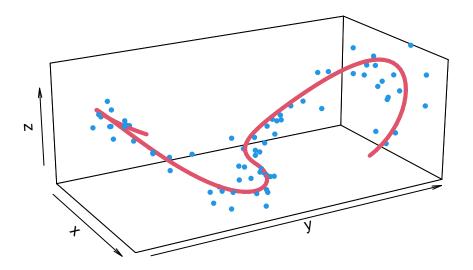
Assignment 2: Nonlinear Dimensionality Reduction

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Dataset

```
t \leftarrow seq(-1.5*pi, 1.5*pi, l=100)
R<- 1
n<-75
sd.eps <- .15
set.seed(1)
y \leftarrow R*sign(t) - R*sign(t)*cos(t/R)
x \leftarrow -R*sin(t/R)
z \leftarrow (y/(2*R))^2
rt <- sort(runif(n)*3*pi - 1.5*pi)
eps <- rnorm(n)*sd.eps
ry <- R*sign(rt) - (R+eps)*sign(rt)*cos(rt/R)</pre>
rx <- -(R+eps)*sin(rt/R)</pre>
rz \leftarrow (ry/(2*R))^2 + runif(n,min=-2*sd.eps,max=2*sd.eps)
XYZ <- cbind(rx,ry,rz)</pre>
distXYZ <- dist(XYZ)</pre>
lines3D(x,y,z,colvar = NULL,
          phi = 20, theta = 60, r =sqrt(3), d =3, scale=FALSE,
          col=2, lwd=4, as=1,
          xlim=range(rx),ylim=range(ry),zlim=range(rz))
points3D(rx,ry,rz,col=4,pch=19,cex=.6,add=TRUE)
```



Local Continuity Meta-criteria

Q1. Write a function that computes MadjK as a function of two distance matrices between points.

```
LC <- function(D, X, K_) {
    # D - high dim. matrix
    # X - euclidean distance matrix
    wD <- as.matrix(dissWeights(D, type = "knn", k = K_))
    wX <- as.matrix(dissWeights(X, type = "knn", k = K_))
    N.K_ = mean(rowSums(wD & wX))
    M.K_ <- N.K_/K_
    M.K_-K_/(n-1)
}</pre>
```

Choosing the tuning parameters in Local MDS

Q2. Choose the pair (K,tau) maximizing the Local Continuity Meta-criteria.

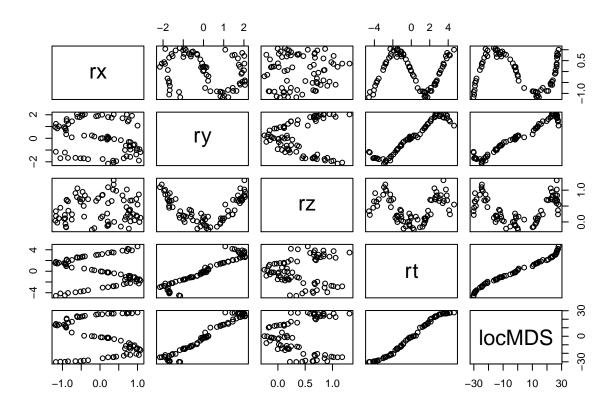
```
Stress.LocalMDS <- function(conf,n,dist.orig,k=5,tau=1){
  require(smacof)
  q<-1
  mconf <- matrix(conf,nrow = n, byrow = FALSE) # configuration matrix</pre>
```

```
Eucl.dist <- dist(mconf)</pre>
  w <- dissWeights(dist.orig, type = "knn", k = k)
  w.1 < (w==1)
  card.N.k \leftarrow sum(w.1)
  card.N.k.c \leftarrow n*(n-1)/2 - card.N.k
  t <- (card.N.k/card.N.k.c)*median(dist.orig[w.1])*tau
  return(sum((dist.orig[w.1]-Eucl.dist[w.1])^2) - t*sum(Eucl.dist[!w.1]))
conf0 <- as.numeric(cmdscale(distXYZ))</pre>
K.search <-c(5,10,15)
tau.search <- c(.1, .5, 1)
best_local_contuinity <- NULL</pre>
for(K in K.search) {
  for(tau in tau.search) {
    localMDS.S.res <- optim(par=conf0, fn=Stress.LocalMDS, n=n, dist.orig=distXYZ, k=K, tau=tau, method
    conf.localMDS.S.res <- matrix(localMDS.S.res$par, nrow = n, byrow = FALSE)</pre>
    K_ <- 10
    local_contuinity <- LC(D=distXYZ, X=dist(conf.localMDS.S.res[,1]), K_)</pre>
    if(is.null(best_local_contuinity) || best_local_contuinity < local_contuinity) {</pre>
      best_local_contuinity <- local_contuinity</pre>
      best_K <- K
      best_tau <- tau
      localMDS.max <- conf.localMDS.S.res</pre>
    }
  }
}
print(best_K)
## [1] 5
print(best_tau)
```

[1] 0.5

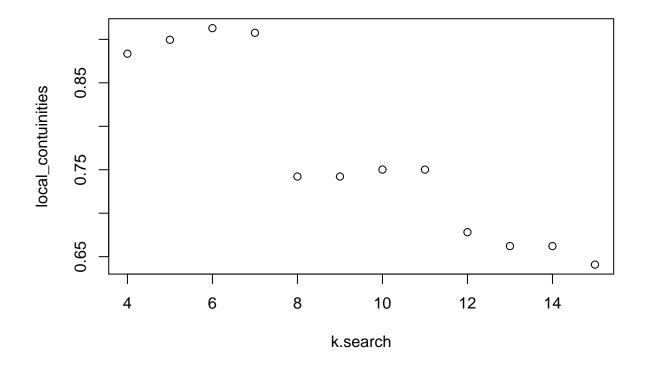
Q3. Graphical representation of the Local MDS output For the optimal K and tau, the output of the Local MDS is a q-dimensional configuration, that is, a $n \times q$ matrix (in our case with q=1).

```
pairs(cbind(XYZ, rt, locMDS=localMDS.max[,1]))
```



Choosing the tuning parameters in ISOMAP

Q4. Choose the parameter k maximizing the Local Continuity Meta-criteria.

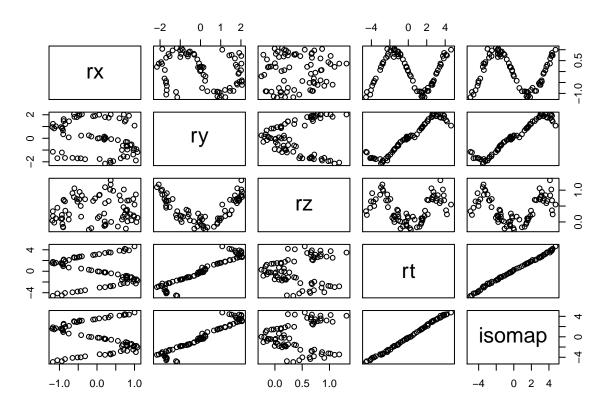


```
best_k <- k.search[which.max(local_contuinities)]
print(best_k)</pre>
```

[1] 6

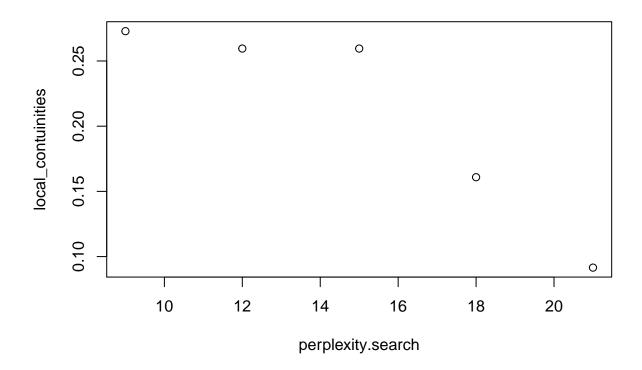
Q5. Graphical representation of the ISOMAP output

```
isomap.max <-isomap(distXYZ, k=best_k)
pairs(cbind(XYZ, rt, isomap=isomap.max$points[,1]))</pre>
```



Choosing the tuning parameters in t-SNE

Q6. Choose the parameter perplexity maximizing the Local Continuity Meta-criteria.

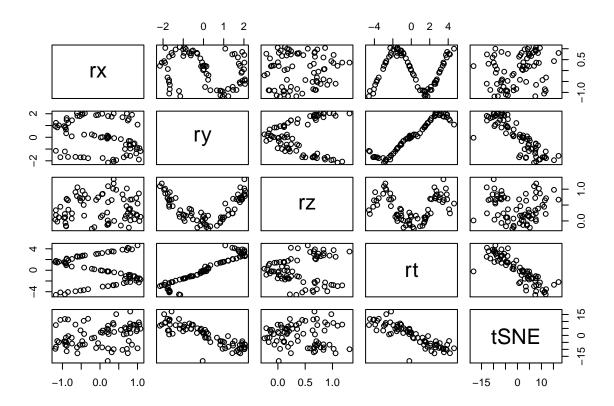


```
best_perplexity <- perplexity.search[which.max(local_contuinities)]
print(best_perplexity)</pre>
```

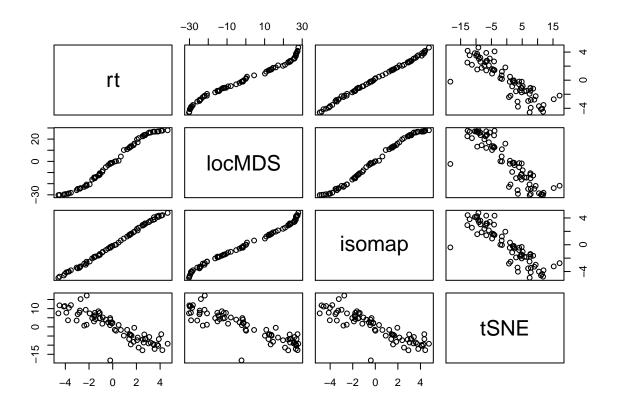
[1] 9

Q7. Graphical representation of the t-SNE output.

```
rtsne.max <- Rtsne(distXYZ, perplexity=best_perplexity, dims=1, theta=0, pca=FALSE, max_iter=200)
pairs(cbind(XYZ, rt, tSNE=rtsne.max$Y[,1]))</pre>
```



Q8. Compare graphically the results of the different techniques.



The result obtained using isomap scaled the data the closest to a linear representation.