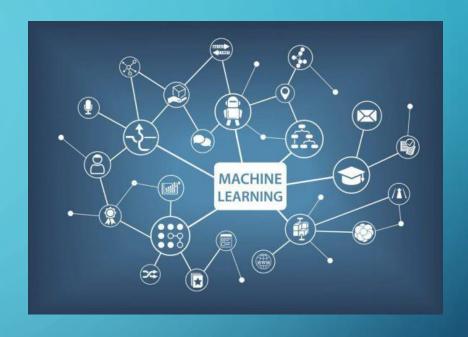
CS5056 TIME SERIES CLUSTERING

HÉCTOR G. CEBALLOS, FRANCISCO J. CANTU

CEBALLOS@TEC.MX, FCANTU@TEC.MX

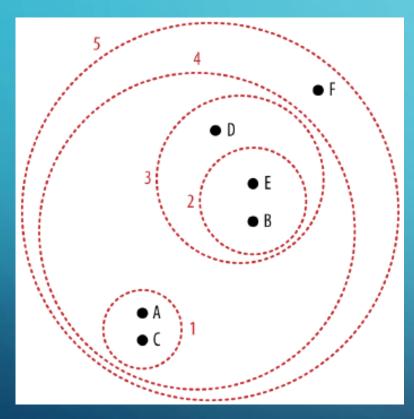




TIME SERIES CLUSTERING



HIERARCHICAL CLUSTERING

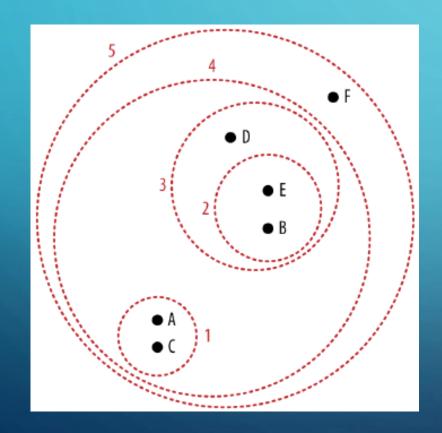


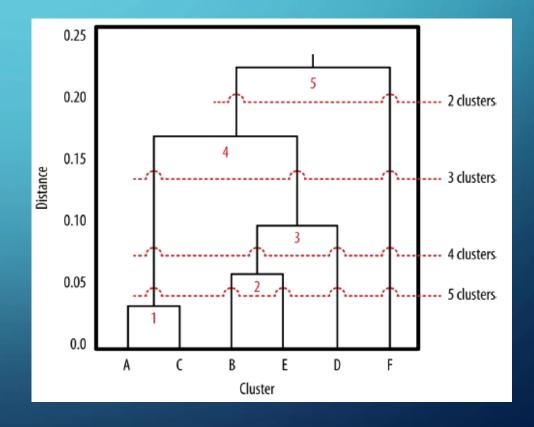
6 objects to classify

• Looks for finding a set of clusters, where elements of each cluster is distinct from elements of each other cluster, and the elements within each cluster are broadly similar to each other.

DENDOGRAMS

Height of horizontal lines indicates how distant is a set of objects from other





SINGLE-LINKAGE CLUSTERING

- Agglomerative (bottom-up) clustering method.
- At each step combines two clusters that contain the closest pair of elements not yet belonging to the same cluster as each other.
- Drawback: nearby elements of the same cluster have small distances, but elements at opposite ends of a cluster may be much farther from each other than two elements of other clusters.

https://en.wikipedia.org/wiki/Single-linkage clustering

SINGLE-LINKAGE CLUSTERING METHOD

- In the beginning, each element is in a cluster of its own.
- The clusters are then sequentially combined into larger clusters, until all elements end up being in the same cluster.
- At each step, the two clusters separated by the shortest distance are combined.
- The function used to determine the distance between two clusters, known as the *linkage function*, is what differentiates the agglomerative clustering methods.

SINGLE-LINKAGE CLUSTERING DISTANCE FUNCTION

• In single-linkage clustering, the distance between two clusters is determined by a single pair of elements: those two elements (one in each cluster) that are closest to each other.

Mathematically, the linkage function – the distance D(X,Y) between clusters X and Y – is described by the expression

$$D(X,Y) = \min_{x \in X, y \in Y} d(x,y),$$

where X and Y are any two sets of elements considered as clusters, and d(x,y) denotes the distance between the two elements x and y.

LINKAGE CLUSTERING SCIPY.CLUSTER.HIERARCHY.LINKAGE

· method='single' assigns

$$d(u, v) = \min(dist(u[i], v[j]))$$

for all points i in cluster u and j in cluster v. This is also known as the Nearest Point Algorithm.

· method='complete' assigns

$$d(u, v) = \max(dist(u[i], v[j]))$$

for all points i in cluster u and j in cluster v. This is also known by the Farthest Point Algorithm or Voor Hees Algorithm.

method='average' assigns

$$d(u, v) = \sum_{ij} \frac{d(u[i], v[j])}{(|u| * |v|)}$$

for all points i and j where |u| and |v| are the cardinalities of clusters u and v, respectively. This is also called the UPGMA algorithm.

· method='weighted' assigns

$$d(u, v) = (dist(s, v) + dist(t, v))/2$$

where cluster u was formed with cluster s and t and v is a remaining cluster in the forest (also called WPGMA).

· method='centroid' assigns

$$dist(s,t) = ||c_s - c_t||_2$$

where c_s and c_t are the centroids of clusters s and t, respectively. When two clusters s and t are combined into a new cluster u, the new centroid is computed over all the original objects in clusters s and t. The distance then becomes the Euclidean distance between the centroid of u and the centroid of a remaining cluster v in the forest. This is also known as the UPGMC algorithm.

• method='median' assigns d(s,t) like the centroid method. When two clusters s and t are combined into a new cluster u, the average of centroids s and t give the new centroid u. This is also known as the WPGMC algorithm.

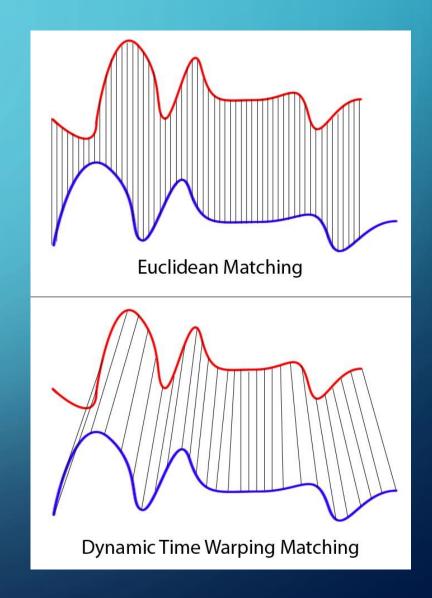
DYNAMIC TIME WARPING

- Dynamic Time Warping (DTW) is one of the algorithms for measuring similarity between two temporal sequences, which may vary in speed.
- DTW has been applied to temporal sequences of video, audio, and graphics data.

https://towardsdatascience.com/dynamic-time-warping-3933f25fcdd

DYNAMIC TIME WARPING

- The idea to compare arrays with different length is to build one-to-many and many-to-one matches so that the total distance can be minimized between the two.
- These two series follow the same pattern, but the blue curve is longer than the red.



DYNAMIC TIME WARPING

• DTW is calculated as the squared root of the sum of squared distances between each element in X and its nearest point in Y. Note that DTW(X, Y) \neq

DTW(Y, X).

$$DTW(x,y) = \min_{\pi} \sqrt{\sum_{(i,j) \in \pi} d(x_i,y_j)^2}$$

where $\pi = [\pi_0, \dots, \pi_K]$ is a path that satisfies the following properties:

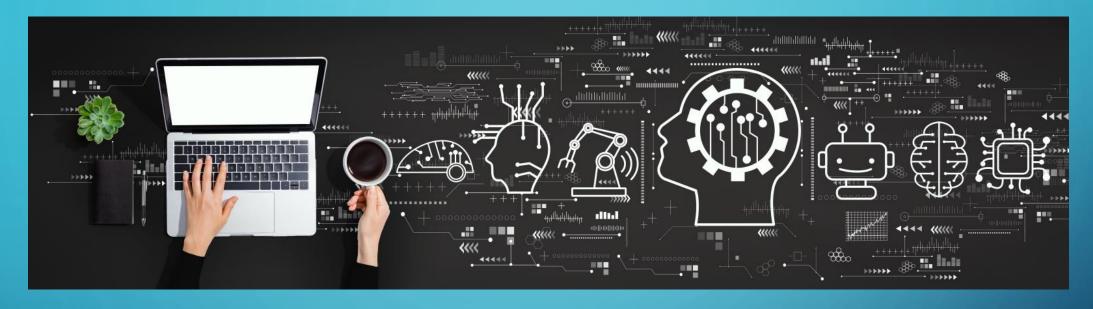
- ullet it is a list of index pairs $\pi_k = (i_k, j_k)$ with $0 \leq i_k < n$ and $0 \leq j_k < m$
- ullet $\pi_0=(0,0)$ and $\pi_K=(n-1,m-1)$
- ullet for all k>0 , $\pi_k=(i_k,j_k)$ is related to $\pi_{k-1}=(i_{k-1},j_{k-1})$ as follows:

$$i_{k-1} \leq i_k \leq i_{k-1} + 1$$

$$j_{k-1} \leq j_k \leq j_{k-1} + 1$$

TIME SERIES CLUSTERING

- In clustering, time series become the data points.
- A distance metric is used for determining if two time series must be grouped together.
- Any clustering method based on metrics can be used, e.g.
 Linkage and K-means.



PRACTICE

DATA SERIES CLUSTERING

DATA SERIES CLUSTERING HANDS-ON EXERCISE

- Generate 6 time series
- Apply linkage clustering to detect the 6 clusters
- Use Pearson and Spearman correlation as distance metric
- Plot the dendogram
- Using the dendogram, predict the composition of clusters on k = [2,3,4,5,7,8]
- Use DTW for linkage clustering.
- Jupyter Notebook: TimeseriesClustering.ipynb