king county housing price modeling

Normalizing

```
In [1]: # import libraries
   import pandas as pd
   import numpy as np
   import seaborn as sns
   import matplotlib.pyplot as plt
   import folium
   plt.style.use('ggplot')
```

Read the clean KC housing data

```
kc = pd.read_csv('data/kc_house data clean.csv')
kc.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21399 entries, 0 to 21398
Data columns (total 20 columns):
id
                 21399 non-null int64
date
                 21399 non-null object
price
                 21399 non-null int64
bedrooms
                 21399 non-null int64
bathrooms
                 21399 non-null float64
sqft lot
                 21399 non-null float64
floors
                 21399 non-null float64
                 21399 non-null float64
waterfront
view
                 21399 non-null float64
condition
                 21399 non-null int64
grade
                 21399 non-null int64
sqft_above
                 21399 non-null float64
                 21399 non-null float64
sqft basement
                 21399 non-null int64
yr built
yr_renovated
                 21399 non-null int64
zipcode
                 21399 non-null int64
lat
                 21399 non-null float64
long
                 21399 non-null float64
sqft living15
                 21399 non-null float64
sqft lot15
                 21399 non-null float64
dtypes: float64(11), int64(8), object(1)
memory usage: 3.3+ MB
```

```
In [3]:
    '''
    price in $ span a large range of numbers while all the features has quite shor
    t range. It could be better to take the log
    scale of the price before fitting.
    also drop id
    '''
    kc = kc.drop(["id"], axis=1)
    kc['price'] = np.log(kc['price'])
```

baseline model

To better gauage the progress let's model without any change to the features

```
In [4]: # import statistical libraries for modelling.
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

simple linear regression

It maybe worthwhile to investigate correlation between each individual feature with the outcome, which is the price

formula = price ~ bedrooms

OLS.	Regression	Results

=========	=======	OLS Re	_			=======	
= Dep. Variable:		pr	ice	R-squ	ared:		0.11
4 Model:			OLS	Adj.	R-squared:		0.11
4 Method:		Least Squa	res	F-sta	tistic:		275
8. Date:	Sur	n, 10 May 2	020	Prob	(F-statistic)	:	0.0
0 Time:		08:50	:36	Log-L	ikelihood:		-1425
6. No. Observatio	ns:	21	.399	AIC:			2.852e+0
4 Df Residuals:		21	.397	BIC:			2.853e+0
4 Df Model:			1				
Covariance Typ	e:	nonrob =======	ust		=========	=======	=======
= 5]	coef	std err		t	P> t	[0.025	0.97
Intercept 3	12.3989	0.012	993	.633	0.000	12.374	12.42
_	0.1883	0.004	52	.513	0.000	0.181	0.19
_	=======		=====	=====	========	======	=======
Omnibus:		73.	399	Durbi	n-Watson:		1.95
Prob(Omnibus):		0.	000	Jarqu	e-Bera (JB):		73.38
9 Skew:		0.	136	Prob(JB):		1.16e-1
6 Kurtosis: 5		2.	910	Cond.	No.		14.
=======================================	=======		=====	=====	========	======	=======
Warnings: [1] Standard E tly specified. ####################################							
formula = pric	e ~ bathro	ooms OLS Re	gress	ion Re	sults =======	=======	=======
= Dep. Variable:		pr	ice	R-squ	ared:		0.27
4			01.6	٠. ٧	D		0.07

OLS Adj. R-squared:

Model:

0.27

```
4
Method:
             Least Squares F-statistic:
                                            806
9.
            Sun, 10 May 2020
                       Prob (F-statistic):
                                            0.0
Date:
Time:
                 08:50:36
                       Log-Likelihood:
                                           -1212
9.
No. Observations:
                   21399
                        AIC:
                                         2.426e+0
Df Residuals:
                   21397
                        BIC:
                                         2.428e+0
Df Model:
                     1
Covariance Type:
                nonrobust
______
          coef std err t P>|t|
                                    [0.025 0.97
5]
.....
Intercept 12.2953 0.009 1412.670 0.000 12.278
                                           12.31
         0.3508 0.004
                      89.830
bathrooms
                             0.000
                                     0.343
                                            0.35
______
Omnibus:
                  94.548 Durbin-Watson:
                                            1.95
Prob(Omnibus):
                   0.000
                        Jarque-Bera (JB):
                                           87.63
Skew:
                   0.124
                       Prob(JB):
                                          9.34e-2
Kurtosis:
                   2.807
                        Cond. No.
                                            7.8
______
Warnings:
```

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

formula = price ~ sqft_lot

OLS Regression Results

______ Dep. Variable: price R-squared: 0.01 Model: 0LS Adj. R-squared: 0.01 Method: Least Squares F-statistic: 216. Sun, 10 May 2020 Prob (F-statistic): Date: 9.06e-4 08:50:36 Log-Likelihood: Time: -1544

No. Observations: 21399 AIC: 3.089e+0Df Residuals: 3.091e+0 21397 BIC: Df Model: 1 Covariance Type: nonrobust ______ P>|t| [0.025 coef std err t 0.97 51 ______ 0.004 3593.374 0.000 Intercept 13.0138 13.007 13.02 sqft lot 1.209e-06 8.22e-08 14.714 0.000 1.05e-06 1.37e-0 ______ Omnibus: 107.332 Durbin-Watson: 1.95 Prob(Omnibus): 0.000 Jarque-Bera (JB): 108.84 Prob(JB): Skew: 0.174 2.31e-2 Kurtosis: 3.018 Cond. No. 4.69e+0

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 4.69e+04. This might indicate that there a re

strong multicollinearity or other numerical problems.

formula = price ~ floors

=======================================		.============	
=			
Dep. Variable:	price	R-squared:	0.09
4			
Model:	OLS	Adj. R-squared:	0.09
4			
Method:	Least Squares	F-statistic:	222
8.			
Date:	Sun, 10 May 2020	Prob (F-statistic):	0.0
0	•		
Time:	08:50:36	Log-Likelihood:	-1449
3.			
No. Observations:	21399	AIC:	2.899e+0
4			
Df Residuals:	21397	BIC:	2.901e+0
4			

Df Model: Covariance Type	:	nonrol	1 bust				
======================================		std err	=====	t	P> t	[0.025	0.97
- Intercept 12	2.6070	0.010	1316	5.542	0.000	12.588	12.62
	0.2851	0.006	47	.197	0.000	0.273	0.29
= Omnibus:		142	.409	Durbir	n-Watson:		1.96
<pre>8 Prob(Omnibus):</pre>		0	.000	Jarque	e-Bera (JB):		144.74
8 Skew: 2		0	.198	Prob(JB):		3.70e-3
Kurtosis:		2	.929	Cond.	No.		6.3
formula = price	~ water	OLS Re	_	ion Res	sults	=======	
= Dep. Variable: 2		рі	rice	R-squa	ared:		0.01
Model:			OLS	Adj. F	R-squared:		0.01
2 Method:		Least Squa	ares	F-stat	istic:		253.
3 Date:	Su	n, 10 May 2	2020	Prob ((F-statistic):	1.04e-5
6 Time:		08:50	ð:36	Log-Li	ikelihood:		-1542
7. No. Observations	5:	2:	1399	AIC:			3.086e+0
4 Df Residuals:		2:	1397	BIC:			3.087e+0
4 Df Model: Covariance Type		nonrol					
=	coef	std err	=====	t	P> t	[0.025	0.97

Intercept 5	13.0282	0.003	3820.869	0.000	13.022	13.03
waterfront 9	0.7822	0.049	15.916	0.000	0.686	0.87
========	=======	=======		=======	=======	=======
= Omnibus: 0		94.	.268 Durbi	n-Watson:		1.95
Prob(Omnibus):	0.	.000 Jarqu	e-Bera (JB):		95.46
Skew:		0.	.163 Prob(ЈВ):		1.86e-2
Kurtosis: 4		2.	.987 Cond.	No.		14.
· ========	=======	=======	.=======		=======	=======
=						

Warnings:

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

formula = price ~ view

	+-
OLS Regression Resul	

=========	======			======			
=							
Dep. Variable 2	:	p	rice	R-squ	iared:		0.09
Model:			OLS	Adi.	R-squared:		0.09
2							
Method:		Least Squ	iares	F-sta	tistic:		215
7.				. 500			
Date:		Sun. 10 May	2020	Prob	(F-statistic)	•	0.0
0					(. 5000=50=5)	•	
Time:		08:5	0:36	Log-L	ikelihood:		-1452
5.							
No. Observati	ons:	2	21399	AIC:			2.905e+0
4							
Df Residuals:		2	21397	BIC:			2.907e+0
4							
Df Model:			1				
Covariance Ty	pe:	nonro	bust				
=========	======	========	=====	======	=========	=======	=======
=							
	coef	std err		t	P> t	[0.025	0.97
5]							
-							
Intercept	12.9870	0.003	3817	7.846	0.000	12.980	12.99
4							
view	0.2071	0.004	46	5.444	0.000	0.198	0.21
6							
=========	======	========		======	=========	=======	=======
=							
_							

Omnibus: 40.802 Durbin-Watson: 1.94 Prob(Omnibus): 0.000 Jarque-Bera (JB): 40.99 Skew: 0.107 Prob(JB): 1.26e-0 Kurtosis: 3.010 Cond. No. 1.4

Warnings:

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

formula = price ~ condition

					======================================		
=							
Dep. Variabl 1	le:	pr	ice	R-squ	area:		0.00
Model:		(OLS	Adi.	R-squared:		0.00
1					- 4		
Method:		Least Squar	res	F-sta	tistic:		27.6
1	c.	10 May 20	220	Durah	/r -+-+:-+:-\.		1 50- 0
Date: 7	St	ın, 10 May 20	020	Prob	(F-statistic):		1.50e-0
, Time:		08:50	:36	Log-L	ikelihood:		-1553
9.				J			
No. Observat	ions:	213	399	AIC:			3.108e+0
4 Df Residuals	• •	21:	397	BIC:			3.110e+0
di Residuais 4	•	21.	331	DIC.			3.1106+0
Df Model:			1				
Covariance T	ype:	nonrobi	ust				
=======================================		:========	====:	=====	========	:=====:	=======
	coef	std err		t	P> t	[0.025	0.97
5]						_	
- Intercent	12.9377	0.018	708	125	0.000	12.902	12.97
3	12.33,,	0.010	, 00	.123	0.000	12.502	12.57
condition	0.0277	0.005	5	.255	0.000	0.017	0.03
8							
======== =	:=======	-======	====:	=====	=========	:======:	=======
Omnibus:		113.1	194	Durbi	n-Watson:		1.95
2							
Prob(Omnibus	5):	0.6	900	Jarqu	e-Bera (JB):		114.92
7 Skew:		a ·	179	Prob(1 R)⋅		1.11e-2
5		0	-,,	1100(55).		1.110 2
Kurtosis:		2.9	993	Cond.	No.		20.

0

=

Warnings:

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

formula = price ~ grade

Tormula = price	grauc	OLS Re	gress:	ion Re	esults		
=======================================	======	========	=====	=====	=========	======	=======
Dep. Variable: 5		pr	ice	R-sq	uared:		0.46
Model:		(0LS	Adj.	R-squared:		0.46
5					•		
Method: 4		Least Squa	res	F-sta	atistic:		1.858e+0
Date:	Su	n, 10 May 2	020	Prob	(F-statistic):		0.0
0							
Time:		08:50	:37	Log-l	Likelihood:		-8866.
No. Observations	5:	21	399	AIC:			1.774e+0
Df Residuals: 4		21	397	BIC:			1.775e+0
Df Model:			1				
Covariance Type:	:	nonrob	ust				
=	======	========	=====			======	=======
_	coef	std err		t	P> t	[0.025	0.97
5]						-	
_							
Intercept 10	7400	0.017	631	.686	0.000	10.707	10.77
grade 6	3004	0.002	136	. 291	0.000	0.296	0.30
=======================================		=======	=====	====			=======
= Omnibus:		36.	605	Durb:	in-Watson:		1.96
2		_		_	-		
Prob(Omnibus): 1		0.	000	Jarqı	ue-Bera (JB):		36.76
Skew:		0.	102	Prob	(JB):		1.04e-0
8		2	004	C =!	No		F3
Kurtosis: 3		3.	004	Cond	. NO.		53.
=======================================		========	=====			======	=======

Warnings:

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

formula	=	price	~	sqft_	_al	bove	5			
							OL S	Regression	Racuil	+c

OLS Regression Results								
_	======		=====	=====	=========	======	=======	
= Dep. Variable 6	:	р	rice	R-sq	uared:		0.32	
Model:			OLS	Adj.	R-squared:		0.32	
Method:		Least Squ	ares	F-st	atistic:		1.033e+0	
Date:		Sun, 10 May	2020	Prob	(F-statistic):		0.0	
Time: 7.		08:5	0:37	Log-	Likelihood:		-1133	
No. Observati	ons:	2	1399	AIC:			2.268e+0	
Df Residuals:		2	1397	BIC:			2.269e+0	
Df Model: Covariance Ty	ne•	nonro	1 hust					
-	•			====	=========	======	=======	
=	coef	std err		t	P> t	[0.025	0.97	
5]								
-								
Intercept 9	12.3951	0.007	1805	.196	0.000	12.382	12.40	
sqft_above 0	0.0004	3.54e-06	101	.649	0.000	0.000	0.00	
=======================================	======		=====	====	=========	======	=======	
Omnibus:		82	.153	Durb	in-Watson:		1.98	
Prob(Omnibus)	:	0	.000	Jarq	ue-Bera (JB):		74.36	
Skew: 7		0	.105	Prob	(JB):		7.10e-1	
Kurtosis:		2	.802	Cond	. No.		4.73e+0	
=======================================	======		=====	====	=========	======	=======	

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 4.73e+03. This might indicate that there a

strong multicollinearity or other numerical problems.

formula = price ~ sqft basement

Dep. Variable: price R-squared: 0.08 OLS Adj. R-squared: Model: 0.08

Method: Least Squares F-statistic: 186

5.

Sun, 10 May 2020 Prob (F-statistic): 0.0

Date:

08:50:37 Log-Likelihood: Time: -1465

8.

No. Observations: 21399 AIC: 2.932e+0

Df Residuals: 21397 BIC: 2.934e+0

Df Model: 1 Covariance Type: nonrobust

std err t P>|t| [0.025 coef 0.

975]

Intercept 12.9396 0.004 3303.693 0.000 12.932 1 2.947 sqft_basement 0.0003 7.66e-06 43.190 0.000 0.000

0.000 ______

Omnibus: 132.547 Durbin-Watson: 1.94

Prob(Omnibus): 0.000 Jarque-Bera (JB): 134.93

0.195 Prob(JB): 5.01e-3 Skew:

Kurtosis: 2.998 Cond. No. 61

Warnings:

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

###

formula = price ~ yr built

OLS Regression Results

price R-squared:

Model: OLS Adj. R-squared: 0.00

Dep. Variable:

0.00

7

