Immersive_Data_Science_Project1_EDA

November 15, 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
from sklearn.model_selection import KFold # import KFold
from sklearn.model_selection import cross_val_score, cross_val_predict
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]:
```
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.

0.7 Waterfront

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.])
```

0.8 View

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

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

0.9 yr_renovated

We continue with the column yr_renovated

[10]:
```
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
```

0.10 sqft_basement

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

[18]:
```
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 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(12), object(1)
memory usage: 3.5+ MB
```

0.11 date

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.

[19]:
```
df['date'] = pd.to_datetime(df['date'])
```

[20]:
```
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')
```

[21]:
```
dates_dummies = pd.get_dummies(dates, drop_first=True)
dates_dummies.head()
```

[21]:
```
   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

[22]:
```
df2 = pd.concat([df, dates_dummies], axis = 1)
df2.head()
```

[22]:
```
           id        date     price  bedrooms  bathrooms  sqft_living  \
0  7129300520 2014-10-13  221900.0         3       1.00         1180
1  6414100192 2014-12-09  538000.0         3       2.25         2570
2  5631500400 2015-02-25  180000.0         2       1.00          770
3  2487200875 2014-12-09  604000.0         4       3.00         1960
4  1954400510 2015-02-18  510000.0         3       2.00         1680

   sqft_lot  floors  waterfront  view  …  yr_built  yr_renovated  \
0      5650     1.0         0.0   0.0  …      1955           0.0
1      7242     2.0         0.0   0.0  …      1951        1991.0
2     10000     1.0         0.0   0.0  …      1933           0.0
3      5000     1.0         0.0   0.0  …      1965           0.0
4      8080     1.0         0.0   0.0  …      1987           0.0

   zipcode      lat     long  sqft_living15  sqft_lot15  spring  summer  \
0    98178  47.5112 -122.257           1340        5650       0       0
1    98125  47.7210 -122.319           1690        7639       0       0
2    98028  47.7379 -122.233           2720        8062       0       0
3    98136  47.5208 -122.393           1360        5000       0       0
4    98074  47.6168 -122.045           1800        7503       0       0

   winter
0       0
1       1
2       1
```

```
3        1
4        1

[5 rows x 24 columns]
```

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

[23]:
```
df2['date'] = pd.DatetimeIndex(df2['date']).year
```

[24]:
```
df2.head()
```

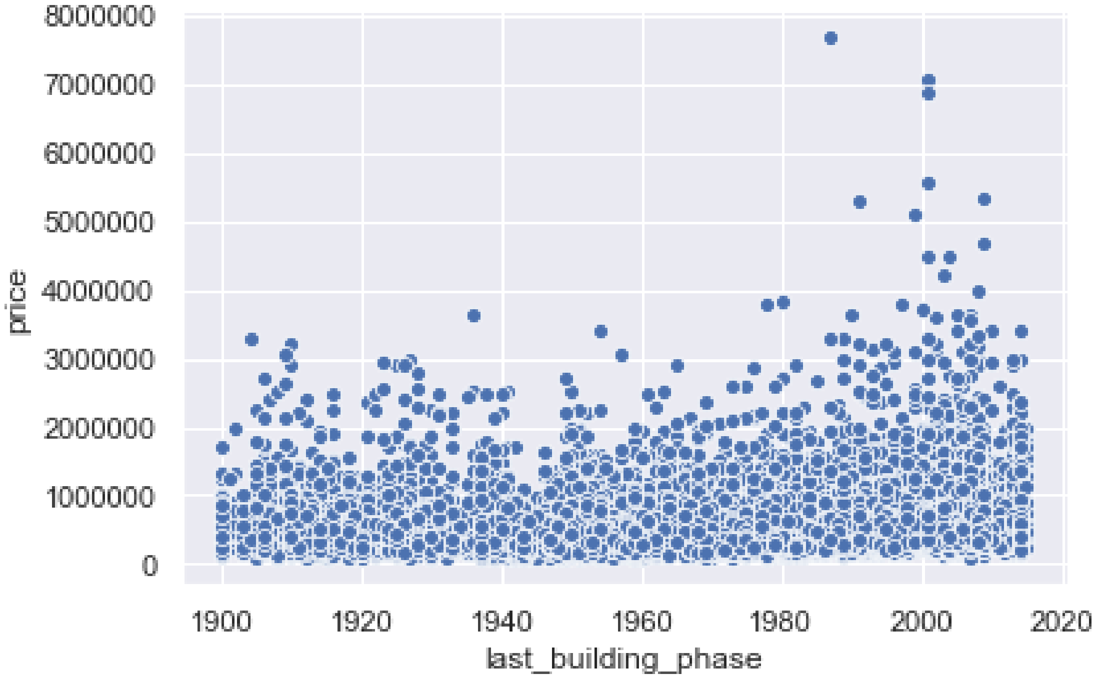
[24]:
```
           id  date     price  bedrooms  bathrooms  sqft_living  sqft_lot  \
0  7129300520  2014  221900.0         3       1.00         1180      5650
1  6414100192  2014  538000.0         3       2.25         2570      7242
2  5631500400  2015  180000.0         2       1.00          770     10000
3  2487200875  2014  604000.0         4       3.00         1960      5000
4  1954400510  2015  510000.0         3       2.00         1680      8080

