Recommendations for First Time Single-Family Home Buyers in King County, WA

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Overview & Business Problem

Our stakeholders are a King County real estate agency and families looking to purchase their very first home. They are looking to find what underlying factors are critical to the perfect home and how these factors may affect the sale price.

Purchasing a home is a huge step in one's life and a big undertaking that requires significant forethought, especially if the home is for a family. Our analysis will provide recommendations and provide assistance to first time single-family home buyers by looking into critically values home features and factors they should focus on in their home journey. Livable square footage, building grade, and condition grade were the focal points of this analysis. By analyzing the correlation of these factors to the price of the home, families can use these results to make an informed purchase with confidence for their very first home to plant their roots within King County, Washington.

King County

The Bottom Line

1. Settle down *out* of Seattle.
2. Bigger homes available at a lower price out of Seattle.
3. Better construction and quality comes at a higher price. Better prices out of Seattle.

Data Understanding

The data used in this analysis was taken from [King County Department of Assessments (https://info.kingcounty.gov/assessor/DataDownload/default.aspx)](https://info.kingcounty.gov/assessor/DataDownload/default.aspx), whereas the `address` , `lat` , and `long` fields have been retrieved using a third-party [geocoding API (https://docs.mapbox.com/api/search/geocoding/)](https://docs.mapbox.com/api/search/geocoding/). The data provided information such as sale price, sale and renovation years, square footage of specific home features, as well as number of bedroomd and bathrooms. The target variable in our analysis was the sale price of the home which laid a foundation for the rest of the analysis and modeling. The dataset contains numerical data, with the instances of categorical data which is then converted into numerical data. Our final dataset had numerous fixed factors as well as the removal of price outliers.

In [1]:
```
# Import packages

import numpy as np
import pandas as pd
import seaborn as sns

import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
import seaborn as sns
import statsmodels.api as sm
import folium

from scipy import stats
from scipy.stats import norm
from sklearn.dummy import DummyRegressor
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler, OneHotEncoder, Ordir
from statsmodels.formula.api import ols
from sklearn.metrics import mean_squared_error as MSE
from sklearn.metrics import r2_score
from sklearn.model_selection import cross_validate, ShuffleSplit
```

In [2]:
```
# Import dataset
data = pd.read_csv("data/kc_house_data.csv")
data
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0
1	8910500230	12/13/2021	920000.0	5	2.5	2770	6703	1.0
2	1180000275	9/29/2021	311000.0	6	2.0	2880	6156	1.0

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

Out[4]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	s
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	

Initial Look at Data to Get Information

In [5]:
```
data['sqft_above'].value_counts()
```

Out[5]:
```
1200    282
1300    282
1060    271
1100    268
1250    265
       ...
1799      1
1783      1
1767      1
7700      1
2049      1
Name: sqft_above, Length: 1187, dtype: int64
```

In [6]:
```
data['heat_source'].value_counts()
```

Out[6]:
```
Gas                  20583
Electricity           6465
Oil                   2899
Gas/Solar               93
Electricity/Solar       59
Other                   20
Oil/Solar                4
Name: heat_source, dtype: int64
```

In [7]:
```
data['sewer_system'].value_counts()
```

Out[7]:
```
PUBLIC                 25777
PRIVATE                 4355
PRIVATE RESTRICTED         6
PUBLIC RESTRICTED          3
Name: sewer_system, dtype: int64
```

In [8]:
```
data['sewer_system'].isnull().sum()
```

Out[8]:
```
14
```

Data Cleaning

- One duplicate in ID, a few nulls in 'sewer_system' and 'heat_source', could drop these since there are only a few.

Dropping the duplicated ID

In [9]:
```
# Check for duplicates
data[data.duplicated(subset=['id'])]
```

Out[9]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
4846	1233100736	9/28/2021	2600000.0	3	4.0	3500	8455	2.0	

1 rows × 25 columns

In [10]:
```
# Verify that duplicate is actually a duplicate
data[data['id'].isin(['1233100736'])]
```

Out[10]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
4845	1233100736	9/28/2021	2600000.0	3	4.0	3500	8455	2.0	
4846	1233100736	9/28/2021	2600000.0	3	4.0	3500	8455	2.0	

2 rows × 25 columns

In [11]:
```
# Dropping duplicate row
data_clean = data.drop_duplicates(subset = ['id'])
data_clean
```

Out[11]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0
1	8910500230	12/13/2021	920000.0	5	2.5	2770	6703	1.0
2	1180000275	9/29/2021	311000.0	6	2.0	2880	6156	1.0

Removing the nulls from 'sewer_System' and 'heat_source'

In [12]:
```
#Drop columns with missing data
data_clean = data_clean.dropna(subset=['sewer_system', 'heat_source'])
data_clean
```

Out[12]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0
1	8910500230	12/13/2021	920000.0	5	2.5	2770	6703	1.0
2	1180000275	9/29/2021	311000.0	6	2.0	2880	6156	1.0

We have elected to drop the rows with missing data instead of imputing it because there are only 3 rows with missing values.

Separating Out Zipcode from the Address

- We wanted to use address to separate out the zip codes of this data set to see if we could draw any insights.

In [13]:
```
data_clean['address']
```

Out[13]:
```
0        2102 Southeast 21st Court, Renton, Washington ...
1        11231 Greenwood Avenue North, Seattle, Washing...
2        8504 South 113th Street, Seattle, Washington 9...
3        4079 Letitia Avenue South, Seattle, Washington...
4        2193 Northwest Talus Drive, Issaquah, Washingt...
                              ...
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, Length: 30110, dtype: object
```

In [14]:
```
# This creates a new column with our zipcodes of the houses
data_clean['postal_code'] = data_clean['address'].str[-20:-15]
data_clean
```

```
<ipython-input-14-ad923d199017>:2: SettingWithCopyWarning:
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-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)
  data_clean['postal_code'] = data_clean['address'].str[-20:-15]
```

Out[14]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0

In [15]:
```
# Verify no missing values -- sanity check
data_clean.isna().sum()
```

Out[15]:
```
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
```

Any homes not within King County?

In [16]:
```
data_clean['postal_code'].value_counts(normalize=True)
```

Out[16]:
```
98042    0.032946
98038    0.028462
98103    0.025274
98115    0.025241
98117    0.024842
           ...
17111    0.000033
68862    0.000033
33138    0.000033
52590    0.000033
94530    0.000033
Name: postal_code, Length: 399, dtype: float64
```

It appears that addresses within King's County begin with Postal Code '98'. Are there any that don't being with '98'? Let's find out.

In [17]:
```
# Find any postal codes not within King County
prefixes = ['98']

data_clean[~data_clean.postal_code.str.startswith(tuple(prefixes))]
```

Out[17]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
12	1797501124	6/25/2021	750000.0	3	2.0	1280	964	3.0
53	7548300606	5/3/2022	960000.0	3	2.0	1280	1221	2.0
62	1934800106	8/24/2021	740000.0	2	2.0	1120	734	3.0
159	856000595	7/8/2021	3730000.0	4	4.5	4820	10800	2.0

There are 911 rows that are not within the King's County area whose postal code does not being with '98'. Let's drop these homes from our dataset and focus on those solely within the county.

In [18]:
```
# Find the indexes of the homes not within King County
prefixes = ['98']
non_king_postals = data_clean[~data_clean.postal_code.str.startswith(t
non_king_postals

# Drop the rows whose postal code does not being with '98'
only_king = data_clean.drop(non_king_postals)
only_king.head()
```

Out[18]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wat
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0	
1	8910500230	12/13/2021	920000.0	5	2.5	2770	6703	1.0	
2	1180000275	9/29/2021	311000.0	6	2.0	2880	6156	1.0	

There might still be some zipcodes present within the dataset that are not within King's County, but are in a neighboring county whose postal code also begins with '98', but let's hone our data some more.

Creating new columns from existing data

Numeric grade value column

In [19]:
```
only_king['grade'].unique()
```

Out[19]:
```
array(['7 Average', '9 Better', '8 Good', '6 Low Average', '10 Very G
ood',
       '5 Fair', '11 Excellent', '12 Luxury', '4 Low', '13 Mansion',
       '3 Poor', '2 Substandard'], dtype=object)
```

In [20]:
```
#To get numeric grade code value
only_king['grade_code'] = only_king['grade'].str[0:2]

#To strip whitespace from the grade code
only_king['grade_code'] = only_king['grade_code'].str.strip()
```

In [21]:
```
#sanity check to make sure no white space
only_king['grade_code'].unique()
```

Out[21]:
```
array(['7', '9', '8', '6', '10', '5', '11', '12', '4', '13', '3', '2'
],
      dtype=object)
```

Numeric condition value column

In [22]:
```
#To get numeric condition code
only_king['condition_code'] = only_king['condition']

# Replace the word to numeric value
only_king.condition_code.replace({'Poor': 1, 'Fair': 2, 'Average': 3,
```

Converting Data Types of New Columns

In [23]:
```
#change postal code to numeric datatype
only_king['postal_code'] = only_king['postal_code'].astype(int)

#To convert to float
only_king['condition_code'] = only_king['condition_code'].astype(int)

#To convert to float
only_king['grade_code'] = only_king['grade_code'].astype(int)
```

Feature engineering

- We want to know the price per sqft of livable sqft to see if we can draw any insights from this. Typically when analyzing pricing of houses, it is a useful metric to have the cost per square foot.

In [24]:

```
only_king['price_sqft'] = only_king['price'] / only_king['sqft_living'
only_king
```

Out[24]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0
1	8910500230	12/13/2021	920000.0	5	2.5	2770	6703	1.0
2	1180000275	9/29/2021	311000.0	6	2.0	2880	6156	1.0
3	1604601802	12/14/2021	775000.0	3	3.0	2160	1400	2.0
4	8562780790	8/24/2021	592500.0	2	2.0	1120	758	2.0
...	...	...	...	...	...	...	...	...
30150	7834800180	11/30/2021	1555000.0	5	2.0	1910	4000	1.5
30151	194000695	6/16/2021	1313000.0	3	2.0	2020	5800	2.0
30152	7960100080	5/27/2022	800000.0	3	2.0	1620	3600	1.0

30153	2781280080	2/24/2022	775000.0	3	2.5	2570	2889	2.0
30154	9557800100	4/29/2022	500000.0	3	1.5	1200	11058	1.0

29199 rows × 29 columns

In [25]:
```
only_king['price_sqft'].describe()
```

Out[25]:
```
count     29199.000000
mean        558.055358
std        3541.243279
min           6.920415
25%         357.754755
50%         487.654321
75%         641.876179
max      601000.000000
Name: price_sqft, dtype: float64
```

Cleaning 'price' to get rid of outliers

- We utilize the Interqurtile range to rid outliers via the formula
- Below: Q1 - 1.5 IQR
- Above: Q3 + 1.5 IQR
- IQR = Q3 – Q1

In [26]:
```
only_king['price'].describe()
```

Out[26]:
```
count    2.919900e+04
mean     1.112959e+06
std      8.954250e+05
min      2.736000e+04
25%      6.450000e+05
50%      8.680000e+05
75%      1.310000e+06
max      3.075000e+07
Name: price, dtype: float64
```

In [27]:

```
# Calculate Q1, Q2, Q3 and IQR
Q1 = np.percentile(only_king['price'], 25, interpolation = 'midpoint')
Q2 = np.percentile(only_king['price'], 50, interpolation = 'midpoint')
Q3 = np.percentile(only_king['price'], 75, interpolation = 'midpoint')

print('Q1 25 percentile of the given data is, ', Q1)
print('Q2 50 percentile of the given data is, ', Q2)
print('Q3 75 percentile of the given data is, ', Q3)

IQR = Q3 - Q1
print('Interquartile range (IQR) is', IQR)
```

```
Q1 25 percentile of the given data is,  645000.0
Q2 50 percentile of the given data is,  868000.0
Q3 75 percentile of the given data is,  1310000.0
Interquartile range (IQR) is 665000.0
```

In [28]:

```
# Find the lower and upper limits
lower_limit = Q1 - 1.5 * IQR
upper_limit = Q3 + 1.5 * IQR
print('Lower limit is', lower_limit)
print('Upper limit is', upper_limit)
```

```
Lower limit is -352500.0
Upper limit is 2307500.0
```

In [29]:
```
# Locate the homes greater than the upper limit
only_king[only_king['price'] >= 2307500]
```

Out[29]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
27	5424700190	2/26/2022	4500000.0	4	3.0	2760	13150	1.5
36	1925059107	6/29/2021	2450000.0	4	3.5	2300	8370	2.0
43	1726059053	3/22/2022	3850000.0	5	3.5	4180	209959	1.0

There are 1874 rows of data that have housing pricing greater than $2,307,500.

In [30]:
```
#Create a copy dataset
df_clean = only_king.copy()

#Filter out the homes beyond the upper limit of price
df_clean = df_clean[df_clean['price'] <= 2307500]
df_clean
```

Out[30]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0
1	8910500230	12/13/2021	920000.0	5	2.5	2770	6703	1.0
2	1180000275	9/29/2021	311000.0	6	2.0	2880	6156	1.0

In [31]:
```
df_clean['price'].median()
```

Out[31]: 835000.0

In [32]:
```
# Wanted to see where price/sqft was equal to 601k
df_clean.loc[df_clean['price_sqft'] == 601000]
```

Out[32]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
14977	1549500215	12/17/2021	1803000.0	4	4.0	3	326701	2.0

1 rows × 29 columns

Filter Criteria

Since this is for a family, we want:

- at least 2 bedrooms
- at least 1 bathroom
- only one floor
- houses built after 1977 due to the asbestos ban
- building grade of 6 and above
- condition code of 3 and above

In [33]:
```
# Wanted to get an idea of our data set size if we find the homes with
df_clean[(df_clean['bedrooms'] >= 2) & (df_clean['bathrooms'] >= 1)]
```

Out[33]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7399300360	5/24/2022	675000.0	4	1.0	1180	7140	1.0
1	8910500230	12/13/2021	920000.0	5	2.5	2770	6703	1.0
2	1180000275	9/29/2021	311000.0	6	2.0	2880	6156	1.0

In [34]:
```
# Filter out homes with less than 2 bedrooms
df_clean = df_clean[df_clean['bedrooms'] >= 2]
```

Filtered to home with at least two rooms to ensure that the house is suiteable for a single family home, one room for the parents and one room for the children.

In [35]:
```
# Filter out the homes with less than 1 bathroom
df_clean = df_clean[df_clean['bathrooms'] >=1]
```

Filtered to homes with atleast one full bath. A place to both shower and use the toilet is important!

In [36]:
```
# Filter to homes with only 1 floor
df_clean = df_clean[df_clean['floors'] == 1]
```

Filtered to homes with only 1 floor to focus on the safety of children. Stairs can be scary!

In [37]:
```
# Filter out homes built after 1977
df_clean = df_clean[df_clean['yr_built'] > 1977]
```

The use of asbestos was banned in 1977. We have filtered the dataset to homes built after 1977 to ensure the house does not contain any asbestos.

In [38]:
```
# Filter to homes that meet building codes - Grade 6 or higher
df_clean = df_clean[df_clean['grade_code'] >= 6]
```

Building grade of 6 is the lowest grade that meets building codes. We want to make sure the house is of code and can surpass inspection.

In [39]:
```
# Filter to homes that are of average and above quality - Condition gr
df_clean = df_clean[df_clean['condition_code'] >= 3]
```

Filtered to homes with condition code of 3 or above to focus on homes that were of Average and above condition.

In [40]:
```
df_clean['condition_code'].unique()
```

Out[40]:
```
array([4, 3, 5])
```

In [41]:
```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2731 entries, 21 to 30152
Data columns (total 29 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   id              2731 non-null   int64  
 1   date            2731 non-null   object 
 2   price           2731 non-null   float64
 3   bedrooms        2731 non-null   int64  
 4   bathrooms       2731 non-null   float64
 5   sqft_living     2731 non-null   int64  
 6   sqft_lot        2731 non-null   int64  
 7   floors          2731 non-null   float64
 8   waterfront      2731 non-null   object 
 9   greenbelt       2731 non-null   object 
 10  nuisance        2731 non-null   object 
 11  view            2731 non-null   object 
 12  condition       2731 non-null   object 
 13  grade           2731 non-null   object 
 14  heat_source     2731 non-null   object 
 15  sewer_system    2731 non-null   object 
 16  sqft_above      2731 non-null   int64  
 17  sqft_basement   2731 non-null   int64  
 18  sqft_garage     2731 non-null   int64  
 19  sqft_patio      2731 non-null   int64  
 20  yr_built        2731 non-null   int64  
 21  yr_renovated    2731 non-null   int64  
 22  address         2731 non-null   object 
 23  lat             2731 non-null   float64
 24  long            2731 non-null   float64
 25  postal_code     2731 non-null   int64  
 26  grade_code      2731 non-null   int64  
 27  condition_code  2731 non-null   int64  
 28  price_sqft      2731 non-null   float64
dtypes: float64(6), int64(13), object(10)
memory usage: 640.1+ KB
```

In [42]:
```
df_clean['price'].describe()
```

Out[42]:
```
count    2.731000e+03
mean     8.426668e+05
std      3.869865e+05
min      4.118100e+04
25%      5.700000e+05
50%      7.300000e+05
75%      1.011000e+06
max      2.301000e+06
Name: price, dtype: float64
```

In [43]:
```
df_clean['yr_built'].describe()
```

Out[43]:
```
count    2731.000000
mean     1987.685829
std         9.918578
min      1978.000000
25%      1980.000000
50%      1985.000000
75%      1992.000000
max      2022.000000
Name: yr_built, dtype: float64
```

In [44]:
```
df_clean.head()
```

Out[44]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
21	2310000170	2/28/2022	750000.0	3	2.0	1590	7754	1.0	
25	2095600170	10/8/2021	580000.0	3	3.0	2020	4482	1.0	
26	8682282030	5/4/2022	2000000.0	3	3.0	2700	7694	1.0	

Exported this cleaned dataset as a .csv, this will be our "master dataset"

In [45]:
```
df_clean.to_csv('data_cleaned.csv')
```

Modeling with Dataset

- We now have our cleaned dataset and would like to model this utilizing sklearn.

In [46]:
```
df = pd.read_csv('data_cleaned.csv')
```

In [47]:
```
df = df.drop(df.columns[0], axis =1)
```

In [48]:
```
# Checked to see how the data looks after import
df.head()
```

Out[48]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterf
0	2310000170	2/28/2022	750000.0	3	2.0	1590	7754	1.0	
1	2095600170	10/8/2021	580000.0	3	3.0	2020	4482	1.0	
2	8682282030	5/4/2022	2000000.0	3	3.0	2700	7694	1.0	
3	5727500011	11/3/2021	785000.0	3	2.0	1350	7354	1.0	
4	1421059003	8/25/2021	1680000.0	3	2.5	5200	206039	1.0	

5 rows × 29 columns

In [49]:
```
# We dropped the variables that we are not interested in exploring
df = df.drop(columns=['date', 'condition', 'grade', 'heat_source', 'se
                                    'yr_renovated', 'sqft_above', 'sqft
                                    'greenbelt', 'nuisance', 'view'])
```

In [50]:
```
# Sanity check that the columns were removed
df
```

Out[50]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_garage
0	2310000170	750000.0	3	2.0	1590	7754	1.0	440
1	2095600170	580000.0	3	3.0	2020	4482	1.0	600
2	8682282030	2000000.0	3	3.0	2700	7694	1.0	530
3	5727500011	785000.0	3	2.0	1350	7354	1.0	460
4	1421059003	1680000.0	3	2.5	5200	206039	1.0	1080
...	...	...	...	...	...	...	...	...
2726	3821400080	500000.0	3	2.5	1610	7250	1.0	490
2727	1761100480	560000.0	3	2.0	1480	8770	1.0	540
2728	2408100010	1011000.0	3	2.0	1460	10995	1.0	460
2729	2539500005	880000.0	4	2.5	2260	5661	1.0	460
2730	7960100080	800000.0	3	2.0	1620	3600	1.0	240

2731 rows × 16 columns

Scaling the data

- We know that the columns that interest us are not on all on the same scale (i.e number of bedrooms vs. price) Therefore we want to scale our data utilizing StandardScaler.

In [51]:
```
numbers_df = df.drop(['postal_code', 'lat', 'long'], axis=1)
```

In [52]:
```
scaled_df = StandardScaler().fit(numbers_df)
new_df = pd.DataFrame(scaled_df.transform(numbers_df), columns= number
new_df
```

Out[52]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_garage	s
0	-0.788063	-0.239501	-0.397810	-0.593686	-0.513990	-0.289056	0.0	-0.131216	·
1	-0.861512	-0.678874	-0.397810	1.098753	0.160401	-0.352063	0.0	0.638273	·
2	1.394924	2.991177	-0.397810	1.098753	1.226879	-0.290212	0.0	0.301622	
3	0.382688	-0.149042	-0.397810	-0.593686	-0.890394	-0.296759	0.0	-0.035030	·
4	-1.092593	2.164124	-0.397810	0.252533	5.147757	3.529187	0.0	2.946741	
...	...	...	...	...	...	...	...	...	
2726	-0.270295	-0.885637	-0.397810	0.252533	-0.482623	-0.298762	0.0	0.109249	
2727	-0.976103	-0.730565	-0.397810	-0.593686	-0.686509	-0.269492	0.0	0.349715	·
2728	-0.754457	0.435064	-0.397810	-0.593686	-0.717876	-0.226647	0.0	-0.035030	·
2729	-0.709442	0.096489	0.892475	0.252533	0.536805	-0.329360	0.0	-0.035030	·
2730	1.147522	-0.110274	-0.397810	-0.593686	-0.466940	-0.369047	0.0	-1.093078	·

2731 rows × 13 columns

In [53]:
```
# Taking a quick look at the correlation values
new_df.corr()
```

Out[53]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	s
id	1.000000	-0.005142	-0.082049	-0.062077	-0.063376	-0.193448	NaN	
price	-0.005142	1.000000	0.176587	0.355532	0.544653	0.174683	NaN	
bedrooms	-0.082049	0.176587	1.000000	0.553038	0.508079	0.012522	NaN	
bathrooms	-0.062077	0.355532	0.553038	1.000000	0.649136	0.053510	NaN	
sqft_living	-0.063376	0.544653	0.508079	0.649136	1.000000	0.230482	NaN	
sqft_lot	-0.193448	0.174683	0.012522	0.053510	0.230482	1.000000	NaN	
floors	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
sqft_garage	-0.035101	0.220684	0.096532	0.241162	0.300379	0.054536	NaN	
sqft_patio	-0.066855	0.273564	0.102776	0.230531	0.391423	0.178182	NaN	
yr_built	0.037681	0.093806	-0.103216	0.045555	0.067360	0.079642	NaN	

In [54]:
```
# Looking to see which variables have the highest correlation with 'pr
new_df.corr()['price'].map(abs).sort_values(ascending=False)
```

Out[54]:
```
price             1.000000
price_sqft        0.673794
grade_code        0.565316
sqft_living       0.544653
bathrooms         0.355532
sqft_patio        0.273564
sqft_garage       0.220684
bedrooms          0.176587
sqft_lot          0.174683
yr_built          0.093806
condition_code    0.028751
id                0.005142
floors                 NaN
Name: price, dtype: float64
```

In [55]:
```
# Setting up our X and y for modeling
X = new_df.drop(columns = ['price', 'floors', 'id'])
y = new_df['price']
```

In [56]:
```
# Checking that our variables were scaled
X.head()
```

Out[56]:

	bedrooms	bathrooms	sqft_living	sqft_lot	sqft_garage	sqft_patio	yr_built	grade_code
0	-0.39781	-0.593686	-0.513990	-0.289056	-0.131216	-0.991004	0.233360	-0.634611
1	-0.39781	1.098753	0.160401	-0.352063	0.638273	-0.502750	0.435038	-0.634611
2	-0.39781	1.098753	1.226879	-0.290212	0.301622	1.613017	1.846789	1.917852
3	-0.39781	-0.593686	-0.890394	-0.296759	-0.035030	-0.502750	-0.270837	-0.634611
4	-0.39781	0.252533	5.147757	3.529187	2.946741	1.735081	1.947629	3.194083

Dummy Regressor Model

In [57]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =

dummy_regr = DummyRegressor()
dummy_regr.fit(X_train, y_train)
dummy_regr.predict(X_train)
dummy_regr.predict(X_test)
dummy_regr.score(X_train, y_train)
dummy_regr.score(X_test, y_test)
dummy_train_RMSE = MSE(y_train,dummy_regr.predict(X_train), squared =
dummy_test_RMSE = MSE(y_test,dummy_regr.predict(X_test), squared = Fal

print()
print(f'Baseline Model Train Score: {dummy_regr.score(X_train, y_trair
print(f'Baseline Model Train RMSE: {round(dummy_train_RMSE)}')
print()
print(f'Baseline Model Test Score: {dummy_regr.score(X_test, y_test)}'
print(f'Baseline Model Test RMSE: {round(dummy_test_RMSE)}')
```

```
Baseline Model Train Score: 0.0
Baseline Model Train RMSE: 1.0

Baseline Model Test Score: -0.00032613851514340375
Baseline Model Test RMSE: 1.0
```

- This first model is pretty low, which is expected as it's the Dummy Regressor. Can only go up from here!

Second Model

- We want to create a model with just one variable at first, testing our highest correlated feature, 'price_sqft'

In [58]:
```
X_train_second_model = X_train[['price_sqft']]
X_test_second_model = X_test[['price_sqft']]

splitter = ShuffleSplit(n_splits=3, test_size=0.25, random_state=1337)

second_model = LinearRegression()
second_model.fit(X_train_second_model,y_train)

second_model_scores = cross_validate(estimator=second_model, X=new_df[

second_predict_train = second_model.predict(X_train_second_model)
second_predict_test = second_model.predict(X_test_second_model)

second_train_RMSE = MSE(y_train,second_predict_train,squared = False)
second_test_RMSE = MSE(y_test,second_predict_test, squared = False)

second_condition_num = sm.OLS(y_train, sm.add_constant(X_train_second_

print(f'Second Model Train score: {second_model_scores["train_score"].
print(f'Second Model Train RMSE: {round(second_train_RMSE)}')
print(f'Second Model Train Condition Number: {second_condition_num}')
print()
print("Second Model Test score: ", second_model_scores["test_score"].m
print(f'Second Model Test RMSE: {round(second_test_RMSE)}')
```

```
Second Model Train score: 0.297543313752787664
Second Model Train RMSE: 1.0
Second Model Train Condition Number: 1.013016249467147

Second Model Test score:  0.29357221571611486
Second Model Test RMSE: 1.0
```

- The results of our second model show that there is a Root Mean Squared Error of approximately 1. We note that our values are scaled, so we need to look at what this means with regards to price. As such we need to check the summary statistics.

In [59]:
```
# Taking a look at 'price' summary statistics
numbers_df['price'].describe()
```

Out[59]:
```
count    2.731000e+03
mean     8.426668e+05
std      3.869865e+05
min      4.118100e+04
25%      5.700000e+05
50%      7.300000e+05
75%      1.011000e+06
max      2.301000e+06
Name: price, dtype: float64
```

- An RSME of 1 std is suggesting that our model is off by approximately 1 standard deviation of price, or approximately 386,987 dollars. From our research we established that the median price of King County houses was approximately 780,000 dollars. We will keep this in mind as we continue modeling.

Get the Coefficient from our Second Model

- We wanted to interpret the coefficient for this variable to see what it means for our price

In [60]:
```
# Find the coefficient value for 'price_sqft'
second_model.coef_
```

Out[60]:
```
array([0.67459603])
```

In [61]:
```
df['price_sqft'].describe()
```

Out[61]:
```
count    2731.000000
mean      450.318617
std       168.290002
min        22.943038
25%       335.714286
50%       418.139535
75%       542.151753
max      1707.317073
Name: price_sqft, dtype: float64
```

In [62]:
```
df['price'].describe()
```

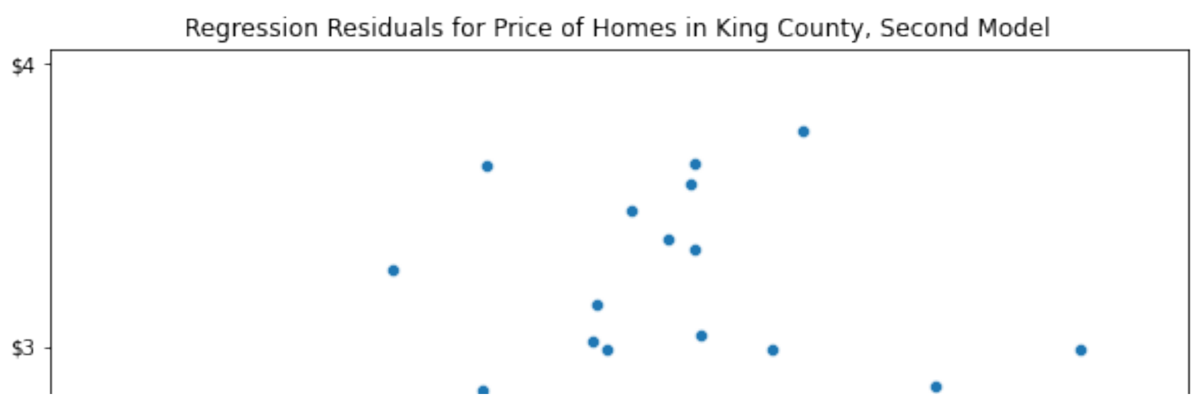
Out[62]:
```
count    2.731000e+03
mean     8.426668e+05
std      3.869865e+05
min      4.118100e+04
25%      5.700000e+05
50%      7.300000e+05
75%      1.011000e+06
max      2.301000e+06
Name: price, dtype: float64
```

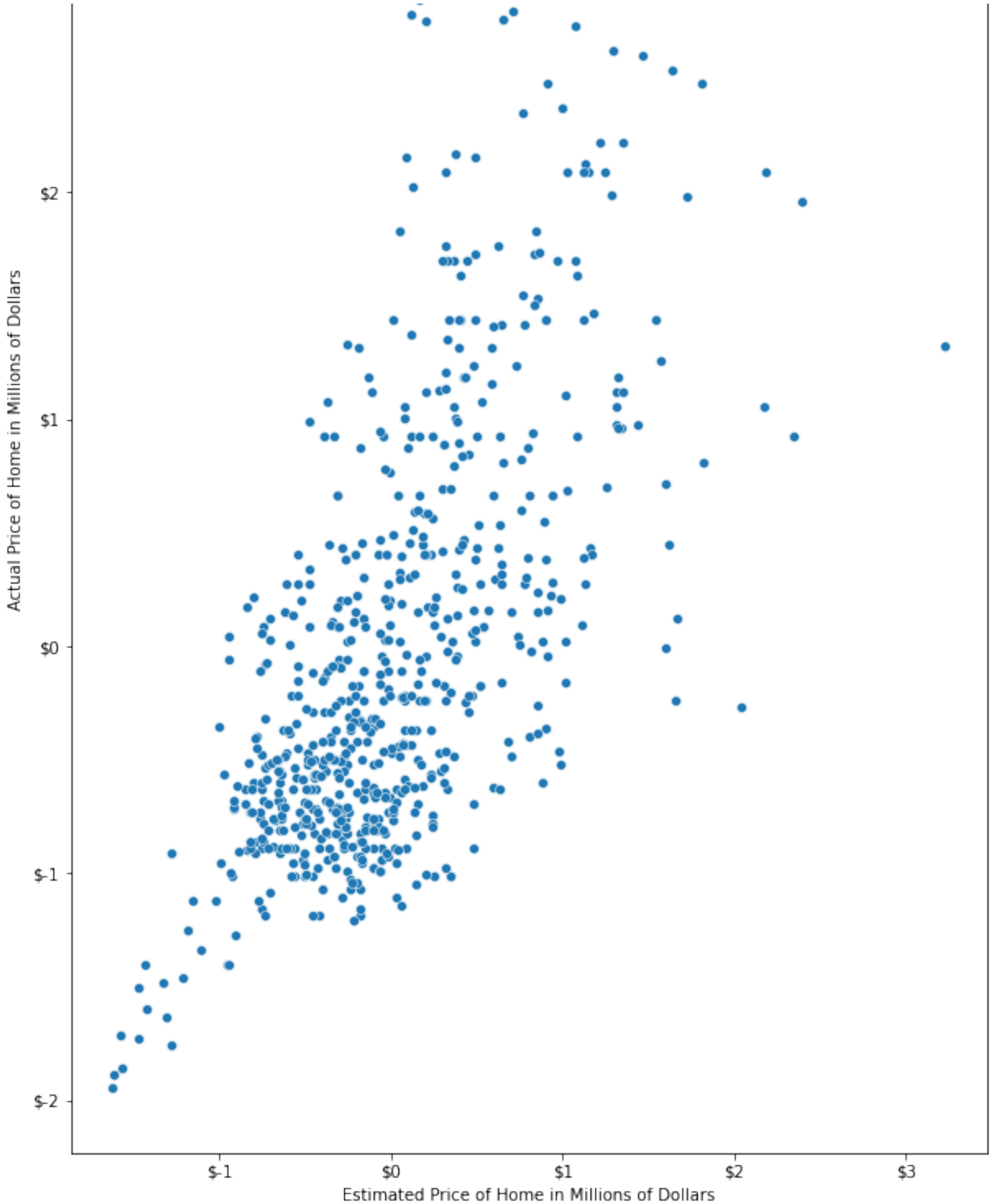
How to Interpret

- For each 1 std increase in price_sqft, we expect to see on average a .675 std increase in the price. (For every increase of 168 dollars/sqft, we expect on average the price to increase by approxmately 261,000 dollars)

Checking Variance of Second Model

In [63]:
```
fig, ax = plt.subplots(figsize = (10,16))

sns.scatterplot(x = second_predict_test, y = y_test, ax=ax)
ax.set_title('Regression Residuals for Price of Homes in King County,
ax.set_xlabel('Estimated Price of Home in Millions of Dollars')
ax.set_ylabel('Actual Price of Home in Millions of Dollars')
ax.ticklabel_format(style='plain')
millions = ticker.FuncFormatter(lambda x, pos: '${0:g}'.format(x))
ax.yaxis.set_major_formatter(millions)
ax.xaxis.set_major_formatter(millions)
x,y = [range(0, 4, 1)],[range(0, 4, 1)]

plt.show()
```





Third Model

- Wanted to plot more variables, 3 highest correlating to price, price/sqft, sqft living, and grade code.

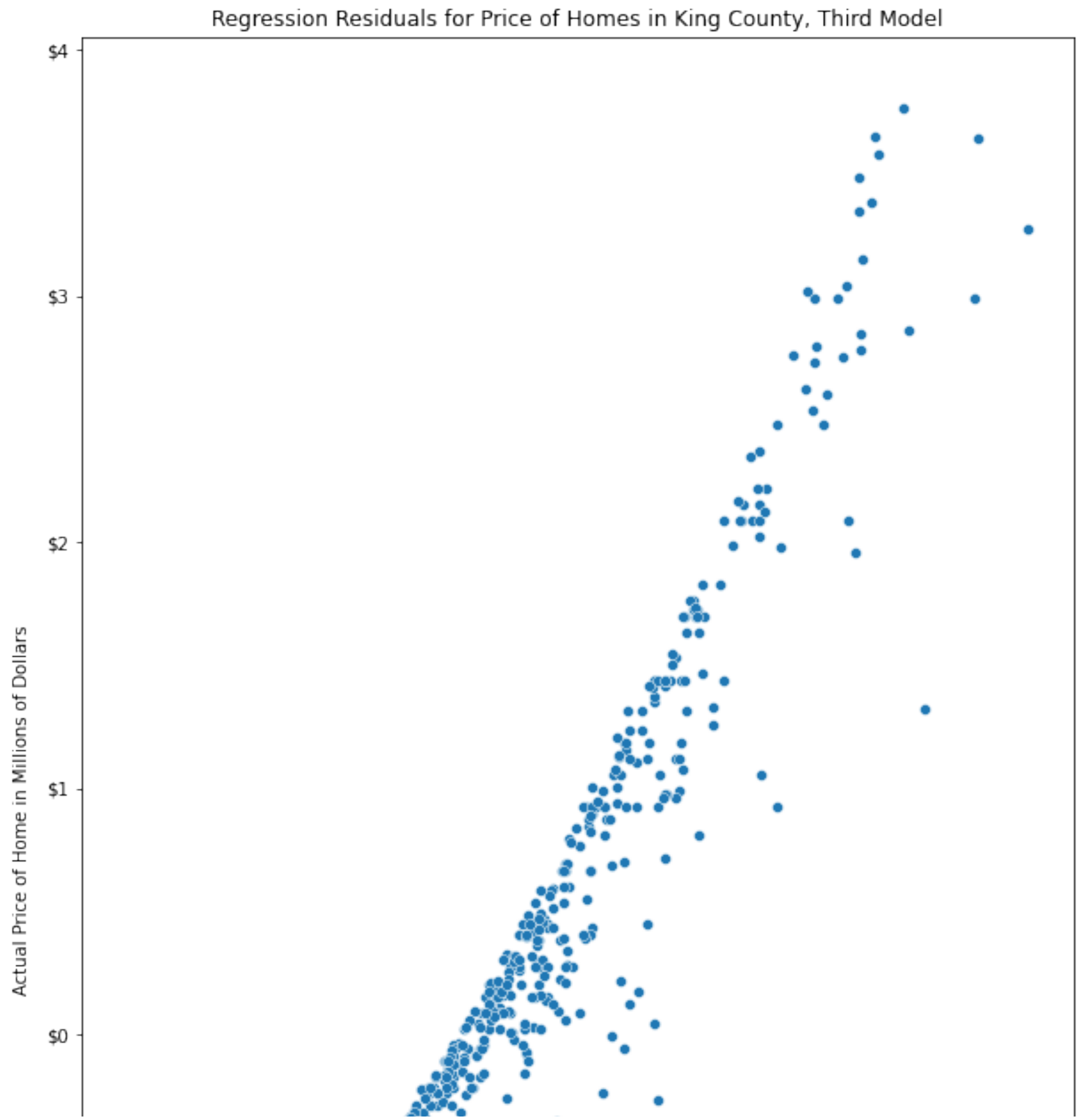
In [64]:
```
X_train_third_model = X_train[['price_sqft','sqft_living', 'grade_code
X_test_third_model = X_test[['price_sqft','sqft_living','grade_code']]

splitter = ShuffleSplit(n_splits=3, test_size=0.25, random_state=1337)

third_model = LinearRegression()
third_model.fit(X_train_third_model,y_train)

third_model_scores = cross_validate(
    estimator=third_model,
    X=new_df[['price_sqft', 'sqft_living', 'grade_code']],
    y=new_df.price,
    return_train_score=True,
    cv=splitter
)

third_predict_train = third_model.predict(X_train_third_model)
third_predict_test = third_model.predict(X_test_third_model)

third_train_RMSE = MSE(y_train,third_predict_train,squared = False)
third_test_RMSE = MSE(y_test,third_predict_test, squared = False)

third_condition_num = sm.OLS(y_train, sm.add_constant(X_train_third_mo

print(f'Third Model Train score: {third_model_scores["train_score"].me
print(f'Third Model Train RMSE: {(third_train_RMSE)}')
print()
print(f'Third Model Train Condition Number: {third_condition_num}')
print()
print("Third Model Test score: ", third_model_scores["test_score"].mea
print(f'Third Model Test RMSE: {(third_test_RMSE)}')
```

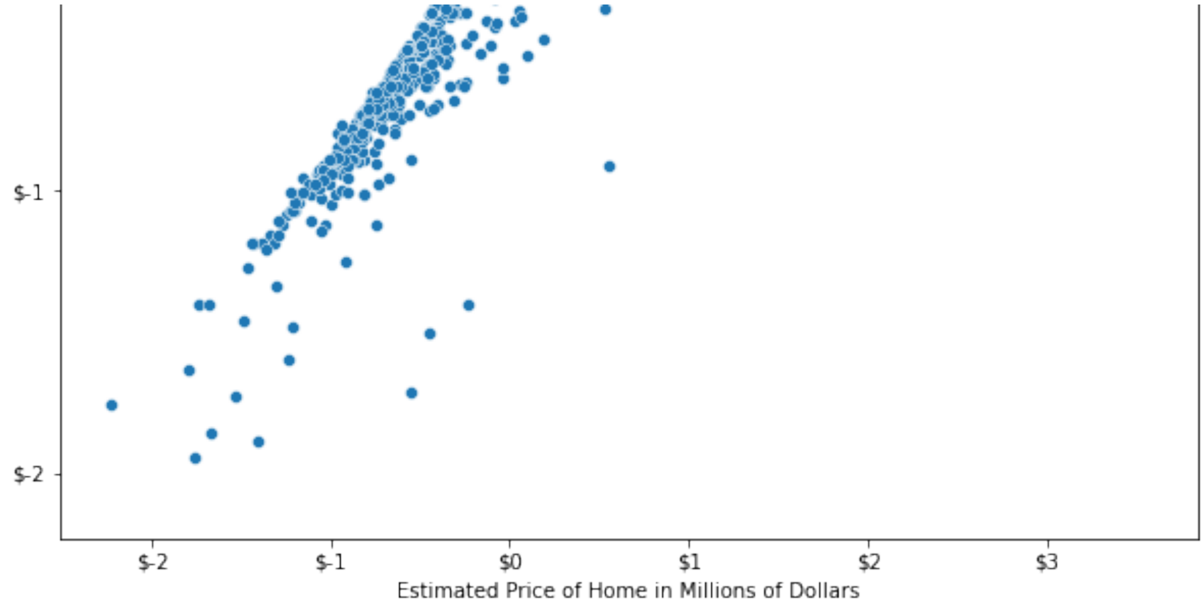
```
Third Model Train score: 0.9309081785724708
Third Model Train RMSE: 0.25989283442071814

Third Model Train Condition Number: 2.3167160847767625

Third Model Test score:  0.9297555396511165
Third Model Test RMSE: 0.273863401619033
```

Checking Variance of Third Model

In [65]:

```
fig, ax = plt.subplots(figsize = (10,16))

sns.scatterplot(x = third_predict_test, y = y_test, ax=ax)
ax.set_title('Regression Residuals for Price of Homes in King County,
ax.set_xlabel('Estimated Price of Home in Millions of Dollars')
ax.set_ylabel('Actual Price of Home in Millions of Dollars')
ax.ticklabel_format(style='plain')
millions = ticker.FuncFormatter(lambda x, pos: '${0:g}'.format(x))
ax.yaxis.set_major_formatter(millions)
ax.xaxis.set_major_formatter(millions)
x,y = [range(0, 4, 1)],[range(0, 4, 1)]

plt.show()
```





Get the Coefficients from our Third Model

In [66]:
```
third_model.coef_
```

Out[66]:
```
array([0.79261726, 0.65838925, 0.05401056])
```

In [67]:
```
df['price'].describe()
```

Out[67]:
```
count    2.731000e+03
mean     8.426668e+05
std      3.869865e+05
min      4.118100e+04
25%      5.700000e+05
50%      7.300000e+05
75%      1.011000e+06
max      2.301000e+06
Name: price, dtype: float64
```

In [68]:
```
df['price_sqft'].describe()
```

Out[68]:
```
count    2731.000000
mean      450.318617
std       168.290002
min        22.943038
25%       335.714286
50%       418.139535
75%       542.151753
max      1707.317073
Name: price_sqft, dtype: float64
```

In [69]:
```
df['sqft_living'].describe()
```

Out[69]:
```
count    2731.000000
mean     1917.726474
std       637.729194
min       770.000000
25%      1460.000000
50%      1810.000000
75%      2245.000000
max      5490.000000
Name: sqft_living, dtype: float64
```

In [70]:
```
df['grade_code'].describe()
```

Out[70]:
```
count    2731.000000
mean        7.497254
std         0.783701
min         6.000000
25%         7.000000
50%         7.000000
75%         8.000000
max        12.000000
Name: grade_code, dtype: float64
```

How to Interpret

For every:

- 168 dollars/sqft increase, we expect the price to increase by 307,000 dollars.
- 638 sqft increase in house size, we expect the price to increase by 255,000 dollars.
- .783 increase in grade code, we expect the price to increase by 21,000 dollars.

Insights

- We observe that we have a high score of approximately 93%, indicated that 93% of the variance seen in our price is due to the three variables highlighted above.
- We believe this is due to multicolinearity between our variables, especially since our feature engineered feature utilizes price per square feet, and we also are modeling against square feet as well.

Fourth Model

- We wanted to try modeling all the variables in our dataset to see if it would improve our score

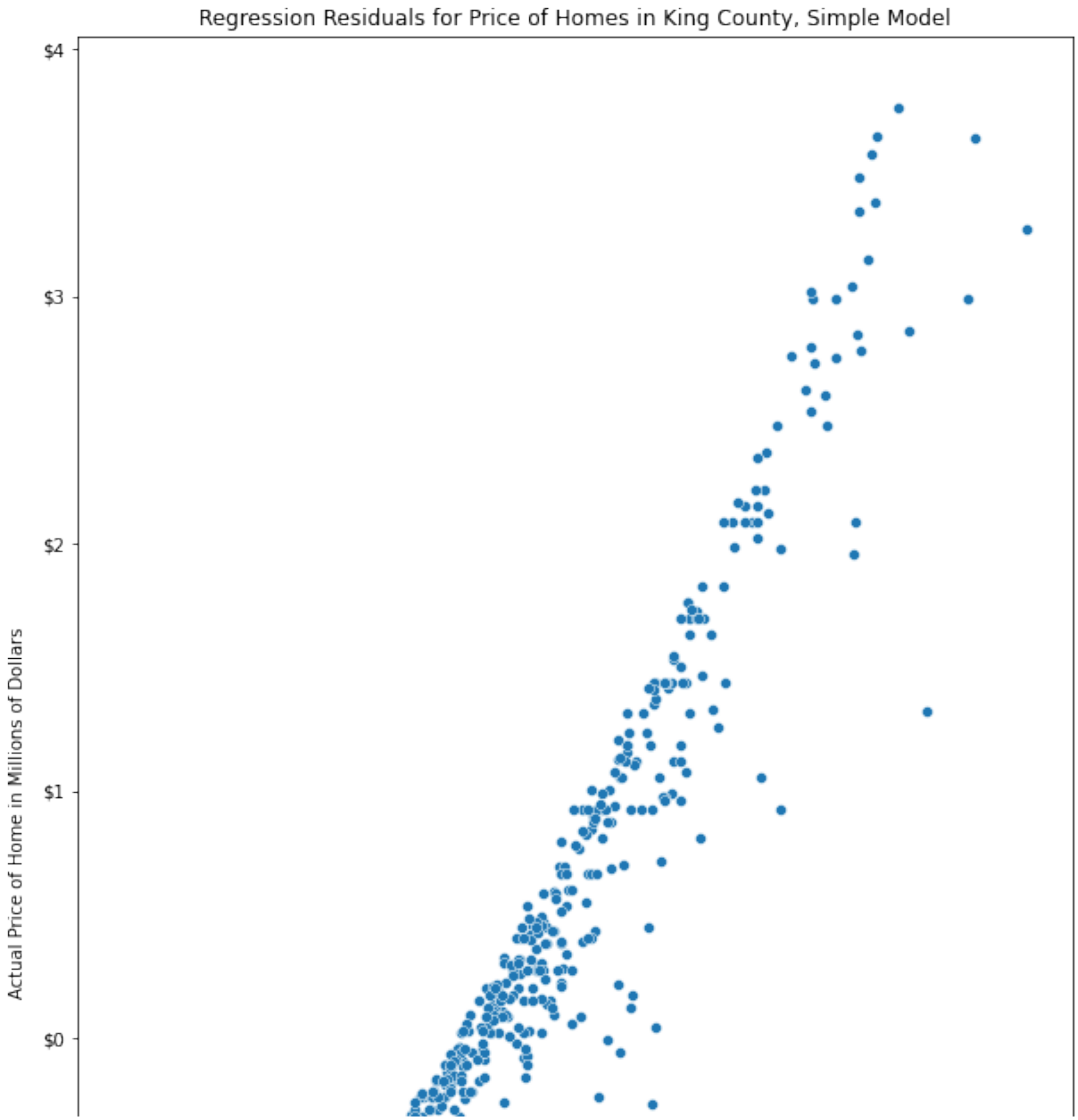
In [71]:
```
X_train_fourth_model = X_train
X_test_fourth_model = X_test

splitter = ShuffleSplit(n_splits=3, test_size=0.25, random_state=1337)

fourth_model = LinearRegression()
fourth_model.fit(X_train_fourth_model,y_train)

fourth_model_scores = cross_validate(
    estimator=fourth_model,
    X=new_df.drop(columns = 'price'),
    y=new_df.price,
    return_train_score=True,
    cv=splitter
)

fourth_predict_train = fourth_model.predict(X_train_fourth_model)
fourth_predict_test = fourth_model.predict(X_test_fourth_model)

fourth_train_RMSE = MSE(y_train,fourth_predict_train,squared = False)
fourth_test_RMSE = MSE(y_test,fourth_predict_test, squared = False)

fourth_condition_num = sm.OLS(y_train, sm.add_constant(X_train_fourth_

print(f'Fourth Model Train score: {fourth_model_scores["train_score"].
print(f'Fourth Model Train RMSE: {(fourth_train_RMSE)}')
print()
print(f'Fourth Model Train Condition Number: {fourth_condition_num}')
print()
print("Fourth Model Test score: ", fourth_model_scores["test_score"].m
print(f'Fourth Model Test RMSE: {(fourth_test_RMSE)}')
```

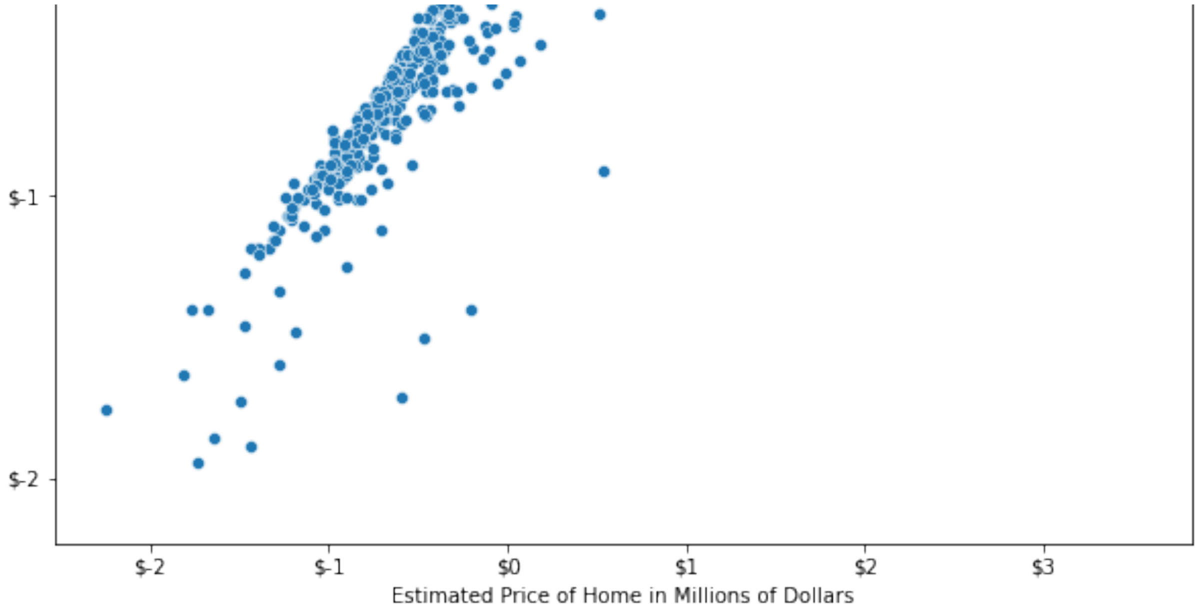
```
Fourth Model Train score: 0.9316003923381965
Fourth Model Train RMSE: 0.25883060687297554

Fourth Model Train Condition Number: 3.7020437513046143

Fourth Model Test score:  0.9298050860104968
Fourth Model Test RMSE: 0.2738572846156539
```

- We can compare our score values and they are similar to our third model, however we see that our condition number has increased. We believe that this indicates that there is multicolinearity between our variables as suggested in our previous example.

Checking the Variance of Fourth Model

In [72]:
```
fig, ax = plt.subplots(figsize = (10,16))

sns.scatterplot(x = fourth_predict_test, y = y_test, ax=ax)
ax.set_title('Regression Residuals for Price of Homes in King County,
ax.set_xlabel('Estimated Price of Home in Millions of Dollars')
ax.set_ylabel('Actual Price of Home in Millions of Dollars')
ax.ticklabel_format(style='plain')
millions = ticker.FuncFormatter(lambda x, pos: '${0:g}'.format(x))
ax.yaxis.set_major_formatter(millions)
ax.xaxis.set_major_formatter(millions)
x,y = [range(0, 4, 1)],[range(0, 4, 1)]

plt.show()
```





Fifth Model

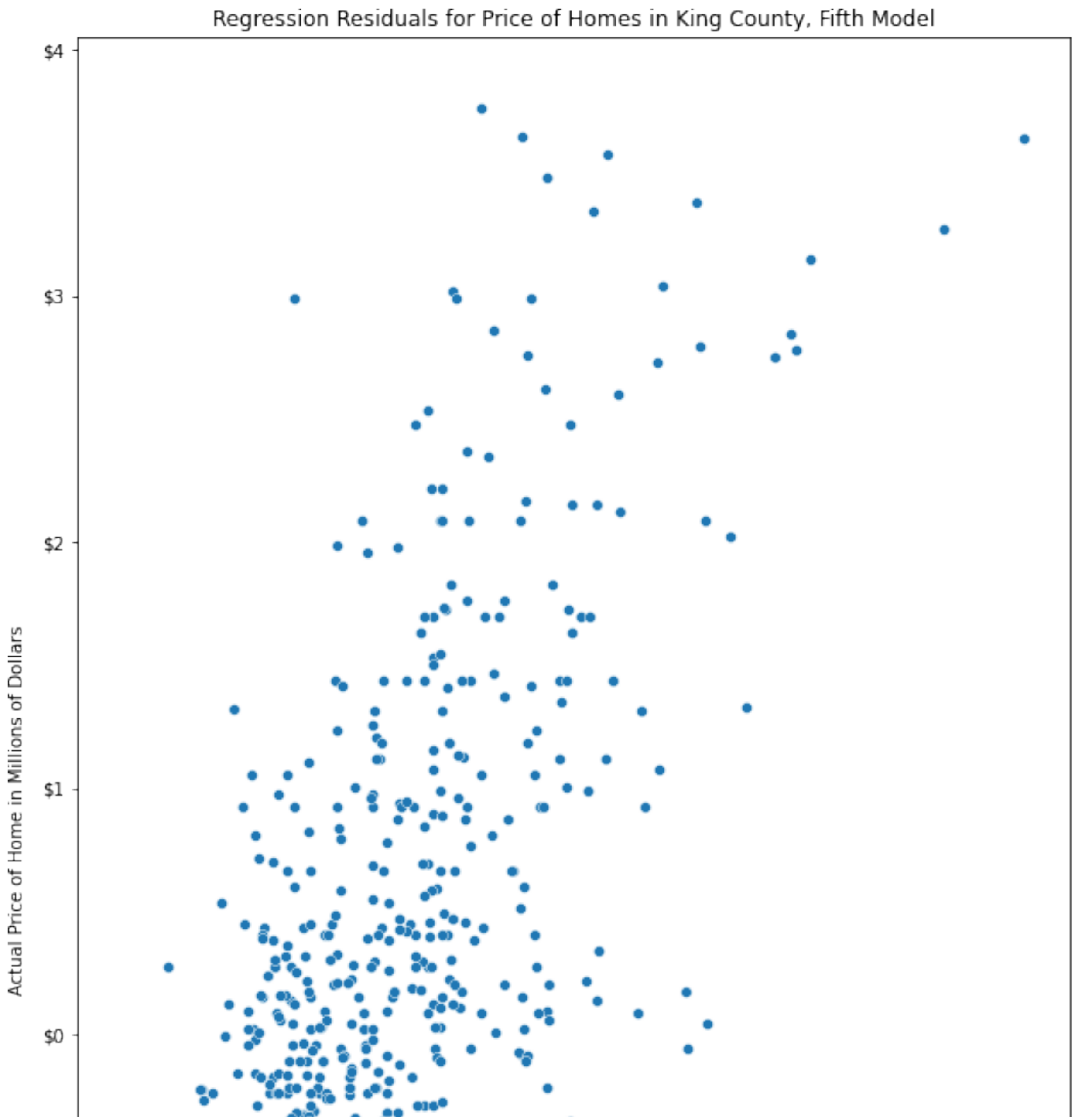
- We believe that there might be too much multicolinearity in our model due to our feature engineered variable. As such we wanted to test how the model looks with this removed.

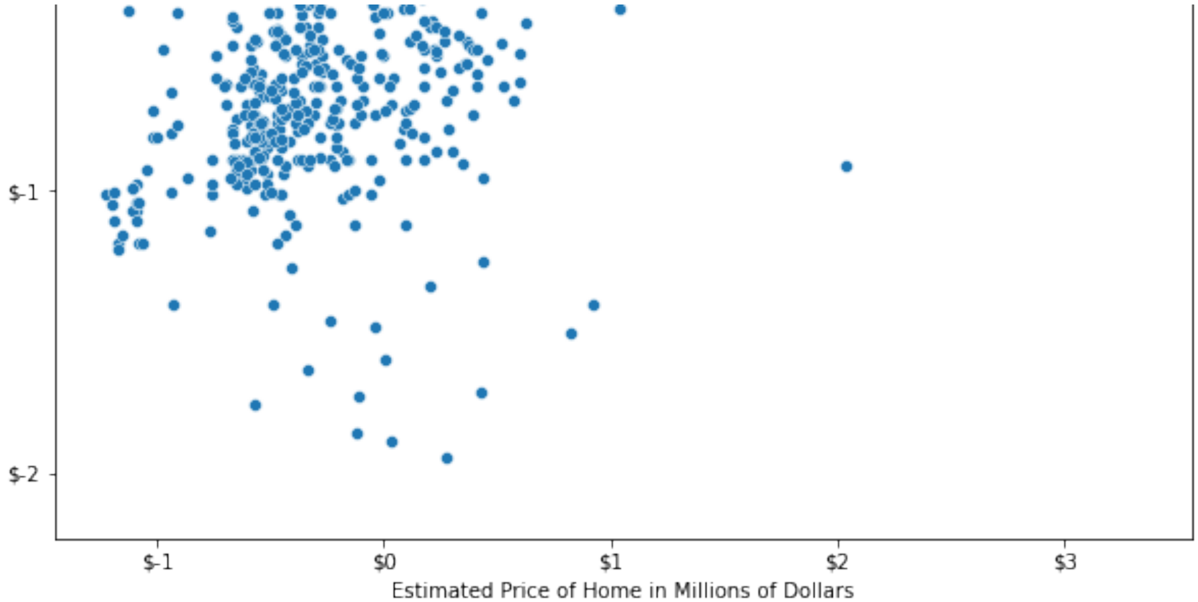
In [73]:
```
X_train_fifth_model = X_train[['sqft_living', 'grade_code']]
X_test_fifth_model = X_test[['sqft_living','grade_code']]

splitter = ShuffleSplit(n_splits=3, test_size=0.25, random_state=1337)

fifth_model = LinearRegression()
fifth_model.fit(X_train_fifth_model,y_train)

fifth_model_scores = cross_validate(
    estimator=fifth_model,
    X=new_df[['sqft_living', 'grade_code']],
    y=new_df.price,
    return_train_score=True,
    cv=splitter
)

fifth_predict_train = fifth_model.predict(X_train_fifth_model)
fifth_predict_test = fifth_model.predict(X_test_fifth_model)

fifth_train_RMSE = MSE(y_train,fifth_predict_train,squared = False)
fifth_test_RMSE = MSE(y_test,fifth_predict_test, squared = False)

fifth_condition_num = sm.OLS(y_train, sm.add_constant(X_train_fifth_mo

print(f'Ffith Model Train score: {fifth_model_scores["train_score"].me
print(f'Fifth Model Train RMSE: {(fifth_train_RMSE)}')
print()
print(f'Fifth Model Train Condition Number: {fifth_condition_num}')
print()
print("Fifth Model Test score: ", fifth_model_scores["test_score"].mea
print(f'Fifth Model Test RMSE: {(fifth_test_RMSE)}')
```

```
Ffith Model Train score: 0.37308899771469123
Fifth Model Train RMSE: 0.7895404447658543

Fifth Model Train Condition Number: 2.1139728340320696

Fifth Model Test score:  0.3906099965951218
Fifth Model Test RMSE: 0.7866608442208449
```

In [74]:

```
fig, ax = plt.subplots(figsize = (10,16))

sns.scatterplot(x = fifth_predict_test, y = y_test, ax=ax)
ax.set_title('Regression Residuals for Price of Homes in King County,
ax.set_xlabel('Estimated Price of Home in Millions of Dollars')
ax.set_ylabel('Actual Price of Home in Millions of Dollars')
ax.ticklabel_format(style='plain')
millions = ticker.FuncFormatter(lambda x, pos: '${0:g}'.format(x))
ax.yaxis.set_major_formatter(millions)
ax.xaxis.set_major_formatter(millions)
x,y = [range(0, 4, 1)],[range(0, 4, 1)]

plt.show()
```





Get the Coefficients from our Fifth Model

In [75]:
```
fifth_model.coef_
```

Out[75]:
```
array([0.32466871, 0.34908435])
```

In [76]:
```
df['sqft_living'].describe()
```

Out[76]:
```
count    2731.000000
mean     1917.726474
std       637.729194
min       770.000000
25%      1460.000000
50%      1810.000000
75%      2245.000000
max      5490.000000
Name: sqft_living, dtype: float64
```

In [77]:
```
df['grade_code'].describe()
```

Out[77]:
```
count    2731.000000
mean        7.497254
std         0.783701
min         6.000000
25%         7.000000
50%         7.000000
75%         8.000000
max        12.000000
Name: grade_code, dtype: float64
```

In [78]:
```
df['price'].describe()
```

Out[78]:
```
count    2.731000e+03
mean     8.426668e+05
std      3.869865e+05
min      4.118100e+04
25%      5.700000e+05
50%      7.300000e+05
75%      1.011000e+06
max      2.301000e+06
Name: price, dtype: float64
```

How to Interpret

For every:

- 638 sqft increase in house size, we expect the price on average to increase by approximately 125,000 dollars.
- .783 increase in grade code, we expect the price to increase by approximately 47,000 dollars.

We notice that taking out the price per sqft decreases our Condition Number for this model, which suggests that there is a decrease in multicolinearity.

Data Visuals Creation

In [79]:
```
# From our earlier data cleaning, we are creating a dataset called dat
data_relevant = df_clean.copy()
```

In [80]:
```
data_relevant = data_relevant.drop(columns=['id', 'date', 'waterfront'
                                    'condition', 'grade', 'heat_source',
                                    'yr_renovated', 'address', 'lat', 'l

data_relevant.head()
```

Out[80]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_garage	sqft_patio	yr_b
21	750000.0	3	2.0	1590	7754	1.0	440	0	19
25	580000.0	3	3.0	2020	4482	1.0	600	120	19
26	2000000.0	3	3.0	2700	7694	1.0	530	640	20
34	785000.0	3	2.0	1350	7354	1.0	460	120	19
39	1680000.0	3	2.5	5200	206039	1.0	1080	670	20

In [81]:
```
data_relevant.describe()
```

Out[81]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_garag
count	2.731000e+03	2731.000000	2731.000000	2731.000000	2731.00000	2731.0	2731.00000
mean	8.426668e+05	3.308312	2.350787	1917.726474	22764.97803	1.0	467.28377
std	3.869865e+05	0.775164	0.590972	637.729194	51940.46294	0.0	207.96823
min	4.118100e+04	2.000000	1.000000	770.000000	1078.00000	1.0	0.00000
25%	5.700000e+05	3.000000	2.000000	1460.000000	7279.50000	1.0	420.00000
50%	7.300000e+05	3.000000	2.500000	1810.000000	9016.00000	1.0	480.00000
75%	1.011000e+06	4.000000	3.000000	2245.000000	13452.00000	1.0	550.00000
max	2.301000e+06	8.000000	7.000000	5490.000000	765753.00000	1.0	2210.00000

Created a column called 'in_Seattle' to determine if postal code of house was in Seattle

In [82]:
```
Seattle_postalcodes = [98133, 98125, 98115, 98117, 98107, 98103, 98105
98195, 98191, 98181, 98154, 98164, 98121, 98101, 98104, 98122, 98134,
98126, 98106, 98108, 98118]

data_relevant['in_Seattle'] = np.where(data_relevant['postal_code'].is
```

In [83]:
```
# Sanity check
data_relevant['in_Seattle'].value_counts()
```

Out[83]:
```
0    2515
1     216
Name: in_Seattle, dtype: int64
```

In [84]:
```
Seattle_Homes = data_relevant.loc[data_relevant['in_Seattle'] == 1]
Seattle_Homes['price'].describe()
```

Out[84]:
```
count    2.160000e+02
mean     8.952342e+05
std      3.145420e+05
min      1.220500e+05
25%      6.999875e+05
50%      8.390000e+05
75%      1.010250e+06
max      2.020000e+06
Name: price, dtype: float64
```

In [85]:
```
NotSeattle_Homes = data_relevant.loc[data_relevant['in_Seattle'] == 0]
NotSeattle_Homes['price'].describe()
```

Out[85]:
```
count    2.515000e+03
mean     8.381521e+05
std      3.923093e+05
min      4.118100e+04
25%      5.600000e+05
50%      7.150000e+05
75%      1.012000e+06
max      2.301000e+06
Name: price, dtype: float64
```

In [86]:
```
data_relevant = data_relevant[data_relevant['condition_code'] >= 3]
```

In [87]:
```
data_relevant['price'].min()
```

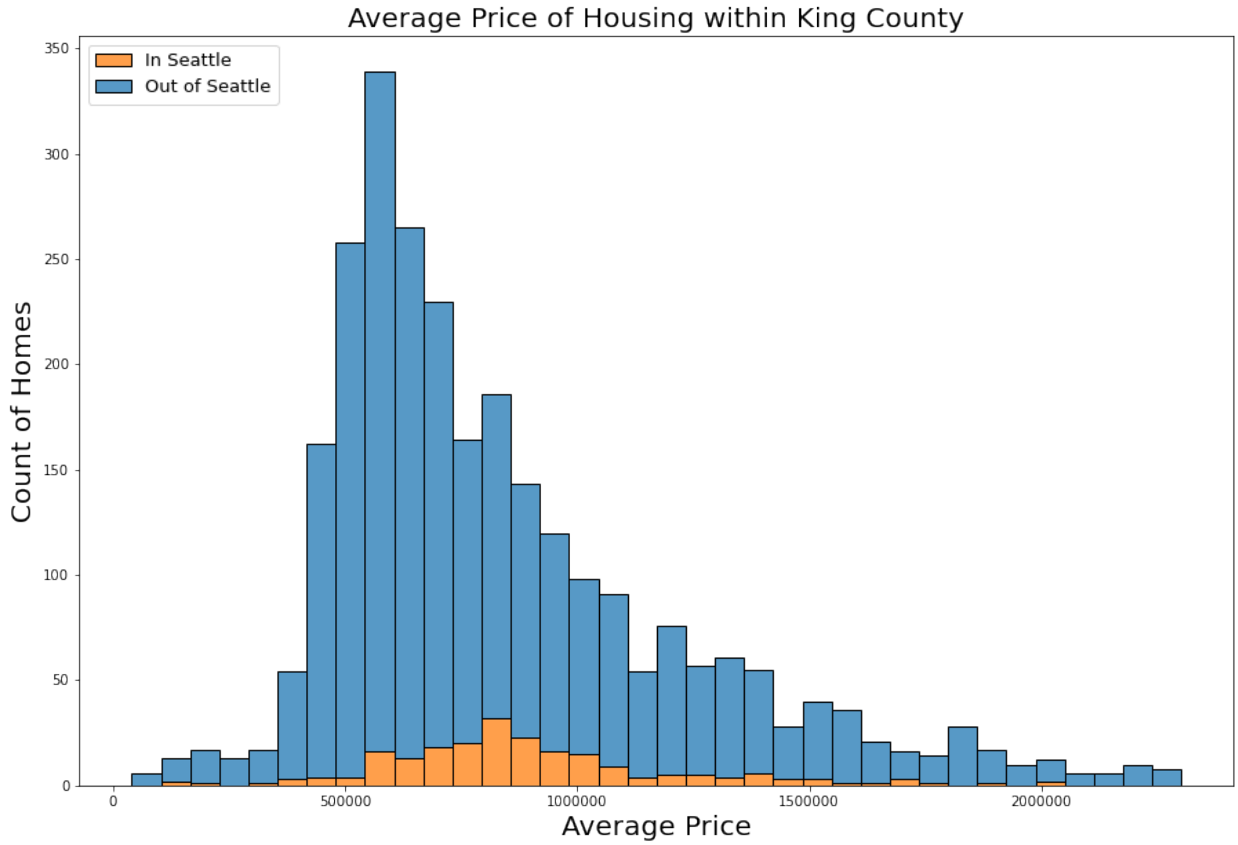
Out[87]: 41181.0

In [88]:
```
data_relevant['price'].max()
```

Out[88]: 2301000.0

Created average price of housing in King County based on if in Seattle or outside Seattle

In [89]:
```
fig, ax = plt.subplots(figsize = (15 , 10))

import matplotlib.ticker as ticker

sns.histplot(data_relevant, x="price", hue="in_Seattle", multiple="sta
plt.legend(loc='upper left', labels=['In Seattle', 'Out of Seattle'],
ax.set_xlabel('Average Price', fontsize = 20)
ax.set_ylabel('Count of Homes', fontsize = 20)
ax.set_title('Average Price of Housing within King County', fontsize =
plt.ticklabel_format(style='plain',axis='x');
```

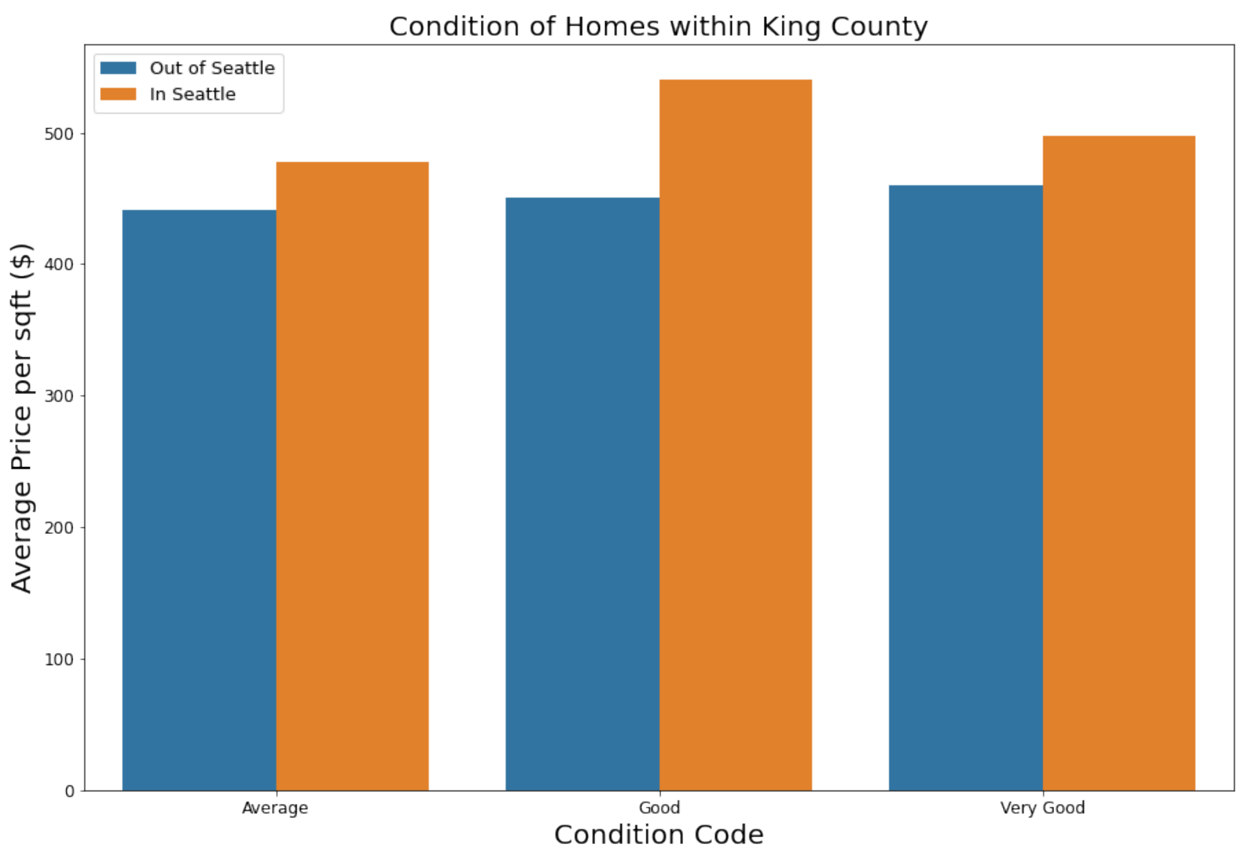


Looking at the average pricing of homes within King County, we see that significantly more families are purchasing homes outside of Seattle compared to purchases within the city. The average price of realty within Seattle is greater than that outside of the city as well which follows the trend of urban realty being more expensive than that of suburb communities.

Created average price per square feet vs. condition code of houses

- We wanted to compare the average price per square foot versus the condition code of the houses based on the locations of the houses.

In [90]:
```
fig, ax = plt.subplots(figsize = (15 , 10))

import matplotlib.ticker as ticker
from matplotlib import pyplot as plt

sns.barplot(x=data_relevant["condition_code"], y=data_relevant['price_
ax.legend(loc='upper left', labels=['Out of Seattle', 'In Seattle'], f
ax.set_xlabel('Condition Code', fontsize = 20)
ax.set_ylabel('Average Price per sqft ($)', fontsize = 20)
ax.set_title('Condition of Homes within King County', fontsize = 20)
plt.ticklabel_format(style='plain',axis='y')
ax.set_xticklabels(['Average','Good', 'Very Good'])
ax.tick_params(axis='both', which='major', labelsize=12);
```

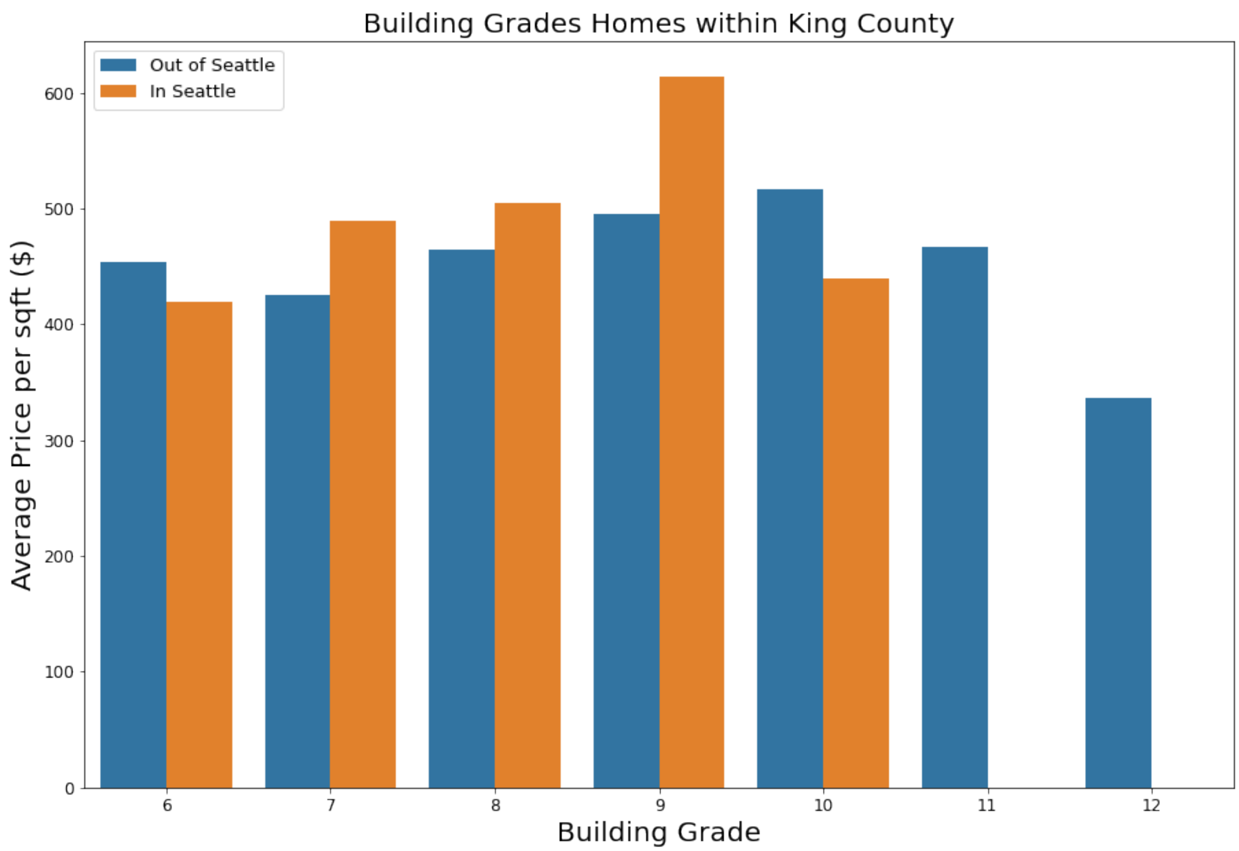


This model focused on homes that were of Average or greater condition to ensure that the families, especially the children are living in suitable conditions and not in homes of disrepair. Homes outside of Seattle have seen a steady incline in price as the conditions increase, whereas those within the city of Seattle have a greater variation in price.

Created average price per square feet vs building grades of homes

- We wanted to compare the average price per square feet against building grade values based on location of the houses.

In [91]:
```
fig, ax = plt.subplots(figsize = (15 , 10))

import matplotlib.ticker as ticker
from matplotlib import pyplot as plt

sns.barplot(x=data_relevant["grade_code"], y=data_relevant['price_sqft
ax.legend(loc='upper left', labels=['Out of Seattle', 'In Seattle'], f
ax.set_xlabel('Building Grade', fontsize = 20)
ax.set_ylabel('Average Price per sqft ($)', fontsize = 20)
ax.set_title('Building Grades Homes within King County', fontsize = 20
plt.ticklabel_format(style='plain',axis='y')
ax.tick_params(axis='both', which='major', labelsize=12);
```



This model focused on homes that had a building grade of 6 and above since the grade 6 is the lowest achievable grade that meetings King County building codes. There is an upward trend of average price per square foot as the building grade increases. However, there are only homes outside of Seattle that are of grade 11 and 12 which can be attributed to real estate is cheaper out of the big city or families customizings their homes more in suburban areas whereaas urban areas have more red tape and limitations. In addition, homes of higher grade begin to approach mansion level, and with more property, the bigger the house can be, which may not be possible within the city since there is less space.

Creating a map of the dataset

New datasets with the In Seattle vs Out of Seattle Breakdown

In [92]:
```
#Create new dataset for mapping dataset
mapdata = df_clean.copy()
```

In [93]:
```
#Create new column noting whether home is in or out of Seattle
Seattle_postalcodes = [98133, 98125, 98115, 98117, 98107, 98103, 98105
98195, 98191, 98181, 98154, 98164, 98121, 98101, 98104, 98122, 98134,
98126, 98106, 98108, 98118]

mapdata['in_Seattle'] = np.where(mapdata['postal_code'].isin(Seattle_p
mapdata.head()
```

Out[93]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
21	2310000170	2/28/2022	750000.0	3	2.0	1590	7754	1.0	
25	2095600170	10/8/2021	580000.0	3	3.0	2020	4482	1.0	
26	8682282030	5/4/2022	2000000.0	3	3.0	2700	7694	1.0	

In [94]:
```
#Create copy of the map dataset
df_seattle = mapdata.copy()

#Create new dataset for homes only in Seattle
Seattle_Homes = df_seattle.loc[df_seattle['in_Seattle'] == 1]
Seattle_Homes.shape
```

Out[94]: (216, 30)

Of the 2,731 homes within the dataset, there are 216 homes in the city of Seattle - roughly 8% of the dataset.

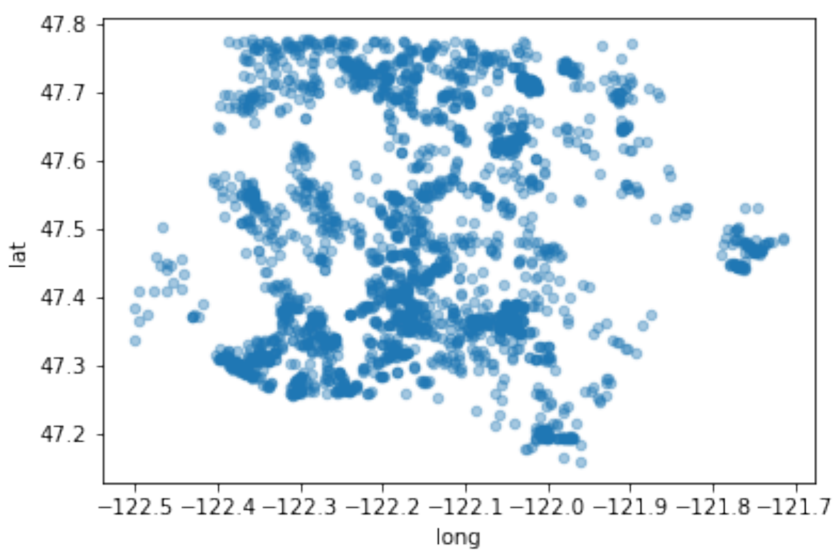
In [95]:
```
#Create copy of the map dataset
df_notseattle = mapdata.copy()

#Create new dataset for homes only in Seattle
NotSeattle_Homes = df_seattle.loc[df_seattle['in_Seattle'] == 0]
NotSeattle_Homes.shape
```

Out[95]: (2515, 30)

Of the 2,731 homes within the dataset, there are 2,515 homes out of Seattle city bounds - roughly 92% of the dataset.

Mapping the homes

In [96]:
```
#Map of all of the datapoints
mapdata.plot(kind="scatter", x="long", y="lat", alpha=0.4)
plt.show();
```



In [97]:
```
#Select only the relevant columns for mapping
seattle_locations = Seattle_Homes[["lat", "long", "id"]]
```

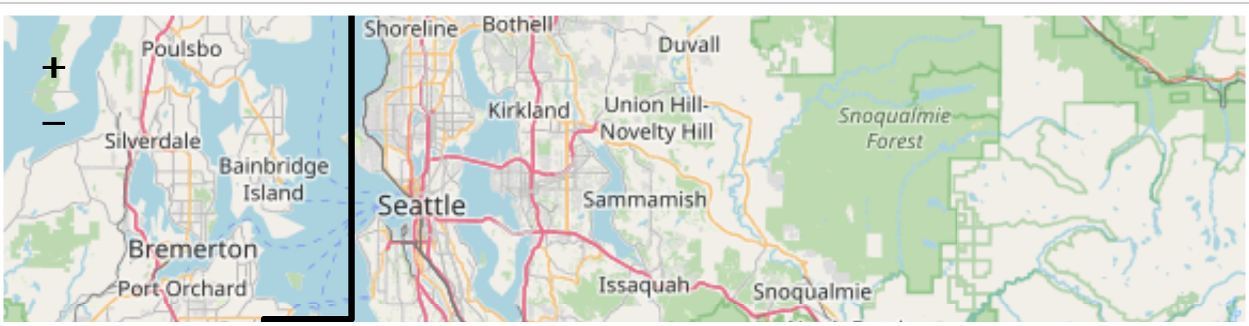
In [98]:
```
#Select only the relevant columns for mapping
notSeattle_locations = NotSeattle_Homes[["lat", "long", "id"]]
```

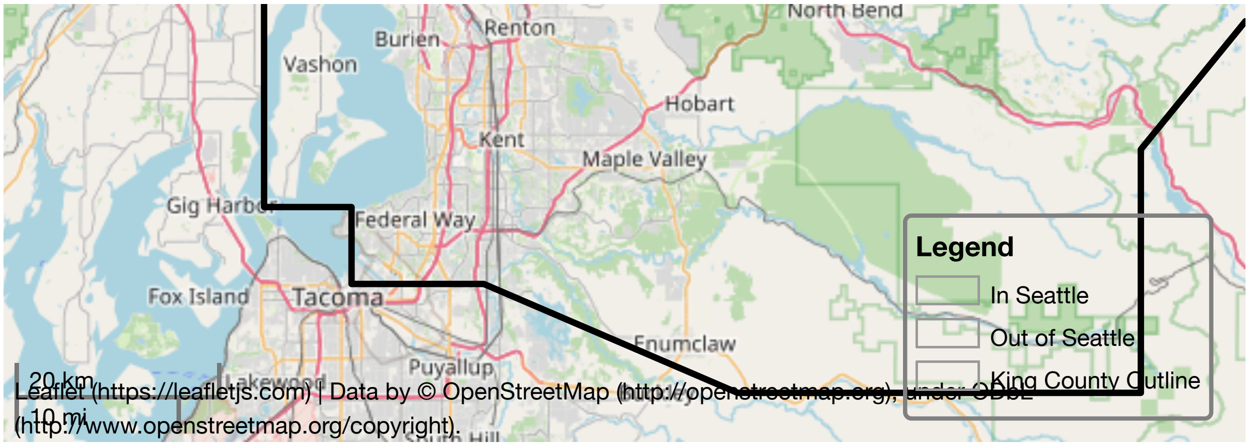
In [99]:
```
#Create an interactive map of homes
import folium
from folium.plugins import FastMarkerCluster
from branca.element import Template, MacroElement

#Create a blank map
map = folium.Map(location=[notSeattle_locations.lat.mean(),
                           notSeattle_locations.long.mean()], zoom_sta

#Index markers for homes Out of Seattle
for index, location_info in notSeattle_locations.iterrows():
    folium.Marker([location_info["lat"], location_info["long"]], popup

#Index markers for homes In Seattle
for index, location_info in seattle_locations.iterrows():
    folium.Marker([location_info["lat"], location_info["long"]], popup

#County outline coordinates
king_county = [
    [47.777799, -121.998473],
    [47.777799, -122.419374],
    [47.734022, -122.419374],
    [47.503347, -122.419374],
    [47.503347, -122.419374],
    [47.503347, -122.533756],
    [47.324233, -122.533756],
    [47.324233, -122.419374],
    [47.257529, -122.419374],
    [47.257529, -122.249917],
    [47.161605, -121.924595],
    [47.161605, -121.404507],
    [47.373455, -121.404507],
    [47.600453, -121.131500],
    [47.777799, -121.131500],
    [47.777799, -121.998473],
]

# Plot county lines using coordinates
my_PolyLine=folium.PolyLine(locations=king_county,weight=3, color = 'b
map.add_child(my_PolyLine)


#Create a draggable legend
template = """
{% macro html(this, kwargs) %}

<!doctype html>
<html lang="en">
<head>
  <meta charset="utf-8">
```

```
  <meta name="viewport" content="width=device-width, initial-scale=1">
  <title>jQuery UI Draggable - Default functionality</title>
  <link rel="stylesheet" href="//code.jquery.com/ui/1.12.1/themes/base

  <script src="https://code.jquery.com/jquery-1.12.4.js"></script>
  <script src="https://code.jquery.com/ui/1.12.1/jquery-ui.js"></scrip

  <script>
  $( function() {
    $( "#maplegend" ).draggable({
                    start: function (event, ui) {
                        $(this).css({
                            right: "auto",
                            top: "auto",
                            bottom: "auto"
                        });
                    }
                });
});

  </script>
</head>
<body>


<div id='maplegend' class='maplegend'
    style='position: absolute; z-index:9999; border:2px solid grey; ba
     border-radius:4px; padding: 4px; font-size:14px; right: 15px; bot

<div class='legend-title'>Legend</div>

<div class='legend-scale'>
  <ul class='legend-labels'>
    <li><span style='background:orange;opacity:1.0;'></span>In Seattle
    <li><span style='background:cadetblue;opacity:1.0;'></span>Out of
    <li><span style='background:black;opacity:1.0;'></span>King County

  </ul>
</div>
</div>

</body>
</html>

<style type='text/css'>
  .maplegend .legend-title {
    text-align: left;
    margin-bottom: 5px;
    font-weight: bold;
    font-size: 90%;
    }
```

```
    }
  .maplegend .legend-scale ul {
    margin: 0;
    margin-bottom: 2px;
    padding: 0;
    float: left;
    list-style: none;
    }
  .maplegend .legend-scale ul li {
    font-size: 80%;
    list-style: none;
    margin-left: 0;
    line-height: 18px;
    margin-bottom: 2px;
    }
  .maplegend ul.legend-labels li span {
    display: block;
    float: left;
    height: 14px;
    width: 30px;
    margin-right: 5px;
    margin-left: 0;
    border: 1px solid #999;
    }
  .maplegend .legend-source {
    font-size: 80%;
    color: #777;
    clear: both;
    }
  .maplegend a {
    color: #777;
    }
</style>
{% endmacro %}"""

macro = MacroElement()
macro._template = Template(template)

map.get_root().add_child(macro)

map
```

Out[99]:





The dataset consisted of 2,731 homes with the numerous fixed factors and price outliers removed. The homes within the city of Seattle is noted in orange markers and the homes outside of Seattle are noted in blue. The outline of King County can be seen noted in a black line.

Conclusion

Our model accounted for approximately 37% of the variability seen in the price of the home after focusing on two main factors, square foot of liveable space and the building grade. As the amount of space in the home and building grade both increase, the average price of the home is expected to increase as well. To be more precise, with one square food increase in liveable space, you should expect to see an increase in the price of the home on average by about two hundred dollars. With one grade increase in the building grade, you should expect to see an increase in the price of the home on average by about sixty thousand dollars.

Recommendations

- **Plant your roots in a town outside of Seattle**
  - On average the prices of homes outside of Seattle are lower compared to those within the city of Seattle, which leaves your bank account with more money. Signficantly more families purchase homes outside of Seattle so you can surround yourself with other growing families in a family friendly neighorhood as well.
- **Opt for a home with more liveable square feet**
  - Although adding more square footage means more dollar signs on the price tag of the home, a home with a larger space would be advantageous to a growing family. A larger home allows each family member to maintain their own space within a single household.
- **Focus on homes with higher condition code or building grade**
  - As both the condition code and building grade increase, the value of a home increases as well. The higher quality and design of the home, the stronger it will be to withstand the forces of nature and your children. A quality home has been maintained properly which means less repairs for you and decreased chances of injuries due to the deferred maintanence or home deterioration.

From the start, our focal point was the price of a home. As such, we believe these results would benefit both real estate agencies and families should they be taken into consideration.

Future Insights & Next Steps

- Consider changes in the Housing Market.
- Explore how the changes in demographics impact real-estate trends and the local area.
- Consider changes in interest rates and how this impacts purchaser's ability to obtain a mortgage and real estate demand.