```
Method:
             Least Squares F-statistic:
                                            153.
            Sun, 10 May 2020
                        Prob (F-statistic):
                                          4.15e-3
Date:
5
                 08:50:37
Time:
                        Log-Likelihood:
                                          -1547
6.
No. Observations:
                   21399
                        AIC:
                                          3.096e+0
Df Residuals:
                   21397
                        BIC:
                                          3.097e+0
Df Model:
                      1
Covariance Type:
                nonrobust
______
          coef std err t P>|t|
                                    [0.025
5]
-----
Intercept 10.1927 0.229 44.456 0.000
                                     9.743
                                           10.64
        0.0014 0.000 12.385
yr built
                             0.000
                                     0.001
                                            0.00
______
Omnibus:
                  150.208 Durbin-Watson:
                                            1.96
Prob(Omnibus):
                        Jarque-Bera (JB):
                   0.000
                                          153.14
Skew:
                   0.206
                        Prob(JB):
                                          5.57e-3
Kurtosis:
                   2.949
                        Cond. No.
                                          1.33e+0
______
```

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.33e+05. This might indicate that there a re

strong multicollinearity or other numerical problems.

formula = price ~ yr_renovated

OLS Regression Results							
=							
Dep. Variable: 9	price	R-squared:	0.00				
Model: 9	OLS	Adj. R-squared:	0.00				
Method: 8	Least Squares	F-statistic:	198.				
Date:	Sun, 10 May 2020	Prob (F-statistic):	6.22e-4				

```
5
Time:
                  08:50:37
                         Log-Likelihood:
                                             -1545
                    21399
                                            3.091e+0
No. Observations:
                         AIC:
Df Residuals:
                    21397
                         BIC:
                                            3.093e+0
4
Df Model:
Covariance Type:
                 nonrobust
_______
                 std err
                            t
                                P>|t|
                                       [0.025
                                               0.9
            coef
751
Intercept 13.0230 0.003 3759.148
                                0.000
                                       13.016
                                               13.
030
         0.0001 9.48e-06 14.098
yr_renovated
                                0.000
                                        0.000
                                                0.
000
______
Omnibus:
                   96.883
                         Durbin-Watson:
                                              1.95
Prob(Omnibus):
                    0.000
                         Jarque-Bera (JB):
                                              98.12
Skew:
                    0.166
                         Prob(JB):
                                             4.92e-2
2
                                               37
Kurtosis:
                    3.005
                         Cond. No.
______
Warnings:
```

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

###

formula = price ~ zipcode

OLS Regression Results							
===========	:==========						
=							
Dep. Variable:	price	R-squared:	0.00				
1							
Model:	OLS	Adj. R-squared:	0.00				
1							
Method:	Least Squares	F-statistic:	22.1				
1	•						
Date:	Sun, 10 May 2020	<pre>Prob (F-statistic):</pre>	2.59e-0				
6	,						
Time:	08:50:37	Log-Likelihood:	-1554				
2.							
No. Observations:	21399	AIC:	3.109e+0				
4	21333	AIC.	3.103010				
Df Residuals:	21397	BIC:	3.110e+0				
	21397	BIC.	3.1106+0				
4							

Df Model:

Covariance Type: nonrobust t P>|t| coef std err [0.025 0.97 5] -----Intercept 42.5197 6.272 6.780 0.000 30.227 54.81 zipcode -0.0003 6.39e-05 -4.702 0.000 -0.000 -0.00 ______ Omnibus: 106.988 Durbin-Watson: 1.95 0.000 Prob(Omnibus): Jarque-Bera (JB): 108.53 Skew: 0.174 Prob(JB): 2.70e-2 Kurtosis: 2.986 Cond. No. 1.80e+0

1

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.8e+08. This might indicate that there are

strong multicollinearity or other numerical problems.

formula = price ~ lat

	J		
===========			========
=			
Dep. Variable:	price	R-squared:	0.21
2			
Model:	OLS	Adj. R-squared:	0.21
2			
Method:	Least Squares	F-statistic:	577
0.	•		
Date:	Sun, 10 May 2020	Prob (F-statistic):	0.0
0			
Time:	08:50:37	Log-Likelihood:	-1299
8.			
No. Observations:	21399	AIC:	2.600e+0
4			
Df Residuals:	21397	BIC:	2.602e+0
4			
Df Model:	1		
Covariance Type:	nonrobust		
=======================================			========

5]	coef	std err	t	P> t	[0.025	0.97
- Intercept 9 lat 2	-65.8959 1.6596	1.039 0.022	-63.416 75.958	0.000 0.000	-67.933 1.617	-63.85 1.70
======================================		452.		n-Watson:	======	1.95
Prob(Omnibu 5 Skew: 2	5):	0.	319 Prob(·		514.03 2.39e-11
Kurtosis: 4 ===================================	========	3.	410 Cond.	No. ======	=======	1.63e+0

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.63e+04. This might indicate that there a re

strong multicollinearity or other numerical problems.

formula = price ~ long

=							
Dep. Variable:	price	R-squared:	0.00				
4	·	·					
Model:	OLS	Adj. R-squared:	0.00				
4							
Method:	Least Squares	F-statistic:	77.3				
0	•						
Date:	Sun, 10 May 2020	<pre>Prob (F-statistic):</pre>	1.58e-1				
8	,	,					
Time:	08:50:37	Log-Likelihood:	-1551				
4.		S					
No. Observations:	21399	AIC:	3.103e+0				
4							
Df Residuals:	21397	BIC:	3.105e+0				
4							
Df Model:	1						
Covariance Type:	nonrobust						
=======================================	=======================================		===========				
=							
	coef std err	t P> t	[0.025 0.97				
5]			-				
-							

> Intercept 2.958 13.198 0.000 33.241 39.0391 44.83 long 0.2128 0.024 8.792 0.000 0.165 0.26 ______ Omnibus: 125.975 Durbin-Watson: 1.95 Prob(Omnibus): 0.000 Jarque-Bera (JB): 128.10 Prob(JB): Skew: 0.189 1.53e-2 Kurtosis: 3.011 Cond. No. 1.06e+0 _______

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correc tly specified.
- [2] The condition number is large, 1.06e+05. This might indicate that there a re

strong multicollinearity or other numerical problems.

###

formula = price ~ sqft_living15

OLS Regression Results							
=======================================	:======	========	========	-=======	:=======	=====	
Dep. Variable:		price	R-squared	1 :		0.35	
8 Model:		OLS	Adj. R-so	quared:		0.35	
8							
Method: 4	Le	ast Squares	F-statist	ic:	1.1	.94e+0	
Date: 0	Sun,	10 May 2020	Prob (F-s	statistic):		0.0	
Time:		08:50:37	Log-Likel	lihood:	-	1080	
<pre>9. No. Observations: 4</pre>		21399	AIC:		2.1	.62e+0	
Df Residuals: 4		21397	BIC:		2.1	.64e+0	
Df Model:		1					
Covariance Type:		nonrobust					
=======================================		========	=======		========	=====	
====	coef	std err	t	P> t	[0 025	0.	
975]	COCT	sta cii	C	17[6]	[0.023	0.	
Intercept 2.165	12.1485	0.009	1422.930	0.000	12.132	1	
	0.0004	4.1e-06	109.265	0.000	0.000		

0.000

______ Omnibus: 107.251 Durbin-Watson: 1.97 Prob(Omnibus): 0.000 Jarque-Bera (JB): 111.13 Skew: 0.158 Prob(JB): 7.38e-2 Kurtosis: 3.158 Cond. No. 6.49e+0 ______

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 6.49e+03. This might indicate that there a re

strong multicollinearity or other numerical problems.

formula = price ~ sqft_lot15

==========		=======				======	=======
= Dep. Variable:		pr	rice	R-squ	uared:		0.00
8 Model:			0LS	Adj.	R-squared:		0.00
8 Method:		Least Squa	ares	F-sta	atistic:		178.
6 Date: 0	Sun	, 10 May 2	2020	Prob	(F-statistic)	:	1.40e-4
Uime: 4.		08:50	9:37	Log-L	ikelihood:		-1546
4. No. Observations 4	s:	21	L399	AIC:			3.093e+0
4 Df Residuals: 4		21	L397	BIC:			3.095e+0
T Df Model: Covariance Type:		nonrot	1 oust				
======================================			=====	t	P> t	[0.025	0.97
	3.0108	0.004	3461.	.771	0.000	13.003	13.01
sqft_lot15 1.66 6	58e-06	1.25e-07	13.	. 365	0.000	1.42e-06	1.91e-0
======================================	:======	110.	. 589	Durbi	in-Watson:	======	1.95

```
Prob(Omnibus):
                           0.000
                                 Jarque-Bera (JB):
                                                           112.22
                                 Prob(JB):
Skew:
                           0.177
                                                           4.27e-2
Kurtosis:
                                 Cond. No.
                           3.003
                                                           3.32e+0
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 3.32e+04. This might indicate that there a
strong multicollinearity or other numerical problems.
###
```

The R2 values between statsmodels.api and statsmodels.formula.api are totally different. statsmodels.api has very high value and statsmodels.formula.api has a very low value. Visual inspection of the data shows most of the features are not linearly related. Thus, it is important to differentiate between these two options in the same statsmodels library.

multiple linear regression

```
In [8]: tmp_kc = kc.drop(["date"], axis=1) # obviously date datatype won't work with 0
LS
    predictors = list(tmp_kc.columns)
    predictors.remove('price')

f = 'price ~ ' + ' + '.join(predictors)
    model = ols(formula=f, data=tmp_kc).fit()
    print(model.summary())
```

=========	:=======	J	=======		=======	======
= Dep. Variable:		price	R-squared	l :		0.75
1 Model:		OLS	Adj. R-sq	uared:		0.75
<pre>0 Method:</pre>	Le	east Squares	F-statist	ic:		378
5. Date:	Sun,	10 May 2020	Prob (F-s	tatistic):		0.0
0 Time: 5		08:50:37	Log-Likel	ihood:		-694.4
No. Observation	ons:	21399	AIC:			142
Df Residuals: 8.		21381	BIC:			156
o. Df Model: Covariance Typ	oe:	17 nonrobust				
=======================================	:=======	========	========	:======:	=======	======
975]	coef	std err	t	P> t	[0.025	0.
 Intercept	-5.9318	3.659	-1.621	0.105	-13.103	
1.239	-2.9310	3.639	-1.021	0.105	-13.103	
bedrooms 0.007	-0.0117	0.002	-4.698	0.000	-0.017	-
bathrooms 0.078	0.0701	0.004	17.096	0.000	0.062	
	4.843e-07	5.97e-08	8.113	0.000	3.67e-07	6.01
floors 0.088	0.0789	0.005	17.475	0.000	0.070	
waterfront 0.406	0.3545	0.026	13.458	0.000	0.303	
view 0.067	0.0616	0.003	22.814	0.000	0.056	
condition 0.069	0.0630	0.003	21.508	0.000	0.057	
grade 0.163	0.1579	0.003	58.198	0.000	0.153	
sqft_above 0.000	0.0001	4.79e-06	27.171	0.000	0.000	
sqft_basement 0.000	0.0001	5.61e-06	26.659	0.000	0.000	
yr_built 0.003	-0.0034	9.04e-05	-37.929	0.000	-0.004	-
yr_renovated e-05	3.718e-05	5.03e-06	7.397	0.000	2.73e-05	4.7
zipcode 0.001	-0.0006	4.12e-05	-14.757	0.000	-0.001	-
lat 1.419	1.3924	0.013	104.101	0.000	1.366	
long 0.107	-0.1394	0.016	-8.488	0.000	-0.172	-

sqft living15 9.631e-05 4.4e-06 21.913 0.000 8.77e-05 0.000 sqft_lot15 -2.233e-07 9.13e-08 0.014 -4.02e-07 -2.447 -4.44 e-08 ______ 314.255 Durbin-Watson: Omnibus: 1.97 Prob(Omnibus): 0.000 Jarque-Bera (JB): 599.11 Skew: -0.030 Prob(JB): 8.00e-13 1 Kurtosis: 3.818 Cond. No. 2.15e+0 _______

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.15e+08. This might indicate that there a re

strong multicollinearity or other numerical problems.

The R2 values of 0.750 from statsmodels.formula.api OLS algorith is much more realistic and reasonable without handling the categorical data and without normalization of any king.

Categorical and Numerical features

The categorical and numerical data must be handled appropriately. Some features such as date sold may be binned into seasons, which makes it easier to handle and much less complicated when fitting. Then all other numerical data may be normalized so that much more reasonable fitting parameters may be obtained when fitting.

Latitude and Longitude is inherently correlated and cannot be treated separately

The zipcode, latitude and longitude all shows the location. While zipcode represents a region and inherently a categorical feature. The latitude+longitude is a much more precise measure of location of a given house. While in a single zipcode there may be a wide range of prices in the close neighborhood prices tend to be similar. Although latitude and longitude separately do not provide much useful information, it can be used to calculate distances relative to a fix point in the region. It should be noted that latitude and longitude are essentially angles and need quite complex conversions to transform them to distances. However, for a small enough region and a county they can be approximated to coordinates in a flat plane without loss of generality. The focal point that makes most sense is the official coordinates of Seattle, which is (47.6062, -122.3321). The '-' on longitude represents 'west'. For a house with coordinates (x1, y1) by applying 'haversine' formula for the distance 'r' can be calculated as follows

```
Haversine a = \sin^2(\Delta \phi/2) + \cos \phi_1 \cdot \cos \phi_2 \cdot \sin^2(\Delta \lambda/2)
formula: c = 2 \cdot \text{atan2}(\sqrt{a}, \sqrt{(1-a)})
d = R \cdot c
```

where φ is latitude, λ is longitude, R is earth's radius (mean radius = 6,371km); note that angles need to be in radians to pass to trig functions!

haversine formula source (https://www.movable-type.co.uk/scripts/latlong.html)

77.348990250629

```
lat long dist

0 47.5112 -122.257 77.348990

1 47.7210 -122.319 77.141575

2 47.7379 -122.233 77.169163

3 47.5208 -122.393 77.274453

4 47.6168 -122.045 77.362968

Index(['date', 'price', 'bedrooms', 'bathrooms', 'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade', 'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15', 'dist'], dtype='object')
```

```
In [11]: # now let's redo the OLS by replacing lattitude and longitude, lat and long wi
    th 'r'
    tmp_kc = kc.drop(["date", 'lat', 'long'], axis=1) # obviously date datatype wo
    n't work with OLS
    predictors = list(tmp_kc.columns)
    predictors.remove('price')

f = 'price ~ ' + ' + '.join(predictors)
    model = ols(formula=f, data=tmp_kc).fit()
    print(model.summary())
```

=========	========	_	:======== :210!!		=======	======
= Dep. Variable:		price	R-squared	i:		0.73
4 Model:		OLS	Adj. R-so	quared:		0.73
4 Method:	Lo	east Squares	F-statist	ic:		368
9. Date:	Sun,	10 May 2020	Prob (F-s	statistic):		0.0
0 Time:		08:50:38	Log-Like	lihood:		-1380.
3 No. Observatio	ns:	21399	AIC:			279
<pre>5. Df Residuals:</pre>		21382	BIC:			293
0. Df Model:		16				
Covariance Typ		nonrobust ======	:=======	=======	========	======
====						
975]	coef	std err	t	P> t	[0.025	0.
Intercept 0.687	231.7099	4.580	50.592	0.000	222.733	24
bedrooms 0.010	-0.0146	0.003	-5.690	0.000	-0.020	-
bathrooms 0.077	0.0688	0.004	16.266	0.000	0.061	
sqft_lot e-07	5.88e-07	6.16e-08	9.551	0.000	4.67e-07	7.09
floors 0.080	0.0708	0.005	15.191	0.000	0.062	
waterfront 0.384	0.3311	0.027	12.177	0.000	0.278	
view 0.059	0.0534	0.003	19.236	0.000	0.048	
condition 0.067	0.0609	0.003	20.133	0.000	0.055	
grade 0.156	0.1503	0.003	53.814	0.000	0.145	
sqft_above 0.000	0.0001	4.92e-06	29.368	0.000	0.000	
sqft_basement 0.000	0.0001	5.79e-06	24.187	0.000	0.000	
yr_built 0.003	-0.0030	9.24e-05	-31.959	0.000	-0.003	-
yr_renovated e-05	3.995e-05	5.19e-06	7.697	0.000	2.98e-05	5.01
zipcode 0.001	-0.0011	4.06e-05	-26.259	0.000	-0.001	-
sqft_living15 0.000	0.0001	4.48e-06	27.349	0.000	0.000	
sqft_lot15 e-07	4.94e-09	9.4e-08	0.053	0.958	-1.79e-07	1.89

dist 1.396	-1.4262	0.015	-94.012	0.000	-1.456	-
=======================================	========		=======	=======	=======	:====
= Omnibus: 3		166.801	Durbin-Wa	tson:		1.98
Prob(Omnibus):		0.000	Jarque-Be	ra (JB):	2	45.41
0 Skew: 4		-0.075	Prob(JB):		5.	13e-5
Kurtosis:		3.503	Cond. No.		2.	61e+0
8						
=======================================	=======		=======	=======	========	:====
=						

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.61e+08. This might indicate that there a re

strong multicollinearity or other numerical problems.

Relacing 'lat' and 'long' with 'r' reduced the R2 from 0.751 to 0.734. Thus, it maybe useful to look at linear regression of each these features to have an accurate estimation.

formula = price ~ zipcode

OLS Regression Results

=========			:====				=======
=							
Dep. Variable	: :	<pre>price R-squared:</pre>					0.00
1							
Model:			0LS	Adj.	R-squared:		0.00
1							
Method:		Least Squa	res	F-st	atistic:		22.1
1							
Date:		Sun, 10 May 2	2020	Prob	(F-statistic):		2.59e-0
6							
Time:		08:50	38:	Log-	Likelihood:		-1554
2.							
No. Observati	ions:	21	.399	AIC:			3.109e+0
4							
Df Residuals:		21	.397	BIC:			3.110e+0
4			_				
Df Model:			1				
Covariance Ty	•	nonrob					
=========		=========	====	=====		======	=======
=	550	E std opp		_	P> t	רם מוד	0.07
c 1	coe	sta err		Ĺ	P> L	[0.025	0.97
5]							
Intoncont	/2 510 ⁻	7 6 272		6 790	0.000	20 227	5 <i>1</i> Q1
2	42.317	0.272		0.760	0.000	30.227	34.61
_	-0 000	3 6 390-05	_	./ 702	0.000	-0 000	-0.00
21pcode 0	-0.000.	0.556-65		4.702	0.000	-0.000	-0.00
=========	.======				=========		
=							
Omnibus:		106.	988	Durb	in-Watson:		1.95
4		200.	200	5 4. 5.	in nacson.		1,33
Prob(Omnibus)):	0.	000	Jarq	ue-Bera (JB):		108.53
7	, ,				ac 20. a (02).		
Skew:		0.	174	Prob	(JB):		2.70e-2
4					(,-		
Kurtosis:		2.	986	Cond	. No.		1.80e+0
8							-
=========	:=====:			======		=======	=======
=							

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.8e+08. This might indicate that there are

strong multicollinearity or other numerical problems.

formula = price ~ lat

OLS Regression Results

=

```
Dep. Variable:
                       price
                            R-squared:
                                                    0.21
2
Model:
                        OLS
                            Adj. R-squared:
                                                    0.21
Method:
                Least Squares
                            F-statistic:
                                                    577
0.
              Sun, 10 May 2020
Date:
                            Prob (F-statistic):
                                                     0.0
                    08:50:38
                            Log-Likelihood:
Time:
                                                   -1299
8.
No. Observations:
                       21399
                            AIC:
                                                 2.600e+0
Df Residuals:
                            BIC:
                                                 2.602e+0
                       21397
Df Model:
                          1
Covariance Type:
                    nonrobust
_______
                                           [0.025
            coef std err
                                   P>|t|
                             t
                                                   0.97
5]
     ______
Intercept -65.8959 1.039 -63.416 0.000 -67.933 -63.85
lat
          1.6596
                   0.022
                          75.958
                                   0.000
                                            1.617
                                                    1.70
Omnibus:
                     452.059
                            Durbin-Watson:
                                                    1.95
Prob(Omnibus):
                       0.000
                            Jarque-Bera (JB):
                                                   514.03
                       0.319
                            Prob(JB):
                                                 2.39e-11
Skew:
2
Kurtosis:
                       3.410
                            Cond. No.
                                                  1.63e+0
______
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 1.63e+04. This might indicate that there a
strong multicollinearity or other numerical problems.
###
formula = price ~ long
                    OLS Regression Results
______
Dep. Variable:
                       price
                            R-squared:
                                                    0.00
4
Model:
                        OLS
                            Adj. R-squared:
                                                    0.00
```

Method:		Le	ast Squa	res	F-sta	tistic:		77.3	
0									
Date:		Sun,	10 May 2	.020	Prob	(F-statistic):		1.58e-1	
8									
Time:			08:50	:38	Log-L	ikelihood:		-1551	
	4.								
No. Observations:			21399		AIC:		3.103e+0		
•	4		24207		576		2 1050		
Df Residuals:			21397		RIC:		3.105e+0		
Df Model:	4		4						
Covariance ⁻	Tyna·		1 nonrobust						
					.=====	:========			
=									
	coe	f s	td err		t	P> t	[0.025	0.97	
5]						. 1 - 1			
-									
-									
Intercept	39.0393	L	2.958	13	.198	0.000	33.241	44.83	
7									
long	0.2128	3	0.024	8	.792	0.000	0.165	0.26	
0									
========	=======	=====	======	=====	=====	=========	======	=======	
=									
Omnibus:			125.975		Durbin-Watson:			1.95	
4	- \ .		0	000	7			120 10	
Prob(Omnibus):			0.000		Jarque-Bera (JB):		128.10		
1 Skew:			α	100	Dnoh/	JD).		1.53e-2	
Skew.		0.189		Prob(JB):			1.55e-2		
Kurtosis:		3 011		Cond. No.			1.06e+0		
5			٠,	011	cona.	110.		1.00010	
	=======		======	=====	=====	=========	=======	=======	
=									

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.06e+05. This might indicate that there a re

strong multicollinearity or other numerical problems.

formula = price ~ dist

old heli eddied							
============		=============	==========				
=							
Dep. Variable:	price	R-squared:	0.12				
1	•	•					
Model:	OLS	Adj. R-squared:	0.12				
1	023	Aug. R Squarea.	0.12				
<u>т</u>	Lanat Causana	F -4-4:-4:	204				
Method:	Least Squares	F-STatistic:	294				
1.							
Date:	Sun, 10 May 2020	<pre>Prob (F-statistic):</pre>	0.0				
0							

Time:

5.			00.30.30		Log Likelinood.		1-11/
No. Observations:		21	21399				2.835e+0
Df Residuals: 4		21397		BIC:			2.837e+0
Df Model:			1				
Covariance Type:		nonrob					
=======================================	=======	=======	=====	=====	========	=======	=======
	coef	std err		t	P> t	[0.025	0.97
5]							
-							
Intercept	106.5319	1.724	61	.790	0.000	103.153	109.91
1							
dist	-1.2091	0.022	-54	.232	0.000	-1.253	-1.16
5							
=======================================	========	========	=====	======		=======	=======
Omnibus:		318.	175	Durbir	n-Watson:		1.95
1							
Prob(Omnibus):		0.	0.000		Jarque-Bera (JB):		334.54
6				5			
Skew: 3		0.	292	Prob(J	JB):		2.26e-7
Kurtosis:		3.182		Cond. No.			4.16e+0
4		J.		20.14			
=======	=======	=======	=====	======		=======	=======
=							

08:50:38

Log-Likelihood:

-1417

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 4.16e+04. This might indicate that there a

strong multicollinearity or other numerical problems.

•

Is the predictor 'r' better than lat+long or zipcode? The feature

- 'long' = 0.004
- 'lat' = 0.212
- 'zipcode' = 0.001
- 'r' = 'r' = 0.121

It's difficult to say weather r is a good indicator or not. Let's keep it for now.

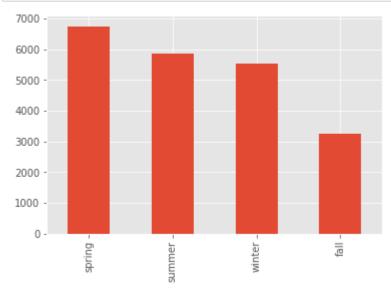
Categorize 'Date' variable to show season

The feature 'date' is the date the souse sold in king county. A date data type will not be included in the regression. Thus, it may be better to categorize the date into season.

