Phase2Pro - Iteration

BUSINESS PROBLEM

King County Realty is a newly established local business in Northwestern America. The business owners and investors are seeking some concrete information regarding what attracts local buyers in this area to purchase new home to assist them with a marketing campaign to cater their services to the community. We will inspect the data set to determine what relationships and connections buyers have to purchasing a home to help King County Realty market their new business to suit.

What motivates buyers in this area to buy higher valued properties in King County?

A linear regression model will be used to understand the connections to the business problem using the OSMIN Model - Obtain, Scrub, Explore, Model and interpret.

In [62]:
```
#Import packages
import numpy as np
import pandas as pd
import statsmodels.api as sm
import scipy.stats as stats
from scipy import stats
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
from matplotlib.lines import Line2D
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from mpl_toolkits import mplot3d
import sklearn.metrics as metrics
import random
from math import sqrt
import seaborn as sns
plt.style.use('seaborn')
```

OBTAIN - Data has been sourced from kc_house_data.csv.

In [63]:
```
#Import data set and reviewed total of null values
data = pd.read_csv('data\\kc_house_data.csv')
data.isnull().sum()
```

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

SCRUB - During this stage, we'll focus on cleaning the data, obtaining critical statistical values and prepping for analysis.

In [64]:
```
#refined dataset and drop unnecessary column data
data.drop(['id', 'date', 'waterfront', 'sqft_above', 'sqft_basement', 'lat', 'lor
```

In [65]:
```
#display first 5 rows
data.head()
```

Out[65]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	yr_built	zipcode
0	221900	3	1	1180	5650	1	3	7	1955	98178
1	538000	3	2.25	2570	7242	2	3	7	1951	98125
2	180000	2	1	770	10000	1	3	6	1933	98028
3	604000	4	3	1960	5000	1	5	7	1965	98136
4	510000	3	2	1680	8080	1	3	8	1987	98074

In [66]:
```
#Removed duplicates and show unique values for column data
data.drop_duplicates(inplace=True)
data.nunique()
```

Out[66]:
```
price          3622
bedrooms         12
bathrooms        29
sqft_living    1034
sqft_lot       9776
floors            6
condition         5
grade            11
yr_built        116
zipcode          70
dtype: int64
```

In [67]:
```
#Observe correlations between variables to identify best predictor with regards t
data.corr()

# I can see the strongest predictor of price is sqft_living with a 70% correlatic
#with grade in close second at 67%, however sqft_lot makes more sense to view bas
#see: https://finance.zacks.com/property-size-increase-home-value-9809.html

#Objectivity here is to find other connections that are not so common - hence the
```

Out[67]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	yr_built	zi
price	1	0.31	0.53	0.70	0.09	0.26	0.04	0.67	0.05	
bedrooms	0.31	1	0.51	0.58	0.03	0.18	0.03	0.36	0.16	
bathrooms	0.53	0.51	1	0.76	0.09	0.50	-0.13	0.67	0.51	
sqft_living	0.70	0.58	0.76	1	0.17	0.35	-0.06	0.76	0.32	
sqft_lot	0.09	0.03	0.09	0.17	1	-0.00	-0.01	0.11	0.05	
floors	0.26	0.18	0.50	0.35	-0.00	1	-0.26	0.46	0.49	
condition	0.04	0.03	-0.13	-0.06	-0.01	-0.26	1	-0.15	-0.36	
grade	0.67	0.36	0.67	0.76	0.11	0.46	-0.15	1	0.45	
yr_built	0.05	0.16	0.51	0.32	0.05	0.49	-0.36	0.45	1	
zipcode	-0.05	-0.15	-0.20	-0.20	-0.13	-0.06	0.00	-0.19	-0.35	

In [68]:
```
#Show current types, convert to integers as all numerical values, display data
print(data.dtypes)
data = data.astype("int64", errors='ignore')
data.info()
```

```
price          float64
bedrooms         int64
bathrooms      float64
sqft_living      int64
sqft_lot         int64
floors         float64
condition        int64
grade            int64
yr_built         int64
zipcode          int64
dtype: object
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21589 entries, 0 to 21596
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   price        21589 non-null  int64
 1   bedrooms     21589 non-null  int64
 2   bathrooms    21589 non-null  int64
 3   sqft_living  21589 non-null  int64
 4   sqft_lot     21589 non-null  int64
 5   floors       21589 non-null  int64
 6   condition    21589 non-null  int64
 7   grade        21589 non-null  int64
 8   yr_built     21589 non-null  int64
 9   zipcode      21589 non-null  int64
dtypes: int64(10)
memory usage: 1.8 MB
```

In [69]:
```
data_preds = data.drop('price', axis=1)
data_target = data['price']
data_preds.head()
```

Out[69]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	yr_built	zipcode
0	3	1	1180	5650	1	3	7	1955	98178
1	3	2	2570	7242	2	3	7	1951	98125
2	2	1	770	10000	1	3	6	1933	98028
3	4	3	1960	5000	1	5	7	1965	98136
4	3	2	1680	8080	1	3	8	1987	98074

In [70]:
```
#use sm,add_constant() to add constant term/y-intercept
predictors = sm.add_constant(data_preds)
predictors
#optimise betas adding another predictor intercept term = bo x const
```

```
C:\Users\racar\anaconda3\lib\site-packages\statsmodels\tsa\tsatools.py:142: Fut
ureWarning: In a future version of pandas all arguments of concat except for th
e argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

Out[70]:

	const	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	yr_built	zipcod
0	1	3	1	1180	5650	1	3	7	1955	9817
1	1	3	2	2570	7242	2	3	7	1951	9812
2	1	2	1	770	10000	1	3	6	1933	9802
3	1	4	3	1960	5000	1	5	7	1965	9813
4	1	3	2	1680	8080	1	3	8	1987	9807
...	...	...	...	...	...	...	...	...	...	
21592	1	3	2	1530	1131	3	3	8	2009	9810
21593	1	4	2	2310	5813	2	3	8	2014	9814
21594	1	2	0	1020	1350	2	3	7	2009	9814
21595	1	3	2	1600	2388	2	3	8	2004	9802
21596	1	2	0	1020	1076	2	3	7	2008	9814

21589 rows × 10 columns

In [71]:
```
model = sm.OLS(data_target, predictors).fit()
model.summary()
```

Out[71]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.620
Model:	OLS	**Adj. R-squared:**	0.620
Method:	Least Squares	**F-statistic:**	3908.
Date:	Mon, 30 May 2022	**Prob (F-statistic):**	0.00
Time:	18:29:08	**Log-Likelihood:**	-2.9684e+05
No. Observations:	21589	**AIC:**	5.937e+05
Df Residuals:	21579	**BIC:**	5.938e+05
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	9.399e+05	3.17e+06	0.297	0.767	-5.27e+06	7.15e+06
bedrooms	-4.767e+04	2105.076	-22.643	0.000	-5.18e+04	-4.35e+04
bathrooms	5.724e+04	3222.411	17.762	0.000	5.09e+04	6.36e+04
sqft_living	187.5490	3.317	56.550	0.000	181.048	194.050
sqft_lot	-0.2426	0.038	-6.333	0.000	-0.318	-0.168
floors	1.912e+04	3758.277	5.088	0.000	1.18e+04	2.65e+04
condition	2.176e+04	2591.018	8.399	0.000	1.67e+04	2.68e+04
grade	1.318e+05	2230.152	59.088	0.000	1.27e+05	1.36e+05
yr_built	-3913.2186	74.269	-52.690	0.000	-4058.791	-3767.646
zipcode	59.9158	31.742	1.888	0.059	-2.301	122.133

Omnibus:	17145.336	**Durbin-Watson:**	1.986
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1176193.052
Skew:	3.312	**Prob(JB):**	0.00
Kurtosis:	38.548	**Cond. No.**	2.04e+08

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.04e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

In [72]:
```
#R squared value is at 0.620, P-values are at 0.00,  we will continue to review t
```

In [73]:
```
data_preds_scaled = (data_preds - np.mean(data_preds)) /np.std(data_preds)
pd.options.display.float_format = lambda x : '{:.0f}'.format(x) if int(x) == x el
```

In [74]:
```
data_preds_scaled.describe()
```

Out[74]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	yr_built	zipcode
count	21589	21589	21589	21589	21589	21589	21589	21589	21589
mean	-0.00	0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00
std	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
min	-2.56	-2.38	-1.86	-0.35	-0.81	-3.70	-3.97	-2.42	-1.44
25%	-0.40	-1.02	-0.71	-0.24	-0.81	-0.63	-0.56	-0.68	-0.84
50%	-0.40	0.34	-0.19	-0.18	-0.81	-0.63	-0.56	0.14	-0.24
75%	0.68	0.34	0.51	-0.11	1.01	0.91	0.29	0.89	0.75
max	31.98	8.51	12.48	39.51	2.82	2.44	4.55	1.50	2.26

In [75]:
```
predictors = sm.add_constant(data_preds_scaled)
model = sm.OLS(data_target, predictors).fit()
model.summary()
```

```
C:\Users\racar\anaconda3\lib\site-packages\statsmodels\tsa\tsatools.py:142: Fut
ureWarning: In a future version of pandas all arguments of concat except for th
e argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

Out[75]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.620
Model:	OLS	**Adj. R-squared:**	0.620
Method:	Least Squares	**F-statistic:**	3908.
Date:	Mon, 30 May 2022	**Prob (F-statistic):**	0.00
Time:	18:29:08	**Log-Likelihood:**	-2.9684e+05
No. Observations:	21589	**AIC:**	5.937e+05
Df Residuals:	21579	**BIC:**	5.938e+05
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	5.403e+05	1542.278	350.331	0.000	5.37e+05	5.43e+05
bedrooms	-4.415e+04	1949.950	-22.643	0.000	-4.8e+04	-4.03e+04
bathrooms	4.202e+04	2365.616	17.762	0.000	3.74e+04	4.67e+04
sqft_living	1.722e+05	3045.243	56.550	0.000	1.66e+05	1.78e+05
sqft_lot	-1.005e+04	1586.642	-6.333	0.000	-1.32e+04	-6938.957
floors	1.055e+04	2072.568	5.088	0.000	6483.729	1.46e+04
condition	1.416e+04	1685.708	8.399	0.000	1.09e+04	1.75e+04
grade	1.546e+05	2616.500	59.088	0.000	1.49e+05	1.6e+05
yr_built	-1.149e+05	2181.302	-52.690	0.000	-1.19e+05	-1.11e+05
zipcode	3206.4537	1698.709	1.888	0.059	-123.142	6536.050

Omnibus:	17145.336	**Durbin-Watson:**	1.986
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1176193.052
Skew:	3.312	**Prob(JB):**	0.00
Kurtosis:	38.548	**Cond. No.**	4.61

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

In [76]:
```
#No difference to R value however some of the coefficients
```

In [77]:
```
ss = StandardScaler()
```

In [78]:
```
ss.fit(data_preds)
data_preds_st_scaled = ss.transform(data_preds_scaled)
```

In [79]:
```
np.allclose(data_preds_st_scaled, data_preds_scaled)
```

Out[79]:
```
False
```

In [80]:
```
data_preds_scaled.head()
```

Out[80]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	yr_built	zipcode
0	-0.40	-1.02	-0.98	-0.23	-0.81	-0.63	-0.56	-0.54	1.87
1	-0.40	0.34	0.53	-0.19	1.01	-0.63	-0.56	-0.68	0.88
2	-1.48	-1.02	-1.43	-0.12	-0.81	-0.63	-1.41	-1.29	-0.93
3	0.68	1.70	-0.13	-0.24	-0.81	2.44	-0.56	-0.20	1.08
4	-0.40	0.34	-0.44	-0.17	-0.81	-0.63	0.29	0.55	-0.07

In [81]:
```
data_target.mean()
```

Out[81]:
```
540308.3467506601
```

In [82]:
```
data_preds_st_scaled[:5, :]
```

Out[82]:
```
array([[-4.07659475e+00, -3.77761637e+00, -2.26681084e+00,
        -3.64669502e-01, -4.08705556e+00, -6.20970663e+00,
        -7.00463484e+00, -6.71268218e+01, -1.83264888e+03],
       [-4.07659475e+00, -1.92206283e+00, -2.26516216e+00,
        -3.64668574e-01, -7.98842164e-01, -6.20970663e+00,
        -7.00463484e+00, -6.71314589e+01, -1.83266739e+03],
       [-5.24203145e+00, -3.77761637e+00, -2.26729714e+00,
        -3.64666966e-01, -4.08705556e+00, -6.20970663e+00,
        -7.73112125e+00, -6.71523258e+01, -1.83270126e+03],
       [-2.91115806e+00, -6.65093003e-02, -2.26588568e+00,
        -3.64669881e-01, -4.08705556e+00, -1.48465996e+00,
        -7.00463484e+00, -6.71152292e+01, -1.83266355e+03],
       [-4.07659475e+00, -1.92206283e+00, -2.26621779e+00,
        -3.64668085e-01, -4.08705556e+00, -6.20970663e+00,
        -6.27814842e+00, -6.70897252e+01, -1.83268520e+03]])
```

In [83]:
```
lr = LinearRegression()
lr.fit(data_preds_st_scaled, data_target)
```

Out[83]:
```
LinearRegression()
```

In [84]:
```
lr.coef_
```

Out[84]:
```
array([-4.08991298e+04,  3.08463823e+04,  1.58122472e+08, -4.16211715e+08,
        5.81584102e+03,  9.21168745e+03,  1.81385689e+05, -3.37559214e+06,
        1.71596651e+05])
```

In [85]:
```
lr.intercept_
```

Out[85]:
```
296151978.4850304
```

In [86]:
```
lr.score(data_preds_st_scaled, data_target)
```

Out[86]:
```
0.6197829380613668
```

In [87]:
```
y_hat = lr.predict(data_preds_st_scaled)
y_hat
```

Out[87]:
```
array([313016.52447158, 662161.5086115 , 228060.61663187, ...,
        80252.96640611, 399918.59277272,  84232.66216922])
```

In [88]:
```
data_preds_st_scaled.shape
```

Out[88]:
```
(21589, 9)
```

In [89]:
```
base_pred = np.zeros(9).reshape(1, -1)
base_pred
```

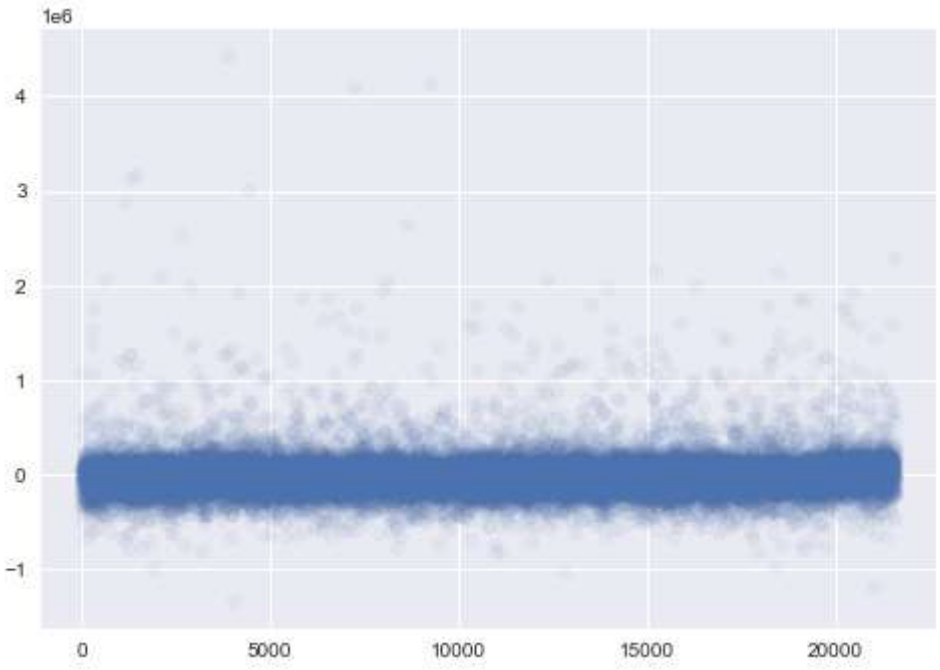
Out[89]:
```
array([[0., 0., 0., 0., 0., 0., 0., 0., 0.]])
```

In [90]:
```
lr.predict(base_pred)
```

Out[90]:
```
array([2.96151978e+08])
```

In [91]:
```
y_hat = lr.predict(data_preds_st_scaled)
resid = (data_target - y_hat)

plt.scatter(x=range(y_hat.shape[0]),y=resid, alpha=0.05)
```

Out[91]:
```
<matplotlib.collections.PathCollection at 0x1d0c4ee2430>
```



In [92]:
```
#patterns in the errors are aspotted near the 0.00
```

In [93]:
```
metrics.r2_score(data_target, lr.predict(data_preds_st_scaled))
```

Out[93]:
```
0.6197829380613668
```

In [94]:
```
avg_quality = np.mean(data_target)
num = len(data_target)
metrics.r2_score(data_target, avg_quality * np.ones(num))
```

Out[94]:
```
0.0
```

In [95]:
```
metrics.mean_absolute_error(data_target, lr.predict(data_preds_st_scaled))
```

Out[95]:
```
144764.04226654395
```

In [96]:
```
#extremely high value of being off on the sqft_living data
metrics.mean_squared_error(data_target, lr.predict(data_preds_st_scaled), squared
```

Out[96]:
```
226557.46000060465
```

In [97]:
```
#discover pop mean (sqft_lot)
population_mean = data.sqft_lot.mean()
population_mean
```

Out[97]:
```
15103.896197137432
```

In [98]:
```
#discover pop mean (Sqft_living)
population_mean = data.sqft_living.mean()
population_mean
```

Out[98]:
```
2080.4155356894717
```

In [99]:
```
# Take a sample of 50 records to test if the hypothesis related to the sqt_lot sh
sample = data.sample(n=50, random_state=22)
# Calculate the sample mean
sample_mean = sample.sqft_lot.mean()
sample_mean
#Sqft_lots in this area appear to be very large at 9925.96 - lets review for outl
```

Out[99]:
```
9925.96
```

In [100]:
```
# Find the difference between the sample and population means
err = np.abs(sample_mean - population_mean)
# Divide by the population mean to find a percent error
per_err = err / population_mean
per_err
```

Out[100]:
```
3.7711429902922884
```

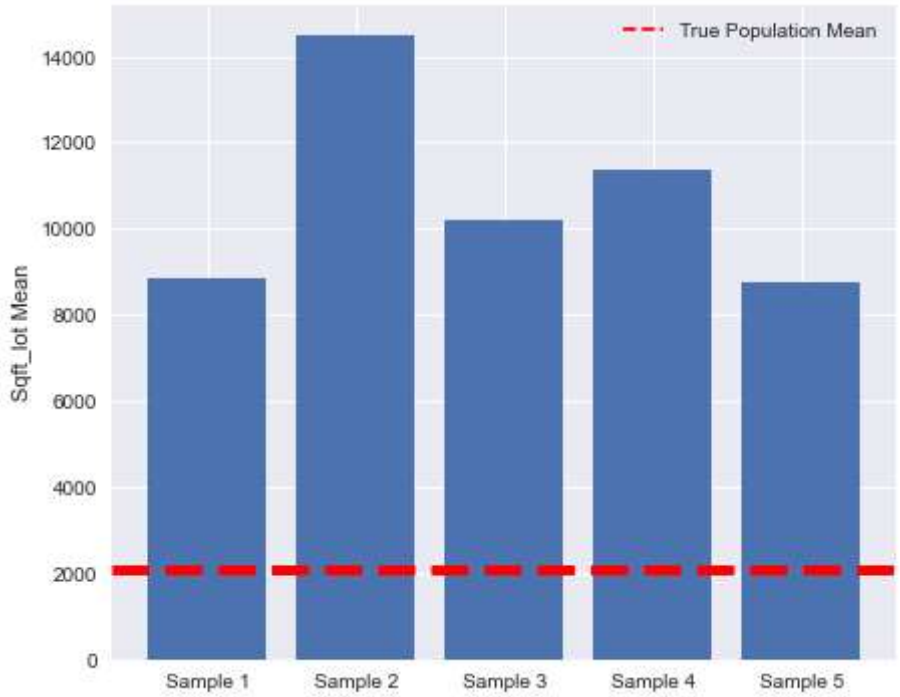
In [101]:
```
#Create sample test
five_sample_means = []
for i in range(5):
    sample = data.sample(n=50, random_state=i+100)
    five_sample_means.append(sample.sqft_lot.mean())

five_sample_means
```

Out[101]:
```
[8854.38, 14481.8, 10178.66, 11351.08, 8747.14]
```

In [102]:
```
#Create sample mean
five_sample_errors = [np.abs(sample_mean-population_mean)/population_mean for sam
five_sample_errors
```

Out[102]:
```
[3.2560631989635493,
 5.961013197394999,
 3.892609108798394,
 4.456159985960753,
 3.2045158046279947]
```

In [103]:
```
#Visualise the
x_labels = [f"Sample {x}" for x in range(1, 6)]

fig, ax = plt.subplots(figsize=(7,6))

ax.bar(x_labels, five_sample_means)
ax.set_ylabel("Sqft_lot Mean")
ax.axhline(y=population_mean, color="red", linewidth=5, linestyle="--")
ax.legend(
    handles=[Line2D([0],[0], color="red", linestyle="--")],
    labels=["True Population Mean"],
    fontsize="medium"
);
#Interesting fact that the population mean roughly displays the mean at 2000 acro
```



In [104]:
```
#View head of the
#lamba function to remove exponential values - Scrub
pd.options.display.float_format = lambda x : '{:.0f}'.format(x) if int(x) == x el
data.describe()
```

Out[104]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	yr_built
count	21589	21589	21589	21589	21589	21589	21589	21589	21589
mean	540,308.35	3.37	1.75	2,080.42	15,103.90	1.45	3.41	7.66	1,970.99
std	367,428.32	0.93	0.73	918.23	41,419.63	0.55	0.65	1.17	29.37
min	78000	1	0	370	520	1	1	3	1900
25%	322000	3	1	1430	5042	1	3	7	1951
50%	450000	3	2	1910	7620	1	3	7	1975
75%	645000	4	2	2550	10688	2	4	8	1997
max	7700000	33	8	13540	1651359	3	5	13	2015

In [105]:
```
#Creating the p-value and the z-score
import math
import scipy.stats as stats
mu = 150
sigma = 100
n=21
x_bar = 151
z = (x_bar - mu)/(sigma/math.sqrt(n))
p = 1 - stats.norm.cdf(z)

p,z

# (p = 0.48, z = 0.045)
```

Out[105]: (0.48172456464754565, 0.04582575694955839)

** HYPOTHESIS **

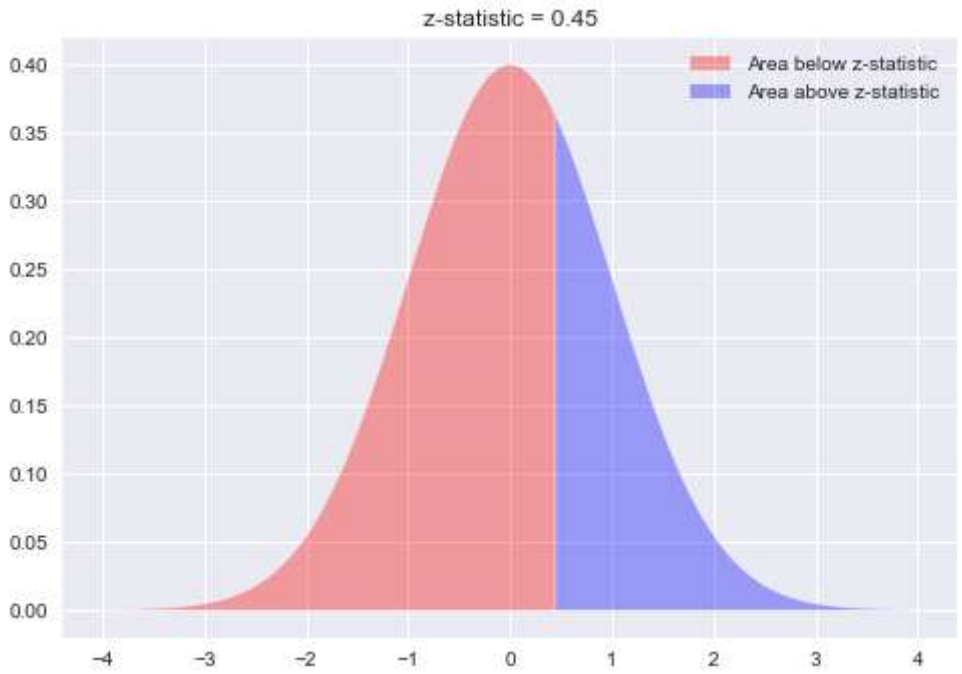
Below we set to explore the data set by deriving statistics and creating visualisation with dummy test data.

Null hypothesis: There is no difference between experimental and control group - when comparing sqft_lot against sqft_living does NOT affect a buyers decision to purchase a home. $\mu 1=\mu 2 \mu 1=\mu 2$

Alternative Hypothesis: There is a difference between experimental and control group - the sqft_living DOES affect a buyers decision when purchasing a home. $\mu 1 \neq \mu 2 \mu 1 \neq \mu 2$

#alpha value is 0.35

In [106]:
```
#running z test visualision to determine area above z stat
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

plt.style.use('seaborn')
plt.fill_between(x=np.arange(-4,0.45,0.01),
                 y1= stats.norm.pdf(np.arange(-4,0.45,0.01)) ,
                 facecolor='red',
                 alpha=0.35,
                 label= 'Area below z-statistic'
                 )

plt.fill_between(x=np.arange(0.45,4,0.01),
                 y1= stats.norm.pdf(np.arange(0.45,4,0.01)) ,
                 facecolor='blue',
                 alpha=0.35,
                 label= 'Area above z-statistic')
plt.legend()
plt.title ('z-statistic = 0.45');
```



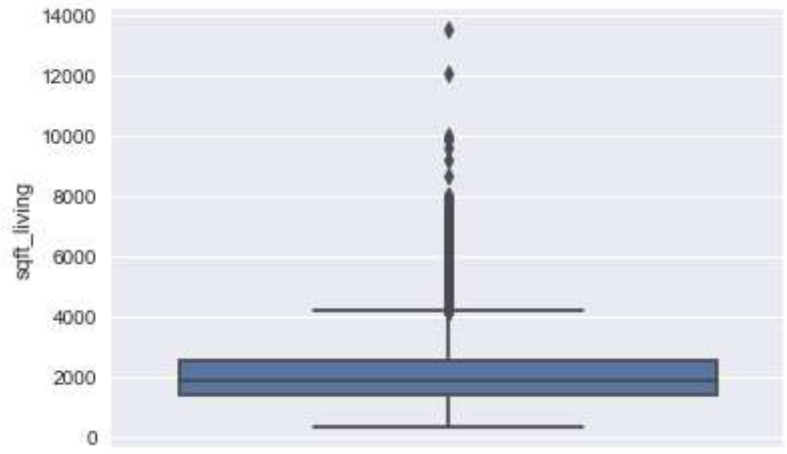
In [107]:
```
#show norm with degree of freedom
stats.norm.cdf(z)
```

Out[107]: 0.5182754353524544

In [108]:
```
#Pvalue minus degree of freedom
pval = 1 - stats.norm.cdf(z)
pval
```

Out[108]: 0.48172456464754565

In [109]:
```
# creating boxplots to see the outliers in the price variable

plt.figure(figsize=(6,4))
sns.boxplot(y=data['sqft_living']).set_title
plt.show()
```



In [110]:
```
#let us numerically draw conclusions
#creating function that can calculate interquartile range of the data
def calc_interquartile(data, column):
    global lower, upper
    #calculating the first and third quartile
    first_quartile, third_quartile = np.percentile(data[column], 25), np.percenti
    #calculate the inter quartile range
    iqr = third_quartile - first_quartile
    # outlier cutoff (1.5 is a generally used as a threshold)
    cutoff = iqr*1.5
    #calculate the lower and upper limits
    lower, upper = first_quartile - cutoff , third_quartile + cutoff
    #remove the outliers from the columns
    upper_outliers = data[data[column] > upper]
    lower_outliers = data[data[column] < lower]
    print('Lower outliers', lower_outliers.shape[0])
    print('Upper outliers', upper_outliers.shape[0])
    return print('total outliers', upper_outliers.shape[0] + lower_outliers.shape
```

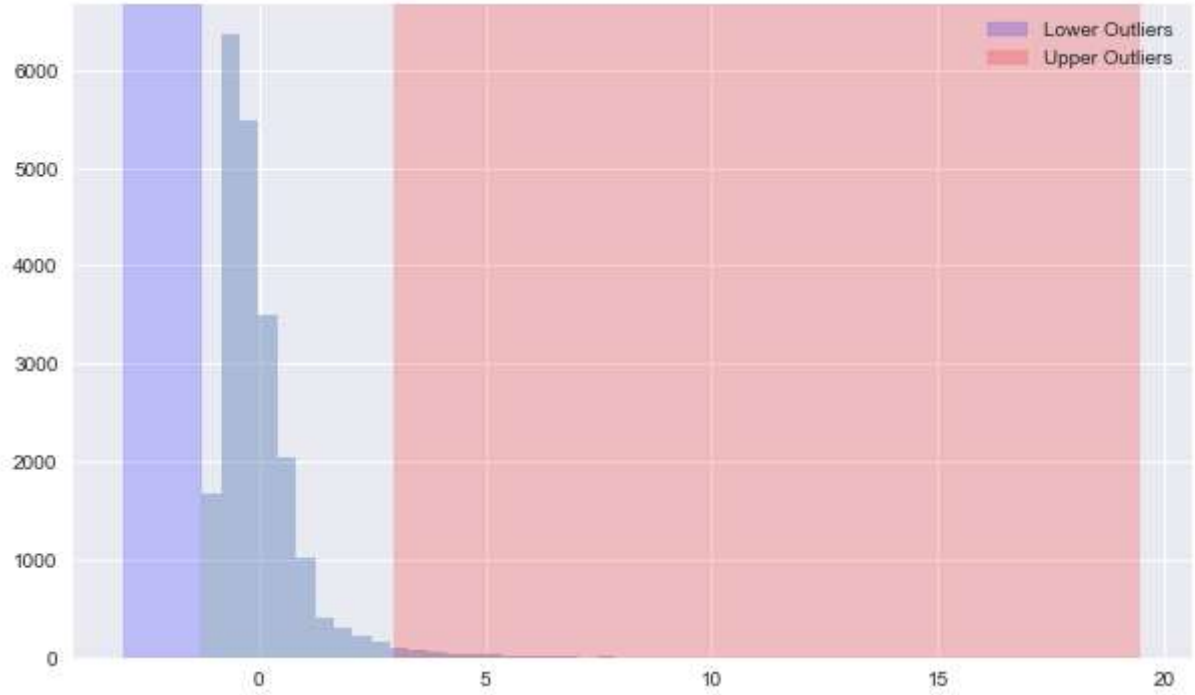
In [111]:
```
#applying the above function on columns to find the total outliers in every featu
for i in data.columns:
    print('Total outliers in ', i)
    calc_interquartile(data, i)
    print()
```

```
Total outliers in  price
Lower outliers 0
Upper outliers 1158
total outliers 1158

Total outliers in  bedrooms
Lower outliers 196
Upper outliers 334
total outliers 530

Total outliers in  bathrooms
Lower outliers 0
Upper outliers 402
total outliers 402

Total outliers in  sqft_living
Lower outliers 0
Upper outliers 571
total outliers 571

Total outliers in  sqft_lot
Lower outliers 0
Upper outliers 2419
total outliers 2419

Total outliers in  floors
Lower outliers 0
Upper outliers 0
total outliers 0

Total outliers in  condition
Lower outliers 29
Upper outliers 0
total outliers 29

Total outliers in  grade
Lower outliers 270
Upper outliers 1635
total outliers 1905

Total outliers in  yr_built
Lower outliers 0
Upper outliers 0
total outliers 0

Total outliers in  zipcode
Lower outliers 0
Upper outliers 0
total outliers 0
```

In [112]:
```
""" creating function for calculating zscore which is subtracting the mean from e
is less than -3 or greater than 3, then to determine if it is an outlier"""

def z_score(data, column):
    #creating global variables for plotting the graph for better demonstration
    global zscore, outlier
    #creating lists to store zscore and outliers
    zscore = []
    outlier =[]
    # for zscore generally taken thresholds are 2.5, 3 or 3.5 - used 3 here
    threshold = 3
    # calculating the mean of the passed column
    mean = np.mean(data[column])
    # calculating the standard deviation of the passed column
    std = np.std(data[column])
    for i in data[column]:
        z = (i-mean)/std
        zscore.append(z)
        #if the zscore is greater than threshold = 3 that means it is an outlier
        if np.abs(z) > threshold:
            outlier.append(i)
    return print('total outliers', len(outlier))
```

In [113]:
```
#plotting outliers graph for 'price' feature
z_score(data, 'price')
plt.figure(figsize = (10,6))
sns.distplot(zscore, kde=False)
print(upper, lower)
plt.axvspan(xmin = -3 ,xmax= min(zscore),alpha=0.2, color='blue', label='Lower Ou
plt.axvspan(xmin = 3 ,xmax= max(zscore),alpha=0.2, color='red', label='Upper Outl
plt.legend()
plt.show()
```

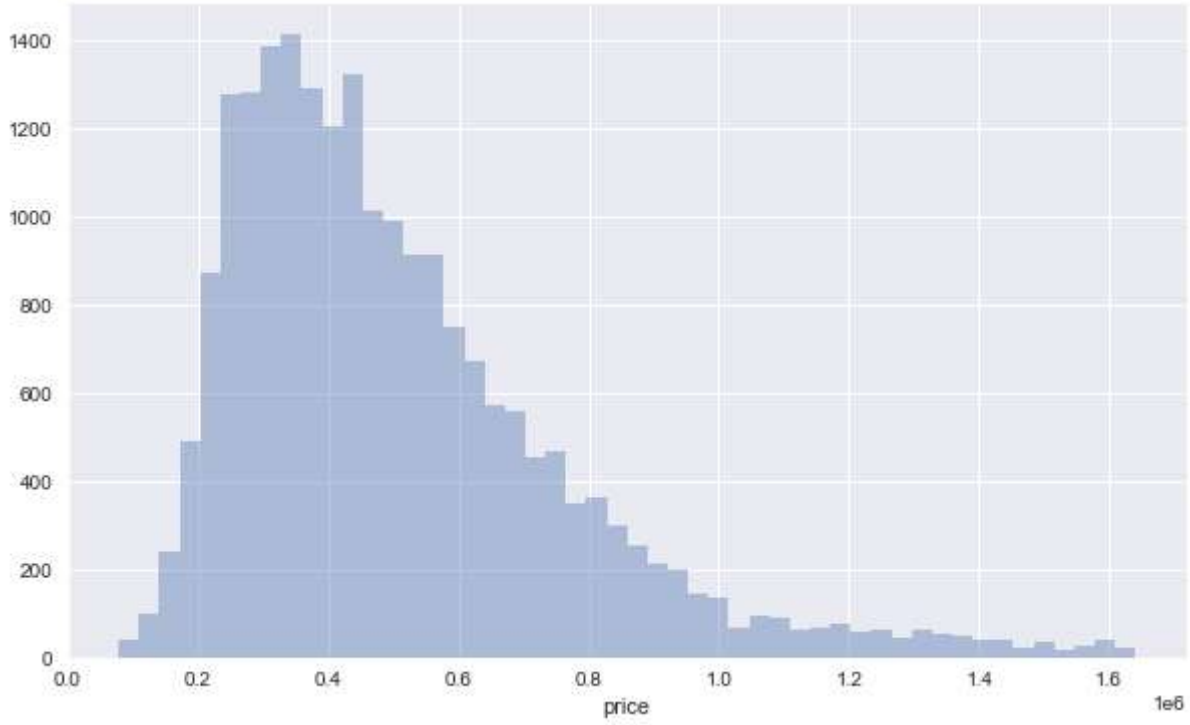
```
total outliers 406
98245.5 97905.5

C:\Users\racar\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Futur
eWarning: `distplot` is a deprecated function and will be removed in a future v
ersion. Please adapt your code to use either `displot` (a figure-level function
with similar flexibility) or `histplot` (an axes-level function for histogram
s).
  warnings.warn(msg, FutureWarning)
```



