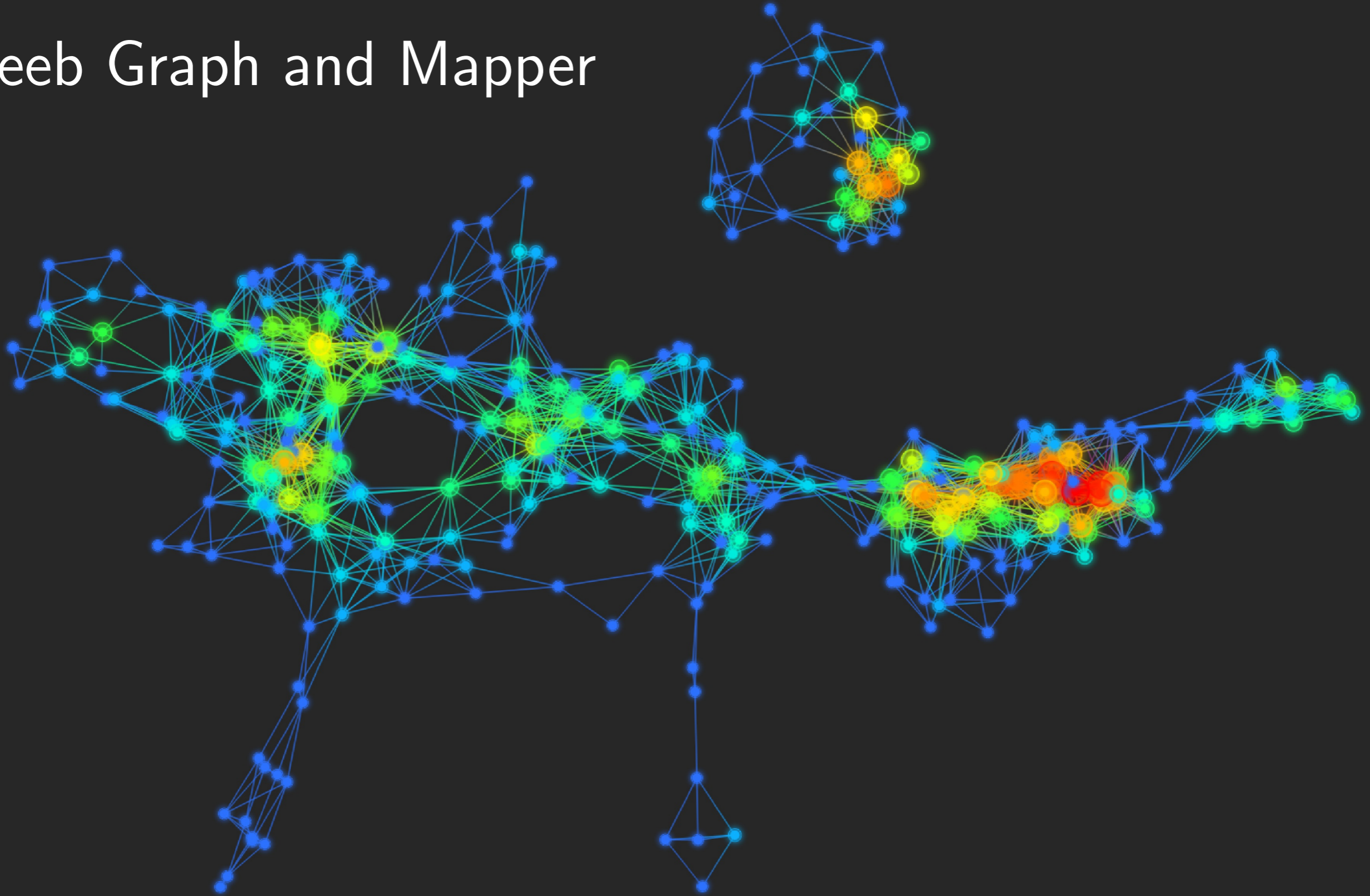


Reeb Graph and Mapper



Motivations

get a higher-level understanding of the structure of data

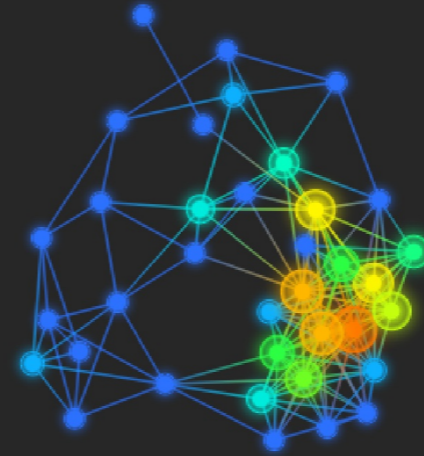
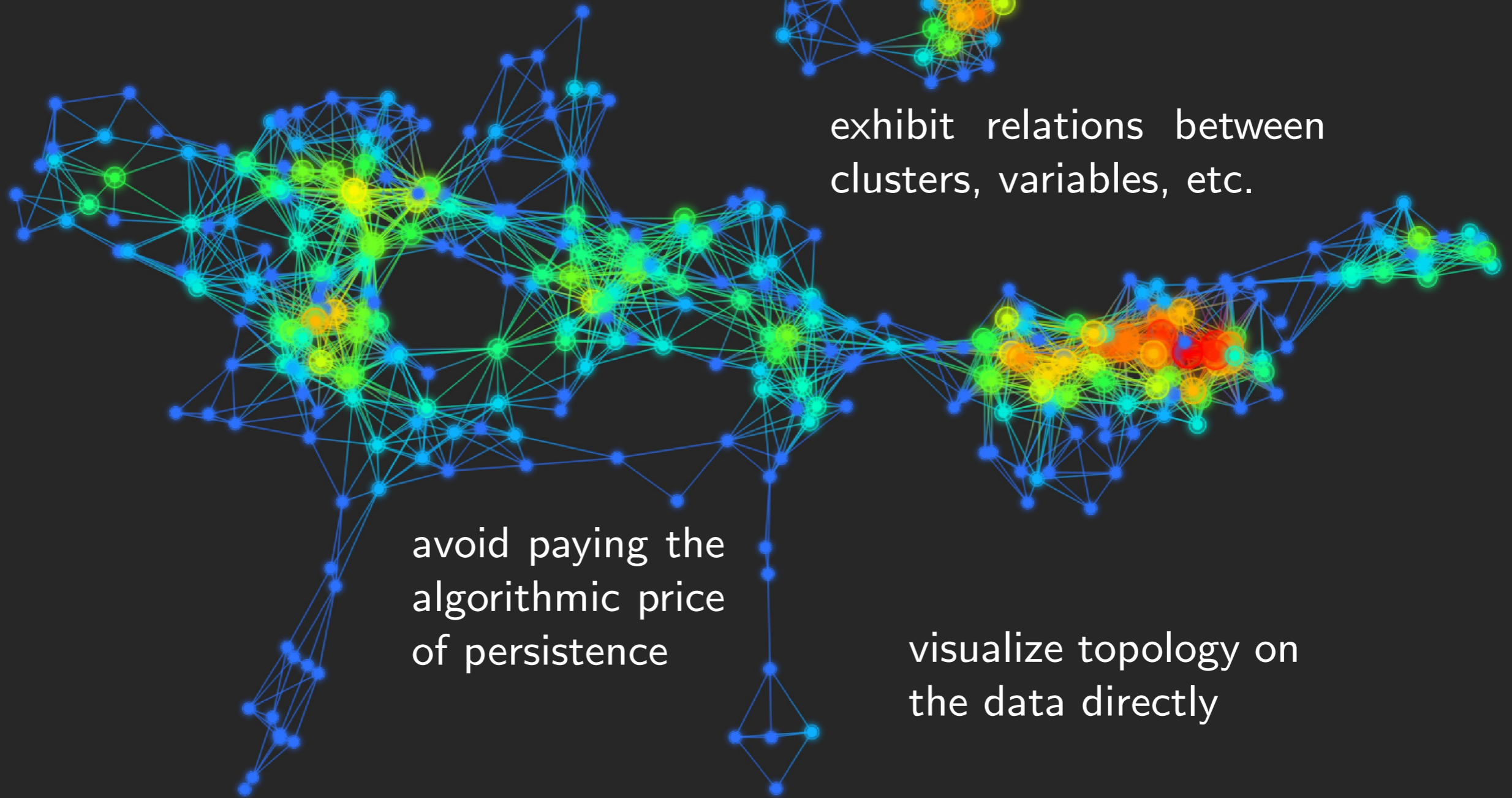


exhibit relations between clusters, variables, etc.



avoid paying the algorithmic price of persistence

visualize topology on the data directly

Motivations

get a higher-level understanding of the structure of data

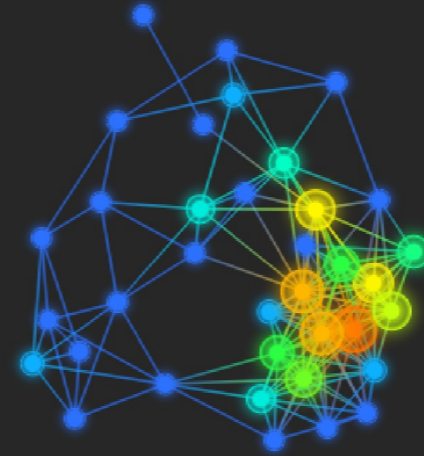
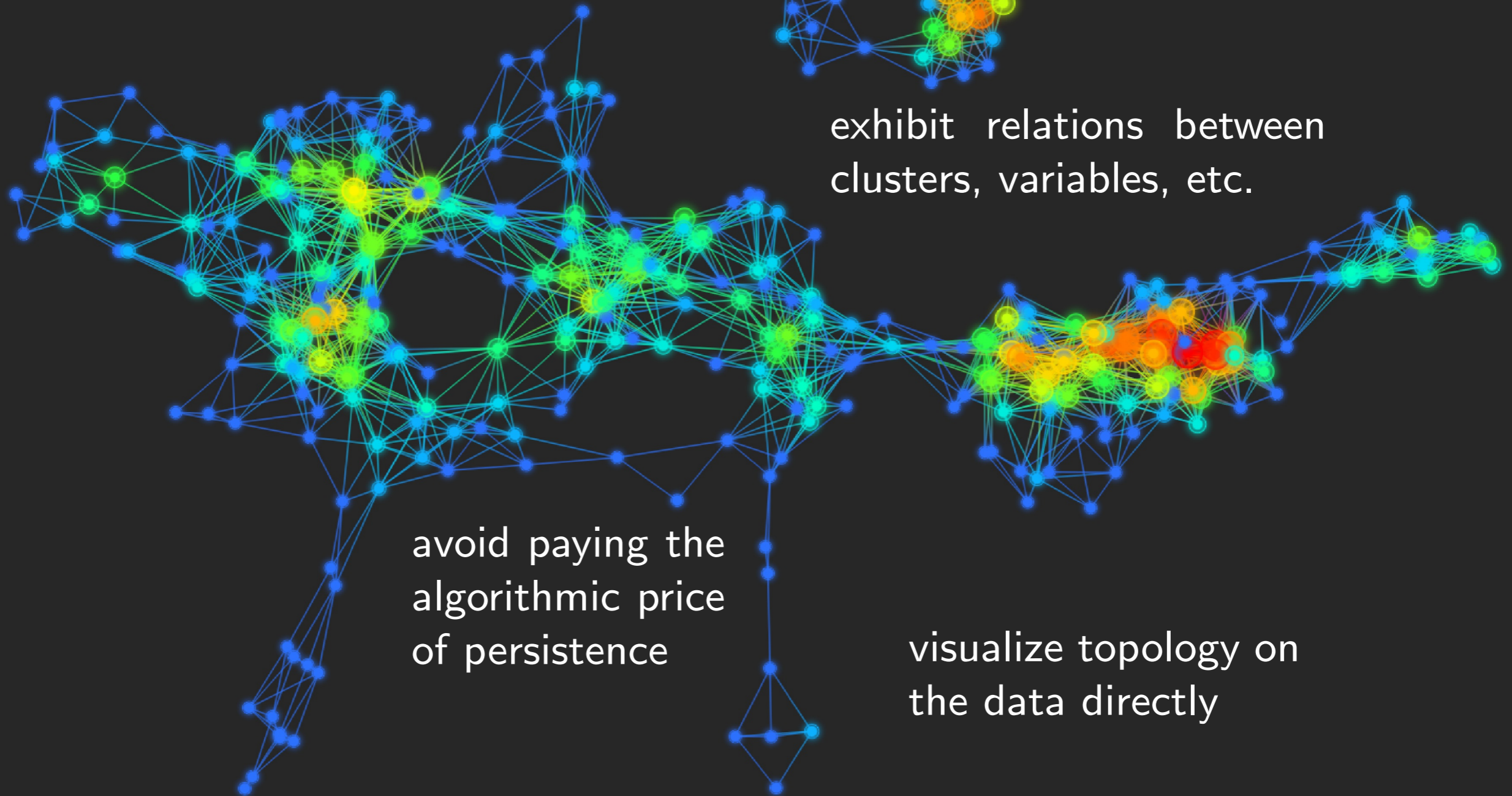


exhibit relations between clusters, variables, etc.



avoid paying the algorithmic price of persistence

visualize topology on the data directly

principle: summarize the topological structure of a map $f : X \rightarrow \mathbb{R}$ through a graph

Mapper in the continuous setting

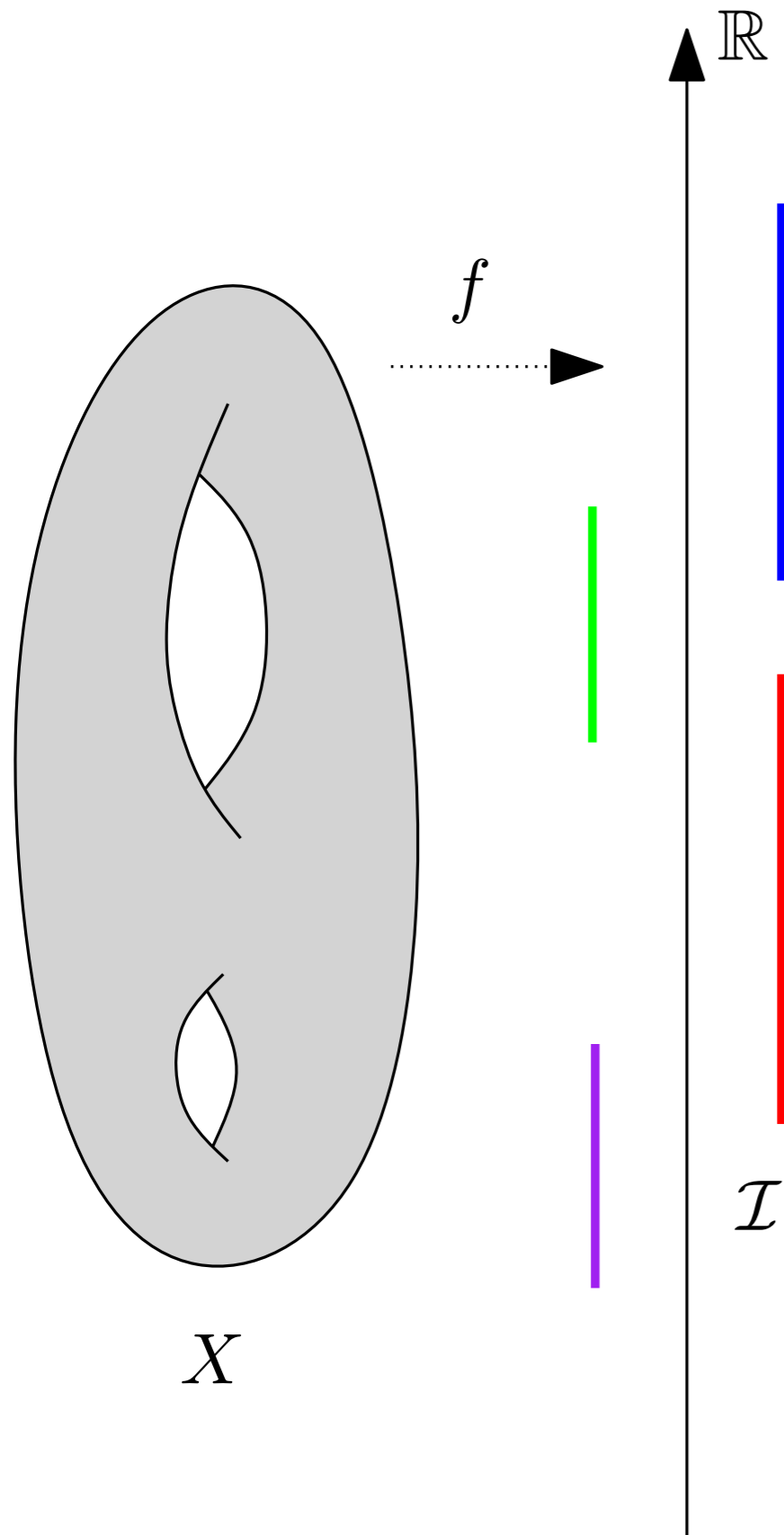
Input:

- continuous function ('filter', 'lens'...) $f : X \rightarrow \mathbb{R}$
- cover \mathcal{I} of $\text{im}(f)$ by open intervals: $\text{im} f \subseteq \bigcup_{I \in \mathcal{I}} I$

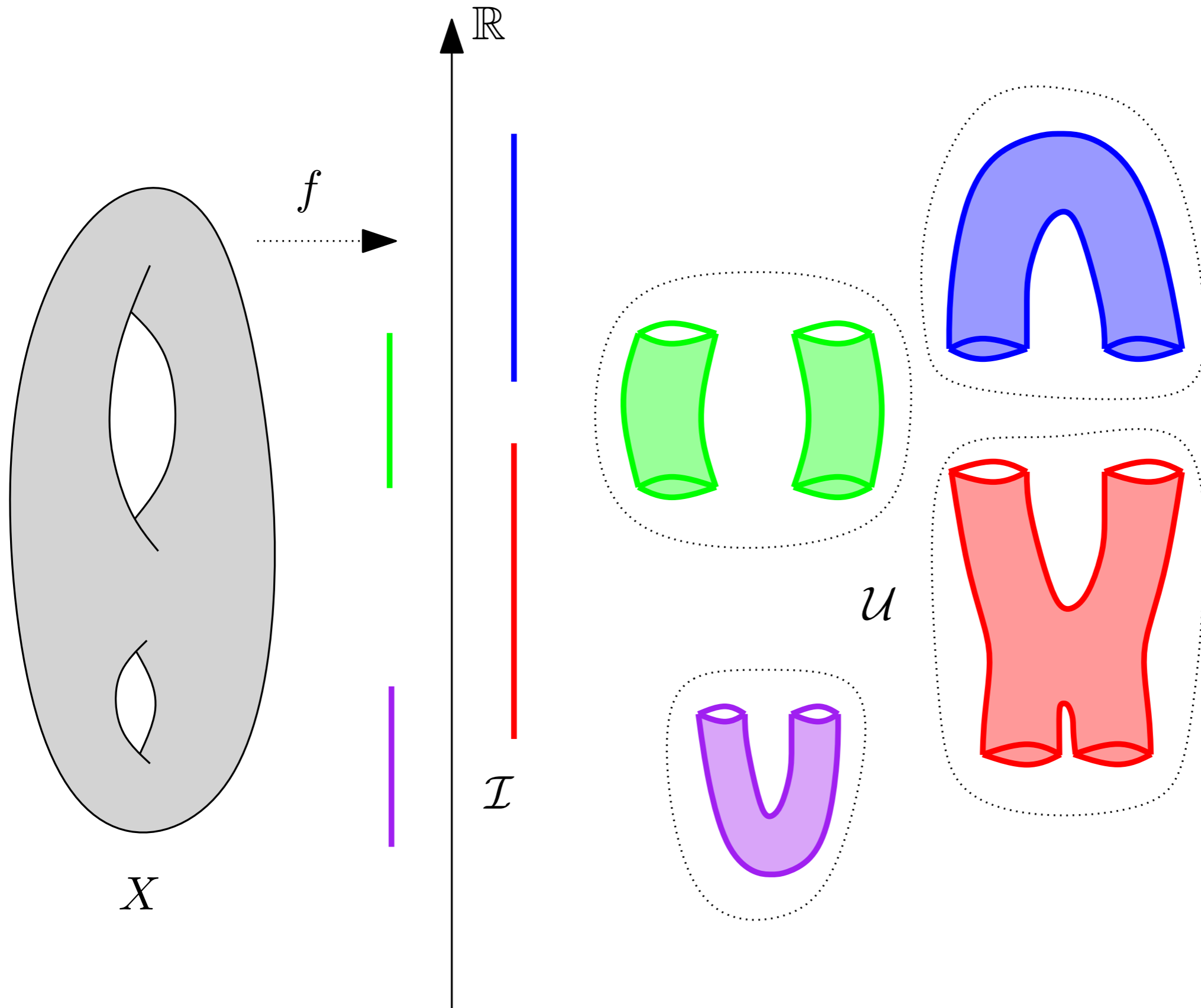
Method:

- Compute *pullback cover* \mathcal{U} of X : $\mathcal{U} = \{f^{-1}(I)\}_{I \in \mathcal{I}}$
- Refine \mathcal{U} by separating each of its elements into its various connected components \rightarrow connected cover \mathcal{V}
- The Mapper is the *nerve* of \mathcal{V} :
 - 1 vertex per element $V \in \mathcal{V}$
 - 1 edge per intersection $V \cap V' \neq \emptyset$, $V, V' \in \mathcal{V}$
 - 1 k -simplex per $(k + 1)$ -fold intersection $\bigcap_{i=0}^k V_i \neq \emptyset$, $V_0, \dots, V_k \in \mathcal{V}$

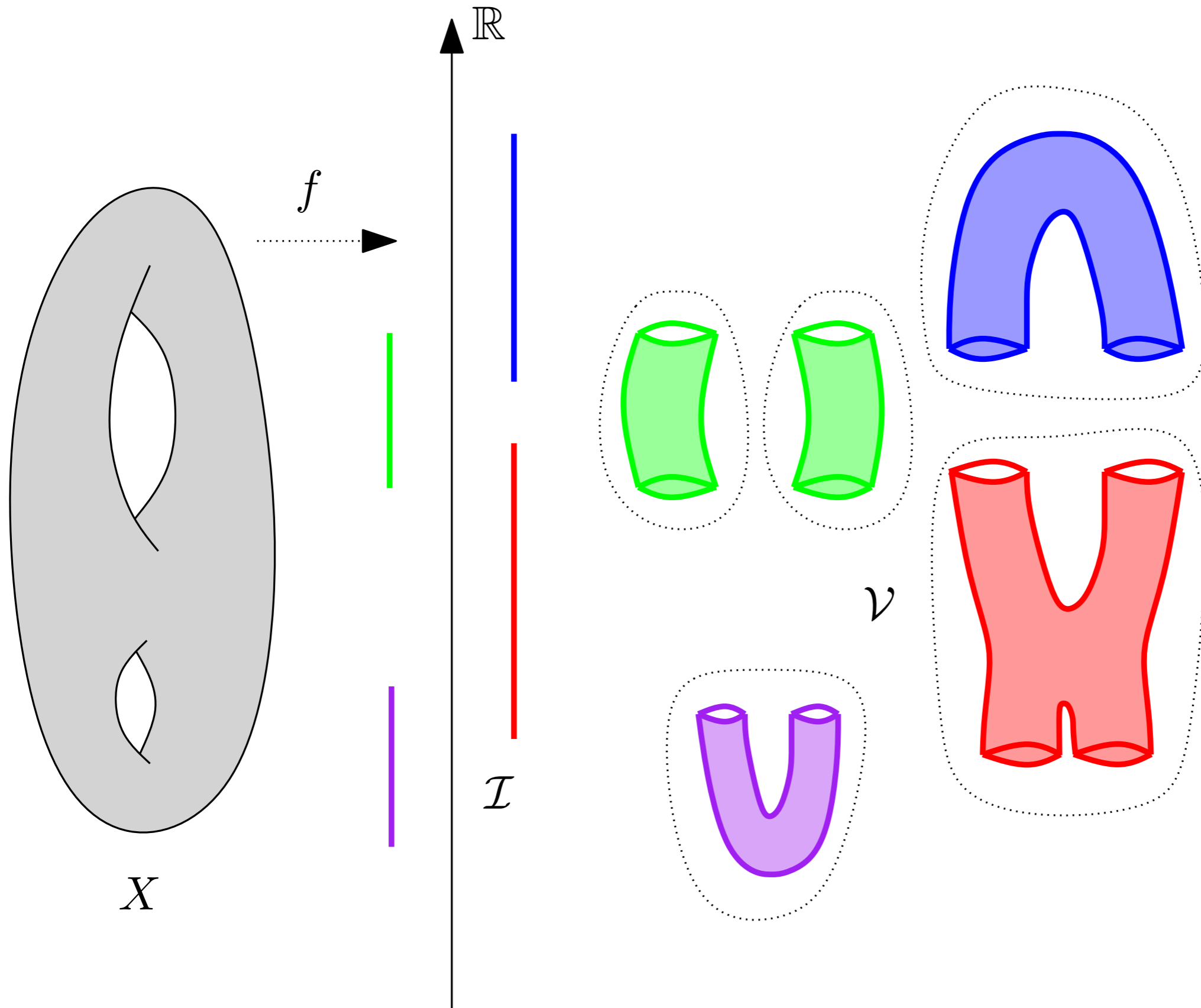
Mapper in the continuous setting



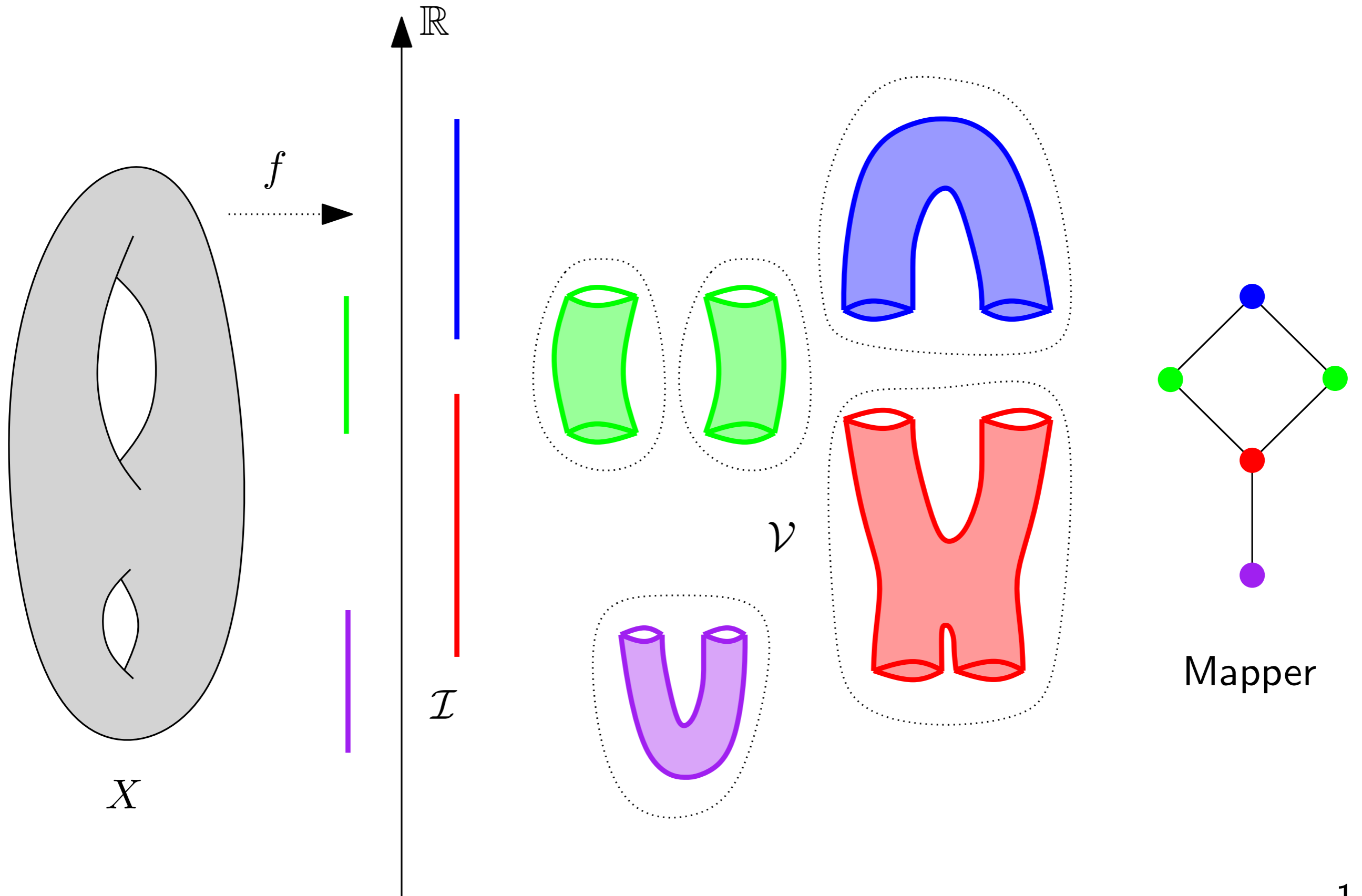
Mapper in the continuous setting



Mapper in the continuous setting



Mapper in the continuous setting



Mapper in practice

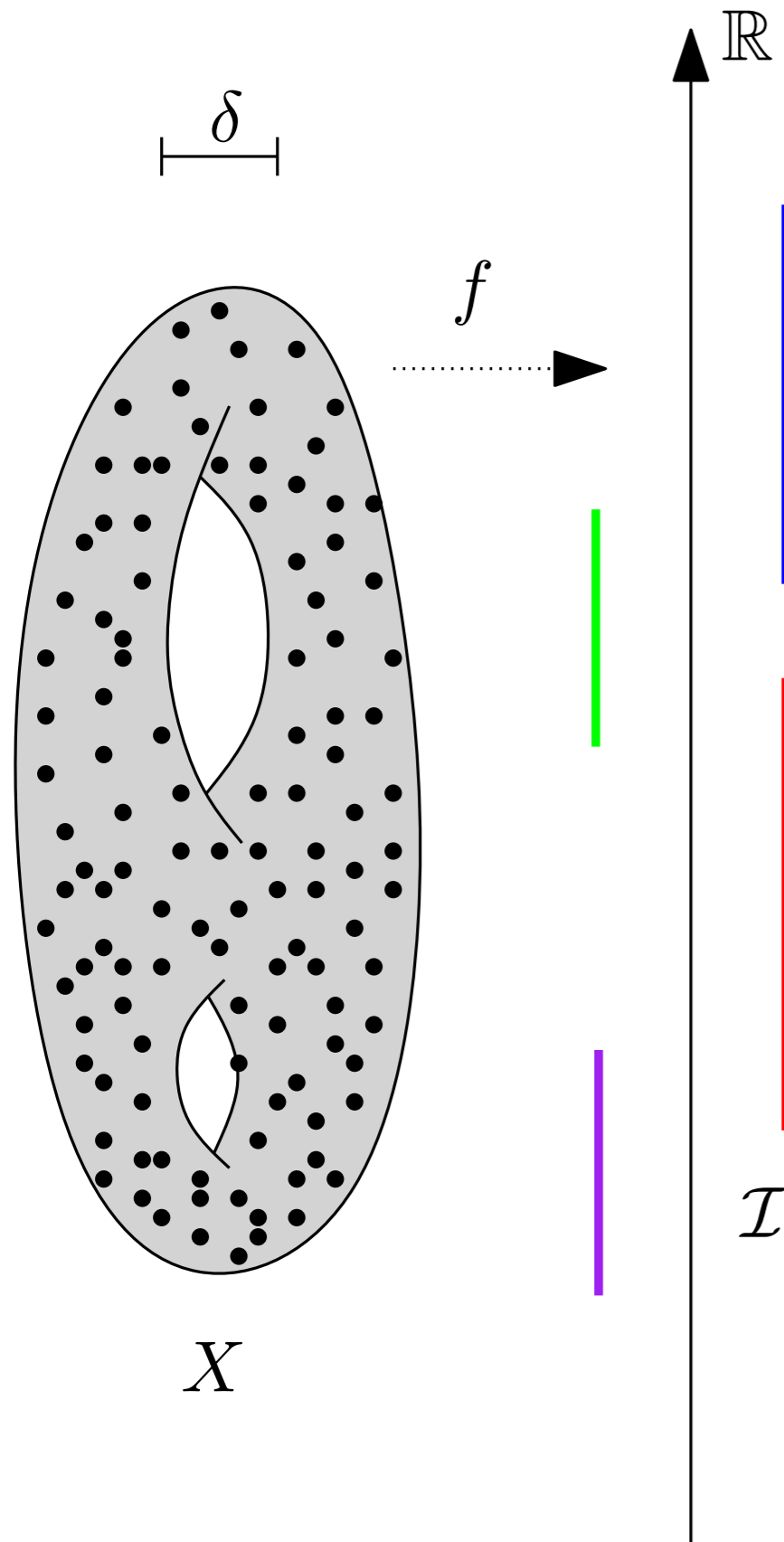
Input: - point cloud P with metric d_P

- continuous function ('filter', 'lens'...) $f : P \rightarrow \mathbb{R}$
- cover \mathcal{I} of $\text{im}(f)$ by open intervals: $\text{im}f \subseteq \bigcup_{I \in \mathcal{I}} I$

Method: • Compute neighborhood graph $G = (P, E)$

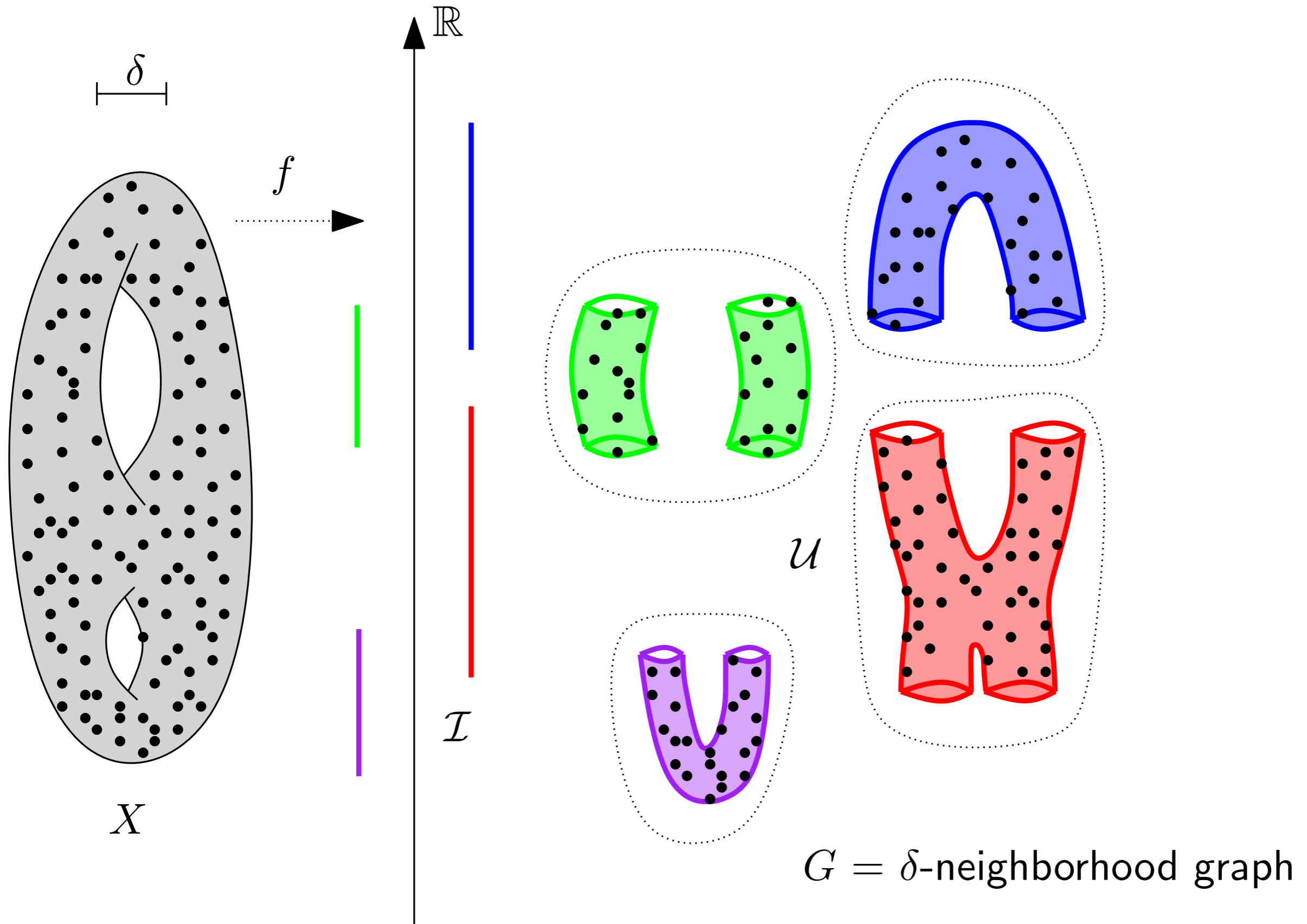
- Compute *pullback cover* \mathcal{U} of P : $\mathcal{U} = \{f^{-1}(I)\}_{I \in \mathcal{I}}$
- Refine \mathcal{U} by separating each of its elements into its various connected components in $G \rightarrow$ connected cover \mathcal{V}
- The Mapper is the *nerve* of \mathcal{V} :
(intersections materialized by data points)
 - 1 vertex per element $V \in \mathcal{V}$
 - 1 edge per intersection $V \cap V' \neq \emptyset, V, V' \in \mathcal{V}$
 - 1 k -simplex per $(k + 1)$ -fold intersection $\bigcap_{i=0}^k V_i \neq \emptyset, V_0, \dots, V_k \in \mathcal{V}$

Mapper in practice

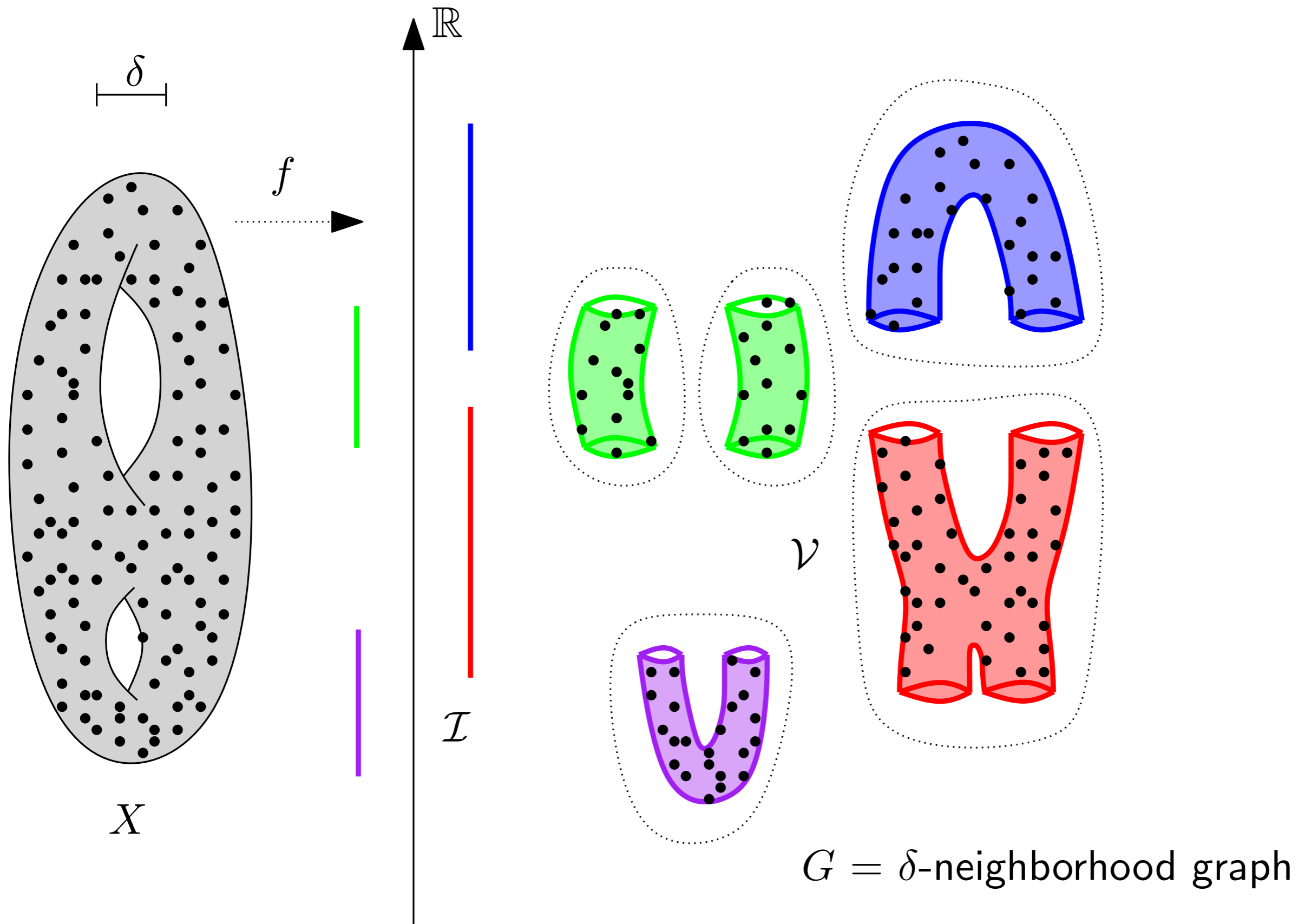


$G = \delta$ -neighborhood graph

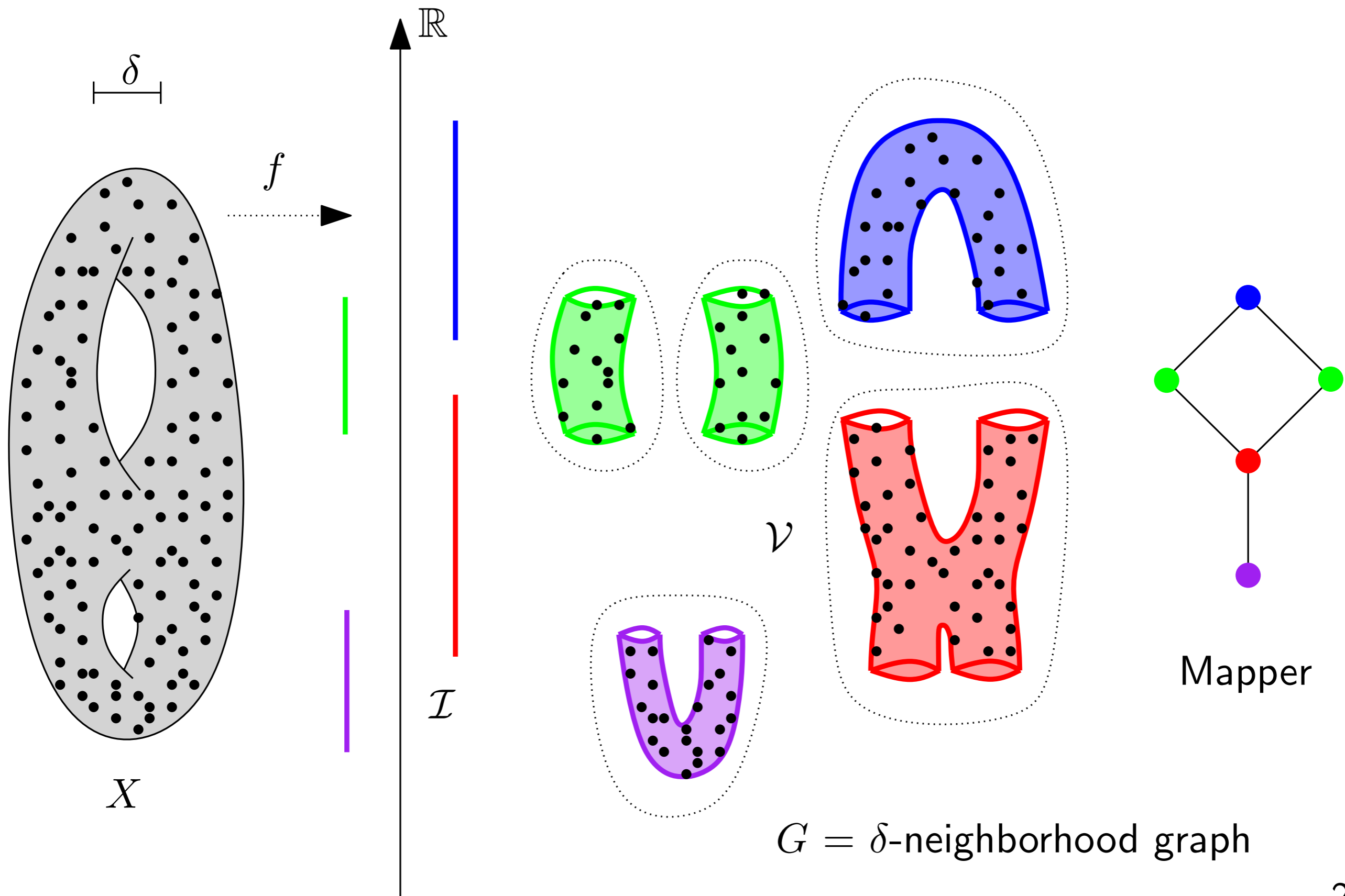
Mapper in practice



Mapper in practice



Mapper in practice



Mapper in practice

Parameters:

- filter $f : P \rightarrow \mathbb{R}$
- cover \mathcal{I} of $\text{im}(f)$ by open intervals
- neighborhood size δ

Mapper in practice

Parameters:

- filter $f : P \rightarrow \mathbb{R}$
- cover \mathcal{I} of $\text{im}(f)$ by open intervals
- neighborhood size δ

geometric scale



range scale



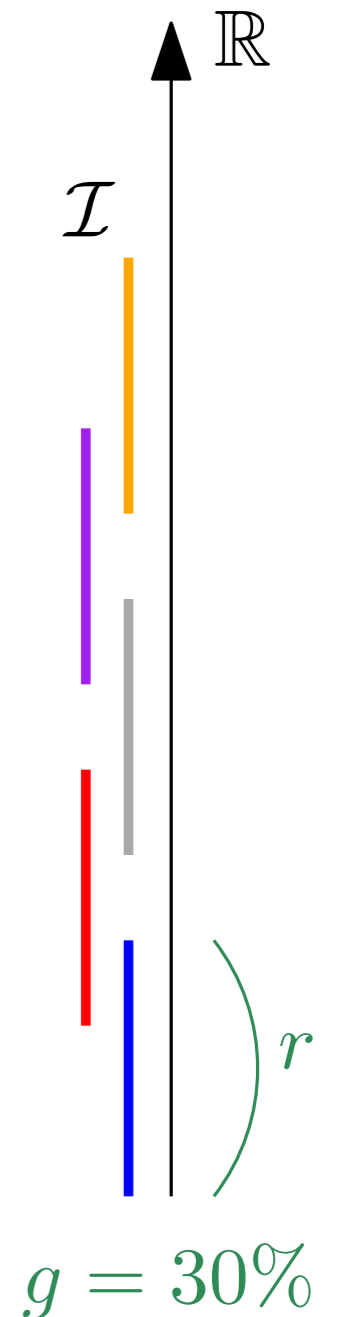
Mapper in practice

Parameters:

- filter $f : P \rightarrow \mathbb{R}$
- cover \mathcal{I} of $\text{im}(f)$ by open intervals
- neighborhood size δ

geometric scale

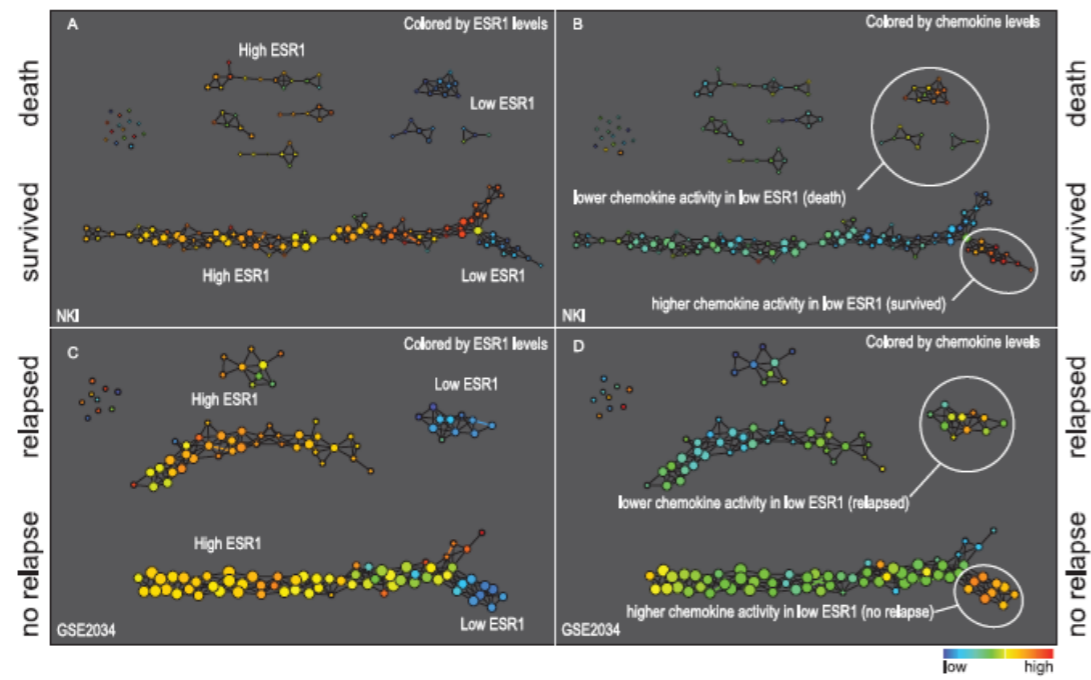
range scale



→ uniform cover \mathcal{I} :

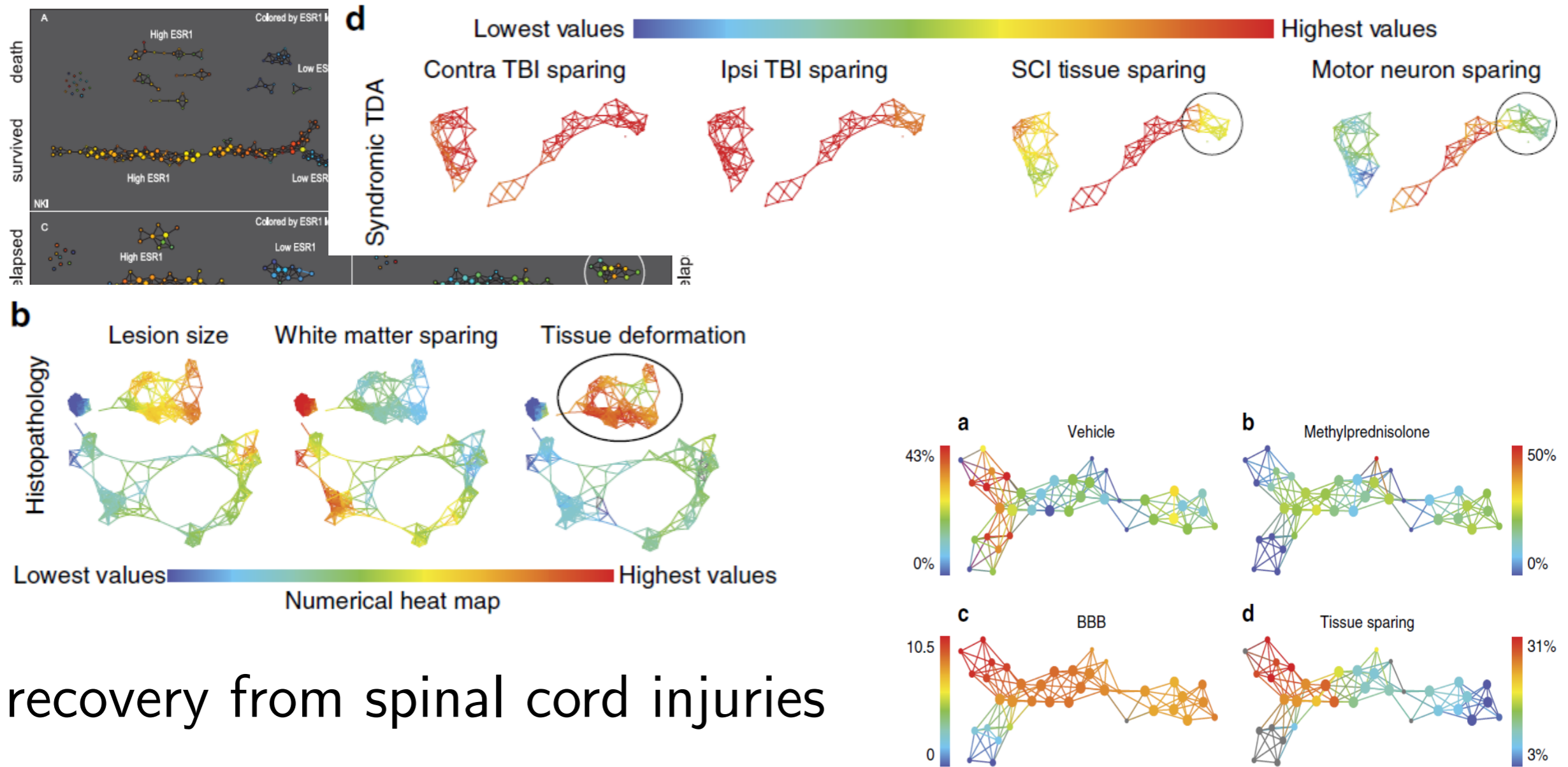
- resolution / granularity: r (diameter of intervals)
- gain: g (percentage of overlap)

Mapper in applications



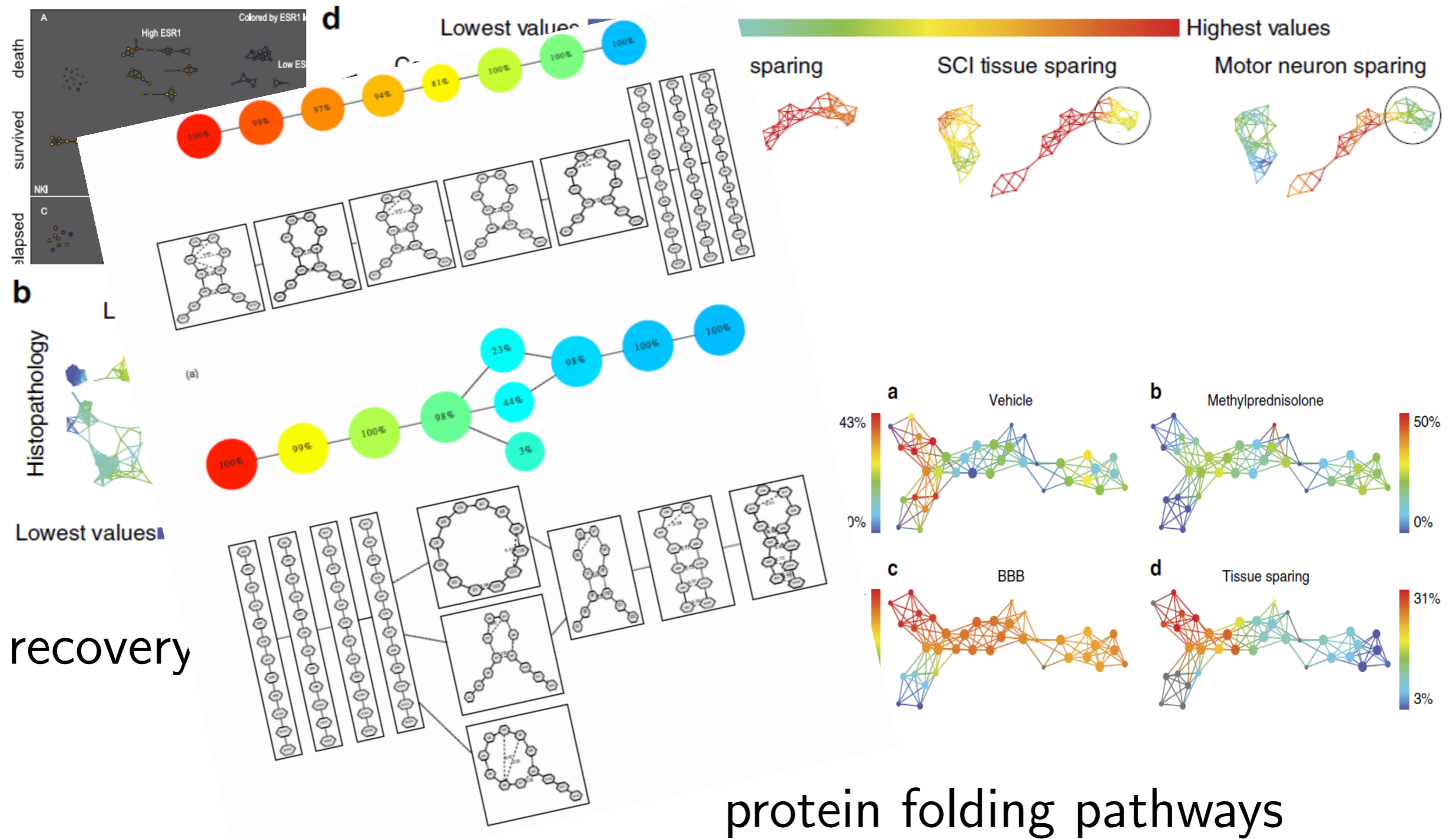
breast cancer subtype

Mapper in applications

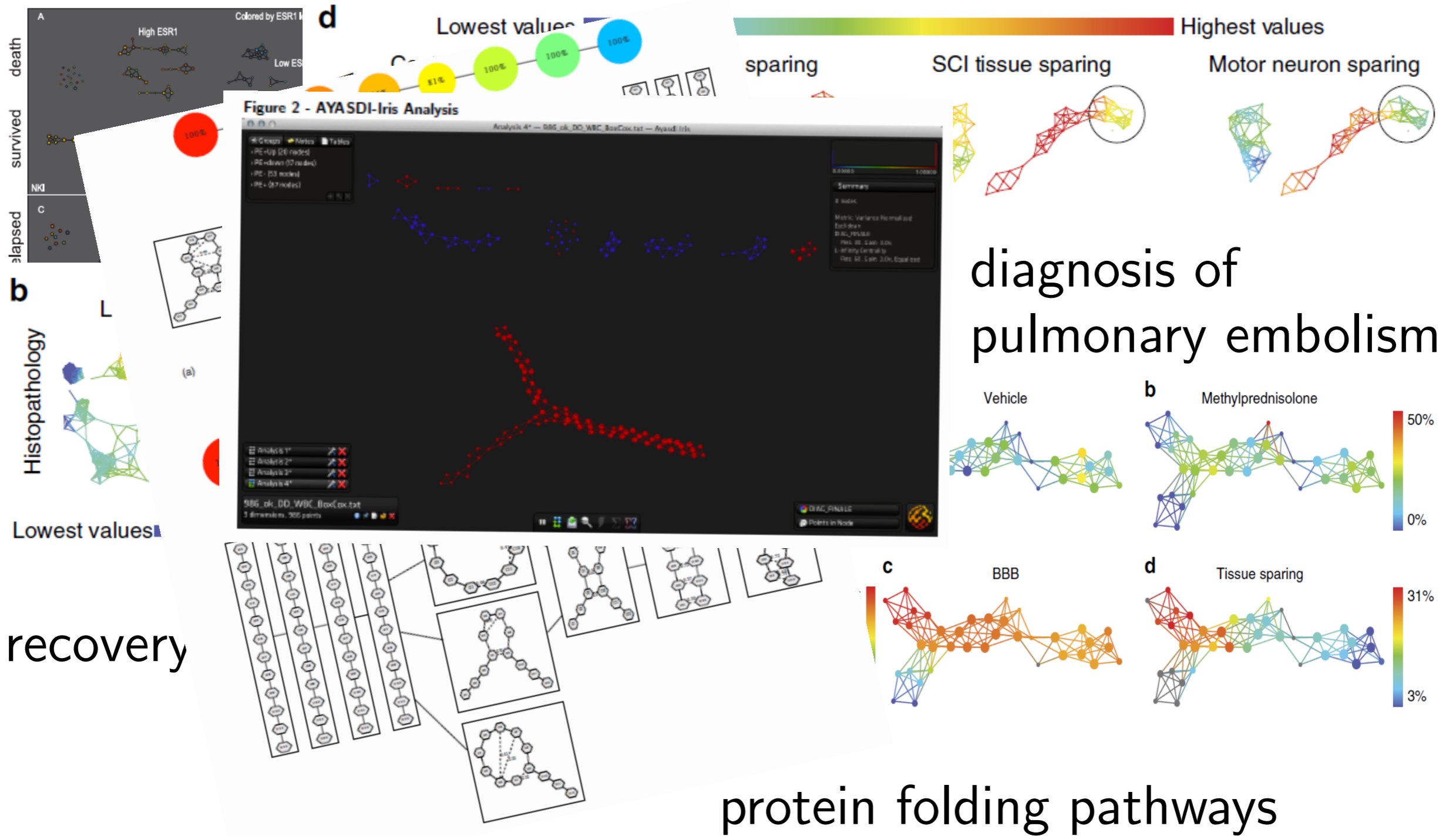


recovery from spinal cord injuries

Mapper in applications

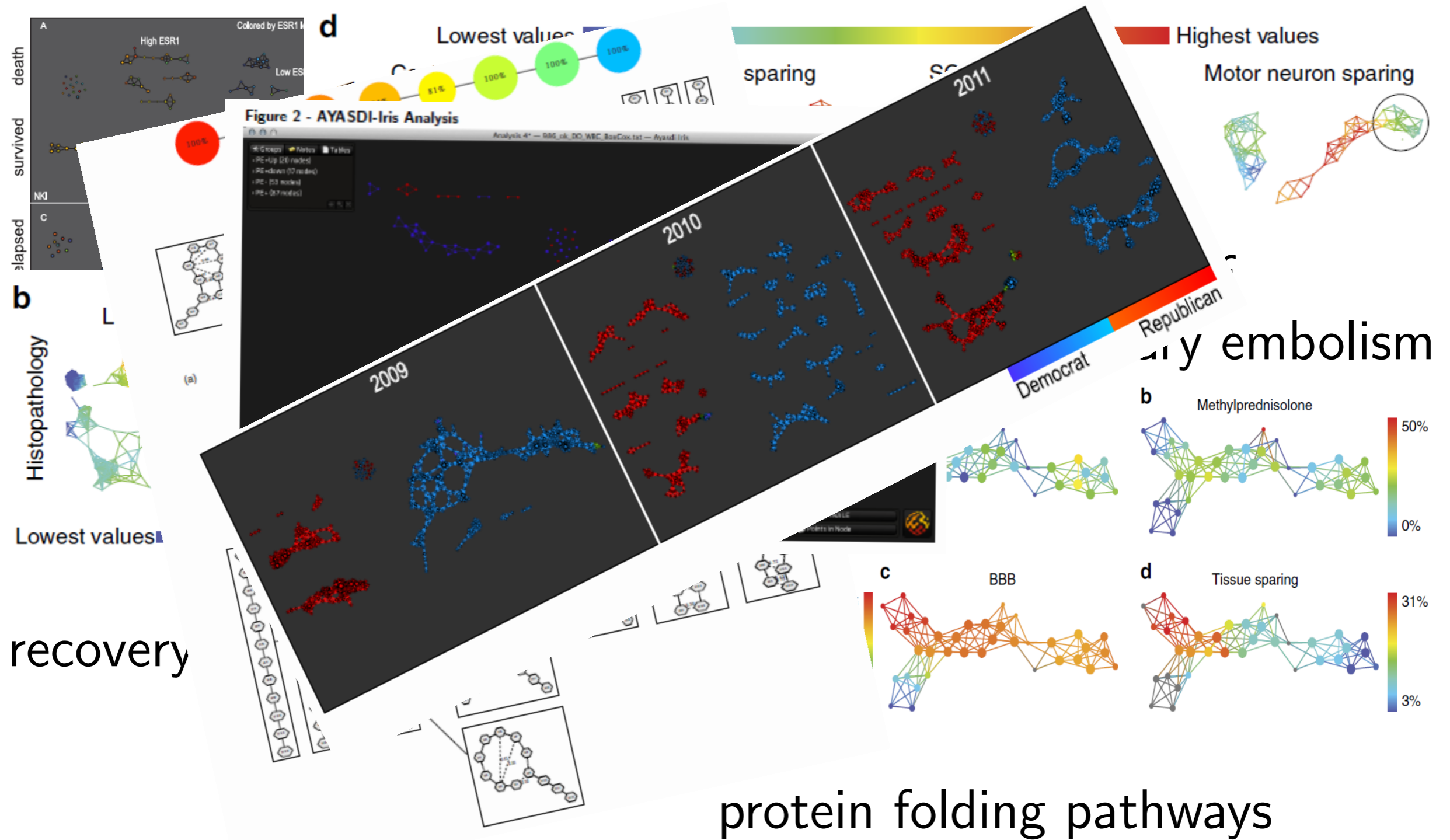


Mapper in applications



Mapper in applications

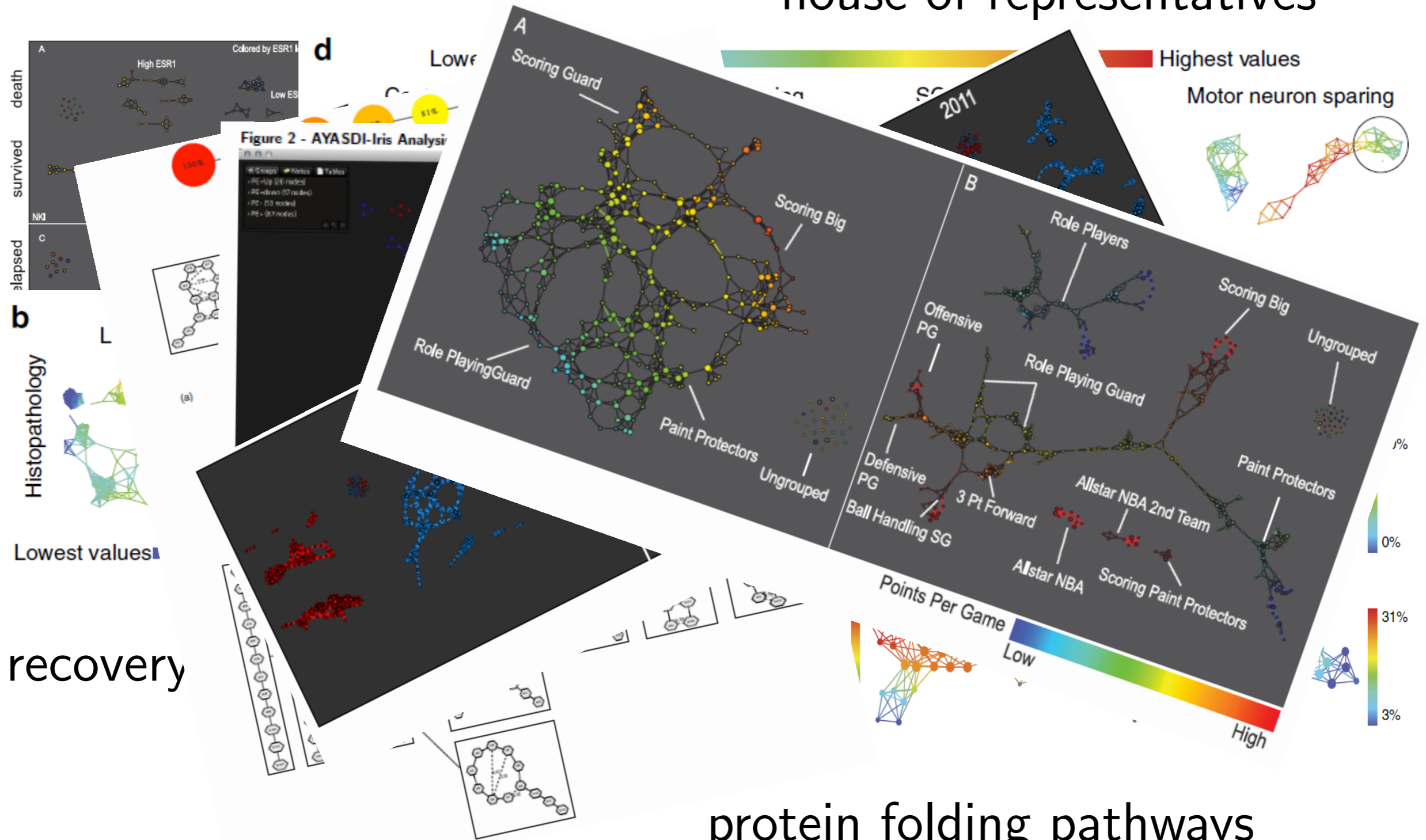
implicit networks in the US house of representatives



Mapper in applications

classification of NBA players

implicit networks in the US house of representatives

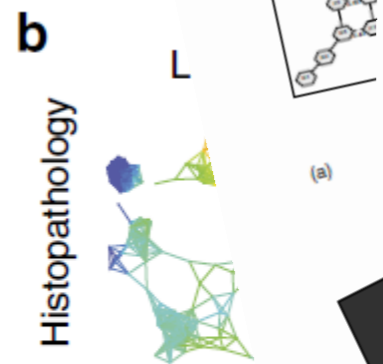
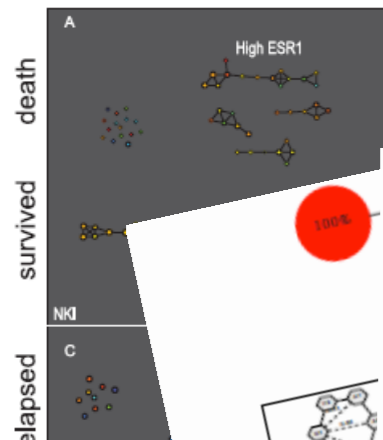


protein folding pathways

Mapper in applications

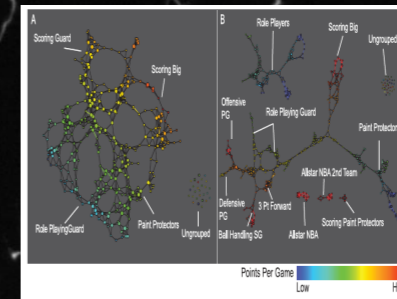
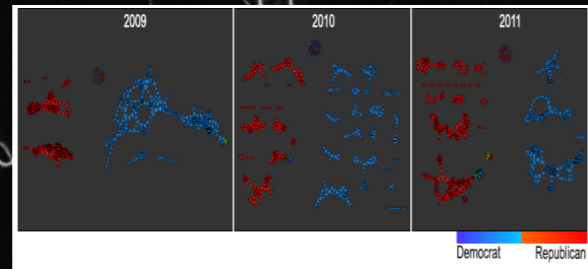
classification of NBA players

implicit networks in the US house of representatives

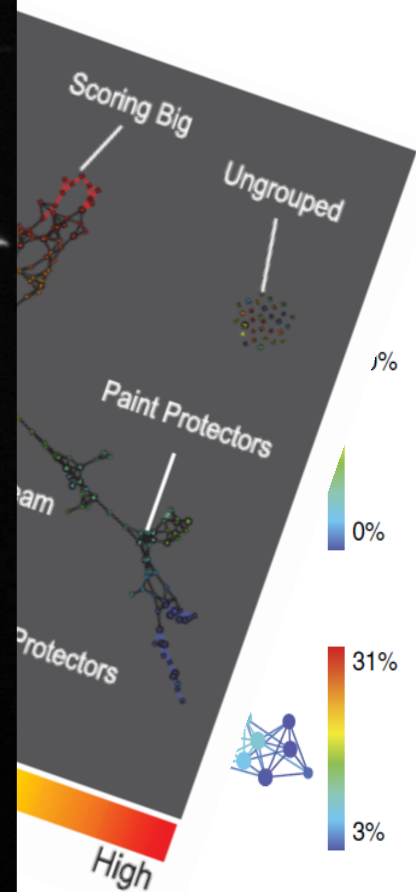
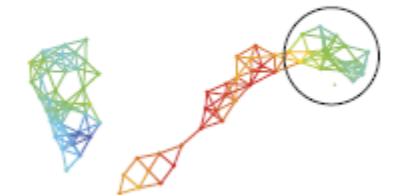


Lowest values

recovery



highest values
Motor neuron sparing



BLACK

MAGIC

ays

Mapper in applications

Extracting insights from the shape of complex data using topology, Lum et al., Nature, 2013

Topological Data Analysis for Discovery in Preclinical Spinal Cord Injury and Traumatic Brain Injury, Nielson et al., Nature, 2015

Using Topological Data Analysis for Diagnosis Pulmonary Embolism, Rucco et al., arXiv preprint, 2014

Topological Methods for Exploring Low-density States in Biomolecular Folding Pathways, Yao et al., J. Chemical Physics, 2009

CD8 T-cell reactivity to islet antigens is unique to type 1 while CD4 T-cell reactivity exists in both type 1 and type 2 diabetes, Sarikonda et al., J. Autoimmunity, 2013

Innate and adaptive T cells in asthmatic patients: Relationship to severity and disease mechanisms, Hinks et al., J. Allergy Clinical Immunology, 2015

Choice of parameters

Parameters:

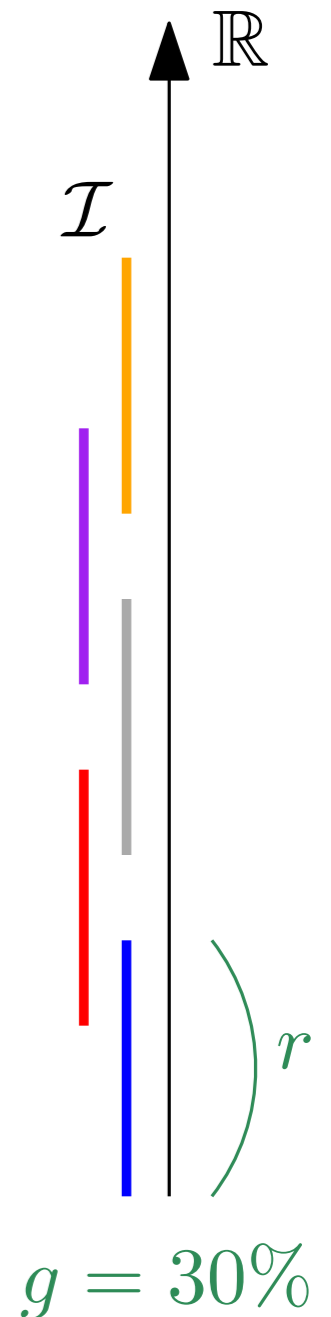
- filter $f : P \rightarrow \mathbb{R}$
- cover \mathcal{I} of $\text{im}(f)$ by open intervals
- neighborhood size δ

geometric scale

range scale

→ uniform cover \mathcal{I} :

- resolution / granularity: r (diameter of intervals)
- gain: g (percentage of overlap)



Choice of parameters

How to choose r , g and δ ?

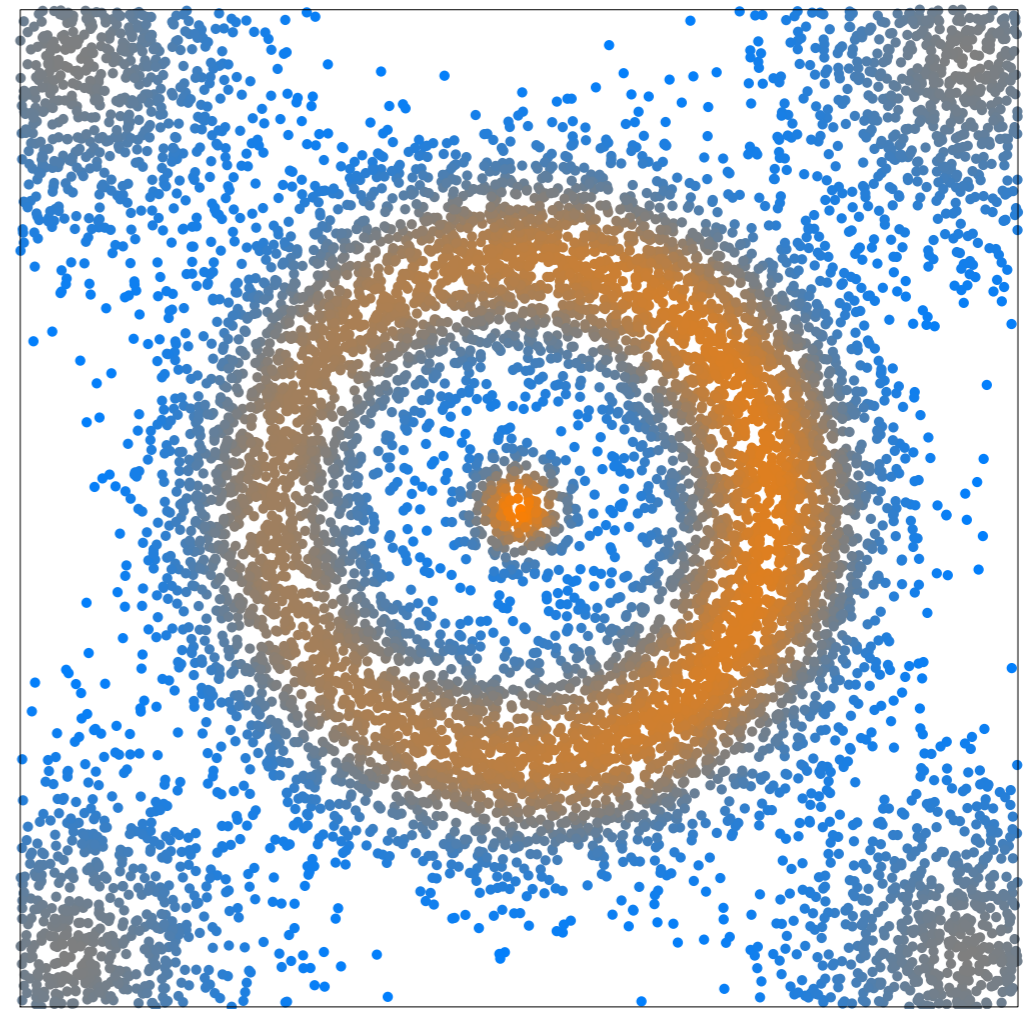
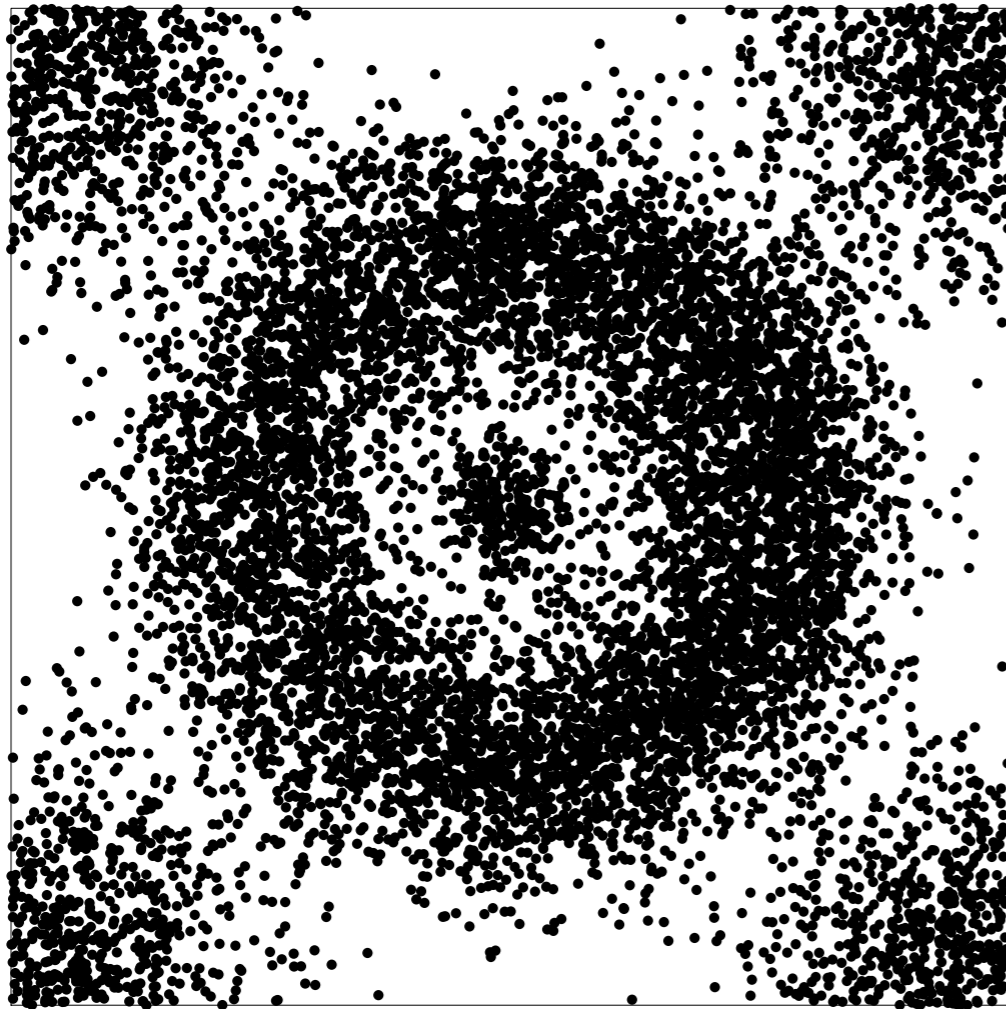
→ in practice: trial-and-error (or some vague procedure)

high-dimensional data sets^{40,48}. This is performed automatically within the software, by deploying an ensemble machine learning algorithm that iterates through overlapping subject bins of different sizes that resample the metric space (with replacement), thereby using a combination of the metric location and similarity of subjects in the network topology. After performing millions of iterations, the algorithm returns the most stable, consensus vote for the resulting ‘golden network’ (Reeb graph), representing the multidimensional data shape^{12,40}.

Topological Data Analysis for Discovery in Preclinical Spinal Cord Injury and Traumatic Brain Injury, Nielson et al., Nature, 2015

Choice of parameters

Illustration: $P \subset \mathbb{R}^2$ sampled from known probability distribution



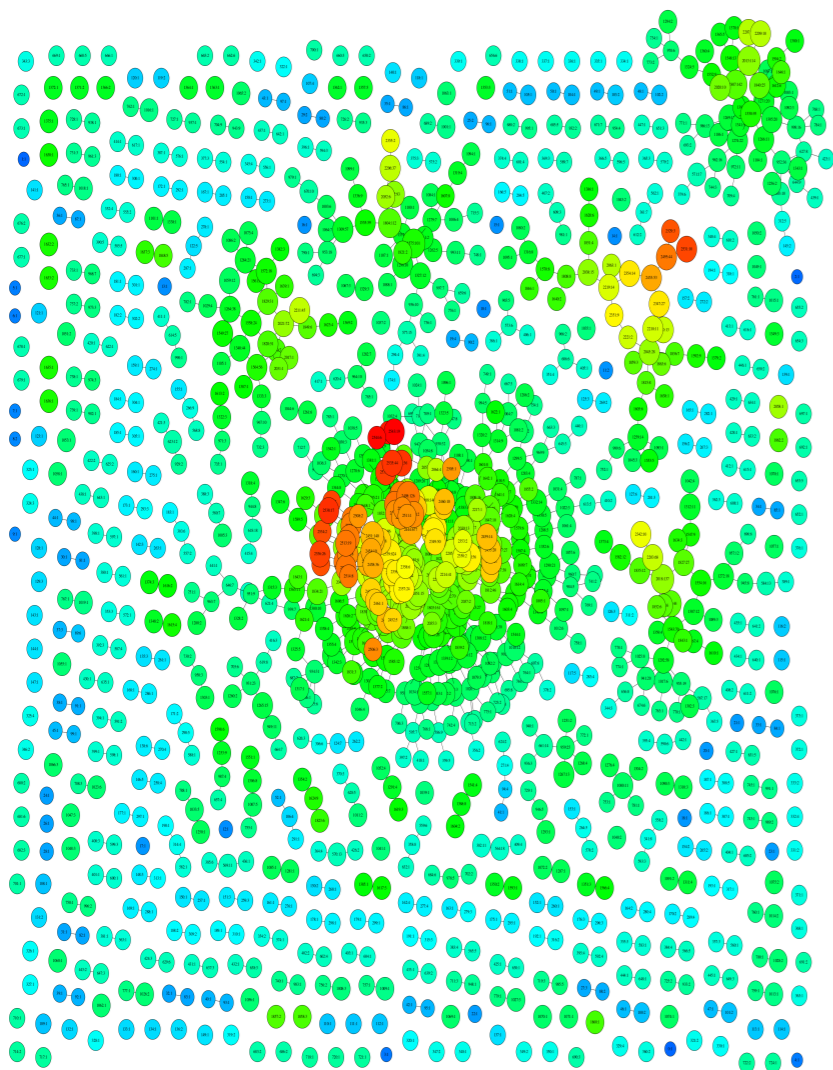
Choice of parameters

Illustration: $P \subset \mathbb{R}^2$ sampled from known probability distribution

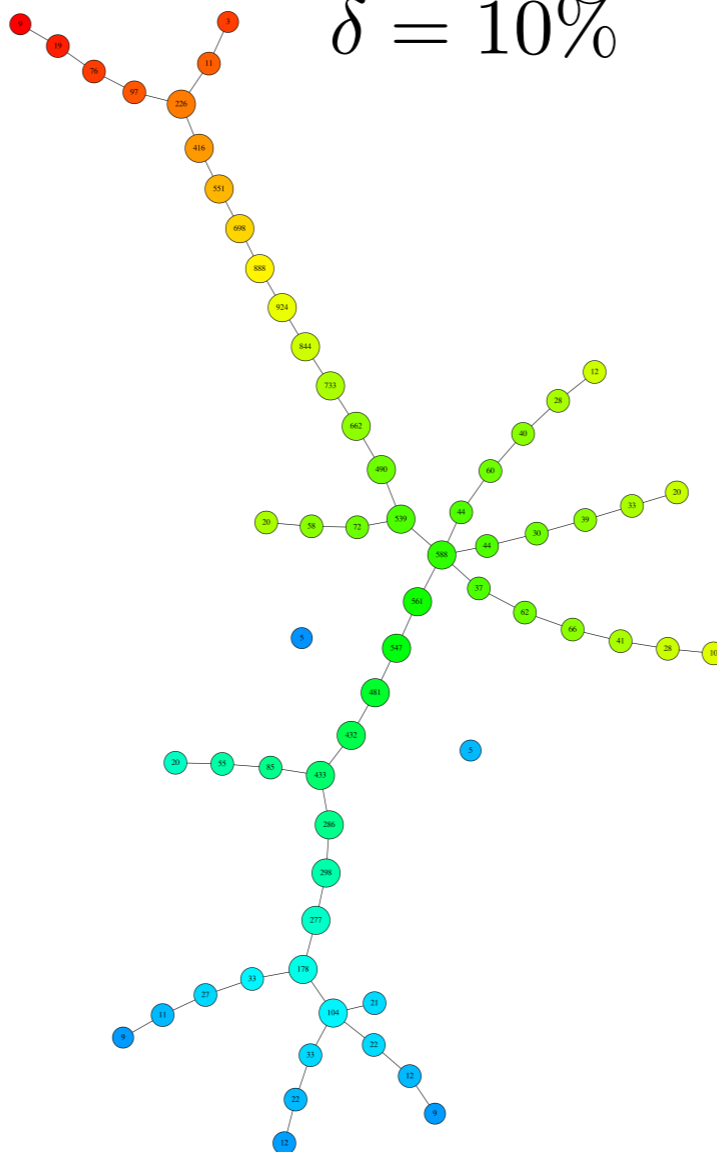
f = density estimator, $r = 1/30$, $g = 20\%$

δ = percentage of the diameter of X

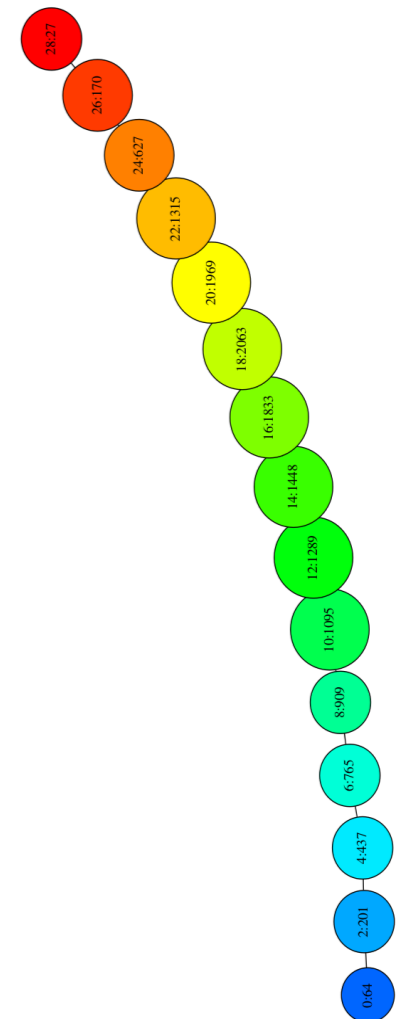
$\delta = 1\%$



$\delta = 10\%$



$\delta = 30\%$



Choice of parameters

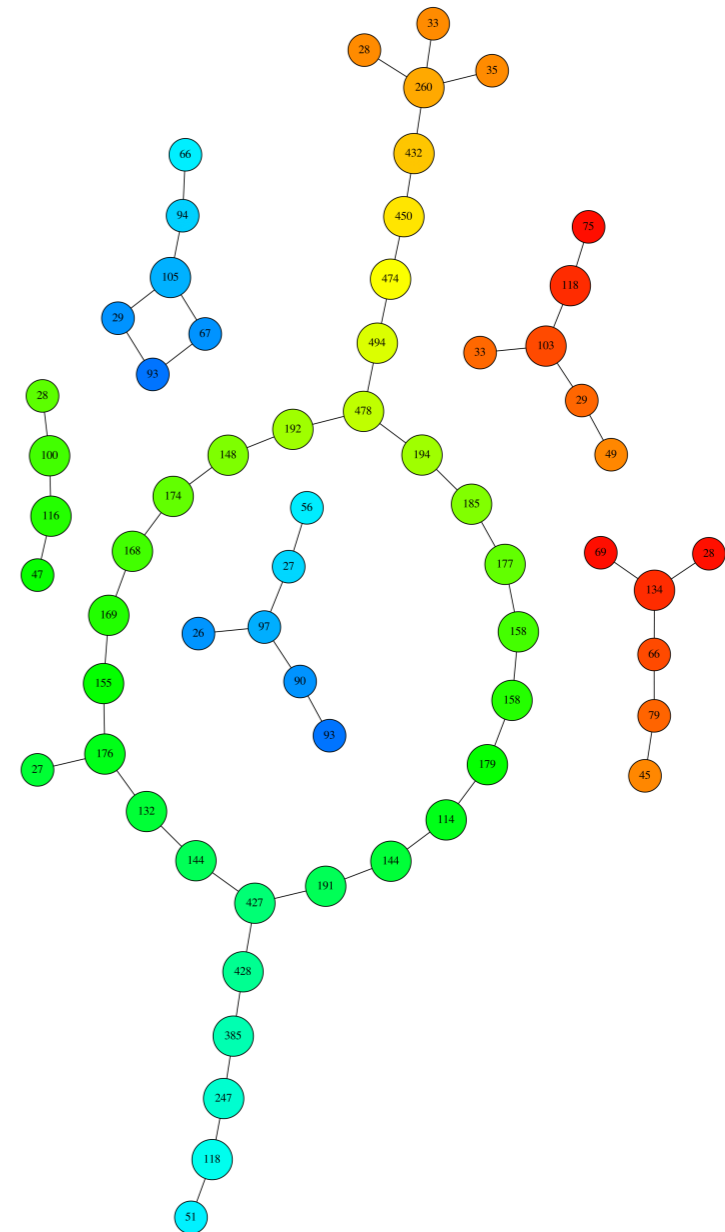
Illustration: $P \subset \mathbb{R}^2$ sampled from known probability distribution

$f =$ abscissa, $r = 1/30$, $g = 10\%$

$\delta =$ percentage of the diameter of X

$$\delta = 1\%$$

+ small cluster removal



Choice of parameters

Structure and Stability of the 1-Dimensional Mapper.

Carrière, O. 2016

- clarifies formally the roles of r and g in the continuous setting
- gives sufficient conditions on δ to get approximation results
- also gives a notion of distance and stability for Mappers...

Choice of parameters

Structure and Stability of the 1-Dimensional Mapper.

Carrière, O. 2016

→ clarifies formally the roles of r and g in the continuous setting

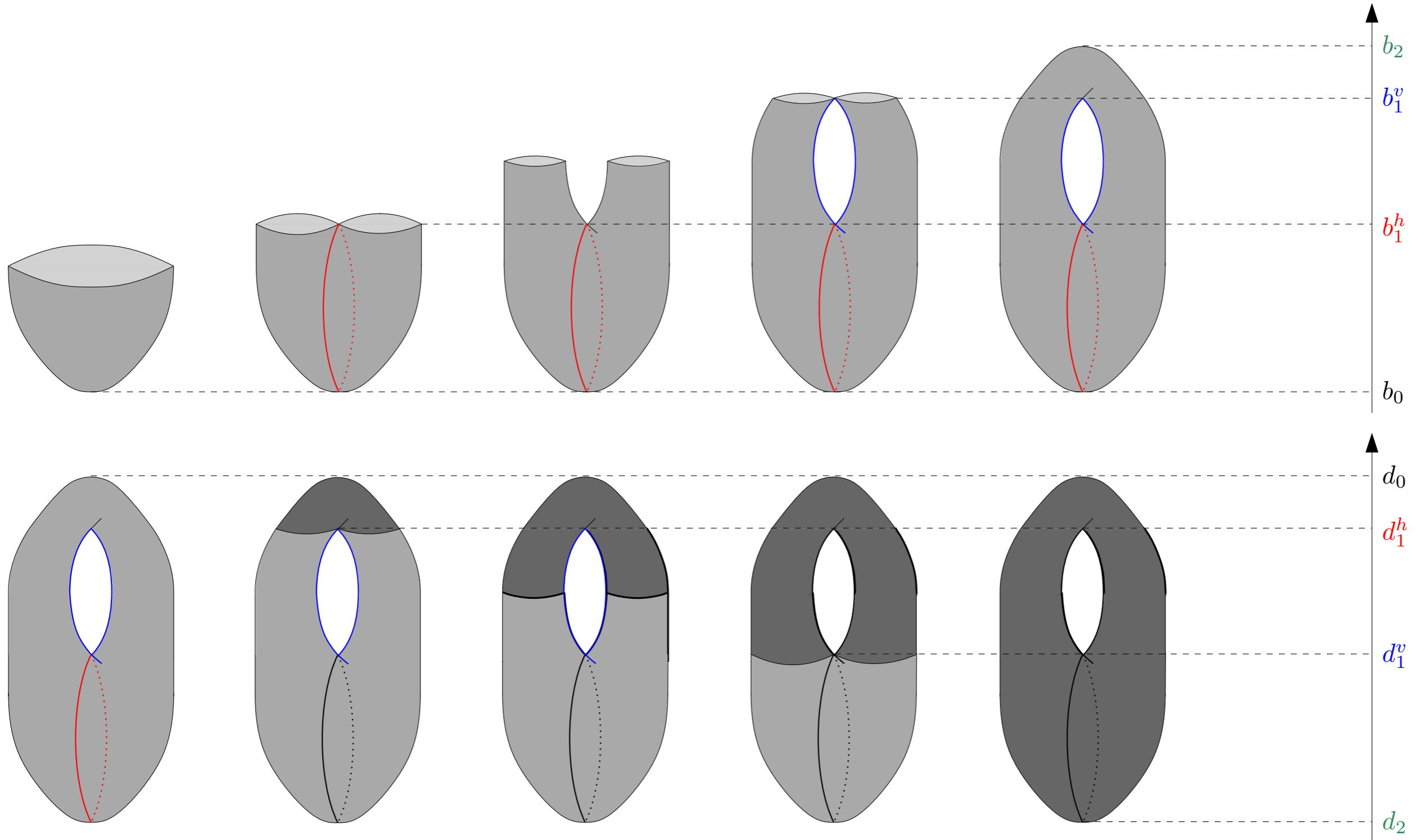
→ gives sufficient conditions on δ to get approximation results

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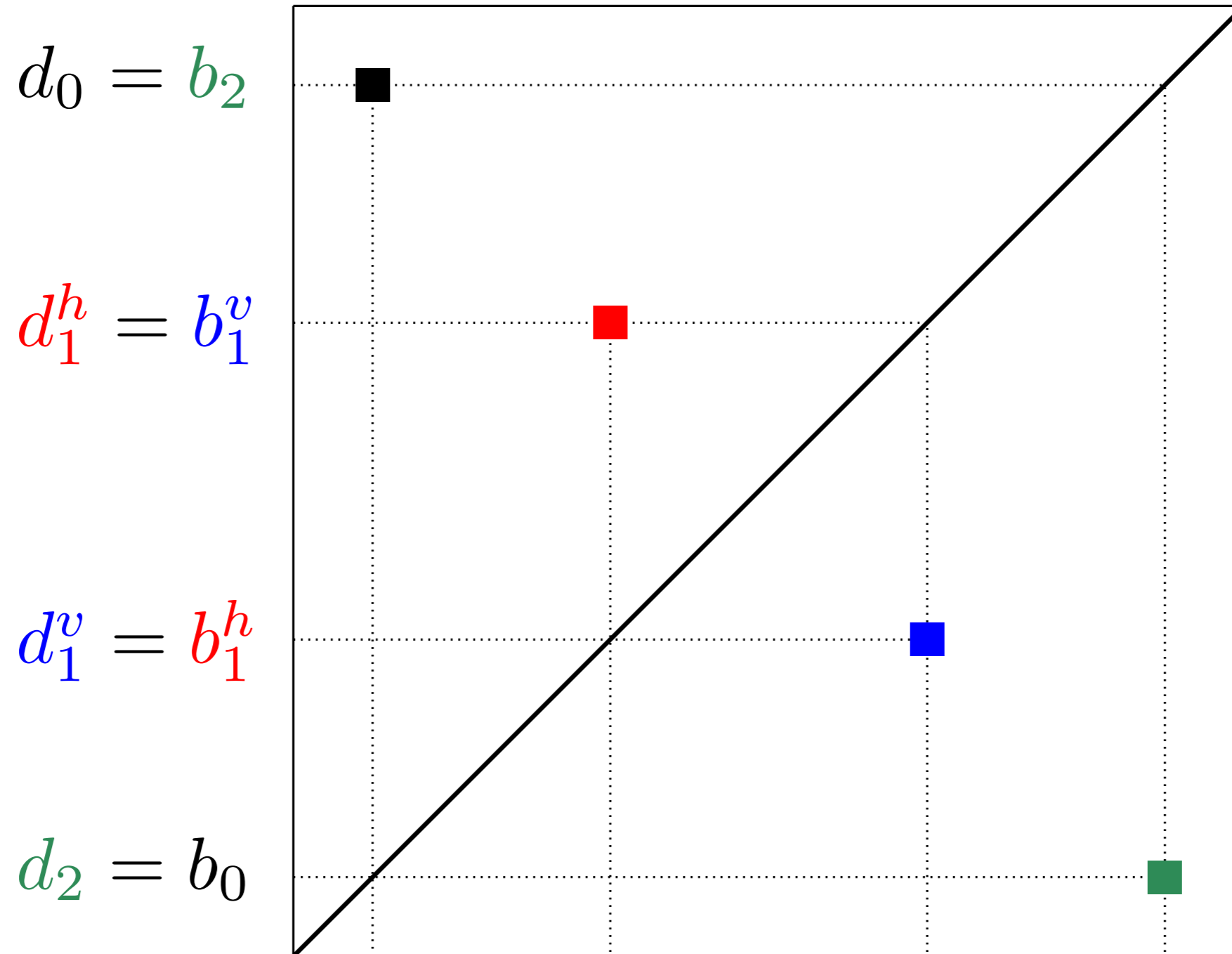
Other publications:

- de Silva, Munch, Patel. *Categorified Reeb Graphs*. 2015
- Munch, Wang. *Convergence between Categorical Representations of Reeb Space and Mapper*. 2016

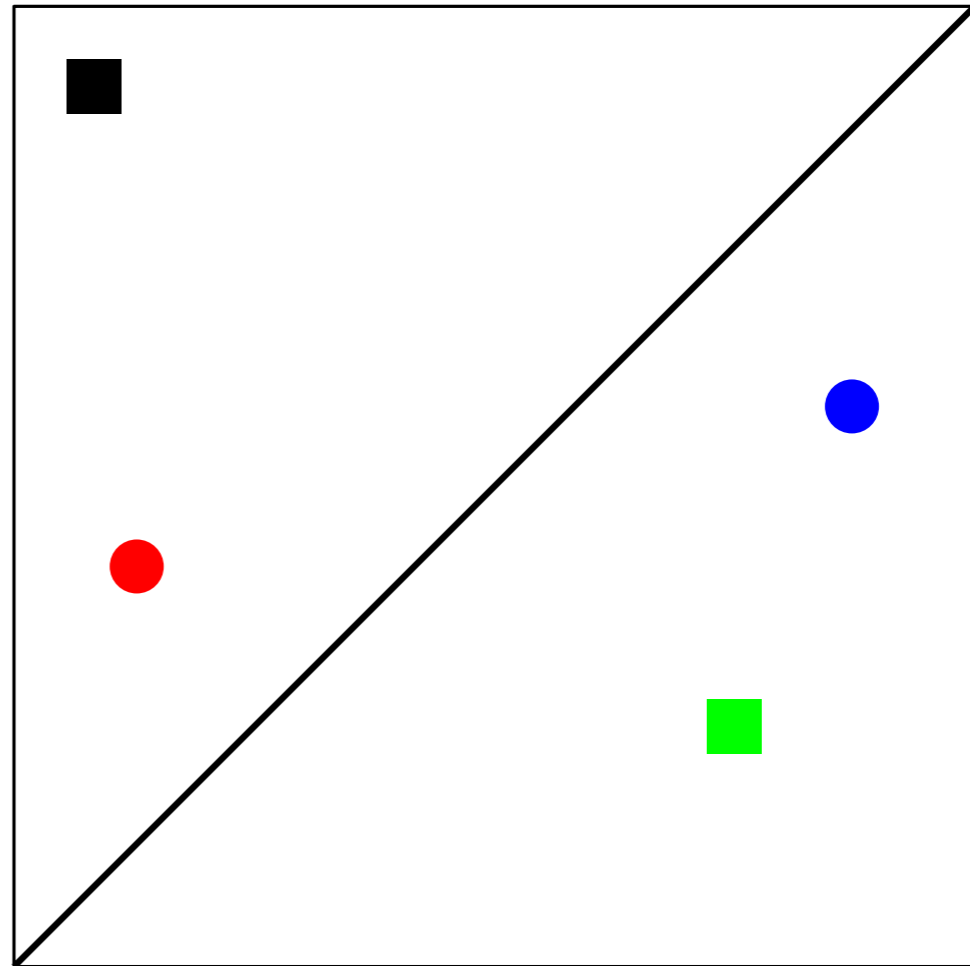
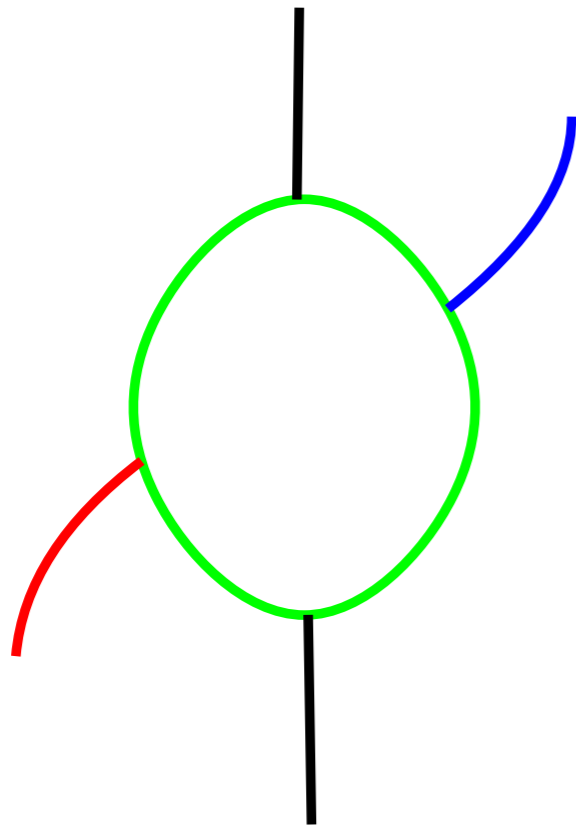
Extended Persistence



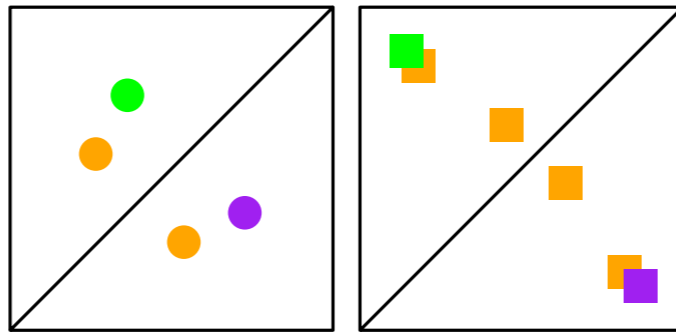
Extended Persistence



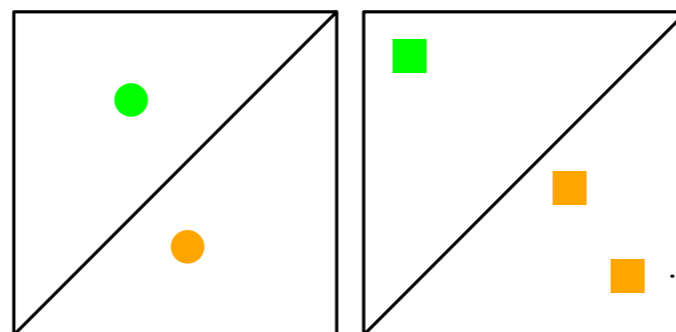
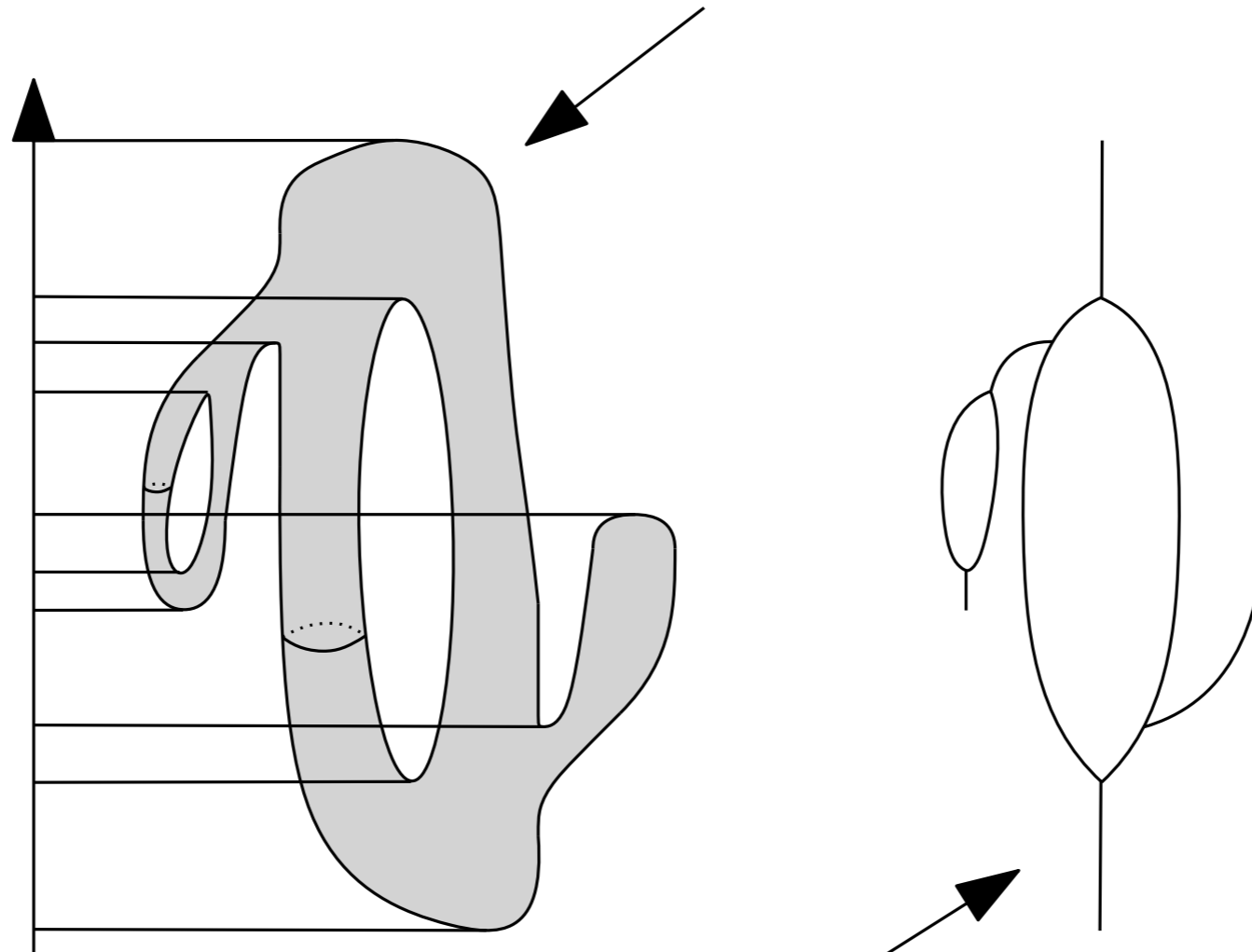
Extended Persistence

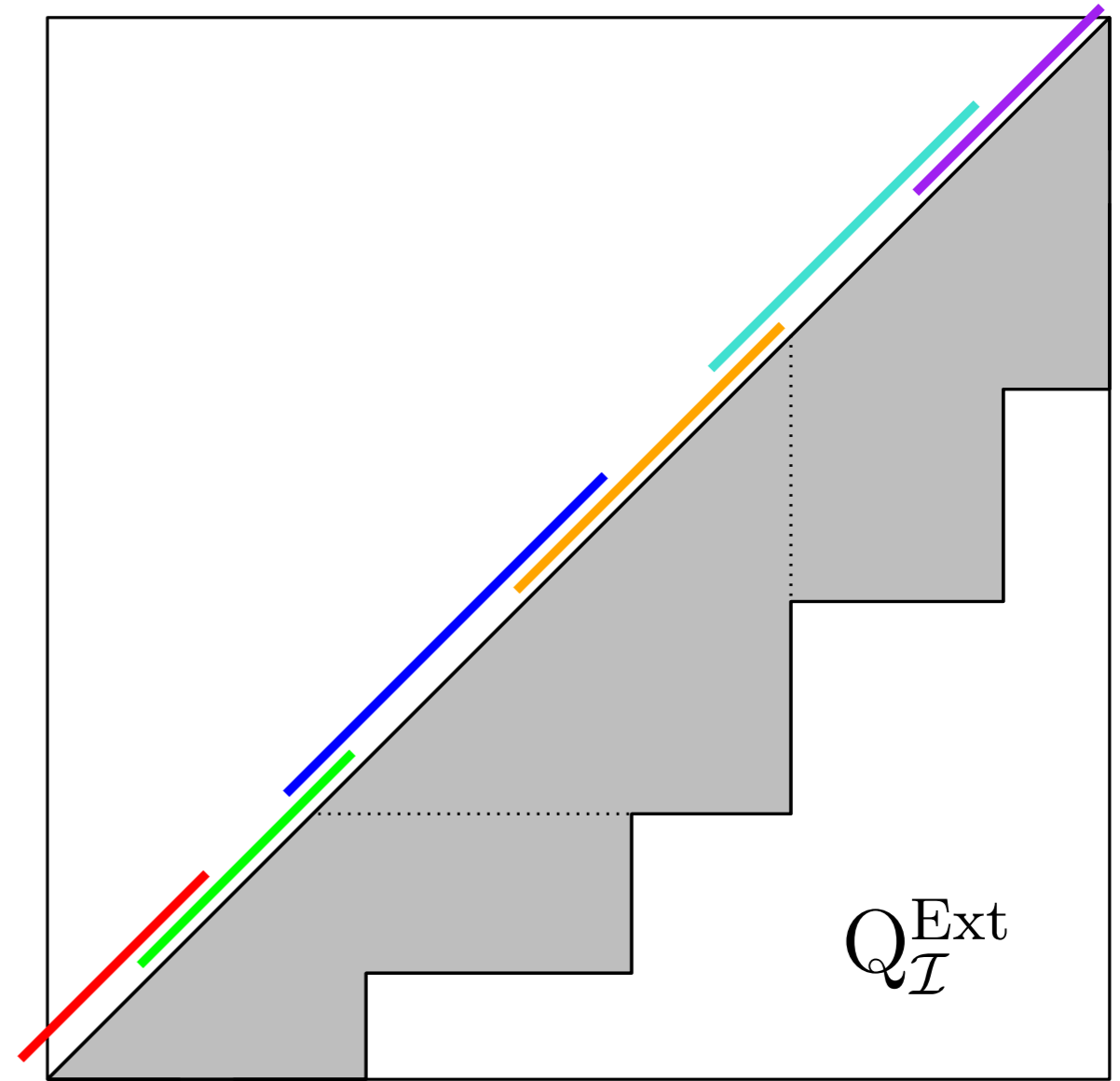
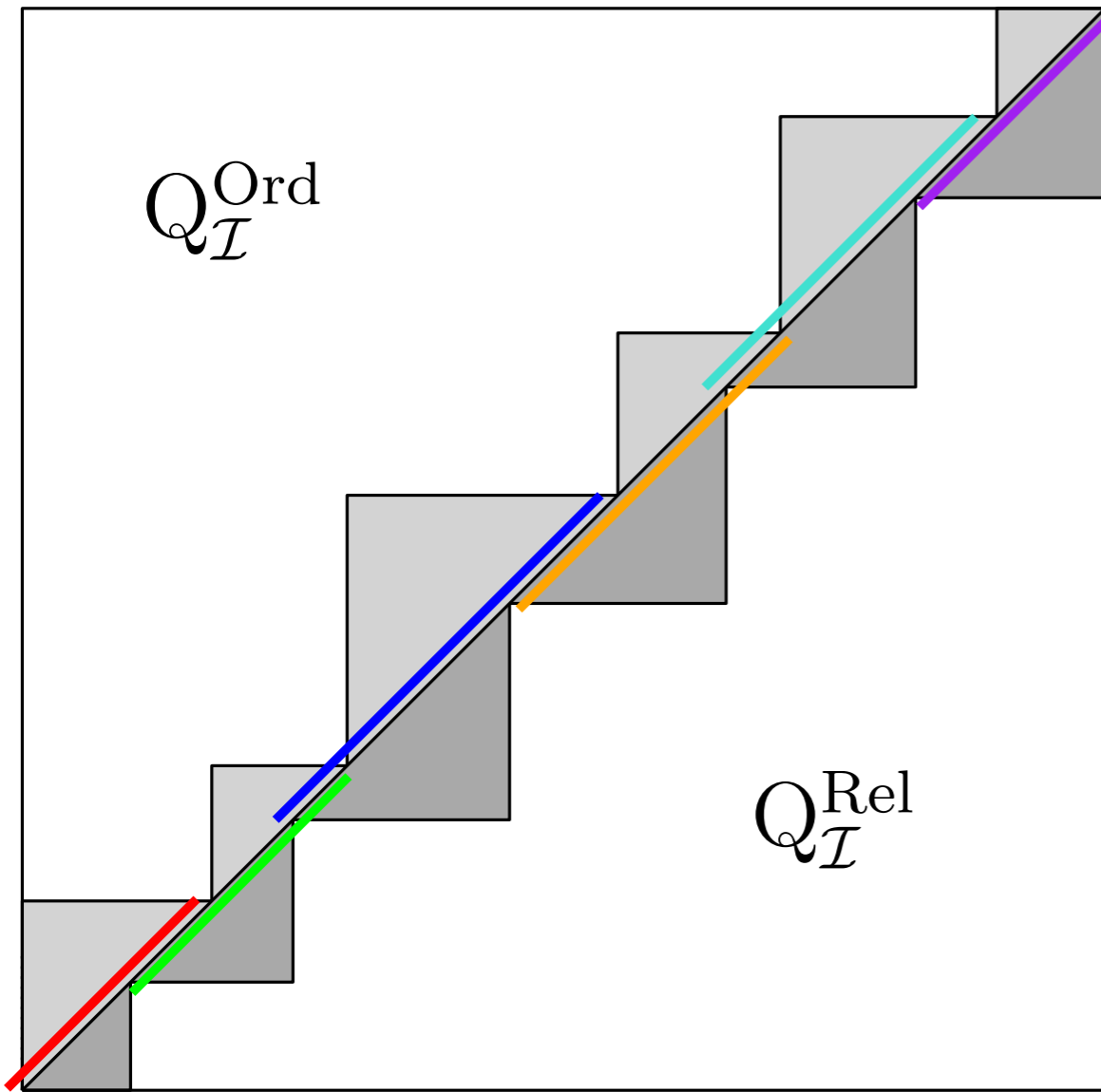


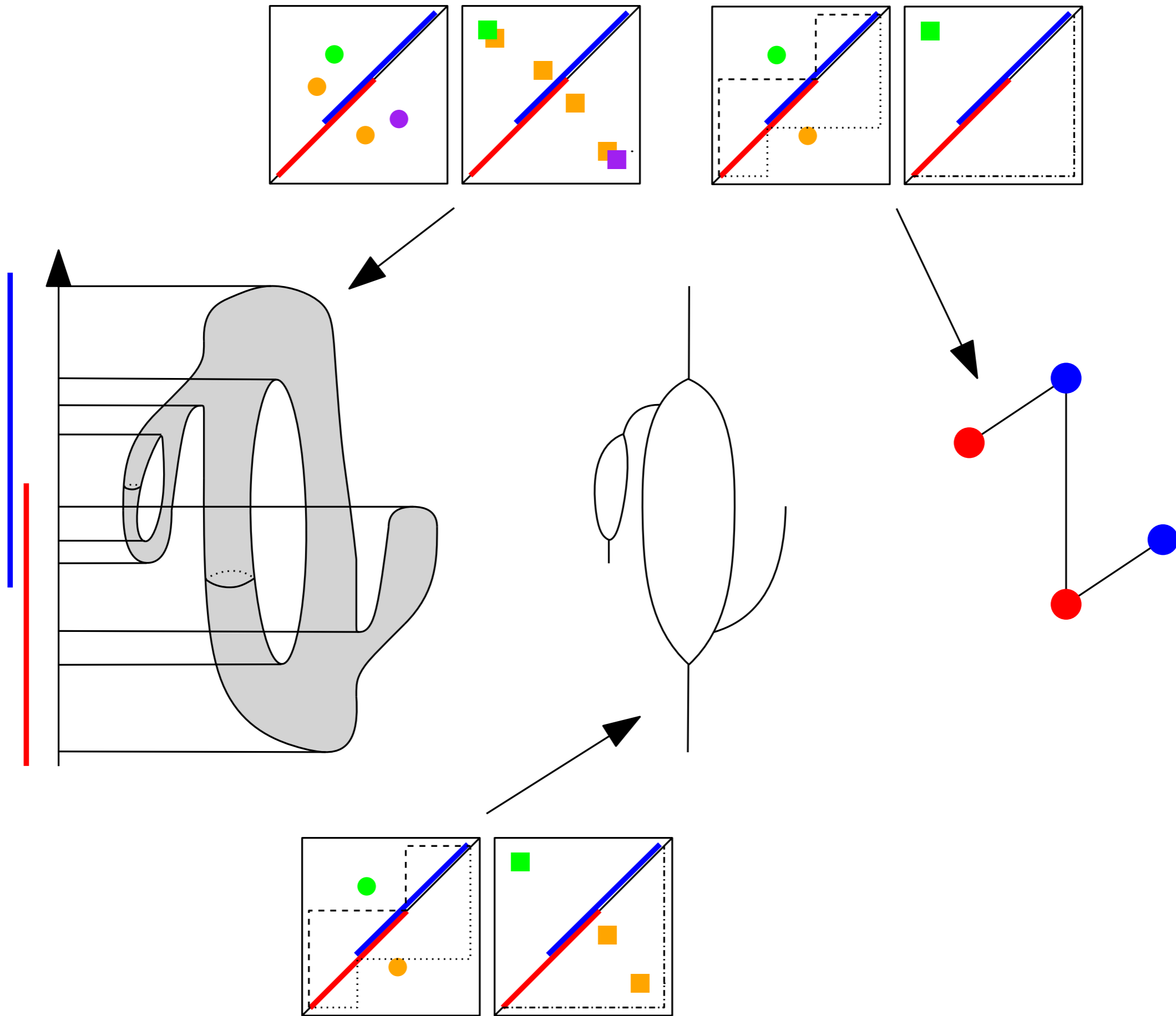
- ordinary / relative
- extended

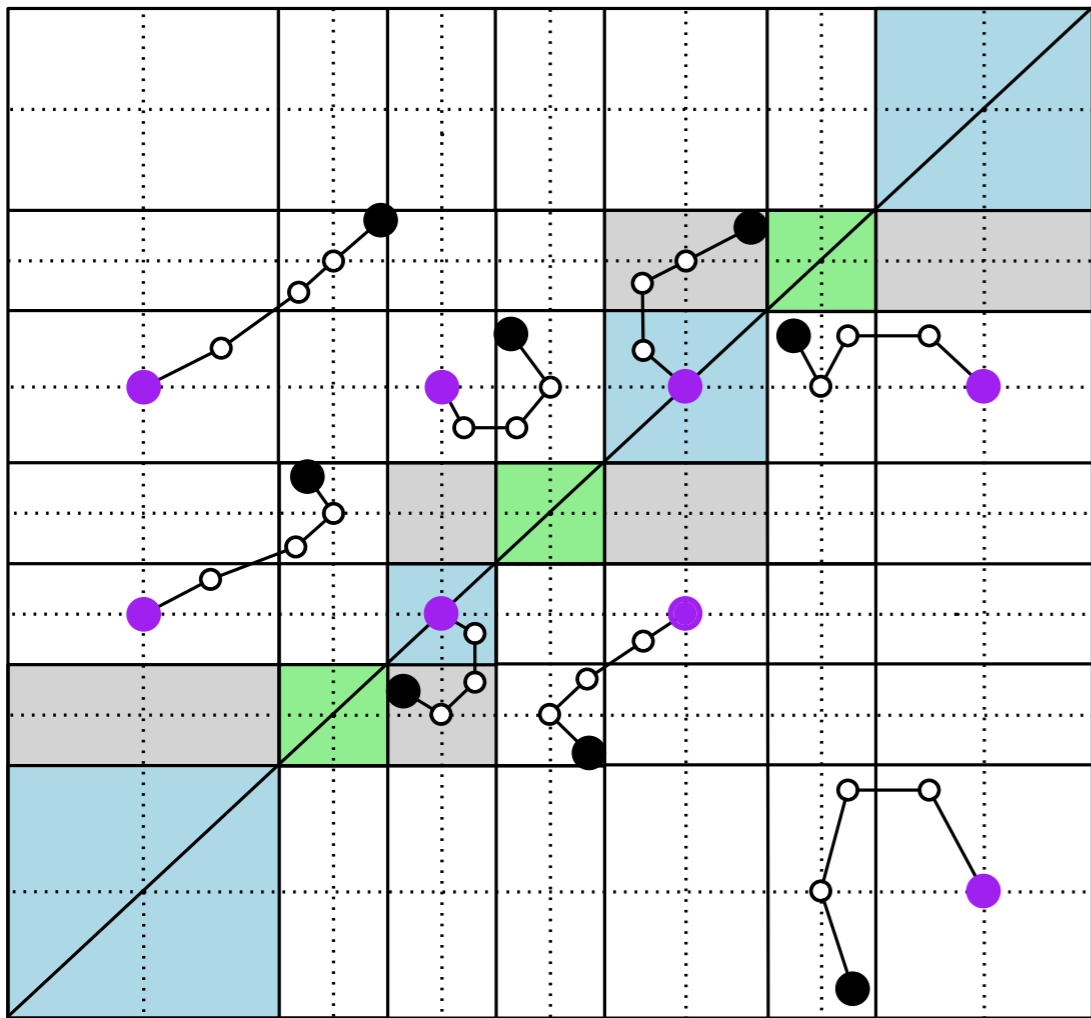


- H_0
- H_1
- H_2

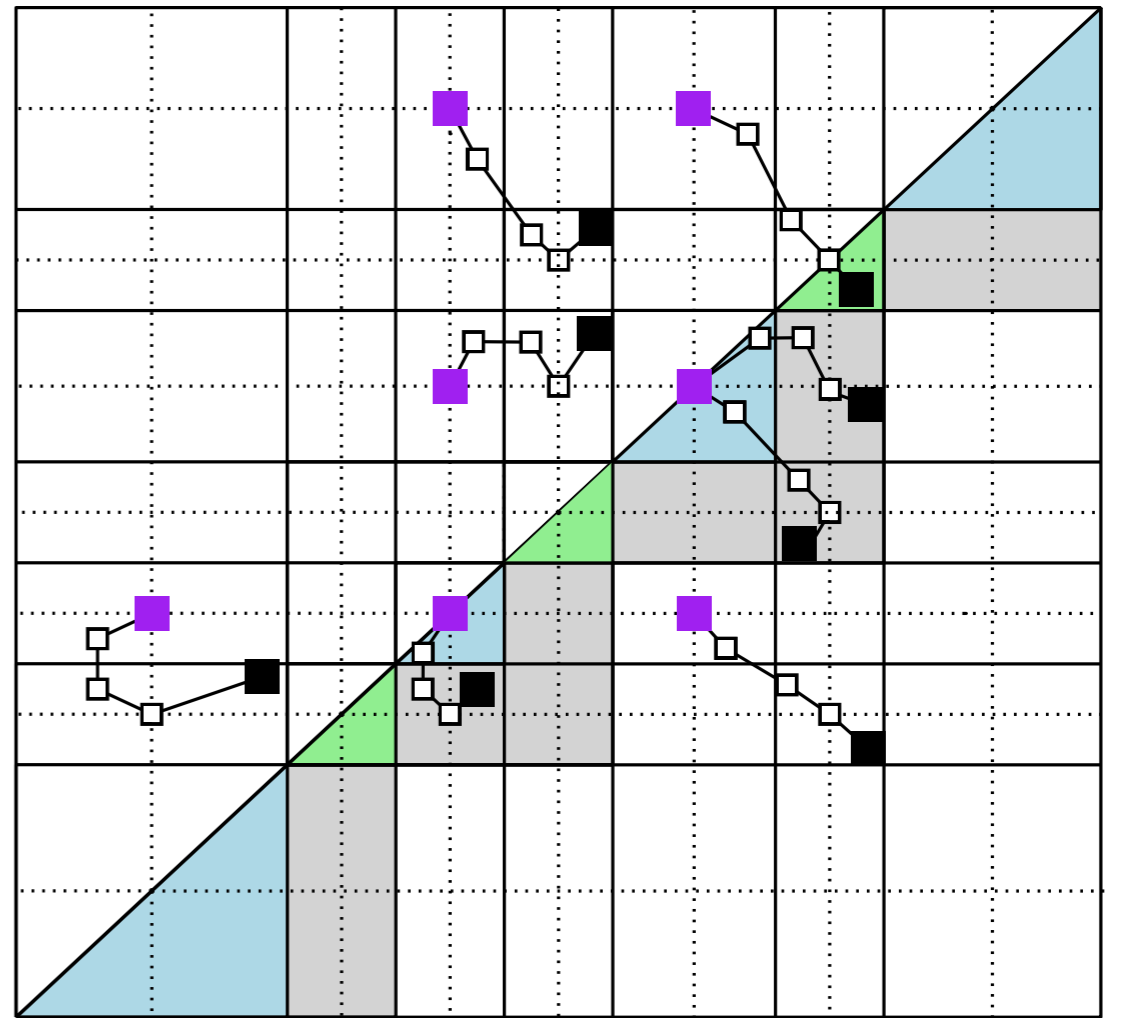








I ————— J



I ————— J

