Dan Journic's Phase 2 Project

This is where I will be writing my code for the Flatiron School's Phase 2 Project. And then later editing and revising. So let's get started: Step 1) import all the libraries necessary for linear regression and graphing

In [1]:

```
import pandas as pd
import numpy as np
# Setting random seed for reproducibility, not sure if I'll need it.
np.random.seed(1000)

import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
from sklearn.model_selection import KFold
from itertools import combinations
```

So before I get too into the problem itself, I wanted to look at the data first.

In [2]:

```
df=pd.read_csv("kc_house_data.csv")
```

In [3]:

```
df.describe()
```

Out[3]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	19221.000000	21
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	0.007596	
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	0.086825	
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	0.000000	
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	0.000000	
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	0.000000	
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	

In [4]:

```
df.head()
```

Out[4]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_abov
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	0.0	...	7	118
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	...	7	217
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0	0.0	...	6	77

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_abov
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	...	7	105
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	...	8	168

5 rows × 21 columns

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
id               21597 non-null int64
date             21597 non-null object
price            21597 non-null float64
bedrooms         21597 non-null int64
bathrooms        21597 non-null float64
sqft_living      21597 non-null int64
sqft_lot         21597 non-null int64
floors           21597 non-null float64
waterfront       19221 non-null float64
view             21534 non-null float64
condition        21597 non-null int64
grade            21597 non-null int64
sqft_above       21597 non-null int64
sqft_basement    21597 non-null object
yr_built         21597 non-null int64
yr_renovated     17755 non-null float64
zipcode          21597 non-null int64
lat              21597 non-null float64
long             21597 non-null float64
sqft_living15    21597 non-null int64
sqft_lot15       21597 non-null int64
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
```

In [6]:

```
df.isna().sum()
```

Out[6]:

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

So the problem here is self-defined (whatever I want it to be). My gut is to take the viewpoint of a potential buyer, and try to predict if the price they're paying is a good deal or not. Almost like the Car-Fax of houses.

It's WAY too much data to really make any sense of it graphically. So I'll need to trim down my data a bit. I'm pretty sure that price is going to be my predicted value, so let's put that in its own variable, and drop it from the main dataframe.

In [7]:

```
price=df['price']
```

In [8]:

```
price
```

Out[8]:

```
0        221900.0
1        538000.0
2        180000.0
3        604000.0
4        510000.0
           ...
21592    360000.0
21593    400000.0
21594    402101.0
21595    400000.0
21596    325000.0
Name: price, Length: 21597, dtype: float64
```

What I'm noticing is that I forgot to remove the categorical variables. I should do that. I was looking at 'view'. It seems to be a grade from 0-4. And I just remembered in the project repository they give us a column set we can use, at least some of the columns they recommend we ignore. It pays to read the directions.

In [9]:

```
col_ign=['id','date','view','sqft_above','sqft_basement','yr_renovated','zipcode','lat',
'long','sqft_living15','sqft_lot15']
```

In [10]:

```
df_s1=df.drop(columns=col_ign,axis=1)
```

In [11]:

```
df_s1
```

Out[11]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr_built
0	221900.0	3	1.00	1180	5650	1.0	NaN	3	7	1955
1	538000.0	3	2.25	2570	7242	2.0	0.0	3	7	1951
2	180000.0	2	1.00	770	10000	1.0	0.0	3	6	1933
3	604000.0	4	3.00	1960	5000	1.0	0.0	5	7	1965
4	510000.0	3	2.00	1680	8080	1.0	0.0	3	8	1987
...	...	...	...	...	...	...	...	...	...	...
21592	360000.0	3	2.50	1530	1131	3.0	0.0	3	8	2009
21593	400000.0	4	2.50	2310	5813	2.0	0.0	3	8	2014
21594	402101.0	2	0.75	1020	1350	2.0	0.0	3	7	2009
21595	400000.0	3	2.50	1600	2388	2.0	NaN	3	8	2004
21596	325000.0	2	0.75	1020	1076	2.0	0.0	3	7	2008

21597 rows × 10 columns

So much better. So let's try to look at that pairplot and maybe even heatmap again, since it should be much

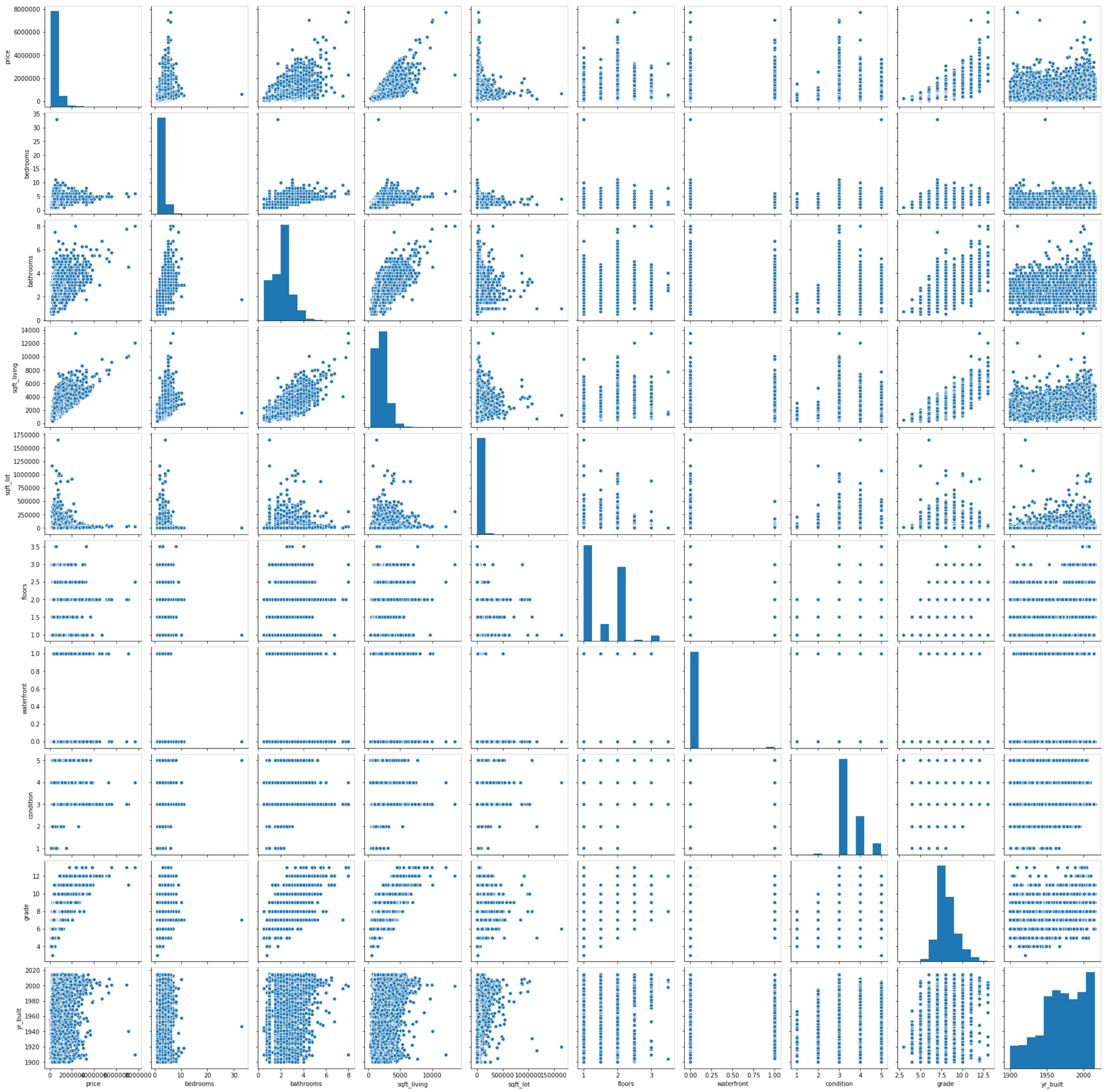
more manageable.

In [12]:

```
sns.pairplot(df_s1)
```

Out[12]:

```
<seaborn.axisgrid.PairGrid at 0x1a7a4505860>
```

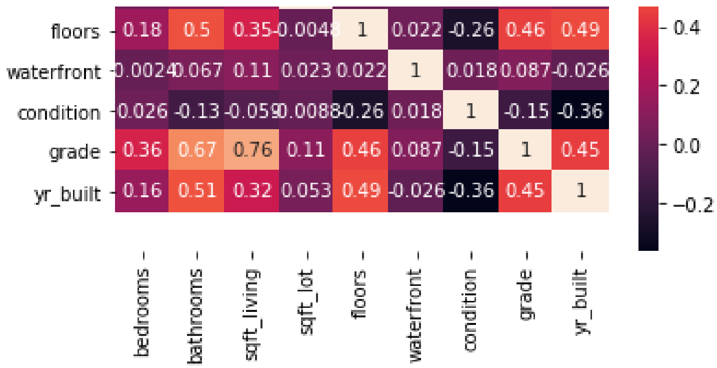


So that still took a bunch of time, and didn't yield anything too telling.

In [13]:

```
ax = sns.heatmap(df_s1.corr(), annot=True)

ax.set_ylim(10,0)
plt.show()
```



Yeah, still a lot. Well, if this were easy everyone would do it. Let's get as simple as we can and make a scatter plot with 2 variables: price and bedrooms. First, let's see what else coorelates with price best.

In [10]:

```
df_s1.corr().price.sort_values(ascending=False)
```

Out[10]:

```
price          1.000000
sqft_living    0.701917
grade          0.667951
bathrooms      0.525906
bedrooms       0.308787
waterfront     0.276295
floors         0.256804
sqft_lot       0.089876
yr_built       0.053953
condition      0.036056
Name: price, dtype: float64
```

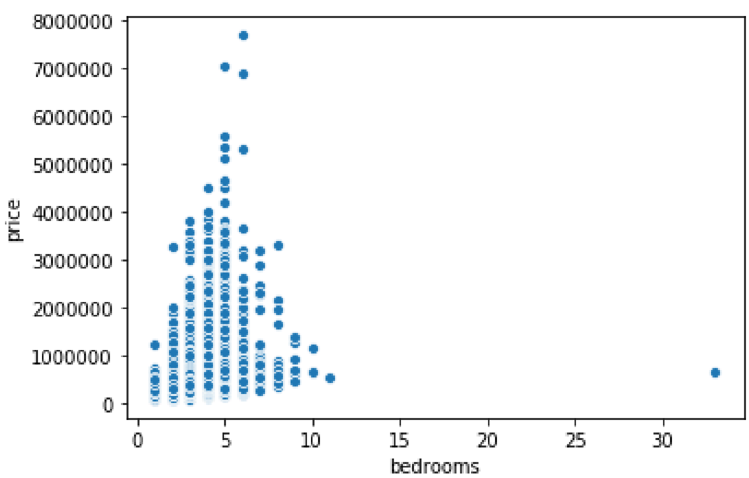
I wanted to use 4 variables for my modeling, but I wanted to keep them somewhat simple. sqft_living, bedrooms and bathrooms are pretty common things folks look for in their house. So I think I'll go with sqft_lot for the final one (folks might care how much of a yard they'll have for, kids, pets etc)

In [11]:

```
sns.scatterplot(data=df_s1, x="bedrooms", y="price")
```

Out[11]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1b8063c7198>
```



There's a house here that has over 30 bedrooms and is priced at a million bucks? That don't look right. I looked back up at the data, there's a house with 33 bedrooms. I'm not sure how you can still call it a house, as opposed to 'hotel'. I may need to drop that one, that might skew the data a little.

In [12]:

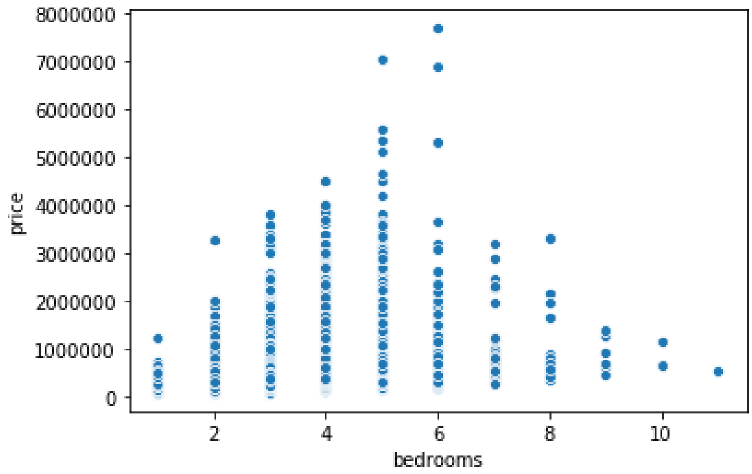
```
df_s1 = df_s1[df_s1.bedrooms != 33]
```

In [13]:

```
sns.scatterplot(data=df_s1, x="bedrooms", y="price")
```

Out[13]:

<matplotlib.axes._subplots.AxesSubplot at 0x1b8063d0860>



Ahhhh, nothing beats some nicely distributed data. Still I find it a little bothersome that there isn't a direct relationship between price and bedrooms. But this wasn't too bad, so let's try another pairing, price and sqft_living:

In [14]:

```
df_s1.head()
```

Out[14]:

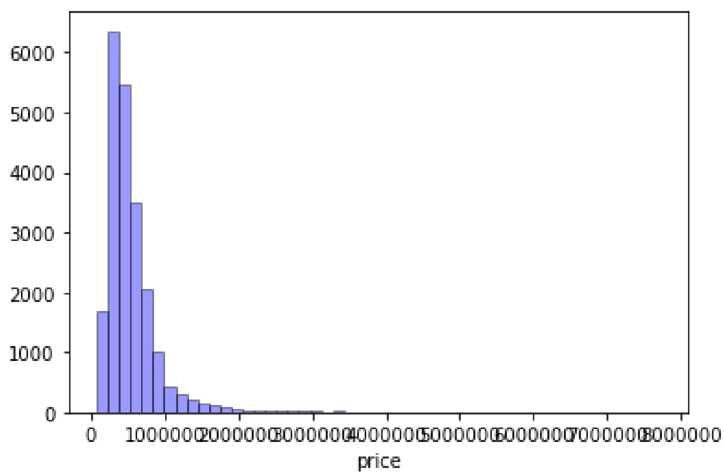
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr_built
0	221900.0	3	1.00	1180	5650	1.0	NaN	3	7	1955
1	538000.0	3	2.25	2570	7242	2.0	0.0	3	7	1951
2	180000.0	2	1.00	770	10000	1.0	0.0	3	6	1933
3	604000.0	4	3.00	1960	5000	1.0	0.0	5	7	1965
4	510000.0	3	2.00	1680	8080	1.0	0.0	3	8	1987

In [15]:

```
sns.distplot(df_s1['price'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[15]:

<matplotlib.axes._subplots.AxesSubplot at 0x1b806449ac8>

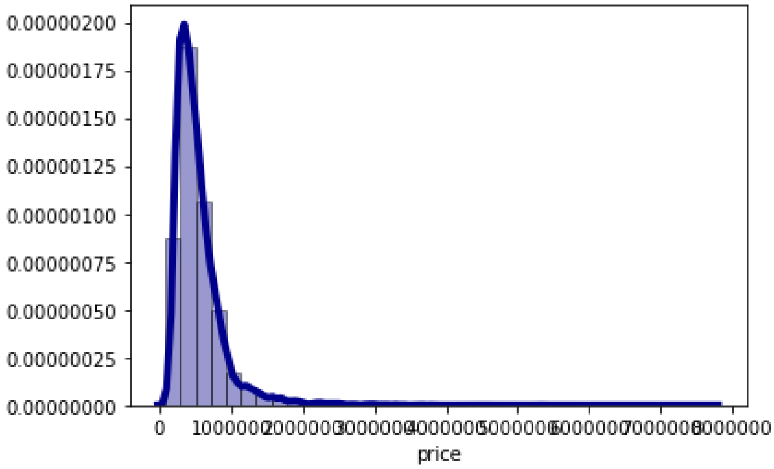


In [16]:

```
sns.distplot(df_s1['price'], hist=True, kde=True,
             bins=int(180/5), color = 'darkblue',
             hist_kws={'edgecolor':'black'},
             kde_kws={'linewidth': 4})
```

Out[16]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1b8068cc940>
```



So this tells me my data isn't very evenly distributed, I'll have to fix that. Two ways seem pretty acceptable: 1) Log transforming the data, 2) cutting the data off at about 1.5 million. I bet if I cut the data off there that'll look a lot more like a normal distribution.

In [17]:

```
price_low=df_s1[df_s1.price<=1500000]
```

In [18]:

```
price_low
```

Out[18]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	grade	yr_built
0	221900.0	3	1.00	1180	5650	1.0	NaN	3	7	1955
1	538000.0	3	2.25	2570	7242	2.0	0.0	3	7	1951
2	180000.0	2	1.00	770	10000	1.0	0.0	3	6	1933
3	604000.0	4	3.00	1960	5000	1.0	0.0	5	7	1965
4	510000.0	3	2.00	1680	8080	1.0	0.0	3	8	1987
...	...	...	...	...	...	...	...	...	...	...
21592	360000.0	3	2.50	1530	1131	3.0	0.0	3	8	2009
21593	400000.0	4	2.50	2310	5813	2.0	0.0	3	8	2014
21594	402101.0	2	0.75	1020	1350	2.0	0.0	3	7	2009
21595	400000.0	3	2.50	1600	2388	2.0	NaN	3	8	2004
21596	325000.0	2	0.75	1020	1076	2.0	0.0	3	7	2008

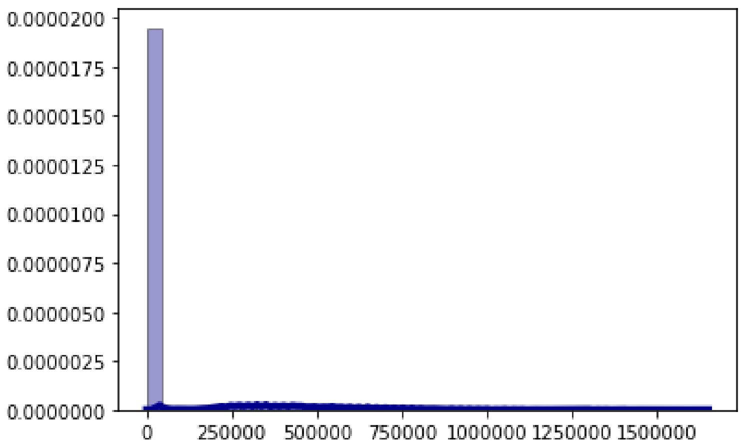
21080 rows × 10 columns

In [27]:

```
sns.distplot(price_low, hist=True, kde=True,
             bins=int(180/5), color = 'darkblue',
             hist_kws={'edgecolor':'black'},
             kde_kws={'linewidth': 4})
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x17465f942b0>
```



Nope. Seems that didn't work at all. So let's do a simple log transform of the price.

In [13]:

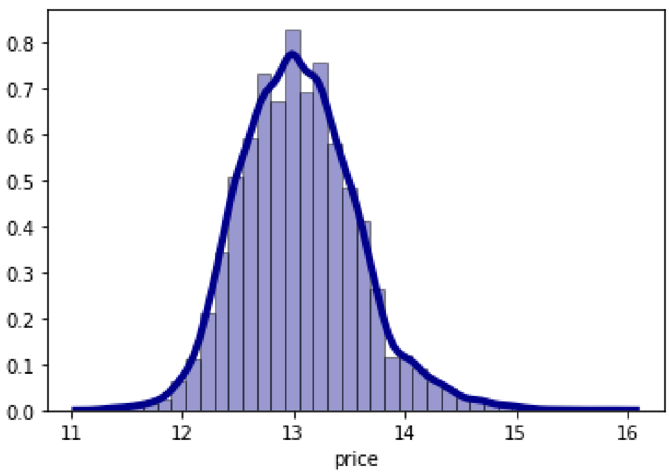
```
price_log=np.log(price)
```

In [14]:

```
sns.distplot(price_log, hist=True, kde=True,
             bins=int(180/5), color = 'darkblue',
             hist_kws={'edgecolor':'black'},
             kde_kws={'linewidth': 4})
```

Out[14]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f6005076a0>
```



Look at how nice that looks, so nicely distributed. So "normally" distributed. Now the plan is to cut off the price data at 1 standard deviation above the mean.

In [21]:

```
price_log.describe()
```

Out[21]:

```
count    21597.000000
mean        13.048211
std          0.526555
min         11.264464
25%         12.682307
50%         13.017003
75%         13.377006
max         15.856731
Name: price, dtype: float64
```

```
Name: price, dtype: float64
```

In [15]:

```
stdv=.526555
cutoff1=price_log.mean() + stdv
cutoff2=price_log.mean() + (stdv*2)
```

Just to be safe, I added a second cutoff at 2 standard deviations. So let's look at them:

In [16]:

```
price_top1=np.exp(cutoff1)
price_top2=np.exp(cutoff2)
print(price_top1)
print(price_top2)
```

```
786042.3433634304
1330840.0826993242
```

Interesting. The cutoffs are either $786,000or$ **1.33 million. Well, I want to keep as much data as possible, so let's use cutoff 2.**

In [17]:

```
price_low=df_s1[df_s1.price<=1330840]
price_hi=df_s1[df_s1.price>1330840]
```

In [18]:

```
price_low.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20869 entries, 0 to 21596
Data columns (total 10 columns):
price          20869 non-null float64
bedrooms       20869 non-null int64
bathrooms      20869 non-null float64
sqft_living    20869 non-null int64
sqft_lot       20869 non-null int64
floors         20869 non-null float64
waterfront     18560 non-null float64
condition      20869 non-null int64
grade          20869 non-null int64
yr_built       20869 non-null int64
dtypes: float64(4), int64(6)
memory usage: 1.8 MB
```

We really didn't trim that much off, so that's a good thing for the model. Only about 1000 or so.

In [19]:

```
20869/21597 #how much of the original data we're keeping.
```

Out[19]:

```
0.9662916145760986
```

In [20]:

```
price_low.describe()
```

Out[20]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	
count	2.086900e+04	20869.000000	20869.000000	20869.000000	2.086900e+04	20869.000000	18560.000000	20869.000000	208
mean	4.921810e+05	3.344434	2.070763	2006.091044	1.468600e+04	1.481695	0.003448	3.407351	

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition
std	2.318026e+05	0.891255	0.723721	806.488218	3.999130e+04	0.587104	0.056622	0.647836
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	0.000000	1.000000
25%	3.182000e+05	3.000000	1.500000	1410.000000	5.000000e+03	1.000000	0.000000	3.000000
50%	4.420000e+05	3.000000	2.250000	1880.000000	7.528000e+03	1.000000	0.000000	3.000000
75%	6.179500e+05	4.000000	2.500000	2475.000000	1.040400e+04	2.000000	0.000000	4.000000
max	1.330000e+06	11.000000	7.500000	7480.000000	1.651359e+06	3.500000	1.000000	5.000000

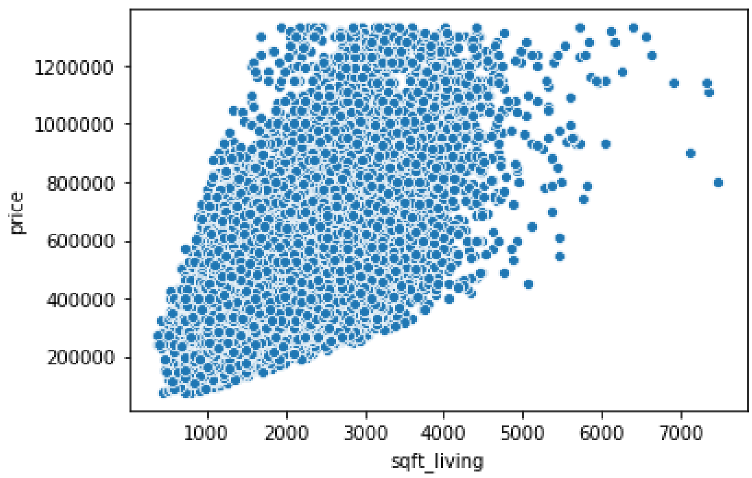
Next step? Well, I got a nice cutoff for price, let's see if we can do some stuff with it.

In [21]:

```
sns.scatterplot(data=price_low, x="sqft_living", y="price")
```

Out[21]:

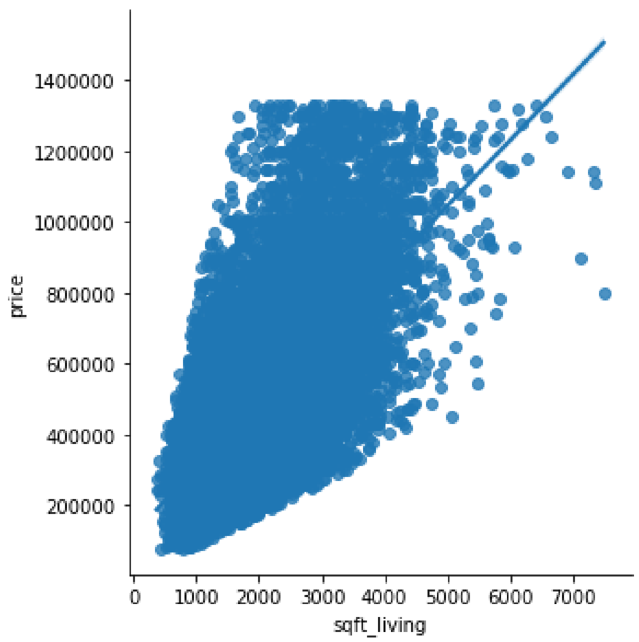
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f60056c940>
```



That's just begging to be linearlly regressed.

In [22]:

```
sns.lmplot(x="sqft_living", y="price", data=price_low)
plt.show()
```



So, just to crawl, let's try a little linear regression with just these 2. First, instantiate it:

In [23]:

```
lr = LinearRegression()
```

In [24]:

```
y = price_low['price'].values
lr.fit(price_low[['sqft_living']], y)
```

Out[24]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [25]:

```
m = lr.coef_
print(m)
```

```
[185.23232919]
```

In [26]:

```
b = lr.intercept_
print(b)
```

```
120588.0741801149
```

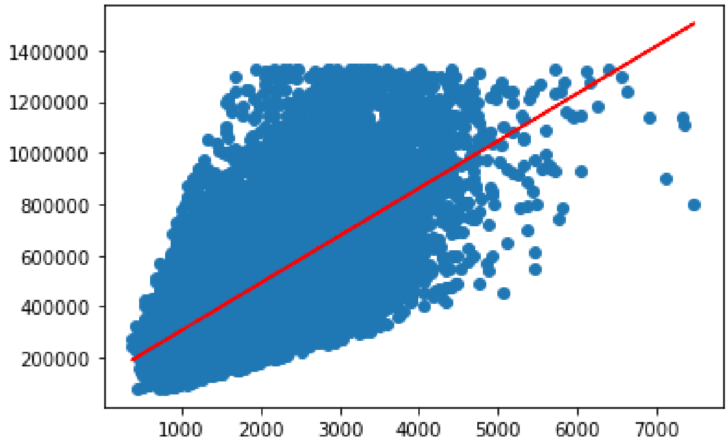
That looks a bit odd, but we'll go with it for now, let's make some equations and graphs and see how it looks.

In [27]:

```
X=price_low['sqft_living'].values
y_eq=m*X+b
```

In [28]:

```
plt.scatter(X, y)
plt.plot(X, y_eq, color='red')
plt.show()
```



For a simple case, this looks pretty good. There's still more to do, more complexity to add in.

In [29]:

```
from sklearn.metrics import r2_score
```

In [30]:

```
r2_score(y, y_eq)
```

Out[30]:

```
0.4153296223007371
```

Meh, not great. But like I said, this is crawl, next we'll walk, then run. Next step is to add a little more complexity: sqft AND bedrooms.

sqft AND bedrooms.

In [31]:

```
att2=['sqft_living','bedrooms']
```

In [32]:

```
X=price_low[att2]
```

In [33]:

```
lr.fit(X, y)
```

Out[33]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [34]:

```
m = lr.coef_
print(m)
b = lr.intercept_
print(b)
```

```
[   204.82657438 -29495.93420606]
179927.44928716472
```

In [35]:

```
preds = lr.predict(X)
```

In [36]:

```
r2_score(y, preds)
```

Out[36]:

```
0.423543662455258
```

So it seems our R2 score actually dropped as we added these other variables. That sucks.

In [37]:

```
import statsmodels.api as sm
X_int = sm.add_constant(X)
model = sm.OLS(y,X_int).fit()
model.summary()
```

```
D:\anaconda3\envs\learn-env\lib\site-packages\numpy\core\fromnumeric.py:2580: FutureWarni
ng: Method .ptp is deprecated and will be removed in a future version. Use numpy.ptp inst
ead.
  return ptp(axis=axis, out=out, **kwargs)
```

Out[37]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.424
Model:	OLS	**Adj. R-squared:**	0.423
Method:	Least Squares	**F-statistic:**	7666.
Date:	Thu, 28 Jan 2021	**Prob (F-statistic):**	0.00
Time:	15:14:05	**Log-Likelihood:**	-2.8167e+05
No. Observations:	20869	**AIC:**	5.633e+05
Df Residuals:	20866	**BIC:**	5.634e+05
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1.799e+05	4744.683	37.922	0.000	1.71e+05	1.89e+05
sqft_living	204.8266	1.890	108.351	0.000	201.121	208.532
bedrooms	-2.95e+04	1710.596	-17.243	0.000	-3.28e+04	-2.61e+04

Omnibus:	2177.873	Durbin-Watson:	1.972
Prob(Omnibus):	0.000	Jarque-Bera (JB):	3348.059
Skew:	0.775	Prob(JB):	0.00
Kurtosis:	4.202	Cond. No.	8.72e+03

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 8.72e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

So it's suggesting there is multicollinearity at work here, and I don't disagree. I think bedrooms, bathrooms and sqft are related. The more bedrooms and/or bathrooms you have, the bigger your house is going to be. Let's get even more complicated; let's split our columns into continuous and categorical: So let's plan out our next steps for the next few days: -Look uo how to deal with colinear variables -include year built in the model -split the data, test and train -Go from there.

In [38]:

```
att3=['sqft_living','bedrooms','bathrooms','sqft_lot']
```

In [39]:

```
X=price_low[att3].values
```

In [40]:

```
y = price_low['price'].values
lr.fit(X, y)
```

Out[40]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [41]:

```
m = lr.coef_
print(m)
b = lr.intercept_
print(b)
```

```
[ 2.00084338e+02 -3.11301011e+04  1.05074290e+04 -1.26130731e-01]
175000.13342293166
```

In [42]:

```
preds = lr.predict(X)
r2_score(y, preds)
```

Out[42]:

```
0.4245556844227749
```

Time to start throwing spaghetti against the wall. An R2 score of 42 just isn't going to cut it. So let's try our regression with the log price.

In [43]:

```
price_low_log=np.log(price_low.price)
```

```
price_low_log=np.log(price_low.price)
```

In [44]:

```
y=price_low_log.values
```

In [45]:

```
lr.fit(X, y)
```

Out[45]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [46]:

```
m = lr.coef_
print(m)
b = lr.intercept_
print(b)
```

```
[ 3.65304586e-04 -5.32337200e-02  5.09053438e-02 -1.75442585e-07]
12.34269171408627
```

In [47]:

```
preds = lr.predict(X)
r2_score(y, preds)
```

Out[47]:

```
0.4022210995475586
```

Somehow, we've gotten worse. Let's log more things, the sqft's. We'll put sqft_living, sqft_lot and price into its own dataframe, log those values, and put them back into the original dataframe. Then run a linear regression on that and see what we get.

In [48]:

```
continuous = ['sqft_living', 'sqft_lot','price']
cont = price_low[continuous]
log_names = [f'{column}_log' for column in cont.columns]
```

In [49]:

```
df_log = np.log(cont)
df_log.columns = log_names
```

In [50]:

```
scaler = StandardScaler()

df_log_norm = scaler.fit_transform(df_log)
```

In [51]:

```
df_log_norm = pd.DataFrame(df_log_norm, columns = df_log.columns)
```

In [52]:

```
df_log_norm.head()
```

Out[52]:

	sqft_living_log	sqft_lot_log	price_log
0	-1.117789	-0.368636	-1.485162
1	0.810548	-0.091637	0.420131
2	-2.175311	0.268433	-1.935373

	sqft_living_log	sqft_lot_log	price_log
3	0.139286	-0.505012	0.669074
4	-0.242597	0.030542	0.305147

In [53]:

```
df_pre = pd.concat([df_log_norm, price_low], axis=1)
df_pre.head()
```

Out[53]:

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	condition	g
0	-1.117789	-0.368636	-1.485162	221900.0	3.0	1.00	1180.0	5650.0	1.0	NaN	3.0	
1	0.810548	-0.091637	0.420131	538000.0	3.0	2.25	2570.0	7242.0	2.0	0.0	3.0	
2	-2.175311	0.268433	-1.935373	180000.0	2.0	1.00	770.0	10000.0	1.0	0.0	3.0	
3	0.139286	-0.505012	0.669074	604000.0	4.0	3.00	1960.0	5000.0	1.0	0.0	5.0	
4	-0.242597	0.030542	0.305147	510000.0	3.0	2.00	1680.0	8080.0	1.0	0.0	3.0	

So now that I've pretty much decided what variables I want to use, I'm going to drop the others from the dataframe.

In [54]:

```
to_drop=['floors','waterfront','condition','grade','yr_built']
```

In [55]:

```
df_final=df_pre.drop(columns=to_drop)
```

In [56]:

```
df_final.describe()
```

Out[56]:

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot
count	2.086900e+04	2.086900e+04	2.086900e+04	2.086900e+04	20869.000000	20869.000000	20869.000000	2.086900e+04
mean	-9.451659e-16	-1.503549e-15	-4.818439e-15	4.921810e+05	3.344434	2.070763	2006.091044	1.468600e+04
std	1.000024e+00	1.000024e+00	1.000024e+00	2.318026e+05	0.891255	0.722731	806.488218	3.999138e+04
min	-3.990919e+00	-3.030577e+00	-3.734425e+00	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02
25%	-6.766364e-01	-5.050121e-01	-7.097054e-01	3.182000e+05	3.000000	1.500000	1410.000000	5.000000e+03
50%	3.604850e-02	-4.841765e-02	-2.711710e-03	4.420000e+05	3.000000	2.250000	1880.000000	7.528000e+03
75%	7.172379e-01	3.126264e-01	7.181967e-01	6.179500e+05	4.000000	2.500000	2475.000000	1.040400e+04
max	3.457152e+00	5.966798e+00	2.367255e+00	1.330000e+06	11.000000	7.500000	7480.000000	1.651359e+06

In [57]:

```
df_final.dropna(inplace=True)
```

In [58]:

```
test=['sqft_living_log','sqft_lot_log','bedrooms','bathrooms']
```

In [59]:

```
X=df_final[test]
y=df_final.price_log
```

In [60]:

```
model = sm.OLS(y, sm.add_constant(X))
```

```
D:\anaconda3\envs\learn-env\lib\site-packages\numpy\core\fromnumeric.py:2580: FutureWarning: Method .ptp is deprecated and will be removed in a future version. Use numpy.ptp instead.
  return ptp(axis=axis, out=out, **kwargs)
```

In [61]:

```
results = model.fit()

results.summary()
```

Out[61]:

OLS Regression Results

Dep. Variable:	price_log	**R-squared:**	0.402
Model:	OLS	**Adj. R-squared:**	0.402
Method:	Least Squares	**F-statistic:**	3388.
Date:	Thu, 28 Jan 2021	**Prob (F-statistic):**	0.00
Time:	15:14:51	**Log-Likelihood:**	-23462.
No. Observations:	20175	**AIC:**	4.693e+04
Df Residuals:	20170	**BIC:**	4.697e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-0.0345	0.022	-1.574	0.116	-0.078	0.008
sqft_living_log	0.6598	0.006	115.070	0.000	0.649	0.671
sqft_lot_log	-0.1073	0.006	-18.750	0.000	-0.119	-0.096
bedrooms	0.0113	0.007	1.591	0.112	-0.003	0.025
bathrooms	-0.0017	0.009	-0.198	0.843	-0.019	0.016

Omnibus:	236.906	**Durbin-Watson:**	1.969
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	153.952
Skew:	-0.069	**Prob(JB):**	3.71e-34
Kurtosis:	2.595	**Cond. No.**	17.3

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

In [62]:

```
X_int = sm.add_constant(X)
model = sm.OLS(y,X_int).fit()
model.summary()
```

Out[62]:

OLS Regression Results

Dep. Variable:	price_log	**R-squared:**	0.402
Model:	OLS	**Adj. R-squared:**	0.402
Method:	Least Squares	**F-statistic:**	3388.
Date:	Thu, 28 Jan 2021	**Prob (F-statistic):**	0.00

Time:	15:14:52	**Log-Likelihood:**	-23462.
No. Observations:	20175	**AIC:**	4.693e+04
Df Residuals:	20170	**BIC:**	4.697e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0345	0.022	-1.574	0.116	-0.078	0.008
sqft_living_log	0.6598	0.006	115.070	0.000	0.649	0.671
sqft_lot_log	-0.1073	0.006	-18.750	0.000	-0.119	-0.096
bedrooms	0.0113	0.007	1.591	0.112	-0.003	0.025
bathrooms	-0.0017	0.009	-0.198	0.843	-0.019	0.016

Omnibus:	236.906	**Durbin-Watson:**	1.969
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	153.952
Skew:	-0.069	**Prob(JB):**	3.71e-34
Kurtosis:	2.595	**Cond. No.**	17.3

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

In [63]:

```
lr.fit(X, y)
preds = lr.predict(X)
```

In [64]:

```
r2_score(y, preds)
```

Out[64]:

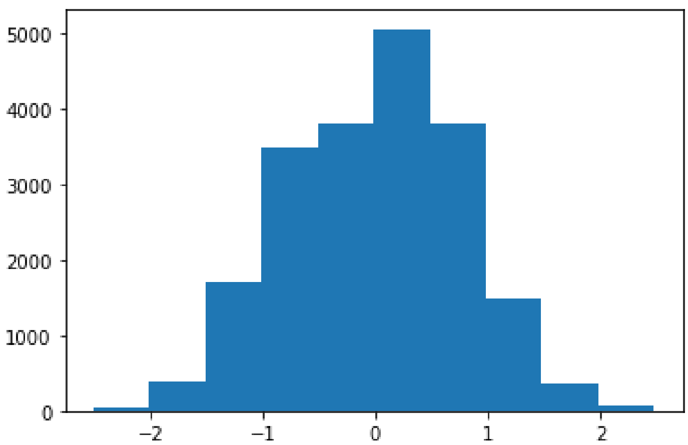
```
0.4018584144443017
```

In [65]:

```
residuals = y-preds
```

In [66]:

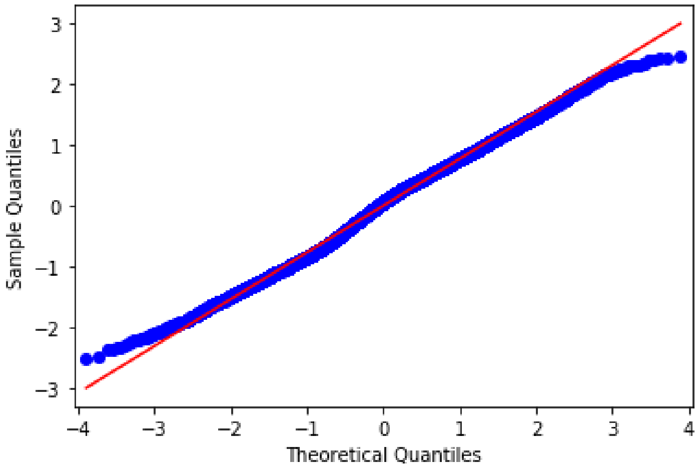
```
plt.hist(residuals)
plt.show()
```



In [72]:

```
fig = sm.qqplot(residuals, line = 'r')
```

```
fig = sm.qqplot(residuals, line = 'r')
```



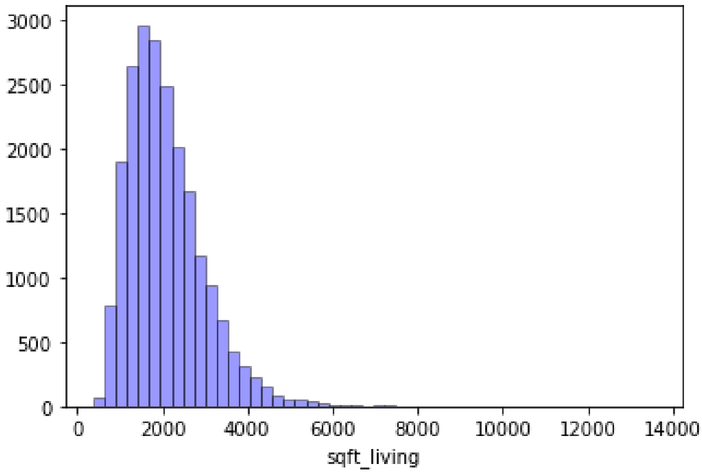
All that stuff is nice and all, but I still need to get that R2 score up. Let's take a step back and see if we can get some more linear relationships with price going. We can start by looking at the distributions of my variables, we already know the log of the price is a normal distribution.

In [67]:

```
sns.distplot(df_s1['sqft_living'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[67]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f601094898>
```

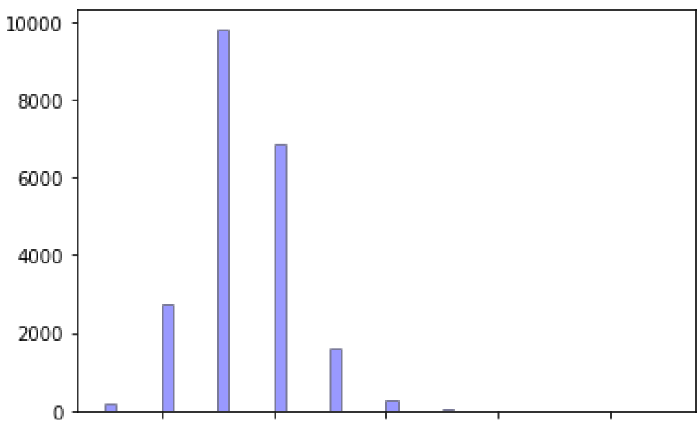


In [76]:

```
sns.distplot(df_s1['bedrooms'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[76]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fba3d792e8>
```

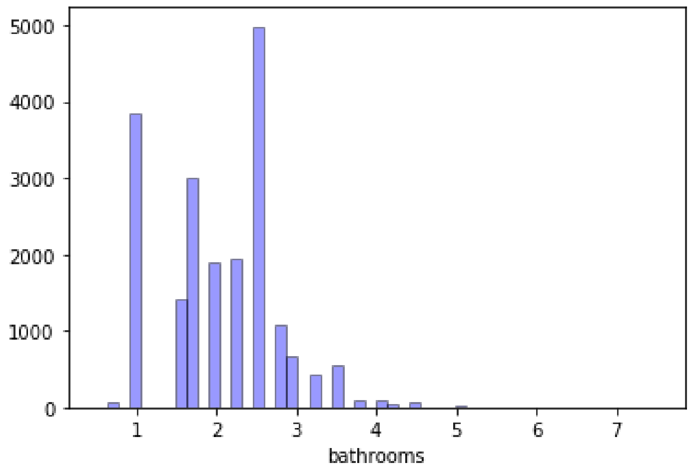


In [77]:

```
sns.distplot(df_final['bathrooms'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[77]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fba1e996d8>
```



In [74]:

```
df_final['bathrooms'].unique()
```

Out[74]:

```
array([1.  , 2.25, 3.  , 2.  , 4.5 , 1.5 , 2.5 , 1.75, 2.75, 3.25, 4.  ,
       3.5 , 0.75, 4.25, 1.25, 3.75, 4.75, 5.  , 0.5 , 5.25, 6.75, 7.5 ,
       5.5 , 5.75, 6.5 ])
```

What's a quarter of a bathroom look like? Or three quarters for that matter? I think I can simplify that some. Make the quarters into halves. I figure 2.25 bathrooms is closer to 2.5 than 2.0, but 3.75 bathrooms would also be closer to 3.4 than to 4. So I'll need to edit this column, more like add another column with just halves. I have an idea how to do that:

In [68]:

```
list1=[1,5,9,13,17,21,25,29,33]
list2=[3,7,11,15,19,23,27,31,35]
```

So these lists are the values when dividing the bathrooms by .25, if your bathrooms are ending in .25 or .75, all I need to do is go over the column see if the value divided by 0.25 yields one of these numbers, if it's in list1, add .25, if it's in list2, subtract .25, otherwise, leave it alone. We'll make a new column for all these values so as to keep the original.

In [76]:

```
g= len(df_final['bathrooms'])
```

In [77]:

```
g
```

Out[77]:

```
20175
```

In [82]:

```
a= df_final['bathrooms'][0]/0.25
```

In [83]:

```
a
```

Out[83]:

```
4.0
```

In [84]:

```
df_final.head()
```

Out[84]:

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot
0	-1.117789	-0.368636	-1.485162	221900.0	3.0	1.00	1180.0	5650.0
1	0.810548	-0.091637	0.420131	538000.0	3.0	2.25	2570.0	7242.0
2	-2.175311	0.268433	-1.935373	180000.0	2.0	1.00	770.0	10000.0
3	0.139286	-0.505012	0.669074	604000.0	4.0	3.00	1960.0	5000.0
4	-0.242597	0.030542	0.305147	510000.0	3.0	2.00	1680.0	8080.0

In [77]:

```
a in list1
```

Out[77]:

```
False
```

In [78]:

```
a in list2
```

Out[78]:

```
False
```

In [69]:

```
df_final['bath_haf']=df_final['bathrooms']
```

In [70]:

```
df_final['bath_haf']
```

Out[70]:

```
0        1.00
1        2.25
2        1.00
3        3.00
4        2.00
         ...
20864    2.25
20865    2.25
20866    2.50
20867    1.50
20868    2.50
Name: bath_haf, Length: 20175, dtype: float64
```

In [71]:

```
df_final['bath_haf'][0]/0.25
```

Out[71]:

```
4.0
```

In [72]:

```
for i in df_final.index:
    a= df_final['bath_haf'][i]
    b= a/.25
    if b in list1:
        df_final['bath_haf'][i]=a + 0.25
    elif b in list2:
        df_final['bath_haf'][i]= a - 0.25
    else:
        df_final['bath_haf'][i]= a
```

In [73]:

```
df_final['bath_haf'].unique()
```

Out[73]:

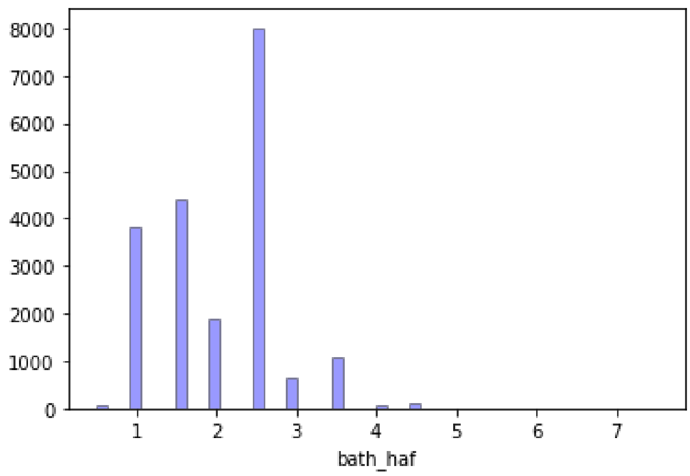
```
array([1. , 2.5, 3. , 2. , 4.5, 1.5, 3.5, 4. , 0.5, 5. , 5.5, 6.5, 7.5])
```

In [74]:

```
sns.distplot(df_final['bath_haf'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[74]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f60117f208>
```



That's a little better.

In [75]:

```
test2=['sqft_living_log','sqft_lot_log','bedrooms','bath_haf']
```

In [76]:

```
X=df_final[test2]
y=df_final.price_log
```

In [77]:

```
lr.fit(X, y)
preds = lr.predict(X)
```

In [78]:

```
r2_score(y, preds)
```

Out[78]:

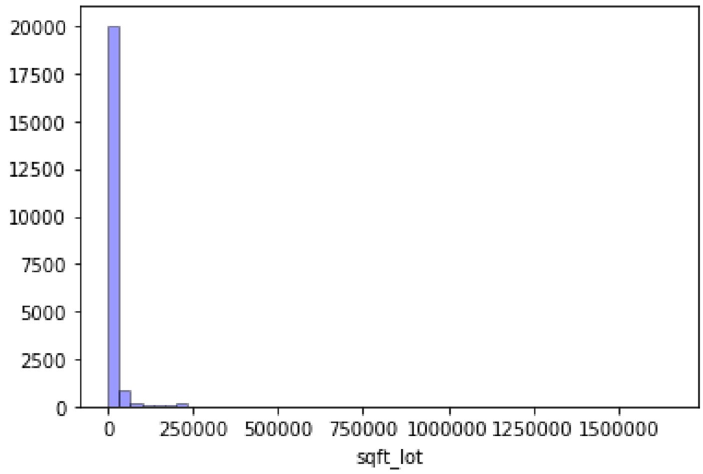
```
0.4018609379250867
```

In [79]:

```python
sns.distplot(df_s1['sqft_lot'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[79]:

<matplotlib.axes._subplots.AxesSubplot at 0x1f6029a6e48>

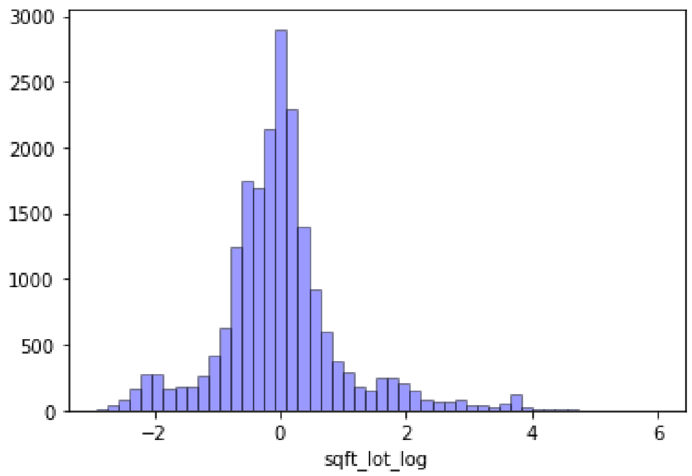


In [96]:

```python
sns.distplot(df_final['sqft_lot_log'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[96]:

<matplotlib.axes._subplots.AxesSubplot at 0x1fba4853e80>

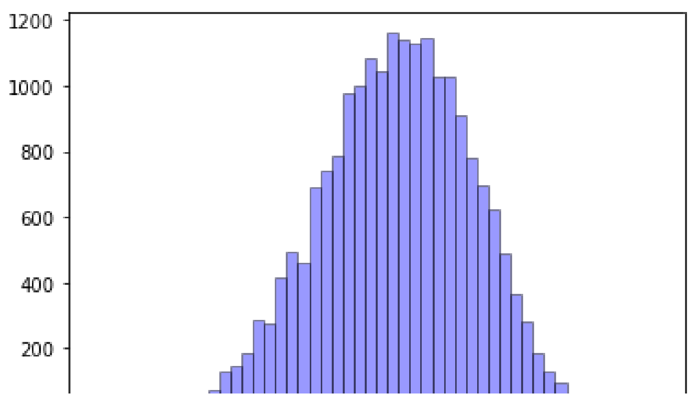


In [88]:

```python
sns.distplot(df_final['sqft_living_log'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[88]:

<matplotlib.axes._subplots.AxesSubplot at 0x1b80a2ef908>

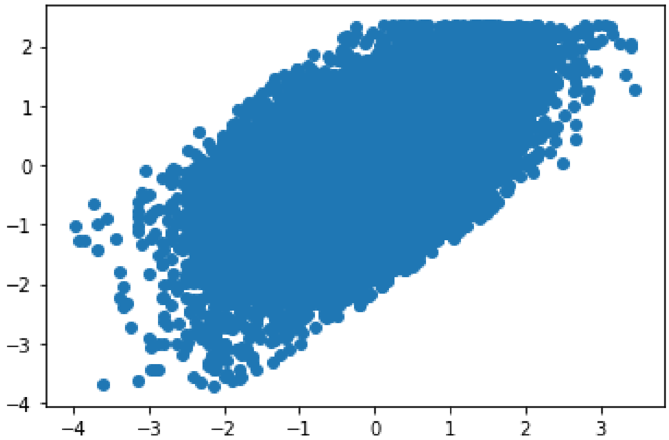


In [98]:

```
q=df_final['sqft_living_log']
u=df_final['price_log']
plt.scatter(q, u)
```

Out[98]:

<matplotlib.collections.PathCollection at 0x1fba4be6828>

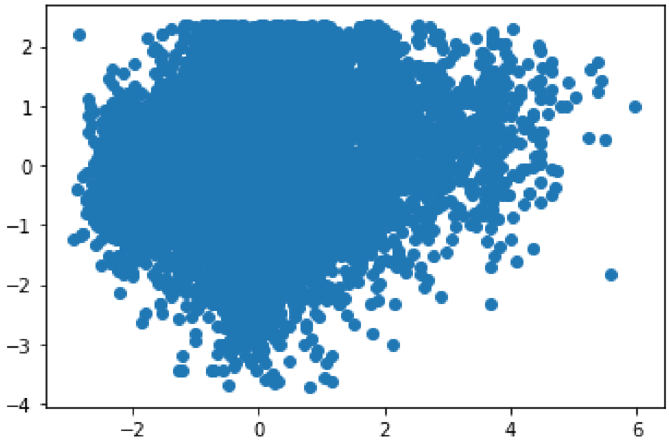


In [99]:

```
plt.scatter(df_final['sqft_lot_log'],u)
```

Out[99]:

<matplotlib.collections.PathCollection at 0x1fba4c53470>



So the problem seems to be bedrooms and bathrooms, they don't seem to want to fit into the model.

In [80]:

```
test3=['sqft_living_log','sqft_lot_log']
```

In [81]:

```
X=df_final[test3]
y=df_final.price_log
```

In [82]:

```
lr.fit(X, y)
preds = lr.predict(X)
r2_score(y, preds)
```

Out[82]:

```
0.40176779261215945
```

In [83]:

```
test4=['sqft_living_log','bathrooms','bedrooms','sqft_lot_log']
X=df_final[test4]
y=df_final.price_log
```

In [84]:

```
lr.fit(X, y)
preds = lr.predict(X)
r2_score(y, preds)
```

Out[84]:

```
0.4018584144443017
```

Desperate times, desperate measures, time to use some scalers:

In [85]:

```
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
```

In [86]:

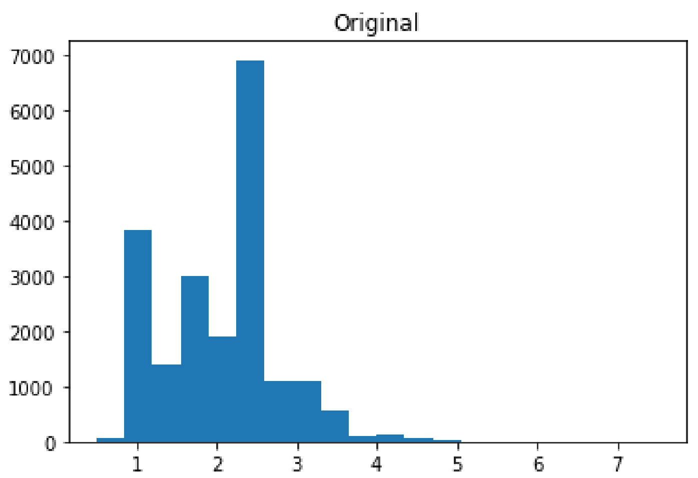
```
stdscaler = StandardScaler()
minmaxscaler = MinMaxScaler()
robscaler = RobustScaler()
```

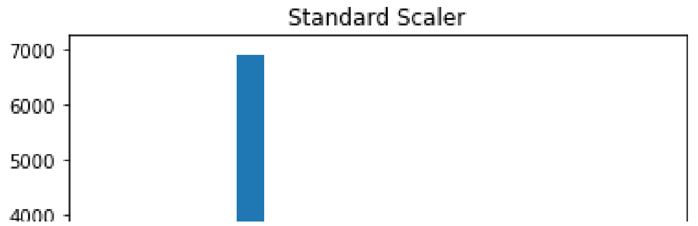
In [87]:

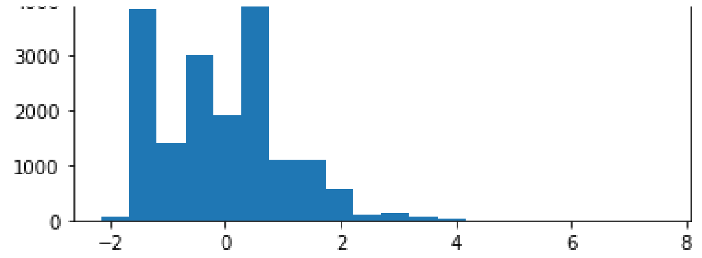
```
X_scaled_std = stdscaler.fit_transform(X['bathrooms'].values.reshape(-1, 1))
X_scaled_mm = minmaxscaler.fit_transform(X['bathrooms'].values.reshape(-1, 1))
X_scaled_rob = robscaler.fit_transform(X['bathrooms'].values.reshape(-1, 1))
```

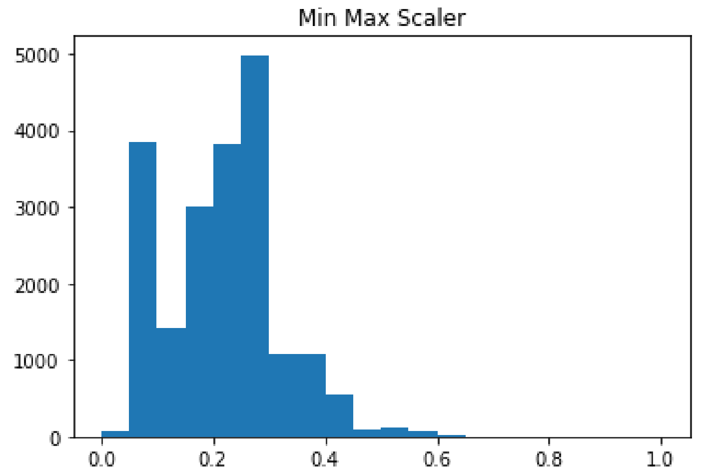
In [88]:

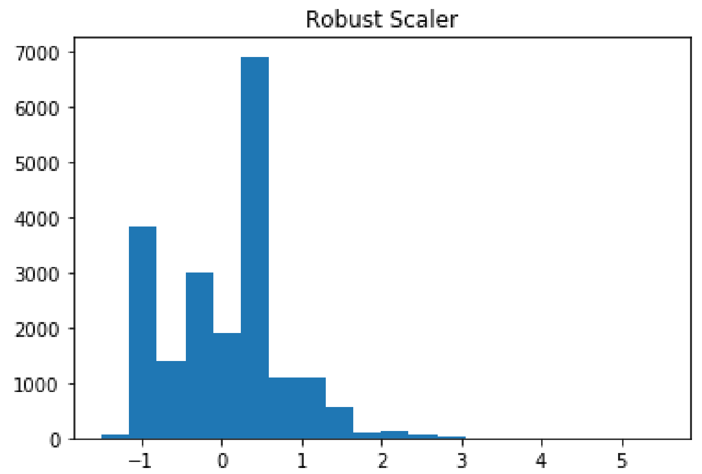
```
scalers = {'Original': X['bathrooms'].values,
           'Standard Scaler': X_scaled_std,
           'Min Max Scaler': X_scaled_mm,
           'Robust Scaler': X_scaled_rob}
for title, data in scalers.items():
    plt.hist(data, bins=20)
    plt.title(f"{title}")
    plt.show()
```











In [89]:

```
scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)
```

In [90]:

```
scaled_model = sm.OLS(y, sm.add_constant(X_scaled))
scaled_results = scaled_model.fit()

scaled_results.summary()
```

Out[90]:

OLS Regression Results

Dep. Variable:	price_log	**R-squared:**	0.402
Model:	OLS	**Adj. R-squared:**	0.402
Method:	Least Squares	**F-statistic:**	3388.
Date:	Thu, 28 Jan 2021	**Prob (F-statistic):**	0.00
Time:	15:16:39	**Log-Likelihood:**	-23462.
No. Observations:	20175	**AIC:**	4.693e+04
Df Residuals:	20170	**BIC:**	4.697e+04
Df Model:	4		

Covariance Type:	nonrobust

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0002	0.005	0.045	0.964	-0.010	0.011
x1	0.6588	0.006	115.070	0.000	0.648	0.670
x2	-0.0013	0.006	-0.198	0.843	-0.014	0.011
x3	0.0101	0.006	1.591	0.112	-0.002	0.023
x4	-0.1075	0.006	-18.750	0.000	-0.119	-0.096

Omnibus:	236.906	Durbin-Watson:	1.969
Prob(Omnibus):	0.000	Jarque-Bera (JB):	153.952
Skew:	-0.069	Prob(JB):	3.71e-34
Kurtosis:	2.595	Cond. No.	1.77

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

In [121]:

```
X
```

Out[121]:

	sqft_living_log	bathrooms	bedrooms	sqft_lot_log
0	-1.117789	1.00	3.0	-0.368636
1	0.810548	2.25	3.0	-0.091637
2	-2.175311	1.00	2.0	0.268433
3	0.139286	3.00	4.0	-0.505012
4	-0.242597	2.00	3.0	0.030542
...	...	...	...	...
20864	-0.474293	2.25	3.0	-2.163533
20865	0.546319	2.25	4.0	-0.336900
20866	-1.478766	2.50	4.0	-1.966026
20867	-0.363467	1.50	3.0	-1.329602
20868	-1.478766	2.50	5.0	-2.219160

20175 rows × 4 columns

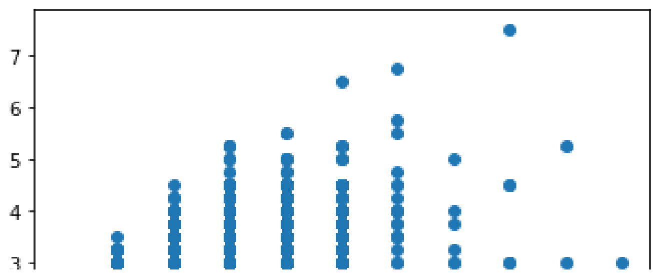
Let's check for some colinearity between bedrooms and bathrooms. I'm pretty sure there will be.

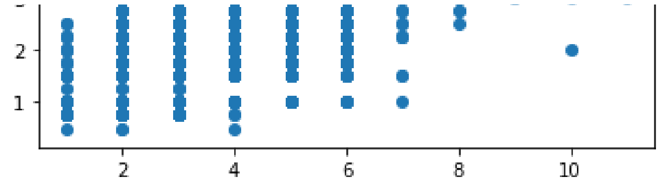
In [100]:

```
plt.scatter(df_final['bedrooms'],df_final['bathrooms'])
```

Out[100]:

<matplotlib.collections.PathCollection at 0x1b80a804a90>



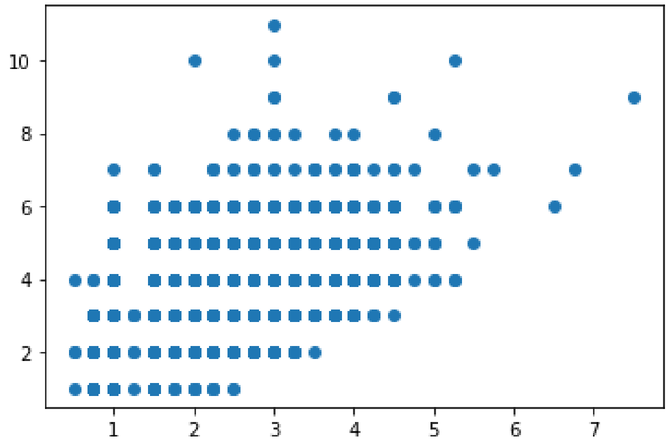


In [123]:

```
plt.scatter(df_final['bathrooms'],df_final['bedrooms'])
```

Out[123]:

```
<matplotlib.collections.PathCollection at 0x1fba5025128>
```



In [130]:

```
df_final.describe()
```

Out[130]:

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	20118.000000	20118.000000	20118.000000	2.011800e+04	20118.000000	20118.000000	20118.000000	2.011800e+04	20
mean	0.001091	0.004489	-0.000214	4.902058e+05	3.331047	2.048576	1993.443782	1.495725e+04	
std	0.998260	1.001896	1.000553	2.316542e+05	0.864057	0.712110	795.447885	4.045743e+04	
min	-3.990919	-2.924226	-3.734425	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	
25%	-0.676636	-0.503228	-0.707678	3.150000e+05	3.000000	1.500000	1400.000000	5.100000e+03	
50%	0.036049	-0.043684	-0.002712	4.400000e+05	3.000000	2.000000	1870.000000	7.620000e+03	
75%	0.712228	0.317549	0.714712	6.150000e+05	4.000000	2.500000	2450.000000	1.051625e+04	
max	3.457152	5.966798	2.367255	1.330000e+06	6.000000	5.000000	7350.000000	1.651359e+06	

Let's do some more cutoffs. Let's cap the bedrooms at 6, and bathrooms at 5. The Brady Bunch lived in a 4 bedroom house.

In [101]:

```
df_final = df_final[df_final.bedrooms <= 6]
```

In [102]:

```
df_final = df_final[df_final.bathrooms <= 5]
```

How can I turn beds and baths into 1 variable, and put that in my model? What if I did a linear regression of the beds and baths, used that as my variable.

In [103]:

```
y = df_final['bathrooms'].values
```

```python
X= df_final[['bedrooms']]
lr.fit(X, y)
```

Out[103]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [104]:

```python
lr = LinearRegression()
```

In [105]:

```python
lr.fit(X, y)
```

Out[105]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [106]:

```python
preds = lr.predict(X)
```

In [107]:

```python
r2_score(y, preds)
```

Out[107]:

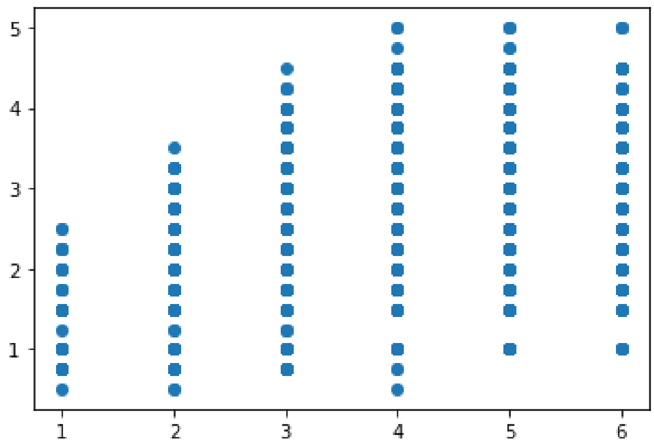
```
0.2590854263404009
```

In [108]:

```python
plt.scatter(df_final['bedrooms'],df_final['bathrooms'])
```

Out[108]:

```
<matplotlib.collections.PathCollection at 0x1b80a862b38>
```



In [109]:

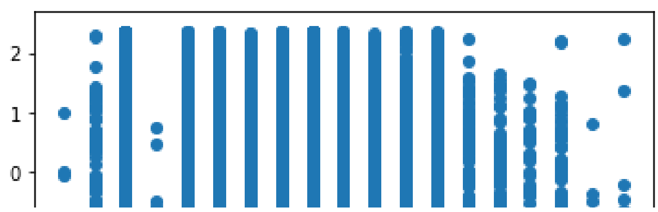
```python
df_final['bath_plus']=np.exp(df_final['bathrooms'])
```

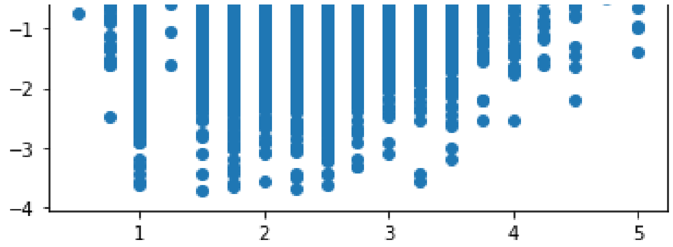
In [110]:

```python
plt.scatter(df_final['bathrooms'],df_final['price_log'])
```

Out[110]:

```
<matplotlib.collections.PathCollection at 0x1b80a8c7518>
```





In [111]:

```
df_final.drop('bath_plus',axis=1, inplace=True)
```

In [112]:

```
df_final['price_100']=df_final['price']/10000
```

In [166]:

```
df_final
```

Out[166]:

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	bath_haf	price_100
0	-1.117789	-0.368636	-1.485162	221900.0	3.0	1.00	1180.0	5650.0	1.0	22.19
1	0.810548	-0.091637	0.420131	538000.0	3.0	2.25	2570.0	7242.0	2.5	53.80
2	-2.175311	0.268433	-1.935373	180000.0	2.0	1.00	770.0	10000.0	1.0	18.00
3	0.139286	-0.505012	0.669074	604000.0	4.0	3.00	1960.0	5000.0	3.0	60.40
4	-0.242597	0.030542	0.305147	510000.0	3.0	2.00	1680.0	8080.0	2.0	51.00
...	...	...	...	...	...	...	...	...	...	...
20864	-0.474293	-2.163533	-0.444179	565000.0	3.0	2.25	1540.0	1005.0	2.5	56.50
20865	0.546319	-0.336900	-0.217513	765000.0	4.0	2.25	2030.0	2222.0	2.5	76.50
20866	-1.478766	-1.966026	-0.206242	644000.0	4.0	2.50	3310.0	4839.0	2.5	64.40
20867	-0.363467	-1.329602	-0.217513	461000.0	3.0	1.50	1270.0	1416.0	1.5	46.10
20868	-1.478766	-2.219160	-0.664215	270500.0	5.0	2.50	2406.0	7093.0	2.5	27.05

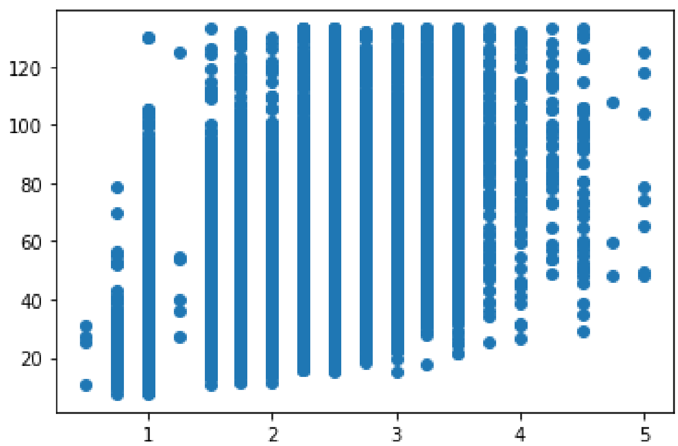
20118 rows × 10 columns

In [167]:

```
plt.scatter(df_final['bathrooms'],df_final['price_100'])
```

Out[167]:

```
<matplotlib.collections.PathCollection at 0x1fba6246dd8>
```



In [113]:

```
y = df_final['price'].values
```

```
y= df_final['price'].values
X= df_final[['bedrooms']]
lr.fit(X, y)
```

Out[113]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [114]:

```
preds = lr.predict(X)
r2_score(y, preds)
```

Out[114]:

```
0.09842077135571392
```

In [115]:

```
df_final['bedrooms'].unique()
```

Out[115]:

```
array([3., 2., 4., 5., 1., 6.])
```

In [116]:

```
df_final['bedrooms']
```

Out[116]:

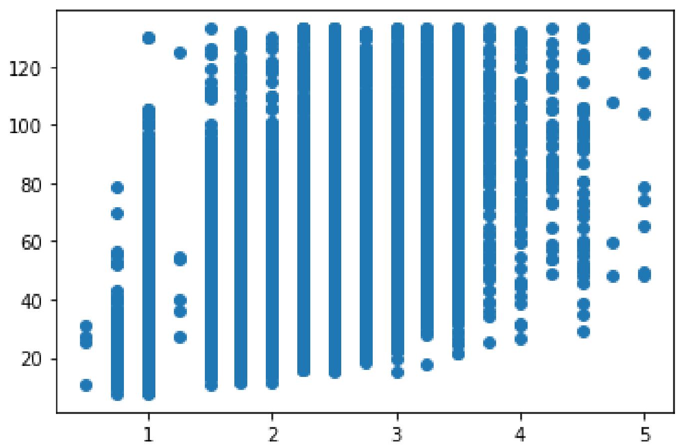
```
0        3.0
1        3.0
2        2.0
3        4.0
4        3.0
        ...
20864    3.0
20865    4.0
20866    4.0
20867    3.0
20868    5.0
Name: bedrooms, Length: 20118, dtype: float64
```

In [117]:

```
plt.scatter(df_final['bathrooms'],df_final['price_100'])
```

Out[117]:

```
<matplotlib.collections.PathCollection at 0x1b80a9266d8>
```



In [118]:

```
df_final.groupby(['bedrooms','bath_haf']).size()
```

Out[118]:

```
bedrooms  bath_haf
```

```
1.0       0.5           28
          1.0          135
          1.5           14
          2.0            5
          2.5            6
2.0       0.5           26
          1.0         1552
          1.5          573
          2.0          210
          2.5          284
          3.0           12
          3.5            7
3.0       0.5           16
          1.0         1777
          1.5         2661
          2.0         1023
          2.5         3455
          3.0          166
          3.5          276
          4.0            7
          4.5            4
4.0       0.5            3
          1.0          325
          1.5          968
          2.0          521
          2.5         3614
          3.0          293
          3.5          502
          4.0           36
          4.5           33
          5.0            2
5.0       1.0           43
          1.5          180
          2.0          109
          2.5          565
          3.0          143
          3.5          244
          4.0           29
          4.5           33
          5.0            3
6.0       1.0            6
          1.5           22
          2.0           24
          2.5           69
          3.0           42
          3.5           38
          4.0            9
          4.5           22
          5.0            3
dtype: int64
```

This might help us. This shows the most common number of bathrooms given the number of bedrooms. In fact, it looks like 2.5 bathrooms seems to be the norm. So here's what we can do: Make yet another column, and that column will be bathrooms, but it'll only have the 3 most common values given the number of bedrooms.

In [119]:

```
df_final['bath_3']=df_final['bath_haf']
```

In [120]:

```
for i in df_final.index:
    group13=[1,1.5,2.5]
    group4=[1.5,2,2.5]
    group5=[1.5,2.5,3.5]
    group6=[2.5,3,3.5]
    a= df_final['bath_3'][i]
    b= df_final['bedrooms'][i]
    if b == 2 and a not in group13:
        df_final['bath_3'][i]= None
```

```
    elif b == 3 and a not in group13:
        df_final['bath_3'][i]= None
    elif b == 4 and a not in group4:
        df_final['bath_3'][i]= None
    elif b == 5 and a not in group5:
        df_final['bath_3'][i]= None
    elif b == 6 and a not in group6:
        df_final['bath_3'][i]= None
```

In [121]:

```
df_final.head()
```

Out[121]:

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	bath_haf	price_100	bath_3
0	-1.117789	-0.368636	-1.485162	221900.0	3.0	1.00	1180.0	5650.0	1.0	22.19	1.0
1	0.810548	-0.091637	0.420131	538000.0	3.0	2.25	2570.0	7242.0	2.5	53.80	2.5
2	-2.175311	0.268433	-1.935373	180000.0	2.0	1.00	770.0	10000.0	1.0	18.00	1.0
3	0.139286	-0.505012	0.669074	604000.0	4.0	3.00	1960.0	5000.0	3.0	60.40	NaN
4	-0.242597	0.030542	0.305147	510000.0	3.0	2.00	1680.0	8080.0	2.0	51.00	NaN

In [122]:

```
df_fin=df_final.dropna()
```

In [123]:

```
df_fin.describe()
```

Out[123]:

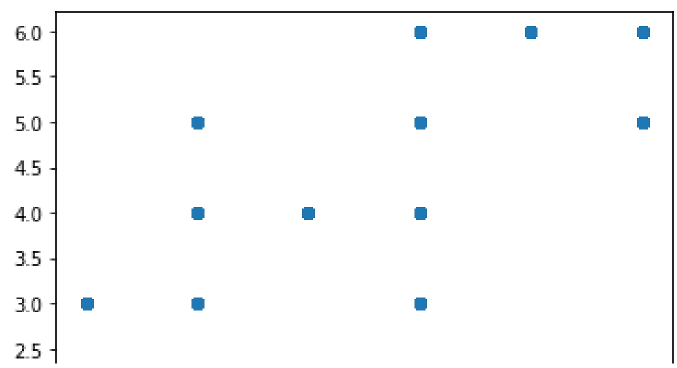
	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	16731.000000	16731.000000	16731.000000	1.673100e+04	16731.000000	16731.000000	16731.00000	1.673100e+04	167
mean	0.000201	0.008051	-0.001213	4.737150e+05	3.283486	1.956996	1930.43530	1.399446e+04	
std	0.997762	0.996267	1.001896	2.185500e+05	0.854524	0.629373	736.23415	3.388182e+04	
min	-3.924853	-2.924226	-3.734425	7.800000e+04	1.000000	0.500000	370.00000	5.200000e+02	
25%	-0.676636	-0.501670	-0.717834	3.100000e+05	3.000000	1.500000	1370.00000	5.178500e+03	
50%	0.036049	-0.043684	-0.005147	4.300000e+05	3.000000	2.000000	1840.00000	7.675000e+03	
75%	0.712228	0.320854	0.723586	5.950000e+05	4.000000	2.500000	2390.00000	1.044000e+04	
max	3.457152	5.966798	2.367255	1.330000e+06	6.000000	3.750000	7350.00000	1.164794e+06	

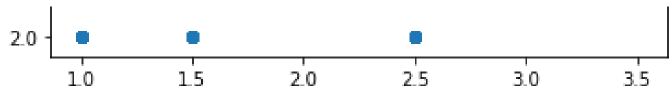
In [191]:

```
plt.scatter(df_fin['bath_3'],df_fin['bedrooms'])
```

Out[191]:

```
<matplotlib.collections.PathCollection at 0x1fba7cfd358>
```





In [124]:

```
y = df_fin['bath_3'].values
X= df_fin[['bedrooms']]
lr.fit(X, y)
```

Out[124]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [125]:

```
preds = lr.predict(X)
r2_score(y, preds)
```

Out[125]:

```
0.3131370670541668
```

Ok, so by doing this, I've tripled my R2 score regarding beds and baths

In [126]:

```
df_fin.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16731 entries, 0 to 20868
Data columns (total 11 columns):
sqft_living_log    16731 non-null float64
sqft_lot_log       16731 non-null float64
price_log          16731 non-null float64
price              16731 non-null float64
bedrooms           16731 non-null float64
bathrooms          16731 non-null float64
sqft_living        16731 non-null float64
sqft_lot           16731 non-null float64
bath_haf           16731 non-null float64
price_100          16731 non-null float64
bath_3             16731 non-null float64
dtypes: float64(11)
memory usage: 1.5 MB
```

In [127]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
id               21597 non-null int64
date             21597 non-null object
price            21597 non-null float64
bedrooms         21597 non-null int64
bathrooms        21597 non-null float64
sqft_living      21597 non-null int64
sqft_lot         21597 non-null int64
floors           21597 non-null float64
waterfront       19221 non-null float64
view             21534 non-null float64
condition        21597 non-null int64
grade            21597 non-null int64
sqft_above       21597 non-null int64
sqft_basement    21597 non-null object
yr_built         21597 non-null int64
yr_renovated     17755 non-null float64
zipcode          21597 non-null int64
lat              21597 non-null float64
long             21597 non-null float64
```

```
sqft_living15    21597 non-null int64
sqft_lot15       21597 non-null int64
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
```

In [196]:

```
16543/21597
```

Out[196]:

```
0.7659860165763763
```

So, we ended up removing about 25% of the original data, but if this works then it'll be worth it.

In [128]:

```
att4=['bedrooms','bath_3','sqft_living_log','sqft_lot_log']
y=df_fin['price_log']
X=df_fin[att4]
```

In [129]:

```
lr.fit(X, y)
```

Out[129]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [130]:

```
preds = lr.predict(X)
r2_score(y, preds)
```

Out[130]:

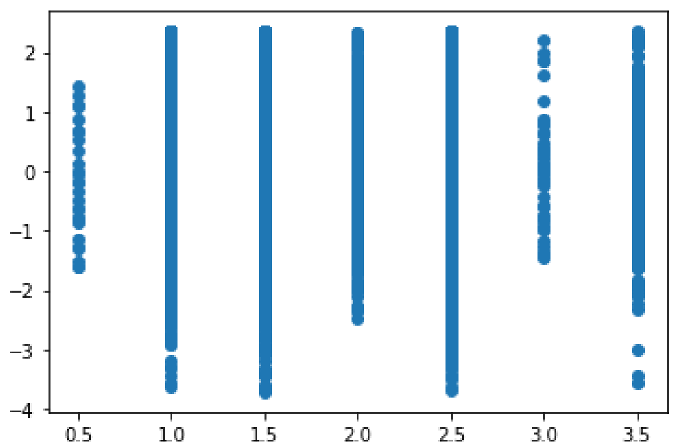
```
0.4026580033819309
```

In [131]:

```
plt.scatter(df_fin['bath_3'],df_fin['price_log'])
```

Out[131]:

```
<matplotlib.collections.PathCollection at 0x1b80a7c85c0>
```



In [132]:

```
df_fin
```

Out[132]:

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	bath_haf	price_100	bath_:
0	-1.117789	-0.368636	-1.485162	221900.0	3.0	1.00	1180.0	5650.0	1.0	22.190	1.

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	bath_half	price_100	bath_
1	0.810548	-0.091637	0.420131	538000.0	3.0	2.25	2570.0	7242.0	2.5	53.800	2.
2	-2.175311	0.268433	-1.935373	180000.0	2.0	1.00	770.0	10000.0	1.0	18.000	1.
6	-0.191516	-0.158793	-1.165059	257500.0	3.0	2.25	1715.0	6819.0	2.5	25.750	2.
7	-1.383472	0.235710	-0.895667	291850.0	3.0	1.50	1060.0	9711.0	1.5	29.185	1.
...	...	...	...	...	...	...	...	...	...	...	.
20864	-0.474293	-2.163533	-0.444179	565000.0	3.0	2.25	1540.0	1005.0	2.5	56.500	2.
20865	0.546319	-0.336900	-0.217513	765000.0	4.0	2.25	2030.0	2222.0	2.5	76.500	2.
20866	-1.478766	-1.966026	-0.206242	644000.0	4.0	2.50	3310.0	4839.0	2.5	64.400	2.
20867	-0.363467	-1.329602	-0.217513	461000.0	3.0	1.50	1270.0	1416.0	1.5	46.100	1.
20868	-1.478766	-2.219160	-0.664215	270500.0	5.0	2.50	2406.0	7093.0	2.5	27.050	2.

16731 rows × 11 columns

In [133]:

```
att5=['sqft_living']
y=df_fin['price']
X=df_fin[att5]
```

In [134]:

```
lr.fit(X,y)
```

Out[134]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [135]:

```
preds = lr.predict(X)
r2_score(y, preds)
```

Out[135]:

```
0.36984663355734293
```

In [136]:

```
att6=['sqft_lot_log']
y=df_fin['price_log']
X=df_fin[att6]
lr.fit(X,y)
```

Out[136]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [137]:

```
preds = lr.predict(X)
r2_score(y, preds)
```

Out[137]:

```
0.008955494006984255
```

In [138]:

```
att7=['sqft_lot']
```

```
y=df_fin['price']
X=df_fin[att7]
lr.fit(X,y)
```

Out[138]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [139]:

```
preds = lr.predict(X)
r2_score(y, preds)
```

Out[139]:

```
0.004726533123860177
```

So my variables are:sqft_living, sqft_lot, bedrooms and bathrooms.

In [140]:

```
att_1=['bedrooms']
y=df_fin['price']
X=df_fin[att_1]
lr.fit(X,y)
```

Out[140]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [141]:

```
preds = lr.predict(X)
r2_score(y, preds)
```

Out[141]:

```
0.10142270009085119
```

In [142]:

```
att_2=['bath_3']
y=df_fin['price']
X=df_fin[att_2]
lr.fit(X,y)
```

Out[142]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [143]:

```
preds = lr.predict(X)
r2_score(y, preds)
```

Out[143]:

```
0.1604912291687941
```

In [160]:

```
att_3=['sqft_living']
y=df_fin['price']
X=df_fin[att4]
lr.fit(X,y)
```

Out[160]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [161]:

```
preds = lr.predict(X)
```

```
r2_score(y, preds)
```

Out[161]:

```
0.17350553445859962
```

So let's try the train-test split:

In [162]:

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

In [163]:

```
len(X_test) + len(X_train) == len(X)
```

Out[163]:

```
True
```

In [164]:

```
scaler = StandardScaler()
```

In [165]:

```
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [166]:

```
lr.fit(X_train_scaled, y_train)
```

Out[166]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [167]:

```
y_train_pred = lr.predict(X_train_scaled)
y_test_pred = lr.predict(X_test_scaled)

print("Training Scores:")
print(f"R2: {r2_score(y_train, y_train_pred)}")

print("Testing Scores:")
print(f"R2: {r2_score(y_test, y_test_pred)}")
```

```
Training Scores:
R2: 0.17658887493395237
Testing Scores:
R2: 0.16227605574188841
```

In [155]:

```
pip install eli5
```

```
Collecting eli5Note: you may need to restart the kernel to use updated packages.
  Downloading eli5-0.10.1-py2.py3-none-any.whl (105 kB)
Requirement already satisfied: six in d:\anaconda3\envs\learn-env\lib\site-packages (from
eli5) (1.15.0)
Requirement already satisfied: jinja2 in d:\anaconda3\envs\learn-env\lib\site-packages (f
rom eli5) (2.11.2)
Collecting tabulate>=0.7.7
  Downloading tabulate-0.8.7-py3-none-any.whl (24 kB)
Requirement already satisfied: scikit-learn>=0.18 in d:\anaconda3\envs\learn-env\lib\site
-packages (from eli5) (0.21.3)
Collecting graphviz
  Downloading graphviz-0.16-py2.py3-none-any.whl (19 kB)
Requirement already satisfied: scipy in d:\anaconda3\envs\learn-env\lib\site-packages (fr
om eli5) (1.5.0)
Requirement already satisfied: numpy>=1.9.0 in d:\anaconda3\envs\learn-env\lib\site-packa
```

```
ges (from eli5) (1.19.1)
Requirement already satisfied: attrs>16.0.0 in d:\anaconda3\envs\learn-env\lib\site-packa
ges (from eli5) (19.3.0)
Requirement already satisfied: MarkupSafe>=0.23 in d:\anaconda3\envs\learn-env\lib\site-p
ackages (from jinja2->eli5) (1.1.1)
Requirement already satisfied: joblib>=0.11 in d:\anaconda3\envs\learn-env\lib\site-packa
ges (from scikit-learn>=0.18->eli5) (0.16.0)
Installing collected packages: tabulate, graphviz, eli5
Successfully installed eli5-0.10.1 graphviz-0.16 tabulate-0.8.7
```

In [157]:

```
import eli5
```

In [168]:

```
eli5.show_weights(lr, feature_names=list(X.columns))
```

Out[168]:

y top features

Weight?	Feature
+470685.143	<BIAS>
+70102.634	bath_3
+31269.392	bedrooms
+85.658	sqft_lot_log
-173.181	sqft_living_log

In [171]:

```
y_train_pred = lr.predict(X_train_scaled)
y_test_pred = lr.predict(X_test_scaled)

print("Training Scores:")
print(f"R2: {r2_score(y_train, y_train_pred)}")
print(f"Mean Absolute Error: {mean_absolute_error(y_train, y_train_pred)}")
print("---")
print("Testing Scores:")
print(f"R2: {r2_score(y_test, y_test_pred)}")
print(f"Mean Absolute Error: {mean_absolute_error(y_test, y_test_pred)}")
print(f"Root Mean Squared Error V1: {np.sqrt(mean_squared_error(y_test, y_test_pred))}")
print(f"Root Mean Squared Error V2: {mean_squared_error(y_test, y_test_pred)}")
```

```
Training Scores:
R2: 0.17658887493395237
Mean Absolute Error: 154152.30131673024
---
Testing Scores:
R2: 0.16227605574188841
Mean Absolute Error: 159574.16803459308
Root Mean Squared Error V1: 203247.85967638547
Root Mean Squared Error V2: 41309692463.031685
```

In [175]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [176]:

```
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns
```

In [177]:

```
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                          for i in range(len(X.columns))]
```

In [178]:

```
print(vif_data)
```

```
          feature        VIF
0        bedrooms  13.279275
1          bath_3  13.280561
2  sqft_living_log   1.105705
3     sqft_lot_log   1.107506
```

Now I'll need to look up what to do with this.

In [179]:

```
df_fin['bb']=df_fin['bedrooms'] + df_fin['bathrooms']
```

```
D:\anaconda3\envs\learn-env\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopyWar
ning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

In [180]:

```
df_fin
```

Out[180]:

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	bath_haf	price_100	bath_
0	-1.117789	-0.368636	-1.485162	221900.0	3.0	1.00	1180.0	5650.0	1.0	22.190	1.
1	0.810548	-0.091637	0.420131	538000.0	3.0	2.25	2570.0	7242.0	2.5	53.800	2.
2	-2.175311	0.268433	-1.935373	180000.0	2.0	1.00	770.0	10000.0	1.0	18.000	1.
6	-0.191516	-0.158793	-1.165059	257500.0	3.0	2.25	1715.0	6819.0	2.5	25.750	2.
7	-1.383472	0.235710	-0.895667	291850.0	3.0	1.50	1060.0	9711.0	1.5	29.185	1.
...	...	...	...	...	...	...	...	...	...	...	.
20864	-0.474293	-2.163533	-0.444179	565000.0	3.0	2.25	1540.0	1005.0	2.5	56.500	2.
20865	0.546319	-0.336900	-0.217513	765000.0	4.0	2.25	2030.0	2222.0	2.5	76.500	2.
20866	-1.478766	-1.966026	-0.206242	644000.0	4.0	2.50	3310.0	4839.0	2.5	64.400	2.
20867	-0.363467	-1.329602	-0.217513	461000.0	3.0	1.50	1270.0	1416.0	1.5	46.100	1.
20868	-1.478766	-2.219160	-0.664215	270500.0	5.0	2.50	2406.0	7093.0	2.5	27.050	2.

16731 rows × 12 columns

In [181]:

```
bb_test=['sqft_living_log','sqft_lot_log','bb']
```

In [184]:

```
y=df_fin['price_log']
X=df_fin[bb_test]
lr.fit(X,y)
```

Out[184]:

Out[184]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [185]:

```
preds = lr.predict(X)
r2_score(y, preds)
```

Out[185]:

```
0.40260571265462886
```

In [186]:

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

In [187]:

```
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [188]:

```
lr.fit(X_train_scaled, y_train)
```

Out[188]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [189]:

```
y_train_pred = lr.predict(X_train_scaled)
y_test_pred = lr.predict(X_test_scaled)

print("Training Scores:")
print(f"R2: {r2_score(y_train, y_train_pred)}")
print(f"Mean Absolute Error: {mean_absolute_error(y_train, y_train_pred)}")
print("---")
print("Testing Scores:")
print(f"R2: {r2_score(y_test, y_test_pred)}")
print(f"Mean Absolute Error: {mean_absolute_error(y_test, y_test_pred)}")
print(f"Root Mean Squared Error V1: {np.sqrt(mean_squared_error(y_test, y_test_pred))}")
print(f"Mean Squared Error V2: {mean_squared_error(y_test, y_test_pred)}")
```

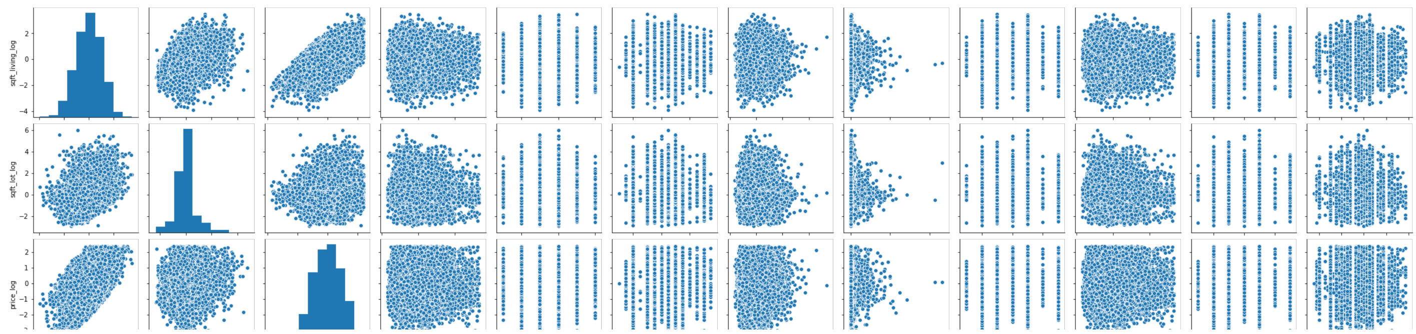
```
Training Scores:
R2: 0.40238726890828724
Mean Absolute Error: 0.6360828622504685
---
Testing Scores:
R2: 0.40312926844689845
Mean Absolute Error: 0.6371330869663714
Root Mean Squared Error V1: 0.7771113440347136
Root Mean Squared Error V2: 0.603902041027439
```

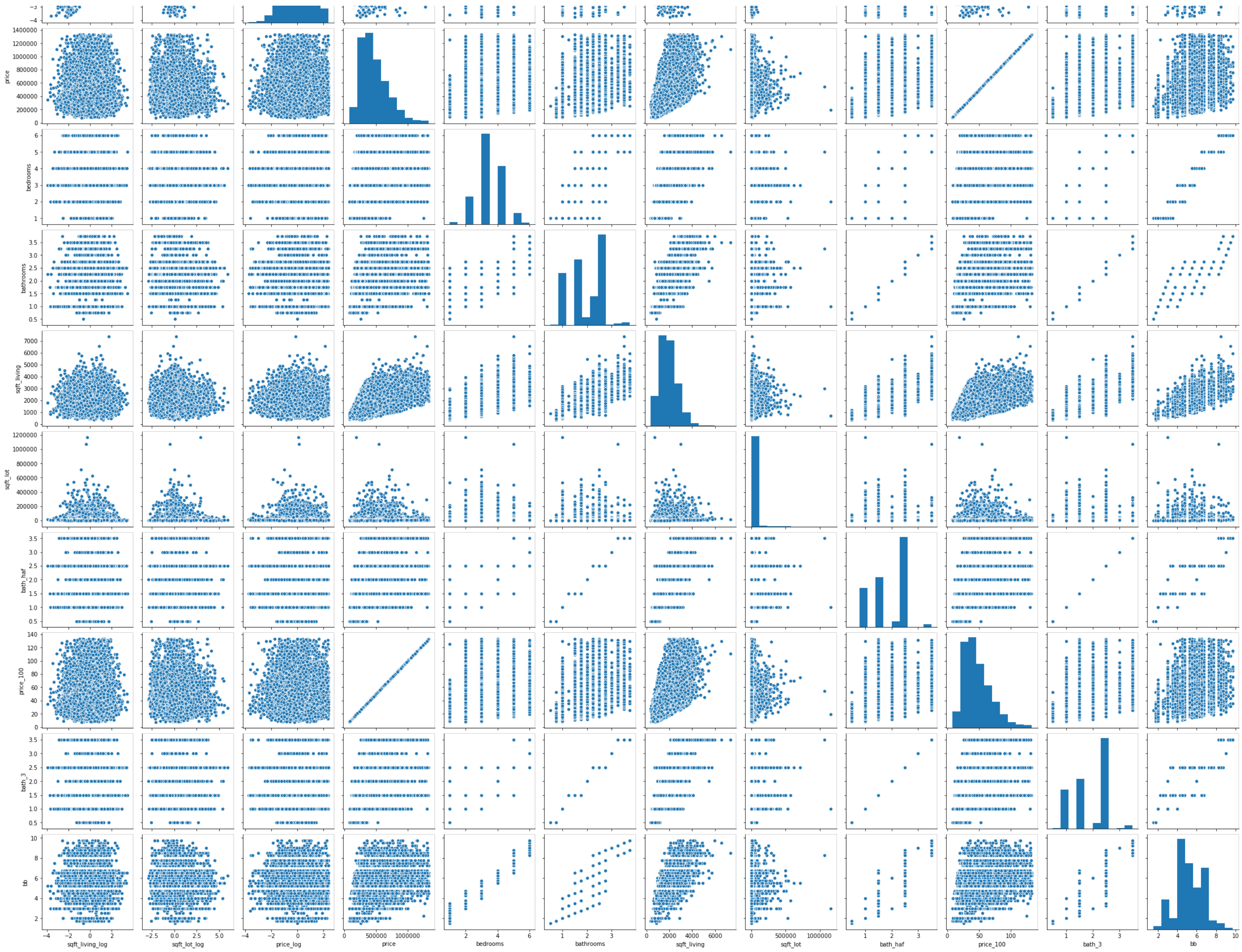
In [190]:

```
sns.pairplot(df_fin)
```

Out[190]:

```
<seaborn.axisgrid.PairGrid at 0x1b80c5105f8>
```





In [ ]:

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