In [ ]:

```
%%javascript
/** Below because this notebook is pretty large */
var rto = 500;
console.log('NB: Increase require timeout to ' + rto + ' seconds');
window.requirejs.config({waitSeconds: rto});
```

Business Problem

The Zillow Failure

As reported on a November 9, 2021 episode of the Wall Street Journal, "The Journal" podcast, Zillow attempted to transform its business in 2018 by buying up thousands of homes all over the country. By utilizing it's massive amount of search data, Zillow hoped to leverage its advantage. According to the podcast,

> Ryan Knutson: So Zillow went huge and bought thousands of homes all over the country. The company would often do some light renovations and turn around and sell them quickly.

Unfortunately, for Zillow, their efforts ultimately failed (the pandemic did not help of course). Zillow has returned to its core efforts.

> Will Parker: So there's a debate right now about whether what happened at Zillow is a Zillow problem or an iBuyer problem. And I think what happens with its competitors, these other companies, is really going to tell us a lot about what the answer to that question really is.

Project Goals

The problem Zillow experienced offer an opportunity for competitors in the market. In this project I will use Linear Regression techniques identify key areas where a real estate competitor could make improvements to tranches of homes in an effort to reliably secure profit. I expect a variety of factors to play a role in the analysis.

Data Understanding

The give Dataset is for King County, Washington. According to Wikipedia:

> King County is located in the U.S. state of Washington. The population was 2,269,675 in the 2020 census, making it the most populous county in Washington, and the 12th-most populous in the United States. The county seat is Seattle, also the state's most populous city.

King County has a mixture of the urban Seattle areas and surrounding Suburbs. Given the size and population I anticipate it will serve as an excellent case study for further modeling projects.

In [23]:

```
import pandas as pd
import matplotlib.pyplot as plt
```

In [24]:

```
pd.reset_option('display.float_format')
```

In [425…:

```
#importing standard packages for intital data analysis
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
data = pd.read_csv('data/kc_house_data.csv')

pd.set_option('display.float_format', lambda x: '%.5f' % x)
```

In [26]:

```
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  object 
 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  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64  
 11  grade          21597 non-null  int64  
 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: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
```

Column Names

The column names are are included in a markdown file that I will make into a readable dataframe.

In [27]:

```
# f = open(, 'r')
# f.readlines()
with open("data/column_name.md") as file:
    lines = file.readlines()
    lines = [line.rstrip() for line in lines]
#creating a list of column names
col_list= []
#adding oher information into an appendix list
#only including the column names and description in list
for line in lines[1:]:
    if "-" in line:
        col_list.append(line.split("-"))
    else:
        col_list.append(line)
```

In [28]:

```
for idx, col in enumerate(col_list):
    if len(col)>2:
        col_list[idx-1].append(col)
```

In [29]:

```
for col in col_list:
    if len(col)>3:
        col_list.remove(col)
```

In [30]:

```
pd.set_option('max_colwidth', 200)
col_names = pd.DataFrame(col_list[1:],columns=['Name','Description','Notes'])
```

In [31]:

```
col_names
```

Out[31]:

	Name	Description	Notes
0	* $date$	Date house was sold	None
1	* $price$	Sale price (prediction target)	None
2	* $bedr\infty ms$	Number of bedrooms	None
3	* $bathr\infty ms$	Number of bathrooms	None
4	* $sqft_liv\in g$	Square footage of living space in the home	None
5	* $sqft_lot$	Square footage of the lot	None
6	* $\lfloor s \rfloor$	Number of floors (levels) in house	None
7	* $wateront$	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
8	* $view$	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
9	* $condition$	How good the overall condition of the house is. Related to maintenance of house.	* See the [King County Assessor Website](https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r) for further explanation of each condition code
10	* ∇e	Overall grade of the house. Related to the construction and design of the house.	* See the [King County Assessor Website](https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r) for further explanation of each building grade code
11	* $sqft_above$	Square footage of house apart from basement	None
12	* $sqft_basement$	Square footage of the basement	None
13	* $yr_bui<$	Year when house was built	None
14	* $yr_renovated$	Year when house was renovated	None
15	* $zipcode$	ZIP Code used by the United States Postal Service	None
16	* lat	Latitude coordinate	None
17	* $long$	Longitude coordinate	None
18	* $sqft_liv\in g15$	The square footage of interior housing living space for the nearest 15 neighbors	None
19	* $sqft_lot15$	The square footage of the land lots of the nearest 15 neighbors	None

This dataframe gives a clear explanation of each of the feautres that I will explore below individually.

Data Exploration

Price

In [32]:

```
data['price'].describe()
```

Out[32]:

```
count     21597.00000
mean     540296.57351
std      367368.14010
min       78000.00000
25%      322000.00000
50%      450000.00000
75%      645000.00000
max     7700000.00000
Name: price, dtype: float64
```

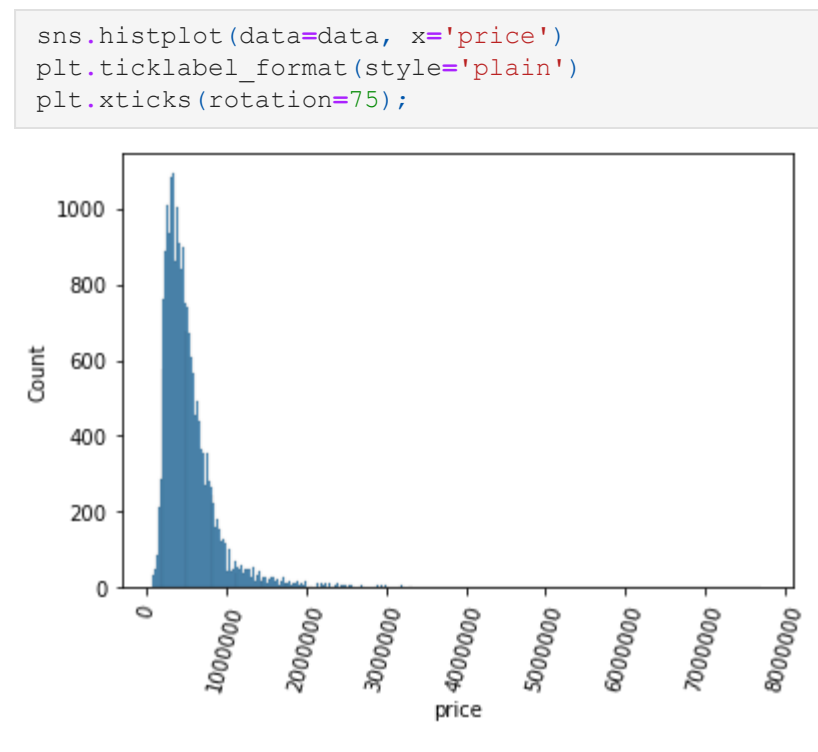
In [33]:

```
average_price = data['price'].mean()
median_price = data['price'].median()

print(f'The average home price in the data set is {average_price}, the median price is {median_price}')
```

```
The average home price in the data set is 540296.5735055795, the median price is 450000.0
```

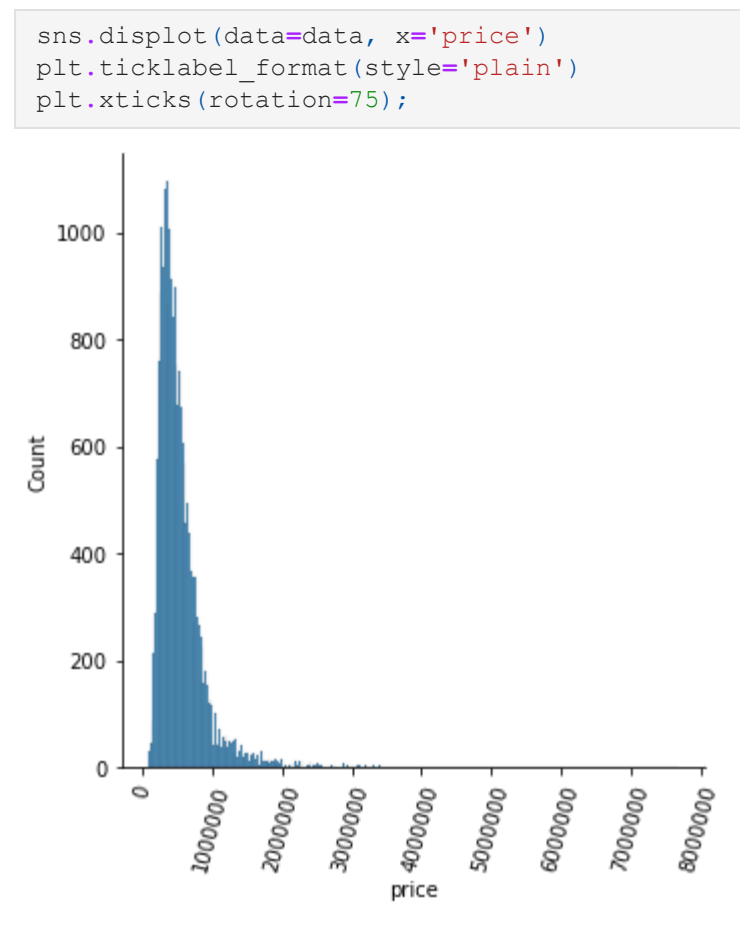
In [34]:

```
sns.histplot(data=data, x='price')
plt.ticklabel_format(style='plain')
plt.xticks(rotation=75);
```



In [35]:

```
sns.displot(data=data, x='price')
plt.ticklabel_format(style='plain')
plt.xticks(rotation=75);
```



The price is the target variable for the Linear Regression Analysis. It is a highly right skewed dataset in this regard.

Year Built Analysis

In [36]:

```
data['yr_built'].sort_values()
```

Out[36]:

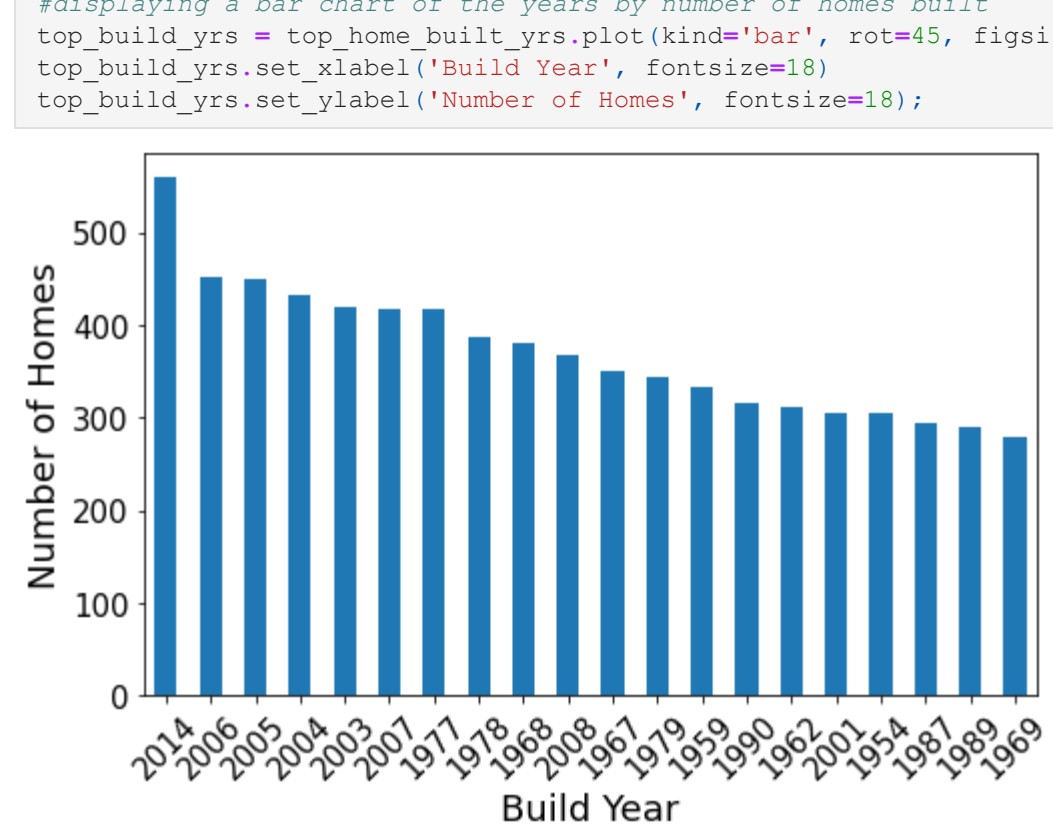
```
14069    1900
14783    1900
10973    1900
115      1900
4693     1900
         ... 
20235    2015
7519     2015
14911    2015
4150     2015
19789    2015
Name: yr_built, Length: 21597, dtype: int64
```

Top Build Years

The data contains both a "date" column and "year" column. The data set starts in 1900 and extends to 2015. So we have a mixture of old homes and new homes. Let's try to get a better sense of what that split.

In [37]:

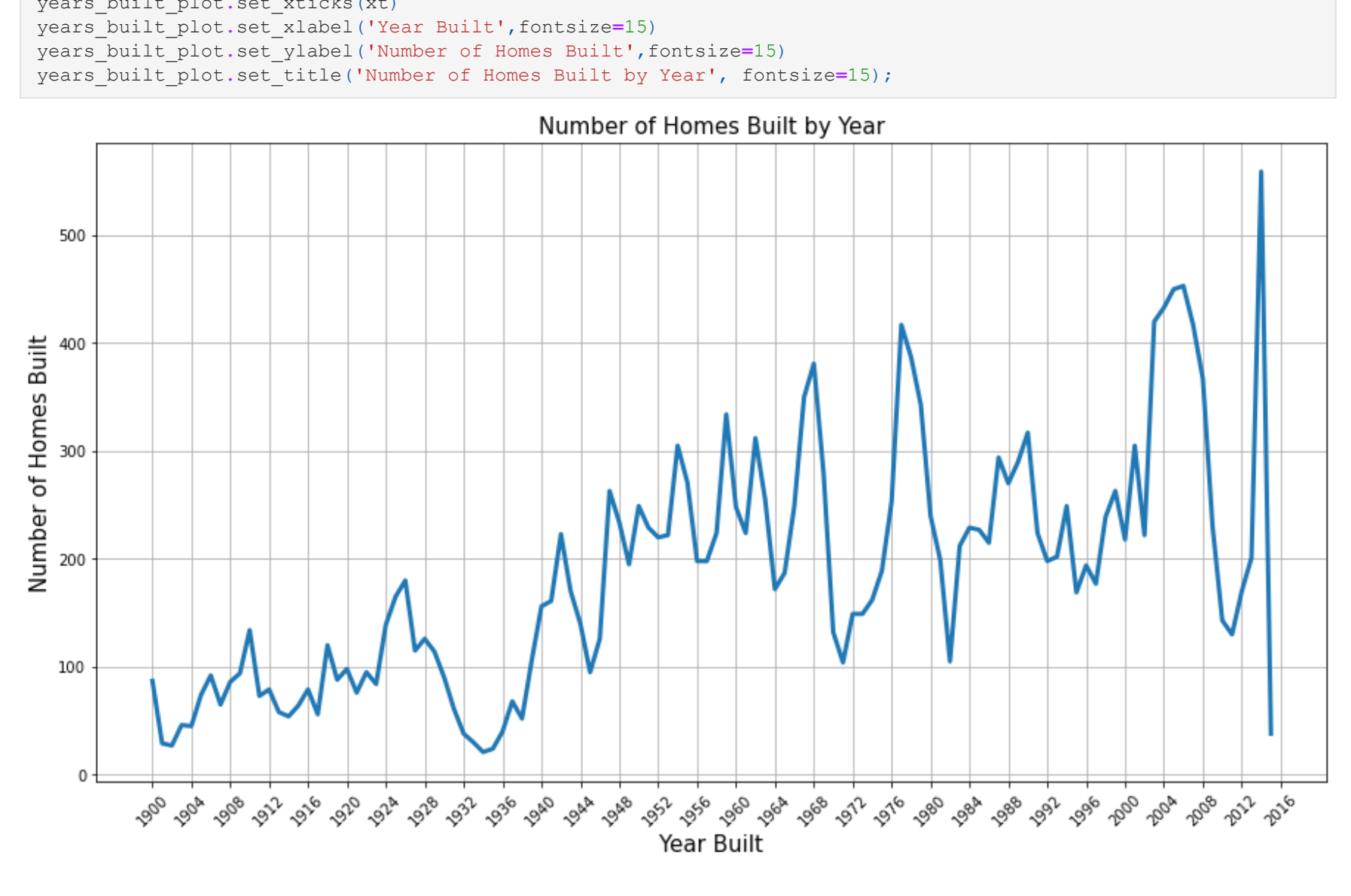
```
#Sorting the year built to show thge top years built with value counts.
top_home_built_yrs = data['yr_built'].value_counts(sort=True).head(20)

#displaying a bar chart of the years by number of homes built
top_build_yrs = top_home_built_yrs.plot(kind='bar', rot=45, figsize = (8,5),fontsize=15)
top_build_yrs.set_xlabel('Build Year', fontsize=18)
top_build_yrs.set_ylabel('Number of Homes', fontsize=18);
```



A quick bar chart reveals that the top five years of home building occurred recently (the past 20 years). This may or may not be relevent later, on. It's interesting, but let's also do a deeper dive to get some information on decade by decade home building maybe.

In [38]:

```
#setting a range for the xticks
xt = list(range(1900,2020,4))

#performing a count of the count of the home build year
years_built = data.yr_built.value_counts()
years_built = years_built.sort_index(ascending=True)

years_built_plot = years_built.plot(kind='line', figsize=(15,8),rot=45,grid=True, linewidth=3)
years_built_plot.set_xticks(xt)
years_built_plot.set_xlabel('Year Built',fontsize=15)
years_built_plot.set_ylabel('Number of Homes Built',fontsize=15)
years_built_plot.set_title('Number of Homes Built by Year', fontsize=15);
```

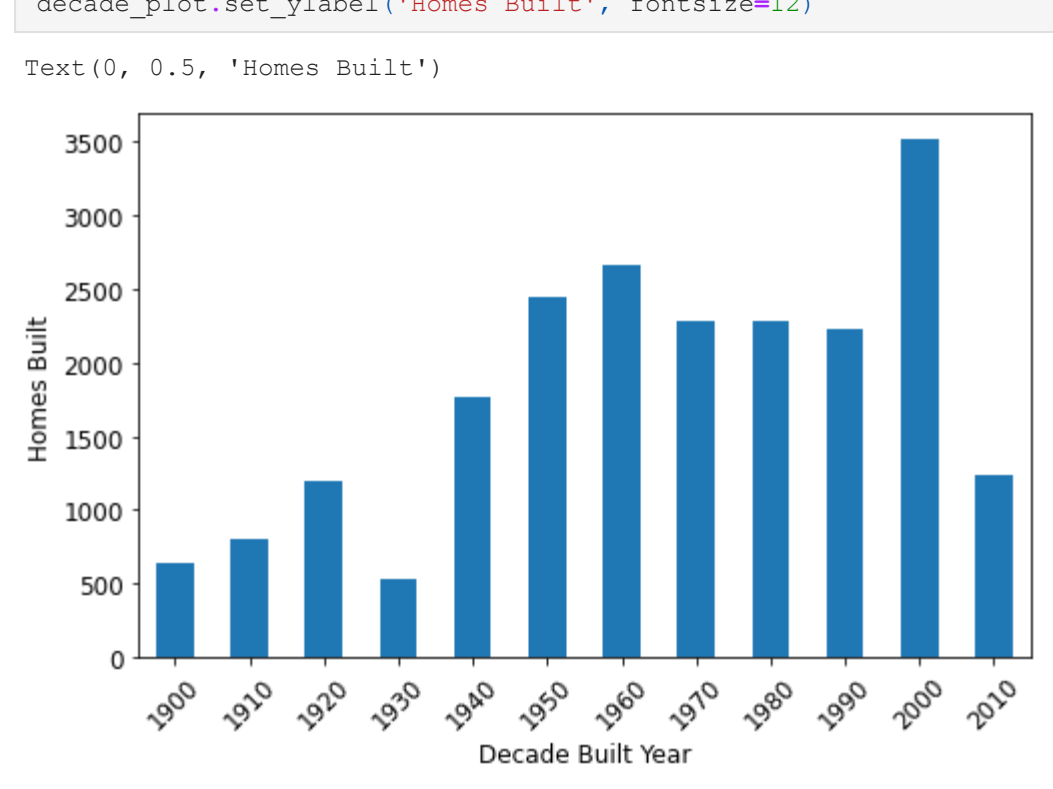


Builds by Decade

In [39]:

```
#Eliminating the last digit on the year built and multiplying by ten
decades = data.yr_built//10*10
decades = decades.value_counts().sort_index(ascending=True)

decade_plot = decades.plot(kind='bar',figsize=(8,5), rot=45, fontsize=12)
decade_plot.set_xlabel('Decade Built Year', fontsize=12)
decade_plot.set_ylabel('Homes Built', fontsize=12)
```

Out[39]: `Text(0, 0.5, 'Homes Built')`



Unsurprsingly home builds have been on the increase with blips of slowdowns - less homes were built during the Great Depression, and after the 2008 financial crisis. The 2010s are incomplete as a dataset goes, so look to be a declning decade on the charts, but 2014 showed to be the highest year of home builds.

This isn't just a sign of when homes were built, this is a data set of the build date of homes that were sold. So Initially there is a sense that more recent homes are perhaps more deseriable.

In [40]:

```
data.yr_built.value_counts()[2015]
```

Out[40]: `38`

The home built year of 38 in 2015 suggests I may consider throwing out the 2015 data, or at least accounting for the year built as incomplete in some way from the end of the data set, I may think of treating 'year built' as categorical. Considering the target of SalePrice, potentially year built will be an important coefficient in this determination.

Date Sold Information

According to the outside chart breakdown, the 'date' column indicates, the year sold information is in the 'date' column.

In [318…:

```
from datetime import datetime
```

In [506…:

```
#Converting date column to datetime column
data['date'] = pd.to_datetime(data['date'])
```

In [43]:

```
earliest_date = datetime.strftime(data['date'].min(), '%B %d%, %Y')
latest_date = datetime.strftime(data['date'].max(), '%B %d%, %Y')

print(f'The earliest sale by date is {earliest_date}, the most recent sale date is {latest_date}.')
```

```
The earliest sale by date is May 02, 2014, the most recent sale date is May 27, 2015.
```

In [44]:

```
#Top 10 correlations
corrs = data.corr()['price'].sort_values(ascending=False)[1:-11]
corrs
```

Out[44]:

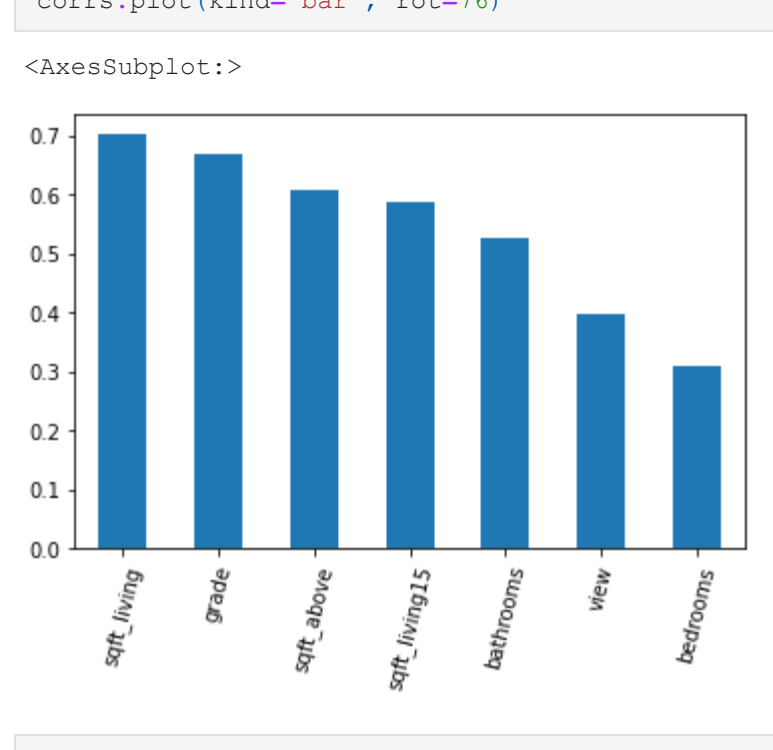
```
sqft_living     0.70192
grade           0.66795
sqft_above      0.60537
sqft_living15   0.58524
bathrooms       0.52591
view            0.39573
bedrooms        0.30879
Name: price, dtype: float64
```

This is a very cursory look at the correlations in the dataset. I will further look at multicollinearties later in the noteboo. But at first glance the best indicators look to be sqft, "grade," and number of bathrooms. Of course, this is uncleansed data, that hasn't been normalized, or invesitaged. I will want to seperate categoricals and continuous, remove multicorrelations.

In [45]:

```
corrs.plot(kind='bar', rot=76)
```

Out[45]: `<AxesSubplot:>`



In [46]:

```
month_sales = data.date.dt.month.value_counts().sort_index(ascending=True)
```

In [47]:

```
month_sale_date = data.date.dt.month.value_counts().sort_index()
month_sale_date
```

Out[47]:

```
1      978
2     1247
3     1875
4     2229
5     2414
6     2178
7     2211
8     1939
9     1771
10    1876
11    1409
12    1470
Name: date, dtype: int64
```

In [48]:

```
import calendar
months = []

for x in range(1,13):
    months.append(calendar.month_name[x])
```

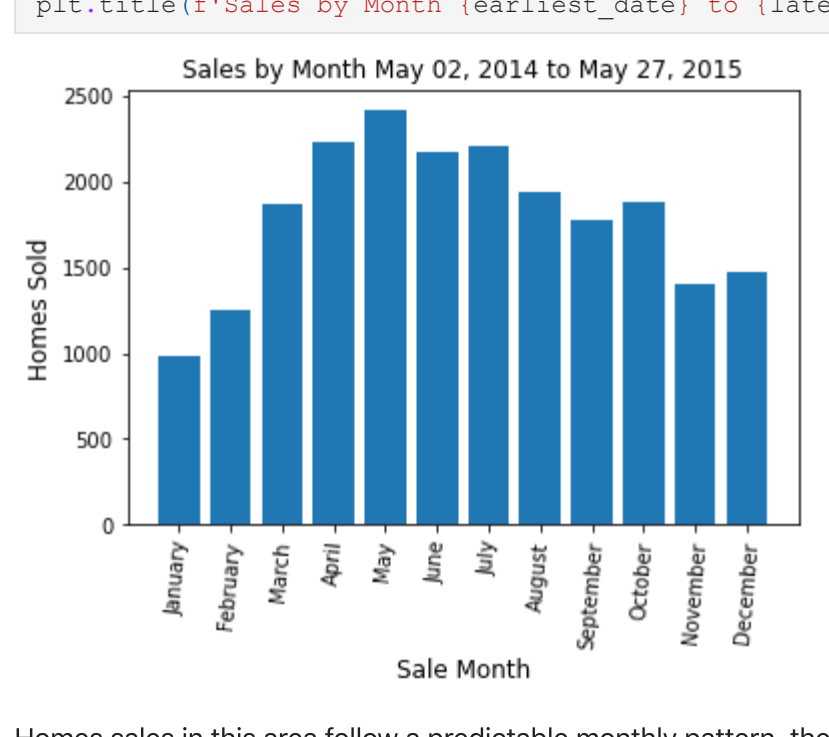
In [49]:

```
import numpy as np
np.array(month_sale_date)
monthly_sales = list(zip(months,month_sale_date))
```

Sales on Monthly Basis

In [50]:

```
monthly_sales =pd.DataFrame(monthly_sales, columns=['Month', 'Sales'])
monthly_sales
plt.bar(x=monthly_sales['Month'],height=monthly_sales['Sales'])
plt.xticks(rotation=85)
plt.xlabel('Sale Month', fontsize=12)
plt.ylabel('Homes Sold', fontsize=12)
plt.title(f'Sales by Month {earliest_date} to {latest_date}');
```



Homes sales in this area follow a predictable monthly pattern, the sales transactions were lowest in the January February, tick up in May and taper off in the Fall months. This may factor into the model, but so far this is the merely looking at when the homes are sold with factoring into price. Let's see if we can do a simple look at sale price vs month.

In [51]:

```
import numpy as np
data["month"] = data['date'].map(lambda x: x.month)
aggs = data.groupby(data.month)['price'].agg([np.mean,np.median])
```

In [52]:

```
aggs.info()
```

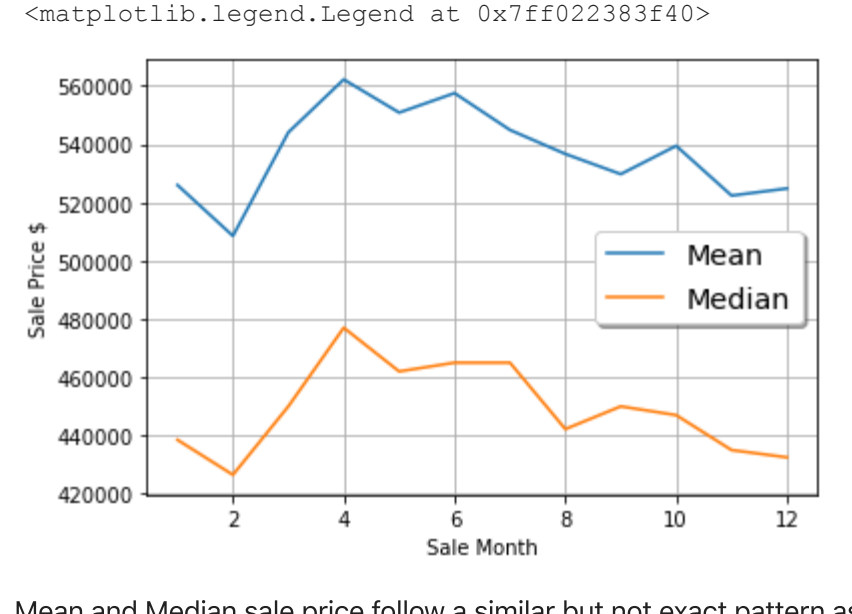
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12 entries, 1 to 12
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   mean    12 non-null     float64
 1   median  12 non-null     float64
dtypes: float64(2)
memory usage: 288.0 bytes
```

Aggregate Monthly Data

In [53]:

```
agg_chart = aggs.plot(kind='line',grid=True)
agg_chart.set_ylabel('Sale Price $')
agg_chart.set_xlabel('Sale Month')
agg_chart.legend(('Mean', 'Median'),loc='center right', shadow=True, fontsize='x-large',fancybox=True)
```

Out[53]: `<matplotlib.legend.Legend at 0x7ff022383f40>`



Mean and Median sale price follow a similar but not exact pattern as well. Sale Price does seem to peak in April, and gradually lowers until December. Not only are fewer homes sold in the colder months, but the average price and the median price declines as well. Perhaps sellers lower the price as the year goes on, or the pricier homes are removed bought up?

In [54]:

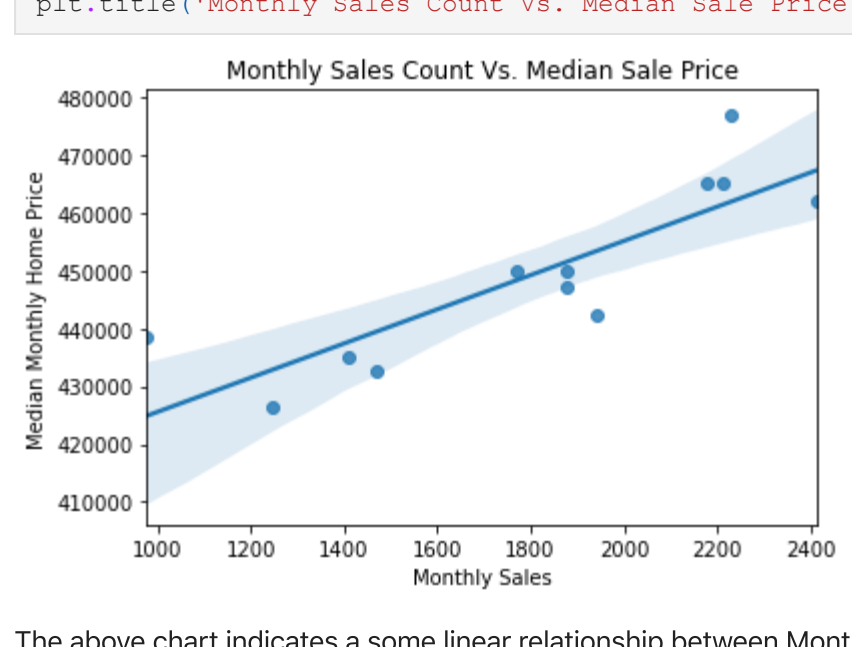
```
monthly_sales
```

Out[54]:

	Month	Sales
0	January	978
1	February	1247
2	March	1875
3	April	2229
4	May	2414
5	June	2178
6	July	2211
7	August	1939
8	September	1771
9	October	1876
10	November	1409
11	December	1470

In [55]:

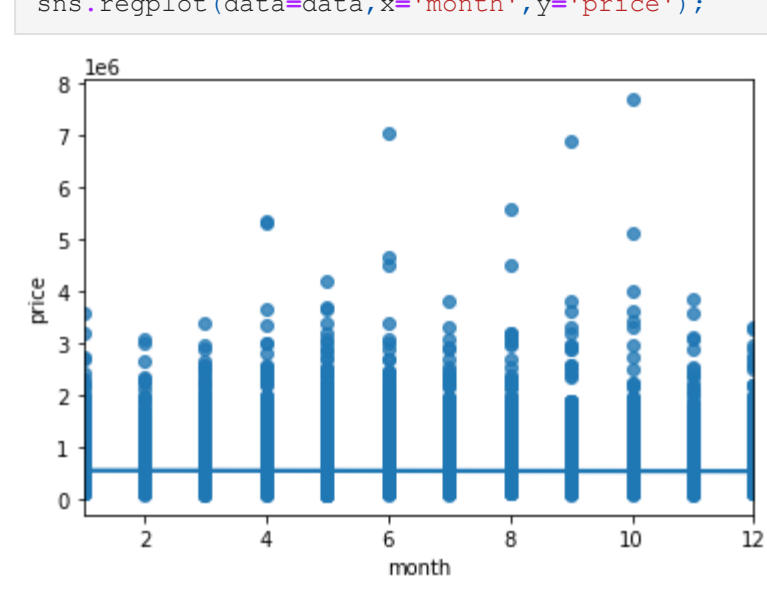
```
sns.regplot(x=monthly_sales.Sales,y=aggs['median'])
plt.xlabel('Monthly Sales')
plt.ylabel('Median Monthly Home Price')
plt.title('Monthly Sales Count Vs. Median Sale Price');
```



The above chart indicates a some linear relationship between Monthly Sales and the Median Sale Price, Perhaps this will be helpful later on for the regression, but, as sales volume is higher, sale price indeed seems to be higher. Let's see if we can look at this on not just a monthly basis.

In [56]:

```
sns.regplot(data=data,x='month',y='price');
```



This scatterplot displays some relationship of month to sale price. The same sort of relationship with some outliers is show. This will be further explored later in the notebook - the potential relationship between various features in the dataset and the sale price on a monthly price.

Renovation Year

In [57]:

```
data['yr_renovated'].describe()
```

Out[57]:

```
count   17755.00000
mean       83.63678
std       399.94641
min         0.00000
25%         0.00000
50%         0.00000
75%         0.00000
max      2015.00000
Name: yr_renovated, dtype: float64
```

In [58]:

```
data['yr_renovated'].value_counts()
```

Out[58]:

```
0.00000       17011
2014.00000       73
2003.00000       31
2013.00000       31
2007.00000       30
              ...  
1946.00000        1
1959.00000        1
1971.00000        1
1951.00000        1
1954.00000        1
Name: yr_renovated, Length: 70, dtype: int64
```

In [59]:

```
data['yr_renovated'].value_counts().head(20)
```

Out[59]:

```
0.00000       17011
2014.00000       73
2003.00000       31
2013.00000       31
2007.00000       30
2000.00000       29
2005.00000       29
1990.00000       22
2004.00000       22
2009.00000       21
1989.00000       20
2006.00000       20
2002.00000       17
1991.00000       16
1998.00000       16
1984.00000       16
1999.00000       15
2008.00000       15
2010.00000       15
2001.00000       15
Name: yr_renovated, dtype: int64
```

Year renovation data reveals that most homes in the dataset haven't been renovated, for this intitial dive, let's remove them from the series to have a better sense of renovation information.

In [60]:

```
#Removing where the "year renovated" is 0
renovation_filtered = data.yr_renovated[data['yr_renovated']!=0].copy()
```

In [61]:

```
renovation_filtered = pd.to_datetime(renovation_filtered, format='%Y').dt.year
```

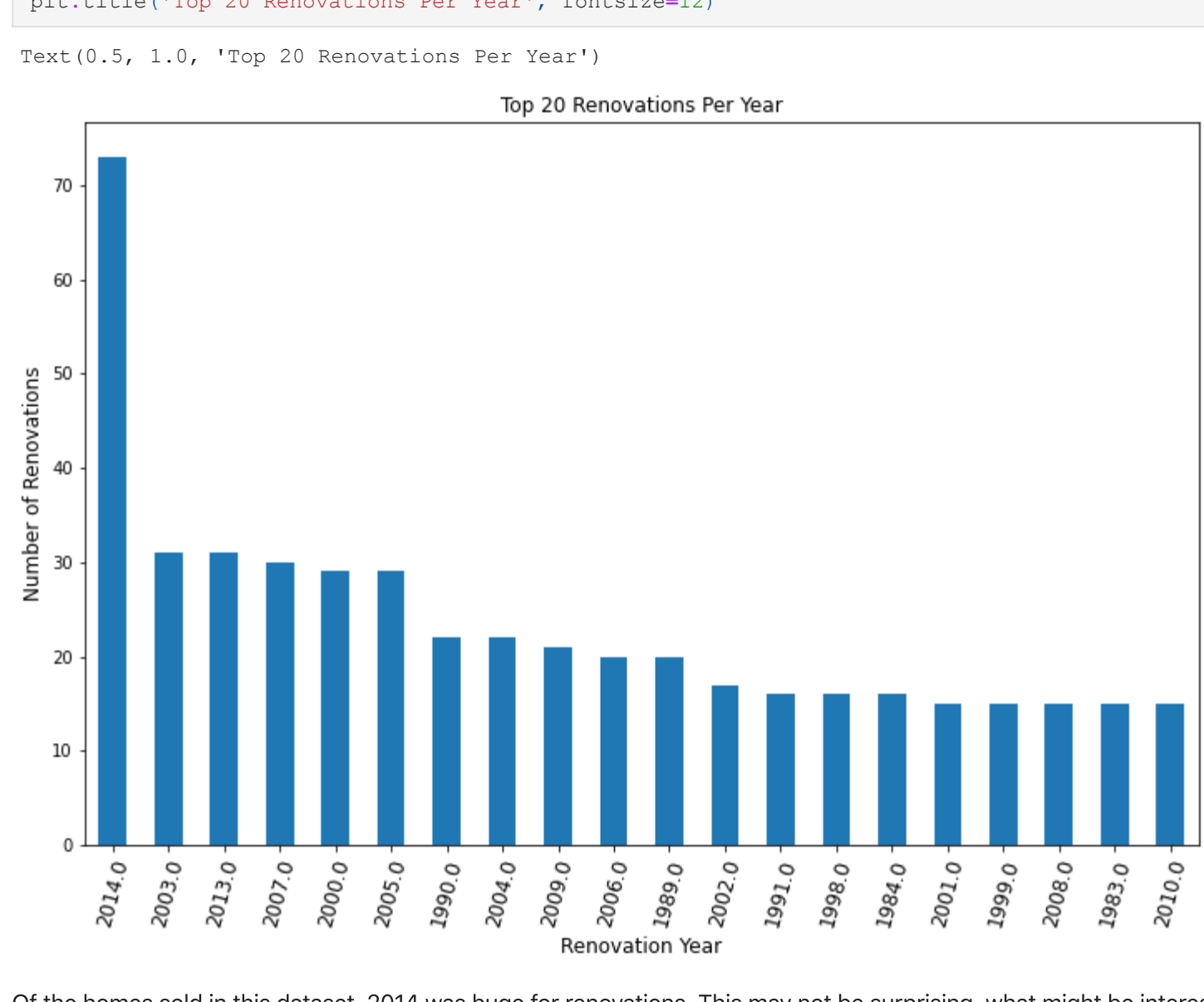
In [62]:

```
top_20_renos = renovation_filtered.value_counts().head(20)
```

In [63]:

```
top_20_renos.plot(kind='bar',rot=75, figsize=(12,8))
plt.xticks(fontsize=12);
plt.xlabel('Renovation Year',fontsize=12)
plt.ylabel('Number of Renovations', fontsize=12)
plt.title('Top 20 Renovations Per Year', fontsize=12)
```

Out[63]: `Text(0.5, 1.0, 'Top 20 Renovations Per Year')`



Of the homes sold in this dataset, 2014 was huge for renovations. This may not be surprising, what might be interesting to look at is what year those homes were constructed.

Renovation Year Vs. Year Built

In [64]:

```
#Working with a dataframe that only has renovated homes
reno_filtered = data[data['yr_renovated']!=0].copy()
```

In [65]:

```
#Top Years Build Years for Renovated Homes
reno_filtered['yr_built'].value_counts().head(20)
```

Out[65]:

```
2014    102
1968     85
1977     84
2003     78
2008     75
1967     74
2006     73
2005     72
1979     71
1947     70
1962     70
2007     70
2004     69
1955     68
1950     67
1942     66
1978     65
1959     65
1954     65
1969     61
Name: yr_built, dtype: int64
```

In [66]:

```
#Average year for renovated home
average_year = str(reno_filtered['yr_built'].mean())[0:4]

#Median year for renovated home
median_year = str(reno_filtered['yr_built'].median())[0:4]

print(f'The average built year for renovated homes is {average_year}, the median year is {median_year}')
```

```
The average built year for renovated homes is 1965, the median year is 1967
```

Perhaps unsurprisingly renovated homes date back to around World War II. Let's look at the average time between build and renovation.

In [67]:

```
int(reno_filtered['yr_renovated'].mean()-reno_filtered['yr_built'].mean())
```

Out[67]: `30`

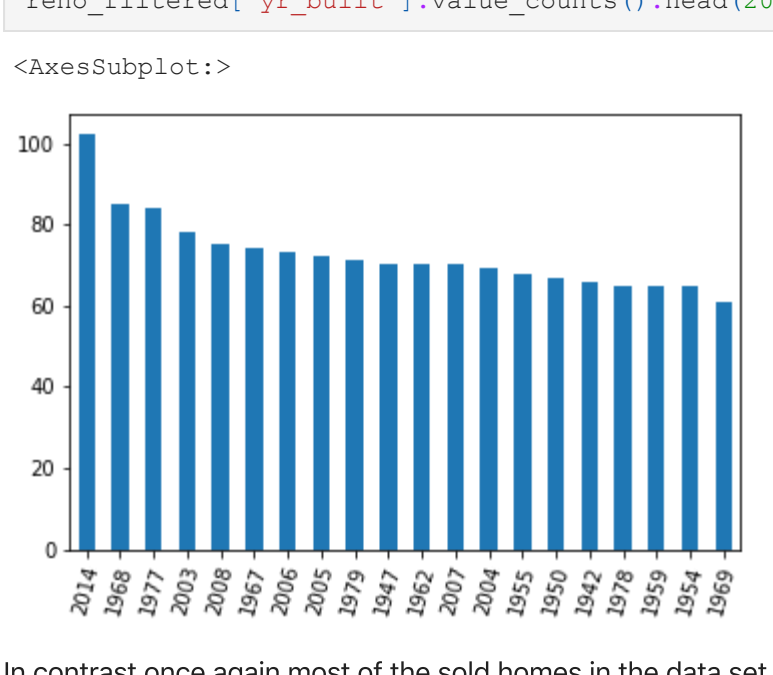
On average it was 56 years between construction and renovation for the renovated properties.

The following chart shows us the top build years of the renovated homes that were sold. No real trends seem to be gleaned here, 1950 tops the chart, but then homes built in 1924 are third on the list.

In [68]:

```
reno_filtered['yr_built'].value_counts().head(20).plot(kind='bar', rot=75)
```

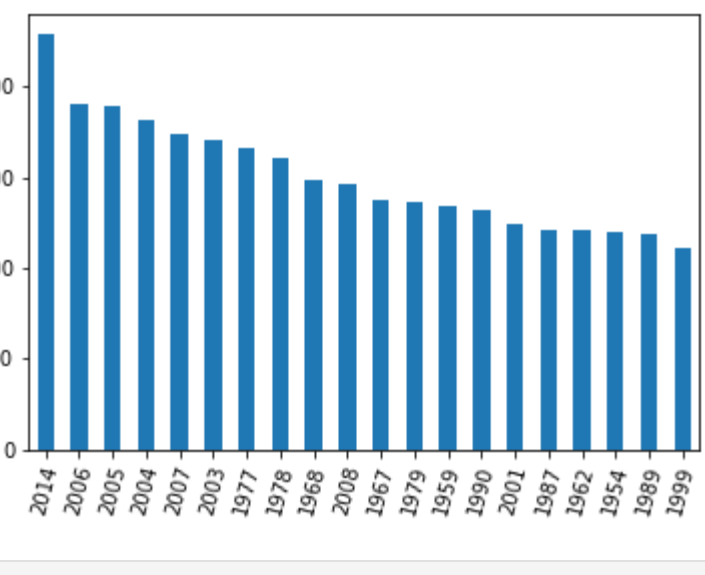
Out[68]: `<AxesSubplot:>`



In contrast once again most of the sold homes in the data set are from 2014, so recent homes seem to be the top homes on the list. Unrenovated homes make up most of the dataset.

In [69]:

