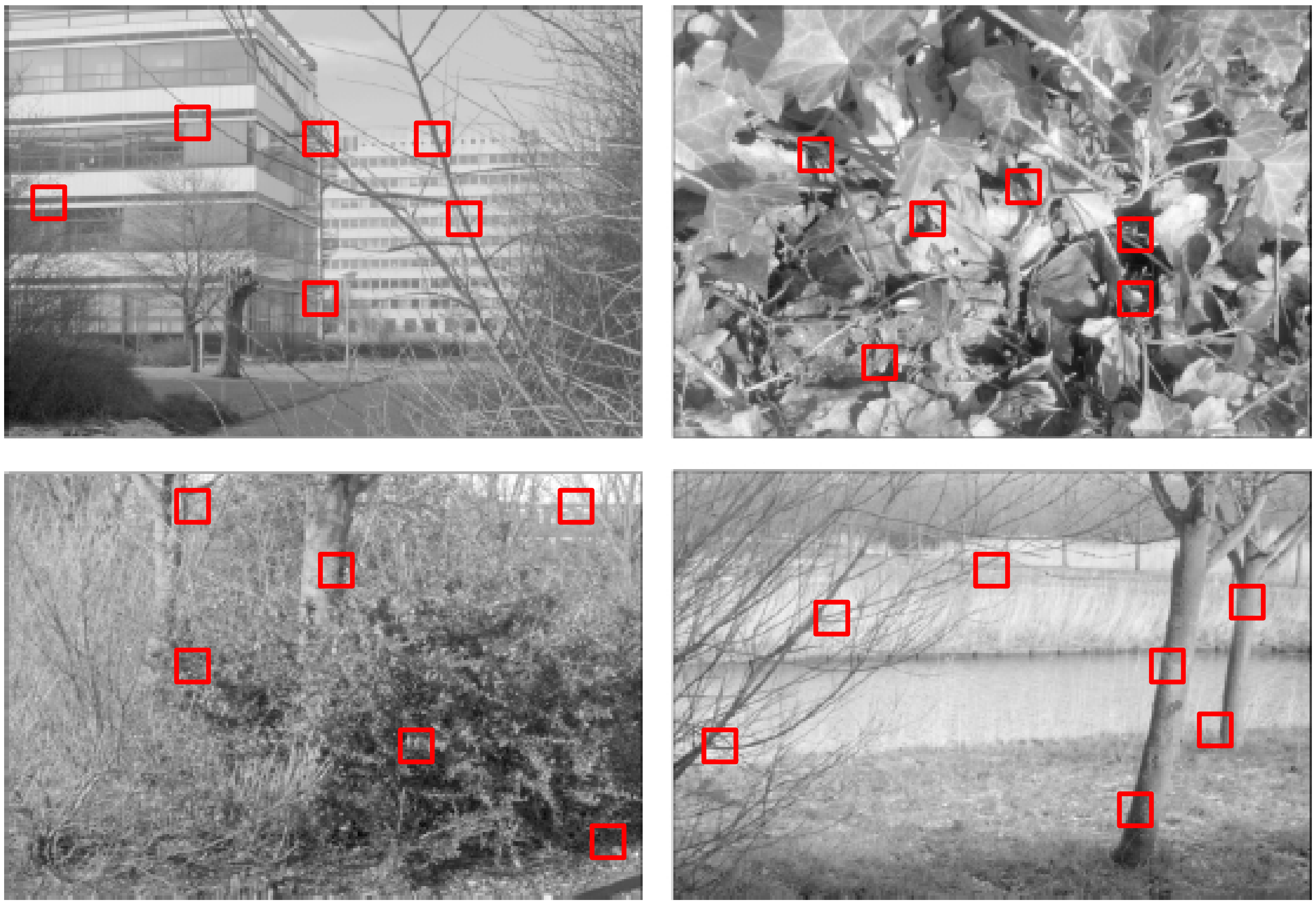
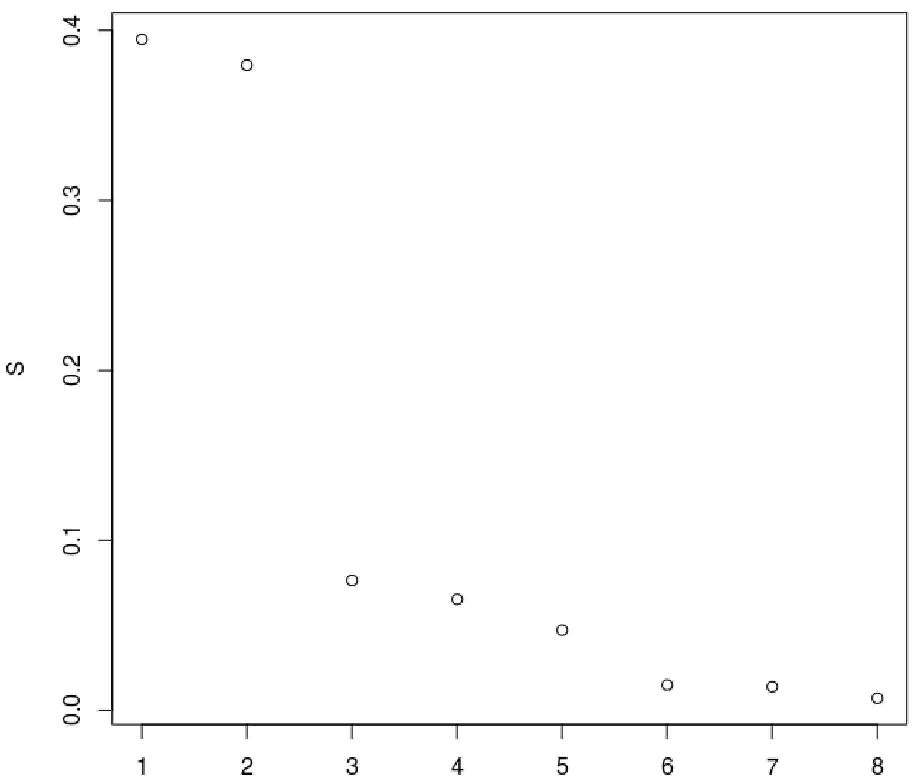
Example: Natural Images Data

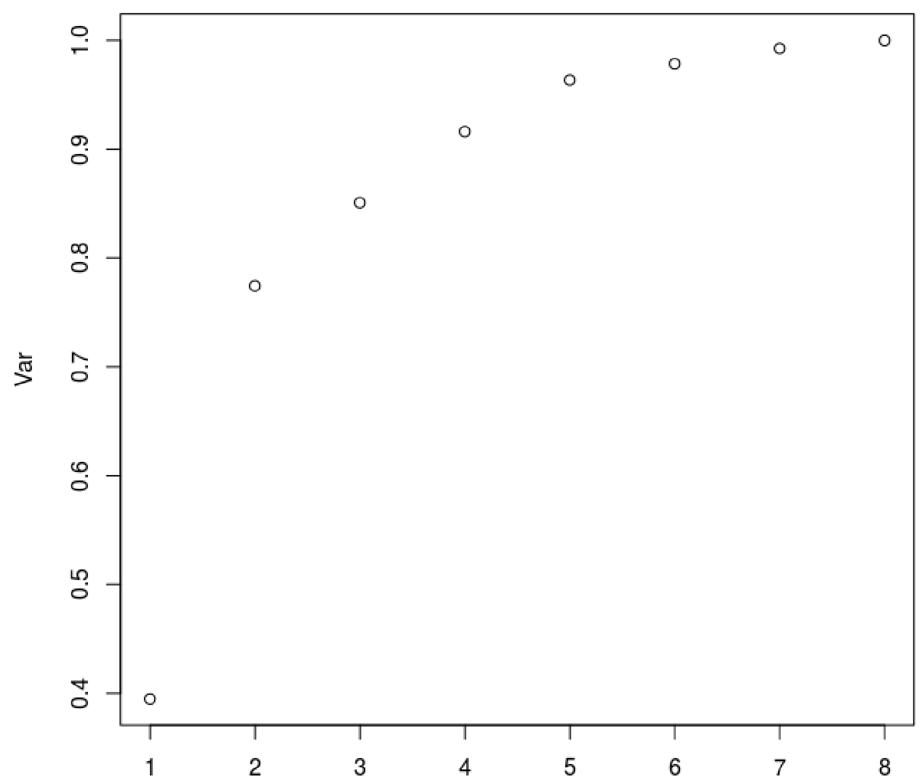
Input: 4 million data points on $\mathbb{S}^7$, coming from high-contrast 3×3 image patches

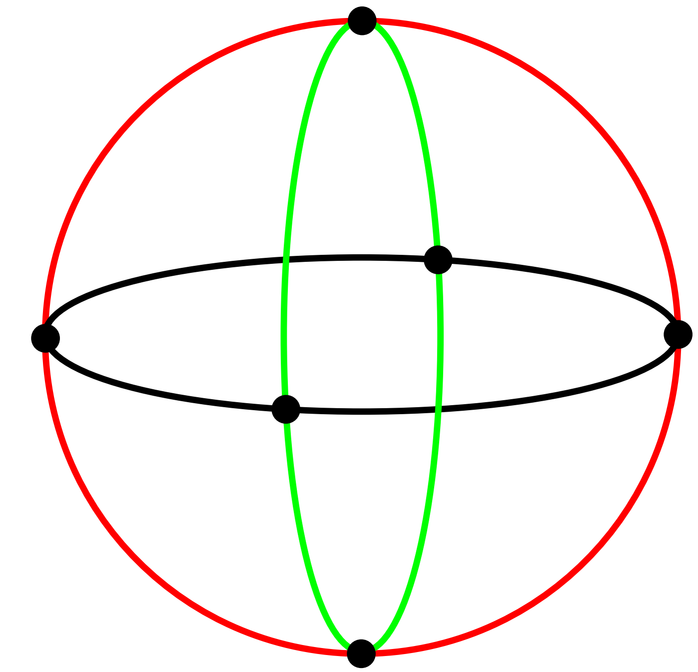


(source: [Lee, Pederson, Mumford 03])

