

# King County, Data Analysis

Please fill out:

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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>

## 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 necessary libraries
import pandas as pd
# Import the necessary 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 sns
sns.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()
```

	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

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

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

```
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.'''

```

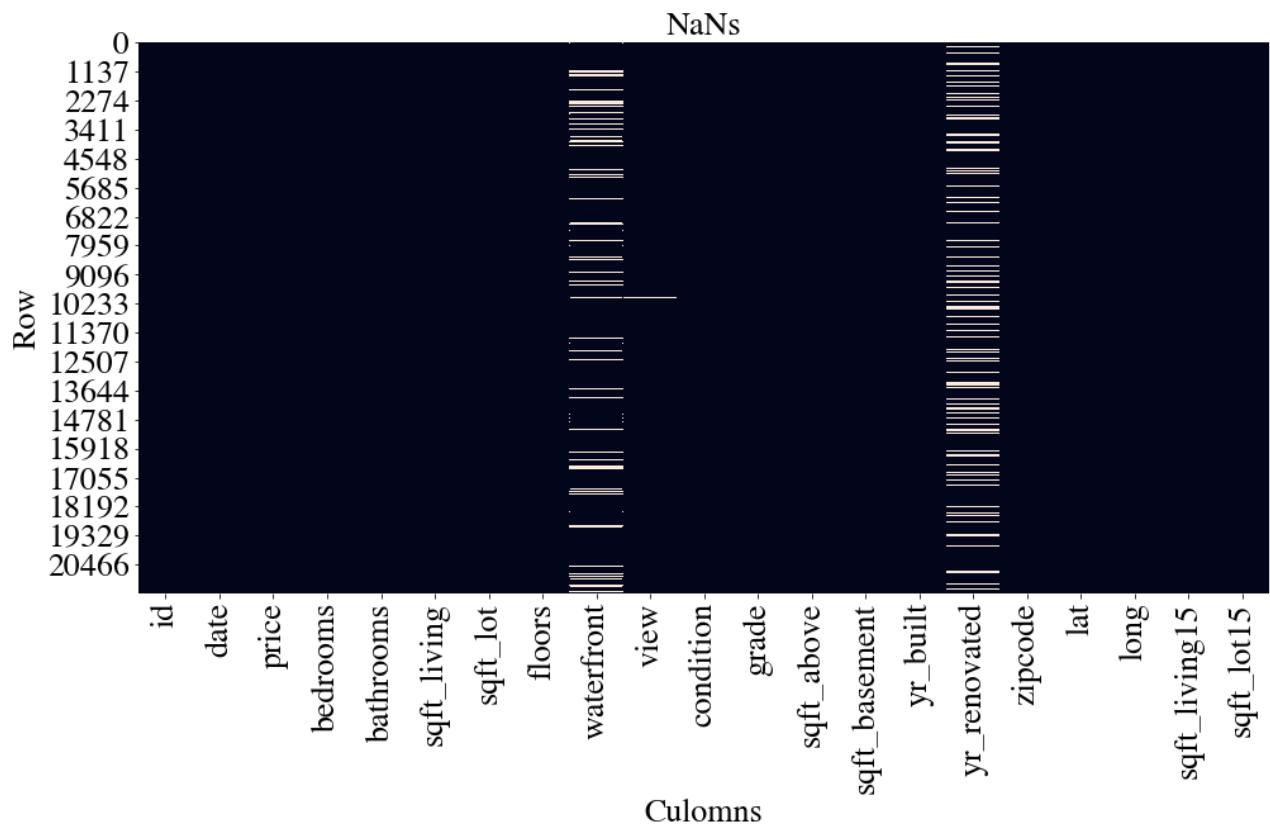
```
fig, ax = plt.subplots(figsize=(16,8))

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()
```



```
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 [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', '2000.0', '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 = True)
```

```
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()
```

#	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. 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]:

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

## 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 [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]:

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

In [36]:

```
# Confirming that there are no missing values.
```

```
missing_value_kc_data
```

Out[36]:

	<b>column_name</b>	<b>percent_missing</b>
	<b>id</b>	0.000000

	column_name	percent_missing
	<b>date</b>	0.000000
	<b>price</b>	0.000000
	<b>bedrooms</b>	0.000000
	<b>bathrooms</b>	0.000000
	<b>sqft_living</b>	0.000000
	<b>sqft_lot</b>	0.000000
	<b>floors</b>	0.000000
	<b>waterfront</b>	11.001528
	<b>view</b>	0.291707
	<b>condition</b>	0.000000
	<b>grade</b>	0.000000
	<b>sqft_above</b>	0.000000
	<b>sqft_basement</b>	0.000000
	<b>yr_built</b>	0.000000
	<b>yr_renovated</b>	17.789508
	<b>zipcode</b>	0.000000
	<b>lat</b>	0.000000
	<b>long</b>	0.000000
	<b>sqft_living15</b>	0.000000
	<b>sqft_lot15</b>	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	view
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]:

		<b>id</b>	<b>date</b>	<b>price</b>	<b>bedrooms</b>	<b>bathrooms</b>	<b>sqft_living</b>	<b>sqft_lot</b>	<b>floors</b>	<b>waterfront</b>	<b>vie</b>
<b>1</b>	6414100192	2014-12-09	0.5380	3.0	2.25	2570	7242	2.0		NO	
<b>3</b>	2487200875	2014-12-09	0.6040	4.0	3.00	1960	5000	1.0		NO	
<b>5</b>	7237550310	2014-05-12	1.2300	4.0	4.50	5420	101930	1.0		NO	
<b>8</b>	2414600126	2015-04-15	0.2295	3.0	1.00	1780	7470	1.0		NO	
<b>11</b>	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_duplicate = kc_data[kc_data.duplicated(subset=['id'], keep=False)]
kc_data_duplicate.head()
```

Out[43]:

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

5 rows × 25 columns

In [44]:

```
kc_data_duplicate = kc_data_duplicate[['id', 'date_month', 'price', 'grade',
                                         'condition']]
kc_data_duplicate
```

Out[44]:

	<b>id</b>	<b>date_month</b>	<b>price</b>	<b>grade</b>	<b>condition</b>
<b>93</b>	6021501535	7	0.430000	8	3

	<b>id</b>	<b>date_month</b>	<b>price</b>	<b>grade</b>	<b>condition</b>
<b>94</b>	6021501535	12	0.700000	8	3
<b>313</b>	4139480200	6	1.380000	11	3
<b>314</b>	4139480200	12	1.400000	11	3
<b>1084</b>	9834200885	7	0.360000	7	5
...	...	...	...	...	...
<b>18689</b>	3558900590	3	0.692500	7	3
<b>18976</b>	7856400300	7	1.410000	10	5
<b>18977</b>	7856400300	3	1.510000	10	5
<b>19536</b>	643300040	11	0.481000	7	4
<b>19537</b>	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.
Consolidating it using group by 'id' where one row 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('p
```

In [46]:

```
kc_group_id.head()
```

Out[46]:

	<b>id</b>	<b>priceprice</b>	<b>pricedate_month</b>	<b>pricegrade</b>	<b>pricecondition</b>				
		<b>price0</b>	<b>price1</b>	<b>price0</b>	<b>price1</b>	<b>price0</b>	<b>price1</b>	<b>price0</b>	<b>price1</b>
<b>0</b>	526059224	0.260	0.470000	9	2	7	7	3	3
<b>1</b>	641900050	0.335	0.499950	8	2	7	7	3	3
<b>2</b>	643300040	0.481	0.719521	11	3	7	7	4	4
<b>3</b>	1139600270	0.300	0.310000	7	3	8	8	3	3
<b>4</b>	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 a multi-index 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.	
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 home_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)

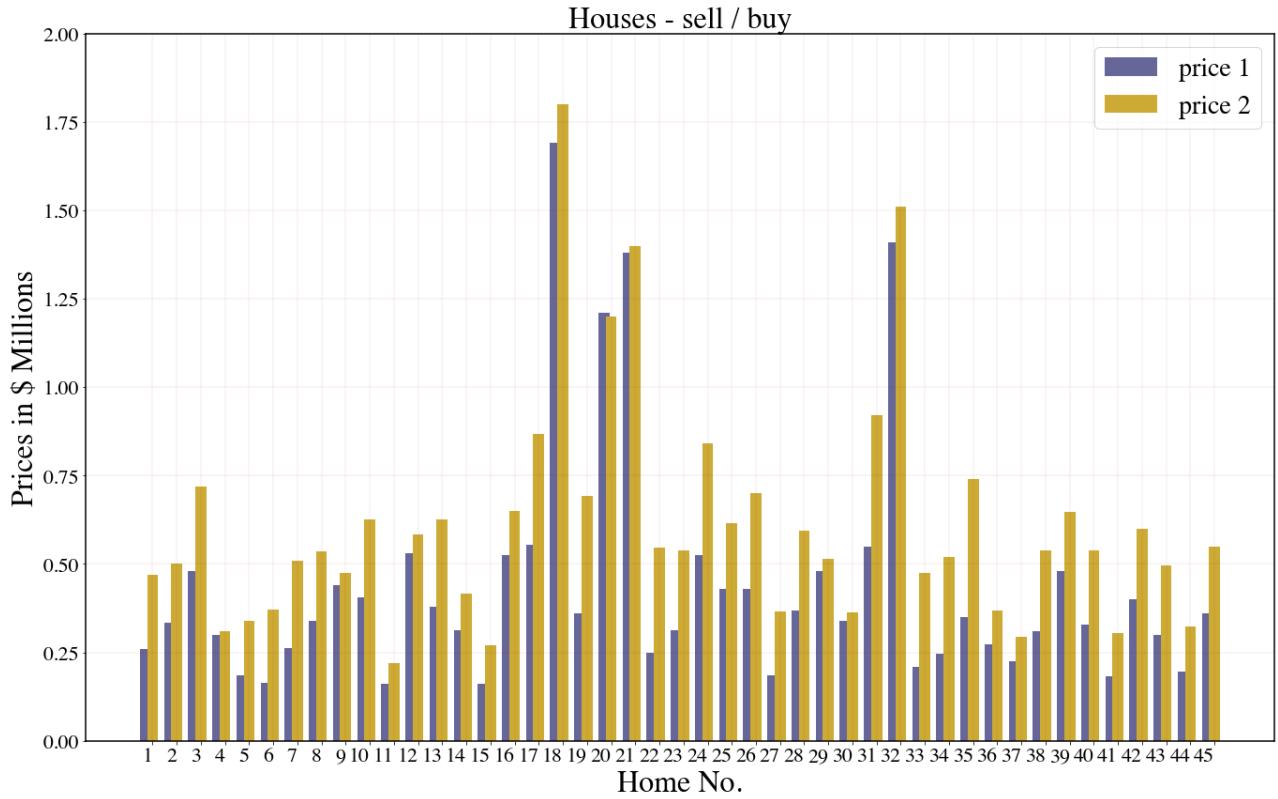
ax.set_xticks(x + bar_width / 2)
ax.set_xticklabels(kc_group_id['home_no.'].unique())

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 profit).

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

```

In [55]:

```
kc_group_id.head()
```

Out[55]:

	<b>id</b>	<b>price_1</b>	<b>price_2</b>	<b>month_1</b>	<b>month_2</b>	<b>cond_1</b>	<b>cond_2</b>	<b>price0</b>	<b>price1</b>	<b>home_no.</b>
<b>0</b>	526059224	0.260	0.470000	9	2	7	7	3	3	1
<b>1</b>	641900050	0.335	0.499950	8	2	7	7	3	3	2
<b>2</b>	643300040	0.481	0.719521	11	3	7	7	4	4	3
<b>3</b>	1139600270	0.300	0.310000	7	3	8	8	3	3	4
<b>4</b>	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]:

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

In [57]:

```
# Creating a function that has bars with range of colors - darker from
# tightest and lighter to the lowest.
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 [59]:

```
# 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"))

# Label 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)

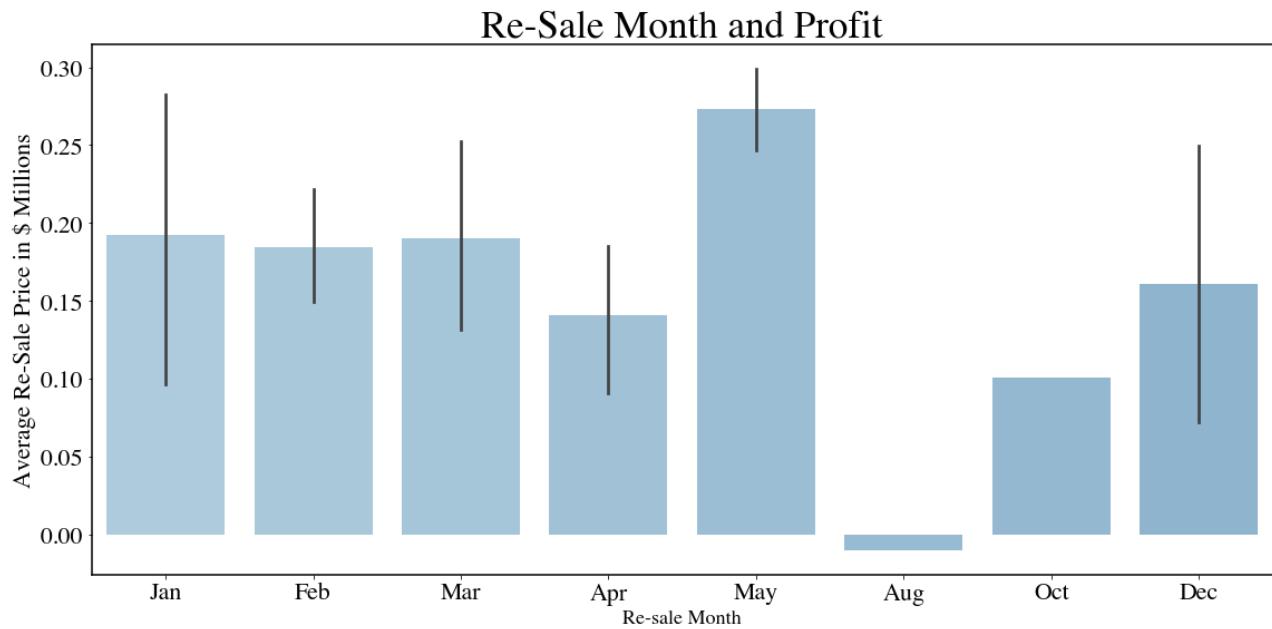
# Set x-axis tick labels.
```

```

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 there is any 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))
sns.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=(20,10))
# the plot gets saved to 'output.png'

plt.title('Price according to Zipcode' )
plt.xticks(rotation = 55)
plt.xlabel('Zipcode', fontsize=20)

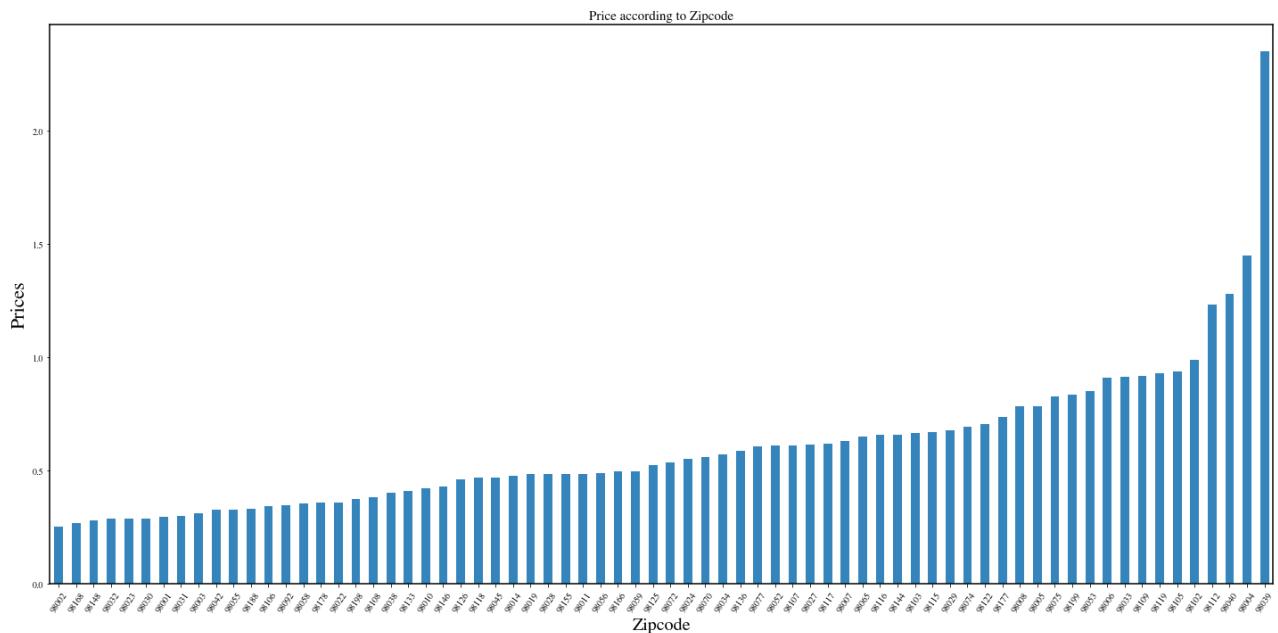
```

```

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]:

		<b>id</b>	<b>date</b>	<b>price</b>	<b>bedrooms</b>	<b>bathrooms</b>	<b>sqft_living</b>	<b>sqft_lot</b>	<b>floors</b>	<b>waterfront</b>
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]:

		<b>id</b>	<b>date</b>	<b>price</b>	<b>bedrooms</b>	<b>bathrooms</b>	<b>sqft_living</b>	<b>sqft_lot</b>	<b>floors</b>	<b>waterfront</b>
--	--	-----------	-------------	--------------	-----------------	------------------	--------------------	-----------------	---------------	-------------------

	<b>id</b>	<b>date</b>	<b>price</b>	<b>bedrooms</b>	<b>bathrooms</b>	<b>sqft_living</b>	<b>sqft_lot</b>	<b>floors</b>	<b>waterfront</b>	<b>v</b>
	<b>7245</b>	6762700020	2014-10-13	7.70	6.0	8.00	12050	27600	2.5	NO
	<b>3910</b>	9808700762	2014-06-11	7.06	5.0	4.50	10040	37325	2.0	YES
	<b>9245</b>	9208900037	2014-09-19	6.89	6.0	7.75	9890	31374	2.0	NO
	<b>4407</b>	2470100110	2014-08-04	5.57	5.0	5.75	9200	35069	2.0	NO
	<b>1446</b>	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")
sns.set_context(fontfamily="times")
top20p.plot(kind="scatter", x="long", y="lat", figsize=(16, 8), c="price",
            cmap="Accent_r", colorbar=True, sharex=False)

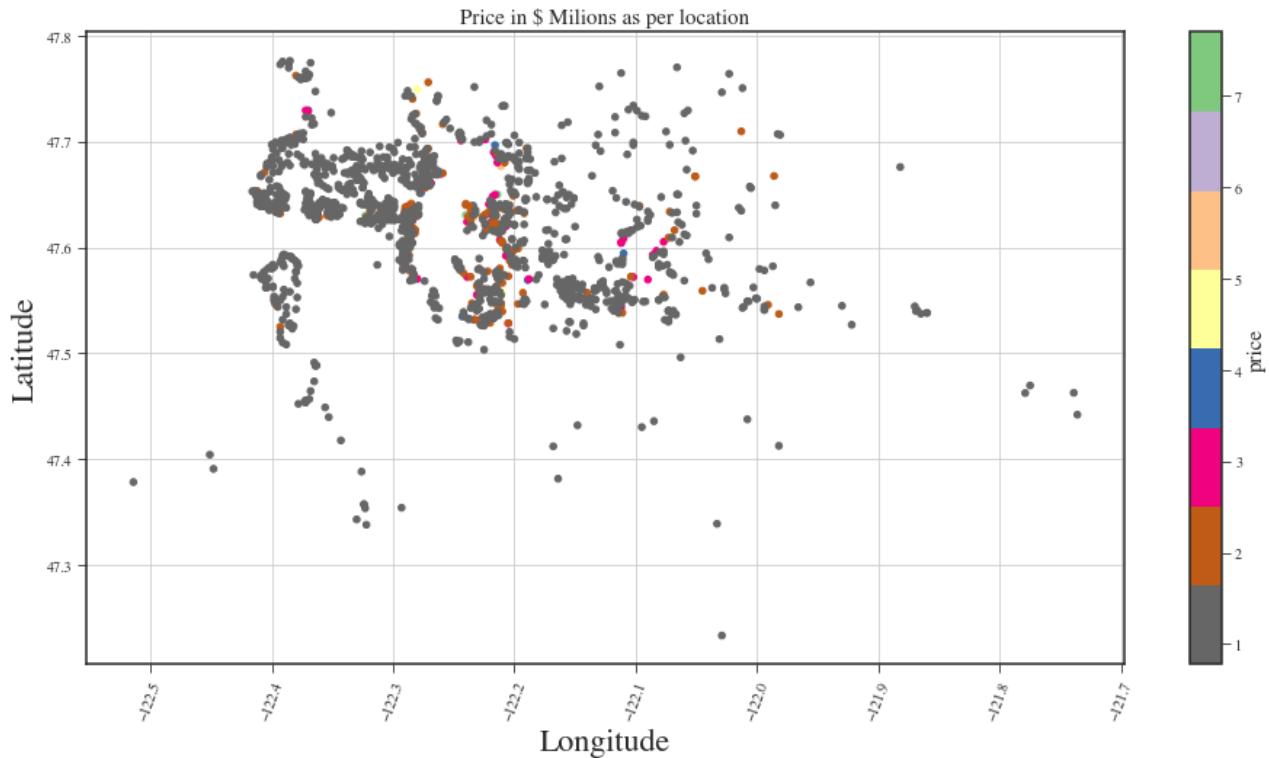
plt.xticks(rotation = 70)
```

```

plt.grid(which='both')
plt.title('Price in $ Millions 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 any pattern of the prices
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)
sns.set_context(fontfamily="times")

```