```
In [14]: kc['date']= pd.to_datetime(kc['date'])
kc['month'] = kc['date'].dt.month # add a month column to the dataframe
kc.month.unique()

Out[14]: array([10, 12, 2, 5, 6, 1, 4, 3, 7, 8, 11, 9], dtype=int64)
```

```
In [15]: plt.style.use('ggplot')
   kc.month = kc.month.replace(12, 0) # change 12 to 0 so that 0-2 represent wint
   er
   #creating bins for the season
   bins = [0, 3, 6, 9, 11]
   kc['season'] = pd.cut(kc['month'], bins, include_lowest = True, labels = ["win ter", "spring", "summer", "fall"])
   kc['season'] = kc['season'].cat.as_unordered()
   kc['season'].value_counts().plot(kind='bar')
   plt.show()
   kc.season
```



```
Out[15]: 0
                     fall
          1
                   winter
          2
                   winter
          3
                   winter
          4
                   winter
                    . . .
          21394
                   spring
          21395
                   winter
         21396
                   spring
         21397
                   winter
         21398
         Name: season, Length: 21399, dtype: category
         Categories (4, object): [winter, spring, summer, fall]
```

prepare other categorical features to sting

```
In [16]: #print(kc.columns[0:20])
    check_cat = ['waterfront', 'condition', 'floors', 'view', 'grade', 'sqft_basem
    ent']

for feature in check_cat:
    print("unique values of \'{}\' predictor".format(feature))
    display(kc[feature].value_counts())
```

```
unique values of 'waterfront' predictor
0.0
       21296
1.0
         103
Name: waterfront, dtype: int64
unique values of 'condition' predictor
3
     13899
4
      5631
5
      1671
2
       169
        29
Name: condition, dtype: int64
unique values of 'floors' predictor
1.0
       10639
2.0
        8106
1.5
        1898
3.0
         607
2.5
         143
3.5
           6
Name: floors, dtype: int64
unique values of 'view' predictor
0.0
       19415
2.0
         930
3.0
         483
1.0
         317
4.0
         254
Name: view, dtype: int64
unique values of 'grade' predictor
7
      8973
      6060
8
9
      2597
      2038
6
10
      1075
       329
11
5
       242
12
        56
        27
4
13
         1
         1
Name: grade, dtype: int64
unique values of 'sqft_basement' predictor
```

```
0.0
          13225
600.0
            215
500.0
            209
700.0
            205
800.0
            200
602.0
              1
1281.0
              1
915.0
2130.0
              1
1890.0
Name: sqft_basement, Length: 291, dtype: int64
```

The numerical variable looks catergorical. However, except wavefront rest can be assumed as a numerical data for the puspose of regression. let's encode wavefront onto string.

```
In [17]: kc['waterfront'] = kc['waterfront'].astype("str")
In [18]: # let's remove unnecessary and binned
kc = kc.drop(['date', 'month'], axis =1 )
```

One-Hot Encoding to handle the categorical features

```
In [19]: kc = pd.get_dummies(kc) #one-hot encoding our data
         kc.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 21399 entries, 0 to 21398
         Data columns (total 24 columns):
                           21399 non-null float64
         bedrooms
                           21399 non-null int64
         bathrooms
                           21399 non-null float64
         sqft lot
                           21399 non-null float64
         floors
                           21399 non-null float64
         view
                           21399 non-null float64
                           21399 non-null int64
         condition
                           21399 non-null int64
         grade
                           21399 non-null float64
         sqft above
         sqft basement
                           21399 non-null float64
         yr built
                           21399 non-null int64
         yr_renovated
                           21399 non-null int64
                           21399 non-null int64
         zipcode
         lat
                           21399 non-null float64
                           21399 non-null float64
         long
         sqft living15
                           21399 non-null float64
         sqft_lot15
                           21399 non-null float64
         dist
                           21399 non-null float64
         waterfront_0.0
                           21399 non-null uint8
         waterfront 1.0
                           21399 non-null uint8
         season_winter
                           21399 non-null uint8
         season spring
                           21399 non-null uint8
         season summer
                           21399 non-null uint8
                           21399 non-null uint8
         season_fall
         dtypes: float64(12), int64(6), uint8(6)
         memory usage: 3.1 MB
In [20]: kc.rename(columns={'waterfront 0.0' : 'waterfront 0', 'waterfront 1.0' : 'water
         rfront_1'}, inplace=True)
In [21]: # to preserve linear dependance let's drop one column from hot encoded feature
         kc = kc.drop(['waterfront_1', 'season_fall'], axis =1 )
```

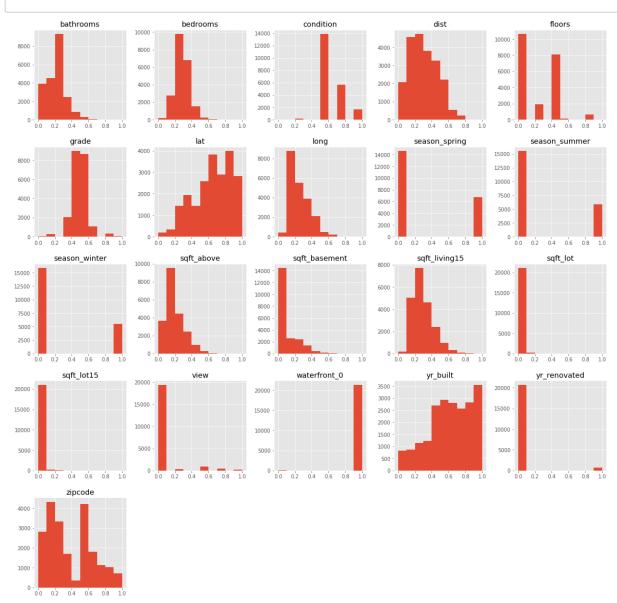
Min-Max Normalization

Min-max normalization make most sense for this data.

```
In [22]: # min-max scaler (normalization using y= (x-min)/(max-min))
from sklearn.preprocessing import MinMaxScaler

#let's drop the price for it's not included in the normalize
kc_norm = kc.drop(['price'], axis =1 )

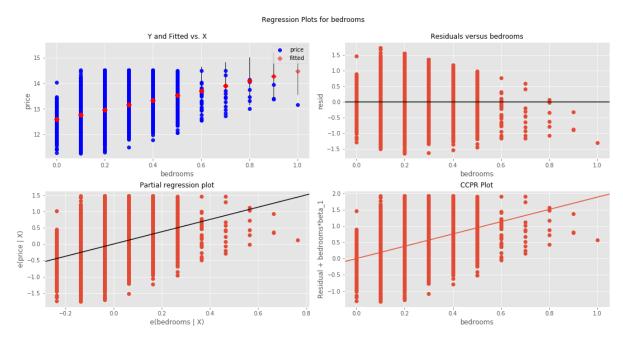
scaler = MinMaxScaler() # instantiate
kc_norm = pd.DataFrame(scaler.fit_transform(kc_norm), columns = kc_norm.column
s)
kc_norm.hist(figsize = (20,20));
```



```
In [23]: #display(kc_norm.columns)
# add the price column to the mean normalized dataset.
kc_norm['price']=kc['price']
#kc_norm=pd.concat([kc_cat, kc_norm], axis=1)
#display(kc_norm.columns)
```

Let's redo OLS after normalization

formula = price ~ bedrooms



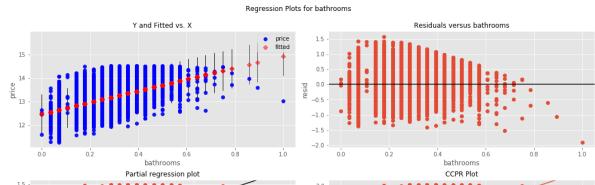
OLS Regression Results

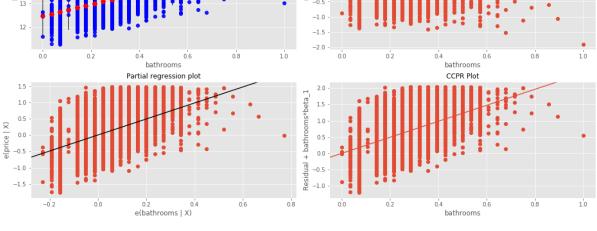
			.======	======	=====	==========	=======	
=								
Dep. Variable:	:		р	rice	R-sq	uared:		0.11
4								
Model:				OLS	Adj.	R-squared:		0.11
4								075
Method:		Le	east Squ	ares	F-st	atistic:		275
8. Date:		Cup	10 May	2020	Dnoh	/Γ c+o+ic+ic).		0.0
Date.		Juii,	10 May	2020	PIOU	(F-statistic):		0.0
Time:			08:5	0:42	l og-	Likelihood:		-1425
6.			00.5	0.72	-06	LIKCIIIIOOU.		1,25
No. Observation	ons:		2	1399	AIC:			2.852e+0
Df Residuals:			2	1397	BIC:			2.853e+0
4 Df Model:				1				
Covariance Typ	٠.		nonro	1 hust				
					====	==========	======	=======
=								
	coef	f s	std err		t	P> t	[0.025	0.97
5]							-	
-								
	12.5872	2	0.009	1389	.000	0.000	12.569	12.60
5	4 000	,	0.026	F-2	E43	0.000	1 013	1 05
bearooms 3	1.882	/	0.036	52	.513	0.000	1.812	1.95
						==========		
=								
Omnibus:			73	. 399	Durb	in-Watson:		1.95
3					2 0 0			
Prob(Omnibus):	:		0	.000	Jarq	ue-Bera (JB):		73.38
9					•	, ,		
Skew:			0	.136	Prob	(JB):		1.16e-1
6								
Kurtosis:			2	.910	Cond	. No.		11.
8								
=========		=====	======	=====	=====	========	======	=======
=								
Warnings:								

Warnings:

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

formula = price ∼ bathrooms





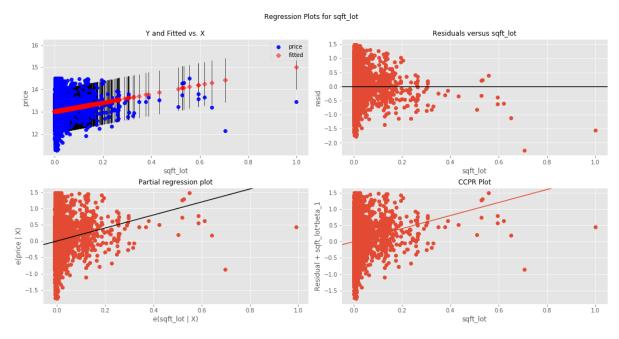
OLS Regression Results

				, 				
=======================================	:=====	======	=====	:====	====	=========	======	=======
Dep. Variable:			pri	.ce	R-sq	uared:		0.27
4 Model:			0	LS	Adi.	R-squared:		0.27
4					, .u. j v	Transfer Co.		• • • •
Method:		Least	Squar	es	F-st	atistic:		806
9. Date:		Sun. 10 I	Mav 20	120	Prob	(F-statistic):		0.0
0		Ju,	,			(. 500.015.10).		
Time:		(08:50:	43	Log-	Likelihood:		-1212
9. No. Observation	ns:		213	99	AIC:			2.426e+0
4								
Df Residuals:			213	97	BIC:			2.428e+0
4 Df Model:				1				
Covariance Typ	e:	n	onrobu	ıst				
	======	======	=====	====	====	=========	======	=======
=	coef	std (err		t	P> t	[0.025	0.97
5]						7 1 - 1	L	
- Intercept	12.4707	0.0	007	1808	.745	0.000	12.457	12.48
4								
bathrooms 0	2.4559	0.	027	89	.830	0.000	2.402	2.51
-	======	:======	=====	:====:	====	=========	=======	=======
=								
Omnibus:			94.5	48	Durb	in-Watson:		1.95
<pre>8 Prob(Omnibus):</pre>			0.0	000	Jarq	ue-Bera (JB):		87.63
5					•	, ,		
Skew:			0.1	.24	Prob	(JB):		9.34e-2
0 Kurtosis:			2.8	807	Cond	. No.		9.8
7								
_	======	======	=====			=========	======	=======
=								
Warnings:								

Warnings:

 $\cite{black} \cite{black}$ Standard Errors assume that the covariance matrix of the errors is correctly specified.

formula = price ~ sqft_lot



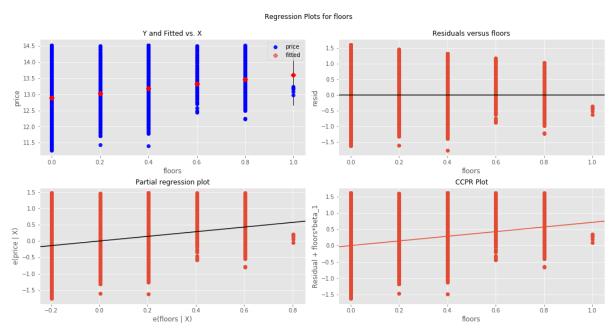
OLS Regression Results

						=======================================		
=								
Dep. Variable:			pr	rice	R-sq	uared:		0.01
Model:				OLS	Adj.	R-squared:		0.01
<pre>0 Method:</pre>		ا معد	+ Saus	nac	F_c+	atistic:		216.
5								
Date:		Sun, 10	May 2	2020	Prob	(F-statistic):		9.06e-4
Time:			08:50	:44	Log-	Likelihood:		-1544
No. Observatio	ns:		21	1399	AIC:			3.089e+0
Df Residuals:			21	1397	BIC:			3.091e+0
Df Model:				1				
Covariance Typ								
=======================================	======	:=====	=====	:====:	====	=========	======	:======
	coef	std	err		t	P> t	[0.025	0.97
5]								
-								
Intercept 1	13.0144	. 0	.004	3607	. 848	0.000	13.007	13.02
sqft_lot 3	1.9966	5 0	.136	14	.714	0.000	1.731	2.26
=========	======	======	=====			========	======	
= Omnibus:			107.	332	Durb	in-Watson:		1.95
4 Prob(Omnibus):			0.	000	Jara	ue-Bera (JB):		108.84
6								
Skew: 4			0.	174	Prob	(JB):		2.31e-2
Kurtosis:			3.	018	Cond	. No.		39.
========	======		=====	=====	====	========	======	
=								
Warnings: [1] Standard F	rrors a	issume t	hat th	ne cova	arian	ce matrix of th	e errors	is correc

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

###

formula = price ~ floors



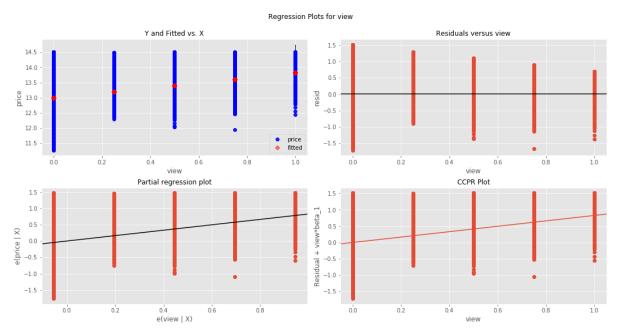
OLS Regression Results

=						=========	======	
Dep. Variable	:		р	rice	R-sq	uared:		0.09
Model:				OLS	Adj.	R-squared:		0.09
4 Method:		دما	st Sau	arec	F_c+	atistic:		222
8.		LCa.	sc squ	ai C3	1 30	aciscic.		222
Date: 0		Sun, 1	0 May	2020	Prob	(F-statistic):		0.0
Time:			08:5	0:46	Log-	Likelihood:		-1449
3. No. Observation	ons:		2	1399	AIC:			2.899e+0
4								
Df Residuals:			2	1397	BIC:			2.901e+0
Df Model: Covariance Type	ne:		nonro	1 hust				
					====	========	======	=======
=	cood	- c+	d onn		+	P> t	[0 025	0.97
5]	coe	50	u em		Ĺ	P> L	[0.025	0.97
-								
Intercept 1	12.8921	L (0.004	2927	.893	0.000	12.883	12.90
_	0.7128	3 (0.015	47	.197	0.000	0.683	0.74
_	======	=====	=====	=====	====		======	=======
= Omnibus:			142	.409	Durb	in-Watson:		1.96
<pre>8 Prob(Omnibus)</pre>	•		0	.000	Jarq	ue-Bera (JB):		144.74
8 Skout			a	100	Dnob	/ ומר /		2 700 2
Skew: 2			О	.198	Prob	(JB):		3.70e-3
Kurtosis: 3			2	.929	Cond	. No.		4.8
=========	======		=====	=====	====		======	=======
=								
Warnings:	_							

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

###

formula = price ~ view



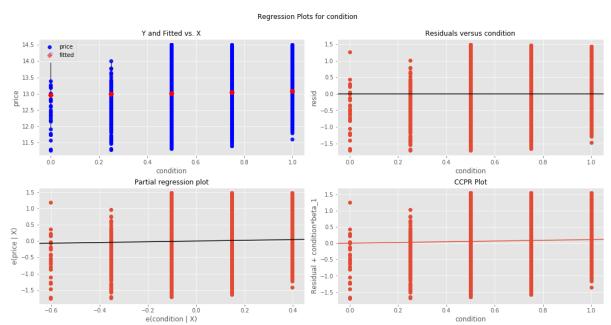
OLS Regression Results

				egi ess.				
=	======		======		=====	:=========	======	
Dep. Variable: 2			p	rice	R-sq	uared:		0.09
Model:				OLS	Adj.	R-squared:		0.09
2 Method:		۵ ا	ast Sai	IZPAC	F_c+	atistic:		215
7.		LC	asc squ	iai es	1-30	aciscic.		213
Date:		Sun,	10 May	2020	Prob	(F-statistic):		0.0
0 Time:			08:5	0:47	Log-	Likelihood:		-1452
5. No. Observatio	nc•		7	21399	AIC:			2.905e+0
4	115.		2	1333	AIC.			2.3036+0
Df Residuals:			2	21397	BIC:			2.907e+0
Df Model:				1				
Covariance Typ			nonro					
=						:=========		
5]	coef	F S	td err		t	P> t	[0.025	0.97
- Intercept	12.9870	a	0.003	3917	816	0.000	12.980	12.99
4	12.5076	,	0.005	3017	.040	0.000	12.500	12.77
view 4	0.8286	5	0.018	46	.444	0.000	0.794	0.86
•	======	=====	======	:=====:	====	.========	======	
= Omnibus:			10	.802	Dunh	oin-Watson:		1.94
3			40	7.002	Duib	in-wacson.		1.54
<pre>Prob(Omnibus): 1</pre>			6	.000	Jarq	ue-Bera (JB):		40.99
Skew:			6	.107	Prob	(ЈВ):		1.26e-0
9 Kurtosis:			3	3.010	Cand	l No		E 1
9			3	.010	Conu	i. NO.		5.4
	======		======	:=====:	====	=========	======	=======
=								
Warnings:	nnone	accumo	+ha+ +	he cov	ani an	uce matrix of th	a annons	is connec

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

###

formula = price ~ condition



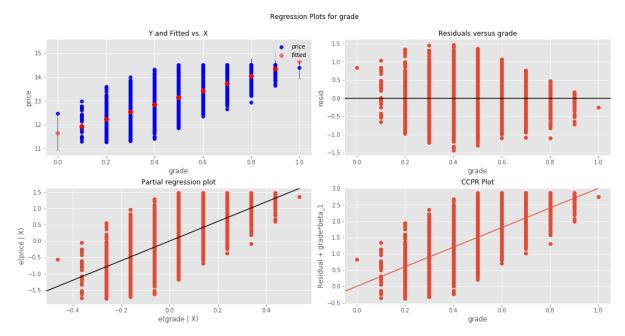
OLS Regression Results

		:=======	======	====	======		=======	
=								
Dep. Variable:	:		pri	ice	R-sq	uared:		0.00
Model:			(OLS	Adj.	R-squared:		0.00
Method:		Least	t Squar	res	F-st	atistic:		27.6
1 Date:		Sun, 10	May 26	ð20	Prob	(F-statistic):		1.50e-0
7 Time:			08:50:	:48	Log-l	Likelihood:		-1553
9. No. Observation	ons:		213	399	AIC:			3.108e+0
4 Df Residuals:			213	397	BIC:			3.110e+0
4 Df Model: Covariance Typ								
=======================================						- 1.1		
5]						P> t	_	
-								
1						0.000		
condition 2	0.1107	7 0.	.021	5	5.255	0.000	0.069	0.15
=========		:=====:	=====	====	=====	=========	======	=======
= Omnibus: 2			113.1	194	Durb:	in-Watson:		1.95
Prob(Omnibus):	:		0.6	900	Jarqı	ue-Bera (JB):		114.92
7 Skew:			0.1	179	Prob	(JB):		1.11e-2
5 Kurtosis:			2.9	993	Cond	. No.		8.4
4	======	.======		====			======	
=						 _	_	_
Warnings:								

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

###

formula = price ~ grade

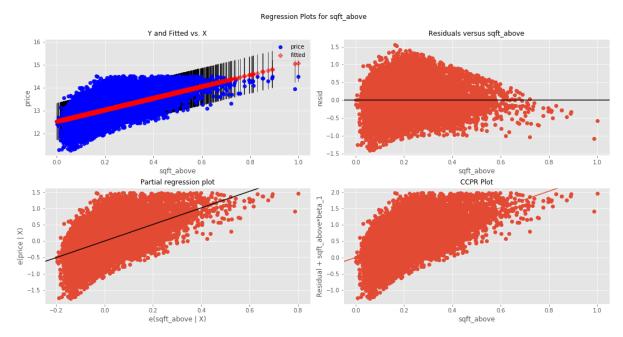


OLS Regression Results

			negie:				
	======	:======	======	=====	=======================================		=======
= Dep. Variable: 5			price	R-sq	uared:		0.46
Model:			OLS	Adj.	R-squared:		0.46
5 Method:		Least S	Squares	F-st	atistic:		1.858e+0
4 Date:		Sun, 10 Ma	ay 2020	Prob	(F-statistic)	:	0.0
0 Time:			3:50:49		Likelihood:		-8866.
3		00	3.30.43	LOG	LIKCIIIIOOU.		0000.
No. Observatio	ns:		21399	AIC:			1.774e+0
Df Residuals:			21397	BIC:			1.775e+0
Df Model:			1				
Covariance Typ	e:	nor	robust				
	======	:======	======	=====	===========		=======
=	coef	std er	rr	+	P> t	[0.025	0.97
5]		364 61	•		. , e	[0.023	
-							
Intercept 2	11.6412	0.01	11	07.950	0.000	11.621	11.66
	3.0040	0.02	22 1	36.291	0.000	2.961	3.04
,	======	:=======	.=====	======	========		=======
=							
Omnibus: 2			36.605	Durb	in-Watson:		1.96
Prob(Omnibus):			0.000	Jarq	ue-Bera (JB):		36.76
Skew:			0.102	Prob	(JB):		1.04e-0
8 Kurtosis:			3.004	Cond	. No.		10.
7							
	======	=======			=========		=======
=							
Warnings:							
	rrors a	ssume that	the co	ovarian	ce matrix of th	ne errors	is correc

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

formula = price ~ sqft_above



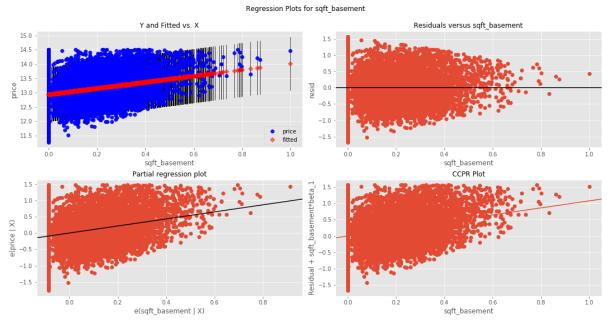
OLS Regression Results

=========	======	=====		=====:	=====	 ==========	=======	=======
=								
Dep. Variable	:		р	rice	R-sq	uared:		0.32
6								
Model:				OLS	Adj.	R-squared:		0.32
6 Method:		١٥	act Cau	2005	Г с+	a+ic+ic.		1 022010
Method:		Le	ast squ	ares	F-5 L	atistic:		1.033e+0
Date:		Sun.	10 May	2020	Prob	(F-statistic):		0.0
0		Ju,				(. 5000=50=0).		
Time:			08:5	0:51	Log-	Likelihood:		-1133
7.								
No. Observation	ons:		2	1399	AIC:			2.268e+0
4			2	1207	DTC.			2 200010
Df Residuals:			2	1397	BIC:			2.269e+0
Df Model:				1				
Covariance Typ	oe:		nonro					
=========	======		======	=====	====	=========	======	=======
=.		_						
-1	coe	f s	td err		t	P> t	[0.025	0.97
5]								
_								
Intercept	12.5284	1	0.006	2199	.790	0.000	12.517	12.54
0								
sqft_above	2.5396	5	0.025	101	.649	0.000	2.491	2.58
9								
=========	======	=====	======	=====	=====	========	======	=======
= Omnibus:			92	152	Dunh	in-Watson:		1.98
2			62	.133	Dui D	III-wacson.		1.98
Prob(Omnibus)	•		0	.000	Jara	ue-Bera (JB):		74.36
8						(, ,		
Skew:			0	.105	Prob	(JB):		7.10e-1
7								
Kurtosis:			2	.802	Cond	. No.		9.2
5								
=======================================		==		_=====	_====	=========	_======	====
Mannings.								

Warnings:

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

formula = price ~ sqft_basement



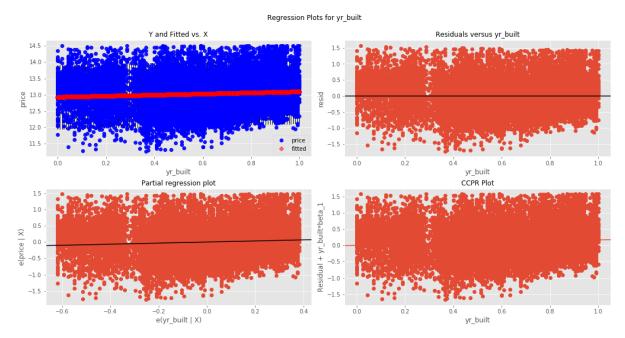
OLS Regression Results

		_	STOIL MESUIC				
=======================================	=======	:=======	:=======	========	:=======	-====	
Dep. Variable:		price	R-squared	:		0.08	
Model:		OLS	Adj. R-sq	uared:		0.08	
0 Method:	Los	net Sauanos	F-statist	ic:		186	
5.	Lea	ist squares	r-statist.		100		
Date: 0	Sun, 1	l0 May 2020	Prob (F-s	tatistic):	0.0		
Time:		08:50:52	Log-Likel	ihood:	-	-1465	
No. Observations:	:	21399	AIC:		2.9	932e+0	
Df Residuals:		21397	BIC:		2.9	934e+0	
Df Model:		1					
Covariance Type:		nonrobust		========			
====							
0751	coef	std err	t	P> t	[0.025	0.	
975]							
 -	12 0206	0.004	2202 602	0.000	42.022	4	
Intercept 2.947	12.9396	0.004	3303.693	0.000	12.932	1	
<pre>sqft_basement 1.128</pre>	1.0789	0.025	43.190	0.000	1.030		
==========	-======		:=======	=======	:=======	-====	
= Omnibus: 0		132.547	Durbin-Wa	tson:		1.94	
Prob(Omnibus):		0.000	Jarque-Be	ra (JB):	1	134.93	
2 Skew:		0.195	Prob(JB):		5.	.01e-3	
0 Kuntasisi		2.998	Cand No			7.6	
Kurtosis: 7		2.998	Cond. No.			7.6	
=======================================	-======		:=======	=======	:=======	=====	
Warnings: [1] Standard Erro	ne secumo	that the co	wanianco ma	tniv of the	onnone is	connoc	
tly specified	n s assume	chac the Co	vai tailCE illa	CLIX OF CHE	EI I OI 2 12 (יוויבר	

tly specified.

###

formula = price ~ yr_built

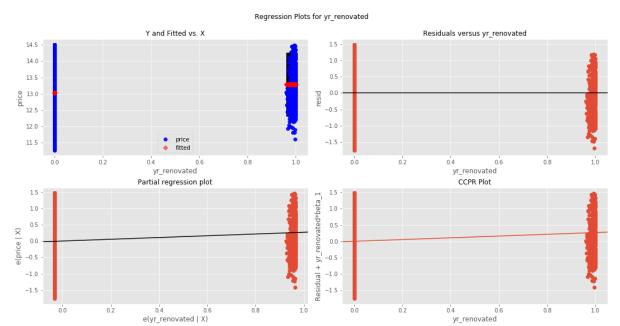


OLS Regression Results

				egi ess.				
=======================================	======	=====	======	=====	=====	==========	======	=======
Dep. Variable	:		р	rice	R-sq	uared:		0.00
Model:				OLS	Adj.	R-squared:		0.00
7 Method:		ا	aast Sou	arec	F_c+	atistic:		153.
4								
Date: 5		Sun,	10 May	2020	Prob	(F-statistic):		4.15e-3
Time:			08:5	0:53	Log-	Likelihood:		-1547
6. No. Observati	ons:		2	1399	AIC:			3.096e+0
4								
Df Residuals:			2	1397	BIC:			3.097e+0
Df Model:				1				
Covariance Ty	•		nonro 			==========		
=								
5]	coef	f s	std err		t	P> t	[0.025	0.97
- Intercept	12 9297	7	0.009	1447	296	0.000	12.912	12.94
7								
yr_built 2	0.1657	7	0.013	12	.385	0.000	0.139	0.19
=========	======			=====			======	=======
= Omnibus:			150	.208	Durb	in-Watson:		1.96
2								
Prob(Omnibus) 3	:		0	.000	Jarq	ue-Bera (JB):		153.14
Skew:			0	.206	Prob	(JB):		5.57e-3
4 Kurtosis:			2	.949	Cond	. No.		5.4
9			_					
=======================================	======	=====	======	=====	====	=========	======	=======
Warnings:	Ennone a	o c c um/	- +h-+ +	he cov	anian	ce matrix of th	a arrors	is correc

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

formula = price ~ yr_renovated

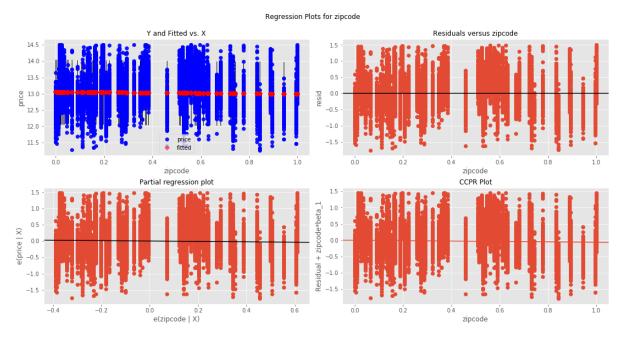


OLS Regression Results

		_		STOIL WESUI			
=======================================	=======	=======	===:	=======	:=======:	======	======
Dep. Variable: 9		pri	ce	R-square	ed:		0.00
Model:		0	LS	Adj. R-s	squared:		0.00
9 Method:	L	east Squar	es	F-statis	stic:		198.
8 Date:	Sun,	10 May 20	20	Prob (F-	·statistic):		6.22e-4
5 Time:		08:50:	55	Log-Like	elihood:		-1545
4.				- 0			
No. Observation 4	s:	213	99	AIC:			3.091e+0
Df Residuals: 4		213	97	BIC:			3.093e+0
Df Model:			1				
Covariance Type	•	nonrobu	st				
	=======	=======	===:	=======		======	======
===	coof	ctd onn		+	P> t	[0.025	0.9
75]	coei	sta en		Ĺ	P> C	[0.023	0.9
Intercept 030	13.0230	0.003	3	759.148	0.000	13.016	13.
	0.2694	0.019		14.098	0.000	0.232	0.
=	=======	=======	===:	=======	:=======	======	======
Omnibus:		96.8	83	Durbin-W	latson:		1.95
Prob(Omnibus):		0.0	00	Jarque-E	Bera (JB):		98.12
6 Skew:		0.1	66	Prob(JB)):		4.92e-2
<pre>2 Kurtosis: 2</pre>		3.0	05	Cond. No).		5.6
==========	=======	=======	===:	=======		======	======
=							
Warnings:							
[1] Standard Er	rors assum	e that the	co	variance m	natrix of the	errors i	is correc

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

formula = price ~ zipcode



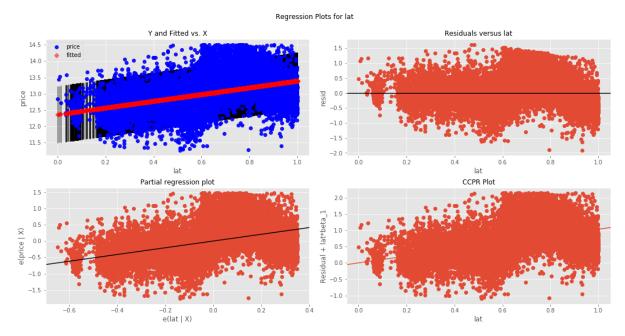
OLS Regression Results

	======			=====	=====	============		
=								
Dep. Variable	:		р	rice	R-sq	uared:		0.00
Model:				OLS	Adj.	R-squared:		0.00
1 Method:		Le	ast Squ	ares	F-st	atistic:		22.1
1 Date:						(F-statistic):		2.59e-0
6		Juli	_					2.596-0
Time: 2.			08:5	0:56	Log-	Likelihood:		-1554
No. Observation	ons:		2	1399	AIC:			3.109e+0
Df Residuals:			2	1397	BIC:			3.110e+0
4 Df Model: Covariance Ty	pe:		nonro	1 bust				
=======================================	======		======	=====	=====	=========	======	=======
-1	coe	f s	td err		t	P> t	[0.025	0.97
5]								
- Intoncont	12 055	ı	0 006	2176	200	0.000	13.043	13.06
7	13,033.	L	0.000	21/0	. 209	0.000	13.043	13.00
zipcode 5	-0.0595	5	0.013	-4	.702	0.000	-0.084	-0.03
=======================================	======	=====	======	=====	=====	========	======	=======
Omnibus:			106	.988	Durb	in-Watson:		1.95
4 Prob(Omnibus)	:		0	.000	Jara	ue-Bera (JB):		108.53
7								
Skew: 4			0	.174	Prob	(JB):		2.70e-2
Kurtosis: 0			2	.986	Cond	. No.		4.3
=========	======	=====	======	=====	=====	========	======	=======
=								
Warnings:								

Warnings:

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

formula = price ~ lat



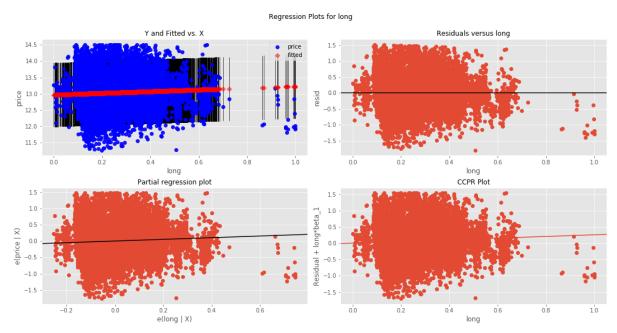
OLS Regression Results

	.=====			=====	=====	=======================================	.======	
=								
Dep. Variable:		price			R-sq	0.21		
Model:		OLS			Adj.	0.21		
2 Method:		Least Squares			F-st	577		
0. Date:		Sun.	10 May	2020	Prob	(F-statistic):		0.0
0		Ju.,	_					
Time: 8.			08:5	0:57	Log-	Likelihood:		-1299
No. Observation	ns:		2	1399	AIC:			2.600e+0
Df Residuals:			2	1397	BIC:			2.602e+0
4 Df Model: Covariance Typ	ne:		nonro	1 bust				
					=====	========	======	=======
=	500	c ,	td onn		+	P> t	[0 025	a 07
5]	coe						_	
-								
Intercept 0	12.3623	1	0.009	1325	.417	0.000	12.344	12.38
lat 8	1.0317	7	0.014	75	.958	0.000	1.005	1.05
=======================================	:=====:		:=====	=====	=====	=========	======	=======
Omnibus:			452	.059	Durb	in-Watson:		1.95
Prob(Omnibus):			0	.000	Jarq	ue-Bera (JB):		514.03
5 Skew:			0	.319	Prob	(JB):		2.39e-11
2								C 4
Kurtosis: 3			3	.410	Cona	. NO.		6.4
=======================================		=====		=====	====	=========	======	=======
Warnings:								

Warnings:

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

formula = price ~ long



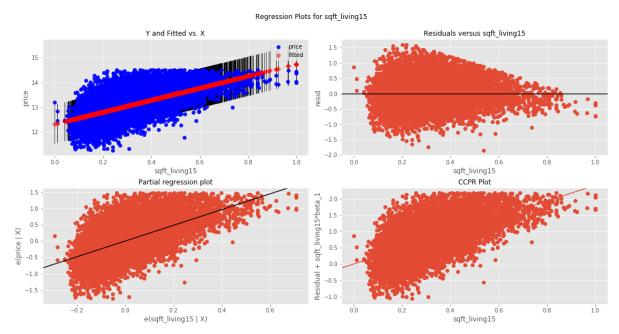
OLS Regression Results

=	====	=====		-===	=====			
Dep. Variable:	:		pı	rice	R-so	quared:		0.00
Model:				OLS	Adj	. R-squared	:	0.00
4 Method:		leas	t Saus	ares	F-s1	tatistic:		77.3
0		LCas	c Sque	ai C3	1 3	tatistic.		
Date: 8		Sun, 10	May 2	2020	Prol	(F-statis	tic):	1.58e-1
Time:			08:50	ð:59	Log	-Likelihood	:	-1551
No. Observation	ons:		23	1399	AIC	:		3.103e+0
Df Residuals:			23	1397	BIC	:		3.105e+0
Df Model: Covariance Typ								
=======================================			:====:	====	=====	=======	========	========
5]	coe-	f sto	l err		t	P> t	[0.025	0.97
Intercept 3	12.967	9 6	.008	159	3.050	0.000	12.951	12.98
long 3	0.2562	2 6	.029		8.792	0.000	0.199	0.31
=========		======	=====		=====		========	=======
= Omnibus:			125	.975	Durl	oin-Watson:		1.95
4 Prob(Omnibus):	:		0	.000	Jaro	que-Bera (J	B):	128.10
1 Skew:			а	.189	Prol	o(JB):		1.53e-2
8								
Kurtosis: 9			3.	.011	Cond	d. No.		9.0
=======================================		======	=====	====	=====	=======	========	=======

Warnings:

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

formula = price ~ sqft_living15



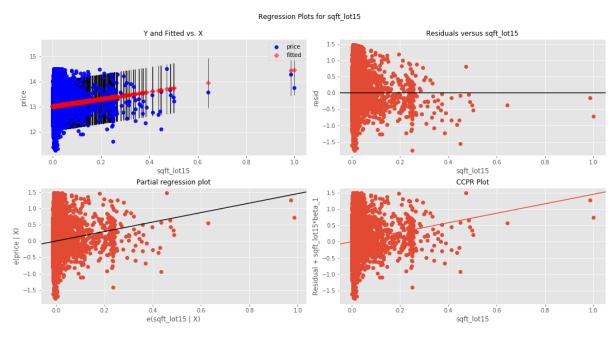
OLS Regression Results

013 Regression Results										
	=======	=======	=======	========	=======	=====				
= Dep. Variable: 8		price	R-squared	l:	0.35					
Model:		OLS	Adj. R-sq	uared:	0.35					
8 Method:	Lea	ast Squares	F-statist	ic:	1.194e+0					
4 Date:	Sun, í	10 May 2020	Prob (F-s	tatistic):	0.0					
0 Time:		08:51:00	Log-Likel	ihood:	-1080					
9. No. Observations:		21399	AIC:		2.:	162e+0				
4 Df Residuals:		21397	BIC:		2.:	164e+0				
4 Df Model:		1								
Covariance Type:		nonrobust								
====						=====				
975]	coef	std err	t	P> t	[0.025	0.				
Intercept 2.341	12.3272	0.007	1758.899	0.000	12.313	1				
sqft_living15 2.458	2.4145	0.022	109.265	0.000	2.371					
=======================================	=======	=======		========	=======	=====				
Omnibus:		107.251	Durbin-Wa	tson:		1.97				
Prob(Omnibus):		0.000	Jarque-Be	era (JB):	:	111.13				
2 Skew:		0.158	Prob(JB):		7	.38e-2				
5 Kurtosis:		3.158	Cond. No.			8.7				
6				:=======	========	=====				
=										
Warnings:										

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

###

formula = price ~ sqft_lot15



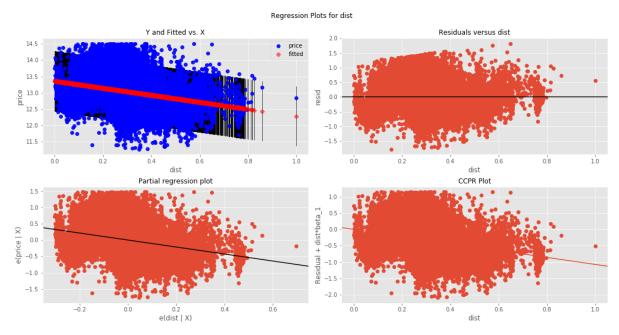
OLS Regression Results

=			=====	=====	====	=========	======	
Dep. Variable 8	:		р	rice	R-sq	uared:		0.00
Model:				OLS	Adj.	R-squared:		0.00
8 Method:		Loo	c+ Cau	2005	Г с+	atistis		178.
Method: 6		Lea	st Squ	ares	F-St	atistic:		1/8.
Date:		Sun, 10	a May	2020	Prob	(F-statistic):		1.40e-4
0 Time:			08:5	1:01	Log-	Likelihood:		-1546
4. No. Observation	ons:		2	1399	AIC:			3.093e+0
4 Df Residuals:			2	1397	BIC:			3.095e+0
4								
Df Model: Covariance Typ			nonro					
=				=====		=========	=====	
5]	coef	sto	d err		t	P> t	[0.025	0.97
Intercept 9	13.0119) (0.004	3493	.252	0.000	13.005	13.01
sqft_lot15 5	1.4523	3 (0.109	13	.365	0.000	1.239	1.66
=========	======		=====	=====	====	========	======	=======
= Omnibus:			110	.589	Durb	in-Watson:		1.95
3 Prob(Omnibus)	:		0	.000	Jarq	ue-Bera (JB):		112.22
8 Skew:			0	.177	Prob	(JB):		4.27e-2
5 Kurtosis:			3	.003	Cond	No		31.
9			J	.005	Cond	. 110		51.
=	======	:=====:	=====	=====	====	========	======	=======
Warnings:	_							

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

###

formula = price ~ dist



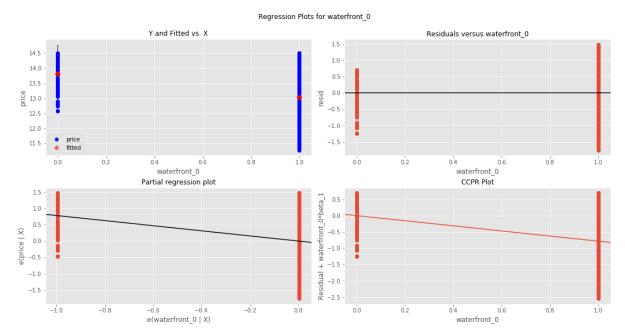
OLS Regression Results

				gi C33.				
=======================================	======	======	=====	=====	=====		======	=======
Dep. Variable	:		pr	rice	R-squ	uared:		0.12
1 Model:				OLS	Adi.	R-squared:		0.12
1								
Method:		Leas	t Squa	ares	F-sta	atistic:		294
1. Date:		Sun, 10	May 2	2020	Prob	(F-statistic):		0.0
0								
Time: 5.			08:51	L:02	Log-L	ikelihood:		-1417
No. Observati	ons:		21	1399	AIC:			2.835e+0
Df Residuals:			21	L397	BIC:			2.837e+0
Df Model:				1				
Covariance Ty	•		nonrob =====					
=								
- 1	coe	f std	err		t	P> t	[0.025	0.97
5]								
-								
Intercept 0	13.357	L 0	.007	1964	.514	0.000	13.344	13.37
_	-1.0734	1 0	.020	-54	.232	0.000	-1.112	-1.03
========	======		=====				======	
= Omnibus:			318.	.175	Durbi	in-Watson:		1.95
1								
Prob(Omnibus)	:		0.	.000	Jarqu	ue-Bera (JB):		334.54
6 Skew:			0.	.292	Prob((JB):		2.26e-7
3								
Kurtosis: 5			3.	.182	Cond.	No.		6.7
_	======		=====				======	=======
=								
Warnings:								

Warnings:

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

formula = price ~ waterfront_0

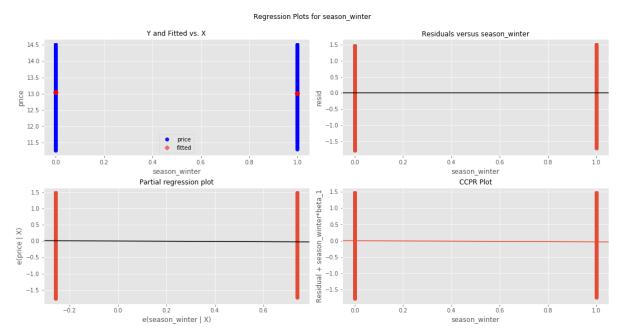


OLS Regression Results

==========	=======	=========	=======		=======	=======		
=								
Dep. Variable: 2		price	R-squai	red:		0.01		
Model:		OLS	Adj. R	-squared:		0.01		
Method:	L	east Squares	F-stat:	istic:		253.		
3 Date:	Sun,	10 May 2020	Prob (I	-statistic):		1.04e-5		
6 Time:		08:51:04	Log-Lil	kelihood:		-1542		
7. No. Observation	s:	21399	AIC:			3.086e+0		
4 Df Residuals:		21397	BIC:			3.087e+0		
4 Df Model: Covariance Type		1 nonrobust						
===========	=======	========	=======	=========	=======			
===	coof	std onn	+	P> t	[0 025	0.9		
75]					[0.025	0.9		
Intercept 907	13.8104	0.049	281.679	0.000	13.714	13.		
waterfront_0 686	-0.7822	0.049	-15.916	0.000	-0.879	-0.		
==========		========	=======					
= Omnibus:		94.268	Durbin-	-Watson:		1.95		
<pre>0 Prob(Omnibus):</pre>		0.000	Jarque	-Bera (JB):		95.46		
5 Skew:		0.163	-			1.86e-2		
1		0,103	1100(01	-,.		2.000 2		
Kurtosis: 8		2.987	Cond. I	No.		28.		
==========	=======	========	=======		=======	======		
=								
Warnings:								

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

formula = price ~ season_winter



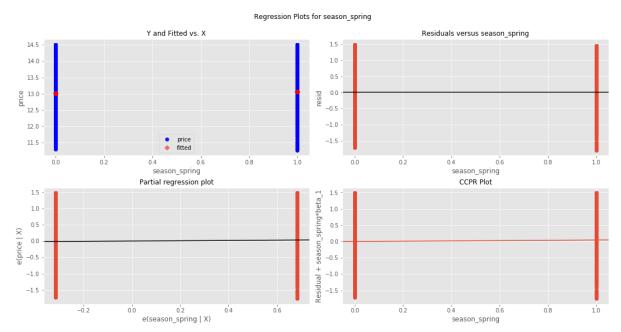
OLS Regression Results

		_	SION NESUIC			
=======================================	=======	:=======	=======	========	:=======	:====
Dep. Variable:		price	R-squared	:		0.00
1 Model:		OLS	Adj. R-sq	uared:		0.00
1 Method:	Lea	st Squares	F-statist	ic:		18.8
5 Date:	Sun 1	.0 May 2020	Proh (F.s	tatistic):	1	42e-0
5	Juli, 1	_	•			
Time: 3.		08:51:05	Log-Likel	ihood:	-	·1554
No. Observations	:	21399	AIC:		3.1	L09e+0
Df Residuals:		21397	BIC:		3.1	11e+0
4 Df Model:		1				
Covariance Type:		nonrobust ======	:=======	=========		:====
====						
975]	coef	std err	t	P> t	[0.025	0.
Intercept 3.049	13.0407	0.004	3284.562	0.000	13.033	1
season_winter 0.019	-0.0339	0.008	-4.342	0.000	-0.049	-
=======================================			=======	========		:====
= Omnibus:		117.342	Durbin-Wa	tson:		1.95
4 Prob(Omnibus):		0.000	Jarque-Be	ra (JB):	1	19.19
4 Skew:		0.183	Prob(JB):		1.	31e-2
6 Kurtosis:		3.002	Cond. No.			2.4
7						
=	==	=====				=
Warnings:						

Warnings:

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

formula = price ~ season_spring



OLS Regression Results

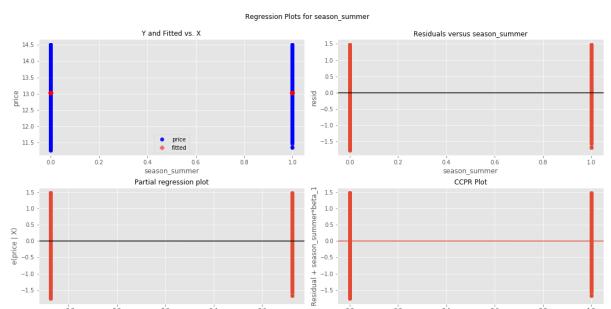
		_	ssion Result			
_		=======	:=======	========	========	:====
= Dep. Variable: 2		price	R-squared	:		0.00
Model:		OLS	Adj. R-sq	uared:		0.00
2 Method:	Lea	ast Squares	F-statist	ic:		37.6
1 Date:	Sun, 1	10 May 2020	Prob (F-s	tatistic):	8.	.78e-1
0 Time:		08:51:07	Log-Likel	ihood:	-	-1553
4.						
No. Observations:	:	21399	AIC:		3.1	L07e+0
Df Residuals: 4		21397	BIC:		3.1	L09e+0
Df Model:		1				
Covariance Type:		nonrobust				
			.=======	========		
====						
	coef	std err	t	P> t	[0.025	0.
975]						
•	13.0177	0.004	3150.172	0.000	13.010	1
3.026	0.0451	0.007	6.133	0.000	0.031	
season_spring 0.060	0.0451	0.007	0.133	0.000	0.031	
==========						
=						
Omnibus:		116.924	Durbin-Wa	tson:		1.95
Prob(Omnibus):		0.000	Jarque-Be	ra (JB):	1	118.76
2 Skew:		0.182	Prob(JB):		1	.63e-2
6		0.102	1100(30).		1.	.030 2
Kurtosis:		3.003	Cond. No.			2.4
2						
===========				========	========	=====
=						
Warnings:					_	
[1] Standard Erro	ors assume	that the co	ovariance ma	trix of the	errors is c	correc

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

formula = price ~ season_summer

-0.2

0.2 0 e(season_summer | X)



0.6

0.4 0.6 season_summer

0.8

OLS Regression Results

		J	ssion kesuit			
_					=======	=====
= Dep. Variable:		price	R-squared	:		0.00
0 Model:		OLS	Adj. R-sq	uared:		-0.00
0						
Method: 9	Lea	ast Squares	F-statist	ic:		0.0194
Date: 9	Sun, 1	l0 May 2020	Prob (F-s	tatistic):		0.88
Time:		08:51:08	Log-Likel	ihood:		-1555
No. Observations:	:	21399	AIC:		3.	111e+0
4 Df Residuals:		21397	BIC:		3.	113e+0
4 Df Model:		1				
Covariance Type:		nonrobust				
			========	=======	=======	=====
====	coef	std err	t	P> t	[0 025	0.
975]	coei	Stu en	· ·	P> C	[0.025	υ.
	13.0323	0.004	3244.940	0.000	13.024	1
season_summer 0.014	-0.0011	0.008	-0.140	0.889	-0.016	
0.014		.=======	.=======	=======	=======	=====
=						
Omnibus: 4		114.680	Durbin-Wa ⁻	tson:		1.95
Prob(Omnibus): 5		0.000	Jarque-Be	ra (JB):		116.45
Skew:		0.181	Prob(JB):		5	.15e-2
Kurtosis:		2.997	Cond. No.			2.4
5						
=					=======	=====
Warnings: [1] Standard Erro	nrs assume	that the co	ovariance ma	trix of the	errors is	correc
tly specified.	n s assume	chat the CC	oval TallCE IIId	CLIX OF CHE	ELLOL,2 12	COLLEC
###############	+#########	!##########	!#########	###########	##########	######

###

```
In [27]: # What's the total R2 after normalization ? drop 'lat' and 'long' first
    tmp_kc = kc_final.drop(['lat', 'long'], axis=1)
    predictors = list(tmp_kc.columns)
    predictors.remove('price')

f = 'price ~ ' + ' + '.join(predictors)
    model = ols(formula=f, data=tmp_kc).fit()
    print(model.summary())
```

OLS Regression Results

			sion Result			
=======================================	=======	=======	=======	:========		======
Dep. Variable: 5		price	R-squared	l:		0.73
Model:		OLS	Adj. R-sq	uared:		0.73
Method: 9.	Le	ast Squares	F-statist	ic:		311
Date:	Sun,	10 May 2020	Prob (F-s	tatistic):		0.0
Time:		08:51:08	Log-Likel	ihood:		-1348.
No. Observations 6.	:	21399	AIC:			273
Df Residuals: 6.		21379	BIC:			289
Df Model:		19				
Covariance Type:		nonrobust				
===========	=======	=======	=======	:=======		======
====	C			p. L. I	[0 00F	
975]	coef	std err	t	P> t	[0.025	0.
Intercept	12.6103	0.031	404.221	0.000	12.549	1
2.671 bedrooms 0.098	-0.1483	0.026	-5.781	0.000	-0.199	-
bathrooms 0.539	0.4812	0.030	16.262	0.000	0.423	
sqft_lot 1.170	0.9713	0.102	9.569	0.000	0.772	
floors 0.200	0.1775	0.012	15.256	0.000	0.155	
view 0.236	0.2140	0.011	19.283	0.000	0.192	
condition 0.268	0.2446	0.012	20.222	0.000	0.221	
grade 1.555	1.5003	0.028	53.787	0.000	1.446	
sqft_above 1.093	1.0247	0.035	29.554	0.000	0.957	
sqft_basement 0.494	0.4568	0.019	24.252	0.000	0.420	
yr_built 0.319	-0.3397	0.011	-31.997	0.000	-0.361	-
yr_renovated 0.101	0.0810	0.010	7.754	0.000	0.061	
zipcode 0.197	-0.2123	0.008	-26.418	0.000	-0.228	-
sqft_living15 0.706	0.6583	0.024	27.285	0.000	0.611	
sqft_lot15 0.160	-0.0001	0.082	-0.002	0.999	-0.160	
dist 1.240	-1.2663	0.013	-94.156	0.000	-1.293	-

			0_			
waterfront_0 0.278	-0.3316	0.027	-12.214	0.000	-0.385	-
season_winter 0.031	0.0198	0.006	3.475	0.001	0.009	
season_spring 0.048	0.0371	0.006	6.747	0.000	0.026	
season_summer 0.018	0.0067	0.006	1.186	0.236	-0.004	
===========	========	=======	=======	========	========	====
=		474 400	5			
Omnibus: 4		174.122	Durbin-Wa	itson:	-	1.98
Prob(Omnibus):		0.000	Jarque-Be	era (JB):	256	6.44
Skew:		-0.081	Prob(JB):		2.00	6e-5
Kurtosis: 2.		3.511	Cond. No.			13
==========		=======		.=======	=========	====
_						

=

Warnings:

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

 $file: ///C: /Users/MYDELL {\sim} 1/AppData/Local/Temp/modeling_1 - 1.html$

