

CS282R - Sepsis Cluster Optimzation

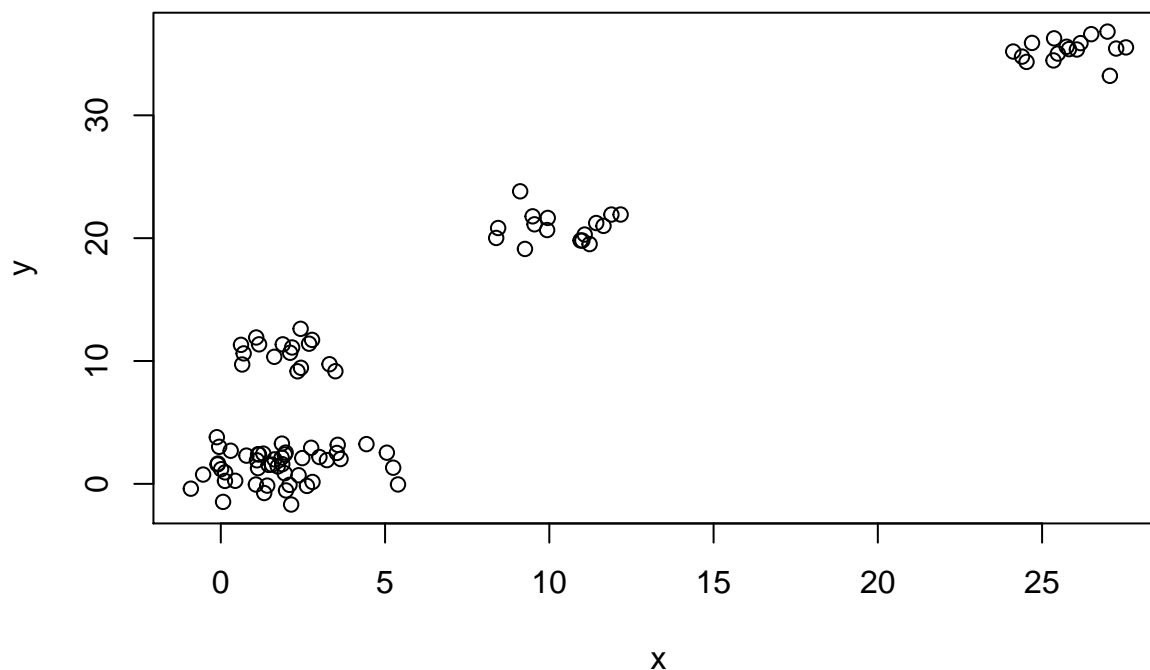
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11/3/2017

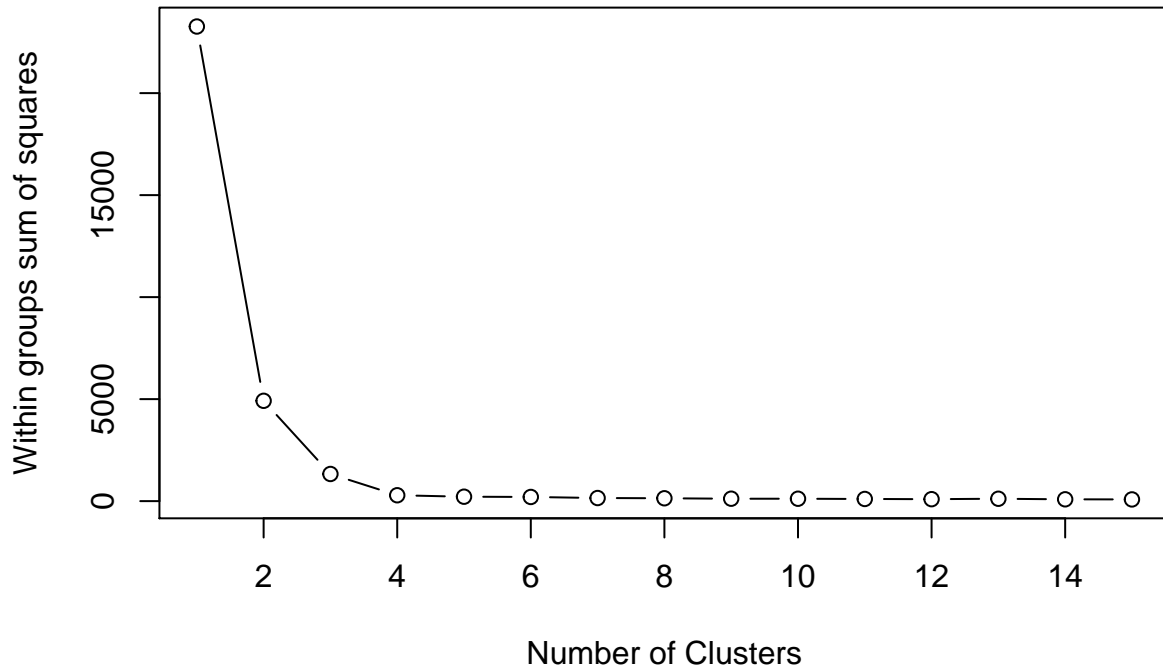
Using the suggestions from [this StackOverflow question](#), this note will attempt to find the optimal clustering for the Sepsis data set.

```
lots_of_clusters = function(d, in_k) {  
  mydata <- d  
  wss <- (nrow(mydata) - 1) * sum(apply(mydata, 2, var))  
  for (i in 2:15)  
    wss[i] <- sum(kmeans(mydata,centers = i)$withinss)  
  plot(1:15,wss,type = "b",xlab = "Number of Clusters",ylab = "Within groups sum of squares")  
  pamk.best <- pamk(d)  
  cat("number of clusters estimated by optimum average silhouette width:",pamk.best$nc,"\n")  
  plot(pam(d, pamk.best$nc))  
  asw <- numeric(20)  
  for (k in 2:20)  
    asw[k] <- pam(d, k)$silinfo$avg.width  
  k.best <- which.max(asw)  
  cat("silhouette-optimal number of clusters:", k.best, "\n")  
}
```

```
# Sample data  
n = 100  
g = 6  
set.seed(g)  
d <- data.frame(x = unlist(lapply(1:g, function(i) rnorm(n/g, runif(1)*i^2))),  
                y = unlist(lapply(1:g, function(i) rnorm(n/g, runif(1)*i^2))))  
plot(d)
```

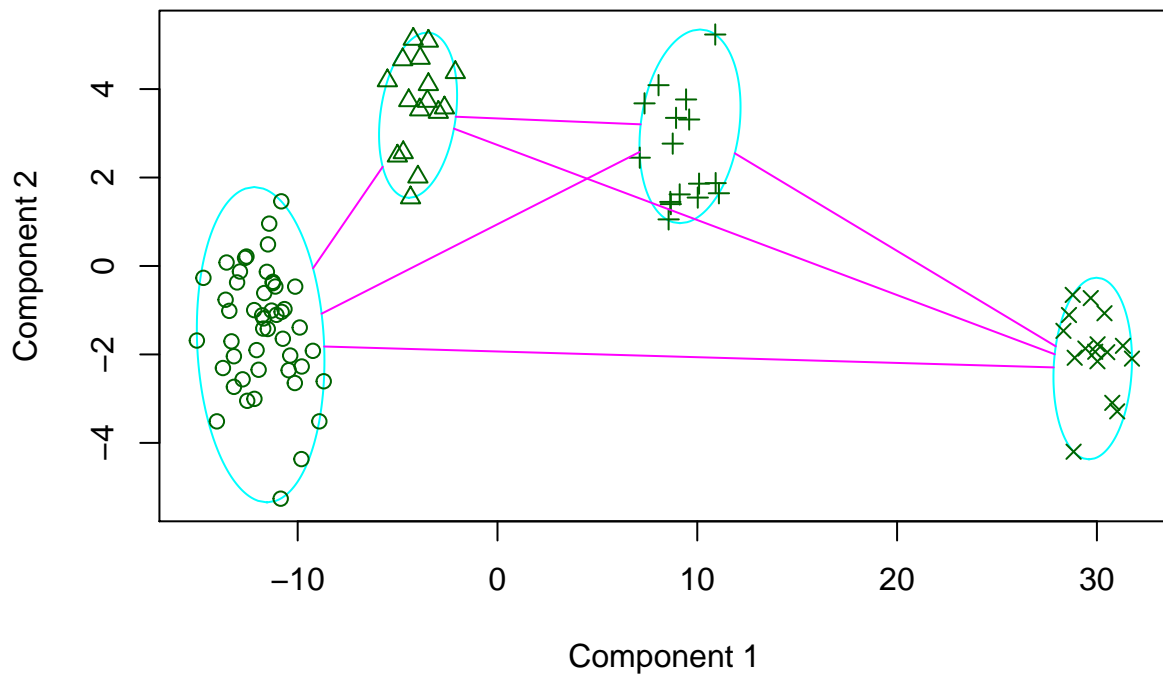


```
lots_of_clusters(d,4)
```



```
## number of clusters estimated by optimum average silhouette width: 4
```

```
clusplot(pam(x = d, k = pamk.best$nc))
```



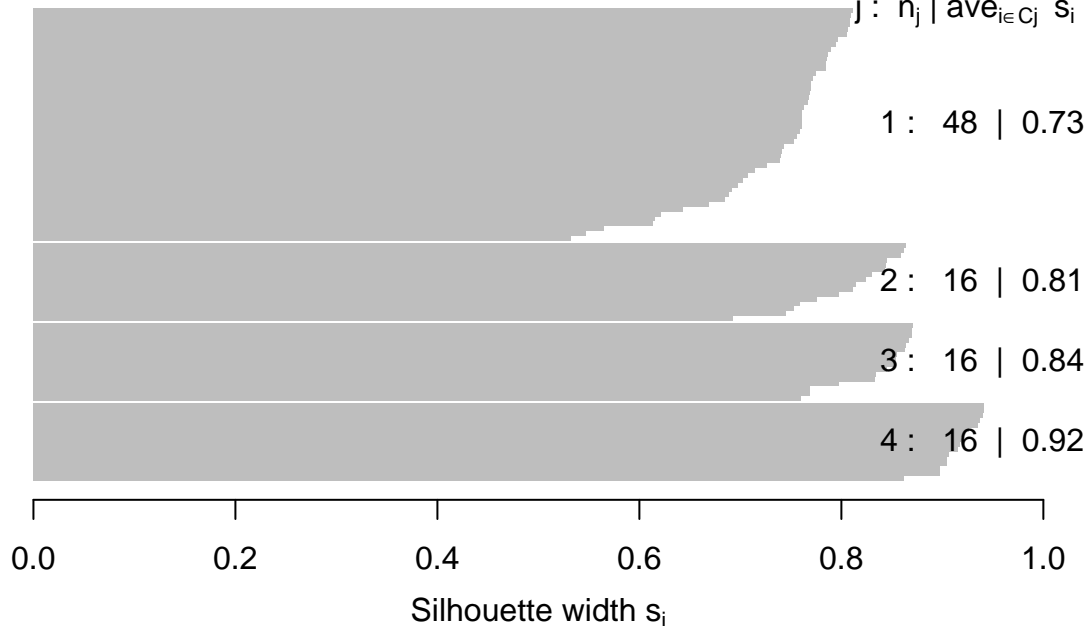
These two components explain 100 % of the point variability.

Silhouette plot of pam(x = d, k = pamk.best\$nc)

n = 96

4 clusters C_j

j : n_j | $\text{ave}_{i \in C_j} s_i$



silhouette-optimal number of clusters: 4

calinsky

```
# fit <- cascadeKM(scale(d, center = TRUE, scale = TRUE), 1, 10, iter = 1000)
```

```
# plot(fit, sortg = TRUE, grpmts.plot = TRUE)
```

```
# calinski.best <- as.numeric(which.max(fit$results[2,]))
```

```
# cat("Calinski criterion optimal number of clusters:", calinski.best, "\n")
```

```
# BIC
```

```
# See http://www.jstatsoft.org/v18/i06/paper
```

```
# http://www.stat.washington.edu/research/reports/2006/tr504.pdf
```

```
#
```

```
# Run the function to see how many clusters
```

```
# it finds to be optimal, set it to search for
```

```
# at least 1 model and up 20.
```

```
# d_clust <- Mclust(as.matrix(d), G=1:20)
```

```
# m.best <- dim(d_clust$z)[2]
```

```
# cat("model-based optimal number of clusters:", m.best, "\n")
```

```
# # 4 clusters
```

```
# plot(d_clust)
```

```
# Affinity Propagation
```

```
# d.apclus <- apcluster(negDistMat(r=2), d)
```

```
# cat("affinity propogation optimal number of clusters:", length(d.apclus@clusters), "\n")
```

```
# # 4
```

```
# heatmap(d.apclus)
```

```
# plot(d.apclus, d)
```

```

# Gap Statistic

# clusGap(d, kmeans, 10, B = 100, verbose = interactive())

# NbClust
# nb <- NbClust(d, diss="NULL", distance = "euclidean",
#             min.nc=2, max.nc=15, method = "kmeans",
#             index = "alllong", alphaBeale = 0.1)
# hist(nb$Best.nc[1,], breaks = max(na.omit(nb$Best.nc[1,])))

# d_dist <- dist(as.matrix(d))    # find distance matrix
# plot(hclust(d_dist))            # apply hierarchical clustering and plot
#
# x <- as.matrix(d)
# d.bclus <- bclus(x, transformed.par = c(0, -50, log(16), 0, 0, 0))
# viplot(imp(d.bclus)$var); plot(d.bclus); ditplot(d.bclus)
# dptplot(d.bclus, scale = 20, horizbar.plot = TRUE, varimp = imp(d.bclus)$var, horizbar.distance = 0, d

# For high dimensional data
# data(Boston)
# boston.pv <- pvclust(Boston)
# plot(boston.pv)

```