



INSTITUTE FOR
MATHEMATICS



STRUCTURES
CLUSTER OF
EXCELLENCE



UNIVERSITÄT
HEIDELBERG
ZUKUNFT
SEIT 1386

Michael Bleher

Institute for Mathematics, Heidelberg University

– 12 DECEMBER 2024, MPI-MCG –

PERSISTENCE AND COARSE-GRAINING IN DYNAMICAL BIOLOGICAL SYSTEMS

A VISION FOR RESEARCH AT MPI-MCG



Homological knot invariants
from 4D gauge theories



M.Sc.

Mathematical Physics

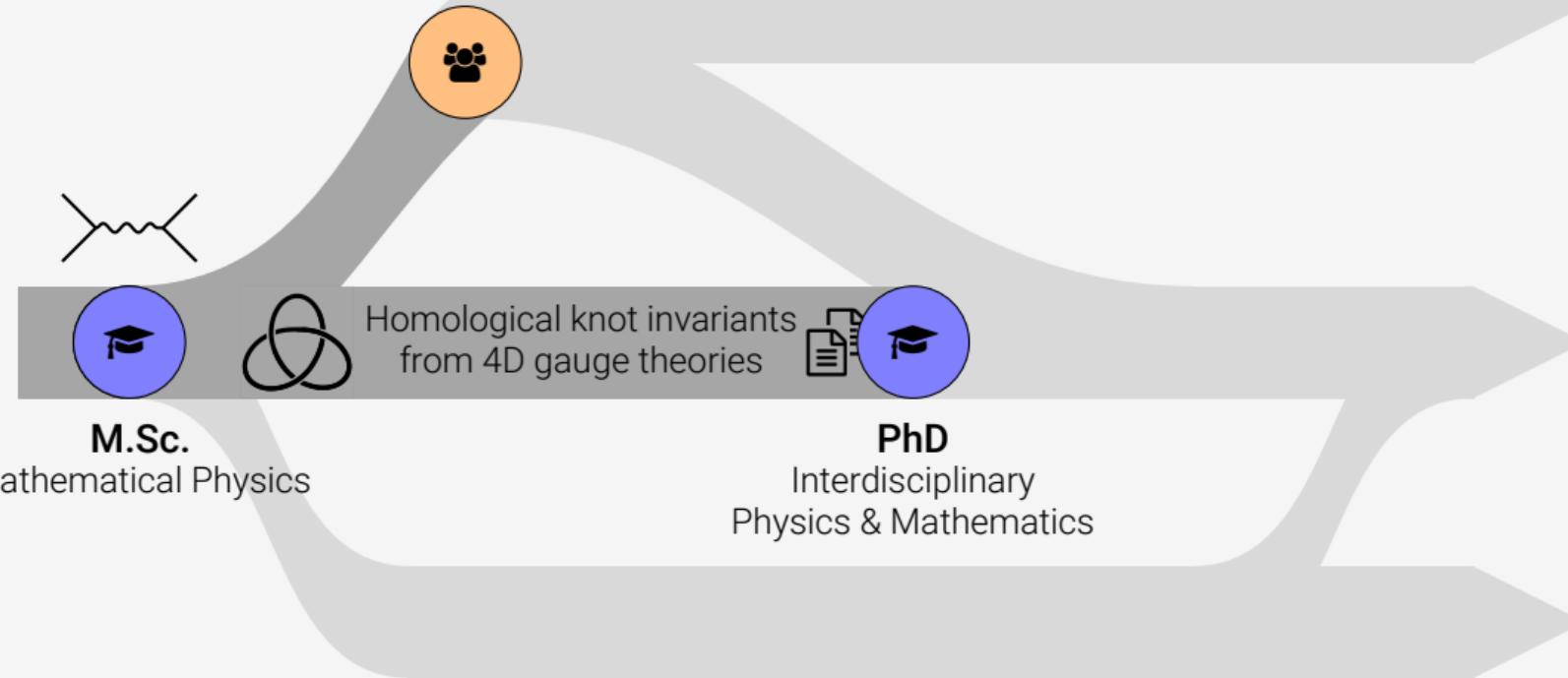
PhD

Interdisciplinary
Physics & Mathematics

TDA Community

EXC STRUCTURES

Seminars, Workshops



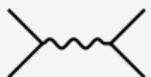
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Topology of
Viral Evolution



Homological knot invariants
from 4D gauge theories



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Viral Evolution - a topologists's perspective

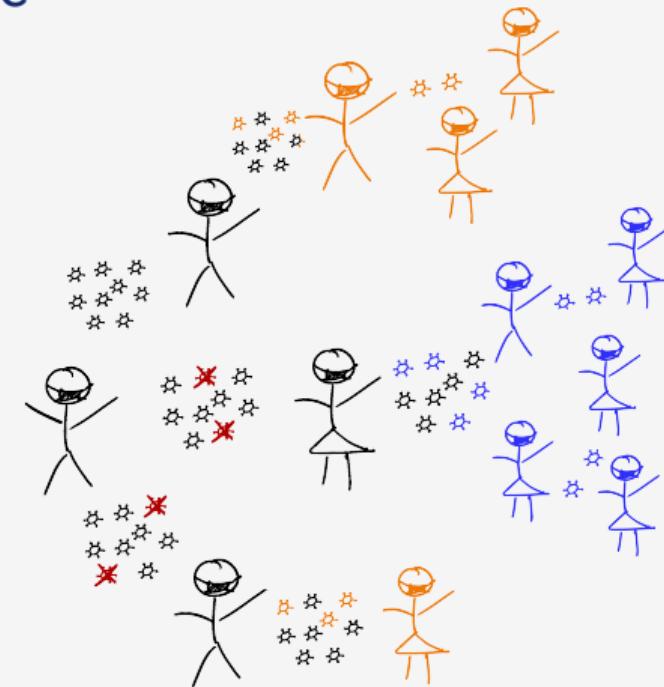
>seq0 date location	>seq3 date location
ATGAAGAGCTTAGTCCTAG	ATGAAGAGCTTAGTCGTAG
>seq1 date location	>seq4 date location
ATGAAGAGCTTGTCTAG	ATGAAGCGCTTGTCTAG

Viral Evolution - a topologists's perspective

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>seq1 date location	>seq4 date location
ATGAAGAGCTT T GTCCTAG	ATGAAGCGCTT T GTC G TAG

Transmission modulates observed mutation frequencies

- not every mutation is beneficial
- wide-spread mutations are not necessarily beneficial (founder effects)
- not every beneficial mutation catches on
- BUT: beneficial mutations tend to **appear repeatedly** (and may then spread more widely)

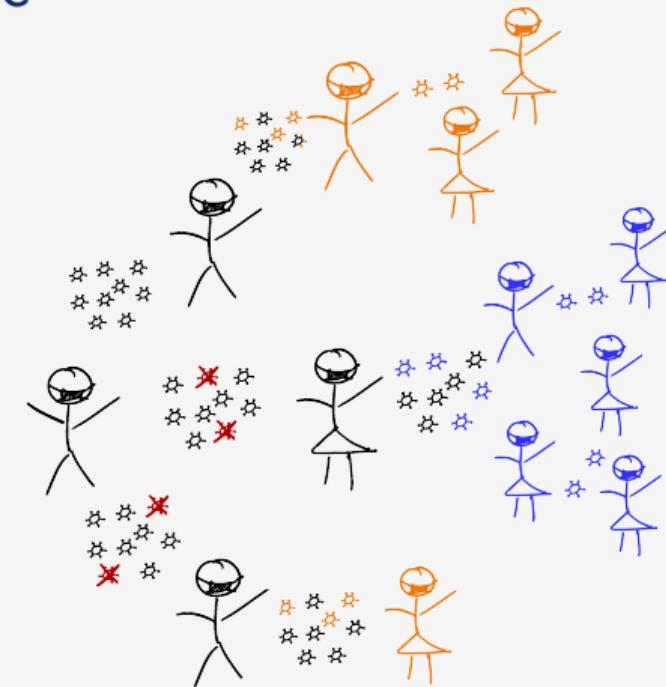


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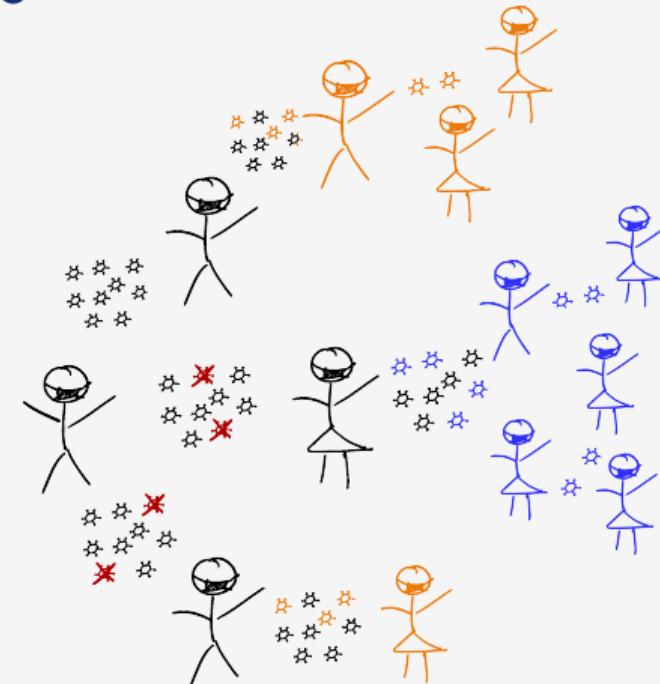
Example: evolution of wings (birds, bats, insects)

Viral Evolution - a topologists's perspective

```
>seq0      >seq3  
..A..C..   ..A..G..  
>seq1      >seq4  
..T..C..   ..T..G..
```

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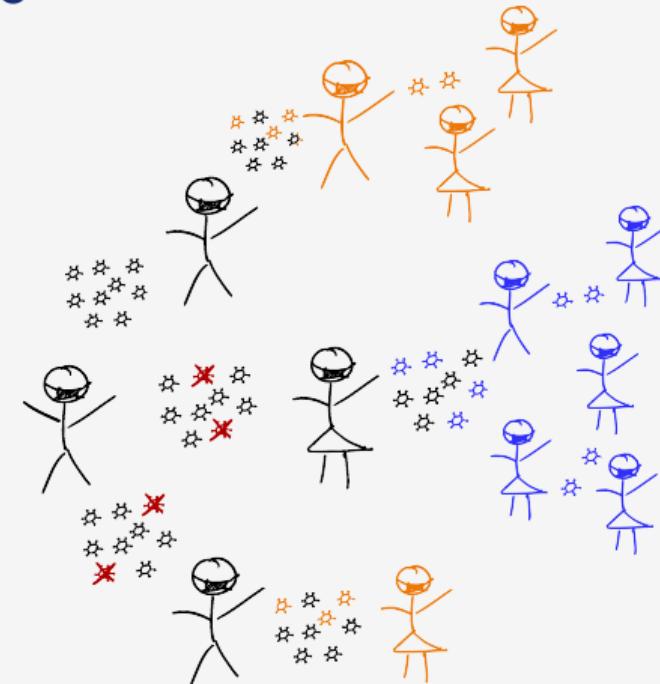
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Viral Evolution - a topologists's perspective

>seq0 ..A..C..	>seq3 ..A..G..	Hamming distance	AC —— AG
>seq1 ..T..C..	>seq4 ..T..G..	→	1
			TC —— TG

Transmission modulates observed mutation frequencies

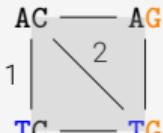
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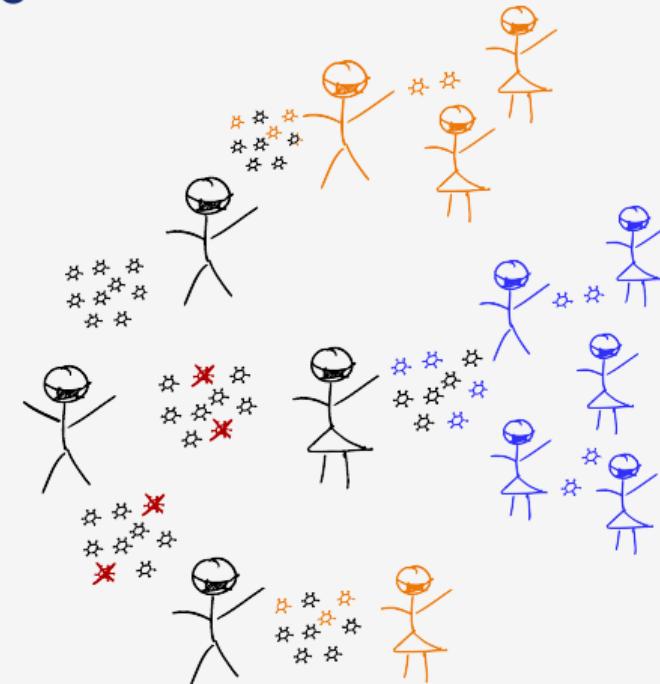
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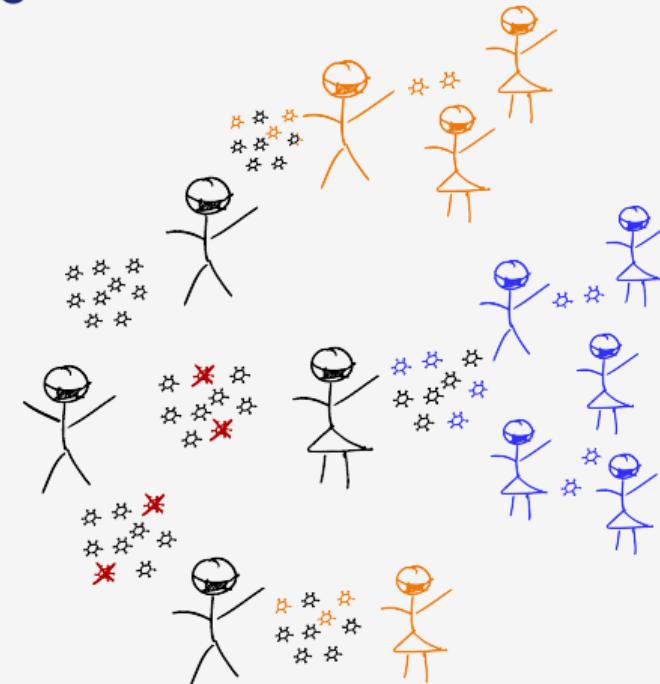
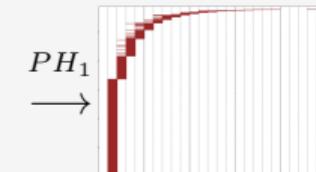


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Topological Recurrence Index (tRI)

arxiv: 2106.07292

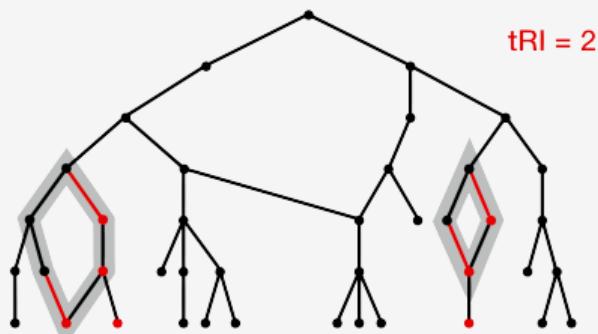
M.B., Lukas Hahn, Maximilian Neumann, Juan Angel Patino-Galindo,
Mathieu Carriere, Ulrich Bauer, Raul Rabadan, Andreas Ott.

Def.

The **topological Recurrence Index (tRI)** of a mutation
is the number of $[1, d]$ -cycles in which it appears.

⇒ tRI counts small scale recurrence

- rare events
- non-homologous ⇒ independent acquisition
- either high mutation rate or fitness advantage



Topological Recurrence Index (tRI)

arxiv: 2207.03394
 Maximilian Neumann, M.B., Lukas Hahn, Samuel Braun,
 Holger Obermaier, Mehmet Soysal, René Caspart, Andreas Ott.

Data include time series information

→ **2-parameter persistence**

All tRI counts appear in 1d subfiltration.

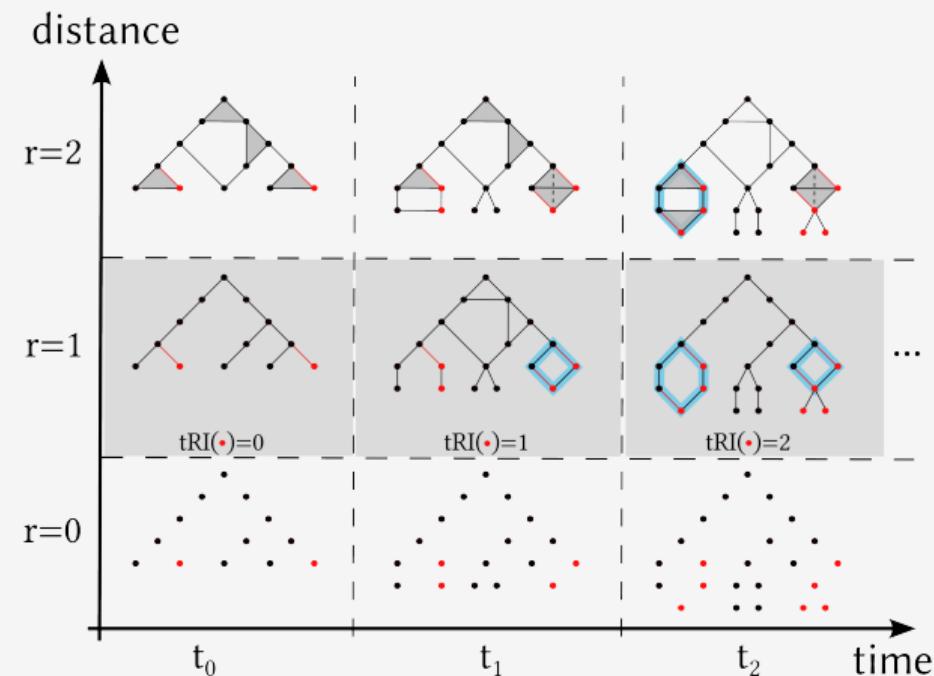
"Thm"

For any multi-filtered flag complex, get
 1d submodules from a deformed metric.

**Multiparameter persistence
 via Rips Transformations (MuRiT)**

Ripser "Add-on":

- distance matrix
 - pointwise poset filtration
 - discrete path in product poset
- 1d persistence submodule



Topological Recurrence Index (tRI)

on-going
Zachary Ardern, M.B., Maximilian Neumann, Andreas Ott.

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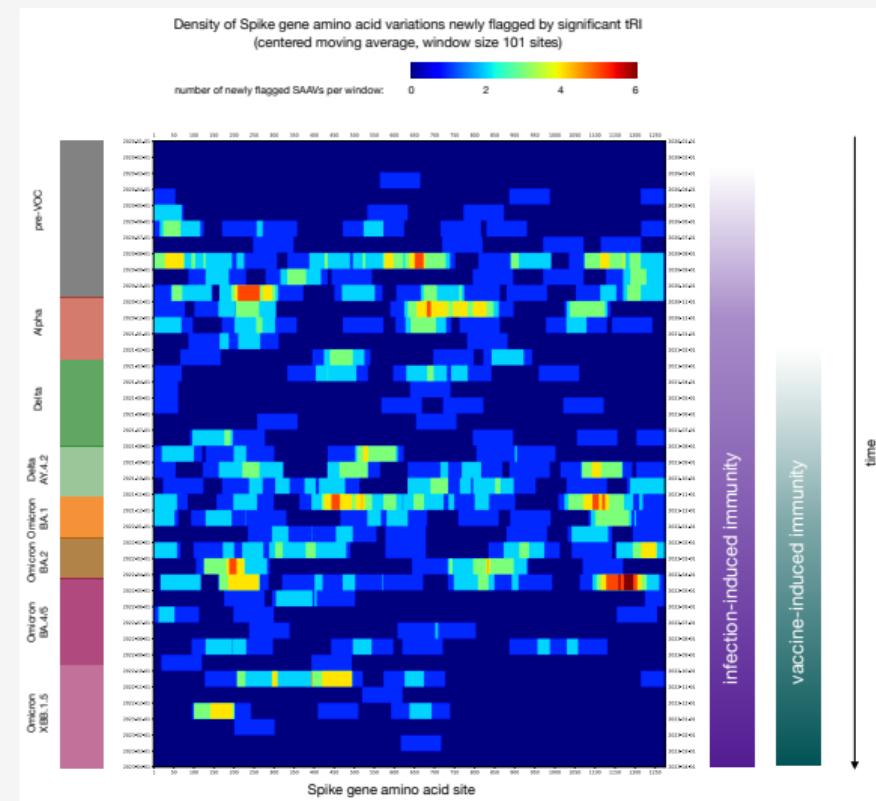
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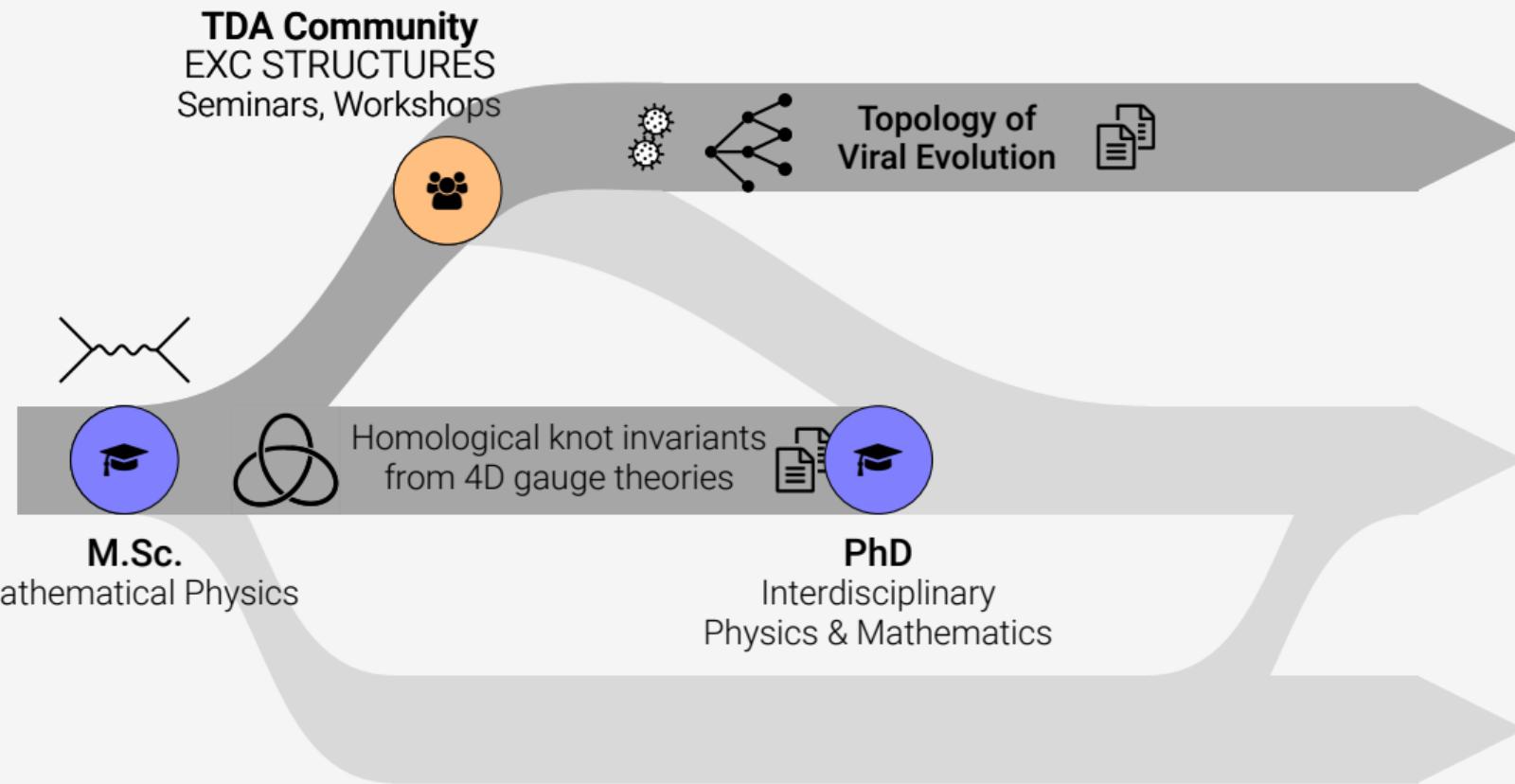
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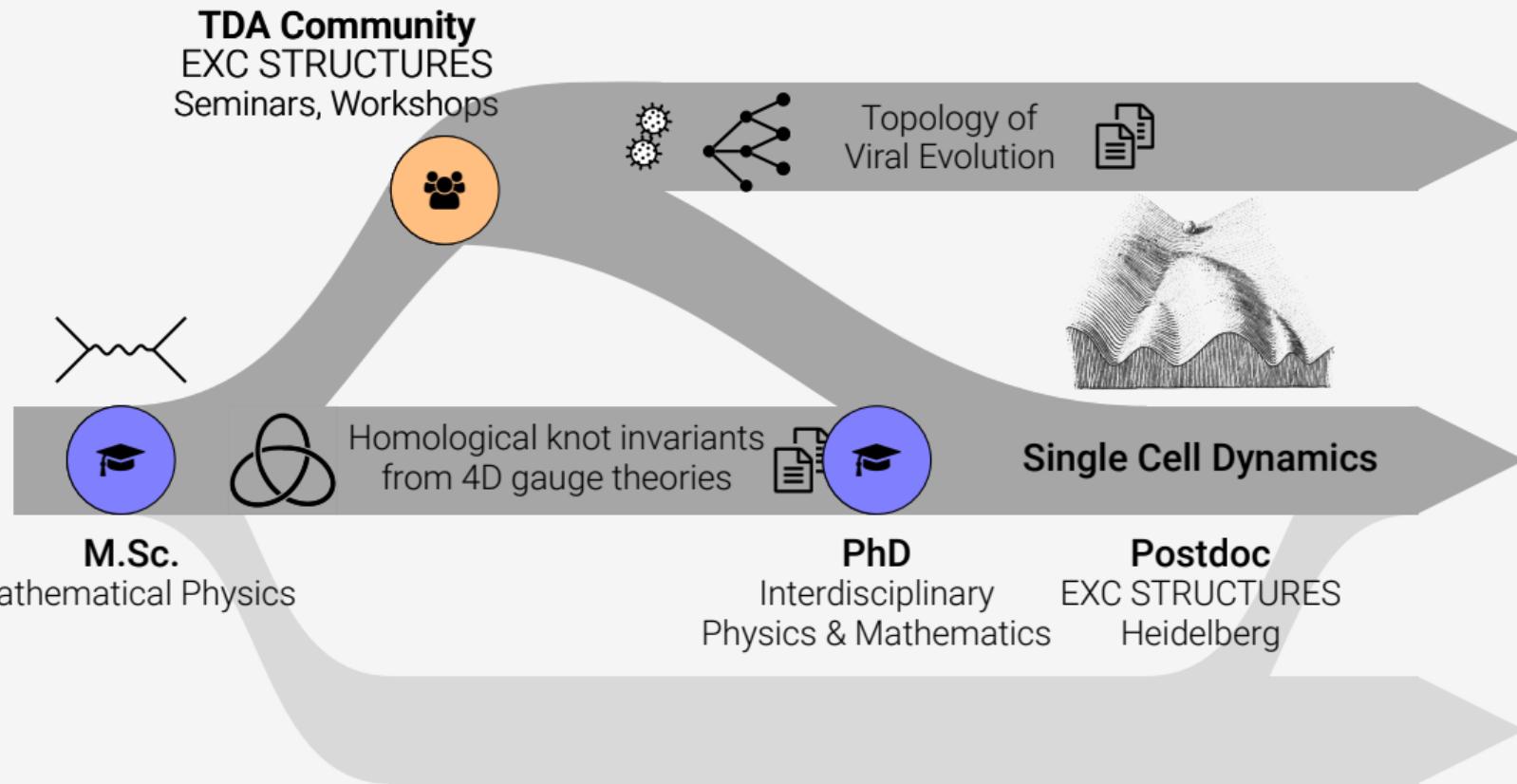
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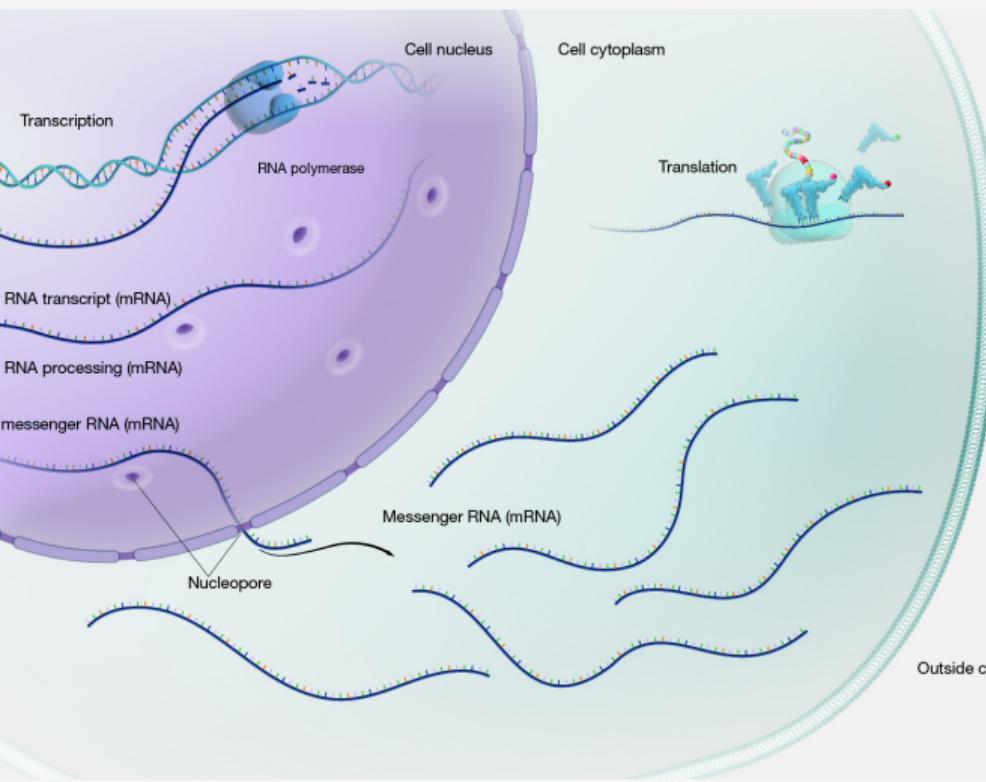






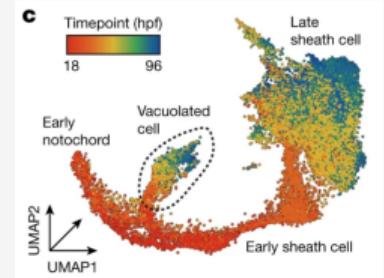
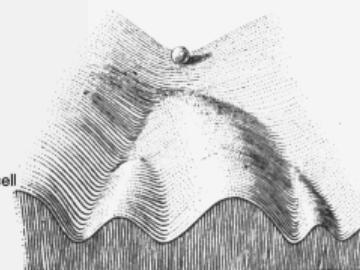
Single Cell Dynamics – a geometer's perspective

on-going
M.B., Fred Hamprecht,
 Anna Marciniak-Czochra, Anna Wienhard.



- **gene expression** = # mRNA
- proxy for cell's current biological state $x_i \in \mathbb{R}^{\# \text{genes}}$
- **RNA velocity** = rate of change in # mRNA
- proxy for cell's current development direction $v_i \in \mathbb{R}^{\# \text{genes}}$

Epigenetic Landscape



Single Cell Dynamics – a geometer's perspective

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Time evolution of individual points $p_i = (x_i, v_i) \in TM$ follows a Hamiltonian flow

$$\dot{\gamma} = X_H, \quad \gamma(0) = p$$

Here H is some Hamiltonian (\simeq energy) and X_H is the associated Hamiltonian vector field defined by

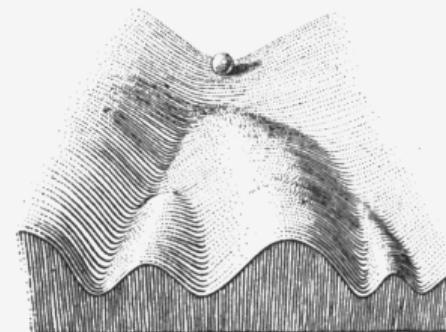
$$\omega(X_H, \cdot) = dH$$

Key Property

Model complex dynamics with few parameters.

Examples

- $H(x, v) = \frac{1}{2}\|v\|^2 \rightsquigarrow$ Geodesics (shortest paths)
- $H(x, v) = V(x) \rightsquigarrow$ Epigenetic Landscape



Single Cell Dynamics – a geometer's perspective

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Challenges

- High-dimensional data (# genes)
- Noise, batch effects
- destructive sampling

Manifold Learning

Hypothesis: Processes take place on low-dimensional submanifold.

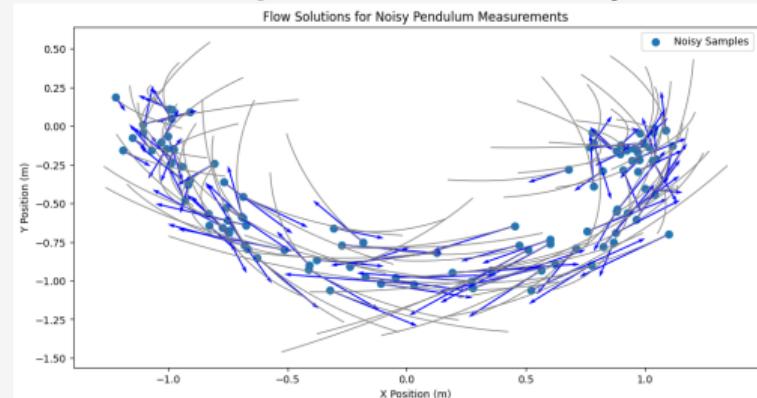
Goal: "Effective Hamiltonian Dynamics"

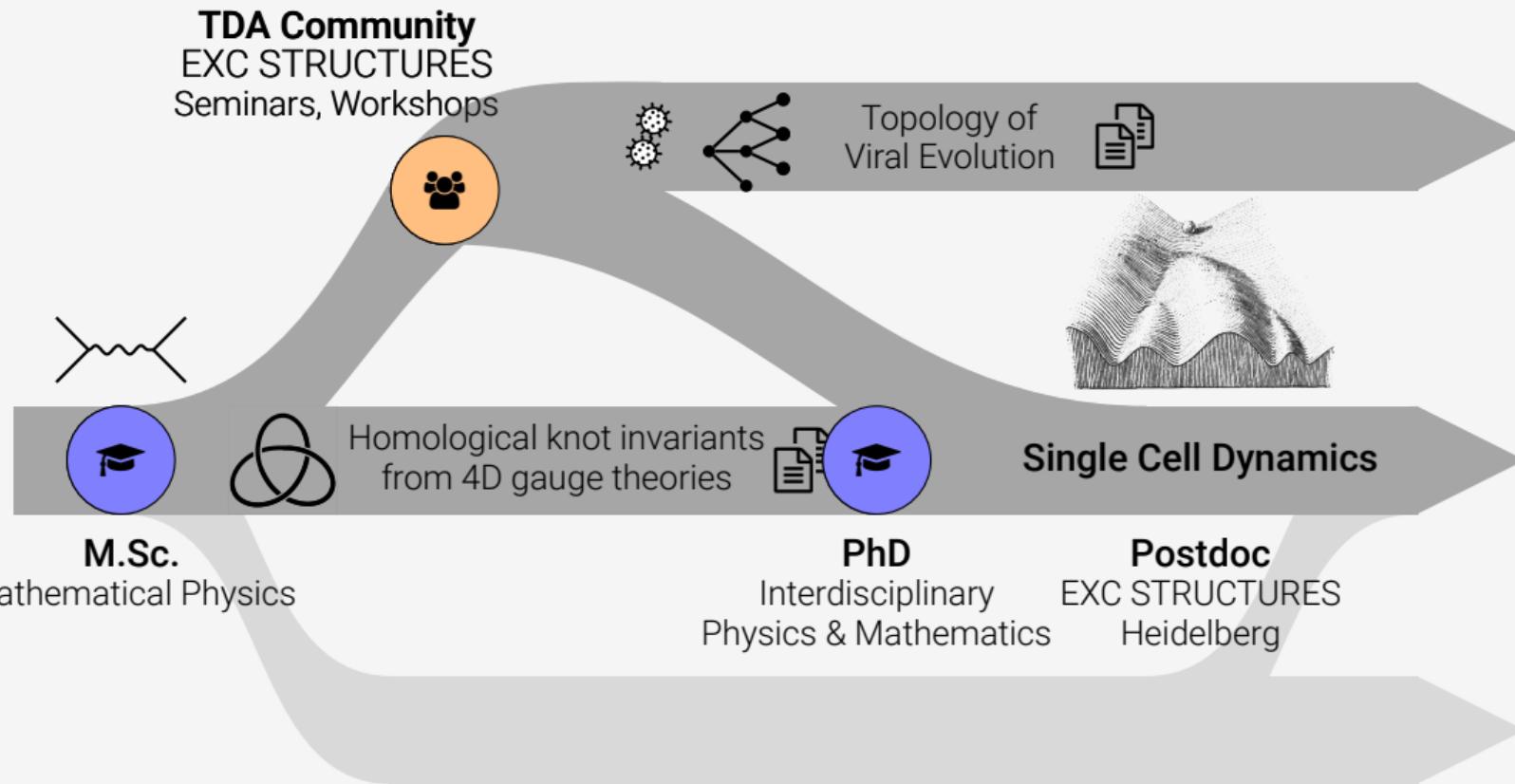
Investigate development and disease through latent space models of differentiation.

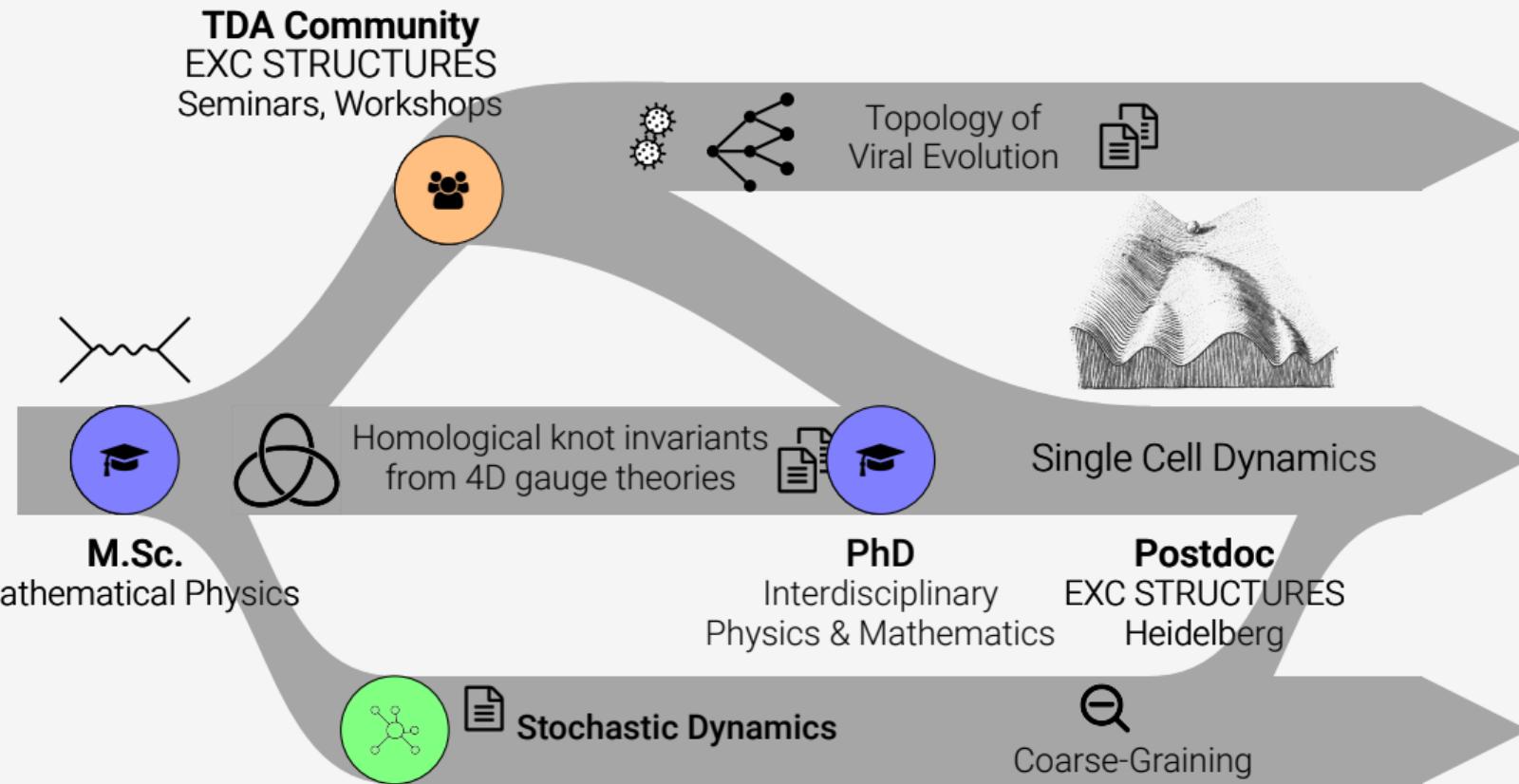
Python Package: gNE

(geometric Neighbour Embeddings)

RNA velocity embeddings in low-dimensions and learning Hamiltonian dynamics.



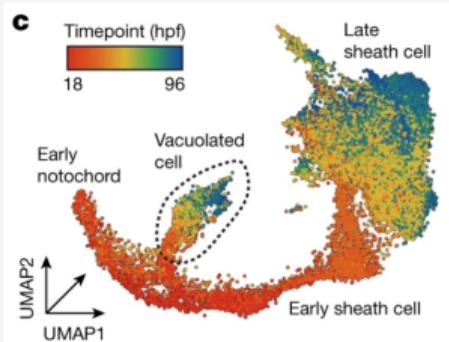




From Single Cells to Populations

on-going
M.B., Diana-Patricia Danciu, Carolin Lindow,
Anna Marciniak-Czochra, Ana Martin-Vilalba.

Zebrafish Embryogenesis (notochord)



Saunders, L.M., Srivatsan, S.R., Duran, M. et al. *Nature* **623**, 782–791 (2023).

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Mouse Neurogenesis (quasi-stationary)



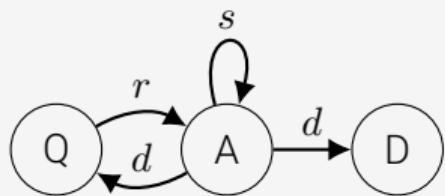
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Population Dynamics



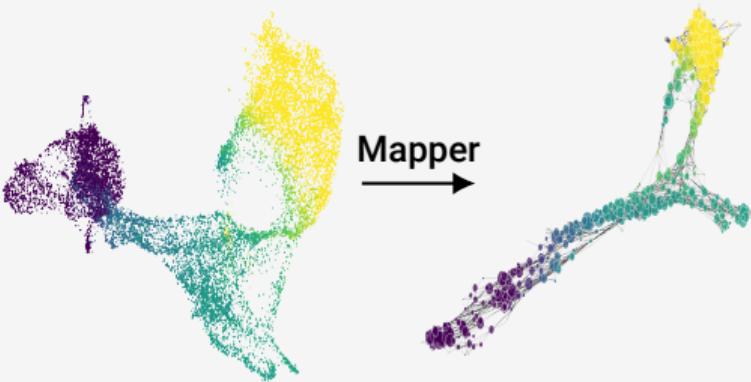
Q : quiescent
 A : active
 D : differentiated

$$\begin{aligned}\frac{d}{dt}Q &= -rQ + sA \\ \frac{d}{dt}A &= rQ - 2dA \\ \frac{d}{dt}D &= dA\end{aligned}$$

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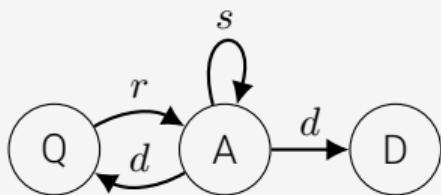
From single cells to population dynamics?

Describe position probability of individual cells
 by continuous time Markov chain

$$\frac{d}{dt} p_i(t) = \sum_j H_{ij} p_j(t)$$

Deduce transition probabilities H_{ij} from data.

Population Dynamics



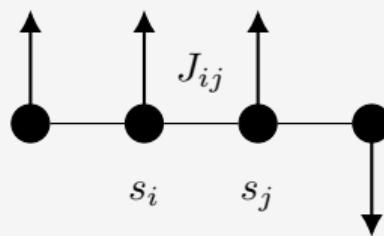
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From Single Cells to Populations - a physicist's perspective

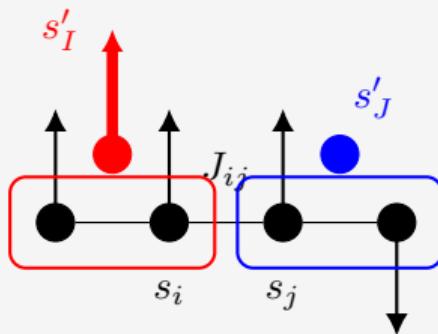
Renormalization, aka Coarse-Graining

Ising model: $s_i \in \{-1, 1\}$, $J_{ij} \in \mathbb{R}$



$$E(J) = \sum_{\langle i,j \rangle} J_{ij} s_i s_j$$

From Single Cells to Populations - a physicist's perspective

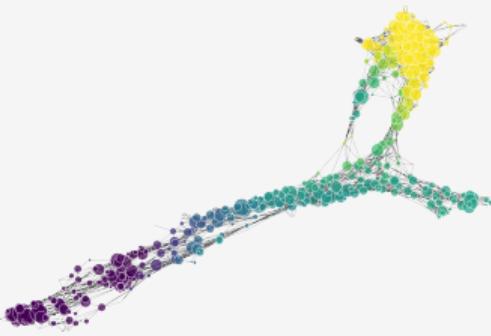


Renormalization, aka Coarse-Graining

Ising model: $s_i \in \{-1, 1\}$, $J_{ij} \in \mathbb{R}$, $s'_I \in \{-1, 0, 1\}$

$$E(J) = \sum_{\langle i,j \rangle} J_{ij} s_i s_j \xrightarrow{s'_I = \frac{1}{|I|} \sum_{i \in I} s_I} E'(J') = \sum_{\langle I,J \rangle} J'_{IJ} s'_I s'_J.$$

From Single Cells to Populations - a physicist's perspective

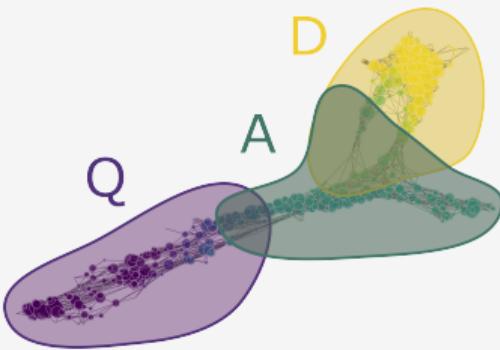


Renormalization, aka Coarse-Graining

Continuous time Markov chain: $p_i \in [0, 1], H_{ij} \in \mathbb{R}$

$$\frac{d}{dt} p_i(t) = \sum_j H_{ij} p_j(t)$$

From Single Cells to Populations - a physicist's perspective

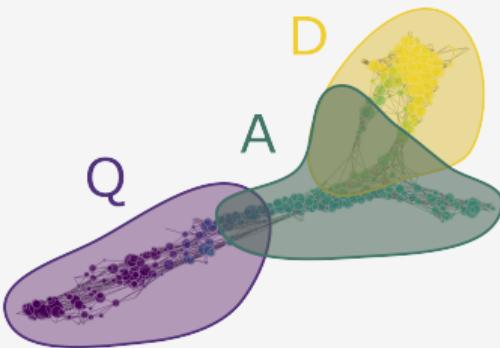


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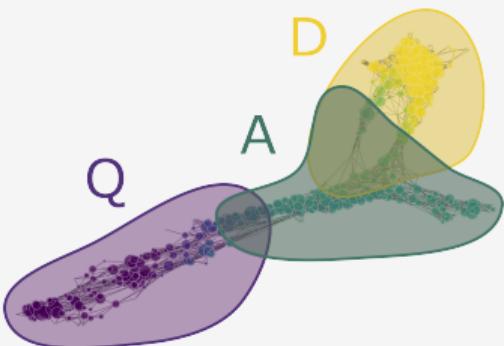
Persistence and coarse-graining in dynamical biological systems?

Small scale
diffusion-drift model
of scRNA-seq



Large scale
population models
of bulk RNA-seq

From Single Cells to Populations - a physicist's perspective

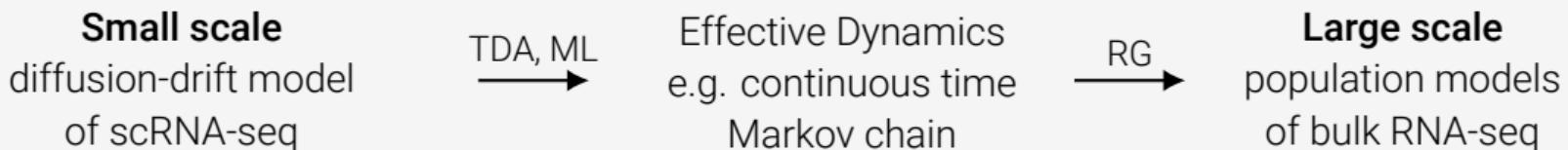


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Persistence and coarse-graining in dynamical biological systems?



persistence tracks **topological** features across scales
renormalization tracks **dynamical** features across scales