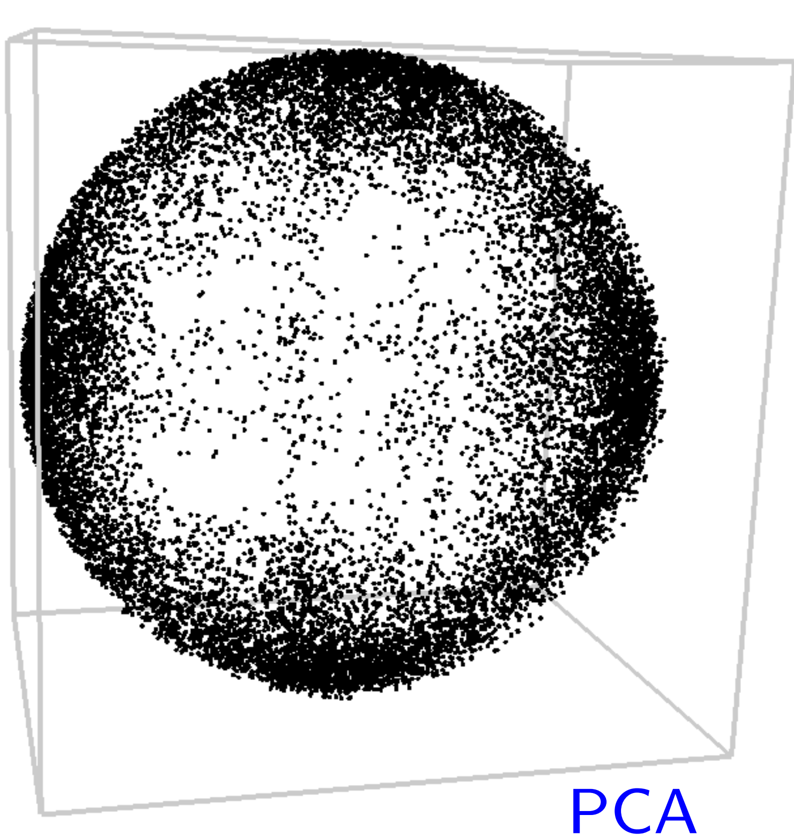
Example: Natural Images Data



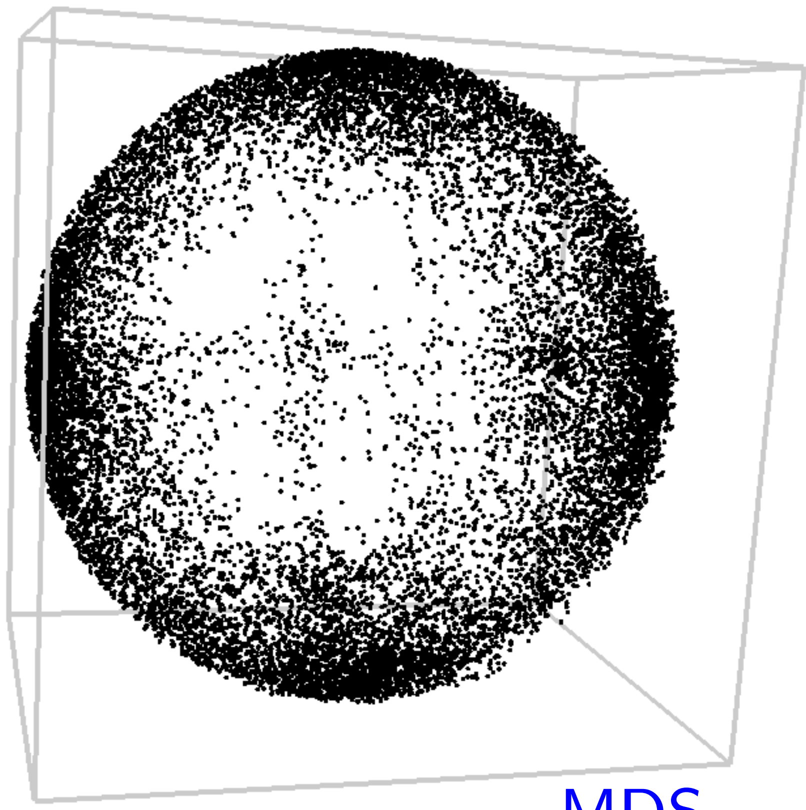




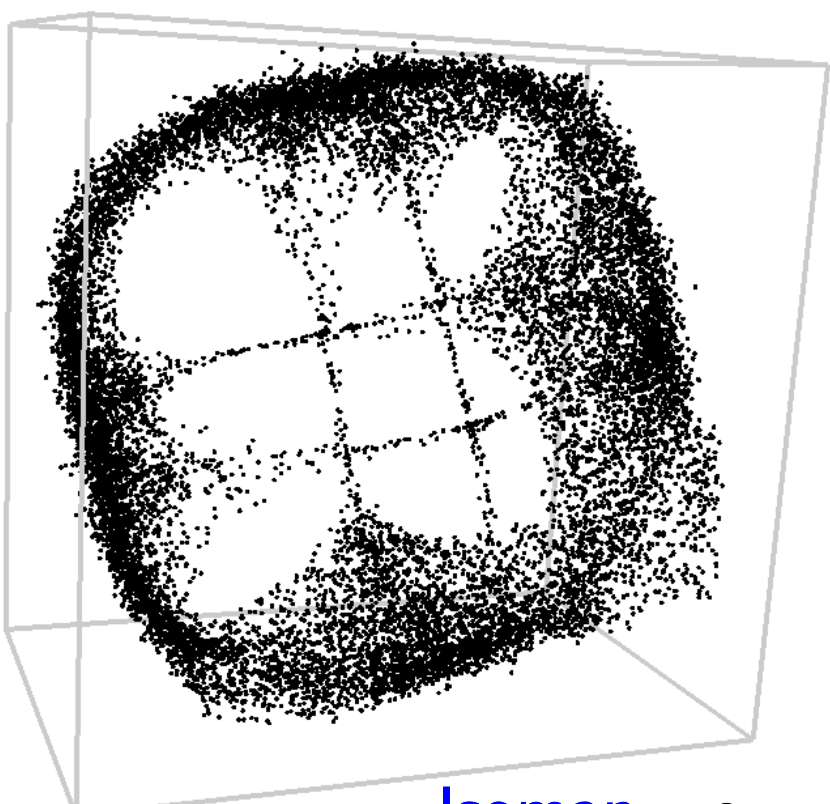
$(\beta_1 = 7)$



PCA

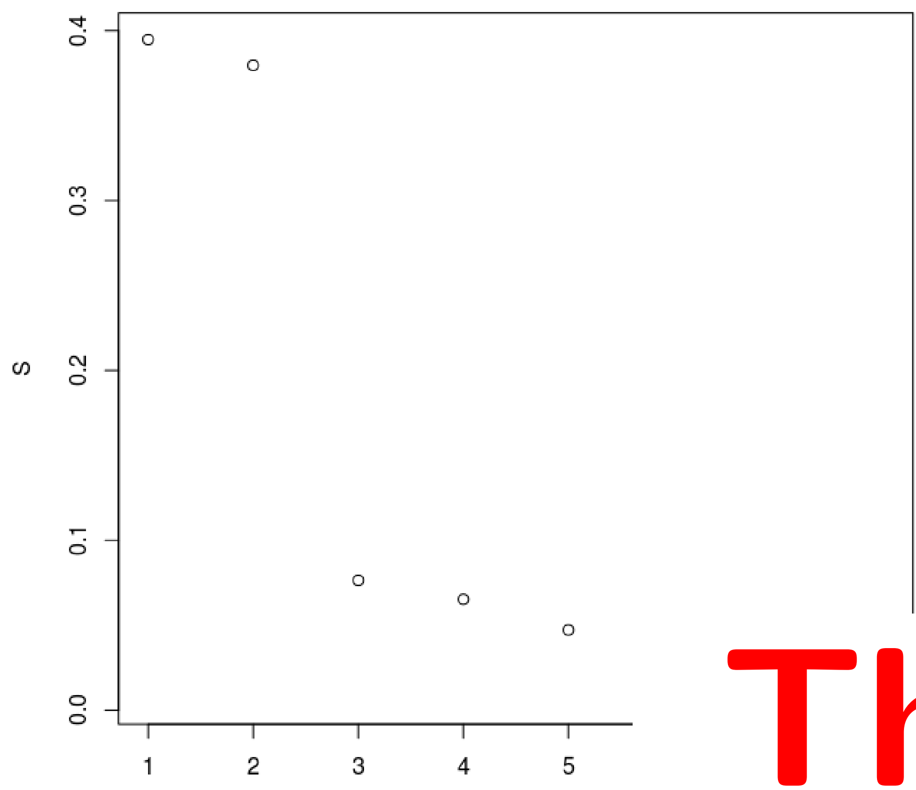


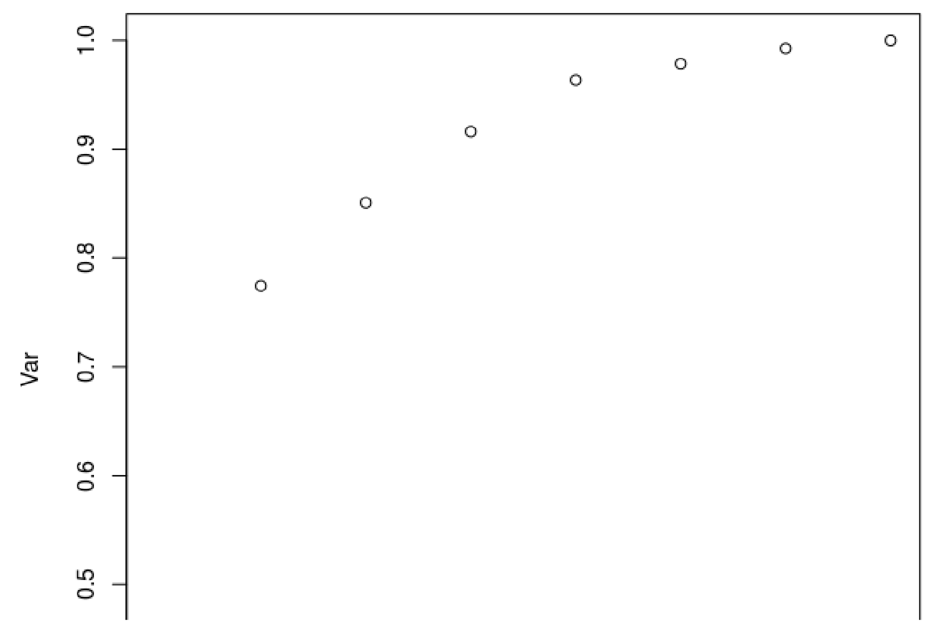
MDS

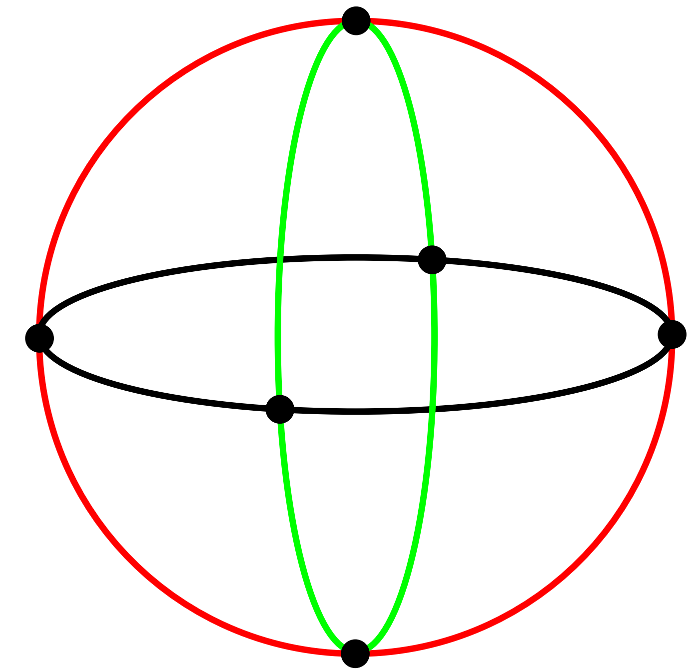


Isomap

Example: Natural Images Data

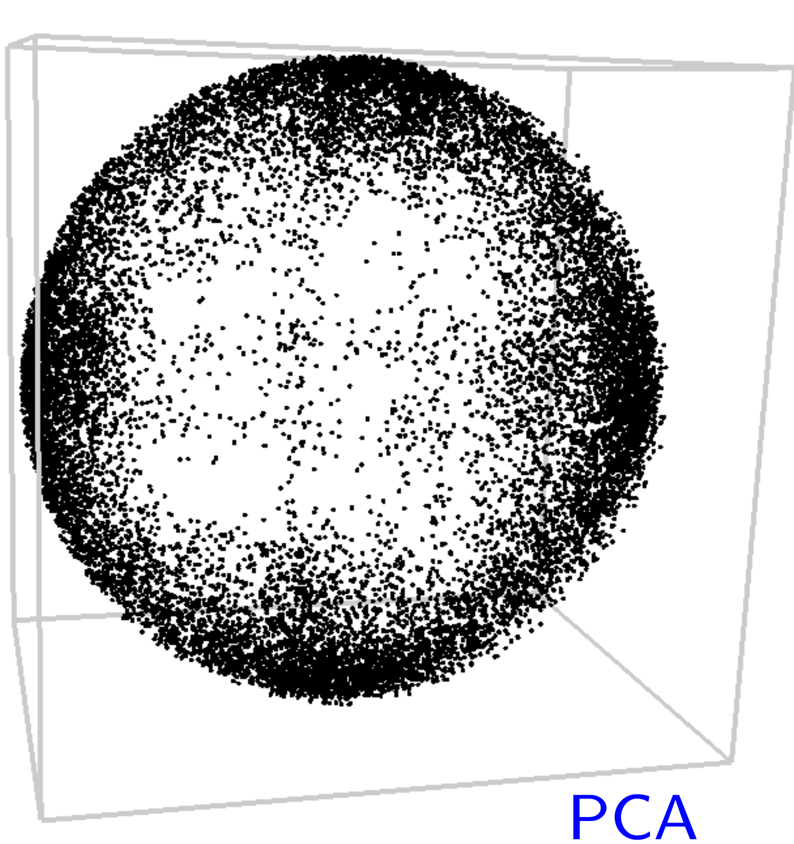


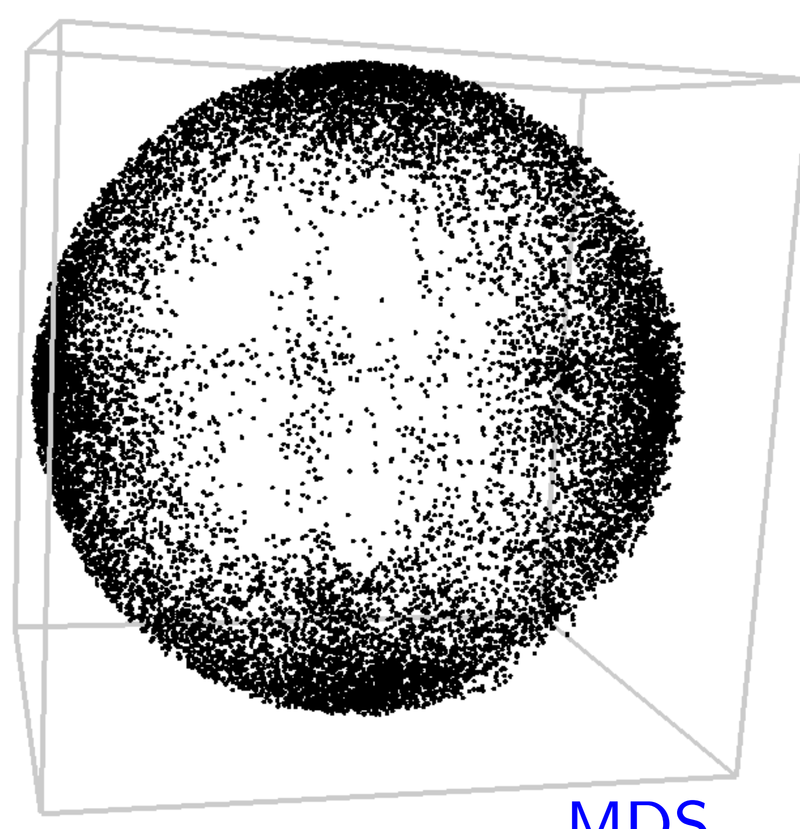


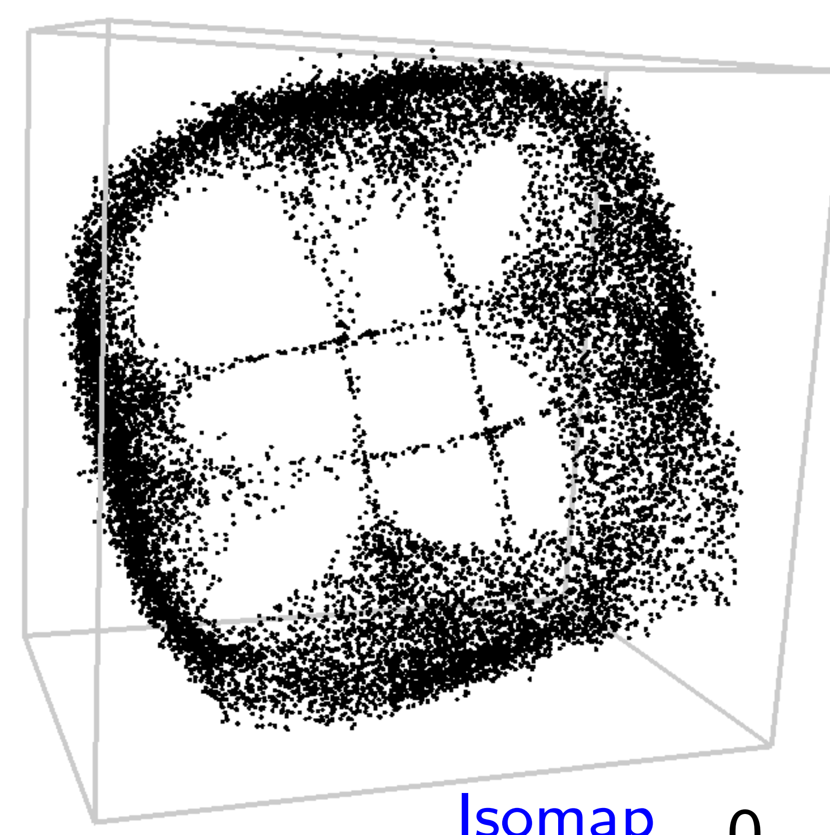


$(\beta_1 = 7)$

This is a lie!





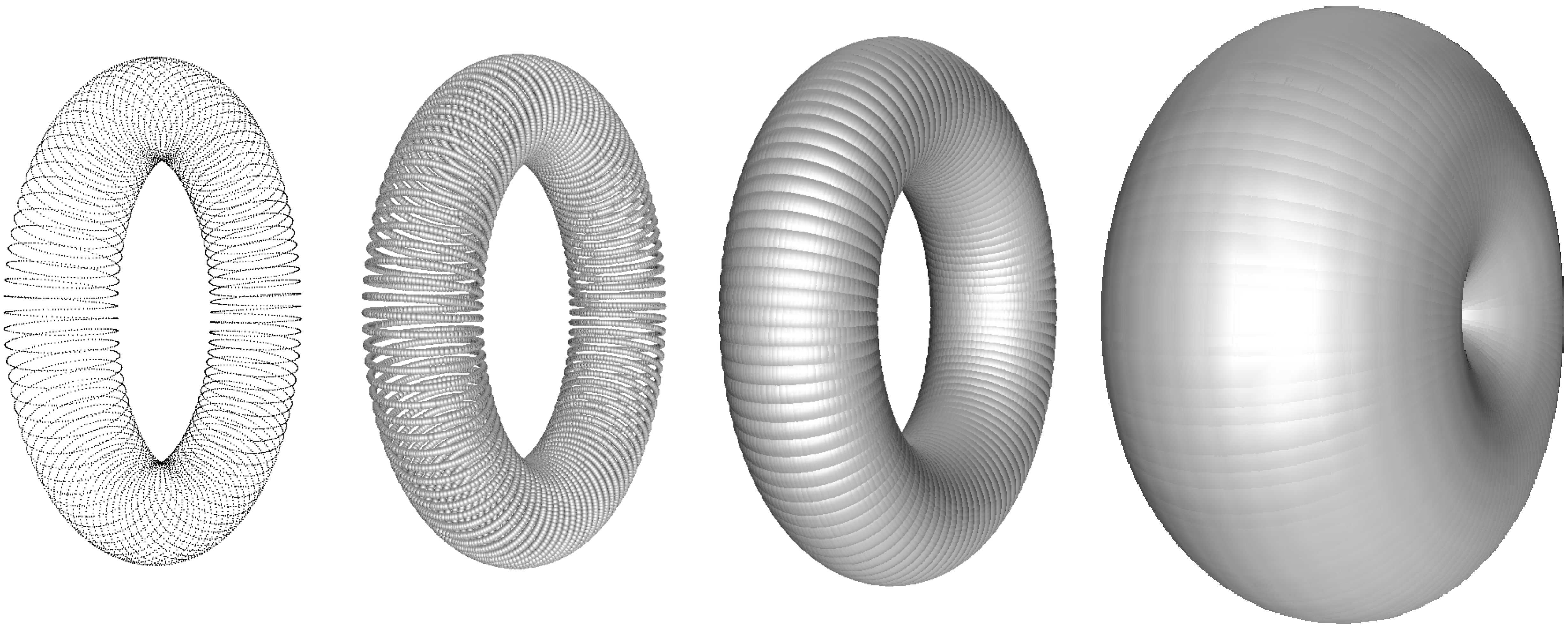


Topology from Data

Input: point cloud $P \subset \mathbb{R}^d$

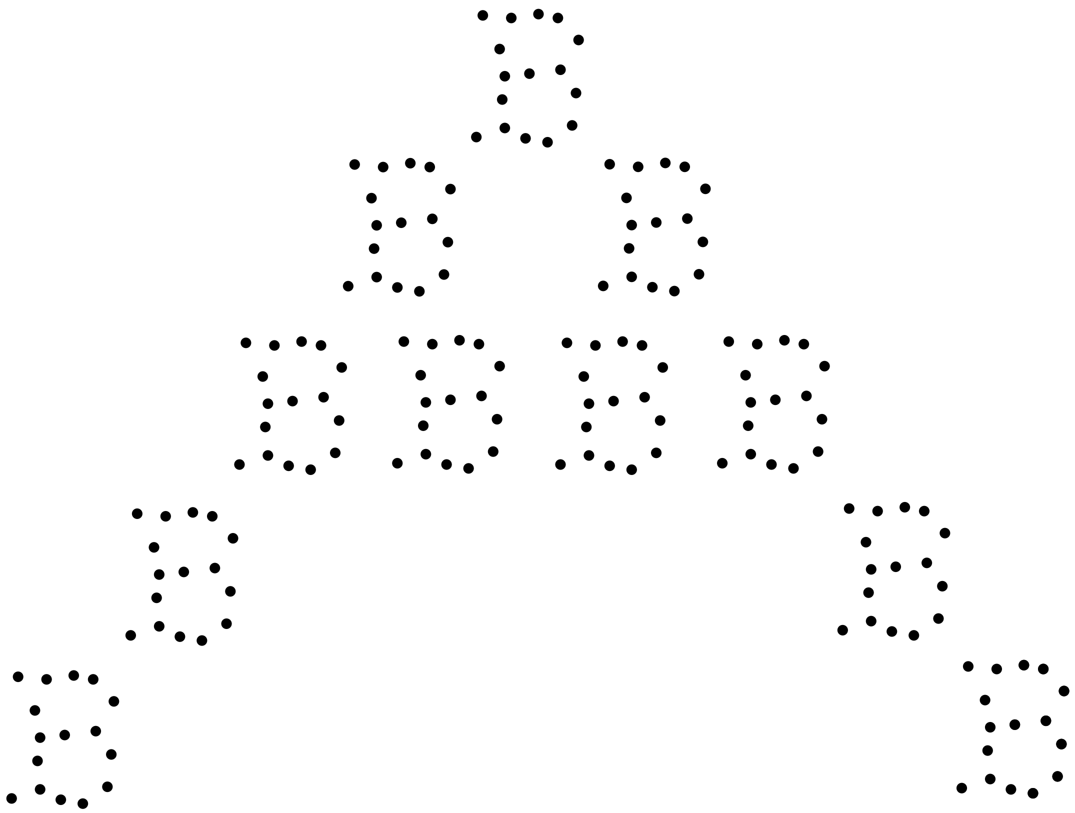
$\rightarrow$ uncover the topological structure of the space(s) underlying the data

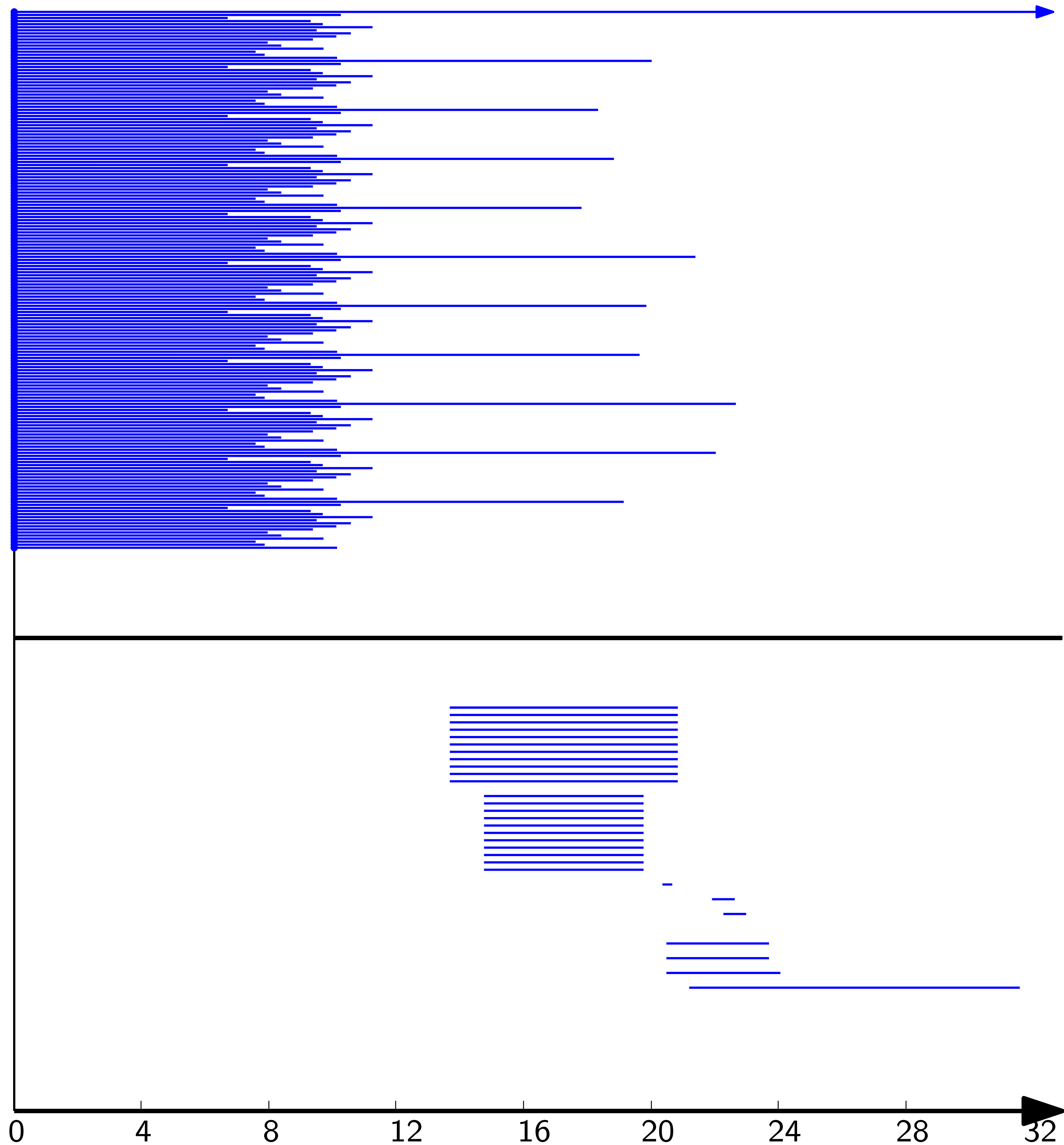
$\rightarrow$ inspect data at all scales and see what 'persists'



Approach: Compute persistence of distance function

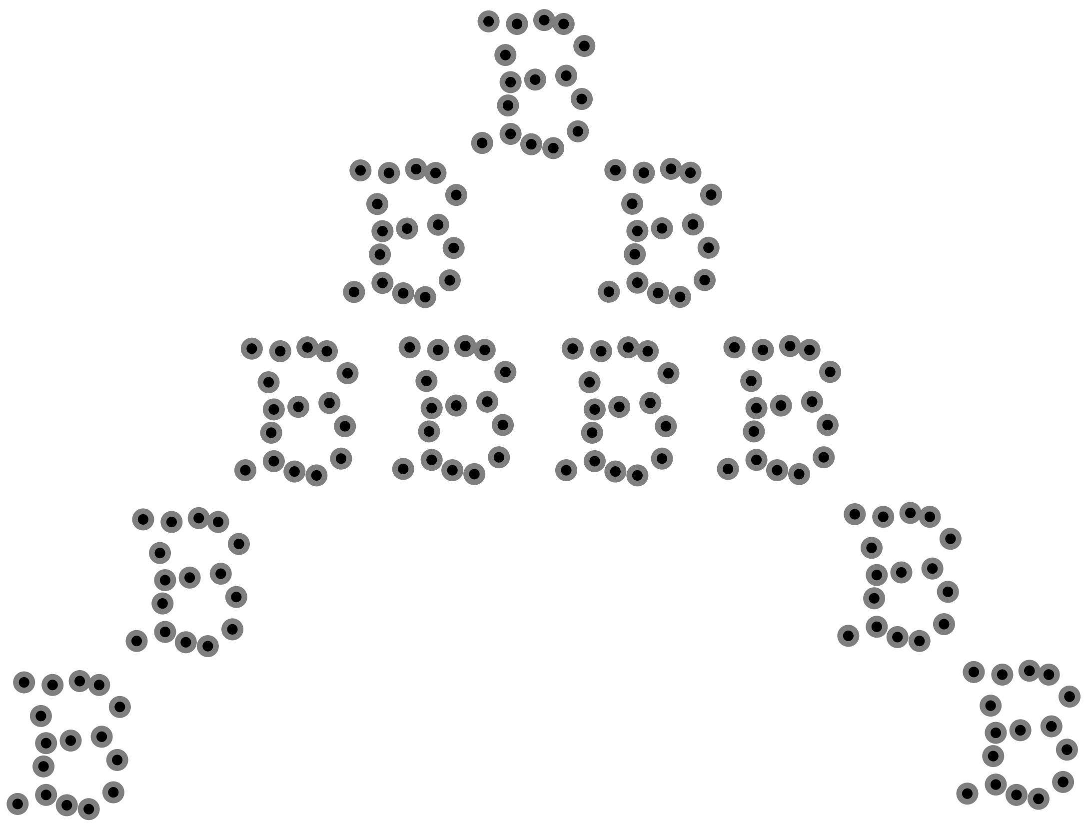
$$\mathrm{d}_P : \quad \mathbb{R}^2 \to \mathbb{R}$$
$$x \mapsto \min_{p \in P} \|x - p\|_2$$

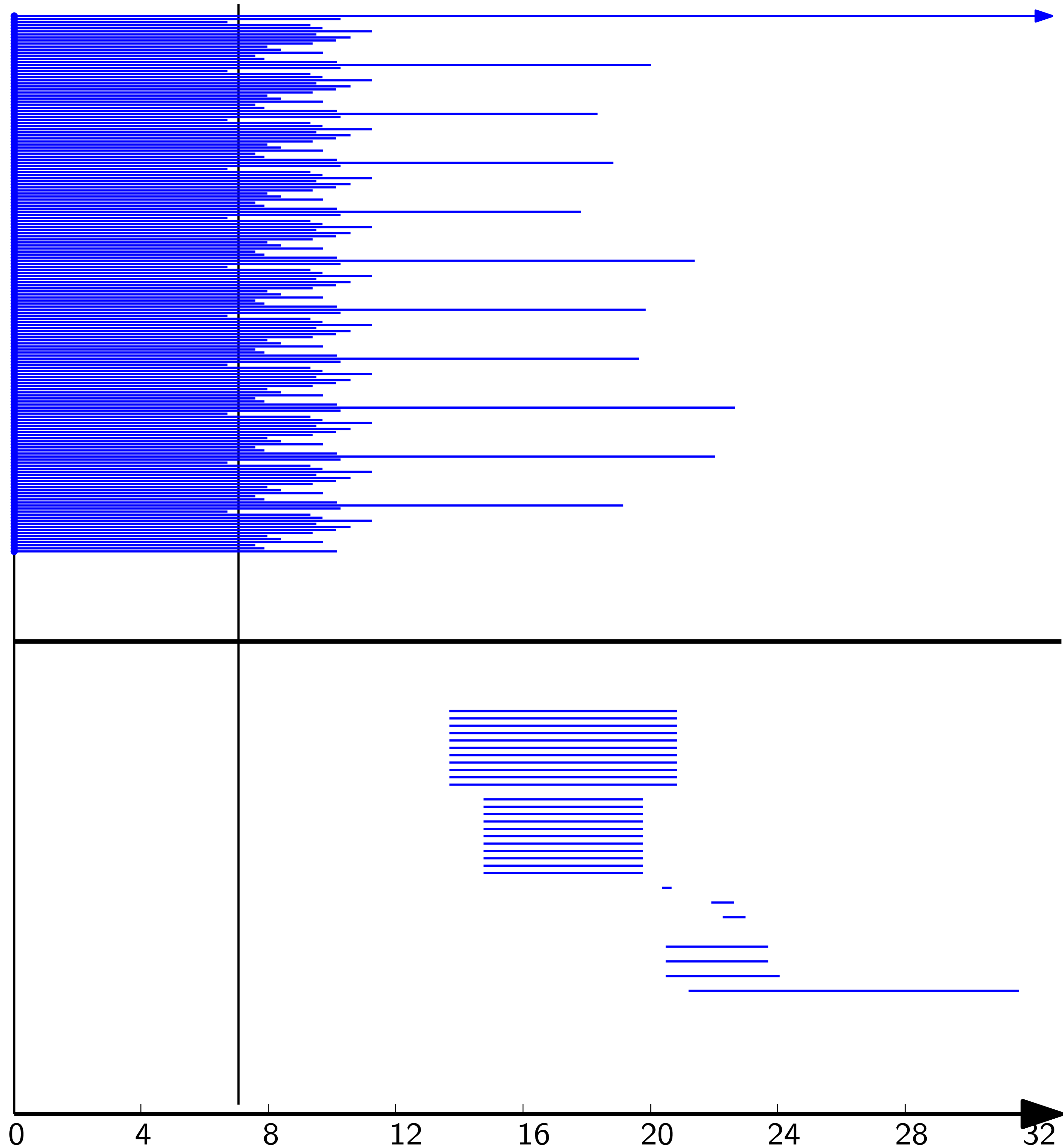




Approach: Compute persistence of distance function

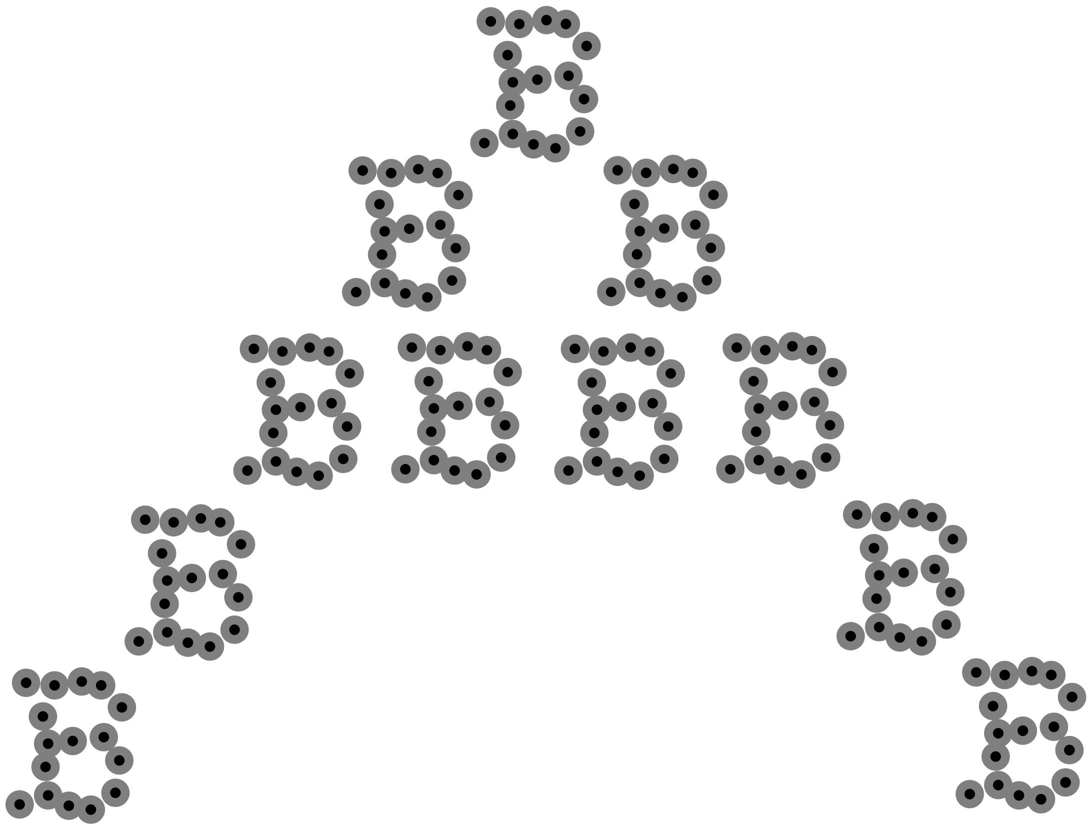
$$\mathrm{d}_P : \quad \mathbb{R}^2 \to \mathbb{R}$$
$$x \mapsto \min_{p \in P} \|x - p\|_2$$

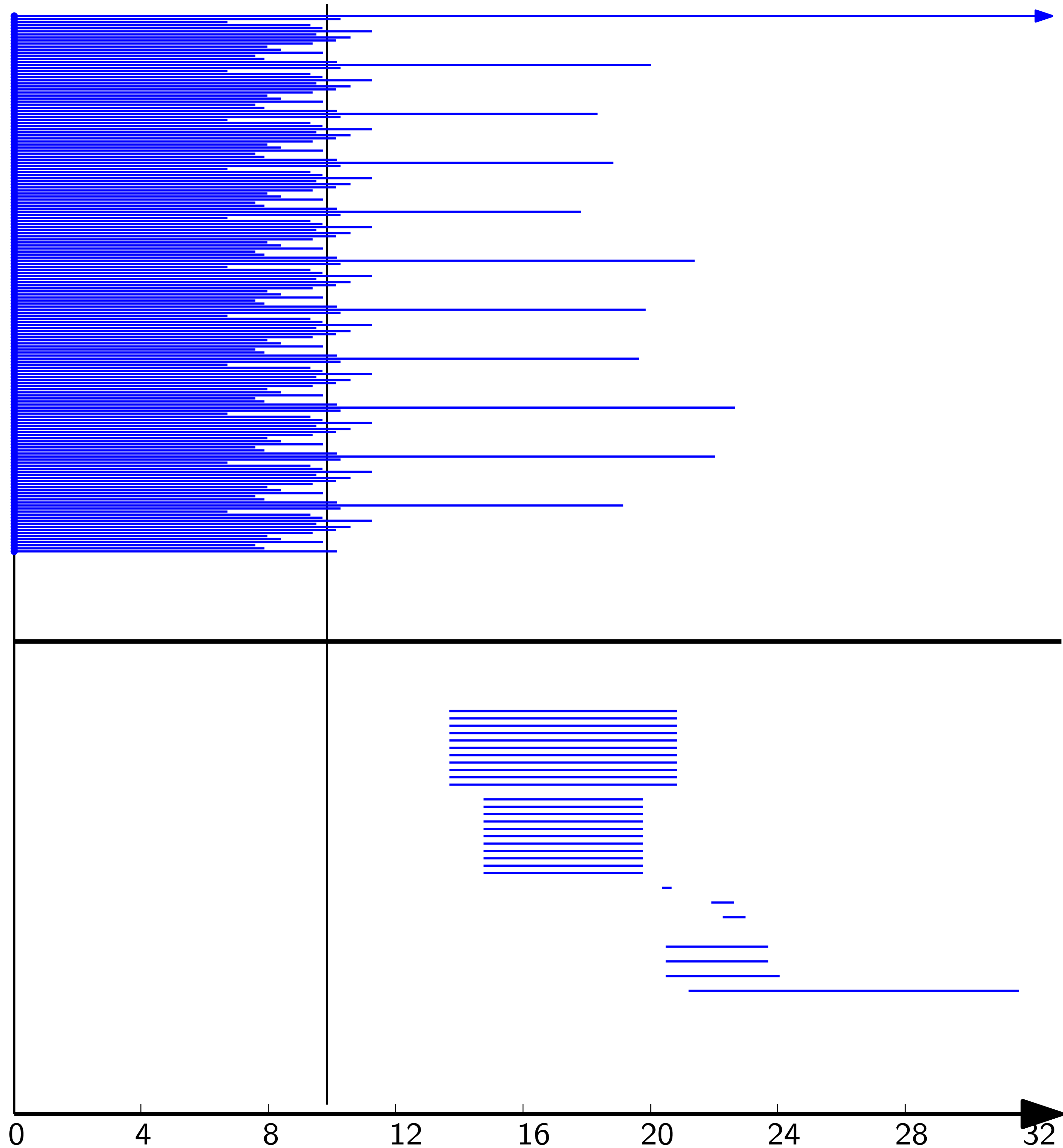




Approach: Compute persistence of distance function

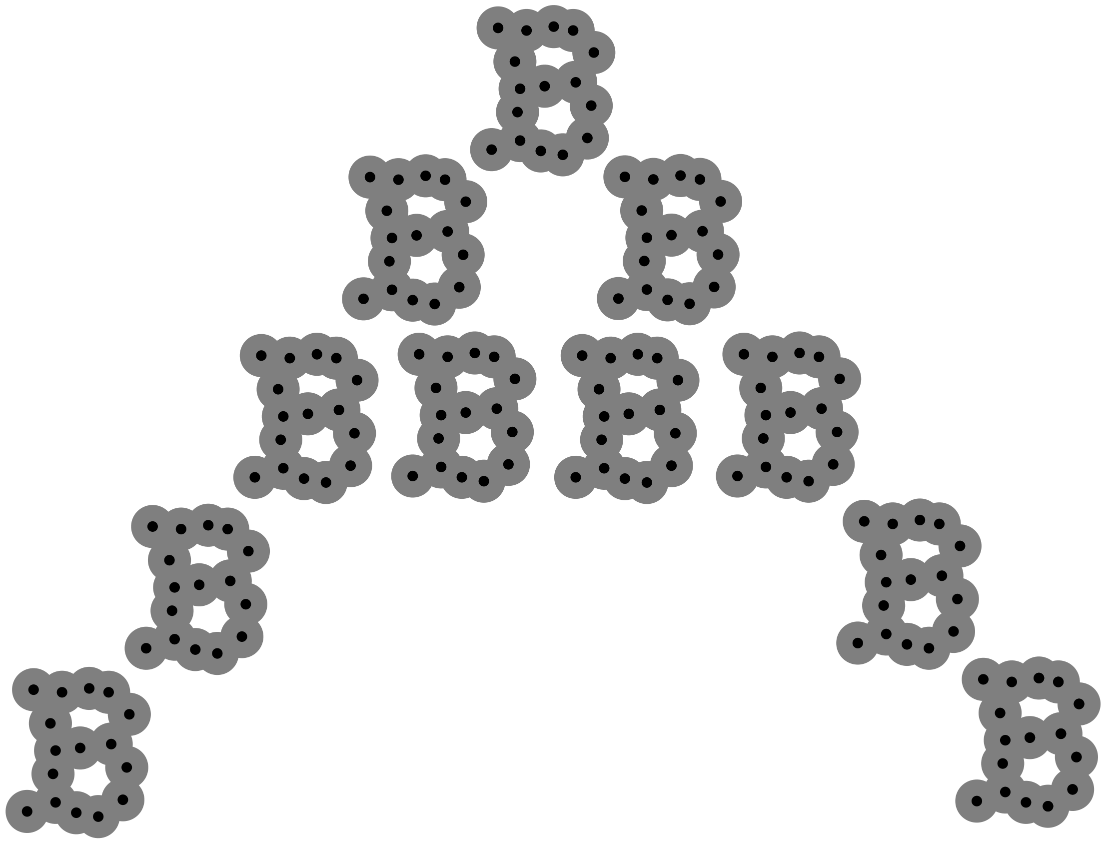
$$\begin{aligned} \mathrm{d}_P : \quad & \mathbb{R}^2 \to \mathbb{R} \\ & x \mapsto \min_{p \in P} \|x - p\|_2 \end{aligned}$$

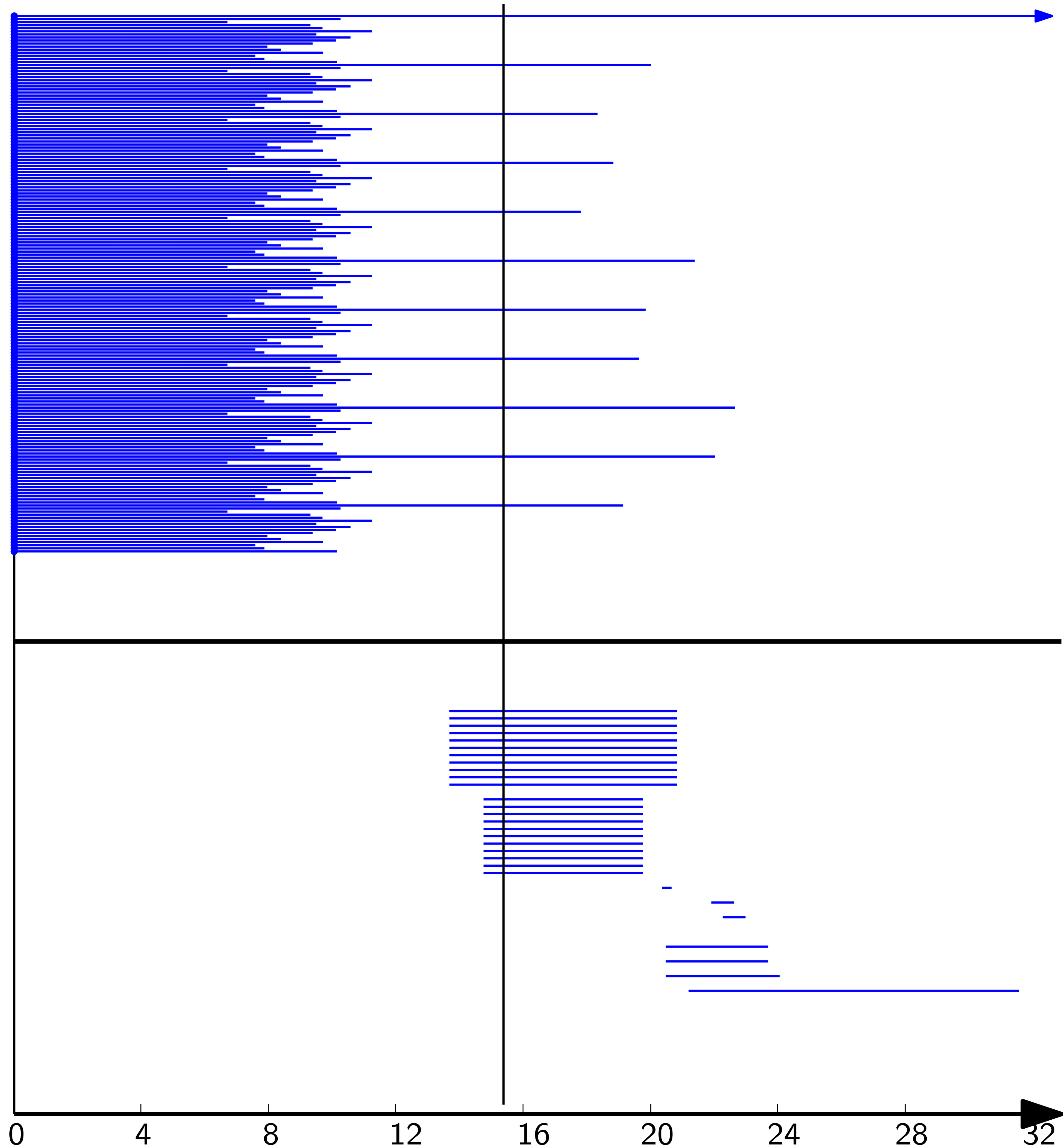




Approach: Compute persistence of distance function

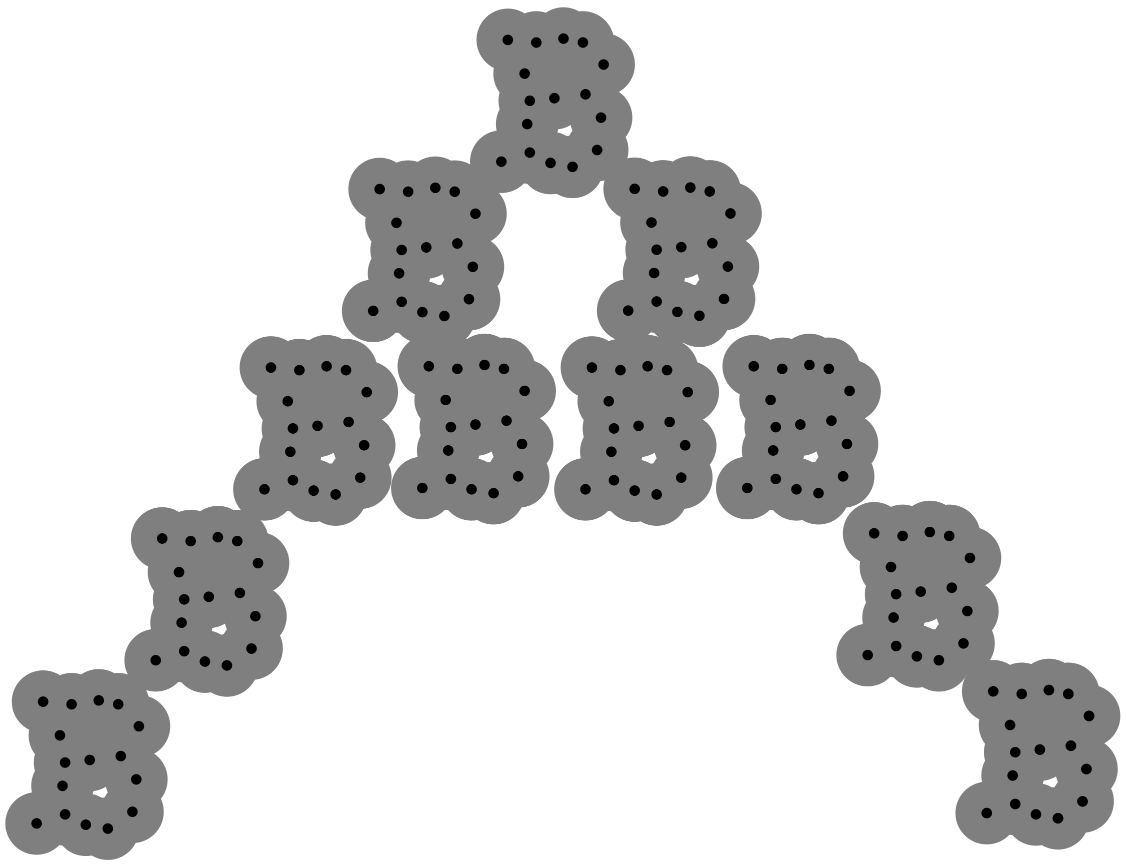
$$\mathrm{d}_P : \quad \mathbb{R}^2 \to \mathbb{R}$$
$$x \mapsto \min_{p \in P} \|x - p\|_2$$

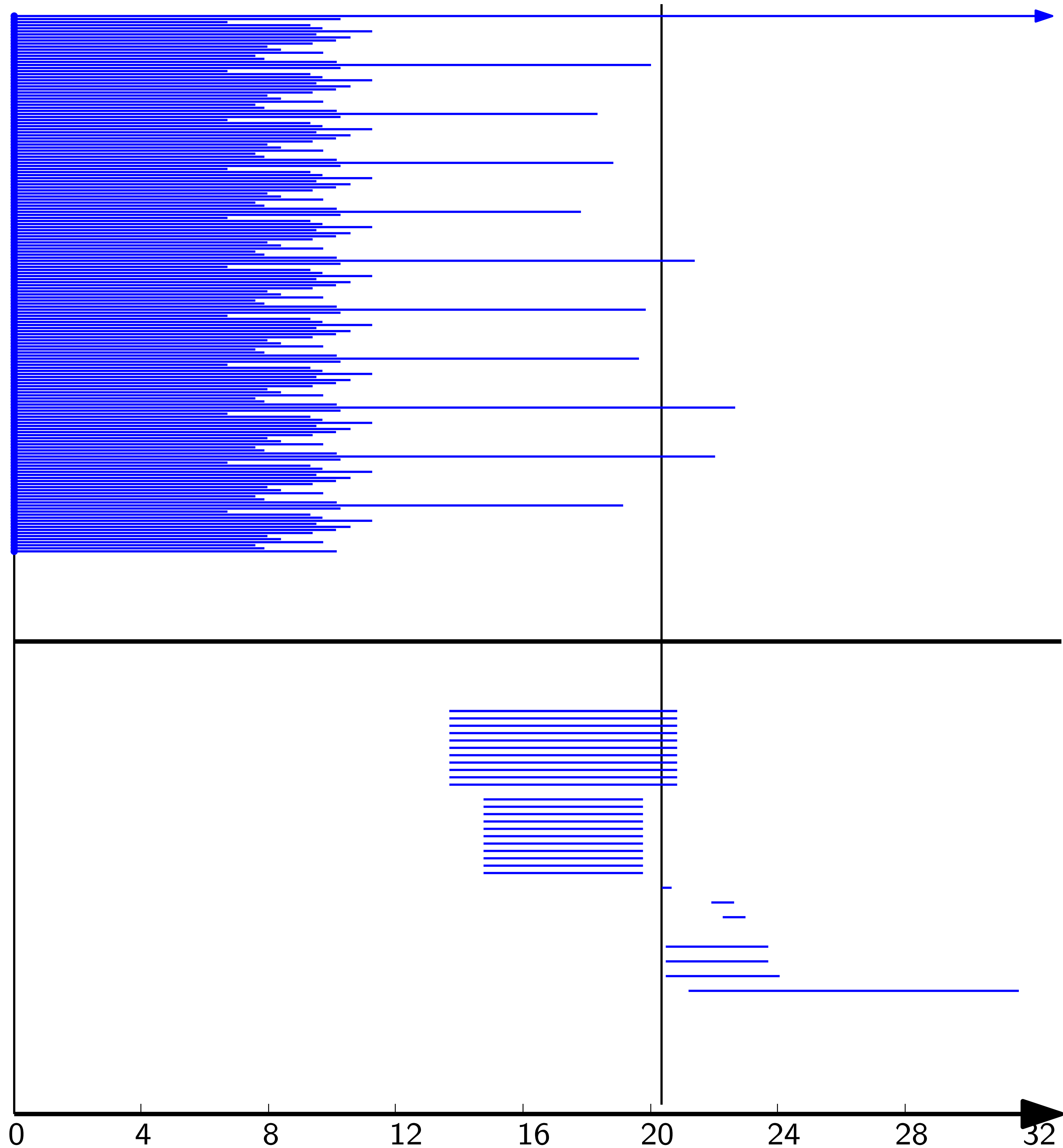




Approach: Compute persistence of distance function

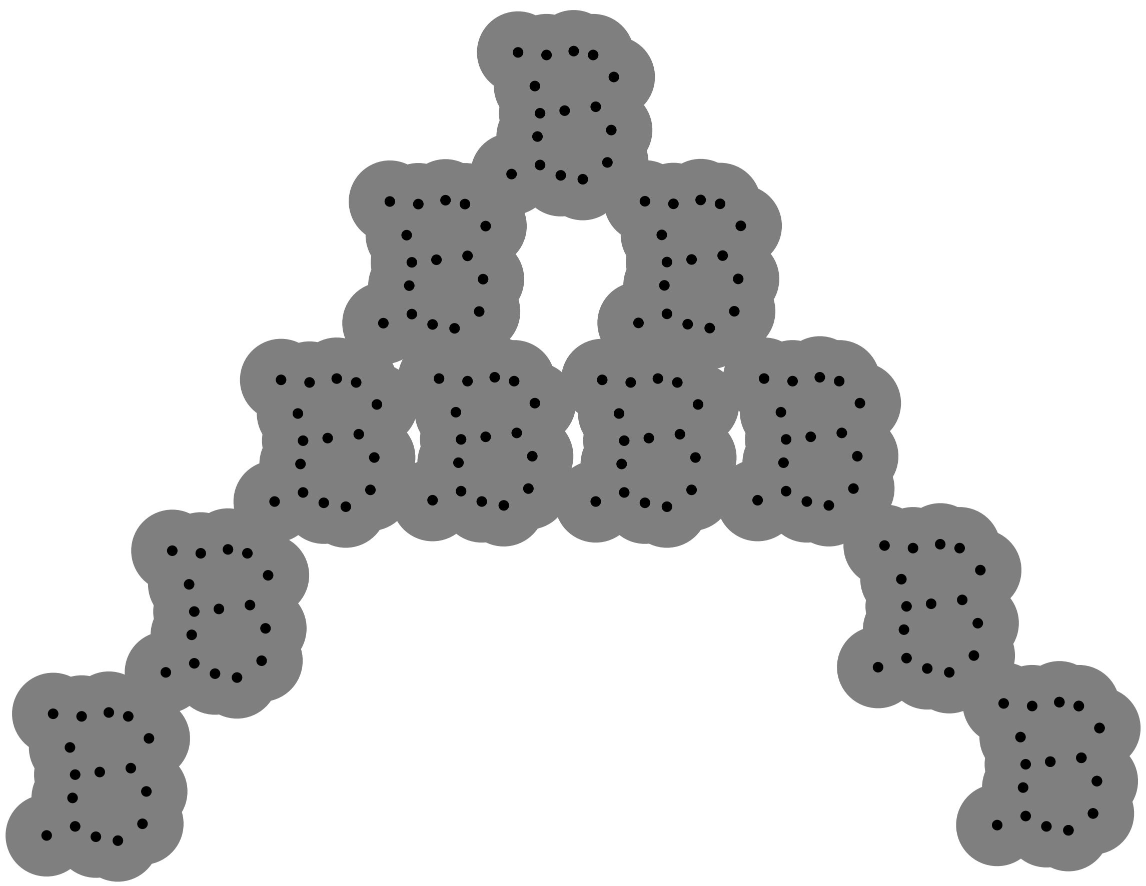
$$\mathrm{d}_P : \quad \mathbb{R}^2 \to \mathbb{R}$$
$$x \mapsto \min_{p \in P} \|x - p\|_2$$

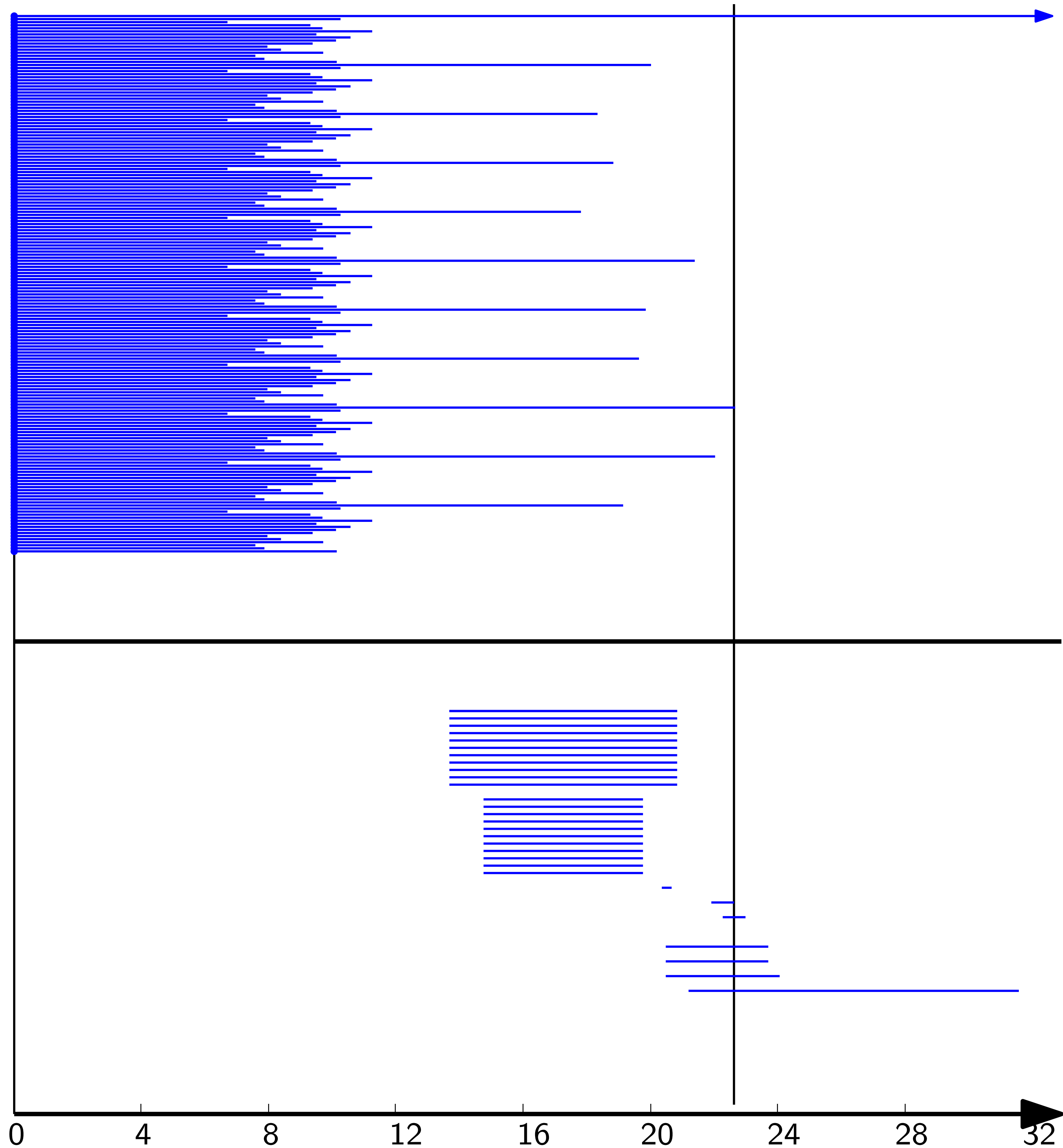




Approach: Compute persistence of distance function

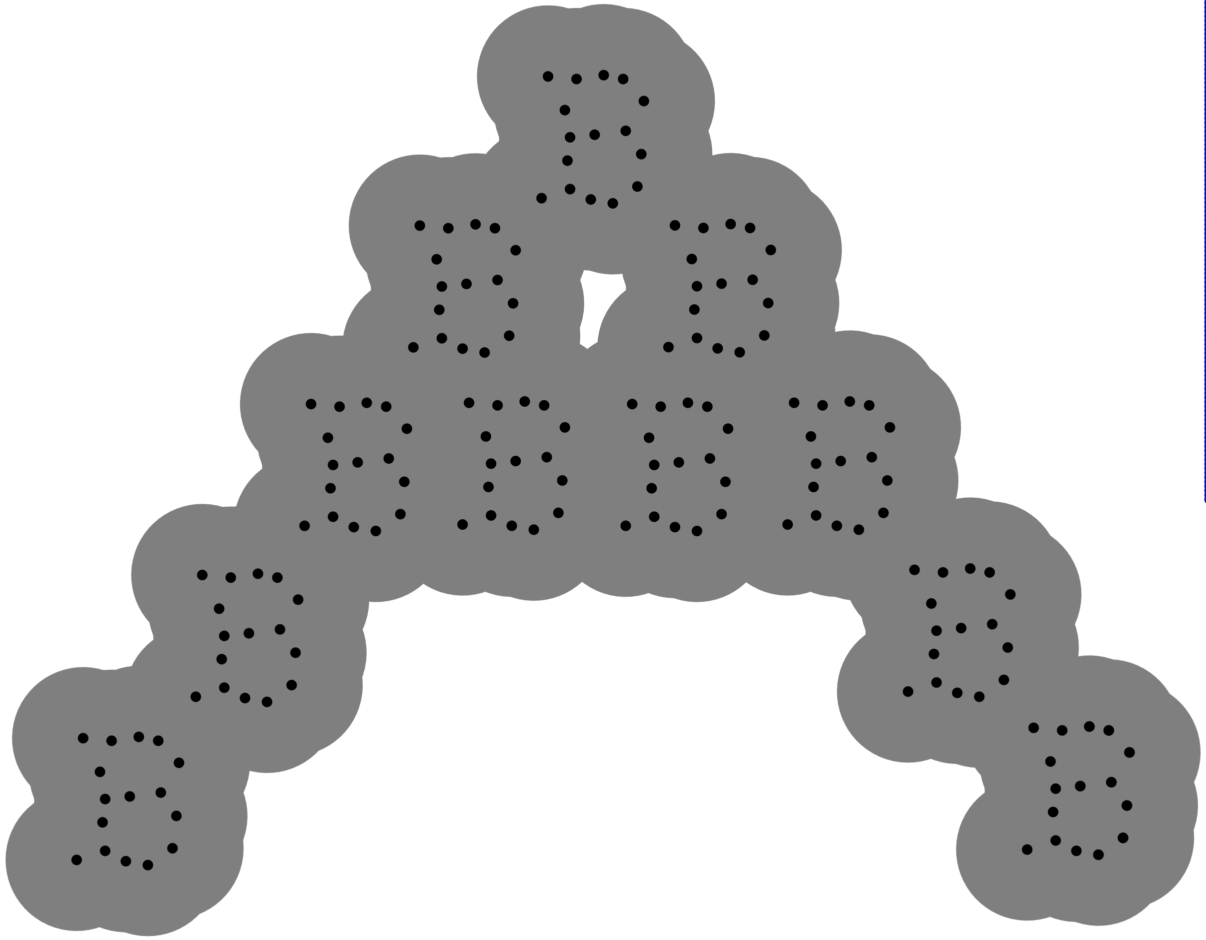
$$\mathrm{d}_P : \quad \mathbb{R}^2 \to \mathbb{R}$$
$$x \mapsto \min_{p \in P} \|x - p\|_2$$

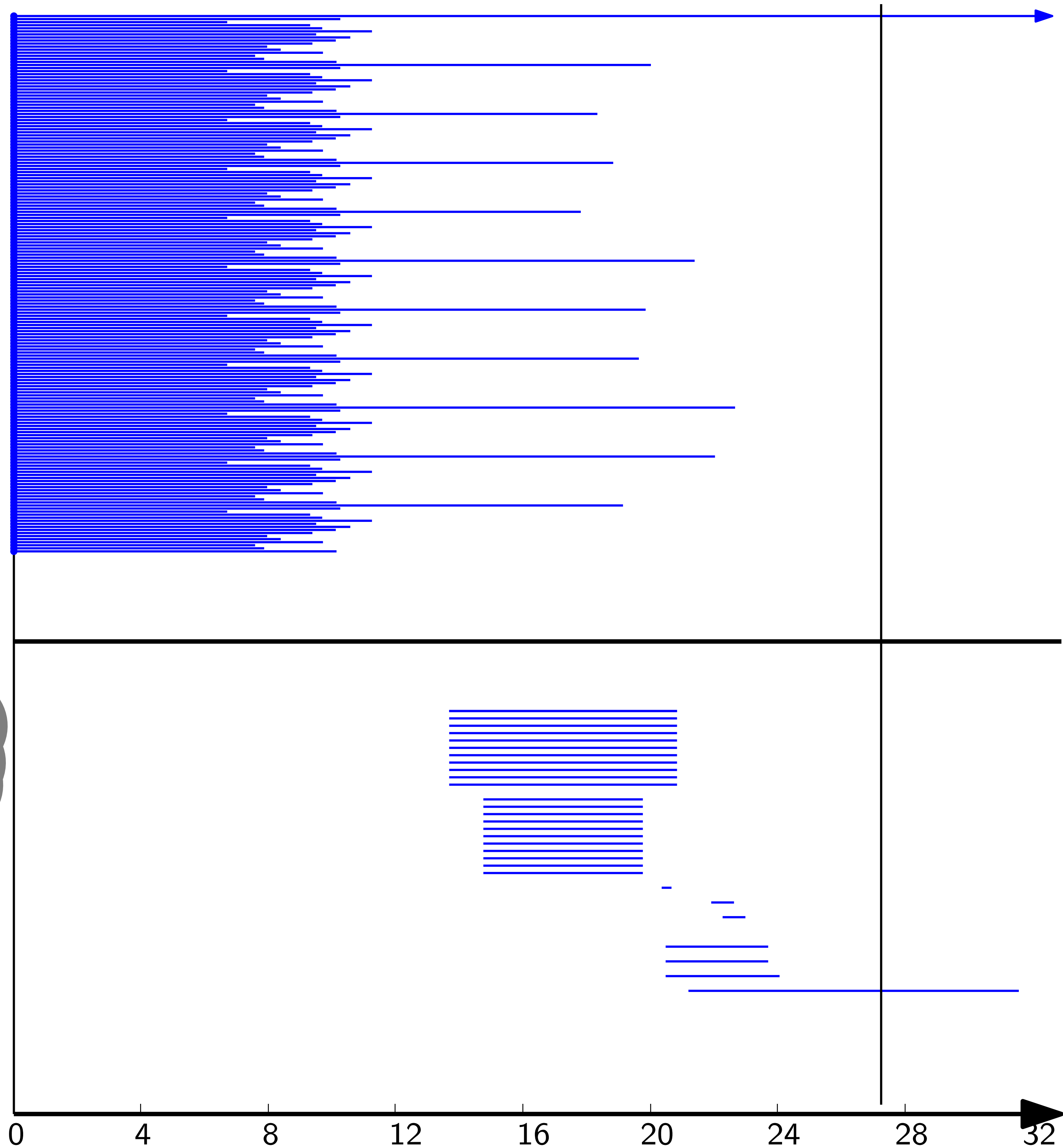




Approach: Compute persistence of distance function

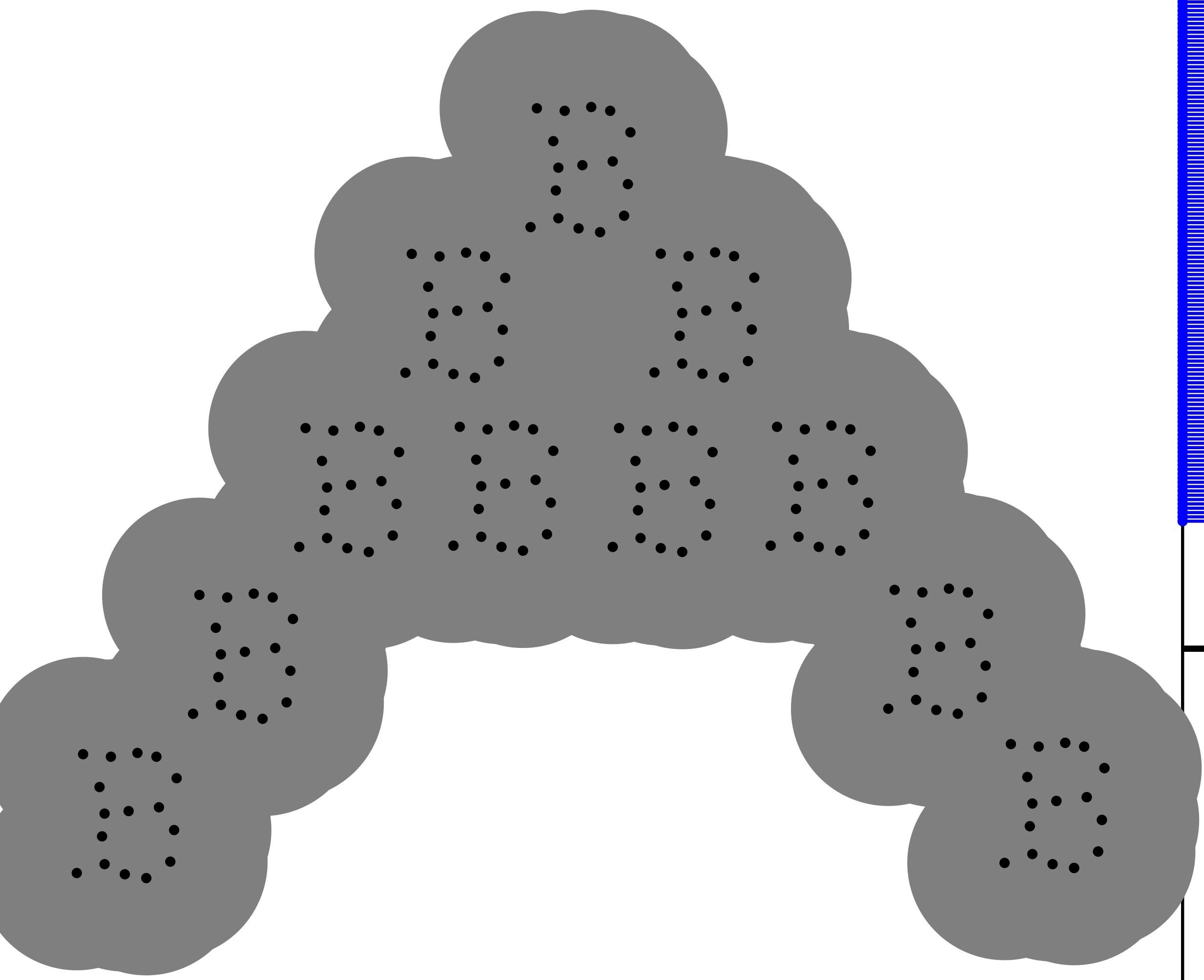
$$\mathrm{d}_P : \quad \mathbb{R}^2 \to \mathbb{R}$$
$$x \mapsto \min_{p \in P} \|x - p\|_2$$

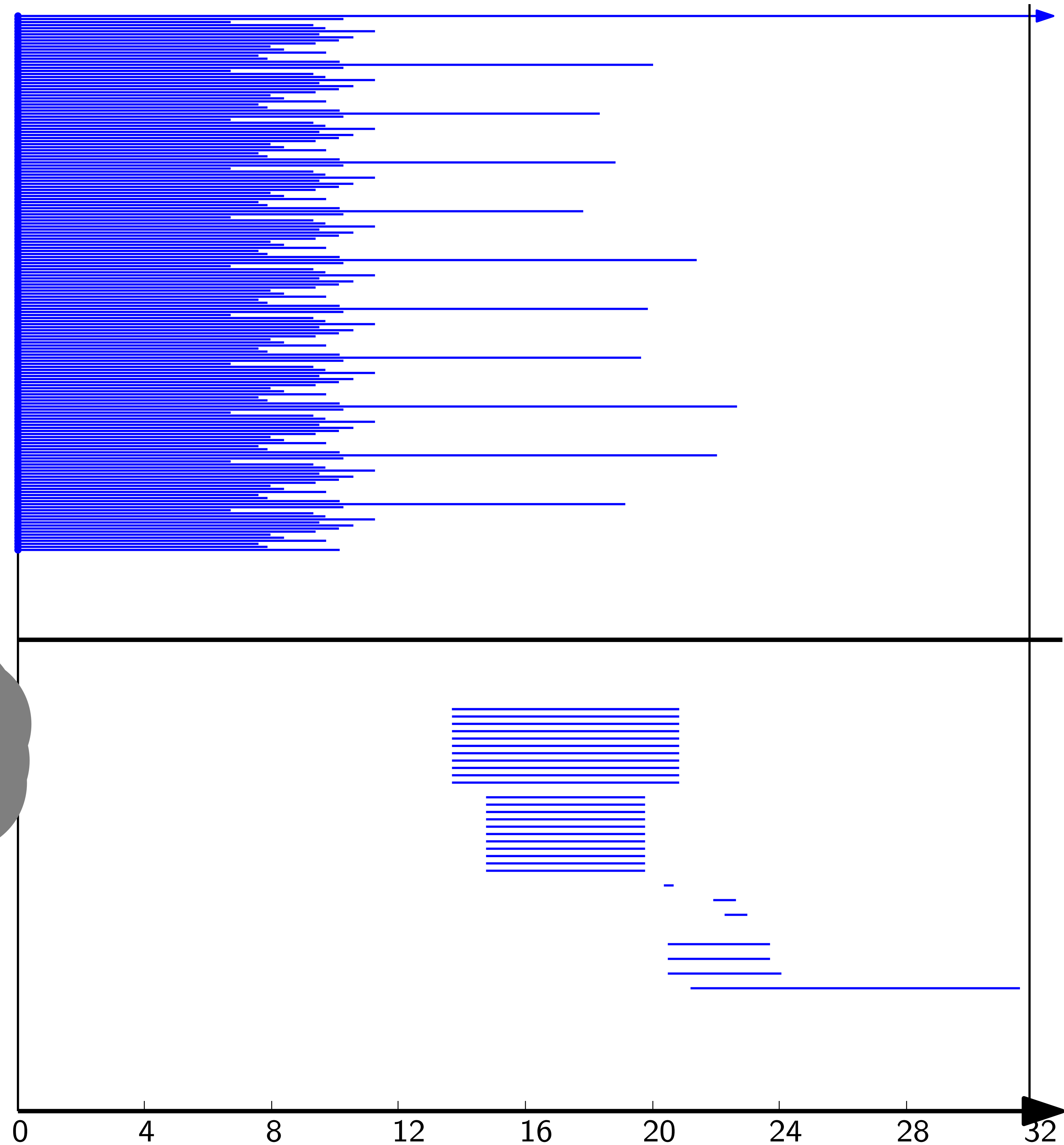




Approach: Compute persistence of distance function

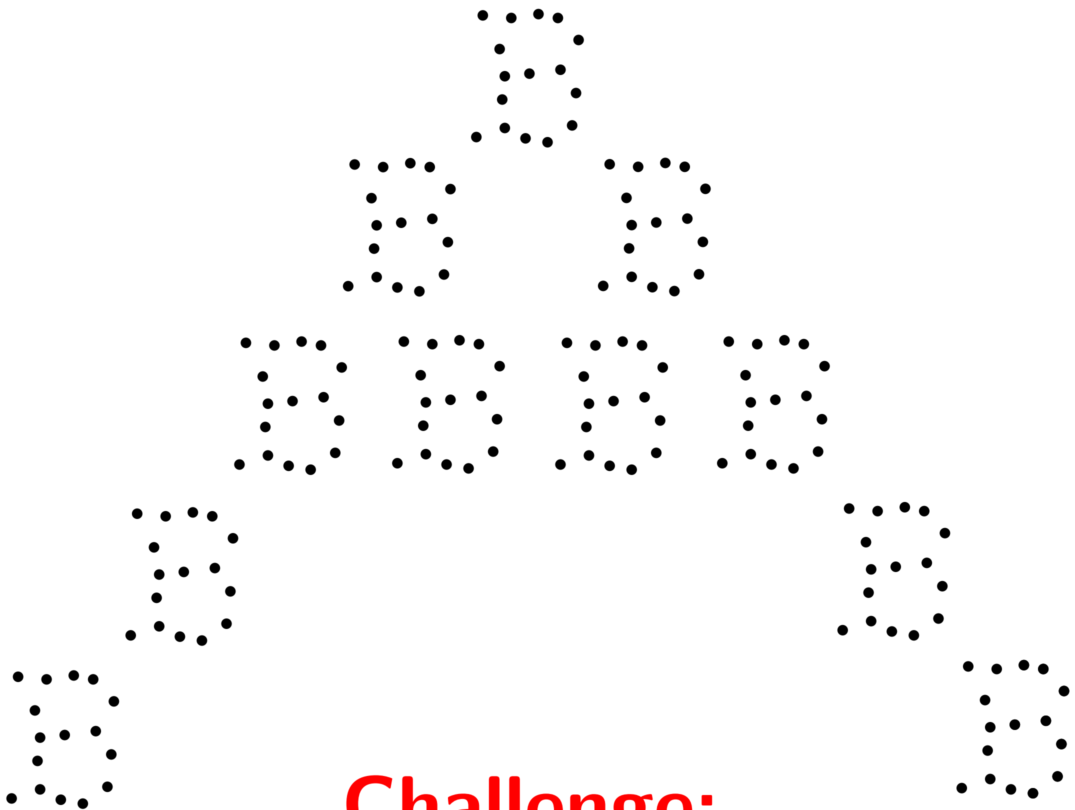
$$\mathrm{d}_P : \quad \mathbb{R}^2 \to \mathbb{R}$$
$$x \mapsto \min_{p \in P} \|x - p\|_2$$





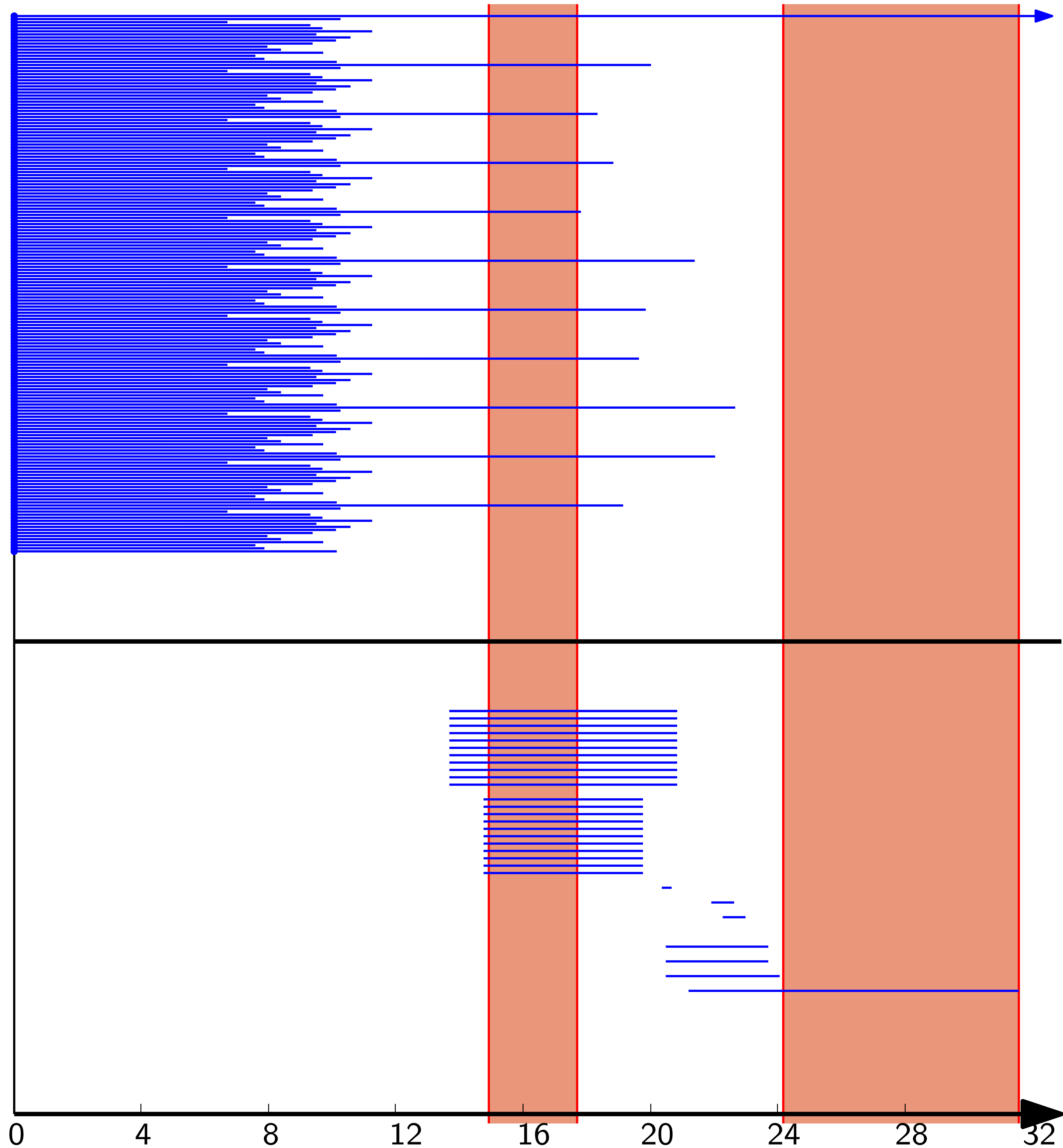
Approach: Compute persistence of distance function

$$\begin{aligned} \mathrm{d}_P : \quad & \mathbb{R}^2 \to \mathbb{R} \\ & x \mapsto \min_{p\in P} \|x-p\|_2 \end{aligned}$$

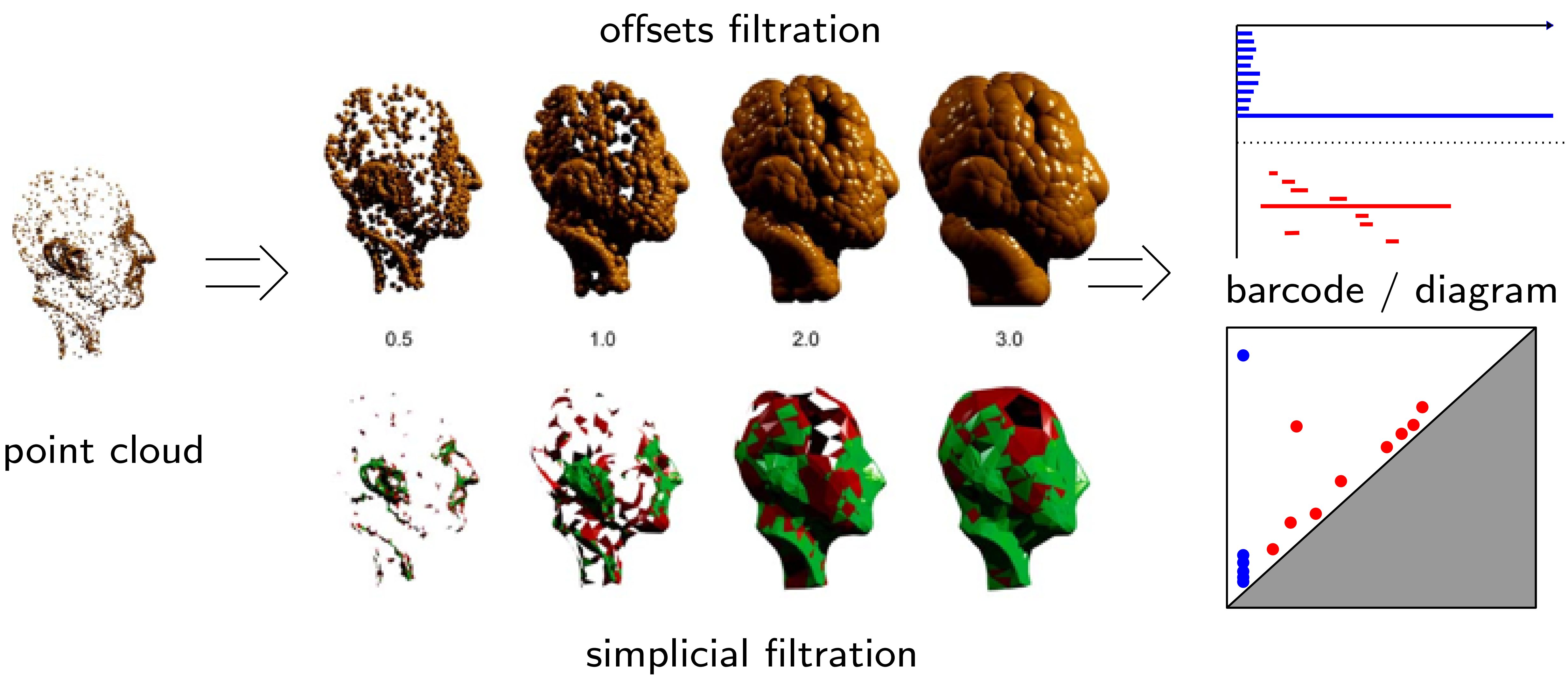


Challenge:
provide theoretical guarantees

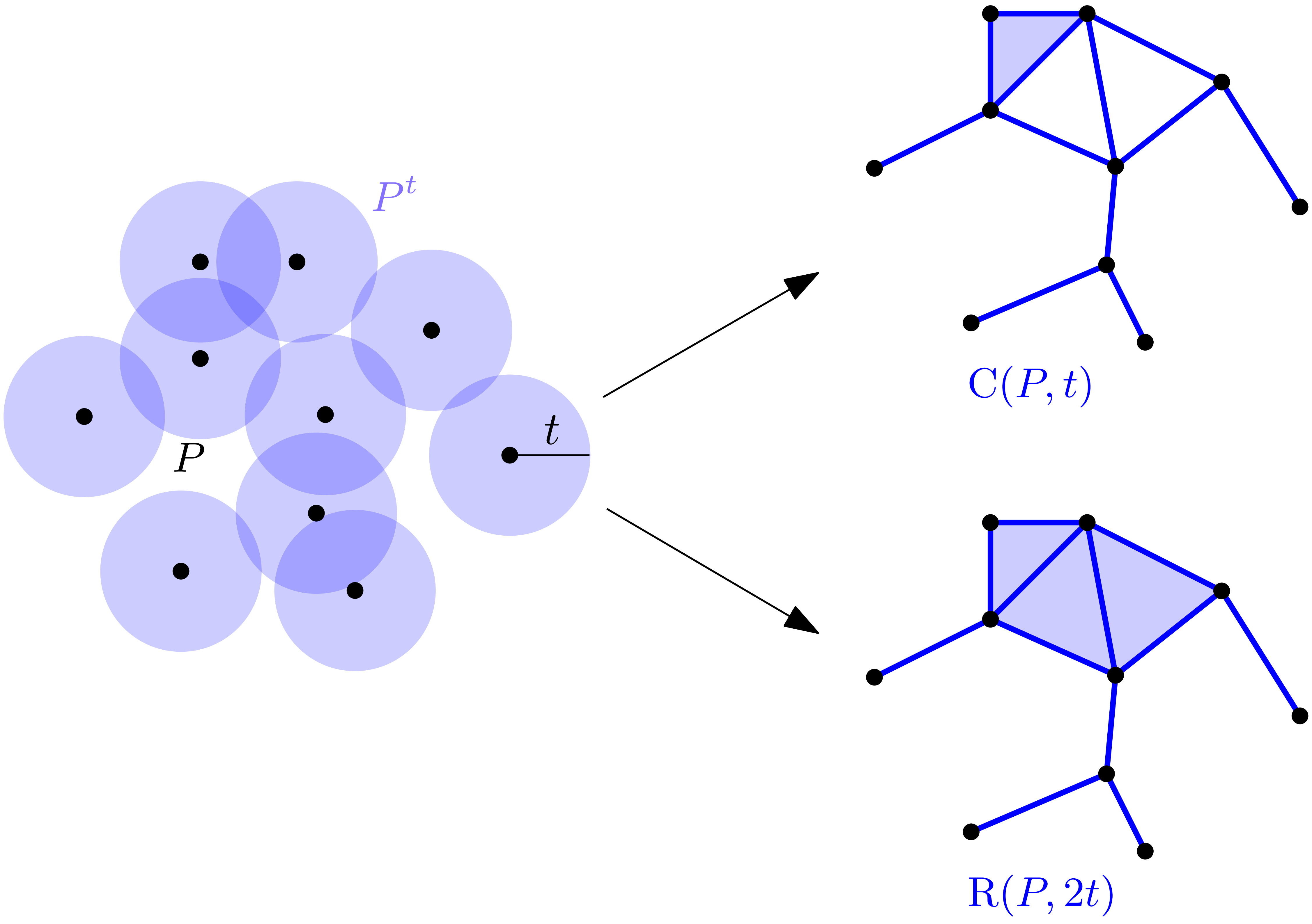
(sufficient sampling conditions under which the barcode of d_P reveals the homology of the underlying space)



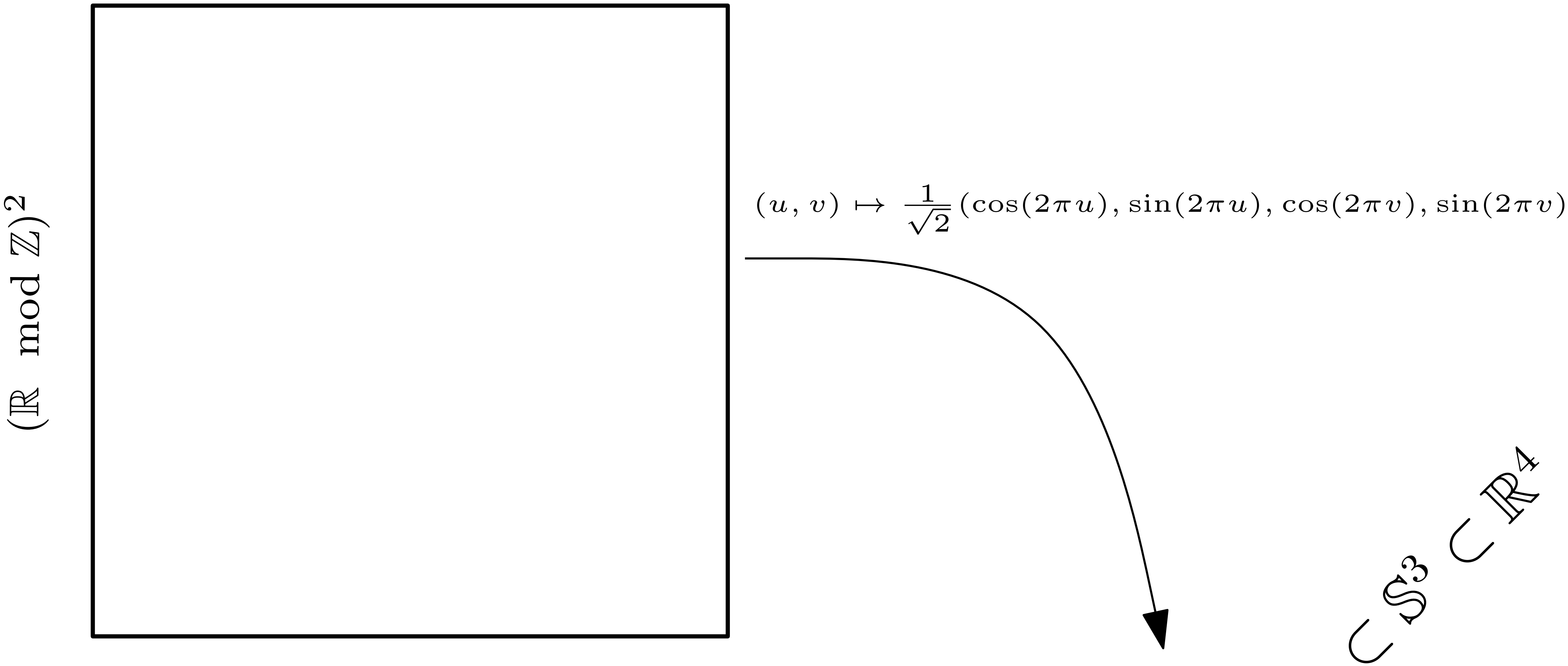
In practice: The inference pipeline

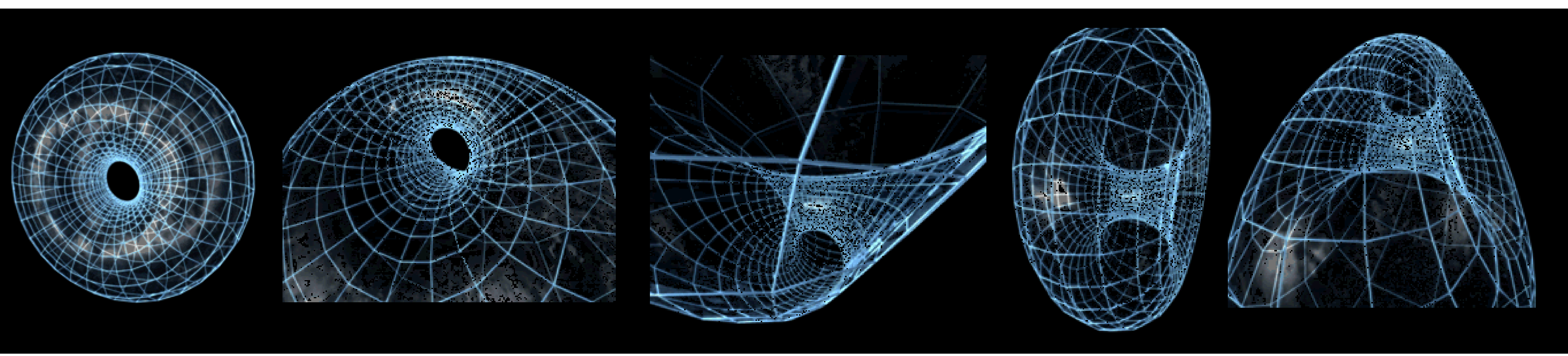


Čech and Rips filtrations



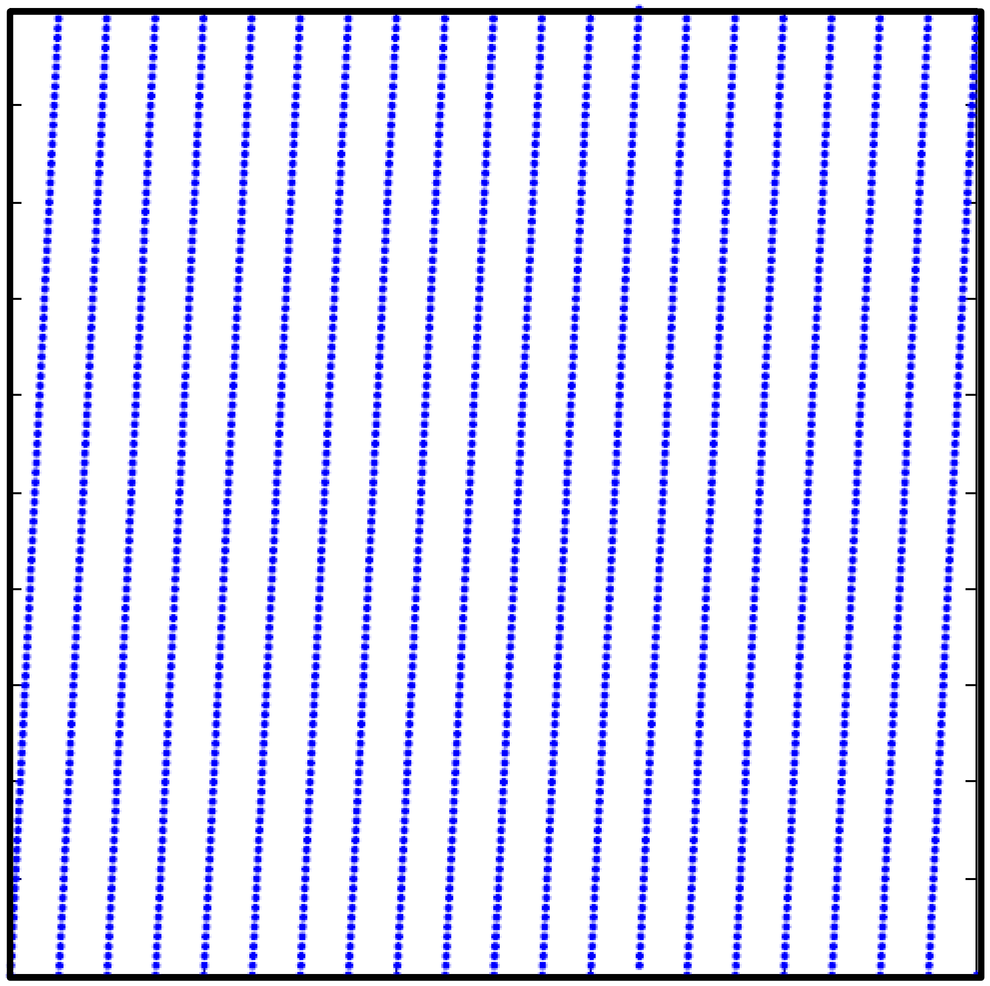
Example (manufactured data)





source: `http://http://en.wikipedia.org/wiki/Clifford_torus`

Example (manufactured data)



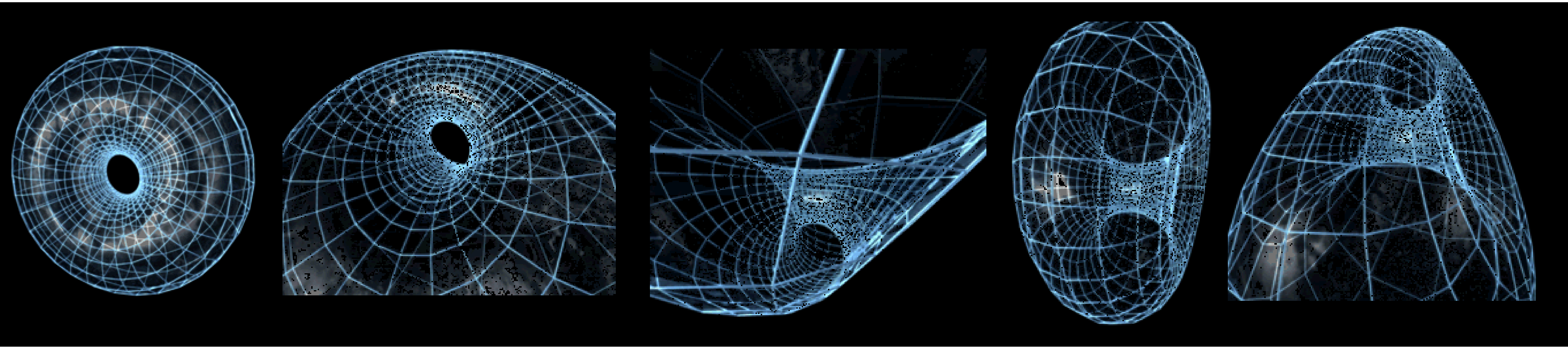
$(u, v) \mapsto \frac{1}{\sqrt{2}}(\cos(2\pi u), \sin(2\pi u), \cos(2\pi v), \sin(2\pi v))$

$n = 2000$ data points

ambient dimension $d = 4$

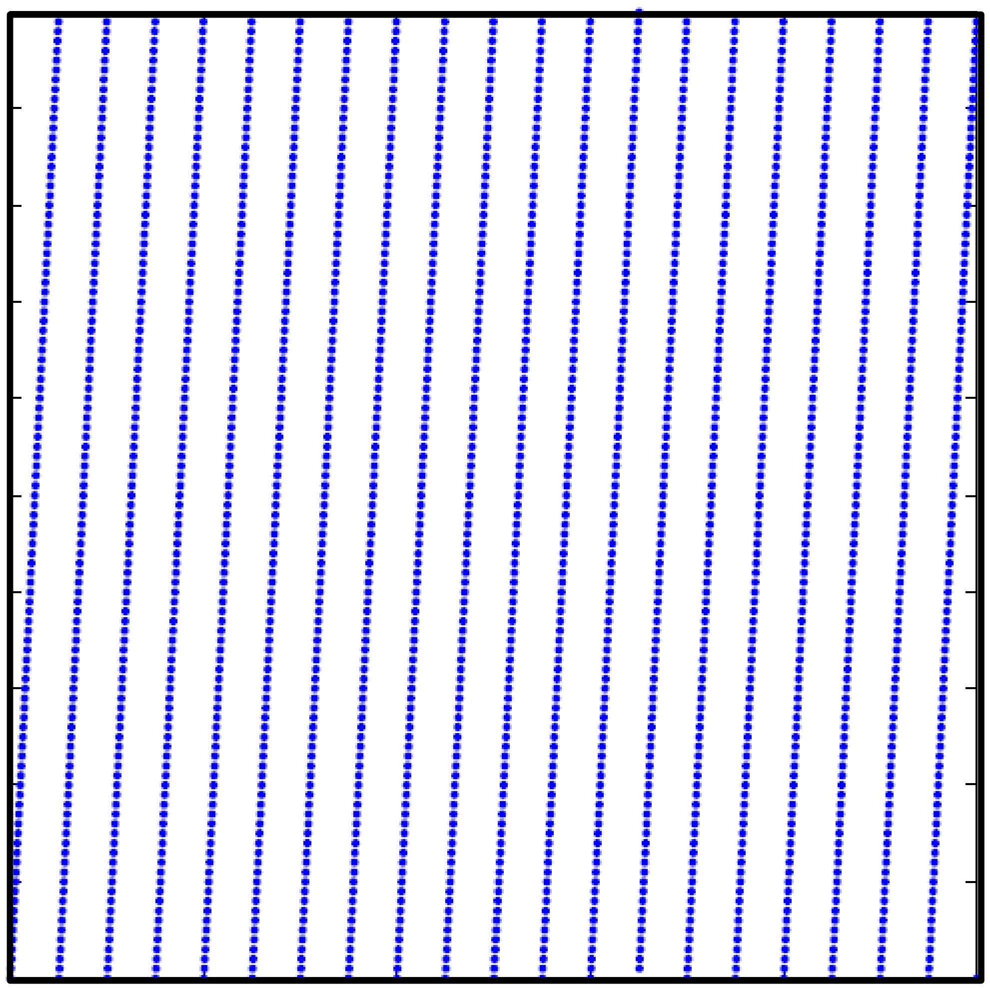
intrinsic dimension $k = 1, 2, 3$

$\subset \mathbb{S}3 \subset \mathbb{R}^4$



source: `http://http://en.wikipedia.org/wiki/Clifford_torus`

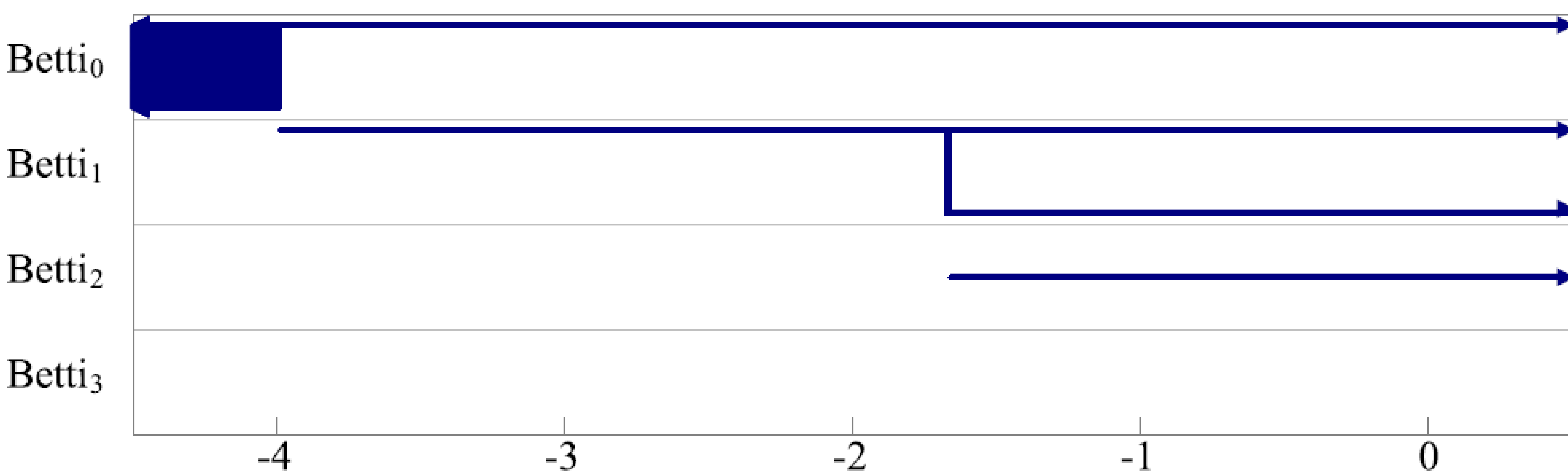
Example (manufactured data)



$n = 2000$ data points

ambient dimension $d = 4$

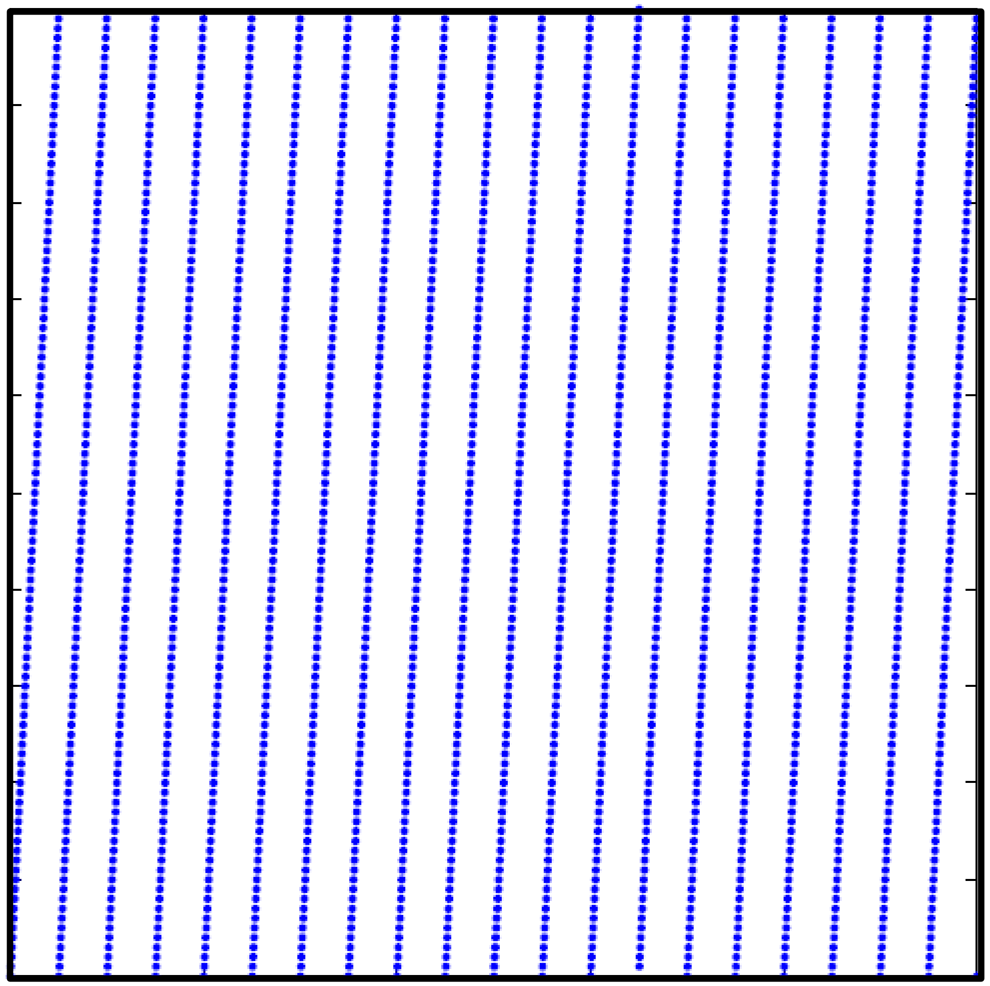
intrinsic dimension $k = 1, 2, 3$



Vietoris-Rips filtration

size $\sim 2^n \mid n^{d+1}$

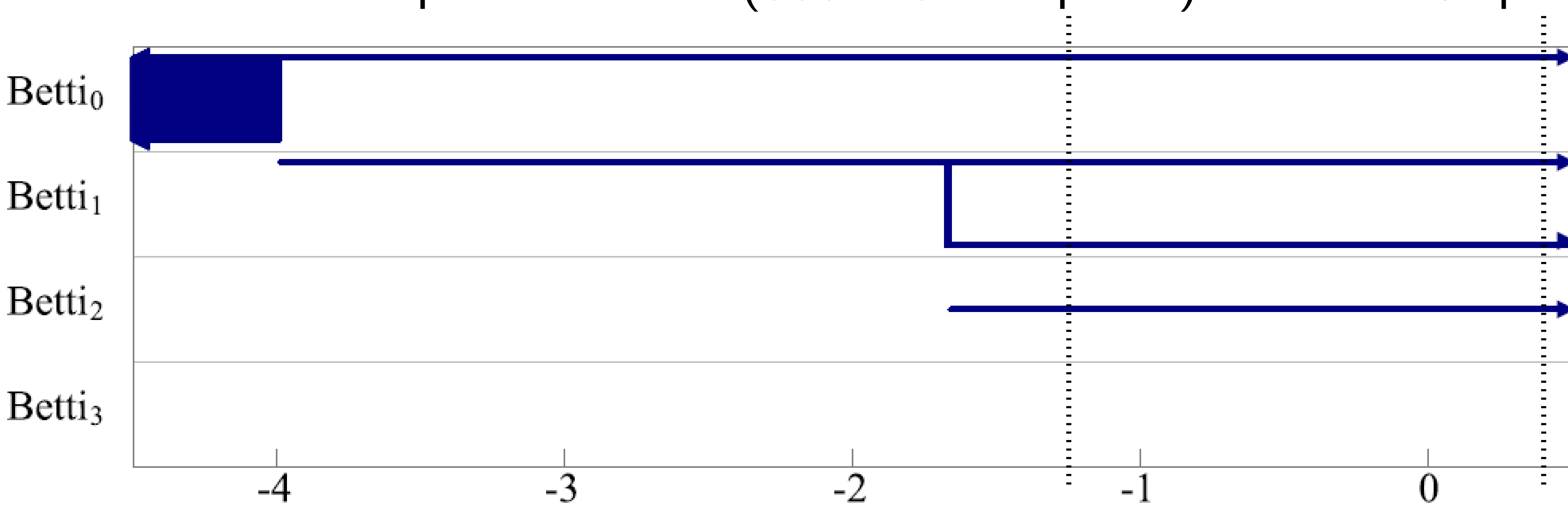
Example (manufactured data)



$n = 2000$ data points
ambient dimension $d = 4$
intrinsic dimension $k = 1, 2, 3$

computation limit $(500 \cdot 10^6$ simplices)

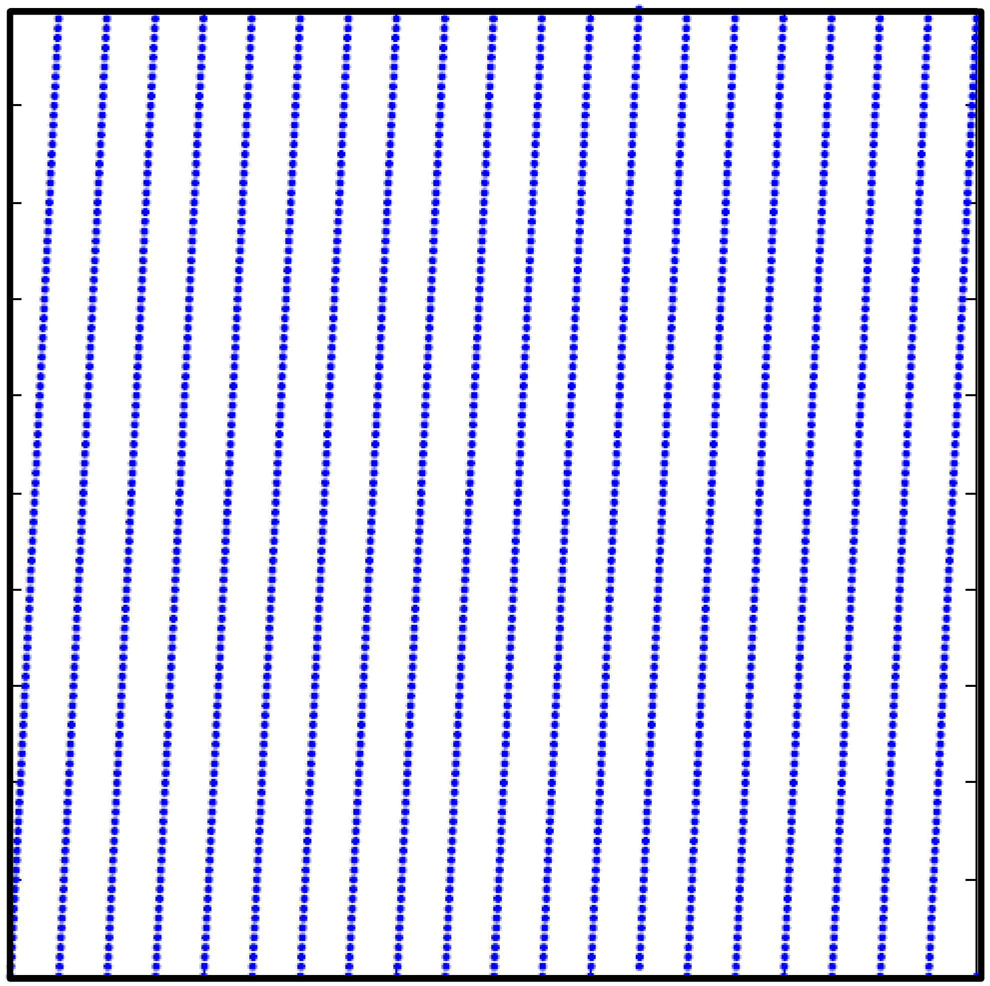
3-sphere $(37 \cdot 10^9$ simplices)



Vietoris-Rips filtration

size $\sim 2^n \mid n^{d+1}$

Example (manufactured data)

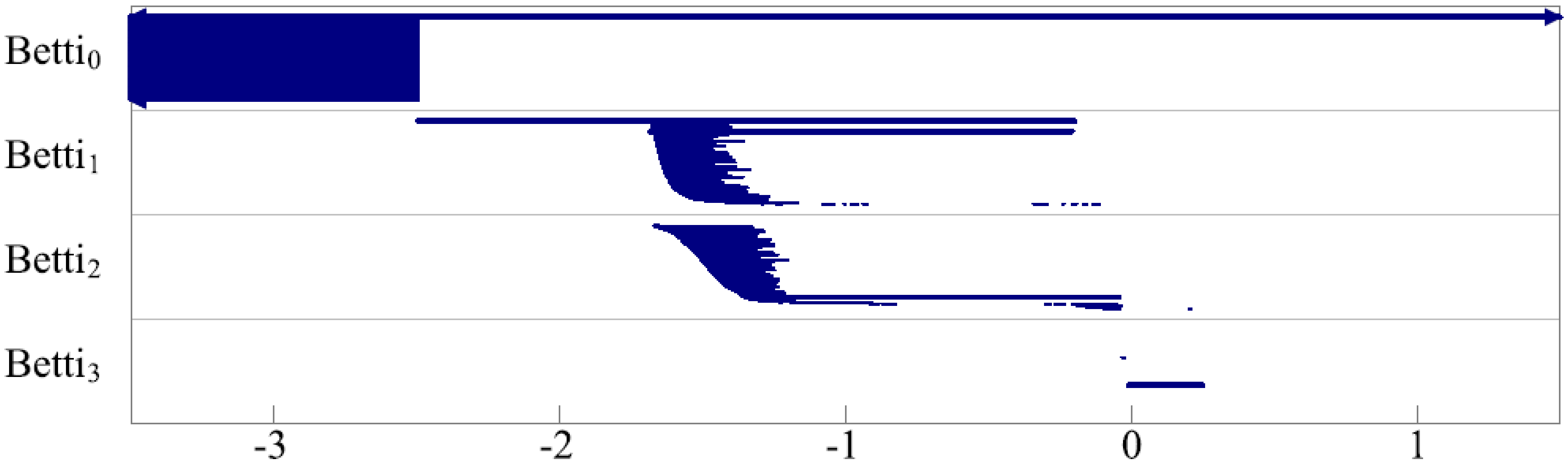


$n = 2000$ data points

ambient dimension $d = 4$

intrinsic dimension $k = 1, 2, 3$

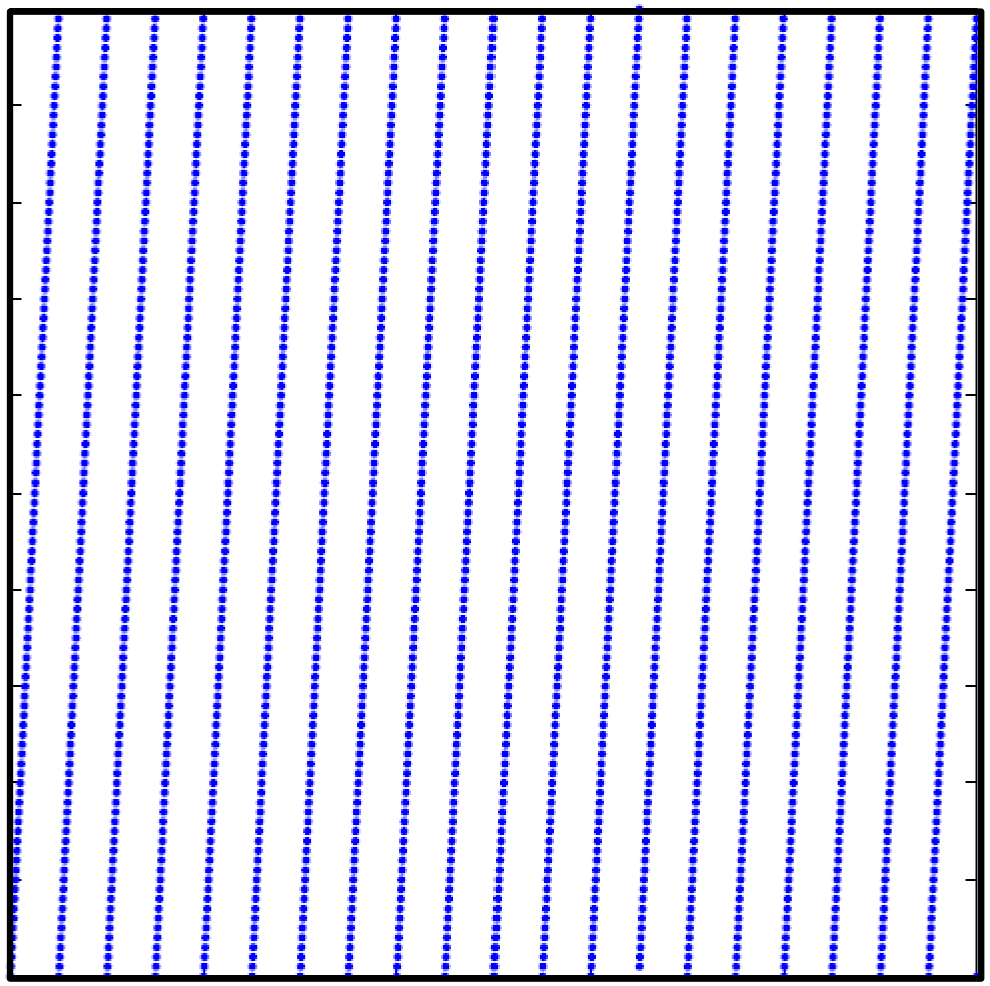
$(12 \cdot 10^6$ simplices$)$



mesh-based filtration

size $\sim 2^{d^2} n$

Example (manufactured data)

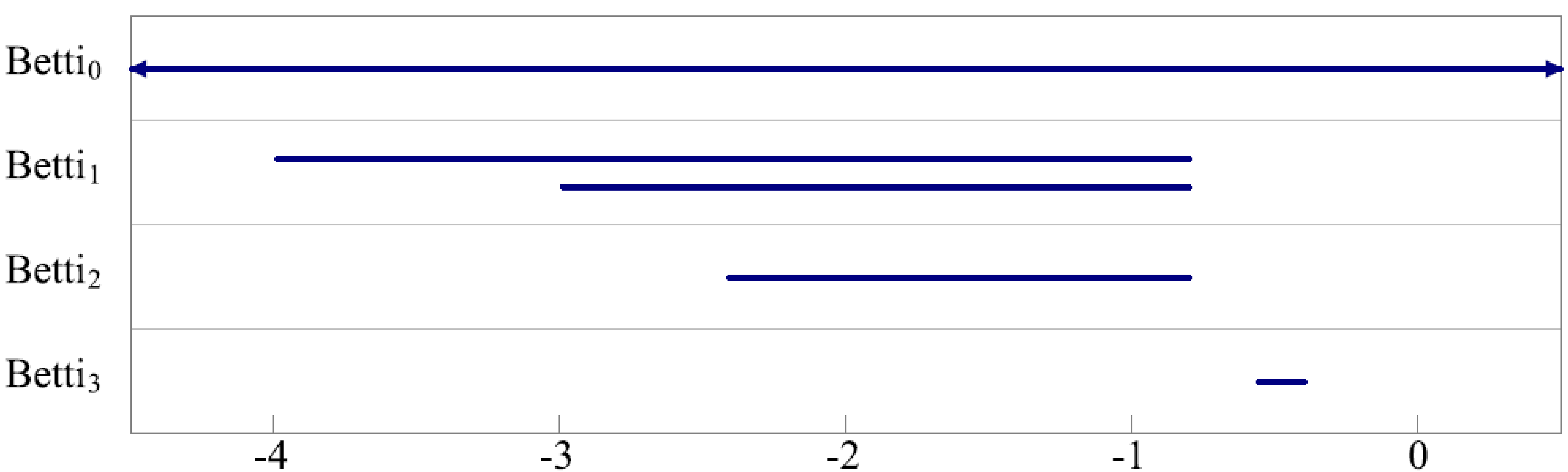


$n = 2000$ data points

ambient dimension $d = 4$

intrinsic dimension $k = 1, 2, 3$

$(200 \cdot 10^3$ simplices)

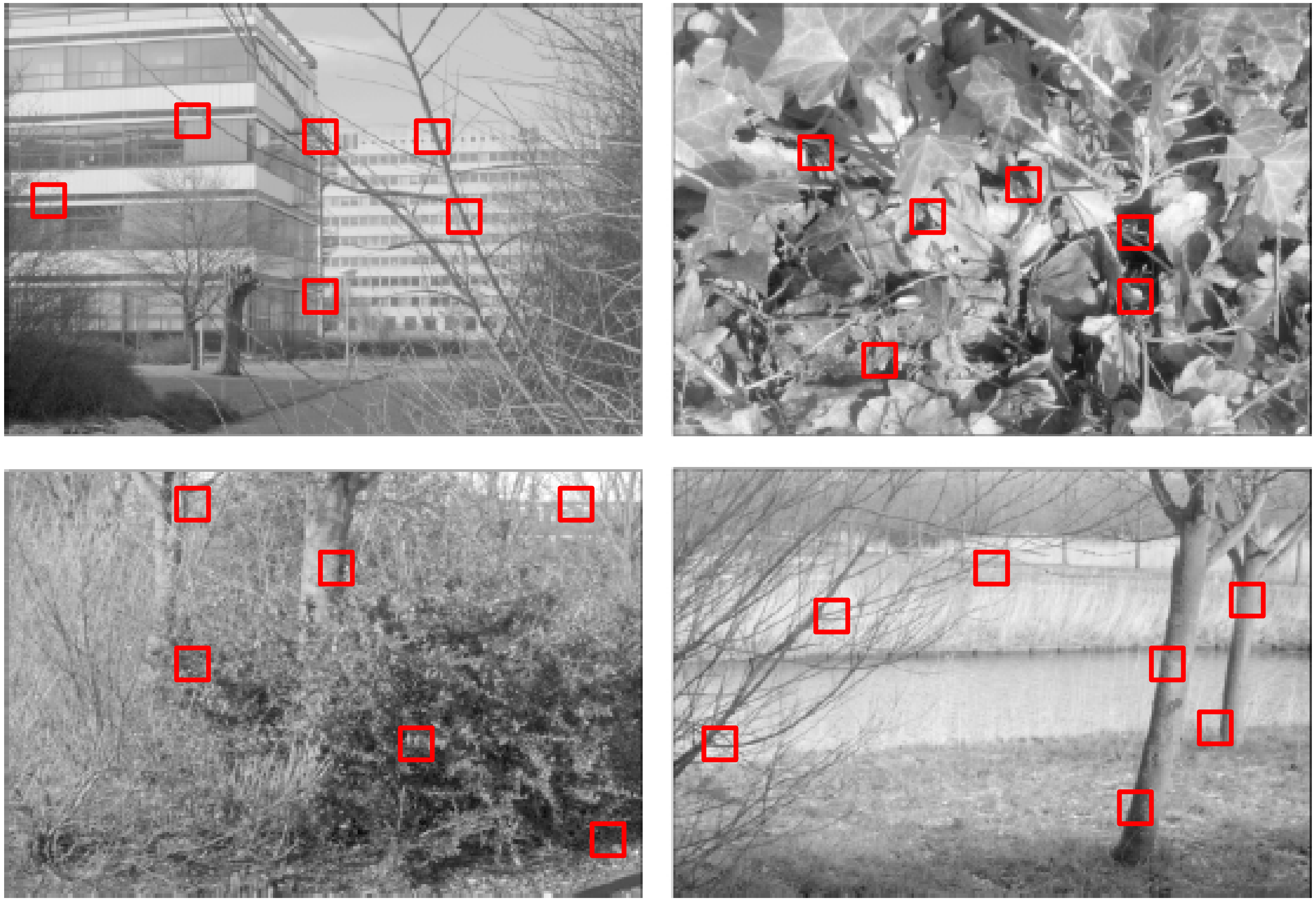


sparse Rips filtration

size $\sim 2^{k^2} n$

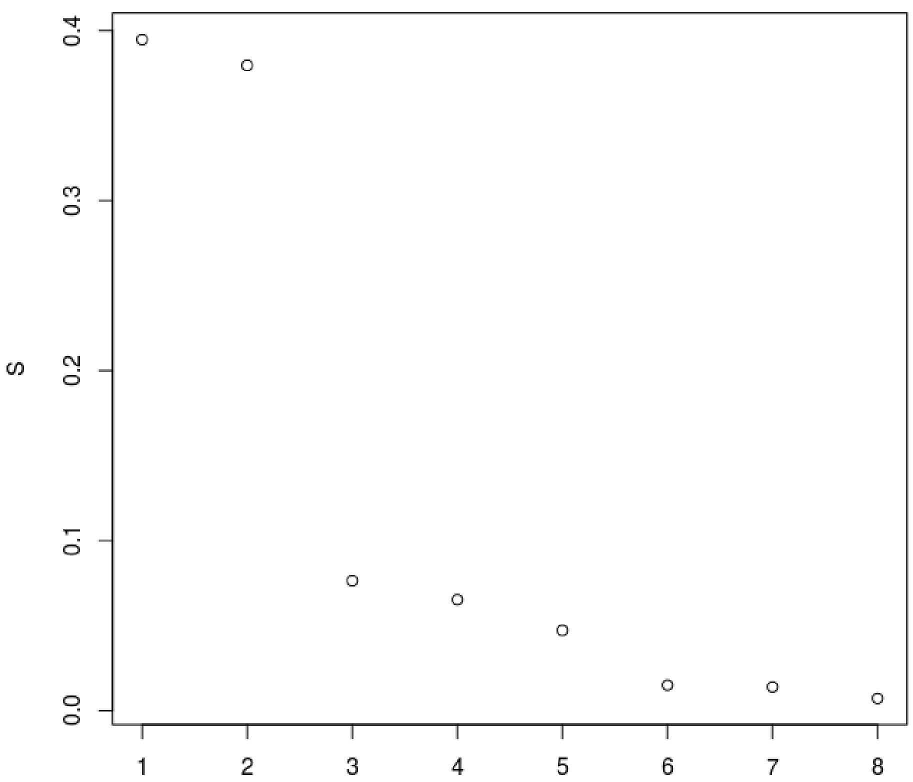
Natural Images Data

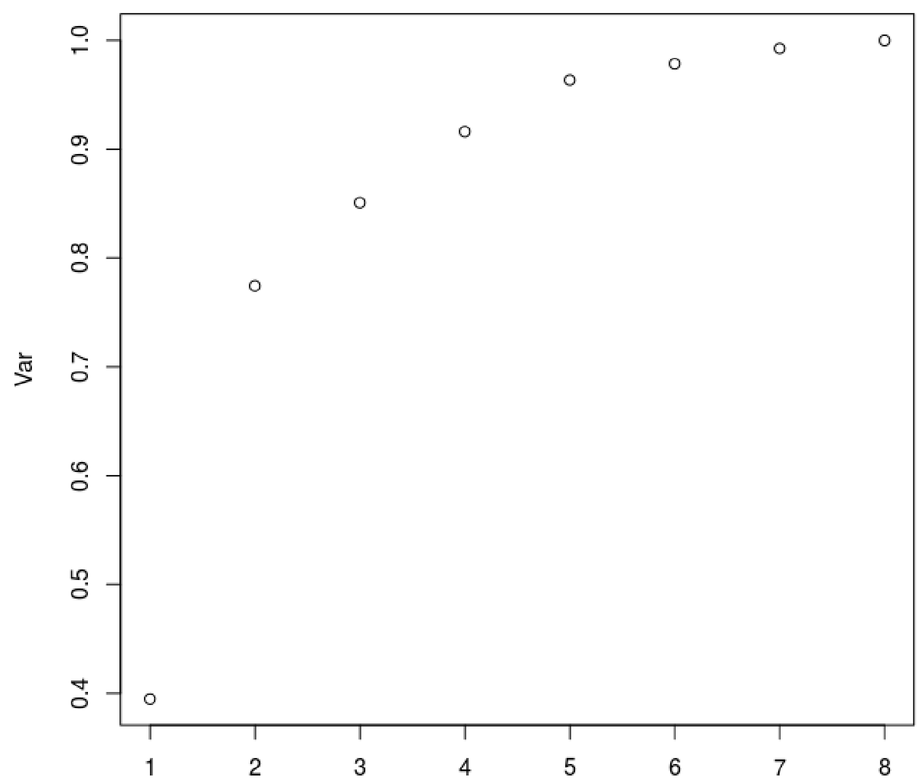
Input: 4 million data points on $\mathbb{S}^7$, coming from high-contrast 3×3 image patches

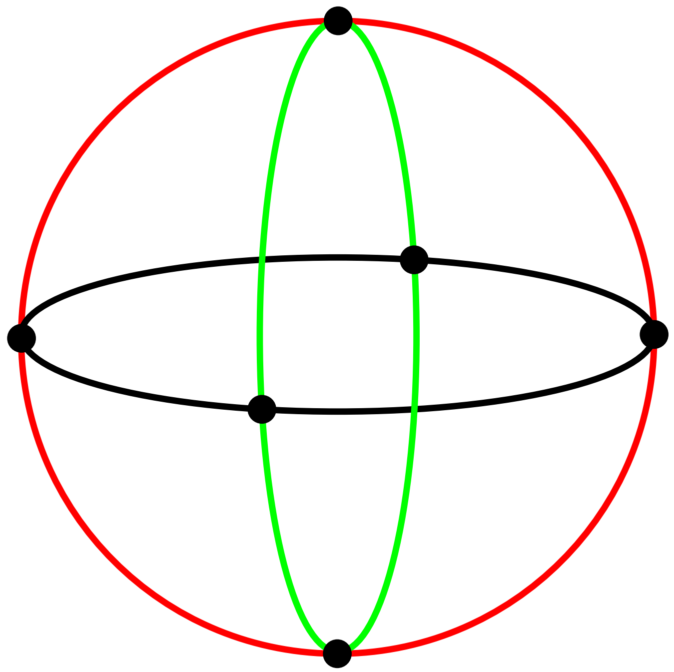


(source: [Lee, Pederson, Mumford 03])

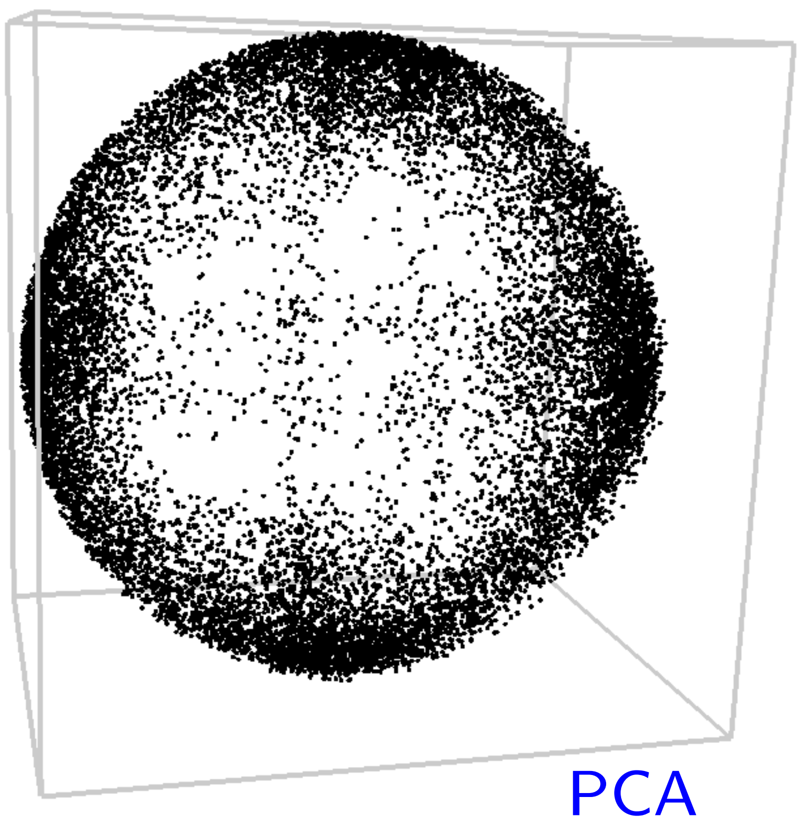
Natural Images Data



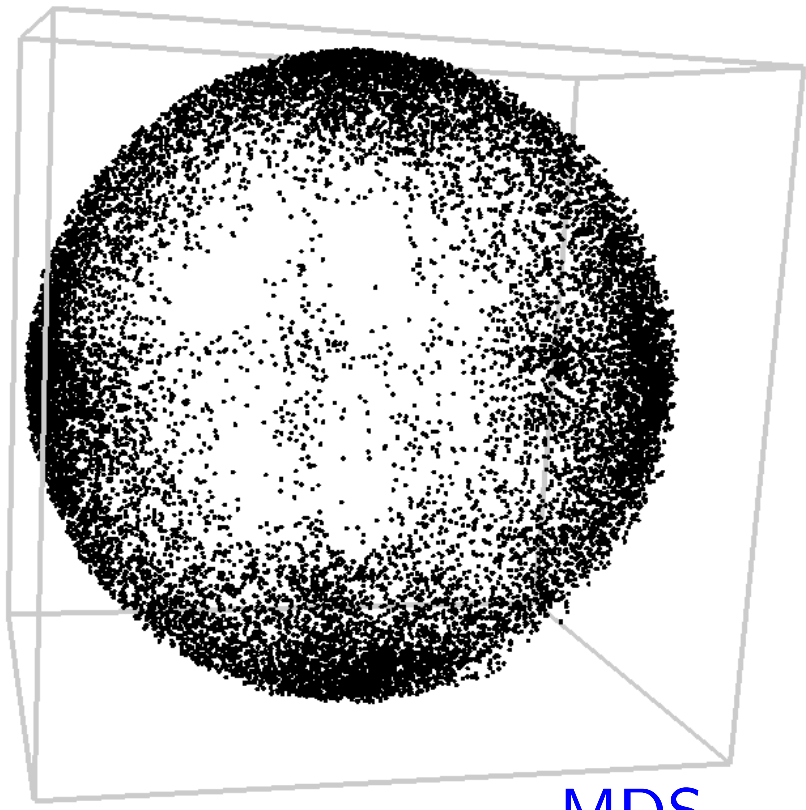




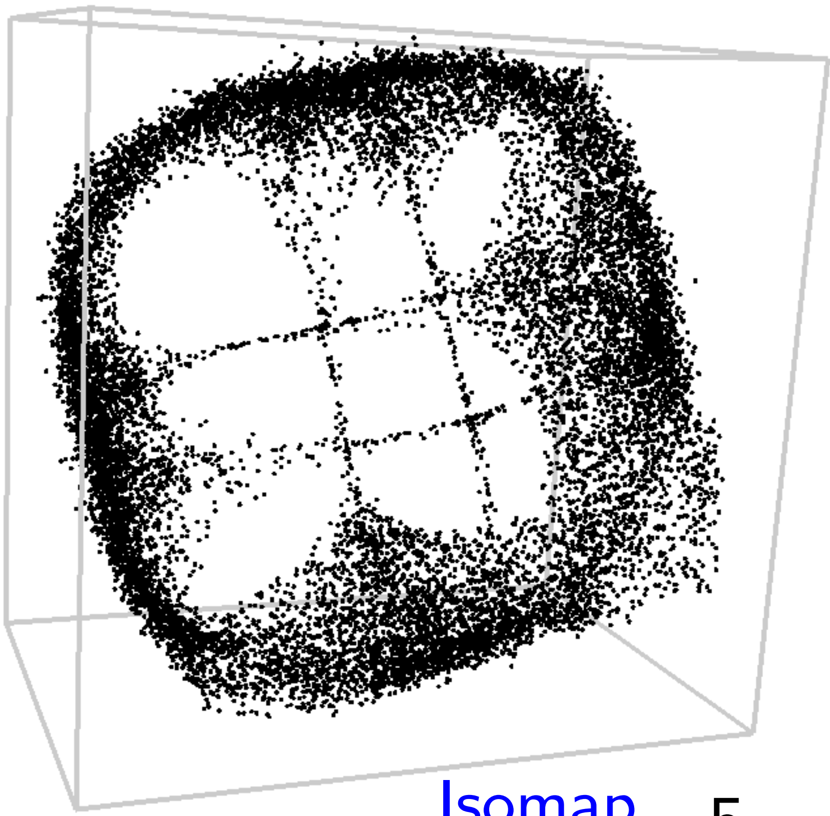
$(\beta_1 = 7)$



PCA



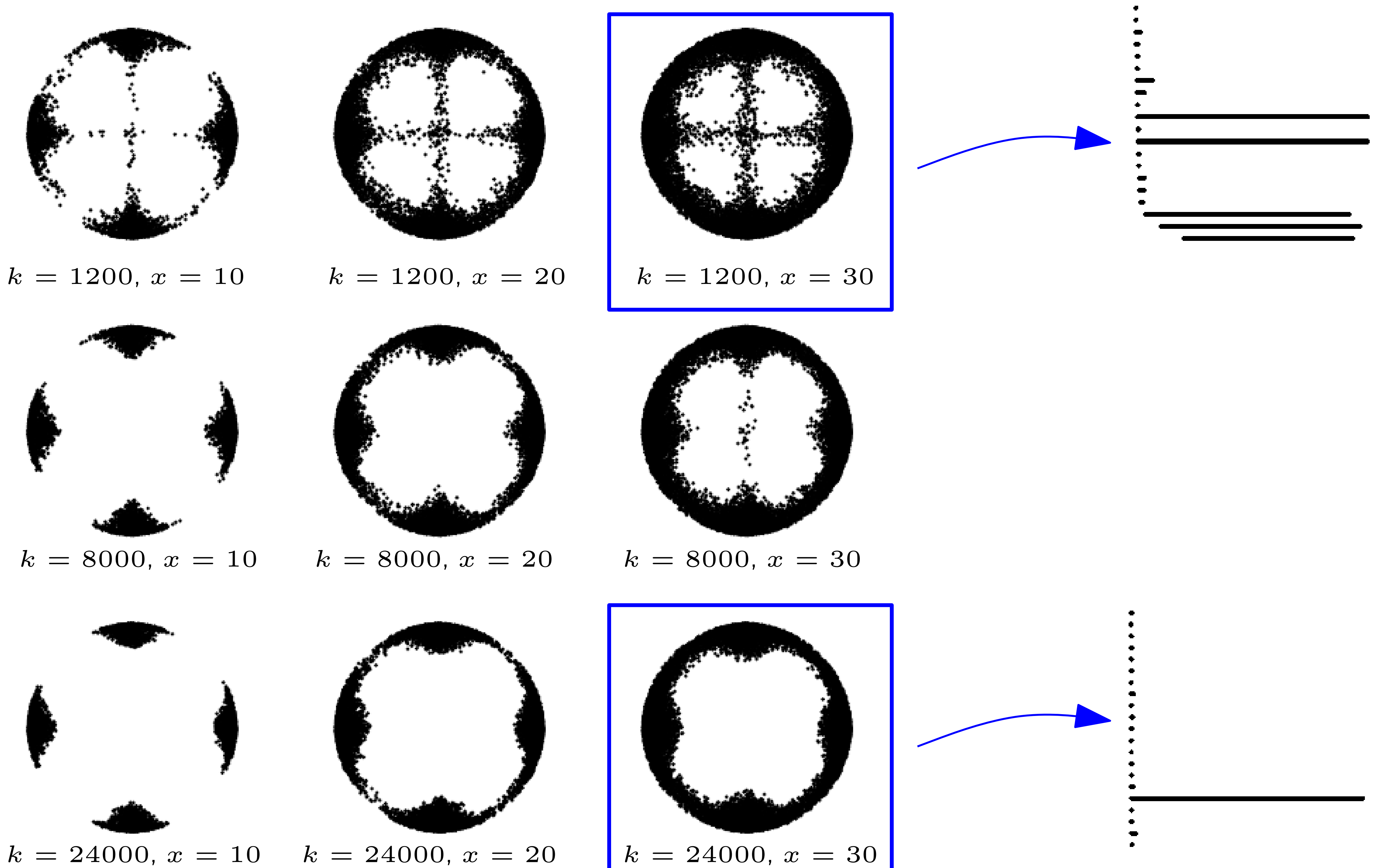
MDS



Isomap

Natural Images Data

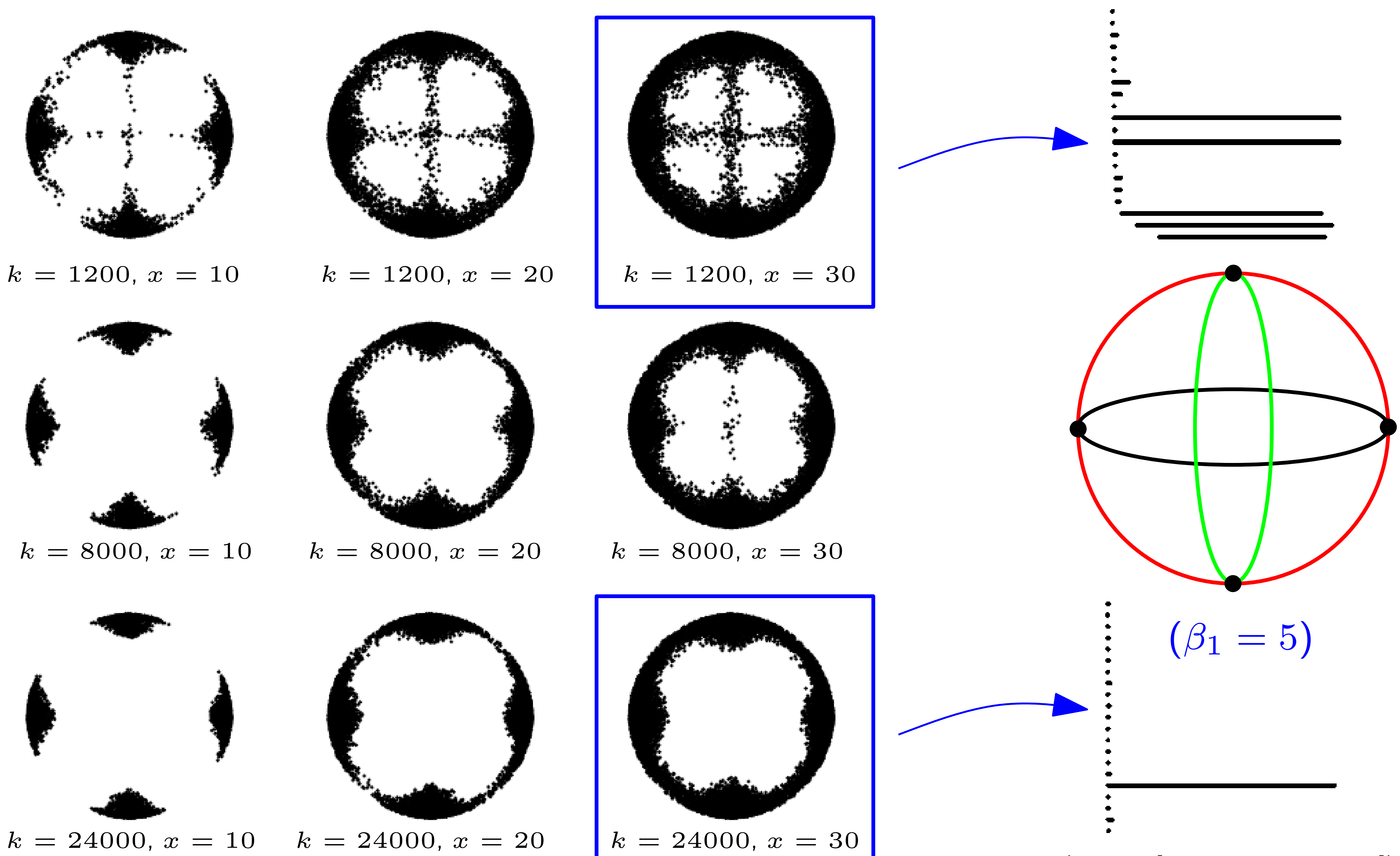
Preprocessing: - select bottom $x\%$ of data points according to k-NN distance
- sample 5000 points uniformly at random from filtered point set



(source: [de Silva, Carlsson 04])

Natural Images Data

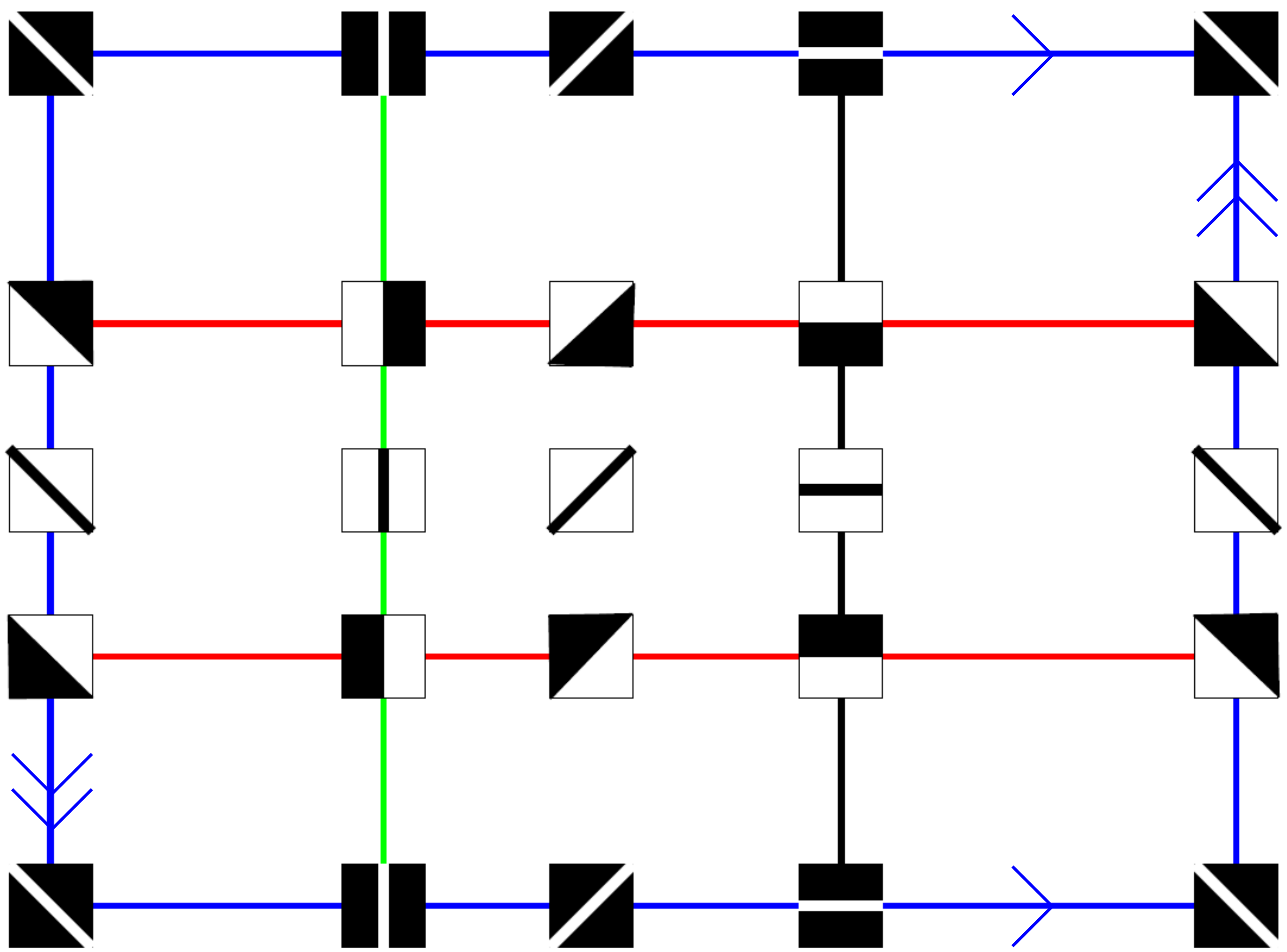
Preprocessing: - select bottom $x\%$ of data points according to k-NN distance
- sample 5000 points uniformly at random from filtered point set

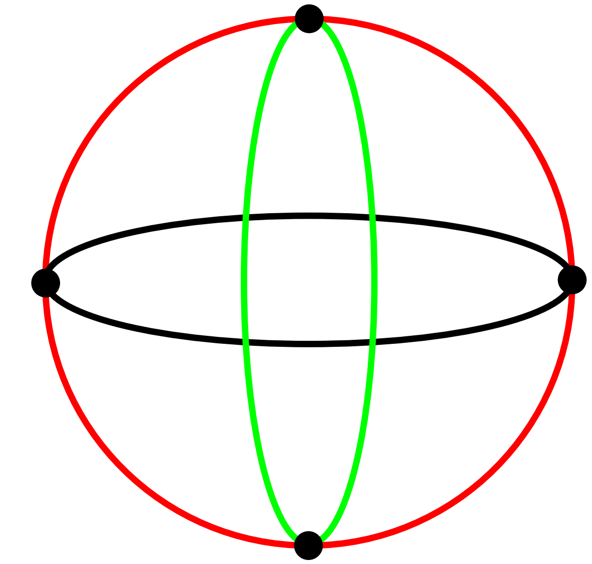


(source: [de Silva, Carlsson 04])

Natural Images Data

Preprocessing: - select bottom $x\%$ of data points according to k-NN distance
- sample 5000 points uniformly at random from filtered point set



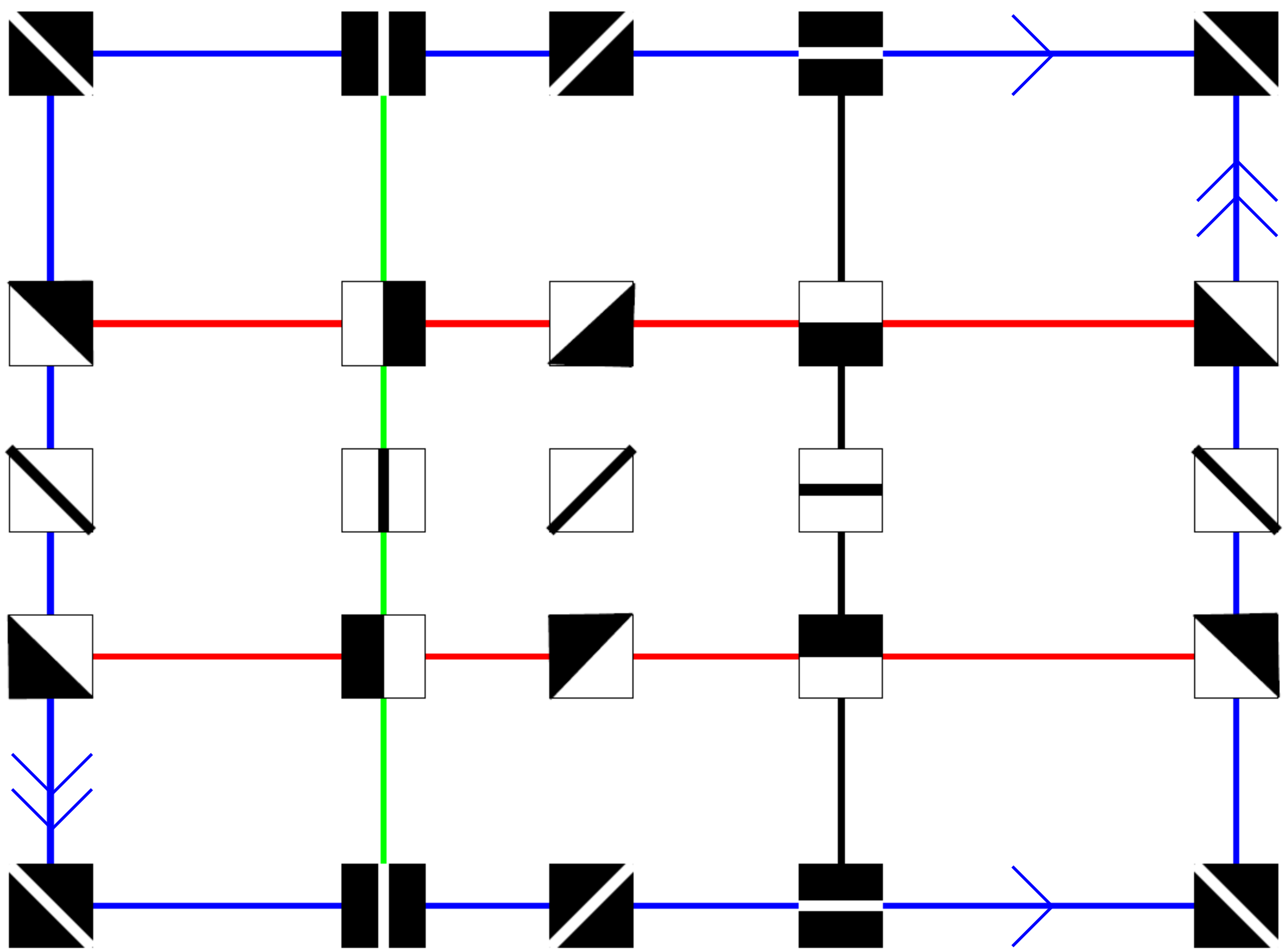


$(\beta_1 = 5)$

(source: [Carlsson, Ishkhanov, de Silva, Zomorodian 2008])

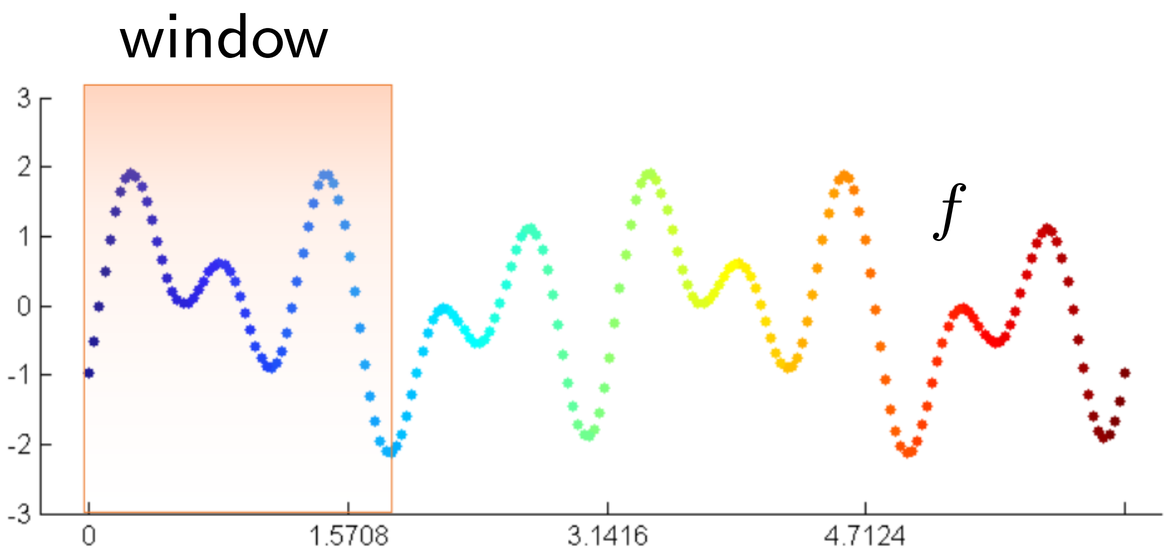
Natural Images Data

Preprocessing: - select bottom $x\%$ of data points according to k-NN distance
- sample 5000 points uniformly at random from filtered point set



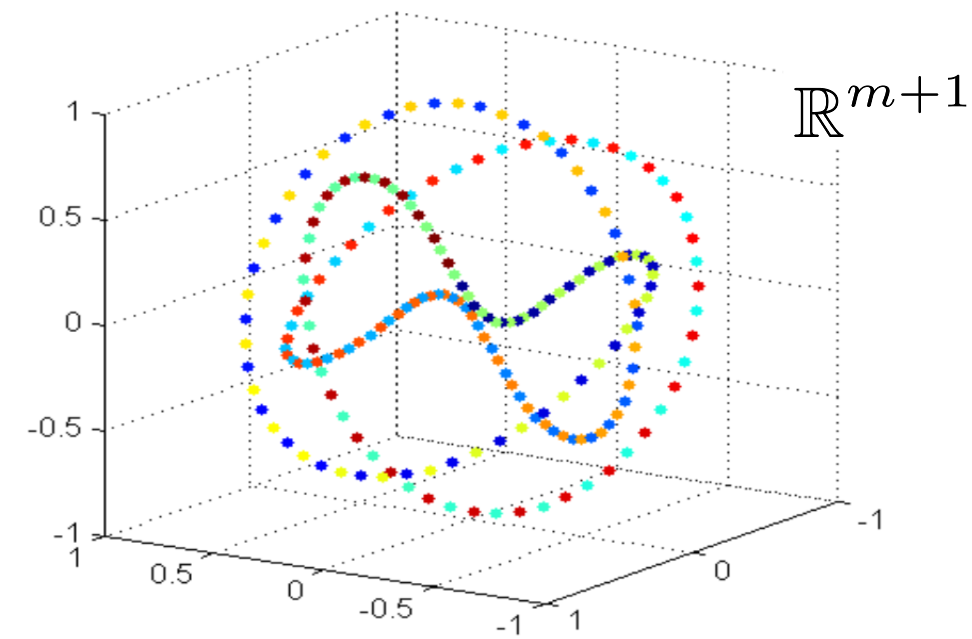
(source: [Carlsson, Ishkhanov, de Silva, Zomorodian 2008])

TDA for time series modeling & analysis



$$\mathrm{TD}_{m,\tau} \Longrightarrow$$

(time-delay embedding)



$f : \mathbb{N} \to \mathbb{R}$

$$\mathrm{TD}_{m,\tau}(f) := \begin{bmatrix} f(t) \\ f(t+\tau) \\ \vdots \\ f(t+m\tau) \end{bmatrix}$$

τ: step / delay

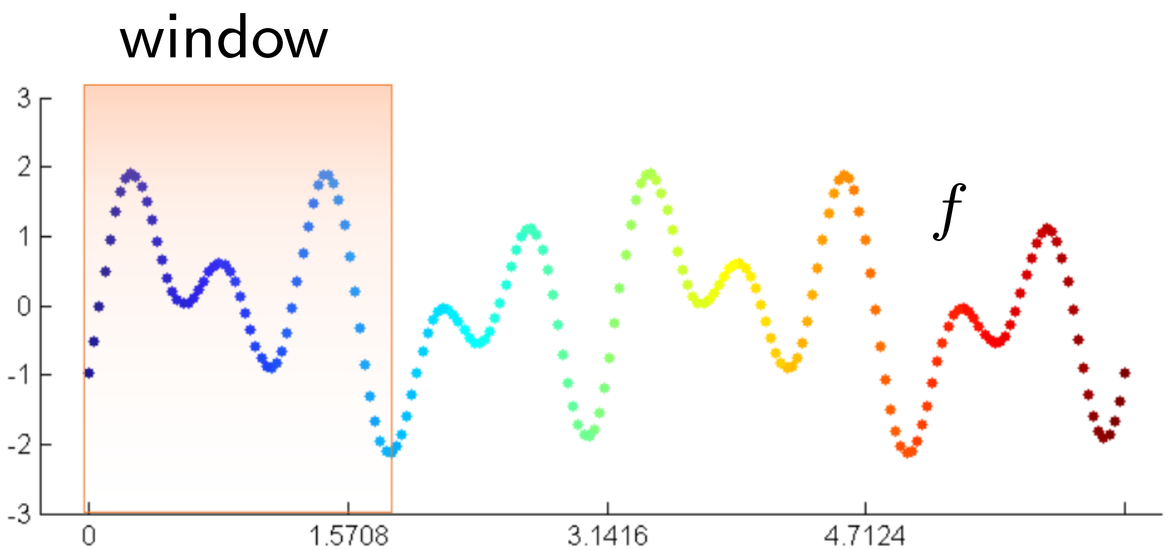
$m\tau$: window size

$m+1$: embedding dimension

signal	**embedded data**
periodicity	circularity
# prominent harmonics (N)	min. ambient dimension ($m \geq 2N$)
# non-commensurate freq.	intrinsic dimension ($\mathbb{S}^1 \times \cdots \times \mathbb{S}^1$)

[J. Perea et al.:"SW1PerS: Sliding windows and 1-persistence scoring", 2015]

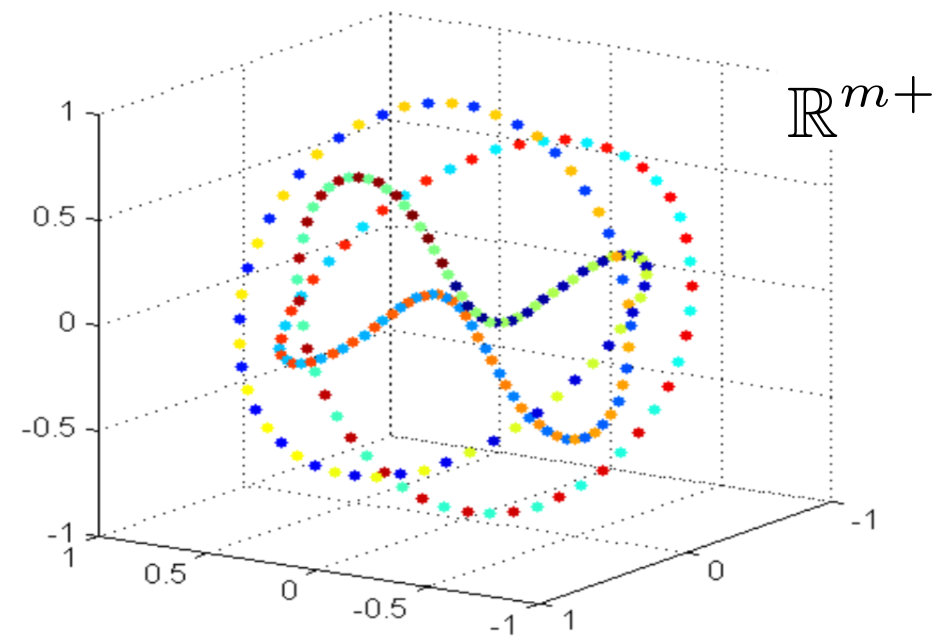
TDA for time series modeling & analysis



$\mathrm{TD}_{m,\tau}$

$\Longrightarrow$

(time-delay embedding)



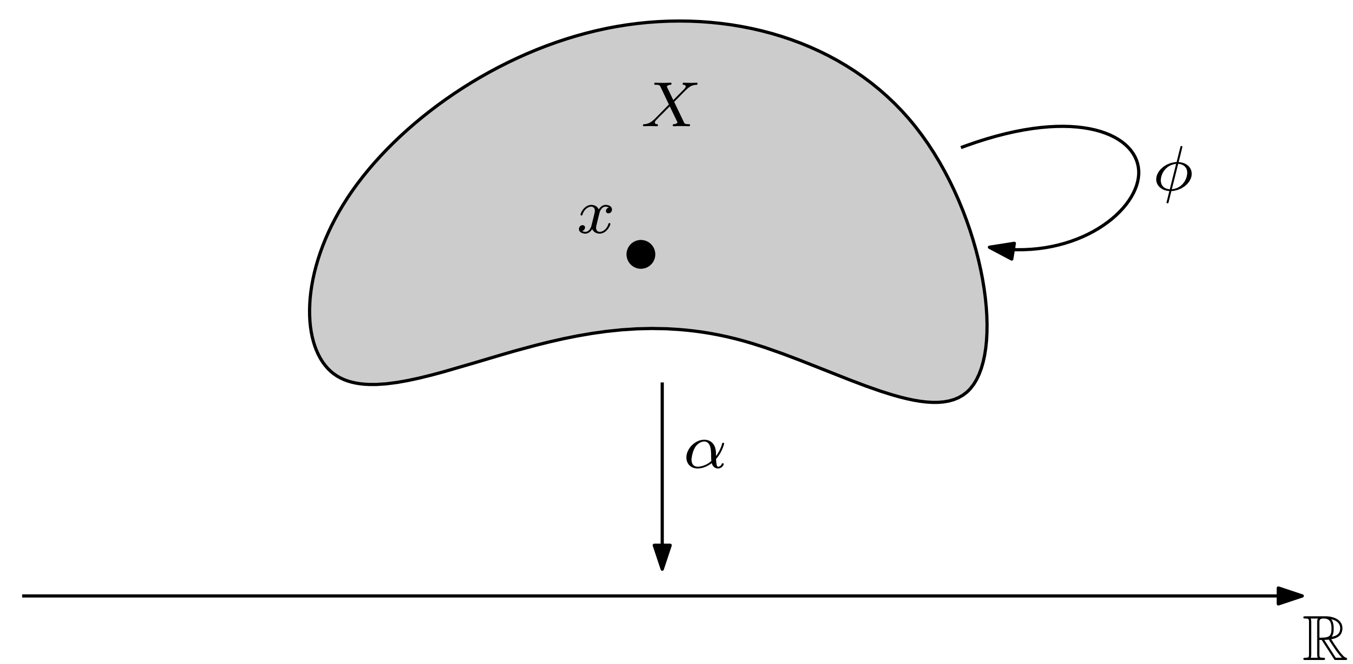
Contributions of TDA:

inference of:

- periodicity
- harmonics
- non-commensurate freq.
- underlying state space

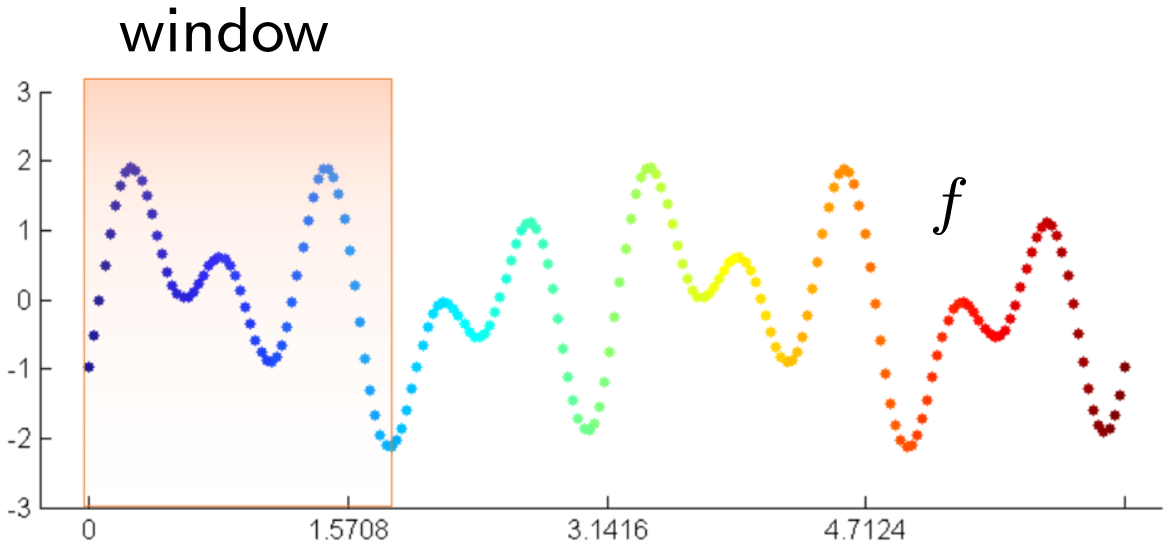
no Fourier transform needed

Dynamical system:



$$f_x(n) := \alpha(\phi^n(x))$$

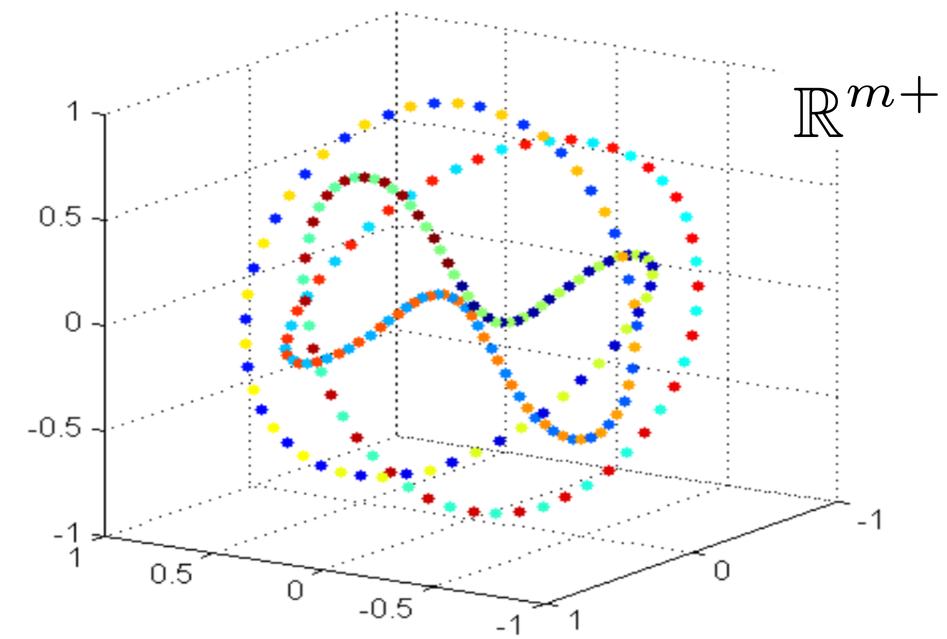
TDA for time series modeling & analysis



$\mathrm{TD}_{m,\tau}$

$\Longrightarrow$

(time-delay embedding)



Contributions of TDA:

inference of:

- periodicity
- harmonics
- non-commensurate freq.
- underlying state space

no Fourier transform needed

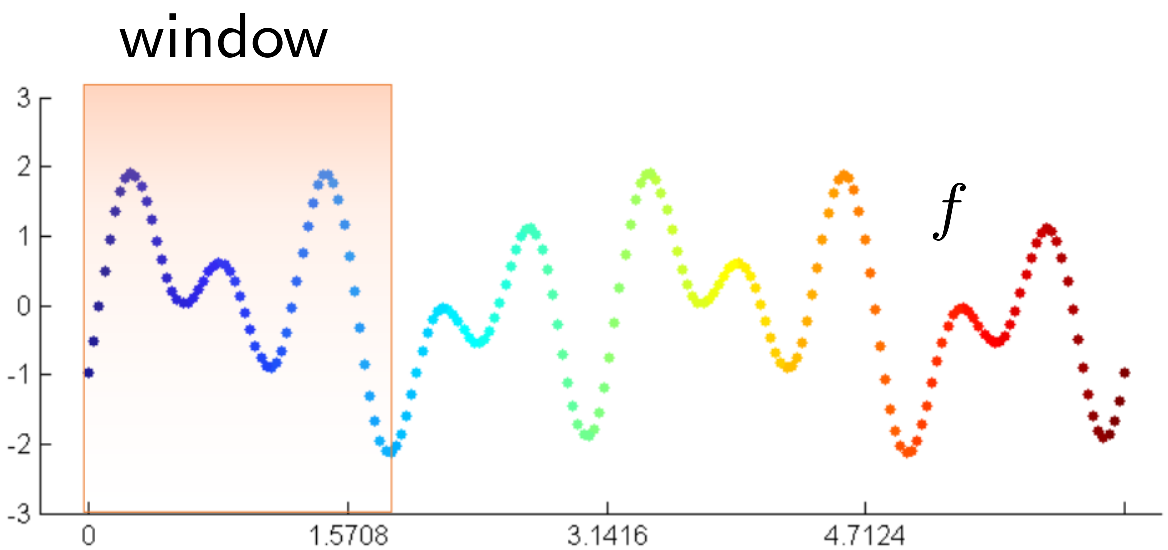
Dynamical system:

Thm: [Nash, Takens]
Given a Riemannian manifold X of dimension $\frac{m}{2}$, it is a **generic property** of $\phi \in \mathrm{Diff}_2(X)$ and $\alpha \in C^2(X, \mathbb{R})$ that

$$X \to \mathbb{R}^{m+1}$$
$$x \mapsto (\alpha(x), \alpha \circ \phi(x), \cdots, \alpha \circ \phi^m(x))$$

is an embedding.

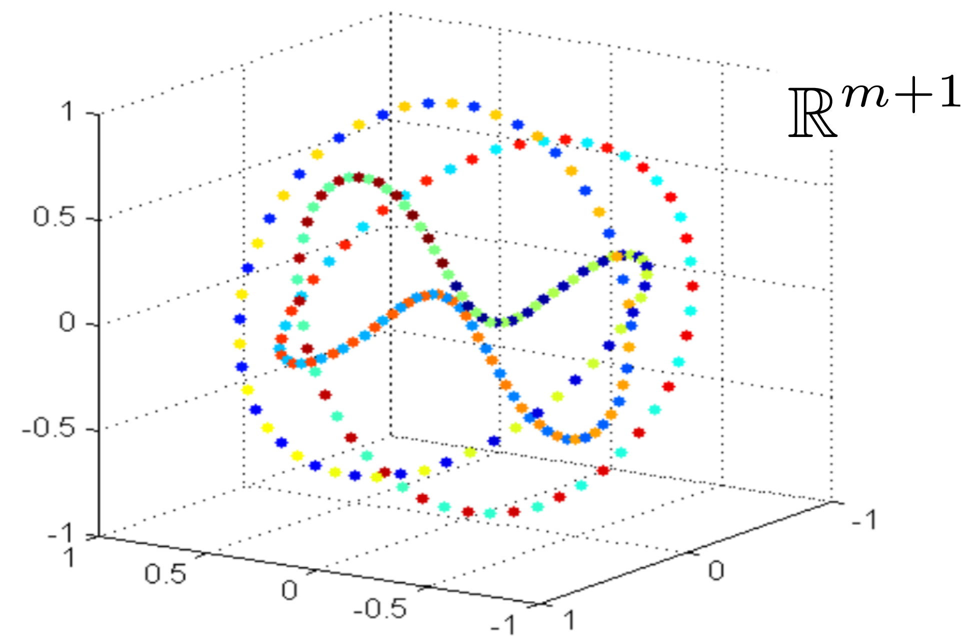
TDA for time series modeling & analysis



$\mathrm{TD}_{m,\tau}$

$\Longrightarrow$

(time-delay embedding)



method / dataset	Gyro sensor	EEG dataset	EMG dataset
SVM + statistical features	67.6 ± 4.7	44.4 ± 19.8	15.0 ± 10.0
SVM + Betti sequence	63.5 ± 11.3	66.7 ± 5.6	49.6 ± 18.2
1-d CNN + dynamic time warping	6.4 ± 5.1	72.4 ± 6.1	15.0 ± 10.0
imaging CNN	18.9 ± 5.2	48.9 ± 4.2	10.0 ± 0.0
1-d CNN + Betti sequence	$\mathbf{79.8} \pm 5.0$	$\mathbf{75.38} \pm 5.7$	$\mathbf{74.4} \pm 10.6$

[Y. Umeda:"Time Series Classification via Topological Data Analysis", 2017]