```
data[data['yr_renovated']==0]['yr_built'].value_counts().head(20).plot(kind='bar',rot=75);
```



In [70]:
```
reno_filtered['price'].mean()
```
Out[70]:
```
575976.7860880942
```

In [71]:
```
#Number of renovated properties
reno_filtered['price'].count()
```
Out[71]:
```
4586
```

The average price for renovated home was 768,901. I think I need to be careful reading into this number, because there is a question of why these homes have been selected for renovation.

In [72]:
```
#Number of unrenovated properties
data[data['yr_renovated']==0]['price'].count()
```
Out[72]:
```
17011
```

The renovated vs. unrenovated properties contrast sharply. Renovated properties are much older, constructed around World War Two. The top properties unrenovated are recent builds - maybe part of large developments, or perhaps new homes are that much more deseriable.

In [73]:
```
reno_filtered[reno_filtered['yr_built']<=1980]
```
Out[73]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	sqft_above	sqft_
1	6414100192	2014-12-09	538000.00000	3	2.25000	2570	7242	2.00000	0.00000	0.00000	...	2170	
2	5631500400	2015-02-25	180000.00000	2	1.00000	770	10000	1.00000	0.00000	0.00000	...	770	
12	114101516	2014-05-28	310000.00000	3	1.00000	1430	19901	1.50000	0.00000	0.00000	...	1430	
26	1794500383	2014-06-26	937000.00000	3	1.75000	2450	2691	2.00000	0.00000	0.00000	...	1750	
28	5101402488	2014-06-24	438000.00000	3	1.75000	1520	6380	1.00000	0.00000	0.00000	...	790	
...	...	...	...	...	...	...	...	...	...	...	...	...	
20428	4305600360	2015-02-25	500012.00000	4	2.50000	2400	9612	1.00000	0.00000	0.00000	...	1230	
20431	3319500628	2015-02-12	356999.00000	3	1.50000	1010	1546	2.00000	nan	0.00000	...	1010	
20946	1278000210	2015-03-11	110000.00000	2	1.00000	828	4524	1.00000	0.00000	0.00000	...	828	
21027	9276200220	2014-07-17	375000.00000	1	1.00000	720	3166	1.00000	0.00000	0.00000	...	720	
21224	7174800094	2015-04-20	525000.00000	1	1.50000	1030	5923	1.00000	nan	0.00000	...	1030	

2990 rows × 22 columns

The vast majority of renovated homes were built before 1980. Just for fun right now let's take a look at homes built before 1980 renovated vs. unrenovated.

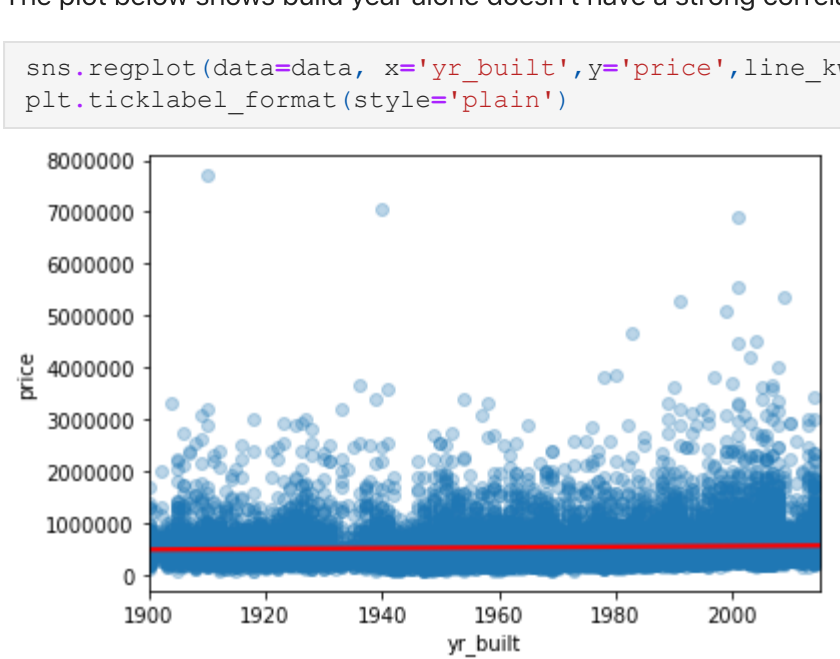
In [74]:
```
reno_filtered[reno_filtered['yr_built']<1980]['price'].mean()
```
Out[74]:
```
563035.372242959
```

In [75]:
```
#creating a dataframe of unrenovated properties
unrenovated_filtered = data[data['yr_renovated']==0].copy()
```

In [76]:
```
#filtering unrenovated properties to find the average price before 1980
unrenovated_filtered[unrenovated_filtered['yr_built']<1980]['price'].mean()
```
Out[76]:
```
486308.97303059377
```

The plot below shows build year alone doesn't have a strong correlation to an increase in price.

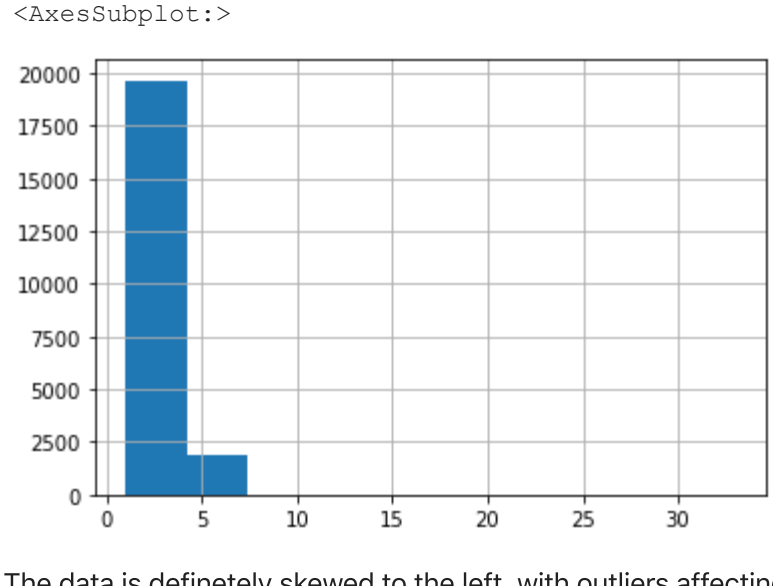
In [77]:
```
sns.regplot(data=data, x='yr_built',y='price',line_kws={"color": "red"},scatter_kws={'alpha':0.3})
plt.ticklabel_format(style='plain')
```



Bedrooms

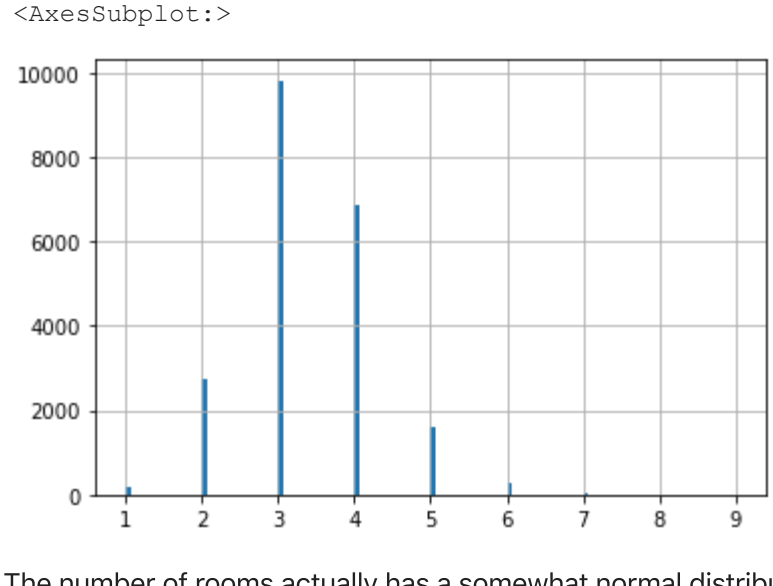
In [78]:
```
#Number of bedrooms per apartment sold
data['bedrooms'].value_counts()
```
Out[78]:
```
3     9824
4     6882
2     2760
5     1601
6      272
1      196
7       38
8       13
9        6
10       3
11       1
33       1
Name: bedrooms, dtype: int64
```

In [79]:
```
data['bedrooms'].hist()
```
Out[79]:
```
<AxesSubplot:>
```



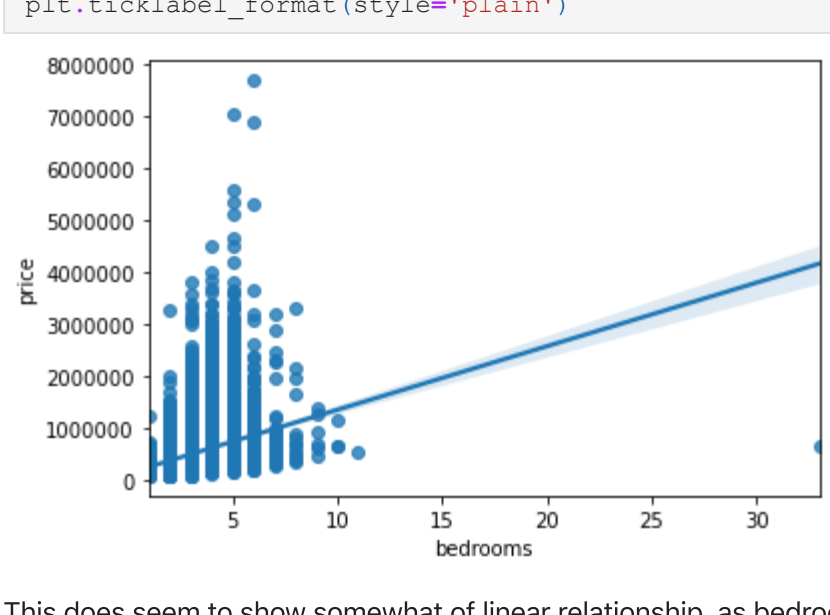
The data is definetely skewed to the left, with outliers affecting the histogram. Let's drop the outliers, to have a better picture.

In [80]:
```
data[data['bedrooms']<10]['bedrooms'].hist(bins='auto')
```
Out[80]:
```
<AxesSubplot:>
```



The number of rooms actually has a somewhat normal distribution in this histogram, I believe we are dealing with a fairly normally distrubted set of bedrooms in each home.

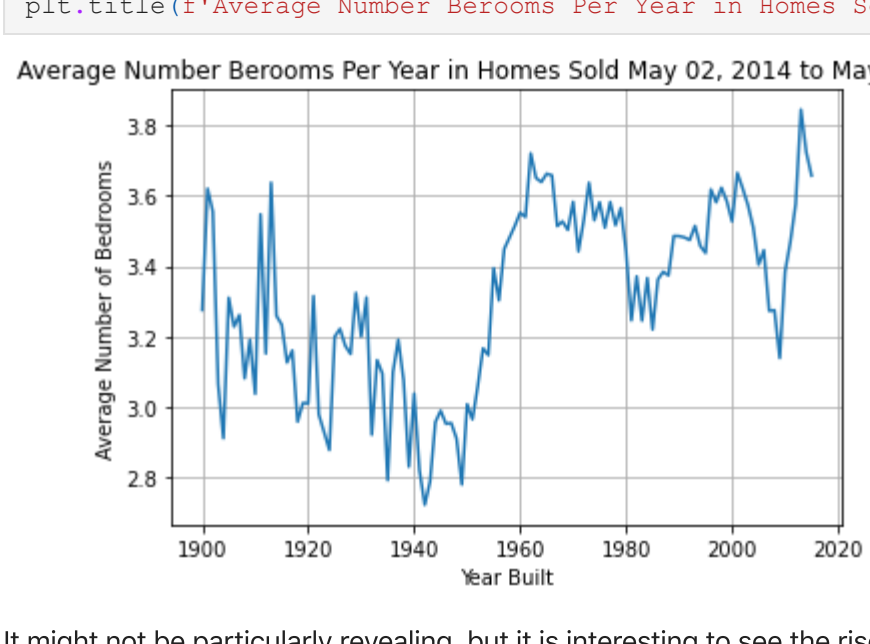
In [81]:
```
sns.regplot(data=data, x='bedrooms',y='price')
plt.ticklabel_format(style='plain')
```



This does seem to show somewhat of linear relationship, as bedrooms go up, price does look to go up a little bit.

In [82]:
```
num_brooms_per_year = data.groupby('yr_built')['bedrooms'].mean().plot(kind='line', grid=True)
num_brooms_per_year
plt.xlabel('Year Built')
plt.ylabel('Average Number of Bedrooms')
plt.title(f'Average Number Berooms Per Year in Homes Sold {earliest_date} to {latest_date}');
```

Average Number Berooms Per Year in Homes Sold May 02, 2014 to May 27, 2015



It might not be particularly revealing, but it is interesting to see the rise and fall of number of bedrooms per houshould in the data set. It indeed appears that homes had more bedrooms, it sank, and rose up in the 60s and 70s. Like many trends it fell around 2008 and went back up.

In [83]:
```
data.groupby('yr_built')['bedrooms'].mean().sort_values(ascending=False).head(10)
```
Out[83]:
```
yr_built
2013   3.84577
2014   3.72451
1962   3.72115
2001   3.66557
1965   3.66310
1966   3.65863
2015   3.65789
1963   3.65098
1964   3.63953
1913   3.63793
Name: bedrooms, dtype: float64
```

In [84]:
```
data.groupby('yr_built')['bedrooms'].mean()[2009]
```
Out[84]:
```
3.139130434782609
```

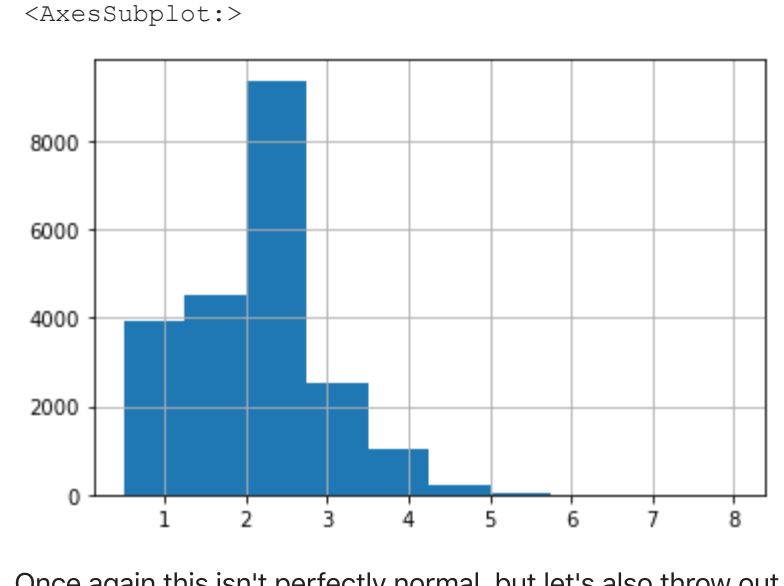
Bathrooms

In [85]:
```
data['bathrooms']
```
Out[85]:
```
0       1.00000
1       2.25000
2       1.00000
3       3.00000
4       2.00000
          ...
21592   2.50000
21593   2.50000
21594   0.75000
21595   2.50000
21596   0.75000
Name: bathrooms, Length: 21597, dtype: float64
```

In [86]:
```
data['bathrooms'].value_counts()
```
Out[86]:
```
2.50000    5377
1.00000    3851
1.75000    3048
2.25000    2047
2.00000    1930
1.50000    1445
2.75000    1185
3.00000     753
3.50000     731
3.25000     589
3.75000     155
4.00000     136
4.50000     100
4.25000      79
0.75000      71
4.75000      23
5.00000      21
5.25000      13
5.50000      10
1.25000       9
6.00000       6
5.75000       4
0.50000       4
8.00000       2
6.25000       2
6.75000       2
6.50000       2
7.50000       1
7.75000       1
Name: bathrooms, dtype: int64
```

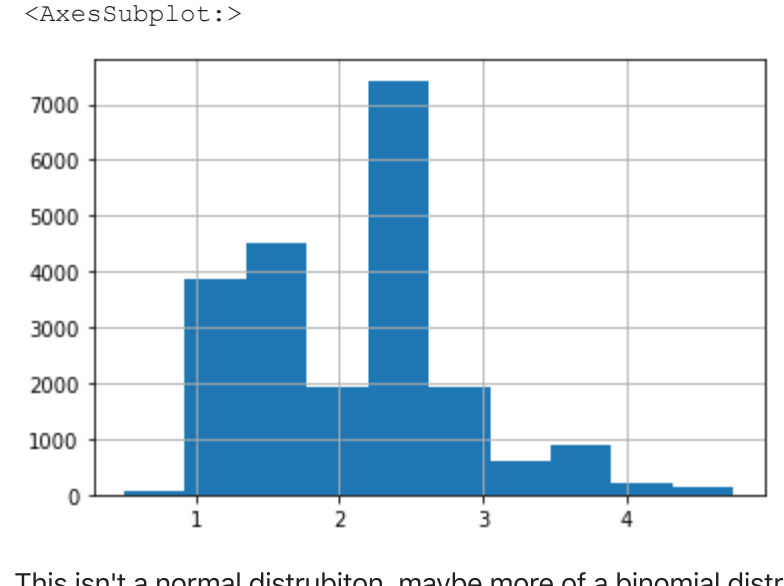
Value counts on the bahhrooms reveals that the top bathroom amount is 2.5 bathrooms. Half and quarter bathrooms are a feeature in some living situations, so this does seem to be an accurate dataset of some kind. Let's look at a histogram.

In [87]:
```
data.bathrooms.hist()
```
Out[87]:
```
<AxesSubplot:>
```



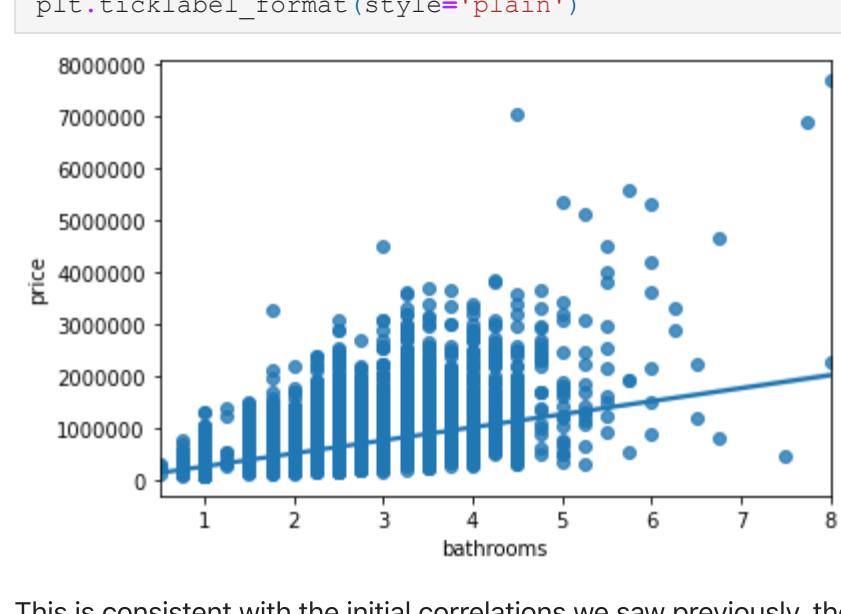
Once again this isn't perfectly normal, but let's also throw out some of the outliers for now.

In [88]:
```
data[data.bathrooms<5].bathrooms.hist()
```
Out[88]:
```
<AxesSubplot:>
```



This isn't a normal distrubiton, maybe more of a binomial distribution? I will have to look more into this, but its tricky since this isn't quiete a categorical or a continuous.

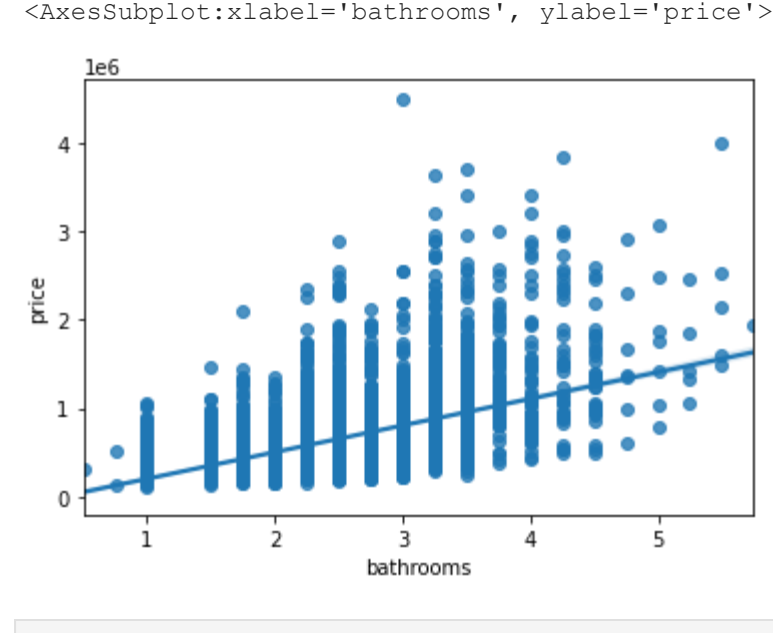
In [89]:
```
sns.regplot(data=data, x='bathrooms',y='price')
plt.ticklabel_format(style='plain')
```



This is consistent with the initial correlations we saw previously, there is some linearity in regards to number of bathrooms and the price of a home, This will be a feature to keep in mind, interestly it has a higher initial correlation than the number of bedrooms. Bathrooms are certainly a neccesisty, but also an ammenitiy. Maybe we can look at home number of home affects homes with similar number of bedrooms? Is that an interaction?

I'm not really sure what to do right now, but for now I am going to look at how bathrooms affect homes of a set number of bedrooms.

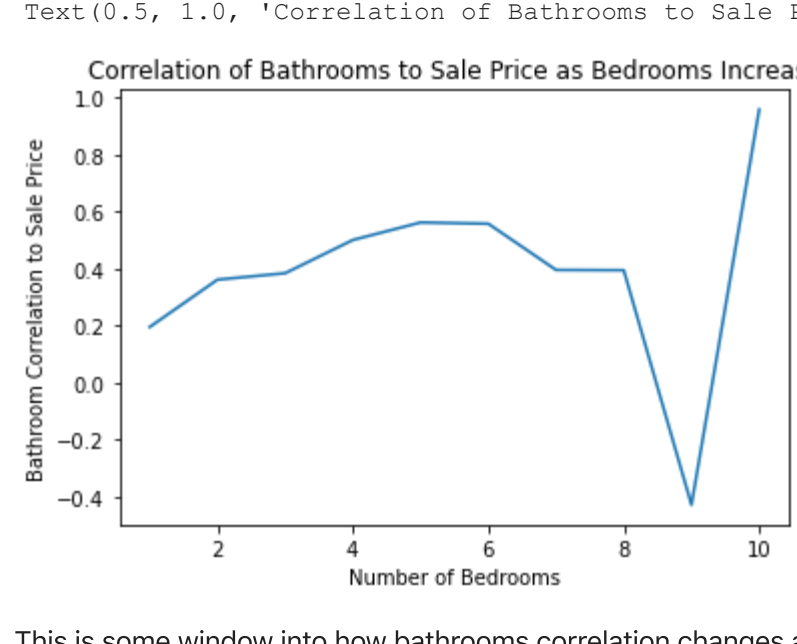
In [90]:
```
sns.regplot(data=data[data['bedrooms']==4], x='bathrooms',y='price')
```
Out[90]:
```
<AxesSubplot:xlabel='bathrooms', ylabel='price'>
```



In [91]:
```
bedroom_range = sorted(data['bedrooms'].value_counts().index)
correlation_per_bdroom = []
for x in bedroom_range:
    correlation_per_bdroom.append(data[data['bedrooms']==x].corr()['price']['bathrooms'])
correlation_per_bdroom = correlation_per_bdroom[0:10]
bedbath_array = list(zip(bedroom_range[0:10],correlation_per_bdroom))
```

In [92]:
```
plt.plot(bedroom_range[0:10],correlation_per_bdroom)
plt.xlabel('Number of Bedrooms')
plt.ylabel('Bathroom Correlation to Sale Price')
plt.title('Correlation of Bathrooms to Sale Price as Bedrooms Increase')
```
Out[92]:
```
Text(0.5, 1.0, 'Correlation of Bathrooms to Sale Price as Bedrooms Increase')
```

Correlation of Bathrooms to Sale Price as Bedrooms Increase



This is some window into how bathrooms correlation changes as the number of bedrooms change. What I am looking for is to see if the value add of bathroom changes as each bedroom number increases. What I do see is it is a better correlation until about 6 bedrooms, but of course we do not have many homes on those higher end in the data set.

I think there is more exploring to be done in the bathroom area and will return to it later.

sqft_living

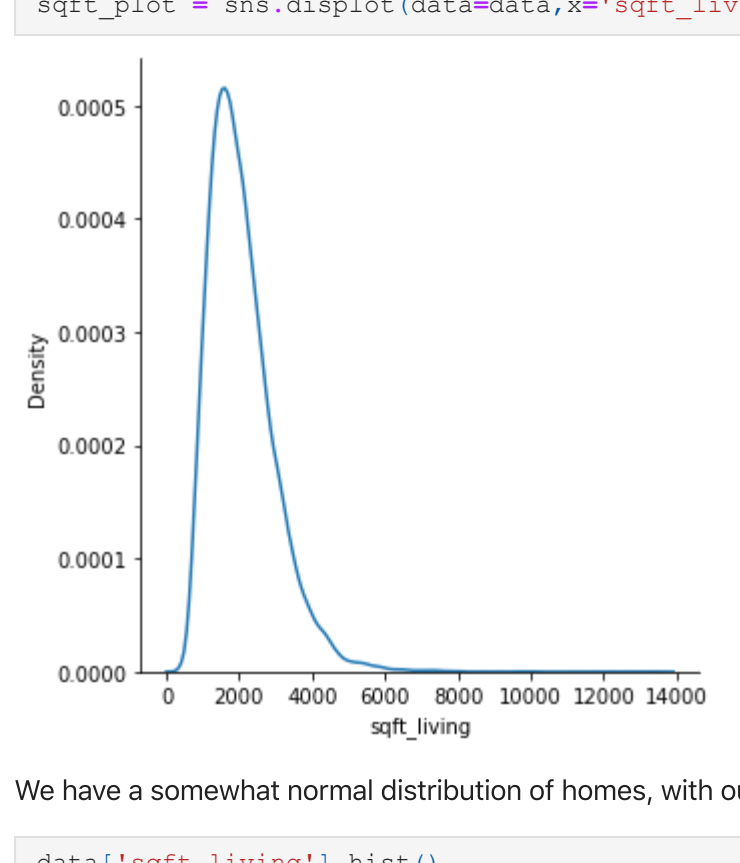
The Square Foot Living represents a major feature as it is the actual living space of the homes that were sold. It also has the highest correlation on our simple correlation list.

In [93]:
```
data.corr()['price']['sqft_living']
```
Out[93]:
```
0.7019173021377597
```

In [94]:
```
data['sqft_living'].describe()
```
Out[94]:
```
count   21597.00000
mean     2080.32185
std       918.10613
min       370.00000
25%      1430.00000
50%      1910.00000
75%      2550.00000
max     13540.00000
Name: sqft_living, dtype: float64
```

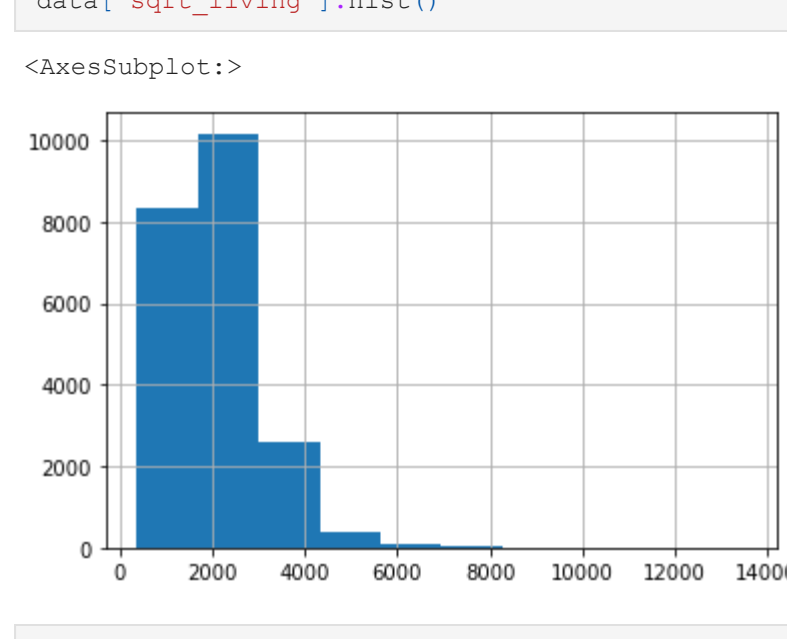
In [95]:
```
data['sqft_living'].value_counts()
```
Out[95]:
```
1300    138
1400    135
1440    133
1660    129
1010    129
        ...
4970      1
2905      1
2793      1
4810      1
1975      1
Name: sqft_living, Length: 1034, dtype: int64
```

In [96]:
```
sqft_plot = sns.displot(data=data,x='sqft_living', kind='kde')
```

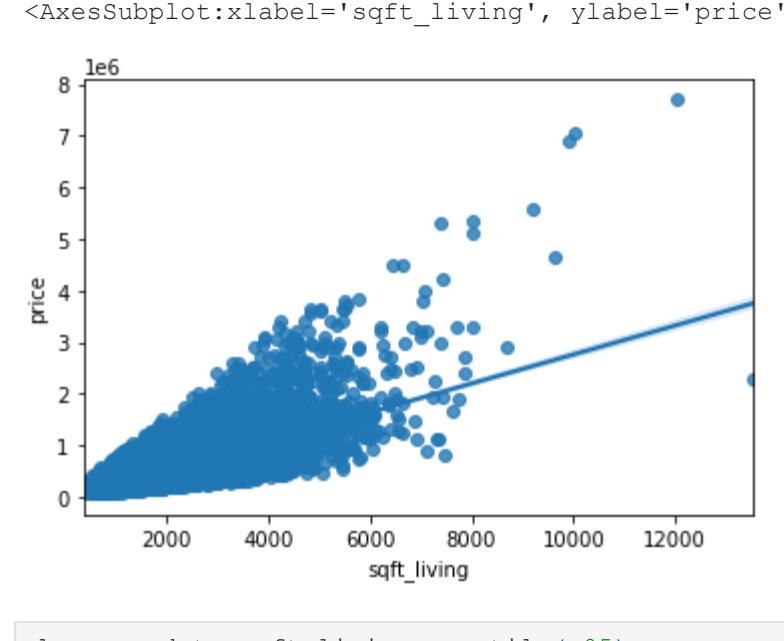


We have a somewhat normal distribution of homes, with outliers affecting the information.

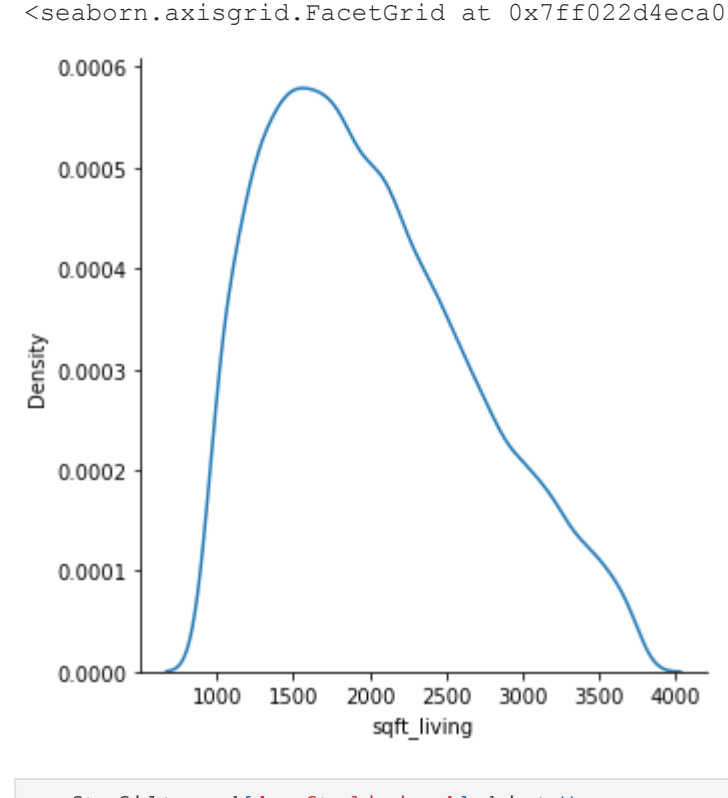
In [97]:
```
data['sqft_living'].hist()
```
Out[97]:
```
<AxesSubplot:>
```



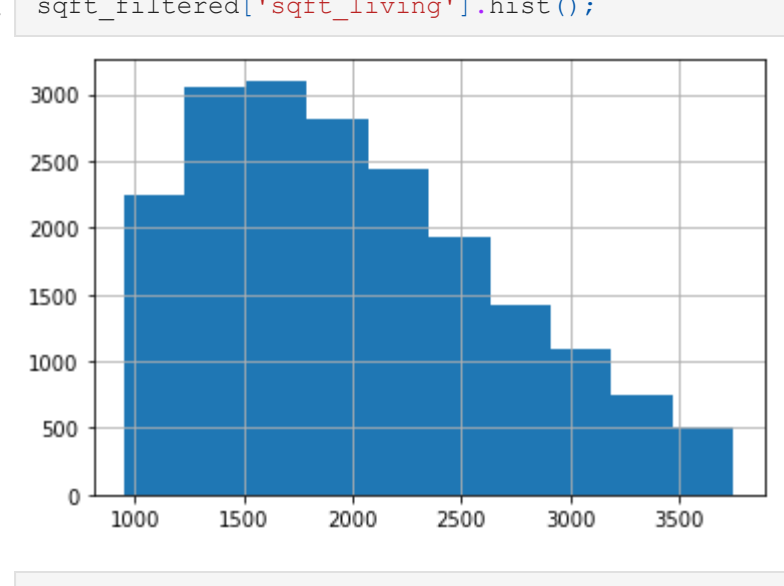
In [98]:
```
sns.regplot(data=data, x='sqft_living',y='price')
```
Out[98]:
```
<AxesSubplot:xlabel='sqft_living', ylabel='price'>
```



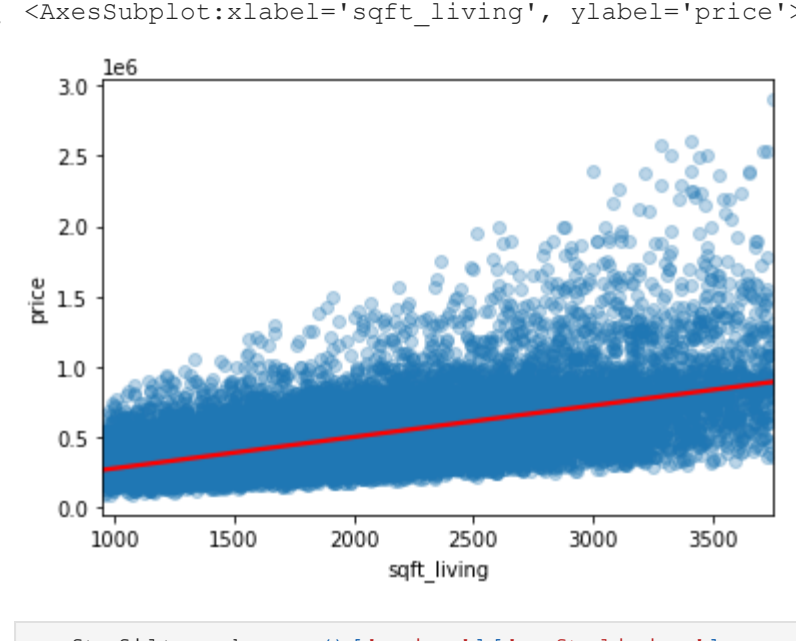
In [99]:
```
lower = data.sqft_living.quantile(.05)
upper = data.sqft_living.quantile(.95)