   floors  waterfront  view  …  yr_built  yr_renovated  zipcode      lat  \
0     1.0         0.0   0.0  …      1955           0.0    98178  47.5112
1     2.0         0.0   0.0  …      1951        1991.0    98125  47.7210
2     1.0         0.0   0.0  …      1933           0.0    98028  47.7379
3     1.0         0.0   0.0  …      1965           0.0    98136  47.5208
4     1.0         0.0   0.0  …      1987           0.0    98074  47.6168

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

[5 rows x 24 columns]
```

0.12 generate new feature: last_building_phase

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

[25]:
```
df2["last_building_phase"] = df2[["yr_built", "yr_renovated"]].max(axis=1)
```

[26]:
```
sns.scatterplot(x="last_building_phase", y="price", data=df2);
```

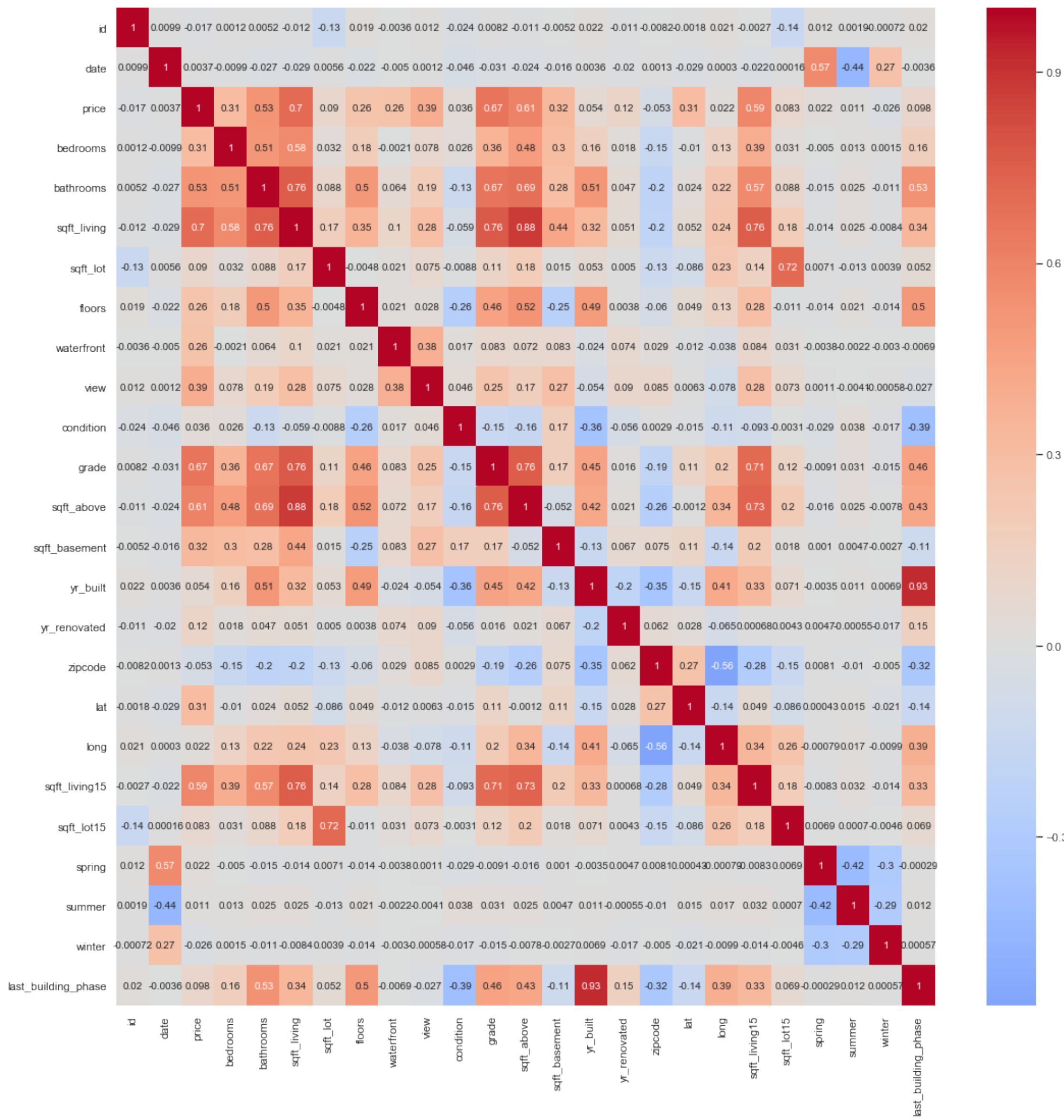


There is a small relationship between price and last_building_phase.

0.13 Visualisation

Lets plot some data

[27]:
```
corr = df2.corr()
f, ax = plt.subplots(figsize = (18,18))
sns.heatmap(data=corr, center = 0, cmap="coolwarm", annot=True);
```

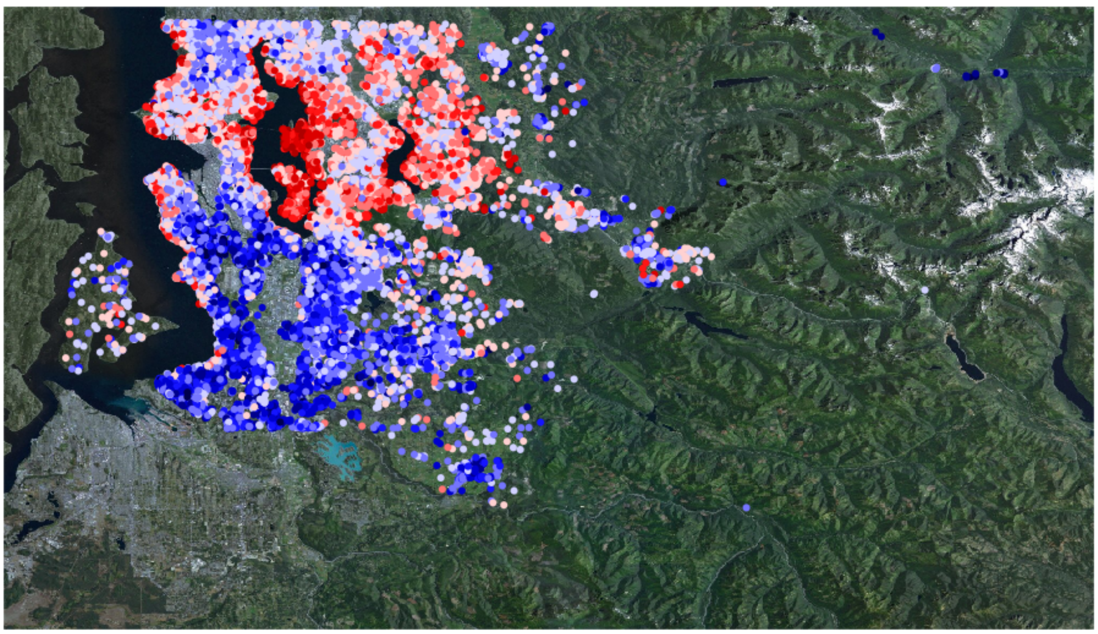


There are variables that have a correlation with price: - bedrooms 0.31 - bathrooms 0.53 - sqft_living 0.7 - sqft_lot 0.09 - floors 0.26 - waterfront 0.26 - view 0.39 - grade 0.67 - sqft_above 0.31 - sqft_basement 0.32 - year_renovated 0.12 - lat 0.31 - sqft_living 0.59 - last_building_phase 0.098

Lets plot the location and the price:

[28]:
```
# 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]
```

