Clustering Analyses: Partitioning

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The 'knit' chunck will allow us to 'knit' the Rmarkdown to a pdf for submission

Clustering Technique: Partitioning

read in Group 4 merged data set from out github folder

```
library(readr)

link='https://raw.githubusercontent.com/Public-Policy-COVID/students_merge/main/Merged_data.csv'

data = read.csv(link)
```

reset indexes to R format:

```
row.names(data)=NULL
```

Partitioning

-We will request a particular number of clusters to the algorithm. The algorithm will put every case in one of those clusters (note: outliers affect output)

For clustering, the variables need to be numeric. Change non-numeric variables (Deaths_COVID & Deaths_total) with integers to numeric.

```
data$Deaths_COVID<-as.numeric(data$Deaths_COVID)

data$Deaths_total<-as.numeric(data$Deaths_total)
```

a. select variables to use for clustering

```
dfClus=data[,c('Number_of_beds','mask_score','Deaths_COVID','Deaths_total','Number_of_hospitals', "blac

summary(dfClus)
```

```
##  Number_of_beds      mask_score     Deaths_COVID   Deaths_total
##  Min.   :    0.0   Min.   :2.470   Min.   :   0   Min.   :    0
##  1st Qu.:   25.0   1st Qu.:3.301   1st Qu.:   0   1st Qu.:    0
##  Median :  131.0   Median :3.464   Median :  22   Median :  637
##  Mean   :  885.4   Mean   :3.428   Mean   : 206   Mean   : 2896
##  3rd Qu.:  553.0   3rd Qu.:3.591   3rd Qu.: 128   3rd Qu.: 2537
##  Max.   :26672.0   Max.   :3.822   Max.   :8034   Max.   :75463
##  Number_of_hospitals black_total_pct  white_total_pct
##  Min.   :  0         Min.   : 0.000   Min.   :49.28
##  1st Qu.:  1         1st Qu.: 0.770   1st Qu.:82.16
##  Median :  2         Median : 1.260   Median :88.64
##  Mean   :  5         Mean   : 2.318   Mean   :85.50
##  3rd Qu.:  4         3rd Qu.: 2.620   3rd Qu.:91.84
```

```
## Max.   :112         Max.   :14.770   Max.   :96.13
```

b. rescale units

```r
dfClus=scale(dfClus)
summary(dfClus)
```

```
##  Number_of_beds      mask_score       Deaths_COVID      Deaths_total
##  Min.   :-0.3334   Min.   :-4.2726   Min.   :-0.2704   Min.   :-0.37704
##  1st Qu.:-0.3240   1st Qu.:-0.5659   1st Qu.:-0.2704   1st Qu.:-0.37704
##  Median :-0.2841   Median : 0.1612   Median :-0.2415   Median :-0.29411
##  Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.00000
##  3rd Qu.:-0.1252   3rd Qu.: 0.7277   3rd Qu.:-0.1024   3rd Qu.:-0.04674
##  Max.   : 9.7118   Max.   : 1.7581   Max.   :10.2736   Max.   : 9.44771
##  Number_of_hospitals black_total_pct   white_total_pct
##  Min.   :-0.44686    Min.   :-0.8976   Min.   :-3.8920
##  1st Qu.:-0.35749    1st Qu.:-0.5994   1st Qu.:-0.3585
##  Median :-0.26812    Median :-0.4097   Median : 0.3379
##  Mean   : 0.00000    Mean   : 0.0000   Mean   : 0.0000
##  3rd Qu.:-0.08937    3rd Qu.: 0.1169   3rd Qu.: 0.6818
##  Max.   : 9.56284    Max.   : 4.8214   Max.   : 1.1428
```

c. rename subset indexes and verify input:

```r
row.names(dfClus)=data$Location
head(dfClus)
```

```
##              Number_of_beds mask_score Deaths_COVID Deaths_total
## Alameda_CA        1.0476322  1.0666781    0.4816583   1.04310240
## Alpine_CA        -0.3334445 -0.6640201   -0.2703586  -0.37704284
## Amador_CA        -0.3138601 -0.1465949   -0.2296736  -0.32301275
## Butte_CA         -0.1251719 -0.2090427   -0.1378042  -0.07590643
## Calaveras_CA     -0.3240289 -0.6104934   -0.2546096  -0.32691854
## Colusa_CA        -0.3153666  0.1790262   -0.2546096  -0.36194046
##              Number_of_hospitals black_total_pct white_total_pct
## Alameda_CA            1.51932965       3.3732540     -3.89196747
## Alpine_CA            -0.44686166      -0.7620594     -1.88666366
## Amador_CA            -0.35748933       0.1401204      0.44640953
## Butte_CA              0.08937233      -0.1618969      0.01654805
## Calaveras_CA         -0.35748933      -0.4794022      0.58611451
## Colusa_CA            -0.35748933      -0.3903458      0.60223432
```

d. set random seed for replicability of results

```r
set.seed(999)
```

e. designate distance method and compute distance matrix

```r
library(cluster)
dfClus_D=cluster::daisy(x=dfClus)
```

f. For the partitioning technique, we need to indicate the number of clusters required

```r
NumCluster=4
res.pam = pam(x=dfClus_D,
              k = NumCluster,
              cluster.only = F)
```

g.Append the clustering results to the dataframe (data)

```r
data$pam=as.factor(res.pam$clustering)
```

h. query the data frame (we will create a table to see the number of counties per cluster and will look at King, County, WA)

```r
table(data$pam)
```

```
##
##  1  2  3  4
## 14 50 39 30
```

```r
data[data$Location=="King_WA",'pam']
```

```
## [1] 1
## Levels: 1 2 3 4
```

Evaluate results

(a)create average sillohuetes

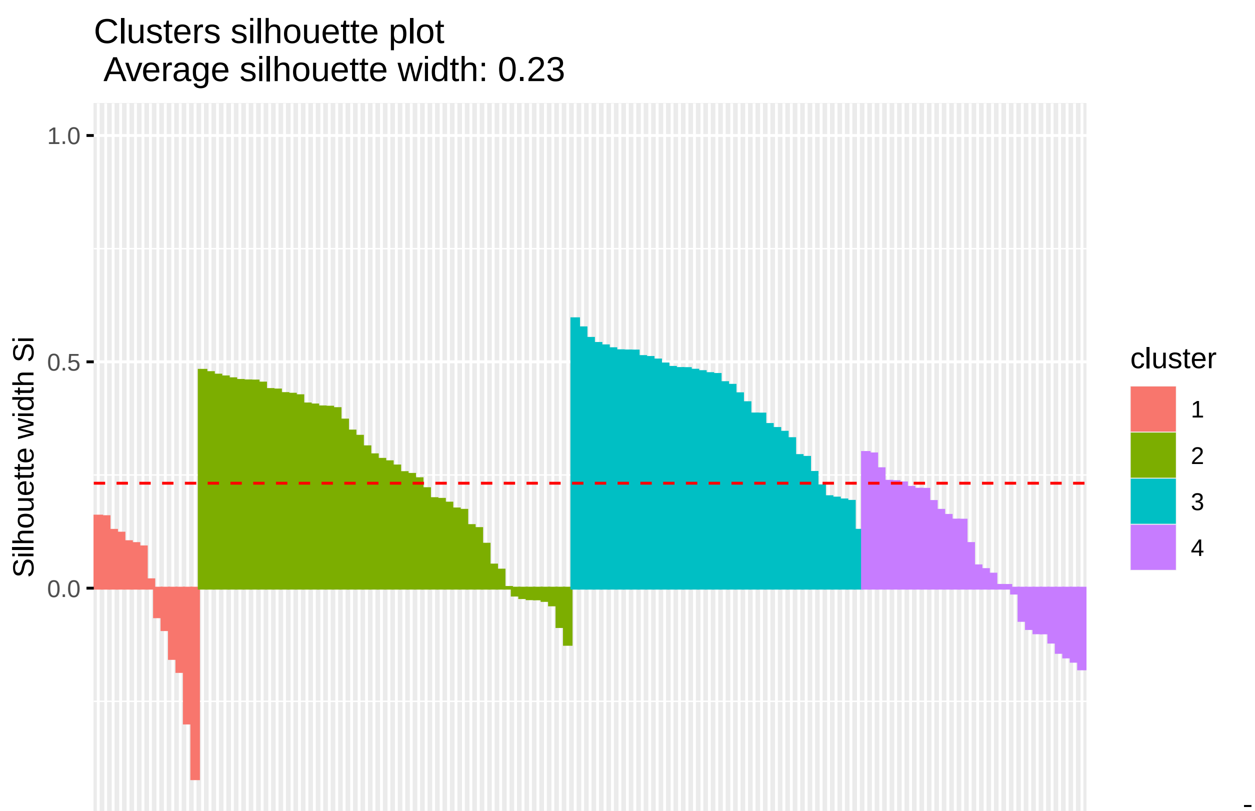
```r
library(factoextra)
```

```
## Loading required package: ggplot2

## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

```r
fviz_silhouette(res.pam)
```

```
##   cluster size ave.sil.width
## 1       1   14         -0.02
## 2       2   50          0.26
## 3       3   39          0.41
## 4       4   30          0.07
```



the average silhouette width is .23

(b) detect anomolies: -save individual silhouettes

```
pamEval=data.frame(res.pam$silinfo$widths)
head(pamEval)
```

```
##                    cluster neighbor sil_width
## Alameda_CA               1        4 0.1591567
## San Bernardino_CA        1        4 0.1579688
## Los Angeles_CA           1        4 0.1277071
## San Diego_CA             1        4 0.1215627
## Sacramento_CA            1        4 0.1027119
## King_WA                  1        4 0.0985324
```

```
-request negative silhouettes.
A negative silhouettes indicates that the item
is poorly clustered
```

```
pamEval[pamEval$sil_width<0,]
```

```
##                   cluster neighbor   sil_width
## Solano_CA               1        4 -0.06312941
## San Francisco_CA        1        4 -0.09158907
## Santa Clara_CA          1        4 -0.15525012
## Contra Costa_CA         1        4 -0.18405269
## San Joaquin_CA          1        4 -0.29794661
## Fresno_CA               1        4 -0.42095642
## Wheeler_OR              2        3 -0.01532344
## Grant_WA                2        3 -0.02085607
## Alpine_CA               2        4 -0.02335024
## Grant_OR                2        3 -0.02363649
## Cowlitz_WA              2        3 -0.02718744
## Franklin_WA             2        3 -0.03694608
## Kittitas_WA             2        3 -0.08484523
## Josephine_OR            2        3 -0.12406058
## Inyo_CA                 4        3 -0.01091712
## Santa Barbara_CA        4        3 -0.07124933
## Sonoma_CA               4        3 -0.08919528
## Humboldt_CA             4        3 -0.09860057
## Imperial_CA             4        3 -0.09878916
## Whitman_WA              4        3 -0.11925089
## Lake_CA                 4        3 -0.14186724
## Placer_CA               4        3 -0.15197878
## Island_WA               4        3 -0.16148989
## Clark_WA                4        3 -0.17829522
```