KingCountyHousing

January 1, 2018

1 Create the dataframe

```
In [8]: import pandas as pd
        housing_data = pd.read_csv("Data/KingCountyHousing.csv")
        # housing_data.head()
```

Here we have 21 Columns with 19 Features, and 21613 Observations.

2 Fix the date

```
In [13]: import datetime
         current_year = datetime.datetime.now().year
         housing_data["age_of_house"] = current_year - pd.to_datetime(
             housing_data["date"]).dt.year
```

We've now added a column for the age of the home, which will help us analyze the pricing.

```
In [14]: housing_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 22 columns):
id               21613 non-null int64
date             21613 non-null object
price            21613 non-null float64
bedrooms         21613 non-null int64
bathrooms        21613 non-null float64
sqft_living      21613 non-null int64
sqft_lot         21613 non-null int64
floors           21613 non-null float64
waterfront       21613 non-null int64
view             21613 non-null int64
condition        21613 non-null int64
grade            21613 non-null int64
sqft_above       21613 non-null int64
sqft_basement    21613 non-null int64
yr_built         21613 non-null int64
```

```
yr_renovated     21613 non-null int64
zipcode          21613 non-null int64
lat              21613 non-null float64
long             21613 non-null float64
sqft_living15    21613 non-null int64
sqft_lot15       21613 non-null int64
age_of_house     21613 non-null int64
dtypes: float64(5), int64(16), object(1)
memory usage: 3.6+ MB
```

In [15]:
```
housing_data.columns
```

Out[15]:
```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15', 'age_of_house'],
      dtype='object')
```

3 Select features and dependent variable

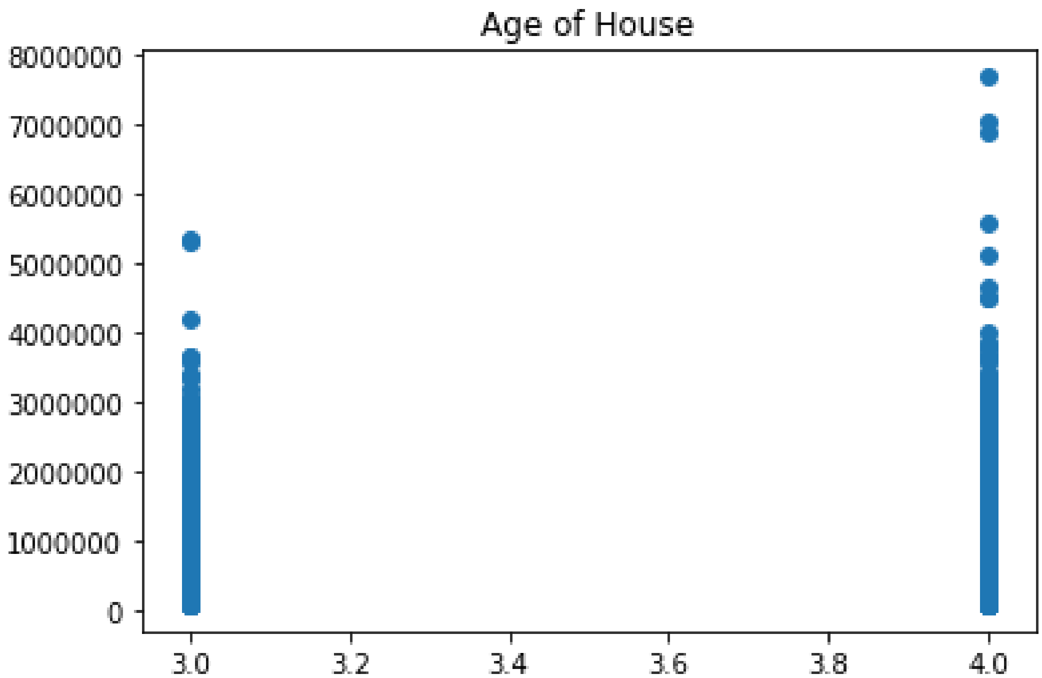
In [65]:
```
feature_cols = [
    u'age_of_house',
    u'bedrooms',
    u'bathrooms',
    u'sqft_living',
    u'sqft_lot',
    u'floors',
    u'waterfront',
    u'view',
    u'condition',
    u'grade',
    u'sqft_above',
    u'sqft_basement',
    u'yr_built',
    u'yr_renovated',
    u'zipcode',
    u'lat',
    u'long',]
x = housing_data[feature_cols]
y = housing_data["price"]
```

4 Visualize the features against the dependent variable

In [19]:
```
import matplotlib.pyplot as plt
%matplotlib inline
```

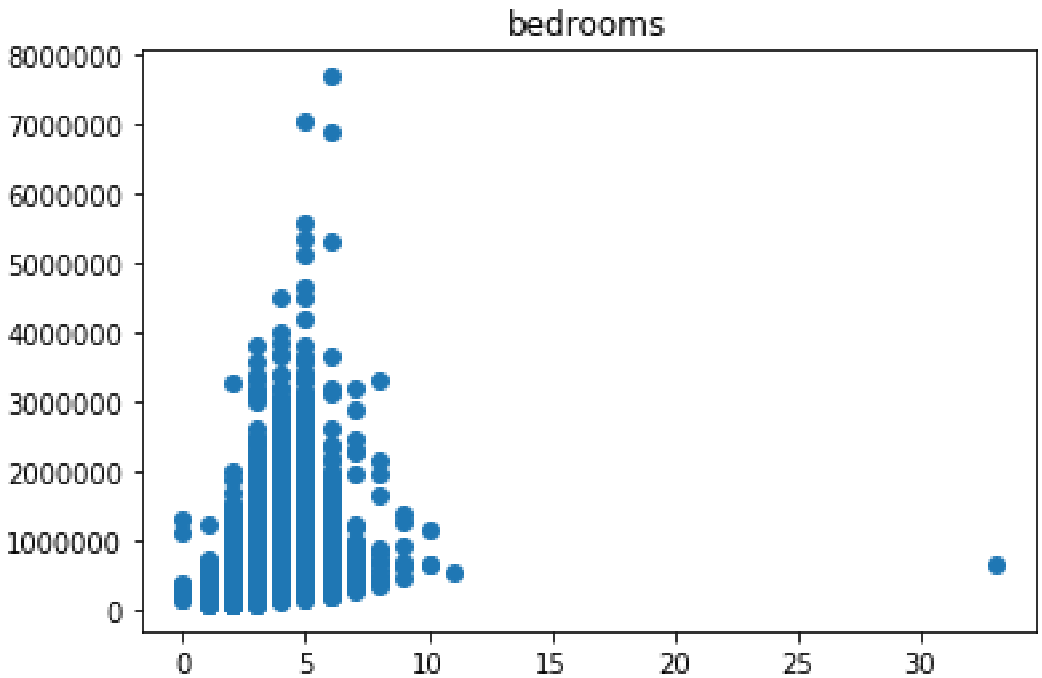
```
plt.title("Age of House")
plt.scatter(housing_data["age_of_house"],housing_data["price"])
```

