



**KTH Computer Science
and Communication**

Towards a topological machine learning

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Overview of existing work

- Stability of persistence
- Persistence of random point clouds
- Distance to measure
- Persistence as ML feature vectors
- Barcode means



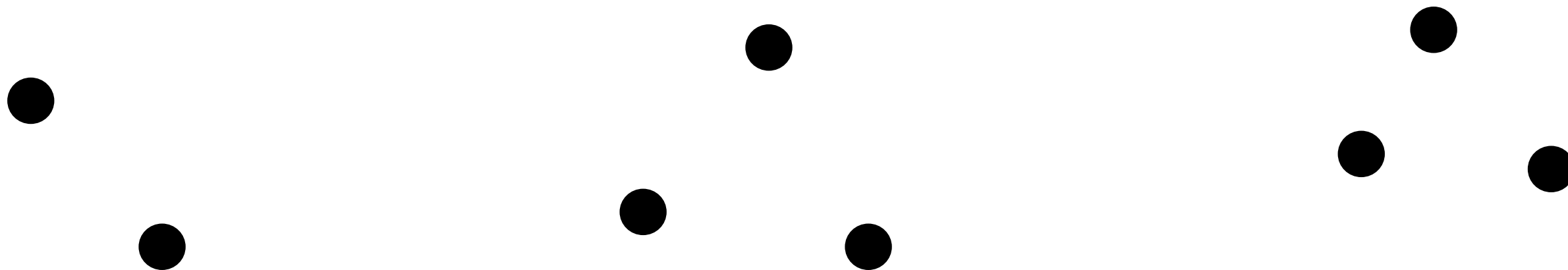
Point cloud cohomology: persistence

- Just computing cohomology: not useful
Discrete points have no interesting structure.
- Instead:
 1. Cover each point with a ball
 2. Compute cohomology of the union of balls

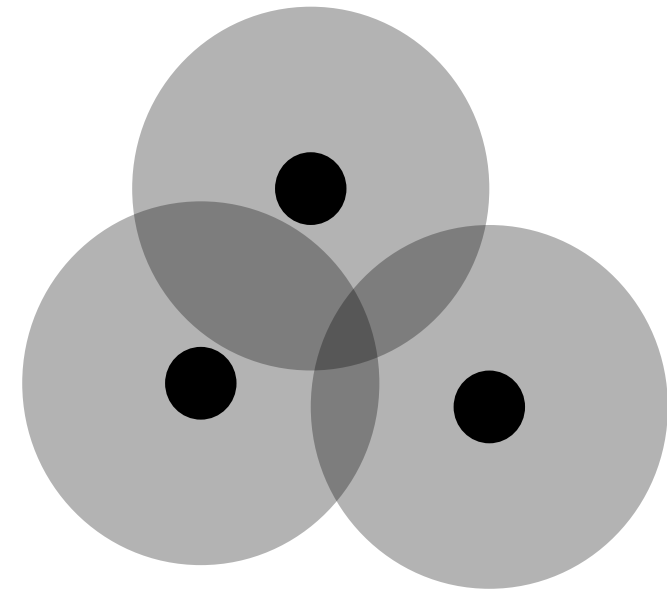
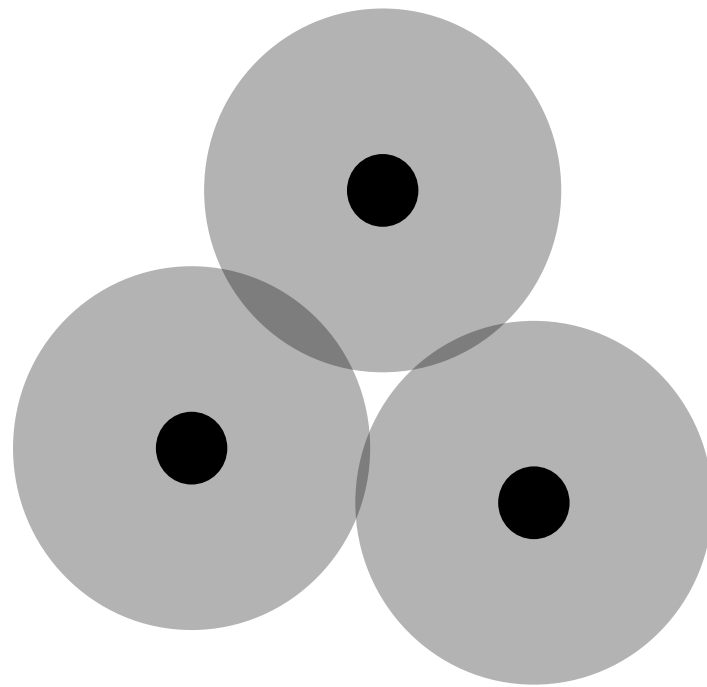
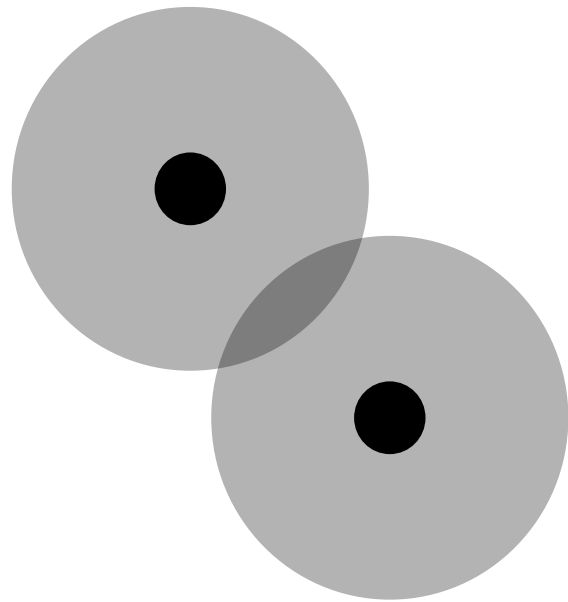


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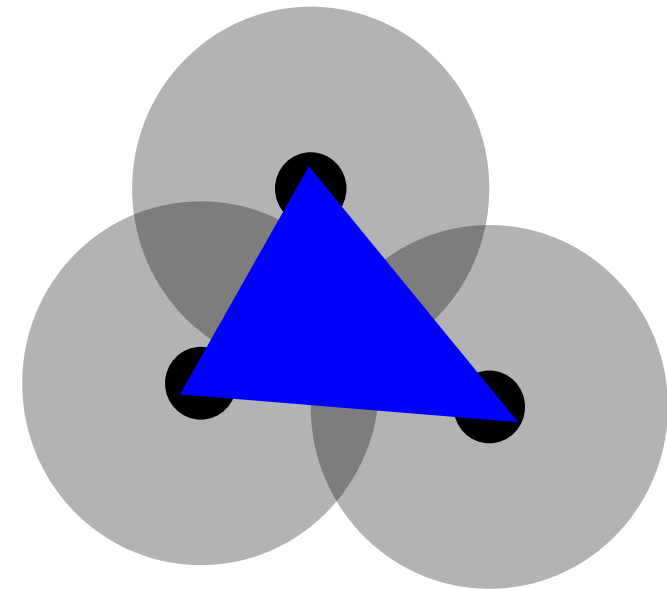
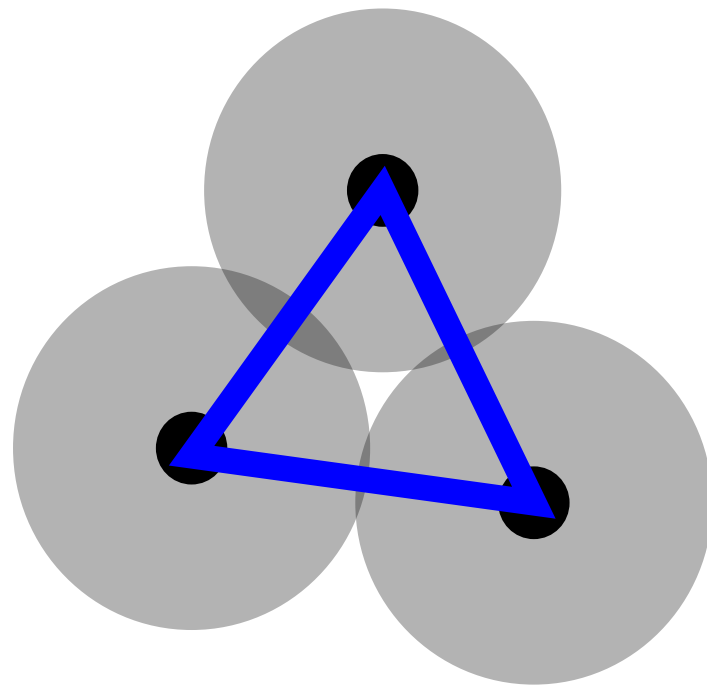
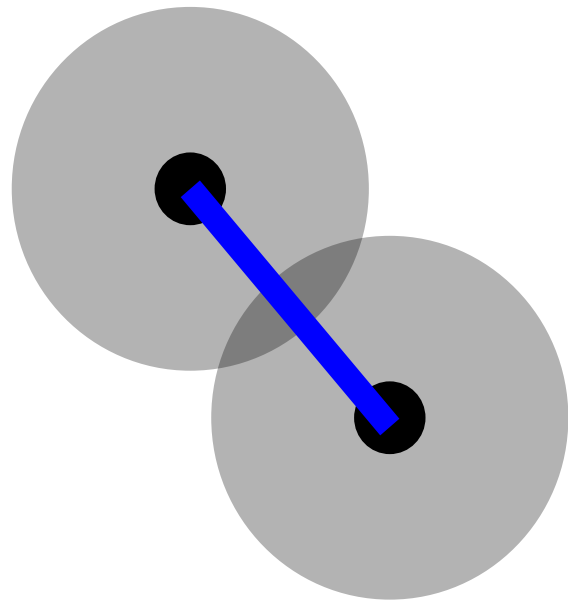
Encoding geometry



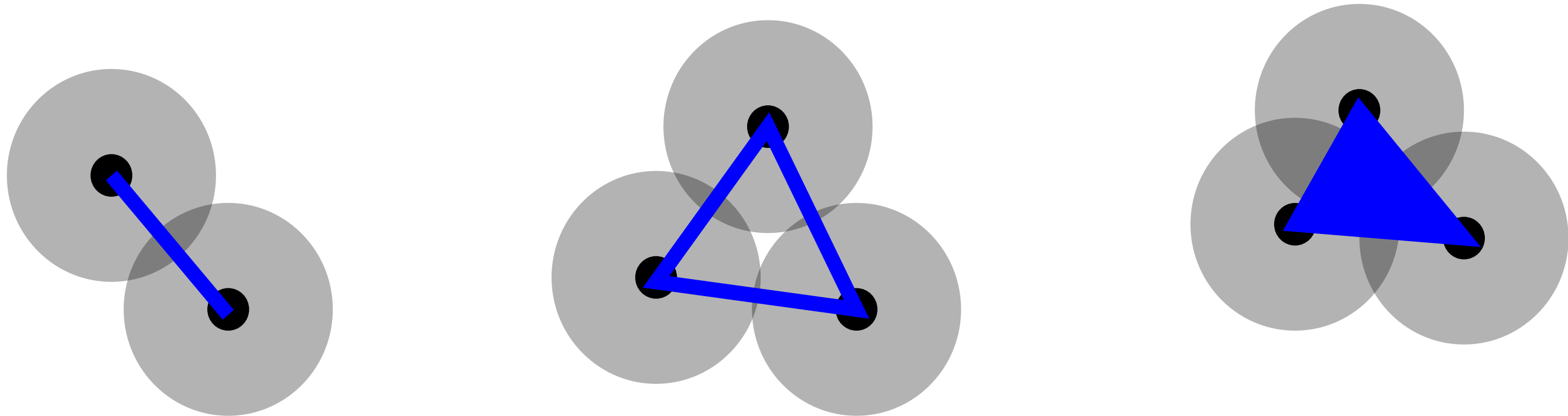
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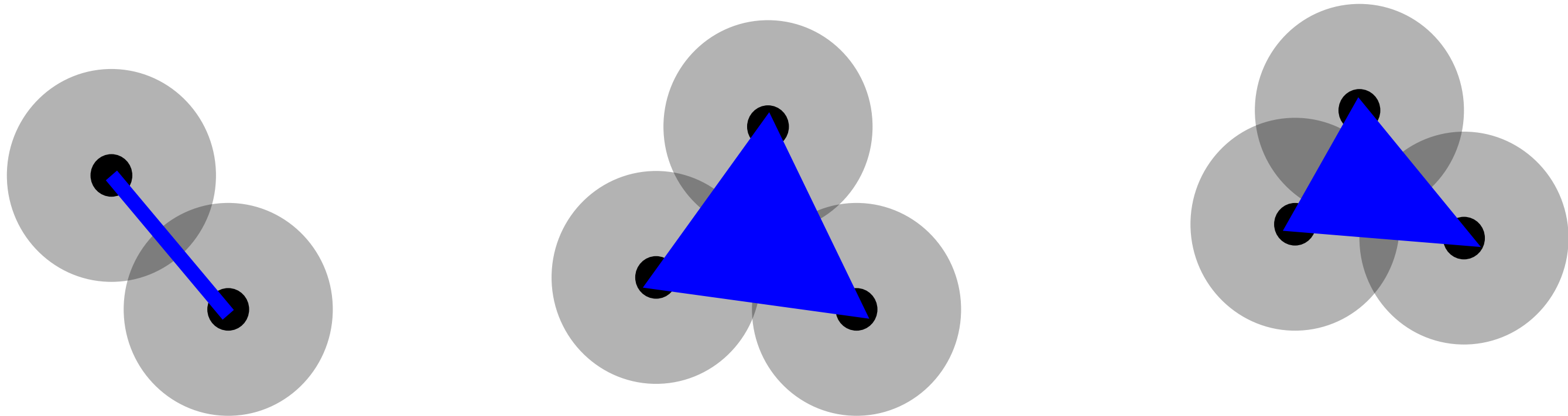
Encoding geometry



The Čech complex of radius r has a simplex for data points x_0, \dots, x_n whenever all the balls of radius r centered around the data points share an intersection. d_i removes x_i .

This generalizes the *single linkage graph*.

Encoding geometry



The Vietoris-Rips complex is completely defined by the single linkage graph: includes a simplex whenever there is a clique in the single linkage graph.
Face maps just like in the Čech case.

Functoriality: algebraic continuity

- If we increase the radius, no cells vanish the complex can only ever increase.

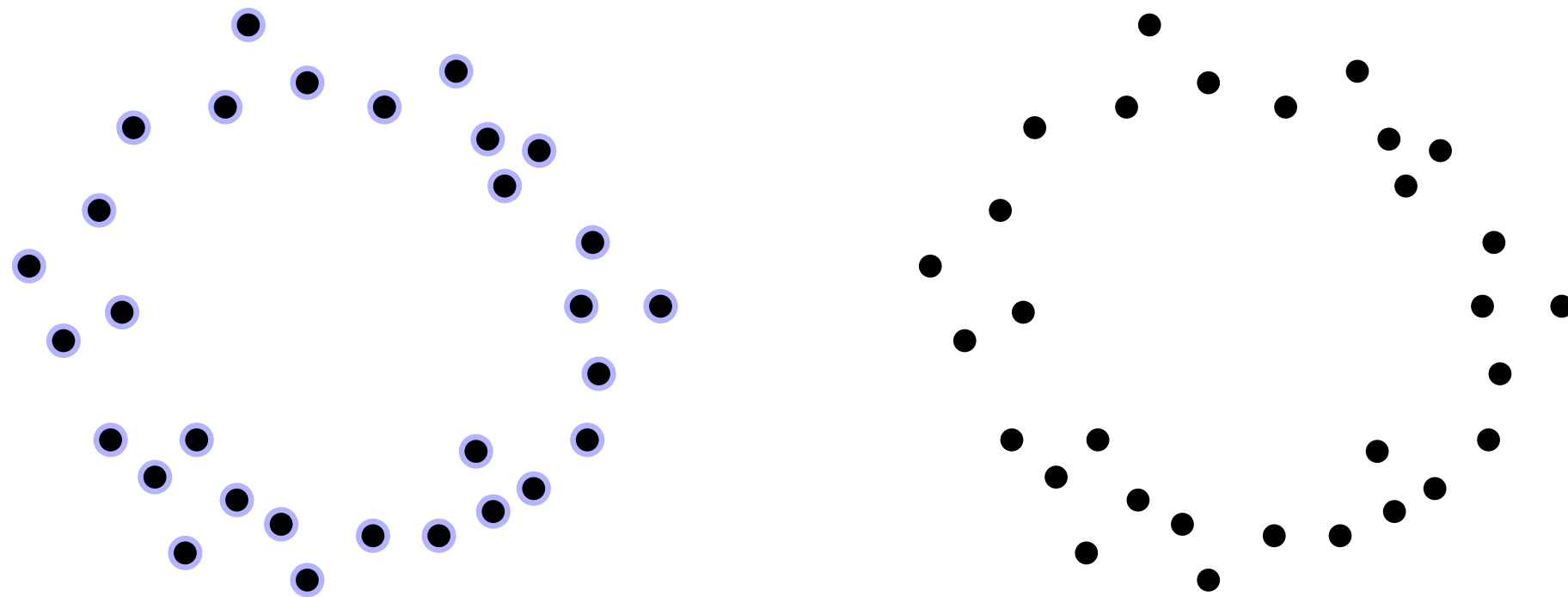
For any $r < r'$ there are inclusion maps
 $\check{C}_r(X) \rightarrow \check{C}_{r'}(X)$

- Computing cohomology is a functor — continuous in an algebraic sense:
if there is a map $X \rightarrow Y$, then there is an induced map
 $H^1 Y \rightarrow H^1 X$

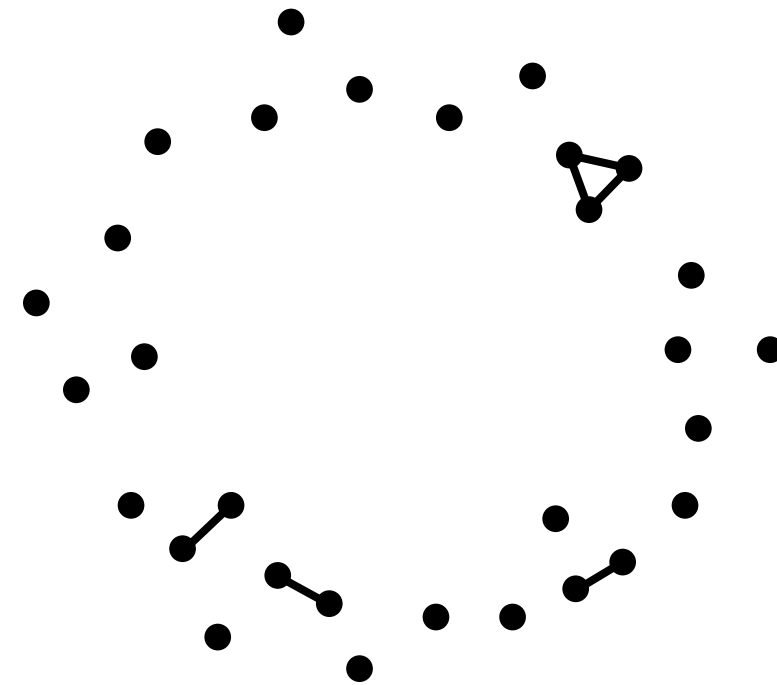
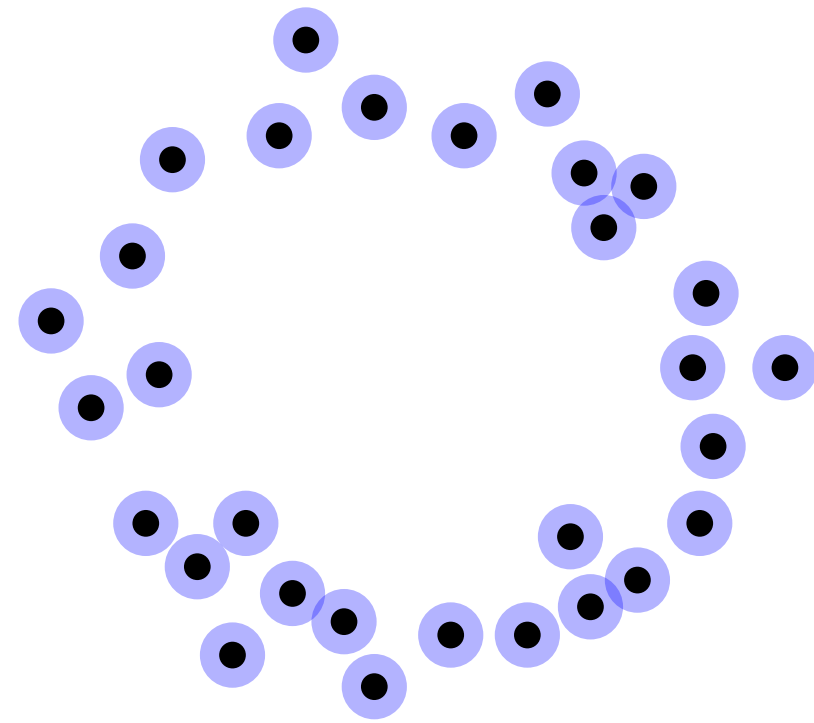


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Persistent cohomology: tracking maps

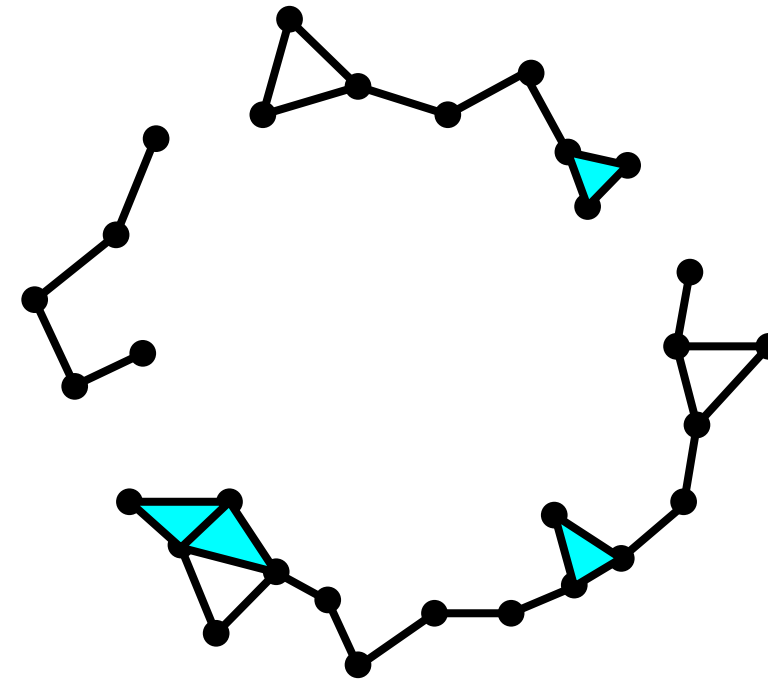
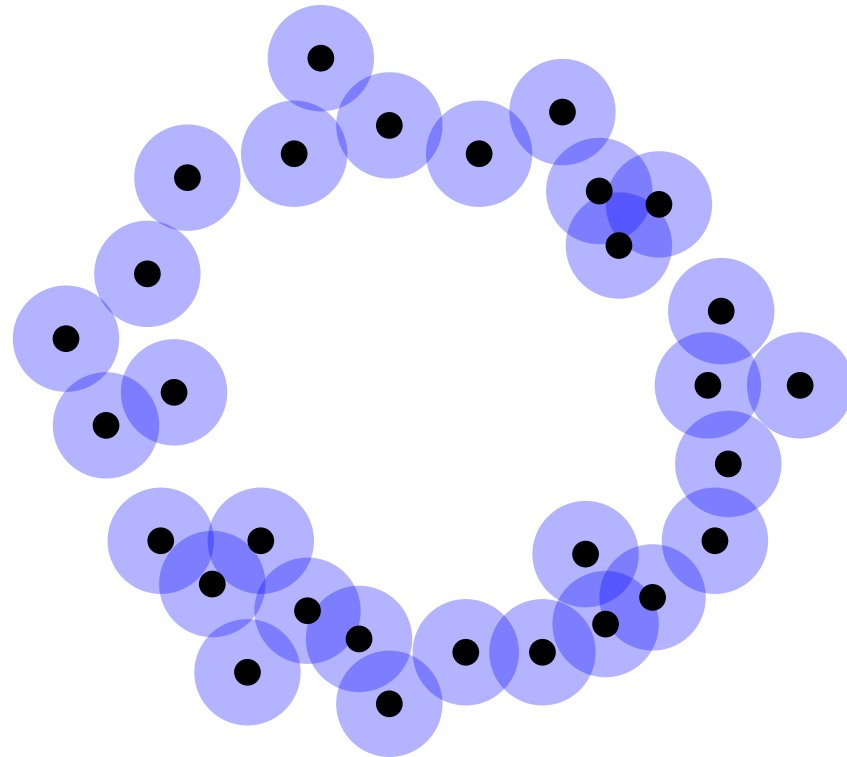


Persistent cohomology: tracking maps



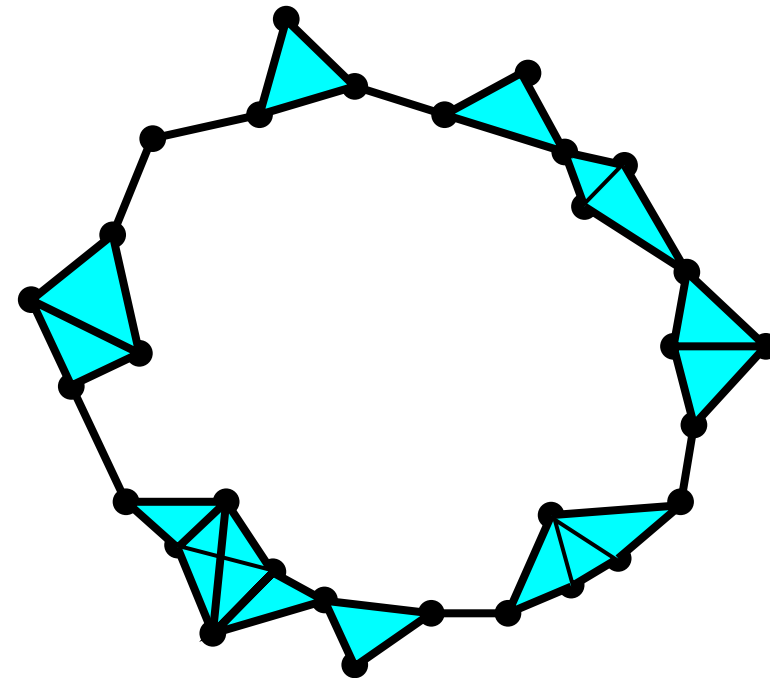
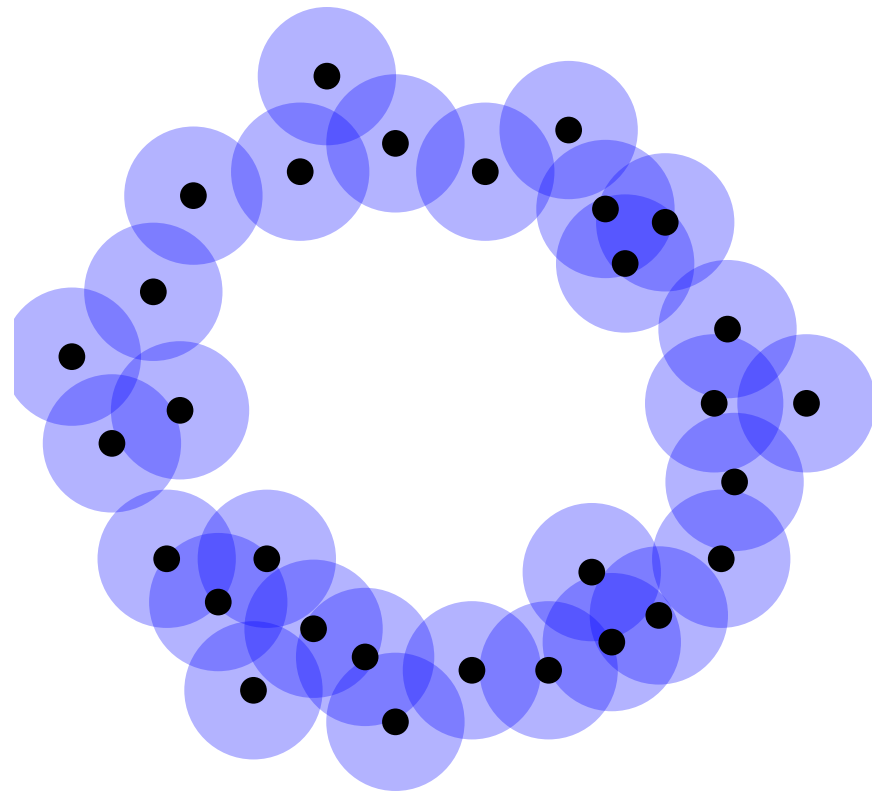
1 loop

Persistent cohomology: tracking maps



3 loops

Persistent cohomology: tracking maps



1 loop

Key point: are loops the same?

- The induced map come to our rescue:
- From a sequence of spaces

$$X_1 \hookrightarrow X_2 \hookrightarrow X_3 \hookrightarrow \dots \hookrightarrow X_n$$

cohomology produces a sequence of vector spaces

$$H^1 X_n \rightarrow \dots \rightarrow H^1 X_3 \rightarrow H^1 X_2 \rightarrow H^1 X_1$$



Algebra glues features

- Theorem (Gabriel, 1972): If M is a collection of vector spaces with linear maps along a path, M decomposes into interval modules.
- Decomposition produces birth/death pairs just like our barcodes.

Interval decompositions produce salient features

- Decomposing a diagram such as

$$H^1X_n \rightarrow \dots \rightarrow H^1X_3 \rightarrow H^1X_2 \rightarrow H^1X_1$$

produces a direct sum diagram where each summand has the shape

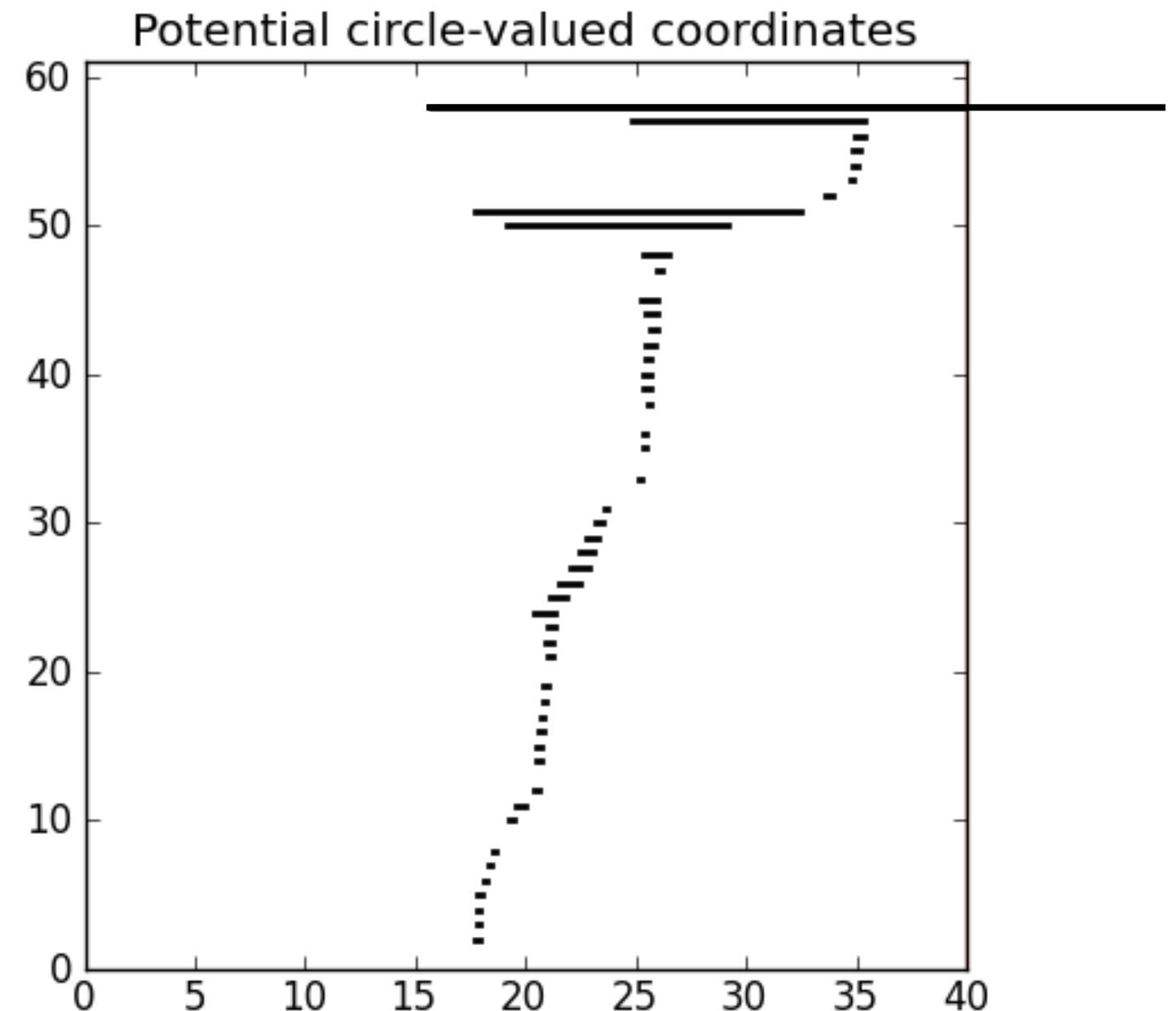
$$0 \rightarrow \dots \rightarrow 0 \rightarrow \mathbb{k} \rightarrow \dots \rightarrow \mathbb{k} \rightarrow 0 \rightarrow 0 \rightarrow 0$$

where all maps $0 \rightarrow 0$ and $\mathbb{k} \rightarrow \mathbb{k}$ are isomorphisms.

- Each such summand is a choice of a (higher dimensional) essential circle coordinate across parameter values that persists across different values.

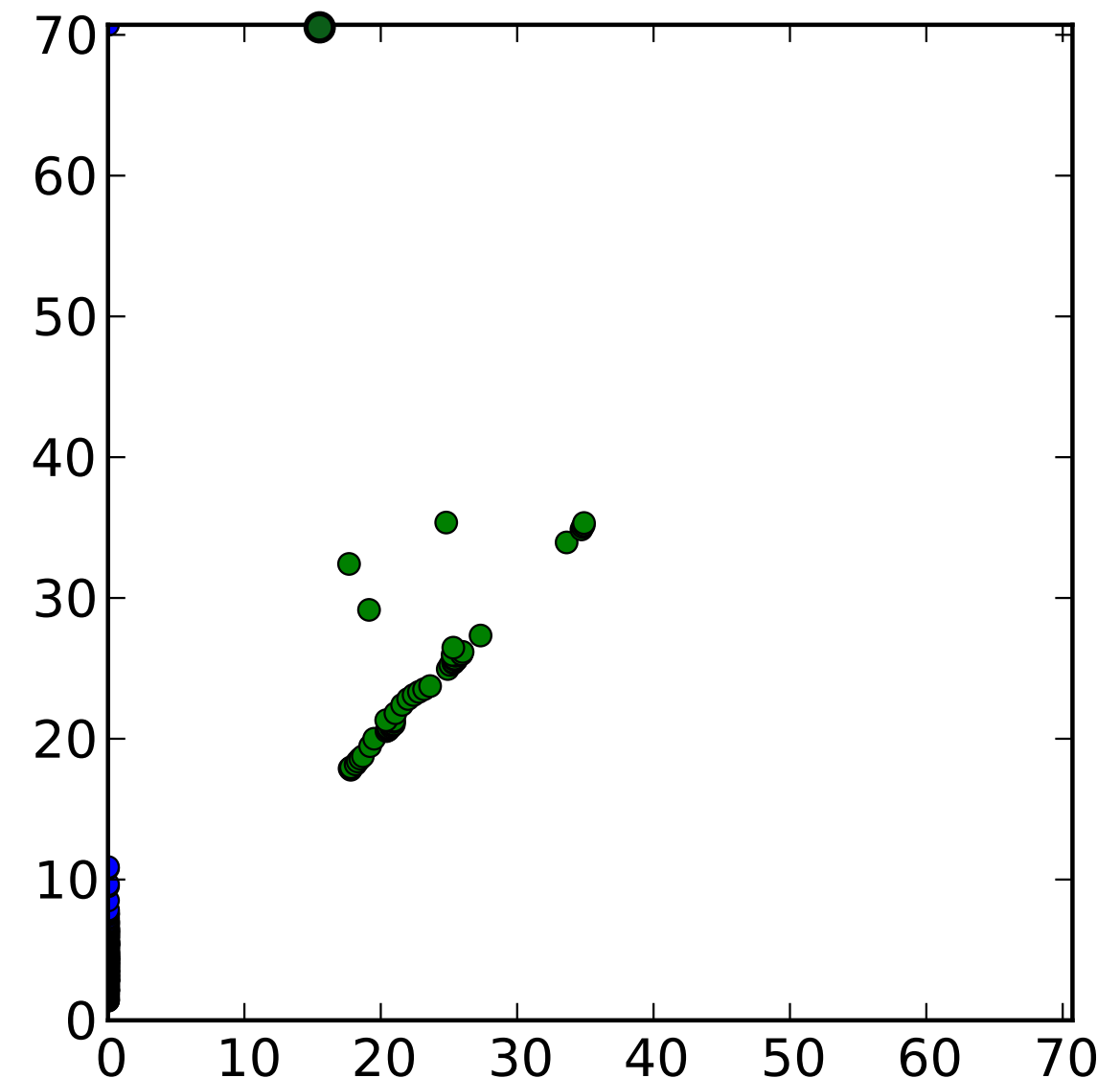
Barcodes and persistence diagrams

- Visualization tools for topological information
- Displays each interval in the decomposition



Barcodes and persistence diagrams

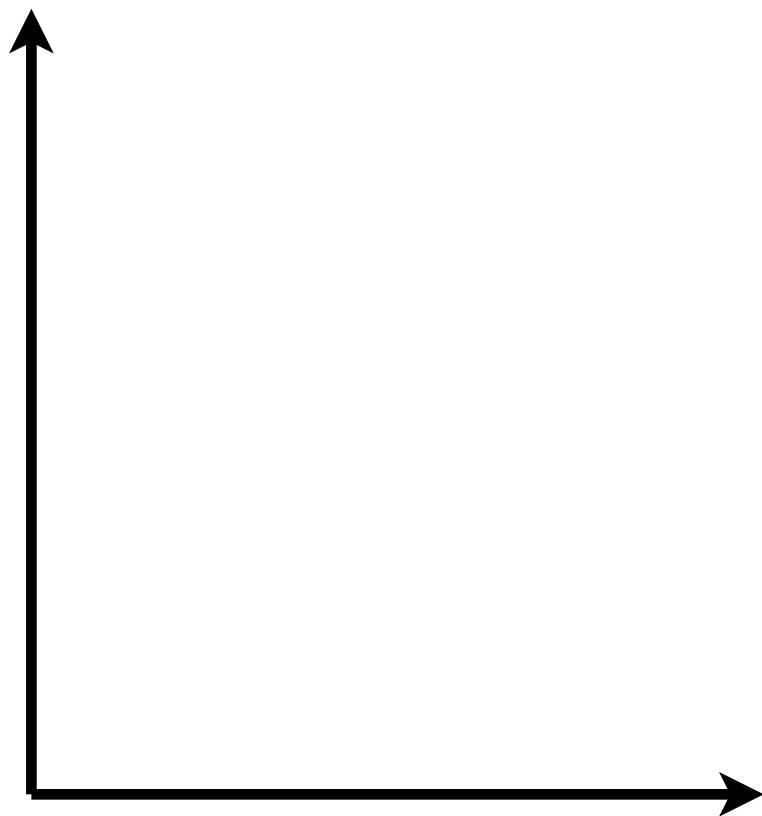
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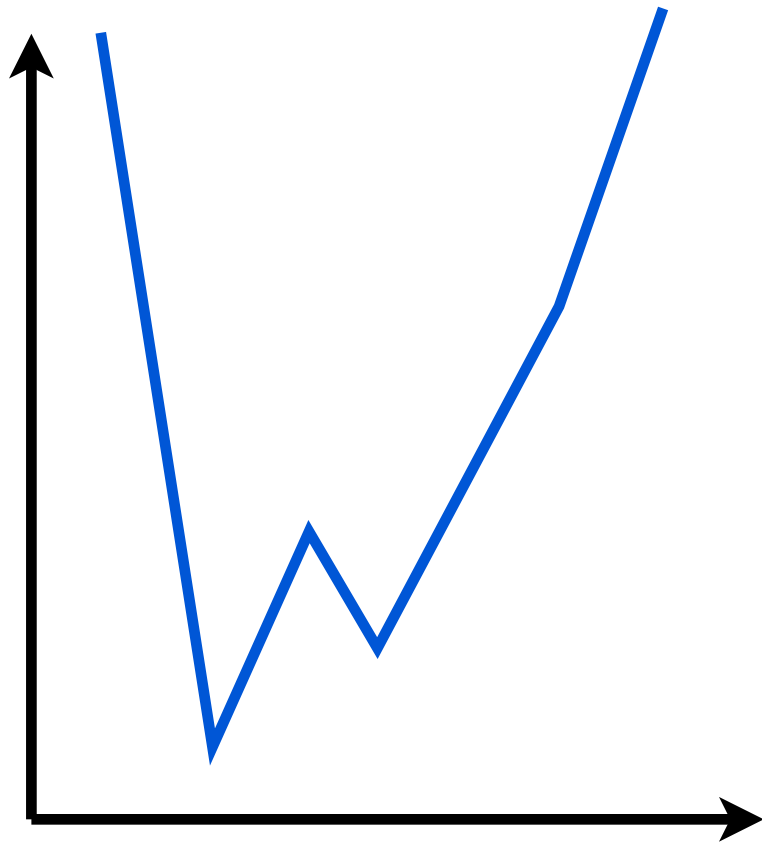
Barcodes are stable



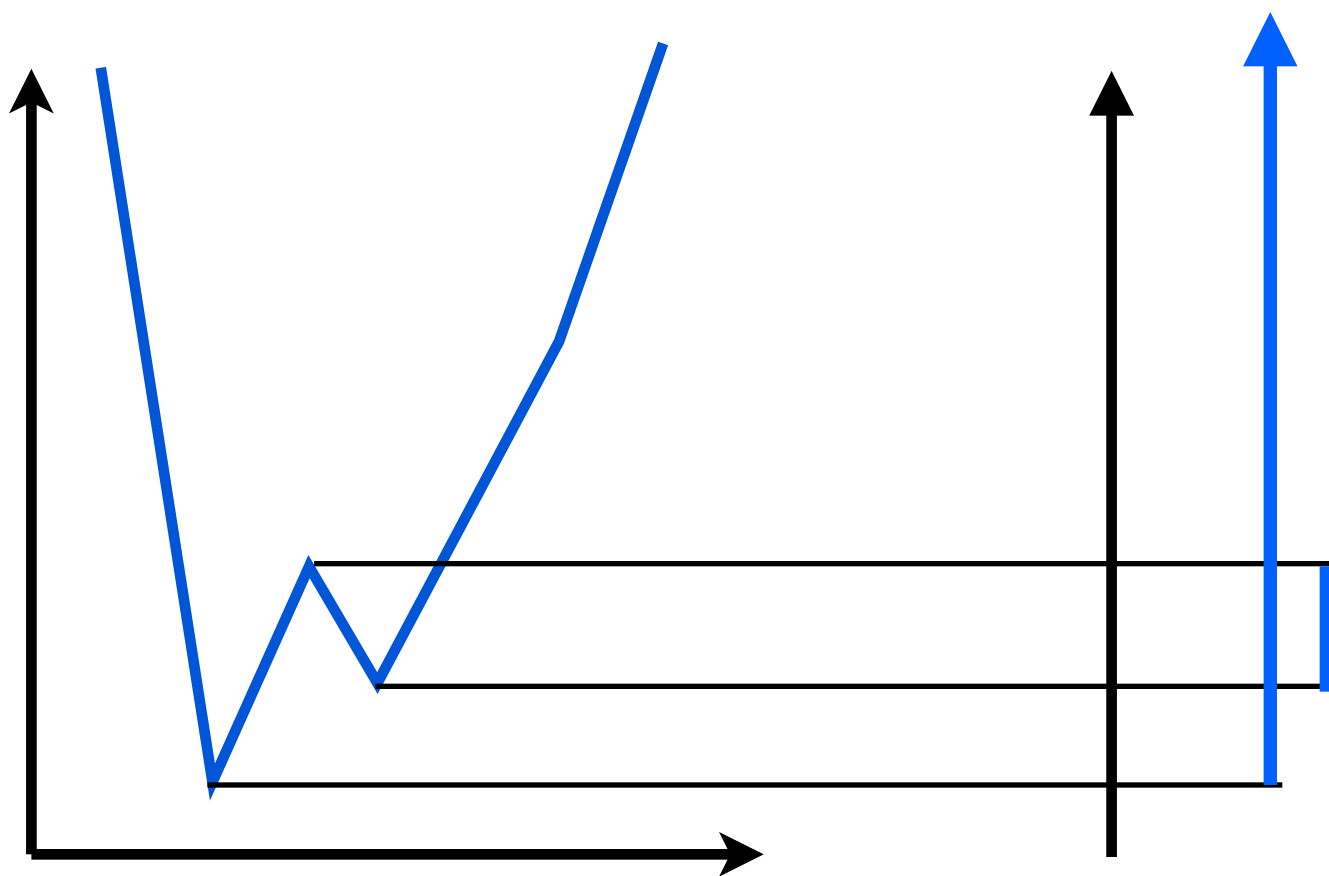


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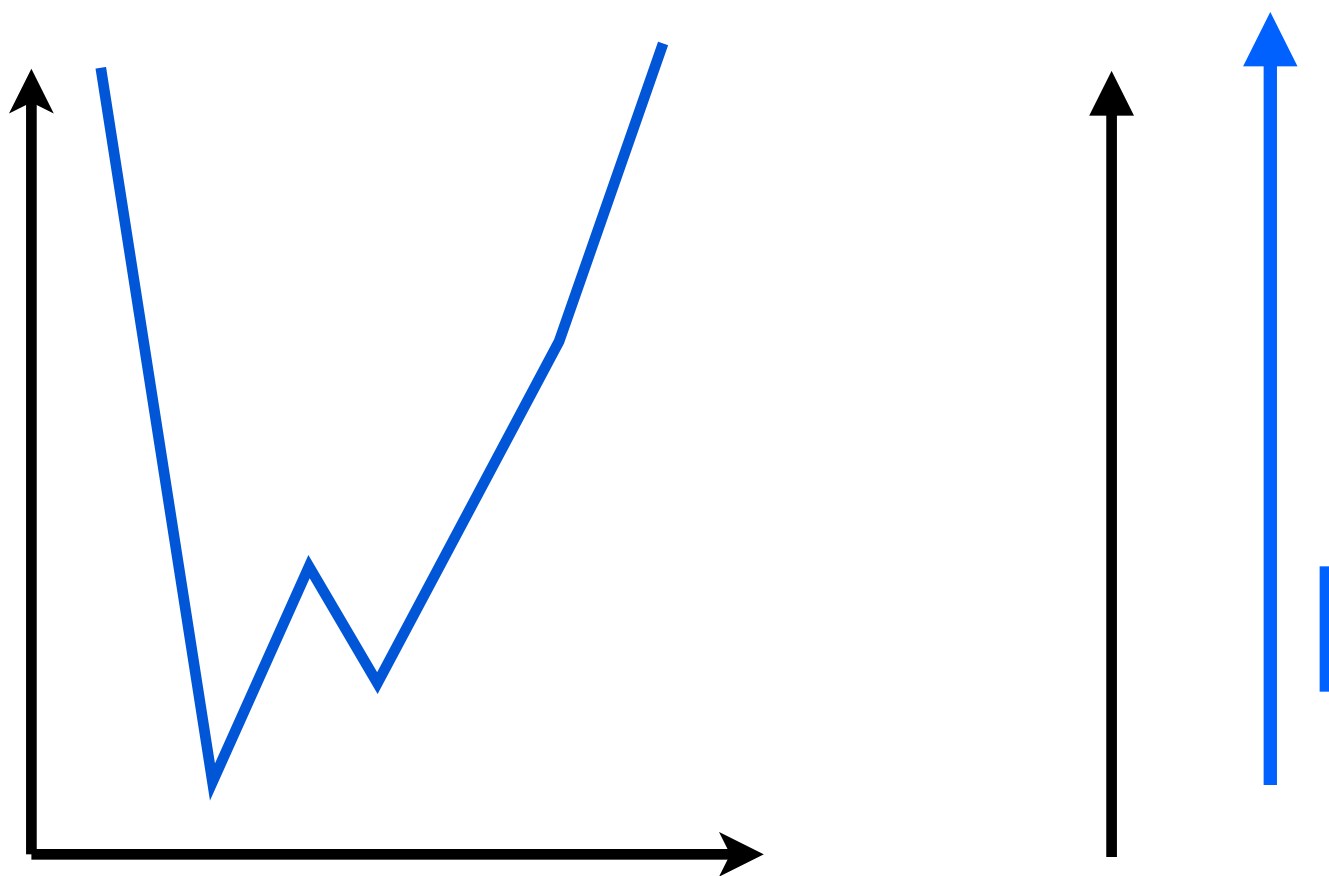
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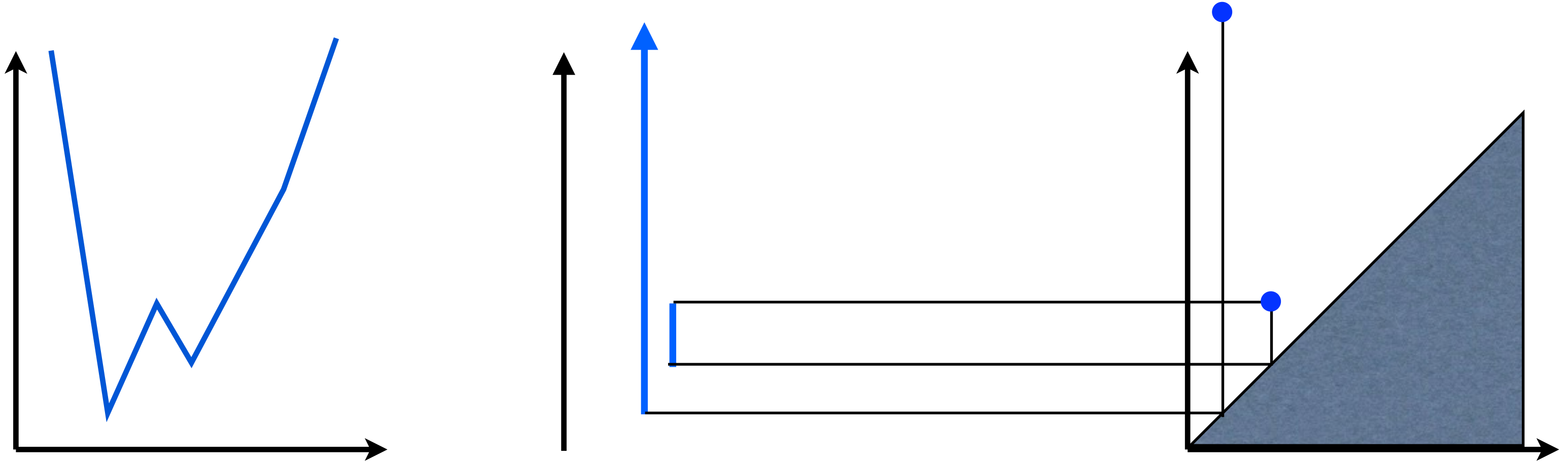
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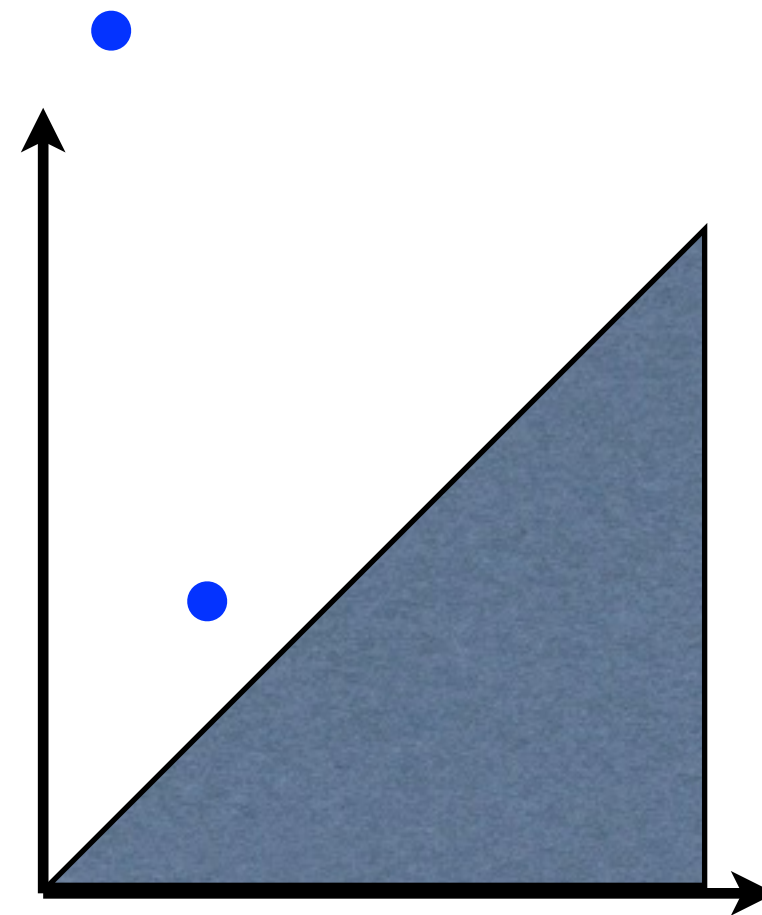
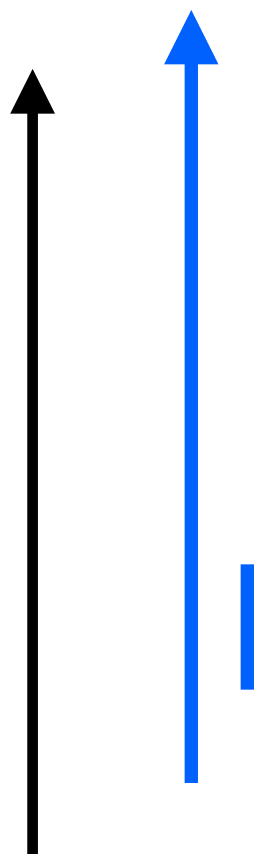
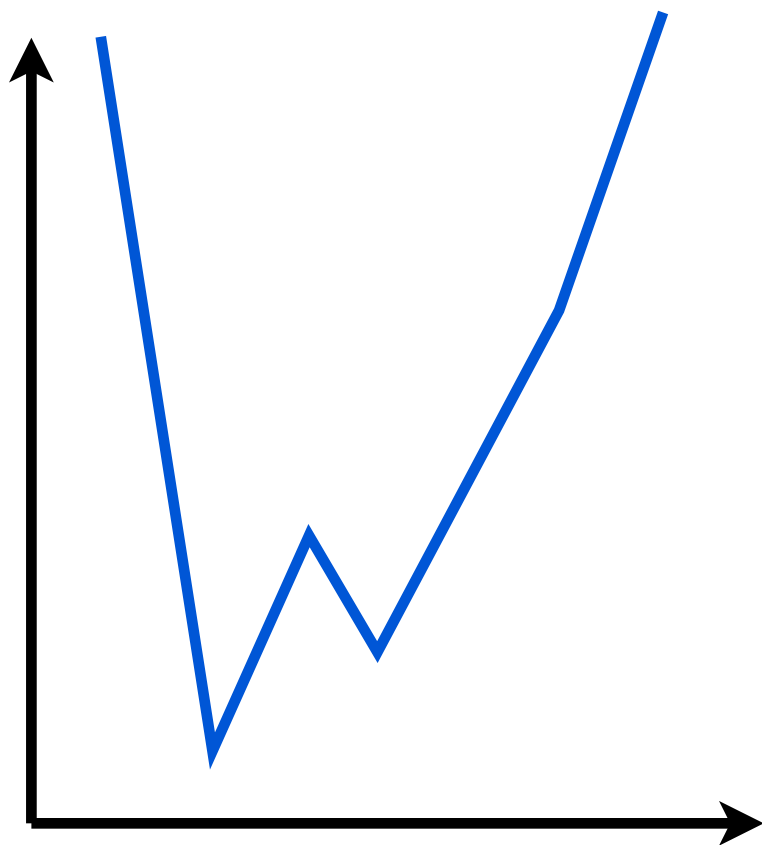
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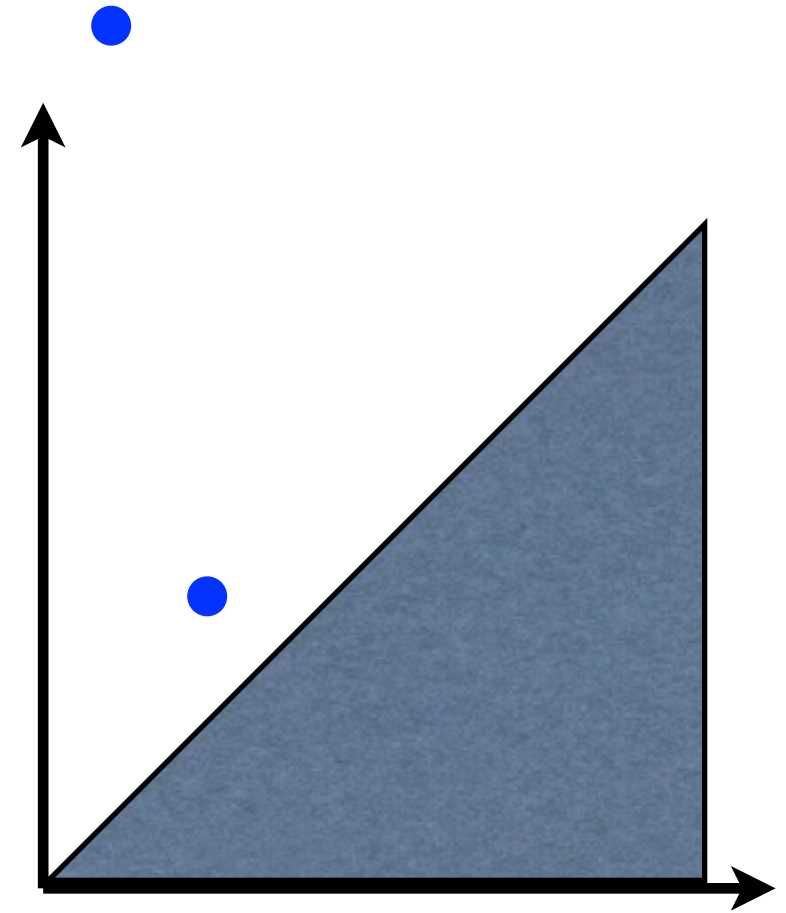
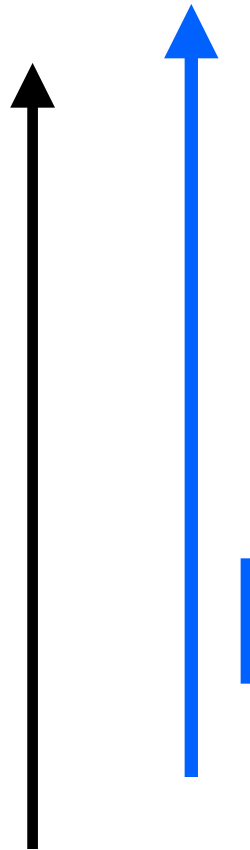
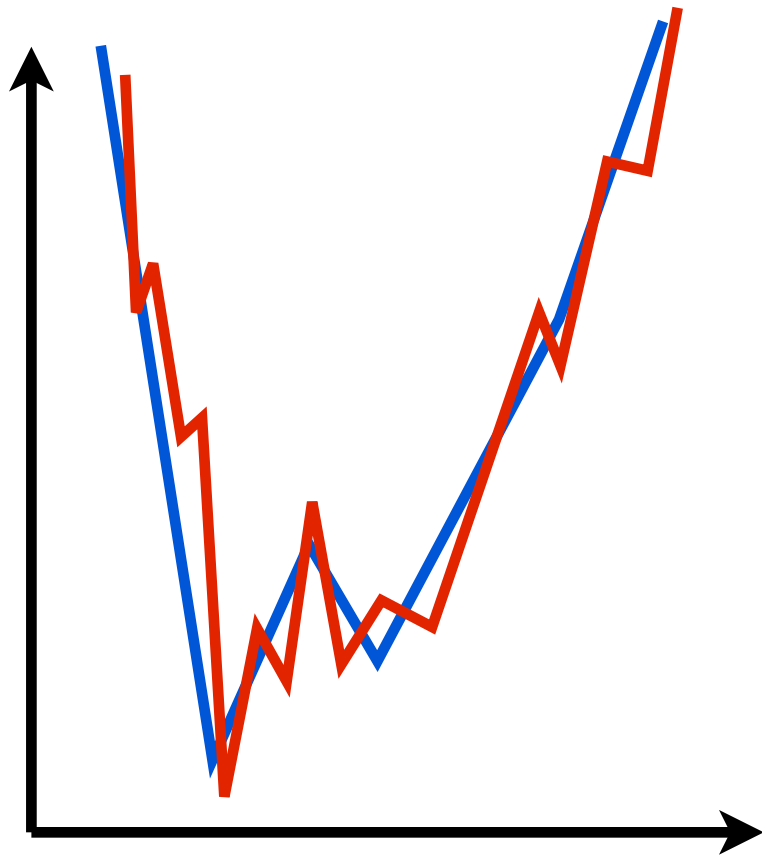
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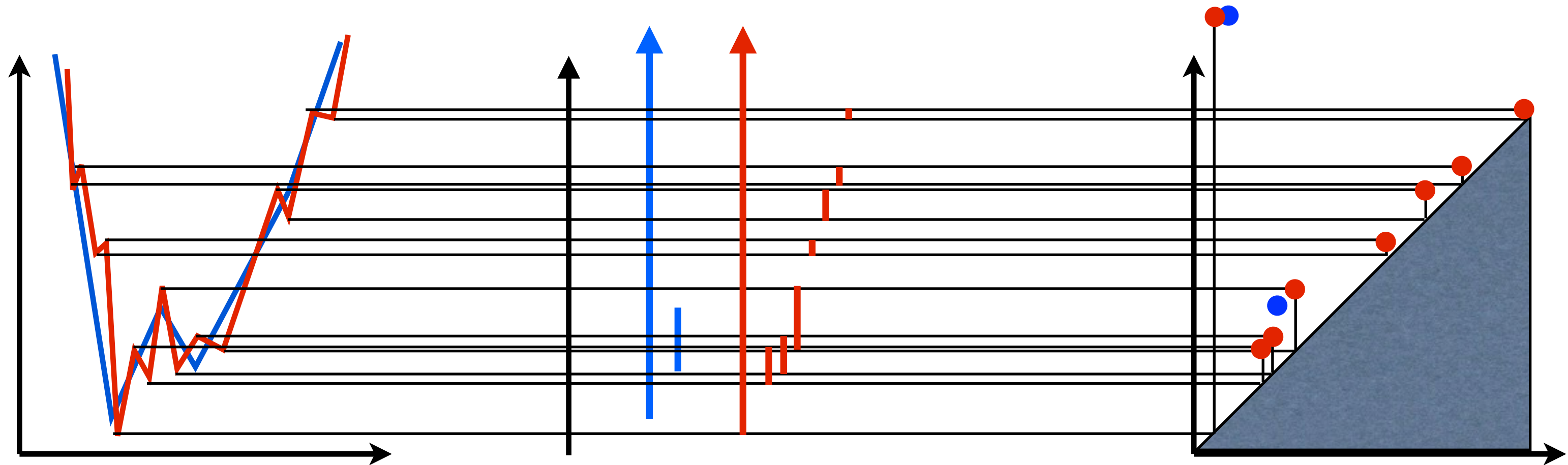
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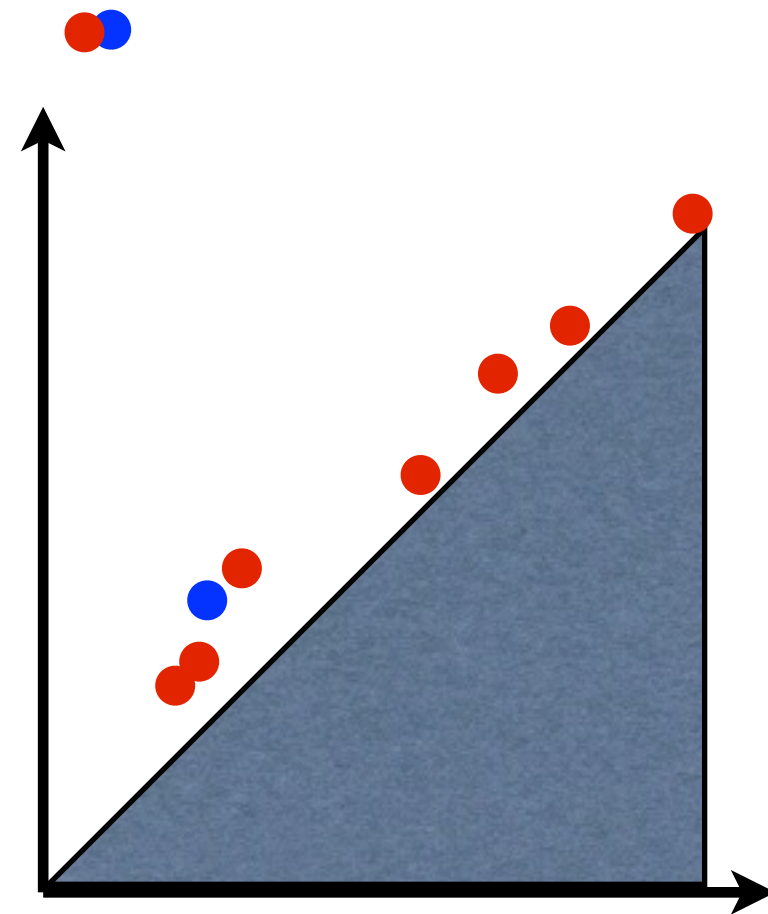
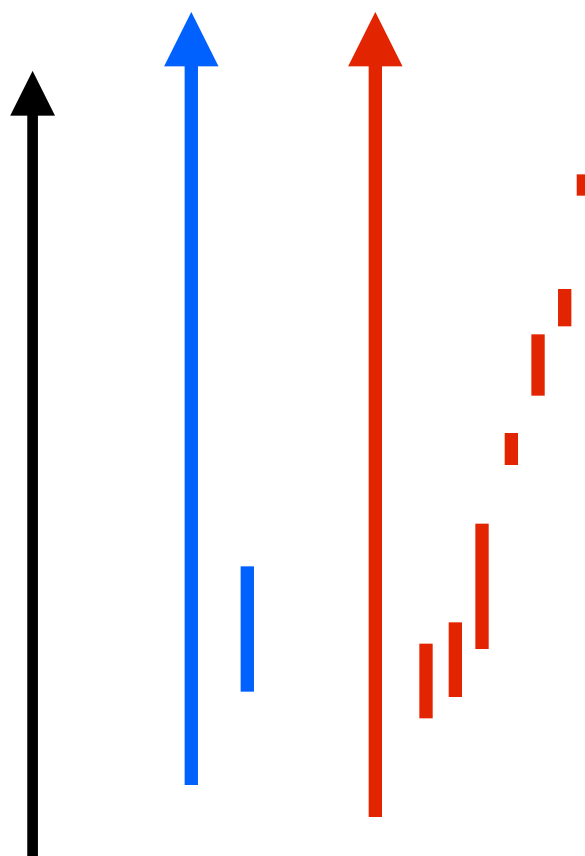
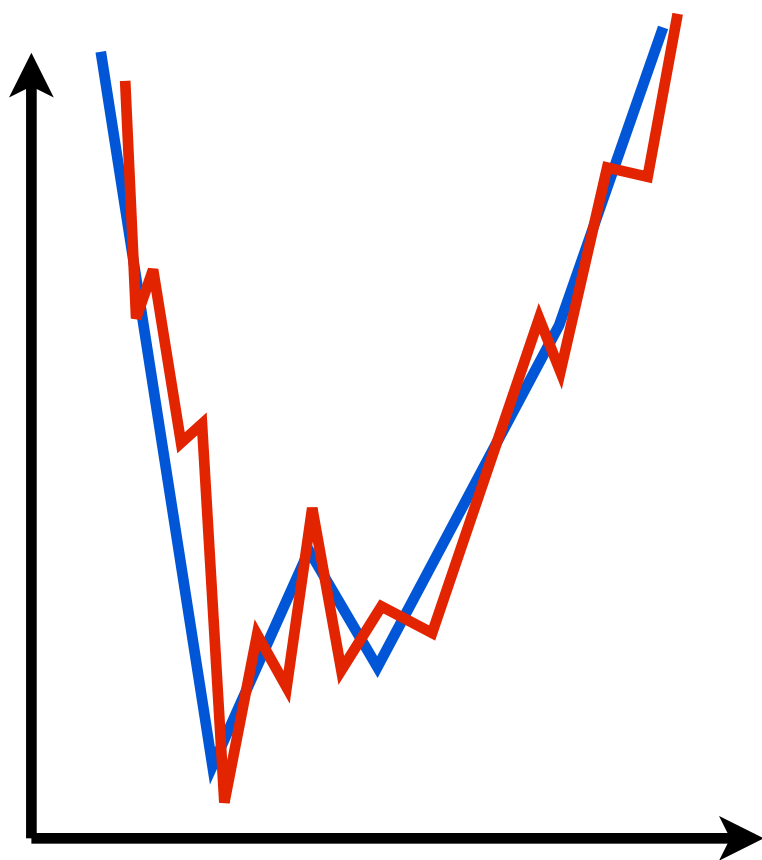
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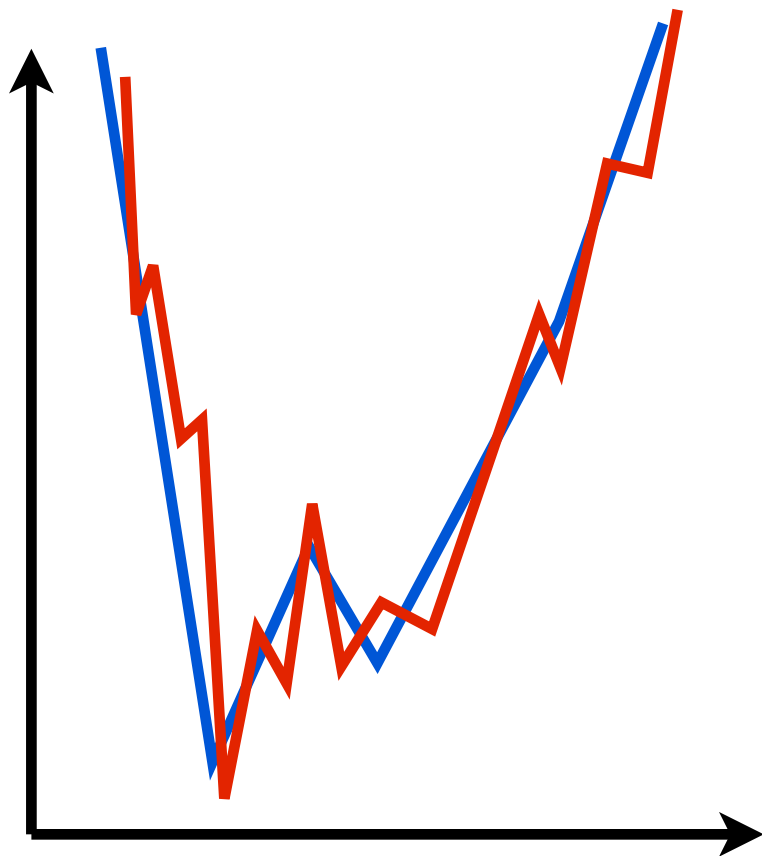
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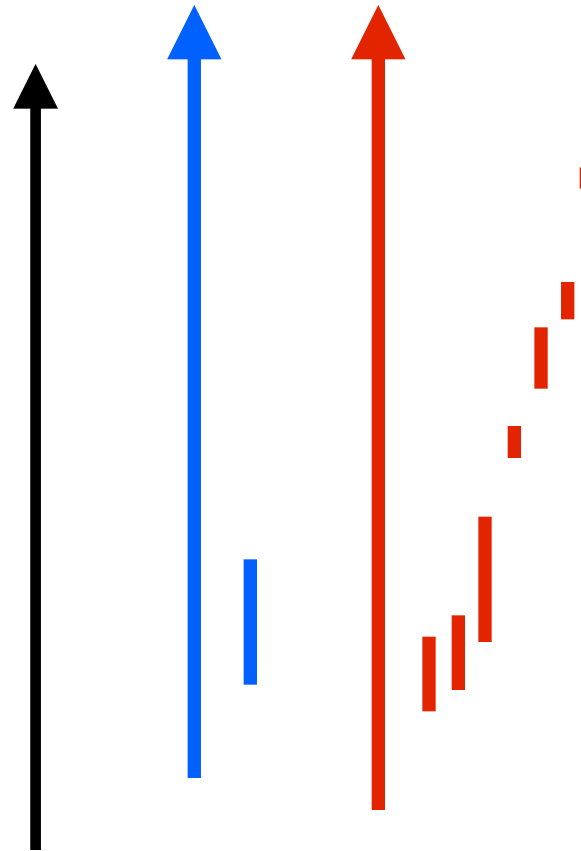
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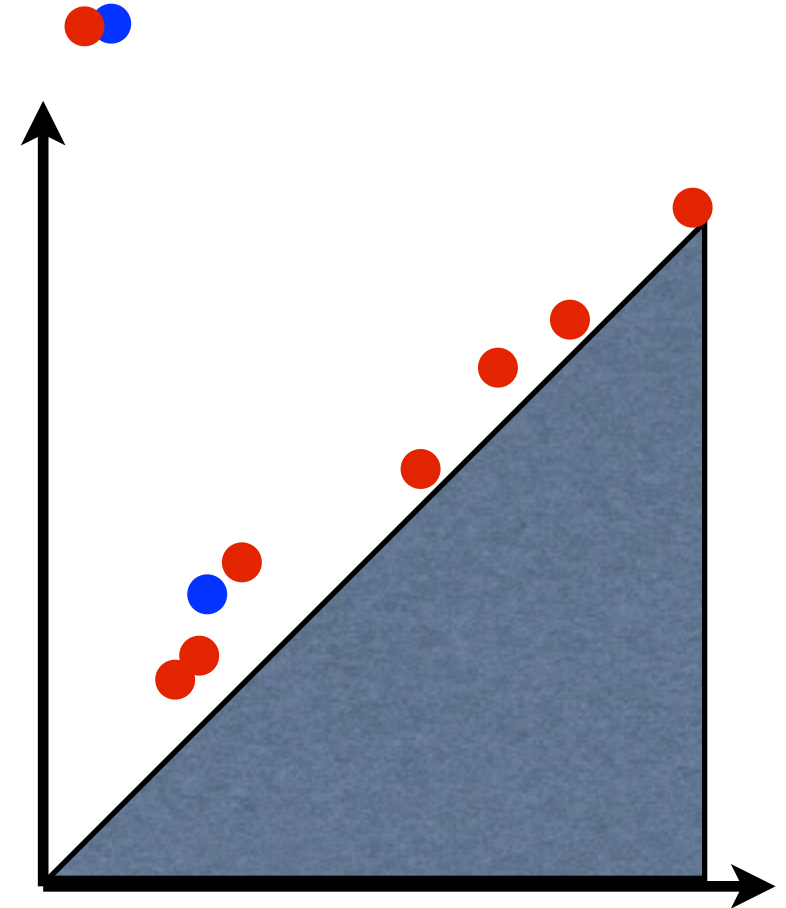
Barcodes are stable



L_∞ distance of functions



upper bound on maximal distance
between points
upper bound on Wasserstein distance
isometric to *interleaving distance*



Stability of persistence

- Persistence is:
the evolution of the topology of sublevel sets of a function on a (sample from a) manifold.
- Stability of persistence:
the mapping from the function-and-manifold to the persistence diagram is
 - Continuous
 - 1-Lipschitz
- Therefore: what persistence computes is related to the original topology. Small features go away with small perturbations.

Persistence of random points

- Zomorodian:
Random flag complex. β_n and β_{n+2} (mostly) don't overlap
- Adler et.al.:
Excursion sets of random fields: Snap, crackle, pop.
- Kahle:
Phase transitions for persistence of random points in \mathbb{R}^d
for a wide family of probability distributions.



Distance to measure

- Consistent, stable and easy to compute estimator of topological features of an underlying probability distribution.
- Connect points to their nearest neighbors. Work with the resulting filtered simplicial complex.
- Chazal, Guibas, Oudot, Skraba (2013)



Machine learning features

- Adcock, Carlsson, Carlsson:
Classify functions on barcodes to make it easier to pick features
- Berwald, Gidea, V-J:
Classify different modes of dynamics using ML on persistence barcodes
- Topology as dimensionality reduction.
- Bubenik: Persistence landscapes

Mean barcode Confidence intervals

- Fasy, Lecci, Rinaldo, Wasserman, Balakrishnan, Singh:
Confidence sets for persistence diagrams
- Turner, Mileyko, Mukherjee, Harer:
Fréchet means for distributions of persistence diagrams
- Munch, Bendich, Turner, Mukherjee, Mattingly, Harer:
Probabilistic Fréchet means and statistics on vineyards
- Mileyko, Mukherjee, Harer:
Probability measures on the space of persistence diagrams



New directions

- Machine learning provides tools that can make persistent homology work better.
- I will describe my latest research ideas next:
using density estimation to build streaming topological learning.



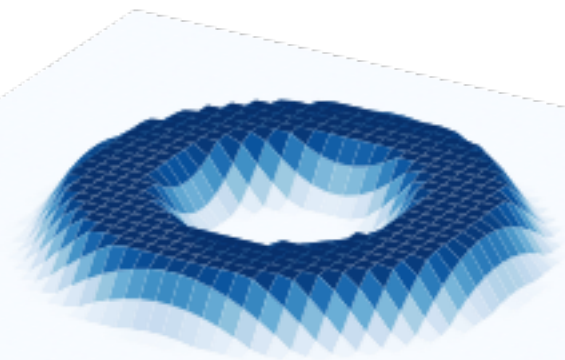
Streaming persistence

- Inspiring example:
 - Tape accelerometer to a shoe.
 - Measure signal:
different closed curves for different steps/gaits.
 - Build a topological model of this recurrence.
- Problem:
 - Want to run data capture for a long time.
 - Persistence behaves badly [$O(n^6)$] with size.
 - 100 runs with 100 points faster than one run with 10 000 points.
- We need to control input size to persistence.



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Streaming persistence



Unknown

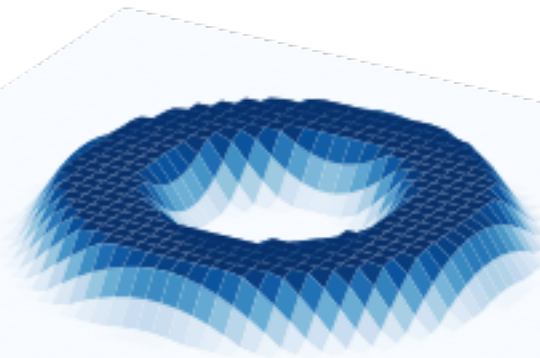


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Streaming persistence

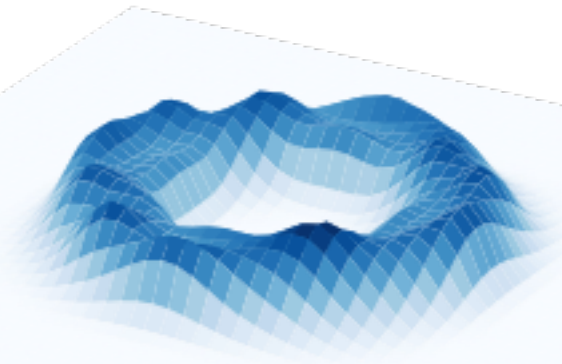


Very large
Appears gradually



Unknown

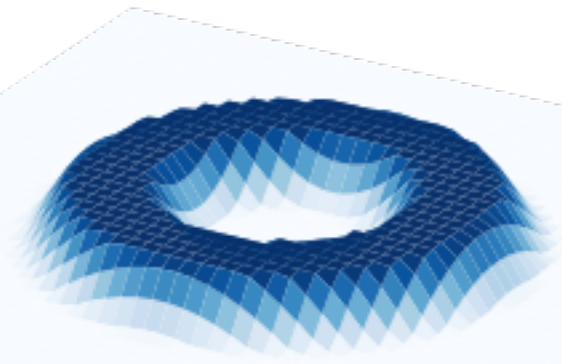
Streaming persistence



Constant size
representation

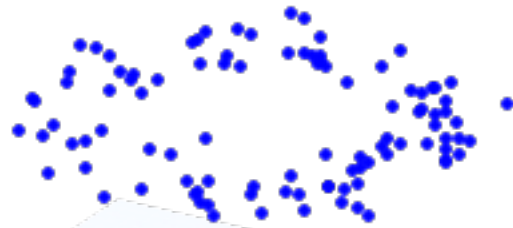


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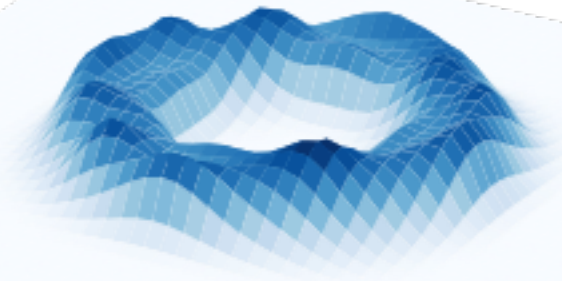


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Streaming persistence



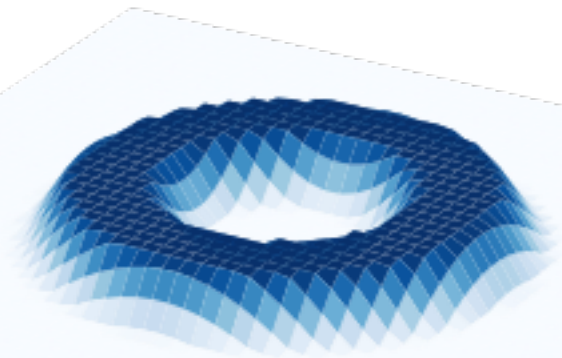
Small enough
for fast persistence



Constant size
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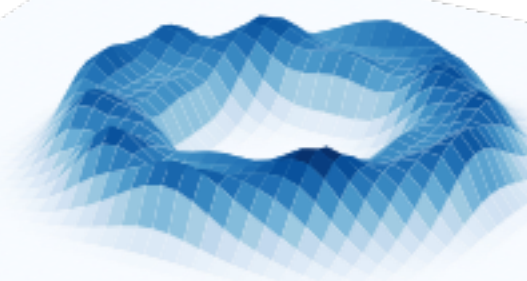


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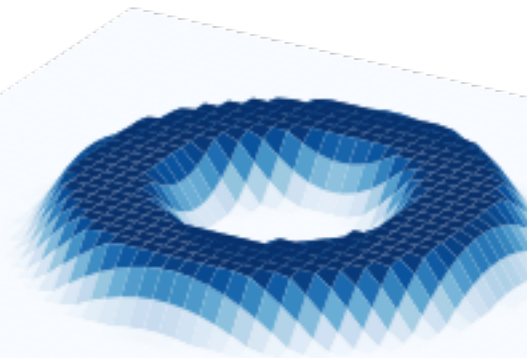
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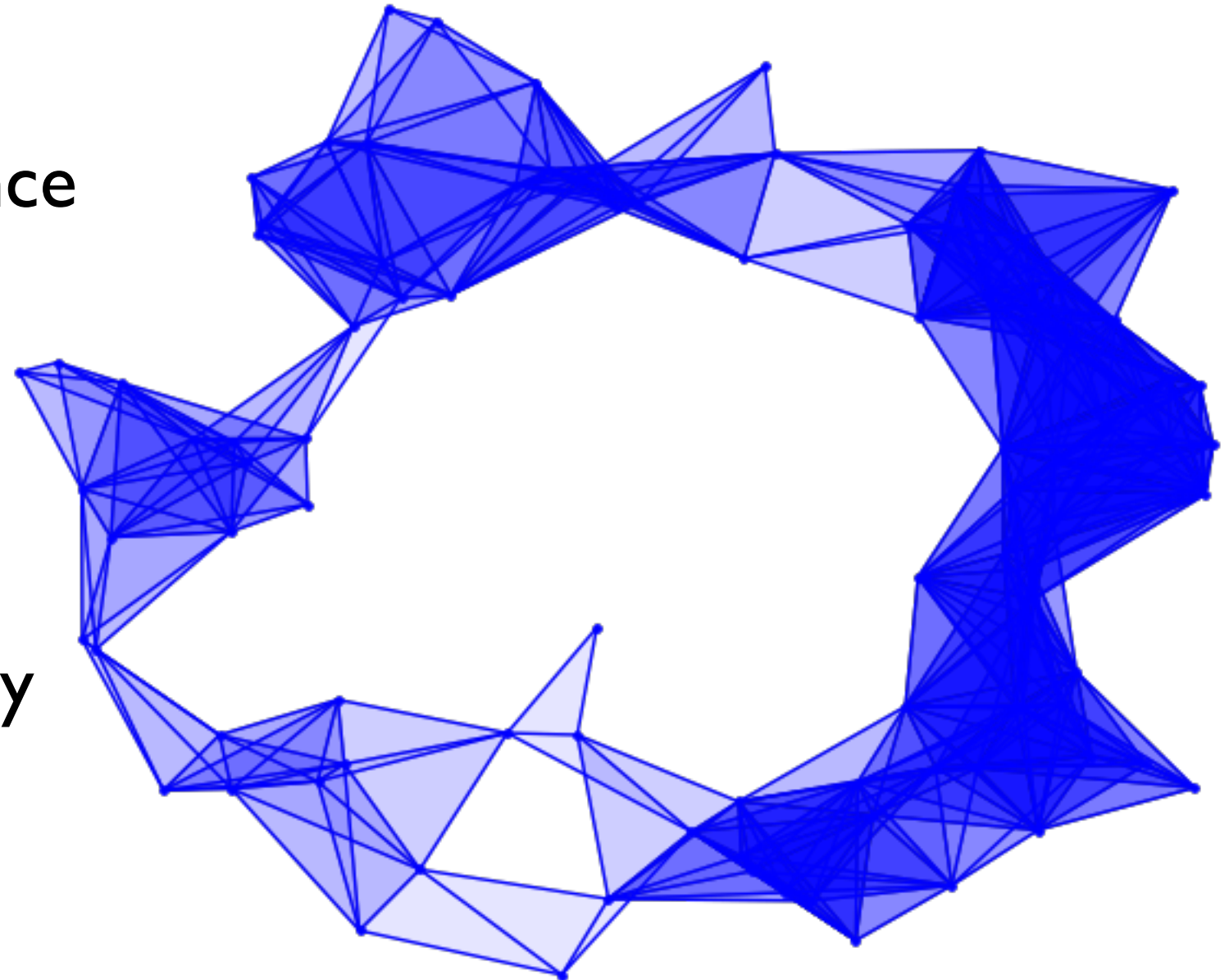
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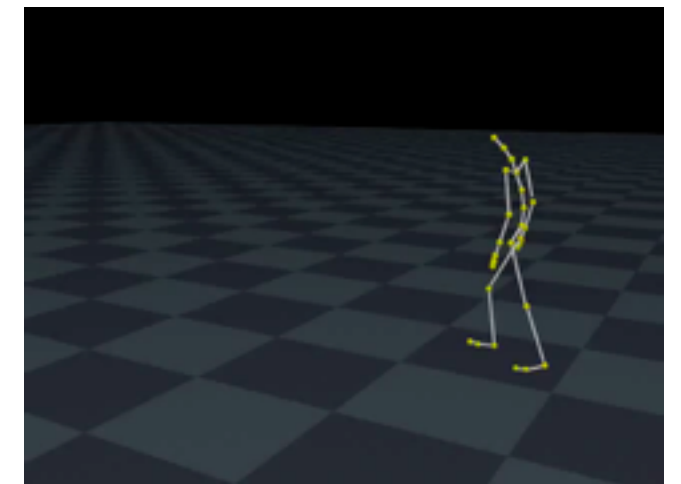
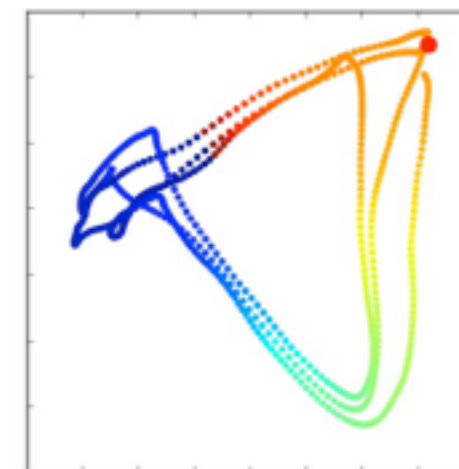
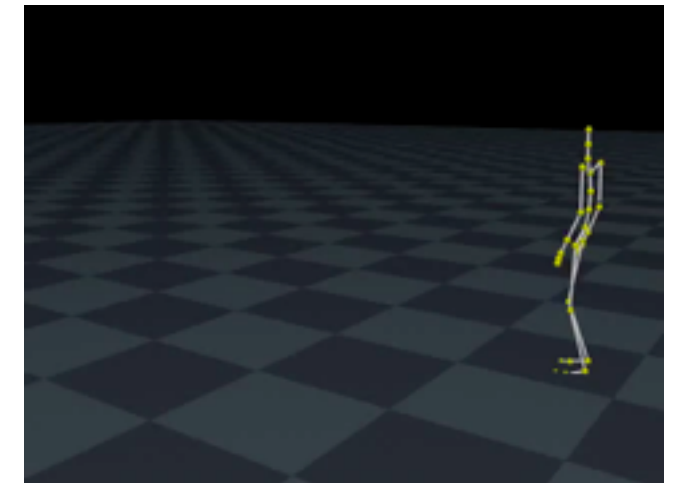
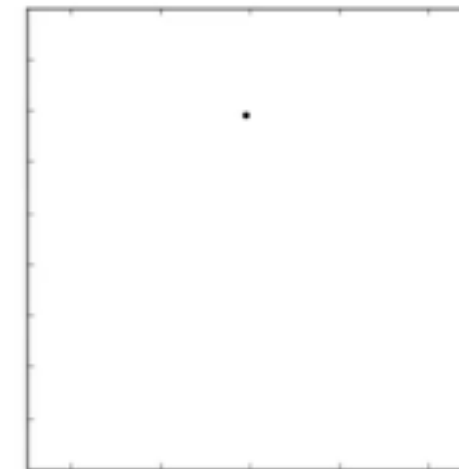
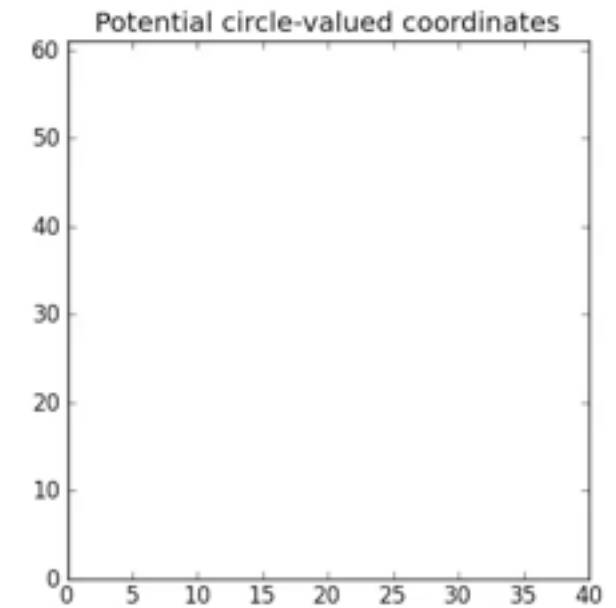
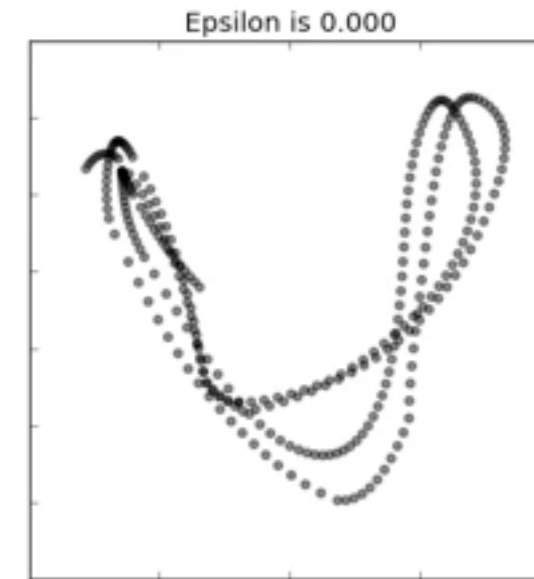


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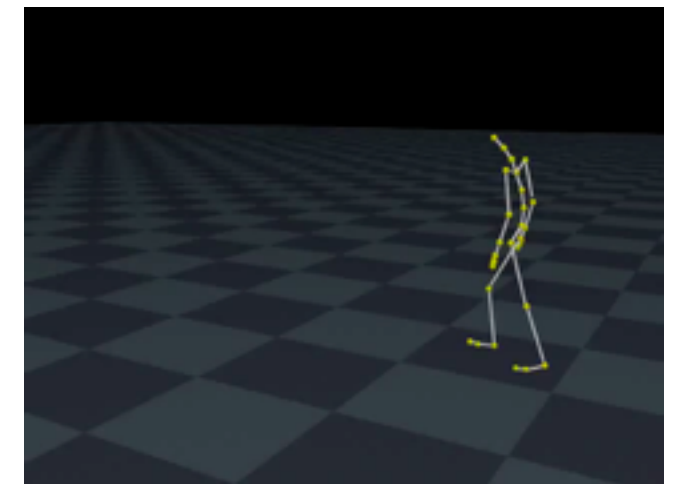
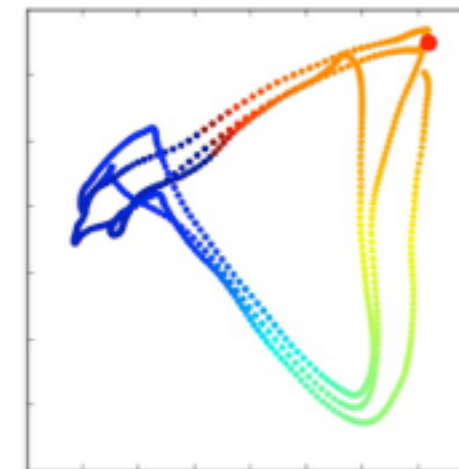
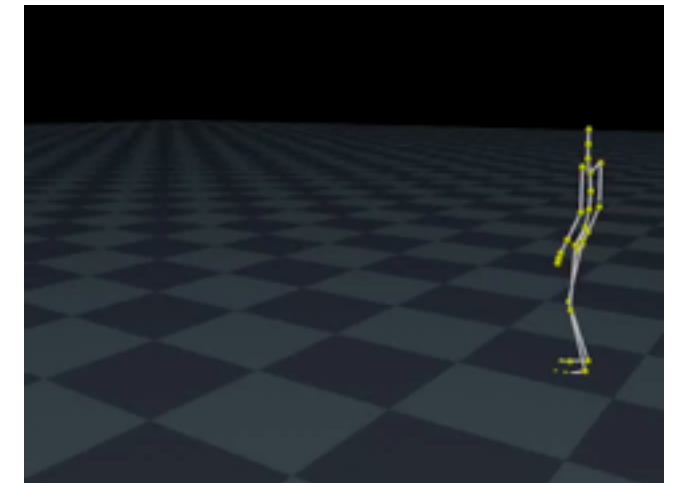
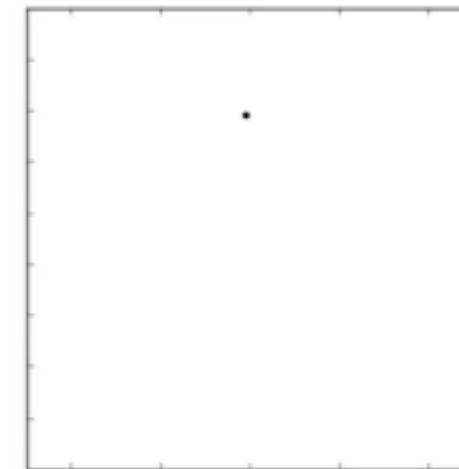
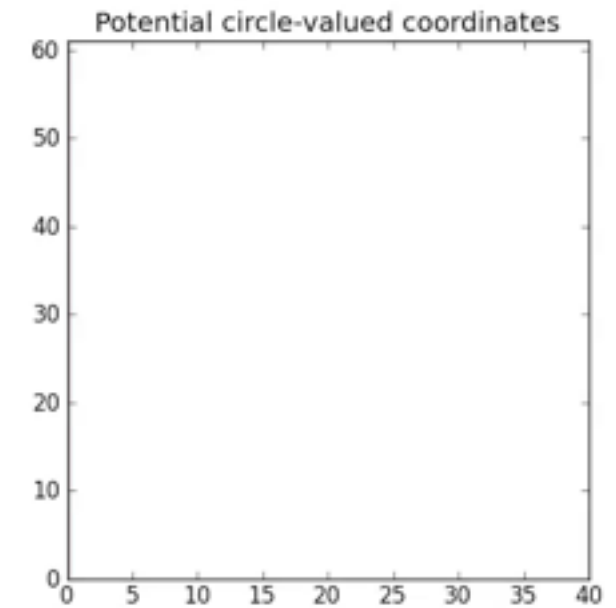
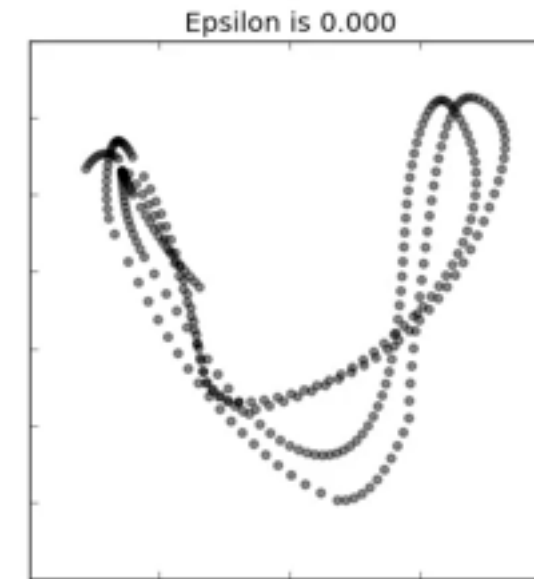
Cohomology

- Produces a topological system for generating circle-valued coordinate functions.
- This improves on state-of-the-art for analyzing recurrence.
- Applicable in motion capture and gait analysis.



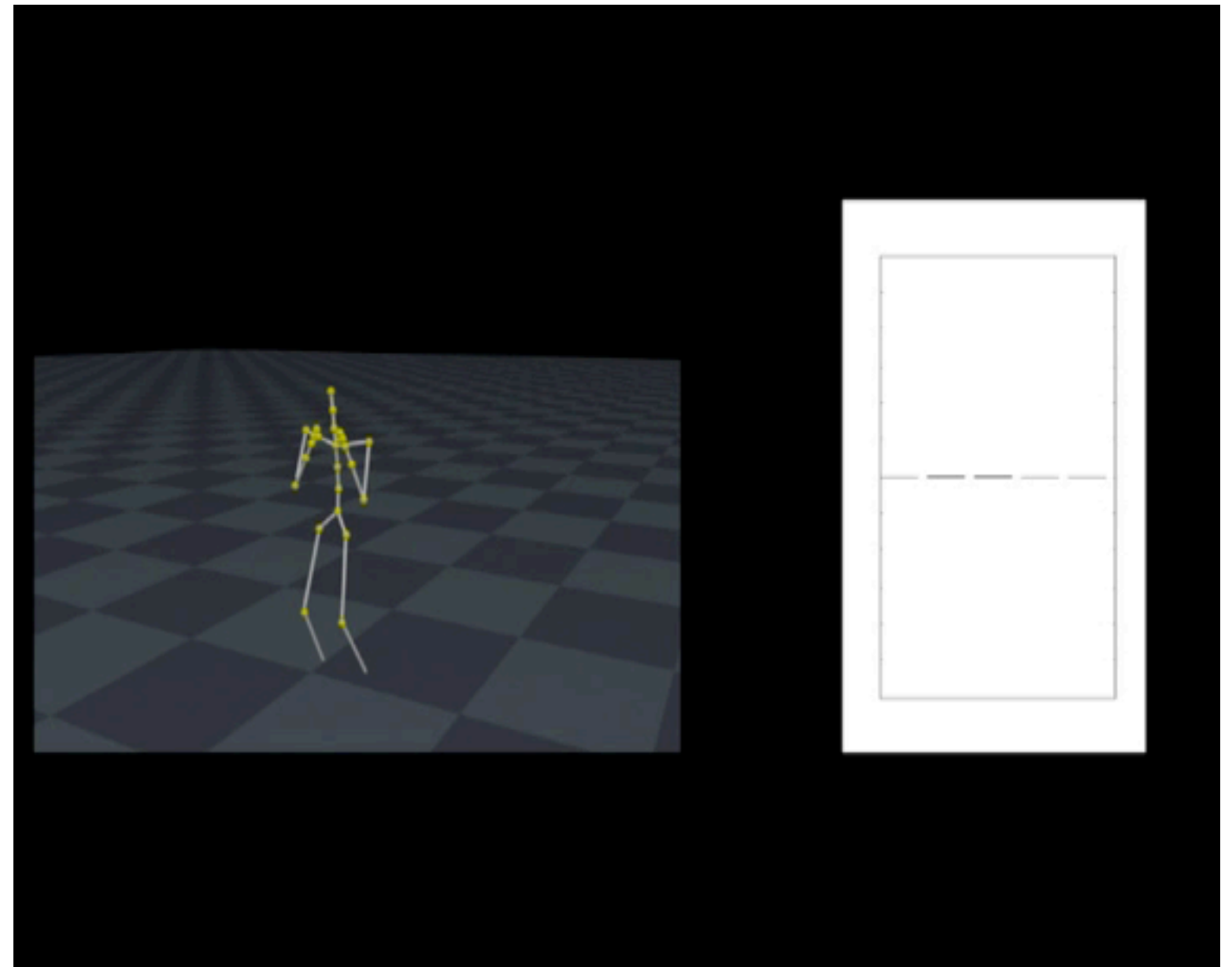
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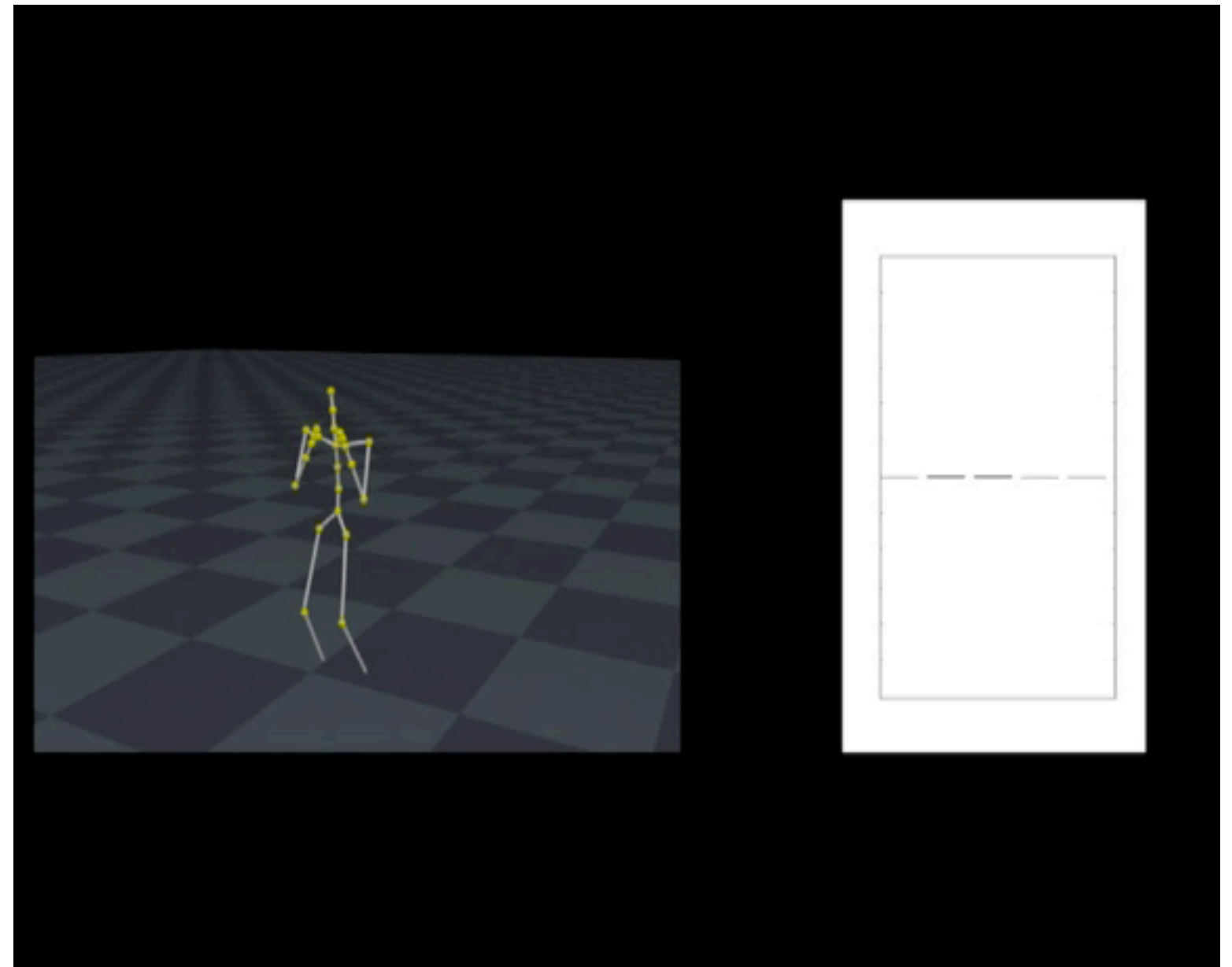
Indicator / feature functions on recurrence

- The functions generated by cohomology work as indicators of different recurrent features.

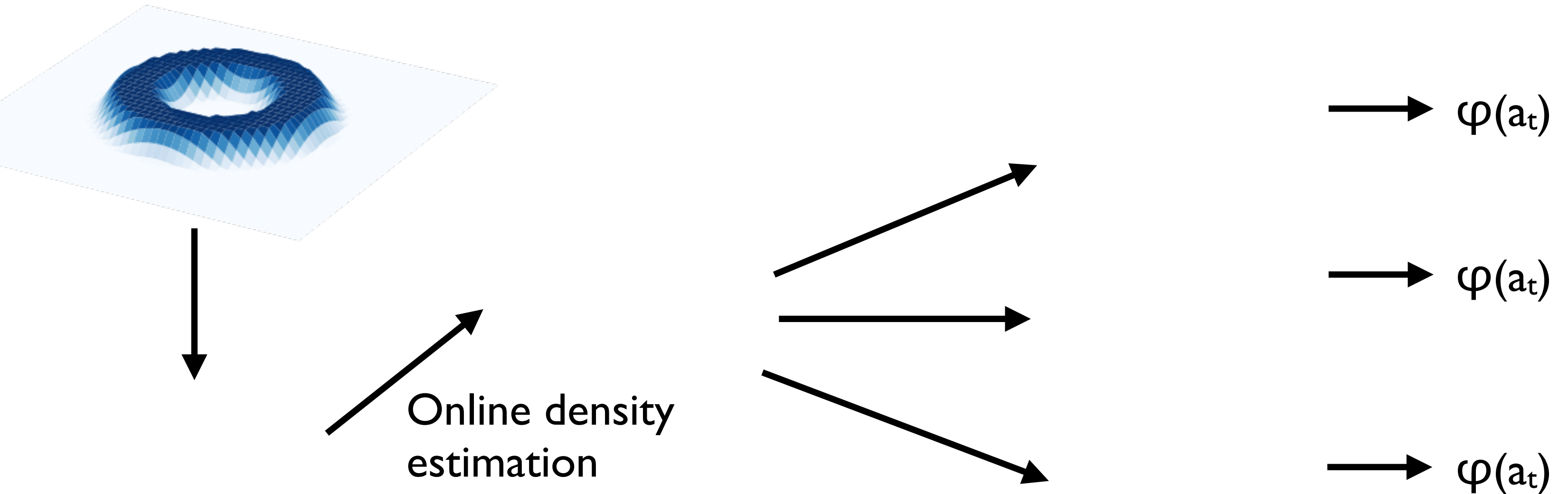


Indicator / feature functions on recurrence

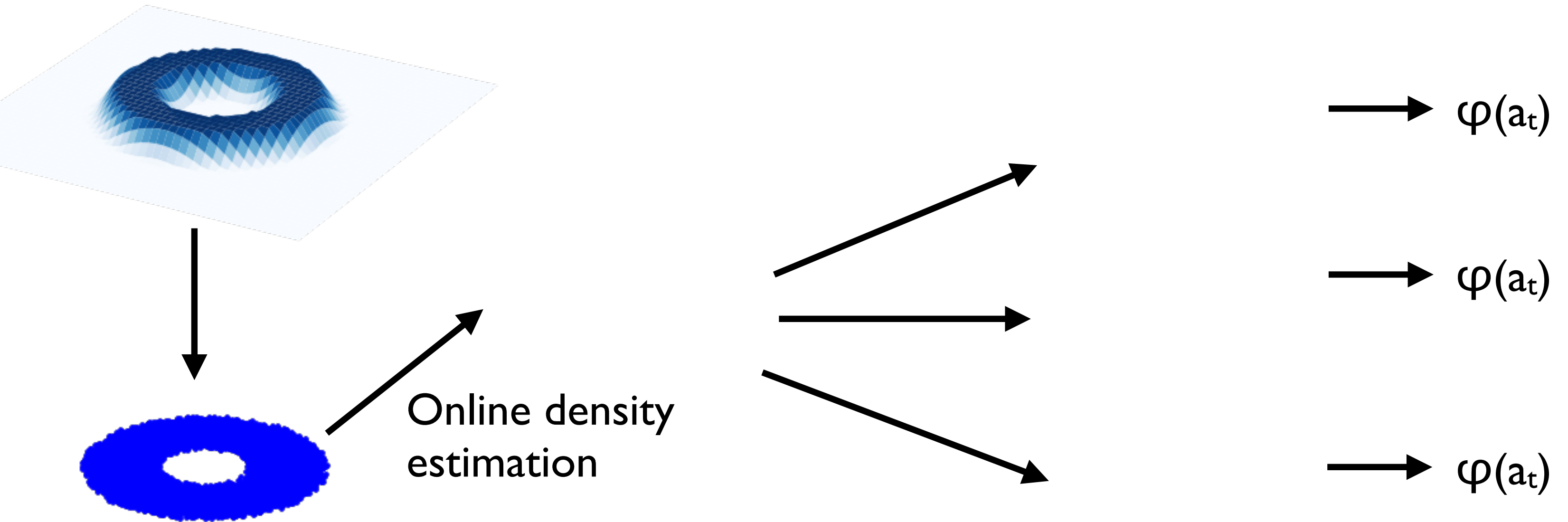
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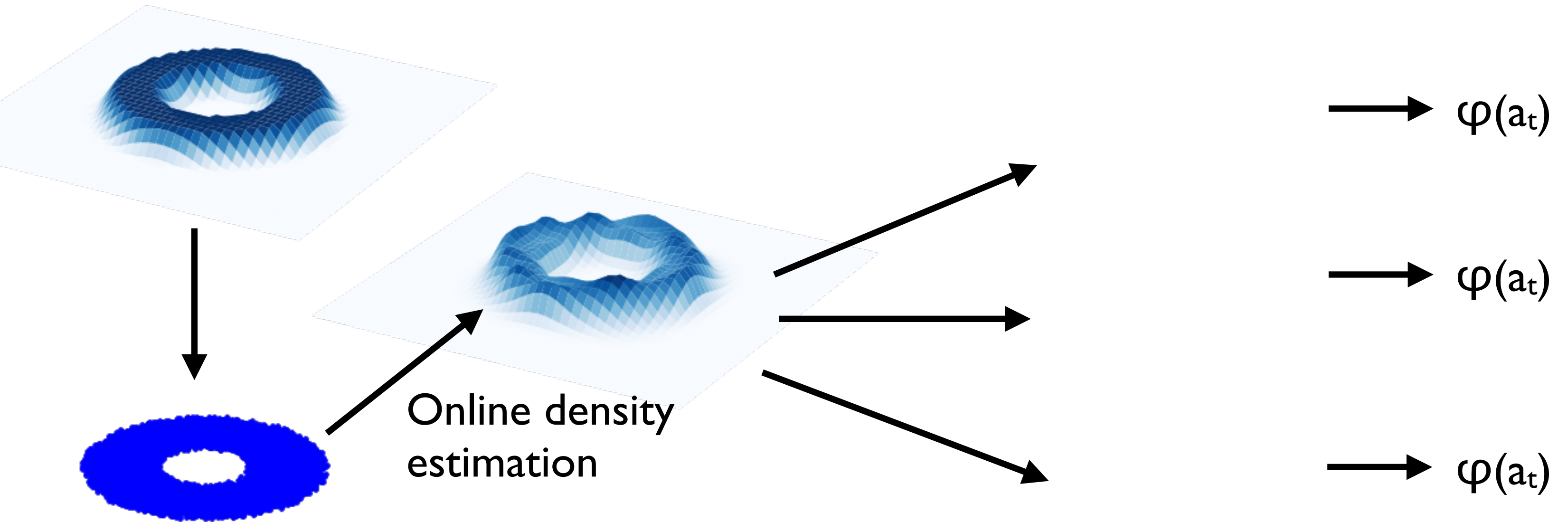
Idea for a pipeline for online topological learning



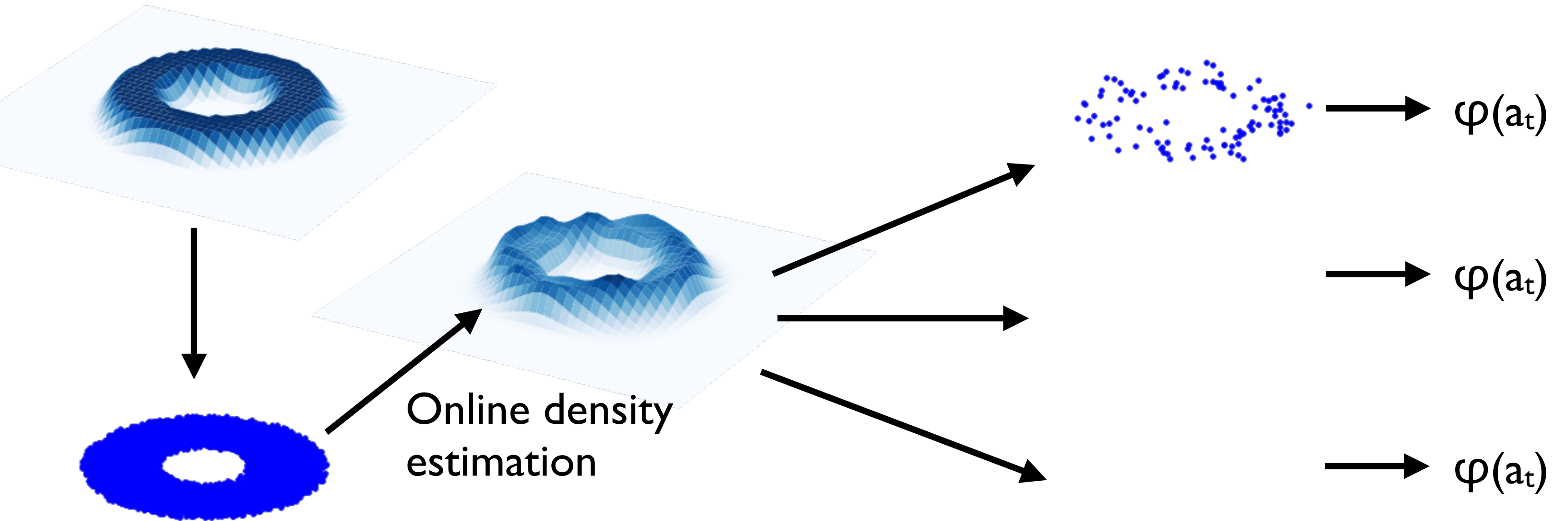
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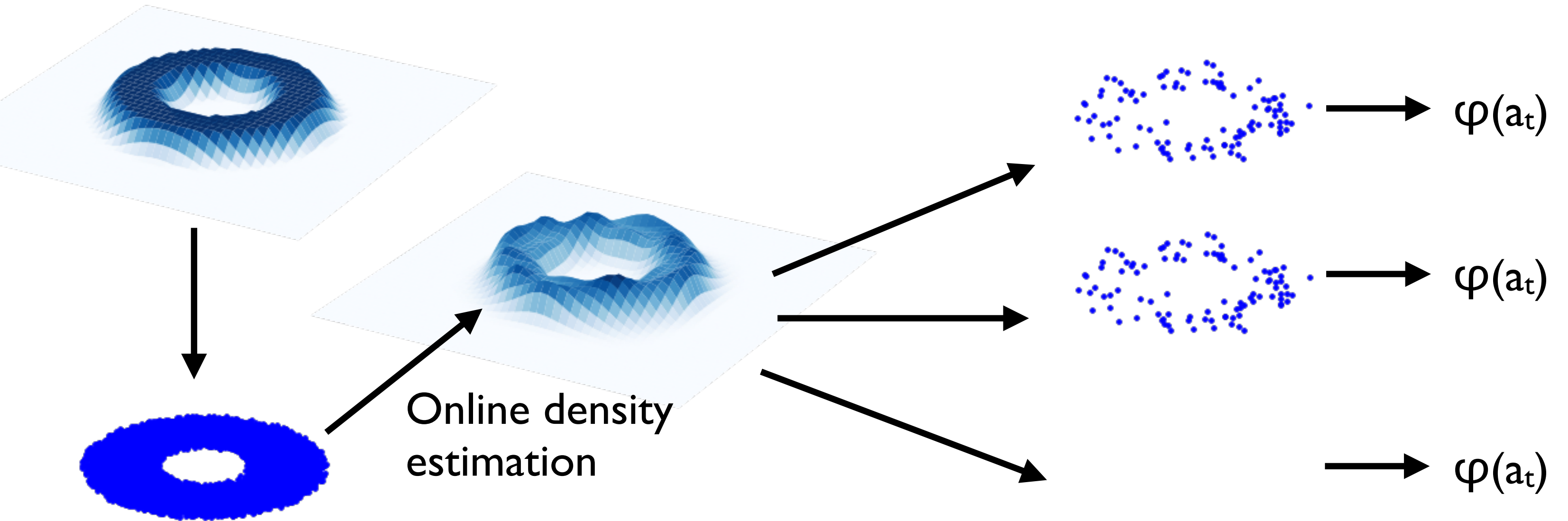
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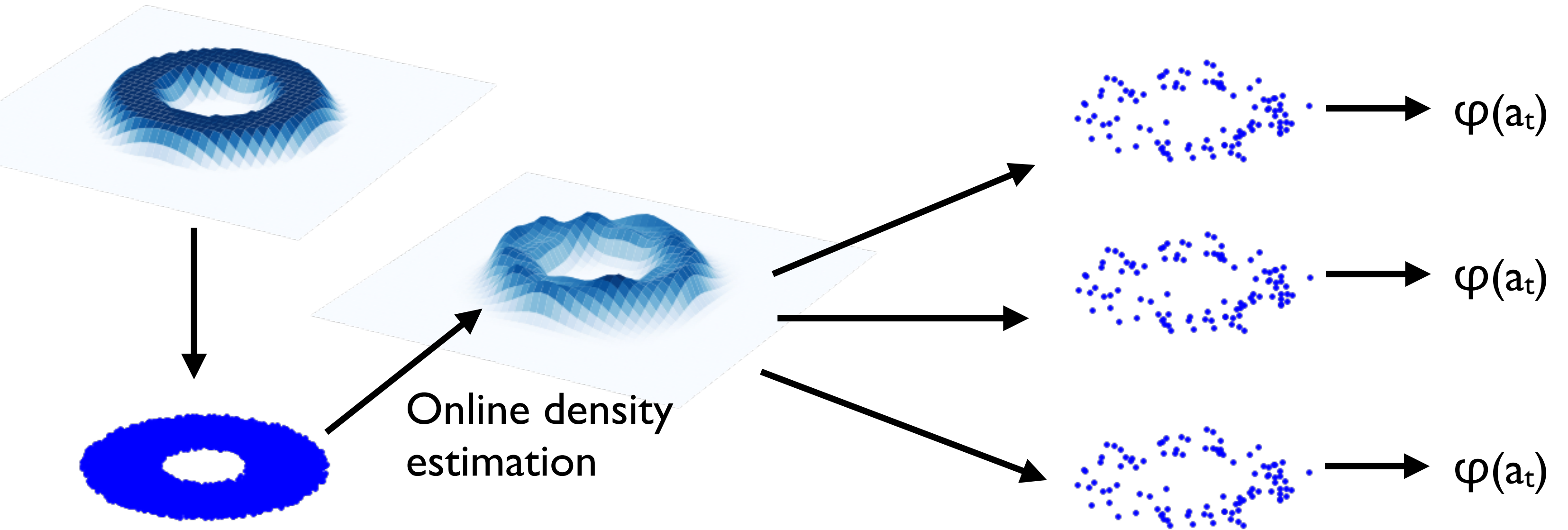
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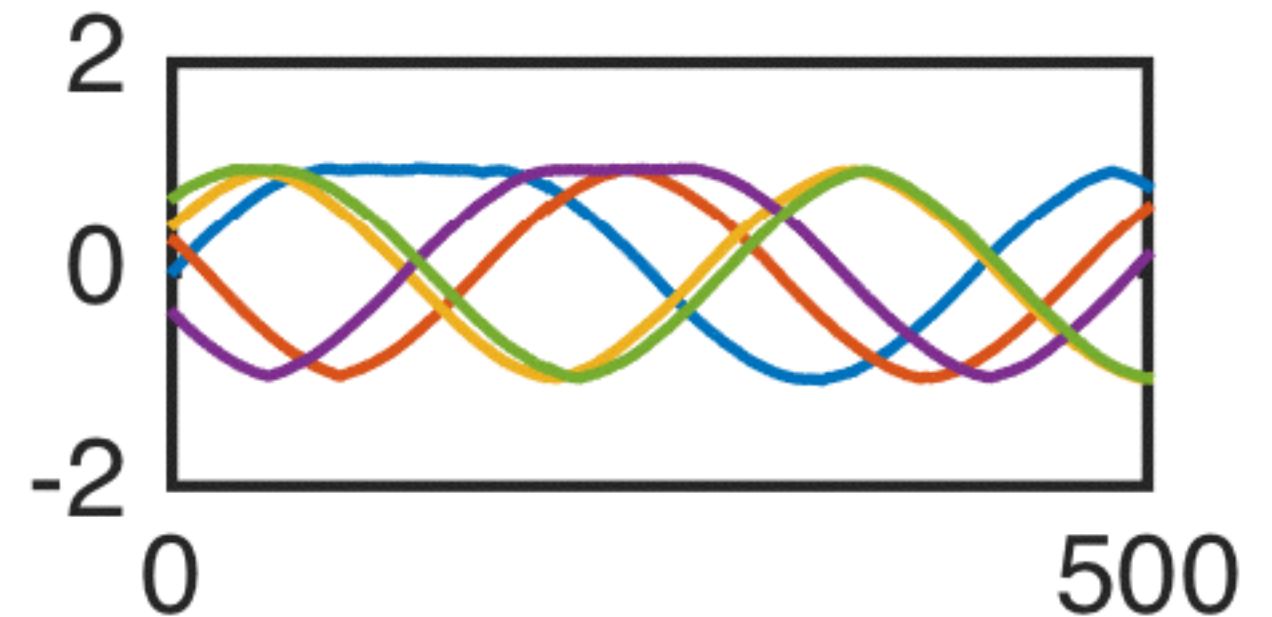
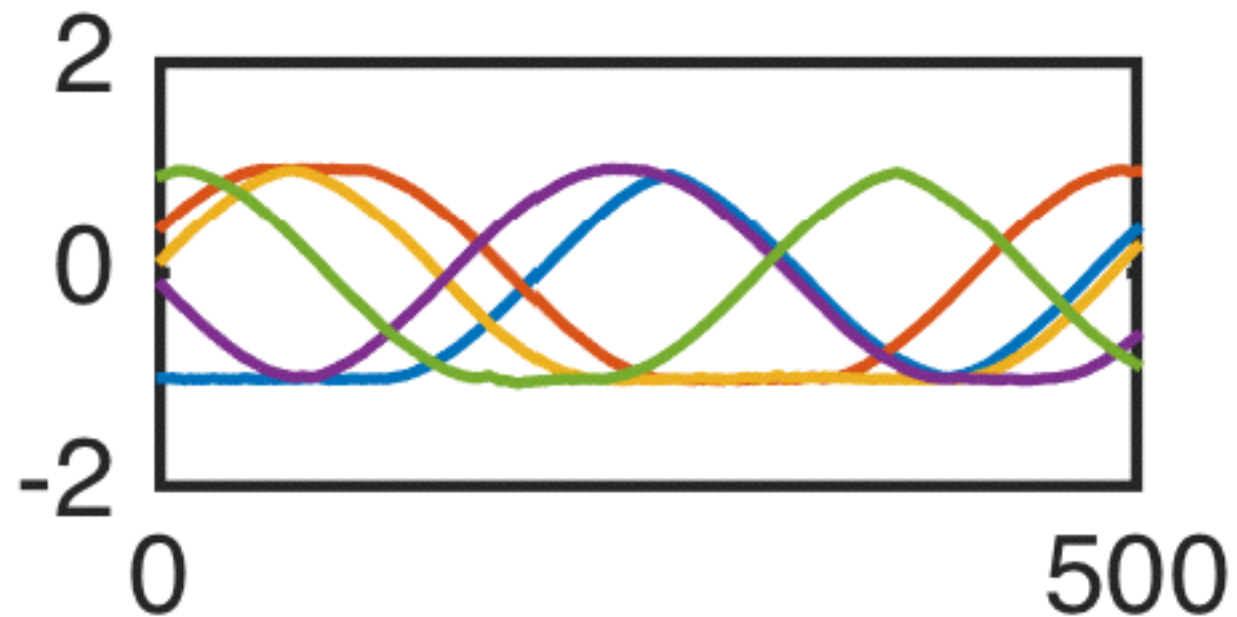
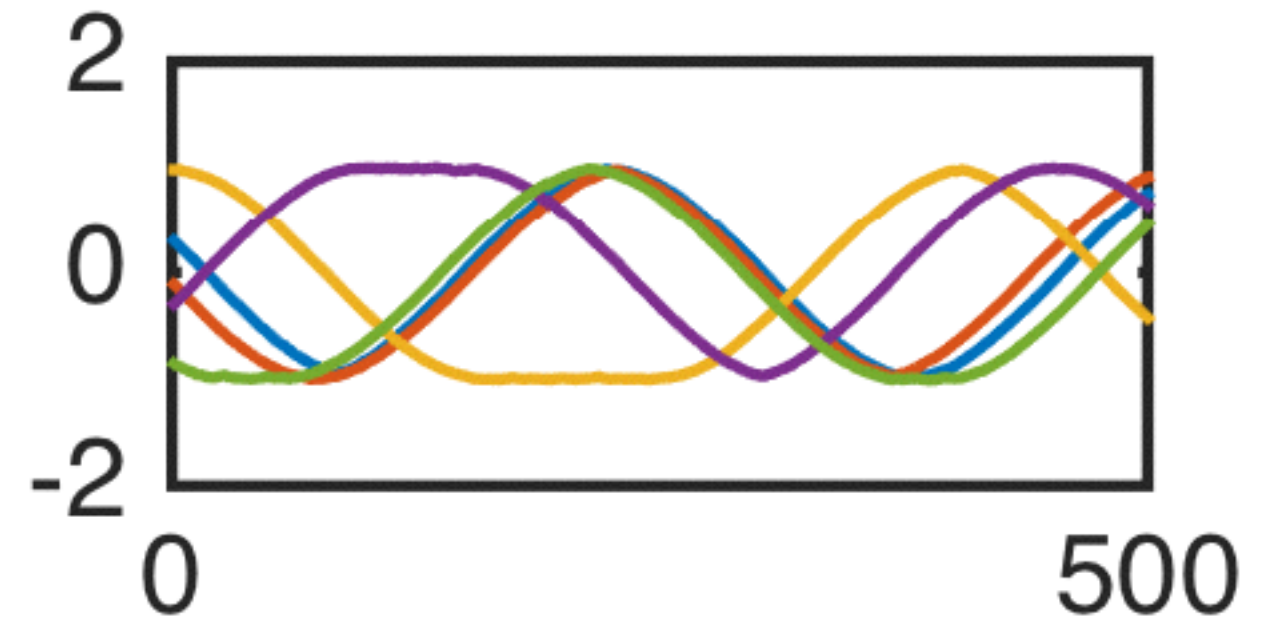
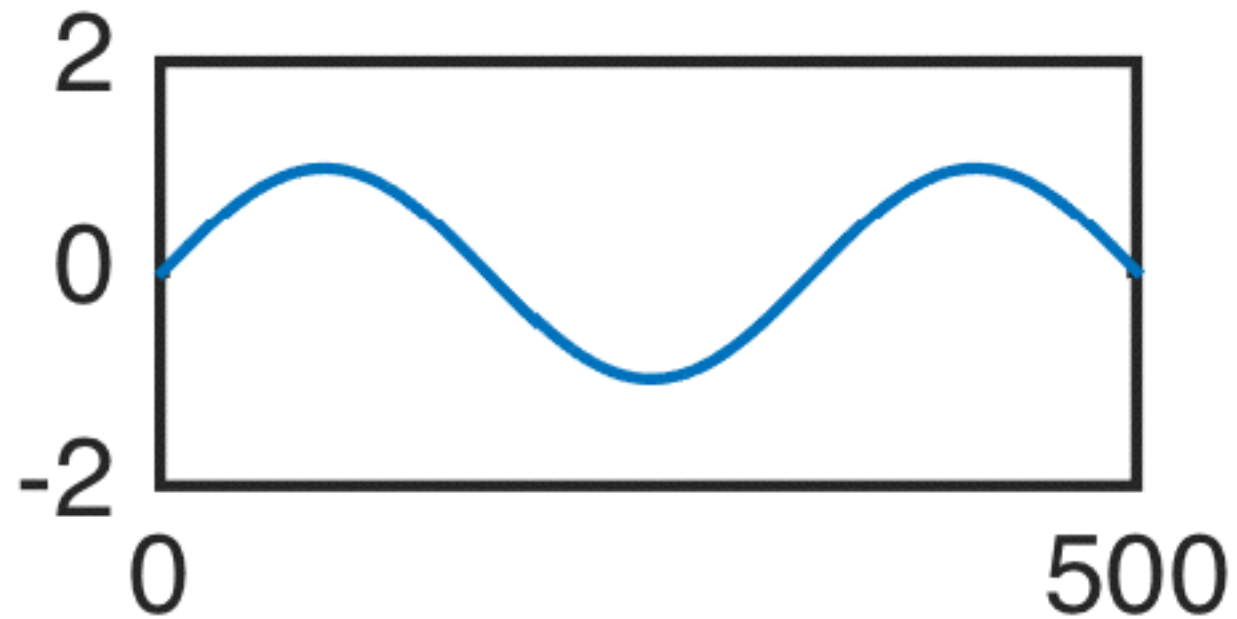
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Idea for a pipeline for online topological learning



Current state

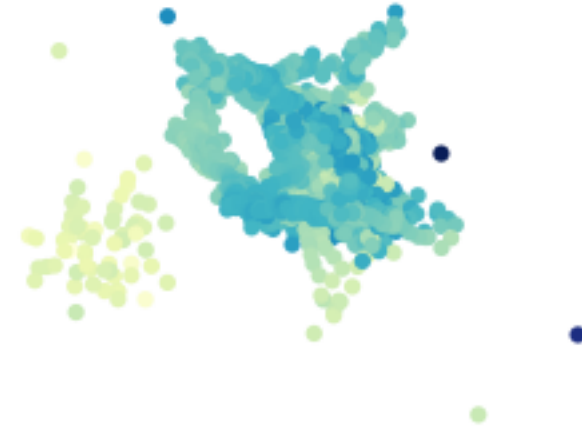


1-d seems doable: learned curves qualitatively similar



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Current state



3d with Gaussian Mixture Models? Not quite...

Next up: try GPLVM

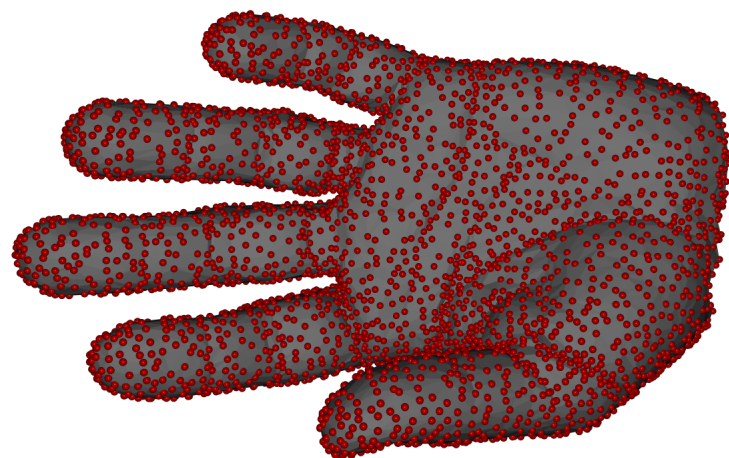
Gaussian Process Latent Variable Models

If anyone has any good ideas — **tell me!**



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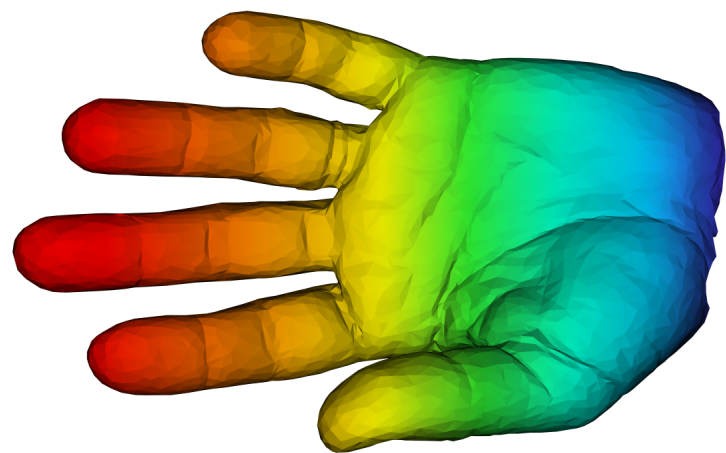
Mapper





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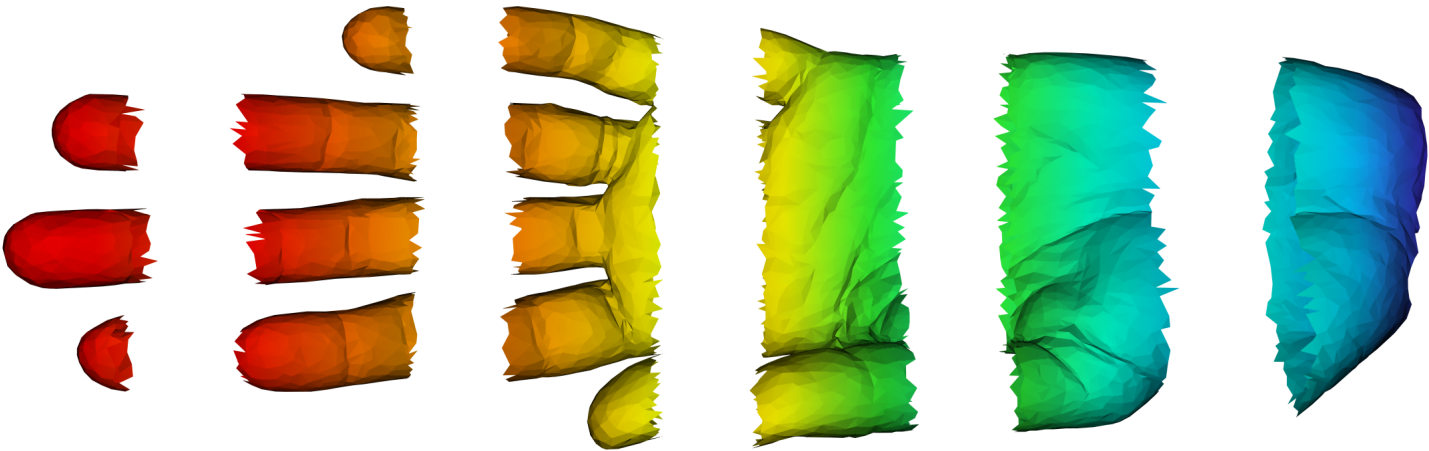
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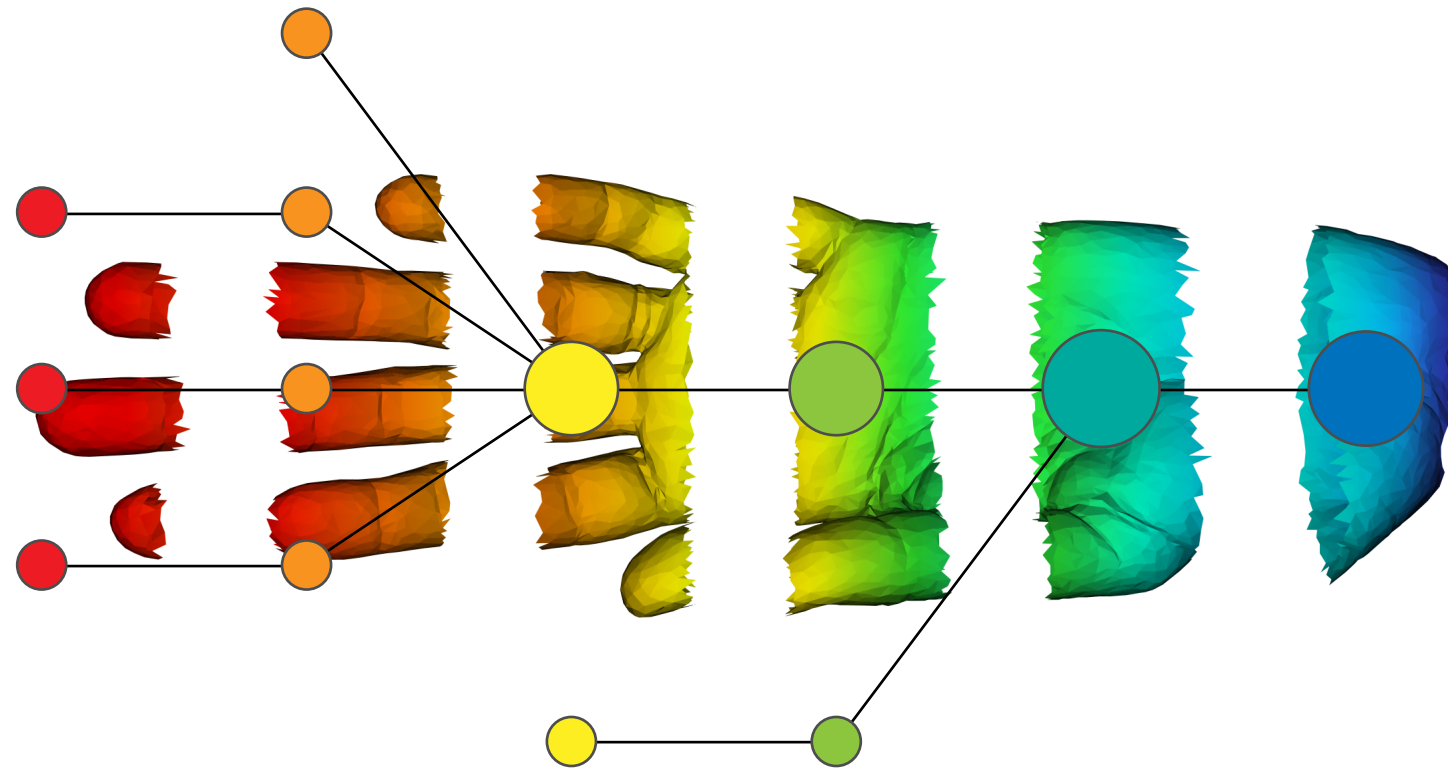


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Mapper



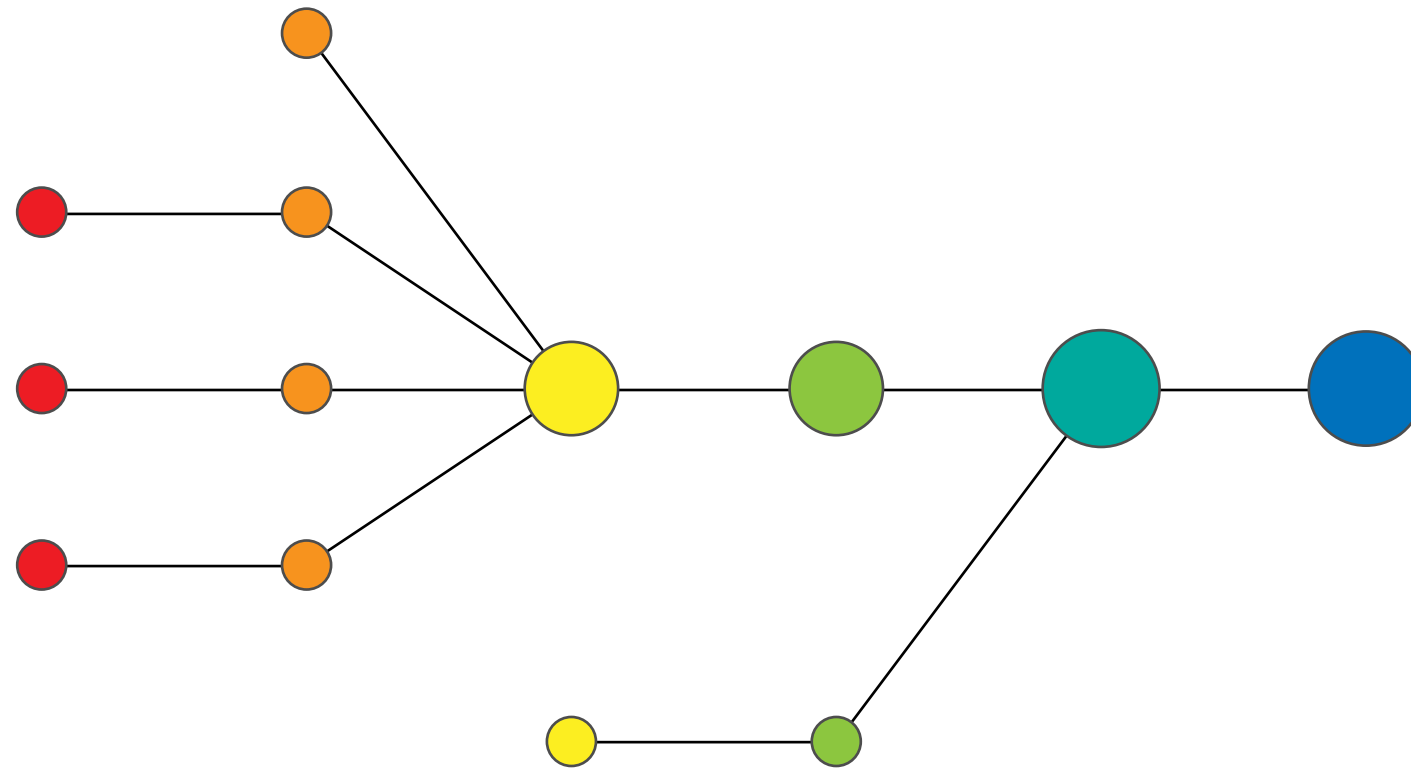
Mapper





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Mapper





Mapper

- Builds automatically a discrete model.
- Stable under permutation of data.
Under permutation of filter functions.
- Persistent topology along varying feature functions:
active research field.
- Strong potential for novel model creation for ML application.
Going beyond Data Analysis.



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Thank you for listening

شكرا لإصغائكم