D. Journic's Phase 2 Project

My first attempt at a notebook started to look more and more like a trainwreck made of nightmares. This is where I will clean it up and make it presentable.

The Business Problem:

Given a certain housing dataset, form a nice linear model from the variables you desire. In this case, I want to make a kind of CarFax for houses: where a potential buyer can input the square footage in the house, and in the lot, the number of bedrooms and the number of bathrooms and my model will give them a price (hopefully a fair one). The reason I chose these and not others was from a brief survey I conducted on my own neighbors, these were the four items they mentioned that were in the data; there were others (proximity to schools, restaurants, etc) but these were the criteria that was included in the data given.

Now that we have some idea what we want to do, let's get to it. Start by importing all the necessary libraries.

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, RobustScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.model_selection import KFold
from itertools import combinations
from statsmodels.stats.outliers_influence import variance_inflation_factor
import eli5
```

In [2]:

```
#Next, read the data
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]:

```
#The target variable is price.
price=df['price']
```

I know the variables I want to use for my data, so I can get rid of all the others.

In [5]:

```
col_ign=['id','date','view','sqft_above','sqft_basement','yr_renovated','zipcode','lat',
'long','sqft_living15','sqft_lot15','floors','waterfront','condition','grade','yr_built'
]
```

In [6]:

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

In [7]:

```
price=df_s1['price'] #updating the target variable
```

In [8]:

```
df_s1
```

Out[8]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot
0	221900.0	3	1.00	1180	5650
1	538000.0	3	2.25	2570	7242
2	180000.0	2	1.00	770	10000
3	604000.0	4	3.00	1960	5000
4	510000.0	3	2.00	1680	8080
...	...	...	...	...	...
21592	360000.0	3	2.50	1530	1131
21593	400000.0	4	2.50	2310	5813
21594	402101.0	2	0.75	1020	1350
21595	400000.0	3	2.50	1600	2388
21596	325000.0	2	0.75	1020	1076

21597 rows × 5 columns

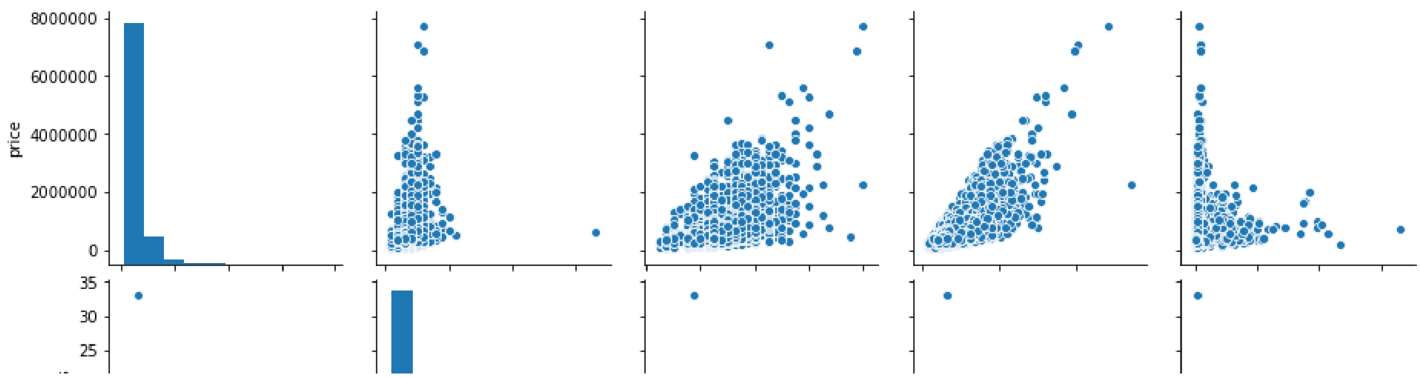
Let's take a look at the relationships between them

