Immersive_Data_Science_Project1_EDA

November 3, 2019

0.1 Final Project Submission

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0.2 What to do

We are given the King County House Sales dataset and we want to predict the prices for houses.

0.3 Importing Python Libraries needed for the project

[1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
from pandas.plotting import scatter_matrix # data processing, scatter matrix
import statsmodels.api as sm # Python module that provides classes and␣
↪functions for the estimation of many different
#statistical models, as well as for conducting statistical tests, and␣
↪statistical data exploration
import matplotlib.pyplot as plt # plotting
import scipy.stats as stats
import sklearn.linear_model as linear_model
from sklearn.model_selection import train_test_split
import seaborn as sns
import statsmodels.api as sms
import statsmodels.formula.api as smf
from statsmodels.formula.api import ols
from mpl_toolkits.basemap import Basemap
sns.set()
%matplotlib inline
```

0.4 Import the data

[2]:
```
df = pd.read_csv('King_County_House_prices_dataset.csv')
df.head()
```

[2]:
```
           id        date     price  bedrooms  bathrooms  sqft_living  \
0  7129300520  10/13/2014  221900.0         3       1.00         1180
1  6414100192   12/9/2014  538000.0         3       2.25         2570
2  5631500400   2/25/2015  180000.0         2       1.00          770
```

```
3  2487200875   12/9/2014  604000.0          4       3.00          1960
4  1954400510   2/18/2015  510000.0          3       2.00          1680

   sqft_lot  floors  waterfront  view     …      grade  sqft_above  \
0      5650     1.0         NaN   0.0     …          7        1180
1      7242     2.0         0.0   0.0     …          7        2170
2     10000     1.0         0.0   0.0     …          6         770
3      5000     1.0         0.0   0.0     …          7        1050
4      8080     1.0         0.0   0.0     …          8        1680

   sqft_basement yr_built  yr_renovated  zipcode      lat     long  \
0            0.0     1955           0.0    98178  47.5112 -122.257
1          400.0     1951        1991.0    98125  47.7210 -122.319
2            0.0     1933           NaN    98028  47.7379 -122.233
3          910.0     1965           0.0    98136  47.5208 -122.393
4            0.0     1987           0.0    98074  47.6168 -122.045

   sqft_living15  sqft_lot15
0           1340        5650
1           1690        7639
2           2720        8062
3           1360        5000
4           1800        7503

[5 rows x 21 columns]
```

0.5 Understanding the data

[3]:
```python
f = open("column_names.md", "r")
print(f.read())
f.close()
```

```
# Column Names and descriptions for Kings County Data Set
* **id** - unique identified for a house
* **dateDate** - house was sold
* **pricePrice** -  is prediction target
* **bedroomsNumber** -  of Bedrooms/House
* **bathroomsNumber** -  of bathrooms/bedrooms
* **sqft_livingsquare** -  footage of the home
* **sqft_lotsquare** -  footage of the lot
* **floorsTotal** -  floors (levels) in house
* **waterfront** - House which has a view to a waterfront
* **view** - Has been viewed
* **condition** - How good the condition is ( Overall )
* **grade** - overall grade given to the housing unit, based on King County
grading system
* **sqft_above** - square footage of house apart from basement
```

```
* **sqft_basement** - square footage of the basement
* **yr_built** - Built Year
* **yr_renovated** - Year when house was renovated
* **zipcode** - zip
* **lat** - Latitude coordinate
* **long** - Longitude coordinate
* **sqft_living15** - The square footage of interior housing living space for
the nearest 15 neighbors
* **sqft_lot15** - The square footage of the land lots of the nearest 15
neighbors
```

0.6 Cleaning the data

Lets get an overview about our data first.

[4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
id               21597 non-null int64
date             21597 non-null object
price            21597 non-null float64
bedrooms         21597 non-null int64
bathrooms        21597 non-null float64
sqft_living      21597 non-null int64
sqft_lot         21597 non-null int64
floors           21597 non-null float64
waterfront       19221 non-null float64
view             21534 non-null float64
condition        21597 non-null int64
grade            21597 non-null int64
sqft_above       21597 non-null int64
sqft_basement    21597 non-null object
yr_built         21597 non-null int64
yr_renovated     17755 non-null float64
zipcode          21597 non-null int64
lat              21597 non-null float64
long             21597 non-null float64
sqft_living15    21597 non-null int64
sqft_lot15       21597 non-null int64
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
```

Sort for nan values

[5]:
```python
df.isna().sum().sort_values()
```

[5]:
```
id                 0
long               0
lat                0
zipcode            0
yr_built           0
sqft_basement      0
sqft_above         0
grade              0
sqft_living15      0
condition          0
floors             0
sqft_lot           0
sqft_living        0
bathrooms          0
bedrooms           0
price              0
date               0
sqft_lot15         0
view              63
waterfront      2376
yr_renovated    3842
dtype: int64
```

We see that there are missing values in the columns view, waterfront and yr_renovated. Let's get an better understanding of the columns before we decide what to do with them.

First we take a look at the column waterfront

[6]:
```
print("Unique values in waterfront:" + str(df.waterfront.unique()))
print("Mean value of waterfront   :" + str(df.waterfront.mean()))
```

```
Unique values in waterfront:[nan  0.  1.]
Mean value of waterfront   :0.007595858696217679
```

Takeaway, basicly it is an boolean saying if a house has waterfront. We can also see that most of the houses have no waterfront.

We asume that a waterfront is an unique selling point and every houseowner would give us the information if the house has one. So we decide to fill the "nan" with zeros.

[7]:
```
df.waterfront.fillna(0, inplace =True)
df.waterfront.unique()
```

[7]:
```
array([0., 1.])
```

We continue with the next column view

[8]:
```
print("Unique values in view : " + str(df.view.unique()))
print("Mean value of view    : " + str(df.view.mean()))
print("Number of Nan for view: " + str(df['view'].isna().sum()))
```

```python
print("Unique count for view : ")
print(df.groupby('view')['id'].nunique())
```

```
Unique values in view : [ 0. nan  3.  4.  2.  1.]
Mean value of view    : 0.23386272870808952
Number of Nan for view: 63
Unique count for view :
view
0.0    19253
1.0      329
2.0      956
3.0      505
4.0      314
Name: id, dtype: int64
```

We can see that most of the houses have not been viewed. We have only 63 nan in the column and we can fill them with zeros.

[9]:
```python
df.view.fillna(0, inplace =True)
df.view.unique()
```

[9]:
```
array([0., 3., 4., 2., 1.])
```

We continue with the column yr_renovated

[10]:
```python
print("Unique values in yr_renovated : " + str(df.yr_renovated.unique()))
print("Number of Nan for yr_renovated: " + str(df['yr_renovated'].isna().sum()))
print("Unique count for yr_renovated : ")
print(df.groupby('yr_renovated')['id'].nunique().head())
```

```
Unique values in yr_renovated : [   0. 1991.   nan 2002. 2010. 1992. 2013. 1994.
1978. 2005. 2003. 1984.
 1954. 2014. 2011. 1983. 1945. 1990. 1988. 1977. 1981. 1995. 2000. 1999.
 1998. 1970. 1989. 2004. 1986. 2007. 1987. 2006. 1985. 2001. 1980. 1971.
 1979. 1997. 1950. 1969. 1948. 2009. 2015. 1974. 2008. 1968. 2012. 1963.
 1951. 1962. 1953. 1993. 1996. 1955. 1982. 1956. 1940. 1976. 1946. 1975.
 1964. 1973. 1957. 1959. 1960. 1967. 1965. 1934. 1972. 1944. 1958.]
Number of Nan for yr_renovated: 3842
Unique count for yr_renovated :
yr_renovated
0.0       16900
1934.0        1
1940.0        2
1944.0        1
1945.0        3
Name: id, dtype: int64
```

We asume that a renovation is an uique selling point and the houseowner would mention it. So we can fill the nan with a zero what means no renovation has taken place.

[11]:
```
df.yr_renovated.fillna(0, inplace = True)
df['yr_renovated'].isna().sum()
```

[11]: 0

So lets take a look at our data:

[12]:
```
df.isna().sum().sort_values()
```

[12]:
```
id               0
long             0
lat              0
zipcode          0
yr_renovated     0
yr_built         0
sqft_basement    0
sqft_above       0
grade            0
sqft_living15    0
condition        0
waterfront       0
floors           0
sqft_lot         0
sqft_living      0
bathrooms        0
bedrooms         0
price            0
date             0
view             0
sqft_lot15       0
dtype: int64
```

We filled all of the missing data.

To be able to work with our data we want to have numeric values in our data. Lets figure out in what format our data is.

