UTILIZING MULTIPLE REGRESSION ANALYSIS TO PREDICT HOUSE PRICES IN KING COUNTY

Business Understanding

Some homeowners are eager to sell, but certain houses are undervalued due to wear and tear. Housing prices can fluctuate based on market trends and buyer preferences. Homeowners aim to increase their property value for higher selling prices, but they lack knowledge and insights on effective strategies to do so.

Our analysis and modelling aimed to help homeowners make informed decisions by assessing how factors like home condition, size, renovations and more can impact their home's estimated value.

Business Questions

1. Does the year the house was built and/or renovated affect the sale price of a house?
2. Do qualitative features of a house (grade, condition e.tc) affect its sale price?
3. Do quantitative features of a house (bedrooms, sqft of spaces) affect it’s sale price ?

Data Understanding

The dataset provided (`kc_house_data.csv`) has information on the features of single-family house sales between 2014 and 2015. More information on this features is found in this link [Residential Glossary of Terms (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r#g)](https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r#g). The file `column_names.md` contains column descriptions.

- The analysis was based on King County data set.
- It had a total of 21,597 records, containing 20 columns and 21,597 rows.
- Timeframe of the data is 2014 to 2015.
- Each row contains data of an individual house, which is indexed by a unique house id.
- The data has numerical and categorical variables.

Data Preparation, Processing, EDA

Libraries

In [47]:

```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
%matplotlib inline

import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split


import warnings
```

Import the Data

In [48]:

```
# import and view the first five records
data = pd.read_csv("kc_house_data.csv")
data.head()
```

Out[48]:

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

5 rows × 21 columns

In [49]:

```
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
```

The data has 21 columns and 21597 rows. The descriptions are in the Residential Glossary of Terms (linked above in the Important links section).

In [50]:

```
data.describe()
```

Out[50]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06

In [51]:

```
data.sample(20)
```

Out[51]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	
11496	2025079037	10/1/2014	510000.0	3	2.25	2750	219542	2.0	NO	N
19274	3416600490	7/31/2014	675000.0	3	2.25	1780	4252	2.0	NO	N
19390	9202650040	9/26/2014	401000.0	3	1.00	1120	8321	1.0	NO	N
498	9274202270	8/18/2014	625000.0	2	1.50	1490	5750	1.5	NO	N
4869	3832710680	7/21/2014	215000.0	4	2.00	1540	7575	1.0	NaN	N
18472	1238500978	9/22/2014	365000.0	3	1.00	950	8450	1.0	NO	N
1746	9424400200	5/15/2014	451555.0	2	1.00	1320	4520	1.0	NO	

Create a Copy of the dataFrame

In [52]:

```
data_copy = data.copy()
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
```

Processing the Data

There are a few issues with the data.

1. Missing values in the `yr_renovated` column.
2. The `sqft_basement` feature has string values instead of numeral values.

Correcting Data Types

There is a problem with the `sqft_basement` feature. There are values denoted as "?" that need to be replaced with 0.

In [53]:

```
data_copy["sqft_basement"] = data_copy.sqft_basement.replace("?", 0.0)
data_copy.sqft_basement.value_counts()
```

Out[53]:

```
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: sqft_basement, Length: 304, dtype: int64
```

In [54]:

```
# check that the data correction was successful

data_copy['sqft_basement']= data_copy.sqft_basement.astype('float64')
data_copy["sqft_basement"].sample(12)
```

Out[54]:

```
6657       0.0
7311       0.0
2332     790.0
10943      0.0
11150      0.0
3000     980.0
11605    600.0
8366     460.0
15644      0.0
2345       0.0
4799     610.0
10846      0.0
Name: sqft_basement, dtype: float64
```

Encoding Categorical Variables

1. `view`

The `view` feature had only 63 missing values. All were replaced with 0 (houses with no views) while the rest of the elements were graded with numbers.

In [55]:

```
data_copy["view"].replace("FAIR", 1, inplace = True)
data_copy["view"].replace("AVERAGE", 2, inplace = True)
data_copy["view"].replace("GOOD", 3, inplace = True)
data_copy["view"].replace("EXCELLENT", 4, inplace = True)
data_copy["view"].replace("NONE", 0, inplace = True)
data_copy["view"].fillna(value = 0, inplace = True)
```

In [56]:

```
data_copy["view"].head(22)
```

Out[56]:

```
0     0.0
1     0.0
2     0.0
3     0.0
4     0.0
5     0.0
6     0.0
7     0.0
8     0.0
9     0.0
10    0.0
11    0.0
12    0.0
13    0.0
14    0.0
15    3.0
16    0.0
17    0.0
18    0.0
19    0.0
20    0.0
21    4.0
Name: view, dtype: float64
```

2. `grade``

In [57]:

```
grading = data_copy["grade"].unique()
grading.sort()
grading
```

Out[57]:

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

In [58]:

```
data_copy["grade_levels"] = data_copy['grade'].str.extract('(\d+)').astype('int64')
print(data_copy.head(10))
```

```
           id        date      price  bedrooms  bathrooms  sqft_living  \
0  7129300520  10/13/2014   221900.0         3       1.00         1180
1  6414100192   12/9/2014   538000.0         3       2.25         2570
2  5631500400   2/25/2015   180000.0         2       1.00          770
3  2487200875   12/9/2014   604000.0         4       3.00         1960
4  1954400510   2/18/2015   510000.0         3       2.00         1680
5  7237550310   5/12/2014  1230000.0         4       4.50         5420
6  1321400060   6/27/2014   257500.0         3       2.25         1715
7  2008000270   1/15/2015   291850.0         3       1.50         1060
8  2414600126   4/15/2015   229500.0         3       1.00         1780
9  3793500160   3/12/2015   323000.0         3       2.50         1890

   sqft_lot  floors waterfront  view  ... sqft_above sqft_basement  yr_bui
lt  \
0      5650     1.0        NaN   0.0  ...       1180           0.0      19
55
1      7242     2.0         NO   0.0  ...       2170         400.0      19
51
2     10000     1.0         NO   0.0  ...        770           0.0      19
33
3      5000     1.0         NO   0.0  ...       1050         910.0      19
65
4      8080     1.0         NO   0.0  ...       1680           0.0      19
87
5    101930     1.0         NO   0.0  ...       3890        1530.0      20
01
6      6819     2.0         NO   0.0  ...       1715           0.0      19
95
7      9711     1.0         NO   0.0  ...       1060           0.0      19
63
8      7470     1.0         NO   0.0  ...       1050         730.0      19
60
9      6560     2.0         NO   0.0  ...       1890           0.0      20
03

   yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15  \
0           0.0    98178  47.5112 -122.257           1340        5650
1        1991.0    98125  47.7210 -122.319           1690        7639
2           NaN    98028  47.7379 -122.233           2720        8062
3           0.0    98136  47.5208 -122.393           1360        5000
4           0.0    98074  47.6168 -122.045           1800        7503
5           0.0    98053  47.6561 -122.005           4760      101930
6           0.0    98003  47.3097 -122.327           2238        6819
7           0.0    98198  47.4095 -122.315           1650        9711
8           0.0    98146  47.5123 -122.337           1780        8113
9           0.0    98038  47.3684 -122.031           2390        7570

   grade_levels
0             7
1             7
2             6
3             7
4             8
5            11
6             7
7             7
8             7
9             7

[10 rows x 22 columns]
```

