

# Machine Learning pour les séries temporelles en Python

## Partie I : comparer des séries temporelles

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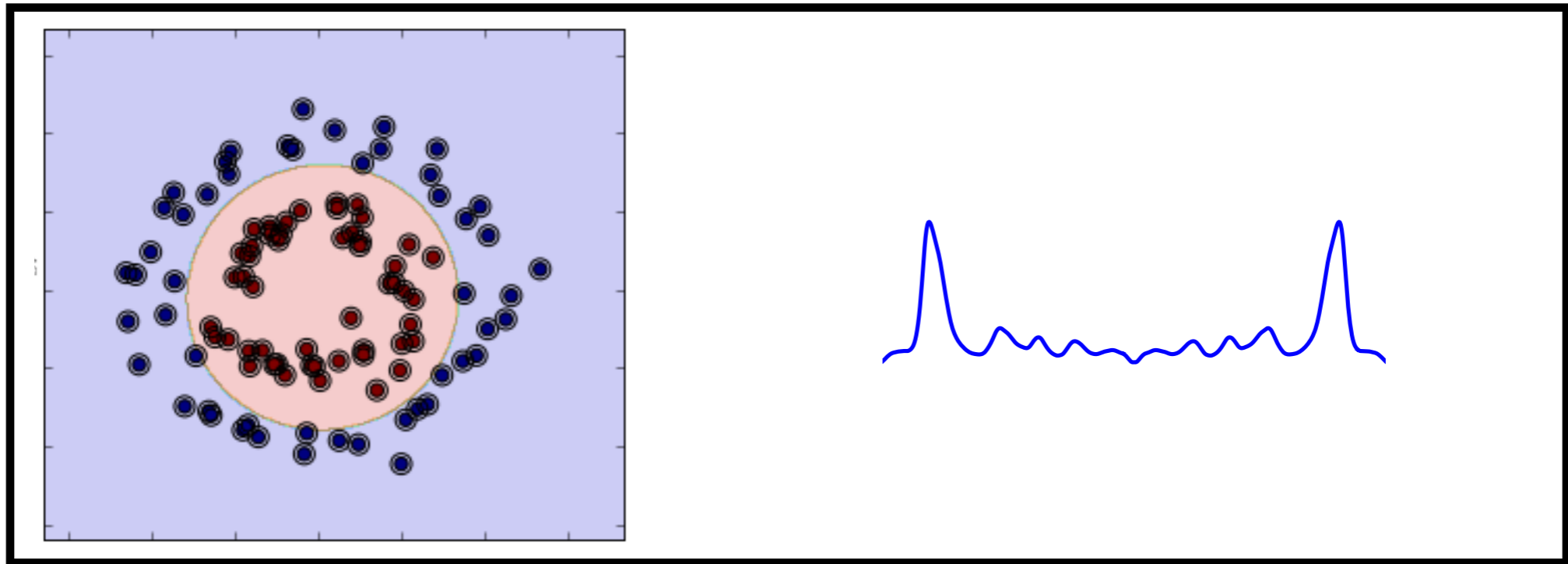
Yann Cabanes, Johann Faouzi, [Romain Tavenard](#)

*Tutoriel présenté à CAp 2023*

[tslearn-team.github.io/tutoriel-cap2023/](https://tslearn-team.github.io/tutoriel-cap2023/)

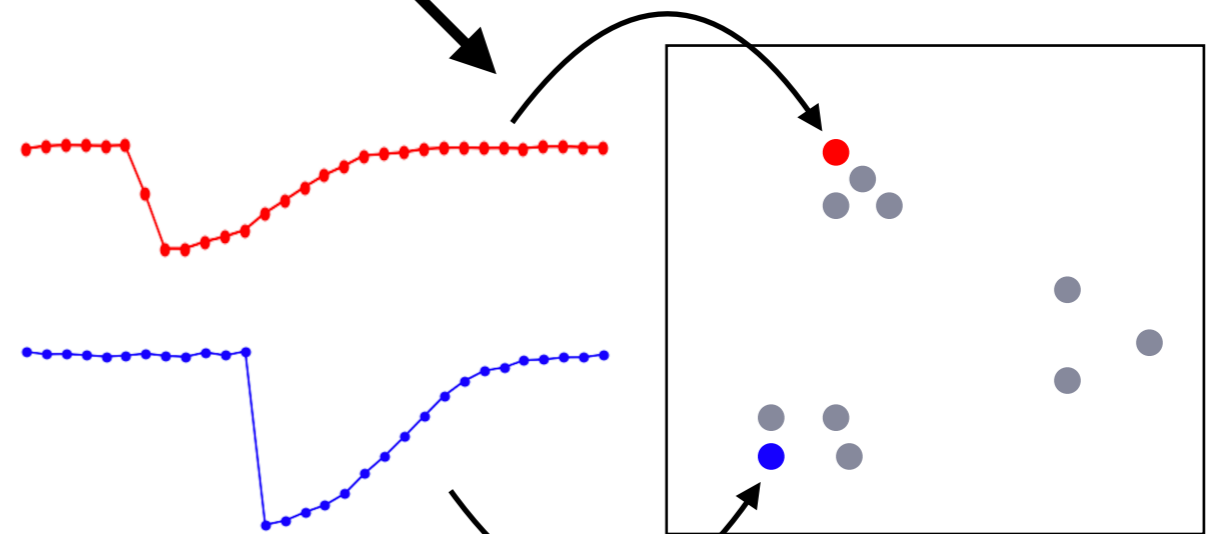
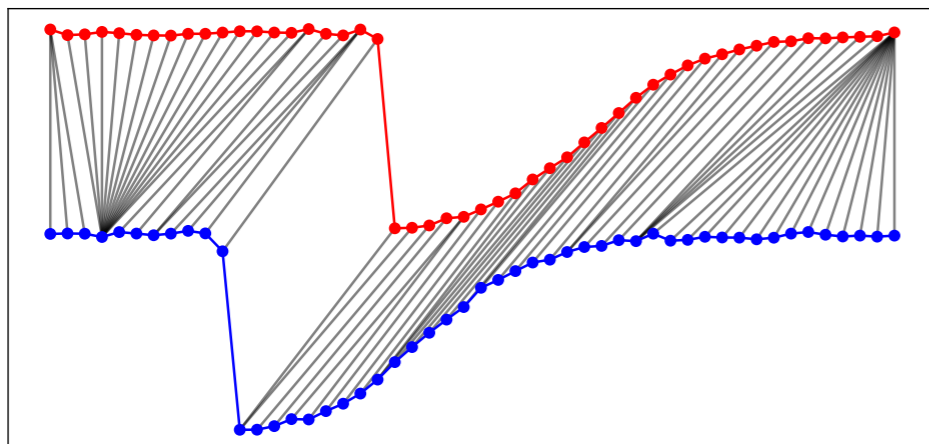


# ML pour les séries temporelles



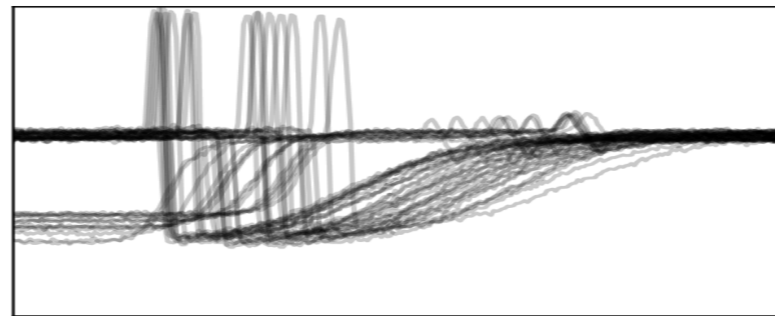
Métrique

Représentation

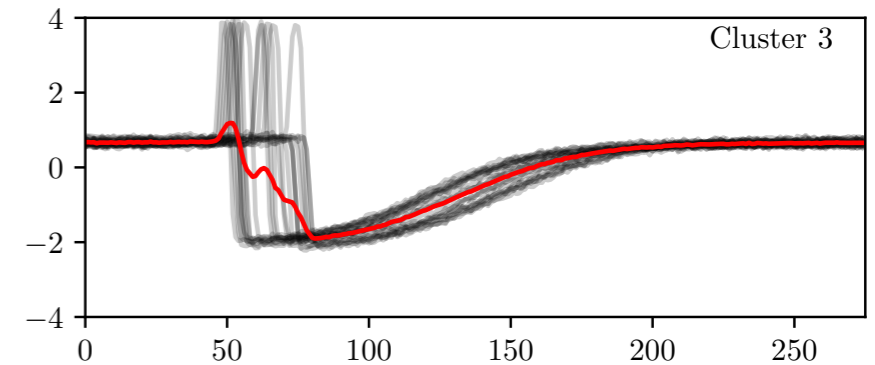
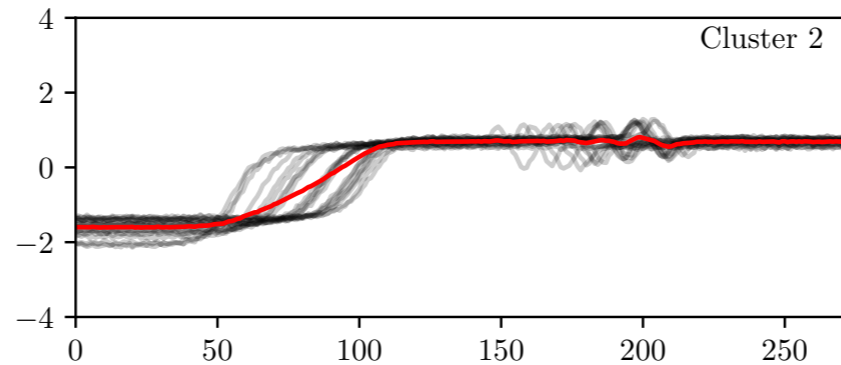
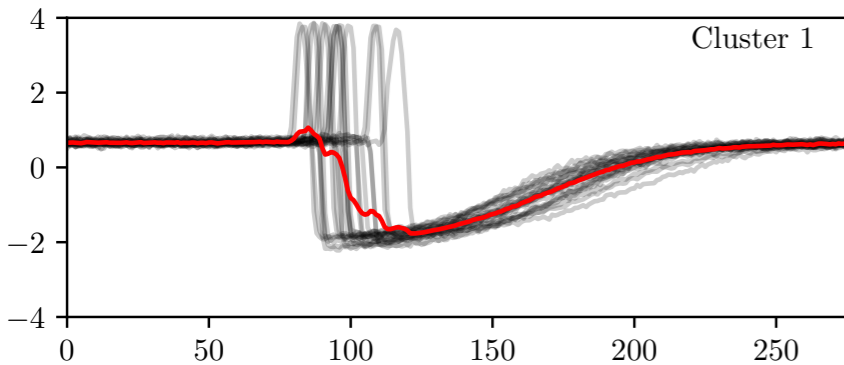


# Comparer des séries temporelles

## Pourquoi utiliser des métriques dédiées ?



Euclidean  $k$ -means



DTW Barycenter Averaging  $k$ -means

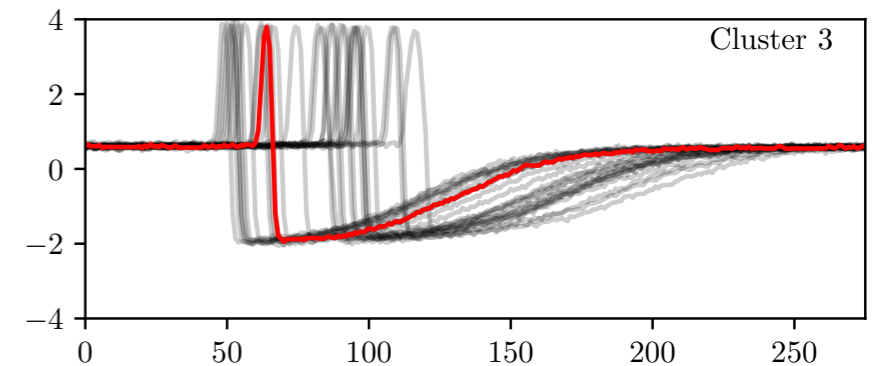
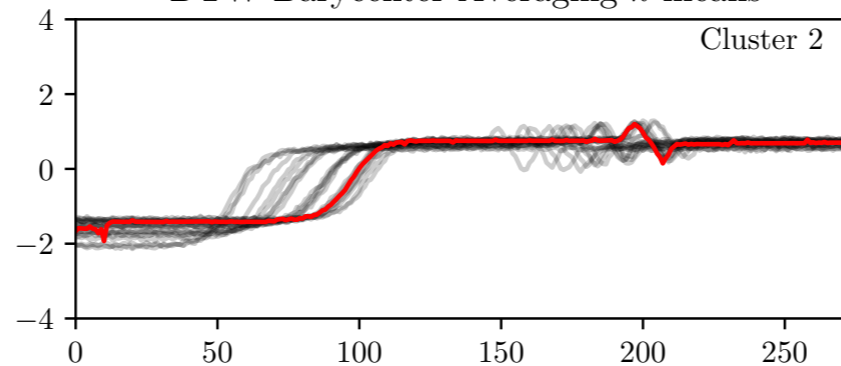
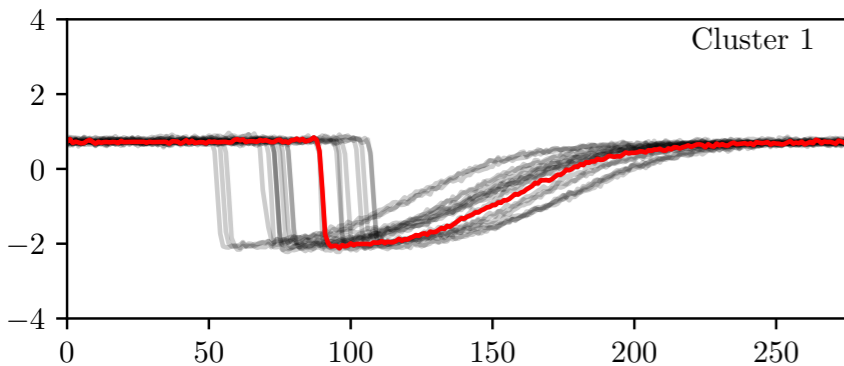


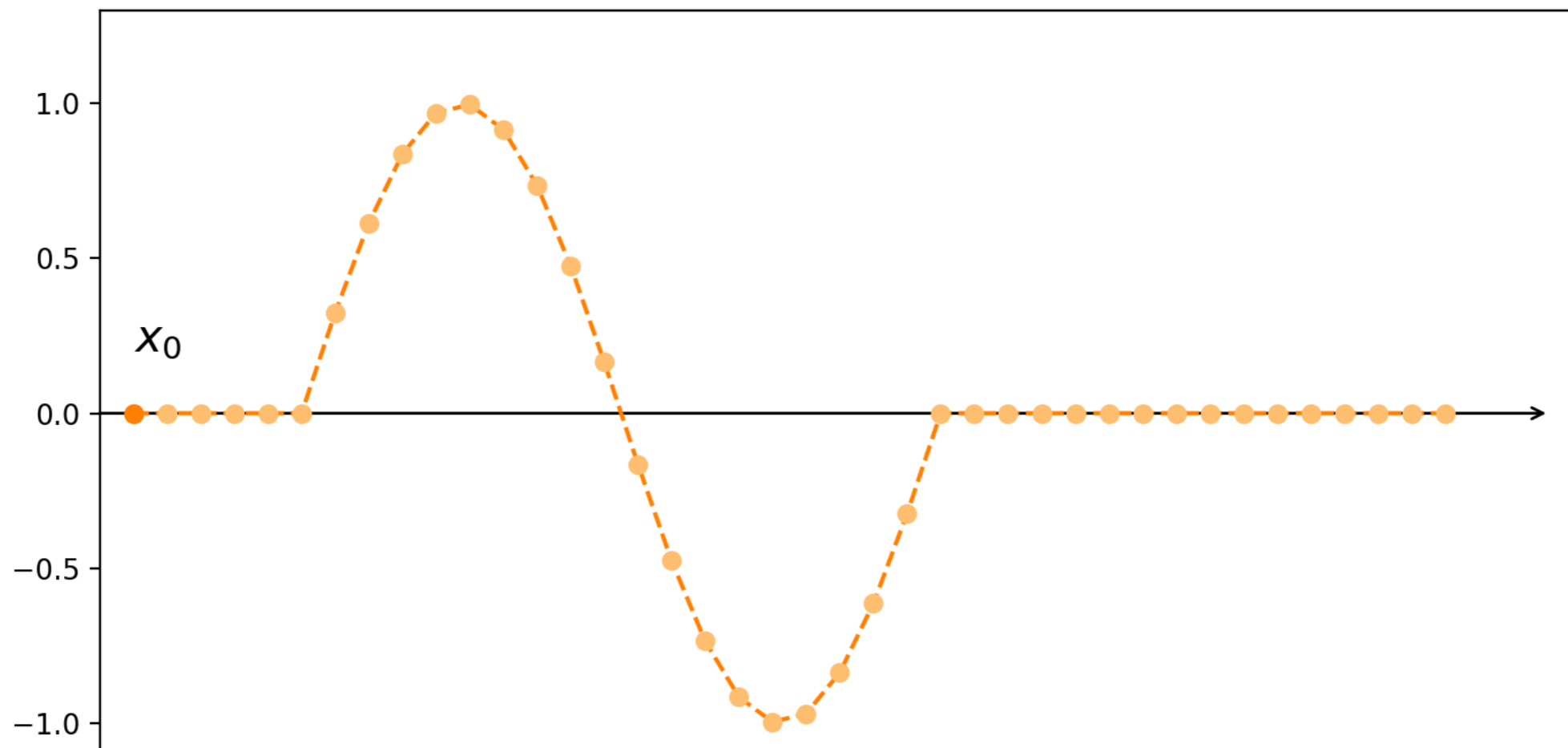
Illustration issue des docs tslearn

# Comparer des séries temporelles

Ce qu'on entend par « série temporelle »

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$$x = (x_0, \dots, x_{n-1})$$

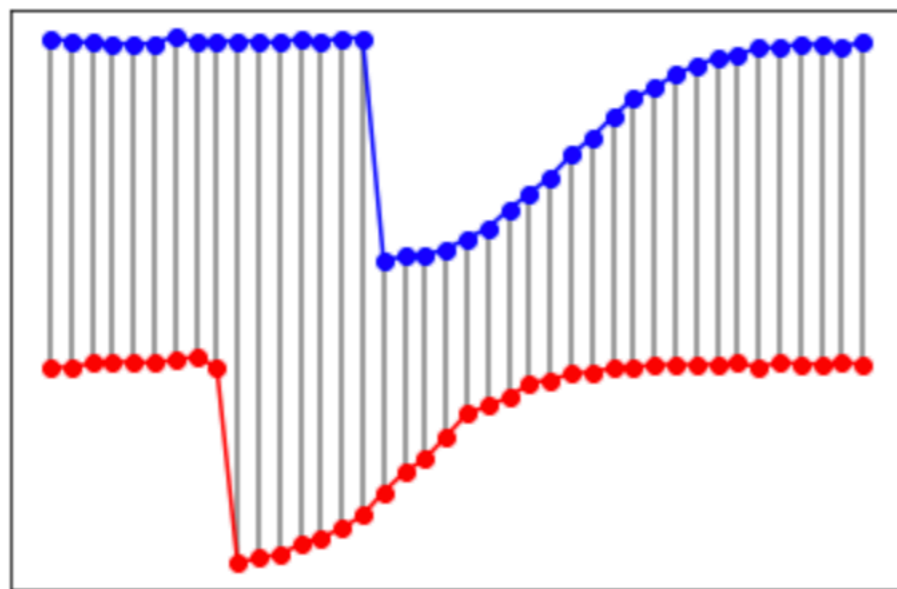


# Comparer des séries temporelles

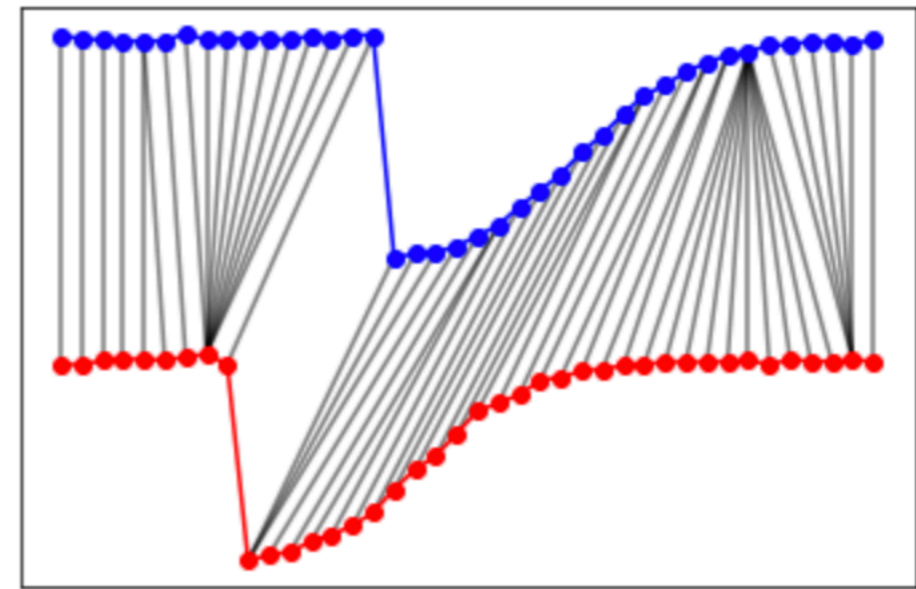
## Dynamic Time Warping (DTW) : intuition



H. Sakoe



Appariement basé distance  
Euclidienne

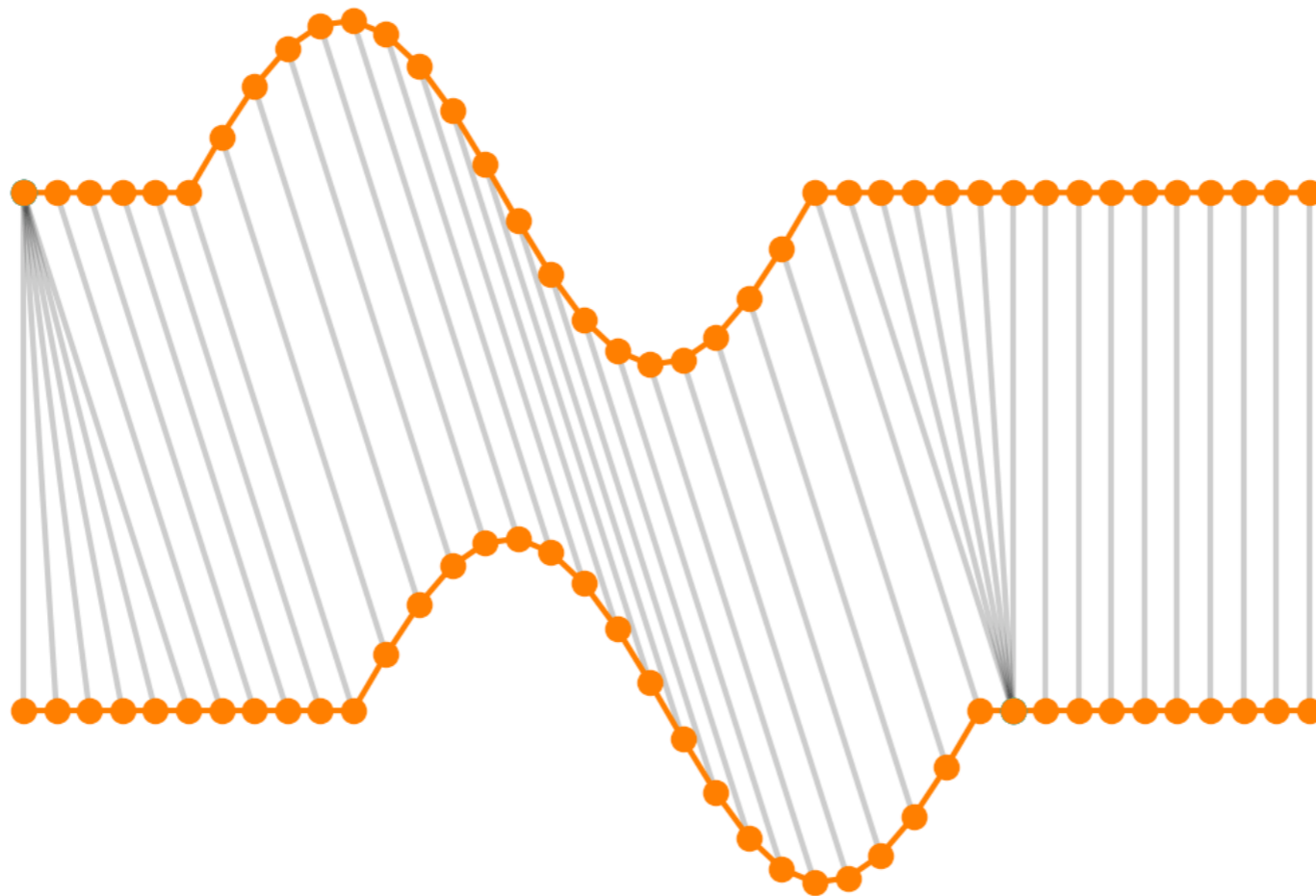


Appariement basé  
Dynamic Time Warping

# Comparer des séries temporelles

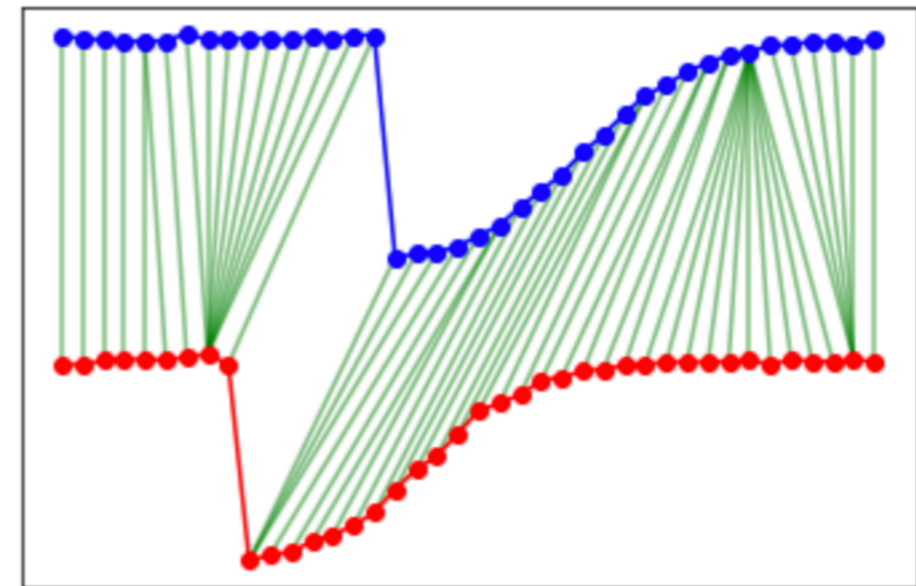
## Dynamic Time Warping (DTW) : intuition

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# Comparer des séries temporelles

## Dynamic Time Warping (DTW)



- DTW Optimization problem

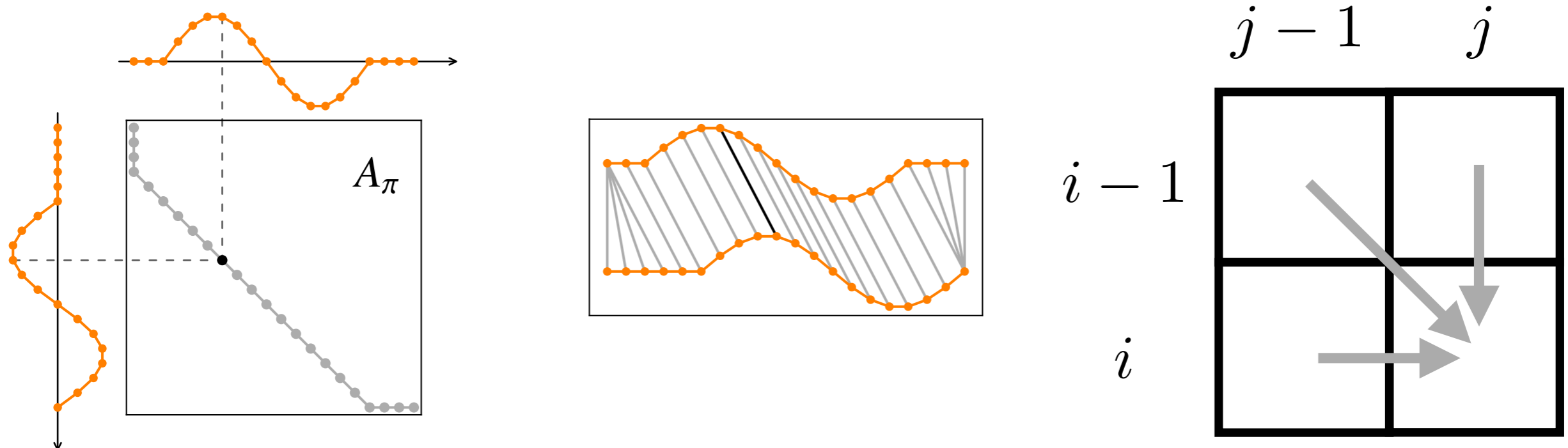
$$DTW_q(\mathbf{x}, \mathbf{x}') = \min_{\pi \in \mathcal{A}(\mathbf{x}, \mathbf{x}')} \left( \sum_{(i,j) \in \pi} d(x_i, x'_j)^q \right)^{\frac{1}{q}}$$

- Optimization on the path  $\pi$ 
  1. Should match beginning (resp. end) of time series
  2. Should be monotonically increasing
  3. Should not skip elements

# Comparer des séries temporelles

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# Comparer des séries temporelles

## Soft-DTW



M. Cuturi



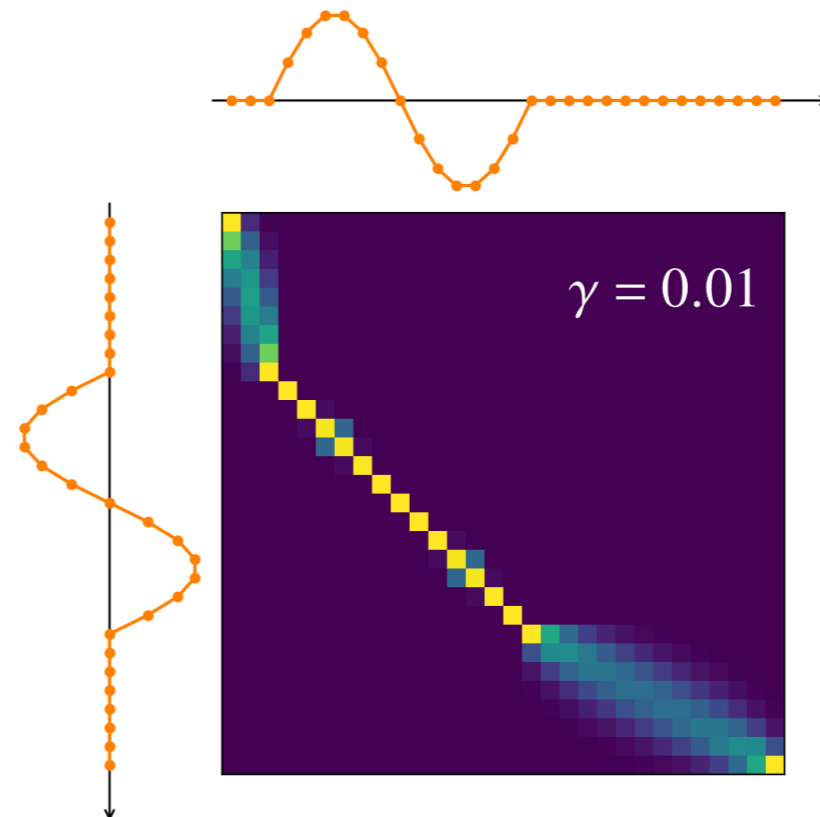
M. Blondel

- DTW Optimization problem

$$DTW_q(\mathbf{x}, \mathbf{x}') = \min_{\pi \in \mathcal{A}(\mathbf{x}, \mathbf{x}')} \left( \sum_{(i,j) \in \pi} d(x_i, x'_j)^q \right)^{\frac{1}{q}}$$

- Differentiable variant: soft-DTW

- Use soft- $\min^\gamma$  in place of  $\min$



# Comparer des séries temporelles

## Un k-means à la sauce DTW

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### Algorithm 3: Lloyd's algorithm ( $k$ -means)

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```
Data:  $(\mathbf{x}^1, \dots, \mathbf{x}^n)$ : time series dataset  
 $\{\mathbf{b}^1, \dots, \mathbf{b}^k\} \leftarrow \text{PickFrom}(\mathbf{x}^1, \dots, \mathbf{x}^n)$  // Or use k-means++ init  
for  $e = 1..n_{iter}$  do  
  for  $i = 1..n$  do  
     $a_i \leftarrow \text{NearestNeighborIndex}(\mathbf{x}^i, \{\mathbf{b}^1, \dots, \mathbf{b}^k\})$   
  end  
  for  $j = 1..k$  do  
     $\mathbf{b}^j \leftarrow \text{Barycenter}(\{\mathbf{x}^i | a_i = j\})$   
  end  
end  
return  $\mathbf{z}$ 
```

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# Comparer des séries temporelles softDTW comme fonction de coût

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- Tâche
  - Prédiction du futur d'une série temporelle
- Outil
  - Réseau de neurone
- Deux possibilités

$$\mathcal{L}_{\text{MSE}}(\mathbf{y}, \hat{\mathbf{y}}) = \sum_{i=1}^T d(y_i, \hat{y}_i)^2$$

$$\mathcal{L}_{\text{soft-DTW}^\gamma}(\mathbf{y}, \hat{\mathbf{y}}) = \text{soft-} \min_{\pi \in \mathcal{A}(T, T)} \sum_{(i, j) \in \pi} d(y_i, \hat{y}_j)^\gamma$$

# Comparer des séries temporelles softDTW comme fonction de coût

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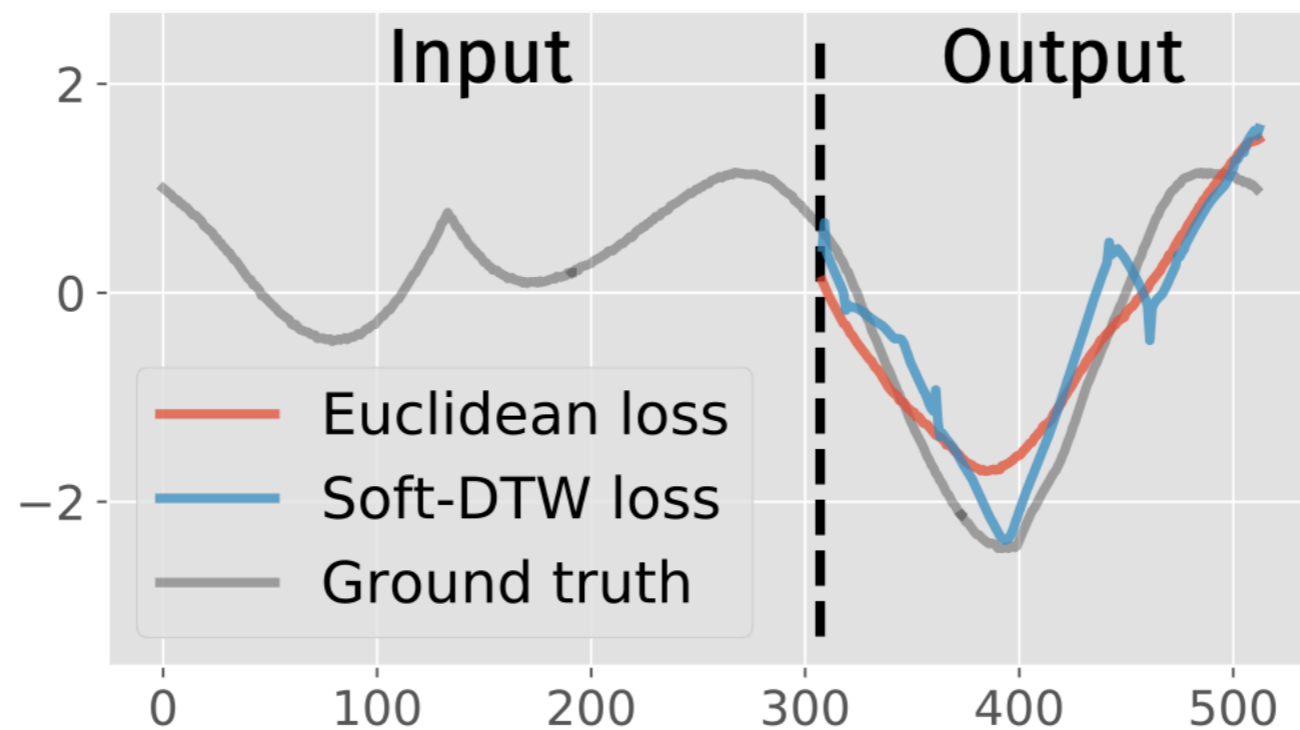


Illustration issue de [Cuturi & Blondel, 2017]

# tslearn: Présentation en 1 diapo

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- Installation

```
pip install tslearn
```

```
conda install -c conda-forge tslearn
```

- Utilisation : à la scikit-learn

```
>>> from tslearn.datasets import UCR_UEA_datasets
>>> from tslearn.clustering import TimeSeriesKMeans
>>>
>>> X_train, y_train, X_test, y_test = UCR_UEA_datasets().load_dataset("TwoPatterns")
>>> print(X_train.shape)
(1000, 128, 1)
>>>
>>> km = TimeSeriesKMeans(n_clusters=3, metric="dtw")
>>> km.fit(X_train)
```