Out[19]: <matplotlib.collections.PathCollection at 0x285dca962b0>



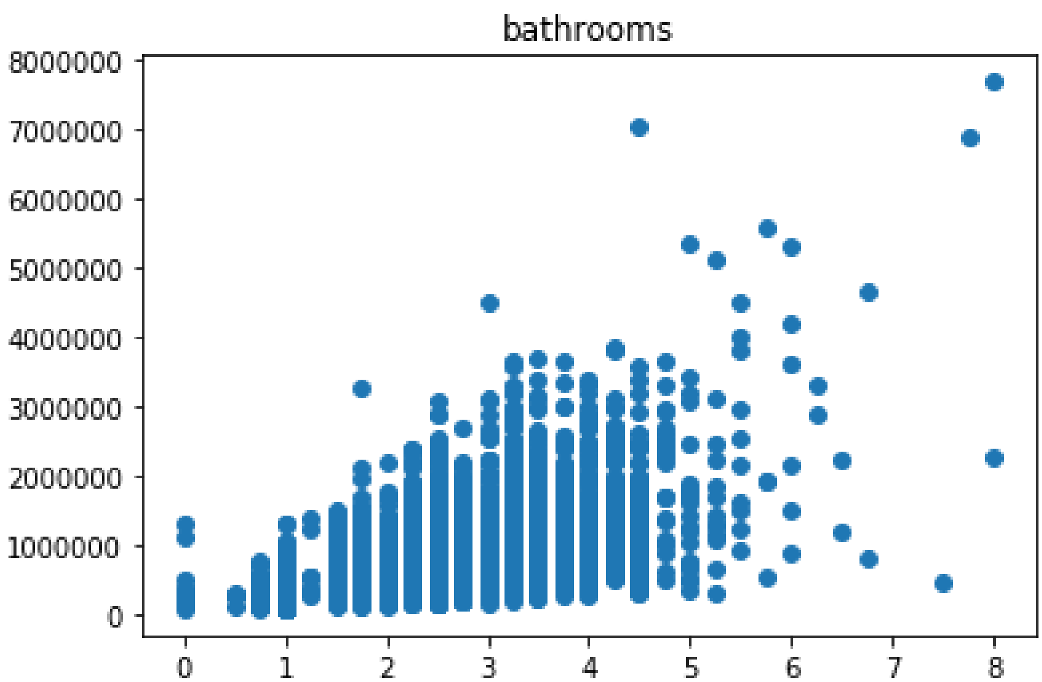
In [20]:
```
plt.title("bedrooms")
plt.scatter(housing_data["bedrooms"],housing_data["price"])
```

Out[20]: <matplotlib.collections.PathCollection at 0x285dcadf320>



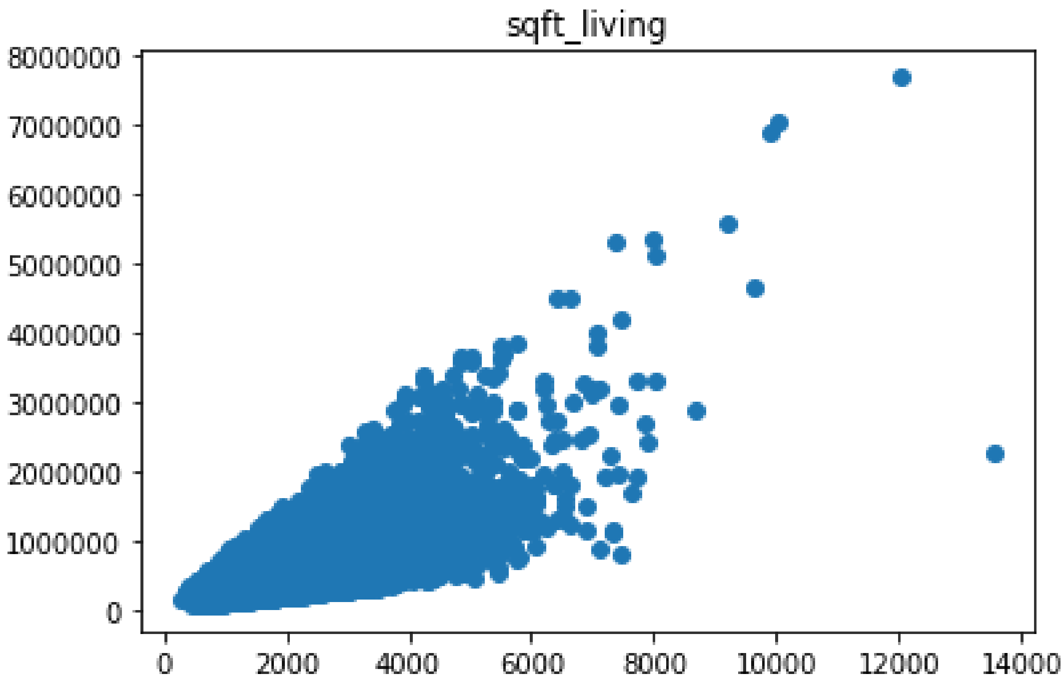

```
In [22]: plt.title("bathrooms")
         plt.scatter(housing_data["bathrooms"],housing_data["price"])

Out[22]: <matplotlib.collections.PathCollection at 0x285dcb53400>
```



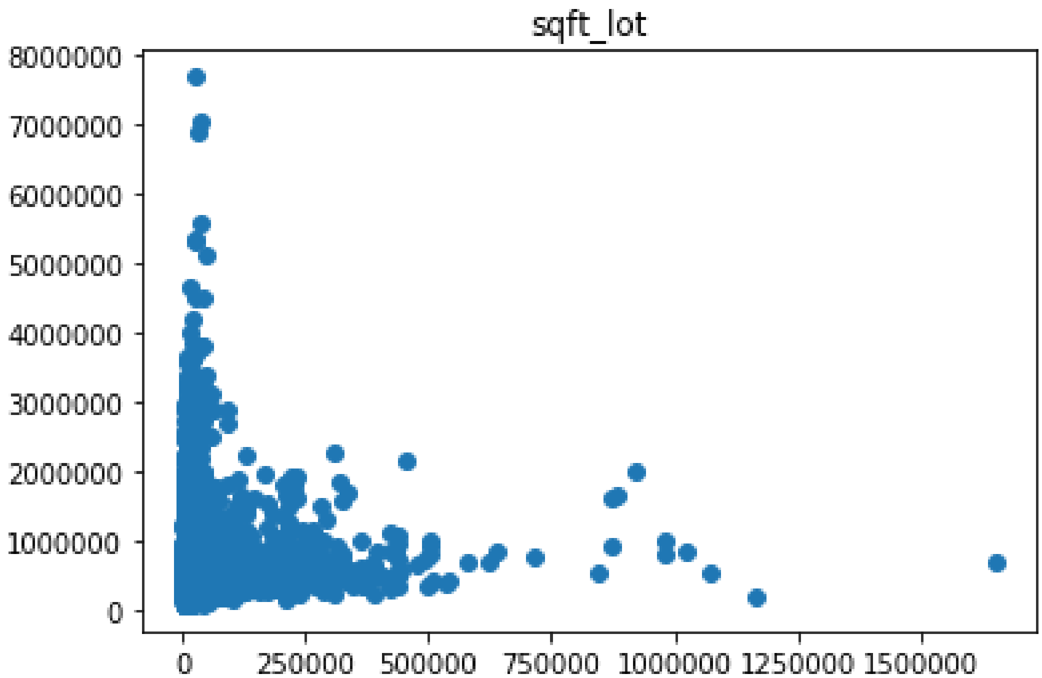
In [23]:
```
plt.title("sqft_living")
plt.scatter(housing_data["sqft_living"],housing_data["price"])
```

Out[23]: <matplotlib.collections.PathCollection at 0x285dcbb9908>



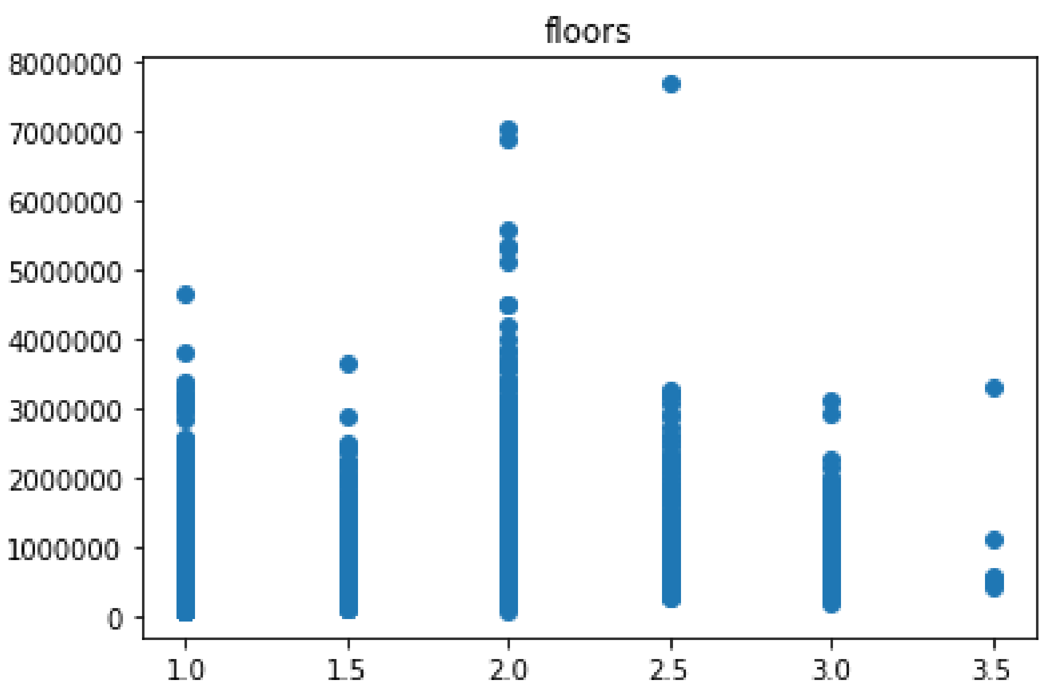
In [24]:
```
plt.title("sqft_lot")
plt.scatter(housing_data["sqft_lot"],housing_data["price"])
```

Out[24]: <matplotlib.collections.PathCollection at 0x285dcc20dd8>



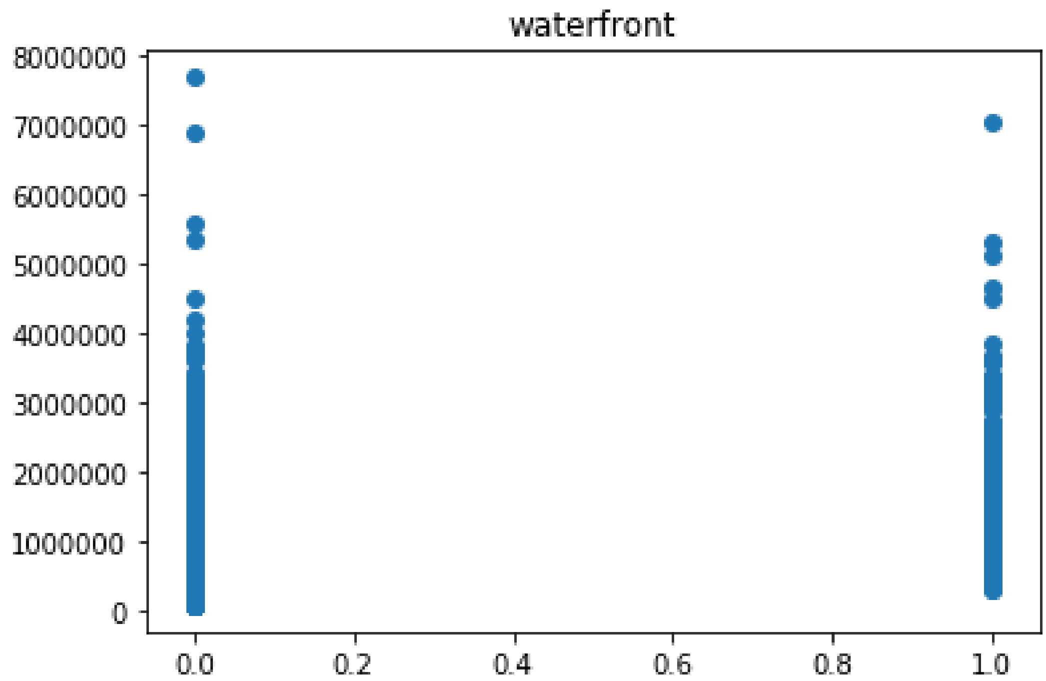

```
In [25]: plt.title("floors")
         plt.scatter(housing_data["floors"],housing_data["price"])

Out[25]: <matplotlib.collections.PathCollection at 0x285dcf58ba8>
```



