Final Project Submission

Group name: Group 5

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Content

Introduction

We are exploring the King County House Sales dataset. The data contains Information on houses sold in the king county in the USA. The data includes various features such as house characteristics, location and sales price.

Objective

The objective of the analysis is to use the King County House Sales dataset tobuild a liner regression model to predict house prices. We will use the Independent Variables to predict the house price through a linear regression model.

Data Preprocessing

In [5]:
```
#import libraries
import pandas as pd
import numpy as np
from scipy import stats as stats
from matplotlib import pyplot as plt
import seaborn as sns
%matplotlib inline

import statsmodels.api as sm

from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.datasets import make_regression
from sklearn.linear_model import LinearRegression
from sklearn import linear_model
from sklearn.neighbors import KNeighborsRegressor
from sklearn import metrics
```

In [6]:
```
#loading and previewing the data
data = pd.read_csv("kc_house_data.csv")
data.head()
```

Out[6]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sq
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	

5 rows × 21 columns

In [7]:
```
# Viewing a summary of the data
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
```

From the summary of the data, there are 21,597 rows and 21 columns. There are null values in three columns i.e. waterfront,view and yr_renovated.

In [8]:
```
# Viewing summary statistics for numerical columns
data.describe()
```

Out[8]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	yr_built
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597.000000	21597.000000
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	1788.596842	1970.999676
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	827.759761	29.375234
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	370.000000	1900.000000
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	1190.000000	1951.000000
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	1560.000000	1975.000000
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	2210.000000	1997.000000
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	9410.000000	2015.000000

Handling missing values

In [9]:
```
#checking for null values
data.isnull().sum()
```

Out[9]:
```
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 [10]:
```
#checking for proportions of the null values
data.isnull().mean()*100
```

Out[10]:
```
id                0.000000
date              0.000000
price             0.000000
bedrooms          0.000000
bathrooms         0.000000
sqft_living       0.000000
sqft_lot          0.000000
floors            0.000000
waterfront       11.001528
view              0.291707
condition         0.000000
grade             0.000000
sqft_above        0.000000
sqft_basement     0.000000
yr_built          0.000000
yr_renovated     17.789508
zipcode           0.000000
lat               0.000000
long              0.000000
sqft_living15     0.000000
sqft_lot15        0.000000
dtype: float64
```

The proportion of the missing values in the yr_renovated and waterfront columns is greater than 10%. We have decided to dropthose columns. For the missing values in view columns are 0.29% we have decided to impute the missing values

In [11]:
```
#dropping null values in the yr_renovated column and waterfront
data.drop(columns=["yr_renovated","waterfront"],inplace = True,axis = 1)
```

In [12]:
```
# Calculating the mode for the view column
view_mode = data.view.mode()[0]
view_mode
```

Out[12]:
```
'NONE'
```

In [13]:
```
#imputing the values for view
data['view'].fillna(view_mode, inplace=True)
```

In [14]:
```
#Confirming there are no more null values
data.isnull().mean()*100
```

Out[14]:
```
id               0.0
date             0.0
price            0.0
bedrooms         0.0
bathrooms        0.0
sqft_living      0.0
sqft_lot         0.0
floors           0.0
view             0.0
condition        0.0
grade            0.0
sqft_above       0.0
sqft_basement    0.0
yr_built         0.0
zipcode          0.0
lat              0.0
long             0.0
sqft_living15    0.0
sqft_lot15       0.0
dtype: float64
```

Feature Engineering

In [15]:
```
# Extracting the numeric part of the grade column
data.grade.unique()
```

Out[15]:
```
array(['7 Average', '6 Low Average', '8 Good', '11 Excellent', '9 Better',
       '5 Fair', '10 Very Good', '12 Luxury', '4 Low', '3 Poor',
       '13 Mansion'], dtype=object)
```

In [16]:
```
#Apply feature engineering to grade column
data.grade.str.split().apply(lambda x : x[0])
```

Out[16]:
```
0        7
1        7
2        6
3        7
4        8
        ..
21592    8
21593    8
21594    7
21595    8
21596    7
Name: grade, Length: 21597, dtype: object
```

In [17]:
```
#replace the grade column with the extracted numbers
data["grade"] = data.grade.str.split().apply(lambda x : x[0])
data.tail()
```

Out[17]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	view	condition	grade	sqft_above	sqft_
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131	3.0	NONE	Average	8	1530	
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813	2.0	NONE	Average	8	2310	
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350	2.0	NONE	Average	7	1020	
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388	2.0	NONE	Average	8	1600	
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076	2.0	NONE	Average	7	1020	

In [18]:
```
# changing the data type of the column grade to integer
data['grade']=data['grade'].astype('int')
```

In [19]:
```
# Viewing the unique values of the condition column
data['condition'].value_counts()
```

Out[19]:
```
condition
Average      14020
Good          5677
Very Good     1701
Fair           170
Poor            29
Name: count, dtype: int64
```

In [20]:
```
# Replacing the condition column with the generated hieracical numbers
data['condition']= data['condition'].map(lambda x: 1 if x=='Poor' else 2 if x=='Fair' else 3
                      if x=='Average' else 4 if x=='Good' else 5 if x=='Very Good' else 0)
```

In [21]:
```

