Phase II Data Science project: Analysis real estate value based on different parameters.

Author: Andrei Mikhailov
email: am@mikhailovandrei.com
Program: Data Science Flex
Instructor name: Abhineet Kulkarni

Overview

During this project, we will be investigating the real estate datasets using multiple linear regression analysis. The customer is a real estate agency who want to give better price recommendations to their customers. For the sake of research, we will use the following dataset (with formats):

- King County, WA Real Estate, CSV

We will employ Pandas, Statsmodel, NumPy, MatPlotLib, and SeaBorn libraries.

Considering the task and dataset natures where we need to predict price against explicitly and relatively limited number of parameters we decided to use **linear regression analysis due to its simplicity, transparency and versatility which makes it appropriate for our task.**

Business Problem

The customer, real estate agency, wants to have a tool for home price prediction based on different parameters, like Living Area, Number of Bedrooms or house conditions.

Data exploration and preparation

In [1]:
```
# Importing libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import warnings
from statsmodels.formula.api import ols
#from sklearn.linear_model import LinearRegression
#from sklearn.model_selection import cross_validate, ShuffleSplit
import statsmodels.api as sm
import statsmodels.graphics.api as smg
from statsmodels.stats.outliers_influence import variance_inflation_factor
import scipy.stats as stats
from sklearn.model_selection import train_test_split
from statsmodels.graphics.regressionplots import plot_leverage_resid2
import statsmodels.stats.api as sms
from statsmodels.compat import lzip

%matplotlib inline

# Importing the data
data = pd.read_csv('data/kc_house_data.csv')
```

```
/Users/andreim/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/s
tatsmodels/tsa/base/tsa_model.py:7: FutureWarning: pandas.Int64Index is d
eprecated and will be removed from pandas in a future version. Use panda
s.Index with the appropriate dtype instead.
  from pandas import (to_datetime, Int64Index, DatetimeIndex, Period,
/Users/andreim/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/s
tatsmodels/tsa/base/tsa_model.py:7: FutureWarning: pandas.Float64Index is
deprecated and will be removed from pandas in a future version. Use panda
s.Index with the appropriate dtype instead.
  from pandas import (to_datetime, Int64Index, DatetimeIndex, Period,
```

In [2]:
```
data.head()
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO

5 rows × 21 columns

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21597 non-null  int64  
 1   date           21597 non-null  object 
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64  
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64  
 6   sqft_lot       21597 non-null  int64  
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  object 
 9   view           21534 non-null  object 
 10  condition      21597 non-null  object 
 11  grade          21597 non-null  object 
 12  sqft_above     21597 non-null  int64  
 13  sqft_basement  21597 non-null  object 
 14  yr_built       21597 non-null  int64  
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64  
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64  
 20  sqft_lot15     21597 non-null  int64  
dtypes: float64(6), int64(9), object(6)
memory usage: 3.5+ MB
```

In [4]:
```
data.isna().sum()
```

Out[4]:
```
id                  0
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
view               63
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated     3842
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

In [5]:
```
data.yr_renovated.unique()
```

Out[5]:
```
array([   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.])
```

As we can see, there are 3842 NaN values in the column 'yr_renovated,' and because it represents the year of renovation we can only drop or replace these values, as applying other methods may be inappropriate. Here we will replace NanN with zero value.

In [6]:
```
data.yr_renovated.fillna(0, inplace=True)
```

In [7]:
```
# Next check sqft_basement column
data.sqft_basement.value_counts()
```

Out[7]:
```
0.0       12826
?           454
600.0       217
500.0       209
700.0       208
          ...
1920.0        1
3480.0        1
2730.0        1
2720.0        1
248.0         1
Name: sqft_basement, Length: 304, dtype: int64
```

Because this column represents a continues variable, and we have only 454 '?' values, we can just drop them.

In [8]:
```
# Drop rows with "?" value
data = data[data.sqft_basement != '?']
#Convert to float
data['sqft_basement'] = data.sqft_basement.astype('float')
```

In [9]:
```
data.sqft_basement.unique()
```

Out[9]:
```
array([   0.,  400.,  910., 1530.,  730., 1700.,  300.,  970.,  760.,
        720.,  700.,  820.,  780.,  790.,  330., 1620.,  360.,  588.,
       1510.,  410.,  990.,  600.,  560.,  550., 1000., 1600.,  500.,
       1040.,  880., 1010.,  240.,  265.,  290.,  800.,  540.,  710.,
        840.,  380.,  770.,  480.,  570., 1490.,  620., 1250., 1270.,
        120.,  650.,  180., 1130.,  450., 1640., 1460., 1020., 1030.,
        750.,  640., 1070.,  490., 1310.,  630., 2000.,  390.,  430.,
        850.,  210., 1430., 1950.,  440.,  220., 1160.,  860.,  580.,
       2060., 1820., 1180.,  200., 1150., 1200.,  680.,  530., 1450.,
       1170., 1080.,  960.,  280.,  870., 1100.,  460., 1400.,  660.,
       1220.,  900.,  420., 1580., 1380.,  475.,  690.,  270.,  350.,
        935., 1370.,  980., 1470.,  160.,  950.,   50.,  740., 1780.,
       1900.,  340.,  470.,  370.,  140., 1760.,  130.,  520.,  890.,
       1110.,  150., 1720.,  810.,  190., 1290.,  670., 1800., 1120.,
       1810.,   60., 1050.,  940.,  310.,  930., 1390.,  610., 1830.,
       1300.,  510., 1330., 1590.,  920., 1320., 1420., 1240., 1960.,
       1560., 2020., 1190., 2110., 1280.,  250., 2390., 1230.,  170.,
        830., 1260., 1410., 1340.,  590., 1500., 1140.,  260.,  100.,
        320., 1480., 1060., 1284., 1670., 1350., 2570., 1090.,  110.,
       2500.,   90., 1940., 1550., 2350., 2490., 1481., 1360., 1135.,
       1520., 1850., 1660., 2130., 2600., 1690.,  243., 1210., 1024.,
       1798., 1610., 1440., 1570., 1650.,  704., 1910., 1630., 2360.,
       1852., 2090., 2400., 1790., 2150.,  230.,   70., 1680., 2100.,
       3000., 1870., 1710., 2030.,  875., 1540., 2850., 2170.,  506.,
        906.,  145., 2040.,  784., 1750.,  374.,  518., 2720., 2730.,
       1840., 3480., 2160., 1920., 2330., 1860., 2050., 4820., 1913.,
         80., 2010., 3260., 2200.,  415., 1730.,  652., 2196., 1930.,
        515.,   40., 2080., 2580., 1548., 1740.,  235.,  861., 1890.,
       2220.,  792., 2070., 4130., 2250., 2240., 1990.,  768., 2550.,
        435., 1008., 2300., 2610.,  666., 3500.,  172., 1816., 2190.,
       1245., 1525., 1880.,  862.,  946., 1281.,  414., 2180.,  276.,
       1248.,  602.,  516.,  176.,  225., 1275.,  266.,  283.,   65.,
       2310.,   10., 1770., 2120.,  295.,  207.,  915.,  556.,  417.,
        143.,  508., 2810.,   20.,  274.,  248.])
```

We have only 63 NaN values in the 'view' column, and we simply drop them.

In [10]:
```
# Drop NaN in the 'view' column.
data.dropna(axis=0, subset=['view'], inplace=True)
```

In [11]:
```
# Checking the 'waterfront variable'
data.waterfront.unique()
# Fill NaN values with 'Unknown'
data.waterfront.fillna('Unknown', inplace=True)
```

In [12]:
```
# Checking NaN values in the dataset
data.isna().sum()
```

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

In [13]:
```
data.head()
```

Out[13]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	Unknown
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO

5 rows × 21 columns

Now we have the dataset cleaned and next we will prepare it for modelling

Dealing with categorical variables

First we need to drop all columns which contain meaningless variables for the sake of our modeling.

In [14]:
```
# Drop columns
col_to_drop = ['id','date','zipcode','lat','long']
# Creating a DataFrame for modeling.
data_for_model = data.drop(col_to_drop, axis=1)
data_for_model.head()
```

Out[14]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grad
0	221900.0	3	1.00	1180	5650	1.0	Unknown	NONE	Average	Averag
1	538000.0	3	2.25	2570	7242	2.0	NO	NONE	Average	Averag
2	180000.0	2	1.00	770	10000	1.0	NO	NONE	Average	6 Lo Averag
3	604000.0	4	3.00	1960	5000	1.0	NO	NONE	Very Good	Averag
4	510000.0	3	2.00	1680	8080	1.0	NO	NONE	Average	8 Goo

In [15]:
```
# Creating the basic dataset with dependent and independent variables.
X_train_base = data_for_model.drop('price', axis=1)
y_train_base = data_for_model['price']
```

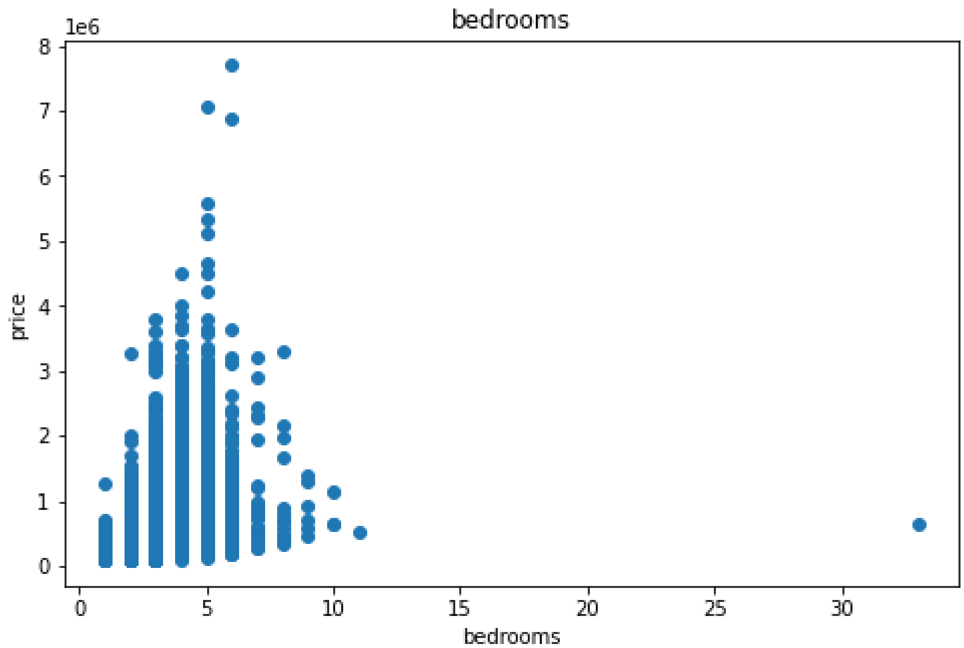
In [16]:
```
# Hot one encoding data in the categorical variables.
waterfront_dummies = pd.get_dummies(data['waterfront'], prefix='wat_f', dro
view_dummies = pd.get_dummies(data['view'], prefix='view', drop_first=True)
condition_dummies = pd.get_dummies(data['condition'], prefix='cond', drop_f
grade_dummies = pd.get_dummies(data['grade'], prefix='grade', drop_first=Tr

X_train_base = pd.concat([X_train_base, waterfront_dummies, view_dummies, c
```

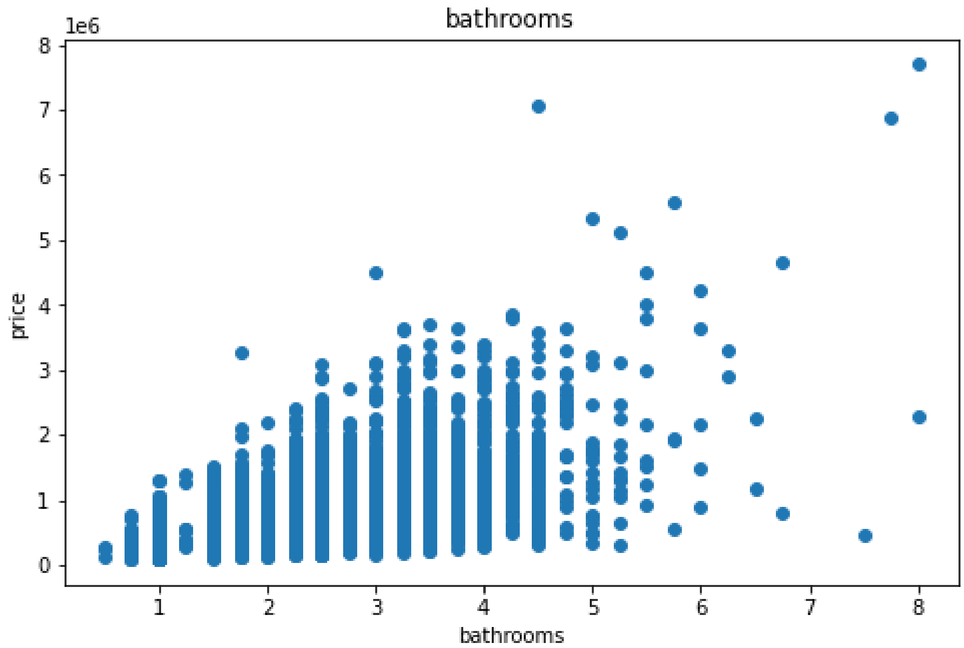
In [17]:
```
# Drop columns with categorical variables.
drop_cat_col = ['waterfront', 'view', 'condition', 'grade']
X_train_base.drop(drop_cat_col, axis=1, inplace=True)
```

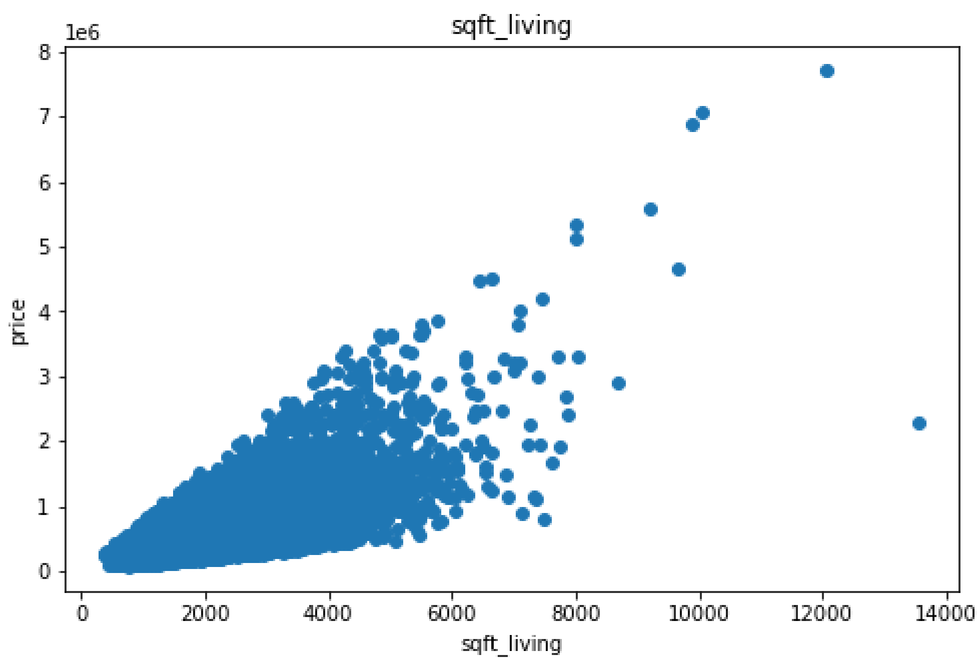
Investigating linearity and correlations

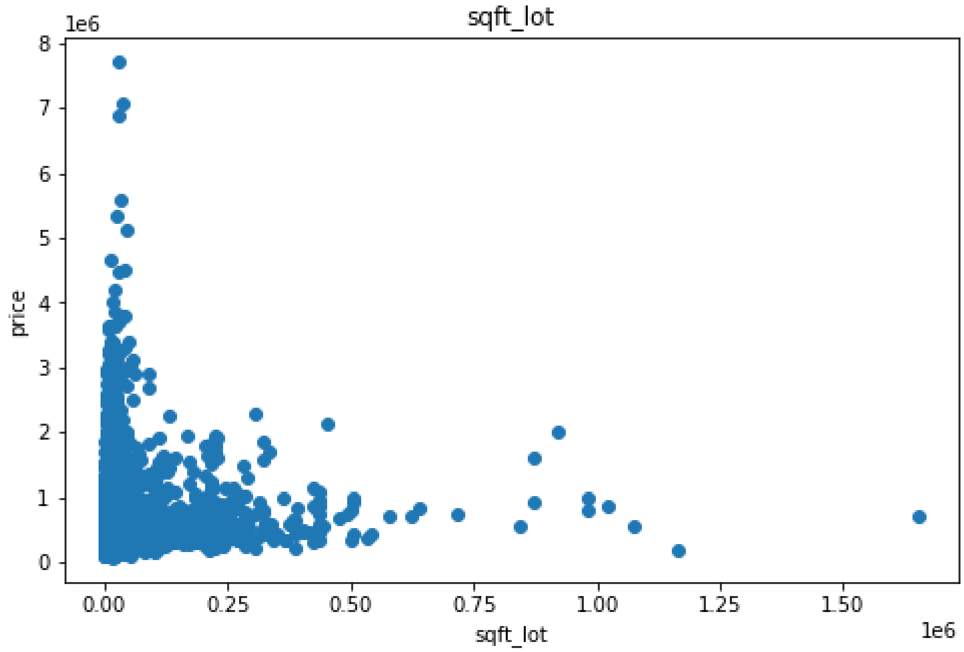
In [18]:
```
# First we plot all independent variables in the basic dataset against pric
for col in X_train_base:
    fig, ax = plt.subplots(figsize=(8, 5))
    ax.scatter(X_train_base[col], y_train_base);

    plt.title(col)
    ax.set_xlabel(col)
    ax.set_ylabel("price")
```

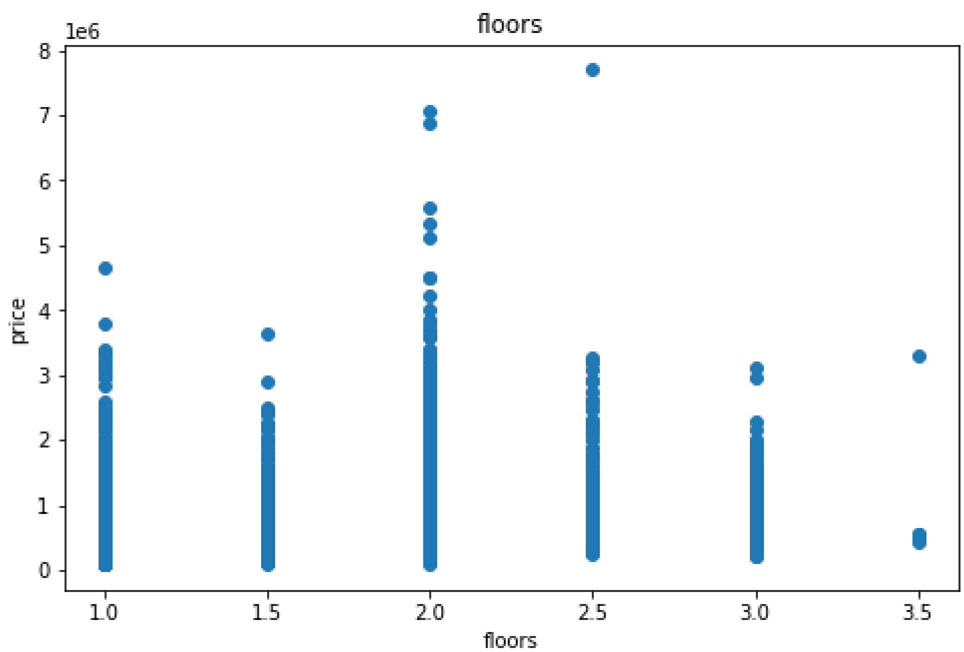
```
<ipython-input-18-e730960b58e7>:3: RuntimeWarning: More than 20 figures h
ave been opened. Figures created through the pyplot interface (`matplotli
b.pyplot.figure`) are retained until explicitly closed and may consume to
o much memory. (To control this warning, see the rcParam `figure.max_open
_warning`).
  fig, ax = plt.subplots(figsize=(8, 5))
```

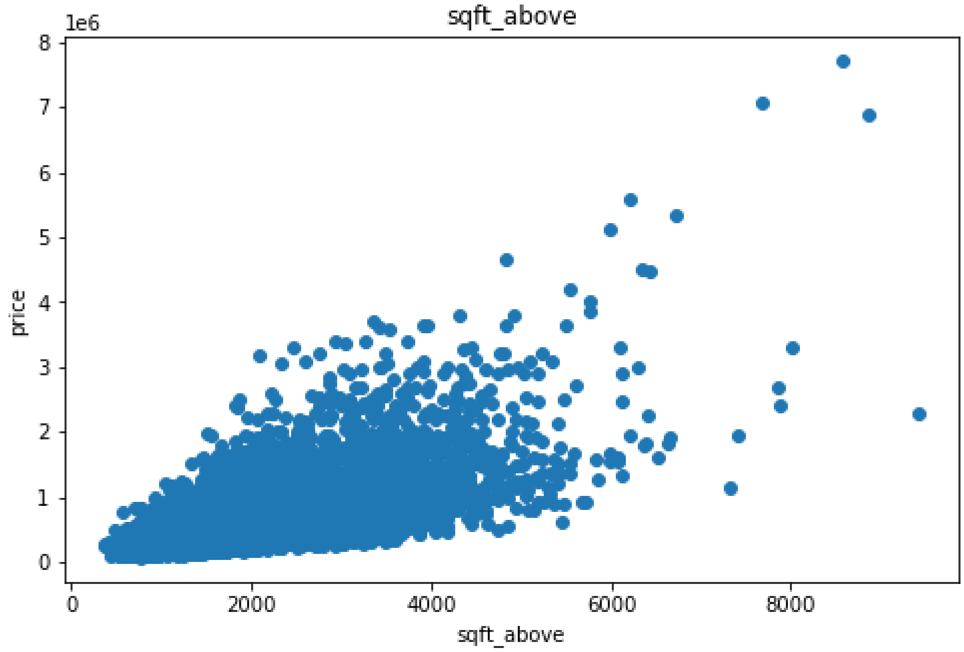


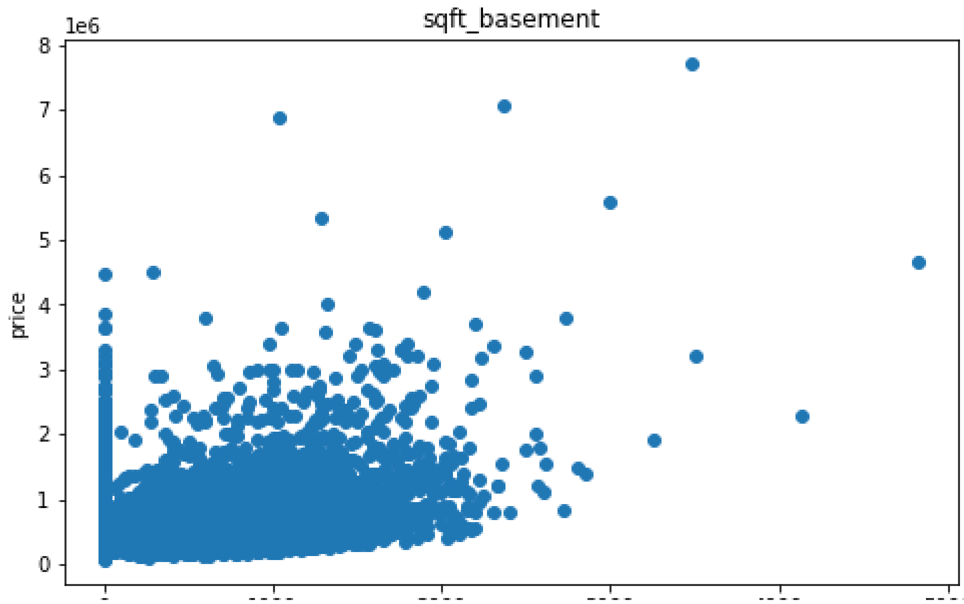

bathrooms
1e6
8
7
6
5
4
3
2
1
0
price
1
2
3
4
5
6
7
8
bathrooms

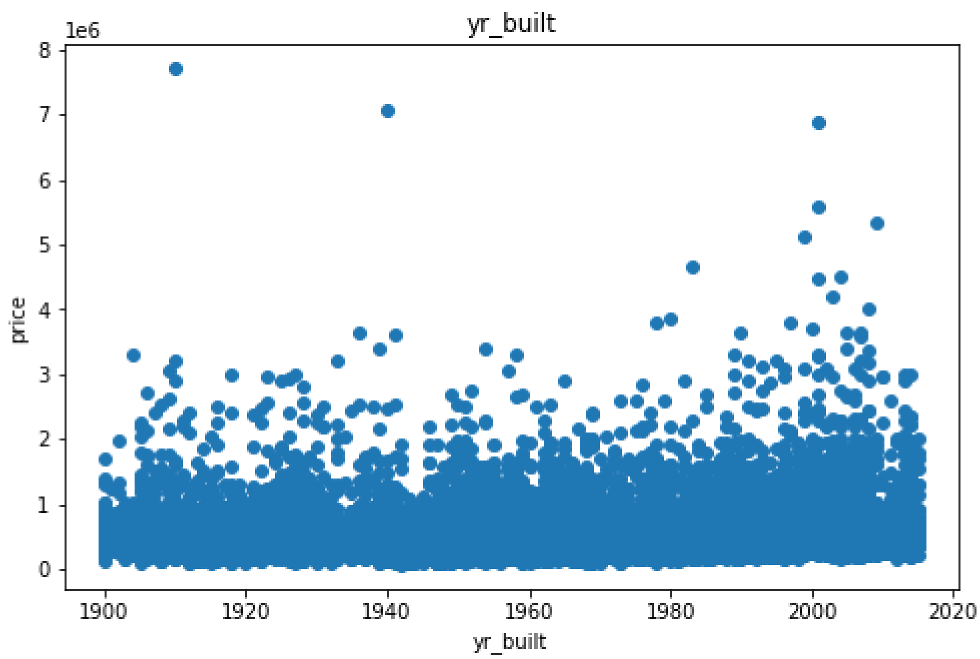

sqft_living
1e6
8
7
6
5
4
3
2
1
0
price
0
2000
4000
6000
8000
10000
12000
14000
sqft_living

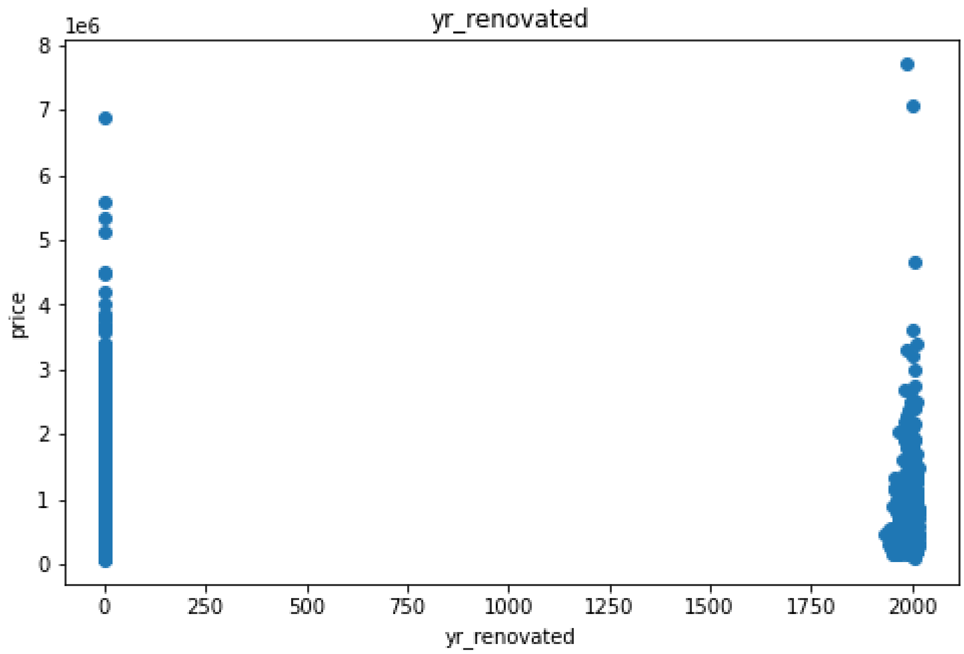

sqft_lot
1e6
price
sqft_lot
1e6
0.00
0.25
0.50
0.75
1.00
1.25
1.50
0
1
2
3
4
5
6
7
8

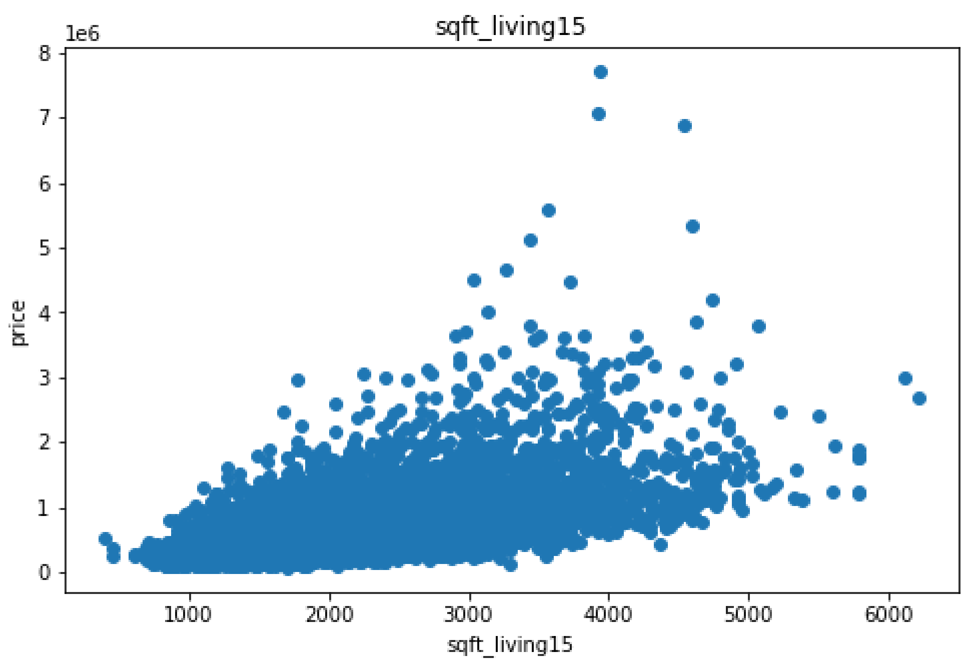

floors
1e6
price
floors
1.0
1.5
2.0
2.5
3.0
3.5
0
1
2
3
4
5
6
7
8

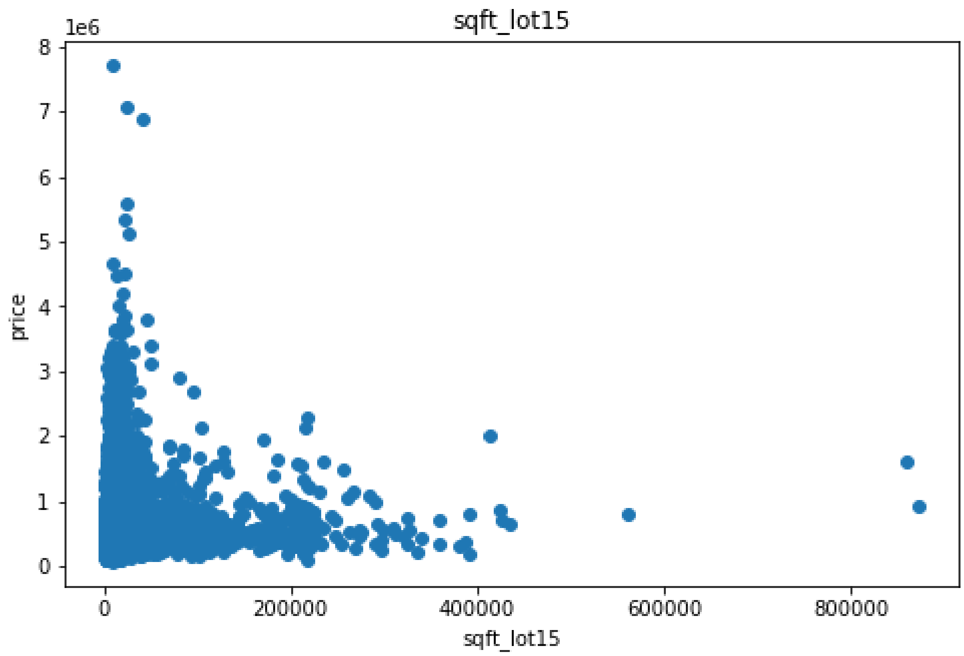

sqft_above
1e6
8
7
6
5
4
3
2
1
0
price
0
2000
4000
6000
8000
sqft_above

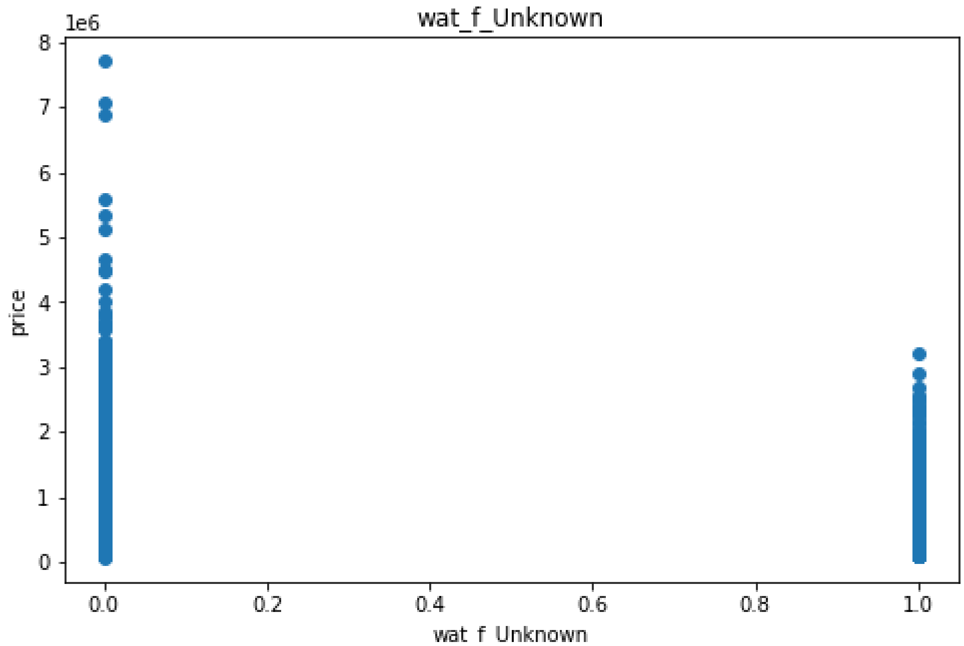

sqft_basement
1e6
price

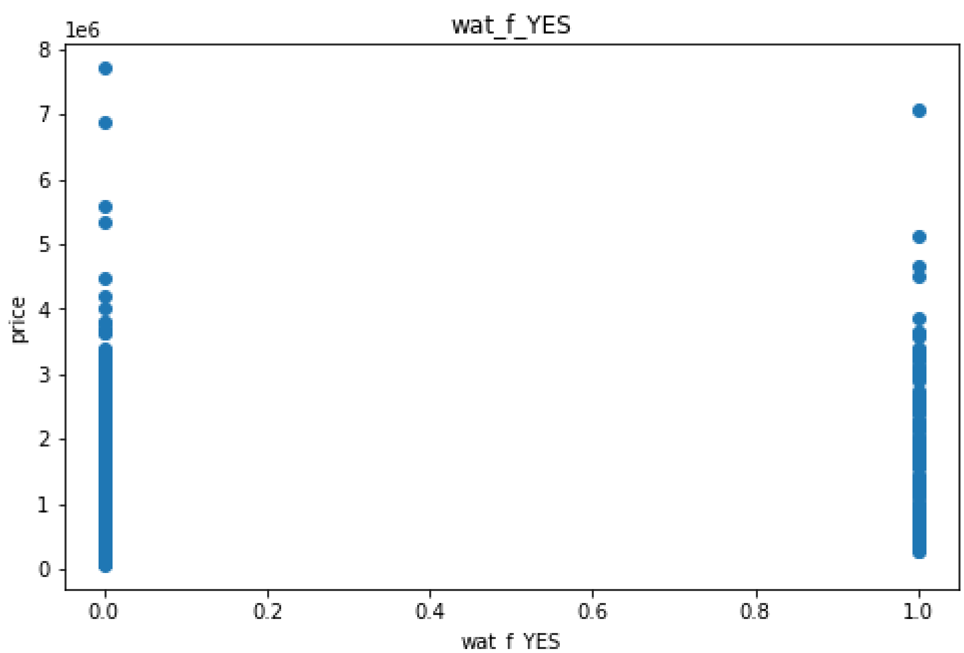

yr_built
1e6
price
yr_built

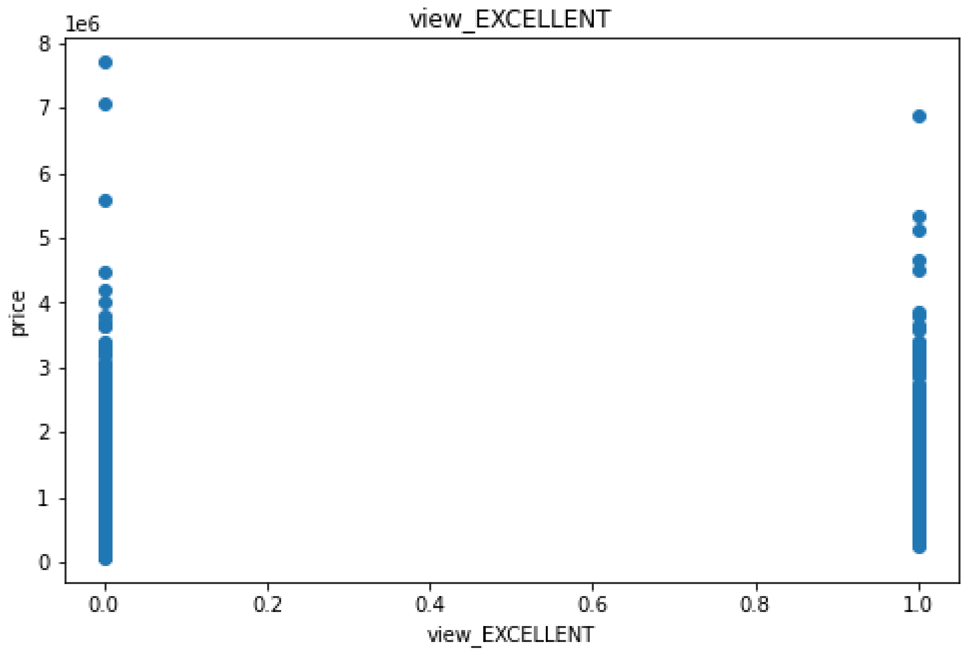

yr_renovated
1e6
price
yr_renovated
0
250
500
750
1000
1250
1500
1750
2000

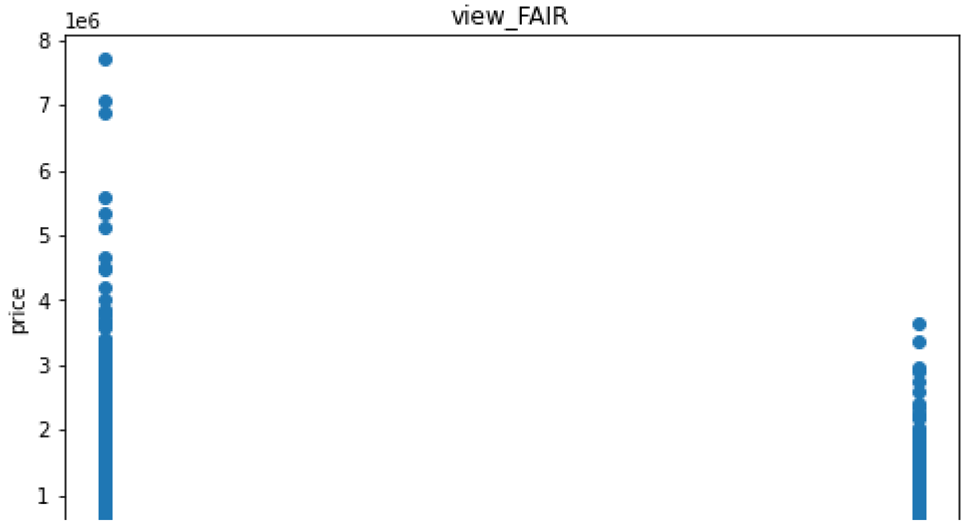

sqft_living15
1e6
price
sqft_living15
1000
2000
3000
4000
5000
6000

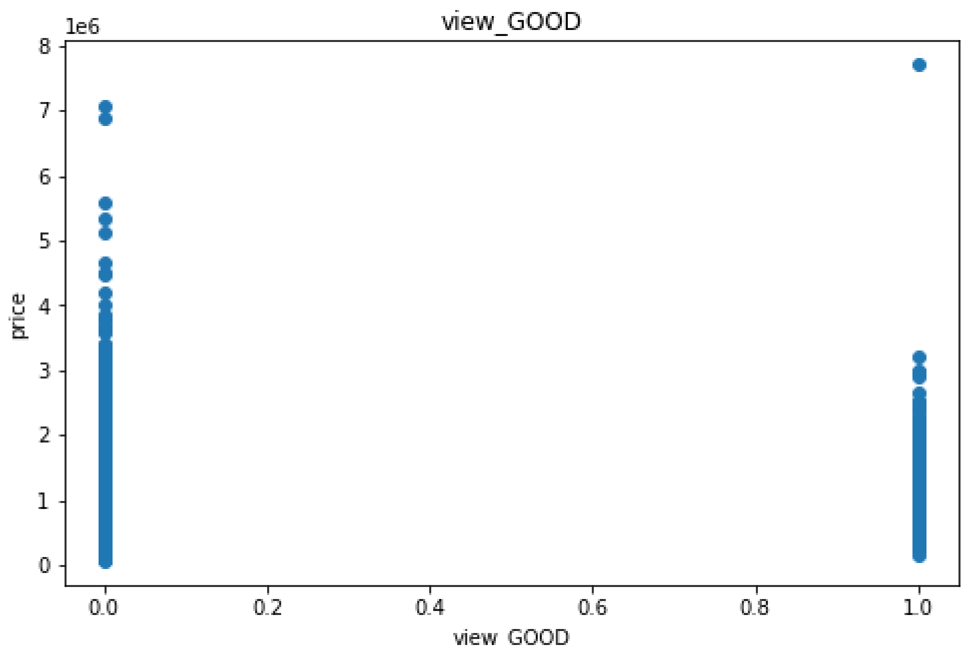

sqft_lot15
1e6
price
sqft_lot15
0
1
2
3
4
5
6
7
8
0
200000
400000
600000
800000

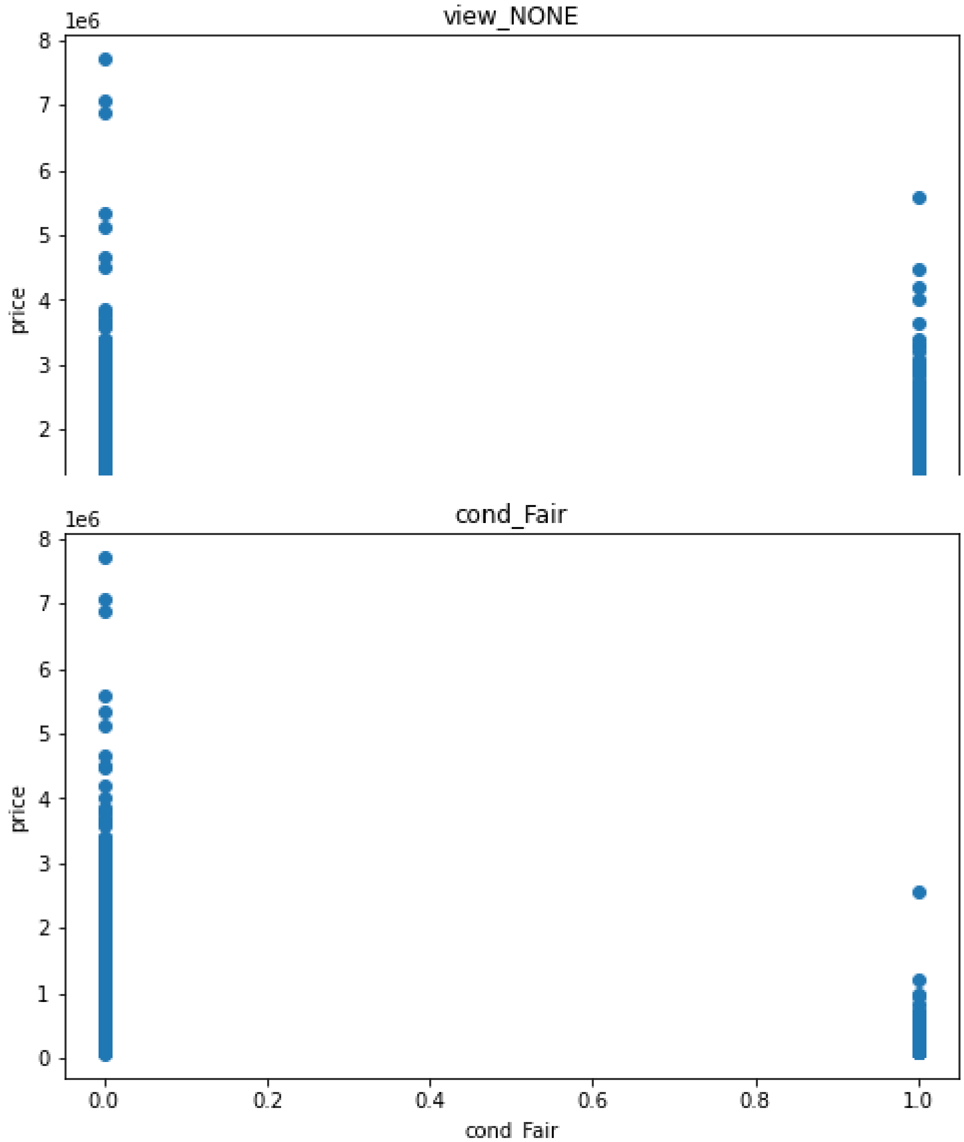

wat_f_Unknown
1e6
8
7
6
5
4
3
2
1
0
price
0.0
0.2
0.4
0.6
0.8
1.0
wat_f_Unknown

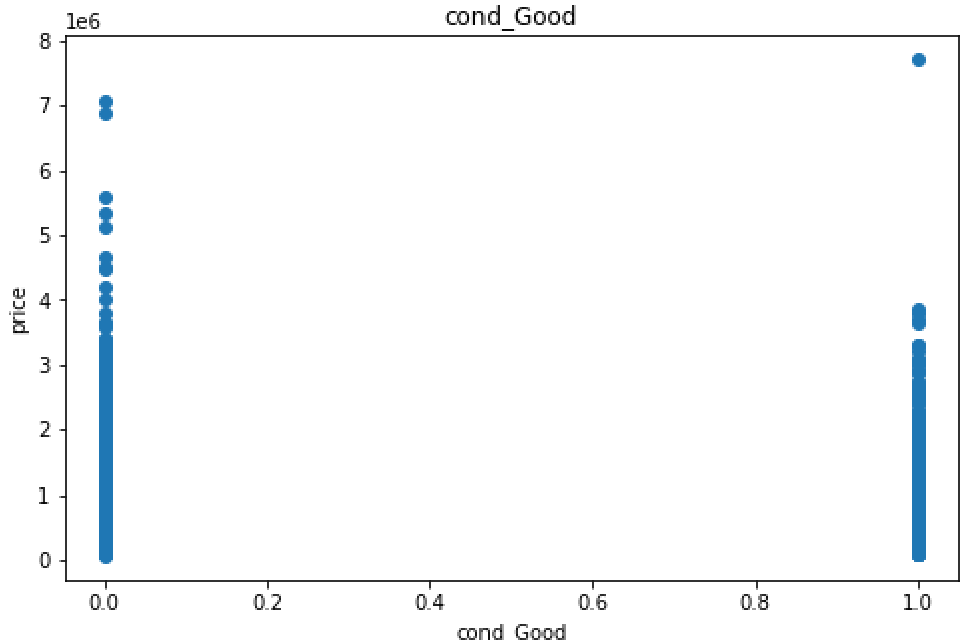

wat_f_YES
1e6
8
7
6
5
4
3
2
1
0
price
0.0
0.2
0.4
0.6
0.8
1.0
wat_f_YES


view_EXCELLENT
1e6
8
7
6
5
4
3
2
1
0
price
0.0
0.2
0.4
0.6
0.8
1.0
view_EXCELLENT

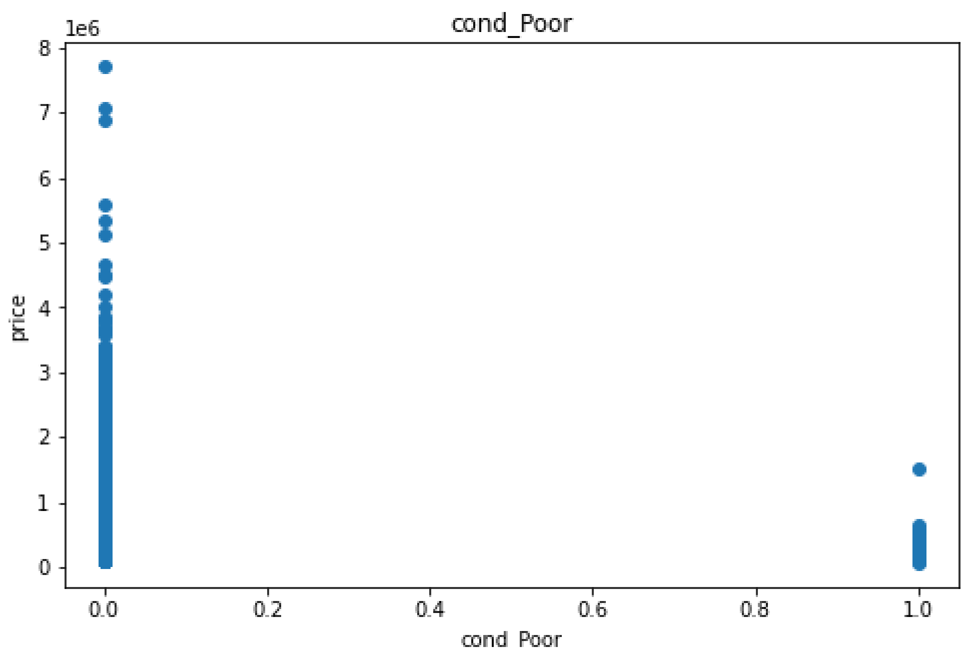

view_FAIR
1e6
8
7
6
5
4
3
2
1
price


view_GOOD
1e6
8
7
6
5
4
3
2
1
0
price
0.0
0.2
0.4
0.6
0.8
1.0
view_GOOD

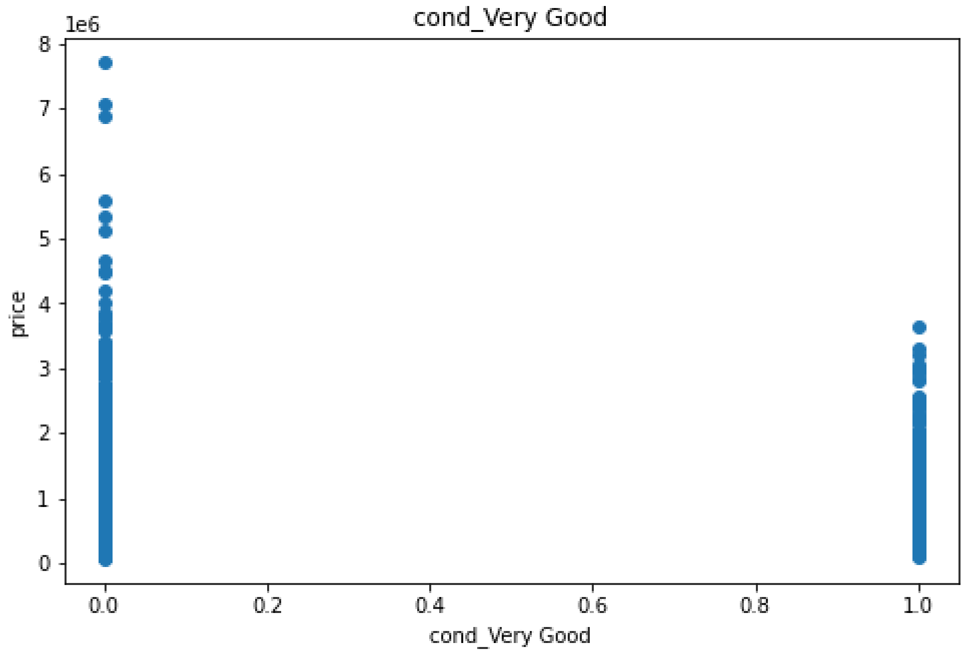

view_NONE
1e6
price
8
7
6
5
4
3
2
cond_Fair
1e6
price
8
7
6
5
4
3
2
1
0
0.0
0.2
0.4
0.6
0.8
1.0
cond_Fair

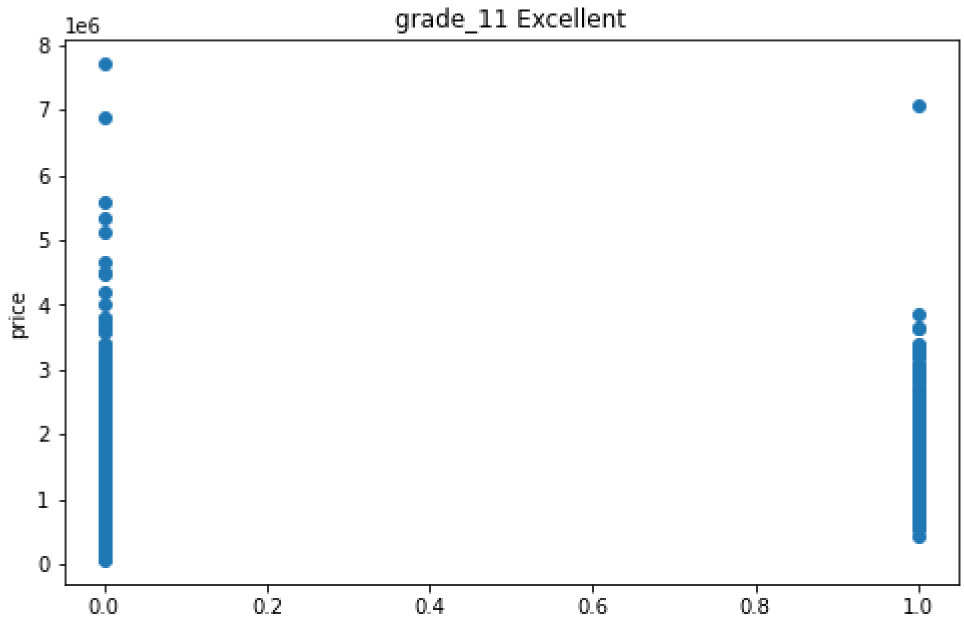


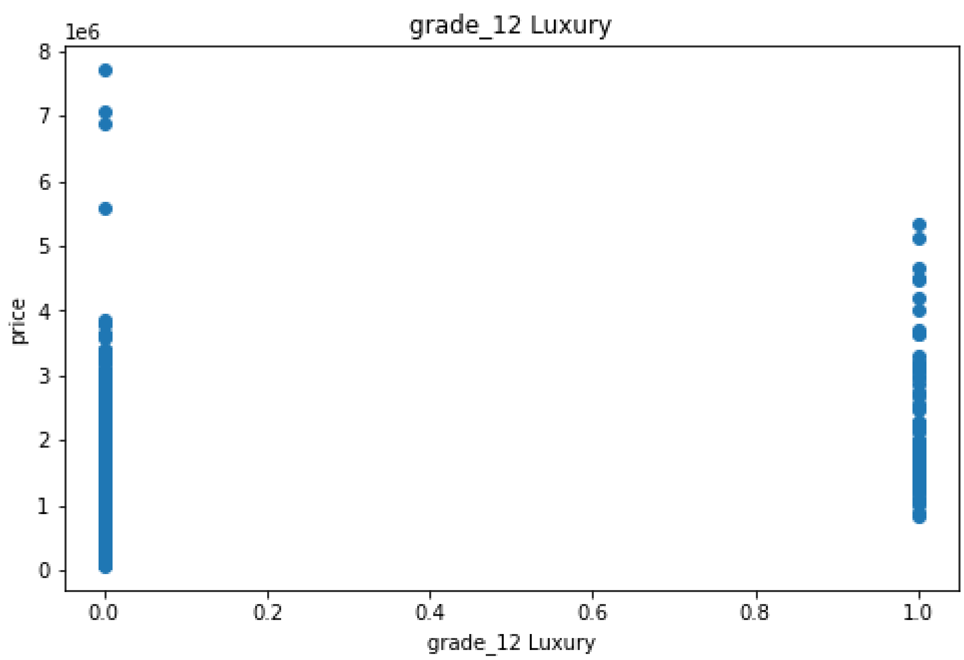
cond_Good
1e6
price
cond_Good

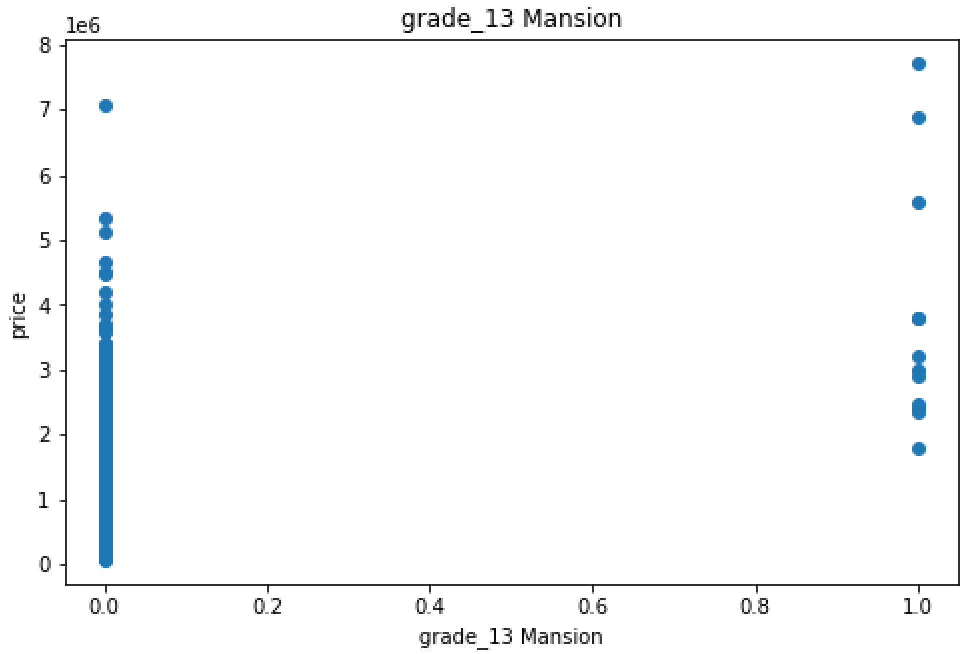


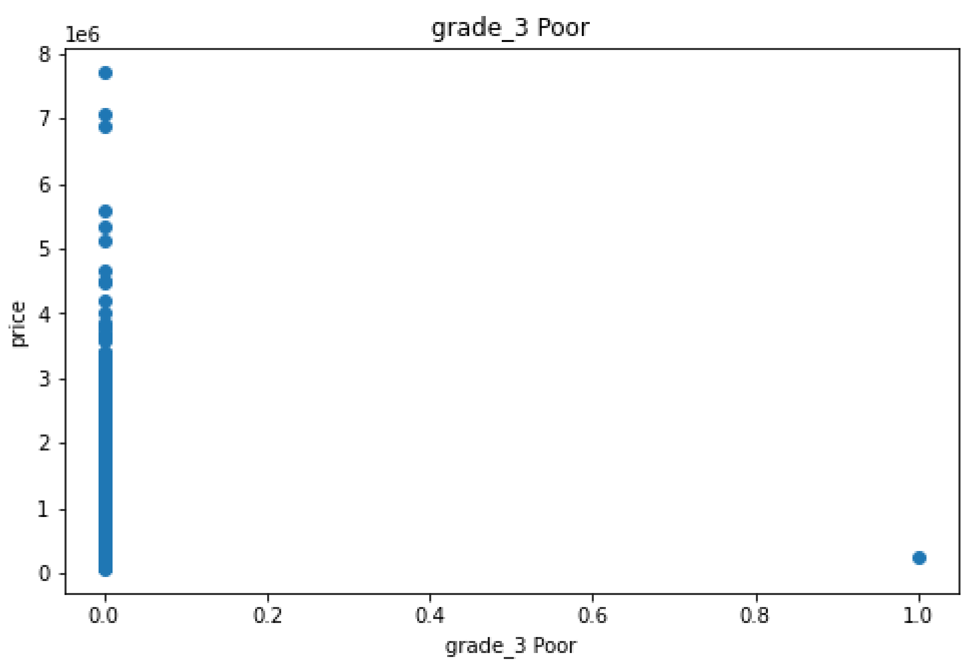
cond_Poor
1e6
price
cond_Poor

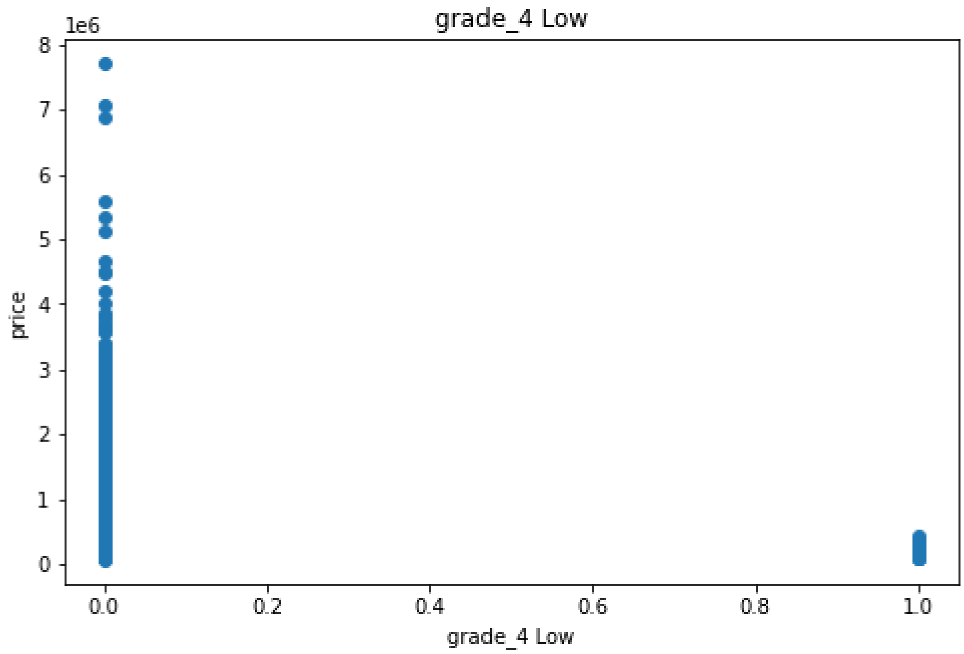

cond_Very Good
1e6
8
7
6
5
4
3
2
1
0
price
0.0
0.2
0.4
0.6
0.8
1.0
cond_Very Good

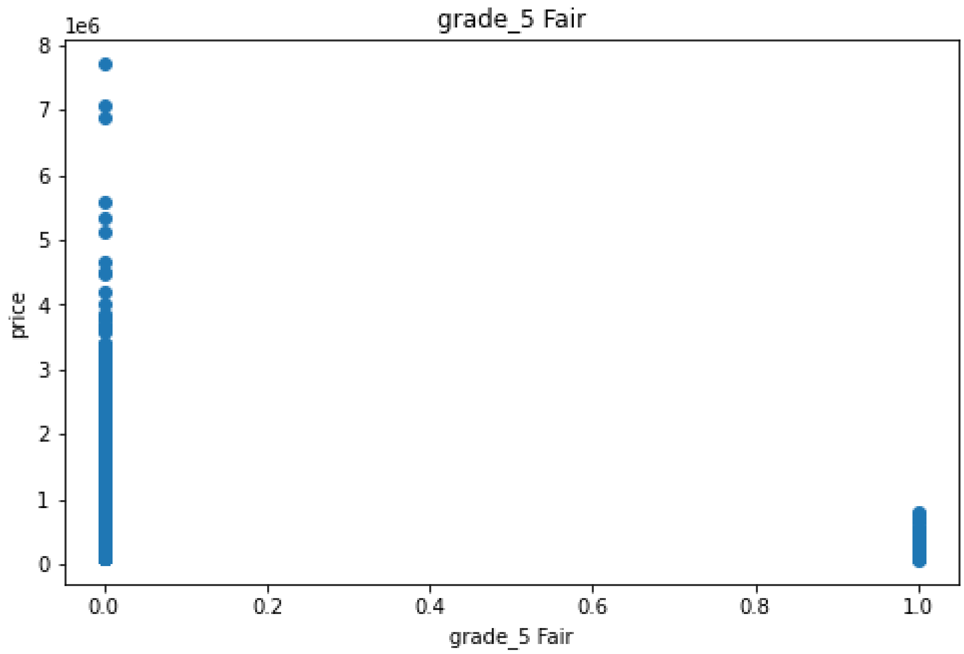

grade_11 Excellent
1e6
price
0.0
0.2
0.4
0.6
0.8
1.0

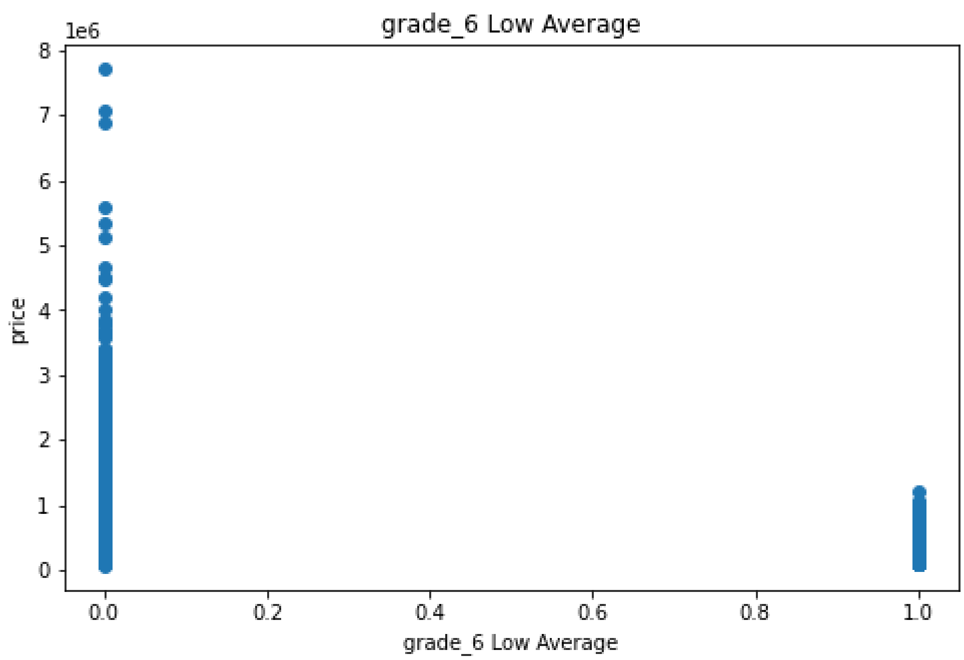

grade_12 Luxury
1e6
price
grade_12 Luxury

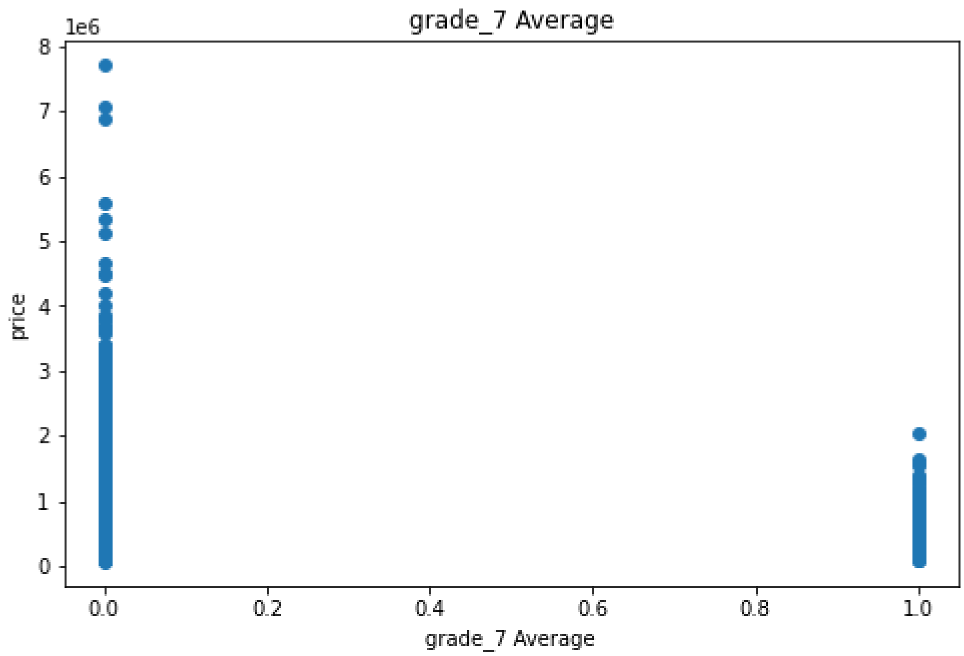

grade_13 Mansion
1e6
8
7
6
5
4
3
2
1
0
price
0.0
0.2
0.4
0.6
0.8
1.0
grade_13 Mansion

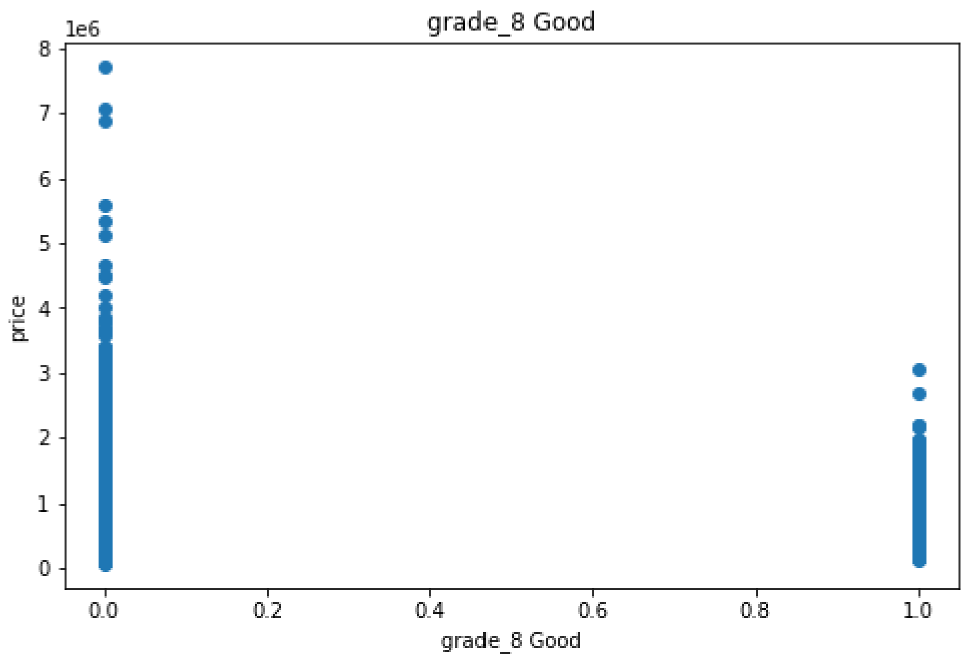

grade_3 Poor
1e6
8
7
6
5
4
3
2
1
0
price
0.0
0.2
0.4
0.6
0.8
1.0
grade_3 Poor

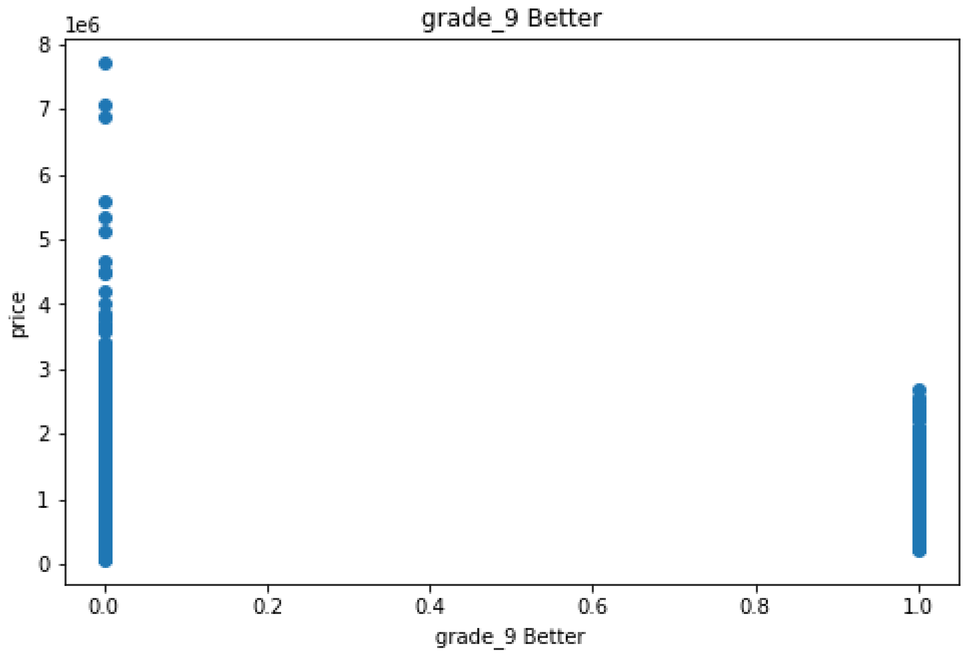

grade_4 Low
1e6
8
7
6
5
4
3
2
1
0
price
0.0
0.2
0.4
0.6
0.8
1.0
grade_4 Low


grade_5 Fair
1e6
price
grade_5 Fair


grade_6 Low Average
1e6
price
grade_6 Low Average


grade_7 Average
1e6
price
grade_7 Average


grade_8 Good
1e6
price
grade_8 Good


grade_9 Better
1e6
8
7
6
5
4
3
2
1
0
price
0.0
0.2
0.4
0.6
0.8
1.0
grade_9 Better

It looks like sqft_living shows strongest linearity. We will check it using seaborn heatmap and correlation matrix.

In [19]:
```
# Merged databases for creating a correlation matrix
data_for_model_num = pd.concat([y_train_base, X_train_base], axis=1)
# Creating a matrix
corr_matr = data_for_model_num.corr()
# Then we will select the most relevant features giving the assumption that
# not less than or equal 0.3the
most_rel_features = corr_matr[corr_matr['price'] >=0.3].drop('price', axis=
most_rel_features.sort_values('price', ascending=False)
```

Out[19]:

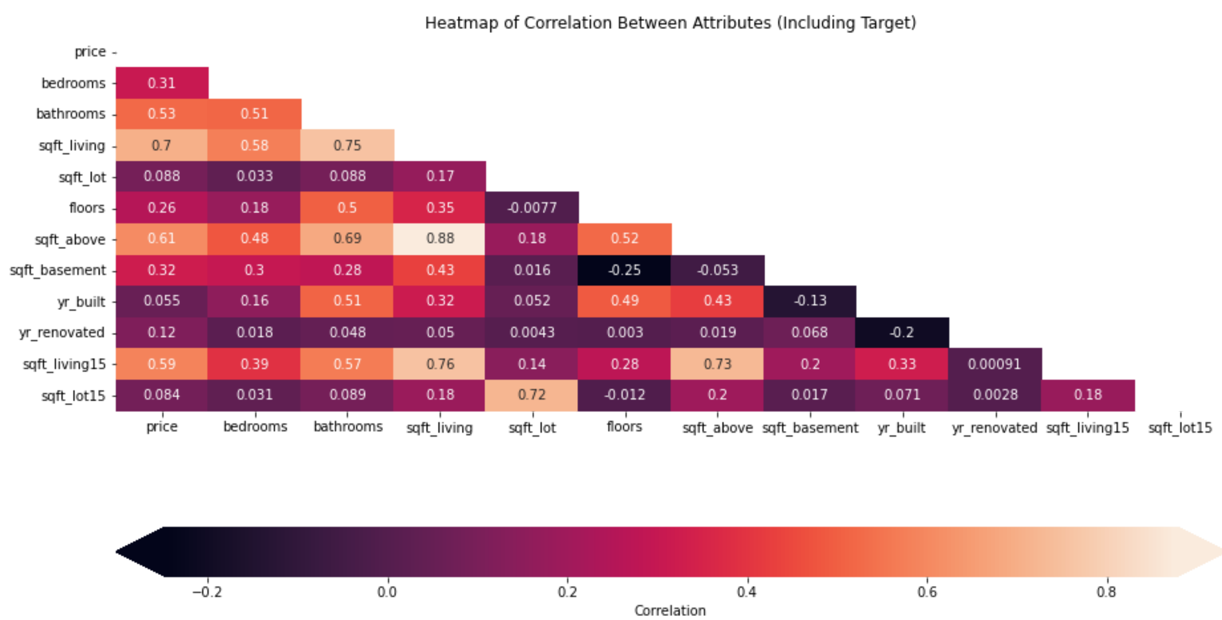
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft
sqft_living	0.702004	0.577696	0.754793	1.000000	0.173266	0.354260	0.876787	
sqft_above	0.605481	0.478967	0.685959	0.876787	0.183653	0.523594	1.000000	
sqft_living15	0.586495	0.391936	0.569396	0.756199	0.143815	0.279379	0.730794	
bathrooms	0.525029	0.513694	1.000000	0.754793	0.088451	0.503796	0.685959	
grade_11 Excellent	0.356823	0.115891	0.245449	0.344909	0.071959	0.118923	0.341766	
sqft_basement	0.323018	0.301987	0.281813	0.433369	0.015612	-0.245628	-0.053403	
bedrooms	0.308454	1.000000	0.513694	0.577696	0.032531	0.178518	0.478967	
view_EXCELLENT	0.307035	0.036234	0.108054	0.169713	0.019024	0.025156	0.107270	

8 rows × 32 columns

Then we plot heatmap matrix for better visual inspection of correlations

In [20]:
```
heatmap_data = data_for_model
corr = heatmap_data.corr()

# Set up figure and axes
fig, ax = plt.subplots(figsize=(15, 8))

# Plot a heatmap of the correlation matrix, with both
# numbers and colors indicating the correlations
sns.heatmap(
    # Specifies the data to be plotted
    data=corr,
    # The mask means we only show half the values,
    # instead of showing duplicates. It's optional.
    mask=np.triu(np.ones_like(corr, dtype=bool)),
    # Specifies that we should use the existing axes
    ax=ax,
    # Specifies that we want labels, not just colors
    annot=True,
    # Customizes colorbar appearance
    cbar_kws={"label": "Correlation", "orientation": "horizontal", "pad": .
)

# Customize the plot appearance
ax.set_title("Heatmap of Correlation Between Attributes (Including Target)"
```

```
<ipython-input-20-5611bc5c717b>:2: FutureWarning: The default value of nu
meric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numer
ic_only to silence this warning.
  corr = heatmap_data.corr()
```



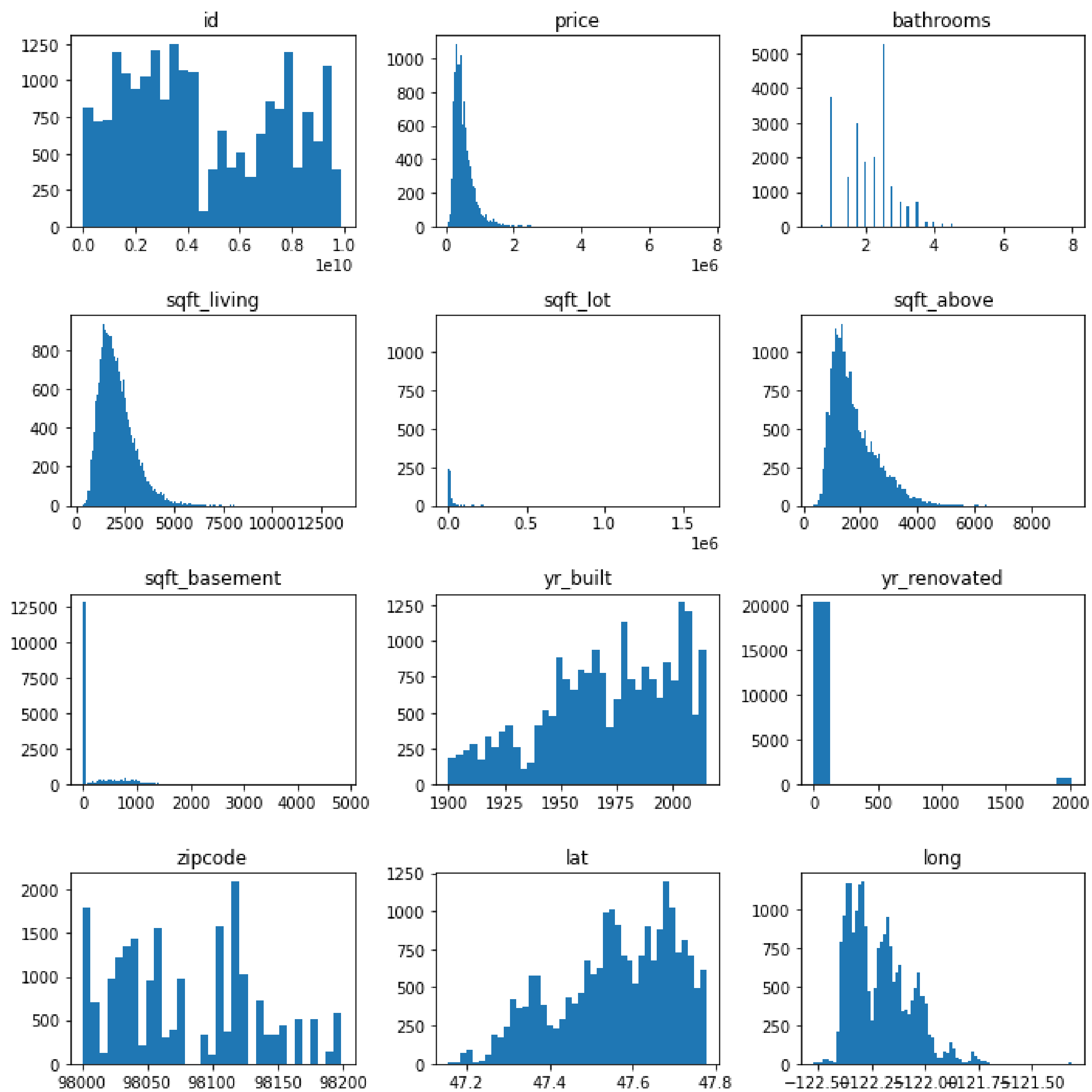
Conclusions

After investigating linearity and correlation we found that 'bathrooms', 'grade_11 Excellent', 'bedrooms', 'view_EXCELLENT', 'sqft_above', 'sqft_basement', and 'grade_11 EXCELLENT' have strongest correlations with price. But we also notice strong correlation between 'sqft_above' and 'sqft_living', which are probably represents very simmilar things therefore we will drop the latter to reduce multicollinearity.

Values' distribution investigation.

We will also check distribution of all values we plan to use for modeling.

In [21]:
```
# Checking distribution of the independent variables
cat_data = data.loc[:, ((data.dtypes != 'object') & (data.nunique() > 20))]

fig, axes = plt.subplots(nrows=(cat_data.shape[1] // 3), ncols=3, figsize=(

categoricals = [column for column in cat_data.columns if column != 'Id']

for col, ax in zip(categoricals, axes.flatten()):
    ax.hist(data[col].dropna(), bins='auto')
    ax.set_title(col)

fig.tight_layout()
```



Conclusions

All variables have non-normal distributions.

Modeling

Building a basic model

First we build an OLS model for the most correlated feature. We will use it as a baseline.

In [22]:
```
# Build a model
most_corr_data = data_for_model_num['sqft_living']
model_ols_base = sm.OLS(y_train_base, sm.add_constant(X_train_base['sqft_li
model_ols_base.summary()
```

```
/Users/andreim/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/s
tatsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of pan
das all arguments of concat except for the argument 'objs' will be keywor
d-only.
  x = pd.concat(x[::order], 1)
```

Out[22]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.493
Model:	OLS	**Adj. R-squared:**	0.493
Method:	Least Squares	**F-statistic:**	2.048e+04
Date:	Wed, 26 Oct 2022	**Prob (F-statistic):**	0.00
Time:	21:24:44	**Log-Likelihood:**	-2.9287e+05
No. Observations:	21082	**AIC:**	5.857e+05
Df Residuals:	21080	**BIC:**	5.858e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-4.327e+04	4456.393	-9.709	0.000	-5.2e+04	-3.45e+04
sqft_living	280.4877	1.960	143.116	0.000	276.646	284.329

Omnibus:	14303.984	**Durbin-Watson:**	1.986
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	509767.330
Skew:	2.786	**Prob(JB):**	0.00
Kurtosis:	26.437	**Cond. No.**	5.63e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.63e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

As we can see, R-squared value is 0.493 that can be a result of true noise or a relatively high number of observations. Next we will build a model included our most correlated features (with the correlation coefficient which is equal or more 0.3).

In [23]:

```
# Create a list of most correlated columns
most_correlated_column = ['sqft_living15', 'bathrooms',
                          'grade_11 Excellent', 'sqft_basement', 'bedrooms'

# Build a dataset
X_train_mcc = pd.concat([X_train_base['sqft_living'], X_train_base[most_cor

# Build a model
model_ols_most_corr = sm.OLS(y_train_base, sm.add_constant(X_train_mcc)).fi
model_ols_most_corr.summary()
```

```
/Users/andreim/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/s
tatsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of pan
das all arguments of concat except for the argument 'objs' will be keywor
d-only.
  x = pd.concat(x[::order], 1)
```

Out[23]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.557
Model:	OLS	**Adj. R-squared:**	0.557
Method:	Least Squares	**F-statistic:**	3782.
Date:	Wed, 26 Oct 2022	**Prob (F-statistic):**	0.00
Time:	21:24:44	**Log-Likelihood:**	-2.9145e+05
No. Observations:	21082	**AIC:**	5.829e+05
Df Residuals:	21074	**BIC:**	5.830e+05
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.684e+04	7560.032	6.195	0.000	3.2e+04	6.17e+04
sqft_living	231.8536	4.066	57.022	0.000	223.884	239.823
sqft_living15	57.1426	3.860	14.802	0.000	49.576	64.709
bathrooms	1.255e+04	3387.273	3.705	0.000	5910.243	1.92e+04
grade_11 Excellent	3.069e+05	1.35e+04	22.801	0.000	2.81e+05	3.33e+05
sqft_basement	34.6542	4.380	7.912	0.000	26.069	43.239
bedrooms	-4.53e+04	2281.116	-19.857	0.000	-4.98e+04	-4.08e+04
view_EXCELLENT	5.405e+05	1.43e+04	37.833	0.000	5.12e+05	5.68e+05

Omnibus:	13900.409	**Durbin-Watson:**	1.992
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	606684.680
Skew:	2.597	**Prob(JB):**	0.00
Kurtosis:	28.762	**Cond. No.**	2.63e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.63e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

As we have seen above, our data variables are not normally distributed and have significant differences in values. We will next perform a logarithmic transformation.

Applying log transformation

In [24]:
```
# We use only the most correlated feature.
X_train_mcc_cont = X_train_mcc['sqft_living']

# Combining data first to avoid mismatching number of rows after performing
# assuming that we won't include any rows with zero value, avoiding '-inf'
data_log = pd.concat([y_train_base, X_train_mcc_cont], axis=1)
data_log = np.log(data_log, where=(data_log>0))
# Add 'log_' prefix to the column names
data_log = data_log.add_prefix('log_')

data_log.head()
```

Out[24]:

	log_price	log_sqft_living
0	12.309982	7.073270
1	13.195614	7.851661
2	12.100712	6.646391
3	13.311329	7.580700
4	13.142166	7.426549

In [25]:
```python
# Create a model based on logarithmically transformed values
X_log_base = data_log.drop(['log_price'], axis=1)
y_log_base = data_log['log_price']
model_best_fit_log = sm.OLS(y_log_base, sm.add_constant(X_log_base)).fit()
model_best_fit_log.summary()
```

```
/Users/andreim/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/s
tatsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of pan
das all arguments of concat except for the argument 'objs' will be keywor
d-only.
  x = pd.concat(x[::order], 1)
```

Out[25]:

OLS Regression Results

Dep. Variable:	log_price	**R-squared:**	0.455
Model:	OLS	**Adj. R-squared:**	0.455
Method:	Least Squares	**F-statistic:**	1.759e+04
Date:	Wed, 26 Oct 2022	**Prob (F-statistic):**	0.00
Time:	21:24:44	**Log-Likelihood:**	-9989.5
No. Observations:	21082	**AIC:**	1.998e+04
Df Residuals:	21080	**BIC:**	2.000e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	6.7255	0.048	140.854	0.000	6.632	6.819
log_sqft_living	0.8374	0.006	132.627	0.000	0.825	0.850

Omnibus:	121.177	**Durbin-Watson:**	1.980
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	112.122
Skew:	0.144	**Prob(JB):**	4.50e-25
Kurtosis:	2.789	**Cond. No.**	137.

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

As we may see after performing the transformation, we have worsened R-squared but better Cond. (137).

In [26]:
```
# Now we want to add best fitted categorial variables to the log-transforme
# We will use only encoded categorical variables for concatination.

# Create a list most relevant categorical variables.
best_fit_cat_var = ['bathrooms', 'grade_11 Excellent', 'bedrooms', 'view_EX

# Build a dataset
X_log_final = pd.concat([X_log_base, X_train_mcc[best_fit_cat_var]], axis=1
X_log_final.head()
```

Out[26]:

	log_sqft_living	bathrooms	grade_11 Excellent	bedrooms	view_EXCELLENT
0	7.073270	1.00	0	3	0
1	7.851661	2.25	0	3	0
2	6.646391	1.00	0	2	0
3	7.580700	3.00	0	4	0
4	7.426549	2.00	0	3	0

In [27]:
```
# Building a final log model

model_final_log = sm.OLS(y_log_base, sm.add_constant(X_log_final)).fit()
model_final_log.summary()
```

```
/Users/andreim/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/s
tatsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of pan
das all arguments of concat except for the argument 'objs' will be keywor
d-only.
  x = pd.concat(x[::order], 1)
```

Out[27]:

OLS Regression Results

Dep. Variable:	log_price	**R-squared:**	0.494
Model:	OLS	**Adj. R-squared:**	0.494
Method:	Least Squares	**F-statistic:**	4109.
Date:	Wed, 26 Oct 2022	**Prob (F-statistic):**	0.00
Time:	21:24:45	**Log-Likelihood:**	-9212.2
No. Observations:	21082	**AIC:**	1.844e+04
Df Residuals:	21076	**BIC:**	1.848e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	7.1655	0.068	106.071	0.000	7.033	7.298
log_sqft_living	0.7889	0.010	75.449	0.000	0.768	0.809
bathrooms	0.0601	0.005	11.520	0.000	0.050	0.070
grade_11 Excellent	0.3758	0.020	18.801	0.000	0.337	0.415
bedrooms	-0.0642	0.004	-17.917	0.000	-0.071	-0.057
view_EXCELLENT	0.5490	0.022	25.336	0.000	0.506	0.591

Omnibus:	83.462	**Durbin-Watson:**	1.981
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	77.270
Skew:	0.115	**Prob(JB):**	1.66e-17
Kurtosis:	2.813	**Cond. No.**	229.

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

We havebetter R-squared value than a base model, but slightly worse multicollinearity.

Finally, we will build a model using the same variables as for the previous one, but not performing log transformation

In [28]:
```
# Building final datasets
X_final = pd.concat([X_train_mcc['sqft_living'], X_train_mcc[best_fit_cat_v
y_final = y_train_base

# Building a final model
model_final = sm.OLS(y_final, sm.add_constant(X_final)).fit()
model_final.summary()
```

```
/Users/andreim/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/s
tatsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of pan
das all arguments of concat except for the argument 'objs' will be keywor
d-only.
  x = pd.concat(x[::order], 1)
```

Out[28]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.552
Model:	OLS	**Adj. R-squared:**	0.552
Method:	Least Squares	**F-statistic:**	5187.
Date:	Wed, 26 Oct 2022	**Prob (F-statistic):**	0.00
Time:	21:24:45	**Log-Likelihood:**	-2.9157e+05
No. Observations:	21082	**AIC:**	5.831e+05
Df Residuals:	21076	**BIC:**	5.832e+05
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	9.312e+04	6739.937	13.817	0.000	7.99e+04	1.06e+05
sqft_living	272.5097	3.132	87.007	0.000	266.371	278.649
bathrooms	1.069e+04	3393.441	3.149	0.002	4033.833	1.73e+04
grade_11 Excellent	3.119e+05	1.35e+04	23.154	0.000	2.86e+05	3.38e+05
bedrooms	-4.638e+04	2282.776	-20.316	0.000	-5.09e+04	-4.19e+04
view_EXCELLENT	5.586e+05	1.43e+04	39.111	0.000	5.31e+05	5.87e+05

Omnibus:	13217.471	**Durbin-Watson:**	1.991
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	488165.457
Skew:	2.459	**Prob(JB):**	0.00
Kurtosis:	26.055	**Cond. No.**	1.92e+04

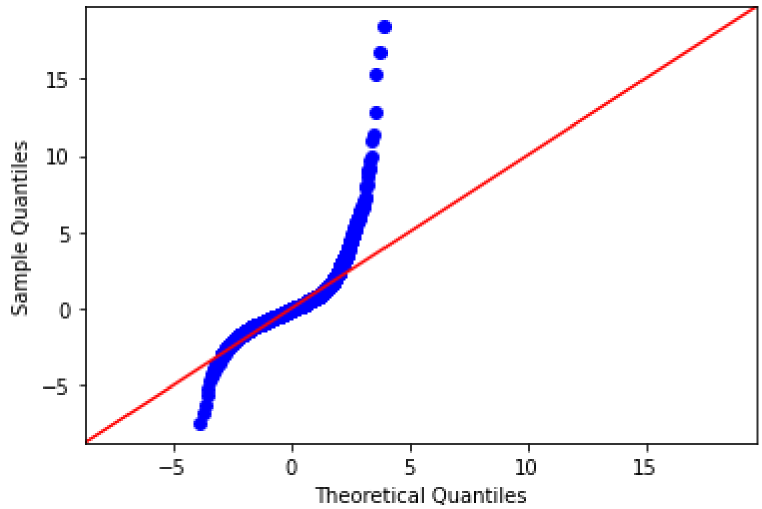
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.92e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

Validating models

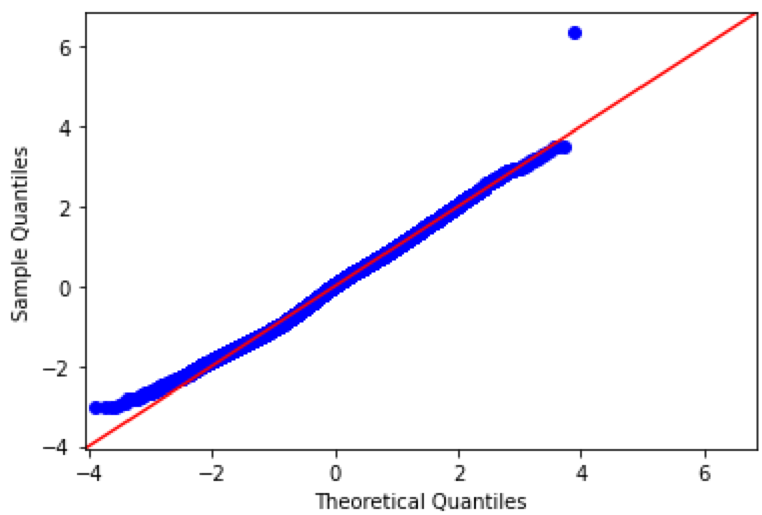
During this step we will visually and formally validate our model.

Investigating Normality

In [29]:
```
# Q-Q plot for the ols model
resid = model_final.resid
resid_log = model_final_log.resid
fig = sm.graphics.qqplot(resid, dist=stats.norm, line='45', fit=True)
```



In [30]:
```
# Q-Q plot for the log ols model.
fig = sm.graphics.qqplot(resid_log, dist=stats.norm, line='45', fit=True)
```



As we can see there are a vast number of outliers, therefore we can consider the violation of the normality assumption.

Investigating Multicollinearity

In [34]:
```
# Checking multicollinearity
vif = [variance_inflation_factor(X_final.values, i) for i in range(X_final.
pd.Series(vif, index=X_final.columns)
```

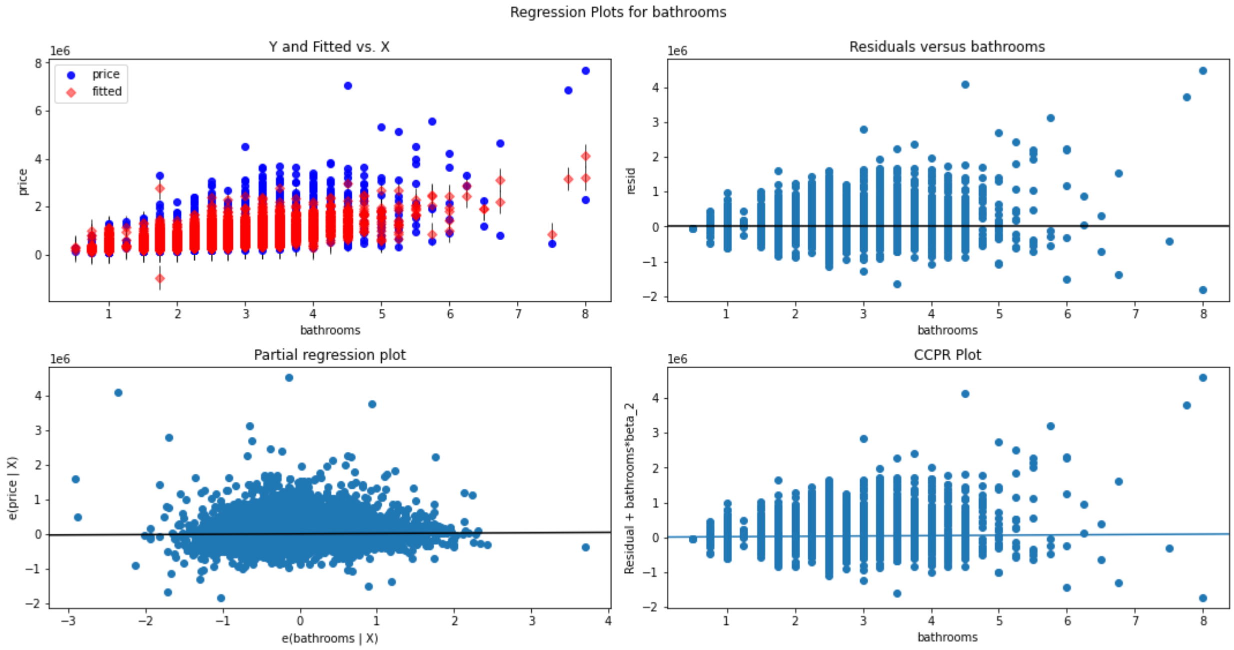
Out[34]:
```
sqft_living            17.452817
bathrooms              18.593786
grade_11 Excellent      1.160730
bedrooms               12.808323
view_EXCELLENT          1.052018
dtype: float64
```

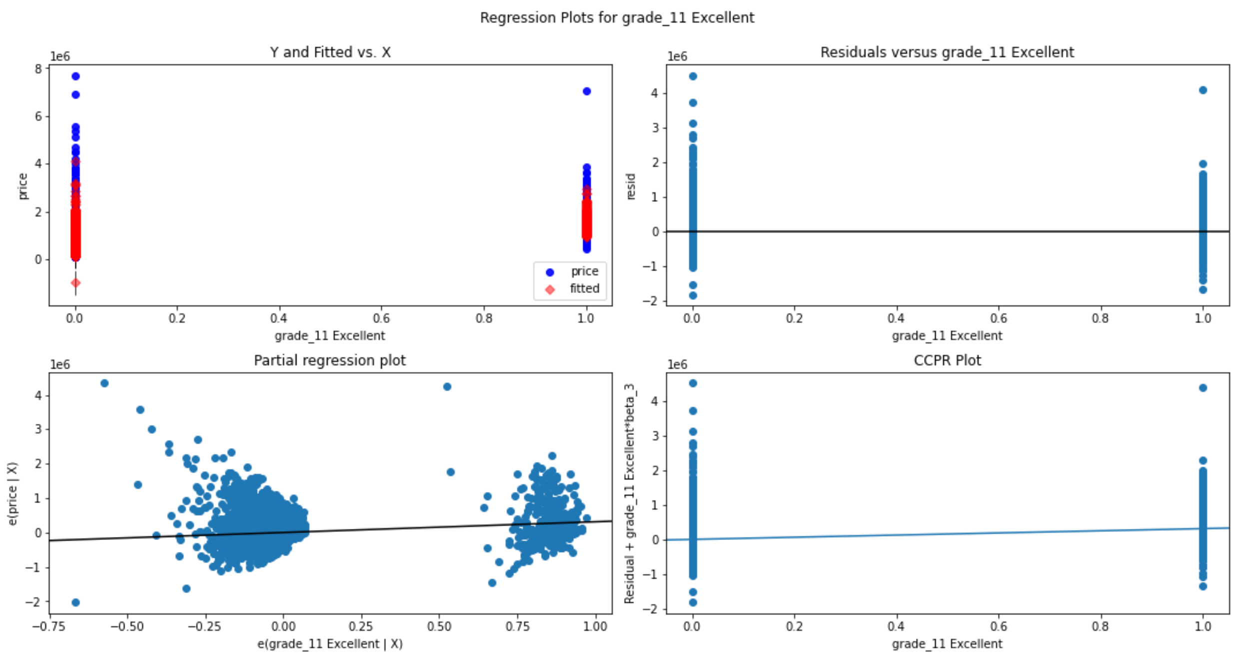
The numbers above show significant multicollinearities for all variables besides 'grade_11 Excellent' and 'view_EXCELLENT'.

Plotting regression results

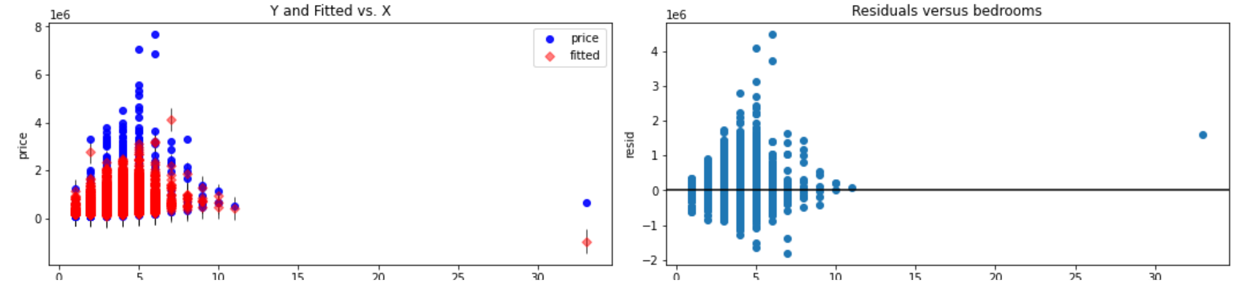
Finally, we will plot residuals against all variables for both models.

In [32]:
```python
# Iterating over each variable for normal ols model
for param in best_fit_cat_var:
    fig = plt.figure(figsize=(15,8))
    fig = sm.graphics.plot_regress_exog(model_final, param , fig=fig)
    plt.show()
```

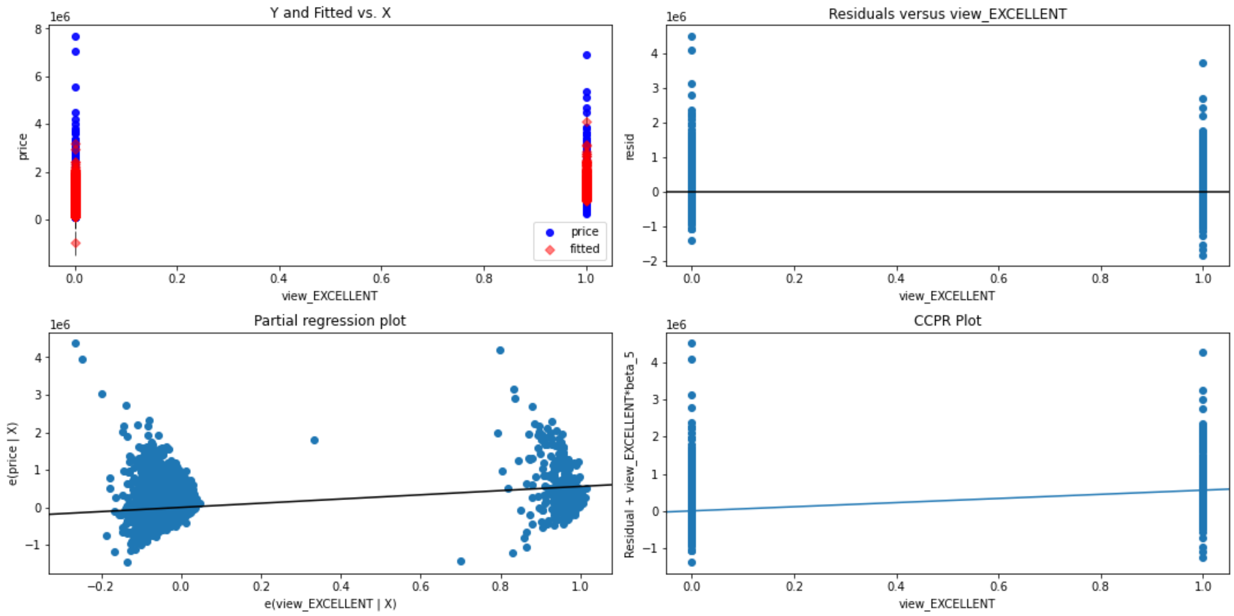




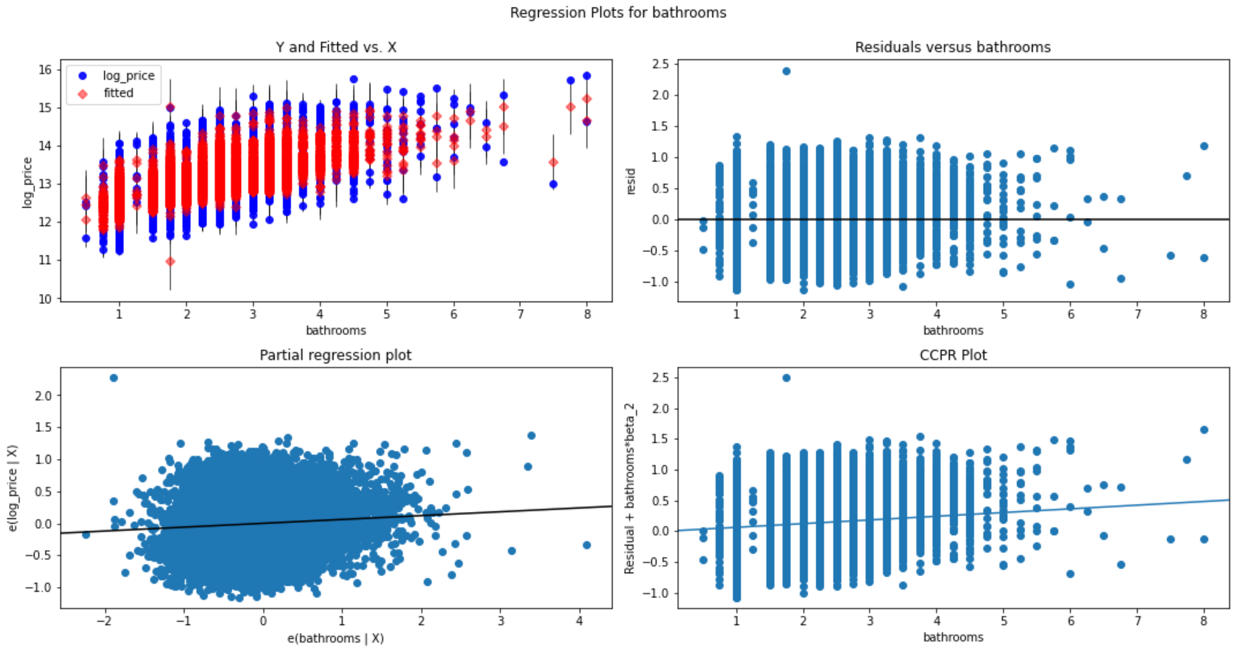
Regression Plots for bedrooms

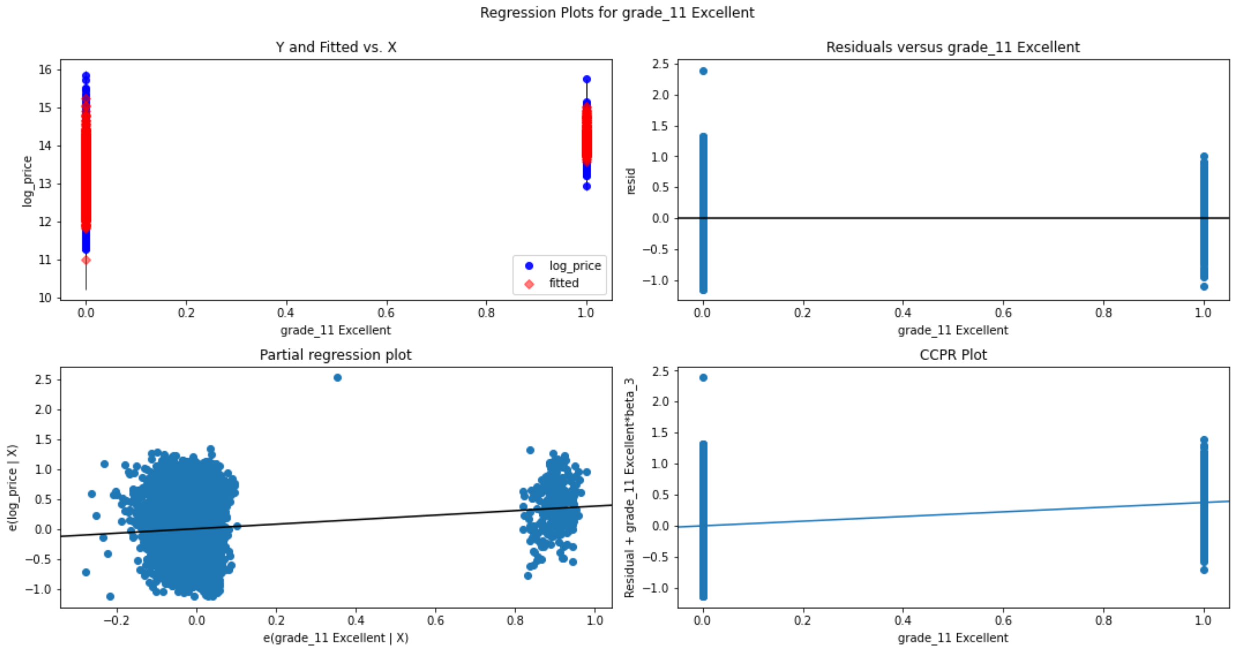


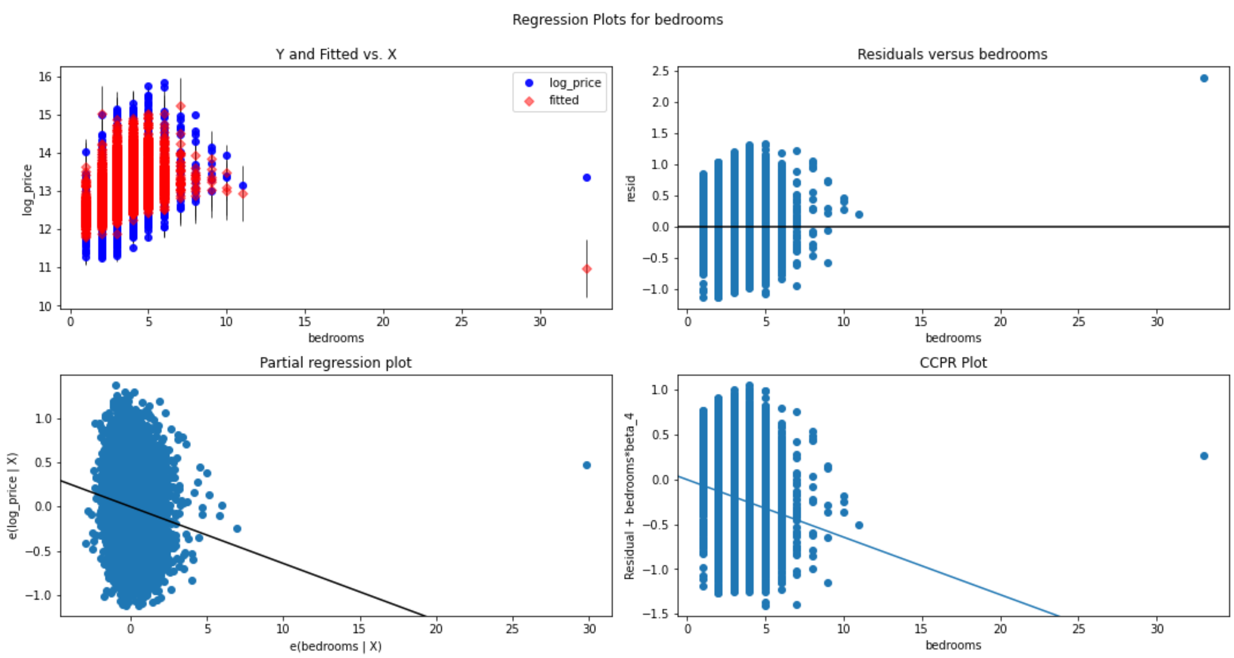
Regression Plots for view_EXCELLENT

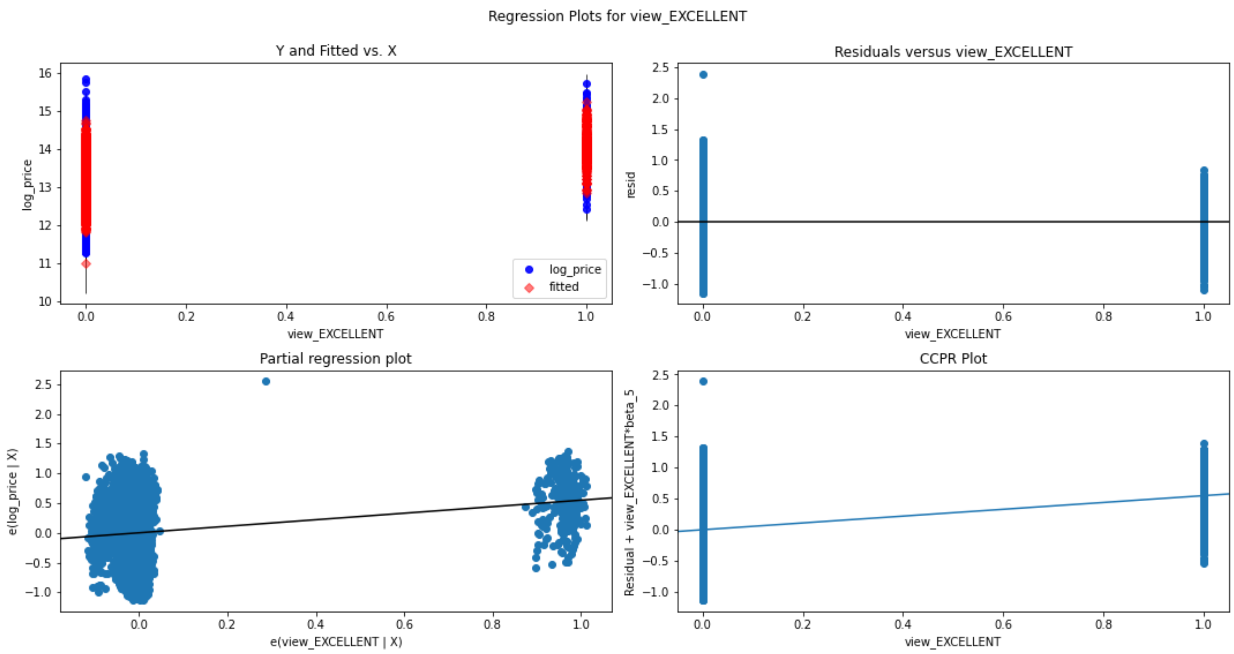


In [33]:
```
# Iterating over each variable for normal ols model

for param in best_fit_cat_var:
    fig = plt.figure(figsize=(15,8))
    fig = sm.graphics.plot_regress_exog(model_final_log, param , fig=fig)
    plt.show()
```




Regression Plots for grade_11 Excellent
Y and Fitted vs. X
log_price
fitted
grade_11 Excellent
Residuals versus grade_11 Excellent
resid
grade_11 Excellent
Partial regression plot
e(log_price | X)
e(grade_11 Excellent | X)
CCPR Plot
Residual + grade_11 Excellent*beta_3
grade_11 Excellent


Regression Plots for bedrooms
Y and Fitted vs. X
log_price
fitted
bedrooms
Residuals versus bedrooms
resid
bedrooms
Partial regression plot
e(log_price | X)
e(bedrooms | X)
CCPR Plot
Residual + bedrooms*beta_4
bedrooms



Conclusions

After validating the models we may see a relatively moderate R-Squared value, which can be result of some noise in our dataset. For both models we have strong multicollinearity for all features, besides grade_11 Excellent and view_EXCELLENT. Normality test demonstrates that residuals distribution arn't normal.

Summary

In this report, we were building a linear regression model based on OLS methods, using The King County real estate dataset to test which parameters have (if any) a statistically significant effect on the dependent variable 'price'.

The overall regression was statistically significant ($R2 = .552$, $p < .000$).

It was found that the Square Footage of the Living Area significantly predicted price ($\beta = 272.5097$, $p < .000$). It was also found that:

- Number of bathrooms significantly predicted price ($\beta = 1.069e+04$, $p < .000$)
- Number of bedrooms significantly predicted price ($\beta = -4.638e+04$, $p < .000$).

We suggest further investigation how features as 'Grade' and 'View' affect home prices.