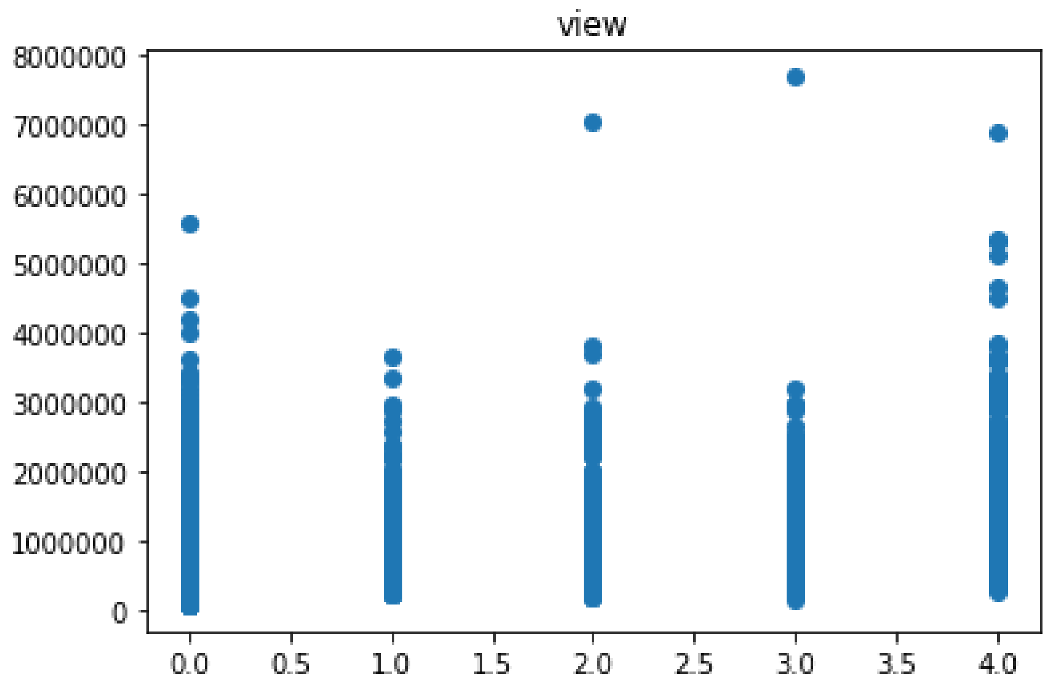
```
In [26]: plt.title("waterfront")
         plt.scatter(housing_data["waterfront"],housing_data["price"])
```

```
Out[26]: <matplotlib.collections.PathCollection at 0x285dcf96ba8>
```



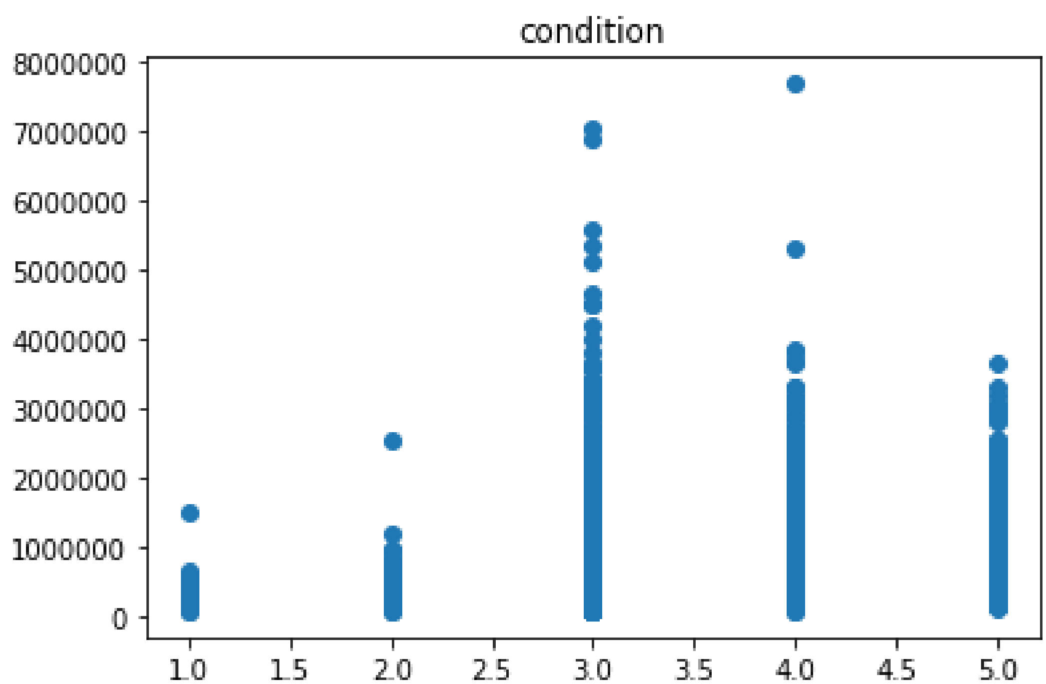

```
In [27]: plt.title("view")
         plt.scatter(housing_data["view"],housing_data["price"])
```

```
Out[27]: <matplotlib.collections.PathCollection at 0x285dd028080>
```



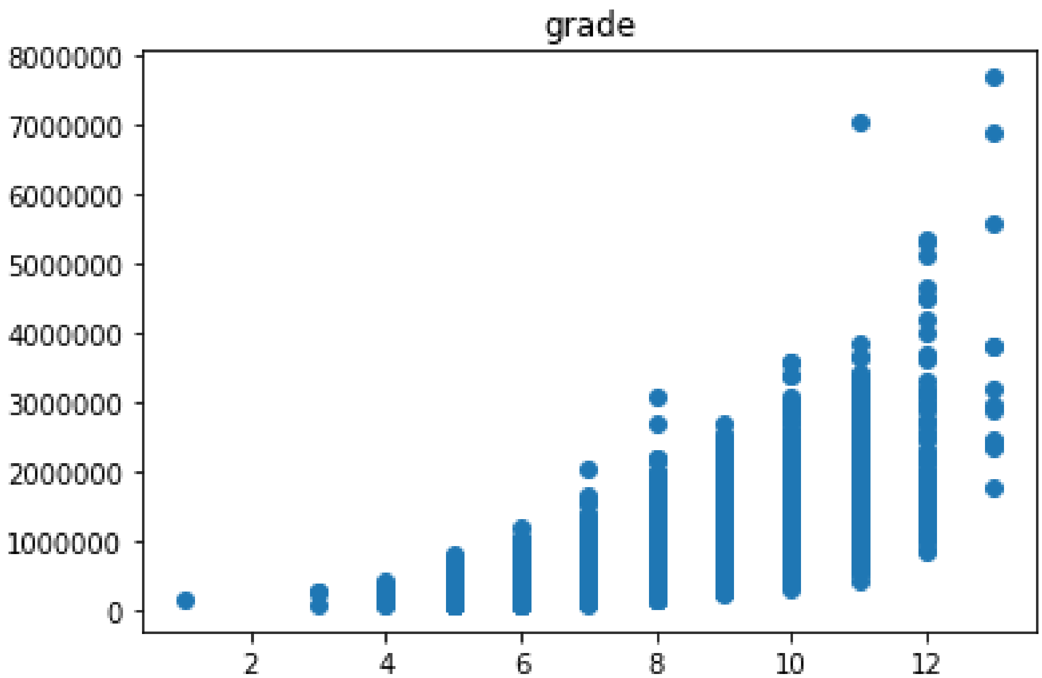

```
In [28]: plt.title("condition")
         plt.scatter(housing_data["condition"],housing_data["price"])

Out[28]: <matplotlib.collections.PathCollection at 0x285dd08d8d0>
```



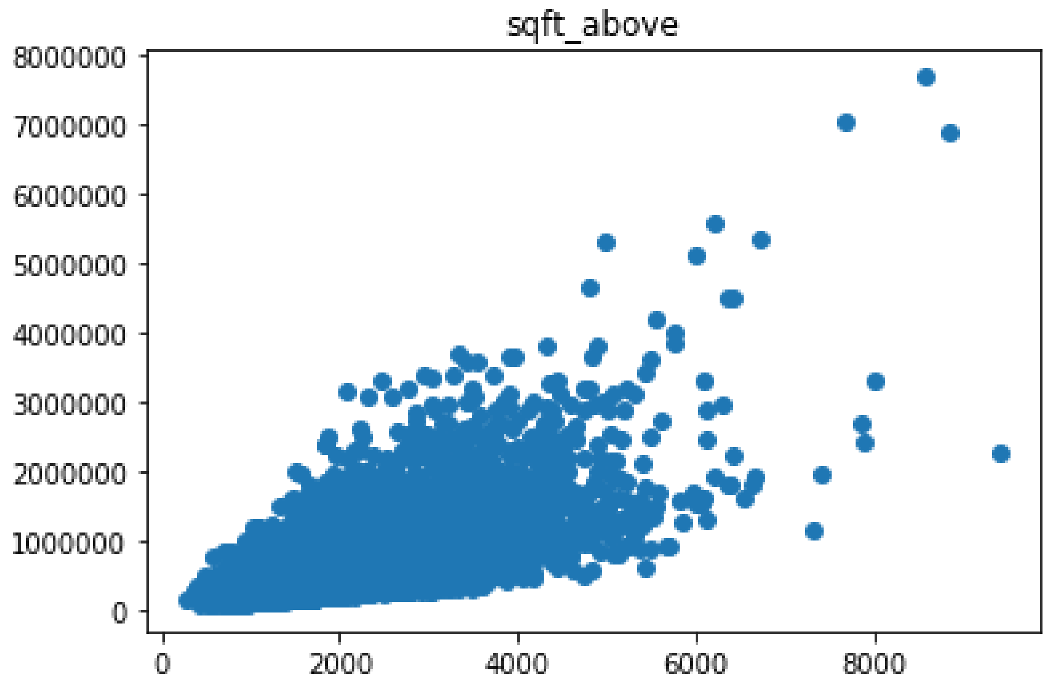
In [29]:
```
plt.title("grade")
plt.scatter(housing_data["grade"],housing_data["price"])
```

Out[29]: <matplotlib.collections.PathCollection at 0x285dd0fe198>



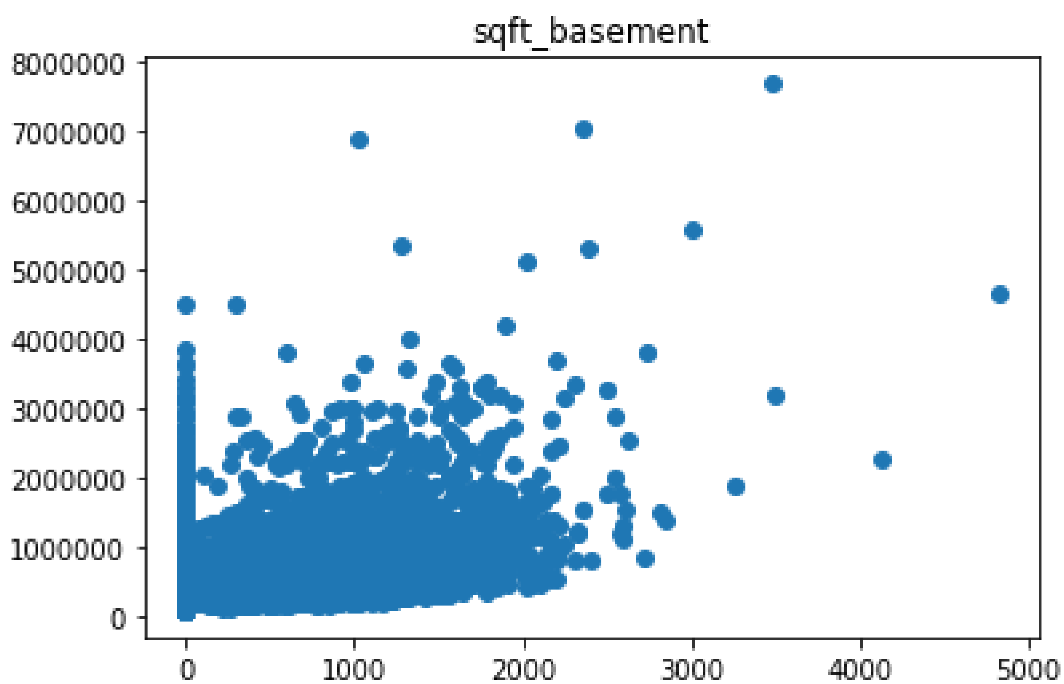
In [30]:
```
plt.title("sqft_above")
plt.scatter(housing_data["sqft_above"],housing_data["price"])
```

Out[30]: <matplotlib.collections.PathCollection at 0x285dd15e860>



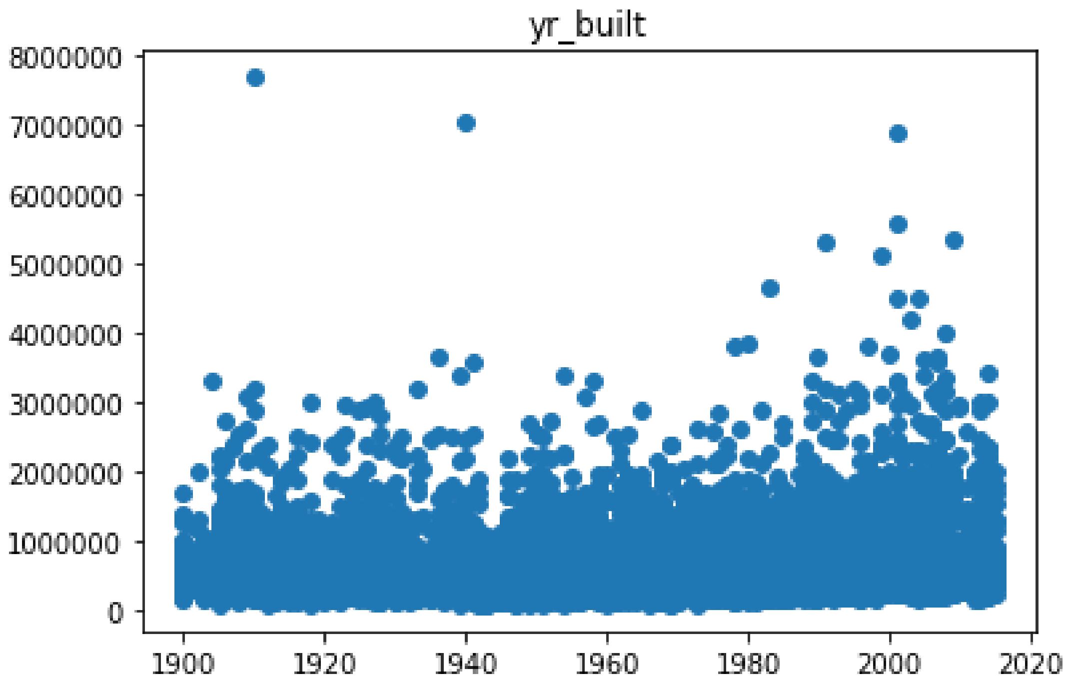

```
In [31]: plt.title("sqft_basement")
         plt.scatter(housing_data["sqft_basement"],housing_data["price"])

Out[31]: <matplotlib.collections.PathCollection at 0x285dd1bce48>
```



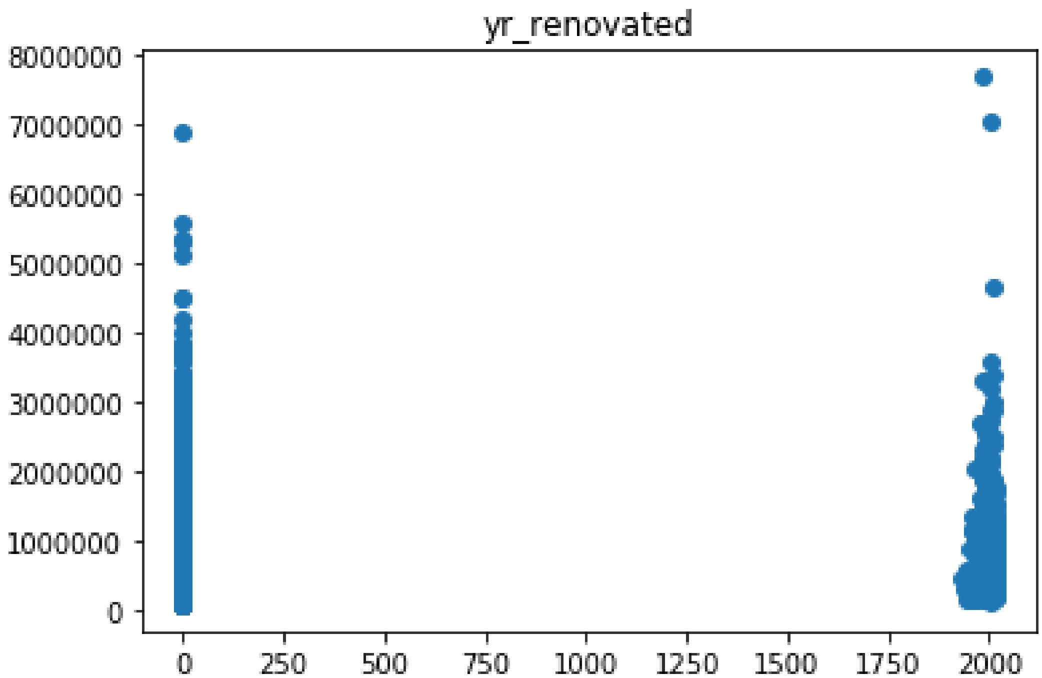
```
In [32]: plt.title("yr_built")
         plt.scatter(housing_data["yr_built"],housing_data["price"])
```

```
Out[32]: <matplotlib.collections.PathCollection at 0x285dd2267b8>
```



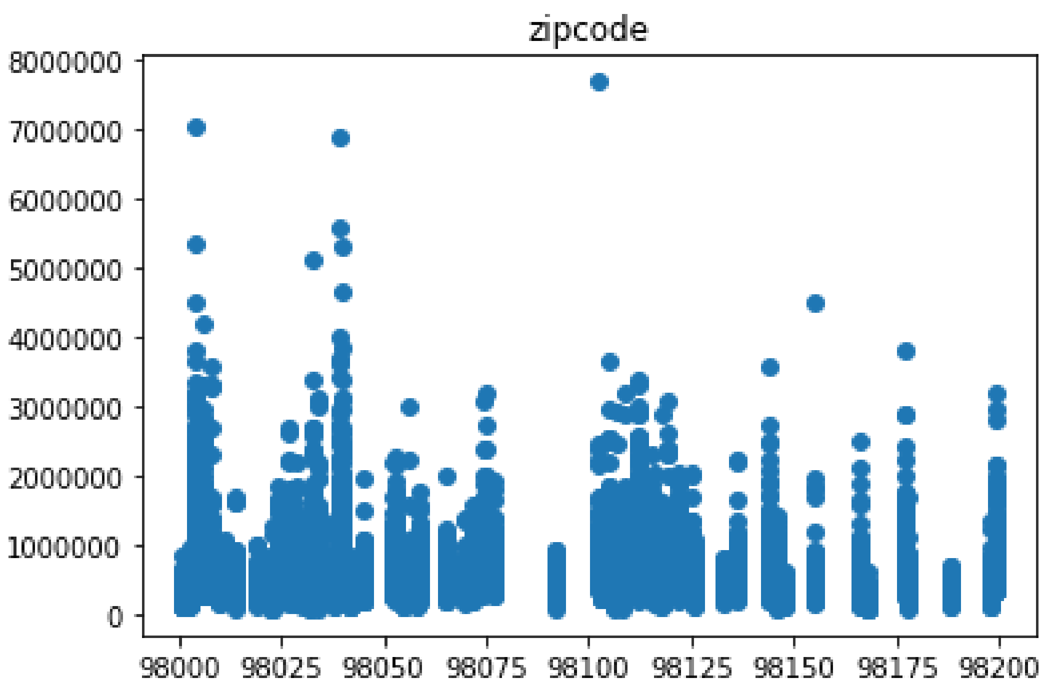

```
In [33]: plt.title("yr_renovated")
         plt.scatter(housing_data["yr_renovated"],housing_data["price"])
```

```
Out[33]: <matplotlib.collections.PathCollection at 0x285dd28d6a0>
```



