

ATMCS 2010, Münster, June 25

Stability of Persistence Diagrams

Application to Scalar Fields Analysis

Steve Y. Oudot — Geometrica group, INRIA Saclay – Île-de-France



Some References

- [1] Chazal, Cohen-Steiner, Glisse, Guibas, O., *Proximity of persistence modules and their diagrams*, Proc. SoCG 2009.
- [2] Chazal, Guibas, O., Skraba, *Analysis of scalar fields over point cloud data*, Proc. SODA 2009.
- [3] Chazal, Guibas, O., Skraba, "Persistence-Based Clustering in Riemannian Manifolds", INRIA Research report 6968, June 2009.

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Logical order: 1 - 2 - 3

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Historical order: 2 - 1 - 2 - 3

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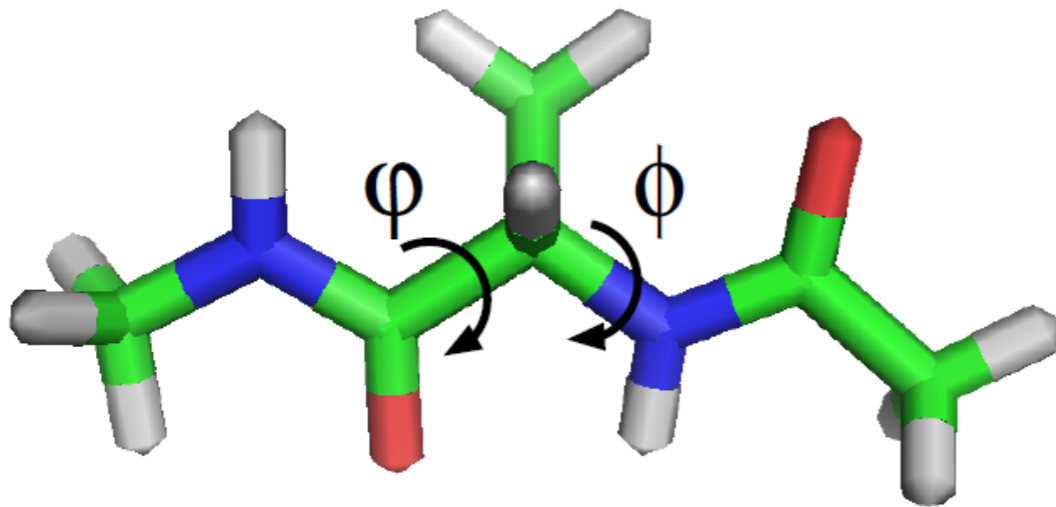
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Today's order: 3 - 2 - (1) - 2 - 3

The Alanine-Dipeptide Dataset

The alanine-dipeptide:

- 7 heavy atoms (C, N) and 13 light atoms (O, H)
- only the 7 heavy atoms play a role in conformational dynamics
 - each conformation is represented as a point in \mathbb{R}^{21}
- conformation space endowed with Root Mean-Squared Deviation (RMSD)

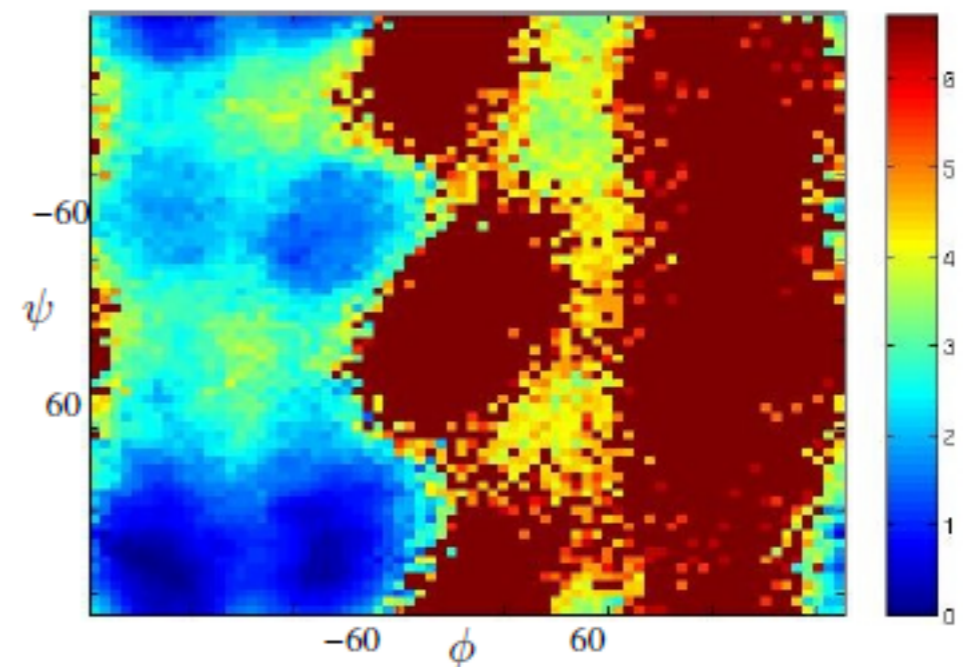
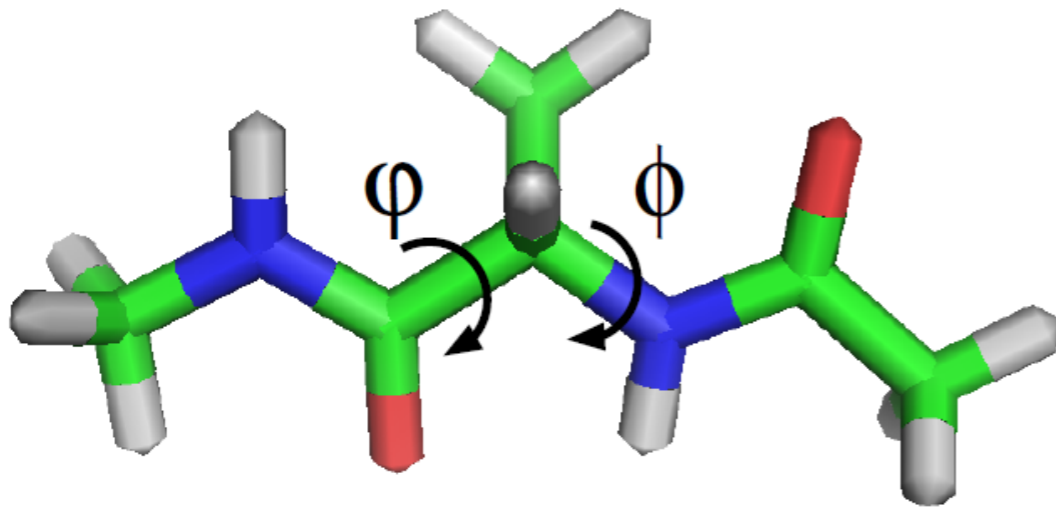


(from [Chodera et al. 2007], courtesy of the *Folding@Home* project)

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- only the 7 heavy atoms play a role in conformational dynamics
 - each conformation is represented as a point in \mathbb{R}^{21}
- conformation space endowed with Root Mean-Squared Deviation (RMSD)
- only two relevant DOFs (angles ϕ , ψ)
- underlying free energy landscape exhibits 6 major minima (*metastable states*)

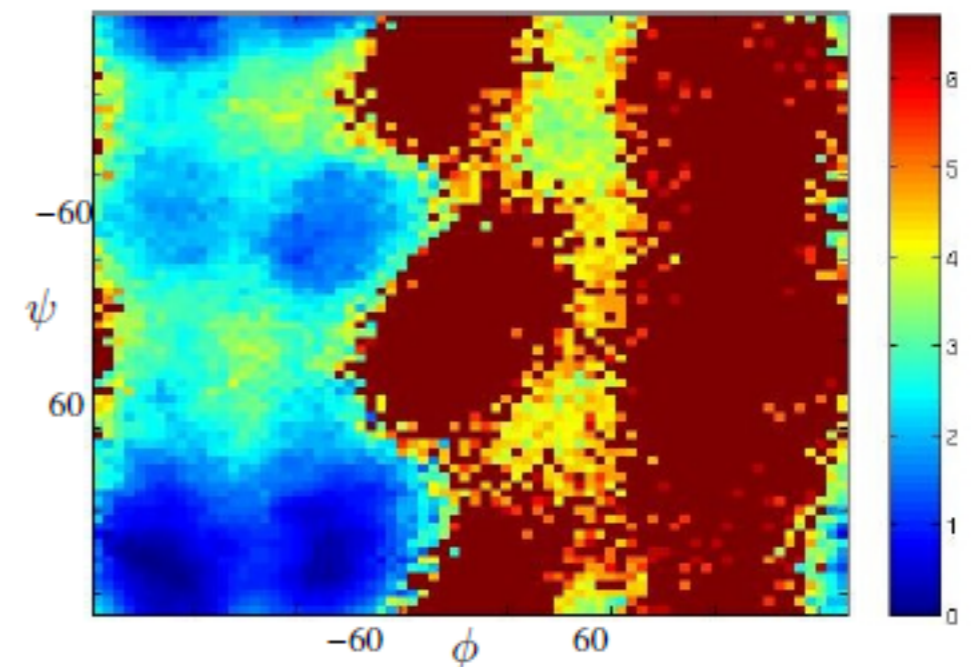
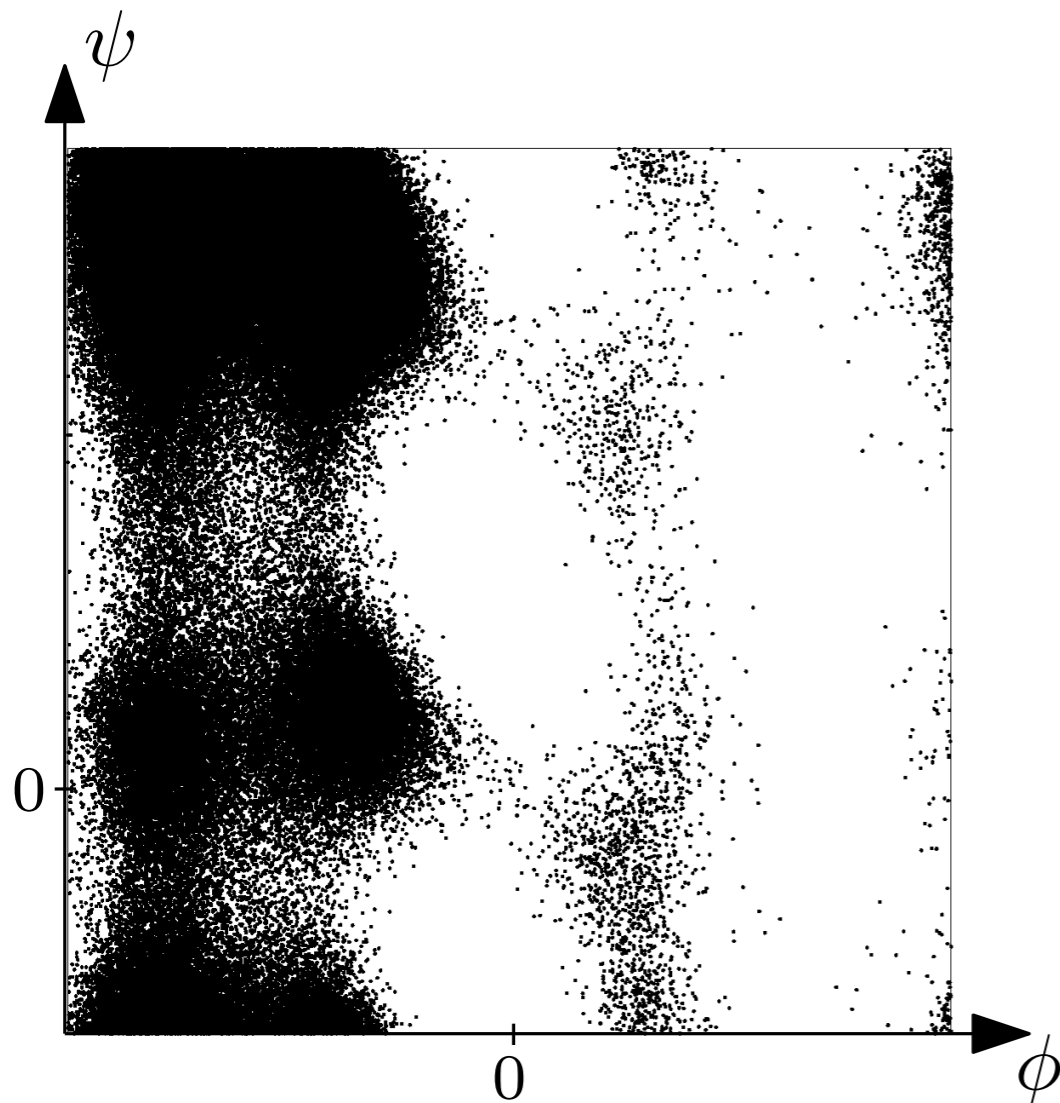


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The Alanine-Dipeptide Dataset

Input:

- 192,000 points in \mathbb{R}^{21} obtained from simulations at picosecond scale
- RMSD used as distance between conformations



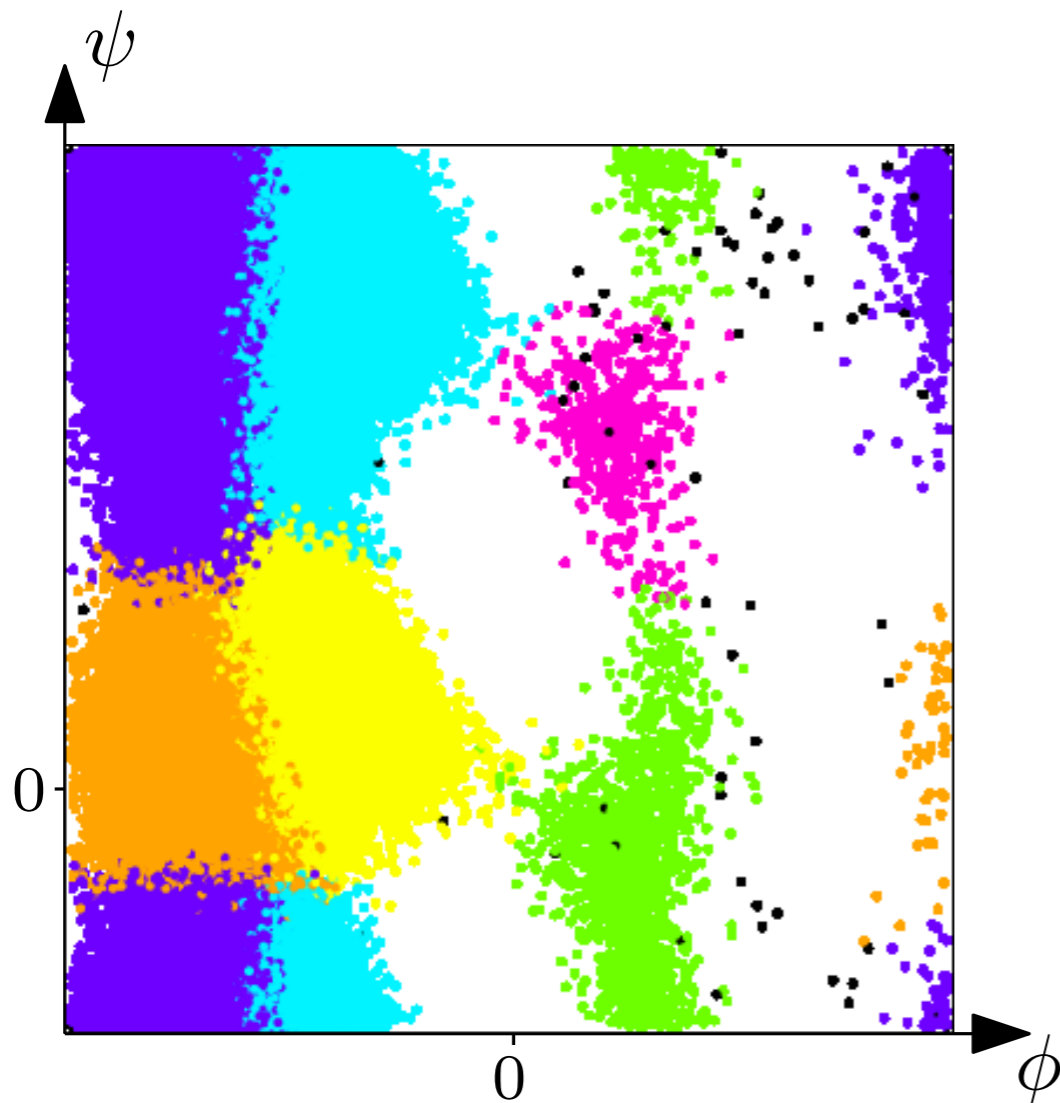
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Goal:

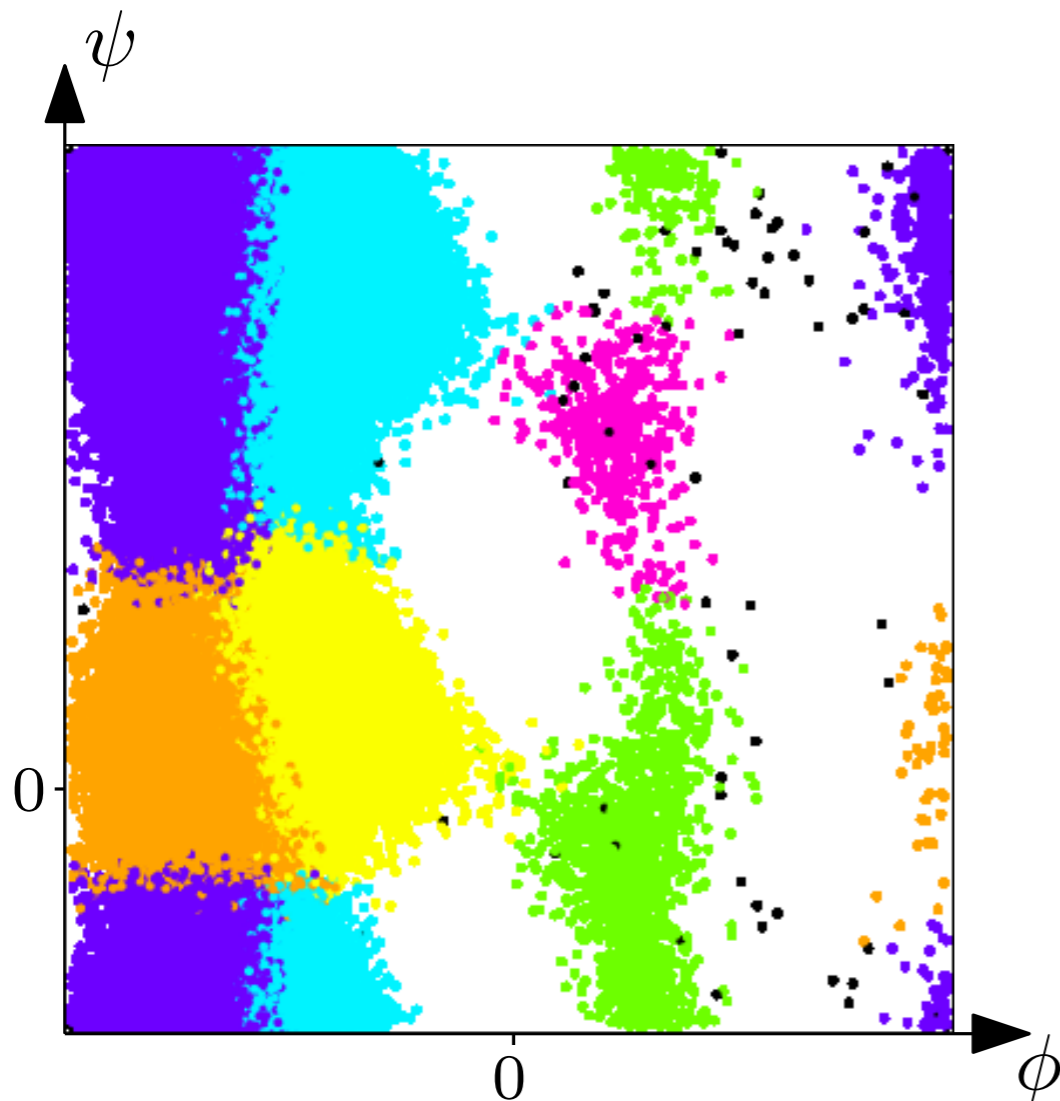
- cluster data into *metastable states*
- states gathered into Markovian model
- enables simulations at millisecond scale



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Challenges:

- low-dim. data embedded in higher dim.
- non-trivial topology
- ambient space is non-Euclidean
- prominences of density peaks differ a lot

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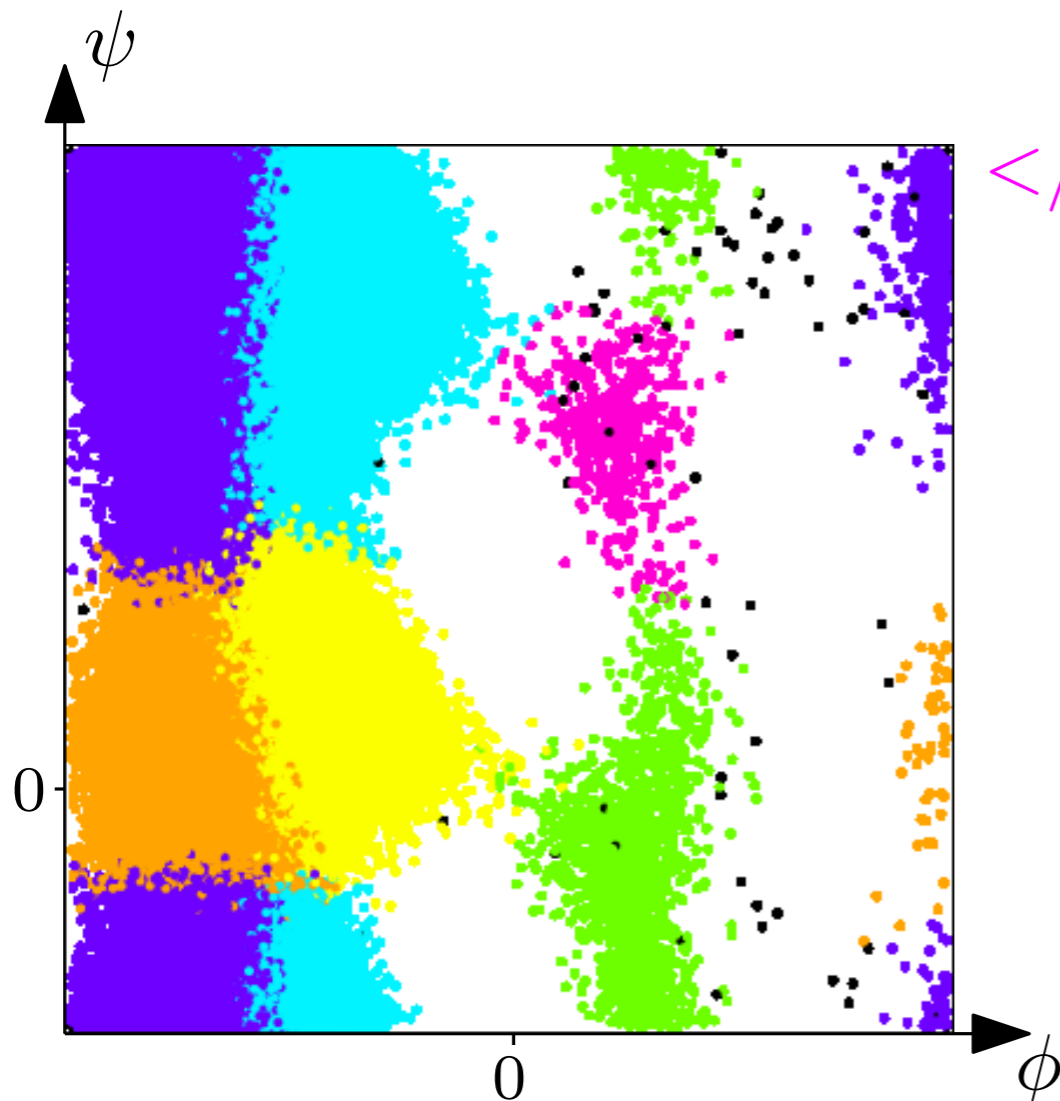
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<advertising>

previous attempts took \geq week of tweaking
our approach worked out of the box (10 minutes)

</advertising>

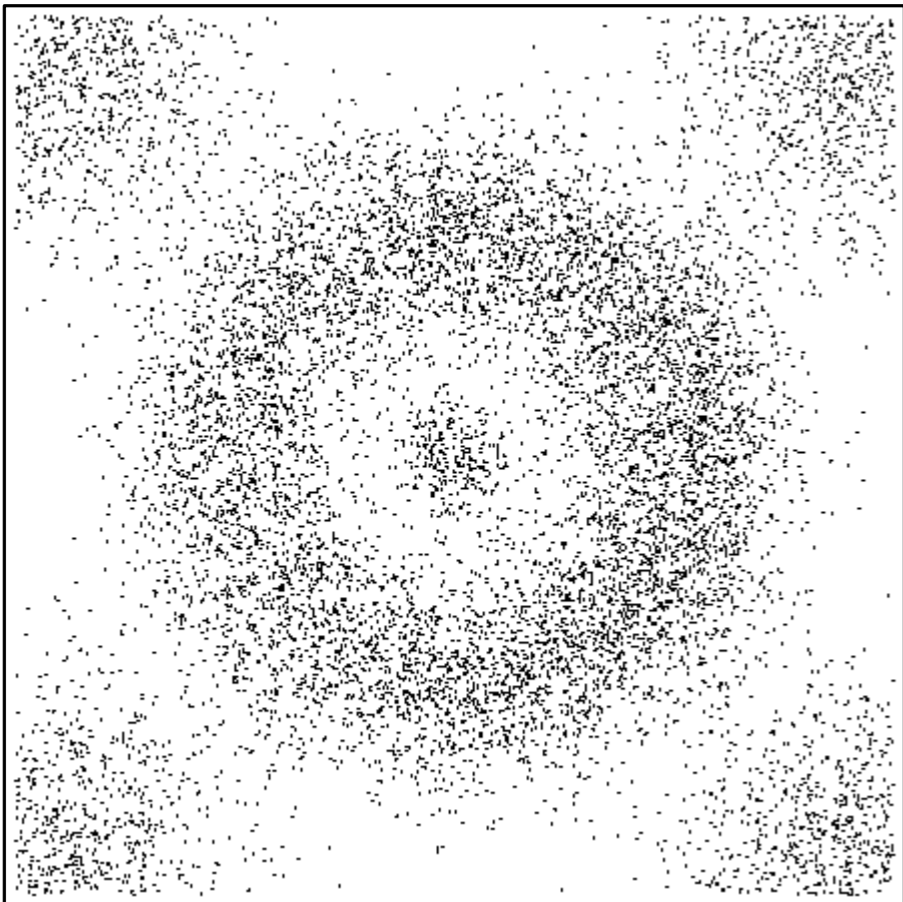


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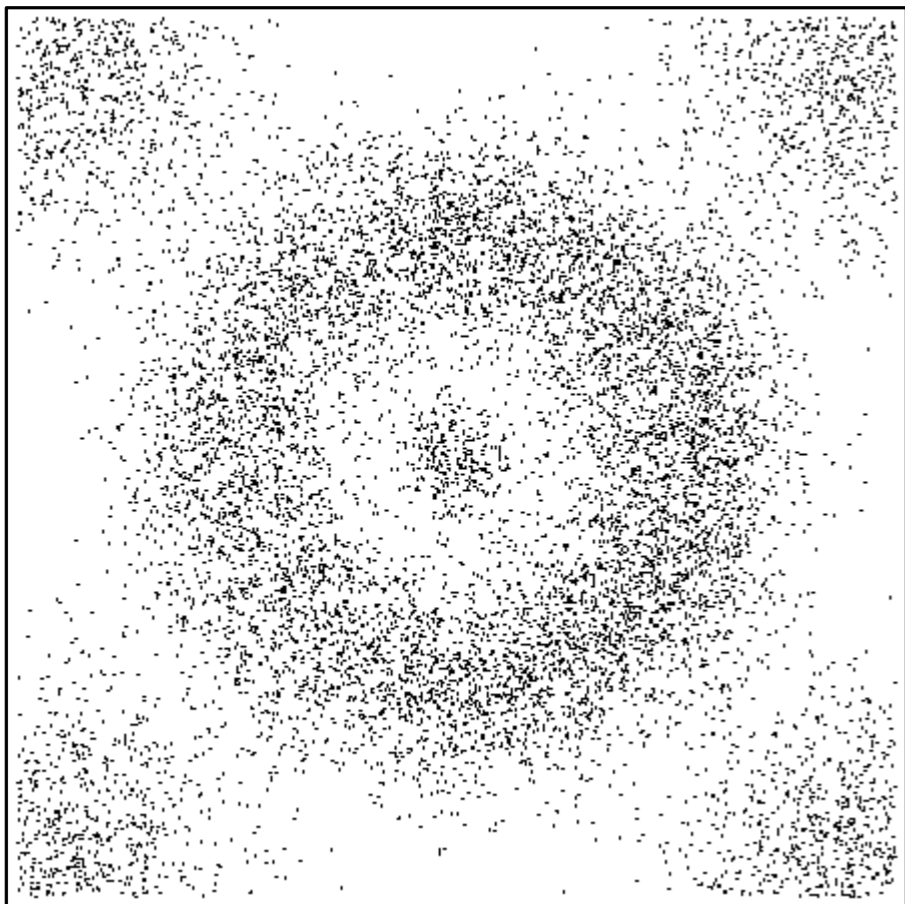
Our Formalism

- \mathbb{X} is a Riemannian manifold
- points are drawn from an unknown probability distribution of density $f : \mathbb{X} \rightarrow \mathbb{R}$
- sole input: the pairwise geodesic distances between the data points

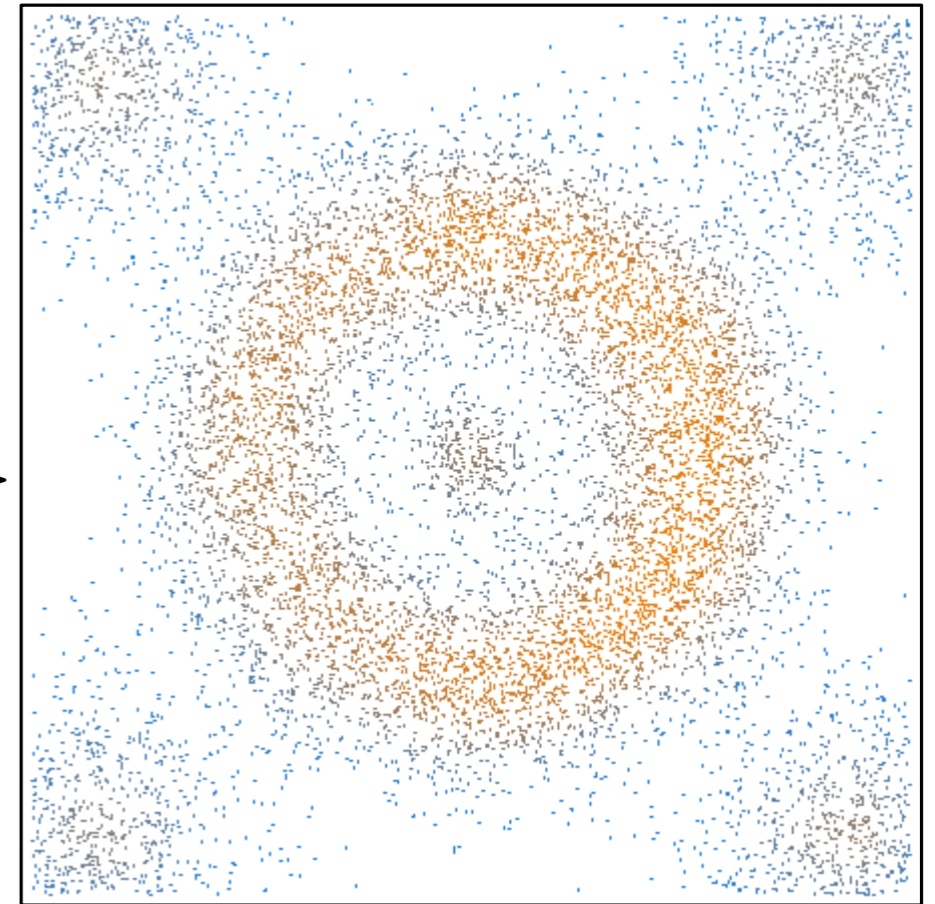


Our Formalism

- \mathbb{X} is a Riemannian manifold
- points are drawn from an unknown probability distribution of density $f : \mathbb{X} \rightarrow \mathbb{R}$
- sole input: the pairwise geodesic distances between the data points
- approximate f through some density estimator \hat{f}
- cluster data points according to basins of attraction of *prominent* peaks of \hat{f}



density
estimation

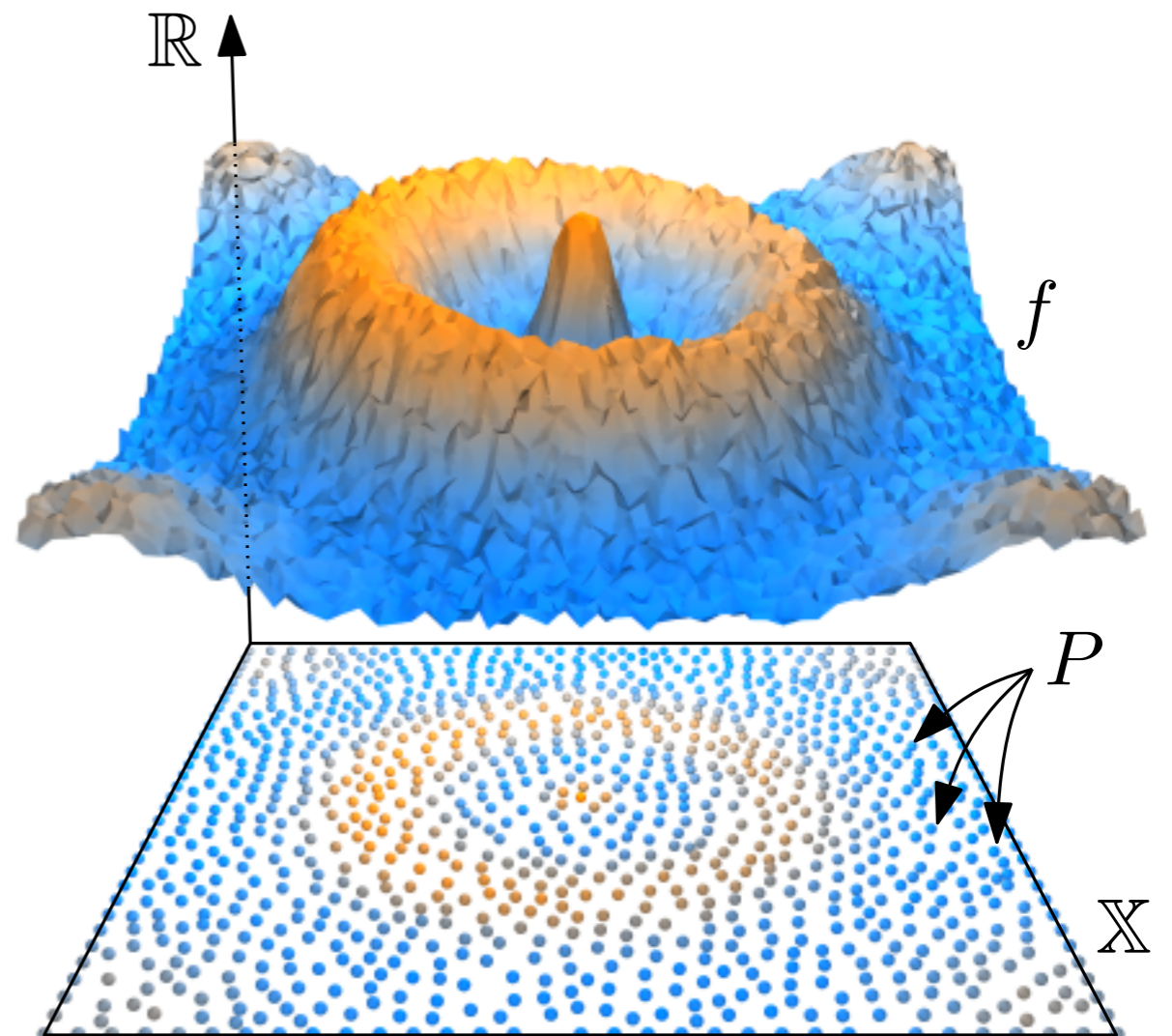


Link with Scalar Fields Analysis

Setting: \mathbb{X} a metric space, $f : \mathbb{X} \rightarrow \mathbb{R}$ a *regular* function

P a finite point cloud in \mathbb{X}

Input: pairwise distances between points of P , values of f at P



Link with Scalar Fields Analysis

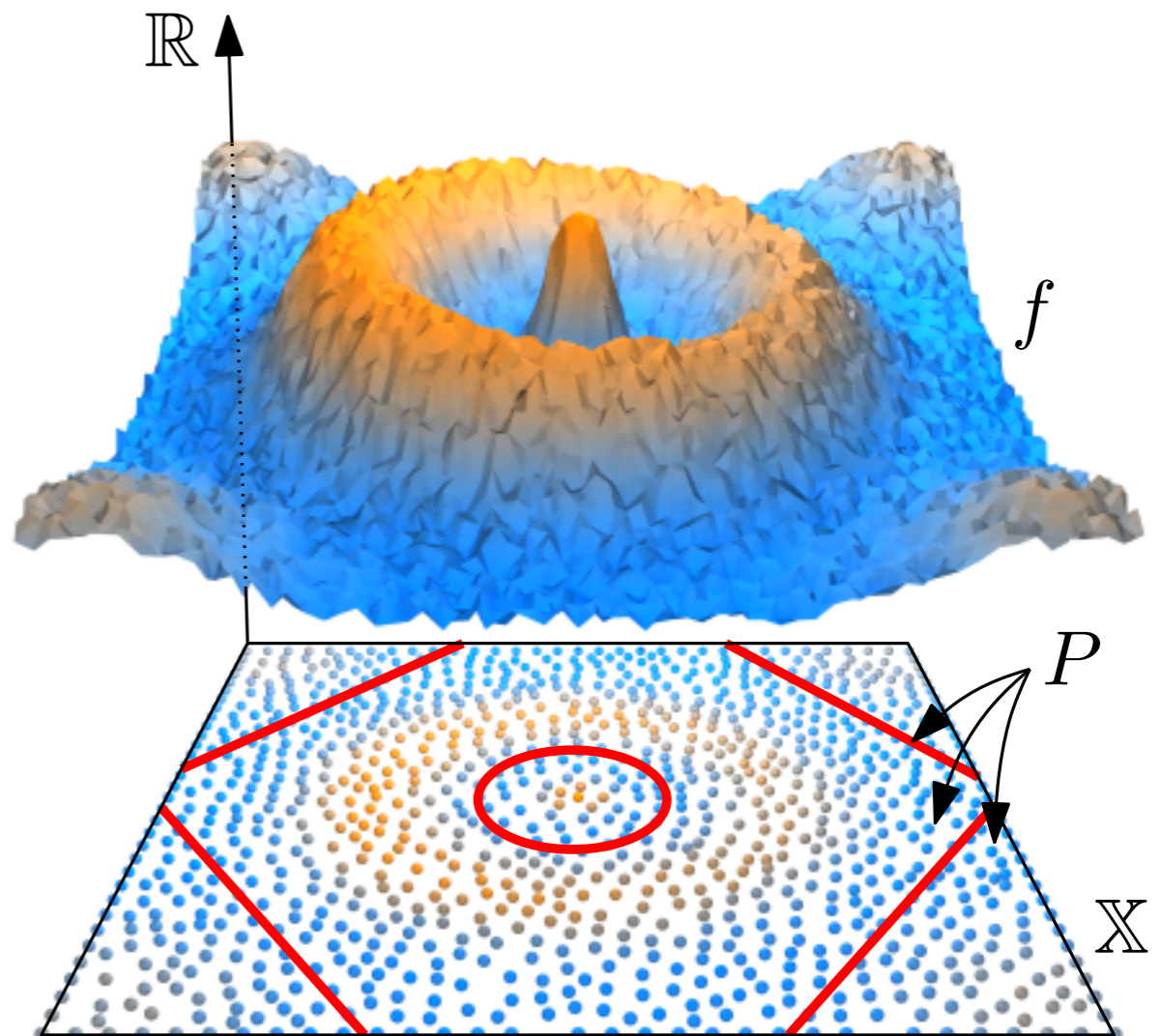
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- stable/unstable manifolds



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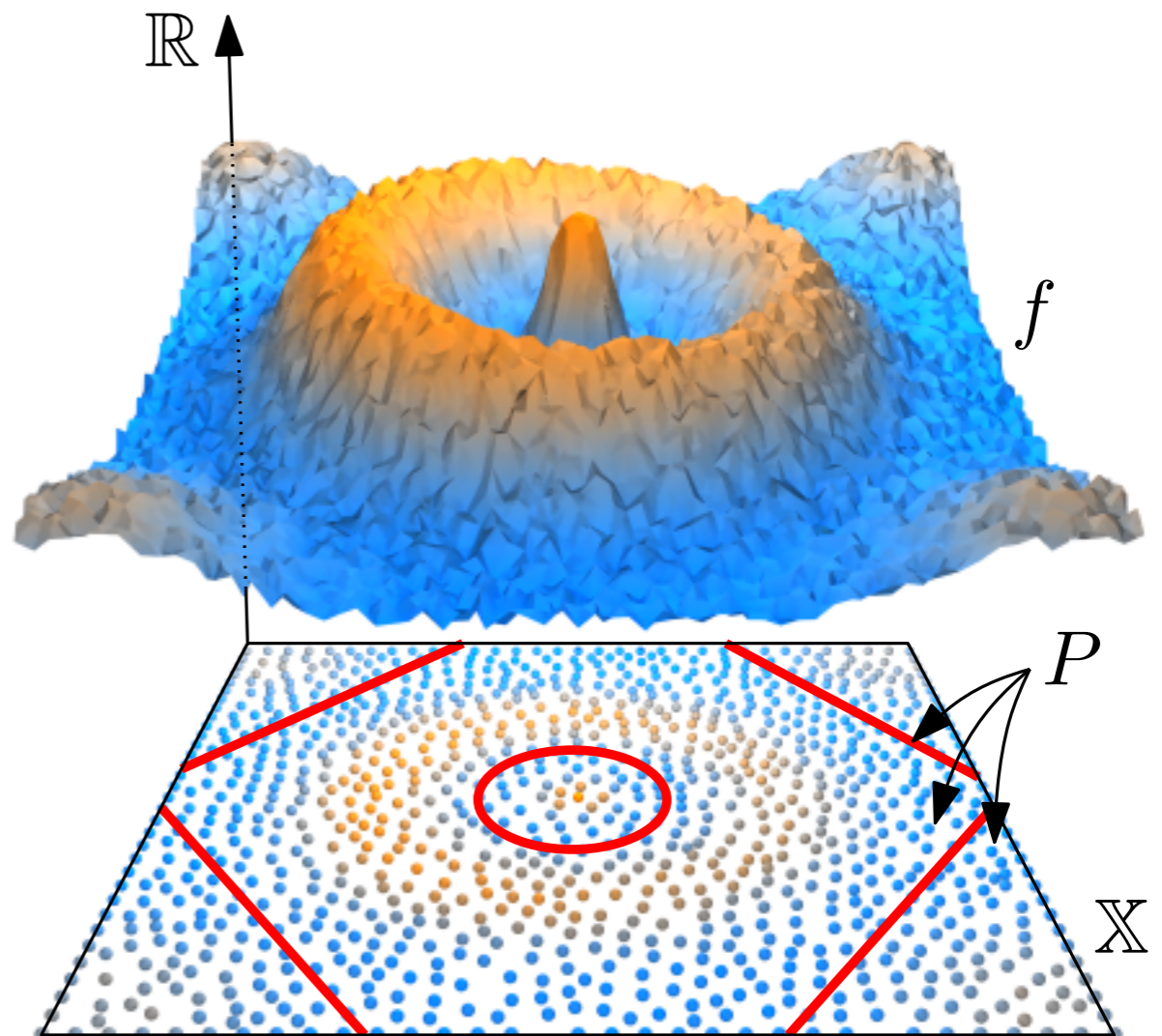
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No triangulation of \mathbb{X} is available

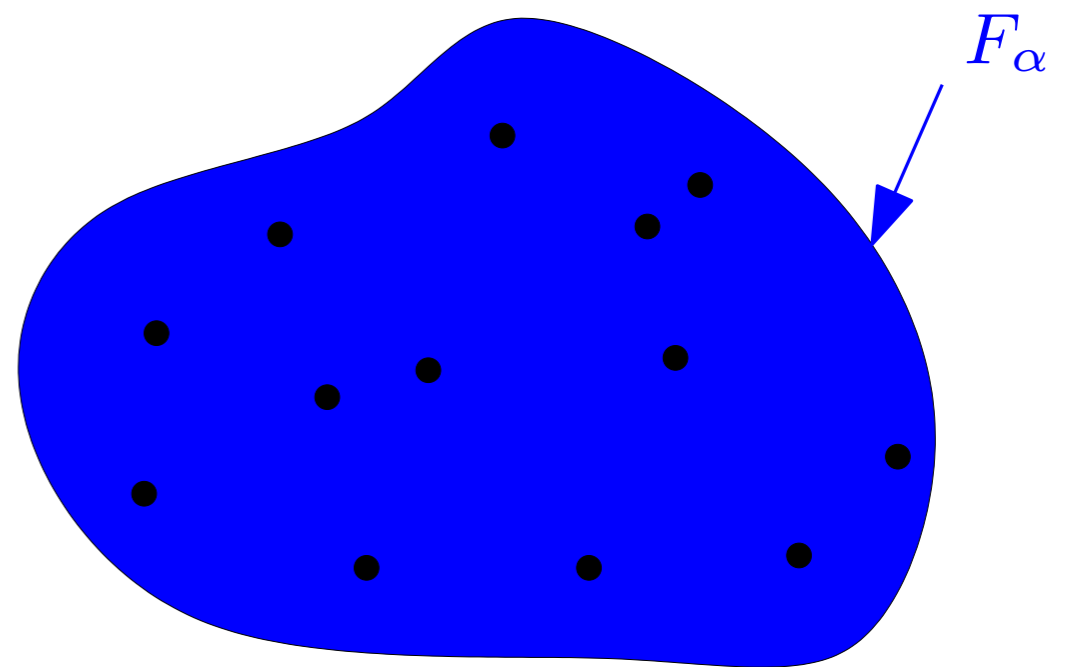


Unions of Balls

Assume \mathbb{X} is a metric space, $f : \mathbb{X} \rightarrow \mathbb{R}$ is c -Lipschitz,
 P is an ε -sample of \mathbb{X} for some (unknown) $\varepsilon > 0$.

$$\left| \begin{array}{l} F_\alpha := f^{-1}((-\infty, \alpha]) \\ P_\alpha := P \cap F_\alpha \\ P_\alpha^\varepsilon := \bigcup_{p \in P_\alpha} B_{\mathbb{X}}(p, \varepsilon) \end{array} \right.$$

$$\forall \alpha \in \mathbb{R}, P_\alpha^\varepsilon \subseteq F_{\alpha+c\varepsilon}$$

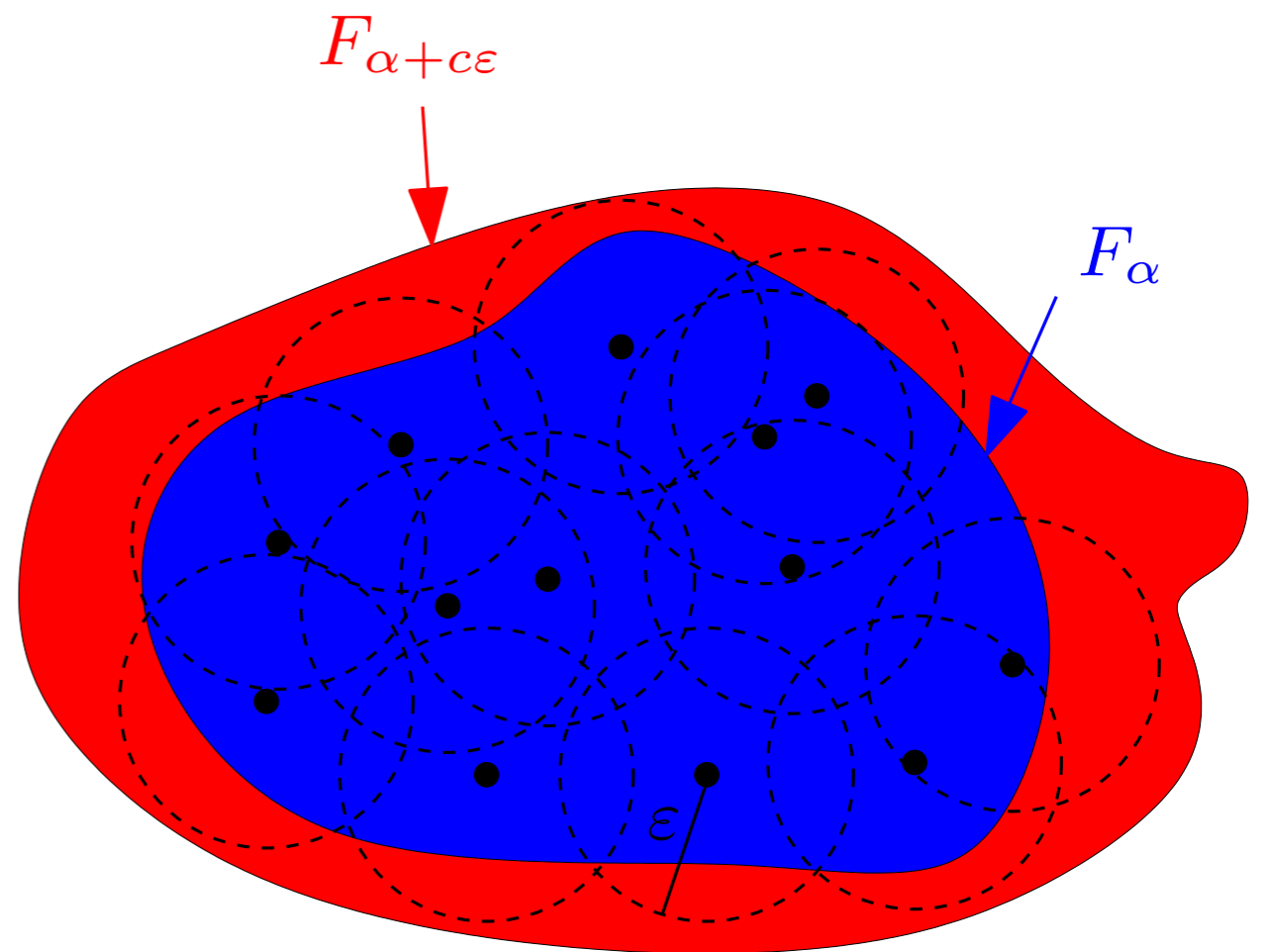


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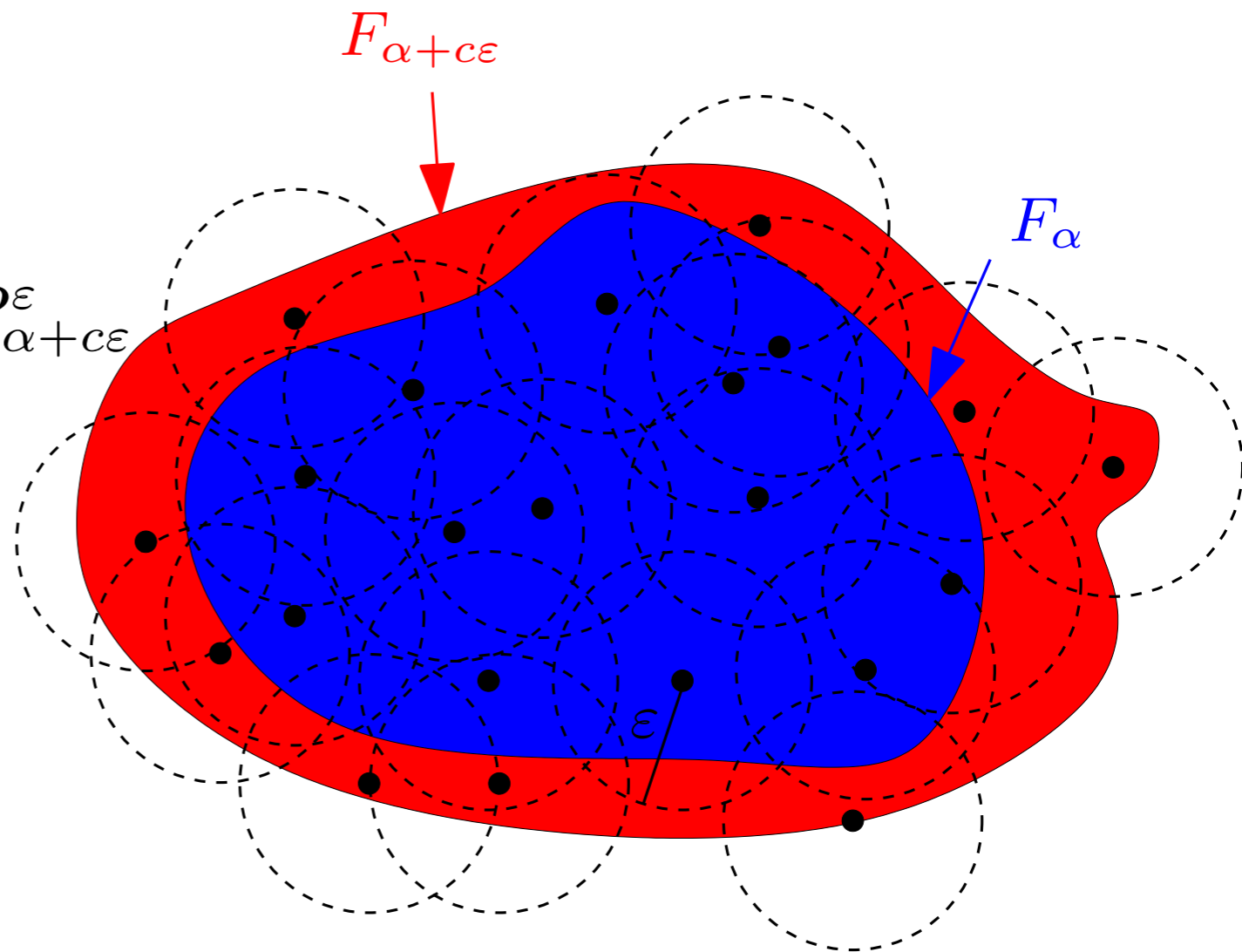


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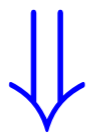
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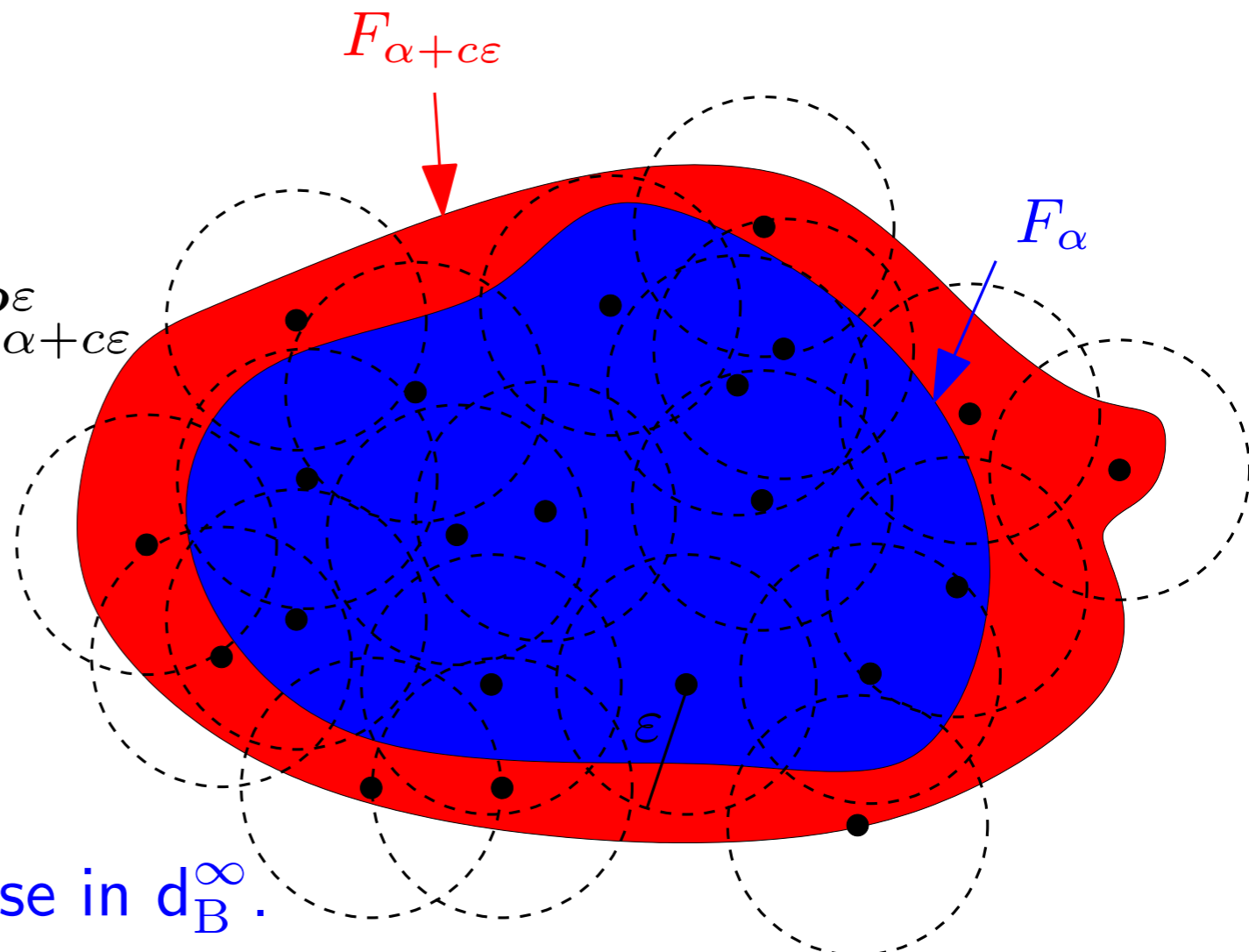
$$\forall \alpha \in \mathbb{R}, P_\alpha^\varepsilon \subseteq F_{\alpha+c\varepsilon} \text{ and } F_\alpha \subseteq P_{\alpha+c\varepsilon}^\varepsilon$$

the nested families of spaces
 $\{F_\alpha\}_{\alpha \in \mathbb{R}}$ and $\{P_\alpha^\varepsilon\}_{\alpha \in \mathbb{R}}$
 are $c\varepsilon$ -interleaved w.r.t. inclusion



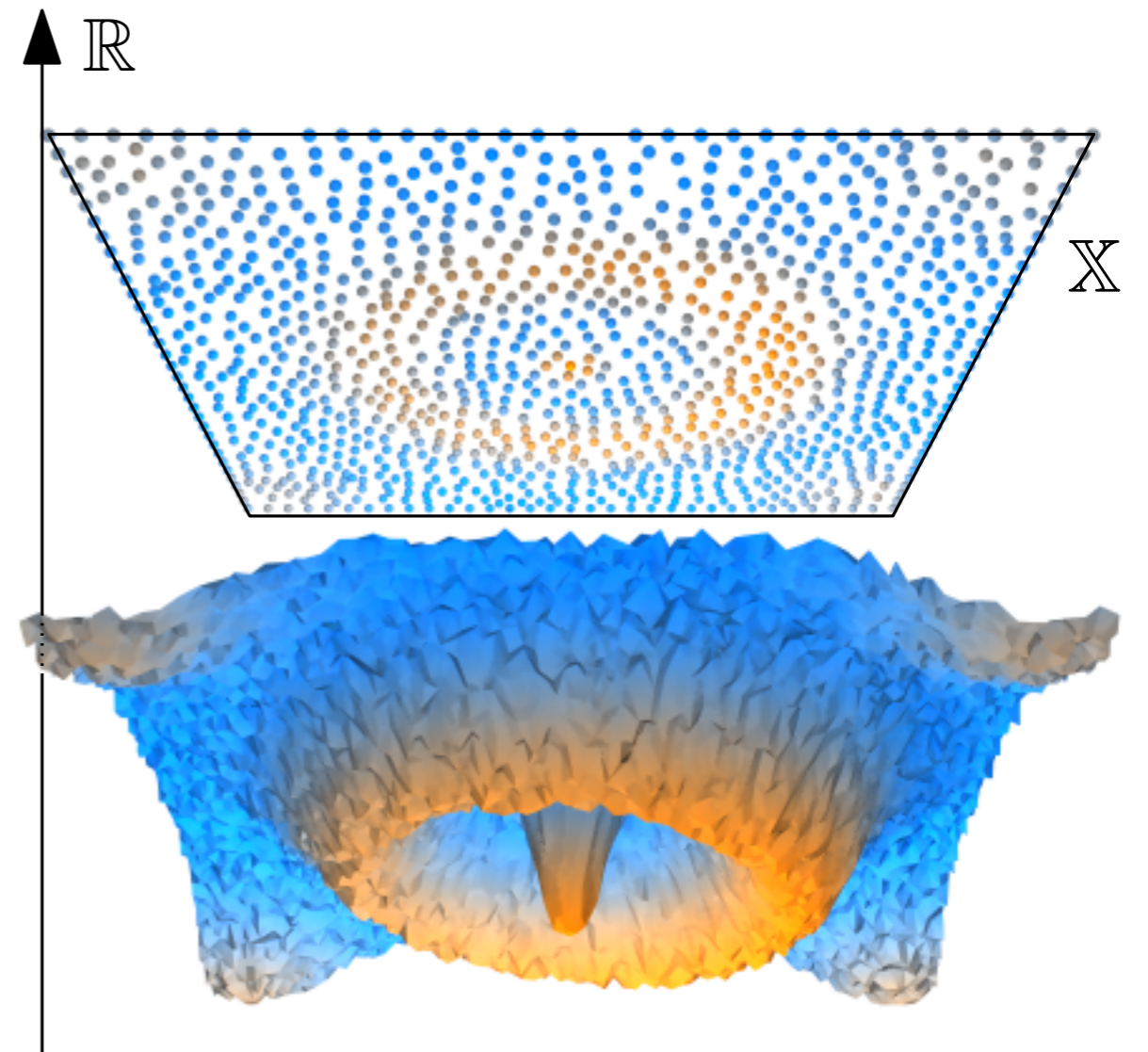
their persistence diagrams are $c\varepsilon$ -close in d_B^∞ .

[Cohen-Steiner, Edelsbrunner, Harer '05] [Chazal, Cohen-Steiner, Glisse, Guibas, O. '09]



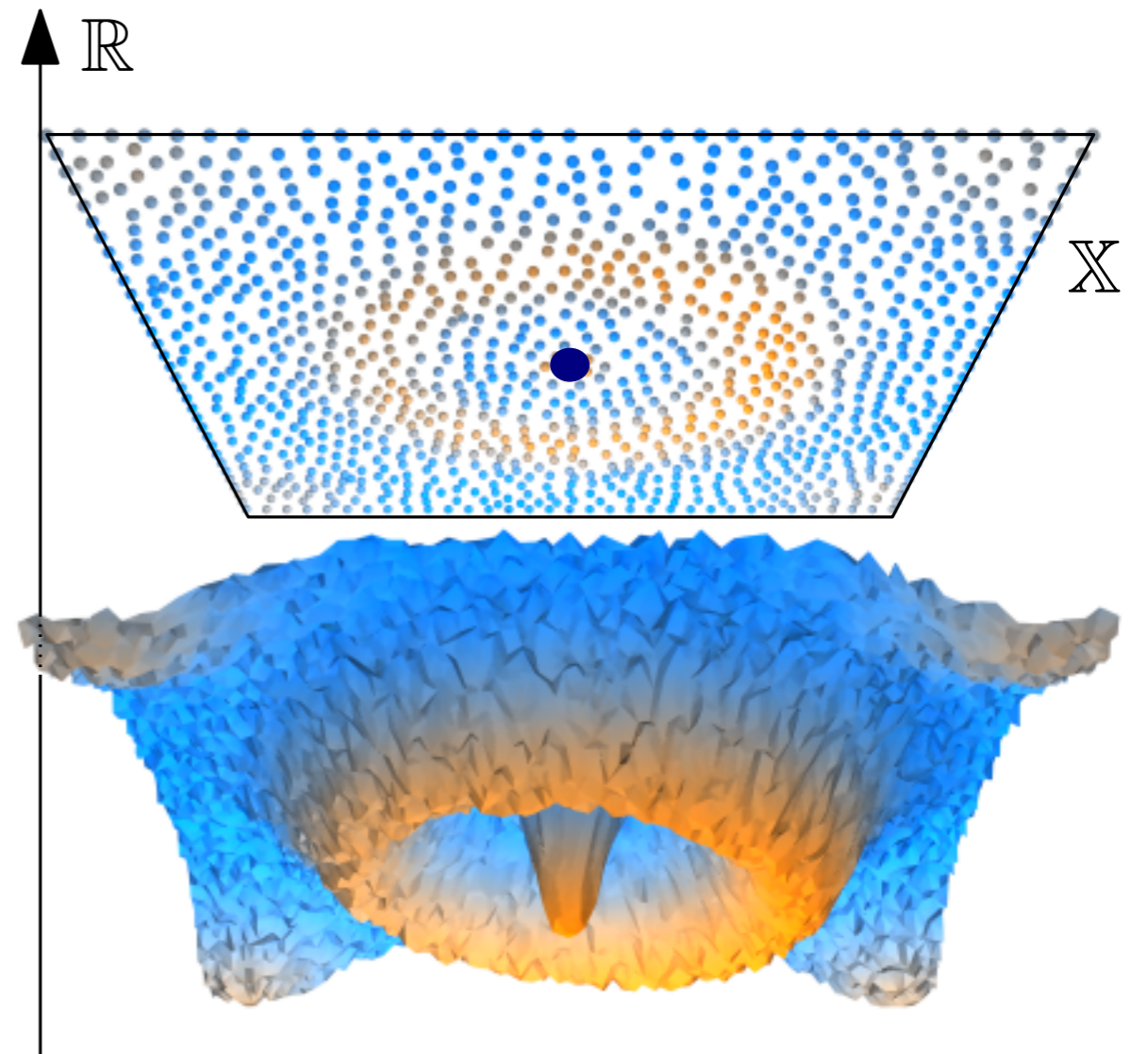
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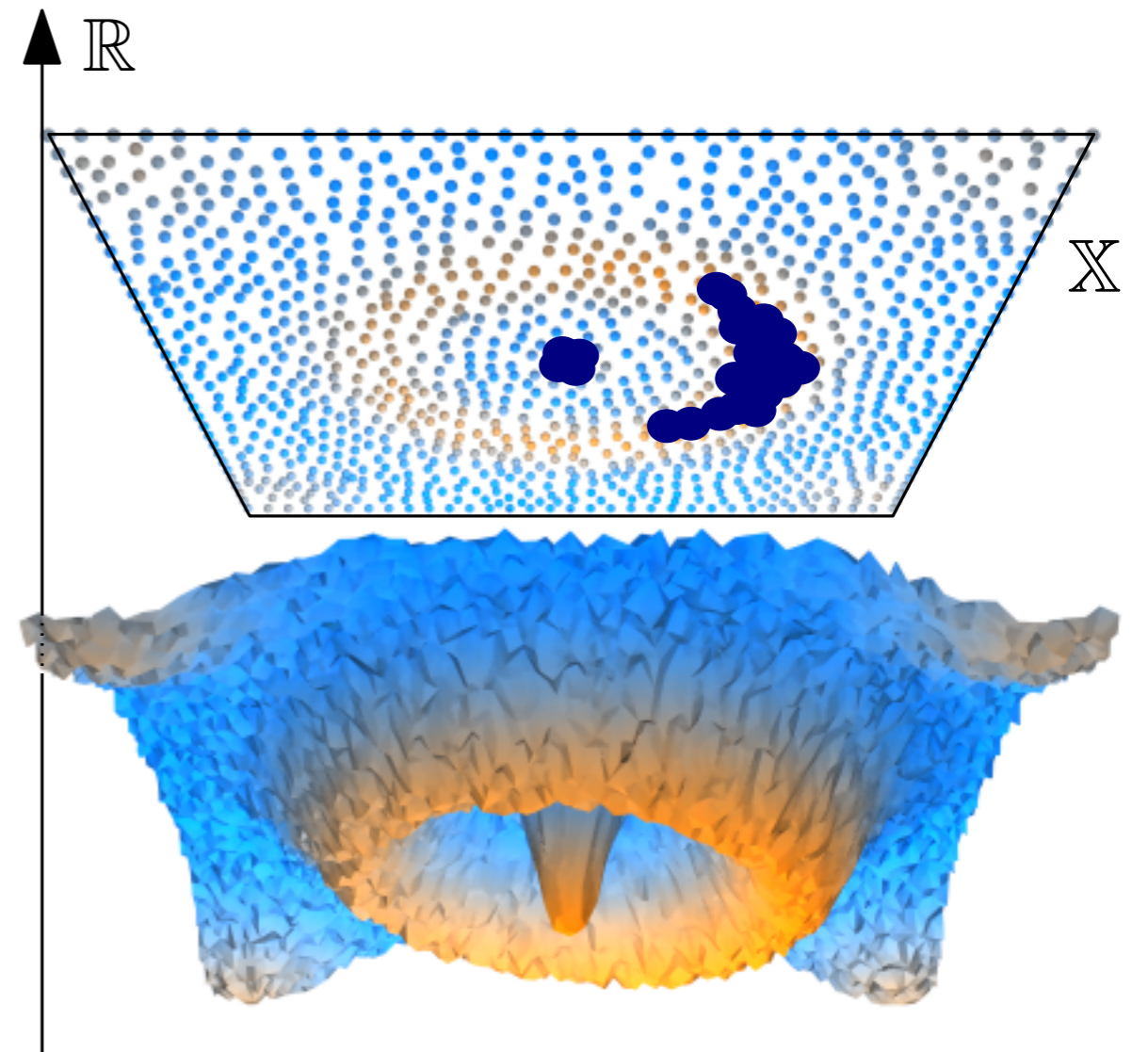
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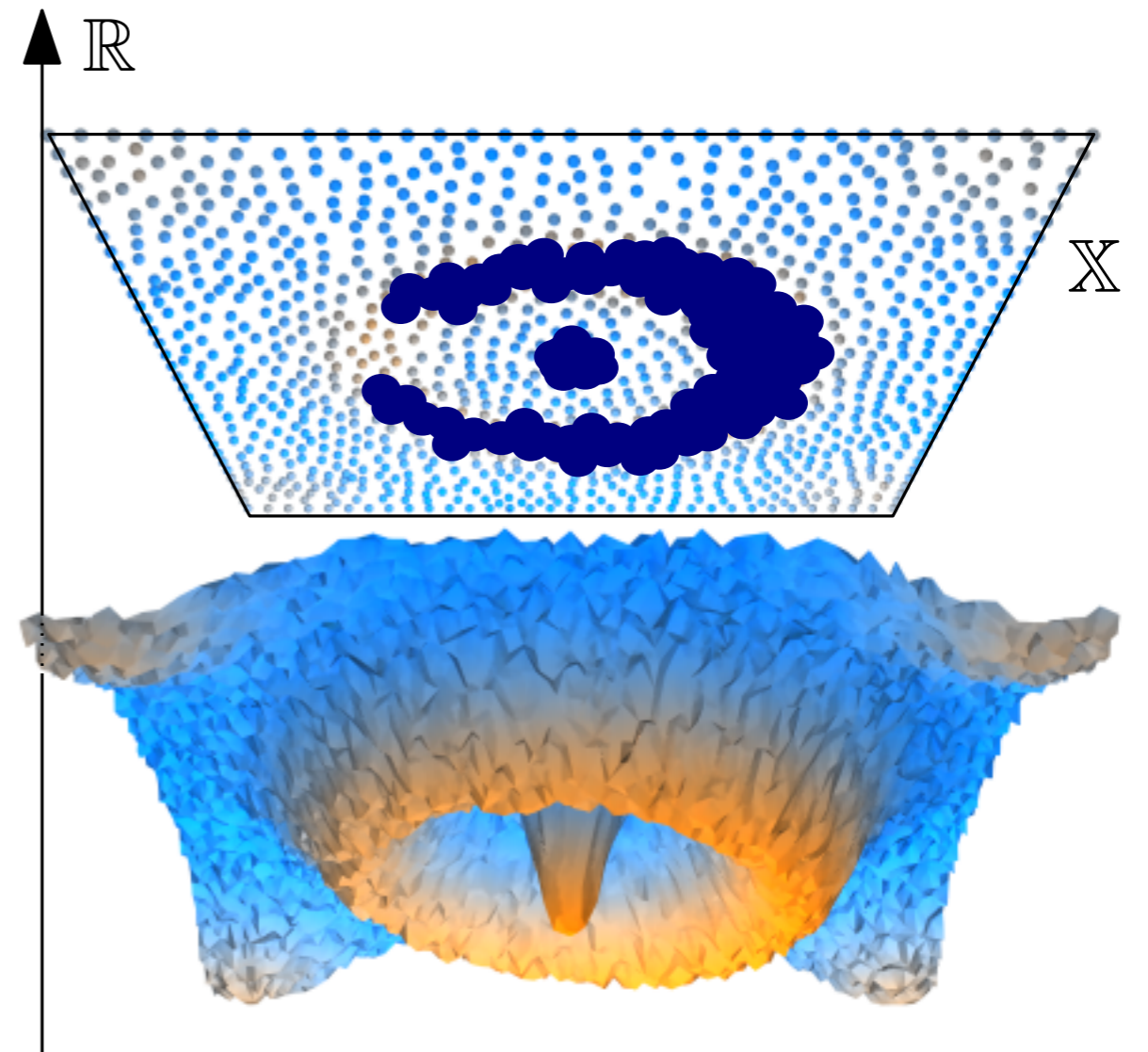
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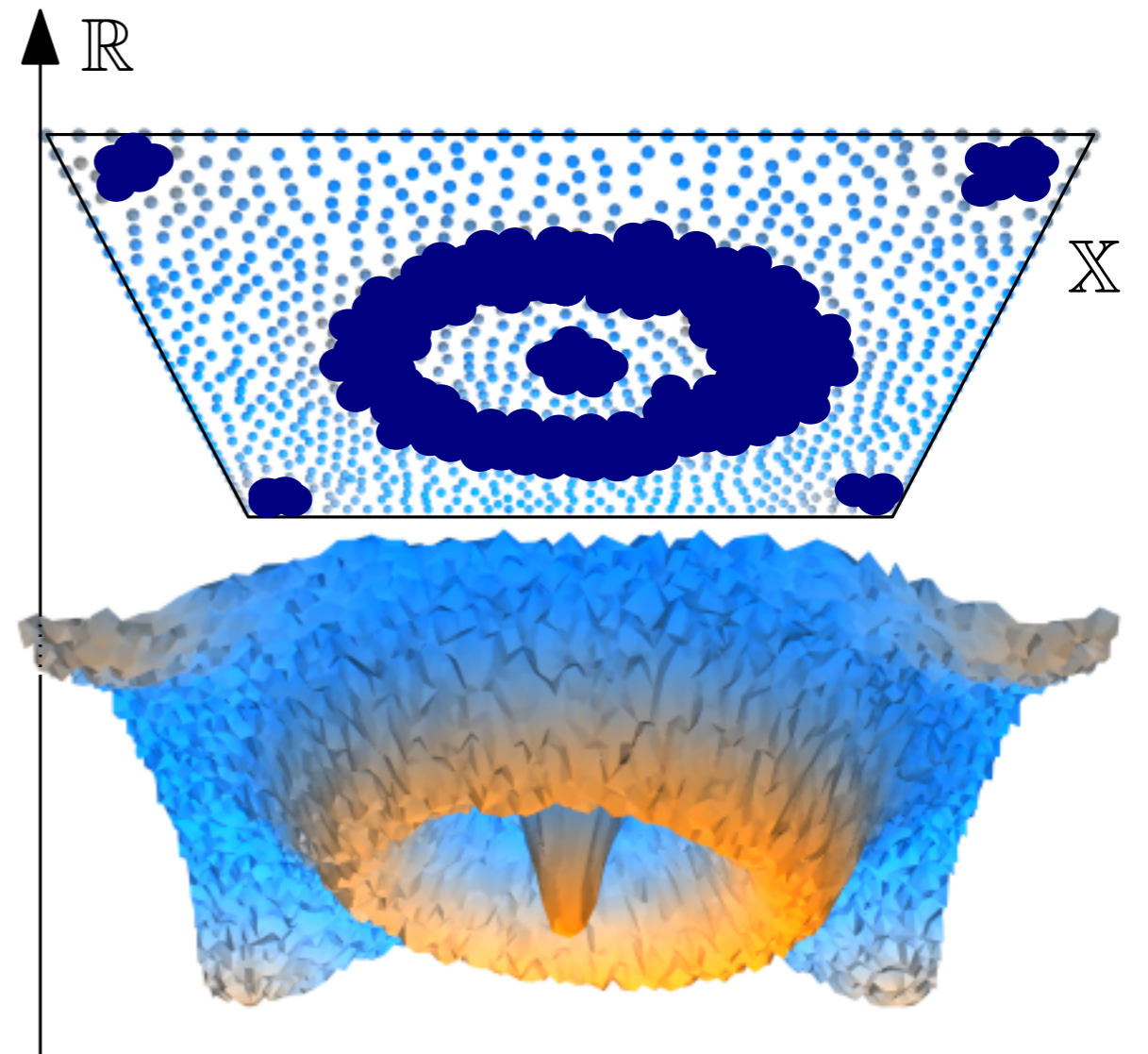
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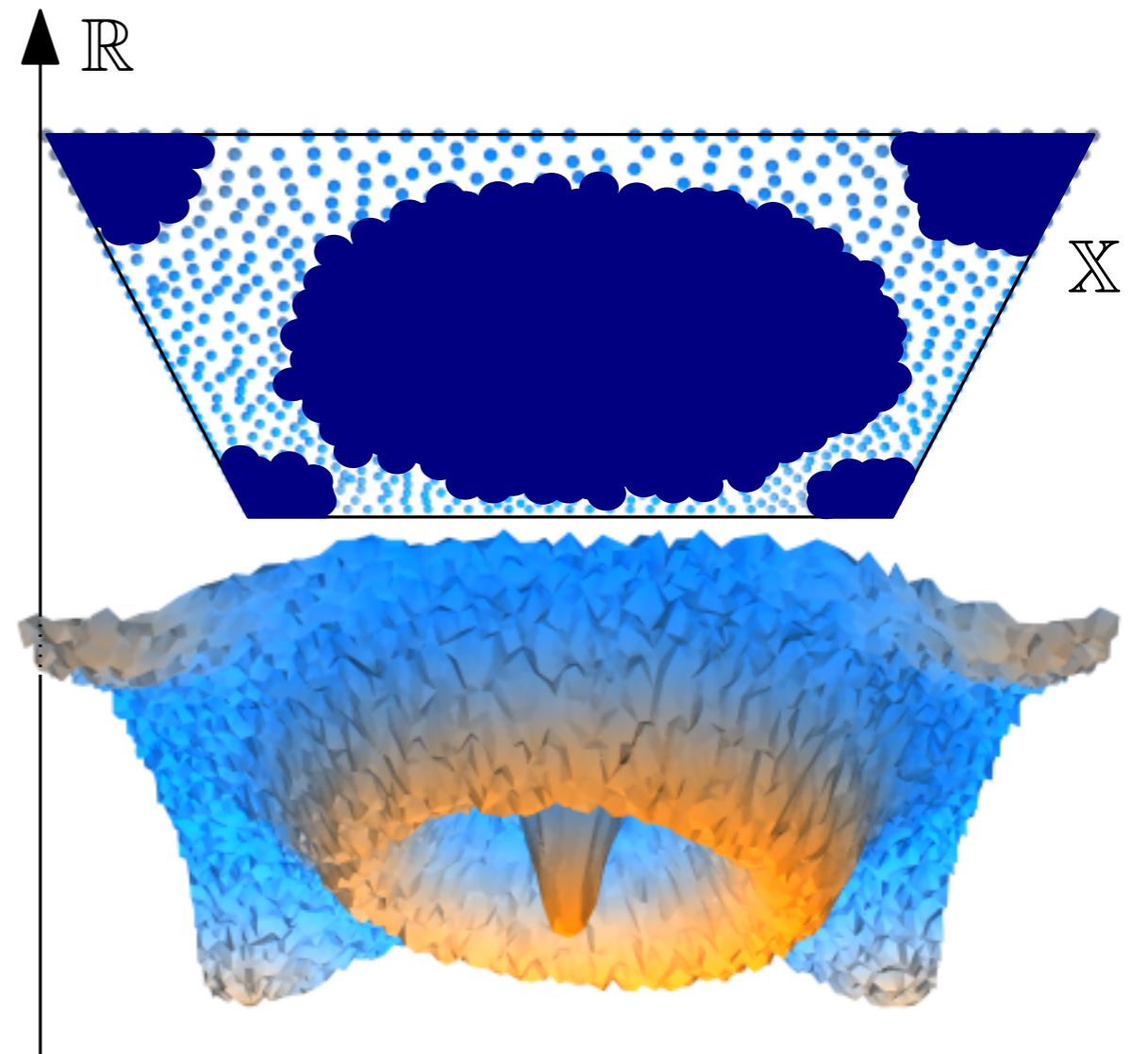
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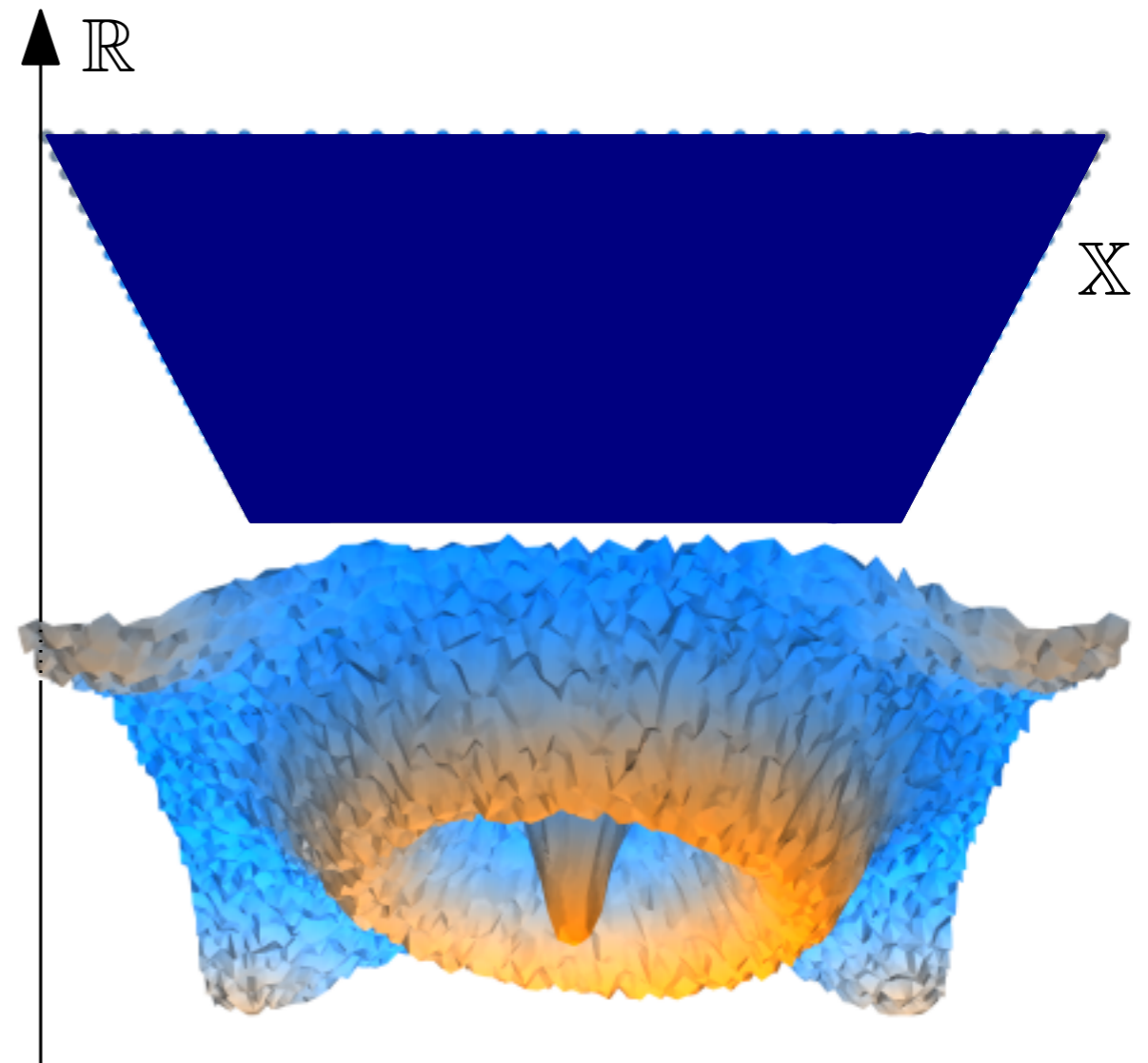
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Algorithm: choose parameter $\delta \geq 0$

1. Sort the data points such that $f(p_1) \leq f(p_2) \leq \dots \leq f(p_n)$,
2. For $i = 1, \dots, n$, build the union of balls $\{p_1, \dots, p_i\}^\delta$,
3. Compute the persistent homology of the nested family of spaces:

$$\{p_1\}^\delta \hookrightarrow \{p_1, p_2\}^\delta \hookrightarrow \{p_1, p_2, p_3\}^\delta \hookrightarrow \dots \hookrightarrow \{p_1, p_2, \dots, p_n\}^\delta$$

Unions of Balls

Riemannian manifold

Assume \mathbb{X} is a ~~metric space~~, $f : \mathbb{X} \rightarrow \mathbb{R}$ is c -Lipschitz,

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$$0 < \varepsilon < \rho_c(\mathbb{X})$$

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or equivalently its nerve $\mathcal{N}^\delta(p_1, \dots, p_i)$,
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$$\mathcal{N}^\delta(p_1) \hookrightarrow \mathcal{N}^\delta(p_1, p_2) \hookrightarrow \mathcal{N}^\delta(p_1, p_2, p_3) \hookrightarrow \dots \hookrightarrow \mathcal{N}^\delta(p_1, p_2, \dots, p_n)$$

Unions of Balls

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→ if $\varepsilon \leq \delta < \varrho_c(\mathbb{X})$, we obtain a $c\delta$ -approximation of the diagram of f in d_B^∞

Unions of Balls

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or equivalent $\mathcal{N}^\delta(p_1, \dots, p_i)$,

3. Compute the persistent \mathcal{H}_k of the nested family of spaces:

$$\mathcal{N}^\delta(p_1) \hookrightarrow \mathcal{N}^\delta(p_1, p_2) \hookrightarrow \mathcal{N}^\delta(p_1, p_2, p_3) \hookrightarrow \dots \hookrightarrow \mathcal{N}^\delta(p_1, p_2, \dots, p_n)$$

Intractable in practice $\leq \rho_c(\mathbb{X})$

Pairs of Rips Complexes

Assume \mathbb{X} is a Riemannian manifold, $f : \mathbb{X} \rightarrow \mathbb{R}$ is c -Lipschitz,

P is an ε -sample of \mathbb{X} for some (unknown) $0 < \varepsilon < \frac{1}{4} \rho_c(\mathbb{X})$.

→ apply sandwiching idea from [Chazal, O. 08]:

$\forall i = 1, \dots, n$, replace $\mathcal{N}^\delta(p_1, \dots, p_i)$ by

$$\mathcal{R}^\delta(p_1, \dots, p_i) \subseteq \mathcal{N}^\delta(p_1, \dots, p_i) \subseteq \mathcal{R}^{2\delta}(p_1, \dots, p_i)$$

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3. Apply the persistence algorithm **for images** to the pair of filtrations.

[Cohen-Steiner, Edelsbrunner, Harer, Morozov '09]

$$\begin{array}{ccccccc}
 \mathcal{R}^{2\delta}(p_1) & \hookrightarrow & \mathcal{R}^{2\delta}(p_1, p_2) & \hookrightarrow & \dots & \hookrightarrow & \mathcal{R}^{2\delta}(p_1, p_2, \dots, p_n) \\
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 \end{array}$$

$\{\text{im } H_k(\mathcal{R}^\delta(p_1, \dots, p_i)) \rightarrow H_k(\mathcal{R}^{2\delta}(p_1, \dots, p_i))\}_{1 \leq i \leq n}$

Pairs of Rips Complexes

Assume \mathbb{X} is a Riemannian manifold, $f : \mathbb{X} \rightarrow \mathbb{R}$ is c -Lipschitz,
 P is an ε -sample of \mathbb{X} for some (unknown) $0 < \varepsilon < \frac{1}{4} \varrho_c(\mathbb{X})$.

Guarantees: $\forall \delta \in [2\varepsilon, \frac{1}{2} \varrho_c(\mathbb{X})]$,

$\{H_k(F_\alpha)\}_{\alpha \in \mathbb{R}}$ and $\{\text{im } H_k(\mathcal{R}^\delta(P_\alpha)) \rightarrow H_k(\mathcal{R}^{2\delta}(P_\alpha))\}_{\alpha \in \mathbb{R}}$ are $2c\delta$ -interleaved:

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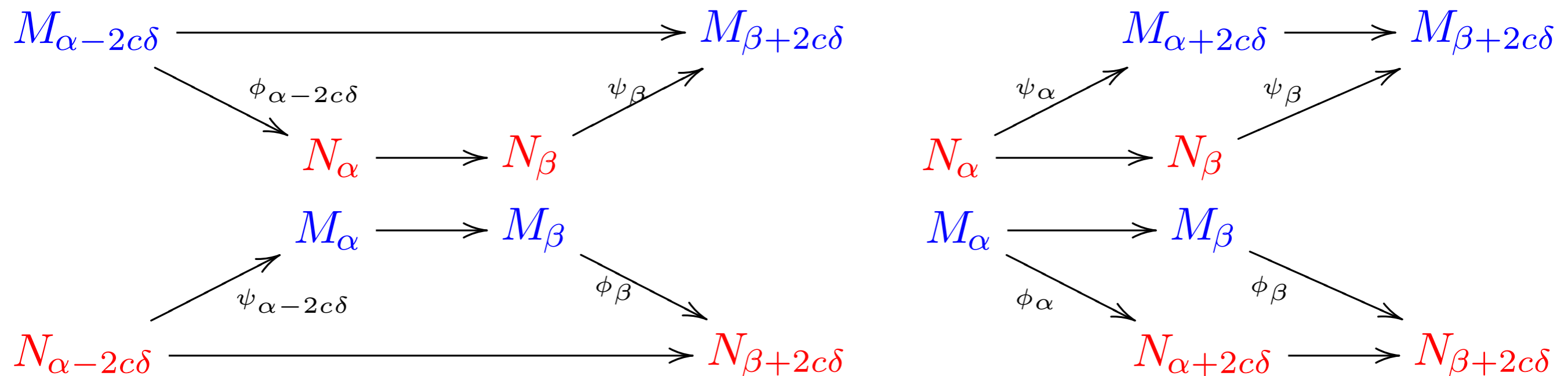
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Letting $M_\alpha = H_k(F_\alpha)$ and $N_\alpha = \text{im } H_k(\mathcal{R}^\delta(P_{\alpha+2c\delta})) \rightarrow H_k(\mathcal{R}^{2\delta}(P_{\alpha+2c\delta}))$,

$\exists \{\phi_\alpha : M_\alpha \rightarrow N_{\alpha+2c\delta}\}_{\alpha \in \mathbb{R}}$ and $\{\psi_\alpha : N_\alpha \rightarrow M_{\alpha+2c\delta}\}_{\alpha \in \mathbb{R}}$

s.t. the following diagrams commute $\forall \alpha \leq \beta$:



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 \mathcal{R}^{2\delta}(p_1) & \hookrightarrow & \mathcal{R}^{2\delta}(p_1, p_2) & \hookrightarrow & \dots & \hookrightarrow & \mathcal{R}^{2\delta}(p_1, p_2, \dots, p_n) \\
 \uparrow & & \uparrow & & & & \uparrow \\
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 \end{array}$$

Pairs of Rips Complexes

Assume \mathbb{X} is a Riemannian manifold, $f : \mathbb{X} \rightarrow \mathbb{R}$ is c -Lipschitz,

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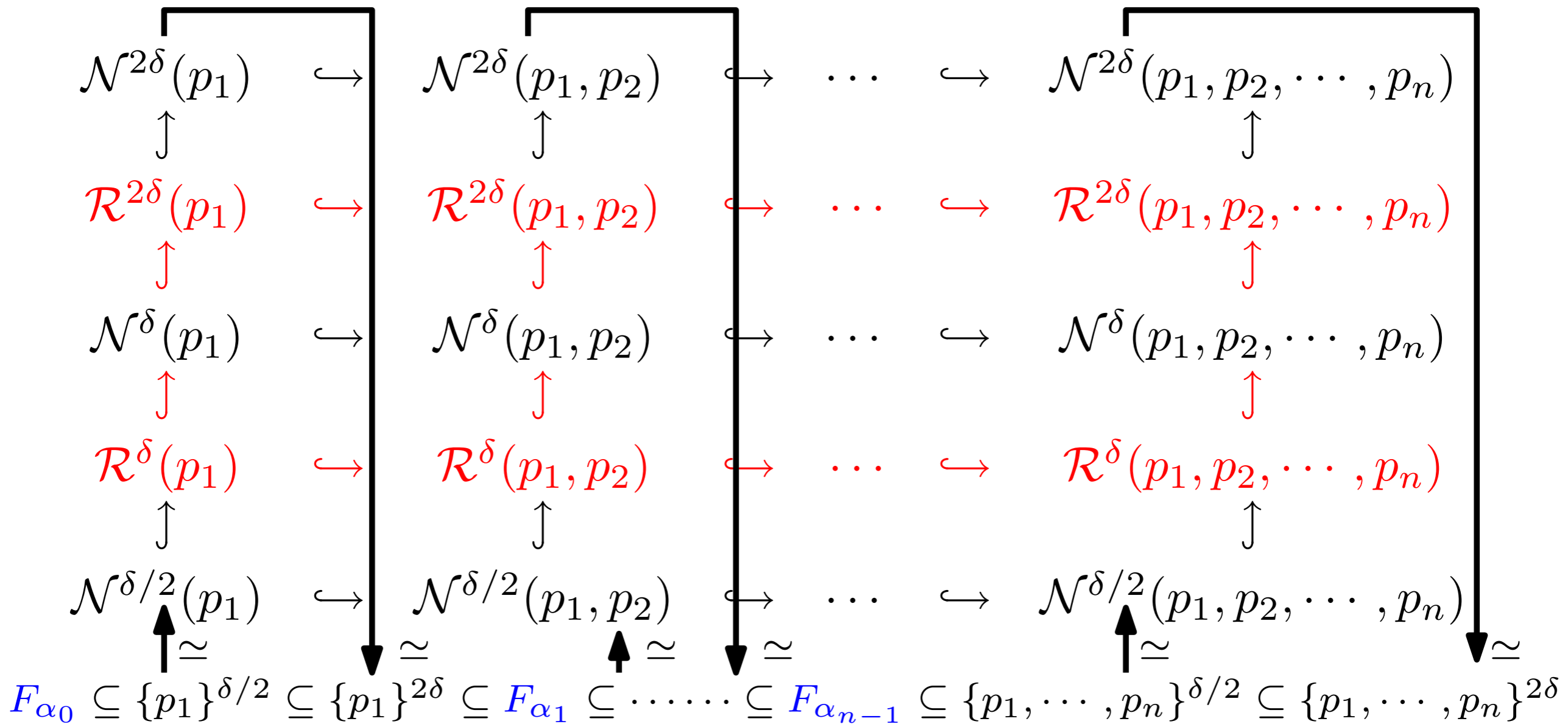
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 \uparrow & & \uparrow & & & & \uparrow \\
 \mathcal{N}^{\delta/2}(p_1) & \hookrightarrow & \mathcal{N}^{\delta/2}(p_1, p_2) & \hookrightarrow & \dots & \hookrightarrow & \mathcal{N}^{\delta/2}(p_1, p_2, \dots, p_n)
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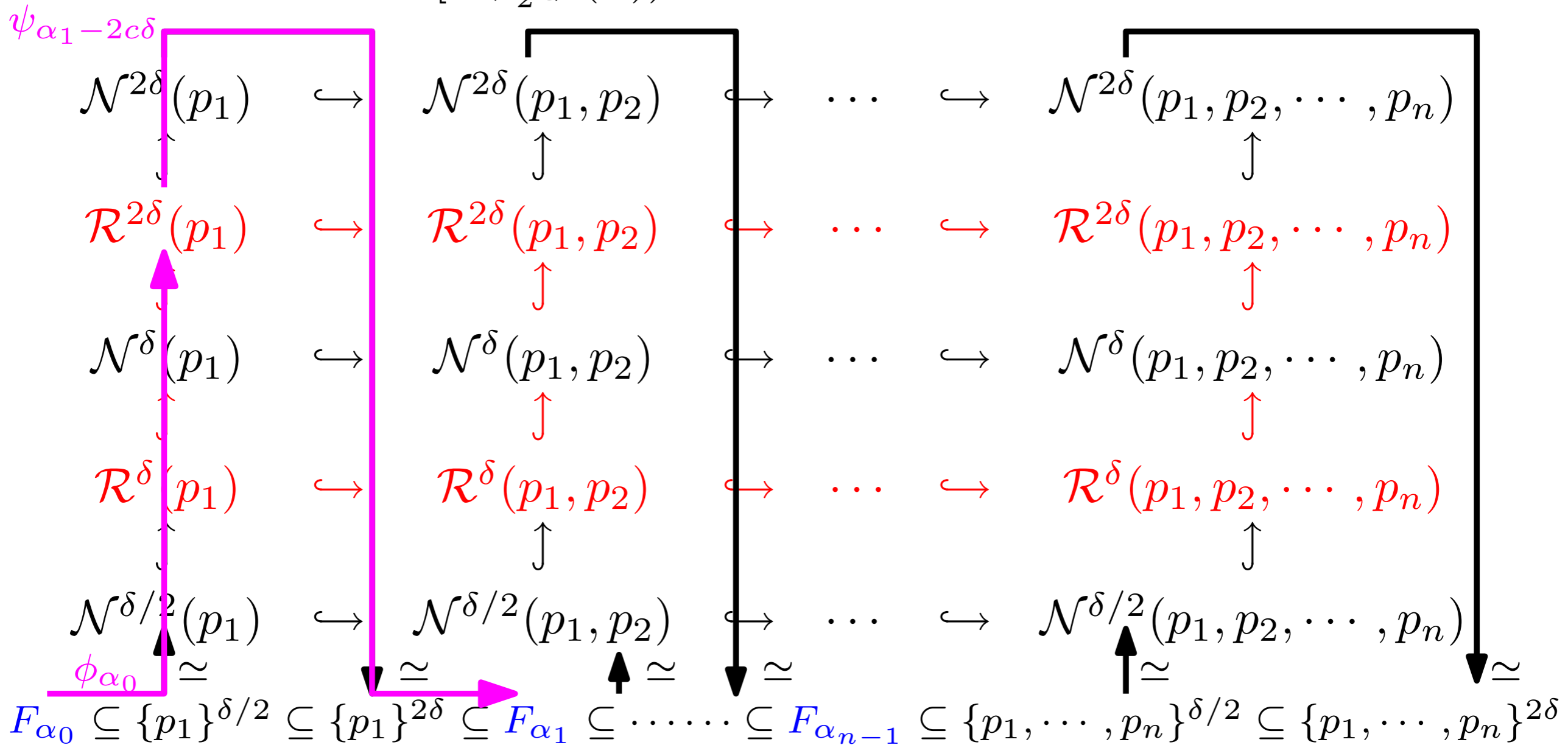


Pairs of Rips Complexes

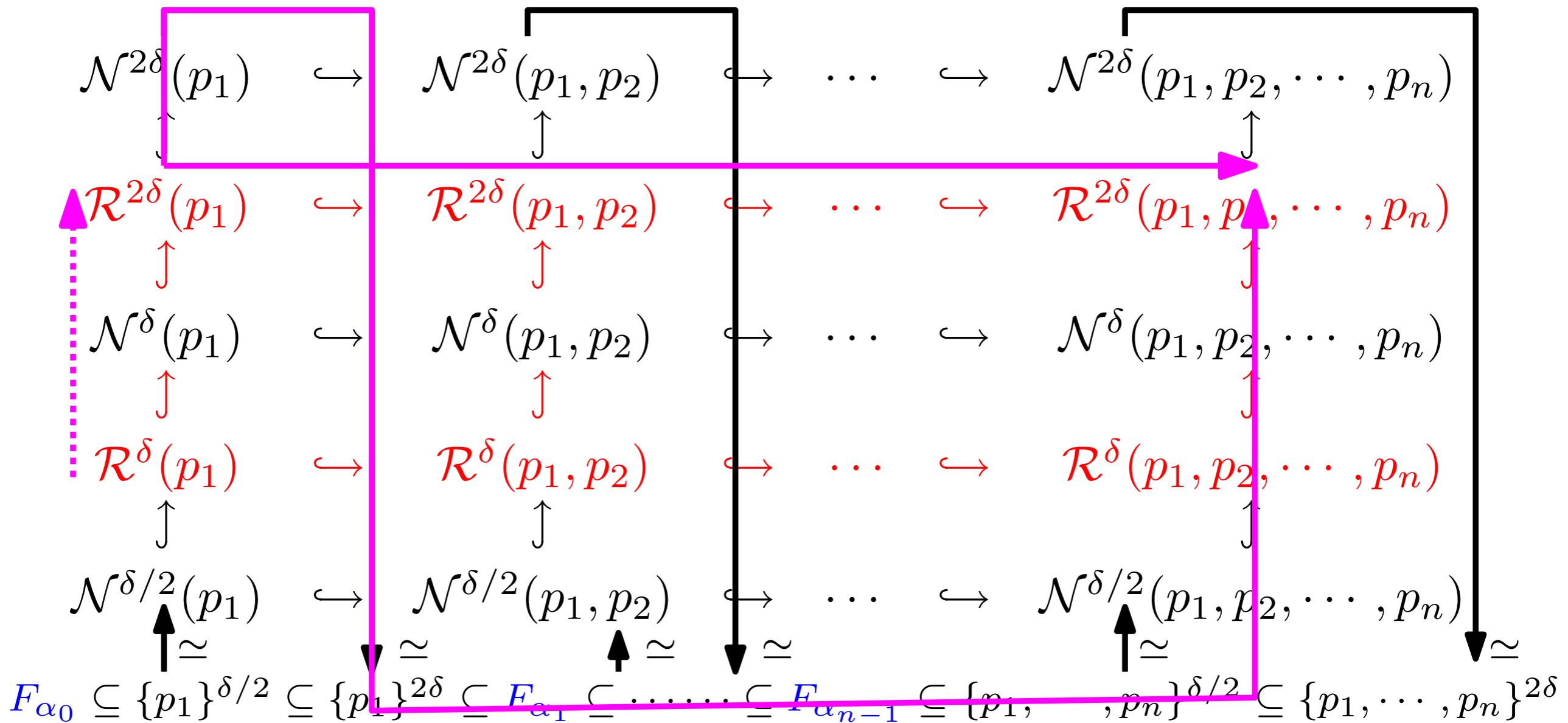
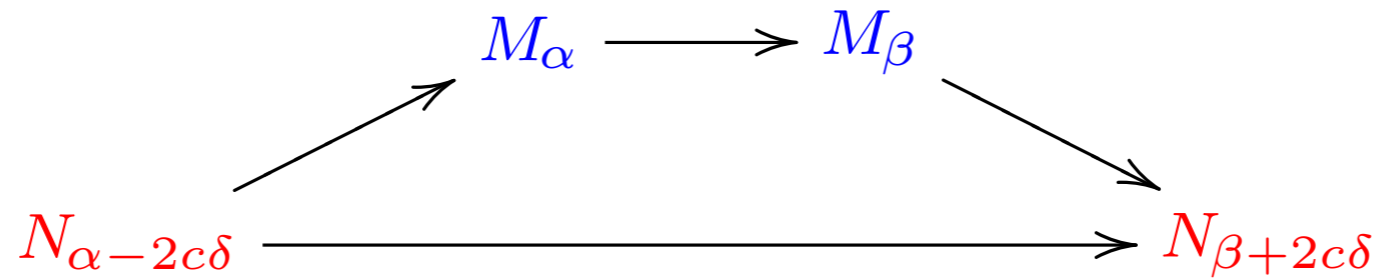
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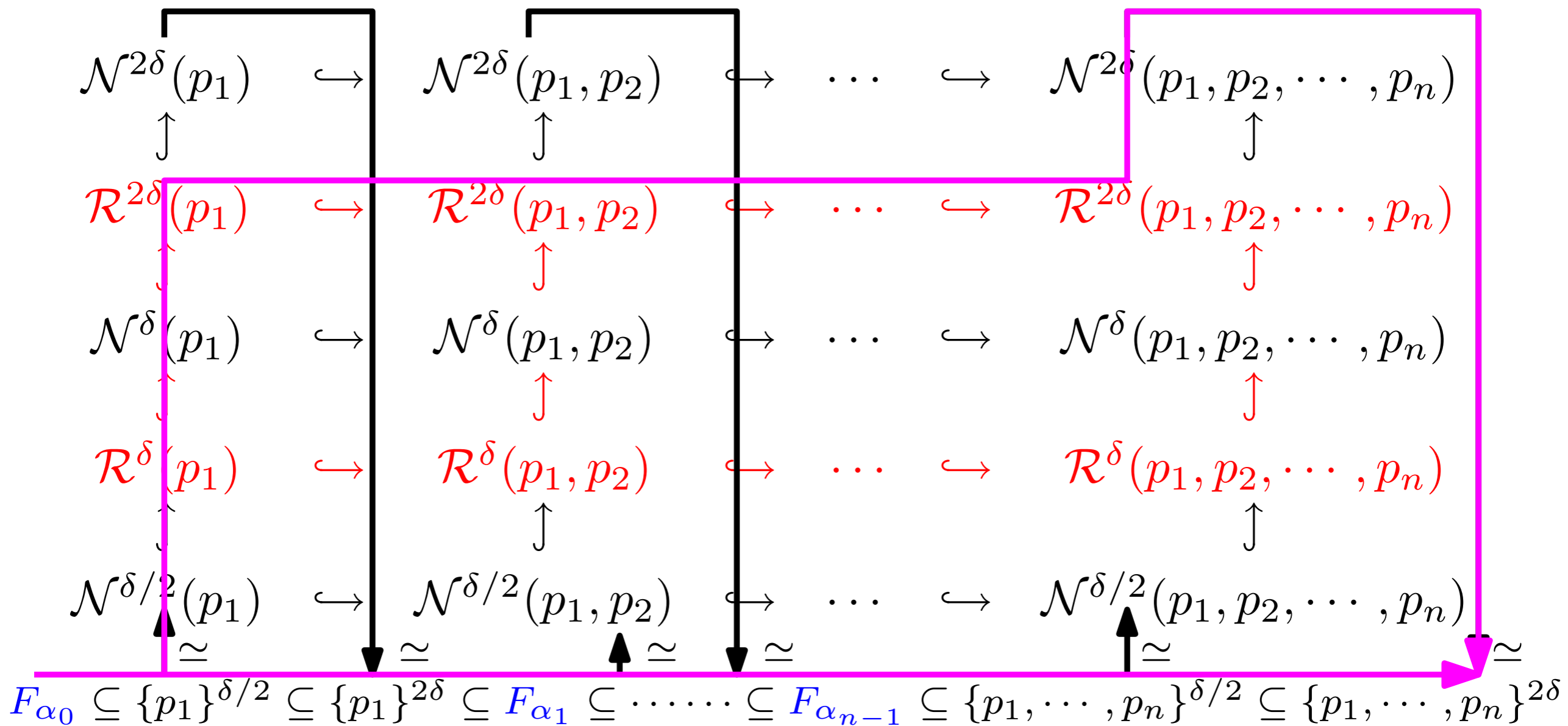
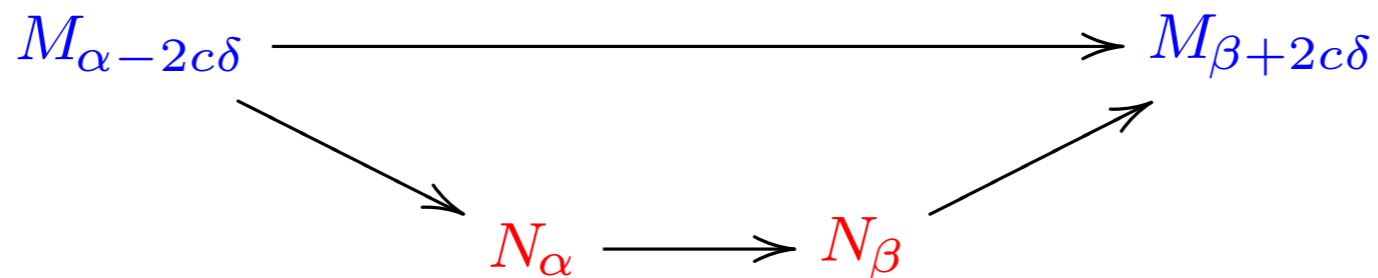
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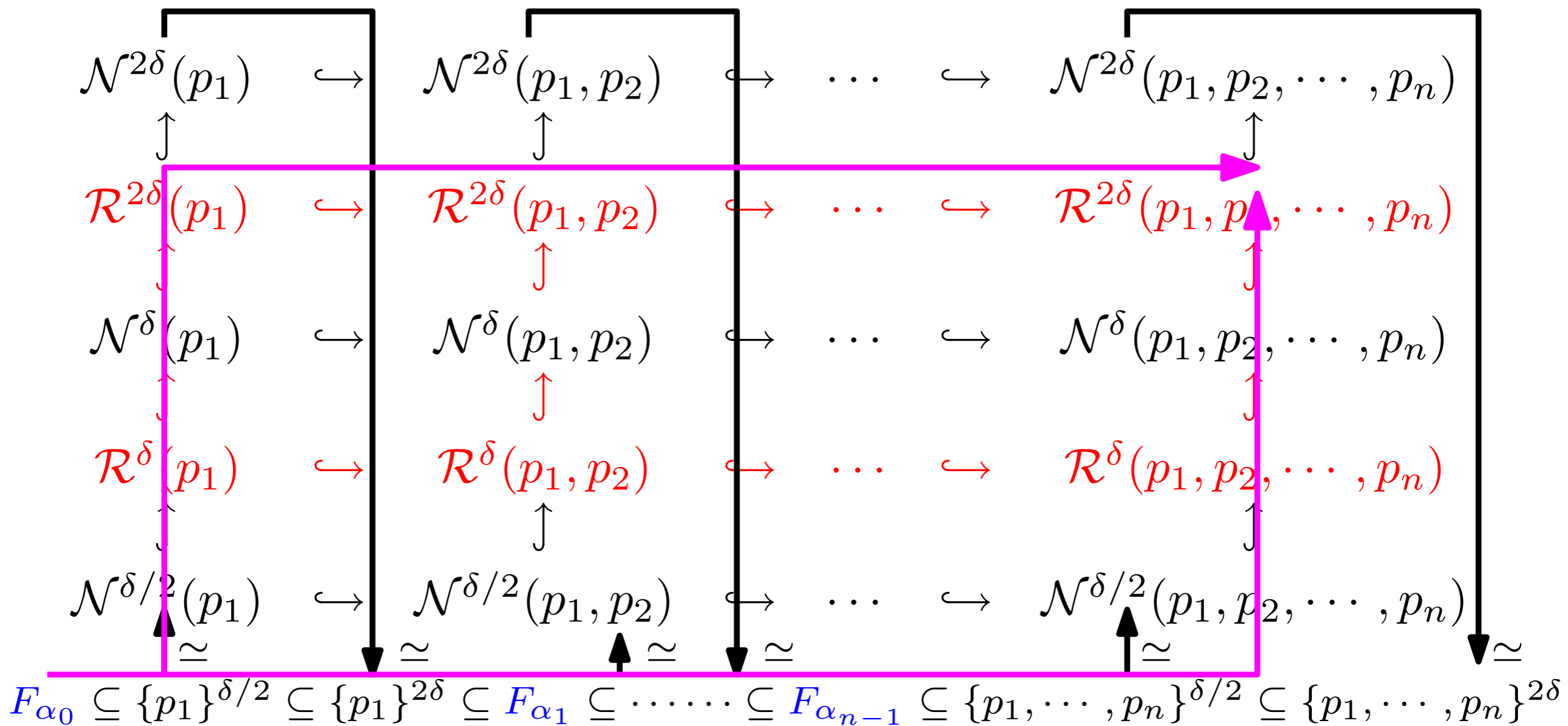
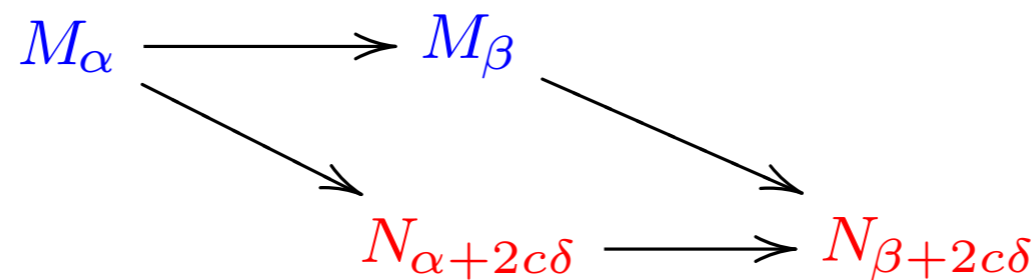
Pairs of Rips Complexes



Pairs of Rips Complexes

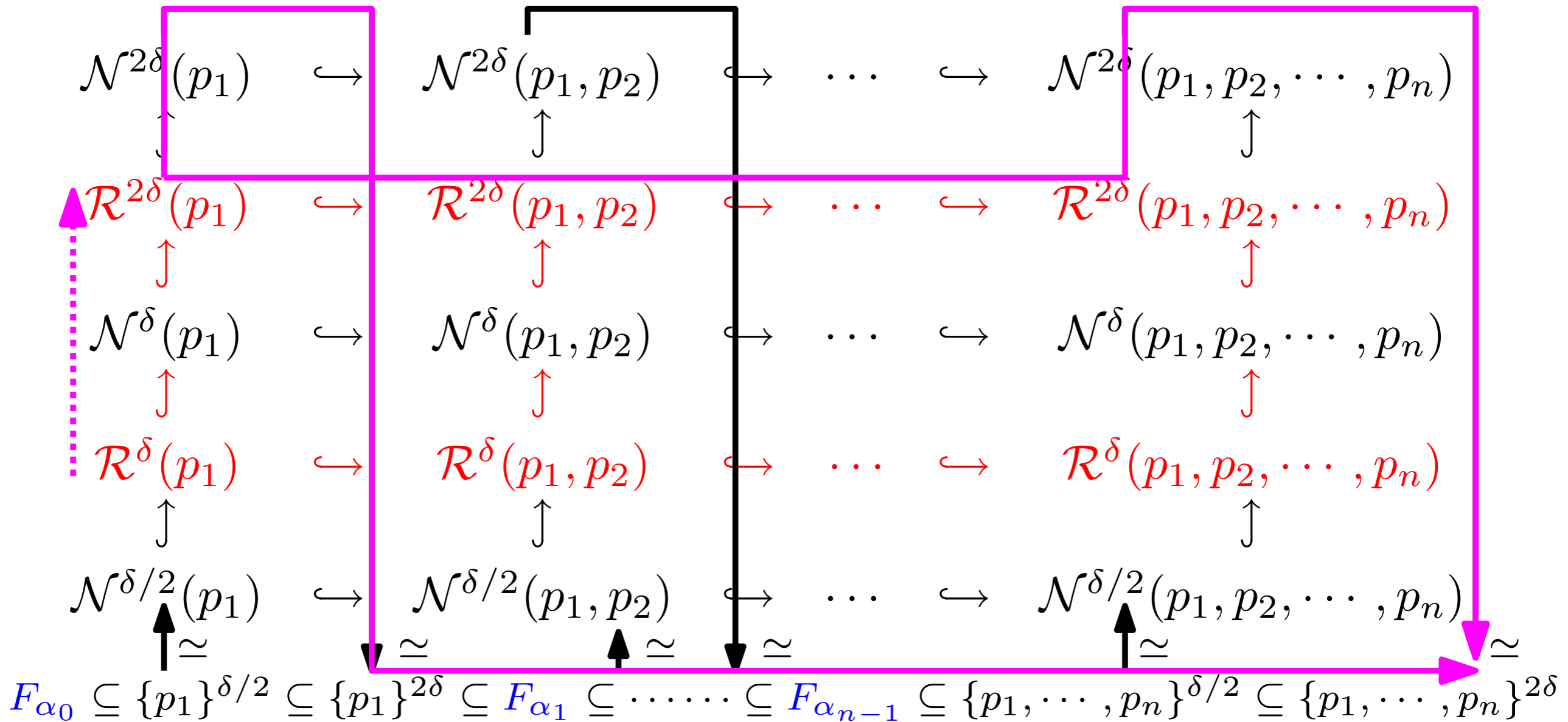


Pairs of Rips Complexes



Pairs of Rips Complexes

$$\begin{array}{ccc}
 & M_{\alpha+2c\delta} & \longrightarrow & M_{\beta+2c\delta} \\
 N_{\alpha} & \nearrow & & \nearrow \\
 & N_{\beta} & \longrightarrow &
 \end{array}$$



Pairs of Rips Complexes

Assume \mathbb{X} is a Riemannian manifold, $f : \mathbb{X} \rightarrow \mathbb{R}$ is c -Lipschitz,
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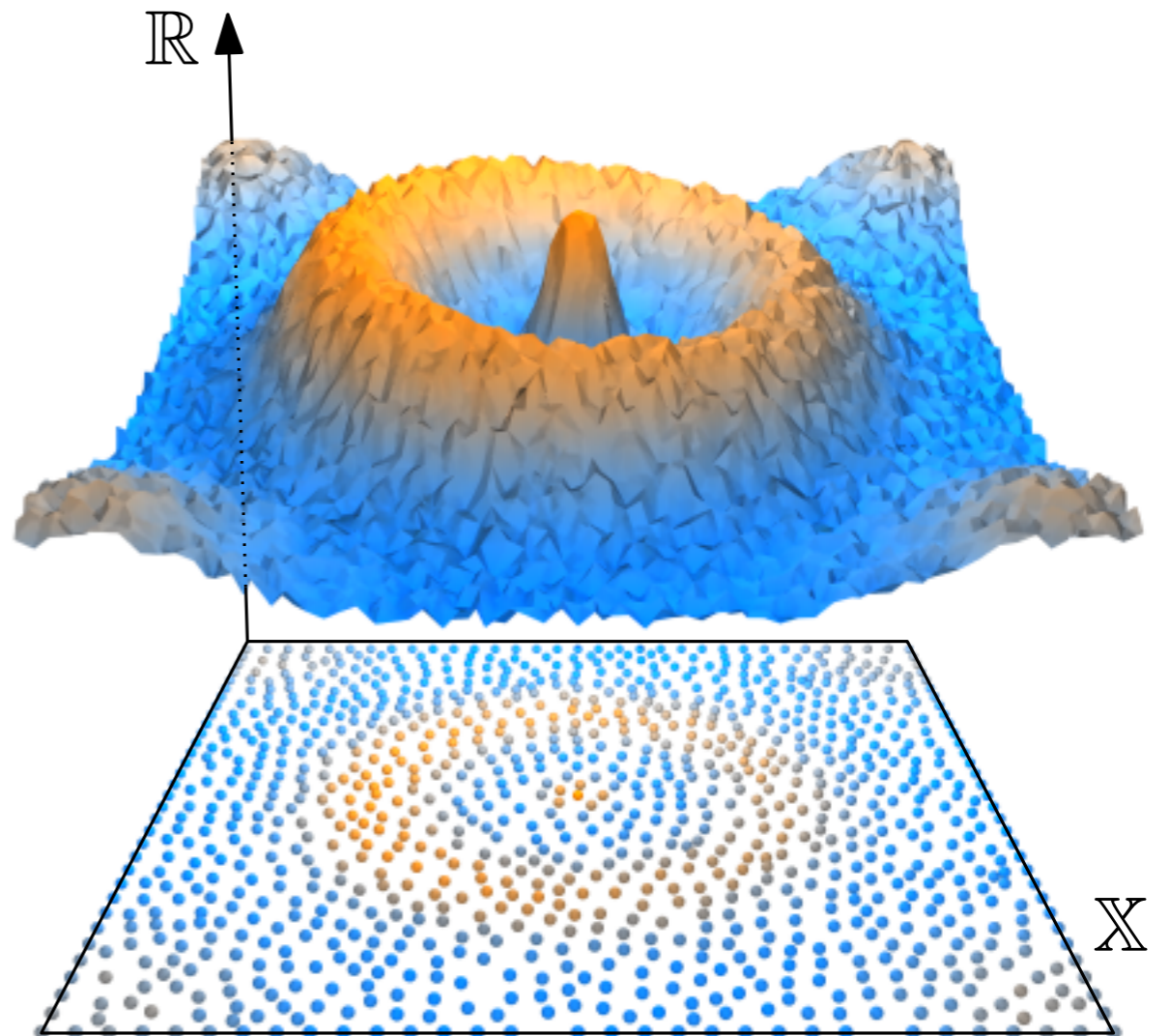
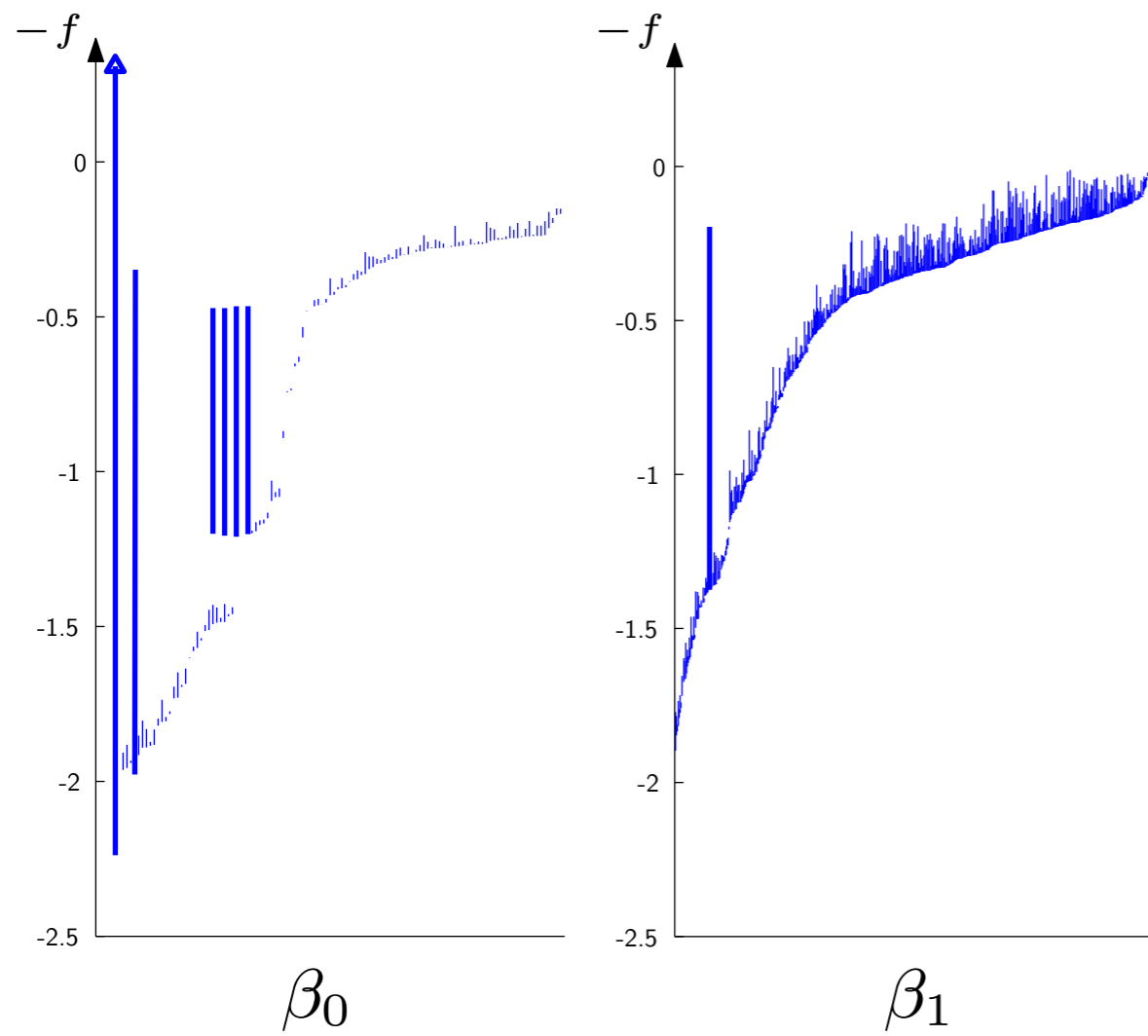
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$\{H_k(F_\alpha)\}_{\alpha \in \mathbb{R}}$ and $\{\text{im } H_k(\mathcal{R}^\delta(P_\alpha)) \rightarrow H_k(\mathcal{R}^{2\delta}(P_\alpha))\}_{\alpha \in \mathbb{R}}$ are $2c\delta$ -interleaved:

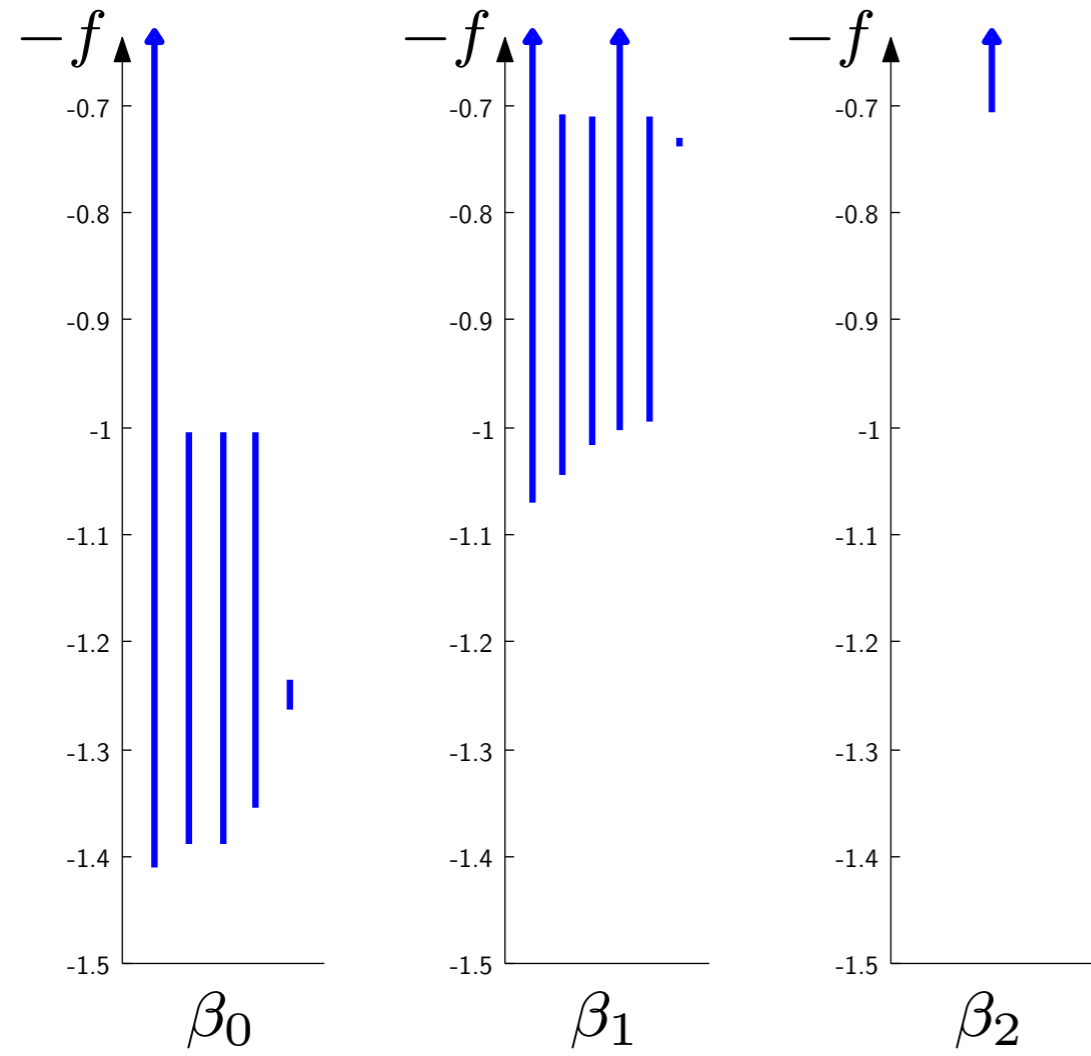
\Downarrow [Chazal, Cohen-Steiner, Glisse, Guibas, O. '09]

their persistence diagrams are $2c\delta$ -close.

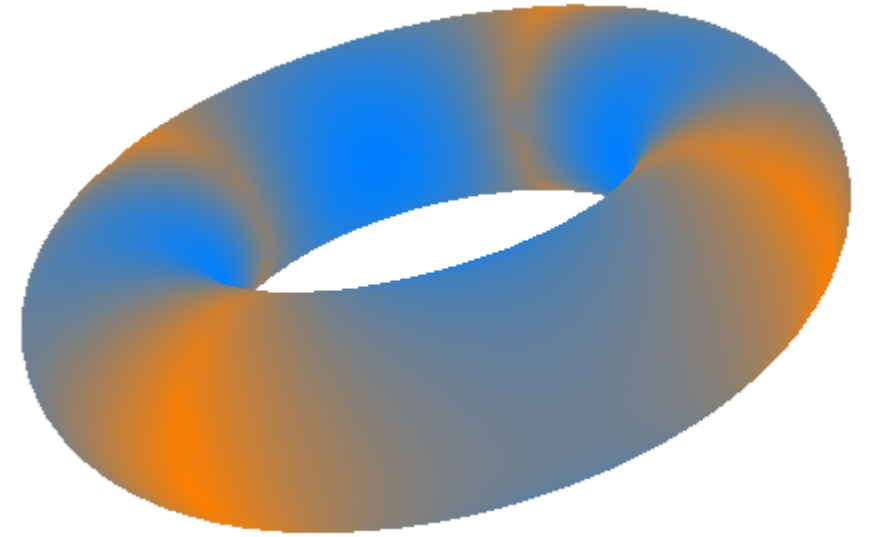
Some Results



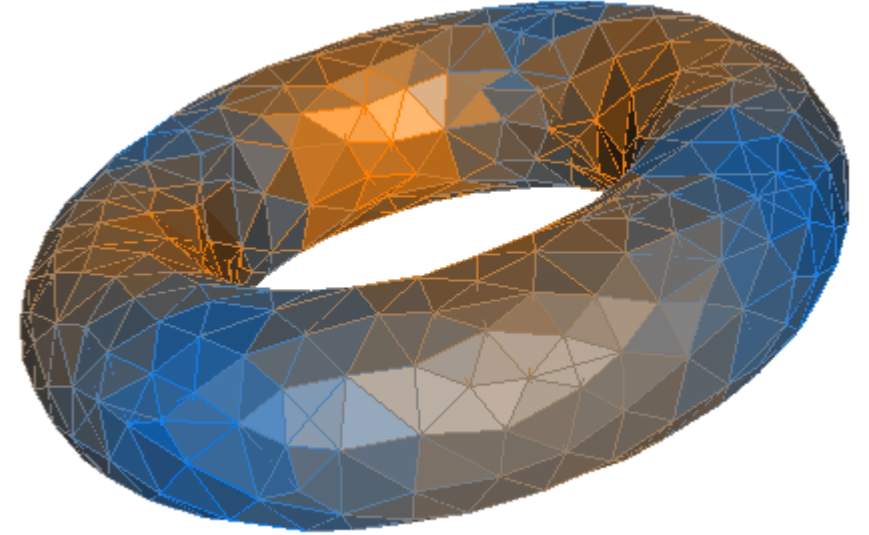
Some Results



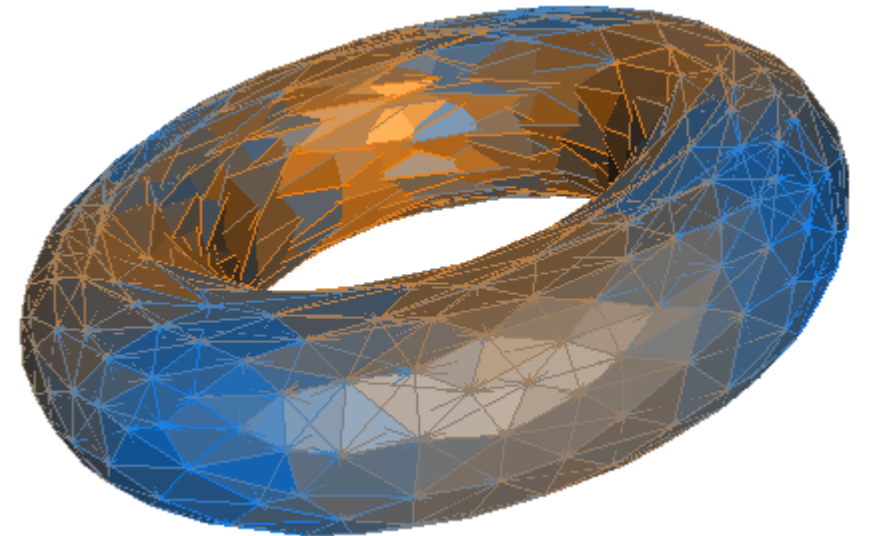
(\mathbb{X}, f)



$\mathcal{R}^\delta(P)$



$\mathcal{R}^{2\delta}(P)$



Back to the Algorithm

Assume \mathbb{X} is a Riemannian manifold, $f : \mathbb{X} \rightarrow \mathbb{R}$ is c -Lipschitz,
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Algorithm: choose parameter $\delta \geq 0$

1. Sort the data points such that $f(p_1) \leq f(p_2) \leq \dots \leq f(p_n)$,
2. For $i = 1, \dots, n$, build $\mathcal{R}^\delta(p_1, \dots, p_i) \subseteq \mathcal{R}^{2\delta}(p_1, \dots, p_i)$,
3. Apply the persistence algorithm for images to the pair of filtrations.

$$\begin{array}{ccccccc}
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Obs.: At 0th homology level, the vertical maps induce surjective homomorphisms

Back to the Algorithm

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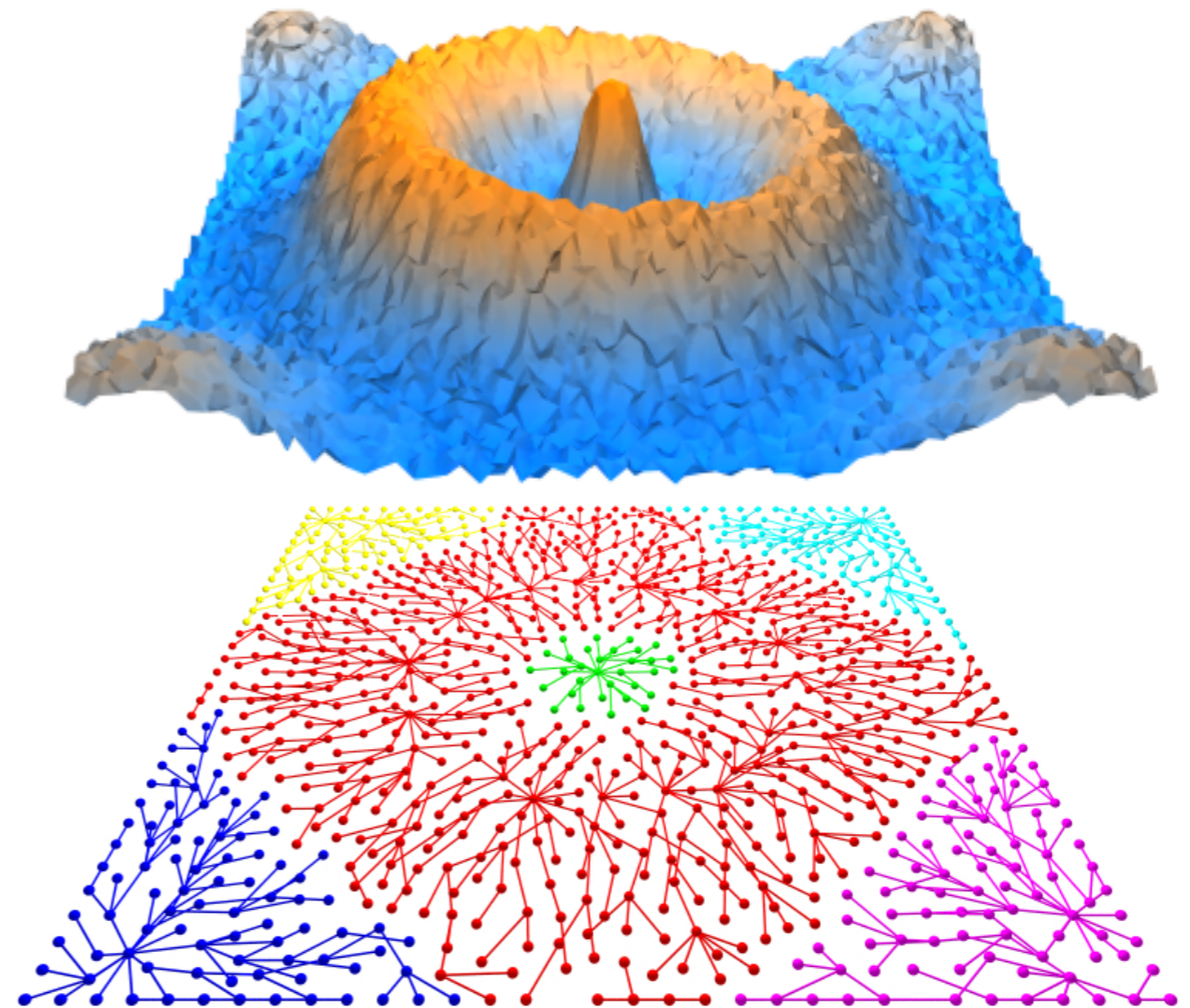
1. Sort the data points such that $f(p_1) \leq f(p_2) \leq \dots \leq f(p_n)$,
2. For $i = 1, \dots, n$, build the 1-skeleton of $\mathcal{R}^{2\delta}(p_1, \dots, p_i)$,
3. Apply the persistence algorithm to the filtration:

$$\mathcal{R}^{2\delta}(p_1) \hookrightarrow \mathcal{R}^{2\delta}(p_1, p_2) \hookrightarrow \dots \hookrightarrow \mathcal{R}^{2\delta}(p_1, p_2, \dots, p_n)$$

Obs.: At 0th homology level, the vertical maps induce surjective homomorphisms

Basins of Attraction

Goal: approximate basins of attraction of significant peaks of f
→ cluster the input point cloud P



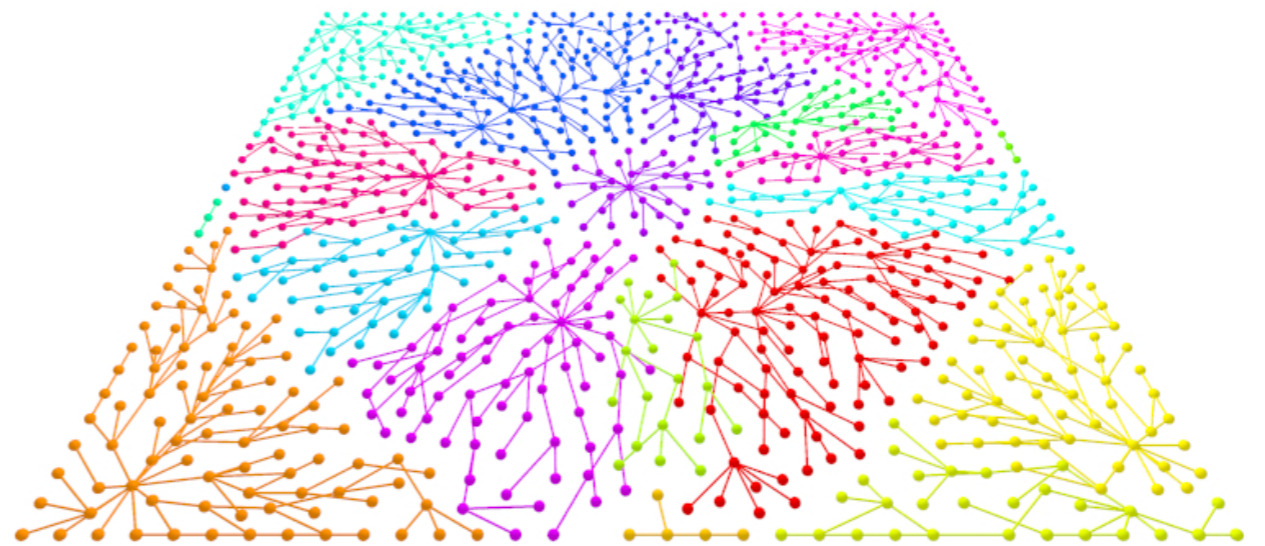
Basins of Attraction

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Approach:

- simulate effect of ∇f by connecting vertex to highest neighbor in Rips graph
→ gives a forest, the roots of which are local maxima of f in the graph



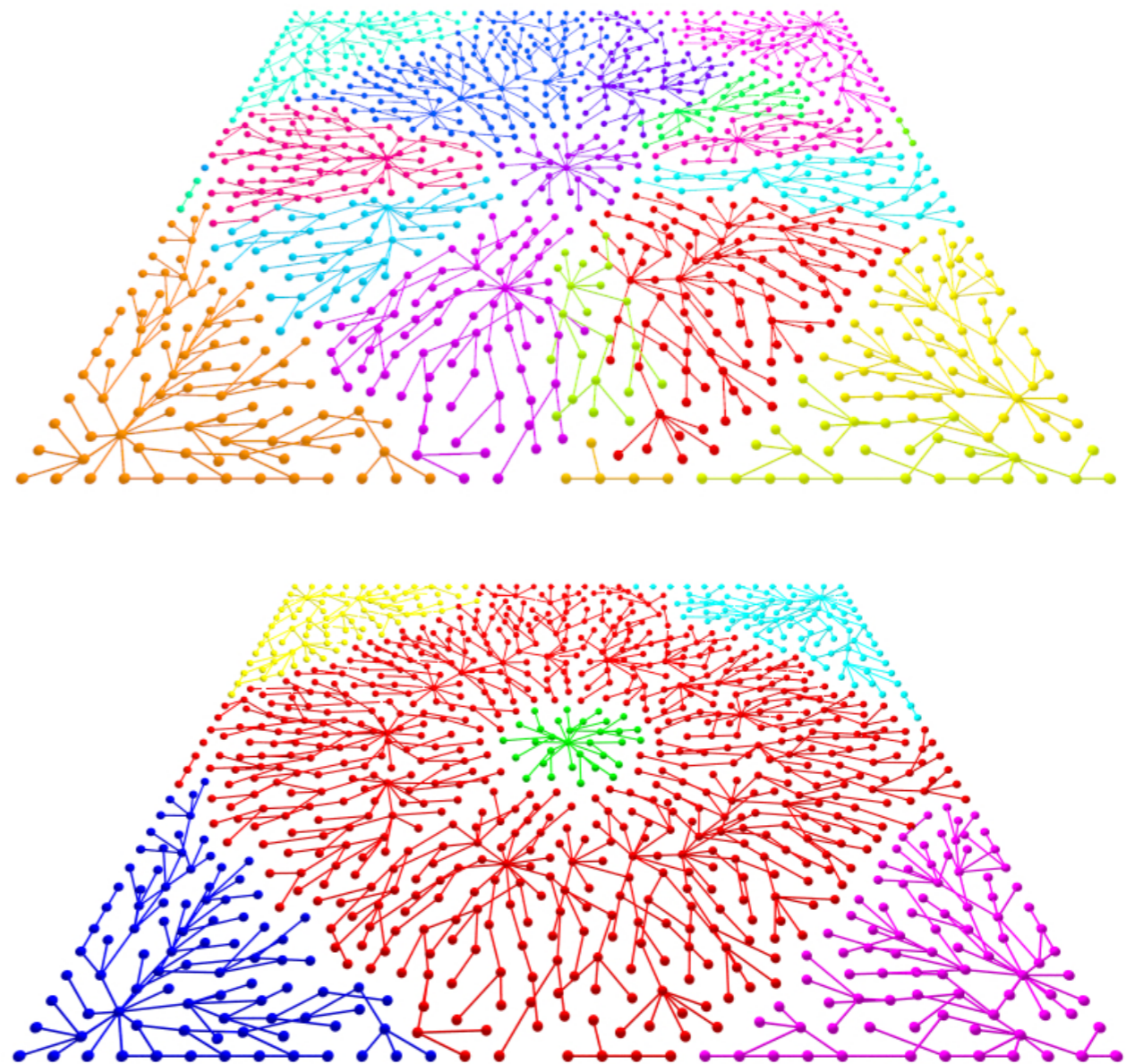
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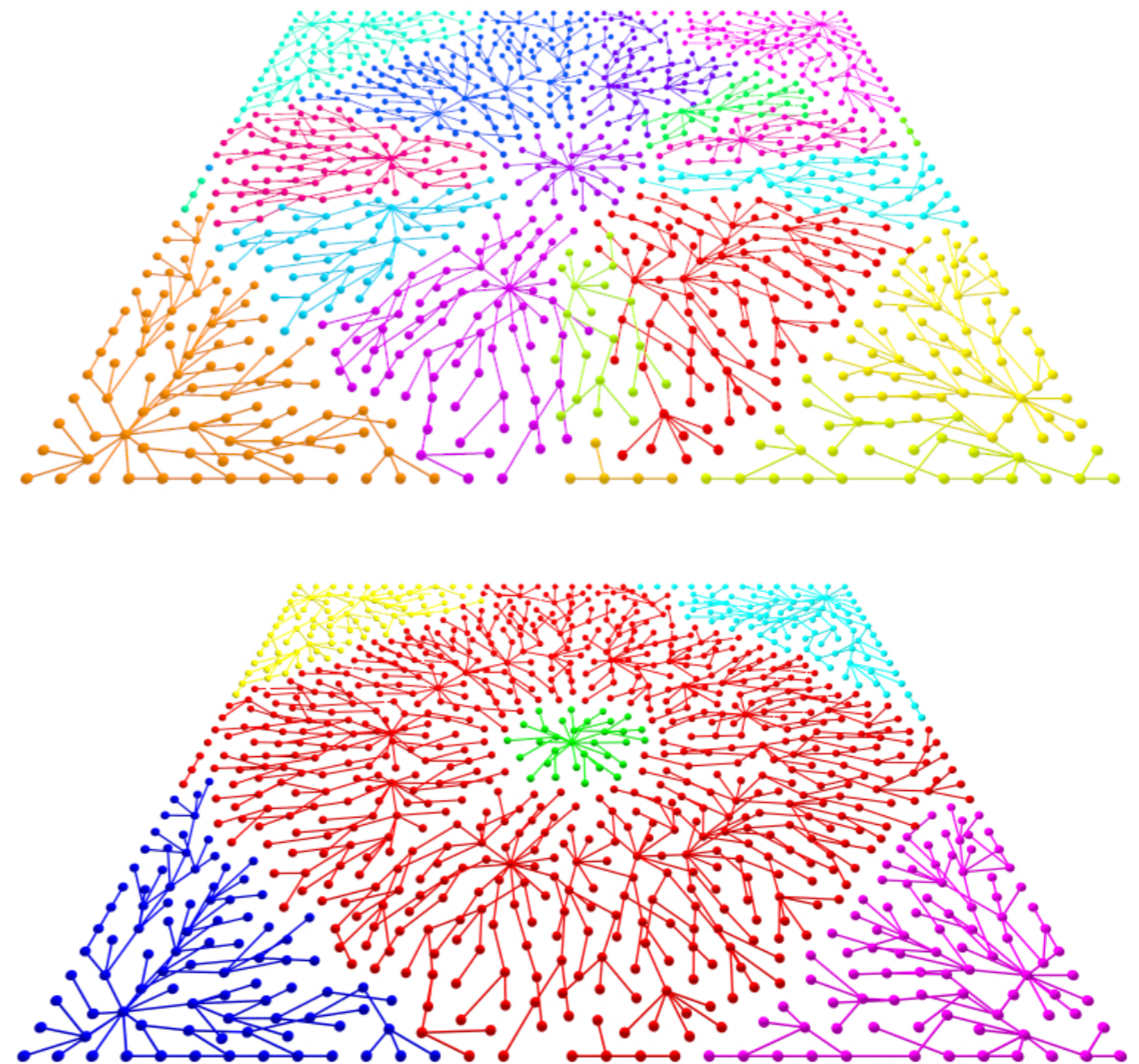
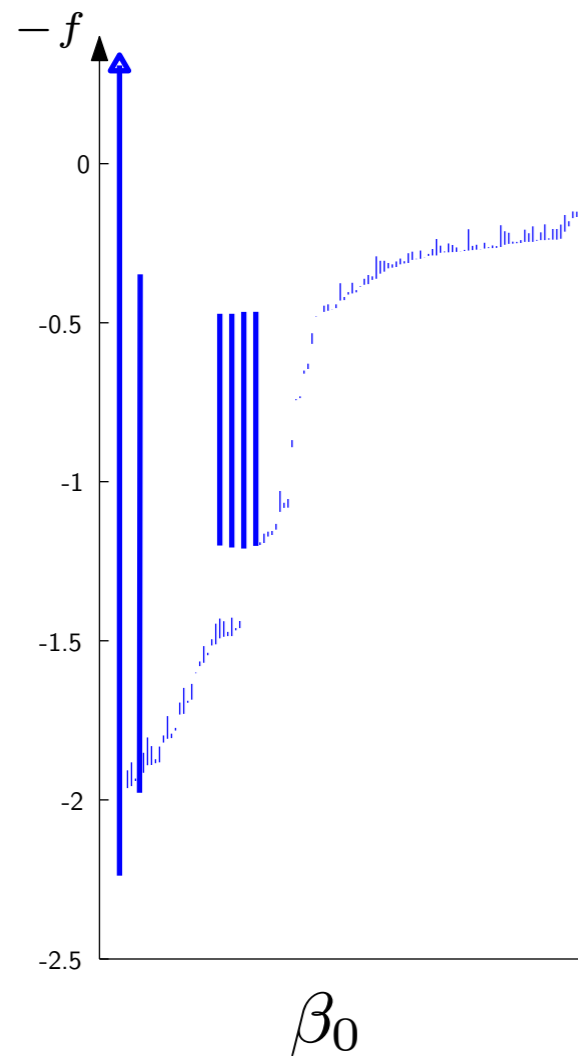
- simulate effect of ∇f by connecting vertex to highest neighbor in Rips graph
→ gives a forest, the roots of which are local maxima of f in the graph
- apply 0-dimensional algorithm to $-f$
→ clusters are merged by persistence algorithm (union-find data structure)
- do not merge clusters that are more persistent than a given threshold τ



Basins of Attraction

Goal: approximate basins of attraction of significant peaks of f

→ cluster the input point cloud P

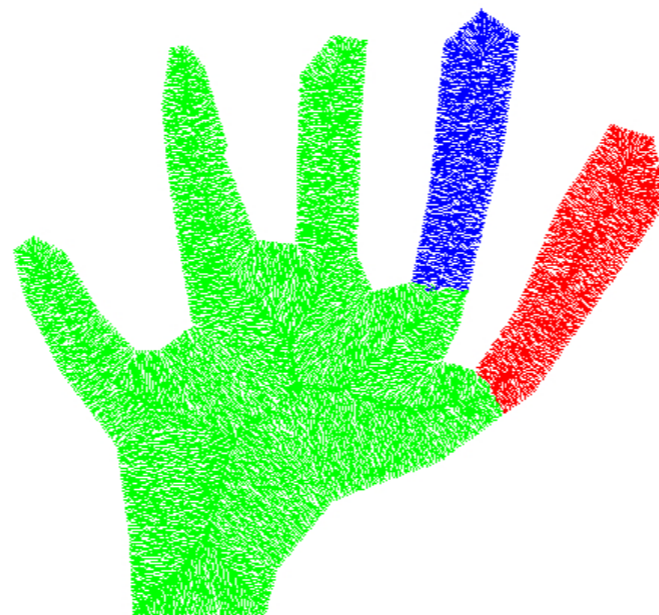
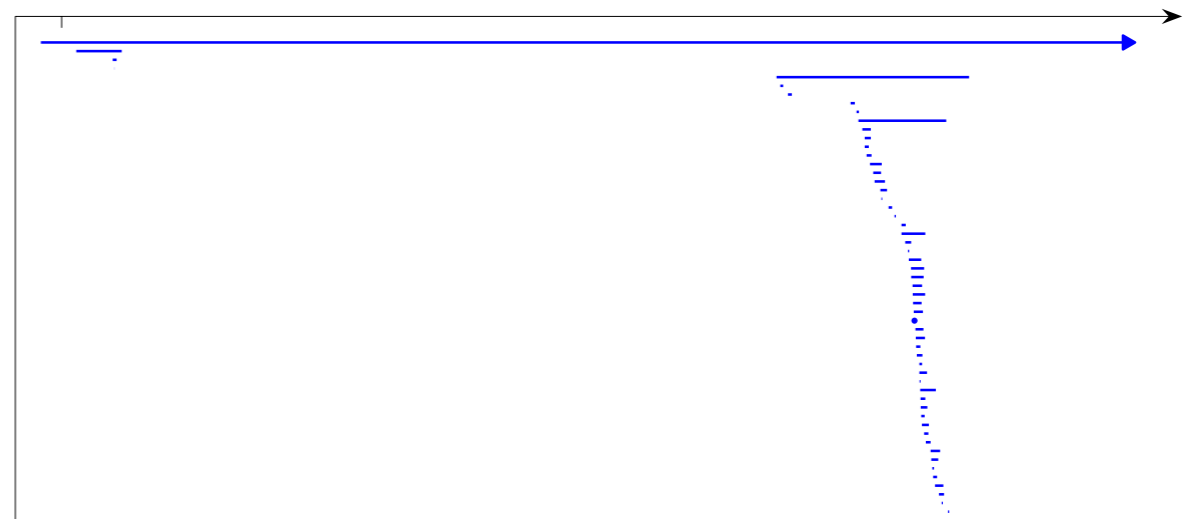


→ the user can use the 0-dim. persistence diagram to choose τ (two runs)

Application to Shape Segmentation

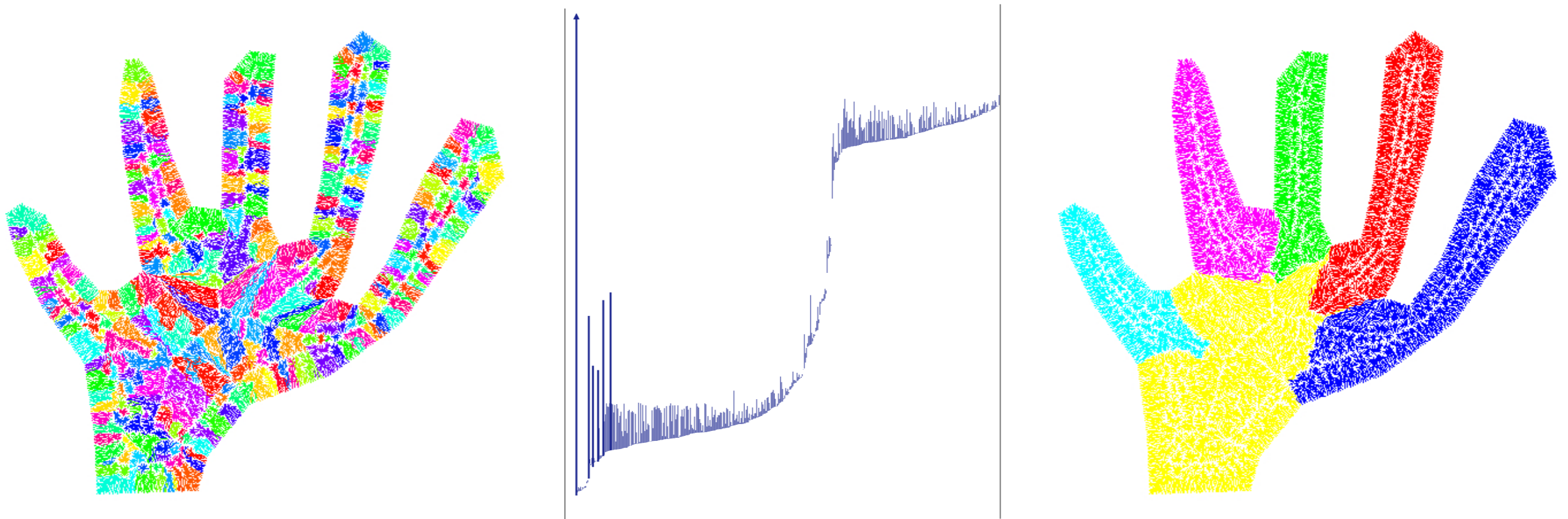
- Goal: partition a sampled shape into its most *natural parts* (ill-posed)
- Problem is cast into the one of finding a *good* segmentation function

→ distance to the boundary:



Application to Shape Segmentation

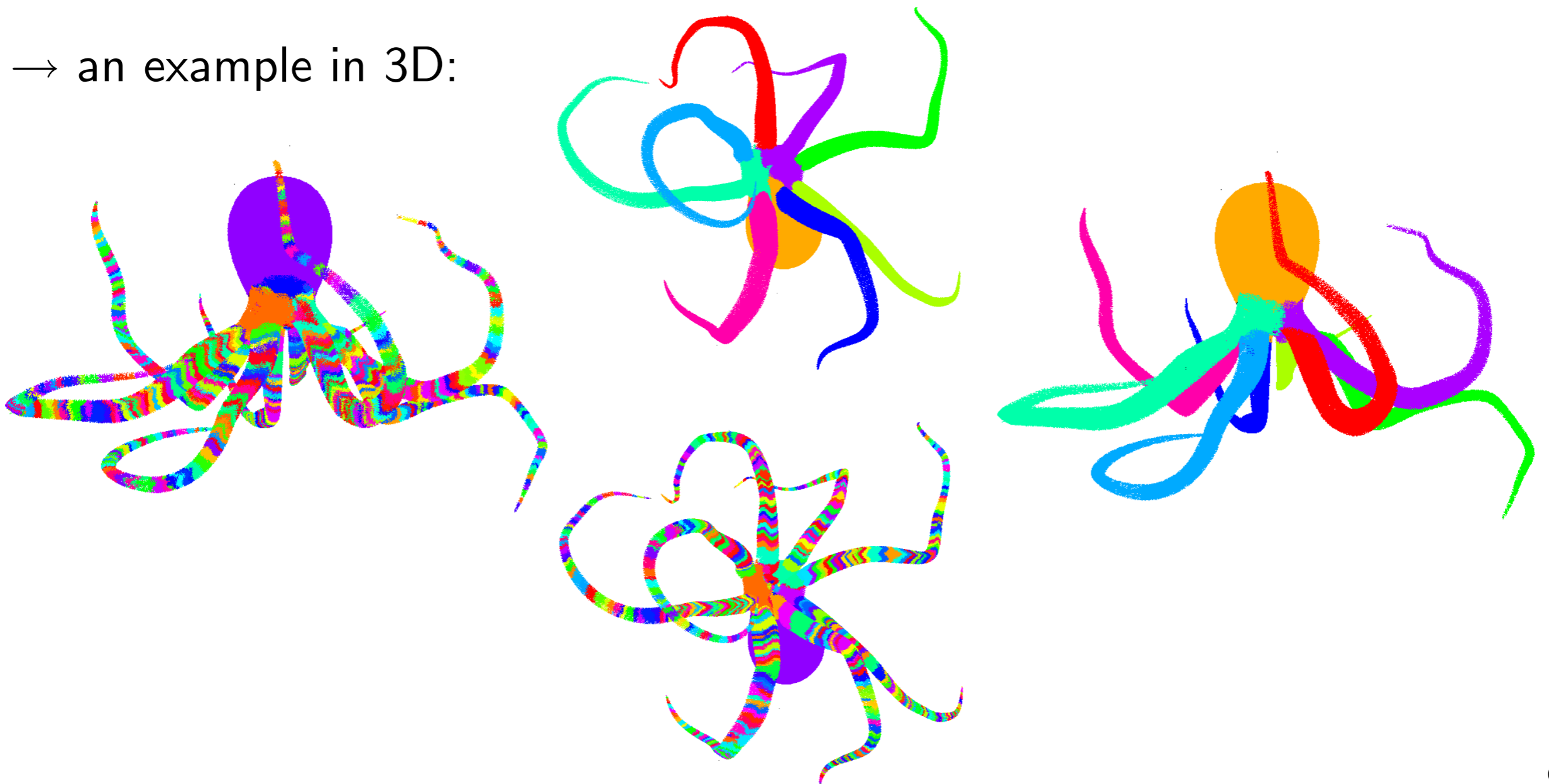
- Goal: partition a sampled shape into its most *natural parts* (ill-posed)
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→ normalized diameter of nearest boundary points:



Application to Shape Segmentation

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- Problem is cast into the one of finding a *good* segmentation function

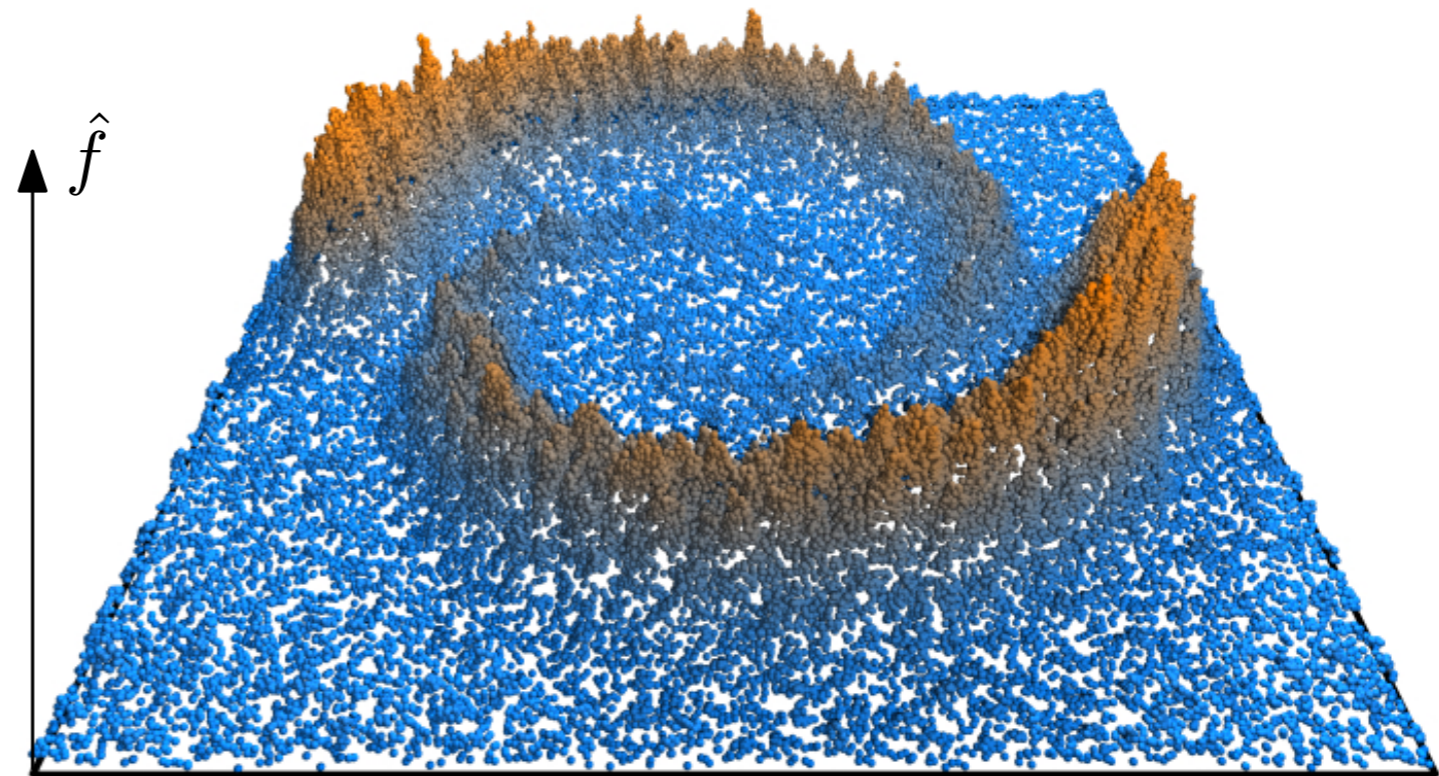
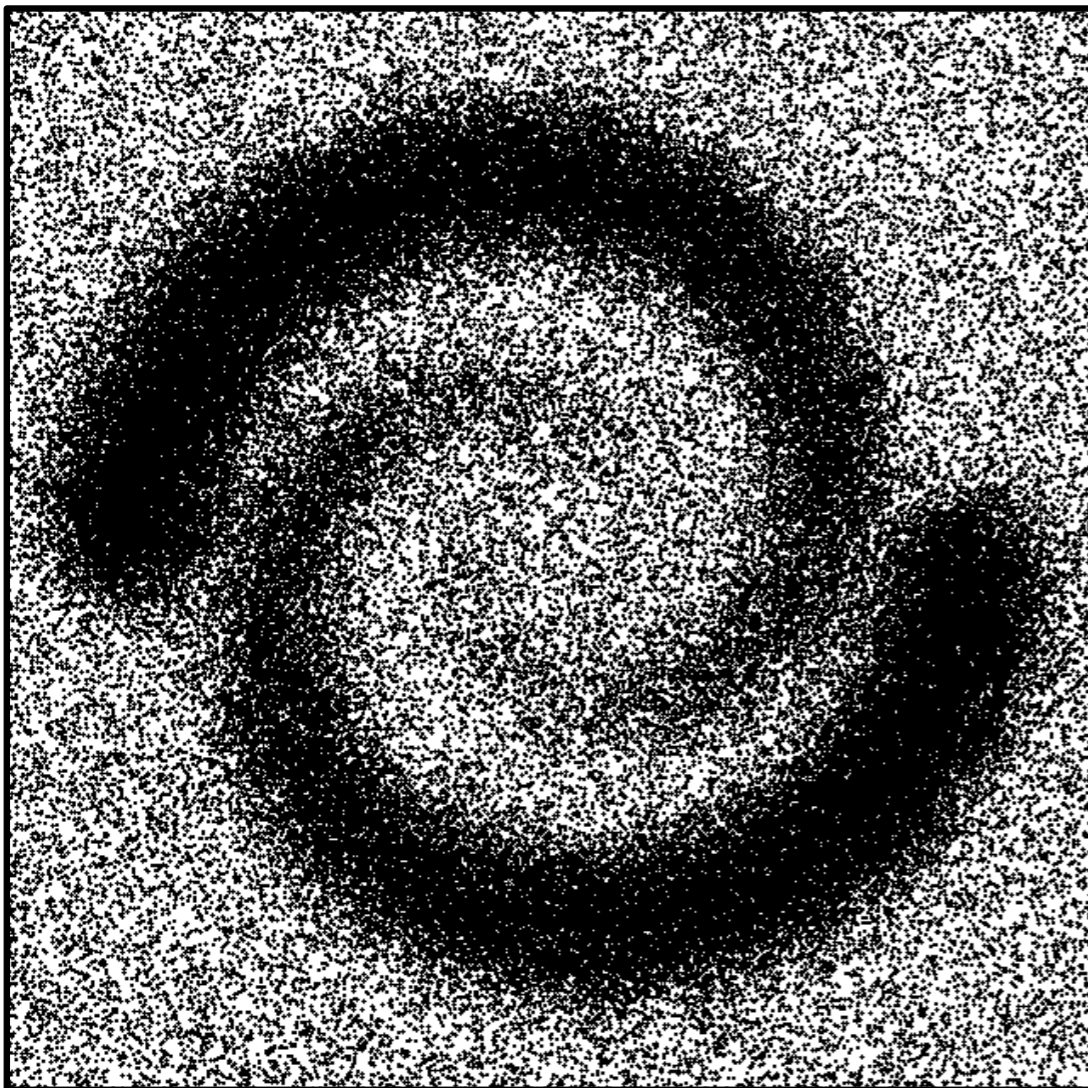
→ an example in 3D:



Application to Clustering

Input: $\mathbb{X} = [0, 1]^2$; $|P| = 100,000$;

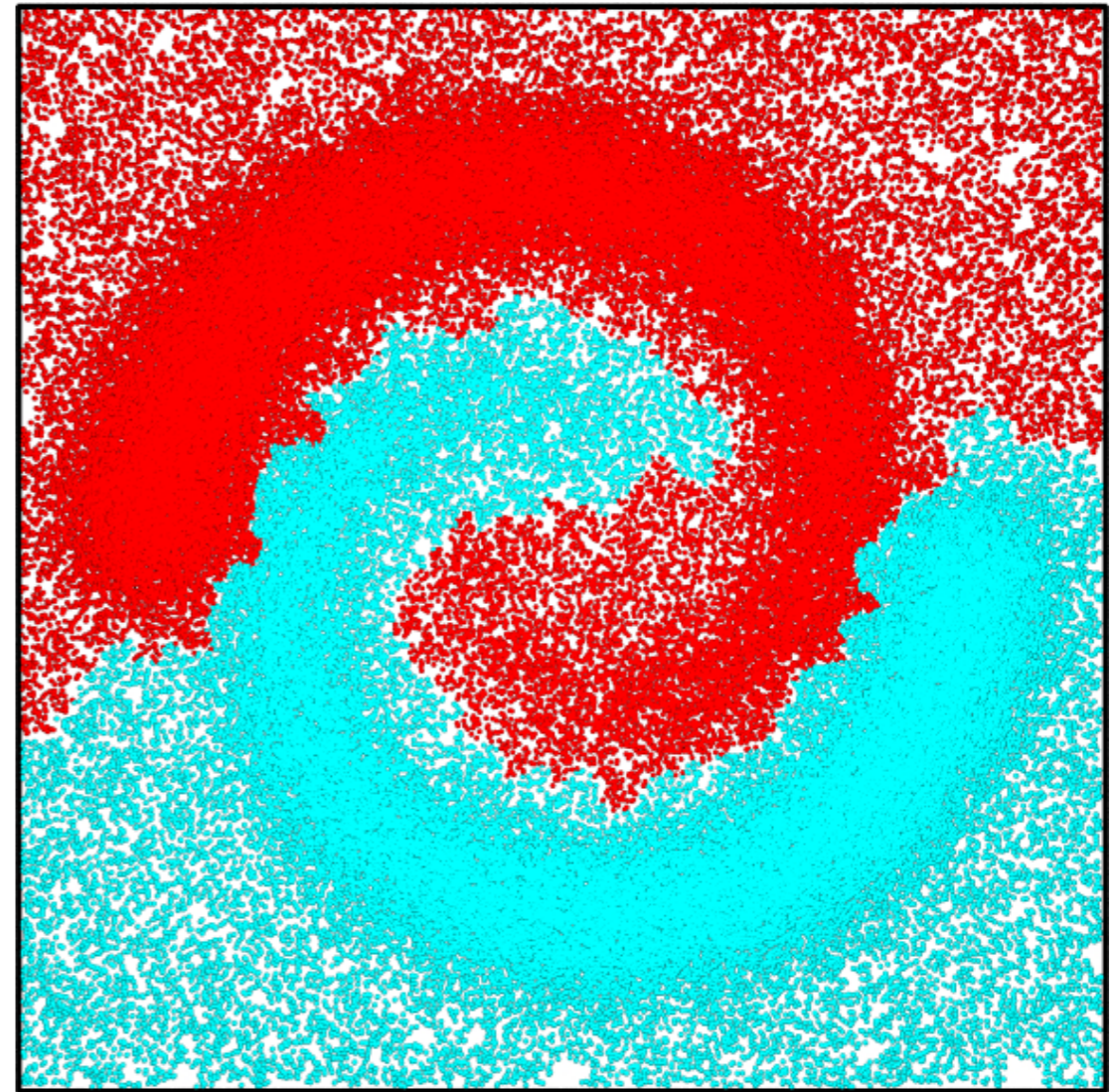
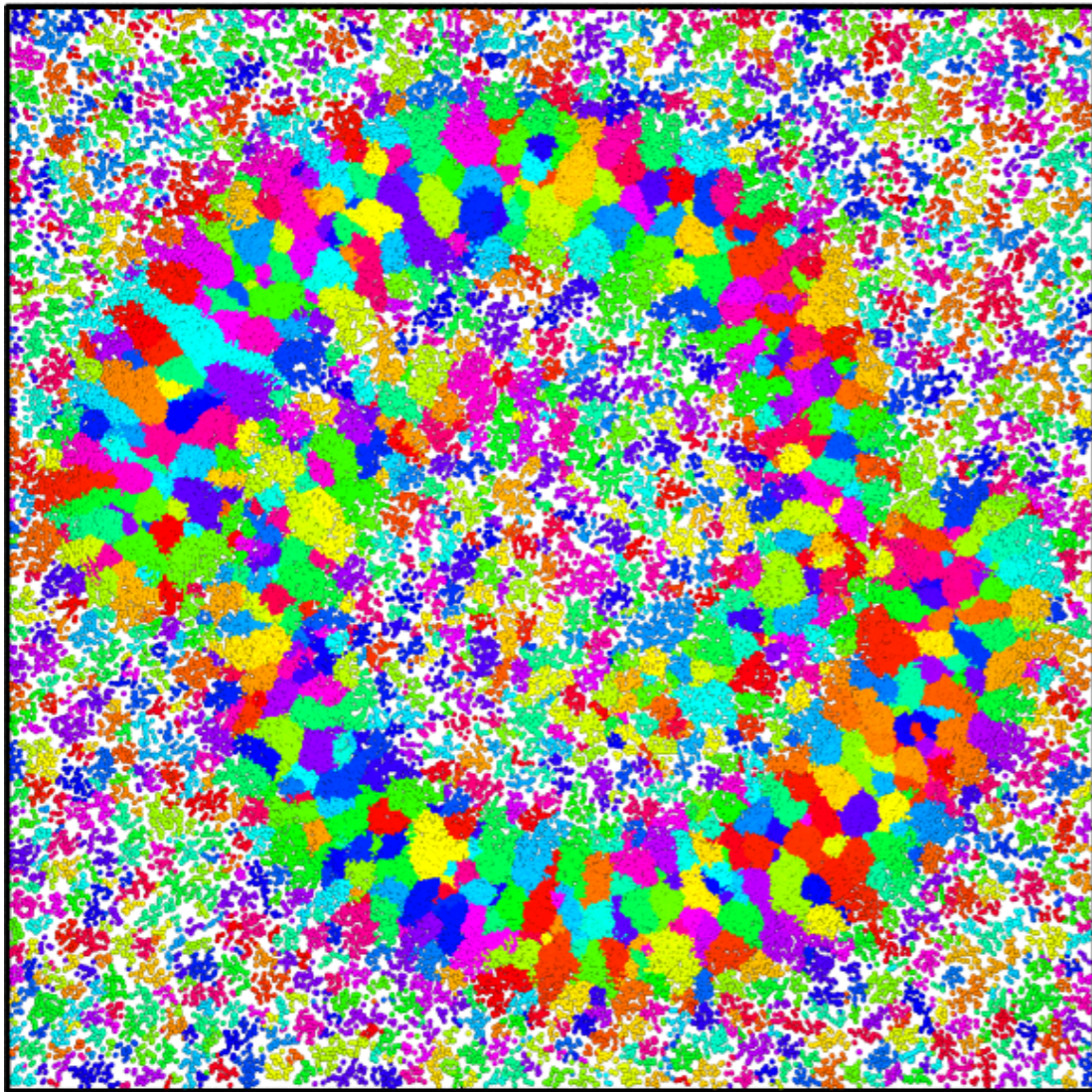
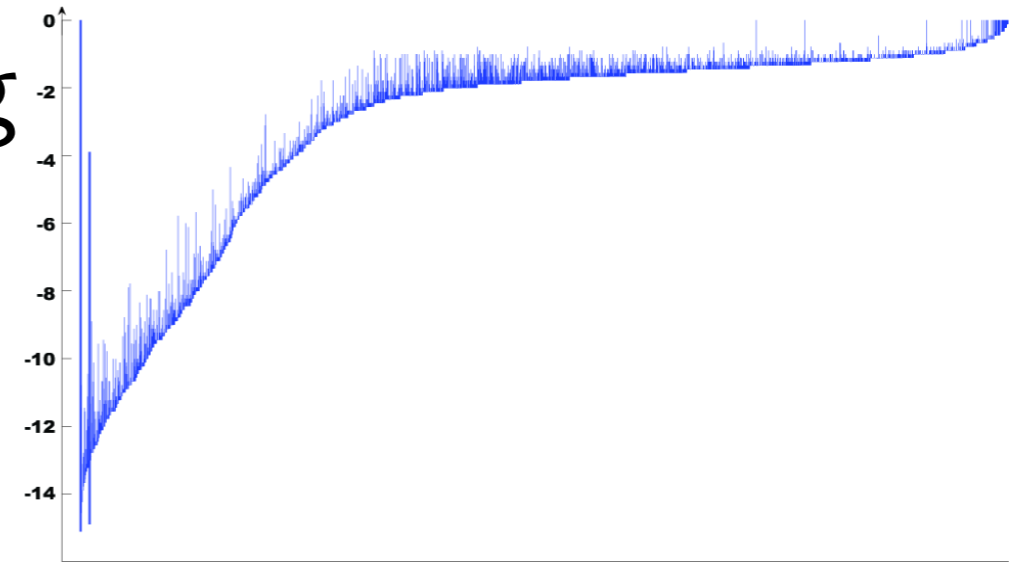
$\hat{f} = \# \{ \text{data pts in fixed-radius ball} \}$



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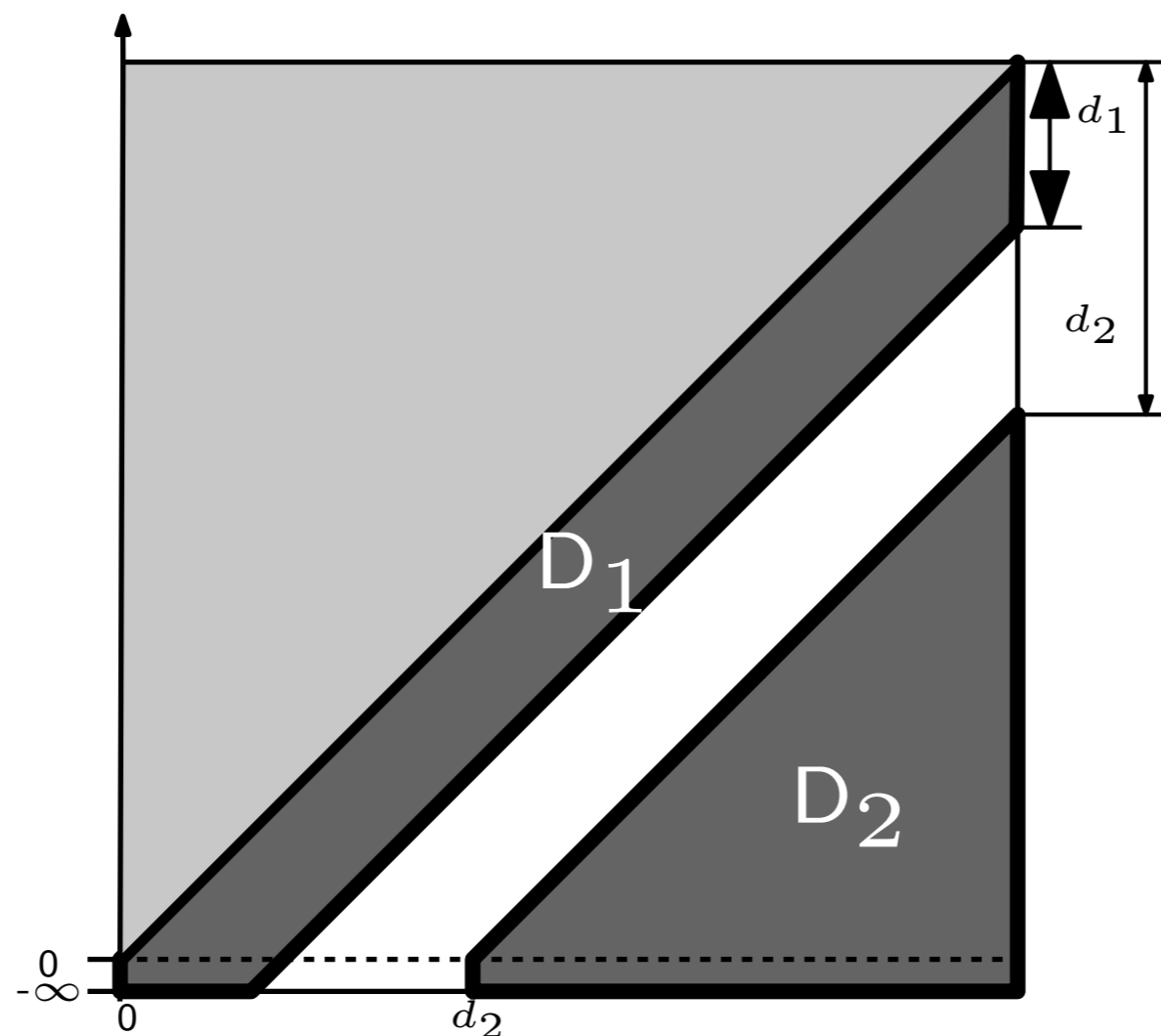
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Application to Clustering

Main challenges:

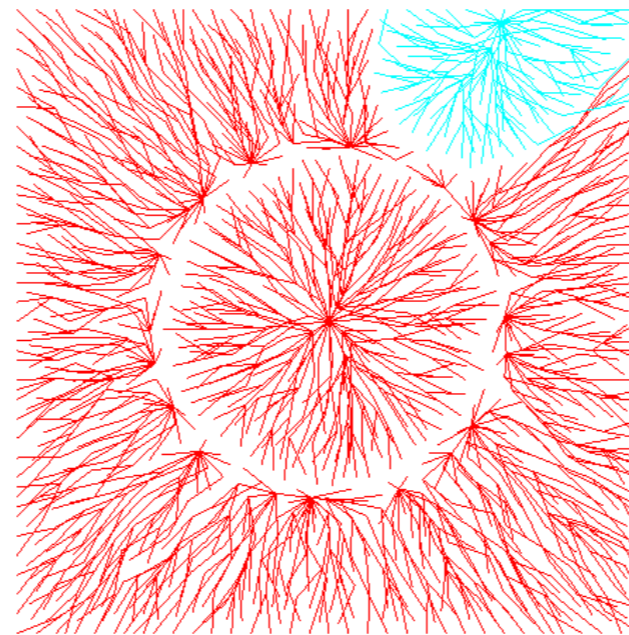
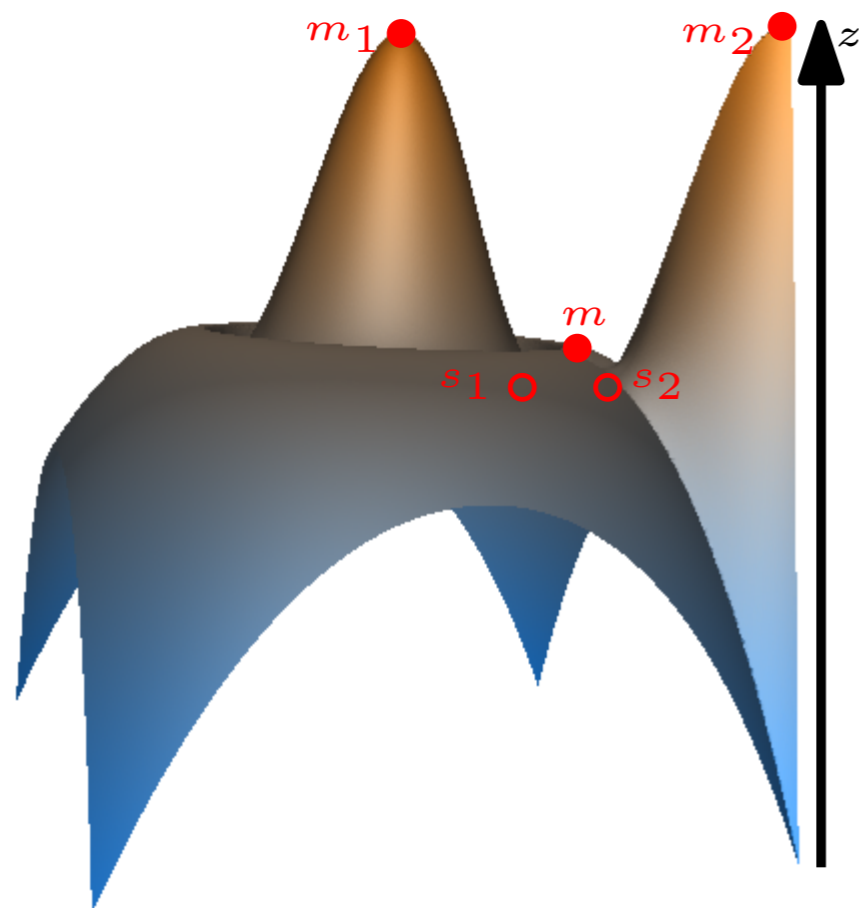
- finding the *correct* number of clusters (separation theorem)



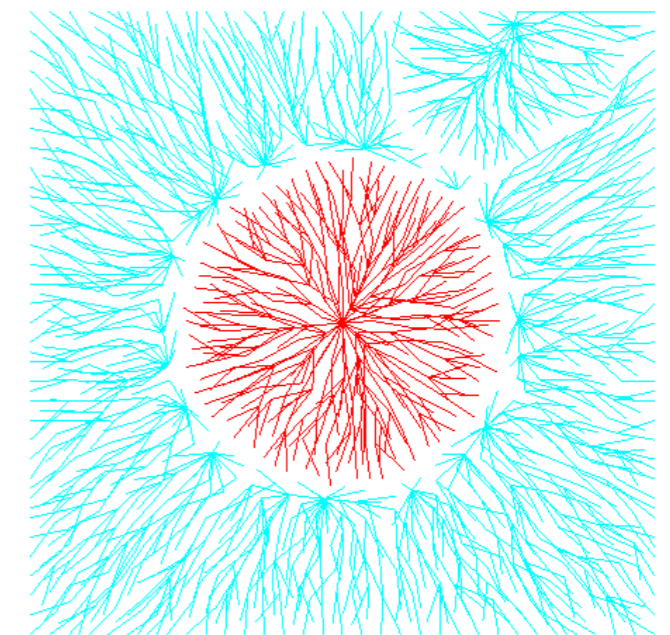
Application to Clustering

Main challenges:

- finding the *correct* number of clusters (separation theorem)
- approximating the basins of attraction (partial approximation result)



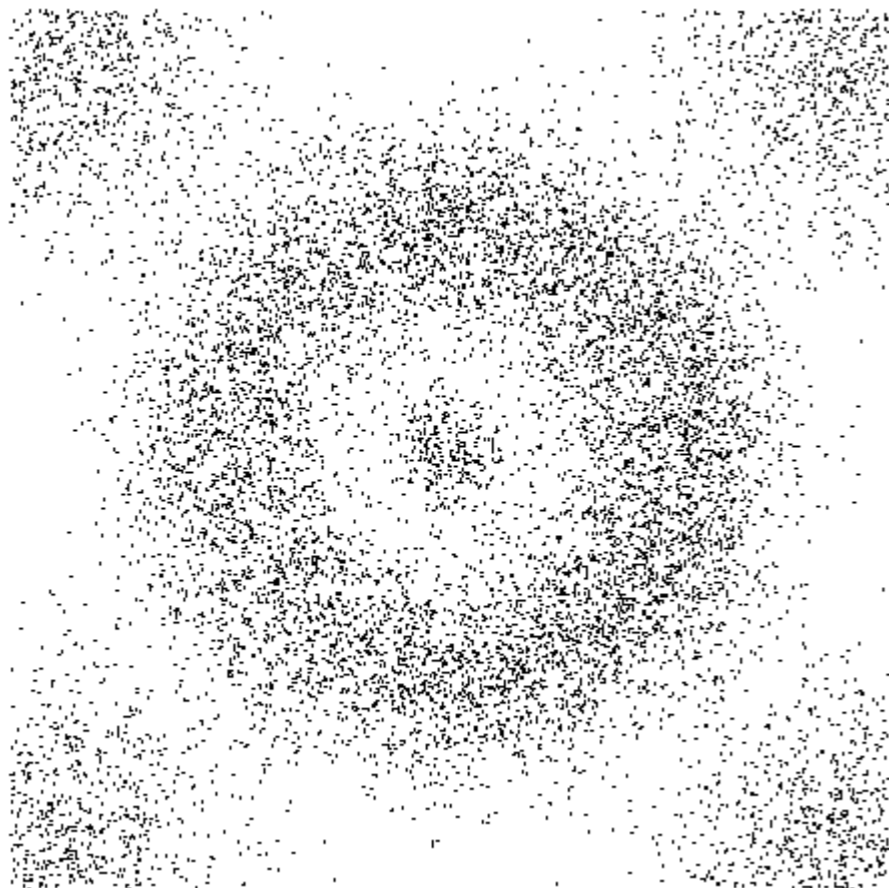
VS.



Application to Clustering

Main challenges:

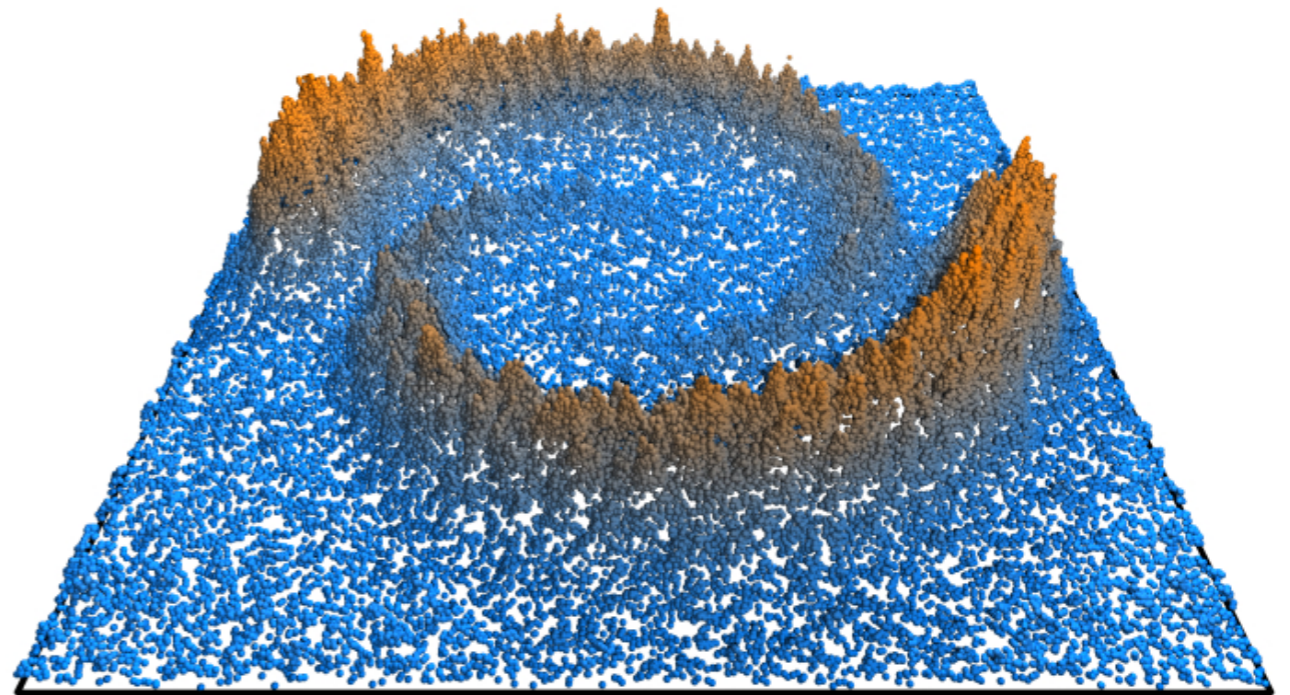
- finding the *correct* number of clusters (separation theorem)
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- \mathbb{X} may be partially sampled (yet some superlevel-set is well-sampled)



Application to Clustering

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Application to Clustering

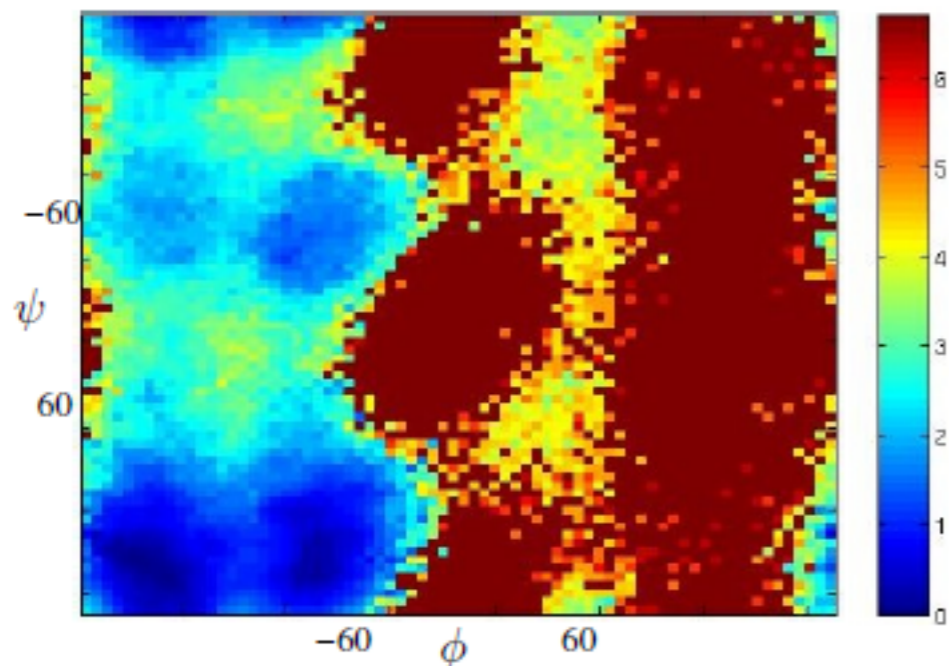
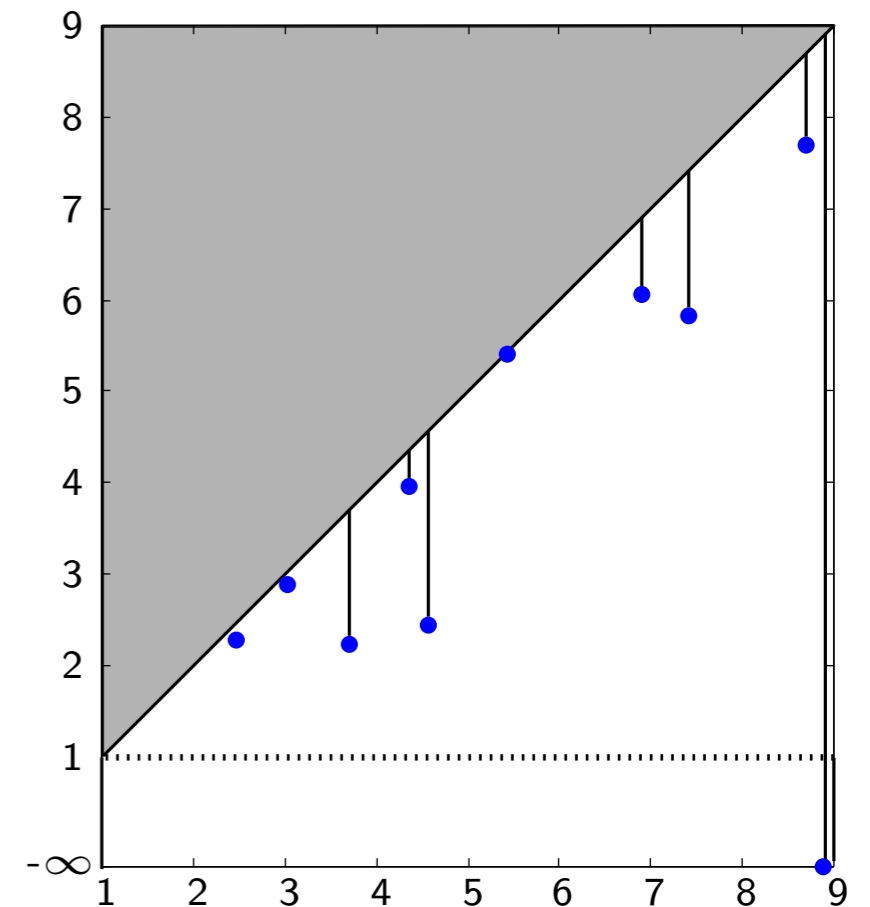
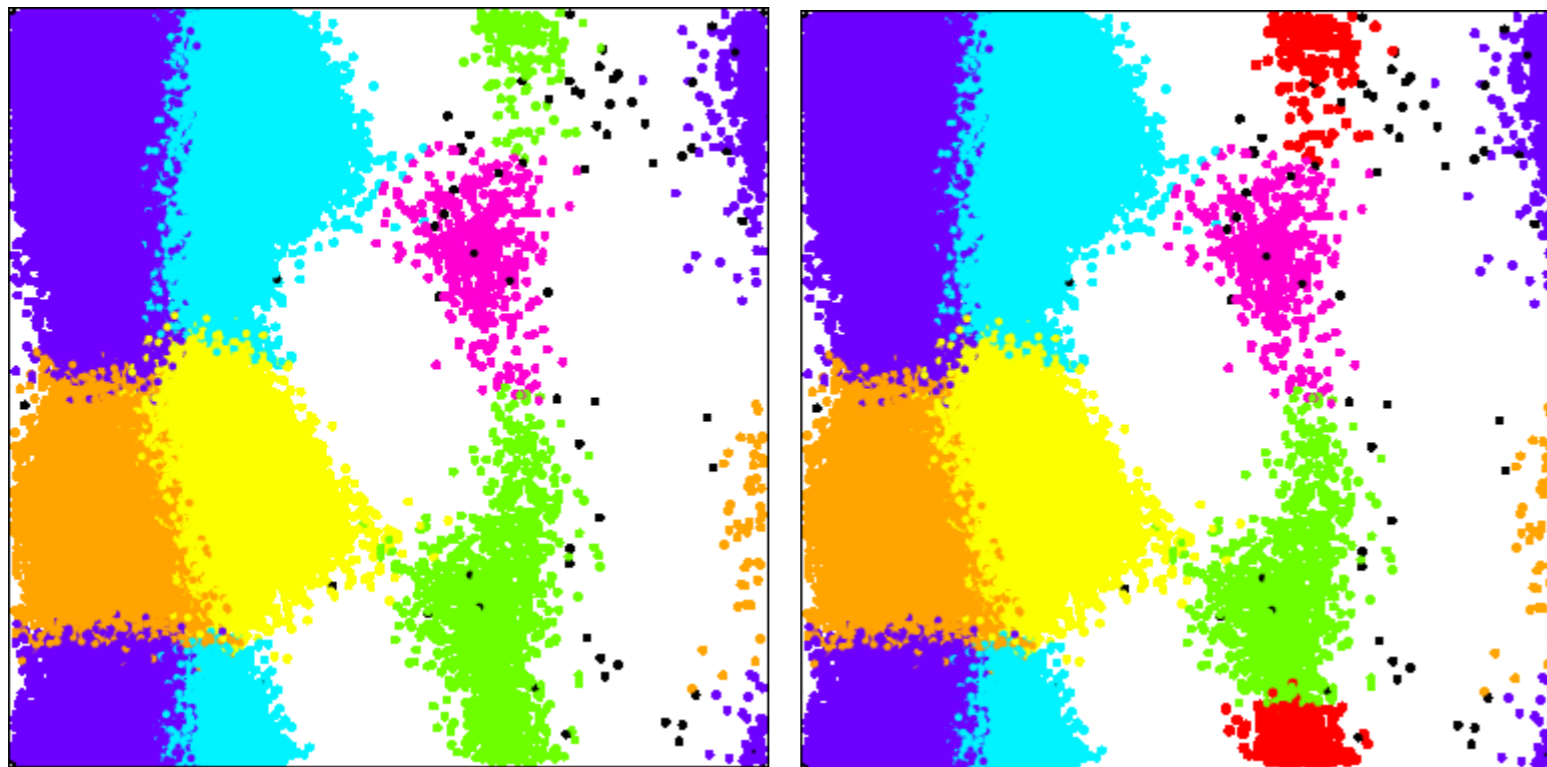
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- \mathbb{X} may be partially sampled (yet some superlevel-set is well-sampled)
- density is only known through some noisy estimator (stability results)
- pairwise distances are often approximated (GH-stability)

Application to Clustering

Back to the Alanine-dipeptide dataset:

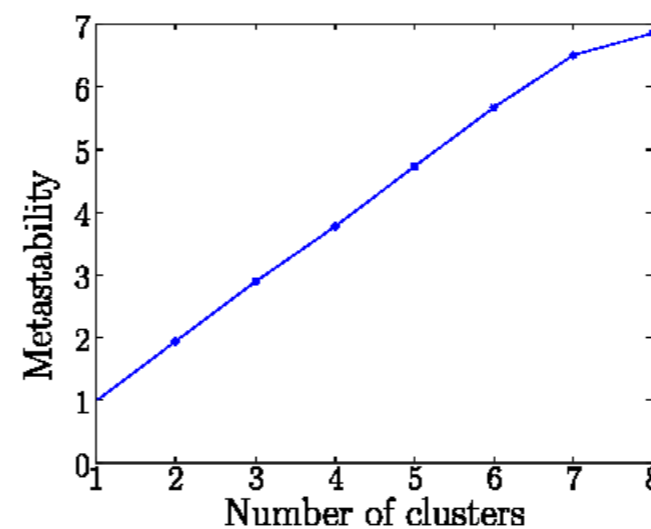
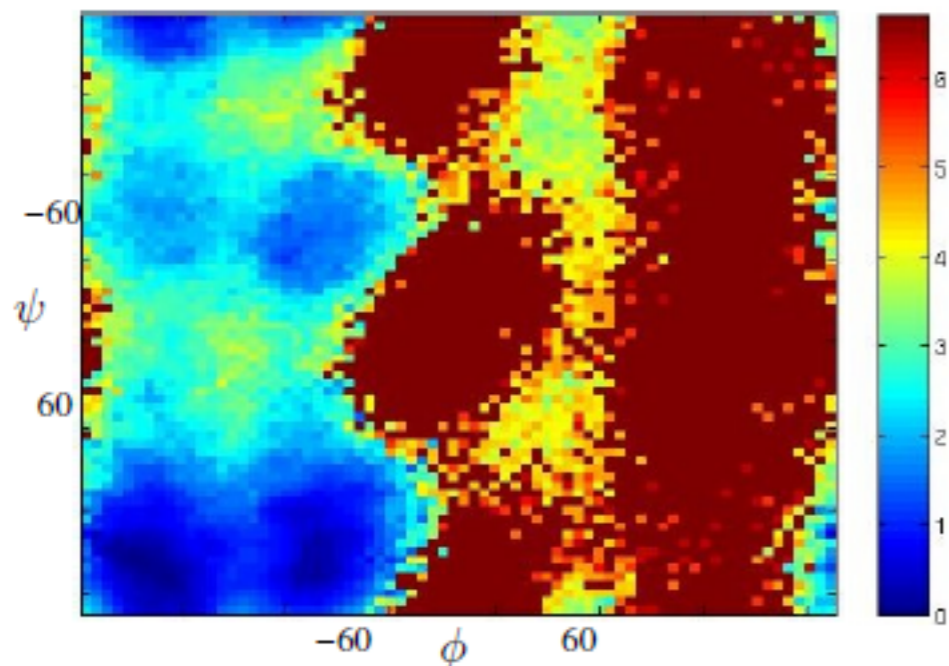
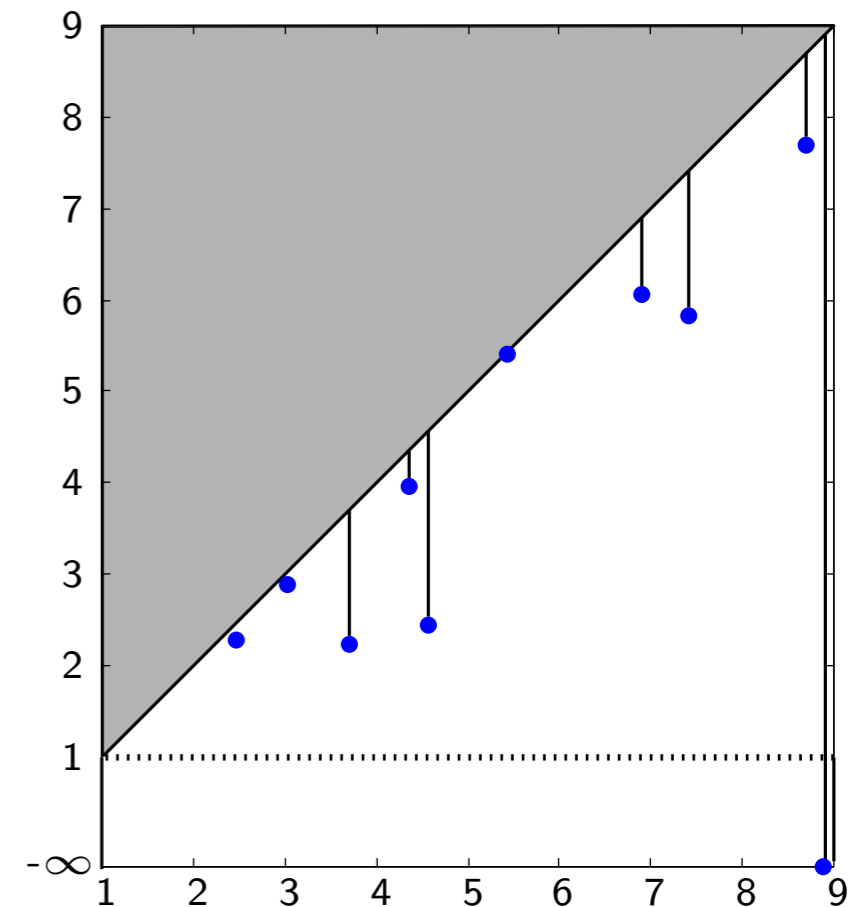
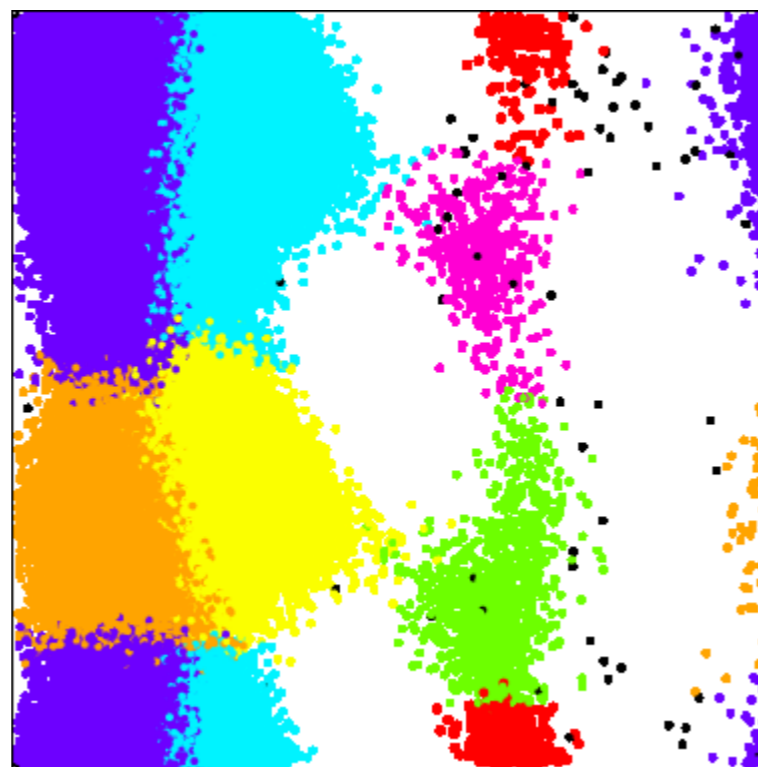
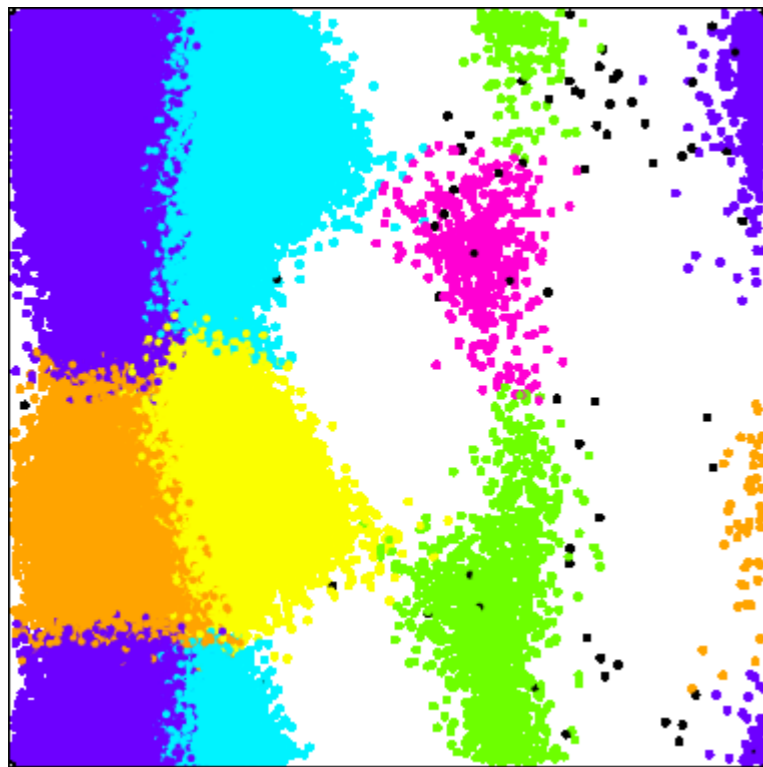
- clustering performed in R^{21} ; persistence diagram plotted on a log/log scale



Application to Clustering

Back to the Alanine-dipeptide dataset:

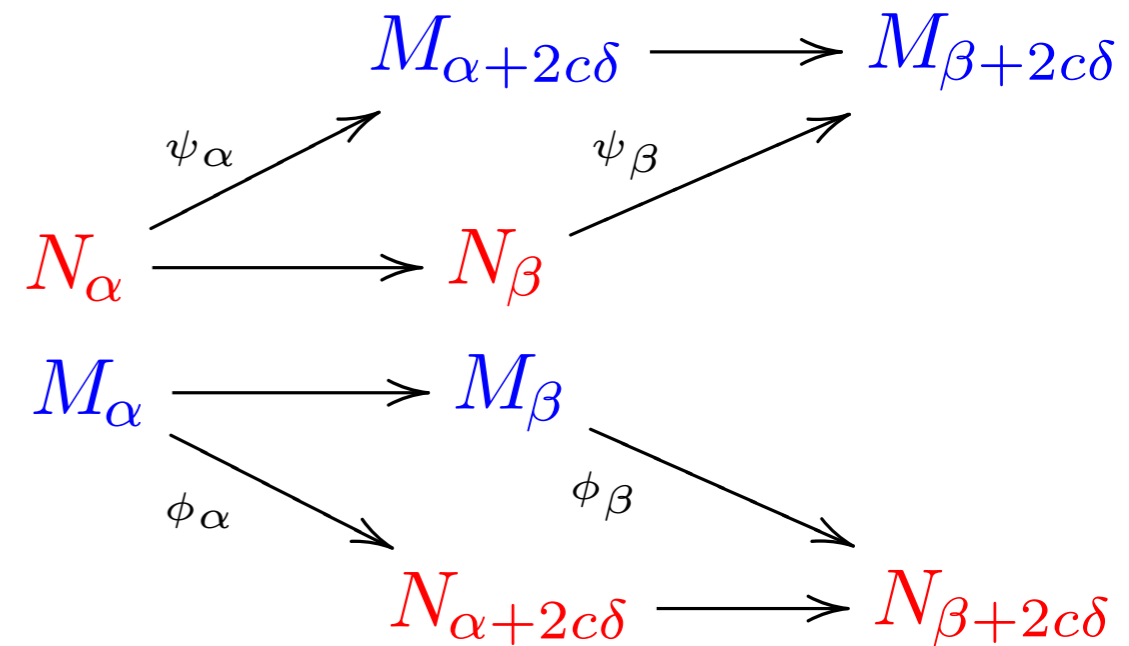
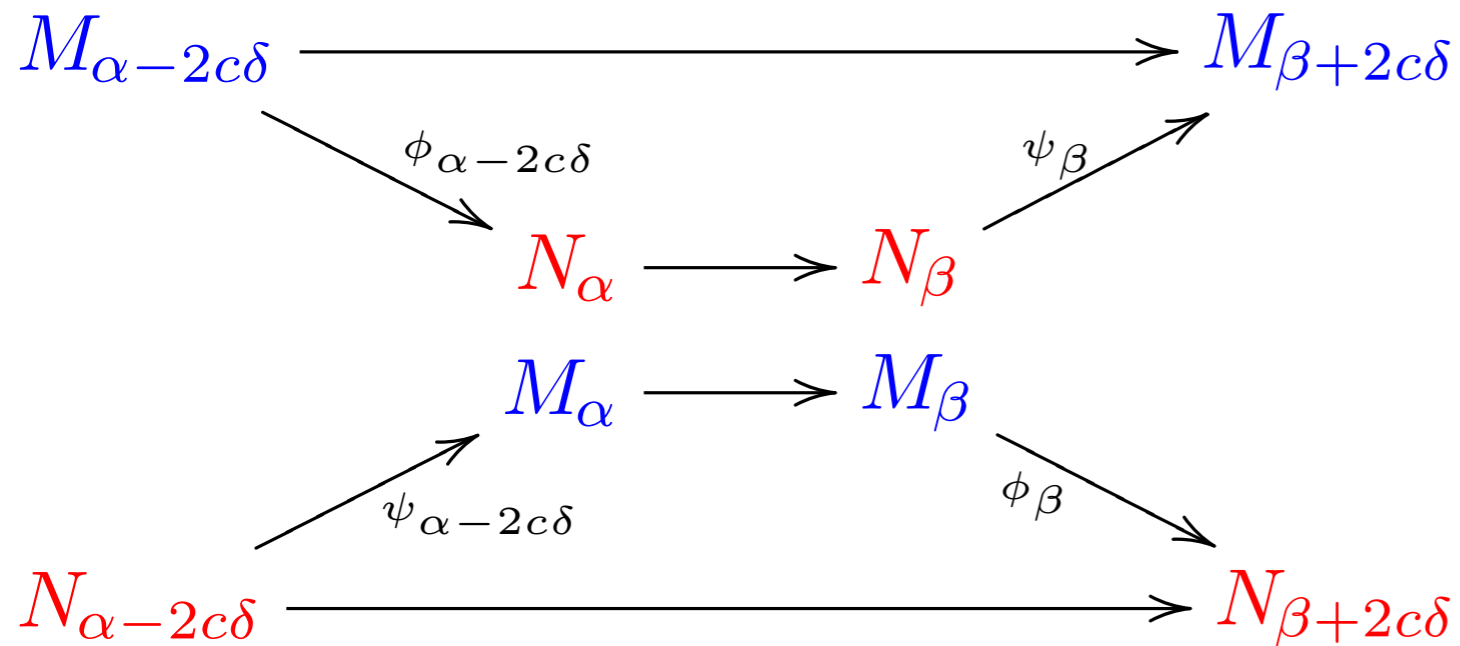
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Interlude: Proof of Stability

$\exists \{\phi_\alpha : M_\alpha \rightarrow N_{\alpha+2c\delta}\}_{\alpha \in \mathbb{R}}$ and $\{\psi_\alpha : N_\alpha \rightarrow M_{\alpha+2c\delta}\}_{\alpha \in \mathbb{R}}$

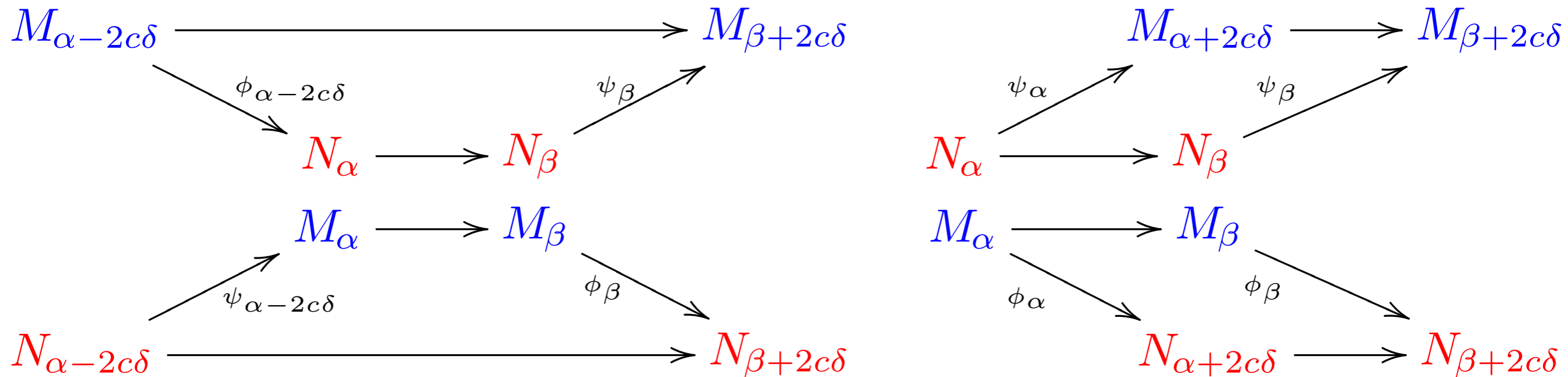
s.t. the following diagrams commute $\forall \alpha \leq \beta$:



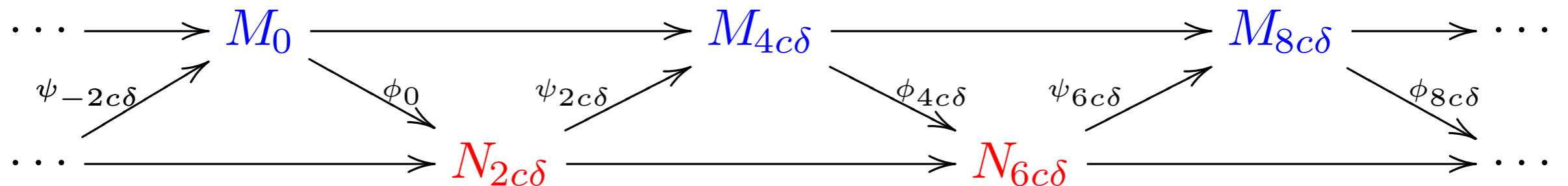
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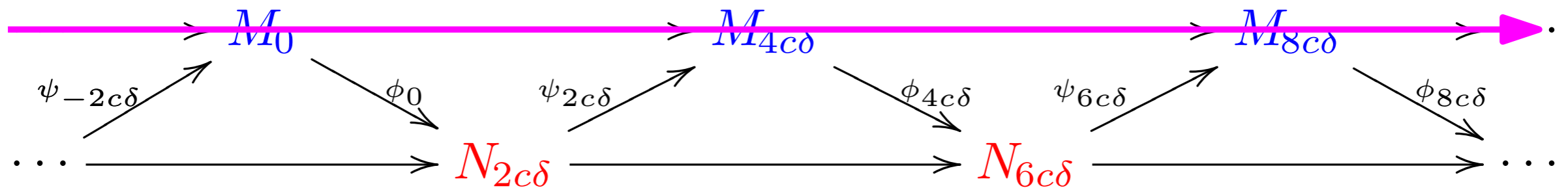


Fix $\alpha_0 = 0$ and consider the following commutative diagram:



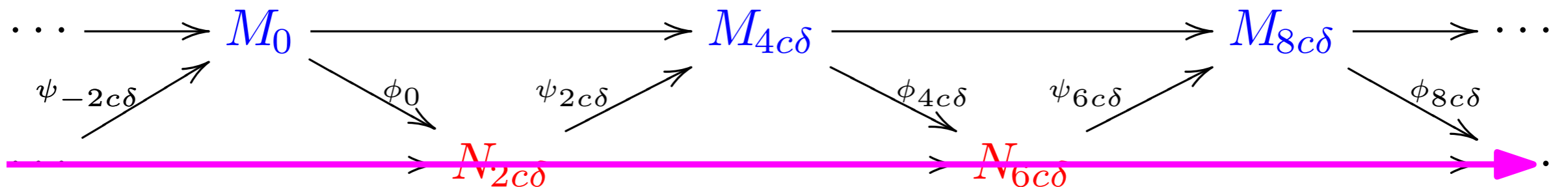
Interlude: Proof of Stability

- $\{M_{4kc\delta}\}_{k \in \mathbb{Z}}$ is a $4c\delta$ -discretization of $\{M_\alpha\}_{\alpha \in \mathbb{R}}$



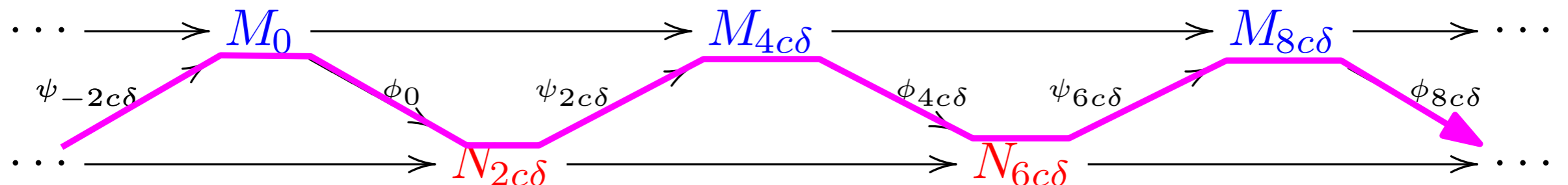
Interlude: Proof of Stability

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- $\{N_{(4k+2)c\delta}\}_{k \in \mathbb{Z}}$ is a $4c\delta$ -discretization of $\{N_\alpha\}_{\alpha \in \mathbb{R}}$



Interlude: Proof of Stability

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- $\{M_{4kc\delta}\}_{k \in \mathbb{Z}}$ and $\{N_{(4k+2)c\delta}\}_{k \in \mathbb{Z}}$ are $4c\delta$ -discretizations of
 $\dots \rightarrow M_0 \rightarrow N_{2c\delta} \rightarrow M_{4c\delta} \rightarrow N_{6c\delta} \rightarrow M_{8c\delta} \rightarrow \dots$

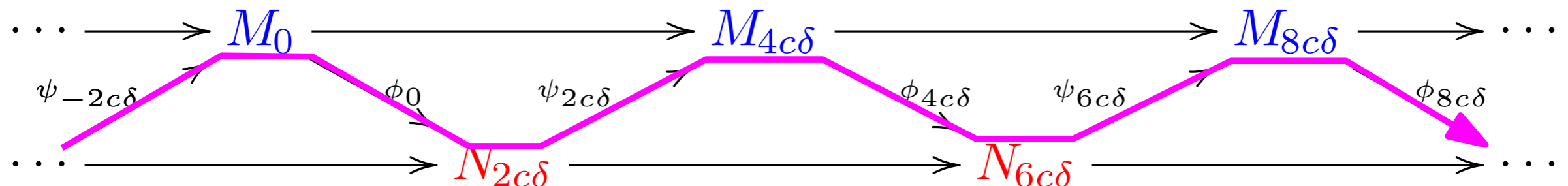


Interlude: Proof of Stability

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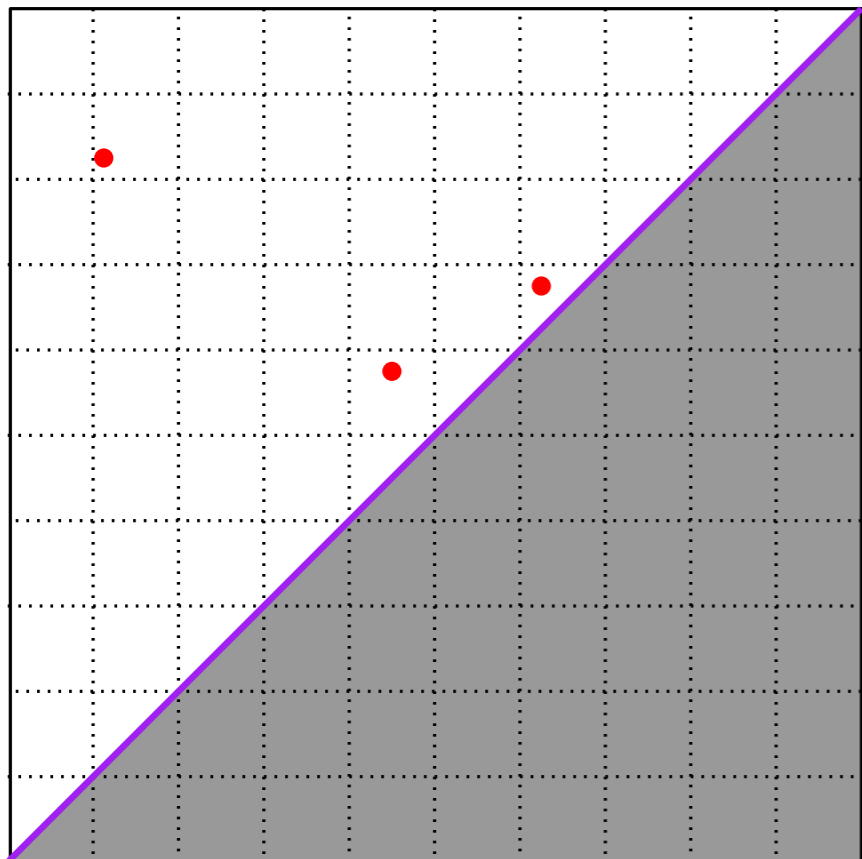
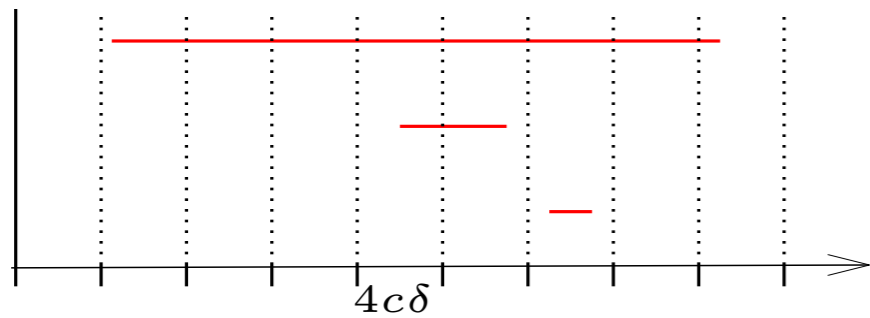
$$\dots \rightarrow M_0 \rightarrow N_{2c\delta} \rightarrow M_{4c\delta} \rightarrow N_{6c\delta} \rightarrow M_{8c\delta} \rightarrow \dots$$

→ **goal:** relate diagrams of persistence module and of its $4c\delta$ -discretizations



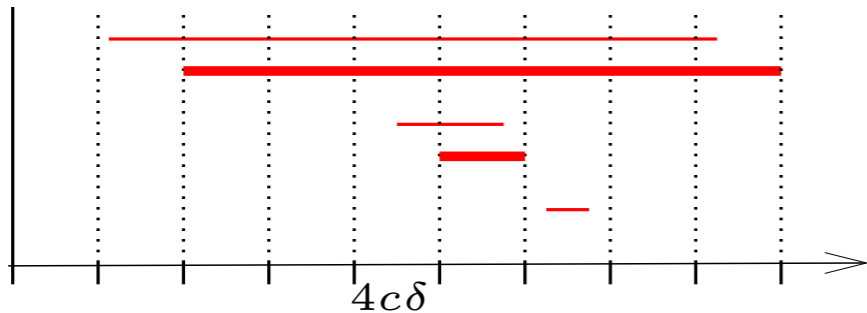
Interlude: Proof of Stability

→ Effect of the discretization of a module on its persistence diagram:



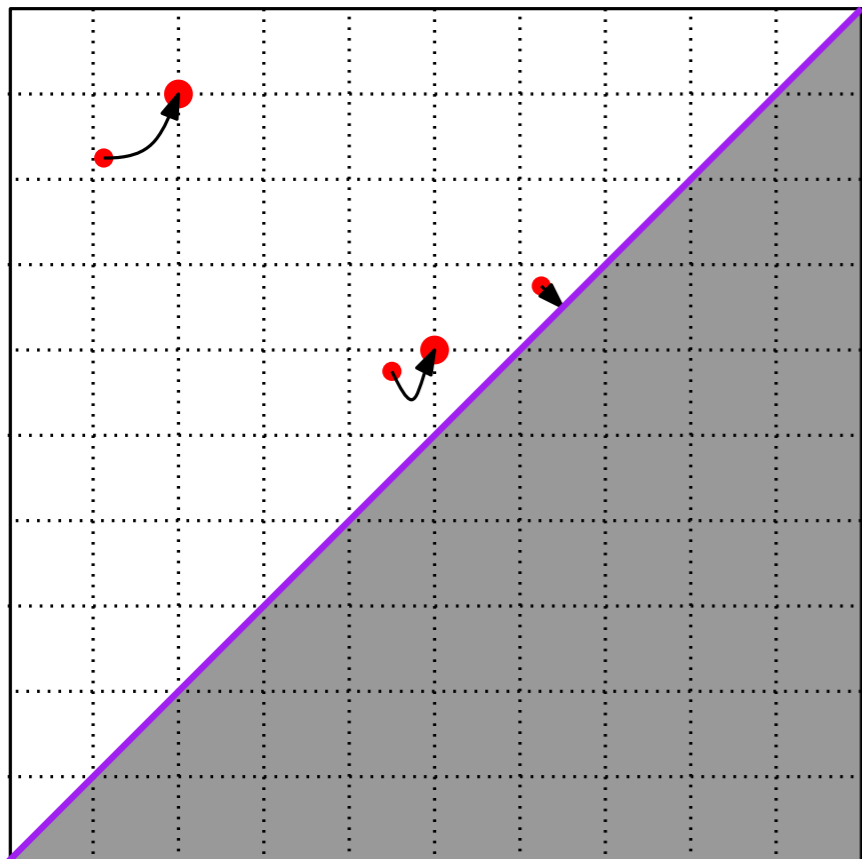
Interlude: Proof of Stability

→ Effect of the discretization of a module on its persistence diagram:



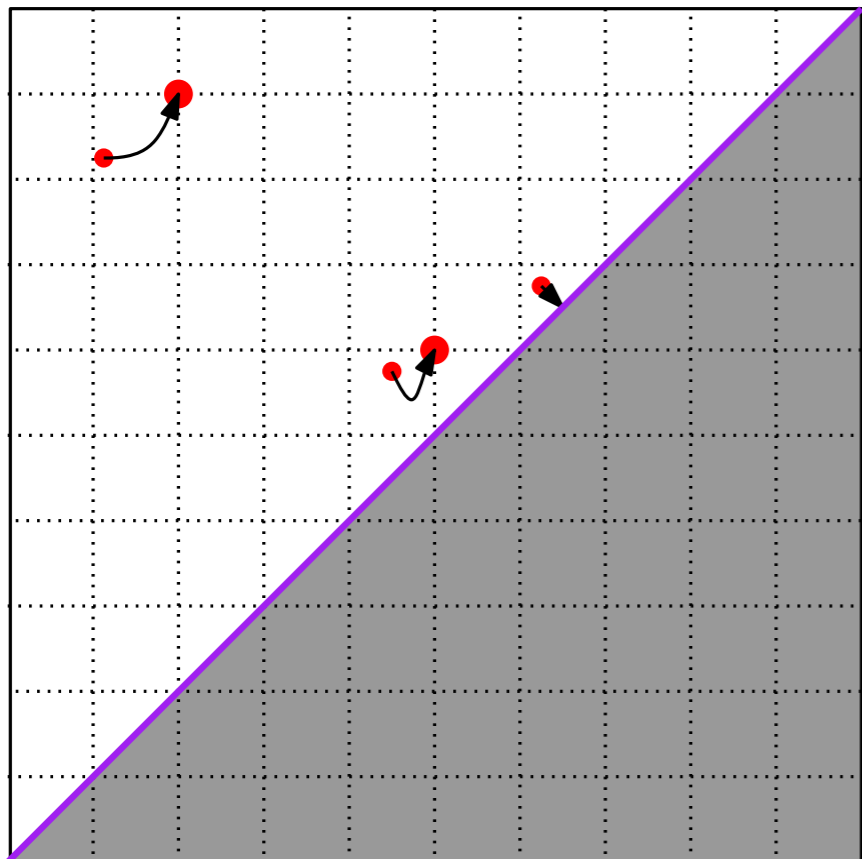
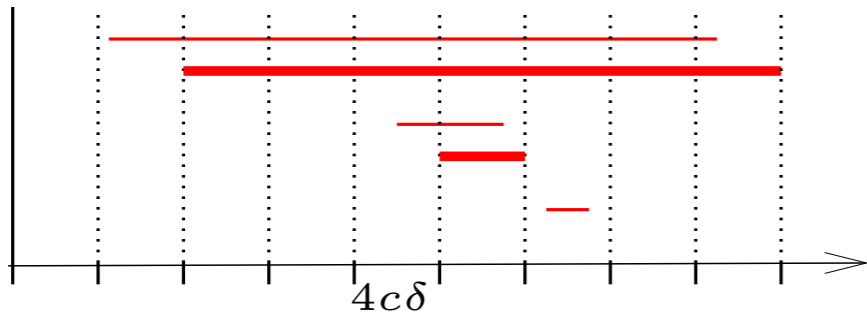
Pixelization map: $\forall \alpha \leq \beta,$

$$\pi_{4c\delta}(\alpha, \beta) = \begin{cases} (\lceil \frac{\alpha}{4c\delta} \rceil 4c\delta, \lceil \frac{\beta}{4c\delta} \rceil 4c\delta) & \text{if } \lceil \frac{\beta}{4c\delta} \rceil > \lceil \frac{\alpha}{4c\delta} \rceil \\ (\frac{\alpha+\beta}{2}, \frac{\alpha+\beta}{2}) & \text{if } \lceil \frac{\beta}{4c\delta} \rceil = \lceil \frac{\alpha}{4c\delta} \rceil \end{cases}$$



Interlude: Proof of Stability

→ Effect of the discetization of a module on its persistence diagram:



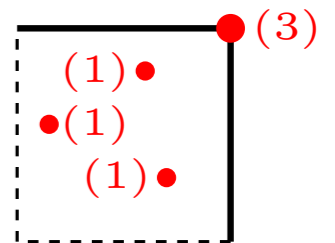
Pixelization map: $\forall \alpha \leq \beta$,

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Theorem: $\pi_{4c\delta}$ induces a multi-bijection

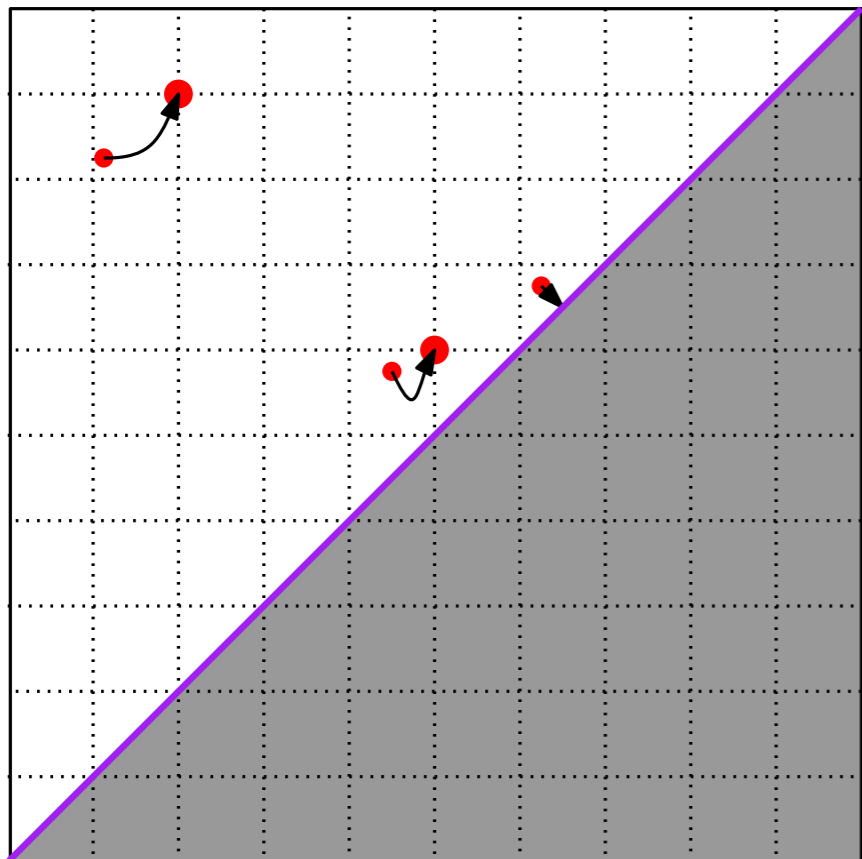
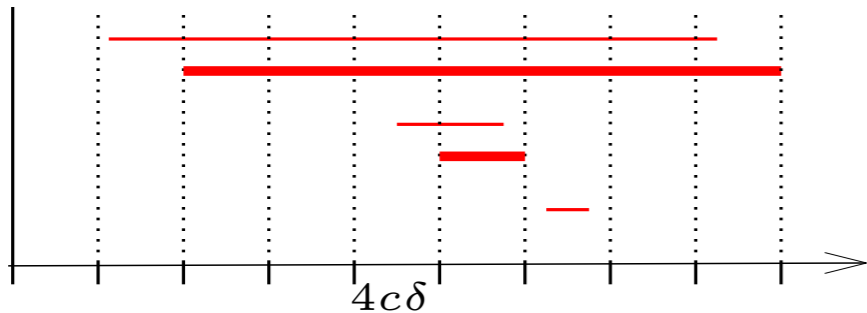
→ proof: show that the multiplicities of both diagrams are the same inside each half-open grid cell that does not intersect the diagonal.

The case of diagonal cells is trivial.



Interlude: Proof of Stability

→ Effect of the discretization of a module on its persistence diagram:



Pixelization map: $\forall \alpha \leq \beta$,

$$\pi_{4c\delta}(\alpha, \beta) = \begin{cases} (\lceil \frac{\alpha}{4c\delta} \rceil 4c\delta, \lceil \frac{\beta}{4c\delta} \rceil 4c\delta) & \text{if } \lceil \frac{\beta}{4c\delta} \rceil > \lceil \frac{\alpha}{4c\delta} \rceil \\ (\frac{\alpha+\beta}{2}, \frac{\alpha+\beta}{2}) & \text{if } \lceil \frac{\beta}{4c\delta} \rceil = \lceil \frac{\alpha}{4c\delta} \rceil \end{cases}$$

Theorem: $\pi_{4c\delta}$ induces a multi-bijection

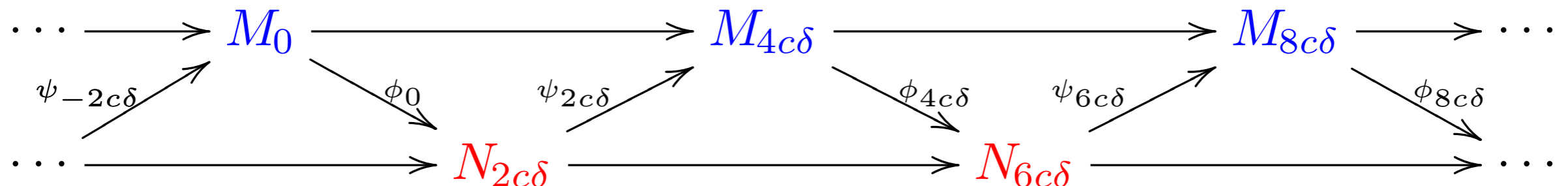
\Rightarrow the bottleneck distance is at most $4c\delta$

Interlude: Proof of Stability

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→ theorem + triangle inequality $\Rightarrow d_B^\infty(\text{Dgm } \{M_\alpha\}_\alpha, \text{Dgm } \{N_\alpha\}_\alpha) \leq 16c\delta$



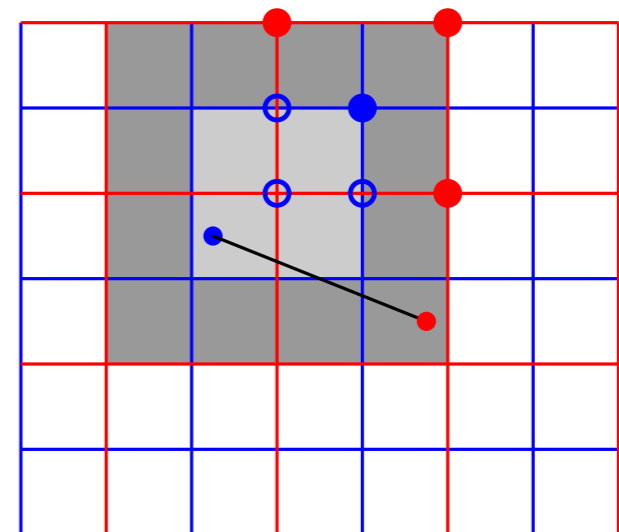
Interlude: Proof of Stability

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\rightarrow theorem + triangle inequality $\Rightarrow d_B^\infty(\text{Dgm } \{M_\alpha\}_\alpha, \text{Dgm } \{N_\alpha\}_\alpha) \leq 16c\delta$

Improvement:

$$d_B^\infty(\text{Dgm } \{M_\alpha\}_\alpha, \text{Dgm } \{N_\alpha\}_\alpha) \leq 6c\delta$$



Some References

[1] Chazal, Cohen-Steiner, Glisse, Guibas, O., *Proximity of persistence modules and their diagrams*, Proc. SoCG 2009.

[2] Chazal, Guibas, O., Skraba, *Analysis of scalar fields over point cloud data*, Proc. SODA 2009.

[3] Chazal, Guibas, O., Skraba, "Persistence-Based Clustering in Riemannian Manifolds", INRIA Research report 6968, June 2009.

→ code integrated to the CULT library (many thanks to P. Skraba)
<https://gforge.inria.fr/projects/cult/>