

# Combinatorial and numerical methods for studying global dynamics in gene regulatory networks

Shane Kepley  
VU Amsterdam

VU Mathematics Colloquium  
October 20, 2021

# Acknowledgments

Based on joint work with

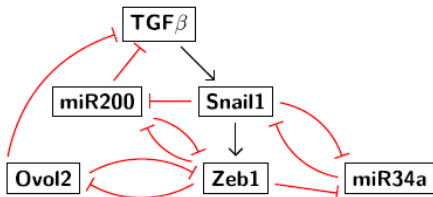
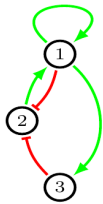
- Konstantin Mischaikow and Marcio Gameiro (Rutgers)
- Elena Quierolo (TU Munich)
- Tomas Gedeon and Bree Cummins (Minnesota State University)

# Outline

- 1 Gene regulatory networks
- 2 Hill function models
- 3 Combinatorial dynamics
- 4 Returning to ODE models
- 5 Analysis of the Toggle Switch

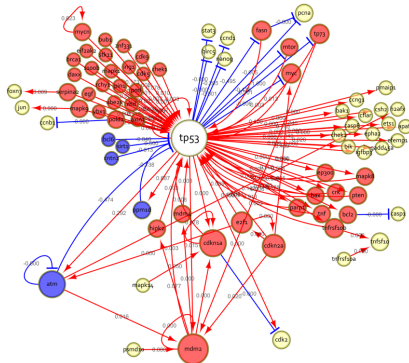
# Gene regulatory networks

- A gene regulatory network (GRN) is a collection of genes which mutually regulate their own gene expression levels or protein production.
- We represent a GRN as a directed graph. Each node represents a gene or protein and the edges between them describe (transcriptional) regulation.
- $A \rightarrow B$  ( $A \dashv B$ ) means  $A$  activates (represses)  $B$  (i.e. more  $A$  increases (decreases) production rate of  $B$ ).
- Examples:



# A more interesting example

- A modern GRN of “known” p53 interactions (G. Chen, M. Cairelli, et al, PLoS CompBio 2014).
- The apparent complexity of a typical GRN actually promotes robust dynamics.
- Central question: What dynamics are imposed by the topology of the GRN?



## Main challenge

No first principles. How do we solve  $\dot{x} = \boxed{?}$

- 1 Define a framework for transcribing GRNs into nonlinear ODEs with relatively simple response functions for each interaction.
- 2 These ODE models have very high parameter dimension.
- 3 Compute “combinatorial dynamics” to obtain a coarse but global description of the dynamics for all parameters.
- 4 Use the combinatorial dynamics to identify subsets of the parameter space with interesting dynamics.
- 5 Return to the ODE model: Apply numerical methods restricted to these parameter subsets to study dynamics classically (i.e. orbits, invariant sets, bifurcations, etc).

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# From networks to ODEs

- For a GRN with  $N$  genes we consider a nonlinear ODE:

$$\dot{x} = f(x, \lambda), \quad x \in X := [0, \infty)^N, \quad \lambda \in \Lambda := (0, \infty)^M.$$

- For  $1 \leq i \leq N$ , the variable  $x_i$  denotes the protein concentration or gene expression level of node  $i$ .
- Assume that each protein or gene degrades at a rate proportional to its own concentration/expression level, i.e.

$$\dot{x}_i = -\gamma_i x_i + \text{nonlinear/inhomogeneous production},$$

where the *decay rate* is  $\gamma_i > 0$ , which is unknown.

- For transcriptional interactions the biology suggests the functional form

$$\dot{x}_i = -\gamma_i x_i + \sum_{\substack{\text{interaction} \\ \text{groups}}} \prod_{\substack{\text{interactions} \\ \text{with } x_i}} g_{i,j}(x_j, \lambda).$$



# Modeling the nonlinear production

## Definition

A polynomial,  $p \in \mathbb{R}[z_1, \dots, z_N]$  is called an **interaction function** if it has the form

$$p = \prod_{m=1}^q p_m, \quad \text{where} \quad p_m = \sum_{j \in I_m} z_j,$$

and  $\{I_1, \dots, I_q\}$  is an integer partition of  $\{1, \dots, N\}$ . The linear polynomial  $p_m$  is called the  $m^{\text{th}}$  **summand** of  $p$ .

- Informally, an interaction function is a “product of sums”. Interactions with similar mechanisms are combined in the same summand.
- Interaction functions provide control over how the contributions from multiple regulators are combined.
- Example:  $p = (z_1 + z_2)(z_3 + z_4)z_5$  where

$$q = 3, \quad N = 5, \quad I_1 = \{1, 2\}, \quad I_2 = \{3, 4\}, \quad I_3 = \{5\}.$$

# Hill response functions

## Definition

Let  $H^+ : [0, \infty) \rightarrow (0, \infty)$  denote the **activating Hill function** defined by the formula

$$H^+(x) := \ell + \delta \frac{x^d}{\theta^d + x^d}.$$

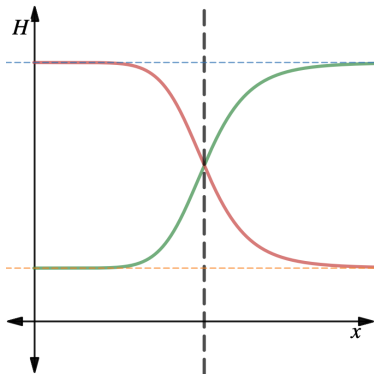
$H^- : [0, \infty) \rightarrow (0, \infty)$  denotes the **repressing Hill function** defined by the formula

$$H^-(x) := \ell + \delta \frac{\theta^d}{\theta^d + x^d}$$

- $H^*$  depends on 4 positive real parameters,  $\{\ell, \delta, \theta, d\}$ .
- $d$  is called the *Hill coefficient* (or Hill exponent).
- Aliases: Holling type II and type III (ecology), Michaelis-Menten or Monod ( $d = 1$ ) functions.

# Properties of Hill functions

- $H^+$  is increasing and  $H^-$  is decreasing.
- $H^+(0) = \ell = \lim_{x \rightarrow \infty} H^-(x)$ .
- $H^-(0) = \ell + \delta = \lim_{x \rightarrow \infty} H^+(x)$ .
- $H^*(\theta) = \ell + \frac{1}{2}\delta$  (half saturation).
- Increasing  $d$  produces a steeper response.
- $H^*$  is hyperbolic when  $1 \leq d \leq 2$  and sigmoidal for  $d > 2$ .



## Definition

A **Hill model** is an ODE of the form

$$\dot{x} = f(x, \lambda) = -\Gamma x + \mathcal{H}(x, \lambda),$$

where

$$\Gamma := \begin{pmatrix} \gamma_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \gamma_N \end{pmatrix}, \quad \mathcal{H}_i(x) = p_i(H_{i,1}^*(x_1) \dots, H_{i,N}^*(x_N)),$$

$p_i$  is an interaction function, and  $H_{i,j}^*$  is a Hill function,  $1 \leq i, j \leq N$ .

- If there is a directed edge from node  $j$  to node  $i$ , then  $H_{i,j}^*$  contributes 4 parameters to the model,  $\{\ell_{i,j}, \delta_{i,j}, \theta_{i,j}, d_{i,j}\}$ .
- If  $j \dashv i$  then  $H_{i,j}^* = H^-$  and if  $j \rightarrow i$  then  $H_{i,j}^* = H^+$ .
- Parameter space dimension:  $M = N + 4 \cdot \#E$ .

# Example: the Toggle Switch



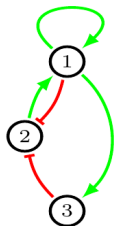
$$\dot{x}_1 = -\gamma_1 x_1 + \ell_{1,2} + \delta_{1,2} \frac{\theta_{1,2}^{d_{1,2}}}{\theta_{1,2}^{d_{1,2}} + x_2^{d_{1,2}}} = -\gamma_1 x_1 + H_{1,2}^-(x_2)$$

$$\dot{x}_2 = -\gamma_2 x_2 + \ell_{2,1} + \delta_{2,1} \frac{\theta_{2,1}^{d_{2,1}}}{\theta_{2,1}^{d_{2,1}} + x_1^{d_{2,1}}} = -\gamma_2 x_2 + H_{2,1}^-(x_1)$$

$$x = (x_1, x_2) \in [0, \infty)^2.$$

$$\lambda = (\gamma_1, \ell_{1,2}, \delta_{1,2}, \theta_{1,2}, d_{1,2}, \gamma_2, \ell_{2,1}, \delta_{2,1}, \theta_{2,1}, d_{2,1}) \in (0, \infty)^{10}.$$

# A three node GRN example



$$f(x, \lambda) = - \underbrace{\begin{pmatrix} \gamma_1 & 0 & 0 \\ 0 & \gamma_2 & 0 \\ 0 & 0 & \gamma_3 \end{pmatrix}}_{\text{linear decay}} x + \underbrace{\begin{pmatrix} H_{1,1}^+(x_1) + H_{2,1}^+(x_2) \\ H_{1,2}^-(x_1)H_{3,2}^-(x_3) \\ H_{1,3}^+(x_1) \end{pmatrix}}_{\text{nonlinear production}}.$$

$$x = (x_1, x_2, x_3) \in [0, \infty)^3.$$

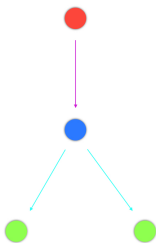
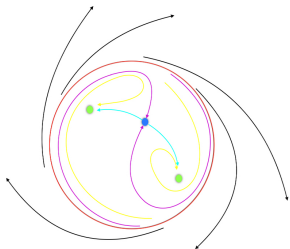
$$\lambda = (\gamma_1, \ell_{1,1}, \delta_{1,1}, \theta_{1,1}, d_{1,1}, \ell_{2,1}, \delta_{2,1}, \theta_{2,1}, d_{2,1}, \gamma_2, \ell_{1,2}, \delta_{1,2}, \theta_{1,2}, d_{1,2}, \ell_{3,2}, \delta_{3,2}, \theta_{3,2}, d_{3,2}, \gamma_3, \ell_{1,3}, \delta_{1,3}, \theta_{1,3}, d_{1,3}) \in (0, \infty)^{23}.$$

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# Combinatorial dynamics

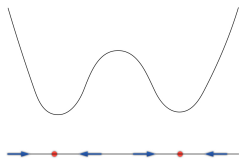
- Main idea: When  $\Lambda$  is high dimensional or parameters are difficult to estimate it is impractical to study invariant sets.
- Give up (temporarily) on studying invariant sets (e.g. orbits, equilibria, invariant manifolds, connections, etc).
- Study robust dynamical descriptions (e.g. attractor/repeller pairs, isolating blocks, Morse decompositions, Conley indices, etc).



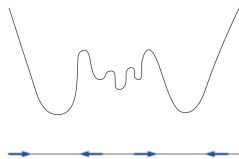
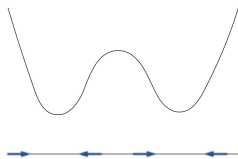


# Attractors vs invariant sets

What we think we see.



What we actually see.



# Model coarseness and robustness

- Informally, *combinatorial dynamics* refers to broadly observable dynamic phenotypes which depend only on the topology of the GRN.
- Let  $x_I$  denote the vector of state variables which regulate  $x_i$  (i.e. source nodes for edges incoming to node  $i$ ). We imagine a system of ODEs of the form

$$\dot{x}_i = -\gamma_i x_i + f_i(x_I, \lambda)$$

where  $f_i$  is some unknown (monotone?) function.

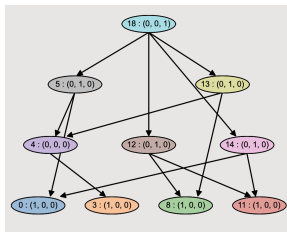
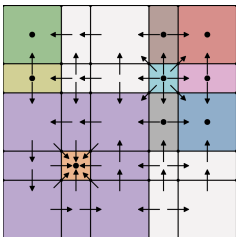
- Combinatorial dynamics are coarse descriptions which are relatively insensitive to the choice of  $f_i$  or  $\lambda$ .
- These take the form of computable dynamical invariants for equivalence classes of models  $[f_i]$  which are robust over large subsets of parameters.
- The dynamics computed are rigorous for all models in  $[f_i]$ .

