

# Mining and Processing Biomedical Data

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adiunkt naukowy

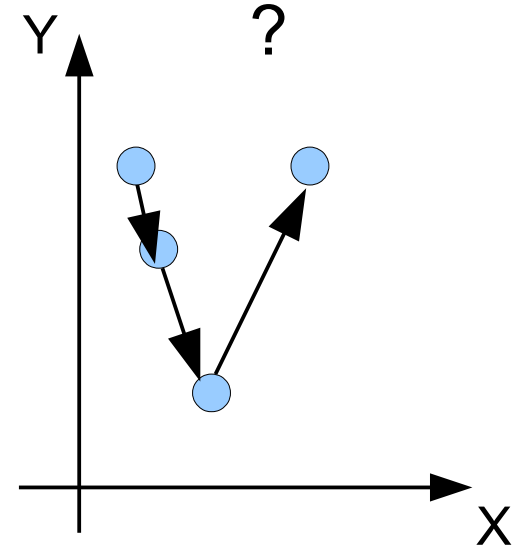
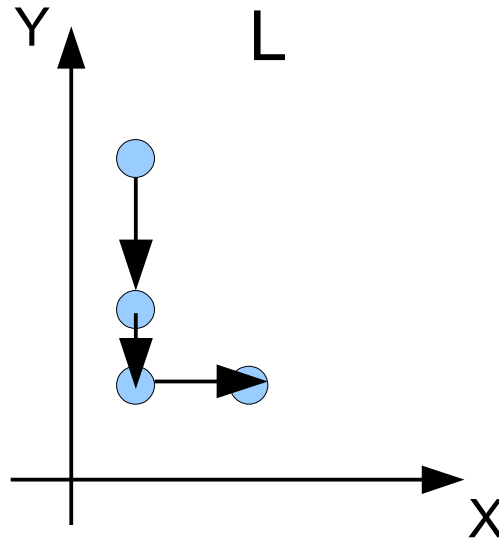
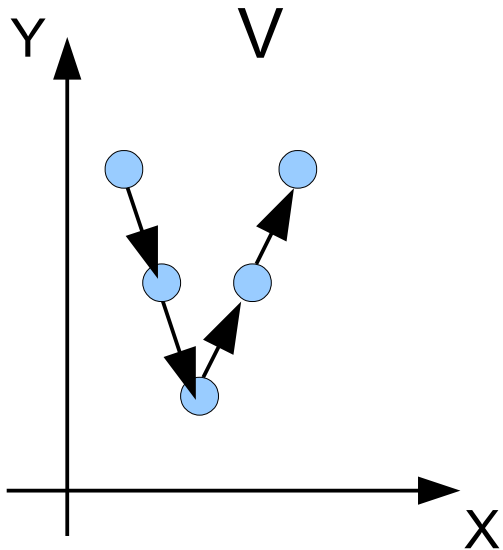
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# Multivariate DTW

# Example: handwriting recognition



Time series (deltaX, deltaY):

(1,-2), (1, -2), (1, 2), (1, 2)

(0,-3), (0, -1), (3, 0)

(0.5,-1), (1.5, -3), (2, 4)

# DTW on multivariate time series

(0.5, -1)

(1.5, -3)

(2, 4)

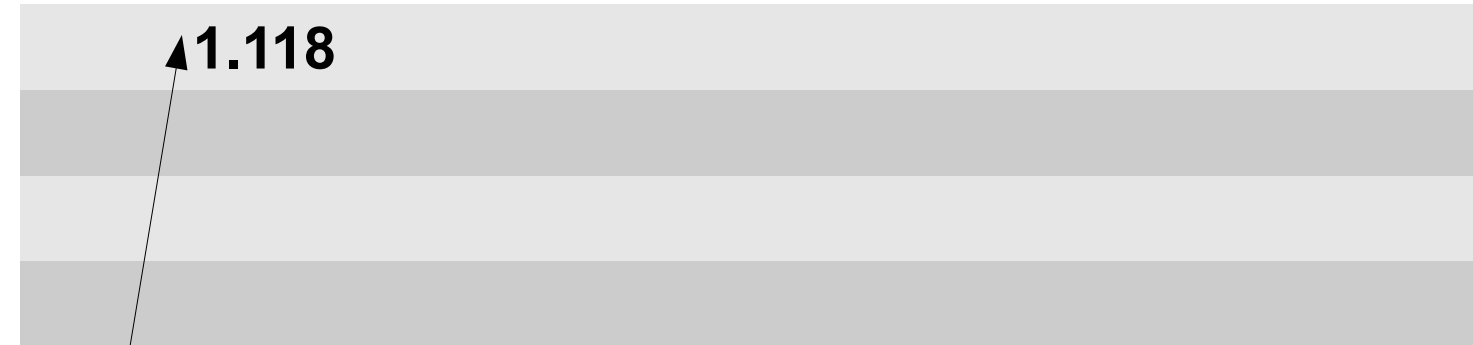
(1, -2)

1.118

(1, -2)

(1, 2)

(1, 2)



$$\sqrt{(1 - 0.5)^2 + ((-2) - (-1))^2}$$

# DTW on multivariate time series

**(0.5, -1)**

(1.5, -3)

(2, 4)

(1, -2)

**1.118**

**(1, -2)**

**2.236**

(1, 2)

(1, 2)

$$1.118 + \sqrt{(1 - 0.5)^2 + ((-2) - (-1))^2}$$

# DTW on multivariate time series

**(0.5, -1)**

(1.5, -3)

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**1.118**

(1, -2)

**2.236**

**(1, 2)**

**5.277**

(1, 2)

$$2.236 + \sqrt{(1 - 0.5)^2 + (2 - (-1))^2}$$

# DTW on multivariate time series

**(0.5, -1)**

(1.5, -3)

(2, 4)

(1, -2)

**1.118**

(1, -2)

**2.236**

(1, 2)

**5.277**

**(1, 2)**

**8.318**

$$5.277 + \sqrt{(1 - 0.5)^2 + (2 - (-1))^2}$$

# DTW on multivariate time series

	(0.5, -1),	(1.5, -3),	(2, 4)
(1, -2)	1.118	2.236	
(1, -2)	2.236		
(1, 2)	5.277		
(1, 2)	8.318		

$$1.118 + \sqrt{(1 - 1.5)^2 + ((-2) - (-3))^2}$$



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	(0.5, -1),	(1.5, -3),	(2, 4)
(1, -2)	1.118	2.236	
(1, -2)	2.236	2.236	
(1, 2)	5.277		
(1, 2)	8.318		

$$1.118 + \sqrt{(1 - 1.5)^2 + ((-2) - (-3))^2}$$

↑  
Min {1.118, 2.236, 2.236}

# DTW on multivariate time series

	(0.5, -1),	(1.5, -3),	(2, 4)
(1, -2)	1.118	2.236	
(1, -2)	2.236	2.236	
(1, 2)	5.277	7.261	
(1, 2)	8.318		

$$2.236 + \sqrt{(1 - 1.5)^2 + (2 - (-3))^2}$$

↑  
Min {5.277, 2.236, 2.236}

# DTW on multivariate time series

	(0.5, -1),	(1.5, -3),	(2, 4)
(1, -2)	1.118	2.236	
(1, -2)	2.236	2.236	
(1, 2)	5.277	7.261	
(1, 2)	8.318	12.286	

$$5.277 + \sqrt{(1 - 1.5)^2 + (2 - (-3))^2}$$

↑  
Min {5.277, 7.261, 8.318}

# DTW on multivariate time series

	(0.5, -1),	(1.5, -3),	(2, 4)
(1, -2)	1.118	2.236	8.319
(1, -2)	2.236	2.236	8.319
(1, 2)	5.277	7.261	4.472
(1, 2)	8.318	12.286	6.708

- What if the time-series have more than two channels (ECG, EEG)?
- Euclidean distance vs. cosine distance

# Speeding-up nearest neighbor classification of time-series

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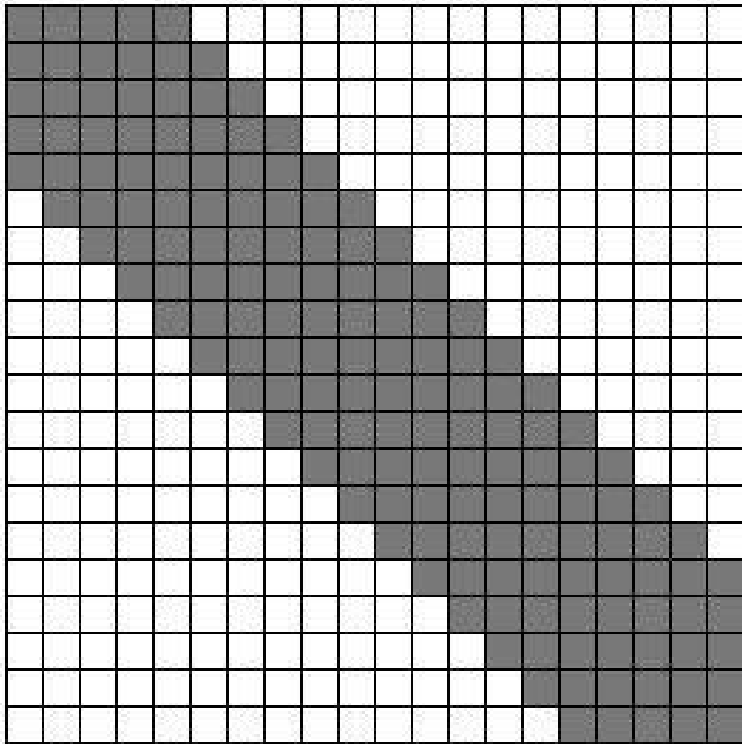
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  - Numerosity reduction / instance selection

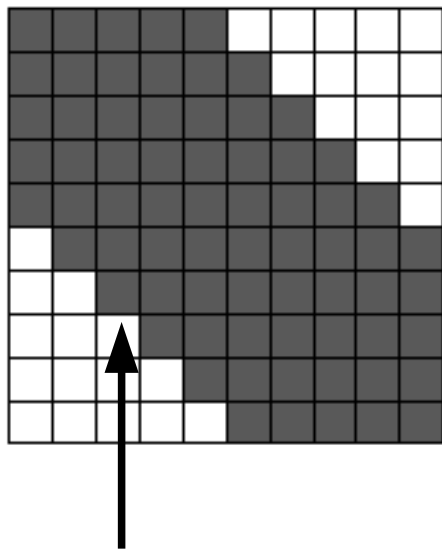
# Constrained DTW



- Calculate only the marked entries of the DTW-matrix, i.e., the ones that are „close“ to the diagonal of the matrix
- „Extreme“ variant of this idea: Lucky Time Warping (Spiegel, 2014)

Spiegel, Stephan, Brijnesh-Johannes Jain, and Sahin Albayrak.  
"Fast Time Series Classification under Lucky Time Warping Distance."  
SAC 2014.

# Early Stop



This column was just calculated. If all the entries in this column are larger than  $d$ , we do not need to calculate the rest of the matrix.

- We want to determine the nearest neighbors of the time series  $t^*$
- We are in an intermediate step, i.e., we already calculated the distance between  $t^*$  and some of the time series of the training data  $\rightarrow$  we know that the distance between  $t^*$  and some other time series is  $d$
- We are calculating the distance between  $t^*$  and the currently considered time series.
- If the DTW matrix has only entries being greater than  $d$  in the column that was calculated last  $\rightarrow$  stop the calculations (the currently considered time series can not be the nearest neighbor anyway).

# Nearest Neighbor Classification with Lower Bounding

$t^*$  – Time series to be classified

$d^*$  – distance of the currently found closest time series

$d^* \leftarrow \text{infinity}$

**for each** time series  $t$  of the training data {

$d \leftarrow \text{estimate\_distance}(t^*, t)$

(  $d$  is a lower bound, i.e., the estimation is done in a way that the true distance is greater than or equal to  $d$  )

if (  $d > d^*$  ) **continue**;

$d1 \leftarrow \text{DTW}(t^*, t)$

if (  $d1 < d^*$  ) {

$d^* \leftarrow d1$ ;  $\text{nearest\_neighbor} \leftarrow t$ ;

}

}

See also:

Rath, Toni M., and R. Manmatha. "Lower-bounding of dynamic time warping distances for multivariate time series." (2003).