sqft_filtered = data[(data['sqft_living']>lower) & (data['sqft_living']<upper)]

sns.displot(data=sqft_filtered, x='sqft_living', kind='kde')
```
Out[99]:
```
<seaborn.axisgrid.FacetGrid at 0x7ff022d4eca0>
```



In [100]:
```
sqft_filtered['sqft_living'].hist();
```



In [101]:
```
sns.regplot(data=sqft_filtered, x='sqft_living',y='price', line_kws={"color": "red"},scatter_kws={'alpha':0.3})
```
Out[101]:
```
<AxesSubplot:xlabel='sqft_living', ylabel='price'>
```



In [102]:
```
sqft_filtered.corr()['price']['sqft_living']
```
Out[102]:
```
0.5785532312360123
```

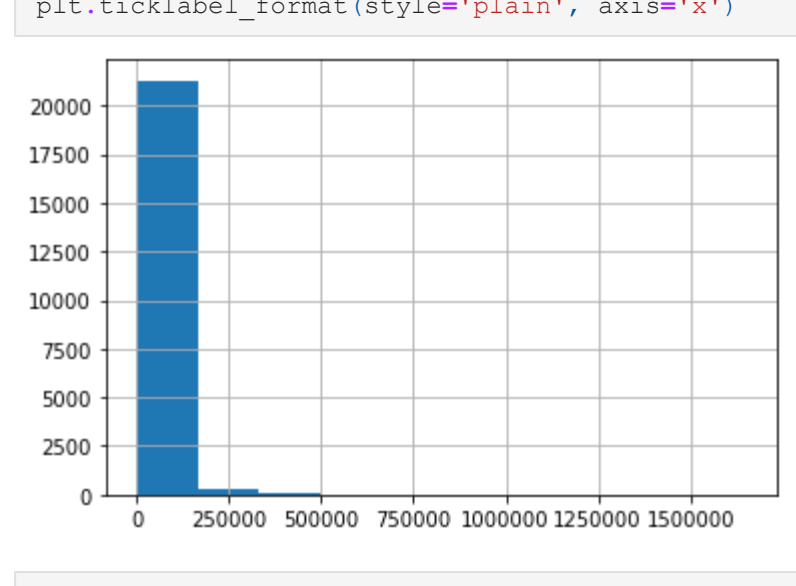
Dropping the outliers of the dataset showed less of correlation with price. Perhaps square footage is a bigger drive of price at the tail of the dataset.

Square Foot Lot

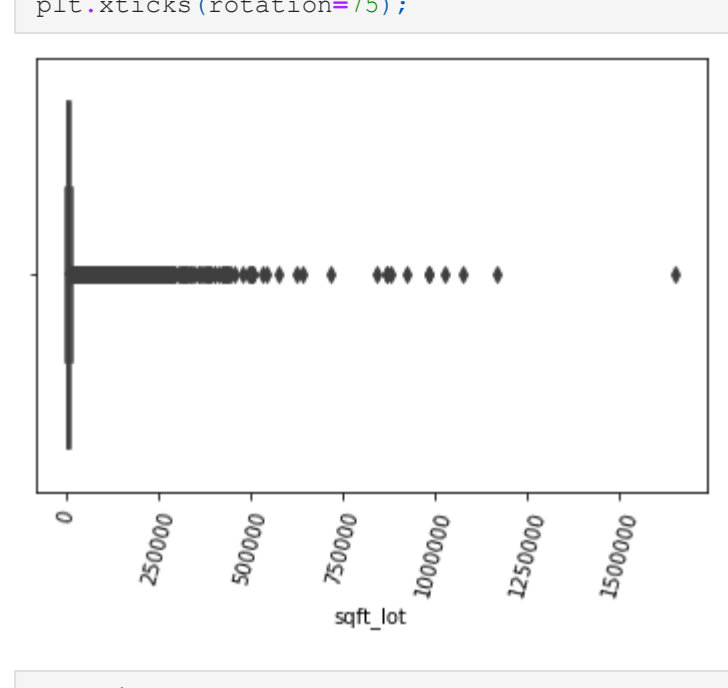
In [103]:
```
data['sqft_lot']
```
Out[103]:
```
0         5650
1         7242
2        10000
3         5000
4         8080
          ...
21592     1131
21593     5813
21594     1350
21595     2388
21596     1076
Name: sqft_lot, Length: 21597, dtype: int64
```

In [104]:
```
data['sqft_lot'].describe()
```
Out[104]:
```
count     21597.00000
mean      15099.40876
std       41412.63688
min         520.00000
25%        5040.00000
50%        7618.00000
75%       10685.00000
max     1651359.00000
Name: sqft_lot, dtype: float64
```

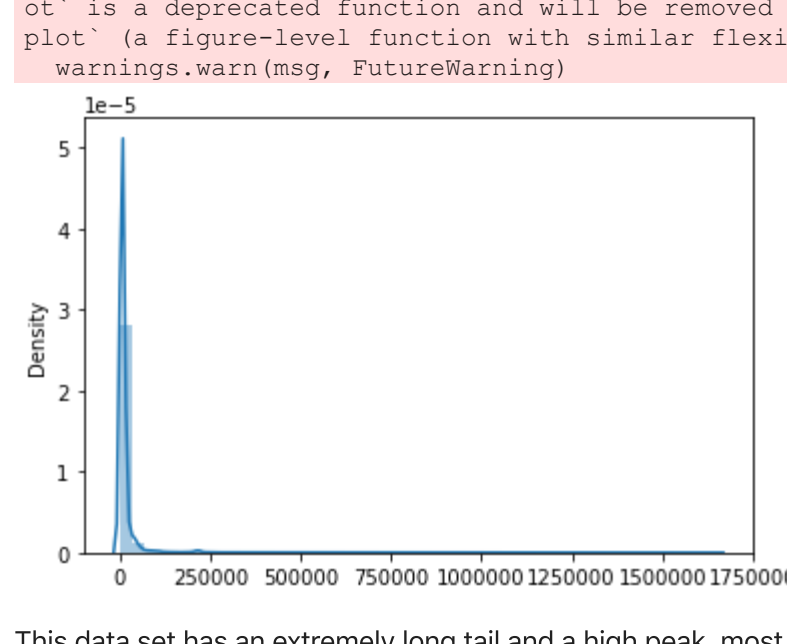
In [105]:
```
data['sqft_lot'].hist()
plt.ticklabel_format(style='plain', axis='x')
```



In [106]:
```
sns.boxplot(data=data, x='sqft_lot')
plt.ticklabel_format(style='plain', axis='x')
plt.xticks(rotation=75);
```

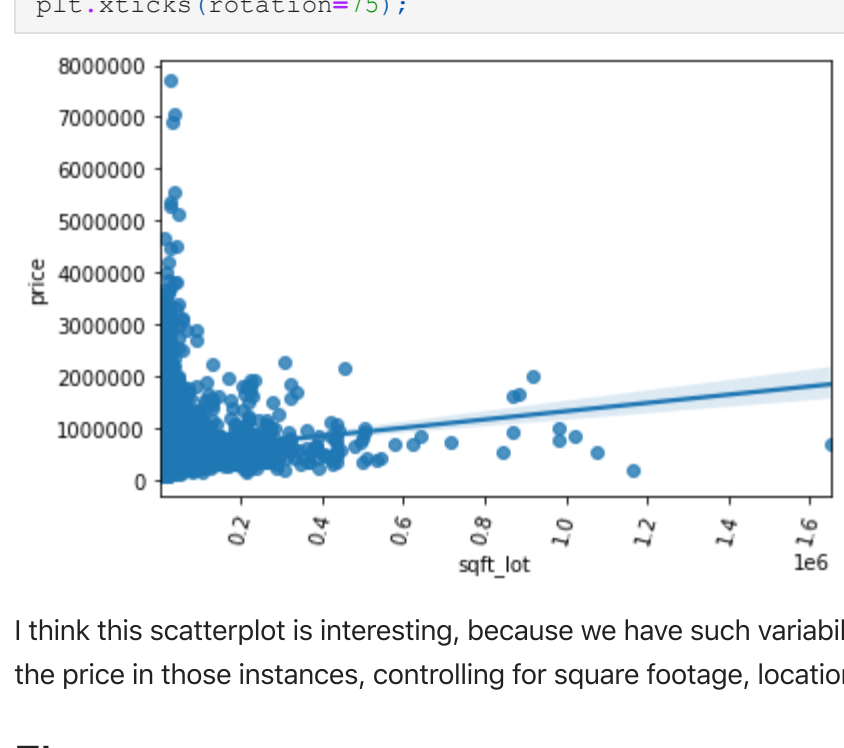


In [107]:
```
sns.distplot(x=data['sqft_lot'])
plt.ticklabel_format(style='plain', axis='x')
```
```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



This data set has an extremely long tail and a high peak, most of the values are still skewed to the lower end of the data set. This means most homes are on smaller lots, but we have a long trail off of larger and larger homes.

In [108]:
```
sns.regplot(data=data, x='sqft_lot',y='price')

plt.ticklabel_format(style='plain', axis='y')
plt.xticks(rotation=75);
```



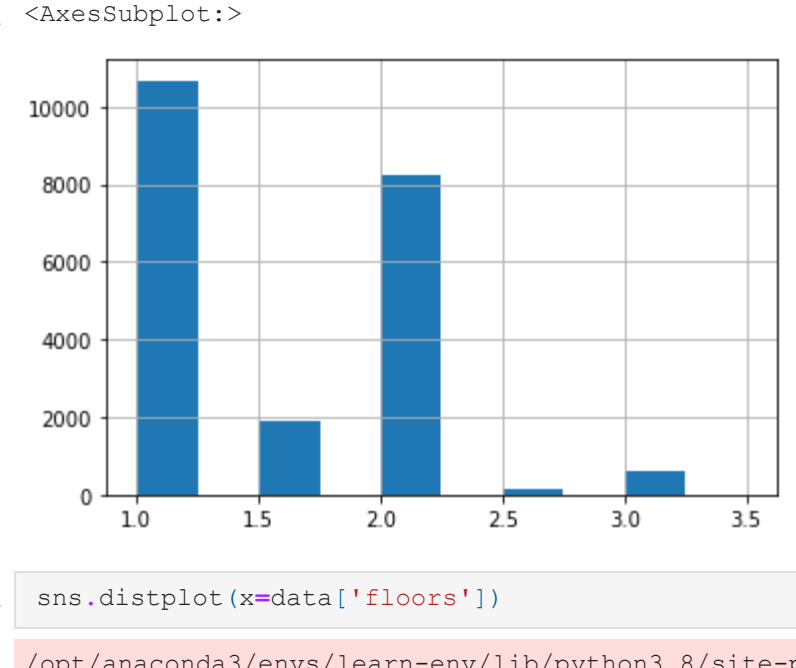
I think this scatterplot is interesting, because we have such variability in the low end of lot square footage. Some other factor is affecting the price in those instances, controlling for square footage, location, bathrooms, bedrooms, there is another factor at play.

Floors

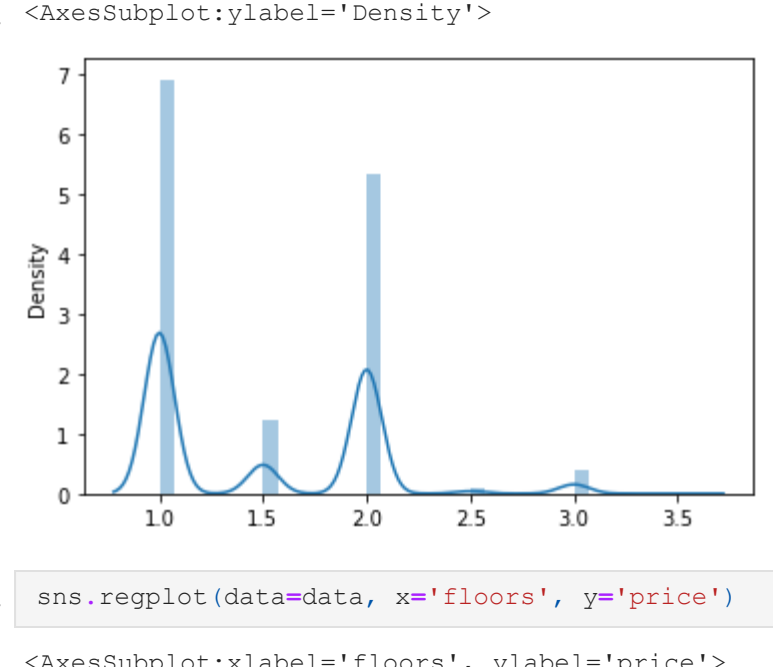
In [109]:
```
data['floors']
```
Out[109]:
```
0       1.00000
1       2.00000
2       1.00000
3       1.00000
4       1.00000
          ...
21592   3.00000
21593   2.00000
21594   2.00000
21595   2.00000
21596   2.00000
Name: floors, Length: 21597, dtype: float64
```

In [110]:
```
data['floors'].describe()
```
Out[110]:
```
count   21597.00000
mean        1.49410
std         0.53968
min         1.00000
25%         1.00000
50%         1.50000
75%         2.00000
max         3.50000
Name: floors, dtype: float64
```

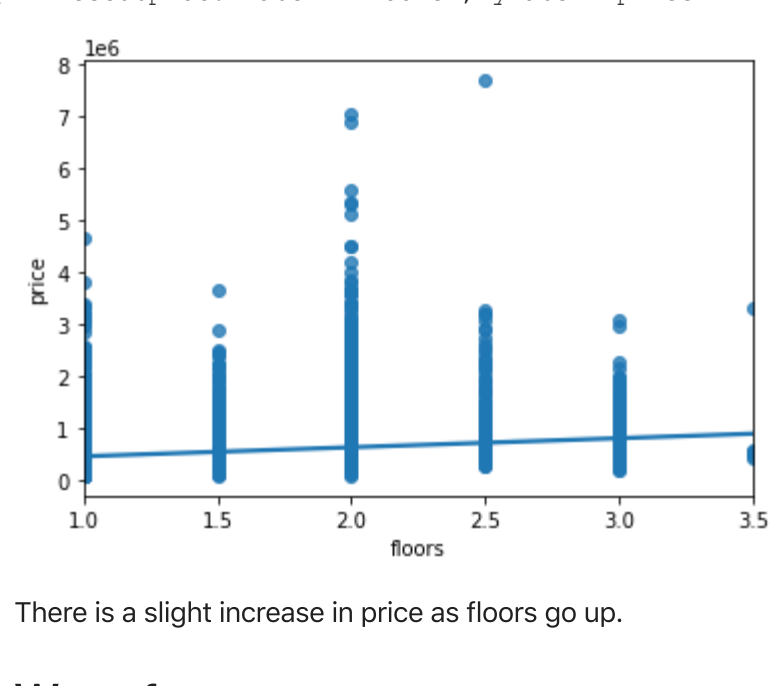
In [111]:
```
data['floors'].hist()
```
Out[111]:
```
<AxesSubplot:>
```



In [112]:
```
sns.distplot(x=data['floors'])
```
```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```
Out[112]:
```
<AxesSubplot:ylabel='Density'>
```



In [113]:
```
sns.regplot(data=data, x='floors', y='price')
```
Out[113]:
```
<AxesSubplot:xlabel='floors', ylabel='price'>
```

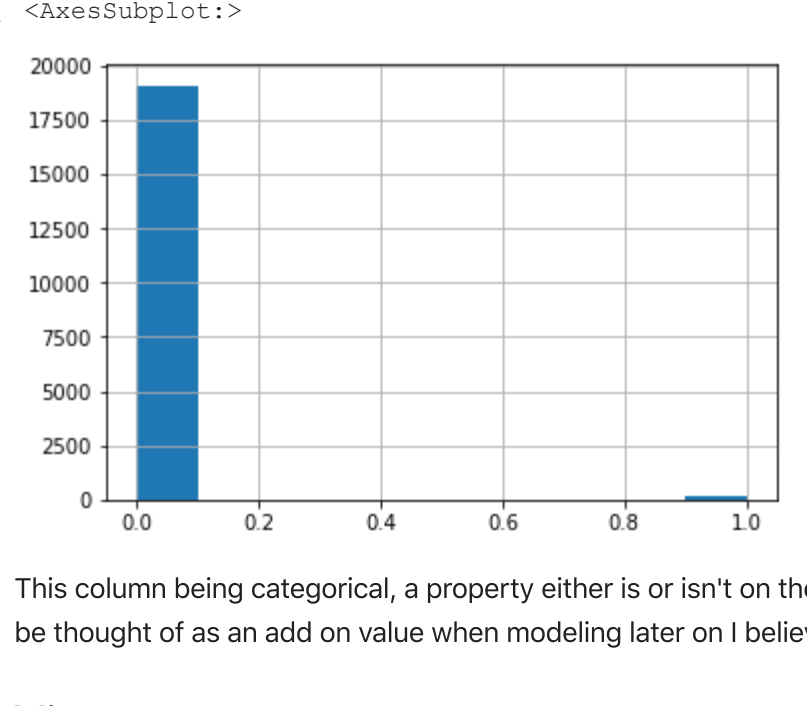


There is a slight increase in price as floors go up.

Waterfront

In [114]:
```
data['waterfront']
```
Out[114]:
```
0           nan
1       0.00000
2       0.00000
3       0.00000
4       0.00000
          ...
21592   0.00000
21593   0.00000
21594   0.00000
21595       nan
21596   0.00000
Name: waterfront, Length: 21597, dtype: float64
```

In [115]:
```
data['waterfront'].hist()
```
Out[115]:
```
<AxesSubplot:>
```



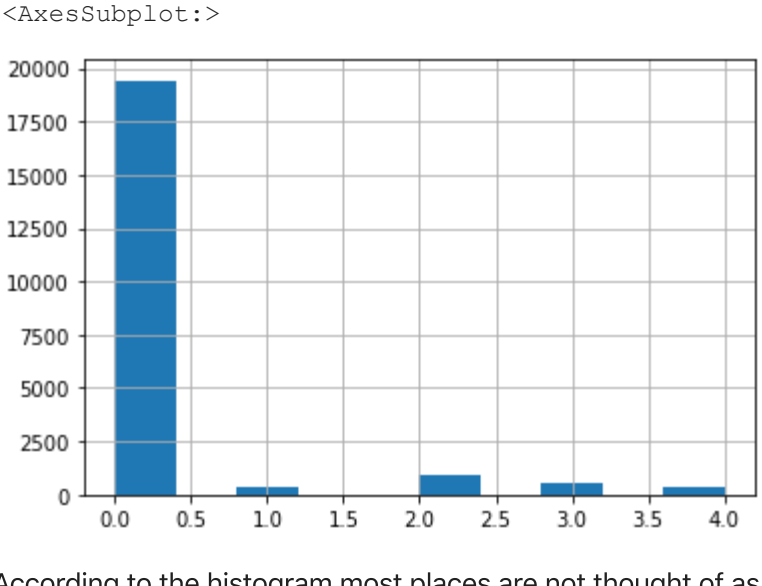
This column being categorical, a property either is or isn't on the waterfront, it doesn't offer as much chance for exploration and this will be thought of as an add on value when modeling later on I believe.

View

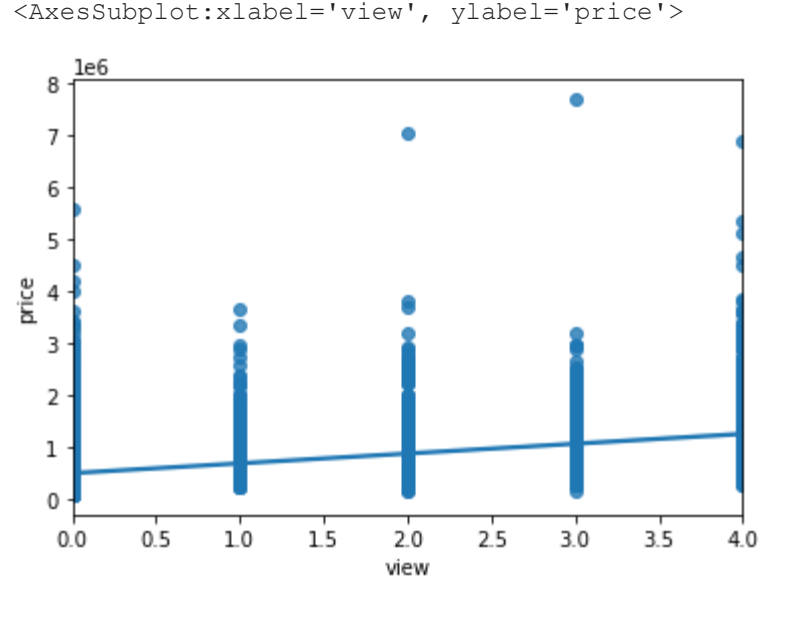
In [116]:
```
data['view'].value_counts()
```

Out [116…
```
0.00000    19422
2.00000      957
3.00000      508
1.00000      330
4.00000      317
Name: view, dtype: int64
```

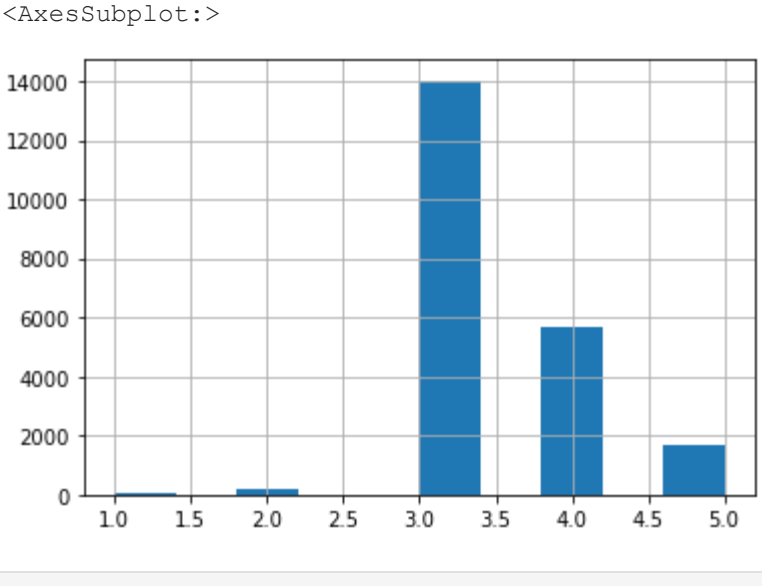
According to the value counts most homes are not thought of as having a nice view, and this might not be something that could be adjusted in home construction.

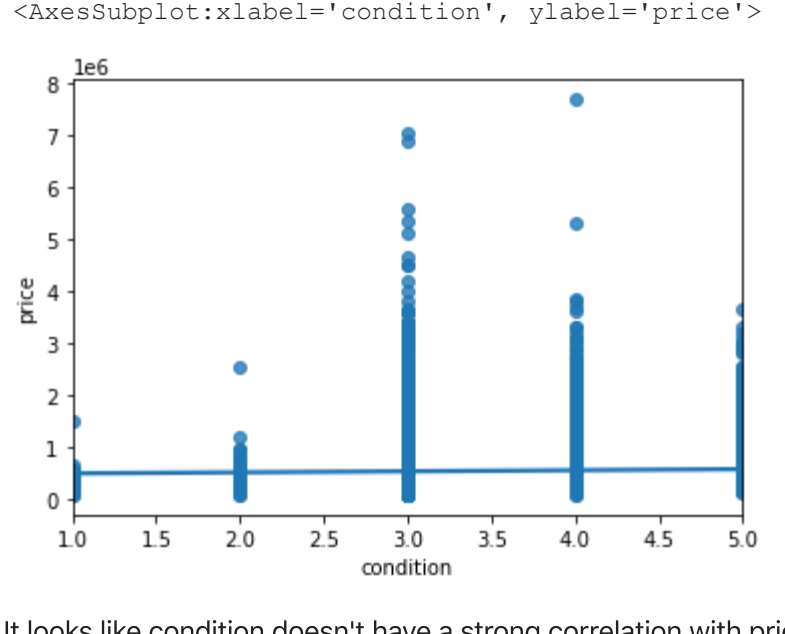
In [117…
```
data['view'].hist()
```
Out [117…
```
<AxesSubplot:>
```


According to the histogram most places are not thought of as really having a "view." I think this will later on be encoded as a categorical column when thinking about price.

In [118…
```
sns.regplot(data=data, x='view', y='price')
```
Out [118…
```
<AxesSubplot:xlabel='view', ylabel='price'>
```


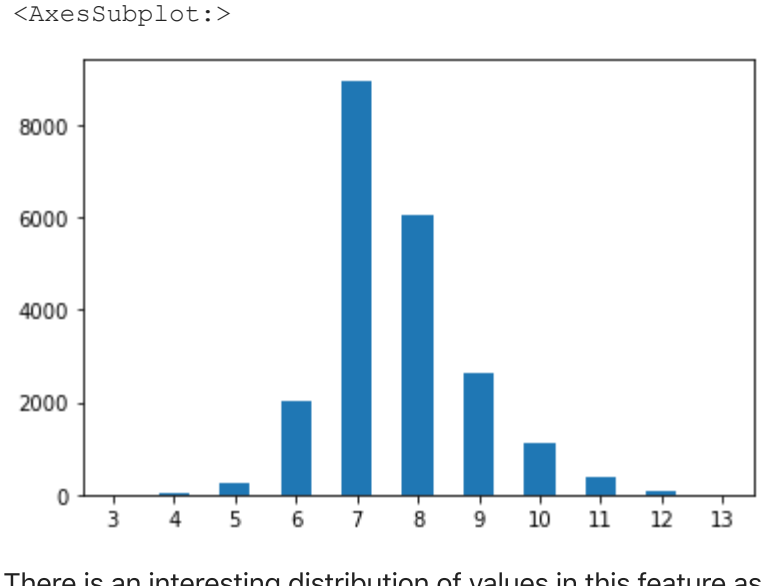
Condition

In [119…
```
data['condition']
```
Out [119…
```
0        3
1        3
2        3
3        5
4        3
        ..
21592    3
21593    3
21594    3
21595    3
21596    3
Name: condition, Length: 21597, dtype: int64
```
In [120…
```
data['condition'].value_counts()
```
Out [120…
```
3    14020
4     5677
5     1701
2      170
1       29
Name: condition, dtype: int64
```
In [121…
```
data['condition'].hist()
```
Out [121…
```
<AxesSubplot:>
```


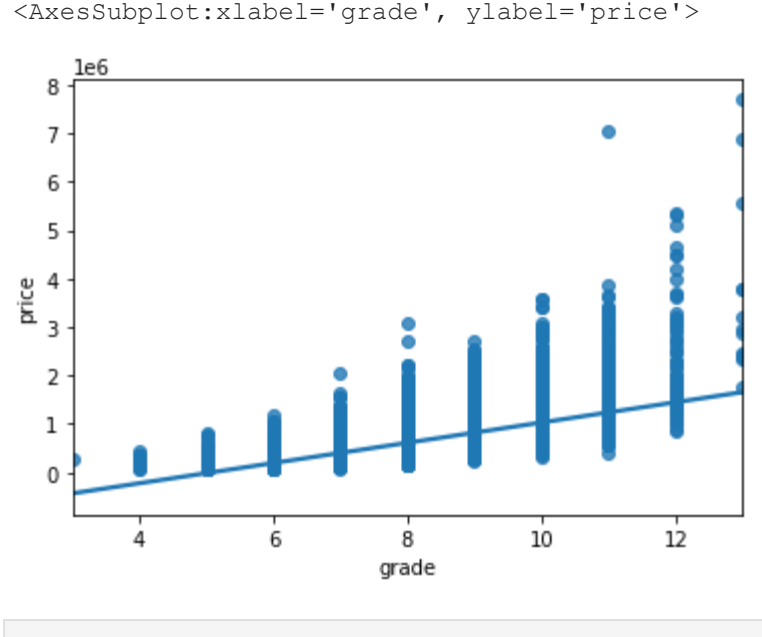
In [122…
```
sns.regplot(data=data, x='condition',y='price')
```
Out [122…
```
<AxesSubplot:xlabel='condition', ylabel='price'>
```


It looks like condition doesn't have a strong correlation with price, as 3.0 homes show the highest condition.

Grade

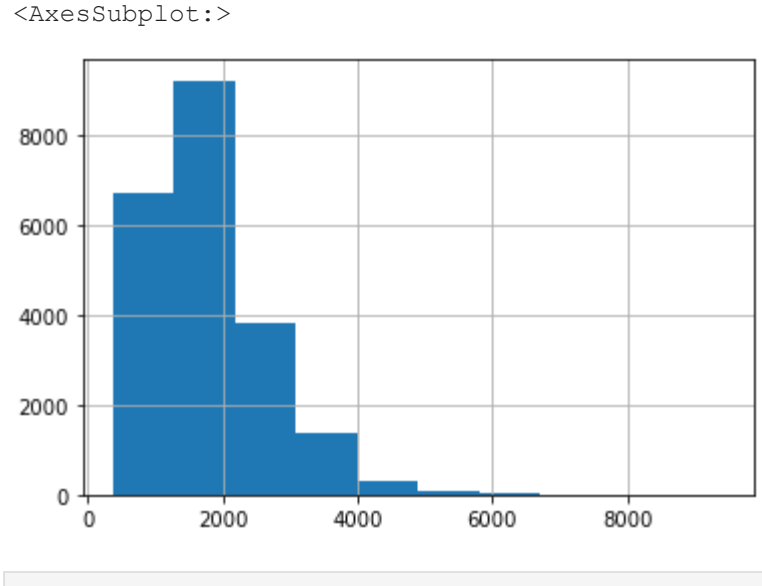
In [123…
```
data['grade']
```
Out [123…
```
0        7
1        7
2        6
3        7
4        8
        ..
21592    8
21593    8
21594    7
21595    8
21596    7
Name: grade, Length: 21597, dtype: int64
```
In [124…
```
data['grade'].value_counts().sort_index(ascending=True)
```
Out [124…
```
3        1
4       27
5      242
6     2038
7     8974
8     6065
9     2615
10    1134
11     399
12      89
13      13
Name: grade, dtype: int64
```
In [125…
```
data['grade'].value_counts().sort_index(ascending=True).plot(kind='bar',rot=360)
```
Out [125…
```
<AxesSubplot:>
```


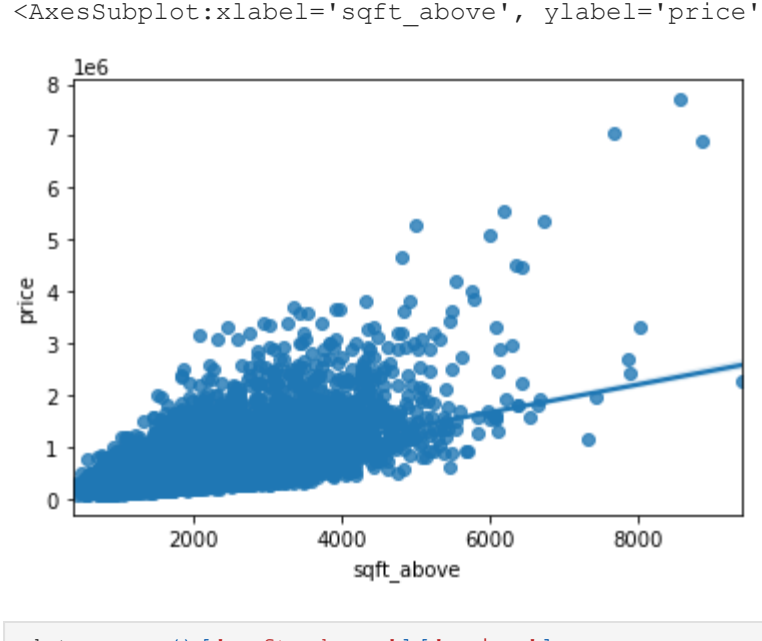
There is an interesting distribution of values in this feature as well, but there is a central grouping.

In [126…
```
sns.regplot(data=data, x='grade',y='price')
```
Out [126…
```
<AxesSubplot:xlabel='grade', ylabel='price'>
```


In [127…
```
data.corr()['price']['grade']
```
Out [127…
```
0.6679507713877846
```
In [128…
```
data['combined_score'] = data['grade']+data['condition']
data.corr()['price']['combined_score']
```
Out [128…
```
0.6430319774785247
```
In [129…
```
data.corr()['price']['condition']
```
Out [129…
```
0.03605637548609834
```

Square Feet Above and Square Feet Basement

In [130…
```
data['sqft_above']
```
Out [130…
```
0        1180
1        2170
2         770
3        1050
4        1680
         ...
21592    1530
21593    2310
21594    1020
21595    1600
21596    1020
Name: sqft_above, Length: 21597, dtype: int64
```
In [131…
```
data['sqft_above'].hist()
```
Out [131…
```
<AxesSubplot:>
```


In [132…
```
sns.regplot(data=data, x='sqft_above', y='price')
```
Out [132…
```
<AxesSubplot:xlabel='sqft_above', ylabel='price'>
```


In [133…
```
data.corr()['sqft_above']['price']
```
Out [133…
```
0.6053679437051825
```
In [134…
```
data['sqft_basement'].value_counts()
```
Out [134…
```
0.0       12826
?           454
600.0       217
500.0       209
700.0       208
          ...
4820.0        1
1525.0        1
1275.0        1
1281.0        1
1008.0        1
Name: sqft_basement, Length: 304, dtype: int64
```
In [135…
```
data[data['sqft_basement']=='?']=0.0
```
In [136…
```
data[data['sqft_basement']==0]=0.0
```
In [137…
```
data['sqft_basement'].value_counts()
```
Out [137…
```
0.0       12826
0.0         454
600.0       217
500.0       209
700.0       208
          ...
4820.0        1
1525.0        1
1275.0        1
1281.0        1
1008.0        1
Name: sqft_basement, Length: 304, dtype: int64
```
In [138…
```
data['sqft_basement'] = data['sqft_basement'].astype(float)
```
In [139…
```
data['sqft_basement'].value_counts()
```
Out [139…
```
0.00000       13280
600.00000       217
500.00000       209
700.00000       208
800.00000       201
              ...
915.00000         1
295.00000         1
1281.00000        1
2130.00000        1
906.00000         1
Name: sqft_basement, Length: 303, dtype: int64
```
In [140…
```
data.corr()['sqft_basement']['price']
```
Out [140…
```
0.3362627873444643
```

I changed the "?" values in the dataset to "0.0," does that alter the dataset too much? I could look at what the 0.0 columns look like and see if I can figure out what they are like in comparison to the '?' mark columns. This is an area to work on before making the baseline model. This is apart of the preprocessing part of this task.

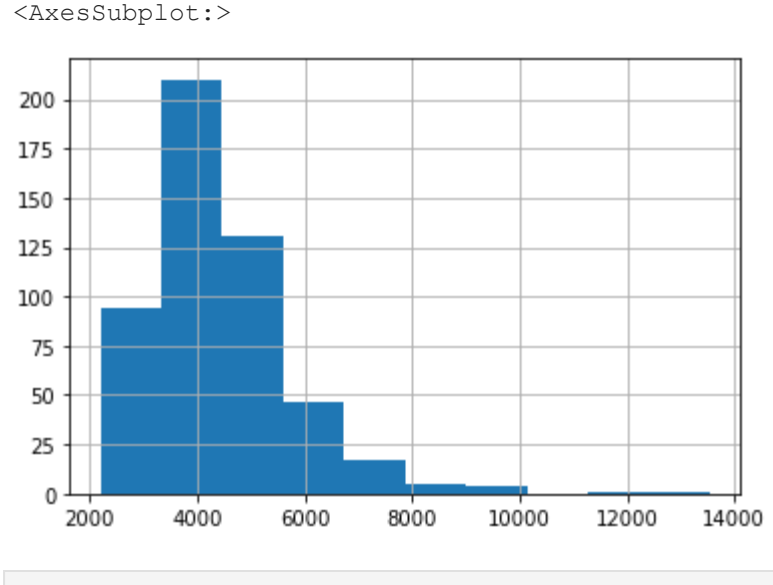
Zipcode

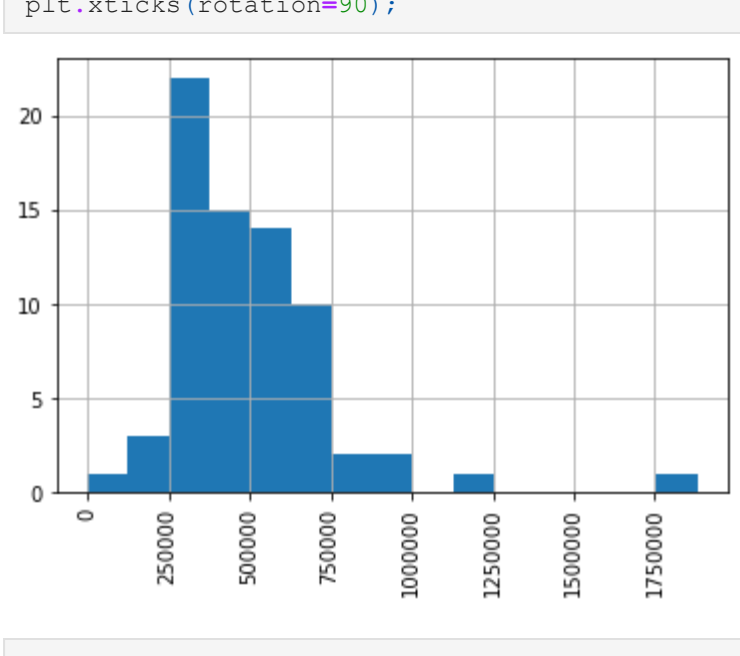
In [141…
```
data['zipcode'].value_counts()
```
Out [141…
```
98103    588
98038    574
98115    568
98052    562
98042    542
        ...
98102    100
98010     98
98024     79
98148     55
98039     49
Name: zipcode, Length: 71, dtype: int64
```

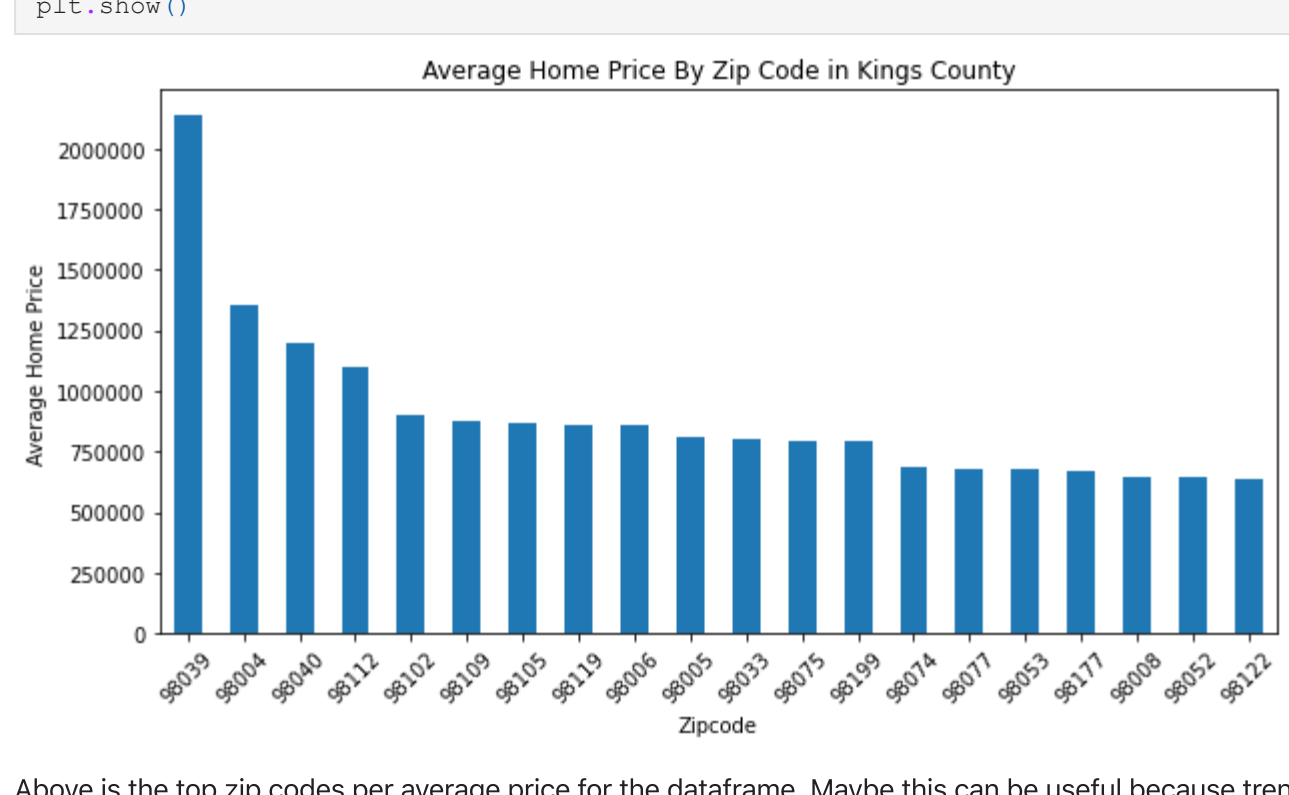
It will be interesting as to how to deal with the zip code column as the zip code is not a continium in the sense that it can be averaged and have the same sort of centrla tendencies. It is going to be like our other location information and be thought of as a sort of categorical data in and of itself maybe?

In [142…
```
data.corr()['zipcode']['price']
```
Out [142…
```
0.20805130503859007
```

I am not surprised that the correlation between zipcode and price is not very high.

In [144…
```
top_10_zips = data.groupby('zipcode')['price'].mean().sort_values(ascending=False).head(20)
```
In [145…
```
data[data['price']>1500000]['sqft_living'].hist()
```
Out [145…
```
<AxesSubplot:>
```


In [146…
```
data.groupby('zipcode')['price'].median().hist(bins='auto')
plt.ticklabel_format(style='plain')
plt.xticks(rotation=90);
```


In [147…
```
data['sqft_living'].mean()
```
Out [147…
```
2037.1767838125666
```
In [148…
```
plt.rc('axes.formatter', useoffset=False);


fig, ax = plt.subplots()

ax.ticklabel_format(useOffset=False, style='plain')

top_10_zips.plot(kind='bar',rot=45,figsize=(10,5),ax=ax)
plt.title('Average Home Price By Zip Code in Kings County')
plt.ylabel('Average Home Price')
plt.xlabel('Zipcode')

plt.show()
```


Above is the top zip codes per average price for the dataframe. Maybe this can be useful because trends might apply differently to different areas in the dataset as opposed to other less pricey zip code, or there might be some dividing by zip code at some point.

What can be assessed regarding the zip code information. How likely is it that location in one of these zip codes leads to meaningful rise in price? Is it easy to say that location is the determiner in the dataset, but am I going to treat this like a categorical value?

Latitude and Longtitude

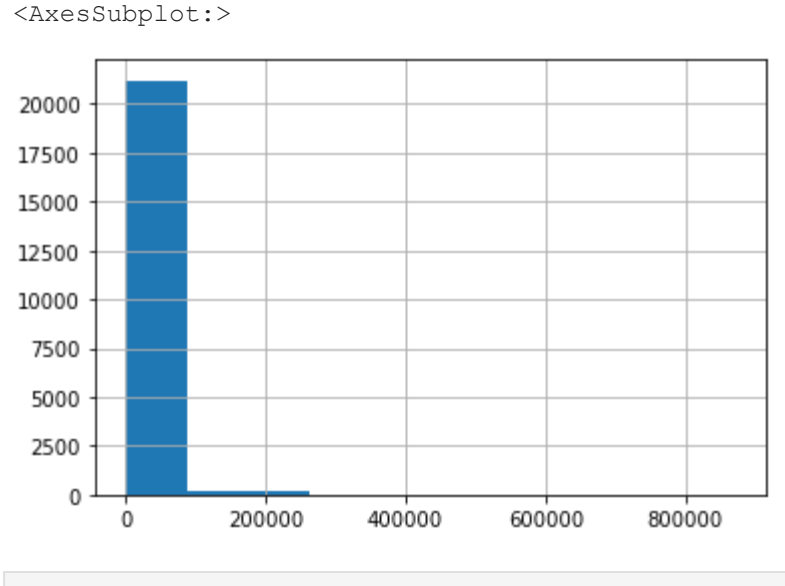
In [149…
```
data['long'].value_counts()
```
Out [149…
```
0.00000       454
-122.29000    113
-122.30000    109
-122.36200    104
-122.29100     98
             ...
-121.76000      1
-122.45900      1
-122.49600      1
-121.32500      1
-121.78500      1
Name: long, Length: 751, dtype: int64
```
In [150…
```
data['lat'].value_counts()
```
Out [150…
```
0.00000     454
47.66240     17
47.53220     17
47.54910     17
47.69550     16
           ...
47.44260      1
47.62570      1
47.38920      1
47.38610      1
47.27150      1
Name: lat, Length: 5019, dtype: int64
```

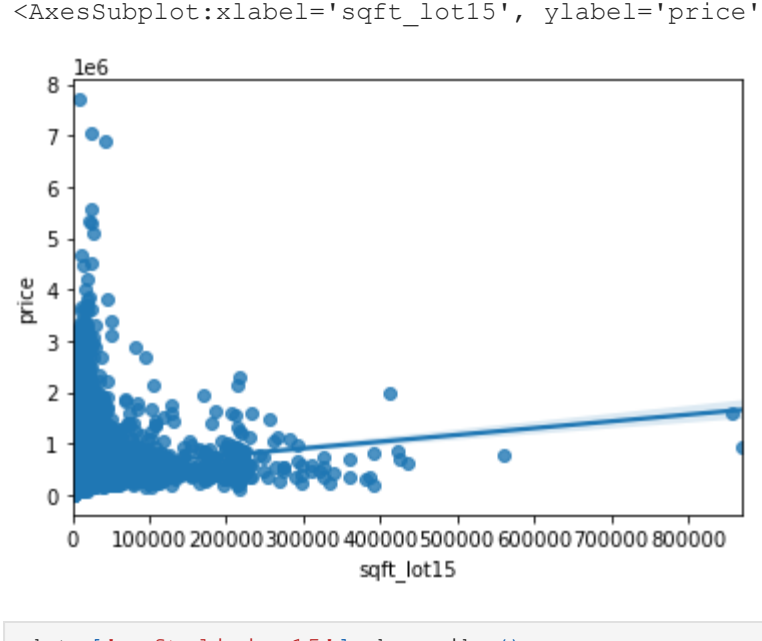
There are 454 locations without longtitude, and latitudal information. Should thse be combined into one column and used to asses the location in any way? Then it can be plotted or something like that?

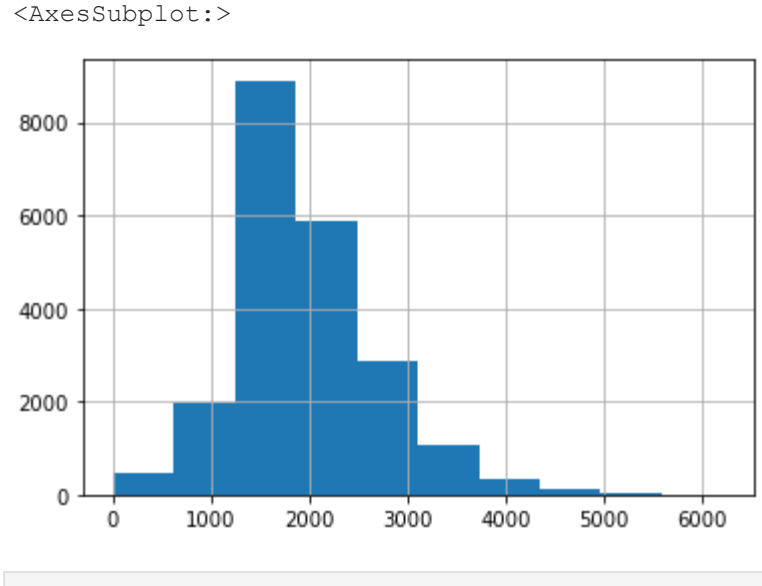
In [151…
```
data.groupby('long')['price'].mean()
```
Out [151…
```
long
-122.51900   575000.00000
-122.51500   565000.00000
-122.51400   999000.00000
-122.51200   290000.00000
-122.51100   370000.00000
                 ...
-121.32100   375000.00000
-121.31900   241000.00000
-121.31600   155000.00000
-121.31500   158500.00000
0.00000           0.00000
Name: price, Length: 751, dtype: float64
```
In [152…
```
data['long_lat'] = list(zip(data['long'],data['lat']))
data['long_lat'].value_counts().head(20)
```
Out [152…
```
(0.0, 0.0)                              454
(-122.28399999999999, 47.6647)            4
(-122.01700000000001, 47.5446)            4
(-122.34700000000001, 47.5171)            4
(-122.146, 47.6599)                       4
(-122.338, 47.6652)                       4
(-122.354, 47.6536)                       4
(-122.363, 47.6689)                       3
(-122.346, 47.6533)                       3
(-122.387, 47.5402)                       3
(-122.324, 47.6966)                       3
(-122.02600000000001, 47.54)              3
(-122.175, 47.6897)                       3
(-122.33, 47.4562)                        3
(-122.295, 47.5925)                       3
(-122.334, 47.7321)                       3
(-121.884, 47.5415)                       3
(-122.35700000000001, 47.7274)            3
(-122.069, 47.5345)                       3
(-122.196, 47.5184)                       3
Name: long_lat, dtype: int64
```
In [153…
```
data['lat'].round().value_counts()
```
Out [153…
```
48.00000    14686
47.00000     6457
0.00000       454
Name: lat, dtype: int64
```
In [154…
```
data['long'].round().value_counts()
```
Out [154…
```
-122.00000    21109
0.00000         454
-123.00000       18
-121.00000       16
Name: long, dtype: int64
```

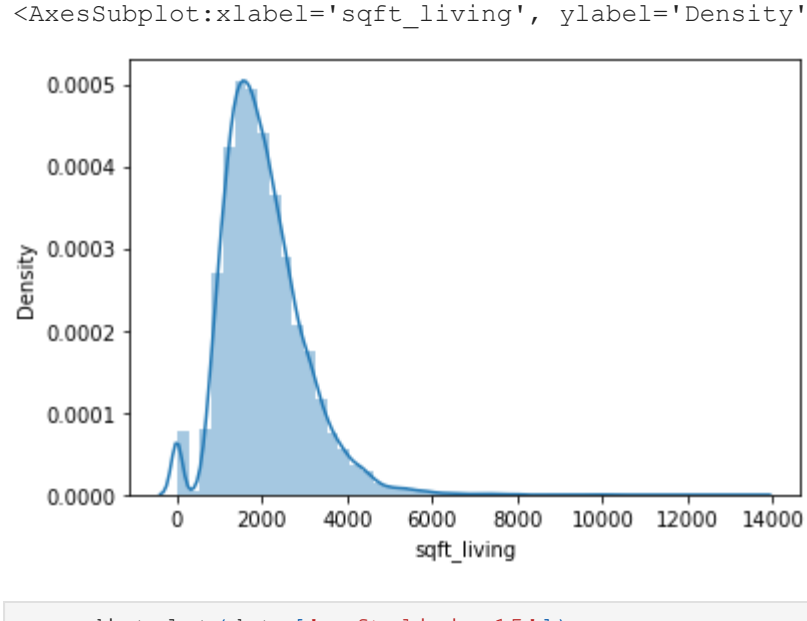
This is one of the most linear relationships in the data set, but values are likely to correlate with grade, grade is also a score assigned by the county, so it make take into account other values already.

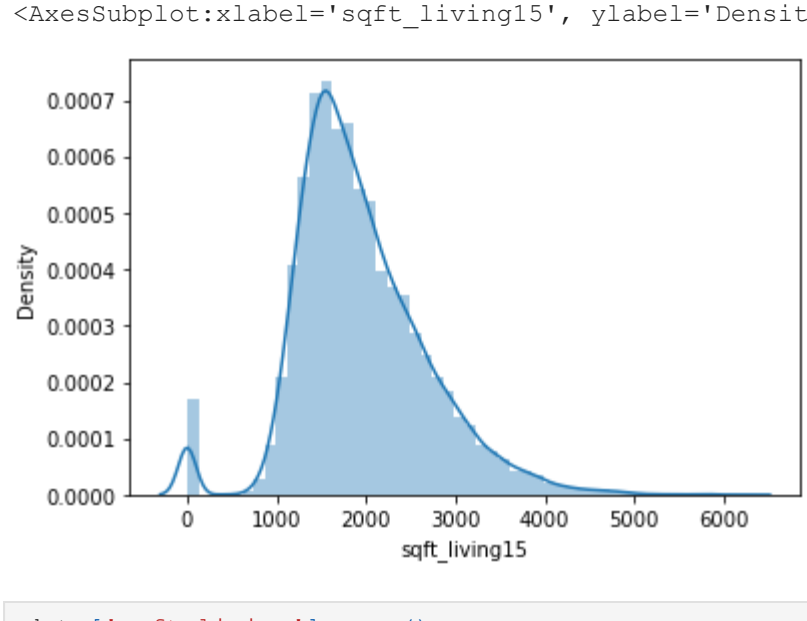
Neighboring Lots and Square Footage

In [155…
```
data['sqft_lot15'].describe()
```
Out [155…
```
count    21597.00000
mean     12471.15109
std      26944.22285
min          0.00000
25%       5000.00000
50%       7560.00000
75%      10009.00000
max     871200.00000
Name: sqft_lot15, dtype: float64
```
In [156…
```
data['sqft_lot15'].hist()
```
Out [156…
```
<AxesSubplot:>
```


In [157…
```
sns.regplot(data=data,x='sqft_lot15',y='price')
```
Out [157…
```
<AxesSubplot:xlabel='sqft_lot15', ylabel='price'>
```


In [158…
```
data['sqft_living15'].describe()
```
Out [158…
```
count   21597.00000
mean     1945.49609
std       735.89246
min         0.00000
25%      1460.00000
50%      1820.00000
75%      2350.00000
max      6210.00000
Name: sqft_living15, dtype: float64
```
In [159…
```
data['sqft_living15'].hist()
```
Out [159…
```
<AxesSubplot:>
```


In [160…
```
sns.distplot(data['sqft_living'])
```
```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distpl
ot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `dis
plot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```
Out [160…
```
<AxesSubplot:xlabel='sqft_living', ylabel='Density'>
```


In [161…
```
sns.distplot(data['sqft_living15'])
```
```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distpl
ot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `dis
plot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```
Out [161…
```
<AxesSubplot:xlabel='sqft_living15', ylabel='Density'>
```


In [162…
```
data['sqft_living'].mean()
```
Out [162…
```
2037.1767838125666
```
In [163…
```
data['sqft_living15'].mean()
```
Out [163…
```
1945.496087419549
```
In [164…
```
data[data['sqft_living']>data['sqft_living15']]['price'].mean()
```
Out [164…
```
630903.587252154
```
In [165…
```
data[data['sqft_living']<data['sqft_living15']]['price'].mean()
```
Out [165…
```
461329.6978113543
```
In [166…
```
data[data['sqft_living']<data['sqft_living15']].corr()['price']
```
Out [166…
```
id                0.01685
price             1.00000
bedrooms          0.32327
bathrooms         0.42609
sqft_living       0.64722
sqft_lot          0.04872
floors            0.23872
waterfront        0.21932
view              0.36462
condition         0.06027
grade             0.61653
sqft_above        0.55742
sqft_basement     0.27244
yr_built          0.03551
yr_renovated      0.11334
zipcode          -0.10211
lat               0.34931
long              0.06991
sqft_living15     0.66893
sqft_lot15        0.06154
month            -0.02057
combined_score    0.59382
Name: price, dtype: float64
```
In [167…
```
len(data[data['sqft_living']>data['sqft_living15']])/len(data)
```
Out [167…
```
0.4460341714126962
```
In [168…
```
len(data[data['sqft_lot']>data['sqft_lot15']])/len(data)
```
Out [168…
```
0.38954484419132285
```
In [169…
```
data[data['sqft_lot']>data['sqft_lot15']]['price'].mean()
```
Out [169…
```
566092.1641507192
```
In [170…
```
data[data['sqft_lot']<data['sqft_lot15']]['price'].mean()
```
Out [170…
```
527085.3203106332
```

The same situation with living size does not apply to lot size. Maybe we deal with apartments in some instances?

In [171…
```
len(data['sqft_lot'].unique())
```
Out [171…
```
9644
```
In [172…
```
len(data['sqft_living'].unique())
```
Out [172…
```
1026
```
In [173…
```
len(data['sqft_lot15'].unique())
```
Out [173…
```
8573
```
In [174…
```
len(data['sqft_living15'].unique())
```
Out [174…
```
774
```
In [175…
```
data['sqft_living'].value_counts()
```
Out [175…
```
0       454
1300    135
1400    134
1440    130
1010    127
       ...
4970      1
2905      1
2793      1
4810      1
1975      1
Name: sqft_living, Length: 1026, dtype: int64
```
In [176…
```
data['sqft_lot'].value_counts()
```
Out [176…
```
0         454
5000      348
6000      286
4000      244
7200      218
         ...
11212       1
9165        1
41300       1
17377       1
315374      1
Name: sqft_lot, Length: 9644, dtype: int64
```

Missing Values and Nulls

This data set contains 21,597 entries of housing data. There is a mixture of numeric and object columns. "Data" and "sqft_basement" are indicated as objects and will probably need to be transformed into floats or integers.

In [426…
```
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  object
 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  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64
 11  grade          21597 non-null  int64
 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: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
```

Watefront

In [427…
```
len(data[data['waterfront'].isna()])/len(data)
```
Out [427…
```
0.11001527989998611
```

11 % of the Waterfront Column in the dataset is currently null. That's a high percentage. But let's look again at the value counts for the column.

In [428…
```
data['waterfront'].value_counts()
```
Out [428…
```
0.00000    19075
1.00000      146
Name: waterfront, dtype: int64
```
In [429…
```
np.sum(data['waterfront']==0)/len(data)
```
Out [429…
```
0.8832245219243413
```
In [430…
```
np.sum(data['waterfront']==1)/len(data)
```
Out [430…
```
0.006760198175672547
```

88% of the waterfront data is not on the waterfront, and an exceedingly small .006% of the homes are indeed on the waterfront, I think at this time it is a safe option to fill those nulls as 0. This will be changed to categorical value anyway.

In [431…
```
data['waterfront'] = data['waterfront'].fillna(0)
```
In [432…
```
data['waterfront'].value_counts()
```
Out [432…
```
0.00000    21451
1.00000      146
Name: waterfront, dtype: int64
```
In [433…
```
len(data[data['waterfront'].isna()])/len(data)
```
Out [433…
```
0.0
```

View

In [434…
```
data['view'].value_counts()
```
Out [434…
```
0.00000    19422
2.00000      957
3.00000      508
1.00000      330
4.00000      317
Name: view, dtype: int64
```
In [435…
```
len(data[data['view'].isna()])/len(data)
```
Out [435…
```
0.0029170718155299346
```

A very small amount of the view column are null values, in an effort not to drop these from the dataset, I'm going to think about imputing these values in some fashion.

In [436…
```
data['view'].describe()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20439 entries, 0 to 21596
Data columns (total 23 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   id                   20439 non-null  int64  
 1   date                 20439 non-null  object 
 2   price                20439 non-null  float64
 3   bedrooms             20439 non-null  int64  
 4   bathrooms            20439 non-null  float64
 5   sqft_living          20439 non-null  int64  
 6   sqft_lot             20439 non-null  int64  
 7   floors               20439 non-null  float64
 8   waterfront           20439 non-null  float64
 9   view                 20439 non-null  float64
 10  condition            20439 non-null  int64  
 11  grade                20439 non-null  int64  
 12  sqft_above           20439 non-null  int64  
 13  sqft_basement        20439 non-null  float64
 14  yr_built             20439 non-null  int64  
 15  yr_renovated         20439 non-null  float64
 16  zipcode              20439 non-null  int64  
 17  lat                  20439 non-null  float64
 18  long                 20439 non-null  float64
 19  sqft_living15        20439 non-null  int64  
 20  sqft_lot15           20439 non-null  int64  
 21  sqft_living_compared 20439 non-null  float64
 22  sqft_lot_compared    20439 non-null  float64
dtypes: float64(11), int64(11), object(1)
memory usage: 3.7+ MB
```

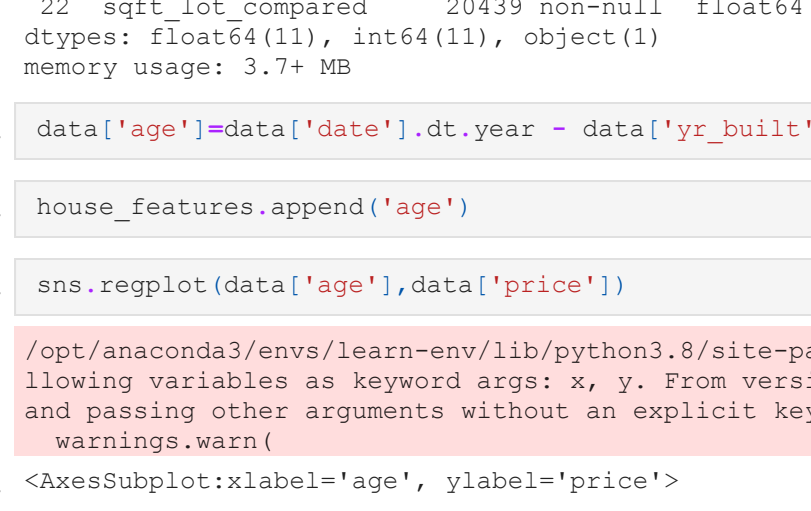
In [507…
```
data['age']=data['date'].dt.year - data['yr_built']
```

In [508…
```
house_features.append('age')
```

In [509…
```
sns.regplot(data['age'],data['price'])
```

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[509…
```
<AxesSubplot:xlabel='age', ylabel='price'>
```



I do not believe age meets the standard of linearity that is needed for performing regression.

In [510…
```
house_features.remove('age')
```

Renovation Status

Another available column of information is renovation. Many of the homes were not renovated, but I can still create a renovatoin feature.

In [511…
```
data['renovated']=data['yr_renovated']>1
```

In [512…
```
data['renovated']=data['renovated']*1
```

Model Fitter

In [513…
```
def model_iteration(X, y):
    #import sklearn train/test split
    from sklearn.model_selection import train_test_split

    X_train, X_test, y_train, y_test = train_test_split(X, y)

#     #Importing the Standard Scalar
#     from sklearn.preprocessing import StandardScaler

    from sklearn.linear_model import LinearRegression
    #Instatiating the Baseline Model
    model = LinearRegression()
    model.fit(X_train, y_train)
    return model, X_train, X_test, y_train, y_test
```

In [514…
```
X = data[house_features]
y = data['price']
```

In [515…
```
second_model, X_train, X_test, y_train, y_test = model_iteration(X,y)
```

In [516…
```
def scaled_X(X_train,X_test):
    scaler = StandardScaler()
    scaled_data = scaler.fit_transform(X_train)

#     Creating a new data frame with the scaled data. Getting the column names from the X_train dataframe.
    scaled_X_train = pd.DataFrame(scaled_data, columns = X_train.columns,index=X_train.index)
    scaled_X_test = scaler.transform(X_test)

    return scaled_X_train, scaled_X_test
```

MultiCollinearity Check

In [517…
```
df=X.corr().abs().stack().reset_index().sort_values(0, ascending=False)

df['pairs'] = list(zip(df.level_0, df.level_1))

df.set_index(['pairs'], inplace = True)
df.drop(columns=['level_1', 'level_0'], inplace = True)

df.columns = ['cc']
df.drop_duplicates(inplace=True)
df
abs(df.corr()) > 0.75
df=X.corr().abs().stack().reset_index().sort_values(0, ascending=False)
df[(df[0]>.75) & (df[0] <1)]
```

Out[517…

level_0	level_1	0

Model Score

In [518…
```
def model_score(model, X_train, X_test, y_train, y_test):
    train_score = model.score(X_train, y_train)
    test_score = model.score(X_test, y_test)

    return f'Train Score = {train_score}, Test Score = {test_score}'
```

In [519…
```
model_score(second_model, X_train, X_test, y_train, y_test)
```

Out[519…
```
'Train Score = 0.5054460285367008, Test Score = 0.49330562646352305'
```

Residual Helpers

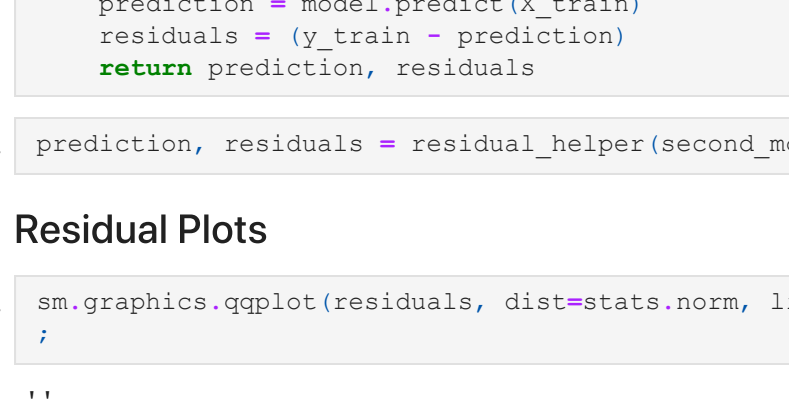
In [520…
```
def residual_helper(model,X_train,y_train):
    prediction = model.predict(X_train)
    residuals = (y_train - prediction)
    return prediction, residuals
```

In [521…
```
prediction, residuals = residual_helper(second_model,X_train,y_train)
```

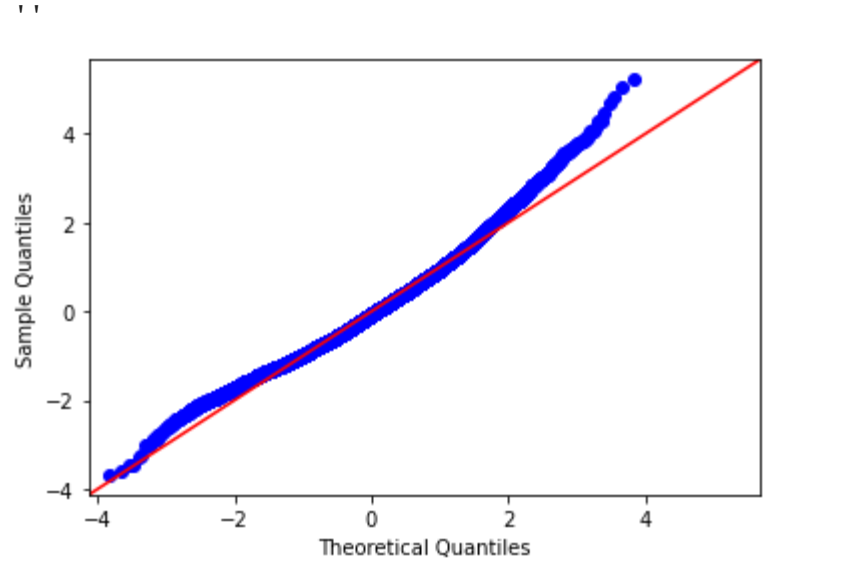
Residual Plots

In [522…
```
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True);
;
```

Out[522…
```
''
```



In [523…
```
# Run this cell without changes
fig, ax = plt.subplots()

ax.scatter(prediction, residuals, alpha=0.5)
ax.plot(prediction, [0 for i in range(len(X_train))])
ax.set_xlabel("Predicted Value")
ax.set_ylabel("Residuals")
ax.set_title('Homoscedasticity Test');
```



Stats Models Helper

In [526…
```
def Stats_Mod_Helper(y_train,X_train):
    stats_mod = sm.OLS(y_train,X_train)
    results = stats_mod.fit()

    return sm.OLS(y_train, sm.add_constant(X_train)).fit().summary()
```

In [527…
```
Stats_Mod_Helper(y_train,X_train)
```

Out[527…

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.505
Model:	OLS	**Adj. R-squared:**	0.505
Method:	Least Squares	**F-statistic:**	1423.
Date:	Fri, 07 Jan 2022	**Prob (F-statistic):**	0.00
Time:	05:07:39	**Log-Likelihood:**	-2.0409e+05
No. Observations:	15329	**AIC:**	4.082e+05
Df Residuals:	15317	**BIC:**	4.083e+05
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-4.14e+05	1.44e+04	-28.785	0.000	-4.42e+05	-3.86e+05
bedrooms	-7139.9164	1648.788	-4.330	0.000	-1.04e+04	-3908.095
bathrooms	-1.959e+04	2689.736	-7.283	0.000	-2.49e+04	-1.43e+04
sqft_living	102.4033	3.192	32.082	0.000	96.147	108.660
floors	3.153e+04	3036.078	10.385	0.000	2.56e+04	3.75e+04
waterfront	1.026e+05	2.54e+04	4.035	0.000	5.28e+04	1.52e+05
view	3.364e+04	1968.734	17.087	0.000	2.98e+04	3.75e+04
condition	4.171e+04	1922.366	21.695	0.000	3.79e+04	4.55e+04
grade	7.917e+04	1839.145	43.046	0.000	7.56e+04	8.28e+04
sqft_basement	49.0394	3.804	12.890	0.000	41.582	56.497
sqft_living_compared	-520.6329	50.614	-10.286	0.000	-619.842	-421.424
sqft_lot_compared	23.5455	8.879	2.652	0.008	6.142	40.949

Omnibus:	777.481	**Durbin-Watson:**	1.989
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	954.210
Skew:	0.529	**Prob(JB):**	6.25e-208
Kurtosis:	3.612	**Cond. No.**	4.63e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.63e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

Second Model Assesment

The second model displayed a lower R Squared, but seemed to show a better adherence to the assumptions of normality and homoscedasticity. Trimming the outliers seems to have helped the model, but maybe some of the features were not helpful. I will definitely drop the square foot basement, and see what other features can be dropped.

Feature Selection

In [528…
```
from sklearn.feature_selection import RFECV
from sklearn.model_selection import cross_validate, ShuffleSplit
splitter = ShuffleSplit(n_splits=3, test_size=0.25, random_state=0)
```

In [529…
```
# Importances are based on coefficient magnitude, so
# we need to scale the data to normalize the coefficients
X_train_for_RFECV = StandardScaler().fit_transform(X_train)

model_for_RFECV = LinearRegression()

# Instantiate and fit the selector
selector = RFECV(model_for_RFECV, cv=splitter)
selector.fit(X_train_for_RFECV, y_train)

# Print the results
print("Was the column selected?")
for index, col in enumerate(X_train.columns):
    print(f"{col}: {selector.support_[index]}")
```

```
Was the column selected?
bedrooms: True
bathrooms: True
sqft_living: True
floors: True
waterfront: True
view: True
condition: True
grade: True
sqft_basement: True
sqft_living_compared: True
sqft_lot_compared: False
```

I will be dropping the Square Foot Basement column, the Square Foot Lot Compared feature.

In [530…
```
to_drop = ['sqft_lot_compared']
```

In [531…
```
# Run this cell without changes
print(f"X_train is a DataFrame with {X_train.shape[0]} rows and {X_train.shape[1]} columns")
print(f"y_train is a Series with {y_train.shape[0]} values")

# We always should have the same number of rows in X as values in y
assert X_train.shape[0] == y_train.shape[0]
```

```
X_train is a DataFrame with 15329 rows and 11 columns
y_train is a Series with 15329 values
```

Third Model Iteration

Categorical Feature Engineering

Location Information

The first two iterations of the model did not utilize location information, but location most likely plays a role in the valuation of homes. Currently the dataset features 70 zip codes. In order to reduce the number of features and make them interpretable I will add join the zip codes to city names.

I will also add some information about seasonality of sale to give some additional information to the model to improve the R-Squared. I hope that dropping the insignificant features and adding this categorical information will show improvement.

In [532…
```
len(data['zipcode'].value_counts())
```

Out[532…
```
70
```

In [533…
```
zip_df = pd.read_csv('data/uszips.csv')
```

In [534…
```
zip_df
```

Out[534…

	zip	lat	lng	city	state_id	state_name	zcta	parent_zcta	population	density	county_fips	county_nam
0	601	18.18005	-66.75218	Adjuntas	PR	Puerto Rico	True	nan	17113.00000	102.70000	72001	Adjunta
1	602	18.36074	-67.17519	Aguada	PR	Puerto Rico	True	nan	37751.00000	476.00000	72003	Aguad
2	603	18.45440	-67.12201	Aguadilla	PR	Puerto Rico	True	nan	47081.00000	574.90000	72005	Aguadill
3	606	18.16721	-66.93828	Maricao	PR	Puerto Rico	True	nan	6392.00000	58.30000	72093	Marica
4	610	18.29032	-67.12244	Anasco	PR	Puerto Rico	True	nan	26686.00000	286.90000	72011	Añasc
...	...	...	...	...	...	...	...	...	...	...	...	...
33115	99923	55.97796	-130.03671	Hyder	AK	Alaska	True	nan	14.00000	0.30000	2198	Prince o Wales-Hyde
33116	99925	55.55796	-132.97482	Klawock	AK	Alaska	True	nan	908.00000	6.30000	2198	Prince o Wales-Hyde
33117	99926	55.12617	-131.48928	Metlakatla	AK	Alaska	True	nan	1654.00000	4.80000	2198	Prince o Wales-Hyde
33118	99927	56.25100	-133.37572	Point Baker	AK	Alaska	True	nan	0.00000	0.00000	2198	Prince o Wales-Hyde
33119	99929	56.36950	-131.93648	Wrangell	AK	Alaska	True	nan	2502.00000	0.40000	2275	Wrange

33120 rows × 18 columns

The zip code Data Frame contains a lot of information I probably won't use, so I will only make a Data Frame of columns that seem relevant.

In [535…
```
zip_df = zip_df[['zip','city','state_name','population','density','county_name']]
```

This is a large data set and I will narrow it down to only Kings County zip codes.

In [536…
```
data['zipcode'].value_counts().index
```

Out[536…
```
Int64Index([98103, 98038, 98052, 98115, 98042, 98117, 98034, 98118, 98023,
            98133, 98058, 98059, 98155, 98074, 98056, 98006, 98125, 98027,
            98053, 98033, 98001, 98126, 98092, 98106, 98075, 98144, 98029,
            98116, 98065, 98146, 98028, 98003, 98198, 98031, 98199, 98122,
            98168, 98055, 98008, 98072, 98107, 98178, 98136, 98030, 98166,
            98022, 98177, 98045, 98002, 98011, 98019, 98077, 98108, 98105,
            98112, 98040, 98004, 98119, 98005, 98007, 98188, 98032, 98014,
            98070, 98010, 98102, 98109, 98024, 98148, 98039],
           dtype='int64')
```

In [537…
```
#Creating a list of zips to filter from
kings_zips = list(data['zipcode'].value_counts().index)
```

In [538…
```
zip_df = zip_df[zip_df['zip'].isin(kings_zips)]
```

In [539…
```
zip_df
```

Out[539…

	zip	city	state_name	population	density	county_name
32286	98001	Auburn	Washington	33699.00000	699.30000	King
32287	98002	Auburn	Washington	33468.00000	1797.10000	King
32288	98003	Federal Way	Washington	49533.00000	1644.40000	King
32289	98004	Bellevue	Washington	36202.00000	1985.40000	King
32290	98005	Bellevue	Washington	19223.00000	987.70000	King
...	...	...	...	...	...	...
32373	98177	Seattle	Washington	20676.00000	1409.10000	King
32374	98178	Seattle	Washington	27335.00000	2178.20000	King
32375	98188	Seattle	Washington	25175.00000	1290.80000	King
32377	98198	Seattle	Washington	37966.00000	1901.30000	King
32378	98199	Seattle	Washington	22720.00000	2094.40000	King

70 rows × 6 columns

In [540…
```
#Creating a dataframe of zipcodes and cities
zip_city = zip_df[['zip','city']].sort_values(by='city')
```

In [541…
```
zip_city
```

Out[541…

	zip	city
32286	98001	Auburn
32287	98002	Auburn
32339	98092	Auburn
32289	98004	Bellevue
32290	98005	Bellevue
...	...	...
32346	98107	Seattle
32331	98065	Snoqualmie
32333	98070	Vashon
32337	98077	Woodinville
32334	98072	Woodinville

70 rows × 2 columns

In [542…
```
#Making a dictionary of zip codes and cities
zip_dict = dict(zip(zip_city.zip, zip_city.city))
zip_dict
```

Out[542…
```
{98001: 'Auburn',
 98002: 'Auburn',
 98092: 'Auburn',
 98004: 'Bellevue',
 98005: 'Bellevue',
 98006: 'Bellevue',
 98007: 'Bellevue',
 98008: 'Bellevue',
 98010: 'Black Diamond',
 98011: 'Bothell',
 98014: 'Carnation',
 98019: 'Duvall',
 98022: 'Enumclaw',
 98024: 'Fall City',
 98023: 'Federal Way',
 98003: 'Federal Way',
 98027: 'Issaquah',
 98029: 'Issaquah',
 98028: 'Kenmore',
 98030: 'Kent',
 98031: 'Kent',
 98032: 'Kent',
 98042: 'Kent',
 98033: 'Kirkland',
 98034: 'Kirkland',
 98038: 'Maple Valley',
 98039: 'Medina',
 98040: 'Mercer Island',
 98045: 'North Bend',
 98052: 'Redmond',
 98053: 'Redmond',
 98055: 'Renton',
 98056: 'Renton',
 98058: 'Renton',
 98059: 'Renton',
 98074: 'Sammamish',
 98075: 'Sammamish',
 98125: 'Seattle',
 98126: 'Seattle',
 98133: 'Seattle',
 98136: 'Seattle',
 98144: 'Seattle',
 98146: 'Seattle',
 98168: 'Seattle',
 98155: 'Seattle',
 98166: 'Seattle',
 98122: 'Seattle',
 98177: 'Seattle',
 98178: 'Seattle',
 98188: 'Seattle',
 98148: 'Seattle',
 98119: 'Seattle',
 98199: 'Seattle',
 98117: 'Seattle',
 98198: 'Seattle',
 98102: 'Seattle',
 98103: 'Seattle',
 98118: 'Seattle',
 98106: 'Seattle',
 98105: 'Seattle',
 98108: 'Seattle',
 98109: 'Seattle',
 98112: 'Seattle',
 98115: 'Seattle',
 98116: 'Seattle',
 98107: 'Seattle',
 98065: 'Snoqualmie',
 98070: 'Vashon',
 98077: 'Woodinville',
 98072: 'Woodinville'}
```

In [543…
```
data['city'] = data['zipcode'].map(zip_dict)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20439 entries, 0 to 21596
Data columns (total 26 columns):
 #   Column                Non-Null Count  Dtype         
---  ------                --------------  -----         
 0   id                    20439 non-null  int64         
 1   date                  20439 non-null  datetime64[ns]
 2   price                 20439 non-null  float64       
 3   bedrooms              20439 non-null  int64         
 4   bathrooms             20439 non-null  float64       
 5   sqft_living           20439 non-null  int64         
 6   sqft_lot              20439 non-null  int64         
 7   floors                20439 non-null  float64       
 8   waterfront            20439 non-null  float64       
 9   view                  20439 non-null  float64       
 10  condition             20439 non-null  int64         
 11  grade                 20439 non-null  int64         
 12  sqft_above            20439 non-null  int64         
 13  sqft_basement         20439 non-null  float64       
 14  yr_built              20439 non-null  int64         
 15  yr_renovated          20439 non-null  float64       
 16  zipcode               20439 non-null  int64         
 17  lat                   20439 non-null  float64       
 18  long                  20439 non-null  float64       
 19  sqft_living15         20439 non-null  int64         
 20  sqft_lot15            20439 non-null  int64         
 21  sqft_living_compared  20439 non-null  float64       
 22  sqft_lot_compared     20439 non-null  float64       
 23  age                   20439 non-null  int64         
 24  renovated             20439 non-null  int64         
 25  city                  20439 non-null  object        
dtypes: datetime64[ns](1), float64(11), int64(13), object(1)
memory usage: 4.2+ MB
```

One Hot Encoding "City"

In [544…
```
len(data['city'].value_counts())
```

Out[544…
```
24
```

For this iteration I will be one hot encoding the cities as seperate features. There will be 23 features that I will be modeled along with house features.

In [545…
```
city_dummies = pd.get_dummies(data['city'],drop_first=True)
```

In [546…
```
city_cols = list(city_dummies.columns)
```

In [547…
```
data = pd.concat([data, city_dummies], axis=1)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20439 entries, 0 to 21596
Data columns (total 49 columns):
 #   Column                Non-Null Count  Dtype         
---  ------                --------------  -----         
 0   id                    20439 non-null  int64         
 1   date                  20439 non-null  datetime64[ns]
 2   price                 20439 non-null  float64       
 3   bedrooms              20439 non-null  int64         
 4   bathrooms             20439 non-null  float64       
 5   sqft_living           20439 non-null  int64         
 6   sqft_lot              20439 non-null  int64         
 7   floors                20439 non-null  float64       
 8   waterfront            20439 non-null  float64       
 9   view                  20439 non-null  float64       
 10  condition             20439 non-null  int64         
 11  grade                 20439 non-null  int64         
 12  sqft_above            20439 non-null  int64         
 13  sqft_basement         20439 non-null  float64       
 14  yr_built              20439 non-null  int64         
 15  yr_renovated          20439 non-null  float64       
 16  zipcode               20439 non-null  int64         
 17  lat                   20439 non-null  float64       
 18  long                  20439 non-null  float64       
 19  sqft_living15         20439 non-null  int64         
 20  sqft_lot15            20439 non-null  int64         
 21  sqft_living_compared  20439 non-null  float64       
 22  sqft_lot_compared     20439 non-null  float64       
 23  age                   20439 non-null  int64         
 24  renovated             20439 non-null  int64         
 25  city                  20439 non-null  object        
 26  Bellevue              20439 non-null  uint8         
 27  Black Diamond         20439 non-null  uint8         
 28  Bothell               20439 non-null  uint8         
 29  Carnation             20439 non-null  uint8         
 30  Duvall                20439 non-null  uint8         
 31  Enumclaw              20439 non-null  uint8         
 32  Fall City             20439 non-null  uint8         
 33  Federal Way           20439 non-null  uint8         
 34  Issaquah              20439 non-null  uint8         
 35  Kenmore               20439 non-null  uint8         
 36  Kent                  20439 non-null  uint8         
 37  Kirkland              20439 non-null  uint8         
 38  Maple Valley          20439 non-null  uint8         
 39  Medina                20439 non-null  uint8         
 40  Mercer Island         20439 non-null  uint8         
 41  North Bend            20439 non-null  uint8         
 42  Redmond               20439 non-null  uint8         
 43  Renton                20439 non-null  uint8         
 44  Sammamish             20439 non-null  uint8         
 45  Seattle               20439 non-null  uint8         
 46  Snoqualmie            20439 non-null  uint8         
 47  Vashon                20439 non-null  uint8         
 48  Woodinville           20439 non-null  uint8         
dtypes: datetime64[ns](1), float64(11), int64(13), object(1), uint8(23)
memory usage: 4.7+ MB
```

The DataSet know contains the additional features for a the second iteration of modeling. Having now droppe the outliers, and one-hot encoded the cities, it may be time for another pass at modeling.

I will be making some helper functions for the second iteration of the model.

Month of Sale

In [548…
```
data['month_sale']=data['date'].dt.month
data['month_sale']
```

Out[548…
```
0        10
1        12
2         2
3        12
4         2
         ..
21592     5
21593     2
21594     6
21595     1
21596    10
Name: month_sale, Length: 20439, dtype: int64
```

In [549…
```
def season_of_date(date_UTC):
    year = str(date_UTC.year)
    seasons = {'spring': pd.date_range(start= year +'-03-21 00:00:00', end=year + '-06-20 00:00:00'),
               'summer': pd.date_range(start= year + '-06-21 00:00:00', end= year + '-09-22 00:00:00'),
               'autumn': pd.date_range(start= year + '-09-23 00:00:00', end= year + '-12-20 00:00:00')}
    if date_UTC in seasons['spring']:
        return 'spring'
    if date_UTC in seasons['summer']:
        return 'summer'
    if date_UTC in seasons['autumn']:
        return 'autumn'
    else:
        return 'winter'

data['season'] = data.date.map(season_of_date)
```

One Hot Encoding Season

In [550…
```
season_dummies = pd.get_dummies(data['season'],drop_first=True)
```

In [551…
```
season_cols = list(season_dummies.columns)
```

In [552…
```
data = pd.concat([data, season_dummies], axis=1)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20439 entries, 0 to 21596
Data columns (total 54 columns):
 #   Column                Non-Null Count  Dtype         
---  ------                --------------  -----         
 0   id                    20439 non-null  int64         
 1   date                  20439 non-null  datetime64[ns]
 2   price                 20439 non-null  float64       
 3   bedrooms              20439 non-null  int64         
 4   bathrooms             20439 non-null  float64       
 5   sqft_living           20439 non-null  int64         
 6   sqft_lot              20439 non-null  int64         
 7   floors                20439 non-null  float64       
 8   waterfront            20439 non-null  float64       
 9   view                  20439 non-null  float64       
 10  condition             20439 non-null  int64         
 11  grade                 20439 non-null  int64         
 12  sqft_above            20439 non-null  int64         
 13  sqft_basement         20439 non-null  float64       
 14  yr_built              20439 non-null  int64         
 15  yr_renovated          20439 non-null  float64       
 16  zipcode               20439 non-null  int64         
 17  lat                   20439 non-null  float64       
 18  long                  20439 non-null  float64       
 19  sqft_living15         20439 non-null  int64         
 20  sqft_lot15            20439 non-null  int64         
 21  sqft_living_compared  20439 non-null  float64       
 22  sqft_lot_compared     20439 non-null  float64       
 23  age                   20439 non-null  int64         
 24  renovated             20439 non-null  int64         
 25  city                  20439 non-null  object        
 26  Bellevue              20439 non-null  uint8         
 27  Black Diamond         20439 non-null  uint8         
 28  Bothell               20439 non-null  uint8         
 29  Carnation             20439 non-null  uint8         
 30  Duvall                20439 non-null  uint8         
 31  Enumclaw              20439 non-null  uint8         
 32  Fall City             20439 non-null  uint8         
 33  Federal Way           20439 non-null  uint8         
 34  Issaquah              20439 non-null  uint8         
 35  Kenmore               20439 non-null  uint8         
 36  Kent                  20439 non-null  uint8         
 37  Kirkland              20439 non-null  uint8         
 38  Maple Valley          20439 non-null  uint8         
 39  Medina                20439 non-null  uint8         
 40  Mercer Island         20439 non-null  uint8         
 41  North Bend            20439 non-null  uint8         
 42  Redmond               20439 non-null  uint8         
 43  Renton                20439 non-null  uint8         
 44  Sammamish             20439 non-null  uint8         
 45  Seattle               20439 non-null  uint8         
 46  Snoqualmie            20439 non-null  uint8         
 47  Vashon                20439 non-null  uint8         
 48  Woodinville           20439 non-null  uint8         
 49  month_sale            20439 non-null  int64         
 50  season                20439 non-null  object        
 51  spring                20439 non-null  uint8         
 52  summer                20439 non-null  uint8         
 53  winter                20439 non-null  uint8         
dtypes: datetime64[ns](1), float64(11), int64(14), object(2), uint8(26)
memory usage: 5.0+ MB
```

Third Model Iteration

In [573…
```
house_features
```

Out[573…
```
['bedrooms',
 'bathrooms',
 'sqft_living',
 'floors',
 'waterfront',
 'view',
 'condition',
 'sqft_basement',
 'sqft_living_compared']
```

In [574…
```
house_features = [element for element in house_features if element not in to_drop]
```

In [579…
```
X = data[house_features+city_cols+season_cols]
y = data['price']
```

In [580…
```
third_model, X_train, X_test, y_train, y_test = model_iteration(X,y)
```

Scoring Third Model

In [581…
```
model_score(third_model, X_train, X_test, y_train, y_test)
```

Out[581…
```
'Train Score = 0.6960352210702934, Test Score = 0.7063994618858418'
```

In [582…
```
# Run this cell without changes
from sklearn.model_selection import cross_val_score

cross_val_score = cross_val_score(third_model, X_train, y_train, cv=8)
cross_val_score.mean()
```

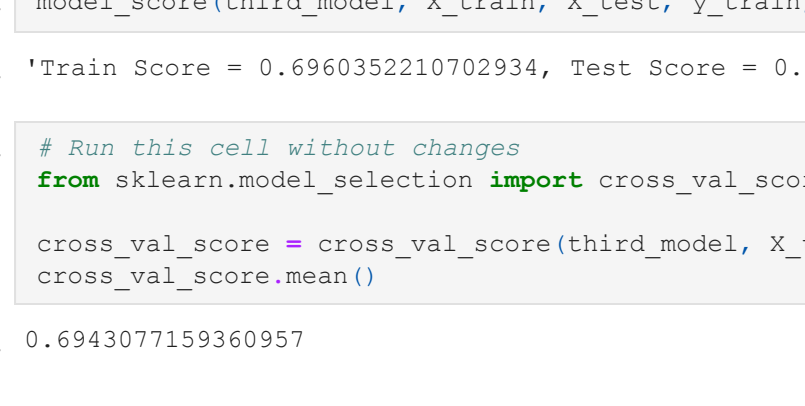
Out[582…
```
0.6943077159360957
```

Residual Tests

In [583…
```
prediction, residuals = residual_helper(third_model,X_train,y_train)
```

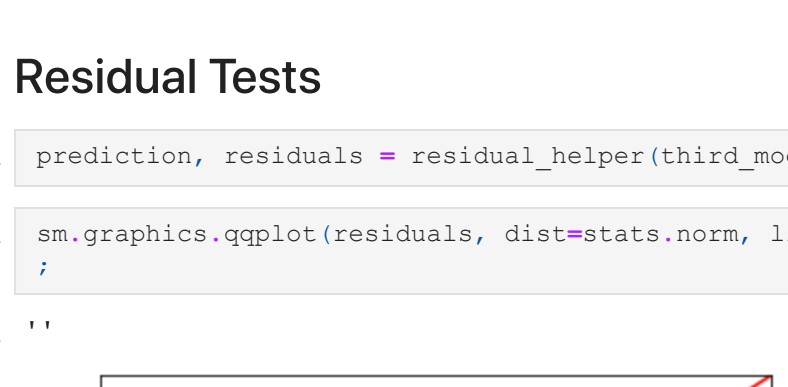
In [584…
```
sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True);
;
```

Out[584…
```
''
```

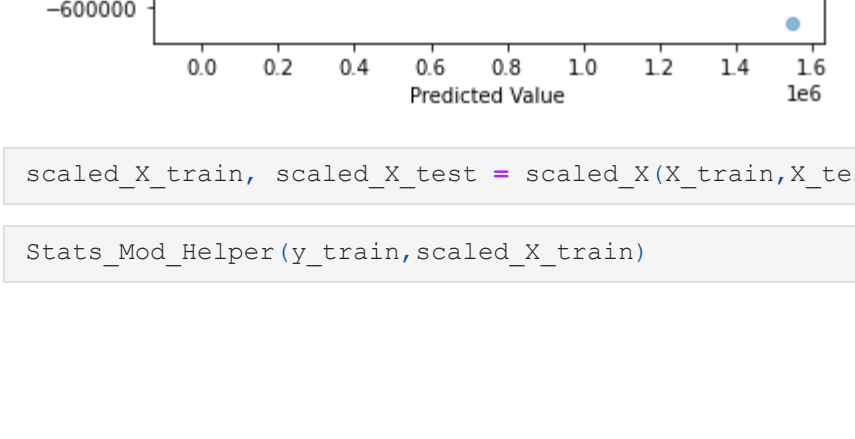


In [585…
```
plt.hist(residuals, bins=100)
;
```

Out[585…
```
''
```



In [586…
```
# Run this cell without changes
fig, ax = plt.subplots()

ax.scatter(prediction, residuals, alpha=0.5)
ax.plot(prediction, [0 for i in range(len(X_train))])
ax.set_xlabel("Predicted Value")
ax.set_ylabel("Residuals")
ax.set_title('Homoscedasticity Test');
```



In [587…
```
scaled_X_train, scaled_X_test = scaled_X(X_train,X_test)
```

In [588…
```
Stats_Mod_Helper(y_train,scaled_X_train)
```

Out[588...

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.696
Model:	OLS	**Adj. R-squared:**	0.695
Method:	Least Squares	**F-statistic:**	972.7
Date:	Fri, 07 Jan 2022	**Prob (F-statistic):**	0.00
Time:	05:17:39	**Log-Likelihood:**	-2.0034e+05
No. Observations:	15329	**AIC:**	4.008e+05
Df Residuals:	15292	**BIC:**	4.010e+05
Df Model:	36		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.778e+05	927.793	515.001	0.000	4.76e+05	4.8e+05
bedrooms	-7621.3444	1219.395	-6.250	0.000	-1e+04	-5231.186
bathrooms	2976.6549	1520.429	1.958	0.050	-3.567	5956.877
sqft_living	9.74e+04	2075.070	46.939	0.000	9.33e+04	1.01e+05
floors	6297.1748	1323.422	4.758	0.000	3703.111	8891.239
waterfront	5151.6933	988.907	5.209	0.000	3213.317	7090.069
view	1.857e+04	1027.991	18.064	0.000	1.66e+04	2.06e+04
condition	2.541e+04	994.092	25.558	0.000	2.35e+04	2.74e+04
sqft_basement	-5926.4246	1283.988	-4.616	0.000	-8443.194	-3409.655
sqft_living_compared	-1.516e+04	1272.797	-11.907	0.000	-1.77e+04	-1.27e+04
grade	6.046e+04	1539.644	39.268	0.000	5.74e+04	6.35e+04
Bellevue	6.759e+04	1363.330	49.580	0.000	6.49e+04	7.03e+04
Black Diamond	6630.0476	974.964	6.800	0.000	4719.002	8541.093
Bothell	1.408e+04	1017.004	13.843	0.000	1.21e+04	1.61e+04
Carnation	1.031e+04	980.426	10.512	0.000	8384.630	1.22e+04
Duvall	1.035e+04	1020.658	10.145	0.000	8353.791	1.24e+04
Enumclaw	1810.0521	1044.886	1.732	0.083	-238.049	3858.154
Fall City	1.156e+04	965.063	11.974	0.000	9663.733	1.34e+04
Federal Way	-3366.1730	1238.572	-2.718	0.007	-5793.921	-938.425
Issaquah	3.54e+04	1226.183	28.869	0.000	3.3e+04	3.78e+04
Kenmore	1.521e+04	1047.461	14.520	0.000	1.32e+04	1.73e+04
Kent	1199.5403	1365.811	0.878	0.380	-1477.613	3876.693
Kirkland	4.984e+04	1278.005	39.000	0.000	4.73e+04	5.23e+04
Maple Valley	6602.7026	1179.804	5.596	0.000	4290.146	8915.259
Medina	8660.6464	930.377	9.309	0.000	6836.997	1.05e+04
Mercer Island	3.828e+04	1021.955	37.457	0.000	3.63e+04	4.03e+04
North Bend	1.23e+04	1032.270	11.916	0.000	1.03e+04	1.43e+04
Redmond	5.154e+04	1310.080	39.340	0.000	4.9e+04	5.41e+04
Renton	1.987e+04	1462.436	13.586	0.000	1.7e+04	2.27e+04
Sammamish	4.075e+04	1265.375	32.202	0.000	3.83e+04	4.32e+04
Seattle	1.102e+05	2313.182	47.655	0.000	1.06e+05	1.15e+05
Snoqualmie	1.495e+04	1078.946	13.854	0.000	1.28e+04	1.71e+04
Vashon	1.024e+04	1009.192	10.142	0.000	8257.040	1.22e+04
Woodinville	2.701e+04	1137.784	23.735	0.000	2.48e+04	2.92e+04
spring	8520.3226	1189.738	7.162	0.000	6188.294	1.09e+04
summer	-556.8421	1181.079	-0.471	0.637	-2871.899	1758.214
winter	3376.8585	1122.481	3.008	0.003	1176.662	5577.055

Omnibus:	1549.817	**Durbin-Watson:**	2.003
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3321.279
Skew:	0.640	**Prob(JB):**	0.00
Kurtosis:	4.888	**Cond. No.**	8.03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Model Assessment

The final model showed a marked improvement on the R-Squared score. The residuals look normally distributed, with still some skew. Heteroscedasticity remains an issue so I believe that calls the model into question. The p-values for "summer" in the categorical season is above the desired level, as is the cities of Kent and Enumclaw. I would weigh these against the low p-values of the features in the same category.

In [589...
```
results_summary = Stats_Mod_Helper(y_train,scaled_X_train)

results_as_html = results_summary.tables[1].as_html()
Results_df = pd.read_html(results_as_html, header=0, index_col=0)[0]
```

In [590...
```
Results_df
```

Out[590...

	coef	std err	t	P>|t|	[0.025	0.975]
const	477800.00000	927.79300	515.00100	0.00000	476000.00000	480000.00000
bedrooms	-7621.34440	1219.39500	-6.25000	0.00000	-10000.00000	-5231.18600
bathrooms	2976.65490	1520.42900	1.95800	0.05000	-3.56700	5956.87700
sqft_living	97400.00000	2075.07000	46.93900	0.00000	93300.00000	101000.00000
floors	6297.17480	1323.42200	4.75800	0.00000	3703.11100	8891.23900
waterfront	5151.69330	988.90700	5.20900	0.00000	3213.31700	7090.06900
view	18570.00000	1027.99100	18.06400	0.00000	16600.00000	20600.00000
condition	25410.00000	994.09200	25.55800	0.00000	23500.00000	27400.00000
sqft_basement	-5926.42460	1283.98800	-4.61600	0.00000	-8443.19400	-3409.65500
sqft_living_compared	-15160.00000	1272.79700	-11.90700	0.00000	-17700.00000	-12700.00000
grade	60460.00000	1539.64400	39.26800	0.00000	57400.00000	63500.00000
Bellevue	67590.00000	1363.33000	49.58000	0.00000	64900.00000	70300.00000
Black Diamond	6630.04760	974.96400	6.80000	0.00000	4719.00200	8541.09300
Bothell	14080.00000	1017.00400	13.84300	0.00000	12100.00000	16100.00000
Carnation	10310.00000	980.42600	10.51200	0.00000	8384.63000	12200.00000
Duvall	10350.00000	1020.65800	10.14500	0.00000	8353.79100	12400.00000
Enumclaw	1810.05210	1044.88600	1.73200	0.08300	-238.04900	3858.15400
Fall City	11560.00000	965.06300	11.97400	0.00000	9663.73300	13400.00000
Federal Way	-3366.17300	1238.57200	-2.71800	0.00700	-5793.92100	-938.42500
Issaquah	35400.00000	1226.18300	28.86900	0.00000	33000.00000	37800.00000
Kenmore	15210.00000	1047.46100	14.52000	0.00000	13200.00000	17300.00000
Kent	1199.54030	1365.81100	0.87800	0.38000	-1477.61300	3876.69300
Kirkland	49840.00000	1278.00500	39.00000	0.00000	47300.00000	52300.00000
Maple Valley	6602.70260	1179.80400	5.59600	0.00000	4290.14600	8915.25900
Medina	8660.64640	930.37700	9.30900	0.00000	6836.99700	10500.00000
Mercer Island	38280.00000	1021.95500	37.45700	0.00000	36300.00000	40300.00000
North Bend	12300.00000	1032.27000	11.91600	0.00000	10300.00000	14300.00000
Redmond	51540.00000	1310.08000	39.34000	0.00000	49000.00000	54100.00000
Renton	19870.00000	1462.43600	13.58600	0.00000	17000.00000	22700.00000
Sammamish	40750.00000	1265.37500	32.20200	0.00000	38300.00000	43200.00000
Seattle	110200.00000	2313.18200	47.65500	0.00000	106000.00000	115000.00000
Snoqualmie	14950.00000	1078.94600	13.85400	0.00000	12800.00000	17100.00000
Vashon	10240.00000	1009.19200	10.14200	0.00000	8257.04000	12200.00000
Woodinville	27010.00000	1137.78400	23.73500	0.00000	24800.00000	29200.00000
spring	8520.32260	1189.73800	7.16200	0.00000	6188.29400	10900.00000
summer	-556.84210	1181.07900	-0.47100	0.63700	-2871.89900	1758.21400
winter	3376.85850	1122.48100	3.00800	0.00300	1176.66200	5577.05500

House Features Assessment

Scaled Comparison

In [591...
```
House_Sum = Results_df.loc[house_features,:]
```

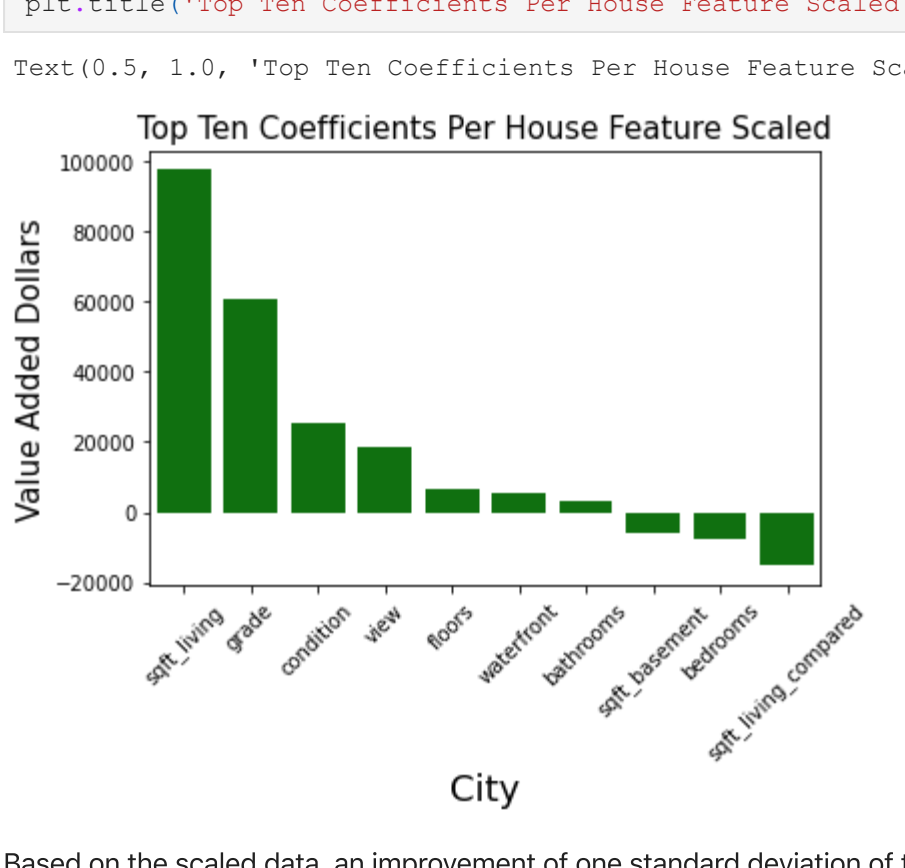
In [610...
```
House_Sum = House_Sum.sort_values(by='coef',ascending=False)
House_Sum = House_Sum.reset_index()
House_Sum
```

Out[610...

	index	coef	std err	t	P>|t|	[0.025	0.975]
0	sqft_living	97400.00000	2075.07000	46.93900	0.00000	93300.00000	101000.00000
1	grade	60460.00000	1539.64400	39.26800	0.00000	57400.00000	63500.00000
2	condition	25410.00000	994.09200	25.55800	0.00000	23500.00000	27400.00000
3	view	18570.00000	1027.99100	18.06400	0.00000	16600.00000	20600.00000
4	floors	6297.17480	1323.42200	4.75800	0.00000	3703.11100	8891.23900
5	waterfront	5151.69330	988.90700	5.20900	0.00000	3213.31700	7090.06900
6	bathrooms	2976.65490	1520.42900	1.95800	0.05000	-3.56700	5956.87700
7	sqft_basement	-5926.42460	1283.98800	-4.61600	0.00000	-8443.19400	-3409.65500
8	bedrooms	-7621.34440	1219.39500	-6.25000	0.00000	-10000.00000	-5231.18600
9	sqft_living_compared	-15160.00000	1272.79700	-11.90700	0.00000	-17700.00000	-12700.00000

In [611...
```
sns.barplot(data=House_Sum.iloc[:10],x='index',y='coef', color='Green')
plt.xlabel('City', fontsize=18)
plt.ylabel('Value Added Dollars',fontsize=15)
plt.xticks(rotation=45);
plt.title('Top Ten Coefficients Per House Feature Scaled',size=15)
```

Out[611...
```
Text(0.5, 1.0, 'Top Ten Coefficients Per House Feature Scaled')
```



Based on the scaled data, an improvement of one standard deviation of the square-foot living space would add 97,400 dollars to the value of a home. The grade and condition column are the next ranked coefficients when scaled. View also ranks as another feature, but certainly one that cannot be altered.

I would think it best to use these coefficients to look at their real dollar value.

Real Dollar Coefficients

In [608...
```
real_results_summary = Stats_Mod_Helper(y_train,X_train)

real_results_as_html = real_results_summary.tables[1].as_html()
real_Results_df = pd.read_html(real_results_as_html, header=0, index_col=0)[0]
```

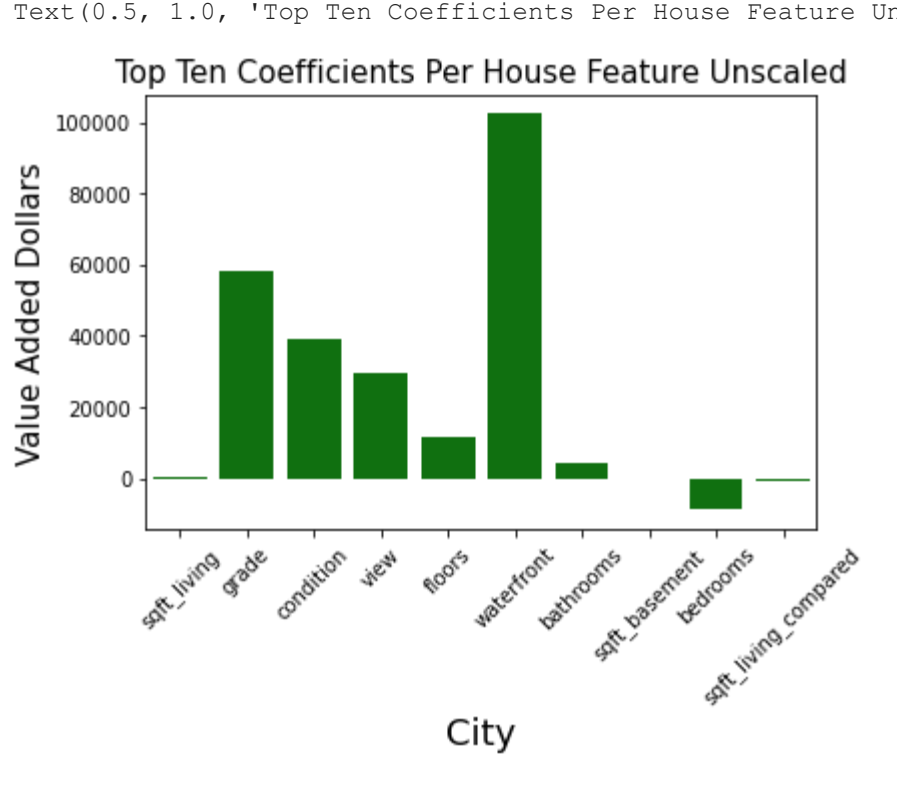
In [594...
```
order = House_Sum.index
```

In [602...
```
real_Results_df
real_House_Sum = real_Results_df.loc[house_features,:]
real_House_Sum = real_House_Sum.reindex(index=order).reset_index()
```

In the unscaled version of the model, ranked by the scaled values. An additional square footage of living space would add 126 to a property with only a standard error of $2.66. An additional floor would add 11,700. Certainly an improvement of Grade or Condition would yield value, but these may be harder to practically achieve.

In [604...
```
sns.barplot(data=real_House_Sum.iloc[:10],x='index',y='coef', color='Green')
plt.xlabel('City', fontsize=18)
plt.ylabel('Value Added Dollars',fontsize=15)
plt.xticks(rotation=45);
plt.title('Top Ten Coefficients Per House Feature Unscaled',size=15)
```

Out[604...
```
Text(0.5, 1.0, 'Top Ten Coefficients Per House Feature Unscaled')
```



Location Assessment

In [596...
```
Location_Sum = Results_df.loc[city_cols,:]
Location_Sum = Location_Sum.sort_values(by='coef',ascending=False)
Location_Sum = Location_Sum.reset_index()
```

Examining the One-hot encoded coefficients, the value added to the home price is displayed in the above dataframe.

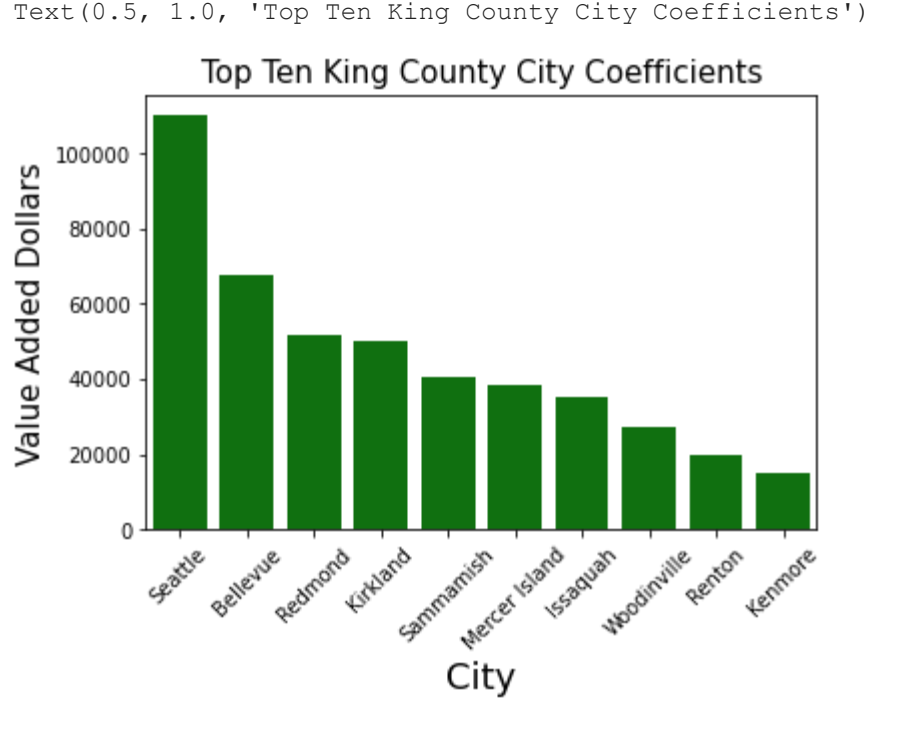
In [597...
```
Location_Sum.iloc[:10]
```

Out[597...

	index	coef	std err	t	P>|t|	[0.025	0.975]
0	Seattle	110200.00000	2313.18200	47.65500	0.00000	106000.00000	115000.00000
1	Bellevue	67590.00000	1363.33000	49.58000	0.00000	64900.00000	70300.00000
2	Redmond	51540.00000	1310.08000	39.34000	0.00000	49000.00000	54100.00000
3	Kirkland	49840.00000	1278.00500	39.00000	0.00000	47300.00000	52300.00000
4	Sammamish	40750.00000	1265.37500	32.20200	0.00000	38300.00000	43200.00000
5	Mercer Island	38280.00000	1021.95500	37.45700	0.00000	36300.00000	40300.00000
6	Issaquah	35400.00000	1226.18300	28.86900	0.00000	33000.00000	37800.00000
7	Woodinville	27010.00000	1137.78400	23.73500	0.00000	24800.00000	29200.00000
8	Renton	19870.00000	1462.43600	13.58600	0.00000	17000.00000	22700.00000
9	Kenmore	15210.00000	1047.46100	14.52000	0.00000	13200.00000	17300.00000

In [598...
```
sns.barplot(data=Location_Sum.iloc[:10],x='index',y='coef', color='Green')
plt.xlabel('City', fontsize=18)
plt.ylabel('Value Added Dollars',fontsize=15)
plt.xticks(rotation=45);
plt.title('Top Ten King County City Coefficients',size=15)
```

Out[598...
```
Text(0.5, 1.0, 'Top Ten King County City Coefficients')
```



Conclusions

- The model showed an R-Squared of nearly 70%, with what appeared to be close to normality of residuals and some problems with Heteroskedasticity. Outliers were dropped from the dataset and I believe the model struggled with higher priced homes.
- I superior model could have dealt with location data differently, as its my belief location plays a strong role in the price. I think there might be a city interaction that could have been built into the model.
- As always more recent data, especially during and after Covid would be helpful.

In [ ]: