In [4]:

```
# 1. Explore this dataset using what you have learned in data preprocessing and data visual
import numpy as np #linear algebra
import pandas as pd #datapreprocessing, CSV file I/O
import seaborn as sns #for plotting graphs
import matplotlib.pyplot as plt
df=pd.read_csv('kc_house_data.csv')
df.head()
```

Out[4]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0

5 rows × 21 columns

In [2]:

```
#some general information about the data columns and values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
```

#	Column	Non-Null Count	Dtype				
0	id	21613 non-null	int64				
1	date	21613 non-null	object				
2	price	21613 non-null	float64				
3	bedrooms	21613 non-null	int64				
4	bathrooms	21613 non-null	float64				
5	sqft_living	21613 non-null	int64				
6	sqft_lot	21613 non-null	int64				
7	floors	21613 non-null	float64				
8	waterfront	21613 non-null	int64				
9	view	21613 non-null	int64				
10	condition	21613 non-null	int64				
11	grade	21613 non-null	int64				
12	sqft_above	21613 non-null	int64				
13	sqft_basement	21613 non-null	int64				
14	yr_built	21613 non-null	int64				
15	yr_renovated	21613 non-null	int64				
16	zipcode	21613 non-null	int64				
17	lat	21613 non-null	float64				
18	long	21613 non-null	float64				
19	sqft_living15	21613 non-null	int64				
20	sqft_lot15	21613 non-null	int64				
dtypes: float64(5), int64(15), object(1)							
memory usage: 3 5+ MB							

memory usage: 3.5+ MB

In [3]:

```
#Finding missing values
df.isnull().sum()
```

Out[3]:

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

In [5]:

```
#Finding the count of no of bedrooms
df['bedrooms'].value_counts()
```

Out[5]:

```
9824
3
4
       6882
2
       2760
5
       1601
6
        272
        199
1
7
         38
8
         13
0
         13
9
          6
10
          3
11
          1
          1
33
```

Name: bedrooms, dtype: int64

In [6]:

```
#Finding the count of grade
df['grade'].value_counts()
Out[6]:
7
      8981
      6068
8
      2615
9
6
      2038
10
      1134
       399
11
5
       242
        90
12
        29
13
        13
```

Name: grade, dtype: int64

3 1

In [7]:

3

```
#Finding the count of condition
df['condition'].value_counts()
```

Out[7]:

3 14031 4 5679 5 1701 2 172 1 30

Name: condition, dtype: int64

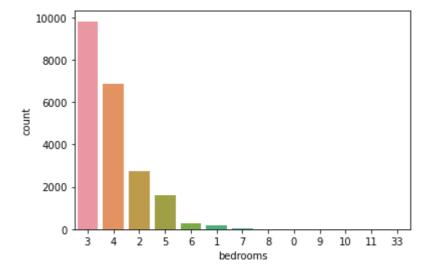
In [8]:

```
#A countplot is plotted for bedrooms
sns.countplot(df.bedrooms,order=df['bedrooms'].value_counts().index)
```

C:\Users\pc-H\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureW arning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argumen ts without an explicit keyword will result in an error or misinterpretation. warnings.warn(

Out[8]:

<AxesSubplot:xlabel='bedrooms', ylabel='count'>



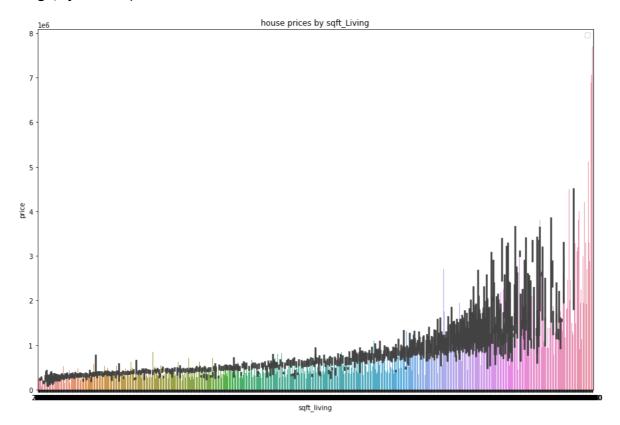
In [10]:

```
#A barplot is plotted between sqft living and prices to get an overview of how the price ch
fig,axes=plt.subplots(nrows=1,ncols=1,figsize=(15,10))
plt.title("house prices by sqft_Living")
plt.xlabel('sqft_living')
plt.ylabel('house prices')
plt.legend()
sns.barplot(x='sqft_living',y='price',data=df)
```

No handles with labels found to put in legend.

Out[10]:

<AxesSubplot:title={'center':'house prices by sqft_Living'}, xlabel='sqft_li
ving', ylabel='price'>



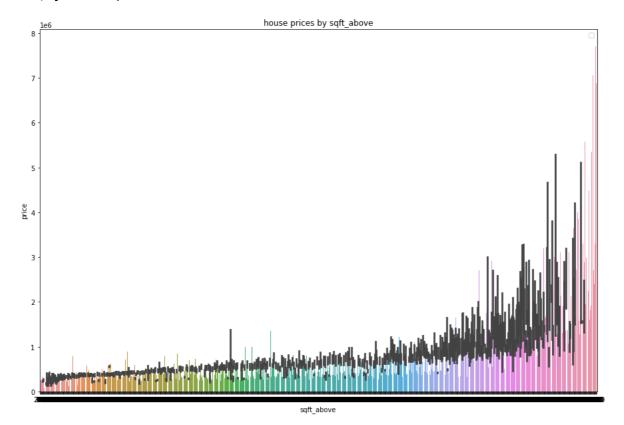
In [11]:

```
#A barplot is plotted between the sqft above and prices to see how the price changes with t
fig,axes=plt.subplots(nrows=1,ncols=1,figsize=(15,10))
plt.title("house prices by sqft_above")
plt.xlabel('sqft_above')
plt.ylabel('house prices')
plt.legend()
sns.barplot(x='sqft_above',y='price',data=df)
```

No handles with labels found to put in legend.

Out[11]:

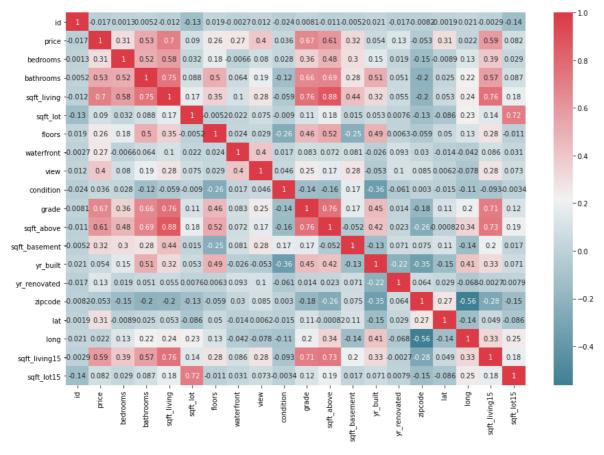
<AxesSubplot:title={'center':'house prices by sqft_above'}, xlabel='sqft_abo
ve', ylabel='price'>



In [12]:

```
def correlation_heatmap(df1):
    _,ax=plt.subplots(figsize=(15,10))
    colormap=sns.diverging_palette(220,10,as_cmap=True)
    sns.heatmap(df.corr(),annot=True,cmap=colormap)

correlation_heatmap(df)
```

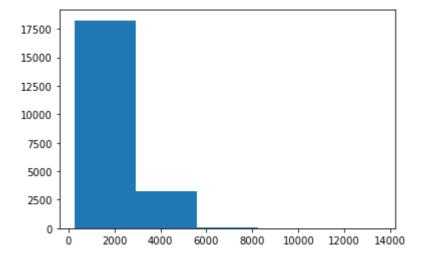


In [13]:

```
#A histogram is plotted for sqft living
plt.hist('sqft_living',data=df,bins=5)
```

Out[13]:

```
(array([1.825e+04, 3.255e+03, 1.010e+02, 5.000e+00, 2.000e+00]),
array([ 290., 2940., 5590., 8240., 10890., 13540.]),
<BarContainer object of 5 artists>)
```



In [14]:

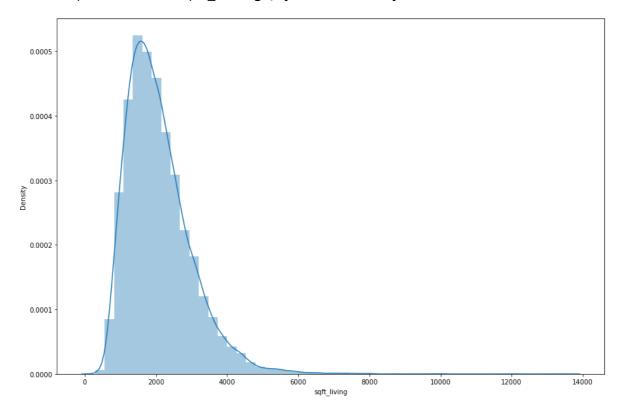
```
#A distplot is plotted for sqft living to see if the data is skewed or not
fig,axes=plt.subplots(nrows=1,ncols=1,figsize=(15,10))
sns.distplot(df['sqft_living'],hist=True,kde=True,rug=False,label='sqft_living',norm_hist=T
```

C:\Users\pc-H\anaconda3\lib\site-packages\seaborn\distributions.py:2551: Fut ureWarning: `distplot` is a deprecated function and will be removed in a fut ure 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[14]:

<AxesSubplot:xlabel='sqft_living', ylabel='Density'>



In [15]:

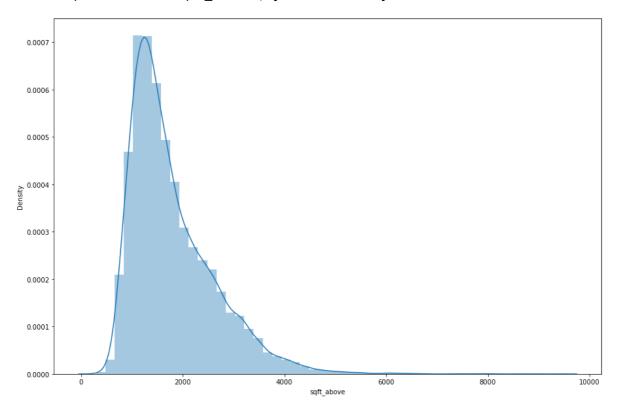
```
#A distplot is plotted for sqft above to see if the data is skewed or not
fig,axes=plt.subplots(nrows=1,ncols=1,figsize=(15,10))
sns.distplot(df['sqft_above'],hist=True,kde=True,rug=False,label='sqft_above',norm_hist=Tru
```

C:\Users\pc-H\anaconda3\lib\site-packages\seaborn\distributions.py:2551: Fut ureWarning: `distplot` is a deprecated function and will be removed in a fut ure 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[15]:

<AxesSubplot:xlabel='sqft_above', ylabel='Density'>



```
In [16]:
```

```
#Finding the mean, mode and median of sqft living.
print('Mean',round(df['sqft_living'].mean(),2))
print('Median',df['sqft_living'].median())
print('Mode',df['sqft_living'].mode()[0])
```

Mean 2079.9 Median 1910.0 Mode 1300

In [17]:

```
#Through graphs we observe that the sqft living=1300 has more values.
len(df[df['sqft_living']==1300])
```

Out[17]:

138

In [18]:

```
#3. Split your dataset into a training set and a testing set.

from sklearn.model_selection import train_test_split

from sklearn import linear_model

from sklearn.neighbors import KNeighborsRegressor

from sklearn.preprocessing import PolynomialFeatures

from sklearn import metrics

from mpl_toolkits.mplot3d import Axes3D

%matplotlib inline
```

In [19]:

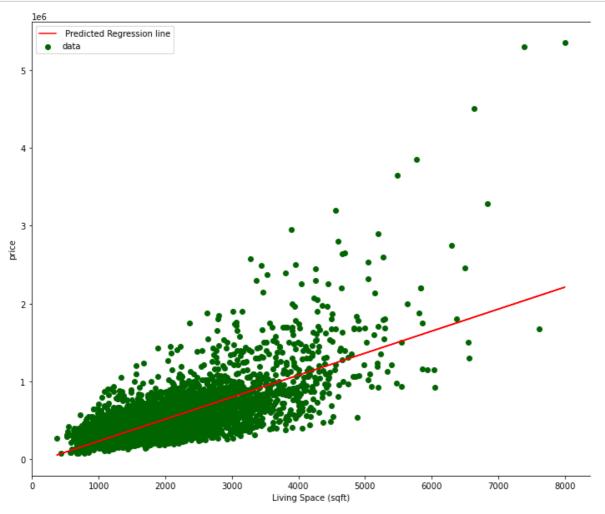
```
train_data,test_data=train_test_split(df,train_size=0.8,random_state=3)
reg=linear_model.LinearRegression()
x_train=np.array(train_data['sqft_living']).reshape(-1,1)
y_train=np.array(train_data['price']).reshape(-1,1)
reg.fit(x_train,y_train)

x_test=np.array(test_data['sqft_living']).reshape(-1,1)
y_test=np.array(test_data['price']).reshape(-1,1)
pred=reg.predict(x_test)
print('linear model')
mean_squared_error=metrics.mean_squared_error(y_test,pred)
print('Sqaured mean error', round(np.sqrt(mean_squared_error),2))
print('R squared training',round(reg.score(x_train,y_train),3))
print('R sqaured testing',round(reg.score(x_test,y_test),3))
print('intercept',reg.intercept_)
print('coefficient',reg.coef_)
```

```
linear model
Sqaured mean error 254289.15
R squared training 0.492
R sqaured testing 0.496
intercept [-47235.8113029]
coefficient [[282.2468152]]
```

In [20]:

```
_, ax = plt.subplots(figsize= (12, 10))
plt.scatter(x_test, y_test, color= 'darkgreen', label = 'data')
plt.plot(x_test, reg.predict(x_test), color='red', label= 'Predicted Regression line')
plt.xlabel('Living Space (sqft)')
plt.ylabel('price')
plt.legend()
plt.legend()
plt.gca().spines['right'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
```



In [21]:

```
train_data,test_data=train_test_split(df,train_size=0.8,random_state=3)
reg=linear_model.LinearRegression()
x_train=np.array(train_data['grade']).reshape(-1,1)
y_train=np.array(train_data['price']).reshape(-1,1)
reg.fit(x_train,y_train)

x_test=np.array(test_data['grade']).reshape(-1,1)
y_test=np.array(test_data['price']).reshape(-1,1)
pred=reg.predict(x_test)
print('linear model')
mean_squared_error=metrics.mean_squared_error(y_test,pred)
print('squared mean error',round(np.sqrt(mean_squared_error),2))
print('R squared training',round(reg.score(x_train,y_train),3))
print('R squared testing',round(reg.score(x_test,y_test),3))
print('intercept',reg.intercept_)
print('coeeficient',reg.coef_)
```

```
linear model
squared mean error 263387.61
R squared training 0.442
R squared testing 0.46
intercept [-1061459.62144314]
coeeficient [[209225.48270386]]
```

In []:

#Multi-linear Regression Code

In [23]:

```
features1=['bedrooms','grade','sqft_living','sqft_above']
reg=linear_model.LinearRegression()
reg.fit(train_data[features1],train_data['price'])
pred=reg.predict(test_data[features1])
print('complex_model 1')
mean_squared_error=metrics.mean_squared_error(y_test,pred)
print('mean squared error(MSE)', round(np.sqrt(mean_squared_error),2))
print('R squared training',round(reg.score(train_data[features1],train_data['price']),3))
print('R squared training', round(reg.score(test_data[features1],test_data['price']),3))
print('Intercept: ', reg.intercept_)
print('Coefficient:', reg.coef_)
```

```
complex_model 1
mean squared error(MSE) 239014.4
R squared training 0.548
R squared training 0.555
Intercept: -523645.7841467742
Coefficient: [-4.33050242e+04 1.03455986e+05 2.73023590e+02 -8.38875593e+0
1]
```

In [24]:

```
features2 = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront', 'view','
reg= linear_model.LinearRegression()
reg.fit(train_data[features1], train_data['price'])
pred = reg.predict(test_data[features1])
print('Complex Model_2')
mean_squared_error = metrics.mean_squared_error(y_test, pred)
print('Mean Squared Error (MSE) ', round(np.sqrt(mean_squared_error), 2))
print('R-squared (training) ', round(reg.score(train_data[features1], train_data['price']),
print('R-squared (testing) ', round(reg.score(test_data[features1], test_data['price']), 3)
print('Intercept: ', reg.intercept_)
print('Coefficient:', reg.coef_)
```

```
Complex Model_2
Mean Squared Error (MSE) 239014.4
R-squared (training) 0.548
R-squared (testing) 0.555
Intercept: -523645.7841467742
Coefficient: [-4.33050242e+04 1.03455986e+05 2.73023590e+02 -8.38875593e+0
1]
```

In []:

#Polynomial Regression

In [25]:

```
#For degree=2, the linear modelis built. The mean squared error is calculated and r squared
polyfeat=PolynomialFeatures(degree=2)
xtrain_poly=polyfeat.fit_transform(train_data[features1])
xtest_poly=polyfeat.fit_transform(test_data[features1])

poly=linear_model.LinearRegression()
poly.fit(xtrain_poly,train_data['price'])
polypred=poly.predict(xtest_poly)

print('Complex Model_3')
mean_squared_error = metrics.mean_squared_error(test_data['price'], polypred)
print('Mean Squared Error (MSE) ', round(np.sqrt(mean_squared_error), 2))
print('R-squared (training) ', round(poly.score(xtrain_poly, train_data['price']), 3))
print('R-squared (testing) ', round(poly.score(xtest_poly, test_data['price']), 3))
```

```
Complex Model_3
Mean Squared Error (MSE) 221965.07
R-squared (training) 0.614
R-squared (testing) 0.616
```

In []:

#Desciption:

#the most important features selected are: price, bedrooms', 'grade', 'sqft_living', 'sqft_abov #A heatmap is a two-dimensional graphical representation of data where the individual value #Scikit-learn provides a range of supervised and unsupervised learning algorithms via a con #we splitting the data into 80:20 ratio of which train_size is 80%, test_size is 20%. train #Polynomial Regression is a form of linear regression in which the relationship between the #For degree=2, the linear modelis built. The mean squared error is calculated and r squared #Polynomial Regression provides the best approximation of the relationship between the depe

localhost:8889/notebooks/First step into ML Haithem Habachi.ipynb#