ASSIGNMENT 3B

1. **Consider the BCP dataset and its class variable with values "R" (Recurrence Occurred) and "N" (No Recurrence Occurred so far). Ignore the attribute that gives the number of years after which recurrence occurred or the number of years for which the patient has been free of recurrence. There are thirty other attribute values given as features measured for every patient. Use only these thirty attributes.**

   CODE:

```
data = pd.read_csv('wpbc.data.csv')

# Considering only 30 attributes
X = data.loc[:,'M_radius':'fractal dimension']
y = data['Outcome']
X.info()
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 194 entries, 0 to 193
Data columns (total 30 columns):
M_radius                194 non-null float64
M_texture               194 non-null float64
M_perimeter             194 non-null float64
M_area                  194 non-null float64
M_smoothness            194 non-null float64
M_compactness           194 non-null float64
M_concavity             194 non-null float64
M_concave points        194 non-null float64
M_symmetry              194 non-null float64
M_fractal dimension     194 non-null float64
SE_radius               194 non-null float64
SE_texture              194 non-null float64
SE_perimeter            194 non-null float64
SE_area                 194 non-null float64
SE_smoothness           194 non-null float64
SE_compactness          194 non-null float64
SE_concavity            194 non-null float64
SE_concave points       194 non-null float64
SE_symmetry             194 non-null float64
SE_fractal dimension    194 non-null float64
radius                  194 non-null float64
texture                 194 non-null float64
perimeter               194 non-null float64
area                    194 non-null float64
smoothness              194 non-null float64
compactness             194 non-null float64
concavity               194 non-null float64
concave points          194 non-null float64
symmetry                194 non-null float64
fractal dimension       194 non-null float64
dtypes: float64(30)
memory usage: 45.5 KB
```

a. Run k-means algorithm with this dataset for k=4. Run it three different times and for each run show the cluster centers and the SSE values for each cluster and also the total SSE value for the clustering.

FOR 1st RUN:

```
K_Means_1 = KMeans(n_clusters=4,init='random', random_state=30).fit(X)
center = K_Means_1.cluster_centers_
indx = K_Means_1.labels_
clusters_SSE1 = []
print('Below are SSE values for each cluster of K_Means_1 clustering\n')
for i in range(4):
    SSE = np.sum(np.sum((X[indx == i] - center[i])**2))
    print('SSE of cluster ' + str(i) + ' = \t' + str(SSE))
    clusters_SSE1.append(SSE)
K_Means_1_SSE = K_Means_1.inertia_
print('Total SSE for 1st run \t' + str(K_Means_1_SSE))
print('\n Cluster centers for 1st run:\n' + str(K_Means_1.cluster_centers_))
```

OUTPUT:

```
Below are SSE values for each cluster of K_Means_1 clustering

SSE of cluster 0 =    2795136.257930213
SSE of cluster 1 =    3744386.7368627535
SSE of cluster 2 =    2462018.7541844267
SSE of cluster 3 =    2567115.4151013456
Total SSE for 1st run        11568657.164078739

 Cluster centers for 1st run:
[[2.35563636e+01 2.46300000e+01 1.56118182e+02 1.74590909e+03
  1.01784545e-01 1.58554545e-01 2.21609091e-01 1.34490909e-01
  1.84372727e-01 5.93345455e-02 1.12993636e+00 1.27262727e+00
  7.74863636e+00 1.76058182e+02 5.47018182e-03 2.63345455e-02
  3.70290909e-02 1.49672727e-02 1.78472727e-02 3.35472727e-03
  3.09372727e+01 3.29990909e+01 2.06809091e+02 2.95145455e+03
  1.38245455e-01 3.48081818e-01 4.66627273e-01 2.26745455e-01
  2.95609091e-01 8.28236364e-02 2.77272727e+00 1.90909091e+00]
 [2.04033333e+01 2.25075000e+01 1.35312500e+02 1.29415833e+03
  1.01379375e-01 1.58957500e-01 1.95429375e-01 1.09532292e-01
  1.96485417e-01 6.07245833e-02 7.78566667e-01 1.23975417e+00
  5.54252083e+00 1.00741042e+02 6.68050000e-03 3.41447917e-02
  4.61258333e-02 1.63574583e-02 2.16468750e-02 3.97083333e-03
  2.49175000e+01 2.94935417e+01 1.67431250e+02 1.90250000e+03
  1.39456458e-01 3.80918750e-01 4.78495833e-01 2.01351667e-01
  3.24829167e-01 8.63220833e-02 3.46666667e+00 3.97916667e+00]
 [1.41684507e+01 2.16912676e+01 9.32536620e+01 6.25071831e+02
  1.05981127e-01 1.39403803e-01 1.31486479e-01 6.66121127e-02
  1.94956338e-01 6.65381690e-02 4.01209859e-01 1.22968028e+00
  2.89861972e+00 3.54732394e+01 6.96430986e-03 3.17556620e-02
  3.89342254e-02 1.39222394e-02 2.09582958e-02 4.15969014e-03
  1.67556338e+01 3.02914085e+01 1.12257183e+02 8.63574648e+02
  1.53298169e-01 3.99116338e-01 4.44295493e-01 1.64238732e-01
  3.39373239e-01 1.01006056e-01 2.32957746e+00 3.01408451e+00]
 [1.76814062e+01 2.24221875e+01 1.16160938e+02 9.73425000e+02
  1.00433281e-01 1.31261406e-01 1.43283125e-01 8.39731250e-02
  1.89348437e-01 6.06314062e-02 6.07687500e-01 1.34821562e+00
  4.20525000e+00 6.79087500e+01 6.92489063e-03 2.95979375e-02
  3.99081250e-02 1.56422187e-02 1.99180156e-02 3.96907812e-03
  2.10351562e+01 3.00875000e+01 1.39135938e+02 1.35689062e+03
  1.37841094e-01 3.16809375e-01 3.89692344e-01 1.68736250e-01
  3.05900000e-01 8.41370312e-02 3.03125000e+00 3.07812500e+00]]
```

FOR 2ND RUN:

```
K_Means_2 = KMeans(n_clusters=4,init='random', random_state=10).fit(X)
center2 = K_Means_2.cluster_centers_
indx2 = K_Means_2.labels_
clusters_SSE2 = []
print('Below are SSE values for each cluster of K_Means_2 clustering\n')
for i in range(4):
    SSE2 = np.sum(np.sum((X[indx2 ==i] - center2[i])**2))
    print('SSE of cluster ' + str(i) + ' = \t' + str(SSE2))
    clusters_SSE2.append(SSE2)
K_Means_2_SSE = K_Means_2.inertia_
print('Total SSE for 1st run \t' + str(K_Means_2_SSE))
print('\n Cluster centers for 2nd run:\n' + str(K_Means_2.cluster_centers_))
```

OUTPUT:

```
Below are SSE values for each cluster of K_Means_2 clustering

SSE of cluster 0 =    2795136.257930213
SSE of cluster 1 =    3852709.6162770456
SSE of cluster 2 =    2369170.0050529144
SSE of cluster 3 =    2555245.9802285926
Total SSE for 1st run        11572261.859488767

 Cluster centers for 2nd run:
[[2.35563636e+01 2.46300000e+01 1.56118182e+02 1.74590909e+03
  1.01784545e-01 1.58554545e-01 2.21609091e-01 1.34490909e-01
  1.84372727e-01 5.93345455e-02 1.12993636e+00 1.27262727e+00
  7.74863636e+00 1.76058182e+02 5.47018182e-03 2.63345455e-02
  3.70290909e-02 1.49672727e-02 1.78472727e-02 3.35472727e-03
  3.09372727e+01 3.29990909e+01 2.06809091e+02 2.95145455e+03
  1.38245455e-01 3.48081818e-01 4.66627273e-01 2.26745455e-01
  2.95609091e-01 8.28236364e-02 2.77272727e+00 1.90909091e+00]
 [2.03908163e+01 2.25608163e+01 1.35212245e+02 1.29207347e+03
  1.01381837e-01 1.58956327e-01 1.96634898e-01 1.09641837e-01
  1.96969388e-01 6.07328571e-02 7.72785714e-01 1.23892245e+00
  5.48583673e+00 9.99775510e+01 6.64687755e-03 3.40967347e-02
  4.61548980e-02 1.62364898e-02 2.15271429e-02 3.95559184e-03
  2.48708163e+01 2.95769388e+01 1.67048980e+02 1.89610204e+03
  1.39212449e-01 3.81024490e-01 4.80308163e-01 2.00777143e-01
  3.24944898e-01 8.62879592e-02 3.45714286e+00 4.12244898e+00]
 [1.41374286e+01 2.17038571e+01 9.30230000e+01 6.22147143e+02
  1.06022286e-01 1.39125286e-01 1.30837714e-01 6.63564286e-02
  1.94911429e-01 6.65440000e-02 4.02715714e-01 1.22926143e+00
  2.90748571e+00 3.55652857e+01 6.97068571e-03 3.18521714e-02
  3.89065714e-02 1.39291286e-02 2.10009857e-02 4.16731429e-03
  1.67252857e+01 3.02677143e+01 1.12019429e+02 8.60411429e+02
  1.53283857e-01 3.99880857e-01 4.42102571e-01 1.63952143e-01
  3.39101429e-01 1.01024000e-01 2.34857143e+00 3.04285714e+00]
 [1.76275000e+01 2.23548438e+01 1.15832813e+02 9.67765625e+02
  1.00458281e-01 1.31261406e-01 1.42070625e-01 8.34982813e-02
  1.89003125e-01 6.07095312e-02 6.04570313e-01 1.34915312e+00
  4.19764063e+00 6.73728125e+01 6.94809375e-03 2.94918437e-02
  3.98037500e-02 1.56892500e-02 1.99522344e-02 3.97535938e-03
  2.09765625e+01 3.00620313e+01 1.38826562e+02 1.34901563e+03
  1.38259844e-01 3.16176562e-01 3.90168906e-01 1.68909688e-01
  3.06335937e-01 8.43729687e-02 3.00000000e+00 2.92187500e+00]]
```

FOR 3rd RUN:

```
K_Means_3 = KMeans(n_clusters=4,init='random', random_state=20).fit(X)
center = K_Means_3.cluster_centers_
indx = K_Means_3.labels_
clusters_SSE3 = []
print('Below are SSE values for each cluster of K_Means_3 clustering\n')
for i in range(4):
    SSE = np.sum(np.sum((X[indx ==i] - center[i])**2))
    print('SSE of cluster ' + str(i) + ' = \t' + str(SSE))
    clusters_SSE3.append(SSE)
K_Means_3_SSE = K_Means_3.inertia_
print('Total SSE for 1st run \t' + str(K_Means_3_SSE))
print('\n Cluster centers for 2nd run:\n' + str(K_Means_3.cluster_centers_))
```

OUTPUT:

```
Below are SSE values for each cluster of K_Means_3 clustering

SSE of cluster 0 =    2462018.7541844267
SSE of cluster 1 =    3642638.9674575753
SSE of cluster 2 =    2672064.0493349275
SSE of cluster 3 =    2795136.257930213
Total SSE for 1st run        11571858.028907144

 Cluster centers for 2nd run:
[[1.41684507e+01 2.16912676e+01 9.32536620e+01 6.25071831e+02
  1.05981127e-01 1.39403803e-01 1.31486479e-01 6.66121127e-02
  1.94956338e-01 6.65381690e-02 4.01209859e-01 1.22968028e+00
  2.89861972e+00 3.54732394e+01 6.96430986e-03 3.17556620e-02
  3.89342254e-02 1.39222394e-02 2.09582958e-02 4.15969014e-03
  1.67556338e+01 3.02914085e+01 1.12257183e+02 8.63574648e+02
  1.53298169e-01 3.99116338e-01 4.44295493e-01 1.64238732e-01
  3.39373239e-01 1.01006056e-01 2.32957746e+00 3.01408451e+00]
 [2.04317021e+01 2.24585106e+01 1.35461702e+02 1.29820426e+03
  1.01604255e-01 1.57680000e-01 1.95104468e-01 1.09743404e-01
  1.95751064e-01 6.06670213e-02 7.74257447e-01 1.23068511e+00
  5.47257447e+00 1.00652553e+02 6.68331915e-03 3.27308511e-02
  4.50385106e-02 1.61442128e-02 2.09727660e-02 3.89263830e-03
  2.49351064e+01 2.94153191e+01 1.67219149e+02 1.90785106e+03
  1.39770426e-01 3.73185106e-01 4.73268085e-01 2.00331489e-01
  3.21804255e-01 8.59502128e-02 3.49148936e+00 4.06382979e+00]
 [1.77027692e+01 2.24589231e+01 1.16347692e+02 9.75433846e+02
  1.00285231e-01 1.32611231e-01 1.44320308e-01 8.42136923e-02
  1.89989231e-01 6.07744615e-02 6.13432308e-01 1.35310462e+00
  4.27640000e+00 6.84778462e+01 6.91909231e-03 3.06902769e-02
  4.07900000e-02 1.58074154e-02 2.04320462e-02 4.02564615e-03
  2.10821538e+01 3.01349231e+01 1.39724615e+02 1.36141538e+03
  1.37638923e-01 3.23387692e-01 3.94838615e-01 1.69975692e-01
  3.08378462e-01 8.44395385e-02 3.02000000e+00 3.03076923e+00]
 [2.35563636e+01 2.46300000e+01 1.56118182e+02 1.74590909e+03
  1.01784545e-01 1.58554545e-01 2.21609091e-01 1.34490909e-01
  1.84372727e-01 5.93345455e-02 1.12993636e+00 1.27262727e+00
  7.74863636e+00 1.76058182e+02 5.47018182e-03 2.63345455e-02
  3.70290909e-02 1.49672727e-02 1.78472727e-02 3.35472727e-03
  3.09372727e+01 3.29990909e+01 2.06809091e+02 2.95145455e+03
  1.38245455e-01 3.48081818e-01 4.66627273e-01 2.26745455e-01
  2.95609091e-01 8.28236364e-02 2.77272727e+00 1.90909091e+00]]
```

b. Select the best of the above three clustering's and explain how you chose the best candidate.

The best clustering is K_Means_1, as the Total SSE for 1st run is 11568657.164078, which is lowest compared to 2nd and 3rd run, which are 11572261.859488767, 11 571858.028907144.

c. For the best candidate clustering chosen by you plot the Silhouette coefficient for the clustering. Compute and report the average Silhouette coefficient for each cluster of the chosen clustering.

Best Clustering candidate = K_Means_1

CODE:

```
AvgSilhouetteScoreOfCluster = silhouette_score(X, K_Means_1.labels_)
print('Mean Silhouette Coefficient of all samples:='+ str(AvgSilhouetteScoreOfCluster))
```

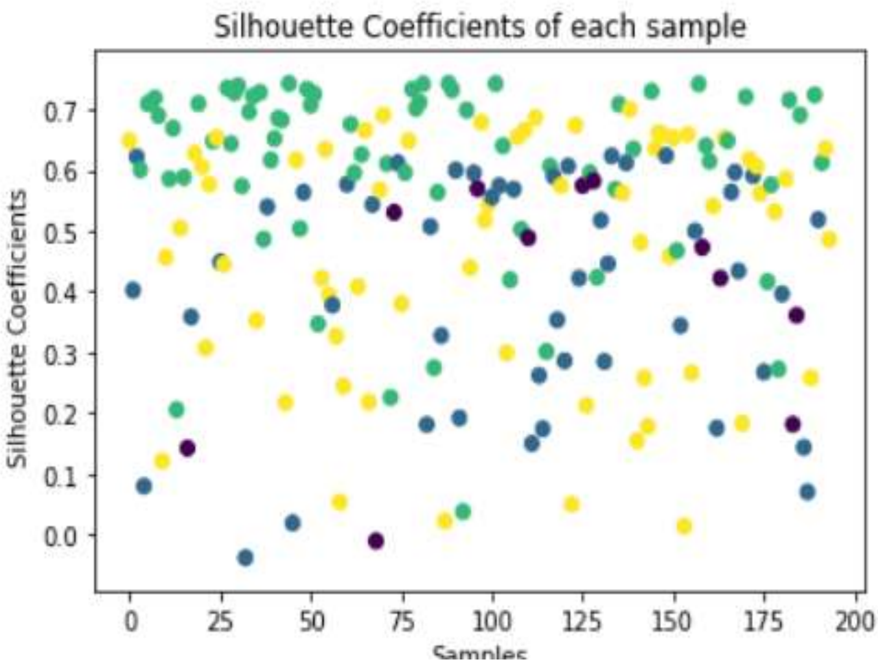
OUTPUT:

```
mean Silhouette Coefficient of all samples:=0.5008996425644388
```

CODE:

```
silhouettePerSample = silhouette_samples(X, K_Means_1.labels_)
%matplotlib inline
plt.scatter(range(len(X)),silhouettePerSample, c=K_Means_1.labels_)
plt.figsize = (35,25)
plt.xlabel("Samples")
plt.ylabel("Silhouette Coefficients ")
plt.title("Silhouette Coefficients of each sample")
```

OUTPUT:



- **Silhouette Coefficient for each cluster**

CODE:

```
for i in range(4):
   cluster_samples = silhouettePerSample[K_Means_1.labels_ == i]
   avg_cluster_silhouette = np.sum(cluster_samples, axis=0)/len(cluster_samples)
   print("Silhoutte Coefficient for cluster "+str(i)+" = "+str(avg_cluster_silhouette))
```

OUTPUT:

```
Silhoutte Coefficient for cluster 0 = 0.39235086742978814
Silhoutte Coefficient for cluster 1 = 0.41175448713040125
Silhoutte Coefficient for cluster 2 = 0.6095792912961995
Silhoutte Coefficient for cluster 3 = 0.4658488445544381
```

d. Now consider the class label for each data point in each cluster ("R" or "N"). To each cluster assign the label that belongs to most of the data points in that cluster. Report the cluster center, its SSE, and its class label, and the fraction of points that have the class label.

CODE:

```
Class = []
sse = clusters_SSE1
for i in range(4):
    print('\n\nFor Cluster ' + str(i+1))
    print('Cluster center: \n' + str(K_Means_1.cluster_centers_[i]))
    print('SSE: \t' + str(sse[i]))
    print('CLASS LABEL:= ' + str(labels.idxmax()))
    labels = (y[K_Means_1.labels_ == i]).value_counts()
    Class.append(labels.idxmax())
    fraction = labels.max()/(labels.max()+labels.min())
    print('Fraction of points that have the class label: \t'+ str(fraction))
```

OUTPUT:

```
For Cluster 1
Cluster center:
[2.35563636e+01 2.46300000e+01 1.56118182e+02 1.74590909e+03
 1.01784545e-01 1.58554545e-01 2.21609091e-01 1.34490909e-01
 1.84372727e-01 5.93345455e-02 1.12993636e+00 1.27262727e+00
 7.74863636e+00 1.76058182e+02 5.47018182e-03 2.63345455e-02
 3.70290909e-02 1.49672727e-02 1.78472727e-02 3.35472727e-03
 3.09372727e+01 3.29990909e+01 2.06809091e+02 2.95145455e+03
 1.38245455e-01 3.48081818e-01 4.66627273e-01 2.26745455e-01
 2.95609091e-01 8.28236364e-02 2.77272727e+00 1.90909091e+00]
SSE:	2795136.257930213
CLASS LABEL:= N
Fraction of points that have the class label:	0.5454545454545454


For Cluster 2
Cluster center:
[2.04033333e+01 2.25075000e+01 1.35312500e+02 1.29415833e+03
 1.01379375e-01 1.58957500e-01 1.95429375e-01 1.09532292e-01
 1.96485417e-01 6.07245833e-02 7.78566667e-01 1.23975417e+00
 5.54252083e+00 1.00741042e+02 6.68050000e-03 3.41447917e-02
 4.61258333e-02 1.63574583e-02 2.16468750e-02 3.97083333e-03
 2.49175000e+01 2.94935417e+01 1.67431250e+02 1.90250000e+03
 1.39456458e-01 3.80918750e-01 4.78495833e-01 2.01351667e-01
 3.24829167e-01 8.63220833e-02 3.46666667e+00 3.97916667e+00]
SSE:	3744386.7368627535
CLASS LABEL:= N
Fraction of points that have the class label:	0.7291666666666666


For Cluster 3
Cluster center:
[1.41684507e+01 2.16912676e+01 9.32536620e+01 6.25071831e+02
 1.05981127e-01 1.39403803e-01 1.31486479e-01 6.66121127e-02
 1.94956338e-01 6.65381690e-02 4.01209859e-01 1.22968028e+00
```

```
 2.89861972e+00 3.54732394e+01 6.96430986e-03 3.17556620e-02
 3.89342254e-02 1.39222394e-02 2.09582958e-02 4.15969014e-03
 1.67556338e+01 3.02914085e+01 1.12257183e+02 8.63574648e+02
 1.53298169e-01 3.99116338e-01 4.44295493e-01 1.64238732e-01
 3.39373239e-01 1.01006056e-01 2.32957746e+00 3.01408451e+00]
SSE:   2462018.7541844267
CLASS LABEL:= N
Fraction of points that have the class label:     0.8450704225352113


For Cluster 4
Cluster center:
[1.76814062e+01 2.24221875e+01 1.16160938e+02 9.73425000e+02
 1.00433281e-01 1.31261406e-01 1.43283125e-01 8.39731250e-02
 1.89348437e-01 6.06314062e-02 6.07687500e-01 1.34821562e+00
 4.20525000e+00 6.79087500e+01 6.92489063e-03 2.95979375e-02
 3.99081250e-02 1.56422187e-02 1.99180156e-02 3.96907812e-03
 2.10351562e+01 3.00875000e+01 1.39135938e+02 1.35689062e+03
 1.37841094e-01 3.16809375e-01 3.89692344e-01 1.68736250e-01
 3.05900000e-01 8.41370312e-02 3.03125000e+00 3.07812500e+00]
SSE:   2567115.4151013456
CLASS LABEL:= N
Fraction of points that have the class label:     0.734375
```

e. Now, use the cluster centers and the class labels as a new classifier. Consider each data point again as belonging to your test set. For each data point predict its class label to be the one that belongs to the cluster center that is closest to the data point. Build the confusion matrix for this new classifier and compute its accuracy, precision and recall values.

CODE:

```
confusion_matrix(y, Pred)
```

OUTPUT:

```
array([[148,   0],
       [ 46,   0]], dtype=int64)
```

For non recurrence class, TP = 148, FP = 46, TN = 0, FN = 0

For recurrence calss, TP = 0, FP = 0, TN = 148, FN = 46

CODE:

```
from sklearn.metrics import classification_report
print(classification_report(y, Pred))
accuracy = accuracy_score(y, Pred)
print('\nAccuracy:=  ' + str(accuracy))
```

	precision	recall	f1-score	support
N	0.76	1.00	0.87	148
R	0.00	0.00	0.00	46
avg / total	0.58	0.76	0.66	194

```
Accuracy:=  0.7628865979381443
```

f. Compare these performance results with those obtained by you in HW3 Q1. Comment on the possible causes for the differences between the two sets of performance values.

```
FOR HW3 Q1,
Mean Accuracy using four fold: 0.763 (std: 0.008)

For Non-Recurrence class Precision 0.8154761904761905
Recall 0.925675675 F1 Score 0.8670886075949368

For Recurrence class Precision 0.5769230769230769
Recall 0.326086 F1 Score 0.4166666666666663

FOR HW3B,

Accuracy: = 0.7628865979381443
```

Class	precision	recall	f1-score	support
N	0.76	1.00	0.87	148
R	0.00	0.00	0.00	46

- **Accuracy is nearly same for clustering and Decision Tree algorithm But, there is large difference between the precision and recall values of recurrence class. Since, clustering predicts all recurrence dataset as non-recurrence, precision and recall value is zero for this class, whereas decision tree correctly predicts few of recurrence class datasets.**

2. Mix the datasets for the red and white wines in one dataset. Perform k-means clustering on this large dataset for the values of k to be: 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, and 14. For each value of k report the lowest total SSE value after selecting the best of the 3-runs for each value of k. Plot the SSE value vs. the value of k. What can you infer from this plot?

CODE:

```
dataW = pd.read_csv("winequality-white.csv")
dataR = pd.read_csv("winequality-red.csv")
data = pd.concat([dataW, dataR], axis=0)
num_clusters = [3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14]
SSEVal = []
min_SSE= []
for i in num_clusters:
    print(" For No of clusters(k)= " + str(i))
    for k in range(3):
        K_Means = KMeans(n_clusters=i, init='random').fit(data)
        SSE = K_Means.inertia_
        SSEVal.append(SSE)
        min_sse = min(SSEVal)
    min_SSE.append(min_sse)
    print(" Minimum SSE:     "+ str(min_sse) + "\n")
```

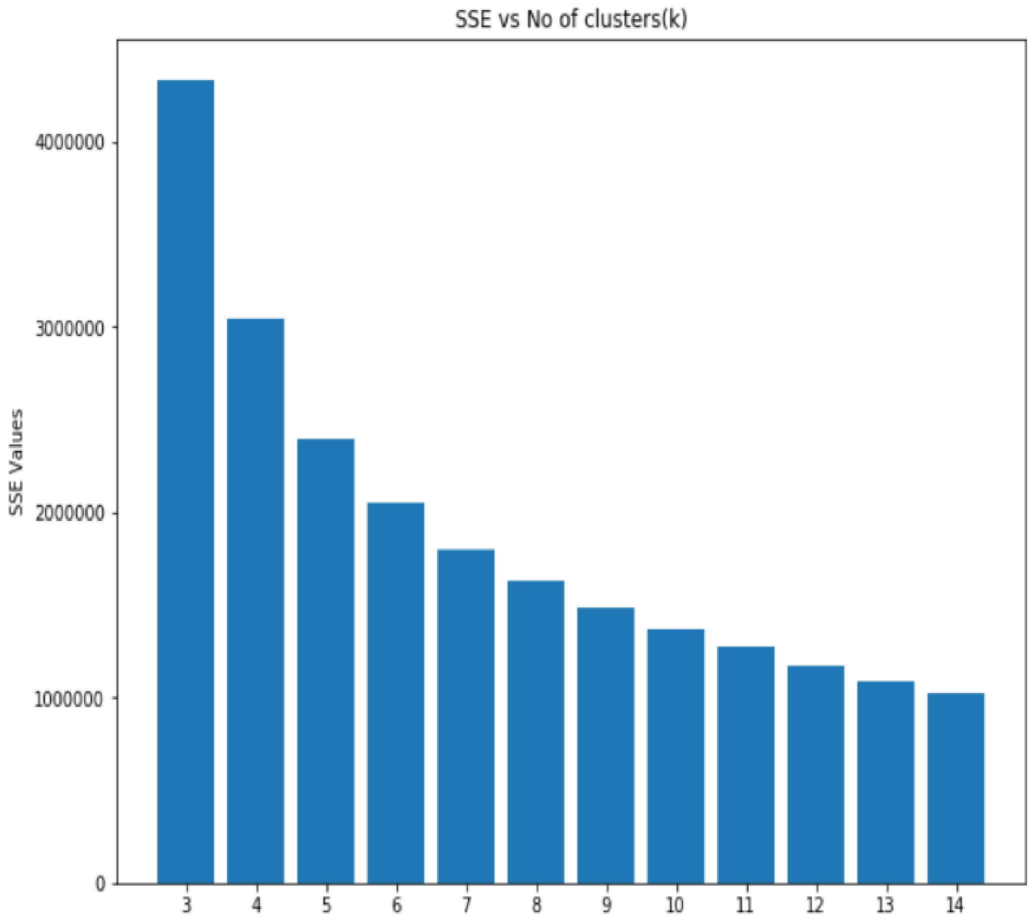
OUTPUT:

```
For No of clusters(k)= 3
Minimum SSE:     4336387.441652566

For No of clusters(k)= 4
Minimum SSE:     3043516.8905087877

For No of clusters(k)= 5
Minimum SSE:     2398851.170080419

For No of clusters(k)= 6
Minimum SSE:     2046427.9092727543

For No of clusters(k)= 7
Minimum SSE:     1801340.7858560903

For No of clusters(k)= 8
Minimum SSE:     1628570.0455626736

For No of clusters(k)= 9
Minimum SSE:     1487998.6982805221

For No of clusters(k)= 10
Minimum SSE:     1371831.0411858177

For No of clusters(k)= 11
Minimum SSE:     1272185.5117560178

For No of clusters(k)= 12
Minimum SSE:     1185073.8043305934

For No of clusters(k)= 13
Minimum SSE:     1117115.8245017577

For No of clusters(k)= 14
Minimum SSE:     1028438.9697431189
```

CODE:

```
plt.figure(figsize = (10,8))
plt.bar(np.arange(12),min_SSE)
plt.xticks(np.arange(12), num_clusters)
plt.xlabel("No of clusters(k)")
plt.ylabel("SSE Values")
plt.title("SSE vs No of clusters(k)")
plt.show()
```

OUTPUT:



- **As seen from above graph, the SSE value decreases as the number of clusters are increased, this is because as the number of cluster increases the number of datasets per cluster decreases and so the distance between the cluster centre and cluster points.**