data['condition'].value_counts()
```

Out[21]:
```
condition
3    14020
4     5677
5     1701
2      170
1       29
Name: count, dtype: int64
```

In [22]:
```
# unique columns for the view column
data['view'].value_counts()
```

Out[22]:
```
view
NONE         19485
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: count, dtype: int64
```

In [23]:
```
# Replacing the view column with the generated hieracical numbers
data['view']= data['view'].map(lambda x: 1 if x=='NONE' else 2 if x=='FAIR' else 3
                        if x=='AVERAGE' else 4 if x=='GOOD' else 5 if x=='EXCELLENT' else 0)
```

In [24]:
```
# Generating Age of the house at the time of selling
data['Year_sold']=data['date'].apply(lambda x: x[-4:])
data['Year_sold']=data['Year_sold'].astype('int')
data['Age']=data['Year_sold']-data['yr_built']
```

In [25]:
```
# Viewing the new features
data.head()
```

Out[25]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	view	condition	...	sqft_above	sqft_basement
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	1	3	...	1180	0.0
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	1	3	...	2170	400.0
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	1	3	...	770	0.0
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	1	5	...	1050	910.0
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	1	3	...	1680	0.0

5 rows × 21 columns

In [26]:
```
# Viweing unique values in the sqft_basement column
data["sqft_basement"].value_counts()
```

Out[26]:
```
sqft_basement
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: count, Length: 304, dtype: int64
```

In [27]:
```
# Cleaning the data frame and removing any ? mark
data = data.applymap(lambda x : 0.0 if x == "?" else x)
data["sqft_basement"].value_counts()
```

Out[27]:
```
sqft_basement
0.0       12826
0.0         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: count, Length: 304, dtype: int64
```

In [28]:
```
# changing the sqft_basement column to float
data["sqft_basement"] = data["sqft_basement"].astype(float)
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   view           21597 non-null  int64  
 9   condition      21597 non-null  int64  
 10  grade          21597 non-null  int64  
 11  sqft_above     21597 non-null  int64  
 12  sqft_basement  21597 non-null  float64
 13  yr_built       21597 non-null  int64  
 14  zipcode        21597 non-null  int64  