3. condition

In [59]:

```
data_copy["condition"].unique()
```

Out[59]:

```
array(['Average', 'Very Good', 'Good', 'Poor', 'Fair'], dtype=object)
```

In [60]:

```
condition_mapping = {
    'Average': 0,
    'Very Good': 1,
    'Good': 2,
    'Poor': 3,
    'Fair': 4
}

# Assuming you have a pandas DataFrame named 'kc_data'
data_copy['condition_numeric'] = data_copy['condition'].map(condition_mapping)
```

4. waterfront

The `waterfront` feature also has NaN values. Since the feature is a string, the elements were replaced with numerical values and the missing values replaced with 0 to denote that the house has no waterfront.

In [61]:

```
# There was YES, NO or NaN

data_copy['waterfront'].replace("YES", 1, inplace = True)
data_copy['waterfront'].replace("NO", 0, inplace = True)
data_copy['waterfront'].fillna(value = 0, inplace = True)
```

Missing Values

The `yr_renovated` missing values can be replaced with zero to indicate that renovation has not been done.

In [62]:

```
data_copy.yr_renovated.fillna(0.0, inplace=True)
```

In [63]:

```
data_copy.waterfront.isna().sum()
```

Out[63]:

```
0
```

In [64]:

```
data_copy.isna().sum()
```

Out[64]:

```
id               0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
```

Outliers

- The bedroom feature had some houses with 11 and 33 bedrooms. This may affect the quality of the graph. Hence, the rows will be dropped.

In [65]:

```
data_copy = data_copy[data_copy["bedrooms"] <= 10]
data_copy.bedrooms.value_counts()
```

Out[65]:

```
3     9824
4     6882
2     2760
5     1601
6      272
1      196
7       38
8       13
9        6
10       3
Name: bedrooms, dtype: int64
```

Dropping Some Columns

In [66]:

```
data_copy.columns
```

Out[66]:

```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcod
e',
       'lat', 'long', 'sqft_living15', 'sqft_lot15', 'grade_levels',
       'condition_numeric'],
      dtype='object')
```

We decided to keep specific columns as predictor variables of the price variable. Hence, we dropped the other columns early on in the analysis by creating a dataframe with the selected columns. Our columns of choice were: `price` , `sqft_living` , `sqft_lot` , `sqft_basement` , `sqft_above` , `yr_built` , `bedrooms` , `bathrooms` , `yr_renovated` , `grade` , `condition` , `waterfront` , `view` , `floors` .

Henceforth, `id` , `date` , `zipcode` , `lat` , `long` , `sqft_living15` , `sqft_lot15` were dropped as they were not relevant to our modelling.

In [67]:

```
kc_data = data_copy[["price", "bedrooms", "bathrooms", "sqft_living", "sqft_lot", "sqft_b
print(kc_data.dtypes)
```

```
price                float64
bedrooms               int64
bathrooms            float64
sqft_living            int64
sqft_lot               int64
sqft_basement        float64
sqft_above             int64
yr_built               int64
yr_renovated         float64
grade                 object
condition             object
waterfront           float64
view                 float64
floors               float64
grade_levels           int64
condition_numeric      int64
dtype: object
```

In [68]:

```
kc_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21595 entries, 0 to 21596
Data columns (total 16 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   price              21595 non-null  float64
 1   bedrooms           21595 non-null  int64  
 2   bathrooms          21595 non-null  float64
 3   sqft_living        21595 non-null  int64  
 4   sqft_lot           21595 non-null  int64  
 5   sqft_basement      21595 non-null  float64
 6   sqft_above         21595 non-null  int64  
 7   yr_built           21595 non-null  int64  
 8   yr_renovated       21595 non-null  float64
 9   grade              21595 non-null  object 
 10  condition          21595 non-null  object 
 11  waterfront         21595 non-null  float64
 12  view               21595 non-null  float64
 13  floors             21595 non-null  float64
 14  grade_levels       21595 non-null  int64  
 15  condition_numeric  21595 non-null  int64  
dtypes: float64(7), int64(7), object(2)
memory usage: 2.8+ MB
```

In [69]:

```
kc_data.head()
```

Out[69]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	sqft_basement	sqft_above	yr_built
0	221900.0	3	1.00	1180	5650	0.0	1180	1955
1	538000.0	3	2.25	2570	7242	400.0	2170	1951
2	180000.0	2	1.00	770	10000	0.0	770	1933
3	604000.0	4	3.00	1960	5000	910.0	1050	1965
4	510000.0	3	2.00	1680	8080	0.0	1680	1987

In [70]:

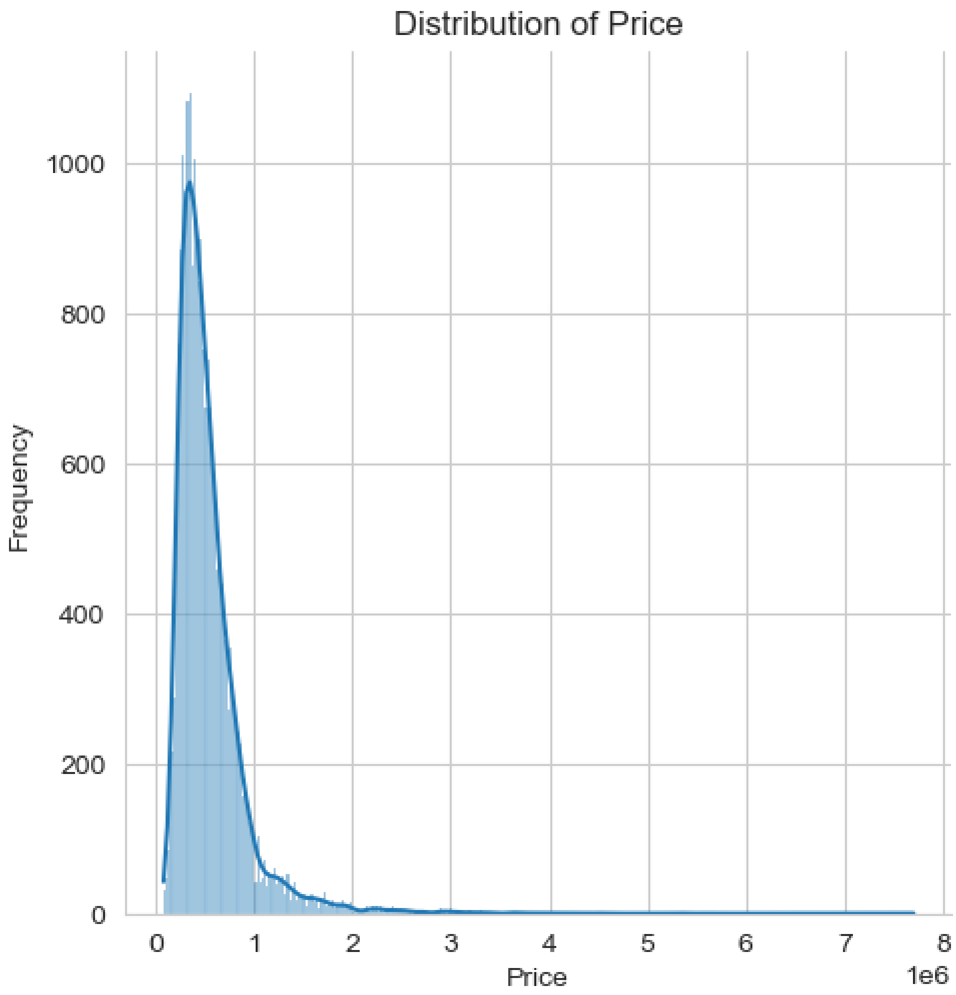
```
kc_data.describe()
```

Out[70]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	sqft_basement
count	2.159500e+04	21595.000000	21595.000000	21595.000000	2.159500e+04	21595.000000
mean	5.402929e+05	3.371475	2.115802	2080.300579	1.510030e+04	285.688400
std	3.673845e+05	0.902643	0.768992	918.121966	4.141445e+04	439.830437
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	0.000000
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	0.000000
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.620000e+03	0.000000
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068600e+04	550.000000
max	7.700000e+06	10.000000	8.000000	13540.000000	1.651359e+06	4820.000000

In [71]:

```
#Set plot style
sns.set_style("whitegrid")

# Create distribution plot
sns.displot(kc_data['price'], kde=True)

# Set plot title and labels
plt.title("Distribution of Price")
plt.xlabel("Price")
plt.ylabel("Frequency")

# Show plot
plt.show()
```



Visualizing the Categorical Variables - Grade, Waterfront

Observations

Most houses sold were of average grade and condition.

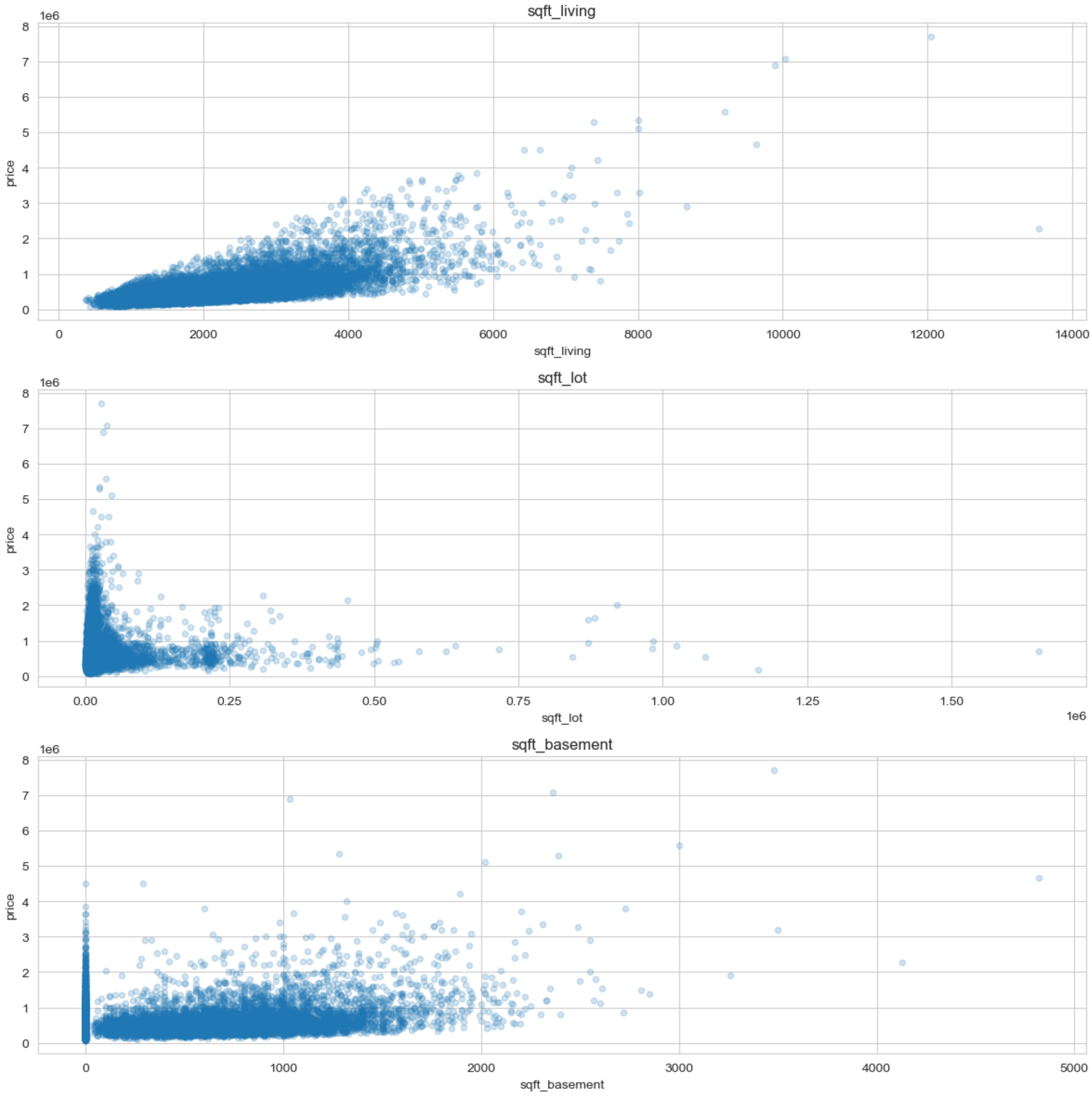
Most did not have a waterfront.

Majority sold had no view.

Visualizing the Continuous Variables vs `price` - `sqft_living`, `sqft_lot`, `sqft_basement`

In [72]:

```
fig, axes = plt.subplots(nrows=3, ncols=1, figsize=(12,12))

for xcol, ax in zip(["sqft_living", "sqft_lot", "sqft_basement"], axes):
    kc_data.plot(kind = "scatter", x = xcol, y = "price", ax = ax, alpha=0.2)

    ax.set_title(xcol)

fig.tight_layout()
```



Observation

`sqft_living` and `sqft_basement` have a linear relationship with the `price`.

