Final Project Submission

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- Student pace: Flex
- Scheduled project review date/time: August 8, 2022 13:30 - 14:15 (CDT)
- Instructor name: Morgan Jones
- 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. 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 Bon Jovi Real Estate Advisors
- Bon Jovi real estate agents that will use the dashboard

Background

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 catagorical 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 regresion to assess the relationship between features of homes and sale price. OLS fits a linear model on data by minimizing the sum of the squared difference between the observed dependent variable and the predicted response $(\hat{y})$

$$\text{To calculate } \hat{y},$$

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

where n is the number of predictors, β_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 catagorical data needs to be coded correctly. The assumptions of OLS linear regression are then checked and models are built. These models are compared using, coefficient of determination, prediction intervals, and Root Mean Squared Error to compare and determine wich 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

## 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 paramaters 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)
```

Table 1 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
`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

Variable	Data Type	Description
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

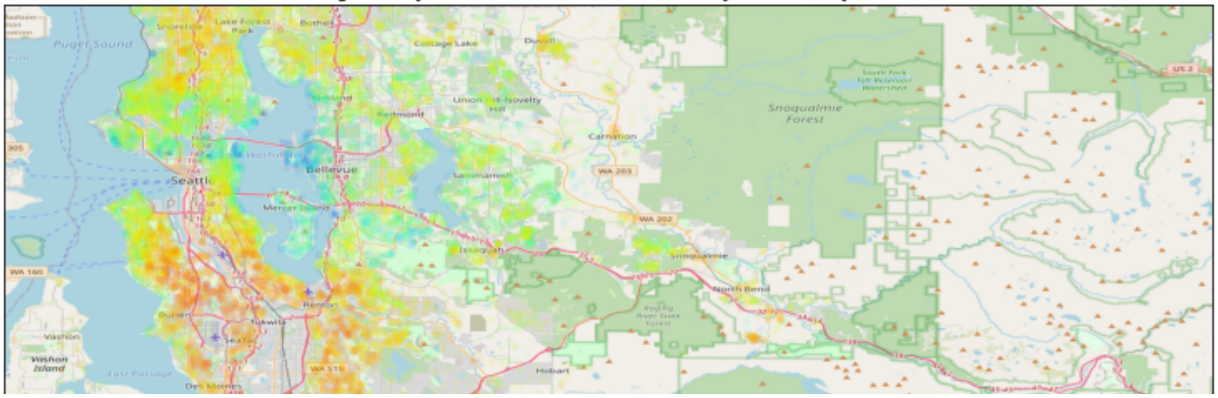
Location of King County, WA home sales

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-

# 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') # titl
# Remove x, y ticks and labels
ax.tick_params(axis='both', which='both',
               bottom=False, top=False, left=False, right=False,
               labelbottom=False, labeltop=False, labelleft=False, labelright

# 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 0x7f8b3c239f70>

King County, WA home sales between May 2014 - May 2015



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 examinter's subjective experience.
- As the map shows, home sales are a mix of urban and rural houses, but much more homes are clustered together. The models may not be able to accurately predict rural house prices because of the lack of data for rural homes.

Data Cleanup

Identify and remove duplicated records

In [5]:
```
# Any dulplicated 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	waterfron
2495	1000102	4/22/2015	300000.0	6	3.0	2400	9373	2.0	NC
2494	1000102	9/16/2014	280000.0	6	3.0	2400	9373	2.0	Nal
16800	7200179	10/16/2014	150000.0	2	1.0	840	12750	1.0	NC
16801	7200179	4/24/2015	175000.0	2	1.0	840	12750	1.0	NC

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 occuring 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
 350000.0    0.007964
450000.0    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
1660    0.005973
1010    0.005973
1800    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
7500    0.005510
4800    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
300.0     0.006575
900.0     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
2003.0    0.001746
2013.0    0.001746
2007.0    0.001690
2000.0    0.001633
2005.0    0.001633
1990.0    0.001239
2004.0    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
1800    0.007686
1720    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
4500    0.005140
3600    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
```

Table 2: 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 `int` 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`	oridinal	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 `yr_built` . Subtract current year from `yr_built` . Drop `yr_built`
`yr_since_reno`	discrete	Create variable from `yr_renovated` . Subtract current year from `yr_renovated` . `0` is the most common value with over 95% of values. If never renovated then subtract from `yr_built` . Drop `yr_renovated` .

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']) # subtract
    if row['yr_renovated'] > 0 # if the property has been renovated
    else row['home_age'], axis = 1) # else the property has not been renovate
df.drop('yr_renovated', axis=1, inplace=True)
```

```
/home/kevinspring/anaconda3/envs/learn-env/lib/python3.8/site-packages/pandas
/core/indexing.py:670: 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
  iloc._setitem_with_indexer(indexer, value)
```

Outliers

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

Out[12]:

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

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]:
```python
df[df['bedrooms'] > 30]
```

Out[13]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	gr
15856	640000.0	33	1.75	1620	6000	1.0	0	0	4	

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

Out[14]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	gr
15856	640000.0	3	1.75	1620	6000	1.0	0	0	4	

Exploratory Data Analysis

Cleaned Data Description

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

Out[15]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	co
count	21597	21597	21597	21597	21597	21597	21597	21597	

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	co
mean	540297	3.37181	2.11583	2080.32	15099.4	1.4941	0.0067602	0.233181	2
std	367368	0.904096	0.768984	918.106	41412.6	0.539683	0.0819439	0.764673	0.(
min	78000	1	0.5	370	520	1	0	0	
25%	322000	3	1.75	1430	5040	1	0	0	
50%	450000	3	2.25	1910	7618	1.5	0	0	
75%	645000	4	2.5	2550	10685	2	0	0	

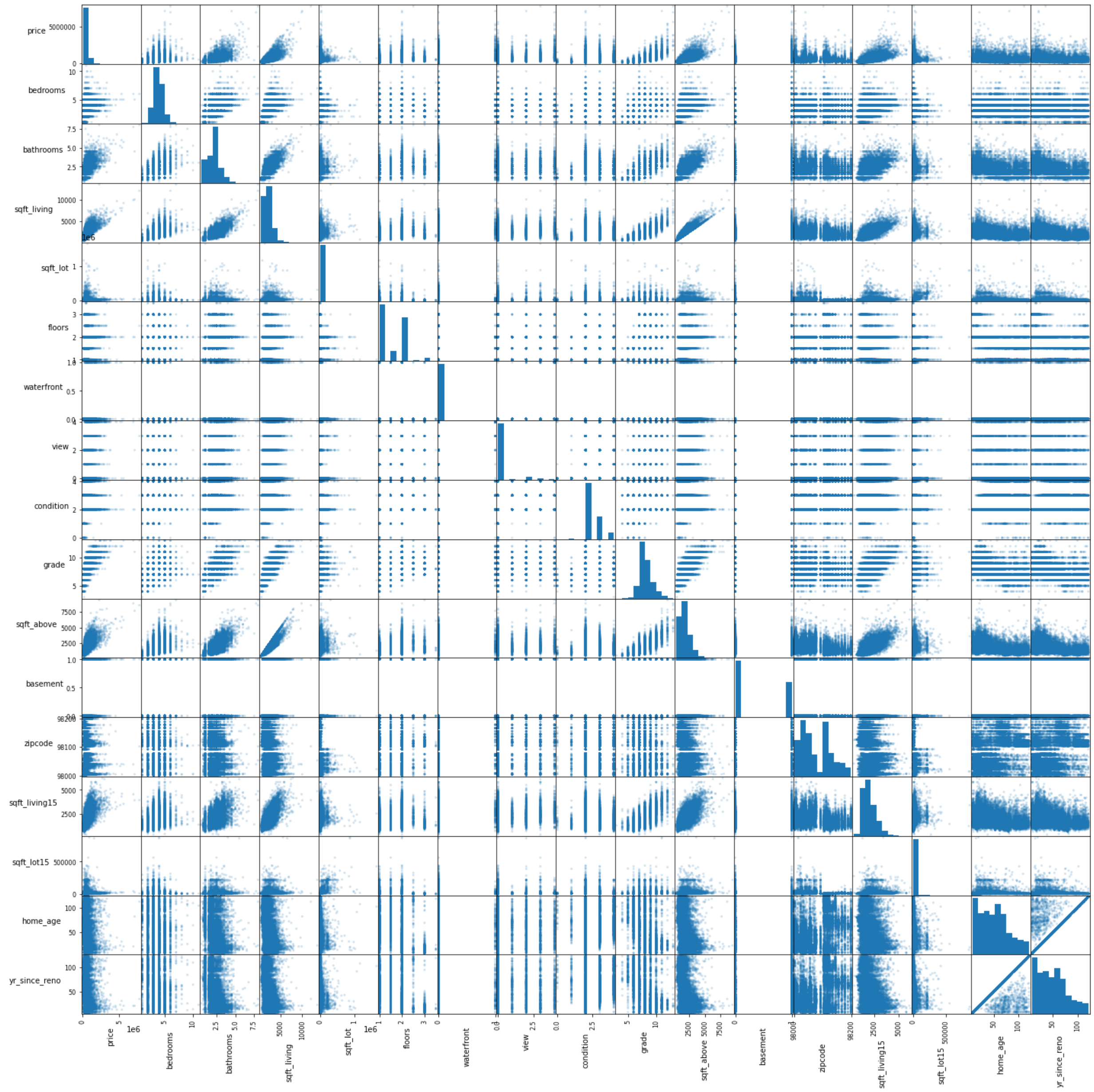
About the data

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

A scatter matrix will return both histograms and scatterplots lined up for each variable. The diaganol represents the histograms of that variable to visualize the distribution and the rest are scatterplots to visualize the relationships between variables.

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

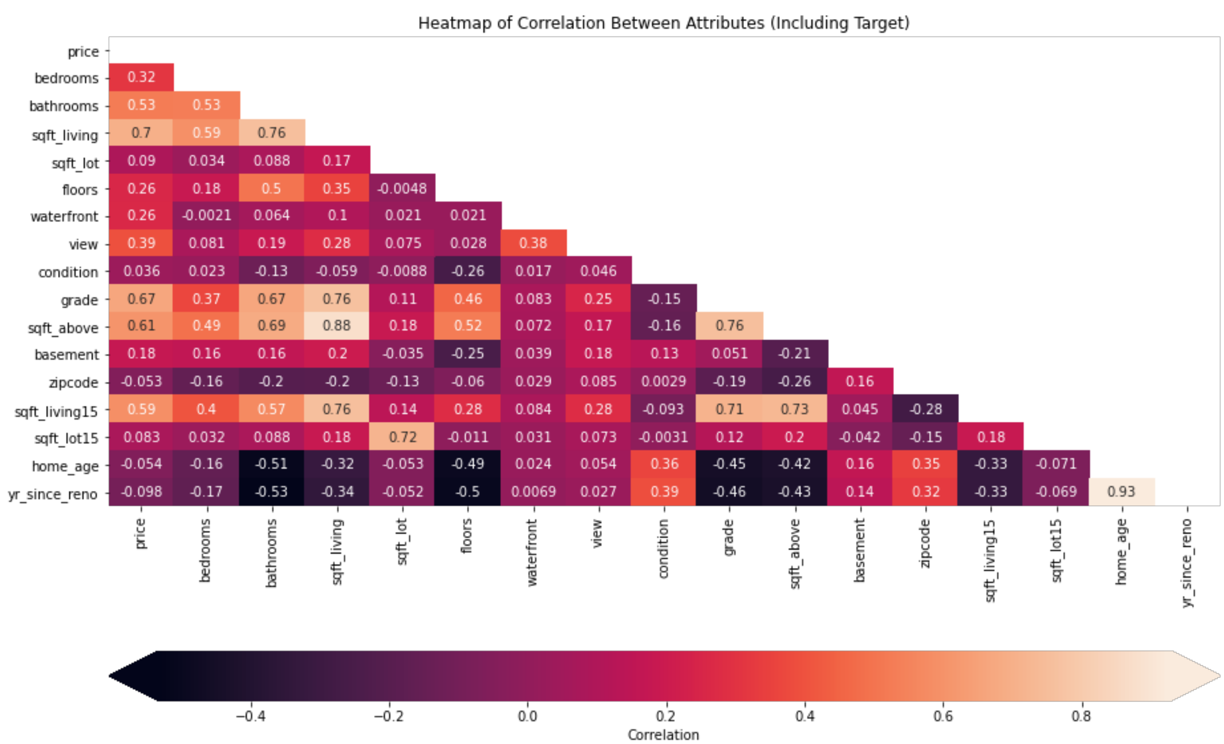
Scatterplot

Looking at the first row, the variables with the strongest positive coorelation 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 exists. This heatmap has a dark color for negatively correlated variables and a light color for positively correlated variables.

In [17]:
```python
# 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,
)

# 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 catagorical variables with regression analysis. The variable `zipcode` is a catagorical 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. This procedure will result in almost all independent variables, excluding some the dummy variables for zipcode, being chosen.
M3	M1 with interaction effects

Table 3: OLS 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. This allows statistical hypothesis testing to be done. As I am developing a prediciton 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 plots.

Specifing Model 1 (M1)

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

In [19]:
```
# Features correlated
# Source doe from Flatiron
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': feat

print('Table 4: Independent Variables Highly Correlated (>0.6) With Price')
display(corr_with_price)
```

```
Table 4: Independent Variables Highly Correlated (>0.6) With Price
```

	Correlations	Features
0	0.701917	sqft_living
1	0.667951	grade
2	0.605368	sqft_above

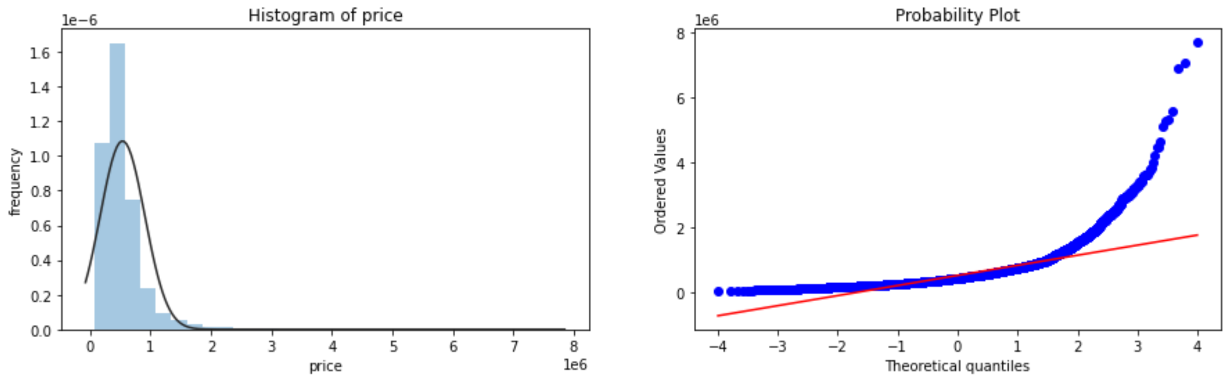
Distribution of dependent variable price

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-aa
'''
    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 the 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 porportionally with the variable.

Residual plot

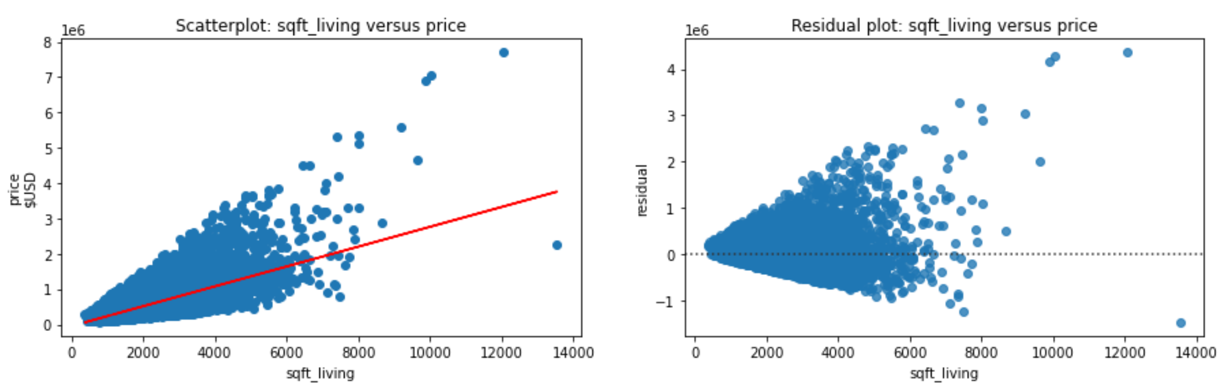
A residual plot is produced for the independent variables with the highest correlation to `price` . Residual plots show the residual error plotted against the actual sale price. This will allow me to assess heteroskedasticity as residual plots will have a random pattern around 0 with homoskedasticity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

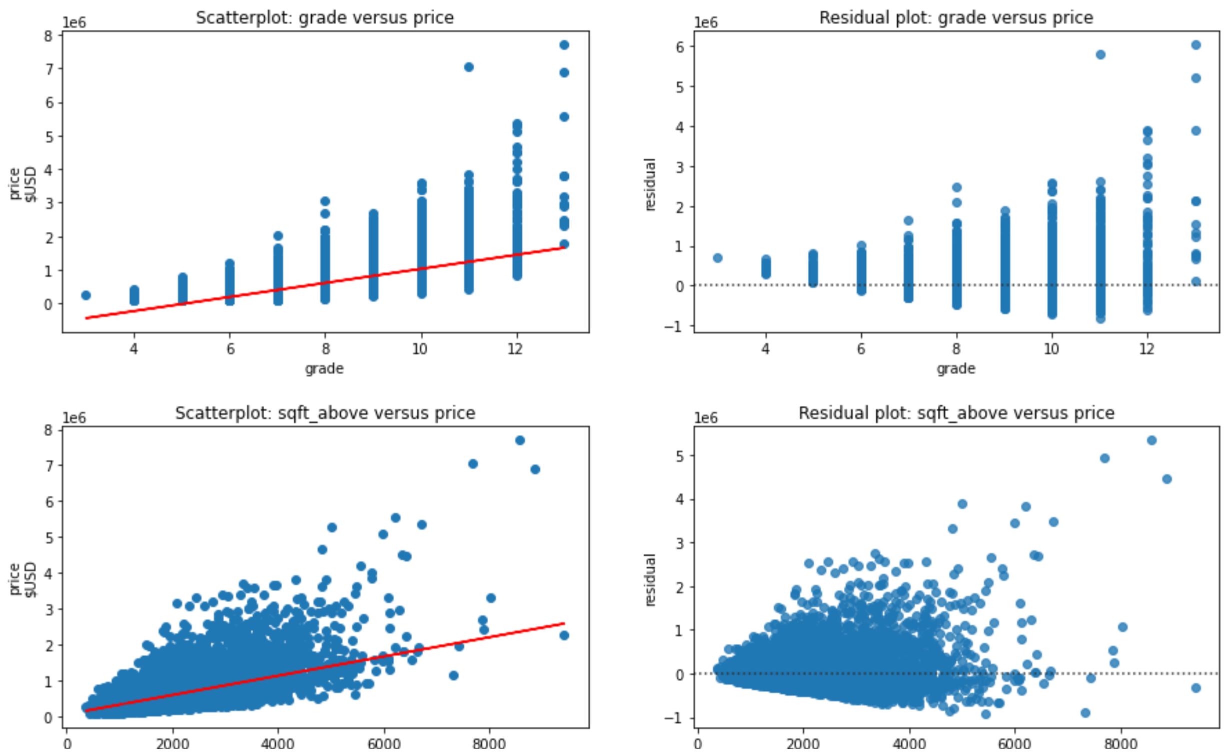
In [22]:

```
# 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]

    # set label for x-axis if ind var is logged
    if xlogged:
        label_x = f'log({X})'
    else: # not logged
        label_x = f'{X}'
    # set label for y-axis if dep var is logged
    if ylogged:
        label_y = f'log({Y})\n$USD'
    else: # not logged
        label_y = f'{Y}\n$USD'

    # make plots
    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
    # title of scatterplot
    ax1.title.set_text(f'Scatterplot: {X} versus {Y}')
    # title of residual plot
    ax2.title.set_text(f'Residual plot: {X} versus {Y}')
    ax2.set(ylabel='residual', xlabel=label_x) # residual plot y-axis label
```

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. This will make th emodel linear and remove unequal variance.

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

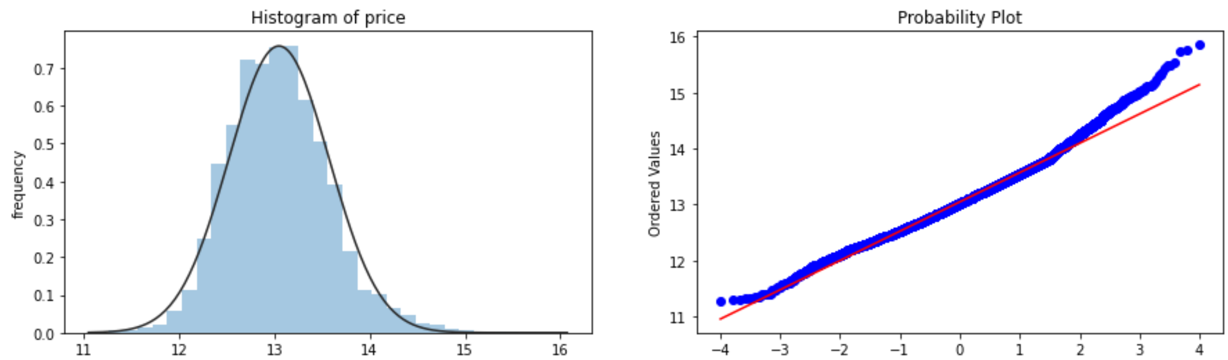
In [25]:
```
# Log transform the rest of the continuous right-skewed area variables
df_clean['sqft_living'] = np.log(df_clean['sqft_living'])
df_clean['sqft_above'] = np.log(df_clean['sqft_above'])
df_clean['sqft_lot15'] = np.log(df_clean['sqft_lot15'])
df_clean['sqft_lot'] = np.log(df_clean['sqft_lot'])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

Histogram of log transformed `price` variable

The distirubtion of the dependent variable, `price` , is normally distributed after being log transformed.

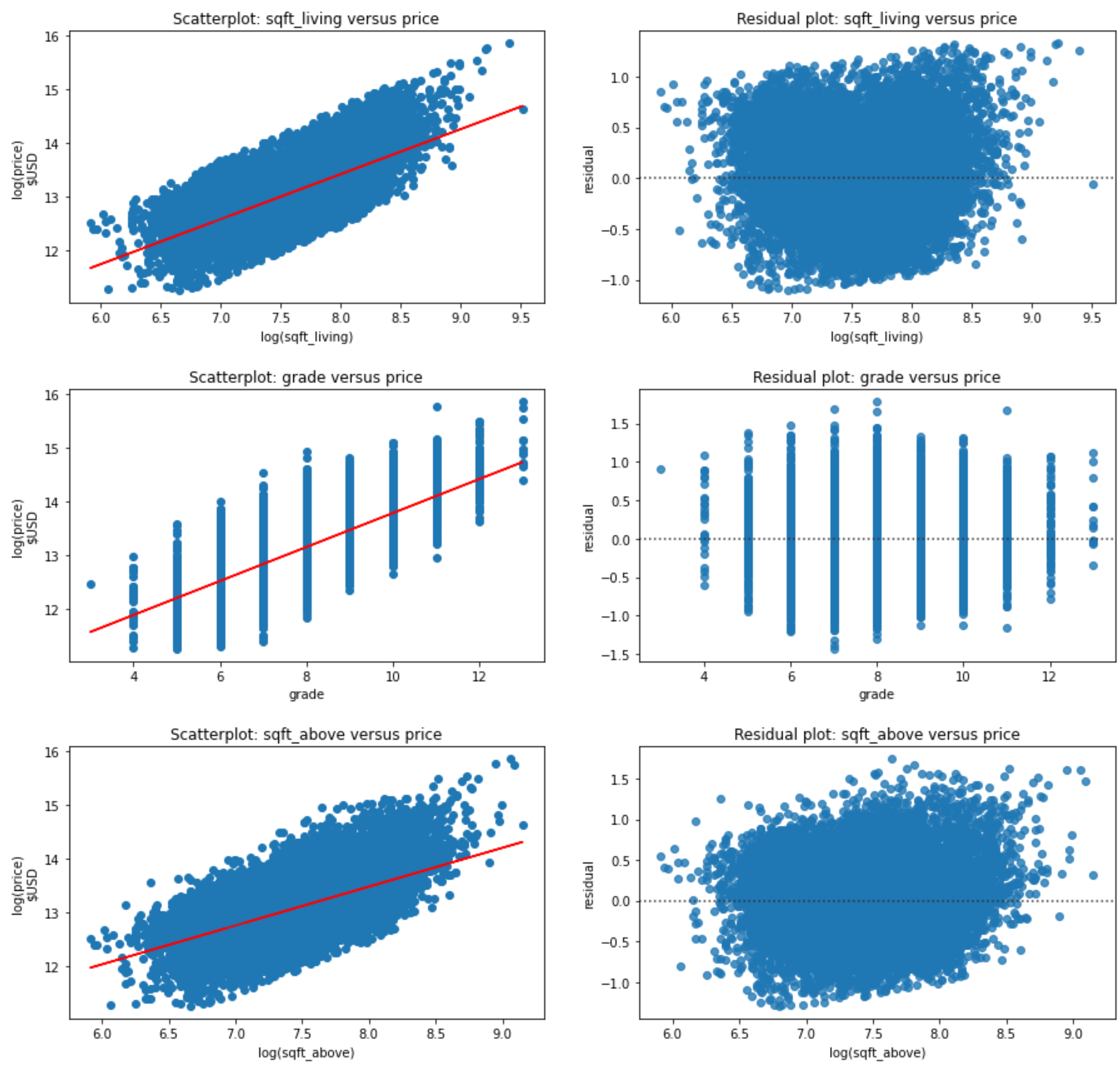
In [26]:
```
# Histogram of log transformed price independent variable
hist_plot(df_clean, 'price')
```

```
EDA of price variable
Skewness: 0.4310041773299232
Kurtosis: 0.691048515911131
```



Residual plots with log transformation

In [27]:
```python
# 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 elemination 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-e369
    '''
    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-val
        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 th
        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 whether the house is 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 correlation between `sqft_above` and `sqft_living` .

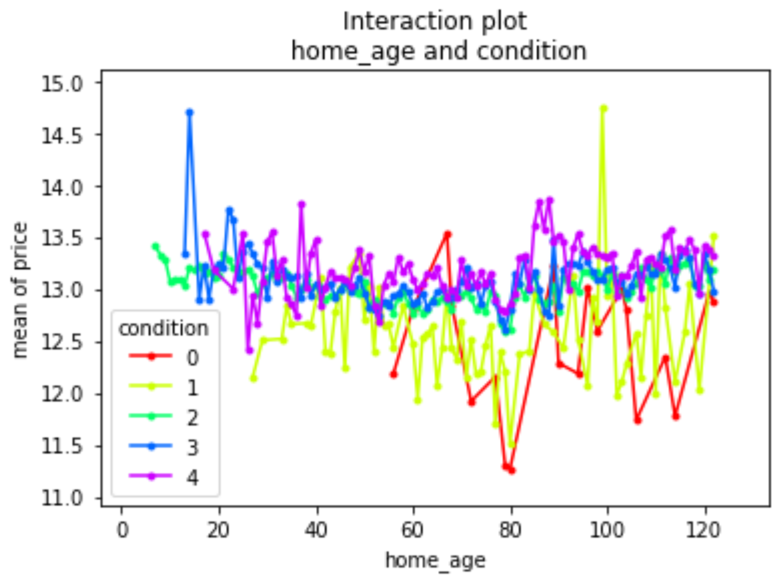
The graphs below are interaction plots. This plot displays the fitted values of the dependent variable (`price`) on the y-axis and one of the predictor variables on the x-axis. The lines between the points represents the other predictor variable. If the lines remain parallel to each other then there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

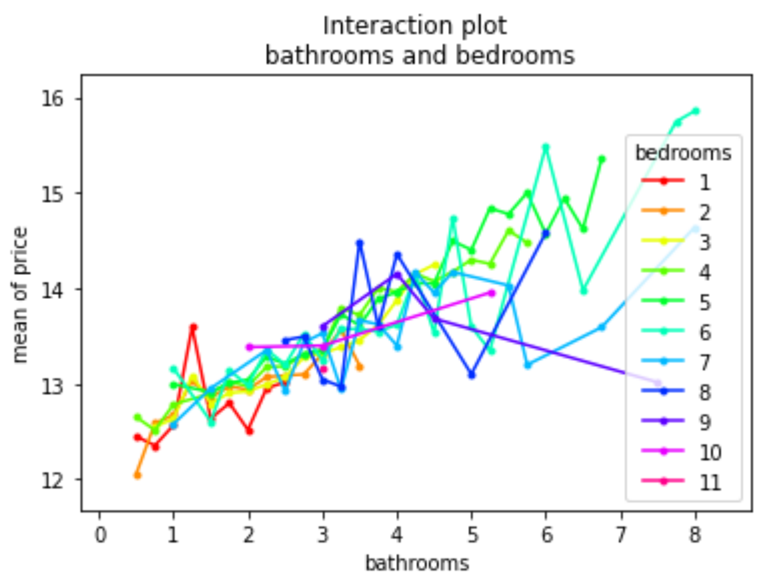
In [29]:

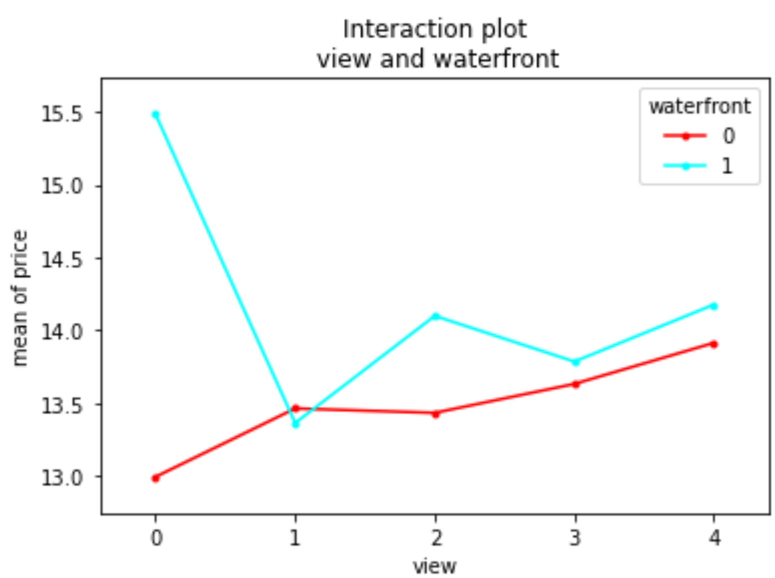
```
def interaction_analysis(data, var1, var2):
    '''
    Produces an interaction plot with programically determined
    title.
    Input:
         data: Pandas dataframe
         var1: column name of first variable
         var2: column name of second variable
    Output:
         interaction plot with title using 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
```

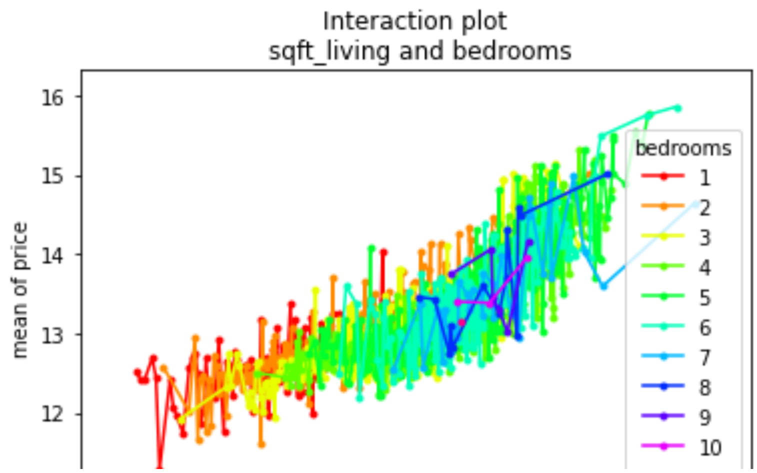
In [30]:

```
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 plot
home_age and condition
mean of price
home_age
condition
0
1
2
3
4


Interaction plot
bathrooms and bedrooms
mean of price
bathrooms
bedrooms
1
2
3
4
5
6
7
8
9
10
11


Interaction plot
view and waterfront
mean of price
view
waterfront
0
1



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 because the view variable is measuring the view of the mountains in Washington and not the view of a waterfront property. This data also may be too subjective or variable from different observers.

Modeling and Regression Results

Linear Regression Helper Function

In [31]:

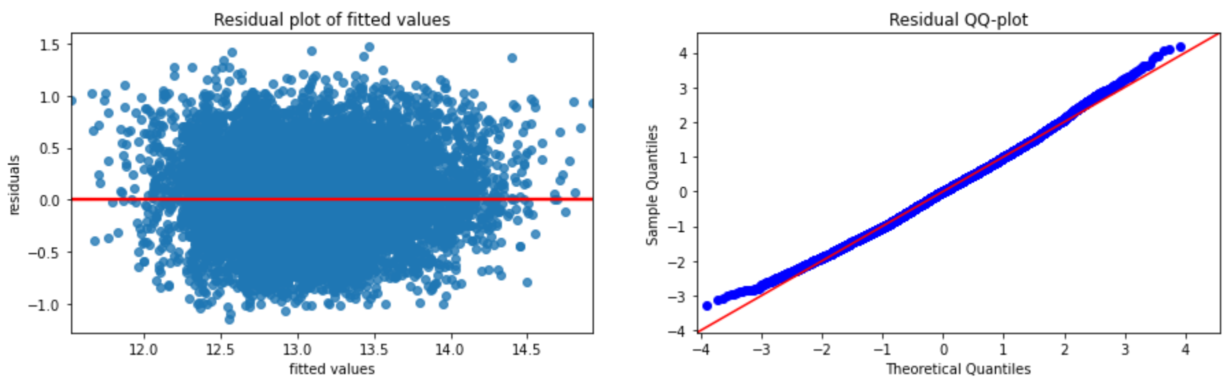
```
def lin_reg_model(data, features, model_name, formula):
    '''
    Runs OLS linear regression
    Input:
        - data: clean data
        - features: independent variables that will be included in model
        - formula: regression formula in R-style
        - model_name: Name you will call the 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

    # 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_err
    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={'col
    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=
    plt.show() # see https://github.com/statsmodels/statsmodels/issues/5493 f
    #fig.suptitle(f'{model_name} Residual QQ-plot')
```

```
    #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(f'Root Mean Squared Error: {RMSE:.2f}')

    return model, r2, interval, RMSE
```

M1 Results

In [32]:

```
# Model 1 features (highest correlated)
model_1_features = corr_with_price['Features'].values
formula_1 = 'price ~' + '+'.join(model_1_features) # model formula

# 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, 'Model 1', formula_1)
```




```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                  price   R-squared:                       0.55
5
Model:                            OLS   Adj. R-squared:                  0.55
5
Method:                 Least Squares   F-statistic:                     896
9.
Date:                Fri, 05 Aug 2022   Prob (F-statistic):               0.0
0
Time:                        23:06:08   Log-Likelihood:                -8054.
1
No. Observations:               21597   AIC:                         1.612e+0
4
Df Residuals:                   21593   BIC:                         1.615e+0
4
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
==
                  coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
--
Intercept       8.6531      0.052    167.137      0.000       8.552       8.7
```

```
55
sqft_living     0.5833      0.012     49.552      0.000       0.560       0.6
06
grade           0.2215      0.003     69.431      0.000       0.215       0.2
28
sqft_above     -0.2306      0.012    -19.733      0.000      -0.254      -0.2
08
==============================================================================
=
Omnibus:                      103.808   Durbin-Watson:                   1.97
4
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              105.19
7
Skew:                           0.170   Prob(JB):                    1.43e-2
3
Kurtosis:                       3.025   Cond. No.                          28
7.
==============================================================================
=

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


R-squared: 0.55
Prediction Interval: 0.69
```

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:

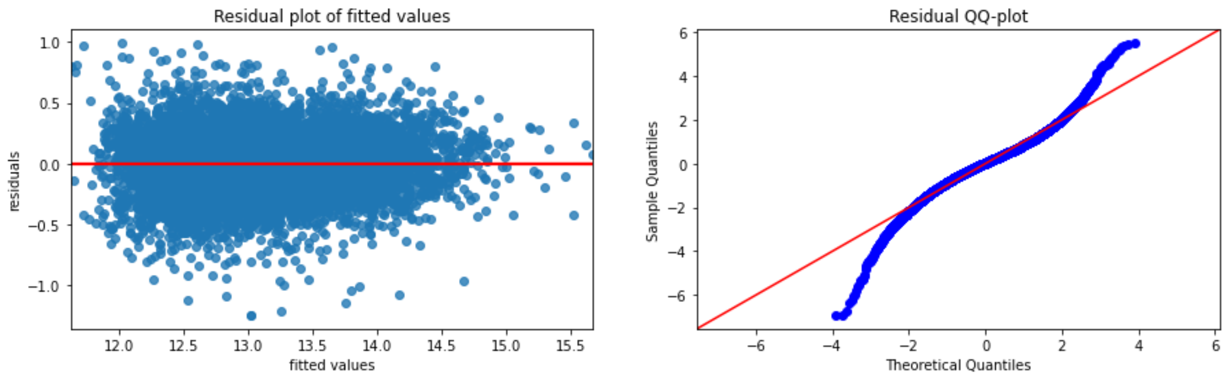
$$\hat{y}_{\substack{sales\\price}} = 0.58X_{\substack{sqft\\living}} + 0.22X_{grade} - 0.23X_{\substack{sqft\\above}} + 8.6531$$

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 multicolinearity 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]:
```python
# Model 2 features (Stepwise backward Design)
model_2_features = backward_elimination(df_clean, df_clean[['price']])
formula_2 = 'price ~' + '+'.join(model_2_features) # model formula

# 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_
```




```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                  price   R-squared:                       0.88
3
Model:                            OLS   Adj. R-squared:                  0.88
3
Method:                 Least Squares   F-statistic:                     203
7.
Date:                Fri, 05 Aug 2022   Prob (F-statistic):               0.0
0
Time:                        23:06:11   Log-Likelihood:                 6411.
2
No. Observations:               21597   AIC:                        -1.266e+0
4
Df Residuals:                   21516   BIC:                        -1.201e+0
4
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:                   2.00
3
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             7091.18
9
Skew:                          -0.199   Prob(JB):                         0.0
0
Kurtosis:                       5.779   Cond. No.                     3.32e+0
3
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 3.32e+03. This might indicate that there a
re
strong multicollinearity or other numerical problems.


R-squared: 0.88
Prediction Interval: 0.35
Root Mean Squared Error: 0.18
```

M2 Interpretation

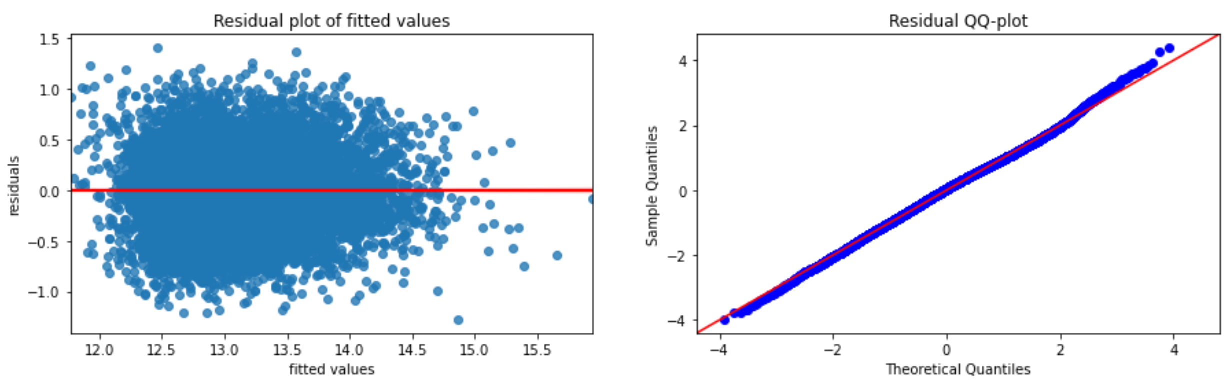
R^2 and adjusted R^2 is 0.89 for M2. This is tremendous improvement over M1. There are many more independent variables used in M2 as compared to M1, which may overfit the data. This model used all the independent variables expect for some of the Zipcodes after recoding Zipcode to dummy variables. Thought there are many variables, the p-values indicate that each of the variables chosen has a statistical 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 ever one-unit in condition of a house the sale price is expected to increase on average 5%. Some of the highest coefficients 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 indicate 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 umnecessary 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', 'h
formula_3 = 'price ~' + '+'.join(model_3_features) + '+ home_age*condition +
model_3_reg, model_3_r2, model_3_pi, m3_RMSE = lin_reg_model(df_clean, model_
```




```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                  price   R-squared:                       0.63
0
Model:                            OLS   Adj. R-squared:                  0.63
0
Method:                 Least Squares   F-statistic:                     524
5.
Date:                Fri, 05 Aug 2022   Prob (F-statistic):               0.0
0
Time:                        23:06:12   Log-Likelihood:                -6064.
0
No. Observations:               21597   AIC:                         1.214e+0
4
Df Residuals:                   21589   BIC:                         1.221e+0
4
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
===========
```

```
                              coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----------
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:                   1.96
2
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               55.95
7
Skew:                          -0.053   Prob(JB):                     7.07e-1
3
Kurtosis:                       3.225   Cond. No.                     1.06e+0
4
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 1.06e+04. This might indicate that there a
re
strong multicollinearity or other numerical problems.


R-squared: 0.62
Prediction Interval: 0.63
```

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. The p-values indicate which variables has a statistical significant relationship with the dependent variable. While there are interactions between these variables, that interaction does not have a significant effect in this model. 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 coefficient for `sqft_living` is 0.25. This means for every 1% increase in square feet of living space in a house there is a 0.25% increase in sale price. The coefficient for `condition` with M3 is -0.0635. This means that for ever one-unit in condition of a house the sale price is expected to decrease about 6% on average.

The residual plot has a random pattern so there is homoskedasticity. The QQ-plot of the residuals indicate that they are normally distributed. These reults 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), prediciton 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 5: Regression Results Table')
results
```

```
Table 5: Regression Results Table
```

Out[35]:

	R_squared	PI	RMSE
M1	0.554774	0.688652	0.351407
M2	0.883369	0.352465	0.180767
M3	0.629711	0.628029	0.323521

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 porportion of variation in the dependent variable that is predictive from the independent variable. I measured R^2 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 5 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 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 indpendent variables. The prediciton interval can be use to assess if the predicitons 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,

$$PI = 1.96 \times s,$$
$$\text{where s is the sample standard deviation calculated by}$$
$$s = \sqrt{\frac{1}{N-2} \times RSS}$$

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 indpendent variables. The smaller the predictive interval the more confidence the true sale price is in that region. M1 and M2 had resonably 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. The smaller the RMSE value, the closer the fitted line from the linear equation is to the actual data. It is the square root of the average squared difference between the predicted dependent value and the actual values in the dataset. 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 it 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.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2},$$
$$\text{where } (\hat{y_1}, \hat{y_2}, \ldots, \hat{y_n}) \text{ are the predicted values,}$$
$$(y_1, y_2, \ldots, y_n) \text{ are the observed values}$$
$$\text{and } (n) \text{is the number of observations}$$

RMSE is estimated using K-Fold cross validation. M2 is almost half the RMSE score of M1 and M2 indicating it produces better prediction 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 one of the three models, the new home features, and the prediction interval. This function returns the predicted house sale price and 95% prediction interval range according to that model and new data.

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+waterfron
                     view+condition+grade+sqft_above+basement+sqft_living15+s
                     home_age+yr_since_reno+zipcode

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

    Input:
          model_no: Statsmodel linear regression model results
          new_data: Pandas Series with variables needed for the regression mo
          pi: prediction interval for that model
    Output:
          Predicted sale price
          Predicted sale price range
    '''
    price_ln = model_no.predict(new_data).values[0] # predicted price
    price = round(np.exp(price_ln))
    price_low = round(np.exp(price_ln - pi)) # prediction lower bound
    price_up = round(np.exp(price_ln + pi)) # prediction upper bound

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

Demonstration

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

In [38]:
```
data = df_clean.sample().squeeze() # Randomly sample data for prediction
data.head(10) # new house features
```

Out[38]:
```
price          13.561908
bedrooms        4.000000
bathrooms       2.500000
sqft_living     8.019613
sqft_lot        8.767952
floors          2.000000
waterfront      0.000000
view            0.000000
condition       2.000000
grade           8.000000
Name: 21480, dtype: float64
```

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 prediciton fu
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: 570048.0, range: 286308.0 - 1134982.0
Actual sale price: 776000.0
```

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: 695922.0, range: 489200.0 - 989997.0
Actual sale price: 776000.0
```

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: 524294.0, range: 279786.0 - 982482.0
Actual sale price: 776000.0
```

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