1 Housing Sale Analysis

By: Brian Lee

1.1 Business Problem

A King County real estate agency has requested us for help in predicting housing prices. They would like to figure out which factors have the greatest effect on the price of the home. They want to cater to average home buyers. You must then translate those findings into actionable insights that the real estate agency can use to better sell the homes in the market.

1.2 Data Understanding

This project uses the King County House Sales dataset, which can be found in kc_house_data.csv in the data folder in this repo. The description of the column names can be found in column_names.md in the same folder.

In [1]:
```
# Import necessary packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from statsmodels.formula.api import ols
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm
import scipy.stats as stats
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
from sklearn import metrics
from sklearn.metrics import mean_absolute_error
```
executed in 1.78s, finished 04:27:43 2021-03-28

Let's first load the housing data set into a DataFrame

In [2]:
```
data = pd.read_csv('data/kc_house_data.csv')
data.head()
```

executed in 79ms, finished 04:27:44 2021-03-28

Out[2]:

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

5 rows × 21 columns

The dataset columns are defined below:

- **id** - unique identified for a house
- **date** - house was sold
- **price** - is prediction target
- **bedrooms** - of Bedrooms/House
- **bathrooms** - of bathrooms/bedrooms
- **sqft_living** - footage of the home
- **sqft_lot** - footage of the lot
- **floors** - floors (levels) in house
- **waterfront** - House which has a view to a waterfront
- **view** - Has been viewed
- **condition** - How good the condition is (Overall)
- **grade** - overall grade given to the housing unit, based on King County grading system
- **sqft_above** - square footage of house apart from basement
- **sqft_basement** - square footage of the basement
- **yr_built** - Built Year
- **yr_renovated** - Year when house was renovated
- **zipcode** - zip
- **lat** - Latitude coordinate
- **long** - Longitude coordinate
- **sqft_living15** - The square footage of interior housing living space for the nearest 15 neighbors
- **sqft_lot15** - The square footage of the land lots of the nearest 15 neighbors

1.3 Data Preparation

We need to first clean up the dataset so that we can properly analyze the housing price factors.

Lets take a quick look at the data we are given:

In [3]:
```
display(data.info())
display(data.describe())
```

executed in 91ms, finished 04:27:44 2021-03-28

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21597 non-null  int64  
 1   date           21597 non-null  object 
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64  
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64  
 6   sqft_lot       21597 non-null  int64  
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64  
 11  grade          21597 non-null  int64  
 12  sqft_above     21597 non-null  int64  
 13  sqft_basement  21597 non-null  object 
 14  yr_built       21597 non-null  int64  
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64  
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64  
 20  sqft_lot15     21597 non-null  int64  
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB

None
```

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	C
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3

There seems to be too many columns. Let's specify what columns we need for our analysis

Removing the following:

Removing the following:

- date
- view
- sqft_above
- sqft_basement
- zipcode
- lat
- long
- sqft_living15
- sqft_lot15

In [4]:
```
# Dropping extraneous columns
data.drop(columns=['id','date','view','sqft_above','sqft_basement','zipcode','lat
```
executed in 15ms, finished 04:27:44 2021-03-28

We need to find missing values and replace them with appropriate values:

In [5]:
```
# Find missing value columns
data.isna().sum()
```
executed in 15ms, finished 04:27:44 2021-03-28

Out[5]:
```
price              0
bedrooms           0
bathrooms          0
sqft_living        0
sqft_lot           0
floors             0
waterfront      2376
condition          0
grade              0
yr_built           0
yr_renovated    3842
dtype: int64
```

In [6]:
```
# Analyze for replacements for 'waterfront' and 'yr_renovated'
data.describe()
```
executed in 45ms, finished 04:27:44 2021-03-28

Out[6]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
count	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	19221
mean	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	0
std	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	0
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	0
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	0
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	0
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1

We can see that waterfront and yr_renovated are missing values. We should feel comfortable with replacing the values with the median values of 0 for both seeing that both the median and 25/75 quartiles all equate to 0.

In [7]:
```
for col in data.columns:
    try:
        median = data[col].median()
        data[col] = data[col].fillna(value=median)
    except:
        continue

# Rechecking missing values and confirm none left.
data.isna().sum()
```
executed in 14ms, finished 04:27:44 2021-03-28

Out[7]:
```
price           0
bedrooms        0
bathrooms       0
sqft_living     0
sqft_lot        0
floors          0
waterfront      0
condition       0
grade           0
yr_built        0
yr_renovated    0
dtype: int64
```

Taking a look at **'yr_renovated'**, we can see that rather than needing to see the specific year of renovation, it may be more effective to see this as a "renovated" category.

In [8]:
```
# Converting yr_renovated into renovated
data['renovated'] = data['yr_renovated'].apply(lambda x: 1 if x>0 else x)
```
executed in 14ms, finished 04:27:44 2021-03-28

In [9]:
```
# Dropping original column yr_renovated
data.drop(columns=['yr_renovated'], inplace=True)
```
executed in 14ms, finished 04:27:44 2021-03-28

In [10]:
```
# Taking a look at the cleaned data
data.head()
```
executed in 15ms, finished 04:27:44 2021-03-28

Out[10]:

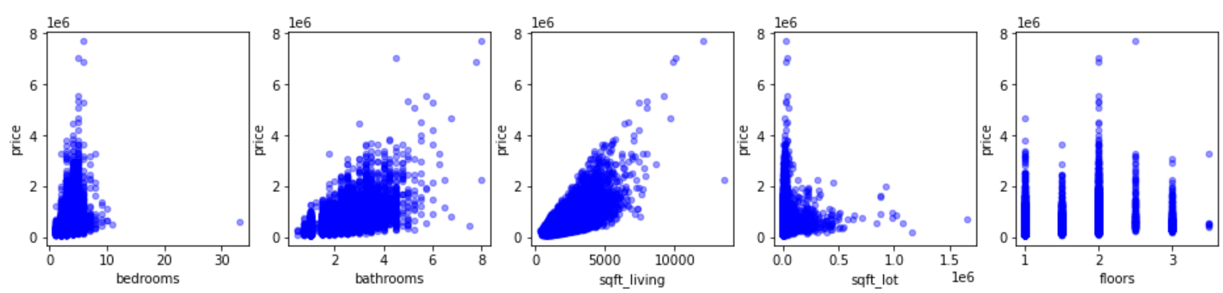
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr_bu
0	221900.0	3	1.00	1180	5650	1.0	0.0	3	7	19
1	538000.0	3	2.25	2570	7242	2.0	0.0	3	7	19
2	180000.0	2	1.00	770	10000	1.0	0.0	3	6	19
3	604000.0	4	3.00	1960	5000	1.0	0.0	5	7	19
4	510000.0	3	2.00	1680	8080	1.0	0.0	3	8	19

1.4 Exploratory Data Analysis

Now that we have cleaned the data, let's examine the distributitions of the columns and examine the descriptive statisitics for the dataset

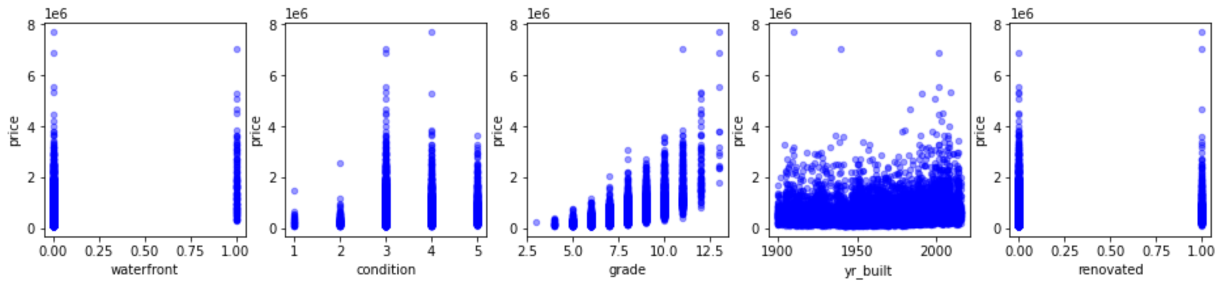
Lets do a basic plot to see trends to the sale price of the home to the columns

In [11]:
```
# Creates subplots comparing price and each column
fig, axes = plt.subplots(nrows=1, ncols=5, figsize=(16,3))

for xcol, ax in zip(['bedrooms','bathrooms','sqft_living','sqft_lot','floors'], a
    data.plot(kind='scatter', x=xcol, y='price', ax=ax, alpha=0.4, color='b')
```
executed in 720ms, finished 04:27:44 2021-03-28



In [12]:
```
# Creates subplots comparing price and each column
fig, axes = plt.subplots(nrows=1, ncols=5, figsize=(16,3))

for xcol, ax in zip(['waterfront','condition','grade','yr_built','renovated'], ax
    data.plot(kind='scatter', x=xcol, y='price', ax=ax, alpha=0.4, color='b')
```

executed in 663ms, finished 04:27:45 2021-03-28

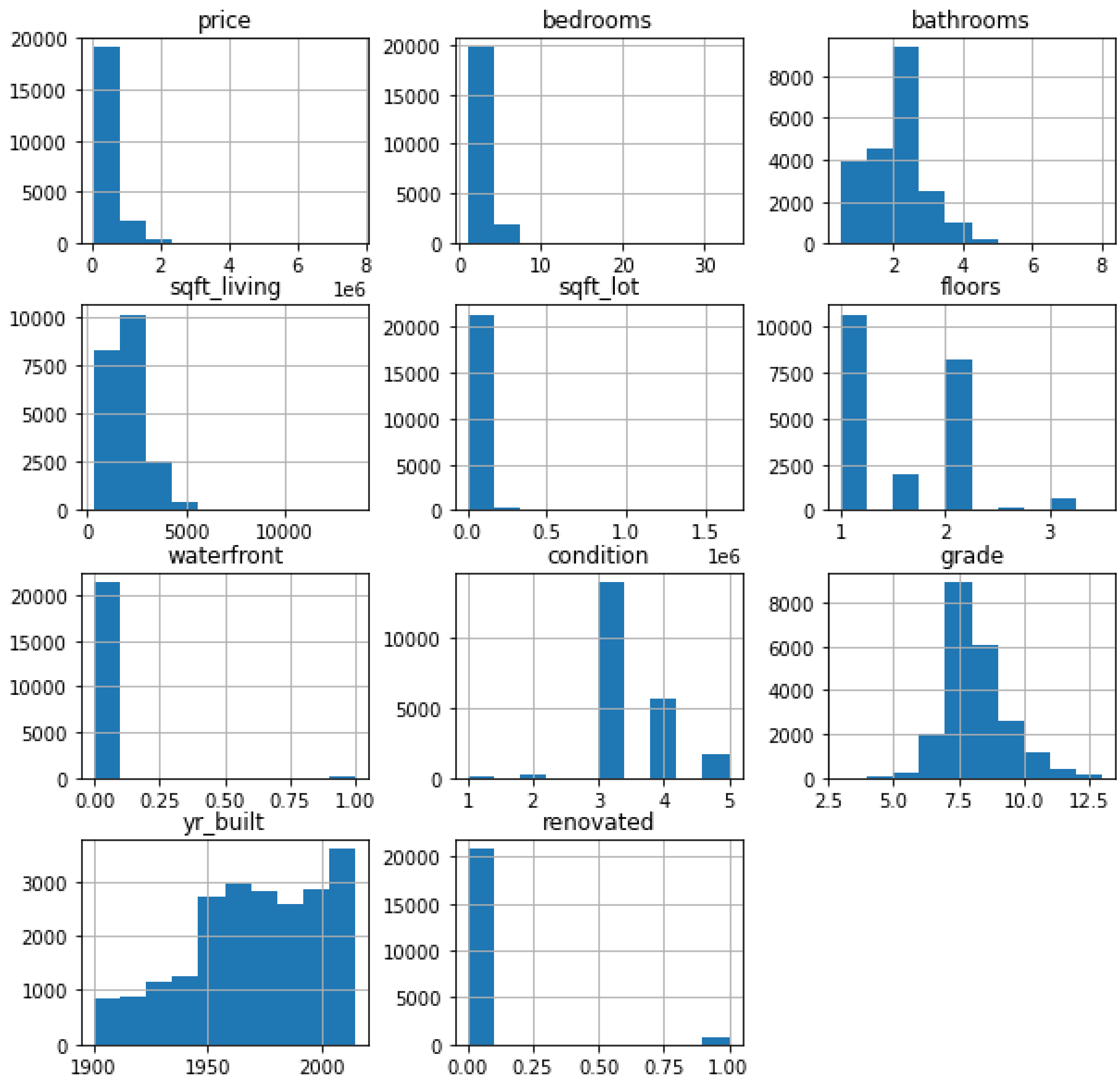


We can see there are some columns that appear to be categorical at first glance.

- floors
- waterfront
- condition
- grade
- renovated

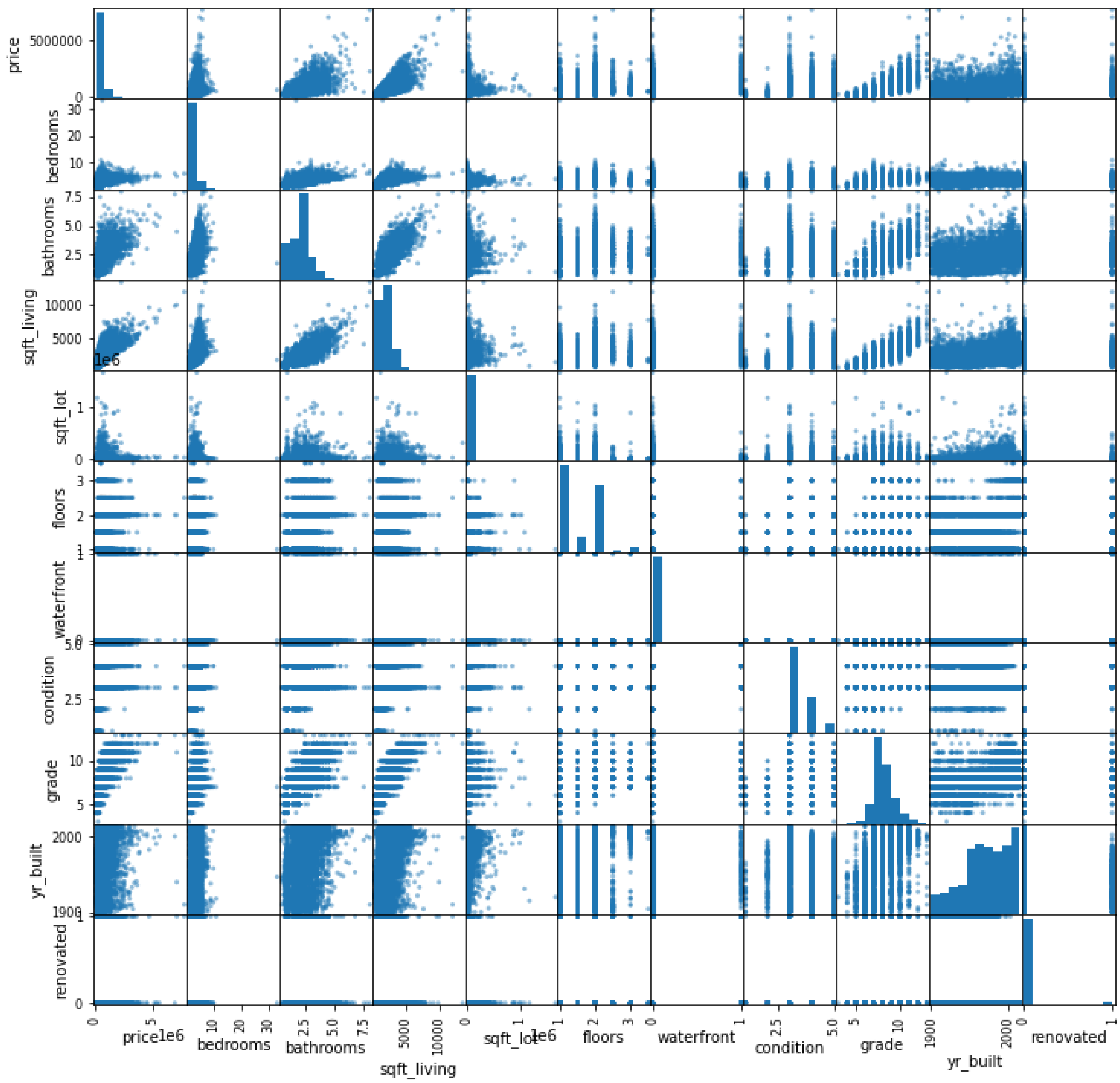
There may be a few outliers in the dataset as well, in particular **'bedrooms'**

In [13]:
```
# Creates a histogram for each variable
import warnings
warnings.filterwarnings('ignore')
fig = plt.figure(figsize = (10,10))
ax = fig.gca()
data.hist(ax = ax);
```
executed in 1.30s, finished 04:27:46 2021-03-28



In [14]:
```
# Creates a scatter matrix
pd.plotting.scatter_matrix(data, figsize=[12,12]);
plt.show()
```

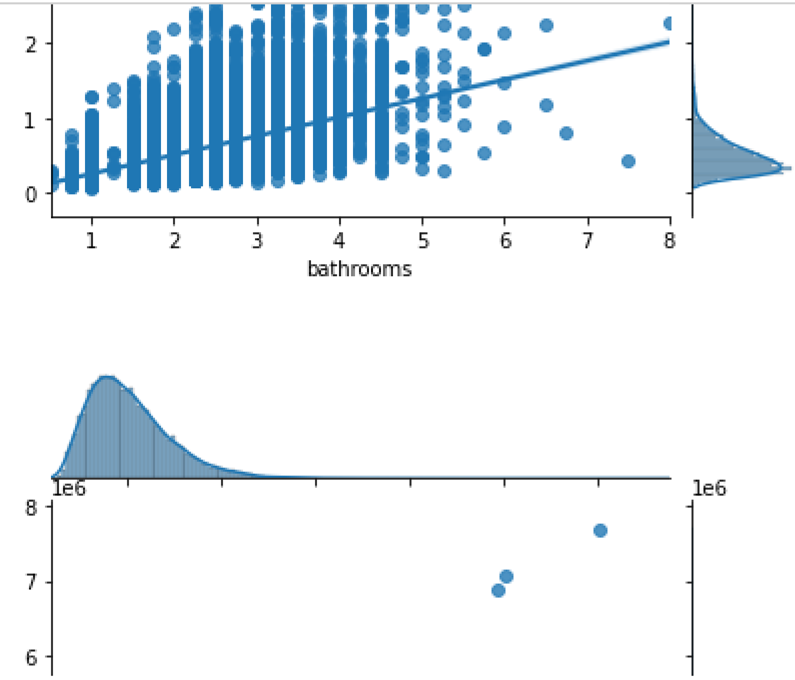
executed in 13.0s, finished 04:27:59 2021-03-28



Let's check for **Linearity**

In [15]:
```
for col in data.columns[1:]:
    sns.jointplot(x=col, y='price', data=data, kind='reg');
```

executed in 24.6s, finished 04:28:24 2021-03-28



- The non-categorical factors appear to be relatively linear

Let's check for **Multicollinearity**.

In [16]:
```python
# Displays if correlation coefficient values is greater than 0.75
data.corr()
abs(data.corr()) > 0.75
```
executed in 30ms, finished 04:28:24 2021-03-28

Out[16]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade
price	True	False	False	False	False	False	False	False	False
bedrooms	False	True	False	False	False	False	False	False	False
bathrooms	False	False	True	True	False	False	False	False	False
sqft_living	False	False	True	True	False	False	False	False	True
sqft_lot	False	False	False	False	True	False	False	False	False
floors	False	False	False	False	False	True	False	False	False
waterfront	False	False	False	False	False	False	True	False	False
condition	False	False	False	False	False	False	False	True	False
grade	False	False	False	True	False	False	False	False	True
yr_built	False	False	False	False	False	False	False	False	False
renovated	False	False	False	False	False	False	False	False	False

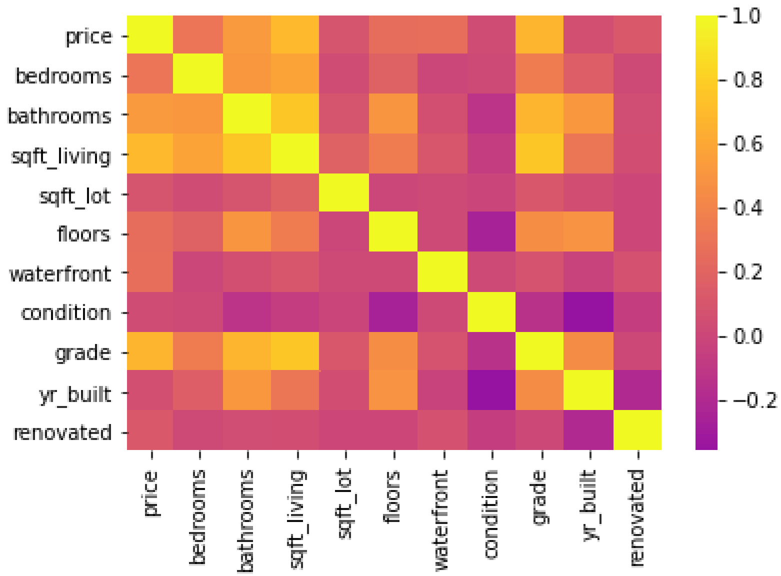
In [17]:
```python
# Finds which column pairs have a CC values > 0.75
df_mc = data.corr().abs().stack().reset_index().sort_values(0, ascending=False)

df_mc['pairs'] = list(zip(df_mc.level_0, df_mc.level_1))

df_mc.set_index(['pairs'], inplace = True)

df_mc.drop(columns=['level_1', 'level_0'], inplace = True)

# cc for correlation coefficient
df_mc.columns = ['cc']

df_mc.drop_duplicates(inplace=True)

df_mc[(df_mc.cc>.75) & (df_mc.cc<1)]
```
executed in 31ms, finished 04:28:24 2021-03-28

Out[17]:

pairs	cc
(grade, sqft_living)	0.762779
(sqft_living, bathrooms)	0.755758

The correlation table tells us that it may be better to drop **sqft_living** as it is highly correlated with other variables.

In [18]:
```
# Heatmap for correlation values
import seaborn as sns
sns.heatmap(data.corr(), cmap='plasma', center=0);
```
executed in 315ms, finished 04:28:24 2021-03-28



1.5 Modeling

Now that we have explored the data, we can finally move on to create models to properly see the effects of each of the factors on housing sale prices.

1.5.1 Model 1: Initial Regression model

Let's model for a non-editted clean dataset

In [19]:
```
#Bring in a clean copy of dataset
data_1 = data.copy()
data_1.head()
```
executed in 15ms, finished 04:28:24 2021-03-28

Out[19]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr_bı
0	221900.0	3	1.00	1180	5650	1.0	0.0	3	7	19
1	538000.0	3	2.25	2570	7242	2.0	0.0	3	7	19
2	180000.0	2	1.00	770	10000	1.0	0.0	3	6	19
3	604000.0	4	3.00	1960	5000	1.0	0.0	5	7	19
4	510000.0	3	2.00	1680	8080	1.0	0.0	3	8	19

In [20]:
```
# Define the problem
outcome = 'price'
x_cols = ['bedrooms','bathrooms','sqft_living','sqft_lot','floors','waterfront',
          'condition','grade','yr_built','renovated']
```
executed in 15ms, finished 04:28:24 2021-03-28

In [21]:
```
# Brief preprocessing (normalize)
data_1.columns = [col.replace(' ', '_') for col in data_1.columns]
for col in x_cols:
    data_1[col] = (data_1[col] - data_1[col].mean())/data_1[col].std()
data_1.head()
```
executed in 31ms, finished 04:28:25 2021-03-28

Out[21]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	gra
0	221900.0	-0.402894	-1.451039	-0.980629	-0.228177	-0.915531	-0.082498	-0.629972	-0.5607
1	538000.0	-0.402894	0.174482	0.533357	-0.189735	0.937409	-0.082498	-0.629972	-0.5607
2	180000.0	-1.482459	-1.451039	-1.427201	-0.123137	-0.915531	-0.082498	-0.629972	-1.4131
3	604000.0	0.676671	1.149794	-0.131054	-0.243873	-0.915531	-0.082498	2.444371	-0.5607
4	510000.0	-0.402894	-0.150622	-0.436030	-0.169499	-0.915531	-0.082498	-0.629972	0.2915

In [22]:
```
# Fitting the actual model
predictors = '+'.join(x_cols)
formula = outcome + '~' + predictors
model = ols(formula=formula, data=data_1).fit()
model.summary()
```
executed in 61ms, finished 04:28:25 2021-03-28

Out[22]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.646
Model:	OLS	**Adj. R-squared:**	0.646
Method:	Least Squares	**F-statistic:**	3936.
Date:	Sun, 28 Mar 2021	**Prob (F-statistic):**	0.00
Time:	04:28:25	**Log-Likelihood:**	-2.9618e+05
No. Observations:	21597	**AIC:**	5.924e+05
Df Residuals:	21586	**BIC:**	5.925e+05
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	5.403e+05	1488.046	363.091	0.000	5.37e+05	5.43e+05
bedrooms	-3.926e+04	1899.954	-20.661	0.000	-4.3e+04	-3.55e+04
bathrooms	3.797e+04	2676.661	14.186	0.000	3.27e+04	4.32e+04
sqft_living	1.628e+05	3032.354	53.681	0.000	1.57e+05	1.69e+05
sqft_lot	-1.009e+04	1523.012	-6.626	0.000	-1.31e+04	-7106.699
floors	1.109e+04	1868.274	5.937	0.000	7430.270	1.48e+04
waterfront	6.161e+04	1506.519	40.893	0.000	5.87e+04	6.46e+04
condition	1.313e+04	1636.323	8.023	0.000	9920.488	1.63e+04
grade	1.525e+05	2529.246	60.278	0.000	1.47e+05	1.57e+05
yr_built	-1.11e+05	2051.663	-54.096	0.000	-1.15e+05	-1.07e+05
renovated	5148.1096	1568.491	3.282	0.001	2073.751	8222.469

Omnibus:	15847.561	**Durbin-Watson:**	1.976
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1006961.287
Skew:	2.936	**Prob(JB):**	0.00
Kurtosis:	35.932	**Cond. No.**	4.77

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [23]:
```
# Create a function for getting linear regression information from housing datase
def linear_reg_sum(data):
    df = data.copy()

    y = df['price']
    X = df.drop(['price'], axis=1)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ranc

    # Training
    linreg = LinearRegression()
    linreg.fit(X_train, y_train)
    y_hat_train = linreg.predict(X_train)
    y_hat_test = linreg.predict(X_test)

    # Significant score calculations
    print(f'R^2 Score of Train: {metrics.r2_score(y_train, y_hat_train)}')
    print(f'RMSE of Train: {np.sqrt(metrics.mean_squared_error(y_train, y_hat_tra
    print(f'RMSE of Test: {np.sqrt(metrics.mean_squared_error(y_test, y_hat_test)
    print(f'Mean Absolute Error of Train: {metrics.mean_absolute_error(y_train, y
    print(f'Mean Absolute Error of Test: {metrics.mean_absolute_error(y_test, y_h

    return metrics.r2_score(y_train, y_hat_train), np.sqrt(metrics.mean_squared_e
```

executed in 12ms, finished 04:28:25 2021-03-28

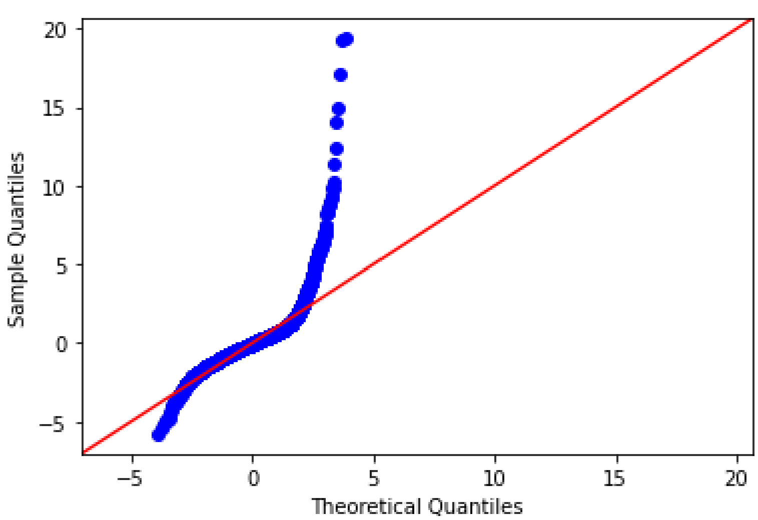
In [24]:
```
a1, b1, c1, d1, e1 = linear_reg_sum(data_1)
```

executed in 29ms, finished 04:28:25 2021-03-28

```
R^2 Score of Train: 0.6462647629327138
RMSE of Train: 218410.57979528894
RMSE of Test: 219640.70438864545
Mean Absolute Error of Train: 141998.8727712253
Mean Absolute Error of Test: 141160.0030755568
```

In [25]:
```
# Q-Q plot
fig = sm.graphics.qqplot(model.resid, dist=stats.norm, line='45', fit=True)
```

executed in 219ms, finished 04:28:25 2021-03-28

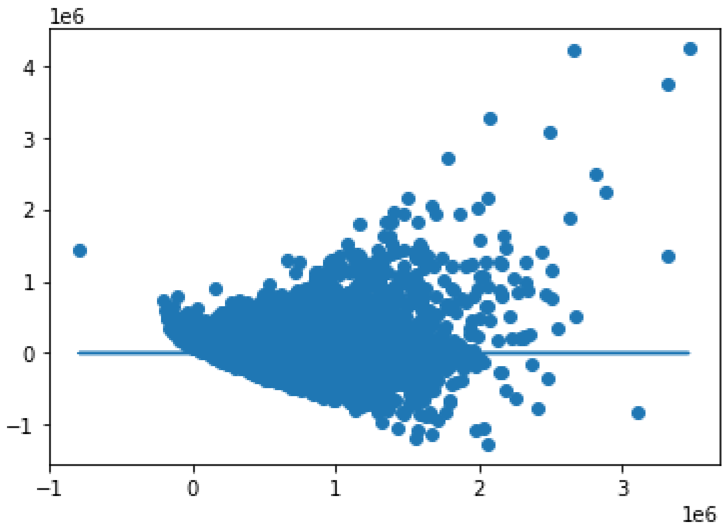


- There were no p-values that were above 0.05. Factors were significant to price
- 'bedrooms','sqft_lot', and 'yr_built' appear to be **negatively** correlated to price
- 'bathrooms,'sqft_living','floors','waterfront','condition','grade', and 'renovated' are **positively** correlated
- The training and test model RMSE has a difference of 1,000. **Not Overfit**
- The price residuals are quite large. There appears to be large outliers on the high end of price and a few on the lower end.

Let's check for **Homoscedasticity**:

In [26]:
```
plt.scatter(model.predict(data_1[x_cols]), model.resid)
plt.plot(model.predict(data_1[x_cols]), [0 for i in range(len(data_1))])
```
executed in 206ms, finished 04:28:25 2021-03-28

Out[26]: [<matplotlib.lines.Line2D at 0x163ae3bdfa0>]



Model does not look good it is spreading out in a specific pattern. Cone-like spread.

1.5.2 Model 2: Price Outliers

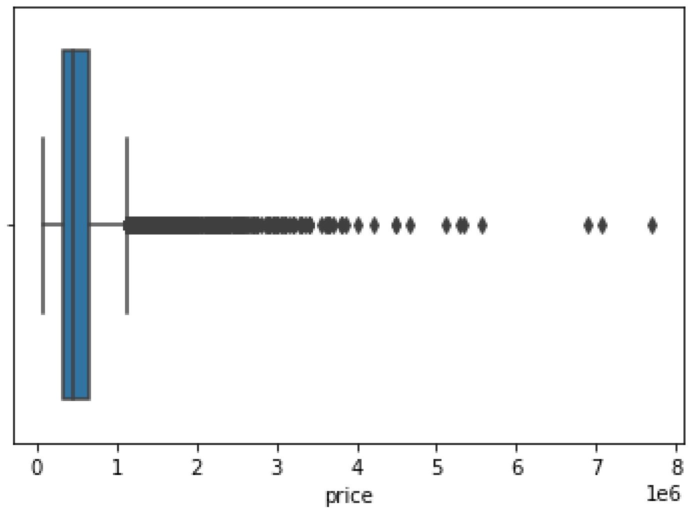
As we have observed on the previous model, let's address the price outliers we saw. This should lead to a better Q-Q plot.

In [27]:
```
# Make a copy of data for Model 2
data_2 = data.copy()
```
executed in 14ms, finished 04:28:25 2021-03-28

We need to look at the distribution of **'price'** to see what outliers we can remove.

In [28]:
```
# Boxplot of price
sns.boxplot(x=data_2['price'])
```
executed in 125ms, finished 04:28:25 2021-03-28

Out[28]:
```
<AxesSubplot:xlabel='price'>
```



We can see that there are clearly several high priced homes that are outliers.

Let's use the z-score to appropriately remove the outliers

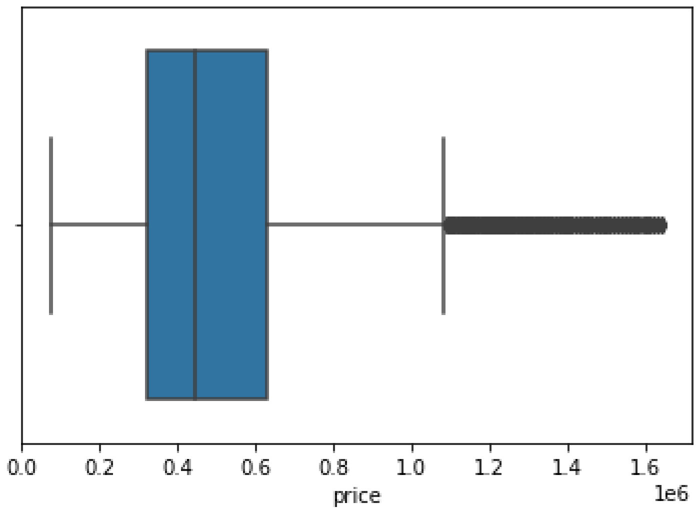
In [29]:
```
# Calculate z-score
z = np.abs(stats.zscore(data_2.price))
z
```
executed in 15ms, finished 04:28:25 2021-03-28

Out[29]:
```
array([0.86671627, 0.00625157, 0.98077344, ..., 0.37618606, 0.38190525,
       0.58606486])
```

In [30]:
```
# Removing data with price z-score > 3
data_2_clean = data_2[(z<3)]
```
executed in 14ms, finished 04:28:25 2021-03-28

In [31]:
```
# Checking cleaned data
sns.boxplot(x=data_2_clean['price'])
```
executed in 125ms, finished 04:28:25 2021-03-28

Out[31]: <AxesSubplot:xlabel='price'>



In [32]:
```
# Clean copy of data 2 (no normalization)
data_2_no_norm = data_2_clean.copy()
```
executed in 14ms, finished 04:28:25 2021-03-28

In [33]:
```
# Brief preprocessing (normalize)
data_2_clean.columns = [col.replace(' ', '_') for col in data_2_clean.columns]
for col in x_cols:
    data_2_clean[col] = (data_2_clean[col] - data_2_clean[col].mean())/data_2_cle
data_2_clean.head()
```
executed in 31ms, finished 04:28:25 2021-03-28

Out[33]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	gra
0	221900.0	-0.388103	-1.477557	-1.018820	-0.227141	-0.904441	-0.061557	-0.628831	-0.5458
1	538000.0	-0.388103	0.220763	0.642392	-0.187736	0.953270	-0.061557	-0.628831	-0.5458
2	180000.0	-1.477989	-1.477557	-1.508818	-0.119471	-0.904441	-0.061557	-0.628831	-1.4476
3	604000.0	0.701784	1.239755	-0.086629	-0.243230	-0.904441	-0.061557	2.453293	-0.5458
4	510000.0	-0.388103	-0.118901	-0.421262	-0.166994	-0.904441	-0.061557	-0.628831	0.3559

Let's see our new model

In [34]:
```
# Define the problem
X = data_2_clean.drop(['price'], axis=1)
y = data_2_clean['price']
```
executed in 14ms, finished 04:28:25 2021-03-28

In [35]:
```
# Fitting the actual model
X_int = sm.add_constant(X)
model_2 = sm.OLS(y,X_int).fit()
model_2.summary()
```

executed in 46ms, finished 04:28:25 2021-03-28

Out[35]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.616
Model:	OLS	**Adj. R-squared:**	0.616
Method:	Least Squares	**F-statistic:**	3400.
Date:	Sun, 28 Mar 2021	**Prob (F-statistic):**	0.00
Time:	04:28:25	**Log-Likelihood:**	-2.8410e+05
No. Observations:	21191	**AIC:**	5.682e+05
Df Residuals:	21180	**BIC:**	5.683e+05
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	5.07e+05	1104.544	459.022	0.000	5.05e+05	5.09e+05
bedrooms	-1.944e+04	1414.903	-13.739	0.000	-2.22e+04	-1.67e+04
bathrooms	2.673e+04	1927.026	13.872	0.000	2.3e+04	3.05e+04
sqft_living	9.199e+04	2151.404	42.758	0.000	8.78e+04	9.62e+04
sqft_lot	-2695.8273	1130.445	-2.385	0.017	-4911.586	-480.069
floors	1.84e+04	1391.265	13.226	0.000	1.57e+04	2.11e+04
waterfront	1.845e+04	1110.050	16.618	0.000	1.63e+04	2.06e+04
condition	1.307e+04	1212.529	10.781	0.000	1.07e+04	1.54e+04
grade	1.334e+05	1803.797	73.928	0.000	1.3e+05	1.37e+05
yr_built	-9.262e+04	1537.667	-60.233	0.000	-9.56e+04	-8.96e+04
renovated	3096.1535	1162.382	2.664	0.008	817.797	5374.510

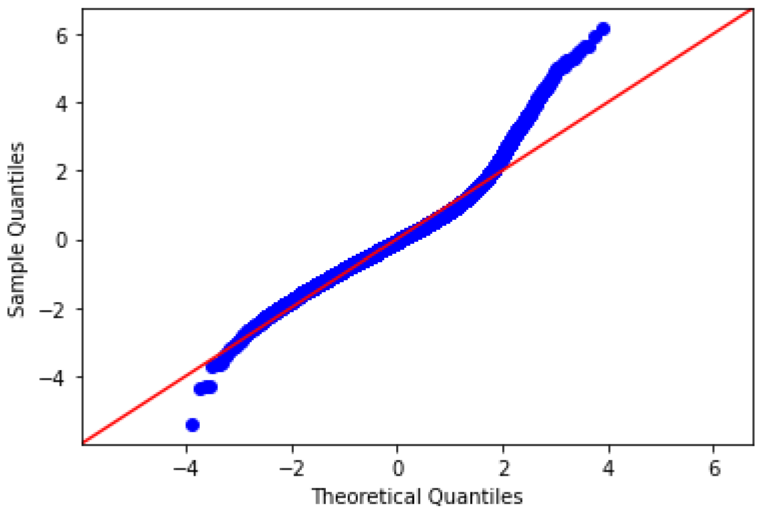
Omnibus:	3269.616	**Durbin-Watson:**	1.961
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	9201.933
Skew:	0.832	**Prob(JB):**	0.00
Kurtosis:	5.766	**Cond. No.**	4.55

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [36]:
```
a2, b2, c2, d2, e2 = linear_reg_sum(data_2_clean)
```
executed in 31ms, finished 04:28:25 2021-03-28

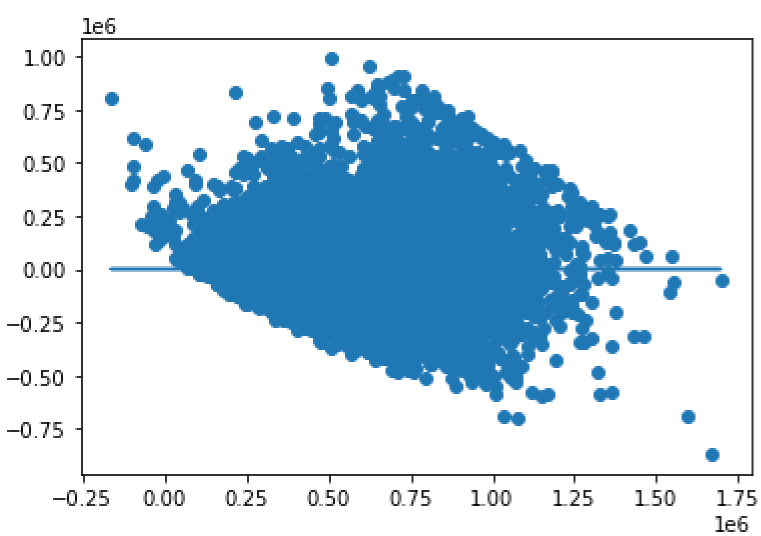
```
R^2 Score of Train: 0.61677598306974
RMSE of Train: 161831.05989699255
RMSE of Test: 156441.12149477913
Mean Absolute Error of Train: 119508.01948349786
Mean Absolute Error of Test: 116192.0940057343
```

In [37]:
```
# Q-Q plot
fig = sm.graphics.qqplot(model_2.resid, dist=stats.norm, line='45', fit=True)
```
executed in 218ms, finished 04:28:26 2021-03-28



In [38]:
```
plt.scatter(model_2.predict(X_int), model_2.resid)
plt.plot(model_2.predict(X_int), [0 for i in range(len(X_int))])
```
executed in 203ms, finished 04:28:26 2021-03-28

Out[38]: [<matplotlib.lines.Line2D at 0x163ae536a30>]



- Q-Q plot is much more normal than before
- R-squared value has reduced due to the removal of datapoints

- P-values are still below 0.05. All factors still significant.
- RMSE difference between Train and Test are still fine (5k difference)
- Homoscedasticity has improved. There is still a trend, but may be improved on with further refining

1.5.3 Model 3: Categorical Variables

Let's appropriately analyse the factors again with a few appropriately identified as categoricals.

In [39]:
```
# Iterating on Model 1 data
data_3 = data_2_no_norm.copy()
```
executed in 14ms, finished 04:28:26 2021-03-28

In [40]:
```
# List out the continuous and categorical variables
continuous = ['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'yr_bu
categoricals = ['floors', 'waterfront', 'condition', 'grade','renovated']
```
executed in 15ms, finished 04:28:26 2021-03-28

In [41]:
```
# Change to str for dummies
data_3['floors'] = data_3['floors'].apply(str)
data_3['waterfront'] = data_3['waterfront'].apply(lambda x: 'yes' if x>0 else 'no
data_3['condition'] = data_3['condition'].apply(str)
data_3['grade'] = data_3['grade'].apply(str)
data_3['renovated'] = data_3['renovated'].apply(lambda x: 'yes' if x>0 else 'no')
```
executed in 31ms, finished 04:28:26 2021-03-28

In [42]:
```
# Create Dummies for categorical variables
data_ohe = pd.get_dummies(data_3[categoricals], prefix=categoricals, drop_first=T
data_ohe.columns
```
executed in 31ms, finished 04:28:26 2021-03-28

Out[42]:
```
Index(['floors_1.5', 'floors_2.0', 'floors_2.5', 'floors_3.0', 'floors_3.5',
       'waterfront_yes', 'condition_2', 'condition_3', 'condition_4',
       'condition_5', 'grade_11', 'grade_12', 'grade_3', 'grade_4', 'grade_5',
       'grade_6', 'grade_7', 'grade_8', 'grade_9', 'renovated_yes'],
      dtype='object')
```

In [43]:
```
# normalize the continuous data
data_cont = data_3[continuous]

# normalize (subract mean and divide by std)

def normalize(feature):
    return (feature - feature.mean()) / feature.std()

data_norm = data_cont.apply(normalize)
```
executed in 14ms, finished 04:28:26 2021-03-28

In [44]:
```
# Combine data for new dataset for Model 2
data_3_pc = pd.concat([data_norm, data_ohe], axis=1)
data_3_pc.head()
```

executed in 635ms, finished 04:28:27 2021-03-28

Out[44]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	yr_built	floors_1.5	floors_2.0	floors_
0	-1.098851	-0.388103	-1.477557	-1.018820	-0.227141	-0.543841	0	0	
1	0.119438	-0.388103	0.220763	0.642392	-0.187736	-0.680428	0	1	
2	-1.260339	-1.477989	-1.477557	-1.508818	-0.119471	-1.295072	0	0	
3	0.373811	0.701784	1.239755	-0.086629	-0.243230	-0.202372	0	0	
4	0.011523	-0.388103	-0.118901	-0.421262	-0.166994	0.548859	0	0	

5 rows × 26 columns

In [45]:
```
X = data_3_pc.drop('price', axis=1)
y = data_3_pc['price']
```

executed in 14ms, finished 04:28:27 2021-03-28

In [46]:
```
X_int = sm.add_constant(X)
model_3 = sm.OLS(y,X_int).fit()
model_3.summary()
```

executed in 63ms, finished 04:28:27 2021-03-28

Out[46]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.624
Model:	OLS	**Adj. R-squared:**	0.623
Method:	Least Squares	**F-statistic:**	1403.
Date:	Sun, 28 Mar 2021	**Prob (F-statistic):**	0.00
Time:	04:28:27	**Log-Likelihood:**	-19714.
No. Observations:	21191	**AIC:**	3.948e+04
Df Residuals:	21165	**BIC:**	3.969e+04
Df Model:	25		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.0619	0.117	9.046	0.000	0.832	1.292
bedrooms	-0.0601	0.006	-10.907	0.000	-0.071	-0.049
bathrooms	0.1142	0.007	15.327	0.000	0.100	0.129
sqft_living	0.3401	0.009	39.864	0.000	0.323	0.357
sqft_lot	-0.0132	0.004	-3.042	0.002	-0.022	-0.005
yr_built	-0.3434	0.007	-52.681	0.000	-0.356	-0.331
floors_1.5	0.0498	0.016	3.054	0.002	0.018	0.082
floors_2.0	0.0480	0.012	3.977	0.000	0.024	0.072
floors_2.5	0.2437	0.054	4.546	0.000	0.139	0.349
floors_3.0	0.4606	0.028	16.313	0.000	0.405	0.516
floors_3.5	0.4144	0.251	1.650	0.099	-0.078	0.906
waterfront_yes	1.1402	0.069	16.488	0.000	1.005	1.276
condition_2	-0.0843	0.124	-0.681	0.496	-0.327	0.158
condition_3	0.0780	0.115	0.678	0.498	-0.148	0.304
condition_4	0.1281	0.115	1.113	0.266	-0.097	0.354
condition_5	0.2695	0.116	2.328	0.020	0.043	0.496
grade_11	0.4815	0.042	11.501	0.000	0.399	0.564
grade_12	1.1011	0.111	9.934	0.000	0.884	1.318
grade_3	-2.2059	0.615	-3.588	0.000	-3.411	-1.001
grade_4	-2.0649	0.122	-16.900	0.000	-2.304	-1.825
grade_5	-2.0950	0.049	-42.620	0.000	-2.191	-1.999
grade_6	-1.8891	0.031	-61.281	0.000	-1.950	-1.829

grade_7	-1.5159	0.026	-59.286	0.000	-1.566	-1.466
grade_8	-1.0884	0.024	-46.283	0.000	-1.135	-1.042
grade_9	-0.4837	0.023	-20.586	0.000	-0.530	-0.438
renovated_yes	0.0869	0.025	3.462	0.001	0.038	0.136

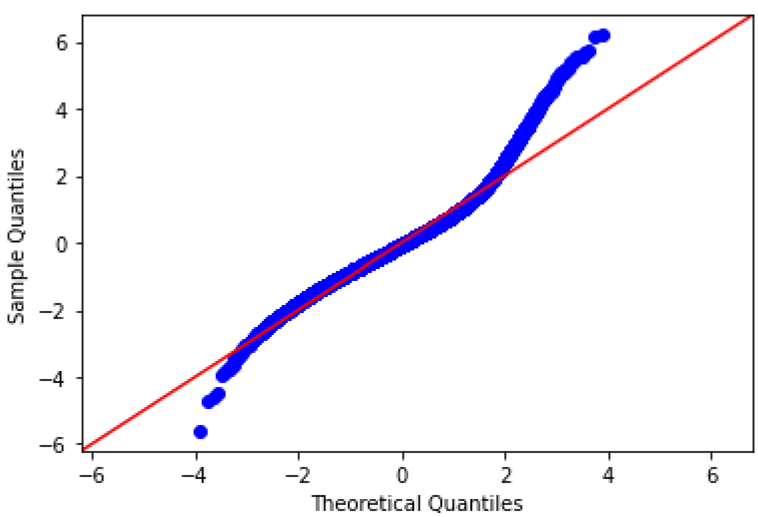
Omnibus:	3197.698	**Durbin-Watson:**	1.961
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	9274.025
Skew:	0.806	**Prob(JB):**	0.00
Kurtosis:	5.812	**Cond. No.**	238.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [47]:
```
a3, b3, c3, d3, e3 = linear_reg_sum(data_3_pc)
```
executed in 31ms, finished 04:28:27 2021-03-28

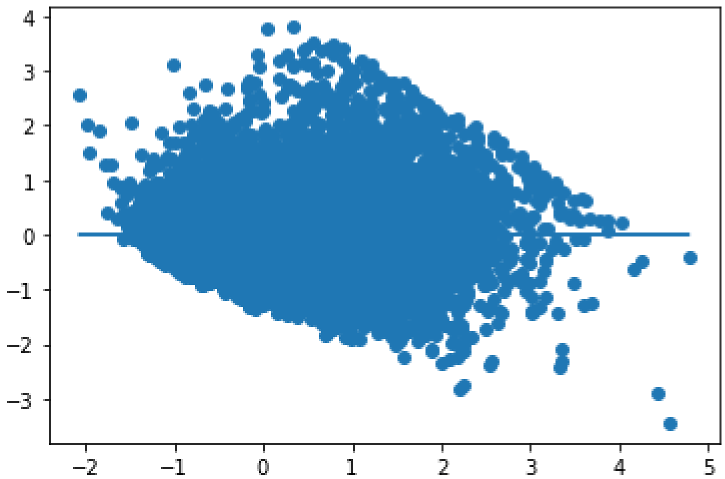
```
R^2 Score of Train: 0.6253793942236275
RMSE of Train: 0.6166762713232646
RMSE of Test: 0.6014094935086501
Mean Absolute Error of Train: 0.4560913291046095
Mean Absolute Error of Test: 0.4471718886215013
```

In [48]:
```
# Q-Q plot
fig = sm.graphics.qqplot(model_3.resid, dist=stats.norm, line='45', fit=True)
```
executed in 217ms, finished 04:28:27 2021-03-28



In [49]:
```
plt.scatter(model_3.predict(X_int), model_3.resid)
plt.plot(model_3.predict(X_int), [0 for i in range(len(data_3_pc))])
```
executed in 187ms, finished 04:28:27 2021-03-28

Out[49]: [<matplotlib.lines.Line2D at 0x163ad3a1910>]



- Q-Q plot is similar to Model 2
- R-squared value has increased from Model 2
- P-values for **'floor_3.5', 'condition_2', 'condition_3', and 'condition_4'** were above 0.05. These factors can be ignored as they are not significantly impacting price
- RMSE difference between Train and Test are still fine. Not overfit.
- Homoscedasticity has slightly improved. There is still a trend, but may be improved on with additional changes

1.5.4 Model 4: Log Transform

Let's log transform the model data to transform the skewed data to normal

In [50]:
```
# Iterating on Model 1 data
data_4 = data_2_no_norm.copy()
```
executed in 13ms, finished 04:28:27 2021-03-28

In [51]:
```
# List out the continuous and categorical variables
continuous = ['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'yr_bu
categoricals = ['floors', 'waterfront', 'condition', 'grade','renovated']
```
executed in 14ms, finished 04:28:27 2021-03-28

In [52]:
```
# Change to str for dummies
data_4['floors'] = data_4['floors'].apply(str)
data_4['waterfront'] = data_4['waterfront'].apply(lambda x: 'yes' if x>0 else 'no
data_4['condition'] = data_4['condition'].apply(str)
data_4['grade'] = data_4['grade'].apply(str)
data_4['renovated'] = data_4['renovated'].apply(lambda x: 'yes' if x>0 else 'no')
```

executed in 45ms, finished 04:28:27 2021-03-28

In [53]:
```
# Create Dummies for categorical variables
data_ohe = pd.get_dummies(data_4[categoricals], prefix=categoricals, drop_first=T
data_ohe.columns
```

executed in 29ms, finished 04:28:27 2021-03-28

Out[53]:
```
Index(['floors_1.5', 'floors_2.0', 'floors_2.5', 'floors_3.0', 'floors_3.5',
       'waterfront_yes', 'condition_2', 'condition_3', 'condition_4',
       'condition_5', 'grade_11', 'grade_12', 'grade_3', 'grade_4', 'grade_5',
       'grade_6', 'grade_7', 'grade_8', 'grade_9', 'renovated_yes'],
      dtype='object')
```

In [54]:
```
# Log transform and normalize
data_cont = data_4[continuous]

# log features
log_names = [f'{column}_log' for column in data_cont.columns]

data_log = np.log(data_cont)
data_log.columns = log_names

# normalize (subract mean and divide by std)

def normalize(feature):
    return (feature - feature.mean()) / feature.std()

data_log_norm = data_log.apply(normalize)
```

executed in 14ms, finished 04:28:27 2021-03-28

In [55]:
```
# Combine data for new dataset for Model 3
data_4_pc = pd.concat([data_log_norm, data_ohe], axis=1)
data_4_pc.head()
```
executed in 31ms, finished 04:28:27 2021-03-28

Out[55]:

	price_log	bedrooms_log	bathrooms_log	sqft_living_log	sqft_lot_log	yr_built_log	floors_1.5	fl
0	-1.463747	-0.263828	-1.725013	-1.124885	-0.375587	-0.536613	0	
1	0.365886	-0.263828	0.372979	0.772925	-0.099188	-0.673950	0	
2	-1.896080	-1.700993	-1.725013	-2.165666	0.260100	-1.295470	0	
3	0.604944	0.755857	1.117254	0.112289	-0.511667	-0.194497	0	
4	0.255468	-0.263828	0.068258	-0.263548	0.022726	0.552070	0	

5 rows × 26 columns

In [56]:
```
X = data_4_pc.drop('price_log', axis=1)
y = data_4_pc['price_log']
```
executed in 15ms, finished 04:28:27 2021-03-28

In [57]:
```
display(X.head())
display(y.head())
```
executed in 31ms, finished 04:28:27 2021-03-28

	bedrooms_log	bathrooms_log	sqft_living_log	sqft_lot_log	yr_built_log	floors_1.5	floors_2.0	f
0	-0.263828	-1.725013	-1.124885	-0.375587	-0.536613	0	0	
1	-0.263828	0.372979	0.772925	-0.099188	-0.673950	0	1	
2	-1.700993	-1.725013	-2.165666	0.260100	-1.295470	0	0	
3	0.755857	1.117254	0.112289	-0.511667	-0.194497	0	0	
4	-0.263828	0.068258	-0.263548	0.022726	0.552070	0	0	

5 rows × 25 columns

```
0   -1.463747
1    0.365886
2   -1.896080
3    0.604944
4    0.255468
Name: price_log, dtype: float64
```

In [58]:
```
X_int = sm.add_constant(X)
model_4 = sm.OLS(y,X_int).fit()
model_4.summary()
```
executed in 60ms, finished 04:28:27 2021-03-28

Out[58]:

OLS Regression Results

Dep. Variable:	price_log	**R-squared:**	0.602
Model:	OLS	**Adj. R-squared:**	0.601
Method:	Least Squares	**F-statistic:**	1280.
Date:	Sun, 28 Mar 2021	**Prob (F-statistic):**	0.00
Time:	04:28:27	**Log-Likelihood:**	-20310.
No. Observations:	21191	**AIC:**	4.067e+04
Df Residuals:	21165	**BIC:**	4.088e+04
Df Model:	25		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.7789	0.121	6.453	0.000	0.542	1.015
bedrooms_log	-0.0889	0.006	-14.977	0.000	-0.101	-0.077
bathrooms_log	0.0924	0.008	11.750	0.000	0.077	0.108
sqft_living_log	0.3955	0.009	42.447	0.000	0.377	0.414
sqft_lot_log	-0.0728	0.005	-13.931	0.000	-0.083	-0.063
yr_built_log	-0.3462	0.007	-51.145	0.000	-0.360	-0.333
floors_1.5	0.0571	0.017	3.387	0.001	0.024	0.090
floors_2.0	0.0449	0.013	3.514	0.000	0.020	0.070
floors_2.5	0.1174	0.055	2.121	0.034	0.009	0.226
floors_3.0	0.3893	0.031	12.735	0.000	0.329	0.449
floors_3.5	0.4204	0.258	1.627	0.104	-0.086	0.927
waterfront_yes	0.8908	0.071	12.498	0.000	0.751	1.031
condition_2	-0.0496	0.127	-0.389	0.697	-0.299	0.200
condition_3	0.2595	0.118	2.192	0.028	0.027	0.492
condition_4	0.2983	0.118	2.519	0.012	0.066	0.530
condition_5	0.4206	0.119	3.532	0.000	0.187	0.654
grade_11	0.3050	0.043	7.144	0.000	0.221	0.389
grade_12	0.5673	0.114	4.996	0.000	0.345	0.790
grade_3	-1.7915	0.633	-2.831	0.005	-3.032	-0.551
grade_4	-2.2013	0.126	-17.413	0.000	-2.449	-1.954
grade_5	-2.2102	0.051	-43.478	0.000	-2.310	-2.111
grade_6	-1.8675	0.031	-59.702	0.000	-1.929	-1.806

grade_7	-1.3915	0.025	-55.398	0.000	-1.441	-1.342
grade_8	-0.9111	0.023	-39.196	0.000	-0.957	-0.866
grade_9	-0.3646	0.024	-15.268	0.000	-0.411	-0.318
renovated_yes	0.0137	0.026	0.530	0.596	-0.037	0.064

Omnibus:	93.917	**Durbin-Watson:**	1.965
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	107.397
Skew:	-0.112	**Prob(JB):**	4.77e-24
Kurtosis:	3.267	**Cond. No.**	243.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [59]:
```
# Create a function for getting linear regression information from housing datase
def linear_reg_sum_log(data):
    df = data.copy()

    y = df['price_log']
    X = df.drop(['price_log'], axis=1)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ranc

    # Training
    linreg = LinearRegression()
    linreg.fit(X_train, y_train)
    y_hat_train = linreg.predict(X_train)
    y_hat_test = linreg.predict(X_test)

    # Significant score calculations
    print(f'R^2 Score of Train: {metrics.r2_score(y_train, y_hat_train)}')
    print(f'RMSE of Train: {np.sqrt(metrics.mean_squared_error(y_train, y_hat_tra
    print(f'RMSE of Test: {np.sqrt(metrics.mean_squared_error(y_test, y_hat_test)
    print(f'Mean Absolute Error of Train: {metrics.mean_absolute_error(y_train, y
    print(f'Mean Absolute Error of Test: {metrics.mean_absolute_error(y_test, y_h

    return metrics.r2_score(y_train, y_hat_train), np.sqrt(metrics.mean_squared_e
```

executed in 14ms, finished 04:28:27 2021-03-28

In [60]:
```
a4, b4, c4, d4, e4 = linear_reg_sum_log(data_4_pc)
```

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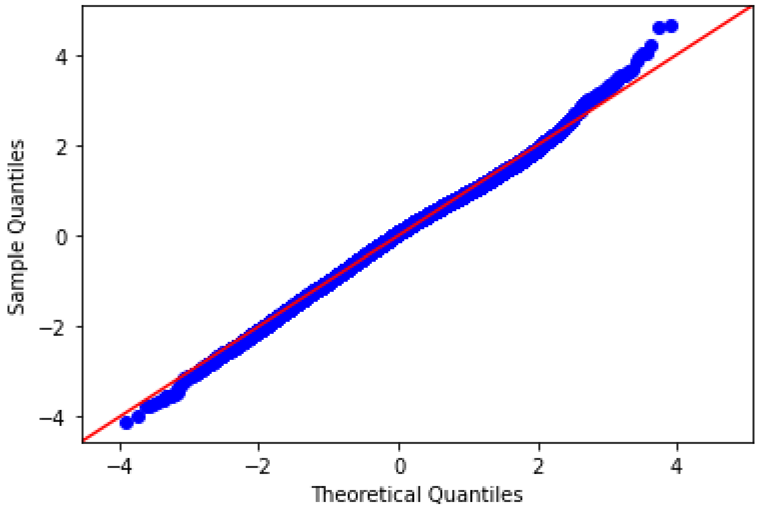
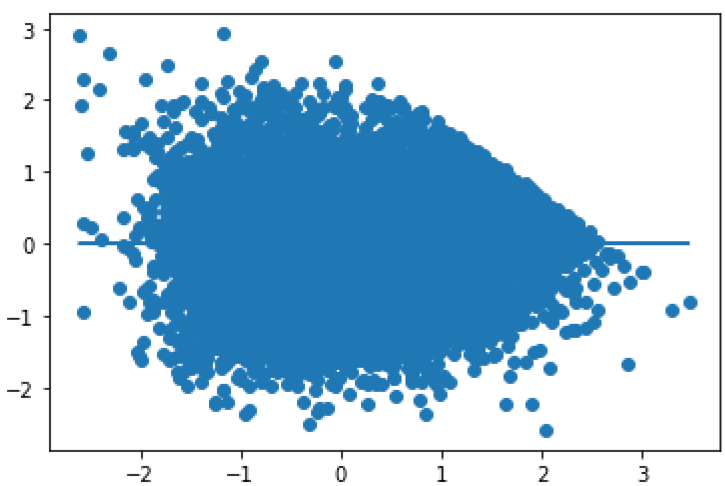
```
R^2 Score of Train: 0.6023678834040344
RMSE of Train: 0.6325323400670484
RMSE of Test: 0.6251384954320163
Mean Absolute Error of Train: 0.5021571256144449
Mean Absolute Error of Test: 0.4956449547618317
```

In [61]:
```
# Q-Q plot
fig = sm.graphics.qqplot(model_4.resid, dist=stats.norm, line='45', fit=True)
```
executed in 185ms, finished 04:28:28 2021-03-28



In [62]:
```
plt.scatter(model_4.predict(X_int), model_4.resid)
plt.plot(model_4.predict(X_int), [0 for i in range(len(data_4_pc))])
```
executed in 170ms, finished 04:28:28 2021-03-28

Out[62]: [<matplotlib.lines.Line2D at 0x163aa611eb0>]



- R-squared value went down from Model 3, but not by a large amount. **60% of the variation in price can be explained by the factors in the model**
- P-values for **'floors_3.5', 'condition_2', and 'renovated_yes'** were above 0.05 and thus were not significantly affecting price and can be ignored.
- Q-Q plot appears to be linear. It is very close to 0 residuals. **Best Q-Q plot thus far!**
- Homoscedasticity has improved from Model 3. **Best Homoscedasticity thus far!**
- Largest factors for better home prices are **whether the home is along a waterfront** and having a good **grade** and **condition** of the home.

Model 4 with the previous iterations is the best model to observe the effects of the variables on Housing sale prices.

Let's see how our models have progressed through each iteration

In [63]:
```
metric_values = {'Model':[1,2,3,4], 'R^2':[a1, a2, a3, a4], 'RMSE Train':[b1, b2,

metrics_df = pd.DataFrame(data=metric_values)
display(metrics_df)
```

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	Model	R^2	RMSE Train	RMSE Test	MAE Train	MAE Test
0	1	0.646265	218410.579795	219640.704389	141998.872771	141160.003076
1	2	0.616776	161831.059897	156441.121495	119508.019483	116192.094006
2	3	0.625379	0.616676	0.601409	0.456091	0.447172
3	4	0.602368	0.632532	0.625138	0.502157	0.495645

Let's get the Coefficient values from Model 4 for our final observations

In [64]:
```
# Let's get the coefficients from the best model
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()
linreg.fit(X, y)
```

executed in 29ms, finished 04:28:28 2021-03-28

Out[64]:
```
LinearRegression()
```

In [65]:
```
linreg.coef_
```

executed in 15ms, finished 04:28:28 2021-03-28

Out[65]:
```
array([-0.08887593,  0.09242832,  0.39547839, -0.0728257 , -0.3462355 ,
        0.05710396,  0.04492364,  0.11741703,  0.38928367,  0.42043744,
        0.89081643, -0.04957772,  0.25946036,  0.29825495,  0.42064787,
        0.30495806,  0.56732451, -1.79150016, -2.2013249 , -2.21024722,
       -1.86750937, -1.39154091, -0.91114017, -0.36455841,  0.01368457])
```

In [66]:
```
coeff_df = pd.DataFrame(linreg.coef_, X.columns, columns = ['coefficient'])
```

executed in 14ms, finished 04:28:28 2021-03-28

In [67]:
```
coeff_df.value_counts()
```
executed in 13ms, finished 04:28:28 2021-03-28

Out[67]:
```
coefficient
 0.890816     1
 0.013685     1
-2.201325     1
-1.867509     1
-1.791500     1
-1.391541     1
-0.911140     1
-0.364558     1
-0.346235     1
-0.088876     1
-0.072826     1
-0.049578     1
 0.044924     1
 0.567325     1
 0.057104     1
 0.092428     1
 0.117417     1
 0.259460     1
 0.298255     1
 0.304958     1
 0.389284     1
 0.395478     1
 0.420437     1
 0.420648     1
-2.210247     1
dtype: int64
```

In [68]:

```
# Create a barplot of positive impacting factors
ax = coeff_df[coeff_df['coefficient'] > 0].sort_values(by=['coefficient'], ascend
ax.set_title("Positive Impact of Variables on House Prices", fontsize = 20, fontw
ax.set_xlabel("Variables", fontsize=16, fontweight='bold')
ax.set_ylabel("Coefficient - Impact of Variables", fontsize=16, fontweight='bold'

plt.xticks(rotation=-65, fontsize=12, fontweight='bold')
plt.yticks(fontsize=12, fontweight='bold')
plt.grid(color='#95a5a6', linestyle='--', linewidth=2, axis='y', alpha=0.3)
```

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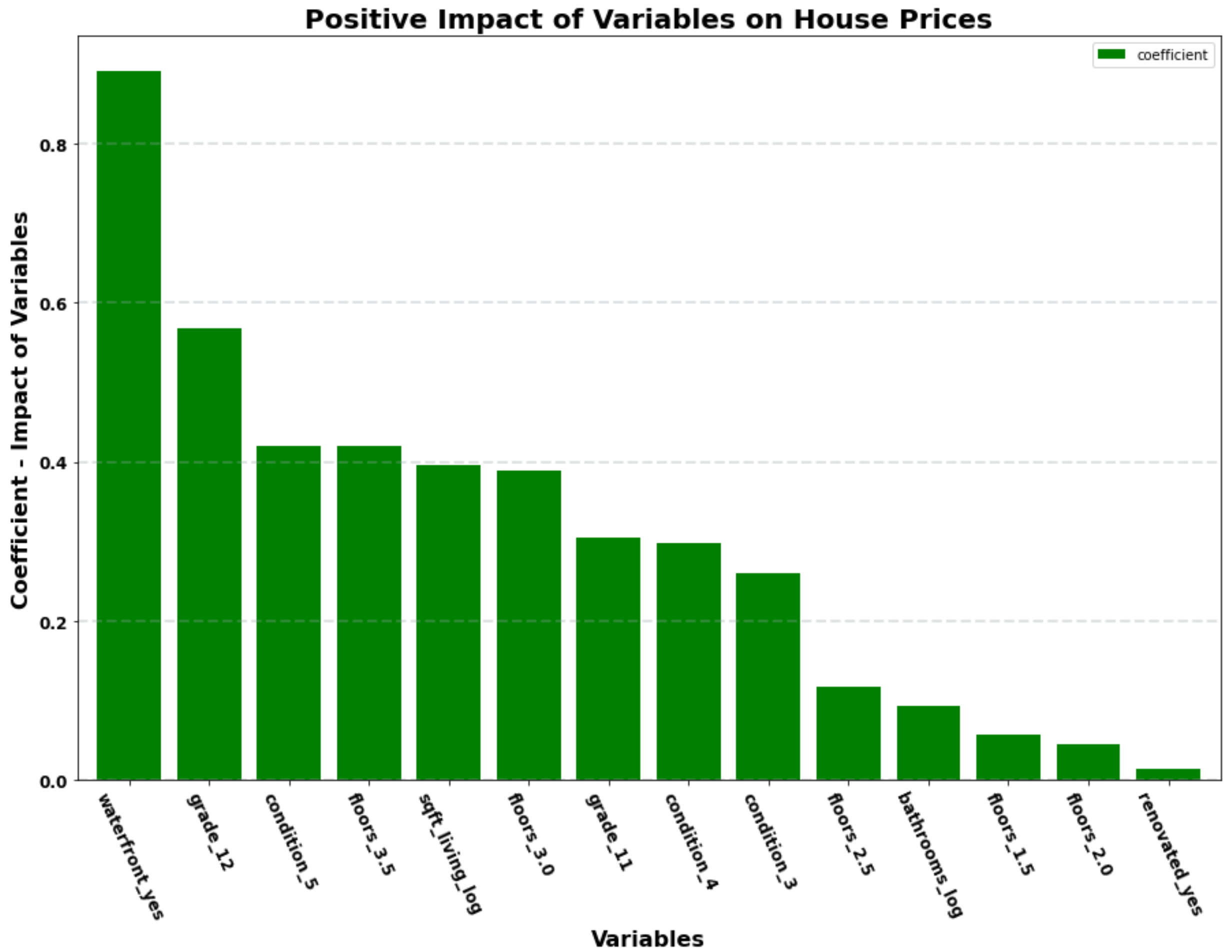

In [69]:
```
# Create a barplot of positive impacting factors
ax = coeff_df[coeff_df['coefficient'] < 0].sort_values(by=['coefficient']).plot(k
ax.set_title("Negative Impact of Variables on House Prices", fontsize=20, fontwei
ax.set_xlabel("Variables", fontsize=16, fontweight='bold')
ax.set_ylabel("Coefficient - Impact of Variables", fontsize=16, fontweight='bold'
ax.legend(loc='lower right')

plt.xticks(rotation=-65, fontsize=12, fontweight='bold')
plt.yticks(fontsize=12, fontweight='bold')
plt.grid(color='#95a5a6', linestyle='--', linewidth=2, axis='y', alpha=0.3)
```

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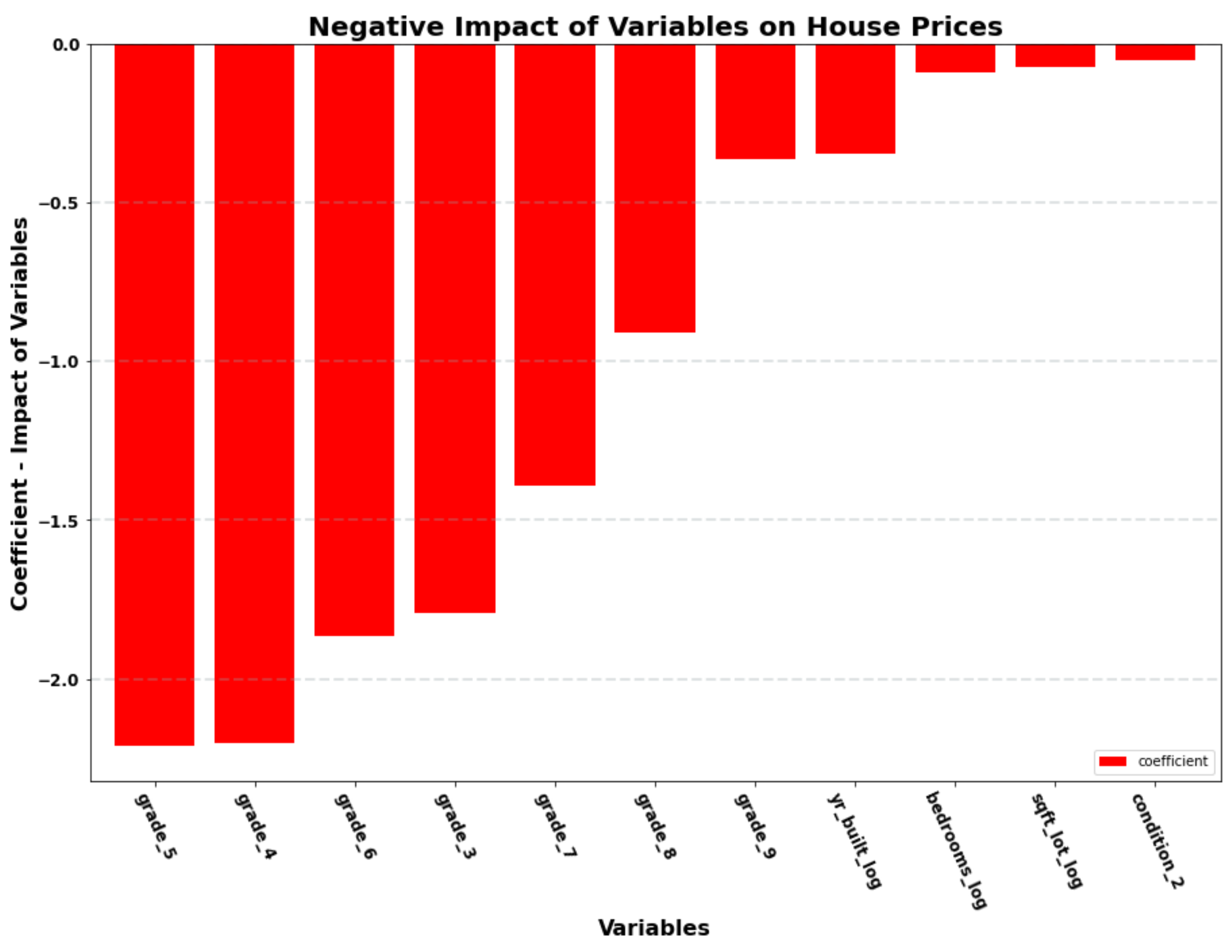

1.6 Conclusions

The analysis of the housing sale price datasets resulted in the following conclusions:

- Having a **Waterfront** has the largest impact on house sale prices. It may be good to increase prices on these homes as customers are more willing to pay the premium.
- A great **Condition** and **Grade** of a home are the second most important to a higher price payed for the home. Thus, **Renovations** increases the prices if it provides an improvement to the overall condition and grade. Random renovations may not have a great impact on the price of a home.
- Having a larger living space as seen with increase **Sq.ft.of Living Space** and more **Floors** can increase the price of the home. It makes sense as people will pay for more space.

1.7 Next Steps

Further analyses of the housing price dataset could yield additional insights to other recommendations:

- **Finding the best locations in King County that yield higher house sale prices**
- **Creating an estimation tool for a home based on inputting the correlated factors**
- **Analyzing factors further to estimate homes for a lower budget customer**