```python
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 house data, with color reflecting prizes
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.

0.14 generate dummies for longitude and latitude

Lets group our houses for longitude and latitude

[29]:
```python
#seperate the latitude into seven parts
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')
```

[30]:
```
#seperate the longitude into seven parts
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')
```

[31]:
```
#introduce dummy variables
lat_dummies = pd.get_dummies(lat, drop_first=True)
long_dummies = pd.get_dummies(long, drop_first=True)
long_dummies.head()
```

[31]:

	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

[32]:
```
lat_long = pd.concat([lat_dummies, long_dummies], axis = 1)
lat_long.head()
```

[32]:
```
   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
```

[33]:
```python
# join our dataframe with the dummies
df3 = pd.concat([df2, lat_long], axis = 1)
```

0.15 Model a linear Regression

First we take the variables with the highest correlation with the price and our dummies for the location

[34]:
```python
X = df3[[ 'bedrooms', 'bathrooms', 'sqft_living',
       '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()
```

[34]:
```
<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:                Mon, 04 Nov 2019   Prob (F-statistic):               0.00
Time:                        15:56:31   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_living     128.5872      2.005     64.125      0.000     124.657
132.518
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      101.6745      2.035     49.965      0.000      97.686
105.663
sqft_basement    26.9127      2.530     10.636      0.000      21.953
31.872
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.                     7.81e+16
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 6.89e-21. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
"""
```

