khwilliamkim Final Finished Lab History

1 contributor

1.62 MB

Final Project Submission

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Kings County Housing Analysis with Multiple Linear Regression

Overview

A young couple is planning on selling their home, they want to increase the home value as much as possible but have limited capital for renovations. The couple decided to use Multiple Linear Regression Modeling to analyze and predict house sales in King County based on certain features or variables, so that they can be used to make profitable decisions.

After careful evaluation and various iterations of our linear regression models, we have determined that square feet of living space and building grade are the most correlated with a higher selling house price.

Business Problem

Our stakeholders are seeking advice for new homeowners about how home renovations might increase the estimated value of their homes and by what amount.

This analysis will help homeowners buy and/or sell homes. We will be reviewing building grade and square-footage of living space and various factors to determine which features are highly correlated with home sale prices.

Hypothesis

Null Hypothesis - There is no relationship between our independent variables and our dependent variable (target)

Alternative Hypothesis - There is a relationship between our independent variables and our dependent variable (target)

*Note The significance level - alphas of 0.05 was used to determine our final recommendations.

Questions to be analyzed

Q1: What features have the highest correlation to the home price?

Q2: What features have the strongest correlations with other predicting variables?

Q3: What combinations of features is the best fit for price predictions?

Data Understanding

The data used for this analysis is the King County Housing data set. The data set contained information and features for more than 21,000 homes in King County. Each home in the set contained information regarding features such as number of bedrooms/bathrooms/floors, square footage of living space and lot, zip-code, building grade, condition and etc.

The King County Housing Data Set consists of multiple features that attributes to the final sale price for homes in King County. The descriptions of the features are listed below.

King County Housing Data Columns

- `id` - Unique identifier for a house
- `date` - Date house was sold – (Ignored)
- `price` - Sale price (prediction target)
- `bedrooms` - Number of bedrooms
- `bathrooms` - Number of bathrooms
- `sqft_living` - Square footage of living space in the home
- `sqft_lot` - Square footage of the lot
- `floors` - Number of floors (levels) in house
- `waterfront` - Whether the house is on a waterfront
- `view` - Quality of view from house – (Ignored)
- `condition` - How good the overall condition of the house is.
- `grade` - Overall grade of the house.
- `sqft_above` - Square footage of house apart from basement – (Ignored)
- `sqft_basement` - Square footage of the basement – (Ignored)
- `yr_built` - Year when house was built
- `yr_renovated` - Year when house was renovated – (Ignored)

- `zipcode` - ZIP Code used by the United States Postal Service – (Ignored)
- `lat` - Latitude coordinate – (Ignored)
- `long` - Longitude coordinate – (Ignored)
- `sqft_living15` - The square footage of interior housing living space for the nearest 15 neighbors – (Ignored)
- `sqft_lot15` - The square footage of the land lots of the nearest 15 neighbors – (Ignored)

Explotory Data Analyis

Lets start the exploration process by importing data.

In [1]:

```
#Load necessary modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import scipy.stats as stats
import statsmodels.formula.api as smf
import statsmodels.stats.api as sms
import statsmodels.api as sm
from statsmodels.formula.api import ols
from sklearn import datasets, linear_model
import seaborn as sns
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn import metrics
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error, make_scor
from sklearn.model_selection import cross_val_score
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings('ignore')
```

Removing irrelvant columns

In [2]:

```
# reading the csv file
# drop irrelevant columns
df = pd.read_csv('data/kc_house_data.csv').drop(['date',
                                                  'view',
                                                  'sqft_al
                                                  'sqft_ba
                                                  'yr_ren
                                                  'zipcod
                                                  'lat',
                                                  'long',
                                                  'sqft_l
                                                  'sqft_l
# previewing the DataFrame
df.head()
```

Out[2]: id price bedrooms bathrooms sqft_living sqft_lo

Out[2]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lo
0	7129300520	221900.0	3	1.00	1180	565
1	6414100192	538000.0	3	2.25	2570	724
2	5631500400	180000.0	2	1.00	770	1000
3	2487200875	604000.0	4	3.00	1960	500
4	1954400510	510000.0	3	2.00	1680	808

In [3]:

```
df.shape
```

Out[3]:

```
(21597, 11)
```

The dataset contains 21,597 houses with 11 features.

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   id           21597 non-null  int64  
 1   price        21597 non-null  float64
 2   bedrooms     21597 non-null  int64  
 3   bathrooms    21597 non-null  float64
 4   sqft_living  21597 non-null  int64  
 5   sqft_lot     21597 non-null  int64  
 6   floors       21597 non-null  float64
 7   waterfront   19221 non-null  object 
 8   condition    21597 non-null  object 
 9   grade        21597 non-null  object 
 10  yr_built     21597 non-null  int64  
dtypes: float64(3), int64(5), object(3)
memory usage: 1.8+ MB
```

In [5]:

```
df.describe()
```

Out[5]:

	id	price	bedrooms	bathrooms	
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2
std	2.876736e+09	3.673681e+05	0.926299	0.768984	
min	1.000102e+06	7.800000e+04	1.000000	0.500000	
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13

In [6]:
```
# descriptive statistics for our target price.
df['price'].describe()
```

Out[6]:
```
count    2.159700e+04
mean     5.402966e+05
std      3.673681e+05
min      7.800000e+04
25%      3.220000e+05
50%      4.500000e+05
75%      6.450000e+05
max      7.700000e+06
Name: price, dtype: float64
```

The average price of homes in the data set is 540,297 dollars. The prices ranges from 78,000 to 8,000,000 dollars and the median house price is 450,000 dollars

In [7]:
```
# descriptive statistics for square footage
df['sqft_living'].describe()
```

Out[7]:
```
count    21597.000000
mean      2080.321850
std        918.106125
min        370.000000
25%       1430.000000
50%       1910.000000
75%       2550.000000
max      13540.000000
Name: sqft_living, dtype: float64
```

The mean square-feet of living space is 2,080 sq-ft and the range of living space ranges from 370 sq-ft to 13,540 sq-ft. The median sq footage is 1,910.

In [8]:
```
df['bedrooms'].value_counts()
```

Out[8]:
```
3     9824
4     6882
2     2760
5     1601
6      272
1      196
7       38
8       13
9        6
10       3
11       1
33       1
Name: bedrooms, dtype: int64
```

The bedroom counts range from 1 bedroom to 33

In [9]:
```
df['bathrooms'].value_counts()
```

Out[9]:
```
2.50    5377
1.00    3851
1.75    3048
2.25    2047
```

```
2.00    1930
1.50    1445
2.75    1185
3.00     753
3.50     731
3.25     589
3.75     155
4.00     136
4.50     100
4.25      79
0.75      71
4.75      23
5.00      21
5.25      13
5.50      10
1.25       9
6.00       6
0.50       4
5.75       4
6.75       2
8.00       2
6.25       2
6.50       2
7.50       1
7.75       1
Name: bathrooms, dtype: int64
```

In [10]:

```
df['floors'].value_counts()
```

Out[10]:

```
1.0    10673
2.0     8235
1.5     1910
3.0      611
2.5      161
3.5        7
Name: floors, dtype: int64
```

In [11]:

```
df['sqft_lot'].value_counts()
```

Out[11]:

```
5000     358
6000     290
4000     251
7200     220
4800     119
        ...
22605      1
25248      1
9934       1
9142       1
1076       1
Name: sqft_lot, Length: 9776, dtype: int64
```

In [12]:

```
df['sqft_lot'].describe()
```

Out[12]:

```
count    2.159700e+04
mean     1.509941e+04
std      4.141264e+04
min      5.200000e+02
25%      5.040000e+03
50%      7.618000e+03
75%      1.068500e+04
max      1.651359e+06
Name: sqft_lot, dtype: float64
```

In [13]:

```
df['yr_built'].value_counts()
```

Out[13]:

```
2014    559
2006    453
2005    450
2004    433
2003    420
       ...
1933     30
1901     29
1902     27
1935     24
1934     21
Name: yr_built, Length: 116, dtype: int64
```

The year built ranges from 1934 to 2014.

In [14]:

```
df['condition'].value_counts()
```

Out[14]:

```
Average      14020
Good          5677
Very Good     1701
Fair           170
Poor            29
Name: condition, dtype: int64
```

In [15]:

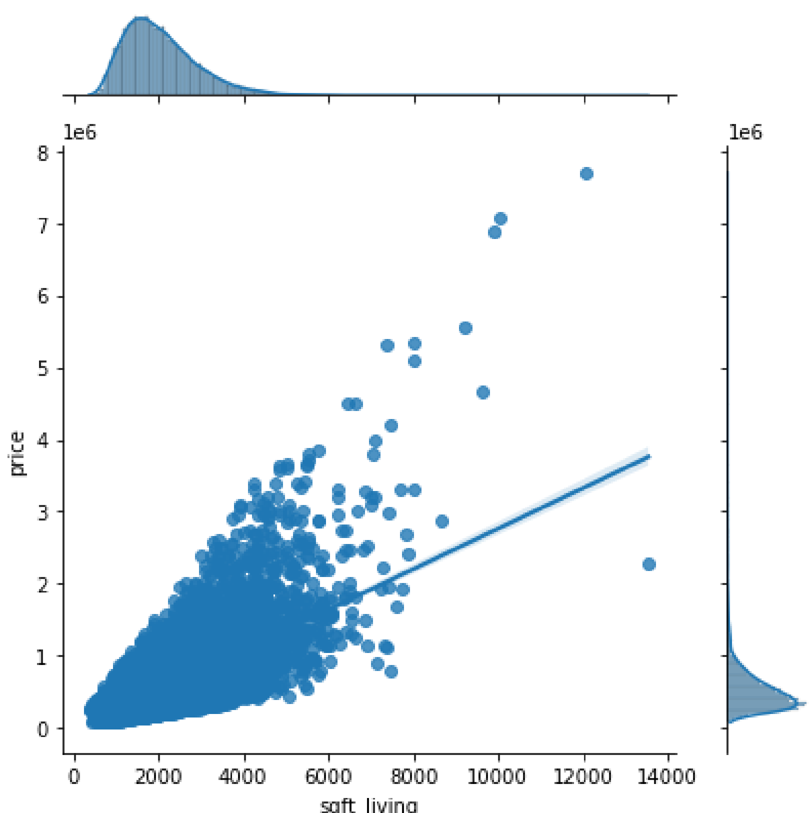
```
df['waterfront'].value_counts()
```

Out[15]:

```
NO     19075
YES      146
Name: waterfront, dtype: int64
```

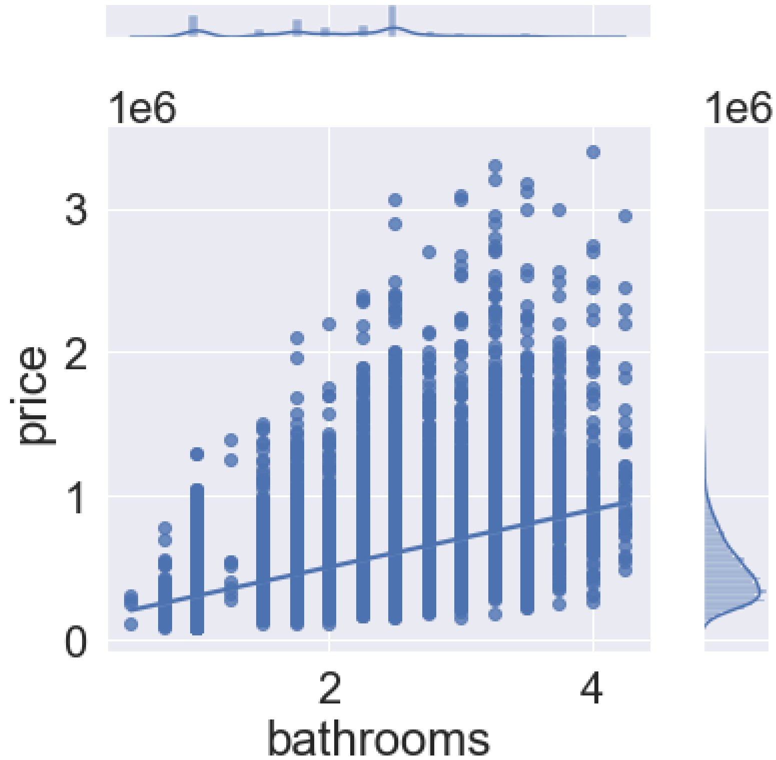
In [16]:

```
# examining the relationship between sqft_living and pri
sns.jointplot('sqft_living','price', data=df, kind='reg'
plt.tight_layout()
```



In [169…

```
sns.jointplot('bathrooms','price', data=df, kind='reg')
plt.tight_layout()
```



Data Preperation

Data Preparation Fundamentals - Applying appropriate preprocessing and feature engineering steps to tabular data in preparation for statistical modeling

Data Cleaning Steps Handling Missing Values: Identify and address and missing values using techniques such as dropping or replacing data.

Handling Non-Numeric Data: A Linear regression model needs all of the features to be numeric, not categorical. Identify the data type 'object' and address them using techniques such as ordinal or one-hot encoding.

This notebook contains a breakdown of the step-by-step processes that we used to compile, scrub, and transform our data. It includes variations of narrowing our scope and explorations into the impacts that our different transformations have on the data.

Preprocessing with Scikit-learn

Let explore and clean our data set to prep for our Linear Regression Model. Preprocessing Steps.

1. Handle Missing Values
2. Convert Categorical Features into Numbers
3. Find and Remove Outliers

Handling Missing Values

Below, let's check to see if there are any NaNs in our data

In [17]:
```
#locate missing values
df.isna().sum()
```

Out[17]:
```
id                  0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
condition           0
grade               0
yr_built            0
dtype: int64
```

In [18]:
```
#dealing with missing values
for column in df.columns:
    percentage_of_nan = (sum(df[column].isnull())/len(df
    print(column, percentage_of_nan)
```

```
id 0.0
price 0.0
bedrooms 0.0
bathrooms 0.0
sqft_living 0.0
sqft_lot 0.0
floors 0.0
waterfront 11.00152798999861
condition 0.0
grade 0.0
yr_built 0.0
```

The feature 'waterfront' is the only feature with missing values and about 11% of the values have NaNs. Lets investigate this feature to handle it's missing values

In [19]:
```
df['waterfront'].value_counts()
```

Out[19]:
```
NO      19075
YES       146
Name: waterfront, dtype: int64
```

We can see that the 'waterfront' feature only has two values, yes or no. Thus NaN values can be considered no because they do not exist in their homes.

In [20]:
```
df['waterfront'].fillna('NO', inplace=True)
```

In [21]:

```
df['waterfront'].value_counts()
```

Out[21]:

```
NO     21451
YES      146
Name: waterfront, dtype: int64
```

In [22]:

```
#recheck for missing values
df.isna().sum()
```

Out[22]:

```
id              0
price           0
bedrooms        0
bathrooms       0
sqft_living     0
sqft_lot        0
floors          0
waterfront      0
condition       0
grade           0
yr_built        0
dtype: int64
```

Convert Categorical Features into Numbers

Our model would crash because some of the columns are non-numeric. Features with a numeric data type will work with our model, but these features need to be converted:

- waterfront (object)
- condition (object)
- grade (object)

Let's inspect the value counts of the specified features:

In [23]:

```
print(df['waterfront'].value_counts())
print()
print(df['condition'].value_counts())
print()
print(df['grade'].value_counts())
```

```
NO     21451
YES      146
Name: waterfront, dtype: int64

Average      14020
Good          5677
Very Good     1701
Fair           170
Poor            29
Name: condition, dtype: int64

7 Average        8974
8 Good           6065
9 Better         2615
6 Low Average    2038
10 Very Good     1134
11 Excellent      399
5 Fair            242
12 Luxury          89
4 Low              27
13 Mansion         13
```

```
3 Poor              1
Name: grade, dtype: int64
```

split function to seperate the numeric value of 'grade'

The Grade feature is an object data type however the numeric grade is listed in the front. We will use a simple string split function to isolate the numeric part of the feature.

Waterfront has only 2 categories and can be converted into binary in place, whereas Condition has more than 2 categories and will need to be expanded into multiple columns.

In [24]:

```
df = df.assign(grade=df.grade.str.split(' ')).explode('gr
```

In [25]:

```
df.duplicated().value_counts()
```

Out[25]:

```
False    46360
True         6
dtype: int64
```

In [26]:

```
df = df.drop_duplicates()
```

In [27]:

```
df.shape
```

Out[27]:

```
(46360, 11)
```

In [28]:

```
df = df.drop_duplicates(subset='id')
```

In [29]:

```
df.dropna()
```

Out[29]:

	id	price	bedrooms	bathrooms	sqft_living	sc
0	7129300520	221900.0	3	1.00	1180	
1	6414100192	538000.0	3	2.25	2570	
2	5631500400	180000.0	2	1.00	770	
3	2487200875	604000.0	4	3.00	1960	
4	1954400510	510000.0	3	2.00	1680	
...	...	...	...	...	...	
21592	263000018	360000.0	3	2.50	1530	
21593	6600060120	400000.0	4	2.50	2310	
21594	1523300141	402101.0	2	0.75	1020	
21595	291310100	400000.0	3	2.50	1600	
21596	1523300157	325000.0	2	0.75	1020	

21420 rows × 11 columns

In [30]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21420 entries, 0 to 21596
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   id           21420 non-null  int64
 1   price        21420 non-null  float64
 2   bedrooms     21420 non-null  int64
 3   bathrooms    21420 non-null  float64
 4   sqft_living  21420 non-null  int64
 5   sqft_lot     21420 non-null  int64
 6   floors       21420 non-null  float64
 7   waterfront   21420 non-null  object
 8   condition    21420 non-null  object
 9   grade        21420 non-null  object
 10  yr_built     21420 non-null  int64
dtypes: float64(3), int64(5), object(3)
memory usage: 2.0+ MB
```

In [31]:

```
df['grade'].value_counts()
```

Out[31]:

```
7     8889
8     6041
9     2606
6     1995
10    1130
11     396
5      234
12      88
4       27
13      13
3        1
Name: grade, dtype: int64
```

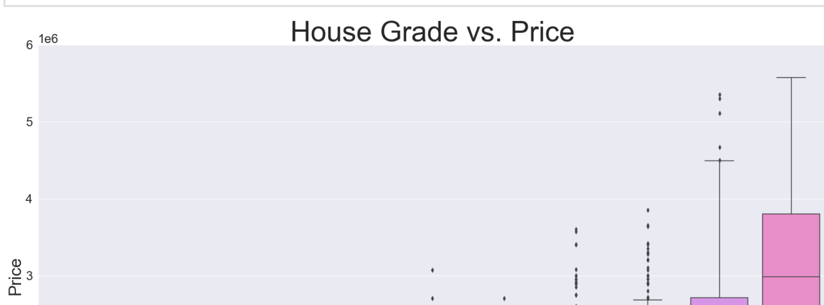
The most common buiding grade is a 7

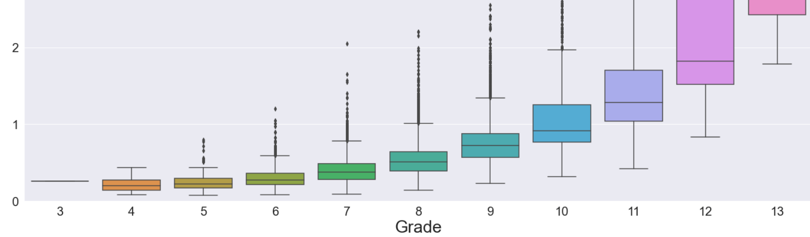
In [32]:

```
# Change the data type from object to int.
df['grade'] = df['grade'].astype(int)
```

In [33]:

```
#grade
plt.figure(figsize=(25,15))
sns.set(font_scale=2)
ax = sns.boxplot(x="grade", y="price", data=df)
ax.set_title('House Grade vs. Price', fontsize=50)
ax.set_ylabel('Price', fontsize=30)
ax.set_xlabel('Grade', fontsize=30)
ax.set_ylim(bottom=0, top=6000000);
```





When we look at grade, we can see that as the categorical building grade designation improves, the house price does indeed rise as well.

Binary Categories : OrdinalEncoder

For Binary categories, we will use an OrdinalEncoder to convert the category Waterfront into binary values by following these steps.

1. Identify data to be transformed
2. Instantiate the transformer object
3. Fit the transformer object
4. Transform data using the transformer object

In [34]:

```
# create a variable waterfront_train that contains the
# relevant column from df
waterfront_train = df[['waterfront']]

# Initiate an OrdinalEncoder
encoder_waterfront = OrdinalEncoder()

# Fit the encoder on waterfront_train
encoder_waterfront.fit(waterfront_train)

# Inspect the categories of the fitted encoder
encoder_waterfront.categories_[0]
```

Out[34]:

```
array(['NO', 'YES'], dtype=object)
```

In [35]:

```
# Transform waterfront_train using the encoder and
# assign the result to waterfront_encoded_train
waterfront_encoded_train = encoder_waterfront.transform(

# Flatten for appropriate shape
waterfront_encoded_train = waterfront_encoded_train.flat

#Visually inspect waterfront_encoded_train
waterfront_encoded_train
```

Out[35]:

```
array([0., 0., 0., ..., 0., 0., 0.])
```

In [36]:

```
# Replace value of Street
df['waterfront'] = waterfront_encoded_train

# Visually inspect df
df
```

Out[36]:

	id	price	bedrooms	bathrooms	sqft_living	sq

	id	price	bedrooms	bathrooms	sqft_living
0	7129300520	221900.0	3	1.00	1180
1	6414100192	538000.0	3	2.25	2570
2	5631500400	180000.0	2	1.00	770
3	2487200875	604000.0	4	3.00	1960
4	1954400510	510000.0	3	2.00	1680
...	...	...	...	...	...
21592	263000018	360000.0	3	2.50	1530
21593	6600060120	400000.0	4	2.50	2310
21594	1523300141	402101.0	2	0.75	1020
21595	291310100	400000.0	3	2.50	1600
21596	1523300157	325000.0	2	0.75	1020

21420 rows × 11 columns

In [37]:

```
df['waterfront'].value_counts()
```

Out[37]:

```
0.0    21274
1.0      146
Name: waterfront, dtype: int64
```

Transforming the confition column using .map()

In [38]:

```
df['condition'].value_counts()
```

Out[38]:

```
Average      13900
Good          5643
Very Good     1687
Fair           162
Poor            28
Name: condition, dtype: int64
```

In [39]:

```
condition_mapping = {
    "Average": 3,
    "Good": 4,
    "Very Good": 5,
    "Fair": 2,
    "Poor": 1
}
```

In [40]:

```
df['condition'].map(condition_mapping)
```

Out[40]:

```
0        3
1        3
2        3
3        5
4        3
        ..
21592    3
21593    3
21594    3
```

```
21595    3
21596    3
Name: condition, Length: 21420, dtype: int64
```

In [41]:

```
df['condition'] = df['condition'].map(condition_mapping)
df['condition'].value_counts()
```

Out[41]:

```
3    13900
4     5643
5     1687
2      162
1       28
Name: condition, dtype: int64
```

In [42]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21420 entries, 0 to 21596
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   id           21420 non-null  int64  
 1   price        21420 non-null  float64
 2   bedrooms     21420 non-null  int64  
 3   bathrooms    21420 non-null  float64
 4   sqft_living  21420 non-null  int64  
 5   sqft_lot     21420 non-null  int64  
 6   floors       21420 non-null  float64
 7   waterfront   21420 non-null  float64
 8   condition    21420 non-null  int64  
 9   grade        21420 non-null  int32  
 10  yr_built     21420 non-null  int64  
dtypes: float64(4), int32(1), int64(6)
memory usage: 2.4 MB
```

Dealing with Outliers

Its seems as the data set is containing both Single-Family and Multi-Family units. For example more than 8 bedrooms or more than 5 bathrooms. It would be better to separate the two different types of buildings and analyze. Thus we have decided to remove the rows with any outlier values.

In [43]:

```
# define function to describe outliers
def outliers_description(df):
    print('Outlier Data Description')
    describe = df.describe()

    describe.loc['+3_std'] = describe.loc['mean'] + (desc
    describe.loc['-3_std'] = describe.loc['mean'] - (desc
    print(describe)
```

In [44]:

```
outliers_description(df)
```

```
Outlier Data Description
                   id         price       bedrooms      bath
rooms   sqft_living  \
count   2.142000e+04  2.142000e+04  21420.000000  21420.0
00000  21420.000000
```

```
mean     4.580940e+09  5.407393e+05        3.373950        2.1
18429    2083.132633
std      2.876761e+09  3.679311e+05        0.925405        0.7
68720     918.808412
min      1.000102e+06  7.800000e+04        1.000000        0.5
00000     370.000000
25%      2.123537e+09  3.225000e+05        3.000000        1.7
50000    1430.000000
50%      3.904921e+09  4.500000e+05        3.000000        2.2
50000    1920.000000
75%      7.308900e+09  6.450000e+05        4.000000        2.5
00000    2550.000000
max      9.900000e+09  7.700000e+06       33.000000        8.0
00000   13540.000000
+3_std   1.321122e+10  1.644533e+06        6.150163        4.4
24589    4839.557868
-3_std  -4.049344e+09 -5.630540e+05        0.597736       -0.1
87731    -673.292602

             sqft_lot        floors     waterfront       cond
ition           grade  \
count    2.142000e+04  21420.000000  21420.000000  21420.0
00000   21420.000000
mean     1.512804e+04      1.495985      0.006816        3.4
10784       7.662792
std      4.153080e+04      0.540081      0.082280        0.6
50035       1.171971
min      5.200000e+02      1.000000      0.000000        1.0
00000       3.000000
25%      5.040000e+03      1.000000      0.000000        3.0
00000       7.000000
50%      7.614000e+03      1.500000      0.000000        3.0
00000       7.000000
75%      1.069050e+04      2.000000      0.000000        4.0
00000       8.000000
max      1.651359e+06      3.500000      1.000000        5.0
00000      13.000000
+3_std   1.397204e+05      3.116228      0.253655        5.3
60890      11.178705
-3_std  -1.094644e+05     -0.124258     -0.240022        1.4
60679       4.146878

             yr_built
count    21420.000000
mean      1971.092997
std         29.387141
min       1900.000000
25%       1952.000000
50%       1975.000000
75%       1997.000000
max       2015.000000
+3_std    2059.254419
-3_std    1882.931575
```

Remove outliers more than 3 standard deviations away from the mean

In [45]:

```
def remove_outliers(df, features):
    print("Outliers Removed Count")

    x = len(df)

    for feature in features:
        df[feature + '_zscore'] = np.abs(stats.zscore(df
        y = df.loc[np.abs(df[feature + '_zscore']) > 3]
```

```
        y = df.loc[np.abs(df[feature + '_zscore']) > 3]
        percent = round((len(y) * 100) / x, 3)

        print(len(y), "outliers removed for", feature)

        df = df.loc[np.abs(df[feature + '_zscore']) < 3]

        df = df.drop([feature + '_zscore'], axis=1)

    return df
```

In [46]:

```
outliers = df[['bedrooms', 'bathrooms', 'sqft_living']]
df = remove_outliers(df, outliers)
```

```
Outliers Removed Count
62 outliers removed for bedrooms
171 outliers removed for bathrooms
209 outliers removed for sqft_living
```

In [47]:

```
def plot_histogram(df, column, title, xlabel, ylabel):
    # Extract the relevant data
    data = df[column]
    mean = data.mean()
    # Set up plot
    fig, ax = plt.subplots(figsize=(10,7))
    # Plot histogram
    ax.hist(data, bins="auto")
    # Plot vertical line
    ax.axvline(mean, color="black")
    # Customize title and axes labels
    ax.set_title(title)
    ax.set_xlabel(xlabel)
    ax.set_ylabel(ylabel)

plot_histogram(
    df,
    "price",
    "Distribution of Sale Prices",
    "Sale Price",
    "Number of Houses"
)
```

In [48]:

```
def print_stats(df, column):
    print("Mean:                ", df[column].mean())
```

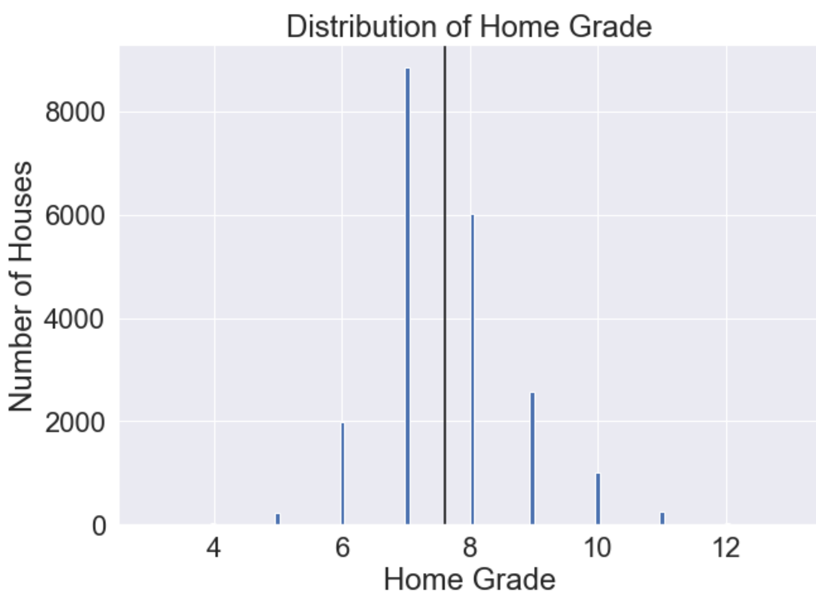
```
    print("Mean:                ", df[column].mean())
    print("Median:              ", df[column].median())
    print("Standard Deviation:", df[column].std())

print_stats(df, "price")
```

```
Mean:               518066.6351415769
Median:             447000.0
Standard Deviation: 301071.6722828131
```

Looks like a log normal distribution. Most houses in this sample are clustered around the median value of 447,000 dollars, but the higher-end homes are pulling the mean up to over 518,066 dollars

In [49]:

```
plot_histogram(
    df,
    "grade",
    "Distribution of Home Grade",
    "Home Grade",
    "Number of Houses"
)
```



In [50]:

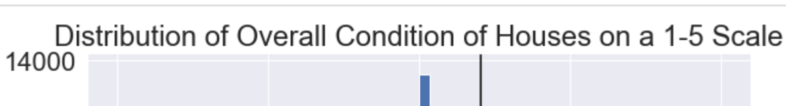
```
print_stats(df, 'grade')
```

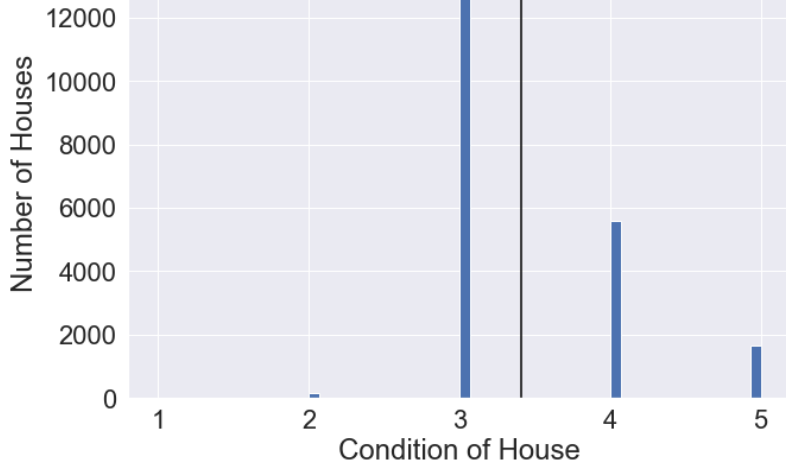
```
Mean:               7.610115358947469
Median:             7.0
Standard Deviation: 1.1050580688804281
```

Grade is approximately normally distributed.

In [51]:

```
plot_histogram(
    df,
    "condition",
    "Distribution of Overall Condition of Houses on a 1-!
    "Condition of House",
    "Number of Houses"
)
```





In [52]:

```
print_stats(df, 'condition')
```

```
Mean:                  3.4131947754790732
Median:                3.0
Standard Deviation: 0.6509397347766206
```

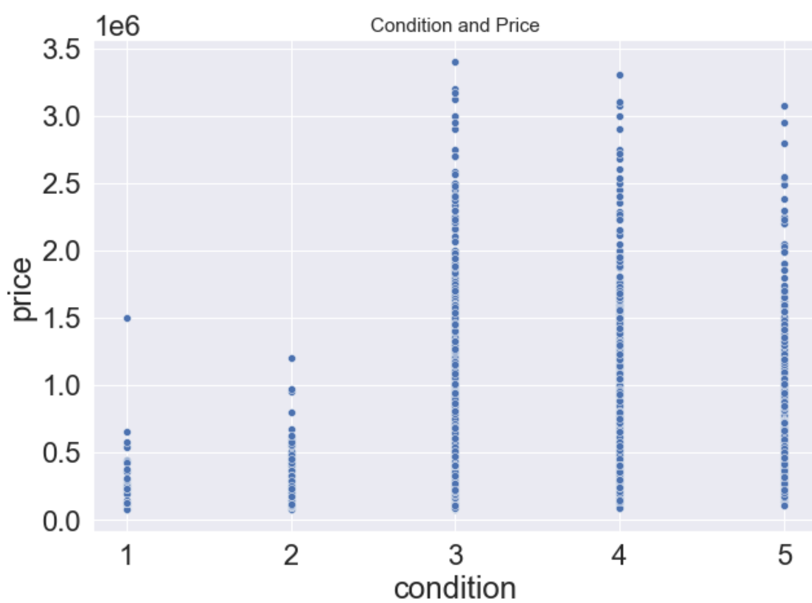
Most homes have a condition of 3. It seems like we should treat this as a categorical rather than numeric variable, since the difference between conditions is so abrupt

In [53]:

```
plt.figure(figsize=(10,7))
sns.scatterplot(df['condition'], df['price'])
plt.title('Condition and Price', fontsize=15)
```

Out[53]:

```
Text(0.5, 1.0, 'Condition and Price')
```



The condition variable in the dataset that we would expect to be highly related with price, but which doesn't have a clear linear relationship.

One useful way to explore a categorical variable is to create subsets of the full dataset based on that categorical variable, then plot their distributions based on some other variable.

In [54]:

```python
below_average_condition = df[df["condition"] < 3]
average_condition = df[df["condition"] == 3]
above_average_condition = df[df["condition"] > 3]
```

In [55]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20978 entries, 0 to 21596
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   id           20978 non-null  int64  
 1   price        20978 non-null  float64
 2   bedrooms     20978 non-null  int64  
 3   bathrooms    20978 non-null  float64
 4   sqft_living  20978 non-null  int64  
 5   sqft_lot     20978 non-null  int64  
 6   floors       20978 non-null  float64
 7   waterfront   20978 non-null  float64
 8   condition    20978 non-null  int64  
 9   grade        20978 non-null  int32  
 10  yr_built     20978 non-null  int64  
dtypes: float64(4), int32(1), int64(6)
memory usage: 1.8 MB
```

In [56]:

```python
# Change the data type from object to int.
df['price'] = df['price'].astype(int)
```

In [57]:

```python
# Set up plot
fig, ax = plt.subplots(figsize=(15,5))

# Create custom bins so all are on the same scale
bins = range(df["price"].min(), df["price"].max(), int(d

# Plot three histograms, with reduced opacity (alpha) so
# can see them overlapping
ax.hist(
    x=above_average_condition["price"],
    label="above average condition",
    bins=bins,
    color="cyan",
    alpha=0.5
)
ax.hist(
    x=average_condition["price"],
    label="average condition",
    bins=bins,
    color="gray",
    alpha=0.3
)
ax.hist(
    x=below_average_condition["price"],
    label="below average condition",
    bins=bins,
    color="yellow",
    alpha=0.5
)

# Customize labels
ax.set_title("Distributions of Sale Price Grouped by Conc
ax.set_xlabel("Sale Price")
ax.set_ylabel("Number of Houses")
```

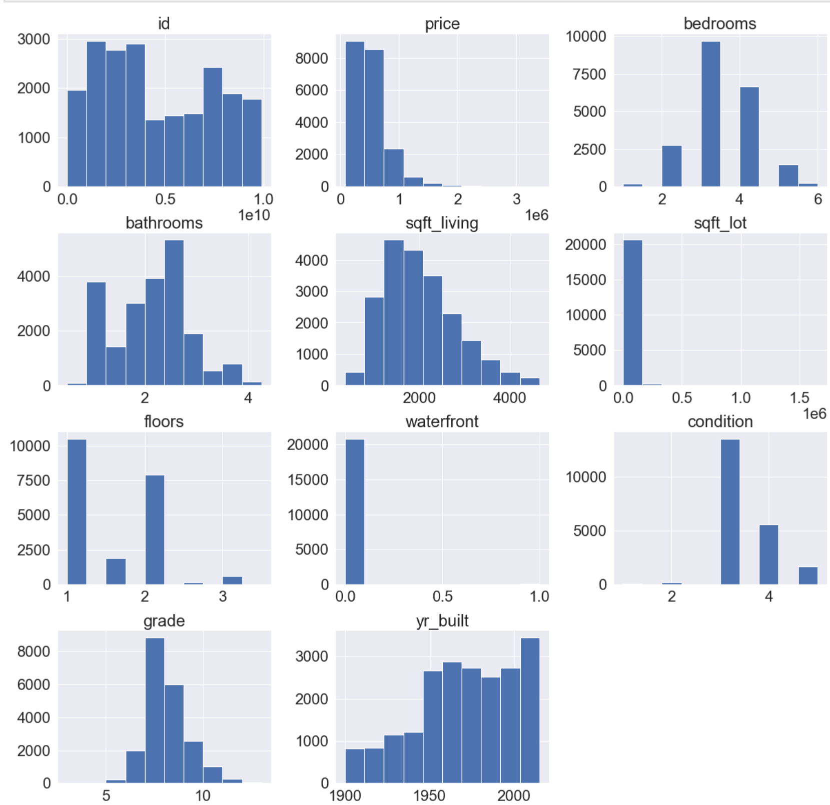
```
ax.legend();
```

But what might be surprising is that above-average condition houses do not seem to have higher average sale prices than average condition houses. We might want to investigate further to understand what kinds of houses are rated as above-average condition, since this goes against a standard assumption that better condition would mean higher cost.

Assumptions

Now that we have finished cleaning the data set let's begin to make our initial assumptions. We'll test the normality of distribution for several independent variables as well as their linearity to the Price. If the variable appears to be normally distributed and linear we will use that in our initial model.

In [58]:
```
#review distribution of variables
df.hist(figsize=(20,20));
```



Reviewing Correlations and Addressing Multicollinearity

The objective is finding out which variables are most strongly correlated with price, as these variables will be good candidates for inclusion in our model. One of the assumptions of a multiple linear regression model, however, is that there is no multicollinearity among the explanatory variables. Below, we create a correlation matrix of price and continuous variables in the dataset to visualize correlations.

Explore Correlations

To understand more about what features of these homes lead to higher sale prices, let's look at some correlations.

In [59]:

```
# Get a list of correlations with SalePrice, sorted from
# to largest
correlation_series = df.corr()['price'].sort_values()
# Select second to last correlation, since the highest (
# correlation will be SalePrice correlating 100% with it:
max_corr_value = correlation_series.iloc[-2]
max_corr_column = correlation_series.index[-2]
print("Most Positively Correlated Column:", max_corr_colu
print("Maximum Correlation Value:", max_corr_value)
```

```
Most Positively Correlated Column: grade
Maximum Correlation Value: 0.6515434324583883
```

In [60]:

```
correlation_series = df.corr()['price'].sort_values()
max_corr_value = correlation_series.iloc[-3]
max_corr_column = correlation_series.index[-3]
print("Second Most Positively Correlated Column:", max_co
print("Maximum Correlation Value:", max_corr_value)
```

```
Second Most Positively Correlated Column: sqft_living
Maximum Correlation Value: 0.6472777070874484
```

In [61]:

```
correlation_series = df.corr()['price'].sort_values()
max_corr_value = correlation_series.iloc[-4]
max_corr_column = correlation_series.index[-4]
print("Third Most Positively Correlated Column:", max_co
print("Maximum Correlation Value:", max_corr_value)
```

```
Third Most Positively Correlated Column: bathrooms
Maximum Correlation Value: 0.4696317325722415
```

Q1: What features have the highest correlation to the home price?

The houses grade, sqft_living, and bathrooms have the highest correlation with price.

In [62]:

```
# We can just find the smallest value, not the second sma
# since we aren't avoiding the perfect correlation with
min_corr_value = correlation_series.iloc[1]
min_corr_column = correlation_series.index[1]

print("Most Negatively Correlated Column:", min_corr_colu
print("Minimum Correlation Value:", min_corr_value)
```

```
Most Negatively Correlated Column: yr_built
Minimum Correlation Value: 0.03304060821765139
```

In [63]:

```python
min_corr_value = correlation_series.iloc[2]
min_corr_column = correlation_series.index[2]

print("Second Most Negatively Correlated Column:", min_c
print("Minimum Correlation Value:", min_corr_value)
```

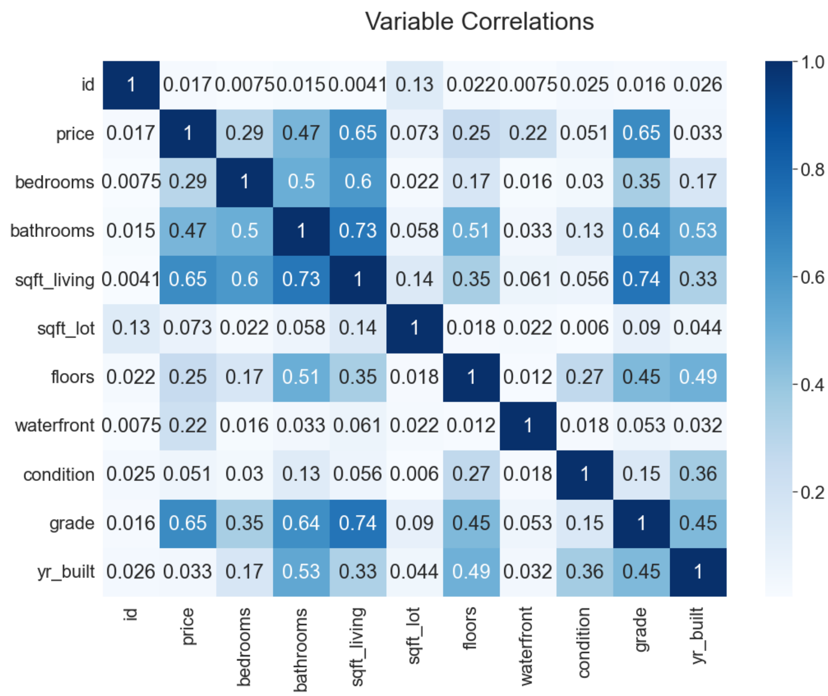
```
Second Most Negatively Correlated Column: condition
Minimum Correlation Value: 0.05131668178239331
```

In [64]:

```python
corr = df.corr().abs()
fig, ax=plt.subplots(figsize=(17,12))
fig.suptitle('Variable Correlations', fontsize=30, y=.95
heatmap = sns.heatmap(corr, cmap='Blues', annot=True)
heatmap
```

Out[64]:

```
<AxesSubplot:>
```



In [65]:

```python
# create and display dataframes that narrow down the most
features = []
correlations = []
for idx, correlation in corr['price'].T.iteritems():
    if correlation >= .30 and idx != 'price':
        features.append(idx)
        correlations.append(correlation)
corr_price_df = pd.DataFrame({'Correlations':correlation
                              'Features': features}).sor
```

In [66]:

```python
Multicollinear_Features = []
Multicollinear_Corr = []
def check_multicollinearity(feature):
    for idx, correlation in corr[feature].T.iteritems():
        if correlation >= .70 and idx != feature:
            Multicollinear_Features.append([feature, idx
            Multicollinear_Corr.append(correlation)
```

```
for feature in corr:
    check_multicollinearity(feature)
MC_df = pd.DataFrame({'Correlations':Multicollinear_Corr
                      'Features': Multicollinear_Feature:
```

In [67]:

```
print('Correlations with Price')
display(corr_price_df)
print('Multicollinear Features')
display(MC_df)
```

```
Correlations with Price
```

	Correlations	Features
2	0.651543	grade
1	0.647278	sqft_living
0	0.469632	bathrooms

```
Multicollinear Features
```

	Correlations	Features
2	0.737053	[sqft_living, grade]
3	0.737053	[grade, sqft_living]
0	0.725613	[bathrooms, sqft_living]
1	0.725613	[sqft_living, bathrooms]

Q2: What features have the strongest correlations with other predicting variables?

None of our features have a correlation over 0.75 so multicollinearity is not an issue. Sqft_livng and grade have the highest correlations in our data.

In [68]:

```
df.corr()
```

Out[68]:

	id	price	bedrooms	bathrooms	sqft_living
id	1.000000	-0.017185	0.007509	0.015375	-0.004123
price	-0.017185	1.000000	0.294247	0.469632	0.647278
bedrooms	0.007509	0.294247	1.000000	0.502386	0.598196
bathrooms	0.015375	0.469632	0.502386	1.000000	0.725613
sqft_living	-0.004123	0.647278	0.598196	0.725613	1.000000
sqft_lot	-0.131456	0.072836	0.022481	0.058334	0.143944
floors	0.022023	0.251965	0.166861	0.505936	0.346984
waterfront	-0.007457	0.216155	-0.015706	0.033232	0.060978
condition	-0.025194	0.051317	0.029669	-0.128354	-0.056413
grade	0.016228	0.651543	0.349646	0.637203	0.737053
yr_built	0.025617	0.033041	0.165938	0.529347	0.330360

Data Modeling

There are 3 assumptions about the data that must be checked before building any linear regression model:

There should be a linear relationship between the explanatory and response variable. The data should be homoscedastic (i.e., the residuals have equal variance around the regression line on a scatterplot). The model residuals should follow a normal distribution (i.e. the residuals fall along a relatively straight line on a QQ plot). All of the above assumptions, in addition to the assumption of no multicollinearity, also apply to multiple regression.

In addition to checking for these assumptions, we will also look at two values in the model summary:

R-squared: This value tells us what proportion of the variability of y around its mean can be explained by the model. It can fall between 0 and 1, and a higher r-squared value indicates higher predictive power.

p-value: The null hypothesis for linear regression is that there is no relationship between the chosen explanatory variables and the response variable. Therefore, we want the model to have a p-value lower than .05 so we can reject the null hypothesis.

Model #1: Baseline Model

Build a baseline model using the top two features correlated to price

In [69]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20978 entries, 0 to 21596
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   id           20978 non-null  int64  
 1   price        20978 non-null  int32  
 2   bedrooms     20978 non-null  int64  
 3   bathrooms    20978 non-null  float64
 4   sqft_living  20978 non-null  int64  
 5   sqft_lot     20978 non-null  int64  
 6   floors       20978 non-null  float64
 7   waterfront   20978 non-null  float64
 8   condition    20978 non-null  int64  
 9   grade        20978 non-null  int32  
 10  yr_built     20978 non-null  int64  
dtypes: float64(3), int32(2), int64(6)
memory usage: 1.8 MB
```

In [70]:

```
home_preds0 = df.drop(['price',
                       'id',
                       'bathrooms',
                       'bedrooms',
                       'waterfront',
                       'sqft_lot',
                       'floors',
                       'condition',
                       'yr_built'], axis=1)
home_target0 = df['price']
home_preds0.head()
```

Out[70]:

	sqft_living	grade
0	1180	7
1	2570	7
2	770	6
3	1960	7
4	1680	8

In [71]:

```
predictors0 = sm.add_constant(home_preds0)
predictors0
```

Out[71]:

	const	sqft_living	grade
0	1.0	1180	7
1	1.0	2570	7
2	1.0	770	6
3	1.0	1960	7
4	1.0	1680	8
...	...	...	...
21592	1.0	1530	8
21593	1.0	2310	8
21594	1.0	1020	7
21595	1.0	1600	8
21596	1.0	1020	7

20978 rows × 3 columns

In [72]:

```
modelbaseline = sm.OLS(home_target0, predictors0).fit()
```

In [73]:

```
modelbaseline.summary()
```

Out[73]: OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.486
Model:	OLS	**Adj. R-squared:**	0.486

Method:	Least Squares	**F-statistic:**	9901.
Date:	Fri, 27 May 2022	**Prob (F-statistic):**	0.00
Time:	15:14:34	**Log-Likelihood:**	-2.8743e+05
No. Observations:	20978	**AIC:**	5.749e+05
Df Residuals:	20975	**BIC:**	5.749e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.97
const	-5.521e+05	1.18e+04	-46.786	0.000	-5.75e+05	-5.29e+
sqft_living	137.6391	2.758	49.914	0.000	132.234	143.0
grade	1.041e+05	1996.367	52.128	0.000	1e+05	1.08e+

Omnibus:	10657.564	**Durbin-Watson:**	1.974
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	129013.168
Skew:	2.160	**Prob(JB):**	0.00
Kurtosis:	14.355	**Cond. No.**	1.74e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.74e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

the baseline model's R Squared value is 0.486, lets try to increase the accuracy.

Model #2: using train_test_split

In [74]:

```
y = df['price']
X = df.drop('price', axis=1)
```

In [75]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y
```

In [76]:

```
print(f"X_train is a DataFrame with {X_train.shape[0]} r
print(f"y_train is a Series with {y_train.shape[0]} valu

# We always should have the same number of rows in X as 
assert X_train.shape[0] == y_train.shape[0]
```

```
X_train is a DataFrame with 15733 rows and 10 columns
```

y_train is a Series with 15733 values

In [77]:
```
# Declare relevant columns
relevant_columns = [
    'bedrooms',
    'bathrooms',
    'sqft_living',
    'sqft_lot',
    'waterfront',
    'floors',
    'condition',
    'grade',
    'yr_built'
]

# Reassign X_train so that it only contains relevant colu
X_train = X_train.loc[:, relevant_columns]

# Visually inspect X_train
X_train
```

Out[77]:

	bedrooms	bathrooms	sqft_living	sqft_lot	waterfront	flo
4438	4	2.50	2770	6000	0.0	
15353	4	1.50	2480	6383	0.0	
6845	4	2.50	2320	7800	0.0	
18197	3	1.50	1930	11092	0.0	
2198	4	3.75	4490	34982	0.0	
...	...	...	...	...	...	
11604	4	2.75	2640	35070	0.0	
12305	2	1.50	1140	1149	0.0	
5551	2	2.00	1060	4000	0.0	
889	3	2.50	3000	25341	0.0	
16247	3	1.00	1400	8710	0.0	

15733 rows × 9 columns

There might be a clearer linear relationship between price and specific condition values, which we can explore more effectively by one-hot encoding the variable.

Multiple Categories

Unlike the 'waterfront' feature, 'condition' has more than two categories. We will need to create multiple columns that are each representing one category. To do this we will use

OneHotEncoder from sklearn.preprocessing

In [78]:
```
# Create a variable condition_train
# extrated from X_train
condition_train = X_train[['condition']]
```

```
# Instantiate a OneHotEncoder
ohe = OneHotEncoder(categories='auto', sparse=False, han

# Fit the encoder on condition_train
ohe.fit(condition_train)

# Inspect the categories of the fitted encoder
ohe.categories_
```

Out[78]:

```
[array([1, 2, 3, 4, 5], dtype=int64)]
```

In [79]:

```
# Transform condition_train using the encoder and
# assign the result to condition_encoded_train
condition_encoded_train = ohe.transform(condition_train)

condition_encoded_train
```

Out[79]:

```
array([[0., 0., 1., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 1., 0., 0.],
       ...,
       [0., 1., 0., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.]])
```

In [80]:

```
# Make the transformed data into a datafram
condition_encoded_train = pd.DataFrame(
    condition_encoded_train,
    columns=ohe.categories_[0],
    index=X_train.index
)

condition_encoded_train
```

Out[80]:

	1	2	3	4	5
4438	0.0	0.0	1.0	0.0	0.0
15353	0.0	0.0	1.0	0.0	0.0
6845	0.0	0.0	1.0	0.0	0.0
18197	0.0	0.0	1.0	0.0	0.0
2198	0.0	0.0	1.0	0.0	0.0
...	...	...	...	...	...
11604	0.0	0.0	1.0	0.0	0.0
12305	0.0	0.0	1.0	0.0	0.0
5551	0.0	1.0	0.0	0.0	0.0
889	0.0	0.0	1.0	0.0	0.0
16247	0.0	0.0	0.0	1.0	0.0

15733 rows × 5 columns

In [81]:

```
# Drop original condition column
X_train.drop('condition', axis=1, inplace=True)
X_train
```

Out[81]:

	bedrooms	bathrooms	sqft_living	sqft_lot	waterfront	flo
4438	4	2.50	2770	6000	0.0	
15353	4	1.50	2480	6383	0.0	
6845	4	2.50	2320	7800	0.0	
18197	3	1.50	1930	11092	0.0	
2198	4	3.75	4490	34982	0.0	
...	...	...	...	...	...	
11604	4	2.75	2640	35070	0.0	
12305	2	1.50	1140	1149	0.0	
5551	2	2.00	1060	4000	0.0	
889	3	2.50	3000	25341	0.0	
16247	3	1.00	1400	8710	0.0	

15733 rows × 8 columns

In [82]:

```
# Concatenate the new dataframe with current df
X_train = pd.concat([X_train, condition_encoded_train], a
X_train
```

Out[82]:

	bedrooms	bathrooms	sqft_living	sqft_lot	waterfront	flo
4438	4	2.50	2770	6000	0.0	
15353	4	1.50	2480	6383	0.0	
6845	4	2.50	2320	7800	0.0	
18197	3	1.50	1930	11092	0.0	
2198	4	3.75	4490	34982	0.0	
...	...	...	...	...	...	
11604	4	2.75	2640	35070	0.0	
12305	2	1.50	1140	1149	0.0	
5551	2	2.00	1060	4000	0.0	
889	3	2.50	3000	25341	0.0	
16247	3	1.00	1400	8710	0.0	

15733 rows × 13 columns

In [83]:

```
# dropping a column related to condition to avoid the du
X_train.drop(1, axis=1, inplace=True)
X_train
```

Out[83]:

	bedrooms	bathrooms	sqft_living	sqft_lot	waterfront	flo
4438	4	2.50	2770	6000	0.0	

4438	4	2.50	2770	6000	0.0
15353	4	1.50	2480	6383	0.0
6845	4	2.50	2320	7800	0.0
18197	3	1.50	1930	11092	0.0
2198	4	3.75	4490	34982	0.0
...	...	...	...	...	...
11604	4	2.75	2640	35070	0.0
12305	2	1.50	1140	1149	0.0
5551	2	2.00	1060	4000	0.0
889	3	2.50	3000	25341	0.0
16247	3	1.00	1400	8710	0.0

15733 rows × 12 columns

In [84]:

```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15733 entries, 4438 to 16247
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   bedrooms     15733 non-null  int64  
 1   bathrooms    15733 non-null  float64
 2   sqft_living  15733 non-null  int64  
 3   sqft_lot     15733 non-null  int64  
 4   waterfront   15733 non-null  float64
 5   floors       15733 non-null  float64
 6   grade        15733 non-null  int32  
 7   yr_built     15733 non-null  int64  
 8   2            15733 non-null  float64
 9   3            15733 non-null  float64
 10  4            15733 non-null  float64
 11  5            15733 non-null  float64
dtypes: float64(7), int32(1), int64(4)
memory usage: 1.5 MB
```

In [85]:

```
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[85]:

```
LinearRegression()
```

In [86]:

```
# use cross validation to take a look at the model's per
cross_val_score(model, X_train, y_train, cv=3)
```

Out[86]:

```
array([0.61210062, 0.60849282, 0.59087099])
```

Preprocess for Test Data

Apply same steps on Test Data

In [87]:

```
# Preprocess Test Data
X_test = X_test.loc[:, relevant_columns]
```

```
X_test = X_test.loc[:, relevant_columns]
```

In [88]:
```
X_test
```

Out[88]:

	bedrooms	bathrooms	sqft_living	sqft_lot	waterfront	floo
2597	2	1.00	900	7620	0.0	
4481	4	2.50	2020	7277	0.0	
7616	3	1.75	1300	7735	0.0	
8953	4	2.25	3190	11597	0.0	
5575	4	1.75	1780	9794	0.0	
...	...	...	...	...	...	
3088	2	2.00	1780	3810	0.0	
8182	5	2.50	1970	8605	0.0	
18357	2	1.75	950	15219	0.0	
1319	3	1.50	1380	6657	0.0	
5802	3	2.50	2130	12245	0.0	

5245 rows × 9 columns

In [89]:
```
# One-hot encode condition
condition_test = X_test[["condition"]]
condition_encoded_test = ohe.transform(condition_test)
condition_encoded_test = pd.DataFrame(
    condition_encoded_test,
    columns=ohe.categories_[0],
    index=X_test.index
)
X_test.drop("condition", axis=1, inplace=True)
X_test = pd.concat([X_test, condition_encoded_test], axi

# Visually inspect X_test
X_test
```

Out[89]:

	bedrooms	bathrooms	sqft_living	sqft_lot	waterfront	floo
2597	2	1.00	900	7620	0.0	
4481	4	2.50	2020	7277	0.0	
7616	3	1.75	1300	7735	0.0	
8953	4	2.25	3190	11597	0.0	
5575	4	1.75	1780	9794	0.0	
...	...	...	...	...	...	
3088	2	2.00	1780	3810	0.0	
8182	5	2.50	1970	8605	0.0	
18357	2	1.75	950	15219	0.0	
1319	3	1.50	1380	6657	0.0	

5802	3	2.50	2130	12245	0.0

5245 rows × 13 columns

In [90]:

```
X_test.drop(1, axis=1, inplace=True)
X_test
```

Out[90]:

	bedrooms	bathrooms	sqft_living	sqft_lot	waterfront	floo
2597	2	1.00	900	7620	0.0	
4481	4	2.50	2020	7277	0.0	
7616	3	1.75	1300	7735	0.0	
8953	4	2.25	3190	11597	0.0	
5575	4	1.75	1780	9794	0.0	
...	...	...	...	...	...	
3088	2	2.00	1780	3810	0.0	
8182	5	2.50	1970	8605	0.0	
18357	2	1.75	950	15219	0.0	
1319	3	1.50	1380	6657	0.0	
5802	3	2.50	2130	12245	0.0	

5245 rows × 12 columns

In [91]:

```
model.fit(X_train, y_train)
model.score(X_test, y_test)
```

Out[91]:

```
0.6172888187559109
```

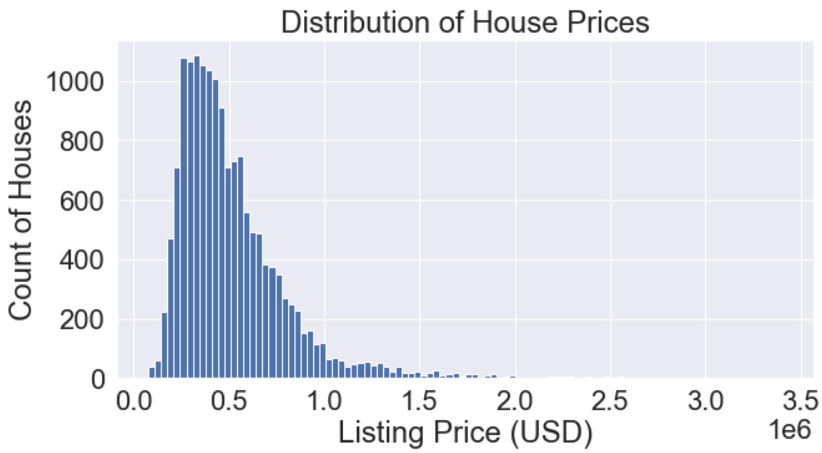
In [92]:

```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15733 entries, 4438 to 16247
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   bedrooms     15733 non-null  int64  
 1   bathrooms    15733 non-null  float64
 2   sqft_living  15733 non-null  int64  
 3   sqft_lot     15733 non-null  int64  
 4   waterfront   15733 non-null  float64
 5   floors       15733 non-null  float64
 6   grade        15733 non-null  int32  
 7   yr_built     15733 non-null  int64  
 8   2            15733 non-null  float64
 9   3            15733 non-null  float64
 10  4            15733 non-null  float64
 11  5            15733 non-null  float64
dtypes: float64(7), int32(1), int64(4)
memory usage: 1.5 MB
```

In [93]:

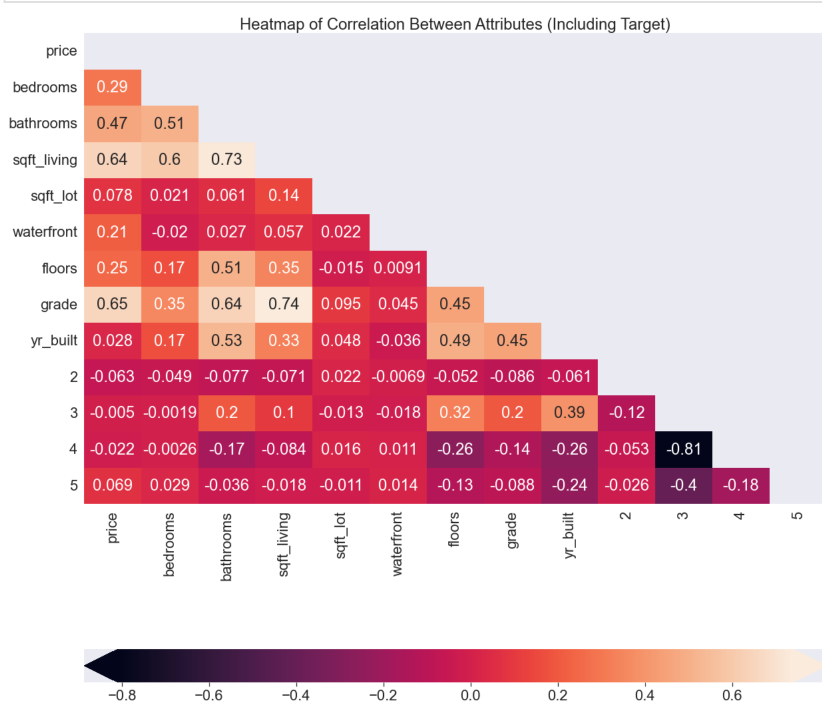
```
# A visualization of the distribution of the target vari
fig, ax = plt.subplots(figsize=(10, 5))

ax.hist(y_train, bins=100)

ax.set_xlabel("Listing Price (USD)")
ax.set_ylabel("Count of Houses")
ax.set_title("Distribution of House Prices");
```



Interpret a Correlation Heatmap

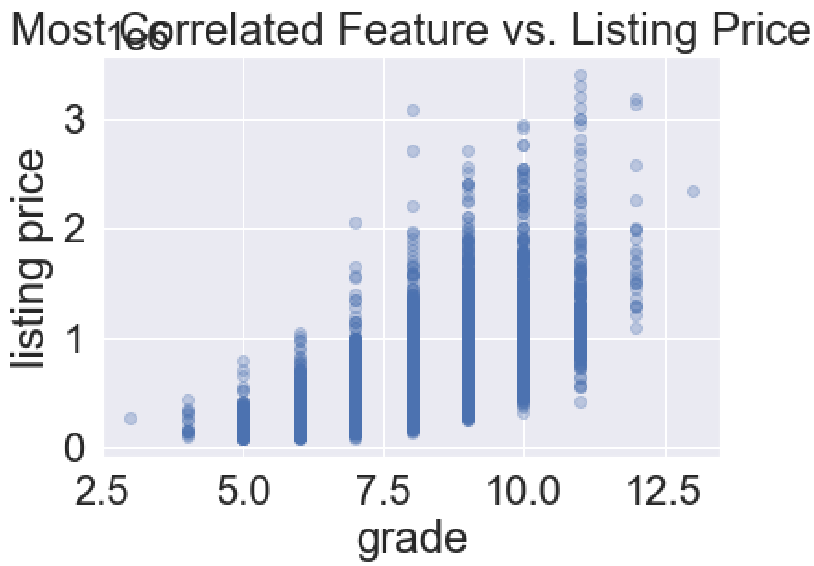
In [94]:

```
heatmap_data = pd.concat([y_train, X_train], axis=1)
corr = heatmap_data.corr()

# Set up figure and axes
fig, ax = plt.subplots(figsize=(20, 20))

sns.heatmap(
    data=corr,
    mask=np.triu(np.ones_like(corr, dtype=bool)),
    ax=ax,
    annot=True,
    cbar_kws={"label": "Correlation", "orientation": "hor
)

ax.set_title("Heatmap of Correlation Between Attributes
```



In [95]:
```
most_correlated_feature = 'grade'
```

In [96]:
```
fig, ax = plt.subplots()

ax.scatter(X_train[most_correlated_feature], y_train, al
ax.set_xlabel(most_correlated_feature)
ax.set_ylabel("listing price")
ax.set_title("Most Correlated Feature vs. Listing Price"
```



In [97]:
```
baseline_model = LinearRegression()
```

In [98]:
```
from sklearn.model_selection import cross_validate, Shuf

splitter = ShuffleSplit(n_splits=3, test_size=0.25, rand

baseline_scores = cross_validate(
    estimator=baseline_model,
    X=X_train[[most_correlated_feature]],
    y=y_train,
    return_train_score=True,
    cv=splitter
)

print("Train score:     ", baseline_scores["train_score"
print("Validation score:", baseline_scores["test_score"]
```

```
Train score:      0.4219222881153983
Validation score: 0.41992301320322056
```

In [99]:
```
w = X_train
k = y_train
```

In [100…
```
X_intw = sm.add_constant(w)
X_intw
```

Out[100…

	const	bedrooms	bathrooms	sqft_living	sqft_lot	waterfro
4438	1.0	4	2.50	2770	6000	(

15353	1.0	4	1.50	2480	6383	(
6845	1.0	4	2.50	2320	7800	(
18197	1.0	3	1.50	1930	11092	(
2198	1.0	4	3.75	4490	34982	(
...	...	...	...	...	...	
11604	1.0	4	2.75	2640	35070	(
12305	1.0	2	1.50	1140	1149	(
5551	1.0	2	2.00	1060	4000	(
889	1.0	3	2.50	3000	25341	(
16247	1.0	3	1.00	1400	8710	(

15733 rows × 13 columns

In [101…

```
model1 = sm.OLS(k,X_intw).fit()
```

In [102…

```
model1.summary()
```

Out[102…

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.605
Model:	OLS	**Adj. R-squared:**	0.605
Method:	Least Squares	**F-statistic:**	2010.
Date:	Fri, 27 May 2022	**Prob (F-statistic):**	0.00
Time:	15:14:57	**Log-Likelihood:**	-2.1360e+05
No. Observations:	15733	**AIC:**	4.272e+05
Df Residuals:	15720	**BIC:**	4.273e+05
Df Model:	12		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.97**
const	6.248e+06	1.36e+05	45.958	0.000	5.98e+06	6.51e+
bedrooms	-3.418e+04	2300.737	-14.854	0.000	-3.87e+04	-2.97e+
bathrooms	4.541e+04	3685.584	12.320	0.000	3.82e+04	5.26e+
sqft_living	134.6878	3.685	36.554	0.000	127.465	141.9
sqft_lot	-0.0739	0.038	-1.963	0.050	-0.148	-0.0
waterfront	6.071e+05	1.99e+04	30.437	0.000	5.68e+05	6.46e+
floors	2.776e+04	3554.094	7.809	0.000	2.08e+04	3.47e+
grade	1.343e+05	2254.597	59.571	0.000	1.3e+05	1.39e+
yr_built	-3604.5959	68.996	-52.243	0.000	-3739.837	-3469.3

2	2.458e+04	4.41e+04	0.557	0.577	-6.19e+04	1.11e+
3	4.773e+04	4.09e+04	1.168	0.243	-3.23e+04	1.28e+
4	6.359e+04	4.09e+04	1.556	0.120	-1.65e+04	1.44e+
5	1.004e+05	4.11e+04	2.442	0.015	1.98e+04	1.81e+

Omnibus:	7150.736	**Durbin-Watson:**	1.990
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	86958.778
Skew:	1.863	**Prob(JB):**	0.00
Kurtosis:	13.898	**Cond. No.**	3.98e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.98e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

the R Squared value increased to 0.605

Model #3: Dropping multicollinear features

In [103…

```
X_train.info()
```

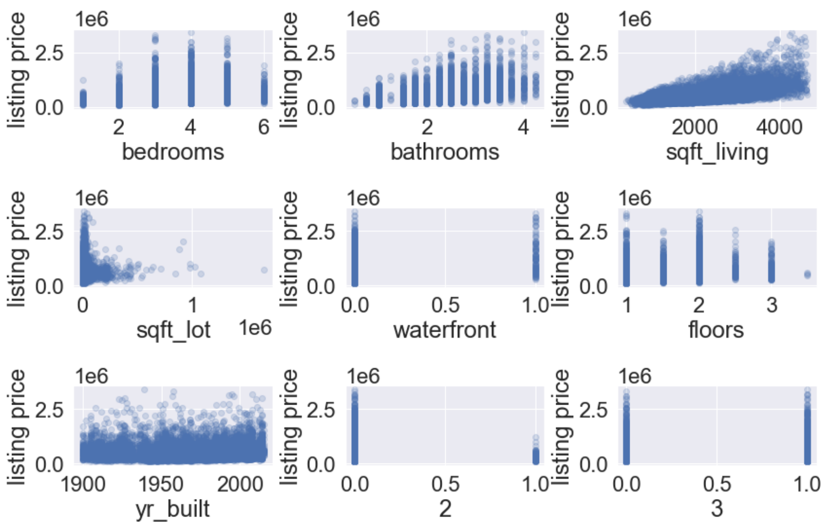
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15733 entries, 4438 to 16247
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   bedrooms     15733 non-null  int64  
 1   bathrooms    15733 non-null  float64
 2   sqft_living  15733 non-null  int64  
 3   sqft_lot     15733 non-null  int64  
 4   waterfront   15733 non-null  float64
 5   floors       15733 non-null  float64
 6   grade        15733 non-null  int32  
 7   yr_built     15733 non-null  int64  
 8   2            15733 non-null  float64
 9   3            15733 non-null  float64
 10  4            15733 non-null  float64
 11  5            15733 non-null  float64
dtypes: float64(7), int32(1), int64(4)
memory usage: 1.5 MB
```

In [104…

```
scatterplot_data = X_train.drop("grade", axis=1)

fig, axes = plt.subplots(ncols=3, nrows=3, figsize=(12, 
fig.set_tight_layout(True)

for index, col in enumerate(scatterplot_data.columns):
```

```
    ax = axes[index//3][index%3]
    ax.scatter(X_train[col], y_train, alpha=0.2)
    ax.set_xlabel(col)
    ax.set_ylabel("listing price")
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_8052/2401537943.py in <module>
      5
      6 for index, col in enumerate(scatterplot_data.columns):
----> 7     ax = axes[index//3][index%3]
      8     ax.scatter(X_train[col], y_train, alpha=0.2)
      9     ax.set_xlabel(col)

IndexError: index 3 is out of bounds for axis 0 with size 3
```



In [105…

```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15733 entries, 4438 to 16247
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   bedrooms     15733 non-null  int64  
 1   bathrooms    15733 non-null  float64
 2   sqft_living  15733 non-null  int64  
 3   sqft_lot     15733 non-null  int64  
 4   waterfront   15733 non-null  float64
 5   floors       15733 non-null  float64
 6   grade        15733 non-null  int32  
 7   yr_built     15733 non-null  int64  
 8   2            15733 non-null  float64
 9   3            15733 non-null  float64
 10  4            15733 non-null  float64
 11  5            15733 non-null  float64
dtypes: float64(7), int32(1), int64(4)
memory usage: 1.5 MB
```

In [106…

```
X_train_second_model = X_train.drop(['sqft_living',
                                     'yr_built', 2, 3, 4

X_train_second_model
```

Out[106…

	bedrooms	bathrooms	sqft_lot	waterfront	floors	grade
4438	4	2.50	6000	0.0	2.0	8
15353	4	1.50	6383	0.0	1.0	7
6845	4	2.50	7800	0.0	2.0	8
18197	3	1.50	11092	0.0	1.0	7
2198	4	3.75	34982	0.0	2.0	12
...	...	...	...	...	...	...
11604	4	2.75	35070	0.0	1.5	8
12305	2	1.50	1149	0.0	2.0	7
5551	2	2.00	4000	0.0	1.0	7
889	3	2.50	25341	0.0	2.0	9
16247	3	1.00	8710	0.0	1.0	7

15733 rows × 6 columns

In [107…

```
second_model = LinearRegression()

second_model_scores = cross_validate(
    estimator=second_model,
    X=X_train_second_model,
    y=y_train,
    return_train_score=True,
    cv=splitter
)

print("Current Model")
print("Train score:     ", second_model_scores["train_sc
print("Validation score:", second_model_scores["test_sco
print()
print("Model #2")
print("Train score:     ", baseline_scores["train_score"
print("Validation score:", baseline_scores["test_score"]
```

```
Current Model
Train score:      0.46954786364807233
Validation score: 0.4603851781117901

Model #2
Train score:      0.4219222881153983
Validation score: 0.41992301320322056
```

In [108…

```
# use StatsModels to fit and evaluate a linear regressio
# features used in the second model.
sm.OLS(y_train, sm.add_constant(X_train_second_model)).f
```

Out[108… OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.467
Model:	OLS	**Adj. R-squared:**	0.467
Method:	Least Squares	**F-statistic:**	2300.
Date:	Fri, 27 May 2022	**Prob (F-statistic):**	0.00

Time:	15:15:07	**Log-Likelihood:**	-2.1596e+05
No. Observations:	15733	**AIC:**	4.319e+05
Df Residuals:	15726	**BIC:**	4.320e+05
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.9
const	-8.163e+05	1.36e+04	-60.204	0.000	-8.43e+05	-7.9e+
bedrooms	1.767e+04	2405.816	7.346	0.000	1.3e+04	2.24e+
bathrooms	3.947e+04	3733.831	10.570	0.000	3.21e+04	4.68e+
sqft_lot	0.0655	0.043	1.516	0.130	-0.019	0.1
waterfront	7.362e+05	2.31e+04	31.905	0.000	6.91e+05	7.81e+
floors	-4.452e+04	3912.360	-11.379	0.000	-5.22e+04	-3.69e+
grade	1.65e+05	2139.292	77.116	0.000	1.61e+05	1.69e+

Omnibus:	7255.448	**Durbin-Watson:**	1.986
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	70378.748
Skew:	1.977	**Prob(JB):**	0.00
Kurtosis:	12.577	**Cond. No.**	5.71e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.71e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

Model #4: Using significant Features

In [109…

```
significant_features = ["sqft_living", "grade", "bathroo
```

In [110…

```
third_model = LinearRegression()
X_train_third_model = X_train[significant_features]

third_model_scores = cross_validate(
    estimator=third_model,
    X=X_train_third_model,
    y=y_train,
    return_train_score=True,
    cv=splitter
)

print("Current Model")
print("Train score:      ", third_model_scores["train_sco
```

```
print("Validation score:", third_model_scores["test_scor
print()
print("Model #3")
print("Train score:     ", second_model_scores["train_sc
print("Validation score:", second_model_scores["test_sco
print()
print("Model #2")
print("Train score:     ", baseline_scores["train_score"
print("Validation score:", baseline_scores["test_score"]
```

```
Current Model
Train score:      0.48532525501683654
Validation score: 0.4807175934734418

Model #3
Train score:      0.46954786364807233
Validation score: 0.4603851781117901

Model #2
Train score:      0.4219222881153983
Validation score: 0.41992301320322056
```

Selecting Features with sklearn

In [111…

```
from sklearn.feature_selection import RFECV
from sklearn.preprocessing import StandardScaler

# Importances are based on coefficient magnitude, so
# we need to scale the data to normalize the coefficient
X_train_for_RFECV = StandardScaler().fit_transform(X_tra

model_for_RFECV = LinearRegression()

# Instantiate and fit the selector
selector = RFECV(model_for_RFECV, cv=splitter)
selector.fit(X_train_for_RFECV, y_train)

# Print the results
print("Was the column selected?")
for index, col in enumerate(X_train_second_model.columns
    print(f"{col}: {selector.support_[index]}")
```

```
Was the column selected?
bedrooms: True
bathrooms: True
sqft_lot: False
waterfront: True
floors: True
grade: True
```

In [112…

```
from itertools import combinations

features = ["sqft_living", "grade", "bathrooms", "bedroo

# Make a dataframe to hold the results (not strictly nec
# but it makes the output easier to read)
results_df = pd.DataFrame(columns=features)

# Selecting just piece_count
results_df = results_df.append({
    "train_score": baseline_scores["train_score"].mean()
    "val_score": baseline_scores["test_score"].mean()
}, ignore_index=True)
```

```python
# Selecting 1 additional feature
for feature in features[1:]:
    scores = cross_validate(
        estimator=second_model,
        X=X_train[["sqft_living", feature]],
        y=y_train,
        return_train_score=True,
        cv=splitter
    )
    # Note: this technique of appending to a df is quite
    # Here it works because it's only happening 6 times,
    # doing this for a whole dataset
    results_df = results_df.append({
        feature: "Yes",
        "train_score": scores["train_score"].mean(),
        "val_score": scores["test_score"].mean()
    }, ignore_index=True)

# Selecting 2 additional features
for (feature1, feature2) in list(combinations(features[1
    scores = cross_validate(
        estimator=second_model,
        X=X_train[["sqft_living", feature1, feature2]],
        y=y_train,
        return_train_score=True,
        cv=splitter
    )
    results_df = results_df.append({
        feature1: "Yes",
        feature2: "Yes",
        "train_score": scores["train_score"].mean(),
        "val_score": scores["test_score"].mean()
    }, ignore_index=True)

# Fill in remaining values where appropriate
results_df["sqft_living"] = "Yes"
results_df.fillna("No", inplace=True)

results_df
```

Out[112...

	sqft_living	grade	bathrooms	bedrooms	floors	train_score
0	Yes	No	No	No	No	0.421922
1	Yes	Yes	No	No	No	0.481754
2	Yes	No	Yes	No	No	0.414831
3	Yes	No	No	Yes	No	0.430300
4	Yes	No	No	No	Yes	0.415664
5	Yes	Yes	Yes	No	No	0.485325
6	Yes	Yes	No	Yes	No	0.488349
7	Yes	Yes	No	No	Yes	0.484683
8	Yes	No	Yes	Yes	No	0.430500
9	Yes	No	Yes	No	Yes	0.415866
10	Yes	No	No	Yes	Yes	0.430801

The best model uses sqft_living, grade, and bathrooms. It has a validation score of 0.4807

Q3: What combinations of features is the best fit for price predictions?

Grade, sqft_living and bathrooms are the best fit for a multiple regression model. These features are highly correlated with price, have relatively low multicollinearity, and can together account for more than half of the variability of price. All multiple regression assumptions are satisfied with these features included.

Model #5: Using relevant features & OneHotEncoding

In [113…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20978 entries, 0 to 21596
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   id           20978 non-null  int64
 1   price        20978 non-null  int32
 2   bedrooms     20978 non-null  int64
 3   bathrooms    20978 non-null  float64
 4   sqft_living  20978 non-null  int64
 5   sqft_lot     20978 non-null  int64
 6   floors       20978 non-null  float64
 7   waterfront   20978 non-null  float64
 8   condition    20978 non-null  int64
 9   grade        20978 non-null  int32
 10  yr_built     20978 non-null  int64
dtypes: float64(3), int32(2), int64(6)
memory usage: 1.8 MB
```

In [114…

```
condition_train2 = df[['condition']]

ohe2 = OneHotEncoder(categories='auto', sparse=False, ha

ohe2.fit(condition_train2)

ohe2.categories_
```

Out[114…

```
[array([1, 2, 3, 4, 5], dtype=int64)]
```

In [115…

```
condition_encoded_train2 = ohe.transform(condition_train

condition_encoded_train2
```

Out[115…

```
array([[0., 0., 1., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 1., 0., 0.],
       ...,
       [0., 0., 1., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 1., 0., 0.]])
```

In [116…

```
condition_encoded_train2 = pd.DataFrame(
    condition_encoded_train2,
    columns=ohe2.categories_[0],
    index=df.index
)

condition_encoded_train2
```

Out[116…

	1	2	3	4	5
0	0.0	0.0	1.0	0.0	0.0
1	0.0	0.0	1.0	0.0	0.0
2	0.0	0.0	1.0	0.0	0.0
3	0.0	0.0	0.0	0.0	1.0
4	0.0	0.0	1.0	0.0	0.0
...	...	...	...	...	...
21592	0.0	0.0	1.0	0.0	0.0
21593	0.0	0.0	1.0	0.0	0.0
21594	0.0	0.0	1.0	0.0	0.0
21595	0.0	0.0	1.0	0.0	0.0
21596	0.0	0.0	1.0	0.0	0.0

20978 rows × 5 columns

In [117…

```
df.drop('condition', axis=1, inplace=True)
df
```

Out[117…

	id	price	bedrooms	bathrooms	sqft_living	sqf
0	7129300520	221900	3	1.00	1180	
1	6414100192	538000	3	2.25	2570	
2	5631500400	180000	2	1.00	770	1(
3	2487200875	604000	4	3.00	1960	
4	1954400510	510000	3	2.00	1680	
...	...	...	...	...	...	
21592	263000018	360000	3	2.50	1530	
21593	6600060120	400000	4	2.50	2310	
21594	1523300141	402101	2	0.75	1020	
21595	291310100	400000	3	2.50	1600	
21596	1523300157	325000	2	0.75	1020	

20978 rows × 10 columns

In [118…

```
df = pd.concat([df, condition_encoded_train2], axis=1)
```

```
df
```

Out[118…

	id	price	bedrooms	bathrooms	sqft_living	sqf
0	7129300520	221900	3	1.00	1180	
1	6414100192	538000	3	2.25	2570	
2	5631500400	180000	2	1.00	770	1
3	2487200875	604000	4	3.00	1960	
4	1954400510	510000	3	2.00	1680	
...	...	...	...	...	...	
21592	263000018	360000	3	2.50	1530	
21593	6600060120	400000	4	2.50	2310	
21594	1523300141	402101	2	0.75	1020	
21595	291310100	400000	3	2.50	1600	
21596	1523300157	325000	2	0.75	1020	

20978 rows × 15 columns

In [119…

```
df.drop(1, axis=1, inplace=True)
df
```

Out[119…

	id	price	bedrooms	bathrooms	sqft_living	sqf
0	7129300520	221900	3	1.00	1180	
1	6414100192	538000	3	2.25	2570	
2	5631500400	180000	2	1.00	770	1
3	2487200875	604000	4	3.00	1960	
4	1954400510	510000	3	2.00	1680	
...	...	...	...	...	...	
21592	263000018	360000	3	2.50	1530	
21593	6600060120	400000	4	2.50	2310	
21594	1523300141	402101	2	0.75	1020	
21595	291310100	400000	3	2.50	1600	
21596	1523300157	325000	2	0.75	1020	

20978 rows × 14 columns

In [120…

```
df1 = df.drop('id', axis=1)
df1
```

Out[120…

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	221900	3	1.00	1180	5650	1.0

1	538000	3	2.25	2570	7242	2.0
2	180000	2	1.00	770	10000	1.0
3	604000	4	3.00	1960	5000	1.0
4	510000	3	2.00	1680	8080	1.0
...	...	...	...	...	...	...
21592	360000	3	2.50	1530	1131	3.0
21593	400000	4	2.50	2310	5813	2.0
21594	402101	2	0.75	1020	1350	2.0
21595	400000	3	2.50	1600	2388	2.0
21596	325000	2	0.75	1020	1076	2.0

20978 rows × 13 columns

In [121…

```
home_preds = df1.drop(['price'], axis=1)
home_target = df1['price']
home_preds.head()
```

Out[121…

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	3	1.00	1180	5650	1.0	0.0
1	3	2.25	2570	7242	2.0	0.0
2	2	1.00	770	10000	1.0	0.0
3	4	3.00	1960	5000	1.0	0.0
4	3	2.00	1680	8080	1.0	0.0

In [122…

```
# use sm.add_constant() to add constant term/y-intercept
predictors = sm.add_constant(home_preds)
predictors
```

Out[122…

	const	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	1.0	3	1.00	1180	5650	1.0
1	1.0	3	2.25	2570	7242	2.0
2	1.0	2	1.00	770	10000	1.0
3	1.0	4	3.00	1960	5000	1.0
4	1.0	3	2.00	1680	8080	1.0
...	...	...	...	...	...	...
21592	1.0	3	2.50	1530	1131	3.0
21593	1.0	4	2.50	2310	5813	2.0
21594	1.0	2	0.75	1020	1350	2.0
21595	1.0	3	2.50	1600	2388	2.0
21596	1.0	2	0.75	1020	1076	2.0

20978 rows × 13 columns

In [123…

```
model_last = sm.OLS(home_target, predictors).fit()
```

In [124…

```
model_last.summary()
```

Out[124…

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.608
Model:	OLS	**Adj. R-squared:**	0.608
Method:	Least Squares	**F-statistic:**	2714.
Date:	Fri, 27 May 2022	**Prob (F-statistic):**	0.00
Time:	15:15:37	**Log-Likelihood:**	-2.8457e+05
No. Observations:	20978	**AIC:**	5.692e+05
Df Residuals:	20965	**BIC:**	5.693e+05
Df Model:	12		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.9**
const	6.271e+06	1.17e+05	53.444	0.000	6.04e+06	6.5e+
bedrooms	-3.297e+04	1964.610	-16.782	0.000	-3.68e+04	-2.91e+
bathrooms	4.428e+04	3155.827	14.032	0.000	3.81e+04	5.05e+
sqft_living	136.4605	3.161	43.168	0.000	130.264	142.6
sqft_lot	-0.1020	0.033	-3.078	0.002	-0.167	-0.0
floors	2.771e+04	3048.120	9.091	0.000	2.17e+04	3.37e+
waterfront	6.05e+05	1.74e+04	34.702	0.000	5.71e+05	6.39e+
grade	1.324e+05	1916.038	69.122	0.000	1.29e+05	1.36e+
yr_built	-3585.1348	59.361	-60.396	0.000	-3701.486	-3468.7
2	-2.727e+04	3.86e+04	-0.706	0.480	-1.03e+05	4.84e+
3	-3446.1909	3.58e+04	-0.096	0.923	-7.36e+04	6.67e+
4	1.041e+04	3.58e+04	0.291	0.771	-5.97e+04	8.05e+
5	4.853e+04	3.6e+04	1.349	0.177	-2.2e+04	1.19e+

Omnibus:	9066.183	**Durbin-Watson:**	1.975
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	102134.623
Skew:	1.772	**Prob(JB):**	0.00
Kurtosis:	13.212	**Cond. No.**	3.93e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.93e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [150…

```
X3_train, X3_test, y3_train, y3_test = train_test_split(
```

In [151…

```
print(f"X3_train is a DataFrame with {X3_train.shape[0]}
print(f"y3_train is a Series with {y3_train.shape[0]} va

# We always should have the same number of rows in X as
assert X3_train.shape[0] == y3_train.shape[0]
```

```
X3_train is a DataFrame with 15733 rows and 12 columns
y3_train is a Series with 15733 values
```

In [152…

```
X3_train_final = X3_train
X3_test_final = X3_test
```

In [153…

```
final_model1 = LinearRegression()

final_model1.fit(X3_train_final, y3_train)

final_model1.score(X3_test_final, y3_test)
```

Out[153…

```
0.6172888187559094
```

In [154…

```
print(pd.Series(final_model1.coef_, index=X3_train_final
print()
print("Intercept:", final_model1.intercept_)
```

```
bedrooms        -34176.178912
bathrooms        45405.475771
sqft_living        134.687758
sqft_lot            -0.073950
floors           27755.688990
waterfront      607066.744164
grade           134307.611086
yr_built         -3604.595878
2                24583.808899
3                47732.087851
4                63586.399956
5               100360.721272
Name: Coefficients, dtype: float64

Intercept: 6248401.9943853
```

Model #6: Final Model

Using relevant features, dropping multicollinear feature, log transform, and Onehotencoding.

In [125…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20978 entries, 0 to 21596
Data columns (total 14 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   id           20978 non-null  int64  
 1   price        20978 non-null  int32  
 2   bedrooms     20978 non-null  int64  
 3   bathrooms    20978 non-null  float64
 4   sqft_living  20978 non-null  int64  
 5   sqft_lot     20978 non-null  int64  
 6   floors       20978 non-null  float64
 7   waterfront   20978 non-null  float64
 8   grade        20978 non-null  int32  
 9   yr_built     20978 non-null  int64  
 10  2            20978 non-null  float64
 11  3            20978 non-null  float64
 12  4            20978 non-null  float64
 13  5            20978 non-null  float64
dtypes: float64(7), int32(2), int64(5)
memory usage: 2.2 MB
```

In [126…

```
df = df.drop('id', axis=1)
df.head()
```

Out[126…

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wat
0	221900	3	1.00	1180	5650	1.0	
1	538000	3	2.25	2570	7242	2.0	
2	180000	2	1.00	770	10000	1.0	
3	604000	4	3.00	1960	5000	1.0	
4	510000	3	2.00	1680	8080	1.0	

In [127…

```
continuous = ['sqft_living', 'sqft_lot', 'price']
categoricals = ['bedrooms', 'bathrooms', 'floors', 'wate
```

In [128…

```
df[continuous]
```

Out[128…

	sqft_living	sqft_lot	price
0	1180	5650	221900
1	2570	7242	538000
2	770	10000	180000
3	1960	5000	604000
4	1680	8080	510000
...	...	...	...
21592	1530	1131	360000
21593	2310	5813	400000

21594	1020	1350	402101
21595	1600	2388	400000
21596	1020	1076	325000

20978 rows × 3 columns

In [129…

```
# Log transform and normalize
home_cont2 = df[continuous]

# log features
log_names2 = [f'{column}_log' for column in home_cont2.co

home_log2 = np.log(home_cont2)
home_log2.columns = log_names2

# normalize (subract mean and divide by std)

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

home_log_norm2 = home_log2.apply(normalize)
```

In [130…

```
#remove multicollinear feature
home_ohe2 = df.drop('sqft_living', axis=1)
```

In [131…

```
preprocessed2 = pd.concat([home_log_norm2, home_ohe2], ax
preprocessed2.head()
```

Out[131…

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathr
0	-1.136064	-0.372410	-1.430051	221900	3	
1	0.789421	-0.094105	0.337619	538000	3	
2	-2.192023	0.267662	-1.847742	180000	2	
3	0.119151	-0.509429	0.568580	604000	4	
4	-0.262167	0.028650	0.230940	510000	3	

In [132…

```
X2 = preprocessed2.drop('price', axis=1)
X2.head()
```

Out[132…

	sqft_living_log	sqft_lot_log	price_log	bedrooms	bathrooms	s
0	-1.136064	-0.372410	-1.430051	3	1.00	
1	0.789421	-0.094105	0.337619	3	2.25	
2	-2.192023	0.267662	-1.847742	2	1.00	
3	0.119151	-0.509429	0.568580	4	3.00	
4	-0.262167	0.028650	0.230940	3	2.00	

In [133…

```
X2 = X2.drop('sqft_lot', axis=1)
```

```
X2 = X2.drop('sqft_lot', axis=1)
X2.head()
```

Out[133...

	sqft_living_log	sqft_lot_log	price_log	bedrooms	bathrooms	fl
0	-1.136064	-0.372410	-1.430051	3	1.00	
1	0.789421	-0.094105	0.337619	3	2.25	
2	-2.192023	0.267662	-1.847742	2	1.00	
3	0.119151	-0.509429	0.568580	4	3.00	
4	-0.262167	0.028650	0.230940	3	2.00	

In [134...

```
X2 = X2.drop('price_log', axis=1)
X2.head()
```

Out[134...

	sqft_living_log	sqft_lot_log	bedrooms	bathrooms	floors	wate
0	-1.136064	-0.372410	3	1.00	1.0	
1	0.789421	-0.094105	3	2.25	2.0	
2	-2.192023	0.267662	2	1.00	1.0	
3	0.119151	-0.509429	4	3.00	1.0	
4	-0.262167	0.028650	3	2.00	1.0	

In [135...

```
y2 = preprocessed2['price_log']
```

In [136...

```
X_int2 = sm.add_constant(X2)
model6 = sm.OLS(y2,X_int2).fit()
model6.summary()
```

Out[136...

OLS Regression Results

Dep. Variable:	price_log	**R-squared:**	0.613
Model:	OLS	**Adj. R-squared:**	0.613
Method:	Least Squares	**F-statistic:**	2767.
Date:	Fri, 27 May 2022	**Prob (F-statistic):**	0.00
Time:	15:16:03	**Log-Likelihood:**	-19810.
No. Observations:	20978	**AIC:**	3.965e+04
Df Residuals:	20965	**BIC:**	3.975e+04
Df Model:	12		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	19.7594	0.387	51.104	0.000	19.002	20.517
sqft_living_log	0.3609	0.009	40.552	0.000	0.343	0.378
sqft_lot_log	-0.0734	0.005	-14.580	0.000	-0.083	-0.064

bedrooms	-0.0941	0.007	-14.123	0.000	-0.107	-0.081
bathrooms	0.1649	0.011	15.504	0.000	0.144	0.186
floors	0.0936	0.011	8.756	0.000	0.073	0.115
waterfront	1.1089	0.058	19.238	0.000	0.996	1.222
grade	0.4661	0.006	76.113	0.000	0.454	0.478
yr_built	-0.0120	0.000	-61.587	0.000	-0.012	-0.012
2	-0.0574	0.128	-0.450	0.652	-0.307	0.193
3	0.2412	0.118	2.041	0.041	0.010	0.473
4	0.2890	0.118	2.446	0.014	0.057	0.521
5	0.4016	0.119	3.379	0.001	0.169	0.635

Omnibus:	71.580	**Durbin-Watson:**	1.971
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	93.291
Skew:	-0.037	**Prob(JB):**	5.52e-21
Kurtosis:	3.318	**Cond. No.**	1.81e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.81e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

R-squared: The r-squared value, 0.613, indicates that the model can account for about 61% of the variability of price around its mean.

the features have a high p-value, lets remove condition 2.

Model #7: Final Model Fix

In [137...

```
X2 = X2.drop(2, axis=1)
X2.head()
```

Out[137...

	sqft_living_log	sqft_lot_log	bedrooms	bathrooms	floors	wate
0	-1.136064	-0.372410	3	1.00	1.0	
1	0.789421	-0.094105	3	2.25	2.0	
2	-2.192023	0.267662	2	1.00	1.0	
3	0.119151	-0.509429	4	3.00	1.0	
4	-0.262167	0.028650	3	2.00	1.0	

In [138...

```
X_int2 = sm.add_constant(X2)
```

```
model7 = sm.OLS(y2,X_int2).fit()
model7.summary()
```

Out[138… OLS Regression Results

Dep. Variable:	price_log	**R-squared:**	0.613
Model:	OLS	**Adj. R-squared:**	0.613
Method:	Least Squares	**F-statistic:**	3018.
Date:	Fri, 27 May 2022	**Prob (F-statistic):**	0.00
Time:	15:16:10	**Log-Likelihood:**	-19810.
No. Observations:	20978	**AIC:**	3.964e+04
Df Residuals:	20966	**BIC:**	3.974e+04
Df Model:	11		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	19.7143	0.373	52.794	0.000	18.982	20.446
sqft_living_log	0.3609	0.009	40.555	0.000	0.343	0.378
sqft_lot_log	-0.0734	0.005	-14.578	0.000	-0.083	-0.064
bedrooms	-0.0942	0.007	-14.127	0.000	-0.107	-0.081
bathrooms	0.1649	0.011	15.505	0.000	0.144	0.186
floors	0.0937	0.011	8.763	0.000	0.073	0.115
waterfront	1.1092	0.058	19.247	0.000	0.996	1.222
grade	0.4661	0.006	76.115	0.000	0.454	0.478
yr_built	-0.0120	0.000	-61.610	0.000	-0.012	-0.012
3	0.2901	0.046	6.269	0.000	0.199	0.381
4	0.3379	0.046	7.279	0.000	0.247	0.429
5	0.4505	0.048	9.334	0.000	0.356	0.545

Omnibus:	71.581	**Durbin-Watson:**	1.971
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	93.354
Skew:	-0.036	**Prob(JB):**	5.35e-21
Kurtosis:	3.319	**Cond. No.**	1.71e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.71e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

R-squared: The r-squared value, 0.613, indicates that the

model can account for about 61% of the variability of price around its mean.

p-value: All of the p-values are less than 0.5, which means we can reject the null hypothesis.

In [139…
```
X2_train, X2_test, y2_train, y2_test = train_test_split(X
```

In [140…
```
print(f"X2_train is a DataFrame with {X2_train.shape[0]}
print(f"y2_train is a Series with {y2_train.shape[0]} va

# We always should have the same number of rows in X as
assert X2_train.shape[0] == y2_train.shape[0]
```

```
X2_train is a DataFrame with 15733 rows and 11 columns
y2_train is a Series with 15733 values
```

In [141…
```
X2_train_final = X2_train
X2_test_final = X2_test
```

In [142…
```
final_model = LinearRegression()

final_model.fit(X2_train_final, y2_train)

final_model.score(X2_test_final, y2_test)
```

Out[142…
```
0.6145468303796924
```

In [143…
```
# use cross validation to take a look at the model's per
cross_val_score(final_model, X2_train, y2_train, cv=3)
```

Out[143…
```
array([0.61118744, 0.61761319, 0.60586161])
```

Regression Results

In [144…
```
# user friendly metrics
from sklearn.metrics import mean_squared_error

mean_squared_error(y2_test, final_model.predict(X2_test_
```

Out[144…
```
0.6218011343164459
```

This means that for an average house, this algorithm will be off by about 104,012 dollars.

In [145…
```
# Interpret the Final Model
print(pd.Series(final_model.coef_, index=X2_train_final.
print()
print("Intercept:", final_model.intercept_)
```

```
sqft_living_log    0.354131
sqft_lot_log      -0.069461
bedrooms          -0.095418
bathrooms          0.163152
floors             0.098707
waterfront         1.144082
```

```
grade                0.469890
yr_built            -0.012007
3                    0.325523
4                    0.380132
5                    0.485771
Name: Coefficients, dtype: float64

Intercept: 19.566478652566683
```

According to our model, the log price of an average house will go up by 0.16 dollars by one increase in bathrooms and 0.35 dollars by increasing the log sqft_living.

Evaluation

1. Investigate Linearity
2. Investigate Normality - QQ Plot
3. Investigate Multicollinearity
4. Investigate Homoscedasticity

In [146…

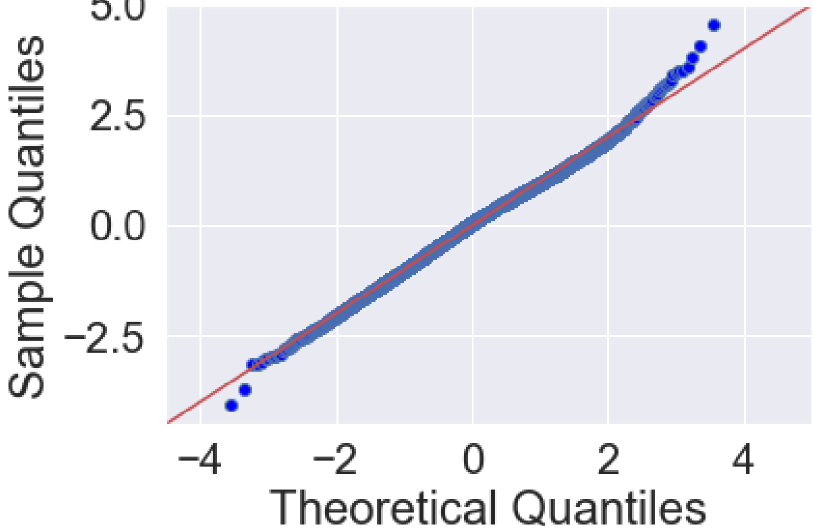
```python
# Investigating Linearity
preds = final_model.predict(X2_test_final)
fig, ax = plt.subplots()

ax.scatter(y2_test, preds, alpha=0.5)
ax.set_xlabel("Actual Price")
ax.set_ylabel("Predicted Price")
ax.legend();
```

```
No handles with labels found to put in legend.
```

We have some outliers that are all over the place, but in general it looks like we have a linear relationship (not violating this assumption)

In [147…

```python
# Investigating Normality QQPlot
import scipy.stats as stats

residuals = (y2_test - preds)
sm.graphics.qqplot(residuals, dist=stats.norm, line='45'
```



Since almost all of the datapoints fall along a straight line in this QQ-plot, we can consider the normality assumption satisfied

In [148…

```
# Investigating Multicollinearity
from statsmodels.stats.outliers_influence import varianc
vif = [variance_inflation_factor(X2_train_final.values, i
pd.Series(vif, index=X2_train_final.columns, name="Variar
```

Out[148…

```
sqft_living_log       4.303137
sqft_lot_log          1.368904
bedrooms             28.306718
bathrooms            27.008616
floors               14.863076
waterfront            1.015819
grade               121.295582
yr_built            270.868190
3                    72.086166
4                    29.072516
5                     9.478880
Name: Variance Inflation Factor, dtype: float64
```

In [155…

```
print('Multicollinear Features')
display(MC_df)
```

Multicollinear Features

	Correlations	Features
2	0.737053	[sqft_living, grade]
3	0.737053	[grade, sqft_living]
0	0.725613	[bathrooms, sqft_living]
1	0.725613	[sqft_living, bathrooms]

Although we still have a couple pairs of highly correlated variables, they each come out well below the acceptable correlation value of 0.75 suggesting that we in fact do not have an issue of high multi-collinearity.

In [149…

```
# Investigating Homoscedasticity
fig, ax = plt.subplots()

ax.scatter(preds, residuals, alpha=0.5)
```

```
ax.plot(preds, [0 for i in range(len(X2_test))])
ax.set_xlabel("Predicted Value")
ax.set_ylabel("Actual - Predicted Value");
```