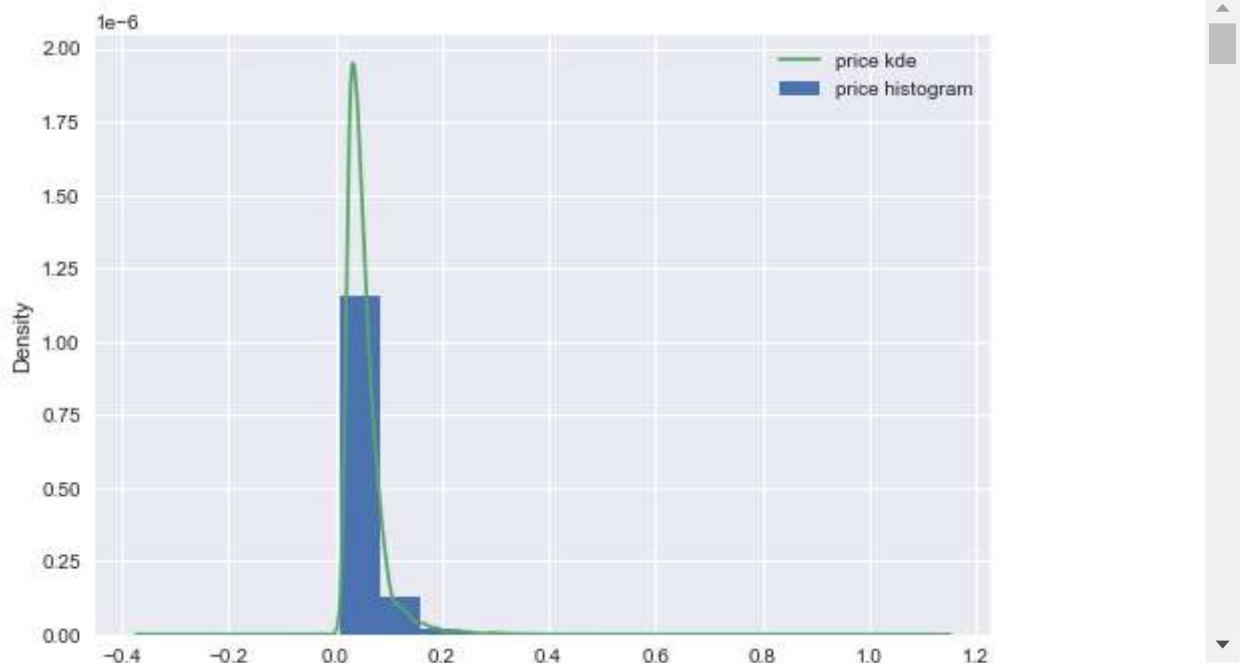
In [114]:
```
#remove the outliers from price using zscore
dj=[]
for i in data.price:
    if i in set(outlier):
        dj.append(0.0)
    else:
        dj.append(i)

data['P'] = dj

x = data.drop(data[data['P'] == 0.0].index)
x.shape
```

Out[114]: (21183, 11)

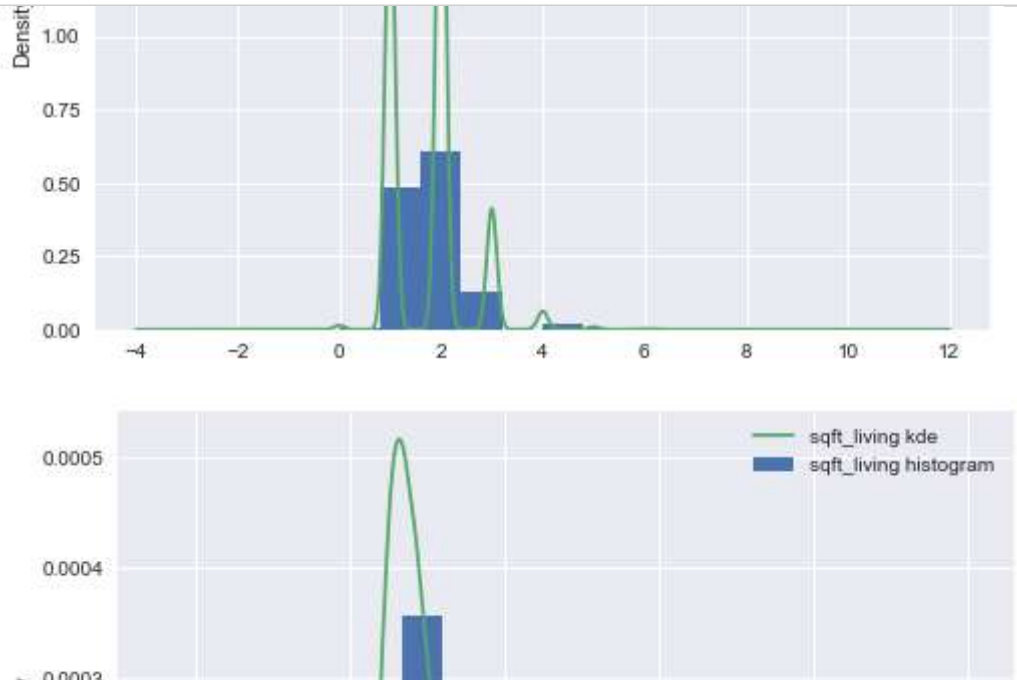
In [115]:
```
plt.figure(figsize = (10,6))
sns.distplot(x['price'], kde=False)
plt.show()
```



In [116]:
```
#Plotted KDE - Explore
for column in data:
    data[column].plot.hist(density=True, label = column+' histogram')
    data[column].plot.kde(label =column+' kde')
    plt.legend()
    plt.show()
```



In [117]:
```
#Plotted KDE - Explore
for column in data:
    data[column].plot.hist(density=True, label = column+' histogram')
    data[column].plot.kde(label =column+' kde')
    plt.legend()
    plt.show()
```



In [118]:
```
# import libraries for OLS - Obtain
import statsmodels.api as sm
import statsmodels.formula.api as smf

# build the formula - Explore
f = 'price~grade'
# create a fitted model in one line
model = smf.ols(formula=f, data=data).fit()
#Display OLS Summary - Explore
model.summary()
```

Out[118]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.446
Model:	OLS	**Adj. R-squared:**	0.446
Method:	Least Squares	**F-statistic:**	1.740e+04
Date:	Mon, 30 May 2022	**Prob (F-statistic):**	0.00
Time:	18:29:24	**Log-Likelihood:**	-3.0090e+05
No. Observations:	21589	**AIC:**	6.018e+05
Df Residuals:	21587	**BIC:**	6.018e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-1.062e+06	1.23e+04	-86.419	0.000	-1.09e+06	-1.04e+06
grade	2.092e+05	1586.012	131.916	0.000	2.06e+05	2.12e+05

Omnibus:	19872.369	**Durbin-Watson:**	1.969
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2042951.569
Skew:	4.081	**Prob(JB):**	0.00
Kurtosis:	49.952	**Cond. No.**	52.0

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

In [119]:
```
# import libraries for OLS - Obtain
import statsmodels.api as sm
import statsmodels.formula.api as smf

# build the formula - Explore
f = 'price~sqft_living'
# create a fitted model in one line
model = smf.ols(formula=f, data=data).fit()
#Display OLS Summary - Explore
model.summary()
```

Out[119]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.493
Model:	OLS	**Adj. R-squared:**	0.493
Method:	Least Squares	**F-statistic:**	2.097e+04
Date:	Mon, 30 May 2022	**Prob (F-statistic):**	0.00
Time:	18:29:24	**Log-Likelihood:**	-2.9995e+05
No. Observations:	21589	**AIC:**	5.999e+05
Df Residuals:	21587	**BIC:**	5.999e+05
Df Model:	1		
Covariance Type:	nonrobust		

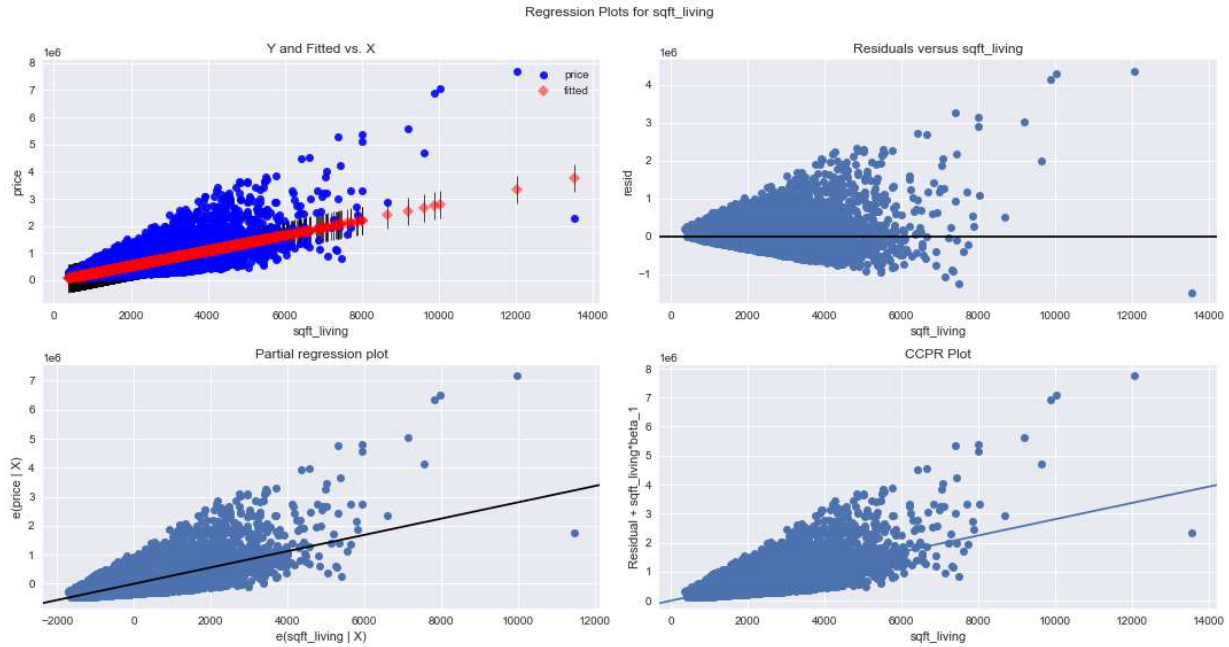
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-4.404e+04	4411.108	-9.984	0.000	-5.27e+04	-3.54e+04
sqft_living	280.8815	1.940	144.801	0.000	277.079	284.684

Omnibus:	14794.997	**Durbin-Watson:**	1.982
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	542159.026
Skew:	2.819	**Prob(JB):**	0.00
Kurtosis:	26.894	**Cond. No.**	5.63e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.63e+03. This might indicate that there are strong multicollinearity or other numerical problems.

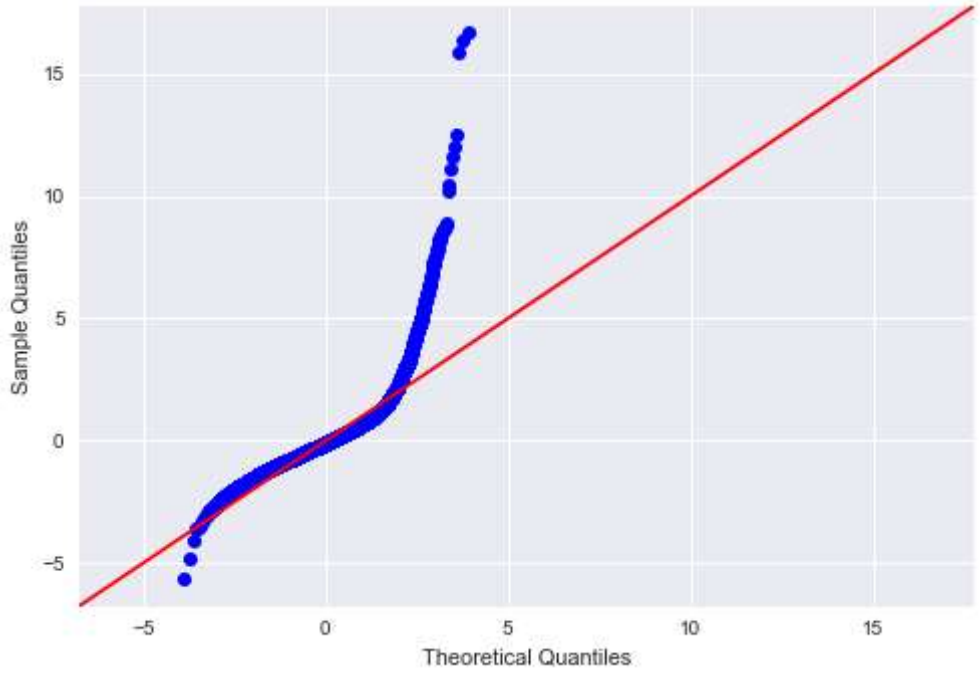
Note that the R squared value is between 0 and 1 with a value of 0.493. This is a great sign that the "sqft_lot" coefficient has a strong relationship to sale price aswell as the sqft_lot R squared testing above. This info will add value to further research regarding understanding the relationships connecting Kings County homebuyers' requirements of buying a property.

In [120]:
```
#visualisation
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "sqft_living", fig=fig)
plt.show()
```



In [121]:
```
#graphical representation stipulating residual data
import scipy.stats as stats
residuals = model.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
fig.show()
```

```
C:\Users\racar\anaconda3\lib\site-packages\statsmodels\graphics\gofplots.py:99
3: UserWarning: marker is redundantly defined by the 'marker' keyword argument
and the fmt string "bo" (-> marker='o'). The keyword argument will take precede
nce.
  ax.plot(x, y, fmt, **plot_style)
C:\Users\racar\AppData\Local\Temp/ipykernel_7616/1756778277.py:5: UserWarning:
Matplotlib is currently using module://matplotlib_inline.backend_inline, which
is a non-GUI backend, so cannot show the figure.
  fig.show()
```



In [122]:
```
def kfolds(data, k):
    # push data as pandas DataFrame
    data = pd.DataFrame(data)
    num_observations = len(data)
    fold_size = num_observations//k
    leftovers = num_observations%k
    folds = []
    start_obs = 0
    for fold_n in range(1,k+1):
        if fold_n <= leftovers:
            #Fold Size will be 1 larger to account for leftovers
            fold =  data.iloc[start_obs : start_obs+fold_size+1]
            folds.append(fold)
            start_obs +=  fold_size + 1
        else:
            fold =  data.iloc[start_obs : start_obs+fold_size]
            folds.append(fold)
            start_obs +=  fold_size

    return folds
```

In [123]:
```
data_data = pd.concat([X.reset_index(drop=True), y], axis=1)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_7616/3828648012.py in <module>
----> 1 data_data = pd.concat([X.reset_index(drop=True), y], axis=1)

NameError: name 'X' is not defined
```

In [ ]:
```
data_folds = kfolds(data_data, 5)
```

In [ ]:
```
#Created a scatter plot for linearity - Explore
fig, axs = plt.subplots(1, 3, sharey=True, figsize=(18, 6))
for idx, channel in enumerate(['sqft_living', 'grade', 'sqft_lot']):
    data.plot(kind='scatter', x=channel, y='price', ax=axs[idx], label=channel)
plt.legend()
plt.show()
```

As we can see, compared amongst the three variables that the sqft_living relationship is linear in some way across the data. There are some outliers here, however if outliers are removed, you can discern that the size of sqft_lot does have a relationship with price as well as grade and sqft_living.

