

# **Statistical Data Mining**

## **Spring**

### **Assignment -2**

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**Class No 05**

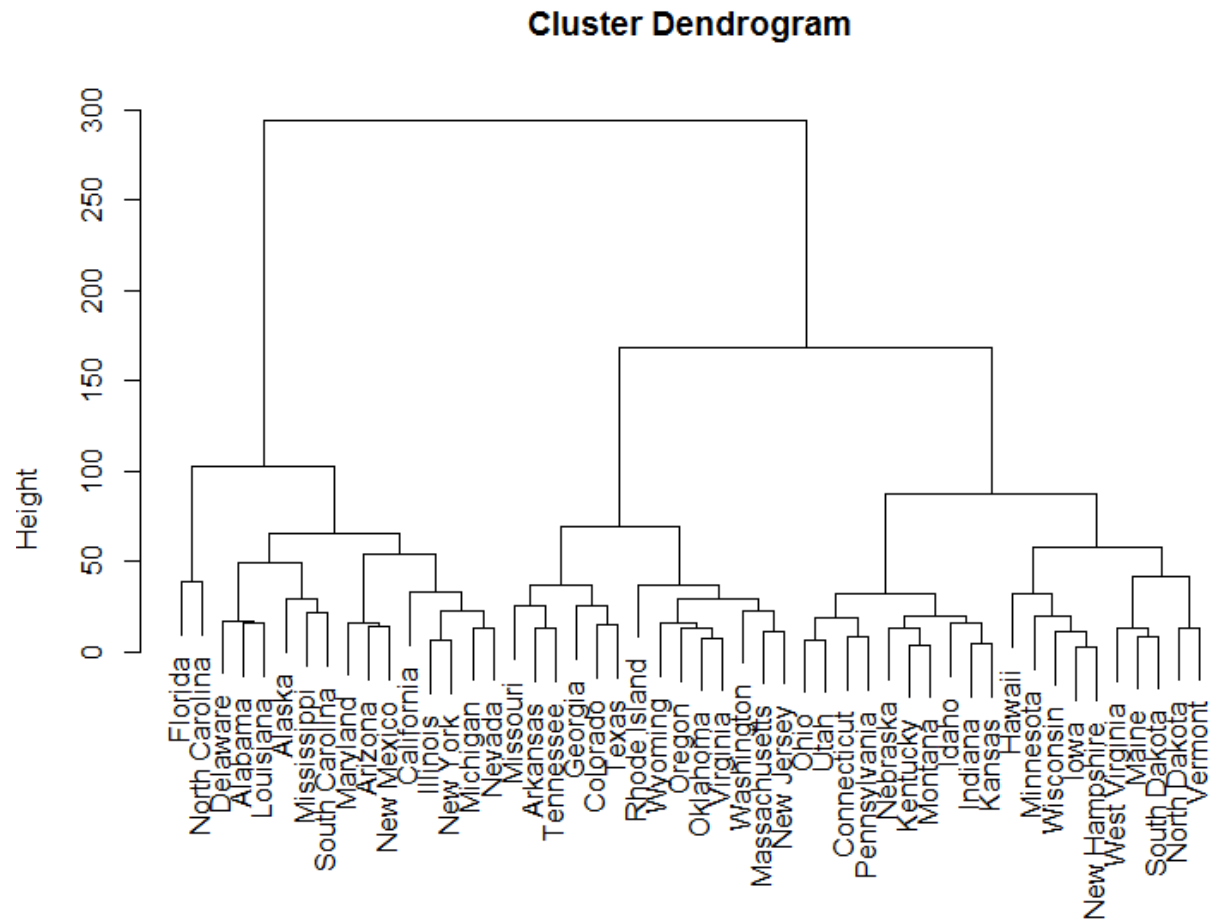
The State University of New York at Buffalo

Engineering Sciences - Data Science

**Question 1** Consider the **USArrests** data. We will now perform hierarchical clustering on the states.

(a) Using hierarchical clustering with complete linkage and Euclidean distance, cluster the states.

Step1 Hierarchical Clustering





- d. What effect does scaling the variables have on the hierarchical clustering obtained ?  
In your opinion, should the variables be scaled before the inter-observation dissimilarities are computed ? Provide a justification for your answer.

```
> cutree(heri_comp_scaled, 3)
Alabama      Alaska      Arizona      Arkansas      California      Colorado      Connecticut      Delaware
1            1            2            3            2            2            3            3
Florida      Georgia      Hawaii      Idaho      Illinois      Indiana      Iowa      Kansas
2            1            3            3            2            3            3            3
Kentucky      Louisiana      Maine      Maryland      Massachusetts      Michigan      Minnesota      Mississippi
3            1            3            2            3            2            3            1
Missouri      Montana      Nebraska      Nevada      New Hampshire      New Jersey      New Mexico      New York
3            3            3            2            3            3            2            2
North Carolina      North Dakota      Ohio      Oklahoma      Oregon      Pennsylvania      Rhode Island      South Carolina
1            3            3            3            3            3            3            1
South Dakota      Tennessee      Texas      Utah      Vermont      Virginia      Washington      West Virginia
3            1            2            3            3            3            3            3
Wisconsin      Wyoming
3            3
```

```
> table(cutree(heri_comp_scaled, 3), cutree(heri_comp_scaled, 3))
      1  2  3
1    8  0  0
2    0 11  0
3    0  0 31
> |
```

After scaling the cluster are having different value but the tree is similar so it is advisable to scale the data first and then do clustering. As all the features would be on same scale.

**Question 2** On the book website, [www.StatLearning.com](http://www.StatLearning.com), there is a gene expression data set (Ch10Ex11.csv) that consists of 40 tissue samples with measurements on 1,000 genes. The first 20 samples are from healthy patients, while the second 20 are from a diseased group.

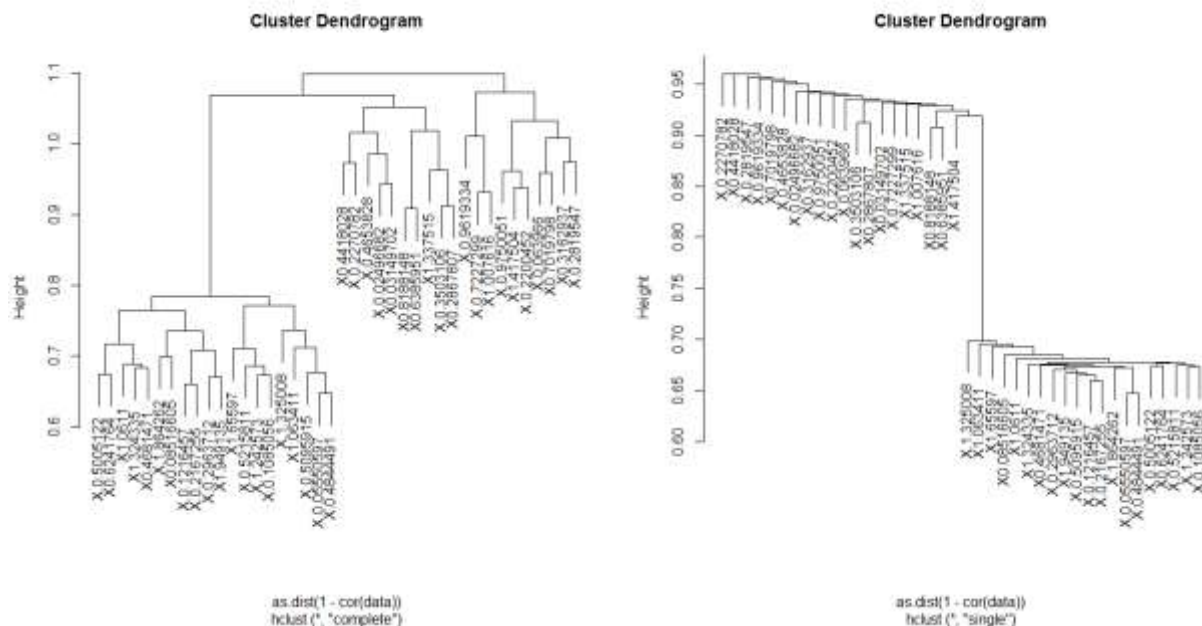
Solution 2

Step 1 ) Load the data set

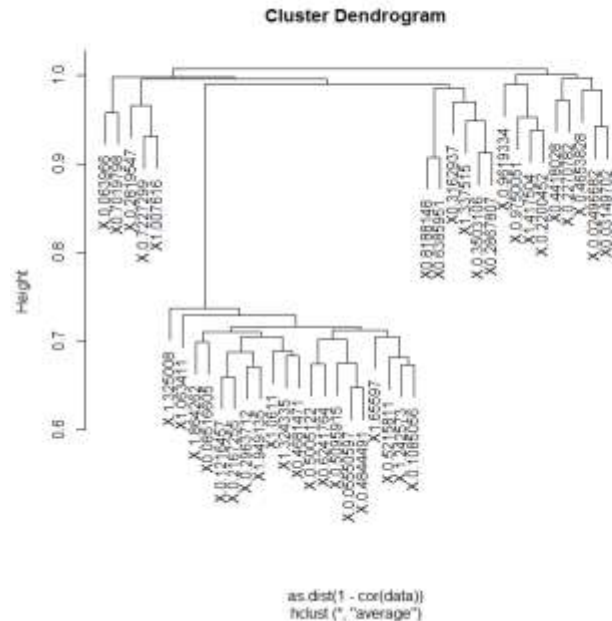
```
balanced Accuracy      1.0000      1.0000      0.9203      0.
> data <- read.csv('Ch10Ex11.csv',header =TRUE)
> |
```

Step 2) Applying hierarchal clustering using three methods single, complete and average

Complete hierarchal clustering and Single Clustering plots



Plot for average hierarchal clustering



From the above plot we can see that results are different for all three methods

Clustering	single	complete	average
No of cluster	2	2	3

Step 3) Doing PCA can help understand which genes differ the most and will capture the max variation in each components from pc1 onwards as shown

	head(pca.data\$rotation)															
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8								
[1,]	-0.002020577	-0.026729160	0.050923384	-0.025335813	0.002540427	-0.003845007	-0.036264394	-0.021687824								
[2,]	-0.011323705	-0.006375876	0.014463864	0.054334418	-0.020430305	0.026024237	0.071661302	0.046283318								
[3,]	-0.011818181	-0.002698934	0.033669694	-0.012669666	0.005993466	-0.003124366	-0.001993498	-0.005750509								
[4,]	0.007295620	-0.011506243	-0.008541655	-0.001656472	0.005898937	-0.019434963	0.002023317	0.049955321								
[5,]	0.017925282	-0.027195193	-0.020230126	-0.023628687	-0.019715348	-0.047743565	-0.040426164	-0.006254015								
[6,]	0.002431410	-0.080527984	-0.045067008	-0.033022683	-0.036120073	-0.017473524	0.017128909	-0.011174570								
	PC9	PC10	PC11	PC12	PC13	PC14	PC15	PC16								
[1,]	0.005413988	-0.01241626	0.089905979	0.03416619	-0.009418017	0.024673821	-0.040654553	0.03726500								
[2,]	-0.01311219	-0.025990037	0.015388740	0.021917274	-0.010281512	0.003914036	-0.006259321	-0.01767650								
[3,]	-0.010031756	-0.01748695	0.006036607	0.02582668	0.085603154	0.008495326	-0.046722012	0.01912605								
[4,]	-0.009329362	0.01950252	0.048478336	-0.07576305	0.054437344	-0.010566001	0.063164802	0.04190348								
[5,]	-0.005873346	0.02371620	-0.022867535	-0.01490424	-0.019137859	-0.004722886	-0.02513212	0.01076301								
[6,]	0.016898872	0.028406677	-0.011376237	-0.03138241	-0.026675291	0.013475190	0.037666948	0.01376594								
	PC17	PC18	PC19	PC20	PC21	PC22	PC23	PC24								
[1,]	0.013405021	-0.018148069	-0.02171085	-0.001871207	-0.001787212	0.005831217	-0.006867130	-0.038552270								
[2,]	0.007094665	-0.026699275	-0.02057786	0.013803662	0.010021512	-0.039755267	-0.060629437	-0.02887159								
[3,]	0.012236082	-0.032214354	-0.05211059	-0.036741162	0.077080616	0.001732929	0.070134403	-0.006380881								
[4,]	0.038867738	-0.039679957	-0.01219022	0.018292071	-0.038262274	-0.023098630	-0.048254710	0.002980197								
[5,]	0.035919094	-0.028369572	-0.028117223	0.009850524	-0.004041523	0.013165695	-0.013431695	-0.019222502								
[6,]	-0.025107250	0.004694277	-0.02000222	0.010055779	-0.022060884	-0.012907933	-0.036313946	0.042035021								
	PC25	PC26	PC27	PC28	PC29	PC30	PC31	PC32								
[1,]	-0.006731389	0.041015530	0.03994101	-0.009034578	-0.024621894	-0.007557639	-0.04542839	0.014528075								
[2,]	0.035427922	-0.064429449	-0.01893297	0.036050765	0.004615966	0.004120397	0.03053793	0.02509743								
[3,]	-0.00421179	0.025859282	-0.0145592	0.075857504	0.010257575	0.016446668	-0.0415866	0.017560605								

```
> load_overall = apply(pca_data$rotation, 1, sum)
> row= order(abs(load_overall), decreasing = TRUE)
> row[1:10]
[1] 979 864 67 11 910 236 623 716 896 523
>
```

**Question 3) Access the data “primate.scapulae” a) Cluster the data based on single-linkage, average linkage, and complete-linkage agglomerative hierarchical clustering. Decide on the groupings, and justify it, for all three methods. Calculate the misclassification rate. Which method performed the best and which method performed the worst? Was the result in line with your expectations?**

Solution 3)

Step1 ) Load the data

Step 2) Removing the na there are 40 missing values

```
> sum(is.na(primate.scapulae$gamma))
[1] 40
```

After removing missing value check

```
> sum(is.na(primate.scapulae$gamma))
[1] 0
```

Step 3) Scaling the data

Step 4) Calculating the distance matrix

```

      1      2      3      4      5      6      7      8      9
2  2.4206671
3  3.2392671 2.1859726
4  1.7276718 3.9409410 4.4379195
5  1.1021311 2.0217118 2.9025877 2.0976657
6  3.4451515 3.7141324 3.0684798 3.6691877 3.0902276
7  1.6869368 3.1366878 3.2265082 1.7114336 1.3914419 2.9266307
8  2.2802608 2.7983255 2.3799098 3.0124301 2.3459054 1.6441837 2.4679415
9  1.5744628 2.5124795 2.6141864 2.1600912 0.9688386 2.5126984 1.0131145 1.9925767
10 1.9022662 3.3799795 3.4018825 1.6724827 1.7276831 2.4726412 1.2559171 2.1645063 1.1495184
```

step 5) calculating for single linkage hierarchal clustering, displaying table and printing confusion matrix

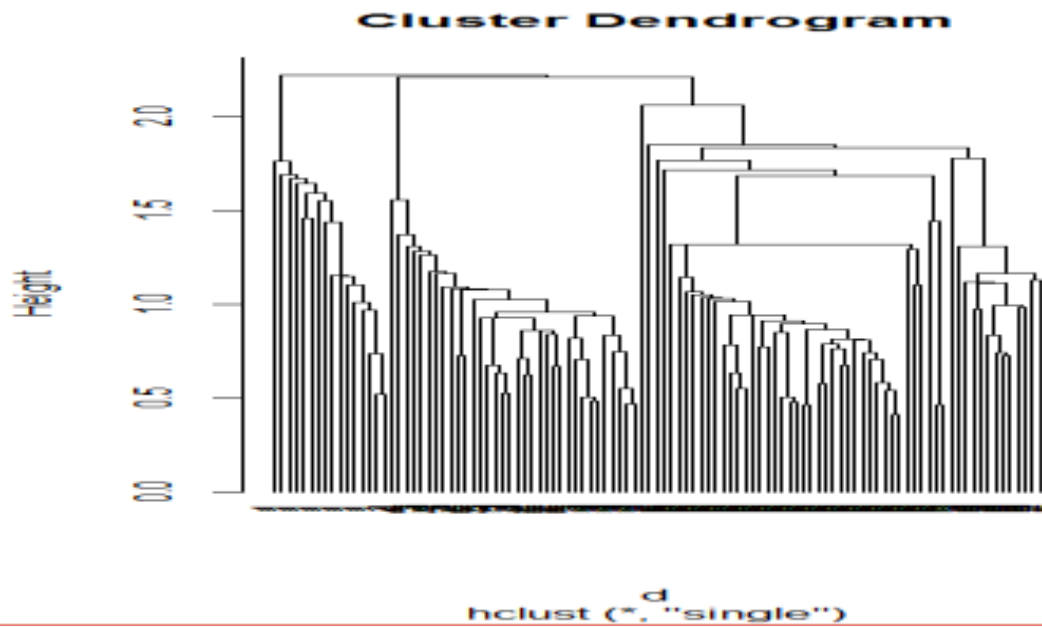


Table for single linkage as we can see 2 samples were misclassified

```
> table(cutree(heri_clust_single, k=5), primate.scapulae$classdigit)
```

	1	2	3	4	5
1	16	0	0	0	0
2	0	13	0	0	40
3	0	1	0	0	0
4	0	1	0	0	0
5	0	0	20	14	0

overall statistics

```
Accuracy : 0.2762
95% CI : (0.1934, 0.372)
No Information Rate : 0.381
P-Value [Acc > NIR] : 0.9908
```

```
Kappa : 0.0699
```

```
Mcnemar's Test P-Value : NA
```

statistics by class:

	Class: 1	Class: 2	Class: 3	Class: 4	Class: 5
Sensitivity	1.0000	0.8667	0.000000	0.000000	0.0000
Specificity	1.0000	0.5556	0.988235	0.989011	0.4769
Pos Pred Value	1.0000	0.2453	0.000000	0.000000	0.0000
Neg Pred Value	1.0000	0.9615	0.807692	0.865385	0.4366
Prevalence	0.1524	0.1429	0.190476	0.133333	0.3810
Detection Rate	0.1524	0.1238	0.000000	0.000000	0.0000
Detection Prevalence	0.1524	0.5048	0.009524	0.009524	0.3238
Balanced Accuracy	1.0000	0.7111	0.494118	0.494505	0.2385

```
> |
```



Step 6) Calculating **Average clustering** linkage , plotting the cluster and display confusion matrix

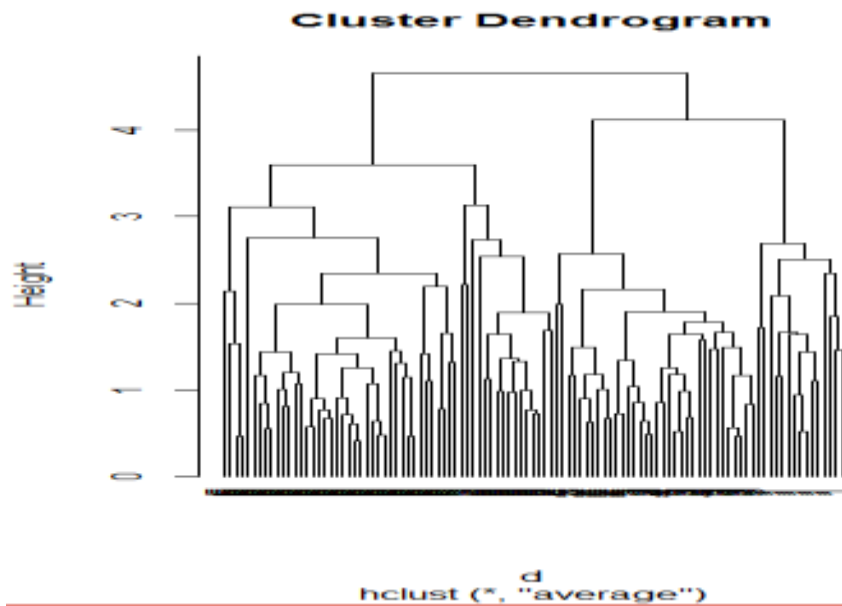


Table for the Average hierarchical clustering as we can see 2 were miss classified

```
> table(cutree(heri_clust_avg, k=5), primate.scapulae$classdigit)
```

```

      1  2  3  4  5
1 15  0  0  0  0
2  1  1  0  0  0
3  0 14  0  0  0
4  0  0 20 14  0
5  0  0  0  0 40
> |
```

Confusion Matrix for Average hierarchical clustering

#### Overall Statistics

```

Accuracy : 0.6667
95% CI : (0.568, 0.7557)
No Information Rate : 0.381
P-value [Acc > NIR] : 2.927e-09
```

```
Kappa : 0.5624
```

```
Mcnemar's Test P-value : NA
```

#### Statistics by Class:

	Class: 1	Class: 2	Class: 3	Class: 4	Class: 5
Sensitivity	0.9375	0.066667	0.0000	1.0000	1.000
Specificity	1.0000	0.988889	0.8353	0.7802	1.000
Pos Pred Value	1.0000	0.500000	0.0000	0.4118	1.000
Neg Pred Value	0.9889	0.864078	0.7802	1.0000	1.000
Prevalence	0.1524	0.142857	0.1905	0.1333	0.381
Detection Rate	0.1429	0.009524	0.0000	0.1333	0.381
Detection Prevalence	0.1429	0.019048	0.1333	0.3238	0.381
Balanced Accuracy	0.9688	0.527778	0.4176	0.8901	1.000

Step 7 ) Calculating for **complete** hierarchical clustering  
as we can see 3 were misclassified

```
> heri_clust_comp1 <- hclust(d, method = "complete")
> table(cutree(heri_clust_comp1, k=5), primate.scapulae$classdigit)
```

```
      1  2  3  4  5
1 14  0  0  0  0
2  2  1  0  0  0
3  0 14  0  0  0
4  0  0 20 14  0
5  0  0  0  0 40
```

overall statistics

```
Accuracy : 0.6571
 95% CI : (0.5581, 0.747)
No Information Rate : 0.381
P-Value [Acc > NIR] : 9.417e-09
```

```
Kappa : 0.55
```

```
Mcnemar's Test P-Value : NA
```

Statistics by Class:

```
      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
Sensitivity    0.8750 0.066667  0.0000  1.0000  1.000
Specificity    1.0000 0.977778  0.8353  0.7802  1.000
Pos Pred Value 1.0000 0.333333  0.0000  0.4118  1.000
Neg Pred Value 0.9780 0.862745  0.7802  1.0000  1.000
Prevalence     0.1524 0.142857  0.1905  0.1333  0.381
Detection Rate 0.1333 0.009524  0.0000  0.1333  0.381
Detection Prevalence 0.1333 0.028571  0.1333  0.3238  0.381
Balanced Accuracy 0.9375 0.522222  0.4176  0.8901  1.000
> |
```

Average hierarchical clustering has the best accuracy with 65% among all the three clustering method, Yes average was the best way to calculate compared to single and complete clustering method.

## Question 3 b

Cluster the data based on K-means or K-medoids. Use an analytical technique to justify your choice in “k”. How did the performance compare to the hierarchical clustering of part a? Which did you feel was a better method for this data?

Step1 ) Clustering the data based on k mediods

Step 2) Optimal value of K

```
> # optimal value of k
> kmediods$nc
[1] 5
```

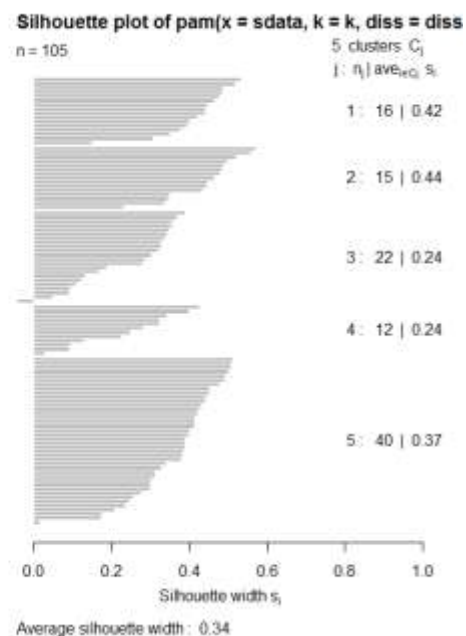
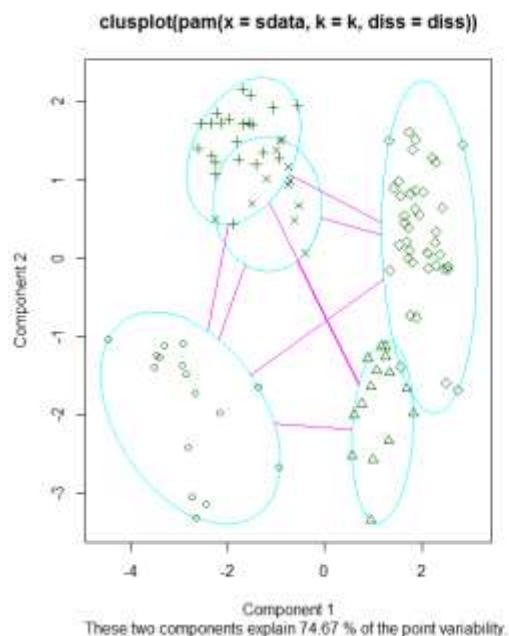
Step 3) tabulating the results

```
> table(kmediods$pamobject$clustering, primate.scapulae$classdigit)
```

```
      1  2  3  4  5
1 16  0  0  0  0
2  0 15  0  0  0
3  0  0 18  4  0
4  0  0  2 10  0
5  0  0  0  0 40
```

```
> |
```

Step 4) Plotting the results



## Step 5) Confusion Matrix observations

## overall Statistics

Accuracy : 0.9429  
95% CI : (0.8798, 0.9787)  
No Information Rate : 0.381  
P-value [Acc > NIR] : < 2.2e-16

Kappa : 0.9244

Mcnemar's Test P-value : NA

## statistics by class:

	class: 1	class: 2	class: 3	class: 4	class: 5
Sensitivity	1.0000	1.0000	0.9000	0.71429	1.000
Specificity	1.0000	1.0000	0.9529	0.97802	1.000
Pos Pred Value	1.0000	1.0000	0.8182	0.83333	1.000
Neg Pred Value	1.0000	1.0000	0.9759	0.95699	1.000
Prevalence	0.1524	0.1429	0.1905	0.13333	0.381
Detection Rate	0.1524	0.1429	0.1714	0.09524	0.381
Detection Prevalence	0.1524	0.1429	0.2095	0.11429	0.381
Balanced Accuracy	1.0000	1.0000	0.9265	0.84615	1.000

Accuracy is 94% as per the accuracy K-medoids way is better.

**Question 4** Run a batch-SOM analysis on the Wisconsin Breast-Cancer data ([https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+\(Prognostic\)](https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Prognostic))). Describe how well the SOM methods cluster the tumor cases into benign and malignant. Compute the U-matrix and discuss its representation for these data.

Step1) Load the data

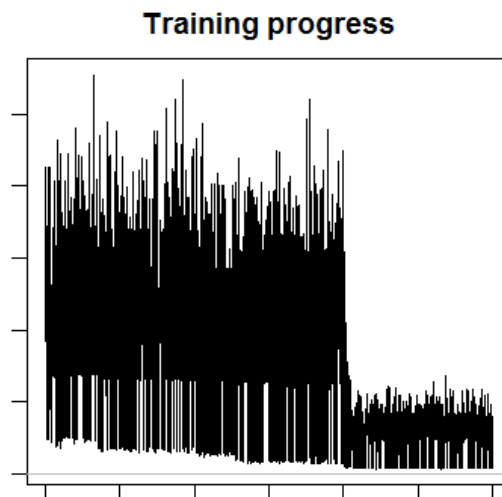
Step 2) Converting the data types to numeric

Step 3) Scaling the data

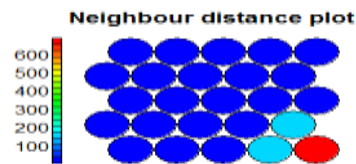
Step4 ) making the som grid applying the som model

```
> som_map_grid <- somgrid(xdim = 5, ydim = 5, topo = "hexagonal")  
> cancer_data_som <- som(cancer_data_scaled, grid = som_map_grid, rlen = 3000)
```

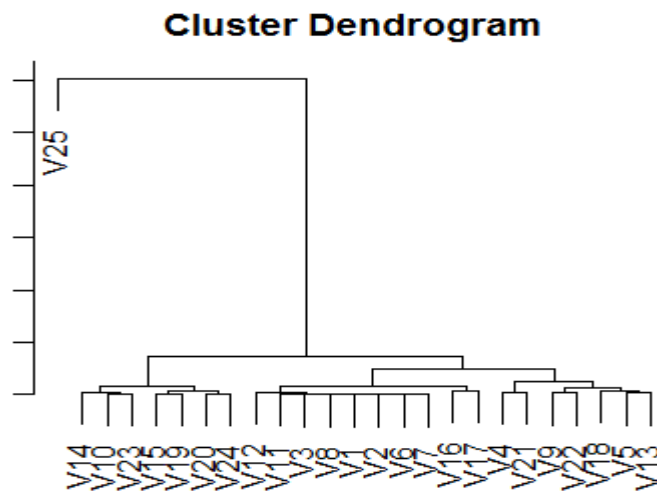
Step 5) Plotting the som codes with type as changes and we can see it converges after 2000 iterations



Step 7) SOM U matrix plot as we can see the dark blue nodes are near by based on Euclidean distance , light blue are bit further and red are at extremes.



Step 8) Clustering the codes



Step 9) Plotting the results and we see two clusters are formed clearly

**Mapping plot**