[13]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
id               21597 non-null int64
date             21597 non-null object
price            21597 non-null float64
bedrooms         21597 non-null int64
bathrooms        21597 non-null float64
sqft_living      21597 non-null int64
sqft_lot         21597 non-null int64
```

```
floors           21597 non-null float64
waterfront       21597 non-null float64
view             21597 non-null float64
condition        21597 non-null int64
grade            21597 non-null int64
sqft_above       21597 non-null int64
sqft_basement    21597 non-null object
yr_built         21597 non-null int64
yr_renovated     21597 non-null float64
zipcode          21597 non-null int64
lat              21597 non-null float64
long             21597 non-null float64
sqft_living15    21597 non-null int64
sqft_lot15       21597 non-null int64
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
```

So the columns date and sqft_basement are objects. We want to change that. First we take a look at sqft_basement. I would expect an numeric value. Lets explore sqft_basement

[14]:
```
print(df.groupby('sqft_basement')['id'].nunique())
```

```
sqft_basement
0.0       12718
10.0          1
100.0        42
1000.0      146
1008.0        1
1010.0       62
1020.0       51
1024.0        1
1030.0       44
1040.0       54
1050.0       41
1060.0       58
1070.0       51
1080.0       31
1090.0       32
110.0        18
1100.0       78
1110.0       35
1120.0       43
1130.0       30
1135.0        1
1140.0       28
1150.0       26
1160.0       26
1170.0       30
```

```
1180.0      28
1190.0      24
120.0       53
1200.0      68
1210.0      18
            …
80.0        20
800.0      201
810.0       55
820.0       62
830.0       56
840.0       82
850.0       69
860.0       79
861.0        1
862.0        1
870.0       48
875.0        1
880.0       69
890.0       52
90.0        21
900.0      141
906.0        1
910.0       69
915.0        1
920.0       65
930.0       41
935.0        1
940.0       71
946.0        1
950.0       62
960.0       65
970.0       44
980.0       55
990.0       51
?          454
Name: id, Length: 304, dtype: int64
```

We see the unique sqrt_basement values and detect that in 454 rows is a "?". Thats why the datatype of the column is an object. We definetly want to change that.

So lets try to find some information about the houses with basement, without basement and we don't know about the basement.

[15]:
```
df[['sqft_basement','sqft_above','sqft_living']].head()
```

[15]:

	sqft_basement	sqft_above	sqft_living
0	0.0	1180	1180
1	400.0	2170	2570

```
2          0.0         770          770
3        910.0        1050         1960
4          0.0        1680         1680
```

[16]:
```python
basement = df[['sqft_basement','sqft_above','sqft_living']]
basement['sqft_living-above'] = basement['sqft_living'] - basement['sqft_above']
basement
```

```
/Users/flori/anaconda3/envs/nf/lib/python3.6/site-
packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
```

[16]:

	sqft_basement	sqft_above	sqft_living	sqft_living-above
0	0.0	1180	1180	0
1	400.0	2170	2570	400
2	0.0	770	770	0
3	910.0	1050	1960	910
4	0.0	1680	1680	0
5	1530.0	3890	5420	1530
6	?	1715	1715	0
7	0.0	1060	1060	0
8	730.0	1050	1780	730
9	0.0	1890	1890	0
10	1700.0	1860	3560	1700
11	300.0	860	1160	300
12	0.0	1430	1430	0
13	0.0	1370	1370	0
14	0.0	1810	1810	0
15	970.0	1980	2950	970
16	0.0	1890	1890	0
17	0.0	1600	1600	0
18	?	1200	1200	0
19	0.0	1250	1250	0
20	760.0	860	1620	760
21	720.0	2330	3050	720
22	0.0	2270	2270	0
23	0.0	1070	1070	0
24	0.0	2450	2450	0
25	0.0	1710	1710	0
26	700.0	1750	2450	700
27	0.0	1400	1400	0
28	730.0	790	1520	730

```
29              0.0         2570        2570             0
...             ...         ...         ...             ...
21567           0.0          710         710             0
21568         320.0          940        1260           320
21569           0.0         1870        1870             0
21570           0.0         1430        1430             0
21571           0.0         1520        1520             0
21572         190.0         1020        1210           190
21573           0.0         2540        2540             0
21574        1800.0         3110        4910          1800
21575           0.0         2770        2770             0
21576           0.0         1190        1190             0
21577           0.0         4170        4170             0
21578           0.0         2500        2500             0
21579          50.0         1480        1530            50
21580           0.0         3600        3600             0
21581             ?         3410        3410             0
21582           0.0         3118        3118             0
21583           0.0         3990        3990             0
21584           0.0         4470        4470             0
21585           0.0         1425        1425             0
21586           0.0         1500        1500             0
21587           0.0         2270        2270             0
21588           0.0         1490        1490             0
21589           0.0         2520        2520             0
21590         910.0         2600        3510           910
21591         130.0         1180        1310           130
21592           0.0         1530        1530             0
21593           0.0         2310        2310             0
21594           0.0         1020        1020             0
21595           0.0         1600        1600             0
21596           0.0         1020        1020             0

[21597 rows x 4 columns]
```

Seems like the sqft_basement is just calculated by subtracting sqft_above from sqft_living

[17]:
```python
df['sqft_basement'] = basement['sqft_living'] - basement['sqft_above']
```

So sqft_living is just the sum of sqft_aboce and sqft_basement we can just drop it.

[18]:
```python
df.drop('sqft_living', axis = 1, inplace = True)
```

[19]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 20 columns):
```

```
id                21597 non-null int64
date              21597 non-null object
price             21597 non-null float64
bedrooms          21597 non-null int64
bathrooms         21597 non-null float64
sqft_lot          21597 non-null int64
floors            21597 non-null float64
waterfront        21597 non-null float64
view              21597 non-null float64
condition         21597 non-null int64
grade             21597 non-null int64
sqft_above        21597 non-null int64
sqft_basement     21597 non-null int64
yr_built          21597 non-null int64
yr_renovated      21597 non-null float64
zipcode           21597 non-null int64
lat               21597 non-null float64
long              21597 non-null float64
sqft_living15     21597 non-null int64
sqft_lot15        21597 non-null int64
dtypes: float64(8), int64(11), object(1)
memory usage: 3.3+ MB
```

Now we have to look at the date column. To be able to work with it we have to change it to an numeriv value. Therefore we want to seperate between spring, summer, autumn and winter. We asume that the winter starts at december 1st, spring starts at march 1st, summer starts at june 1st and autumn at september 1st.

[20]:
```
df['date'] = pd.to_datetime(df['date'])
```

[21]:
```
dates = []
for i in (range(len(df))):
    if(df['date'][i].month == 12 or df['date'][i].month == 1 or df['date'][i].
 ↪month == 2):
        dates.append('winter')
    elif(df['date'][i].month == 3 or df['date'][i].month == 4 or df['date'][i].
 ↪month == 5):
        dates.append('spring')
    elif(df['date'][i].month == 6 or df['date'][i].month == 7 or df['date'][i].
 ↪month == 8):
        dates.append('summer')
    else:
        dates.append('autumn')
```

[22]:
```
dates_dummies = pd.get_dummies(dates, drop_first=True)
dates_dummies.head()
```

```
[22]:    spring  summer  winter
      0       0       0       0
      1       0       0       1
      2       0       0       1
      3       0       0       1
      4       0       0       1
```

We generated our dummy variables. Now we want to join our dummy variables with our dataset

```python
[23]: df2 = pd.concat([df, dates_dummies], axis = 1)
      df2.head()
```

```
[23]:            id        date     price  bedrooms  bathrooms  sqft_lot  floors  \
      0  7129300520  2014-10-13  221900.0         3       1.00      5650     1.0
      1  6414100192  2014-12-09  538000.0         3       2.25      7242     2.0
      2  5631500400  2015-02-25  180000.0         2       1.00     10000     1.0
      3  2487200875  2014-12-09  604000.0         4       3.00      5000     1.0
      4  1954400510  2015-02-18  510000.0         3       2.00      8080     1.0

         waterfront  view  condition  …  yr_built  yr_renovated  zipcode  \
      0         0.0   0.0          3  …      1955           0.0    98178
      1         0.0   0.0          3  …      1951        1991.0    98125
      2         0.0   0.0          3  …      1933           0.0    98028
      3         0.0   0.0          5  …      1965           0.0    98136
      4         0.0   0.0          3  …      1987           0.0    98074

             lat     long  sqft_living15  sqft_lot15  spring  summer  winter
      0  47.5112 -122.257           1340        5650       0       0       0
      1  47.7210 -122.319           1690        7639       0       0       1
      2  47.7379 -122.233           2720        8062       0       0       1
      3  47.5208 -122.393           1360        5000       0       0       1
      4  47.6168 -122.045           1800        7503       0       0       1

      [5 rows x 23 columns]
```

Now we want to drop the month and day part of the date, so we just have the year left.

```python
[24]: df2['date'] = pd.DatetimeIndex(df2['date']).year
```

```python
[25]: df2.head()
```

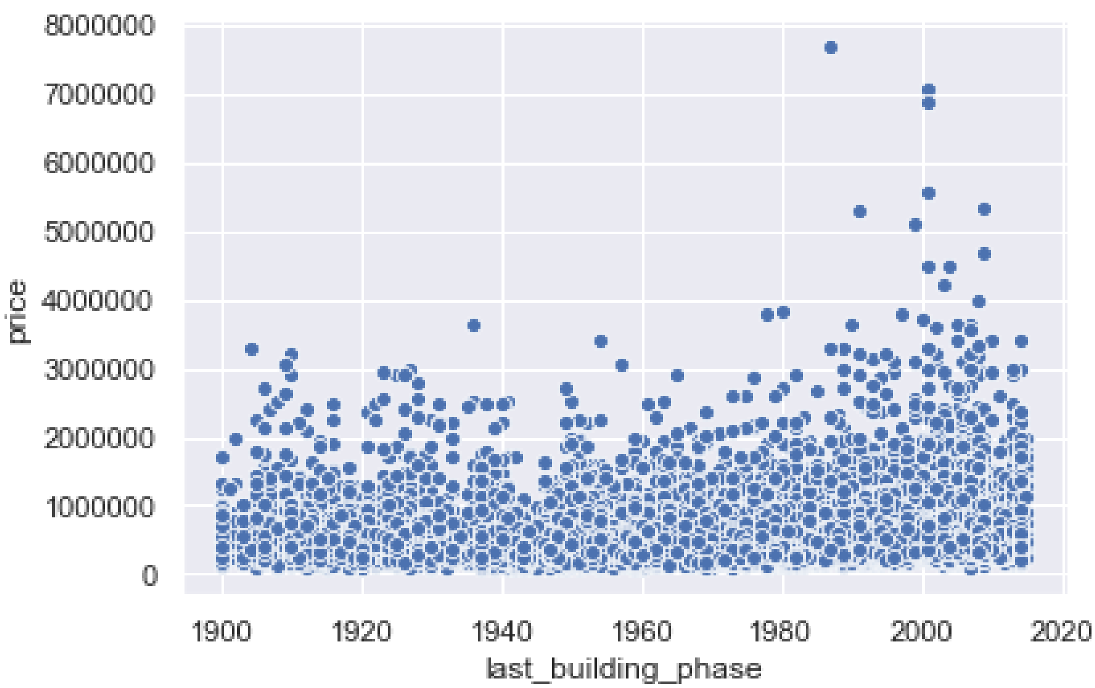
```
[25]:            id  date     price  bedrooms  bathrooms  sqft_lot  floors  \
      0  7129300520  2014  221900.0         3       1.00      5650     1.0
      1  6414100192  2014  538000.0         3       2.25      7242     2.0
      2  5631500400  2015  180000.0         2       1.00     10000     1.0
      3  2487200875  2014  604000.0         4       3.00      5000     1.0
      4  1954400510  2015  510000.0         3       2.00      8080     1.0
```

```
   waterfront  view  condition  ...   yr_built  yr_renovated  zipcode  \
0         0.0   0.0          3  ...       1955           0.0    98178
1         0.0   0.0          3  ...       1951        1991.0    98125
2         0.0   0.0          3  ...       1933           0.0    98028
3         0.0   0.0          5  ...       1965           0.0    98136
4         0.0   0.0          3  ...       1987           0.0    98074

       lat     long  sqft_living15  sqft_lot15  spring  summer  winter
0  47.5112 -122.257           1340        5650       0       0       0
1  47.7210 -122.319           1690        7639       0       0       1
2  47.7379 -122.233           2720        8062       0       0       1
3  47.5208 -122.393           1360        5000       0       0       1
4  47.6168 -122.045           1800        7503       0       0       1

[5 rows x 23 columns]
```