# Dynamic Signatures Generated by Regulatory Networks (DSGRN)

- DSGRN is a computational platform for computing global combinatorial dynamics for GRN models.
- DSGRN uses a *simple model* for which the following can be done explicitly, efficiently, and rigorously.
  - 1 Discretize  $X$ : Compute a coarse description (Morse graph) of the gradient-like dynamics on  $X$  for an arbitrary parameter.
  - 2 Discretize  $\Lambda$ : Decompose  $\Lambda$  into open, semi-algebraic subsets on which the Morse graph is constant.
- Both steps are highly nontrivial.
- The combinatorial description of the global dynamics is a collection of parameter regions which partition  $\Lambda$ , and a Morse graph associated to each region.
- The combinatorial dynamics computed using DSGRN are valid for infinite Hill coefficients (i.e.  $d_{i,j} \rightarrow \infty$  for all  $i, j$ ).

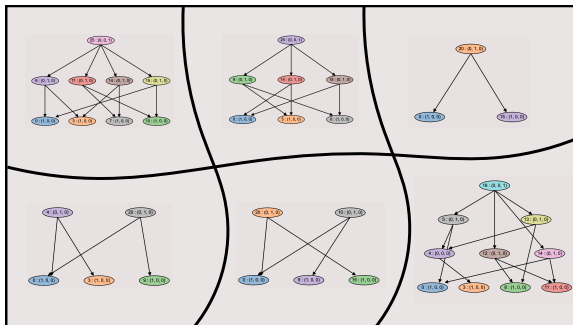
# Discretizing state space

- Partition  $X$  into top cells with transverse faces.
- Build a graph representation of the dynamics (state transition graph) and compute its lattice of attractors.
- Attractor lattices are robust and their algebraic structure encodes topological (and therefore dynamical) properties. (W. Kalies, K. Mischaikow, R.C.A.M. Vandervorst).
- Compute the associated Morse graph which is a robust description of the coarse dynamical phenotype.



# Discretizing parameter space

- A combinatorial **parameter space decomposition** (PSD) is a partition of  $\Lambda$  into subsets on which the Morse graph is constant.
- For the simple model these subsets are semi-algebraic sets given by explicit inequalities.
- Unfortunately, there are a lot of these subsets, most of them are empty, and there is no efficient algorithm for determining whether an arbitrary semi-algebraic set is nonempty.



# Connections to Algebraic Geometry and Order Theory

- Consider a semi-algebraic set  $\Xi \subset \mathbb{R}^d$ , and a collection of polynomials  $\mathcal{P} := \{p_1, \dots, p_K\} \subset \mathbb{R}[x_1, \dots, x_d]$ .
- Equip  $\mathcal{P}$  with a partial order such that if  $p \prec q$ , then

$$p(\xi) < q(\xi) \quad \text{for all } \xi \in \Xi.$$

- A permutation  $\sigma \in S_K$  defines a linear extension of this partial order,  $\prec_\sigma$ , satisfying

$$p_{\sigma(1)} \prec_\sigma p_{\sigma(2)} \prec_\sigma \dots \prec_\sigma p_{\sigma(K)}.$$

- We define the *realizable set* associated to  $\sigma$  by

$$\Xi_\sigma := \{\xi \in \Xi : p_{\sigma(k)}(\xi) < p_{\sigma(k+1)}(\xi) \text{ for all } 1 \leq k \leq K - 1\}.$$

## The algebraically constrained linear extension problem (ACLEP)

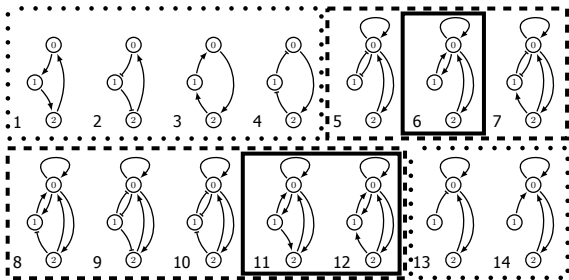
Given  $(\mathcal{P}, \prec, \Xi)$ , rigorously compute the set of all permutations with nonempty realizable sets.

# Relationship between ACLEP and PSD

- Computing a combinatorial PSD for the simple model is equivalent to a specific instance of the ACLEP.
- Surprisingly, these instances of the ACLEP can be solved “efficiently” (S.K., K. Mischaikow, L. Zhang, 2020 SIAGA).
- This problem only needs to be solved once for each distinct configuration of incoming edges to a GRN node and the results stored in a database.
- The current version of DSGRN has rigorous solutions stored for a node with up to 5 incoming (transcriptional) edges with any interaction function **except**  $p = (z_1 + z_2 + z_3)(z_4 + z_5)$ .
- We have also solved PSD problems for “non-transcriptional” regulation modeling ubiquitination and phosphorylation (B. Cummins, M. Gameiro, T. Gedeon, S.K., K. Mischaikow, 2021).

# Combinatorial dynamics of three node networks

- Top 14 hysteretic switch designs out of 19,683 three node GRNs (M. Gameiro, T. Gedeon, S.K., K. Mischaikow, PLoS CompBio 2020)
- Synthetic Biology labs at UW and UC Santa Barbara are actually building these designs.





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- *HillCont*: An open source Python library for numerical analysis of Hill models (coauthored with Elena Queirolo).
- Implement Hill function ODE models given only GRN topology for arbitrary state/parameter dimension.
- Efficient evaluation of Hill models and the following derivatives

$$D_x f, D_\lambda f, D_{xx} f, D_{\lambda x} f, D_{\lambda\lambda} f, D_{xxx} f, D_{\lambda xx} f, D_{\lambda\lambda x}.$$

via automatic differentiation (i.e. without formulas or calculus).

- Main features:
  - 1 Automatically search for equilibria, saddle-node bifurcations, Hopf bifurcations, and pitchfork bifurcations.
  - 2 Constrained parameter optimization and/or continuation along equilibria/bifurcations.
  - 3 Rigorous enclosures of equilibria for biologically relevant GRNs via the “bootstrap map”.

# The bootstrap map

## Definition

A continuous function  $g: [0, \infty)^N \rightarrow (0, \infty)^N$  has a **monotone factorization** if for each  $i = 1, \dots, N$ ,  $g_i$  factors as

$$g_i(x) = g_i^+(x)g_i^-(x) \quad \text{for all } x \in [0, \infty)^N,$$

where  $g_i^+: [0, \infty)^N \rightarrow (0, \infty)^N$  is bounded and strictly increasing and  $g_i^-: [0, \infty)^N \rightarrow (0, \infty)^N$  is bounded and strictly decreasing as a function of each variable  $x_1, \dots, x_N$ .

## Definition

If  $f(x) = -\Gamma x + \mathcal{H}(x)$  and  $\mathcal{H}$  has a monotone factorization, then the **bootstrap map** for  $f$  is  $\Phi: \mathbb{R}^{2N} \rightarrow \mathbb{R}^{2N}$  defined by the formula

$$\Phi_i(\alpha, \beta) = \frac{1}{\gamma_i} \mathcal{H}_i^+(\alpha) \mathcal{H}_i^-(\beta) \quad \text{and} \quad \Phi_{N+i}(\alpha, \beta) = \frac{1}{\gamma_i} \mathcal{H}_i^+(\beta) \mathcal{H}_i^-(\alpha),$$

where  $\alpha, \beta \in \mathbb{R}^N$  and  $i = 1, \dots, N$ .

# Rigorous equilibrium enclosures

## Theorem (S.K., K. Mischaikow, E. Queirolo)

Consider  $f$  and  $\Phi$  as previously defined and assume that  $\liminf_{\|x\| \rightarrow \infty} g_i^-(x) > 0$  for all  $i = 1, \dots, N$ . Then, the following are true.

- (i)  $x \in [0, \infty)^N$  is a zero of  $f$  if and only if  $(x, x) \in [0, \infty^{2N})$  is a fixed point of  $\Phi$ .
- (ii) Define  $(\alpha^{(0)}, \beta^{(0)}) \in \mathbb{R}^{2N}$  coordinate wise by

$$\alpha_i^{(0)} := \frac{1}{\gamma_i} g_i^+(0) \liminf_{\|x\| \rightarrow \infty} g_i^-(x), \quad \beta_i^{(0)} := \frac{1}{\gamma_i} \limsup_{\|x\| \rightarrow \infty} g_i^+(x) g_i^-(0)$$

for  $i = 1, \dots, N$ . Iteratively, define  $(\alpha^{n+1}, \beta^{n+1}) = \Phi(\alpha^n, \beta^n)$  for  $n \geq 1$ . Then  $(\hat{\alpha}, \hat{\beta}) := \lim_{n \rightarrow \infty} (\alpha^n, \beta^n)$  exists and  $(\hat{\alpha}, \hat{\beta})$  is a fixed point of  $\Phi$ .

- (iii) If  $f(\hat{x}) = 0$ , then

$$\hat{x} \in \hat{R} := \prod_{i=1}^N [\hat{\alpha}_i, \hat{\beta}_i].$$

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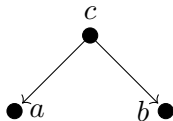
# DSGRN analysis of the Toggle Switch

- $\Lambda = (0, \infty)^{10}$  is partitioned into 9 semi-algebraic subsets  $\{R_1, \dots, R_9\}$  with constant Morse graphs.
- Example:  $R_5$  is defined by the inequalities

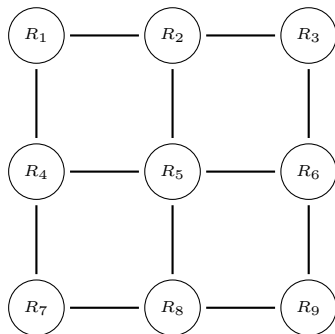
$$\ell_{1,2} < \gamma_1 \theta_{2,1} < \ell_{1,2} + \delta_{1,2}$$

$$\ell_{2,1} < \gamma_2 \theta_{1,2} < \ell_{2,1} + \delta_{2,1}$$

and has associated Morse graph



- The remaining 8 regions have Morse graphs with a unique minimal attractor of “FP” type.



# Predicting ODE dynamics from combinatorial dynamics

- The Toggle Switch Hill model is

$$\dot{x} = f(x, \lambda) = \begin{pmatrix} -\gamma_1 & 0 \\ 0 & -\gamma_2 \end{pmatrix} x + \begin{pmatrix} H_{1,2}^-(x_2) \\ H_{2,1}^-(x_1) \end{pmatrix}$$

with  $\lambda = (\gamma_1, \ell_{1,2}, \delta_{1,2}, \theta_{1,2}, d_{1,2}, \gamma_2, \ell_{2,1}, \delta_{2,1}, \theta_{2,1}, d_{2,1})$ .

- We identify both Hill coefficients (i.e.  $d_{1,2} = d_{2,1} = d$ ).
- At  $d = 1$ ,  $f$  has a unique globally attracting stable equilibrium.
- The DSGRN analysis holds in the limit  $d \rightarrow \infty$ .
- Assume  $f$  has no codimension-1 bifurcations other than saddle-node bifurcations.
- If the combinatorial dynamics were a perfect predictor of the ODE dynamics, then we expect to find saddle-node bifurcations when continuing parameters in  $R_5$ .
- Using *HillCont* we can quantify the correlation between the combinatorial and ODE dynamics with statistical analysis.

# Constructive saddle-node bifurcation theorem

Theorem (J.B. van den Berg, M. Gameiro, J.P. Lessard, J.D. Mireles James, K. Mischaikow)

Let  $g : X \times \mathbb{R} \rightarrow TX$  be a one parameter family of vector fields. Define  $G : \mathbb{R}^{2N+1} \rightarrow \mathbb{R}^{2N+1}$  by the formula

$$G(x, v, s) := \begin{pmatrix} g(x, s) \\ D_x g(x, s)v \\ v^T v - 1 \end{pmatrix} \quad x, v \in \mathbb{R}^N, s \in \mathbb{R}.$$

Suppose  $\hat{u} = (\hat{x}, \hat{v}, \hat{s}) \in \mathbb{R}^N \times \mathbb{R}^N \times \mathbb{R}$  satisfies

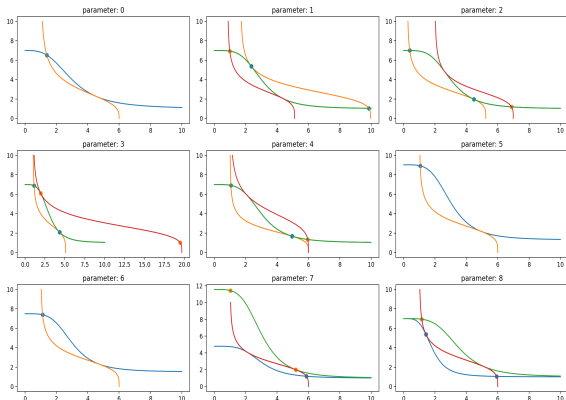
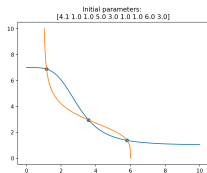
- 1  $G(\hat{u}) = 0$ .
- 2  $D_u G(\hat{u})$  is an isomorphism.
- 3 Every nonzero eigenvalue of  $D_x g(\hat{x}, \hat{s})$  has nonzero real part.

Then,  $g$  undergoes a saddle-node bifurcation at  $(\hat{x}, \hat{s})$  and

$$\ker D_x g(\hat{x}, \hat{s}) = \text{span}(\{\hat{v}\}).$$



# Searching for saddle-node bifurcations for $\lambda \in R_5$

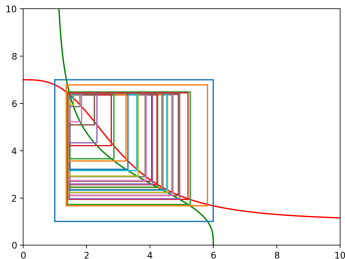
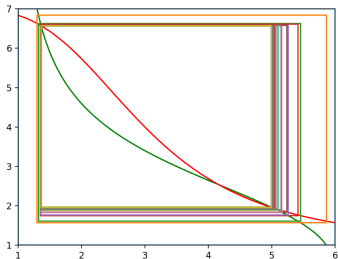


# Rigorous equilibria for the Toggle Switch

Theorem (S.K., K. Mischaikow, E. Queirolo)

Let  $\Phi : \mathbb{R}^4 \rightarrow \mathbb{R}^4$  be the bootstrap map for Toggle Switch. Suppose the bootstrap iteration converges to  $(\hat{\alpha}, \hat{\beta}) \in \mathbb{R}^2 \times \mathbb{R}^2$  and let  $\hat{R} := [\hat{\alpha}_1, \hat{\beta}_1] \times [\hat{\alpha}_2, \hat{\beta}_2]$ . Then, either  $\hat{R}$  is degenerate and  $f$  is monostable with unique equilibrium  $\hat{x} = (\hat{\alpha}_1, \hat{\alpha}_2)$ , or  $f$  is bistable with stable equilibria at the corners of  $\hat{R}$  with coordinates

$$\hat{x}_1 = (\hat{\alpha}_1, \hat{\beta}_2), \quad \hat{x}_2 = (\hat{\beta}_1, \hat{\alpha}_2).$$



## $\chi^2$ hypothesis testing

We test the null hypothesis that  $\lambda \in R_5$  is independent of the existence of a saddle-node bifurcation along the parameterized path  $\gamma : [1, \infty] \rightarrow \Lambda$  defined by

$$\gamma(s) = (\gamma_1, \ell_{1,2}, \delta_{1,2}, \theta_{1,2}, s, \gamma_2, \ell_{2,1}, \delta_{2,1}, \theta_{2,1}, s).$$

- Contingency table for 1,000 randomly chosen parameters:

	SNB found	No SNB found	Bisection fail	Bad parity
$\lambda \in R_5$	86	0	30	5
$\lambda \notin R_5$	2	875	0	2

- $\chi^2$  test statistic: 968.19
- $p$ -value:  $p \approx 1.4 \times 10^{-209}$

# Thank you for your attention!

