

Topological Data Analysis of Stochastic Collective Motion

Chad Topaz (Williams College)

Lori Ziegelmeier, Tom Halverson (Macalester College)

NSF DMS-1412674



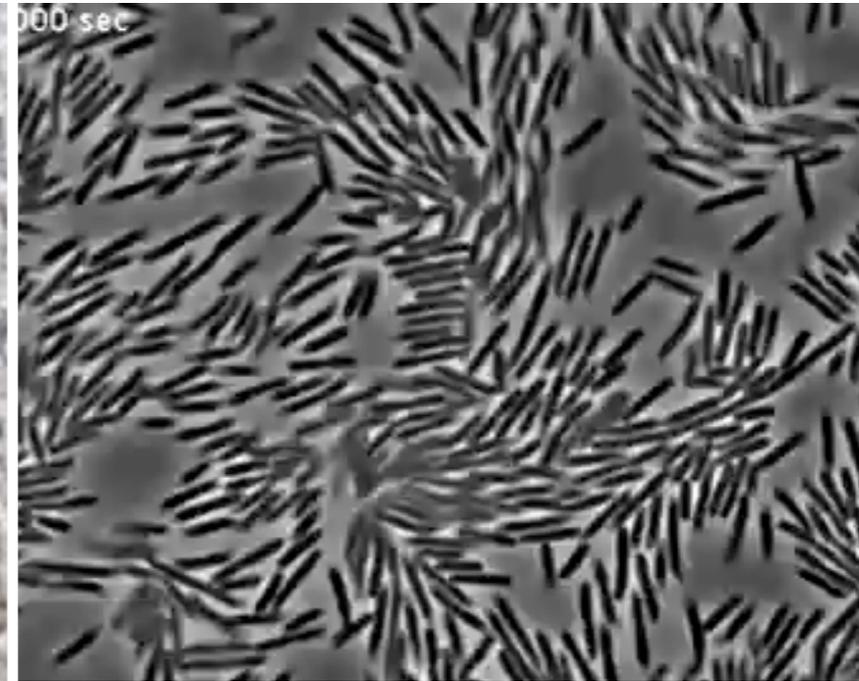
Owen Humphries/PA Wire

Main point of this tutorial.

- **Topological data analysis** (TDA) is a powerful tool for computing and describing the topology of data.
- TDA of time series aids the analysis of **large data sets** arising from collective motion.
- Topological time series of collective motion models have a **coherent average**.

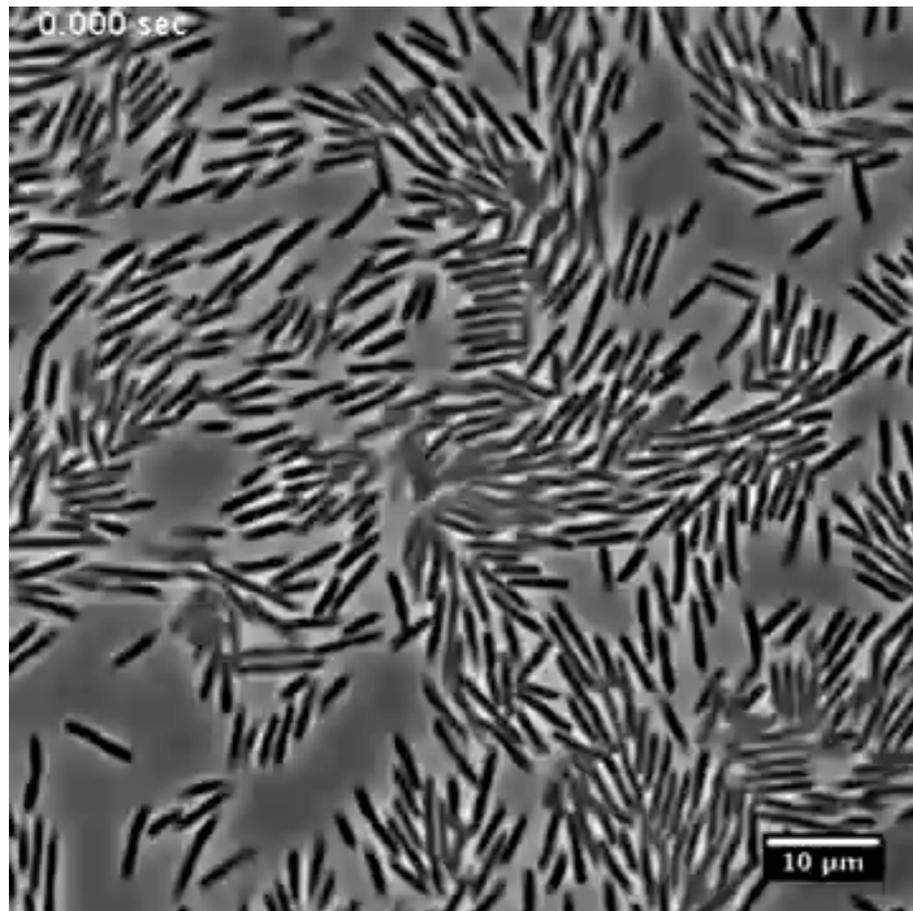


Collective motion occurs across the natural world.



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. Inside the envelope, the following text is displayed:

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

240,000 pieces of information

MS78

Topological Data Analysis of Time Series from Dynamical Systems

8:30-8:55 Topological Data Analysis of Stochastic Collective Motion
Chad M. Topaz, Macalester College, USA

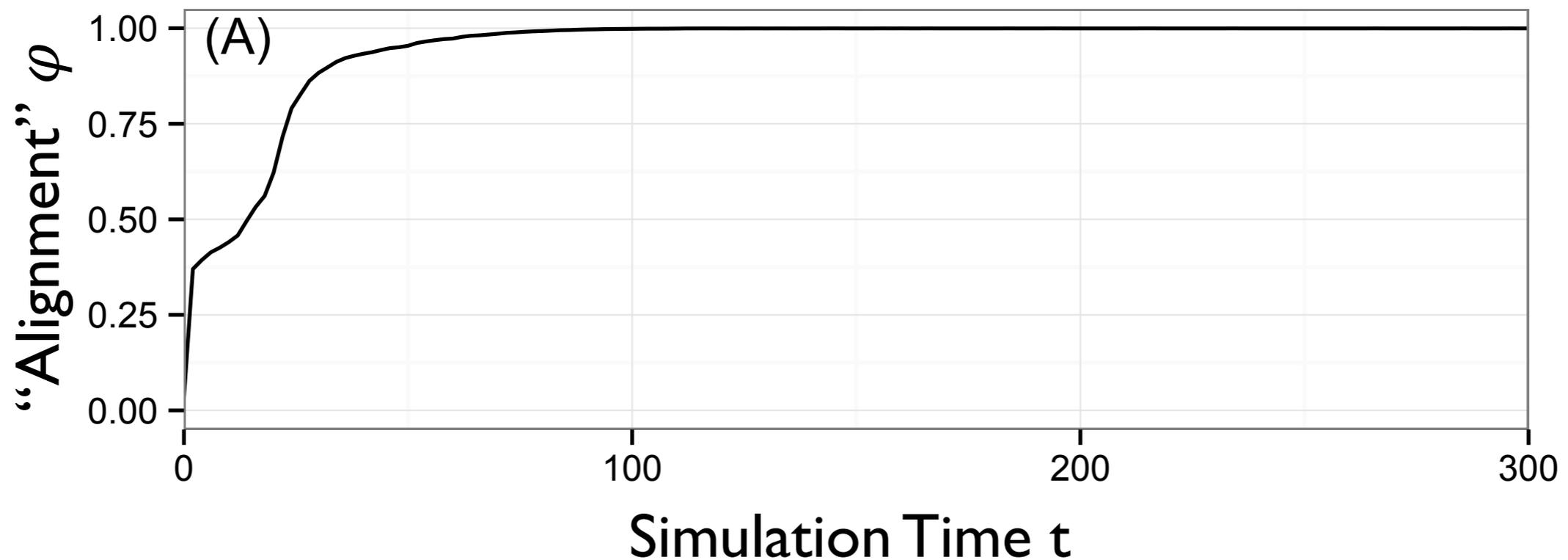
9:00-9:25 Combinatorial Approx. and Discrete-Time Dynamics
Sarah Day, College of William & Mary, USA

9:30-9:55 Classification of Pattern-Forming Systems Using Persistence
Rachel Neville and *Patrick Shipman*, Colorado State University, USA

10:00-10:25 Witness Complexes for Time Series Analysis
Nicole Sanderson, University of Colorado, USA

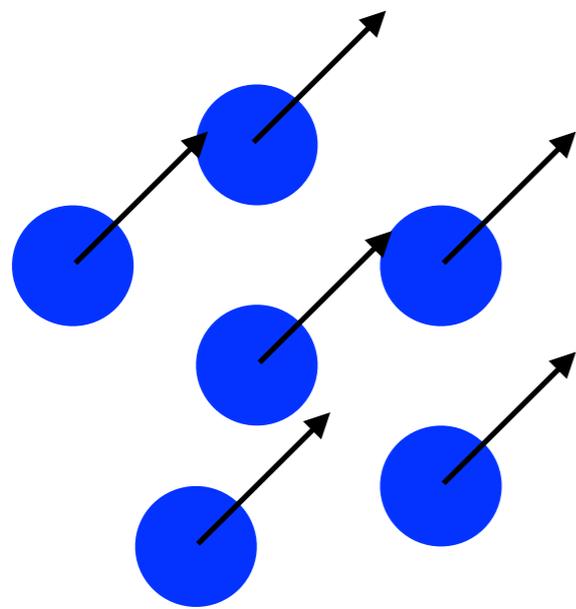
Dynamics are often assessed via order parameter time series.

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

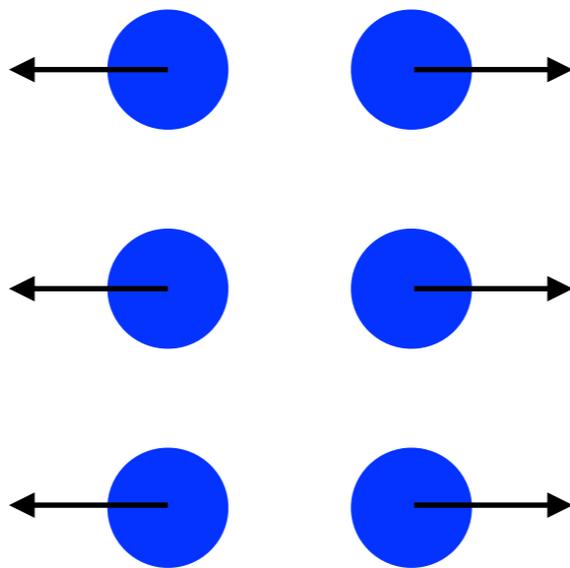


Dynamics are often assessed via order parameter time series.

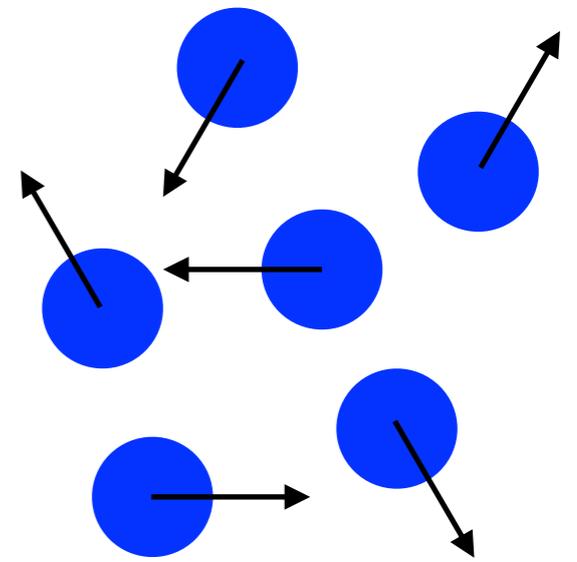
Alignment order parameter: $\varphi(t) = \frac{1}{Nv_0} \left| \sum_{i=1}^N \mathbf{v}_i(t) \right|$



$$\varphi = 1$$



$$\varphi = 0$$

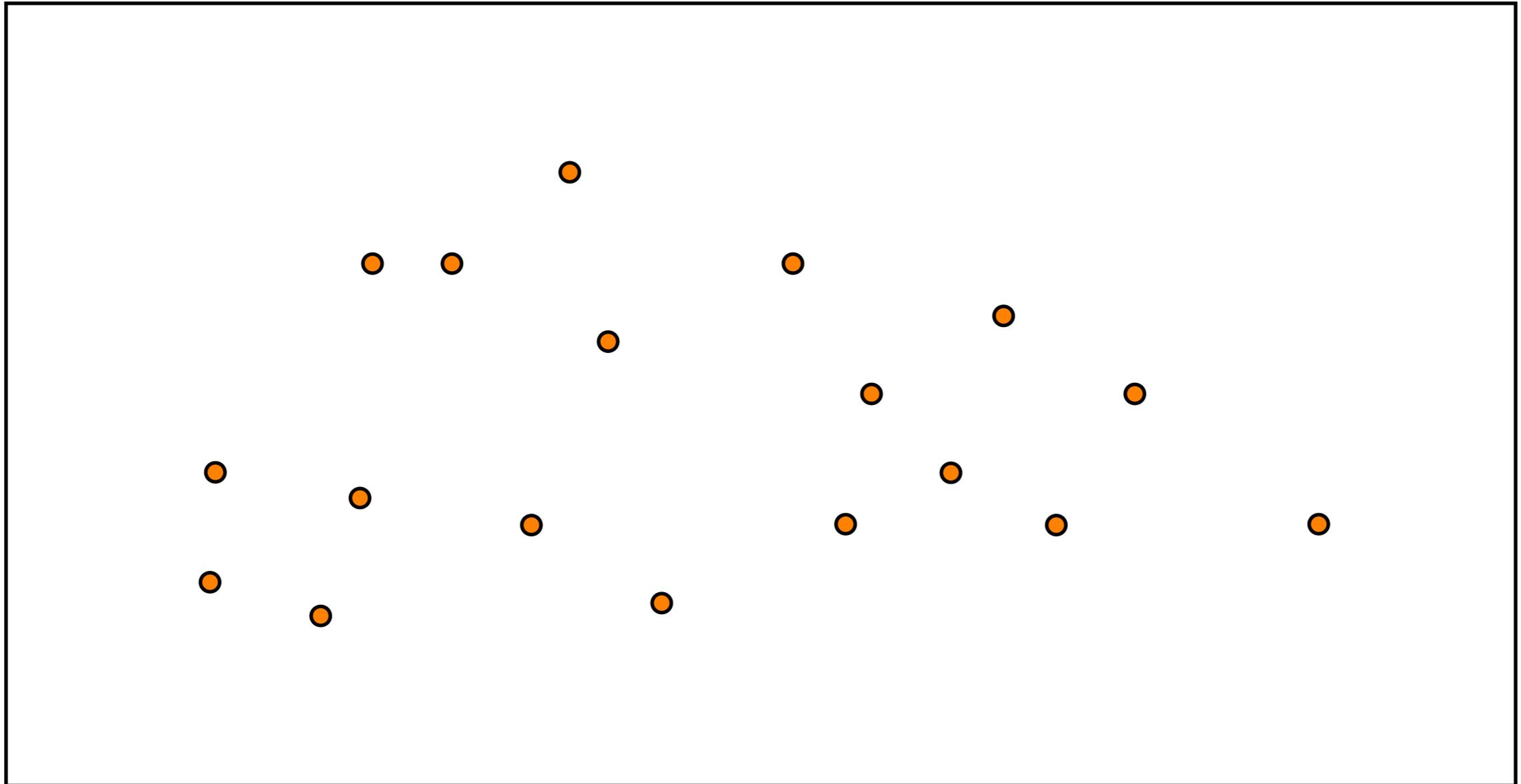


$$\varphi = 0$$

Study data via topology.

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



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Topological Data Analysis of Time Series from Dynamical Systems

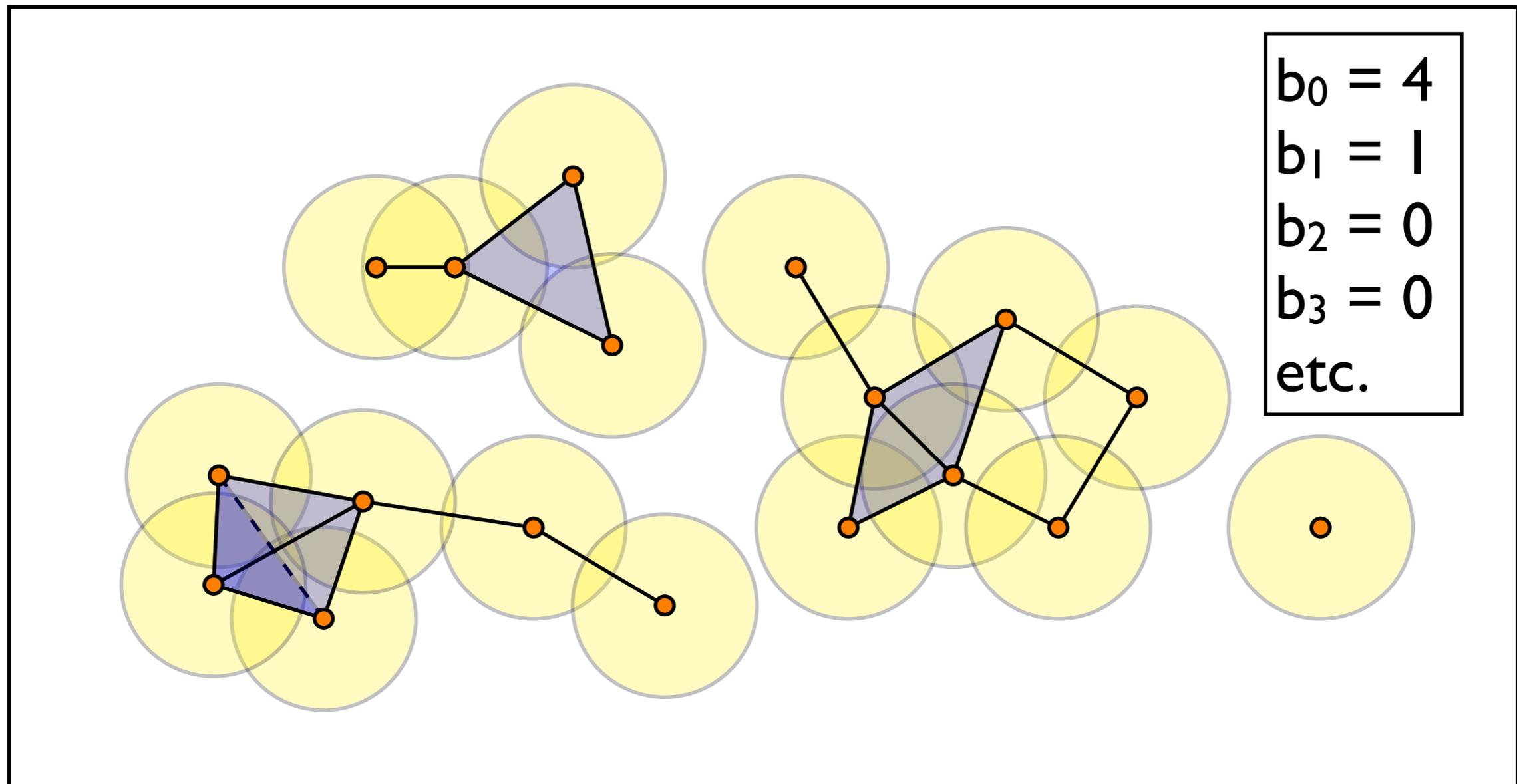
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Step 3: Calculate Betti numbers



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

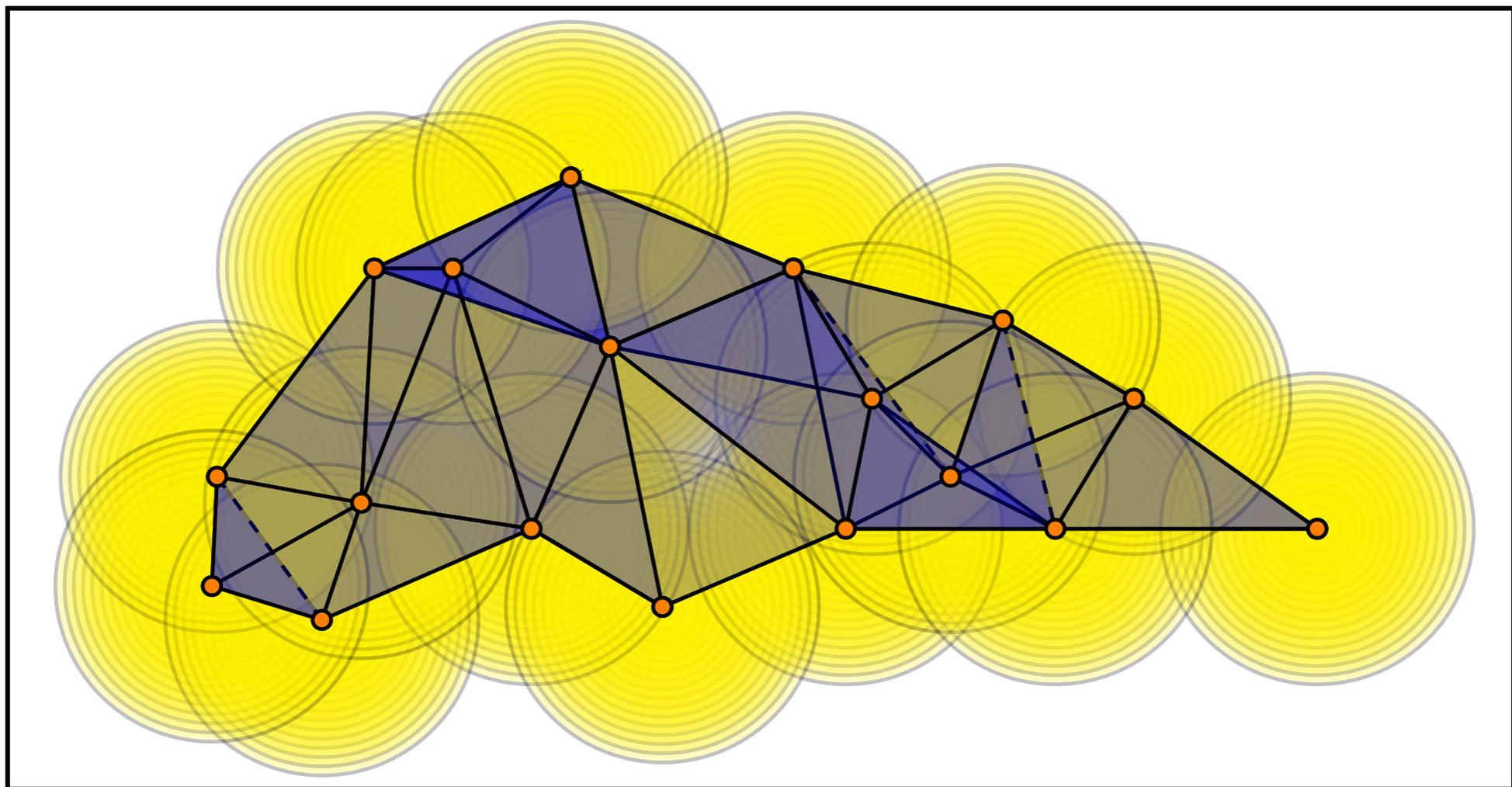
A full-color Extravaganza



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



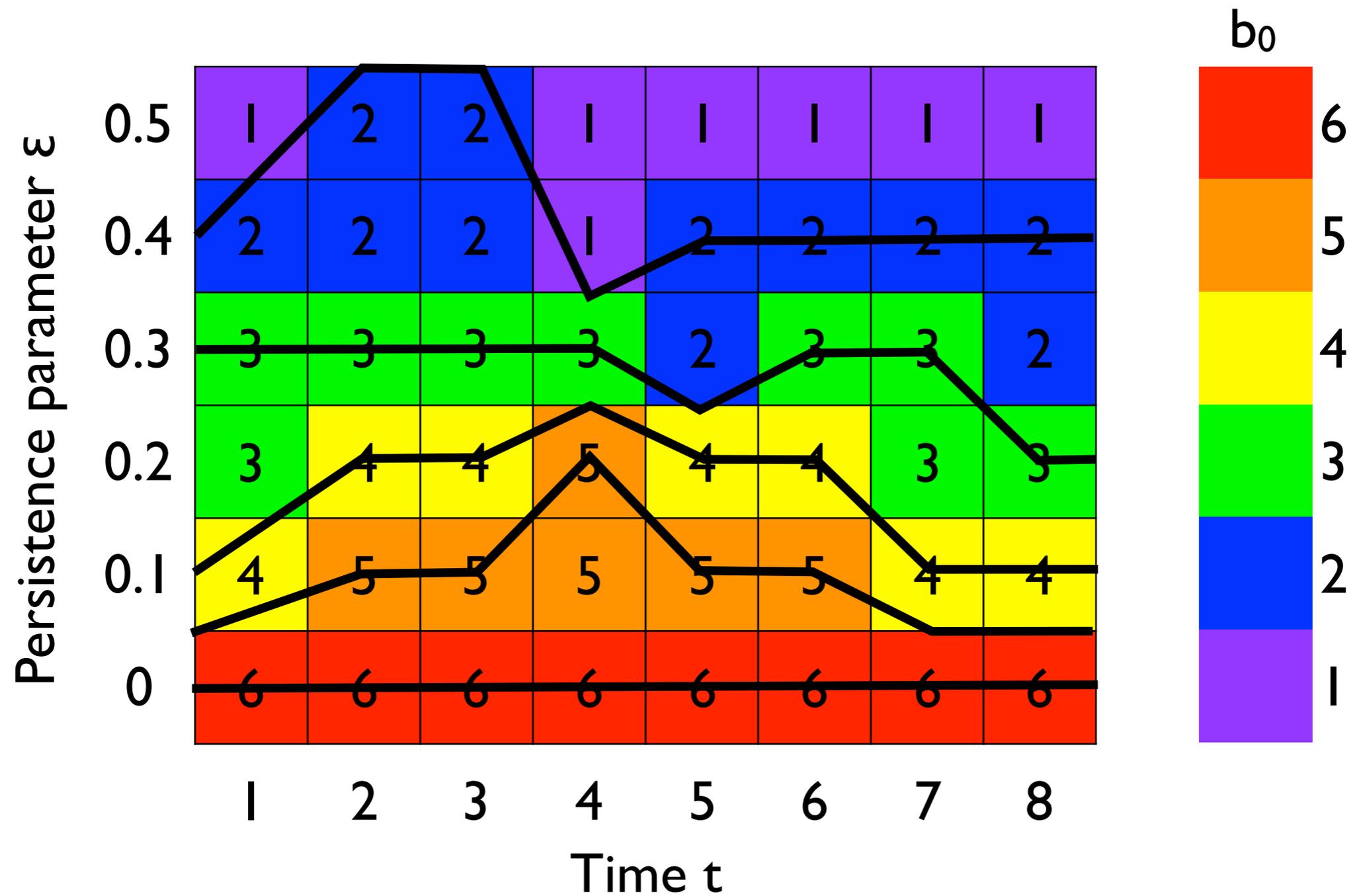
Step 4: Find persistent homology



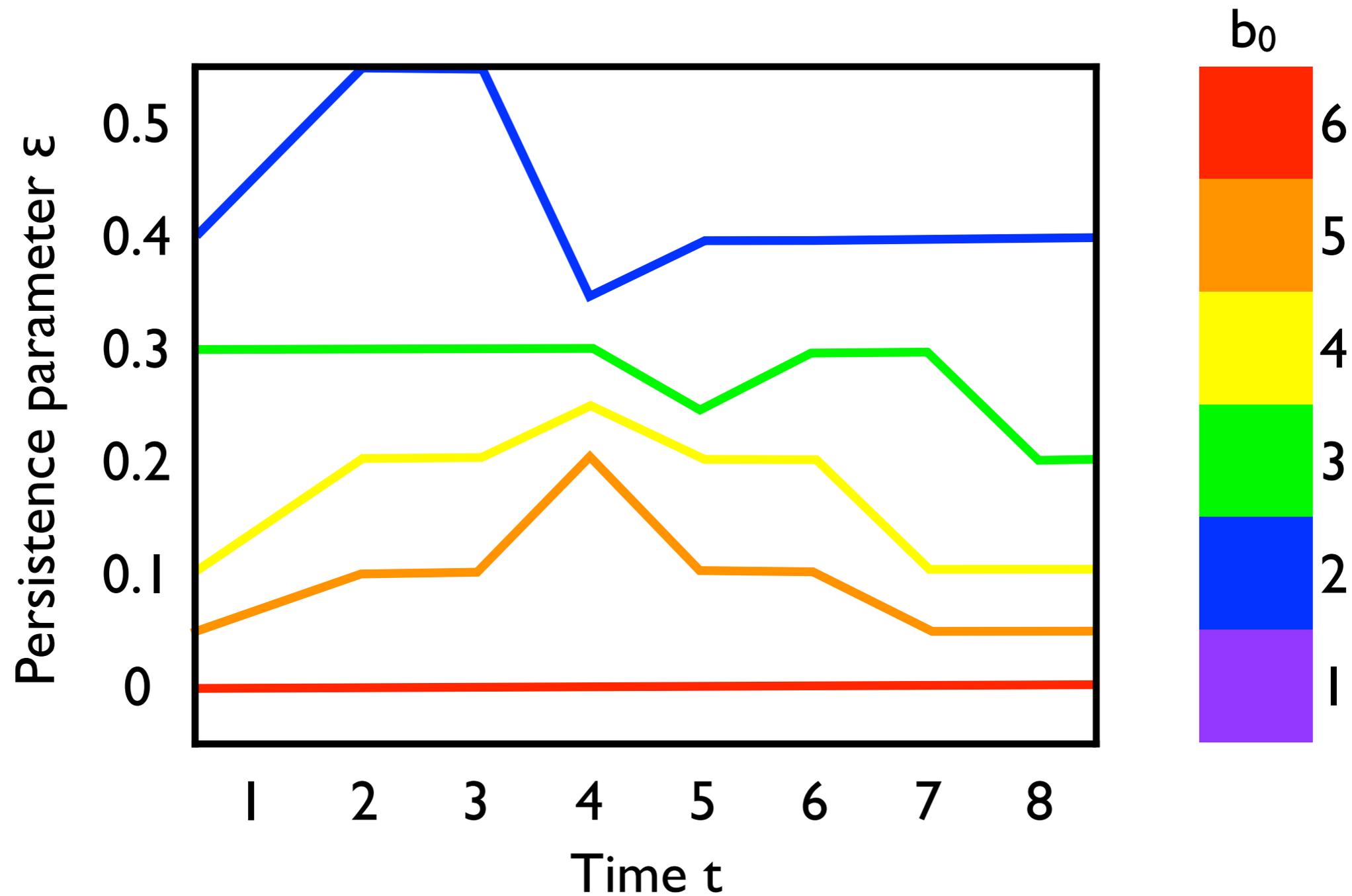
Step 4: Find persistent homology



Step 5: Evolve in time



Step 5: Evolve in time





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Topological Data Analysis of Time Series from Dynamical Systems

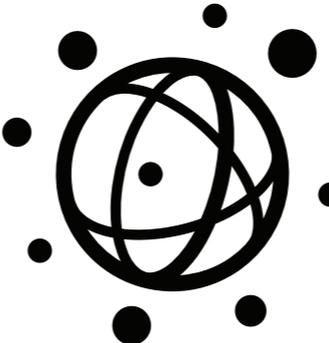
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RESEARCH ARTICLE

Topological Data Analysis of Biological Aggregation Models

Chad M. Topaz*, Lori Ziegelmeier, Tom Halverson



topologist



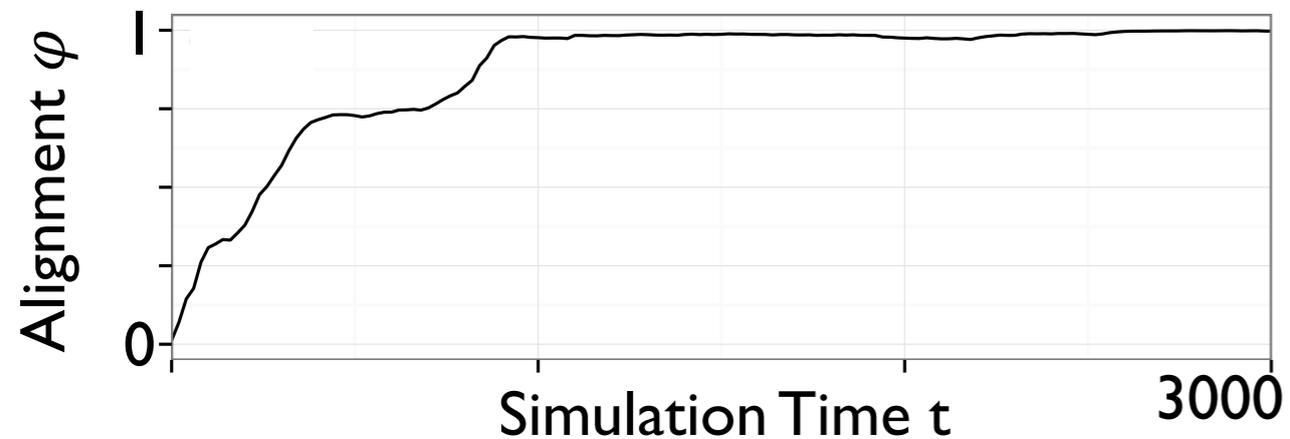
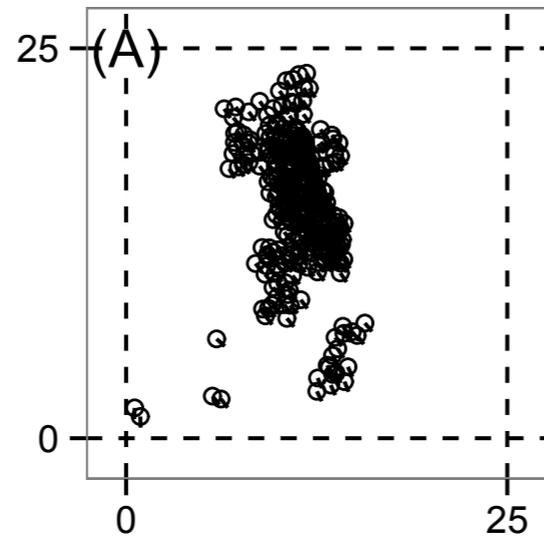
teaches topology



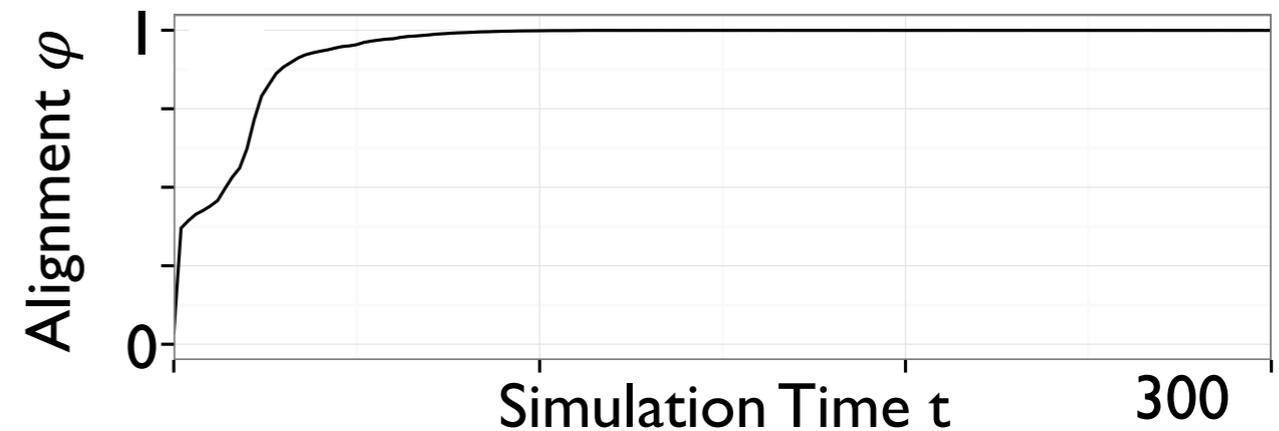
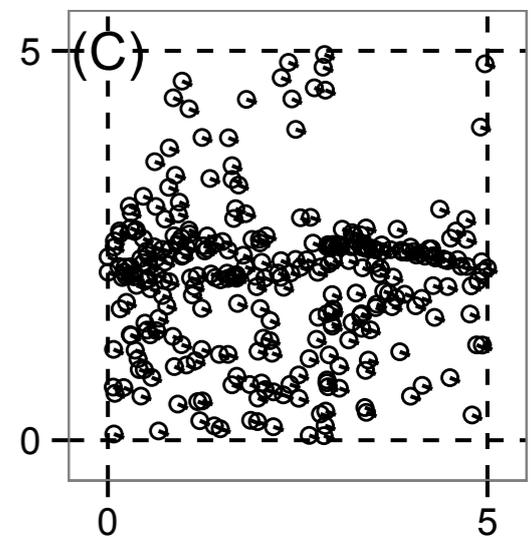
never even took topology

Order parameter time series that look similar...

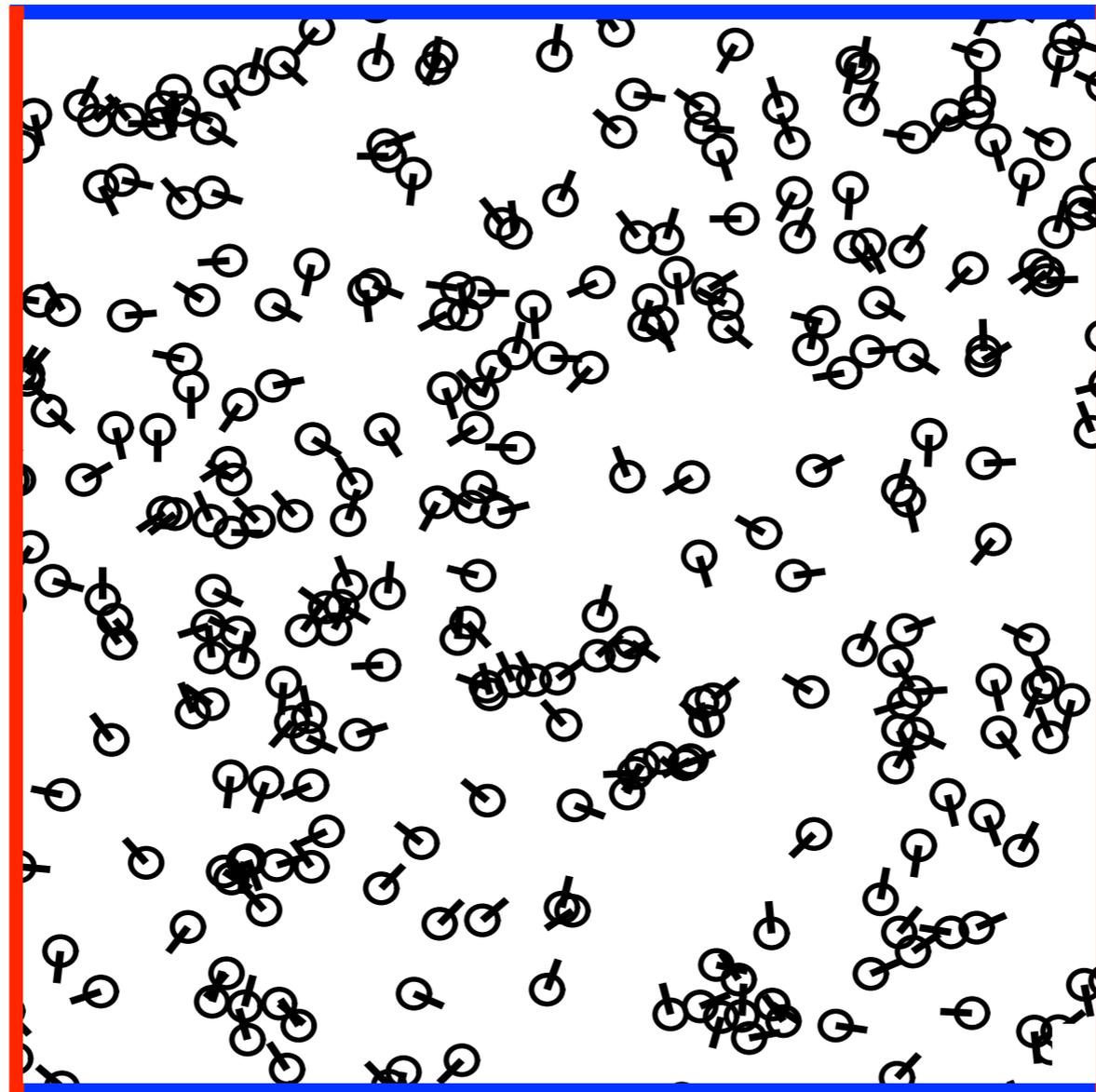
Parameter
Set #1



Parameter
Set #2



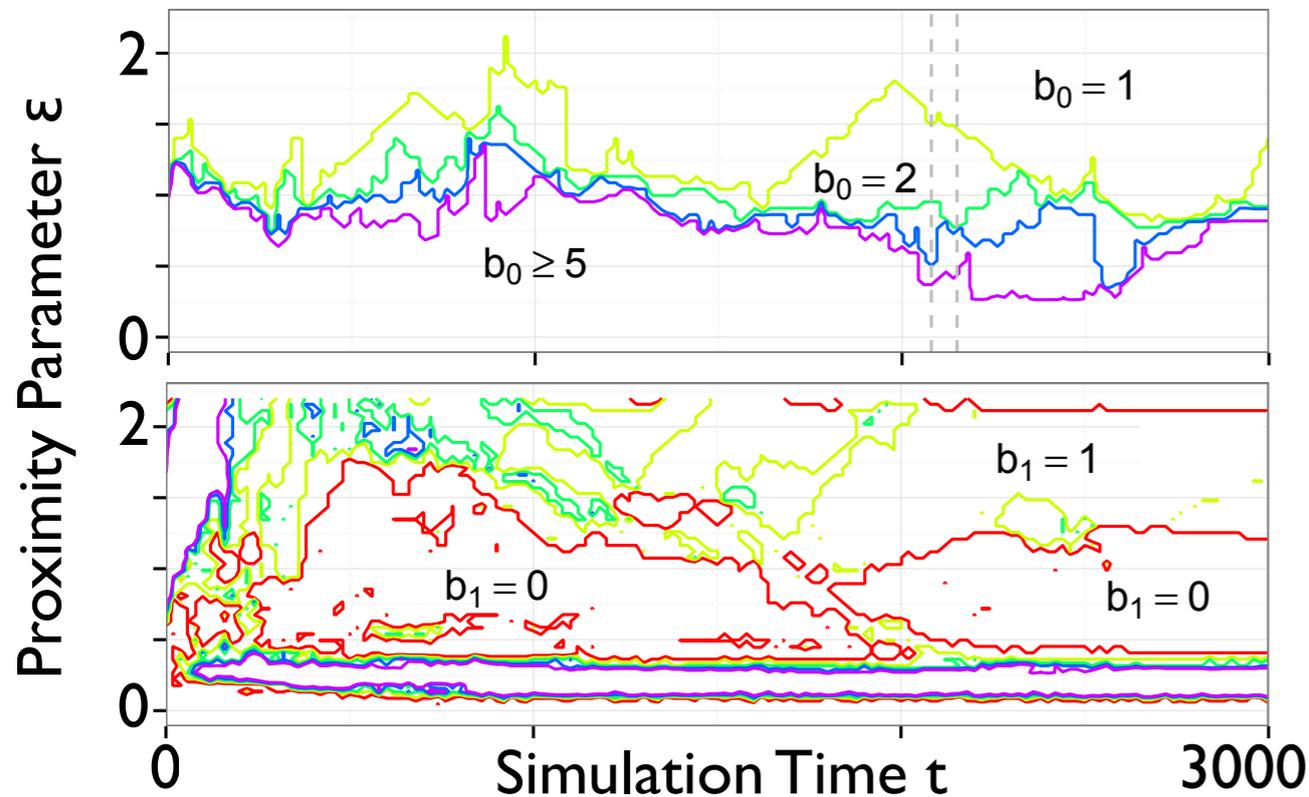
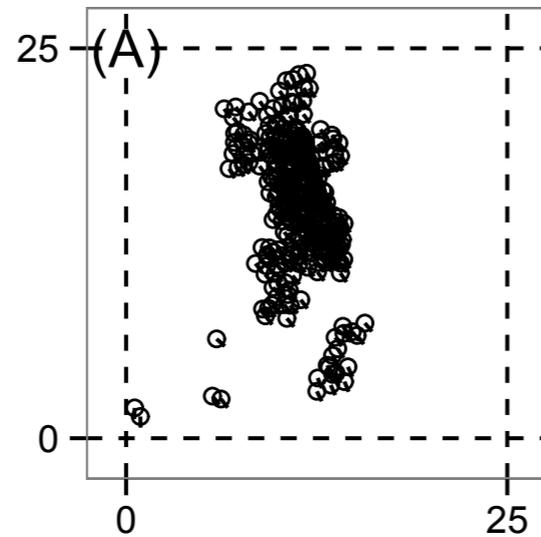
Random initial cond. for Vicsek model covers a three-torus.



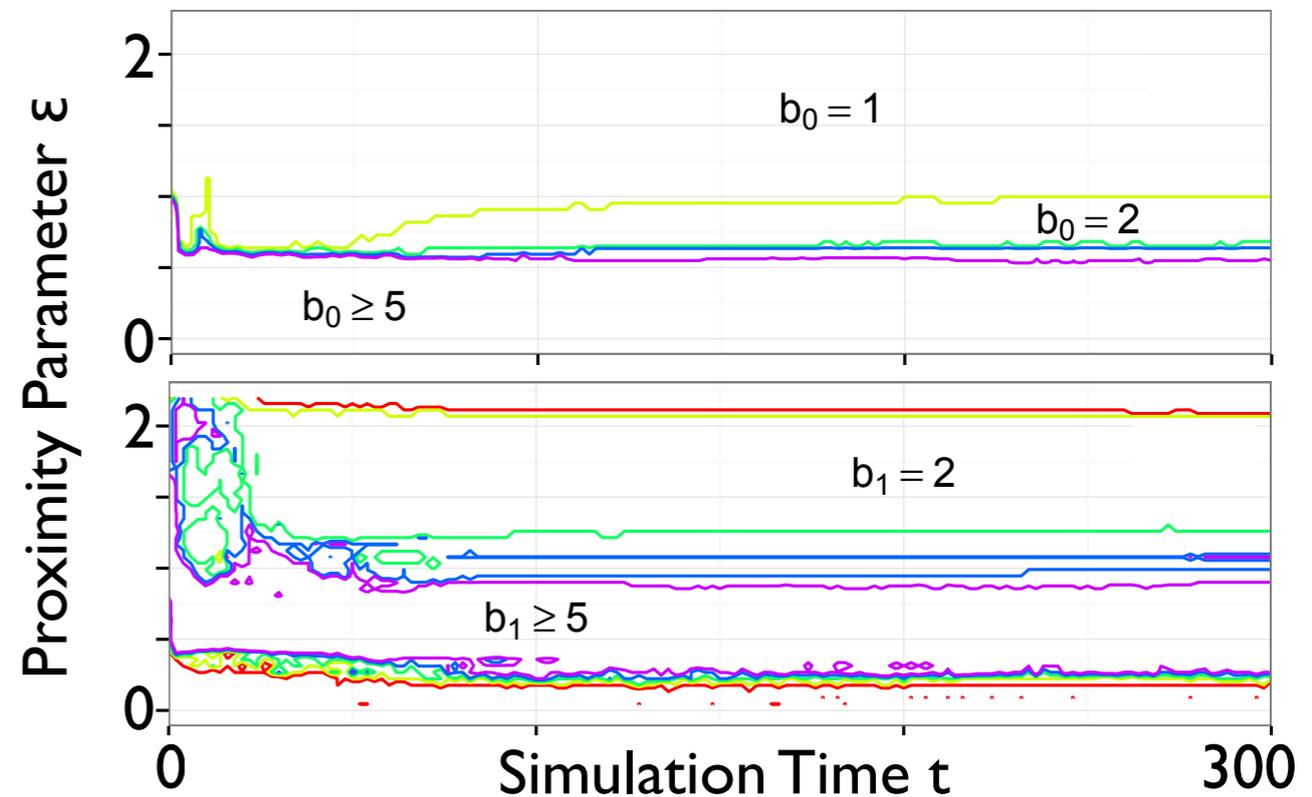
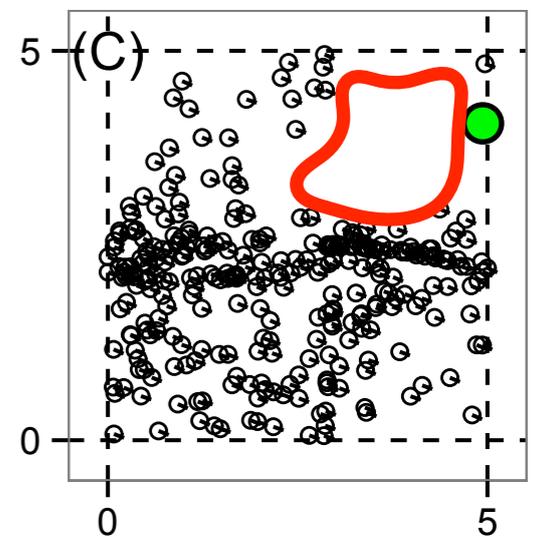
Three-torus T^3
 $b = (1, 3, 3, 1, 0, \dots)$

...can have drastically different topological signatures.

Parameter Set #1



Parameter Set #2



Main points of this tutorial-style talk:

- **Topological data analysis** (TDA) is a set of tools for computing and describing the shape of data ✓
- TDA of time series aids the classification of **large data sets** arising from collective motion ✓
- Topological time series of collective motion models have a **coherent average**



XII.P.

HECEST HORRENDA
CARIBDIS

D

F

HUST

LOIOT

VAST

DIA

HELGALA
TERRA NOBILIVM

ROOPEDVM

STEK

NISCA

HORV PISCI
CAPITIBVS
VTVNTVR
LOCO LIGNI

NYGAVIK

GAMBIA

DUVANES

TANVANES TRODANES

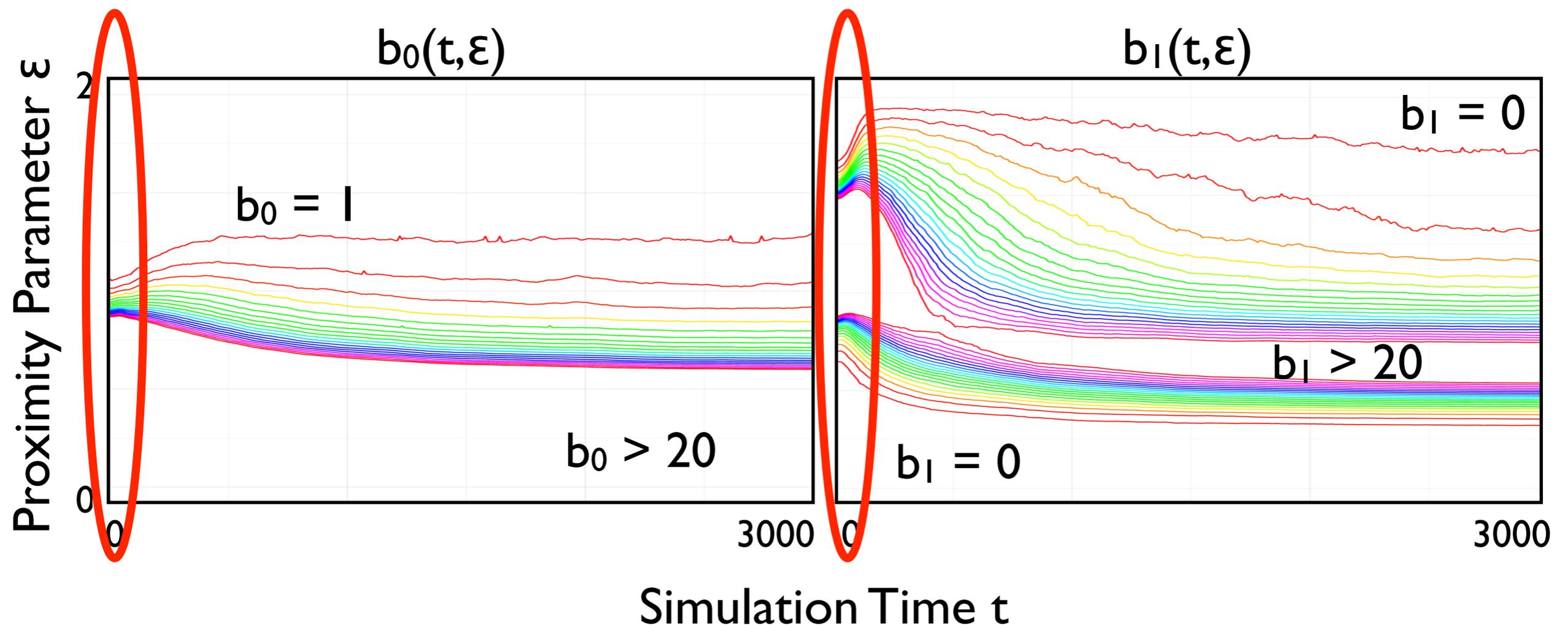
Main point this tutorial-st



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Do time series of random processes have average homology?

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



What is the homology of a random complex?

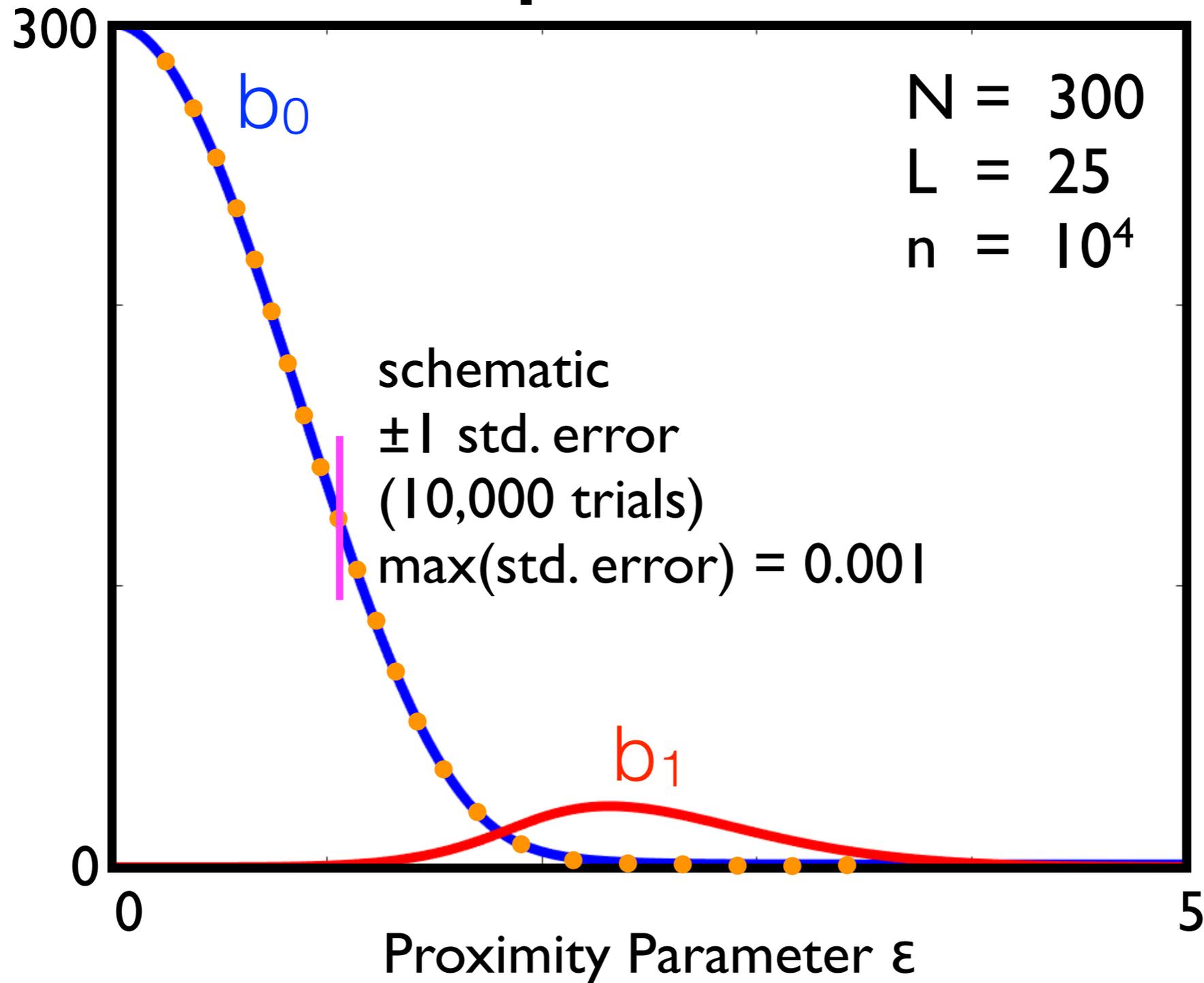
Topology of random simplicial complexes:
A Survey (Matthew Kahle, preprint, 2014)

THEOREM 4.3. *Let $\alpha > 0$ be fixed, $p = n^{-\alpha}$,
and $X \sim X(n, p)$. If $1/(k+1) < \alpha < 1/k$, then*

$$\frac{\mathbb{E}[\beta_k]}{\binom{n}{k+1} p^{\binom{k+1}{2}}} \rightarrow 1,$$

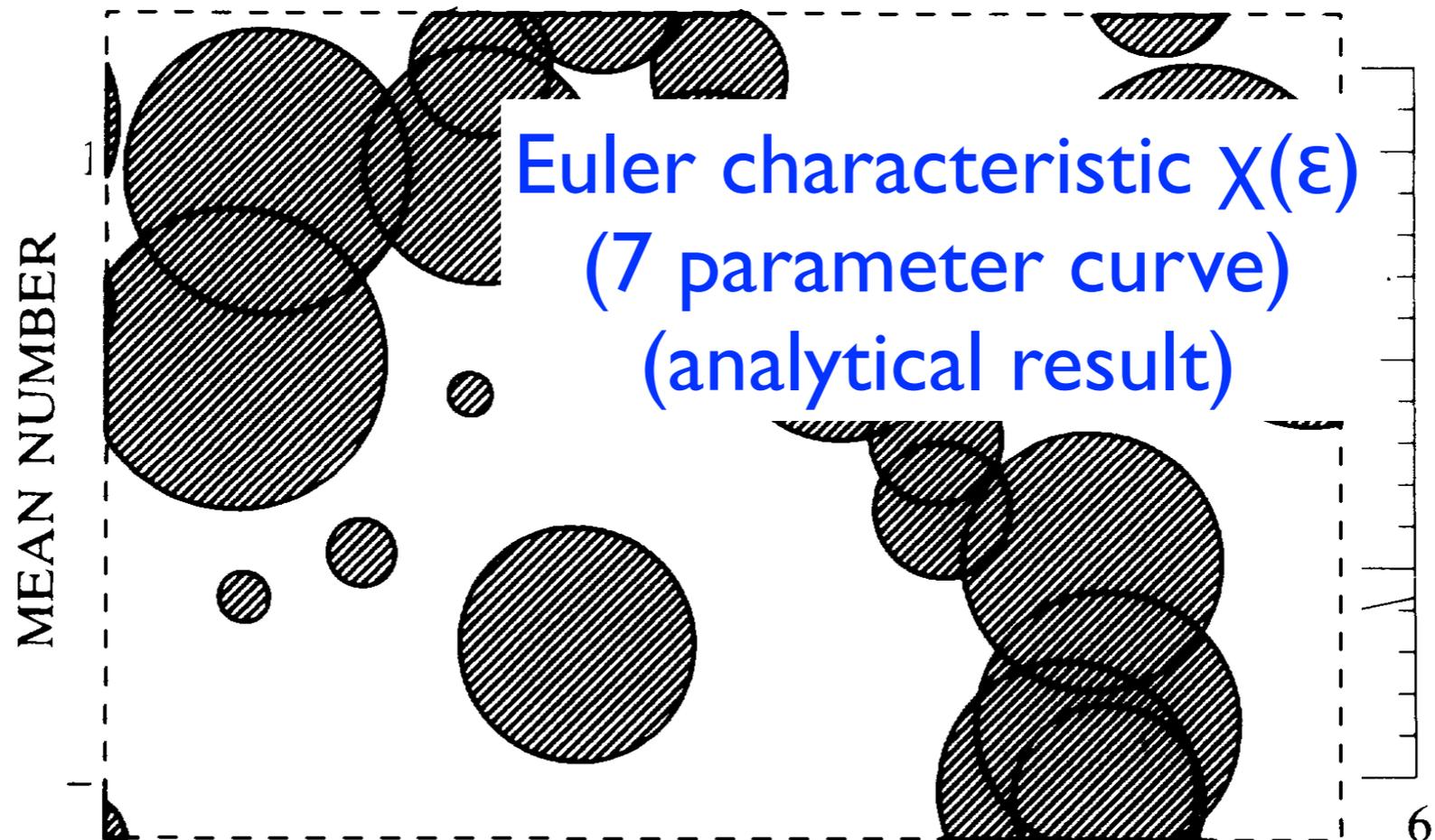
as $n \rightarrow \infty$.

What is the homology of a random complex with N finite?



Euler characteristic is known for poisson points in the plane.

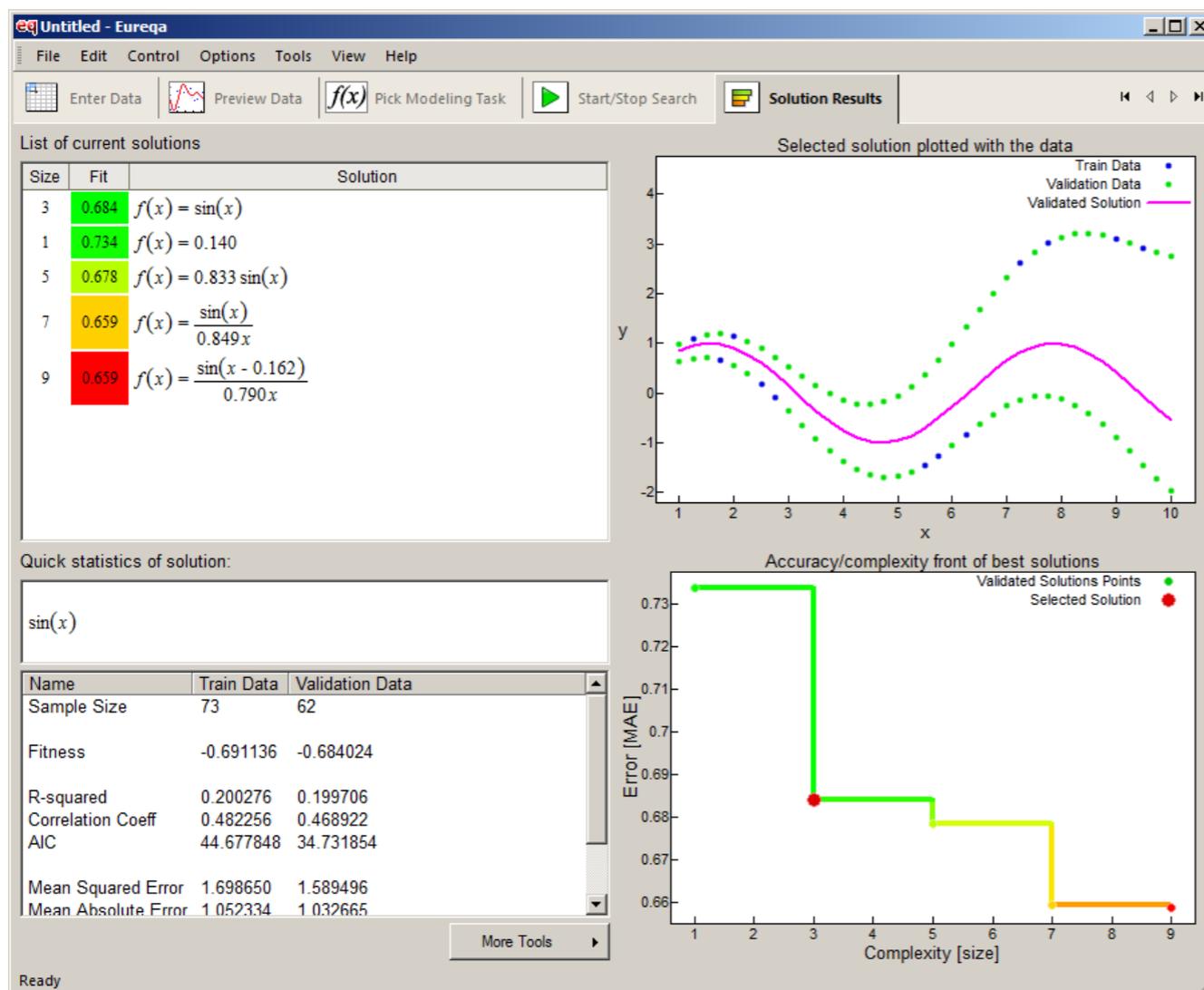
On the number of clumps resulting from the overlap of randomly placed figures in a plane
(A.M. Kellerer, J.Appl. Prob., 1983)



Dimensional analysis + limiting behavior + machine learning?

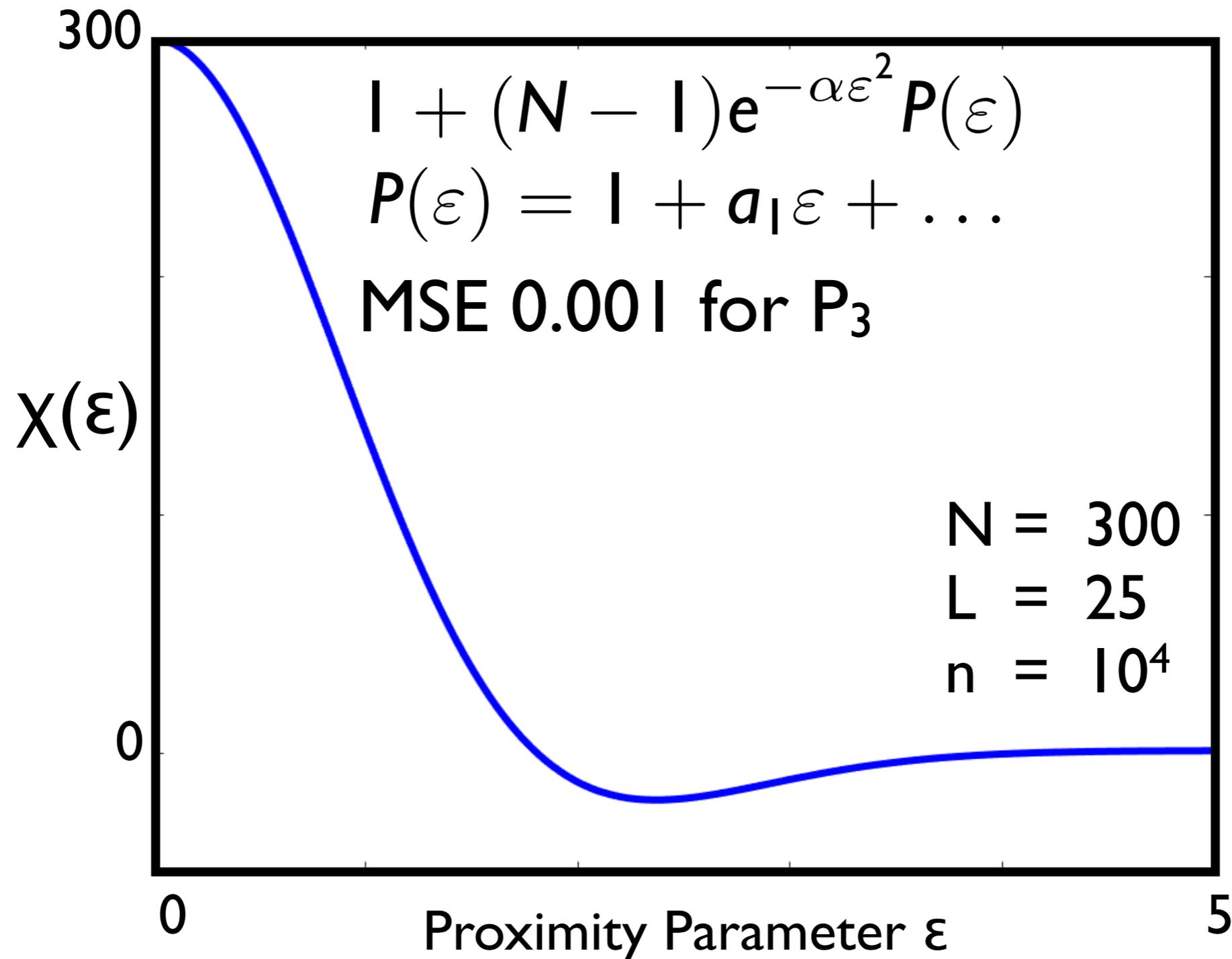
$$\chi(\varepsilon; N, L) = 1 + (N - 1)f(\varepsilon/L, N)$$

$$f(0, N) = 1 \quad \lim_{\varepsilon \rightarrow \infty} f(\varepsilon/L, N) = 0$$



Eureka
see SIAM DSI5 Plenary
“Automating Discovery”
by Hod Lipson

Computer-generated model provides a reasonable fit.



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- **Topological data analysis** (TDA) is a set of tools for computing and describing the shape of data ✓
- TDA of time series aids the classification of **large data sets** arising from collective motion ✓
- Topological time series of collective motion models have a **coherent average**... what is it? ✓

<http://www.ams.org/profession/2018MRC-Agent>

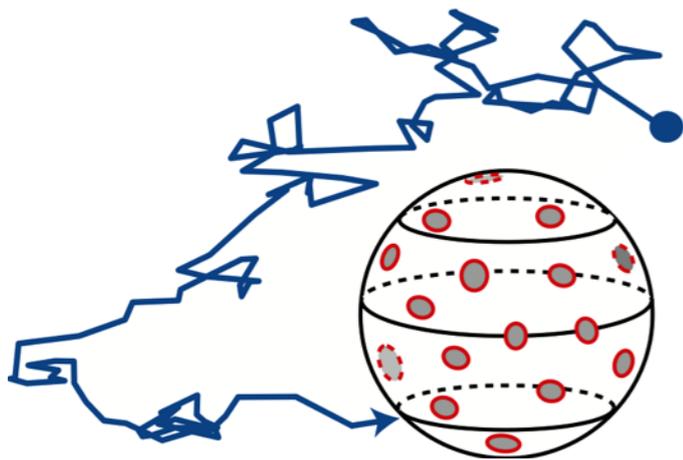
American Mathematical Society Mathematics Research Community

Agent-Based Modeling in Biological and Social Systems

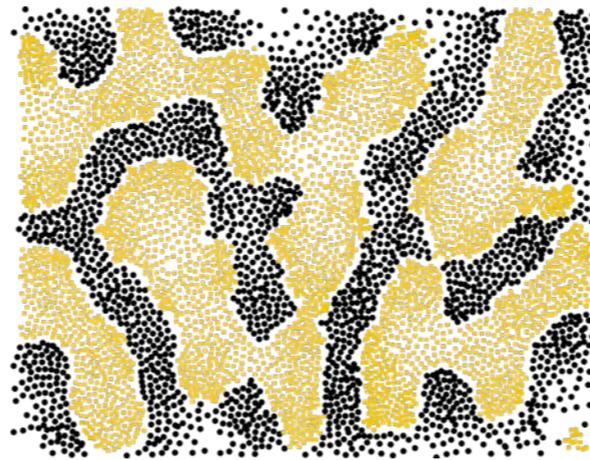
A practicum for graduate students and recent PhD's
June 17 - 23, 2018

Whispering Pines Conference Center, West Greenwich, Rhode Island

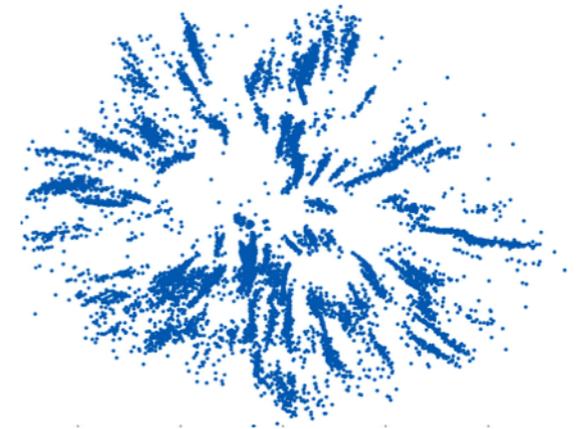
Andrew Bernoff (Harvey Mudd College), Leah Edelstein-Keshet (University of British Columbia), Alan Lindsay (University of Notre Dame), Chad Topaz (Williams College), Alexandria Volkening, (MBI @ Ohio State), Lori Ziegelmeier (Macalester College)



Diffusive signaling problems in chemoreception
(Bernoff & Lindsay 2017)



Agent-based model of zebrafish stripes
(Volkening & Sandstede 2015)



Agent-based model of locust hopper bands
(Bernoff, Devore, Jones, Zhang & Topaz 2017)