Create new column "last_building_phase" include the max of yr_built and yr_renovated

[26]:
```python
df2["last_building_phase"] = df2[["yr_built", "yr_renovated"]].max(axis=1)
```

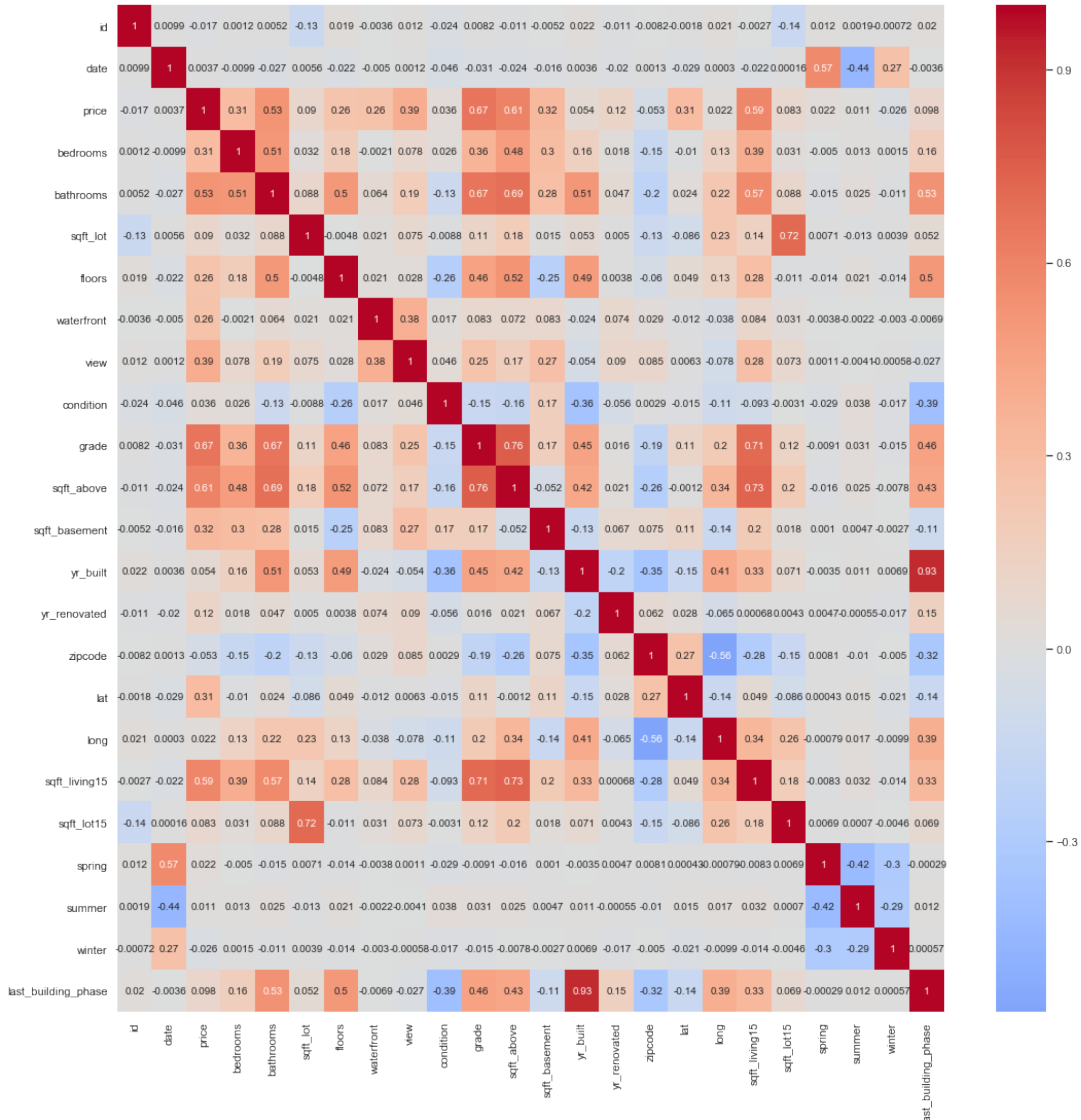
[27]:
```python
sns.scatterplot(x="last_building_phase", y="price", data=df2);
```



There is a small relationship between price and last_building_phase.

Lets plot some data

[28]:
```python
corr = df2.corr()
f, ax = plt.subplots(figsize = (18,18))
sns.heatmap(data=corr, center = 0, cmap="coolwarm", annot=True);
```



There are variables that have a correlation with price:

-bedrooms 0.31

-bathrooms 0.53

-sqft-lot 0.09

-floors 0.26

-waterfront 0.26

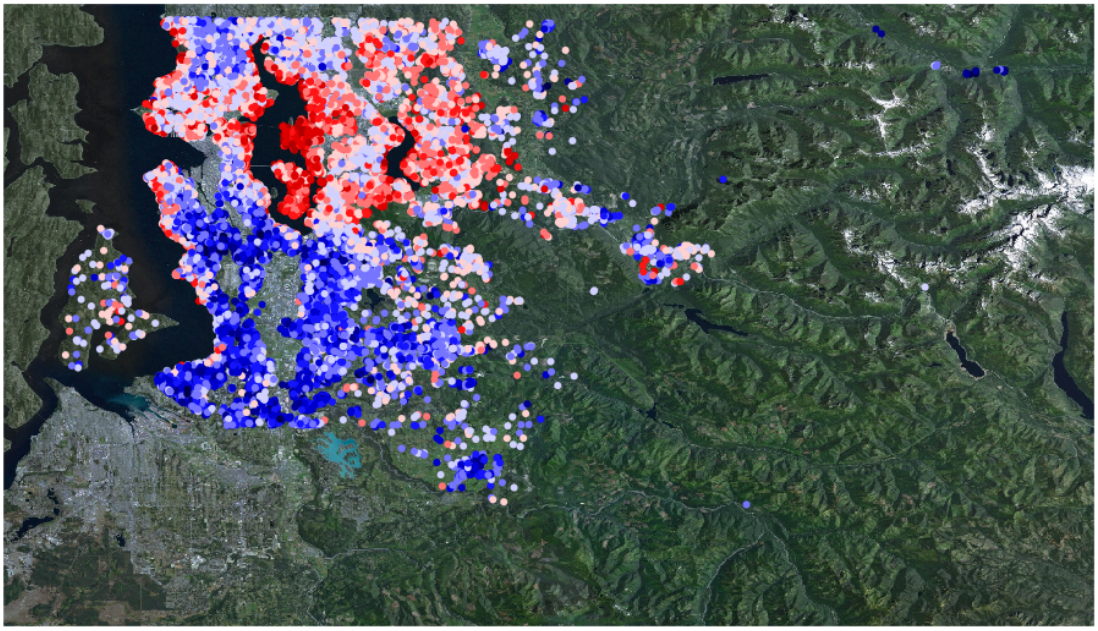
-view 0.39

-grade 0.67

```
-sqft_above 0.31
-sqft_basement 0.32
-year_renovated 0.12
-lat 0.31
-sqft_living 0.59
-last_building_phase 0.098
```

Lets plot the location and the price:

[29]:
```
# Extract the data we're interested in
lat = df['lat'].values
lon = df['long'].values
bins = [0, 150000, 200000, 250000, 300000, 400000, 550000 ,750000, 1000000,␣
↪1500000, 2500000, 5000000, 10000000]
c = pd.cut(df['price'], bins, labels = range(12))
# 1. Draw the map background
fig = plt.figure(figsize=(16, 16))
m = Basemap(projection='merc', resolution='h', llcrnrlon = -122.6, llcrnrlat =␣
↪47, urcrnrlon = -121.2, urcrnrlat = 47.8,
            lon_0= -121.7,
            lat_0= 47.4,
            epsg=4269)
m.arcgisimage(service='ESRI_Imagery_World_2D', xpixels = 2000)

# 2. scatter city data, with color reflecting population
# and size reflecting area
lons, lats = m(lon, lat)
m.scatter(lons, lats,zorder=1, linewidths=0.07, cmap = 'seismic', c = c)

plt.show()
```



We see that there is a correlation between location and price.