```
In [28]: # What's the total R2 after normalization ? drop 'r'
tmp_kc = kc_final.drop(['dist'], axis=1) # remove id
predictors = list(tmp_kc.columns)
predictors.remove('price')

f = 'price ~ ' + ' + '.join(predictors)
model = ols(formula=f, data=tmp_kc).fit()
print(model.summary())
```

OLS Regression Results

===========		ols Regres			=======	======
=						
Dep. Variable: 1		price	R-squared	l:		0.75
Model: 1		OLS	Adj. R-so	quared:		0.75
Method:	Le	ast Squares	F-statist	ic:		323
0. Date:	Sun,	10 May 2020	Prob (F-s	statistic):		0.0
0 Time:		08:51:08	Log-Likel	ihood:		-660.7
5 No. Observations	•	21399	AIC:			136
3.	•					
<pre>Df Residuals: 1.</pre>		21378	BIC:			153
Df Model: Covariance Type:		20 nonrobust				
• •		========	=======	.=======		======
====	coef	std err	t	P> t	[0.025	0.
975]	COCT	364 611	C	17[6]	[0.023	0.
Intercept	11.7381	0.030	387.185	0.000	11.679	1
1.797 bedrooms	-0.1194	0.025	-4.804	0.000	-0.168	-
0.071 bathrooms	0.4902	0.029	17.106	0.000	0.434	
0.546 sqft_lot	0.7989	0.098	8.118	0.000	0.606	
0.992 floors	0.1980	0.011	17.556	0.000	0.176	
0.220						
view 0.268	0.2464	0.011	22.854	0.000	0.225	
condition 0.276	0.2535	0.012	21.640	0.000	0.231	
grade	1.5761	0.027	58.186	0.000	1.523	
1.629 sqft_above	0.9215	0.034	27.353	0.000	0.856	
0.988 sqft_basement	0.4880	0.018	26.724	0.000	0.452	
0.524 yr_built	-0.3943	0.010	-37.978	0.000	-0.415	_
0.374 yr_renovated	0.0755	0.010	7.468	0.000	0.056	
0.095						
zipcode 0.105	-0.1214	0.008	-14.895	0.000	-0.137	-
lat	0.8658	0.008	104.260	0.000	0.850	
0.882 long	-0.1681	0.020	-8.514	0.000	-0.207	-
0.129 sqft_living15 0.564	0.5173	0.024	21.863	0.000	0.471	

sqft_lot15 0.043	-0.1981	0.079	-2.497	0.013	-0.354	-
waterfront_0 0.303	-0.3550	0.026	-13.497	0.000	-0.407	-
season_winter 0.032	0.0213	0.006	3.852	0.000	0.010	
season_spring 0.046	0.0351	0.005	6.590	0.000	0.025	
season_summer 0.015	0.0042	0.005	0.768	0.442	-0.007	
=======================================	========	=======	=======		=======	====
Omnibus:		323.087	Durbin-Wa	ntson:		1.98
Prob(Omnibus):		0.000	Jarque-Be	era (JB):	6	19.38
Skew: 5		-0.037	Prob(JB):		3.1	.8e-13
Kurtosis: 9.		3.830	Cond. No.			13
=========	========	=======	=======	========	=======	=====
=						
Warnings: [1] Standard Er	rors assume	that the co	variance ma	atrix of the	errors is c	orrec

tly specified.

The distance feature 'r' is reduce the R2 just a little compared to 'lat' and 'long'. Let's still keep it for now and choose in feature engineering.

All data is normalized and ready for validation

Save the clean data to a kc_house_data_clean.csv file

```
In [29]: kc_final.to_csv('data/kc_house_data_normalized.csv', index=False)
```

Please open validation.ipynb next for final model