Step 1: Our Stakeholder and the Business Problem.

HGTV SHOW

-HGTV is launching a show based on homes in kings county. The goal of the show is to show homeowners what predictors lead to a higher listing price so the owner can sell and maximize profit.The goal is getting homes with good grades and base quality that may need a couple of alterations to maximize it's value.

IMPORTING LIBRARIES

In [1]:
```
#importing the necessary libraries for the project.
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFE
from sklearn.preprocessing import PolynomialFeatures, StandardScaler
import statsmodels
from statsmodels.formula.api import ols
from sklearn.model_selection import train_test_split
from sklearn.dummy import DummyRegressor
from statsmodels.tools.eval_measures import rmse
from statsmodels.api import qqplot
from scipy import stats
from sklearn.preprocessing import OneHotEncoder
from folium.plugins import FastMarkerCluster
import folium
from sklearn.metrics import r2_score
import branca.colormap as cm
```

In [2]:
```
#loading in the data and making a pandas dataframe.
df = pd.read_csv('data/kc_house_data.csv')
df.info()
```

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

EDA(EXPLORITORY DATA ANALYSIS)

In [3]:

```
#Exploring the columns and values.
df.head()
```

Out[3]:

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

5 rows × 21 columns

-Exploring some low hanging data. some standouts: Avaerage house in this county have 3 bedrooms and 2 bathrooms. -Theres a hosue in the set that gas 33 bedrooms and 8 bathroom which will defiently be an outlier. -Oldest house is dated to 1900. While he most recent hosue was built in 2015.

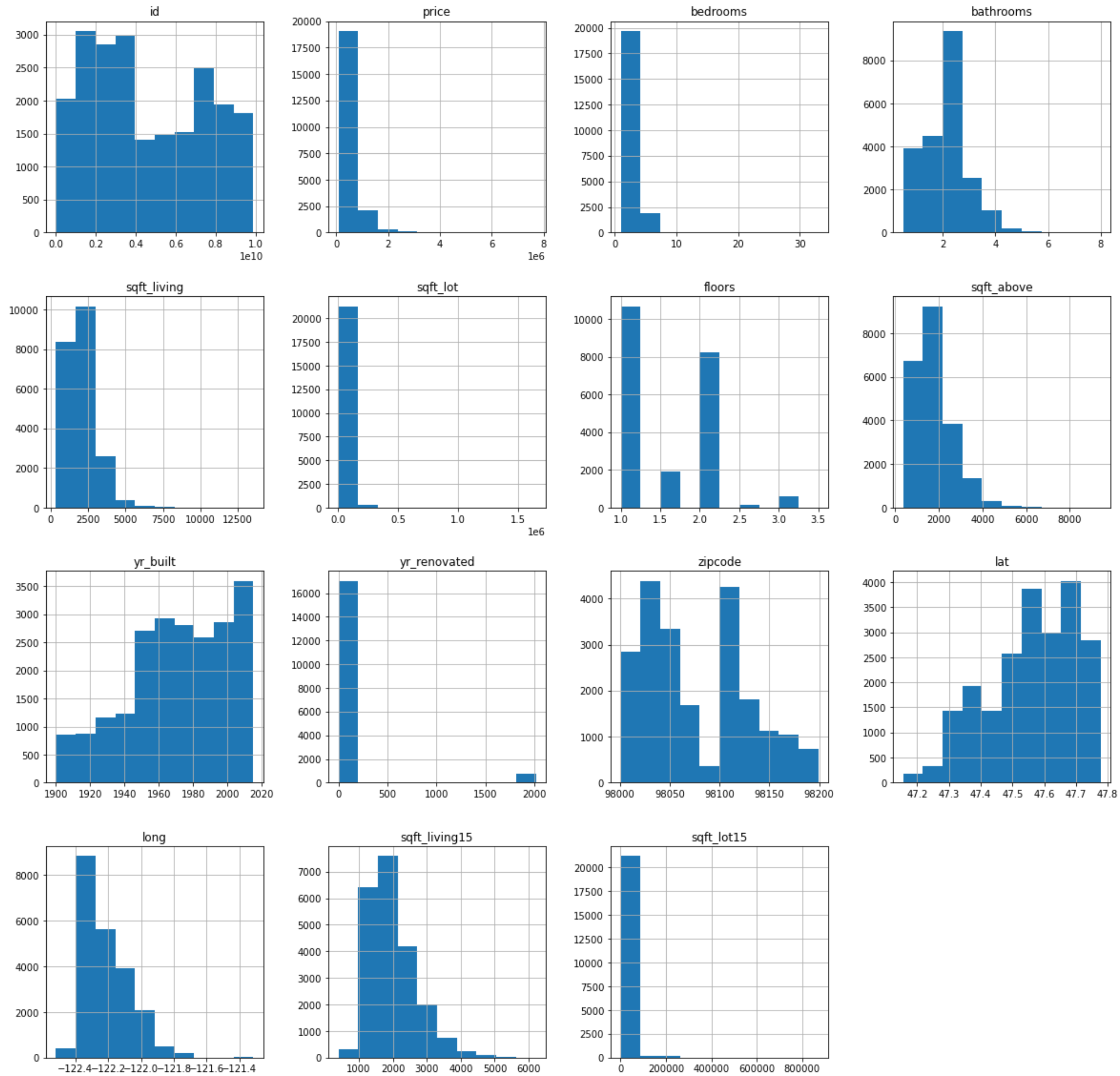
In [6]:
```
df.describe()
```

Out[6]:

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

Running a histogram of the dataframe. So visibily see the distribution. Apart from Latitude and Year Built. Most of the variables distrubte the right.

In [5]:
```
df.hist(figsize=(20,20));
```



-Dropping houses that are repeated. some houses are repeated if they had rennovations done. -Filling in waterfront's NA values with 0 -Dropping years renovated column because a large amount og

In [7]:
```
#exploring and filtering

df.drop_duplicates(subset='id',keep='first',inplace=True)
df['waterfront'].fillna(0, inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21420 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21420 non-null  int64
 1   date           21420 non-null  object
 2   price          21420 non-null  float64
 3   bedrooms       21420 non-null  int64
 4   bathrooms      21420 non-null  float64
 5   sqft_living    21420 non-null  int64
 6   sqft_lot       21420 non-null  int64
 7   floors         21420 non-null  float64
 8   waterfront     21420 non-null  object
 9   view           21357 non-null  object
 10  condition      21420 non-null  object
 11  grade          21420 non-null  object
 12  sqft_above     21420 non-null  int64
 13  sqft_basement  21420 non-null  object
 14  yr_built       21420 non-null  int64
 15  yr_renovated   17616 non-null  float64
 16  zipcode        21420 non-null  int64
 17  lat            21420 non-null  float64
 18  long           21420 non-null  float64
 19  sqft_living15  21420 non-null  int64
 20  sqft_lot15     21420 non-null  int64
dtypes: float64(6), int64(9), object(6)
memory usage: 3.6+ MB
```

In [8]:

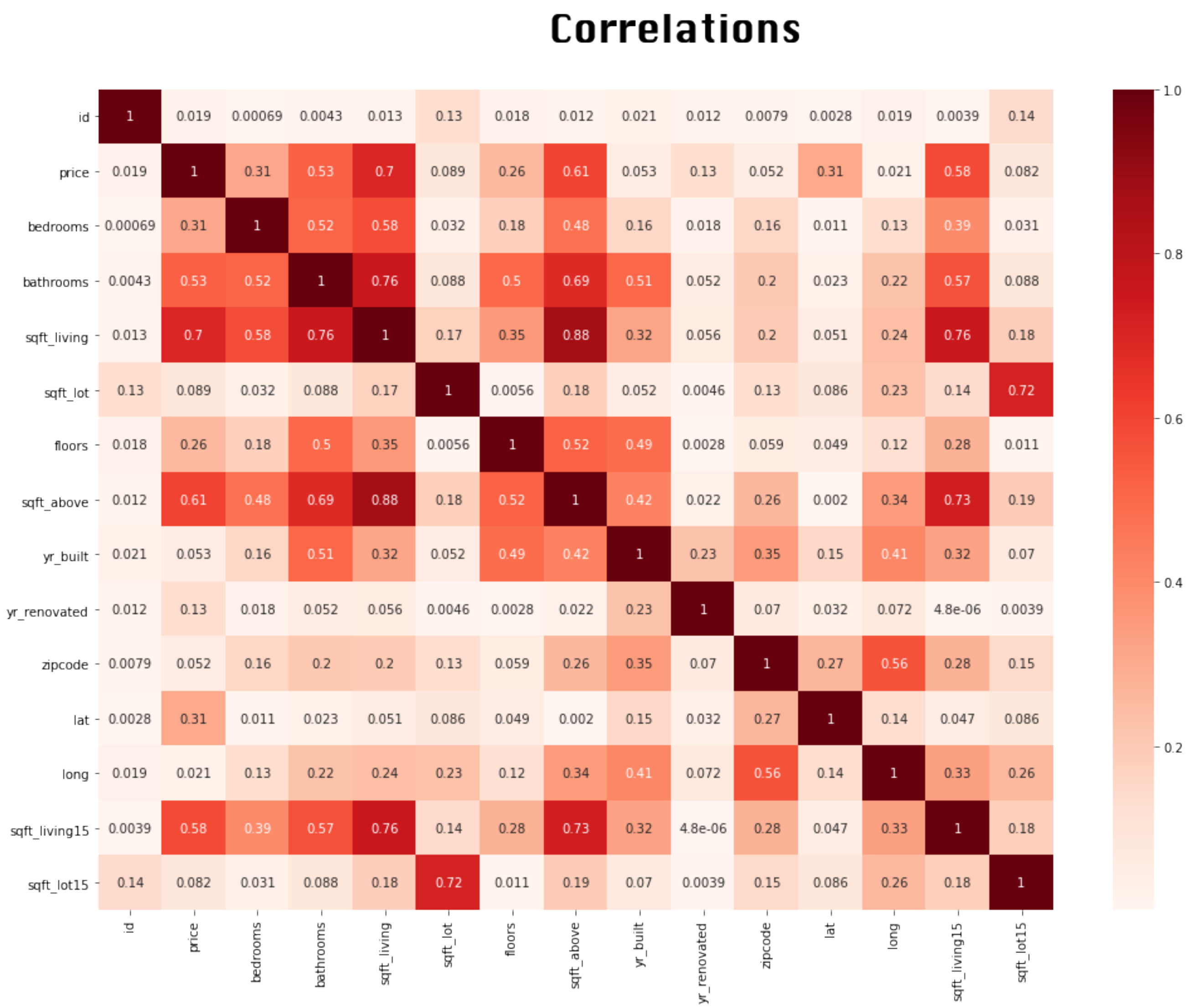
```
for column in list(df.columns):
    print(column, sum(df[column].isnull()))
```

```
id 0
date 0
price 0
bedrooms 0
bathrooms 0
sqft_living 0
sqft_lot 0
floors 0
waterfront 0
view 63
condition 0
grade 0
sqft_above 0
sqft_basement 0
yr_built 0
yr_renovated 3804
zipcode 0
lat 0
long 0
sqft_living15 0
sqft_lot15 0
```

Pre Model Assumptions

In [12]:

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



In [13]:
```
features = []
correlations = []
for idx, correlation in corr['price'].T.iteritems():
    if correlation >= .30 and idx != 'price':
        features.append(idx)
        correlations.append(correlation)
corr_with_price = pd.DataFrame({'Correlations':correlations, 'Features': feat

Multicollinear_Features = []
Multicollinear_Corr = []
def check_multicollinearity(feature):
    for idx, correlation in corr[feature].T.iteritems():
        if correlation >= .80 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': Multico
print('Multicollinear Features')
display(MC_df)
print('Correlations with Price')
display(MC_df)
```

```
Multicollinear Features
```

	Correlations	Features
0	0.876533	[sqft_living, sqft_above]
1	0.876533	[sqft_above, sqft_living]

```
Correlations with Price
```

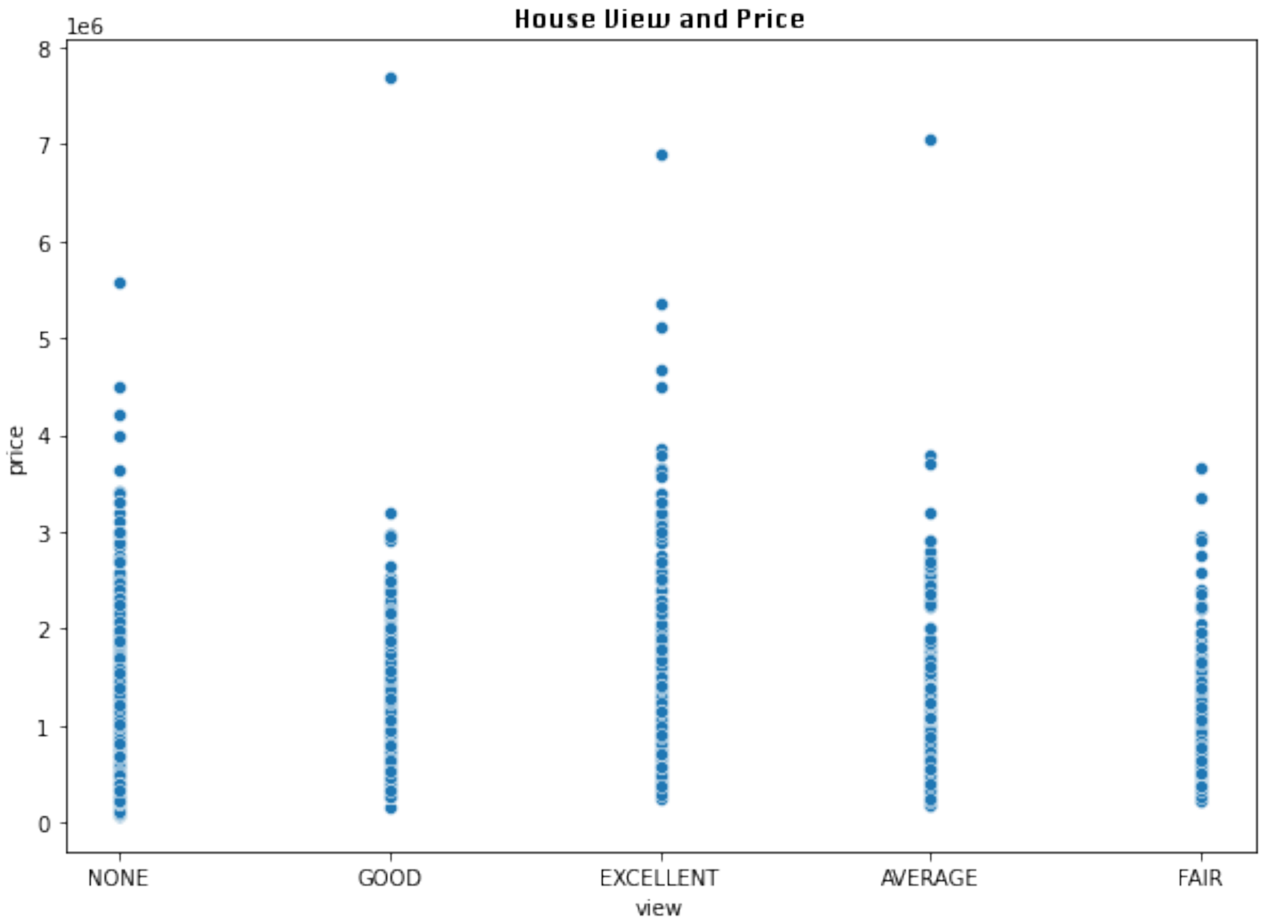
	Correlations	Features
0	0.876533	[sqft_living, sqft_above]
1	0.876533	[sqft_above, sqft_living]

In [14]:
```
plt.figure(figsize=(10,7))
sns.scatterplot(df['view'], df['price'])
plt.title('House View and Price', fontsize=12, fontname='silom')
```

```
/Users/olamideholayinka/opt/anaconda3/envs/learn-env/lib/python3.8/site-packag
es/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as k
eyword args: x, y. From version 0.12, the only valid positional argument will
be `data`, and passing other arguments without an explicit keyword will result
in an error or misinterpretation.
  warnings.warn(
```

Out[14]:

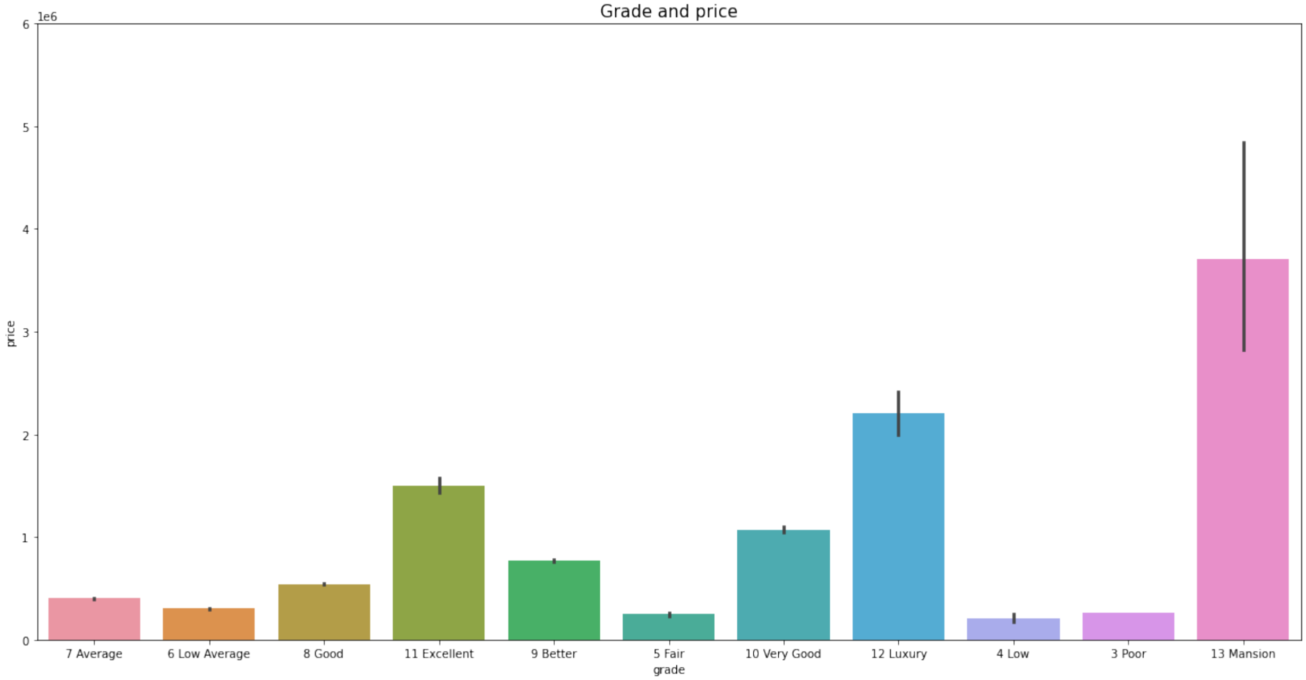
```
Text(0.5, 1.0, 'House View and Price')
```



In [13]:

```
fig, ax = plt.subplots(figsize =(20,10))
y = df['price']
x = df['grade']
sns.barplot(x,y)
ax.set_ylim(bottom=0,top=6000000)
plt.title('Grade and price', fontsize=15, fontname='silom');
```

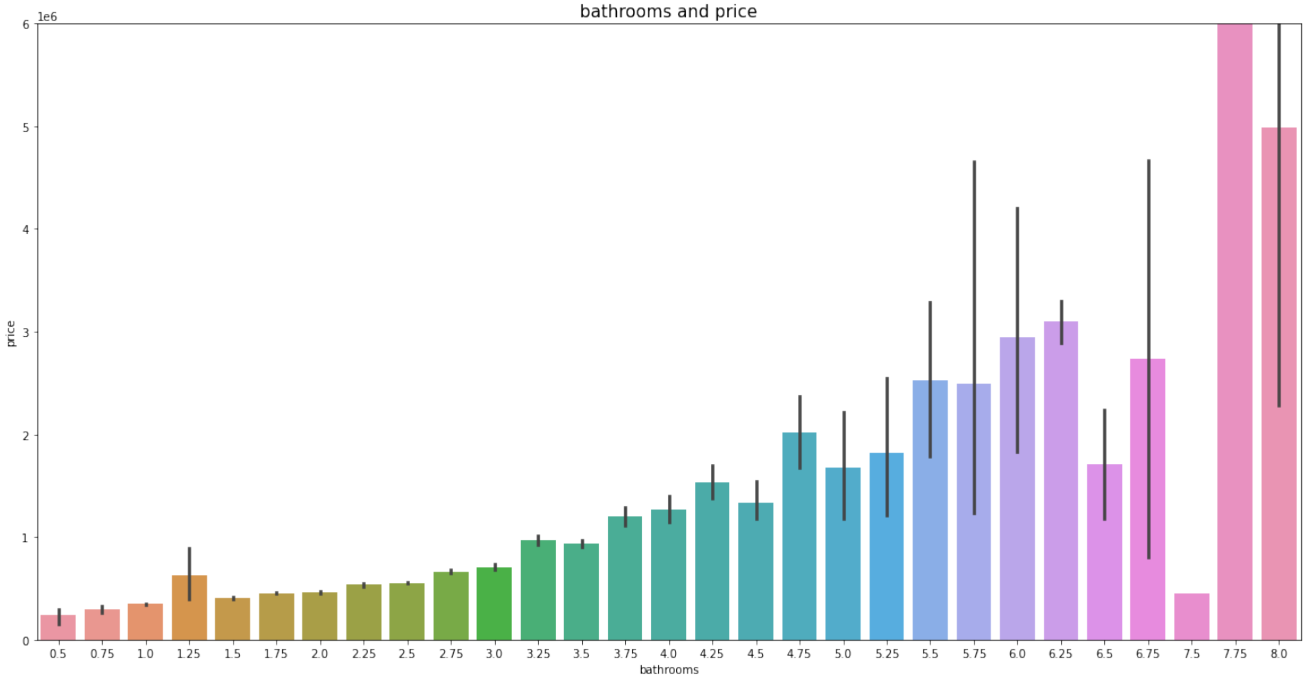
```
C:\Users\ilene\anaconda3\envs\learn-env\lib\site-packages\seaborn\_decorators.
py:36: FutureWarning: Pass the following variables as keyword args: x, y. From
version 0.12, the only valid positional argument will be `data`, and passing o
ther arguments without an explicit keyword will result in an error or misinter
pretation.
  warnings.warn(
```



In [30]:

```
fig, ax = plt.subplots(figsize =(20,10))
y = df['price']
x = df['bathrooms']
sns.barplot(x,y)
ax.set_ylim(bottom=0,top=6000000)
plt.title('bathrooms and price', fontsize=15, fontname='silom');
```

```
C:\Users\ilene\anaconda3\envs\learn-env\lib\site-packages\seaborn\_decorators.
py:36: FutureWarning: Pass the following variables as keyword args: x, y. From
version 0.12, the only valid positional argument will be `data`, and passing o
ther arguments without an explicit keyword will result in an error or misinter
pretation.
  warnings.warn(
```



In [15]:
```
def get_center_latlong(df):
    centerlat = (df['lat'].max() + df['lat'].min()) / 2
    centerlong =  (df['long'].max() + df['long'].min()) / 2
    return centerlat, centerlong
```

In [16]:
```
center = get_center_latlong(df)
```

In [17]:
```
colormap = cm.LinearColormap(colors=['darkblue', 'orange', 'yellow', 'lightye


sqft_map = folium.Map(location=center, zoom_start=10)
for i in range(len(df)):
    folium.Circle(
    location=[df.iloc[i]['lat'], df.iloc[i]['long']],
        radius=10,
        fill=True,
        color=colormap(df.iloc[i]['sqft_living']),
        fill_opacity=0.2).add_to(sqft_map)

sqft_map.add_child(colormap)
```

Out[17]: Make this Notebook Trusted to load map: File -> Trust Notebook

In [35]:
```
df = df[(df["bathrooms"] == 7.5)]
df
```

Out[35]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wa
8537	424049043	8/11/2014	450000.0	9	7.5	4050	6504	2.0	

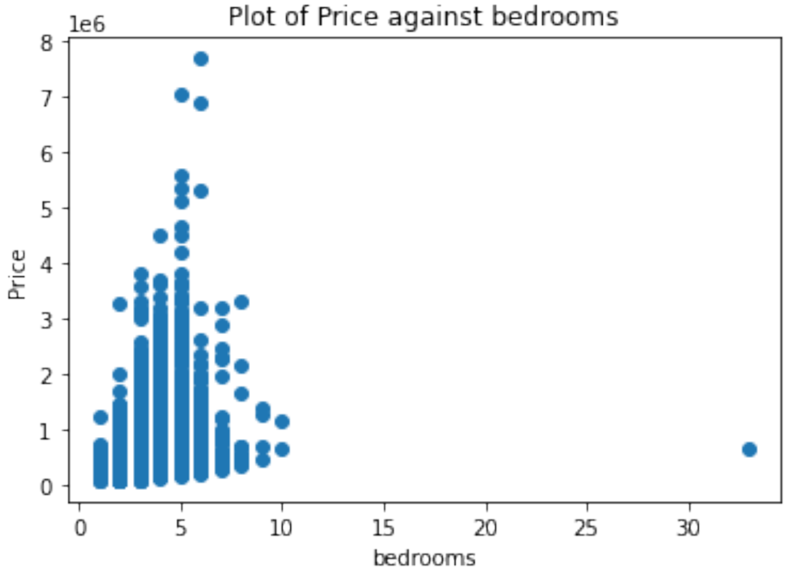
1 rows × 21 columns

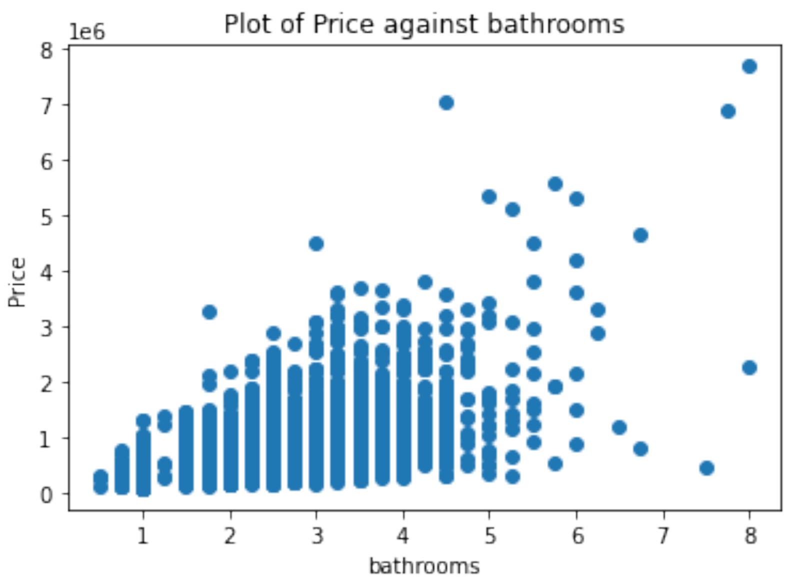
In [37]:
```
df.sqft_living.describe()
```

Out[37]:
```
count       1.0
mean     4050.0
std         NaN
min      4050.0
25%      4050.0
50%      4050.0
75%      4050.0
max      4050.0
Name: sqft_living, dtype: float64
```

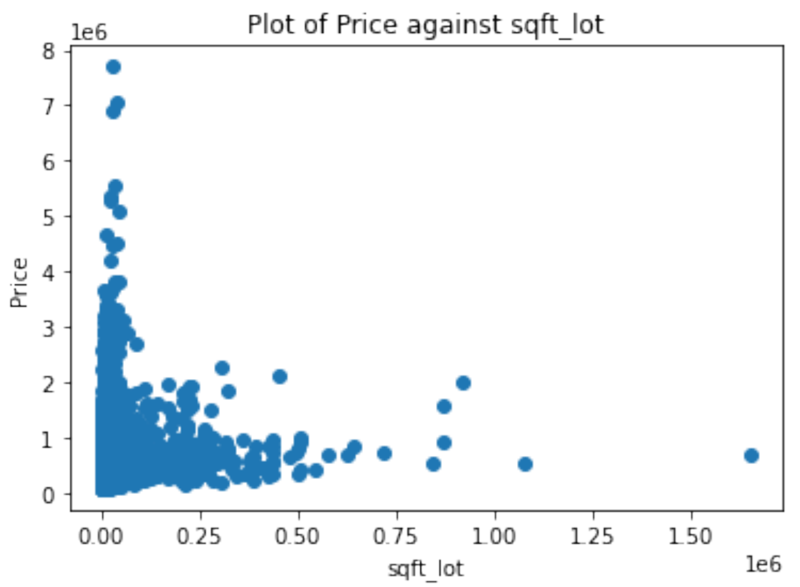
In [ ]:
```
# CHECKING FOR LINEARITY
```

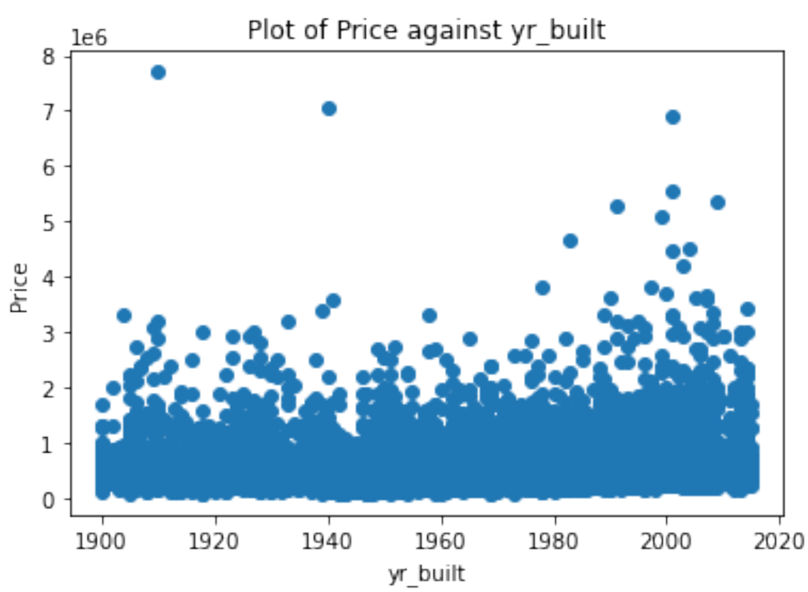
In [22]:
```
features = X_train.columns

for x in features:
    plt.scatter(X_train[x], y_train)
    plt.title(f'Plot of Price against {x}')
    plt.xlabel(x)
    plt.ylabel('Price')
    plt.show()

# also plot sales against itself
plt.scatter(y_train.index, y_train)
plt.hlines(y_train.mean(), 0, 200)
plt.xlabel('Index Value')
plt.ylabel('Price')
plt.title('Variance of Price')
plt.show()
```

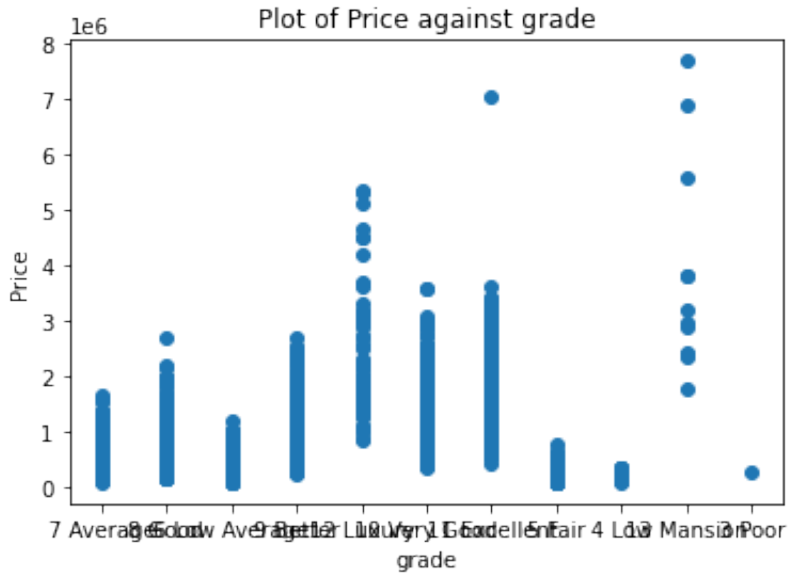





Plot of Price against sqft_living
1e6
Price
sqft_living
0
2000
4000
6000
8000
10000
12000
14000

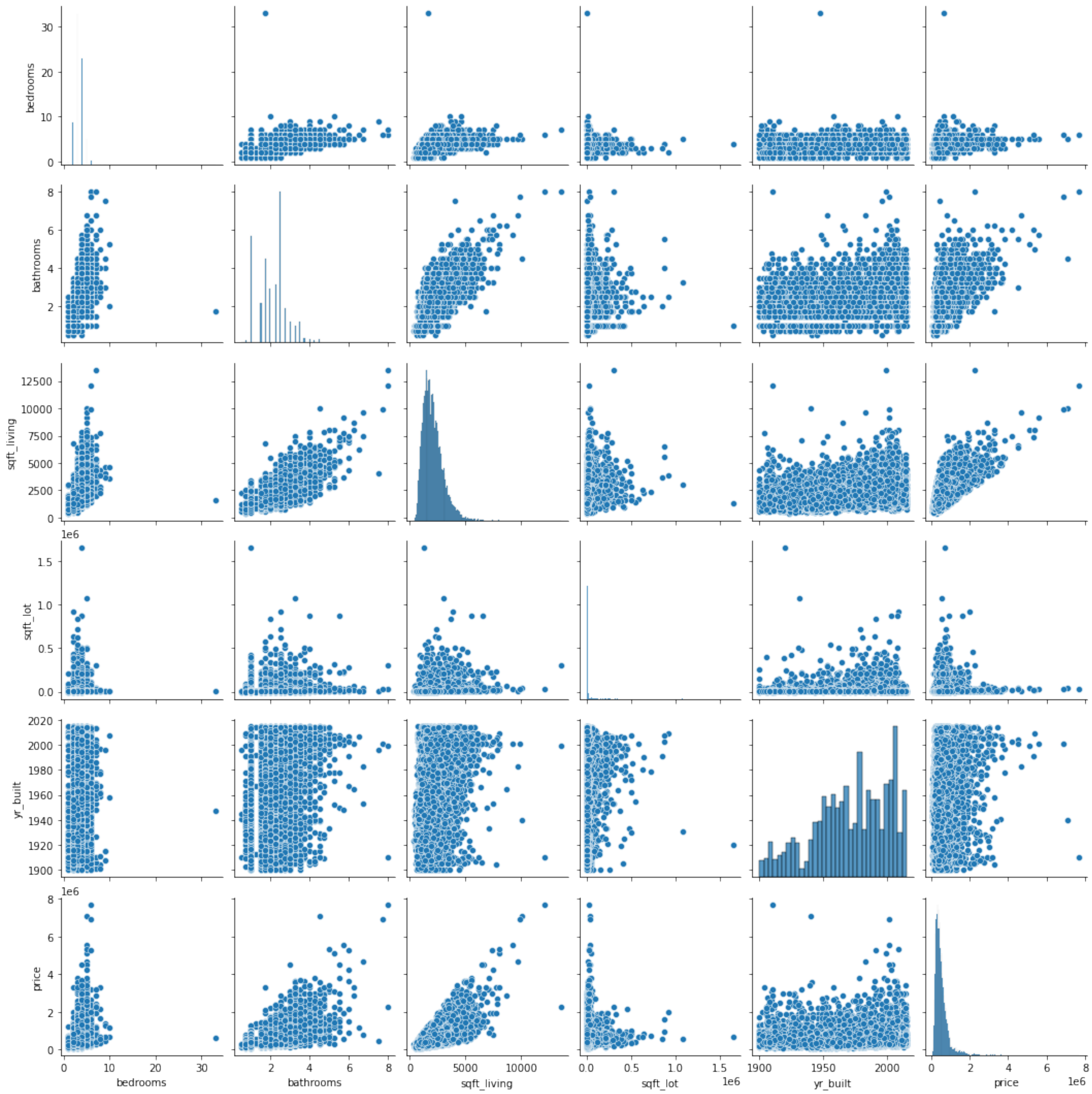

Plot of Price against sqft_lot
1e6
Price
sqft_lot
1e6
0.00
0.25
0.50
0.75
1.00
1.25
1.50


Plot of Price against yr_built
1e6
Price
yr_built
1900
1920
1940
1960
1980
2000
2020



In [23]:
```
train_df = pd.concat([X_train, y_train], axis =1)
```

In [24]:
```
sns.pairplot(train_df)
plt.show()
```



STEP 3 TRAIN TEST SPLIT

In [21]:
```
y = df.price
X = df[['bedrooms', 'bathrooms', 'sqft_living','sqft_lot','yr_built','grade'
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.20, random_state=42)
```

In [ ]:

STEP 4 ONE HOT ENCODE CATEGORICAL VARIABLE

In [ ]:
```
#grade
```

In [25]:
```
ohe = OneHotEncoder()
ohe.fit_transform(X_train)
```

Out[25]:
```
<17136x9494 sparse matrix of type '<class 'numpy.float64'>'
	with 102816 stored elements in Compressed Sparse Row format>
```

In [ ]:
```
```

In [26]:
```
train_df.corr()
```

Out[26]:

	bedrooms	bathrooms	sqft_living	sqft_lot	yr_built	price
bedrooms	1.000000	0.512126	0.575100	0.040754	0.152713	0.308335
bathrooms	0.512126	1.000000	0.756116	0.091503	0.503744	0.526030
sqft_living	0.575100	0.756116	1.000000	0.180099	0.314592	0.702331
sqft_lot	0.040754	0.091503	0.180099	1.000000	0.050806	0.092713
yr_built	0.152713	0.503744	0.314592	0.050806	1.000000	0.052383
price	0.308335	0.526030	0.702331	0.092713	0.052383	1.000000

STEP 5 CREATING DUMMY BASELINE

In [27]:
```
#Dummy Regressor for the baseline. DUMMY IS ONLY APPLIED ON TRAINING SET
dummy_regr = DummyRegressor(strategy='mean')
dummy_regr.fit(X_train, y_train)
dummy_regr.predict(X_train)
```

Out[27]:
```
array([542950.3173436, 542950.3173436, 542950.3173436, ...,
       542950.3173436, 542950.3173436, 542950.3173436])
```

In [28]:
```
dummy_regr.score(X_train, y_train)# the R score is zero.  The mean of Y expla
```

Out[28]:
```
0.0
```

In [ ]:
```
y_train.shape
y_train
```

RUNNING A SIMPLE MODEL WTIH VARIABLES []. THESE VARIBALES WERE CHOSEN BASED ON RFE OR VARS THAT ARE HIGHLY CORRELATED WITH SALES.

In [ ]:
```
# NOW CREATE FIRST SIMPLE MODEL THAT DOES BETTER THAN DUMMY REGRESSOR MEAN.
#EXAMPLES; RECURSIVE FEATURE ELIMINATION. LOOK AT HIGH CORRELATIONS VARIABLES

#MODEL 1
```

In [30]:
```
y = df.price
X = df[['bedrooms', 'bathrooms', 'sqft_living','sqft_lot','yr_built','grade',
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.20, random_state=42)
```

In [31]:
```
dummy_regr = DummyRegressor(strategy='mean')
dummy_regr.fit(X_train, y_train)
dummy_regr.predict(X_train)
```

Out[31]:
```
array([542950.3173436, 542950.3173436, 542950.3173436, ...,
       542950.3173436, 542950.3173436, 542950.3173436])
```

In [32]:
```
dummy_regr.score(X_train, y_train)
```

Out[32]:
```
0.0
```

In [33]:
```
grade_trial = pd.DataFrame()
grade_test = pd.DataFrame()
```

In [34]:
```
ohe = OneHotEncoder(sparse=False, handle_unknown='ignore')
grade_trial['grade'] = X_train['grade']
grade_trial['ID'] = len(X_train.values)
ohe_data = pd.DataFrame(ohe.fit_transform(grade_trial))
#grade_trial
ohe_data.columns = ohe.get_feature_names(['grade', 'ID'])
ohe_data = ohe_data.drop('ID_17136', axis=1)
#ohe_data

grade_test['grade'] = X_test['grade']
grade_test['ID'] = len(X_test.values)
ohe_test = pd.DataFrame(ohe.transform(grade_test))
ohe_test.columns = ohe.get_feature_names(['grade', 'ID'])
ohe_test = ohe_test.drop('ID_17136', axis=1)
```

In [ ]:

In [35]:
```
np.random.seed(42)

y = df.price
X = df[['bedrooms', 'bathrooms', 'sqft_living','sqft_lot','yr_built','grade',

# Train test split with random_state=42 and test_size=0.2

X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=42)

# Scale appropriately on TRAINING DATA

ss = StandardScaler()
ss.fit(X_train.drop('grade', axis=1))
Testpreds = ss.transform(X_test.drop('grade', axis=1))
X_preds_st_scaled = ss.transform(X_train.drop('grade', axis=1))

lr = LinearRegression()

# fit and score the model (checkout the test set if there is time)
lr.fit(X_preds_st_scaled, y_train)
lr.coef_
lr.score(X_preds_st_scaled, y_train)
```

Out[35]: 0.5547264615853337

In [36]:
```
combined_x = ohe_data.join(pd.DataFrame(X_preds_st_scaled))
combined_test = ohe_test.join(pd.DataFrame(Testpreds))
```

In [37]:
```
type(combined_test)
```

Out[37]: pandas.core.frame.DataFrame

In [38]:
```
lr = LinearRegression()

# fit and score the model (checkout the test set if there is time)
lr.fit(combined_x.values, y_train)
lr.coef_
lr.score(combined_x.values, y_train)
```

Out[38]: 0.6479566533507228

In [39]:
```
model1 = lr.predict(combined_test.values)
lr.coef_
lr.score(combined_test.values, y_test)
```

Out[39]: 0.6313406870043061

In [40]:
```
def sk_metrics(y, model):
    from sklearn.metrics import mean_squared_error, mean_absolute_error

    print("Metrics:")
    # R2
    print(f"R2: {r2_score(y, model):.3f}")
    # MAE
    print(f"Mean Absolute Error: {mean_absolute_error(y, model):.3f}")
    # MSE
    print(f"Mean Squared Error: {mean_squared_error(y, model):.3f}")
    # RMSE - just MSE but set squared=False
    print(f"Root Mean Squared Error: {mean_squared_error(y, model, squared=Fa
    return
```

In [41]:
```
sk_metrics(y_test, model1)
```

```
Metrics:
R2: 0.631
Mean Absolute Error: 136819.122
Mean Squared Error: 44643315242.166
Root Mean Squared Error: 211289.648
```

In [42]:
```
display(X_train.head())
display(X_test.head())
```

	bedrooms	bathrooms	sqft_living	sqft_lot	yr_built	grade	floors
13634	4	2.50	2240	4616	2001	7 Average	2.0
13631	2	2.25	2470	7658	1954	8 Good	1.0
5717	5	3.50	3530	218472	1999	7 Average	2.0
15431	4	1.50	1580	10230	1945	6 Low Average	1.0
17294	4	2.50	2070	10244	1969	8 Good	1.0

	bedrooms	bathrooms	sqft_living	sqft_lot	yr_built	grade	floors
6132	3	1.00	1020	6000	1900	7 Average	1.5
8993	3	1.75	1620	5500	1950	7 Average	1.0
559	4	2.50	2050	10271	1998	7 Average	2.0
11931	3	2.50	2510	5186	2001	7 Average	2.0
15176	2	2.00	1390	12530	1959	8 Good	1.0

In [43]:
```
# SECOND MODEL .R squared is lower than our first.
```

In [64]:
```
Model_2 = ols(formula="price ~bathrooms + bedrooms", data=df).fit()
Model_2.summary()
```

Out[64]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.279
Model:	OLS	**Adj. R-squared:**	0.279
Method:	Least Squares	**F-statistic:**	4142.
Date:	Thu, 17 Feb 2022	**Prob (F-statistic):**	0.00
Time:	15:32:08	**Log-Likelihood:**	-3.0140e+05
No. Observations:	21420	**AIC:**	6.028e+05
Df Residuals:	21417	**BIC:**	6.028e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-3.547e+04	8361.541	-4.242	0.000	-5.19e+04	-1.91e+04
bathrooms	2.39e+05	3240.812	73.754	0.000	2.33e+05	2.45e+05
bedrooms	2.07e+04	2692.095	7.691	0.000	1.54e+04	2.6e+04

Omnibus:	17197.290	**Durbin-Watson:**	1.969
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	897026.537
Skew:	3.474	**Prob(JB):**	0.00
Kurtosis:	33.932	**Cond. No.**	17.0

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

In [65]:

```
Model_3 = ols(formula="price ~sqft_living + sqft_living15 + sqft_lot ", data=
Model_3.summary()
#better r squared than our second but not better than our first
```

Out[65]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.501
Model:	OLS	**Adj. R-squared:**	0.500
Method:	Least Squares	**F-statistic:**	7155.
Date:	Thu, 17 Feb 2022	**Prob (F-statistic):**	0.00
Time:	15:32:08	**Log-Likelihood:**	-2.9747e+05
No. Observations:	21420	**AIC:**	5.949e+05
Df Residuals:	21416	**BIC:**	5.950e+05
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-1.004e+05	5456.168	-18.400	0.000	-1.11e+05	-8.97e+04
sqft_living	245.0885	2.970	82.528	0.000	239.268	250.909
sqft_living15	68.0150	3.962	17.168	0.000	60.250	75.780
sqft_lot	-0.3078	0.043	-7.085	0.000	-0.393	-0.223

Omnibus:	15375.814	**Durbin-Watson:**	1.989
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	666369.950
Skew:	2.967	**Prob(JB):**	0.00
Kurtosis:	29.672	**Cond. No.**	1.36e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.36e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

In [66]:

```
Model_4 = ols(formula="price ~sqft_living + sqft_living15", data=df).fit()
Model_4.summary()
```

Out[66]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.499
Model:	OLS	**Adj. R-squared:**	0.499
Method:	Least Squares	**F-statistic:**	1.068e+04
Date:	Thu, 17 Feb 2022	**Prob (F-statistic):**	0.00
Time:	15:32:09	**Log-Likelihood:**	-2.9749e+05
No. Observations:	21420	**AIC:**	5.950e+05
Df Residuals:	21417	**BIC:**	5.950e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-9.958e+04	5461.213	-18.234	0.000	-1.1e+05	-8.89e+04
sqft_living	243.0141	2.959	82.136	0.000	237.215	248.813
sqft_living15	67.4359	3.965	17.006	0.000	59.663	75.208

Omnibus:	15441.551	**Durbin-Watson:**	1.989
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	675536.703
Skew:	2.984	**Prob(JB):**	0.00
Kurtosis:	29.857	**Cond. No.**	9.43e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.43e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

POST MODEL ANALYSIS

In [ ]:

```

```