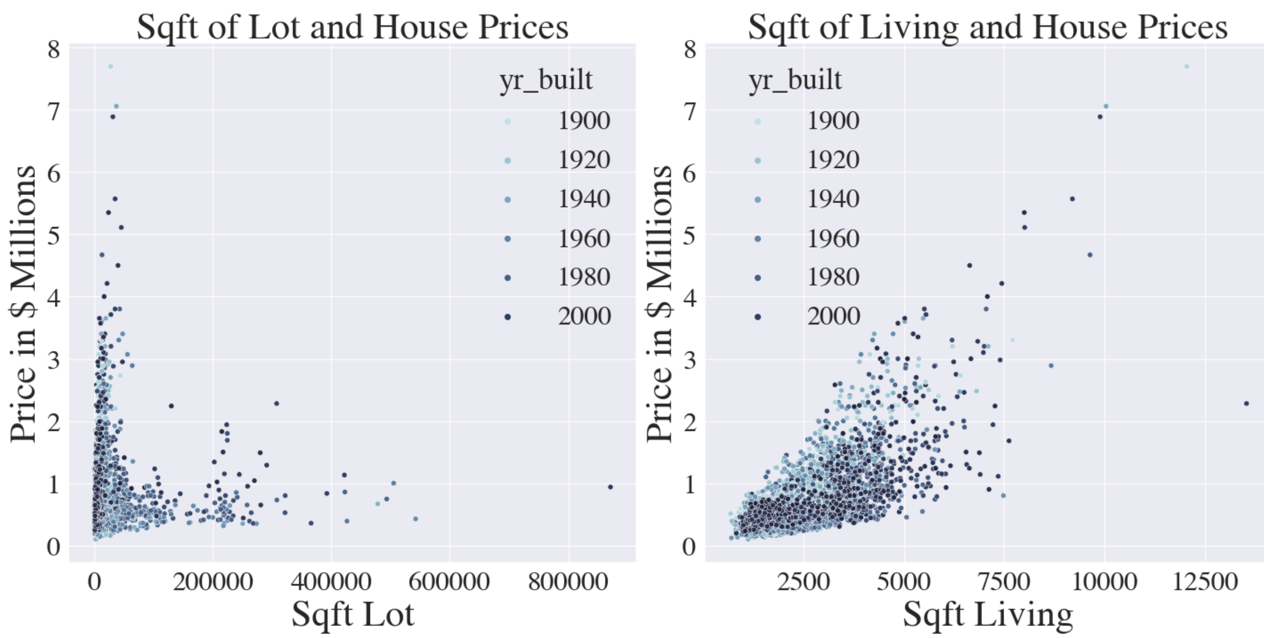
Out[83]: Text(0, 0.5, 'Price in $ Millions')



In [84]:

```
# 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 [85]:

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

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

Out[85]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
id	1.00	-0.02	0.01	0.00	-0.02	-0.13	0.02	NaN	0.01
price	-0.02	1.00	0.26	0.53	0.72	0.07	0.35	NaN	0.45
bedrooms	0.01	0.26	1.00	0.46	0.52	0.06	0.08	NaN	0.10
bathrooms	0.00	0.53	0.46	1.00	0.70	0.13	0.47	NaN	0.24
sqft_living	-0.02	0.72	0.52	0.70	1.00	0.23	0.33	NaN	0.37
sqft_lot	-0.13	0.07	0.06	0.13	0.23	1.00	-0.02	NaN	0.07
floors	0.02	0.35	0.08	0.47	0.33	-0.02	1.00	NaN	0.12
waterfront	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
view	0.01	0.45	0.10	0.24	0.37	0.07	0.12	NaN	1.00
condition	-0.02	0.08	0.07	-0.06	0.03	-0.01	-0.16	NaN	0.03
grade	0.01	0.69	0.26	0.64	0.73	0.13	0.46	NaN	0.38

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
sqft_above	-0.02	0.72	0.43	0.70	0.92	0.21	0.50	NaN	0.33
sqft_basement	-0.02	0.41	0.46	0.41	0.72	0.16	-0.11	NaN	0.29
yr_built	0.01	-0.01	0.03	0.39	0.17	0.09	0.29	NaN	-0.01
yr_renovated	-0.00	0.15	0.05	0.09	0.09	0.00	0.07	NaN	0.09
zipcode	-0.03	-0.06	-0.15	-0.18	-0.20	-0.18	0.09	NaN	0.06
lat	-0.03	0.24	0.00	0.03	0.03	-0.11	0.10	NaN	-0.02
long	-0.00	0.02	0.13	0.19	0.23	0.33	-0.05	NaN	-0.04
sqft_living15	-0.01	0.60	0.33	0.51	0.72	0.20	0.18	NaN	0.41
sqft_lot15	-0.12	0.05	0.04	0.11	0.21	0.79	-0.02	NaN	0.06
dateyear	0.00	0.00	-0.01	-0.03	-0.03	0.01	-0.03	NaN	-0.01
date_month	-0.00	-0.00	0.00	0.01	0.02	-0.02	0.03	NaN	-0.00
year	0.00	0.00	-0.01	-0.03	-0.03	0.01	-0.03	NaN	-0.01
month	-0.00	-0.00	0.00	0.01	0.02	-0.02	0.03	NaN	-0.00

24 rows × 24 columns

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

Other elements to cosider - How New should the house be? under what condition?

In [86]:

```
kc_data['condition'].unique()
```

Out[86]:

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

In [87]:

```
group_condition = kc_data.groupby(['condition']).mean()
group_condition = pd.DataFrame.reset_index(group_condition)
#group_condition['price'] = group_condition['price']/1000000
group_condition
```

Out[87]:

	condition	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floo
0	1	5.337300e+09	0.324333	3.333333	1.666667	1850.000000	19043.000000	1.00000
1	2	5.097944e+09	0.417773	3.200000	1.800000	1861.400000	26088.940000	1.05000
2	3	4.642844e+09	0.612184	3.514252	2.350058	2313.367290	12714.375000	1.4154
3	4	4.575608e+09	0.603976	3.590193	2.118534	2281.827260	14584.501125	1.1736
4	5	4.486960e+09	0.751617	3.691267	2.318182	2425.753071	11056.217445	1.2794

5 rows × 24 columns

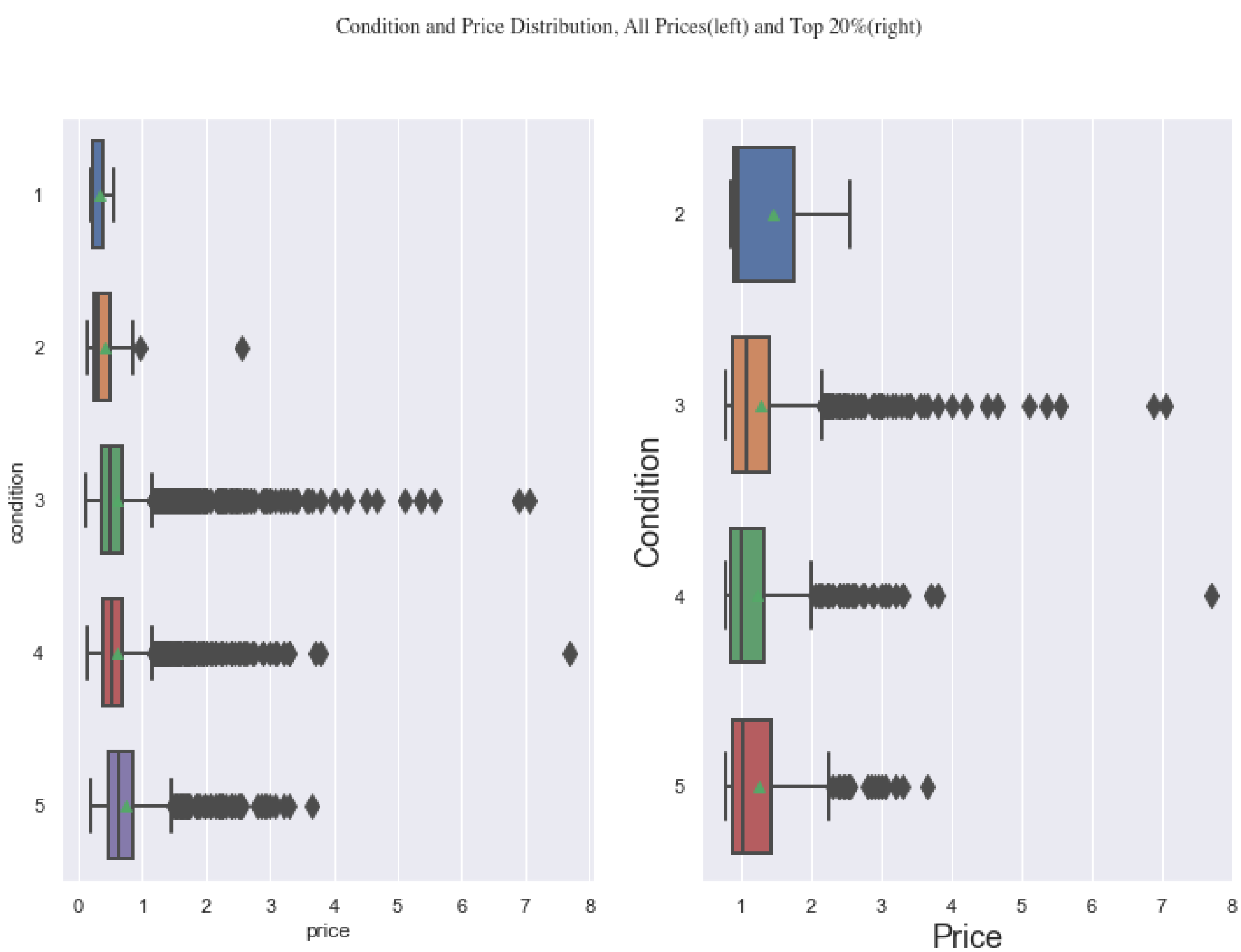
In [88]:

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

In [89]:

```
sns.set() # Setting seaborn as default style even if use only matplotlib

fig, axes = plt.subplots(1, 2, figsize=(12,8))

isns.set_context(fontfamily="times")

fig.suptitle('Condition and Price Distribution, All Prices(left) and Top 20%(righ

sns.boxplot(ax=axes[0], y = kc_data['condition'], x =kc_data['price'],
            width = 0.7, orient ='h', showmeans = True, linewidth = 2, fliersize

plt.xlabel('Condition', fontsize=18)
plt.ylabel('Price in $ Milllions', fontsize=18)


isns.set_context(fontfamily="times")
sns.boxplot(ax=axes[1], y = top20p['condition'], x = top20p['price'],
            width = 0.7, orient ='h', showmeans = True, linewidth = 2, fliersize

plt.xlabel('Price', fontsize=18)
plt.ylabel('Condition', fontsize=18)


#sns.boxplot(y = kc_data['condition'], x = kc_data['price'], ax = axes[0, 0])
```

Out[89]: Text(0, 0.5, 'Condition')



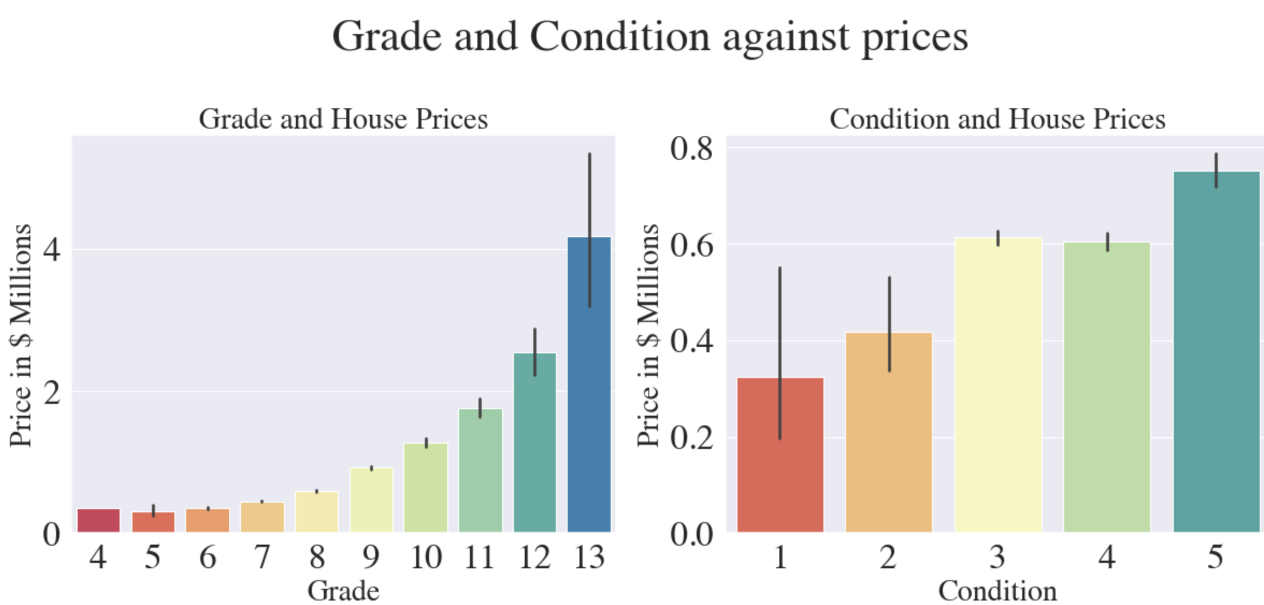
In [90]:

```
## Condition and Grade
```

In [91]:

```python
from matplotlib.gridspec import GridSpec


#sns.set_color_codes("Spectral")

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 in $ Millions', fontsize=28)



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.suptitle('Grade and Condition against prices', fontsize=42)
```

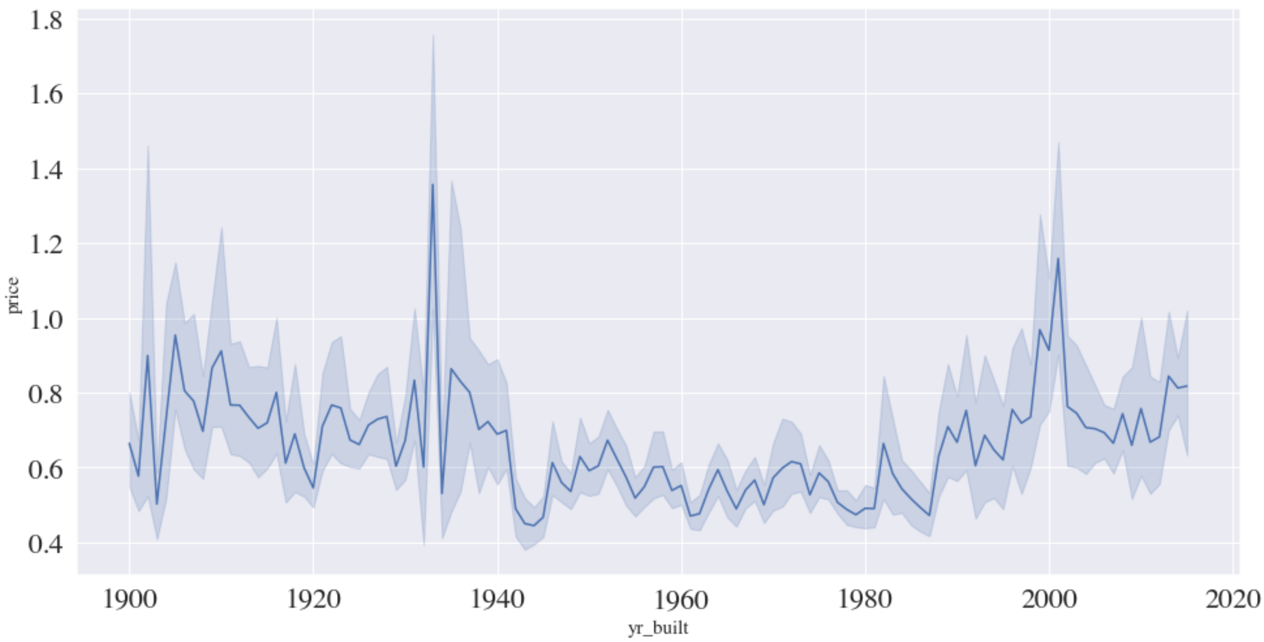
Out[91]: Text(0.5, 0.98, 'Grade and Condition against prices')



Year Built/Renovated

In [92]:
```
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'>
```



In [93]:
```
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
```

In [95]:

```
year_price = kc_data[['yr_renovated','price']]
year_price
```

Out[95]:

	yr_renovated	price
1	1991	0.5380
3	0	0.6040
5	0	1.2300
8	0	0.2295
11	0	0.4680
...	...	...
21572	0	0.4145
21574	0	1.2200
21579	0	0.5200
21590	0	1.0100
21591	0	0.4750

7370 rows × 2 columns

In [96]:
```
reno_years  = year_price.replace(0, pd.np.nan).dropna(axis=0, how='any').fillna(0
```

In [97]:
```
group_yr_reno= reno_years.groupby(['yr_renovated']).mean()
group_yr_reno = pd.DataFrame.reset_index(group_yr_reno)
```

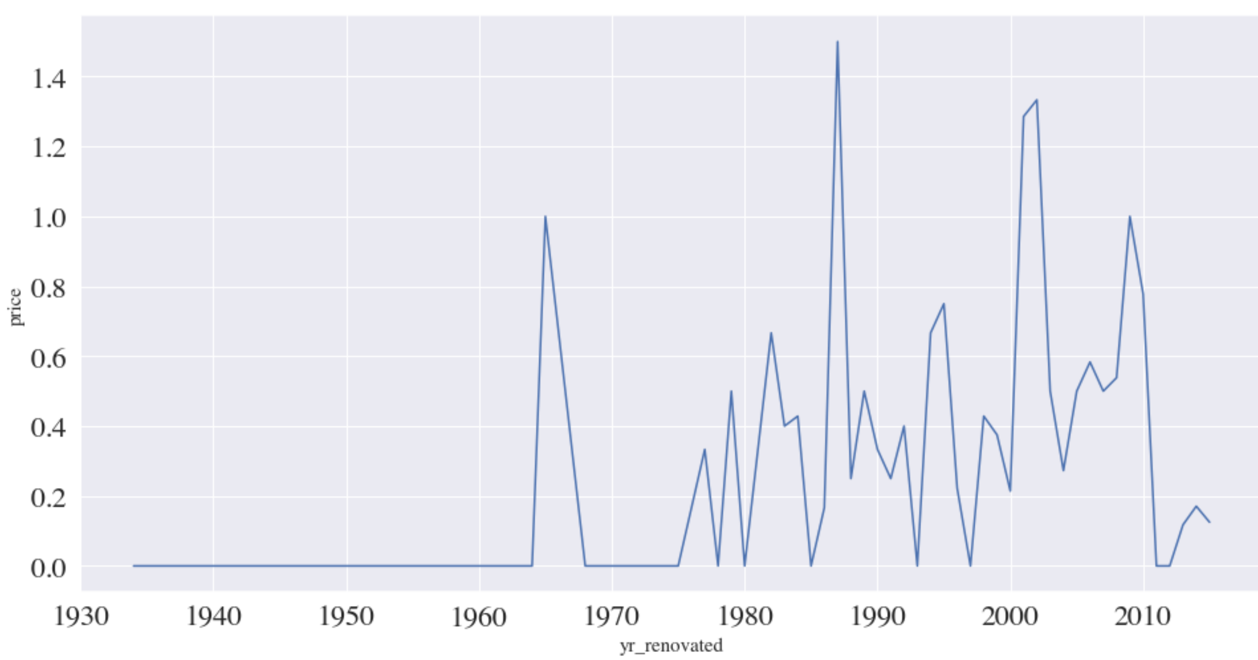
In [98]:
```
group_yr_reno.head()
```

Out[98]:

	yr_renovated	price
0	1934	0.0
1	1940	0.0
2	1955	0.0
3	1956	0.0
4	1957	0.0

In [99]:
```
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=group_yr_reno, x="yr_renovated", y="price")
```

Out[99]: <AxesSubplot:xlabel='yr_renovated', ylabel='price'>



In [100…
```
# Let's check yr_built stats and asses the virable.
top20p.yr_built.describe()
```

Out[100…
```
count    1474.000000
mean     1965.005427
```

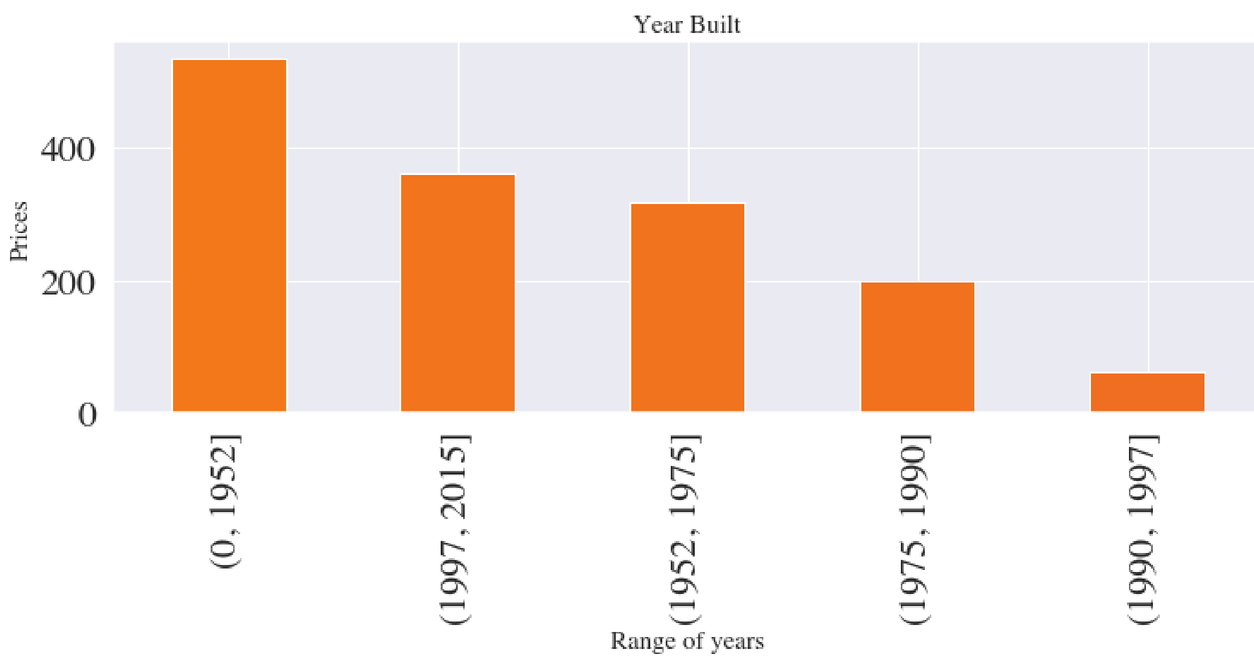
```
std        33.081355
min      1900.000000
25%      1937.000000
50%      1967.000000
75%      1996.000000
max      2015.000000
Name: yr_built, dtype: float64
```

In [101…

```
# Here are the  bins  based on the values observed above. 5 values will result in

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 [102…

```
#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=Fa
plt.xlabel('Range of years')
plt.ylabel('Prices')
plt.title('Year Built')
#plt.legend()
plt.show()
```



Preparing for Modeling

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

```
* Ensure that there is no multicollinearity that none of the
independent variables are correlated.
* Handle categorical valuables by eitheruse dummy encoding or use
one-hot-encoding.
* Scaling and normalizing the data.
```

In [103…

```
# We will extract all the variables beside the target variable.
kc_pred = kc_data.iloc[:,3:55]
kc_pred.head()
```

Out[103…

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_ab
1	3.0	2.25	2570	7242	2.0	0	1	3	7	
3	4.0	3.00	1960	5000	1.0	0	1	5	7	1
5	4.0	4.50	5420	101930	1.0	0	1	3	11	3
8	3.0	1.00	1780	7470	1.0	0	1	3	7	1
11	2.0	1.00	1160	6000	1.0	0	1	4	7	

5 rows × 22 columns

In [104…

```
kc_pred.isnull().sum()
```

Out[104…

```
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
year             0
month            0
dtype: int64
```

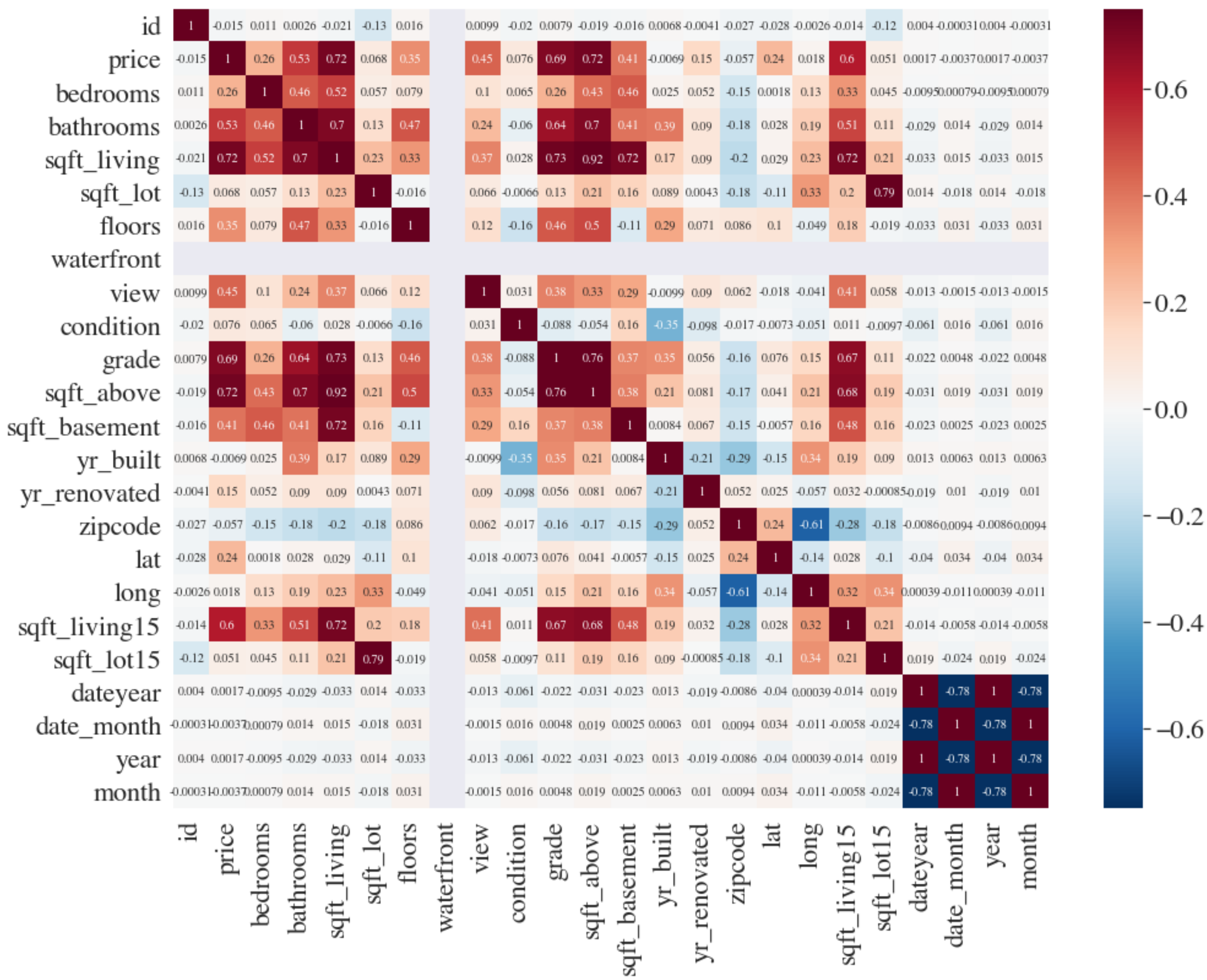
In [105…

```
kc_pred.dropna(subset=['bedrooms'], inplace=True)
```

In [106…

```
# Checking for correlation among the variables using a heat map.

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
```



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 [107…

```
mc_variables = []  # Creating an empty list for variables
mc_corr = [] # Creating an empty list for corr number

def check_mc(feature):
    for idx, correlation in corr[feature].T.iteritems():  # Loop through the vari
        if correlation >= .60 and idx != feature:
            mc_variables.append([feature, idx]) # Add to the list
            mc_corr.append(correlation)


# Establishing a dataframe to show the results.

for feature in corr:
    check_mc(feature)
mc_df = pd.DataFrame({'Correlations':mc_corr,
                      'Features': mc_variables}).sort_values(by=['Correlations'],
```

In [108…

```
print('Multicollinear Features')
display(mc_df)
```

```
Multicollinear Features
```

	Correlations	Features
31	1.000000	[month, date_month]
30	1.000000	[year, dateyear]
29	1.000000	[date_month, month]
28	1.000000	[dateyear, year]
9	0.920198	[sqft_living, sqft_above]
20	0.920198	[sqft_above, sqft_living]
27	0.794075	[sqft_lot15, sqft_lot]
12	0.794075	[sqft_lot, sqft_lot15]
21	0.759163	[sqft_above, grade]
16	0.759163	[grade, sqft_above]
15	0.730471	[grade, sqft_living]
8	0.730471	[sqft_living, grade]
2	0.721493	[price, sqft_above]
18	0.721493	[sqft_above, price]
6	0.718413	[sqft_living, price]
0	0.718413	[price, sqft_living]
11	0.716863	[sqft_living, sqft_living15]
24	0.716863	[sqft_living15, sqft_living]
23	0.715406	[sqft_basement, sqft_living]
10	0.715406	[sqft_living, sqft_basement]
7	0.700149	[sqft_living, bathrooms]
3	0.700149	[bathrooms, sqft_living]
19	0.696547	[sqft_above, bathrooms]
5	0.696547	[bathrooms, sqft_above]
1	0.692124	[price, grade]
13	0.692124	[grade, price]
22	0.680532	[sqft_above, sqft_living15]
26	0.680532	[sqft_living15, sqft_above]
17	0.672676	[grade, sqft_living15]
25	0.672676	[sqft_living15, grade]
14	0.639196	[grade, bathrooms]
4	0.639196	[bathrooms, grade]

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 [109…

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

    VIF_Scores = pd.DataFrame()
    VIF_Scores["Independent Features"] = kc_pred.columns
    VIF_Scores["VIF Scores"] = [variance_inflation_factor(kc_pred.values,i) for i
    return VIF_Scores

vif_scores(kc_pred)
```

Out[109…

	Independent Features	VIF Scores
0	bedrooms	2.329040e+01
1	bathrooms	2.673418e+01
2	sqft_living	inf
3	sqft_lot	3.300548e+00
4	floors	1.708991e+01
5	waterfront	NaN
6	view	4.100013e+00
7	condition	3.312603e+01
8	grade	1.661402e+02
9	sqft_above	inf
10	sqft_basement	inf
11	yr_built	9.545120e+03
12	yr_renovated	1.203020e+00
13	zipcode	5.263925e+06
14	lat	1.707336e+05
15	long	2.068590e+06
16	sqft_living15	2.811552e+01
17	sqft_lot15	3.434316e+00
18	dateyear	inf
19	date_month	inf
20	year	inf
21	month	inf

In [110…

```
kc_data = kc_data[['price','sqft_living','waterfront','condition','grade','view',
```

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

- view
- condition
- grade
- yr_built

In [111…

```
WF_dummies = pd.get_dummies(kc_data["waterfront"], prefix="WV")
View_dummies = pd.get_dummies(kc_data["view"], prefix="View")
Con_dummies = pd.get_dummies(kc_data["condition"], prefix="Con")
Grade_dummies = pd.get_dummies(kc_data["grade"], prefix="Grade")
Month_dummies = pd.get_dummies(kc_data["month"], prefix="Month")
```

In [112…

```
kc_data.drop(['waterfront','view','condition','grade','month'], axis =1, inplace=
```

In [113…

```
# Add the new dummy variables to the data frame
kc_data = pd.concat([kc_data, WF_dummies , View_dummies, Con_dummies,Grade_dummie

kc_data.head()
```

Out[113…

	price	sqft_living	sqft_lot	WV_0	View_1	View_2	View_3	View_4	View_5	Con_1	...	Mon
1	0.5380	2570	7242	1	1	0	0	0	0	0	...	
3	0.6040	1960	5000	1	1	0	0	0	0	0	...	
5	1.2300	5420	101930	1	1	0	0	0	0	0	...	
8	0.2295	1780	7470	1	1	0	0	0	0	0	...	
11	0.4680	1160	6000	1	1	0	0	0	0	0	...	

5 rows × 36 columns

In [114…

```
kc_data.head()
```

Out[114…

	price	sqft_living	sqft_lot	WV_0	View_1	View_2	View_3	View_4	View_5	Con_1	...	Mon
1	0.5380	2570	7242	1	1	0	0	0	0	0	...	
3	0.6040	1960	5000	1	1	0	0	0	0	0	...	
5	1.2300	5420	101930	1	1	0	0	0	0	0	...	
8	0.2295	1780	7470	1	1	0	0	0	0	0	...	
11	0.4680	1160	6000	1	1	0	0	0	0	0	...	

5 rows × 36 columns

In [115…

```
kc_data.isnull().sum()
```

Out[115…

```
price              0
```

```
sqft_living    0
sqft_lot       0
WV_0           0
View_1         0
View_2         0
View_3         0
View_4         0
View_5         0
Con_1          0
Con_2          0
Con_3          0
Con_4          0
Con_5          0
Grade_4        0
Grade_5        0
Grade_6        0
Grade_7        0
Grade_8        0
Grade_9        0
Grade_10       0
Grade_11       0
Grade_12       0
Grade_13       0
Month_1        0
Month_2        0
Month_3        0
Month_4        0
Month_5        0
Month_6        0
Month_7        0
Month_8        0
Month_9        0
Month_10       0
Month_11       0
Month_12       0
dtype: int64
```

Last few steps before applying linear regression model:

    Splitting the data into 75% training and 25% testing.

    Checking that the split occurred correctly.

    Normalizing distribution by using log function.

    Checking log transformation.

In [116…

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

In [117…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,  random
```

In [118…

```
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(5527, 35) (5527,) (1843, 35) (1843,)
```

In [119…

```
kc_train = pd.concat([X_train, y_train], axis = 1)
```

```
kc_train.head()
```

Out[119…

	sqft_living	sqft_lot	WV_0	View_1	View_2	View_3	View_4	View_5	Con_1	Con_2	...
9542	2230	9640	1	1	0	0	0	0	0	0	...
6285	2400	9537	1	1	0	0	0	0	0	0	...
3895	2100	9984	1	1	0	0	0	0	0	0	...
9092	2670	6780	1	0	0	0	1	0	0	0	...
18304	2880	213444	1	1	0	0	0	0	0	0	...

5 rows × 36 columns

Applying log transformation for the continuous variables that are not normally distributed.

In [120…

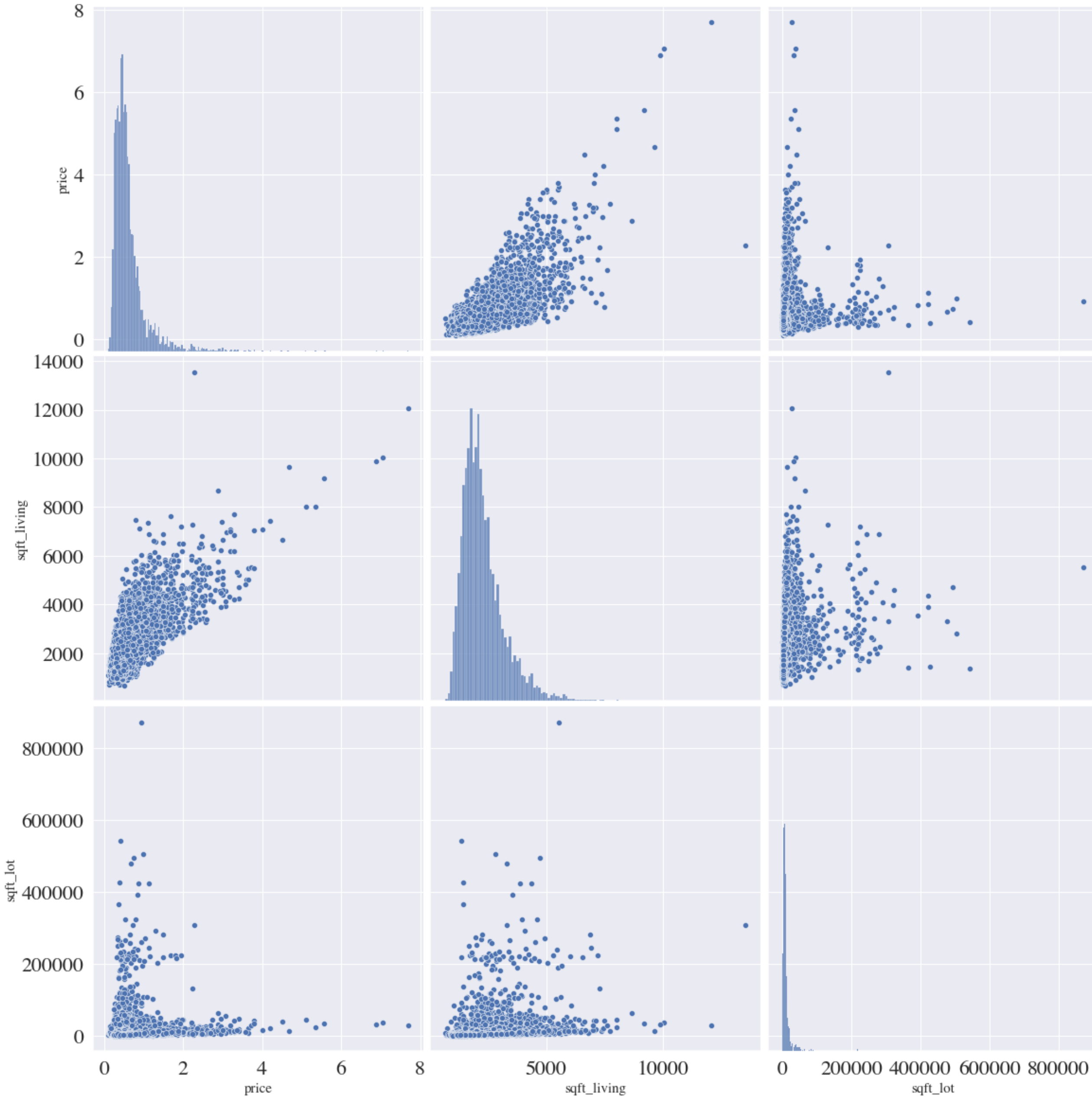
```
kc_train['price'] = np.log(kc_train['price'])
kc_train['sqft_living'] = np.log(kc_train['sqft_living'])
kc_train['sqft_lot'] = np.log(kc_train['sqft_lot'])
```

In [121…

```
check_log = kc_data[['price','sqft_living','sqft_lot']]
```

In [122…

```
sns.pairplot(check_log, height=5.5, aspect=1)

sns.set(font_scale=2)
```



Applying StandardScaler into a function in order to standardize the data into the same units.

In [123…
```
# Let's create a StandardScaler object to scale our data for us.
ss = StandardScaler()
```

In [124…
```
# Get scaling parameters with the train sample exclusively, using the Scaler.fit(
ss.fit(kc_train)
```

Out[124… StandardScaler()

In [125…
```
kc_train_scaled = pd.DataFrame(ss.transform(kc_train))
```

In [126…
```
kc_train_scaled.describe()
```

Out[126…

	0	1	2	3	4	5	
ount	5.527000e+03	5.527000e+03	5527.0	5.527000e+03	5.527000e+03	5.527000e+03	5.527000
nean	5.107162e-16	3.078574e-16	0.0	-4.774642e-16	-4.061645e-17	-2.697217e-16	9.51131‹
std	1.000090e+00	1.000090e+00	0.0	1.000090e+00	1.000090e+00	1.000090e+00	1.000090
min	-3.123039e+00	-2.843785e+00	0.0	-2.239229e+00	-1.743209e-01	-2.717157e-01	-2.036C
25%	-6.703544e-01	-4.724627e-01	0.0	4.465823e-01	-1.743209e-01	-2.717157e-01	-2.036C
50%	-6.523868e-02	-6.805300e-03	0.0	4.465823e-01	-1.743209e-01	-2.717157e-01	-2.036C
75%	6.162702e-01	3.867076e-01	0.0	4.465823e-01	-1.743209e-01	-2.717157e-01	-2.036C
max	4.988731e+00	5.339827e+00	0.0	4.465823e-01	5.736547e+00	3.680317e+00	4.911489

rows × 36 columns

Model and Interpret the Data

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

In [127…

```
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
            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_p

            # 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
            if not changed:
                break
        return included
```

In [128…

```
#predictors = kc_train_scaled.drop('price', axis=1)
```

In [129…

```
X_train.shape
```

Out[129… (5527, 35)

The function has chosen the following features.

In [130…

```
result = stepwise_selection(X_train, y_train, verbose = True)
print('resulting features:')
print(result)
```

```
Add  sqft_living                    with p-value 0.0
Add  View_5                         with p-value 1.09148e-106
Add  Grade_11                       with p-value 4.21949e-37
Add  Grade_12                       with p-value 8.98278e-40
Add  Grade_10                       with p-value 1.46685e-50
Add  Grade_13                       with p-value 2.29835e-46
Add  Grade_9                        with p-value 1.17225e-60
Add  WV_0                           with p-value 4.50713e-29
Add  sqft_lot                       with p-value 4.5142e-27
Add  Con_5                          with p-value 1.74473e-23
Add  Grade_8                        with p-value 8.8622e-21
Add  View_1                         with p-value 4.21565e-16
Add  Con_4                          with p-value 3.12956e-07
Add  View_3                         with p-value 0.00089122
Add  Month_4                        with p-value 0.00327365
Add  Month_3                        with p-value 0.00175463
resulting features:
['sqft_living', 'View_5', 'Grade_11', 'Grade_12', 'Grade_10', 'Grade_13', 'Grade_
9', 'WV_0', 'sqft_lot', 'Con_5', 'Grade_8', 'View_1', 'Con_4', 'View_3', 'Month_
4', 'Month_3']
```

In [131…
```
best_features = ['WV_0', 'sqft_living', 'Grade_7', 'View_1', 'Grade_6', 'Grade_8'
                 'View_5', 'Grade_5', 'Grade_9', 'Con_4', 'sqft_lot', 'Grade_10',
                 'Month_4', 'Con_2','View_3']
```

Running the OLS regression model.

In [132…
```
X_train_fin = X_train[best_features] # Using the best features for the model
X_train_int = sm.add_constant(X_train_fin) #Fitting the training data
model = sm.OLS(y_train, X_train_int).fit()
model.summary()
```

Out[132…

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.640
Model:	OLS	**Adj. R-squared:**	0.639
Method:	Least Squares	**F-statistic:**	612.1
Date:	Tue, 20 Sep 2022	**Prob (F-statistic):**	0.00
Time:	21:41:59	**Log-Likelihood:**	-441.76
No. Observations:	5527	**AIC:**	917.5
Df Residuals:	5510	**BIC:**	1030.
Df Model:	16		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
WV_0	1.0659	0.038	28.157	0.000	0.992	1.140
sqft_living	0.0002	5.72e-06	30.353	0.000	0.000	0.000
Grade_7	-0.8674	0.029	-30.129	0.000	-0.924	-0.811
View_1	-0.1120	0.015	-7.703	0.000	-0.141	-0.084
Grade_6	-0.8893	0.033	-26.632	0.000	-0.955	-0.824
Grade_8	-0.8010	0.027	-29.151	0.000	-0.855	-0.747
Con_5	0.1311	0.012	10.993	0.000	0.108	0.155
View_5	0.3857	0.025	15.349	0.000	0.336	0.435
Grade_5	-0.9180	0.082	-11.240	0.000	-1.078	-0.758
Grade_9	-0.6324	0.027	-23.644	0.000	-0.685	-0.580
Con_4	0.0366	0.008	4.571	0.000	0.021	0.052
sqft_lot	-1.176e-06	1.16e-07	-10.153	0.000	-1.4e-06	-9.49e-07
Grade_10	-0.4419	0.028	-16.023	0.000	-0.496	-0.388
Month_3	0.0383	0.013	3.036	0.002	0.014	0.063
Month_4	0.0345	0.012	2.980	0.003	0.012	0.057
Con_2	-0.0120	0.042	-0.283	0.777	-0.095	0.071
View_3	-0.0598	0.019	-3.142	0.002	-0.097	-0.023

Omnibus:	3557.926	**Durbin-Watson:**	2.010
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	205410.265
Skew:	2.386	**Prob(JB):**	0.00
Kurtosis:	32.482	**Cond. No.**	8.64e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.64e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Evaluating and Interpreting the Regression Model

In [133…
```
X_train_final = X_train[best_features]
X_test_final = X_test[best_features]
```

R Squared

In [134…
```
final_model = LinearRegression()

# Fit the model on X_train_final and y_train
final_model.fit(X_train_final, y_train)

# Score the model on test data applying built-in .score method)
final_model.score(X_test_final, y_test)
```

Out[134… 0.6470202388867357

The R-Squared for the testing data is 0.65 which is very close to 0.64 that we got in the training data.

Mean Squared Error

In [135…
```
mean_squared_error(y_test, final_model.predict(X_test_final), squared=False)
```

Out[135… 0.2887858740795608

In [136…
```
print(pd.Series(final_model.coef_, index=X_train_final.columns, name="Coefficient
print("Model's Intercept:", final_model.intercept_)
```

```
WV_0           0.000000
sqft_living    0.000174
Grade_7       -0.867442
View_1        -0.112014
Grade_6       -0.889255
Grade_8       -0.800978
Con_5          0.131145
View_5         0.385743
Grade_5       -0.918013
Grade_9       -0.632385
Con_4          0.036637
```

```
sqft_lot       -0.000001
Grade_10       -0.441933
Month_3         0.038302
Month_4         0.034455
Con_2          -0.011996
View_3         -0.059841
Name: Coefficients, dtype: float64
Model's Intercept: 1.0658936676178987
```

The model’s intercept which is the base price for a house is roughly $1.06 Million. The prices varies depending on the increase or decrease of each variable.

In [137…

```python
linreg = LinearRegression()

linreg.fit(X_train_final, y_train)
y_hat_test = linreg.predict(X_test_final)
```

In [138…

```python
y_hat_train = linreg.predict(X_train_final)
```

In [139…

```python
train_error = y_train-y_hat_train
```

In [140…

```python
# We will use sklearn.metrics to calculate the test data Mean Square Error

from sklearn.metrics import mean_squared_error
test_residuals = y_hat_test - y_test
train_residuals = y_hat_train - y_train
test_mse = mean_squared_error(y_test, y_hat_test)
```

In [141…

```python
# create and print mean squared error variable

print('\nTraining Mean Squared Error is', mean_squared_error(y_train,y_hat_train)
print('Testing Mean Squared Error is', mean_squared_error(y_test,y_hat_test))

# Creating and printing root mean squared error

print('\nTraining Root Mean Squared Error is', np.sqrt(mean_squared_error(y_train
print('Testing Root Mean Squared Error is', np.sqrt(mean_squared_error(y_test,y_h

# create and view training and testing r squared

print('\nTraining R squared is', r2_score(y_train,y_hat_train))
print('Testing R squared is',r2_score(y_test,y_hat_test))
```

```
Training Mean Squared Error is 0.06869881197184738
Testing Mean Squared Error is 0.08339728106789594

Training Root Mean Squared Error is 0.26210458212676746
Testing Root Mean Squared Error is 0.2887858740795608

Training R squared is 0.6399582088928608
Testing R squared is 0.6470202388867357
```

Mean Squared Error - the average(squared) discrepancy of house prices in this model will be roughly $68K per house.

Root Mean Squared Error - the average deviation between the predicted house and the actual house price is roughly $262K.

R squared - 64% 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.

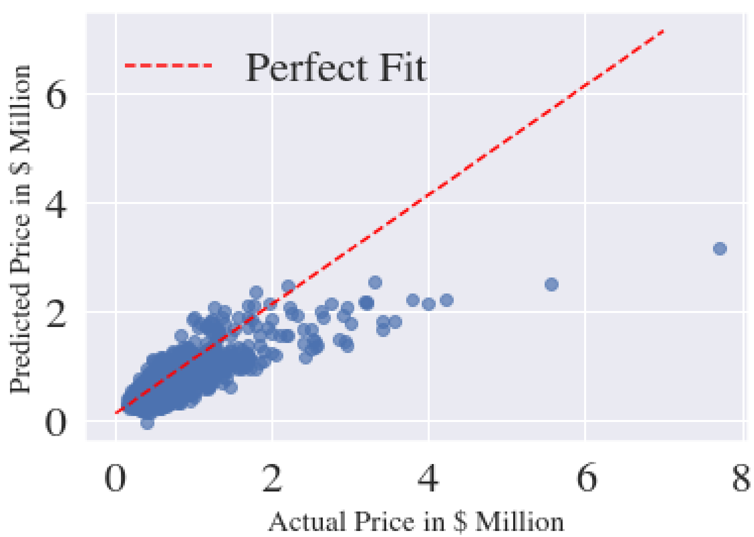
All of the above training and testing evaluation resutls are very close to one another which suggests that our model is not overfitted or underfitted.

Testing if the linear assumption is violated. The graph shows that the relationship between actual prices and predictable prices is linear.

In [142…

```
sns.set(font_scale=2)
isns.set_context(fontfamily="times")
plt.figure(figsize=(22, 18))


preds = final_model.predict(X_test_final)
fig, ax = plt.subplots()

linear_line = np.arange(y_test.min(), y_test.max())
ax.plot(linear_line, linestyle="--", color="red", label="Perfect Fit")
ax.scatter(y_test, preds, alpha=0.7)
ax.set_xlabel("Actual Price in $ Million")
ax.set_ylabel("Predicted Price in $ Million")
ax.legend();
```

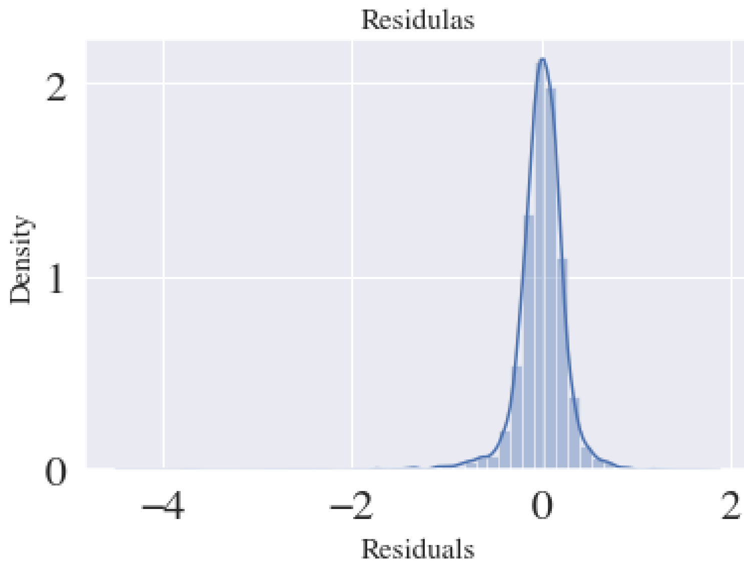
```
<Figure size 1584x1296 with 0 Axes>
```



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

In [143…

```
sns.distplot(train_residuals)
plt.title('Residulas' )
plt.xlabel('Residuals')
plt.ylabel('Density')
plt.show()
```



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, and buy in the months of January and February

GRADE AND CONDITION: 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.