 15  lat            21597 non-null  float64
 16  long           21597 non-null  float64
 17  sqft_living15  21597 non-null  int64  
 18  sqft_lot15     21597 non-null  int64  
 19  Year_sold      21597 non-null  int64  
 20  Age            21597 non-null  int64  
dtypes: float64(6), int64(14), object(1)
memory usage: 3.5+ MB
```

Exploratory Data Analysis (EDA)

In [29]:
```
#correlation between price and the other variables
# data.corr()
data.select_dtypes (['float','int']).corr()['price']
# data.corr()["price"]
```

Out[29]:
```
id              -0.016772
price            1.000000
bedrooms         0.308787
bathrooms        0.525906
sqft_living      0.701917
sqft_lot         0.089876
floors           0.256804
view             0.393497
condition        0.036056
grade            0.667951
sqft_above       0.605368
sqft_basement    0.321108
yr_built         0.053953
zipcode         -0.053402
lat              0.306692
long             0.022036
sqft_living15    0.585241
sqft_lot15       0.082845
Year_sold        0.003727
Age             -0.053890
Name: price, dtype: float64
```

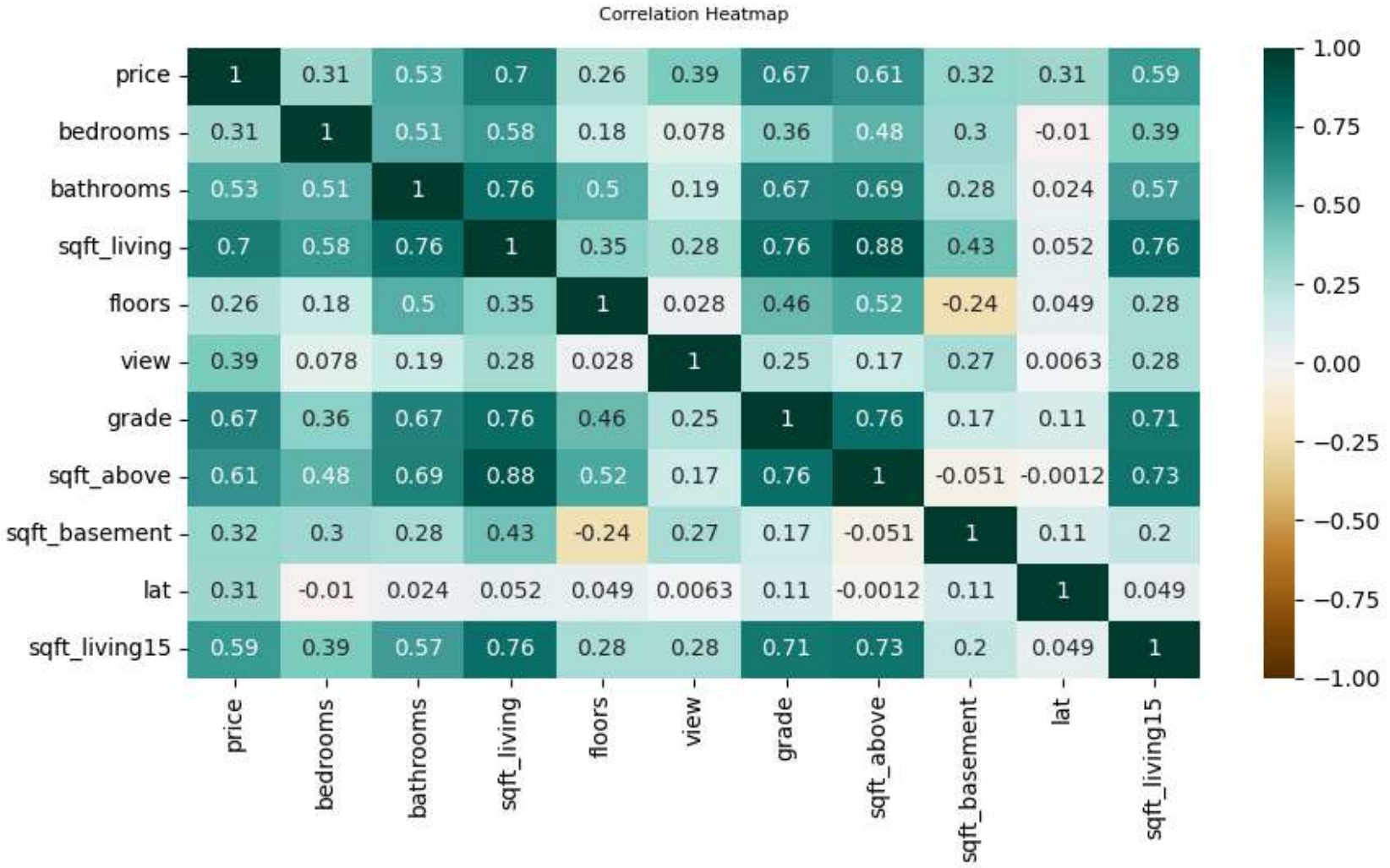
In [30]:
```
#list of the columns to drop that have a low correlation to the price
columns_to_drop = ['date',"id", "sqft_lot","yr_built","long","sqft_lot15","zipcode",'condition','Age','Year_s
```

In [31]:
```
#dropping the columns
data.drop(columns = columns_to_drop, inplace = True)
```

In [32]:
```
# Viewing the correlation between price and other variables
data.select_dtypes (['float','int']).corr()['price']
```

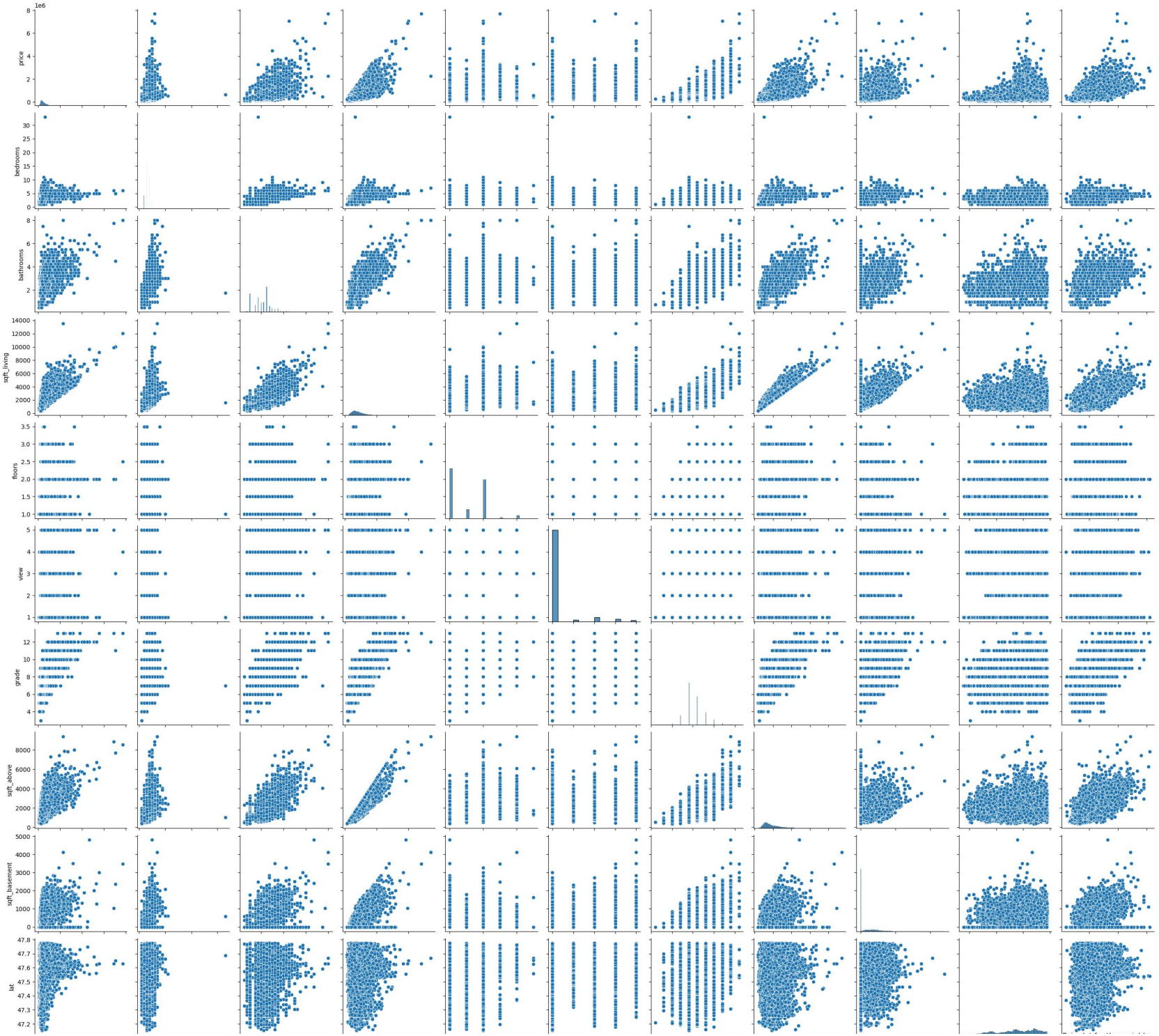
Out[32]:
```
price            1.000000
bedrooms         0.308787
bathrooms        0.525906
sqft_living      0.701917
floors           0.256804
view             0.393497
grade            0.667951
sqft_above       0.605368
sqft_basement    0.321108
lat              0.306692
sqft_living15    0.585241
Name: price, dtype: float64
```

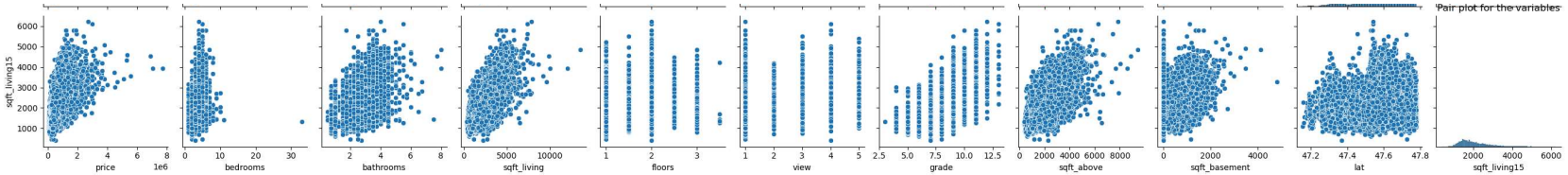
In [181]:
```
# Visualize relationships between key features and house prices
plt.figure(figsize=(10, 5))
heatmap = sns.heatmap(data.select_dtypes (['float','int']).corr(), vmin=-1, vmax=1, annot=True, cmap='BrBG')
heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':8}, pad=12);
```



In [33]:
```
# Viewing the relationship amongst variables using a pair plot
sns.pairplot(data)
plt.title('Pair plot for the variables');
```