In [ ]:
```
# create a DataFrame with the minimum and maximum values of Sqft_Living - Model
X_new = pd.DataFrame({'sqft_living': [data.sqft_living.min(), data.sqft_living.ma
print(X_new.head())

# make predictions for those x values and store them - Model
preds = model.predict(X_new)
print (preds)

# first, plot the observed data and the least squares line - Model
data.plot(kind='scatter', x='sqft_living', y='price')
plt.plot(X_new, preds, c='red', linewidth=2)
plt.show()
```

In [ ]:
```
# Split the data into training and test sets (assign 20% to test set)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20)
```

In [ ]:
```
# A brief preview of train-test split to create test training data and dummy data
print(len(X_train), len(X_test), len(y_train), len(y_test))
```

In [ ]:
```
#apply model to the train set created
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()

linreg.fit(X_train, y_train)
y_hat_test = linreg.predict(X_test)
```

In [ ]:
```
#calculate training and test MSE
from sklearn.metrics import mean_squared_error
test_residuals = y_hat_test - y_test

test_mse = mean_squared_error(y_test, y_hat_test)
test_mse
```

MSE is calculated by taking the average of the square of the difference between the original and predicted values of the data. The mean squared error is used to determine the model's performance.

##Explore: the data set by deriving statistics and creating visualisation with dummy test data

In [ ]:
```
from sklearn.metrics import mean_squared_error, make_scorer
from sklearn.model_selection import cross_val_score
mse = make_scorer(mean_squared_error)
cv_5_results = cross_val_score(linreg, X, y, cv=5, scoring=mse)
```

In [ ]:
```
cv_5_results.mean()
```

In [ ]:
```
import random
random.seed(110)

train_err = []
test_err = []
t_sizes = list(range(5,100,5))
for t_size in t_sizes:
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=t_size/10
    linreg.fit(X_train, y_train)
    y_hat_train = linreg.predict(X_train)
    y_hat_test = linreg.predict(X_test)
    train_err.append(mean_squared_error(y_train, y_hat_train))
    test_err.append(mean_squared_error(y_test, y_hat_test))
plt.scatter(t_sizes, train_err, label='Housing Training Error')
plt.scatter(t_sizes, test_err, label='Housing Testing Error')
plt.legend()
```

In [ ]:
```
#train set 2
random.seed(900)

train_err = []
test_err = []
t_sizes = range(5,100,5)
for t_size in t_sizes:
    temp_train_err = []
    temp_test_err = []
    for i in range(10):
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=t_siz
        linreg.fit(X_train, y_train)
        y_hat_train = linreg.predict(X_train)
        y_hat_test = linreg.predict(X_test)
        temp_train_err.append(mean_squared_error(y_train, y_hat_train))
        temp_test_err.append(mean_squared_error(y_test, y_hat_test))
    train_err.append(np.mean(temp_train_err))
    test_err.append(np.mean(temp_test_err))
plt.scatter(t_sizes, train_err, label='Housing Training Error')
plt.scatter(t_sizes, test_err, label='Housing Testing Error')
plt.legend()
```

In [ ]:
```
#Paired sample t-test

data = pd.read_csv('data\\kc_house_data.csv')
data[['price','sqft_living', 'sqft_lot']].describe()
ttest,pval = stats.ttest_rel(data['price'], data['sqft_living'])
print(pval)
if pval<0.05:
    print("reject null hypothesis")
else:
    print("accept null hypothesis")
```

```
** ALTERNATIVE HYPOTHESIS CONFIRMED **
```

Below we set to explore the data set by deriving statistics and creating visualisation with dummy test data.

Null hypothesis: There is no difference between experimental and control group - when comparing sqft_lot against sqft_living does NOT affect a buyers decision to purchase a home. μ1=μ2μ1=μ2

Alternative Hypothesis: There is a difference between experimental and control group - the sqft_living and sqft_Lot DOES affect a buyers decision when purchasing a home by

μ1≠μ2μ1≠μ2 #alpha value is 0.35

In [ ]:
```
#import scipy.stats as stats
residuals = model.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
fig.show()
```

In [ ]:
```
#visualisation used to model and interpret the data
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "sqft_living", fig=fig)
plt.show()
```

In [ ]:
```
#setting predictors location
data_pred = data.iloc[:,0:12]
data_pred.head()
```

In [ ]:
```
#visualse value of correlation percentage
data_pred.corr()
```

In [ ]:
```
#check for connections
abs(data_pred.corr()) >= 0.70
```

In [ ]:
```
#Compare linearity between 2 variables for further analysis
sns.set_theme(color_codes=True)
plt.rcParams['figure.figsize'] = [8,5]
plt.rcParams['font.size'] =14
plt.rcParams['font.weight']= 'bold'
plt.style.use('seaborn-whitegrid')
data = pd.read_csv('data\\kc_house_data.csv')
f = plt.figure(figsize=(14,6))
ax = f.add_subplot(121)
sns.scatterplot(x='grade',y='price',data=data,palette='Set1',ax=ax)
ax.set_title('Scatter plot of grade vs price')

ax = f.add_subplot(122)
sns.scatterplot(x='sqft_living',y='price',data=data,palette='viridis')
ax.set_title('Scatter plot of sqft_living vs price')
plt.savefig('sc.png');
```

In [ ]:
```
#Cleaning data for prediction
data=data_pred.corr().abs().stack().reset_index().sort_values(0, ascending=False)
# combine the variable name columns (Which were only named level_0 and level_1 by
data['pairs'] = list(zip(data.level_0, data.level_1))
# set index to pairs
data.set_index(['pairs'], inplace = True)
#drop level columns
data.drop(columns=['level_1', 'level_0'], inplace = True)
# renamed correlation column to cc
data.columns = ['cc']
# drop duplicates.
data.drop_duplicates(inplace=True)
```

In [ ]:
```
#quick preview to confirm
data[(data.cc>=.70) & (data.cc <1)]
```

In [ ]:
```
#creating a heatmap to learn even more
import seaborn as sns
sns.heatmap(data_pred.corr(), center=0);
```

Each square shows the correlation between the variables on each axis. Correlation ranges from -2 to +1. Data closer to zero means there is no linear relationship between the two variables.

3 important parameter estimates or statistics. Sqft_living : R value square = 0.493 Sqft_lot: Common knowledge/speculation based on market reasearch indicates that the lot size of a house directly effects the cost of house sales greater than a living area size - however this theory proved incorrect based on the data set for this area. Based on data the true population mean for the sqft_living area was 2000 feet squared.