```

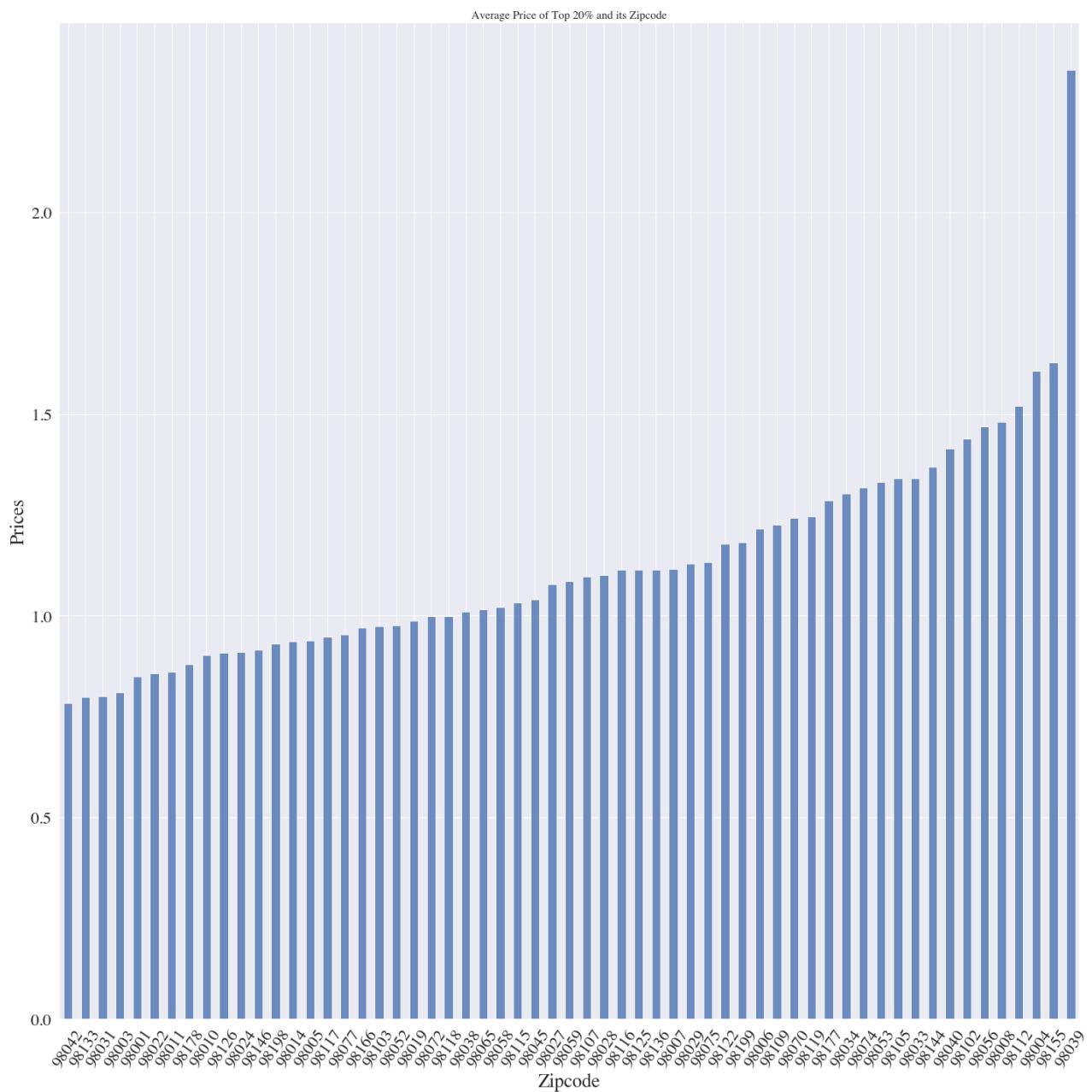
group_zipcode = group_zipcode.sort_values()
group_zipcode.plot(kind='bar',x='zipcode',y='price',align='center',
                    alpha=0.8,figsize=(20,20))
# the plot gets saved to 'output.png'

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

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]:

		<b>id</b>	<b>date</b>	<b>price</b>	<b>bedrooms</b>	<b>bathrooms</b>	<b>sqft_living</b>	<b>sqft_lot</b>	<b>floors</b>	<b>waterfront</b>	
		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]:

		<b>id</b>	<b>date</b>	<b>price</b>	<b>bedrooms</b>	<b>bathrooms</b>	<b>sqft_living</b>	<b>sqft_lot</b>	<b>floors</b>	<b>waterfront</b>	
		9430	4302201085	2014-09-18	0.24800	3.0	1.00	1470	7680	1.0	NO

		<b>id</b>	<b>date</b>	<b>price</b>	<b>bedrooms</b>	<b>bathrooms</b>	<b>sqft_living</b>	<b>sqft_lot</b>	<b>floors</b>	<b>waterfront</b>
1619	1310500550	2014-12-20	0.24800	4.0	2.25	2320	8760	1.0	No	
8412	2172000846	2014-06-19	0.24800	4.0	2.00	2080	13510	1.0	No	
4834	5151600480	2015-04-02	0.24800	3.0	1.75	1840	19501	1.0	No	
4295	2122059160	2015-04-27	0.24800	5.0	1.75	2190	16788	1.0	No	
...	...	...	...	...	...	...	...	...	...	.
2350	7229700105	2015-04-24	0.17250	2.0	2.00	1510	20685	1.0	No	
19547	42000245	2014-06-13	0.17100	4.0	2.00	1520	19672	1.0	No	
9865	1219000473	2014-06-26	0.16495	3.0	1.75	1570	15330	1.0	No	
8716	7883603425	2014-05-29	0.15500	3.0	1.00	1250	6250	1.0	No	
5811	7568700480	2015-03-23	0.15300	2.0	1.00	1140	10152	1.0	No	

135 rows × 25 columns

In [72]:

```

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

# plt.figure(figsize=(18, 12))
sns.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)

```

```

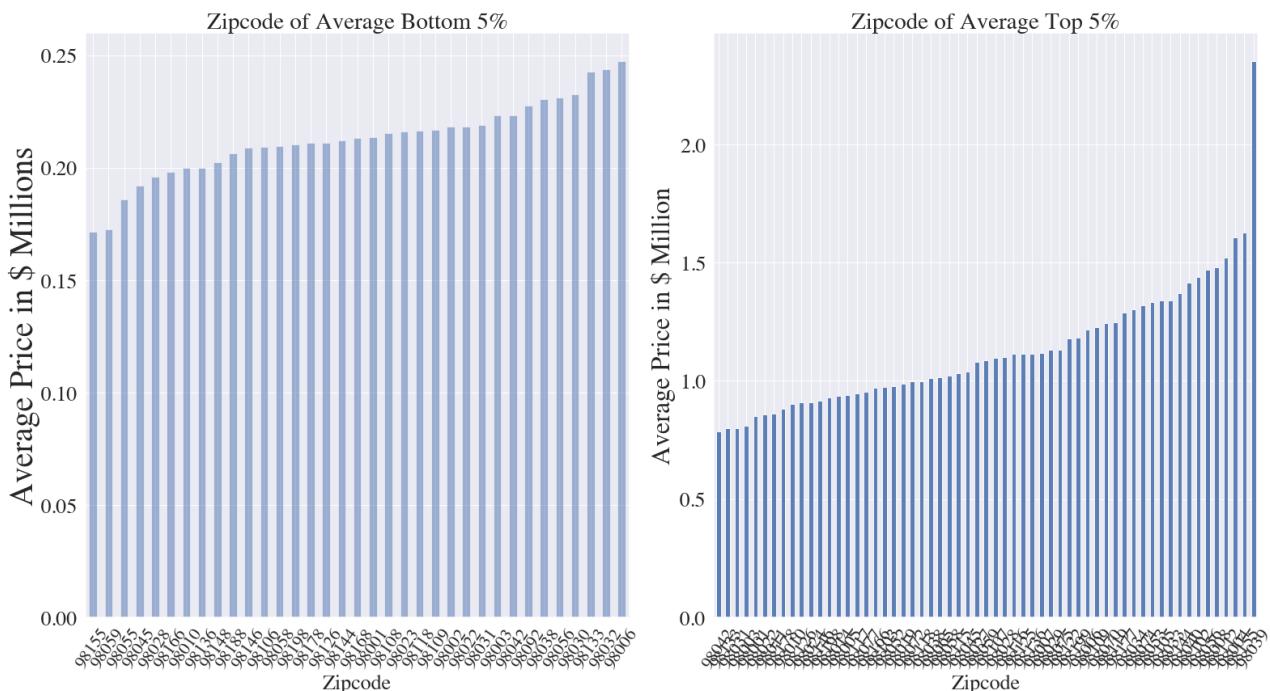
plt.subplot(1,2,2)
group_zipcode = group_zipcode.sort_values()
group_zipcode.plot(kind='bar',x='zipcode',y='price',
                    alpha=0.9,figsize=(22,12))

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]:

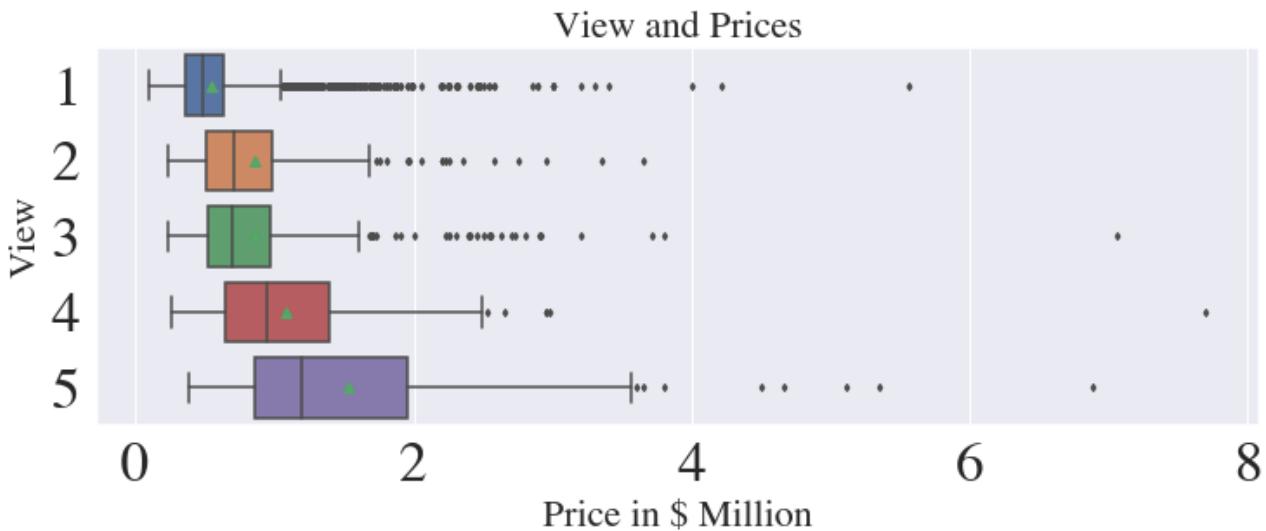
```

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

```
#We would need to visualize the data to clearly see where the data rests. Let's use
#the boxplot function from Seaborn to do just that.

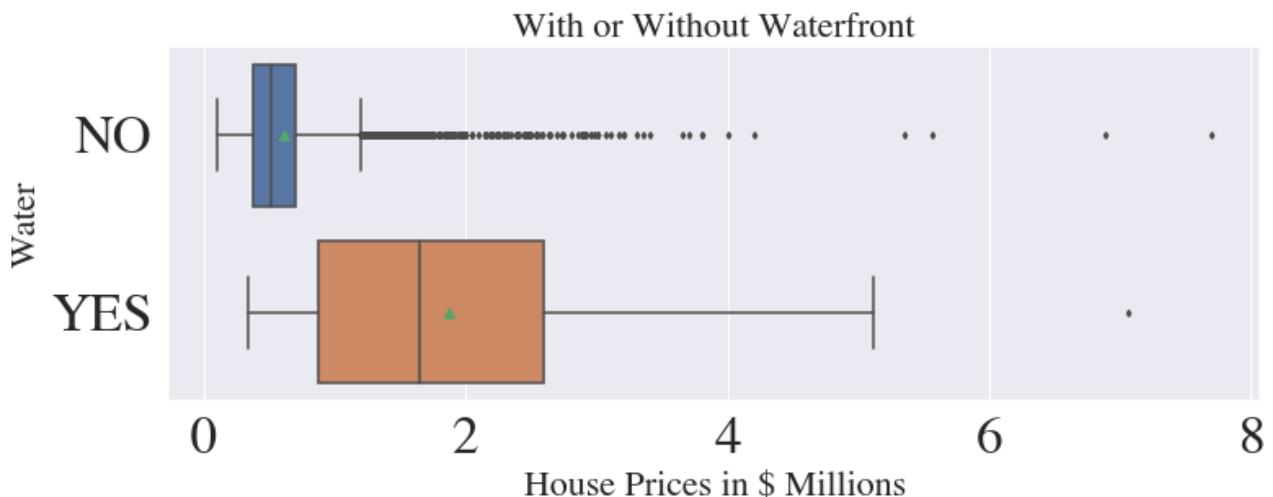
from scipy import stats, linalg

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 [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)
sns.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='--')

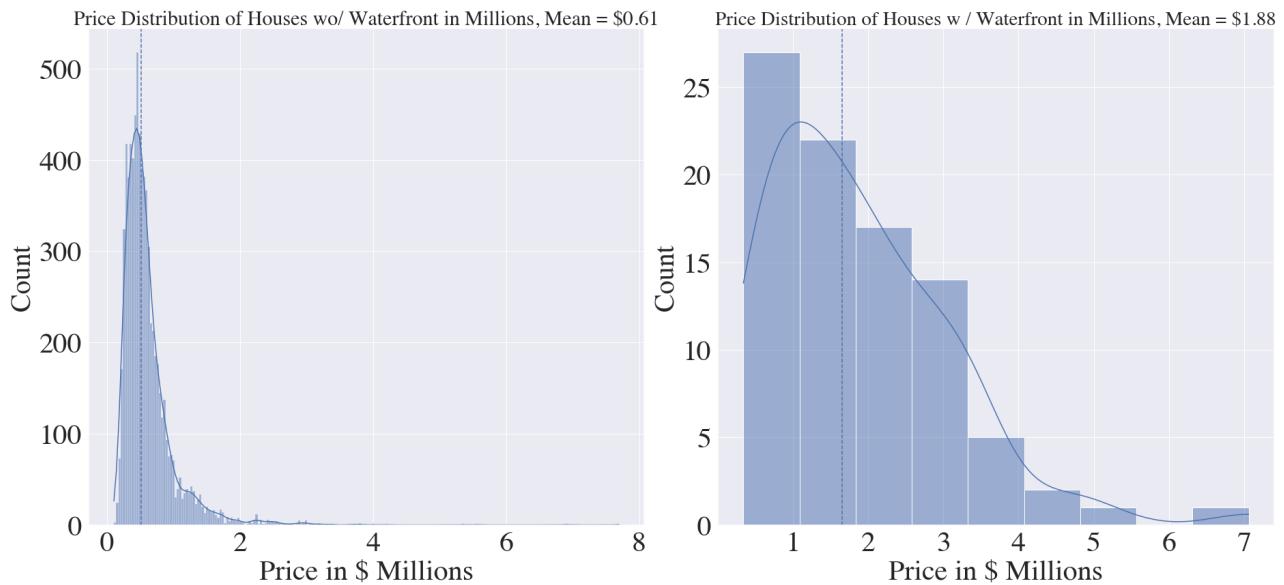
m = np.mean(waterfront)
m = round(m,2)

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()

```



## 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

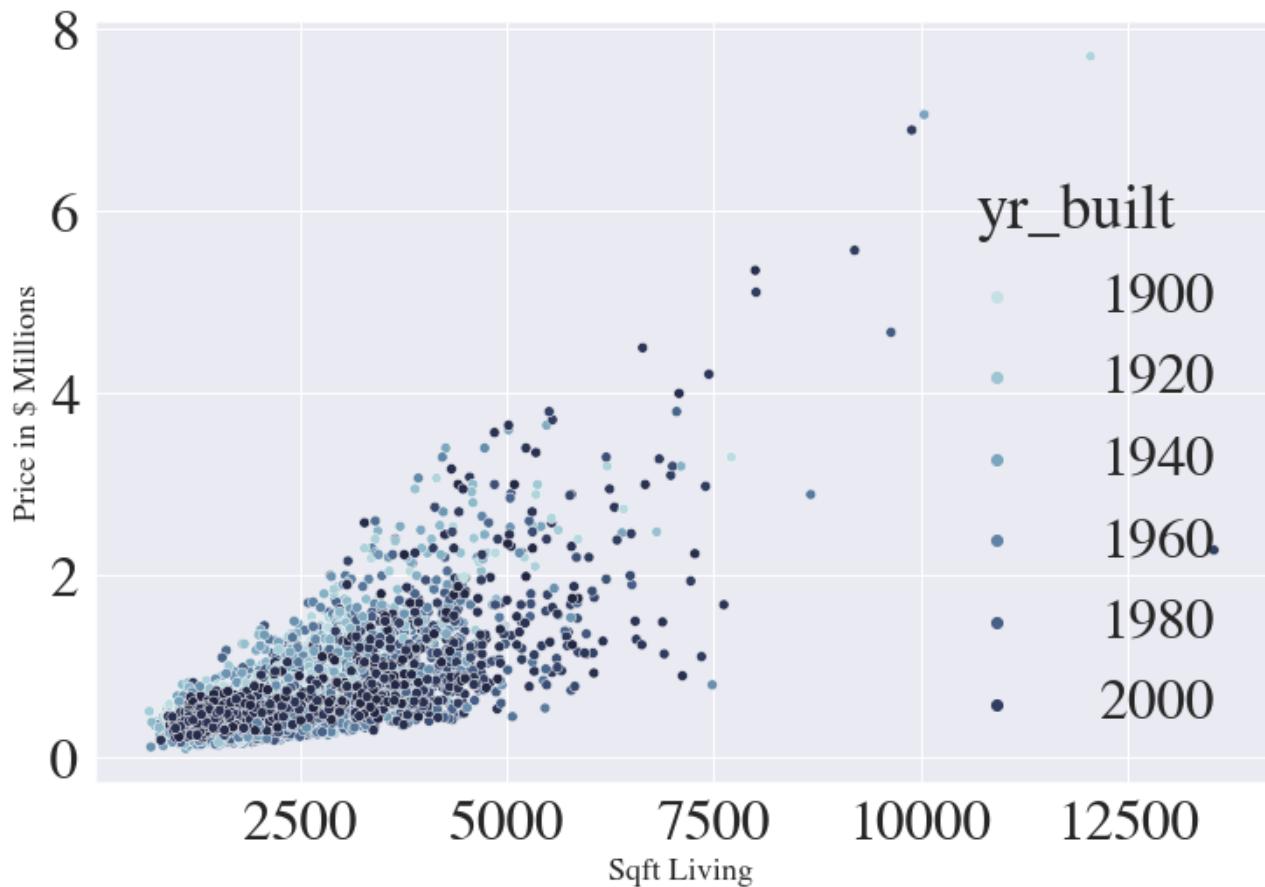
unexpectedly, the year a house was built did not show a relationship to price.

In [82]:

```
plt.subplots(figsize=(12,8))
sns.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')



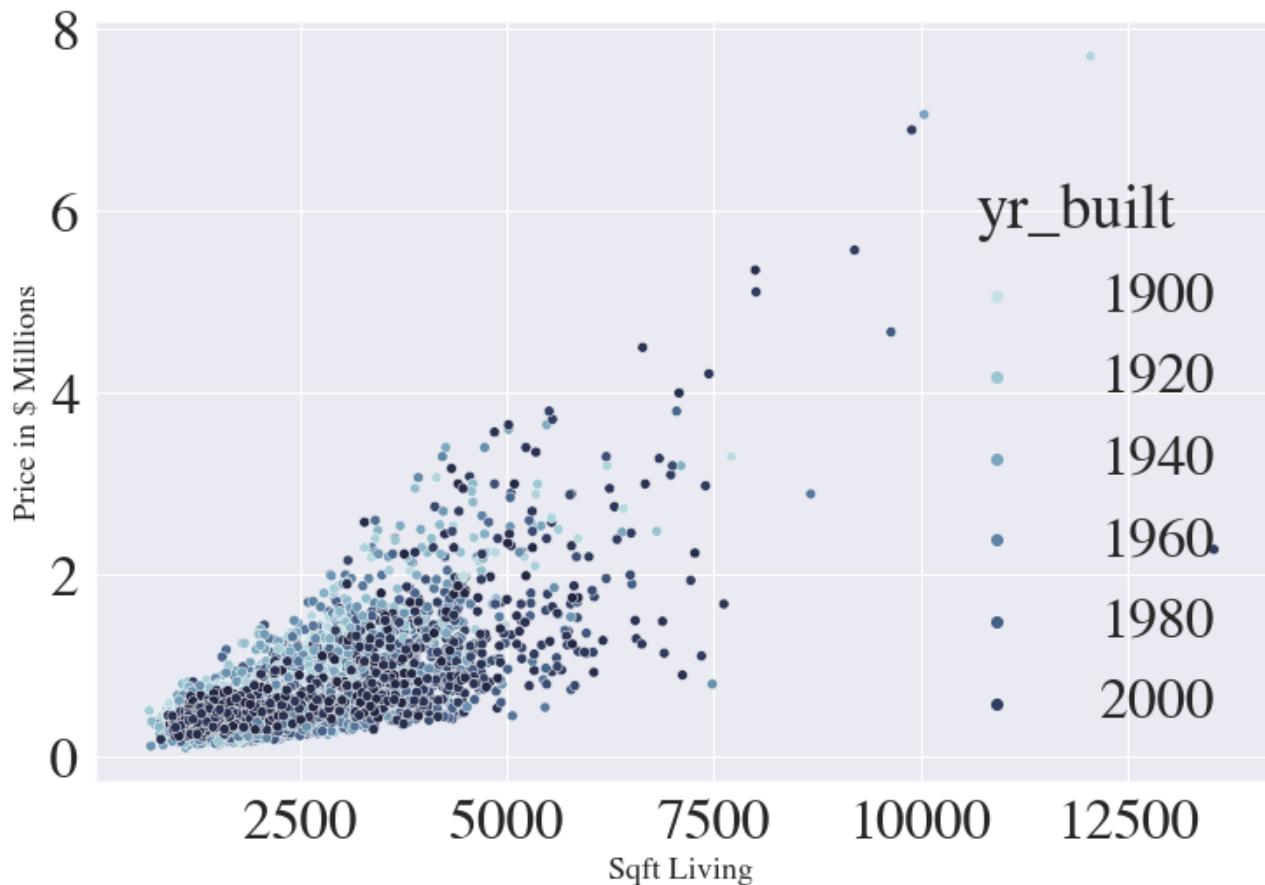
In [83]:

```
plt.subplots(figsize=(12,8))

sns.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)

sns.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)

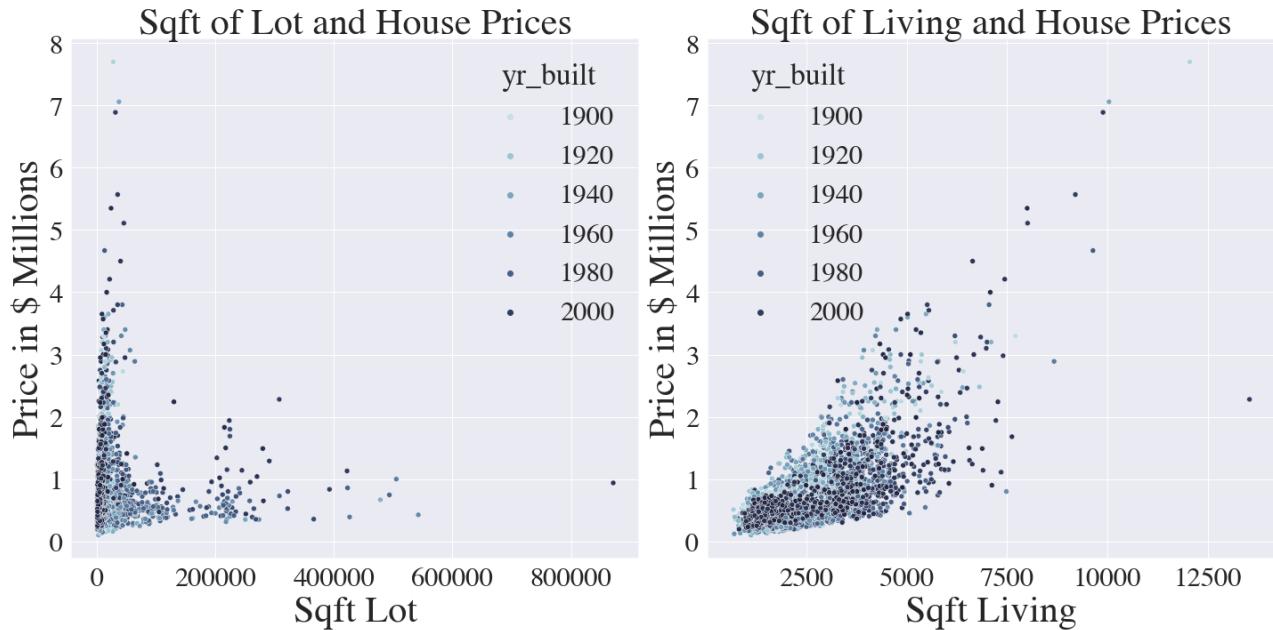
plt.subplot(1,2,2)
```

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

sns.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]:

	<b>id</b>	<b>price</b>	<b>bedrooms</b>	<b>bathrooms</b>	<b>sqft_living</b>	<b>sqft_lot</b>	<b>floors</b>	<b>waterfront</b>	<b>view</b>
<b>id</b>	1.00	-0.02	0.01	0.00	-0.02	-0.13	0.02	NaN	0.01
<b>price</b>	-0.02	1.00	0.26	0.53	0.72	0.07	0.35	NaN	0.45
<b>bedrooms</b>	0.01	0.26	1.00	0.46	0.52	0.06	0.08	NaN	0.10
<b>bathrooms</b>	0.00	0.53	0.46	1.00	0.70	0.13	0.47	NaN	0.24
<b>sqft_living</b>	-0.02	0.72	0.52	0.70	1.00	0.23	0.33	NaN	0.37
<b>sqft_lot</b>	-0.13	0.07	0.06	0.13	0.23	1.00	-0.02	NaN	0.07
<b>floors</b>	0.02	0.35	0.08	0.47	0.33	-0.02	1.00	NaN	0.12
<b>waterfront</b>	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
<b>view</b>	0.01	0.45	0.10	0.24	0.37	0.07	0.12	NaN	1.00

	<b>id</b>	<b>price</b>	<b>bedrooms</b>	<b>bathrooms</b>	<b>sqft_living</b>	<b>sqft_lot</b>	<b>floors</b>	<b>waterfront</b>	<b>view</b>
<b>condition</b>	-0.02	0.08	0.07	-0.06	0.03	-0.01	-0.16	NaN	0.03
<b>grade</b>	0.01	0.69	0.26	0.64	0.73	0.13	0.46	NaN	0.38
<b>sqft_above</b>	-0.02	0.72	0.43	0.70	0.92	0.21	0.50	NaN	0.33
<b>sqft_basement</b>	-0.02	0.41	0.46	0.41	0.72	0.16	-0.11	NaN	0.29
<b>yr_built</b>	0.01	-0.01	0.03	0.39	0.17	0.09	0.29	NaN	-0.01
<b>yr_renovated</b>	-0.00	0.15	0.05	0.09	0.09	0.00	0.07	NaN	0.09
<b>zipcode</b>	-0.03	-0.06	-0.15	-0.18	-0.20	-0.18	0.09	NaN	0.06
<b>lat</b>	-0.03	0.24	0.00	0.03	0.03	-0.11	0.10	NaN	-0.02
<b>long</b>	-0.00	0.02	0.13	0.19	0.23	0.33	-0.05	NaN	-0.04
<b>sqft_living15</b>	-0.01	0.60	0.33	0.51	0.72	0.20	0.18	NaN	0.41
<b>sqft_lot15</b>	-0.12	0.05	0.04	0.11	0.21	0.79	-0.02	NaN	0.06
<b>dateyear</b>	0.00	0.00	-0.01	-0.03	-0.03	0.01	-0.03	NaN	-0.01
<b>date_month</b>	-0.00	-0.00	0.00	0.01	0.02	-0.02	0.03	NaN	-0.00
<b>year</b>	0.00	0.00	-0.01	-0.03	-0.03	0.01	-0.03	NaN	-0.01
<b>month</b>	-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 consider - 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
```

	<b>condition</b>	<b>id</b>	<b>price</b>	<b>bedrooms</b>	<b>bathrooms</b>	<b>sqft_living</b>	<b>sqft_lot</b>	<b>flo</b>
<b>0</b>	1	5.337300e+09	0.324333	3.333333	1.666667	1850.000000	19043.000000	1.000000
<b>1</b>	2	5.097944e+09	0.417773	3.200000	1.800000	1861.400000	26088.940000	1.050000
<b>2</b>	3	4.642844e+09	0.612184	3.514252	2.350058	2313.367290	12714.375000	1.415400
<b>3</b>	4	4.575608e+09	0.603976	3.590193	2.118534	2281.827260	14584.501125	1.173600
<b>4</b>	5	4.486960e+09	0.751617	3.691267	2.318182	2425.753071	11056.217445	1.279400

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))

sns.set_context(fontfamily="times")

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

sns.boxplot(ax=axes[0], y = kc_data['condition'],
            x =kc_data['price'],
            width = 0.7, orient ='h', showmeans = True,
            linewidth = 2, fliersize =10)

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

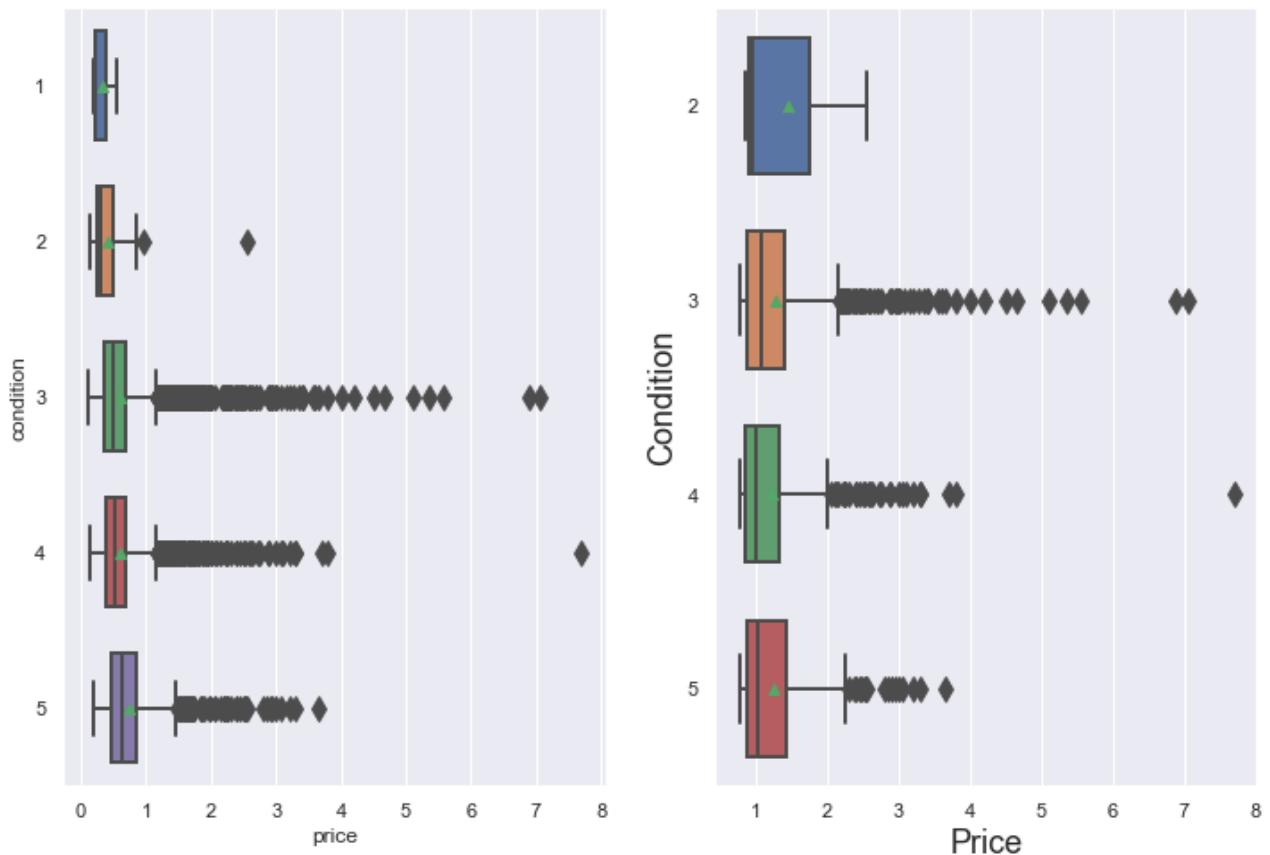
sns.set_context(fontfamily="times")
sns.boxplot(ax=axes[1], y = top20p['condition'], x = top20p['price'],
            width = 0.7, orient ='h',
            showmeans = True, linewidth = 2, fliersize =10)

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')

## Condition and Price Distribution, All Prices(left) and Top 20%(right)



```
In [90]: ## Condition and Grade
```

```
In [91]: from matplotlib.gridspec import GridSpec
```

```
#sns.set_color_codes("Spectral")

sns.set(font_scale=3)
sns.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')
```

```

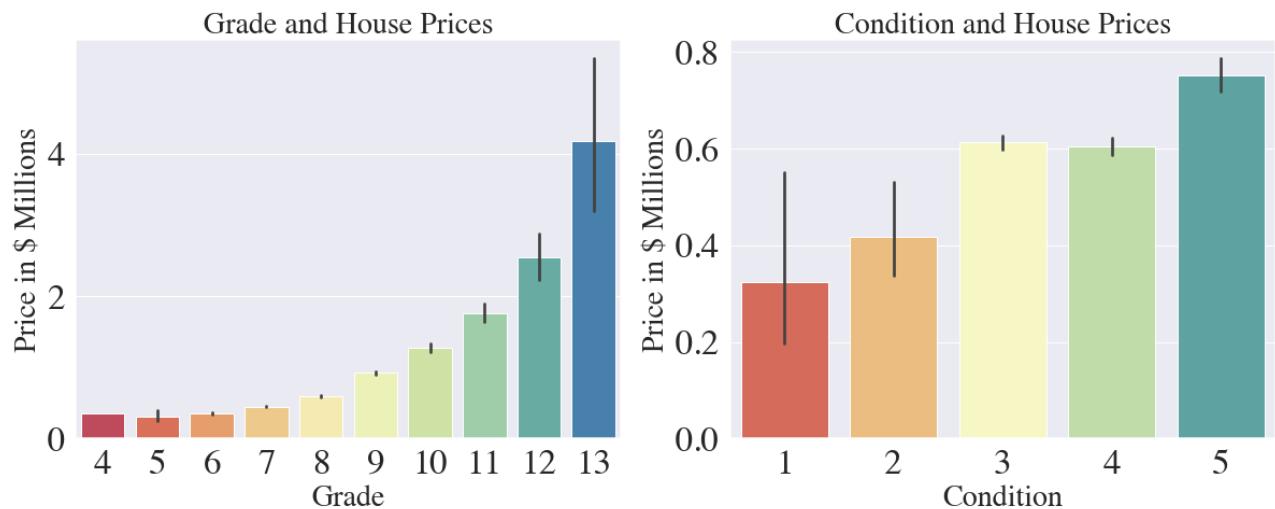
plt.title('Grade and House Prices' , fontsize=28)
plt.xlabel('Grade' , fontsize=28)
plt.ylabel('Price in $ Millions' , fontsize=28)

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

```

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

## Grade and Condition against prices



## Year Built/Renovated

```

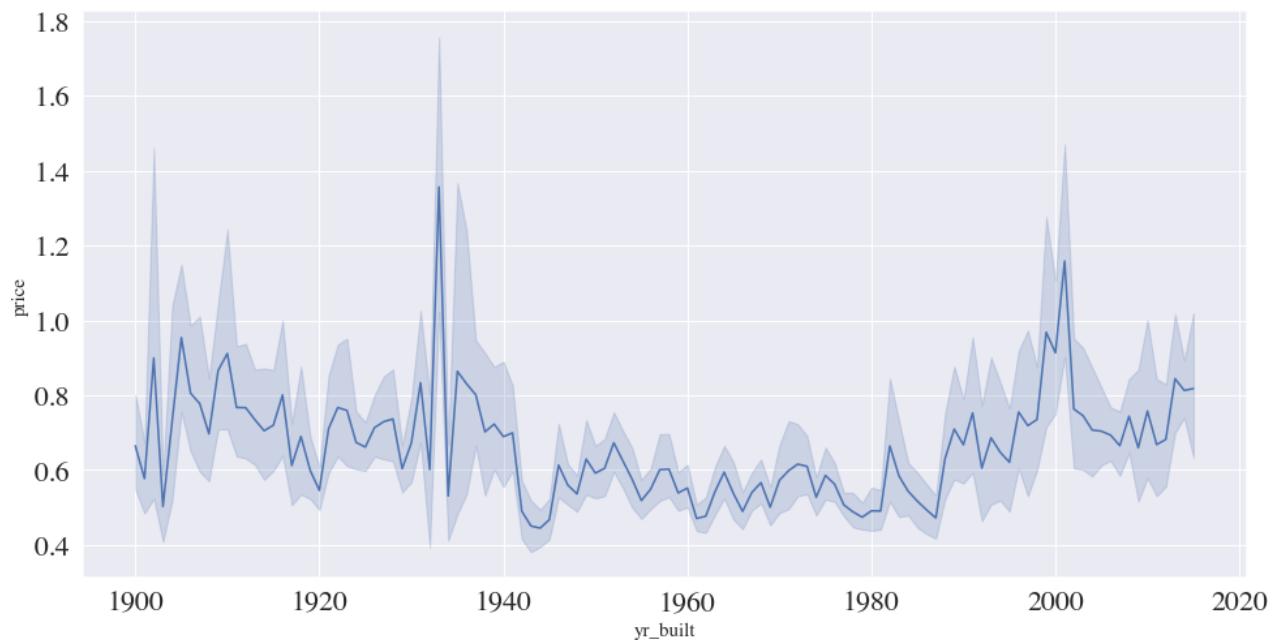
In [92]: sns.set_style('whitegrid')
sns.set_color_codes("pastel")
sns.set(font_scale=2)
sns.set_context(fontfamily="times")

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).astype
```

```
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]:

```

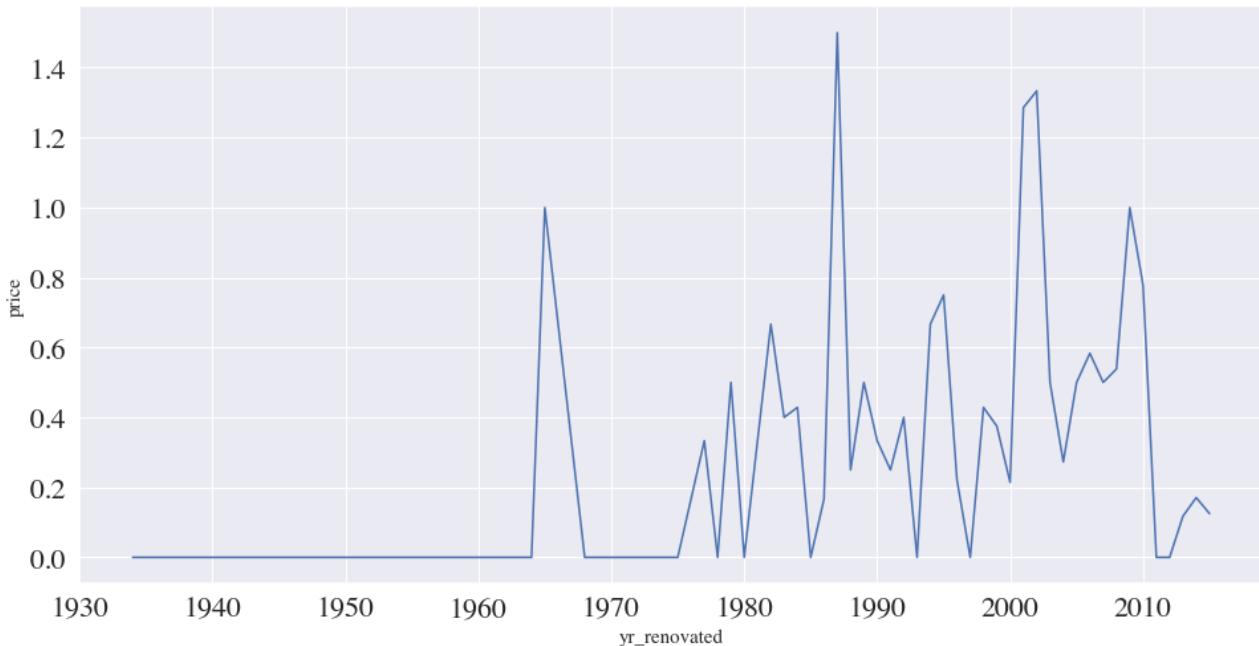
sns.set_style('whitegrid')
sns.set_color_codes("pastel")
sns.set(font_scale=2)
sns.set_context(fontfamily="times")

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

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

```

Out[99]:



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 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_ordered()
#bins_yr_built.head()

```

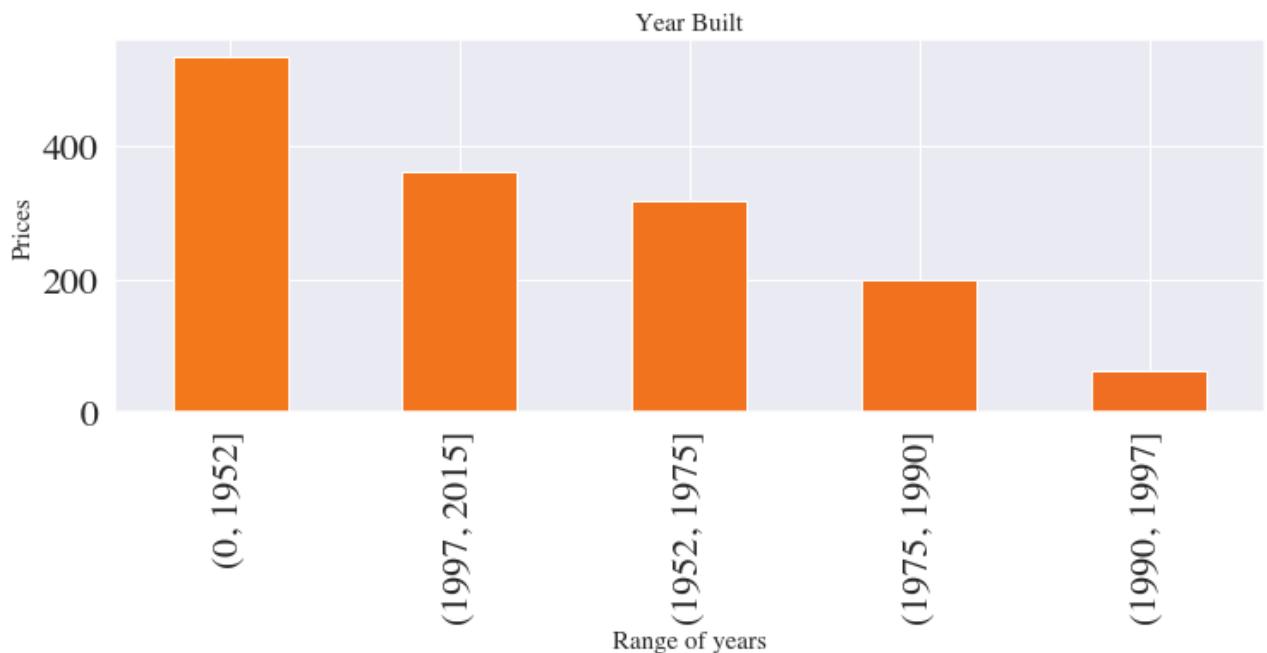
In [102...]

```

#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))
sns.set_context(fontfamily="times")
bins_yr_built.value_counts().plot(kind='bar', stacked=True, color=color, legend=False)
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 variables by either use 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_above	sqft_basement	yr_built	yr_renovated	zipcode	lat	long	sqft_living15	sqft_lot15	dateyear	date_month	year	month	dtype: int64
1	3.0	2.25	2570	7242	2.0	0	1	3	7	1	0	1900	0	98033	47.6	-122.1	2560	7242	2010	1	2010	1	
3	4.0	3.00	1960	5000	1.0	0	1	5	7	1	0	1200	0	98033	47.6	-122.1	1700	5000	2010	1	2010	1	
5	4.0	4.50	5420	101930	1.0	0	1	3	11	3	0	1200	0	98033	47.6	-122.1	1700	5000	2010	1	2010	1	
8	3.0	1.00	1780	7470	1.0	0	1	3	7	1	0	1200	0	98033	47.6	-122.1	1700	7470	2010	1	2010	1	
11	2.0	1.00	1160	6000	1.0	0	1	4	7	1	0	1200	0	98033	47.6	-122.1	1700	6000	2010	1	2010	1	

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

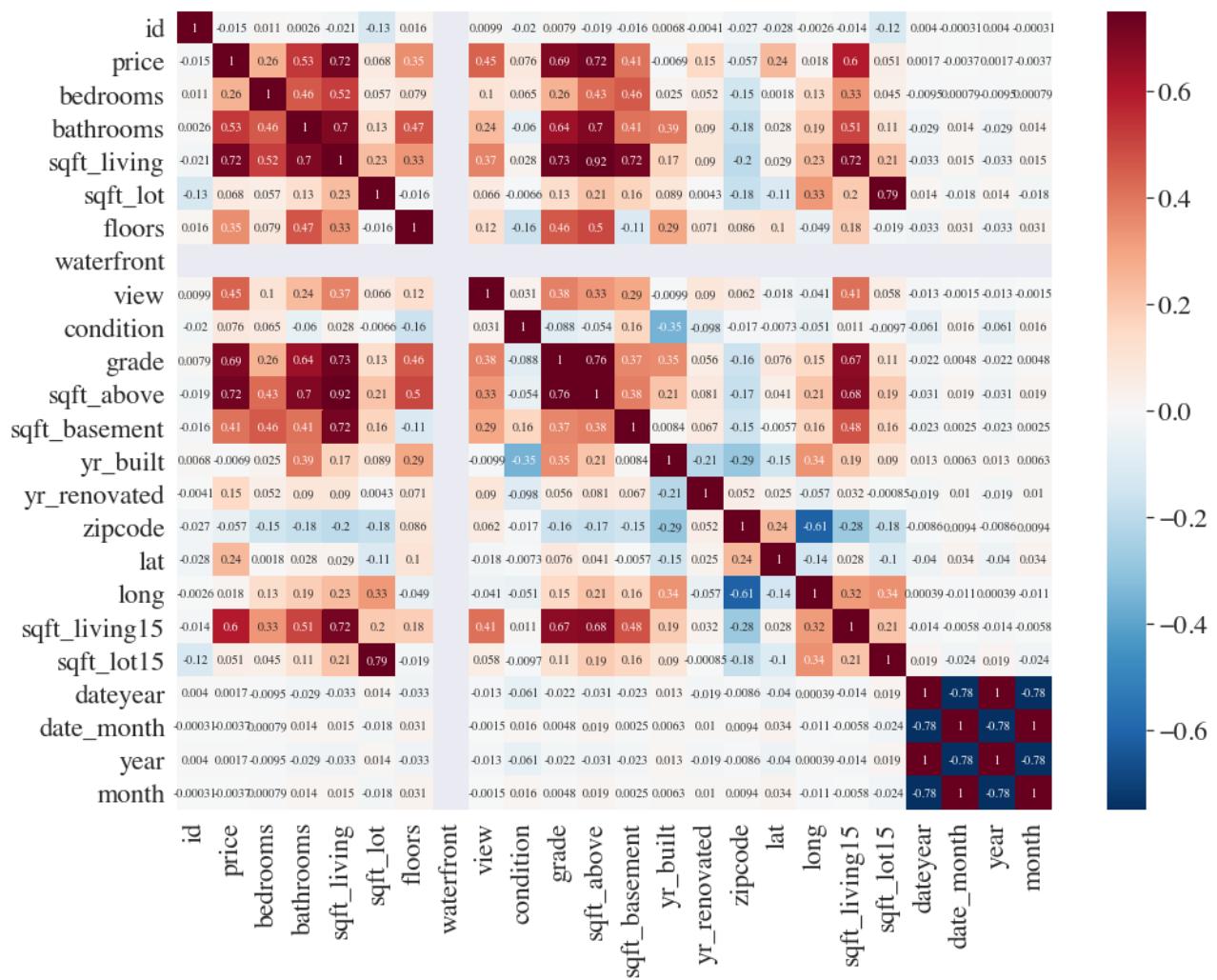
In [105...]

```
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)
sns.set_context(fontfamily="times")
heatmap = sns.heatmap(corr, annot=True, linewidths=0, vmin=-0.75,
                      vmax=0.75, cmap="RdBu_r")
```



Creating a function that generates a list of two variables and the respective correlation to check for multicolliniartiy. 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 variables
        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**

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

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=True)
```

```
In [113... # Add the new dummy variables to the data frame
kc_data = pd.concat([kc_data, WF_dummies , View_dummies, Con_dummies,
Grade_dummies, Month_dummies], axis=1)

kc_data.head()
```

	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	0	...
3	0.6040	1960	5000	1	1	0	0	0	0	0	0	...
5	1.2300	5420	101930	1	1	0	0	0	0	0	0	...
8	0.2295	1780	7470	1	1	0	0	0	0	0	0	...
11	0.4680	1160	6000	1	1	0	0	0	0	0	0	...

5 rows × 36 columns

```
In [114... kc_data.head()
```

	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	0	...
3	0.6040	1960	5000	1	1	0	0	0	0	0	0	...
5	1.2300	5420	101930	1	1	0	0	0	0	0	0	...
8	0.2295	1780	7470	1	1	0	0	0	0	0	0	...
11	0.4680	1160	6000	1	1	0	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_state=42)
```

```
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	...

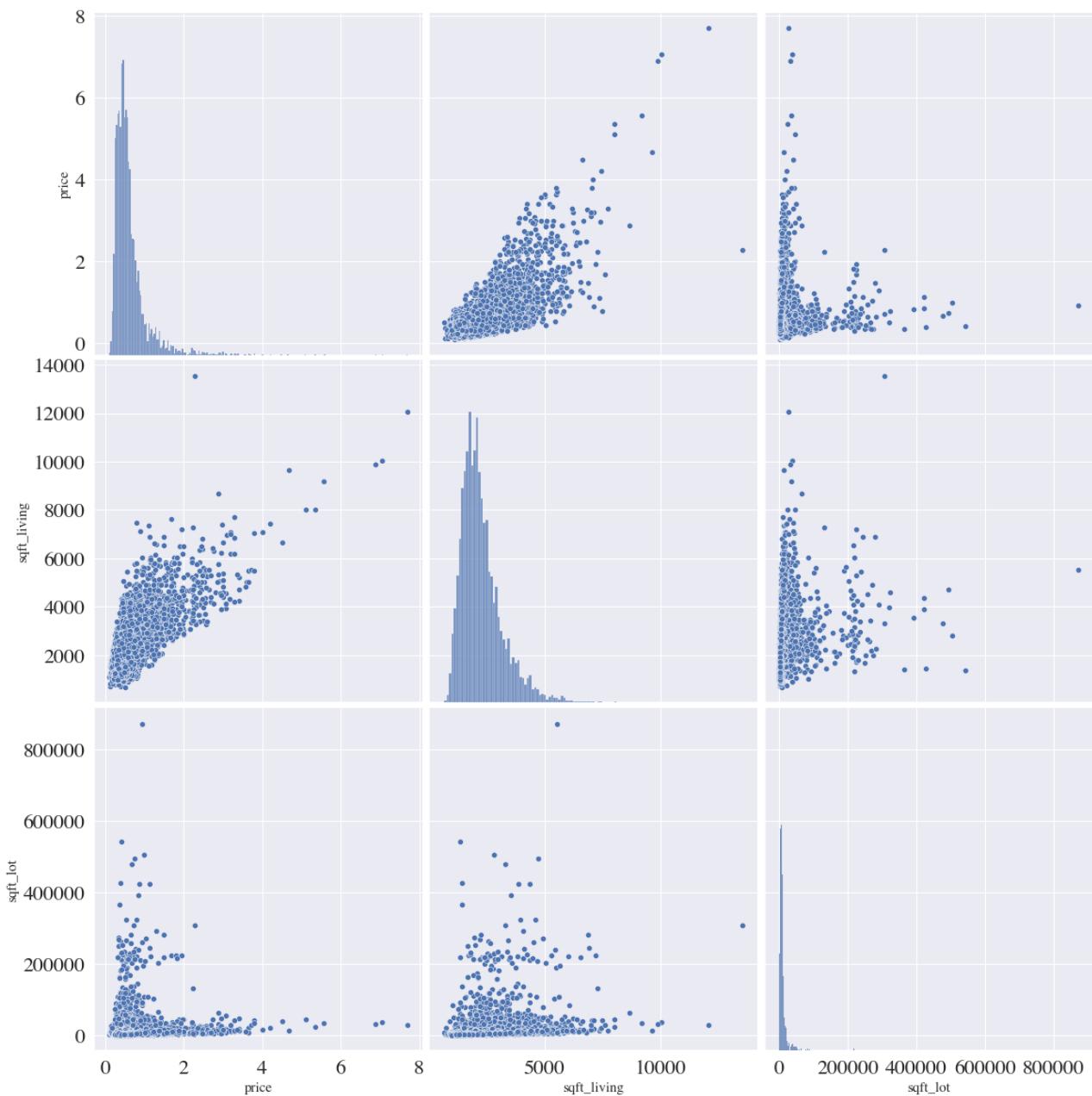
5 rows × 36 columns

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() function
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
<b>count</b>	5.527000e+03	5.527000e+03	5527.0	5.527000e+03	5.527000e+03	5.527000e+03
<b>mean</b>	5.107162e-16	3.078574e-16	0.0	-4.774642e-16	-4.061645e-17	-2.697217e-16
<b>std</b>	1.000090e+00	1.000090e+00	0.0	1.000090e+00	1.000090e+00	1.000090e+00
<b>min</b>	-3.123039e+00	-2.843785e+00	0.0	-2.239229e+00	-1.743209e-01	-2.717157e-01
<b>25%</b>	-6.703544e-01	-4.724627e-01	0.0	4.465823e-01	-1.743209e-01	-2.717157e-01
<b>50%</b>	-6.523868e-02	-6.805300e-03	0.0	4.465823e-01	-1.743209e-01	-2.717157e-01
<b>75%</b>	6.162702e-01	3.867076e-01	0.0	4.465823e-01	-1.743209e-01	-2.717157e-01
<b>max</b>	4.988731e+00	5.339827e+00	0.0	4.465823e-01	5.736547e+00	3.680317e+00

8 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', 'Con_5', 'View_5', 'Grade_5', 'Grade_9', 'Con_4',
                     'sqft_lot', 'Grade_10', 'Month_3', '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()
```

OLS Regression Results									
Dep. Variable:	price	R-squared:	0.640 <th data-cs="3" data-kind="parent"></th> <th data-kind="ghost"></th> <th data-kind="ghost"></th>						
Model:	OLS	Adj. R-squared:	0.639 <th data-cs="3" data-kind="parent"></th> <th data-kind="ghost"></th> <th data-kind="ghost"></th>						
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]			
<b>WV_0</b>	1.0659	0.038	28.157	0.000	0.992	1.140			
<b>sqft_living</b>	0.0002	5.72e-06	30.353	0.000	0.000	0.000			
<b>Grade_7</b>	-0.8674	0.029	-30.129	0.000	-0.924	-0.811			
<b>View_1</b>	-0.1120	0.015	-7.703	0.000	-0.141	-0.084			
<b>Grade_6</b>	-0.8893	0.033	-26.632	0.000	-0.955	-0.824			
<b>Grade_8</b>	-0.8010	0.027	-29.151	0.000	-0.855	-0.747			
<b>Con_5</b>	0.1311	0.012	10.993	0.000	0.108	0.155			
<b>View_5</b>	0.3857	0.025	15.349	0.000	0.336	0.435			
<b>Grade_5</b>	-0.9180	0.082	-11.240	0.000	-1.078	-0.758			
<b>Grade_9</b>	-0.6324	0.027	-23.644	0.000	-0.685	-0.580			
<b>Con_4</b>	0.0366	0.008	4.571	0.000	0.021	0.052			
<b>sqft_lot</b>	-1.176e-06	1.16e-07	-10.153	0.000	-1.4e-06	-9.49e-07			
<b>Grade_10</b>	-0.4419	0.028	-16.023	0.000	-0.496	-0.388			
<b>Month_3</b>	0.0383	0.013	3.036	0.002	0.014	0.063			
<b>Month_4</b>	0.0345	0.012	2.980	0.003	0.012	0.057			
<b>Con_2</b>	-0.0120	0.042	-0.283	0.777	-0.095	0.071			
<b>View_3</b>	-0.0598	0.019	-3.142	0.002	-0.097	-0.023			

<b>Omnibus:</b>	<b>Durbin-Watson:</b>	2.010
<b>Prob(Omnibus):</b>	0.000	<b>Jarque-Bera (JB):</b> 205410.265
<b>Skew:</b>	2.386	<b>Prob(JB):</b> 0.00
<b>Kurtosis:</b>	32.482	<b>Cond. No.</b> 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="Coefficients"))
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... linreg = LinearRegression()

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

In [138... y_hat_train = linreg.predict(X_train_final)

In [139... train_error = y_train-y_hat_train

In [140... # 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... # 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,y_hat_train)))
print('Testing Root Mean Squared Error is',
      np.sqrt(mean_squared_error(y_test,y_hat_test)))

# 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 results are very close to one another which suggests that our model is not overfitted or underfitted.

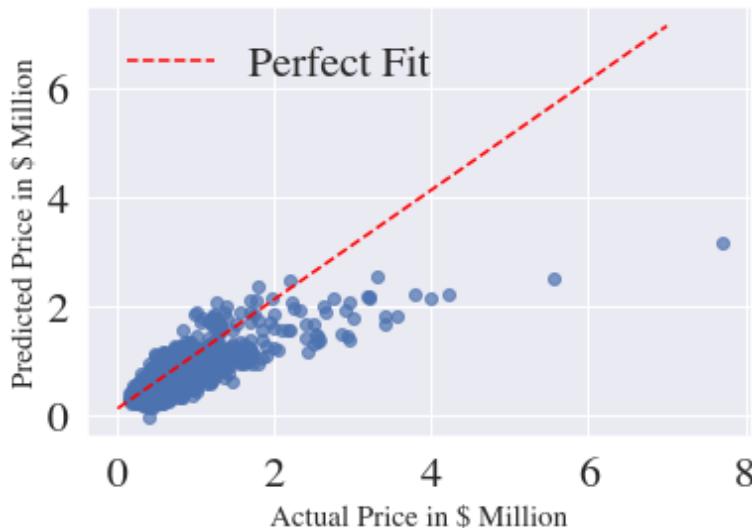
Testing if the linear assumption is violated. The graph shows that the relationship between actual prices and predictable prices is linear.

```
In [142...]: 
sns.set(font_scale=2)
sns.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();
```

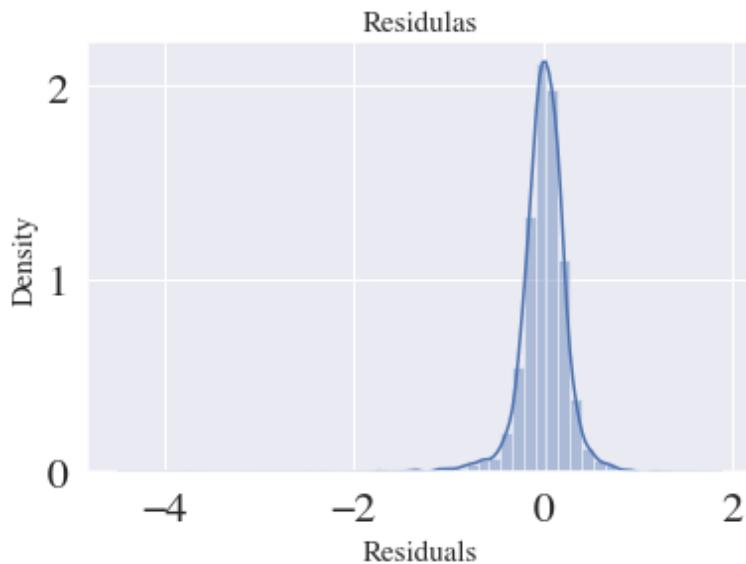
<Figure size 1584x1296 with 0 Axes>



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.