Time series clustering

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Introduction

Clustering

The **goal of clustering** is to create homogeneous group of obsevations, s.t.:

- observations within a group are as similar as possible
- groups are as different as possible from each other

The groups are called **clusters**.

Use of clustering

- Clustering is an unsupervised technique.
- It aims to explore the data and to discover some typical pattern.
- It is often used as a preliminary step between supervised approach.

The data

Our goal is to cluster time series.

For instance, the number of new cases of Covid19 in the different countries of the world.

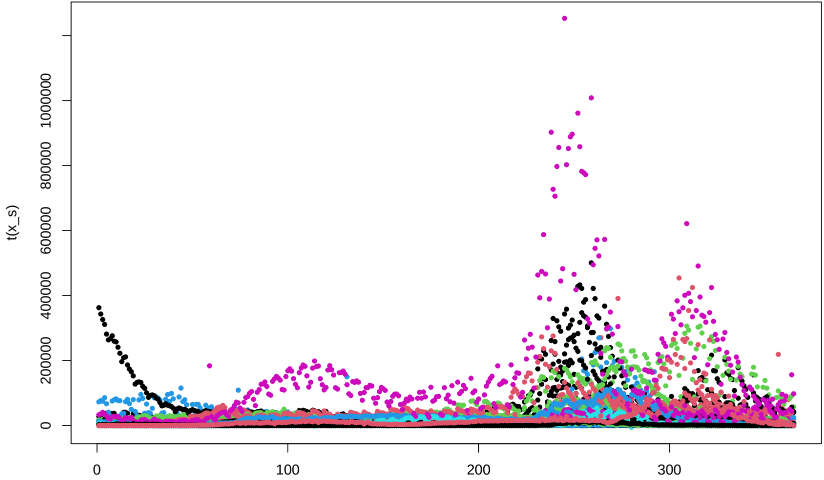
```
covid19 = read.csv("data/2022-05-13-WHO-COVID-19-global-dat
x=matrix(covid19$New_cases,ncol = 861,byrow = TRUE)
rownames(x)=unique(covid19$Country_code)
x_s=x[,(861-364):861]
x_s=x_s[rowMeans(x_s)>1000,]
```

For the example, a subset of countries having large number of cases are selected

The data

We have 80 time series, observed on 365 points

```r
matplot(t(x_s),pch=20)
```



We want to cluster them into homogeneous group

Basics of Time Series Clustering

Time serie clustering

An easy way is to use usual algorithms:

- kmeans,
- hierarchical clustering,

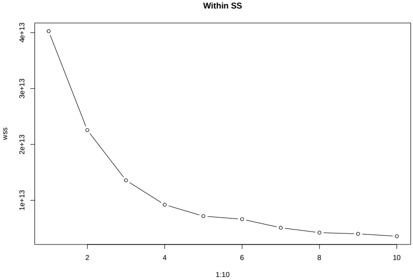
applied on a given distance for time series:

- either the usual Euclidean distance
- or specific distances as DTW

Kmeans with Euclidean distance

We can apply the usual kmeans algorithm using the Euclidean distance between time series:

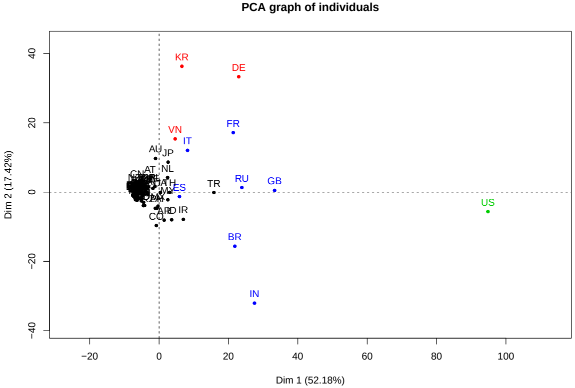
```
wss=NULL
for (k in 1:10){
  tmp=kmeans(x_s,centers=k)
  wss=c(wss,tmp$tot.withinss)
}
plot(1:10,wss,main="Within SS",type="b")
```



May be 4 clusters ?

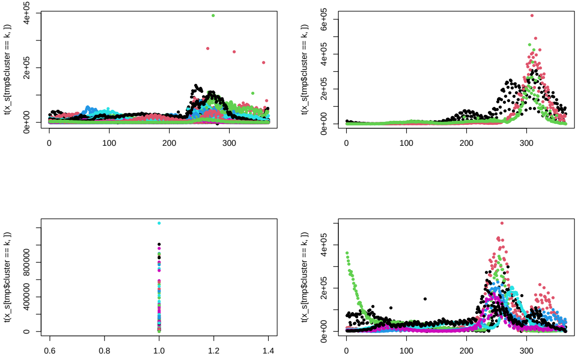
Kmeans with Euclidean distance

```
tmp=kmeans(x_s,centers=4)
library(FactoMineR)
pca<- PCA(x_s, graph = FALSE)
plot(pca,choix = "ind",col.ind = tmp$cluster,
     graph.type = "classic")
```



Kmeans with Euclidean distance

```r
par(mfrow=c(2,2))
for (k in 1:4){
 matplot(t(x_s[tmp$cluster==k,]),pch=20)
}
```



Dynamic Time Warping

The Euclidean distance is influenced by non-alignment of time series:

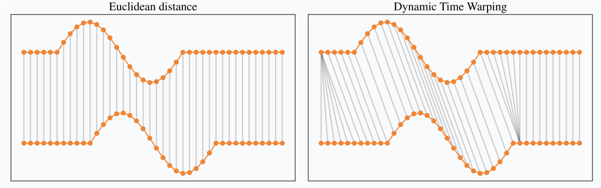


Figure from https://rtavenar.github.io/blog/dtw.html

Dynamic Time Warping look for the best alignment of the 2 time series.

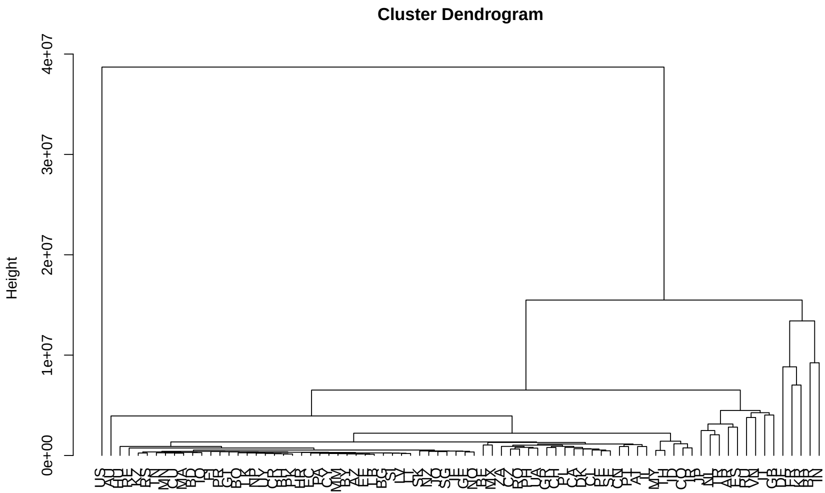
A distance can be build by measuring the distance between the best time series alignement.

```
library(dtw)
distMatrix <- dist(x_s, method="DTW")
```

Hierarchical clustering

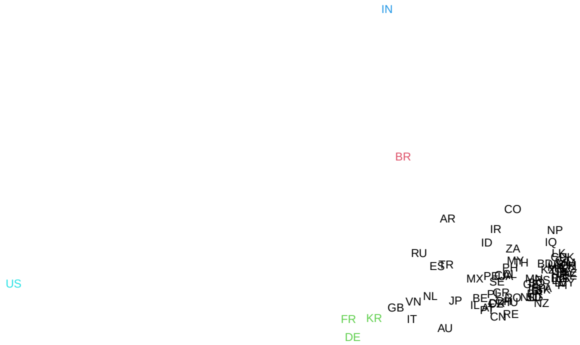
We can then apply any clustering algorithm using this DTW distance

```
hc <- hclust(distMatrix, method="average")
plot(hc, hang = -1)
```



Clustering representation

```r
cluster=cutree(hc,5)
mds2 <- -cmdscale(distMatrix)
plot(mds2, type="n", axes=FALSE, ann=FALSE)
text(mds2, labels=rownames(x_s), xpd = NA,col = cluster)
```

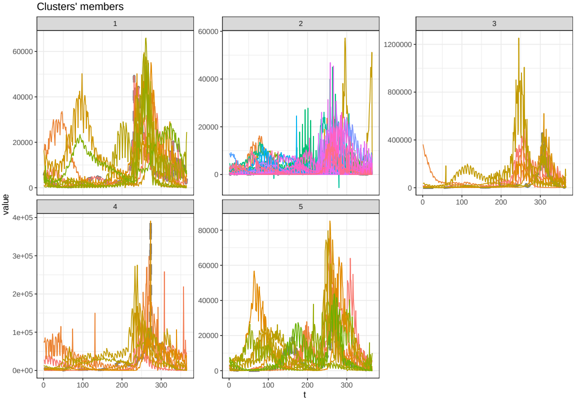


To go further

The dtwclust package

The following package allows different type of clustering, based on DTW distances:

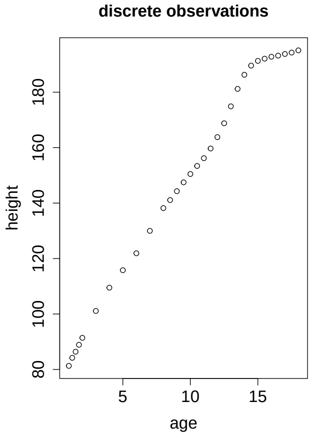
```
library(dtwclust)
tmp=tsclust(x_s,k=5)
plot(tmp)
```

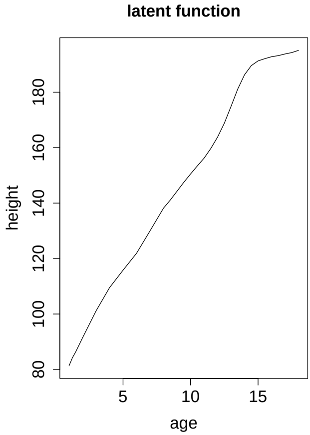


Functional data approach

An alternative way to work with time series is to assumes that $x_i(t_1), \ldots, x_i(t_m)$ are **discrete observations of a function**:

$$x_i(t) \qquad \text{with } t \in [0, T]$$





This is the **functional data approach**

The funHDDC package

The funHDDC package provides clustering algorithm for functional data

```r
library(funHDDC)
```

```
## Registered S3 method overwritten by 'funHDDC':
##   method  from
##   plot.fd fda

##
## Attaching package: 'funHDDC'

## The following object is masked from 'package:fda':
##
##     plot.fd
```