Discovering frequent patterns in time series through unsupervised data mining techniques: the case of the energy profiling in buildings

Marco Savino Piscitelli

marco.piscitelli@polito.it

TEBE TECHNOLOGY ENERGY BUILDING ENVIRONMENT

POLITECNICO DI TORINO

BAEDA Lab — Building Automation Energy Data Analytics

PyData

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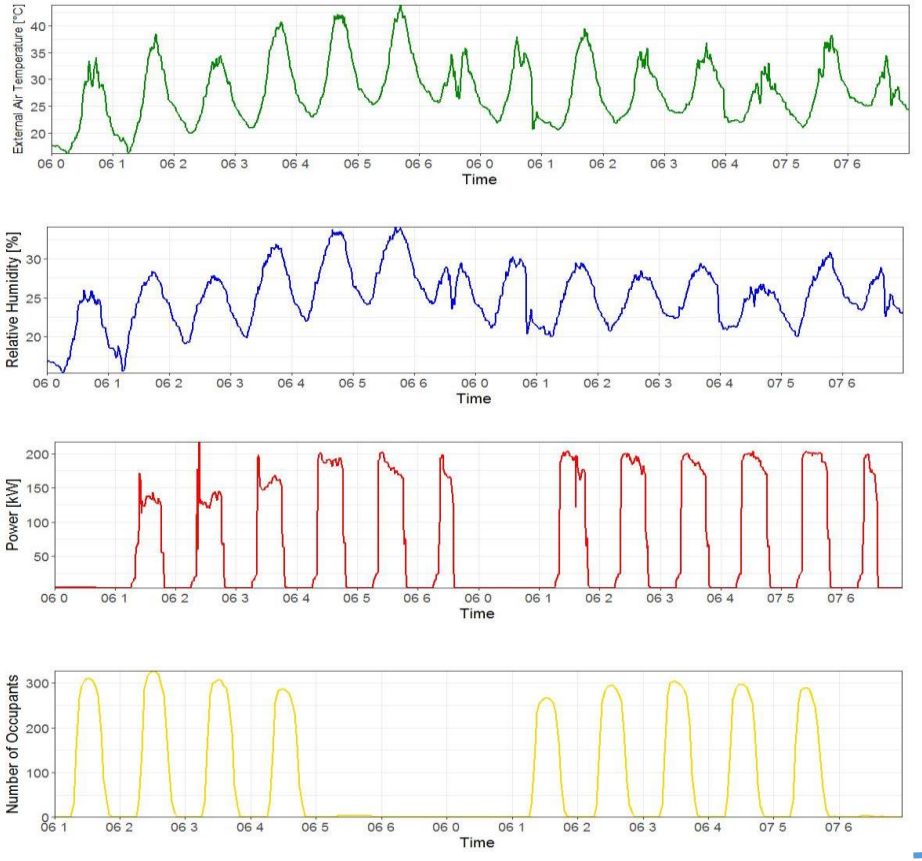
Energy profiling

The increasing implementation of ICT and EMS in the current ***paradigm of smart buildings in smart cities*** has enabled an easier availability of a huge amount of heterogeneous and complex building-related data in form of time series.

Climatic data

Operational data

User related data



What is a time series?

*A **time series** is a **series** of data points listed in **time** order. Most commonly, a **time series** is a sequence taken at successive equally spaced points in **time**.*

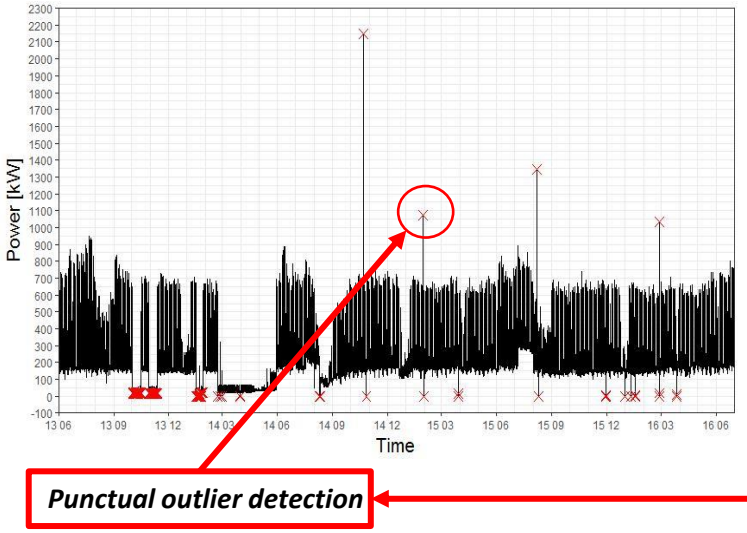
Temporal Data Mining

The mining of ***time series data*** has recently gained high attention as a way to describe and deeply ***characterise*** typical operational patterns and trends of ***energy consumption in buildings.***

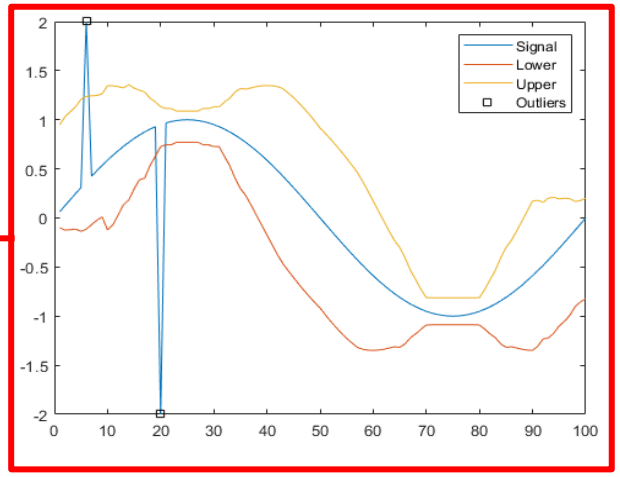
Data pre-processing

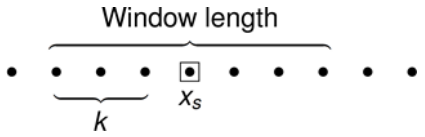
In a first step, the collected raw data in form of time series are analysed through different statistical methods to identify potential **missing values and punctual outliers** that must be replaced or removed.

DATA CLEANING

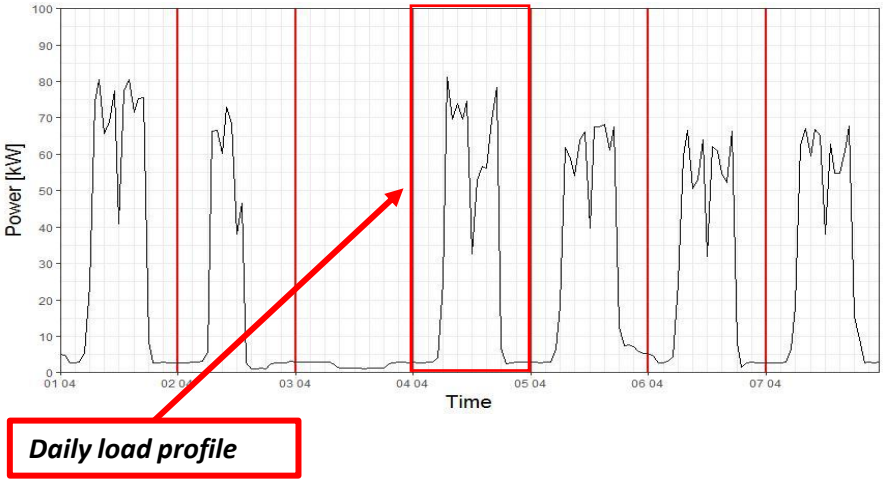


HAMPEL FILTER





TIME-SERIES CHUNKING



In a second step, the original **time series is chunked in fixed length windows** (sub-sequences). The sub-sequences, representing the daily load profiles, are **organized into a MxN matrix** where M is the number of daily load profiles while N depends from the data granularity.

The load profiles (M by N) matrix

date	time	Power [kW]
20/09/2018	00:00	10
20/09/2018	06:00	20
20/09/2018	12:00	34
20/09/2018	18:00	20
21/09/2018	00:00	6
21/09/2018	06:00	15
21/09/2018	12:00	67
21/09/2018	18:00	30
22/09/2018	00:00	9
22/09/2018	06:00	12
22/09/2018	12:00	21
22/09/2018	18:00	9

KEY VALUE

N - dimension

date	00:00	06:00	12:00	18:00
20/09/2018	10	20	34	20
21/09/2018	6	15	67	30
22/09/2018	9	12	21	9

M - dimension

N – dimension = depends from the timestep of the time series
(e.g. for hourly time series N = 24)

M – dimension = depends from the number of days

Typical load profiles identification

This phase of the framework is performed at individual building/customer level and it is aimed at **identifying groups of homogenous profiles in the M by N matrix** through a data segmentation phase.

The typical profiles can be then evaluated through statistical measures (e.g. mean, median) calculated in each group of homogenous daily load profiles identified in the data segmentation phase. To this purpose, data segmentation may be performed following:

1. **Domain expert based approach.**
2. **Data mining approach by using unsupervised techniques.**
3. **Indirect clustering through data reduction methods.**

Cluster analysis

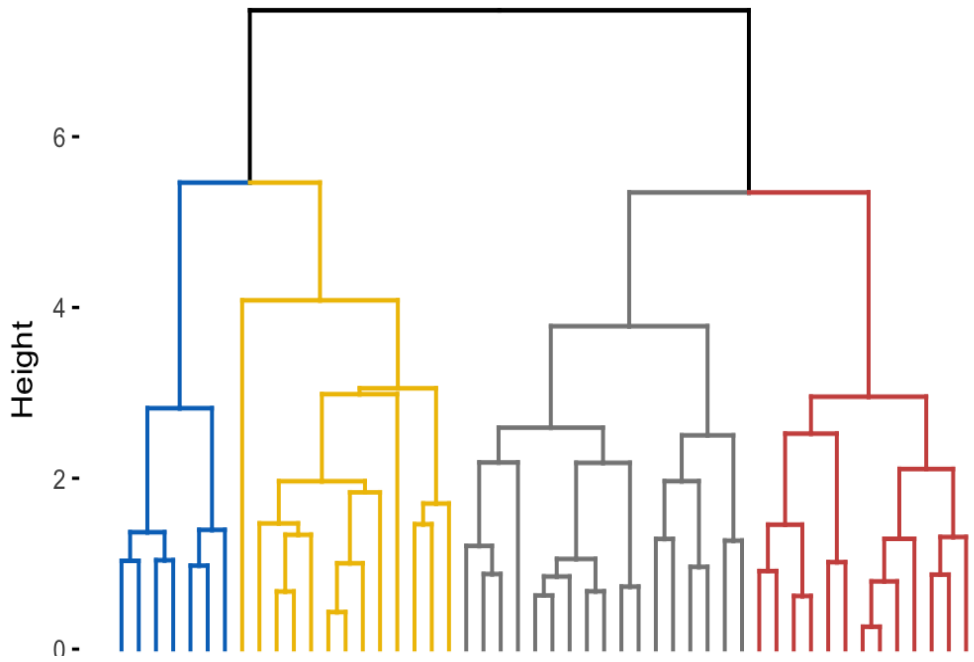
- Clustering allows to segment a set of data objects into clusters based on a concept of **similarity/proximity among data**.

- The objective of any clustering algorithm consists in **dividing a set of data composed of n multidimensional objects** {x1, . . ., xn} **into K clusters** {C1, . . ., CK}, in order to group similar objects in the same cluster and dissimilar objects into different clusters.

- The set of clusters P = {C1, . . ., CK} is referred as data partition.

Hierarchical clustering

- A set of nested clusters organized as a hierarchical bottom/up (agglomerative) or top/down (divisive) tree



Cluster analysis

MxN matrix

N - dimension

M - dimension

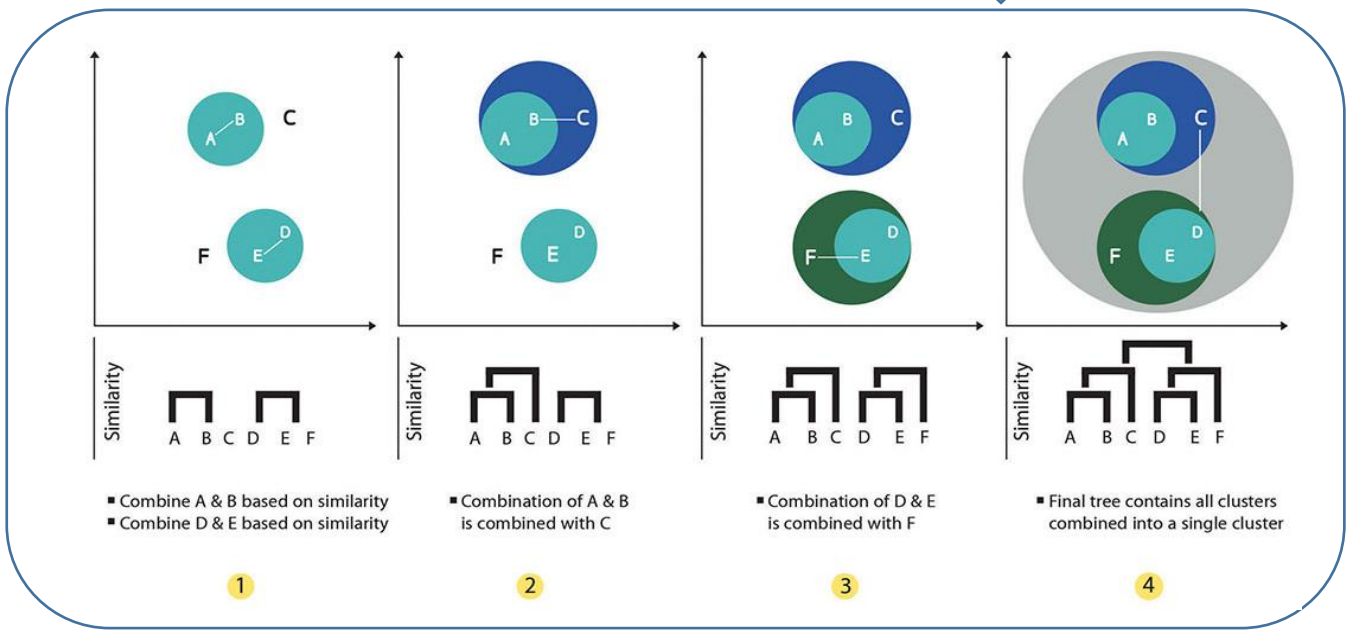
date	00:00	06:00	12:00
20/09/2018	10	20	34
21/09/2018	6	15	67
22/09/2018	9	12	21
23/09/2018	10	20	34
24/09/2018	6	15	67
25/09/2018	9	12	21

distance matrix

Euclidean distance

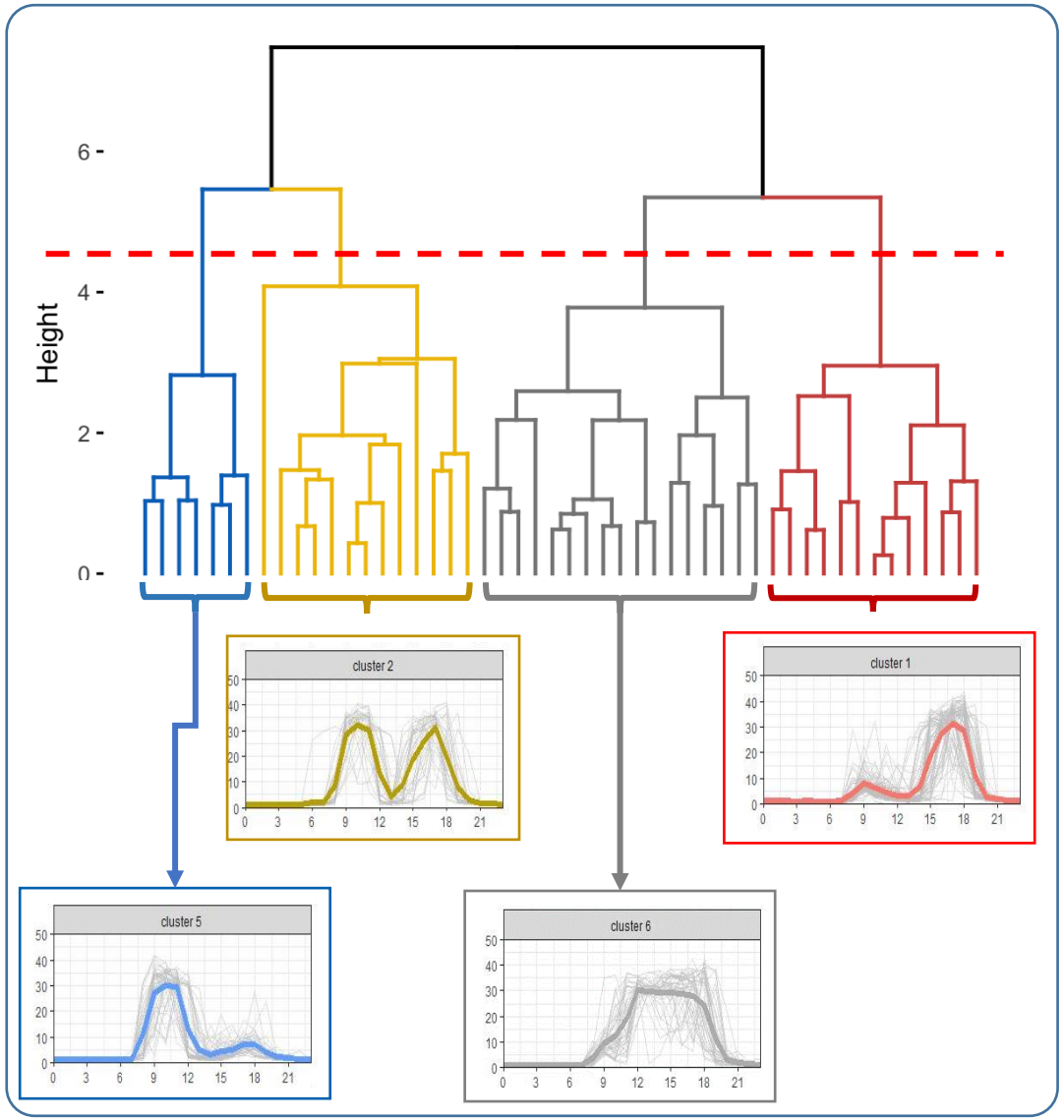
$$d_{ED}(X,Y) = \sqrt{\sum_{i=1}^{n}(xi - yi)^2}$$

$$A = \begin{bmatrix} 0 & d_{12}^2 & d_{13}^2 & \dots & d_{1n}^2 \\ d_{21}^2 & 0 & d_{23}^2 & \dots & d_{2n}^2 \\ d_{31}^2 & d_{32}^2 & 0 & \dots & d_{3n}^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d_{n1}^2 & d_{n2}^2 & d_{n3}^2 & \dots & 0 \end{bmatrix}$$



https://www.brandidea.com/hierarchicalclustering.html

Cut of the cluster dendrogram



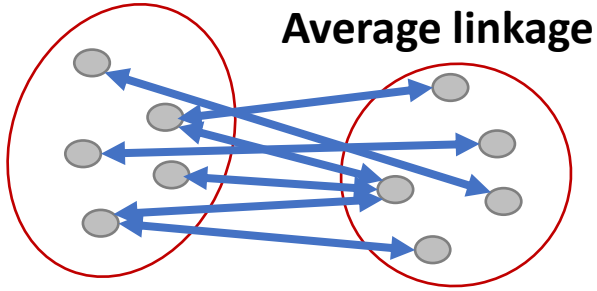
Cluster analysis hierarchical algorithms

Average linkage hierarchical clustering: In this type, two clusters whose merger has the smallest average distance between data points are merged in each step.

Complete linkage hierarchical clustering: In this type, two clusters whose merger has the smallest diameter are merged in each step.

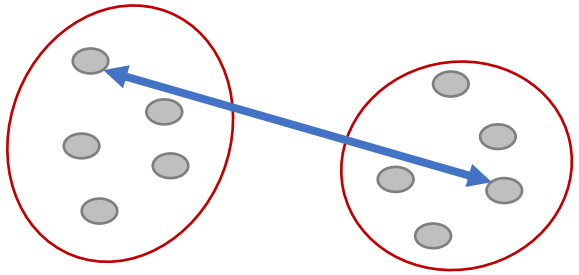
Single linkage hierarchical clustering: In this linkage type, two clusters whose two closest members have the shortest distance are merged in each step.

Average linkage



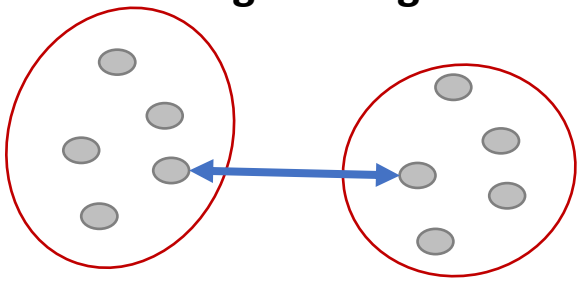
$$L(r,t) = \frac{1}{n_r n_t} \sum_{i=1}^{n_r} \sum_{j=1}^{n_t} D(x_{ri}, x_{tj})$$

Complete linkage



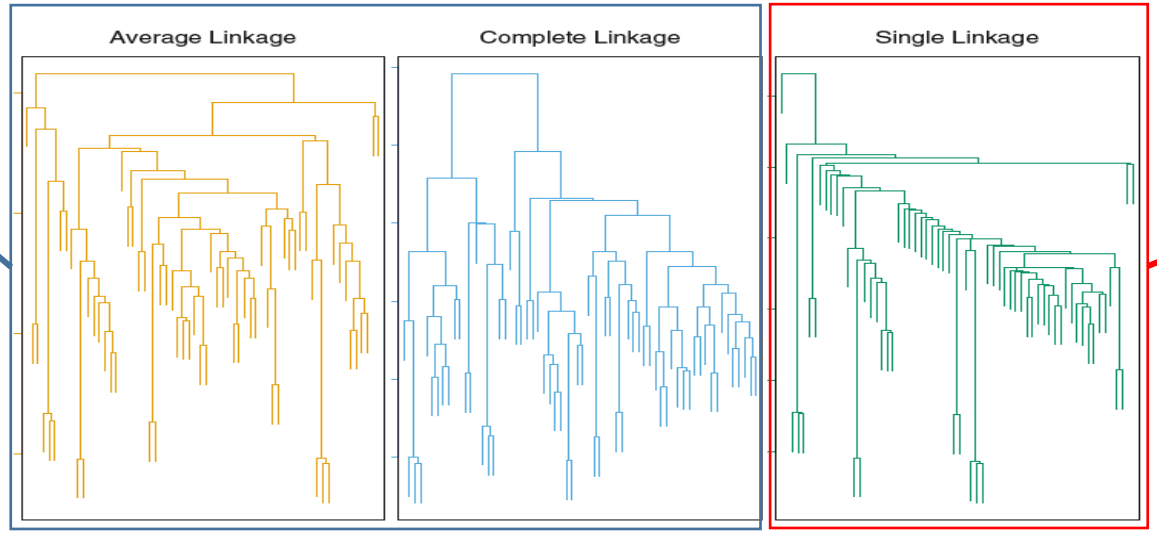
$$L(r,t) = \max(D(x_{ri}, x_{tj})$$

Single linkage



$$L(r,t) = min(D(x_{ri}, x_{tj})$$

Average and **Complete** produce more balanced dendrograms.



Single is more sensitive to outliers.

https:/,

Cluster analysis – optimal number of clusters

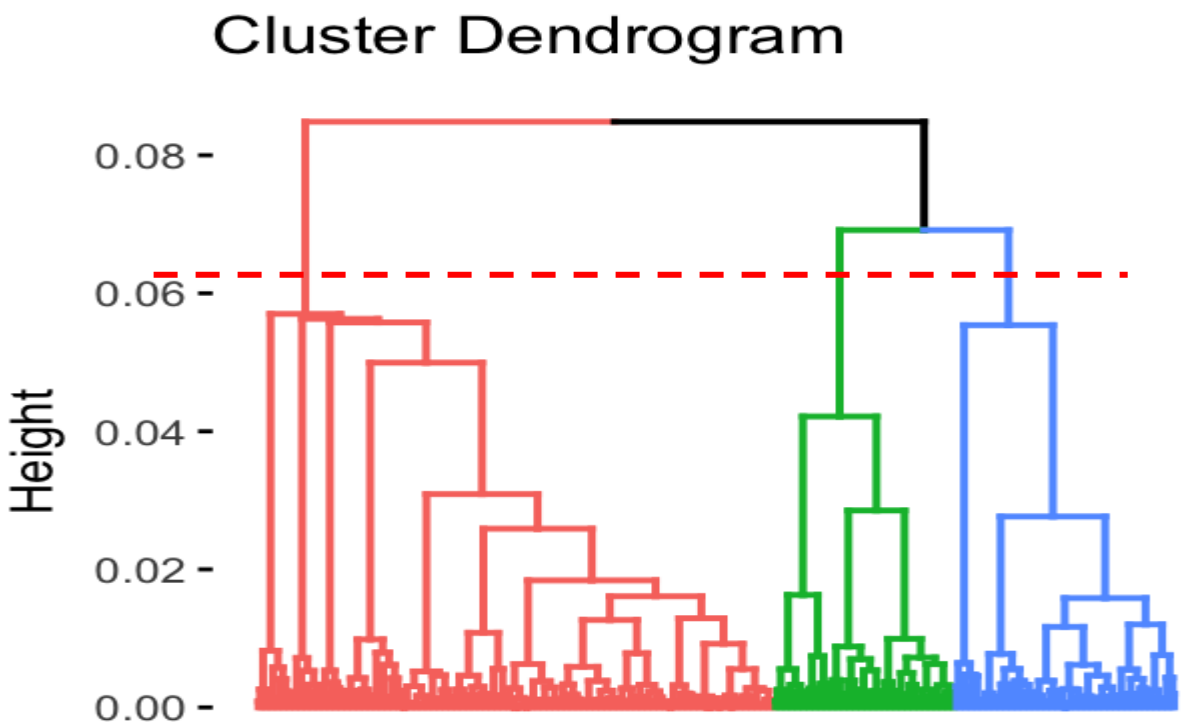
Select the validation metrics

	Name of the index in **NbClust**	Optimal number of clusters
1.	"ch" (Calinski and Harabasz 1974)	Maximum value of the index
2.	"duda" (Duda and Hart 1973)	Smallest number of clusters such that index > criticalValue
3.	"pseudot2" (Duda and Hart 1973)	Smallest number of clusters such that index < criticalValue
4.	"cindex" (Hubert and Levin 1976)	Minimum value of the index
5.	"gamma" (Baker and Hubert 1975)	Maximum value of the index
6.	"beale" (Beale 1969)	Number of clusters such that critical value >= alpha
7.	"ccc" (Sarle 1983)	Maximum value of the index
8.	"ptbiserial" (Milligan 1980, 1981)	Maximum value of the index
9.	"gplus" (Rohlf 1974; Milligan 1981)	Minimum value of the index
10.	"db" (Davies and Bouldin 1979)	Minimum value of the index
11.	"frey" (Frey and Van Groenewoud 1972)	Cluster level before index value < 1.00
12.	"hartigan" (Hartigan 1975)	Maximum difference between hierarchy levels of the index
13.	"tau" (Rohlf 1974; Milligan 1981)	Maximum value of the index
14.	"ratkowsky" (Ratkowsky and Lance 1978)	Maximum value of the index
15.	"scott" (Scott and Symons 1971)	Maximum difference between hierarchy levels of the index
16.	"marriot" (Marriot 1971)	Max. value of second differences between levels of the index
17.	"ball" (Ball and Hall 1965)	Maximum difference between hierarchy levels of the index
18.	"trcovw" (Milligan and Cooper 1985)	Maximum difference between hierarchy levels of the index
19.	"tracew" (Milligan and Cooper 1985)	Max. value of second differences between levels
20.	"friedman" (Friedman and Rubin 1967)	Maximum difference between hierarchy levels of the index
21.	"mcclain" (McClain and Rao 1975)	Minimum value of the index
22.	"rubin" (Friedman and Rubin 1967)	Minimum value of second differences between levels
23.	"kl" (Krzanowski and Lai 1988)	Maximum value of the index
24.	"silhouette" (Rousseeuw 1987)	Maximum value of the index
25.	"gap" (Tibshirani *et al.* 2001)	Smallest number of clusters such that criticalValue >= 0
26.	"dindex" (Lebart *et al.* 2000)	Graphical method
27.	"dunn" (Dunn 1974)	Maximum value of the index
28.	"hubert" (Hubert and Arabie 1985)	Graphical method
29.	"sdindex" (Halkidi *et al.* 2000)	Minimum value of the index
30.	"sdbw" (Halkidi and Vazirgiannis 2001)	Minimum value of the index

Table 2: Overview of the indices implemented in the **NbClust** package.

Select the search space (e.g. from 2 to 15 clusters)

the 70% of cluster analyses result in less than 7 clusters



Supervised classification – Decision trees

The **cluster label** is defined **as a categorical dependent variable** which can be predicted with a classification model using additional attributes for the **supervised classification process**.

Explanatory variables

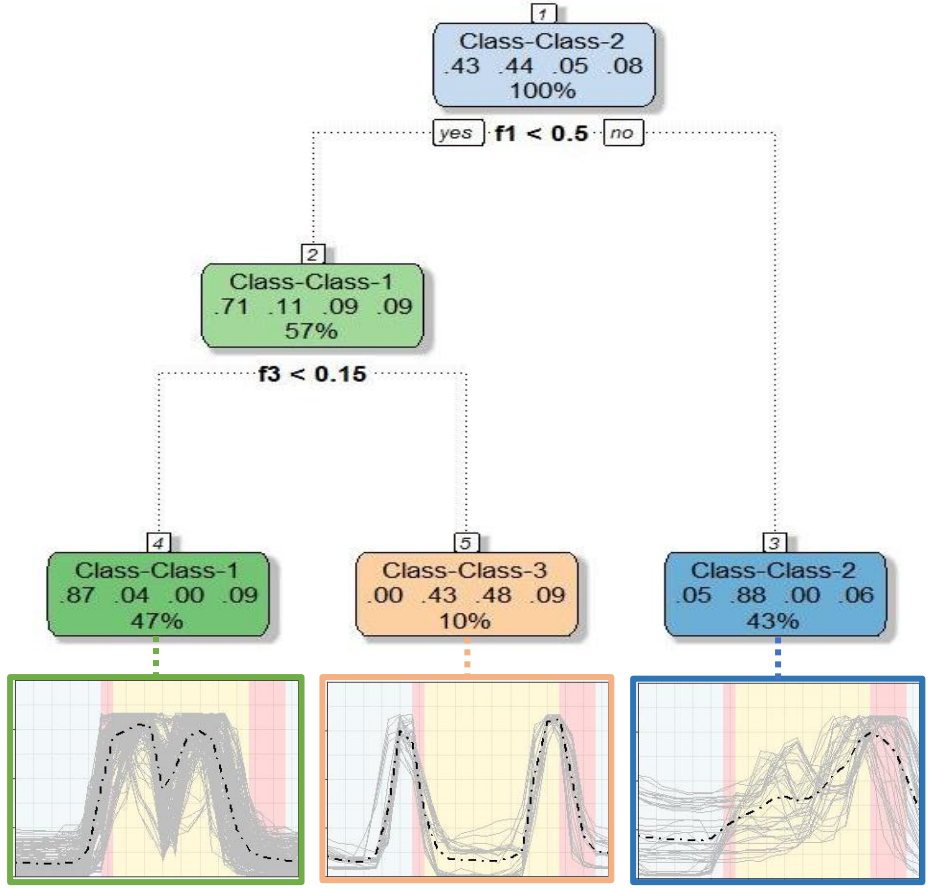
- **Time variables**
- **Energy consumption influencing variables**

$daily\ average\ solar\ radiation$

$type\ of\ the\ day\ (working, no-working)$

$daily\ average\ external\ temperature$

$day\ of\ the\ week$



Classification and regression trees

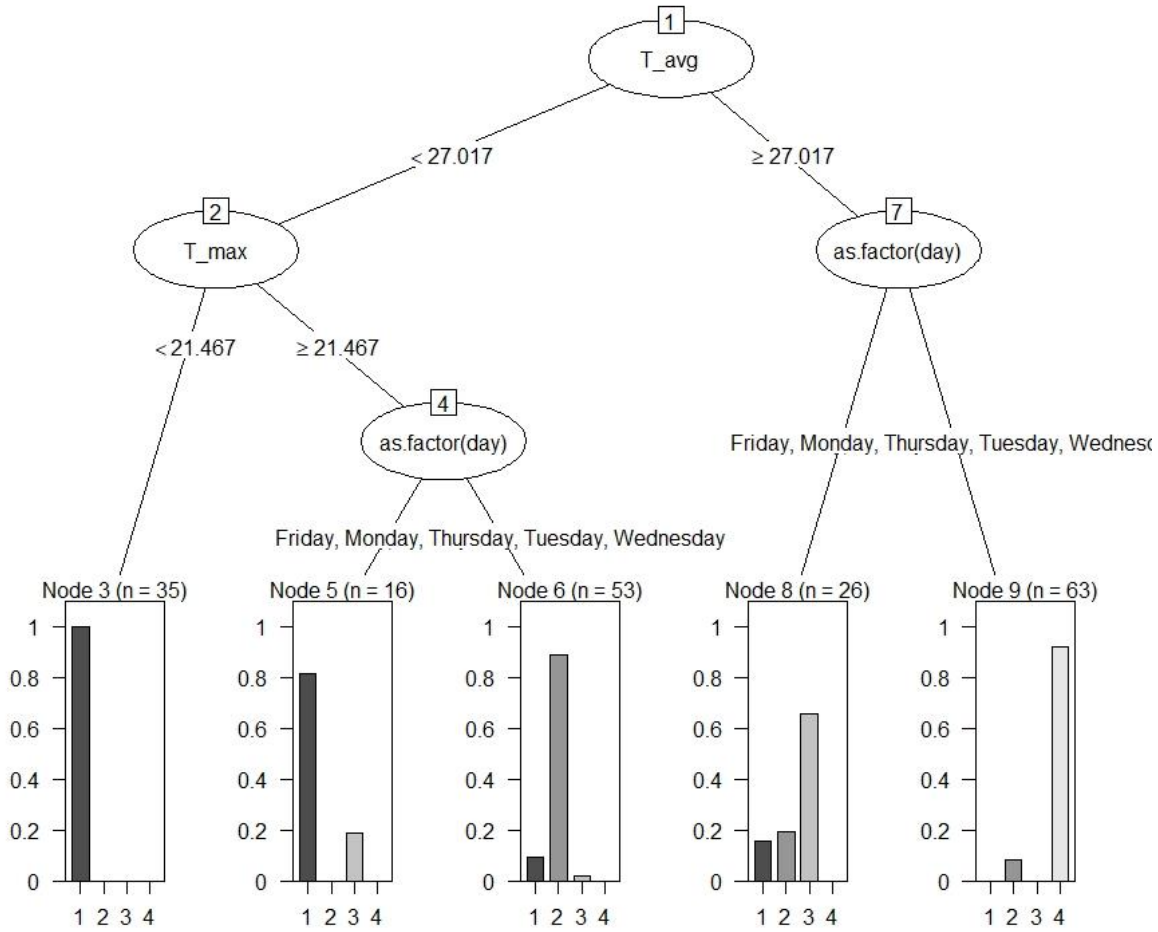
- The task of classification consists in develop a model capable to assign objects to one of different predefined class, and to predict for a new statistical object its class membership accordingly.

- The objective of a classification model consists in learning a function or a set of rules, which allows to **predict** for a new unlabeled statistical object its **class membership** and provide a **description of the data features** that characterize **objects with the same label**.

Decision trees

- Starting from the **root node**, at each node of the tree model, the data are successively splitted.
- At each split the model identify which data feature, and threshold value, better discriminate labels in the corresponding subset of data according to impurity measures.
- Tree models where the output variable takes class label are called **classification trees**, while Decision trees where the output variable takes continuous values are called **regression trees**

Classification Tree



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Data pre-processing

- **Replace missing values**
- **Construction of MxN matrix**
- **Data normalization**

2

Load profile clustering

- **Construction of the distance matrix**
- **Hierarchical clustering analysis**
- **Evaluation of cluster centroids**

3

Cluster label classification

- **Enrichment of the dataset with predictive variables**
- **Development of a classification tree**

Advanced data visualization

Let’s code!