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– EPFL Topology Seminar – 2 April 2026 –

Single cells, population dynamics, and Euler characteristic profiles

Motivation

Cell population dynamics is crucial in:

- Stem cell biology
- Cancer treatment
- Regenerative medicine

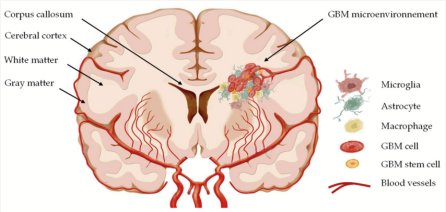
Example: Glioblastoma

Glioblastoma tumours (GBM) arise from neural stem cell dynamics 'gone wrong'.

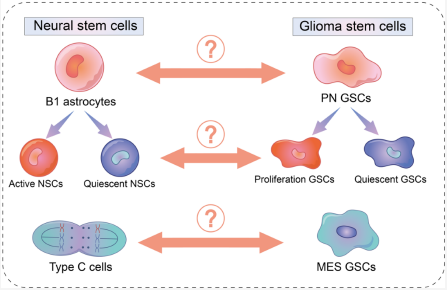
Roughly: dysregulated differentiation process.

High 'stemness' of tumour cells
$\rightarrow$ therapy resistance, relapse, poor prognosis.

w/ Ana Martin-Vilalba (DKFZ),
Anna Marciniak-Czochra (Heidelberg)

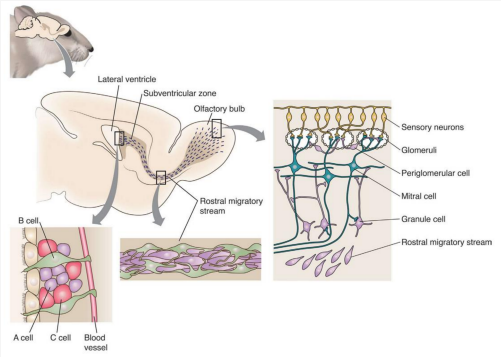


el Kheir et al., 2022



Wang et al., 2021

Model System: Neurogenesis in mature mice



Sanes et al., 2019

(Main) Cell Types

- Quiescent Neural Stem Cells (Q)
- Active Neural Stem Cells (A)
- Differentiated Cells, e.g. Neurons (D)

Questions

- How do cells transition between
$$Q \leftrightarrow A \leftrightarrow D$$
- How do transitions depend on population size (signalling), time (aging), external factors (e.g., inflammation)?
- How do these dynamics change in disease?

Population Dynamics

Compartmental models are determined by:

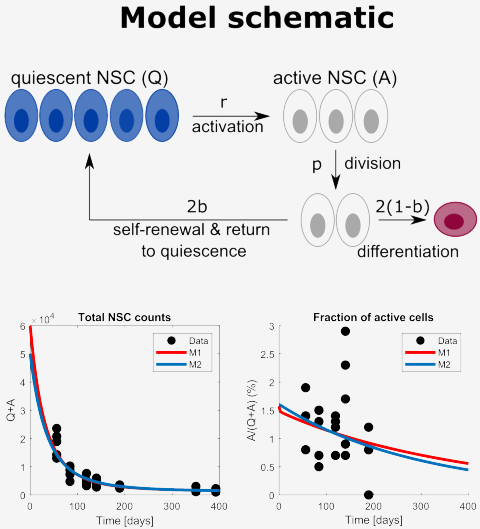
- Graph (compartments + transitions)
- Transition rates between compartments

$$\frac{dQ}{dt} = -rQ + 2bpA$$
$$\frac{dA}{dt} = rQ - pA$$
$$\frac{dD}{dt} = 2(1-p)bA$$

Problem

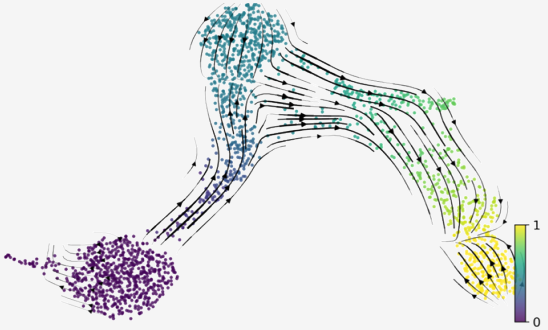
Population dynamics not identifiable from data.

Many models fit the same population data.
(different graphs, rates, non-linearities, ...)

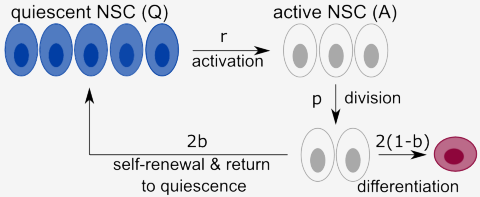


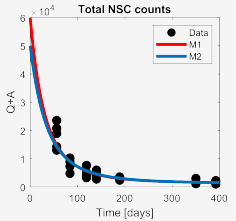
Population Dynamics

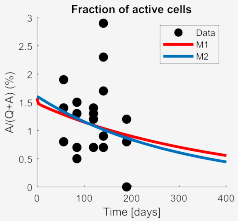
Q: Can single-cell data help?



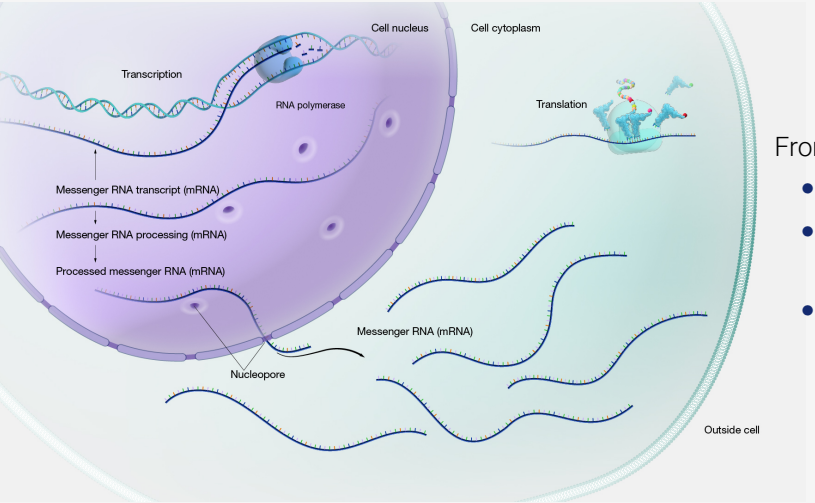
Model schematic







Single-cell Gene Expression



From code to function

- DNA $\rightarrow$ mRNA $\rightarrow$ proteins
- gene expression
  $\simeq$ # mRNA snippets
- proxy for cell's current biological state $x_i \in \mathbb{R}^N$

Single-cell dynamics: a minimal picture

1. Cell state dynamics

Each cell can be in one of several cell states

$$z \in \{Q, A, D, \ldots\}$$

determines transcription rate $\alpha_{z,g}$ for each gene g

State probability follows a continuous-time Markov chain:

$$\frac{d}{dt} p_z(t) = \sum_{z'} H_{zz'} p_{z'}(t)$$

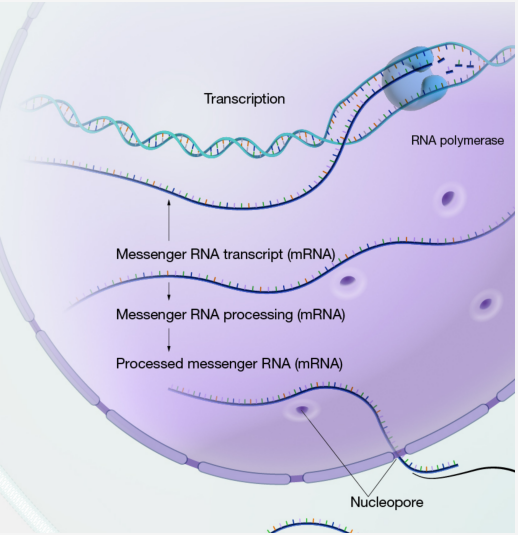
2. Gene transcription dynamics

Gene expression follows a transcription-degradation process:

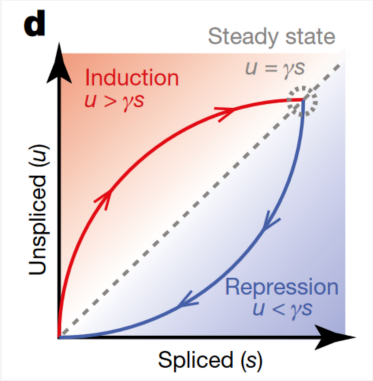
$$\frac{dx_g}{dt} = \alpha_{z(t),g} - \gamma x_g$$

- x_g: expression of gene g
- α_{g,z_t}: transcription rate
- γ: degradation rate

RNA velocity



La Manno, G. et al. (2018) 'RNA velocity of single cells', Nature, 560(7719), pp. 494–498. Fig 1.



$\rightsquigarrow v_i \in \mathbb{R}^N$ **RNA velocity**

Single-cell dynamics: a slightly extended picture

1. Cell state dynamics

Each cell can be in one of several cell states

$$z \in \{Q, A, D, \ldots\}$$

determines transcription rate $\alpha_{z,g}$ for each gene g

State probability follows a continuous-time Markov chain:

$$\frac{d}{dt}p_z(t) = \sum_{z'} H_{zz'}p_{z'}(t)$$

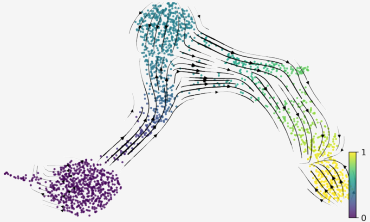
2. Gene transcription dynamics

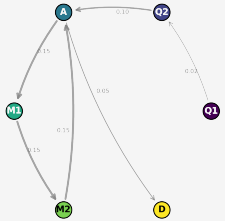
Gene expression follows a transcription-splicing-degradation process:

$$\frac{du_g}{dt} = \alpha_{z(t),g} - \beta u_g$$
$$\frac{ds_g}{dt} = \beta u_g - \gamma s_g$$

- u_g/s_g: unspliced/spliced expression
- α_{g,z_t}: transcription rate
- β: splicing rate
- γ: degradation rate

From single cells to populations





Single-cell level

Continuous-time Markov Chain (CTMC)

(interacting particles / mean field)

$$\frac{d}{dt}\begin{pmatrix} p_Q \\ p_A \\ p_D \end{pmatrix} = \begin{pmatrix} -\lambda_{QA} & \lambda_{AQ} & 0 \\ \lambda_{QA} & -(\lambda_{AQ}+\lambda_{AD}) & \lambda_{DA} \\ 0 & \lambda_{AD} & -\lambda_{DA} \end{pmatrix}\begin{pmatrix} p_Q \\ p_A \\ p_D \end{pmatrix}$$

$\xrightarrow{LLN}$

Population level

Occupation number ODEs

(non-linear in population sizes)

$$\frac{d}{dt}\begin{pmatrix} Q \\ A \\ D \end{pmatrix} = \begin{pmatrix} -f_{QA} & f_{AQ} & 0 \\ f_{QA} & -(f_{AQ}+f_{AD}) & f_{DA} \\ 0 & f_{AD} & -f_{DA} \end{pmatrix}\begin{pmatrix} Q \\ A \\ D \end{pmatrix}$$

A Hierarchy of Problems

Linking scRNA-seq data to population dynamics requires answering

1. What **compartments/states** can individual cells be in?
2. What **transitions** occur between these states?
   For example: can cells move back into (deep) quiescence or do they remain active?
3. What are the **rates** of these transitions?
4. How do rates **depend on** population size, time, external factors?

Problems 1 & 2: Graph structure $\rightarrow$ Topology

Can we differentiate between candidate graphs using TDA?

Approach: Euler Characteristic Profiles.

with Marta Marszweska (Gdansk, Warsaw), Justyna Signerska-Rynkowska (Gdansk), Pawel Dlotko (Warsaw)

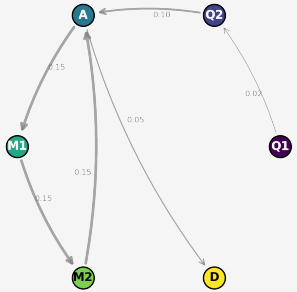
Application Goal: Uncovering Cell State Transitions

The Biological Question

After benchmarking validates the method, we can apply it to answer:

Consider the (Q, A, D) system:

- Does an $A \to Q2$ transition exist? How about an $A \to Q1$ transition? Or an $M2 \to Q1$ transition?
- That is: can cells land in (deep) quiescence after division?



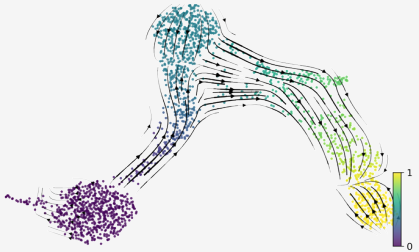
From labeled points to filtered graphs

What We Have (at least in principle)

For each cell

- current gene expression $x_i \in \mathbb{R}^N$
- RNA velocity $v_i \in T_{x_i}\mathbb{R}^N$

$$X = \{(x_i, v_i)\} \subset T\mathbb{R}^N$$



What We Want

- Graph structure of the Markov chain on cell states

The Key Question

How do we extract the transition graph from X?

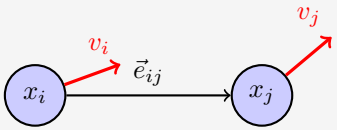
From labeled points to filtered graphs

Construct symmetric kNN graph $\Gamma_{kNN}(\{x_i\})$.

For each edge $(x_i, x_j) \in \Gamma_{kNN}$ set $\vec{e}_{ij} = x_j - x_i$, define

$$a_{ij} = d_{\cos}(\vec{e}_{ij}, v_i), \qquad b_{ij} = d_{\cos}(\vec{e}_{ij}, v_j),$$

with *cosine distance* $d_{\cos}(u, v) = 1 - \frac{u \cdot v}{\|u\|\|v\|} \in [0, 2]$.



Edge bifiltration

$$f(x_i, x_j) = \big(\min(a_{ij}, b_{ij}),\ \max(a_{ij}, b_{ij})\big) \in [0, 2] \times [0, 2]$$

Interpretation

Small filtration $\rightarrow$ pairwise velocity alignment $\rightarrow$ signal of state transition.

From filtered graphs to filtered complexes

For a graph $\Gamma = (V, E)$, its **clique** / **flag complex** is

$$K(\Gamma) = \big\{\sigma \subseteq V \mid \{u, v\} \in E \text{ for all } u, v \in \sigma\big\}.$$

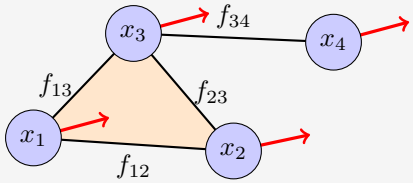
$$(p+1)\text{-clique in } \Gamma \iff p\text{-simplex in } K(\Gamma)$$

Filtration

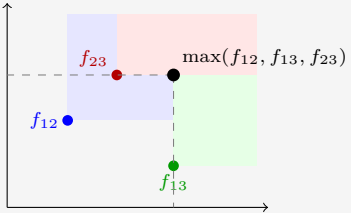
- Vertices: $f(x_i) = (0, 0)$
- Edges: $f(x_i, x_j) = (\min, \max)$
- Higher simplices when all faces are present:

$$f(\sigma) = \max_{(x,x') \subseteq \sigma} f(x, x')$$

$$K_{\boldsymbol{\epsilon}}(\Gamma) \coloneqq \{\sigma \in K(\Gamma) \mid f(\sigma) \leq \boldsymbol{\epsilon} = (\epsilon_1, \epsilon_2)\}$$



$$f(\triangle) = \max(f_{12}, f_{13}, f_{23})$$



coordinatewise maximum in $(\mathbb{R}^2, \leq)$

The Euler Characteristic Profile (ECP)

$$K_\bullet(\Gamma) : (P, \leq) \to (\mathrm{SimpComp}, \subseteq)$$

Applying homology $\implies$ multi-parameter persistence module.

Hard to interpret, hard to compute.

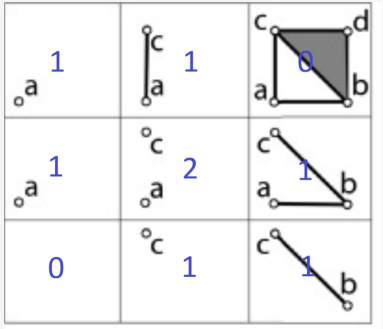
Euler Characteristic Profile

$$ECP: P \to \mathbb{Z}$$

$$(a,b) \mapsto \chi\big(K_{(a,b)}\big) = \sum_{i=0}^{n} (-1)^i \#\{\sigma \in K_{(a,b)} \mid \dim \sigma = i\}$$

$$= \sum_{i=0}^{n} (-1)^i \operatorname{rk} H_i\big(K_{(a,b)}\big)$$

?? to interpret, embarrassingly easy to compute.



ECP of flag complexes via Bron–Kerbosch

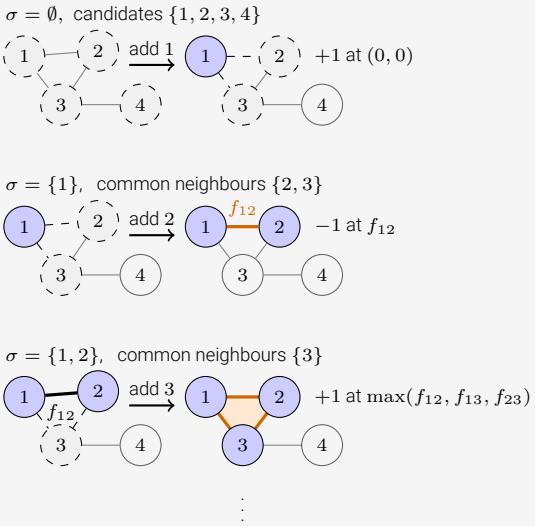
Each simplex σ contributes ± 1 at $f(\sigma)$.

$$ECP = \sum_{\sigma} \phi_\sigma, \quad \phi_\sigma(\epsilon) = (-1)^{\dim \sigma} \mathbf{1}_{\{\epsilon \geq f(\sigma)\}}$$

Bron–Kerbosch algorithm for ECP

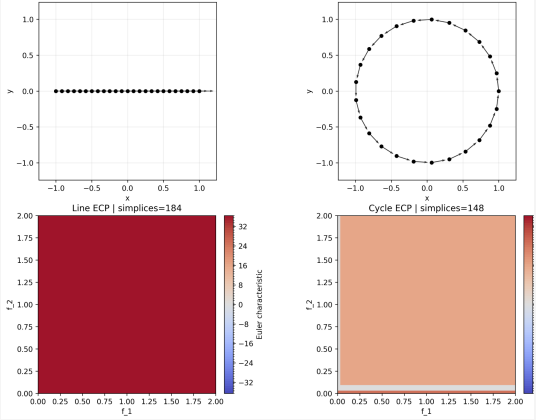
BronKerboschECP(G)
  Extend($\emptyset$, V, $(0,0)$)

Extend(σ, C, f_σ)
  for each $w \in C$:
    $\sigma' \leftarrow \sigma \cup \{w\}$
    $f' \leftarrow \max\{f_\sigma,\ f(v,w) : v \in \sigma\}$
    record $(-1)^{\dim \sigma'}$ **at** f'
    Extend(σ', $C \cap N(w)$, f')

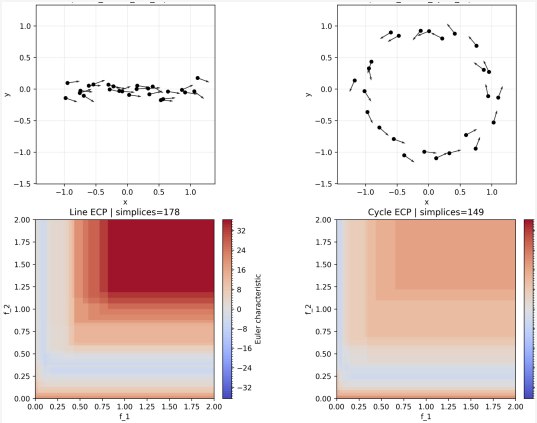


Stability Experiments

no noise

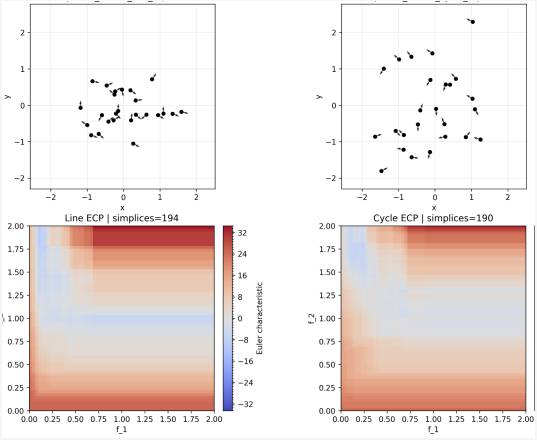


noise ∼ 10% of signal

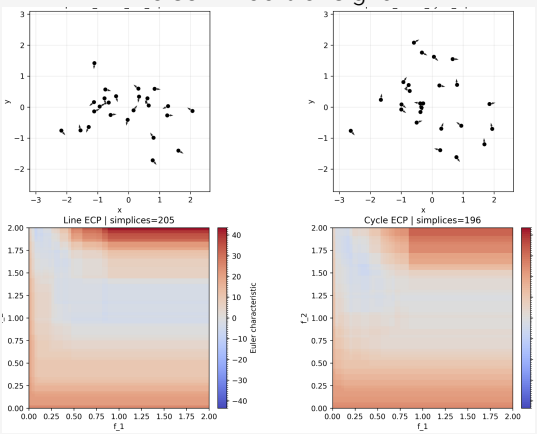


Stability Experiments

noise ∼ 50% of signal



noise ∼ 100% of signal



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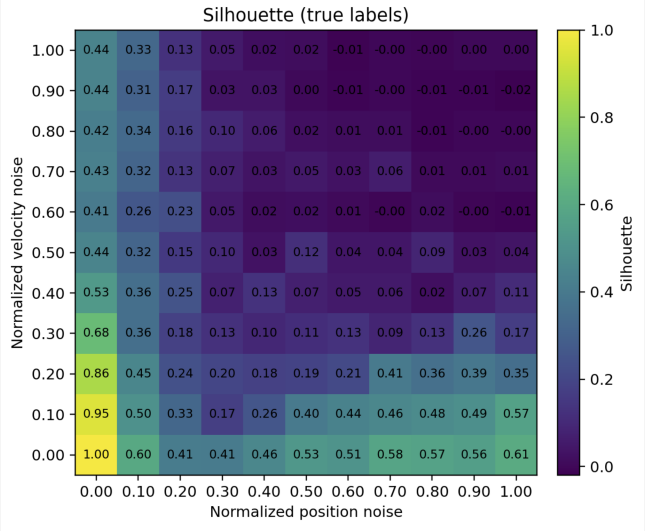
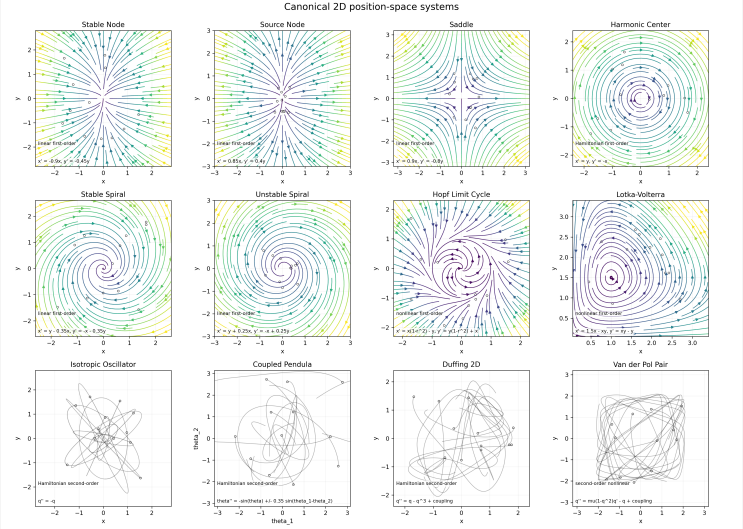


Low-dimensional dynamical systems



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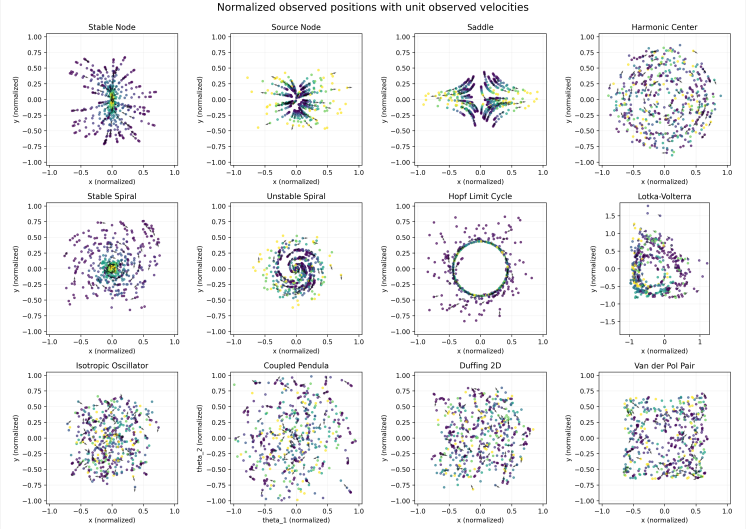

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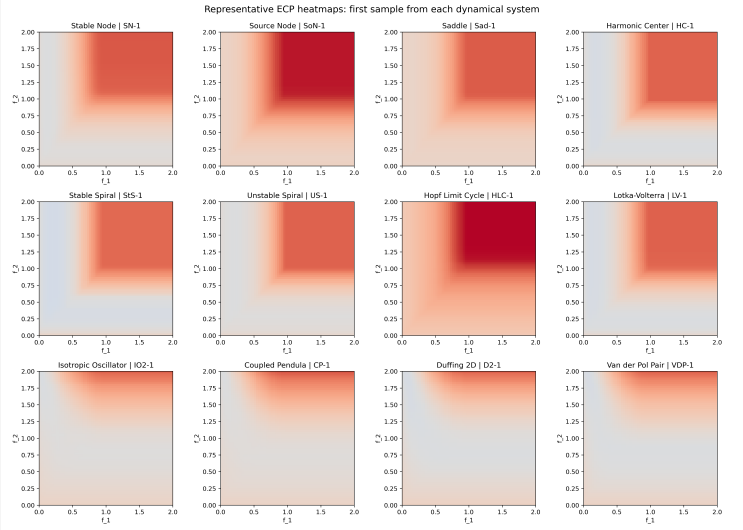
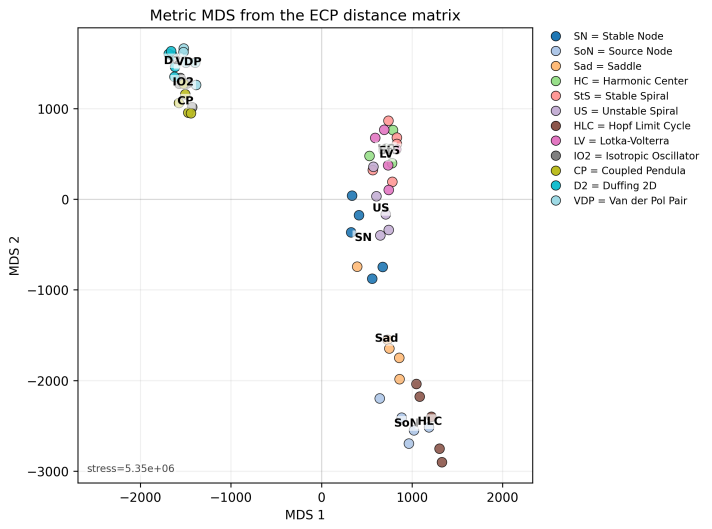
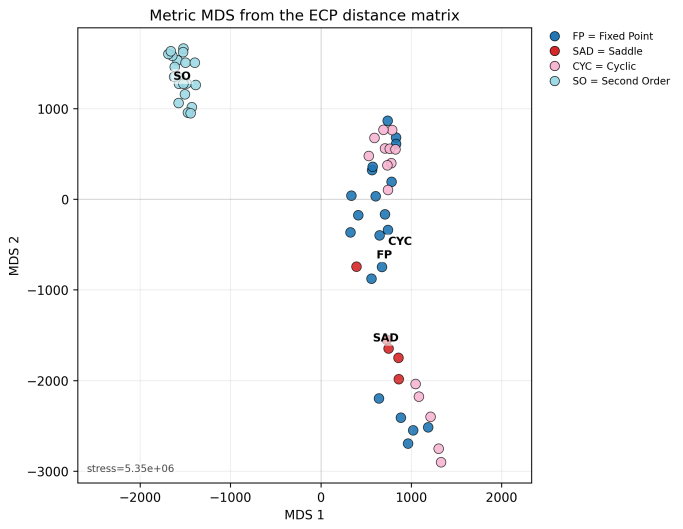


Low-dimensional dynamical systems



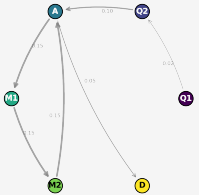
Low-dimensional dynamical systems



Synthetic Data: A Markov-Modulated Splicing Model

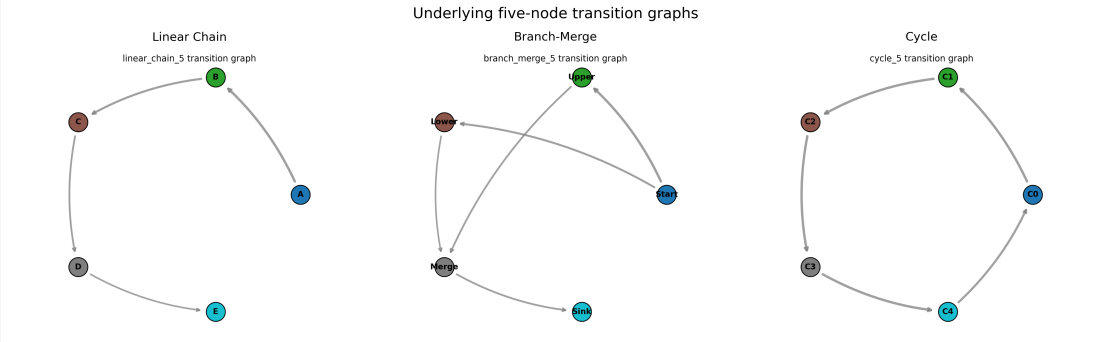
Generate synthetic u/s-counts of single cells using two-level dynamics:

- **Latent state process:**
  Continuous-time Markov chain on a state graph
  - States $z_1, \ldots, z_n$ with probability p_i
  - $\frac{d}{dt} p_i = \sum_j H_{ij} p_j$
  - Asymmetric transition rates $H_{ij} \neq H_{ji}$, encode directionality
- **Gene expression:**
  Standard transcription-splicing-degradation process for cell in state z with state-dependent transcription rate α_z
  - $\frac{du}{dt} = \alpha_z - \beta \cdot u$ (transcription + splicing)
  - $\frac{ds}{dt} = \beta \cdot u - \gamma \cdot s$ (splicing + degradation)

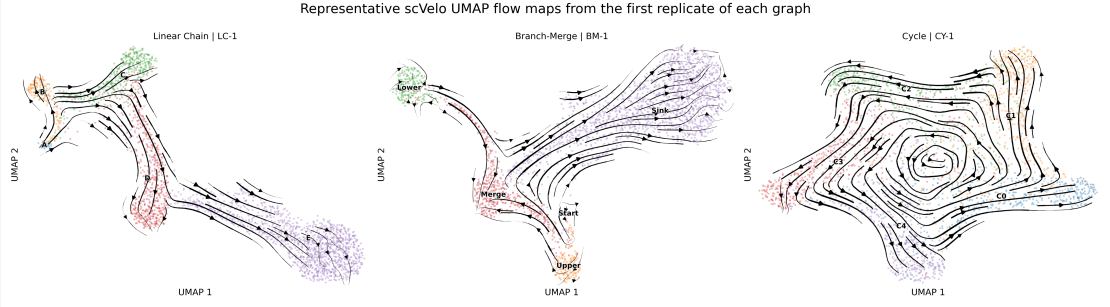


Output: u/s-counts + **current state** for each cell at time t.

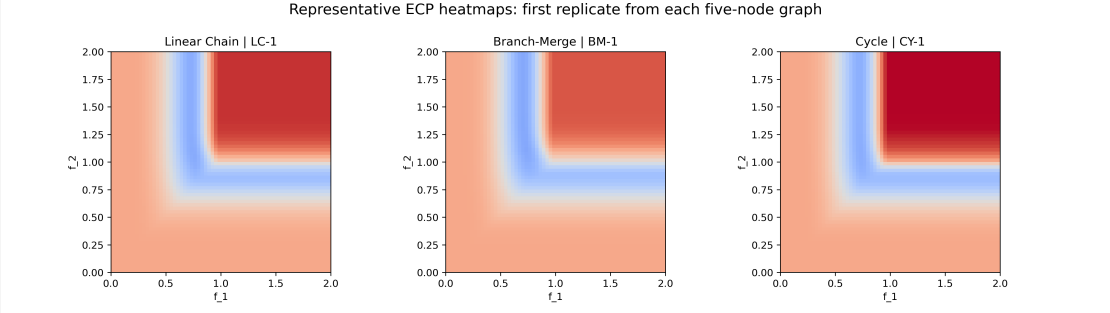
Synthetic scRNA-seq data



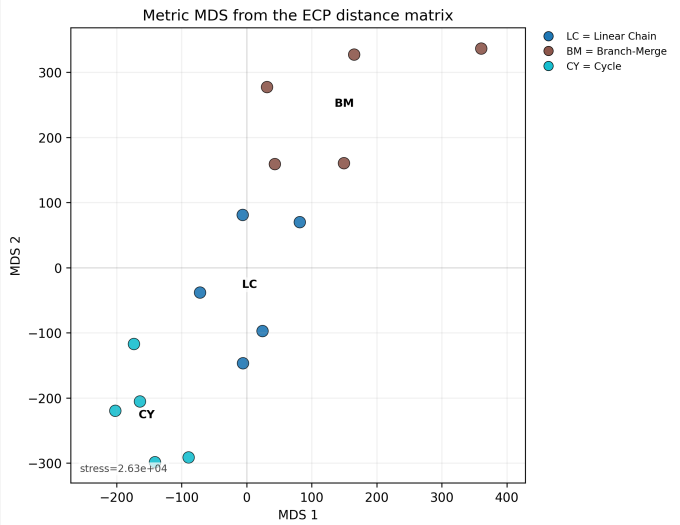
Synthetic scRNA-seq data



Synthetic scRNA-seq data



Synthetic scRNA-seq data



Current Status and Next Steps

What We Have

- Bifiltered complex construction (kNN + velocity alignment)
- ECP computation for bifiltrations
- synthetic data for arbitrary graphs

Next Steps

1. Proper benchmarking
2. Systematic noise sensitivity analysis
3. high-dimensional data is famously noisy; too noisy for ECP to be useful?
4. RNA velocity is famously unreliable; too unreliable for ECP to be useful?
5. Move beyond classification/clustering; can we recover the ground truth?

Thanks for your attention