Checking for Collinearity

In [73]:

```
correlation = kc_data.corr()['price'].map(abs).sort_values(ascending = False)
correlation
```

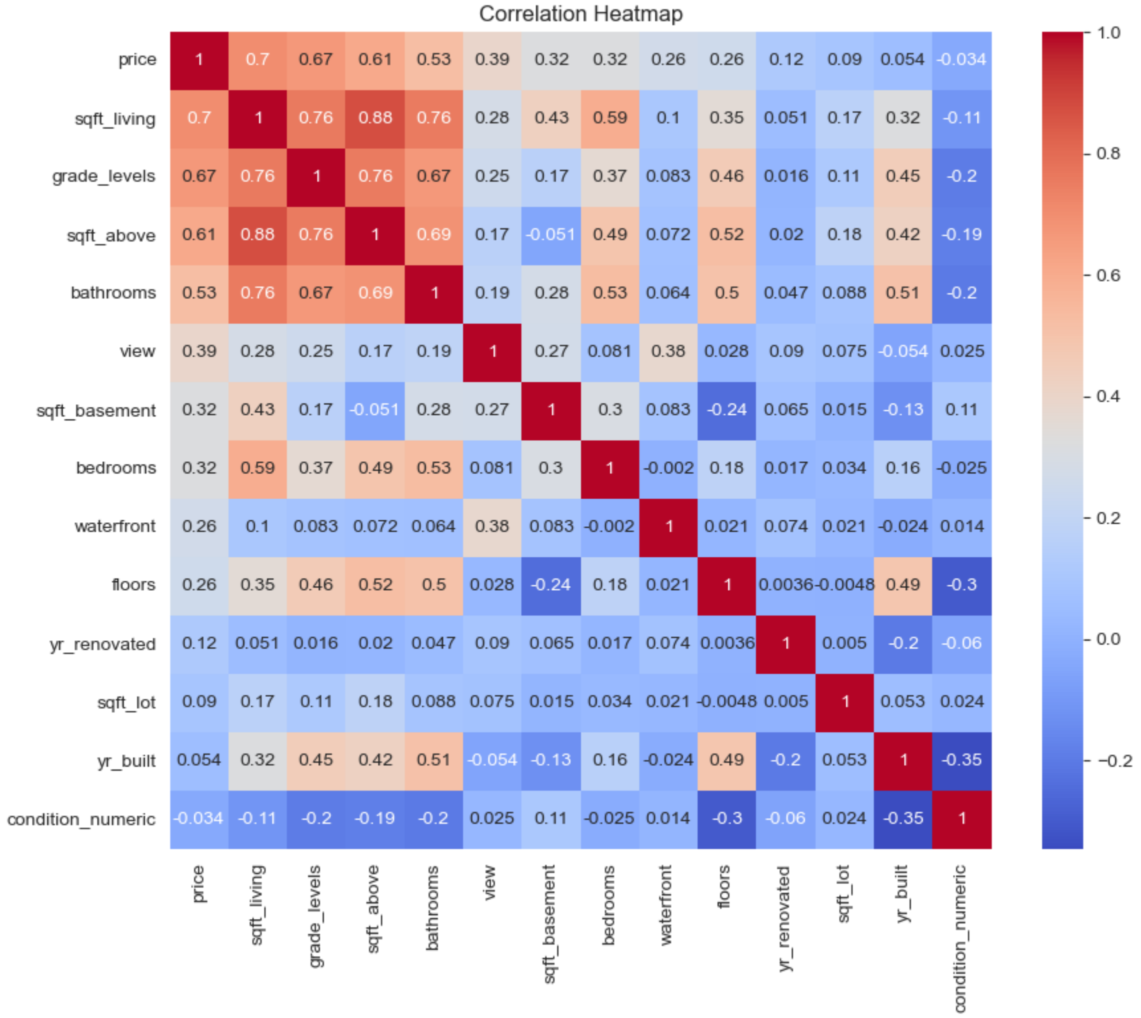
Out[73]:

```
price                1.000000
sqft_living          0.701948
grade_levels         0.667967
sqft_above           0.605401
bathrooms            0.525934
view                 0.393502
sqft_basement        0.321109
bedrooms             0.316504
waterfront           0.264308
floors               0.256828
yr_renovated         0.117948
sqft_lot             0.089879
yr_built             0.053964
condition_numeric    0.034484
Name: price, dtype: float64
```

The strongest correlation with price is with `sqft_living` , `bathrooms` and `sqft_basement` . The heatmap below visualizes this information.

In [74]:

```
correlation_matrix = kc_data[correlation.index].corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```



Feature Engineering

- Adding some columns to help extract more information.

In [75]:

```
kc_data.columns
```

Out[75]:

```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
       'sqft_basement', 'sqft_above', 'yr_built', 'yr_renovated', 'grade',
       'condition', 'waterfront', 'view', 'floors', 'grade_levels',
       'condition_numeric'],
      dtype='object')
```

In [76]:

```
kc_data.loc[:, "house_age"] = 2015 - kc_data["yr_built"].values
kc_data.loc[:, "renovation_status"] = kc_data["yr_renovated"].values - kc_data["yr_built"
kc_data.loc[:, "renovation_status"] = np.where(kc_data["renovation_status"].isnull(), 0,
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_9412\3523992008.py:1: SettingWith
CopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/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)
  kc_data.loc[:, "house_age"] = 2015 - kc_data["yr_built"].values
C:\Users\hp\AppData\Local\Temp\ipykernel_9412\3523992008.py:2: SettingWith
CopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/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)
  kc_data.loc[:, "renovation_status"] = kc_data["yr_renovated"].values - k
c_data["yr_built"].values
C:\Users\hp\AppData\Local\Temp\ipykernel_9412\3523992008.py:3: SettingWith
CopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/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)
  kc_data.loc[:, "renovation_status"] = np.where(kc_data["renovation_statu
s"].isnull(), 0, kc_data["renovation_status"])
```

In [77]:

```
print(data_copy.head(5))
print(data_copy.columns)
```

```
           id        date     price  bedrooms  bathrooms  sqft_living  \
0  7129300520  10/13/2014  221900.0         3       1.00         1180   
1  6414100192   12/9/2014  538000.0         3       2.25         2570   
2  5631500400   2/25/2015  180000.0         2       1.00          770   
3  2487200875   12/9/2014  604000.0         4       3.00         1960   
4  1954400510   2/18/2015  510000.0         3       2.00         1680   

   sqft_lot  floors  waterfront  view  ... sqft_basement yr_built  \
0      5650     1.0         0.0   0.0  ...           0.0     1955   
1      7242     2.0         0.0   0.0  ...         400.0     1951   
2     10000     1.0         0.0   0.0  ...           0.0     1933   
3      5000     1.0         0.0   0.0  ...         910.0     1965   
4      8080     1.0         0.0   0.0  ...           0.0     1987   

   yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15  \
0           0.0    98178  47.5112 -122.257           1340        5650   
1        1991.0    98125  47.7210 -122.319           1690        7639   
2           0.0    98028  47.7379 -122.233           2720        8062   
3           0.0    98136  47.5208 -122.393           1360        5000   
4           0.0    98074  47.6168 -122.045           1800        7503   

   grade_levels  condition_numeric  
0             7                  0  
1             7                  0  
2             6                  0  
3             7                  1  
4             8                  0  

[5 rows x 23 columns]
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcod
e',
       'lat', 'long', 'sqft_living15', 'sqft_lot15', 'grade_levels',
       'condition_numeric'],
      dtype='object')
```

Multicollinearity

In [78]:

```
abs(kc_data.corr()) > .75
```

Out[78]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	sqft_basement	sqft_above	yr_built
price	True	False	False	False	False	False	False	False
bedrooms	False	True	False	False	False	False	False	False
bathrooms	False	False	True	True	False	False	False	False
sqft_living	False	False	True	True	False	False	True	False
sqft_lot	False	False	False	False	True	False	False	False
sqft_basement	False	False	False	False	False	True	False	False
sqft_above	False	False	False	True	False	False	True	False
yr_built	False	False	False	False	False	False	False	True
yr_renovated	False	False	False	False	False	False	False	False
waterfront	False	False	False	False	False	False	False	False

In [79]:

```
data = pd.read_csv("kc_house_data.csv")
data_copy = data.copy()
# kc_data = data_copy[["price", "bedrooms", "bathrooms","sqft_living", "sqft_lot", "sqft_
#                      "condition", "waterfront", "view", "floors", "renovation_status",
```

In [80]:

```
# Creating a new dataframe of the absolute values of the correlations
collinear_pairs = kc_data.corr().abs().stack().reset_index().sort_values(0, ascending=Fal
collinear_pairs['pairs'] = list(zip(collinear_pairs.level_0, collinear_pairs.level_1))
collinear_pairs.set_index(['pairs'], inplace = True)
collinear_pairs.drop(columns=['level_1', 'level_0'], inplace = True)

# cc for correlation coefficient
collinear_pairs.columns = ['cc']
collinear_pairs.drop_duplicates(inplace=True)

# Filter for correlation coefficients less than 1 and greater than 0.76
collinear_pairs[(collinear_pairs.cc>.76) & (collinear_pairs.cc<1)]
```

Out[80]:

	cc
pairs	
(house_age, yr_built)	1.000000
(yr_renovated, renovation_status)	0.996987
(sqft_living, sqft_above)	0.876446
(sqft_living, grade_levels)	0.762825

- To ensure that data interpretation accuracy is addressed, `sqft_living` will be dropped when modelling because it is strongly correlated with two other predictor variables.
- Further, `renovation_status` and `house_age` were dropped since they were a result of feature engineering yet they caused a near perfect collinearity.

In [81]:

```
kc_data = kc_data.drop(columns=["sqft_living", "renovation_status", "house_age"])
```

In [82]:

```
print(kc_data.columns)

print(kc_data.info())
```

```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_lot', 'sqft_basement',
       'sqft_above', 'yr_built', 'yr_renovated', 'grade', 'condition',
       'waterfront', 'view', 'floors', 'grade_levels', 'condition_numeri
c'],
      dtype='object')
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21595 entries, 0 to 21596
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   price             21595 non-null  float64
 1   bedrooms          21595 non-null  int64
 2   bathrooms         21595 non-null  float64
 3   sqft_lot          21595 non-null  int64
 4   sqft_basement     21595 non-null  float64
 5   sqft_above        21595 non-null  int64
 6   yr_built          21595 non-null  int64
 7   yr_renovated      21595 non-null  float64
 8   grade             21595 non-null  object
```

Creating the Models

1. Base Model

- The base model takes into consideration the feature with the strongest correlation with price after `sqft_living` which has auto-correlation with other variables.
- From our analysis, the feature is `grade` . For the purpose of modelling, the column `grade_levels` was used.

In [83]:

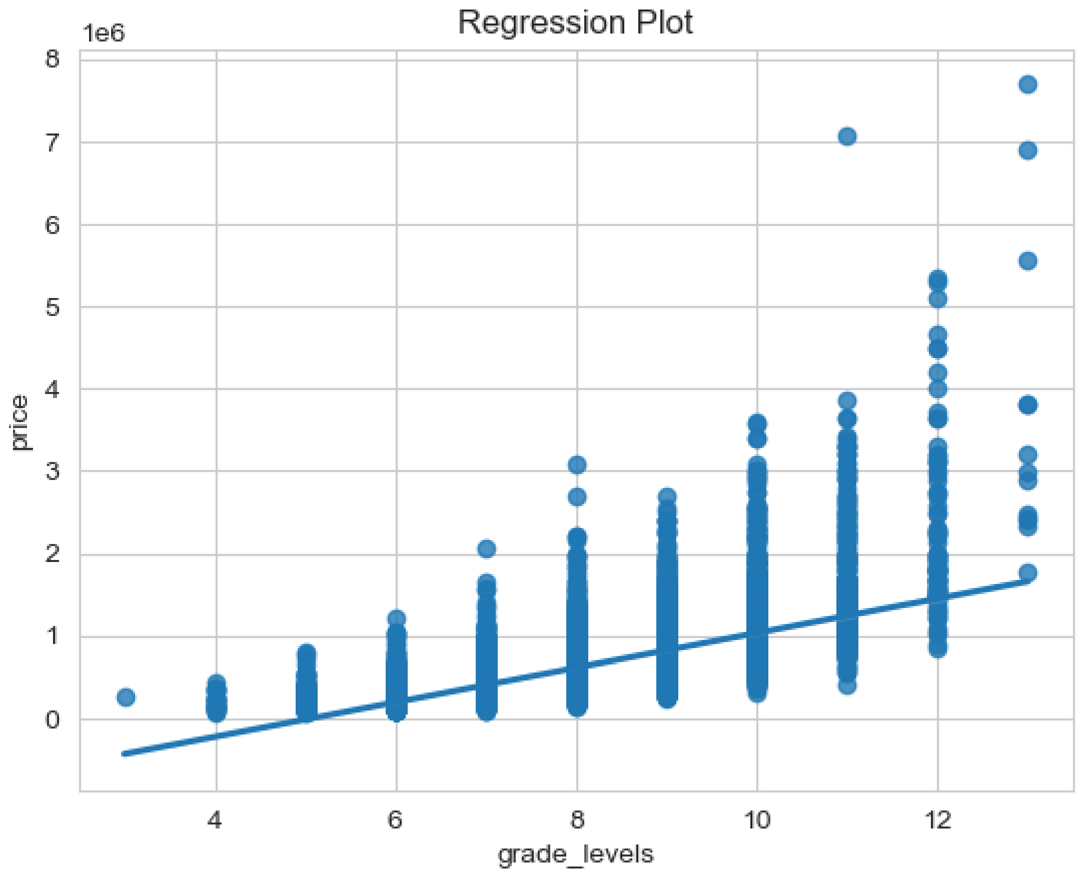
```
# Create our X and y for the baseline model
y = kc_data["price"]
X = kc_data["grade_levels"]
# Add a constant column to the feature matrix for the intercept term
X = sm.add_constant(X)

# Create and fit the linear regression model
model = sm.OLS(y, X).fit()

# Print the summary of the model
print(model.summary())
```

```
                            OLS Regression Results
========================================================================
======
Dep. Variable:                  price   R-squared:
0.446
Model:                            OLS   Adj. R-squared:
0.446
Method:                 Least Squares   F-statistic:                 1.7
40e+04
Date:                Fri, 02 Jun 2023   Prob (F-statistic):
0.00
Time:                        22:19:37   Log-Likelihood:            -3.00
98e+05
No. Observations:               21595   AIC:                         6.0
20e+05
Df Residuals:                   21593   BIC:                         6.0
20e+05
Df Model:                           1
Covariance Type:            nonrobust
```

In [84]:

```
sns.regplot(kc_data['grade_levels'], kc_data['price'])
plt.title("Regression Plot")
print("Grade and price are positively correlated.")
```

```
C:\Users\hp\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureW
arning: Pass the following variables as keyword args: x, y. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterp
retation.
  warnings.warn(

Grade and price are positively correlated.
```



2. Iterating Categorical and Numerical Features

In the cell below, we added one categorical variable after another but the r-squared values were blow 60%, with grade giving us the highest r-squared of 55%.

In [85]:

```
num_cat_features = kc_data[["bedrooms", "bathrooms", "sqft_lot", "sqft_basement", "sqft_a

y = kc_data["price"]
X = num_cat_features

# Add a constant column to the feature matrix for the intercept term
X = sm.add_constant(X)

# Create and fit the linear regression model
model = sm.OLS(y, X).fit()

# Print the summary of the model
print(model.summary())
```

```
                            OLS Regression Results                            
==============================================================================
====
Dep. Variable:                  price   R-squared:                       
0.511
Model:                            OLS   Adj. R-squared:                  
0.511
Method:                 Least Squares   F-statistic:                     3
223.
Date:                Fri, 02 Jun 2023   Prob (F-statistic):              
0.00
Time:                        22:19:38   Log-Likelihood:             -2.9964
e+05
No. Observations:               21595   AIC:                          5.993
e+05
Df Residuals:                   21587   BIC:                          5.994
e+05
Df Model:                           7                                         
Covariance Type:            nonrobust                                         
==============================================================================
===========
                        coef    std err          t      P>|t|      [0.025      
0.975]
------------------------------------------------------------------------------
-----------
const              5.504e+04   8303.369      6.629      0.000    3.88e+04    
7.13e+04
bedrooms          -6.625e+04   2458.164    -26.953      0.000   -7.11e+04   
-6.14e+04
bathrooms          1.475e+04   3844.613      3.835      0.000    7210.228    
2.23e+04
sqft_lot             -0.3731      0.043     -8.587      0.000      -0.458      
-0.288
sqft_basement       331.5323      4.976     66.629      0.000     321.779     
341.285
sqft_above          307.0510      3.368     91.174      0.000     300.450     
313.652
floors             1.578e+04   4370.222      3.610      0.000    7209.573    
2.43e+04
condition_numeric  2.435e+04   1995.032     12.204      0.000    2.04e+04    
2.83e+04
==============================================================================
====
Omnibus:                    14156.231   Durbin-Watson:                   
1.988
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              46468
8.579
Skew:                           2.673   Prob(JB):                        
0.00
Kurtosis:                      25.088   Cond. No.                          2.20
e+05
==============================================================================
====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is cor
rectly specified.
[2] The condition number is large, 2.2e+05. This might indicate that there
are
strong multicollinearity or other numerical problems.
```

In [86]:

```
num_cat_features = kc_data[["bedrooms", "bathrooms", "sqft_lot", "sqft_basement", "sqft_a

y = kc_data["price"]
X = num_cat_features

# Add a constant column to the feature matrix for the intercept term
X = sm.add_constant(X)

# Create and fit the linear regression model
model = sm.OLS(y, X).fit()

# Print the summary of the model
print(model.summary())
```

```
                            OLS Regression Results
==========================================================================
======
Dep. Variable:                  price   R-squared:
0.545
Model:                            OLS   Adj. R-squared:
0.545
Method:                 Least Squares   F-statistic:
3696.
Date:                Fri, 02 Jun 2023   Prob (F-statistic):
0.00
Time:                        22:19:38   Log-Likelihood:          -2.98
86e+05
No. Observations:               21595   AIC:                       5.9
77e+05
Df Residuals:                   21587   BIC:                       5.9
78e+05
Df Model:                           7
Covariance Type:            nonrobust
```

In [87]:

```
num_cat_features = kc_data[["bedrooms", "bathrooms", "sqft_lot", "sqft_basement", "sqft_a

y = kc_data["price"]
X = num_cat_features

# Add a constant column to the feature matrix for the intercept term
X = sm.add_constant(X)

# Create and fit the linear regression model
model = sm.OLS(y, X).fit()

# Print the summary of the model
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
====
Dep. Variable:                  price   R-squared:
0.550
Model:                            OLS   Adj. R-squared:
0.550
Method:                 Least Squares   F-statistic:                     3
775.
Date:                Fri, 02 Jun 2023   Prob (F-statistic):
0.00
Time:                        22:19:38   Log-Likelihood:            -2.9873
e+05
No. Observations:               21595   AIC:                         5.975
e+05
Df Residuals:                   21587   BIC:                         5.975
e+05
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
=======
                    coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
const         -5.173e+05   1.53e+04    -33.733      0.000   -5.47e+05   -
4.87e+05
bedrooms      -4.497e+04   2391.534    -18.802      0.000   -4.97e+04   -
4.03e+04
bathrooms     -1.748e+04   3721.721     -4.696      0.000   -2.48e+04   -
1.02e+04
sqft_lot         -0.2875      0.042     -6.898      0.000      -0.369
-0.206
sqft_basement   271.1924      4.969     54.582      0.000     261.454
280.931
sqft_above      203.0235      3.961     51.254      0.000     195.259
210.788
floors        -1.755e+04   4162.208     -4.218      0.000   -2.57e+04   -9
396.235
grade_levels   1.092e+05   2412.016     45.269      0.000    1.04e+05
1.14e+05
==============================================================================
====
Omnibus:                    16384.104   Durbin-Watson:
1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           89613
2.687
Skew:                           3.153   Prob(JB):
0.00
Kurtosis:                      33.922   Cond. No.                     4.08
e+05
==============================================================================
====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is cor
rectly specified.
[2] The condition number is large, 4.08e+05. This might indicate that ther
e are
strong multicollinearity or other numerical problems.
```

3. Model Using All Features

In [88]:

```
features = kc_data.columns.drop(["price", "grade","condition", "view"])

# Create the feature matrix X and the target vector y
X = kc_data[features]
y = kc_data['price']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create and fit the linear regression model
model = LinearRegression()
model.fit(X, y)

# Add a constant column to the feature matrix for the intercept term
X_train = sm.add_constant(X_train)
X_test = sm.add_constant(X_test)

# Create and fit the linear regression model
model = sm.OLS(y_train, X_train)
results = model.fit()

# Print the summary of the model
print(results.summary())

# Print the coefficients and intercept
print("Coefficients:")
print(results.params.drop('const'))
```

```
                            OLS Regression Results
==========================================================================
====
Dep. Variable:                  price   R-squared:
0.647
Model:                            OLS   Adj. R-squared:
0.647
Method:                 Least Squares   F-statistic:                     2
876.
Date:                Fri, 02 Jun 2023   Prob (F-statistic):
0.00
Time:                        22:19:38   Log-Likelihood:            -2.3695
e+05
No. Observations:               17276   AIC:                         4.739
e+05
Df Residuals:                   17264   BIC:                         4.740
e+05
Df Model:                          11
Covariance Type:            nonrobust
==========================================================================
===========
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------
-----------
const              6.837e+06   1.48e+05     46.223      0.000    6.55e+06
7.13e+06
bedrooms          -4.57e+04   2386.574    -19.147      0.000   -5.04e+04
-4.1e+04
bathrooms          5.309e+04   3946.359     13.453      0.000    4.54e+04
6.08e+04
sqft_lot             -0.2289      0.041     -5.571      0.000      -0.309
-0.148
sqft_basement       191.1348      5.099     37.486      0.000     181.141
201.129
sqft_above          172.8895      3.969     43.557      0.000     165.109
180.670
yr_built          -3891.3905     77.100    -50.472      0.000   -4042.514
-3740.267
yr_renovated          9.1697      4.790      1.914      0.056      -0.220
18.559
waterfront         7.074e+05   2.06e+04     34.374      0.000    6.67e+05
7.48e+05
floors             2.153e+04   4244.557      5.073      0.000    1.32e+04
2.99e+04
grade_levels       1.323e+05   2443.224     54.154      0.000    1.28e+05
1.37e+05
condition_numeric  7112.1185   1965.832      3.618      0.000    3258.889
1.1e+04
==========================================================================
====
Omnibus:                    12649.778   Durbin-Watson:
1.989
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           78801
9.105
Skew:                           2.930   Prob(JB):
0.00
Kurtosis:                      35.563   Cond. No.                     3.94
e+06
==========================================================================
====
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is cor
rectly specified.
[2] The condition number is large, 3.94e+06. This might indicate that ther
e are
strong multicollinearity or other numerical problems.
Coefficients:
bedrooms            -45695.877904
bathrooms            53091.597730
sqft_lot                -0.228944
sqft_basement          191.134756
sqft_above             172.889464
yr_built             -3891.390483
yr_renovated             9.169658
waterfront          707414.074915
floors               21531.580756
grade_levels        132309.486415
condition_numeric     7112.118547
dtype: float64
```

4. Time period: `yr_built` and `yr_renovated`

In [89]:

```
y = kc_data["price"]
X = kc_data[["yr_built", "yr_renovated"]]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create and fit the linear regression model
model = LinearRegression()
model.fit(X, y)

# Add a constant column to the feature matrix for the intercept term
X_train = sm.add_constant(X_train)
X_test = sm.add_constant(X_test)

# Create and fit the linear regression model
model = sm.OLS(y_train, X_train)
results = model.fit()

# Add a constant column to the feature matrix for the intercept term
X_train = sm.add_constant(X)
X_test = sm.add_constant(X_test)

# Create and fit the linear regression model
model = sm.OLS(y, X).fit()

# Print the summary of the model
print(model.summary())
```

```
                            OLS Regression Results
==========================================================================
=============
Dep. Variable:                  price   R-squared (uncentered):
0.689
Model:                            OLS   Adj. R-squared (uncentered):
0.689
Method:                 Least Squares   F-statistic:
2.394e+04
Date:                Fri, 02 Jun 2023   Prob (F-statistic):
0.00
Time:                        22:19:38   Log-Likelihood:
-3.0718e+05
No. Observations:               21595   AIC:
6.144e+05
Df Residuals:                   21593   BIC:
6.144e+05
Df Model:                           2
Covariance Type:            nonrobust
==========================================================================
======
                   coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------
------
yr_built       269.9816      1.279    211.079      0.000     267.475     2
72.489
yr_renovated   123.3517      6.810     18.113      0.000     110.004     1
36.700
==========================================================================
====
Omnibus:                    18929.394   Durbin-Watson:
1.972
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          108358
1.481
Skew:                           3.976   Prob(JB):
0.00
Kurtosis:                      36.779   Cond. No.
5.42
==========================================================================
====

Notes:
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is cor
rectly specified.
```

5. Qualitative Features: `grade` , `waterfront` , `condition` , `view`

In [90]:

```
y = kc_data["price"]
X = kc_data[["grade_levels","waterfront","condition_numeric", "view"]]
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create and fit the linear regression model
model = LinearRegression()

model.fit(X, y)

# Add a constant column to the feature matrix for the intercept term
X_train = sm.add_constant(X_train)
X_test = sm.add_constant(X_test)

# Create and fit the linear regression model
model = sm.OLS(y_train, X_train)
results = model.fit()

# Add a constant column to the feature matrix for the intercept term
X_train = sm.add_constant(X)
X_test = sm.add_constant(X_test)

# Create and fit the linear regression model
model = sm.OLS(y, X).fit()

# Print the summary of the model
print(model.summary())
```

```
                                 OLS Regression Results                                
=======================================================================================
===============
Dep. Variable:                  price   R-squared (uncentered):                   
0.802
Model:                            OLS   Adj. R-squared (uncentered):              
0.802
Method:                 Least Squares   F-statistic:                          
2.187e+04
Date:                Fri, 02 Jun 2023   Prob (F-statistic):                   
0.00
Time:                        22:19:39   Log-Likelihood:                   
-3.0231e+05
No. Observations:               21595   AIC:                              
6.046e+05
Df Residuals:                   21591   BIC:                              
6.047e+05
Df Model:                           4                                         
Covariance Type:            nonrobust                                         
```

6. Quantitative Features: `bedrooms` , `bathrooms` , `sqft_living` , `sqft_lot` , `sqft_basement` , `sqft_above` , `floors`

In [91]:

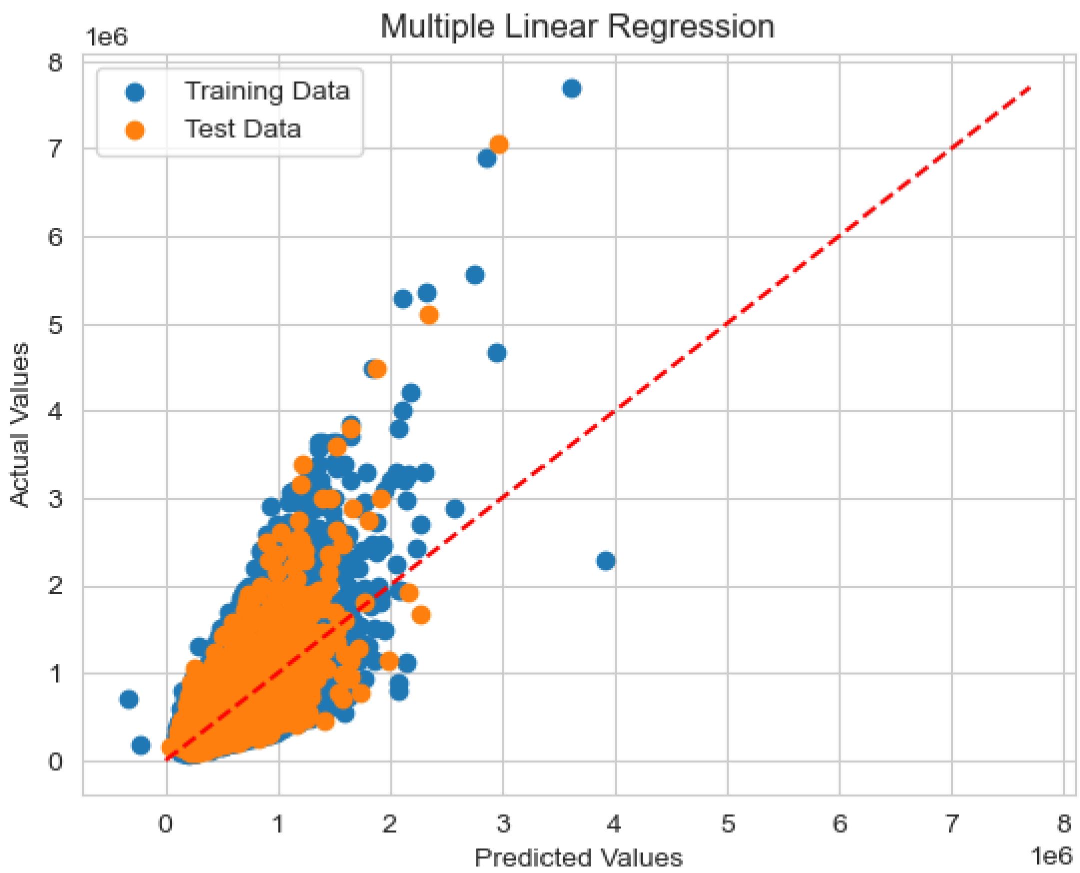
```
y = kc_data["price"]
X = kc_data[["bedrooms", "bathrooms", "sqft_lot", "sqft_basement", "sqft_above", "floors"

# Split the data into training and testing sets
X_train_num, X_test_num, y_train_num, y_test_num = train_test_split(X, y, test_size=0.2,

# Create and fit the linear regression model
model = LinearRegression()

model.fit(X, y)

# Add a constant column to the feature matrix for the intercept term
X_train_num = sm.add_constant(X_train_num)
X_test_num = sm.add_constant(X_test_num)

# Create and fit the linear regression model
model = sm.OLS(y_train_num, X_train_num)
results = model.fit()

# predict on train and test data
target_train_pred = results.predict(X_train_num)
target_test_pred = results.predict(X_test_num)

# Add a constant column to the feature matrix for the intercept term
X_train_num = sm.add_constant(X)
X_test_num = sm.add_constant(X_test_num)

# Create and fit the linear regression model
model = sm.OLS(y, X).fit()

# Print the summary of the model
print(model.summary())
```

```
                                 OLS Regression Results
=======================================================================
===============
Dep. Variable:                  price   R-squared (uncentered):
0.843
Model:                            OLS   Adj. R-squared (uncentered):
0.843
Method:                 Least Squares   F-statistic:
1.939e+04
Date:                Fri, 02 Jun 2023   Prob (F-statistic):
0.00
Time:                        22:19:39   Log-Likelihood:
-2.9977e+05
No. Observations:               21595   AIC:
5.996e+05
Df Residuals:                   21589   BIC:
5.996e+05
Df Model:                           6
Covariance Type:            nonrobust
```

Regression Results

In [92]:

```
fig, ax = plt.subplots()
ax.scatter(target_train_pred, y_train_num, label='Training Data')
ax.scatter(target_test_pred, y_test_num, label='Test Data')
ax.plot([0, np.max(y)], [0, np.max(y)], linestyle='--', color='r')
ax.set_xlabel('Predicted Values')
ax.set_ylabel('Actual Values')
ax.set_title('Multiple Linear Regression')
ax.legend()
plt.show()
```



The model is a good fit since the training data and test data do not over fit or underfit.

Observations

The model that incorporated the numerical features, was the most favorable, with an R squared of 0.84 . Approximately 84.3% of the variation in the dependent variable (price) can be explained by the numerical independent variables.

Other statistics of the model are:

- F-statistic 0f 2.188e+04 – indicating that the regression model is statistically significant
- p-values (below 0.05) – indicating statistical significance of the coefficients.

Co-efficiency

- floors: Houses with an additional floor have a predicted price increase of approximately 27,060 ($p < 0.001$).
- bathrooms: For each additional bathroom, the predicted price increases by approximately 12,640 ($p = 0.001$).
- sqft_basement: For each additional square foot of basement area, the predicted price increases by

Conclusion

- In conclusion, home sellers should take in the following:
  - Consider increasing the space of the house, by increasing the number of floors, bathrooms & the size of basement & above ground area
  - Highly graded houses fetch higher prices. Waterfront and views, also increase the value of houses.
  - The newer the house, the higher the price, similarly, the most recently renovated houses fetch higher prices. Therefore, sellers need to renovated their houses.
- Models that incorporate other features such as proximity to amenities, the nature of geographical features and the locality's weather conditions have an impact on a property's sale value.
- Furthermore, it would be interesting to investigate whether certain months and seasons have an impact on the demand for homes.