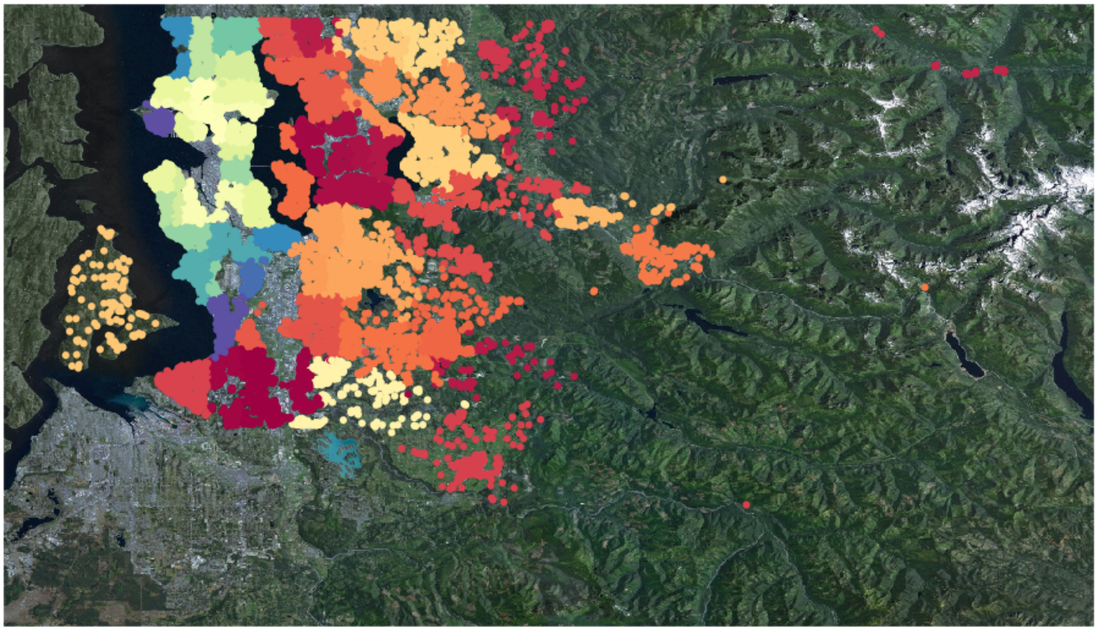
R-squared is 0.727 not bad at all.

0.16 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

[35]:
```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 zipcode areas
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.

[36]:
```
#model with the most correlated variables and dummies for the zipcode
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()
```

[36]:
```
<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:                Mon, 04 Nov 2019   Prob (F-statistic):               0.00
Time:                        15:56:44   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
```

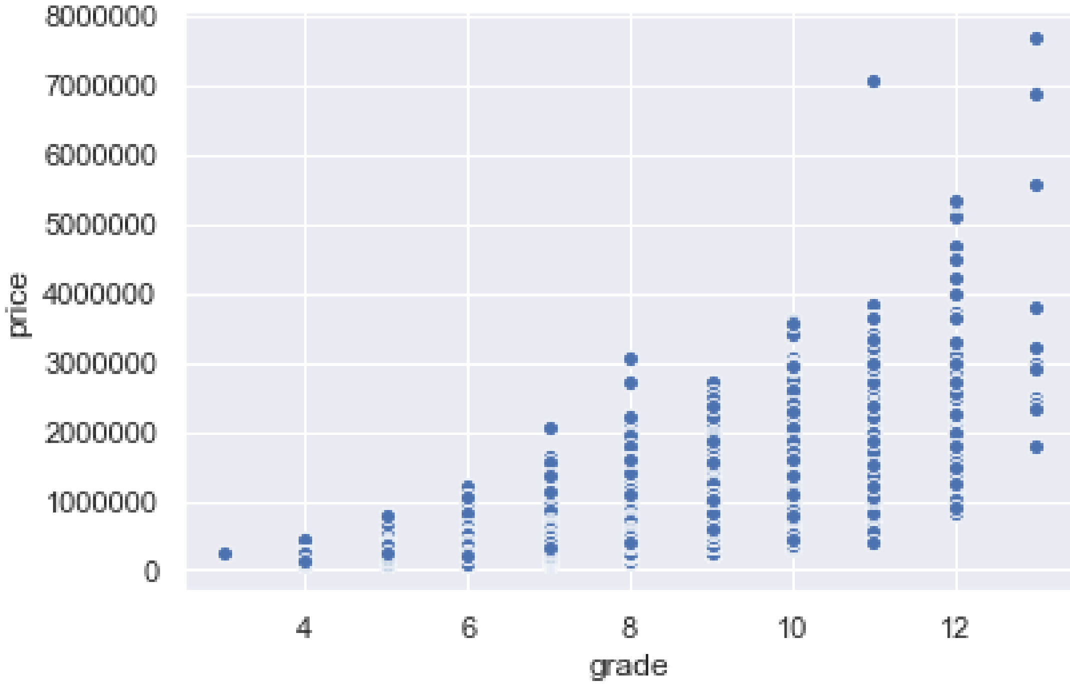
```
C(zipcode)[T.98199]  3.956e+05   1.28e+04     30.999      0.000    3.71e+05
4.21e+05
bedrooms            -2.617e+04   1556.016    -16.822      0.000   -2.92e+04
-2.31e+04
bathrooms            2.389e+04   2654.214      9.000      0.000    1.87e+04
2.91e+04
sqft_lot                0.1804      0.030      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

