Final Project Submission

Boma Yangu Housing Agency House Price Prediction Model

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- Student pace: Full time
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- Blog post URL: My blog (https://www.linkedin.com/in/africandatascientist/)

Overview

This project employes the use of variouse Linear Regression modes to try and predict house prices. Linear Regression is used here due to its ability to perform inference statistic giving us more insight and relationship about the data we are working on. The data used to develop this model is the King County House Sales Dataset which is a CSV file that contains 21597 rows and 21 columns of data. Each column in the data set represents an atttribute about a house and the target variable Price which we will develp a model to try to predict.

The other 20 colums of this dataset will therefor be used to try and develop an accurate model to help the managers of Boma Yangu Housing Agency predict the price of a house given certain parameters.
We will start developing the model by using a simple liner regressor and continue to explore by incorporating multile linear regressors to increase accuracy of the base model while also adding and removing other features from the model.

Business Problem

The recent burst in real estate bubble in the country has made may real estate agencies run into multiple losses. This has been particulerly worsened by the inability of some real estate agencie to provide a reasonable price of a given housing unit. These problems has lead to the recent undervaluation and sometimes over valuation of houses more than the current market prices.

Boma Yangu Housing Agency therefor needs a model that will help them predict the true value of a house not by guessing but by making data driven decissions from already available data.
This model should be accute enough to give a price prediction when certain parameters are fed into the model. This will really help the agency avoids losses by investing in overpriced houses due to the current bubble and make profit by buying and investing in underpriced houses in the current bubblewhic have a potential of selling at high prices after the bubble burst.

Data Understanding

The data used to develop this regression model contains house sale prices for King County, which includes Seattle. It includes homes sold between September 9 2014 and January 1 2015

The data set contains 21597 records and 21 attributes.

We will get a better understanding on the data by investgating the column_names.md file found in the data directory which will give us more idea about the data and the attributes in each column as shown below.

Column Names and Descriptions for King County Data Set

- `id` - Unique identifier for a house
- `date` - Date house was sold
- `price` - Sale price (prediction target)
- `bedrooms` - Number of bedrooms
- `bathrooms` - Number of bathrooms
- `sqft_living` - Square footage of living space in the home
- `sqft_lot` - Square footage of the lot
- `floors` - Number of floors (levels) in house
- `waterfront` - Whether the house is on a waterfront
  - Includes Duwamish, Elliott Bay, Puget Sound, Lake Union, Ship Canal, Lake Washington, Lake Sammamish, other lake, and river/slough waterfronts
- `view` - Quality of view from house
  - Includes views of Mt. Rainier, Olympics, Cascades, Territorial, Seattle Skyline, Puget Sound, Lake Washington, Lake Sammamish, small lake / river / creek, and other
- `condition` - How good the overall condition of the house is. Related to maintenance of house.
  - See the King County Assessor Website (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r) for further explanation of each condition code
- `grade` - Overall grade of the house. Related to the construction and design of the house.
  - See the King County Assessor Website (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r) for further explanation of each building grade code
- `sqft_above` - Square footage of house apart from basement
- `sqft_basement` - Square footage of the basement
- `yr_built` - Year when house was built
- `yr_renovated` - Year when house was renovated

- `zipcode` - ZIP Code used by the United States Postal Service
- `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

In [1]:
```
#Import the relevant packages for this module
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
from scipy.stats import norm
import statsmodels.api as sm
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import mean_absolute_error
%matplotlib inline
```

In [2]:
```
#Read the metadata contained in the column_names.md
with open('data/column_names.md') as f:
    print(f.read())
```

```
# Column Names and Descriptions for King County Data Set
* `id` - Unique identifier for a house
* `date` - Date house was sold
* `price` - Sale price (prediction target)
* `bedrooms` - Number of bedrooms
* `bathrooms` - Number of bathrooms
* `sqft_living` - Square footage of living space in the home
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* `floors` - Number of floors (levels) in house
* `waterfront` - Whether the house is on a waterfront
  * Includes Duwamish, Elliott Bay, Puget Sound, Lake Union, Ship Canal, Lake W
ashington, Lake Sammamish, other lake, and river/slough waterfronts
* `view` - Quality of view from house
  * Includes views of Mt. Rainier, Olympics, Cascades, Territorial, Seattle Sky
line, Puget Sound, Lake Washington, Lake Sammamish, small lake / river / creek,
and other
* `condition` - How good the overall condition of the house is. Related to main
tenance of house.
  * See the [King County Assessor Website](https://info.kingcounty.gov/assesso
r/esales/Glossary.aspx?type=r) for further explanation of each condition code
* `grade` - Overall grade of the house. Related to the construction and design
of the house.
  * See the [King County Assessor Website](https://info.kingcounty.gov/assesso
r/esales/Glossary.aspx?type=r) for further explanation of each building grade c
ode
* `sqft_above` - Square footage of house apart from basement
* `sqft_basement` - Square footage of the basement
* `yr_built` - Year when house was built
* `yr_renovated` - Year when house was renovated
* `zipcode` - ZIP Code used by the United States Postal Service
* `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 neighbor
s
```

The data in column_name.md file explains the attribute found in each of the 21 columns found on the dataset

Lets load the data set to confirm

In [3]:
```
#Loading the data
data = pd.read_csv('data/kc_house_data.csv' ,index_col=0)

#Get the shape of the data and display the first 3 rows
print(data.shape)
data.head(3)
```

```
(21597, 20)
```

Out[3]:

id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	
7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	N
6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	N
5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	N

In [4]:
```
#check the data type of every column
data.dtypes
```

Out[4]:
```
date              object
price            float64
bedrooms           int64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront        object
view              object
condition         object
grade             object
sqft_above         int64
sqft_basement     object
yr_built           int64
yr_renovated     float64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

Some of the data in the data set contain object wich cannot be fed directly to a linear model since they may be categorical values such as the grade column.
The sqft_basement colum seem to have integer values but loaded as an object.

In [5]:
```
#Check the distribution of the data set that contains integer values
data.describe()
```

Out[5]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqf
count	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597
mean	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	1788
std	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	827
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	370
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	1190
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	1560
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	2210
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	9410

Data Preparation

DATA CLEANING

Lets start by cleaning the data set.
Check and fix columns with missing values in the dataset as shown bellow.

In [6]:
```
#Check fo null values in the dataset
data.isna().sum()
```

Out[6]:
```
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
```

The waterfron and yr_renovated variables have alot of missing data and therefore requre cleaning

The view column too has null values and requres futher action

In [7]:
```
#check the number of variables lost when removing then null values
d = data.dropna()
data.shape[0] - d.shape[0]  #thats alot of data signals lost lets try and reduse
```

Out[7]:
```
5835
```

Deleting all columns with empty entries will result into the loss of 5835 records which is quite a reat number and might cause loss of signals in our dataset.

In [8]:
```
#We will add the empty records to the NONE Value since its the majority category
print(data['view'].value_counts())

#replacing null view values with NONE
data["view"].fillna("NONE", inplace = True)
```

```
NONE         19422
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: view, dtype: int64
```

In [9]:
```
#replace the null values with the majority category since it makes scene to have
data['waterfront'].value_counts()
data["waterfront"].fillna("NO", inplace = True)
```

In [10]:
```
#Fill in the missing yr_renovated colum by the mean
yr_mean = data['yr_renovated'].mean()
data["yr_renovated"].fillna(yr_mean, inplace = True)
```

In [11]:
```
#our data now has no null values
print(data.shape)
data.isna().sum()
```

```
(21597, 20)
```

Out[11]:
```
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
```

Now we have a clean dataset without missing values

In [12]:
```
#shape of the new dataset
data.shape
```

Out[12]:
```
(21597, 20)
```

In [13]:
```
#Checking on the correlation to know which features are important for developing
#plt.show()
#for i in data.columns:
#    plt.figure()
#   plt.scatter(data[i],data['price'])
```

In [14]:
```
#check the correlation to choose the best features and arrange in descending orde
data.corr()['price'].sort_values(ascending=False)
```

```
C:\Users\admin\AppData\Local\Temp\ipykernel_4272\3041286634.py:2: FutureWarnin
g: The default value of numeric_only in DataFrame.corr is deprecated. In a futu
re version, it will default to False. Select only valid columns or specify the
value of numeric_only to silence this warning.
  data.corr()['price'].sort_values(ascending=False)
```

Out[14]:
```
price            1.000000
sqft_living      0.701917
sqft_above       0.605368
sqft_living15    0.585241
bathrooms        0.525906
bedrooms         0.308787
lat              0.306692
floors           0.256804
yr_renovated     0.118125
sqft_lot         0.089876
sqft_lot15       0.082845
yr_built         0.053953
long             0.022036
zipcode         -0.053402
Name: price, dtype: float64
```

lets drop some columns we are not intrested using for the model in like:

date, sqft_above, sqft_basement, zipcode, long

In [15]:
```
#drop unused row for this model
data.drop(['date', 'sqft_above', 'sqft_basement', 'zipcode', 'long', 'sqft_lot15'
```

In [16]:
```
#Total number of non categorical variables we will use
print(len(data.columns))
data.columns
```

```
14
```

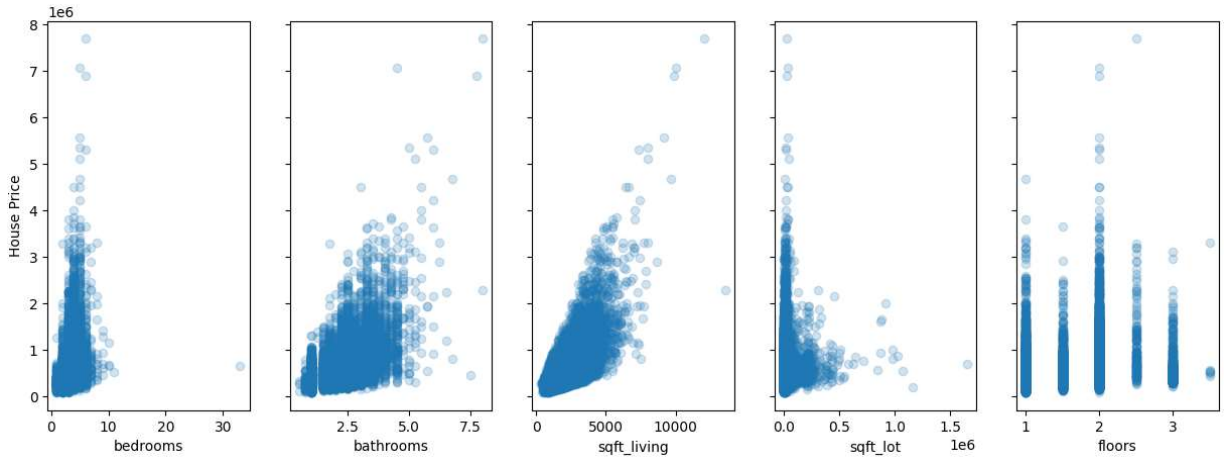
Out[16]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'view', 'condition', 'grade', 'yr_built', 'yr_renovated',
       'lat', 'sqft_living15'],
      dtype='object')
```

sqft_living seem to have the highest correlation with the price column
There seem to be a relationship betwen price and size of the house or rooms

Virtualize the relationship between features and target(house price)

For each numerical feature in the clead data subset create a scatter plot to investigate the leanear relationship with the price variable for best 5 correlations

In [17]:
```
numeric_cols = data[['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
fig, axes = plt.subplots(ncols=5, figsize=(15,5), sharey=True)
axes[0].set_ylabel('House Price')

for i, col in enumerate(numeric_cols.drop("price", axis=1).columns):
    ax = axes[i]
    ax.scatter(numeric_cols[col], numeric_cols['price'], alpha = 0.2)
    ax.set_xlabel(col)
```



There seem to be some linear relationship with price in bathrooms and sqft_living variables. The floor variable seem to contain discrete variables and the yr_built column doesnt seeem to produce a good linear relationship with the target variable price.

DATA MODELING

Base Model

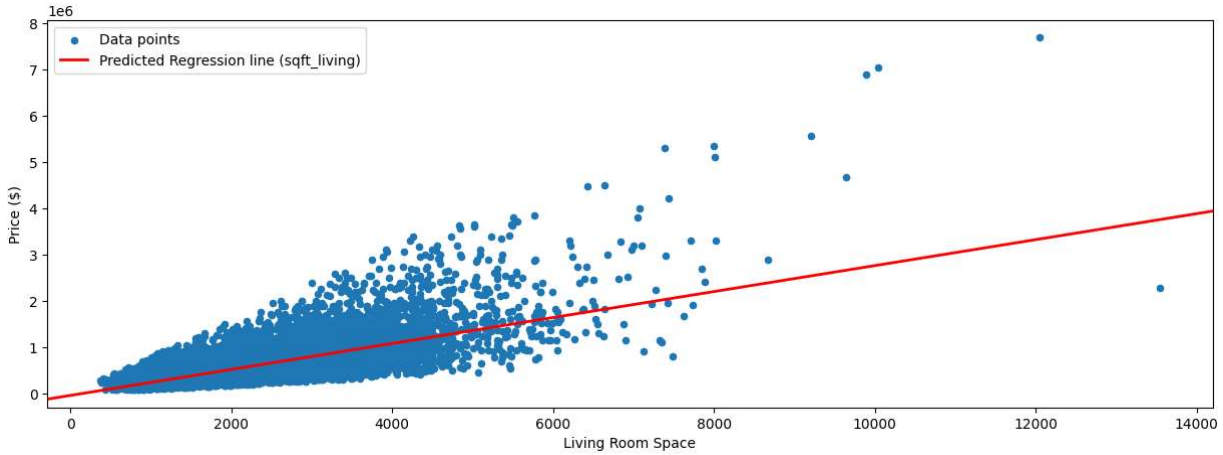
We will now develop a simple linear regression model from which to improve our model on. The sqft_living column shows a strong linear correlation with the house price column so we will develop a linear regression model from these two coloumns to see how accurate the model will be.

In [18]:
```
#set the X varibale to be equal to the independent variable sqft_living and the y
X = data[['sqft_living']]
y = data['price']

#develop the simple linear regression model

base_model =  sm.OLS(y, sm.add_constant(X)).fit()
print(base_model.summary())
```

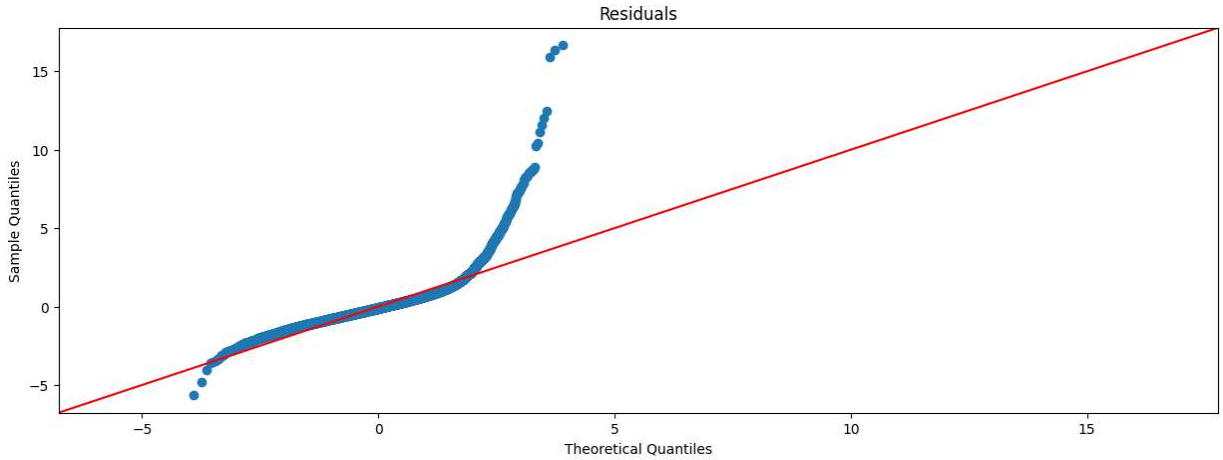
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.493
Model:                            OLS   Adj. R-squared:                  0.493
Method:                 Least Squares   F-statistic:                 2.097e+04
Date:                Fri, 30 Sep 2022   Prob (F-statistic):               0.00
Time:                        14:26:48   Log-Likelihood:            -3.0006e+05
No. Observations:               21597   AIC:                         6.001e+05
Df Residuals:                   21595   BIC:                         6.001e+05
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -4.399e+04   4410.023     -9.975      0.000   -5.26e+04   -3.53e+04
sqft_living   280.8630      1.939    144.819      0.000     277.062     284.664
==============================================================================
Omnibus:                    14801.942   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           542662.604
Skew:                           2.820   Prob(JB):                         0.00
Kurtosis:                      26.901   Cond. No.                     5.63e+03
==============================================================================

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

This model has a p value less than 0.05 hence its statistically significat but it only explains about 50% of the variance in the target data by a r_squared value of 0.49 hence its not really a good model.
The intercept is 4.4 meaning if we had a room with 0 Square footage of living space the price of the house we would expect is
$4.4 < br > The sqft_living coefficient is about 281 meaning for each additional 1 foot of space$
in the house price. This sugdgests the bigger the living space the more expensive the house price.
Let virtualize the model with Square footage of living space as the predictor

In [19]:
```
from cProfile import label

from matplotlib.pyplot import scatter, ylabel


fig, ax = plt.subplots(figsize=(15,5))
data.plot(y='price', x='sqft_living', kind='scatter', label= 'Data points', ax=ax
sm.graphics.abline_plot(model_results=base_model, label='Predicted Regression lir
ax.legend()
plt.show()
```



In [20]:
```
#Plot the residials to see how well the model performes
fig, ax = plt.subplots(figsize=(15,5))
sm.graphics.qqplot(base_model.resid, dist= norm, line='45', fit=True, ax=ax)
ax.set_title('Residuals')
plt.show()
```



In [21]:
```
#calculate the mean absolute error of this model
pre_1 = base_model.predict(sm.add_constant(X))
mean_absolute_error(y, pre_1)
```

Out[21]:
```
173824.8874961748
```

This show how bad our model is since its affected by the outliers in the sqft_living coloum. This can be attributed to the fact that some large houses are vary expensive relative to the average price of housing.

Multi Regression

Lets try and add more features into the module to try and see how goo our model performance will increase
Looking at the correlation mattrix in our previouse code we find that the next value with a higher correlation matrix is bathrooms(0.525906), bedrooms(0.308787), floors(0.256804), sqft_lot (0.089876) and finally yr_built(0.053953)

lets try fitting all these features into our model and see how well it performs relative to the base model above.

This increases our Adj. R-squared value by about 6% indicating an improvement on our model to explain the varience of 12% more of out target variable. The model is also still statistically significan wit a p value less than 0.05

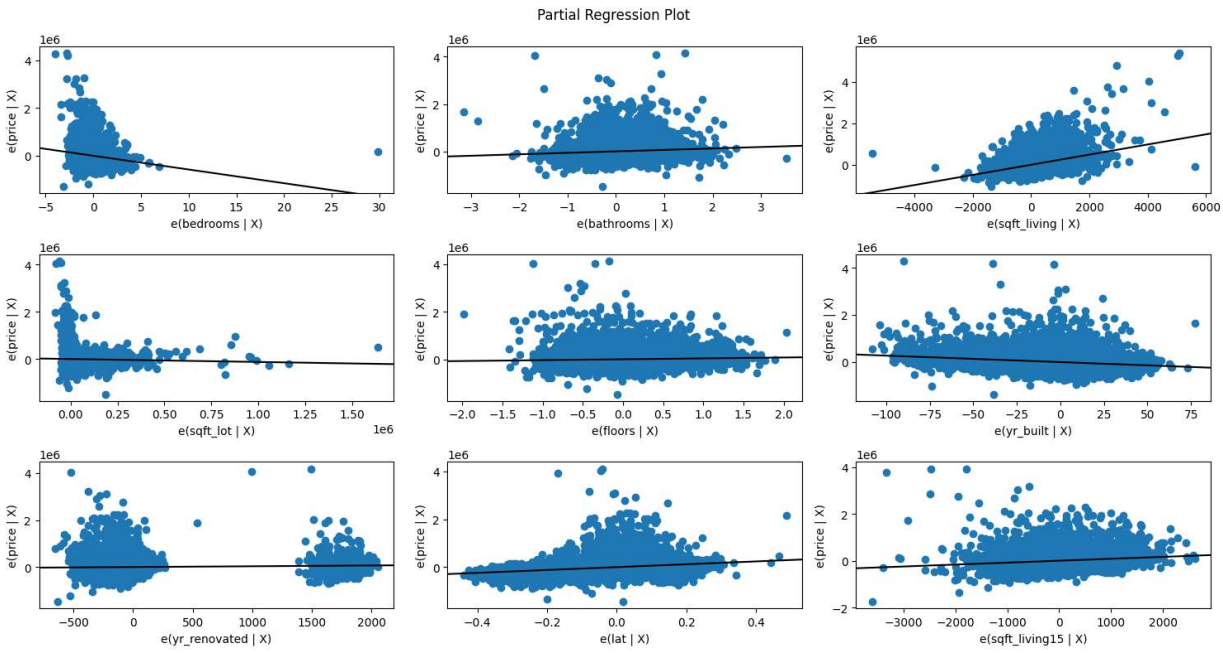
In [22]:
```
#multi regression with all the data points
X_all = data[['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'yr_b
multi_model_all = sm.OLS(y, sm.add_constant(X_all)).fit()
print(multi_model_all.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.616
Model:                            OLS   Adj. R-squared:                  0.616
Method:                 Least Squares   F-statistic:                     3850.
Date:                Fri, 30 Sep 2022   Prob (F-statistic):               0.00
Time:                        14:26:50   Log-Likelihood:            -2.9705e+05
No. Observations:               21597   AIC:                         5.941e+05
Df Residuals:                   21587   BIC:                         5.942e+05
Df Model:                           9
Covariance Type:            nonrobust
==============================================================================
==
                   coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
--
const         -2.314e+07   5.92e+05    -39.053      0.000   -2.43e+07    -2.2e+
07
bedrooms      -5.755e+04   2107.467    -27.306      0.000   -6.17e+04   -5.34e+
04
bathrooms      6.153e+04   3613.566     17.029      0.000    5.45e+04    6.86e+
04
sqft_living     244.9043      3.490     70.178      0.000     238.064     251.7
45
sqft_lot         -0.1256      0.038     -3.266      0.001      -0.201      -0.0
50
floors         3.698e+04   3541.206     10.443      0.000       3e+04    4.39e+
04
yr_built      -2743.5614     69.938    -39.228      0.000   -2880.646   -2606.4
77
yr_renovated     32.7660      4.451      7.361      0.000      24.041      41.4
91
lat            5.975e+05   1.15e+04     51.748      0.000    5.75e+05     6.2e+
05
sqft_living15    82.2603      3.512     23.420      0.000      75.376      89.1
45
==============================================================================
Omnibus:                    17662.005   Durbin-Watson:                   1.994
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1154418.694
Skew:                           3.494   Prob(JB):                         0.00
Kurtosis:                      38.129   Cond. No.                     1.69e+07
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctl
y specified.
[2] The condition number is large, 1.69e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Create a partial Regression Plots for all the features ploted to see how each perform

In [23]:
```
fig = plt.figure(figsize=(15,8))
sm.graphics.plot_partregress_grid(
    multi_model_all,
    exog_idx=list(X_all.columns),
    grid=(3,3),
    fig=fig
)
plt.tight_layout()
plt.show()
```

```
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
eval_env: 1
```



The models trys to fit the data well though there exists some outliers that the linear model does not capture well. There are still some categorical variables not addded in this model. Lets add that and see if the model accuracy will increase

In [24]:
```
#calculate the mean absolute error of this model
pre_2 = multi_model_all.predict(sm.add_constant(X_all))
mean_absolute_error(y, pre_2)
```

Out[24]: 142490.4839760155

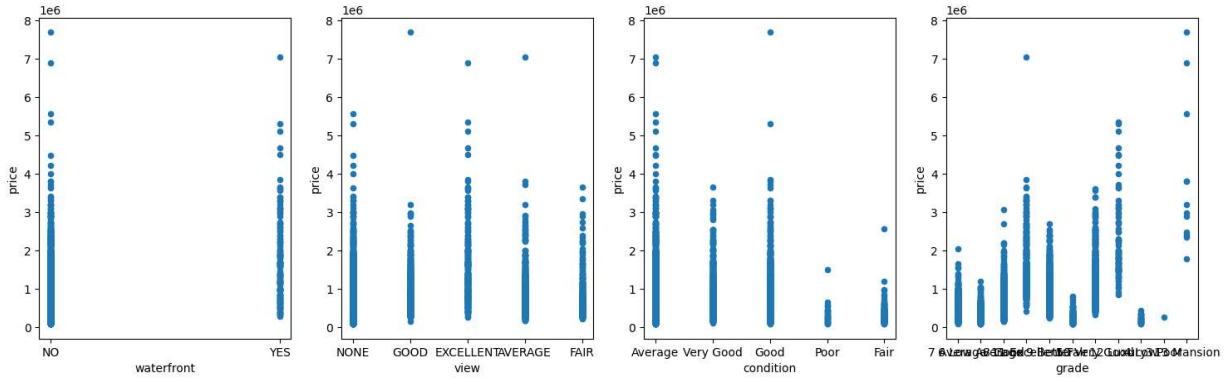
Adding the categorical variables to the model

The model above did not use any categorical variables in the data set. We will use one-hot-encoding to transform the categorical columns to feed them to the model to increase the signal in the data.
Our dataset include 3 categorical columns ['waterfront', 'condition', 'grade']

In [25]:
```
#view the categorical values an their respective categories
cat_data = data[['waterfront','view', 'condition', 'grade']]
for col in cat_data.columns:
    print("the categorical values in " + col + " are:")
    print(cat_data[col].value_counts())
```

```
the categorical values in waterfront are:
NO     21451
YES      146
Name: waterfront, dtype: int64
the categorical values in view are:
NONE         19485
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: view, dtype: int64
the categorical values in condition are:
Average      14020
Good          5677
Very Good     1701
Fair           170
Poor            29
Name: condition, dtype: int64
the categorical values in grade are:
7 Average        8974
8 Good           6065
9 Better         2615
6 Low Average    2038
10 Very Good     1134
11 Excellent      399
5 Fair            242
12 Luxury          89
4 Low              27
13 Mansion         13
3 Poor              1
Name: grade, dtype: int64
```

In [42]:
```
#ploting categorical variables
fig, (ax1, ax2, ax3, ax4) = plt.subplots(ncols=4, figsize=(18,5))

#[['waterfront','view', 'condition', 'grade']]
data.plot.scatter(x='waterfront', y='price', ax =ax1)
data.plot.scatter(x='view', y='price', ax =ax2)
data.plot.scatter(x='condition', y='price', ax =ax3)
data.plot.scatter(x='grade', y='price', ax =ax4);
```



In [27]:
```
#transform the categorical columns using one hot encoding to enable them to be fe
X_3 = data.drop('price', axis= 1)
X_categorical = pd.get_dummies(X_3, columns=['waterfront','view', 'condition', 'g
print(X_3.shape)
print(X_categorical.shape) #We now have more features in our dataset to bust the
X_categorical.head()
```

```
(21597, 13)
(21597, 28)
```

Out[27]:

id	bedrooms	bathrooms	sqft_living	sqft_lot	floors	yr_built	yr_renovated	lat
7129300520	3	1.00	1180	5650	1.0	1955	0.000000	47.5112
6414100192	3	2.25	2570	7242	2.0	1951	1991.000000	47.7210
5631500400	2	1.00	770	10000	1.0	1933	83.636778	47.7379
2487200875	4	3.00	1960	5000	1.0	1965	0.000000	47.5208
1954400510	3	2.00	1680	8080	1.0	1987	0.000000	47.6168

5 rows × 28 columns

In [28]:
```
#Run the full model conatainaing the full data set to see how this will improve t
full_model = sm.OLS(y, sm.add_constant(X_categorical)).fit()
print(full_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.725
Model:                            OLS   Adj. R-squared:                  0.725
Method:                 Least Squares   F-statistic:                     2030.
Date:                Fri, 30 Sep 2022   Prob (F-statistic):               0.00
Time:                        14:26:54   Log-Likelihood:            -2.9345e+05
No. Observations:               21597   AIC:                         5.870e+05
Df Residuals:                   21568   BIC:                         5.872e+05
Df Model:                          28
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -2.261e+07   5.24e+05    -43.116      0.000   -2.36e+07   -2.16e+07
bedrooms   -1.845e+04   1856.336     -9.936      0.000   -2.21e+04   -1.48e+04
bathrooms   4.601e+04   3110.856     14.792      0.000    3.99e+04    5.21e+04
sqft_living  128.0980      3.297     38.855      0.000     121.636     134.560
sqft_lot      -0.1110      0.033     -3.398      0.001      -0.175      -0.047
floors         2.44e+04   3122.041      7.816      0.000    1.83e+04    3.05e+04
yr_built   -2245.4965     66.139    -33.951      0.000   -2375.135   -2115.858
yr_renovated  33.8124      3.842      8.801      0.000      26.282      41.343
lat            5.783e+05   9984.762     57.921      0.000    5.59e+05    5.98e+05
sqft_living15  24.5460      3.186      7.704      0.000      18.301      30.791
waterfront_YES  5.544e+05   1.96e+04     28.342      0.000    5.16e+05    5.93e+05
view_EXCELLENT  1.877e+05   1.46e+04     12.838      0.000    1.59e+05    2.16e+05
view_FAIR      5.44e+04   1.23e+04      4.414      0.000    3.02e+04    7.86e+04
view_GOOD      6.548e+04   1.06e+04      6.164      0.000    4.47e+04    8.63e+04
```

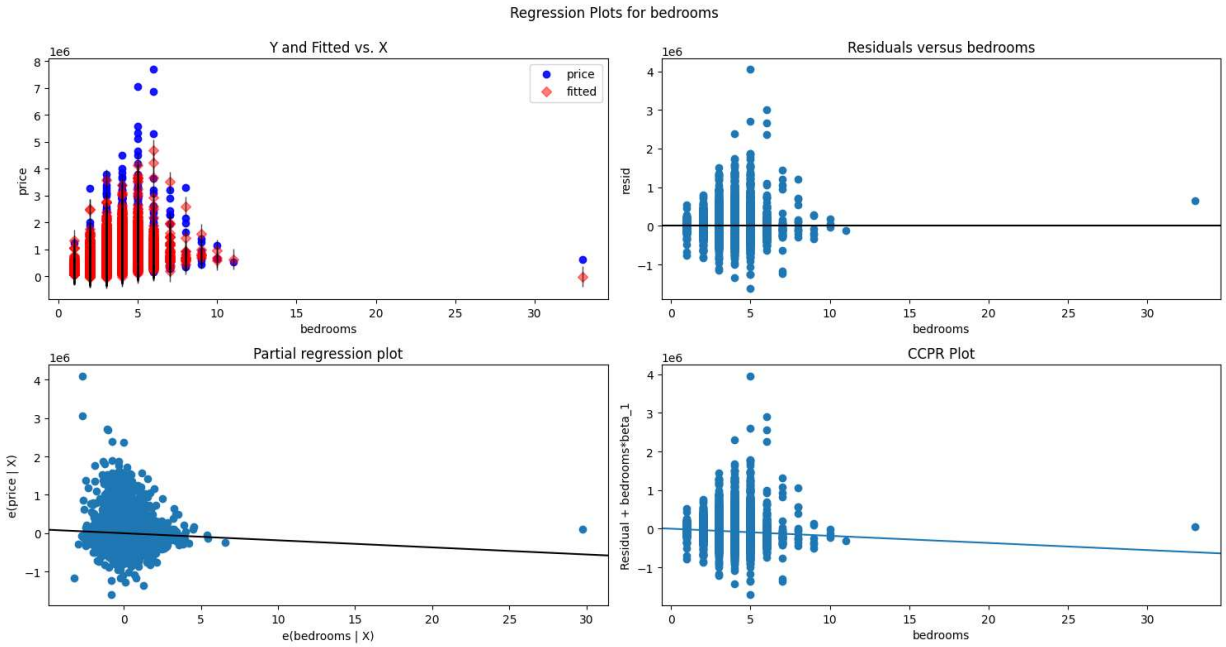
```
view_NONE             -6.79e+04   6547.493    -10.371      0.000   -8.07e+04
-5.51e+04
condition_Fair      -6089.9556   1.51e+04     -0.404      0.686   -3.56e+04
2.34e+04
condition_Good       3.694e+04   3306.399     11.173      0.000    3.05e+04
4.34e+04
condition_Poor      -5.399e+04   3.62e+04     -1.493      0.135   -1.25e+05
1.69e+04
condition_Very Good  7.516e+04   5313.731     14.144      0.000    6.47e+04
8.56e+04
grade_11 Excellent   2.531e+05   1.14e+04     22.104      0.000    2.31e+05
2.76e+05
grade_12 Luxury      7.187e+05   2.19e+04     32.871      0.000    6.76e+05
7.62e+05
grade_13 Mansion     1.919e+06   5.48e+04     35.030      0.000    1.81e+06
2.03e+06
grade_3 Poor        -2.656e+05   1.93e+05     -1.375      0.169   -6.44e+05
1.13e+05
grade_4 Low         -4.173e+05   3.84e+04    -10.874      0.000   -4.93e+05
-3.42e+05
grade_5 Fair        -4.294e+05   1.55e+04    -27.673      0.000    -4.6e+05
-3.99e+05
grade_6 Low Average -4.009e+05   9810.138    -40.869      0.000    -4.2e+05
-3.82e+05
grade_7 Average     -3.525e+05   8056.469    -43.757      0.000   -3.68e+05
-3.37e+05
grade_8 Good        -2.872e+05   7234.460    -39.698      0.000   -3.01e+05
-2.73e+05
grade_9 Better      -1.659e+05   7079.585    -23.439      0.000    -1.8e+05
-1.52e+05
==============================================================================
=
Omnibus:                    14786.198   Durbin-Watson:                   1.98
4
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           807779.77
8
Skew:                           2.677   Prob(JB):                         0.0
0
Kurtosis:                      32.479   Cond. No.                     1.76e+0
7
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 1.76e+07. This might indicate that there a
re
strong multicollinearity or other numerical problems.
```

In [29]:
```
#calculate the mean absolute error of this model
pre_3 = full_model.predict(sm.add_constant(X_categorical))
mean_absolute_error(y, pre_3)
```

Out[29]:
```
119100.49980735894
```

In [47]:
```
# plot the resedual for the bedrooms data to view the model performance
fig = plt.figure(figsize=(15,8))
sm.graphics.plot_regress_exog(full_model, "bedrooms", fig=fig)
plt.show()
```

```
eval_env: 1
```



The model has greately improved by the inclusion of the categorical variables and and the variance in the taget variable can be explained up to about 73%
The model is also statistically significant with a p value of less than 0.05

The mean absolute error of our model has also greately reduced indicating an improvement on our model.

Explainaing the model

Model Summary

- Our model is statistically significant overall, and explains about 73% of the variance in House sales Price.
- On average this model may be off by about $119k in its predictions on home price this is due to the outliers caused by highl expensive houses that affect the model predictive ability.

All of our coefficients are statistically significant

- const: when all the features used in this prediction are zero, we would expect a home sale price of -$22558k. This might not be realistic in real world since we cannot have a house with zero rooms for example

- bedrooms: For each increase 1 bedroom space we see an associated decrease in House price by about $19k. This can be brought about by the fact that houses in towns tend to be small and expenceve while those out of town are big and cheaper.
- bathrooms: For each increase 1 bathroom space we see an associated increase in House price by about $45k.
- sqft_living: For each increase in 1 inch of squarefoot of living room space we see an associated increase in House price by about $129
- sqft_lot: For each increase in 1 inch of Square footage of the lot space we see an associated increase in House price by a small amount of about $0.1. This sudgests that the Square footage of the lot is not a real consern for home owners
- floors : For each increase in 1 house floor, we see an associated increase in House price by about $24k
- yr_built: For each increase in a house's year by 1 we see an associated decrease in House price by about $2k. This can be brought about by the fact that houses built long time ago have a low price than recent houses.
- yr_renovated: For each increase in a house's year of renovation by 1 we see an associated increasw in House price by about $34. This can be brought about by the fact that houses that are recently renewed are much expensive due to the renovations done
- lat: For each increase 1 latitude, we see can associated increase in House price by about $577k. This can be attributed to the fact that tempratures at high latitude areas are favorable for many people hence the higher price house price

Type *Markdown* and LaTeX: α^2