Capstone Regression Project

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Business Understanding

My stakeholder, One Call Concepts, Inc. is wanting to prepare for the next busy season. One Call Concepts,known by many different names, including DigSafe, is ran as Washington Utility Notification Center in Washington state. (http://www.callbeforeyoudig.org/washington/faq.asp#q1 (http://www.callbeforeyoudig.org/washington/faq.asp#q1)) They are the middle man when a contractor, or homeowner, or anyone, wants to move dirt around and the locating companies. They maintain databases of underground facilities and use that information to know who to contact using a proprietary software system.

DigSafe would like to be able to predict the final sale prices of properties currently in areas with no view, needing beautification. Working with King County, Washington they have learned that the county is looking to provide incentives to owners of these properties. This predicting model will allow the county to discern what type or amount of incentive to provide the owners. Encouraging economic growth and a more inviting natural habitation throught the county. Which in turn should increase interest in their county from tourists and possible new residents(constituents).

We will begin narrowing the variables by view. We will then remove the price outliers. From the cleaned dataset we will start with the square footage of the lot, total living area and the area above ground.

Data Understanding

What we'll do is use data gathered on the county from 2021 - 2022 home sales data for King County Washington. https://data.kingcounty.gov/ (https://data.kingcounty.gov/) .

Data Preparation

Loading the Data

In [1]:

```
import pandas as pd
import numpy as np
import statsmodels.api as sm
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set_theme(style="ticks", palette="rocket")

```

In [2]:

```
df = pd.read_csv('data/kc_house_data.csv')
```

Data Exploration

In [3]:

```
#review label, types and for null values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30155 entries, 0 to 30154
Data columns (total 25 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             30155 non-null  int64  
 1   date           30155 non-null  object 
 2   price          30155 non-null  float64
 3   bedrooms       30155 non-null  int64  
 4   bathrooms      30155 non-null  float64
 5   sqft_living    30155 non-null  int64  
 6   sqft_lot       30155 non-null  int64  
 7   floors         30155 non-null  float64
 8   waterfront     30155 non-null  object 
 9   greenbelt      30155 non-null  object 
 10  nuisance       30155 non-null  object 
 11  view           30155 non-null  object 
 12  condition      30155 non-null  object 
 13  grade          30155 non-null  object 
 14  heat_source    30123 non-null  object 
 15  sewer_system   30141 non-null  object 
 16  sqft_above     30155 non-null  int64  
 17  sqft_basement  30155 non-null  int64  
 18  sqft_garage    30155 non-null  int64  
 19  sqft_patio     30155 non-null  int64  
 20  yr_built       30155 non-null  int64  
 21  yr_renovated   30155 non-null  int64  
 22  address        30155 non-null  object 
 23  lat            30155 non-null  float64
 24  long           30155 non-null  float64
dtypes: float64(5), int64(10), object(10)
memory usage: 5.8+ MB
```

In [4]:

```
#Looking for which is carrying the most weight, mean, of the numerical c
df.describe()
```

Out[4]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot
count	3.015500e+04	3.015500e+04	30155.000000	30155.000000	30155.000000	3.015500e+04
mean	4.538104e+09	1.108536e+06	3.413530	2.334737	2112.424739	1.672360e+04
std	2.882587e+09	8.963857e+05	0.981612	0.889556	974.044318	6.038260e+04
min	1.000055e+06	2.736000e+04	0.000000	0.000000	3.000000	4.020000e+02
25%	2.064175e+09	6.480000e+05	3.000000	2.000000	1420.000000	4.850000e+03
50%	3.874011e+09	8.600000e+05	3.000000	2.500000	1920.000000	7.480000e+03
75%	7.287100e+09	1.300000e+06	4.000000	3.000000	2619.500000	1.057900e+04
max	9.904000e+09	3.075000e+07	13.000000	10.500000	15360.000000	3.253932e+06

We see that id is the heaviest, then price, sqft_lot, sqft_living, yr_built, sqft_above. ID is the heaviest, but is not relevant for our problem, so we will drop that column first. Price will be our target. We want to know what percentage of the lot the total living space takes up. And how that takes effects the final price of the property.

In [5]:

```
df.corr()
```

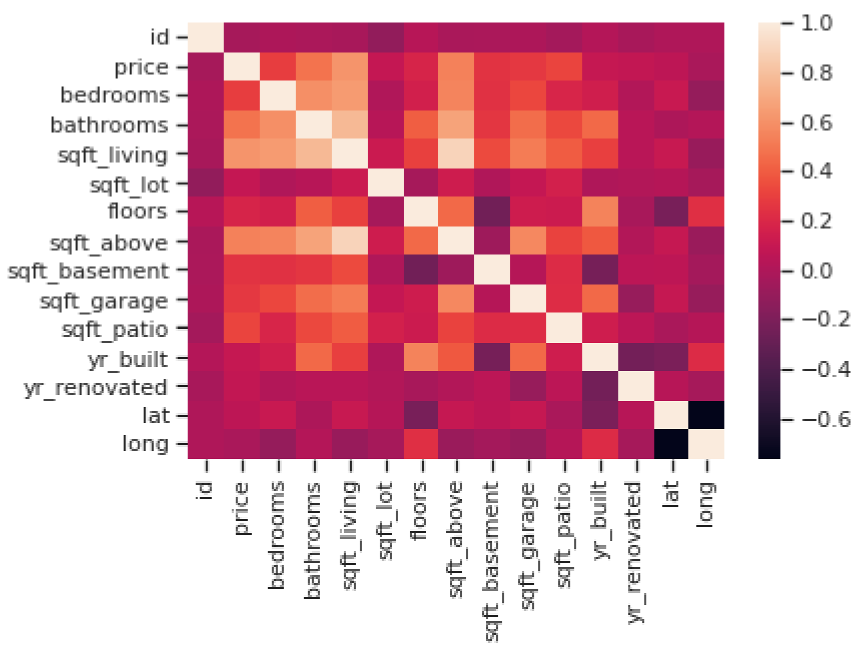
Out[5]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
id	1.000000	-0.034184	-0.006306	-0.012094	-0.027932	-0.119101	0.032043
price	-0.034184	1.000000	0.289204	0.480401	0.608521	0.085730	0.180576
bedrooms	-0.006306	0.289204	1.000000	0.589273	0.637874	0.003306	0.147592
bathrooms	-0.012094	0.480401	0.589273	1.000000	0.772677	0.035886	0.404412
sqft_living	-0.027932	0.608521	0.637874	0.772677	1.000000	0.119563	0.304240
sqft_lot	-0.119101	0.085730	0.003306	0.035886	0.119563	1.000000	-0.032097
floors	0.032043	0.180576	0.147592	0.404412	0.304240	-0.032097	1.000000
sqft_above	-0.023216	0.538651	0.547164	0.674924	0.883984	0.129231	0.448281
sqft_basement	-0.014662	0.245058	0.238502	0.260902	0.338460	0.004111	-0.248093
sqft_garage	-0.007829	0.264169	0.319441	0.457022	0.511740	0.087169	0.132656
sqft_patio	-0.041625	0.313409	0.183439	0.327551	0.396030	0.155250	0.125183
yr_built	0.023071	0.096013	0.146191	0.443648	0.291694	0.001750	0.544646
yr_renovated	-0.029131	0.084786	0.014286	0.040631	0.038499	0.010049	-0.025449
lat	-0.000691	0.063632	0.108758	-0.005225	0.102186	0.030020	-0.218554
long	0.000479	-0.022509	-0.106689	0.017400	-0.087669	-0.034308	0.233781

In [6]:

```
#checking for multicollinearity prior to clean up
sns.heatmap(df.corr())
```

Out[6]: <AxesSubplot:>



In [7]:
```
df.price.corr(df.sqft_lot)
```
Out[7]: 0.0857304213147298

In [8]:
```
df.price.corr(df.sqft_living)
```
Out[8]: 0.6085212366942929

In [9]:
```
#sqft_above is the area of the home that is above ground
df.price.corr(df.sqft_above)
```
Out[9]: 0.5386511734301328

Data Cleaning

In [10]:
```
#check for null values
df.isnull().sum()
```
Out[10]:
```
id                0
date              0
price             0
bedrooms          0
bathrooms         0
sqft_living       0
sqft_lot          0
floors            0
waterfront        0
greenbelt         0
nuisance          0
view              0
condition         0
grade             0
heat_source      32
sewer_system     14
sqft_above        0
sqft_basement     0
sqft_garage       0
```

Our heat_source and sewer_system have a negligent amount of null values in respect to the size of the size of the dataset with 32 and 14 out of 30155 entries. Therefore, we will remove these rows from our dataframe

In [11]:

```
df.dropna(axis = 0, inplace = True)
#confirm null values have been removed
df.isnull().sum()
```

Out[11]:

```
id               0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
greenbelt        0
nuisance         0
view             0
condition        0
grade            0
heat_source      0
sewer_system     0
sqft_above       0
sqft_basement    0
sqft_garage      0
sqft_patio       0
yr_built         0
yr_renovated     0
address          0
lat              0
long             0
dtype: int64
```

In [12]:

```
#check the shape of the data verify as well
df.shape
```

Out[12]:

```
(30111, 25)
```

In [13]:

```
#changing the date column label to date sold to clarify what the informa
sold = {"date" : "datesold"}
df.rename(columns=sold, inplace=True)
df.columns
```

Out[13]:

```
Index(['id', 'datesold', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'greenbelt', 'nuisance', 'view',
       'condition', 'grade', 'heat_source', 'sewer_system', 'sqft_above',
       'sqft_basement', 'sqft_garage', 'sqft_patio', 'yr_built',
       'yr_renovated', 'address', 'lat', 'long'],
      dtype='object')
```

In [14]:
```
#changing our datesold column from type object to type datetime
df.datesold = df.datesold.apply(lambda x: pd.to_datetime(x, yearfirst=Tr
df.dtypes
```

Out[14]:
```
id                        int64
datesold         datetime64[ns]
price                   float64
bedrooms                  int64
bathrooms               float64
sqft_living               int64
sqft_lot                  int64
floors                  float64
waterfront               object
greenbelt                object
nuisance                 object
view                     object
condition                object
grade                    object
heat_source              object
sewer_system             object
sqft_above                int64
sqft_basement             int64
sqft_garage               int64
sqft_patio                int64
yr_built                  int64
yr_renovated              int64
address                  object
lat                     float64
long                    float64
dtype: object
```

In [15]:
```
#creating a new colume, 'age', from the 'yr_renovated' and 'yr_built' co
df["age"] = np.where(df["yr_renovated"] != 0, df.datesold.apply(lambda x
df["datesold"].apply(lambda x:x.year) - df["yr_built"])
df.columns
```

