

Mining Time Series:

Computing Similarity

Mining Massive Datasets

Prof. Carlos Castillo — <https://chato.cl/teach>



Universitat
Pompeu Fabra
Barcelona

Sources

- Data Mining, The Textbook (2015) by Charu Aggarwal (chapter 14)
- Introduction to Time Series Mining (2006) [tutorial](#) by Keogh Eamonn [[alt. link](#)]
- Time Series Data Mining (2006) [slides](#) by Hung Son Nguyen

Using Euclidean distance on time series

Euclidean distance for time series

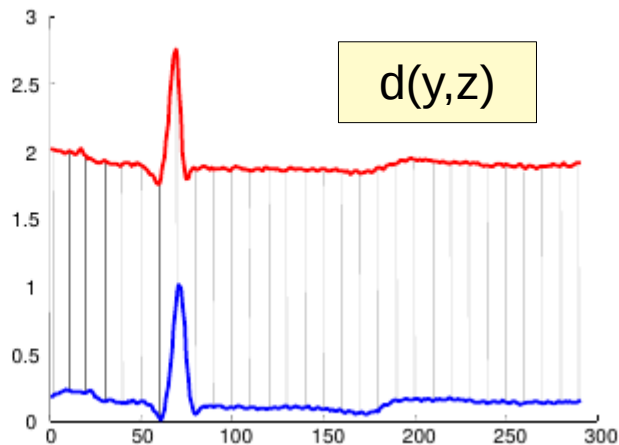
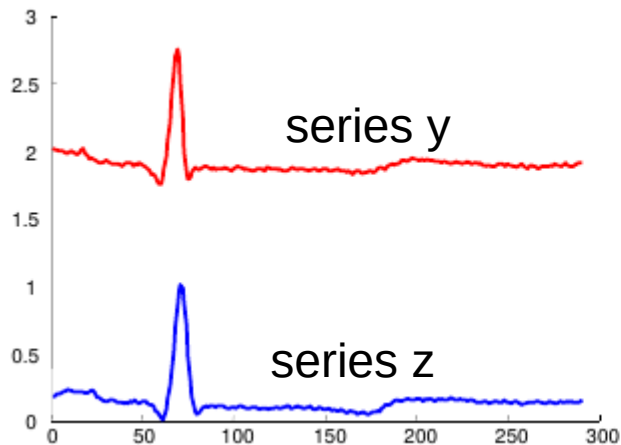
- Euclidean distance between series y and z

$$d(y, z) = \sqrt{\sum_{i=1}^n (y_i - z_i)^2}$$

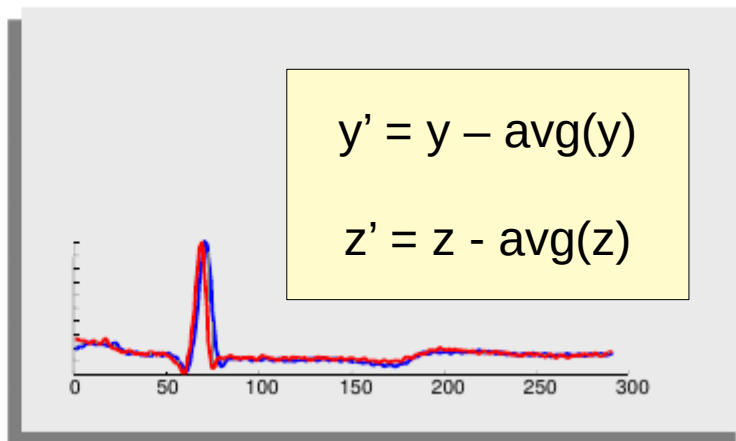
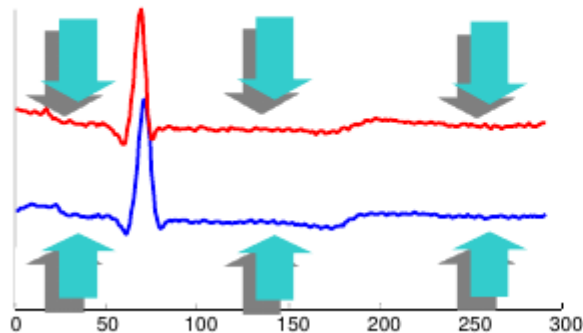
 python
`numpy.linalg.norm(y-z)`

- Sensitive to noise** (see previous slides on how to fix this)
- Sensitive to different offsets, amplitudes, and trends**

Offset translation: subtract the mean

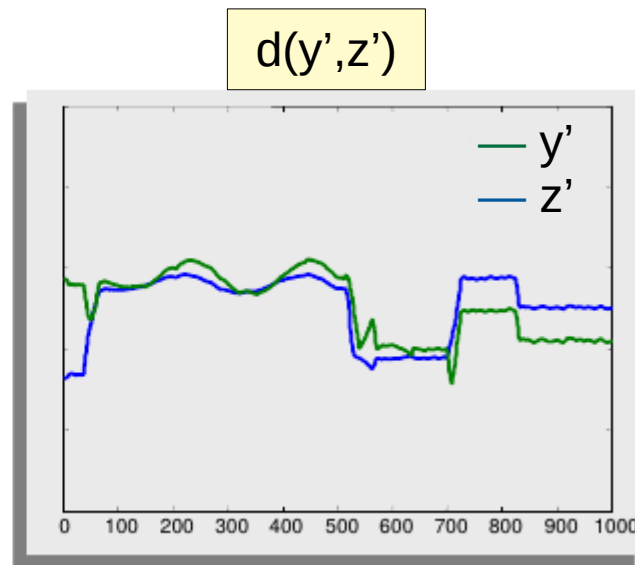
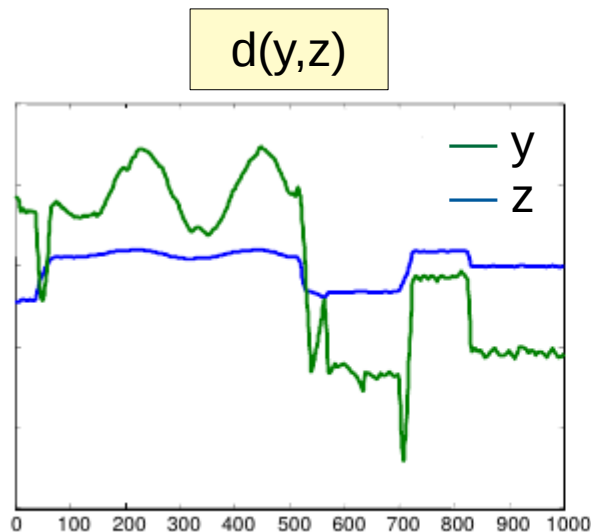


- Series look different



- Series look similar

Amplitude scaling: normalize

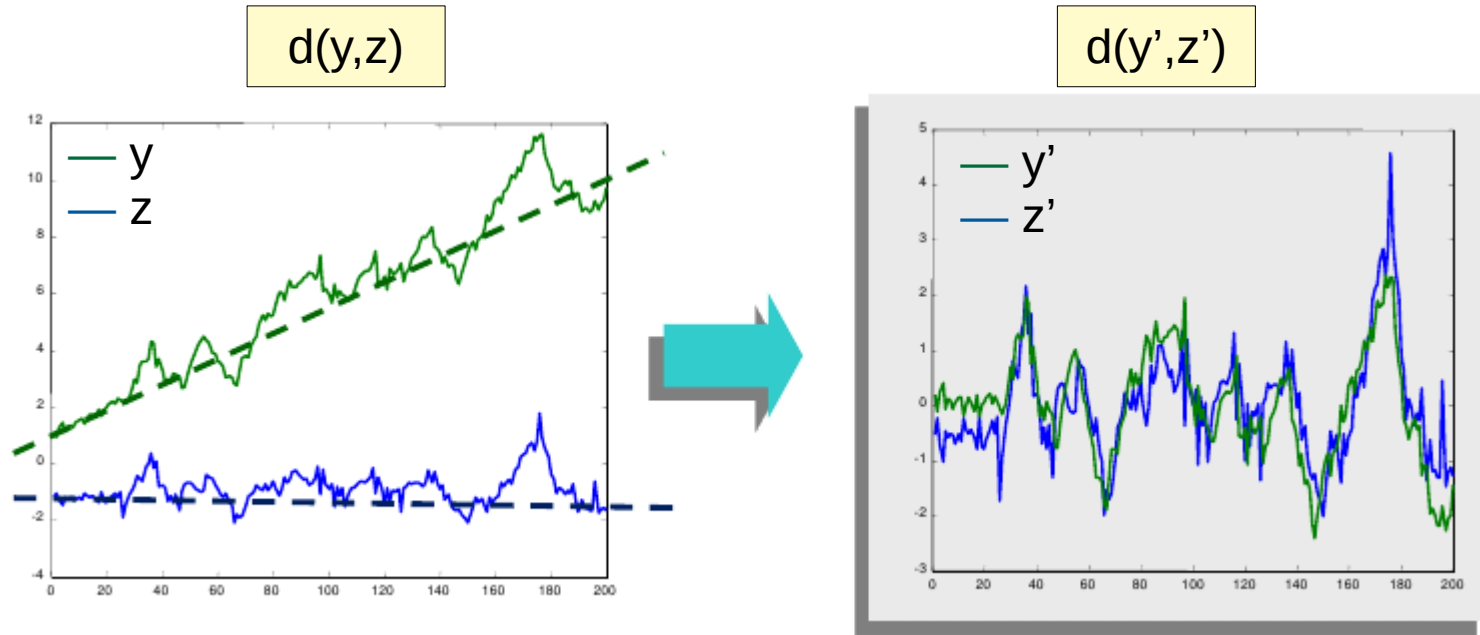


- Standardization
- Range-based normalization

$$y'_i = \frac{y_i - \text{avg}(y)}{\text{std}(y)}$$

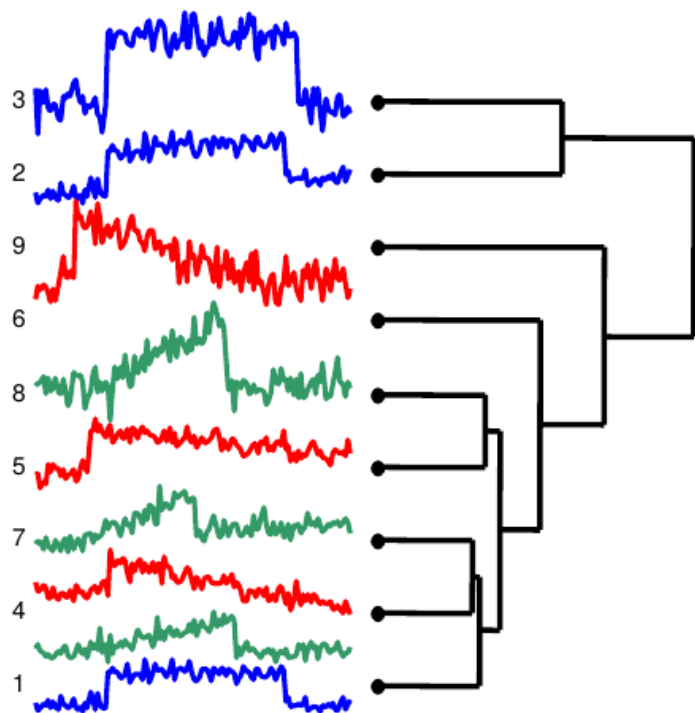
$$y'_i = \frac{y_i - \min(y)}{\max(y) - \min(y)}$$

Trend removal: remove linear trend

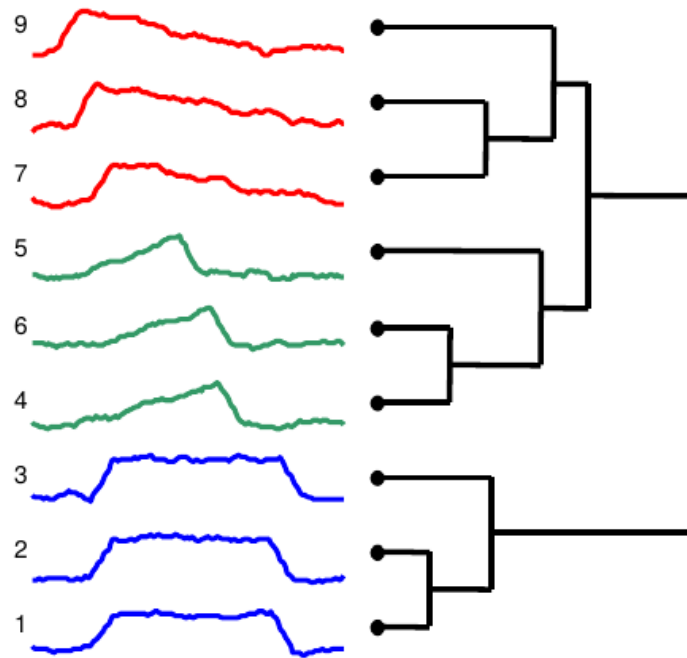


1. Find best straight line fitting data
2. Subtract that line from the data

Example: clustering of time series after using smoothing, offset translation, amplitude scaling, and trend removal



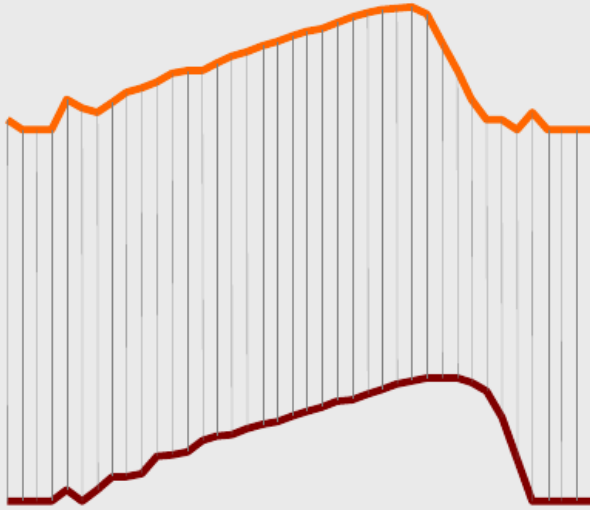
Clustering using euclidean distance on original series



Clustering using euclidean distance on processed series

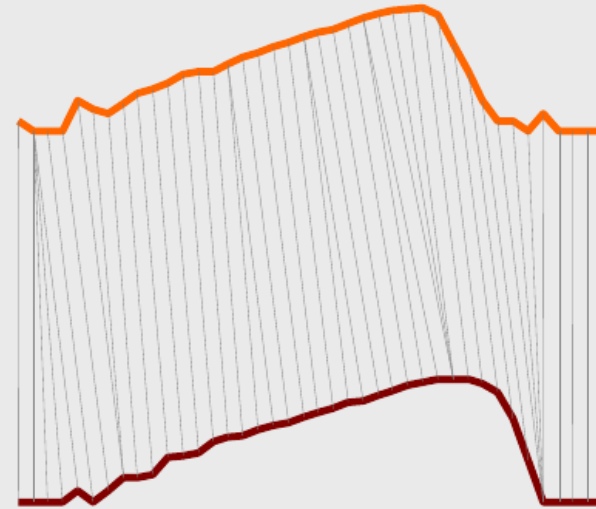
Dynamic time warping

Dynamic time warping



Fixed Time Axis

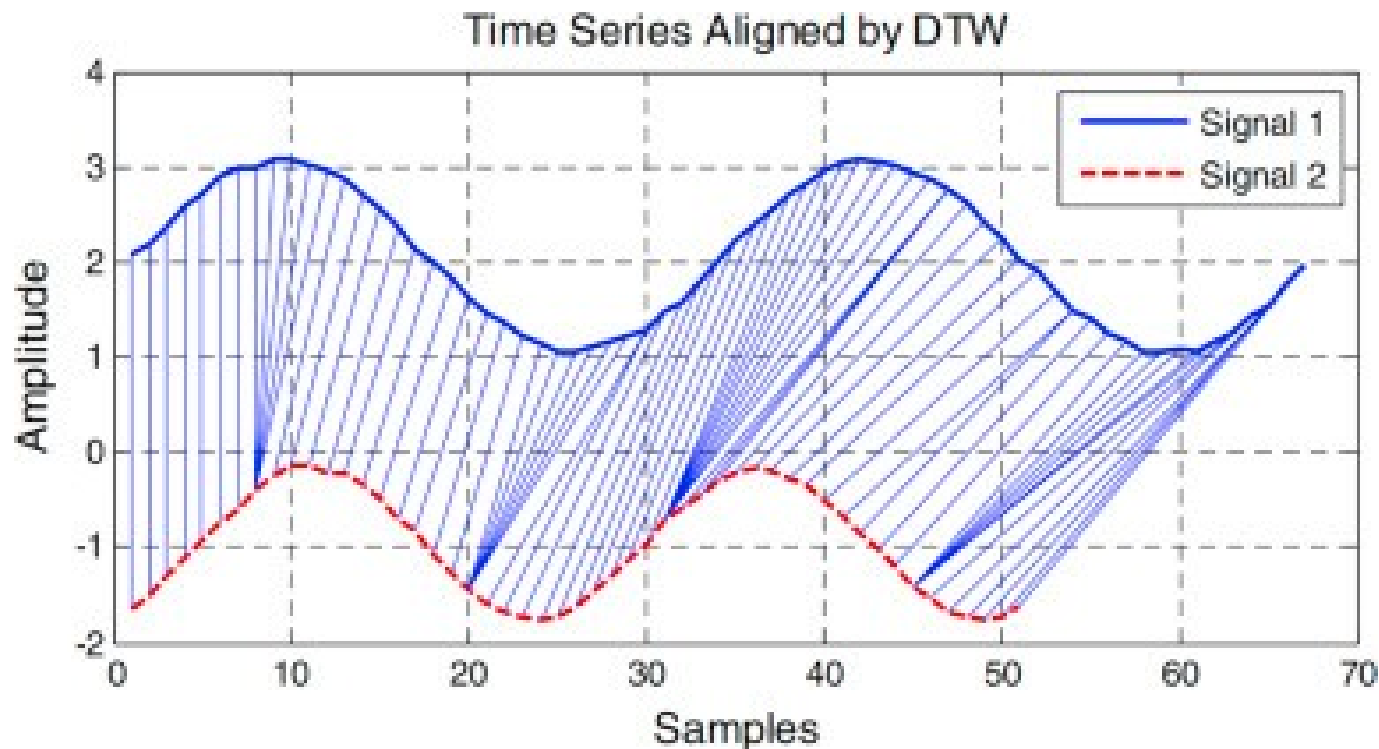
Sequences are aligned “one to one”.



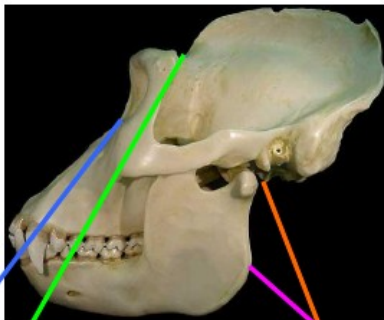
“Warped” Time Axis

Nonlinear alignments are possible.

Dynamic time warping example



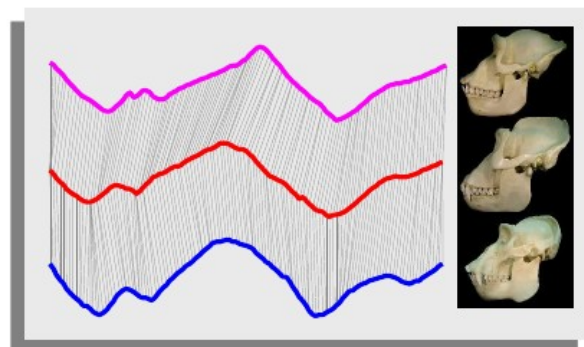
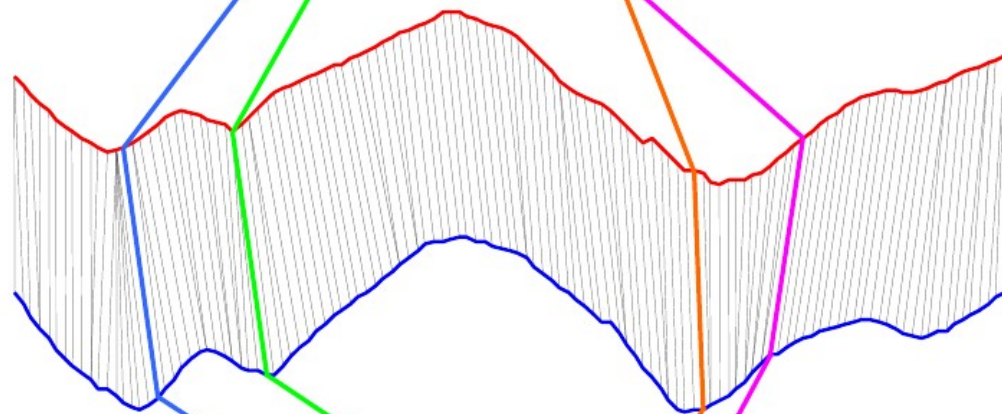
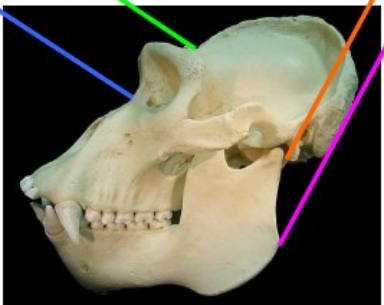
Lowland Gorilla
Gorilla gorilla gorilla



DTW is needed
for most natural
objects...



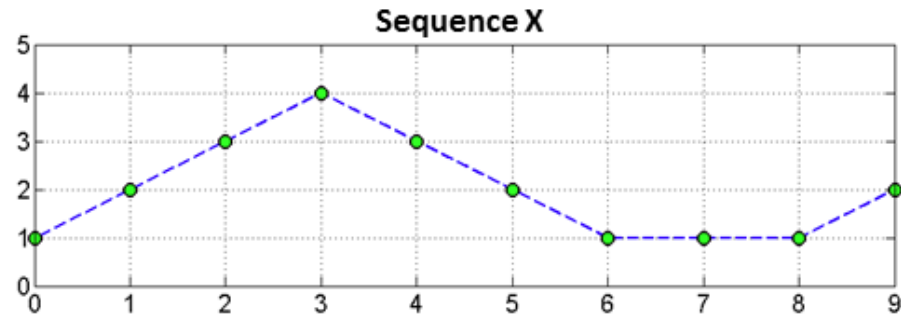
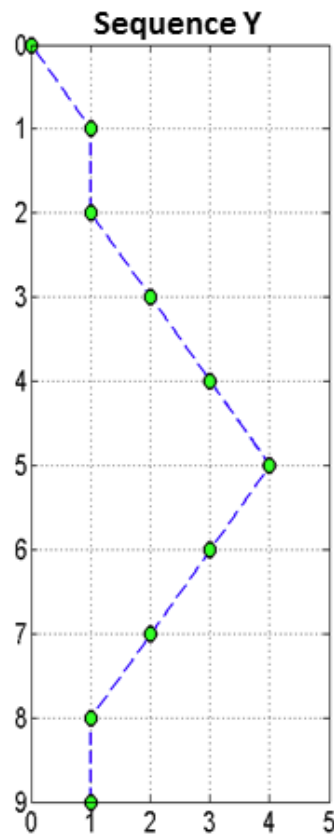
Mountain Gorilla
Gorilla gorilla beringei



Computing DTW(X,Y)

1) Create a matrix M
of size $|X| \times |Y|$

2) Fill-in the matrix
using **dynamic programming**



1	5	14	30						
1	2	6	15						

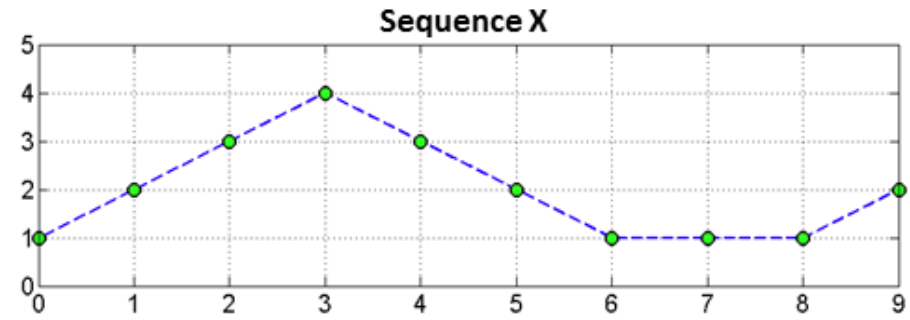
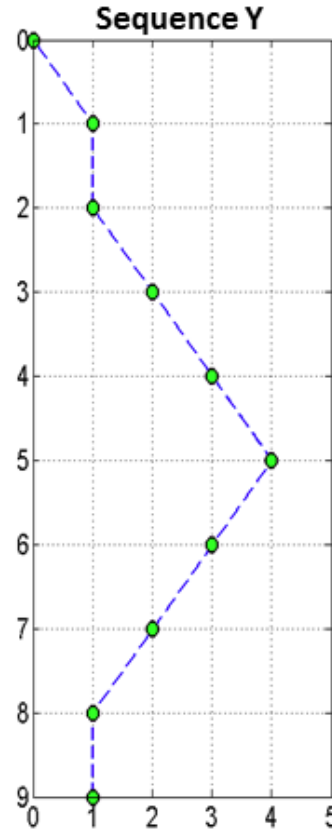
$$M(i, j) = d(y_i, x_j) + \min\{M(i-1, j-1), M(i-1, j), M(i, j-1)\}$$

Computing DTW(X,Y)

(cont.)

- 1) Create a matrix M of size $|X| \times |Y|$
- 2) Fill-in the matrix using dynamic programming
- 3) Find **lighter path**
- 4) Cell (a,b) in path \Rightarrow points a,b should be aligned

[Source]



1	5	14	30	39	43	44	45	46	50
1	2	6	15	19	20	20	20	20	21
1	2	6	15	19	20	20	20	20	21
2	1	2	6	7	7	8	9	10	10
6	2	1	2	2	3	7	11	13	11
15	6	2	1	2	6	12	16	20	15
19	7	2	2	1	2	6	10	14	15
20	7	3	6	2	1	2	3	4	4
20	8	7	12	6	2	1	1	1	2
20	9	11	16	10	3	1	1	1	2

Exercise: Dynamic Time Warping

- Compute DTW these two series
- Create the matrix using the formula (remember first row and first column will be different)
- Mark with color the minimum path

t	1	2	3	4	5	6
Y_t	2	5	2	5	3	--
X_t	0	3	6	0	6	1

$$M(i, j) = d(y_i, x_j) + \min\{M(i-1, j-1), M(i-1, j), M(i, j-1)\}$$

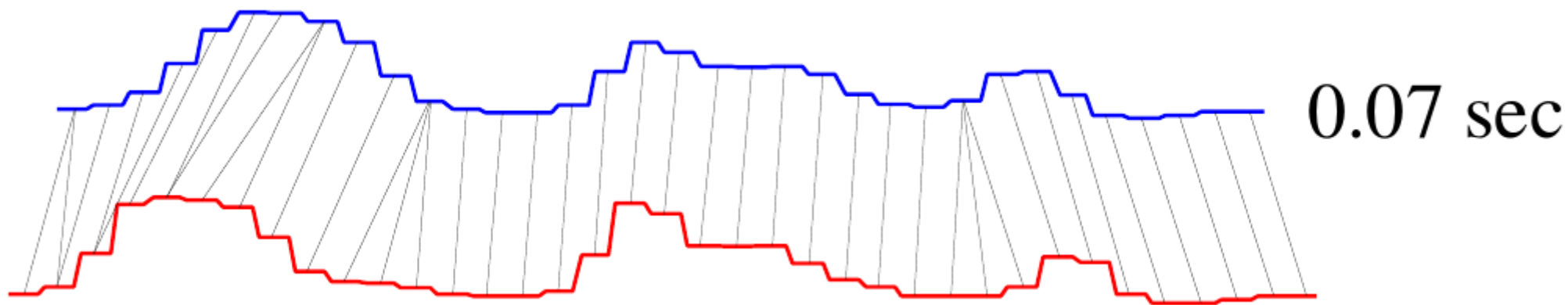
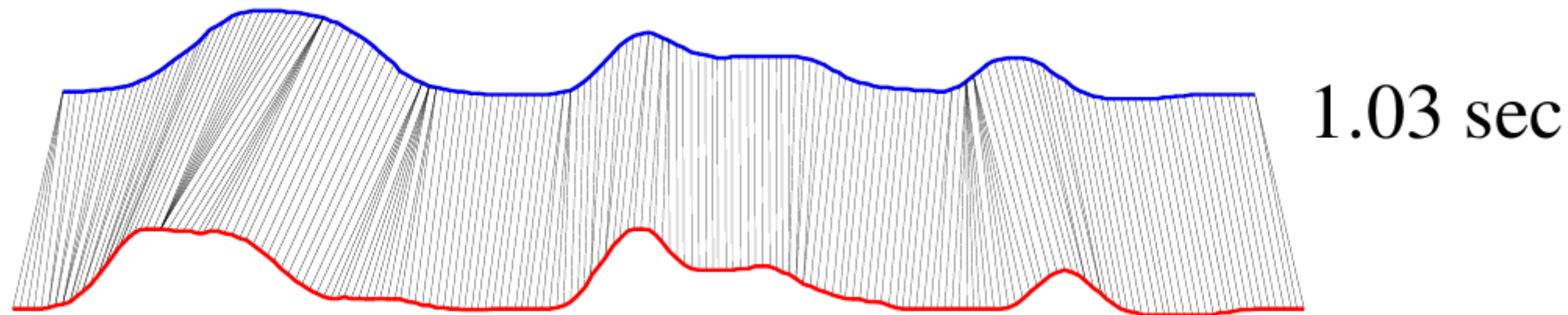


Spreadsheet links: <https://upfbarcelona.padlet.org/chato/hogch321o6pws1fd>

Faster DTW through size reduction

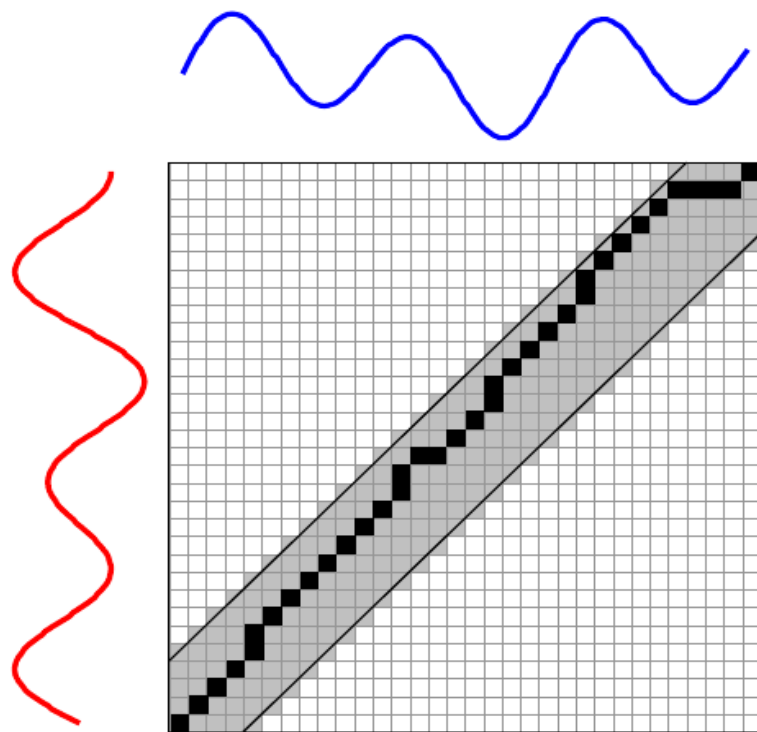
- How to avoid having a large matrix?
- Use less points
 - Sub-sample from original series
 - Bin the original series
- If sampling was done, after doing DTW:
 - Interpolate warpings for intermediate points

Example: faster DTW through sub-sampling

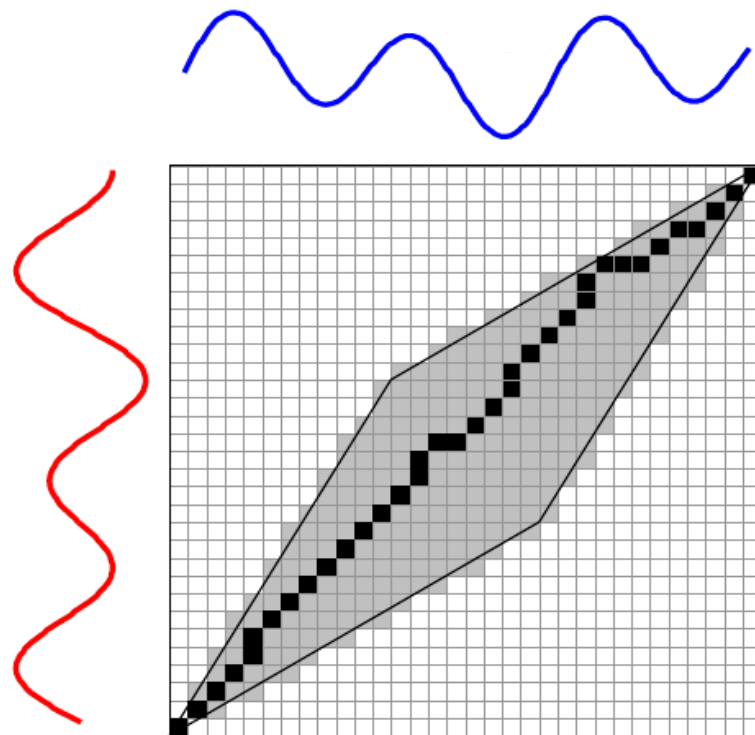


How to avoid **pathological** warpings?

Assume original series cannot be so far apart from each other, using domain knowledge



Sakoe-Chiba Band



Itakura Parallelogram

Summary

Things to remember

- Dynamic time warping

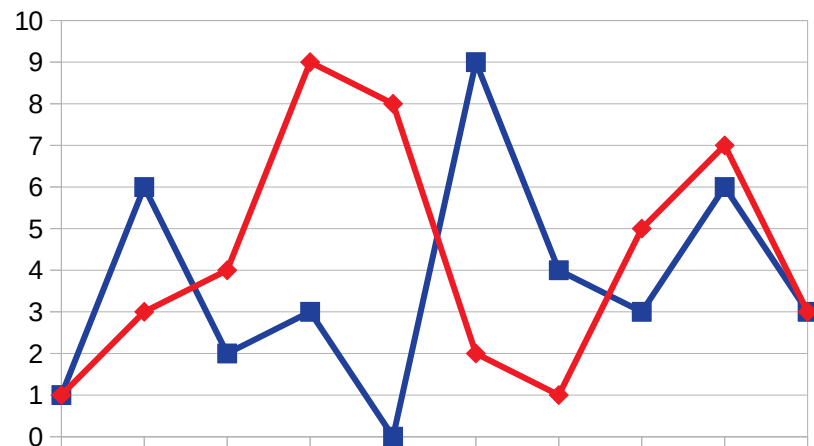
Solved exercise on DTW

- Blue series:

1, 6, 2, 3, 0, 9, 4, 3, 6, 3

- Red series:

1, 3, 4, 9, 8, 2, 1, 5, 7, 3



- First try to do it on your own, then you can watch the solution:

https://youtu.be/_K1OsqCicBY?t=125

Exercises for TT27-TT29

- Data Mining, The Textbook (2015) by Charu Aggarwal
 - Exercises 14.10 \rightarrow 1-6