

Topological Data Analysis

Lecture 13
Topological Data Analysis of Time Series

Oleg Kachan

TDA for time series analysis

Dimensionality

- univariate
- multivariate

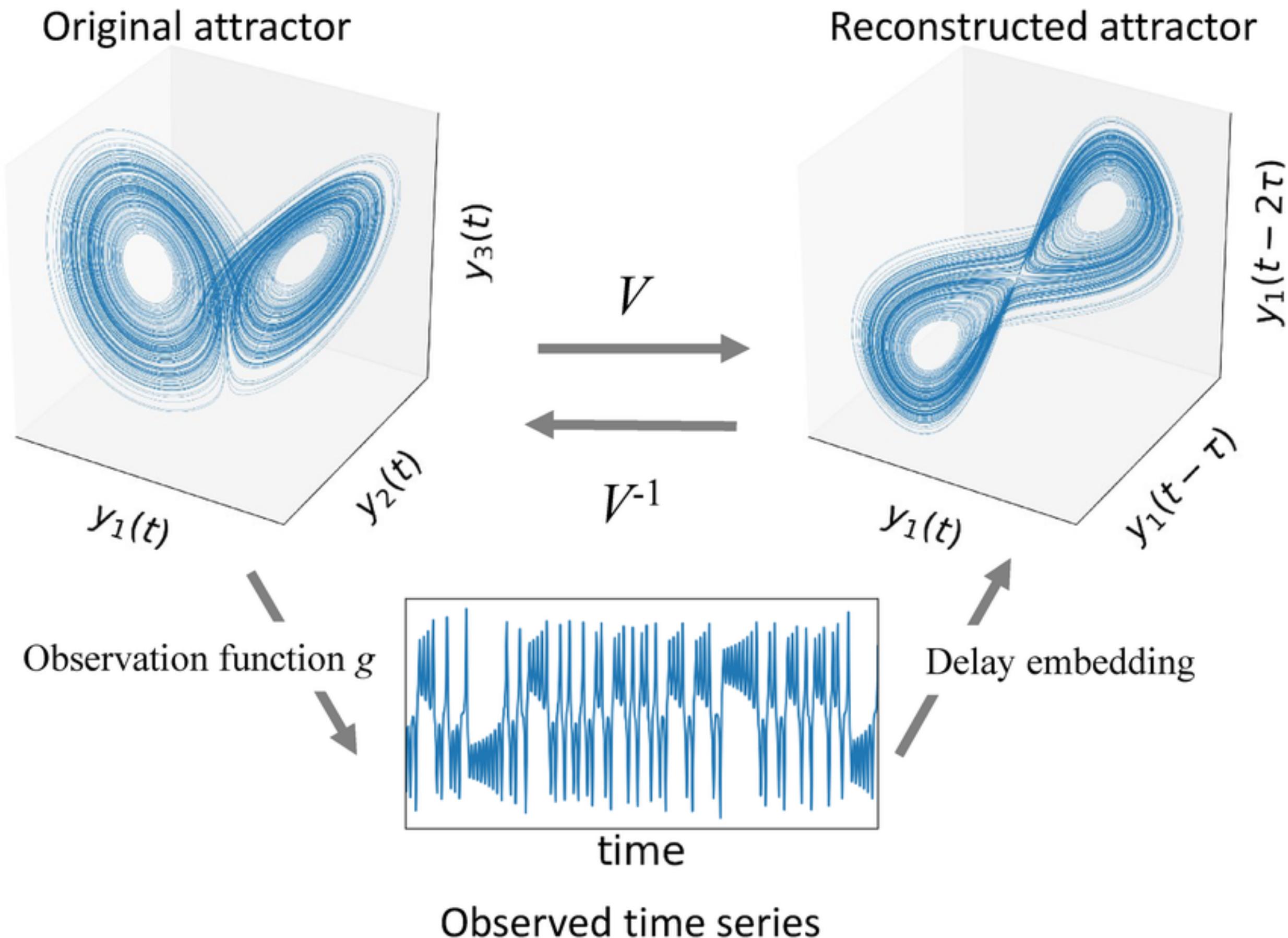
Periodicity

- non-periodic
- periodic

Applications

- medical
- industrial
- financial

Dynamical systems reconstruction



Takens, 1981

Given a time series measurements $g : \mathcal{A} \rightarrow \mathbb{R}$
from a D -dimensional attractor \mathcal{A}
reconstruction map

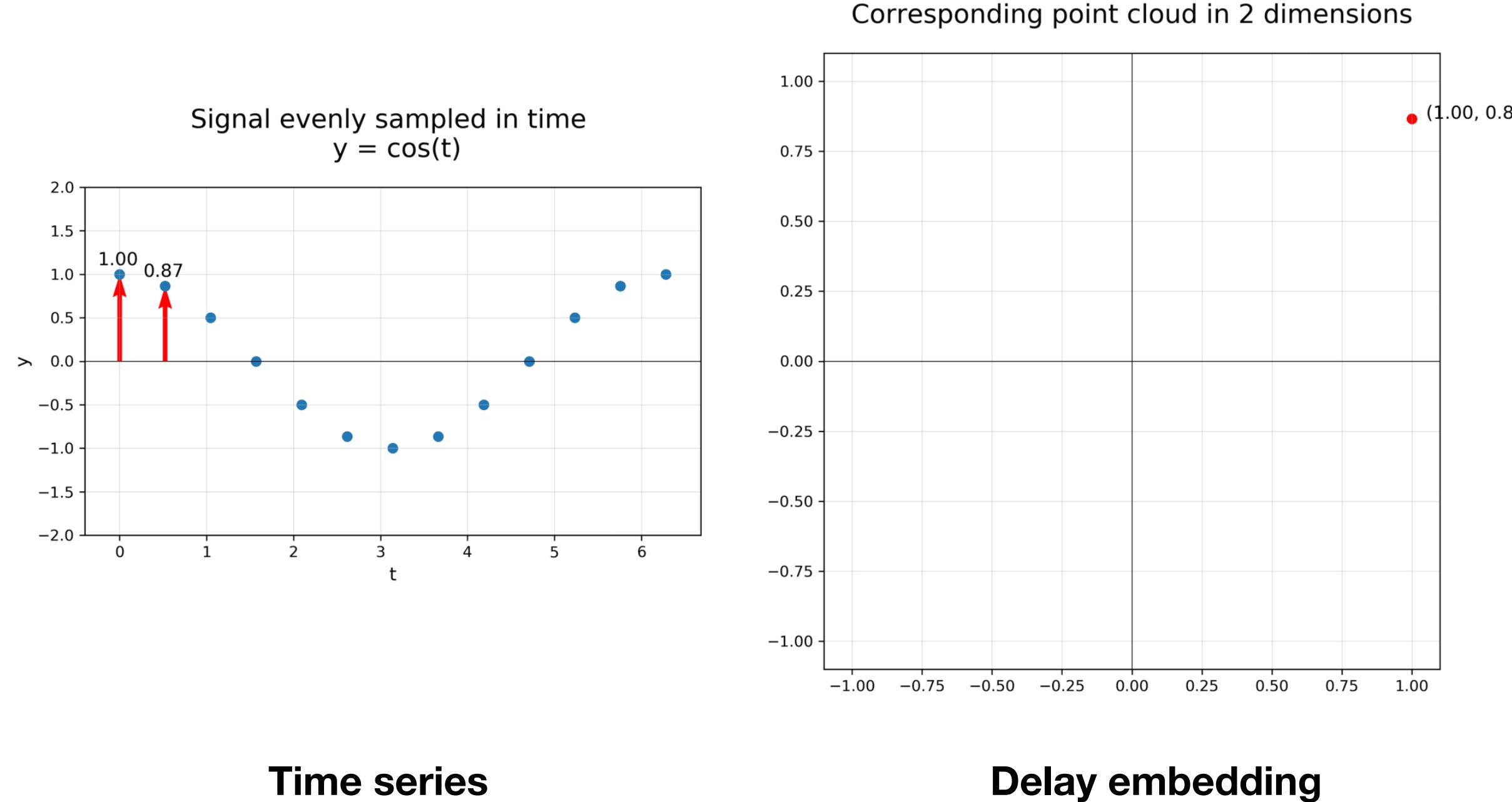
$$f : \mathbb{R} \rightarrow \mathbb{R}^d$$

would be topology-preserving for $d > 2D+1$.

Delay embedding

Given time series $\{x_t\}_{t=1}^N$ a delay embedding, given embedding dimension d and lag τ is defined as

$$DX_t : \mathbb{R} \rightarrow \mathbb{R}^d \quad x_t \mapsto (x_{t-d\tau}, \dots, x_{t-2\tau}, x_{t-\tau})$$



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Choosing τ

Optimal delay is the first minimum of the mutual information between original and delayed time series [Pereira15]

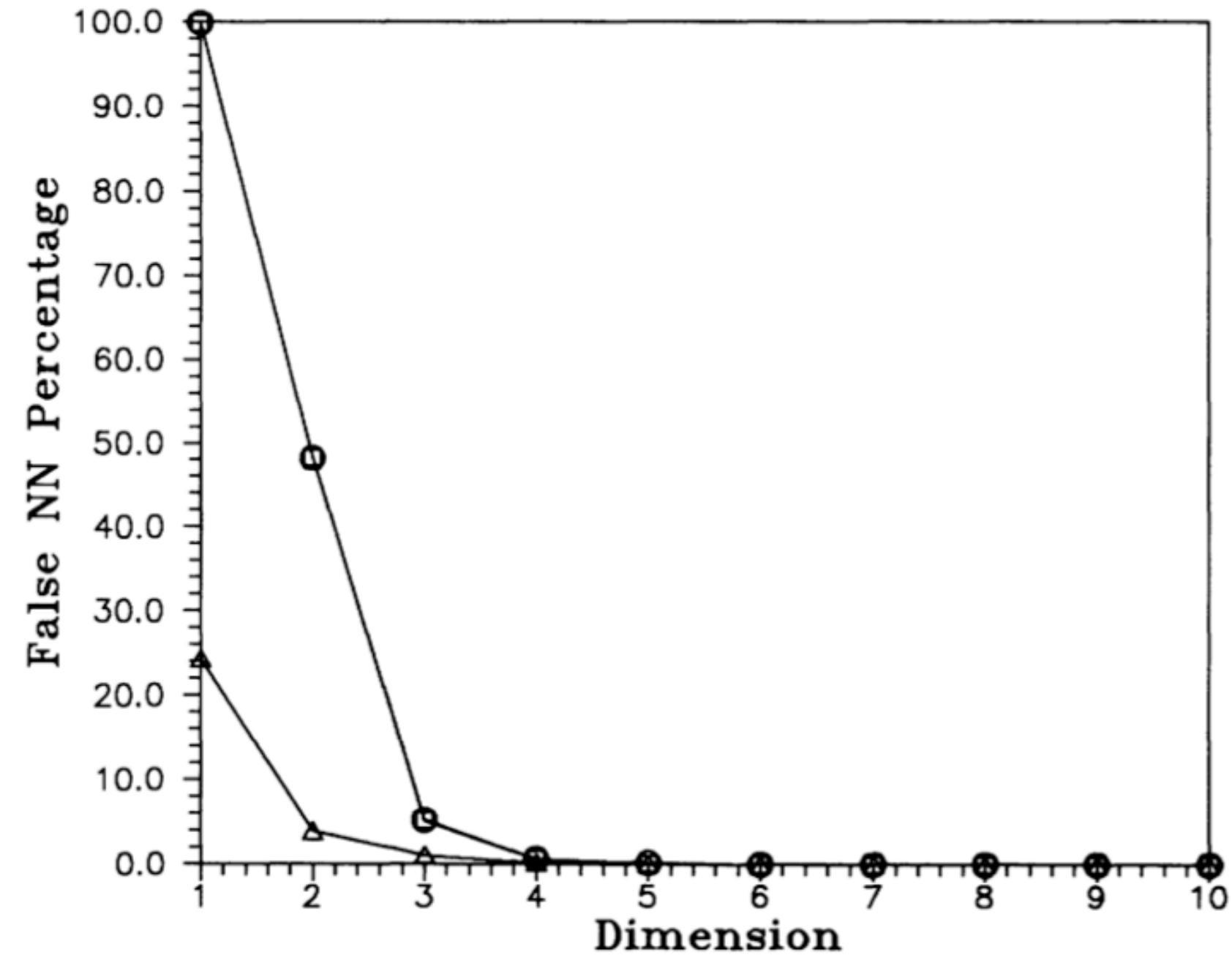
$$\tau^* = \arg \min_{\tau} I(X_t, X_{t-\tau})$$

Delay embedding

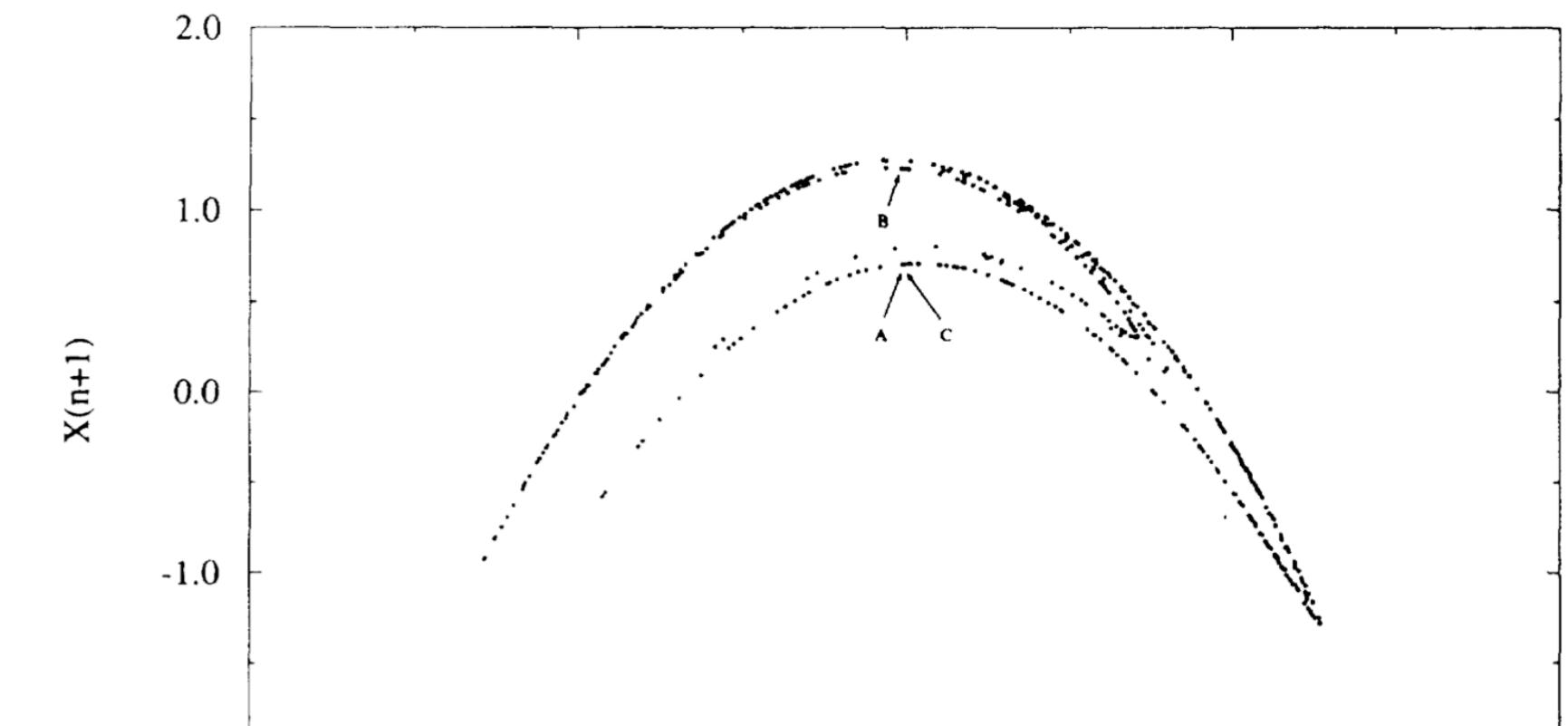
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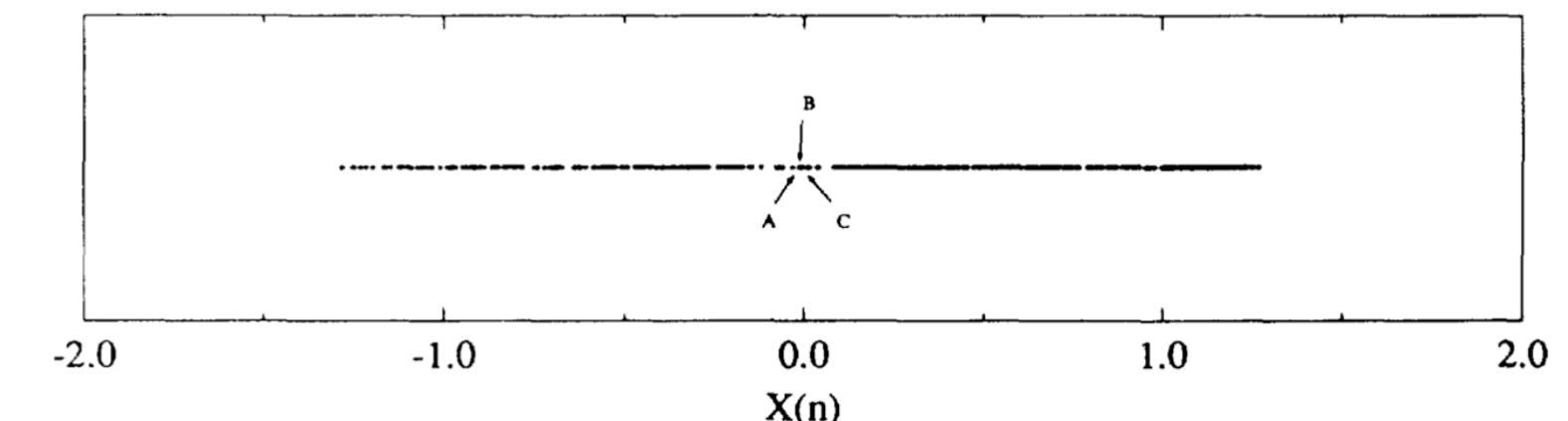
Choosing d



True neighbors in \mathbb{R}^2



False neighbors in \mathbb{R}

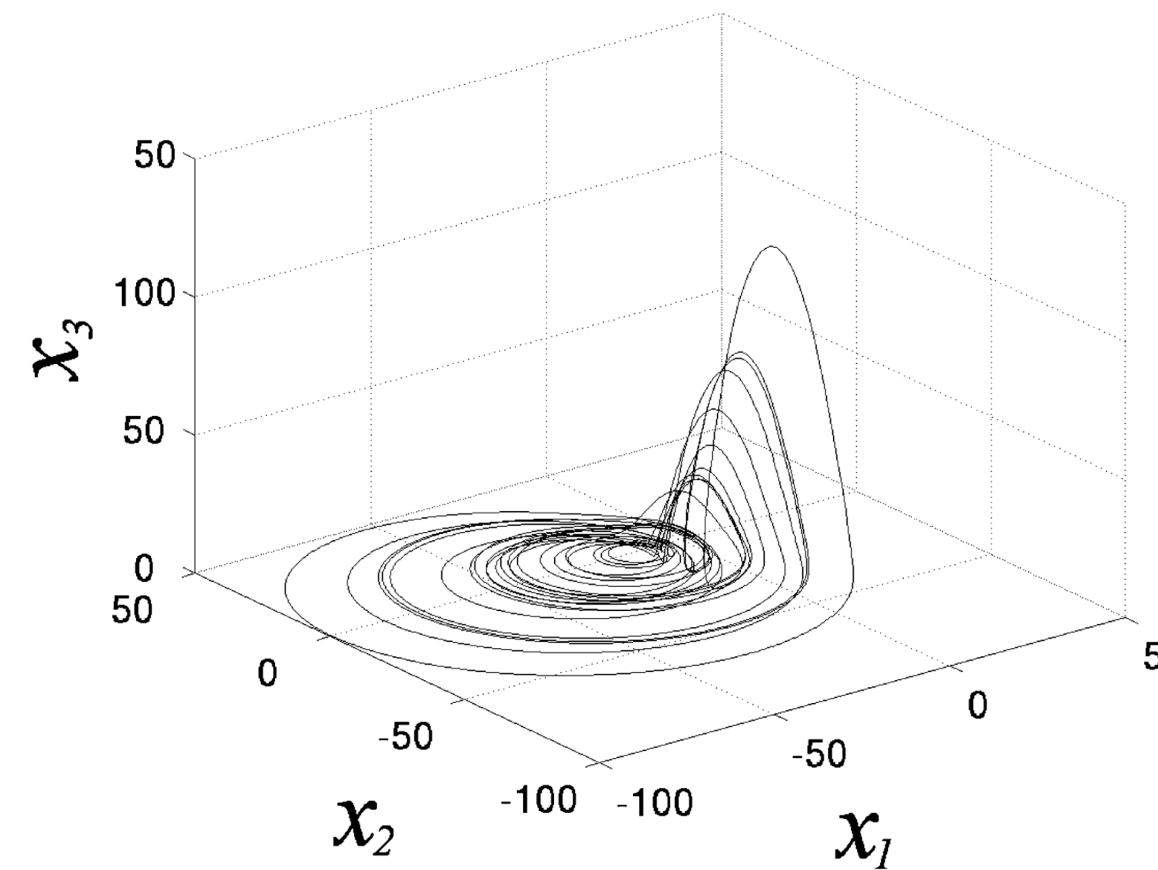
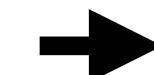


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Time series

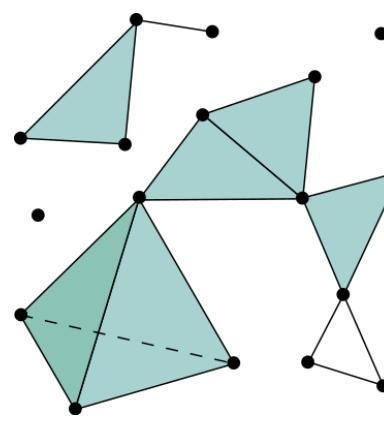
Delay embedding



Persistence diagram

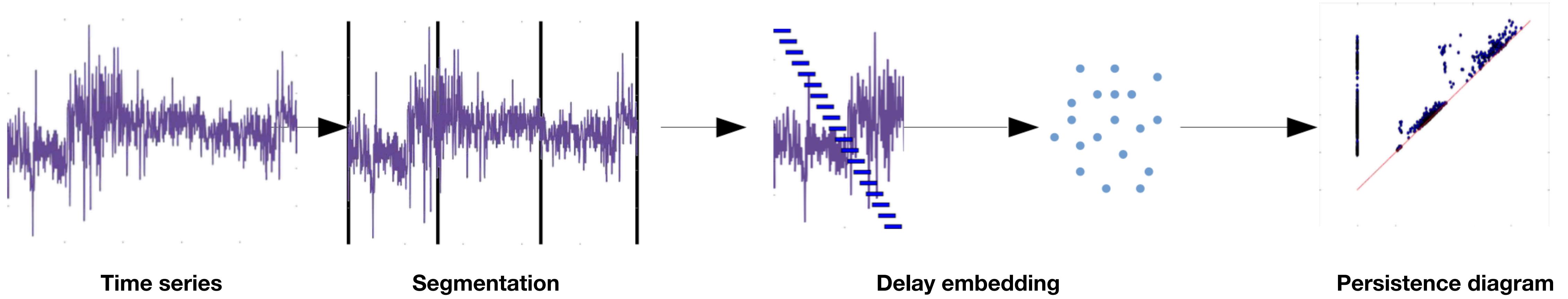


Vector representation
ML task

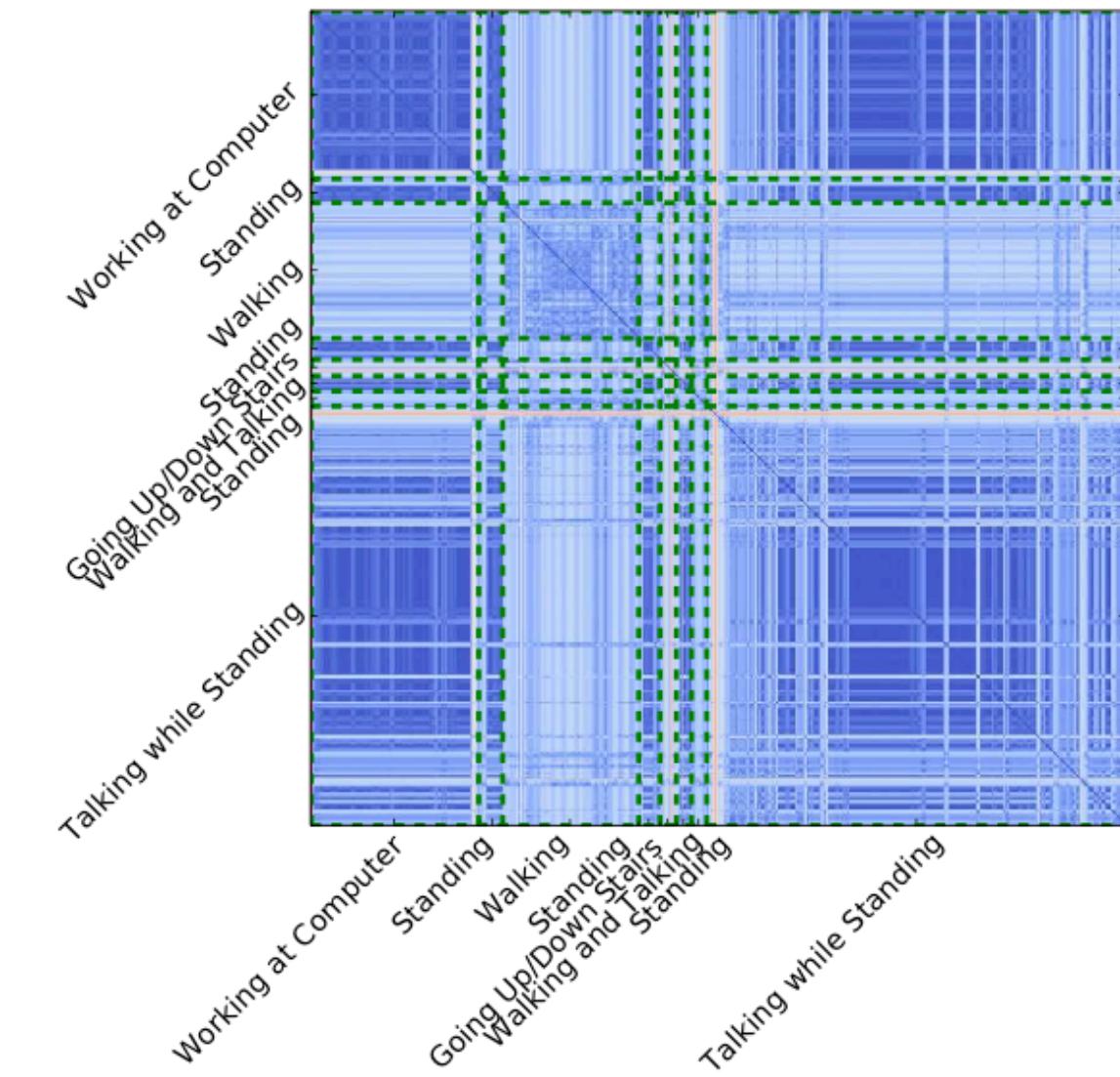


Vietoris-Rips filtration

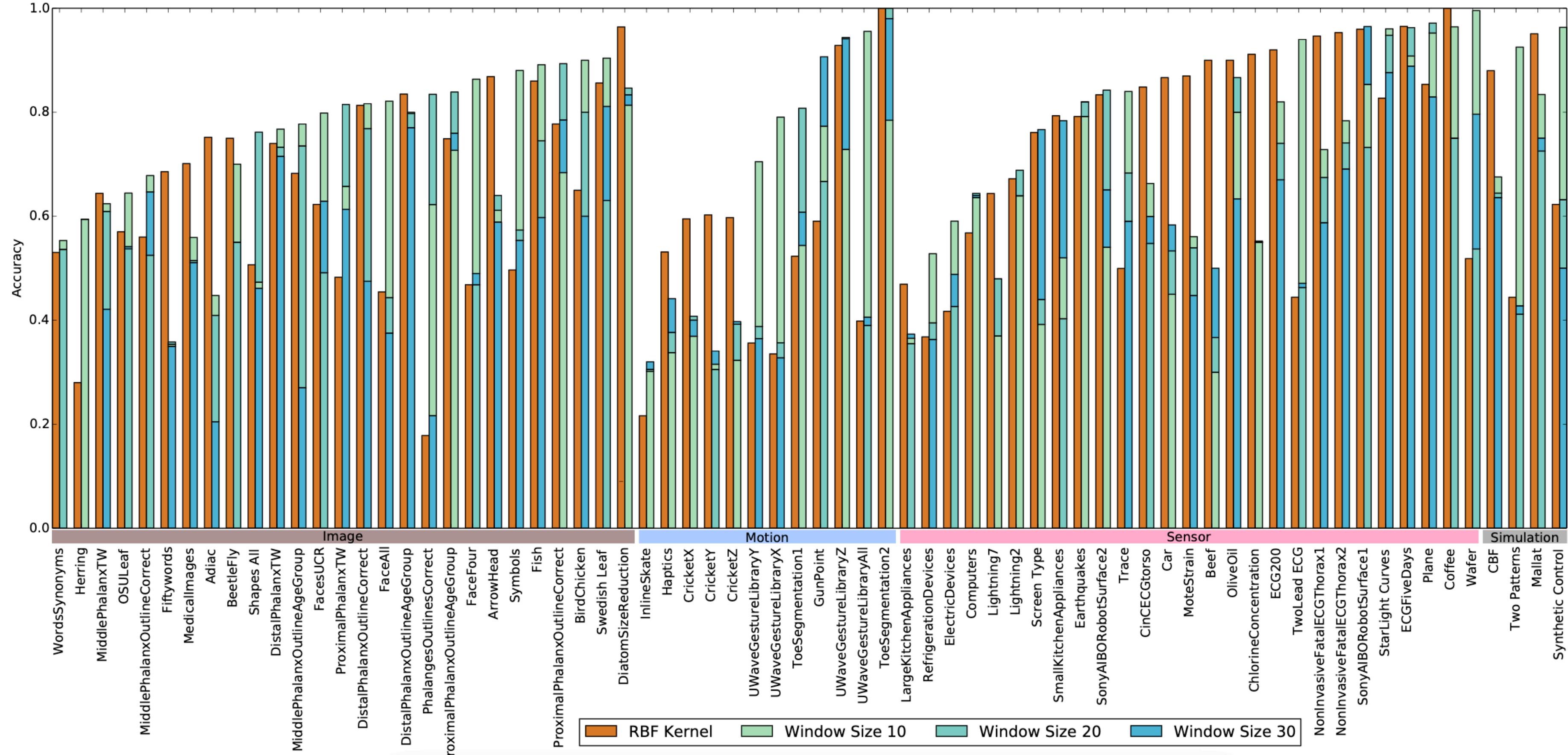
Delay embedding



Dataset	Records	Dim	Classes	Seg. Size	Win. Size	Features
Activity [5]	1,926,896	3	7	1000, 2000	50,100,150	$\text{PD}^{0,1}$
Walking [5]	149,322	3	22	200	15	$\text{PD}^{0,1}$
Mocap [8]	225,551*	62	2*	150	15	$\text{PD}^{0,1}, \text{CI}$
Kitchen [8]	17,726,895	9	5	1000	120	$\text{PD}^{0,1}$
EEG Eye [28]	14,980	16	2	300	20	$\text{PD}^{0,1}$
PAMAP [27]	2,872,533	52	19	1000	20,30,40,50	$\text{PD}^{0,1}$
Bird Sounds [13]	24,050,377	1	16	800	15,30,45	$\text{PD}^{0,1}$



Delay embedding



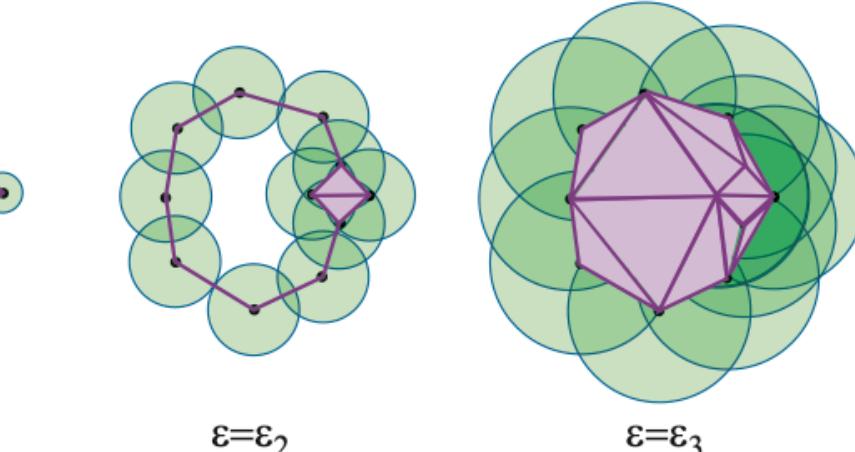
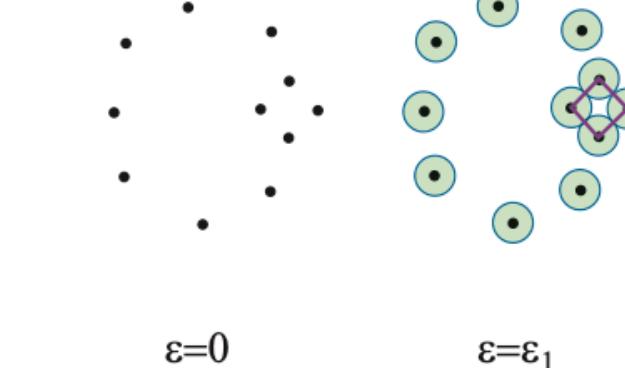
Single-source Continuous Signals:

- **Activity [5]:** Three-dimensional accelerometer measurements capturing movements for 15 human participants and 7 daily activities.
- **Walking [5]:** Three-dimensional accelerometer measurements of 22 people walking along predefined and free-form paths.
- **MOCAP [8]:** Motion capture data capturing multiple types of human motion.
- **Kitchen [8]:** Motion capture data capturing multiple prescribed kitchen tasks.
- **EEG [28]:** EEG sensor data capturing eye state.
- **PAMAP [27]:** Physical Activity Monitoring for Aging People: human motion measurements for 19 different activity types.
- **Bird Sounds [13]:** Audio recordings of different bird species with multiple recordings per species type.

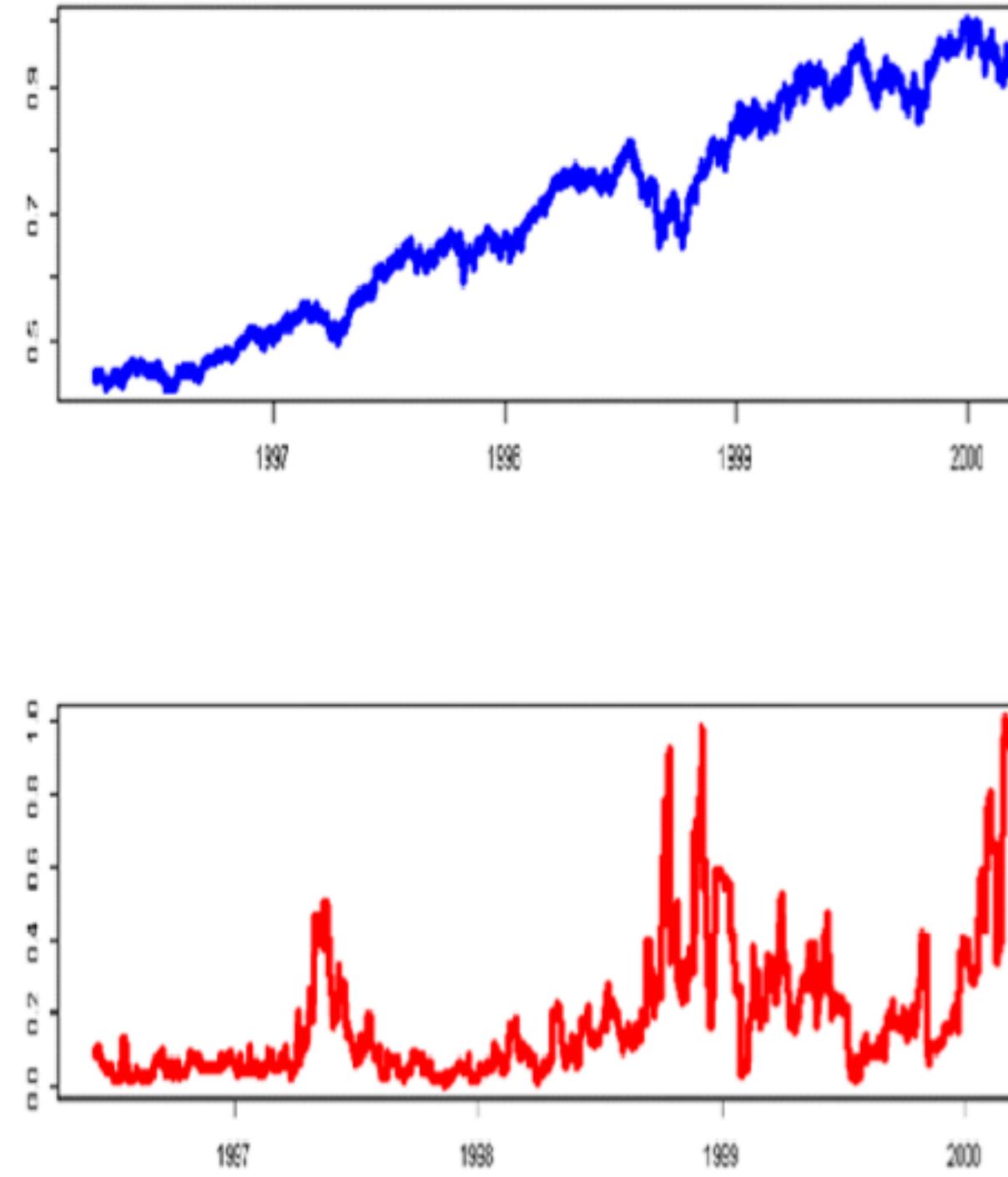
Multi-source Signals:

- **UCR [6]:** 47 time-series datasets broadly categorized by type: Image, Motion, Sensor, & Simulation. The segment size is set to the signal length and the window size is varied. The same features, distances, and kernels are computed, as outlined in Table 1.

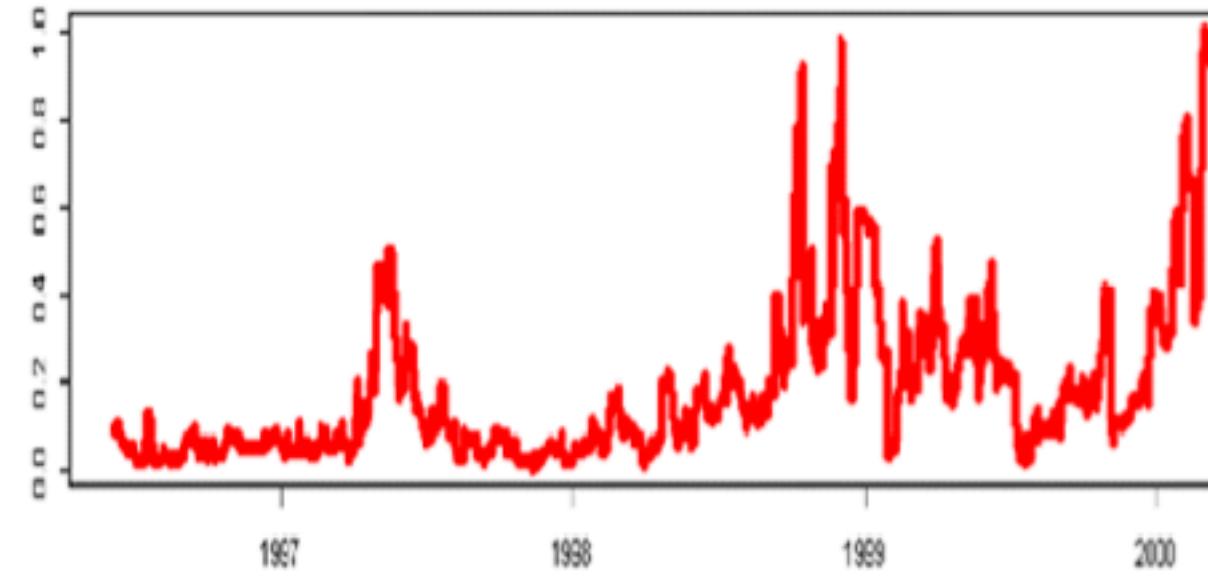
Delay embedding



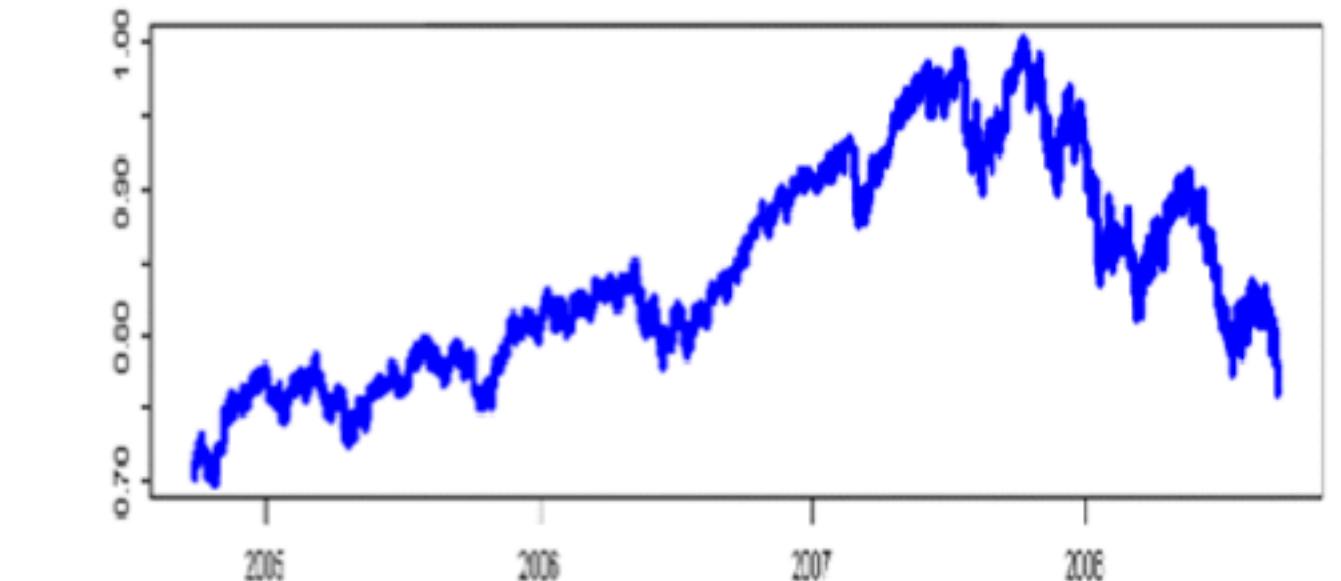
Persistence landscapes



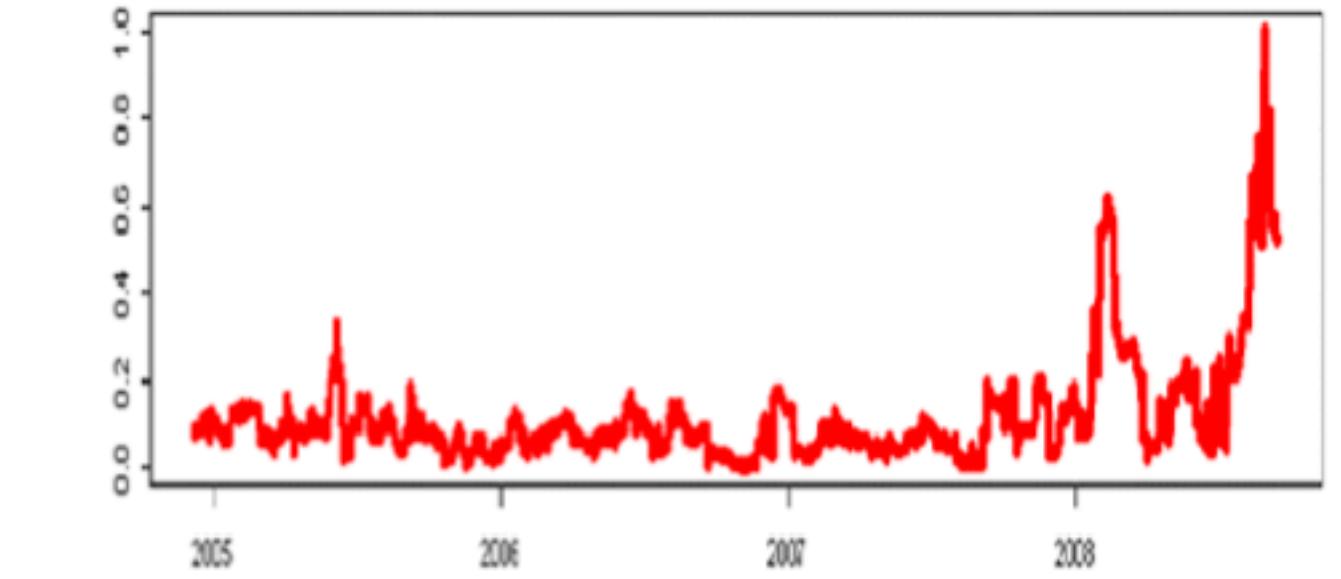
S&P 500



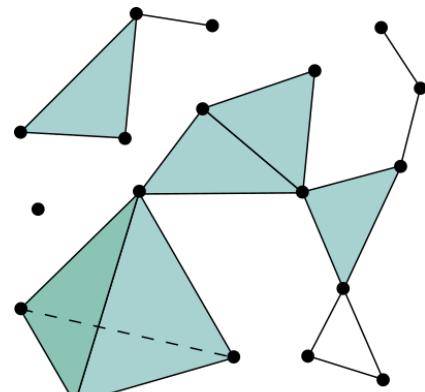
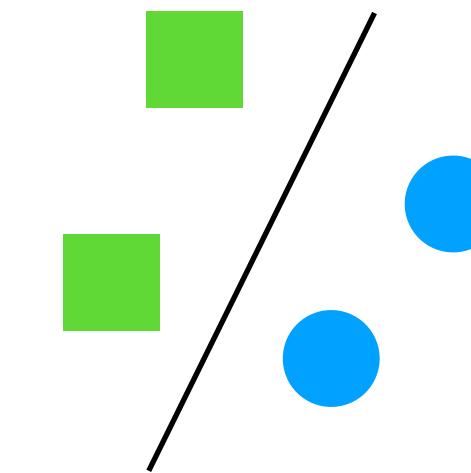
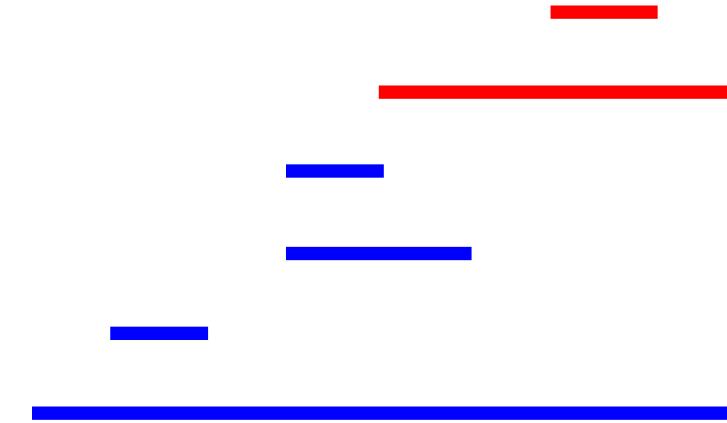
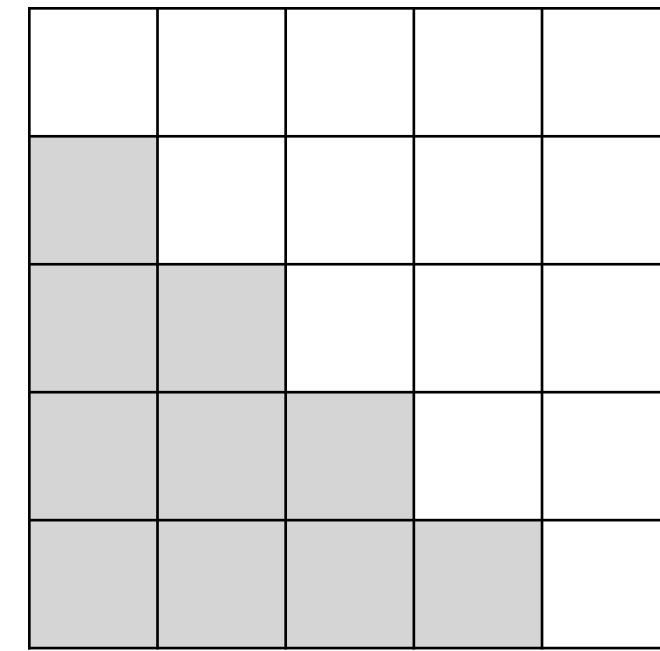
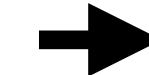
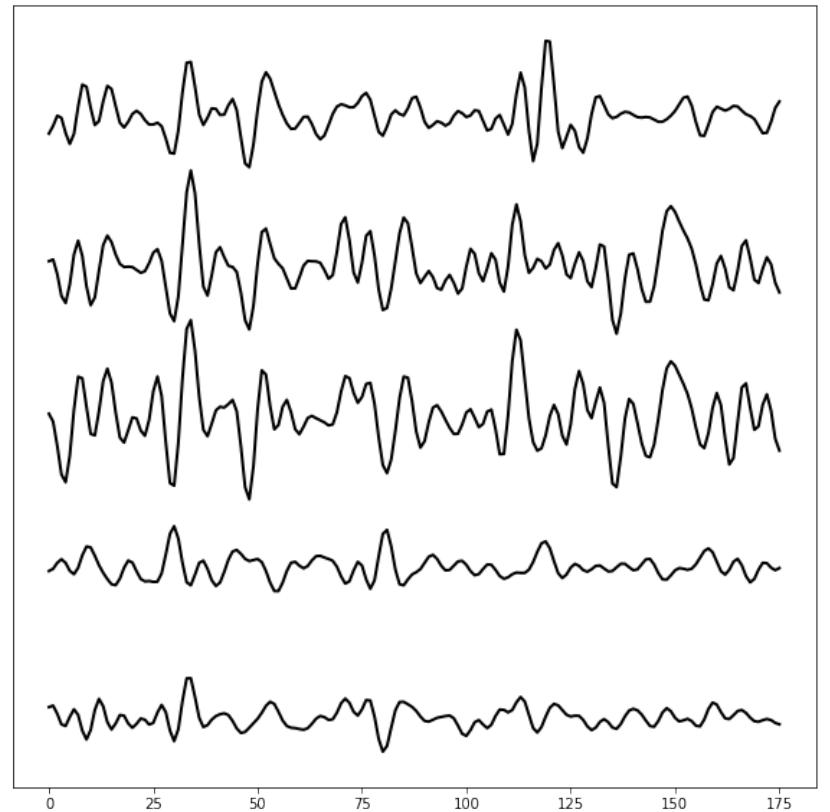
L1 norm of persistence landscapes, $d = 50$



Lehman Brothers crash (2008)



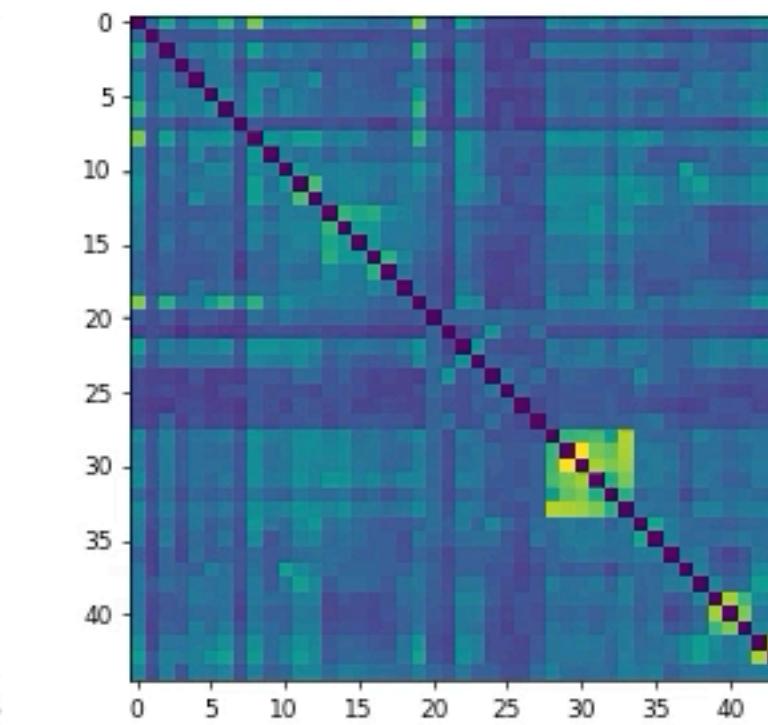
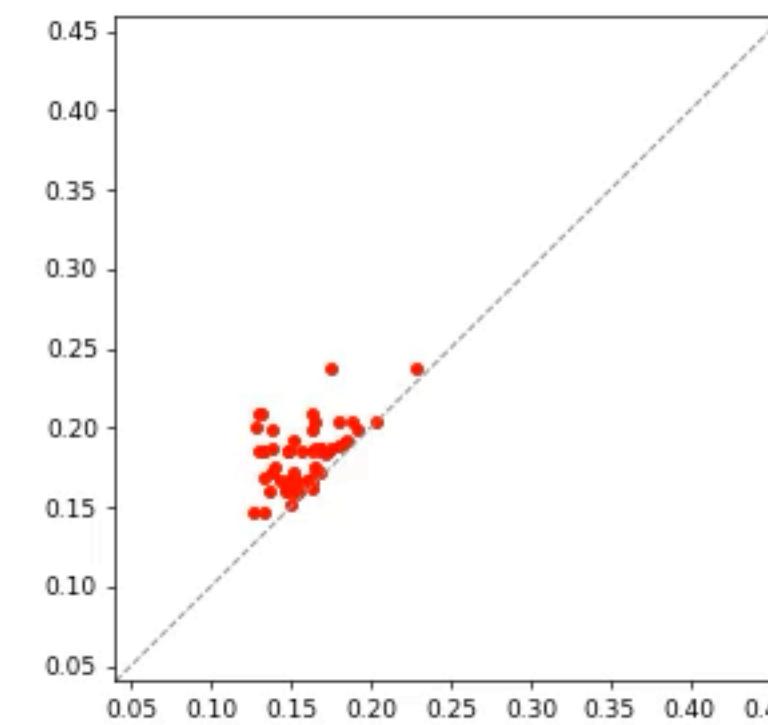
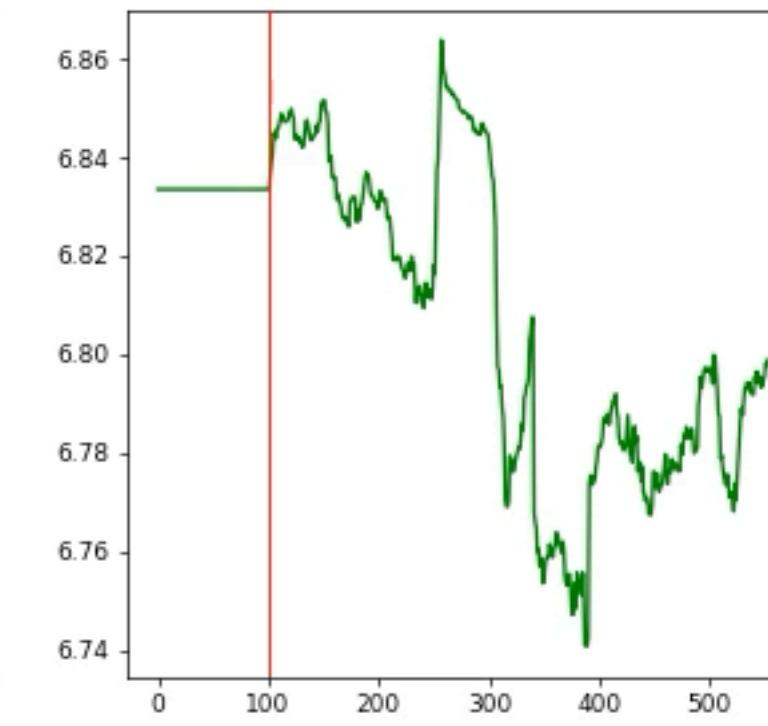
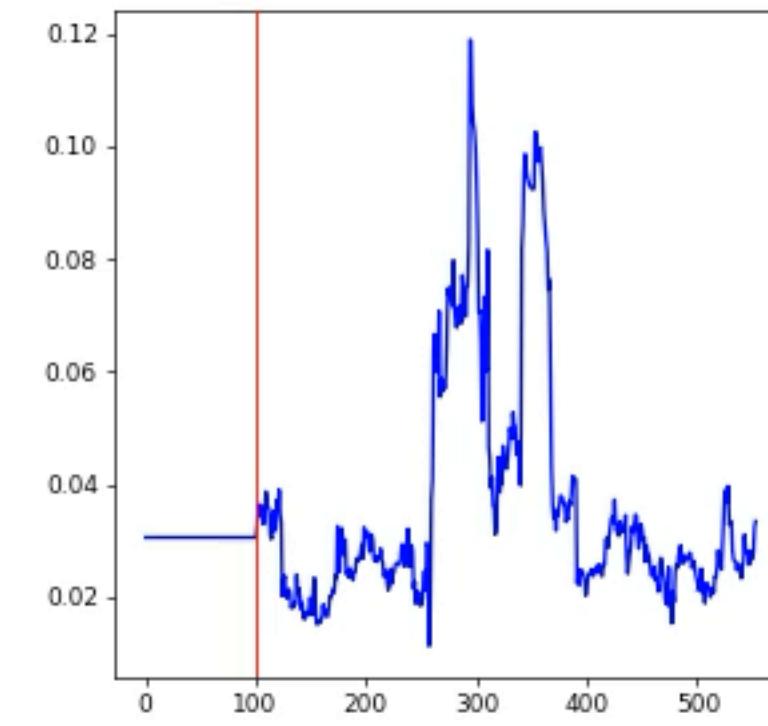
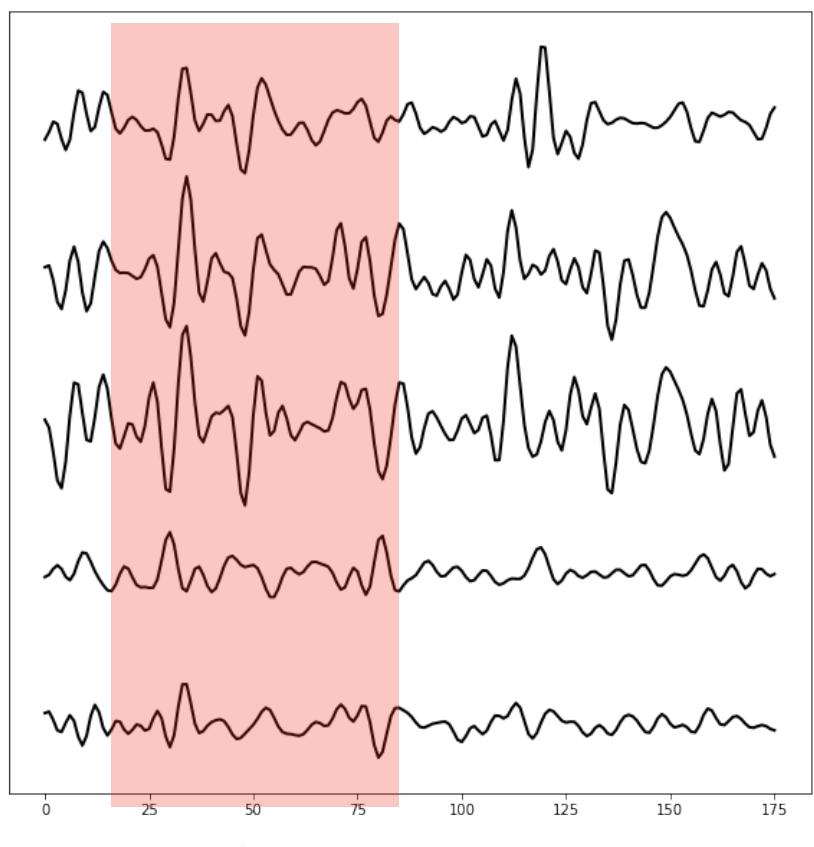
Similarity matrix filtration



$$f(\sigma) = \begin{cases} 0, & \dim(\sigma) = 0, \\ a_{ij}, & \dim(\sigma) = 1, \\ \max(a_{ij}, a_{ik}, a_{jk}), & \dim(\sigma) \geq 2. \end{cases}$$

Similarity matrix filtration

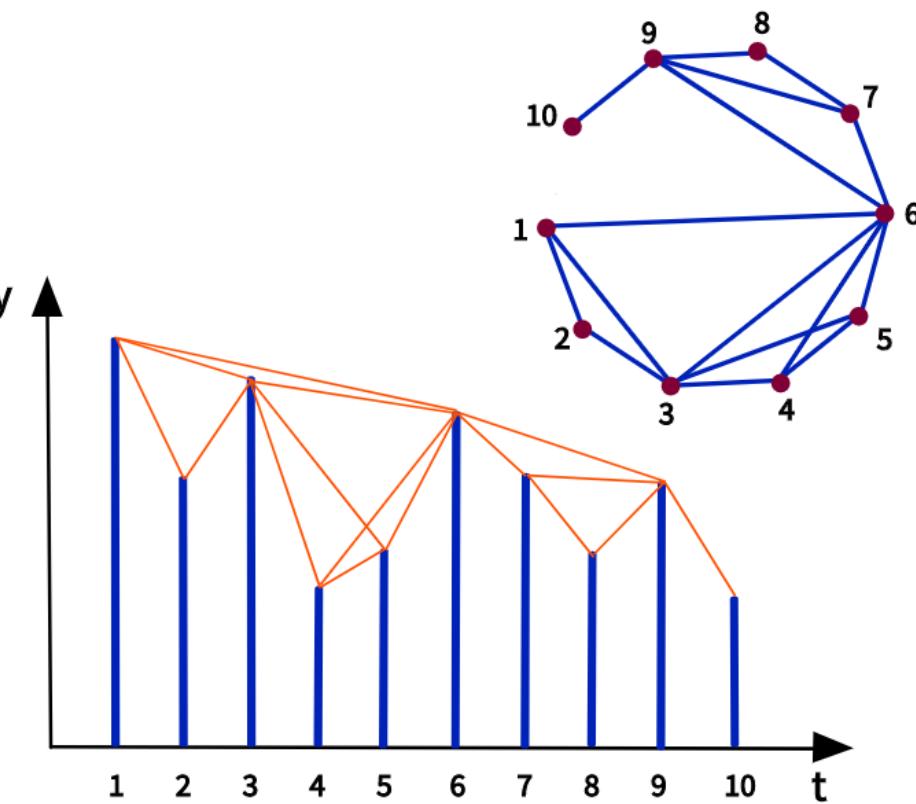
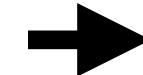
Dynamics



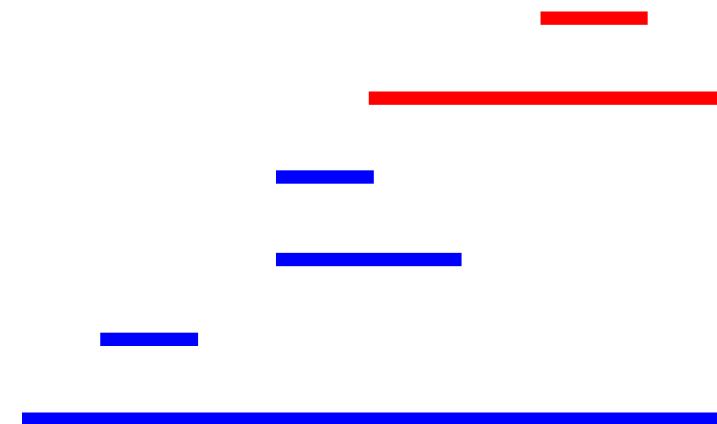
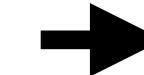
Visibility graph



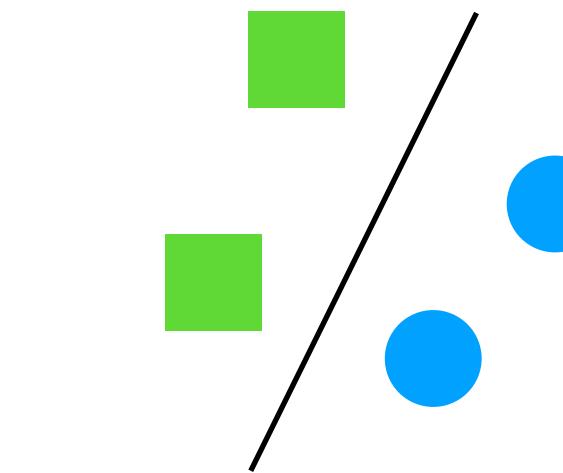
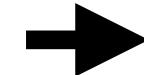
Time series



Visibility graph

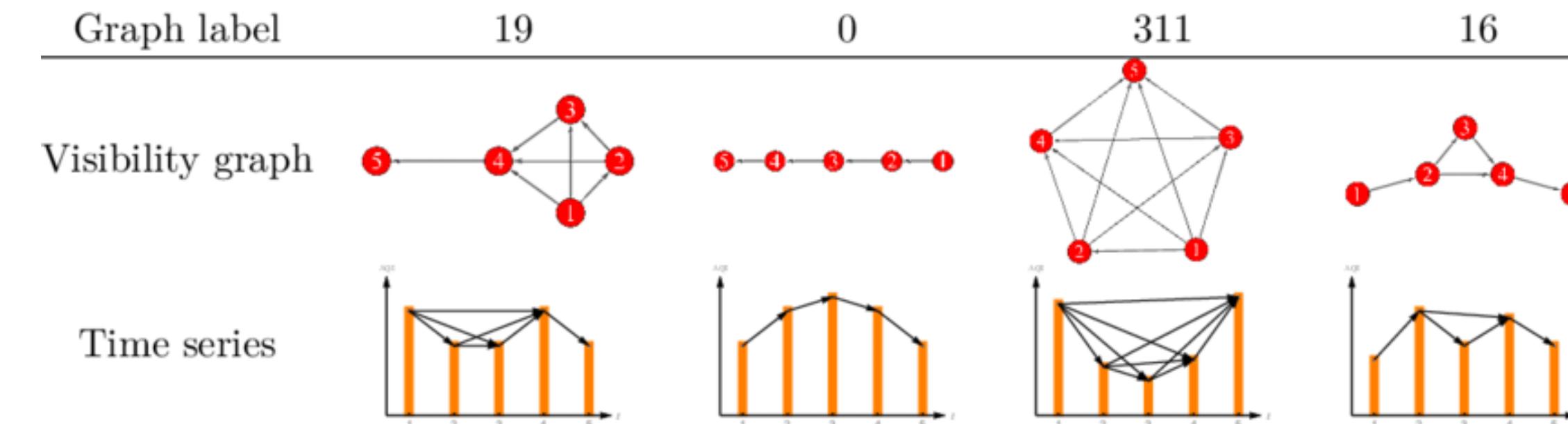
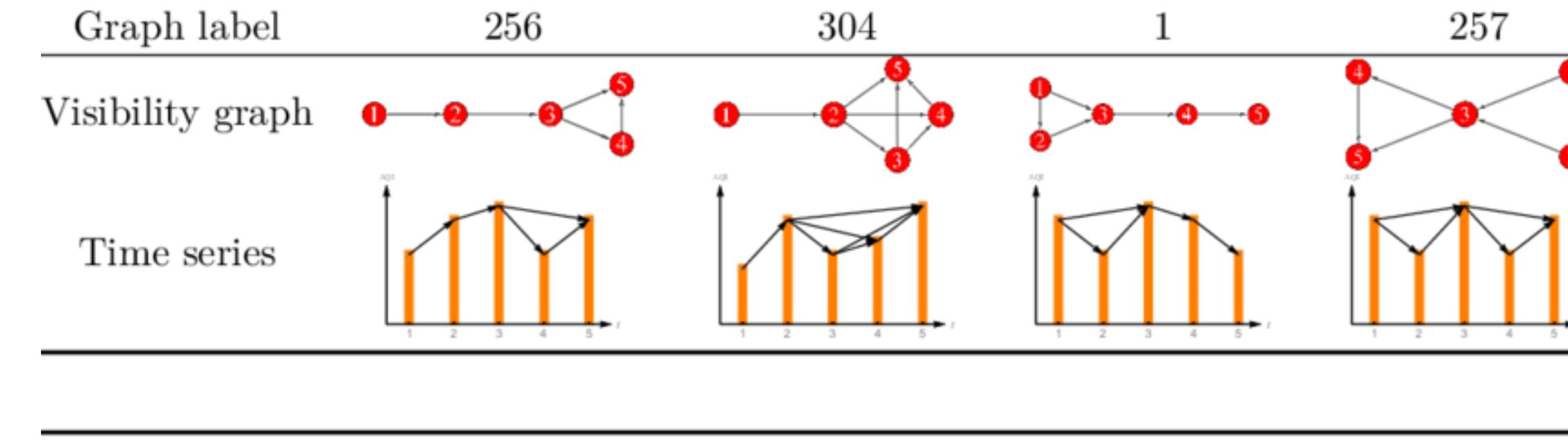
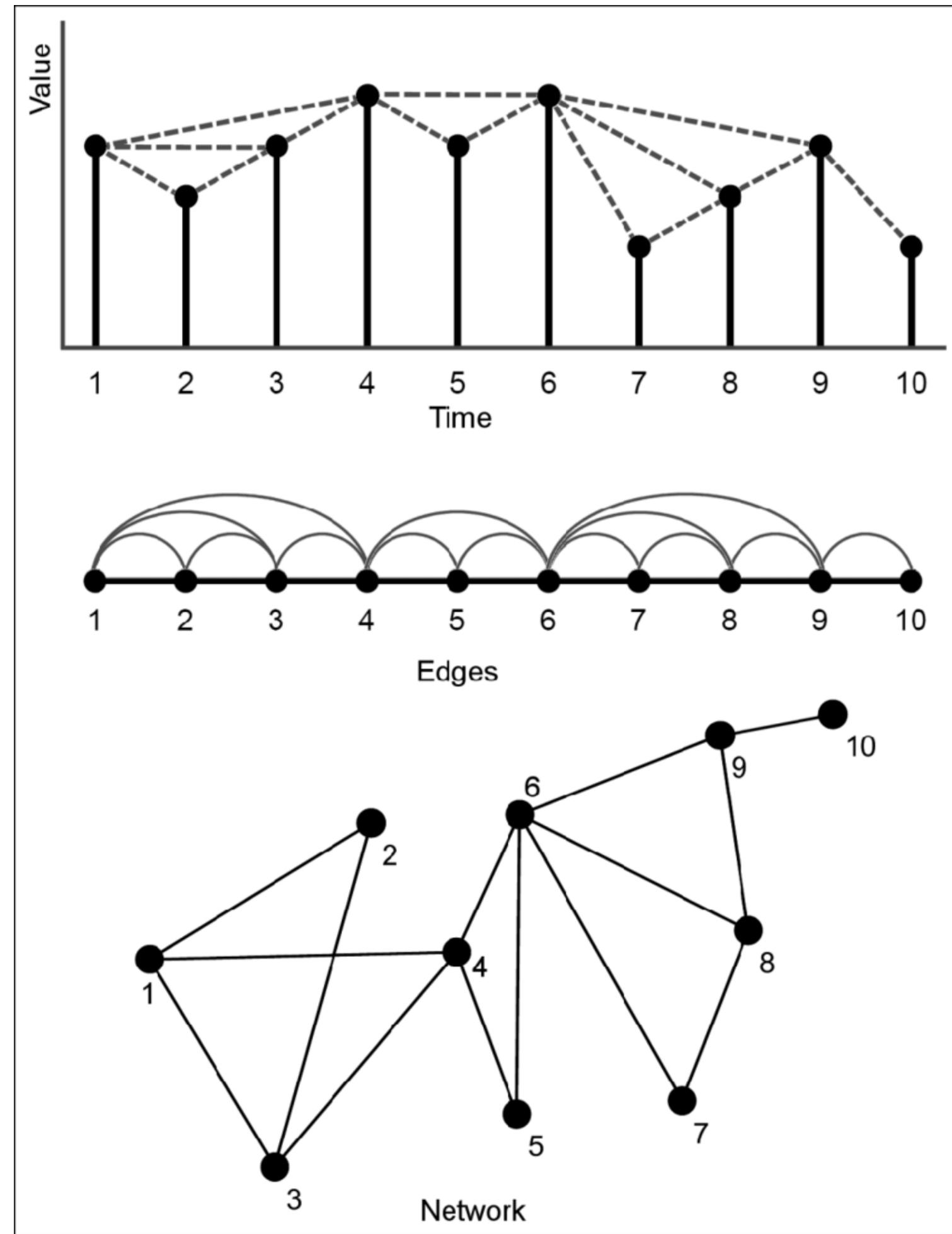


Persistence diagram

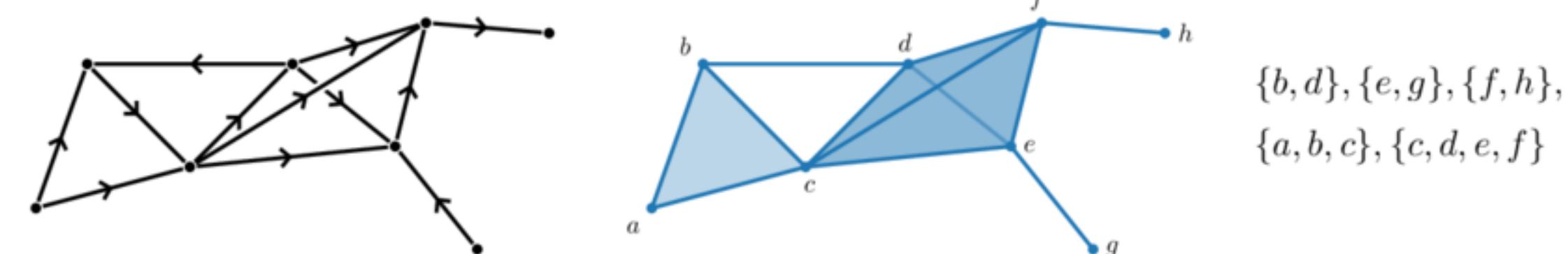


Vector representation
ML task

Visibility graph



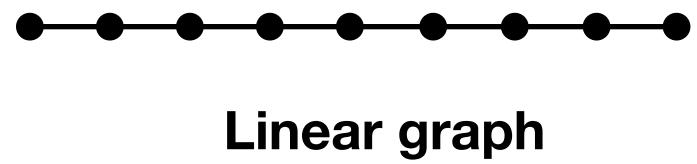
Directed clique complex [Luetgehetmann2019]



Lower star filtration

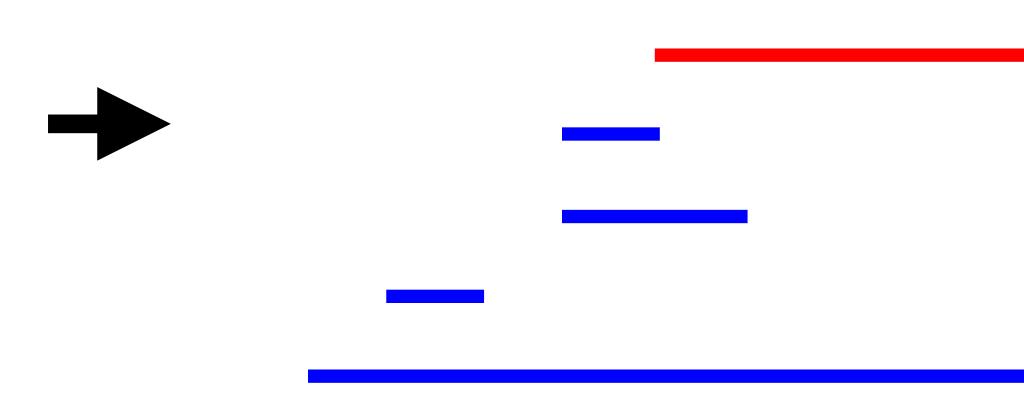


Time series

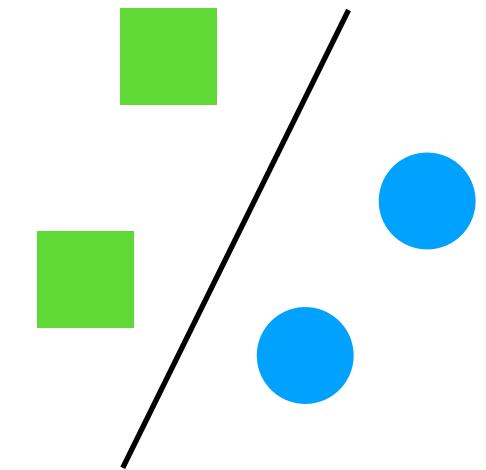


$$f(\sigma) = \begin{cases} x_t, & \dim(\sigma) = 0, \\ \max(x_t, x_{t+1}), & \dim(\sigma) = 1. \end{cases}$$

Lower star filtration

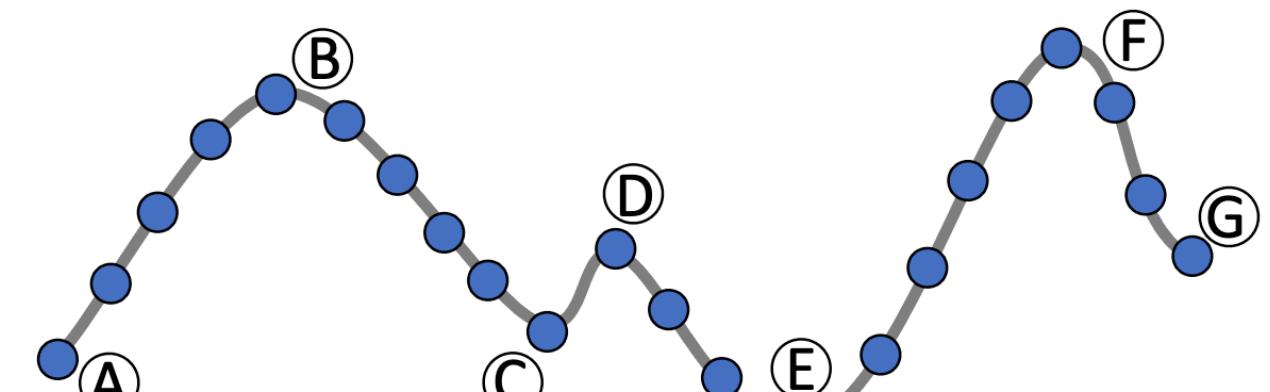


Persistence diagram

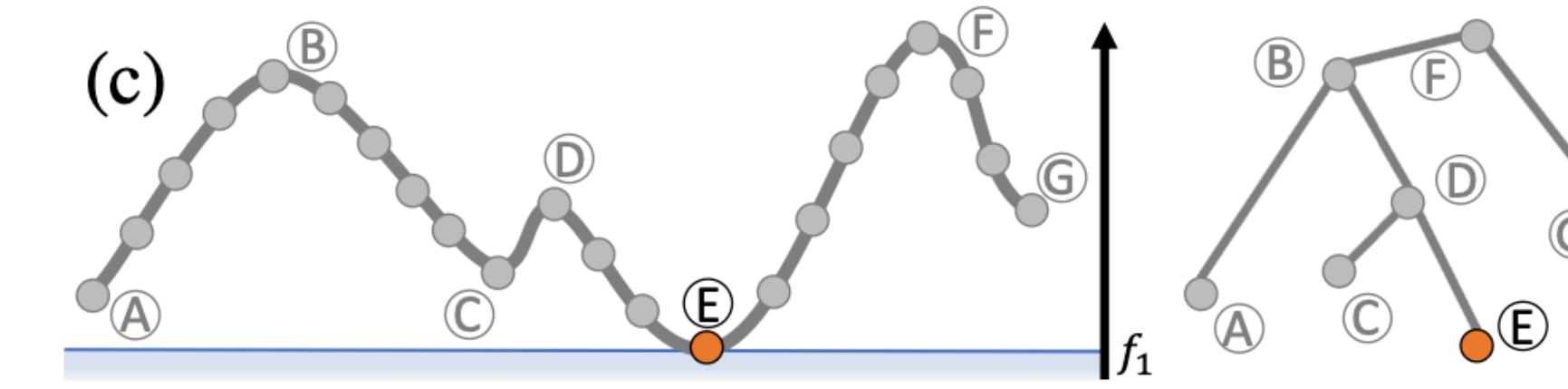


Vector representation
ML task

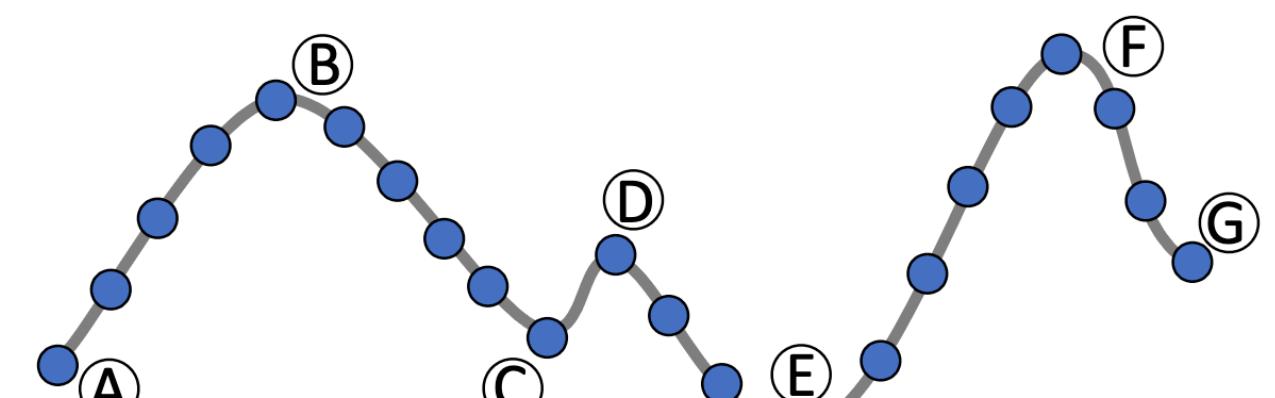
Lower star filtration



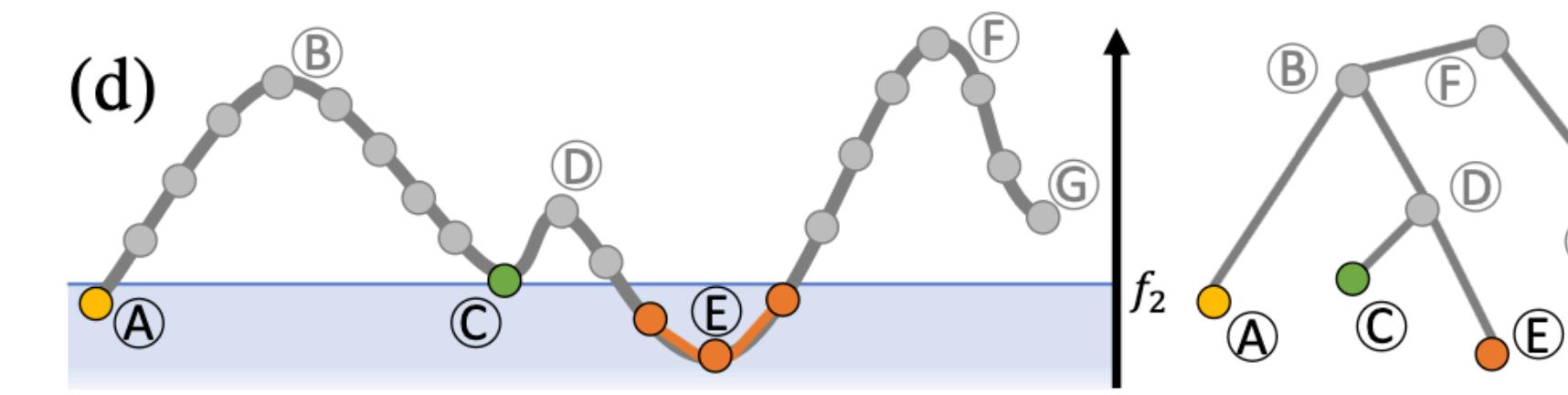
Time series



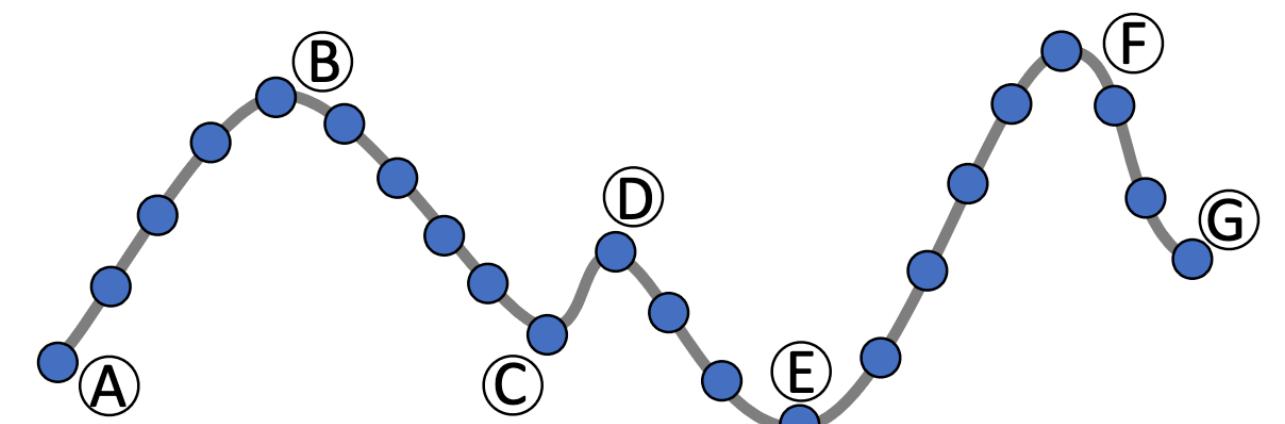
Lower star filtration



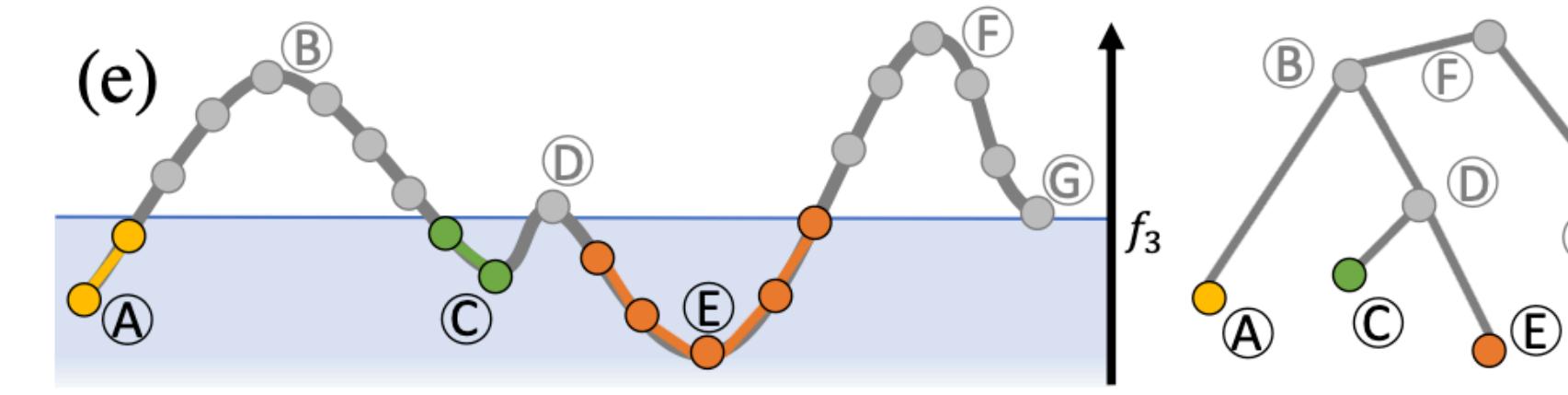
Time series



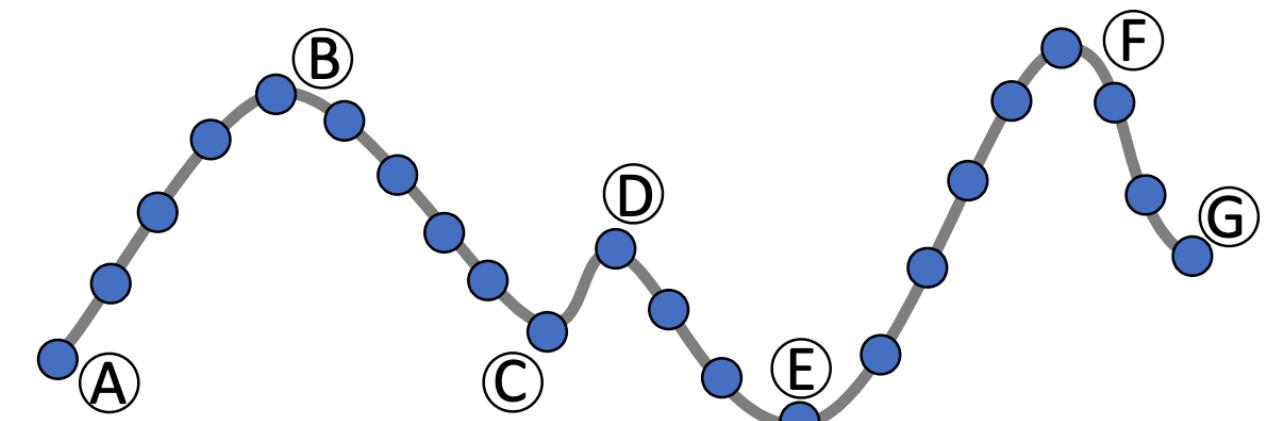
Lower star filtration



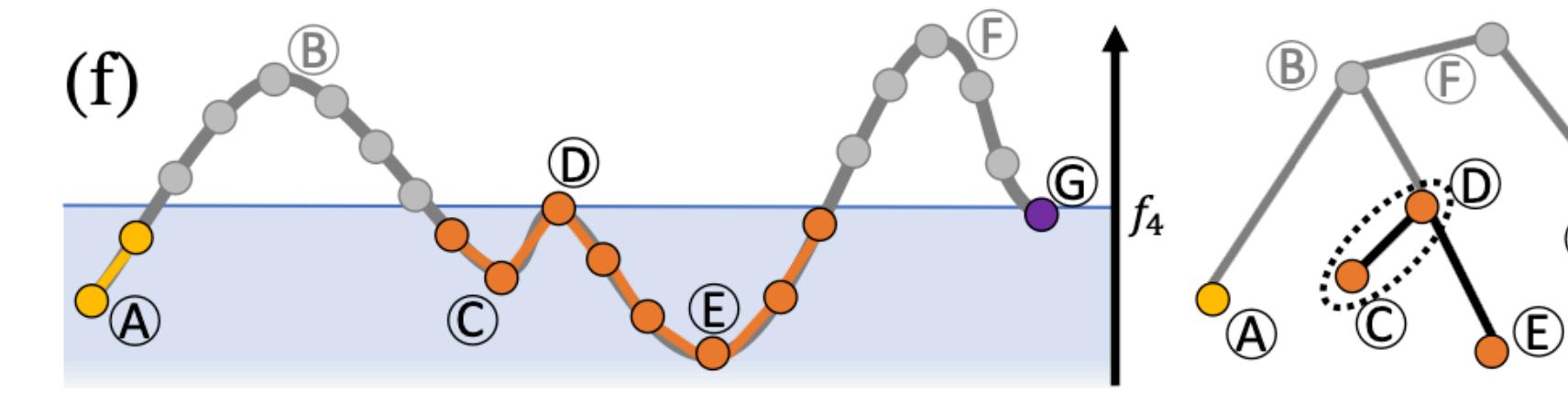
Time series



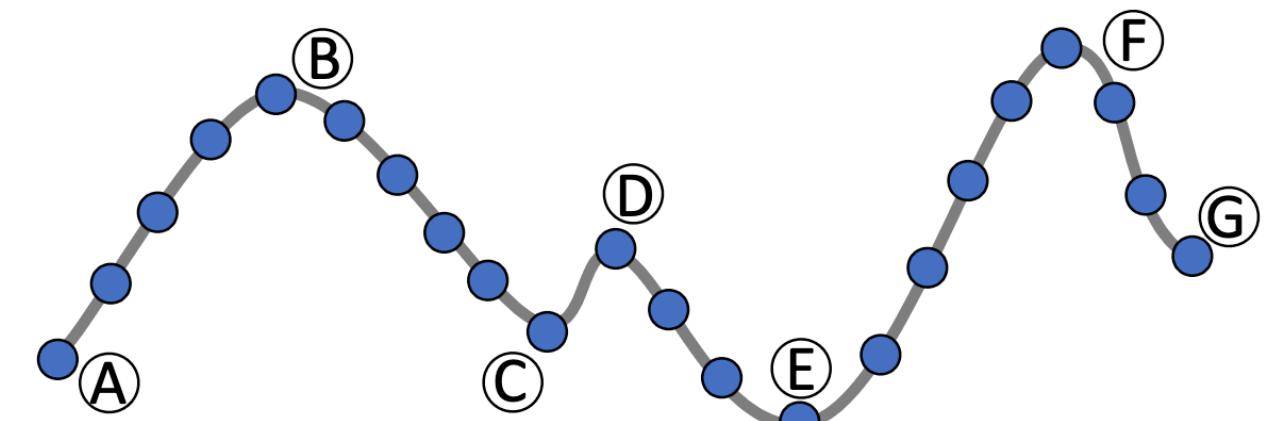
Lower star filtration



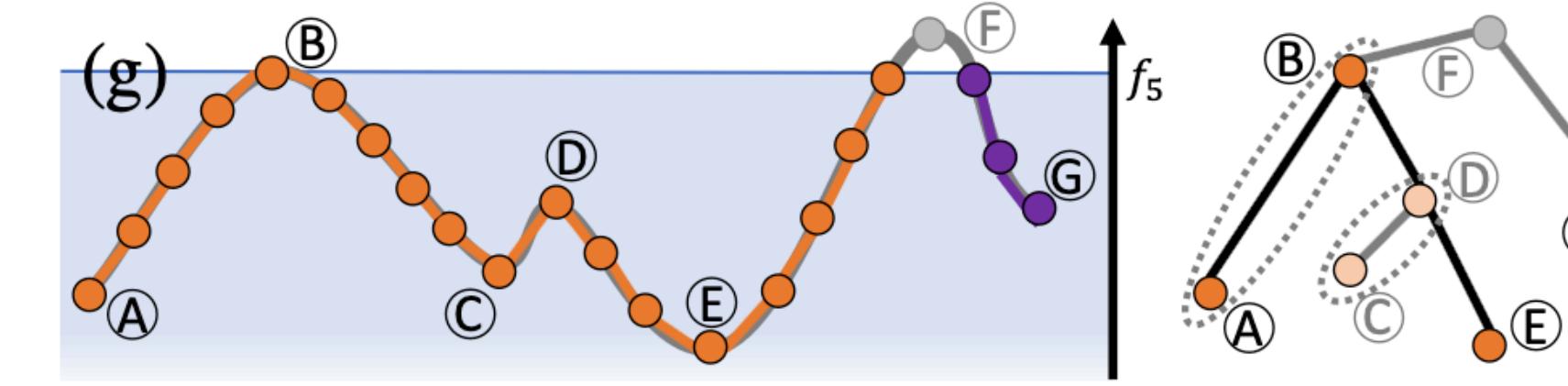
Time series



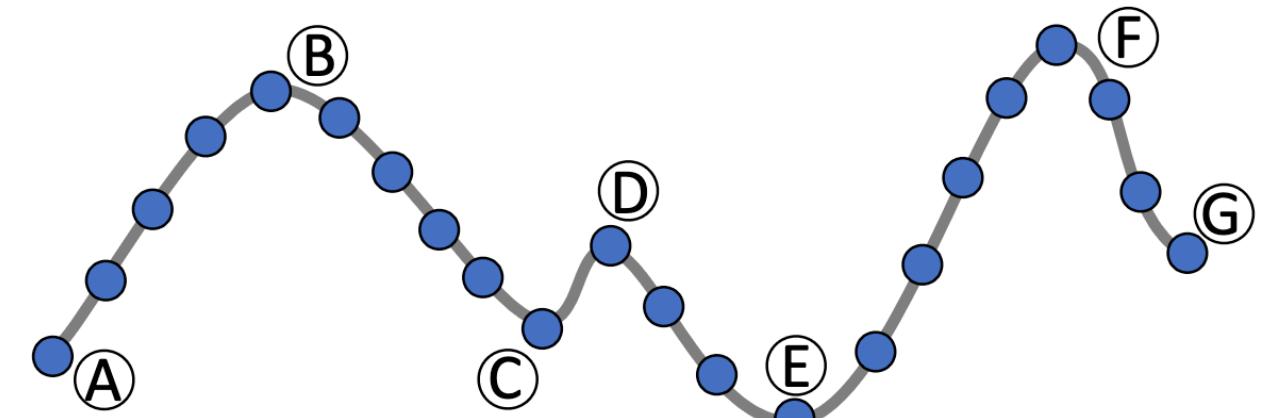
Lower star filtration



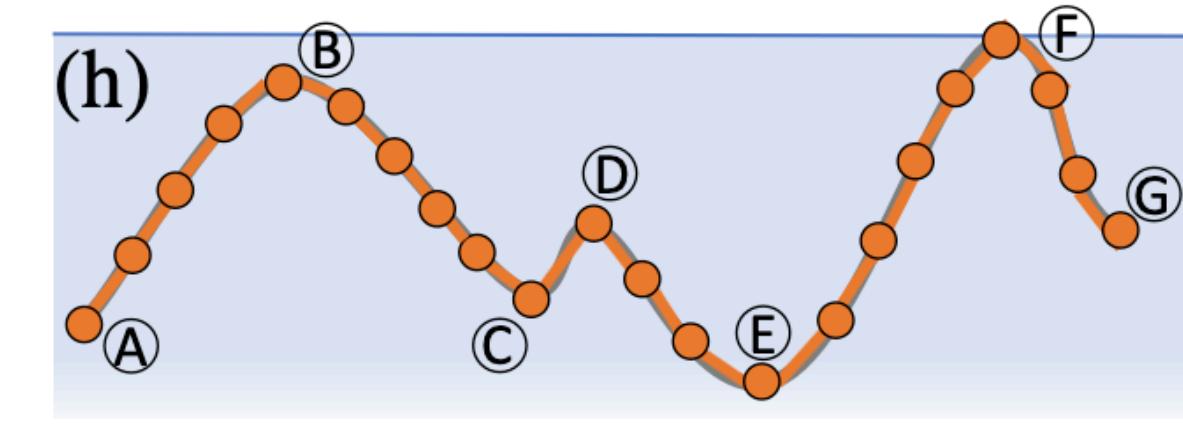
Time series



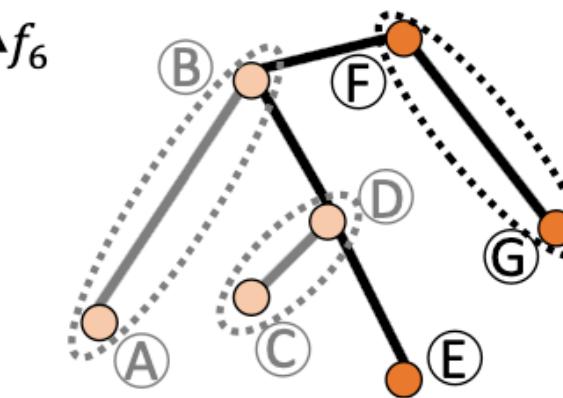
Lower star filtration



Time series

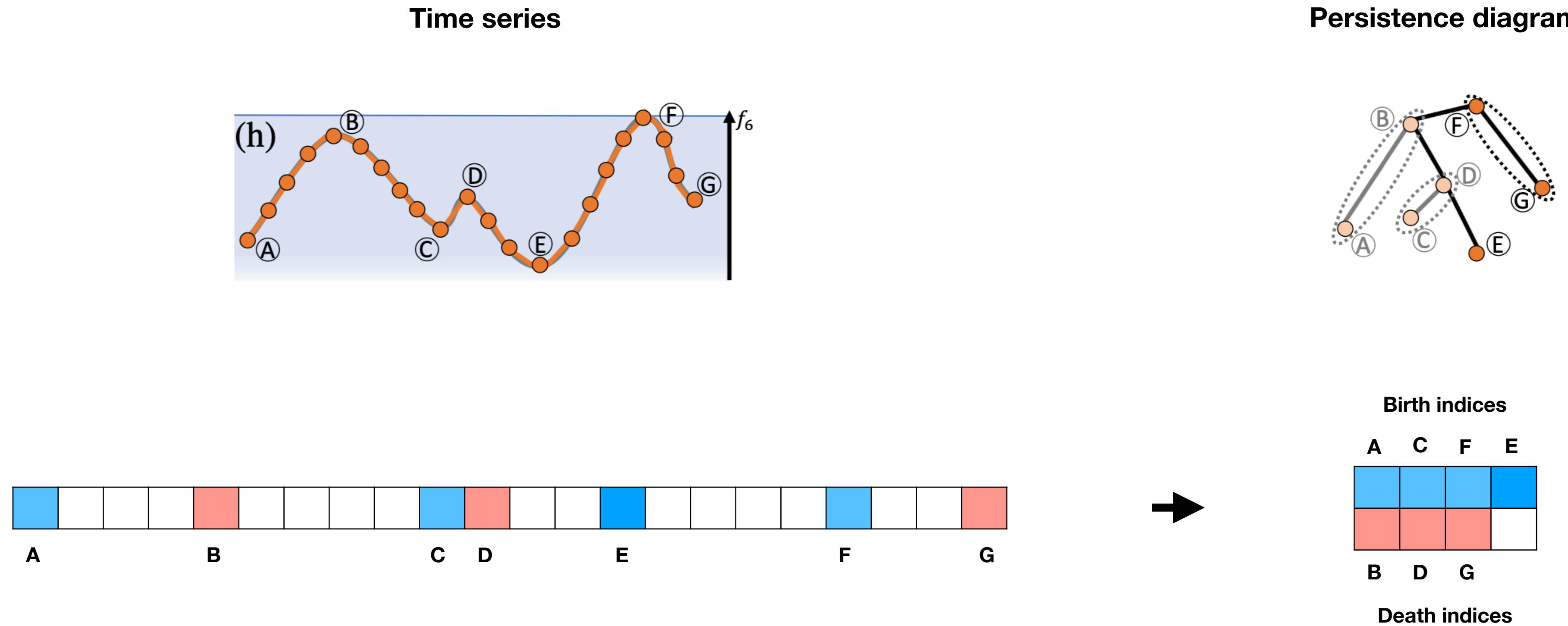


(h)



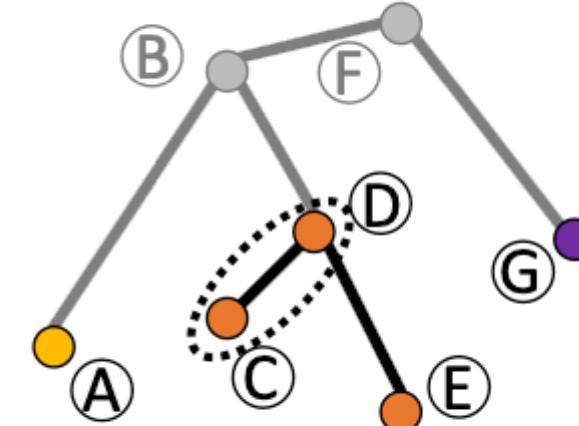
Persistence pairing

Lower star filtration



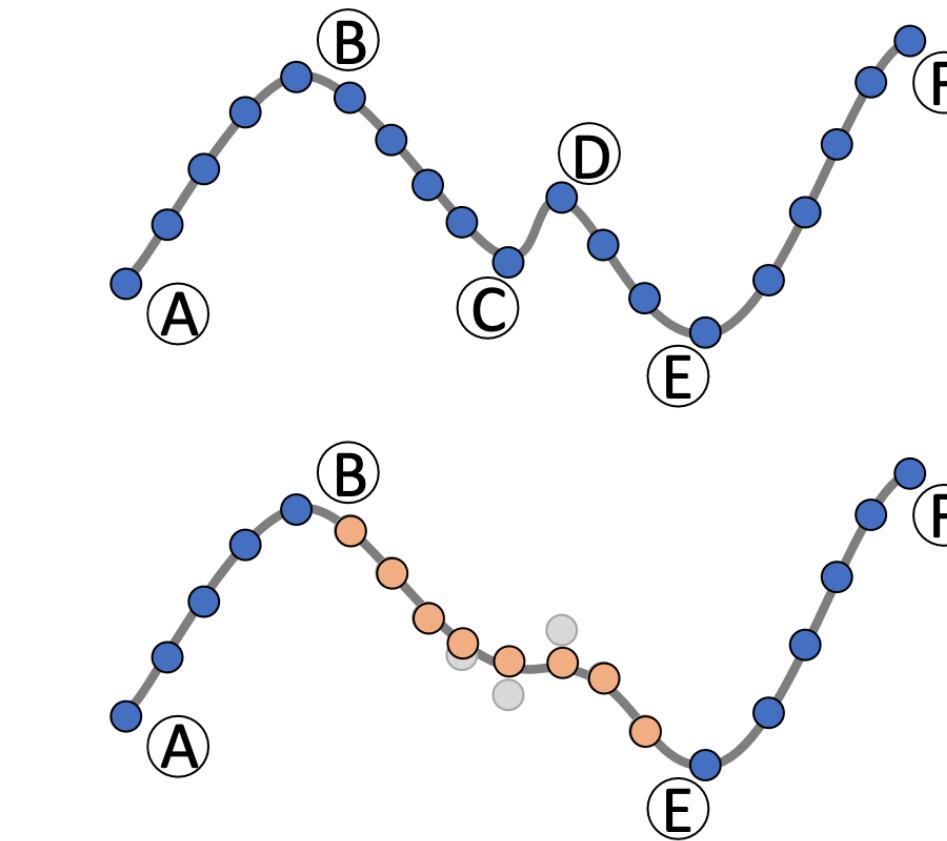
Lower star filtration

Persistence merge tree

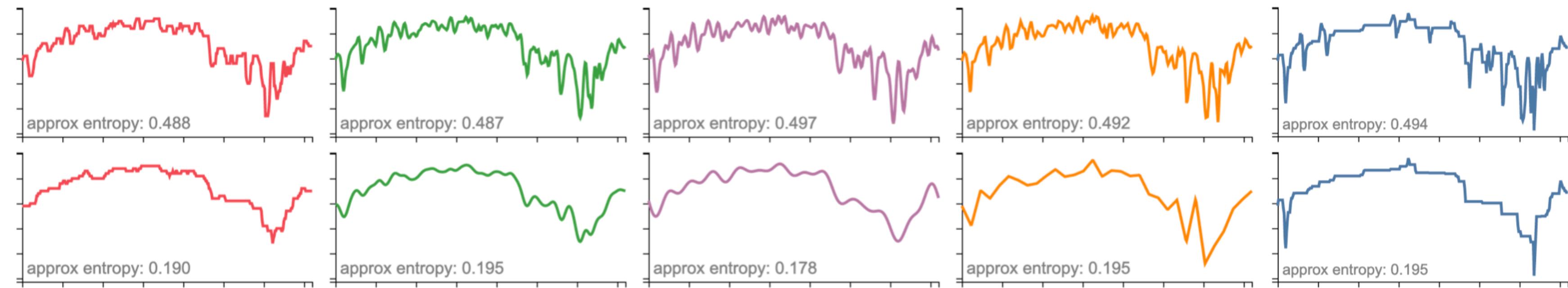
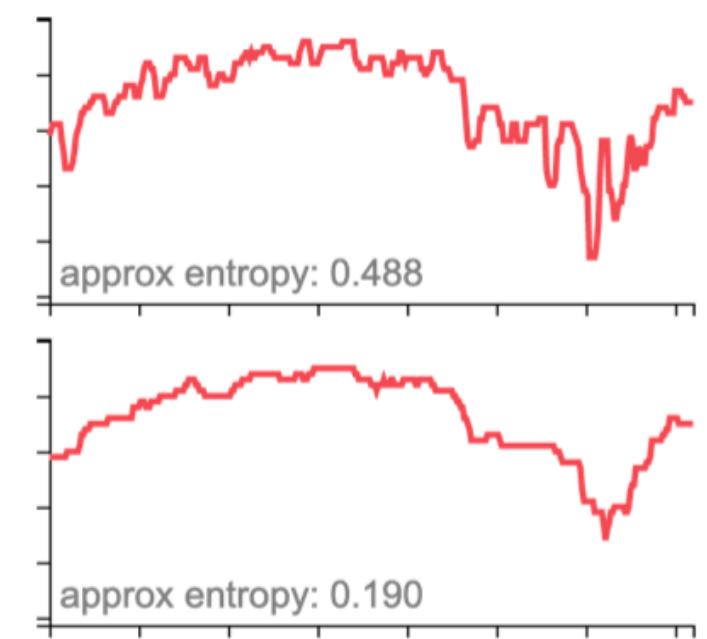
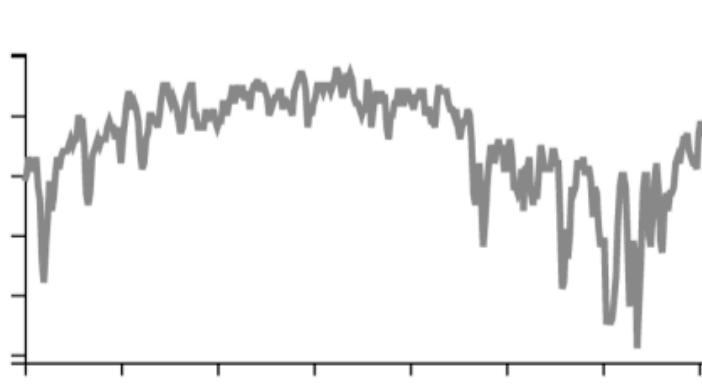


Topological smoothing

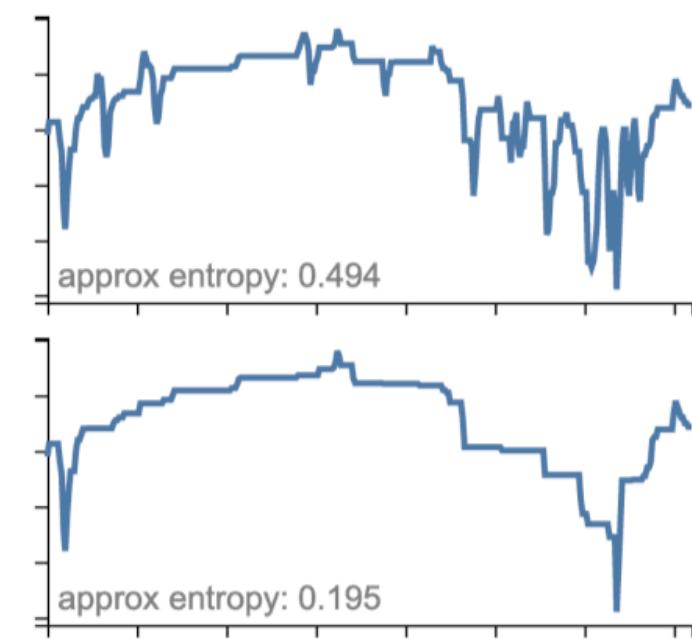
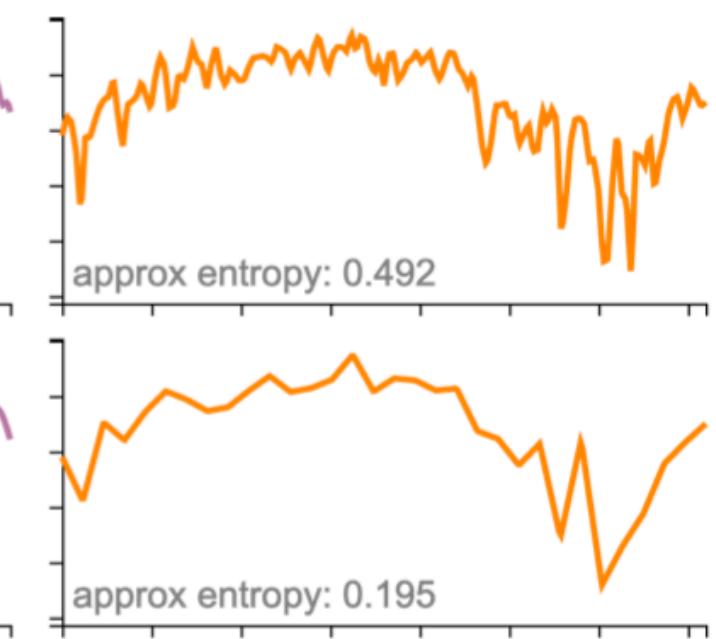
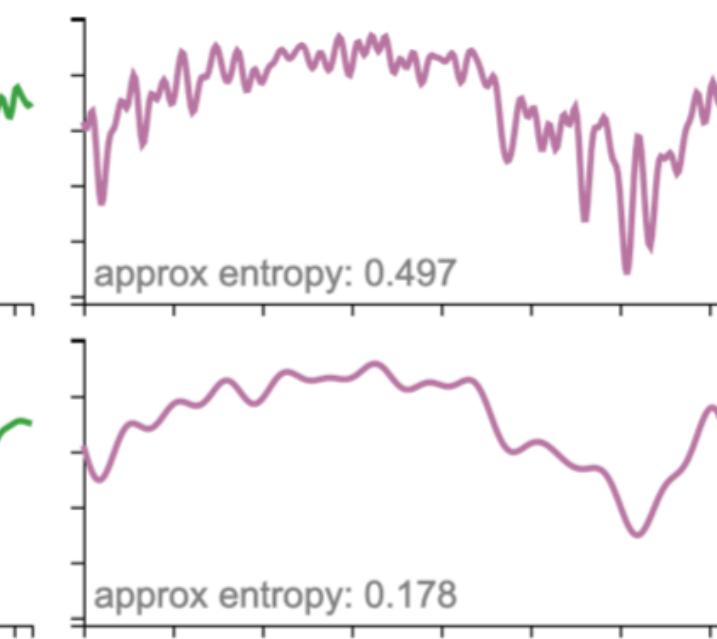
- remove critical pairs with persistence below a threshold t
- enforce monotonicity between neighboring extrema (isotonic regression is used)



Input time series



Smoothed time series



Median

Gaussian

Cutoff

Subsampling

TopoLines

TopoLines: Topological Smoothing for Line Charts

Rosen et al. EuroVis (2020)