[37]:
```python
sns.scatterplot(x="grade", y="price", data=df3);
```



Lets generate dummy variables for grade and model it

[38]:
```
model = ols('price ~ C(grade) + C(zipcode) + bedrooms + bathrooms+ sqft_living␣
↪+ sqft_lot + floors + waterfront + view + sqft_above + sqft_basement +␣
↪last_building_phase', data=df3).fit()

model.summary()
```

[38]:
```
<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:                Mon, 04 Nov 2019   Prob (F-statistic):               0.00
Time:                        15:56:45   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
```

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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_living	99.0743	1.668	59.402	0.000	95.805	102.343
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	74.2902	1.775	41.863	0.000	70.812	77.769
sqft_basement	24.7841	2.050	12.088	0.000	20.765	28.803
last_building_phase	-387.6541	55.856	-6.940	0.000	-497.136	-278.172

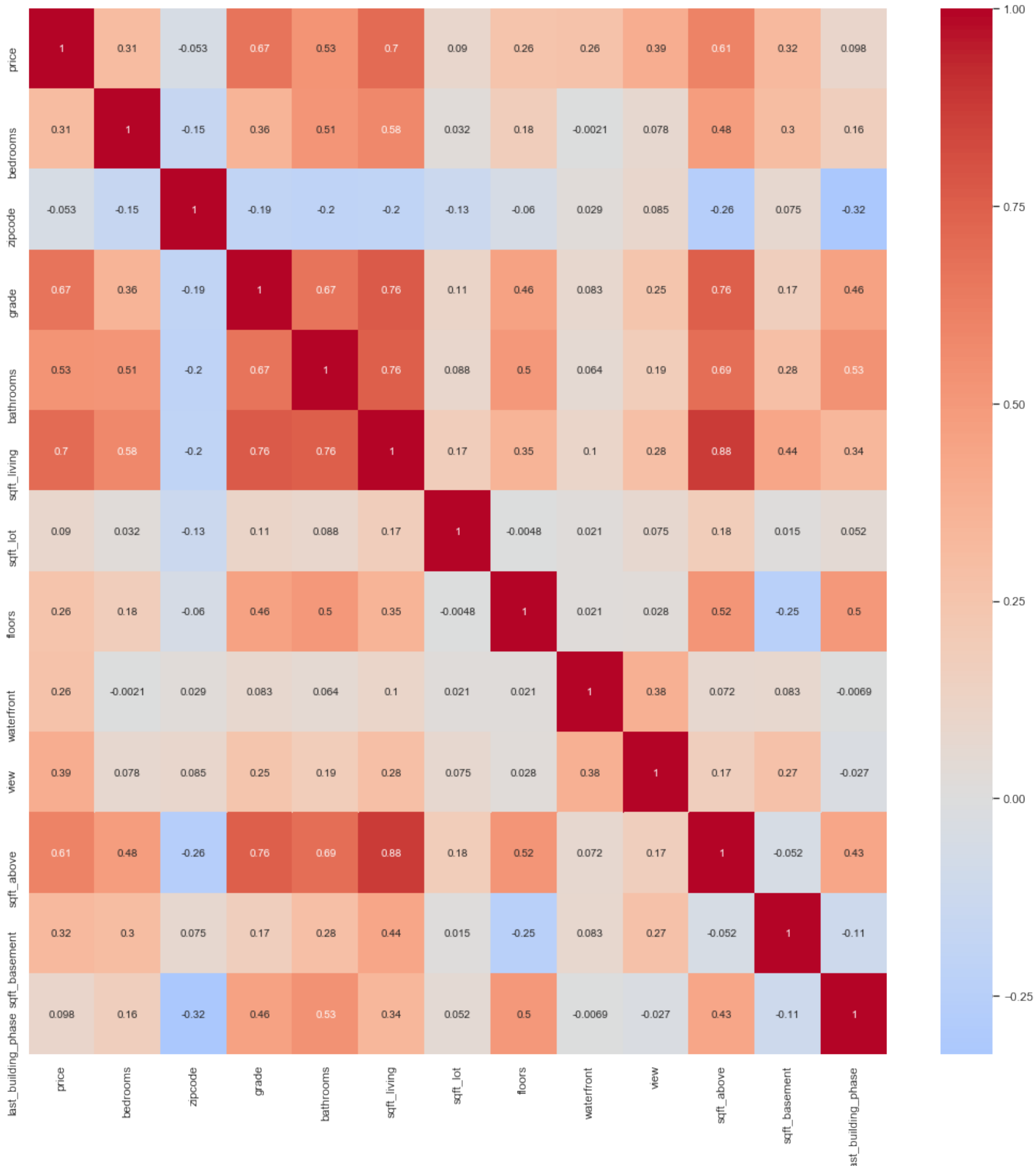
Omnibus:	16351.315	Durbin-Watson:	1.999
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1841059.051
Skew:	2.897	Prob(JB):	0.00
Kurtosis:	47.859	Cond. No.	2.25e+15

```
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 8.28e-18. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
"""
```

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

[39]:
```
corr = df2[['price','bedrooms', 'zipcode','grade','bathrooms','sqft_living',␣
 ↪'sqft_lot','floors','waterfront','view','sqft_above','sqft_basement','last_building_phase']].
 ↪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: - bathrooms - bedrooms - sqft_living - sqft_above - view - sqft_basement

Also we want to keep our categorial variables - zipcode - grade

We also decided to drop bedrooms because bathrooms is defined as bathrooms per bedrooms therefore they have a high correlation. The same goes for sqft_above and sqft_basement, because the sum of them is sqft_living

[40]:
```python
model = ols('price ~ C(grade) + C(zipcode) + bathrooms + sqft_living + view',␣
↪data=df3).fit()

model.summary()
```

[40]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.808
Model:                            OLS   Adj. R-squared:                  0.807
Method:                 Least Squares   F-statistic:                     1101.
Date:                Mon, 04 Nov 2019   Prob (F-statistic):               0.00
Time:                        15:56:46   Log-Likelihood:            -2.8959e+05
No. Observations:               21597   AIC:                         5.794e+05
Df Residuals:                   21514   BIC:                         5.800e+05
Df Model:                          82
Covariance Type:            nonrobust
================================================================================
=======
                          coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
Intercept            1.758e+05   1.62e+05      1.085      0.278   -1.42e+05
4.93e+05
C(grade)[T.4]       -1.812e+05   1.65e+05     -1.099      0.272   -5.04e+05
1.42e+05
C(grade)[T.5]       -2.053e+05   1.62e+05     -1.266      0.205   -5.23e+05
1.13e+05
C(grade)[T.6]       -2.155e+05   1.62e+05     -1.331      0.183   -5.33e+05
1.02e+05
C(grade)[T.7]       -2.239e+05   1.62e+05     -1.383      0.167   -5.41e+05
9.33e+04
C(grade)[T.8]       -2.074e+05   1.62e+05     -1.281      0.200   -5.25e+05
1.1e+05
C(grade)[T.9]       -1.307e+05   1.62e+05     -0.807      0.419   -4.48e+05
1.87e+05
C(grade)[T.10]       3924.9530   1.62e+05      0.024      0.981   -3.14e+05
3.21e+05
C(grade)[T.11]       2.168e+05   1.62e+05      1.337      0.181   -1.01e+05
5.35e+05
C(grade)[T.12]       6.706e+05   1.63e+05      4.113      0.000    3.51e+05
9.9e+05
C(grade)[T.13]       1.711e+06   1.69e+05     10.154      0.000    1.38e+06
2.04e+06
C(zipcode)[T.98002]  1.522e+04   1.43e+04      1.065      0.287   -1.28e+04
```

```
4.32e+04
C(zipcode)[T.98003] -6813.3564   1.29e+04     -0.529      0.597    -3.2e+04
1.84e+04
C(zipcode)[T.98004]  7.798e+05   1.25e+04     62.174      0.000    7.55e+05
8.04e+05
C(zipcode)[T.98005]  3.301e+05   1.52e+04     21.783      0.000       3e+05
3.6e+05
C(zipcode)[T.98006]  2.524e+05   1.13e+04     22.332      0.000     2.3e+05
2.75e+05
C(zipcode)[T.98007]  2.664e+05   1.61e+04     16.589      0.000    2.35e+05
2.98e+05
C(zipcode)[T.98008]  2.835e+05   1.28e+04     22.076      0.000    2.58e+05
3.09e+05
C(zipcode)[T.98010]  7.861e+04   1.83e+04      4.303      0.000    4.28e+04
1.14e+05
C(zipcode)[T.98011]  1.403e+05   1.44e+04      9.769      0.000    1.12e+05
1.69e+05
C(zipcode)[T.98014]  1.029e+05   1.68e+04      6.109      0.000    6.99e+04
1.36e+05
C(zipcode)[T.98019]  9.942e+04   1.45e+04      6.864      0.000     7.1e+04
1.28e+05
C(zipcode)[T.98022]  1622.5155   1.36e+04      0.119      0.905   -2.51e+04
2.83e+04
C(zipcode)[T.98023] -2.225e+04   1.12e+04     -1.992      0.046   -4.41e+04
-351.073
C(zipcode)[T.98024]  1.757e+05      2e+04      8.797      0.000    1.37e+05
2.15e+05
C(zipcode)[T.98027]   1.74e+05   1.17e+04     14.874      0.000    1.51e+05
1.97e+05
C(zipcode)[T.98028]  1.346e+05   1.28e+04     10.495      0.000    1.09e+05
1.6e+05
C(zipcode)[T.98029]  2.225e+05   1.25e+04     17.815      0.000    1.98e+05
2.47e+05
C(zipcode)[T.98030]  9220.0878   1.32e+04      0.699      0.485   -1.66e+04
3.51e+04
C(zipcode)[T.98031]  2.378e+04    1.3e+04      1.835      0.066   -1618.678
4.92e+04
C(zipcode)[T.98032]  6383.0323   1.68e+04      0.381      0.703   -2.65e+04
3.93e+04
C(zipcode)[T.98033]    3.7e+05   1.16e+04     32.031      0.000    3.47e+05
3.93e+05
C(zipcode)[T.98034]   2.06e+05    1.1e+04     18.787      0.000    1.85e+05
2.27e+05
C(zipcode)[T.98038]  4.166e+04   1.08e+04      3.854      0.000    2.05e+04
6.29e+04
C(zipcode)[T.98039]  1.267e+06   2.46e+04     51.485      0.000    1.22e+06
1.31e+06
```

```
C(zipcode)[T.98040]  5.395e+05    1.3e+04     41.518      0.000    5.14e+05
5.65e+05
C(zipcode)[T.98042]  1.801e+04    1.1e+04      1.645      0.100   -3455.576
3.95e+04
C(zipcode)[T.98045]  9.586e+04   1.38e+04      6.938      0.000    6.88e+04
1.23e+05
C(zipcode)[T.98052]  2.519e+05   1.09e+04     23.099      0.000    2.31e+05
2.73e+05
C(zipcode)[T.98053]  2.243e+05   1.18e+04     19.059      0.000    2.01e+05
2.47e+05
C(zipcode)[T.98055]   4.32e+04    1.3e+04      3.316      0.001    1.77e+04
6.87e+04
C(zipcode)[T.98056]  1.026e+05   1.17e+04      8.768      0.000    7.97e+04
1.26e+05
C(zipcode)[T.98058]  4.434e+04   1.14e+04      3.892      0.000     2.2e+04
6.67e+04
C(zipcode)[T.98059]  9.364e+04   1.13e+04      8.252      0.000    7.14e+04
1.16e+05
C(zipcode)[T.98065]   8.97e+04   1.26e+04      7.138      0.000    6.51e+04
1.14e+05
C(zipcode)[T.98070]  1.186e+05   1.73e+04      6.869      0.000    8.47e+04
1.52e+05
C(zipcode)[T.98072]  1.745e+05    1.3e+04     13.436      0.000    1.49e+05
2e+05
C(zipcode)[T.98074]  1.917e+05   1.16e+04     16.546      0.000    1.69e+05
2.14e+05
C(zipcode)[T.98075]  1.938e+05   1.22e+04     15.850      0.000     1.7e+05
2.18e+05
C(zipcode)[T.98077]  1.433e+05   1.44e+04      9.947      0.000    1.15e+05
1.72e+05
C(zipcode)[T.98092] -1.729e+04   1.21e+04     -1.425      0.154   -4.11e+04
6486.229
C(zipcode)[T.98102]  4.874e+05    1.8e+04     27.022      0.000    4.52e+05
5.23e+05
C(zipcode)[T.98103]  3.414e+05   1.08e+04     31.691      0.000     3.2e+05
3.63e+05
C(zipcode)[T.98105]  4.958e+05   1.37e+04     36.305      0.000    4.69e+05
5.23e+05
C(zipcode)[T.98106]  1.117e+05   1.23e+04      9.085      0.000    8.76e+04
1.36e+05
C(zipcode)[T.98107]  3.405e+05   1.31e+04     26.014      0.000    3.15e+05
3.66e+05
C(zipcode)[T.98108]  1.128e+05   1.46e+04      7.738      0.000    8.42e+04
1.41e+05
C(zipcode)[T.98109]  5.041e+05   1.77e+04     28.512      0.000    4.69e+05
5.39e+05
C(zipcode)[T.98112]  6.446e+05   1.31e+04     49.298      0.000    6.19e+05
```

```
6.7e+05
C(zipcode)[T.98115]  3.408e+05   1.08e+04     31.486      0.000     3.2e+05
3.62e+05
C(zipcode)[T.98116]  2.886e+05   1.23e+04     23.399      0.000    2.64e+05
3.13e+05
C(zipcode)[T.98117]  3.208e+05   1.09e+04     29.332      0.000    2.99e+05
3.42e+05
C(zipcode)[T.98118]   1.58e+05   1.12e+04     14.158      0.000    1.36e+05
1.8e+05
C(zipcode)[T.98119]  4.826e+05   1.47e+04     32.881      0.000    4.54e+05
5.11e+05
C(zipcode)[T.98122]  3.484e+05   1.28e+04     27.286      0.000    3.23e+05
3.73e+05
C(zipcode)[T.98125]  2.071e+05   1.17e+04     17.742      0.000    1.84e+05
2.3e+05
C(zipcode)[T.98126]  1.806e+05   1.21e+04     14.896      0.000    1.57e+05
2.04e+05
C(zipcode)[T.98133]  1.682e+05   1.12e+04     15.017      0.000    1.46e+05
1.9e+05
C(zipcode)[T.98136]  2.509e+05   1.31e+04     19.107      0.000    2.25e+05
2.77e+05
C(zipcode)[T.98144]  2.722e+05   1.22e+04     22.324      0.000    2.48e+05
2.96e+05
C(zipcode)[T.98146]  1.026e+05   1.28e+04      8.001      0.000    7.74e+04
1.28e+05
C(zipcode)[T.98148]  7.078e+04    2.3e+04      3.075      0.002    2.57e+04
1.16e+05
C(zipcode)[T.98155]   1.57e+05   1.14e+04     13.724      0.000    1.35e+05
1.79e+05
C(zipcode)[T.98166]  8.926e+04   1.33e+04      6.725      0.000    6.32e+04
1.15e+05
C(zipcode)[T.98168]  4.547e+04   1.31e+04      3.472      0.001    1.98e+04
7.11e+04
C(zipcode)[T.98177]  2.144e+05   1.33e+04     16.139      0.000    1.88e+05
2.4e+05
C(zipcode)[T.98178]   2.97e+04   1.32e+04      2.256      0.024    3900.507
5.55e+04
C(zipcode)[T.98188]  2.539e+04   1.63e+04      1.563      0.118   -6459.828
5.72e+04
C(zipcode)[T.98198]  9608.5824   1.29e+04      0.745      0.456   -1.57e+04
3.49e+04
C(zipcode)[T.98199]  3.836e+05   1.25e+04     30.749      0.000    3.59e+05
4.08e+05
bathrooms            5294.7133   2329.863      2.273      0.023     728.009
9861.418
sqft_living           154.9575      2.323     66.694      0.000     150.403
159.512
```

```
view                  8.339e+04   1581.641     52.723      0.000     8.03e+04
8.65e+04
==============================================================================
Omnibus:                    19120.795   Durbin-Watson:                   1.998
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2895060.214
Skew:                           3.677   Prob(JB):                         0.00
Kurtosis:                      59.242   Cond. No.                     1.11e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.11e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

So we just got down to five variables and we still got a pretty nice R-squared value of 0.808

0.17 trying different models

[41]:
```python
#preparing our dataframe to perform different models
df4 = df2.copy()
y = df4.price.values # define the target variable (dependent variable) as y
df4.drop('price', axis=1, inplace=True)
zipcode_dummies = pd.get_dummies(df4.zipcode, drop_first=True, prefix =␣
 ↪'zipcode') #introduce dummies for zipcode
grade_dummies = pd.get_dummies(df4.grade, drop_first=True, prefix = 'grade')␣
 ↪#introduce dummies for grade
dummies = pd.concat([zipcode_dummies, grade_dummies], axis = 1)
```

[42]:
```python
#drop the features we do not need
df4.drop('sqft_lot', axis=1, inplace=True)
df4.drop('floors', axis=1, inplace=True)
df4.drop('lat', axis=1, inplace=True)
df4.drop('long', axis=1, inplace=True)
df4.drop('zipcode',axis=1, inplace=True)
df4.drop('sqft_living15', axis=1, inplace=True)
df4.drop('sqft_lot15', axis=1, inplace=True)
df4.drop('spring', axis=1, inplace=True)
df4.drop('summer', axis=1, inplace=True)
df4.drop('winter', axis=1, inplace=True)
df4.drop('yr_built', axis=1, inplace=True)
df4.drop('sqft_basement', axis=1, inplace=True)
df4.drop('sqft_above', axis=1, inplace=True)
df4.drop('grade', axis=1, inplace=True)
df4.drop('bedrooms', axis=1, inplace=True)
df4.drop('date', axis=1, inplace=True)
```

```
[43]: #join with our dummies
df4  = pd.concat([df4, dummies], axis = 1)
```

0.18 train/test split

```
[44]: result = []

#split the data
X_train, X_test, y_train, y_test = train_test_split(df4, y, test_size=0.2)

# fit a model
lm = linear_model.LinearRegression()
model = lm.fit(X_train, y_train)
predictions = lm.predict(X_test)
result.append(model.score(X_test, y_test))
print('Train/test split score: ' + str(np.mean(result)))
```

```
Train/test split score: 0.8279509225077162
```

0.19 K-fold cross validation

```
[45]: # Perform 6-fold cross validation
scores = cross_val_score(model, df4, y, cv=6)
print('Cross-validated score:', np.mean(scores))
```

```
Cross-validated score: 0.824289910931233
```

0.20 Summary

After cleaning and exploration of our data we figured out that the most important feature for house prices in King County. Important features. - location - grade - bathrooms - sqft_living - view

Considering this features our linear model got a R-squared value of 0.808

0.21 Buisness recommendations

House sellers: - try to improve the grade of your house - modelling the fair price of the house to get the maximum

House buyers: - be sure about the location the house is based - calculate the fair price of the house to not pay a premium

0.22 Future work

- get more data
- improve data cleaning
  - find a better solution for the cleaning of the waterfront
- get more into detail of the data to find more correlations