Project 2: House Hunting for Families in King County

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Course: Data Science Full Time

Date: 3/26/21 4:30 pm EST

Instructor: Claude Fried

In [296]:
```
# Your code here - remember to use markdown cells for comments as well!
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
import seaborn as sns
import statsmodels.api as sm
import statsmodels.stats.api as sms
import statsmodels.formula.api as smf
from statsmodels.formula.api import ols
from sklearn.linear_model import LinearRegression
import scipy.stats as stats
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.datasets import make_regression
import sklearn.metrics as metrics
from random import gauss
from sklearn.model_selection import train_test_split
from sklearn.linear_model import Lasso
from statsmodels.stats import outliers_influence
from sklearn.metrics import mean_absolute_error
import sklearn
sns.set_theme(color_codes=True)
```

Business Problem

A realtorship is experiencing an influx of smaller families coming into King County as Microsoft has expanded and hired substantial amount of workers. It is your job to find a home for these families, and many also live alone.

Data Observation and Cleaning

Data Keys

id - unique identified for a house
price- Price is prediction target
bedrooms- Number of Bedrooms/House
bathrooms- Number of bathrooms/bedrooms
sqft_living- Square footage of the home
sqft_lot- Square footage of the lot

floors- Total floors (levels) in house
waterfront - House which has a view to a waterfront
condition - How good the condition is (Overall)
grade - overall grade given to the housing unit, based on King County grading system
yr_built - Built Year

Data Prep and Cleaning

First, unnecessary columns are dropped as well as some rows that contained incorrect data across the independent variables. New data series are created as well. The grade and condition columns are changed to type string so that it is seen as categorical data and not numerical.

In [213]:
```
kc_data=pd.read_csv('data/kc_house_data.csv')
kc_new=kc_data.drop(columns=['zipcode','date','view','sqft_above','sqft_basement'
kc_new=kc_new.set_index('id')
kc_new['bldg_age']=2021-kc_new['yr_built']
```

In [ ]:
```
# kc_new.loc[kc_new['bedrooms']==33]=3
#seemed to be an error because there were only 1.75 bathrooms and sqft_living was

# kc_new=kc_new.drop(index=2402100895, axis=0)
#3 beds,baths,sqft_living, etc. everything was 3

# kc_new['bldg_age']=2021-kc_new['yr_built']
# kc_new['grade']=kc_new['grade'].astype('str')         # grade and condition wer
# kc_new['condition']=kc_new['condition'].astype('str') # they are still categori
# kc_new['zipcode']=kc_new['zipcode'].astype('str')
```

In [167]:
```
kc_new.head()
```

Out[167]:

id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	yr_buil
7129300520	221900.0	3	1.00	1180	5650	1.0	3	7	195
6414100192	538000.0	3	2.25	2570	7242	2.0	3	7	195
5631500400	180000.0	2	1.00	770	10000	1.0	3	6	193
2487200875	604000.0	4	3.00	1960	5000	1.0	5	7	196
1954400510	510000.0	3	2.00	1680	8080	1.0	3	8	198

Data Training

In [191]:
```
X_train, X_test, y_train, y_test = train_test_split(predictors,kc_new['price'], t
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

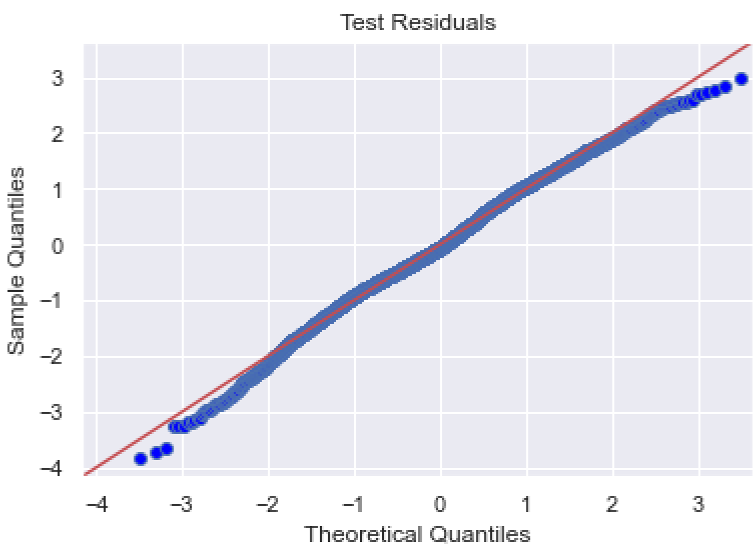
Out[191]:
```
((17276, 6), (4320, 6), (17276,), (4320,))
```

In [306]:
```
lr=LinearRegression()#positive=True)
predictors=kc_new.drop('price',axis=1)
predictors=sm.add_constant(predictors)
# y_train=np.array(y_train).reshape(-1,1)
lr.fit(X_train,y_train)
# predict_ls=fit_lr.predict(predictors)

yhat_train=lr.predict(X_train)
yhat_test=lr.predict(X_test)

train_residuals = yhat_train - y_train
test_residuals = yhat_test - y_test
```

In [237]:
```
mse_train = np.sum((y_train-yhat_train)**2)/len(y_train)
mse_test = np.sum((y_test-yhat_test)**2)/len(y_test)
print('Train Mean Squarred Error:', mse_train)
print('Test Mean Squarred Error:', mse_test)
```

```
Train Mean Squarred Error: 59755332738.083984
Test Mean Squarred Error: 58952013622.75533
```

In [193]:
```
sm.graphics.qqplot(train_residuals,dist=stats.norm,line='45',fit=True)
plt.title('Train Residuals')
sm.graphics.qqplot(test_residuals,dist=stats.norm,line='45',fit=True)
plt.title('Test Residuals')
plt.show()
```




```
We can observe that the difference between the test and train MSE are not too
different, and that the residuals fit well on the Q-Q plot.
```

Data Modeling

After creating a new database, used the OLS function to find the coefficients.

In [215]:
```
outcome = 'price'
predictors = kc_new.drop(['price'], axis=1)
pred_sum = '+'.join(predictors.columns)
formula = outcome + '~' + pred_sum
print(formula)
```

```
price~bedrooms+bathrooms+sqft_living+sqft_lot+floors+condition+grade+yr_built+b
ldg_age
```

In [216]:
```
model = ols(formula=formula, data=kc_new).fit()
model.summary()
```

Out[216]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.618
Model:	OLS	**Adj. R-squared:**	0.618
Method:	Least Squares	**F-statistic:**	4363.
Date:	Mon, 29 Mar 2021	**Prob (F-statistic):**	0.00
Time:	20:58:21	**Log-Likelihood:**	-2.9700e+05
No. Observations:	21597	**AIC:**	5.940e+05
Df Residuals:	21588	**BIC:**	5.941e+05
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.4482	0.032	44.960	0.000	1.385	1.511
bedrooms	-4.915e+04	2123.053	-23.151	0.000	-5.33e+04	-4.5e+04
bathrooms	5.286e+04	3587.694	14.734	0.000	4.58e+04	5.99e+04
sqft_living	187.4021	3.421	54.784	0.000	180.697	194.107
sqft_lot	-0.2459	0.038	-6.439	0.000	-0.321	-0.171
floors	2.128e+04	3592.816	5.922	0.000	1.42e+04	2.83e+04
condition	1.962e+04	2583.883	7.593	0.000	1.46e+04	2.47e+04
grade	1.311e+05	2238.758	58.577	0.000	1.27e+05	1.36e+05
yr_built	-541.9966	8.997	-60.240	0.000	-559.632	-524.361
bldg_age	3468.7420	66.559	52.115	0.000	3338.282	3599.202

Omnibus:	17302.265	**Durbin-Watson:**	1.984
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1207162.645
Skew:	3.353	**Prob(JB):**	0.00
Kurtosis:	39.007	**Cond. No.**	2.45e+19

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 6.99e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

While the R-squared value seemed to show potential, variables such as the yr_built and floors did not seem necessary as well. At this point, I had also noticed that the coefficients were negative for bedrooms and sq. ft lot; however, since I couldn't do much about it, I decided to proceed.

In [217]:
```
outcome = 'price'
predictors = kc_new.drop(['price','yr_built','floors'], axis=1)
pred_sum = '+'.join(predictors.columns)
formula = outcome + '~' + pred_sum
print(formula)
```

```
price~bedrooms+bathrooms+sqft_living+sqft_lot+condition+grade+bldg_age
```

In [218]:
```
model = ols(formula=formula, data=kc_new).fit()
model.summary()
```

Out[218]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.617
Model:	OLS	**Adj. R-squared:**	0.617
Method:	Least Squares	**F-statistic:**	4974.
Date:	Mon, 29 Mar 2021	**Prob (F-statistic):**	0.00
Time:	20:58:25	**Log-Likelihood:**	-2.9702e+05
No. Observations:	21597	**AIC:**	5.941e+05
Df Residuals:	21589	**BIC:**	5.941e+05
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-1.076e+06	1.79e+04	-60.126	0.000	-1.11e+06	-1.04e+06
bedrooms	-4.96e+04	2123.402	-23.356	0.000	-5.38e+04	-4.54e+04
bathrooms	5.798e+04	3484.667	16.639	0.000	5.12e+04	6.48e+04
sqft_living	185.7714	3.412	54.441	0.000	179.083	192.460
sqft_lot	-0.2600	0.038	-6.815	0.000	-0.335	-0.185
condition	1.76e+04	2563.288	6.866	0.000	1.26e+04	2.26e+04
grade	1.334e+05	2206.957	60.457	0.000	1.29e+05	1.38e+05
bldg_age	3925.1267	67.697	57.981	0.000	3792.437	4057.817

Omnibus:	17191.902	**Durbin-Watson:**	1.981
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1180961.717
Skew:	3.324	**Prob(JB):**	0.00
Kurtosis:	38.611	**Cond. No.**	5.14e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.14e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

After observing that the R-squared value seemed to represent a statisticlaly significant model, I checked to see if it passed the 3 assumptions of linear regression. The p-values of the independent variables also seemed to show homoscedesticity, but the model had high condition number, which indicated strong multicollinearity (or other numerical problems).

In [178]:
```
data=kc_new
price_unlog=round(np.exp(data['price']),2)
plot=plt.figure(figsize=(11,6))
ax_beds=sns.regplot(x='bedrooms',y='price',data=data,x_jitter=.1, line_kws={'colo
ax_beds.set_yticklabels(kc_new['price'])
ax_beds.set(xlabel='Number of Bedrooms',ylabel='Price',title='Relationship betwee
```

...

First detected an outlier, a house with more than 30 rooms

In [179]:
```
plot=plt.figure(figsize=(11,6))
ax_baths=sns.regplot(x='bathrooms',y='price',data=data,x_jitter=.1, line_kws={'co
ax_baths.set_yticklabels(kc_new['price'])
ax_baths.set(xlabel='Number of Bathrooms',ylabel='Price',title='Relationship betw
```

...

In [183]:
```
data2=kc_new
plot=plt.figure(figsize=(11,6))
ax_living=sns.regplot(x=data2['sqft_living'],y='price',data=data2,x_jitter=.1, li
ax_living.set_yticklabels(kc_new['price'])
ax_living.set_xticklabels(data2['sqft_living'])
ax_living.set(xlabel='Size of Living Space in Sq. ft.',ylabel='Price',title='Rela
```

...

In [187]:
```
plot=plt.figure(figsize=(11,6))
data2=kc_new
ax_lot=sns.regplot(x='sqft_lot',y='price',data=data2,x_jitter=.1, line_kws={'colo
ax_lot.set_yticklabels(kc_new['price'])
ax_lot.set_xticklabels(data2['sqft_lot'].sort_values())
ax_lot.set(xlabel='Size of Lot Space',ylabel='Price',title='Relationship between
```

...

First located the house with more than 33 rooms and found that it only had 3 bathrooms, and the house was not big enough to have that many rooms, and while checking to see if there were any other errors, found a house with 3 sq. ft of living space, lot, bedrooms, and etc. Decided to drop the entire row.

In [219]:
```
kc_new.loc[kc_new['bedrooms']==33]=3
# seemed to be an error because there were only 1.75 bathrooms and sqft_living wo
kc_new=kc_new.drop(index=2402100895, axis=0)
# 3 beds,baths,sqft_living, etc. everything was 3
```

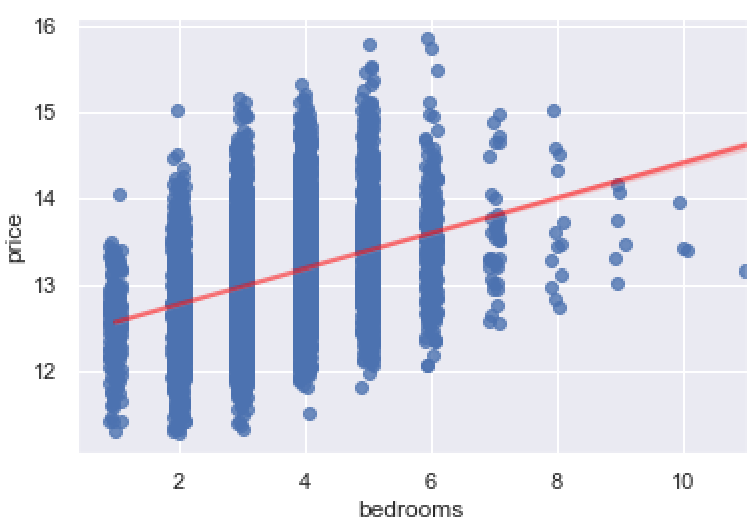
Logarithmic Scaling

The data had to be normalized because the independent variables coefficients were too large. The coefficients were too large and the values were too large (sqft living and lot, price). In order to normalize the data, I created a new database that contained log-scaled values of the original the original data. Not all independent variables were logarithmically scaled, but the dependent variable, price were also log-scaled. This helped normalize the data. Before log scaling and normalizing the values, our data shows no sign of linearity nor homoscedesticity. The regressions of the variables did fit the Q-Q plot; failing to meet 2 of the 3 assumptions of linear regression.

```
After trying to use logged versions, i couldnt so i had to scale them, but
after i did, i had to unscale the price because the price coudlnt be in the
negatives lol
```

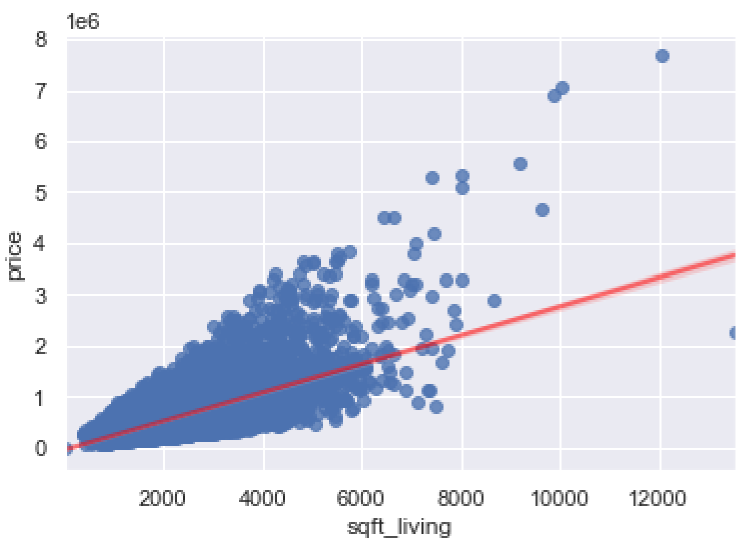
In [241]:
```
logsqft_living=np.log(kc_new['sqft_living'])
logsqft_lot=np.log(kc_new['sqft_lot'])
log_age=np.log(kc_new['bldg_age'])
log_price=np.log(kc_new['price'])

# Creating new database
kc_fin=pd.DataFrame([])
# transferring over varible values
kc_fin['bedrooms']=kc_new['bedrooms']
kc_fin['bathrooms']=kc_new['bathrooms']
kc_fin['sqft_living']=logsqft_living
kc_fin['sqft_lot']=logsqft_lot
kc_fin['condition']=kc_new['condition']
kc_fin['grade']=kc_new['grade']
kc_fin['bldg_age']=log_age


kc_fin=pd.concat([log_price, kc_fin],axis=1)
```

In [222]:
```
data=kc_fin
ax2_beds=sns.regplot(x='bedrooms',y='price',data=data,x_jitter=.1, line_kws={'col
```

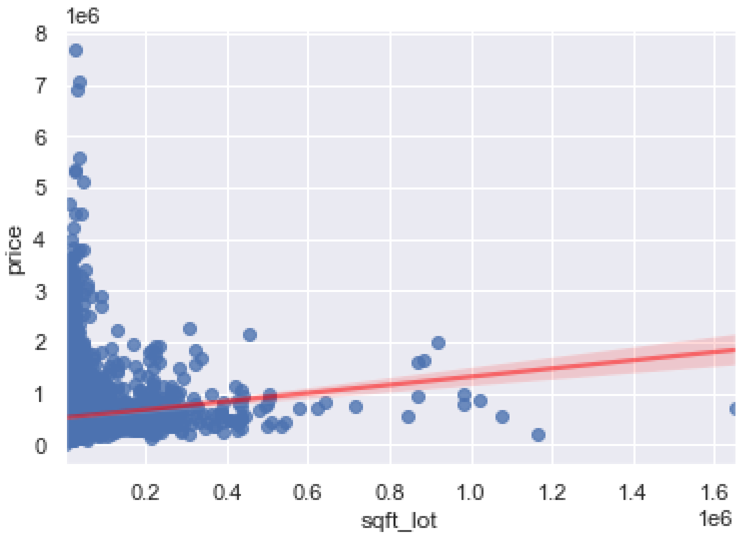


In [223]:
```
ax2_baths=sns.regplot(x='bathrooms',y='price',data=data,x_jitter=.1, line_kws={'c
```

In [224]:
```
ax2_living=sns.regplot(x=data2['sqft_living'],y='price',data=data2,x_jitter=.1, l
```



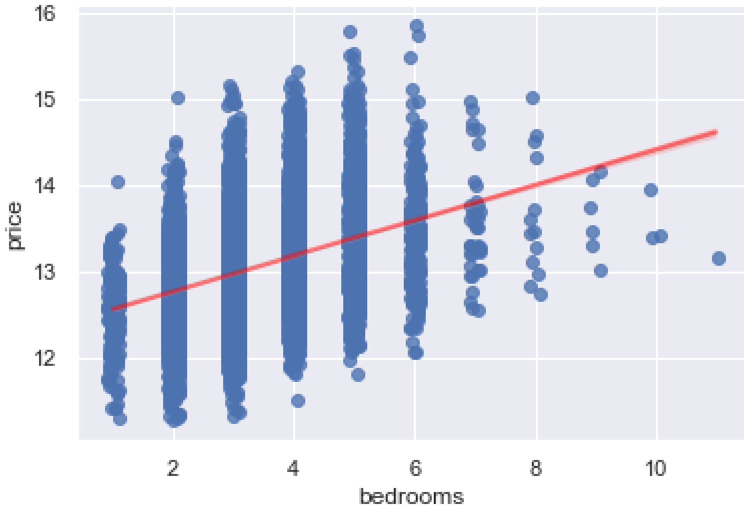
In [225]:
```
ax2_lot=sns.regplot(x='sqft_lot',y='price',data=data2,x_jitter=.1, line_kws={'col
```



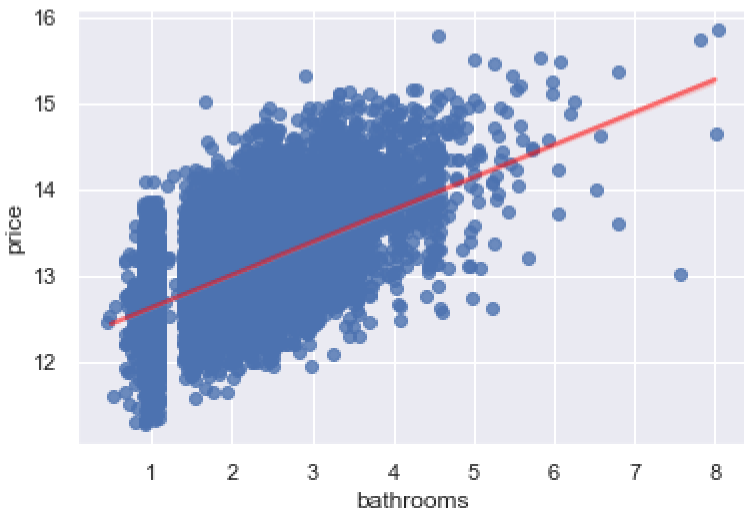
The values were log transformed, but were not scaled.

In [249]:
```
logsqft_living=np.log(kc_new['sqft_living'])
logsqft_lot=np.log(kc_new['sqft_lot'])
log_age=np.log(kc_new['bldg_age'])
log_price=np.log(kc_new['price'])
# Scaling logged values
scaled_living=(logsqft_living-np.mean(logsqft_living))/np.sqrt(np.var(logsqft_liv
scaled_lot=(logsqft_lot-np.mean(logsqft_lot))/np.sqrt(np.var(logsqft_lot))
scaled_age=(log_age-np.mean(log_age))/np.sqrt(np.var(log_age))

kc_fin['bedrooms']=kc_new['bedrooms']
kc_fin['bathrooms']=kc_new['bathrooms']
kc_fin['sqft_living']=scaled_living
kc_fin['sqft_lot']=scaled_lot
kc_fin['condition']=kc_new['condition']
kc_fin['grade']=kc_new['grade']
kc_fin['bldg_age']=scaled_age

kc_fin=pd.concat([log_price, kc_fin],axis=1)
```

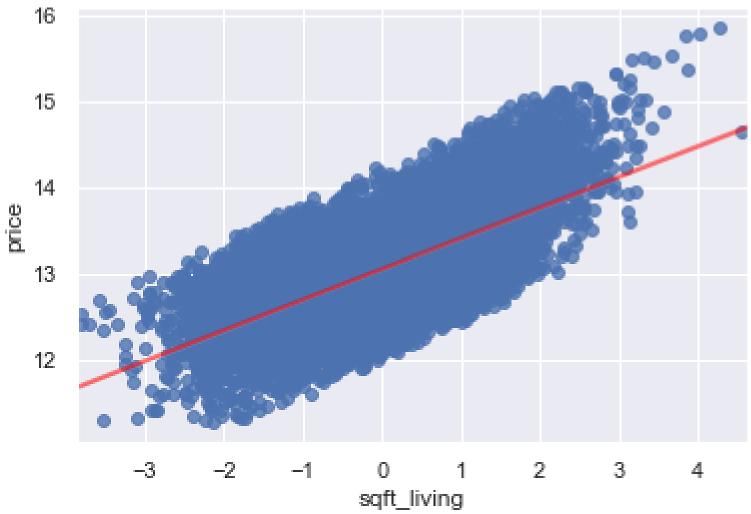
In [243]:
```
data=kc_fin
ax2_beds=sns.regplot(x='bedrooms',y='price',data=data,x_jitter=.1, line_kws={'col
```



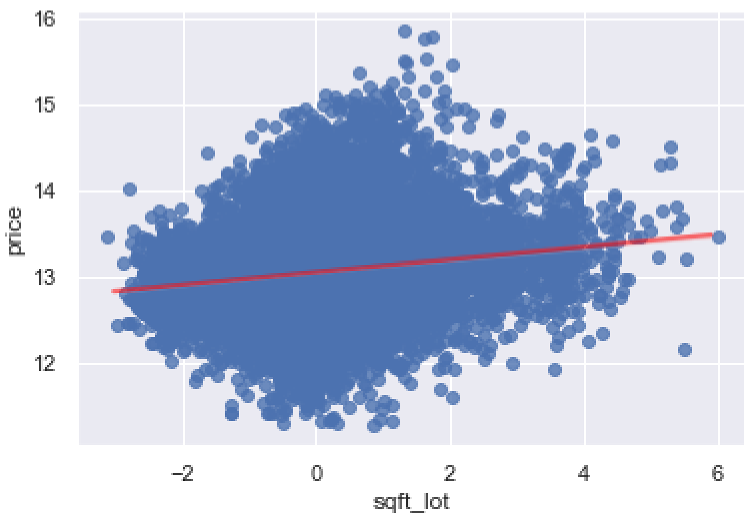
In [244]:
```
ax2_baths=sns.regplot(x='bathrooms',y='price',data=data,x_jitter=.1, line_kws={'c
```



In [245]:
```
ax2_living=sns.regplot(x=data['sqft_living'],y='price',data=data,x_jitter=.1, lir
```



In [246]:
```
ax2_lot=sns.regplot(x='sqft_lot',y='price',data=data,x_jitter=.1, line_kws={'colc
```



After log transforming and scaling the transformed values, the model showed homoscedesticity except in the sqft_lot. This is because many apartments/condos do not have much lot space that is not used for living space. Since many of these apartments/condos are more expensive, there is a much wider variation in price where the sqft lot is near 0.

In [247]:
```
outcome = 'price'
predictors = kc_fin.drop(['price'], axis=1)
pred_sum = '+'.join(predictors.columns)
formula = outcome + '~' + pred_sum
print(formula)
```

```
price~bedrooms+bathrooms+sqft_living+sqft_lot+condition+grade+bldg_age
```

In [248]:
```
model = ols(formula=formula, data=kc_fin).fit()
model.summary()
```

Out[248]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.613
Model:	OLS	**Adj. R-squared:**	0.613
Method:	Least Squares	**F-statistic:**	4888.
Date:	Mon, 29 Mar 2021	**Prob (F-statistic):**	0.00
Time:	21:14:16	**Log-Likelihood:**	-6536.1
No. Observations:	21596	**AIC:**	1.309e+04
Df Residuals:	21588	**BIC:**	1.315e+04
Df Model:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	11.1141	0.031	356.045	0.000	11.053	11.175
bedrooms	-0.0520	0.003	-15.655	0.000	-0.059	-0.046
bathrooms	0.0772	0.005	15.121	0.000	0.067	0.087
sqft_living	0.2076	0.005	43.584	0.000	0.198	0.217
sqft_lot	-0.0657	0.002	-26.443	0.000	-0.071	-0.061
condition	0.0430	0.004	11.479	0.000	0.036	0.050
grade	0.2350	0.003	76.396	0.000	0.229	0.241
bldg_age	0.1463	0.003	49.405	0.000	0.140	0.152

Omnibus:	56.412	**Durbin-Watson:**	1.957
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	70.993
Skew:	0.031	**Prob(JB):**	3.84e-16
Kurtosis:	3.274	**Cond. No.**	133.

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

The model seems to be improving as multicollinearity does not seem to be an issue. While the data cannot be reproduced again for now, condition and/or grade had negative coefficients, meaning that if the grade or the condition of a house was better, it would be cheaper. Later I found out that these types of variables should be set as categorical variables.

In [254]:
```
logsqft_living=np.log(kc_new['sqft_living'])
logsqft_lot=np.log(kc_new['sqft_lot'])
log_age=np.log(kc_new['bldg_age'])
log_price=np.log(kc_new['price'])
# Scaling logged values
scaled_living=(logsqft_living-np.mean(logsqft_living))/np.sqrt(np.var(logsqft_liv
scaled_lot=(logsqft_lot-np.mean(logsqft_lot))/np.sqrt(np.var(logsqft_lot))
scaled_age=(log_age-np.mean(log_age))/np.sqrt(np.var(log_age))

kc_fin=pd.DataFrame([])

kc_fin['bedrooms']=kc_new['bedrooms']
kc_fin['bathrooms']=kc_new['bathrooms']
kc_fin['sqft_living']=scaled_living
kc_fin['sqft_lot']=scaled_lot
kc_fin['bldg_age']=scaled_age

cond_dummies=pd.get_dummies(kc_new['condition'],prefix='cnd',drop_first=True).ast
grade_dummies=pd.get_dummies(kc_new['grade'],prefix='grade',drop_first=True).asty

kc_fin=pd.concat([log_price, kc_fin, cond_dummies, grade_dummies],axis=1)
```

Out[254]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	bldg_age	cnd_2	cnd_3	cnc
id									
7129300520	12.309982	3	1.00	-1.125577	-0.388446	0.689504	0	1	
6414100192	13.195614	3	2.25	0.709431	-0.113256	0.771426	0	1	
5631500400	12.100712	2	1.00	-2.131918	0.244461	1.090038	0	1	
2487200875	13.311329	4	3.00	0.070657	-0.523930	0.460747	0	0	
1954400510	13.142166	3	2.00	-0.292744	0.008125	-0.233989	0	1	
...	...	...	...	...	...	...	...	...	
263000018	12.793859	3	2.50	-0.513225	-2.171614	-1.683985	0	1	
6600060120	12.899220	4	2.50	0.457991	-0.356917	-2.434420	0	1	
1523300141	12.904459	2	0.75	-1.469084	-1.975398	-1.683985	0	1	
291310100	12.899220	3	2.50	-0.407763	-1.343132	-1.199044	0	1	
1523300157	12.691580	2	0.75	-1.469084	-2.226878	-1.572543	0	1	

21596 rows × 20 columns

In [255]:
```
outcome = 'price'
predictors = kc_fin.drop(['price'], axis=1)
pred_sum = '+'.join(predictors.columns)
formula = outcome + '~' + pred_sum
print(formula)
model = ols(formula=formula, data=kc_fin).fit()
model.summary()
```

```
price~bedrooms+bathrooms+sqft_living+sqft_lot+bldg_age+cnd_2+cnd_3+cnd_4+cnd_5+
grade_4+grade_5+grade_6+grade_7+grade_8+grade_9+grade_10+grade_11+grade_12+grad
e_13
```

Out[255]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.617
Model:	OLS	**Adj. R-squared:**	0.617
Method:	Least Squares	**F-statistic:**	1829.
Date:	Mon, 29 Mar 2021	**Prob (F-statistic):**	0.00
Time:	21:21:31	**Log-Likelihood:**	-6428.5
No. Observations:	21596	**AIC:**	1.290e+04
Df Residuals:	21576	**BIC:**	1.306e+04
Df Model:	19		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	12.8057	0.332	38.535	0.000	12.154	13.457
cnd_2[T.1]	-0.0779	0.066	-1.186	0.236	-0.207	0.051
cnd_3[T.1]	0.0476	0.061	0.780	0.435	-0.072	0.167
cnd_4[T.1]	0.0702	0.061	1.149	0.251	-0.050	0.190
cnd_5[T.1]	0.1551	0.061	2.523	0.012	0.035	0.276
grade_4[T.1]	-0.2688	0.332	-0.809	0.418	-0.920	0.382
grade_5[T.1]	-0.2851	0.327	-0.872	0.383	-0.926	0.356
grade_6[T.1]	-0.1618	0.326	-0.496	0.620	-0.801	0.478
grade_7[T.1]	0.0213	0.326	0.065	0.948	-0.618	0.661
grade_8[T.1]	0.2545	0.326	0.780	0.436	-0.385	0.894
grade_9[T.1]	0.5361	0.327	1.642	0.101	-0.104	1.176
grade_10[T.1]	0.7550	0.327	2.311	0.021	0.115	1.395
grade_11[T.1]	0.9813	0.327	3.001	0.003	0.340	1.622
grade_12[T.1]	1.2590	0.329	3.832	0.000	0.615	1.903
grade_13[T.1]	1.4842	0.339	4.376	0.000	0.819	2.149
bedrooms	-0.0487	0.003	-14.671	0.000	-0.055	-0.042
bathrooms	0.0735	0.005	14.276	0.000	0.063	0.084

sqft_living	0.2101	0.005	43.957	0.000	0.201	0.219
sqft_lot	-0.0688	0.003	-27.194	0.000	-0.074	-0.064
bldg_age	0.1465	0.003	48.427	0.000	0.141	0.152

Omnibus:	33.919	**Durbin-Watson:**	1.958
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	40.919
Skew:	0.009	**Prob(JB):**	1.30e-09
Kurtosis:	3.213	**Cond. No.**	2.11e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.11e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

```
I saw that the p-values were generally higher for the grade variable compared
to the condition variable, and the building age variable did not seem to affect
the price. These two variables were removed.
```

In [257]:
```
kc_fin=pd.DataFrame([])

kc_fin['bedrooms']=kc_new['bedrooms']
kc_fin['bathrooms']=kc_new['bathrooms']
kc_fin['sqft_living']=scaled_living
kc_fin['sqft_lot']=scaled_lot

cond_dummies=pd.get_dummies(kc_new['condition'],prefix='cnd',drop_first=True).ast

kc_fin=pd.concat([log_price, kc_fin, cond_dummies],axis=1)

outcome = 'price'
predictors = kc_fin.drop(['price'], axis=1)
pred_sum = '+'.join(predictors.columns)
formula = outcome + '~' + pred_sum
print(formula)
model = ols(formula=formula, data=kc_fin).fit()
model.summary()
```

```
price~bedrooms+bathrooms+sqft_living+sqft_lot+cnd_2+cnd_3+cnd_4+cnd_5
```

Out[257]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.485
Model:	OLS	**Adj. R-squared:**	0.485
Method:	Least Squares	**F-statistic:**	2546.
Date:	Mon, 29 Mar 2021	**Prob (F-statistic):**	0.00
Time:	21:25:55	**Log-Likelihood:**	-9615.8
No. Observations:	21596	**AIC:**	1.925e+04
Df Residuals:	21587	**BIC:**	1.932e+04
Df Model:	8		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	13.1479	0.072	182.727	0.000	13.007	13.289
cnd_2[T.1]	-0.0770	0.076	-1.015	0.310	-0.226	0.072
cnd_3[T.1]	0.0368	0.070	0.523	0.601	-0.101	0.175
cnd_4[T.1]	0.1021	0.070	1.451	0.147	-0.036	0.240
cnd_5[T.1]	0.2094	0.071	2.955	0.003	0.071	0.348
bedrooms	-0.0883	0.004	-23.726	0.000	-0.096	-0.081
bathrooms	0.0621	0.005	11.484	0.000	0.051	0.073
sqft_living	0.3869	0.005	82.139	0.000	0.378	0.396
sqft_lot	-0.0460	0.003	-16.218	0.000	-0.052	-0.040

Omnibus:	94.066	**Durbin-Watson:**	1.978
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	93.154

Skew:	0.148	**Prob(JB):**	5.91e-21
Kurtosis:	2.876	**Cond. No.**	263.

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

Data Selection

Because the majority of the clients are small to mid-size families, houses with more than 5 bedrooms and houses with more than 4 bathrooms were dropped. This also helped with the linear regression model as the before-mentioned houses tended to be outliers

In [258]:
```
kc_fin2=kc_fin.drop(index=kc_fin.loc[kc_fin['bedrooms']>5].index.append(kc_fin.lo
kc_fin2.head()
```

Out[258]:

id	price	bedrooms	bathrooms	sqft_living	sqft_lot	cnd_2	cnd_3	cnd_4	cnd_5
7129300520	12.309982	3	1.00	-1.125577	-0.388446	0	1	0	0
6414100192	13.195614	3	2.25	0.709431	-0.113256	0	1	0	0
5631500400	12.100712	2	1.00	-2.131918	0.244461	0	1	0	0
2487200875	13.311329	4	3.00	0.070657	-0.523930	0	0	0	1
1954400510	13.142166	3	2.00	-0.292744	0.008125	0	1	0	0

In [259]:
```
kc_fin2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21061 entries, 7129300520 to 1523300157
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   price        21061 non-null  float64
 1   bedrooms     21061 non-null  int64
 2   bathrooms    21061 non-null  float64
 3   sqft_living  21061 non-null  float64
 4   sqft_lot     21061 non-null  float64
 5   cnd_2        21061 non-null  category
 6   cnd_3        21061 non-null  category
 7   cnd_4        21061 non-null  category
 8   cnd_5        21061 non-null  category
dtypes: category(4), float64(4), int64(1)
memory usage: 1.0 MB
```

```
After cleaning, transforming, and selecting the data I needed, I constructed an
OLS model that had scaled, normalized data with correct data types and did not
have much multicollinearity issue other than in the categorical variables.
```

In [137]:
```
outcome = 'price'
predictors = kc_fin2.drop(['price','zipcode'], axis=1)
pred_sum = '+'.join(predictors.columns)
formula = outcome + '~' + pred_sum
print(formula)
```

```
price~bedrooms+bathrooms+sqft_living+sqft_lot+cnd_2+cnd_3+cnd_4+cnd_5
```

In [138]:
```
model = ols(formula=formula, data=kc_fin2).fit()
model.summary()
```

Out[138]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.461
Model:	OLS	**Adj. R-squared:**	0.461
Method:	Least Squares	**F-statistic:**	2253.
Date:	Mon, 29 Mar 2021	**Prob (F-statistic):**	0.00
Time:	14:50:33	**Log-Likelihood:**	-9178.8
No. Observations:	21061	**AIC:**	1.838e+04
Df Residuals:	21052	**BIC:**	1.845e+04
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	13.2128	0.073	181.587	0.000	13.070	13.355
cnd_2[T.1]	-0.0868	0.076	-1.136	0.256	-0.237	0.063
cnd_3[T.1]	0.0444	0.071	0.626	0.531	-0.095	0.183
cnd_4[T.1]	0.1066	0.071	1.501	0.133	-0.033	0.246
cnd_5[T.1]	0.2132	0.071	2.984	0.003	0.073	0.353
bedrooms	-0.0968	0.004	-23.666	0.000	-0.105	-0.089
bathrooms	0.0391	0.006	6.785	0.000	0.028	0.050
sqft_living	0.3929	0.005	81.695	0.000	0.384	0.402
sqft_lot	-0.0485	0.003	-16.956	0.000	-0.054	-0.043

Omnibus:	68.943	**Durbin-Watson:**	1.980
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	68.132
Skew:	0.127	**Prob(JB):**	1.60e-15
Kurtosis:	2.887	**Cond. No.**	259.

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

Zipcode

While trying to determine what other factors could play into the house pricing other than the house features themselves, I realized that location mattered greatly. It was an outside variable that was able to provide me with data representing of designated groupings of the locations of the houses.

In [268]:

```
kc_new=kc_data.drop(columns=['date','view','sqft_above','sqft_basement','yr_renov
kc_new['zipcode']=kc_new['zipcode'].astype('str')
kc_new=kc_new.set_index('id')
kc_new
```

Out[268]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	yr_buil
id									
7129300520	221900.0	3	1.00	1180	5650	1.0	3	7	195
6414100192	538000.0	3	2.25	2570	7242	2.0	3	7	195
5631500400	180000.0	2	1.00	770	10000	1.0	3	6	193
2487200875	604000.0	4	3.00	1960	5000	1.0	5	7	196
1954400510	510000.0	3	2.00	1680	8080	1.0	3	8	198
...	...	...	...	...	...	...	...	...	..
263000018	360000.0	3	2.50	1530	1131	3.0	3	8	200
6600060120	400000.0	4	2.50	2310	5813	2.0	3	8	201
1523300141	402101.0	2	0.75	1020	1350	2.0	3	7	200
291310100	400000.0	3	2.50	1600	2388	2.0	3	8	200
1523300157	325000.0	2	0.75	1020	1076	2.0	3	7	200

21597 rows × 10 columns

In [283]:
```
logsqft_living=np.log(kc_new['sqft_living'])
logsqft_lot=np.log(kc_new['sqft_lot'])
log_price=np.log(kc_new['price'])

# Scaling logged values
scaled_living=(logsqft_living-np.mean(logsqft_living))/np.sqrt(np.var(logsqft_liv
scaled_lot=(logsqft_lot-np.mean(logsqft_lot))/np.sqrt(np.var(logsqft_lot))

kc_fin=pd.DataFrame([])

kc_fin['bedrooms']=kc_new['bedrooms']
kc_fin['bathrooms']=kc_new['bathrooms']
kc_fin['sqft_living']=scaled_living
kc_fin['sqft_lot']=scaled_lot
kc_fin['zipcode']=kc_new['zipcode'].astype('str')

cond_dummies=pd.get_dummies(kc_new['condition'],prefix='cnd',drop_first=True).ast
# zip_dummies=pd.get_dummies(kc_new['zipcode'],prefix='zip',drop_first=True).asty


kc_fin=pd.concat([log_price, kc_fin, cond_dummies],axis=1)
```

In [284]:
```
kc_fin2=kc_fin.drop(index=kc_fin.loc[kc_fin['bedrooms']>5].index.append(kc_fin.lo
kc_fin2.head()
```

Out[284]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	zipcode	cnd_2	cnd_3	cnd_
id									
7129300520	12.309982	3	1.00	-1.125582	-0.388439	98178	0	1	
6414100192	13.195614	3	2.25	0.709463	-0.113243	98125	0	1	
5631500400	12.100712	2	1.00	-2.131943	0.244481	98028	0	1	
2487200875	13.311329	4	3.00	0.070676	-0.523926	98136	0	0	
1954400510	13.142166	3	2.00	-0.292732	0.008140	98074	0	1	

In [285]:
```
outcome = 'price'
predictors = kc_fin2.drop('price', axis=1)
pred_sum = '+'.join(predictors.columns)
formula = outcome + '~' + pred_sum
```

In [286]:
```
model_fin = ols(formula=formula, data=kc_fin2).fit()
model_fin.summary()
```

zipcode[T.98004]	1.2340	0.017	74.069	0.000	1.201	1.267
zipcode[T.98005]	0.8073	0.020	40.067	0.000	0.768	0.847
zipcode[T.98006]	0.7722	0.015	51.673	0.000	0.743	0.801
zipcode[T.98007]	0.7153	0.022	33.201	0.000	0.673	0.758
zipcode[T.98008]	0.7274	0.017	42.815	0.000	0.694	0.761
zipcode[T.98010]	0.2264	0.024	9.409	0.000	0.179	0.274
zipcode[T.98011]	0.4667	0.019	24.675	0.000	0.430	0.504
zipcode[T.98014]	0.2561	0.022	11.436	0.000	0.212	0.300
zipcode[T.98019]	0.2944	0.019	15.448	0.000	0.257	0.332
zipcode[T.98022]	0.0737	0.018	4.116	0.000	0.039	0.109
zipcode[T.98023]	0.0056	0.015	0.386	0.700	-0.023	0.034
zipcode[T.98024]	0.3936	0.027	14.564	0.000	0.341	0.447
zipcode[T.98027]	0.5536	0.015	35.949	0.000	0.523	0.584

Creating an unlogged version of the data after unwanted houses were dropped to un-log/un-normalize values to represent real-world values.

In [287]:
```
kc_new2=kc_new.copy()
kc_new2=kc_new2.drop(index=kc_new2.loc[kc_new2['bedrooms']>5].index.append(kc_new
kc_new2
```

...

In [300]:
```
kc_unlog=pd.DataFrame([])
kc_unlog['bedrooms']=kc_new2['bedrooms']
kc_unlog['bathrooms']=kc_new2['bathrooms']
kc_unlog['living']=kc_new2['sqft_living']
kc_unlog['lot']=kc_new2['sqft_lot']
kc_unlog['price_sqft_living']=kc_new2['price']/kc_new2['sqft_living']
kc_unlog['price_sqft_lot']=kc_new2['price']/kc_new2['sqft_lot']
# Shows how much each sq. ft of living space is

zip_dummies=pd.get_dummies(kc_new2['zipcode'],prefix='zip',drop_first=True).astyp
cond_dummies=pd.get_dummies(kc_new2['condition'],prefix='cnd',drop_first=True).as

price=kc_new2['price']

kc_unlog=pd.concat([price,kc_unlog,zip_dummies,cond_dummies],axis=1)
```

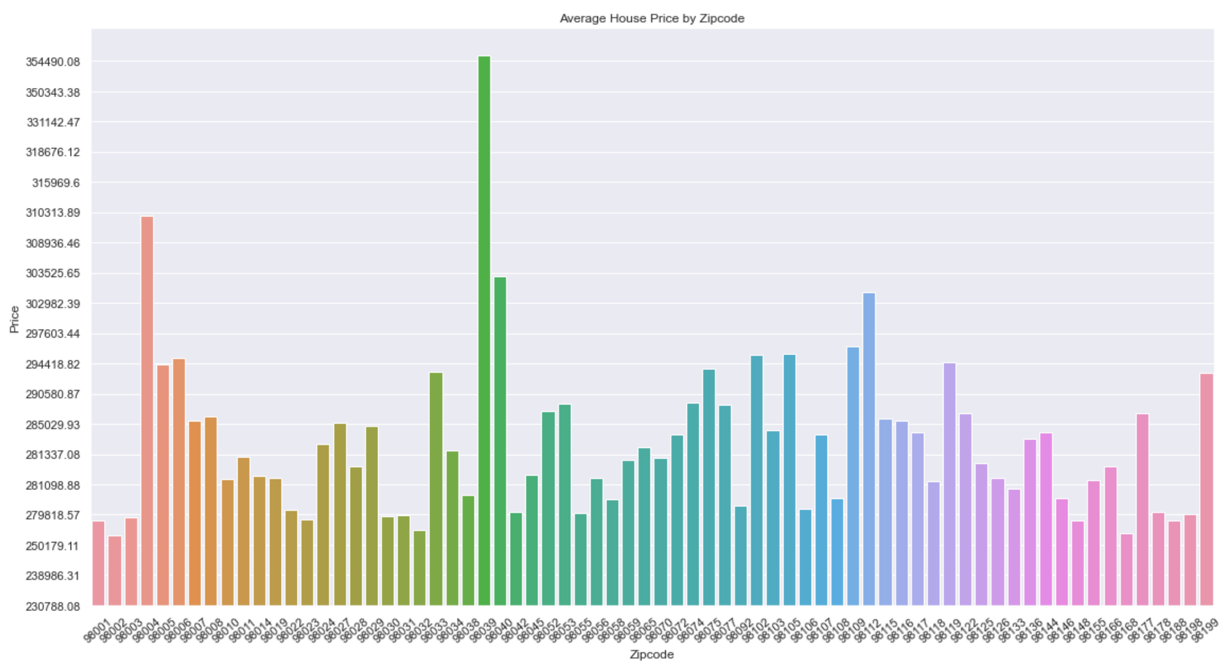
In [301]:
```
kc_unlog
```

...

In [302]:
```
price_by_zipcode=pd.DataFrame([])
price_by_zipcode['zipcode']=pd.concat([kc_new2.groupby(['zipcode'])['price'].mear
price_by_zipcode=price_by_zipcode.set_index('zipcode')
price_by_zipcode['price']=pd.concat([kc_new2.groupby(['zipcode'])['price'].mean()

plot=plt.figure(figsize=(19,10))
zip_price=sns.barplot(x=price_by_zipcode.index,y=price_by_zipcode['price'])
zip_price.set_xticklabels(labels=price_by_zipcode.index, rotation=40)
zip_price.set_yticklabels(labels=round(price_by_zipcode['price'].sort_values(),2)
zip_price.set_yticks(price_by_zipcode['price'])
plt.yticks(np.arange(0,price_by_zipcode['price'].max(), 100000))
zip_price.set(title='Average House Price by Zipcode',xlabel='Zipcode',ylabel='Pri
```

```
<ipython-input-302-44b7a1ab731d>:9: UserWarning: FixedFormatter should only be
used together with FixedLocator
  zip_price.set_yticklabels(labels=round(price_by_zipcode['price'].sort_values
(),2))
```

Out[302]:
```
[Text(0.5, 1.0, 'Average House Price by Zipcode'),
 Text(0.5, 0, 'Zipcode'),
 Text(0, 0.5, 'Price')]
```



Model Check

Using the Mean Absolute Error, determining how accurate the model is in portraying the housing prices in King County

In [330]:
```
lr=LinearRegression()
predictors=kc_new2.drop(['price'],axis=1)
predictors=sm.add_constant(predictors)

X_train, X_test, y_train, y_test = train_test_split(predictors,kc_new2['price'],
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[330]:
```
((10530, 10), (10531, 10), (10530,), (10531,))
```

In [331]:
```
lr.fit(X_train,y_train)

yhat_train=lr.predict(X_train)
yhat_test=lr.predict(X_test)
```

In [336]:
```
mae=mean_absolute_error
mae(yhat_train,np.delete(yhat_test,0))
```

Out[336]:
```
272470.3814412837
```

Using the Mean Absolute Error, we are able to determine that the model has an mean absolute error of $272,470.38.

Multicollinearity Check

The model has some multicollinearity. First between the categorical variables and another between the number of bathrooms and the sqft_living, but that is to be expected. In this model, because the number of bathrooms as well as the sqft_living space is both important in determining the appropriate housing for the clients, neither variables will not be taken out.

In [15]:
```
abs(predictors.corr()) >.75
```

Out[15]:

	bedrooms	bathrooms	sqft_living	sqft_lot
bedrooms	True	False	False	False
bathrooms	False	True	False	False
sqft_living	False	False	True	False
sqft_lot	False	False	False	True

In [16]:
```
kc_pred=kc_fin2.drop(['price'],axis=1)
pred_df=kc_pred.corr().abs().stack().reset_index().sort_values(0, ascending=False

# zip the variable name columns (Which were only named level_0 and level_1 by def
pred_df['pairs'] = list(zip(pred_df.level_0, pred_df.level_1))

# set index to pairs
pred_df.set_index(['pairs'], inplace = True)

#d rop level columns
pred_df.drop(columns=['level_1', 'level_0'], inplace = True)

# rename correlation column as cc rather than 0
pred_df.columns = ['cc']

# drop duplicates. This could be dangerous if you have variables perfectly correl
# for the sake of exercise, kept it in.
pred_df.drop_duplicates(inplace=True)
```

In [17]:
```
pred_df[(pred_df.cc>.75) & (pred_df.cc <1)]
```

...

In [18]:
```
sns.heatmap(predictors.corr(), center=0);
```

...

Linear Regression Assumptions

Proving that the assumptions regarding regression is met using the linear regression model above

Linearity

The scatter plot of the independent variables to the dependent variables show that they have a linear relationship, meeting the linearity assumption. The scatter plots also show that the data is homoscedastic, meeting two of the three assumptions.

In [155]:
```
data=kc_fin2
price_unlog=round(np.exp(data['price']),2)
plot=plt.figure(figsize=(11,6))
ax_beds=sns.regplot(x='bedrooms',y='price',data=data,x_jitter=.1, line_kws={'colo
ax_beds.set_yticklabels(data['price'])
ax_beds.set(xlabel='Number of Bedrooms',ylabel='Price',title='Relationship betwee
```

...

In [154]:
```
plot=plt.figure(figsize=(11,6))

ax_baths=sns.regplot(x='bathrooms',y='price',data=data,x_jitter=.1, line_kws={'co
ax_baths.set_yticklabels(data['price'])
ax_baths.set(xlabel='Number of Bathrooms',ylabel='Price',title='Relationship betw
```

...

In [127]:
```
living_unlog=round(np.exp(logsqft_living),3)
data2=kc_fin2
plot=plt.figure(figsize=(11,6))
ax_living=sns.regplot(x='sqft_living',y='price',data=data2,x_jitter=.1, line_kws=
# ax_living.set_yticklabels(price_unlog)
# ax_living.set_xticklabels('sqft_living')
ax_living.set(xlabel='Size of Living Space in Sq. ft.',ylabel='Price',title='Rela
```

...

While we may assume heteroscedasticity for the sqft_lot, this is because there are many apartments meaning many of these houses have 0 sqft_lot. The price difference between apartments varies significantly depending on location, sqft of living space, commodities, and etc. If we overlook the top and bottom part of the scatter plot where sqft_lot is near 0, the rest of the plot is very linear.

In [156]:
```
plot=plt.figure(figsize=(11,6))
data2=kc_fin2
ax_lot=sns.regplot(x='sqft_lot',y='price',data=data2,x_jitter=.1, line_kws={'colo
ax_lot.set_yticklabels(data['price'])
# ax_lot.set_xticklabels('sqft_lot')
ax_lot.set(xlabel='Size of Lot Space',ylabel='Price',title='Relationship between
```

...

Normality

Q-Q Plot of the residuals

First by building a residuals data frame, I was able to create a Q-Q plot of the residuals using model.resid. The Q-Q plot shows that while it is not perfectly normally distributed, it is quite close.

Without log transforming and normalizing the values, the graphs look like this, however, these graphs do show a relationship between the said independent variable and price with real world values.

In [26]:
```
data=kc_fin2
price_unlog=round(np.exp(data['price']),2)
plot=plt.figure(figsize=(11,6))
ax_beds=sns.regplot(x='bedrooms',y=price_unlog,data=data,x_jitter=.1, line_kws={'
ax_beds.set_yticklabels(price_unlog)
ax_beds.set(xlabel='Number of Bedrooms',ylabel='Price',title='Relationship betwee
```

...

In [27]:
```
plot=plt.figure(figsize=(11,6))

ax_baths=sns.regplot(x='bathrooms',y=price_unlog,data=data,x_jitter=.1, line_kws=
ax_baths.set_yticklabels(price_unlog)
ax_baths.set(xlabel='Number of Bathrooms',ylabel='Price',title='Relationship betw
```

...

In [115]:
```
living_unlog=round(np.exp(logsqft_living),3)
data2=kc_unlog
plot=plt.figure(figsize=(11,6))
ax_living=sns.regplot(x=data2['living'],y=price_unlog,data=data2,x_jitter=.1, lin
ax_living.set_yticklabels(price_unlog)
ax_living.set_xticklabels(data2['living'].sort_values())
ax_living.set(xlabel='Size of Living Space in Sq. ft.',ylabel='Price',title='Rela
```

...

In [116]:
```
plot=plt.figure(figsize=(11,6))
data2=kc_unlog
ax_lot=sns.regplot(x=data2['lot'],y=price_unlog,data=data2,x_jitter=.1, line_kws=
ax_lot.set_yticklabels(price_unlog)
ax_lot.set_xticklabels(data2['lot'].sort_values())
ax_lot.set(xlabel='Size of Lot Space',ylabel='Price',title='Relationship between
```

...

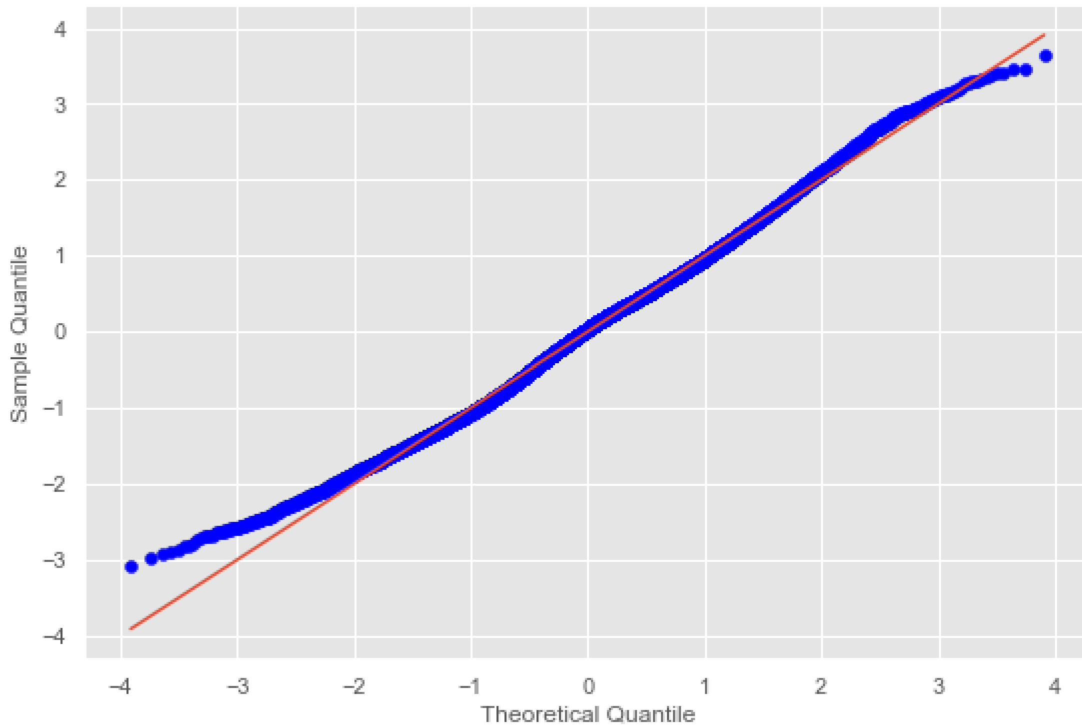
In [297]:
```
residual_df=pd.DataFrame(sorted(model.resid), columns=['residual'])
```

In [298]:
```
residual_df['z_actual']=(residual_df['residual'].map
                         (lambda x: (x-residual_df['residual'].mean())/residual_d
residual_df['rank']=residual_df.index+1
residual_df['percentile']=residual_df['rank'].map(lambda x: x/len(residual_df.res
residual_df['theo']=stats.norm.ppf(residual_df['percentile'])
residual_df['error']=residual_df['z_actual']-residual_df['theo']

residual_df.head()
```

Out[298]:

	residual	z_actual	rank	percentile	theo	error
0	-1.163943	-3.081664	1	0.000046	-3.909181	0.827516
1	-1.120740	-2.967281	2	0.000093	-3.738367	0.771086
2	-1.100164	-2.912804	3	0.000139	-3.635140	0.722337
3	-1.094431	-2.897625	4	0.000185	-3.560295	0.662670
4	-1.084504	-2.871343	5	0.000232	-3.501269	0.629926

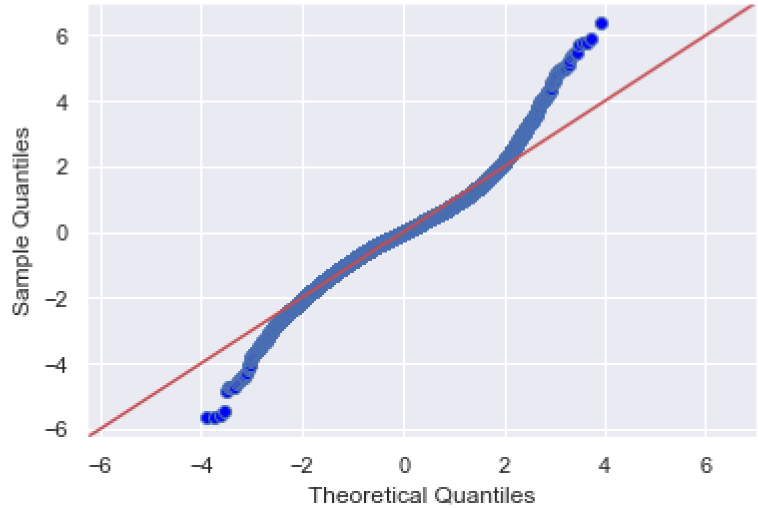
In [299]:
```
with plt.style.context('ggplot'):
    plt.figure(figsize=(9,6))
    plt.scatter(residual_df['theo'],residual_df['z_actual'],color='blue')
    plt.xlabel('Theoretical Quantile')
    plt.ylabel('Sample Quantile')
    plt.plot(residual_df['theo'],residual_df['theo'])
```

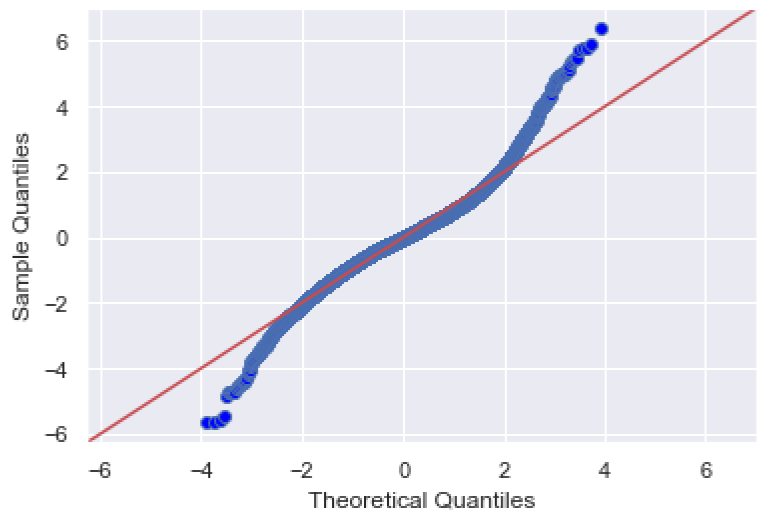


Rechecking normality. While it does seem less normal than before, the model does not seem to be over or underfitting.

In [305]:
```
sm.graphics.qqplot(model_fin.resid, dist=stats.norm, line='45', fit=True)
```

Out[305]:





Histogram of Residuals

Like the Q-Q plots, the histogram of the residuals also shows that the data is nearly normally distributed.

In [148]:
```
sns.histplot(residual_df['residual'],bins=60, kde=True, cbar=True)
plt.xlim((-2,2))
plt.show()
```

...

Visualizing Error Terms

This section has a better visual representation of the linearity and homoscedasticity of the data.

- The Y and Fitted vs. X graph plots the dependent variable against our predicted values with a confidence interval. The positive relationship shows that independent varible and price are correlated, i.e., when one variable increases the other increases.

- The Residuals versus height graph shows our model's errors versus the specified predictor variable. Each dot is an observed value; the line represents the mean of those observed values. If there's no pattern in the distance between the dots and the mean value, the OLS assumption of homoskedasticity holds.
- The Partial regression plot shows the relationship between the independent variable and price, taking in to account the impact of adding other independent variables on our existing coefficient.
- The Component and Component Plus Residual (CCPR) plot is an extension of the partial regression plot. It shows where the trend line would lie after adding the impact of adding our other independent variables on the price.

In [149]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "bedrooms", fig=fig)
plt.show()
```

...

In [150]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "bathrooms", fig=fig)
plt.show()
```

...

In [151]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "sqft_living", fig=fig)
plt.show()
```

...

In [152]:
```
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(model, "sqft_lot", fig=fig)
plt.show()
```

...

Evaluation

By taking bedrooms, bathrooms, size of living space and lot, and the zipcodes, I believe I was able to portray housing prices in King County well. While zipcode had been ignored at start, the price differences between houses of similar specs could not be explained very well, but with the introduction of zip codes, I realized that much of the price difference had been caused by location.

- Because the variable zip codes was categorical, it could not be graphed like condition; however, after observing the mean housing price by zip codes, it was very apparant that zip code played a much bigger role in price determination.

- Because apartments/condos account for higher prices for houses with a lot size of 0(or other very small number), and thus explains the negative relationship between price and lot size.

Conclusion

The biggest challenges were first, trying to figure out why the relationship between lot size and number of bedrooms to the price were negative, and much effort was put into trying to make the coefficients be positive in the model. Realizing that area played an important role in determining housing price was very important as it allowed me to view zip codes as a necessary independent variable. While not having much information regarding the actual geographical location of each area as well as other amenities of each zip code may hinder in providing the best recommendation, knowing that each zip code has different price ranges will help narrowing down potential housing for the clients.

- Organize and categorize different zip codes with housing price range and amenities such as public education, transportation, and other facilities in order to facilitate faster and more suitable recommendations.

- Start oragnizing advertisements targeted to those that are looking to move to the King County area to gain possible clients.

- In the future, having a better understanding of the local traffic, local shopping/food/activities areas, and other factors that clients are looking for in their new neighborhood, would be able to create more fitted lists for the clients.

- Locate houses that are less expensive than those in its neighborhood and are in areas (zip codes) with higher average house price due to a lower condition or etc.

- Using the lot size variable, determine if the housing is an apartment/condo, a town house, or a suburban house.

- When showing possible candidates, show the price of each sq. ft of living space compared to that of zip code average to help the clients determine the price level of the house.