

Topological Data Analysis of Biological Aggregation Dynamics

Chad Topaz (Williams College)

NSF DMS-1412674/1743963



This talk, in a nutshell

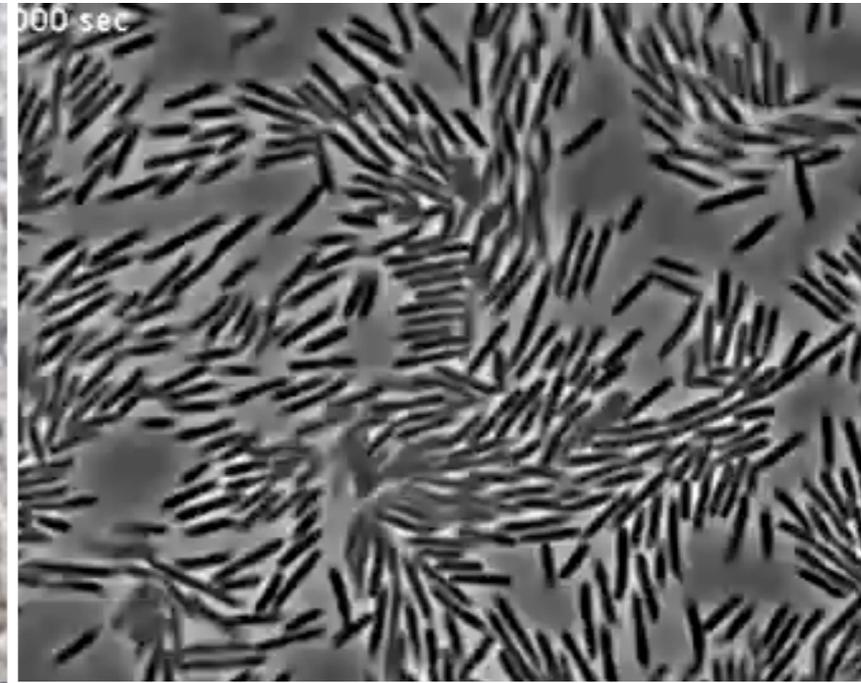
Part I: Applying a topological lens to biological aggregation model data

Message: TDA can be a useful tool for exploratory data analysis.

Part II: Moving towards topological reductions of a complex system

Message: When dynamics are neither highly ordered nor totally random, a topological description might be appropriate, but the approach is analytically challenging.

Biological aggregations abound in nature.



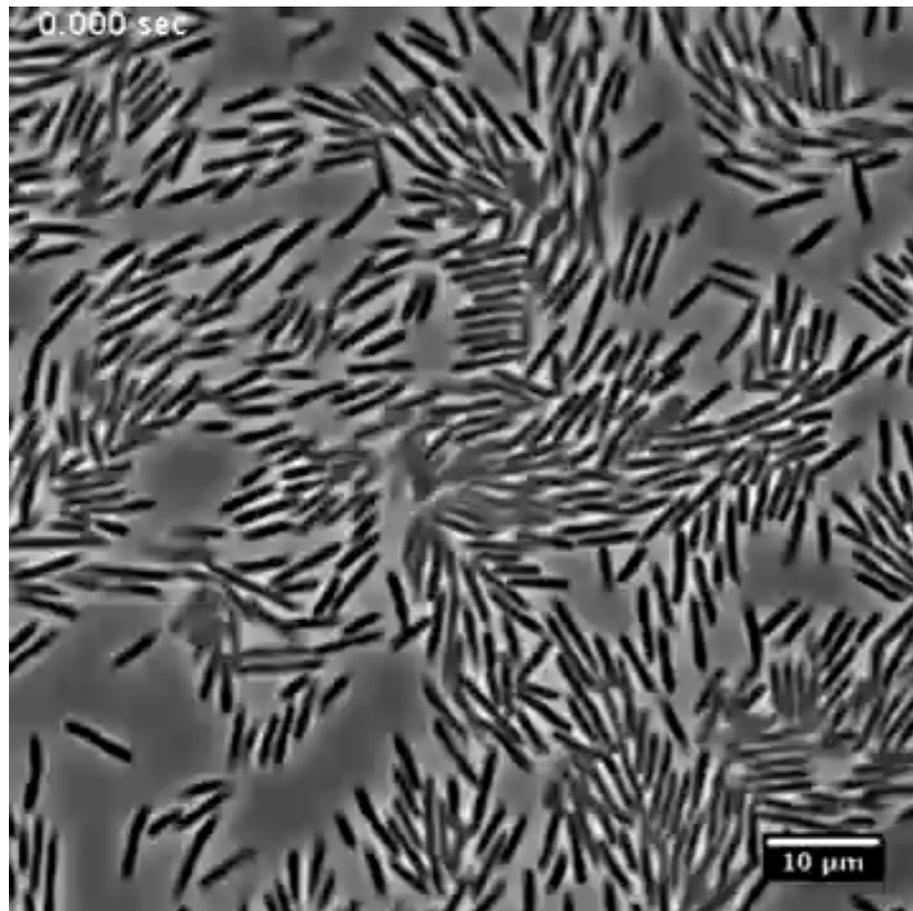
Chad's parsing of biological aggregation research:

1. Determine individual-level behaviors
2. Assess macroscopic group properties
3. Elucidate the connection between these



Quantifying group dynamics is a task suited for data science.

<https://youtu.be/q27Jn3h4kpE>



M. Copeland, University of Wisconsin

A graphic of a yellow envelope with a red and blue striped border. The envelope is open, and the text is written on the inside flap. The text is as follows:

300 bacteria
4 pieces info. / (frame x bacteria)
20 frames / second
10 seconds

240,000 pieces of information

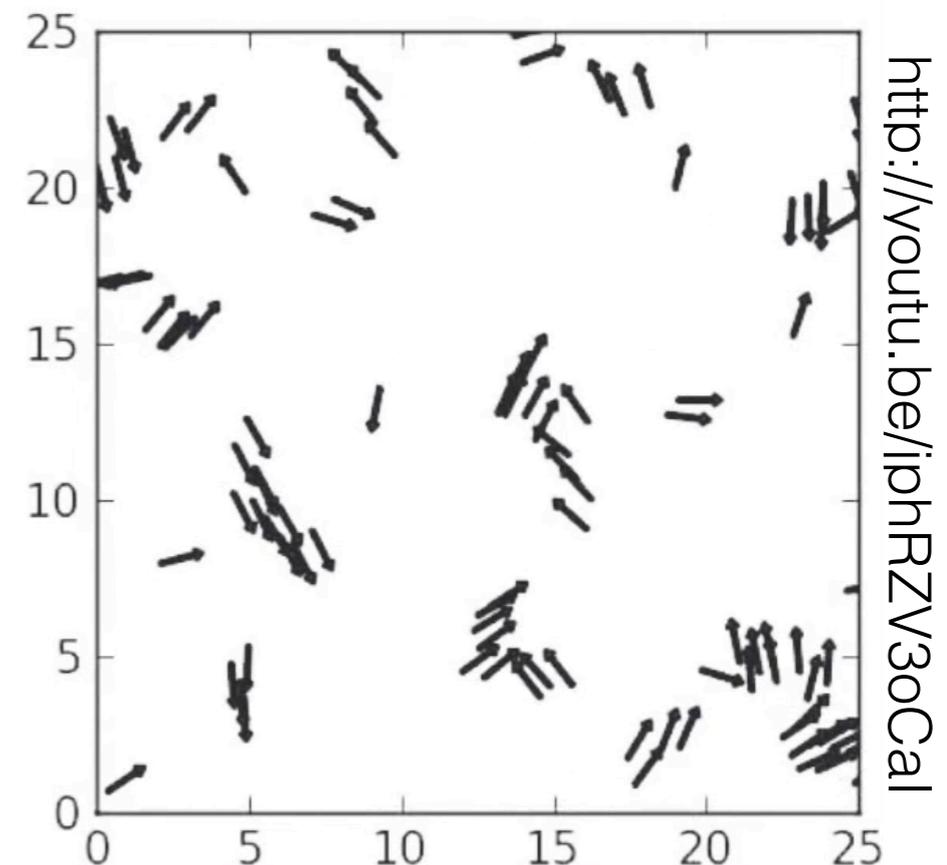
Vicsek's seminal model describes aligning particles.

Novel type of phase transition in a system of self-driven particles

[T Vicsek](#), [A Czirók](#), [E Ben-Jacob](#), [I Cohen](#), [O Shochet](#) - Physical review letters, 1995 - APS

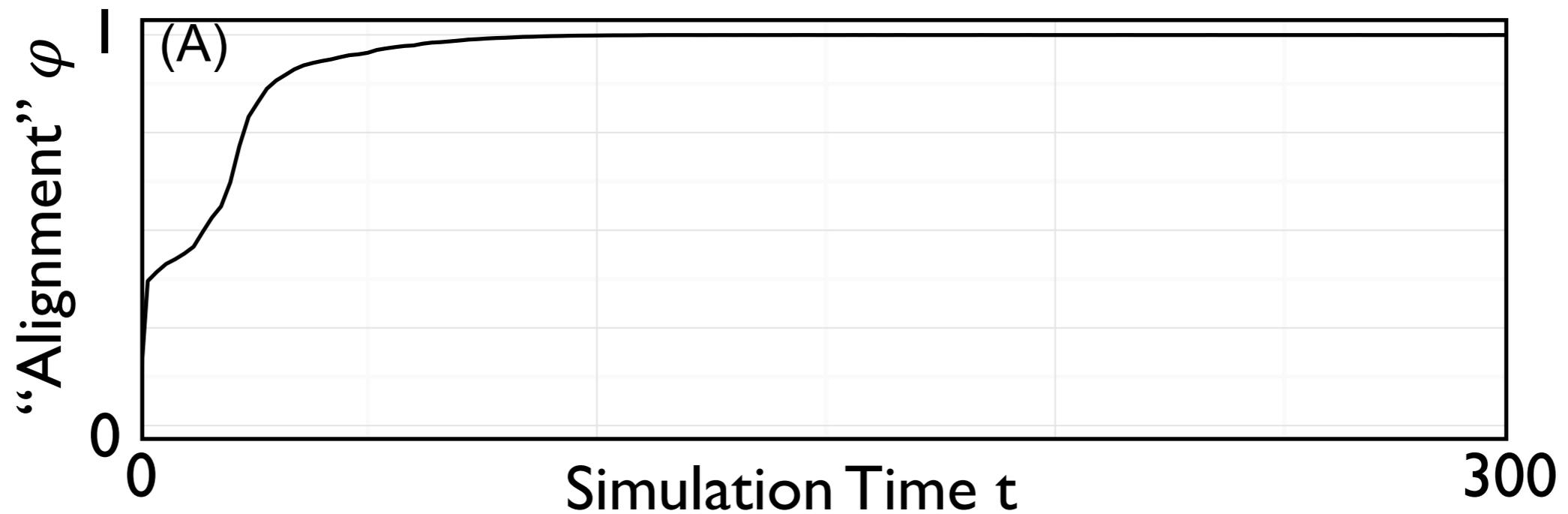
☆ [Cited by 4884](#) [Related articles](#) [All 28 versions](#)

$$\begin{aligned}\theta_i &\leftarrow \underbrace{\langle \theta_j \rangle_{|\mathbf{x}_i - \mathbf{x}_j| \leq R}}_{\text{social alignment}} + \underbrace{U(-\eta/2, \eta/2)}_{\text{uniform noise}} \\ \mathbf{v}_i &\leftarrow v_0 (\cos \theta_i, \sin \theta_i) \\ \mathbf{x}_i &\leftarrow \mathbf{x}_i + \mathbf{v}_i \Delta t\end{aligned}$$



Dynamics are often assessed via order parameter time series.

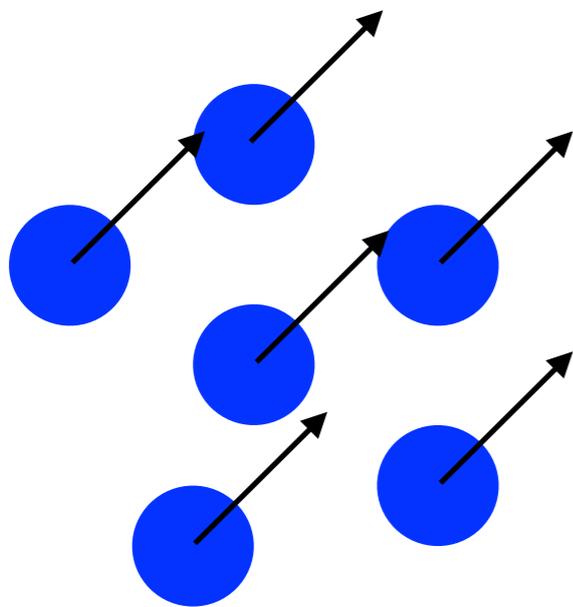
Alignment order parameter: $\phi(t) = \frac{1}{Nv_0} \left| \sum_{i=1}^N \mathbf{v}_i(t) \right|$



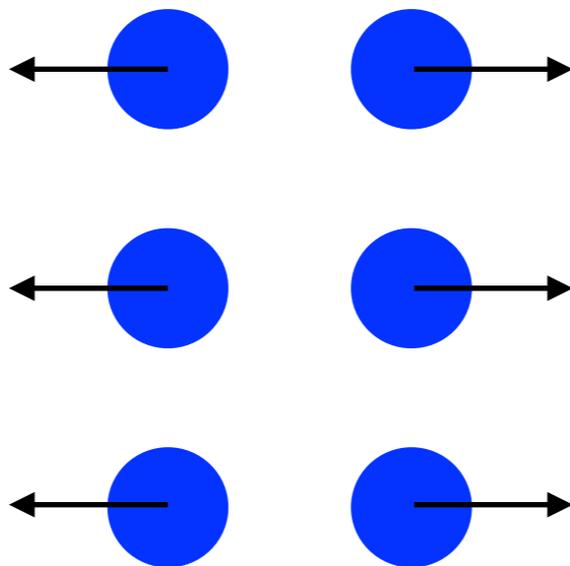


are often assessed via
parameter time series.

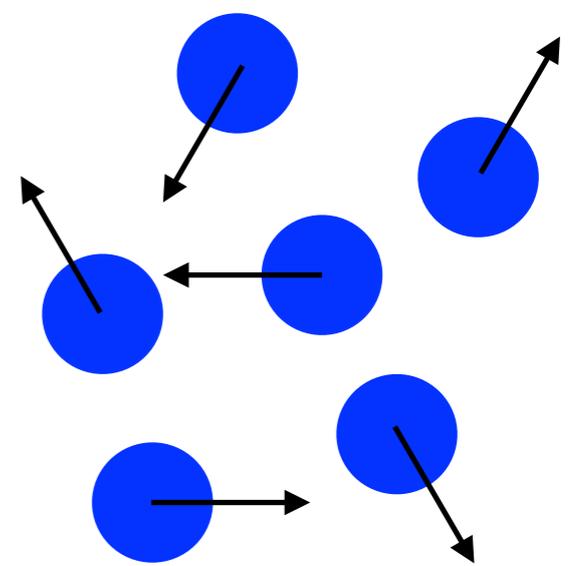
Order parameter:
$$\phi(t) = \frac{1}{Nv_0} \left| \sum_{i=1}^N \mathbf{v}_i(t) \right|$$



$$\varphi = 1$$



$$\varphi = 0$$

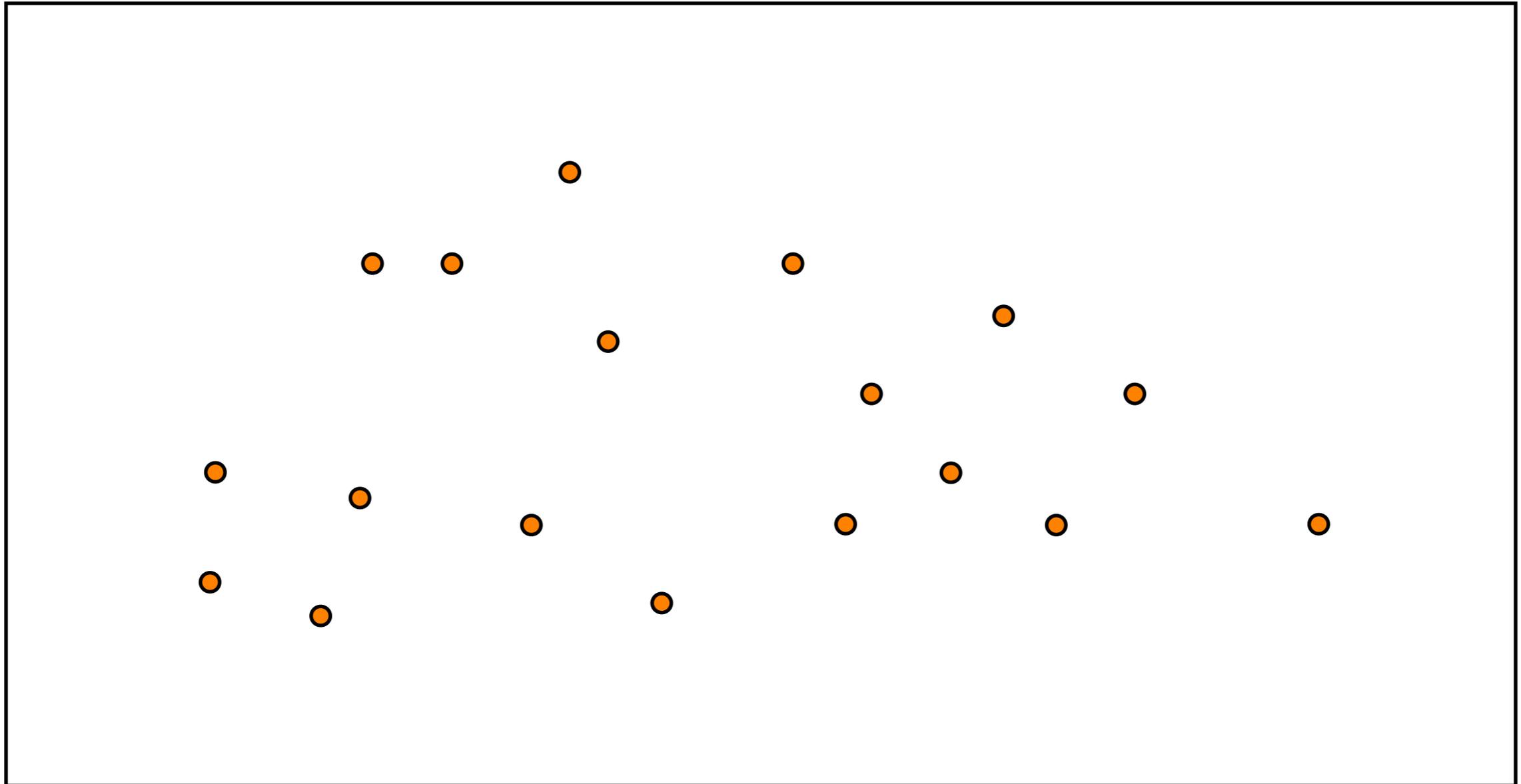


$$\varphi = 0$$

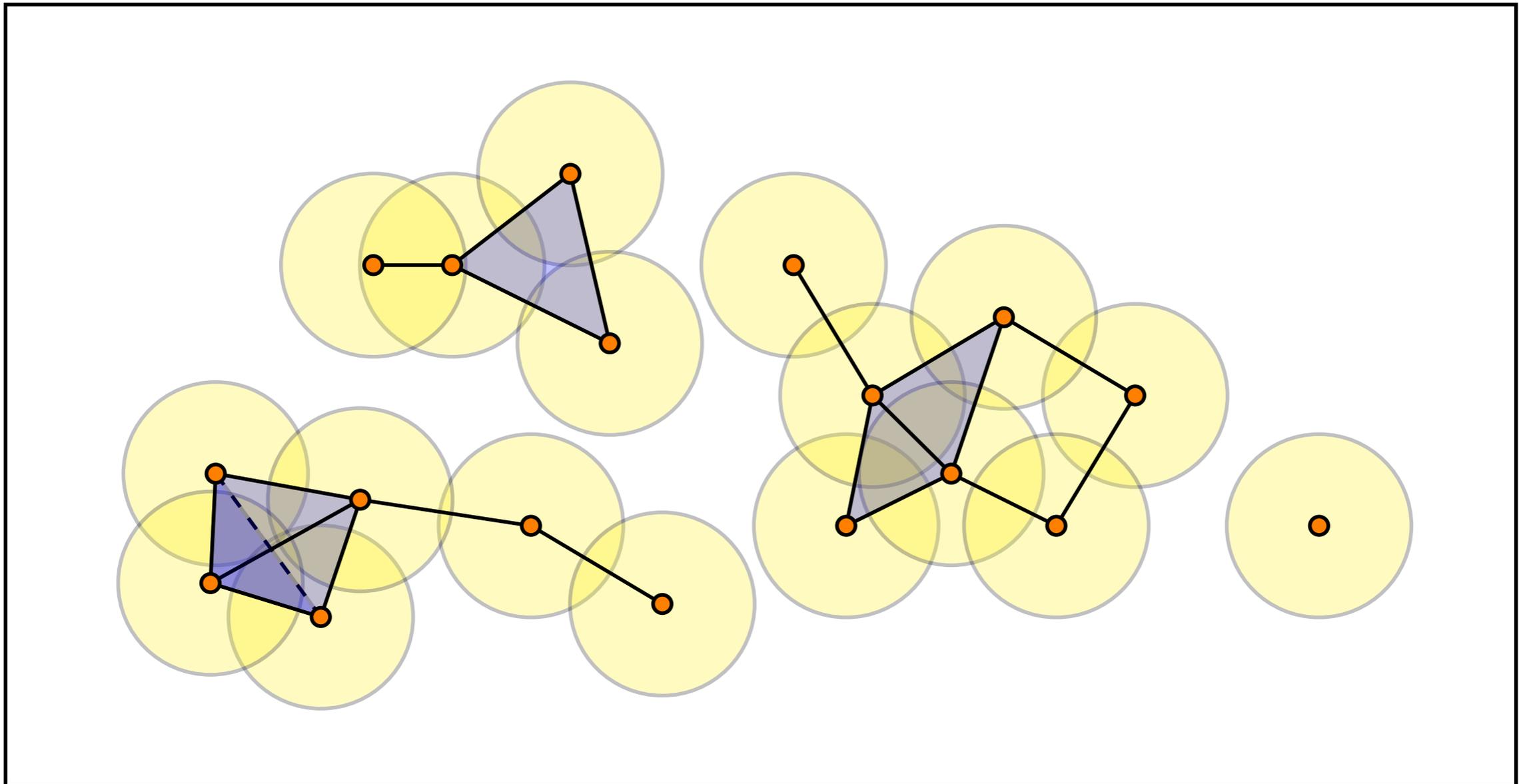
How about using topology as our “order parameter”?

1. Computational Homology
T. Kaczynski, K. Mischaikow, and M. Mrozek. (2004)
2. Computing persistent homology
A. Zomorodian, G. Carlsson. *Disc. & Comp. Geom.* (2005)
3. Barcodes: The persistent topology of data
R. Ghrist. *Bull. Am. Math. Soc.* (2008)
4. Persistent homology: A Survey
H. Edelsbrunner, J. Harer. *Contemp. Math.* (2008)
5. Topology and Data
G. Carlsson. *Bull. Am. Math. Soc.* (2009)

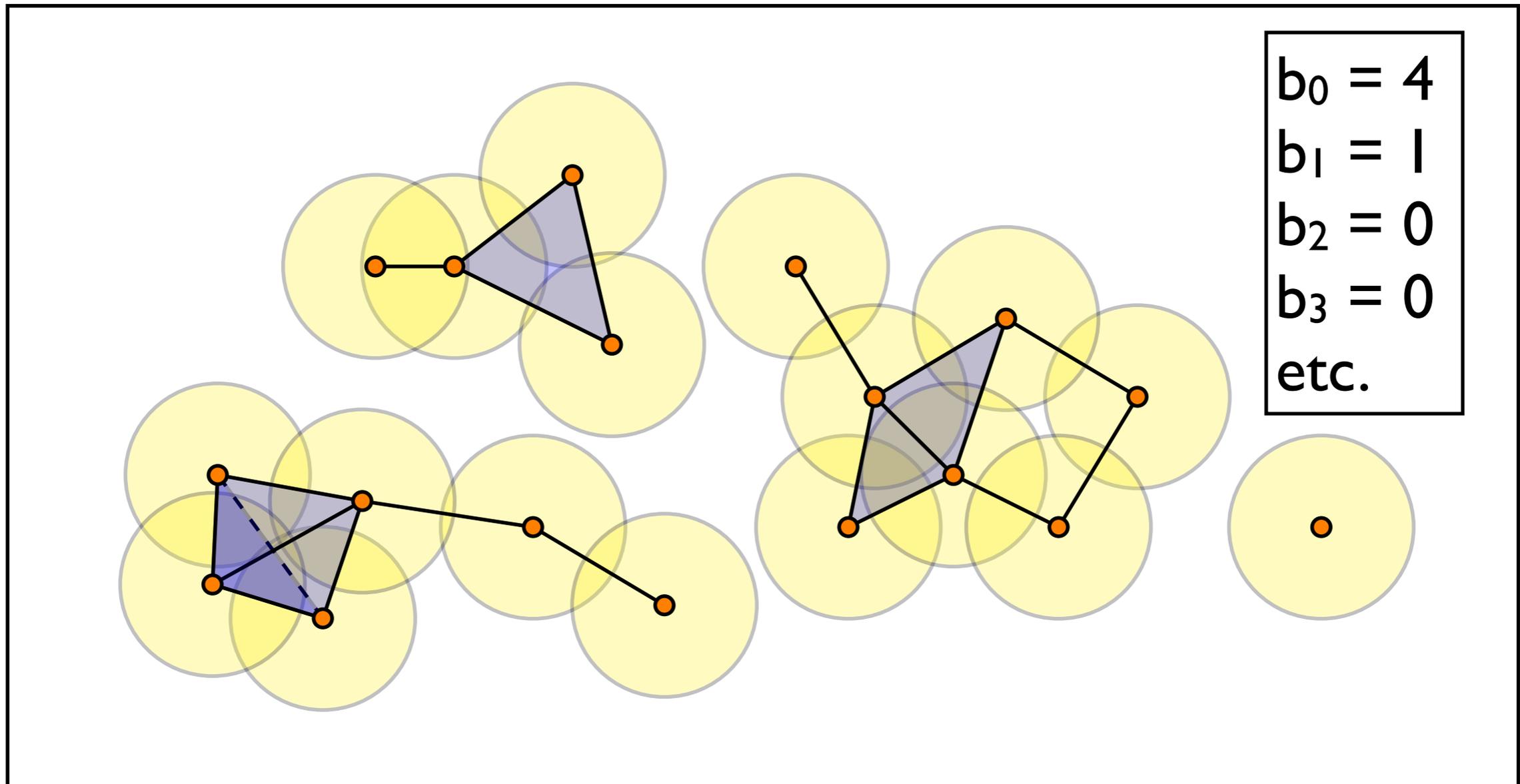
Step 1: Envision data as point cloud



Step 2: Build simplicial complex



Step 3: Calculate Betti numbers



Chad's Self-Help Homology Tutorial For The Simple(x)-Minded

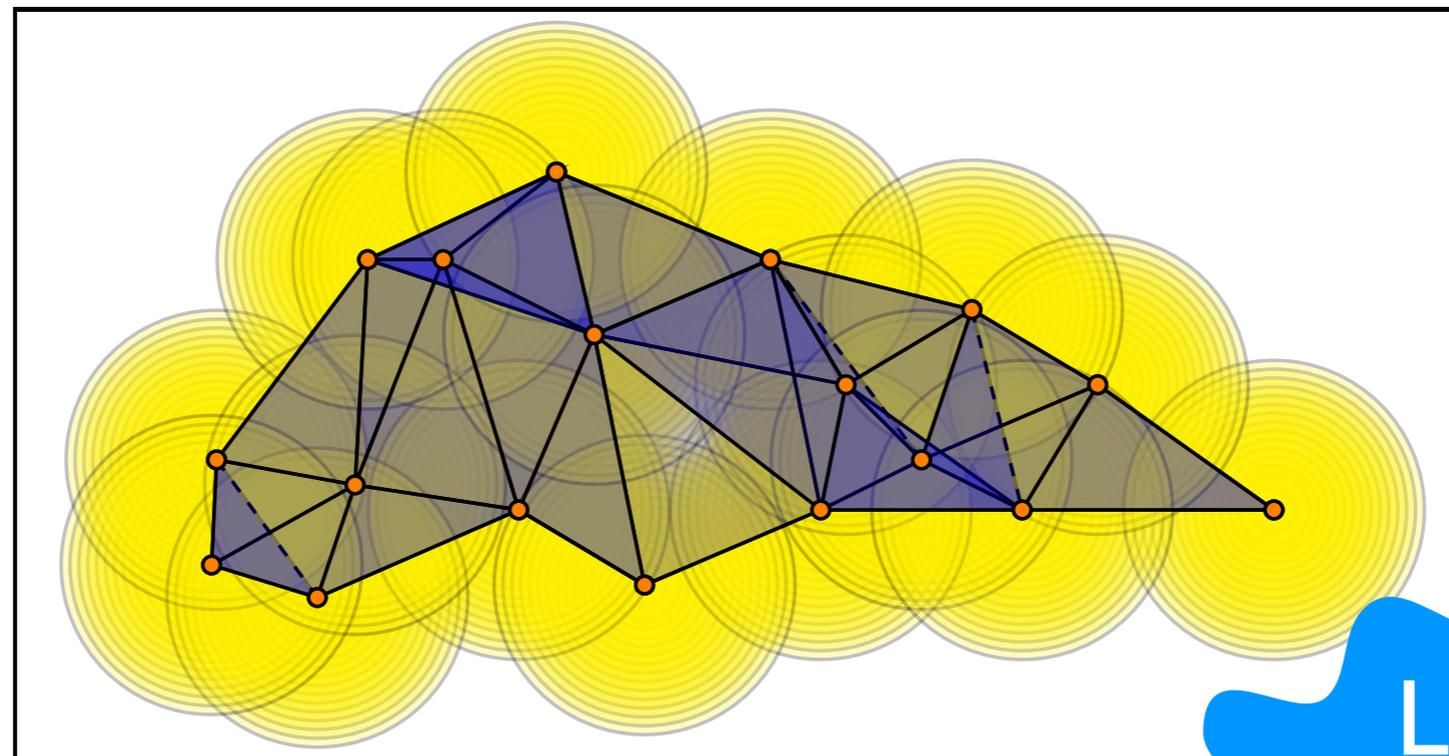
A full-color Extravaganza



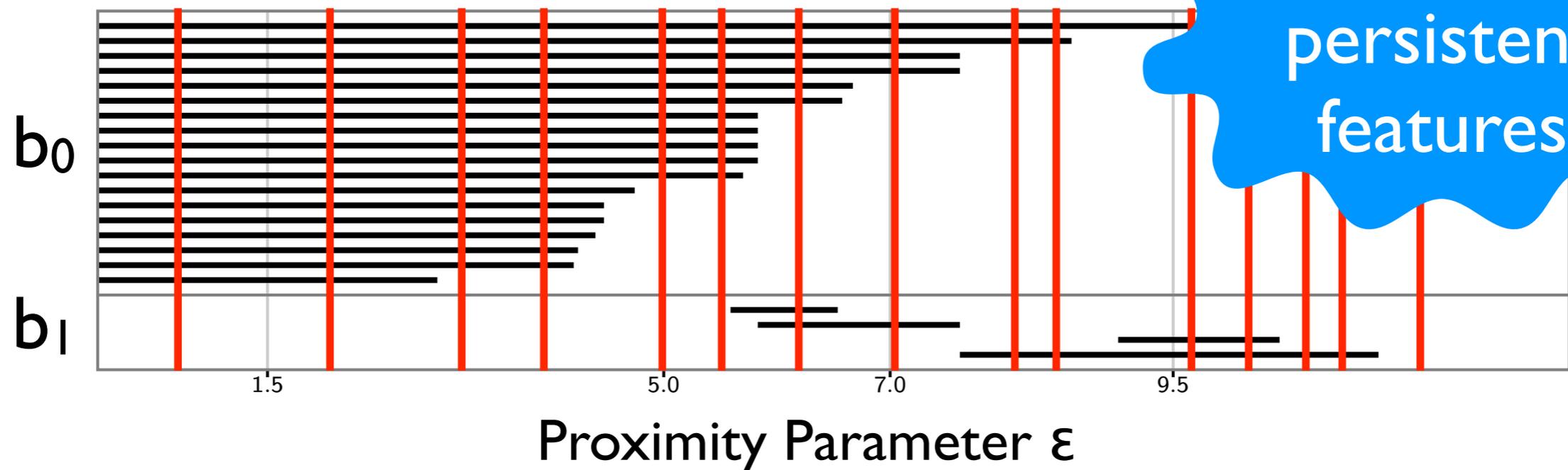
With very sincere thanks and
apologies to Lori Ziegelmeier and
Tom Halverson, who actually know
topology and tried to explain it
to me.



Step 4: Find persistent homology



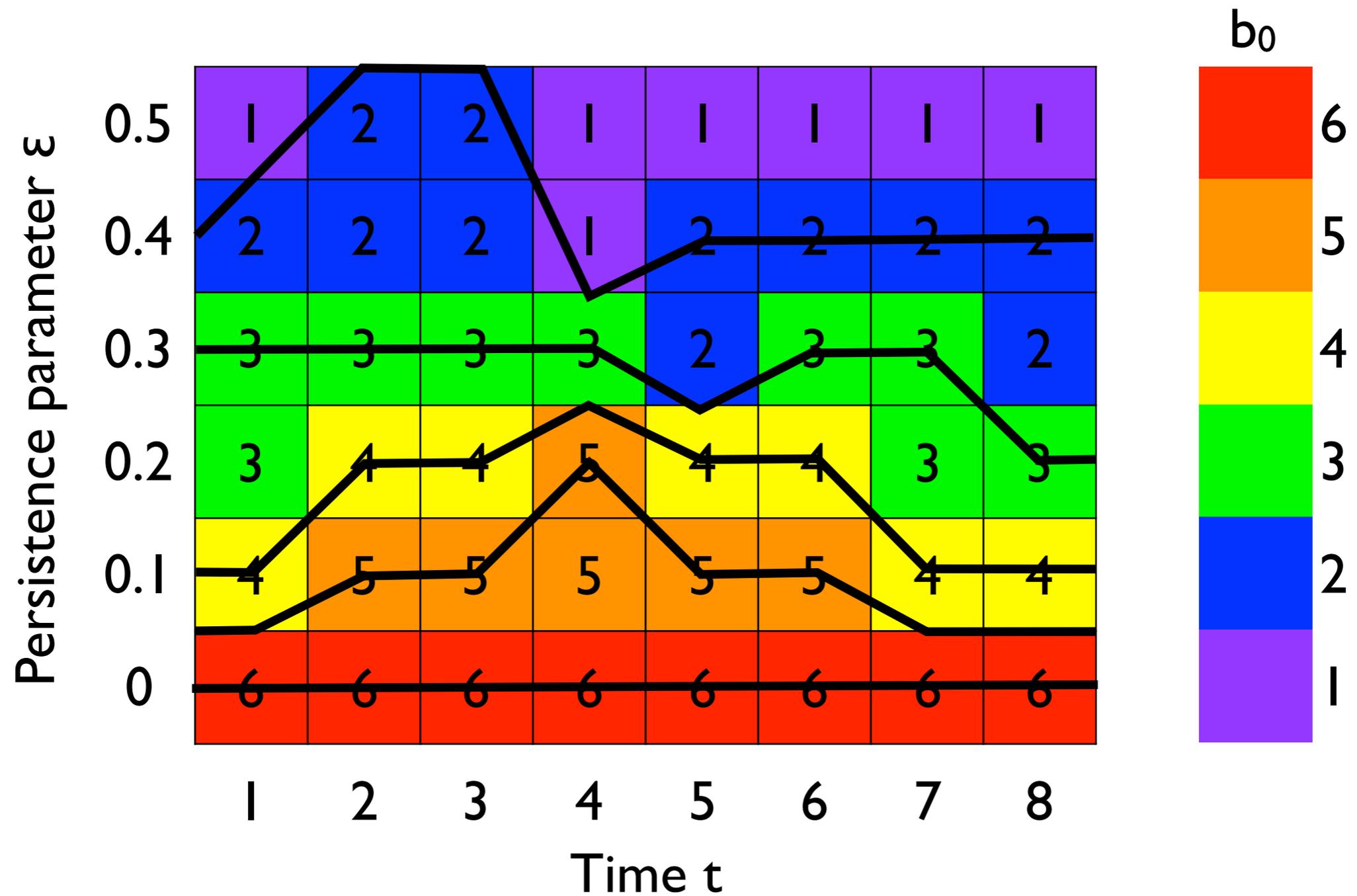
Look for persistent features



Step 4: Find persistent homology



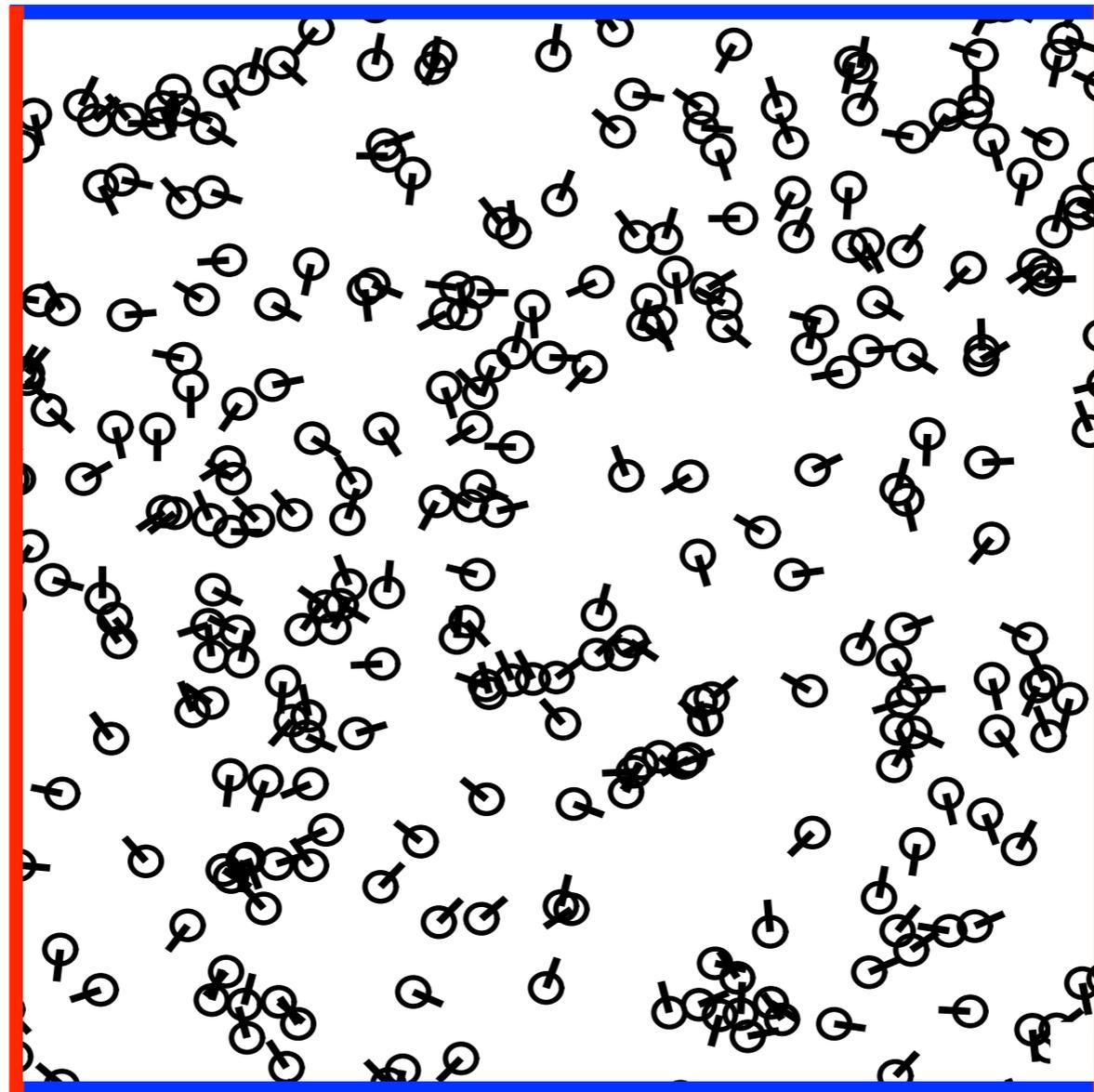
Step 5: Evolve in time



Step 5: Evolve in time (CROCKER)

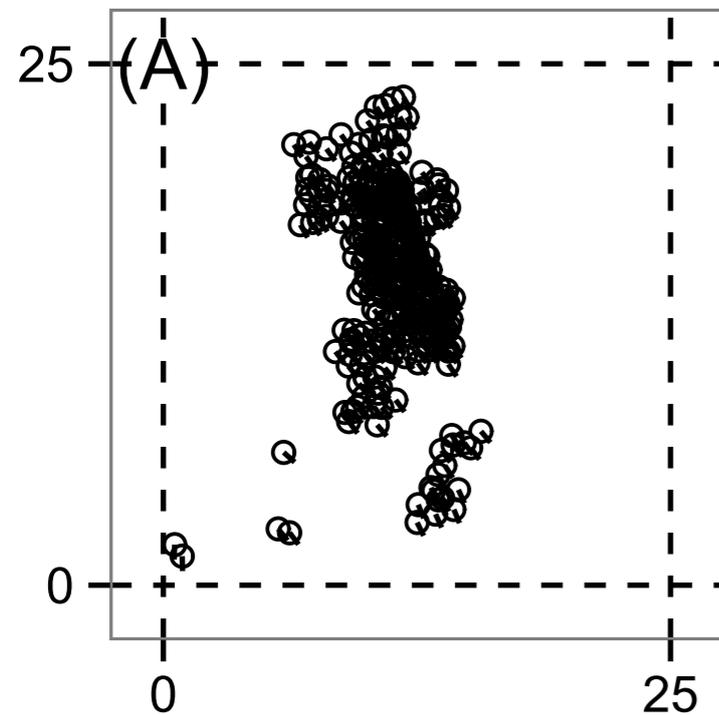


Initial condition for Vicsek model covers a three-torus.

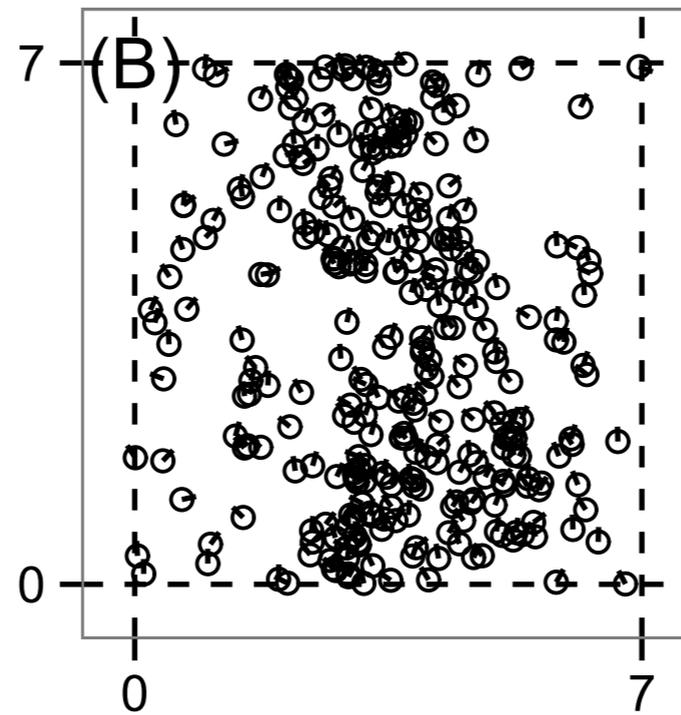


$$b = (1, 3, 3, 1, 0, \dots)$$

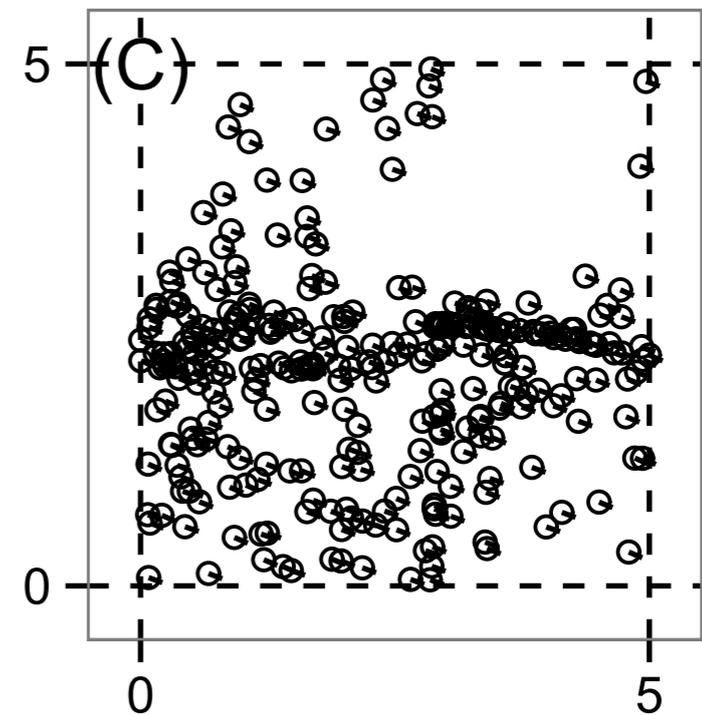
The Vicsek model has several prototypical behaviors.



Clusters?



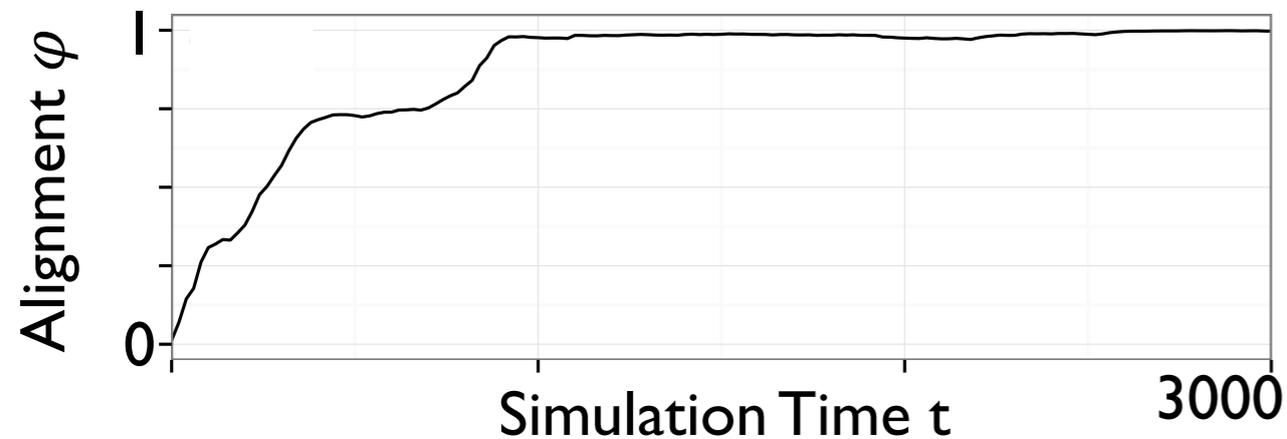
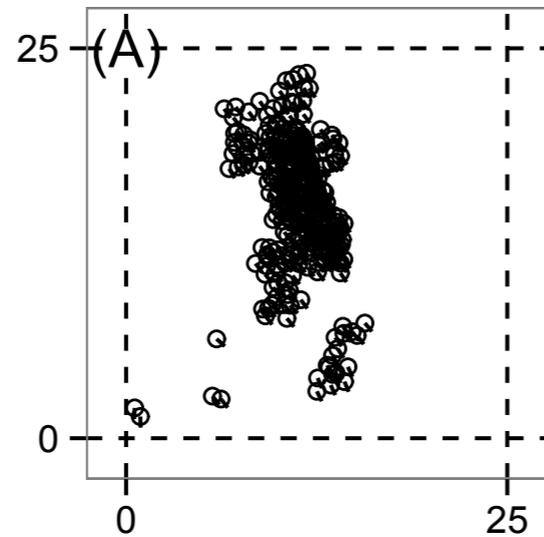
Loose alignment?



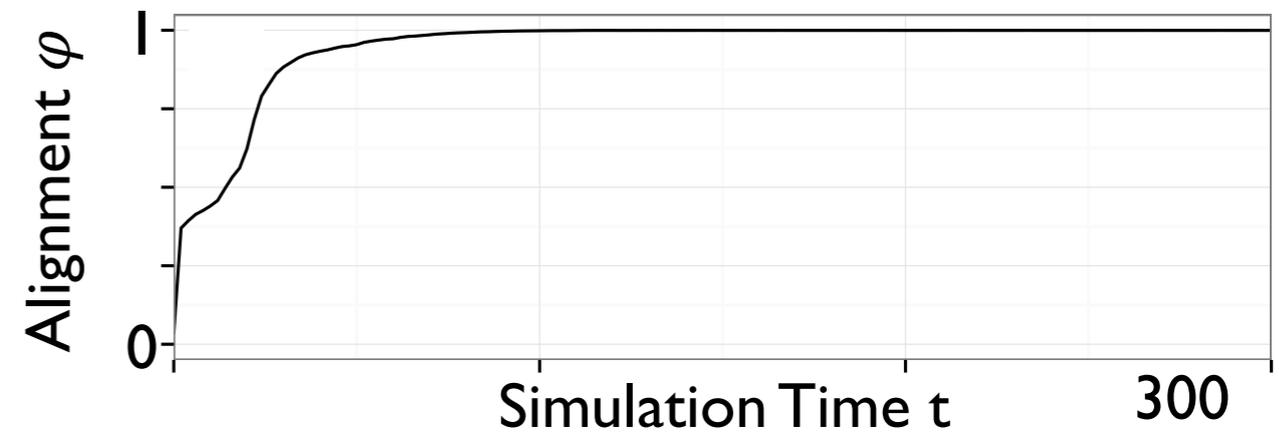
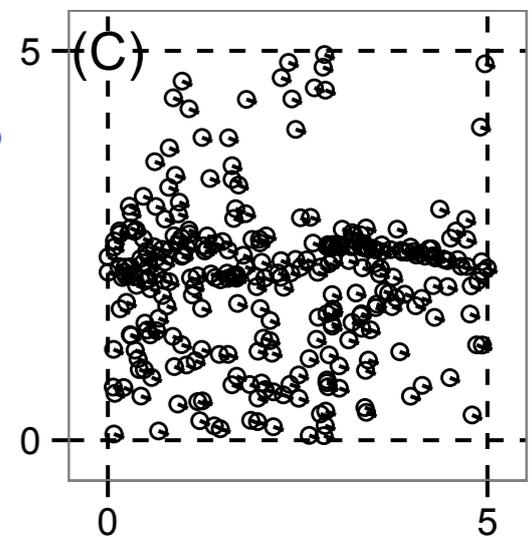
Strong alignment?

Traditional order parameter time series that look similar...

Parameter Set #1
“Clusters”

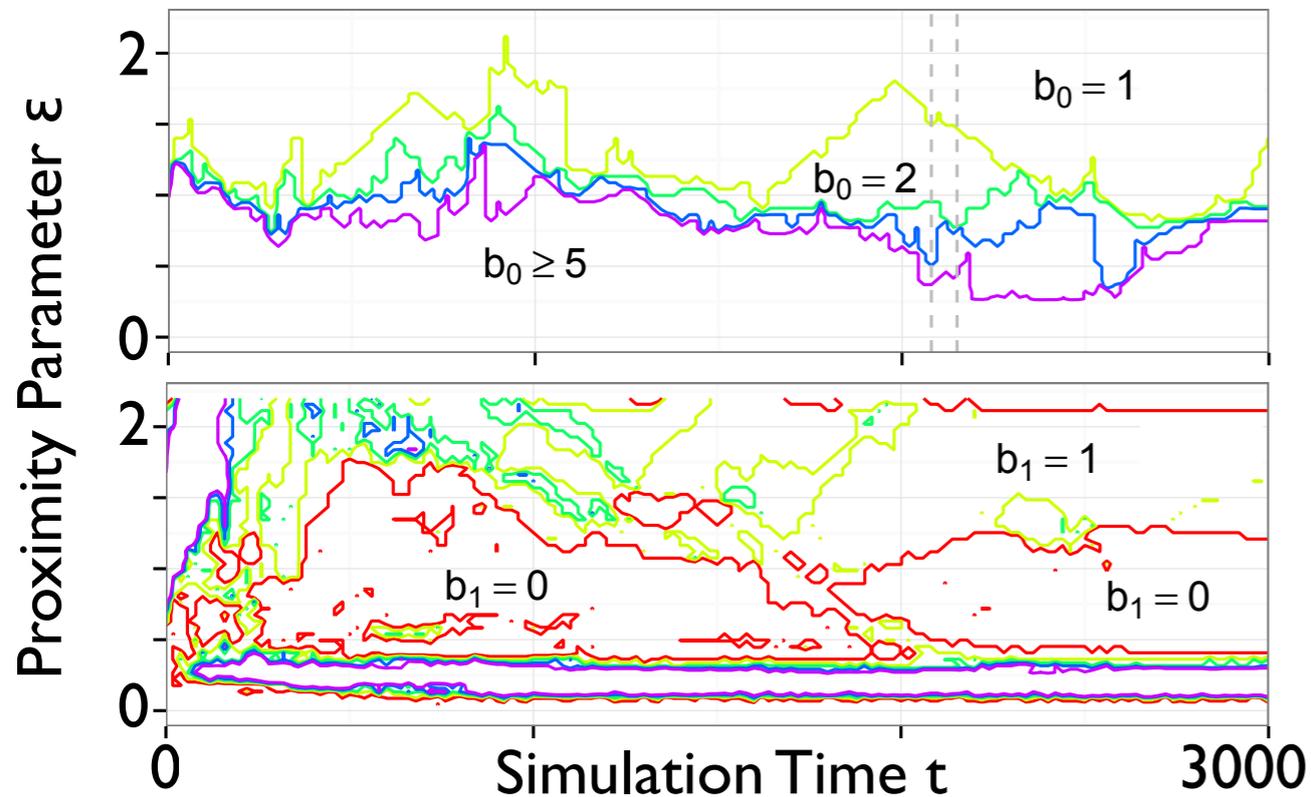
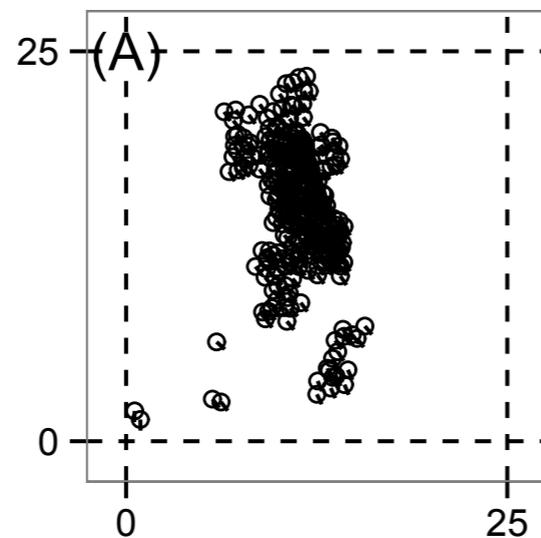


Parameter Set #2
“Strong Alignment”

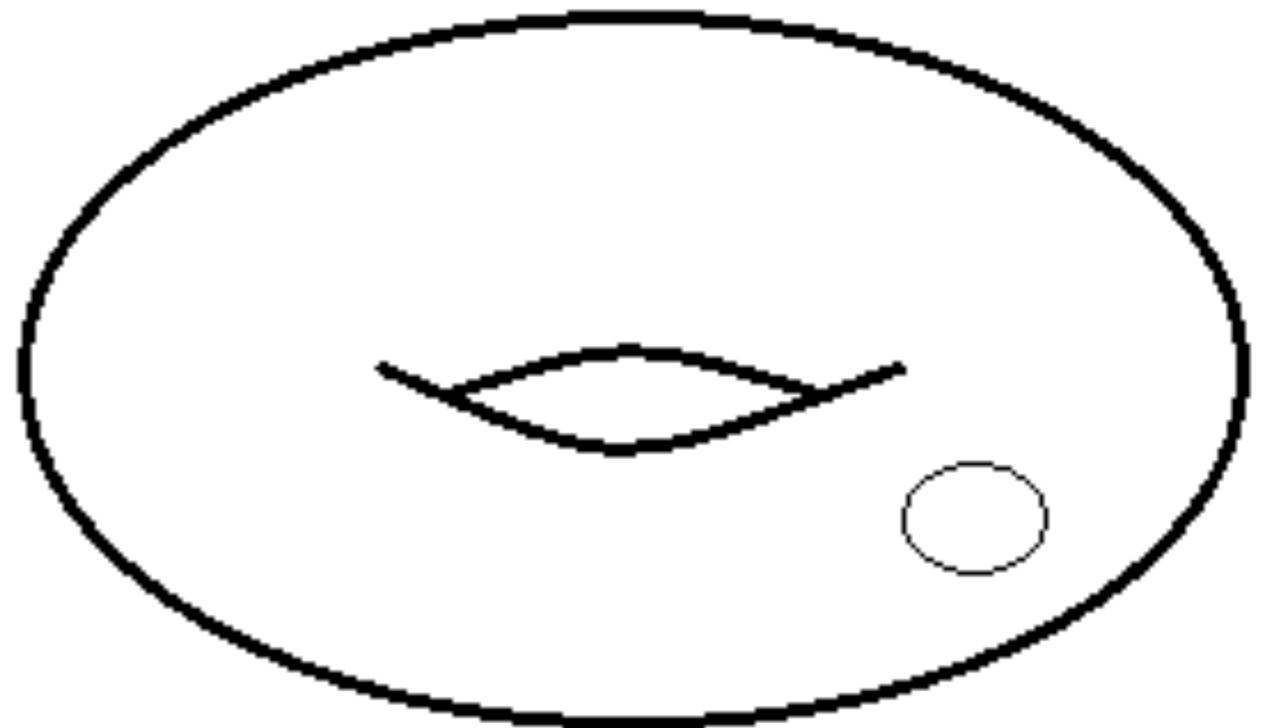
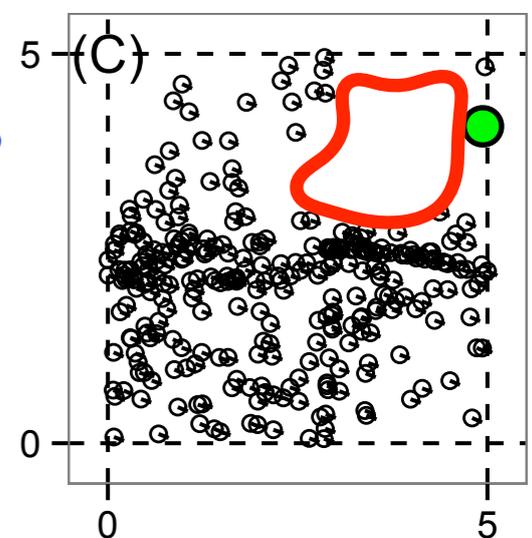


...can have drastically different topological signatures.

Parameter Set #1
“Clusters”



Parameter Set #2
“Strong Alignment”



This talk, in a nutshell

Part I: Applying a topological lens to biological aggregation model data

Message: TDA can be a useful tool for exploratory data analysis.

Part II: Moving towards topological reductions of a complex system

Message: When dynamics are neither highly ordered nor totally random, a topological description might be appropriate, but the approach is analytically challenging.



MARE GLACIALE

VRSI ALBI

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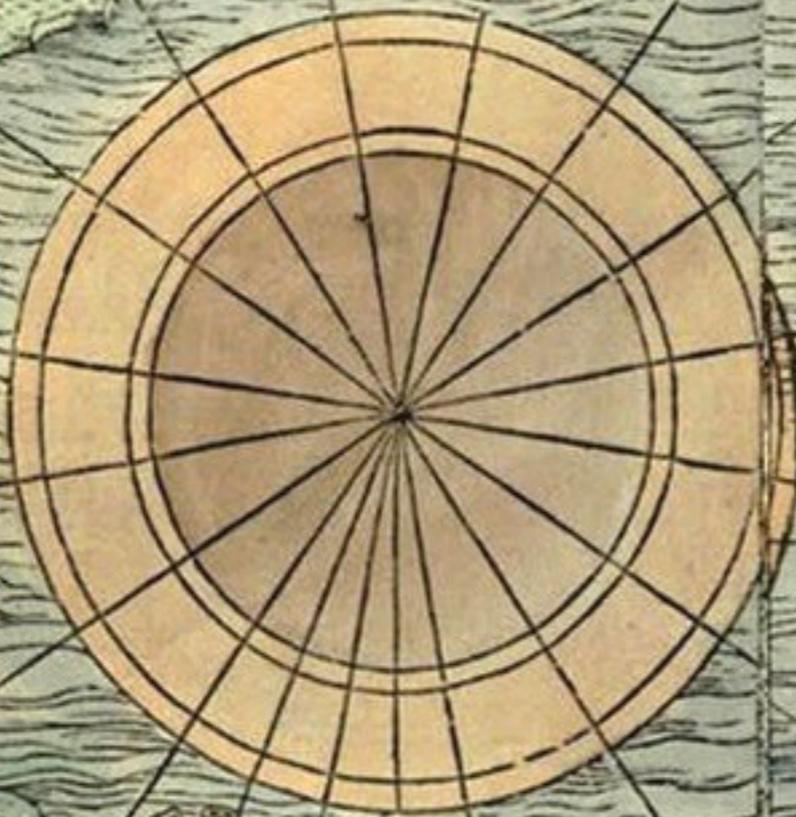
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HELGALA TERRA NOBILIVM

HORVPI CAPITI VT VNT LOCO LI

ESCA

STEK



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COOPEDVM

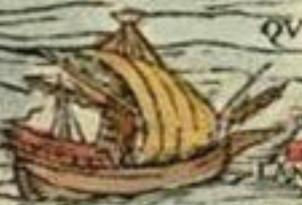
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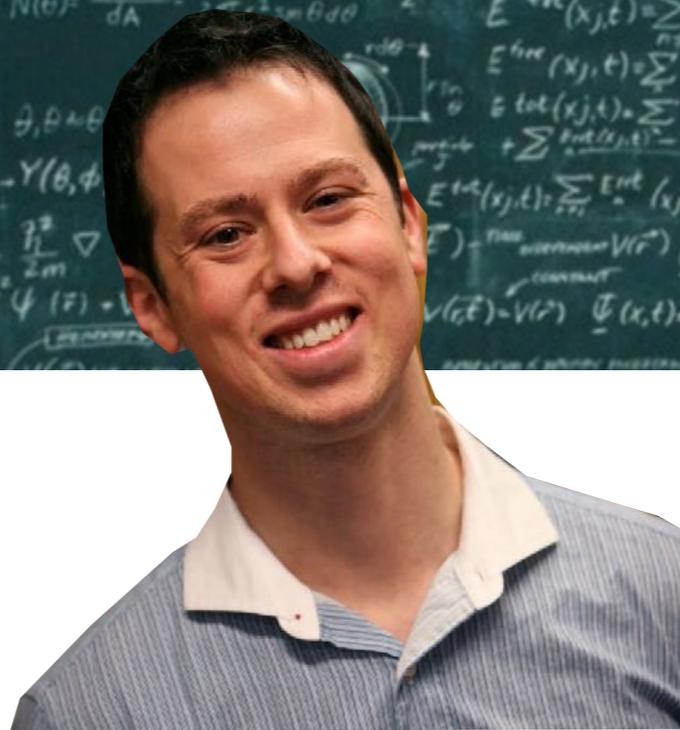
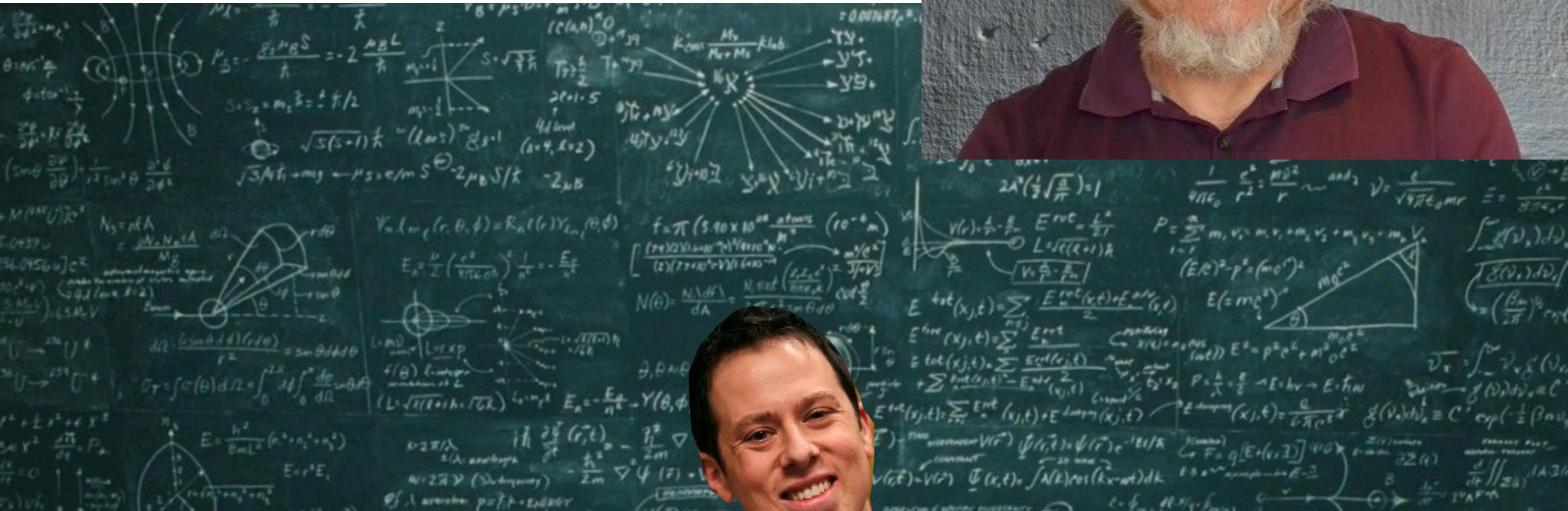


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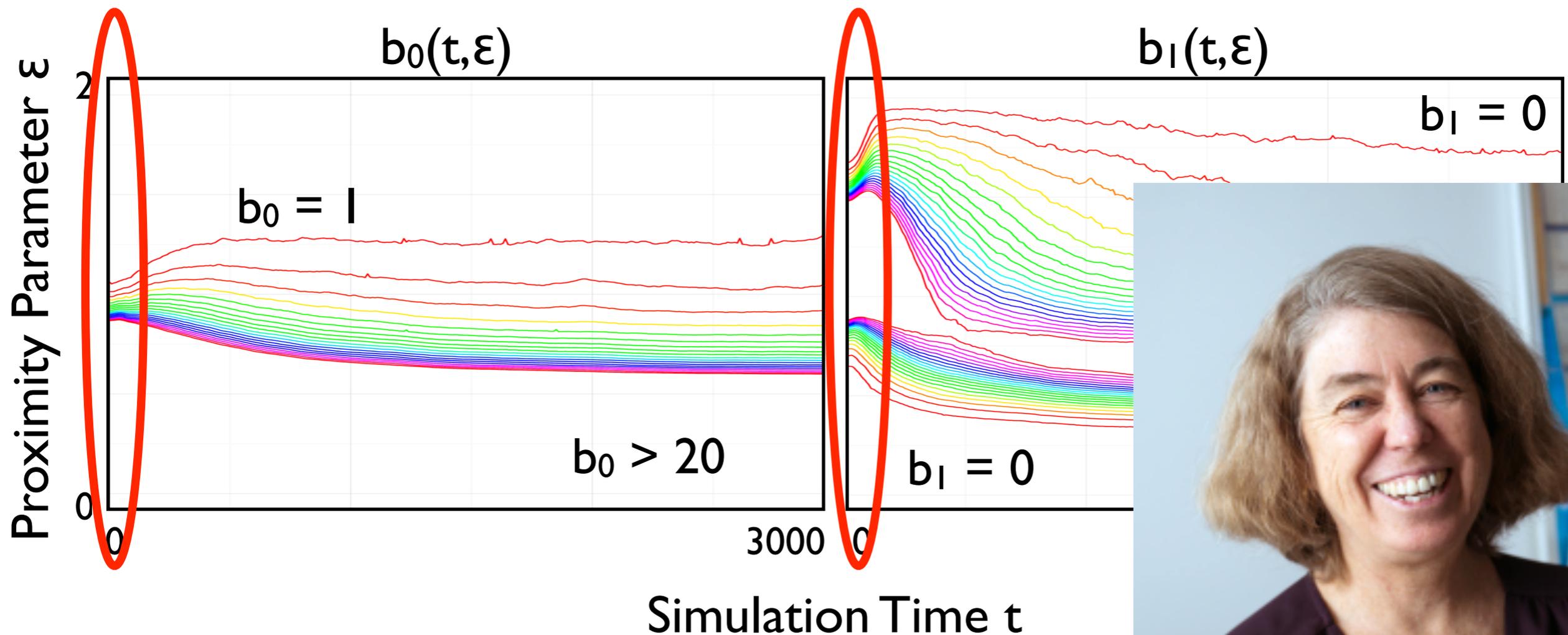
XII.P.



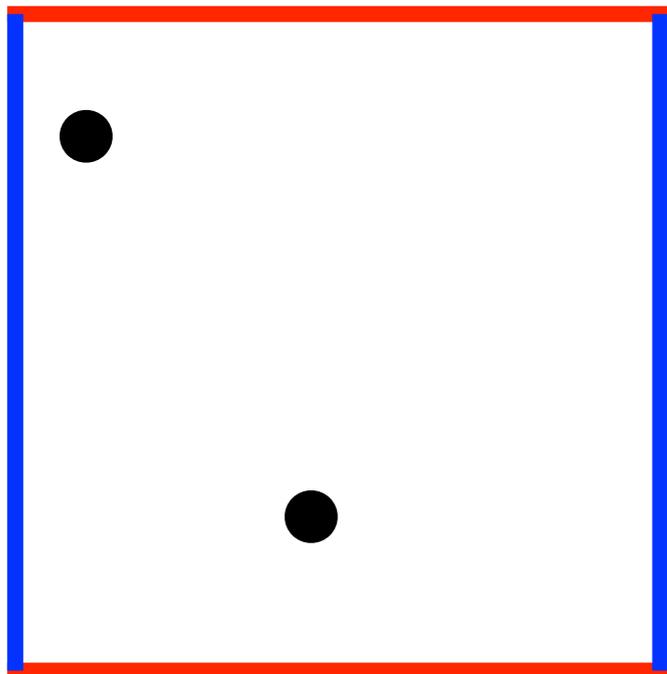


Do time series of random processes have average homology?

Vicsek model (naive) average over $n = 1000$ simulations



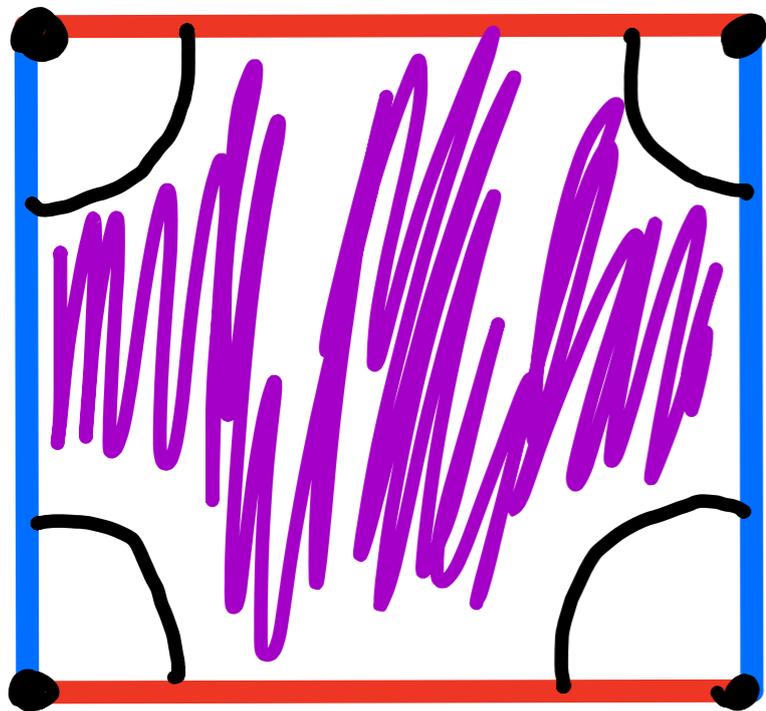
Expected value of $b_0(\epsilon)$ for an impressive ensemble of 2 points?



$$\begin{aligned} b_0(\epsilon) &= 2 \cdot P(\text{disconn.}) + 1 \cdot P(\text{conn.}) \\ &= 2 \cdot [1 - P(\text{conn.})] + P(\text{conn.}) \\ &= 2 - P(\text{conn.}) \end{aligned}$$

$$P(\text{conn.}) = P(\text{conn.}; \epsilon) = ???$$

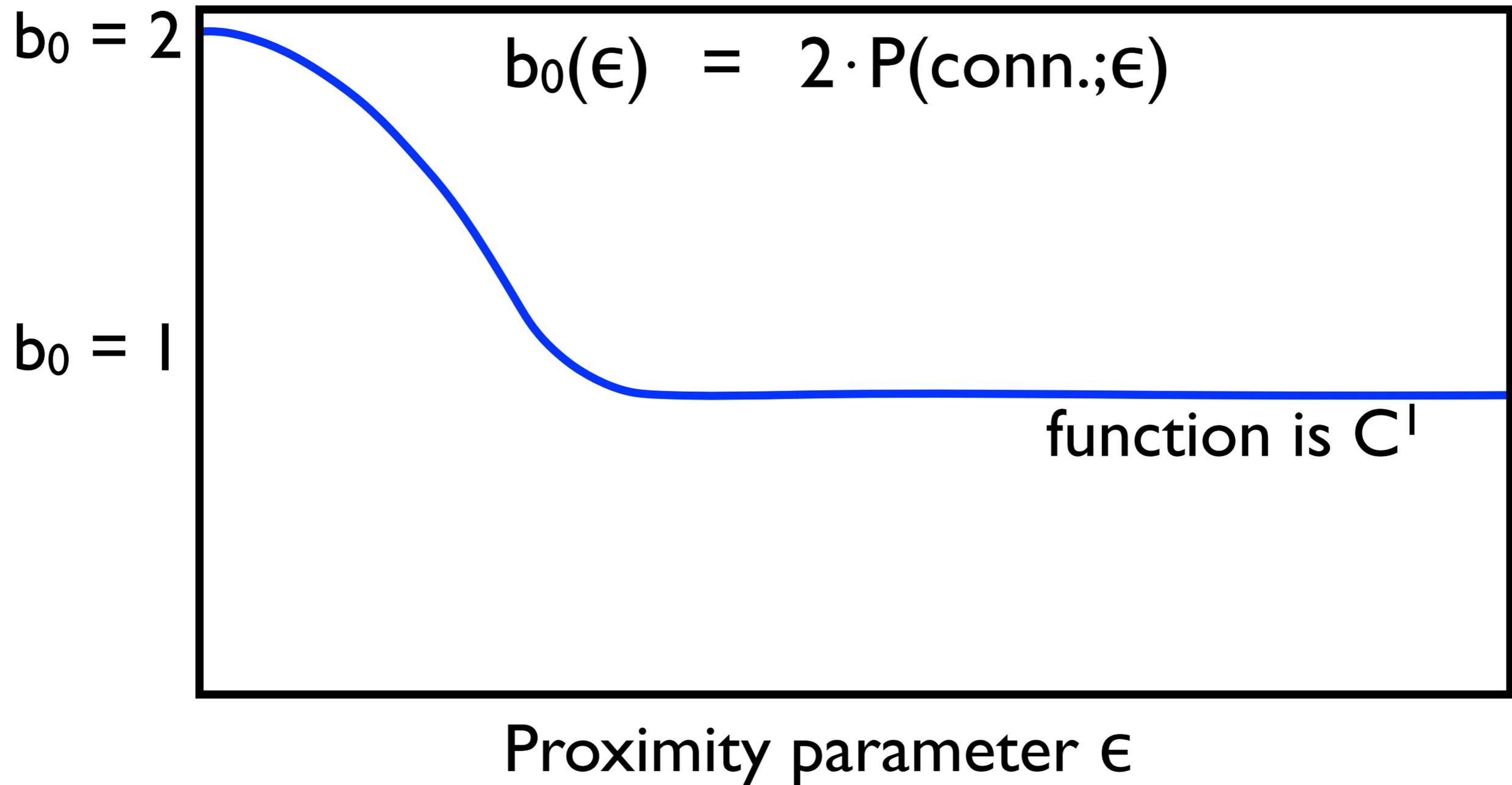
Expected value of $b_0(\epsilon)$ for an
impressive ensemble of 2 points?



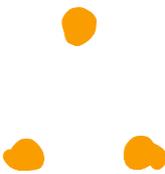
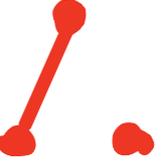
$$\epsilon \leq \frac{1}{2}$$

$$P = \frac{\pi \epsilon^2}{12}$$

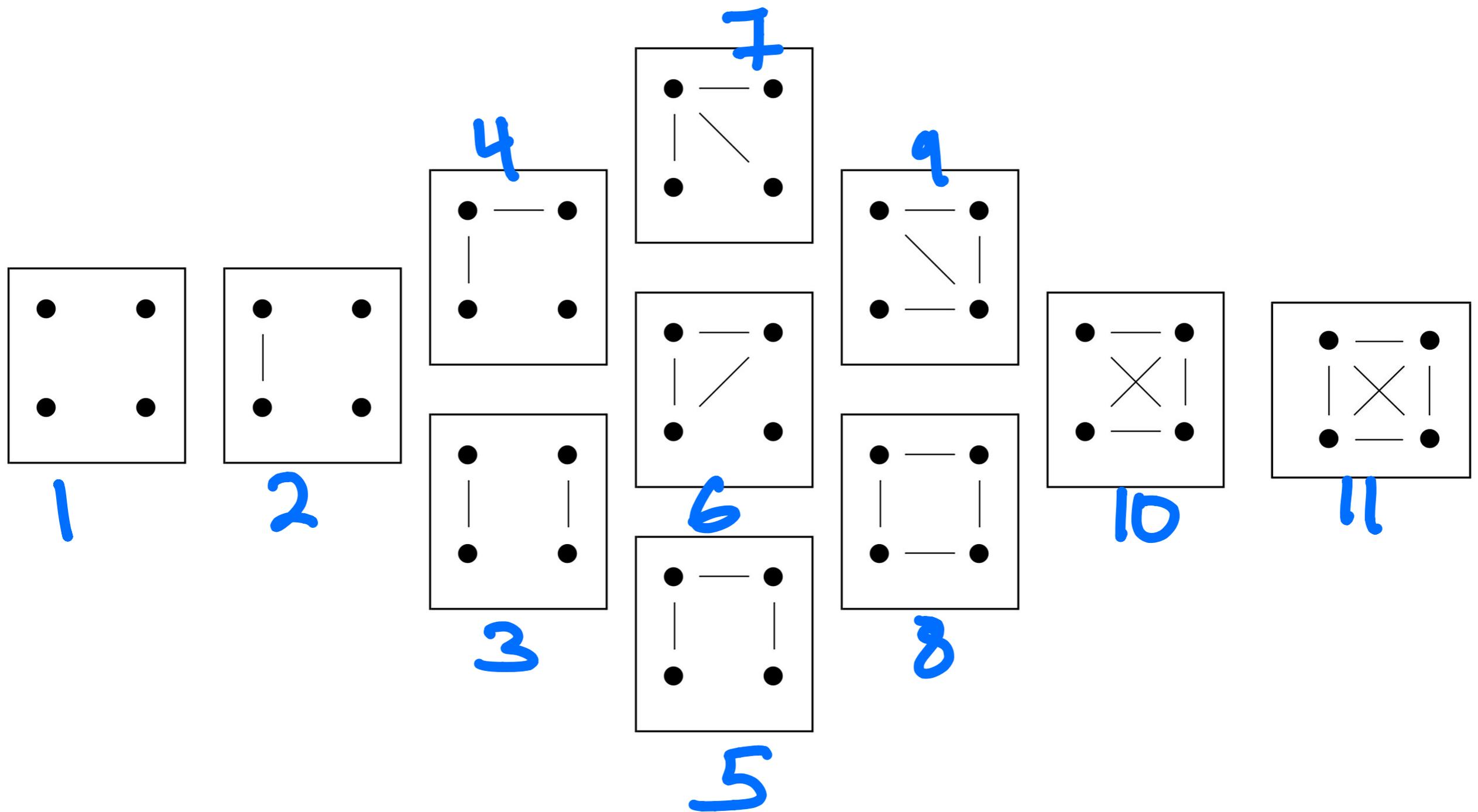
Expected value of $b_0(\epsilon)$ for an impressive ensemble of 2 points?



Expected value of $b_0(\epsilon)$ for an impressive ensemble of 3 points?

Class	# in class	b_0	b_1	Probability
	1	3	0	?
	3	2	0	?
	3	1	0	?
	1	1	0	?

Expected value of $b_0(\epsilon)$ for an
impressive ensemble of 4 points?



Expected value of $b_0(\epsilon)$ for an impressive ensemble of 4 points?

Class	# in class	b_0	b_1	Probability
1	1	4	0	?
2	6	3	0	?
3	3	2	0	?
4	12	2	0	?
5	12	1	0	?
6	4	2	0	?
7	4	1	0	?
8	3	1	1	?
9	12	1	0	?
10	6	1	0	?
11	1	1	0	?

What is the homology of a random geometric graph?

- Random Geometric Graphs [M. Penrose, 2003]
- Topology of random geometric complexes: A Survey [Bobrowski and Kahle, 2014]

Types of results:

- Bounds
- Limiting results ($N \rightarrow \infty, \varepsilon \rightarrow 0$)
- Hard expressions

What is the homology of a random geometric graph?

Theorem 3.2.1 (Penrose, [47]). *If $\Lambda = \lambda \in (0, \infty)$, then:*

$$\frac{\beta_0(n)}{n} \xrightarrow{L^2} \int_{\mathbb{R}^d} \left(\sum_{k=1}^{\infty} k^{-1} p_k(\lambda f(x)) \right) f(x) dx,$$

where

$$p_k(t) = \frac{t^{k-1}}{k!} \int_{(\mathbb{R}^d)^{k-1}} h(0, y_1, \dots, y_{k-1}) e^{-tA(0, y_1, \dots, y_{k-1})} dy_1 \cdots dy_{k-1},$$

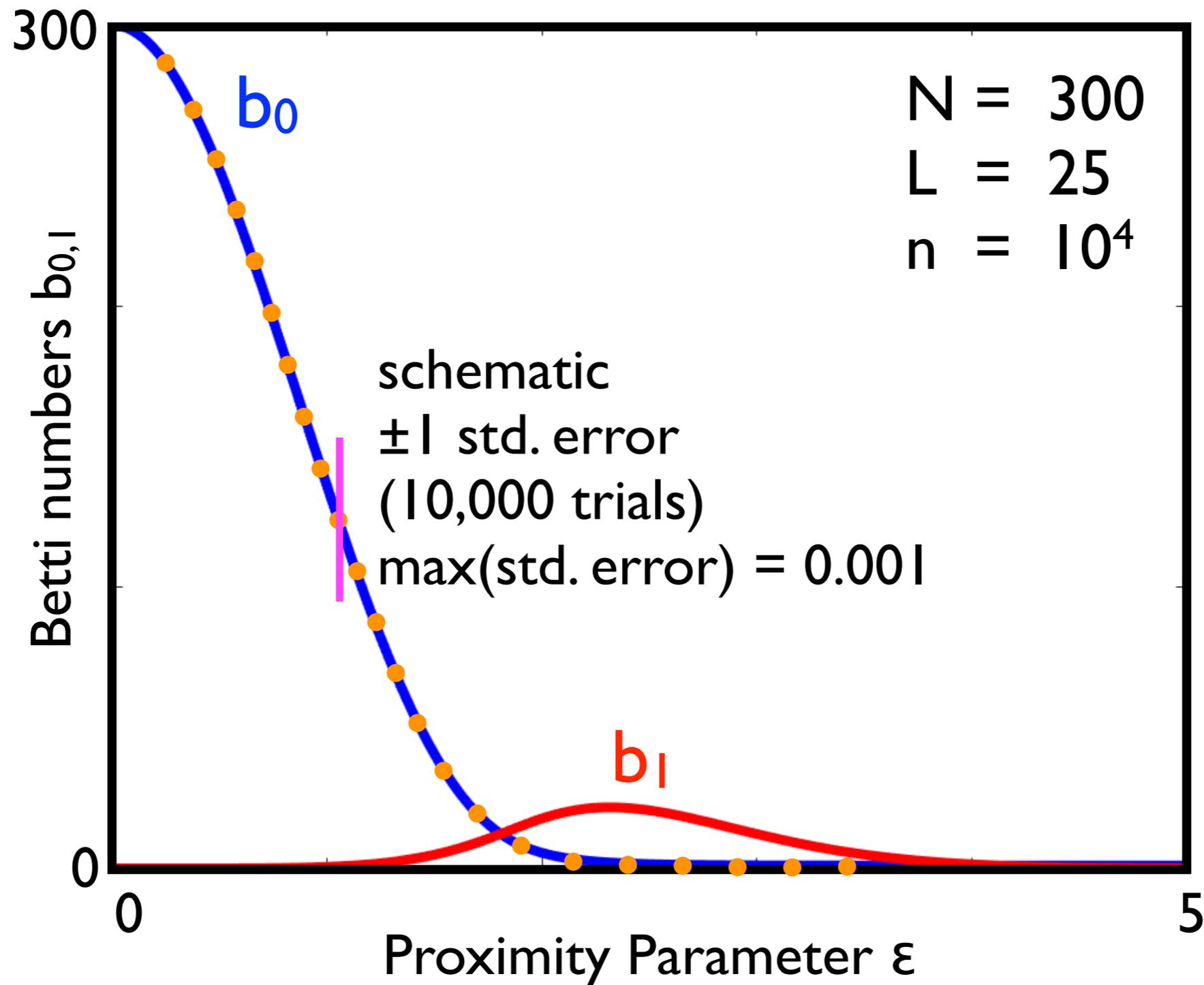
$$h(x_1, x_2, \dots, x_k) = \begin{cases} 1 & G(\{x_1, x_2, \dots, x_k\}, 1) \text{ is connected,} \\ 0 & \text{otherwise,} \end{cases}$$

and

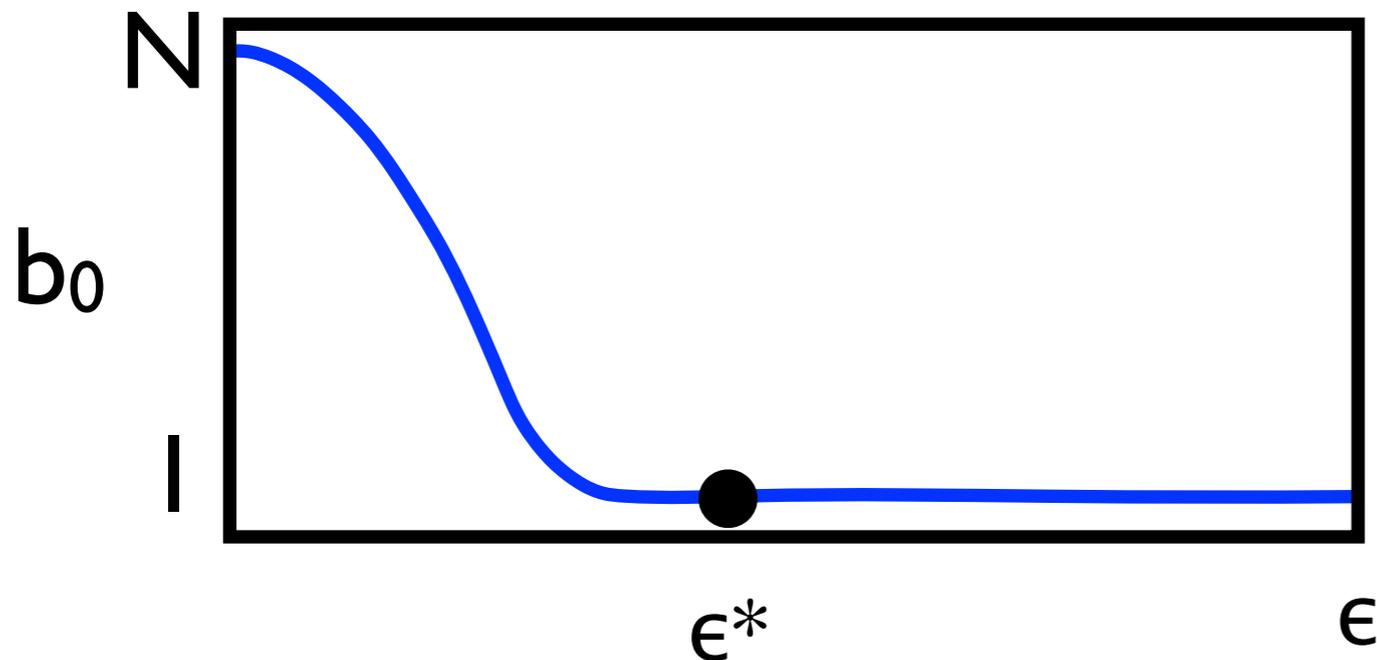
$$A(x_1, x_2, \dots, x_k) := \left| \bigcup_{j=1}^k B_1(x_j) \right|.$$

The infinite sum in (3.2) comes from the fact that we need to count the number of components consisting of any possible number of vertices. The limiting expression provided by the theorem is highly intricate, and at this point impossible to evaluate analytically. Nonetheless, as we will

What is the homology of a random points on flat torus?



Try modeling the topological signature.

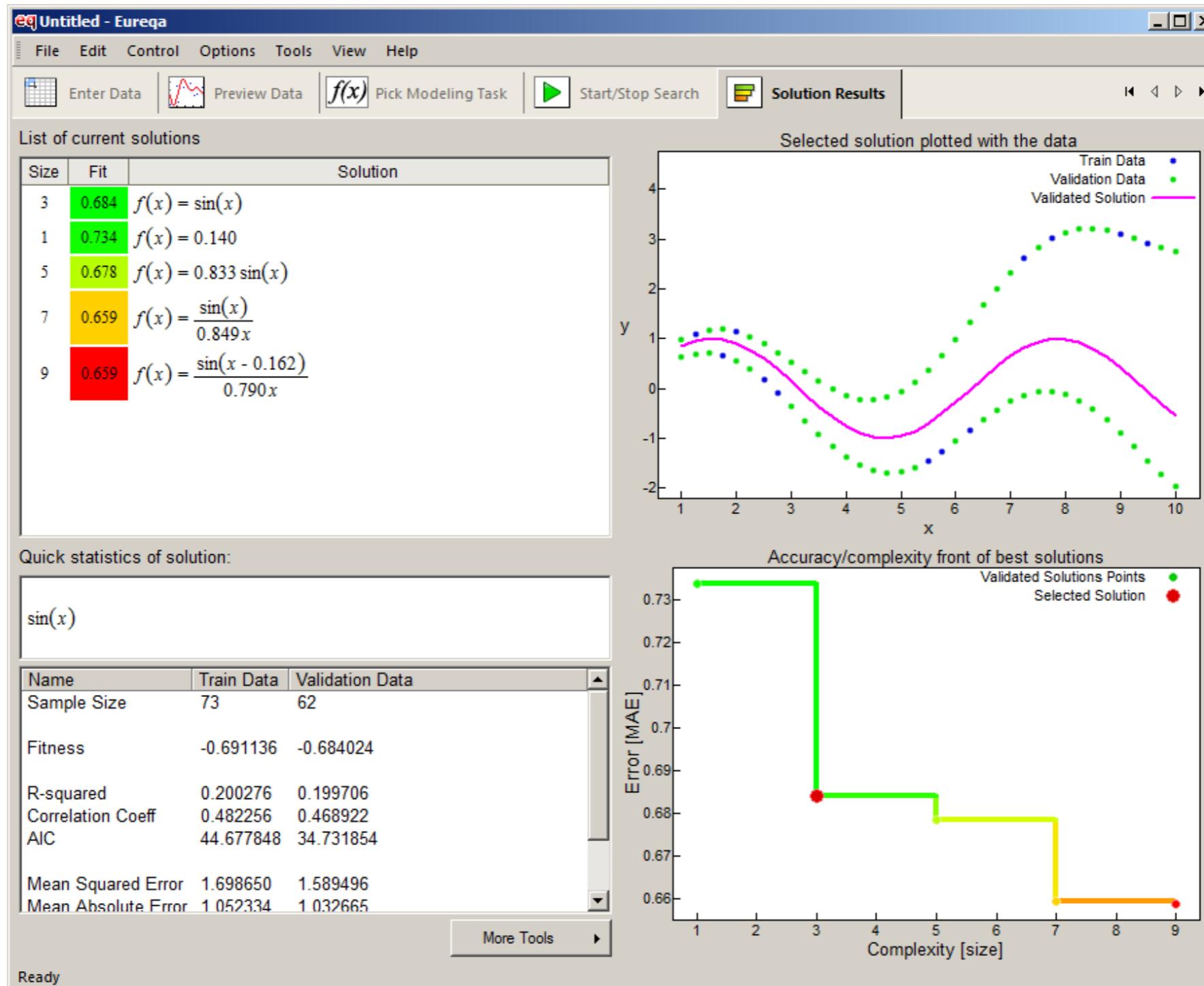


+ dimensional analysis

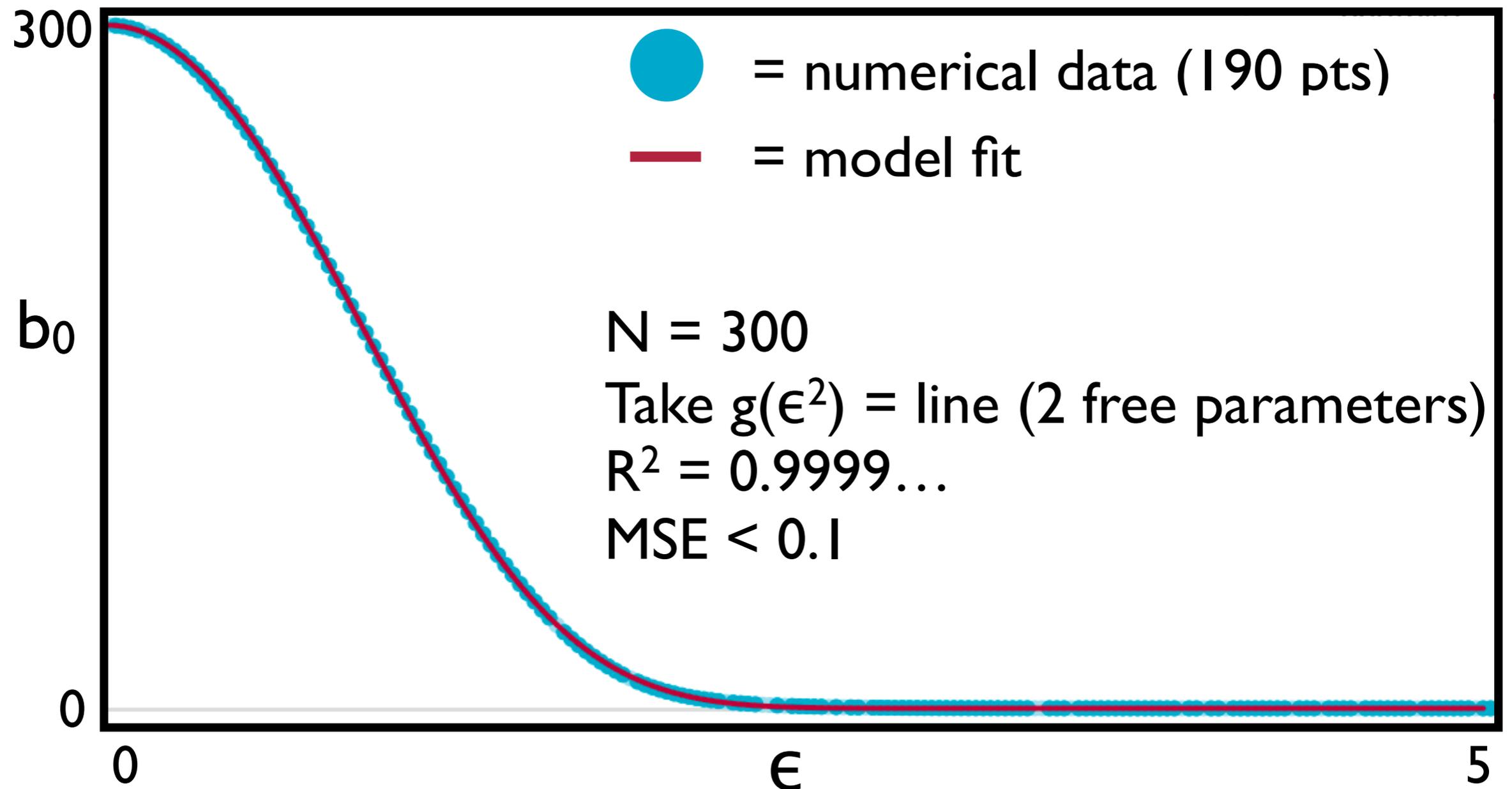
Let $b_0(\epsilon) = 1 + (N - 1) \cdot f(\epsilon^2)$, $f(0) = 1, f(\epsilon^2) = 0$ for $\epsilon \geq \epsilon^*$

$$f(\epsilon^2) = \exp \left[\frac{1}{g(\mathbf{0})\epsilon_*^2} - \frac{1}{\epsilon_*^2 - \epsilon^2} \frac{1}{g(\epsilon^2)} \right]$$

Try modeling the topological signature.



Try modeling the topological signature.



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Message: TDA can be a useful tool for exploratory data analysis

Part II: Moving towards topological reductions of a complex system

Message: When dynamics are neither highly ordered nor totally random, a topological description might be appropriate, but the approach is analytically challenging



Applied mathematical modeling with topological techniques Summer (???) 2019

Organizers:

Henry Adams, Colorado State University

Maria D'Orsogna, Cal State Northridge

Rachel Neville, University of Arizona

Jose Perea, Michigan State University

Chad Topaz, Williams College