```
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layout has chang
ed to tight
  self._figure.tight_layout(*args, **kwargs)
```


price
bedrooms
bathrooms
sqft_living
floors
view
grade
sqft_above
sqft_basement
lat
1e6



In [34]:
```
# Droping variables that have a linear correlation amongst themselves
columns_drop=['sqft_above','sqft_living15']
data.drop(columns=columns_drop,inplace=True)
```

Building Regression Models

In [35]:
```
# baseline dependent and independent variables using sqft_living
# since it has a higer correlation to price as compared to other variables.
y = data["price"]
X = data["sqft_living"]
```

In [36]:
```
#Baseline model
baseline_model = sm.OLS(y,sm.add_constant(X))
baseline_results = baseline_model.fit()
baseline_results.summary()
```

Out[36]:

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:	Sat, 06 Apr 2024	**Prob (F-statistic):**	0.00
Time:	22:15:38	**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 correctly specified.
[2] The condition number is large, 5.63e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

In [37]:
```
# Viewing the baseline parameters
baseline_results.params
```

Out[37]:
```
const         -43988.892194
sqft_living      280.863014
dtype: float64
```

Interpratation of the baseline model

R-squared of 0.493 The model is explaining 49.3% of the change in price.

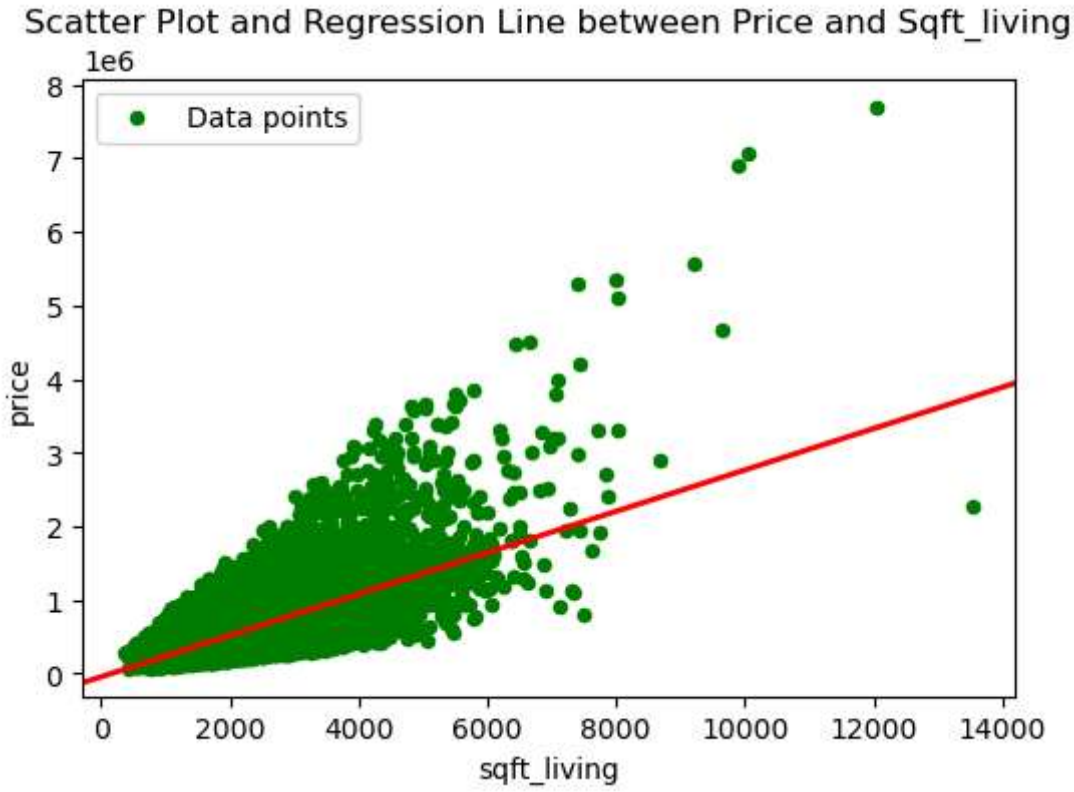
Comapring the P value of F which is 0.00 with the standard alpha of 0.05, our model is statistically significant since the the value is less than the alpha value.

when X is 0 the price will be -43,988

when x increases by 1 unit the price will increase by 280.

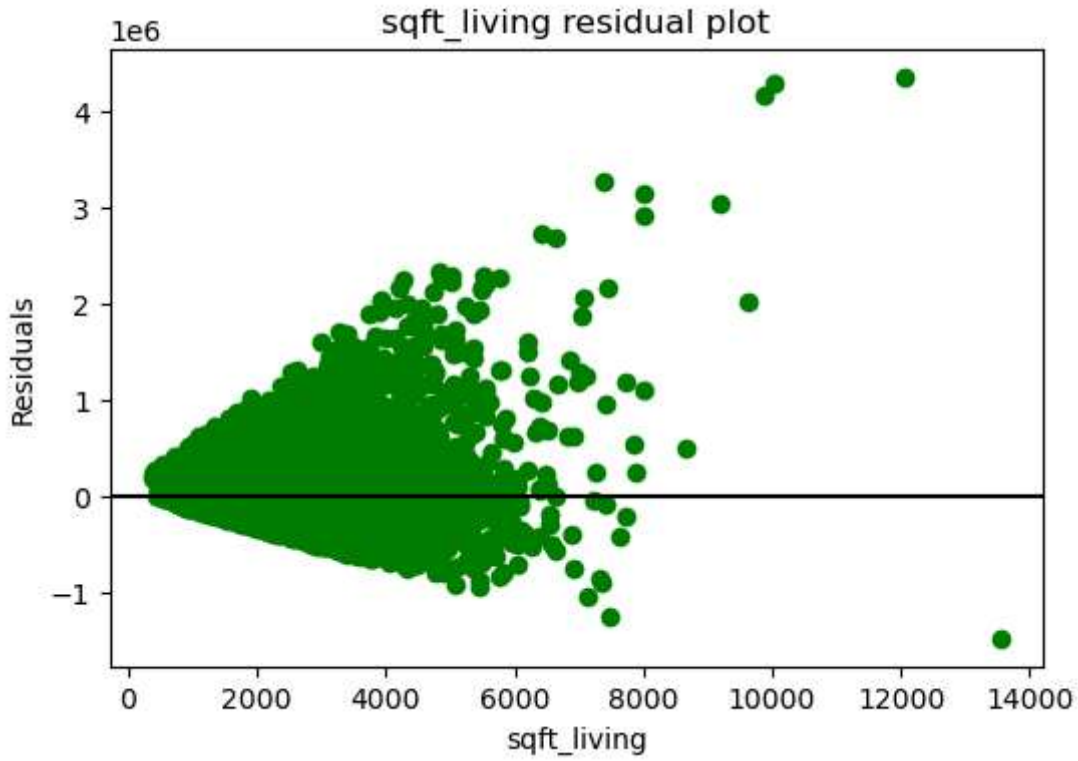
Equation for our model Price = 280.86X - 43988.89

In [38]:
```
# visualising the scatter plot and the line of best fit for the baseline model
fig, ax = plt.subplots(figsize=(6,4))
data.plot(x='sqft_living', y='price', kind="scatter", label="Data points", ax=ax, c='green')
sm.graphics.abline_plot(model_results=baseline_results, label="Regression line (sqft_living)", c="red", linew
ax.legend
plt.title("Scatter Plot and Regression Line between Price and Sqft_living")
plt.show()
```



In [39]:
```
# residual plot for our baseline model
residuals=baseline_results.resid
X=data['sqft_living']