Let s take the squares of the plot and group our houses into them

[30]:
```
lat = []
for i in (range(len(df))):
    if df['lat'][i] < 47.2:
        lat.append('lat_47.2')
    elif df['lat'][i] < 47.3:
        lat.append('lat_47.3')
    elif df['lat'][i] < 47.4:
        lat.append('lat_47.4')
    elif df['lat'][i] < 47.5:
        lat.append('lat_47.5')
    elif df['lat'][i] < 47.6:
        lat.append('lat_47.6')
    elif df['lat'][i] < 47.7:
        lat.append('lat_47.7')
    else:
        lat.append('lat_47.8')
```

[31]:
```
long = []
for i in (range(len(df))):
    if df['long'][i] < -122.4:
        long.append('long_-122.4')
    elif df['long'][i] < -122.2:
        long.append('long_-122.2')
```

```
    elif df['long'][i] < -122:
        long.append('long_-122')
    elif df['long'][i] < -121.8:
        long.append('long_-121.8')
    elif df['long'][i] < -121.6:
        long.append('long_-121.6')
    elif df['long'][i] < -121.4:
        long.append('long_-121.4')
    else:
        long.append('long_-121.2')
```

[32]:
```
lat_dummies = pd.get_dummies(lat, drop_first=True)
long_dummies = pd.get_dummies(long, drop_first=True)
long_dummies.head()
```

[32]:

	long_-121.4	long_-121.6	long_-121.8	long_-122	long_-122.2	long_-122.4
0	0	0	0	0	1	0
1	0	0	0	0	1	0
2	0	0	0	0	1	0
3	0	0	0	0	1	0
4	0	0	0	1	0	0

[33]:
```
lat_long = pd.concat([lat_dummies, long_dummies], axis = 1)
lat_long.head()
```

[33]:

	lat_47.3	lat_47.4	lat_47.5	lat_47.6	lat_47.7	lat_47.8	long_-121.4 \
0	0	0	0	1	0	0	0
1	0	0	0	0	0	1	0
2	0	0	0	0	0	1	0
3	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0

	long_-121.6	long_-121.8	long_-122	long_-122.2	long_-122.4
0	0	0	0	1	0
1	0	0	0	1	0
2	0	0	0	1	0
3	0	0	0	1	0
4	0	0	1	0	0

[34]:
```
df3 = pd.concat([df2, lat_long], axis = 1)
```

0.7 Model a linear Regression

[35]:
```
X = df3[[ 'bedrooms', 'bathrooms',
       'sqft_lot', 'floors', 'waterfront', 'view', 'grade',
       'sqft_above', 'sqft_basement', 'lat_47.8', 'lat_47.3', 'lat_47.4',
       'lat_47.5', 'lat_47.6', 'lat_47.7', 'long_-122.4', 'long_-121.4',
```

```
      'long_-121.6', 'long_-121.8', 'long_-122', 'long_-122.2']]
y = df3[['price']]
X = sms.add_constant(X)
model = sms.OLS(y, X)
results = model.fit()
results.summary()
```

[35]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.727
Model:                            OLS   Adj. R-squared:                  0.727
Method:                 Least Squares   F-statistic:                     2740.
Date:                Sun, 03 Nov 2019   Prob (F-statistic):               0.00
Time:                        10:10:31   Log-Likelihood:            -2.9336e+05
No. Observations:               21597   AIC:                         5.868e+05
Df Residuals:                   21575   BIC:                         5.869e+05
Df Model:                          21
Covariance Type:            nonrobust
================================================================================
=
                    coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-
const         -4.409e+05   6.26e+04     -7.039      0.000   -5.64e+05
-3.18e+05
bedrooms      -2.451e+04   1806.001    -13.570      0.000    -2.8e+04
-2.1e+04
bathrooms      1.454e+04   2936.901      4.952      0.000    8786.795
2.03e+04
sqft_lot          0.1172      0.034      3.485      0.000       0.051
0.183
floors        -7.445e+04   3338.798    -22.299      0.000    -8.1e+04
-6.79e+04
waterfront     6.575e+05   1.73e+04     38.000      0.000    6.24e+05
6.91e+05
view           5.832e+04   1999.164     29.171      0.000    5.44e+04
6.22e+04
grade          6.656e+04   1941.184     34.291      0.000    6.28e+04
7.04e+04
sqft_above      230.2617      3.150     73.103      0.000     224.088
236.436
sqft_basement   155.4998      4.087     38.044      0.000     147.488
163.511
lat_47.8       1.164e+05   2.17e+04      5.370      0.000    7.39e+04
```

```
1.59e+05
lat_47.3      -5.139e+04   2.25e+04     -2.281      0.023   -9.56e+04
-7235.817
lat_47.4      -4.009e+04   2.17e+04     -1.845      0.065   -8.27e+04
2489.904
lat_47.5       1.744e+04   2.17e+04      0.802      0.422   -2.52e+04
6.01e+04
lat_47.6       1.766e+05   2.16e+04      8.192      0.000    1.34e+05
2.19e+05
lat_47.7       3.217e+05   2.16e+04     14.869      0.000    2.79e+05
3.64e+05
long_-122.4    6.164e+04    5.9e+04      1.046      0.296   -5.39e+04
1.77e+05
long_-121.4   -1.014e+05   9.74e+04     -1.041      0.298   -2.92e+05
8.96e+04
long_-121.6    2.389e+04   5.95e+04      0.401      0.688   -9.28e+04
1.41e+05
long_-121.8   -9.844e+04   5.83e+04     -1.689      0.091   -2.13e+05
1.58e+04
long_-122     -2.936e+04   5.81e+04     -0.506      0.613   -1.43e+05
8.45e+04
long_-122.2     4.69e+04    5.8e+04      0.809      0.419   -6.68e+04
1.61e+05
==============================================================================
Omnibus:                    18904.678   Durbin-Watson:                   1.990
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2171070.288
Skew:                           3.701   Prob(JB):                         0.00
Kurtosis:                      51.558   Cond. No.                     5.31e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 5.31e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

R-squared is 0.727 not bad at all.

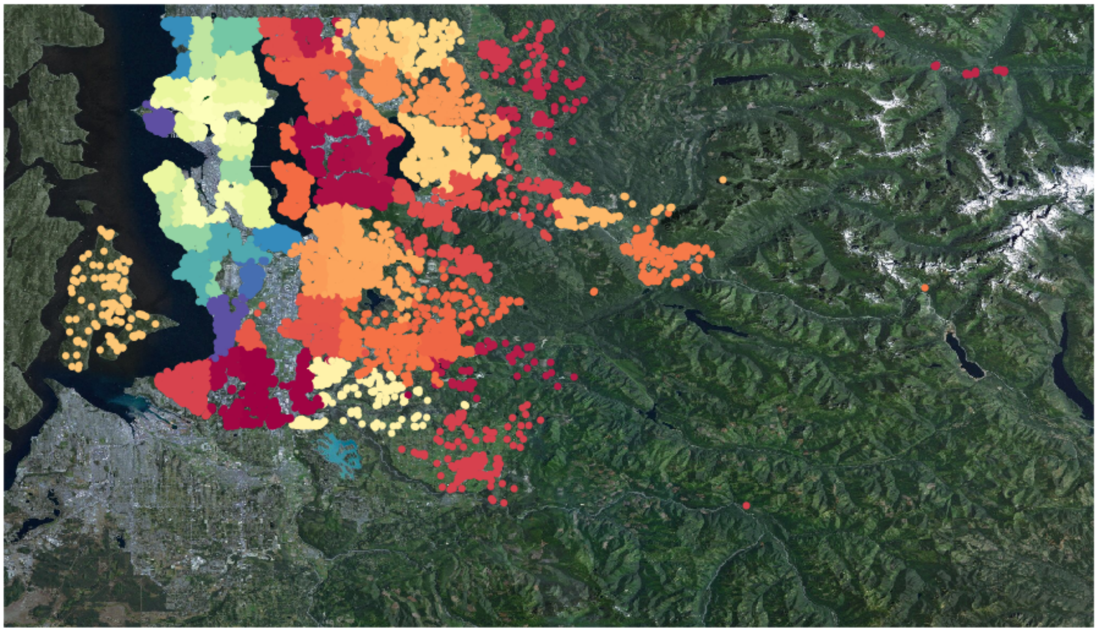
0.8 Improving our approach

We want to introduce dummy variables for the zipcode, because the zipcode is an integer but is actual a categorial variable.

First we plot the zipcode and try to get some insights

[36]:
```python
# Extract the data we're interested in
lat = df['lat'].values
```

```
lon = df['long'].values
# 1. Draw the map background
fig = plt.figure(figsize=(16, 16))
m = Basemap(projection='merc', resolution='h', llcrnrlon = -122.6, llcrnrlat =␣
↪47, urcrnrlon = -121.2, urcrnrlat = 47.8,
            lon_0= -121.7,
            lat_0= 47.4,
            epsg=4269)
m.arcgisimage(service='ESRI_Imagery_World_2D', xpixels = 2000)

# 2. scatter city data, with color reflecting population
# and size reflecting area
lons, lats = m(lon, lat)
m.scatter(lons, lats,zorder=1, linewidths=0.1 , c = df['zipcode'].values, cmap␣
↪= 'Spectral')

plt.show()
```



Seems to work quite good and should be more exact than just the dummies for longitude and latitude.

[37]:
```
model = ols('price ~ C(zipcode) + bedrooms + bathrooms + sqft_lot + floors +␣
↪waterfront + view + grade + sqft_above + sqft_basement +␣
↪last_building_phase', data=df3).fit()

model.summary()
```

[37]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.804
Model:                            OLS   Adj. R-squared:                  0.804
Method:                 Least Squares   F-statistic:                     1119.
Date:                Sun, 03 Nov 2019   Prob (F-statistic):               0.00
Time:                        10:10:54   Log-Likelihood:            -2.8978e+05
No. Observations:               21597   AIC:                         5.797e+05
Df Residuals:                   21517   BIC:                         5.804e+05
Df Model:                          79
Covariance Type:            nonrobust
================================================================================
=======
                          coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
Intercept            1.056e+06   1.13e+05      9.346      0.000    8.34e+05
1.28e+06
C(zipcode)[T.98002]  3.497e+04   1.44e+04      2.429      0.015    6747.289
6.32e+04
C(zipcode)[T.98003] -1.719e+04    1.3e+04     -1.324      0.185   -4.26e+04
8253.120
C(zipcode)[T.98004]  7.868e+05   1.27e+04     62.025      0.000    7.62e+05
8.12e+05
C(zipcode)[T.98005]  3.104e+05   1.53e+04     20.244      0.000     2.8e+05
3.41e+05
C(zipcode)[T.98006]  2.772e+05   1.14e+04     24.239      0.000    2.55e+05
3e+05
C(zipcode)[T.98007]  2.513e+05   1.62e+04     15.488      0.000    2.19e+05
2.83e+05
C(zipcode)[T.98008]  2.538e+05    1.3e+04     19.529      0.000    2.28e+05
2.79e+05
C(zipcode)[T.98010]    7.7e+04   1.84e+04      4.174      0.000    4.08e+04
1.13e+05
C(zipcode)[T.98011]  1.217e+05   1.45e+04      8.398      0.000    9.33e+04
1.5e+05
C(zipcode)[T.98014]  9.283e+04   1.71e+04      5.419      0.000    5.93e+04
1.26e+05
C(zipcode)[T.98019]  8.653e+04   1.46e+04      5.913      0.000    5.78e+04
1.15e+05
C(zipcode)[T.98022] -5201.3953   1.38e+04     -0.376      0.707   -3.23e+04
2.19e+04
C(zipcode)[T.98023] -3.287e+04   1.13e+04     -2.917      0.004    -5.5e+04
-1.08e+04
```

```
C(zipcode)[T.98024]  1.521e+05   2.03e+04      7.498      0.000    1.12e+05
1.92e+05
C(zipcode)[T.98027]  1.708e+05   1.18e+04     14.465      0.000    1.48e+05
1.94e+05
C(zipcode)[T.98028]  1.195e+05   1.29e+04      9.237      0.000    9.42e+04
1.45e+05
C(zipcode)[T.98029]  2.105e+05   1.26e+04     16.720      0.000    1.86e+05
2.35e+05
C(zipcode)[T.98030]  4456.9119   1.33e+04      0.335      0.738   -2.16e+04
3.05e+04
C(zipcode)[T.98031]  1.854e+04   1.31e+04      1.419      0.156   -7068.667
4.42e+04
C(zipcode)[T.98032]  1.034e+04   1.69e+04      0.611      0.541   -2.28e+04
4.35e+04
C(zipcode)[T.98033]  3.705e+05   1.17e+04     31.779      0.000    3.48e+05
3.93e+05
C(zipcode)[T.98034]  2.012e+05   1.11e+04     18.173      0.000    1.79e+05
2.23e+05
C(zipcode)[T.98038]  3.168e+04   1.09e+04      2.900      0.004    1.03e+04
5.31e+04
C(zipcode)[T.98039]  1.332e+06   2.48e+04     53.757      0.000    1.28e+06
1.38e+06
C(zipcode)[T.98040]  5.297e+05   1.32e+04     40.275      0.000    5.04e+05
5.56e+05
C(zipcode)[T.98042]  1.124e+04    1.1e+04      1.017      0.309   -1.04e+04
3.29e+04
C(zipcode)[T.98045]  8.461e+04    1.4e+04      6.055      0.000    5.72e+04
1.12e+05
C(zipcode)[T.98052]  2.285e+05    1.1e+04     20.786      0.000    2.07e+05
2.5e+05
C(zipcode)[T.98053]  1.864e+05   1.19e+04     15.637      0.000    1.63e+05
2.1e+05
C(zipcode)[T.98055]  4.632e+04   1.31e+04      3.524      0.000    2.06e+04
7.21e+04
C(zipcode)[T.98056]  1.046e+05   1.18e+04      8.876      0.000    8.15e+04
1.28e+05
C(zipcode)[T.98058]   3.19e+04   1.15e+04      2.777      0.005    9383.496
5.44e+04
C(zipcode)[T.98059]  8.818e+04   1.14e+04      7.708      0.000    6.58e+04
1.11e+05
C(zipcode)[T.98065]  8.139e+04   1.27e+04      6.406      0.000    5.65e+04
1.06e+05
C(zipcode)[T.98070] -1441.2949   1.77e+04     -0.082      0.935   -3.61e+04
3.32e+04
C(zipcode)[T.98072]  1.516e+05   1.31e+04     11.569      0.000    1.26e+05
1.77e+05
C(zipcode)[T.98074]  1.693e+05   1.17e+04     14.510      0.000    1.46e+05
```

```
1.92e+05
C(zipcode)[T.98075]  1.696e+05   1.23e+04     13.793      0.000    1.46e+05
1.94e+05
C(zipcode)[T.98077]  1.205e+05   1.46e+04      8.274      0.000    9.19e+04
1.49e+05
C(zipcode)[T.98092]   -3.7e+04   1.22e+04     -3.025      0.002    -6.1e+04
-1.3e+04
C(zipcode)[T.98102]  5.228e+05   1.85e+04     28.301      0.000    4.87e+05
5.59e+05
C(zipcode)[T.98103]  3.504e+05   1.12e+04     31.350      0.000    3.29e+05
3.72e+05
C(zipcode)[T.98105]  4.822e+05   1.41e+04     34.288      0.000    4.55e+05
5.1e+05
C(zipcode)[T.98106]  1.485e+05   1.24e+04     11.958      0.000    1.24e+05
1.73e+05
C(zipcode)[T.98107]  3.578e+05   1.34e+04     26.666      0.000    3.32e+05
3.84e+05
C(zipcode)[T.98108]  1.291e+05   1.48e+04      8.729      0.000       1e+05
1.58e+05
C(zipcode)[T.98109]  5.064e+05   1.81e+04     28.019      0.000    4.71e+05
5.42e+05
C(zipcode)[T.98112]  6.362e+05   1.35e+04     46.985      0.000     6.1e+05
6.63e+05
C(zipcode)[T.98115]  3.391e+05   1.11e+04     30.524      0.000    3.17e+05
3.61e+05
C(zipcode)[T.98116]   3.02e+05   1.26e+04     23.964      0.000    2.77e+05
3.27e+05
C(zipcode)[T.98117]  3.261e+05   1.12e+04     29.006      0.000    3.04e+05
3.48e+05
C(zipcode)[T.98118]  1.763e+05   1.13e+04     15.536      0.000    1.54e+05
1.98e+05
C(zipcode)[T.98119]  4.892e+05   1.51e+04     32.445      0.000     4.6e+05
5.19e+05
C(zipcode)[T.98122]  3.503e+05   1.31e+04     26.696      0.000    3.25e+05
3.76e+05
C(zipcode)[T.98125]  2.044e+05   1.18e+04     17.277      0.000    1.81e+05
2.28e+05
C(zipcode)[T.98126]  1.996e+05   1.23e+04     16.212      0.000    1.75e+05
2.24e+05
C(zipcode)[T.98133]  1.749e+05   1.13e+04     15.418      0.000    1.53e+05
1.97e+05
C(zipcode)[T.98136]  2.535e+05   1.34e+04     18.985      0.000    2.27e+05
2.8e+05
C(zipcode)[T.98144]  2.913e+05   1.25e+04     23.344      0.000    2.67e+05
3.16e+05
C(zipcode)[T.98146]  1.137e+05   1.29e+04      8.803      0.000    8.84e+04
1.39e+05
```

```
C(zipcode)[T.98148]  6.286e+04   2.32e+04      2.707      0.007    1.73e+04
1.08e+05
C(zipcode)[T.98155]  1.512e+05   1.16e+04     13.071      0.000    1.29e+05
1.74e+05
C(zipcode)[T.98166]  6.304e+04   1.34e+04      4.702      0.000    3.68e+04
8.93e+04
C(zipcode)[T.98168]  7.529e+04   1.32e+04      5.710      0.000    4.94e+04
1.01e+05
C(zipcode)[T.98177]  2.229e+05   1.34e+04     16.575      0.000    1.97e+05
2.49e+05
C(zipcode)[T.98178]  3.638e+04   1.33e+04      2.736      0.006    1.03e+04
6.24e+04
C(zipcode)[T.98188]  3.495e+04   1.64e+04      2.131      0.033    2804.530
6.71e+04
C(zipcode)[T.98198]  1934.5695    1.3e+04      0.149      0.882   -2.36e+04
2.74e+04
C(zipcode)[T.98199]  3.956e+05   1.28e+04     30.999      0.000    3.71e+05
4.21e+05
bedrooms            -2.617e+04   1556.016    -16.822      0.000   -2.92e+04
-2.31e+04
bathrooms            2.389e+04   2654.214      9.000      0.000    1.87e+04
2.91e+04
sqft_lot                0.1804      0.030      6.111      0.000       0.123
0.238
floors              -5.149e+04   3172.523    -16.230      0.000   -5.77e+04
-4.53e+04
waterfront           6.922e+05   1.49e+04     46.571      0.000    6.63e+05
7.21e+05
view                 5.891e+04   1731.680     34.020      0.000    5.55e+04
6.23e+04
grade                5.668e+04   1774.309     31.943      0.000    5.32e+04
6.02e+04
sqft_above            213.8100      2.836     75.387      0.000     208.251
219.369
sqft_basement         136.9940      3.516     38.962      0.000     130.102
143.886
last_building_phase  -744.5707     59.173    -12.583      0.000    -860.555
-628.586
==============================================================================
Omnibus:                    20673.566   Durbin-Watson:                   1.992
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          4177058.103
Skew:                           4.117   Prob(JB):                         0.00
Kurtosis:                      70.632   Cond. No.                     4.54e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
```

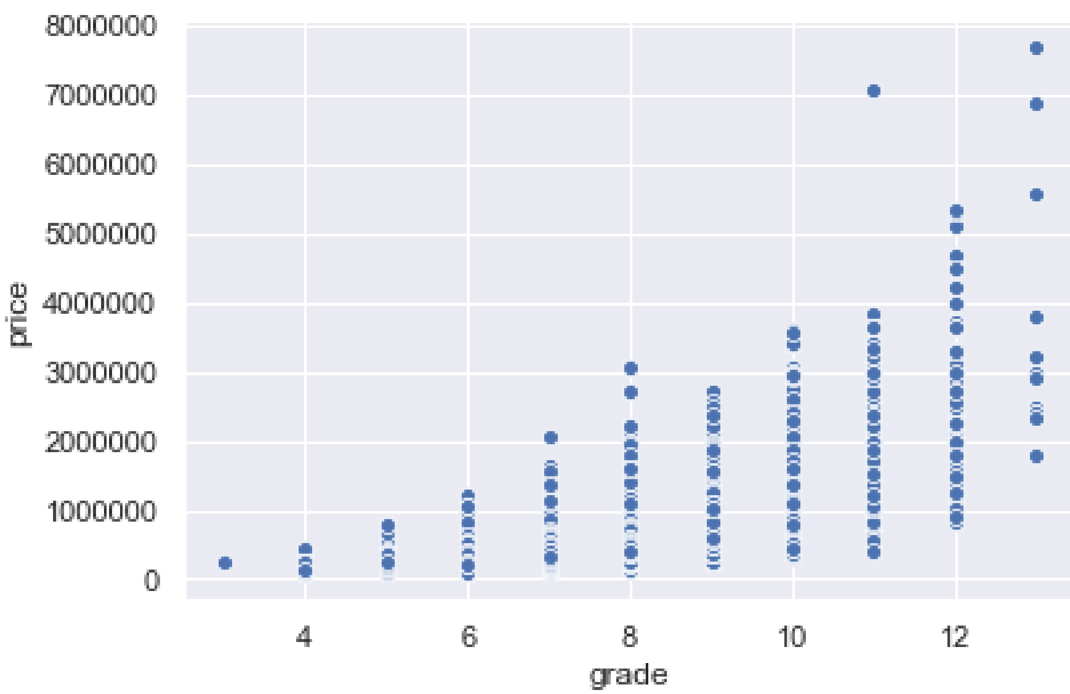
```
specified.
[2] The condition number is large, 4.54e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

R-squared is 0.804 so we got an better result

So making dummies out of a categorial variable improved our model quite good. So lets take a look at other categorial variables.

Lets take a look at grade

[38]:
```
sns.scatterplot(x="grade", y="price", data=df3);
```



Lets generate dummy variables for grade

[39]:
```
model = ols('price ~ C(grade) + C(zipcode) + bedrooms + bathrooms+ sqft_lot +␣
↪floors + waterfront + view + sqft_above + sqft_basement +␣
↪last_building_phase', data=df3).fit()

model.summary()
```

[39]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
```

```
==============================================================================
Dep. Variable:                  price   R-squared:                       0.830
Model:                            OLS   Adj. R-squared:                  0.829
Method:                 Least Squares   F-statistic:                     1191.
Date:                Sun, 03 Nov 2019   Prob (F-statistic):               0.00
Time:                        10:10:55   Log-Likelihood:            -2.8827e+05
No. Observations:               21597   AIC:                         5.767e+05
Df Residuals:                   21508   BIC:                         5.774e+05
Df Model:                          88
Covariance Type:            nonrobust
================================================================================
=======
                         coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
Intercept           9.453e+05   1.86e+05      5.088      0.000    5.81e+05
1.31e+06
C(grade)[T.4]      -1.677e+05   1.55e+05     -1.081      0.280   -4.72e+05
1.36e+05
C(grade)[T.5]      -2.039e+05   1.53e+05     -1.336      0.181   -5.03e+05
9.51e+04
C(grade)[T.6]      -2.024e+05   1.52e+05     -1.329      0.184   -5.01e+05
9.61e+04
C(grade)[T.7]      -2.007e+05   1.52e+05     -1.318      0.187   -4.99e+05
9.78e+04
C(grade)[T.8]      -1.772e+05   1.52e+05     -1.163      0.245   -4.76e+05
1.21e+05
C(grade)[T.9]      -1.031e+05   1.52e+05     -0.677      0.499   -4.02e+05
1.96e+05
C(grade)[T.10]        1.58e+04   1.52e+05      0.104      0.917   -2.83e+05
3.15e+05
C(grade)[T.11]      2.085e+05   1.53e+05      1.366      0.172   -9.08e+04
5.08e+05
C(grade)[T.12]      6.141e+05   1.54e+05      4.000      0.000    3.13e+05
9.15e+05
C(grade)[T.13]      1.712e+06   1.59e+05     10.785      0.000     1.4e+06
2.02e+06
C(zipcode)[T.98002]  1.377e+04   1.34e+04      1.024      0.306   -1.26e+04
4.01e+04
C(zipcode)[T.98003] -7461.9934   1.21e+04     -0.616      0.538   -3.12e+04
1.63e+04
C(zipcode)[T.98004]  7.787e+05   1.18e+04     65.755      0.000    7.55e+05
8.02e+05
C(zipcode)[T.98005]  3.198e+05   1.43e+04     22.328      0.000    2.92e+05
3.48e+05
C(zipcode)[T.98006]  2.635e+05   1.07e+04     24.660      0.000    2.43e+05
```

```
2.84e+05
C(zipcode)[T.98007]  2.622e+05   1.51e+04     17.319      0.000    2.33e+05
2.92e+05
C(zipcode)[T.98008]  2.678e+05   1.21e+04     22.082      0.000    2.44e+05
2.92e+05
C(zipcode)[T.98010]  6.984e+04   1.72e+04      4.056      0.000    3.61e+04
1.04e+05
C(zipcode)[T.98011]  1.372e+05   1.35e+04     10.148      0.000    1.11e+05
1.64e+05
C(zipcode)[T.98014]  8.581e+04    1.6e+04      5.362      0.000    5.44e+04
1.17e+05
C(zipcode)[T.98019]  9.398e+04   1.37e+04      6.882      0.000    6.72e+04
1.21e+05
C(zipcode)[T.98022] -2594.8172   1.29e+04     -0.201      0.841   -2.79e+04
2.27e+04
C(zipcode)[T.98023] -2.733e+04   1.05e+04     -2.598      0.009   -4.79e+04
-6708.254
C(zipcode)[T.98024]  1.518e+05   1.89e+04      8.013      0.000    1.15e+05
1.89e+05
C(zipcode)[T.98027]  1.732e+05    1.1e+04     15.701      0.000    1.52e+05
1.95e+05
C(zipcode)[T.98028]  1.335e+05   1.21e+04     11.054      0.000     1.1e+05
1.57e+05
C(zipcode)[T.98029]  2.239e+05   1.18e+04     19.034      0.000    2.01e+05
2.47e+05
C(zipcode)[T.98030]  7077.1394   1.24e+04      0.570      0.569   -1.73e+04
3.14e+04
C(zipcode)[T.98031]  2.154e+04   1.22e+04      1.767      0.077   -2357.074
4.54e+04
C(zipcode)[T.98032]  8549.9058   1.58e+04      0.541      0.588   -2.24e+04
3.95e+04
C(zipcode)[T.98033]   3.69e+05   1.09e+04     33.910      0.000    3.48e+05
3.9e+05
C(zipcode)[T.98034]  2.018e+05   1.03e+04     19.536      0.000    1.82e+05
2.22e+05
C(zipcode)[T.98038]  3.824e+04   1.02e+04      3.753      0.000    1.83e+04
5.82e+04
C(zipcode)[T.98039]  1.245e+06   2.32e+04     53.722      0.000     1.2e+06
1.29e+06
C(zipcode)[T.98040]  5.305e+05   1.23e+04     43.167      0.000    5.06e+05
5.55e+05
C(zipcode)[T.98042]  1.398e+04   1.03e+04      1.357      0.175   -6220.325
3.42e+04
C(zipcode)[T.98045]  8.979e+04    1.3e+04      6.888      0.000    6.42e+04
1.15e+05
C(zipcode)[T.98052]  2.447e+05   1.03e+04     23.827      0.000    2.25e+05
2.65e+05
```

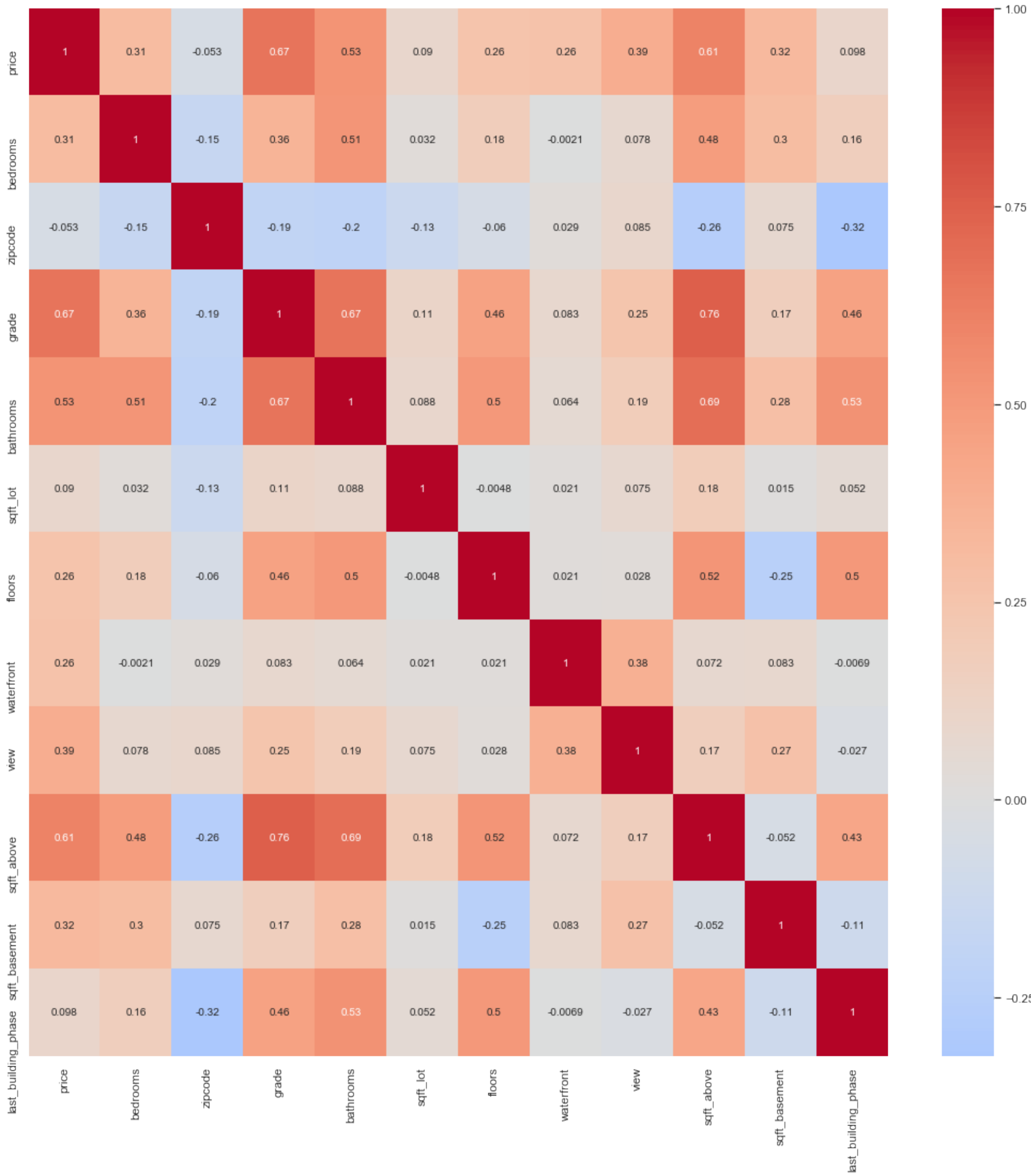
C(zipcode)[T.98053]	2.06e+05	1.11e+04	18.502	0.000	1.84e+05	2.28e+05
C(zipcode)[T.98055]	4.189e+04	1.23e+04	3.415	0.001	1.78e+04	6.59e+04
C(zipcode)[T.98056]	1.01e+05	1.1e+04	9.170	0.000	7.94e+04	1.23e+05
C(zipcode)[T.98058]	3.857e+04	1.07e+04	3.597	0.000	1.75e+04	5.96e+04
C(zipcode)[T.98059]	8.893e+04	1.07e+04	8.325	0.000	6.8e+04	1.1e+05
C(zipcode)[T.98065]	9.264e+04	1.19e+04	7.814	0.000	6.94e+04	1.16e+05
C(zipcode)[T.98070]	9401.1544	1.65e+04	0.570	0.569	-2.29e+04	4.17e+04
C(zipcode)[T.98072]	1.653e+05	1.22e+04	13.518	0.000	1.41e+05	1.89e+05
C(zipcode)[T.98074]	1.803e+05	1.09e+04	16.535	0.000	1.59e+05	2.02e+05
C(zipcode)[T.98075]	1.774e+05	1.15e+04	15.405	0.000	1.55e+05	2e+05
C(zipcode)[T.98077]	1.239e+05	1.36e+04	9.115	0.000	9.72e+04	1.51e+05
C(zipcode)[T.98092]	-2.272e+04	1.14e+04	-1.989	0.047	-4.51e+04	-335.283
C(zipcode)[T.98102]	4.997e+05	1.73e+04	28.957	0.000	4.66e+05	5.33e+05
C(zipcode)[T.98103]	3.534e+05	1.04e+04	33.872	0.000	3.33e+05	3.74e+05
C(zipcode)[T.98105]	4.94e+05	1.31e+04	37.644	0.000	4.68e+05	5.2e+05
C(zipcode)[T.98106]	1.228e+05	1.16e+04	10.574	0.000	1e+05	1.46e+05
C(zipcode)[T.98107]	3.563e+05	1.25e+04	28.454	0.000	3.32e+05	3.81e+05
C(zipcode)[T.98108]	1.194e+05	1.38e+04	8.651	0.000	9.23e+04	1.46e+05
C(zipcode)[T.98109]	5.18e+05	1.69e+04	30.713	0.000	4.85e+05	5.51e+05
C(zipcode)[T.98112]	6.487e+05	1.26e+04	51.337	0.000	6.24e+05	6.74e+05
C(zipcode)[T.98115]	3.461e+05	1.04e+04	33.380	0.000	3.26e+05	3.66e+05
C(zipcode)[T.98116]	3.072e+05	1.18e+04	26.122	0.000	2.84e+05	3.3e+05
C(zipcode)[T.98117]	3.27e+05	1.05e+04	31.181	0.000	3.06e+05	3.48e+05
C(zipcode)[T.98118]	1.635e+05	1.06e+04	15.414	0.000	1.43e+05	

```
1.84e+05
C(zipcode)[T.98119]  5.017e+05   1.41e+04     35.654      0.000    4.74e+05
5.29e+05
C(zipcode)[T.98122]  3.588e+05   1.22e+04     29.301      0.000    3.35e+05
3.83e+05
C(zipcode)[T.98125]  2.051e+05    1.1e+04     18.584      0.000    1.83e+05
2.27e+05
C(zipcode)[T.98126]  1.915e+05   1.15e+04     16.650      0.000    1.69e+05
2.14e+05
C(zipcode)[T.98133]  1.714e+05   1.06e+04     16.188      0.000    1.51e+05
1.92e+05
C(zipcode)[T.98136]  2.576e+05   1.25e+04     20.680      0.000    2.33e+05
2.82e+05
C(zipcode)[T.98144]  2.892e+05   1.16e+04     24.841      0.000    2.66e+05
3.12e+05
C(zipcode)[T.98146]   9.82e+04   1.21e+04      8.129      0.000    7.45e+04
1.22e+05
C(zipcode)[T.98148]  5.993e+04   2.17e+04      2.766      0.006    1.75e+04
1.02e+05
C(zipcode)[T.98155]    1.5e+05   1.08e+04     13.887      0.000    1.29e+05
1.71e+05
C(zipcode)[T.98166]  6.384e+04   1.25e+04      5.099      0.000    3.93e+04
8.84e+04
C(zipcode)[T.98168]  4.702e+04   1.23e+04      3.808      0.000    2.28e+04
7.12e+04
C(zipcode)[T.98177]  2.246e+05   1.26e+04     17.883      0.000       2e+05
2.49e+05
C(zipcode)[T.98178]  2.344e+04   1.24e+04      1.887      0.059    -907.052
4.78e+04
C(zipcode)[T.98188]  2.791e+04   1.53e+04      1.824      0.068   -2079.731
5.79e+04
C(zipcode)[T.98198]   109.6074   1.21e+04      0.009      0.993   -2.37e+04
2.39e+04
C(zipcode)[T.98199]  3.984e+05   1.19e+04     33.455      0.000    3.75e+05
4.22e+05
bedrooms            -1.185e+04   1483.625     -7.989      0.000   -1.48e+04
-8944.530
bathrooms             2.56e+04   2487.376     10.292      0.000    2.07e+04
3.05e+04
sqft_lot                0.1719      0.028      6.240      0.000       0.118
0.226
floors               -3.61e+04   2993.408    -12.061      0.000    -4.2e+04
-3.02e+04
waterfront            6.73e+05   1.39e+04     48.441      0.000    6.46e+05
7e+05
view                 5.624e+04   1618.504     34.751      0.000    5.31e+04
5.94e+04
```

```
sqft_above           173.3644      2.767     62.646      0.000     167.940
178.789
sqft_basement        123.8584      3.290     37.651      0.000     117.410
130.306
last_building_phase  -387.6541     55.856     -6.940      0.000    -497.136
-278.172
==============================================================================
Omnibus:                    16351.315   Durbin-Watson:                   1.999
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1841059.051
Skew:                           2.897   Prob(JB):                         0.00
Kurtosis:                      47.859   Cond. No.                     2.16e+07
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.16e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

Seems like a good model so far. Lets try to drop some variables that have a low correlation with the price. So we take a look at the heatmap again

[40]:
```
corr = df2[['price','bedrooms',␣
 ↪'zipcode','grade','bathrooms','sqft_lot','floors','waterfront','view','sqft_above','sqft_ba
 ↪corr()
f, ax = plt.subplots(figsize = (18,18))
sns.heatmap(data=corr, center = 0, cmap="coolwarm", annot=True);
```



Lets try a model were we just keep variables with a correlation of 0.3 and above:
-bedrooms
-bathrooms
-sqft_above
-view
-sqft_basement
Also we want to keep our categorial variables
-zipcode
-grade

[41]:
```
model = ols('price ~ C(grade) + C(zipcode) + bedrooms + bathrooms + sqft_above␣
 ↪+ view + sqft_basement', data=df3).fit()

model.summary()
```

[41]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.809
Model:                            OLS   Adj. R-squared:                  0.808
Method:                 Least Squares   F-statistic:                     1084.
Date:                Sun, 03 Nov 2019   Prob (F-statistic):               0.00
Time:                        10:10:56   Log-Likelihood:            -2.8952e+05
No. Observations:               21597   AIC:                         5.792e+05
Df Residuals:                   21512   BIC:                         5.799e+05
Df Model:                          84
Covariance Type:            nonrobust
================================================================================
=======
                          coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
Intercept            1.809e+05   1.61e+05      1.120      0.263   -1.36e+05
4.97e+05
C(grade)[T.4]       -1.818e+05   1.64e+05     -1.107      0.268   -5.04e+05
1.4e+05
C(grade)[T.5]       -2.017e+05   1.62e+05     -1.248      0.212   -5.18e+05
1.15e+05
C(grade)[T.6]       -2.117e+05   1.61e+05     -1.313      0.189   -5.28e+05
1.04e+05
C(grade)[T.7]       -2.192e+05   1.61e+05     -1.359      0.174   -5.35e+05
9.69e+04
C(grade)[T.8]       -2.099e+05   1.61e+05     -1.301      0.193   -5.26e+05
1.06e+05
C(grade)[T.9]       -1.436e+05   1.61e+05     -0.890      0.374    -4.6e+05
1.73e+05
C(grade)[T.10]       -1.91e+04   1.61e+05     -0.118      0.906   -3.36e+05
2.97e+05
C(grade)[T.11]       1.816e+05   1.62e+05      1.123      0.261   -1.35e+05
4.99e+05
C(grade)[T.12]       6.193e+05   1.63e+05      3.810      0.000    3.01e+05
9.38e+05
C(grade)[T.13]        1.64e+06   1.68e+05      9.760      0.000    1.31e+06
1.97e+06
C(zipcode)[T.98002]  1.559e+04   1.42e+04      1.095      0.273   -1.23e+04
```

```
4.35e+04
C(zipcode)[T.98003] -4557.8566   1.28e+04     -0.355      0.722   -2.97e+04
2.06e+04
C(zipcode)[T.98004]   7.85e+05   1.25e+04     62.754      0.000    7.61e+05
8.1e+05
C(zipcode)[T.98005]  3.386e+05   1.51e+04     22.389      0.000    3.09e+05
3.68e+05
C(zipcode)[T.98006]  2.609e+05   1.13e+04     23.099      0.000    2.39e+05
2.83e+05
C(zipcode)[T.98007]   2.74e+05    1.6e+04     17.109      0.000    2.43e+05
3.05e+05
C(zipcode)[T.98008]  2.916e+05   1.28e+04     22.759      0.000    2.66e+05
3.17e+05
C(zipcode)[T.98010]  7.431e+04   1.82e+04      4.081      0.000    3.86e+04
1.1e+05
C(zipcode)[T.98011]  1.412e+05   1.43e+04      9.863      0.000    1.13e+05
1.69e+05
C(zipcode)[T.98014]  9.516e+04   1.68e+04      5.665      0.000    6.22e+04
1.28e+05
C(zipcode)[T.98019]  9.333e+04   1.44e+04      6.462      0.000     6.5e+04
1.22e+05
C(zipcode)[T.98022] -2669.3218   1.36e+04     -0.197      0.844   -2.93e+04
2.39e+04
C(zipcode)[T.98023] -1.866e+04   1.11e+04     -1.675      0.094   -4.05e+04
3171.107
C(zipcode)[T.98024]  1.693e+05   1.99e+04      8.500      0.000     1.3e+05
2.08e+05
C(zipcode)[T.98027]  1.761e+05   1.17e+04     15.088      0.000    1.53e+05
1.99e+05
C(zipcode)[T.98028]  1.372e+05   1.28e+04     10.731      0.000    1.12e+05
1.62e+05
C(zipcode)[T.98029]    2.2e+05   1.24e+04     17.671      0.000    1.96e+05
2.44e+05
C(zipcode)[T.98030]  9121.9831   1.32e+04      0.694      0.488   -1.67e+04
3.49e+04
C(zipcode)[T.98031]  2.543e+04   1.29e+04      1.969      0.049     113.321
5.07e+04
C(zipcode)[T.98032]  1.303e+04   1.67e+04      0.779      0.436   -1.97e+04
4.58e+04
C(zipcode)[T.98033]  3.723e+05   1.15e+04     32.332      0.000     3.5e+05
3.95e+05
C(zipcode)[T.98034]    2.1e+05   1.09e+04     19.206      0.000    1.89e+05
2.31e+05
C(zipcode)[T.98038]   3.59e+04   1.08e+04      3.329      0.001    1.48e+04
5.7e+04
C(zipcode)[T.98039]  1.265e+06   2.45e+04     51.592      0.000    1.22e+06
1.31e+06
```

C(zipcode)[T.98040]	5.483e+05	1.3e+04	42.257	0.000	5.23e+05	5.74e+05
C(zipcode)[T.98042]	1.603e+04	1.09e+04	1.468	0.142	-5368.883	3.74e+04
C(zipcode)[T.98045]	9.131e+04	1.38e+04	6.629	0.000	6.43e+04	1.18e+05
C(zipcode)[T.98052]	2.537e+05	1.09e+04	23.340	0.000	2.32e+05	2.75e+05
C(zipcode)[T.98053]	2.115e+05	1.18e+04	17.969	0.000	1.88e+05	2.35e+05
C(zipcode)[T.98055]	4.387e+04	1.3e+04	3.379	0.001	1.84e+04	6.93e+04
C(zipcode)[T.98056]	1.039e+05	1.17e+04	8.907	0.000	8.1e+04	1.27e+05
C(zipcode)[T.98058]	4.686e+04	1.14e+04	4.127	0.000	2.46e+04	6.91e+04
C(zipcode)[T.98059]	9.082e+04	1.13e+04	8.026	0.000	6.86e+04	1.13e+05
C(zipcode)[T.98065]	7.958e+04	1.26e+04	6.340	0.000	5.5e+04	1.04e+05
C(zipcode)[T.98070]	1.119e+05	1.72e+04	6.498	0.000	7.81e+04	1.46e+05
C(zipcode)[T.98072]	1.744e+05	1.29e+04	13.470	0.000	1.49e+05	2e+05
C(zipcode)[T.98074]	1.91e+05	1.15e+04	16.546	0.000	1.68e+05	2.14e+05
C(zipcode)[T.98075]	1.902e+05	1.22e+04	15.601	0.000	1.66e+05	2.14e+05
C(zipcode)[T.98077]	1.391e+05	1.44e+04	9.685	0.000	1.11e+05	1.67e+05
C(zipcode)[T.98092]	-1.979e+04	1.21e+04	-1.637	0.102	-4.35e+04	3900.651
C(zipcode)[T.98102]	4.941e+05	1.8e+04	27.451	0.000	4.59e+05	5.29e+05
C(zipcode)[T.98103]	3.443e+05	1.08e+04	32.031	0.000	3.23e+05	3.65e+05
C(zipcode)[T.98105]	5.047e+05	1.36e+04	37.009	0.000	4.78e+05	5.31e+05
C(zipcode)[T.98106]	1.188e+05	1.23e+04	9.677	0.000	9.47e+04	1.43e+05
C(zipcode)[T.98107]	3.442e+05	1.31e+04	26.355	0.000	3.19e+05	3.7e+05
C(zipcode)[T.98108]	1.195e+05	1.46e+04	8.209	0.000	9.1e+04	1.48e+05
C(zipcode)[T.98109]	5.096e+05	1.76e+04	28.887	0.000	4.75e+05	5.44e+05
C(zipcode)[T.98112]	6.514e+05	1.31e+04	49.860	0.000	6.26e+05	

```
6.77e+05
C(zipcode)[T.98115]  3.469e+05   1.08e+04     32.061      0.000    3.26e+05
3.68e+05
C(zipcode)[T.98116]   2.94e+05   1.23e+04     23.846      0.000     2.7e+05
3.18e+05
C(zipcode)[T.98117]  3.257e+05   1.09e+04     29.794      0.000    3.04e+05
3.47e+05
C(zipcode)[T.98118]  1.637e+05   1.11e+04     14.685      0.000    1.42e+05
1.86e+05
C(zipcode)[T.98119]  4.895e+05   1.47e+04     33.403      0.000    4.61e+05
5.18e+05
C(zipcode)[T.98122]  3.536e+05   1.27e+04     27.744      0.000    3.29e+05
3.79e+05
C(zipcode)[T.98125]  2.113e+05   1.16e+04     18.146      0.000    1.88e+05
2.34e+05
C(zipcode)[T.98126]  1.837e+05   1.21e+04     15.171      0.000     1.6e+05
2.07e+05
C(zipcode)[T.98133]   1.72e+05   1.12e+04     15.395      0.000     1.5e+05
1.94e+05
C(zipcode)[T.98136]  2.545e+05   1.31e+04     19.407      0.000    2.29e+05
2.8e+05
C(zipcode)[T.98144]  2.779e+05   1.22e+04     22.816      0.000    2.54e+05
3.02e+05
C(zipcode)[T.98146]  1.061e+05   1.28e+04      8.303      0.000     8.1e+04
1.31e+05
C(zipcode)[T.98148]   6.98e+04   2.29e+04      3.043      0.002    2.48e+04
1.15e+05
C(zipcode)[T.98155]  1.619e+05   1.14e+04     14.188      0.000     1.4e+05
1.84e+05
C(zipcode)[T.98166]  9.251e+04   1.32e+04      6.992      0.000    6.66e+04
1.18e+05
C(zipcode)[T.98168]  4.958e+04   1.31e+04      3.797      0.000     2.4e+04
7.52e+04
C(zipcode)[T.98177]  2.191e+05   1.33e+04     16.528      0.000    1.93e+05
2.45e+05
C(zipcode)[T.98178]  3.658e+04   1.31e+04      2.785      0.005    1.08e+04
6.23e+04
C(zipcode)[T.98188]  3.047e+04   1.62e+04      1.881      0.060   -1282.700
6.22e+04
C(zipcode)[T.98198]  1.146e+04   1.29e+04      0.892      0.372   -1.37e+04
3.67e+04
C(zipcode)[T.98199]  3.919e+05   1.25e+04     31.367      0.000    3.67e+05
4.16e+05
bedrooms            -1.324e+04   1556.313     -8.505      0.000   -1.63e+04
-1.02e+04
bathrooms            8127.4080   2351.084      3.457      0.001    3519.109
1.27e+04
```

```
sqft_above            174.8861      2.826     61.887      0.000     169.347
180.425
view                 8.473e+04   1602.215     52.882      0.000    8.16e+04
8.79e+04
sqft_basement         146.6707      3.205     45.765      0.000     140.389
152.952
==============================================================================
Omnibus:                    18948.630   Durbin-Watson:                   2.001
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2780571.536
Skew:                           3.629   Prob(JB):                         0.00
Kurtosis:                      58.111   Cond. No.                     9.72e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 9.72e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

So we droped five variabels and we still got a pretty nice R-squared value of 0.809