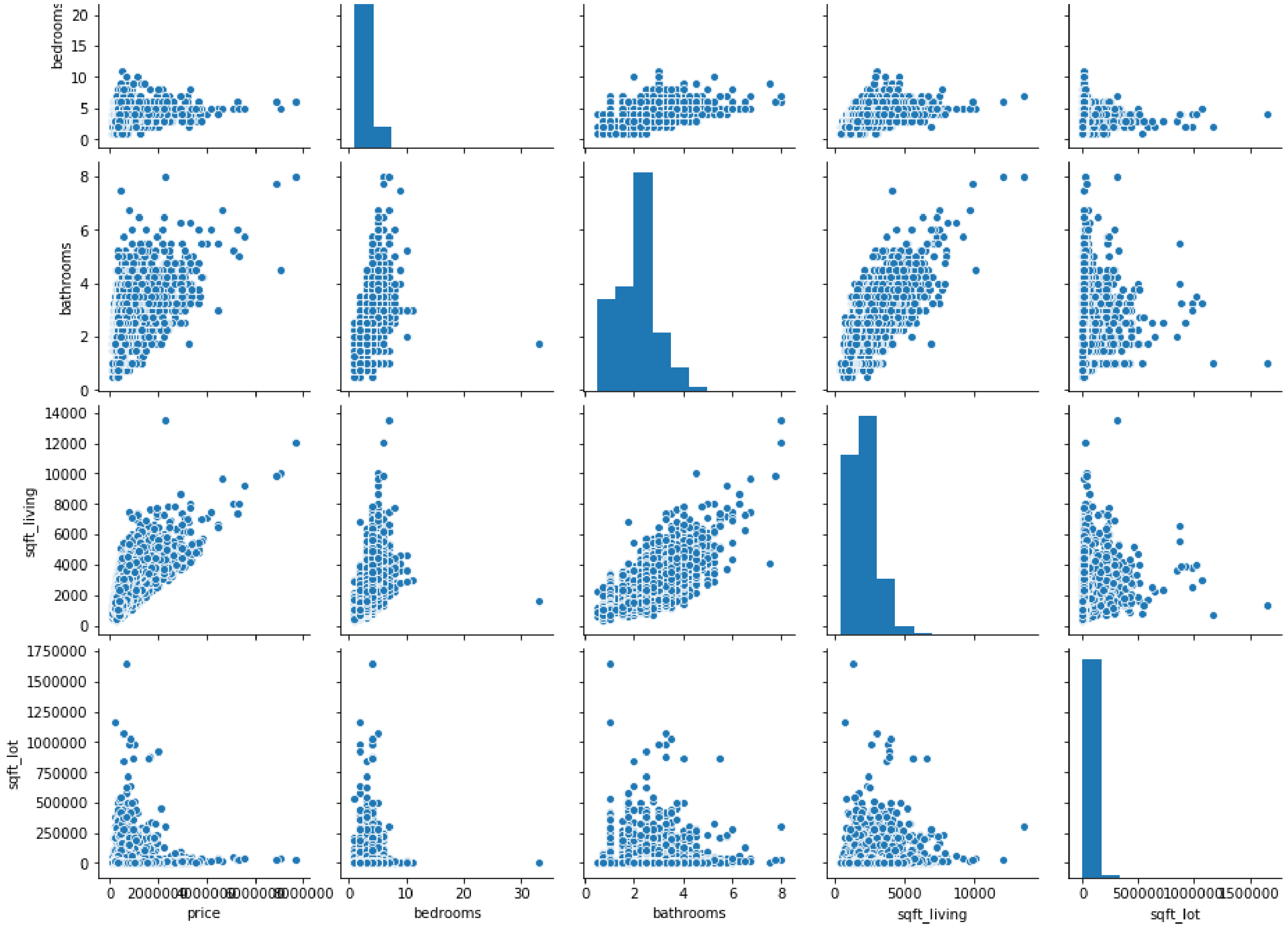
In [9]:

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

Out[9]:

```
<seaborn.axisgrid.PairGrid at 0x27ee7480160>
```

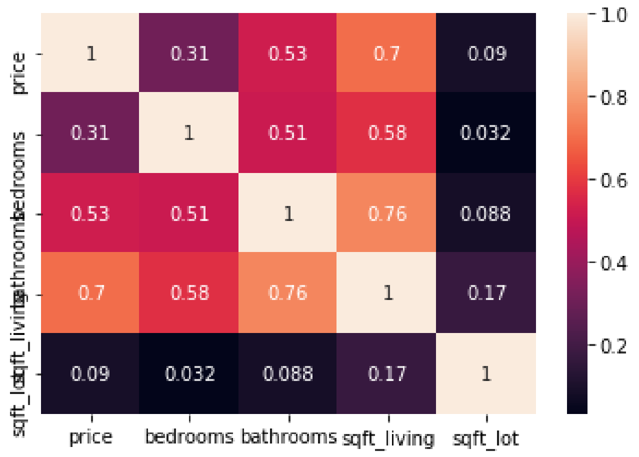




In [10]:

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

ax.set_ylim(5,0)
plt.show()
```



So I noticed 1 particular outlier, in the bedrooms. One of the entries has 33 bedrooms. That will seriously mess up any model I create, so I'm dropping it.

In [11]:

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

So, this being a linear regression project, I see myself doing many linear regressions. To avoid repetitive code, I'll write a function.

In [12]:

```
def lreg (elements,target):
```

```
def lreg(elements,target):
    """This function is designed to take in 2 dataframes: the elements and the target. It will then perform a linear
    regression of the variables, and print out the values of the slope (m), intercept (b), as well as the R2 score. It will also
    return those three variables.
    """
    lr=LinearRegression()
    X=elements.values
    y=target.values
    lr.fit(X,y)
    m = lr.coef_
    print('Slope: {}'.format(m))
    b = lr.intercept_
    print('Intercept: {}'.format(b))
    preds = lr.predict(X)
    r2 = r2_score(y, preds)
    print('R2 score: {}'.format(r2))

    return m,b,r2
```

Let's run it through a simple test:

In [13]:

```
lreg(df_s1[['sqft_living']],df_s1['price'])
```

```
Slope: [280.86880525]
Intercept: -44011.542633763864
R2 score: 0.4927041609539141
```

Out[13]:

```
(array([280.86880525]), -44011.542633763864, 0.4927041609539141)
```

Success. So let's look at a model of the 4 variables I had picked earlier.

In [14]:

```
att1=['sqft_living','sqft_lot','bedrooms','bathrooms']
```

In [16]:

```
price=df_s1['price']
```

In [17]:

```
lreg(df_s1[att1],price)
```

```
Slope: [ 3.17701703e+02 -3.87937456e-01 -6.55939211e+04  7.13655709e+03]
Intercept: 91292.7710924244
R2 score: 0.5102382172847046
```

Out[17]:

```
(array([ 3.17701703e+02, -3.87937456e-01, -6.55939211e+04,  7.13655709e+03]),
 91292.7710924244,
 0.5102382172847046)
```

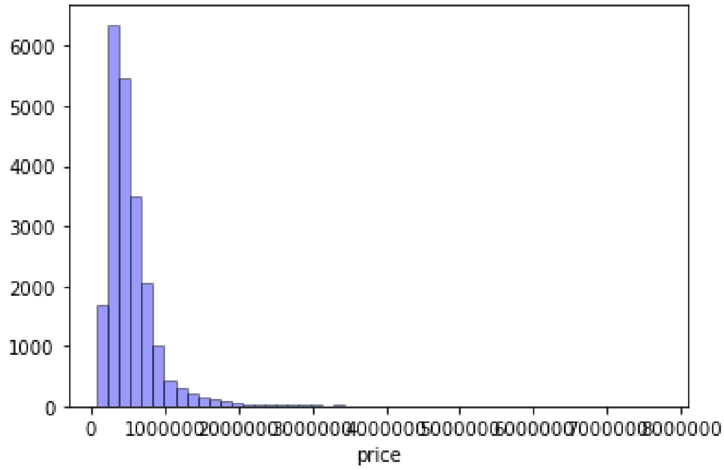
Now let's look at some things we can try to improve that R2 number. We saw from the pairplot that there isn't a very good distribution of the price. Let's look at it again, and see what we can do.

In [18]:

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

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x27ee9ab2908>
```



Let's try a simple log transform:

In [19]:

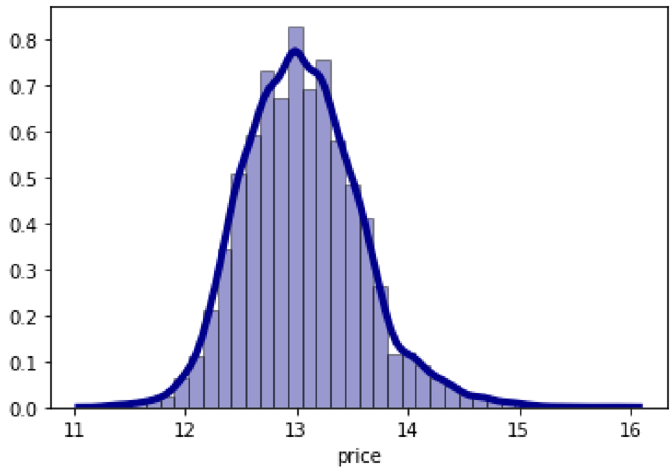
```
price_log=np.log(price)
```

In [20]:

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

Out[20]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x27eeab4add8>
```



Another thing that can be done: cut off the price a bit. We can set the max to be 2 standard deviations from the log mean. This way only the extremely expensive houses will be cut out.

In [21]:

```
price_log.describe()
```

Out[21]:

```
count    21596.000000
mean        13.048196
std          0.526562
min         11.264464
25%         12.682307
50%         13.017003
75%         13.377006
max         15.856731
Name: price, dtype: float64
```

In [22]:

```
price_log
```

Out[22]:

```
0        12.309982
1        13.195614
2        12.100712
3        13.311329
4        13.142166
           ...
21592    12.793859
21593    12.899220
21594    12.904459
21595    12.899220
21596    12.691580
Name: price, Length: 21596, dtype: float64
```

In [23]:

```
stdv=0.526562
cutoff=price_log.mean() + (stdv*2)
price_top=np.exp(cutoff)
print(price_top)
```

```
1330838.9322642826
```

The cutoff is 1.33 Million, that seems like a good top.

In [24]:

```
df_low1=df_s1[df_s1.price<=1330840]
```

In [25]:

```
df_low1.head()
```

Out[25]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot
0	221900.0	3	1.00	1180	5650
1	538000.0	3	2.25	2570	7242
2	180000.0	2	1.00	770	10000
3	604000.0	4	3.00	1960	5000
4	510000.0	3	2.00	1680	8080

In [26]:

```
price=df_low1['price'] #updating the target variable
```

Let's try our first model again, but with the revised price data. I don't expect much of a change if any.

In [27]:

```
lreg(df_low1[att1],price)
```

```
Slope: [ 2.00084338e+02 -1.26130731e-01 -3.11301011e+04  1.05074290e+04]
Intercept: 175000.13342278852
R2 score: 0.4245556844227749
```

Out[27]:

```
(array([ 2.00084338e+02, -1.26130731e-01, -3.11301011e+04,  1.05074290e+04]),
 175000.13342278852,
 0.4245556844227749)
```

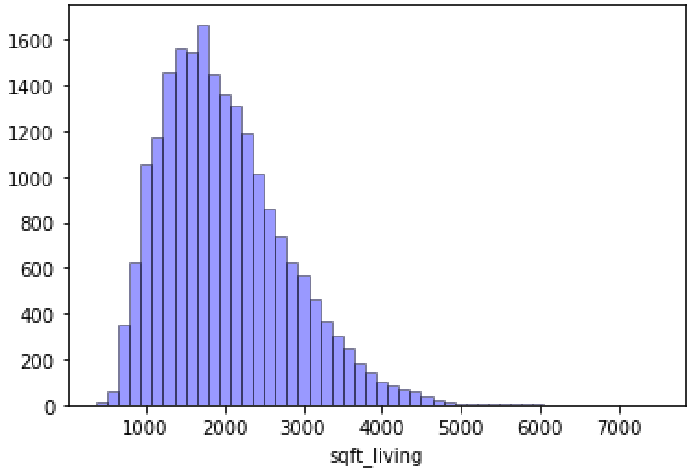
So it got worse. Let's look at the distributions of my other variables, see if something can be done.

In [28]:

```
sns.distplot(df_low1['sqft_living'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[28]:

<matplotlib.axes._subplots.AxesSubplot at 0x27eeab0da58>

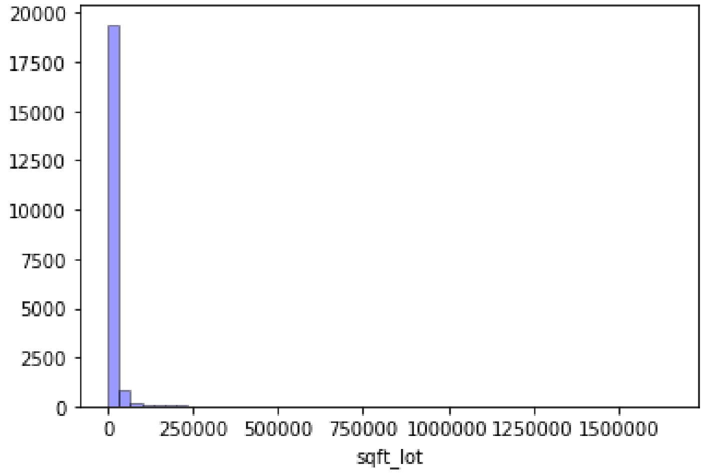


In [29]:

```
sns.distplot(df_low1['sqft_lot'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[29]:

<matplotlib.axes._subplots.AxesSubplot at 0x27eead10f98>

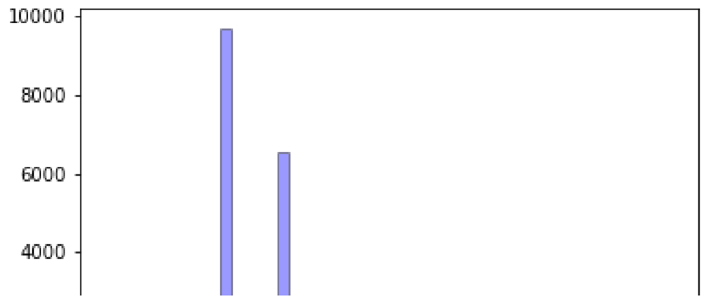


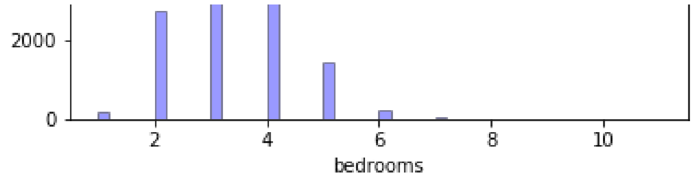
In [30]:

```
sns.distplot(df_low1['bedrooms'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[30]:

<matplotlib.axes._subplots.AxesSubplot at 0x27eead34be0>



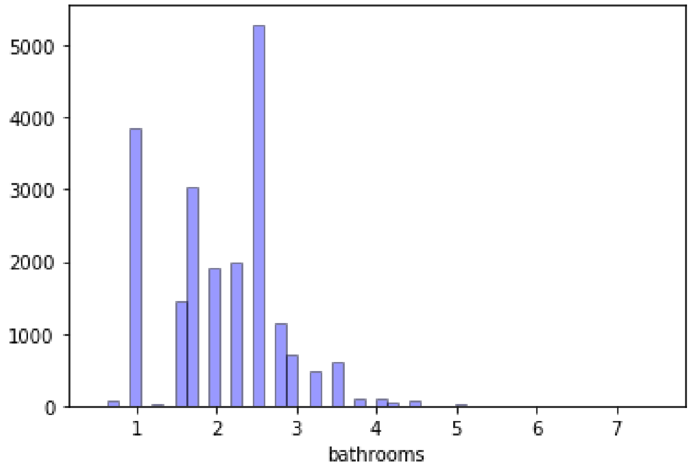


In [31]:

```
sns.distplot(df_low1['bathrooms'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[31]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x27eeadd1f60>
```



Sqft_iving and sqft_lot could probably use a log transform. Bedrooms actually, kind of looks normal, bathrooms is an absolute mess. Since we're doing some more log transforms, I'm going to add the price_log to the dataframe.

In [32]:

```
continuous = ['sqft_living', 'sqft_lot','price']
cont = df_low1[continuous]
log_names = [f'{column}_log' for column in cont.columns]
df_log = np.log(cont)
df_log.columns = log_names
```

In [33]:

```
df_log
```

Out[33]:

	sqft_living_log	sqft_lot_log	price_log
0	7.073270	8.639411	12.309982
1	7.851661	8.887653	13.195614
2	6.646391	9.210340	12.100712
3	7.580700	8.517193	13.311329
4	7.426549	8.997147	13.142166
...	...	...	...
21592	7.333023	7.030857	12.793859
21593	7.745003	8.667852	12.899220
21594	6.927558	7.207860	12.904459
21595	7.377759	7.778211	12.899220
21596	6.927558	6.981006	12.691580

20869 rows × 3 columns

In [34]:

```
scaler = StandardScaler()
df_log_norm = scaler.fit_transform(df_log)
```

In [35]:

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

In [36]:

```
df_pre = pd.concat([df_log_norm, df_low1], axis=1)
df_pre.head()
```

Out[36]:

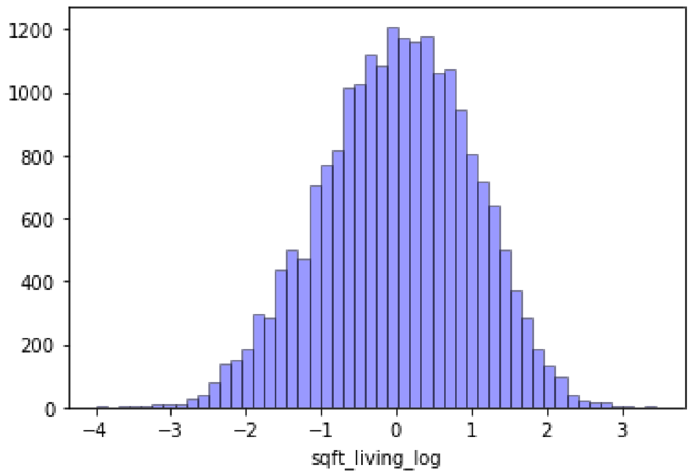
	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot
0	-1.117789	-0.368636	-1.485162	221900.0	3.0	1.00	1180.0	5650.0
1	0.810548	-0.091637	0.420131	538000.0	3.0	2.25	2570.0	7242.0
2	-2.175311	0.268433	-1.935373	180000.0	2.0	1.00	770.0	10000.0
3	0.139286	-0.505012	0.669074	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 [37]:

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

Out[37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x27eeaf98e10>
```



In [38]:

```
att3=['sqft_living_log','sqft_lot_log']
```

In [39]:

```
df_pre.dropna(inplace=True)  #Getting rid of null values
```

In [40]:

```
lreg(df_pre[att1],df_pre['price_log'])
```

```
Slope:  [-2.83383613e-05  5.08508874e-08  1.58521773e-02  3.75333466e-02]
Intercept: -0.07395120392720535
R2 score: 0.0005575945446641972
```

Out[40]:

```
(array([-2.83383613e-05,  5.08508874e-08,  1.58521773e-02,  3.75333466e-02]),
 -0.07395120392720535,
 0.0005575945446641972)
```

In [41]:

```
lreg(df_pre[att3],df_pre['price_log'])
```

```
Slope: [ 0.65982372 -0.10734199]
Intercept: -0.00020435802419986723
R2 score: 0.40176779261215945
```

Out[41]:

```
(array([ 0.65982372, -0.10734199]),
 -0.00020435802419986723,
 0.40176779261215945)
```

In [42]:

```
att4=['sqft_living_log','sqft_lot_log','bedrooms','bathrooms']
```

In [43]:

```
lreg(df_pre[att4],df_pre['price_log'])
```

```
Slope: [ 0.65976503 -0.10731072  0.01134922 -0.00174842]
Intercept: -0.03454783050259746
R2 score: 0.4018584144443017
```

Out[43]:

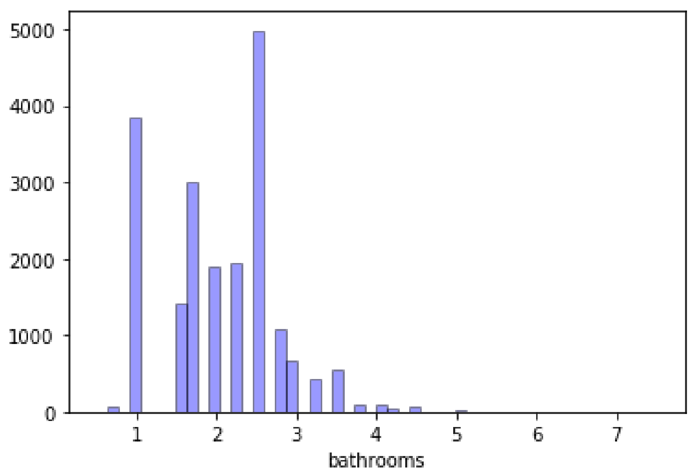
```
(array([ 0.65976503, -0.10731072,  0.01134922, -0.00174842]),
 -0.03454783050259746,
 0.4018584144443017)
```

In [44]:

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

Out[44]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x27eeb0905c0>
```



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 doubt this will help our model, but I don't think it can hurt.

In [45]:

```
list1=[1,5,9,13,17,21,25,29,33]
```

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

If the number of bathrooms ends with .25 or .75, multiplying it by 4 (or dividing by .25) results in the numbers in the lists above. All that needs done is run through our dataframe, and change the value if necessary. If not, leave it alone.

In [46]:

```
df_pre['bath_haf']=df_pre['bathrooms'] #Create a new column for the changed results.
```

In [47]:

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

In [48]:

```
df_pre.head()
```

Out[48]:

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

In [49]:

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

Out[49]:

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

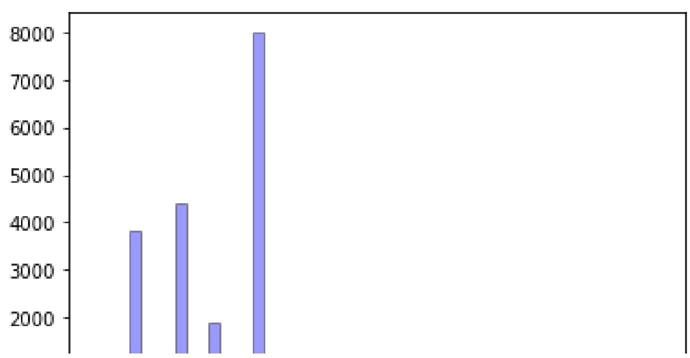
This probably won't help, but nothing wrong with trying things out.

In [50]:

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

Out[50]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x27eeabebba8>
```



So let's try with this new bathroom data.

In [51]:

```
att5=['sqft_living_log','sqft_lot_log','bedrooms','bath_haf']
```

In [52]:

```
lreg(df_pre[att5],df_pre['price_log'])
```

```
Slope: [ 0.65979405 -0.10736254  0.01185104 -0.00294657]
Intercept: -0.033832446322342294
R2 score: 0.4018609379250867
```

Out[52]:

```
(array([ 0.65979405, -0.10736254,  0.01185104, -0.00294657]),
 -0.033832446322342294,
 0.4018609379250867)
```

Basically, no difference.

In [53]:

```
att6=['sqft_living','sqft_lot']
```

In [54]:

```
lreg(df_pre[att6],df_pre['price'])
```

```
Slope: [ 1.87280232e+02 -9.55323818e-02]
Intercept: 118036.90581137297
R2 score: 0.415067489577291
```

Out[54]:

```
(array([ 1.87280232e+02, -9.55323818e-02]),
 118036.90581137297,
 0.415067489577291)
```

Let's try a few more combinations, and see if they yield any better results.

In [55]:

```
att7=['bedrooms','bath_haf']
lreg(df_pre[att7],df_pre['price'])
```

```
Slope: [ 28741.60195985 126620.46384756]
Intercept: 137647.74880899774
R2 score: 0.22521057097961494
```

Out[55]:

```
(array([ 28741.60195985, 126620.46384756]),
 137647.74880899774,
 0.22521057097961494)
```

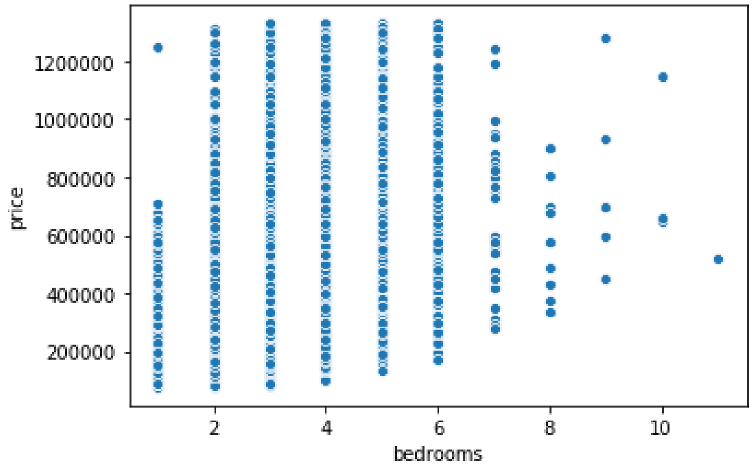
The challenge here is the beds and baths, making the data so it can better fit the model. There's something else I can try:

In [56]:

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

Out[56]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x27eeb09af60>
```

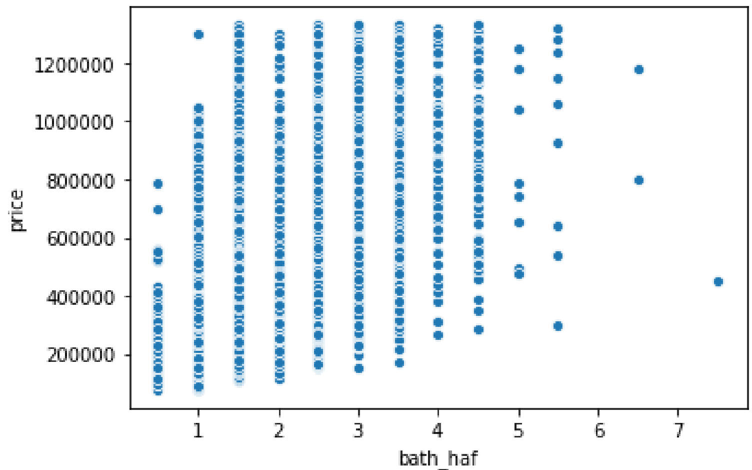


In [57]:

```
sns.scatterplot(data=df_pre, x="bath_haf", y="price")
```

Out[57]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x27eeb146d68>
```



In [58]:

```
df_pre = df_pre[df_pre.bathrooms <= 4]
df_pre = df_pre[df_pre.bedrooms <= 5]   #Setting a cap on the beds and baths
```

In [59]:

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

Out[59]:

```
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
4.0         0.5            3
            1.0          325
            1.5          968
            2.0          521
            2.5         3614
            3.0          293
            3.5          502
            4.0           36
5.0         1.0           43
            1.5          180
            2.0          109
            2.5          565
            3.0          143
            3.5          244
            4.0           29
dtype: int64
```

The idea here is to take the top three values for each bed/bath combination, much like how we got rid of the quarter bathrooms.

In [60]:

```
df_pre['bath_3']=df_pre['bath_haf']
```

In [61]:

```
#This loop is going to evaluate each entry in the bath_3 and bedrooms column, and if the bathrooms do not fall into the top 3
# values (the group lists), it replaces the value with a null. Then a new dataframe is created without the null values.
for i in df_pre.index:
    group1=[.5,1.0,1.5]
    group23=[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_pre['bath_3'][i]
    b= df_pre['bedrooms'][i]
    if b == 2 and a not in group23:
        df_pre['bath_3'][i]= None
    elif b == 3 and a not in group23:
        df_pre['bath_3'][i]= None
    elif b == 4 and a not in group4:
        df_pre['bath_3'][i]= None
    elif b == 5 and a not in group5:
        df_pre['bath_3'][i]= None
    elif b == 6 and a not in group6:
        df_pre['bath_3'][i]= None
    elif b == 1 and a not in group1:
        df_pre['bath_3'][i]= None
df_fin=df_pre.dropna()
```

In [62]:

```
df_fin.head()
```

Out[62]:

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	bath_haf	bath_3
0	-1.117789	-0.368636	-1.485162	221900.0	3.0	1.00	1180.0	5650.0	1.0	1.0
1	0.810548	-0.091637	0.420131	538000.0	3.0	2.25	2570.0	7242.0	2.5	2.5
2	-2.175311	0.268433	-1.935373	180000.0	2.0	1.00	770.0	10000.0	1.0	1.0
6	-0.191516	-0.158793	-1.165059	257500.0	3.0	2.25	1715.0	6819.0	2.5	2.5
7	-1.383472	0.235710	-0.895667	291850.0	3.0	1.50	1060.0	9711.0	1.5	1.5

In [63]:

```
df_fin.describe()
```

Out[63]:

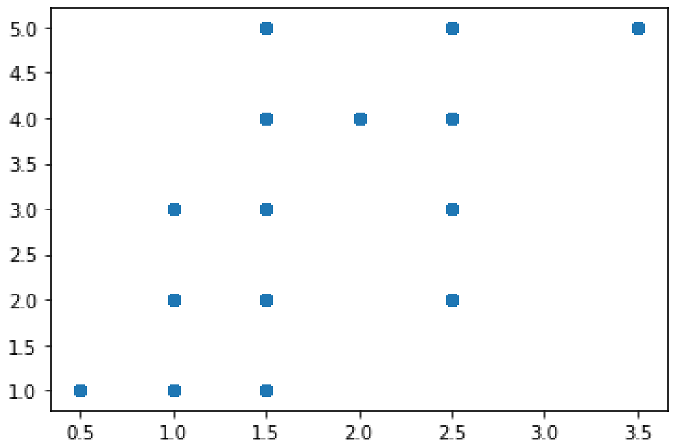
	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	16571.000000	16571.000000	16571.000000	1.657100e+04	16571.000000	16571.000000	16571.000000	1.657100e+04	16
mean	0.000071	0.008281	-0.001425	4.720921e+05	3.260576	1.948193	1920.133003	1.394887e+04	
std	0.997856	0.997517	1.001734	2.174486e+05	0.816651	0.624378	728.108550	3.386753e+04	
min	-3.924853	-2.924226	-3.734425	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	
25%	-0.676636	-0.502003	-0.714443	3.090000e+05	3.000000	1.500000	1360.000000	5.170000e+03	
50%	0.036049	-0.043684	-0.007585	4.287500e+05	3.000000	2.000000	1830.000000	7.665000e+03	
75%	0.712228	0.321706	0.723586	5.900000e+05	4.000000	2.500000	2372.500000	1.040000e+04	
max	3.457152	5.966798	2.367255	1.330000e+06	5.000000	3.750000	7350.000000	1.164794e+06	

In [64]:

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

Out[64]:

```
<matplotlib.collections.PathCollection at 0x27eeb368710>
```



In [65]:

```
att8=['bedrooms','bath_3']
lreg(df_fin[att8],df_fin['price'])
```

```
Slope: [ 35442.44556322 107749.37766631]
Intercept: 149997.17850212712
R2 score: 0.1694480506121243
```

Out[65]:

```
(array([ 35442.44556322, 107749.37766631]),
 149997.17850212712,
 0.1694480506121243)
```

In [66]:

```
att9=['bedrooms','bath_3','sqft_living_log','sqft_lot_log']
lreg(df_fin[att9],df_fin['price'])
```

```
Slope: [ 35384.88298458 107930.76763212  -1723.26741329   1263.95913377]
Intercept: 149826.83614001505
R2 score: 0.16951580426867952
```

Out[66]:

```
(array([ 35384.88298458, 107930.76763212,  -1723.26741329,   1263.95913377]),
 149826.83614001505,
 0.16951580426867952)
```

In [67]:

```
att10=['bedrooms','bath_3','sqft_living_log','sqft_lot_log']
lreg(df_fin[att9],df_fin['price_log'])
```

```
Slope: [ 0.01630268 -0.00521318  0.66210583 -0.10790048]
Intercept: -0.04374214022107247
R2 score: 0.4031199903487501
```

Out[67]:

```
(array([ 0.01630268, -0.00521318,  0.66210583, -0.10790048]),
 -0.04374214022107247,
 0.4031199903487501)
```

So the best R2 value I got from all these attempts was the very first one:

In [68]:

```
lreg(df_s1[att1],df_s1['price'])
```

```
Slope: [ 3.17701703e+02 -3.87937456e-01 -6.55939211e+04  7.13655709e+03]
Intercept: 91292.7710924244
R2 score: 0.5102382172847046
```

Out[68]:

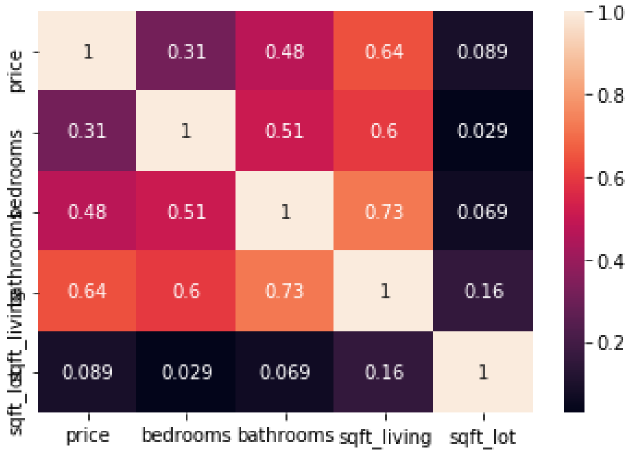
```
(array([ 3.17701703e+02, -3.87937456e-01, -6.55939211e+04,  7.13655709e+03]),
 91292.7710924244,
 0.5102382172847046)
```

Evrything I've done to try to manipulate the data to better fit has only made it worse. There are other things to try, but that will have to wait for another time.

In [69]:

```
ax = sns.heatmap(df_low1.corr(), annot=True)

ax.set_ylim(5,0)
plt.show()
```



In [70]:

```
df_low1.corr().price.sort_values(ascending=False)
```

Out[70]:

```
price          1.000000
sqft_living    0.644461
bathrooms      0.475228
bedrooms       0.314970
sqft_lot       0.089370
```

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

Ok, let's do a train-test split.

In [71]:

```
X=df_s1[att1]
y=df_s1['price']
X_train, X_test, y_train, y_test = train_test_split(X, y)
```

In [72]:

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

Out[72]:

```
True
```

In [73]:

```
scaler = StandardScaler()
```

In [74]:

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

In [75]:

```
lr=LinearRegression()
lr.fit(X_train_scaled, y_train)
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: 0.5088084805078192
Testing Scores:
R2: 0.5144807483918121
```

Again, these numbers do not inspire a lot of confidence in the model. But I think I've done just about as much as I can on manipulating the data. So I'll wrap this up by writing a little code to input those values, and see what comes out.

In [76]:

```
df_s1.describe()
```

Out[76]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot
count	2.159600e+04	21596.000000	21596.000000	21596.000000	2.159600e+04
mean	5.402920e+05	3.371828	2.115843	2080.343165	1.509983e+04
std	3.673760e+05	0.904114	0.768998	918.122038	4.141355e+04
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.619000e+03
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068550e+04
max	7.700000e+06	11.000000	8.000000	13540.000000	1.651359e+06

In [77]:

```
m,b,r2=lreg(X,y)
```

```
Slope: [ 3.17701703e+02 -3.87937456e-01 -6.55939211e+04  7.13655709e+03]
Intercept: 91292.7710924244
R2 score: 0.5102382172847046
```

In [78]:

```
liv_area= float(input("Enter interior square footage (1000-12000): "))
```

```
Enter interior square footage (1000-12000): 2000
```

In [79]:

```
acre= float(input("Enter lot area (550-1600000): "))
```

```
Enter lot area (550-1600000): 1000
```

In [80]:

```
nbeds= float(input("Enter number of bedrooms (1-7): "))
```

```
Enter number of bedrooms (1-7): 5
```

In [81]:

```
nbath= float(input("Enter number of bathrooms (1-8): "))
```

```
Enter number of bathrooms (1-8): 2
```

In [82]:

```
house= pd.DataFrame([[liv_area,acre,nbeds,nbath]],columns=['sqft_living','sqft_lot','bedr
ooms','bathrooms'])
```

In [83]:

```
house.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1 entries, 0 to 0
Data columns (total 4 columns):
sqft_living    1 non-null float64
sqft_lot       1 non-null float64
bedrooms       1 non-null float64
bathrooms      1 non-null float64
dtypes: float64(4)
memory usage: 160.0 bytes
```

In [84]:

```
d_price= m*house+b
```

In [85]:

```
d_price.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1 entries, 0 to 0
Data columns (total 4 columns):
sqft_living    1 non-null float64
sqft_lot       1 non-null float64
bedrooms       1 non-null float64
bathrooms      1 non-null float64
dtypes: float64(4)
memory usage: 160.0 bytes
```

In [86]:

```
est=sum(d_price.values)
```

In [87]:

```
est.tolist()
```

Out[87]:

```
[726696.1774964968, 90904.83363640675, -236676.83440897788, 105565.88526866068]
```

In [88]:

```
est1=sum(est)
```

In [89]:

```
print('Estimated price: {}'.format(est1))
```

```
Estimated price: 686490.0619925865
```

So let's put all that into a nice function:

In [98]:

```
def estimate():
    """This function will allow the user to input 4 values (sqft_living, sqft_lot, bedroo
ms, and bathrooms) and will receive an
    estimated price based off the linear regression function (lreg) earlier in this progr
am. This function will not operate if
    that function isn't already run with valid values for X and y."""
    m,b,r2=lreg(X,y)
    liv_area= float(input("Enter interior square footage (1000-12000): "))
    acre= float(input("Enter lot area (550-1600000): "))
    nbeds= float(input("Enter number of bedrooms (1-7): "))
    nbath= float(input("Enter number of bathrooms (1-8): "))
    house= pd.DataFrame([[liv_area,acre,nbeds,nbath]],columns=['sqft_living','sqft_lot','
bedrooms','bathrooms'])
    d_price= m*house+b
    est=sum(d_price.values)
    est.tolist()
    est1=sum(est)
    print('Estimated price: ${}'.format(round(est1,2)))
    return None
```

In [100]:

```
estimate()
```

```
Slope: [ 3.17701703e+02 -3.87937456e-01 -6.55939211e+04  7.13655709e+03]
Intercept: 91292.7710924244
R2 score: 0.5102382172847046
Enter interior square footage (1000-12000): 1000
Enter lot area (550-1600000): 1000
Enter number of bedrooms (1-7): 5
Enter number of bathrooms (1-8): 3
Estimated price: $686490.06
```

Conclusion:

These models aren't very good. There just isn't a lot of correlation between some of these variables. There's a lot of work left to do, but I'm pretty confident I could make it work, if given enough time.

Some ideas to improve:

Narrowing the scope by zip code, running models for a specific zip code, making that part of the input. I could also narrow the square footage variables a bit more (I noticed quite a range as I was writing the code for the estimator).

In [ ]:

```

```