Time Series Clustering with R

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Clustering Analysis (Data Segmentation)

- **What it is ?**
  - It is an **unsupervised** machine learning technique (unlabeled data).
  - Grouping data into different **clusters**.
  - Minimizing dissimilarity **within** clusters or Maximizing dissimilarity **between** clusters.
- **Applications**
  - Market/ Customers/ Product Segmentation.
  - Recommendation Systems.

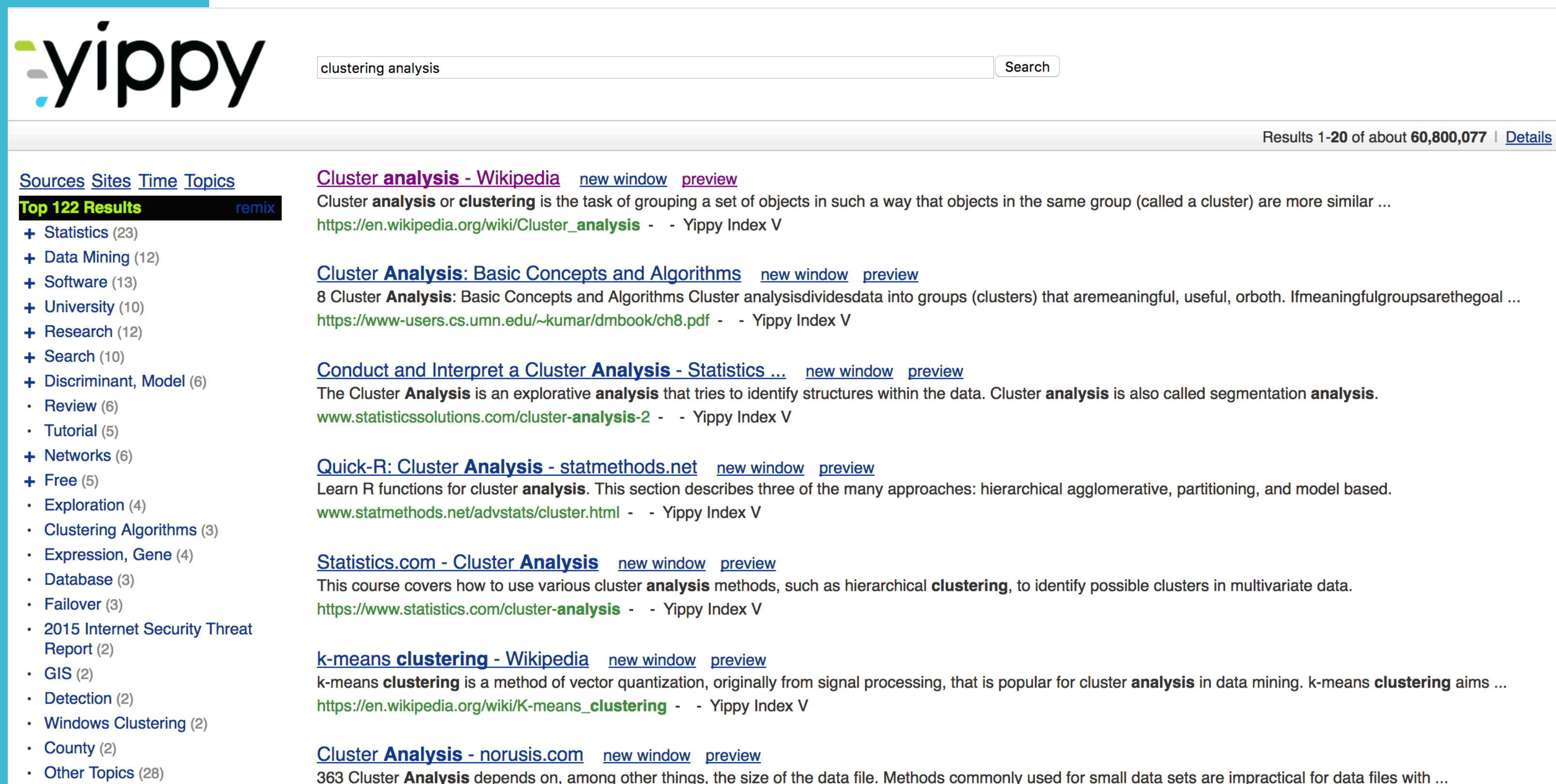
    Ex: *"The similar products you may also like"*

    "RECOMMENDED FOR YOU"
  - Grouping Search Result.

    Ex: Yippy (formerly Clusty)

    Topical Clustering of Search Results

Yippy



yippy
clustering analysis
Search
Results 1-20 of about 60,800,077 | Details
Sources Sites Time Topics
Top 122 Results remix
Statistics (23)
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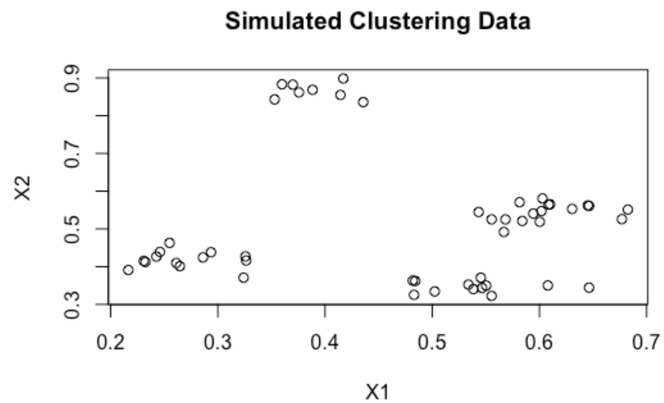
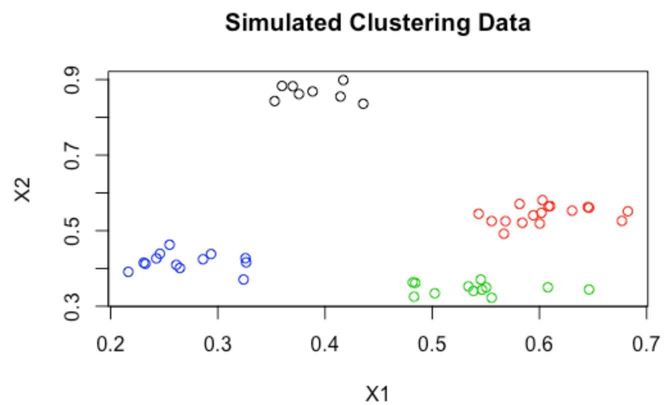
Other Topics (28)
Cluster analysis - Wikipedia new window preview
Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar ...
https://en.wikipedia.org/wiki/Cluster_analysis - - Yippy Index V
Cluster Analysis: Basic Concepts and Algorithms new window preview
8 Cluster Analysis: Basic Concepts and Algorithms Cluster analysisdividesdata into groups (clusters) that aremeaningful, useful, orboth. Ifmeaningfulgroupsarethegoal ...
https://www-users.cs.umn.edu/~kumar/dmbook/ch8.pdf - - Yippy Index V
Conduct and Interpret a Cluster Analysis - Statistics ... new window preview
The Cluster Analysis is an explorative analysis that tries to identify structures within the data. Cluster analysis is also called segmentation analysis.
www.statisticssolutions.com/cluster-analysis-2 - - Yippy Index V
Quick-R: Cluster Analysis - statmethods.net new window preview
Learn R functions for cluster analysis. This section describes three of the many approaches: hierarchical agglomerative, partitioning, and model based.
www.statmethods.net/advstats/cluster.html - - Yippy Index V
Statistics.com - Cluster Analysis new window preview
This course covers how to use various cluster analysis methods, such as hierarchical clustering, to identify possible clusters in multivariate data.
https://www.statistics.com/cluster-analysis - - Yippy Index V
k-means clustering - Wikipedia new window preview
k-means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. k-means clustering aims ...
https://en.wikipedia.org/wiki/K-means_clustering - - Yippy Index V
Cluster Analysis - norusis.com new window preview
363 Cluster Analysis depends on, among other things, the size of the data file. Methods commonly used for small data sets are impractical for data files with ...

Example Data

```r
#### SIMULATED DATA ####
library(MixSim)

set.seed(3)
Q <- MixSim(BarOmega = 0.00002, MaxOmega = NULL , K = 4, p = 2, hom = TRUE)
A = simdataset(n = 50, Pi = Q$Pi, Mu = Q$Mu, S = Q$S)
sim_d = data.frame(A$X)
sim_d$true_cluster = A$id
plot(sim_d[,1:2], main = "Simulated Clustering Data")
plot(sim_d[,1:2], col = sim_d$true_cluster, main = "Simulated Clustering Data")
```

Example Data



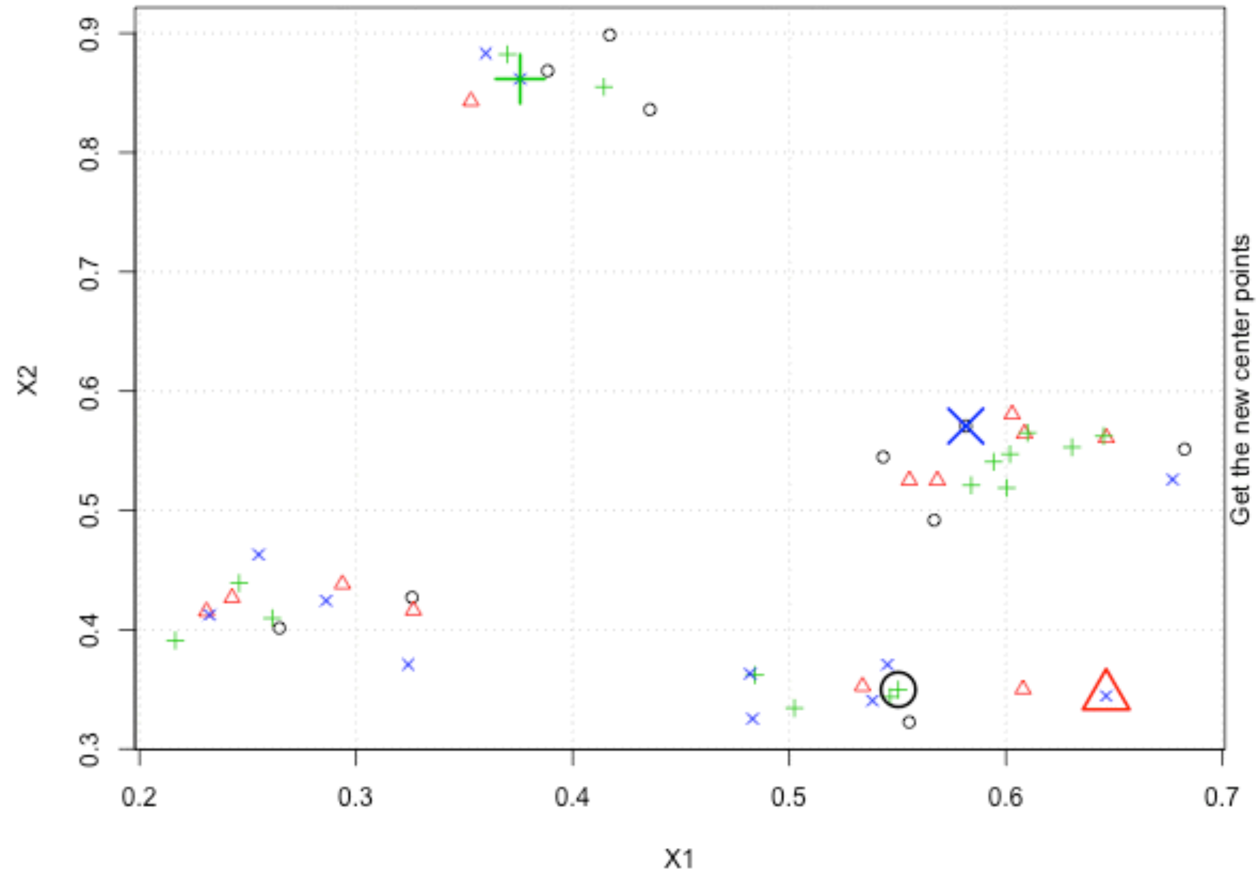


	X1	X2	true_cluster
1	0.4356460	0.8359740	1
2	0.3530190	0.8431142	1
3	0.3757343	0.8616696	1
4	0.3699114	0.8822238	1
5	0.3598940	0.8830917	1
6	0.4144158	0.8550112	1
7	0.3884225	0.8685076	1
8	0.4170783	0.8985235	1
9	0.5942671	0.5407596	2
10	0.6085898	0.5644635	2
11	0.5814696	0.5707407	2
12	0.5433074	0.5447630	2
13	0.6018648	0.5471925	2
14	0.6824566	0.5513103	2
15	0.5668619	0.4918365	2
16	0.6099432	0.5650591	2
17	0.6028487	0.5806603	2
18	0.6769366	0.5259041	2
19	0.5839923	0.5210776	2
20	0.6463144	0.5608912	2
21	0.5683214	0.5251682	2
22	0.6451486	0.5622831	2
23	0.5554161	0.5253096	2
24	0.6003407	0.5188467	2
25	0.6304850	0.5529242	2

Well-Known Methods

- **K-means Clustering**
  1. Specify the number of clusters (K).
  2. Define what is **similar** or **dissimilar**
     → **Distance!**
  3. Algorithm
     1. Random assign all the points to a unique cluster (k), where k = 1,2,3,…K.
     2. Calculate the mean center point for each cluster (m_1, m_2, …, m_K).
     3. Reassign the point to the cluster that it has closest distance to those mean center points.
     4. Repeat 2. ~ 3., until the assignment stop changing.

K-means Animation!



Definition for (Dis)similarity

- Suppose we have a measured point, x_{ij}, where

  Points: $i = 1, 2, 3, \dots, \mathrm{N}$

  Attributes: $j = 1, 2, 3, \dots, \mathrm{p}$

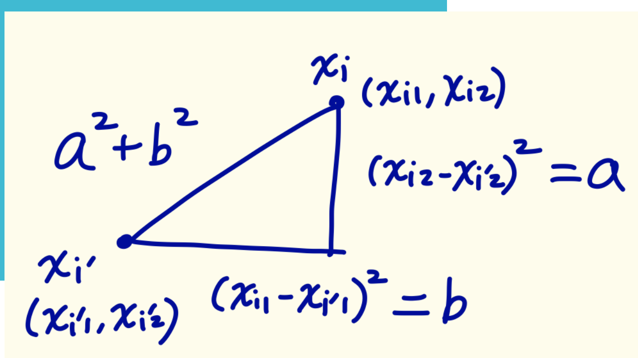
- Dissimilarity between point i and i'

$$D(x_i, x_{i'}) = \sum_{j=1}^{p} d_j(x_{ij}, x_{i'j})$$

- Euclidean Distance

$$d_j(x_{ij}, x_{i'j}) = (x_{ij} - x_{i'j})^2.$$

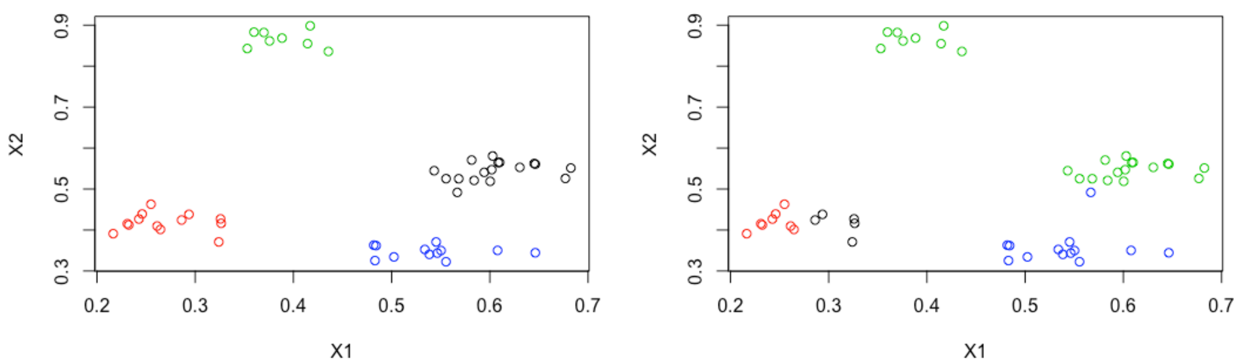
$$d(x_i, x_{i'}) = \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2 = ||x_i - x_{i'}||^2$$



K-means Clustering

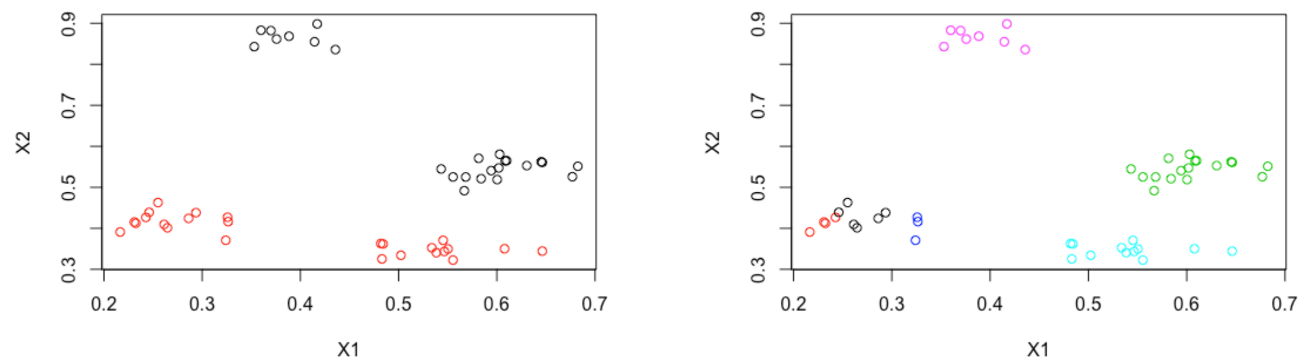
- **Things Need To Be Noticed**
  1. You won't always get the same results. So, do it more times!

```r
#### Things need to be noticed ####
set.seed(2223) # good case
k  = kmeans(sim_d[,1:2], centers=4, nstart = 1)
plot(sim_d[,1:2], col = k$cluster, main = "Good Casse")

set.seed(14) # bad case
k  = kmeans(sim_d[,1:2], centers=4, nstart = 1)
plot(sim_d[,1:2], col = k$cluster, main = "Bad Case")
```



K-means Clustering

- **Things Need To Be Noticed**
  2. How to choose the correct number of clusters ?



$$\sum (x_i - \bar{x})^2 = \sum (x_i - \bar{x_k})^2 + \sum (\bar{x_k} - \bar{x})^2$$

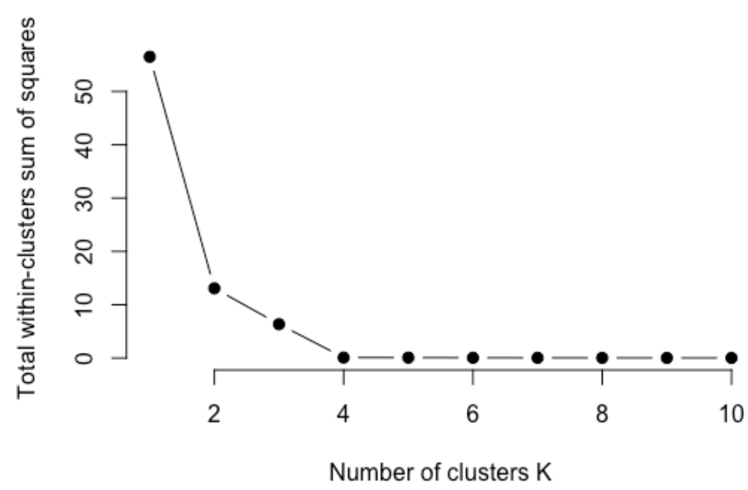
TOTAL Sum of Squares = **WITHIN** Groups SS + **BETWEEN** Groups SS

(**TOTAL** variance = **WITHIN** variance + **BETWEEN** variance)

K-means Clustering

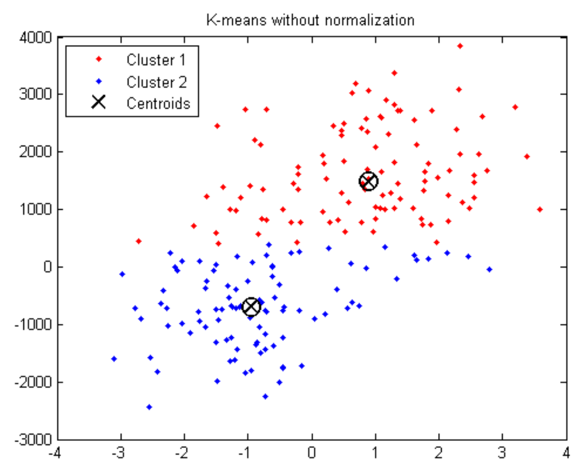
- An Intuitive Method for finding the best k

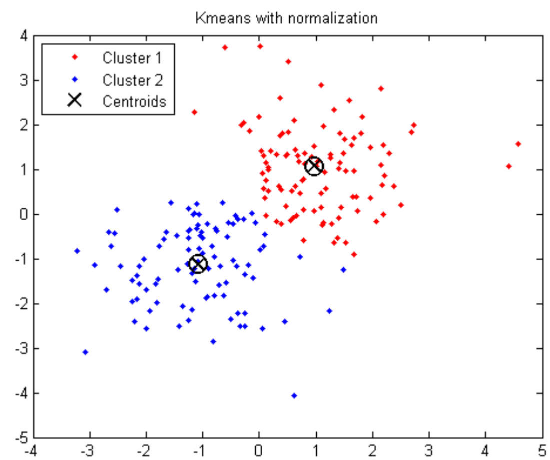
```
# find the best number of cluster
k.max <- 10
wss <- sapply(1:k.max, function(k){
  kmeans(sim_d, k, nstart=30, iter.max = 15 )$tot.withinss
})
plot(1:k.max, wss, type="b", pch = 19, frame = FALSE, xlab="Number of clusters K",
     ylab="Total within-clusters sum of squares")
```



K-means Clustering

- **Things Need To Be Noticed**
  3. Standardize the data or not?



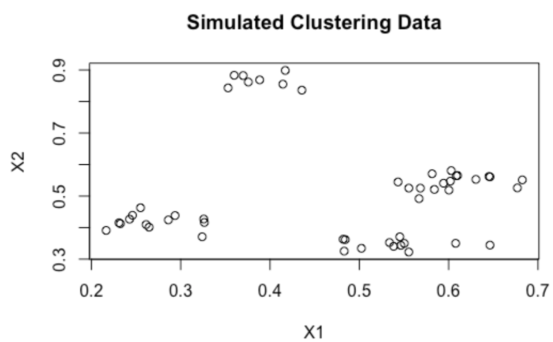


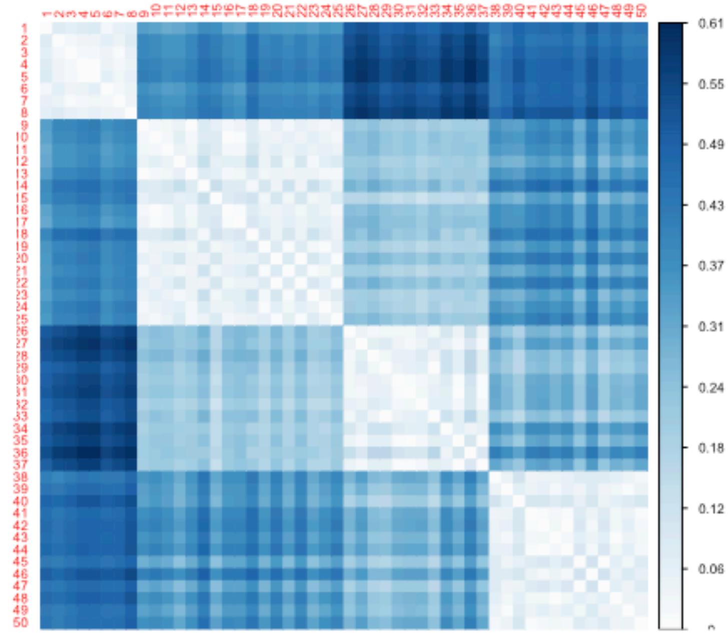
The source of pics : here

Hierarchical Clustering

- **Dissimilarity Matrix**

```r
#### Dissimilarity Matrix ####
library("corrplot")

dst = dist(sim_d[,1:2], method = "euclidean")
corrplot(as.matrix(dst), is.corr = FALSE, method = "color",
         tl.cex = 0.5, cl.cex = 0.5, mar = c(0.5, 0.5, 0.5, 0.5))
```

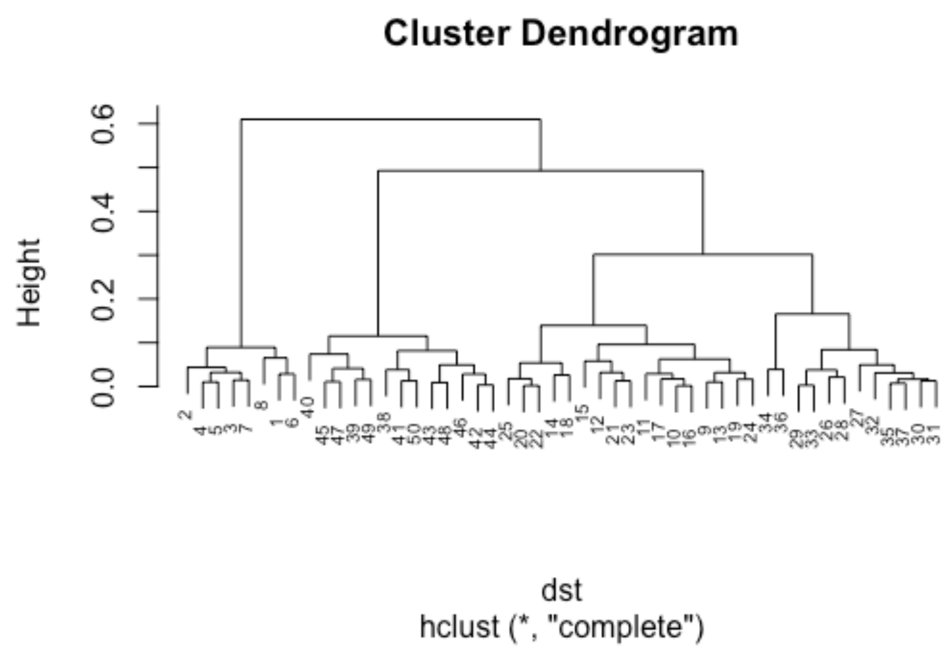




Hierarchical Clustering

- **Algorithm**

```
# Hierachical clustering
dst = dist(sim_d[,1:2], method = "euclidean")
hc = hclust(dst)
plot(hc, cex = 0.6)
rect.hclust(hc, k = 4, border = 2:5)
```



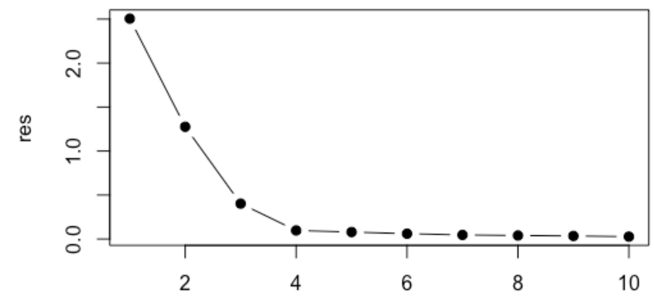
Hierarchical Clustering

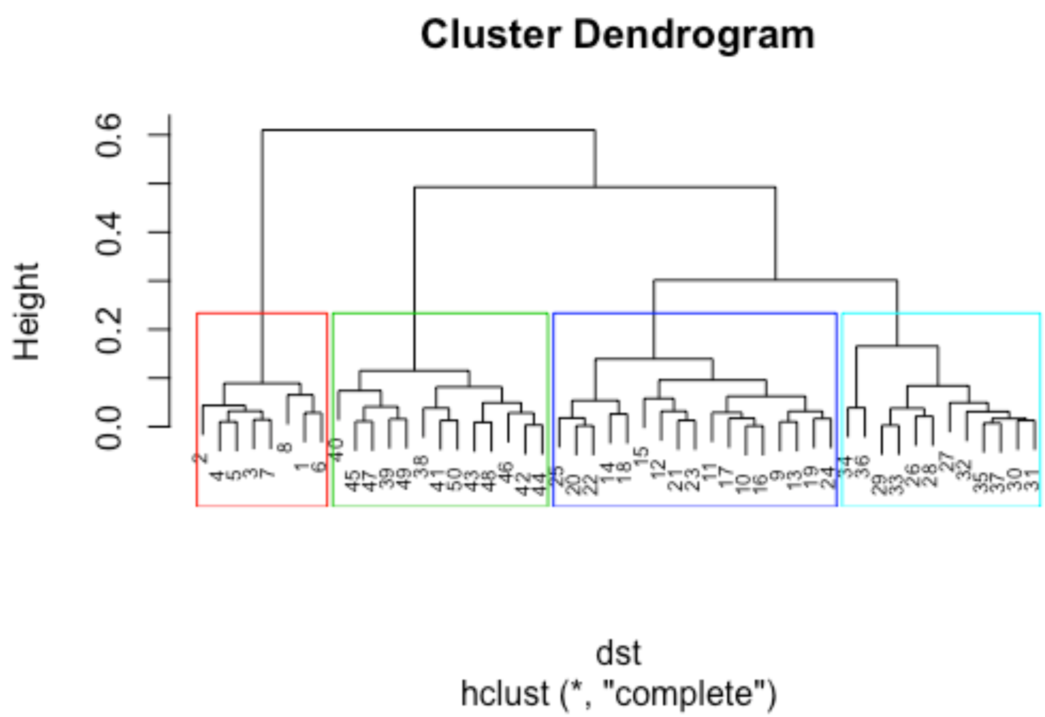
- **Find the Best k**

```r
#### Find the best cluster ####
library(dtw)
dst = dist(sim_d[,1:2], method = "euclidean")
hc = hclust(dst)

wss <- function(d) {
  sum(scale(d, scale = FALSE)^2)
}
wrap = function(i, hc, x) {
  cl = cutree(hc, i)
  spl = split(x, cl)
  wss = sum(sapply(spl, wss))
  wss
}

res = sapply(seq.int(1, 10), wrap, h = hc, x = sim_d[,1:2])
plot(seq_along(res), res, type = "b", pch = 19)

k = 4
plot(hc, cex = 0.6)
rect.hclust(hc, k, border = 2:5)
cutree(hc, k)
```

Hierarchical Clustering

- **Find the Best k**





Hierarchical Clustering

- **Things Need To Know**

  1. No need to specify the number of clusters. One Dendrogram can show many clusters.

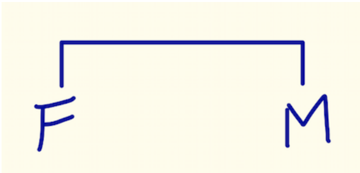
  2. It assumes that all the clusters are nested with a hierarchical structure, but it may not be the case.

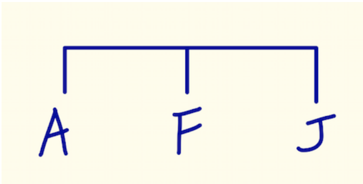
     Ex:

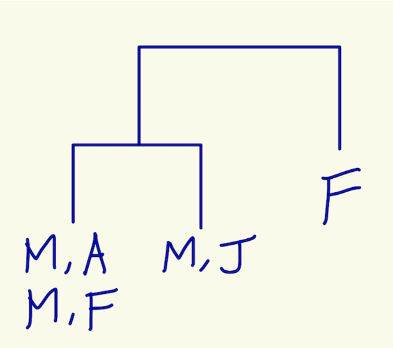
     x1 = { Male, Female }, x2 = { Americans, Japanese, French }

     Best 2 clusters : by Gender

     Best 3 clusters : by Nationality

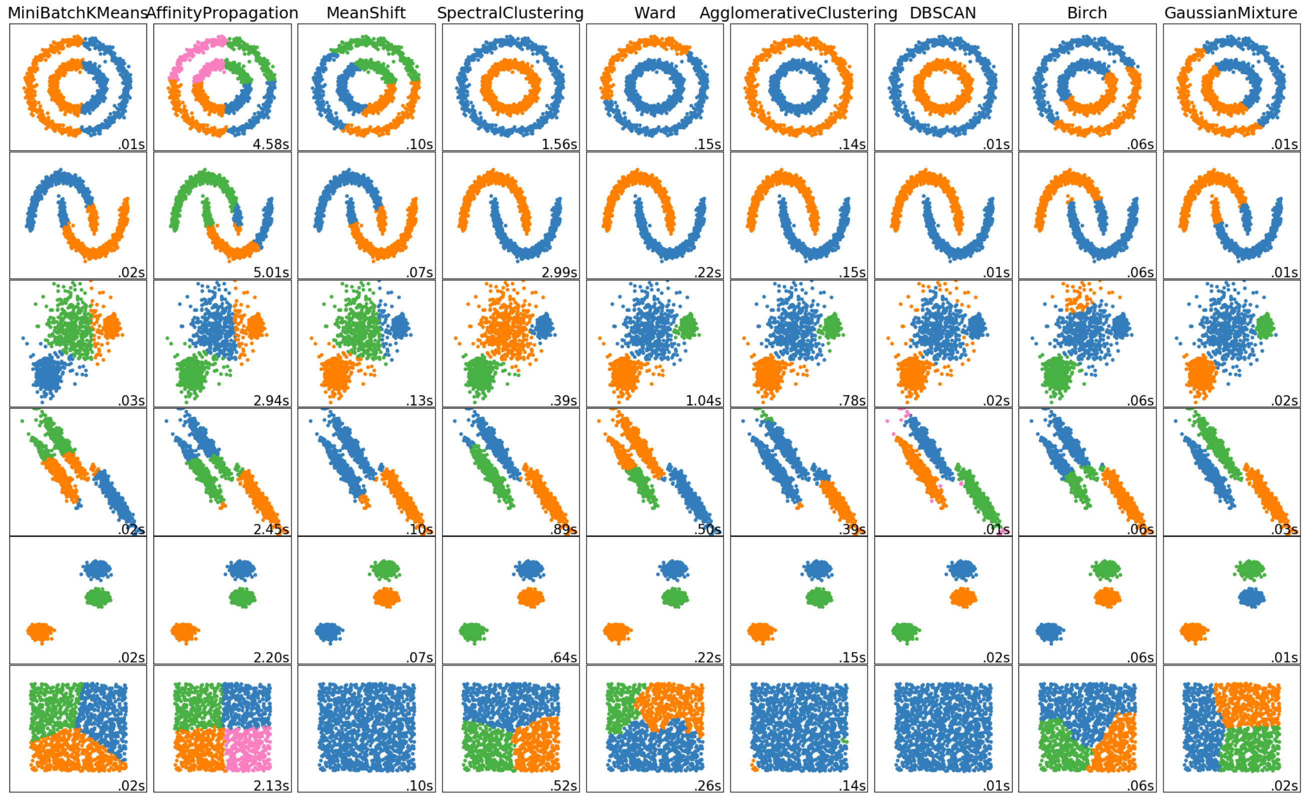






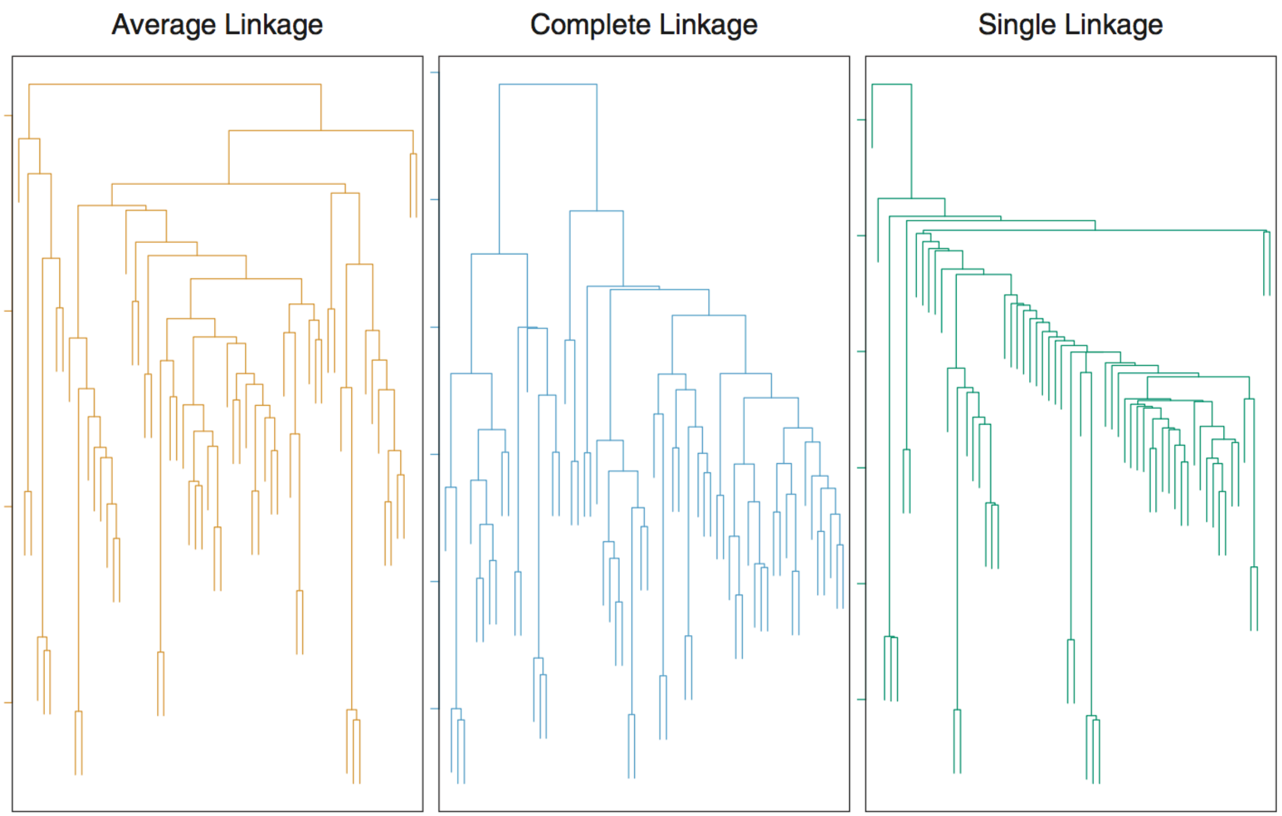
Further Topics

The source of the graph : here



Further Topics

The source of the graph : [here]



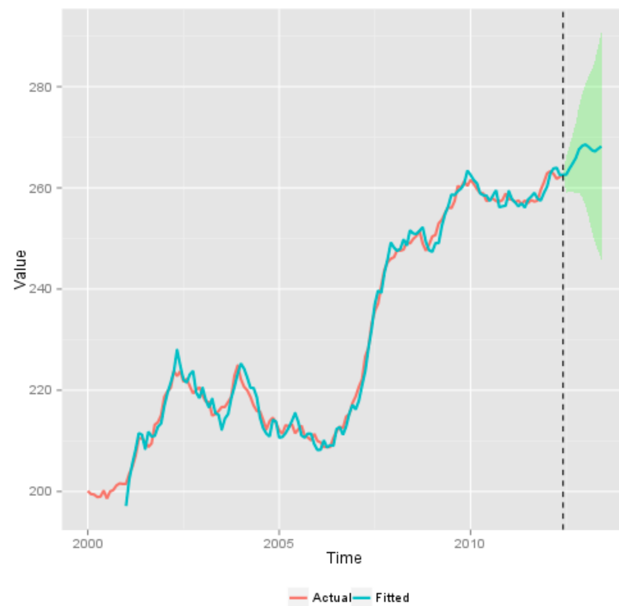
Time Series Data

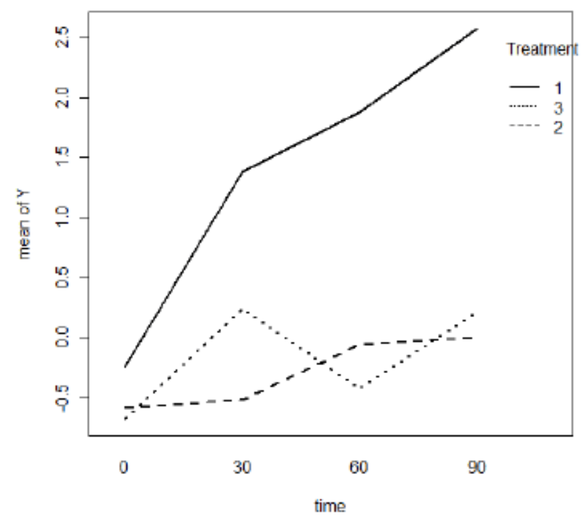
- **General Definition**

  The data is taken by time and believe that time will be an influential factor to the data.

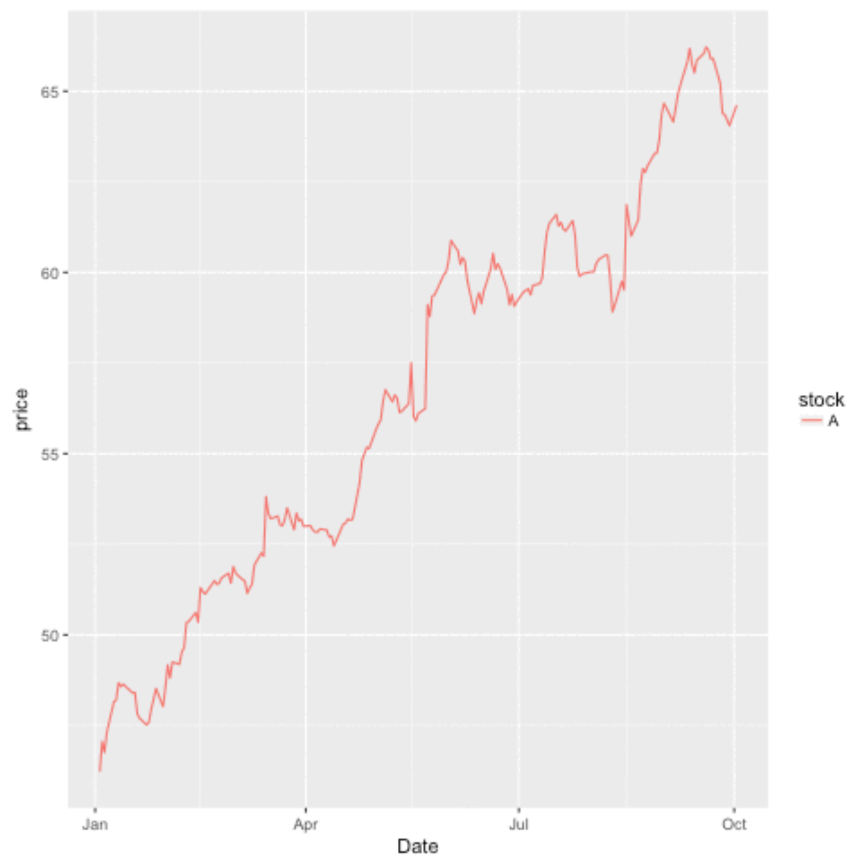
  Ex : Sales data ,

  Difference in temperature under different treatments

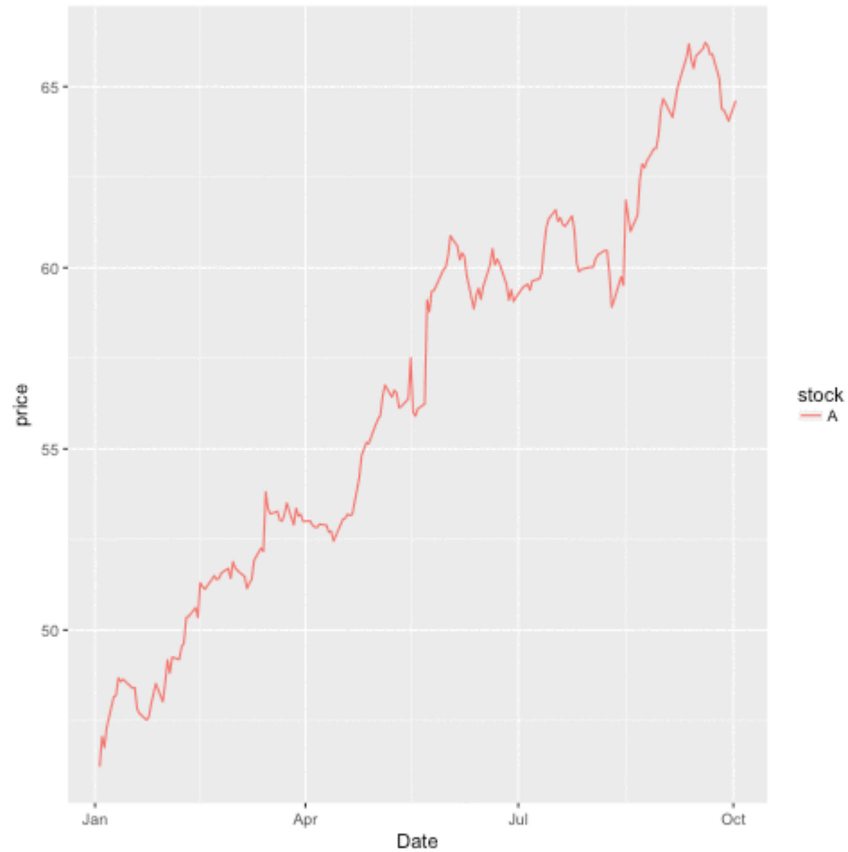




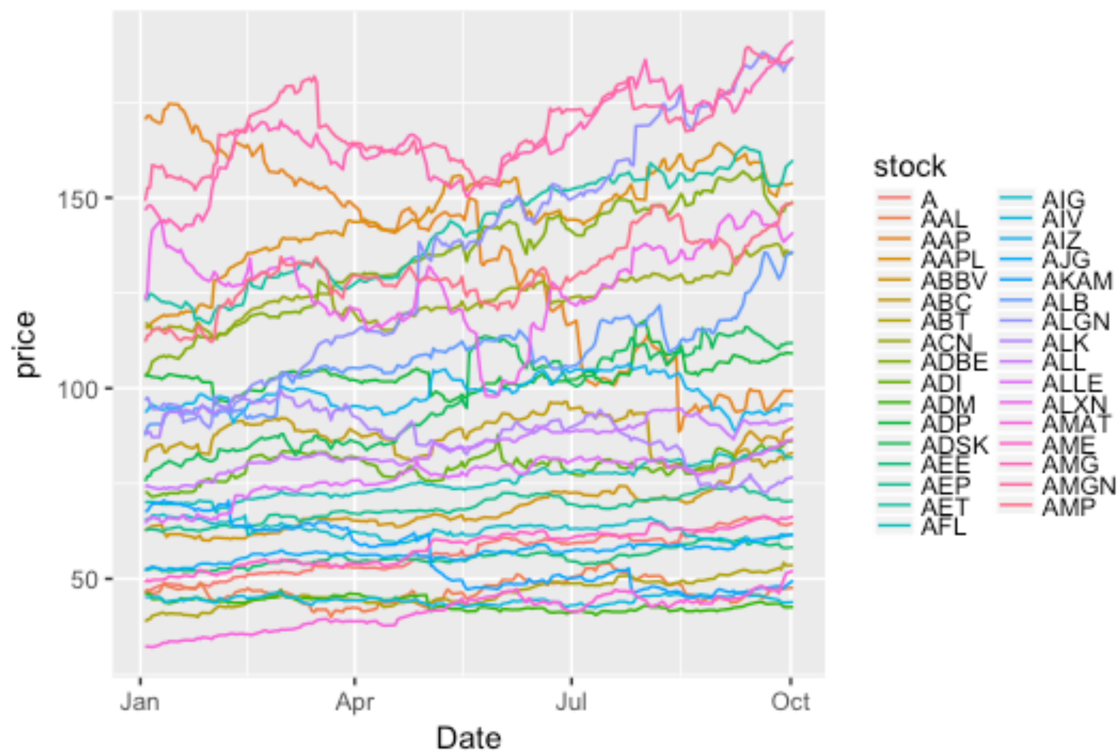
Example Data



Example Data



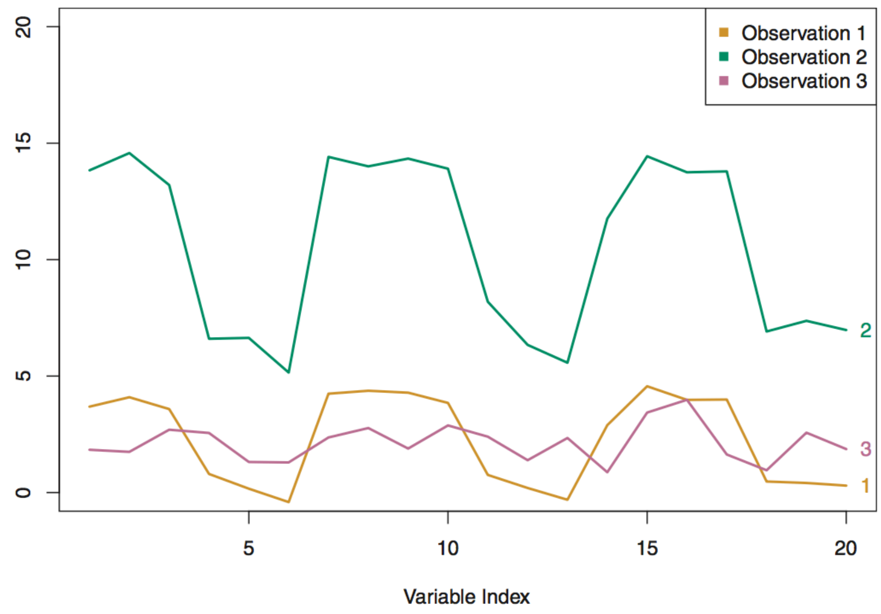
Example Data



Distance between Time Series

- **Euclidean Distance may not be what we want.**

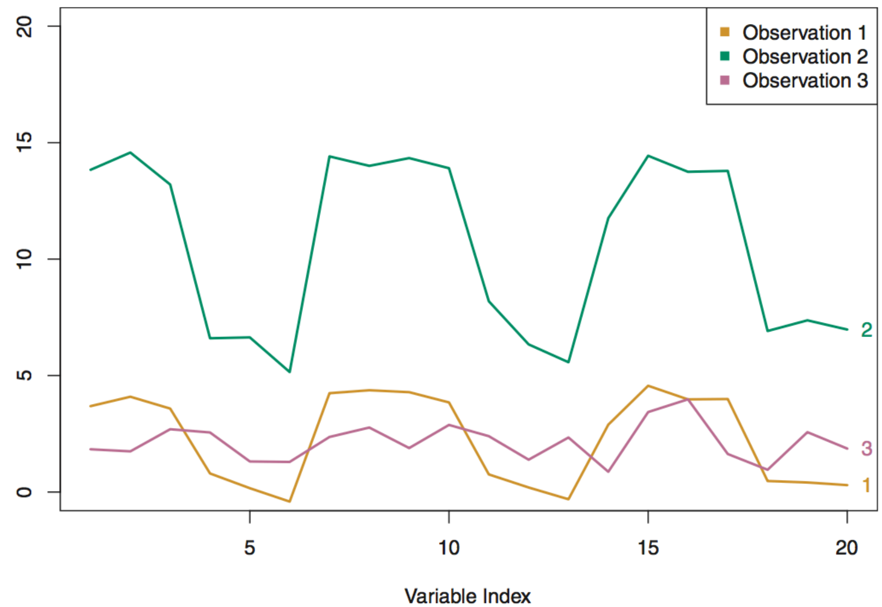
(The source of this pic : here)



Distance between Time Series

- **Think about Correlation**

$$\rho(x_i, x_{i'}) = \frac{\sum_j (x_{ij} - \bar{x}_i)(x_{i'j} - \bar{x}_{i'})}{\sqrt{\sum_j (x_{ij} - \bar{x}_i)^2 \sum_j (x_{i'j} - \bar{x}_{i'})^2}}$$



Distance between Time Series

- **Think about Dynamic Time Warping (DTW) Distance**

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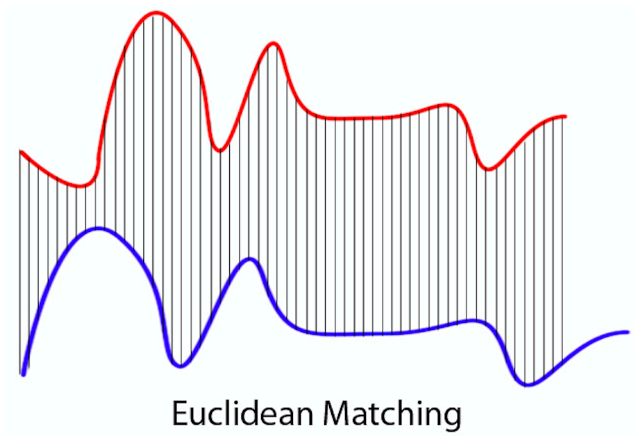
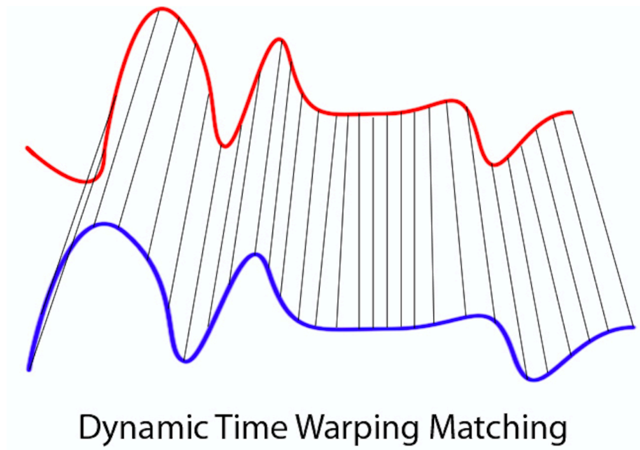
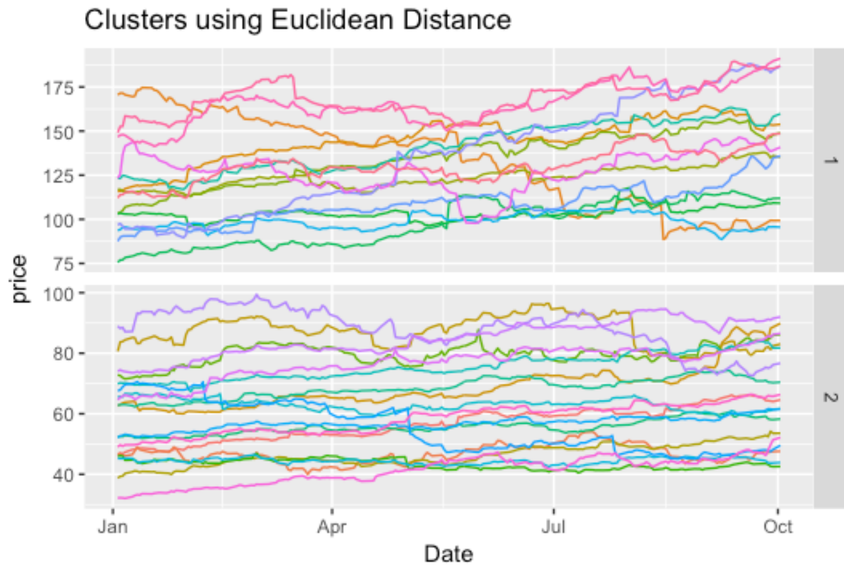
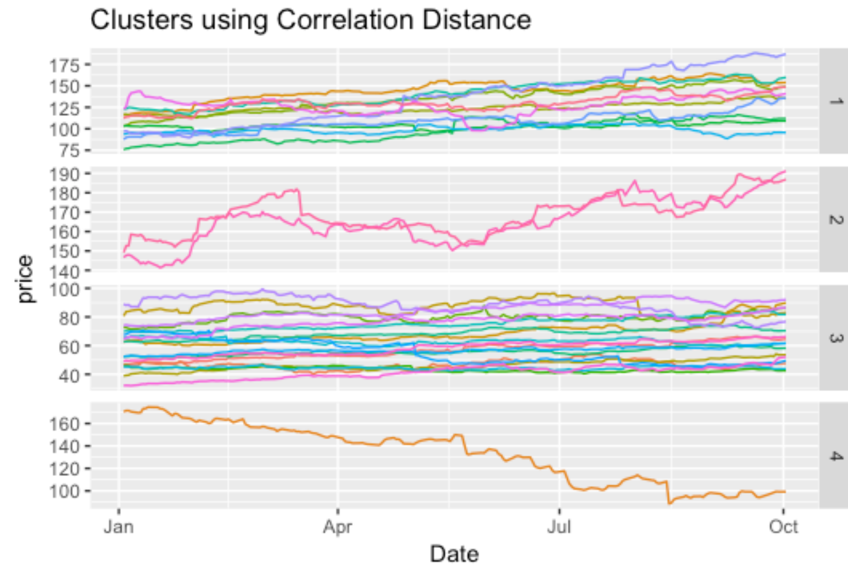




Results


Clusters using Euclidean Distance
price
Date
Jan
Apr
Jul
Oct
1
2


Clusters using Correlation Distance
price
Date
Jan
Apr
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3
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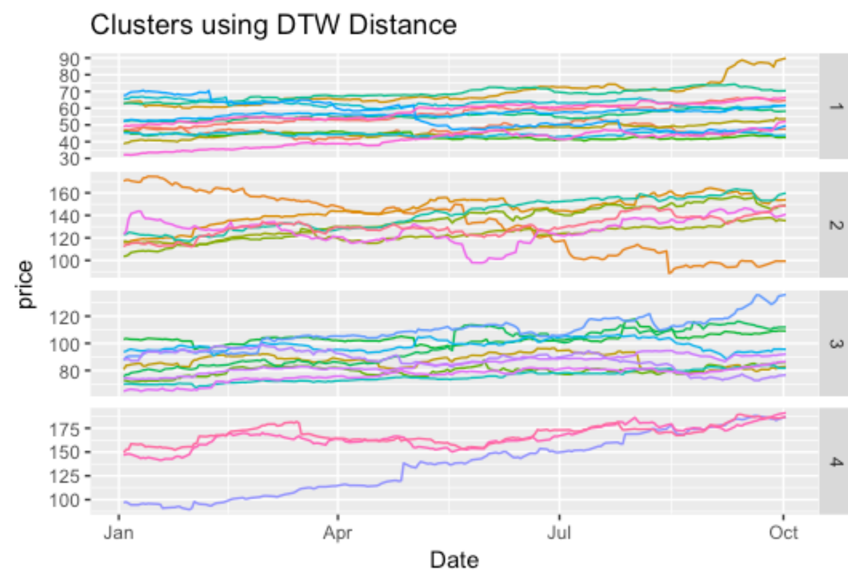
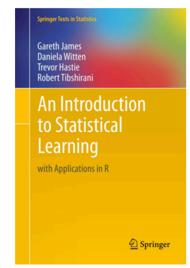
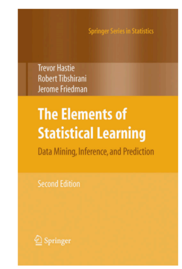

Clusters using DTW Distance
price
Date
Jan
Apr
Jul
Oct
1
2
3
4

References and Resources

- **Books**
  - An Introduction to Statistical Learning with Applications in R
  - The Elements of Statistical Learning: Data Mining, Inference and Prediction





- **R Packages**
  - MixSim – Generate clustering data
  - corrplot – Plot the dissimilarity matrix
  - tidyverse – Data Manipulation
  - ggplot2 – Data Visualization
  - amap – K-means with Correlation Distance

Q and A

- **My personal website and Github**
  - **http://yintingchou.com/**
  - **https://github.com/choux130/EU_TSClustering_101117**

Demo

- **Rstudio!**