King County Housing Sale Price Analysis

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Business Problem

A prominent YouTuber has hired us because she is planning to produce a series of videos on flipping houses. The process of flipping property is essentially purchasing some real estate, investing in it through construction or additions, and selling for a profit. Our client wants to know what features most determine home sale price, so she can give her viewers a guide on how to best invest in the properties they purchase/sell.

Data Understanding

The dataset we are analyzing contains information about real estate in King County. This includes 21,597 entries spanning May 2014 - May 2015. We will use this data to create a multiple linear regression model in order to discover two features that affect home sale price.

Data Preparation

In order to ensure clean data, we will explore the dataset for outliers, missing values, and multicollinearity.

In [1]:

```
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, cross_validate
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Lasso, Ridge, LinearRegression
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
```

In [2]:

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

In [3]:

```
df.head()
```

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfr
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	N
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 [4]:
```python
drop_cols = [
    'date', 'view', 'sqft_above', 'sqft_basement', 'yr_renovated', 'zipcode',
    'lat', 'long', 'sqft_living15', 'sqft_lot15', 'id'
]
df = df.drop(drop_cols, axis=1)
```

In [5]:
```python
df.head()
```

Out[5]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr
0	221900.0	3	1.00	1180	5650	1.0	NaN	3	7	
1	538000.0	3	2.25	2570	7242	2.0	0.0	3	7	
2	180000.0	2	1.00	770	10000	1.0	0.0	3	6	
3	604000.0	4	3.00	1960	5000	1.0	0.0	5	7	
4	510000.0	3	2.00	1680	8080	1.0	0.0	3	8	

In [6]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   price         21597 non-null  float64
 1   bedrooms      21597 non-null  int64  
 2   bathrooms     21597 non-null  float64
 3   sqft_living   21597 non-null  int64  
 4   sqft_lot      21597 non-null  int64  
 5   floors        21597 non-null  float64
 6   waterfront    19221 non-null  float64
 7   condition     21597 non-null  int64  
 8   grade         21597 non-null  int64  
 9   yr_built      21597 non-null  int64  
dtypes: float64(4), int64(6)
memory usage: 1.6 MB
```

In [7]:
```python
# Assume null values for column: waterfront means the property does not have a w
df = df.fillna(0)
```

In [8]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   price         21597 non-null  float64
 1   bedrooms      21597 non-null  int64  
 2   bathrooms     21597 non-null  float64
 3   sqft_living   21597 non-null  int64  
 4   sqft_lot      21597 non-null  int64  
 5   floors        21597 non-null  float64
 6   waterfront    21597 non-null  float64
 7   condition     21597 non-null  int64  
 8   grade         21597 non-null  int64  
 9   yr_built      21597 non-null  int64  
```

```
dtypes: float64(4), int64(6)
memory usage: 1.6 MB
```

In [9]:
```python
df.describe()
```

Out[9]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	
count	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	2
mean	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	
std	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	

In [10]:
```python
df[df['bedrooms'] > 8]
```

Out[10]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grad
4092	599999.0	9	4.50	3830	6988	2.5	0.0	3	
4231	700000.0	9	3.00	3680	4400	2.0	0.0	3	
6073	1280000.0	9	4.50	3650	5000	2.0	0.0	3	
8537	450000.0	9	7.50	4050	6504	2.0	0.0	3	
8748	520000.0	11	3.00	3000	4960	2.0	0.0	3	
13301	1150000.0	10	5.25	4590	10920	1.0	0.0	3	
15147	650000.0	10	2.00	3610	11914	2.0	0.0	4	
15856	640000.0	33	1.75	1620	6000	1.0	0.0	5	
16830	1400000.0	9	4.00	4620	5508	2.5	0.0	3	
18428	934000.0	9	3.00	2820	4480	2.0	0.0	3	
19239	660000.0	10	3.00	2920	3745	2.0	0.0	4	

In [11]:
```python
# Dropping the odd property with 33 bedrooms
df.drop(index=15856,inplace=True)
```

In [12]:
```python
df.describe()
```

Out[12]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	
count	2.159600e+04	21596.000000	21596.000000	21596.000000	2.159600e+04	21596.000000	:
mean	5.402920e+05	3.371828	2.115843	2080.343165	1.509983e+04	1.494119	
std	3.673760e+05	0.904114	0.768998	918.122038	4.141355e+04	0.539685	
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.619000e+03	1.500000
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068550e+04	2.000000
max	7.700000e+06	11.000000	8.000000	13540.000000	1.651359e+06	3.500000

In [13]:
```
df[df['sqft_living'] > 8000]
```

Out[13]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	gra
1162	5110000.0	5	5.25	8010	45517	2.0	1.0	3	
3910	7060000.0	5	4.50	10040	37325	2.0	1.0	3	
4407	5570000.0	5	5.75	9200	35069	2.0	0.0	3	
7245	7700000.0	6	8.00	12050	27600	2.5	0.0	4	
8085	4670000.0	5	6.75	9640	13068	1.0	1.0	3	
9245	6890000.0	6	7.75	9890	31374	2.0	0.0	3	
12764	2280000.0	7	8.00	13540	307752	3.0	0.0	3	
14542	2890000.0	5	6.25	8670	64033	2.0	0.0	3	
18288	3300000.0	5	6.25	8020	21738	2.0	0.0	3	

In [14]:
```
df.isna().sum()
```

Out[14]:
```
price          0
bedrooms       0
bathrooms      0
sqft_living    0
sqft_lot       0
floors         0
waterfront     0
condition      0
grade          0
yr_built       0
dtype: int64
```

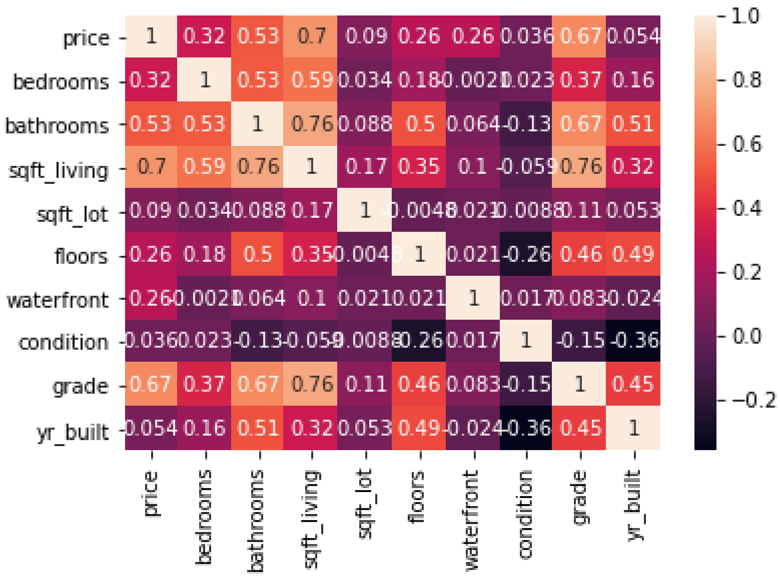
In [15]:
```
sns.pairplot(df)
```

Out[15]:
```
<seaborn.axisgrid.PairGrid at 0x7fd2d0d63490>
```

In [16]:
```
# Possibly some multicollinearity between bed/bath and sqft_living. Will check t
```

In [17]:
```
sns.heatmap(df.corr(), annot=True)
```

Out[17]: <AxesSubplot:>



```
In [18]: df.columns
```

```
Out[18]: Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
                'waterfront', 'condition', 'grade', 'yr_built'],
               dtype='object')
```

Modeling

Here are the strategies we will attempt as we fine tune our baseline linear regression model:

1. Remove features based on coefficient values
2. One hot encode categorical data
3. Check for substantial interaction relationships between features

```
In [19]: # First, create a baseline model
```

```
In [20]: # Define X and y

         used_cols = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'cond

         X = df[used_cols]
         y = df['price']
```

```
In [21]: # Perform a train/test split
         X_train, X_test, y_train, y_test = train_test_split(X,
                                                             y,
                                                             test_size=0.33,
                                                             random_state=42)
```

```
In [22]: # Using a standard scaler
         scaler = StandardScaler()

         # Train our scaler on training data, then fit to testing
         X_train_scaled = scaler.fit_transform(X_train)
         X_test_scaled = scaler.transform(X_test)
```

Baseline Linear Regression Model

In [23]:
```python
# Instantiate a linear regression model
lr = LinearRegression()
```

In [24]:
```python
# Fit our model on our scaled data
lr.fit(X_train_scaled, y_train)
```

Out[24]:
```
LinearRegression()
```

In [25]:
```python
X_train.columns
```

Out[25]:
```
Index(['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'condition', 'grade', 'yr_built'],
      dtype='object')
```

In [26]:
```python
lr.coef_
```

Out[26]:
```
array([ -46383.31360808,   45524.25114741,  170317.06757107,
        -12500.43673523,    9477.74422744,   13599.38780936,
        156948.61215719, -119549.87371116])
```

In [27]:
```python
lr.intercept_
```

Out[27]:
```
542484.1496302438
```

In [28]:
```python
# Predict and evaluate
y_train_pred = lr.predict(X_train_scaled)
y_test_pred = lr.predict(X_test_scaled)

print("Training Scores:")
print(f"R2 Score: {r2_score(y_train, y_train_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_train, y_train_pred):.4f}")
print("---")
print("Testing Scores:")
print(f"R2 Score: {r2_score(y_test, y_test_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_test, y_test_pred):.4f}")
```

```
Training Scores:
R2 Score: 0.6221
MAE: 145780.8104
---
Testing Scores:
R2 Score: 0.6114
MAE: 144377.0921
```

In [29]:
```python
for n in range(10):
    X_train, X_test, y_train, y_test = train_test_split(X,
                                                        y,
                                                        test_size=0.33,
                                                        random_state=n)  # <--
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    lr = LinearRegression()
    lr.fit(X_train_scaled, y_train)

    y_train_pred = lr.predict(X_train_scaled)
    y_test_pred = lr.predict(X_test_scaled)
```

```
    print(f"Random Seed: {n}")
    print(f"Train R2 Score: {r2_score(y_train, y_train_pred):4f}")
    print(f"Test R2 Score: {r2_score(y_test, y_test_pred):4f}")
    print("-----")
```

```
Random Seed: 0
Train R2 Score: 0.613992
Test R2 Score: 0.628440
-----
Random Seed: 1
Train R2 Score: 0.618734
Test R2 Score: 0.618436
-----
Random Seed: 2
Train R2 Score: 0.622474
Test R2 Score: 0.610720
-----
Random Seed: 3
Train R2 Score: 0.623327
Test R2 Score: 0.608108
-----
Random Seed: 4
Train R2 Score: 0.615630
Test R2 Score: 0.624370
-----
Random Seed: 5
Train R2 Score: 0.618184
Test R2 Score: 0.619285
-----
Random Seed: 6
Train R2 Score: 0.624535
Test R2 Score: 0.606820
-----
Random Seed: 7
Train R2 Score: 0.620943
Test R2 Score: 0.613762
-----
Random Seed: 8
Train R2 Score: 0.620639
Test R2 Score: 0.614806
-----
Random Seed: 9
Train R2 Score: 0.619854
Test R2 Score: 0.616460
-----
```

In [30]:

```
# Try less features: remove sqft_lot, floors, condition
```

Modeling

In [31]:

```
# Define X and y

used_cols = ['bedrooms', 'bathrooms', 'sqft_living', 'grade', 'yr_built']

X = df[used_cols]
y = df['price']
```

In [32]:

```
# Perform a train/test split
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=0.33,
                                                    random_state=42)
```

In [33]:
```
# Using a standard scaler
scaler = StandardScaler()

# Train our scaler on training data, then fit to testing
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Remove Features Regression Model

In [34]:
```
# Instantiate a linear regression model
lr = LinearRegression()
```

In [35]:
```
# Fit our model on our scaled data
lr.fit(X_train_scaled, y_train)
```

Out[35]:
```
LinearRegression()
```

In [36]:
```
X_train.columns
```

Out[36]:
```
Index(['bedrooms', 'bathrooms', 'sqft_living', 'grade', 'yr_built'], dtype='obje
ct')
```

In [37]:
```
lr.coef_
```

Out[37]:
```
array([ -44770.61240734,   50953.01605576,  164780.76925863,
        159352.84347056, -122788.79276654])
```

In [38]:
```
lr.intercept_
```

Out[38]:
```
542484.1496302438
```

In [39]:
```
# Predict and evaluate
y_train_pred = lr.predict(X_train_scaled)
y_test_pred = lr.predict(X_test_scaled)

print("Training Scores:")
print(f"R2 Score: {r2_score(y_train, y_train_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_train, y_train_pred):.4f}")
print("---")
print("Testing Scores:")
print(f"R2 Score: {r2_score(y_test, y_test_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_test, y_test_pred):.4f}")
```

```
Training Scores:
R2 Score: 0.6195
MAE: 146412.9767
---
Testing Scores:
R2 Score: 0.6098
MAE: 144820.6720
```

In [40]:
```
for n in range(10):
    X_train, X_test, y_train, y_test = train_test_split(X,
                                                         y,
                                                         test_size=0.33,
                                                         random_state=n)  # <--
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)
```

```
    lr = LinearRegression()
    lr.fit(X_train_scaled, y_train)

    y_train_pred = lr.predict(X_train_scaled)
    y_test_pred = lr.predict(X_test_scaled)

    print(f"Random Seed: {n}")
    print(f"Train R2 Score: {r2_score(y_train, y_train_pred):4f}")
    print(f"Test R2 Score: {r2_score(y_test, y_test_pred):4f}")
    print("-----")
```

```
Random Seed: 0
Train R2 Score: 0.611069
Test R2 Score: 0.628281
-----
Random Seed: 1
Train R2 Score: 0.616293
Test R2 Score: 0.616584
-----
Random Seed: 2
Train R2 Score: 0.620624
Test R2 Score: 0.607708
-----
Random Seed: 3
Train R2 Score: 0.621518
Test R2 Score: 0.604881
-----
Random Seed: 4
Train R2 Score: 0.613212
Test R2 Score: 0.622370
-----
Random Seed: 5
Train R2 Score: 0.615968
Test R2 Score: 0.617080
-----
Random Seed: 6
Train R2 Score: 0.622242
Test R2 Score: 0.604565
-----
Random Seed: 7
Train R2 Score: 0.617888
Test R2 Score: 0.613577
-----
Random Seed: 8
Train R2 Score: 0.618512
Test R2 Score: 0.612618
-----
Random Seed: 9
Train R2 Score: 0.617448
Test R2 Score: 0.614654
-----
```

In [41]:

```
# Less features used, virtually the same result
```

In [42]:

```
# Remove bedrooms and bathrooms because of multicollinearity with sqft_living
```

In [43]:

```
# Define X and y

used_cols = ['sqft_living', 'grade', 'yr_built']

X = df[used_cols]
y = df['price']
```

In [44]:
```python
# Perform a train/test split
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=0.33,
                                                    random_state=42)
```

In [45]:
```python
# Using a standard scaler
scaler = StandardScaler()

# Train our scaler on training data, then fit to testing
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Remove More Features Regression Model

In [46]:
```python
# Instantiate a linear regression model
lr = LinearRegression()
```

In [47]:
```python
# Fit our model on our scaled data
lr.fit(X_train_scaled, y_train)
```

Out[47]:
```
LinearRegression()
```

In [48]:
```python
X_train.columns
```

Out[48]:
```
Index(['sqft_living', 'grade', 'yr_built'], dtype='object')
```

In [49]:
```python
lr.coef_
```

Out[49]:
```
array([ 162435.01934411,  173223.11138616, -109968.72107639])
```

In [50]:
```python
lr.intercept_
```

Out[50]:
```
542484.1496302438
```

In [51]:
```python
# Predict and evaluate
y_train_pred = lr.predict(X_train_scaled)
y_test_pred = lr.predict(X_test_scaled)

print("Training Scores:")
print(f"R2 Score: {r2_score(y_train, y_train_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_train, y_train_pred):.4f}")
print("---")
print("Testing Scores:")
print(f"R2 Score: {r2_score(y_test, y_test_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_test, y_test_pred):.4f}")
```

```
Training Scores:
R2 Score: 0.6069
MAE: 148994.4267
---
Testing Scores:
R2 Score: 0.5962
MAE: 147844.0295
```

In [52]:
```python
for n in range(10):
```

```
    X_train, X_test, y_train, y_test = train_test_split(X,
                                                        y,
                                                        test_size=0.33,
                                                        random_state=n)  # <--

    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    lr = LinearRegression()
    lr.fit(X_train_scaled, y_train)

    y_train_pred = lr.predict(X_train_scaled)
    y_test_pred = lr.predict(X_test_scaled)

    print(f"Random Seed: {n}")
    print(f"Train R2 Score: {r2_score(y_train, y_train_pred):4f}")
    print(f"Test R2 Score: {r2_score(y_test, y_test_pred):4f}")
    print("-----")
```

```
Random Seed: 0
Train R2 Score: 0.597061
Test R2 Score: 0.617750
-----
Random Seed: 1
Train R2 Score: 0.601551
Test R2 Score: 0.607806
-----
Random Seed: 2
Train R2 Score: 0.608913
Test R2 Score: 0.592330
-----
Random Seed: 3
Train R2 Score: 0.607150
Test R2 Score: 0.594974
-----
Random Seed: 4
Train R2 Score: 0.599309
Test R2 Score: 0.611154
-----
Random Seed: 5
Train R2 Score: 0.604076
Test R2 Score: 0.602149
-----
Random Seed: 6
Train R2 Score: 0.611443
Test R2 Score: 0.588099
-----
Random Seed: 7
Train R2 Score: 0.603816
Test R2 Score: 0.602877
-----
Random Seed: 8
Train R2 Score: 0.606214
Test R2 Score: 0.598283
-----
Random Seed: 9
Train R2 Score: 0.604922
Test R2 Score: 0.600616
-----
```

In [53]:
```
# Again, less features used and virtually the same result
```

In [54]:
```
# Analyzing house prices based on the decade it was built in
```

```
df_yr_built = df.copy()
```

In [55]:
```
year = 1900

while year <= 2015:
    df_yr_built.loc[(df_yr_built['yr_built'] >= year)
                    & (df_yr_built['yr_built'] < (year + 10)),
                    'yr_built'] = year
    year += 10
```

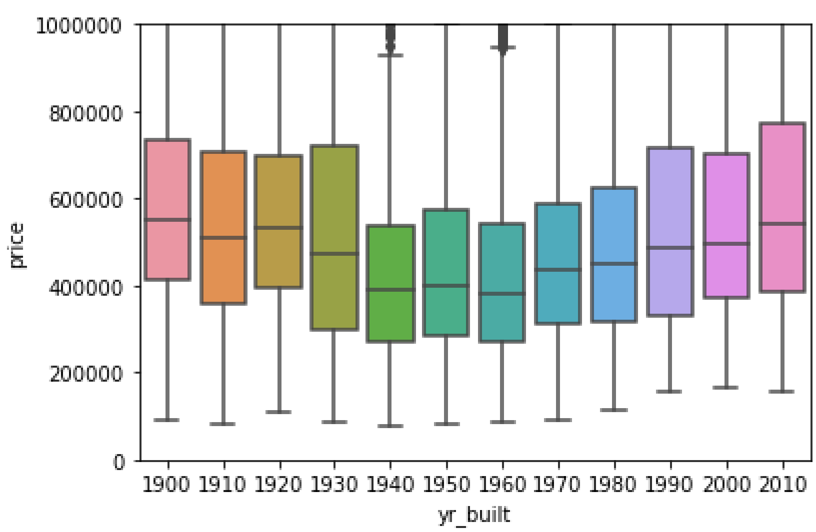
In [56]:
```
df_yr_built.head()
```

Out[56]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr
0	221900.0	3	1.00	1180	5650	1.0	0.0	3	7	
1	538000.0	3	2.25	2570	7242	2.0	0.0	3	7	
2	180000.0	2	1.00	770	10000	1.0	0.0	3	6	
3	604000.0	4	3.00	1960	5000	1.0	0.0	5	7	
4	510000.0	3	2.00	1680	8080	1.0	0.0	3	8	

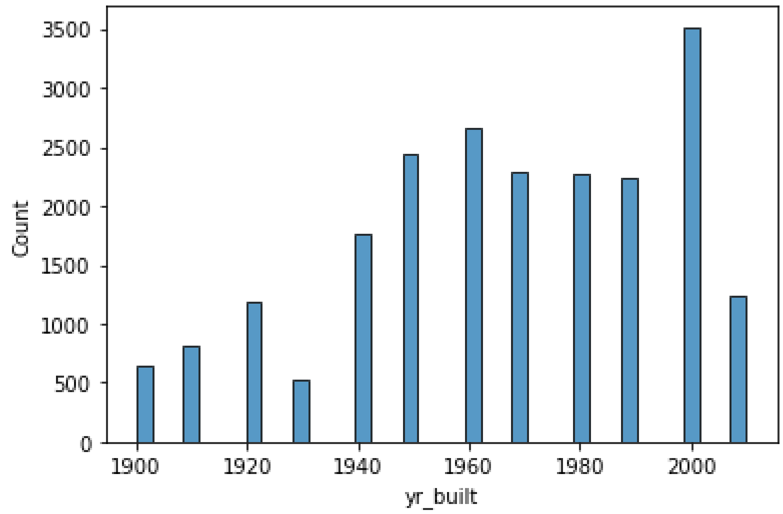
In [57]:
```
sns.boxplot(x='yr_built', y='price',
            data=df_yr_built).ticklabel_format(style='plain',
                                                axis='y',
                                                useOffset=False)
plt.ylim(0, 1000000)
```

Out[57]: (0.0, 1000000.0)



In [58]:
```
sns.histplot(x='yr_built', data=df_yr_built)
```

Out[58]: <AxesSubplot:xlabel='yr_built', ylabel='Count'>



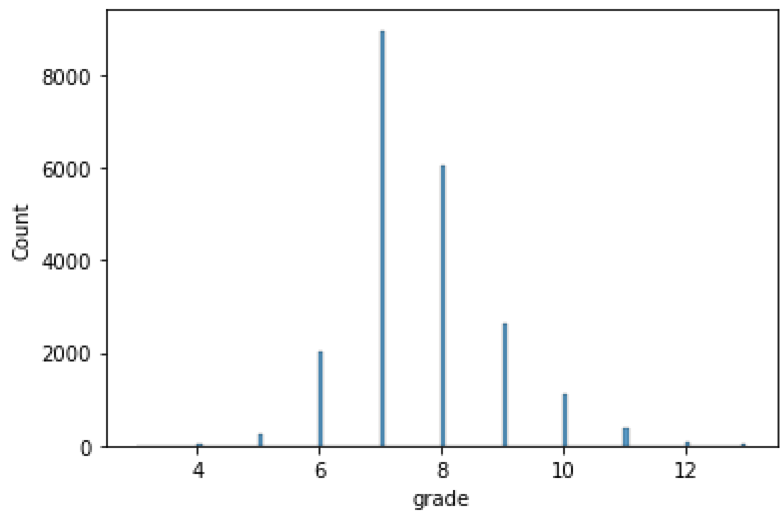
In [59]:
```
# Possibly a non-linear relationship, should consider running a polynomial model
```

In [60]:
```
# Analyzing house prices based on residential building grade
```

In [61]:
```
df_grade = df.copy()
```

In [62]:
```
sns.histplot(x='grade', data=df_grade)
```

Out[62]: <AxesSubplot:xlabel='grade', ylabel='Count'>



In [63]:
```
# We'll define "Average" as grades 7 and 8
```

In [64]:
```
df_grade.loc[df_grade['grade'] <= 6, 'grade_avg'] = 'Below Average'
df_grade.loc[(df_grade['grade'] >= 7) & (df_grade['grade'] <= 8),
             'grade_avg'] = 'Average'
df_grade.loc[df_grade['grade'] >= 9, 'grade_avg'] = 'Above Average'
```

In [65]:
```
df_grade.head()
```

Out[65]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr
0	221900.0	3	1.00	1180	5650	1.0	0.0	3	7	
1	538000.0	3	2.25	2570	7242	2.0	0.0	3	7	

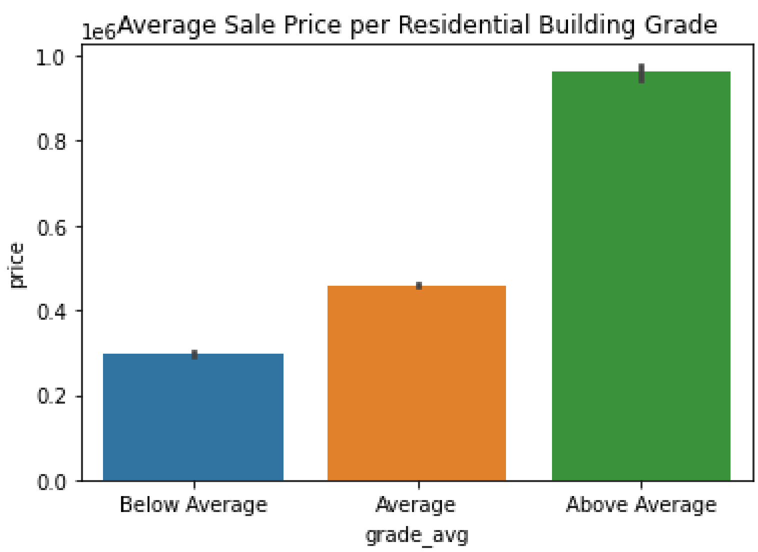
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr
2	180000.0	2	1.00	770	10000	1.0	0.0	3	6	
3	604000.0	4	3.00	1960	5000	1.0	0.0	5	7	
4	510000.0	3	2.00	1680	8080	1.0	0.0	3	8	

In [66]:
```
df_grade['grade_avg'].value_counts()
```

Out[66]:
```
Average          15038
Above Average     4250
Below Average     2308
Name: grade_avg, dtype: int64
```

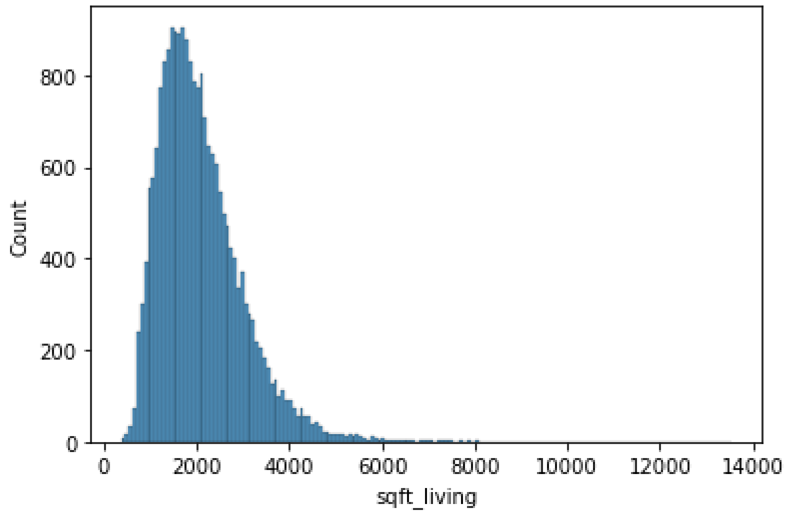
In [67]:
```
sns.barplot(x="grade_avg",
            y="price",
            data=df_grade,
            order=['Below Average', 'Average', 'Above Average'])
plt.title('Average Sale Price per Residential Building Grade')
```

Out[67]:
```
Text(0.5, 1.0, 'Average Sale Price per Residential Building Grade')
```



In [68]:
```
df_sqft = df.copy()
```

In [69]:
```
sns.histplot(x='sqft_living', data=df_sqft);
```



In [70]:
```
df_sqft['sqft_living'].max()
```

Out[70]:
```
13540
```

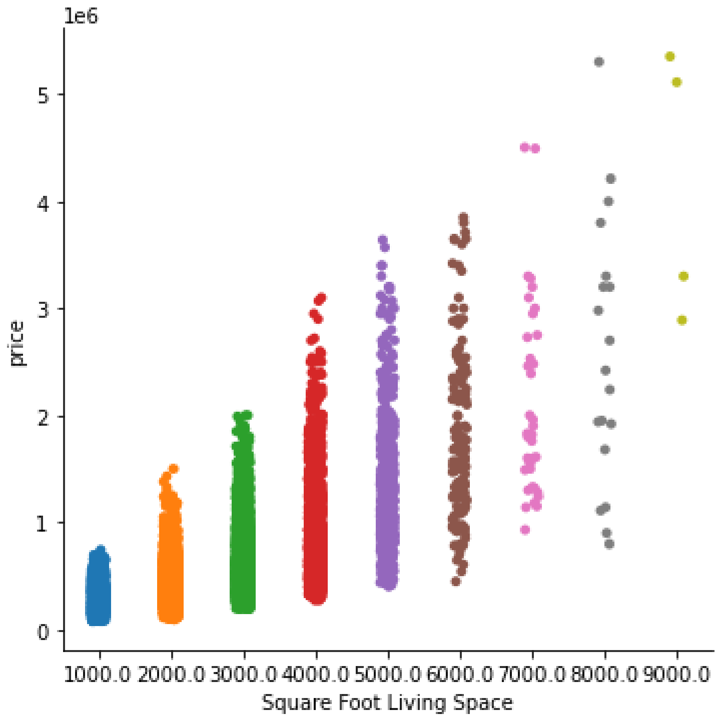
In [71]:
```
# Dividing all properties into 1000 sq ft bins

sqft = 0

while sqft <= 8000:
    df_sqft.loc[(df_sqft['sqft_living'] >= sqft)
                & (df_sqft['sqft_living'] < (sqft + 1000)),
                'Square Foot Living Space'] = (sqft + 1000)
    sqft += 1000

df_sqft.head()
```

Out[71]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr
0	221900.0	3	1.00	1180	5650	1.0	0.0	3	7	
1	538000.0	3	2.25	2570	7242	2.0	0.0	3	7	
2	180000.0	2	1.00	770	10000	1.0	0.0	3	6	
3	604000.0	4	3.00	1960	5000	1.0	0.0	5	7	
4	510000.0	3	2.00	1680	8080	1.0	0.0	3	8	

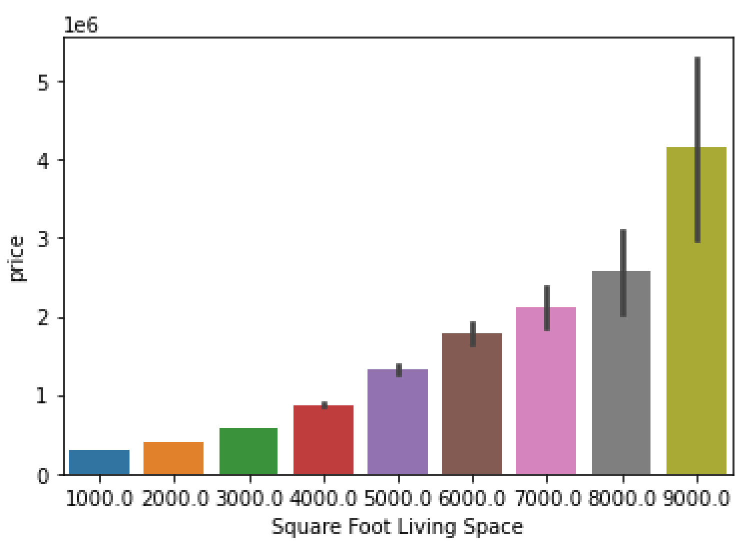
In [72]:
```
sns.catplot(x='Square Foot Living Space', y='price', data=df_sqft)
```

Out[72]:
```
<seaborn.axisgrid.FacetGrid at 0x7fd2c184bb80>
```



In [73]:
```python
sns.barplot(x='Square Foot Living Space', y='price', data=df_sqft)
```

Out[73]: <AxesSubplot:xlabel='Square Foot Living Space', ylabel='price'>



In [74]:
```python
df_sqft.loc[df_sqft['Square Foot Living Space'] == 1000,
            'SQFT Living Space'] = 'Up to 1000'
```

In [75]:
```python
df_sqft.loc[df_sqft['Square Foot Living Space'] == 2000,
            'SQFT Living Space'] = '1000-2000'
df_sqft.loc[df_sqft['Square Foot Living Space'] == 3000,
            'SQFT Living Space'] = '2000-3000'
df_sqft.loc[df_sqft['Square Foot Living Space'] == 4000,
            'SQFT Living Space'] = '3000-4000'
df_sqft.loc[df_sqft['Square Foot Living Space'] == 5000,
            'SQFT Living Space'] = '4000-5000'
df_sqft.loc[df_sqft['Square Foot Living Space'] == 6000,
            'SQFT Living Space'] = '5000-6000'
```

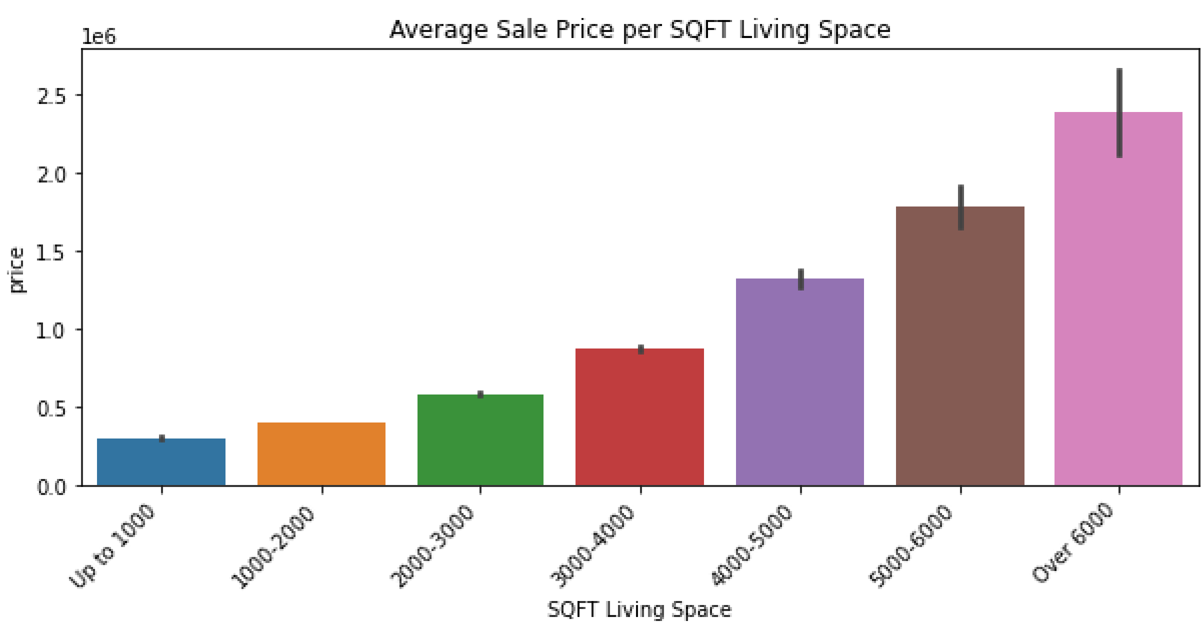
```python
df_sqft.loc[df_sqft['Square Foot Living Space'] > 6000,
            'SQFT Living Space'] = 'Over 6000'
```

In [76]:
```python
df_sqft.head()
```

Out[76]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr
0	221900.0	3	1.00	1180	5650	1.0	0.0	3	7	
1	538000.0	3	2.25	2570	7242	2.0	0.0	3	7	
2	180000.0	2	1.00	770	10000	1.0	0.0	3	6	
3	604000.0	4	3.00	1960	5000	1.0	0.0	5	7	
4	510000.0	3	2.00	1680	8080	1.0	0.0	3	8	

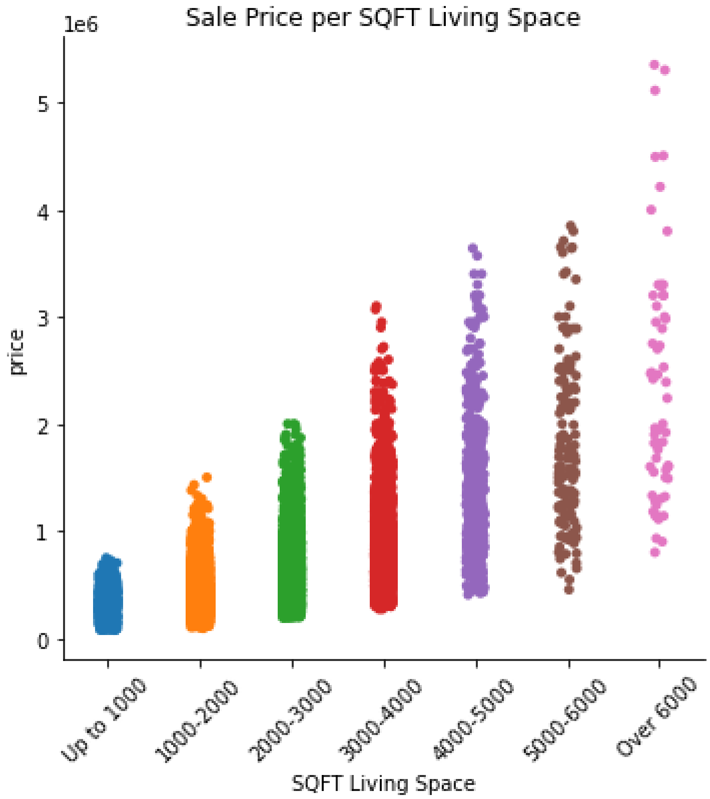
In [77]:
```python
plt.figure(figsize=(10, 4))
sqft_plot = sns.barplot(x='SQFT Living Space',
                        y='price',
                        data=df_sqft,
                        order=[
                            'Up to 1000', '1000-2000', '2000-3000',
                            '3000-4000', '4000-5000', '5000-6000', 'Over 6000'
                        ])
sqft_plot.set_xticklabels(sqft_plot.get_xticklabels(),
                          rotation=45,
                          horizontalalignment='right')
sqft_plot.set_title('Average Sale Price per SQFT Living Space')
plt.show()
```



In [78]:
```python
plt.figure(figsize=(10, 4))
```

```
sqft_plot = sns.catplot(x='SQFT Living Space',
                        y='price',
                        data=df_sqft,
                        order=[
                            'Up to 1000', '1000-2000', '2000-3000',
                            '3000-4000', '4000-5000', '5000-6000', 'Over 6000'
                        ])
plt.title('Sale Price per SQFT Living Space')
plt.xticks(rotation=45)
plt.show()
```

```
<Figure size 720x288 with 0 Axes>
```



Encode Categorical Data

In [79]:
```
df.columns
```

Out[79]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'condition', 'grade', 'yr_built'],
      dtype='object')
```

In [80]:
```
# Explore bedrooms
df['waterfront'].value_counts()
```

Out[80]:
```
0.0    21450
1.0      146
Name: waterfront, dtype: int64
```

In [81]:
```
# Extremely skewed distribution, but worth trying to see if waterfront propertie
```

In [82]:
```
from sklearn.preprocessing import OneHotEncoder

from sklearn.compose import ColumnTransformer
```

In [83]:
```
cat_cols = ['waterfront']
```

In [84]:
```
used_cols = [*used_cols, *cat_cols]
```

In [85]:
```
used_cols
```

Out[85]:
```
['sqft_living', 'grade', 'yr_built', 'waterfront']
```

In [86]:
```
X = df[used_cols]
```

In [87]:
```
X
```

Out[87]:

	sqft_living	grade	yr_built	waterfront
0	1180	7	1955	0.0
1	2570	7	1951	0.0
2	770	6	1933	0.0
3	1960	7	1965	0.0
4	1680	8	1987	0.0
...	...	...	...	...
21592	1530	8	2009	0.0
21593	2310	8	2014	0.0
21594	1020	7	2009	0.0
21595	1600	8	2004	0.0
21596	1020	7	2008	0.0

21596 rows × 4 columns

In [88]:
```
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=0.33,
                                                    random_state=42)
```

In [89]:
```
# Creating an encoder object
encoder = OneHotEncoder(categories='auto', drop='first')

# Creating an columntransformer object

ct = ColumnTransformer(transformers=[('ohe', encoder, cat_cols)],
                       remainder='passthrough')

ct.fit(X_train)

X_train_ohe = ct.transform(X_train)
X_test_ohe = ct.transform(X_test)
```

In [90]:
```
pd.DataFrame(X_train_ohe, columns= ct.get_feature_names()).head()
```

Out[90]:

	ohe__x0_1.0	sqft_living	grade	yr_built

	ohe__x0_1.0	sqft_living	grade	yr_built
0	0.0	2270.0	8.0	1954.0
1	0.0	2360.0	8.0	2008.0
2	0.0	1678.0	7.0	1994.0
3	1.0	1550.0	6.0	1930.0
4	0.0	2770.0	8.0	1967.0

In [91]:
```
# scale our data
scaler = StandardScaler()

# train on train data
scaler.fit(X_train_ohe)

# transform both train and test data
X_train_scaled = scaler.transform(X_train_ohe)
X_test_scaled = scaler.transform(X_test_ohe)
```

Add Waterfront Regression Model

In [92]:
```
lr = LinearRegression()

lr.fit(X_train_scaled, y_train)
```

Out[92]:
```
LinearRegression()
```

In [93]:
```
lr.coef_
```

Out[93]:
```
array([  66815.78575942,  154762.5154394 ,  170944.99704043,
       -104619.64868751])
```

In [94]:
```
lr.intercept_
```

Out[94]:
```
542484.1496302438
```

In [95]:
```
# Predict and evaluate
y_train_pred = lr.predict(X_train_scaled)
y_test_pred = lr.predict(X_test_scaled)

print("Training Scores:")
print(f"R2 Score: {r2_score(y_train, y_train_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_train, y_train_pred):.4f}")
print("---")
print("Testing Scores:")
print(f"R2 Score: {r2_score(y_test, y_test_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_test, y_test_pred):.4f}")
```

```
Training Scores:
R2 Score: 0.6389
MAE: 144941.3861
---
Testing Scores:
R2 Score: 0.6227
MAE: 145451.6261
```

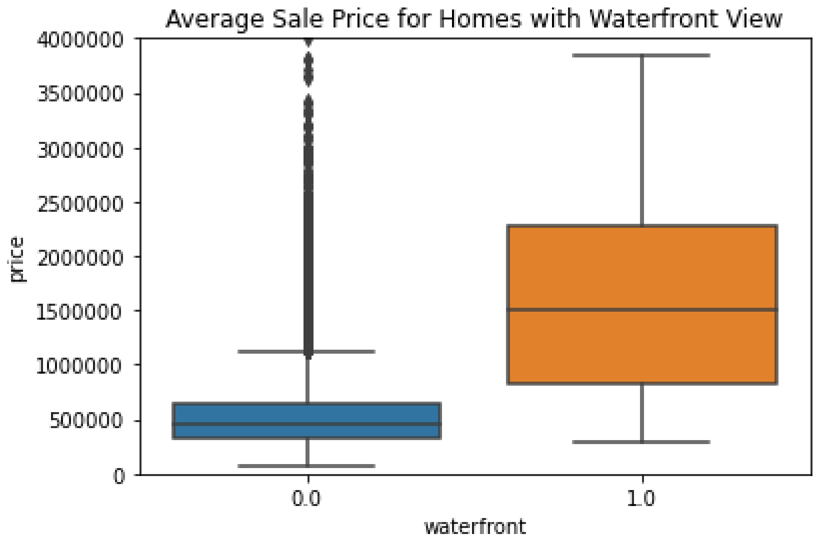
In [96]:
```
for n in range(10):
```

```
    X_train, X_test, y_train, y_test = train_test_split(X,
                                                         y,
                                                         test_size=0.33,
                                                         random_state=n)  # <--
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    lr = LinearRegression()
    lr.fit(X_train_scaled, y_train)

    y_train_pred = lr.predict(X_train_scaled)
    y_test_pred = lr.predict(X_test_scaled)

    print(f"Random Seed: {n}")
    print(f"Train R2 Score: {r2_score(y_train, y_train_pred):4f}")
    print(f"Test R2 Score: {r2_score(y_test, y_test_pred):4f}")
    print("-----")
```

```
Random Seed: 0
Train R2 Score: 0.629788
Test R2 Score: 0.642362
-----
Random Seed: 1
Train R2 Score: 0.632243
Test R2 Score: 0.636882
-----
Random Seed: 2
Train R2 Score: 0.639936
Test R2 Score: 0.620932
-----
Random Seed: 3
Train R2 Score: 0.635497
Test R2 Score: 0.629254
-----
Random Seed: 4
Train R2 Score: 0.632108
Test R2 Score: 0.636436
-----
Random Seed: 5
Train R2 Score: 0.631769
Test R2 Score: 0.636322
-----
Random Seed: 6
Train R2 Score: 0.636032
Test R2 Score: 0.627995
-----
Random Seed: 7
Train R2 Score: 0.633023
Test R2 Score: 0.635192
-----
Random Seed: 8
Train R2 Score: 0.634206
Test R2 Score: 0.632694
-----
Random Seed: 9
Train R2 Score: 0.634848
Test R2 Score: 0.631400
-----
```

In [97]:

```
water_plot = sns.boxplot(x='waterfront', y='price', data=df).ticklabel_format(st
plt.ylim(0, 4000000)
plt.title('Average Sale Price for Homes with Waterfront View');
```



In [98]:
```
# Add interaction feature between condition and grade
```

In [99]:
```
X_interact = X.copy()
```

In [100…
```
X_interact['condition_grade'] = df['condition'] * df['grade']
```

In [101…
```
X_interact.drop(['grade'], axis=1, inplace=True)
```

In [102…
```
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X_interact, y,
                                                    test_size=0.33,
                                                    random_state=42)
```

In [103…
```
# Creating an encoder object
encoder = OneHotEncoder(categories='auto', drop='first')

# Creating an columntransformer object

ct = ColumnTransformer(transformers=[('ohe', encoder, cat_cols)],
                       remainder='passthrough')

ct.fit(X_train)

X_train_ohe = ct.transform(X_train)
X_test_ohe = ct.transform(X_test)
```

In [104…
```
pd.DataFrame(X_train_ohe, columns=ct.get_feature_names()).head()
```

Out[104…

	ohe__x0_1.0	sqft_living	yr_built	condition_grade
0	0.0	2270.0	1954.0	40.0
1	0.0	2360.0	2008.0	24.0
2	0.0	1678.0	1994.0	21.0
3	1.0	1550.0	1930.0	18.0
4	0.0	2770.0	1967.0	24.0

In [105…
```python
# scale our data
scaler = StandardScaler()

# train on train data
scaler.fit(X_train_ohe)

# transform both train and test data
X_train_scaled = scaler.transform(X_train_ohe)
X_test_scaled = scaler.transform(X_test_ohe)
```

Condition/Grade Linear Regression Model

In [106…
```python
lr = LinearRegression()

lr.fit(X_train_scaled, y_train)
```

Out[106…
```
LinearRegression()
```

In [107…
```python
lr.coef_
```

Out[107…
```
array([ 68032.43251284, 237434.74901089, -53547.86006318,  67407.42908584])
```

In [108…
```python
lr.intercept_
```

Out[108…
```
542484.1496302439
```

In [109…
```python
# Predict and evaluate
y_train_pred = lr.predict(X_train_scaled)
y_test_pred = lr.predict(X_test_scaled)

print("Training Scores:")
print(f"R2 Score: {r2_score(y_train, y_train_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_train, y_train_pred):.4f}")
print("---")
print("Testing Scores:")
print(f"R2 Score: {r2_score(y_test, y_test_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_test, y_test_pred):.4f}")
```

```
Training Scores:
R2 Score: 0.5845
MAE: 159163.5410
---
Testing Scores:
R2 Score: 0.5707
MAE: 158815.0562
```

In [110…
```python
for n in range(10):
    X_train, X_test, y_train, y_test = train_test_split(X_interact,
                                                        y,
                                                        test_size=0.33,
                                                        random_state=n)  # <--
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    lr = LinearRegression()
    lr.fit(X_train_scaled, y_train)

    y_train_pred = lr.predict(X_train_scaled)
```

```
    y_test_pred = lr.predict(X_test_scaled)

    print(f"Random Seed: {n}")
    print(f"Train R2 Score: {r2_score(y_train, y_train_pred):4f}")
    print(f"Test R2 Score: {r2_score(y_test, y_test_pred):4f}")
    print("-----")
```

```
Random Seed: 0
Train R2 Score: 0.579860
Test R2 Score: 0.580607
-----
Random Seed: 1
Train R2 Score: 0.579588
Test R2 Score: 0.581301
-----
Random Seed: 2
Train R2 Score: 0.580086
Test R2 Score: 0.580162
-----
Random Seed: 3
Train R2 Score: 0.583529
Test R2 Score: 0.572160
-----
Random Seed: 4
Train R2 Score: 0.578077
Test R2 Score: 0.583728
-----
Random Seed: 5
Train R2 Score: 0.574224
Test R2 Score: 0.589982
-----
Random Seed: 6
Train R2 Score: 0.577435
Test R2 Score: 0.583664
-----
Random Seed: 7
Train R2 Score: 0.579597
Test R2 Score: 0.581259
-----
Random Seed: 8
Train R2 Score: 0.579744
Test R2 Score: 0.580835
-----
Random Seed: 9
Train R2 Score: 0.580384
Test R2 Score: 0.579520
-----
```

In [111…
```
# Ditch this interaction
```

In [ ]:
```

```

In [112…
```
# Add interaction feature between sqft_living and grade
```

In [113…
```
X_interact = X.copy()
```

In [114…
```
X_interact['sqft_living_grade'] = df['sqft_living'] * df['grade']
```

In [115…
```
X_interact.drop(['grade'], axis=1, inplace=True)
X_interact.drop(['sqft_living'], axis=1, inplace=True)
```

In [116…
```
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X_interact,
                                                    y,
                                                    test_size=0.33,
                                                    random_state=42)
```

In [117…
```
# Creating an encoder object
encoder = OneHotEncoder(categories='auto', drop='first')

# Creating an columntransformer object

ct = ColumnTransformer(transformers=[('ohe', encoder, cat_cols)],
                       remainder='passthrough')

ct.fit(X_train)

X_train_ohe = ct.transform(X_train)
X_test_ohe = ct.transform(X_test)
```

In [118…
```
pd.DataFrame(X_train_ohe, columns= ct.get_feature_names()).head()
```

Out[118…

	ohe__x0_1.0	yr_built	sqft_living_grade
0	0.0	1954.0	18160.0
1	0.0	2008.0	18880.0
2	0.0	1994.0	11746.0
3	1.0	1930.0	9300.0
4	0.0	1967.0	22160.0

In [119…
```
# scale our data
scaler = StandardScaler()

# train on train data
scaler.fit(X_train_ohe)

# transform both train and test data
X_train_scaled = scaler.transform(X_train_ohe)
X_test_scaled = scaler.transform(X_test_ohe)
```

Sqft_living/Grade Regression Model

In [120…
```
lr = LinearRegression()

lr.fit(X_train_scaled, y_train)
```

Out[120…
```
LinearRegression()
```

In [121…
```
lr.coef_
```

Out[121…
```
array([ 63395.97262196, -79828.55801811, 298806.427171  ])
```

In [122…
```
lr.intercept_
```

Out[122…
```
542484.1496302438
```

In [123…

```
# Predict and evaluate
y_train_pred = lr.predict(X_train_scaled)
y_test_pred = lr.predict(X_test_scaled)

print("Training Scores:")
print(f"R2 Score: {r2_score(y_train, y_train_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_train, y_train_pred):.4f}")
print("---")
print("Testing Scores:")
print(f"R2 Score: {r2_score(y_test, y_test_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_test, y_test_pred):.4f}")
```

```
Training Scores:
R2 Score: 0.6466
MAE: 147371.9446
---
Testing Scores:
R2 Score: 0.6399
MAE: 146994.7780
```

In [124…

```
for n in range(10):
    X_train, X_test, y_train, y_test = train_test_split(X_interact,
                                                        y,
                                                        test_size=0.33,
                                                        random_state=n)  # <--
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    lr = LinearRegression()
    lr.fit(X_train_scaled, y_train)

    y_train_pred = lr.predict(X_train_scaled)
    y_test_pred = lr.predict(X_test_scaled)

    print(f"Random Seed: {n}")
    print(f"Train R2 Score: {r2_score(y_train, y_train_pred):4f}")
    print(f"Test R2 Score: {r2_score(y_test, y_test_pred):4f}")
    print("-----")
```

```
Random Seed: 0
Train R2 Score: 0.646100
Test R2 Score: 0.640629
-----
Random Seed: 1
Train R2 Score: 0.646501
Test R2 Score: 0.639817
-----
Random Seed: 2
Train R2 Score: 0.640305
Test R2 Score: 0.652344
-----
Random Seed: 3
Train R2 Score: 0.649036
Test R2 Score: 0.634084
-----
Random Seed: 4
Train R2 Score: 0.643463
Test R2 Score: 0.646147
-----
Random Seed: 5
Train R2 Score: 0.638681
Test R2 Score: 0.654483
```

```
-----
Random Seed: 6
Train R2 Score: 0.633431
Test R2 Score: 0.662813
-----
Random Seed: 7
Train R2 Score: 0.646281
Test R2 Score: 0.640445
-----
Random Seed: 8
Train R2 Score: 0.642548
Test R2 Score: 0.648058
-----
Random Seed: 9
Train R2 Score: 0.647176
Test R2 Score: 0.638850
-----
```

In [125…

```
# Succesful interaction
```

In [126…

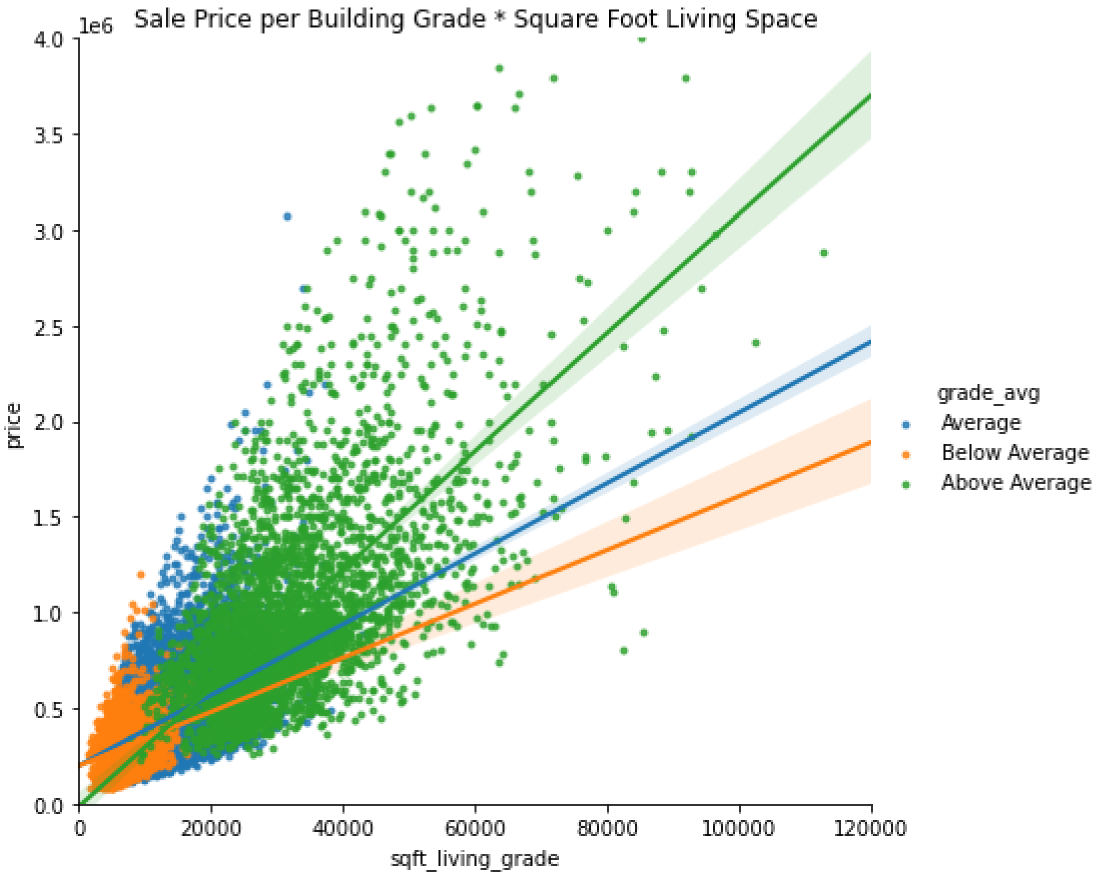
```
df_grade['sqft_living_grade'] = df_grade['sqft_living'] * df_grade['grade']
df_grade.drop(['grade'], axis=1, inplace=True)
df_grade.drop(['sqft_living'], axis=1, inplace=True)
```

In [127…

```
sns.lmplot(x="sqft_living_grade",
           y='price',
           hue='grade_avg',
           height=6,
           truncate=False,
           markers=".",
           data=df_grade).set(ylim=(0, 4000000), xlim=(0, 120000))
plt.title('Sale Price per Building Grade * Square Foot Living Space')
```

Out[127…

```
Text(0.5, 1.0, 'Sale Price per Building Grade * Square Foot Living Space')
```



In [128…

```python
# There is clearly a strong interaction relationship between
# sqft living space and building grade and their affect on sale price
```

In [129…

```python
# Add polynomial
```

In [130…

```python
from sklearn.preprocessing import PolynomialFeatures
```

In [131…

```python
X = X_interact.copy()
```

In [132…

```python
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    test_size=0.33,
                                                    random_state=42)
```

In [133…

```python
# Creating an encoder object
encoder = OneHotEncoder(categories='auto', drop='first')

# Creating an columntransformer object

ct = ColumnTransformer(transformers=[('ohe', encoder, cat_cols)],
                       remainder='passthrough')

ct.fit(X_train)

X_train_ohe = ct.transform(X_train)
X_test_ohe = ct.transform(X_test)
```

In [134…

```python
pd.DataFrame(X_train_ohe, columns= ct.get_feature_names()).head()
```

Out[134...

	ohe__x0_1.0	yr_built	sqft_living_grade
0	0.0	1954.0	18160.0
1	0.0	2008.0	18880.0
2	0.0	1994.0	11746.0
3	1.0	1930.0	9300.0
4	0.0	1967.0	22160.0

In [135...
```
poly = PolynomialFeatures(degree=4, interaction_only=False)
```

In [136...
```
poly.fit(X_train_ohe)
```

Out[136...
```
PolynomialFeatures(degree=4)
```

In [137...
```
X_train_poly = poly.transform(X_train_ohe)
X_test_poly = poly.transform(X_test_ohe)
```

In [138...
```
X_train_poly = pd.DataFrame(X_train_poly, columns=poly.get_feature_names())
X_train_poly.head()
```

Out[138...

	1	x0	x1	x2	x0^2	x0 x1	x0 x2	x1^2	x1 x2	x2^2	...	x(
0	1.0	0.0	1954.0	18160.0	0.0	0.0	0.0	3818116.0	35484640.0	329785600.0	...	
1	1.0	0.0	2008.0	18880.0	0.0	0.0	0.0	4032064.0	37911040.0	356454400.0	...	
2	1.0	0.0	1994.0	11746.0	0.0	0.0	0.0	3976036.0	23421524.0	137968516.0	...	
3	1.0	1.0	1930.0	9300.0	1.0	1930.0	9300.0	3724900.0	17949000.0	86490000.0	...	86
4	1.0	0.0	1967.0	22160.0	0.0	0.0	0.0	3869089.0	43588720.0	491065600.0	...	

5 rows × 35 columns

In [139...
```
# Still need to scale
scaler = StandardScaler()

scaler.fit(X_train_poly)

X_train_poly_sc = scaler.transform(X_train_poly)
X_test_poly_sc = scaler.transform(X_test_poly)
```

Polynomial Regression Model

In [140...
```
lr = LinearRegression()

lr.fit(X_train_poly_sc, y_train)
```

Out[140...
```
LinearRegression()
```

In [141...
```
lr.coef_
```

Out[141...
```
array([-2.02286183e-01, -4.16285647e+16,  4.17771545e+09, -6.99912840e+09,
```

```
         1.46402552e+16,  3.08355643e+15,  1.88463970e+17, -1.26469852e+10,
         2.12224966e+10,  2.14862088e+08,  1.32474520e+16, -1.44515132e+15,
        -9.43110766e+16,  1.02113400e+14,  6.69290265e+12,  3.70635429e+14,
         1.27546427e+10, -2.14527349e+10, -4.38533861e+08,  1.62047250e+06,
         1.37408539e+16, -1.63839458e+15, -9.41528934e+16, -1.02124013e+14,
        -6.69273685e+12, -3.70635428e+14,  3.56762273e+09, -8.27084265e+07,
        -1.00711575e+06,  8.82370000e+04, -4.28531927e+09,  7.22908546e+09,
         2.24214319e+08, -1.97126700e+06,  1.08995000e+05])
```

In [142…

```python
lr.intercept_
```

Out[142…

```
542484.147965386
```

In [143…

```python
# Predict and evaluate
y_train_pred = lr.predict(X_train_poly_sc)
y_test_pred = lr.predict(X_test_poly_sc)

print("Training Scores:")
print(f"R2 Score: {r2_score(y_train, y_train_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_train, y_train_pred):.4f}")
print("---")
print("Testing Scores:")
print(f"R2 Score: {r2_score(y_test, y_test_pred):.4f}")
print(f"MAE: {mean_absolute_error(y_test, y_test_pred):.4f}")
```

```
Training Scores:
R2 Score: 0.6902
MAE: 137663.2167
---
Testing Scores:
R2 Score: 0.6838
MAE: 138325.1017
```

In [144…

```python
n = 1

while n < 9:

    X = X_interact.copy()

    # Train test split
    X_train, X_test, y_train, y_test = train_test_split(X,
                                                         y,
                                                         test_size=0.33,
                                                         random_state=42)

    # Creating an encoder object
    encoder = OneHotEncoder(categories='auto', drop='first')

    # Creating an columntransformer object

    ct = ColumnTransformer(transformers=[('ohe', encoder, cat_cols)],
                           remainder='passthrough')

    ct.fit(X_train)

    X_train_ohe = ct.transform(X_train)
    X_test_ohe = ct.transform(X_test)

    pd.DataFrame(X_train_ohe, columns=ct.get_feature_names()).head()

    poly = PolynomialFeatures(degree=n, interaction_only=False)
```

```python
    poly.fit(X_train_ohe)

    X_train_poly = poly.transform(X_train_ohe)
    X_test_poly = poly.transform(X_test_ohe)

    X_train_poly = pd.DataFrame(X_train_poly, columns=poly.get_feature_names())
    X_train_poly.head()

    # Still need to scale
    scaler = StandardScaler()

    scaler.fit(X_train_poly)

    X_train_poly_sc = scaler.transform(X_train_poly)
    X_test_poly_sc = scaler.transform(X_test_poly)

    # 4th Linear Regression Model

    lr = LinearRegression()

    lr.fit(X_train_poly_sc, y_train)

    lr.coef_

    lr.intercept_

    # Predict and evaluate
    y_train_pred = lr.predict(X_train_poly_sc)
    y_test_pred = lr.predict(X_test_poly_sc)

    print("Polynomial Power {} Training Scores:".format(n))
    print(f"R2 Score: {r2_score(y_train, y_train_pred):.4f}")
    print(f"MAE: {mean_absolute_error(y_train, y_train_pred):.4f}")
    print("---")
    print("Testing Scores:")
    print(f"R2 Score: {r2_score(y_test, y_test_pred):.4f}")
    print(f"MAE: {mean_absolute_error(y_test, y_test_pred):.4f}")
    print("\n")

    n += 1
```

```
Polynomial Power 1 Training Scores:
R2 Score: 0.6466
MAE: 147371.9446
---
Testing Scores:
R2 Score: 0.6399
MAE: 146994.7780


Polynomial Power 2 Training Scores:
R2 Score: 0.6700
MAE: 140568.1545
---
Testing Scores:
R2 Score: 0.6740
MAE: 140622.9850


Polynomial Power 3 Training Scores:
R2 Score: 0.6830
```

```
MAE: 138387.8345
---
Testing Scores:
R2 Score: 0.6763
MAE: 139478.4004


Polynomial Power 4 Training Scores:
R2 Score: 0.6902
MAE: 137663.2167
---
Testing Scores:
R2 Score: 0.6838
MAE: 138325.1017


Polynomial Power 5 Training Scores:
R2 Score: 0.6966
MAE: 137380.8384
---
Testing Scores:
R2 Score: 0.1369
MAE: 141495.6295


Polynomial Power 6 Training Scores:
R2 Score: 0.7014
MAE: 136436.4271
---
Testing Scores:
R2 Score: -6.3257
MAE: 149299.1418


Polynomial Power 7 Training Scores:
R2 Score: 0.7030
MAE: 136424.2706
---
Testing Scores:
R2 Score: -128.0606
MAE: 187431.5009


Polynomial Power 8 Training Scores:
R2 Score: 0.7063
MAE: 135857.0744
---
Testing Scores:
R2 Score: -16279.7141
MAE: 697631.7720
```

Evaluation

After multiple iterations on our model, the resulting findings are:

1. Square Foot Living Space & Residential Building Grade have the strongest relationship with home sale price
2. Waterfront view has a moderate affect on sale price, and is a worthy factor to consider

Recommendations

A house flipper will want to keep the following in mind when allocating their resources towards home improvement:

1. Increase living area square footage - Renovate basement and attic spaces. Add extensions to the home. Build additional living space above the garage
2. Focus on quality of materials and finishes during construction - This includes kitchen countertops, floors, cabinetry design, lighting fixtures, luxury features
3. Keep an eye out for homes with a waterfront view