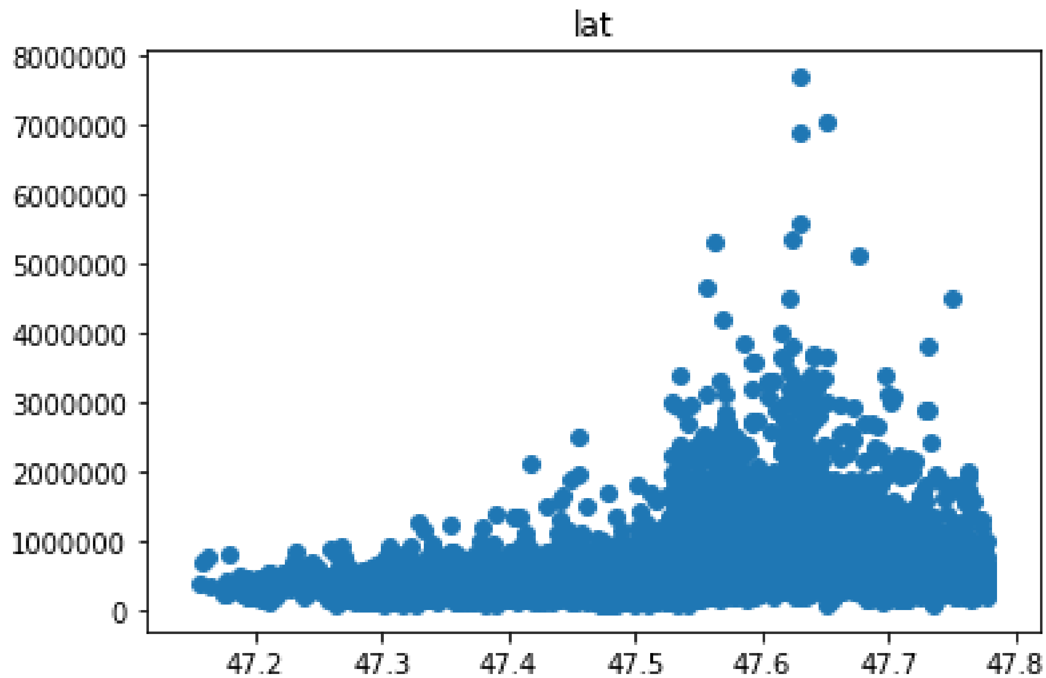

```
In [66]: plt.title("zipcode")
         plt.scatter(housing_data["zipcode"],housing_data["price"])
```

```
Out[66]: <matplotlib.collections.PathCollection at 0x285e5dac390>
```



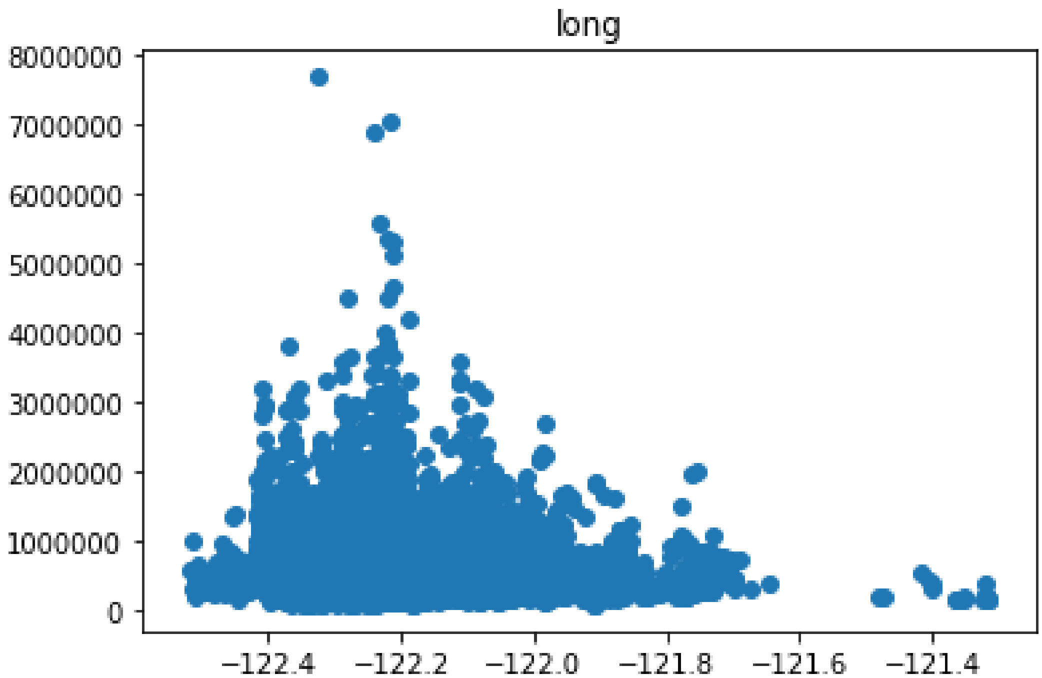
```
In [67]: plt.title("lat")
         plt.scatter(housing_data["lat"],housing_data["price"])
```

```
Out[67]: <matplotlib.collections.PathCollection at 0x285e5e00160>
```




```
In [68]: plt.title("long")
         plt.scatter(housing_data["long"],housing_data["price"])
```

```
Out[68]: <matplotlib.collections.PathCollection at 0x285e5e61588>
```



5 Split the training and test data

```
In [69]: from sklearn.model_selection import train_test_split
         x_train,x_test,y_train,y_test = train_test_split(x, y, test_size=.2, random_state=3)
```

6 Fitting the model to the training set

```
In [70]: from sklearn.linear_model import LinearRegression
         regressor = LinearRegression()
         regressor.fit(x_train, y_train)

         accuracy = regressor.score(x_test, y_test)
         print(accuracy)
```

```
0.709354281043
```

```
In [78]: # Building the optimal model using Backward Elimination
         def backwardElim(X_opt, SL):
             regressor_OLS = sm.OLS(endog = y, exog = X_opt).fit()
             for i in range(np.size(X_opt,1)):
                 if regressor_OLS.pvalues[i] > SL:
                     if regressor_OLS.pvalues[i] == max(regressor_OLS.pvalues):
                         print(regressor_OLS.summary())
```

```
                print("removing: "+str(i)+", with P val: "+str(regressor_OLS.pvalues[i]
                return backwardElim(np.delete(X_opt, i, axis=1), SL)
        return X_opt
```

In [92]:
```
import statsmodels.formula.api as sm
X = np.append(arr =np.ones((21613,1)).astype(int), values = x, axis = 1)
X_opt = X[:, [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17]]
SL = 0.05

X_opt = backwardElim(X_opt, SL)
regressor_OLS = sm.OLS(endog = y, exog = X_opt).fit()
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.700
Model:                            OLS   Adj. R-squared:                  0.700
Method:                 Least Squares   F-statistic:                     3155.
Date:                Mon, 01 Jan 2018   Prob (F-statistic):               0.00
Time:                        15:03:35   Log-Likelihood:            -2.9458e+05
No. Observations:               21613   AIC:                         5.892e+05
Df Residuals:                   21596   BIC:                         5.893e+05
Df Model:                          16
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       9.362e+06   2.88e+06      3.254      0.001    3.72e+06     1.5e+07
x1          -3.04e+04   2932.859    -10.365      0.000   -3.61e+04   -2.47e+04
x2         -3.569e+04   1887.879    -18.905      0.000   -3.94e+04    -3.2e+04
x3           4.11e+04   3247.663     12.656      0.000    3.47e+04    4.75e+04
x4           114.7710      2.127     53.953      0.000     110.601     118.941
x5            -0.0551      0.035     -1.589      0.112      -0.123       0.013
x6          5506.8689   3567.325      1.544      0.123   -1485.352    1.25e+04
x7          5.797e+05    1.73e+04     33.442      0.000    5.46e+05    6.14e+05
x8          5.452e+04   2111.286     25.821      0.000    5.04e+04    5.87e+04
x9          2.692e+04   2350.233     11.452      0.000    2.23e+04    3.15e+04
x10         1.001e+05   2060.886     48.580      0.000    9.61e+04    1.04e+05
x11           74.5709      2.136     34.905      0.000      70.383      78.758
x12           40.2011      2.643     15.212      0.000      35.021      45.381
x13        -2637.2436     72.548    -36.352      0.000   -2779.442   -2495.045
x14           19.3364      3.648      5.301      0.000      12.187      26.486
x15         -603.0424     32.804    -18.383      0.000    -667.341    -538.743
x16         6.098e+05    1.07e+04     56.935      0.000    5.89e+05    6.31e+05
x17        -2.078e+05    1.29e+04    -16.090      0.000   -2.33e+05   -1.82e+05
==============================================================================
Omnibus:                    18172.766   Durbin-Watson:                   1.992
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1785086.012
Skew:                           3.509   Prob(JB):                         0.00
```

```
Kurtosis:                      46.966   Cond. No.                     8.00e+16
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 3.34e-20. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
removing: 6, with P val: 0.122676448789
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.700
Model:                            OLS   Adj. R-squared:                  0.700
Method:                 Least Squares   F-statistic:                     3365.
Date:                Mon, 01 Jan 2018   Prob (F-statistic):               0.00
Time:                        15:03:35   Log-Likelihood:            -2.9458e+05
No. Observations:               21613   AIC:                         5.892e+05
Df Residuals:                   21597   BIC:                         5.893e+05
Df Model:                          15
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        8.47e+06   2.82e+06      3.005      0.003    2.95e+06     1.4e+07
x1         -3.032e+04   2932.545    -10.340      0.000   -3.61e+04   -2.46e+04
x2         -3.576e+04   1887.390    -18.947      0.000   -3.95e+04   -3.21e+04
x3          4.244e+04   3130.401     13.557      0.000    3.63e+04    4.86e+04
x4           114.2382      2.099     54.424      0.000     110.124     118.353
x5            -0.0583      0.035     -1.684      0.092      -0.126       0.010
x6          5.799e+05   1.73e+04     33.451      0.000    5.46e+05    6.14e+05
x7          5.454e+04   2111.312     25.830      0.000    5.04e+04    5.87e+04
x8          2.672e+04   2346.876     11.385      0.000    2.21e+04    3.13e+04
x9          1.003e+05   2057.307     48.757      0.000    9.63e+04    1.04e+05
x10           75.7444      1.996     37.939      0.000      71.831      79.658
x11           38.4927      2.400     16.038      0.000      33.788      43.197
x12        -2612.3789     70.739    -36.930      0.000   -2751.033   -2473.725
x13           19.6660      3.641      5.401      0.000      12.529      26.803
x14         -597.7268     32.624    -18.322      0.000    -661.672    -533.781
x15         6.111e+05   1.07e+04     57.230      0.000     5.9e+05    6.32e+05
x16          -2.1e+05   1.28e+04    -16.353      0.000   -2.35e+05   -1.85e+05
==============================================================================
Omnibus:                    18138.075   Durbin-Watson:                   1.991
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1772812.098
Skew:                           3.499   Prob(JB):                         0.00
Kurtosis:                      46.814   Cond. No.                     7.42e+16
==============================================================================

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

```
[2] The smallest eigenvalue is 3.89e-20. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
removing: 5, with P val: 0.0922781409562
```

In [94]:
```
regressor_OLS.summary()
```

Out[94]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.700
Model:                            OLS   Adj. R-squared:                  0.700
Method:                 Least Squares   F-statistic:                     3604.
Date:                Mon, 01 Jan 2018   Prob (F-statistic):               0.00
Time:                        15:04:38   Log-Likelihood:            -2.9458e+05
No. Observations:               21613   AIC:                         5.892e+05
Df Residuals:                   21598   BIC:                         5.893e+05
Df Model:                          14
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       7.969e+06    2.8e+06      2.843      0.004    2.48e+06    1.35e+07
x1         -3.029e+04   2932.588    -10.328      0.000    -3.6e+04   -2.45e+04
x2         -3.551e+04   1881.707    -18.873      0.000   -3.92e+04   -3.18e+04
x3          4.259e+04   3129.276     13.609      0.000    3.65e+04    4.87e+04
x4           113.8393      2.086     54.579      0.000     109.751     117.928
x5          5.802e+05   1.73e+04     33.472      0.000    5.46e+05    6.14e+05
x6          5.438e+04   2109.328     25.780      0.000    5.02e+04    5.85e+04
x7          2.674e+04   2346.953     11.392      0.000    2.21e+04    3.13e+04
x8          1.004e+05   2057.200     48.782      0.000    9.63e+04    1.04e+05
x9            75.4452      1.989     37.939      0.000      71.547      79.343
x10           38.3951      2.400     16.001      0.000      33.692      43.098
x11        -2605.2632     70.616    -36.894      0.000   -2743.675   -2466.851
x12           19.7064      3.641      5.412      0.000      12.569      26.844
x13         -598.1506     32.625    -18.334      0.000    -662.097    -534.204
x14         6.125e+05   1.06e+04     57.520      0.000    5.92e+05    6.33e+05
x15        -2.137e+05   1.26e+04    -16.908      0.000   -2.39e+05   -1.89e+05
==============================================================================
Omnibus:                    18154.830   Durbin-Watson:                   1.991
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1781798.770
Skew:                           3.503   Prob(JB):                         0.00
Kurtosis:                      46.926   Cond. No.                     7.65e+16
==============================================================================

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

```
[2] The smallest eigenvalue is 3.56e-20. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
"""
```

Removed 'floors' and 'waterfront' 70% accuracy