

# Time Series and Dynamic Time Warping

CSE 4309 – Machine Learning

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# Sequential Data

- Sequential data, as the name implies, are sequences.
- What is the difference between a **sequence** and a **set**?
- A sequence  $X$  is a set of elements, together with a **total order** imposed on those elements.
  - A **total order** describes, for any two elements  $x_1, x_2$ , which of them comes before and which comes after.
- Examples of sequential data:
  - Strings: sequences of characters.
  - Time series: sequences of vectors.

# Time Series

- A **time series** is a **sequence** of observations made over time.
- Examples:
  - Stock market prices (for a single stock, or for multiple stocks).
  - Heart rate of a patient over time.
  - Position of one or multiple people/cars/airplanes over time.
  - Speech: represented as a sequence of audio measurements at discrete time steps.
  - A musical melody: represented as a sequence of pairs (note, duration).

# Applications of Time Series Classification

- Predicting future prices (stock market, oil, currencies...).
- Heart rate of a patient over time:
  - Is it indicative of a healthy heart, or of some disease?
- Position of one or multiple people/cars/airplanes over time.
  - Predict congestion along a route suggested by the GPS.
- Speech recognition.
- Music recognition.
  - Sing a tune to your phone, have it recognize the song.
  - Recognize the genre of a song based on how it sounds.

# Time Series Example: Signs

- 0.5 to 2 million users of American Sign Language (ASL) in the US.
- Different regions in the world use different sign languages.
  - For example, British Sign Language (BSL) is different than American Sign Language.
- These languages have vocabularies of thousands of signs.
- We will use sign recognition as our example application, as we introduce methods for time series classification.

# Example: The ASL Sign for "again"



# Example: The ASL Sign for "bicycle"



# Representing Signs as Time Series

- A sign is a video (or part of a video).
- A video is a sequence of frames.
  - A sequence of images, which, when displayed rapidly in succession, create the illusion of motion.
- At every frame  $i$ , we extract a **feature vector**  $\mathbf{x}_i$ .
  - How should we define the feature vector? This is a (challenging) computer vision problem.
  - The methods we will discuss work with **any** choice we make for the feature vector.
- Then, the entire sign is represented as time series  $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_D)$ .
  - $D$  is the length of the sign video, measured in frames.



# Feature Vectors

- Finding good feature vectors for signs is an active research problem in computer vision.



# Feature Vectors

- We choose a simple approach: the feature vector at each frame is the (x, y) pixel location of the right hand at that frame.



Frame 1:  
Feature vector  
 $\mathbf{x}_1 = (192, 205)$

# Feature Vectors

- We choose a simple approach: the feature vector at each frame is the (x, y) pixel location of the right hand at that frame.



Frame 2:  
Feature vector  
 $\mathbf{x}_2 = (190, 201)$

# Feature Vectors

- We choose a simple approach: the feature vector at each frame is the (x, y) pixel location of the right hand at that frame.



Frame 3:  
Feature vector  
 $\mathbf{x}_3 = (189, 197)$

# Time Series for a Sign

- Using the previous representation, for sign "AGAIN" we end up with this time series:

((192, 205),(190, 201),(190, 194),(191, 188),(194, 182),(205, 183),  
(211, 178),(217, 171),(225, 168),(232, 167),(233, 167),(238, 168),  
(241, 169),(243, 176),(254, 177),(256, 179),(258, 186),(269, 194),  
(271, 202),(274, 206),(276, 207),(277, 208)).

- It is a sequence of 22 2D vectors.

# Time Series for a Sign

- Using the previous representation, for sign "AGAIN" we end up with this time series:

((192, 205),(190, 201),(190, 194),(191, 188),(194, 182),(205, 183),  
(211, 178),(217, 171),(225, 168),(232, 167),(233, 167),(238, 168),  
(241, 169),(243, 176),(254, 177),(256, 179),(258, 186),(269, 194),  
(271, 202),(274, 206),(276, 207),(277, 208))

- It is a sequence of 22 2D vectors.

# Time Series Classification



Training sign  
for "AGAIN".

# Time Series Classification



Training sign  
for "BICYCLE".



# Time Series Classification



Suppose our training set only contains those two signs: "AGAIN" and "BICYCLE".

We get this test sign.

Does it mean "AGAIN", or "BICYCLE"?

# Time Series Classification

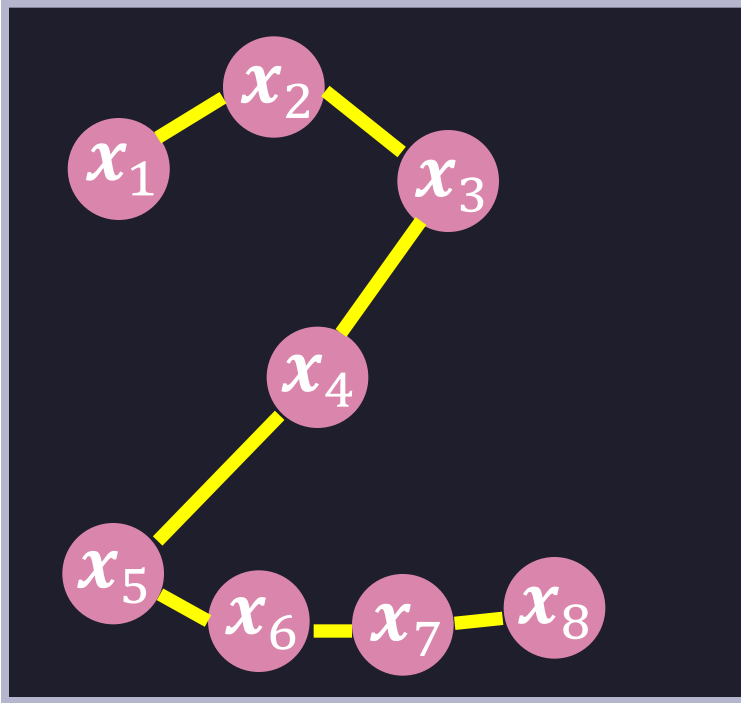


Does this test sign mean "AGAIN", or "BICYCLE"?

We can use nearest-neighbor classification.

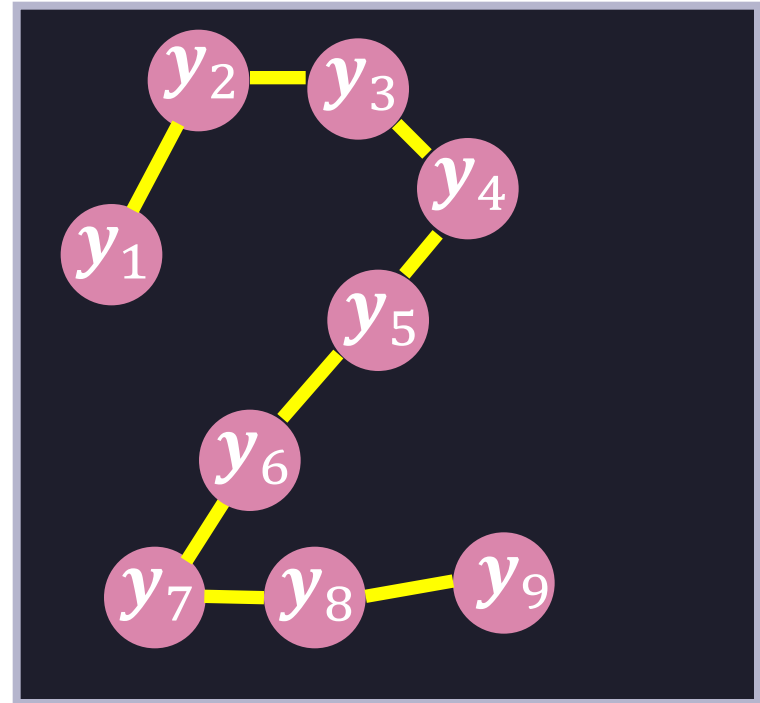
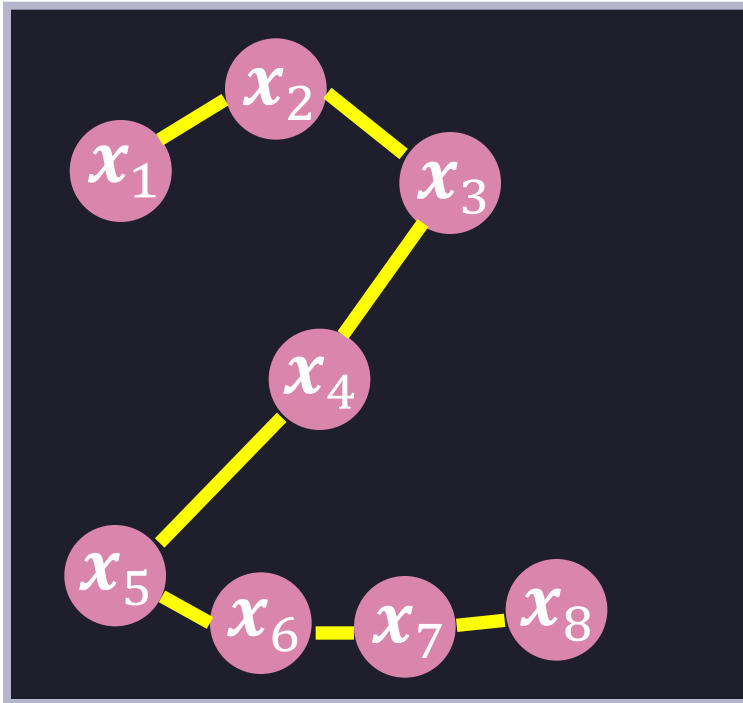
Big question: what distance measure should we choose?

# Visualizing a Time Series



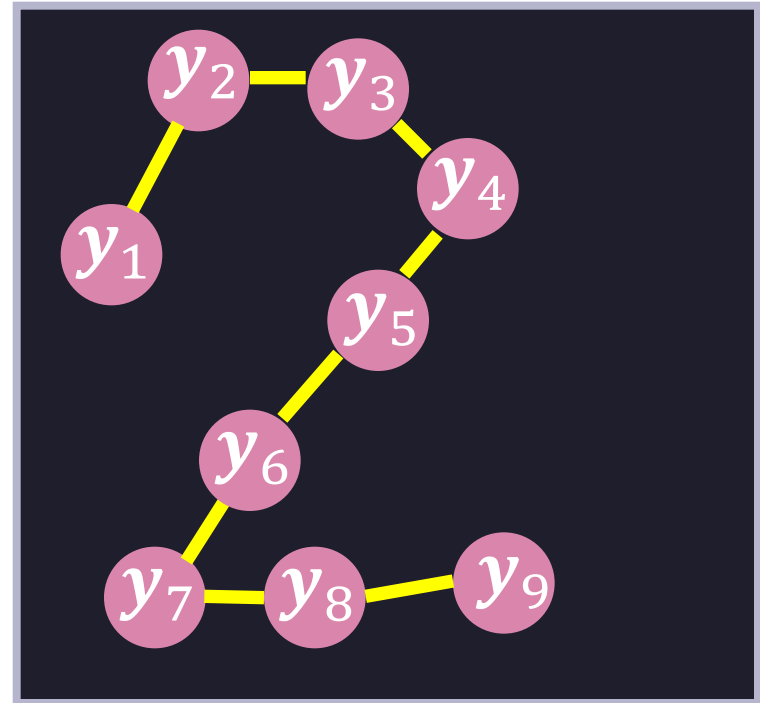
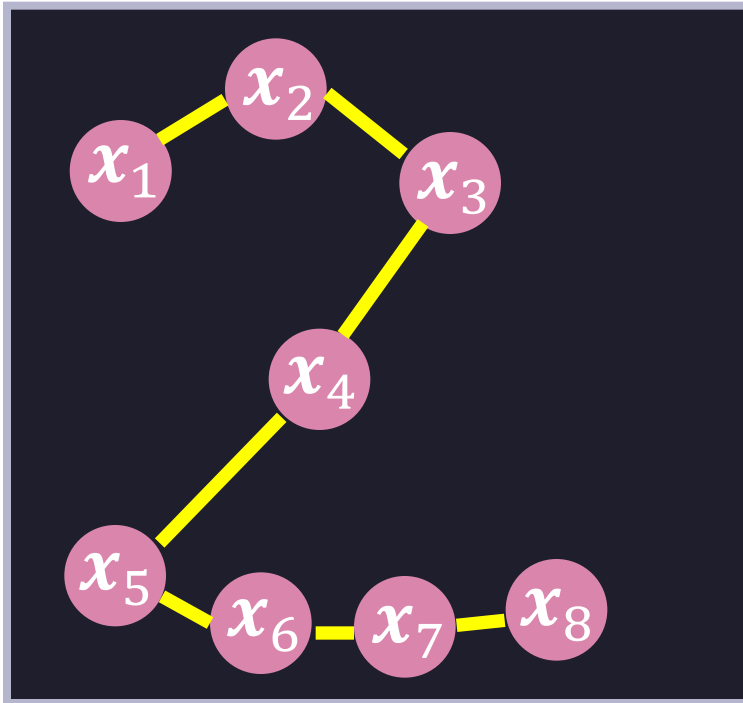
- Here is a visualization of one time series  $X$ .
- Each feature vector (as before) is a point in 2D.
- The time series has eight elements.  $X = (x_1, x_2, \dots, x_D)$ .
- For example,  $x_4$  indicates the position of 2D point  $x_4$ .

# Comparing Time Series



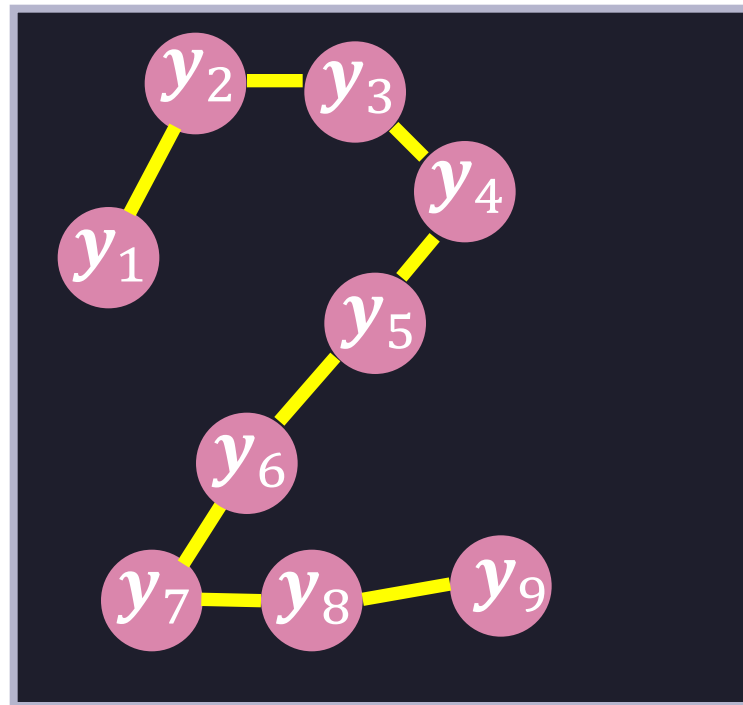
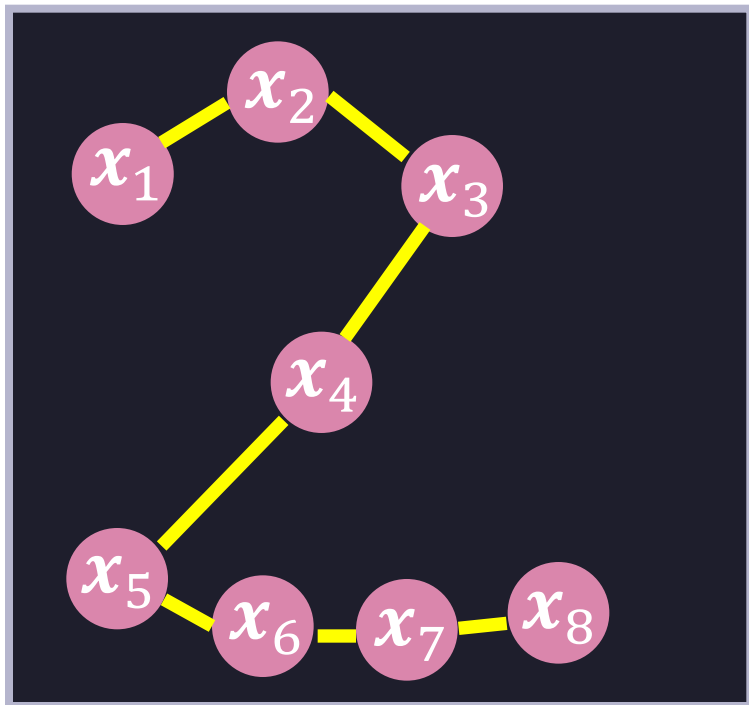
- Here is a visualization of two time series,  $X$  and  $Y$ .
- How do we measure the distance between two time series?

# Comparing Time Series



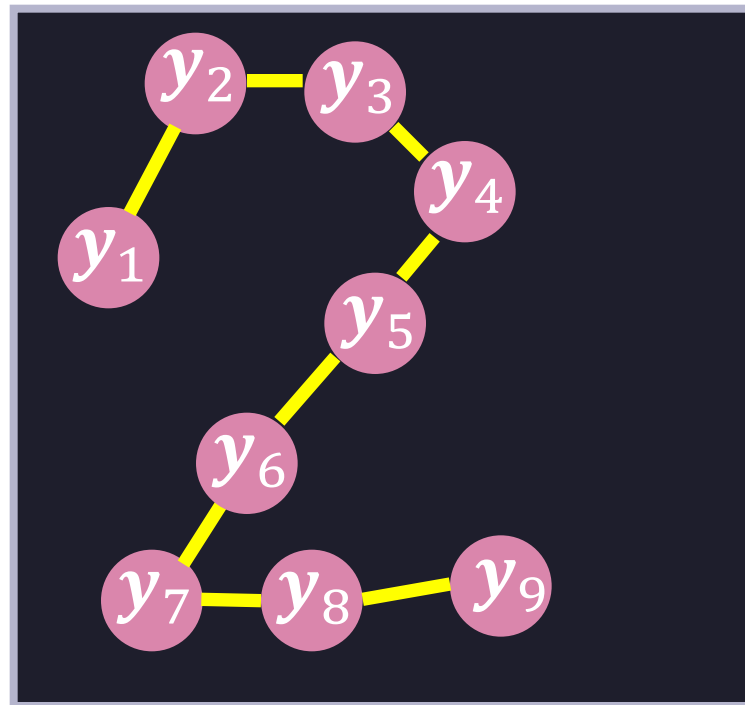
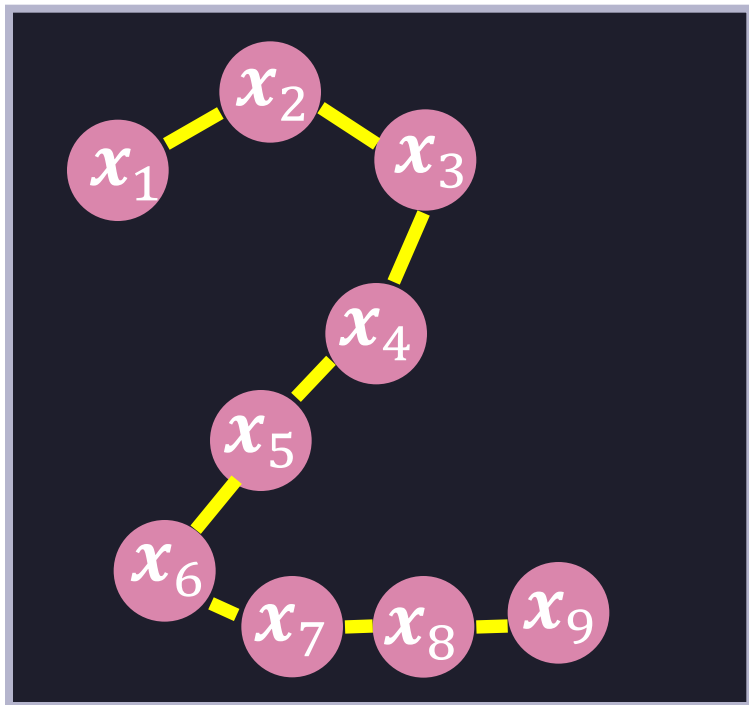
- We could possibly use the Euclidean distance.
  - The first time series is a 16-dimensional vector.
  - The second time series is an 18-dimensional vector.
- However, there are issues...

# Problems with the Euclidean Distance



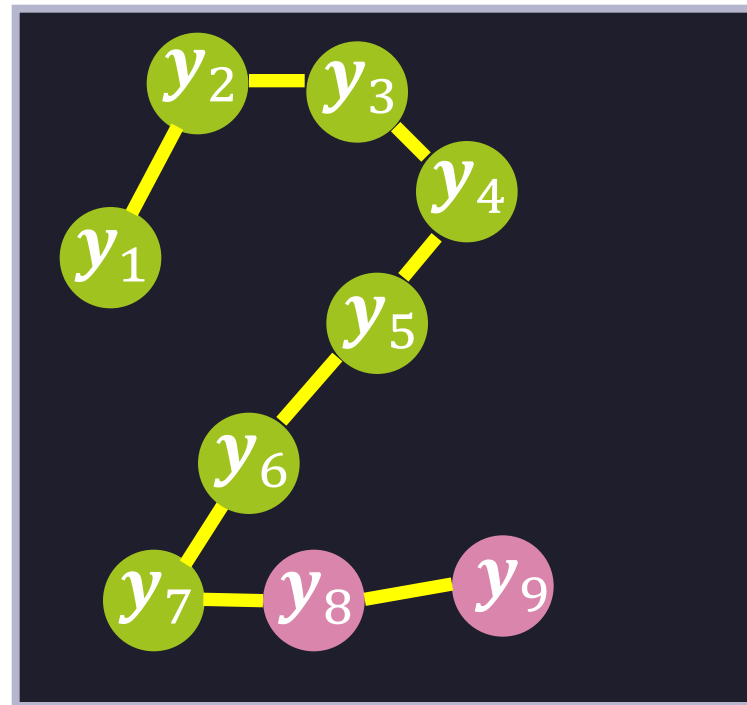
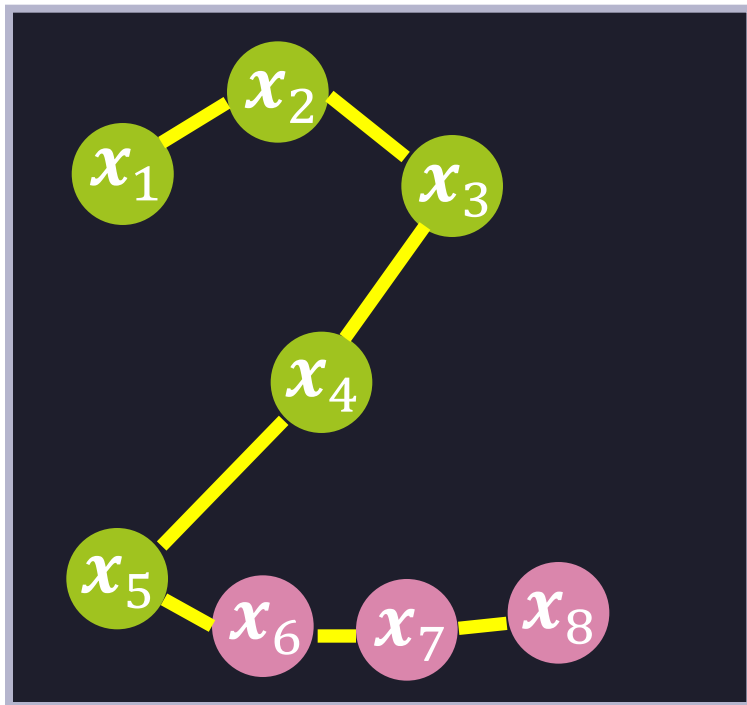
- The two vectors have different numbers of dimensions.
- We could fix that by "stretching" the first time series to also have 9 elements.

# Problems with the Euclidean Distance



- Here, the time series on the left has been converted to have nine elements, using interpolation.
  - We will not explore that option any further, because...

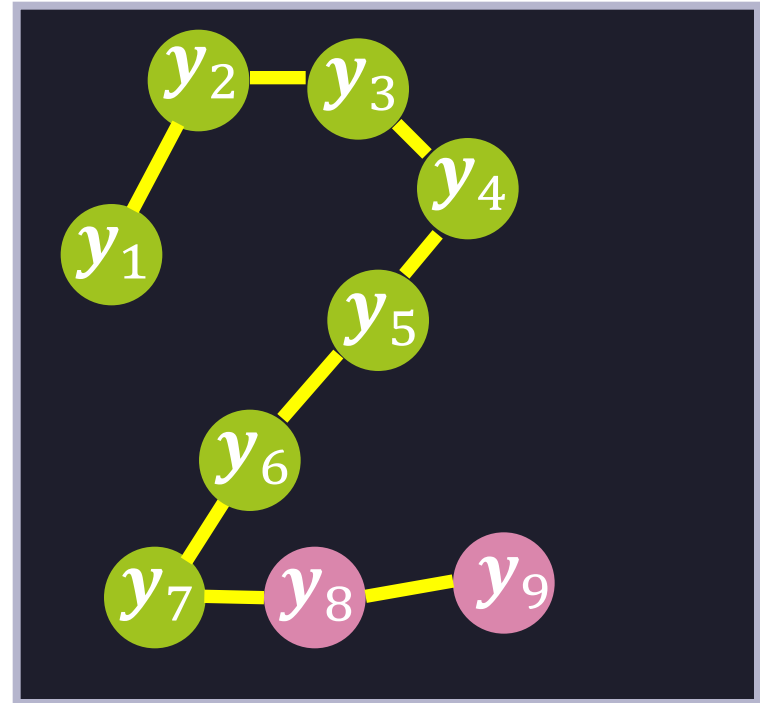
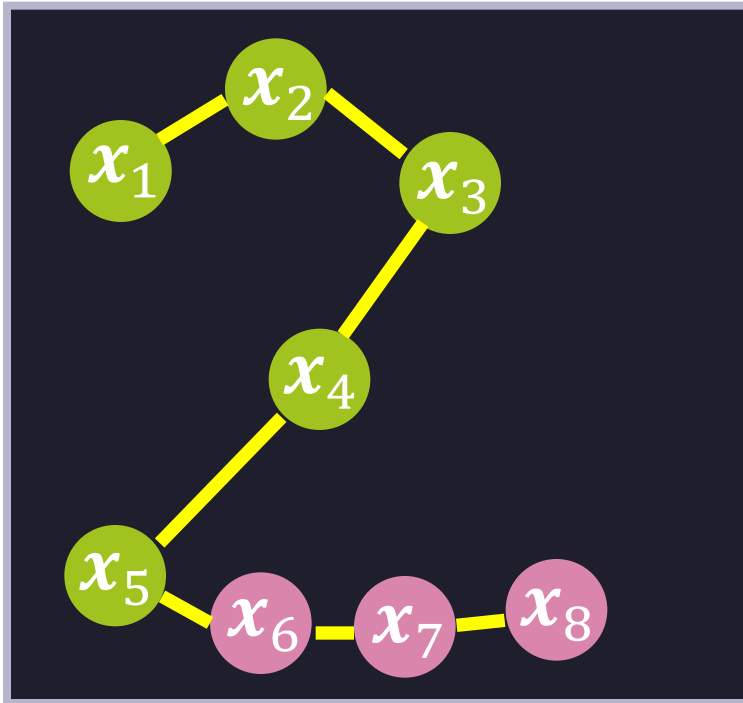
# Problems with the Euclidean Distance



- Bigger problem: the two time series correspond to a similar pattern being performed with **variable speed**.
  - The first five elements of the first time series visually match the first seven elements of the second time series.

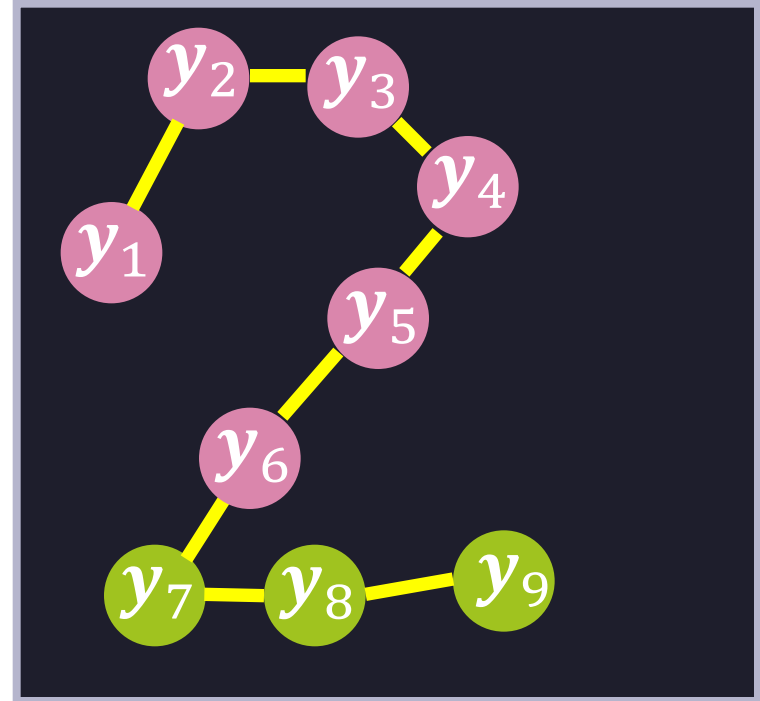
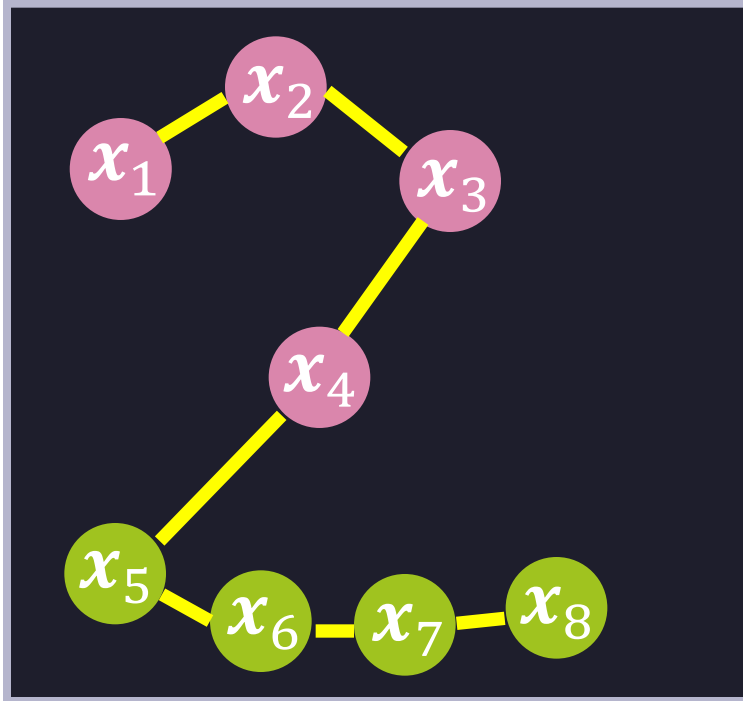


# Problems with the Euclidean Distance



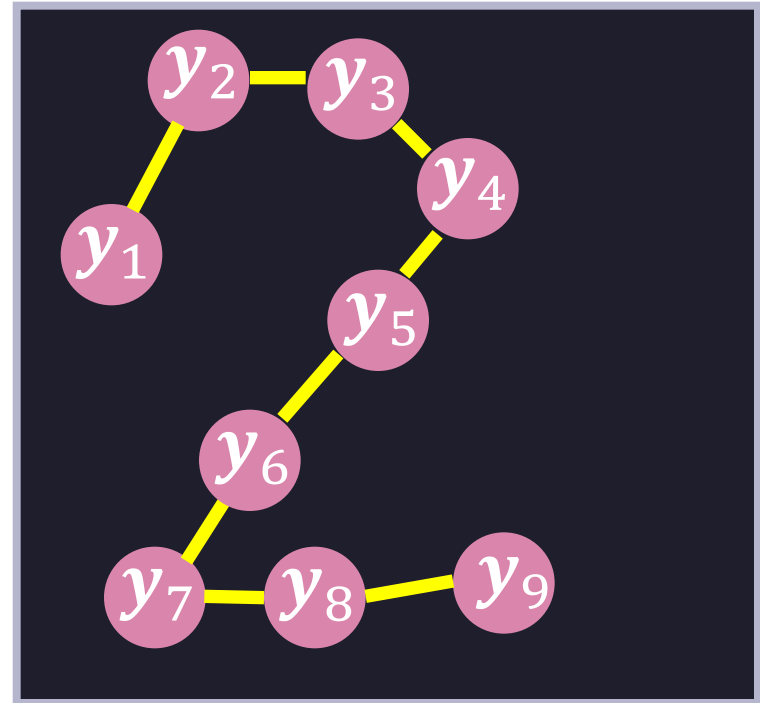
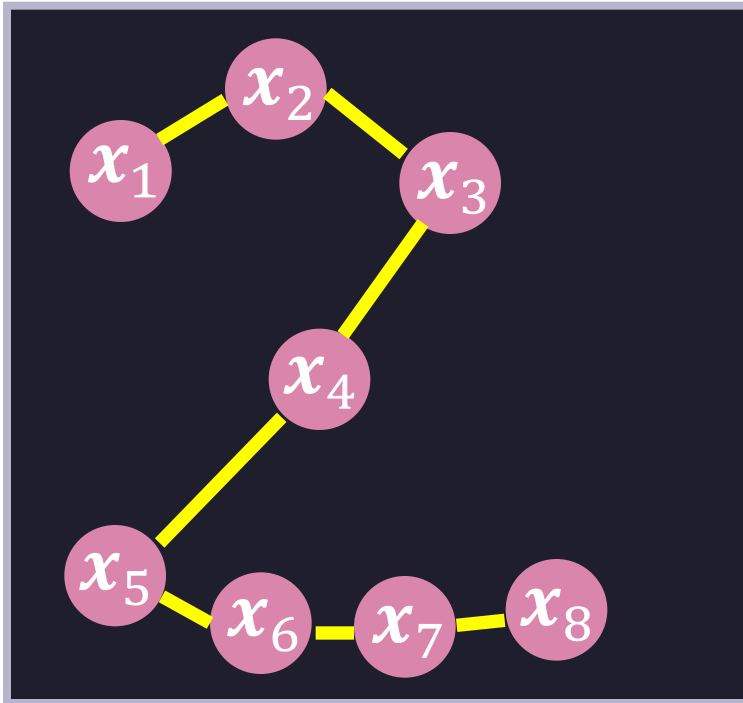
- So, the first time series had a faster speed than the second time series initially.
  - It took 5 time ticks for the first time series, and seven time ticks for the second time series, to move through approximately the same trajectory.

# Problems with the Euclidean Distance



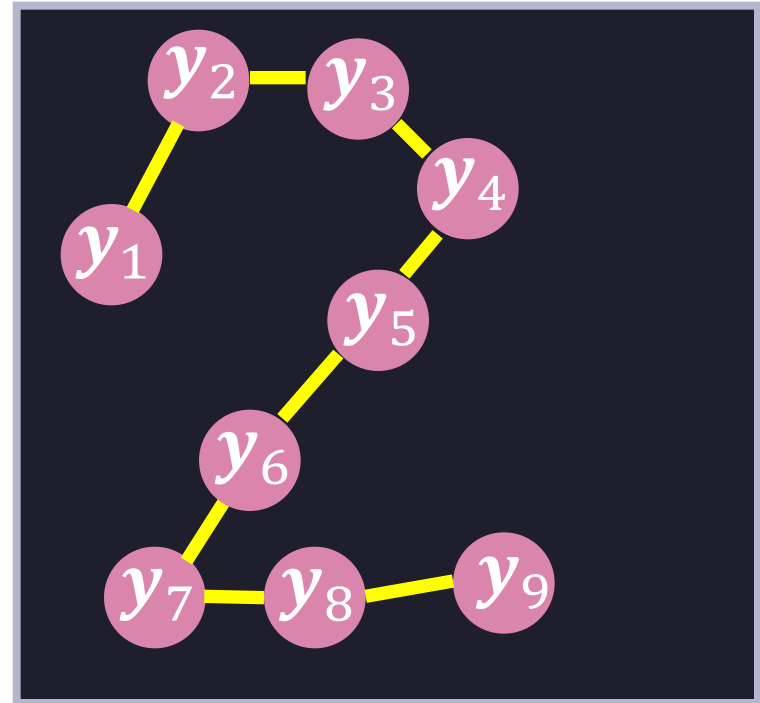
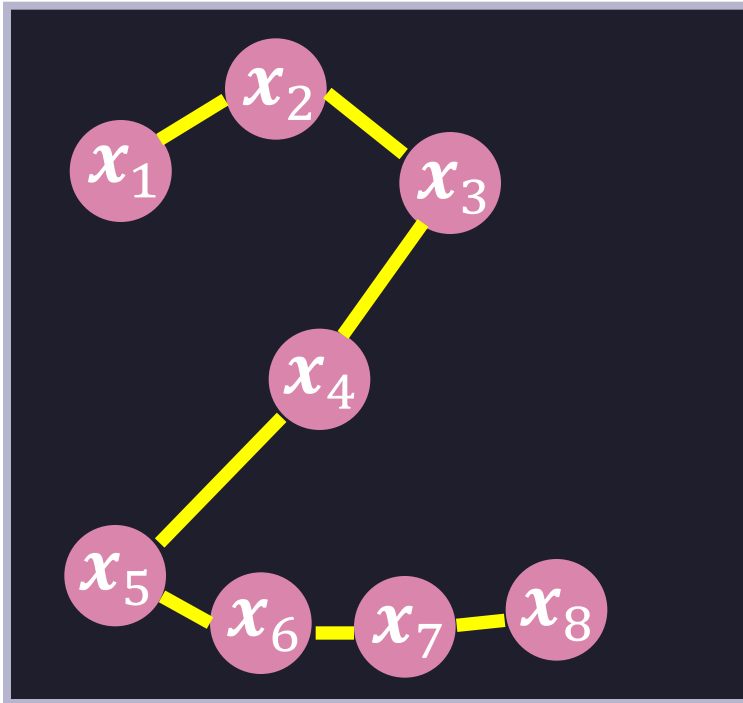
- Similarly, the last four elements of the first time series visually match the last three elements of the second time series.
- So, the first time series had a faster speed than the second time series in the last part.
  - 4 time ticks for the first time series, 3 time ticks for the second one.

# Time Series Alignment



- An alignment is a correspondence between elements of two time series.
- To reliably measure the similarity between two time series, we need to figure out, for each element of the first time series, which elements of the second time series it **corresponds** to.

# Time Series Alignment

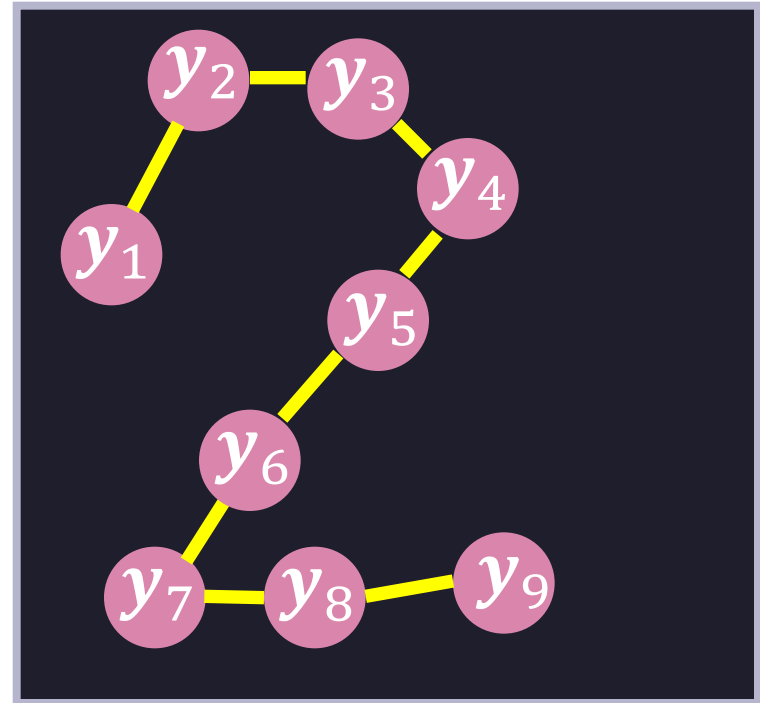
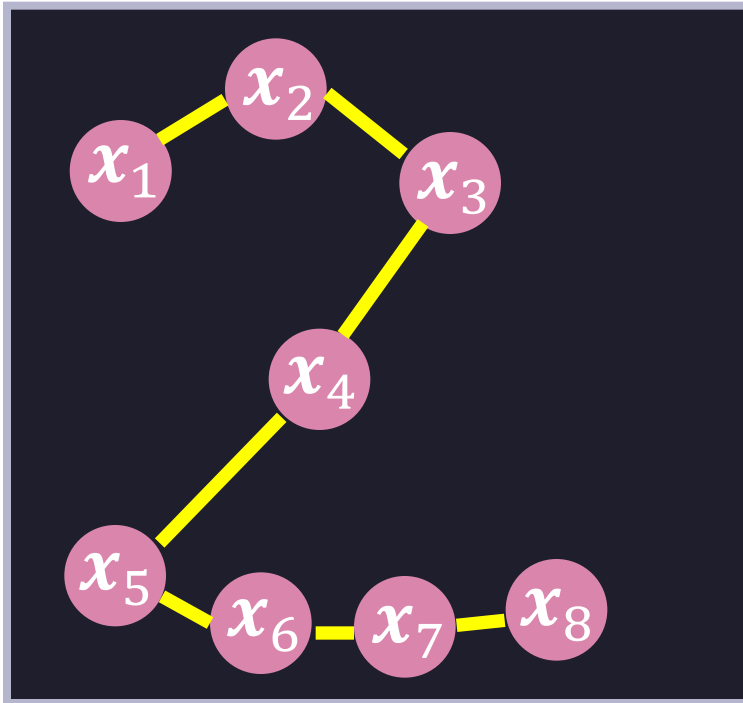


- An alignment  $A$  between  $X$  and  $Y$  is a sequence of pairs of indices:

$$A = \left( (a_{1,1}, a_{1,2}), (a_{2,1}, a_{2,2}), \dots, (a_{R,1}, a_{R,2}) \right)$$

- Element  $(a_{i,1}, a_{i,2})$  of alignment  $A$  specifies that element  $x_{a_{i,1}}$  of  $X$  corresponds to element  $y_{a_{i,2}}$  of the other time series.

# Time Series Alignment

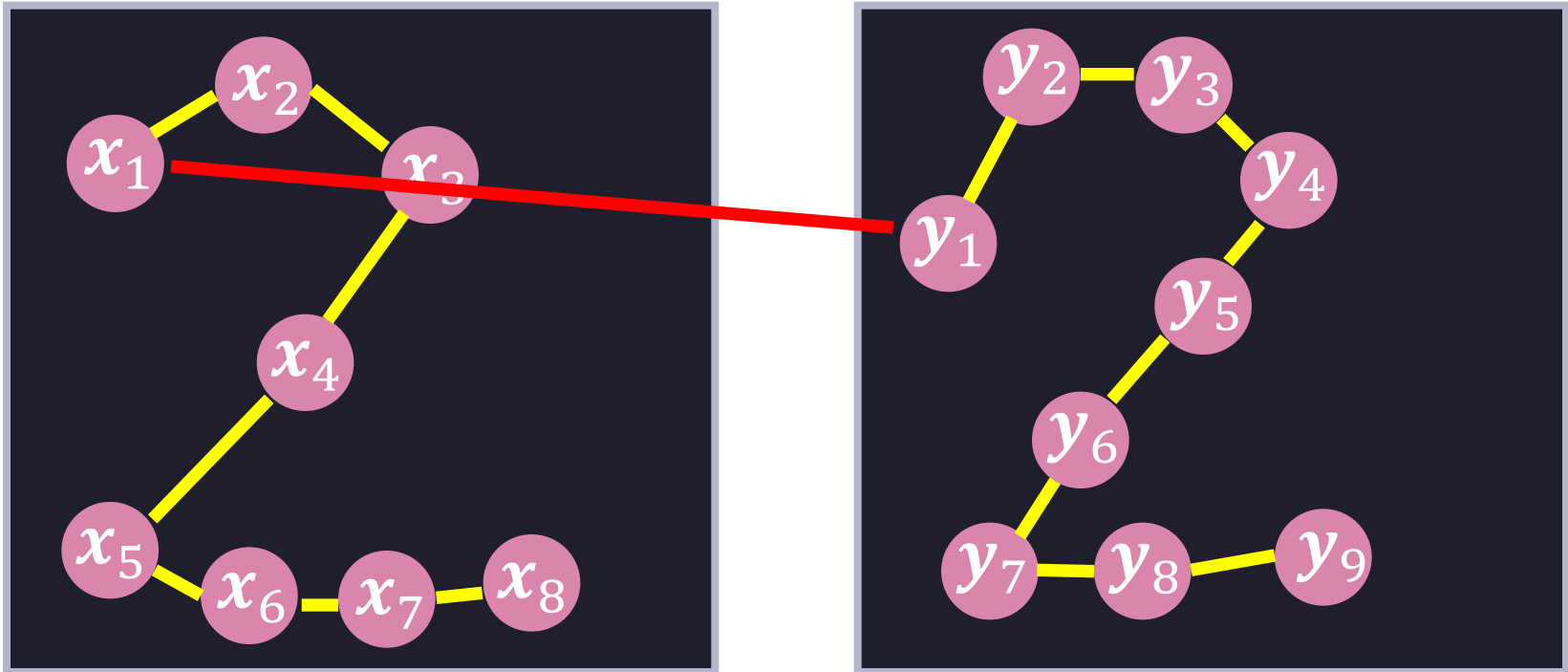


- For example, here is a "good" alignment between the two series:

$((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$

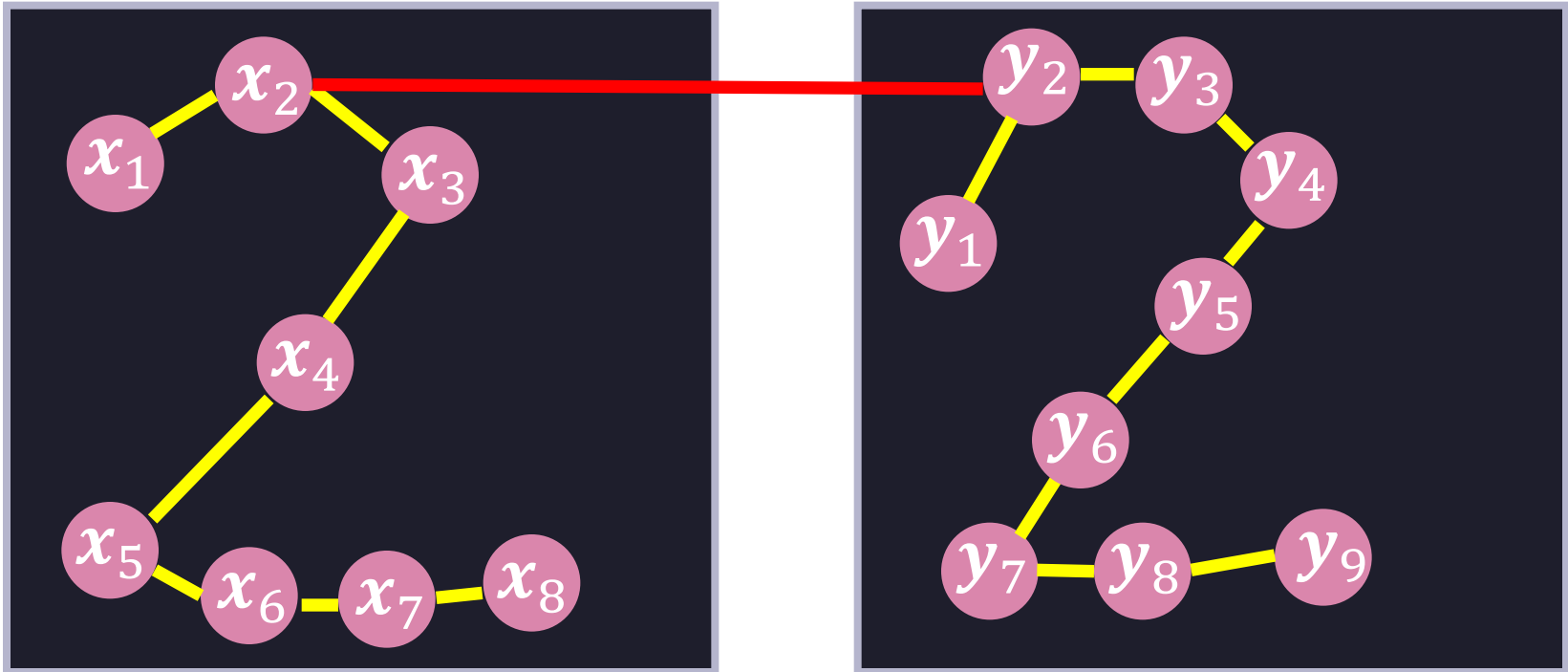
- We will discuss later how to find such an alignment automatically.

# Time Series Alignment



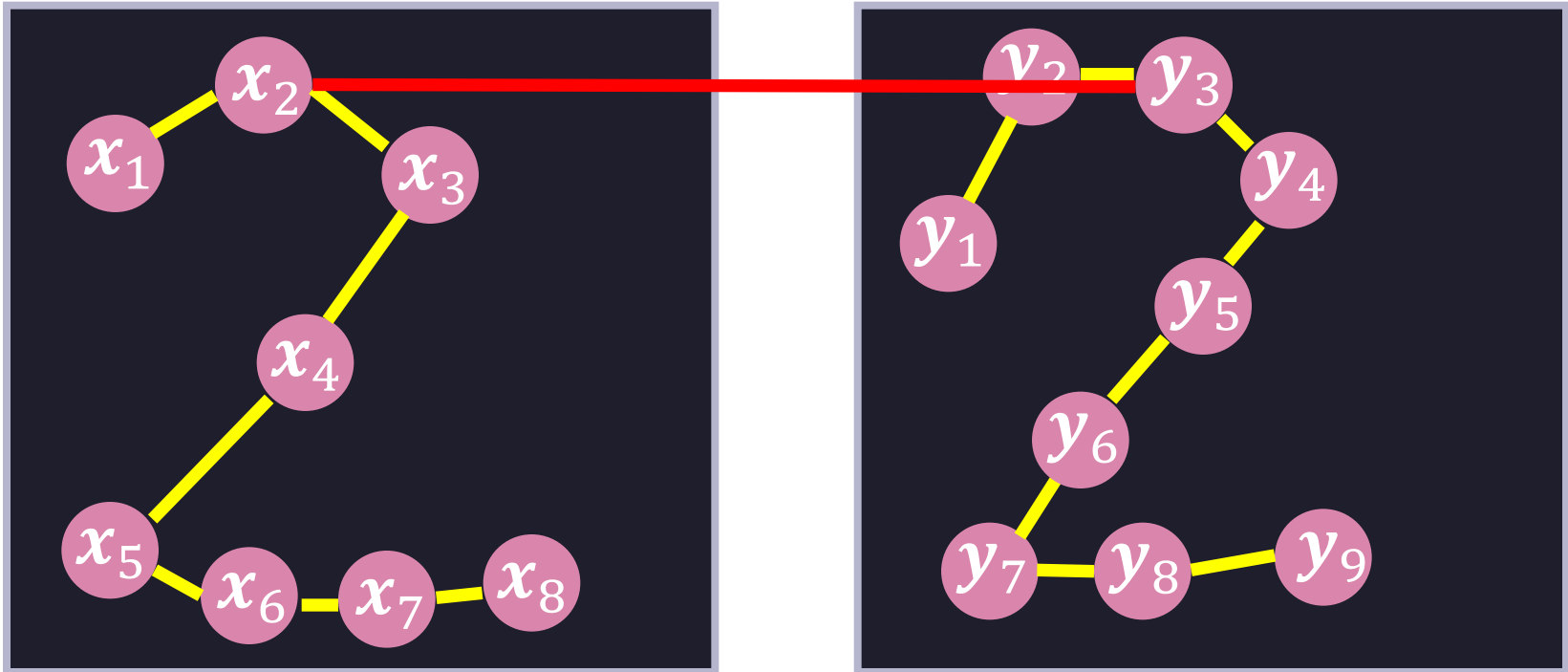
- Alignment:  
 $((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$
- According to this alignment:
  - $x_1$  corresponds to  $y_1$ .

# Time Series Alignment



- Alignment:  
 $((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$
- According to this alignment:
  - $x_2$  corresponds to  $y_2$ .

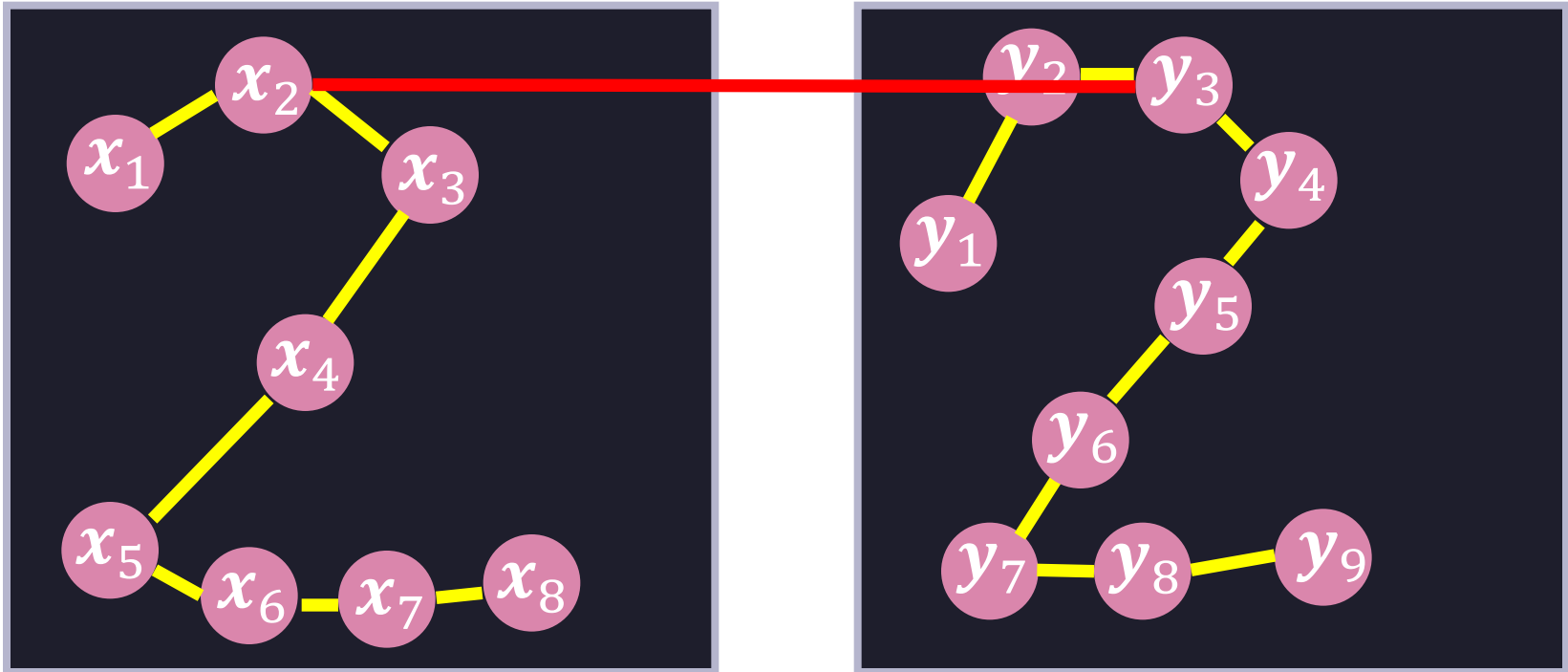
# Time Series Alignment



- Alignment:  
 $((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$
- According to this alignment:
  - $x_2$  also corresponds to  $y_3$ .

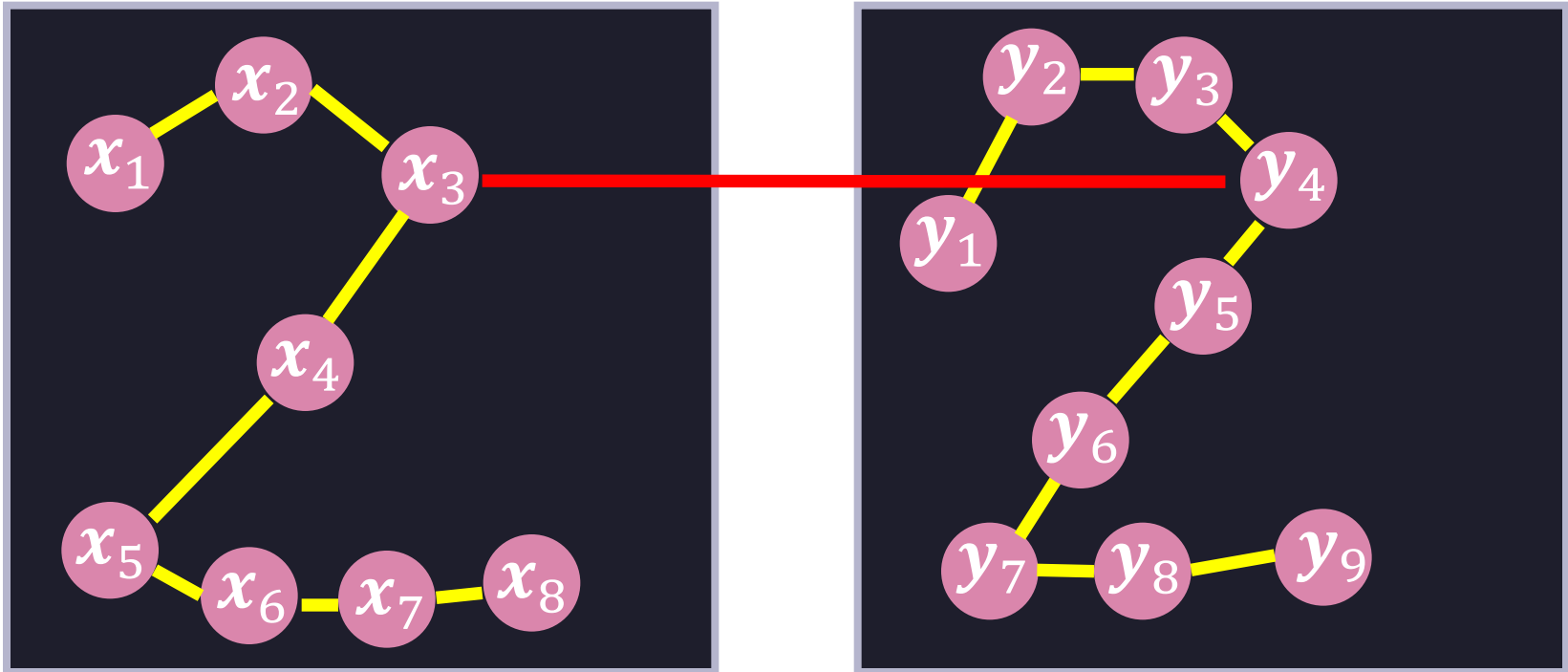


# Time Series Alignment



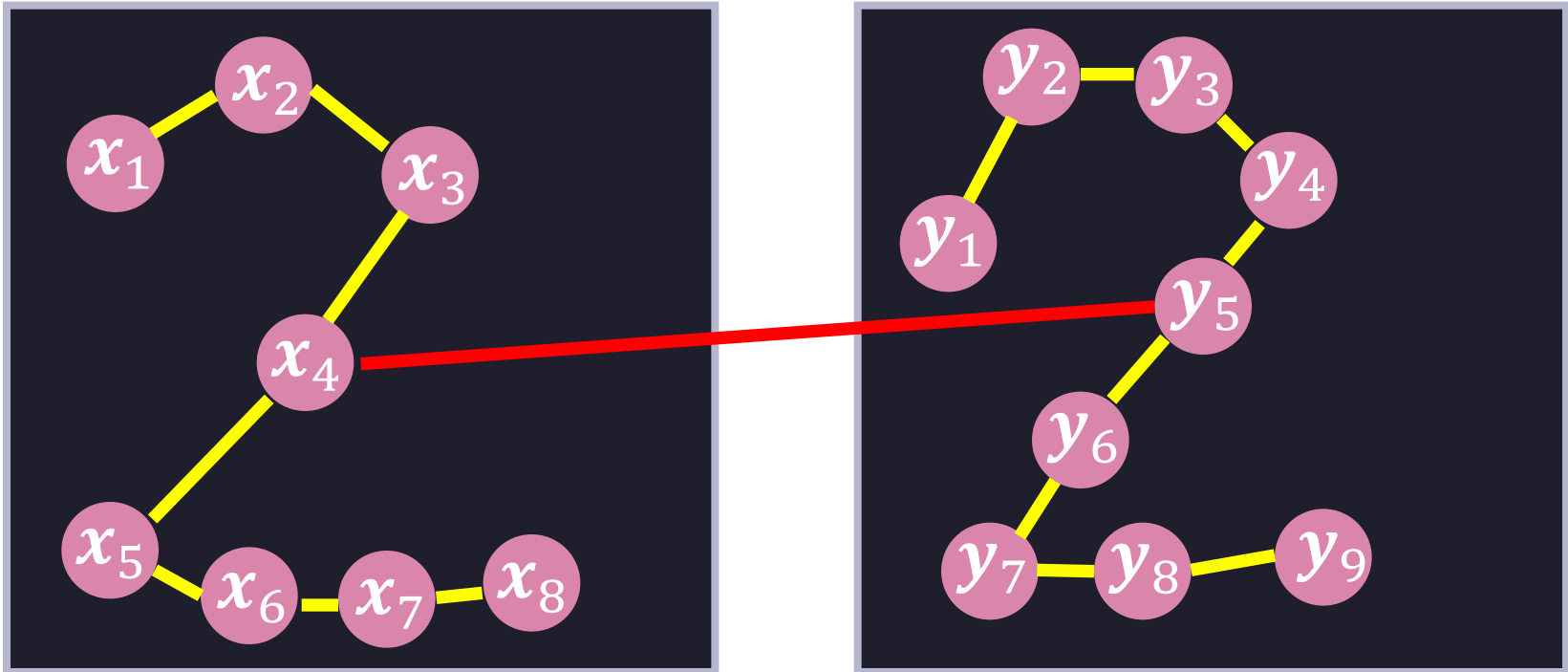
- $x_2$  also corresponds to  $y_3$ .
- One element from one time series can correspond to multiple consecutive elements from the other time series.
  - This captures cases where one series moves slower than the other.
  - For this segment, the first series moves faster than the second one.

# Time Series Alignment



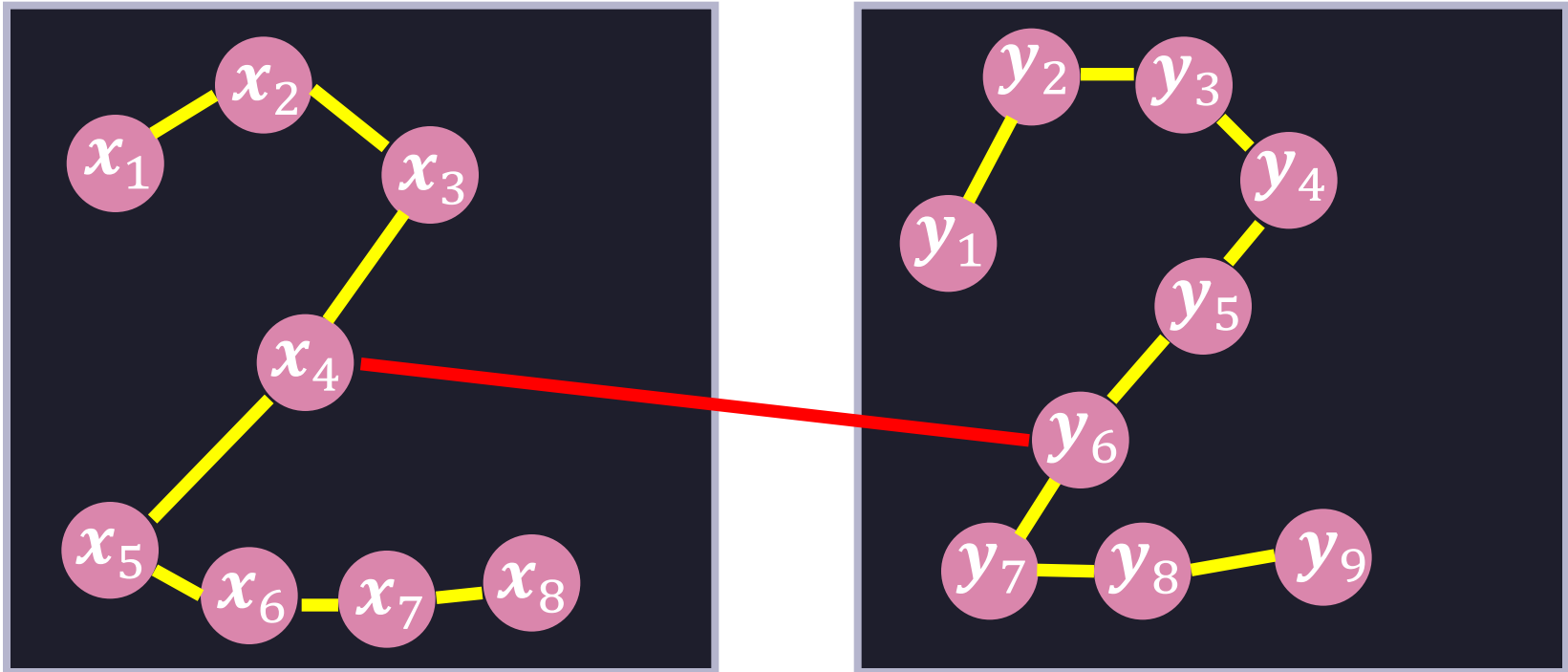
- Alignment:  
 $((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$
- According to this alignment:
  - $x_3$  corresponds to  $y_4$ .

# Time Series Alignment



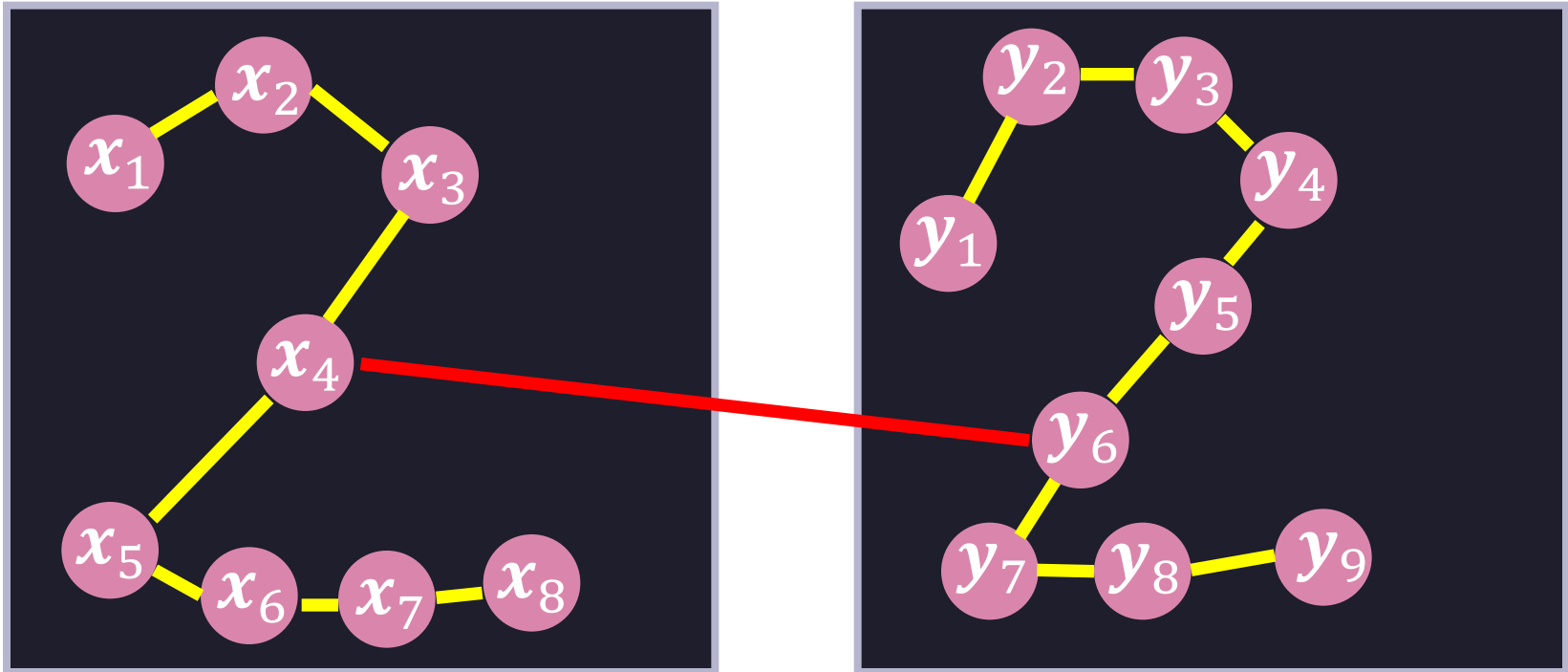
- Alignment:  
 $((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$
- According to this alignment:
  - $x_4$  corresponds to  $y_5$ .

# Time Series Alignment



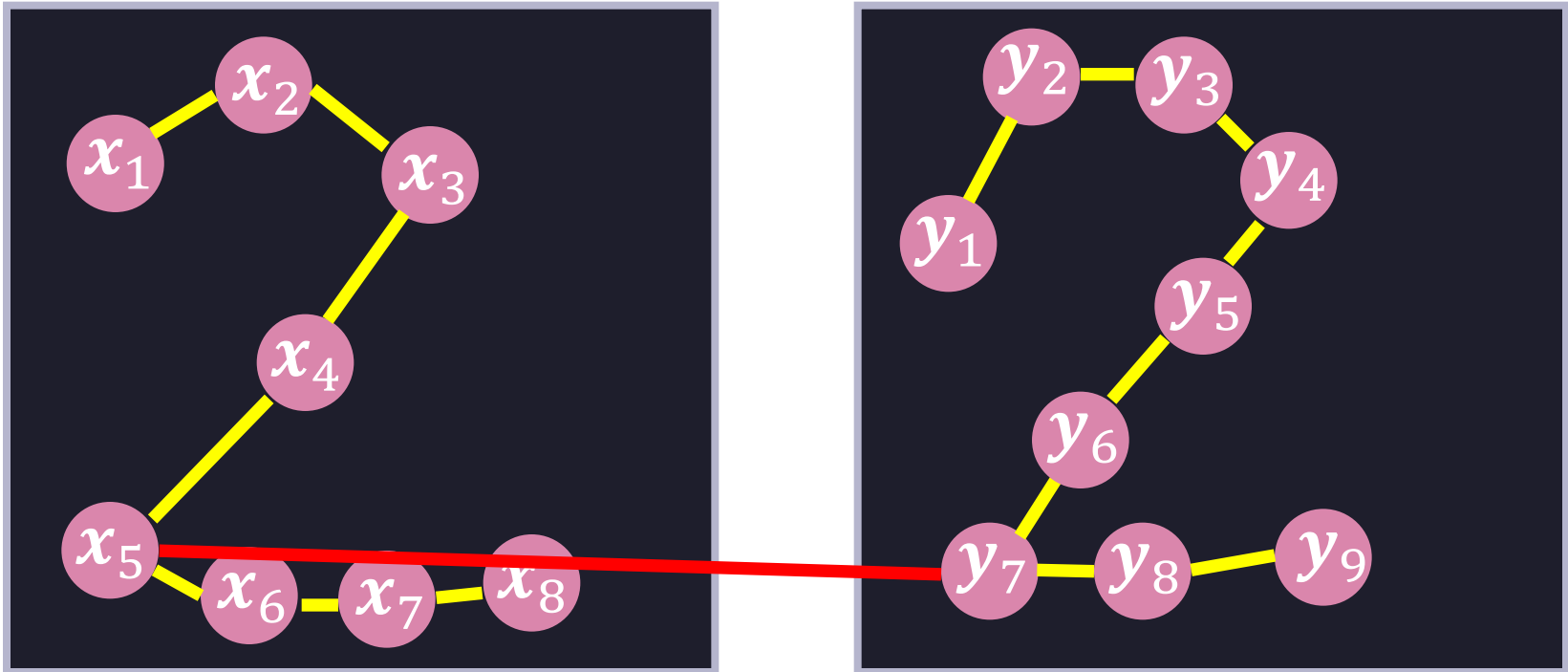
- Alignment:  
 $((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$
- According to this alignment:
  - $x_4$  also corresponds to  $y_6$ .

# Time Series Alignment



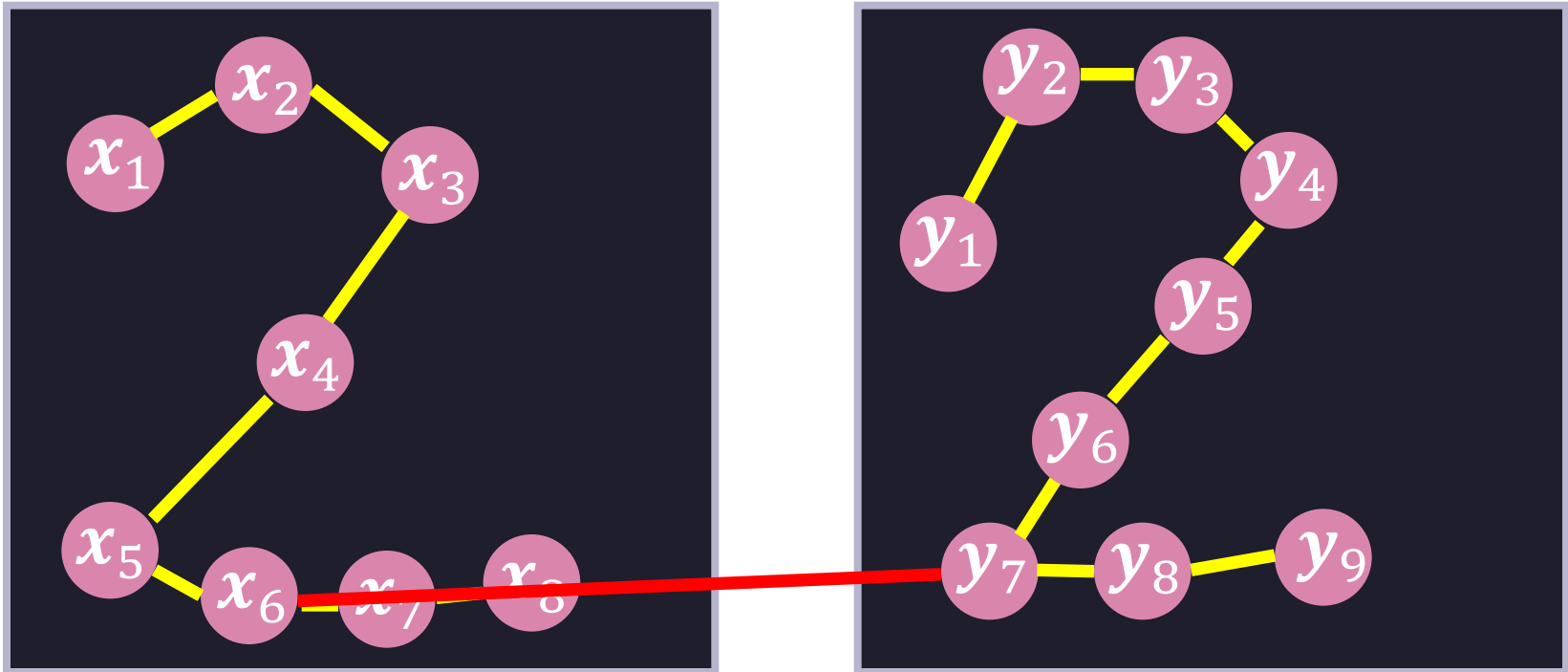
- $x_4$  also corresponds to  $y_6$ .
  - As before, for this segment, the first time series is moving faster than the second one.

# Time Series Alignment



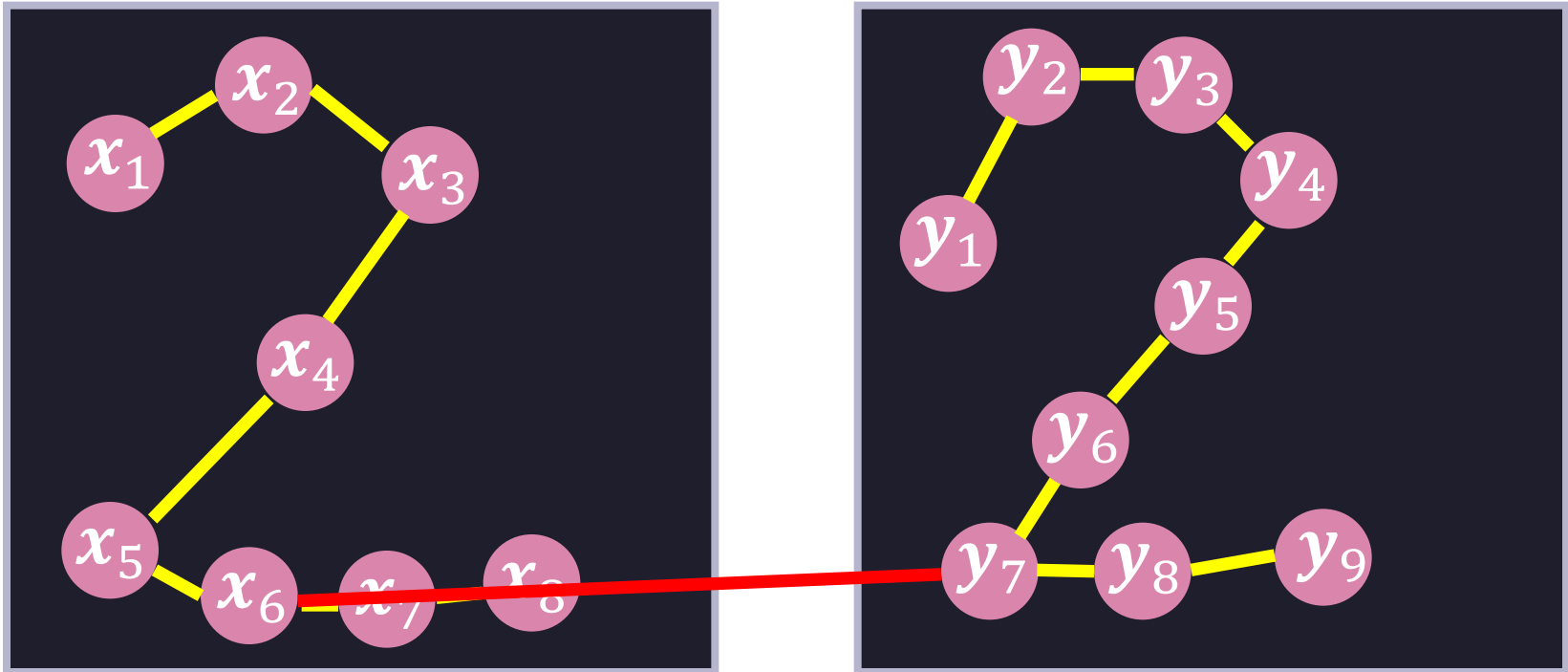
- Alignment:  
 $((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$
- According to this alignment:
  - $x_5$  corresponds to  $y_7$ .

# Time Series Alignment



- Alignment:  
 $((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$
- According to this alignment:
  - $x_6$  also corresponds to  $y_5$ .

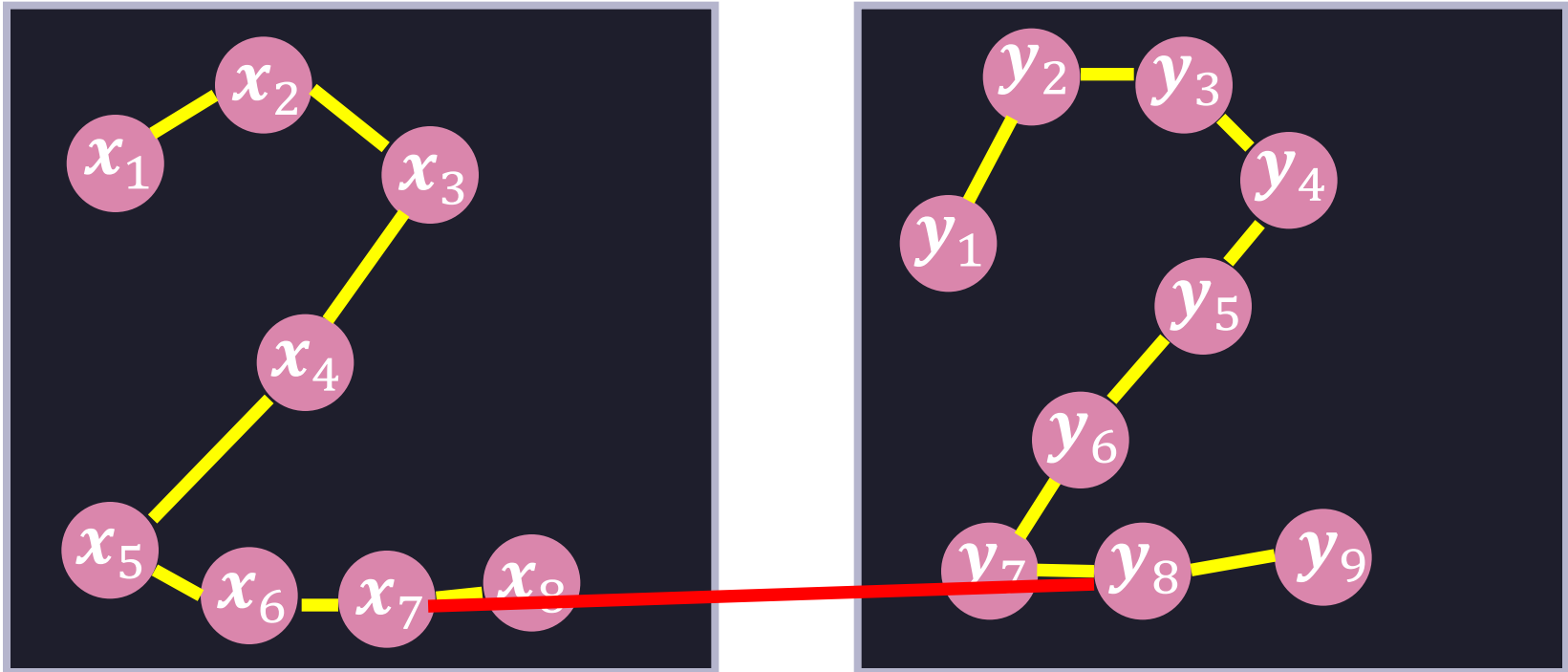
# Time Series Alignment



- Alignment:  
 $((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$
- Here, the first time series is moving slower than the second one, and thus  $x_5$  and  $x_6$  are both matched to  $y_7$ .

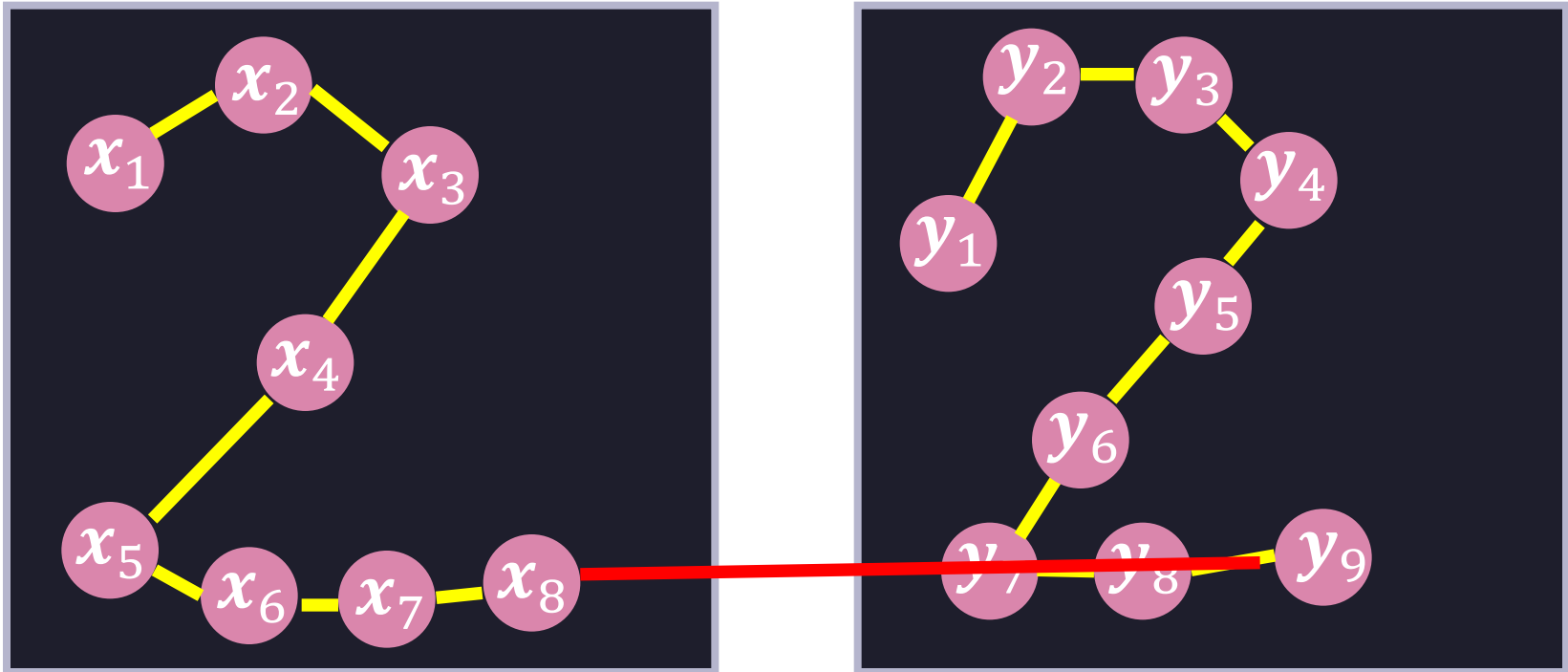


# Time Series Alignment



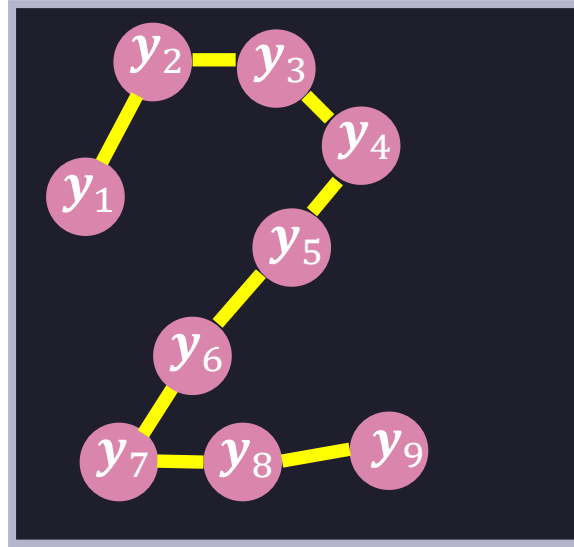
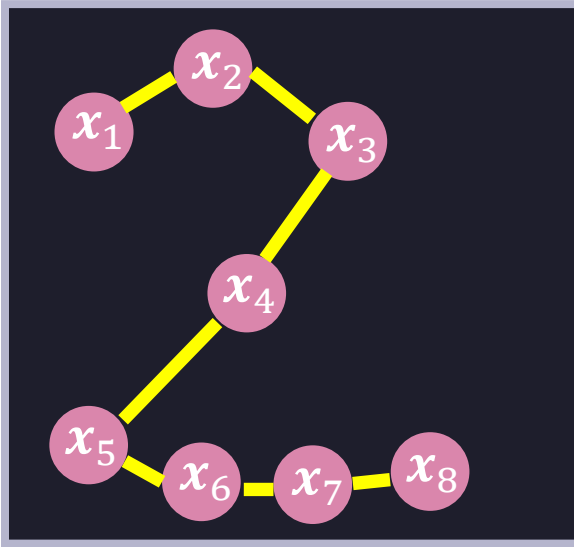
- Alignment:  
 $((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$
- According to this alignment:
  - $x_7$  corresponds to  $y_8$ .

# Time Series Alignment



- Alignment:  
 $((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$
- According to this alignment:
  - $x_8$  corresponds to  $y_9$ .

# The Cost of an Alignment



- An alignment  $A$  is defined as a sequence of pairs

$$A = \left( (a_{1,1}, a_{1,2}), (a_{2,1}, a_{2,2}), \dots, (a_{R,1}, a_{R,2}) \right)$$

- If we are given an alignment  $A$  between two time series  $X$  and  $Y$ , we can compute the cost  $C_{X,Y}(A)$  of that alignment as:

$$C_{X,Y}(A) = \sum_{i=1}^R \text{Cost}(x_{a_{i,1}}, y_{a_{i,2}})$$

# The Cost of an Alignment

- An alignment is defined as a sequence of pairs:

$$\mathbf{A} = \left( (a_{1,1}, a_{1,2}), (a_{2,1}, a_{2,2}), \dots, (a_{R,1}, a_{R,2}) \right)$$

- If we are given an alignment  $\mathbf{A}$  between two time series  $\mathbf{X}$  and  $\mathbf{Y}$ , we can compute the cost  $C_{\mathbf{X},\mathbf{Y}}(\mathbf{A})$  of that alignment as:

$$C_{\mathbf{X},\mathbf{Y}}(\mathbf{A}) = \sum_{i=1}^R \text{Cost}(\mathbf{x}_{a_{i,1}}, \mathbf{y}_{a_{i,2}})$$

- In this formula,  $\text{Cost}(\mathbf{x}_{a_{i,1}}, \mathbf{y}_{a_{i,2}})$  is a black box.
  - You can define it any way you like.
  - For example, if  $\mathbf{x}_{a_{i,1}}$  and  $\mathbf{y}_{a_{i,2}}$  are vectors,  $\text{Cost}(\mathbf{x}_{a_{i,1}}, \mathbf{y}_{a_{i,2}})$  can be the Euclidean distance between  $\mathbf{x}_{a_{i,1}}$  and  $\mathbf{y}_{a_{i,2}}$ .

# The Cost of an Alignment

- An alignment is defined as a sequence of pairs:

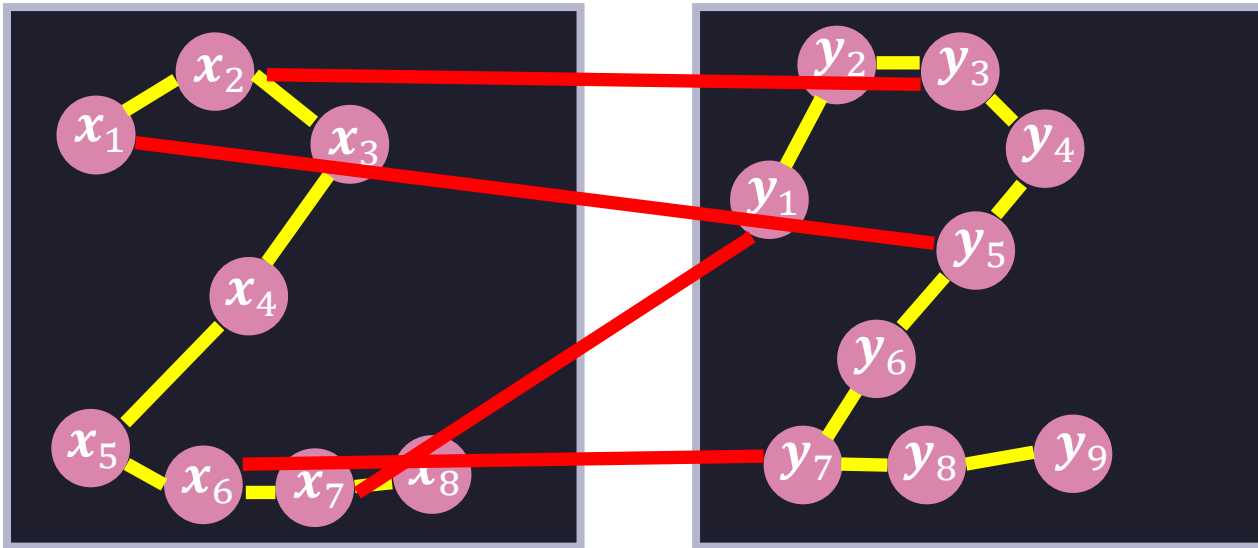
$$\mathbf{A} = \left( (a_{1,1}, a_{1,2}), (a_{2,1}, a_{2,2}), \dots, (a_{R,1}, a_{R,2}) \right)$$

- If we are given an alignment  $\mathbf{A}$  between two time series  $\mathbf{X}$  and  $\mathbf{Y}$ , we can compute the cost  $C_{\mathbf{X},\mathbf{Y}}(\mathbf{A})$  of that alignment as:

$$C_{\mathbf{X},\mathbf{Y}}(\mathbf{A}) = \sum_{i=1}^R \text{Cost}(\mathbf{x}_{a_{i,1}}, \mathbf{y}_{a_{i,2}})$$

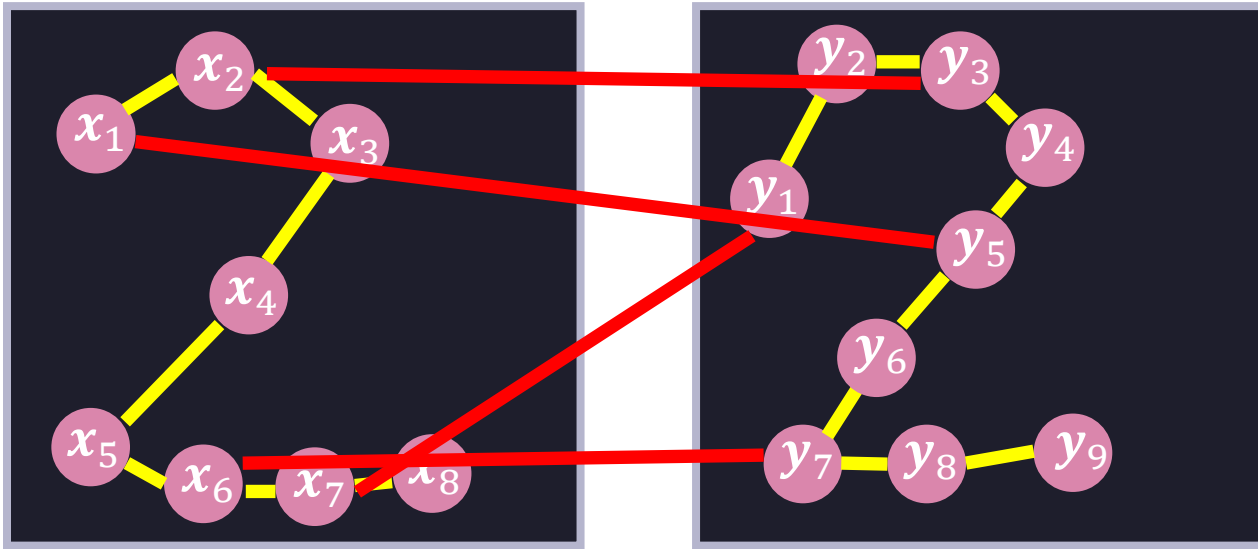
- Notation  $C_{\mathbf{X},\mathbf{Y}}(\mathbf{A})$  indicates that the cost of alignment  $\mathbf{A}$  depends on the specific pair of time series that we are aligning.
  - The cost of an alignment  $\mathbf{A}$  depends on the alignment itself, as well as the two time series  $\mathbf{X}$  and  $\mathbf{Y}$  that we are aligning.

# Rules of Alignment



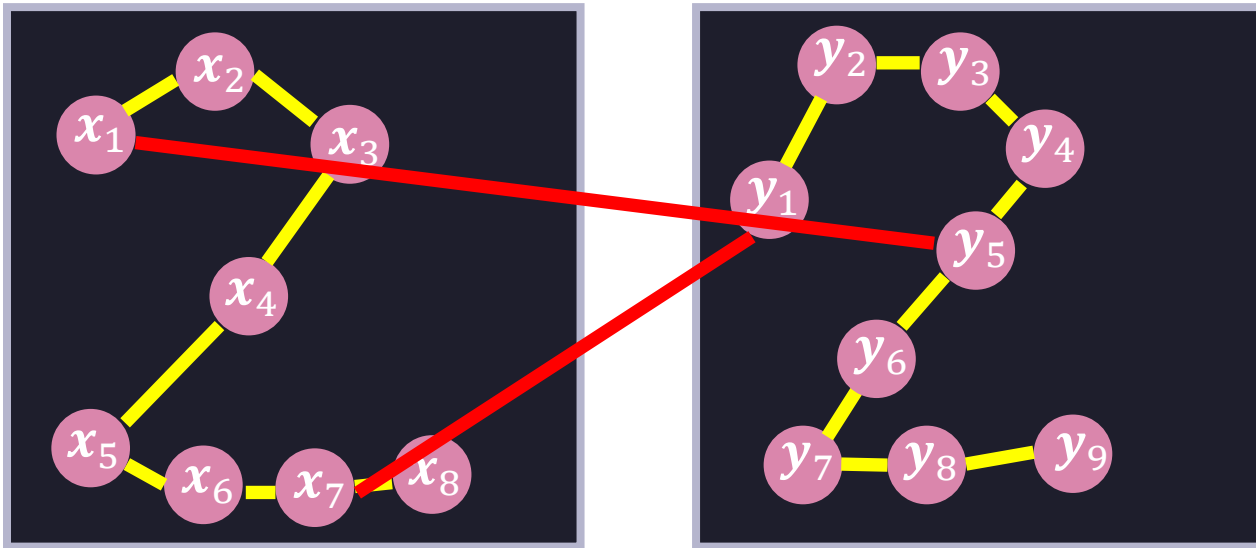
- Should alignment  $((1, 5), (2, 3), (6, 7), (7, 1))$  be legal?
- It always depends on what makes sense for your data.
- Typically, for time series, alignments have to obey certain rules, that this alignment violates.

# Rules of Alignment



- We will require that legal alignments obey three rules:
  - Rule 1: Boundary Conditions.
  - Rule 2: Monotonicity.
  - Rule 3: Continuity
- The next slides define these rules.

# Rule 1: Boundary Conditions

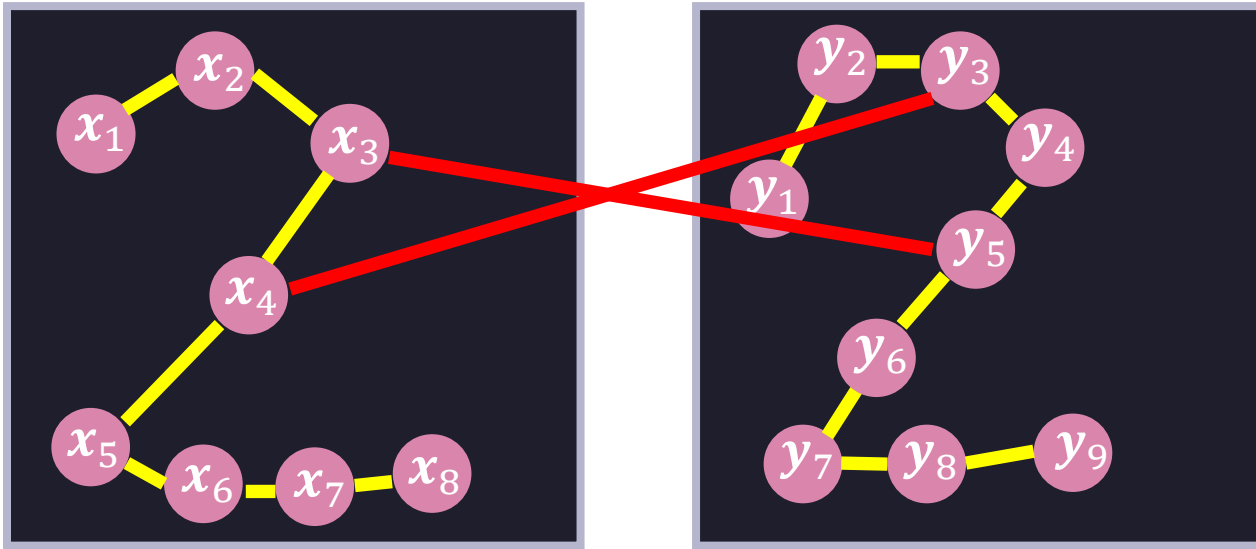


- Illegal alignment (violating boundary conditions):
  - $((1, 5), \dots, (7, 1))$ .
  - $((s_1, t_1), (s_2, t_2), \dots, (s_R, t_R))$
- Alignment rule #1 (boundary conditions):
  - $s_1 = 1, t_1 = 1$ .
  - $s_R = M = \text{length of first time series}$
  - $t_R = N = \text{length of second time series}$

**first elements match  
last elements match**



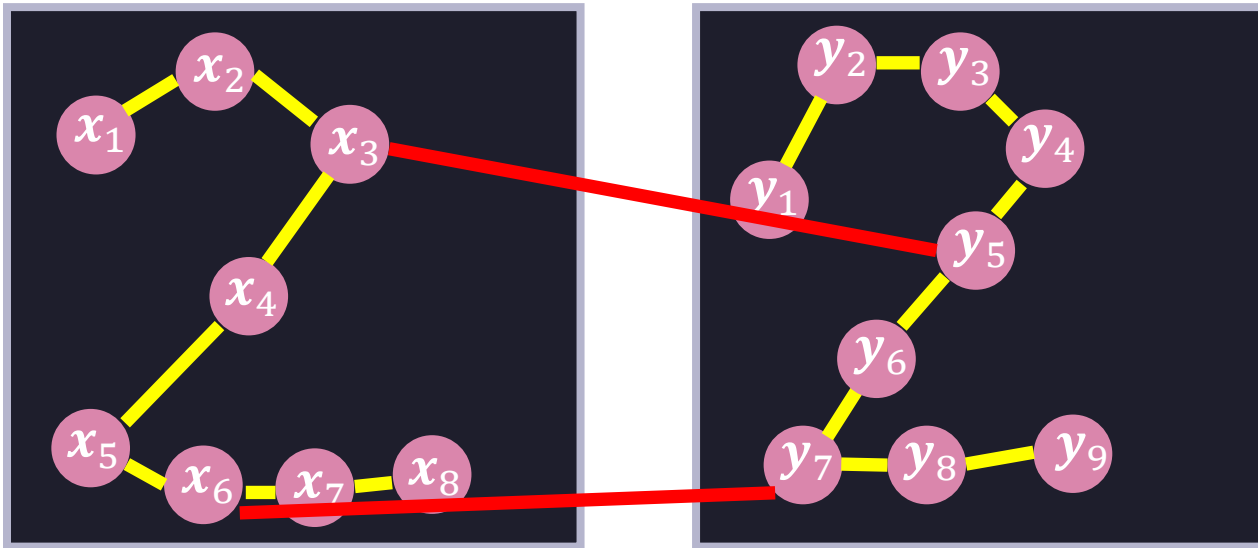
# Rule 2: Monotonicity



- Illegal alignment (violating monotonicity):
  - $(\dots, (3, 5), (4, 3), \dots)$ .
  - $((s_1, t_1), (s_2, t_2), \dots, (s_R, t_R))$
- Alignment rule #2: sequences  $s_1, \dots, s_R$  and  $t_1, \dots, t_R$  are monotonically increasing.
  - $(s_{i+1} - s_i) \geq 0$
  - $(t_{i+1} - t_i) \geq 0$

**The alignment cannot go backwards.**

# Rule 3: Continuity



- Illegal alignment (violating continuity):
  - $(\dots, (3, 5), (6, 7), \dots)$ .
  - $((s_1, t_1), (s_2, t_2), \dots, (s_R, t_R))$
- Alignment rule #3: sequences  $s_1, \dots, s_R$  and  $t_1, \dots, t_R$  cannot increase by more than one at each step.
  - $(s_{i+1} - s_i) \leq 1$
  - $(t_{i+1} - t_i) \leq 1$

**The alignment cannot skip elements.**

# Visualizing a Warping Path

- **Warping path** is an alternative term for an alignment

# Visualizing a Warping Path

$$\mathbf{A} = ((1, 1), (2, 2), (2, 3), (3, 4), (4, 5), (4, 6), (5, 7), (6, 7), (7, 8), (8, 9))$$

- We can visualize a warping path  $\mathbf{A}$  in 2D as follows:
- An element of  $\mathbf{A}$  corresponds to a colored cell in the 2D table.

	$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$	$y_7$	$y_8$	$y_9$
$x_1$									
$x_2$									
$x_3$									
$x_4$									
$x_5$									
$x_6$									
$x_7$									
$x_8$									

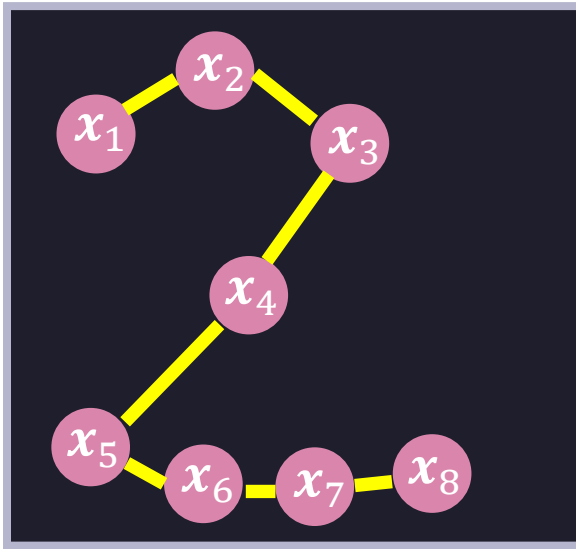
# Dynamic Time Warping

- **Dynamic Time Warping** (DTW) is a distance measure between time series.
- The DTW distance is the cost of the **optimal legal alignment** between the two time series.
- The alignment must be legal: it must obey the three rules of alignments.
  - Boundary conditions.
  - Monotonicity.
  - Continuity.
- The alignment must minimize  $C_{X,Y}(A) = \sum_{i=1}^R \text{Cost}(x_{a_{i,1}}, y_{a_{i,2}})$
- So:

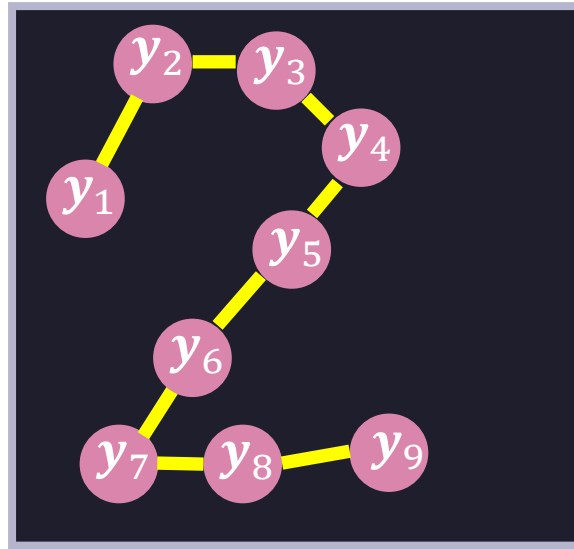
$$\text{DTW}(X, Y) = \min_A C_{X,Y}(A)$$

where  $A$  ranges over all legal alignments between  $X$  and  $Y$ .

# Finding the Optimal Alignment



$X$



$Y$

- $X = (x_1, x_2, \dots, x_M)$ .
  - $X$  is a time series of length  $M$ .
- $Y = (y_1, y_2, \dots, y_N)$ .
  - $Y$  is a time series of length  $N$ .
- Each  $x_i$  and each  $y_i$  are feature vectors.

# Finding the Optimal Alignment

- $X = (x_1, x_2, \dots x_M)$ .
- $Y = (y_1, y_2, \dots y_N)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- Dynamic programming strategy:
  - Break problem up into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots y_j)$ .
- We need to solve every problem( $i, j$ ) for every  $i$  and  $j$ .
- Then, the optimal alignment between  $X$  and  $Y$  is the solution to problem( $M, N$ ).

# Finding the Optimal Alignment

- $X = (x_1, x_2, \dots, x_M)$ .
- $Y = (y_1, y_2, \dots, y_N)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- We break up the problem into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots, y_j)$ .
- How do we start computing the optimal alignment?



# Finding the Optimal Alignment

- $X = (x_1, x_2, \dots, x_M)$ .
- $Y = (y_1, y_2, \dots, y_N)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- We break up the problem into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots, y_j)$ .
- Solve problem(1, 1):
  - How is problem(1, 1) defined?

# Finding the Optimal Alignment

- $X = (x_1, x_2, \dots, x_M)$ .
- $Y = (y_1, y_2, \dots, y_N)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- We break up the problem into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots, y_j)$ .
- Solve problem( $1, 1$ ):
  - Find optimal alignment between  $(x_1)$  and  $(y_1)$ .
  - What is the optimal alignment between  $(x_1)$  and  $(y_1)$ ?

# Finding the Optimal Alignment

- $X = (x_1, x_2, \dots x_M)$ .
- $Y = (y_1, y_2, \dots y_N)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- We break up the problem into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots y_j)$ .
- Solve problem( $1, 1$ ):
  - Find optimal alignment between  $(x_1)$  and  $(y_1)$ .
  - The optimal alignment is the **only legal alignment**:  $((1, 1))$ .

# Alignment for Problem (1, 1)

$$A = ((1, 1) )$$

	$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$	$y_7$	$y_8$	$y_9$
$x_1$									
$x_2$									
$x_3$									
$x_4$									
$x_5$									
$x_6$									
$x_7$									
$x_8$									

# Finding the Optimal Alignment

- $X = (x_1, x_2, \dots, x_M)$ .
- $Y = (y_1, y_2, \dots, y_N)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- We break up the problem into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots, y_j)$ .
- Solve problem( $1, j$ ):
  - How is problem( $1, j$ ) defined?

# Finding the Optimal Alignment

- $X = (x_1, x_2, \dots, x_M)$ .
- $Y = (y_1, y_2, \dots, y_N)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- We break up the problem into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots, y_j)$ .
- Solve problem( $1, j$ ):
  - Find optimal alignment between  $(x_1)$  and  $(y_1, \dots, y_j)$ .
  - What is the optimal alignment between  $(x_1)$  and  $(y_1, \dots, y_j)$ ?

# Finding the Optimal Alignment

- $X = (x_1, x_2, \dots x_M)$ .
- $Y = (y_1, y_2, \dots y_N)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- We break up the problem into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots y_j)$ .
- Solve problem( $1, j$ ):
  - Find optimal alignment between  $(x_1)$  and  $(y_1, \dots y_j)$ .
  - Optimal alignment:  $((1, 1), (1, 2), \dots, (1, j))$ .
  - Here,  $x_1$  is matched with each of the first  $j$  elements of  $Y$ .

# Alignment for Problem (1, 5)

$$A = ((1, 1), (1, 2), (1, 3), (1, 4), (1, 5))$$

	$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$	$y_7$	$y_8$	$y_9$
$x_1$									
$x_2$									
$x_3$									
$x_4$									
$x_5$									
$x_6$									
$x_7$									
$x_8$									



# Finding the Optimal Alignment

- $X = (x_1, x_2, \dots, x_M)$ .
- $Y = (y_1, y_2, \dots, y_N)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- We break up the problem into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots, y_j)$ .
- Solve problem( $i, 1$ ):
  - How is problem( $i, 1$ ) defined?

# Finding the Optimal Alignment

- $X = (x_1, x_2, \dots x_M)$ .
- $Y = (y_1, y_2, \dots y_N)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- We break up the problem into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots y_j)$ .
- Solve problem( $i, 1$ ):
  - Find optimal alignment between  $(x_1, \dots x_i)$  and  $(y_1)$ .
  - What is the optimal alignment between  $(x_1, \dots x_i)$  and  $(y_1)$ ?

# Finding the Optimal Alignment

- $X = (x_1, x_2, \dots x_M)$ .
- $Y = (y_1, y_2, \dots y_N)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- We break up the problem into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots y_j)$ .
- Solve problem( $i, 1$ ):
  - Find optimal alignment between  $(x_1, \dots x_i)$  and  $(y_1)$ .
  - Optimal alignment:  $((1, 1), (2, 1), \dots, (i, 1))$ .
  - Here,  $y_1$  is matched with each of the first  $i$  elements of  $X$ .

# Alignment for Problem (5, 1)

$$A = ((1, 1), (2, 1), (3, 1), (4, 1), (5, 1))$$

	$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$	$y_7$	$y_8$	$y_9$
$x_1$									
$x_2$									
$x_3$									
$x_4$									
$x_5$									
$x_6$									
$x_7$									
$x_8$									

# Finding the Optimal Alignment

- $Y = (y_1, y_2, \dots y_N)$ .
- $X = (x_1, x_2, \dots x_M)$ .
- We want to find the optimal alignment between  $X$  and  $Y$ .
- We break up the problem into a 2D array of smaller, interrelated problems  $(i, j)$ , where  $1 \leq i \leq M, 1 \leq j \leq N$ .
- Problem( $i, j$ ):
  - find optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots y_j)$ .
- Solve problem( $i, j$ ):
  - Here is where dynamic programming comes into play.
  - The solution can be obtained from the solutions to problem( $i, j - 1$ ), problem( $i - 1, j$ ), problem( $i - 1, j - 1$ ).

# Finding the Optimal Alignment

- Solving problem( $i, j$ ):
- Look at the following three alignments:
  - Let  $A_{i,j-1}$  be the solution to problem( $i, j - 1$ ).
  - Let  $A_{i-1,j}$  be the solution to problem( $i - 1, j$ ).
  - Let  $A_{i-1,j-1}$  be the solution to problem( $i - 1, j - 1$ ).
- Let  $A^*_{i,j}$  be the alignment among  $A_{i,j-1}$ ,  $A_{i-1,j}$ , and  $A_{i-1,j-1}$  with the smallest cost.
- Then, the solution to problem( $i, j$ ) is obtained by appending pair ( $i, j$ ) to the end of  $A^*_{i,j}$ .

# Computing DTW( $X, Y$ )

- Input:
  - $X = (x_1, x_2, \dots, x_M)$ .
  - $Y = (y_1, y_2, \dots, y_N)$ .
- Initialization:
  - $C = \text{zeros}(M, N)$ . % Zero matrix, of size  $M \times N$ .
  - $C(1, 1) = \text{Cost}(x_1, y_1)$ .
  - For  $i = 2$  to  $m$ :  $C(i, 1) = C(i - 1, 1) + \text{Cost}(x_i, y_1)$ .
  - For  $j = 2$  to  $n$ :  $C(1, j) = C(1, j - 1) + \text{Cost}(x_1, y_j)$ .
- Main loop:
  - For  $i = 2$  to  $m$ , for  $j = 2$  to  $n$ :
$$C(i, j) = \min\{C(i - 1, j), C(i, j - 1), C(i - 1, j - 1)\} + \text{Cost}(x_i, y_j).$$
- Return  $C(M, N)$ .

# Cost vs. Alignment

- Note: there are two related but different concepts here: **optimal alignment** and **optimal cost**.
  - We may want to find the optimal alignment between two time series, to visualize how elements of those two time series correspond to each other.
  - We may want to compute the DTW distance between two time series  $X$  and  $Y$ , which means finding the cost of the optimal alignment between  $X$  and  $Y$ . We can use such DTW distances, for example, for nearest neighbor classification.
- The pseudocode in the previous slide computes the **cost** of the optimal alignment, **without** explicitly outputting the optimal alignment itself.

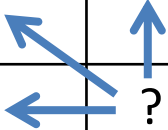


# Cost vs. Alignment

- If you want to compute both the cost of the optimal alignment, and the optimal alignment itself, there are two ways you can modify the pseudocode to do that:
- Option 1: Maintain an **alignment array**  $W$  of size  $M \times N$ .
  - Every time we save a cost at  $C(i, j)$ , we should save the corresponding optimal alignment at  $W(i, j)$ .
  - This alignment is obtained by adding pair  $(i, j)$  to the **end** of the optimal alignment stored at one of  $W(i - 1, j)$ ,  $W(i, j - 1)$ ,  $W(i - 1, j - 1)$ .
- Option 2: Maintain a **backtrack array**  $B$  of size  $M \times N$ .
  - Every time we save a cost to  $C(i, j)$ , we should record at  $B(i, j)$  the choice, among  $(i - 1, j)$ ,  $(i, j - 1)$ ,  $(i - 1, j - 1)$ , that we made.
  - When we are done computing  $C(M, N)$ , we use array  $B$  to **backtrack** and recover the optimal alignment between  $\mathbf{X}$  and  $\mathbf{Y}$ .

# DTW Complexity

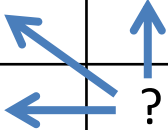
	$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$	$y_7$	$y_8$	$y_9$
$x_1$									
$x_2$									
$x_3$									
$x_4$									
$x_5$									
$x_6$									
$x_7$									
$x_8$									



- For each  $(i, j)$ :
  - Compute optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots, y_j)$ .
  - The solution is computed based on the solutions for  $(i - 1, j)$ ,  $(i, j - 1)$ ,  $(i - 1, j - 1)$ .
  - Time complexity?

# DTW Complexity

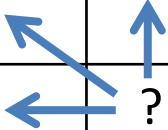
	$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$	$y_7$	$y_8$	$y_9$
$x_1$									
$x_2$									
$x_3$									
$x_4$									
$x_5$									
$x_6$									
$x_7$									
$x_8$									



- For each  $(i, j)$ :
  - Compute optimal alignment between  $(x_1, \dots, x_i)$  and  $(y_1, \dots, y_j)$ .
  - The solution is computed based on the solutions for  $(i-1, j)$ ,  $(i, j-1)$ ,  $(i-1, j-1)$ .
  - Time complexity? Linear to the size of the  $C$  array ( $M \times N$ ).

# DTW Complexity

	$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$	$y_7$	$y_8$	$y_9$
$x_1$									
$x_2$									
$x_3$									
$x_4$									
$x_5$									
$x_6$									
$x_7$									
$x_8$									



- Assume that both time series have approximately the same length  $M$ .
- Then, the time complexity of DTW is  $O(M^2)$ .
  - Improvements and variations have been proposed, with lower time complexity.

# DTW Finds the Optimal Alignment

- Proof:

# DTW Finds the Optimal Alignment

- Proof: by induction.
- Base cases:

# DTW Finds the Optimal Alignment

- Proof: by induction.
- Base cases:
  - $i = 1$  OR  $j = 1$ .

# DTW Finds the Optimal Alignment

- Proof: by induction.
- Base cases:
  - $i = 1$  OR  $j = 1$ .
- Proof of claim for base cases:
  - For any problem( $1, j$ ) and problem( $i, 1$ ), only one legal warping path exists.
    - Unless we consider warping paths with repetitions, like  $((1, 1), (1,1), (1,2))$ , which are legal, but can never have lower cost than their non-repeating versions, like  $((1, 1), (1,2))$ .
  - Therefore, DTW finds the optimal path for problem( $1, j$ ) and problem( $i, 1$ ).
    - It is optimal since it is the *only one*.



# DTW Finds the Optimal Alignment

- Proof: by induction.
- General case:
  - $(i, j)$ , for  $i \geq 2, j \geq 2$ .
- Inductive hypothesis:

# DTW Finds the Optimal Alignment

- Proof: by induction.
- General case:
  - $(i, j)$ , for  $i \geq 2, j \geq 2$ .
- Inductive hypothesis:
  - What we want to prove for  $(i, j)$  is true for  $(i - 1, j), (i, j - 1), (i - 1, j - 1)$ :

# DTW Finds the Optimal Alignment

- Proof: by induction.
- General case:
  - $(i, j)$ , for  $i \geq 2, j \geq 2$ .
- Inductive hypothesis:
  - What we want to prove for  $(i, j)$  is true for  $(i - 1, j), (i, j - 1), (i - 1, j - 1)$ :
  - DTW has computed optimal solutions for problems  $(i - 1, j), (i, j - 1), (i - 1, j - 1)$ .

# DTW Finds the Optimal Alignment

- Proof: by induction.
- General case:
  - $(i, j)$ , for  $i \geq 2, j \geq 2$ .
- Inductive hypothesis:
  - What we want to prove for  $(i, j)$  is true for  $(i - 1, j), (i, j - 1), (i - 1, j - 1)$ :
  - DTW has computed optimal solutions for problems  $(i - 1, j), (i, j - 1), (i - 1, j - 1)$ .
- Proof by contradiction:

# DTW Optimality Proof

- Proof: by induction.
- General case:
  - $(i, j)$ , for  $i \geq 2, j \geq 2$ .
- Inductive hypothesis:
  - What we want to prove for  $(i, j)$  is true for  $(i - 1, j), (i, j - 1), (i - 1, j - 1)$ :
  - DTW has computed optimal solutions for problems  $(i - 1, j), (i, j - 1), (i - 1, j - 1)$ .
- Proof by contradiction:
  - Summary: if solution for  $(i, j)$  is not optimal, then one of the solutions for  $(i - 1, j), (i, j - 1)$ , or  $(i - 1, j - 1)$  was not optimal, which violates the inductive hypothesis.

# DTW Optimality Proof

- Let  $A_{i,j}$  be the DTW solution to problem  $(i, j)$ .
  - We want to prove that  $A_{i,j}$  is optimal, using the inductive hypothesis.
- Let  $A^*_{i,j}$  be the alignment among  $A_{i,j-1}$ ,  $A_{i-1,j}$ , and  $A_{i-1,j-1}$  with the smallest cost.
- Then,  $A_{i,j} = A^*_{i,j} \oplus (i, j)$ .
  - $Q \oplus r$  is the result of appending item  $r$  to the end of list  $Q$ .
- Let  $B_{i,j}$  be the optimal solution to problem  $(i, j)$ .
- $B_{i,j} = B^*_{i,j} \oplus (i, j)$  for some  $B^*$ .
- Assume contradiction ( $B_{i,j} \neq A_{i,j}$ ).

# DTW Optimality Proof

- DTW solution for problem( $i, j$ ):

$$\mathbf{A}_{i,j} = \left( (a_{1,1}, a_{1,2}), (a_{2,1}, a_{2,2}), \dots, (a_{R,1}, a_{R,2}) \right)$$

- Optimal solution for problem( $i, j$ ):

$$\mathbf{B}_{i,j} = \left( (b_{1,1}, b_{1,2}), (b_{2,1}, b_{2,2}), \dots, (b_{S,1}, b_{S,2}) \right)$$

- Assume contradiction:  $\mathbf{A}_{i,j}$  is not optimal. Then,

$$C_{X,Y}(\mathbf{A}_{i,j}) > C_{X,Y}(\mathbf{B}_{i,j})$$

- Why?

– Because  $\mathbf{B}_{i,j}$  is optimal and  $\mathbf{A}_{i,j}$  is not optimal.

# DTW Optimality Proof

- $\mathbf{A}_{i,j} = \left( (a_{1,1}, a_{1,2}), (a_{2,1}, a_{2,2}), \dots, (a_{R,1}, a_{R,2}) \right)$
- $\mathbf{B}_{i,j} = \left( (b_{1,1}, b_{1,2}), (b_{2,1}, b_{2,2}), \dots, (b_{S,1}, b_{S,2}) \right)$

$$C_{X,Y}(\mathbf{A}_{i,j}) > C_{X,Y}(\mathbf{B}_{i,j}) \Rightarrow$$

$$\sum_{i=1}^R \text{Cost}(\mathbf{x}_{a_{i,1}}, \mathbf{y}_{a_{i,2}}) > \sum_{i=1}^S \text{Cost}(\mathbf{x}_{b_{i,1}}, \mathbf{y}_{b_{i,2}})$$

- Why?
  - We are just using the definition of the cost of an alignment.



# DTW Optimality Proof

- $\mathbf{A}_{i,j} = \left( (a_{1,1}, a_{1,2}), (a_{2,1}, a_{2,2}), \dots, (a_{R,1}, a_{R,2}) \right)$
- $\mathbf{B}_{i,j} = \left( (b_{1,1}, b_{1,2}), (b_{2,1}, b_{2,2}), \dots, (b_{S,1}, b_{S,2}) \right)$

$$\sum_{i=1}^R \text{Cost}(\mathbf{x}_{a_{i,1}}, \mathbf{y}_{a_{i,2}}) > \sum_{i=1}^S \text{Cost}(\mathbf{x}_{b_{i,1}}, \mathbf{y}_{b_{i,2}}) \Rightarrow$$

$$\sum_{i=1}^{R-1} \text{Cost}(\mathbf{x}_{a_{i,1}}, \mathbf{y}_{a_{i,2}}) > \sum_{i=1}^{S-1} \text{Cost}(\mathbf{x}_{b_{i,1}}, \mathbf{y}_{b_{i,2}})$$

- Why? The last element of both  $\mathbf{A}_{i,j}$  and  $\mathbf{B}_{i,j}$  is  $(i, j)$ .
  - Both  $\mathbf{A}_{i,j}$  and  $\mathbf{B}_{i,j}$  align  $(\mathbf{x}_1, \dots, \mathbf{x}_i)$  with  $(\mathbf{y}_1, \dots, \mathbf{y}_j)$ .

# DTW Optimality Proof

- $\mathbf{A}_{i,j} = \left( (a_{1,1}, a_{1,2}), (a_{2,1}, a_{2,2}), \dots, (a_{R,1}, a_{R,2}) \right)$
- $\mathbf{B}_{i,j} = \left( (b_{1,1}, b_{1,2}), (b_{2,1}, b_{2,2}), \dots, (b_{S,1}, b_{S,2}) \right)$

$$\sum_{i=1}^{R-1} \text{Cost}(\mathbf{x}_{a_{i,1}}, \mathbf{y}_{a_{i,2}}) > \sum_{i=1}^{S-1} \text{Cost}(\mathbf{x}_{b_{i,1}}, \mathbf{y}_{b_{i,2}}) \Rightarrow$$

$$C_{X,Y}(\mathbf{A}^*_{i,j}) > C_{X,Y}(\mathbf{B}^*_{i,j})$$

- Why? We are just using the definitions of  $\mathbf{A}^*_{i,j}$  and  $\mathbf{B}^*_{i,j}$ .
  - $\mathbf{A}_{i,j} = \mathbf{A}^*_{i,j} \oplus (i, j)$ .
  - $\mathbf{B}_{i,j} = \mathbf{B}^*_{i,j} \oplus (i, j)$

# DTW Optimality Proof

- $\mathbf{A}_{i,j} = \left( (a_{1,1}, a_{1,2}), (a_{2,1}, a_{2,2}), \dots, (a_{R,1}, a_{R,2}) \right)$
- $\mathbf{B}_{i,j} = \left( (b_{1,1}, b_{1,2}), (b_{2,1}, b_{2,2}), \dots, (b_{S,1}, b_{S,2}) \right)$

$$C_{X,Y}(\mathbf{A}^*_{i,j}) > C_{X,Y}(\mathbf{B}^*_{i,j}) \Rightarrow$$

$$\min(C_{X,Y}(\mathbf{A}_{i,j-1}), C_{X,Y}(\mathbf{A}_{i-1,j}), C_{X,Y}(\mathbf{A}_{i-1,j-1})) > C_{X,Y}(\mathbf{B}^*_{i,j})$$

- Why? We are just using the definitions of  $\mathbf{A}^*_{i,j}$  and  $\mathbf{B}^*_{i,j}$ .
  - $\mathbf{A}^*_{i,j} = \operatorname{argmin}(C_{X,Y}(\mathbf{A}_{i,j-1}), C_{X,Y}(\mathbf{A}_{i-1,j}), C_{X,Y}(\mathbf{A}_{i-1,j-1}))$

# DTW Optimality Proof

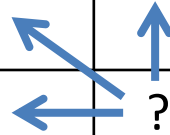
$$\min(C_{X,Y}(A_{i,j-1}), C_{X,Y}(A_{i-1,j}), C_{X,Y}(A_{i-1,j-1})) > C_{X,Y}(B^*_{i,j})$$

**Contradiction!!!**

- The inductive hypothesis was that alignments  $A_{i,j-1}$ ,  $A_{i-1,j}$ ,  $A_{i-1,j-1}$  were the optimal alignments for problems  $(i-1, j)$ ,  $(i, j-1)$ ,  $(i-1, j-1)$ .
- However,  $B^*_{i,j}$  is also an alignment for one of the three problems.
  - Otherwise,  $B_{i,j}$  would break one of the three rules of legal alignments.
- Plus,  $B^*_{i,j}$  has a lower cost than each of  $A_{i,j-1}$ ,  $A_{i-1,j}$ ,  $A_{i-1,j-1}$ , so one of those three alignments is not optimal..
- This contradicts the inductive hypothesis.

# Visualizing $B^*_{i,j}$ for $i = 4, j = 5$

	$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$	$y_7$	$y_8$	$y_9$
$x_1$									
$x_2$									
$x_3$									
$x_4$									
$x_5$									
$x_6$									
$x_7$									
$x_8$									



- $B_{i,j}$  aligns  $(x_1, \dots, x_i)$  with  $(y_1, \dots, y_j)$ .
- $B^*_{i,j}$  is the result of removing the last element from  $B_{i,j}$ .
- Based on the rules of continuity and monotonicity, the last element of  $B^*_{i,j}$  must be  $(i - 1, j)$ ,  $(i, j - 1)$ , or  $(i - 1, j - 1)$ .

# DTW Optimality Proof - Recap

- Proof: by induction.
- The base cases are easy to prove.
- The tricky part is to prove the inductive case.
  - I.e., prove that  $A_{i,j}$ , which is the DTW solution problem  $(i, j)$ , is indeed the optimal alignment for that problem.
- We prove the inductive case by contradiction:
  - Inductive hypothesis: alignments  $A_{i,j-1}$ ,  $A_{i-1,j}$ ,  $A_{i-1,j-1}$  were the optimal alignments for problems  $(i-1, j)$ ,  $(i, j-1)$ ,  $(i-1, j-1)$ .
  - If  $A_{i,j}$  is not optimal, then we prove that one of alignments  $A_{i,j-1}$ ,  $A_{i-1,j}$ ,  $A_{i-1,j-1}$  must not be optimal, which contradicts the inductive hypothesis.

# Dynamic Time Warping, Recap

- It is oftentimes useful to use nearest neighbor classification to classify time series.
  - Especially when we have very few training examples per class, or, in the extreme, only one training example per class.
- However, to use nearest neighbor classification, we need to define a meaningful distance measure between time series.
- The Euclidean distance works poorly because even slight misalignments can lead to large distance values.
- Dynamic Time Warping is based on computing an optimal alignment between two time series, and thus it can tolerate even large misalignments.
- The complexity of Dynamic Time Warping is quadratic to the length of the time series, but more efficient variants can also be used.

# Other Distance Measures

- There are more distance measures that can be used on time series data. For example:
  - Edit Distance with Real Penalty (ERP).

Lei Chen and Raymond Ng. "On the marriage of  $l_p$ -norms and edit distance." In *International Conference on Very Large Data Bases (VLDB)*, pp. 792-803, 2004.

- Time Warp Edit Distance (TWED).

Pierre-François Marteau. "Time warp edit distance with stiffness adjustment for time series matching." *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI)*, 31, no. 2 (2009): 306-318.

- Move-Split-Merge (MSM).

Alexandra Stefan, Vassilis Athitsos, and Gautam Das. "The move-split-merge metric for time series." *IEEE Transactions on Knowledge and Data Engineering (TKDE)*, 25, no. 6 (2013): 1425-1438.