Out[15]:
```
Index(['id', 'datesold', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'greenbelt', 'nuisance', 'view',
       'condition', 'grade', 'heat_source', 'sewer_system', 'sqft_above',
       'sqft_basement', 'sqft_garage', 'sqft_patio', 'yr_built',
       'yr_renovated', 'address', 'lat', 'long', 'age'],
      dtype='object')
```

In [16]:
```
#removing current irrelevant columns
df.drop(axis = 1, labels = {'datesold','id', 'yr_renovated', 'yr_built',
df.columns
```

Out[16]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floor
s',
       'waterfront', 'greenbelt', 'nuisance', 'view', 'condition', 'grade',
       'heat_source', 'sewer_system', 'sqft_above', 'sqft_basement',
       'sqft_garage', 'sqft_patio', 'address', 'age'],
      dtype='object')
```

In [17]:
```
df.dtypes
```

Out[17]:
```
price            float64
bedrooms           int64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront        object
greenbelt         object
nuisance          object
view              object
condition         object
grade             object
heat_source       object
sewer_system      object
sqft_above         int64
sqft_basement      int64
sqft_garage        int64
sqft_patio         int64
address           object
```

In [18]:
```
#review the address data to determine how to create a new zipcode column
df.address.tail()
```

Out[18]:
```
30150    4673 Eastern Avenue North, Seattle, Washington...
30151    4131 44th Avenue Southwest, Seattle, Washingto...
30152    910 Martin Luther King Jr Way, Seattle, Washin...
30153    17127 114th Avenue Southeast, Renton, Washingt...
30154    18615 7th Avenue South, Burien, Washington 981...
Name: address, dtype: object
```

In [19]:
```
df.address[30111][-20:-15]
```

Out[19]:
```
'98115'
```

In [20]:
```
df.address[30111].split(',')[2][-5:]
```

Out[20]:
```
'98115'
```

In [21]:
```
df["zips"] = df.address.apply(lambda x: x[-20:-15])
```

In [22]:
```
#sampling the new 'zips' column to check format
df.zips.sample(5)
```

Out[22]:
```
1040     98107
11620    98001
27833    98103
26301    98115
4091     98199
Name: zips, dtype: object
```

In [23]:
```
df.shape
```

Out[23]:
```
(30111, 21)
```

In [24]:
```python
#now that we've separated the zip codes, we can remove the 'address' col
df.drop(axis = 1, labels = 'address', inplace = True)
```

In [25]:
```python
#verify column removed
df.shape
```

Out[25]:
```
(30111, 20)
```

Modeling

Baseline Model

In [26]:
```python
#review updated dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30111 entries, 0 to 30154
Data columns (total 20 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   price           30111 non-null  float64
 1   bedrooms        30111 non-null  int64
 2   bathrooms       30111 non-null  float64
 3   sqft_living     30111 non-null  int64
 4   sqft_lot        30111 non-null  int64
 5   floors          30111 non-null  float64
 6   waterfront      30111 non-null  object
 7   greenbelt       30111 non-null  object
 8   nuisance        30111 non-null  object
 9   view            30111 non-null  object
 10  condition       30111 non-null  object
 11  grade           30111 non-null  object
 12  heat_source     30111 non-null  object
 13  sewer_system    30111 non-null  object
```

In [27]:
```python
#Checking our 'view' column we see that 'NONE' is the most frequent resp
#at this point we also meet our number of rows, entries, requirements
df.view.describe()
```

Out[27]:
```
count      30111
unique         5
top         NONE
freq       26555
Name: view, dtype: object
```

In [28]:
```
#creating new dataframe with only numerical values
df_num = df[["bedrooms","bathrooms","sqft_living","sqft_lot","floors","s
df_num.dtypes
```

Out[28]:
```
bedrooms           int64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
sqft_above         int64
sqft_basement      int64
sqft_garage        int64
sqft_patio         int64
age                int64
dtype: object
```

In [29]:
```
#using just the initial numerical values to create baseline model
pred = df_num
target = df.price
```

In [30]:
```
#assigning X and y values
X = pred
y = target
```

In [31]:
```
baseline = sm.OLS(y, sm.add_constant(X))
results = baseline.fit()
print(results.summary())
```

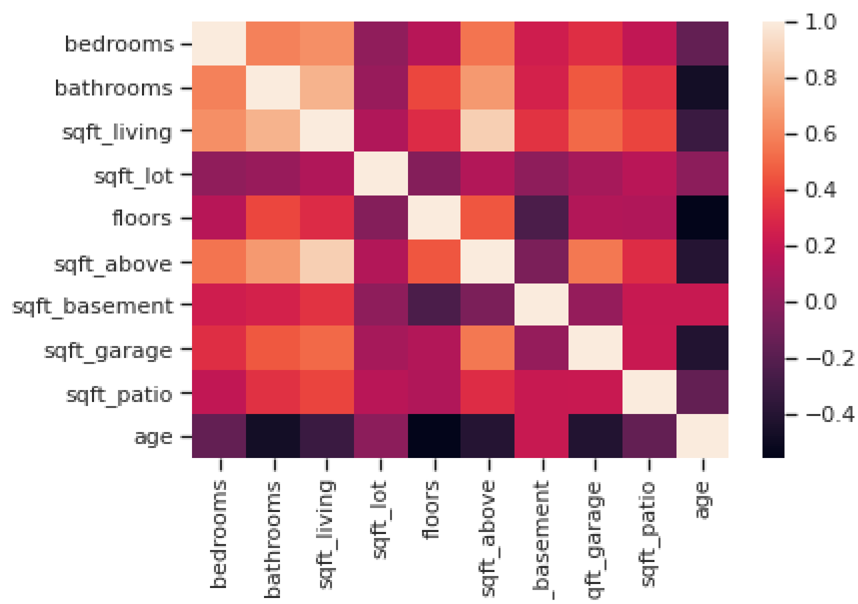
```
=====
Dep. Variable:                  price   R-squared:
0.409
Model:                            OLS   Adj. R-squared:
0.409
Method:                 Least Squares   F-statistic:
2086.
Date:                Mon, 03 Oct 2022   Prob (F-statistic):
0.00
Time:                        02:21:11   Log-Likelihood:             -4.475
1e+05
No. Observations:               30111   AIC:                          8.95
0e+05
Df Residuals:                   30100   BIC:                          8.95
1e+05
Df Model:                          10
Covariance Type:            nonrobust
==========================================================================
========
                    coef    std err          t      P>|t|      [0.025
```

Our R-squared is less 40.9% using just the current numerical values as predictors and 'price' as our target. Our F-statistic and P-values are sbelow .5 as well.

We will create some dummy variables for our catagorical columns

In [32]:
```
#checking for multicollinearity
sns.heatmap(X.corr())
```

Out[32]: <AxesSubplot:>



We see that 'sqft_living' and 'sqft_above' (how many square feet of living space is above ground) are most correlated

In [33]:
```
df.corr()
```

Out[33]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above
price	1.000000	0.288954	0.480337	0.608616	0.086550	0.180589	0.538631
bedrooms	0.288954	1.000000	0.588035	0.637048	0.006215	0.146871	0.546221
bathrooms	0.480337	0.588035	1.000000	0.772226	0.038028	0.404291	0.674239
sqft_living	0.608616	0.637048	0.772226	1.000000	0.122271	0.303911	0.883733
sqft_lot	0.086550	0.006215	0.038028	0.122271	1.000000	-0.031555	0.131756
floors	0.180589	0.146871	0.404291	0.303911	-0.031555	1.000000	0.448245
sqft_above	0.538631	0.546221	0.674239	0.883733	0.131756	0.448245	1.000000
sqft_basement	0.245005	0.237957	0.260684	0.338387	0.004457	-0.248466	-0.067306
sqft_garage	0.263674	0.318110	0.456264	0.510967	0.089318	0.132363	0.559972
sqft_patio	0.313789	0.183660	0.327982	0.396530	0.154575	0.125016	0.312593
age	-0.126909	-0.156650	-0.471854	-0.312269	-0.003427	-0.552862	-0.397502

In [34]:

```
df.sqft_above.corr(df.sqft_living)
```

Out[34]:

```
0.8837330776377422
```

So our baseline model is:

Price = -4477 + -0.0928(sqft_lot) + 301.8909(sqft_above) + 328.2023(sqft_living)

Model Iteration

In [35]:

```
#reviewing data for catagorical columns
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30111 entries, 0 to 30154
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   price          30111 non-null  float64
 1   bedrooms       30111 non-null  int64  
 2   bathrooms      30111 non-null  float64
 3   sqft_living    30111 non-null  int64  
 4   sqft_lot       30111 non-null  int64  
 5   floors         30111 non-null  float64
 6   waterfront     30111 non-null  object 
 7   greenbelt      30111 non-null  object 
 8   nuisance       30111 non-null  object 
 9   view           30111 non-null  object 
 10  condition      30111 non-null  object 
 11  grade          30111 non-null  object 
 12  heat_source    30111 non-null  object 
 13  sewer_system   30111 non-null  object 
 14  sqft_above     30111 non-null  int64  
 15  sqft_basement  30111 non-null  int64  
 16  sqft_garage    30111 non-null  int64  
 17  sqft_patio     30111 non-null  int64  
 18  age            30111 non-null  int64  
 19  zips           30111 non-null  object 
dtypes: float64(3), int64(8), object(9)
memory usage: 5.8+ MB
```

In [36]:

```
#reviewing a sample of the types of values in the catagorical values
df[["waterfront", "greenbelt", "nuisance", "view", "condition", "grade",
```

Out[36]:

```
waterfront  greenbelt  nuisance  view    condition  grade          heat_
source  sewer_system  zips
NO          NO         NO        NONE    Average    8 Good         Gas
PUBLIC        98042    204

98038    184

98010    163

98058    139
                                                    7 Average      Gas
PUBLIC        98038    135

...
                                         Fair       6 Low Average  Oil
PUBLIC        98118      1

98117      1
```

In [37]:

```
#creating a dataframe catagorical dummy values, excluding zipcodes as we
#and they will highly skew our results
cats= ["waterfront", "greenbelt", "nuisance", "view", "condition", "grad
df_dummy= pd.get_dummies(data = df, columns = cats, drop_first=True)
df_dummy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30111 entries, 0 to 30154
Data columns (total 43 columns):
 #   Column                              Non-Null Count  Dtype
---  ------                              --------------  -----
 0   price                               30111 non-null  float64
 1   bedrooms                            30111 non-null  int64
 2   bathrooms                           30111 non-null  float64
 3   sqft_living                         30111 non-null  int64
 4   sqft_lot                            30111 non-null  int64
 5   floors                              30111 non-null  float64
 6   sqft_above                          30111 non-null  int64
 7   sqft_basement                       30111 non-null  int64
 8   sqft_garage                         30111 non-null  int64
 9   sqft_patio                          30111 non-null  int64
 10  age                                 30111 non-null  int64
 11  zips                                30111 non-null  object
 12  waterfront_YES                      30111 non-null  uint8
 13  greenbelt_YES                       30111 non-null  uint8
```

In [38]:

```
#removing spaces from column names and replacing with '_'
df_dummy.columns = df_dummy.columns.str.replace(' ', '_')
df_dummy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30111 entries, 0 to 30154
Data columns (total 43 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   price                           30111 non-null  float64
 1   bedrooms                        30111 non-null  int64  
 2   bathrooms                       30111 non-null  float64
 3   sqft_living                     30111 non-null  int64  
 4   sqft_lot                        30111 non-null  int64  
 5   floors                          30111 non-null  float64
 6   sqft_above                      30111 non-null  int64  
 7   sqft_basement                   30111 non-null  int64  
 8   sqft_garage                     30111 non-null  int64  
 9   sqft_patio                      30111 non-null  int64  
 10  age                             30111 non-null  int64  
 11  zips                            30111 non-null  object 
 12  waterfront_YES                  30111 non-null  uint8  
 13  greenbelt_YES                   30111 non-null  uint8  
```

In [39]:

```
#creating dataframe with only rows where 'view_NONE' is True
nview_df = df_dummy[df_dummy.view_NONE == 1]
nview_df.view_NONE.value_counts()
```

Out[39]:

```
1    26555
Name: view_NONE, dtype: int64
```

In [40]:

```
#confirming it's the entire df
nview_df.shape
```

Out[40]:

```
(26555, 43)
```

In [41]:

```
#remove currently irrelevant 'view' dummy values that are NaN

nview_df.drop(axis = 1, labels = {'view_EXCELLENT','view_FAIR', 'view_GO
#verify columns removed
nview_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26555 entries, 0 to 30154
Data columns (total 39 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   price                            26555 non-null  float64
 1   bedrooms                         26555 non-null  int64  
 2   bathrooms                        26555 non-null  float64
 3   sqft_living                      26555 non-null  int64  
 4   sqft_lot                         26555 non-null  int64  
 5   floors                           26555 non-null  float64
 6   sqft_above                       26555 non-null  int64  
 7   sqft_basement                    26555 non-null  int64  
 8   sqft_garage                      26555 non-null  int64  
 9   sqft_patio                       26555 non-null  int64  
 10  age                              26555 non-null  int64  
 11  zips                             26555 non-null  object 
 12  waterfront_YES                   26555 non-null  uint8  
 13  greenbelt_YES                    26555 non-null  uint8  
 14  nuisance_YES                     26555 non-null  uint8  
 15  condition_Fair                   26555 non-null  uint8  
 16  condition_Good                   26555 non-null  uint8  
 17  condition_Poor                   26555 non-null  uint8  
 18  condition_Very_Good              26555 non-null  uint8  
 19  grade_11_Excellent               26555 non-null  uint8  
 20  grade_12_Luxury                  26555 non-null  uint8  
 21  grade_13_Mansion                 26555 non-null  uint8  
 22  grade_2_Substandard              26555 non-null  uint8  
 23  grade_3_Poor                     26555 non-null  uint8  
 24  grade_4_Low                      26555 non-null  uint8  
 25  grade_5_Fair                     26555 non-null  uint8  
 26  grade_6_Low_Average              26555 non-null  uint8  
 27  grade_7_Average                  26555 non-null  uint8  
 28  grade_8_Good                     26555 non-null  uint8  
 29  grade_9_Better                   26555 non-null  uint8  
 30  heat_source_Electricity/Solar    26555 non-null  uint8  
 31  heat_source_Gas                  26555 non-null  uint8  
 32  heat_source_Gas/Solar            26555 non-null  uint8  
 33  heat_source_Oil                  26555 non-null  uint8  
 34  heat_source_Oil/Solar            26555 non-null  uint8  
 35  heat_source_Other                26555 non-null  uint8  
 36  sewer_system_PRIVATE_RESTRICTED  26555 non-null  uint8  
 37  sewer_system_PUBLIC              26555 non-null  uint8  
 38  sewer_system_PUBLIC_RESTRICTED   26555 non-null  uint8  
dtypes: float64(3), int64(8), object(1), uint8(27)
memory usage: 3.3+ MB
```

```
/opt/conda/lib/python3.9/site-packages/pandas/core/frame.py:4901: Setting
WithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  return super().drop(
```

In [42]:
```python
#checking size of new dataframe
nview_df.shape
```

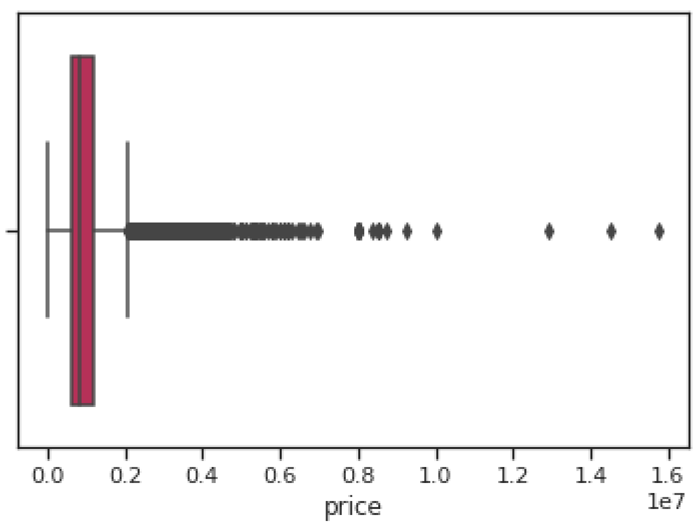
Out[42]:
```
(26555, 39)
```

In [43]:
```python
#determining upper and lower price of these no view property
nview_df.price.describe()
```

Out[43]:
```
count    2.655500e+04
mean     1.018818e+06
std      6.757027e+05
min      2.736000e+04
25%      6.299500e+05
50%      8.299500e+05
75%      1.212968e+06
max      1.574000e+07
Name: price, dtype: float64
```

In [44]:
```python
#plotting 'price' values of range_df
sns.boxplot(data = nview_df, x= 'price', color = "blue", palette = "rock
```

Out[44]:
```
<AxesSubplot:xlabel='price'>
```



In [45]:
```python
#removing unwanted outliers
min_reach, max_reach = nview_df.price.quantile([0.05, 0.95])
min_reach, max_reach
```

Out[45]:
```
(420000.0, 2220000.0)
```

In [46]:

```python
nview_df[nview_df.price > max_reach]
```

Out[46]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_baseme
27	4500000.0	4	3.0	2760	13150	1.5	2760	
36	2450000.0	4	3.5	2300	8370	2.0	2300	
43	3850000.0	5	3.5	4180	209959	1.0	4180	
84	2500000.0	4	3.5	3120	3801	2.0	2540	11
118	3000000.0	3	1.5	2040	14284	1.0	2040	
...	...	...	...	...	...	...	...	
30100	2588000.0	5	4.5	3580	5719	2.0	3580	
30106	2875000.0	3	2.0	1900	8800	1.0	1600	11
30126	3754500.0	4	5.5	5200	10790	2.0	5200	
30130	2435000.0	5	3.0	3920	8414	1.0	2210	22
30140	2650000.0	4	3.5	3270	9200	2.0	2410	10

1324 rows × 39 columns

In [47]:

```python
nview_df[nview_df.price < min_reach]
```

Out[47]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_basemen
45	315000.0	3	1.0	1150	6477	1.0	1150	
52	235000.0	2	1.0	700	14750	1.5	700	
56	37440.0	4	2.5	1670	13703	1.0	1140	110
67	275000.0	4	1.0	1700	7692	1.0	1200	115
81	370000.0	3	1.5	1040	8550	1.0	1040	
...	...	...	...	...	...	...	...	.
30040	315500.0	3	1.0	1290	7500	1.5	1290	
30071	400000.0	1	1.0	760	148975	2.0	760	
30092	345629.0	3	3.5	1430	1078	2.0	1100	33
30125	337500.0	3	1.0	1350	6628	1.0	1350	
30146	380000.0	3	1.0	860	7805	1.0	860	

1295 rows × 39 columns

In [48]:
```python
#creating new dataframe to represent view_NONE values only within our ne
range_df = nview_df[(nview_df.price < max_reach) & (nview_df.price > min
range_df
```

Out[48]:

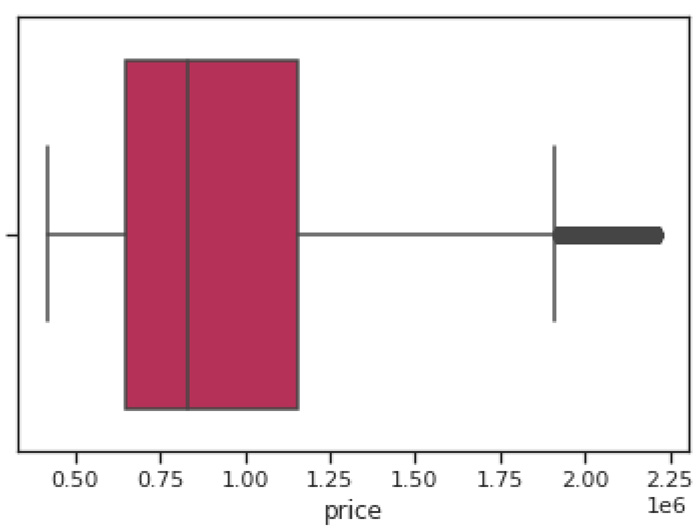
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_base
0	675000.0	4	1.0	1180	7140	1.0	1180	
4	592500.0	2	2.0	1120	758	2.0	1120	
5	625000.0	2	1.0	1190	5688	1.0	1190	
7	820000.0	3	2.5	2214	3506	2.0	2214	
8	780000.0	4	2.5	2340	8125	2.0	2340	
...	...	...	...	...	...	...	...	
30149	719000.0	3	2.5	1270	1141	2.0	1050	
30150	1555000.0	5	2.0	1910	4000	1.5	1600	
30152	800000.0	3	2.0	1620	3600	1.0	940	
30153	775000.0	3	2.5	2570	2889	2.0	1830	
30154	500000.0	3	1.5	1200	11058	1.0	1200	

In [49]:
```python
range_df.shape
```

Out[49]: (23879, 39)

In [50]:
```python
#plotting 'price' values of range_df update
sns.boxplot(data = range_df, x= 'price', color = "blue", palette = "rock
```

Out[50]: <AxesSubplot:xlabel='price'>



In [51]:

```
#reviewing for values of 0, removing these values and zips at this time
range_df.sum()
```

Out[51]:

```
price                                                           2253
3040432.0
bedrooms
80524
bathrooms
53920.0
sqft_living
47050176
sqft_lot
331211730
floors
36903.0
sqft_above
40897434
sqft_basement
10000265
sqft_garage
7673447
sqft_patio
4601616
age
1024226
zips                                9805598027981339803098023981449803168106
980929...
waterfront_YES
39
greenbelt_YES
608
nuisance_YES
4030
condition_Fair
148
condition_Good
6378
condition_Poor
29
condition_Very_Good
2581
grade_11_Excellent
65
grade_12_Luxury
5
grade_13_Mansion
0
grade_2_Substandard
0
grade_3_Poor
3
grade_4_Low
21
grade_5_Fair
228
grade_6_Low_Average
2173
```

```
grade_7_Average
10177
grade_8_Good
8000
grade_9_Better
2667
heat_source_Electricity/Solar
37
heat_source_Gas
16412
heat_source_Gas/Solar
54
heat_source_Oil
2187
heat_source_Oil/Solar
3
heat_source_Other
10
sewer_system_PRIVATE_RESTRICTED
1
sewer_system_PUBLIC
20681
sewer_system_PUBLIC_RESTRICTED
2
dtype: object
```

In [52]:

```
#create new df removing currently irrelevant dummy, 'zips' columns
clean_df = range_df.drop(axis = 1, labels = {'zips','grade_12_Luxury', '
#verify columns removed
clean_df.info()
```

```
Data columns (total 35 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   price                           23879 non-null  float64
 1   bedrooms                        23879 non-null  int64
 2   bathrooms                       23879 non-null  float64
 3   sqft_living                     23879 non-null  int64
 4   sqft_lot                        23879 non-null  int64
 5   floors                          23879 non-null  float64
 6   sqft_above                      23879 non-null  int64
 7   sqft_basement                   23879 non-null  int64
 8   sqft_garage                     23879 non-null  int64
 9   sqft_patio                      23879 non-null  int64
 10  age                             23879 non-null  int64
 11  waterfront_YES                  23879 non-null  uint8
 12  greenbelt_YES                   23879 non-null  uint8
 13  nuisance_YES                    23879 non-null  uint8
 14  condition_Fair                  23879 non-null  uint8
 15  condition_Good                  23879 non-null  uint8
 16  condition_Poor                  23879 non-null  uint8
```

In [53]:

```
preds_2 = clean_df.drop(labels = ['price'], axis = 1)
target_2 = clean_df.price
```

In [54]:
```
X_2 = preds_2
y_2 = target_2
```

In [55]:
```
model_2 = sm.OLS(y_2, sm.add_constant(X_2))
results_2 = model_2.fit()
print(results_2.summary())
```

```
                            OLS Regression Results
=========================================================================
=====
Dep. Variable:                  price   R-squared:
0.429
Model:                            OLS   Adj. R-squared:
0.428
Method:                 Least Squares   F-statistic:
526.6
Date:                Mon, 03 Oct 2022   Prob (F-statistic):
0.00
Time:                        02:21:13   Log-Likelihood:           -3.350
1e+05
No. Observations:               23879   AIC:                        6.70
1e+05
Df Residuals:                   23844   BIC:                        6.70
4e+05
Df Model:                          34
Covariance Type:            nonrobust
```

Our R-squared using is now 42.9%, F-statistic is below 0. We have mostly P-statistics above .5, but some are above this max. Looking at our values for 'sqft_lot', 'sqft_living' and 'sqft_above', their P-statistics are below 0. So, we can move forward using those as our predictor values.

In [56]:
```
# Check our current data's correlations with price
clean_df.price.corr(df.sqft_lot)
```

Out[56]: 0.0897269272686582

In [57]:
```
clean_df.price.corr(df.sqft_living)
```

Out[57]: 0.5559064554200225

In [58]:
```
clean_df.price.corr(df.sqft_above)
```

Out[58]: 0.4862121999941026

In [59]:

```
1 clean_df.price.describe()
```

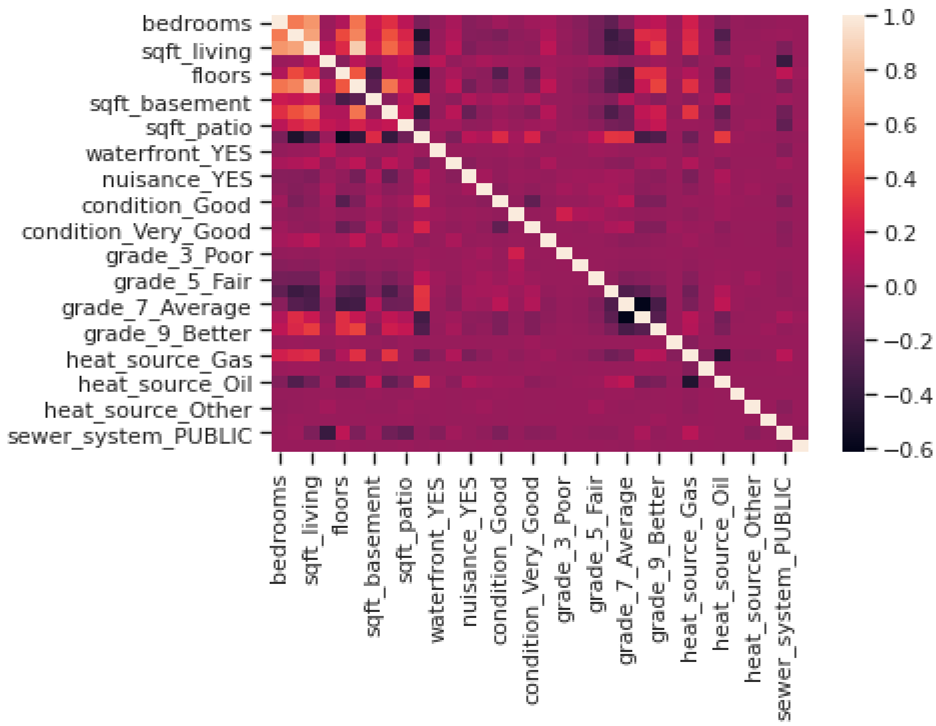
Out[59]:

```
count    2.387900e+04
mean     9.436342e+05
std      3.965928e+05
min      4.210000e+05
25%      6.500000e+05
50%      8.299500e+05
75%      1.155000e+06
max      2.215000e+06
Name: price, dtype: float64
```

In [60]:

```
1 sns.heatmap(X_2.corr())
```

Out[60]: <AxesSubplot:>



Final Model

Regression Results

The model represented is:

Price = 812,600 + 0.3841(sqft_lot) + 96.8246(sqft_above) + 94.7702(sqft_living)

Keeping in mind we are reviewing data only pertaining to original entries listed as view_NONE between the 95th and 5th percentiles of

price:

Overall, this model is statistically significant with a t-statistic p-value and overall F_p-value still below 5%.

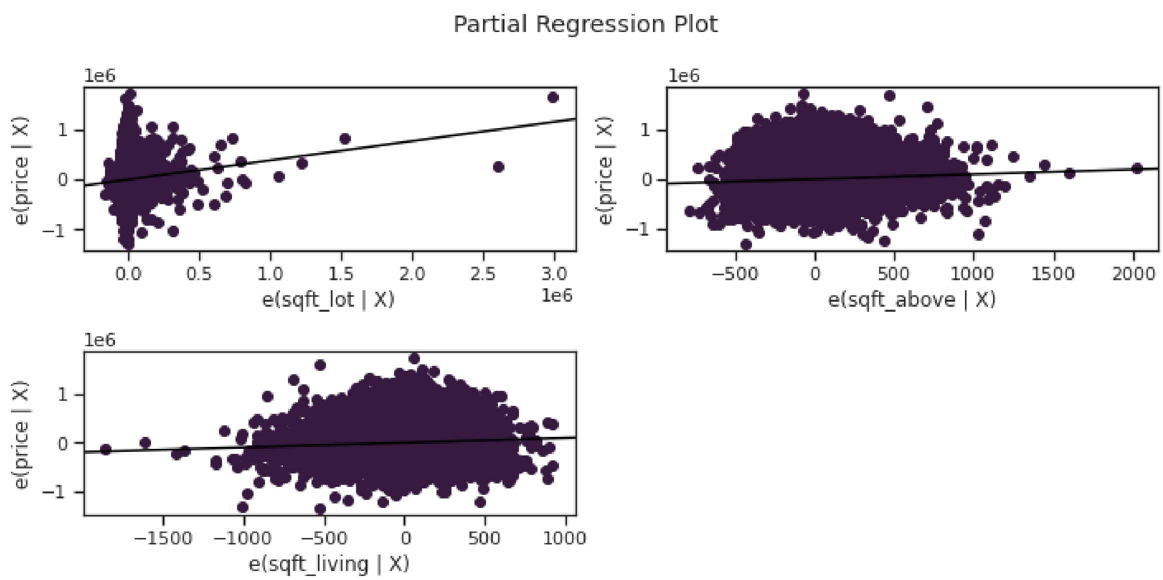
This shows our sqft_lot, sqft_above and sqft_living parameters each significantly impact price

For each sf of increase in sqft_Lot we only gain .38 units in Price, even though it's p-value is still below 5%.

This shows us that sqft_lot is not a good fit for this linear regression model

In [61]:

```
# This will model our chosen predictors alone without the effects of the
fig = plt.figure(figsize=(10,5))
sm.graphics.plot_partregress_grid(results_2, exog_idx=["sqft_lot", "sqft
plt.tight_layout()
plt.show()
```



Conclusion

In conclusion, we can see that our initially chosen parameters sqft_lot, sqft_above, and sqft_living have some significance in determining final home selling price. With that said sqft_lot for this particular set of data, does not seem to add much to the price. However, their may be other factors that we may want to consider. We need to discern if the view values of 'NONE' are accurate, really NaN values, or are misleading in some other fashion. Other considerations may be the factors of condition and grade as they have p-values below 5% as well, we also see a larger stastistically significant impact on sales price of these homes.

Thank you,

Scharmaine Chappell