fig, ax=plt.subplots(figsize=(6,4))
ax.scatter(X,residuals,c='green')
ax.axhline(y=0,c='black')
ax.set_xlabel('sqft_living')
ax.set_ylabel('Residuals')
plt.title('sqft_living residual plot');
```



In [40]:

```
# Mutliple linear regression model based using all numerical field

columns_int=data.select_dtypes( 'int')
columns_int
columns_float=data.select_dtypes( 'float')
columns_float

columns_int_float =list(columns_int.columns) + list(columns_float.columns)
columns_int_float.remove('price')


y=data['price']
X=data[columns_int_float]

second_model=sm.OLS(endog=y,exog=sm.add_constant(X))
second_results=second_model.fit()
second_results.summary()
```

Out[40]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.640
Model:	OLS	**Adj. R-squared:**	0.640
Method:	Least Squares	**F-statistic:**	4803.
Date:	Sat, 06 Apr 2024	**Prob (F-statistic):**	0.00
Time:	22:15:40	**Log-Likelihood:**	-2.9635e+05
No. Observations:	21597	**AIC:**	5.927e+05
Df Residuals:	21588	**BIC:**	5.928e+05
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-3.218e+07	5.25e+05	-61.282	0.000	-3.32e+07	-3.12e+07
bedrooms	-2.901e+04	2059.575	-14.087	0.000	-3.31e+04	-2.5e+04
sqft_living	199.5426	3.489	57.199	0.000	192.705	206.380
view	9.39e+04	2103.379	44.642	0.000	8.98e+04	9.8e+04
grade	8.178e+04	2187.692	37.384	0.000	7.75e+04	8.61e+04
bathrooms	-4158.0755	3345.798	-1.243	0.214	-1.07e+04	2399.937
floors	-2.764e+04	3713.135	-7.443	0.000	-3.49e+04	-2.04e+04
sqft_basement	-1.7950	4.491	-0.400	0.689	-10.598	7.008
lat	6.669e+05	1.11e+04	60.214	0.000	6.45e+05	6.89e+05

Omnibus:	18735.051	**Durbin-Watson:**	1.995
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1702719.450
Skew:	3.729	**Prob(JB):**	0.00
Kurtosis:	45.855	**Cond. No.**	8.06e+05

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.06e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

In [41]:
```
# viewing the coefficients for the multiple linear regression
second_results.params
```

Out[41]:
```
const           -3.218420e+07
bedrooms        -2.901335e+04
sqft_living      1.995426e+02
view             9.389958e+04
grade            8.178408e+04
bathrooms       -4.158075e+03
floors          -2.763731e+04
sqft_basement   -1.795045e+00
lat              6.668567e+05
dtype: float64
```

Interpratation of the mutliple linear regression model

R-squared of 0.64 The model is now explaining 64% of the change in price.

Comapring the P value of F which is 0.00 with the standard alpha of 0.05, our model is statistically significant since the the value is less than the alpha value.

when all independent variables are 0 the price will be -3,218,420

In [42]:
```
# Revising the model by droping variables that have a P(t) greater than a standard alpha of 0.05
data.drop(columns=['sqft_basement','bathrooms'],inplace=True)


columns_int=data.select_dtypes( 'int')
columns_int
columns_float=data.select_dtypes( 'float')
columns_float

columns_int_float =list(columns_int.columns) + list(columns_float.columns)
columns_int_float.remove('price')

# Revising the mutliple linear regression model
y=data['price']
X=data[columns_int_float]

revised_second_model=sm.OLS(y,sm.add_constant(X))
revised_second_model_results=revised_second_model.fit()
revised_second_model_results.summary()
```

Out[42]:

OLS Regression Results

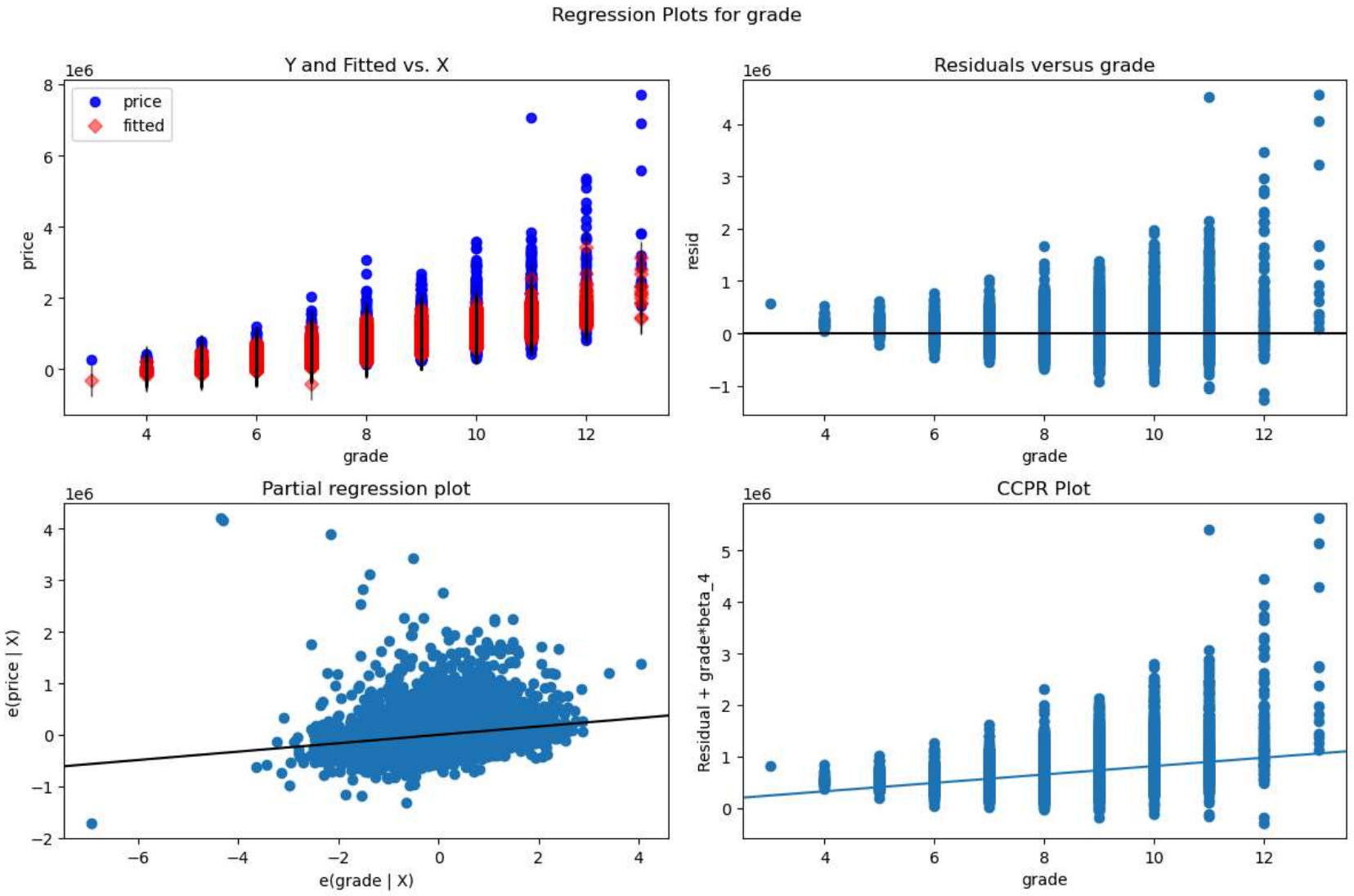
Dep. Variable:	price	**R-squared:**	0.640
Model:	OLS	**Adj. R-squared:**	0.640
Method:	Least Squares	**F-statistic:**	6403.
Date:	Sat, 06 Apr 2024	**Prob (F-statistic):**	0.00
Time:	22:15:40	**Log-Likelihood:**	-2.9635e+05
No. Observations:	21597	**AIC:**	5.927e+05
Df Residuals:	21590	**BIC:**	5.928e+05
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-3.218e+07	5.18e+05	-62.105	0.000	-3.32e+07	-3.12e+07
bedrooms	-2.955e+04	2021.669	-14.616	0.000	-3.35e+04	-2.56e+04
sqft_living	197.2828	2.979	66.234	0.000	191.445	203.121
view	9.376e+04	2068.421	45.329	0.000	8.97e+04	9.78e+04
grade	8.157e+04	2123.408	38.413	0.000	7.74e+04	8.57e+04
floors	-2.851e+04	3143.876	-9.069	0.000	-3.47e+04	-2.24e+04
lat	6.668e+05	1.09e+04	61.076	0.000	6.45e+05	6.88e+05

Omnibus:	18733.272	**Durbin-Watson:**	1.995
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1700656.549
Skew:	3.729	**Prob(JB):**	0.00
Kurtosis:	45.828	**Cond. No.**	7.86e+05

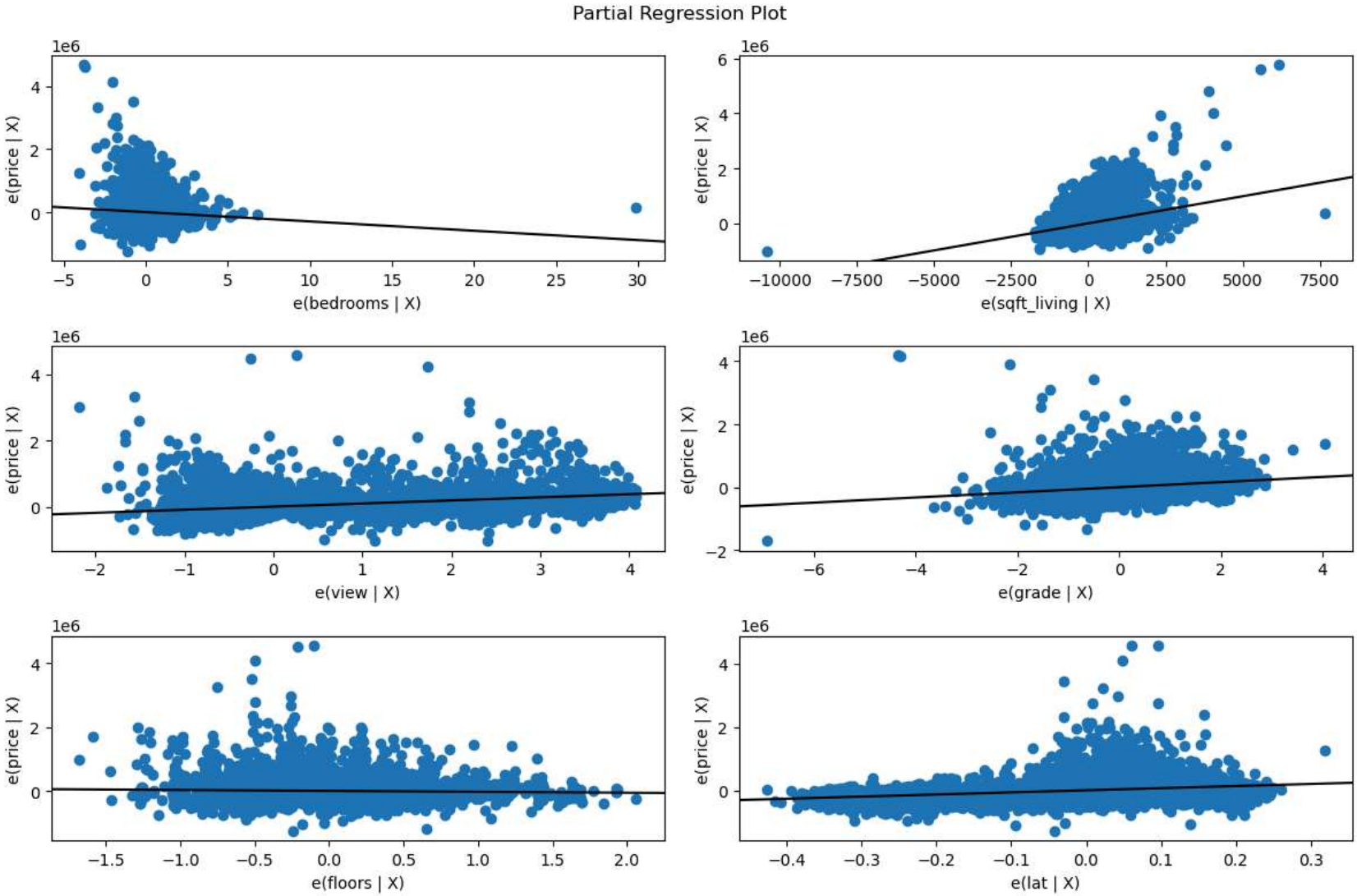
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.86e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

In [43]:
```
# Plotting the fitted
#checking resideual for caret variable
sm.graphics.plot_regress_exog(revised_second_model_results, 'grade', fig=plt.figure(figsize=(12,8)));
```



In [44]:
```
# ploting partial Regression plots for the multiple linear regression.
fig=plt.figure(figsize=(12,8))
sm.graphics.plot_partregress_grid(revised_second_model_results,exog_idx=list(X.columns),fig=fig)
plt.tight_layout();
```

```
C:\Users\ken19189\AppData\Local\Temp\ipykernel_11240\1730839349.py:4: UserWarning: The figure layout has cha
nged to tight
  plt.tight_layout();
```



In [45]:
```
# generating a list for the columns to one hot encode
columns_to_ohe=list(data.select_dtypes(include='object').columns)[1:]
columns_to_ohe
```

Out[45]:
```
[]
```

Polynomial regression

In [46]:
```
# polynimial regression 2 degrees
train_data,test_data=train_test_split(data,train_size=0.8,random_state=3)
reg=linear_model.LinearRegression()

features1=['bedrooms','grade','sqft_living','floors','lat','view']

polyfeat=PolynomialFeatures(degree=2)
xtrain_poly=polyfeat.fit_transform(train_data[features1])
xtest_poly=polyfeat.fit_transform(test_data[features1])

poly=linear_model.LinearRegression()
poly.fit(xtrain_poly,train_data['price'])
polypred=poly.predict(xtest_poly)

print('PR_Model_2')
mean_squared_error = metrics.mean_squared_error(test_data['price'], polypred)
print('Mean Squared Error (MSE) ', round(np.sqrt(mean_squared_error), 2))
print('R-squared (training) ', round(poly.score(xtrain_poly, train_data['price']), 3))
print('R-squared (testing) ', round(poly.score(xtest_poly, test_data['price']), 3))
```

```
PR_Model_2
Mean Squared Error (MSE)  200710.51
R-squared (training)  0.715
R-squared (testing)  0.708
```

In [47]:
```
# polynimial regression 3 degrees
train_data,test_data=train_test_split(data,train_size=0.8,random_state=3)
reg=linear_model.LinearRegression()

features1=['bedrooms','grade','sqft_living','floors','lat','view']

polyfeat=PolynomialFeatures(degree=3)
xtrain_poly=polyfeat.fit_transform(train_data[features1])
xtest_poly=polyfeat.fit_transform(test_data[features1])

poly=linear_model.LinearRegression()
poly.fit(xtrain_poly,train_data['price'])
polypred=poly.predict(xtest_poly)

print('PR_Model_3')
mean_squared_error = metrics.mean_squared_error(test_data['price'], polypred)
print('Mean Squared Error (MSE) ', round(np.sqrt(mean_squared_error), 2))
print('R-squared (training) ', round(poly.score(xtrain_poly, train_data['price']), 3))
print('R-squared (testing) ', round(poly.score(xtest_poly, test_data['price']), 3))
```

```
PR_Model_3
Mean Squared Error (MSE)  192833.88
R-squared (training)  0.738
R-squared (testing)  0.731
```

In [48]:
```
# polynimial regression 4 degrees
train_data,test_data=train_test_split(data,train_size=0.8,random_state=3)
reg=linear_model.LinearRegression()

features1=['bedrooms','grade','sqft_living','floors','lat','view']

polyfeat=PolynomialFeatures(degree=4)
xtrain_poly=polyfeat.fit_transform(train_data[features1])
xtest_poly=polyfeat.fit_transform(test_data[features1])

poly=linear_model.LinearRegression()
poly.fit(xtrain_poly,train_data['price'])
polypred=poly.predict(xtest_poly)

print('PR_Model_4')
mean_squared_error = metrics.mean_squared_error(test_data['price'], polypred)
print('Mean Squared Error (MSE) ', round(np.sqrt(mean_squared_error), 2))
print('R-squared (training) ', round(poly.score(xtrain_poly, train_data['price']), 3))
print('R-squared (testing) ', round(poly.score(xtest_poly, test_data['price']), 3))
```

```
PR_Model_4
Mean Squared Error (MSE)  192863.54
R-squared (training)  0.749
R-squared (testing)  0.73
```

In [49]:
```
# polynimial regression 5 degrees
train_data,test_data=train_test_split(data,train_size=0.8,random_state=3)
reg=linear_model.LinearRegression()

features1=['bedrooms','grade','sqft_living','floors','lat','view']

polyfeat=PolynomialFeatures(degree=5)
xtrain_poly=polyfeat.fit_transform(train_data[features1])
xtest_poly=polyfeat.fit_transform(test_data[features1])

poly=linear_model.LinearRegression()
poly.fit(xtrain_poly,train_data['price'])
polypred=poly.predict(xtest_poly)

print('PR_Model_5')
mean_squared_error = metrics.mean_squared_error(test_data['price'], polypred)
print('Mean Squared Error (MSE) ', round(np.sqrt(mean_squared_error), 2))
print('R-squared (training) ', round(poly.score(xtrain_poly, train_data['price']), 3))
print('R-squared (testing) ', round(poly.score(xtest_poly, test_data['price']), 3))
```

```
PR_Model_5
Mean Squared Error (MSE)  223277.49
R-squared (training)  0.752
R-squared (testing)  0.639
```

Polynomial regression findings

PR_Model_3 gives us R-squared (testing) score of 0.731. From above reports, we can conclude that Polynomial regression is best solution.

A polynomial regression model can be used to explain a 73.1% change in price as a result of renovation at a mean sales price of $192,833.78

Findings and Conclusion

Square footage of living space in the home is the highest determinant in house pricing.

The other factors included

Construction and design of the house

Number of floors

Number of bedrooms

Quality of view from house

Location

In [ ]: