

# Final Project Submission

Please fill out:

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- Scheduled project review date/time: August 8, 2022 13:30 - 14:15 (CDT)
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- Blog post URL: <https://medium.com/@kevinjspring/predicting-home-sale-prices-using-linear-regression-4ebf079a48e8>

## Summary

- Our client wants to be able to predict sales price.
- Ordinary least squares linear regression was used to create three models.
- The three models were compared using  $R^2$ , Prediction Intervals (PI), and Root Mean Squared Error (RMSE).
- Model 2 (M2) is the best model as it has the best predictive capabilities, R-squared 0.88, low RMSE and PI.
- M2 could be used to prototype a client dashboard for real estate agents to predict sales price for new data.
- More data and variables should be collected to improve the model's predictive power.
- Communicate with client about internal real estate data that can be used to further train the model.

## Actionable Recommendations

1. M2 could be used for a client dashboard prototype for Bon Jovi real estate agents to predict sales price.
2. M2 can be used to measure the cost-benefit analysis of making improvements to the home. For example, a one-unit increase in the condition of the home will increase the sale price by about 5%.
3. M2 can help Bon Jovi real estate agents locate customers and properties that have the highest sale price potential. For example, homes in Zipcode 98039 sold for over 200% more than homes in Zipcode 98003 so those customers in 98039 likely have a higher sales price.

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## Business Problem

Our client is a residential real estate broker in King County, WA interested in finding a solution for their customers. Many of their customers come to them needing to sell their home but are unsure of the market value of their home. The client wants us to design and implement a model where they can take in the features of a seller's home and determine which price to begin listing discussion.

## Stakeholders

- President of brokerage firm
- Real estate agents that will use the dashboard

## Methods Summary

Our client wants us to predict a continuous value, sales price, from features of the house their customer gives them in the form of continuous and categorical data. Regression analysis is a statistical process to estimate the relationship between a dependent variable (response) and a continuous independent variables (predictors).

In this analysis I will use ordinary least squares (OLS) linear regression to assess the relationship between features of homes for sale price. OLS minimizes the sum of the squared difference between the observed dependent variable and the predicted response ( $\hat{y}$ )

To calculate  $\hat{y}$ ,

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^n x_n \hat{\beta}_n$$

where  $n$  is the number of predictors,  $\beta_0$  is the intercept,  $\hat{x}_n$  is the  $n^{th}$  predictor, and  $\hat{y}$  are the predicted value associated with the dependent variables.

The linear equation that is returned can be used to predict the response value using new data.

To perform OLS linear regression the data needs to be clean with no missing values and categorical data needs to be coded correctly. The assumptions of OLS linear regression are checked and models are built. These models are compared using, coefficient of determination, prediction intervals, and Root Mean Squared Error to compare and determine which model is the most suited for our client.

```
In [1]: # Import Libraries
        from datetime import date

        ## Data analysis
        import pandas as pd
        import numpy as np

        ## Statistical analysis
        from scipy import stats
        from scipy.stats import norm
        import statsmodels.api as sm
        import statsmodels.formula.api as smf
        from statsmodels.formula.api import ols
        #from statsmodels.stats.outliers_influence import variance_inflation_factor
        #from sklearn.metrics import mean_squared_error
        #from sklearn.model_selection import train_test_split

        ## Model Validation
        from sklearn.linear_model import LinearRegression
        from sklearn.model_selection import KFold
        from sklearn.model_selection import cross_val_score

        ## Visualization
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline

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

## Data

### Description

The data is a collection of single family homes in the King County, WA area sold between May 2014 and May 2015 (1). The data contains 21 variables and 21,597 records. This data will be suitable to create a model to predict sale price for homes within the parameters of this dataset.

```
In [2]: df.shape
```

Out[2]: (21597, 21)

In [3]: *#inspect data*  
df.info()

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

## Variable Names and Descriptions for King County Data Set

See the [King County Assessor Website](#) for further explanation of each condition code

Variable	Data Type	Description
id	catagorical	Unique identifier for a house
date	continuous	Date house was sold
price	continuous	Sale price (prediction target)
bedrooms	discrete	Number of bedrooms
bathrooms	discrete	Number of bathrooms
sqft_living	continuous	Square footage of living space in the home
sqft_lot	continuous	Square footage of the lot
floors -	discrete	Number of floors (levels) in house
waterfront	ordinal	Whether the house is on a waterfront

Variable	Data Type	Description
view	ordinal	Quality of view from house
condition	ordinal	How good the overall condition of the house is. Related to maintenance of house
grade	ordinal	Overall grade of the house. Related to the construction and design of the house
sqft_above	continuous	Square footage of house apart from basement
sqft_basement	continuous	Square footage of the basement
yr_built	catagorical	Year when house was built
yr_renovated	catagorical	Year when house was renovated
zipcode	catagorical	ZIP Code used by the United States Postal Service
lat	catagorical	Latitude coordinate
long	catagorical	Longitude coordinate
sqft_living15	continuous	The square footage of interior housing living space for the nearest 15 neighbors
sqft_lot15	continuous	The square footage of the land lots of the nearest 15 neighbors

## Location of King County, WA home sales

```
In [4]: ## Map of home sales between May 2014 and May 2015
# code adapted from
# Ahmed Qassim,
# https://towardsdatascience.com/easy-steps-to-plot-geographic-data-on-a-map-python-11

# Define bounding box
BBox = ((df.long.min(), df.long.max(),
        df.lat.min(), df.lat.max() ))

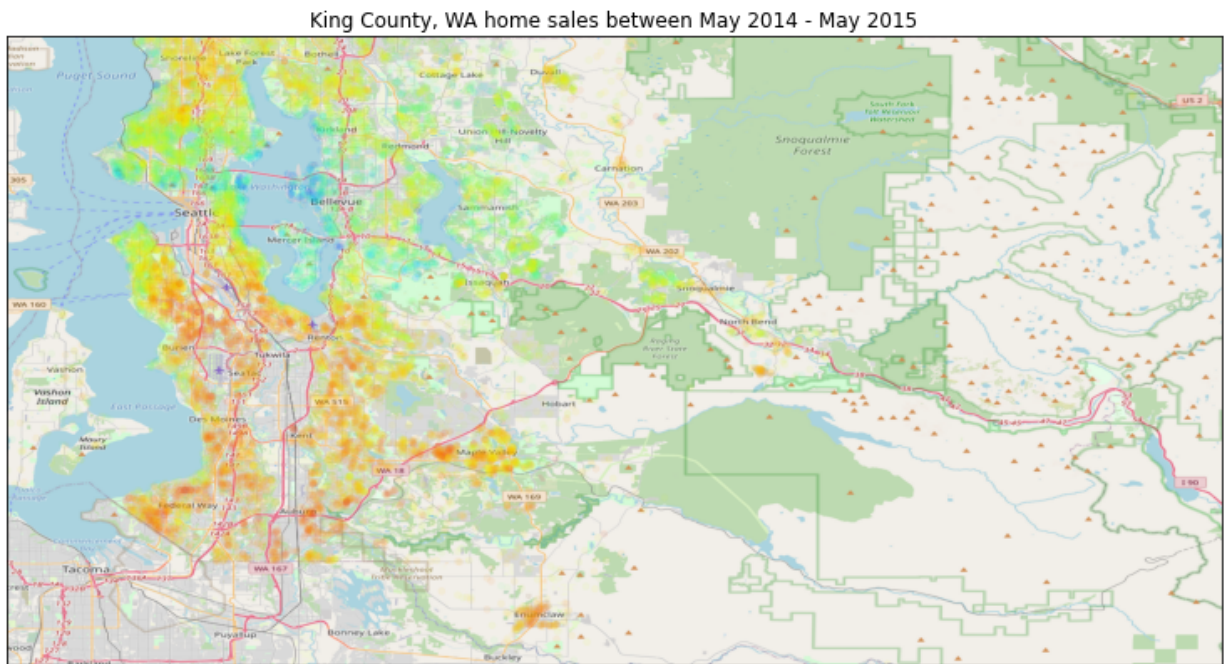
# Make scatterplot
fig, ax = plt.subplots(figsize = (13,12))
ax.scatter(df.long, df.lat, c = np.log(df.price), alpha=.075, s=20, edgecolors='none',
          cmap= plt.cm.get_cmap('jet_r'))
# Plot paramaters
ax.set_title('King County, WA home sales between May 2014 - May 2015') # title
ax.tick_params(axis='both', which='both', # Remove x, y ticks
              bottom=False, top=False, left=False, right=False,
              labelbottom=False, labeltop=False, labelleft=False, labelright=False)

# Set x and y-axis limits to bounding box
ax.set_xlim(BBox[0],BBox[1])
ax.set_ylim(BBox[2],BBox[3])

# Set area map
ruh_m=plt.imread('img/King_County_map.png')
ax.imshow(ruh_m, zorder=0, extent = BBox, aspect= 'equal') #

# plt.savefig('img/KC_home_sale_map.png', dpi=600) # save the image
```

Out[4]: <matplotlib.image.AxesImage at 0x1f80e9bb700>



## Data Limitations

- Data is only from 2014 to 2015. Models to predict future sales price would need to be updated with newer data.
- Some data might be missing, such as for-sale-by-owner or owner-financed sales.
- Ordinal data might be highly variable based on examiner's subjective experience.

## Data Cleanup

### Identify and remove duplicated records

```
In [5]: # Any duplicated homes?
duplicates_len = len(df[df.duplicated(subset=['id'], keep=False)].sort_values(by='id'))

print(f"Results:\nThere are {duplicates_len} duplicated records.")
df[df.duplicated(subset=['id'], keep=False)].sort_values(by='id').head(4)
```

Results:

There are 353 duplicated records.

Out[5]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfr
2495	1000102	4/22/2015	300000.0	6	3.0	2400	9373	2.0	
2494	1000102	9/16/2014	280000.0	6	3.0	2400	9373	2.0	N
16800	7200179	10/16/2014	150000.0	2	1.0	840	12750	1.0	
16801	7200179	4/24/2015	175000.0	2	1.0	840	12750	1.0	

4 rows × 21 columns

## Duplicate home ID discussion

The duplicated records based on ID are from the same homes that sold within the same year. These homes have the same attributes except for sale `date`. These may be homes that were flipped or sold quickly after an initial sale. I will keep these records as I am interested in predicting a home's sale price and these give more data for the true value of a house.

## Remove Unnecessary variables

The following variables will be deleted from this analysis as they are unnecessary to my analysis.

- `id` - This is an unique identifier for each home. Too unique.
- `date` - This is the sale date and time will not be analyzed due to the single year of the data.
- `lat` - This is the latitude of the home sold. Will use Zipcode for location.
- `long` - same reasoning as `lat`

```
In [6]: # delete unnecessary columns
df.drop(['id', 'date', 'lat', 'long'], axis=1, inplace=True)
```

## Identify Missing data

```
In [7]: # How many columns have NaN?
print(df.isna().sum())
```

```
price          0
bedrooms       0
bathrooms      0
sqft_living    0
sqft_lot       0
floors         0
waterfront     2376
view           63
condition      0
grade          0
sqft_above     0
sqft_basement  0
yr_built       0
yr_renovated   3842
zipcode        0
sqft_living15  0
sqft_lot15     0
dtype: int64
```

```
In [8]: # Any placeholders?
# Look for top occurring values
print('King County, WA \n Home Sales Dataframe\n')
for col in df.columns:
    print(col, '\n', df[col].value_counts(normalize = True).head(10), '\n')
```



King County, WA  
Home Sales Dataframe

price

450000.0	0.007964
350000.0	0.007964
550000.0	0.007362
500000.0	0.007038
425000.0	0.006945
325000.0	0.006853
400000.0	0.006714
375000.0	0.006390
300000.0	0.006158
525000.0	0.006066

Name: price, dtype: float64

bedrooms

3	0.454878
4	0.318655
2	0.127796
5	0.074131
6	0.012594
1	0.009075
7	0.001760
8	0.000602
9	0.000278
10	0.000139

Name: bedrooms, dtype: float64

bathrooms

2.50	0.248970
1.00	0.178312
1.75	0.141131
2.25	0.094782
2.00	0.089364
1.50	0.066907
2.75	0.054869
3.00	0.034866
3.50	0.033847
3.25	0.027272

Name: bathrooms, dtype: float64

sqft\_living

1300	0.006390
1400	0.006251
1440	0.006158
1800	0.005973
1660	0.005973
1010	0.005973
1820	0.005927
1480	0.005788
1720	0.005788
1540	0.005742

Name: sqft\_living, dtype: float64

sqft\_lot

5000	0.016576
6000	0.013428
4000	0.011622
7200	0.010187

```
4800    0.005510
7500    0.005510
4500    0.005279
8400    0.005140
9600    0.005047
3600    0.004769
Name: sqft_lot, dtype: float64
```

```
floors
1.0    0.494189
2.0    0.381303
1.5    0.088438
3.0    0.028291
2.5    0.007455
3.5    0.000324
Name: floors, dtype: float64
```

```
waterfront
NO      0.992404
YES     0.007596
Name: waterfront, dtype: float64
```

```
view
NONE      0.901923
AVERAGE  0.044441
GOOD      0.023591
FAIR      0.015325
EXCELLENT 0.014721
Name: view, dtype: float64
```

```
condition
Average    0.649164
Good       0.262861
Very Good  0.078761
Fair       0.007871
Poor       0.001343
Name: condition, dtype: float64
```

```
grade
7 Average    0.415521
8 Good       0.280826
9 Better     0.121082
6 Low Average 0.094365
10 Very Good 0.052507
11 Excellent 0.018475
5 Fair       0.011205
12 Luxury    0.004121
4 Low        0.001250
13 Mansion   0.000602
Name: grade, dtype: float64
```

```
sqft_above
1300    0.009816
1010    0.009724
1200    0.009538
1220    0.008890
1140    0.008520
1400    0.008334
1060    0.008242
1180    0.008196
```

```
1340    0.008149
1250    0.008057
Name: sqft_above, dtype: float64
```

```
sqft_basement
0.0    0.593879
?      0.021021
600.0   0.010048
500.0   0.009677
700.0   0.009631
800.0   0.009307
400.0   0.008520
1000.0  0.006853
900.0   0.006575
300.0   0.006575
Name: sqft_basement, dtype: float64
```

```
yr_built
2014    0.025883
2006    0.020975
2005    0.020836
2004    0.020049
2003    0.019447
2007    0.019308
1977    0.019308
1978    0.017919
1968    0.017641
2008    0.016993
Name: yr_built, dtype: float64
```

```
yr_renovated
0.0    0.958096
2014.0  0.004112
2013.0  0.001746
2003.0  0.001746
2007.0  0.001690
2000.0  0.001633
2005.0  0.001633
2004.0  0.001239
1990.0  0.001239
2009.0  0.001183
Name: yr_renovated, dtype: float64
```

```
zipcode
98103    0.027874
98038    0.027272
98115    0.026994
98052    0.026578
98117    0.025605
98042    0.025328
98034    0.025235
98118    0.023475
98023    0.023105
98006    0.023059
Name: zipcode, dtype: float64
```

```
sqft_living15
1540    0.009122
1440    0.009029
1560    0.008890
```

```
1500    0.008334
1460    0.007825
1580    0.007733
1610    0.007686
1720    0.007686
1800    0.007686
1620    0.007594
Name: sqft_living15, dtype: float64
```

```
sqft_lot15
5000    0.019771
4000    0.016484
6000    0.013335
7200    0.009724
4800    0.006714
7500    0.006575
8400    0.005371
3600    0.005140
4500    0.005140
5100    0.005047
Name: sqft_lot15, dtype: float64
```

## Missing value results

- NaN
  - waterfront
    - Binary categorical variable ( YES or NO )
    - replace NaN with mode of NO as most likely these properties are not waterfront
  - view
    - Ordinal categorical variable
    - replace NaN with NONE
  - yr\_renovated
    - Will be converted to a countable numerical variable
    - 0 is the most common value with over 95% of values.
    - Replace NaN with 0 value
- Placeholder
  - yr\_renovated has 0 for missing or unknown values.
  - sqft\_basement has ? for missing or unknown values.

```
In [9]: # replacing waterfront NaN with 'NO'
df['waterfront'].fillna('NO', inplace=True)

# replace yr_renovated NaN with 'Unknown'
df['yr_renovated'].fillna(0, inplace=True)

# replace `NaN` with `NONE` for column `view`
df['view'].fillna('NONE', inplace=True)
```

```
In [10]: # Confirm no more NaN values
print(df.isna().sum())
```

```

price          0
bedrooms       0
bathrooms      0
sqft_living    0
sqft_lot       0
floors         0
waterfront     0
view           0
condition      0
grade          0
sqft_above     0
sqft_basement  0
yr_built       0
yr_renovated   0
zipcode        0
sqft_living15  0
sqft_lot15     0
dtype: int64

```

## Coding ordinal, binary, and count data

variable	Data Type	Plan
condition	ordinal	Recode to dictionary. { 'Poor': 0, 'Fair': 1, 'Average': 2, 'Good': 3, 'Very Good': 4 }
grade	ordinal	Delete the descriptor, keep the number, and convert it to <code>int</code> datatype. Example: 7 Average becomes 7
basement	binary	If there is a basement (sq.ft > 0) the value will be set to 1. No basement (sq.ft = 0) set to 0. ? makes up about 2% of values and the current value of 0 makes up almost 60%. Replace ? with the mode of 0.
view	ordinal	Recode to dictionary. { 'NONE': 0, 'FAIR': 1, 'AVERAGE': 2, 'GOOD': 3, 'EXCELLENT': 4 }
waterfront	binary	Recode to dictionary. { 'NO': 0, 'YES': 1 }.
home_age	discrete	Create variable from <code>yr_built</code> . Subtract current year from <code>yr_built</code> . Drop <code>yr_built</code>
yr_since_reno	discrete	Create variable from <code>yr_renovated</code> . Subtract current year from <code>yr_renovated</code> . 0 is the most common value with over 95% of values. If never renovated then subtract from <code>yr_built</code> . Drop <code>yr_renovated</code> .

```

In [11]: # -----#
# Encoding ordinal, binary, and count variables
# Code condition to ordinal data

```

```

# Map condition variable to dictionary
condition_dict = {'Poor': 0, 'Fair': 1, 'Average': 2, # Map
                  'Good': 3, 'Very Good': 4}
df['condition'] = df['condition'].map(condition_dict) # Use map to
                                                    # code values

# Code Grade to ordinal data
# Strip out by spaces and keep the first string, which is the value
df['grade'] = df['grade'].apply(lambda x: x.split(' ', 1)[0]).astype(int)

# Code sqft_basement to binary data
# sqft_basement has '?' as a placeholder. Set this to 0.
df['sqft_basement'].replace('?', 0, inplace=True)
# change to numerical type
df['sqft_basement'] = df['sqft_basement'].astype(float)
# With a basement then code as 1
df['sqft_basement'].loc[df['sqft_basement'] > 0] = 1
# rename column
df.rename(columns={'sqft_basement': 'basement'}, inplace=True)

# Code view to ordinal data
# Map ordinal variable to dictionary
view_dict = {'NONE': 0,
             'FAIR': 1,
             'AVERAGE': 2,
             'GOOD': 3,
             'EXCELLENT': 4} # map
df['view'] = df['view'].map(view_dict) # Recode

# Recode waterfront to binary data
# Map binary variable to dictionary
waterfront_dict = {'NO': 0, 'YES': 1} # map
df['waterfront'] = df['waterfront'].map(waterfront_dict) # Recode

# Recode home_age to discrete data
# Calculate home age
current_year = date.today().year # assign current year
df['home_age'] = current_year - df['yr_built'] # Calculate year since built
df.drop('yr_built', axis=1, inplace=True) # drop old column

# Recode yr_since_reno to discrete data
# subtraction function
def sub(a, b):
    return a - b
# Calculate years since last renovation
df['yr_since_reno'] = df.apply(lambda row : sub(current_year, row['yr_renovated'])) if
df.drop('yr_renovated', axis=1, inplace=True)

```

D:\ProgramData\Anaconda3\lib\site-packages\pandas\core\indexing.py:1732: SettingWithCopyWarning:

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

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

```
self._setitem_single_block(indexer, value, name)
```

In [12]: `df.describe().apply(lambda s: s.apply(lambda x: format(x, 'g')))` # Data description to

```
Out[12]:
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade
<b>count</b>	21597	21597	21597	21597	21597	21597	21597	21597	21597	21597
<b>mean</b>	540297	3.3732	2.11583	2080.32	15099.4	1.4941	0.0067602	0.233181	2.4	6.7
<b>std</b>	367368	0.926299	0.768984	918.106	41412.6	0.539683	0.0819439	0.764673	0.6	1.1
<b>min</b>	78000	1	0.5	370	520	1	0	0	1	3
<b>25%</b>	322000	3	1.75	1430	5040	1	0	0	1	4
<b>50%</b>	450000	3	2.25	1910	7618	1.5	0	0	2	5
<b>75%</b>	645000	4	2.5	2550	10685	2	0	0	3	6
<b>max</b>	7.7e+06	33	8	13540	1.65136e+06	3.5	1	4	4	11

## Outliers

There is an outlier that may be due to a data entry mistake. One house has 33 bedrooms. I was expecting it to be a mansion but it has an average grade (7), 1.75 bathrooms, and only 1,620 square feet of living space. I think this house had a miskey and the number of bedrooms should be 3.

```
In [13]: df[df['bedrooms'] > 30]
```

```
Out[13]:
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade
<b>15856</b>	640000.0	33	1.75	1620	6000	1.0	0	0	4	7

```
In [14]: df.at[15856, 'bedrooms'] = 3
df.loc[[15856]]
```

```
Out[14]:
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade
<b>15856</b>	640000.0	3	1.75	1620	6000	1.0	0	0	4	7

## Exploratory Data Analysis

### Cleaned Data Description

```
In [15]: df.describe().apply(lambda s: s.apply(lambda x: format(x, 'g')))
```

Out[15]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condo
<b>count</b>	21597	21597	21597	21597	21597	21597	21597	21597	21597
<b>mean</b>	540297	3.37181	2.11583	2080.32	15099.4	1.4941	0.0067602	0.233181	2.4
<b>std</b>	367368	0.904096	0.768984	918.106	41412.6	0.539683	0.0819439	0.764673	0.6
<b>min</b>	78000	1	0.5	370	520	1	0	0	0
<b>25%</b>	322000	3	1.75	1430	5040	1	0	0	0
<b>50%</b>	450000	3	2.25	1910	7618	1.5	0	0	0
<b>75%</b>	645000	4	2.5	2550	10685	2	0	0	0
<b>max</b>	7.7e+06	11	8	13540	1.65136e+06	3.5	1	4	4

## About the data

The median house sold in King County, WA between 2014 to 2015 was for \$450,000. The median house sold was 1910 square feet, 3 bedroom, 2.25 bathrooms, and 47 years old. The home sale price range was \$78,000 to \$7,700,000.

## Variable scatter matrix

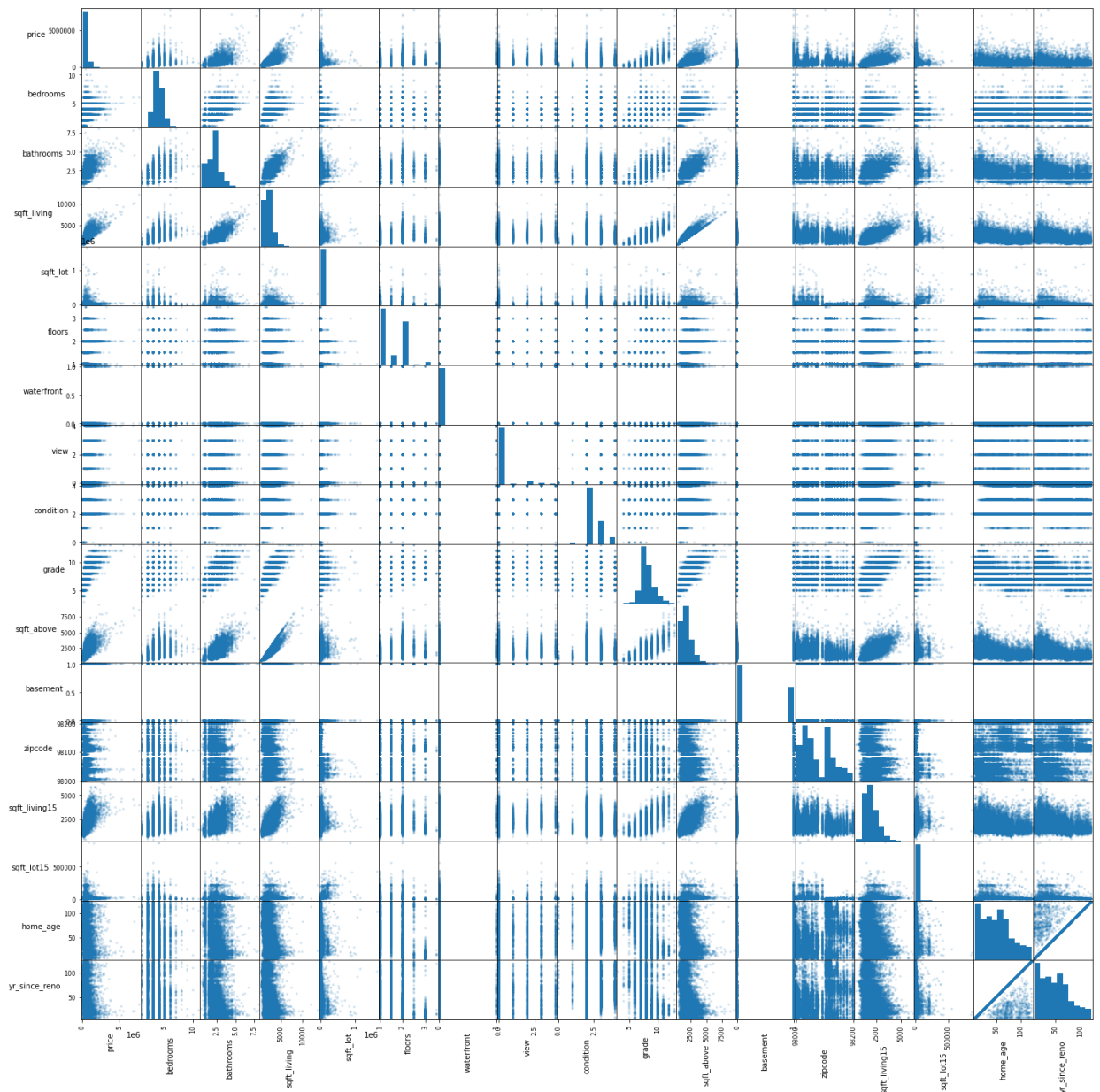
```
In [16]: # Visualize the data using scatter plot and histogram

import warnings
warnings.filterwarnings('ignore') # Ignore warnings

# Create scatter matrix
axes = pd.plotting.scatter_matrix(df, alpha = 0.2, figsize = [20, 20])
for ax in axes.flatten():
    ax.xaxis.label.set_rotation(90)
    ax.yaxis.label.set_rotation(0)
    ax.yaxis.label.set_ha('right')

plt.tight_layout()
plt.gcf().subplots_adjust(wspace=0, hspace=0)
plt.show()
```





## Scatter Matrix Results

### Histogram

The diagonal plots are the histogram and indicate that most of the variables are right-skewed, including the dependent variable, price.

### Scatterplot

Looking at the first row, the variables with the strongest positive correlation with price are for the number of bathrooms, grade, and square footage of the living space in the house.

## Correlation Matrix Heatmap

A correlation heatmap calculates the Pearson correlation between variables. A Pearson correlation measures the relationship between two variables. A value of 1 means a complete

positive correlation, a value of 0 means no correlation, and -1 means a negative correlation. This heatmap has a dark color for negatively correlated variables and a light color for positively correlated variables.

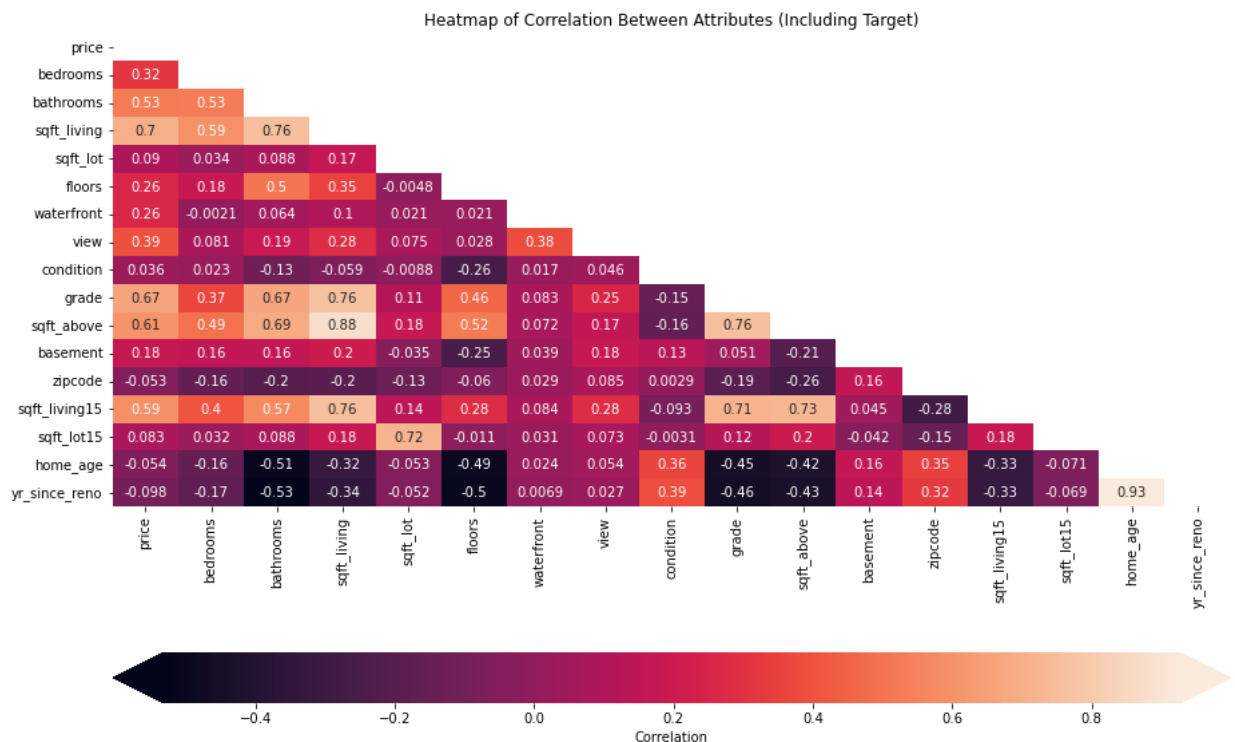
```
In [17]: # Make heatmap
# Code adapted from Flatiron Data Science

# compute the correlation matrix
corr = df.corr()

# Set up figure and axes
fig, ax = plt.subplots(figsize=(15, 10))

# Plot a heatmap of the correlation matrix, with both
# numbers and colors indicating the correlations
sns.heatmap(
    # Specifies the data to be plotted
    data=corr,
    # The mask means we only show half the values,
    # instead of showing duplicates. It's optional.
    mask=np.triu(np.ones_like(corr, dtype=bool)),
    # Specifies that we should use the existing axes
    ax=ax,
    # Specifies that we want labels, not just colors
    annot=True,
    # Customizes colorbar appearance
    cbar_kws={"label": "Correlation", "orientation": "horizontal", "pad": .2, "extend"
)

# Customize the plot appearance
ax.set_title("Heatmap of Correlation Between Attributes (Including Target)");
```



## Dummy variables for ZipCode

Dummy variables or One-hot-encoding is a way to use categorical variables with regression analysis. The variable `zipcode` is a categorical variable and must be converted to a numerical data. Each Zipcode will become its own variable and be either a 'no' (0) or 'yes' (1).

```
In [18]: # Convert zipcode variable to Dummy variables
df_clean = df.copy()
cat_col = ['zipcode']

# Label columns as category
df[cat_col] = df[cat_col].astype('category')
ohe_df = pd.get_dummies(df[cat_col], drop_first=True)

# merge ohe_df with df_clean and drop old zip_code column
df_clean = pd.concat([df_clean, ohe_df], axis=1)
df_clean.drop(cat_col, axis=1, inplace=True)
```

## Model Specification

In this section I will specify which variable to include in the model to predict sales price. After checking the assumptions and correcting variables to fit the assumptions, I will start building the models

Model	Description
M1	Use variables highly correlated (>0.6) with sale price
M2	A backward stepwise regression to choose variables and find that this procedure chooses almost all independent variables, excluding some the dummy variables for zipcode
M3	M1 with interaction effects

## Model Assumptions (2)

Assumption	Description
1	The regression model is linear in the coefficients and error term
2	There is a random sampling of observations
3	Error term has a population mean of zero
4	There is no multi-collinearity (or perfect collinearity)
5	The error term has a constant variance (no heteroskedasticity)
6 (optional)	The error term is normally distributed. Allows me to perform statistical hypothesis testing. As I am developing a prediction model this assumption is unnecessary.

Assumption 2 is met with the collection of the data. The data may lack private sales by owner but the majority of house sales occur through real estate agents. Assumptions 1, 3, 4, 5 and 6 will be checked with residual plots.

# Specifying Model 1 (M1)

I will specify M1 variables using the variables with a Pearson's correlation of 0.6 or greater.

```
In [19]: # Features correlated
features = []
correlations = []
for idx, correlation in corr['price'].T.iteritems():
    if correlation >= .6 and idx != 'price':
        features.append(idx)
        correlations.append(correlation)
corr_with_price = pd.DataFrame({'Correlations': correlations, 'Features': features})

print('Independent Variables Highly Correlated (>0.6) With Price')
display(corr_with_price)
```

Independent Variables Highly Correlated (>0.6) With Price

	Correlations	Features
0	0.701917	sqft_living
1	0.667951	grade
2	0.605368	sqft_above

## Distribution of dependent variable price

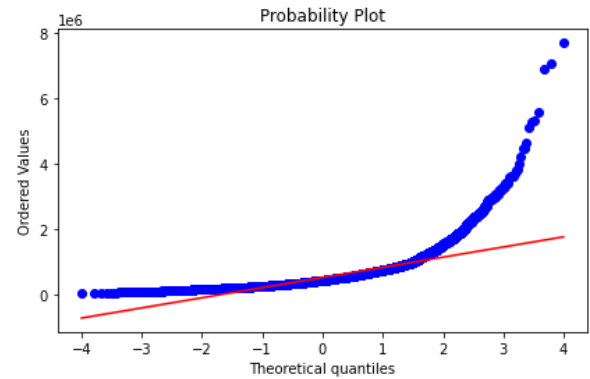
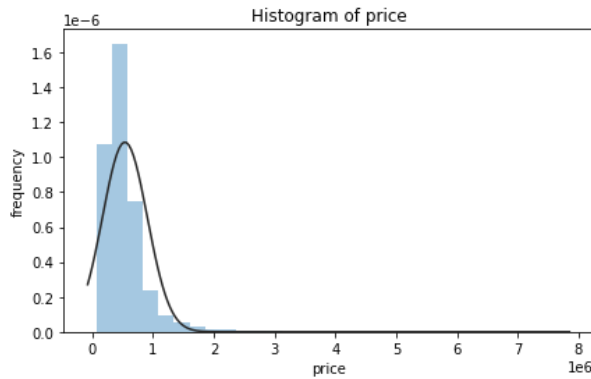
```
In [20]: def hist_plot(data, Y):
    ...
    Histogram plot function
    Input:
        data: pandas dataframe
        Y: column of variable for the histogram
    Output:
        Histogram plot
        Skewness and kurtosis value
    Citation:
        Atanu Dan
        https://medium.com/@atanudan/kurtosis-skew-function-in-pandas-aa63d72e20c
    ...

    y = data[Y]
    # Plot code
    fig, ax = plt.subplots(1,2, figsize=(15,4))
    sns.distplot(y, fit=norm, bins=30, kde=False, ax=ax[0]);
    ax[0].title.set_text(f'Histogram of {Y}')
    ax[0].set(xlabel=f'{Y}', ylabel='frequency')
    res = stats.probplot(df_clean['price'], plot=ax[1])

    ## Skewness and Kurtosis
    print(f'EDA of {Y} variable')
    print(f'Skewness: {y.skew()}')
    print(f'Kurtosis: {y.kurt()}')
```

```
In [21]: #histogram of price
hist_plot(df_clean, 'price')
```

EDA of price variable  
Skewness: 4.023364652271239  
Kurtosis: 34.54135857673376



## Interpretation

The data in the variable `price` is highly right-skewed and does not follow a normal distribution as shown in the histogram and QQ-plot. This may result in a high level of **heteroskedasticity** because there are many orders of magnitude between the lowest and highest sale price. Heteroskedasticity results when variance is not equal across the range of dependent variable. This may cause higher variance in high sale price houses in contrast to low sale price houses. In other words, the variance is unequal as it is changing proportionally with the variable.

## Residual plot

A residual plot is produced for the independent variables with the highest correlation to `price`. Residual plots show the residual error plotted against the actual sale price. This will allow me to assess heteroskedasticity as residual plots will have a random pattern around 0 with homoskedasticity but a cone shape pattern with heteroskedasticity.

```
In [22]: # Residual plot
def residual_plot(data, X, Y, xlogged=False, ylogged=False):
    """
    Residual Plot Function
    Input:
        data = Pandas dataframe
        X: independent variable
        Y: dependent variable
        logged: Is the axis logged?
    Output:
        Residual plot
    """
    x = data[X]
    y = data[Y]
    if xlogged:
        label_x = f'log({X})'
    else:
        label_x = f'{X}'
    if ylogged:
        label_y = f'log({Y})\n$USD'
    else:
```

```

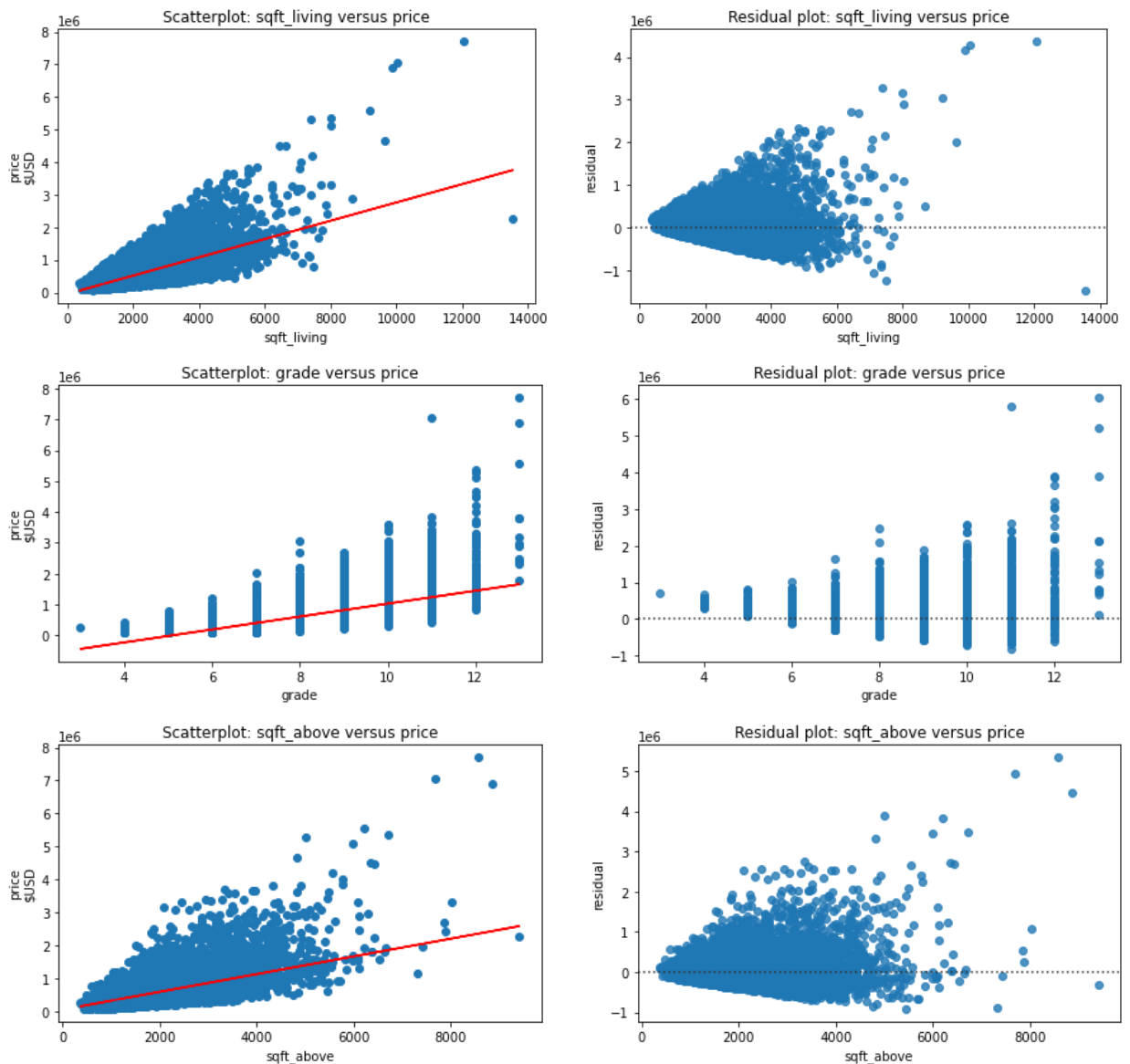
label_y = f'{Y}\n$USD'
fig, (ax1, ax2) = plt.subplots(1,2, figsize=(15,4))
ax1.scatter(x, y)
m, b = np.polyfit(x, y, 1) # regression line
ax1.plot(x, m*x+b, color='red') # plot regression line
ax1.set(xlabel=label_x, ylabel=label_y)
sns.residplot(x=x, y = y, ax=ax2) # residual plot
ax1.title.set_text(f'Scatterplot: {X} versus {Y}')
ax2.title.set_text(f'Residual plot: {X} versus {Y}')
ax2.set(ylabel='residual', xlabel=label_x)

```

```

In [23]: # Residual plot
residual_plot(df_clean, 'sqft_living', 'price', False, False)
residual_plot(df_clean, 'grade', 'price', False, False)
residual_plot(df_clean, 'sqft_above', 'price', False, False)

```



## Interpretation

The fitted line plot to the left of the scatterplots for each of these variables indicates that the relationships are not linear. The fan shape in the residual plot indicates that there is a high level

of heteroskedasticity which would violate an assumption of ordinary least squares regression. To fix this the `price` variable and variables associated with square feet will be log transformed to take into account the change in magnitude of the variance at higher values.

```
In [24]: # Log transform price data
df_clean['price'] = np.log(df_clean['price'])
```

```
In [25]: # Log transform the rest of the continuous right-skewed area variables
df_clean['sqft_living'] = np.log(df_clean['sqft_living'])
df_clean['sqft_above'] = np.log(df_clean['sqft_above'])
df_clean['sqft_lot15'] = np.log(df_clean['sqft_lot15'])
df_clean['sqft_lot'] = np.log(df_clean['sqft_lot'])
df_clean['sqft_living15'] = np.log(df_clean['sqft_living15'])
```

## Histogram of log transformed `price` variable

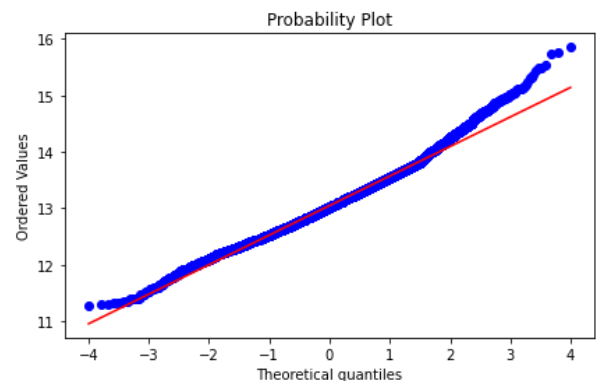
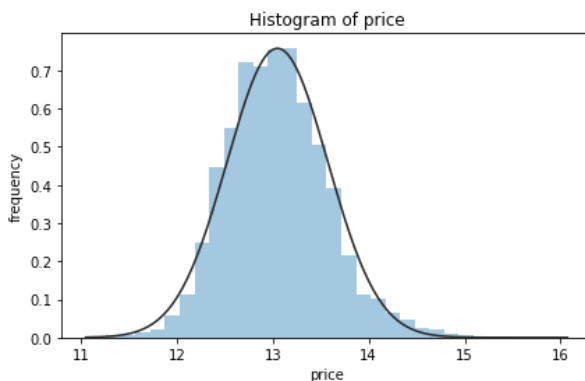
The distribution of the dependent variable, `price`, is not normally distributed after being log transformed.

```
In [26]: # Histogram of Log transformed price independent variable
hist_plot(df_clean, 'price')
```

EDA of price variable

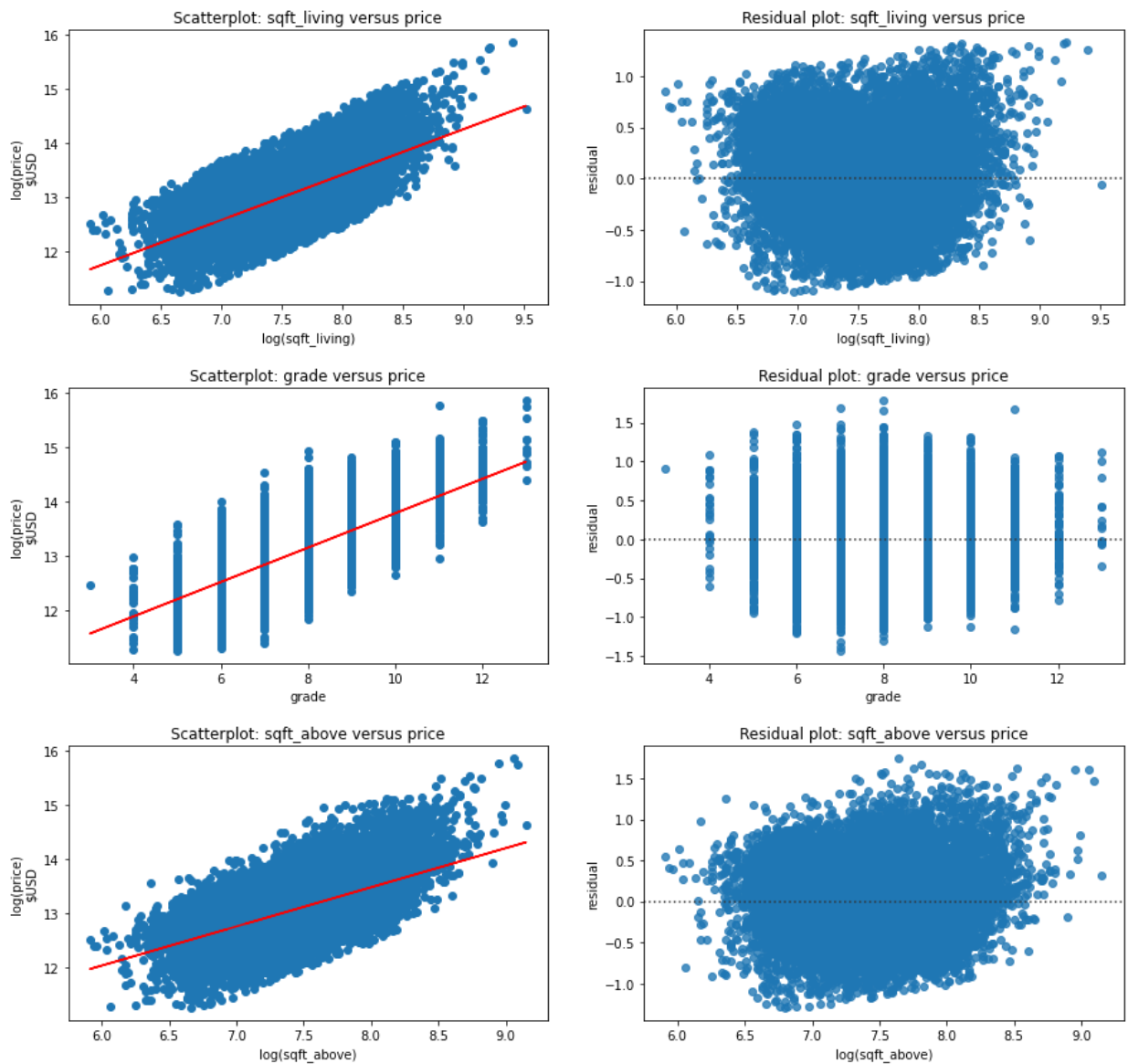
Skewness: 0.4310041773299232

Kurtosis: 0.691048515911131



## Residual plots with log transformation

```
In [27]: # Residual plot
residual_plot(df_clean, 'sqft_living', 'price', True, True)
residual_plot(df_clean, 'grade', 'price', False, True)
residual_plot(df_clean, 'sqft_above', 'price', True, True)
```



## Interpretation

After log transforming the sales price data and the continuous data associated with area, the residual plot has a random pattern which indicates it meets the homoskedasticity assumption for ordinary least square regression. `grade` was not log transformed but the residual plot shows homoskedasticity when `price` is log transformed. `grade` also now appears to have a linear relationship with `price` as shown in the fitted-line plot.

## Model 2 (M2)

Since a simple model like M1 did not produce a high  $R^2$  value, M2 uses an automated stepwise backward elimination feature selection strategy. All the variables are fed into the model and fitted. The independent variable with highest p-value is removed if the p-value is greater than 0.05. A p-value greater than 0.05 indicates that variable's effect is not statistically significant. This is repeated until all the p-values of the predictor variables are less than 0.05, meaning they are significant.



```
In [28]: #Backward Elimination function
def backward_elimination(df, y):
    """
    Backward Elimination
    Feed all the possible features to the model at first. We check
    the performance of the model and then iteratively remove the worst
    performing features one by one till the overall performance of the
    model comes in acceptable range. The performance metric used here to
    evaluate feature performance is p-value. If the pvalue is above 0.05
    then we remove the feature, else we keep it.

    Input:
        df = Pandas dataframe of your data
        y = dependent variable
    Output:
        list of independent variables in the model

    Citation:
        Abhini Shetye
        https://towardsdatascience.com/feature-selection-with-pandas-e3690ad8504b
    """
    X = df.copy()
    X.drop(y.columns, axis=1, inplace=True)
    cols = list(X.columns) # get all of the column names
    pmax = 1
    while (len(cols)>0): # while there are entries in the cols list
        p= [] # initialize p-value list
        X_1 = X[cols] # create new dataframe
        X_1 = sm.add_constant(X_1) # add constant for y-intercept
        model = sm.OLS(y,X_1).fit() # OLS regression model on the data
        p = pd.Series(model.pvalues.values[1:],index = cols) # save the p-values
        pmax = max(p) # assign maximum p-valuse
        feature_with_p_max = p.idxmax() # get that p-value's index
        if(pmax > 0.05): # check if the max p-value is greater than 5
            cols.remove(feature_with_p_max) # if it is then remove it from the cols list
        else:
            break # otherwise all p-values are less than 0.05
    return cols # return the features
```

## Model 3 (M3)

Interaction effects occur when the effect of one predictor variable depends on the value of another variable. For example, condition of a home may be dependent on the age of the home. There may be a dependency between the view and the house on waterfront property. M3 builds on M1 by adding interaction effects to the main effects. It also removes `sqft_above` as a predictor variable due to high multicollinearity between `sqft_above` and `sqft_living`.

The graphs below are interaction plots. This plot displays the fitted values of the dependent variable ( `price` ) on the y-axis and one of the predictor variables on the x-axis. The lines between the points represents the other predictor variable. If the lines remain parallel to each other then there is not an interaction between these variables. If the lines cross that indicates there could be an interaction.

```
In [29]: def interaction_analysis(data, var1, var2):
```

```

'''
Produces an interaction plot with programically determined
title.
Input:
    data: Pandas dataframe
    var1: column name of first variable
    var2: column name of second variable
Output:
    interaction plot with title of var1 and var2
'''

# Import Library
from statsmodels.graphics.factorplots import interaction_plot

# Make interaction plot
fig = interaction_plot(data[var1], df_clean[var2], data['price'])
plt.title(f'Interaction plot\n {var1} and {var2}') # set title

```

```

In [30]: import pandas as pd
from statsmodels.graphics.factorplots import interaction_plot

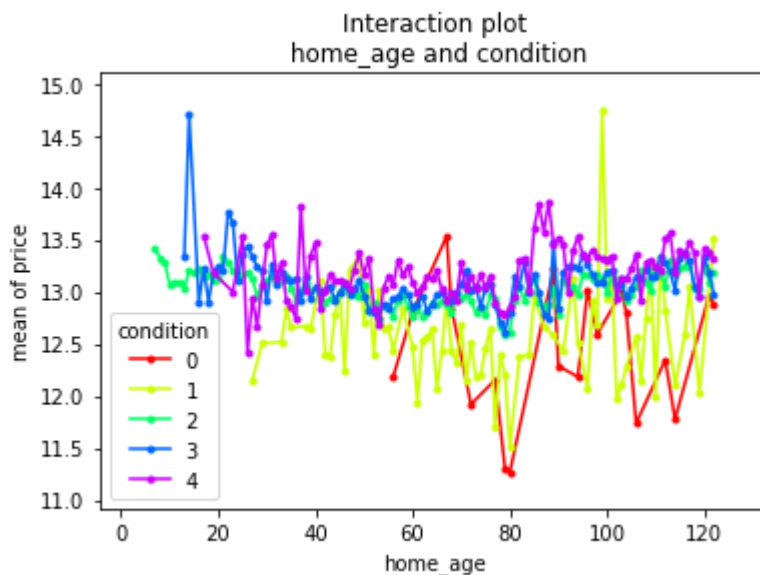
# Interaction of home age and condition
interaction_analysis(df_clean, 'home_age', 'condition')

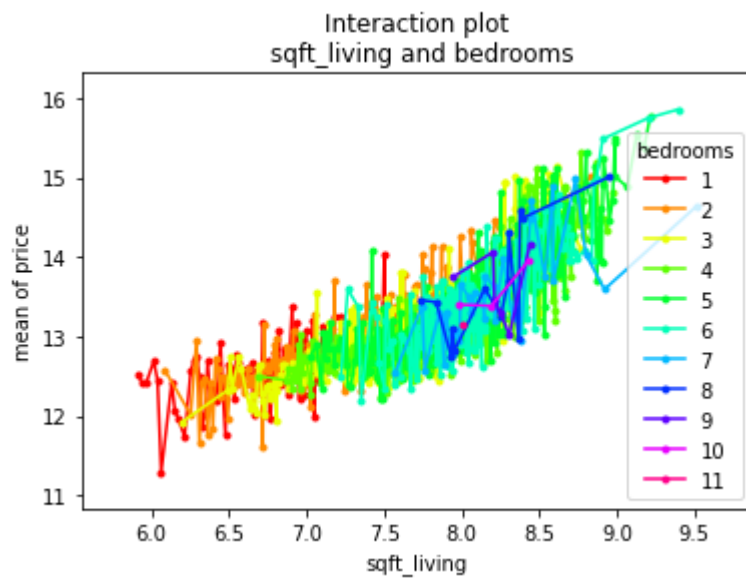
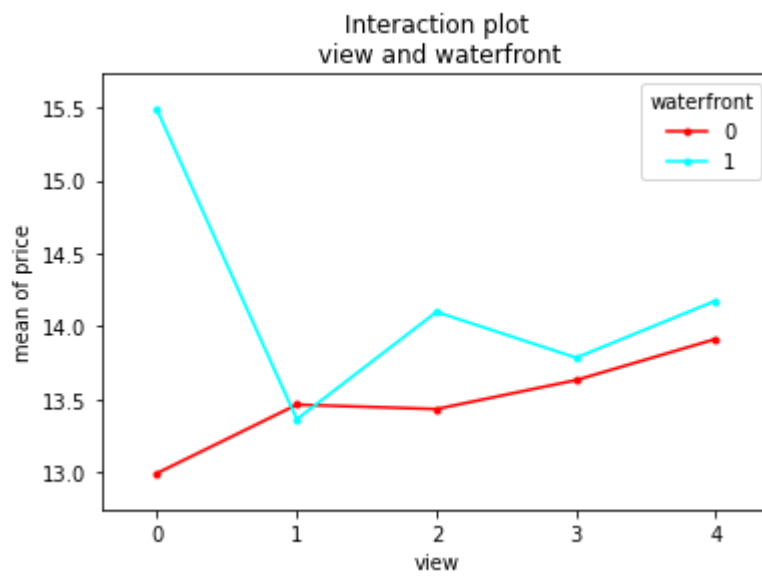
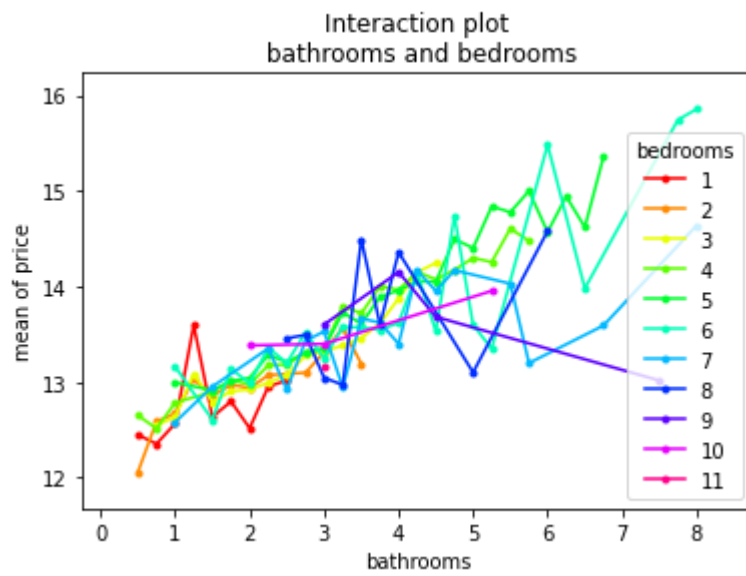
# Interaction of bathrooms and bedrooms
interaction_analysis(df_clean, 'bathrooms', 'bedrooms')

# interaction of view and waterfront
interaction_analysis(df_clean, 'view', 'waterfront')

# Interaction of sqft_living and bedrooms
interaction_analysis(df_clean, 'sqft_living', 'bedrooms')

```





## Interaction Effects Interpretation

On an interaction plot, parallel lines indicate that there is no interaction effect while different slopes and lines that cross suggest that an interaction may be present. 'home\_age' and 'condition', 'bathrooms' and 'bedrooms', and 'sqft\_living' and 'bedrooms' each show interaction effects. This means a third variable influences the relationship between a dependent and independent variable. The relationship changes depending on the value of the third variable.

'view' and 'waterfront' shows a slight interactive effect but only for view of 1 with no waterfront property. This may be because the view variable is measuring the view of the mountains in Washington and not the view of a waterfront property.

## Modeling and Regression Results

### Linear Regression Helper Function

```
In [31]: def lin_reg_model(data, features, model_name, formula):  
    ...  
    Runs OLS linear regression  
    Input:  
        - data: clean data  
        - features: independent variables that will be included in model  
        - formula: regression formula in R-style  
        - model_name: Name you will call the model (ex. Model 1, Model 2)  
    Output:  
        - OLS summary  
        - Residual QQ-plot  
        - OLS model object  
        - Prediction interval  
        - R-squared  
        - Root Mean Squared Error  
    ...  
    target = 'price'  
    y = data[target] # outcome data  
    X = data[features]  
  
    # Linear Regression using statsmodel Library  
    data = sm.add_constant(data)  
    model = sm.OLS.from_formula(formula=formula, data=data).fit()  
  
    # Predict values from the model  
    y_predict = model.predict(X)  
  
    # Create K-Fold cross-validation object  
    kf = KFold(n_splits=5, shuffle=True) #K-Fold of 5, shuffle data, 20% test data  
  
    # Regression model using sklearn  
    lm = LinearRegression()  
  
    # Cross-validated R-squared calculation  
    r2_scores = cross_val_score(lm, X, y, cv=kf, scoring = 'r2')  
    r2 = np.mean(np.absolute(r2_scores)) # calculate the mean r-squared  
  
    # Calculate prediction interval  
    sum_errs = np.sum((y - y_predict) ** 2) # Sum of errors
```

```

stdev = np.sqrt(1/(len(y)-2) * sum_errs) # Standard deviation
interval = 1.96 * stdev # Prediction interval

# Cross-validated Root Mean Squared Error
scores = cross_val_score(lm, X, y, cv=kf, scoring = 'neg_mean_squared_error')
RMSE = np.sqrt(np.mean(np.absolute(scores)))

# Plotting
fig, ax = plt.subplots(1, 2, figsize=(15,4))

# Residual plot
sns.regplot(x=model.fittedvalues, y=model.resid, ax=ax[0], line_kws={'color':'r'})
ax[0].title.set_text('Residual plot of fitted values')
ax[0].set(ylabel='residuals', xlabel='fitted values')
ax[1].title.set_text('Residual QQ-plot')

# Plot residual qq-plot
sm.graphics.qqplot(model.resid, dist=stats.norm, line='45', fit=True, ax=ax[1])
plt.show() # see https://github.com/statsmodels/statsmodels/issues/5493 for bug
#fig.suptitle(f'{model_name} Residual QQ plot')

print(model.summary())
print('\n')
print(f'R-squared: {r2:.2f}')
print(f'Prediction Interval: {interval:.2f}')
print('Root Mean Squared Error:', RMSE)

return model, r2, interval, RMSE

```

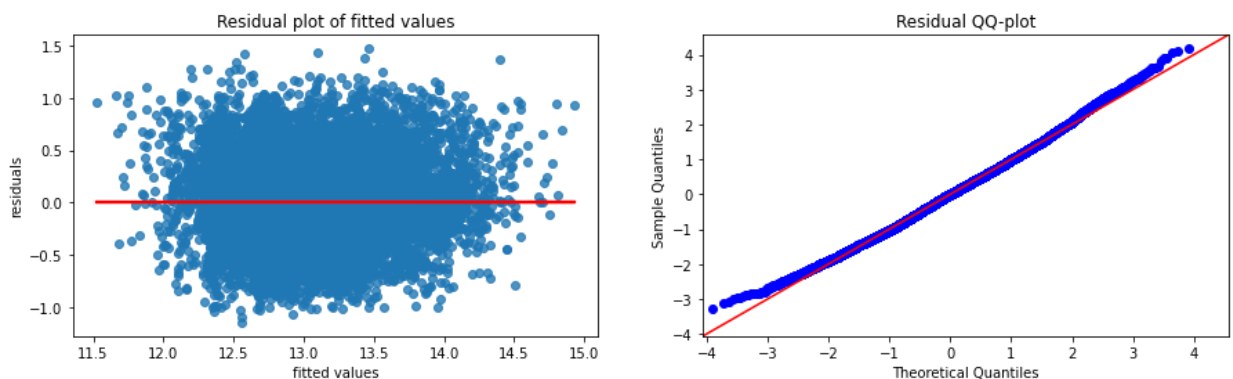
## M1 Results

```

In [32]: # Model 1
model_1_features = corr_with_price['Features'].values # Highest correlated features
formula_1 = 'price ~' + '+' .join(model_1_features)

# get regression model results, prediction interval, and RMSE score
model_1_reg, model_1_r2, model_1_pi, m1_RMSE = lin_reg_model(df_clean, model_1_features)

```



```

                                OLS Regression Results
=====
Dep. Variable:                  price    R-squared:                  0.555
Model:                          OLS      Adj. R-squared:             0.555
Method:                        Least Squares  F-statistic:               8969.
Date:                          Wed, 03 Aug 2022  Prob (F-statistic):      0.00
Time:                          07:39:24    Log-Likelihood:            -8054.1
No. Observations:              21597      AIC:                      1.612e+04
Df Residuals:                  21593      BIC:                      1.615e+04
Df Model:                      3
Covariance Type:               nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
Intercept          8.6531         0.052    167.137      0.000         8.552         8.755
sqft_living         0.5833         0.012     49.552      0.000         0.560         0.606
grade              0.2215         0.003     69.431      0.000         0.215         0.228
sqft_above        -0.2306         0.012    -19.733      0.000        -0.254        -0.208
=====
Omnibus:                 103.808    Durbin-Watson:              1.974
Prob(Omnibus):            0.000    Jarque-Bera (JB):           105.197
Skew:                     0.170    Prob(JB):                   1.43e-23
Kurtosis:                 3.025    Cond. No.                   287.
=====

```

Notes:

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

R-squared: 0.55

Prediction Interval: 0.69

Root Mean Squared Error: 0.35141130451037417

## M1 Interpretation

The p-values indicate that each of the variables chosen has a statistical significant relationship with the dependent variable, but the  $R^2$  value is low at 0.55. For a predictive model the  $R^2$  needs to be higher. The linear function of M1 is:

$$\hat{y}_{sales} = 0.58X_{sqft_{living}} + 0.22X_{grade} - 0.23X_{sqft_{above}} + 8.6531$$

The coefficient for `sqft_living` is 0.58. This means for every 1% increase in square feet of living space in a house, there is a 0.58% increase in sale price. For every 1% increase in the square feet in the above ground area of a house there is a 0.22% reduction in sale price.

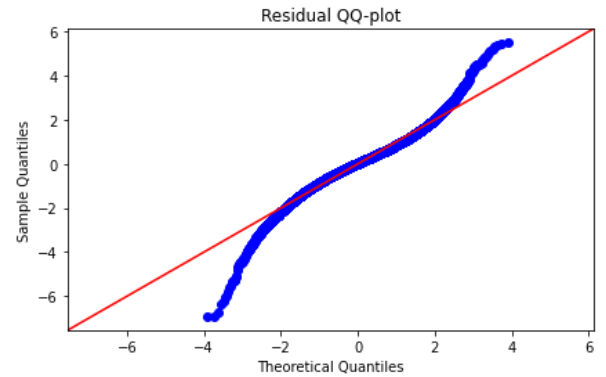
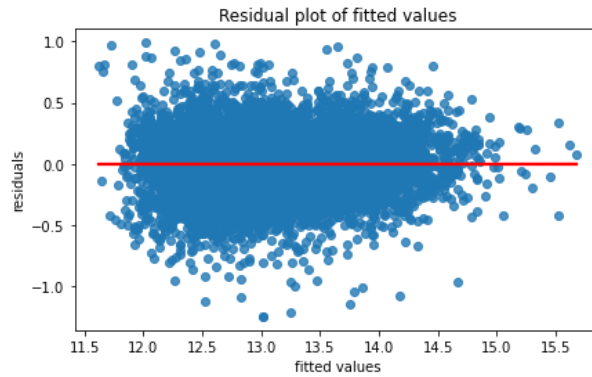
Interestingly, the area of the space above the home is penalized. This may be due to multicollinearity between the `sqft_living` and `sqft_above`. For every one-unit increase in the grade of the home, there is a 24.6% increase in sales price. Calculated by,  $(e^{0.22} - 1) \times 100$  (3).

The residual plot has a random pattern so there is homoskedasticity and the QQ-plot of the residuals indicate that they are normally distributed, meeting the assumptions of OLS.

## Model 2 Results

```
In [33]: model_2_features = backward_elimination(df_clean, df_clean[['price']]) # feature
formula_2 = 'price ~' + '+'.join(model_2_features)

# get regression model results, prediction interval, and RMSE score
model_2_reg, model_2_r2, model_2_pi, m2_RMSE = lin_reg_model(df_clean, model_2_features)
```



# OLS Regression Results

```

=====
Dep. Variable:          price      R-squared:          0.883
Model:                  OLS        Adj. R-squared:       0.883
Method:                 Least Squares  F-statistic:       2037.
Date:                   Wed, 03 Aug 2022  Prob (F-statistic): 0.00
Time:                   07:39:27      Log-Likelihood:    6411.2
No. Observations:      21597        AIC:               -1.266e+04
Df Residuals:          21516        BIC:               -1.201e+04
Df Model:               80
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	6.8154	0.047	145.176	0.000	6.723	6.907
bedrooms	-0.0155	0.002	-8.289	0.000	-0.019	-0.012
bathrooms	0.0400	0.003	13.679	0.000	0.034	0.046
sqft_living	0.2318	0.012	18.771	0.000	0.208	0.256
sqft_lot	0.0709	0.004	19.529	0.000	0.064	0.078
floors	-0.0223	0.004	-5.952	0.000	-0.030	-0.015
waterfront	0.4828	0.016	29.325	0.000	0.451	0.515
view	0.0617	0.002	32.017	0.000	0.058	0.065
condition	0.0527	0.002	24.347	0.000	0.048	0.057
grade	0.0937	0.002	47.211	0.000	0.090	0.098
sqft_above	0.2001	0.012	16.450	0.000	0.176	0.224
basement	0.0243	0.005	4.747	0.000	0.014	0.034
sqft_living15	0.1551	0.007	23.365	0.000	0.142	0.168
sqft_lot15	-0.0190	0.004	-4.763	0.000	-0.027	-0.011
home_age	0.0014	0.000	12.040	0.000	0.001	0.002
yr_since_reno	-0.0012	0.000	-9.933	0.000	-0.001	-0.001
zipcode_98004	1.1205	0.012	97.301	0.000	1.098	1.143
zipcode_98005	0.7150	0.015	47.879	0.000	0.686	0.744
zipcode_98006	0.6357	0.010	65.038	0.000	0.617	0.655
zipcode_98007	0.6439	0.016	40.145	0.000	0.612	0.675
zipcode_98008	0.6469	0.012	54.343	0.000	0.624	0.670
zipcode_98010	0.2342	0.019	12.441	0.000	0.197	0.271
zipcode_98011	0.4381	0.014	31.564	0.000	0.411	0.465
zipcode_98014	0.2983	0.017	17.335	0.000	0.265	0.332
zipcode_98019	0.3114	0.014	22.118	0.000	0.284	0.339
zipcode_98022	0.0344	0.013	2.652	0.008	0.009	0.060
zipcode_98023	-0.0326	0.009	-3.433	0.001	-0.051	-0.014
zipcode_98024	0.4187	0.021	19.944	0.000	0.378	0.460
zipcode_98027	0.5055	0.010	49.155	0.000	0.485	0.526
zipcode_98028	0.4088	0.012	34.522	0.000	0.386	0.432
zipcode_98029	0.5999	0.011	52.547	0.000	0.578	0.622
zipcode_98030	0.0435	0.012	3.530	0.000	0.019	0.068
zipcode_98031	0.0644	0.012	5.364	0.000	0.041	0.088
zipcode_98033	0.7842	0.010	77.897	0.000	0.764	0.804
zipcode_98034	0.5405	0.009	58.616	0.000	0.522	0.559
zipcode_98038	0.1629	0.009	18.051	0.000	0.145	0.181
zipcode_98039	1.2983	0.026	49.541	0.000	1.247	1.350
zipcode_98040	0.8723	0.012	71.742	0.000	0.848	0.896
zipcode_98042	0.0567	0.009	6.165	0.000	0.039	0.075
zipcode_98045	0.3113	0.013	23.521	0.000	0.285	0.337
zipcode_98052	0.6273	0.009	68.744	0.000	0.609	0.645
zipcode_98053	0.5760	0.010	55.122	0.000	0.556	0.596
zipcode_98055	0.1488	0.012	12.268	0.000	0.125	0.173
zipcode_98056	0.3251	0.010	31.671	0.000	0.305	0.345
zipcode_98058	0.1562	0.010	15.922	0.000	0.137	0.175
zipcode_98059	0.3348	0.010	34.237	0.000	0.316	0.354



zipcode_98065	0.4045	0.012	34.888	0.000	0.382	0.427
zipcode_98070	0.2938	0.018	16.358	0.000	0.259	0.329
zipcode_98072	0.4629	0.012	38.283	0.000	0.439	0.487
zipcode_98074	0.5464	0.010	54.104	0.000	0.527	0.566
zipcode_98075	0.5528	0.011	50.198	0.000	0.531	0.574
zipcode_98077	0.4209	0.014	29.888	0.000	0.393	0.449
zipcode_98102	1.0026	0.019	52.582	0.000	0.965	1.040
zipcode_98103	0.8630	0.010	88.559	0.000	0.844	0.882
zipcode_98105	0.9715	0.014	71.553	0.000	0.945	0.998
zipcode_98106	0.3922	0.011	34.637	0.000	0.370	0.414
zipcode_98107	0.8880	0.013	69.651	0.000	0.863	0.913
zipcode_98108	0.3936	0.014	27.411	0.000	0.365	0.422
zipcode_98109	1.0213	0.019	54.997	0.000	0.985	1.058
zipcode_98112	1.0725	0.013	82.767	0.000	1.047	1.098
zipcode_98115	0.8456	0.010	88.963	0.000	0.827	0.864
zipcode_98116	0.7906	0.012	68.050	0.000	0.768	0.813
zipcode_98117	0.8487	0.010	87.017	0.000	0.830	0.868
zipcode_98118	0.4966	0.010	50.590	0.000	0.477	0.516
zipcode_98119	1.0080	0.015	67.452	0.000	0.979	1.037
zipcode_98122	0.8420	0.012	67.509	0.000	0.818	0.866
zipcode_98125	0.5843	0.010	56.317	0.000	0.564	0.605
zipcode_98126	0.5914	0.011	52.795	0.000	0.569	0.613
zipcode_98133	0.4797	0.010	49.550	0.000	0.461	0.499
zipcode_98136	0.7131	0.013	56.801	0.000	0.689	0.738
zipcode_98144	0.7113	0.012	61.725	0.000	0.689	0.734
zipcode_98146	0.3019	0.012	25.439	0.000	0.279	0.325
zipcode_98148	0.1632	0.024	6.682	0.000	0.115	0.211
zipcode_98155	0.4378	0.010	44.014	0.000	0.418	0.457
zipcode_98166	0.3077	0.012	24.700	0.000	0.283	0.332
zipcode_98168	0.0943	0.012	7.725	0.000	0.070	0.118
zipcode_98177	0.5915	0.013	47.246	0.000	0.567	0.616
zipcode_98178	0.1692	0.012	13.683	0.000	0.145	0.193
zipcode_98188	0.1072	0.016	6.588	0.000	0.075	0.139
zipcode_98198	0.0671	0.012	5.631	0.000	0.044	0.091
zipcode_98199	0.8818	0.012	74.678	0.000	0.859	0.905
=====						
Omnibus:	1555.735	Durbin-Watson:	2.003			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	7091.189			
Skew:	-0.199	Prob(JB):	0.00			
Kurtosis:	5.779	Cond. No.	3.32e+03			
=====						

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 3.32e+03. This might indicate that there are strong multicollinearity or other numerical problems.

R-squared: 0.88

Prediction Interval: 0.35

Root Mean Squared Error: 0.18068327675820967

## M2 Interpretation

$R^2$  and adjusted  $R^2$  is 0.89 for M2. This is tremendous improvement over M1. There are many more independent variables used in M2 as compared to M1, though. This model used all the independent variables expect for some of the Zipcodes after recoding this variable to dummy

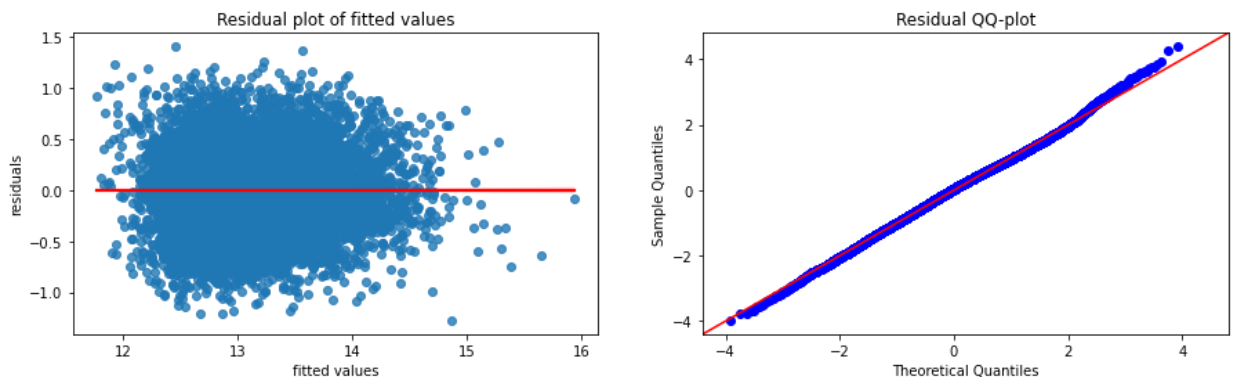
variables. Though there are many variables, the p-values indicate that each of the variables chosen has a statistically significant relationship with the dependent variable. This  $R^2$  score is good for a predictive model.

The coefficient for `condition` for M2 is 0.0527. This means that for every increase in one-unit of the condition value there is about a 5% increase in the home sale price. Some of the highest coefficients are in the Zipcode variables. For example, with all other independent variables held constant a home in 98039 would sell for 266% more than Zipcode 98003.

The residual plot has a random pattern so there is homoskedasticity. The QQ-plot of the residuals indicates that they are not normally distributed. This could cause problems with the predictive model for predictions of features that are at the extreme ends of the data range compared to the training data, but assumption 6 is only optional and necessary for explorative models and not necessary for predictive models.

## M3 Results

```
In [34]: model_1_features_del_sqftabove = np.delete(model_1_features, 2)
model_3_features = np.append(model_1_features_del_sqftabove, ['bedrooms', 'home_age',
formula_3 = 'price ~' + '+'.join(model_3_features) + '+ home_age*condition + sqft_livi
model_3_reg, model_3_r2, model_3_pi, m3_RMSE = lin_reg_model(df_clean, model_3_feature
```



```

                                OLS Regression Results
=====
Dep. Variable:                  price    R-squared:                  0.630
Model:                          OLS      Adj. R-squared:             0.630
Method:                        Least Squares  F-statistic:                5245.
Date:                          Wed, 03 Aug 2022  Prob (F-statistic):      0.00
Time:                          07:39:29    Log-Likelihood:             -6064.0
No. Observations:                21597    AIC:                       1.214e+04
Df Residuals:                    21589    BIC:                       1.221e+04
Df Model:                        7
Covariance Type:                nonrobust
=====
===
                                coef      std err          t      P>|t|      [0.025      0.9
75]
-----
---
Intercept                      9.3395      0.130      72.027      0.000      9.085      9.
594
sqft_living                    0.2455      0.018     13.955      0.000      0.211      0.
280
grade                          0.2441      0.003     80.865      0.000      0.238      0.
250
bedrooms                      -0.6645      0.038    -17.375      0.000     -0.739     -0.
590
home_age                       0.0015      0.000      4.897      0.000      0.001      0.
002
condition                     -0.0635      0.009     -6.724      0.000     -0.082     -0.
045
home_age:condition             0.0015      0.000     11.404      0.000      0.001      0.
002
sqft_living:bedrooms           0.0820      0.005     16.489      0.000      0.072      0.
092
=====
Omnibus:                      47.633    Durbin-Watson:              1.962
Prob(Omnibus):                 0.000    Jarque-Bera (JB):           55.957
Skew:                          -0.053    Prob(JB):                   7.07e-13
Kurtosis:                      3.225    Cond. No.                    1.06e+04
=====

```

Notes:

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

[2] The condition number is large, 1.06e+04. This might indicate that there are strong multicollinearity or other numerical problems.

R-squared: 0.62

Prediction Interval: 0.63

Root Mean Squared Error: 0.32358401681948173

## M3 Interpretation

When analyzing M3 the p-value of the interaction effect of **bedrooms** with **bathrooms** is greater than 0.05 which indicates it is not a significant effect. While there are interactions between these variables, that interaction does not have a significant effect in this model. The p-values indicate which variables has a statistical significant relationship with the dependent

variable. The variables `bedrooms` and `bathrooms` were removed and model 3 was run without them.

$R^2$  and adjusted  $R^2$  for M3 is 0.63. This is an improvement over M1 but is less than M2. The interaction effects between some variables does seem to help increase  $R^2$ .

The residual plot has a random pattern so there is homoskedasticity. The QQ-plot of the residuals indicate that they are normally distributed. These results show the model meets the assumptions of OLS.

RMSE is similar to M1 (0.352) and higher than M2 (0.180).

## Conclusions

### Model Analysis and Comparisons

I will use coefficient of determination ( $R^2$ ), prediction intervals, and root means squared error to compare the models and determine which model meets the needs of our client. This includes the most accurate predictive power with a tight range in possibilities.

```
In [35]: # Table of model's R-squared, PI, and Cross-validated RMSE
r2 = [model_1_reg.rsquared, model_2_reg.rsquared, model_3_reg.rsquared]
pi = [model_1_pi, model_2_pi, model_3_pi]
rmse = [m1_RMSE, m2_RMSE, m3_RMSE]
results = pd.DataFrame({'R_squared': r2,
                        'PI': pi,
                        'RMSE': rmse},
                        index = ['M1', 'M2', 'M3'])
print('Table 4: Regression Results Table')
results
```

Table 4: Regression Results Table

```
Out[35]:
```

	<b>R_squared</b>	<b>PI</b>	<b>RMSE</b>
<b>M1</b>	0.554774	0.688652	0.351411
<b>M2</b>	0.883369	0.352465	0.180683
<b>M3</b>	0.629711	0.628029	0.323584

### Coefficient of Determination ( $R^2$ )

$R^2$  is a statistical estimate of how close the observed data is to the regression line of each model. It is the proportion of variation in the dependent variable that is predictive from the independent variable.  $R^2$  is measured using 5-fold cross-validation.

$$R^2 = 1 - \frac{\text{Residual Sum of Squares (RSS)}}{\text{Total Sum of Squares (TSS)}}$$

$$= 1 - \frac{\sum (y_i - \hat{y})^2}{\sum (y_i - \bar{y})^2}$$

As Table 4 above shows, the model with the highest  $R^2$  is M2 at 0.88. This is a great score for a predictive model, the higher the better. M1 has the lowest  $R^2$  score at 0.55, M2 is highest at 0.88, and M3 is 0.63.

## Prediction Interval

A prediction interval (PI) is the range where a single new observation is likely to fall given specific values of the independent variables. The prediction interval can be used to assess if the predictions are sufficiently in a narrow range to satisfy the client's requirement. Prediction intervals can be compared across models. Smaller intervals indicate tighter predictive range. Large prediction intervals tell us the model could have a wide range in its predictions and would not meet the client's needs.

The prediction interval is calculated by,

$$PI = 1.96 \times s,$$

where  $s$  is the sample standard deviation calculated by

$$s = \sqrt{\frac{1}{N-2} \times RSS}$$

M2 also has the lowest predictive intervals. A prediction interval is the range where a single new observation is likely (95%) to fall given specific values of the independent variables. The smaller the predictive interval the more confidence the true sale price is in that region. M1 and M2 had reasonably similar prediction intervals and twice the value as M2.

## Root Mean Squared Error

RMSE is a measure of the mean error rate of a regression model that penalizes larger errors. It is the square root of the average squared difference between the predicted dependent value and the actual values in the dataset. The smaller the RMSE value, the closer the fitted line from the linear equation is to the actual data. Like Mean Squared Error (MSE), this statistic squares the residual error before it is averaged, which gives a high weight to large errors, but because the square root is taken, the statistic is in the same units as the dependent variable, sale price (\$USD). The lower the score of RMSE the closer the model fits the data.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2},$$

where  $(\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n)$  are the predicted values,  
 $(y_1, y_2, \dots, y_n)$  are the observed values  
 and  $(n)$  is the number of observations

RMSE is estimated using K-Fold cross validation. M2 is almost half the RMSE score of M1 and M2 indicating it produces less error between the actual and predicted values.

## Prediction Application

The prediction of Model 2 seems the most reliable of the three models. Below is the `price_predictor` function that input as one of the three models, the new home features, and the prediction interval.

```
In [36]: def price_predictor(model_no, new_data, pi):
    ...
    This function takes in a model and Pandas series object and returns
    an estimated price range for the house to be listed.

    Model 1: price ~ ln(sqft_living) + ln(sqft_above) + grade

    Model 2: price ~ bedrooms+bathrooms+sqft_living+sqft_lot+floors+waterfront+
              view+condition+grade+sqft_above+basement+sqft_living15+sqft_lot15
              home_age+yr_since_reno+zipcode

    Model 3: price ~ sqft_living+grade+sqft_above+ home_age*condition + sqft_living*be

    Input:
        model_no: Statsmodel linear regression model results
        new_data: Pandas Series with variables needed for the regression model
        pi: prediction interval for that model

    Output:
        Predicted sale price
        Predicted sale price range
    ...
    price_ln = model_no.predict(new_data).values[0]
    price = round(np.exp(price_ln))
    price_low = round(np.exp(price_ln - pi))
    price_up = round(np.exp(price_ln + pi))

    return f'Predicted price: {price}, range: {price_low} - {price_up}'
```

## Demonstration

```
In [37]: #data = df_clean.iloc[8677]
```

```
In [38]: data = df_clean.sample().squeeze() # Randomly sample data for prediction
```

```
In [39]: # Model 1 prediction
data_new = data.drop('price') # Remove actual price
print(price_predictor(model_1_reg, data_new, model_1_pi)) # Run prediction function
sale_price = round(np.exp(data['price'])) # assign actual sale price
print(f'Actual sale price: {sale_price}') # print out actual sale price
```

Predicted price: 338530, range: 170028 - 674024  
Actual sale price: 369000

```
In [40]: # Model 2 Prediction function
print(price_predictor(model_2_reg, data_new, model_2_pi))
```

```
print(f'Actual sale price: {sale_price}')
```

Predicted price: 328555, range: 230958 - 467392

Actual sale price: 369000

```
In [41]: # Model 3 prediction function
print(price_predictor(model_3_reg, data_new, model_3_pi))
print(f'Actual sale price: {sale_price}')
```

Predicted price: 302181, range: 161257 - 566262

Actual sale price: 369000

## Recommendations

### Summary

- Our client wants to be able to predict sales price.
- Ordinary least squares linear regression was used to create three models.
- The three models were compared using  $R^2$ , Prediction Intervals (PI), and Root Mean Squared Error (RMSE).
- Model 2 (M2) is the best model as it has the best predictive capabilities, R-squared 0.88, low RMSE and PI.
- M2 could be used to prototype a client dashboard for real estate agents to predict sales price for new data.
- More data and variables should be collected to improve the model's predictive power.
- Communicate with client about internal real estate data that can be used to further train the model.

### Actionable Recommendations

1. M2 could be used for a client dashboard prototype for Bon Jovi real estate agents to predict sales price.
2. M2 can be used to measure the cost-benefit analysis of making improvements to the home. For example, a one-unit increase in the condition of the home will increase the sale price by about 5%.
3. M2 can help Bon Jovi real estate agents locate customers and properties that have the highest sale price potential. For example, homes in Zipcode 98039 sold for over 200% more than homes in Zipcode 98003 so those customers in 98039 likely have a higher sales price.

### Next Steps

This model could be improved to make better predictions by adding more data additional features, such as crime rate in the geographic location of the home, the zoned public school ranking, and time the house was on the market until it was sold. The GPS coordinates of the sold house could be used to collect the first two of these variables. The Multiple Listing Service

may be a source for more recent data and on how long a house was on the market from day of listing to closing date.

Another source of data could be in the internal data of our brokerage client. They possibly have data of properties they have sold or bid on, this would include the data of the asking and bidding price of the property.

## References

1. Kaggle, [Kaggle, House Sales in King County, USA](#)
2. Albert, [Key Assumptions of OLS: Econometrics Review](#)
3. University of Virginia, [Interpreting Log Transformations in a Linear Model](#)