D. Journic Phase 2 Project, Rev 1

This notebook is to have the revisions to my Phase 2 Project after the initial evaluation. This will be a trimmed down notebook, containing some of the original notebooks, along with the corrections.

Step 1: Import the necessary libraries

In [1]:

```
import pandas as pd
import numpy as np
# Setting random seed for reproducibility
np.random.seed(1000)

import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score
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 statsmodels.api as sm
import eli5
```

Step 1a: Read the data

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.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
```

I know the variables I want to use. But this time, I think I'll keep the zip code, for future changes.

In [5]:

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

In [6]:

```
df_s1=df.drop(columns=col_ign,axis=1) #The first cut of the data
```

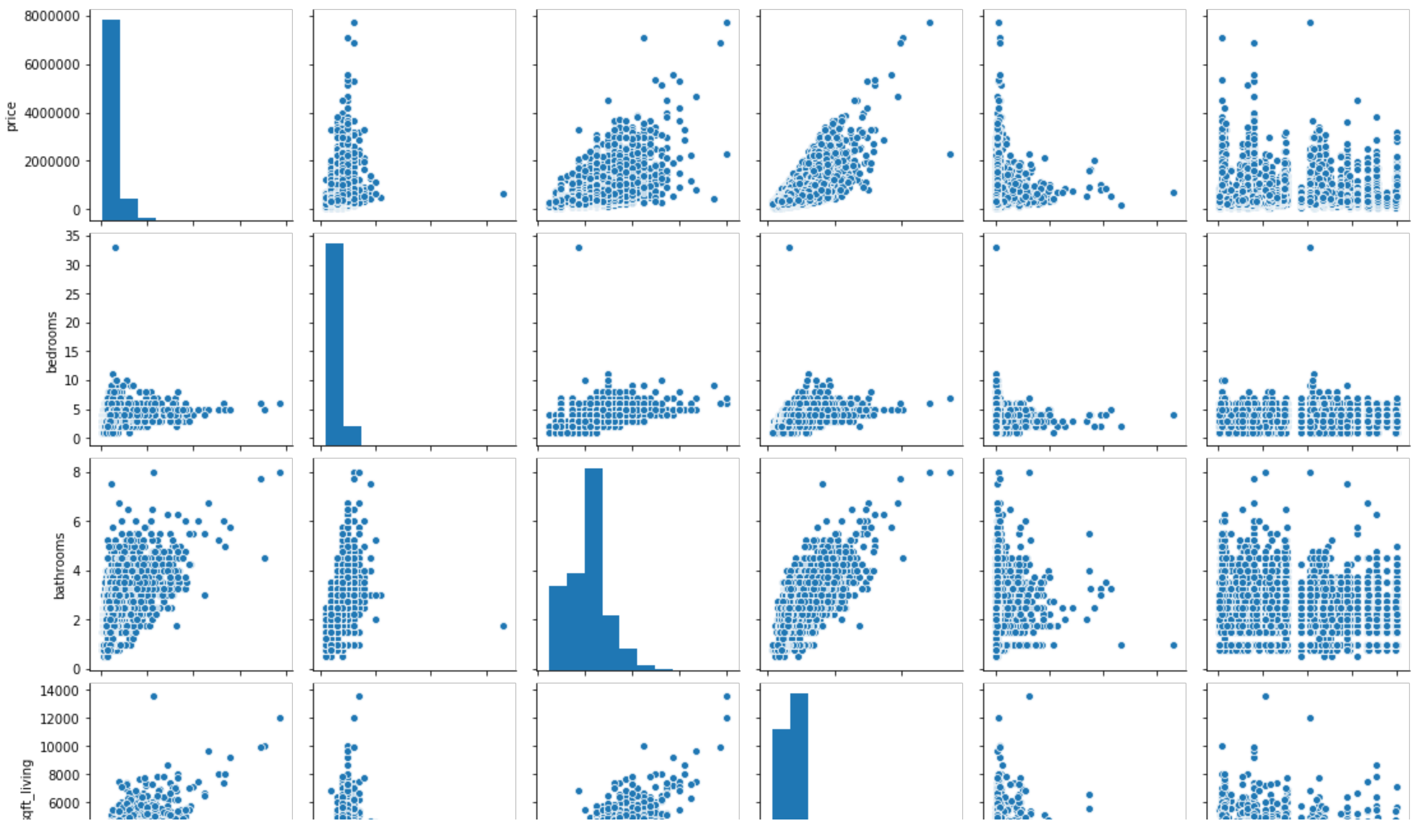
Originally, here's where I did the first train/test split, instead I'm going to put it in the linear regression function. So here is where I look at the data in a pairplot.

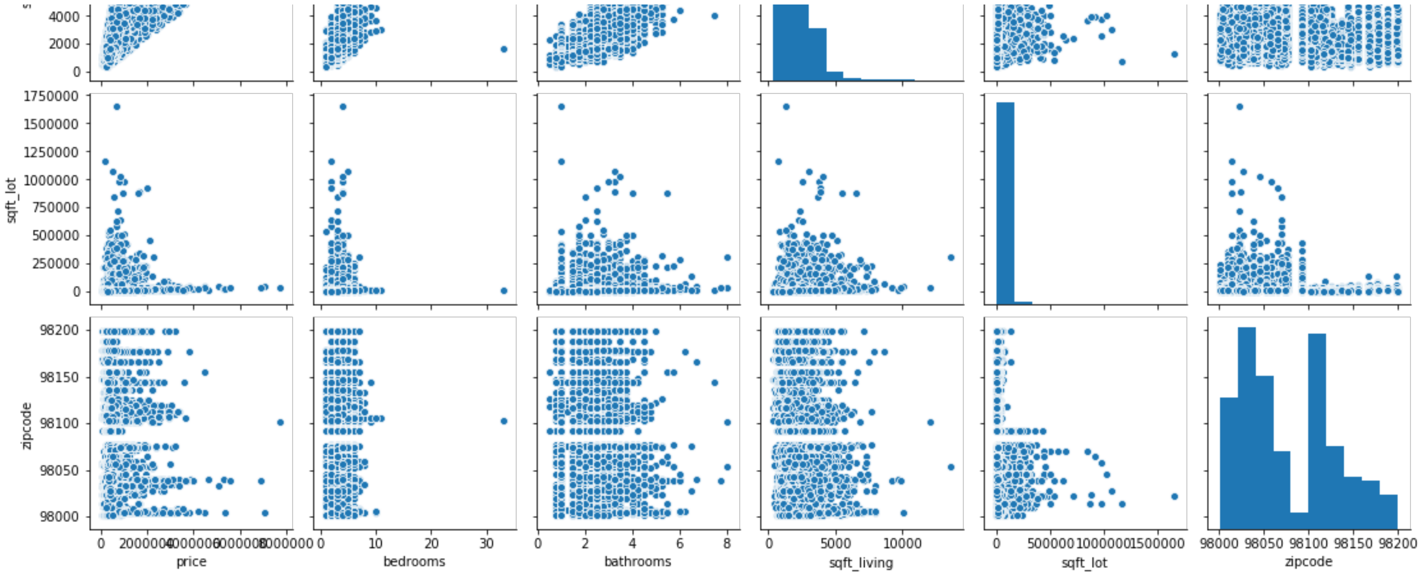
In [7]:

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

Out[7]:

```
<seaborn.axisgrid.PairGrid at 0x1865649d908>
```



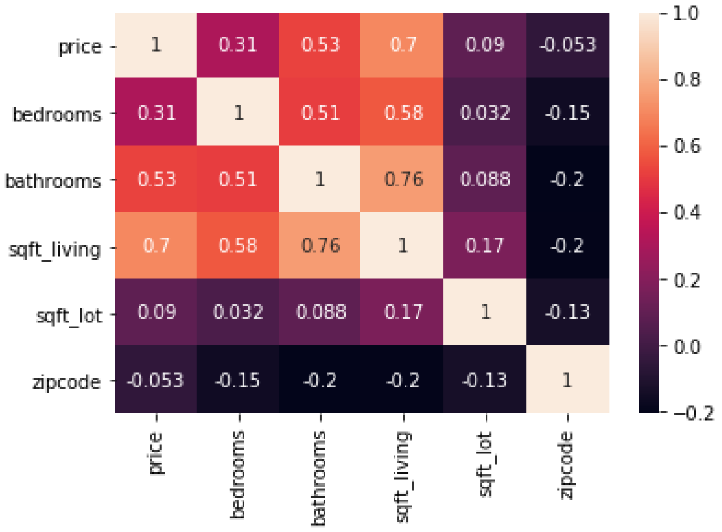


Then I created a little heatmap to help show the correlation:

In [8]:

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

ax.set_ylim(6,0)
plt.show()
```



There is the obvious outlier in the bedrooms, so I can cut that out.

In [9]:

```
df_s2 = df_s1[df_s1.bedrooms != 33] #Second cut of data
```

So here is where I needed to make changes. I introduced the train/test split into my linear regression function.

In [10]:

```
df_s2a=df_s2.drop(columns='price') #Dropping my target variable from the dataframe
```

In [11]:

```
price=df_s2['price']
```

In [12]:

```
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.
    It will also perform a train/test split on the data, scale and then provide R2 scores
.
    """
    lr=LinearRegression()
    X=elements.values
    y=target.values
    X_train, X_test, y_train, y_test = train_test_split(X, y)
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)
    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)}")
    m = lr.coef_
    print('Slope: {}'.format(m))
    b = lr.intercept_
    print('Intercept: {}'.format(b))
    r2 = r2_score(y_test, y_test_pred)

    return m,b,r2
```

So, just to test the function's functionality:

In [13]:

```
lreg(df_s2a[['sqft_living']],df_s2['price'])
```

```
Training Scores:
R2: 0.4927660295248324
Testing Scores:
R2: 0.49251276727464477
Slope: [258583.79288285]
Intercept: 540443.3199975304
```

Out[13]:

```
(array([258583.79288285]), 540443.3199975304, 0.49251276727464477)
```

Ok, so the first time through this, I got an R2 of -2.54, so I went back up to it and made some more changes. I finally managed to get an R2 value of .49, which is close to what I was getting before. So here is where I start trying with different data combinations.

In [14]:

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

In [15]:

```
lreg(df_s2a[att1],price)
```

```
Training Scores:
R2: 0.5113237277729574
Testing Scores:
R2: 0.5058950367297197
Slope: [296889.47455057 -19542.62189265 -61241.80960343   6074.19763475]
Intercept: 541448.5726986479
```

Out[15]:

```
(array([296889.47455057, -19542.62189265, -61241.80960343,   6074.19763475]),
 541448.5726986479,
 0.5058950367297197)
```

So this does give me simliar data to the first run of the program

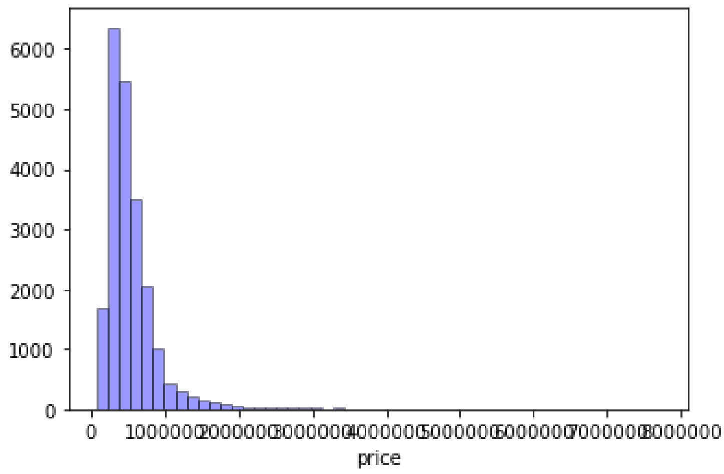
So this does give me similar data to the first run of the program.

In [16]:

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

Out[16]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x18657e89b00>
```



In [17]:

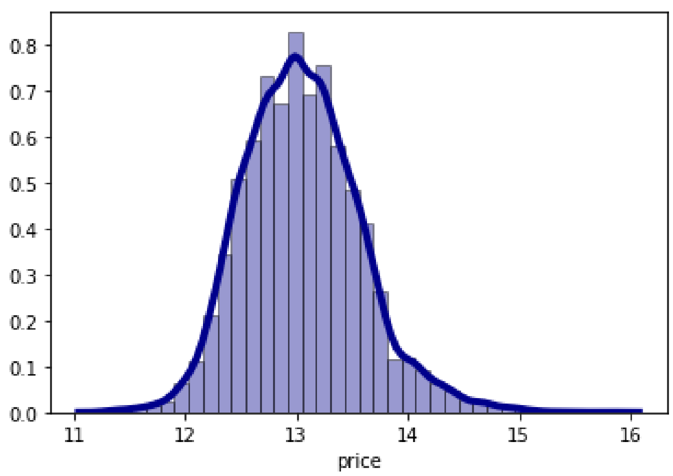
```
price_log=np.log(price) #Log transform of the price
```

In [18]:

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

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x18657f7c860>
```



Here is where I figure out the limits I'm going to use for the price data. I'm going to use 2 standard deviations above the mean as the upper limit.

In [19]:

```
price_log.describe()
```

Out[19]:

```
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 [20]:

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

```
1330838.9322642826
```

In [21]:

```
df_s3=df_s2[df_s2.price<=1336364] #Third cut of data
```

In [22]:

```
price=df_s3['price'] #Updating target variable
df_s3a=df_s3.drop(columns='price')
```

So, let's try the linear regression function with the third cut of data

In [23]:

```
lreg(df_s3a[att1],price)
```

```
Training Scores:
R2: 0.4252021215787616
Testing Scores:
R2: 0.4224100426968639
Slope: [162218.86149959  -6100.90066156 -29008.17492804   7689.73266928]
Intercept: 492055.42553191487
```

Out[23]:

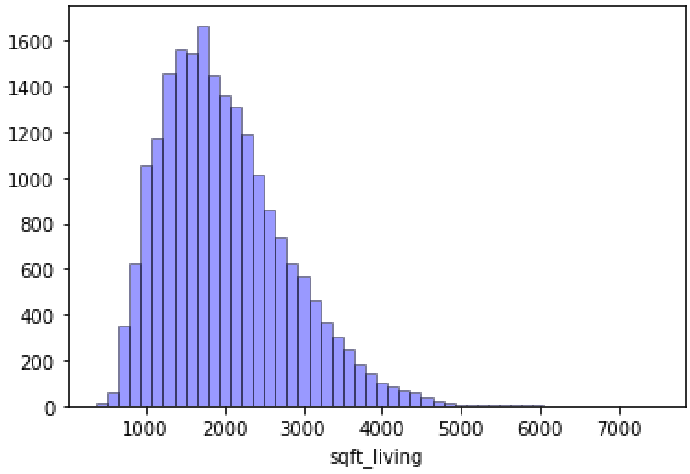
```
(array([162218.86149959,  -6100.90066156, -29008.17492804,   7689.73266928]),
 492055.42553191487,
 0.4224100426968639)
```

In [24]:

```
sns.distplot(df_s3a['sqft_living'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[24]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x18658076fd0>
```



In [25]:

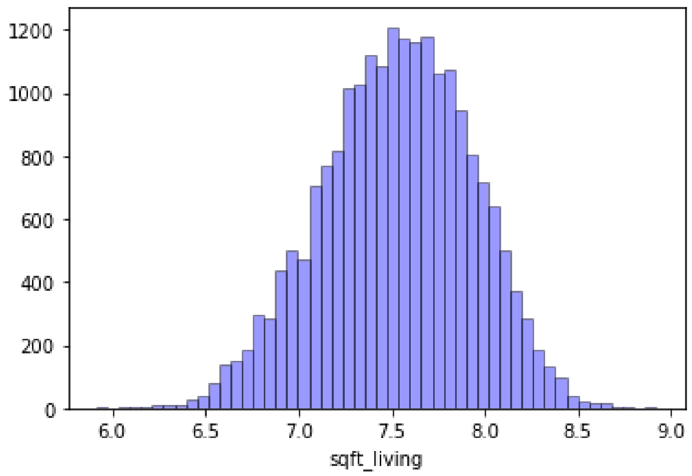
```
living_log=np.log(df_s3a['sqft_living'])
```

In [26]:

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

Out[26]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1865804cd30>
```

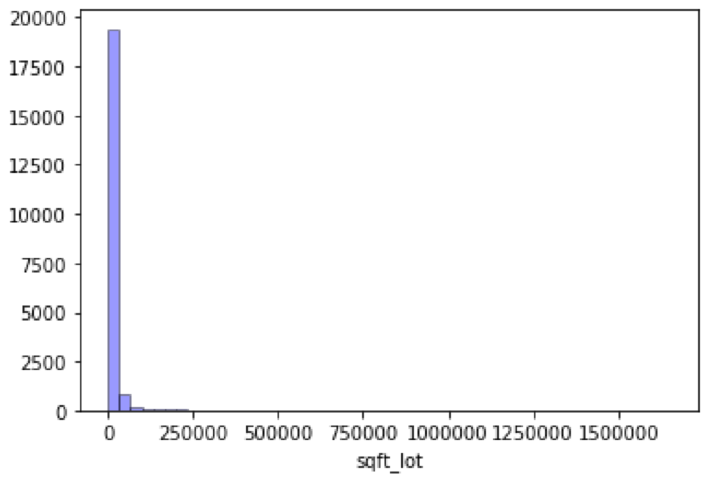


In [27]:

```
sns.distplot(df_s3a['sqft_lot'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1865b6bbdd8>
```



In [28]:

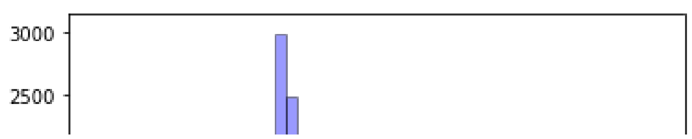
```
acre_log=np.log(df_s3a['sqft_lot'])
```

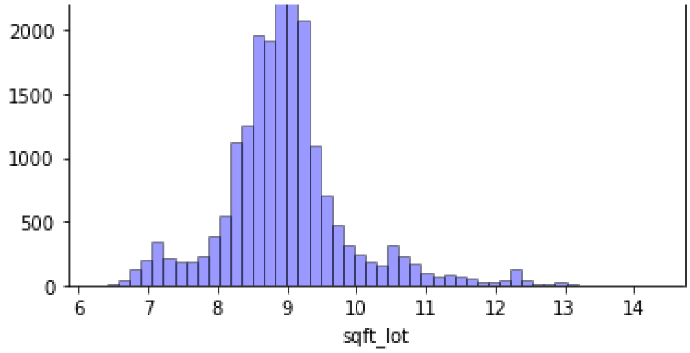
In [29]:

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

Out[29]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1865b7b05c0>
```





In [30]:

```
df_s3a['sqft_living'].describe()
```

Out[30]:

```
count    20869.000000
mean      2006.091044
std        806.488218
min        370.000000
25%       1410.000000
50%       1880.000000
75%       2475.000000
max       7480.000000
Name: sqft_living, dtype: float64
```

In [31]:

```
df_s3a['sqft_lot'].describe()
```

Out[31]:

```
count    2.086900e+04
mean     1.468600e+04
std      3.999138e+04
min      5.200000e+02
25%      5.000000e+03
50%      7.528000e+03
75%      1.040400e+04
max      1.651359e+06
Name: sqft_lot, dtype: float64
```

In [32]:

```
acre_log.describe()
```

Out[32]:

```
count    20869.000000
mean         8.969776
std          0.896203
min          6.253829
25%          8.517193
50%          8.926385
75%          9.249946
max         14.317109
Name: sqft_lot, dtype: float64
```

This was something I brought up in my 'future considerations', putting an upper cap on the lot area

In [33]:

```
lot_sdev= 0.896203
cutoff_lot=acre_log.mean() + (lot_sdev*2)
lot_top=np.exp(cutoff_lot)
print(lot_top)
```

```
47201.53443503135
```

So this is the upper limit for sqft_lot, I'm not sure if I want to use it, but it's here.

In [34]:

```
df_s3a['sqft_lot_cap']=df_s3a['sqft_lot']
```

In [35]:

```
df_s3a.head()
```

Out[35]:

	bedrooms	bathrooms	sqft_living	sqft_lot	zipcode	sqft_lot_cap
0	3	1.00	1180	5650	98178	5650
1	3	2.25	2570	7242	98125	7242
2	2	1.00	770	10000	98028	10000
3	4	3.00	1960	5000	98136	5000
4	3	2.00	1680	8080	98074	8080

In [36]:

```
df_s3.head()
```

Out[36]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	zipcode
0	221900.0	3	1.00	1180	5650	98178
1	538000.0	3	2.25	2570	7242	98125
2	180000.0	2	1.00	770	10000	98028
3	604000.0	4	3.00	1960	5000	98136
4	510000.0	3	2.00	1680	8080	98074

In [37]:

```
df_s3['sqft_lot_cap']=df_s3['sqft_lot']
```

```
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 [38]:

```
df_s4=df_s3[df_s3.sqft_lot_cap<=47201.5344]
```

In [39]:

```
df_s4.head()
```

Out[39]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	zipcode	sqft_lot_cap
0	221900.0	3	1.00	1180	5650	98178	5650
1	538000.0	3	2.25	2570	7242	98125	7242
2	180000.0	2	1.00	770	10000	98028	10000
3	604000.0	4	3.00	1960	5000	98136	5000
4	510000.0	3	2.00	1680	8080	98074	8080

	price	bedrooms	bathrooms	sqft_living	sqft_lot	zipcode	sqft_lot_cap
4	510000.0	3	2.00	1680	8080	98074	8080

In [40]:

```
df_s4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19971 entries, 0 to 21596
Data columns (total 7 columns):
price           19971 non-null float64
bedrooms        19971 non-null int64
bathrooms       19971 non-null float64
sqft_living     19971 non-null int64
sqft_lot        19971 non-null int64
zipcode         19971 non-null int64
sqft_lot_cap    19971 non-null int64
dtypes: float64(2), int64(5)
memory usage: 1.2 MB
```

In [41]:

```
price=df_s4['price'] #Updating target variable
df_s4a=df_s4.drop(columns='price')
```

In [42]:

```
df_s4a.head()
```

Out[42]:

	bedrooms	bathrooms	sqft_living	sqft_lot	zipcode	sqft_lot_cap
0	3	1.00	1180	5650	98178	5650
1	3	2.25	2570	7242	98125	7242
2	2	1.00	770	10000	98028	10000
3	4	3.00	1960	5000	98136	5000
4	3	2.00	1680	8080	98074	8080

In [43]:

```
df_s4a['sqft_lot_cap'].describe()
```

Out[43]:

```
count    19971.000000
mean      8861.691953
std       7144.404522
min        520.000000
25%       5000.000000
50%       7350.000000
75%       9898.500000
max      47179.000000
Name: sqft_lot_cap, dtype: float64
```

In [44]:

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

In [45]:

```
lreg(df_s4a[att2],price)
```

```
Training Scores:
R2: 0.4185906988102046
Testing Scores:
R2: 0.42196226383730073
Slope: [-17302.42667779 167814.7512755  -30378.51058879   2369.05453172]
Intercept: 487641.26011483517
```

Out[45]:

```
(array([-17302.42667779, 167814.7512755 , -30378.51058879,   2369.05453172]),
 487641.26011483517,
 0.42196226383730073)
```

In [46]:

```
lreg(df_s4a[att1],price)
```

```
Training Scores:
R2: 0.4172301393007969
Testing Scores:
R2: 0.4259552876096456
Slope: [166550.20083677 -17374.59855282 -27707.89194786   1724.5589506 ]
Intercept: 486902.5964748297
```

Out[46]:

```
(array([166550.20083677, -17374.59855282, -27707.89194786,   1724.5589506 ]),
 486902.5964748297,
 0.4259552876096456)
```

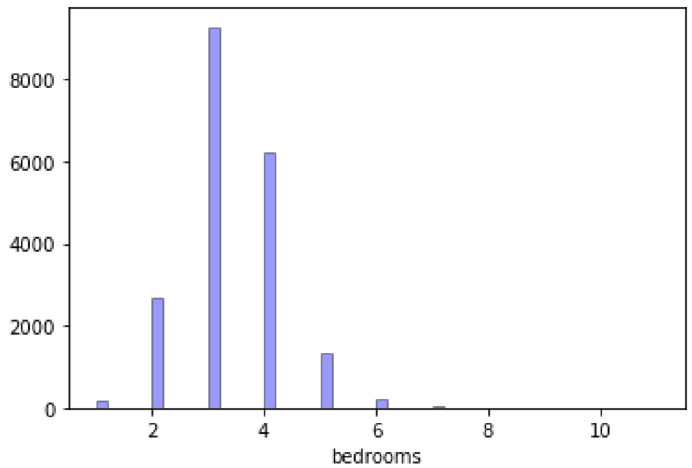
So that change did almost nothing, but that's not too surprising. Since I already know the biggest influencer on price is living area.

In [47]:

```
sns.distplot(df_s4a['bedrooms'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[47]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1865b892ef0>
```

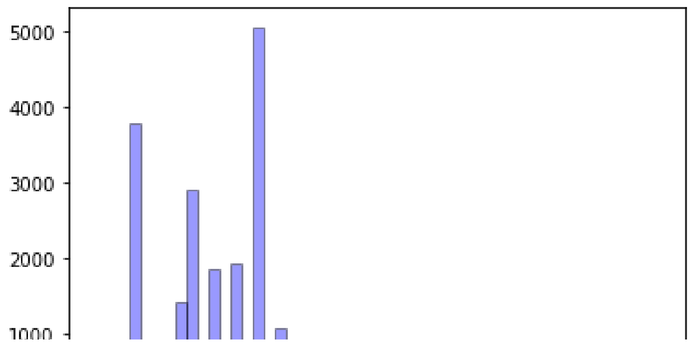


In [48]:

```
sns.distplot(df_s4a['bathrooms'], hist=True, kde=False,
             bins=int(50), color = 'blue',
             hist_kws={'edgecolor':'black'})
```

Out[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1865b988940>
```



In [49]:

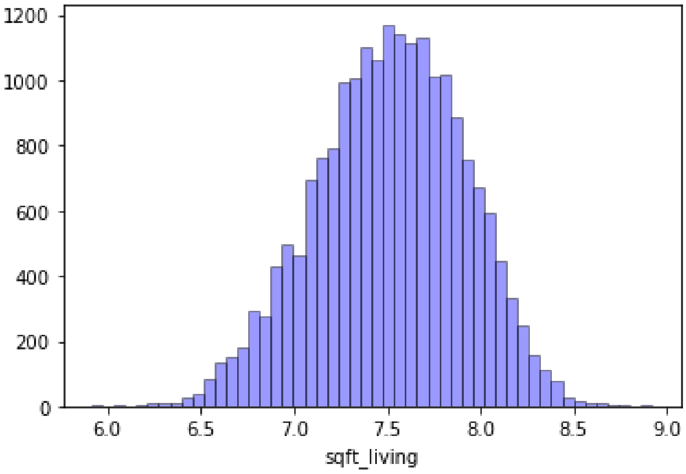
```
liv_log=np.log(df_s4a['sqft_living'])
```

In [50]:

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

Out[50]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1865ba60080>
```



In [51]:

```
liv_log.describe()
```

Out[51]:

```
count    19971.000000
mean         7.512109
std          0.399006
min          5.913503
25%          7.244228
50%          7.522941
75%          7.799753
max          8.919988
Name: sqft_living, dtype: float64
```

In [52]:

```
liv_sdev= 0.399006
cutoff_liv=liv_log.mean() + (liv_sdev*2)
liv_top=np.exp(cutoff_liv)
print(liv_top)
```

```
4064.8050610884347
```

In [53]:

```
df_s4['sqft_liv_cap']=df_s4['sqft_living']
```

```
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.
```

```
  Entry point for launching an IPython kernel.
```

In [54]:

```
df_s5=df_s4[df_s4.sqft_liv_cap<=4064.805]
```

In [55]:

```
df_s5.head()
```

Out[55]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	zipcode	sqft_lot_cap	sqft_liv_cap
0	221900.0	3	1.00	1180	5650	98178	5650	1180
1	538000.0	3	2.25	2570	7242	98125	7242	2570
2	180000.0	2	1.00	770	10000	98028	10000	770
3	604000.0	4	3.00	1960	5000	98136	5000	1960
4	510000.0	3	2.00	1680	8080	98074	8080	1680

In [56]:

```
df_s5['sqft_liv_cap'].describe()
```

Out[56]:

```
count    19697.000000
mean      1941.561913
std        723.507840
min        370.000000
25%       1390.000000
50%       1840.000000
75%       2410.000000
max       4060.000000
Name: sqft_liv_cap, dtype: float64
```

In [57]:

```
att3=['sqft_liv_cap','sqft_lot_cap','bedrooms','bathrooms']
```

In [58]:

```
price=df_s5['price'] #Updating target variable
df_s5a=df_s5.drop(columns='price')
```

In [59]:

```
lreg(df_s5a[att3],price)
```

```
Training Scores:
R2: 0.3899637140263539
Testing Scores:
R2: 0.38664340183747203
Slope: [157888.04549327 -17011.79915397 -29517.78226218    960.85520732]
Intercept: 480391.68081505544
```

Out[59]:

```
(array([157888.04549327, -17011.79915397, -29517.78226218,    960.85520732]),
 480391.68081505544,
 0.38664340183747203)
```

Ok, so again, what I'm doing seems to be moving things in the wrong direction.

In [60]:

```
continuous = ['sqft_living', 'sqft_lot','price']
cont = df_s5[continuous]
log_names = [f'{column}_log' for column in cont.columns]
```

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

In [61]:

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

In [62]:

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

In [63]:

```
df_s6 = pd.concat([df_log_norm, df_s5], axis=1)
df_s6.head()
```

Out[63]:

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	zipcode	sqft_lot_cap	sqft_liv_c
0	-1.101972	-0.290009	-1.461747	221900.0	3.0	1.00	1180.0	5650.0	98178.0	5650.0	118
1	0.910677	0.066490	0.470489	538000.0	3.0	2.25	2570.0	7242.0	98125.0	7242.0	257
2	-2.205733	0.529900	-1.918324	180000.0	2.0	1.00	770.0	10000.0	98028.0	10000.0	77
3	0.210065	-0.465526	0.722953	604000.0	4.0	3.00	1960.0	5000.0	98136.0	5000.0	196
4	-0.188515	0.223734	0.353878	510000.0	3.0	2.00	1680.0	8080.0	98074.0	8080.0	168

In [64]:

```
df_s6.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21423 entries, 0 to 21596
Data columns (total 11 columns):
sqft_living_log    19697 non-null float64
sqft_lot_log       19697 non-null float64
price_log          19697 non-null float64
price              19697 non-null float64
bedrooms           19697 non-null float64
bathrooms          19697 non-null float64
sqft_living        19697 non-null float64
sqft_lot           19697 non-null float64
zipcode            19697 non-null float64
sqft_lot_cap       19697 non-null float64
sqft_liv_cap       19697 non-null float64
dtypes: float64(11)
memory usage: 2.0 MB
```

In [65]:

```
df_s6.dropna(inplace=True)
```

In [66]:

```
p_drop=['price','price_log']
```

In [67]:

```
df_s6.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 17971 entries, 0 to 19696
Data columns (total 11 columns):
sqft_living_log    17971 non-null float64
sqft_lot_log       17971 non-null float64
price_log          17971 non-null float64
```

```
price_log          17971 non-null float64
price              17971 non-null float64
bedrooms           17971 non-null float64
bathrooms          17971 non-null float64
sqft_living        17971 non-null float64
sqft_lot           17971 non-null float64
zipcode            17971 non-null float64
sqft_lot_cap       17971 non-null float64
sqft_liv_cap       17971 non-null float64
dtypes: float64(11)
memory usage: 1.6 MB
```

In [68]:

```
df_s6a=df_s6.drop(columns=p_drop,axis=1) #6th subset of dataframe, dropping the target va
riable
```

In [69]:

```
df_s6a.head()
```

Out[69]:

	sqft_living_log	sqft_lot_log	bedrooms	bathrooms	sqft_living	sqft_lot	zipcode	sqft_lot_cap	sqft_liv_cap
0	-1.101972	-0.290009	3.0	1.00	1180.0	5650.0	98178.0	5650.0	1180.0
1	0.910677	0.066490	3.0	2.25	2570.0	7242.0	98125.0	7242.0	2570.0
2	-2.205733	0.529900	2.0	1.00	770.0	10000.0	98028.0	10000.0	770.0
3	0.210065	-0.465526	4.0	3.00	1960.0	5000.0	98136.0	5000.0	1960.0
4	-0.188515	0.223734	3.0	2.00	1680.0	8080.0	98074.0	8080.0	1680.0

In [70]:

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

In [71]:

```
lreg(df_s6a[att4],df_s6['price_log'])
```

```
Training Scores:
R2: 0.37936737914947216
Testing Scores:
R2: 0.38859138778367985
Slope: [ 0.63937083 -0.15543547]
Intercept: 0.0016298209088611568
```

Out[71]:

```
(array([ 0.63937083, -0.15543547]), 0.0016298209088611568, 0.38859138778367985)
```

In [72]:

```
lr=LinearRegression()
X=df_s6a[att1]
y=df_s6['price']
lr.fit(X,y)
```

Out[72]:

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

In [73]:

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

Out[73]:

y top features

Weight?	Feature
+180352.741	<BIAS>

Weight	Feature
+223.018	sqft_living
-2.639	sqft_lot
-2173.362	bathrooms
-30983.156	bedrooms

In [74]:

```
df_s6.corr().price.sort_values(ascending=False)
```

Out[74]:

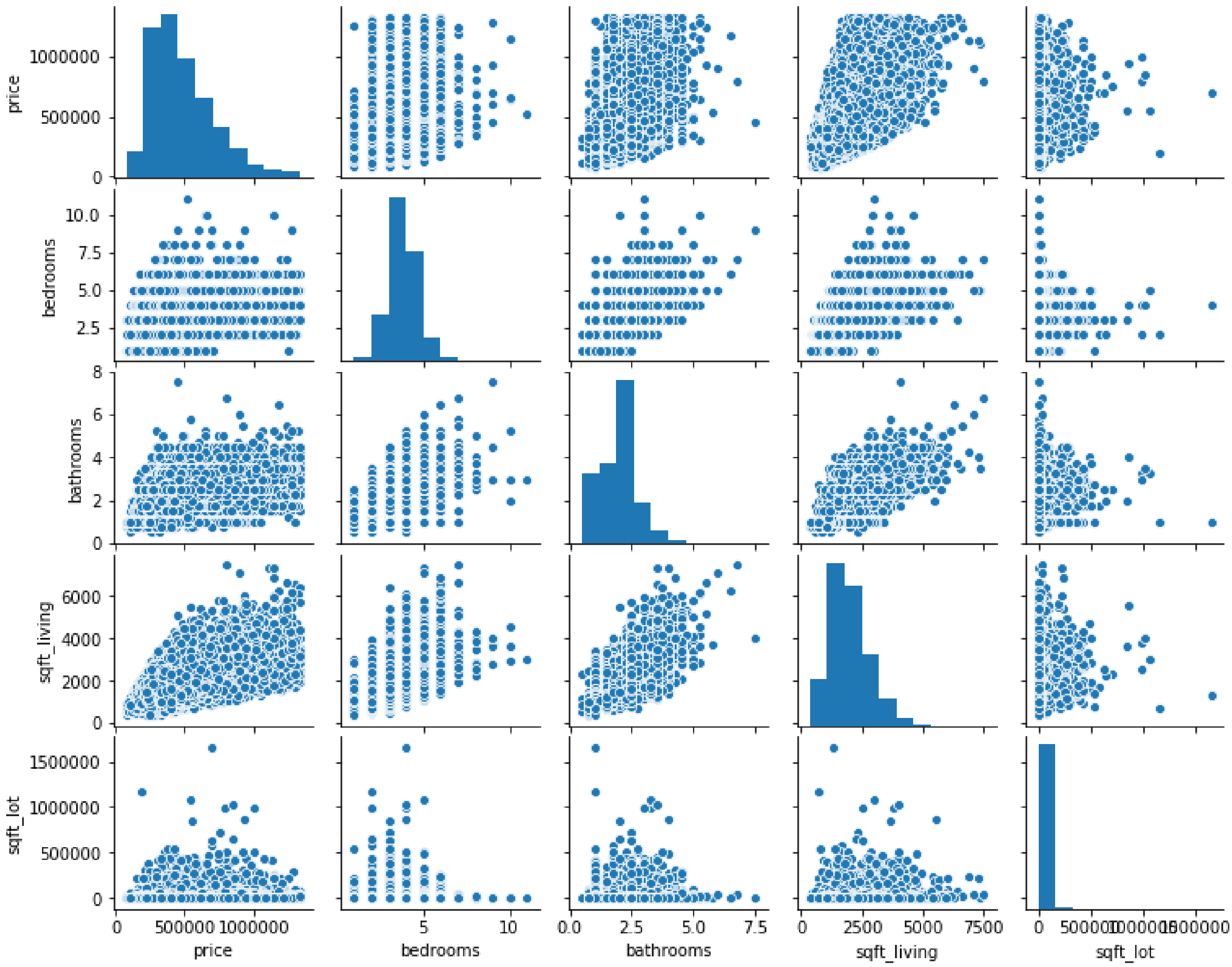
```
price              1.000000
sqft_liv_cap       0.609157
sqft_living        0.609157
bathrooms          0.433743
bedrooms           0.290793
sqft_lot_cap       0.080425
sqft_lot           0.080425
zipcode            0.003984
price_log         -0.000984
sqft_lot_log      -0.009182
sqft_living_log   -0.012766
Name: price, dtype: float64
```

In [75]:

```
df_s3b=df_s3.drop(columns='sqft_lot_cap') #This is just to get a visual for the presentat
ion
df_s3b=df_s3b.drop(columns='zipcode')
```

In [76]:

```
g=sns.pairplot(df_s3b) #This will be the visual,maybe
g.fig.set_size_inches(10,8)
```



In [77]:

```
df_s6.corr()
```

Out[77]:

	sqft_living_log	sqft_lot_log	price_log	price	bedrooms	bathrooms	sqft_living	sqft_lot	zipcode	sqft_lot
sqft_living_log	1.000000	0.272464	0.599398	-0.012766	-0.008814	-0.003372	-0.002625	0.002506	-0.006013	0.00
sqft_lot_log	0.272464	1.000000	0.019152	-0.009182	-0.003917	-0.009134	-0.004333	0.006909	-0.013905	0.00
price_log	0.599398	0.019152	1.000000	-0.000984	-0.004494	-0.008755	0.003695	0.010656	-0.013644	0.01
price	-0.012766	-0.009182	-0.000984	1.000000	0.290793	0.433743	0.609157	0.080425	0.003984	0.08
bedrooms	-0.008814	-0.003917	-0.004494	0.290793	1.000000	0.506689	0.601970	0.123465	-0.140169	0.12
bathrooms	-0.003372	-0.009134	-0.008755	0.433743	0.506689	1.000000	0.717945	0.077563	-0.203013	0.07
sqft_living	-0.002625	-0.004333	0.003695	0.609157	0.601970	0.717945	1.000000	0.253521	-0.175260	0.25
sqft_lot	0.002506	0.006909	0.010656	0.080425	0.123465	0.077563	0.253521	1.000000	-0.208665	1.00
zipcode	-0.006013	-0.013905	-0.013644	0.003984	-0.140169	-0.203013	-0.175260	-0.208665	1.000000	-0.20
sqft_lot_cap	0.002506	0.006909	0.010656	0.080425	0.123465	0.077563	0.253521	1.000000	-0.208665	1.00
sqft_liv_cap	-0.002625	-0.004333	0.003695	0.609157	0.601970	0.717945	1.000000	0.253521	-0.175260	0.25

Residuals, not the money kind.

So here I'm going to check some residuals plots to see how the model works.

In [78]:

```
X=df_s6a[att1]
```

In [79]:

```
vif = pd.DataFrame() #Creating an empty dataframe
vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))]
vif["features"] = df_s6a[att1].columns
```

In [80]:

```
vif
```

Out[80]:

	VIF	features
0	21.596201	sqft_living
1	2.782188	sqft_lot
2	15.185925	bedrooms
3	18.533256	bathrooms

In [81]:

```
y=df_s6['price']
```

In [82]:

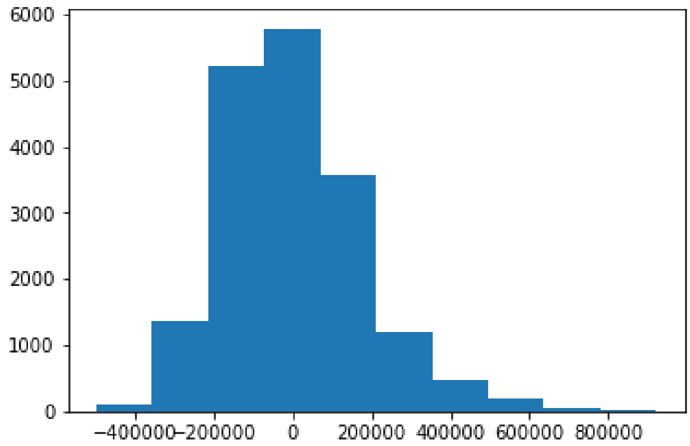
```
lr = LinearRegression()
lr.fit(X, y)
preds = lr.predict(X)
```

In [83]:

```
residuals = y-preds
```

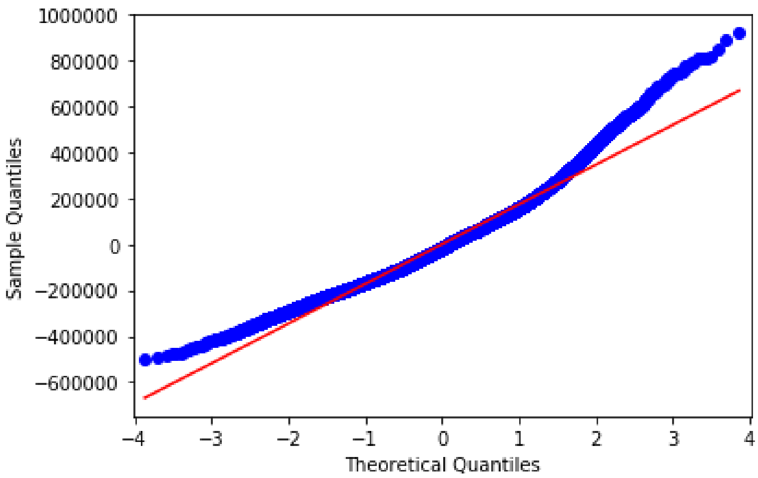
In [84]:

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



In [85]:

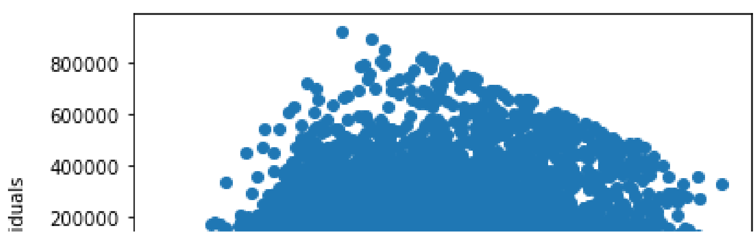
```
fig = sm.qqplot(residuals, line = 'r')
```

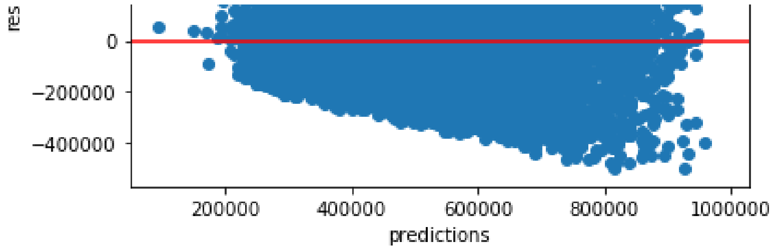


I don't know much about qq plots, but that doesn't look too hot.

In [86]:

```
plt.scatter(preds, residuals)
plt.axhline(y=0, color = 'red', label = '0')
plt.xlabel('predictions')
plt.ylabel('residuals')
plt.show()
```



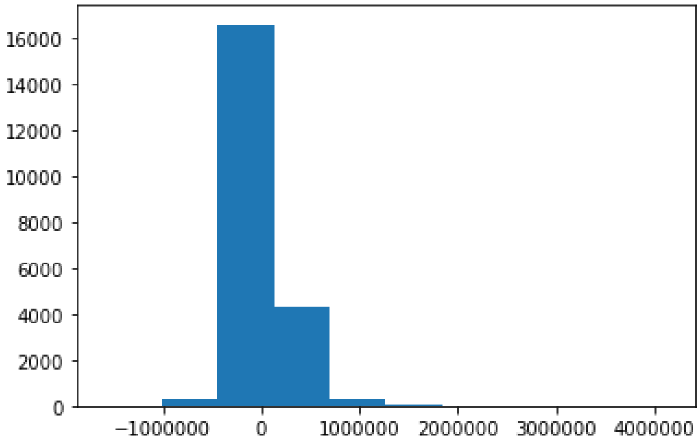


In [87]:

```
X=df_s2a[att1]
y=df_s2['price']
lr = LinearRegression()
lr.fit(X, y)
preds = lr.predict(X)
```

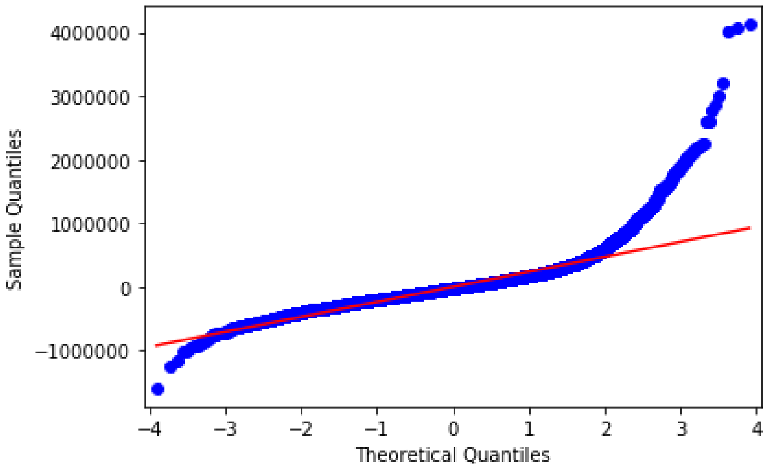
In [88]:

```
residuals = y-preds
plt.hist(residuals)
plt.show()
```



In [89]:

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



This is some obviously skewed data. But we sort of knew that the data wasn't going to fit well to begin with.

One last time, just for "fun"

I'm going to narrow it down to 1 zipcode, the most popular one, and run the model through that, and get a qq and residuals plot, and that should just about wrap things up.

In [95]:

```
df_s2a['zipcode'].value_counts().idxmax()
```

Out[95]:

```
98103
```

In [97]:

```
df_s2z=df_s2[df_s2.zipcode==98103]
```

In [98]:

```
df_s2z.head()
```

Out[98]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	zipcode
17	485000.0	4	1.00	1600	4300	98103
111	570000.0	3	1.75	1260	3328	98103
116	518500.0	3	3.50	1590	1102	98103
128	822500.0	5	3.50	2320	4960	98103
149	511000.0	3	1.00	1430	3455	98103

In [99]:

```
df_s2zip_var=df_s2z.drop(columns='price')
```

In [100]:

```
y=df_s2z.price
```

In [101]:

```
lreg(df_s2zip_var[att1],y)
```

```
Training Scores:
R2: 0.5544726602686663
Testing Scores:
R2: 0.5976829582495553
Slope: [176300.65649927  19512.6195159  -29238.89988495  -7257.21516036]
Intercept: 586433.7111111111
```

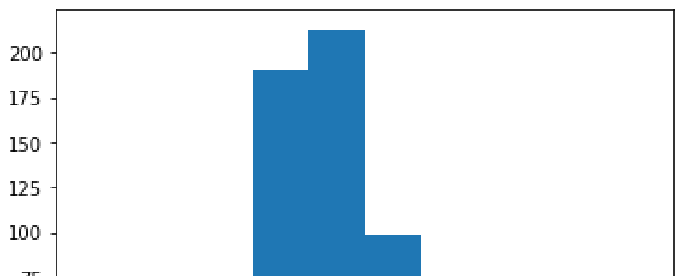
Out[101]:

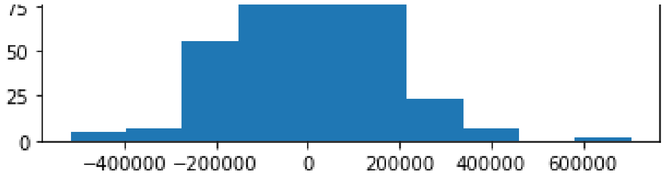
```
(array([176300.65649927,  19512.6195159 , -29238.89988495,  -7257.21516036]),
 586433.7111111111,
 0.5976829582495553)
```

So we got a little bump to the R2 score.

In [102]:

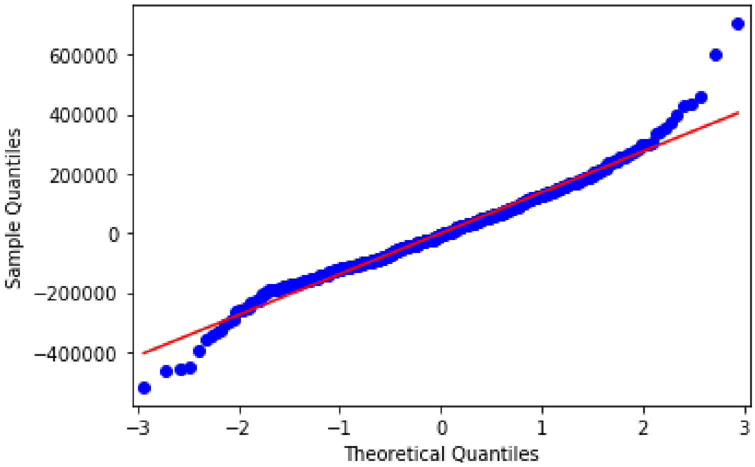
```
X=df_s2zip_var[att1]
lr = LinearRegression()
lr.fit(X, y)
preds = lr.predict(X)
residuals = y-preds
plt.hist(residuals)
plt.show()
```





In [103]:

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



That looks better.

In conclusion:

Hopefully I was able to demonstrate a better understanding of linear modeling, and make the improvements necessary to move on.

In [ ]: