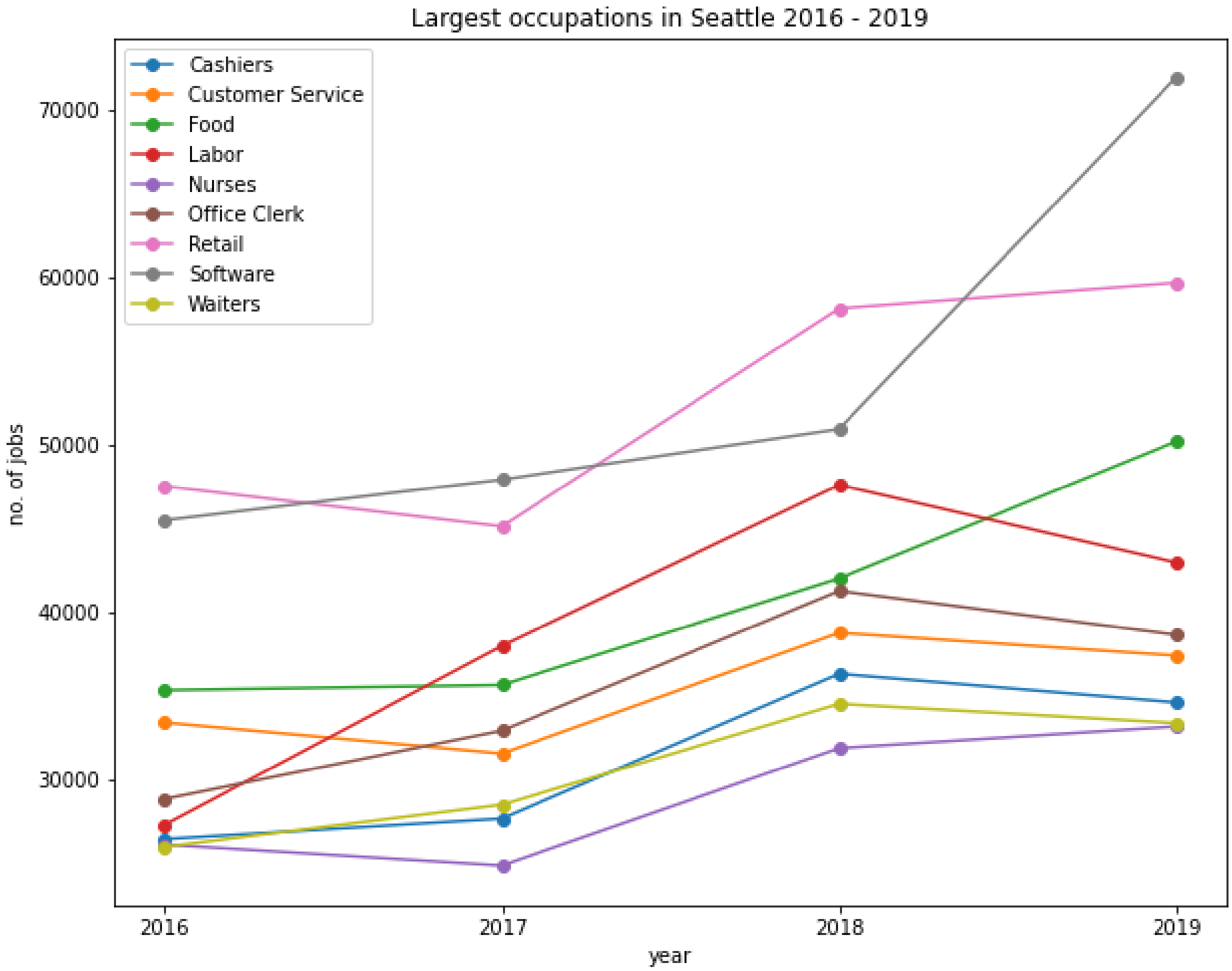
In [1]:
```
# Import packages
import pandas as pd # Reading csv file
import matplotlib.pyplot as plt # for plotting
import numpy as np
```

In [2]:
```
# data sourced from US Bureau of Labor & Statistics www.bls.gov
df = pd.read_csv('data/Largest_occupations_Seattle-Bellevue-Everett_2016-2019.
df['Year'] = df['Year'].astype('int64')
df = df.sort_values(by=['Year'])
df.head(3)
```

Out[2]:

	Description	Group	Employment	Year
35	Waiters and Waitresses	Waiters	25990	2016
18	Registered Nurses	Nurses	26120	2016
3	Cashiers	Cashiers	26450	2016

In [3]:
```
# graph occupations by year
xlabels = []
fig, ax = plt.subplots(figsize=(10,8))
for key, grp in df.groupby(['Group']):
    ax.plot(grp['Year'], grp['Employment'], label=key, marker='o')
plt.title('Largest occupations in Seattle 2016 - 2019')
plt.xticks(np.arange(2016, 2020))
ax.legend(loc="best")
ax.set_xlabel('year')
ax.set_ylabel('no. of jobs')
plt.show()
```


Largest occupations in Seattle 2016 - 2019
Cashiers
Customer Service
Food
Labor
Nurses
Office Clerk
Retail
Software
Waiters
70000
60000
50000
40000
30000
no. of jobs
2016
2017
2018
2019
year

```
In [ ]:
```

In [1]:
```
# Import packages
import pandas as pd # Reading csv file
from shapely.geometry import Point # Shapely for converting latitude/longtitud
import geopandas as gpd # To create GeodataFrame
import matplotlib.pyplot as plt # for plotting
from pyproj import CRS
```

In [2]:
```
# import housing data
df_all = pd.read_csv('data/kc_house_data.csv')
df_all.head(10)
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
0	7129300520	10/13/2014	221900	3	1.00	1180	5650	1.0	
1	6414100192	12/9/2014	538000	3	2.25	2570	7242	2.0	
2	5631500400	2/25/2015	180000	2	1.00	770	10000	1.0	
3	2487200875	12/9/2014	604000	4	3.00	1960	5000	1.0	
4	1954400510	2/18/2015	510000	3	2.00	1680	8080	1.0	
5	7237550310	5/12/2014	1230000	4	4.50	5420	101930	1.0	
6	1321400060	6/27/2014	257500	3	2.25	1715	6819	2.0	
7	2008000270	1/15/2015	291850	3	1.50	1060	9711	1.0	
8	2414600126	4/15/2015	229500	3	1.00	1780	7470	1.0	
9	3793500160	3/12/2015	323000	3	2.50	1890	6560	2.0	

10 rows × 21 columns

In [9]:
```
# clean data--convert "NaN" to 0 and replace "?" with 0
df_all = df_all.fillna(0).replace('?',0)
df_all.head(10)
```

Out[9]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
0	7129300520	10/13/2014	221900	3	1.00	1180	5650	1.0	
1	6414100192	12/9/2014	538000	3	2.25	2570	7242	2.0	
2	5631500400	2/25/2015	180000	2	1.00	770	10000	1.0	
3	2487200875	12/9/2014	604000	4	3.00	1960	5000	1.0	
4	1954400510	2/18/2015	510000	3	2.00	1680	8080	1.0	
5	7237550310	5/12/2014	1230000	4	4.50	5420	101930	1.0	
6	1321400060	6/27/2014	257500	3	2.25	1715	6819	2.0	

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
7	2008000270	1/15/2015	291850	3	1.50	1060	9711	1.0	
8	2414600126	4/15/2015	229500	3	1.00	1780	7470	1.0	
9	3793500160	3/12/2015	323000	3	2.50	1890	6560	2.0	

10 rows × 21 columns

In [16]:

```python
# filter properties
df = df_all[(df_all['price'] <= 1050000) &
            (df_all['price'] >= 105000)]
df
```

Out[16]:

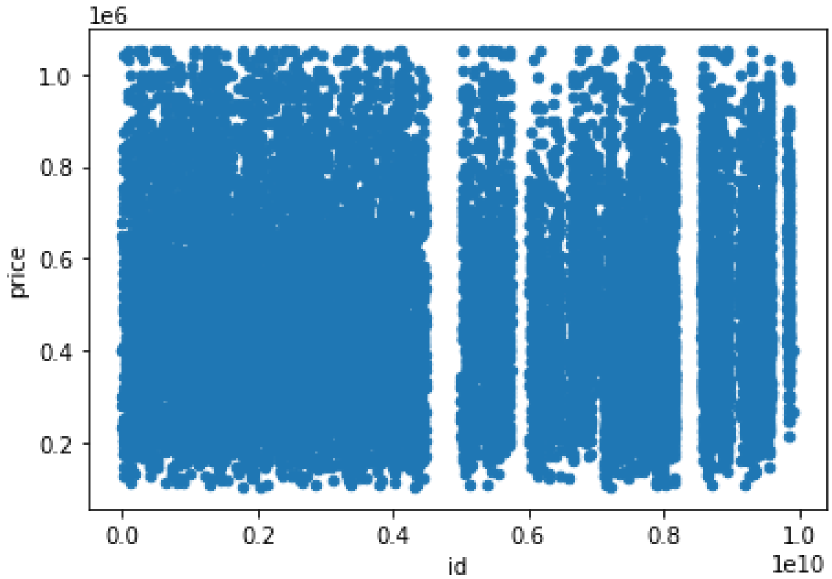
	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7129300520	10/13/2014	221900	3	1.00	1180	5650	1.0
1	6414100192	12/9/2014	538000	3	2.25	2570	7242	2.0
2	5631500400	2/25/2015	180000	2	1.00	770	10000	1.0
3	2487200875	12/9/2014	604000	4	3.00	1960	5000	1.0
4	1954400510	2/18/2015	510000	3	2.00	1680	8080	1.0
...	...	...	...	...	...	...	...	...
21592	263000018	5/21/2014	360000	3	2.50	1530	1131	3.0
21593	6600060120	2/23/2015	400000	4	2.50	2310	5813	2.0
21594	1523300141	6/23/2014	402101	2	0.75	1020	1350	2.0
21595	291310100	1/16/2015	400000	3	2.50	1600	2388	2.0
21596	1523300157	10/15/2014	325000	2	0.75	1020	1076	2.0

20250 rows × 21 columns

In [17]:

```python
# want to look at price range
df.plot(kind='scatter', x='id', y='price')
```

Out[17]: <AxesSubplot:xlabel='id', ylabel='price'>



In [18]:

```
# function to create GeoDataFrame
def add_geo_col(df):
    # create a geometry column
    geometry = [Point(xy) for xy in zip(df['long'], df['lat'])]

    # Coordinate reference system : WGS84 (the GPS model for conversion)
    crs = CRS('epsg:4326')

    # Creating a Geographic data frame
    gdf = gpd.GeoDataFrame(df, crs=crs, geometry=geometry).reset_index()
    return gdf
```

In [19]:

```
gdf = add_geo_col(df)
gdf.head()
```

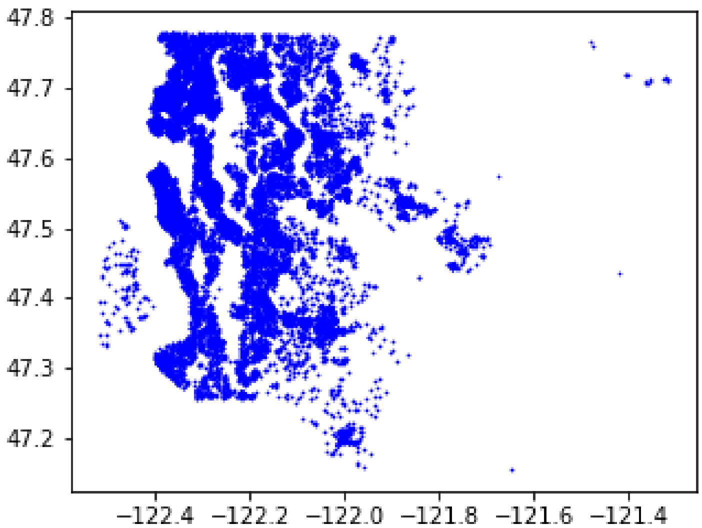
Out[19]:

	index	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floo
0	0	7129300520	10/13/2014	221900	3	1.00	1180	5650	1.
1	1	6414100192	12/9/2014	538000	3	2.25	2570	7242	2.
2	2	5631500400	2/25/2015	180000	2	1.00	770	10000	1.
3	3	2487200875	12/9/2014	604000	4	3.00	1960	5000	1.
4	4	1954400510	2/18/2015	510000	3	2.00	1680	8080	1.

5 rows × 23 columns

In [20]:
```
# Plot all points
gdf.plot(marker='o', color='b', markersize=0.5)
```

Out[20]: <AxesSubplot:>



In [10]:
```
# check what projection is used
gdf.crs
```

Out[10]:
```
<Geographic 2D CRS: EPSG:4326>
Name: WGS 84
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
Area of Use:
- name: World
- bounds: (-180.0, -90.0, 180.0, 90.0)
Datum: World Geodetic System 1984
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

In [21]:
```
# function to convert meters to miles
def m_2_mi(meters):
    return meters * 0.00062137
```

In [22]:
```
# function to find distance between two Points
def dist_to_point(point1, point2):
    pt1_gdf = gpd.GeoSeries([point1], crs=4326)
    pt2_gdf = gpd.GeoSeries([point2], crs=4326)
    pt1_gdf = pt1_gdf.to_crs(3857)
    pt2_gdf = pt2_gdf.to_crs(3857)
    distance = m_2_mi(pt1_gdf.distance(pt2_gdf))
    return round(distance.at[0], 3)
```

In [13]:
```
# Want to compile list of top 5 employers in Seattle area with a centralized c
```

```
# Source is https://www.huduser.gov/portal/publications/pdf/SeattleWA-CHMA-19.
# df_top10_employers = pd.read_csv('data/top_employers.csv')
# df_central5 = df_top10_employers[df_top10_employers['centralized_campus']==
# df_central5 = add_geo_col(df_central5)
# df_central5
```

Out[13]:

	level_0	index	rank	employer	no_employees	long	lat	centralized_cam
0	0	0	1	The Boeing Company	64,300	-122.312023	47.532685	
1	1	1	2	Amazon.com, Inc.	45,000	-122.339688	47.615875	
2	2	2	3	Microsoft Corporation	43,031	-122.339688	47.645744	
3	3	3	4	University of Washington	30,200	-122.303644	47.655544	
4	4	7	8	Starbucks Corporation	11,239	-122.336000	47.580700	

In [14]:

```
# function to find the average distance of a house to the top 5 employers
# def avg_dists(point1, gdf):
#     dists = [dist_to_point(point1, point2) for point2 in gdf['geometry']]
#     avg = sum(dists)/len(dists)
#     return avg
```

In [23]:

```
downtown = Point(-122.3344, 47.6050) # coordinates for center of downtown Seat

# Calculate average distance of each property to central downtown
gdf['dist_2_downtown'] = [dist_to_point(point, downtown) for point in gdf['geo
```

In [16]:

```
# Calculate average distance of each property to the top 5 employers
# gdf['avg_dists'] = [avg_dists(point, df_central5) for point in gdf['geometry
```

In [24]:

```
gdf.head()
```

Out[24]:

	index	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floor
0	0	7129300520	10/13/2014	221900	3	1.00	1180	5650	1.
1	1	6414100192	12/9/2014	538000	3	2.25	2570	7242	2.

	index	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floo
2	2	5631500400	2/25/2015	180000	2	1.00	770	10000	1.
3	3	2487200875	12/9/2014	604000	4	3.00	1960	5000	1.
4	4	1954400510	2/18/2015	510000	3	2.00	1680	8080	1.

5 rows × 24 columns

In [25]:
```
gdf.to_pickle('data/geodata.pkl')
```

In [ ]:

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
import numpy as np
from statsmodels.stats.outliers_influence import variance_inflation_factor
import scipy.stats as stats
from statsmodels.formula.api import ols
from statsmodels.stats.diagnostic import het_white
from matplotlib.cbook import boxplot_stats
```

In [2]:
```
# Load data from other notebook
gdf = pd.read_pickle('data/geodata.pkl')
df = pd.DataFrame(gdf)
```

In [3]:
```
df.columns
```

Out[3]:
```
Index(['index', 'id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15', 'geometry',
       'dist_2_downtown'],
      dtype='object')
```

In [4]:
```
df = df.fillna(0).replace('?',0).replace('"?',0)
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20250 entries, 0 to 20249
Data columns (total 24 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   index           20250 non-null  int64
 1   id              20250 non-null  int64
 2   date            20250 non-null  object
 3   price           20250 non-null  int64
 4   bedrooms        20250 non-null  int64
 5   bathrooms       20250 non-null  float64
 6   sqft_living     20250 non-null  int64
 7   sqft_lot        20250 non-null  int64
 8   floors          20250 non-null  float64
 9   waterfront      20250 non-null  float64
 10  view            20250 non-null  float64
 11  condition       20250 non-null  int64
 12  grade           20250 non-null  int64
 13  sqft_above      20250 non-null  object
 14  sqft_basement   20250 non-null  object
 15  yr_built        20250 non-null  int64
 16  yr_renovated    20250 non-null  float64
 17  zipcode         20250 non-null  int64
 18  lat             20250 non-null  float64
 19  long            20250 non-null  float64
 20  sqft_living15   20250 non-null  int64
 21  sqft_lot15      20250 non-null  int64
```

```
 22  geometry         20250 non-null  object 
 23  dist_2_downtown  20250 non-null  float64
dtypes: float64(8), int64(12), object(4)
memory usage: 3.7+ MB
```

In [6]:
```
# Clean up the data to change strings to integers and delete unnecessary colum
df['sqft_above'] = df['sqft_above'].astype(int)
df['sqft_basement'] = df['sqft_basement'].astype(int)
df = df.drop(columns=['index', 'id', 'geometry'])
df['yr_renovated'] = df['yr_renovated'].astype(int)
```

In [7]:
```
# Converting date to datetime
df['date'] = pd.to_datetime(df['date'])
df['date'] = df['date'].dt.month
```

In [8]:
```
df_b4_dummies = df.copy()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20250 entries, 0 to 20249
Data columns (total 21 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   date             20250 non-null  int64  
 1   price            20250 non-null  int64  
 2   bedrooms         20250 non-null  int64  
 3   bathrooms        20250 non-null  float64
 4   sqft_living      20250 non-null  int64  
 5   sqft_lot         20250 non-null  int64  
 6   floors           20250 non-null  float64
 7   waterfront       20250 non-null  float64
 8   view             20250 non-null  float64
 9   condition        20250 non-null  int64  
 10  grade            20250 non-null  int64  
 11  sqft_above       20250 non-null  int32  
 12  sqft_basement    20250 non-null  int32  
 13  yr_built         20250 non-null  int64  
 14  yr_renovated     20250 non-null  int32  
 15  zipcode          20250 non-null  int64  
 16  lat              20250 non-null  float64
 17  long             20250 non-null  float64
 18  sqft_living15    20250 non-null  int64  
 19  sqft_lot15       20250 non-null  int64  
 20  dist_2_downtown  20250 non-null  float64
dtypes: float64(7), int32(3), int64(11)
memory usage: 3.0 MB
```

In [9]:
```
df_b4_dummies.head(3)
```

Out[9]:

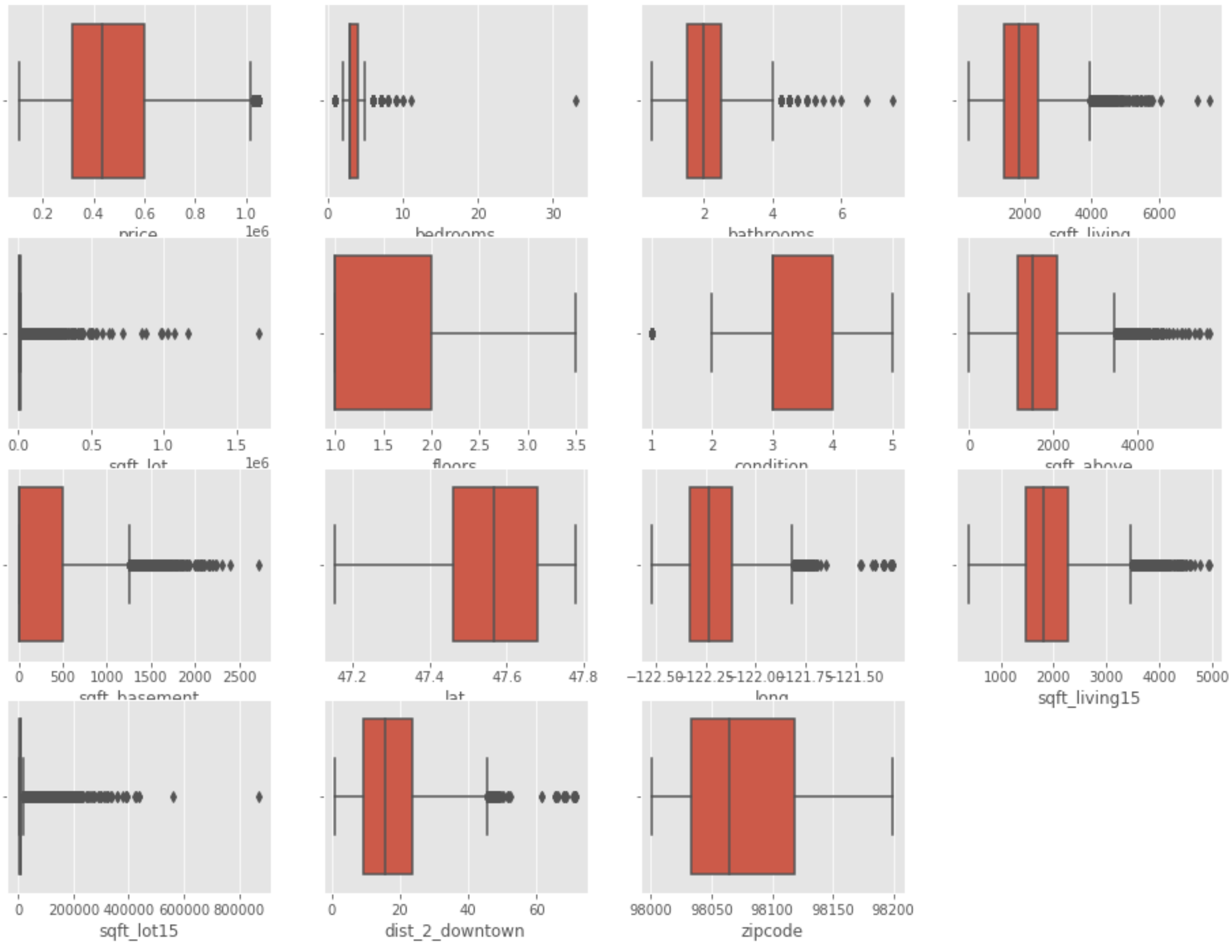
	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	cond
0	10	221900	3	1.00	1180	5650	1.0	0.0	0.0	
1	12	538000	3	2.25	2570	7242	2.0	0.0	0.0	
2	2	180000	2	1.00	770	10000	1.0	0.0	0.0	

3 rows × 21 columns

In [10]:
```
plt.style.use('ggplot')
```

In [11]:
```
# Remove outliers first
cols_to_limit = ['price', 'bedrooms', 'bathrooms', 'sqft_living',
                 'sqft_lot', 'floors', 'condition', 'sqft_above',
                 'sqft_basement', 'lat', 'long', 'sqft_living15',
                 'sqft_lot15', 'dist_2_downtown', 'zipcode']

plot_no = 1
plt.figure(figsize=(16,12))
feat_ranges = []
for col in cols_to_limit:
    plt.subplot(4, 4, plot_no)
    sns.boxplot(x=df_b4_dummies[col])
    feat_ranges.append([col, boxplot_stats(df_b4_dummies[col]).pop(0)['whislo'
                   boxplot_stats(df_b4_dummies[col]).pop(0)['whishi']])
    plot_no += 1

print(feat_ranges)
```

```
[['price', 105000, 1020000], ['bedrooms', 2, 5], ['bathrooms', 0.5, 4.0], ['sq
ft_living', 370, 3950], ['sqft_lot', 520, 18205], ['floors', 1.0, 3.5], ['cond
ition', 2, 5], ['sqft_above', 0, 3470], ['sqft_basement', 0, 1250], ['lat', 4
7.1559, 47.7776], ['long', -122.51899999999999, -121.815], ['sqft_living15', 3
99, 3470], ['sqft_lot15', 651, 17085], ['dist_2_downtown', 1.065, 45.357], ['z
ipcode', 98001, 98199]]
```



In [12]:
```python
# Remove rows with outliers from dataframe
for feat in feat_ranges:
    df_b4_dummies = df_b4_dummies[(df_b4_dummies[feat[0]] >= feat[1])
                                  & (df_b4_dummies[feat[0]] <= feat[2])]
df_b4_dummies
```

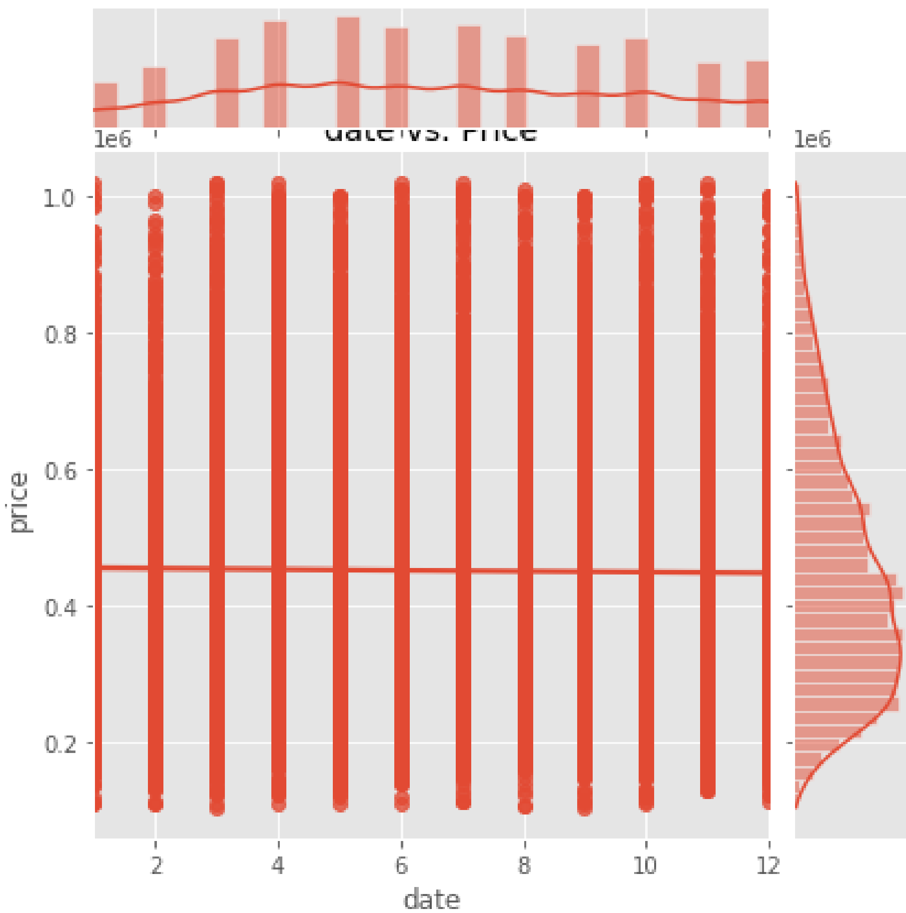
Out[12]:

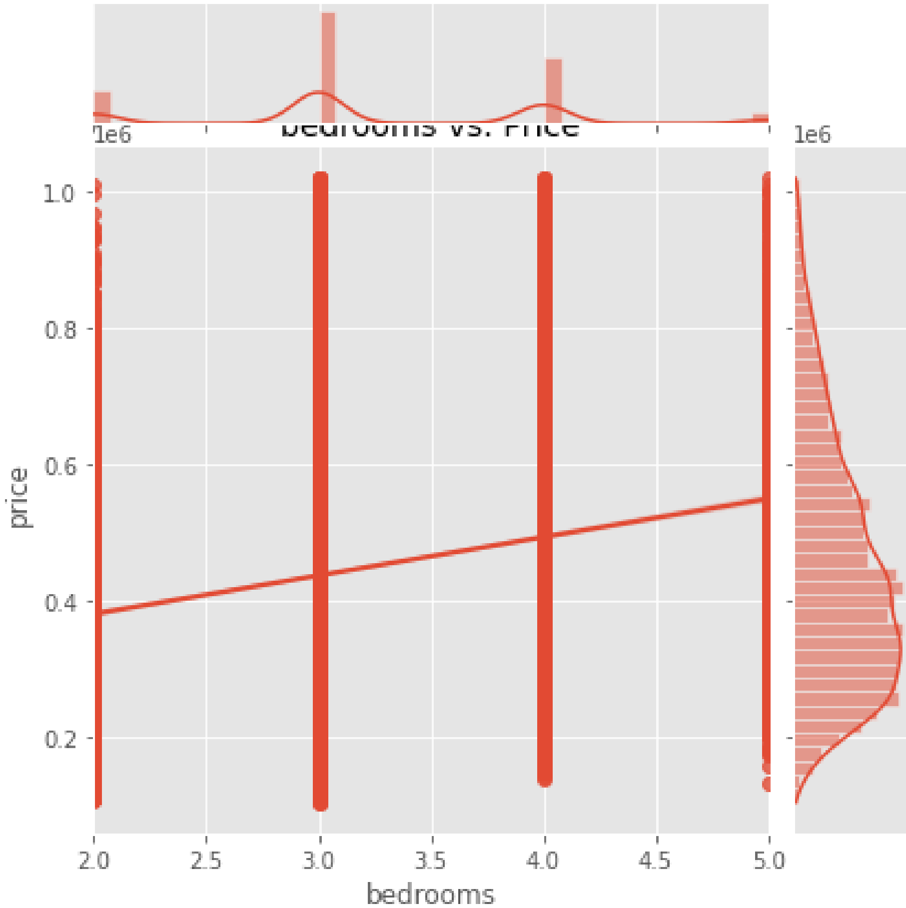
	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
0	10	221900	3	1.00	1180	5650	1.0	0.0	0.0
1	12	538000	3	2.25	2570	7242	2.0	0.0	0.0
2	2	180000	2	1.00	770	10000	1.0	0.0	0.0
3	12	604000	4	3.00	1960	5000	1.0	0.0	0.0
4	2	510000	3	2.00	1680	8080	1.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...
20245	5	360000	3	2.50	1530	1131	3.0	0.0	0.0
20246	2	400000	4	2.50	2310	5813	2.0	0.0	0.0
20247	6	402101	2	0.75	1020	1350	2.0	0.0	0.0
20248	1	400000	3	2.50	1600	2388	2.0	0.0	0.0
20249	10	325000	2	0.75	1020	1076	2.0	0.0	0.0

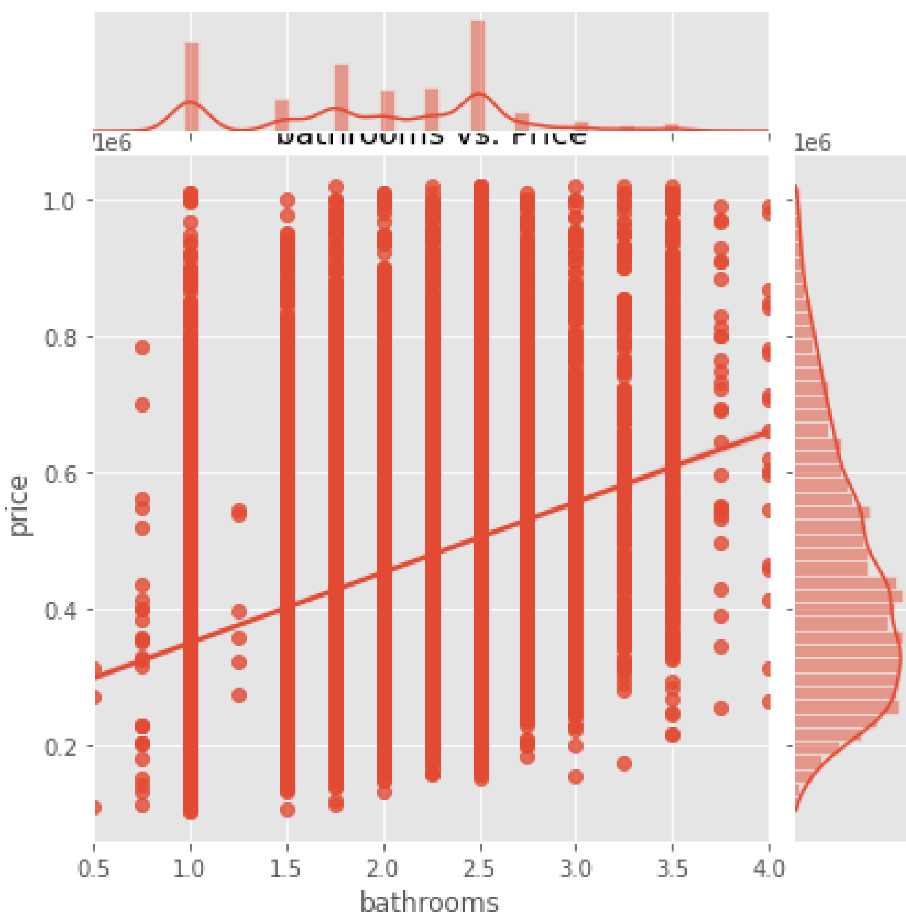
16363 rows × 21 columns

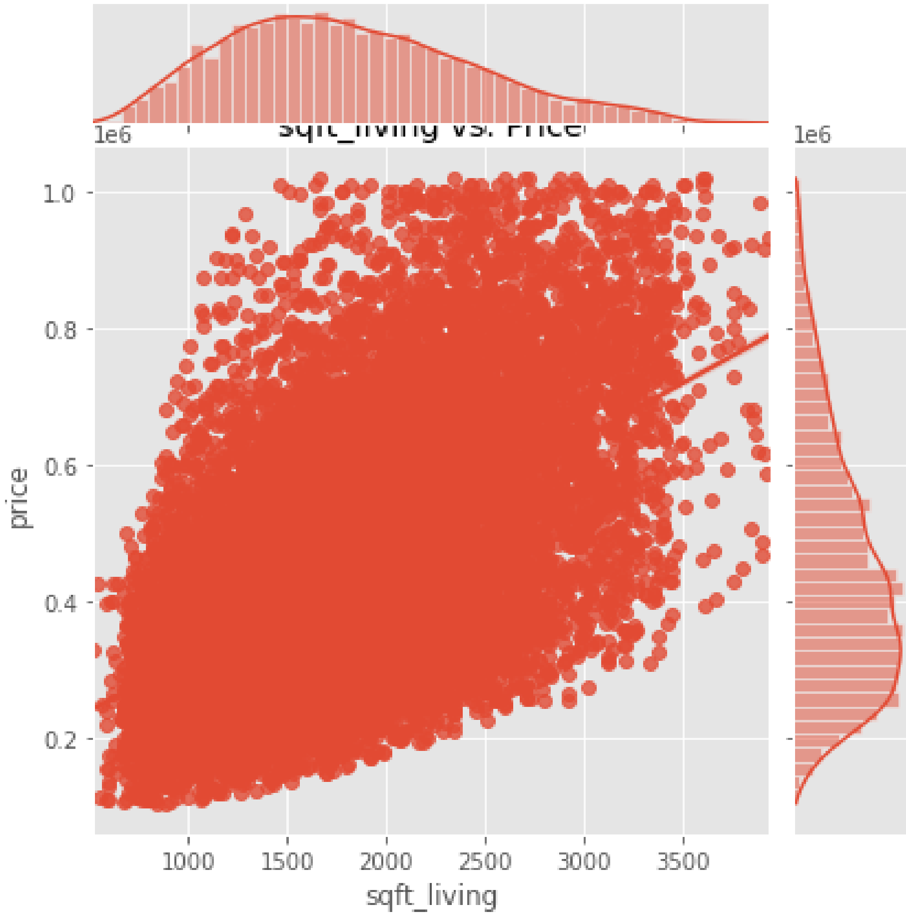
In [13]:
```
# look at features vs. price to get a sense what the influencers are
cols = list(df_b4_dummies.columns)
cols.remove('price')
print(cols)
for col in cols:
    sns.jointplot(x=col, y='price', data=df_b4_dummies, kind='reg')
    title = col+' vs. Price'
    plt.title(title)
```

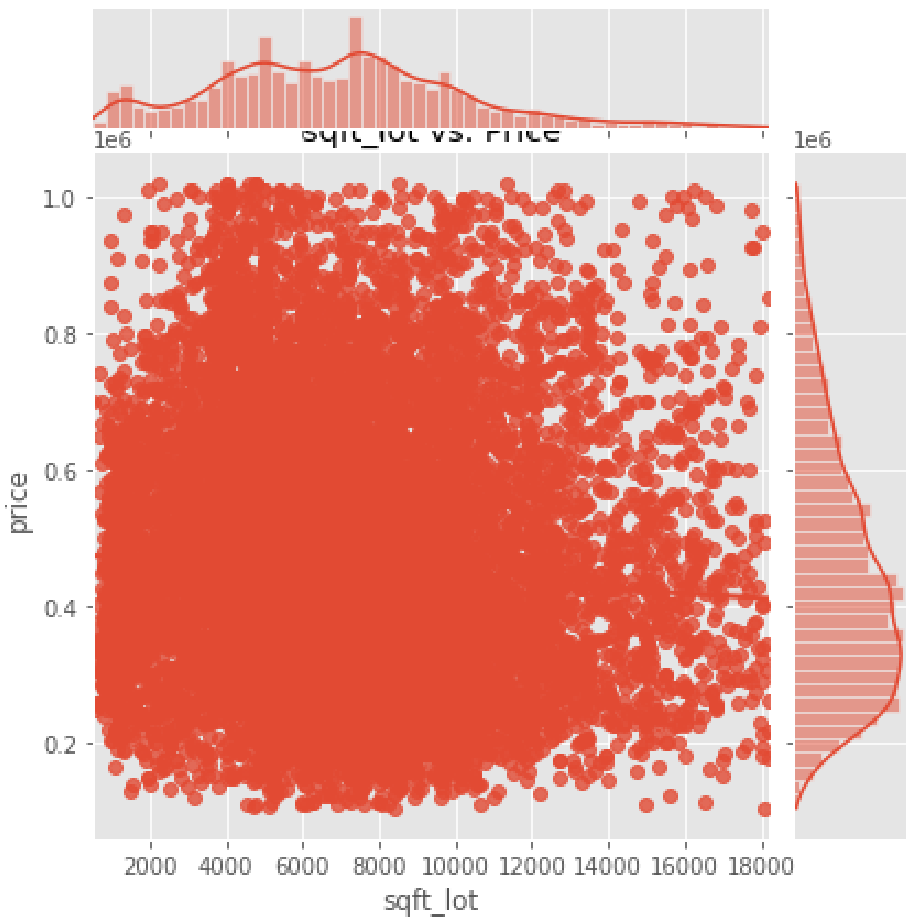
```
['date', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterf
ront', 'view', 'condition', 'grade', 'sqft_above', 'sqft_basement', 'yr_buil
t', 'yr_renovated', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15',
'dist_2_downtown']
```

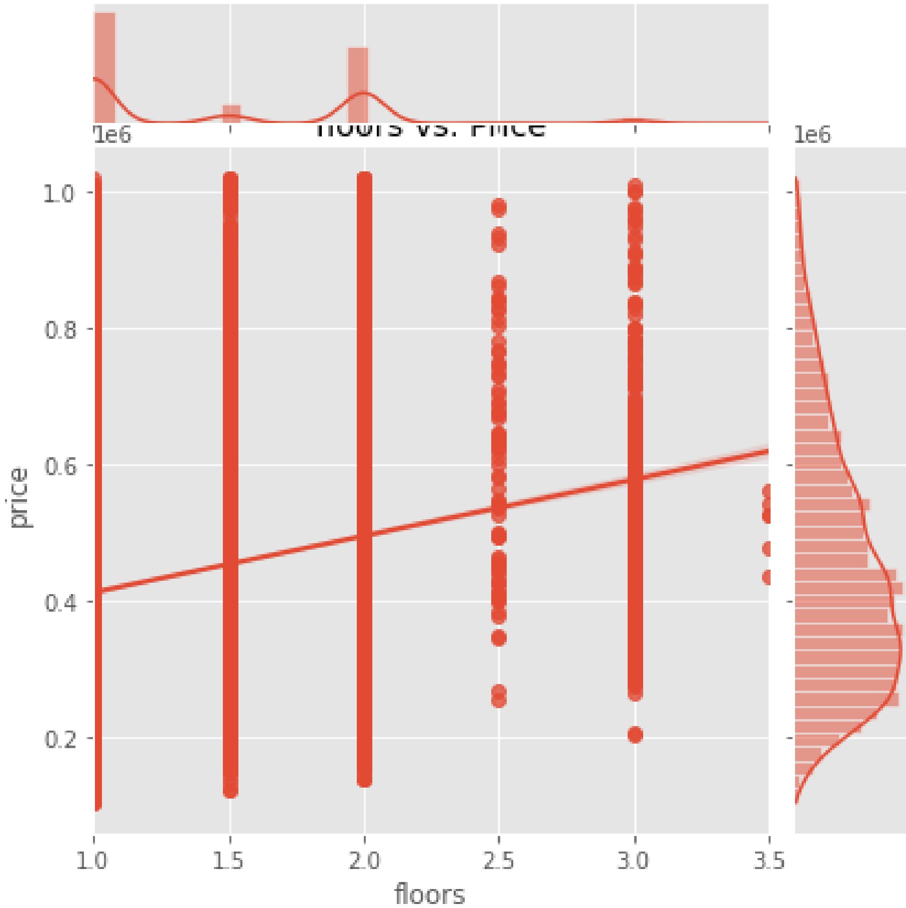


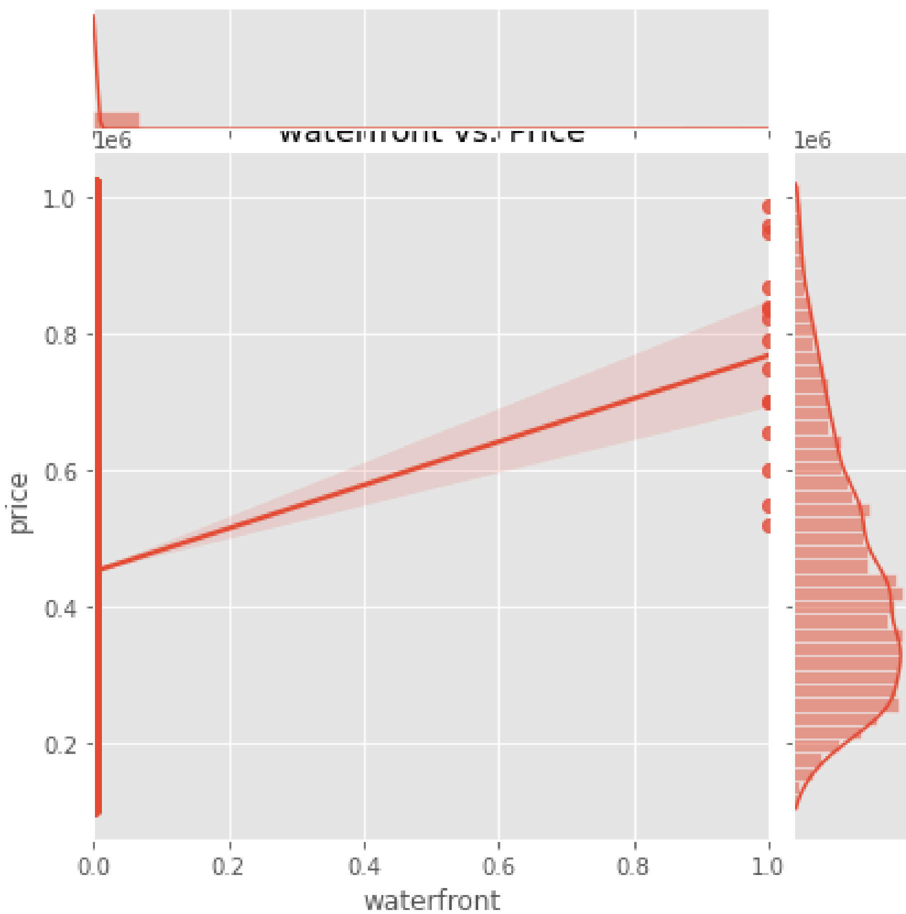

bedrooms vs. Price
1e6
1e6
price
bedrooms
1.0
0.8
0.6
0.4
0.2
2.0
2.5
3.0
3.5
4.0
4.5
5.0

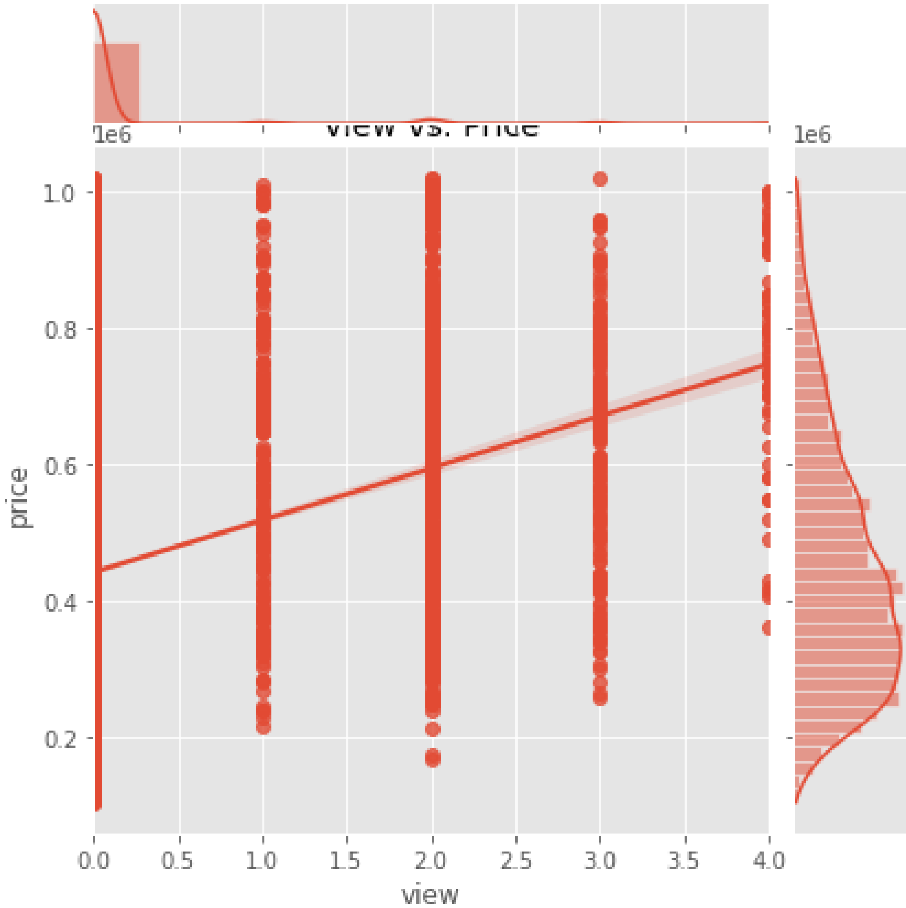

bathrooms vs. Price
1e6
1e6
price
bathrooms
1.0
0.8
0.6
0.4
0.2
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

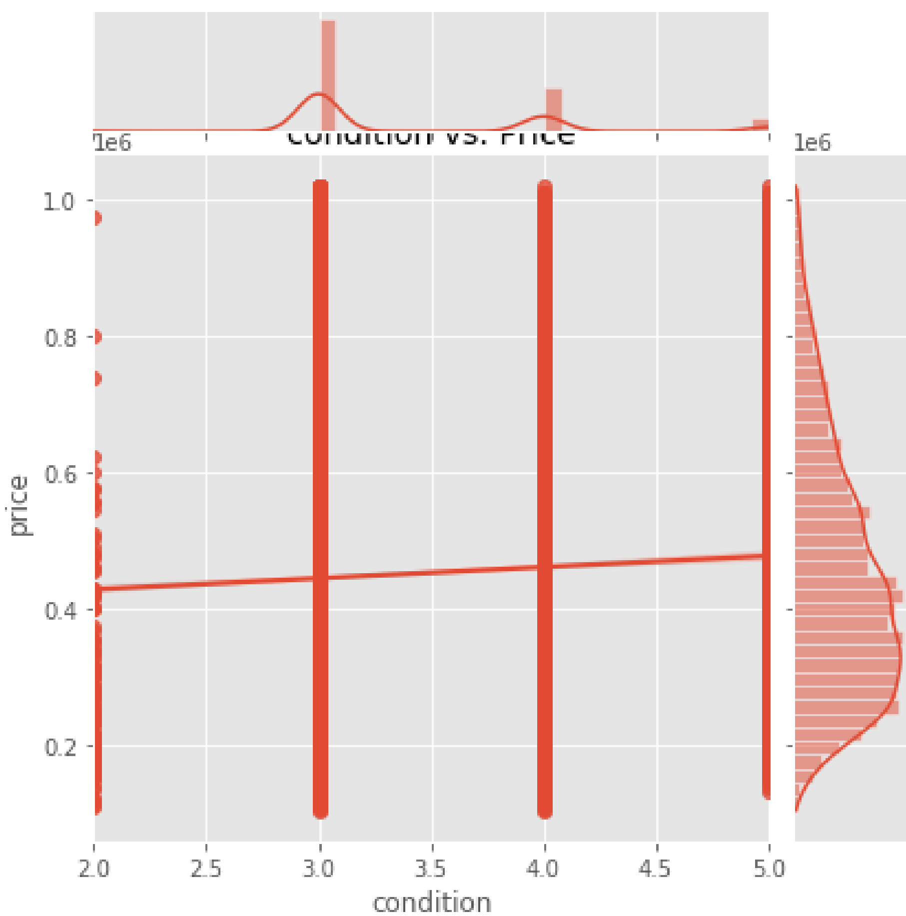

1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
1000
1500
2000
2500
3000
3500
sqft_living

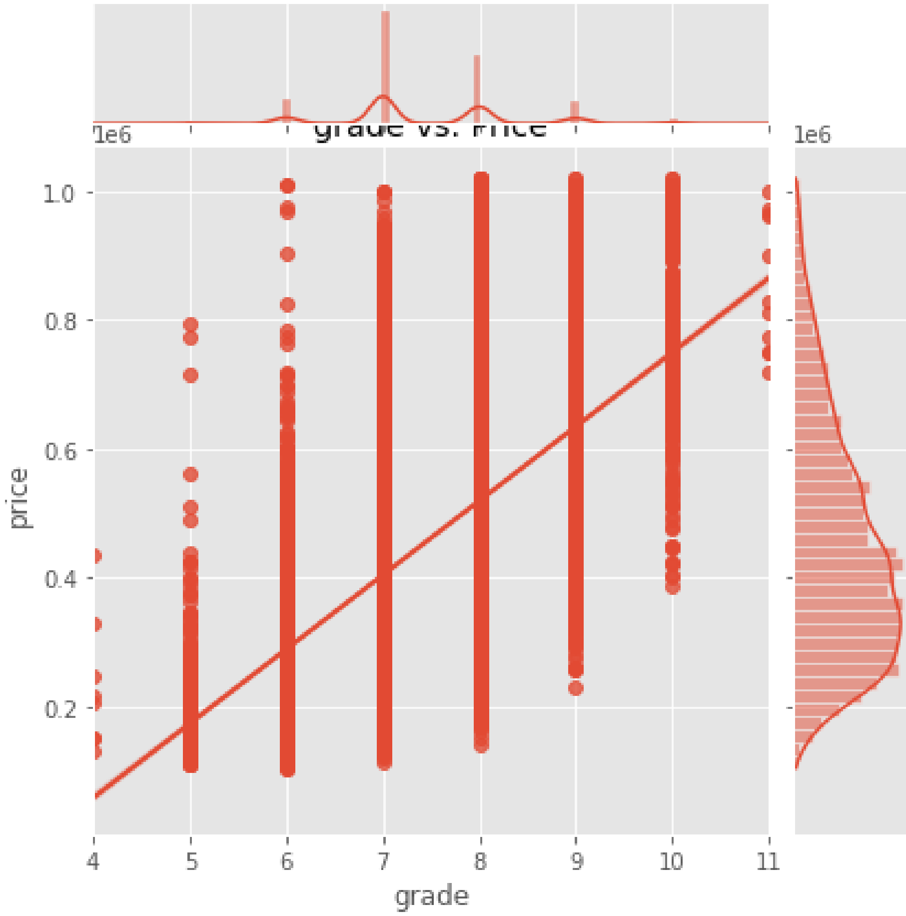

1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
2000
4000
6000
8000
10000
12000
14000
16000
18000
sqft_lot

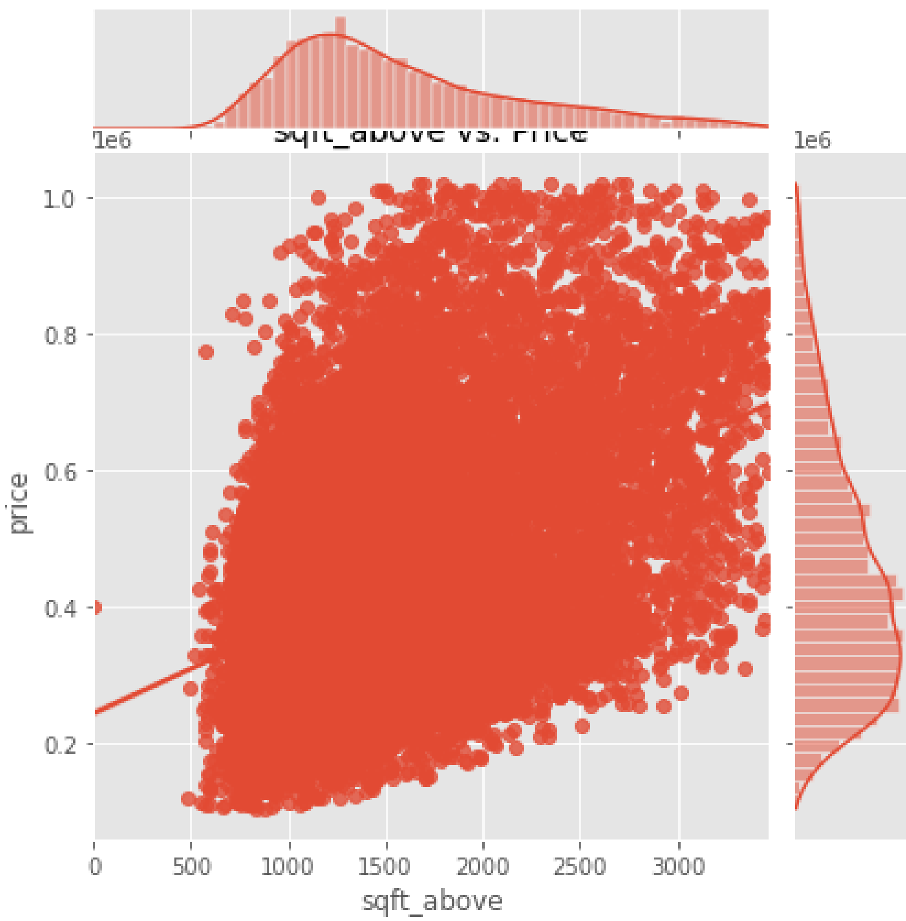

1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
1.0
1.5
2.0
2.5
3.0
3.5
floors

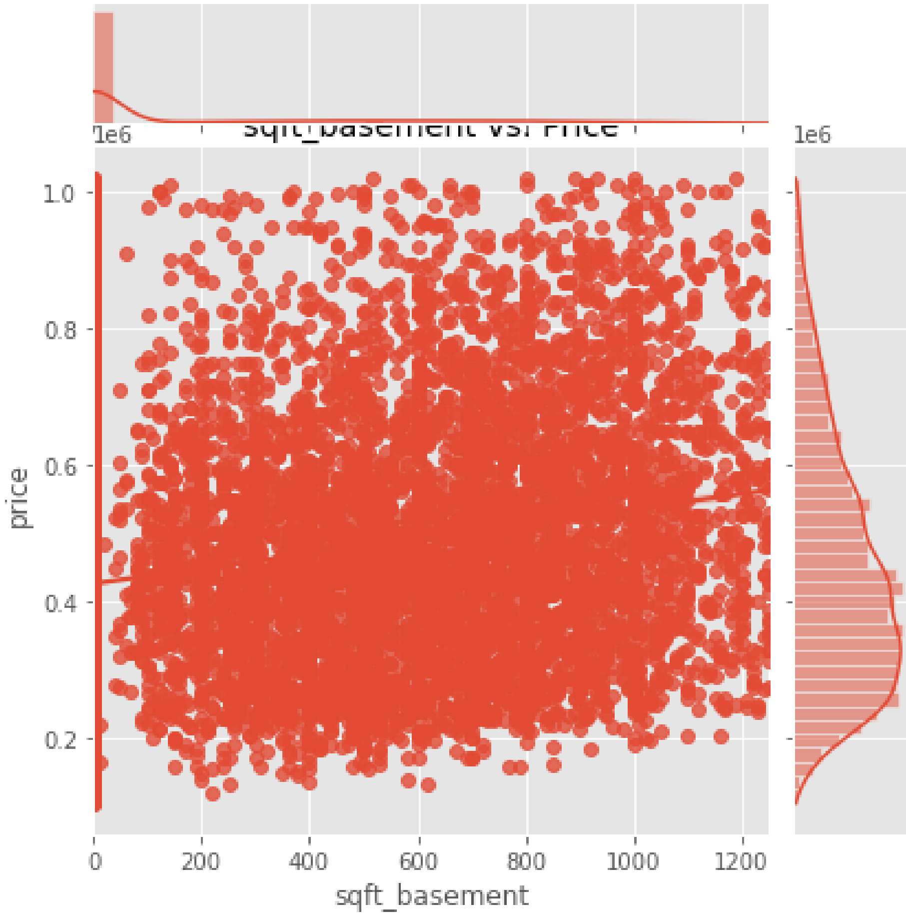

1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
0.0
0.2
0.4
0.6
0.8
1.0
waterfront

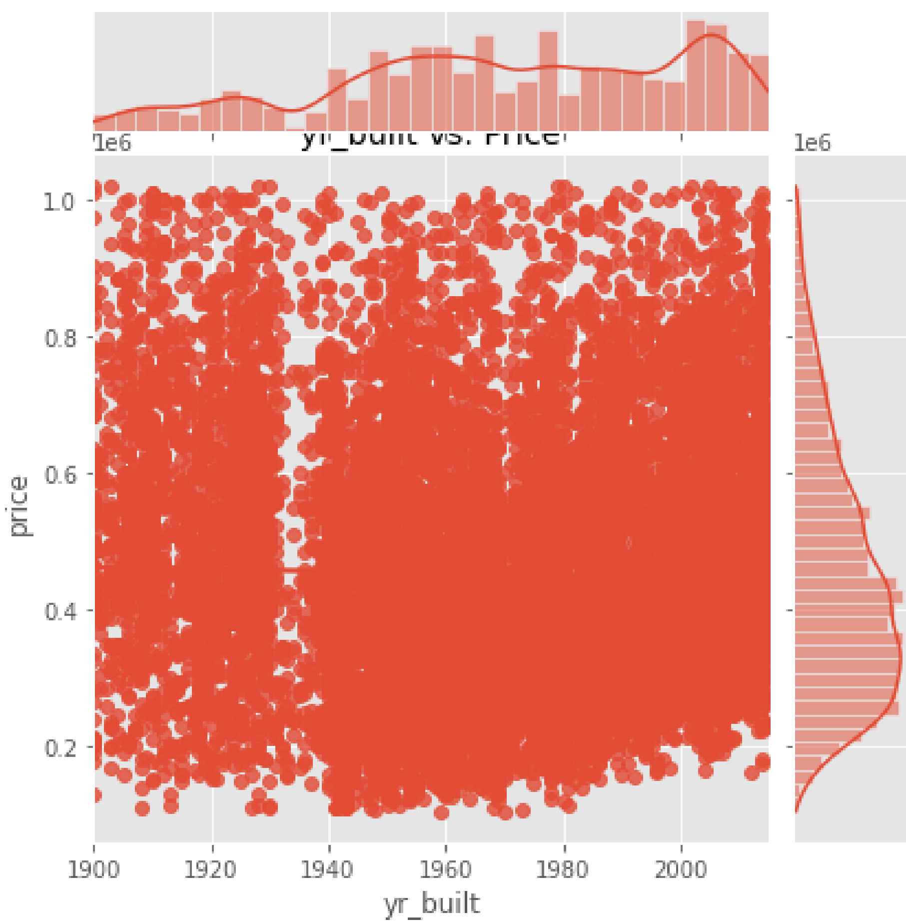

1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
view

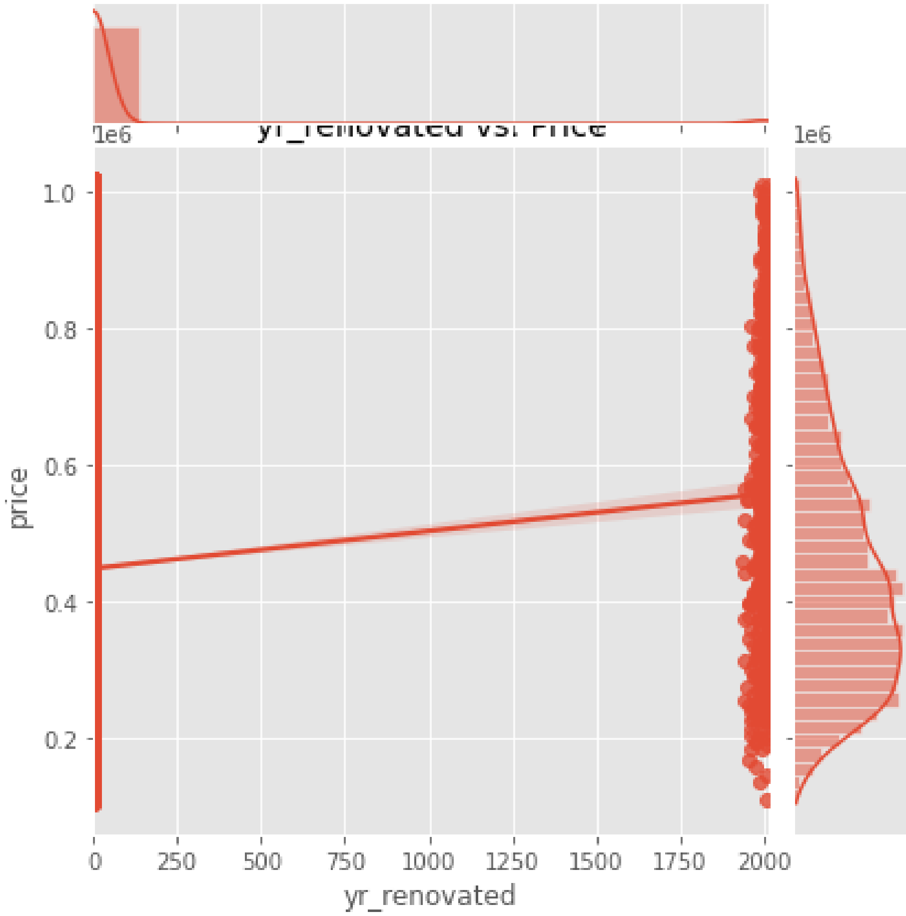

1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
2.0
2.5
3.0
3.5
4.0
4.5
5.0
condition

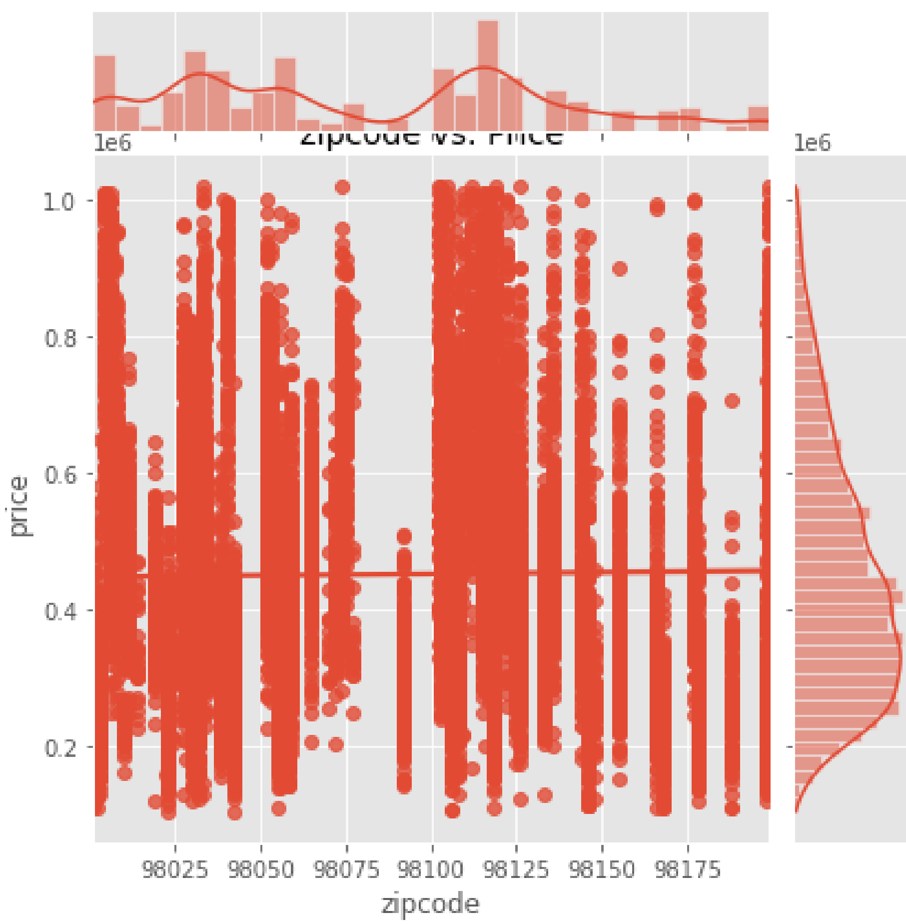

1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
4
5
6
7
8
9
10
11
grade

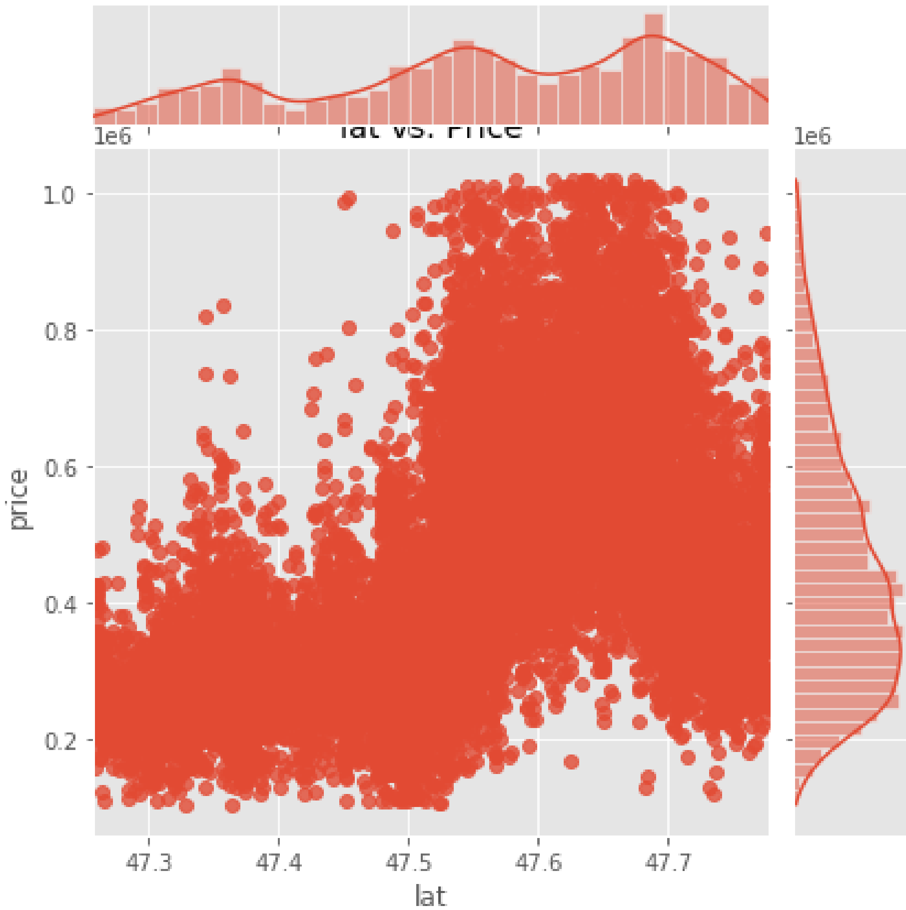

1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
0
500
1000
1500
2000
2500
3000
sqft_above

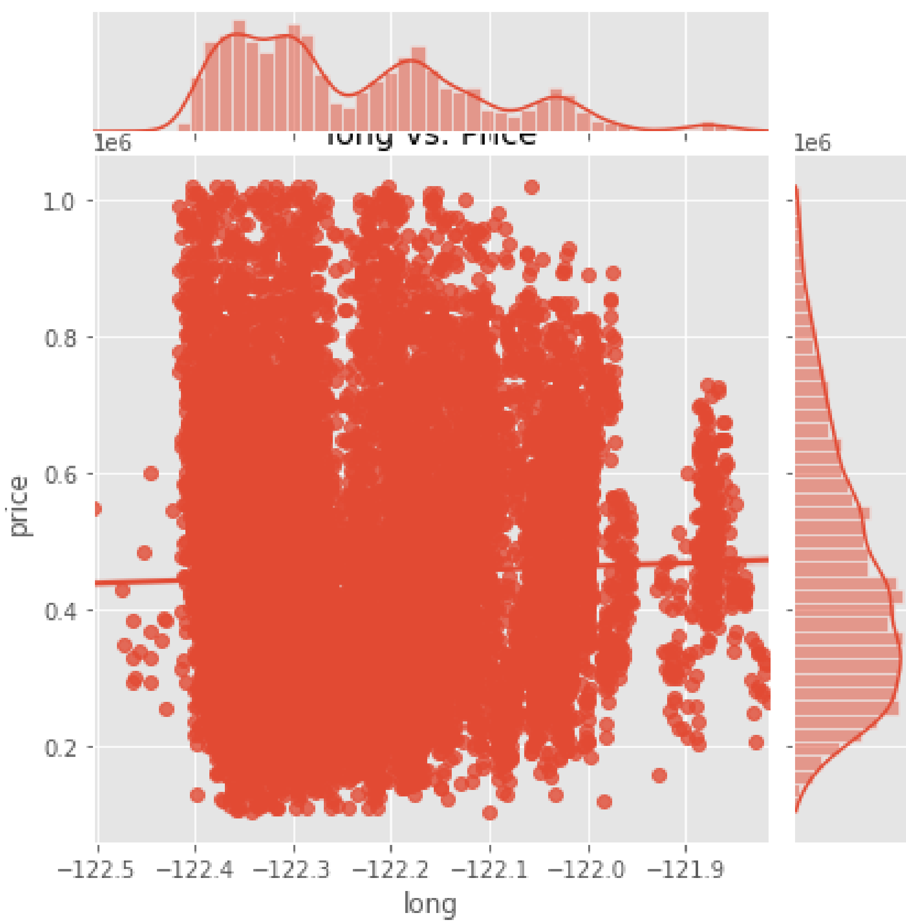

sqft_basement vs. Price
1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
0
200
400
600
800
1000
1200
sqft_basement

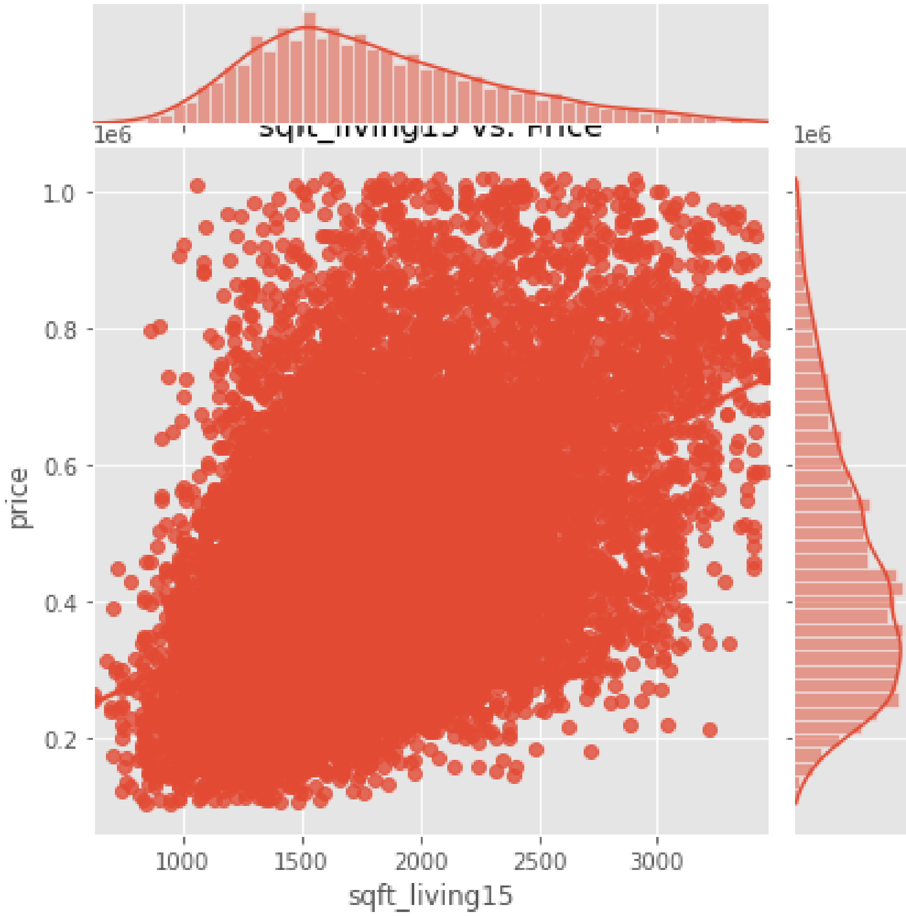

yr_built vs. Price
1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
1900
1920
1940
1960
1980
2000
yr_built

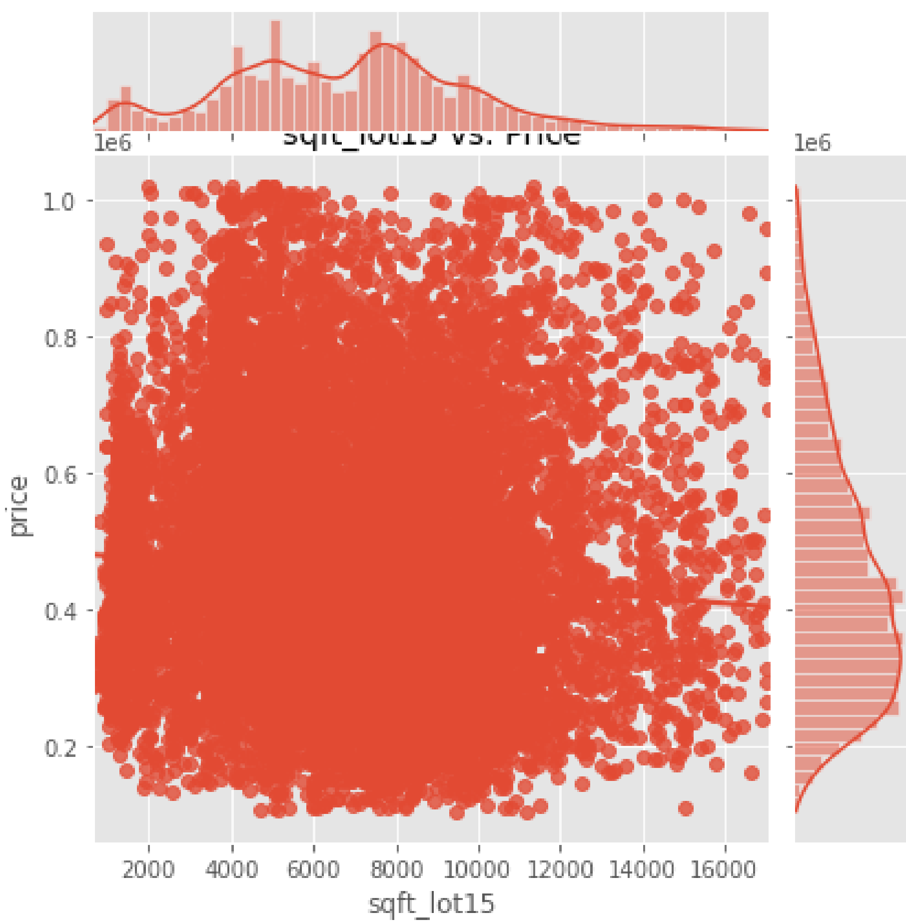

1e6
1e6
price
1.0
0.8
0.6
0.4
0.2
0
250
500
750
1000
1250
1500
1750
2000
yr_renovated

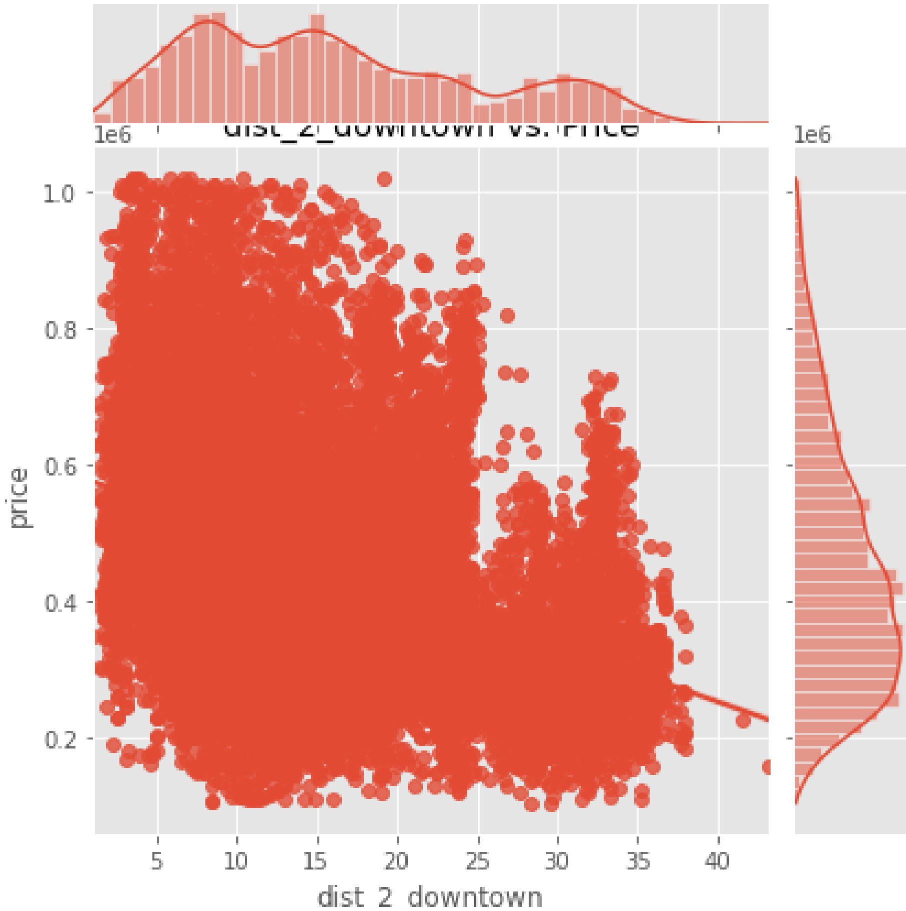

1e6
1e6
price
1.0
0.8
0.6
0.4
0.2
98025
98050
98075
98100
98125
98150
98175
zipcode


1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
47.3
47.4
47.5
47.6
47.7
lat


1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
−122.5
−122.4
−122.3
−122.2
−122.1
−122.0
−121.9
long


sqft_living15 vs. Price
1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
1000
1500
2000
2500
3000
sqft_living15

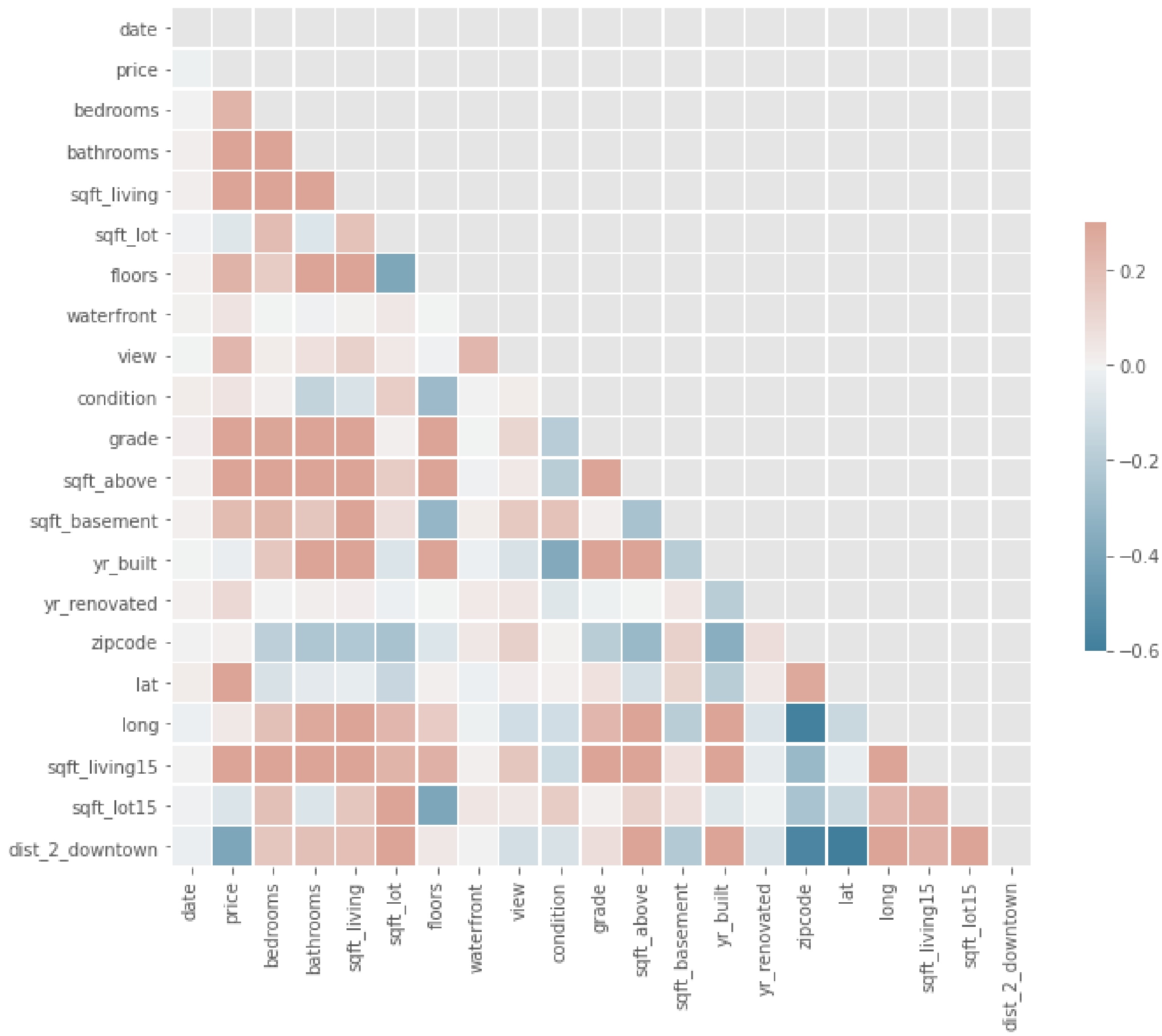

sqft_lot15 vs. Price
1e6
1e6
1.0
0.8
0.6
0.4
0.2
price
2000
4000
6000
8000
10000
12000
14000
16000
sqft_lot15



In [14]:

```
# Create a heatmap to identify any features with obvious multicollinearity

corr = df_b4_dummies.corr()

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype=bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[14]: <AxesSubplot:>



In [15]:
```
# Check for Multicollinearity
cols = list(df_b4_dummies.columns)
cols.remove('price')
X = df_b4_dummies[cols]
vif = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
list(zip(cols, vif))
```

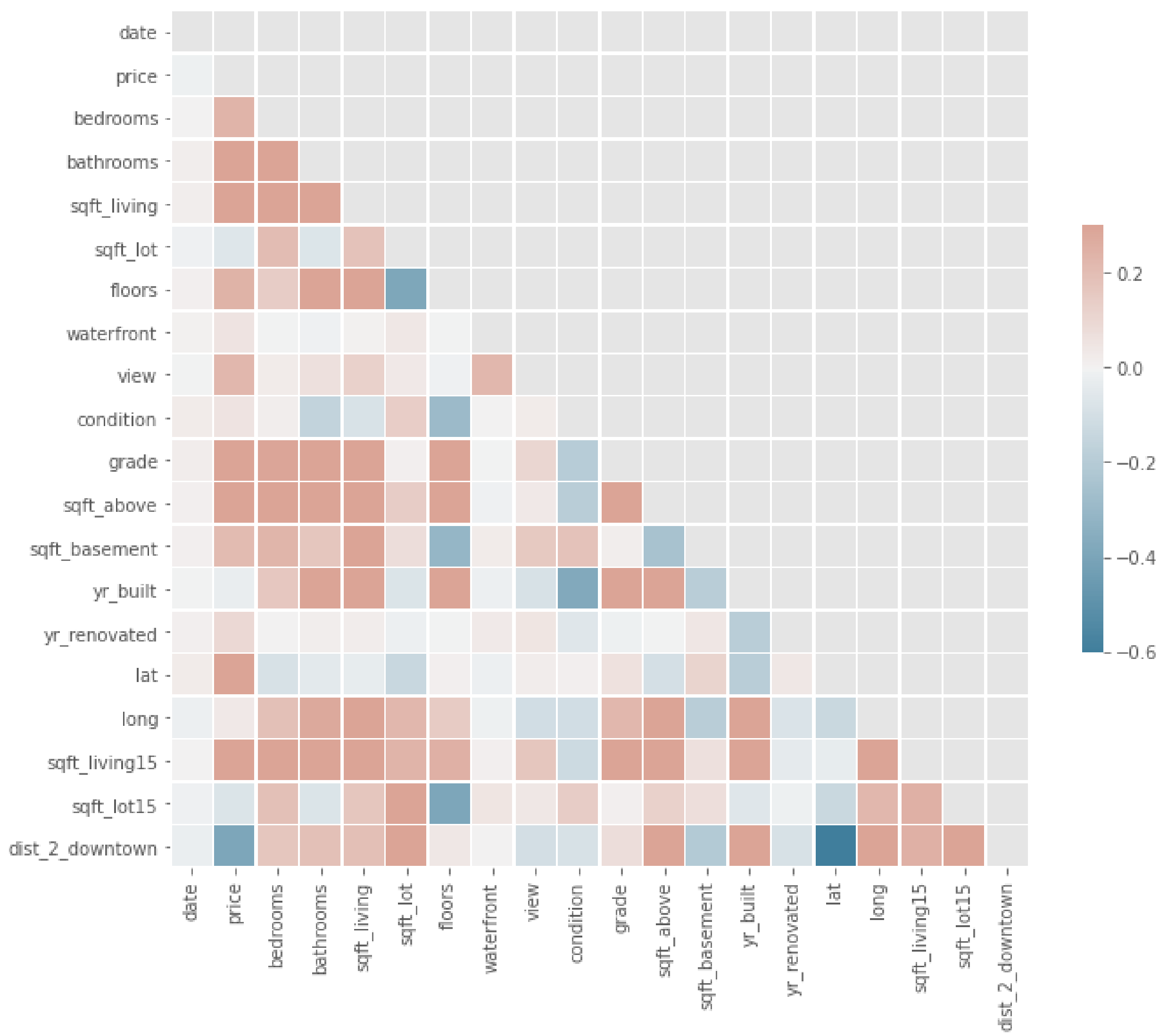
Out[15]:
```
[('date', 5.427906964820898),
 ('bedrooms', 31.625437529691265),
 ('bathrooms', 29.476658559136723),
 ('sqft_living', 904.6142468883447),
 ('sqft_lot', 24.960479391174058),
 ('floors', 22.728808628566043),
 ('waterfront', 1.0584945221909234),
 ('view', 1.2160235503031127),
 ('condition', 36.579883403067946),
 ('grade', 172.59117505076833),
 ('sqft_above', 699.4802751163973),
 ('sqft_basement', 41.54200617688805),
 ('yr_built', 12137.995857422487),
 ('yr_renovated', 1.1323170181402764),
 ('zipcode', 2522913.612925252),
 ('lat', 201501.25243492762),
```

```
('long', 1989633.5705918972),
('sqft_living15', 35.12230238770869),
('sqft_lot15', 29.369390536629286),
('dist_2_downtown', 11.12353795197118)]
```

In [16]:
```
# Drop location-related columns, drop zipcode and latitude
df_b4_dummies = df_b4_dummies.drop(columns=['zipcode'])
```

In [17]:
```
# Check heatmap again
corr = df_b4_dummies.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(11, 9))
cmap = sns.diverging_palette(230, 20, as_cmap=True)
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[17]: <AxesSubplot:>



In [18]:
```
df = df_b4_dummies.copy()
```

In [19]:
```
df.describe()
```

Out[19]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot
count	16363.000000	1.636300e+04	16363.000000	16363.000000	16363.000000	16363.000000
mean	6.562366	4.517670e+05	3.255638	1.983285	1827.464585	6971.636741
std	3.123924	1.860190e+05	0.774378	0.659509	620.560299	3323.913730
min	1.000000	1.050000e+05	2.000000	0.500000	520.000000	520.000000
25%	4.000000	3.065000e+05	3.000000	1.500000	1350.000000	4680.500000
50%	6.000000	4.200000e+05	3.000000	2.000000	1760.000000	6984.000000
75%	9.000000	5.650000e+05	4.000000	2.500000	2240.000000	8924.500000
max	12.000000	1.020000e+06	5.000000	4.000000	3940.000000	18205.000000

In [20]:

```
# Marking Categories
df.waterfront = df.waterfront.astype('category')
df.view = df.view.astype('category')
df.condition = df.condition.astype('category')
df.grade = df.grade.astype('category')
df.bedrooms = df.bedrooms.astype('category')
df.floors = df.floors.astype('category')
df.bathrooms = df.bathrooms.astype('category')
```

In [21]:

```
# Making Dummies
waterfront = pd.get_dummies(df.waterfront, prefix='waterfront', drop_first=Tru
view = pd.get_dummies(df.view, prefix='view', drop_first=True)
condition = pd.get_dummies(df.condition, prefix='condition', drop_first=True)
grade = pd.get_dummies(df.grade, prefix='grade', drop_first=True)
bedrooms = pd.get_dummies(df.bedrooms, prefix='bedrooms', drop_first=True)
floors = pd.get_dummies(df.floors, prefix='floors', drop_first=True)
bathrooms = pd.get_dummies(df.bathrooms, prefix='bathrooms', drop_first=True)

# Take care of dates
mos = ['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec'
df['date'] = [mos[mo-1] for mo in df['date']]
df['date'] = df['date'].astype(str)
date = pd.get_dummies(df.date, prefix='date', drop_first=True)

# Adding dummies to the dataset and removing original features
df = df.join([waterfront, view, condition, grade, bedrooms, floors, bathrooms,
df.drop(['waterfront','view','condition','grade','bedrooms', 'floors', 'bathro
df.head()
```

Out[21]:

	price	sqft_living	sqft_lot	sqft_above	sqft_basement	yr_built	yr_renovated	lat
0	221900	1180	5650	1180	0	1955	0	47.5112
1	538000	2570	7242	2170	400	1951	1991	47.7210
2	180000	770	10000	770	0	1933	0	47.7379

	price	sqft_living	sqft_lot	sqft_above	sqft_basement	yr_built	yr_renovated	lat
3	604000	1960	5000	1050	910	1965	0	47.5208
4	510000	1680	8080	1680	0	1987	0	47.6168

5 rows × 60 columns

In [22]:

```
df.columns = df.columns.str.replace(".", "_")
df.head()
```

Out[22]:

	price	sqft_living	sqft_lot	sqft_above	sqft_basement	yr_built	yr_renovated	lat
0	221900	1180	5650	1180	0	1955	0	47.5112
1	538000	2570	7242	2170	400	1951	1991	47.7210
2	180000	770	10000	770	0	1933	0	47.7379
3	604000	1960	5000	1050	910	1965	0	47.5208
4	510000	1680	8080	1680	0	1987	0	47.6168

5 rows × 60 columns

1st Model

In [23]:

```
# First Model
outcome = 'price' # dependent variable
x_cols = list(df.columns)
x_cols.remove('price')# independence variables --> everything except price
# Fitting the actual model using OLS
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=df).fit()
model.summary()
```

Out[23]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.722
Model:	OLS	**Adj. R-squared:**	0.721
Method:	Least Squares	**F-statistic:**	716.8
Date:	Sat, 26 Dec 2020	**Prob (F-statistic):**	0.00
Time:	19:16:42	**Log-Likelihood:**	-2.1129e+05
No. Observations:	16363	**AIC:**	4.227e+05
Df Residuals:	16303	**BIC:**	4.232e+05

Df Model:	59
Covariance Type:	nonrobust

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.732e+07	1.3e+06	13.289	0.000	1.48e+07	1.99e+07
sqft_living	69.1177	12.003	5.758	0.000	45.590	92.645
sqft_lot	-0.1089	0.499	-0.218	0.827	-1.087	0.869
sqft_above	27.4052	11.999	2.284	0.022	3.885	50.925
sqft_basement	-1.2451	11.862	-0.105	0.916	-24.496	22.006
yr_built	-1179.6058	48.138	-24.505	0.000	-1273.962	-1085.250
yr_renovated	20.3160	2.502	8.120	0.000	15.412	25.220
lat	3.071e+05	7733.767	39.712	0.000	2.92e+05	3.22e+05
long	2.409e+05	9124.720	26.397	0.000	2.23e+05	2.59e+05
sqft_living15	49.9025	2.469	20.214	0.000	45.064	54.741
sqft_lot15	-4.4249	0.560	-7.901	0.000	-5.523	-3.327
dist_2_downtown	-7629.0980	162.092	-47.066	0.000	-7946.816	-7311.380
waterfront_1_0	2.032e+05	2.91e+04	6.987	0.000	1.46e+05	2.6e+05
view_1_0	6.303e+04	7028.602	8.967	0.000	4.92e+04	7.68e+04
view_2_0	4.999e+04	4437.507	11.266	0.000	4.13e+04	5.87e+04
view_3_0	4.849e+04	7646.855	6.341	0.000	3.35e+04	6.35e+04
view_4_0	1.554e+05	1.41e+04	11.040	0.000	1.28e+05	1.83e+05
condition_3	2.95e+04	9528.093	3.096	0.002	1.08e+04	4.82e+04
condition_4	6.312e+04	9563.179	6.600	0.000	4.44e+04	8.19e+04
condition_5	8.378e+04	9849.156	8.506	0.000	6.45e+04	1.03e+05
grade_5	-1.341e+04	3.7e+04	-0.362	0.717	-8.59e+04	5.91e+04
grade_6	9924.8634	3.63e+04	0.273	0.785	-6.13e+04	8.11e+04
grade_7	7.307e+04	3.63e+04	2.011	0.044	1864.761	1.44e+05
grade_8	1.396e+05	3.64e+04	3.834	0.000	6.82e+04	2.11e+05
grade_9	2.218e+05	3.66e+04	6.065	0.000	1.5e+05	2.94e+05
grade_10	2.802e+05	3.7e+04	7.566	0.000	2.08e+05	3.53e+05
grade_11	3.194e+05	4.73e+04	6.757	0.000	2.27e+05	4.12e+05
bedrooms_3	-1349.4951	2578.404	-0.523	0.601	-6403.450	3704.460

bedrooms_4	-1.109e+04	3135.363	-3.538	0.000	-1.72e+04	-4946.788
bedrooms_5	-2.735e+04	4568.799	-5.986	0.000	-3.63e+04	-1.84e+04
floors_1_5	7788.6738	3208.460	2.428	0.015	1499.741	1.41e+04
floors_2_0	-6187.0589	2953.403	-2.095	0.036	-1.2e+04	-398.066
floors_2_5	1.111e+04	1.15e+04	0.968	0.333	-1.14e+04	3.36e+04
floors_3_0	-676.1106	5582.105	-0.121	0.904	-1.16e+04	1.03e+04
floors_3_5	-8196.1999	4.04e+04	-0.203	0.839	-8.74e+04	7.1e+04
bathrooms_0_75	3.686e+04	6.01e+04	0.613	0.540	-8.1e+04	1.55e+05
bathrooms_1_0	4.766e+04	5.69e+04	0.838	0.402	-6.38e+04	1.59e+05
bathrooms_1_25	8791.2791	6.96e+04	0.126	0.900	-1.28e+05	1.45e+05
bathrooms_1_5	5.436e+04	5.69e+04	0.955	0.340	-5.72e+04	1.66e+05
bathrooms_1_75	6.528e+04	5.69e+04	1.147	0.251	-4.63e+04	1.77e+05
bathrooms_2_0	6.692e+04	5.69e+04	1.176	0.240	-4.47e+04	1.78e+05
bathrooms_2_25	7.326e+04	5.69e+04	1.287	0.198	-3.83e+04	1.85e+05
bathrooms_2_5	7.468e+04	5.69e+04	1.312	0.190	-3.69e+04	1.86e+05
bathrooms_2_75	8.455e+04	5.7e+04	1.483	0.138	-2.72e+04	1.96e+05
bathrooms_3_0	7.424e+04	5.71e+04	1.300	0.194	-3.77e+04	1.86e+05
bathrooms_3_25	8.847e+04	5.73e+04	1.545	0.122	-2.38e+04	2.01e+05
bathrooms_3_5	1.146e+05	5.72e+04	2.002	0.045	2419.338	2.27e+05
bathrooms_3_75	1.049e+05	5.98e+04	1.753	0.080	-1.24e+04	2.22e+05
bathrooms_4_0	1.054e+05	6.13e+04	1.720	0.085	-1.47e+04	2.25e+05
date_Aug	-3.167e+04	3501.514	-9.046	0.000	-3.85e+04	-2.48e+04
date_Dec	-3.492e+04	3799.986	-9.189	0.000	-4.24e+04	-2.75e+04
date_Feb	-2.465e+04	3950.777	-6.240	0.000	-3.24e+04	-1.69e+04
date_Jan	-3.138e+04	4341.550	-7.229	0.000	-3.99e+04	-2.29e+04
date_Jul	-2.721e+04	3396.901	-8.010	0.000	-3.39e+04	-2.05e+04
date_Jun	-2.559e+04	3419.953	-7.484	0.000	-3.23e+04	-1.89e+04
date_Mar	-6086.4314	3519.212	-1.729	0.084	-1.3e+04	811.610
date_May	-2.436e+04	3329.978	-7.317	0.000	-3.09e+04	-1.78e+04
date_Nov	-3.151e+04	3842.752	-8.199	0.000	-3.9e+04	-2.4e+04
date_Oct	-3.523e+04	3529.897	-9.980	0.000	-4.21e+04	-2.83e+04
date_Sep	-3.203e+04	3594.655	-8.909	0.000	-3.91e+04	-2.5e+04

Omnibus:	964.082	**Durbin-Watson:**	1.977
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1586.180
Skew:	0.477	**Prob(JB):**	0.00
Kurtosis:	4.189	**Cond. No.**	1.90e+07

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.9e+07. This might indicate that there are
strong multicollinearity or other numerical problems.

Model Refinement 1

Normalize and standardize data

In [24]:
```
# Create histograms to get a sense of data
df.hist(figsize = (20,18));
```

In [25]:
```
df_b4_scale = df.copy() #save unscaled df for later
```

In [26]:
```
# Normalize features that we can
feats_4_log = ['price', 'sqft_living', 'lat', 'long',
               'sqft_living15', 'sqft_lot15', 'dist_2_downtown']

df['long'] = df['long']*-1

for feat in feats_4_log:
    df[feat] = np.log(df[feat])
```

In [27]:
```
df.describe()
```

Out[27]:

	price	sqft_living	sqft_lot	sqft_above	sqft_basement	yr_built
count	16363.000000	16363.000000	16363.000000	16363.000000	16363.000000	16363.000000
mean	12.935661	7.450935	6971.636741	1591.236693	230.948665	1969.898735
std	0.418902	0.352283	3323.913730	606.013212	348.763516	29.919001
min	11.561716	6.253829	520.000000	0.000000	0.000000	1900.000000

	price	sqft_living	sqft_lot	sqft_above	sqft_basement	yr_built
25%	12.632973	7.207860	4680.500000	1140.000000	0.000000	1950.000000
50%	12.948010	7.473069	6984.000000	1440.000000	0.000000	1971.000000
75%	13.244581	7.714231	8924.500000	1930.000000	460.000000	1997.000000
max	13.835313	8.278936	18205.000000	3470.000000	1250.000000	2015.000000

8 rows × 60 columns

In [28]:

```
def scale_feat(series):
    return (series - series.min())/(series.max() - series.min())
```

In [29]:

```
cols = list(df.columns)

for feat in cols:
    df[feat] = scale_feat(df[feat])
df.describe()
```

Out[29]:

	price	sqft_living	sqft_lot	sqft_above	sqft_basement	yr_built
count	16363.000000	16363.000000	16363.000000	16363.000000	16363.000000	16363.000000
mean	0.604305	0.591132	0.364808	0.458570	0.184759	0.607815
std	0.184246	0.173958	0.187951	0.174644	0.279011	0.260165
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.471173	0.471102	0.235256	0.328530	0.000000	0.434783
50%	0.609736	0.602062	0.365507	0.414986	0.000000	0.617391
75%	0.740177	0.721148	0.475233	0.556196	0.368000	0.843478
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

8 rows × 60 columns

In [30]:

```
# See what normalization & scaling did
df.hist(figsize = (20,18));
```

In [31]:

```python
outcome = 'price' # dependent variable

# Fitting the model again
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=df).fit()
model.summary()
```

Out[31]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.764
Model:	OLS	**Adj. R-squared:**	0.763
Method:	Least Squares	**F-statistic:**	894.4
Date:	Sat, 26 Dec 2020	**Prob (F-statistic):**	0.00
Time:	19:17:04	**Log-Likelihood:**	16273.
No. Observations:	16363	**AIC:**	-3.243e+04
Df Residuals:	16303	**BIC:**	-3.196e+04
Df Model:	59		

Covariance Type: nonrobust

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.3467	0.063	5.527	0.000	0.224	0.470
sqft_living	0.2283	0.022	10.368	0.000	0.185	0.272
sqft_lot	-0.0227	0.007	-3.305	0.001	-0.036	-0.009
sqft_above	0.1325	0.021	6.375	0.000	0.092	0.173
sqft_basement	0.0007	0.008	0.085	0.932	-0.015	0.016
yr_built	-0.0904	0.005	-17.521	0.000	-0.101	-0.080
yr_renovated	0.0324	0.005	7.042	0.000	0.023	0.041
lat	0.2444	0.003	76.859	0.000	0.238	0.251
long	-0.1602	0.005	-29.151	0.000	-0.171	-0.149
sqft_living15	0.1683	0.007	24.339	0.000	0.155	0.182
sqft_lot15	-0.0185	0.009	-2.076	0.038	-0.036	-0.001
dist_2_downtown	-0.3915	0.007	-55.833	0.000	-0.405	-0.378
waterfront_1_0	0.2076	0.027	7.827	0.000	0.156	0.260
view_1_0	0.0617	0.006	9.628	0.000	0.049	0.074
view_2_0	0.0411	0.004	10.157	0.000	0.033	0.049
view_3_0	0.0453	0.007	6.507	0.000	0.032	0.059
view_4_0	0.1089	0.013	8.482	0.000	0.084	0.134
condition_3	0.0491	0.009	5.650	0.000	0.032	0.066
condition_4	0.0827	0.009	9.481	0.000	0.066	0.100
condition_5	0.1024	0.009	11.393	0.000	0.085	0.120
grade_5	-0.0191	0.034	-0.566	0.571	-0.085	0.047
grade_6	0.0257	0.033	0.773	0.440	-0.039	0.091
grade_7	0.0903	0.033	2.716	0.007	0.025	0.156
grade_8	0.1469	0.033	4.406	0.000	0.082	0.212
grade_9	0.2040	0.033	6.099	0.000	0.138	0.270
grade_10	0.2410	0.034	7.121	0.000	0.175	0.307
grade_11	0.2540	0.043	5.885	0.000	0.169	0.339
bedrooms_3	-0.0111	0.002	-4.555	0.000	-0.016	-0.006
bedrooms_4	-0.0149	0.003	-5.050	0.000	-0.021	-0.009

bedrooms_5	-0.0310	0.004	-7.398	0.000	-0.039	-0.023
floors_1_5	-0.0003	0.003	-0.094	0.925	-0.006	0.006
floors_2_0	-0.0138	0.003	-5.024	0.000	-0.019	-0.008
floors_2_5	-0.0101	0.011	-0.955	0.340	-0.031	0.011
floors_3_0	-0.0130	0.005	-2.422	0.015	-0.023	-0.002
floors_3_5	-0.0129	0.037	-0.350	0.727	-0.085	0.059
bathrooms_0_75	0.0817	0.055	1.489	0.137	-0.026	0.189
bathrooms_1_0	0.1038	0.052	2.001	0.045	0.002	0.206
bathrooms_1_25	0.0663	0.064	1.044	0.296	-0.058	0.191
bathrooms_1_5	0.1035	0.052	1.993	0.046	0.002	0.205
bathrooms_1_75	0.1211	0.052	2.333	0.020	0.019	0.223
bathrooms_2_0	0.1183	0.052	2.277	0.023	0.016	0.220
bathrooms_2_25	0.1273	0.052	2.450	0.014	0.025	0.229
bathrooms_2_5	0.1344	0.052	2.589	0.010	0.033	0.236
bathrooms_2_75	0.1385	0.052	2.663	0.008	0.037	0.240
bathrooms_3_0	0.1279	0.052	2.454	0.014	0.026	0.230
bathrooms_3_25	0.1397	0.052	2.674	0.008	0.037	0.242
bathrooms_3_5	0.1574	0.052	3.015	0.003	0.055	0.260
bathrooms_3_75	0.1416	0.055	2.594	0.009	0.035	0.249
bathrooms_4_0	0.1467	0.056	2.626	0.009	0.037	0.256
date_Aug	-0.0319	0.003	-9.972	0.000	-0.038	-0.026
date_Dec	-0.0342	0.003	-9.880	0.000	-0.041	-0.027
date_Feb	-0.0251	0.004	-6.958	0.000	-0.032	-0.018
date_Jan	-0.0340	0.004	-8.573	0.000	-0.042	-0.026
date_Jul	-0.0291	0.003	-9.387	0.000	-0.035	-0.023
date_Jun	-0.0266	0.003	-8.534	0.000	-0.033	-0.021
date_Mar	-0.0077	0.003	-2.390	0.017	-0.014	-0.001
date_May	-0.0240	0.003	-7.894	0.000	-0.030	-0.018
date_Nov	-0.0323	0.004	-9.212	0.000	-0.039	-0.025
date_Oct	-0.0355	0.003	-11.017	0.000	-0.042	-0.029
date_Sep	-0.0319	0.003	-9.739	0.000	-0.038	-0.026

Omnibus:	525.368	**Durbin-Watson:**	1.996
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	968.644
Skew:	-0.257	**Prob(JB):**	4.59e-211
Kurtosis:	4.076	**Cond. No.**	689.

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

Model Refinement 2

Remove unecessary features (p-value > 0.05)

In [32]:
```
# Get new columns
p_vals = pd.DataFrame(model.pvalues)
x_cols = p_vals[p_vals[0]<=0.05][1:].index # independent variables
```

In [33]:
```
# Keep columns with p-value less than 0.05
outcome = 'price' # dependent variable

# Fitting the model again
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=df).fit()
model.summary()
```

Out[33]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.763
Model:	OLS	**Adj. R-squared:**	0.763
Method:	Least Squares	**F-statistic:**	1032.
Date:	Sat, 26 Dec 2020	**Prob (F-statistic):**	0.00
Time:	19:17:04	**Log-Likelihood:**	16255.
No. Observations:	16363	**AIC:**	-3.241e+04
Df Residuals:	16311	**BIC:**	-3.200e+04
Df Model:	51		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.4284	0.019	22.221	0.000	0.391	0.466
sqft_living	0.2339	0.010	23.700	0.000	0.215	0.253

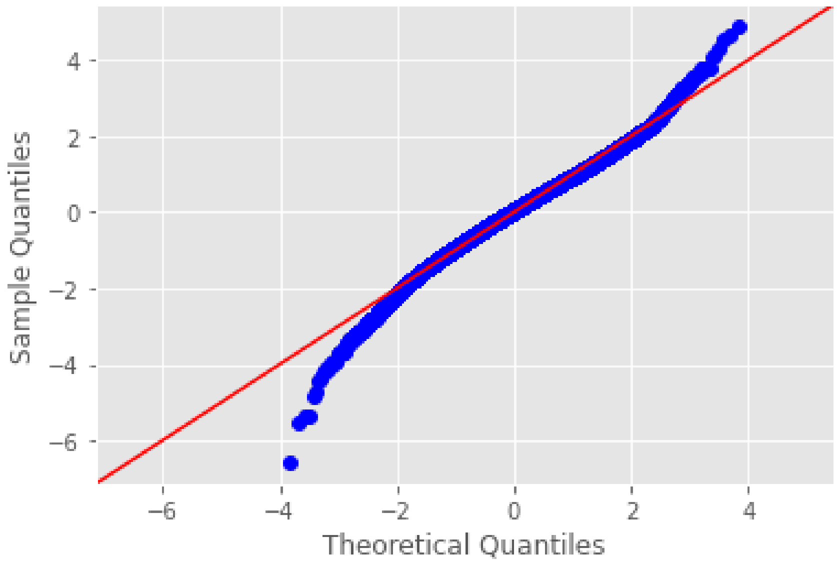
sqft_lot	-0.0219	0.007	-3.188	0.001	-0.035	-0.008
sqft_above	0.1290	0.009	13.812	0.000	0.111	0.147
yr_built	-0.0886	0.005	-18.013	0.000	-0.098	-0.079
yr_renovated	0.0326	0.005	7.105	0.000	0.024	0.042
lat	0.2449	0.003	77.015	0.000	0.239	0.251
long	-0.1587	0.005	-28.916	0.000	-0.169	-0.148
sqft_living15	0.1684	0.007	24.369	0.000	0.155	0.182
sqft_lot15	-0.0182	0.009	-2.072	0.038	-0.035	-0.001
dist_2_downtown	-0.3924	0.007	-56.069	0.000	-0.406	-0.379
waterfront_1_0	0.2101	0.027	7.918	0.000	0.158	0.262
view_1_0	0.0614	0.006	9.597	0.000	0.049	0.074
view_2_0	0.0411	0.004	10.157	0.000	0.033	0.049
view_3_0	0.0453	0.007	6.500	0.000	0.032	0.059
view_4_0	0.1077	0.013	8.389	0.000	0.083	0.133
condition_3	0.0516	0.009	5.935	0.000	0.035	0.069
condition_4	0.0851	0.009	9.763	0.000	0.068	0.102
condition_5	0.1047	0.009	11.658	0.000	0.087	0.122
grade_7	0.0675	0.003	25.121	0.000	0.062	0.073
grade_8	0.1236	0.003	36.978	0.000	0.117	0.130
grade_9	0.1806	0.004	41.335	0.000	0.172	0.189
grade_10	0.2175	0.007	32.037	0.000	0.204	0.231
grade_11	0.2306	0.028	8.341	0.000	0.176	0.285
bedrooms_3	-0.0108	0.002	-4.531	0.000	-0.015	-0.006
bedrooms_4	-0.0147	0.003	-5.048	0.000	-0.020	-0.009
bedrooms_5	-0.0311	0.004	-7.442	0.000	-0.039	-0.023
floors_2_0	-0.0133	0.003	-5.111	0.000	-0.018	-0.008
floors_3_0	-0.0127	0.005	-2.436	0.015	-0.023	-0.002
bathrooms_1_0	0.0389	0.015	2.582	0.010	0.009	0.068
bathrooms_1_5	0.0384	0.015	2.516	0.012	0.008	0.068
bathrooms_1_75	0.0558	0.015	3.678	0.000	0.026	0.086
bathrooms_2_0	0.0528	0.015	3.465	0.001	0.023	0.083
bathrooms_2_25	0.0615	0.015	4.015	0.000	0.031	0.092

bathrooms_2_5	0.0686	0.015	4.480	0.000	0.039	0.099
bathrooms_2_75	0.0727	0.016	4.666	0.000	0.042	0.103
bathrooms_3_0	0.0618	0.016	3.903	0.000	0.031	0.093
bathrooms_3_25	0.0735	0.016	4.496	0.000	0.041	0.106
bathrooms_3_5	0.0911	0.016	5.615	0.000	0.059	0.123
bathrooms_3_75	0.0754	0.023	3.314	0.001	0.031	0.120
bathrooms_4_0	0.0811	0.026	3.155	0.002	0.031	0.132
date_Aug	-0.0316	0.003	-9.886	0.000	-0.038	-0.025
date_Dec	-0.0342	0.003	-9.852	0.000	-0.041	-0.027
date_Feb	-0.0251	0.004	-6.948	0.000	-0.032	-0.018
date_Jan	-0.0341	0.004	-8.606	0.000	-0.042	-0.026
date_Jul	-0.0289	0.003	-9.330	0.000	-0.035	-0.023
date_Jun	-0.0264	0.003	-8.452	0.000	-0.033	-0.020
date_Mar	-0.0074	0.003	-2.318	0.020	-0.014	-0.001
date_May	-0.0238	0.003	-7.844	0.000	-0.030	-0.018
date_Nov	-0.0324	0.004	-9.232	0.000	-0.039	-0.026
date_Oct	-0.0353	0.003	-10.951	0.000	-0.042	-0.029
date_Sep	-0.0317	0.003	-9.676	0.000	-0.038	-0.025

Omnibus:	529.936	**Durbin-Watson:**	1.997
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	961.921
Skew:	-0.264	**Prob(JB):**	1.32e-209
Kurtosis:	4.064	**Cond. No.**	188.

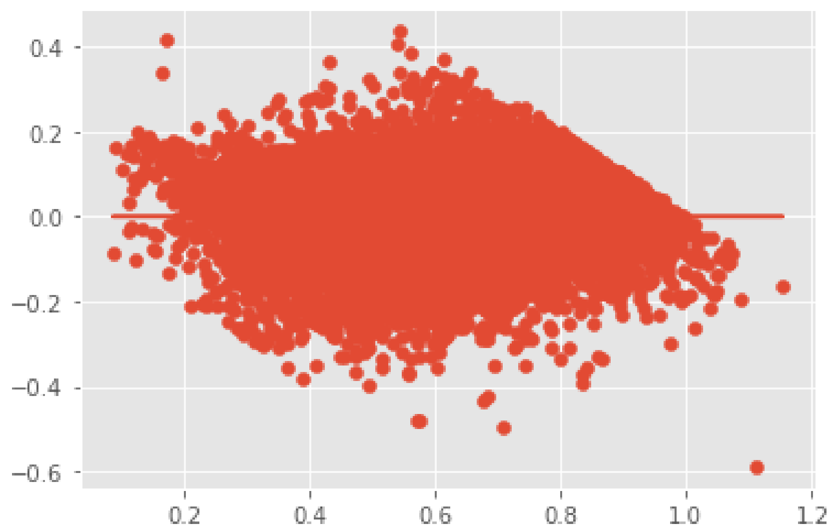
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [34]:
```
# Q-Q Plot to check normality of residuals
residuals = model.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
```



In [35]:
```
# Checking for Homoscedasticity
plt.scatter(model.predict(df[x_cols]), model.resid)
plt.plot(model.predict(df[x_cols]), [0 for i in range(len(df))])
```

Out[35]: [<matplotlib.lines.Line2D at 0x2445bc7ee20>]



Model Refinement 3

Improve residual normality and heteroscedasticity

In [36]:
```
# Finding a cutoff point to narrow the price range
xmin=11.561716
xmax=13.835313

for i in range(0, 25, 1):
    q = i / 100
    price = np.exp(df['price']*(xmax-xmin)+xmin)  # get back to meaningful val
    print('{} percentile: {}'.format(q, price.quantile(q=q)))

print('---')
```

```
for i in range(75, 101, 1):
    q = i / 100
    price = np.exp(df['price']*(xmax-xmin)+xmin)  # get back to meaningful val
    print('{} percentile: {}'.format(q, price.quantile(q=q)))
```

```
0.0 percentile: 105000.03894034293
0.01 percentile: 156848.4227721934
0.02 percentile: 175000.04303472006
0.03 percentile: 190000.04290148403
0.04 percentile: 200000.0426501934
0.05 percentile: 208955.04232114536
0.06 percentile: 215000.04204569408
0.07 percentile: 222000.0416748515
0.08 percentile: 229000.04125001185
0.09 percentile: 234753.04086157965
0.1 percentile: 240000.04047724814
0.11 percentile: 245000.040084874
0.12 percentile: 250000.0396675398
0.13 percentile: 253000.03940536638
0.14 percentile: 258000.03894912492
0.15 percentile: 262500.03851822816
0.16 percentile: 267000.038068462
0.17 percentile: 270000.0377582919
0.18 percentile: 275000.037223267
0.19 percentile: 280000.0366660045
0.2 percentile: 285000.0360869022
0.21 percentile: 289950.0354924526
0.22 percentile: 294950.03487101494
0.23 percentile: 299900.03423536656
0.24 percentile: 301500.0340256149
---
0.75 percentile: 564999.9769662684
0.76 percentile: 574999.9740910776
0.77 percentile: 579999.9726374826
0.78 percentile: 589999.9696987554
0.79 percentile: 599999.9667185666
0.8 percentile: 608619.9641169005
0.81 percentile: 619999.9606365543
0.82 percentile: 628839.9578976792
0.83 percentile: 639999.954396708
0.84 percentile: 649999.9512191516
0.85 percentile: 659999.9480039636
0.86 percentile: 672999.9437688929
0.87 percentile: 684999.9398050511
0.88 percentile: 698999.9351156388
0.89 percentile: 709999.9313829138
0.9 percentile: 724999.9262257792
0.91 percentile: 739999.9209927277
0.92 percentile: 751999.9167526646
0.93 percentile: 770702.7500510826
0.94 percentile: 789999.9030202533
0.95 percentile: 809999.8956116732
0.96 percentile: 834999.8861814148
0.97 percentile: 864999.8746238704
0.98 percentile: 902759.8597159835
0.99 percentile: 951999.8396976517
1.0 percentile: 1019999.8110343539
```

In [37]:
```
# Keep values between 1% and 80%
lower = df['price'].quantile(q=.03)
upper = df['price'].quantile(q=.9)

subset = df[(df['price'] >= lower) & (df['price'] <= upper)].reset_index()
print('Percent removed:',(len(df) - len(subset))/len(df))

predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=subset).fit()
model.summary()
```

```
Percent removed: 0.1272993949764713
```

Out[37]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.708
Model:	OLS	**Adj. R-squared:**	0.707
Method:	Least Squares	**F-statistic:**	676.6
Date:	Sat, 26 Dec 2020	**Prob (F-statistic):**	0.00
Time:	19:17:05	**Log-Likelihood:**	15791.
No. Observations:	14280	**AIC:**	-3.148e+04
Df Residuals:	14228	**BIC:**	-3.109e+04
Df Model:	51		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.5044	0.019	26.269	0.000	0.467	0.542
sqft_living	0.1868	0.009	19.782	0.000	0.168	0.205
sqft_lot	-0.0296	0.007	-4.462	0.000	-0.043	-0.017
sqft_above	0.1068	0.009	11.661	0.000	0.089	0.125
yr_built	-0.0892	0.005	-18.265	0.000	-0.099	-0.080
yr_renovated	0.0142	0.005	2.979	0.003	0.005	0.024
lat	0.2272	0.003	76.626	0.000	0.221	0.233
long	-0.1554	0.005	-30.330	0.000	-0.165	-0.145
sqft_living15	0.1534	0.007	22.601	0.000	0.140	0.167
sqft_lot15	-0.0180	0.008	-2.145	0.032	-0.034	-0.002
dist_2_downtown	-0.3392	0.007	-50.108	0.000	-0.352	-0.326
waterfront_1_0	0.2147	0.038	5.598	0.000	0.140	0.290
view_1_0	0.0578	0.007	8.752	0.000	0.045	0.071

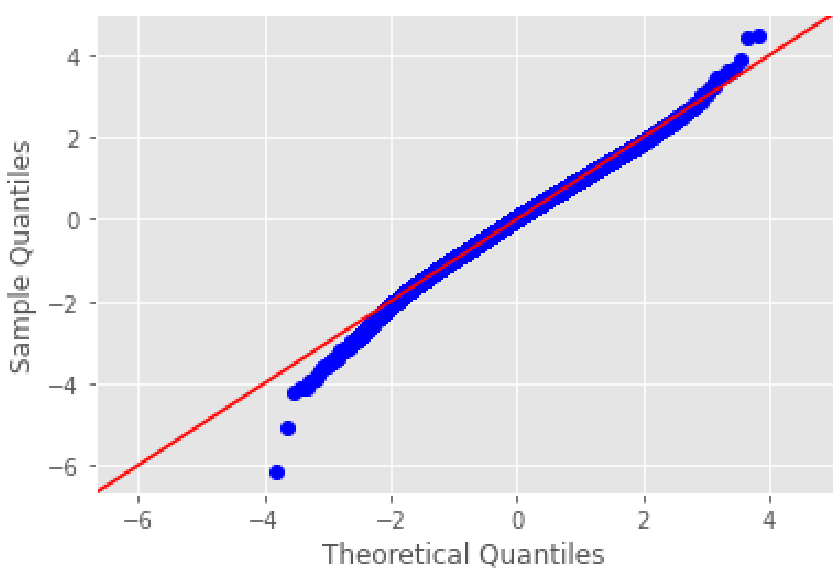
view_2_0	0.0367	0.004	8.713	0.000	0.028	0.045
view_3_0	0.0497	0.007	6.758	0.000	0.035	0.064
view_4_0	0.1124	0.020	5.742	0.000	0.074	0.151
condition_3	0.0218	0.009	2.434	0.015	0.004	0.039
condition_4	0.0471	0.009	5.233	0.000	0.029	0.065
condition_5	0.0630	0.009	6.814	0.000	0.045	0.081
grade_7	0.0568	0.003	22.301	0.000	0.052	0.062
grade_8	0.1091	0.003	34.342	0.000	0.103	0.115
grade_9	0.1533	0.004	35.320	0.000	0.145	0.162
grade_10	0.1959	0.009	22.934	0.000	0.179	0.213
grade_11	0.1802	0.080	2.242	0.025	0.023	0.338
bedrooms_3	-0.0114	0.002	-5.047	0.000	-0.016	-0.007
bedrooms_4	-0.0138	0.003	-4.988	0.000	-0.019	-0.008
bedrooms_5	-0.0312	0.004	-7.576	0.000	-0.039	-0.023
floors_2_0	-0.0112	0.003	-4.363	0.000	-0.016	-0.006
floors_3_0	-0.0109	0.005	-2.191	0.028	-0.021	-0.001
bathrooms_1_0	0.0204	0.015	1.356	0.175	-0.009	0.050
bathrooms_1_5	0.0163	0.015	1.075	0.282	-0.013	0.046
bathrooms_1_75	0.0348	0.015	2.306	0.021	0.005	0.064
bathrooms_2_0	0.0317	0.015	2.090	0.037	0.002	0.061
bathrooms_2_25	0.0385	0.015	2.526	0.012	0.009	0.068
bathrooms_2_5	0.0493	0.015	3.242	0.001	0.020	0.079
bathrooms_2_75	0.0540	0.016	3.481	0.001	0.024	0.084
bathrooms_3_0	0.0407	0.016	2.587	0.010	0.010	0.072
bathrooms_3_25	0.0531	0.016	3.250	0.001	0.021	0.085
bathrooms_3_5	0.0583	0.016	3.559	0.000	0.026	0.090
bathrooms_3_75	0.0533	0.026	2.070	0.038	0.003	0.104
bathrooms_4_0	0.0448	0.028	1.612	0.107	-0.010	0.099
date_Aug	-0.0268	0.003	-8.756	0.000	-0.033	-0.021
date_Dec	-0.0276	0.003	-8.361	0.000	-0.034	-0.021
date_Feb	-0.0168	0.003	-4.914	0.000	-0.024	-0.010
date_Jan	-0.0257	0.004	-6.728	0.000	-0.033	-0.018

date_Jul	-0.0218	0.003	-7.331	0.000	-0.028	-0.016
date_Jun	-0.0214	0.003	-7.153	0.000	-0.027	-0.016
date_Mar	-0.0042	0.003	-1.348	0.178	-0.010	0.002
date_May	-0.0169	0.003	-5.794	0.000	-0.023	-0.011
date_Nov	-0.0286	0.003	-8.517	0.000	-0.035	-0.022
date_Oct	-0.0298	0.003	-9.640	0.000	-0.036	-0.024
date_Sep	-0.0234	0.003	-7.460	0.000	-0.029	-0.017

Omnibus:	216.268	**Durbin-Watson:**	2.006
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	276.664
Skew:	-0.219	**Prob(JB):**	8.38e-61
Kurtosis:	3.522	**Cond. No.**	286.

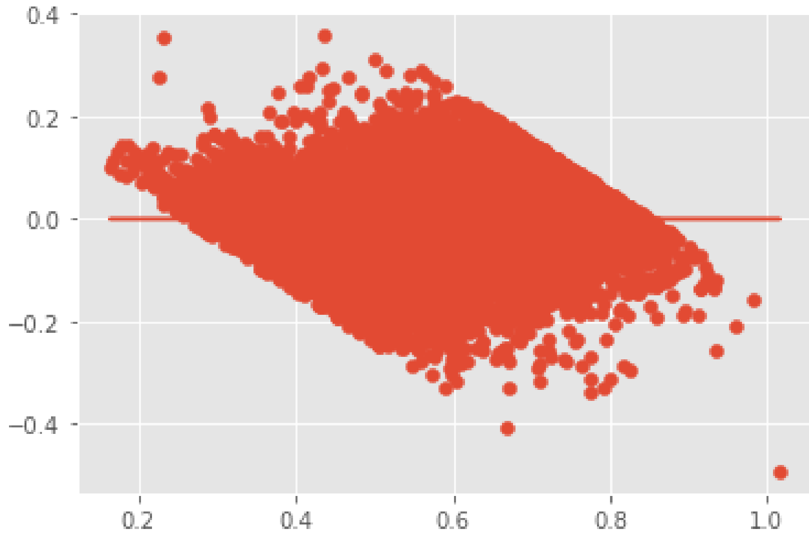
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [38]:
```
# Check Q-Q again
fig = sm.graphics.qqplot(model.resid, dist=stats.norm, line='45', fit=True)
```



In [39]:
```
# Check heteroscedasticity again
plt.scatter(model.predict(subset[x_cols]), model.resid)
plt.plot(model.predict(subset[x_cols]), [0 for i in range(len(subset))])
```

Out[39]: [<matplotlib.lines.Line2D at 0x24458ee8df0>]



Test/train

In [40]:
```
# train test
from statsmodels.formula.api import ols
import statsmodels.api as sm
import scipy.stats as stats
from sklearn.model_selection import train_test_split
```

In [41]:
```
# split data into train and test sets
train, test = train_test_split(subset)
print(len(train), len(test))
```

```
10710 3570
```

In [42]:
```
# Fitting the model to train data
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=train).fit()
model.summary()
```

Out[42]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.707
Model:	OLS	**Adj. R-squared:**	0.705
Method:	Least Squares	**F-statistic:**	513.9
Date:	Sat, 26 Dec 2020	**Prob (F-statistic):**	0.00
Time:	19:17:07	**Log-Likelihood:**	11844.
No. Observations:	10710	**AIC:**	-2.359e+04
Df Residuals:	10659	**BIC:**	-2.321e+04
Df Model:	50		
Covariance Type:	nonrobust		

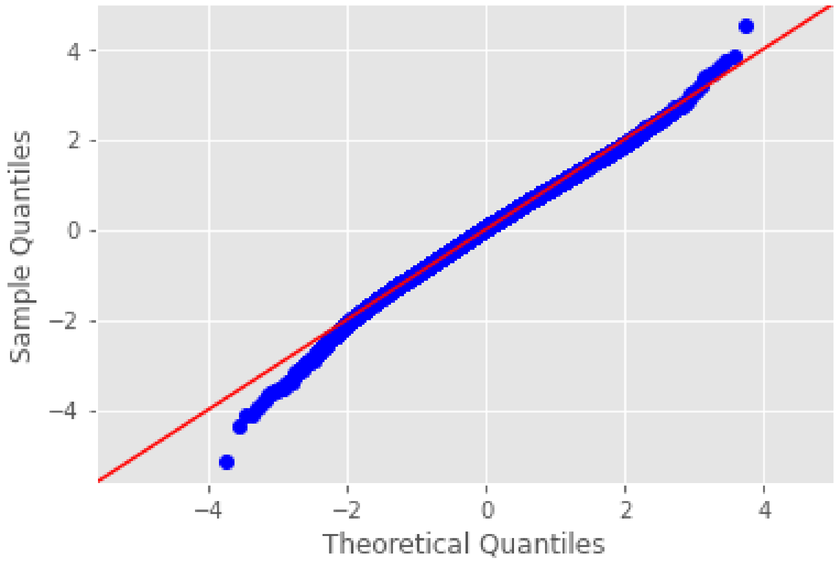
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.4972	0.022	22.114	0.000	0.453	0.541
sqft_living	0.1789	0.011	16.381	0.000	0.157	0.200
sqft_lot	-0.0307	0.008	-3.999	0.000	-0.046	-0.016
sqft_above	0.1059	0.011	9.976	0.000	0.085	0.127
yr_built	-0.0865	0.006	-15.298	0.000	-0.098	-0.075
yr_renovated	0.0241	0.006	4.279	0.000	0.013	0.035
lat	0.2252	0.003	65.959	0.000	0.218	0.232
long	-0.1527	0.006	-25.840	0.000	-0.164	-0.141
sqft_living15	0.1621	0.008	20.814	0.000	0.147	0.177
sqft_lot15	-0.0201	0.010	-2.079	0.038	-0.039	-0.001
dist_2_downtown	-0.3435	0.008	-44.204	0.000	-0.359	-0.328
waterfront_1_0	0.2059	0.046	4.481	0.000	0.116	0.296
view_1_0	0.0611	0.008	7.995	0.000	0.046	0.076
view_2_0	0.0366	0.005	7.667	0.000	0.027	0.046
view_3_0	0.0514	0.009	5.972	0.000	0.035	0.068
view_4_0	0.1085	0.022	5.018	0.000	0.066	0.151
condition_3	0.0216	0.011	2.029	0.042	0.001	0.043
condition_4	0.0479	0.011	4.479	0.000	0.027	0.069
condition_5	0.0629	0.011	5.730	0.000	0.041	0.084
grade_7	0.0546	0.003	18.509	0.000	0.049	0.060
grade_8	0.1069	0.004	29.062	0.000	0.100	0.114
grade_9	0.1497	0.005	29.683	0.000	0.140	0.160
grade_10	0.1964	0.010	19.583	0.000	0.177	0.216
grade_11	4.464e-16	9.57e-17	4.665	0.000	2.59e-16	6.34e-16
bedrooms_3	-0.0123	0.003	-4.700	0.000	-0.017	-0.007
bedrooms_4	-0.0135	0.003	-4.197	0.000	-0.020	-0.007
bedrooms_5	-0.0299	0.005	-6.335	0.000	-0.039	-0.021
floors_2_0	-0.0125	0.003	-4.182	0.000	-0.018	-0.007
floors_3_0	-0.0162	0.006	-2.823	0.005	-0.028	-0.005
bathrooms_1_0	0.0287	0.018	1.619	0.105	-0.006	0.063
bathrooms_1_5	0.0271	0.018	1.516	0.130	-0.008	0.062

bathrooms_1_75	0.0446	0.018	2.504	0.012	0.010	0.080
bathrooms_2_0	0.0426	0.018	2.383	0.017	0.008	0.078
bathrooms_2_25	0.0482	0.018	2.683	0.007	0.013	0.083
bathrooms_2_5	0.0602	0.018	3.354	0.001	0.025	0.095
bathrooms_2_75	0.0608	0.018	3.324	0.001	0.025	0.097
bathrooms_3_0	0.0529	0.019	2.853	0.004	0.017	0.089
bathrooms_3_25	0.0632	0.019	3.275	0.001	0.025	0.101
bathrooms_3_5	0.0748	0.019	3.894	0.000	0.037	0.113
bathrooms_3_75	0.0608	0.028	2.174	0.030	0.006	0.116
bathrooms_4_0	0.0627	0.030	2.075	0.038	0.003	0.122
date_Aug	-0.0254	0.004	-7.084	0.000	-0.032	-0.018
date_Dec	-0.0269	0.004	-6.993	0.000	-0.034	-0.019
date_Feb	-0.0140	0.004	-3.513	0.000	-0.022	-0.006
date_Jan	-0.0190	0.004	-4.318	0.000	-0.028	-0.010
date_Jul	-0.0174	0.003	-5.059	0.000	-0.024	-0.011
date_Jun	-0.0189	0.003	-5.446	0.000	-0.026	-0.012
date_Mar	-0.0022	0.004	-0.625	0.532	-0.009	0.005
date_May	-0.0134	0.003	-3.991	0.000	-0.020	-0.007
date_Nov	-0.0285	0.004	-7.346	0.000	-0.036	-0.021
date_Oct	-0.0263	0.004	-7.351	0.000	-0.033	-0.019
date_Sep	-0.0203	0.004	-5.636	0.000	-0.027	-0.013

Omnibus:	138.464	**Durbin-Watson:**	1.990
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	167.279
Skew:	-0.212	**Prob(JB):**	4.74e-37
Kurtosis:	3.441	**Cond. No.**	1.11e+16

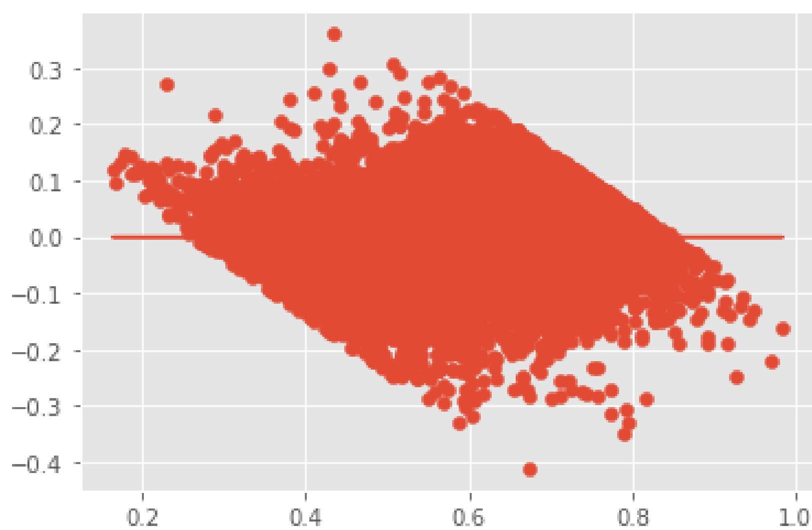
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 4.95e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [43]:
```
fig = sm.graphics.qqplot(model.resid, dist=stats.norm, line='45', fit=True)
```



In [44]:
```
plt.scatter(model.predict(train[x_cols]), model.resid)
plt.plot(model.predict(train[x_cols]), [0 for i in range(len(train))])
```

Out[44]: [<matplotlib.lines.Line2D at 0x24459351fd0>]



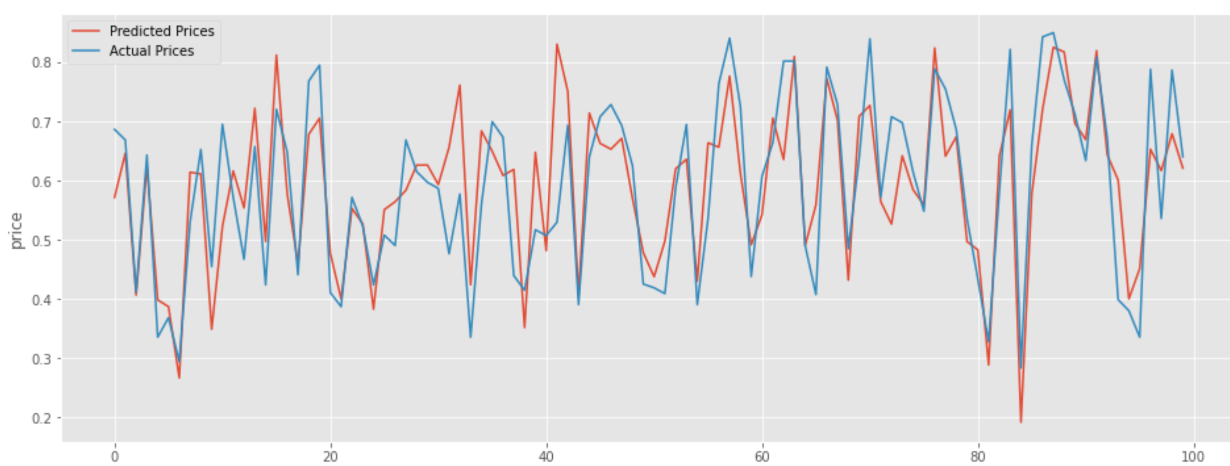
In [45]:
```
# Most significant features
coeffs = pd.DataFrame(model.params, columns=['coeffs'])
coeffs['abs'] = coeffs.abs()
coeffs = coeffs.sort_values('abs', ascending=False)
coeffs.head(10)
```

Out[45]:

	coeffs	abs
Intercept	0.497250	0.497250
dist_2_downtown	-0.343534	0.343534
lat	0.225159	0.225159
waterfront_1_0	0.205905	0.205905

	coeffs	abs
grade_10	0.196366	0.196366
sqft_living	0.178862	0.178862
sqft_living15	0.162060	0.162060
long	-0.152748	0.152748
grade_9	0.149680	0.149680
view_4_0	0.108460	0.108460

In [46]:
```
# Use the test set to see how the train set did
X = test[x_cols].sort_index()
ypred = model.predict(X)
bot = 1100
top = 1200

x = range(top-bot)
ypred = ypred[bot:top]
yactual = test['price'].sort_index()[bot:top]

plt.figure(figsize=(16,6))
sns.lineplot(x=x, y=ypred, label='Predicted Prices')
sns.lineplot(x=x, y=yactual, label='Actual Prices')
plt.show()
```



In [47]:
```
print('R^2 Score:',round(model.rsquared, 5))
print('Average Predicted Price:', round(ypred.mean(),4))
print('Average Actual Price:', round(yactual.mean(), 4))
```

```
R^2 Score: 0.70681
Average Predicted Price: 0.5905
Average Actual Price: 0.5886
```

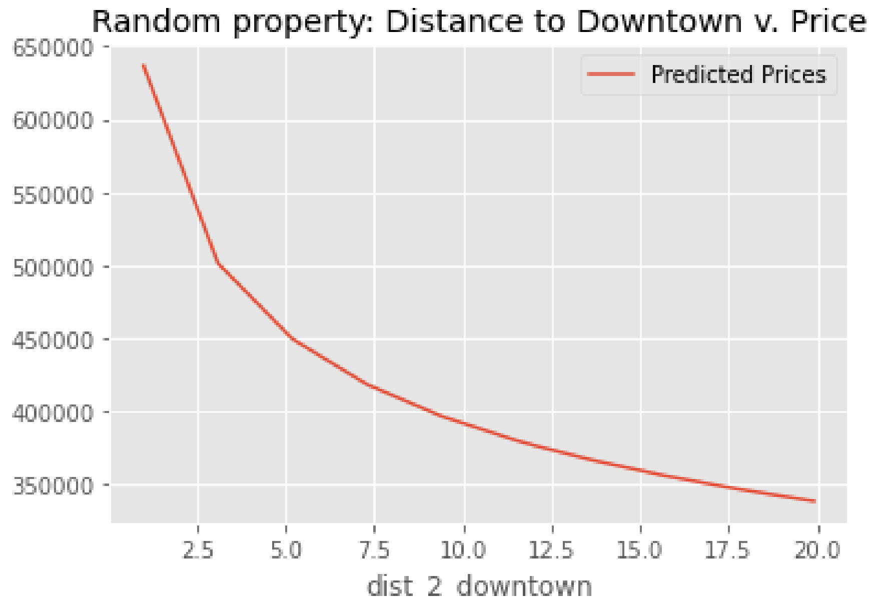
Model Evaluation

In [48]:
```
# function to take a random property and make a graph by adjusting a selected
```

```
def predict_feat(feat, maxfeat, minfeat, title):
    df_copy = df_b4_scale[(df_b4_scale[feat]<=maxfeat) & (df_b4_scale[feat]>=m
    i = int(len(df_copy)/2) # take a house from middle of set
    df_dist = pd.DataFrame(df_copy.iloc[i]).transpose()
    step = minfeat

    for row in range(1,11):
        df_dist = df_dist.append(df_copy.iloc[i].transpose(), ignore_index=Tru
        df_dist[feat][row] = step
        step += (maxfeat - minfeat)/10
    actual_feat = df_dist[feat][0]
    actual_price = df_dist['price'][0]

    df_dist['long'] = df_dist['long']*-1

    for feat3 in feats_4_log:
        df_dist[feat3] = np.log(df_dist[feat3])

    for feat2 in list(df_dist.columns):
        if feat2 == 'long':
            featmax = max(np.log(df_b4_scale[feat2]*-1))
            featmin = min(np.log(df_b4_scale[feat2]*-1))
            df_dist[feat2] = (df_dist[feat2] - featmin) / (featmax - featmin)
            continue
        if feat2 in feats_4_log:
            featmax = max(np.log(df_b4_scale[feat2]))
            featmin = min(np.log(df_b4_scale[feat2]))
            df_dist[feat2] = (df_dist[feat2] - featmin) / (featmax - featmin)
            continue
        else:
            featmax = max(df_b4_scale[feat2])
            featmin = min(df_b4_scale[feat2])
            df_dist[feat2] = (df_dist[feat2] - featmin) / (featmax - featmin)

    maxprice = 13.835313
    minprice = 11.561716
    maxfeat = max(np.log(df_b4_scale[feat]))
    minfeat = min(np.log(df_b4_scale[feat]))

    x=np.exp(df_dist[feat] * (maxfeat-minfeat) + minfeat)
    ypred_feat = model.predict(df_dist)
    ypred_feat = np.exp(ypred_feat * (maxprice-minprice) + minprice)
    print('Actual Price: ${}, Actual Feat: {}.'.format(int(actual_price), actu
    plt.figure(figsize=(6,4))
    plt.title(('{} v. Price').format(title))
    sns.lineplot(x=x, y=ypred_feat, label='Predicted Prices', markers=True)
    return (x, ypred_feat)
```

In [49]:
```
x_dists, prices_v_dists = predict_feat('dist_2_downtown', 22, 1, 'Random prope
```

```
Actual Price: $318000, Actual Feat: 12.074.
```



In [50]:
```
x_dists
```

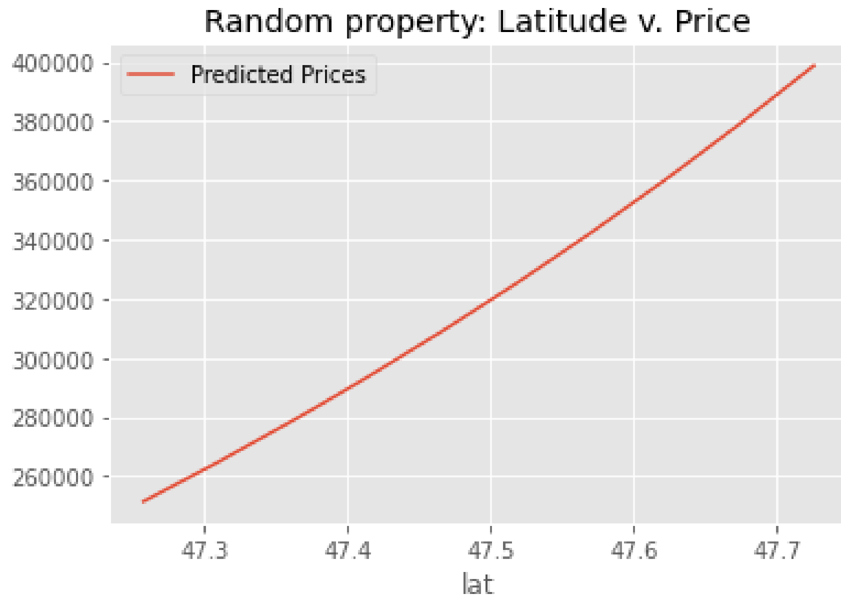
Out[50]:
```
0     12.074
1      1.000
2      3.100
3      5.200
4      7.300
5      9.400
6     11.500
7     13.600
8     15.700
9     17.800
10    19.900
Name: dist_2_downtown, dtype: float64
```

In [51]:
```
prices_v_dists
```

Out[51]:
```
0     376463.558048
1     636670.208638
2     501502.493816
3     449666.066366
4     418616.610001
5     396876.717628
6     380351.164740
7     367130.617693
8     356177.960191
9     346870.391405
10    338806.231080
dtype: float64
```

In [52]:
```
current_feat = 'lat'
x_lat, prices_v_lat = predict_feat(current_feat, max(df_b4_scale[current_feat]
                                   min(df_b4_scale[current_feat]), 'Random pro
```

```
Actual Price: $291000, Actual Feat: 47.3768.
```

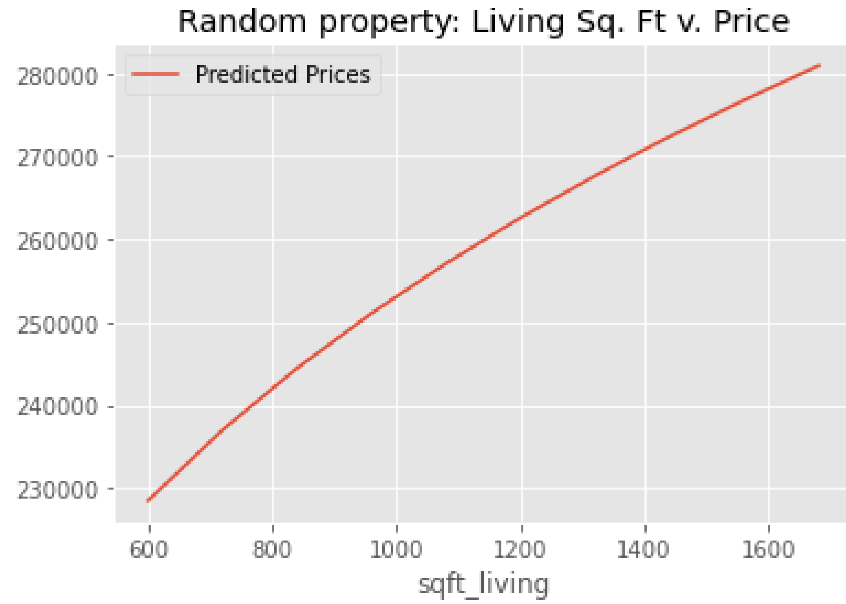


In [53]:
```
print(x_lat)
print(prices_v_lat)
```

```
0     47.37680
1     47.25740
2     47.30942
3     47.36144
4     47.41346
5     47.46548
6     47.51750
7     47.56952
8     47.62154
9     47.67356
10    47.72558
Name: lat, dtype: float64
0     282972.333273
1     251477.391731
2     264753.187261
3     278714.070203
4     293394.582628
5     308830.967395
6     325061.249899
7     342125.323634
8     360065.039778
9     378924.300956
10    398749.159394
dtype: float64
```

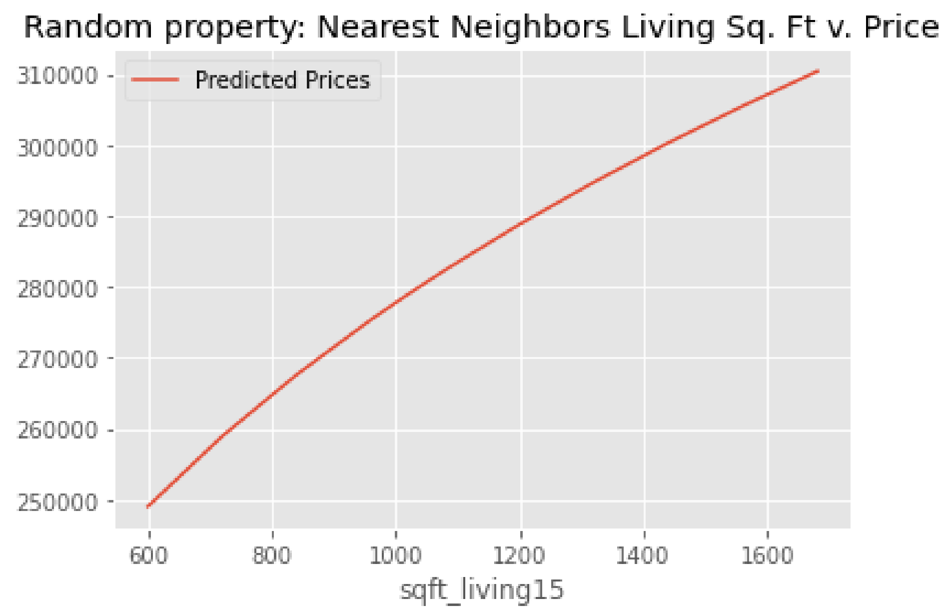
In [54]:
```
x_sgft, prices_v_sgft = predict_feat('sqft_living', 1800, 600, 'Random propert
```

```
Actual Price: $295832, Actual Feat: 1410.0.
```



In [55]:
```
x_sgft15, prices_v_sgft15 = predict_feat('sqft_living15', 1800, 600, 'Random p
```

Actual Price: $281000, Actual Feat: 1020.0.



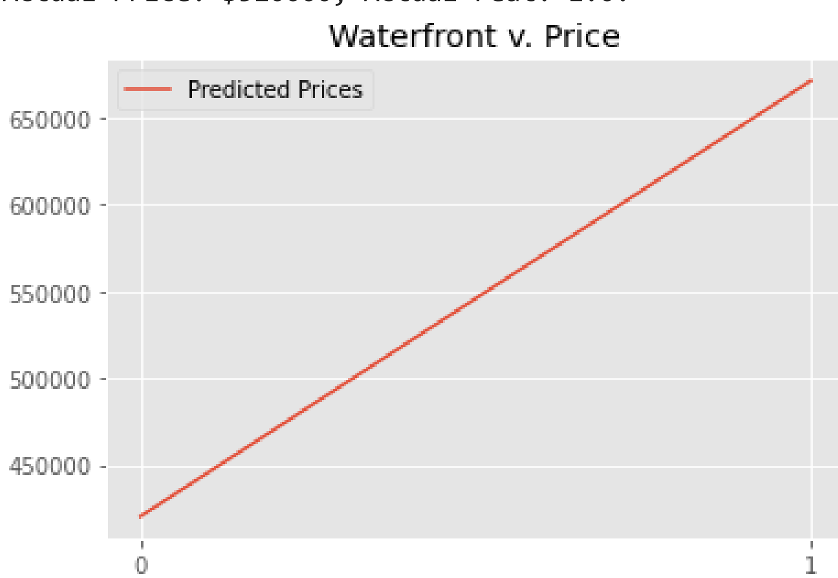
In [56]:
```
def predict_categorical(feat, pricemax, pricemin, feat_true, title):
    df_copy = df_b4_scale[(df_b4_scale[feat]==feat_true) &(df_b4_scale['price'
    i = int(len(df_copy)/2) # take a house from middle of set

    df_cat = pd.DataFrame(df_copy.iloc[i]).transpose()
    df_cat = df_cat.append(df_copy.iloc[i].transpose(), ignore_index=True)
    df_cat[feat][1] = (df_cat[feat][0] - 1)*-1

    actual_feat = df_cat[feat][0]
    actual_price = df_cat['price'][0]

    df_cat['long'] = df_cat['long']*-1

    for feat3 in feats_4_log:
        df_cat[feat3] = np.log(df_cat[feat3])
```

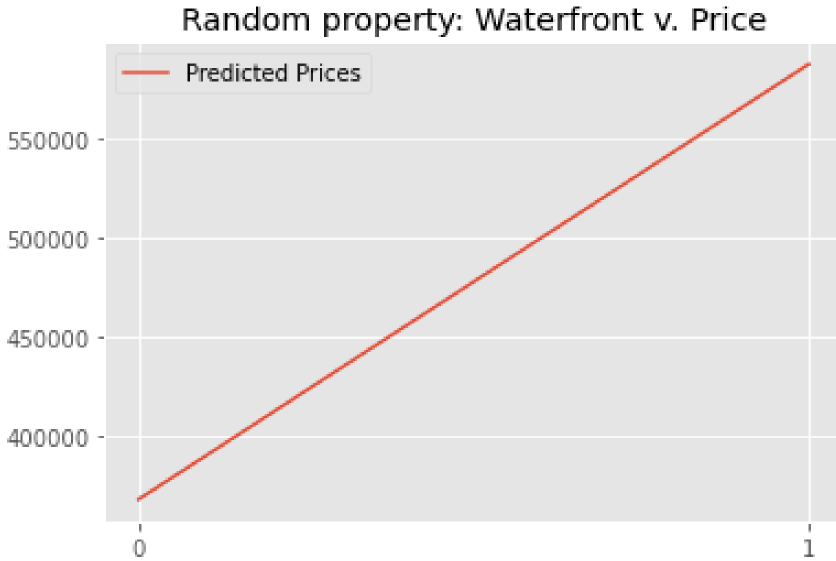
```
    for feat2 in list(df_cat.columns):
        if feat2 == 'long':
            featmax = max(np.log(df_b4_scale[feat2]*-1))
            featmin = min(np.log(df_b4_scale[feat2]*-1))
            df_cat[feat2] = (df_cat[feat2] - featmin) / (featmax - featmin)
            continue
        if feat2 in feats_4_log:
            featmax = max(np.log(df_b4_scale[feat2]))
            featmin = min(np.log(df_b4_scale[feat2]))
            df_cat[feat2] = (df_cat[feat2] - featmin) / (featmax - featmin)
            continue
        else:
            featmax = max(df_b4_scale[feat2])
            featmin = min(df_b4_scale[feat2])
            df_cat[feat2] = (df_cat[feat2] - featmin) / (featmax - featmin)

    maxprice = 13.835313
    minprice = 11.561716
    maxfeat = 0
    minfeat = 1

    x=[df_cat[feat][0], df_cat[feat][1]]
    ypred_feat = model.predict(df_cat)
    ypred_feat = np.exp(ypred_feat * (maxprice-minprice) + minprice)
    print('Actual Price: ${}, Actual Feat: {}.'.format(int(actual_price), actu
    plt.figure(figsize=(6,4))
    g=sns.lineplot(x=x, y=ypred_feat, label='Predicted Prices')
    g.set_xticks([0,1])
    plt.title(('{} v. Price').format(title))
#     plt.show()
    return (x, ypred_feat)
```

In [57]:

```
x_water1, y_water1 = predict_categorical('waterfront_1_0', 5*10**5, 2*10**5, 0
x_water2, y_water2 = predict_categorical('waterfront_1_0', 5.5*10**5, 2*10**5,
```

```
Actual Price: $443000, Actual Feat: 0.0.
Actual Price: $520000, Actual Feat: 1.0.
```



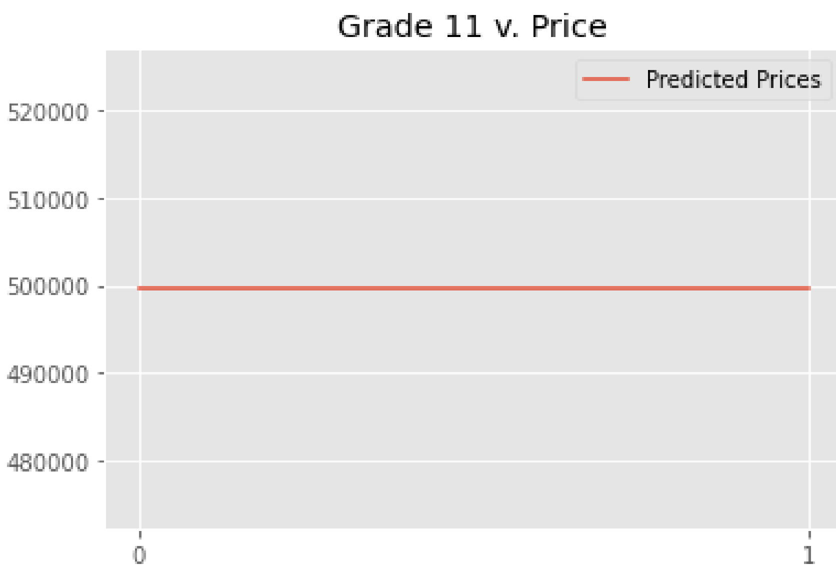


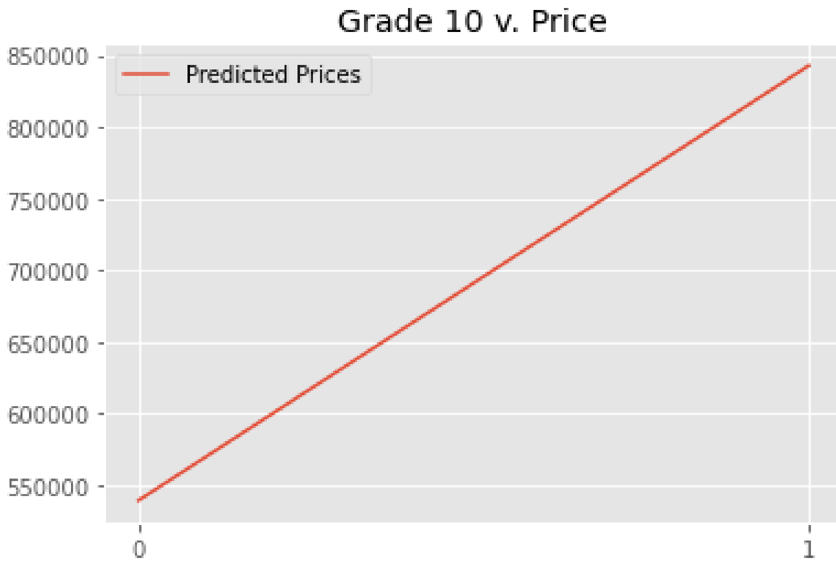
In [58]:
```
print(y_water1)
print(y_water2)
```

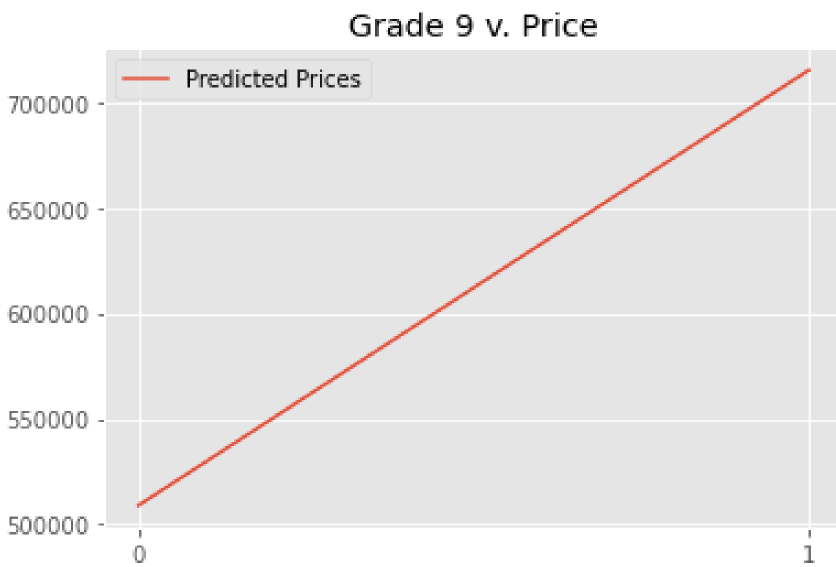
```
0    420299.776075
1    671231.313808
dtype: float64
0    588071.760047
1    368228.394563
dtype: float64
```

In [59]:
```
x_g11, y_g11 = predict_categorical('grade_11', 1*10**6, 2*10**5, 1, 'Grade 11'
x_g10, y_g10 = predict_categorical('grade_10', 1*10**6, 2*10**5, 1, 'Grade 10'
x_g9, y_g9 = predict_categorical('grade_9', 1*10**6, 2*10**5, 1, 'Grade 9')
```

```
Actual Price: $965000, Actual Feat: 1.0.
Actual Price: $746500, Actual Feat: 1.0.
Actual Price: $600000, Actual Feat: 1.0.
```







In [60]:
```
# create additional graphics
from shapely.geometry import Point # Shapely for converting latitude/longtitud
import geopandas as gpd # To create GeodataFram
import pandas as pd
from pyproj import CRS
import matplotlib.pyplot as plt
```

In [61]:
```
def add_geo_col(df):
    # create a geometry column
    geometry = [Point(xy) for xy in zip(df['long'], df['lat'])]

    # Coordinate reference system : WGS84 (the GPS model for conversion)
    crs = CRS('epsg:4326')

    # Creating a Geographic data frame
    gdf = gpd.GeoDataFrame(df, crs=crs, geometry=geometry).reset_index()
    return gdf
```

In [62]:
```
gdf2 = pd.read_pickle('data/geodata.pkl')
```

In [63]:
```
df_top10_employers = pd.read_csv('data/top_employers.csv')
df3 = df_top10_employers[df_top10_employers['centralized_campus']=='y'].reset_
gdf3 = add_geo_col(df3)
```

In [64]:
```
downtown = Point(-122.3244, 47.6150)
gdf4 = gpd.GeoSeries(downtown, crs=4326)
```

In [65]:
```
fig, ax = plt.subplots(ncols=1, sharex=True, sharey=True, figsize=(11, 20))
gdf4.plot(ax=ax, marker='o', color='#FFA12A', markersize=500, label='downtown'
gdf2.plot(ax=ax, marker='s', color='#333333', markersize=1, label='properties'
gdf3.plot(ax=ax, marker='*', color='r', markersize=100, label='employer')
ax.title.set_text('Map of Properties and Key Locations')
ax.legend()
```

Out[65]: <matplotlib.legend.Legend at 0x2445c4d0220>