

Modeling Neural Stem Cell Dynamics

Mathematical Description of Spatiotemporal Homeostasis maintaining in the Zebrafish Brain

HGS MathComp Membership Colloquium

Théo André (P.I.: Prof. Dr. Anna Marciniak-Czochra)

Heidelberg University

October 28th, 2024.



HGS MathComp



UNIVERSITÄT
HEIDELBERG
ZUKUNFT
SEIT 1386

ABOUT ME



Théo André
Ph.D. student

EDUCATION

2018

2019

2020

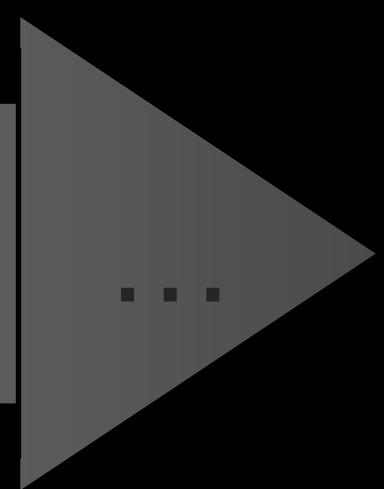
2021

2022

2023

2024

...



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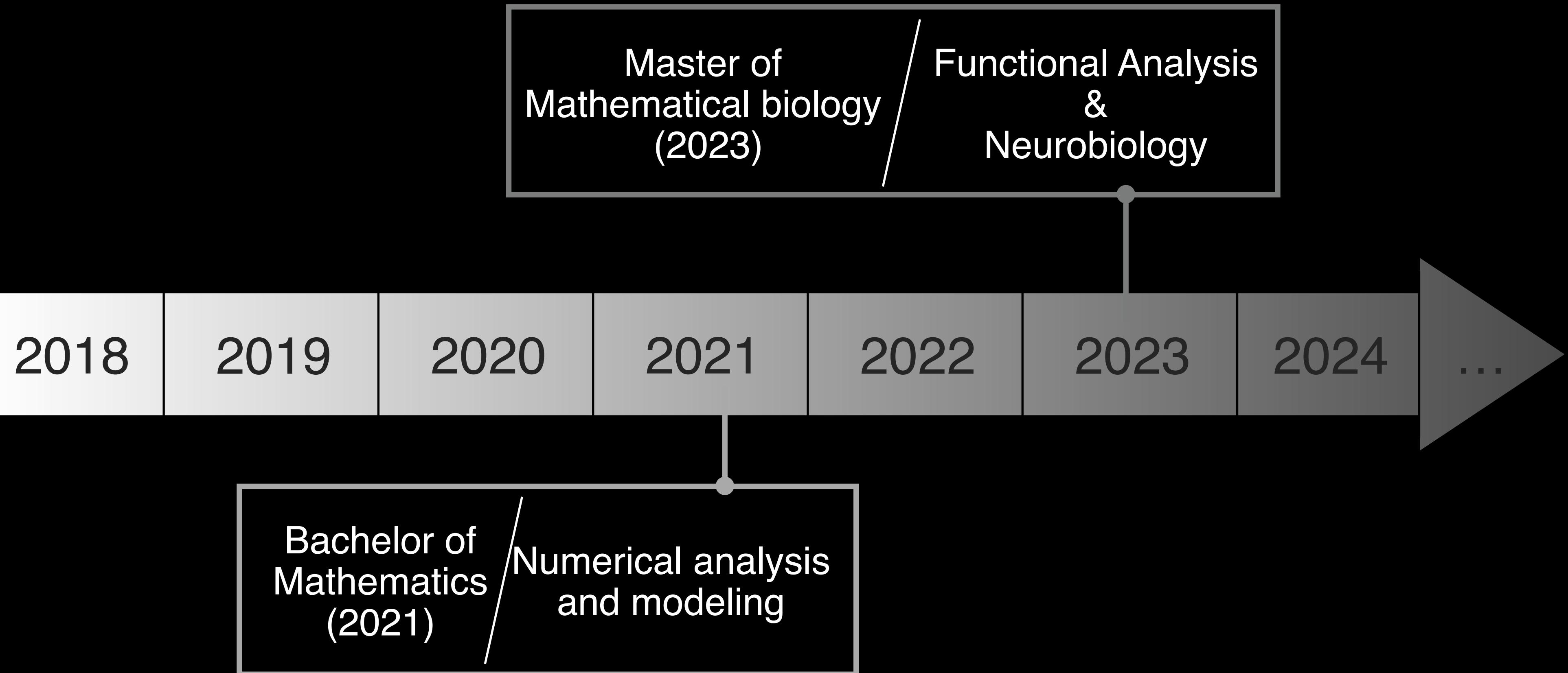
Bachelor of
Mathematics
(2021) / Numerical analysis
and modeling

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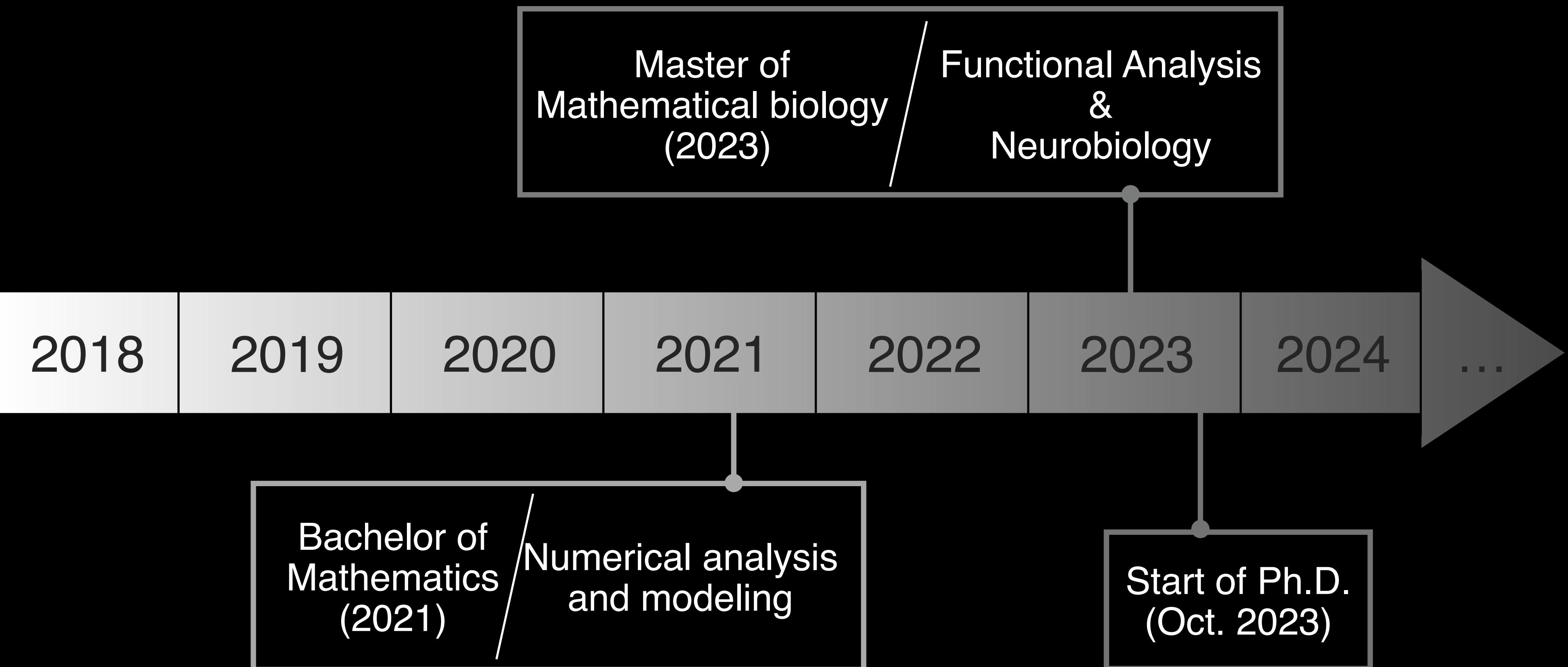


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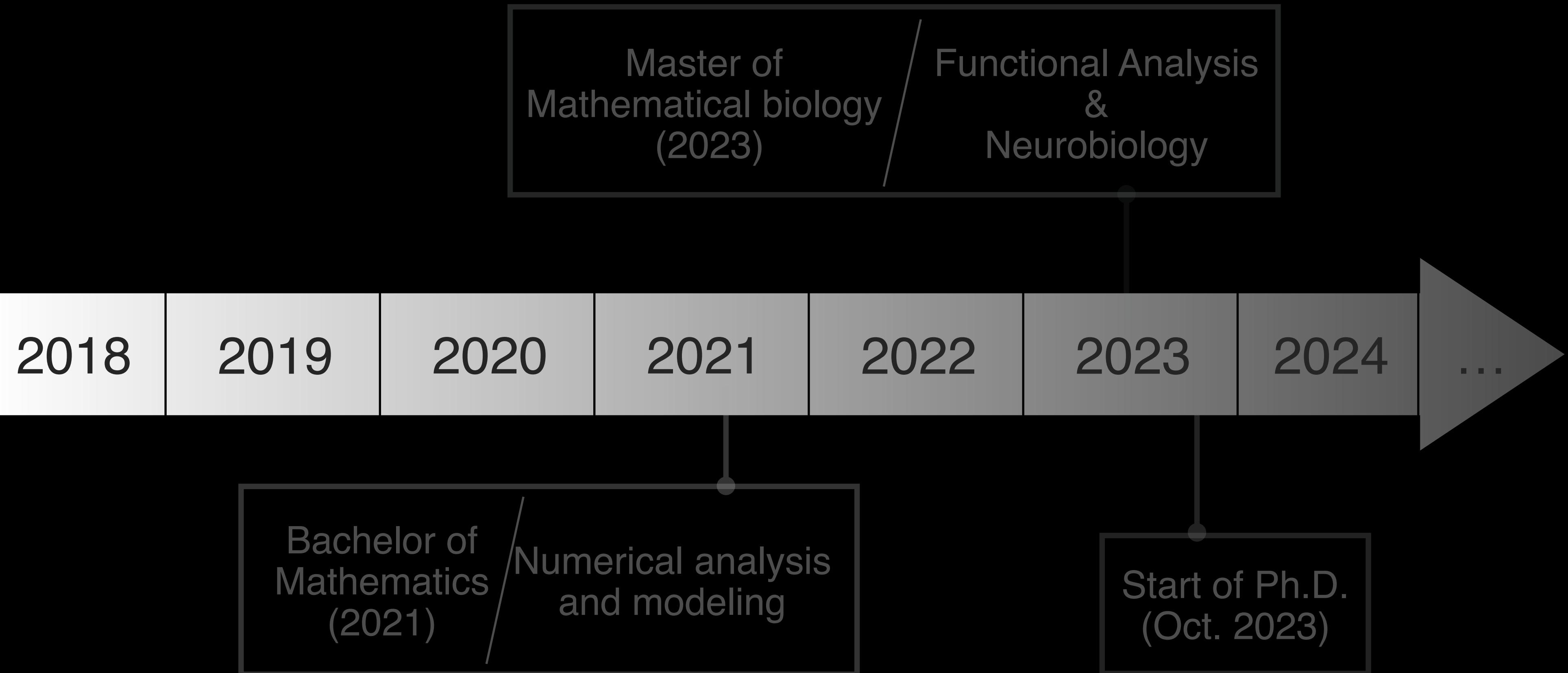


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RESEARCH WORK



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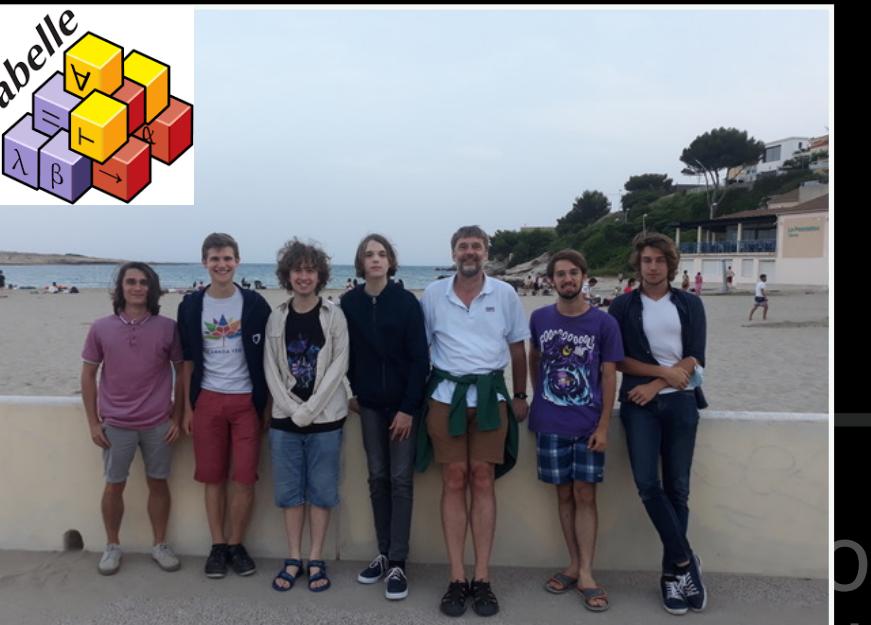
RESEARCH WORK

42 JONAS, MALTE, THÉO, THOMAS, YURI, AND DIERK
7. NEW UNIVERSAL PAIRS

There are several ways to reduce the degree of diophantine equations by introducing new variables. For example, the degree nine equation $A = X^9$ can be replaced by two equations of degree three and with three variables, $A = Y^3$ and $Y = X^3$. In this section, we present a method how to significantly reduce the degree of our universal pair with 11 variables by only slightly increasing the number of variables. This will result in a new, more compact universal pair.

Notice as well that finding a universal pair (ν, δ) can be achieved by constructing a universal diophantine equation - indeed, let $(W_\nu)_\nu$ be an enumeration of all diophantine sets : if one finds a polynomial $P \in \mathbb{Z}[X_0, Y, X_1, \dots, X_\nu]$ such that $x \in W_\nu \iff \exists \mathbf{z} \in \mathbb{Z}^\nu : P(x, \nu, \mathbf{z}) = 0$, and $\deg(P) = \delta$, then

$$P_{W_\nu} := P(., \nu, .)$$
 is a polynomial with ν variables and one parameter realizing the universal pair (ν, δ)
The main term responsible for the immense degree is $\mathfrak{B}^{(\delta+1)^\nu}$ occurring in Definition 2.2. We want to replace this term by an exponential relation $\Theta = \mathfrak{B}^{B_1}$, where $B_1 = (\delta + 1)^\nu$. And we know that exponential relations are equivalent to diophantine expressions. In the following, we will elegantly add this exponential relation to our statements from Theorem II. Firstly, we present the following lemma:



Bounds on Diophantine Equations and
Formalization of Hilbert Xth Problem's proof in
Isabelle
(D. Schleicher, Y. Matiyassevich)

mathematical biology
2023

Functional Analysis
&
Neurobiology

2018

2019

2020

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2024

...

Bachelor of
Mathematics
(2021)

Numerical analysis
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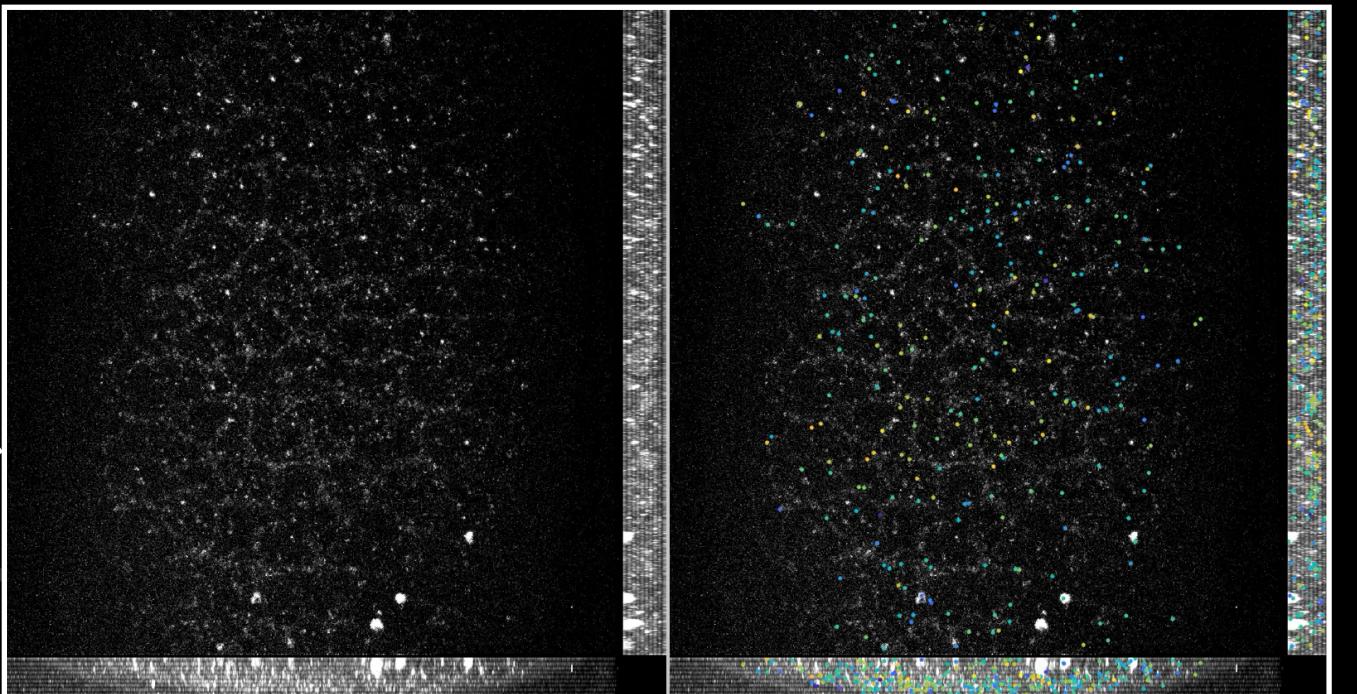
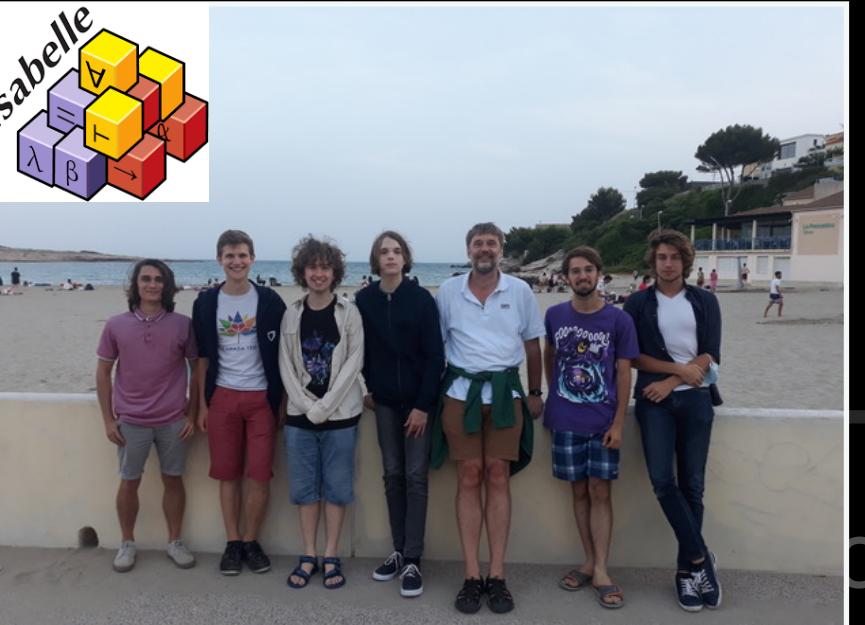
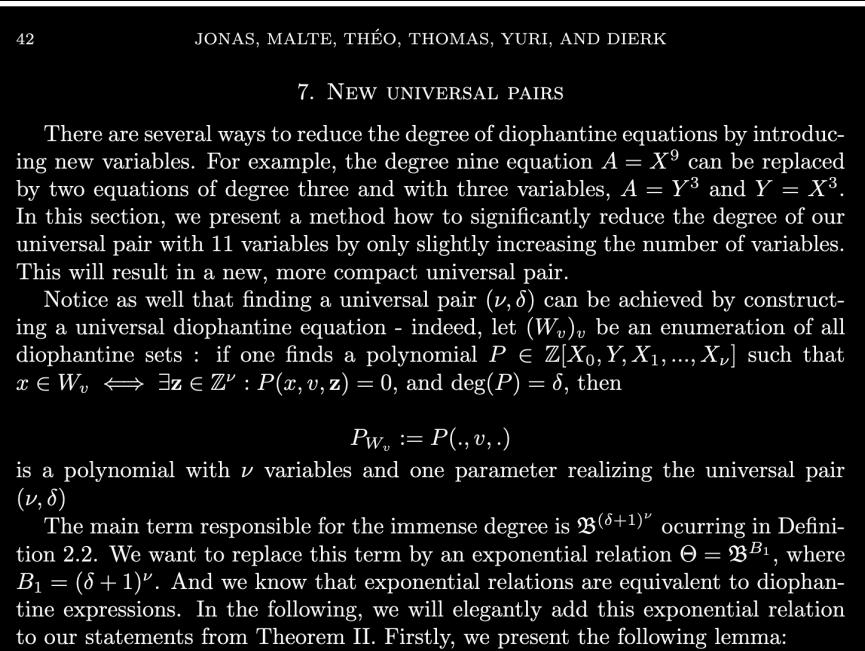
Start of Ph.D.
(Oct. 2023)

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Ph.D. student

RESEARCH WORK



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Bayesian Filtering and Multiscale Tracking
of Endocytosis across biological scales
(T.Lecuit, P. Roudot, C. Collinet)

2018 2019 2020 2021 2022 2023 2024

Bachelor of
Mathematics
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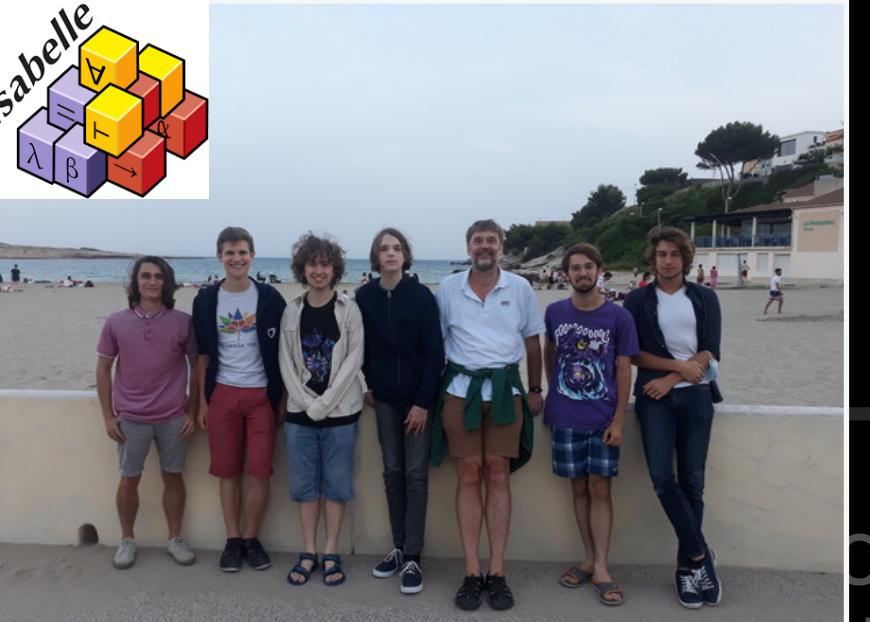
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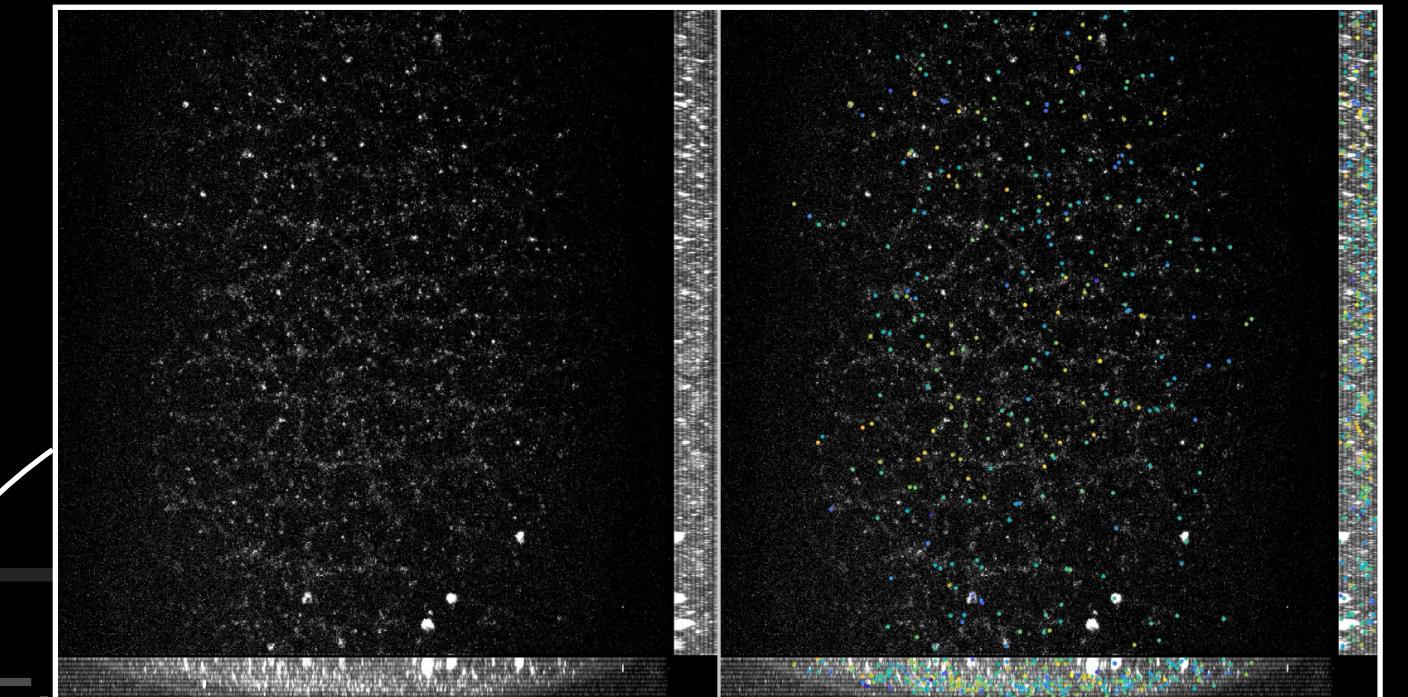
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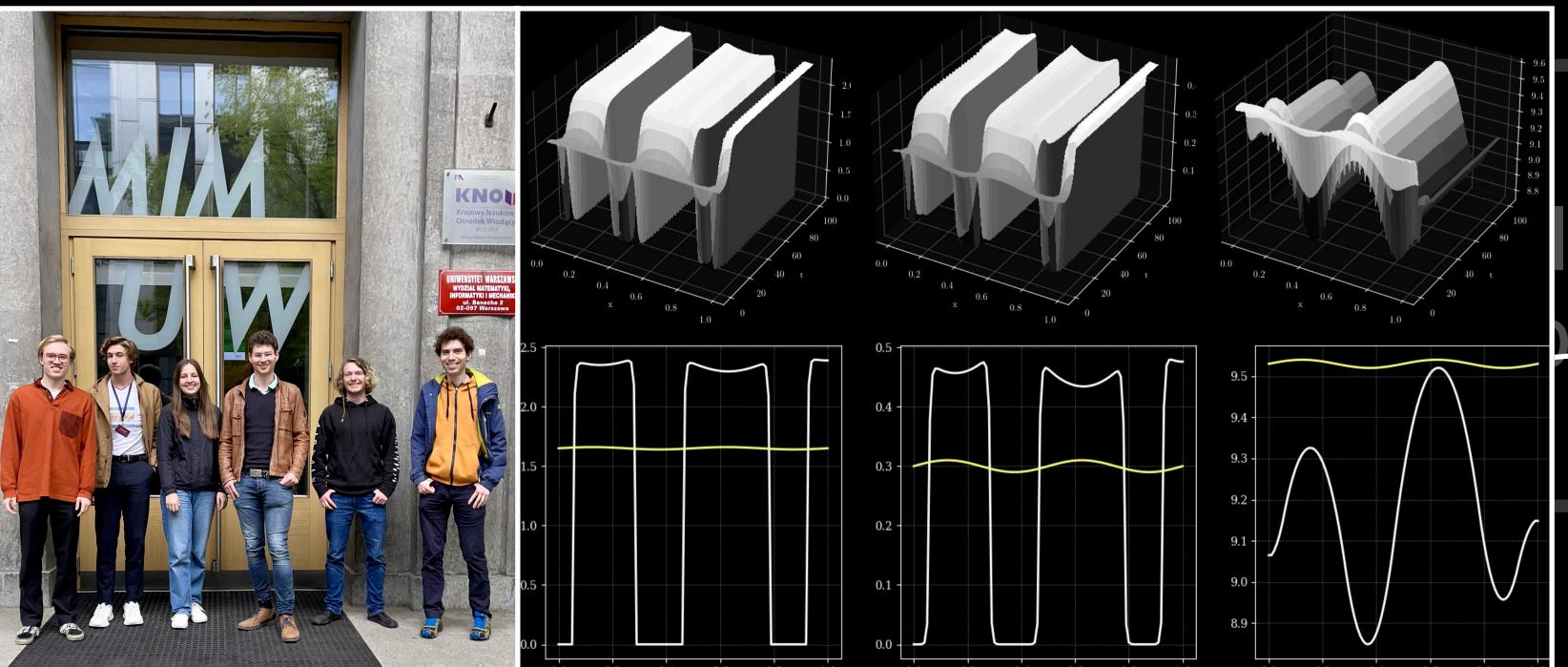
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Functional Analysis
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2023

Bayesian Filtering and Multiscale Tracking
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2018 2019 2020 2021 2022 2023 2024 ...



analysis
modeling

Start of Ph.D.
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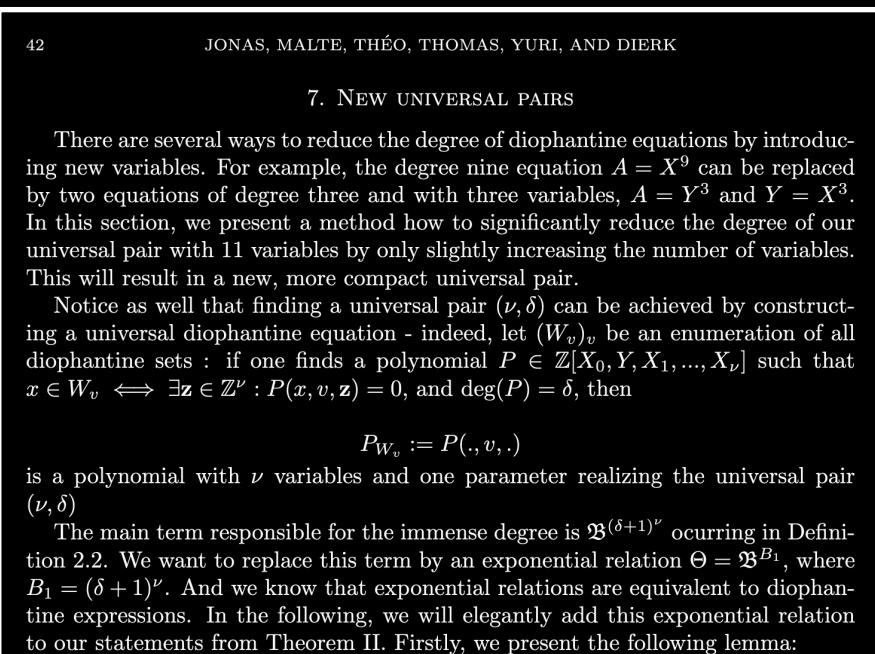
Diffusion-Driven Instability and Pattern formation in
Reaction-Diffusion Equations with two diffusive
components
(A. Marciniak-Czochra)

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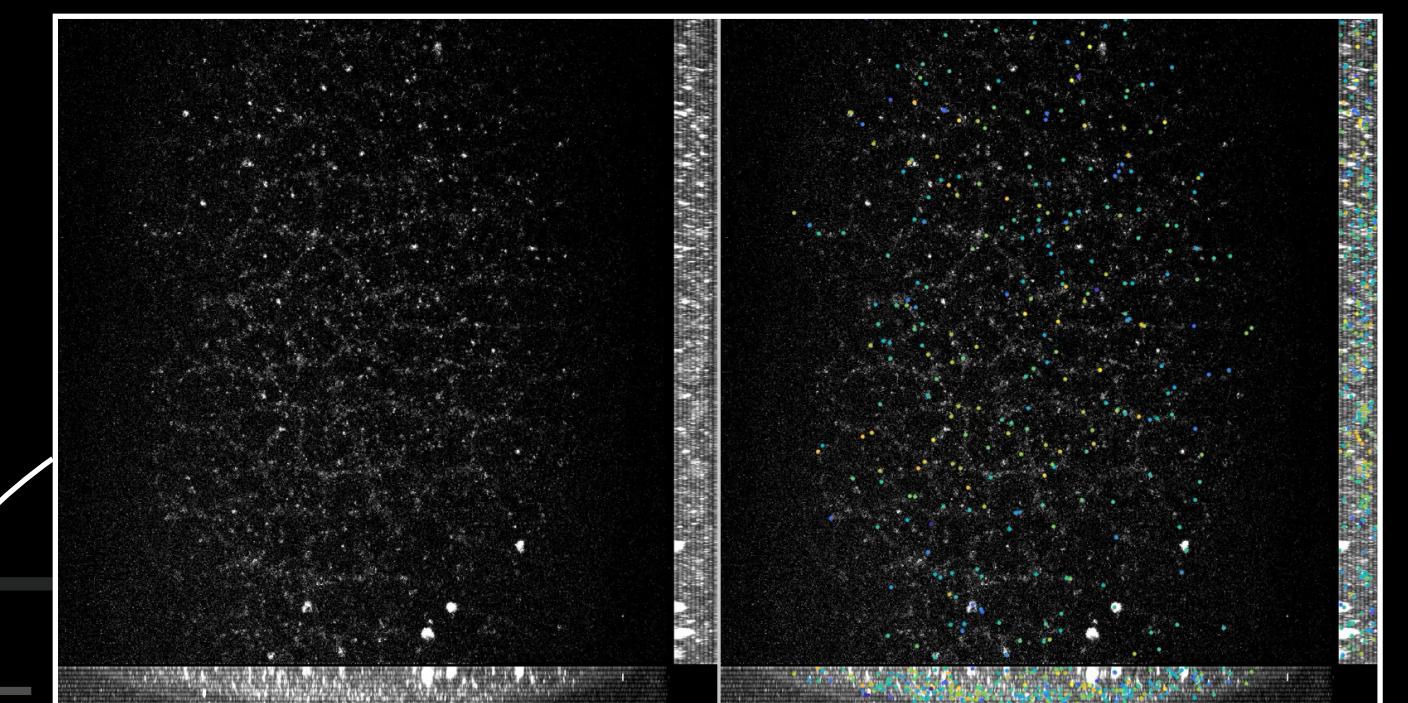


Théo André
Ph.D. student

RESEARCH WORK

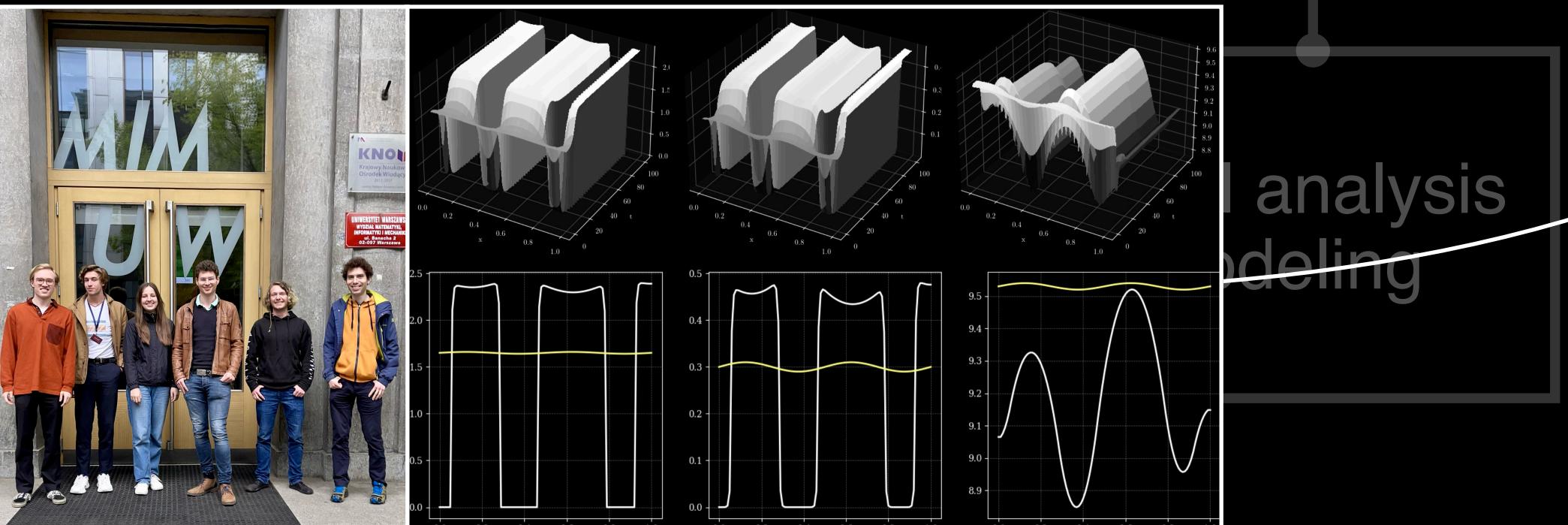


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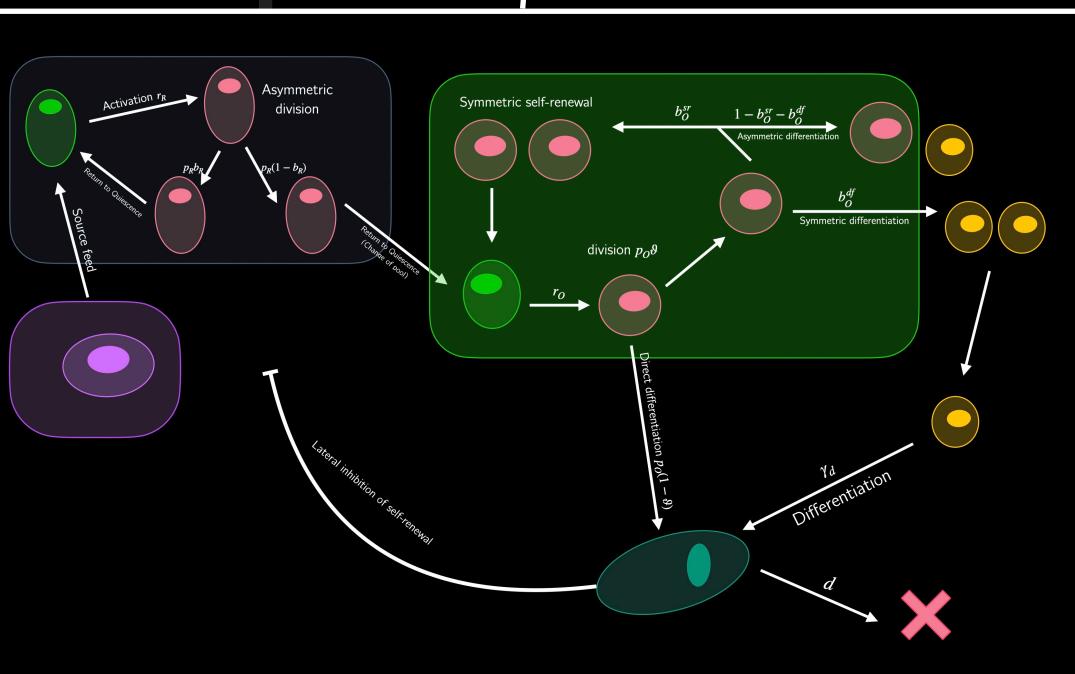


Functional Analysis
of mathematical biology

Bayesian Filtering and Multiscale Tracking
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Diffusion-Driven Instability and Pattern formation in
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Spatiotemporal modeling of Neurogenesis and
maintaining of homeostasis in adult *Danio Rerio*
(A. Marciniak-Czochra) (Ongoing...)

Modeling Neural Stem Cell Dynamics

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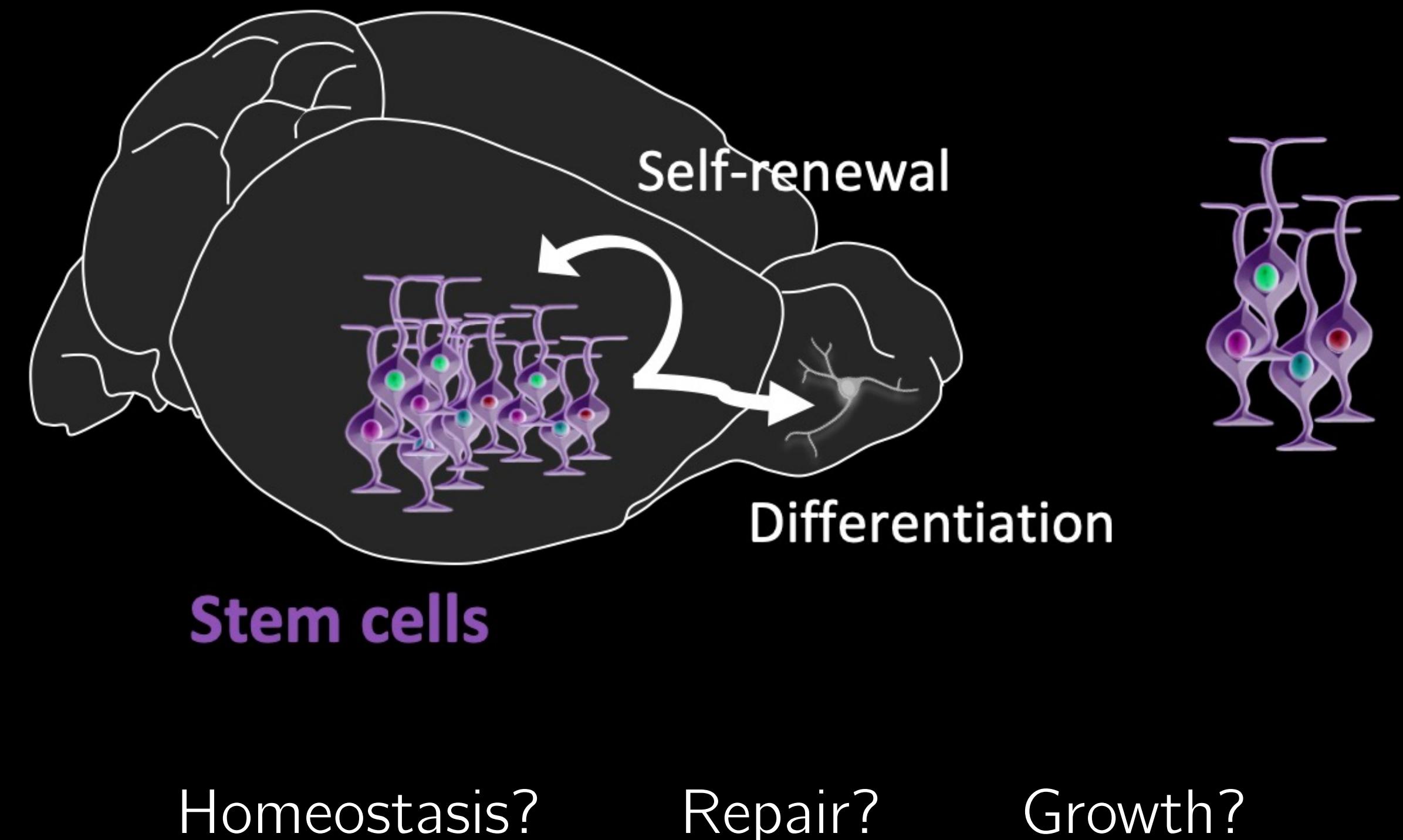


HGS MathComp



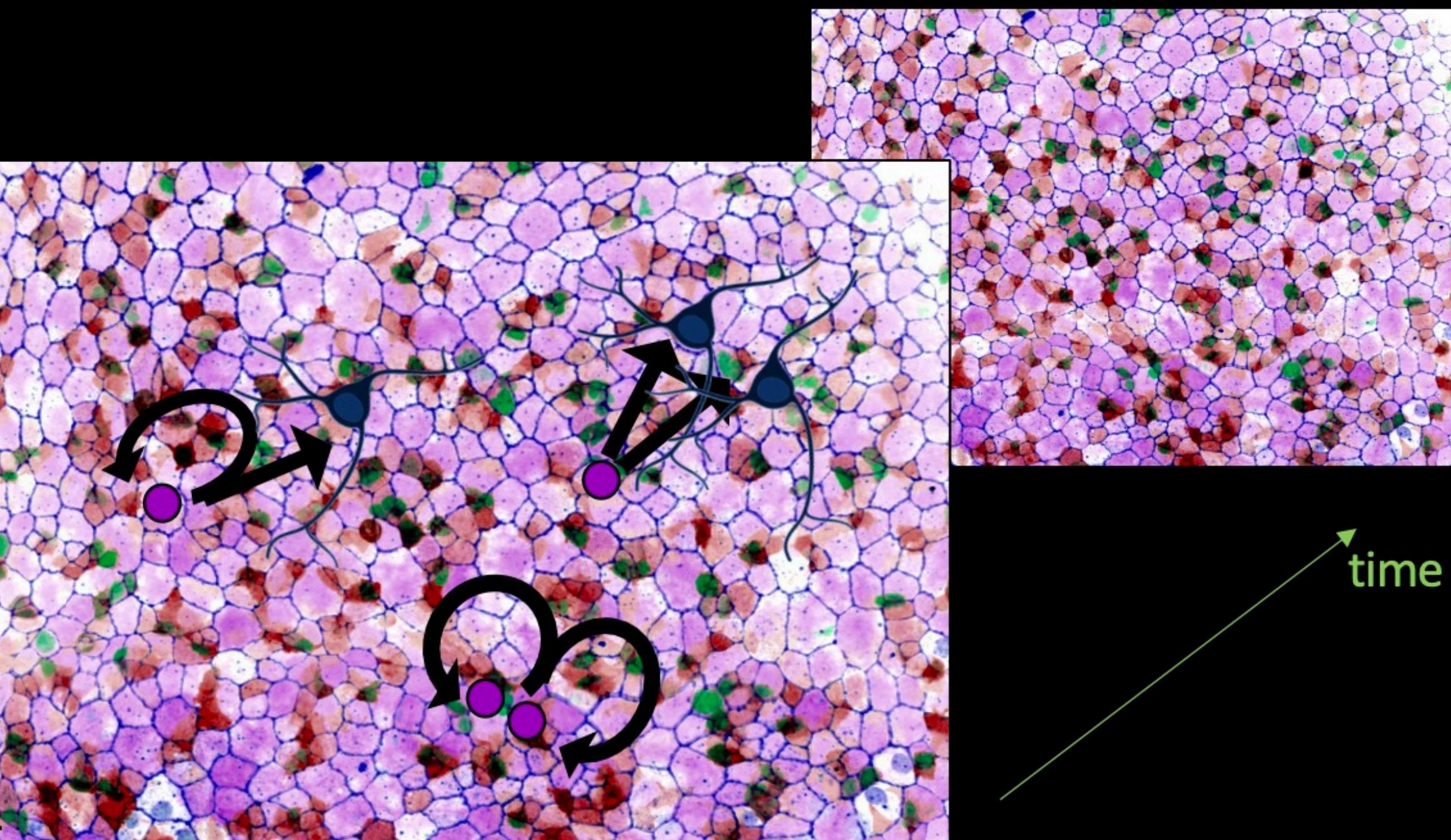
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GOAL: Develop mathematical methodology
for modelling and analysis of spatially-
distributed stem cell (SC) systems.



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MOTIVATION: SC systems are complex. Description of their spatio-temporal dynamics NEEDS a robust mathematical framework.



Connecting disconnected observations?

Stemness maintenance?

GOAL: Develop mathematical methodology for modelling and analysis of spatially-distributed stem cell (SC) systems.

MOTIVATION: SC systems are complex. Description of their spatio-temporal dynamics NEEDS a robust mathematical framework.

WHY? Applications to biology, e.g., *post-injury regeneration* and, sometimes, *cancers dynamics*.

Journal of Mathematical Biology (2019) 79:1587–1621
<https://doi.org/10.1007/s00285-019-01404-w>

Mathematical Biology



A structured population model of clonal selection in acute leukemias with multiple maturation stages

Tommaso Lorenzi¹ · Anna Marciniak-Czochra² · Thomas Stiehl³

Received: 27 September 2018 / Revised: 5 July 2019 / Published online: 26 July 2019
© Springer-Verlag GmbH Germany, part of Springer Nature 2019

Abstract

Recent progress in genetic techniques has shed light on the complex co-evolution of malignant cell clones in leukemias. However, several aspects of clonal selection still remain unclear. In this paper, we present a multi-compartmental continuously structured population model of selection dynamics in acute leukemias, which consists of a system of coupled integro-differential equations. Our model can be analysed in a more efficient way than classical models formulated in terms of ordinary differential equations. Exploiting the analytical tractability of this model, we investigate how clonal selection is shaped by the self-renewal fraction and the proliferation rate of leukemic cells at different maturation stages. We integrate analytical results with numerical solutions of a calibrated version of the model based on real patient data. In summary, our

Applications to biology: Focus on Neural Stem Cell (NSC) systems.

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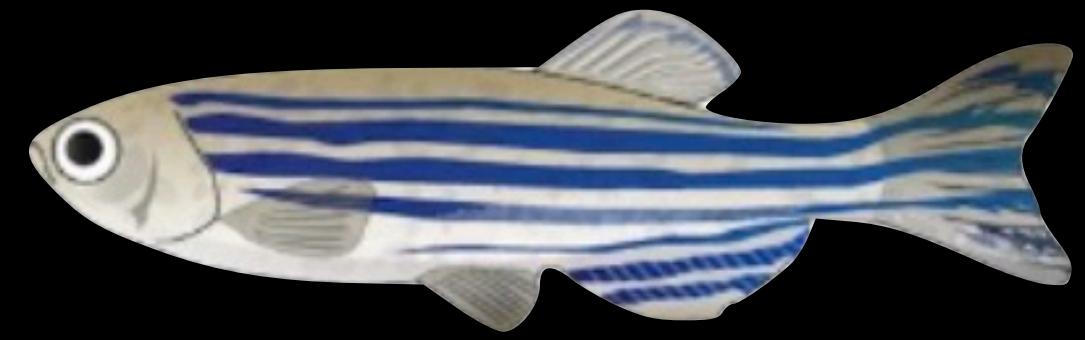
MOUSE



Well-established collaboration
with **Ana Martin Villalba's**
group (Heidelberg)

ZEBRAFISH

(*DANIO RERIO*)



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Observation: Decay / Exhaustion of NSC pool over time



Diana-Patricia
Danciu



Joaa
Hooli

+

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Villalba's
group

$$r = r_{max} \cdot S_1$$

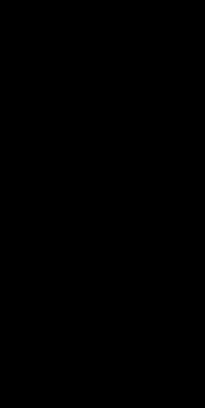
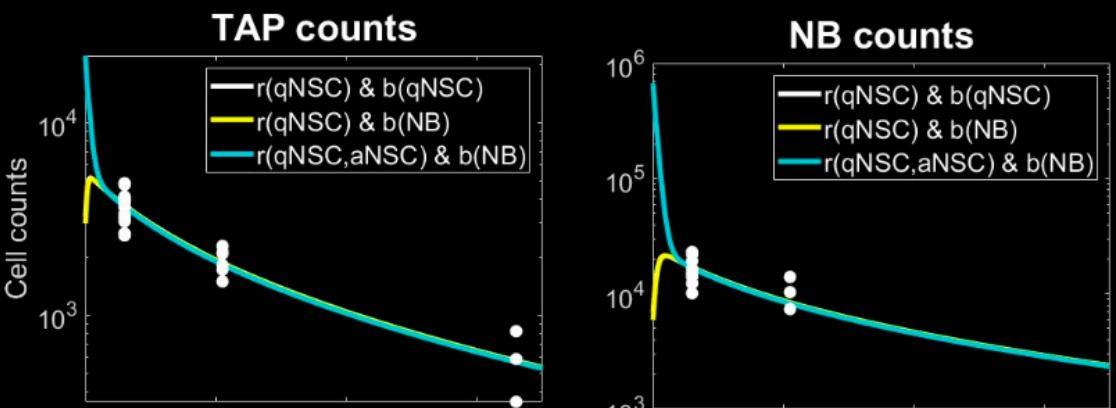
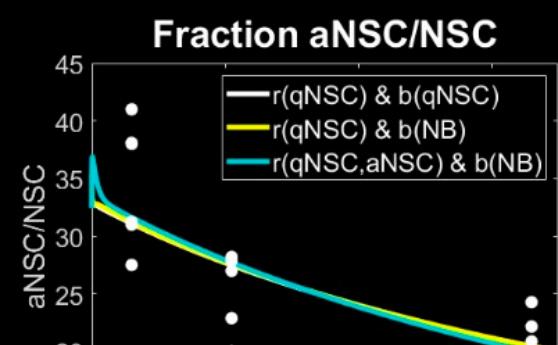
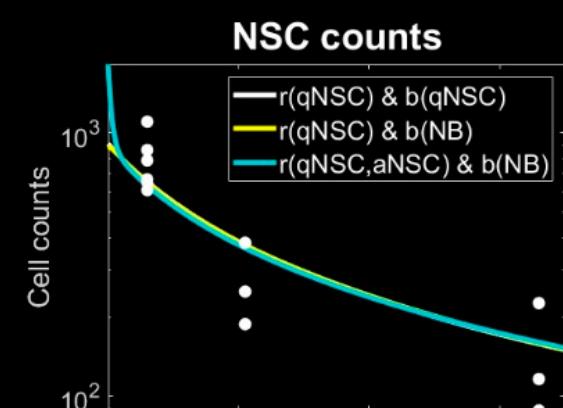
$$\frac{dS_1}{dt} = \underbrace{\text{cells}(t)}_{\text{Production by lineage cells}} - \underbrace{K_r S_1(t)}_{\text{Degradation}} - \underbrace{\text{cells}(t) S_1(t)}_{\text{Consumption by lineage cells}}$$

Production by
lineage cells Degradation Consumption by
lineage cells

$$b = b_{max} \cdot S_2$$

$$\frac{dS_2}{dt} = \underbrace{\text{The picture can't be displayed.}}_{\text{Production by niche (non-lineage cells)}} - \underbrace{S_2(t)}_{\text{Degr.}} - \underbrace{\beta_b \cdot \text{cells}(t) S_2(t)}_{\text{Consumption by lineage cells}}$$

Production by
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Applications to biology: Focus on Neural Stem Cell (NSC) systems.

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Diana-Patricia
Danciu

+



Joaa
Hooli

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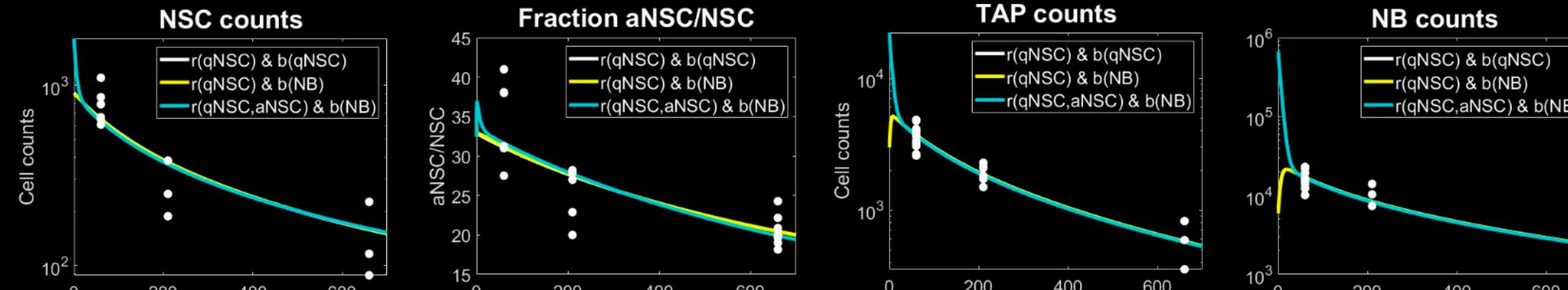
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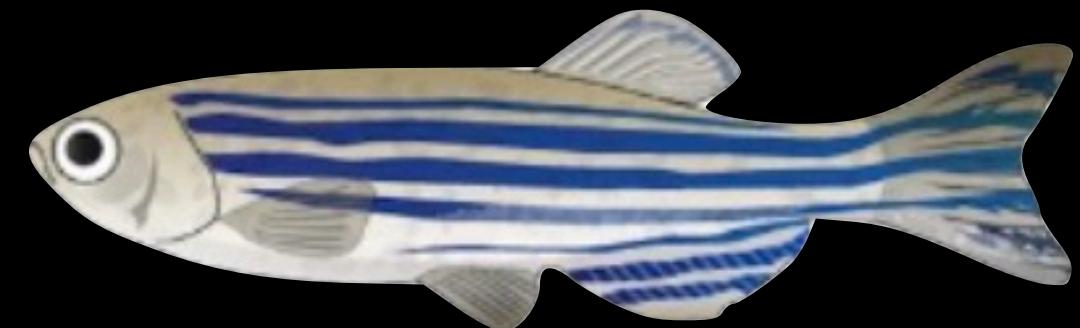
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All the credit goes to Diana-Patricia Danciu for the pictures

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Observation: dynamical *homeostasis* of NSC pool over time



T.
A.

Laure Bally-
Cuif's
group

+

More?

**Dense
biological
literature!**

STEM CELLS

Apical size and *deltaA* expression predict adult neural stem cell decisions along lineage progression

Laure Mancini^{1,2*}, Boris Guirao³, Sara Ortica¹, Miriam Labusch^{1,2}, Felix Cheysson^{4,†}, Valentin Bonnet^{5,6}, Minh Son Phan⁷, Sébastien Herbert^{7\$}, Pierre Mahou⁸, Emilie Menant Sébastien Bedu¹, Jean-Yves Tinevez⁷, Charles Baroud^{5,6}, Emmanuel Beaurepaire⁸, Yohanns Bellaïche³, Laure Bally-Cuif^{1*}, Nicolas Dray^{1*}

Cell Stem Cell

Dynamic spatiotemporal coordination of neural stem cell fate decisions occurs through local feedback in the adult vertebrate brain

**Neural stem cell pools in the vertebrate adult brain:
Homeostasis from cell-autonomous decisions or community rules?**

Nicolas Dray¹ | Emmanuel Than-Trong^{1,2} | Laure Bally-Cuif¹

Lineage hierarchies and stochasticity ensure the long-term maintenance of adult neural stem cells

Emmanuel Than-Trong^{1,2}, Bahareh Kiani³, Nicolas Dray¹, Sara Ortica¹, Benjamin Simons^{4,5,6}, Steffen Rulands^{3,7}, Alessandro Alunni^{1,*†}, Laure Bally-Cuif^{1,*†}

Applications to biology: Focus on Neural Stem Cell (NSC) systems.

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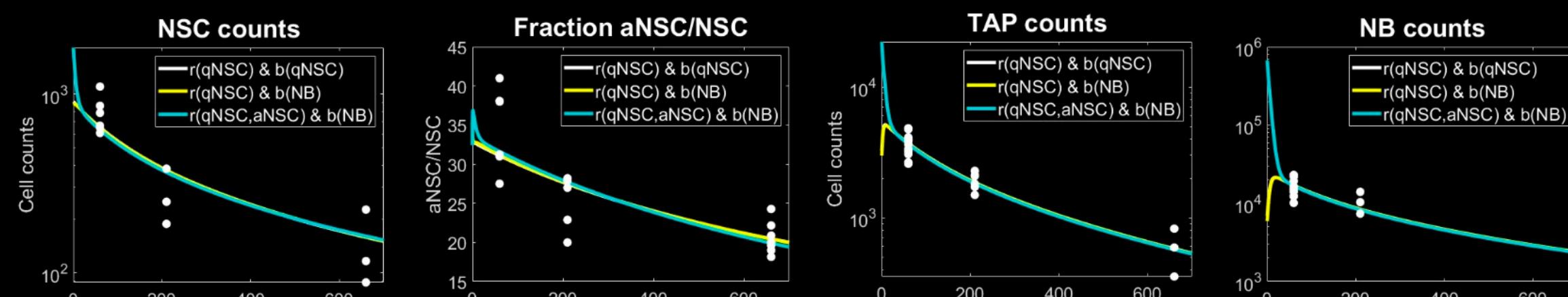
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WHAT ARE THE MECHANISMS MAINTAINING
HOMEOSTASIS IN THE ZEBRAFISH BRAIN?

Neural stem cell pools in the vertebrate adult brain:
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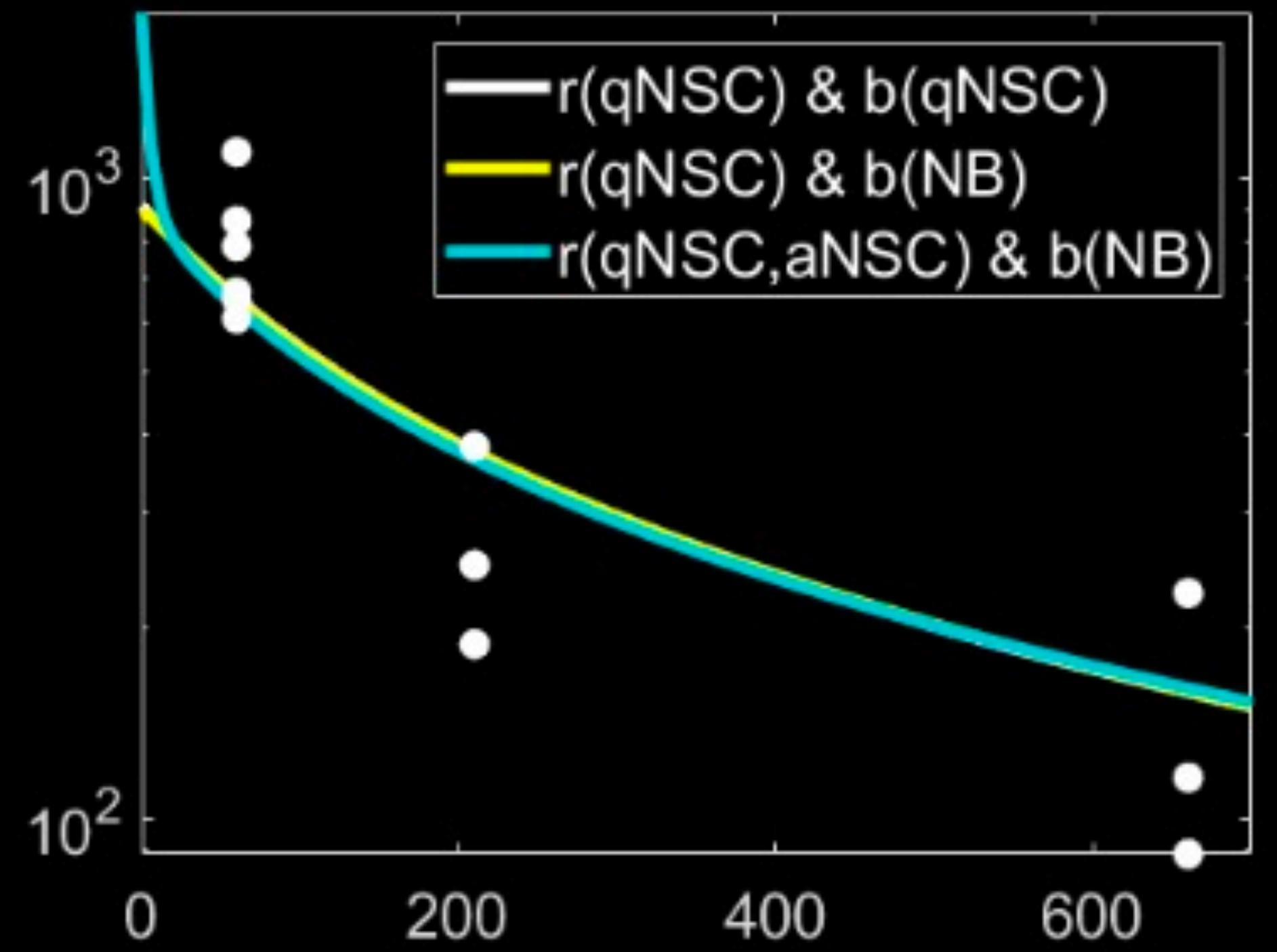
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Current State of NSC Modeling:

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Ordinary Differential Equations

Population scale but no space



Captures
general
behavior

s

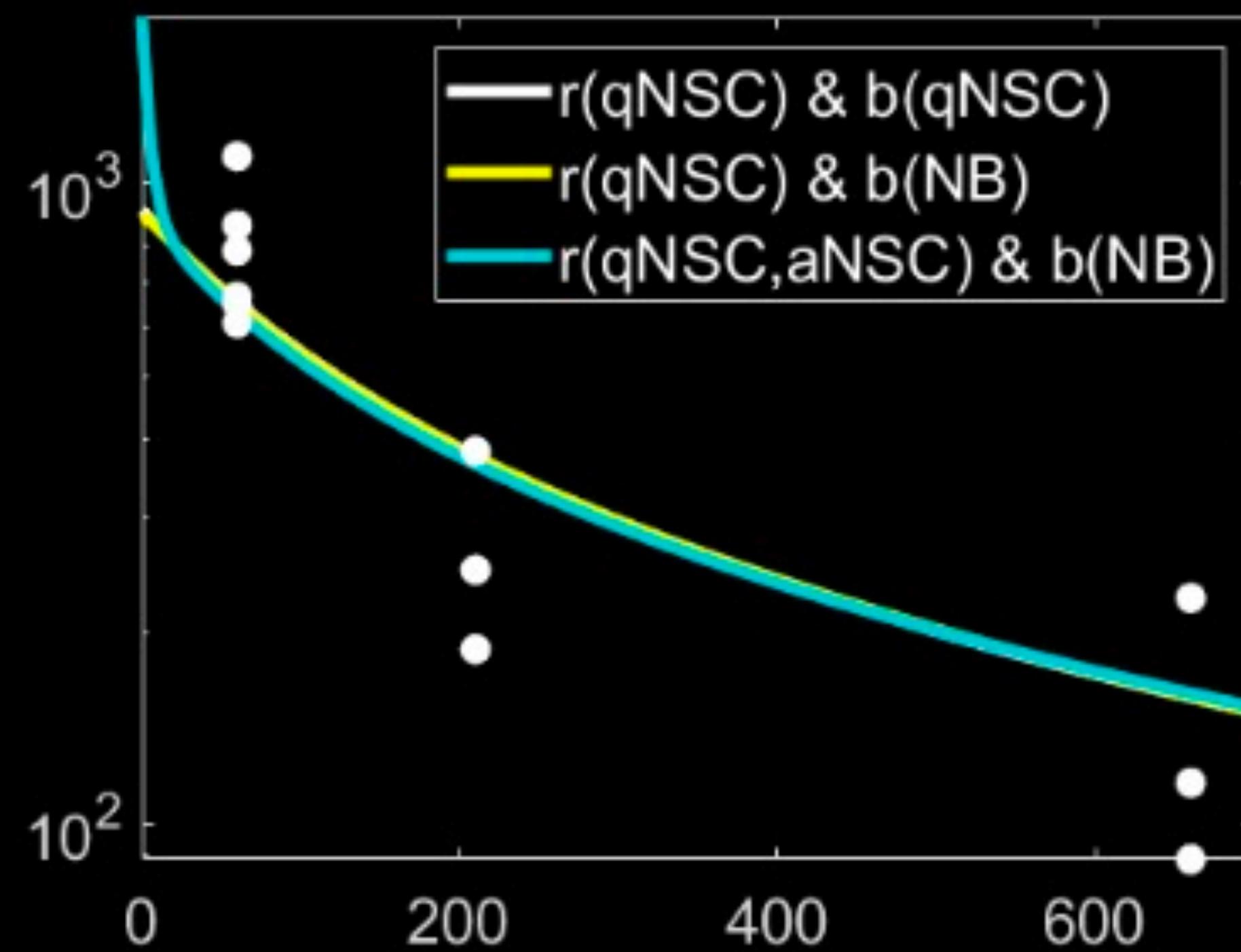
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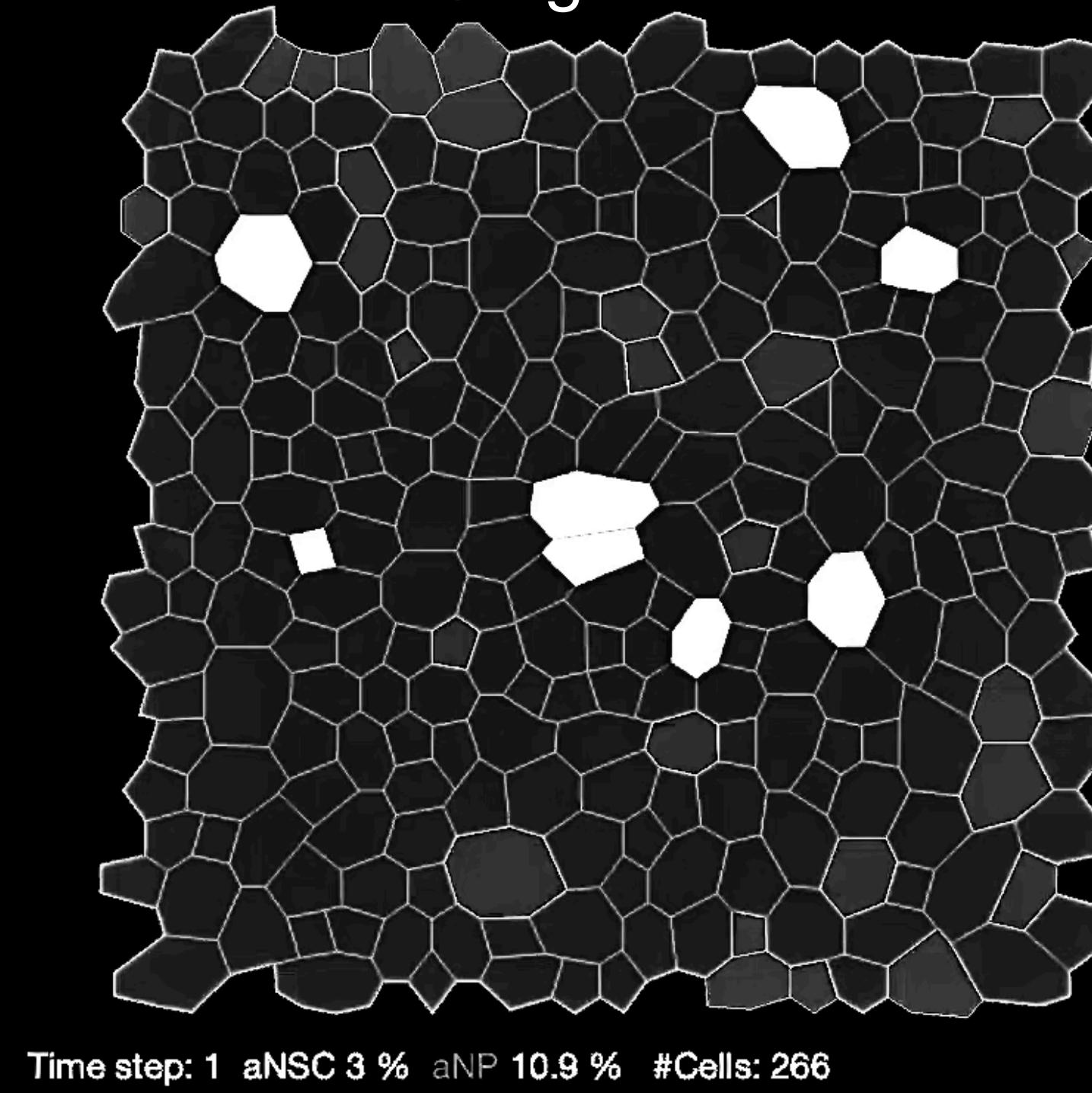


Captures
general
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Individual-Based Models

Single-cell scale and space
integration

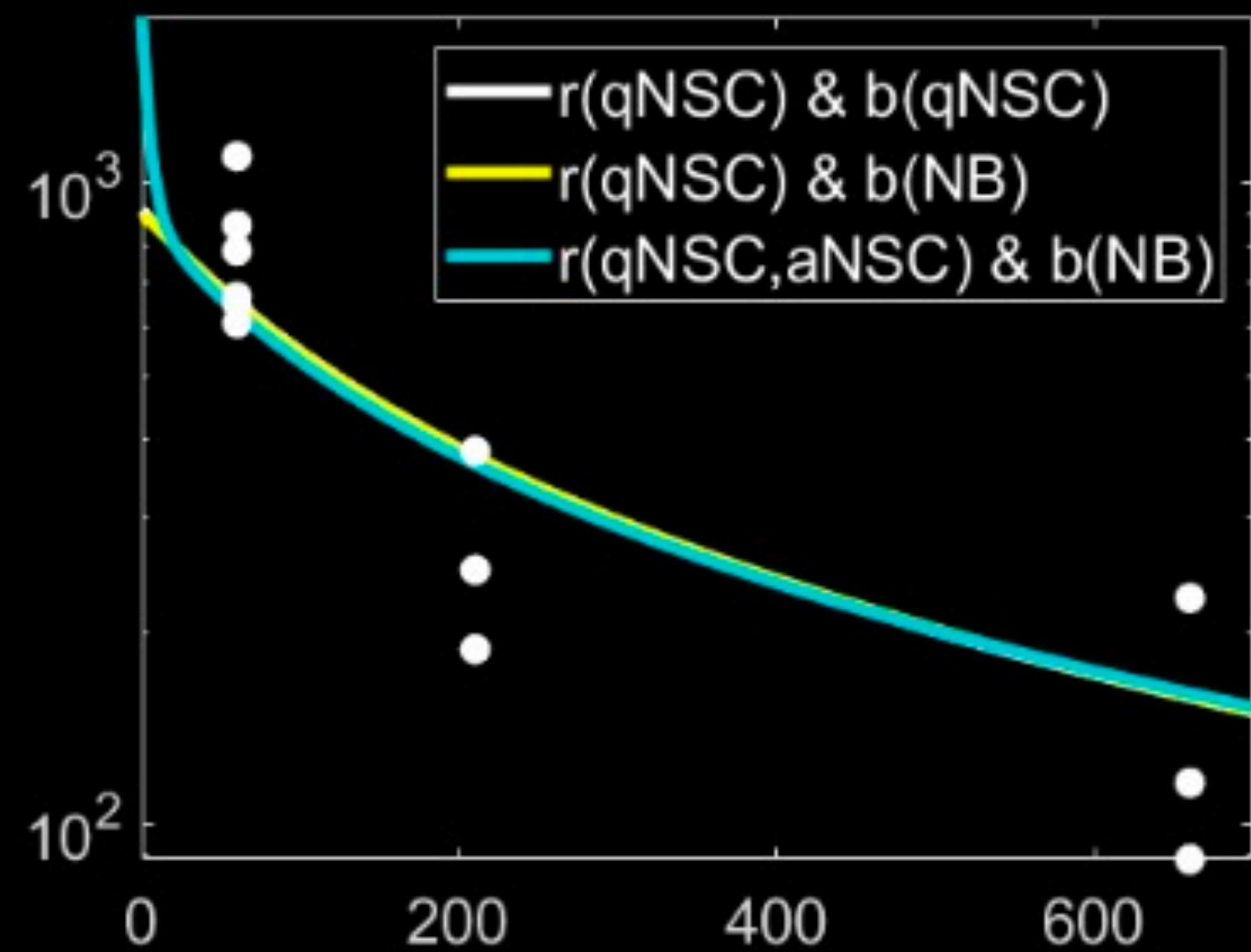


(But no tools for param. estimation or analysis)

Current State of NSC Modeling:

Ordinary Differential Equations

Population scale but no space

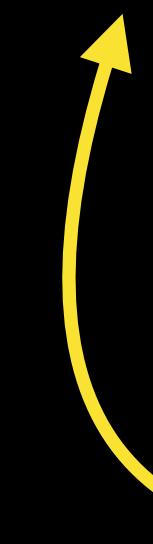
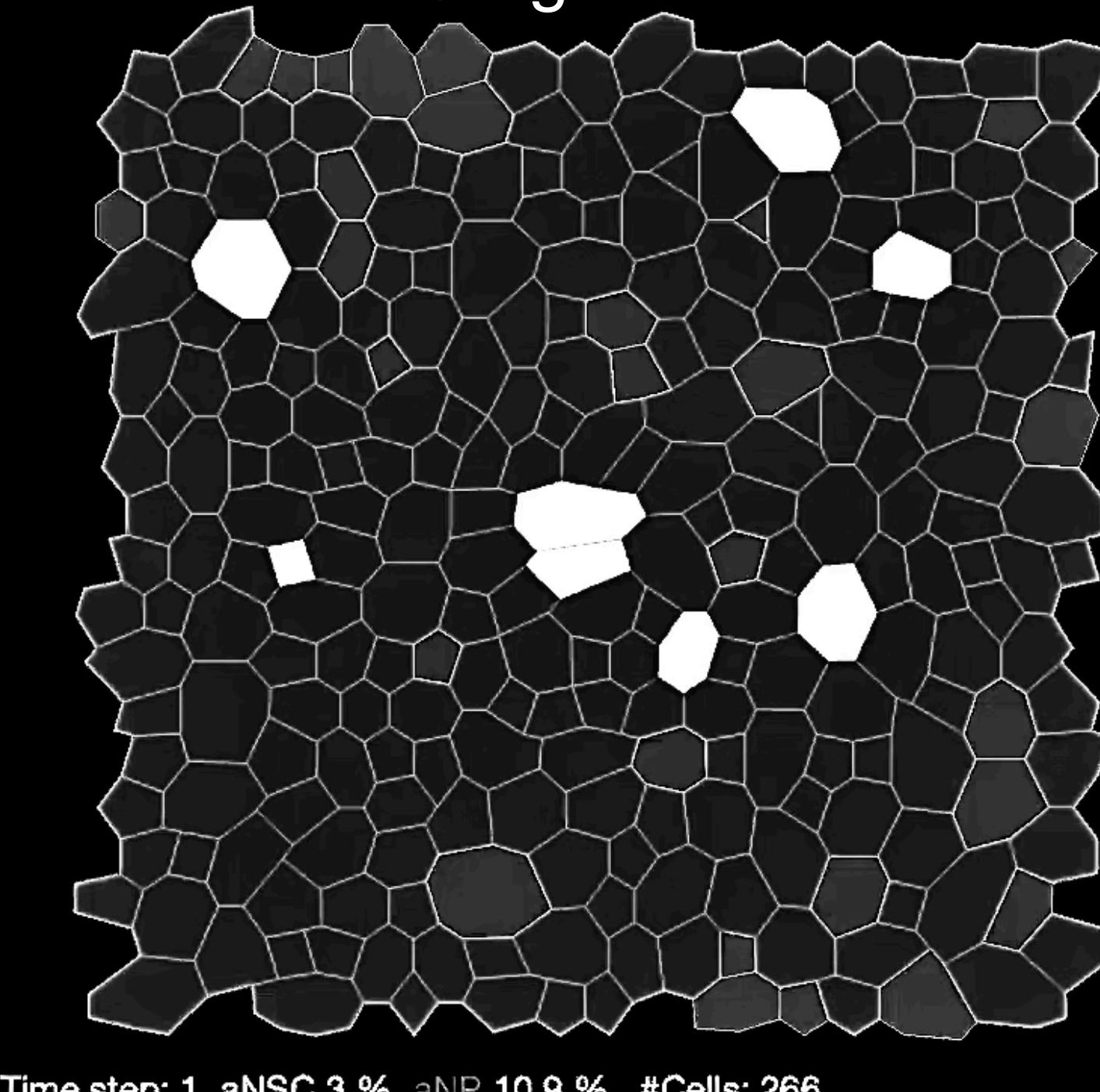


Captures
general
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s

(But not space...)

Individual-Based Models

Single-cell scale and space
integration



Captures (some)
geometry, and spatial
and individual details

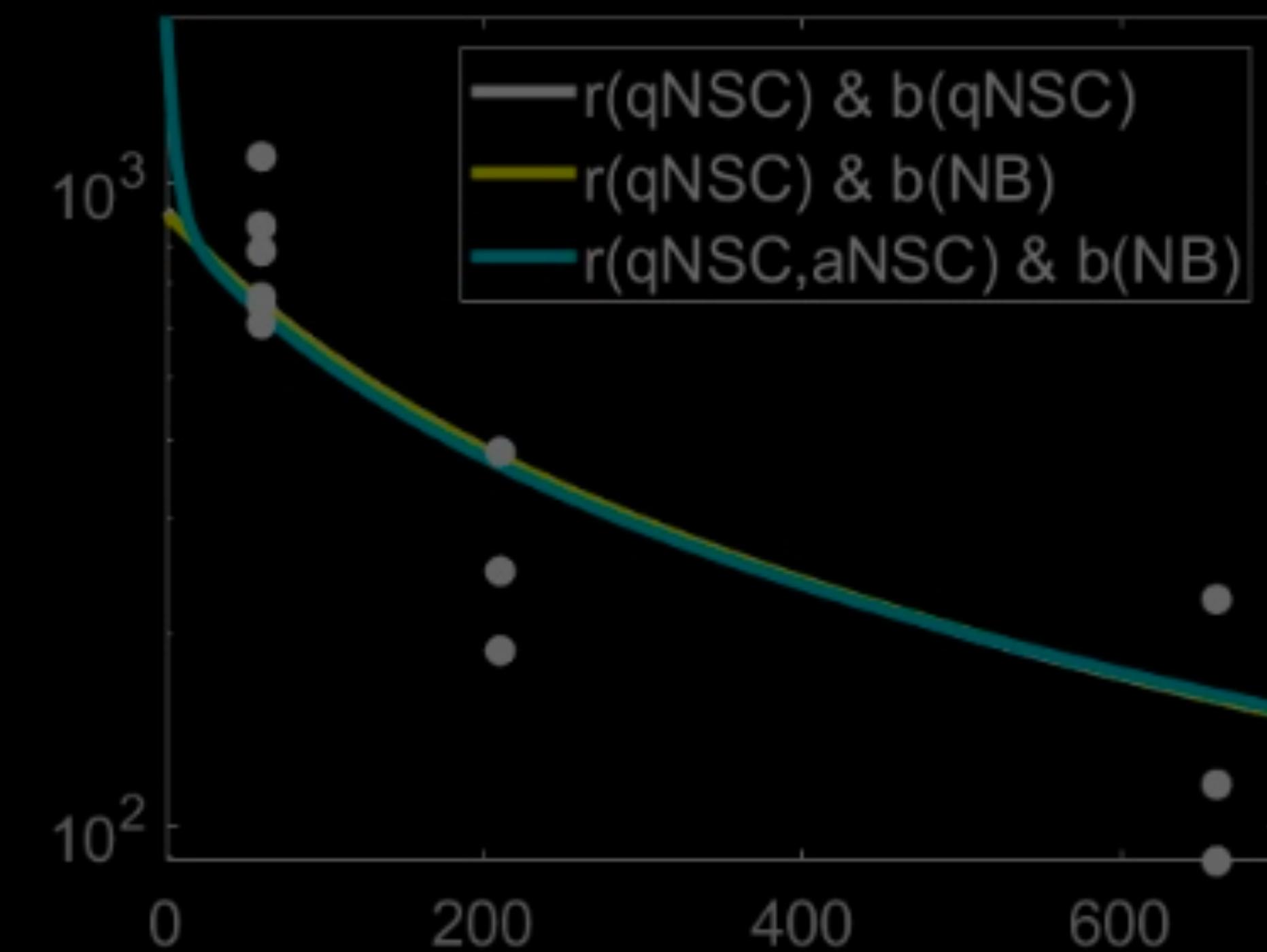
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CAN WE GET BOTH?

Current State of NSC Modeling:

Ordinary Differential Equations

Population scale but no space

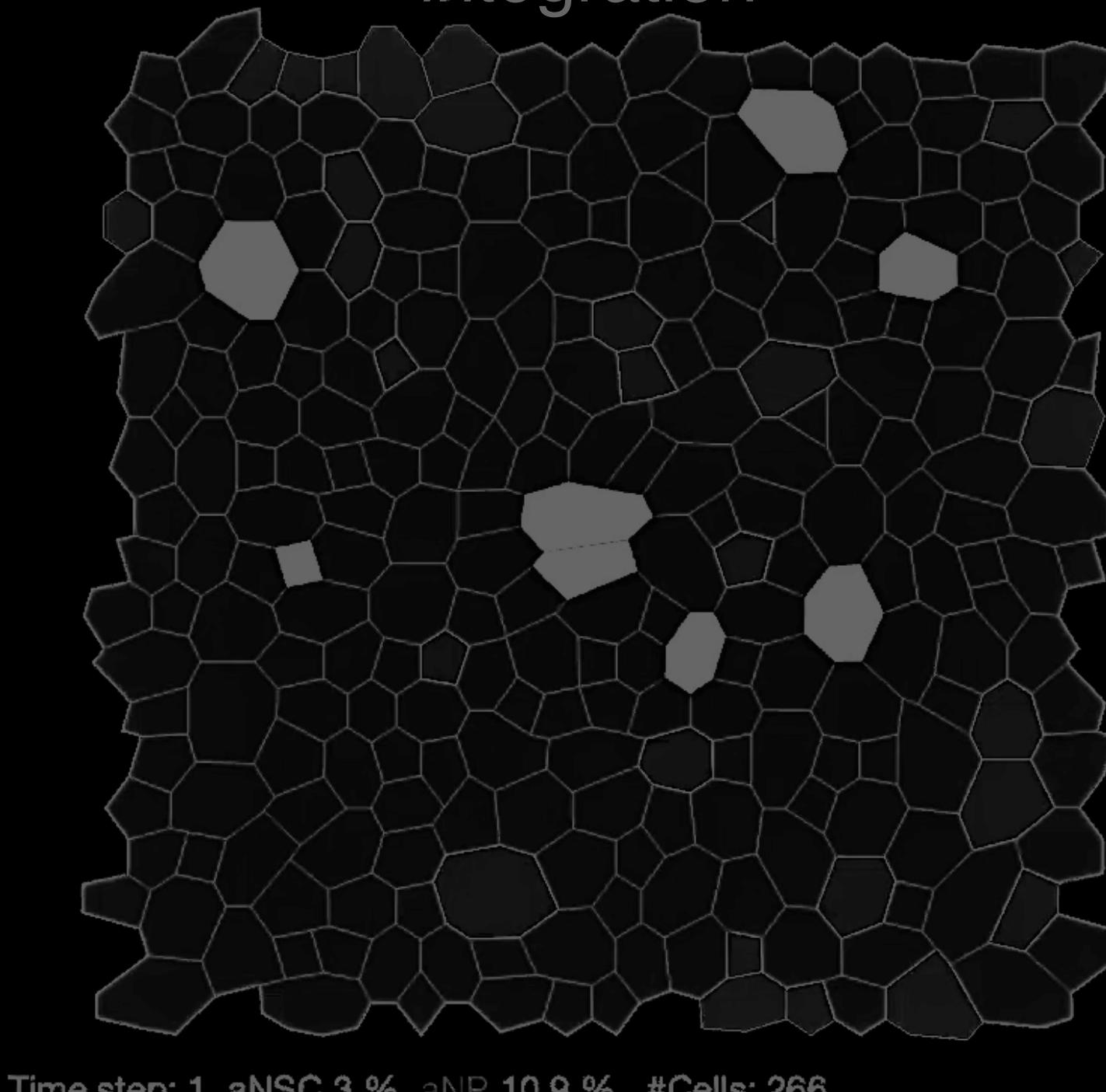


Captures general behavior
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Individual-Based Models

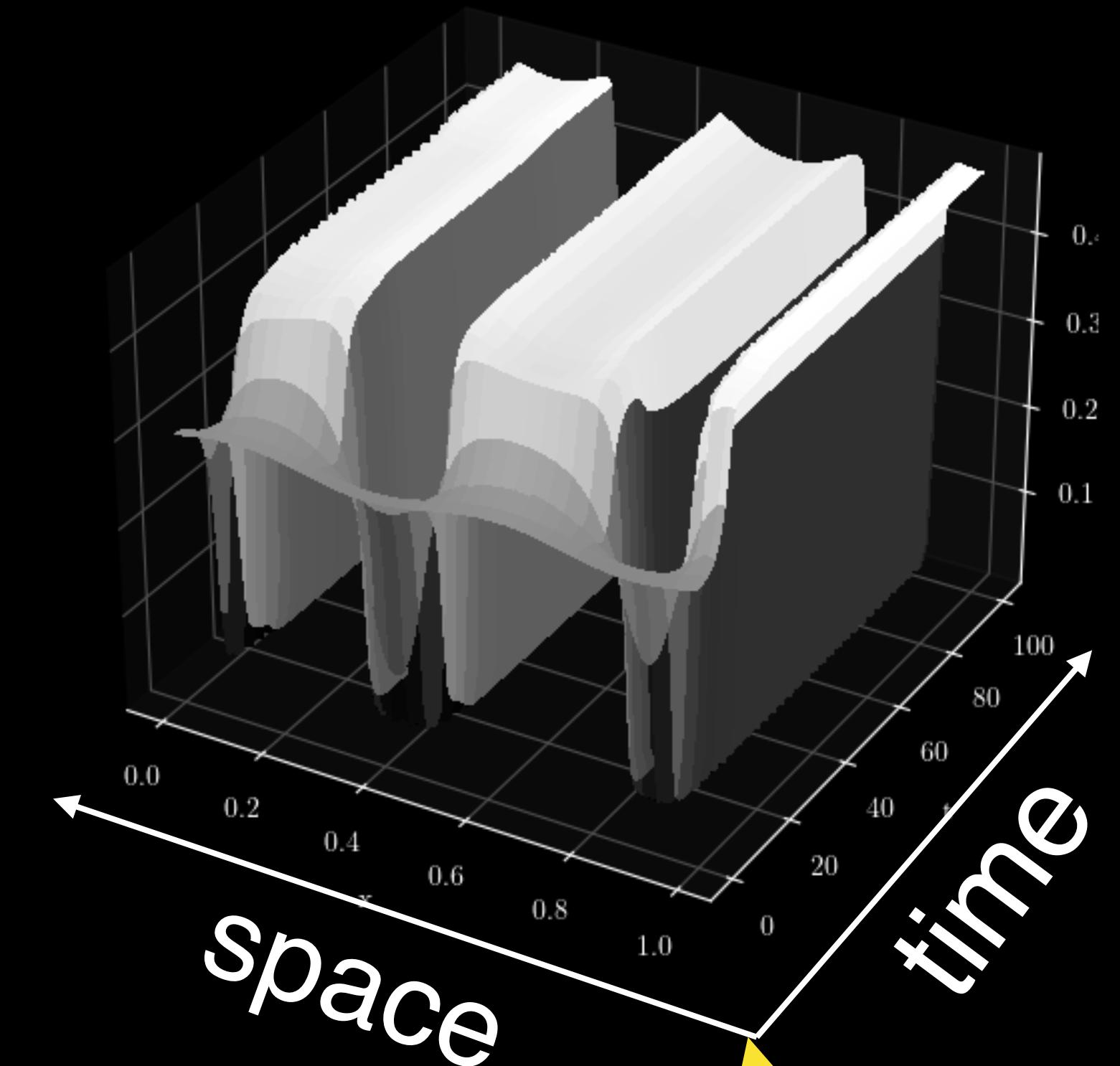
Single-cell scale and space integration



(But no tools for param. estimation or analysis)

Partial Differential Equations

Population scale AND space

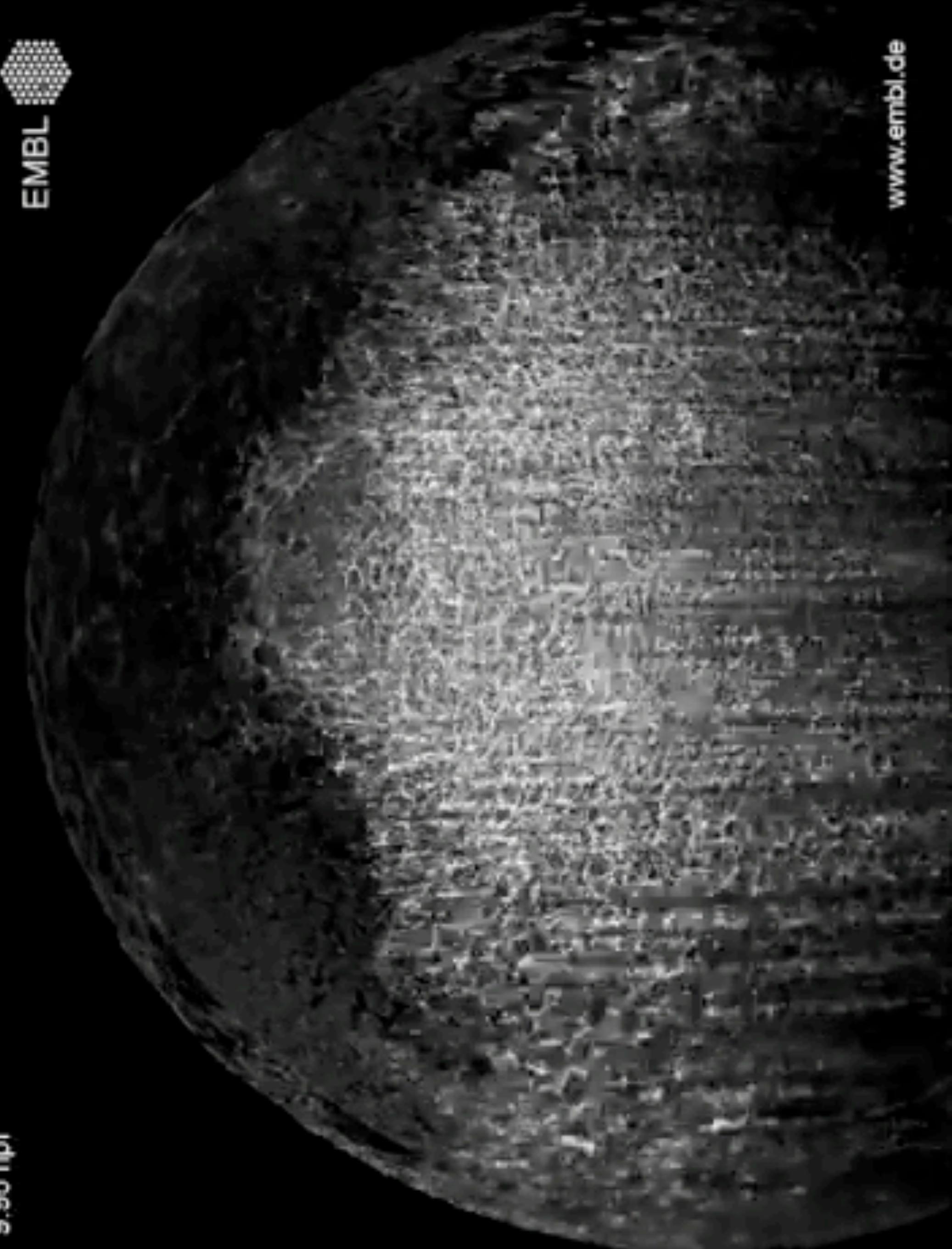


Integrates the geometry and captures general behaviors!

Many phenomena to take into account:

- Cellular motion/migration,
- Stochasticity,
- Local cell-cell interactions,
- Long-range feedback signaling,
- Nonlinear interactions
- ...

9.90 hpf

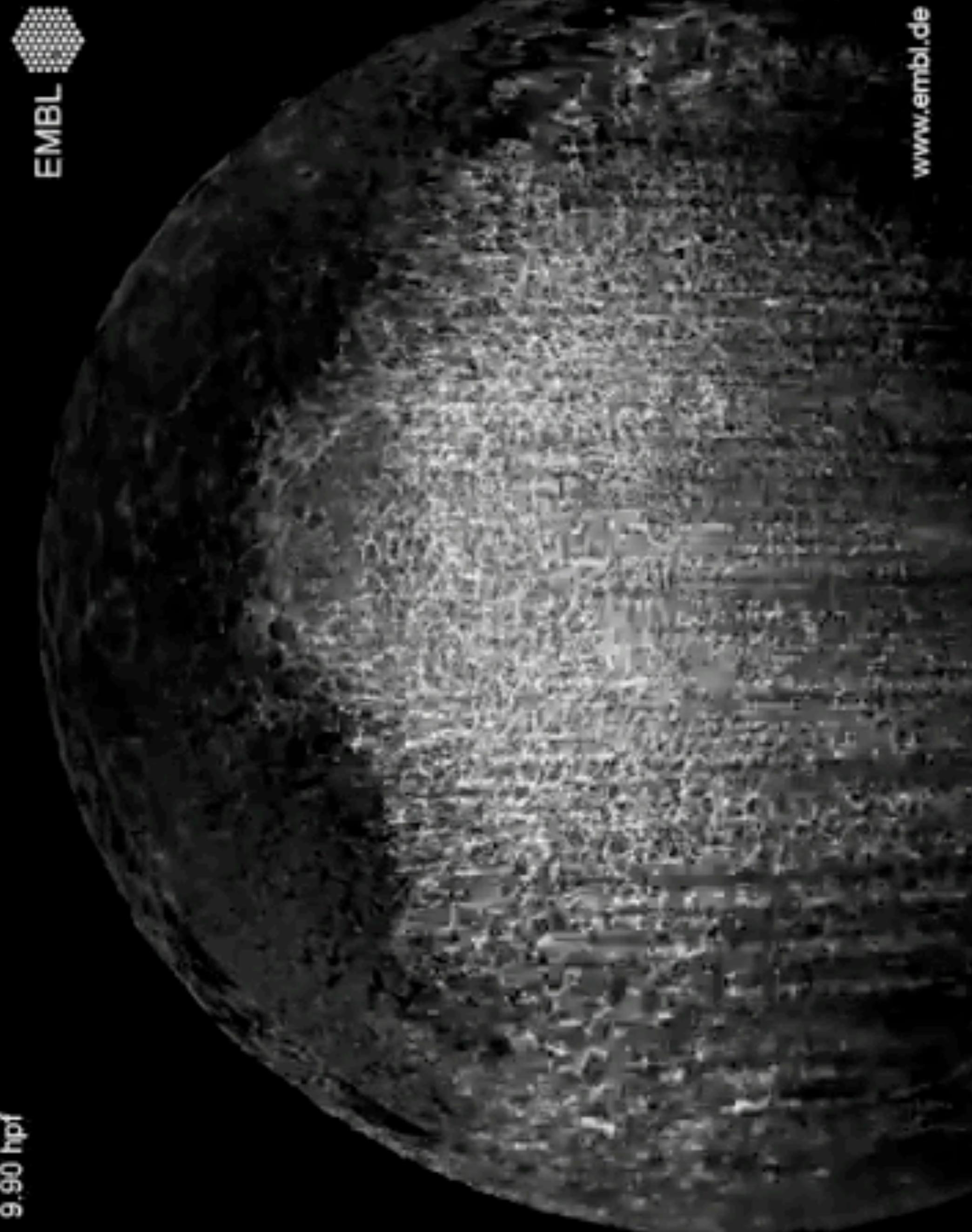


Many phenomena to take into account:

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Coupling between local and global dynamics

- Systems of PDEs coupled to multiple infinite families of ODEs,
- Sparse literature and few results,
- Mechanism of pattern formation is poorly understood...



9.90 hpf

Preliminary project:

(inspired by) AMC. Developmental models with cell surface receptor densities defining morphological position. [2004]

$$\left\{ \begin{array}{l} \text{Free Receptors} \\ \text{Ligands} \\ \text{Enzymes} \end{array} \right\} \quad \left\{ \begin{array}{l} \frac{\partial u}{\partial t} = -\mu_f u + m_1 \frac{uv}{1+uv} - \mu_b uv & \text{for } x \in \Omega, t > 0 \\ \frac{\partial v}{\partial t} = d_1 \Delta v - \mu_l v + m_2 \frac{uv}{1+uv} - \mu_b uv - vw & \text{for } x \in \Omega, t > 0 \\ \frac{\partial w}{\partial t} = d_2 \Delta w - \mu_e w + m_3 \frac{uv}{1+uv} & \text{for } x \in \Omega, t > 0 \\ \frac{\partial v}{\partial \nu} = 0, \quad \frac{\partial w}{\partial \nu}(t, x) = 0 & \text{for } x \in \partial\Omega, t \geq 0 \\ u(0, x) = u_0, \quad v(0, x) = v_0, \quad w(0, x) = w_0 & \text{for } x \in \Omega \end{array} \right.$$

Preliminary project: (inspired by) AMC. Developmental models with cell surface receptor densities defining morphological position. [2004]

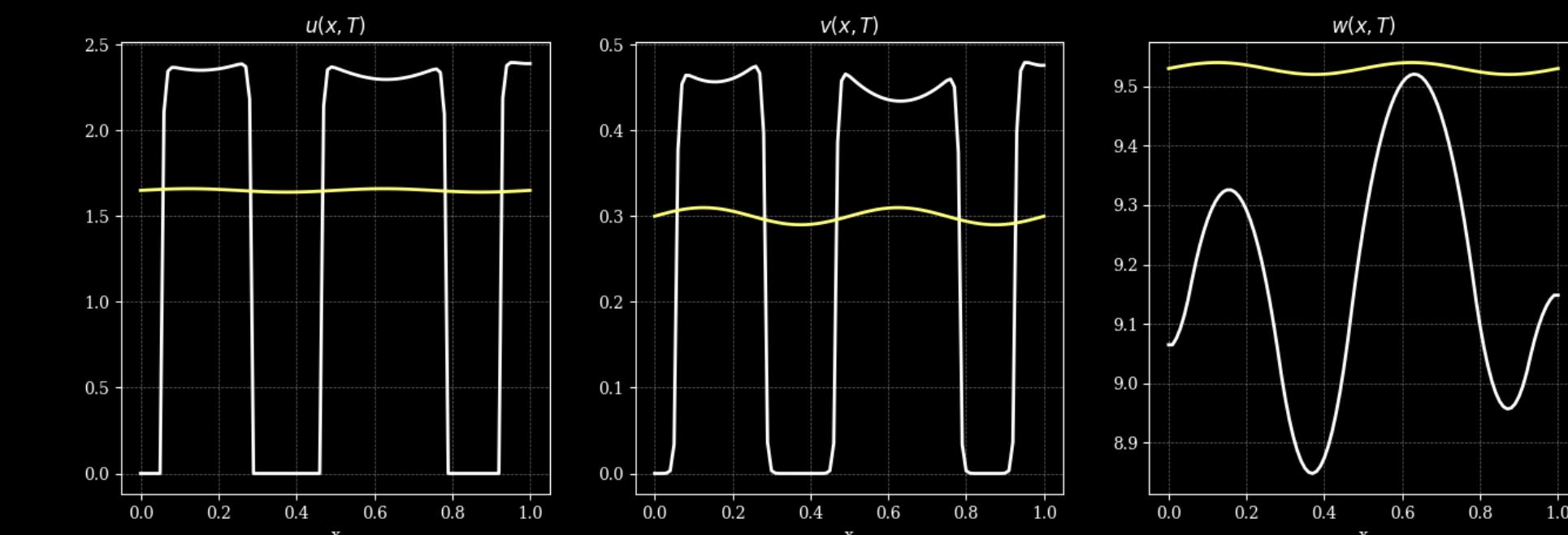
Free Receptors
Ligands
Enzymes

Boundary Conditions

Initial Conditions

$$\left\{ \begin{array}{l} \frac{\partial u}{\partial t} = -\mu_f u + m_1 \frac{uv}{1+uv} - \mu_b uv \quad \text{for } x \in \Omega, t > 0 \\ \frac{\partial v}{\partial t} = d_1 \Delta v - \mu_l v + m_2 \frac{uv}{1+uv} - \mu_b uv - vw \quad \text{for } x \in \Omega, t > 0 \\ \frac{\partial w}{\partial t} = d_2 \Delta w - \mu_e w + m_3 \frac{uv}{1+uv} \quad \text{for } x \in \Omega, t > 0 \\ \frac{\partial v}{\partial \nu} = 0, \quad \frac{\partial w}{\partial \nu}(t, x) = 0 \quad \text{for } x \in \partial\Omega, t \geq 0 \\ u(0, x) = u_0, \quad v(0, x) = v_0, \quad w(0, x) = w_0 \quad \text{for } x \in \Omega \end{array} \right.$$

Can we obtain Turing-like patterns? →



Results: Methodology for obtaining (jump-) patterns in models featuring 1ODE and 2PDEs

1. Bistability and hysteresis:

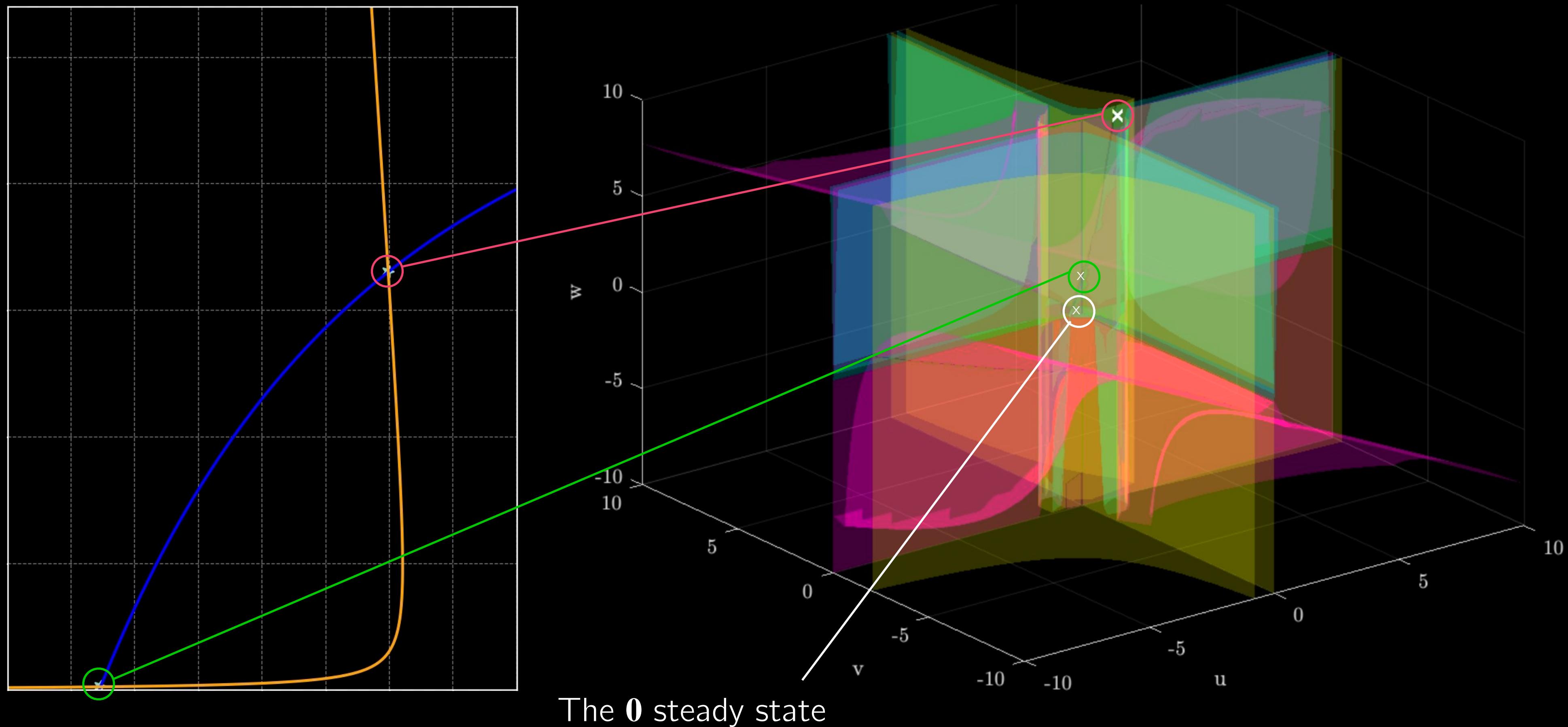


Figure: Existence of three positive steady states. The origin, $\mathbf{0}$, and two additional $\bar{\mathbf{X}}_{2,3}$, given by the intersection of nullclines (left). The right plot represents the manifold $\mathcal{M} = \{(u, v, w) \mid f(u, v) = g(u, v, w) = h(u, v, w) = 0\}$

Results:

Methodology for obtaining (jump-) patterns in models featuring 1ODE and 2PDEs

1. Bistability and hysteresis:

2. Turing Instability:

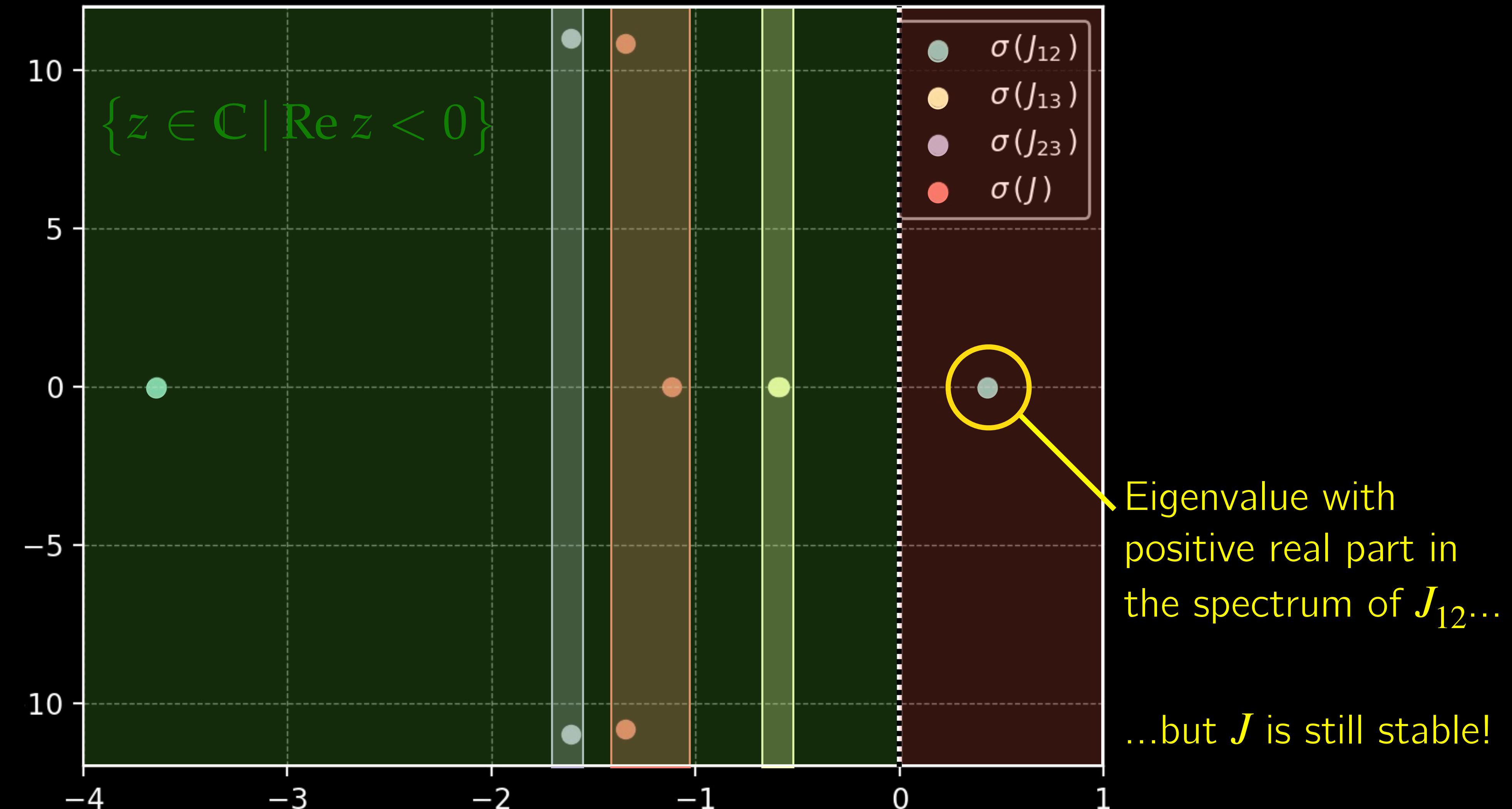


Figure: Spectra of J and its principal minors. One sees J_{12} has a positive eigenvalue while $s(J) < 0$

Results:

Methodology for obtaining (jump-) patterns in models featuring 1ODE and 2PDEs

1. Bistability and hysteresis:
2. Turing Instability:
3. The right diffusion regime:

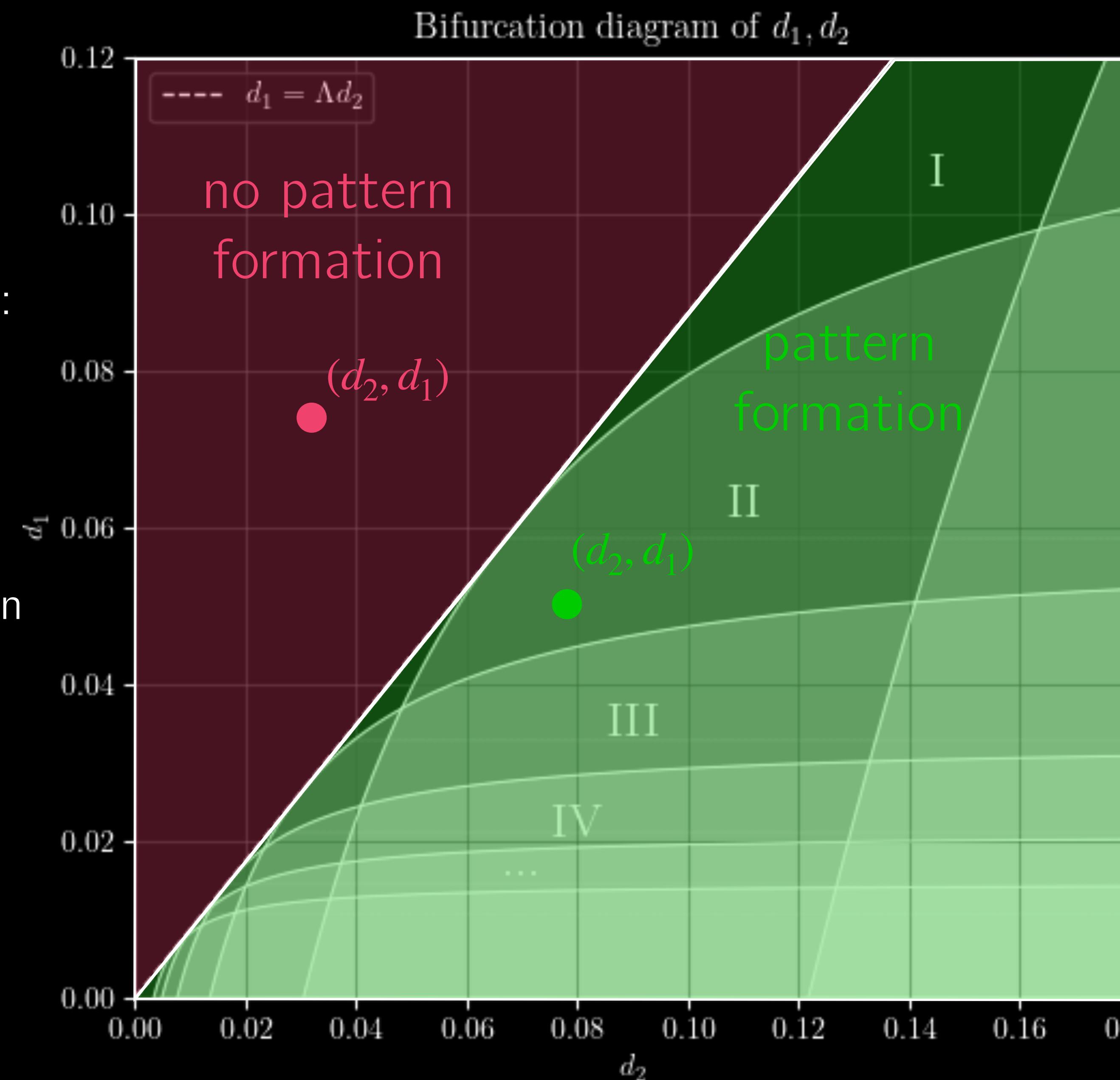
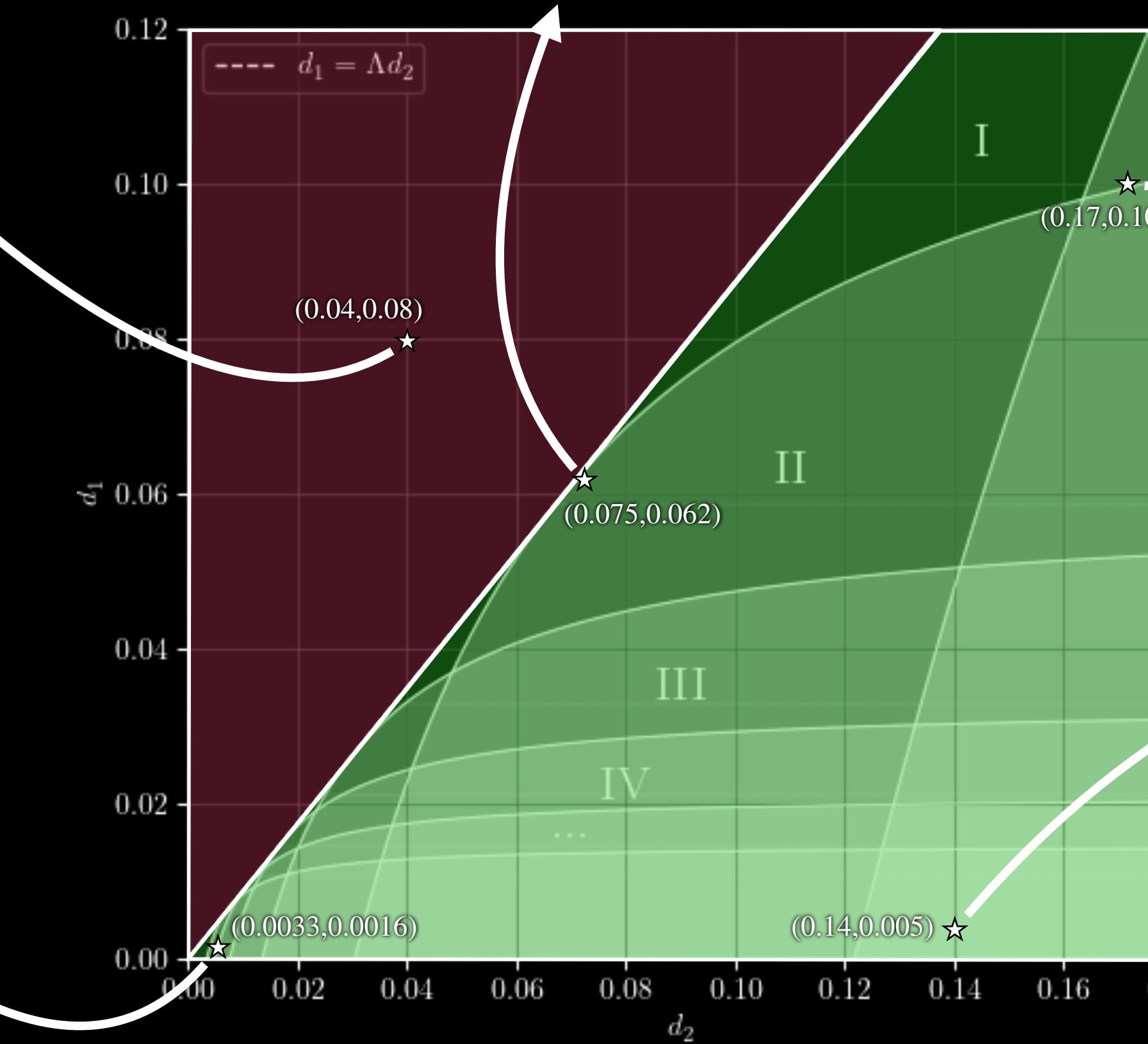
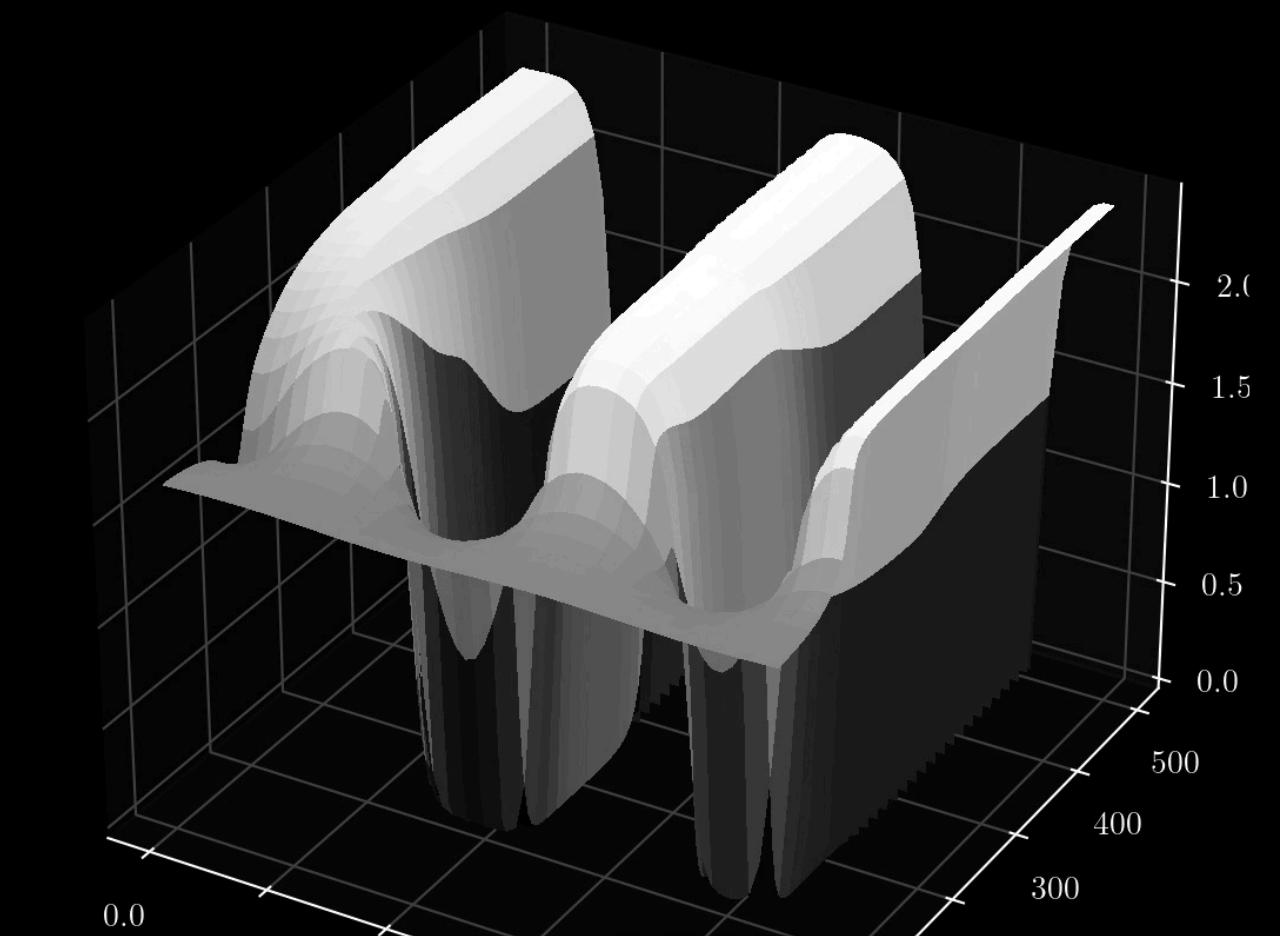
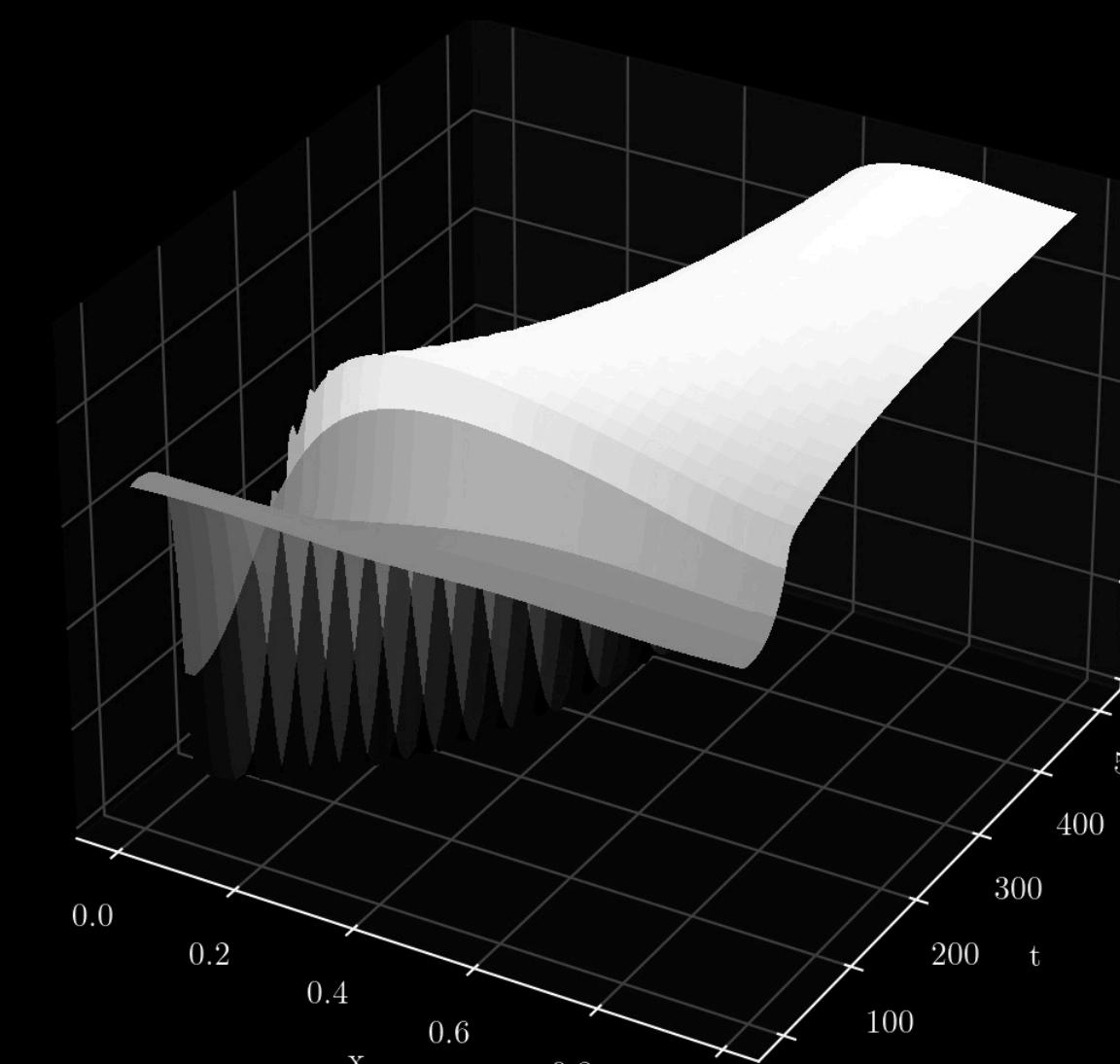
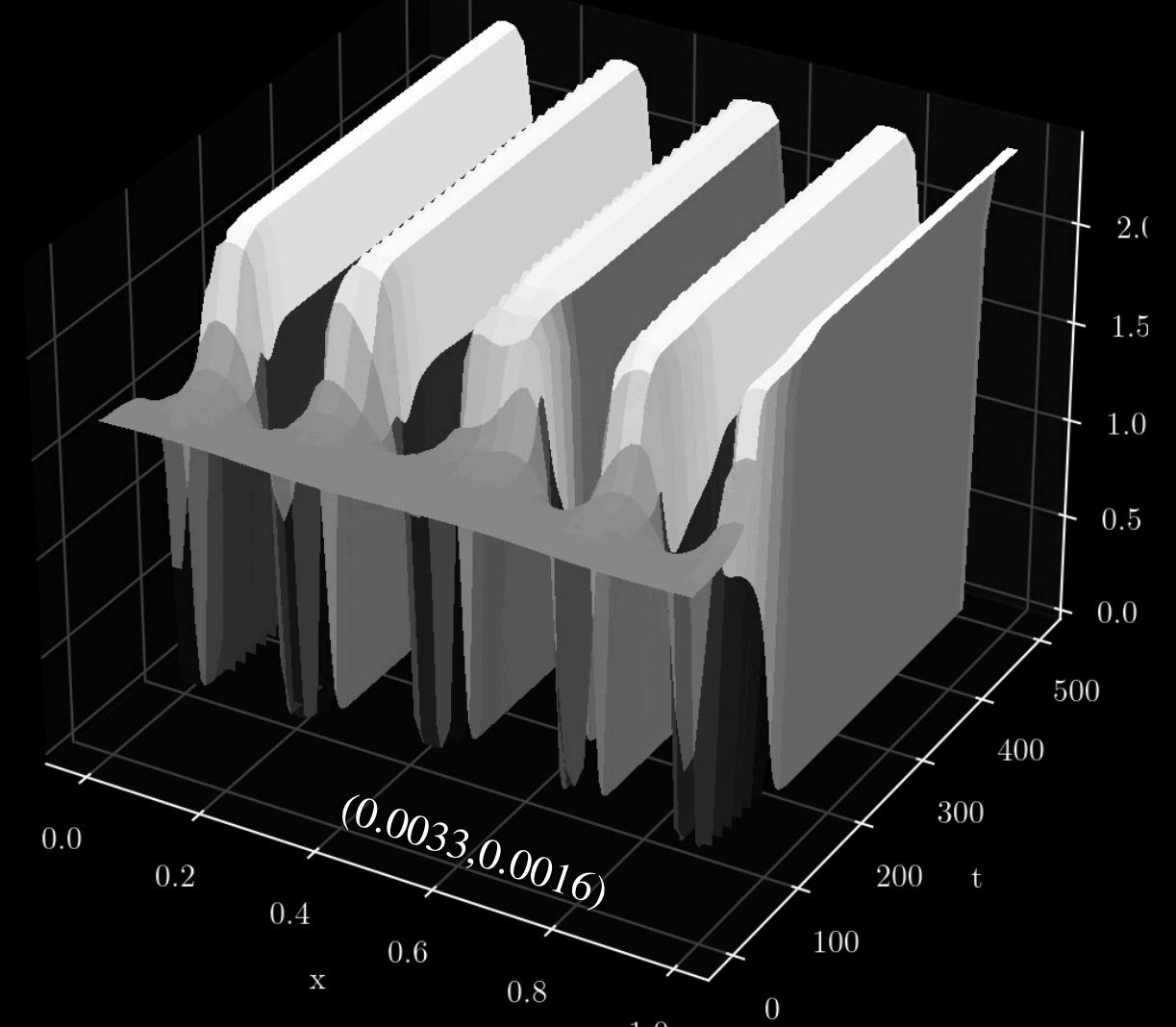
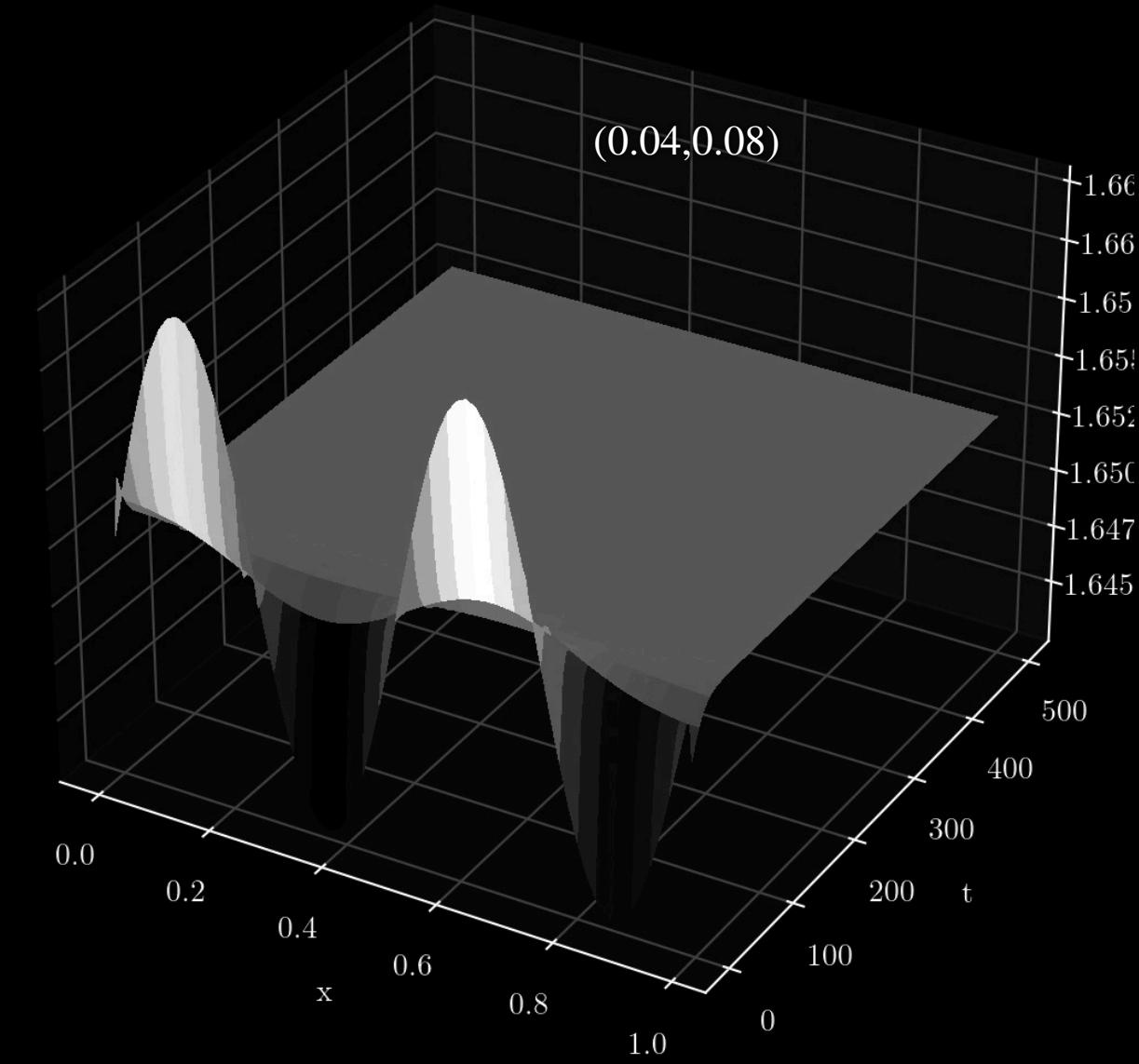
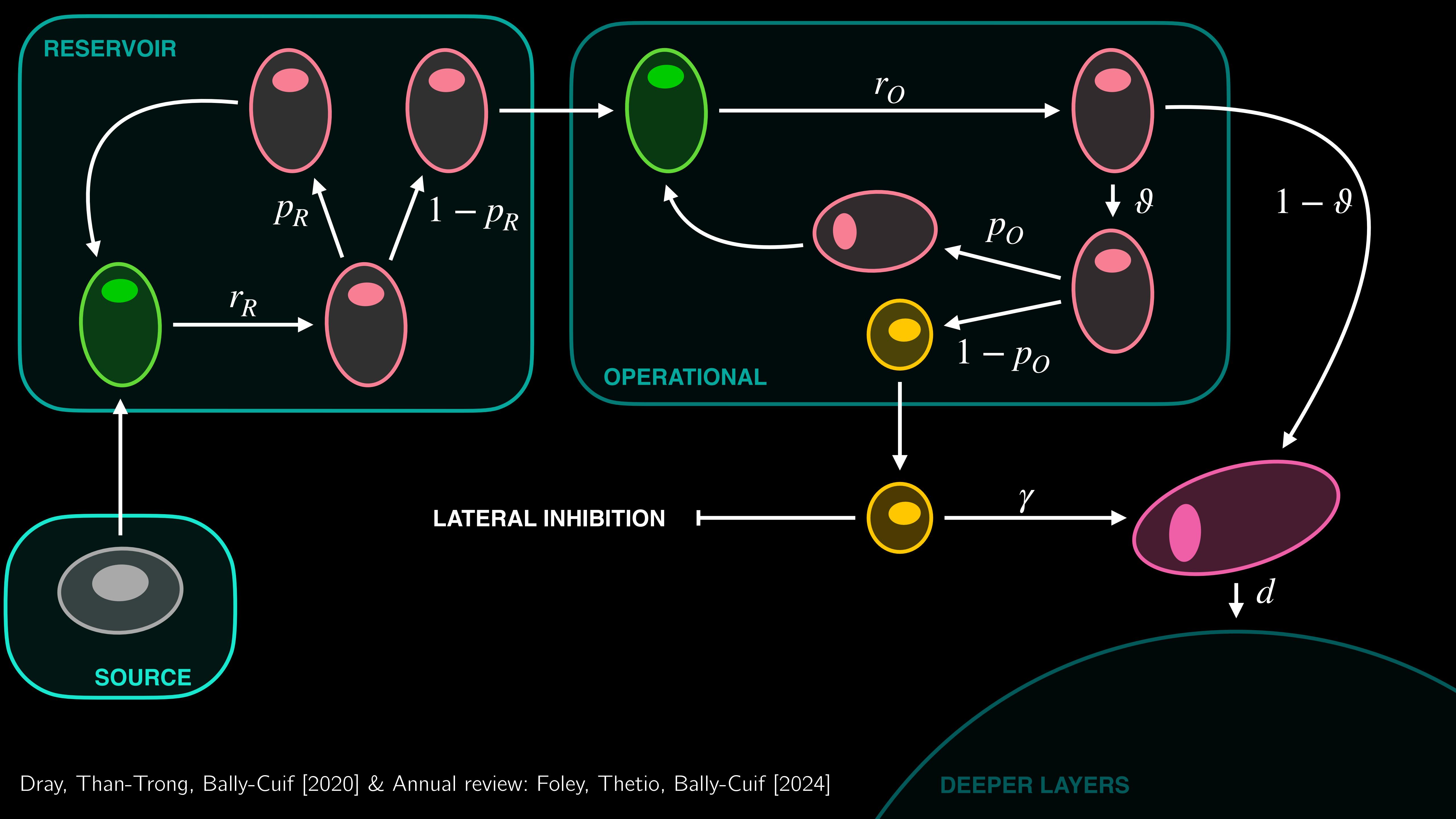


Figure: Bifurcation diagram for diffusion coefficients d_1, d_2 . Subdivisions inside the green area classifies more precisely how many eigenvalues are unstable.

More unstable eigenvalues => More complex patterns

Results:

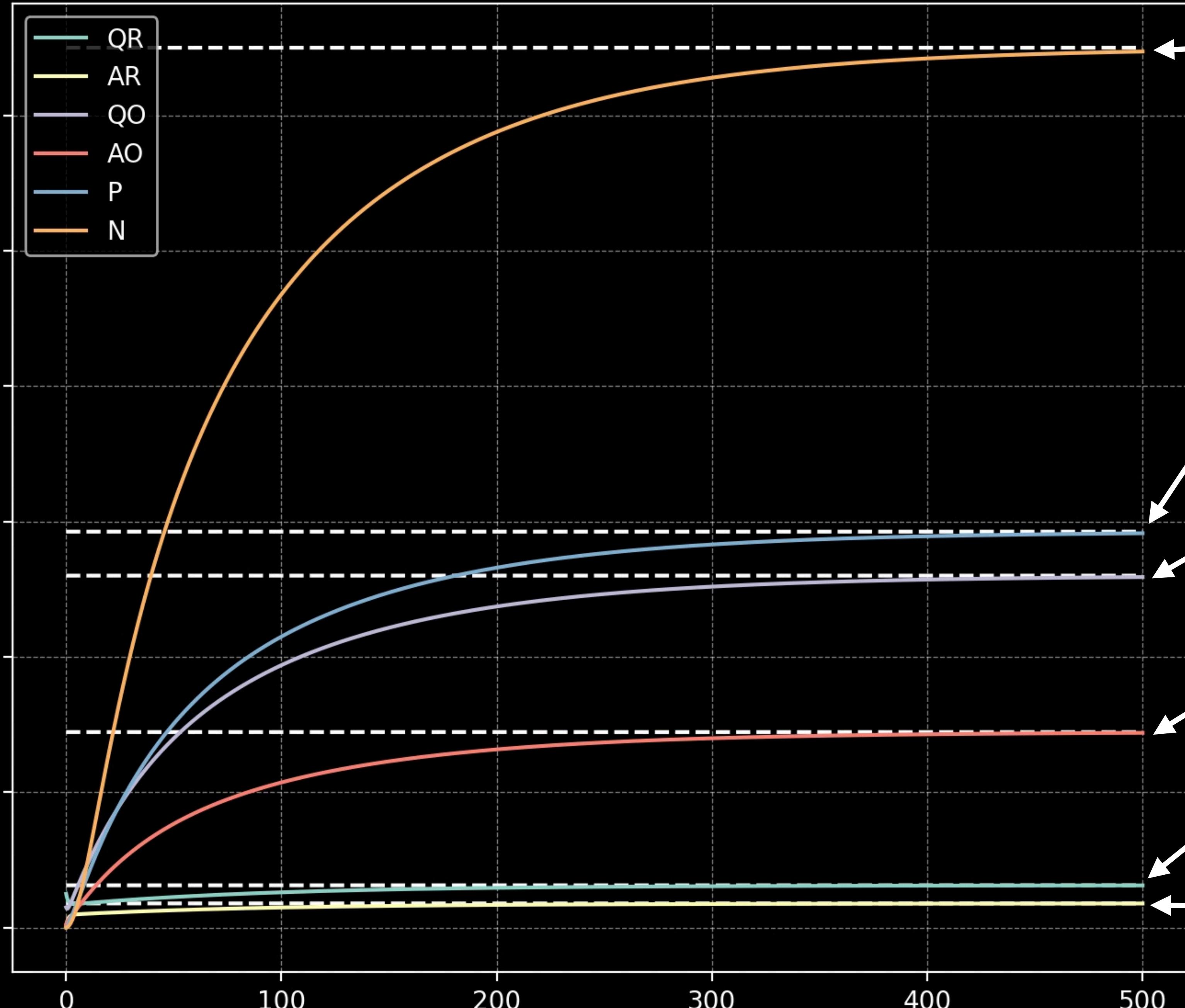




Full system:

$$\left\{ \begin{array}{l} \frac{\partial Q_R}{\partial t} = -r_R Q_R + 2b_R p_R A_R + S \\ \frac{\partial A_R}{\partial t} = r_R Q_R - p_R A_R \\ \frac{\partial Q_O}{\partial t} = -r_O Q_O + (1 + b_O^{sr} - b_O^{df}) \vartheta p_O A_O + 2(1 - b_R) p_R A_R \\ \frac{\partial A_O}{\partial t} = r_O Q_O - p_O A_O \\ \frac{\partial P}{\partial t} = -\gamma_d P + (1 - b_O^{sr} + b_O^{df}) \vartheta p_O A_O \\ \frac{\partial N}{\partial t} = -dN + (1 - \vartheta) p_O A_O + \gamma_d P \end{array} \right.$$

Steady states:



$$\bar{N} = \frac{1}{d} \frac{2(1 - b_R)(1 - \vartheta(b_O^{sr} - b_O^{df}))S}{(1 - 2b_R)[1 - (1 + b_O^{sr} - b_O^{df})\vartheta]}$$

$$\bar{Q}_O = \frac{2(1 - b_R)S}{(1 - 2b_R)[1 - (1 + b_O^{sr} - b_O^{df})\vartheta]} r_O$$

$$\bar{P} = \frac{1}{\gamma_d} \frac{2(1 - b_R)(1 - b_O^{sr} + b_O^{df})\vartheta S}{(1 - 2b_R)[1 - (1 + b_O^{sr} - b_O^{df})\vartheta]}$$

$$\bar{A}_0 = \frac{2(1 - b_R)S}{(1 - 2b_R)[1 - (1 + b_O^{sr} - b_O^{df})\vartheta]} p_O$$

$$\bar{Q}_R = \frac{S}{(1 - 2b_R)r_R}$$

$$\bar{A}_R = \frac{S}{(1 - 2b_R)p_R}$$

Thank you for your attention!

questions?