

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [2]: house_details=pd.read_csv("House_Price.csv")
```

```
In [3]: house_details.head(10)
```

```
Out[3]:
```

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	price
0	3	1	1180	5650	1	221900
1	3	2	2570	7242	2	538000
2	2	1	770	10000	1	180000
3	4	3	1960	5000	1	604000
4	3	2	1680	8080	1	510000
5	4	5	5420	101930	1	1225000
6	3	2	1715	6819	2	257500
7	3	2	1060	9711	1	291850
8	3	1	1780	7470	1	229500
9	3	3	1890	6560	2	323000

In [4]: `house_details.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 6 columns):
#   Column          Non-Null Count  Dtype
---  -
0   bedrooms        21613 non-null  int64
1   bathrooms        21613 non-null  int64
2   sqft_living      21613 non-null  int64
3   sqft_lot         21613 non-null  int64
4   floors           21613 non-null  int64
5   price            21613 non-null  int64
dtypes: int64(6)
memory usage: 1013.2 KB
```

In [5]: `house_details.describe()`

Out[5]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	price
count	21613.000000	21613.000000	21613.000000	2.161300e+04	21613.000000	2.161300e+04
mean	3.370842	2.312543	2079.899736	1.510697e+04	1.542405	5.400881e+05
std	0.930062	0.865405	918.440897	4.142051e+04	0.567504	3.671272e+05
min	0.000000	0.000000	290.000000	5.200000e+02	1.000000	7.500000e+04
25%	3.000000	2.000000	1427.000000	5.040000e+03	1.000000	3.219500e+05
50%	3.000000	2.000000	1910.000000	7.618000e+03	2.000000	4.500000e+05
75%	4.000000	3.000000	2550.000000	1.068800e+04	2.000000	6.450000e+05
max	33.000000	8.000000	13540.000000	1.651359e+06	4.000000	7.700000e+06

```
In [6]: house_details.isnull().sum()
```

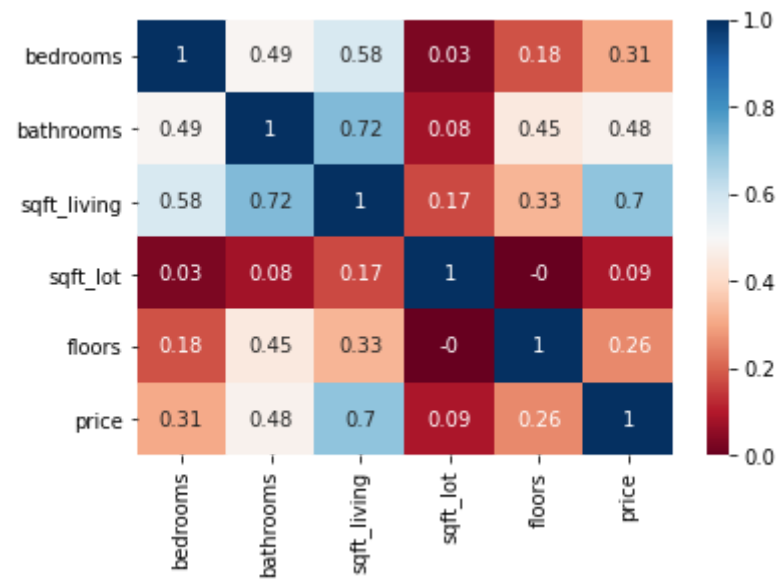
```
Out[6]: bedrooms      0  
bathrooms      0  
sqft_living     0  
sqft_lot        0  
floors          0  
price           0  
dtype: int64
```

```
In [7]: house_info=house_details.corr().round(2)  
house_info
```

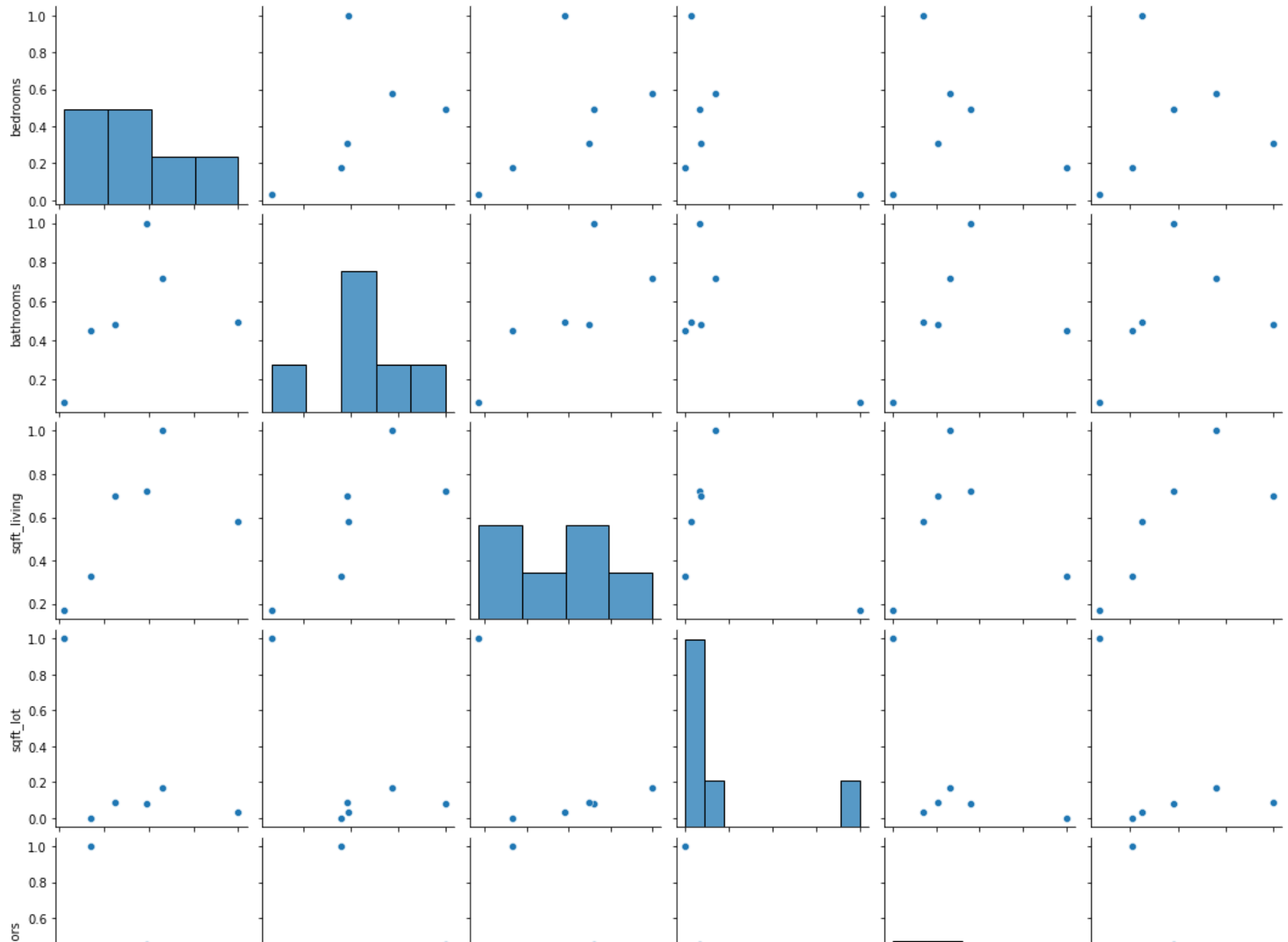
```
Out[7]:
```

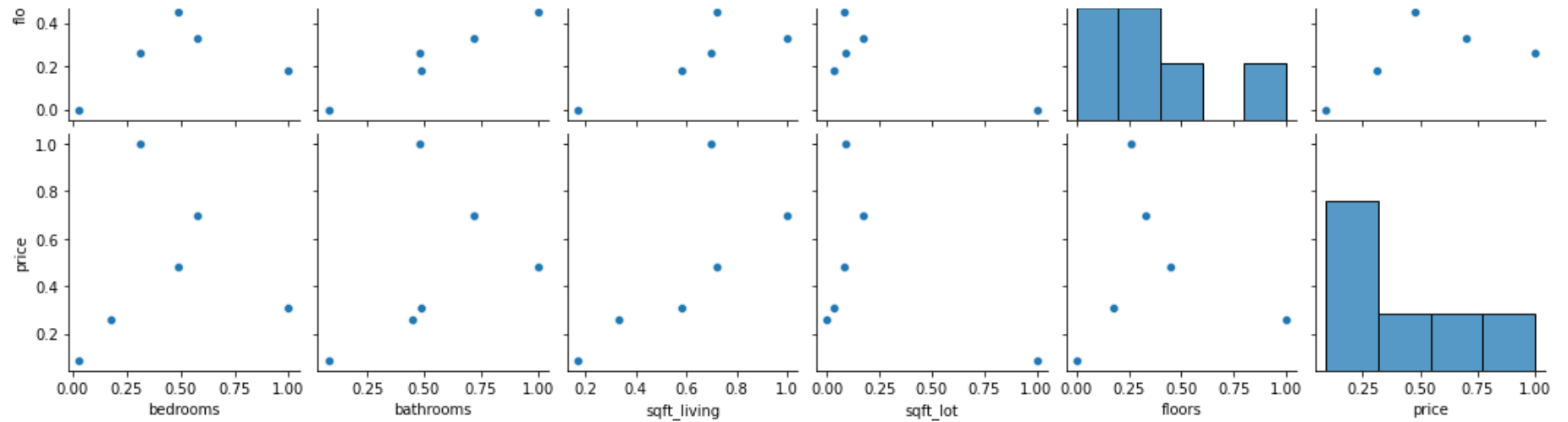
	bedrooms	bathrooms	sqft_living	sqft_lot	floors	price
bedrooms	1.00	0.49	0.58	0.03	0.18	0.31
bathrooms	0.49	1.00	0.72	0.08	0.45	0.48
sqft_living	0.58	0.72	1.00	0.17	0.33	0.70
sqft_lot	0.03	0.08	0.17	1.00	-0.00	0.09
floors	0.18	0.45	0.33	-0.00	1.00	0.26
price	0.31	0.48	0.70	0.09	0.26	1.00

```
In [8]: sns.heatmap(house_info,annot=True,cmap='RdBu');
```

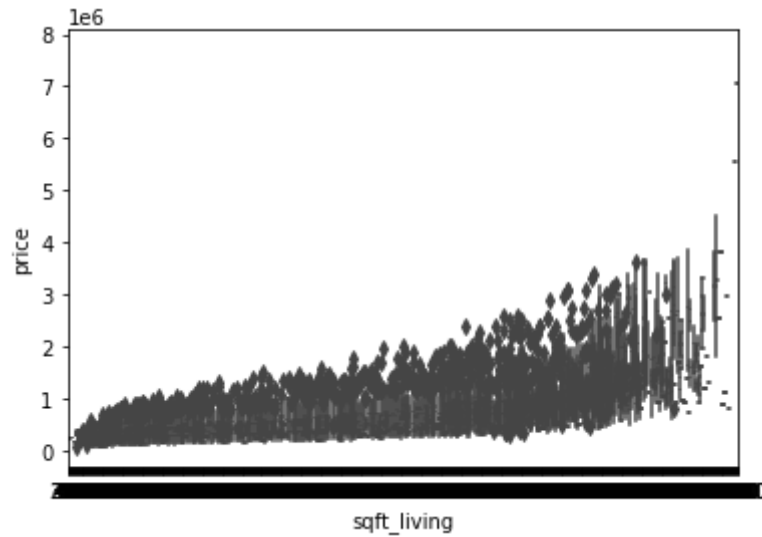


```
In [9]: sns.pairplot(house_info); #By seeing this pairplot we can say, sqft_living has high correlation with price(dependent variable)
```

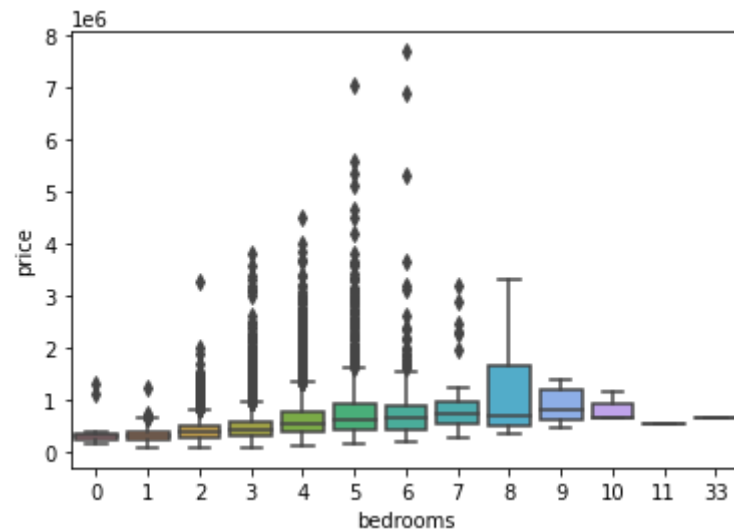




```
In [10]: sns.boxplot(x="sqft_living",y="price",data=house_details);
```

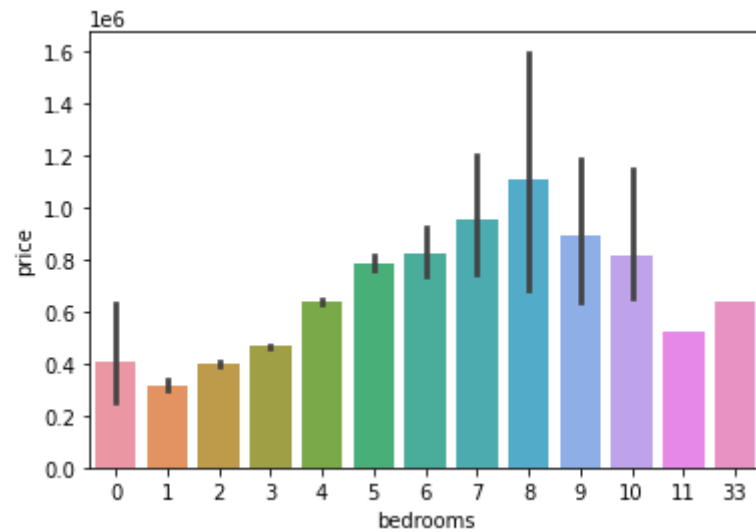


```
In [11]: sns.boxplot(x="bedrooms",y="price",data=house_details);
```



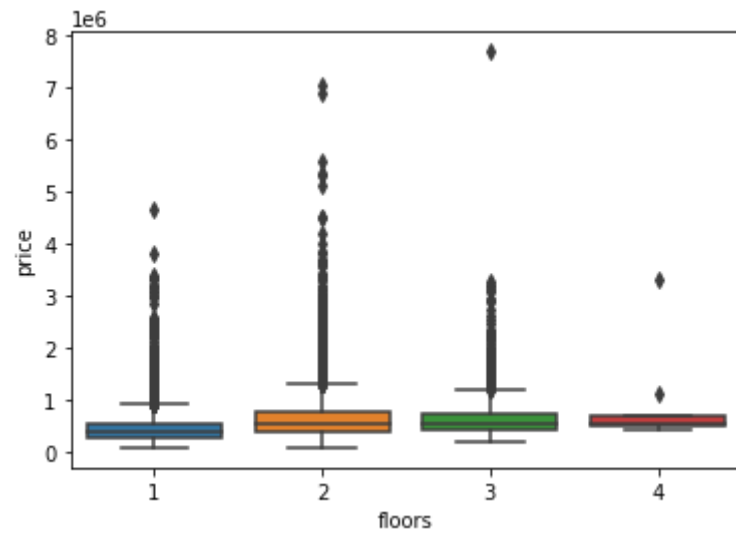
from boxplot it seems price deflections(outliers) are high where houses have 4,5 and 6 bedrooms.

```
In [12]: sns.barplot(x="bedrooms",y="price",data=house_details);
```



from barplot we conclude house with 8 bedrooms have high price


```
In [13]: sns.boxplot(x="floors",y="price",data=house_details);
```



price deflection are high in houses having 2 floors

```
In [14]: ss=pd.DataFrame(house_details)
ss
```

```
Out[14]:
```

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	price
0	3	1	1180	5650	1	221900
1	3	2	2570	7242	2	538000
2	2	1	770	10000	1	180000
3	4	3	1960	5000	1	604000
4	3	2	1680	8080	1	510000
...
21608	3	3	1530	1131	3	360000
21609	4	3	2310	5813	2	400000
21610	2	1	1020	1350	2	402101
21611	3	3	1600	2388	2	400000
21612	2	1	1020	1076	2	325000

21613 rows × 6 columns

just found the max price

```
In [15]: column = ss["price"]
max_value = column.max()
print(max_value)
```

7700000

```
In [16]: ss[ss['price']==ss['price'].max()]
```

```
Out[16]:
```

	bedrooms	bathrooms	sqft_living	sqft_lot	floors	price
7252	6	8	12050	27600	3	7700000

seperating dependent and independent variables

```
In [17]: y_dep=house_details.price
y_dep
```

```
Out[17]: 0      221900
1      538000
2      180000
3      604000
4      510000
...
21608   360000
21609   400000
21610   402101
21611   400000
21612   325000
Name: price, Length: 21613, dtype: int64
```

```
In [18]: x_indep=house_details.drop("price",axis=1) #DROPPING THE DEPENDENT VARIABLE  
x_indep
```

```
Out[18]:
```

	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	3	1	1180	5650	1
1	3	2	2570	7242	2
2	2	1	770	10000	1
3	4	3	1960	5000	1
4	3	2	1680	8080	1
...
21608	3	3	1530	1131	3
21609	4	3	2310	5813	2
21610	2	1	1020	1350	2
21611	3	3	1600	2388	2
21612	2	1	1020	1076	2

21613 rows × 5 columns

CHECKING p-value

```
In [19]: import statsmodels.api as sm
```

```
In [20]: model=sm.OLS(y_dep,x_indep)
```

```
In [21]: my_fit=model.fit()
```

In [22]: `my_fit.summary()`

Out[22]: OLS Regression Results

Dep. Variable:	price	R-squared (uncentered):	0.845
Model:	OLS	Adj. R-squared (uncentered):	0.845
Method:	Least Squares	F-statistic:	2.352e+04
Date:	Fri, 20 Aug 2021	Prob (F-statistic):	0.00
Time:	19:19:14	Log-Likelihood:	-2.9992e+05
No. Observations:	21613	AIC:	5.999e+05
Df Residuals:	21608	BIC:	5.999e+05
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
bedrooms	-4.195e+04	1798.147	-23.329	0.000	-4.55e+04	-3.84e+04
bathrooms	-2.337e+04	3106.713	-7.524	0.000	-2.95e+04	-1.73e+04
sqft_living	324.7097	2.975	109.141	0.000	318.878	330.541
sqft_lot	-0.3486	0.043	-8.103	0.000	-0.433	-0.264
floors	4.002e+04	3138.743	12.750	0.000	3.39e+04	4.62e+04

Omnibus:	13945.067	Durbin-Watson:	1.984
Prob(Omnibus):	0.000	Jarque-Bera (JB):	457933.849
Skew:	2.609	Prob(JB):	0.00
Kurtosis:	24.938	Cond. No.	9.37e+04

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

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

[3] The condition number is large, $9.37e+04$. This might indicate that there are strong multicollinearity or other numerical problems.

From summary we conclude, R-square value is 0.8 so correlation is high and none of the independent variables have $p > 0.05$ so all the independent variables have high correlation with dependent variable.

PREDICTION

```
In [63]: my_fit.predict(x_indep).round()
```

```
Out[63]: 0      271987.0
          1      739423.0
          2      179288.0
          3      436790.0
          4      410120.0
          ...
          21608    420501.0
          21609    590174.0
          21610    303501.0
          21611    402773.0
          21612    303596.0
          Length: 21613, dtype: float64
```

here python predicted the price of each houses

```
In [24]: my_fit.predict(x_indep).round().head(10)
```

```
Out[24]: 0      271987.0  
1      739423.0  
2      179288.0  
3      436790.0  
4      410120.0  
5     1479743.0  
6      461944.0  
7      208232.0  
8      466178.0  
9      495484.0  
dtype: float64
```

MACHINE LEARNING

#Machine learning is performed to check whether the predicted values are correct or not.

```
In [25]: import sklearn  
from sklearn import model_selection  
from sklearn.model_selection import train_test_split
```

splitting 100% data into 80% of data for fitting and 20% for prediction

```
In [26]: x_train,x_test,y_train,y_test=train_test_split(x_indep,y_dep,train_size=0.8,random_state=1)
```

```
In [27]: my_data=sm.OLS(y_train,x_train)
```

```
In [28]: my_fit1=my_data.fit()
```

just checking the R-sq and p values of 80% of data

In [29]: `my_fit1.summary()`

Out[29]: OLS Regression Results

Dep. Variable:	price	R-squared (uncentered):	0.850
Model:	OLS	Adj. R-squared (uncentered):	0.850
Method:	Least Squares	F-statistic:	1.963e+04
Date:	Fri, 20 Aug 2021	Prob (F-statistic):	0.00
Time:	19:19:15	Log-Likelihood:	-2.3938e+05
No. Observations:	17290	AIC:	4.788e+05
Df Residuals:	17285	BIC:	4.788e+05
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
bedrooms	-3.773e+04	1942.300	-19.427	0.000	-4.15e+04	-3.39e+04
bathrooms	-2.63e+04	3383.120	-7.773	0.000	-3.29e+04	-1.97e+04
sqft_living	317.3245	3.278	96.810	0.000	310.900	323.749
sqft_lot	-0.3065	0.045	-6.808	0.000	-0.395	-0.218
floors	4.419e+04	3404.985	12.979	0.000	3.75e+04	5.09e+04

Omnibus:	9379.778	Durbin-Watson:	2.002
Prob(Omnibus):	0.000	Jarque-Bera (JB):	165630.922
Skew:	2.220	Prob(JB):	0.00
Kurtosis:	17.498	Cond. No.	9.72e+04

Notes:

[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.

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

[3] The condition number is large, $9.72e+04$. This might indicate that there are strong multicollinearity or other numerical problems.

In [30]: x_train

Out[30]:

	bedrooms	bathrooms	sqft_living	sqft_lot	floors
7291	3	2	2190	7021	1
14835	3	3	2370	6840	2
15880	2	1	1230	3800	1
8812	4	2	2510	9963	1
17220	3	1	1160	7491	1
...
10955	3	3	1920	3867	2
17289	4	5	3420	7440	3
5192	3	2	1970	54450	1
12172	3	2	1980	8775	1
235	5	4	3760	28040	2

17290 rows × 5 columns

```
In [31]: y_train
```

```
Out[31]: 7291      353000
14835     300523
15880     435000
8812      800000
17220     417500
...
10955     571000
17289    1350000
5192      650000
12172     437000
235       1025000
Name: price, Length: 17290, dtype: int64
```

IMPORTING LINEAR REGRESSION

```
In [32]: from sklearn import linear_model
from sklearn.linear_model import LinearRegression
```

```
In [33]: data=LinearRegression()
```

```
In [34]: data.fit(x_train,y_train)
```

```
Out[34]: LinearRegression()
```

predicting price with 20% of the independent variables(x_test)

```
In [35]: y_pred=data.predict(x_test)
y_pred
```

```
Out[35]: array([ 731166.67967974,  409898.60570831,  669252.27860429, ...,
        478178.67569015, 1472510.04262538,  363850.457691  ])
```

```
In [36]: comp=pd.DataFrame({"actual_price":y_test,"machine_pred_price":y_pred}) #giving column names  
comp
```

```
Out[36]:
```

	actual_price	machine_pred_price
15544	459000	7.311667e+05
17454	445000	4.098986e+05
21548	1057000	6.692523e+05
3427	732350	5.637444e+05
8809	235000	4.046212e+05
...
13597	965000	9.325628e+05
9648	359950	5.967553e+05
18627	260000	4.781787e+05
9553	1795000	1.472510e+06
14200	418000	3.638505e+05

4323 rows × 2 columns

Finding residual(error) by taking difference from machine calculated value to actual calculated value.

```
In [37]: res=y_pred-y_test  
res.round()
```

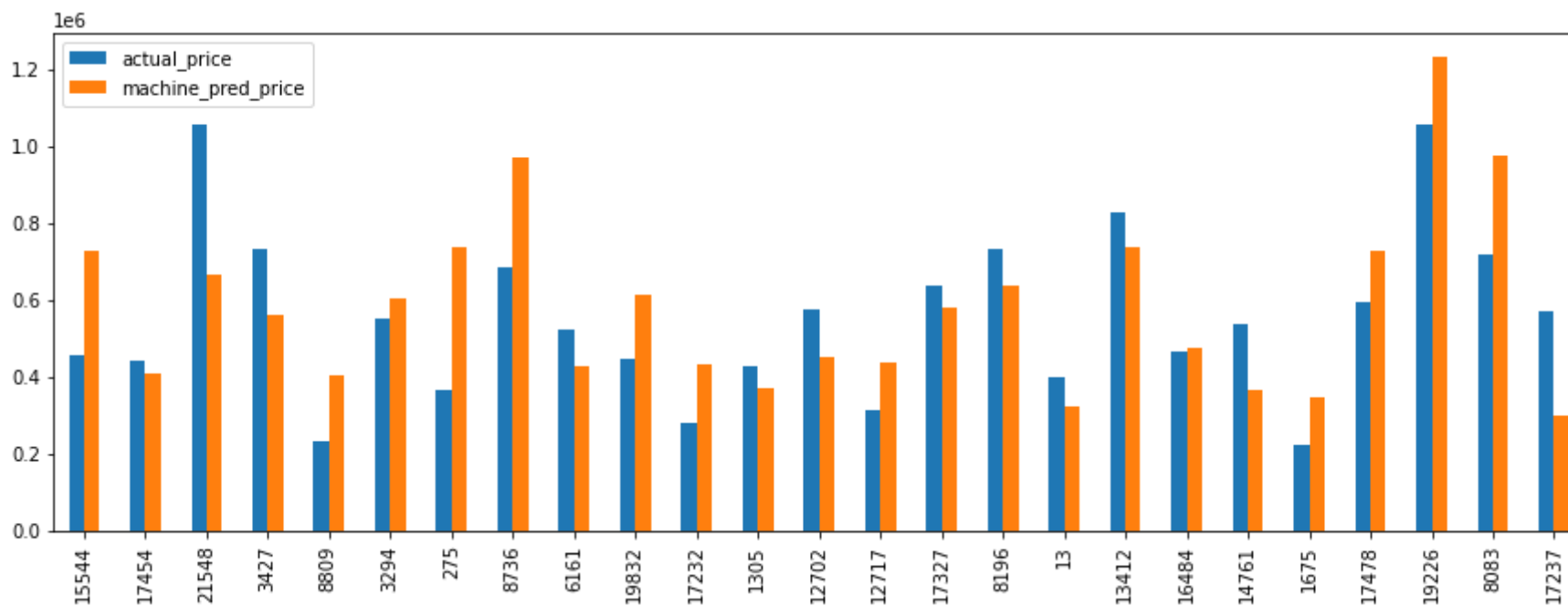
```
Out[37]: 15544    272167.0  
17454    -35101.0  
21548   -387748.0  
3427    -168606.0  
8809     169621.0  
      ...  
13597    -32437.0  
9648     236805.0  
18627     218179.0  
9553    -322490.0  
14200    -54150.0  
Name: price, Length: 4323, dtype: float64
```

here are the errors or differences from machine calc and actual calc

GRAPHS

```
In [38]: com_lmt=comp.head(25)
```

```
In [39]: com_lmt.plot(kind="bar",figsize=(15,5));
```



There is only minimum difference b/w actual and predicted values

```
In [40]: sns.distplot(comp["actual_price"])
sns.distplot(comp["machine_pred_price"])
plt.legend(["actual_price", "machine_pred_price"])
```

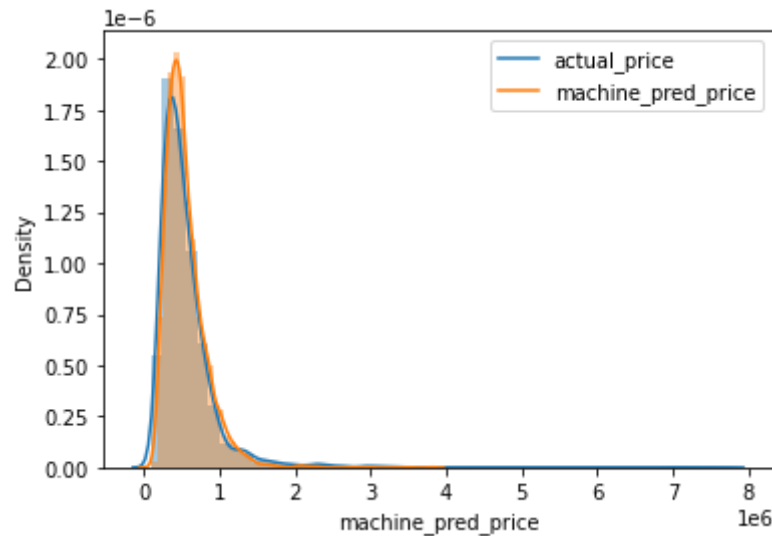
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

warnings.warn(msg, FutureWarning)

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

warnings.warn(msg, FutureWarning)

Out[40]: <matplotlib.legend.Legend at 0x115deb0f8b0>

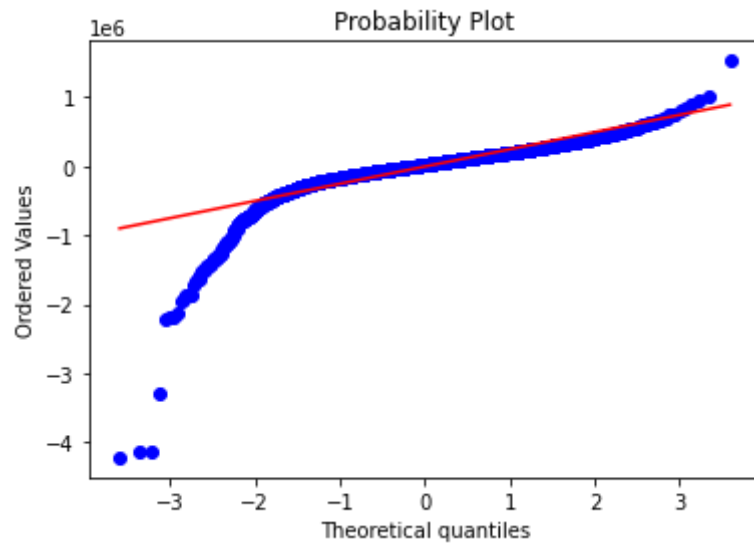


from this graph we can see that both the bell curves are nearer to each other, there is only less variation b/w both values

ASSUMPTIONS IN LINEAR REGRESSION

```
In [41]: # NORMALITY CHECK
import scipy.stats as sps
sps.probplot(res,dist="norm",plot=plt)
```

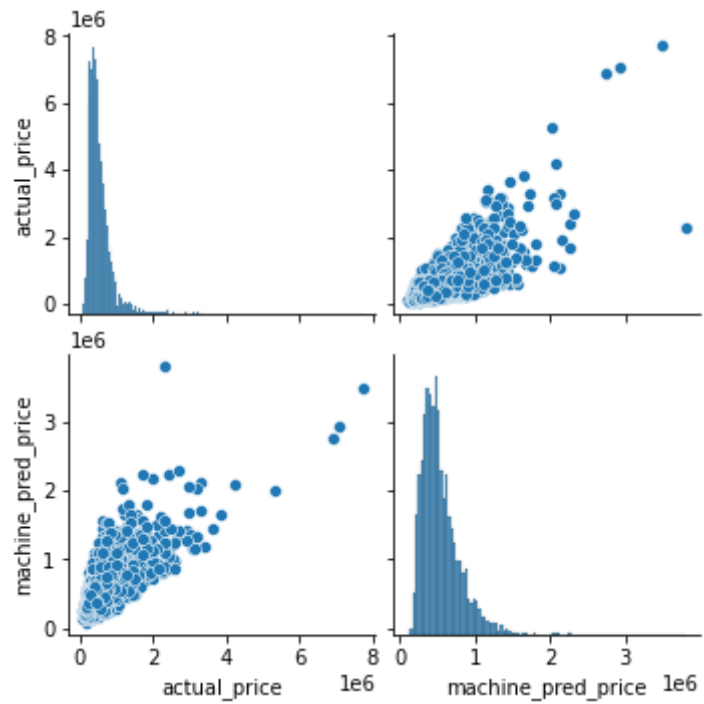
```
Out[41]: ((array([-3.59801667, -3.36038867, -3.22930113, ...,  3.22930113,
                  3.36038867,  3.59801667]),
          array([-4221931.46193083, -4132071.6104107 , -4123216.48079273, ...,
                  965453.51862481,  1002997.08966016,  1530206.98421065])),
         (249171.33518121368, -3865.5587791720936, 0.8659735742459718))
```



Finally i conclude most of the errors are equal to 1 and near by 1 so the predicted values can be taken into account. The predicted dependent variables values are good

```
In [42]: sns.pairplot(comp)
```

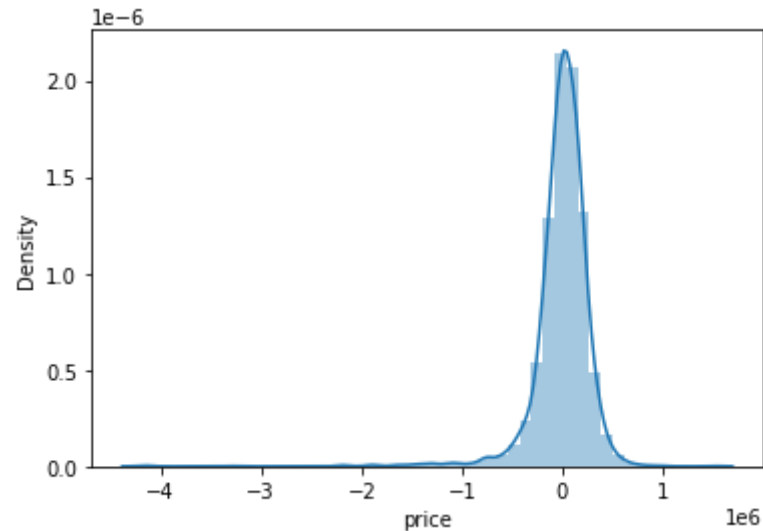
```
Out[42]: <seaborn.axisgrid.PairGrid at 0x115e4199220>
```




```
In [43]: sns.distplot(res)
```

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
warnings.warn(msg, FutureWarning)

```
Out[43]: <AxesSubplot:xlabel='price', ylabel='Density'>
```



```
In [44]: from sklearn.metrics import mean_squared_error  
mean_squared_error(y_test,y_pred)
```

```
Out[44]: 82680872234.52504
```

```
In [45]: mse = np.mean((y_test - y_pred)**2)
mse
```

```
Out[45]: 82680872234.525
```

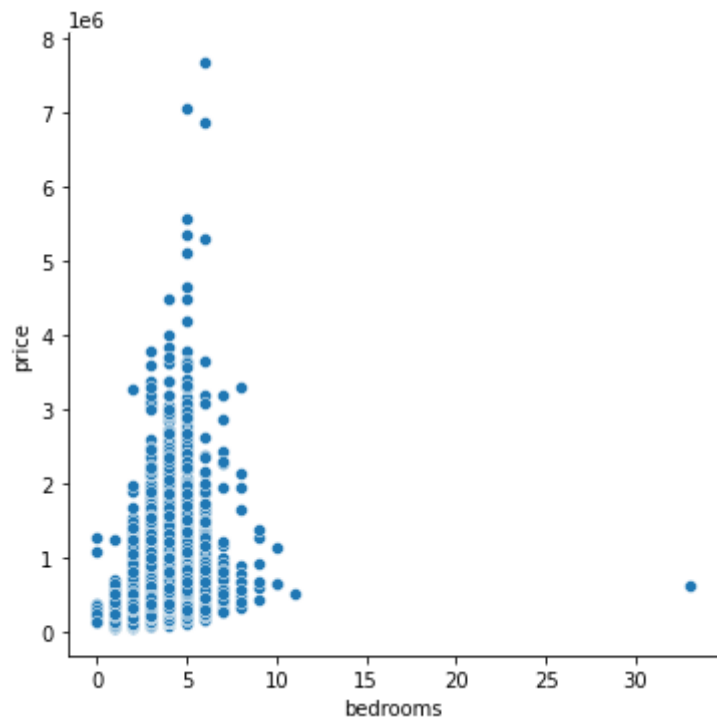
```
In [46]: rmse = mean_squared_error(y_test,[0 for _ in y_test], squared=False)
rmse
```

```
Out[46]: 688412.0089742545
```

Below are just for practice

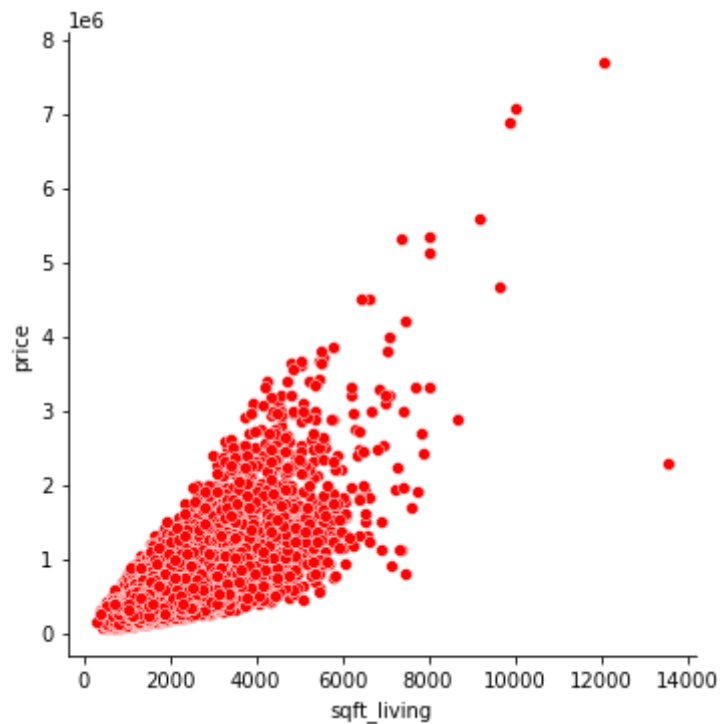
```
In [47]: sns.relplot(x="bedrooms",y="price",data=house_details)
```

```
Out[47]: <seaborn.axisgrid.FacetGrid at 0x115ded2a3a0>
```



```
In [48]: sns.relplot(x="sqft_living",y="price",color="red",data=house_details)
```

```
Out[48]: <seaborn.axisgrid.FacetGrid at 0x115de82f2b0>
```



```
In [49]: sns.barplot(x="bedrooms",y="price",kind="violin",data=house_details);
```

```
-----
AttributeError                                Traceback (most recent call last)
```

```
<ipython-input-49-bd7413dc1e5e> in <module>
```

```
----> 1 sns.barplot(x="bedrooms",y="price",kind="violin",data=house_details);
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py in inner_f(*args, **kwargs)
```

```
44         )
45         kwargs.update({k: arg for k, arg in zip(sig.parameters, args)})
--> 46         return f(**kwargs)
47     return inner_f
48
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py in barplot(x, y, hue, data, order, hue_order, estimator, ci, n_boot, units, seed, orient, color, palette, saturation, errcolor, errwidth, capsize, dodge, ax, **kwargs)
```

```
3185         ax = plt.gca()
3186
-> 3187     plotter.plot(ax, kwargs)
3188     return ax
3189
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py in plot(self, ax, bar_kws)
```

```
1637     def plot(self, ax, bar_kws):
1638         """Make the plot."""
-> 1639     self.draw_bars(ax, bar_kws)
1640     self.annotate_axes(ax)
1641     if self.orient == "h":
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\categorical.py in draw_bars(self, ax, kws)
```

```
1602
1603         # Draw the bars
-> 1604         barfunc(barpos, self.statistic, self.width,
1605                 color=self.colors, align="center", **kws)
1606
```

```
C:\ProgramData\Anaconda3\lib\site-packages\matplotlib\__init__.py in inner(ax, data, *args, **kwargs)
```

```
1445     def inner(ax, *args, data=None, **kwargs):
1446         if data is None:
-> 1447             return func(ax, *map(sanitize_sequence, args), **kwargs)
1448
```

```
1449         bound = new_sig.bind(ax, *args, **kwargs)
```

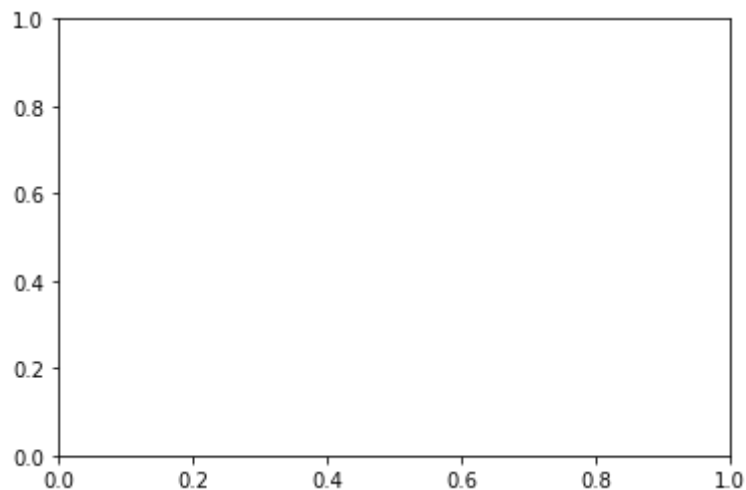
```
C:\ProgramData\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py in bar(self, x, height, width, bottom, align, **kwargs)
```

```
2486         label='_nolegend_',
2487     )
-> 2488     r.update(kwargs)
2489     r.get_path()._interpolation_steps = 100
2490     if orientation == 'vertical':
```

```
C:\ProgramData\Anaconda3\lib\site-packages\matplotlib\artist.py in update(self, props)
```

```
994         func = getattr(self, f"set_{k}", None)
995         if not callable(func):
-> 996             raise AttributeError(f"{type(self).__name__!r} object "
997                                f"has no property {k!r}")
998         ret.append(func(v))
```

AttributeError: 'Rectangle' object has no property 'kind'



```
In [ ]: plt.scatter(x="sqft_living",y="price",color="red",data=house_details);
```

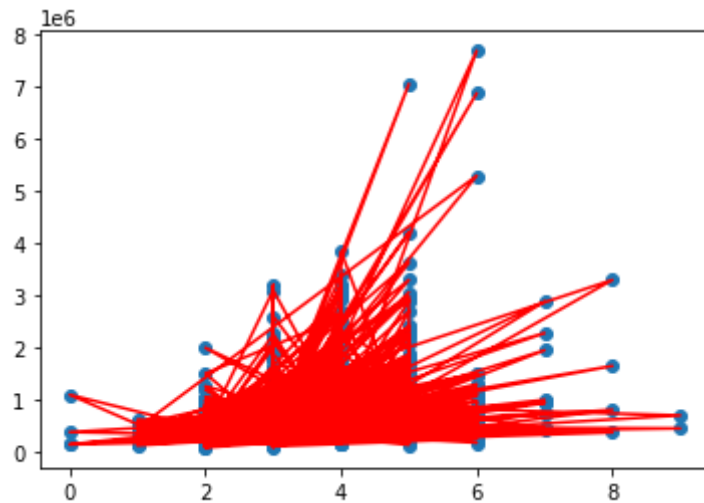
```
In [ ]: plt.xlabel("actual_price")  
plt.ylabel("machine_pred_price")  
plt.scatter(comp.actual_price, comp.machine_pred_price)
```

```
In [ ]: y_pred.intercept_
```

```
In [ ]: sns.distplot(house_details)
```

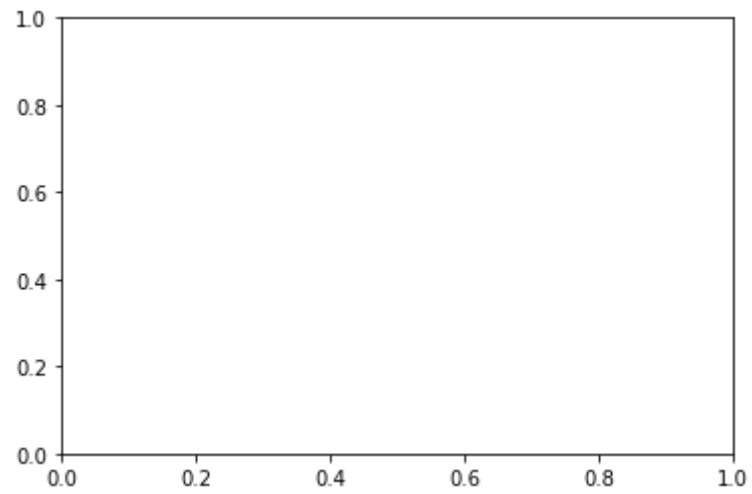
```
In [68]: k=x_test.bedrooms
```

```
In [69]: plt.scatter(k, y_test)  
plt.plot(k, y_test, color='red')  
plt.show()
```



```
In [53]: plt.plot(x="bedrooms" , y="sqft_living", color='red')
```

```
-----  
TypeError                                Traceback (most recent call last)  
<ipython-input-53-6d57da7c7a70> in <module>  
----> 1 plt.plot(x="bedrooms" , y="sqft_living", color='red')  
  
C:\ProgramData\Anaconda3\lib\site-packages\matplotlib\pyplot.py in plot(scalex, scaley, data, *args, **kwargs)  
    2838 @_copy_docstring_and_deprecators(Axes.plot)  
    2839 def plot(*args, scalex=True, scaley=True, data=None, **kwargs):  
-> 2840     return gca().plot(  
    2841         *args, scalex=scalex, scaley=scaley,  
    2842         **({"data": data} if data is not None else {}), **kwargs)  
  
C:\ProgramData\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py in plot(self, scalex, scaley, data, *args, **kwargs)  
    1741     """  
    1742     kwargs = cbook.normalize_kwargs(kwargs, mlines.Line2D)  
-> 1743     lines = [*self._get_lines(*args, data=data, **kwargs)]  
    1744     for line in lines:  
    1745         self.add_line(line)  
  
C:\ProgramData\Anaconda3\lib\site-packages\matplotlib\axes\_base.py in __call__(self, data, *args, **kwargs)  
    212     for pos_only in "xy":  
    213         if pos_only in kwargs:  
-> 214             raise TypeError("{} got an unexpected keyword argument {!r}"  
    215                             .format(self.command, pos_only))  
    216  
  
TypeError: plot got an unexpected keyword argument 'x'
```



In []: