```
In [1]: import pandas as pd
   import numpy as np
   from numpy import linalg as la
   from sklearn import decomposition
   from sklearn.decomposition import PCA
   from sklearn.neighbors import KNeighborsRegressor
   from sklearn.preprocessing import StandardScaler
   from matplotlib import*
   import matplotlib.pyplot as plt
   from sklearn.model_selection import train_test_split
```

In [2]: #raw\_data
 df = pd.read\_csv("kc\_house\_data.csv")
 df.head(3)

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	1
C	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	Ī
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	:
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	

3 rows × 21 columns

In [3]: #pre-processing and cleaning
 #drop id and zipcode
 df=df.drop(['id','date','zipcode','yr\_renovated','view','waterfront'],1)
 df.head(3)

Out[3]:

		price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	sqft_ab
(	0	221900.0	3	1.00	1180	5650	1.0	3	7	1180
	1	538000.0	3	2.25	2570	7242	2.0	3	7	2170
4	2	180000.0	2	1.00	770	10000	1.0	3	6	770

In [4]: df.shape

Out[4]: (21613, 15)

In [5]: X=df.drop(['price'],1)
 Y=df[['price']]

In [6]: # df\_n=(df-df.min())/((df.max())-(df.min()))
 Xs=(X-X.mean())/(X.std())
 Xs.head(3)

Out[6]:

		bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	sqft_ab
(	)	-0.398728	-1.447430	-0.979812	-0.228316	-0.915406	-0.629172	-0.558823	-0.73469
,	1	-0.398728	0.175603	0.533622	-0.189881	0.936484	-0.629172	-0.558823	0.46083
2	2	-1.473925	-1.447430	-1.426221	-0.123296	-0.915406	-0.629172	-1.409554	-1.22980

In [7]: Xs\_cov=Xs.cov()

In [8]: Xs\_cov.head(3)

Out[8]:

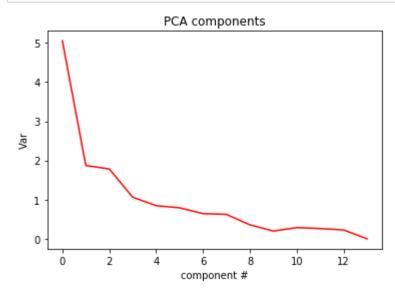
	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade
bedrooms	1.000000	0.515884	0.576671	0.031703	0.175429	0.028472	0.356967
bathrooms	0.515884	1.000000	0.754665	0.087740	0.500653	-0.124982	0.664983
sqft_living	0.576671	0.754665	1.000000	0.172826	0.353949	-0.058753	0.762704

In [9]: eigen\_value,eigen\_vector=la.eig(Xs\_cov)
print(eigen\_value[:])

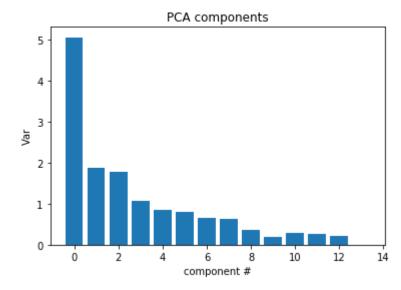
[ 5.05098374e+00 1.87016338e+00 1.78387613e+00 1.06173180e+00 8.46223892e-01 7.91520746e-01 6.43049873e-01 6.23275717e-01 3.57342162e-01 1.97983067e-01 2.85894277e-01 2.61373183e-01 2.26582035e-01 -3.47668819e-16]

•

```
In [10]: index = np.arange(len(eigen_value))
    plt.plot(index, eigen_value, color='r')
    plt.xlabel('component #')
    plt.ylabel('Var')
    plt.title('PCA components')
    plt.show()
```



```
In [11]: index = np.arange(len(eigen_value))
    plt.bar(index, eigen_value)
    plt.xlabel('component #')
    plt.ylabel('Var')
    plt.title('PCA components')
    plt.show()
```



A good number of PCA would be 6.

```
In [12]: X_train, X_test, y_train, y_test = train_test_split(Xs, Y, test_size=0.2, rand
om_state=0)
```

```
In [13]: pca=PCA(n_components=6)
    X_train=pca.fit_transform(X_train)
    X_test=pca.transform(X_test)

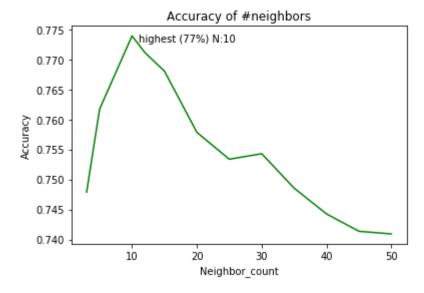
In [14]: #KNN model

In [15]: accuracy_values=[]
    neighbor_count=[3,5,10,12,15,20,25,30,35,40,45,50]
    for i in neighbor_count:
        neigh = KNeighborsRegressor(n_neighbors = i, metric = 'euclidean')
        neigh.fit(X_train,y_train)
        PRED=neigh.predict(X_test)
        ten_score=neigh.score(X_test,y_test)
        accuracy_values.append(ten_score)
```

## In [16]: print accuracy\_values

[0.7479055812734365, 0.7617455364358612, 0.7739490041290873, 0.77114547336347 73, 0.76807469746629, 0.757863388380646, 0.7533808823565806, 0.75430160684516 97, 0.7485568777792191, 0.744254971983161, 0.7413575045397784, 0.740919820783 1815]

```
In [17]: plt.plot(neighbor_count,accuracy_values,color='g')
    plt.xlabel('Neighbor_count')
    plt.ylabel('Accuracy')
    plt.title('Accuracy of #neighbors')
    plt.text(11,0.773, r'highest (77%) N:10')
    plt.show()
```



From the plot its cleara to say an optimal number of nearest neighbours would be 10.

```
In [18]: #training the final model
    neigh = KNeighborsRegressor(n_neighbors = 10, metric = 'euclidean')
    neigh.fit(X,Y)
```