

Automata and The Criticality Hypothesis:



key events coming up

- **Labs: 35% (ISE-483)**
 - Complete 5 (best 4 graded) assignments based on algorithms presented in class
 - Lab 3: March 11th
 - Cellular Automata and Boolean Networks (Assignment 3)
 - Delivered by SSIE583 Group 3
 - Due: March 25th
- **SSIE – 583 -Presentation and Discussion: 25%**
 - Present and lead the discussion of an article related to the class materials
 - Enginet students post/send video or join by Zoom
 - Dates TBA
 - Conrad, M. [1990]. "The geometry of evolution." *Biosystems* **24**: 61-81.
 - Mario Franco
 - Stanley, Kenneth O., Jeff Clune, Joel Lehman, and Risto Miikkulainen. "Designing Neural Networks through Neuroevolution." *Nature Machine Intelligence* **1**, no. 1 (January 2019): 24–35.
 - Jessica Lasebikan
 - Lindgren, K. [1991]. "Evolutionary Phenomena in Simple Dynamics." In: *Artificial Life II*. Langton et al (Eds). Addison-wesley, pp. 295-312.
 - Akshay Gangadhar
 - Salahshour, Mohammad. "Interaction between Games Give Rise to the Evolution of Moral Norms of Cooperation." *PLOS Computational Biology* **18**, no. 9 (September 29, 2022): e1010429
 - Srikanth Iyer
 - Discussion by all



until now

- **Class Book**

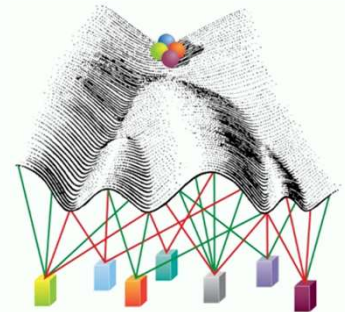
- Floreano, D. and C. Mattiussi [2008]. *Bio-Inspired Artificial Intelligence: Theories, Methods, and Technologies*. MIT Press. Preface, **Chapter 2**.
 - Nunes de Castro, Leandro [2006]. *Fundamentals of Natural Computing: Basic Concepts, Algorithms, and Applications*. Chapman & Hall. **Chapter 1**, pp. 1-23. Chapter 7, sections 7.1-7.4, **Appendix B.3.1**, **Chapter 2**, Chapter 8, sections 8.1, 8.2, 8.3.10

- **Lecture notes**

- Chapter 1: What is Life?
- Chapter 2: The logical Mechanisms of Life
- Chapter 3: Formalizing and Modeling the World
- Chapter 4: Self-Organization and Emergent Complex Behavior
 - posted online @ <http://informatics.indiana.edu/rocha/i-bic>

- **Papers and other materials**

- Dynamical Systems
 - Kauffman, S.A. [1969]. "Metabolic stability and epigenesis in randomly constructed genetic nets". *Journal of Theoretical Biology* 22(3):437-467.
- Optional
 - Prusinkiewicz and Lindenmeyer [1996] *The algorithmic beauty of plants*.
 - Chapter 1
 - Flake's [1998], *The Computational Beauty of Life*. MIT Press.
 - Chapters 10, 11, 14 – Dynamics, Attractors and chaos



bit.ly/atBIC

■ Projects

- Due by May 6th in Brightspace, “Final Project Paper” assignment
 - ALIFE 2023
 - Not to submit to actual conference due date (April 3rd , 2024)
 - <https://2024.alife.org/>
 - 8 pages, author guidelines:
 - https://2024.alife.org/call_paper.html
 - MS Word and Latex/Overleaf templates
 - Preliminary ideas **by March 15**
 - Submit to “Project Idea” assignment in Brightspace.
- Individual or group
 - With very definite tasks assigned per member of group

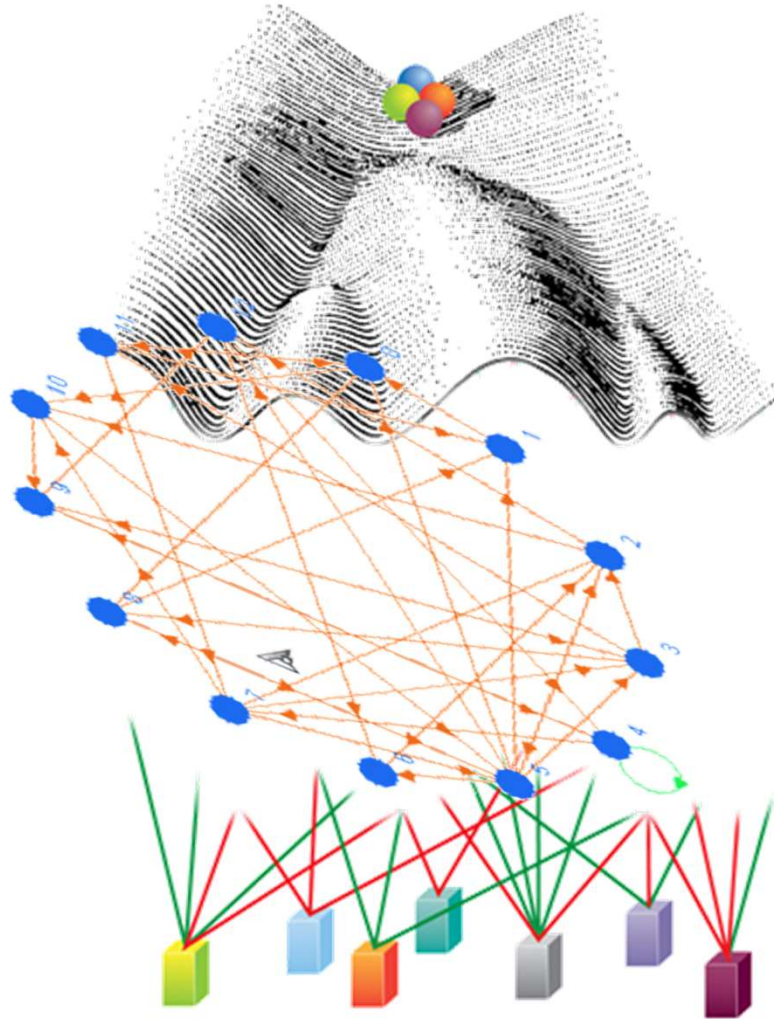
ALIFE 2024

Tackle a real problem using bio-inspired algorithms, such as those used in the labs.



self-organization easily chaotic

evolution requires life in critical regime which is small, how come life is not chaotic?



Kauffman, S. A. (1984). *Phys. D Nonlinear Phen.* **10**, 145–156. Waddington CH (1942). *Nature.* **150** (3811):563–565

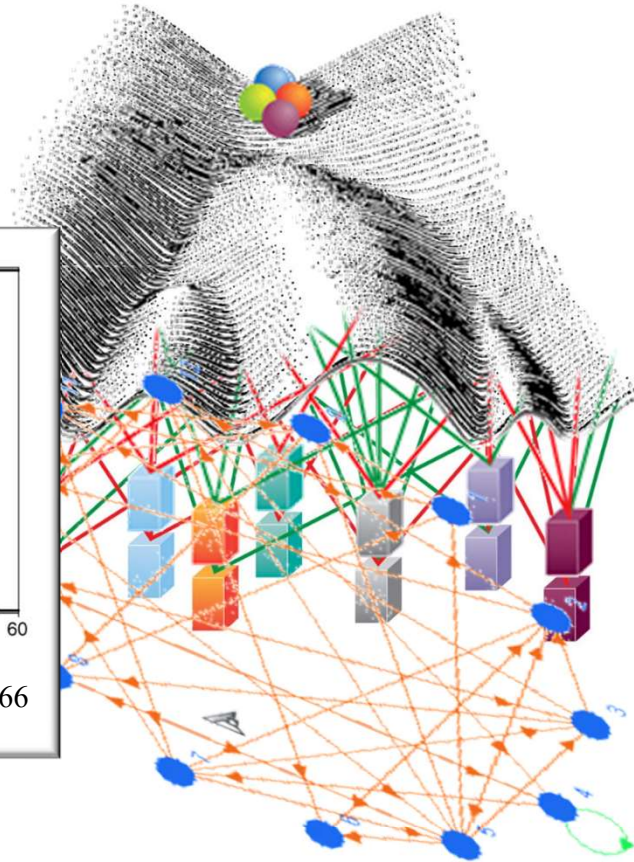
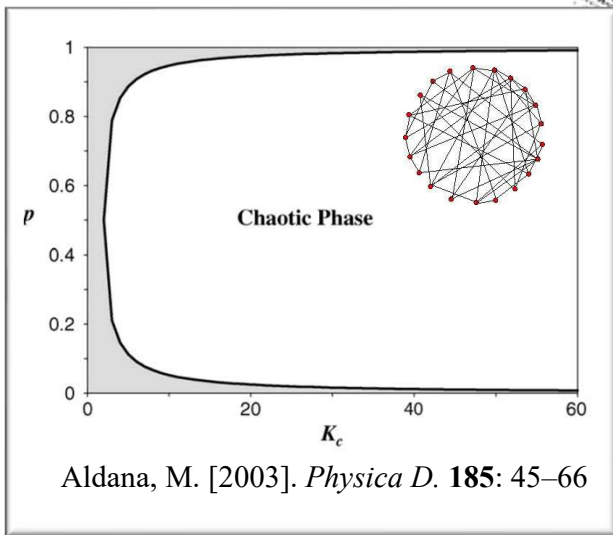
robustness of phenotypes is the result of a **buffering** of the developmental process.

dynamics of gene networks provides buffering (**self-organization**). But still easily chaotic.

Structure (**topological organization**), can provide larger stable or critical universe, but still easily chaotic.

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The Criticality Hypothesis

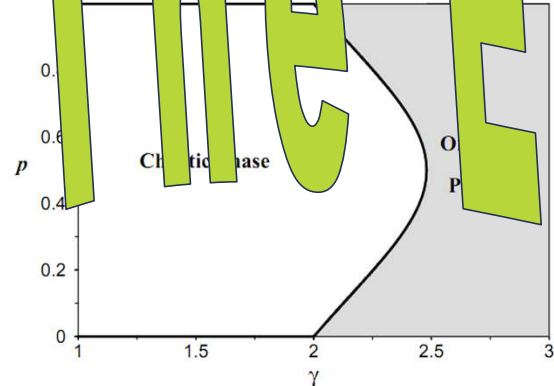
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self-organization easily chaotic

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The Edge of Chaos?



Aldana, M. [2003]. *Physica D*. **185**: 45–66



Kauffman, S. A. (1984). *Phys. D*. Vaddington CH (1942).
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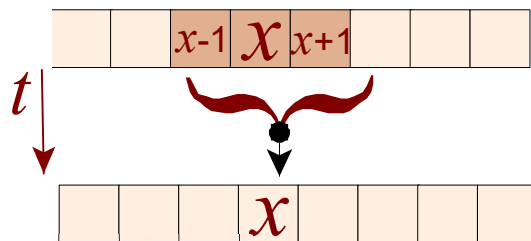
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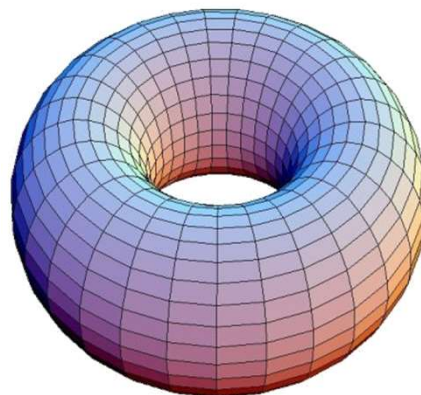
homogenous lattice of state-determined systems

Cellular Automata



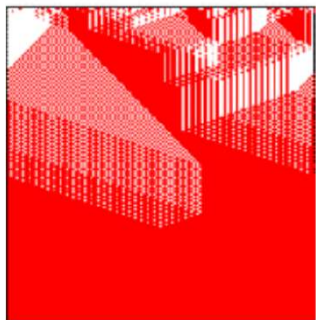
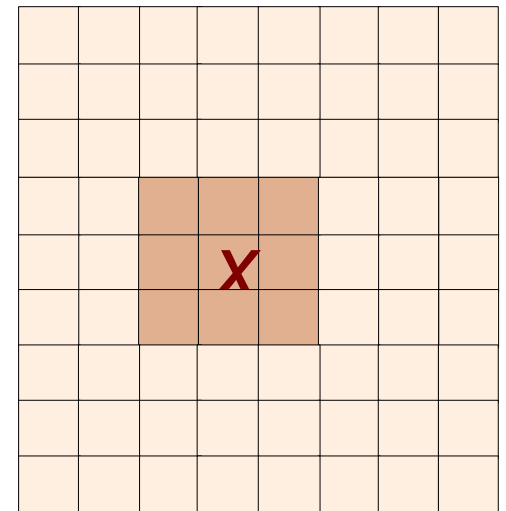
1-D
$$x_i^t = f(x_{i-r}, \dots, x_i, \dots, x_{i+r})^{t-1}$$

$$x \in \{0, 1, 2, \dots, s\}$$



Toroidal Lattice

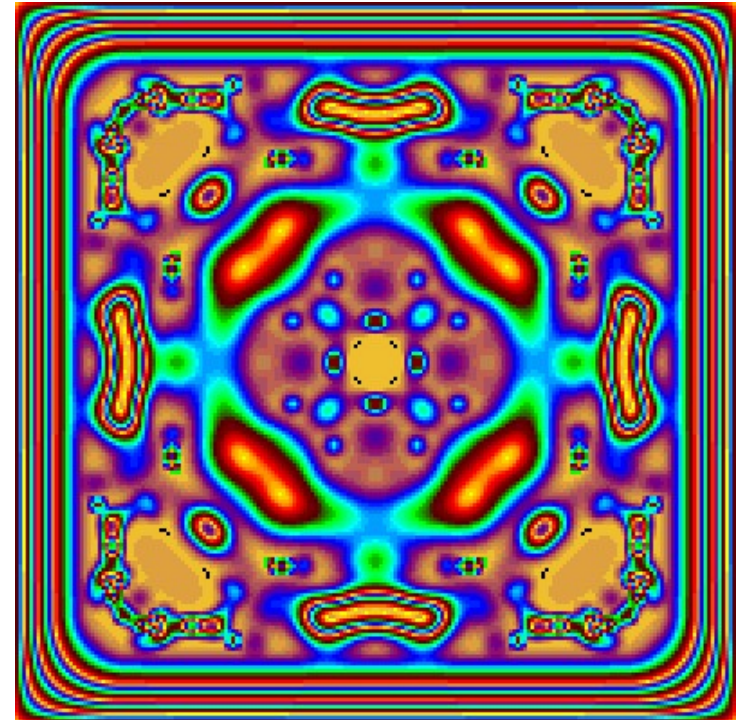
2-D



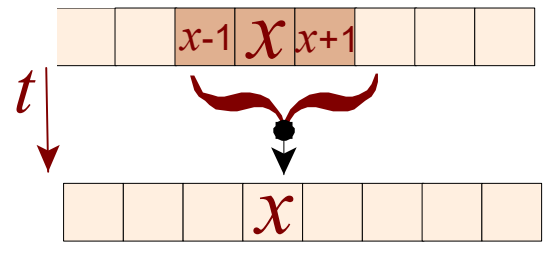
Space-time diagram

$$x_{i,j}^t = f(x_{i-r_x, j-r_y}, \dots, x_{i,j}, \dots, x_{i+r_x, j+r_y})^{t-1}$$

- Parallel updating
- Artificial physics
 - Local interactions only
 - No actions at a distance
 - Homogeneous
- Unpredictable global behavior
 - Emergence
 - 2-levels: rules (micro-level) and attractor behavior (macro-level)
 - Irreversible
- Self-organization
- Example rules
 - Rug (diffusion)
 - 256 states
 - Average of 8 neighbors in 2-d grid, if state is 255 \rightarrow 0.
 - Vote/majority
 - binary

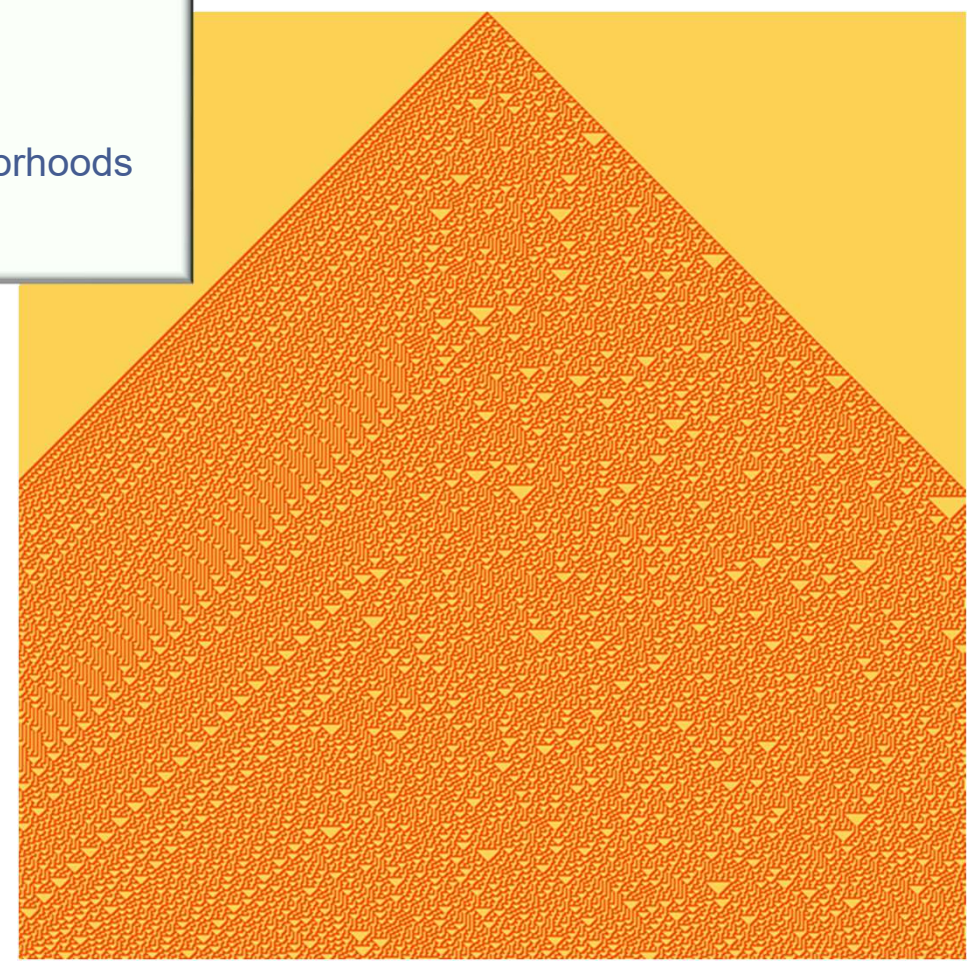
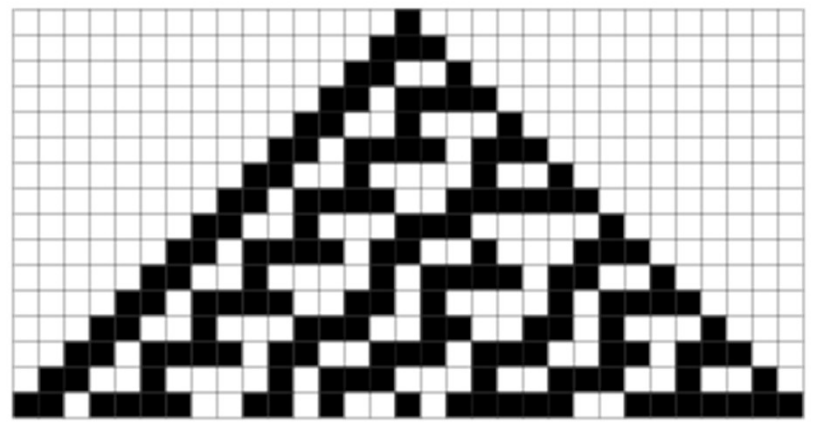
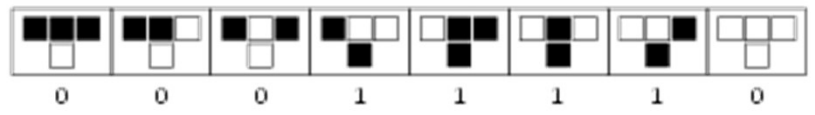


Cellular Automata



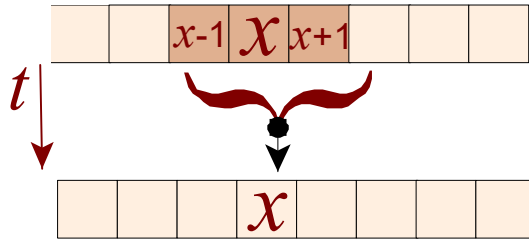
- Radius 1
 - Neighborhood = 3
- Binary
 - $2^3 = 8$ input neighborhoods
 - $2^8 = 256$ rules

rule 30



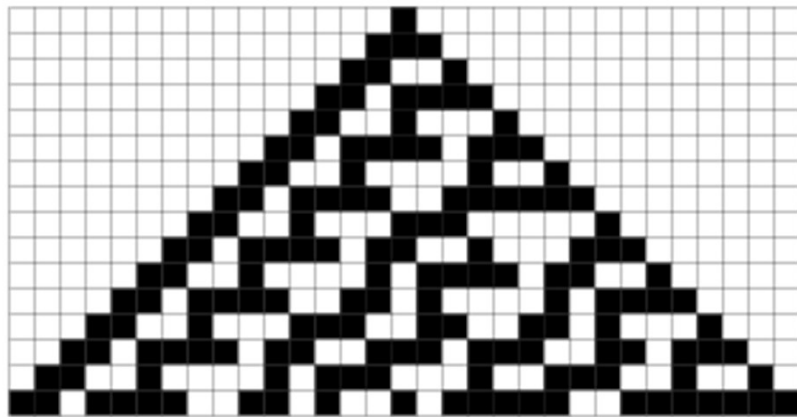
<http://mathworld.wolfram.com/CellularAutomaton.html>

Cellular Automata



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state-determined transitions

If a cell and its neighbours look like this at time t

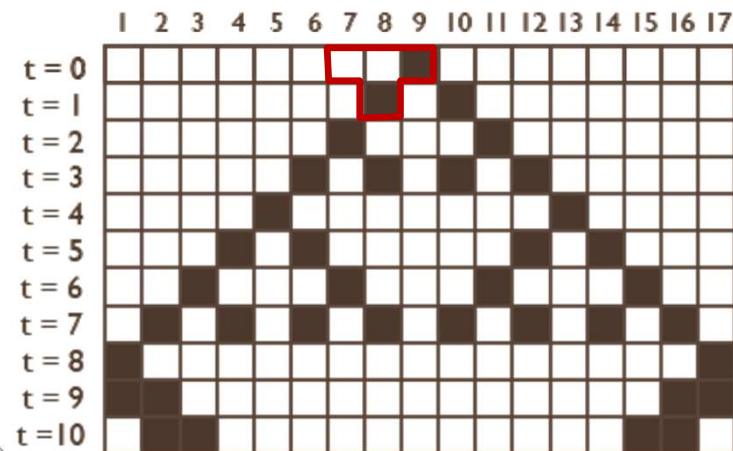
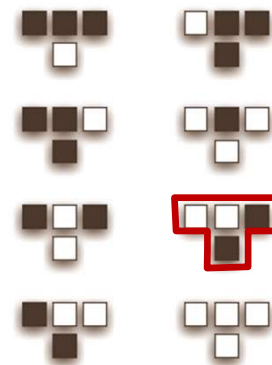


then the cell will look like this on the next row (at time $t+1$)



look-up table
each entry is a
condition-action rule

ECA Rule 90



state-determined transitions

If a cell and its neighbours look like this at time t

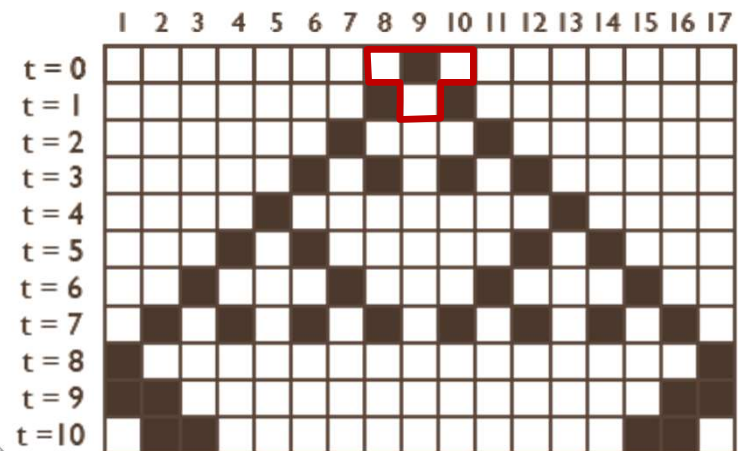
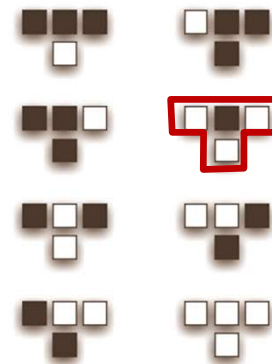


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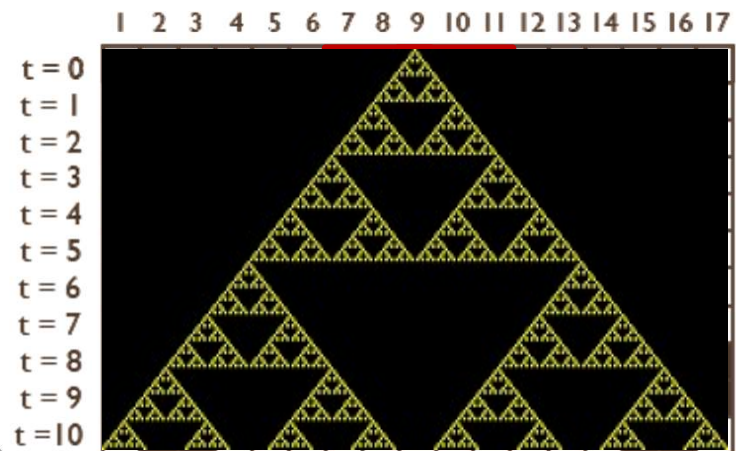
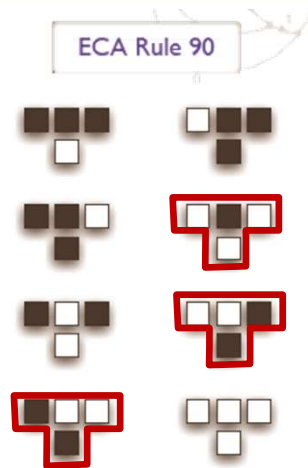
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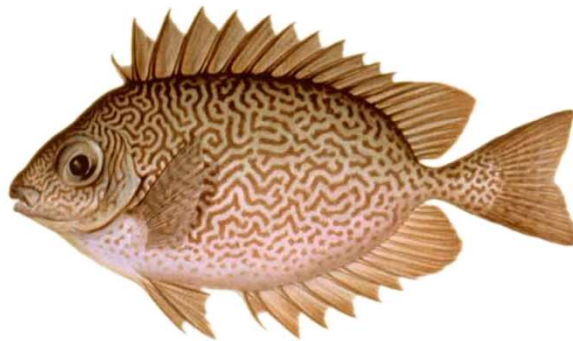
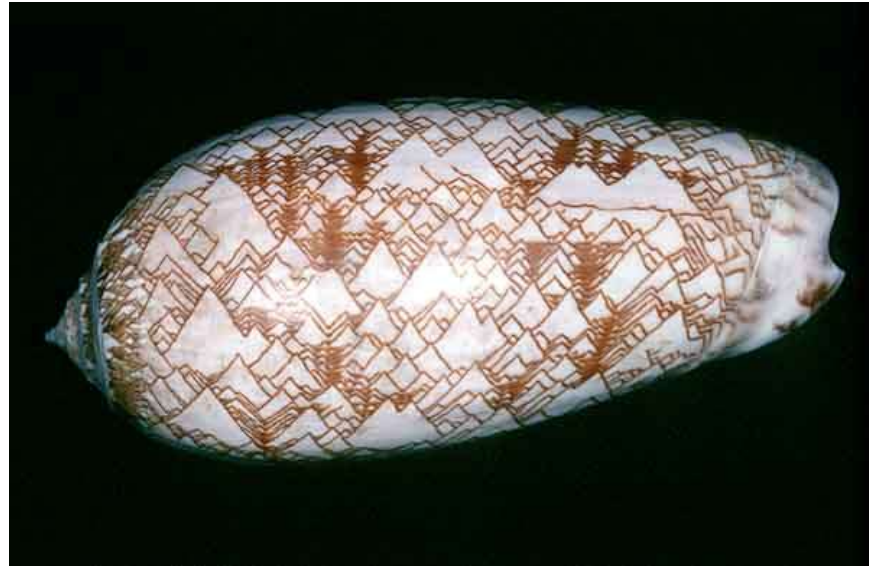
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Living patterns easily replicated in CA

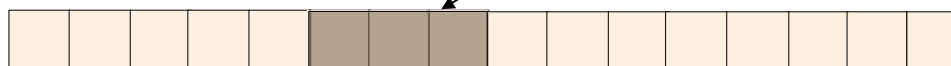


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more formally

D -dimensional lattice L with a finite **automaton** in each lattice site (cell) Neighborhood template N



- State-determined system
 - finite number of states Σ : $K=|\Sigma|$
 - E.g. $\Sigma = \{0,1\}$
 - finite input alphabet α
 - transition function $\Delta: \alpha \rightarrow \Sigma$
 - uniquely ascribes state s in Σ to input patterns α

Example (ECA)
 $K=2, N=3,$
 $|\alpha|=2^3=8$
 $D = 2^8=256$



$$\alpha \in \Sigma^N, |\alpha| = K^N$$

Number of possible neighborhood states

$$D = K^{K^N}$$

Number of possible transition functions

more formally

D -dimensional lattice L with a finite **automaton** in each lattice site (cell) Neighborhood template N



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Example
 $K=8$
 $N=5$
 $|\alpha|=37,768$
 $D \approx 10^{30,000}$



$$\alpha \in \Sigma^N, |\alpha| = K^N$$

Number of possible neighborhood states

$$D = K^{K^N}$$

Number of possible transition functions

Finding the structure of all possible transition functions

- **Statistical analysis**
 - Identify classes of transition functions with similar behavior
 - Similar dynamics (statistically)
 - Via Higher level statistical observables
 - Like Kauffman
- **The Lambda Parameter (similar to bias in BN)**
 - Select a subset of D characterized by λ
 - Arbitrary **quiescent state**: s_q
 - Usually 0
 - A particular function Δ has n transitions to this state and $(K^N - n)$ transitions to other states s of Σ
 - $(1 - \lambda)$ is the probability of having a s_q in every position of the rule table

$$\lambda = \frac{K^N - n}{K^N}$$

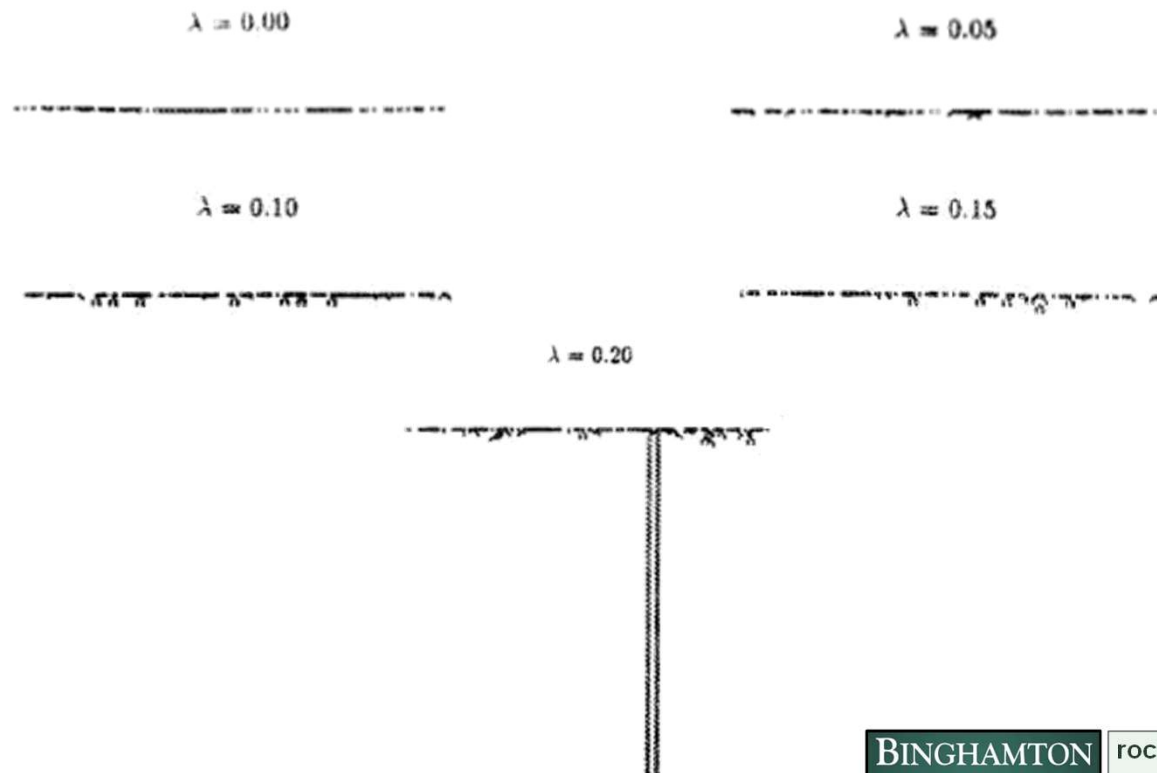
$\lambda = 0$: all transitions lead to s_q ($n = K^N$)

$\lambda = 1$: no transitions lead to s_q ($n = 0$)

$\lambda = 1 - 1/K$: equally probable states ($n = 1/K \cdot K^N$)

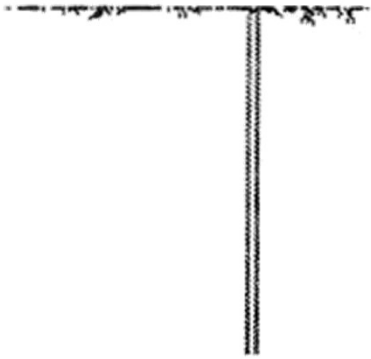
Range: from most homogeneous to most heterogeneous

- λ only correlates well with dynamic behavior for fairly large values of K and N
 - E.g. $K \geq 4$ and $N \geq 5$
- Experiments
 - $K=4, N=5$

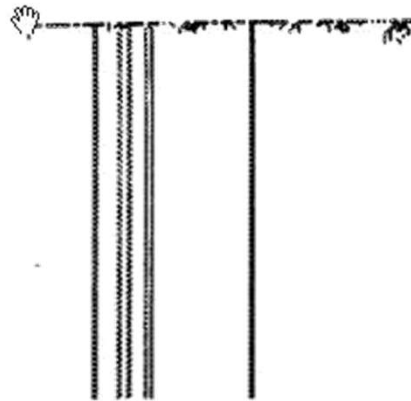


Langton's results

$\lambda = 0.20$



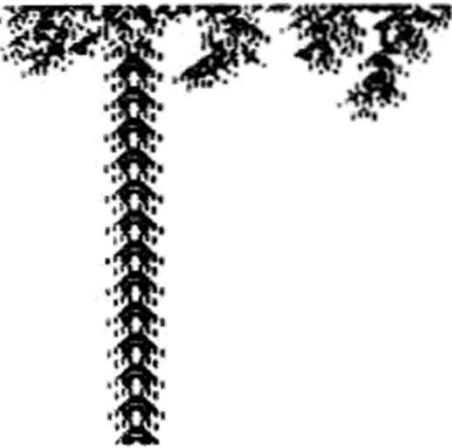
$\lambda = 0.25$



$\lambda = 0.30$

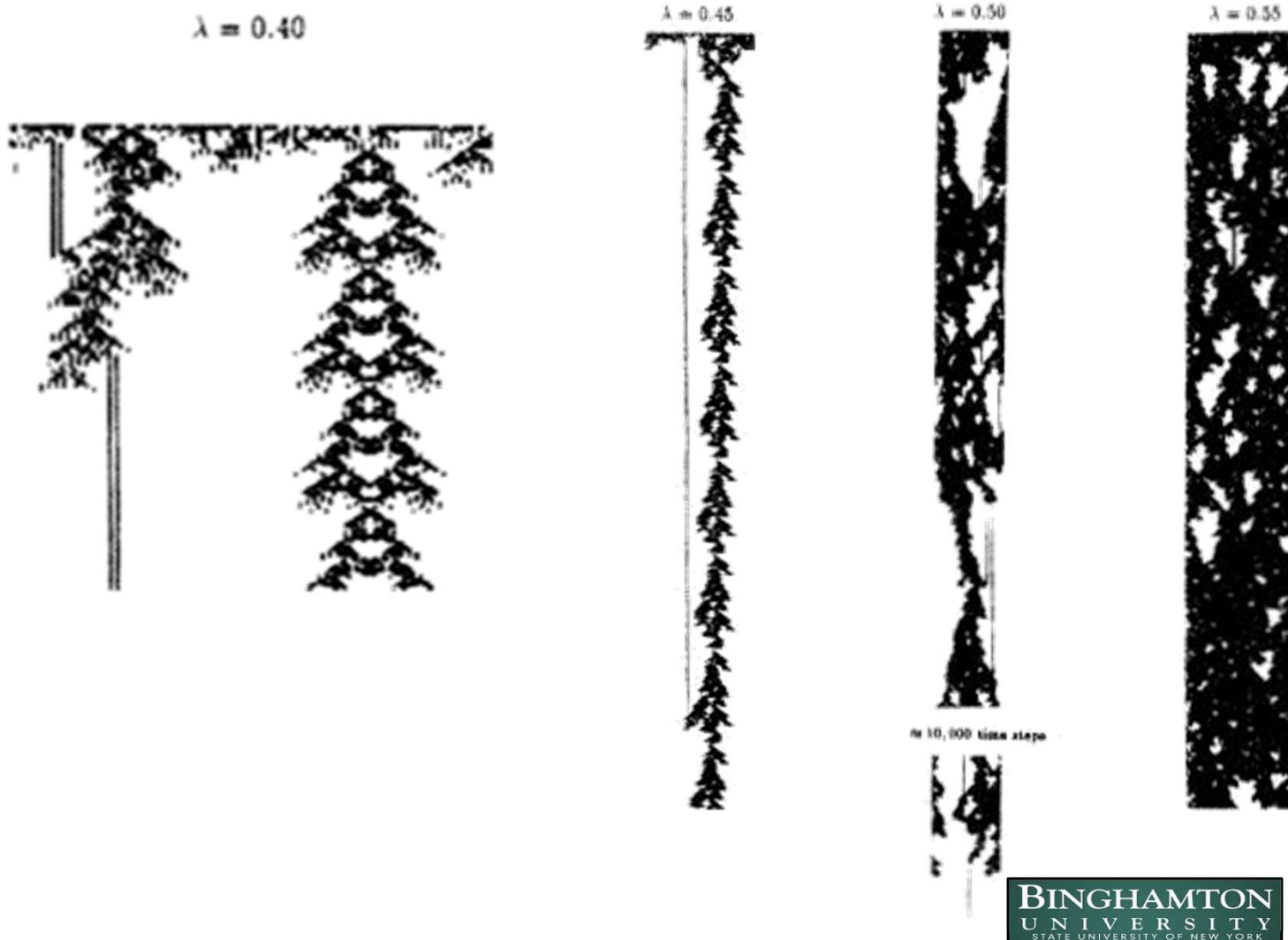


$\lambda = 0.35$



$\lambda = 0.40$





Approximate time when density is within 1% of long-term behavior

$\lambda = 0.55$



$\lambda = 0.60$



$\lambda = 0.65$



Approximate
time when
density is
within 1% of
long-term
behavior

$\lambda = 0.70$

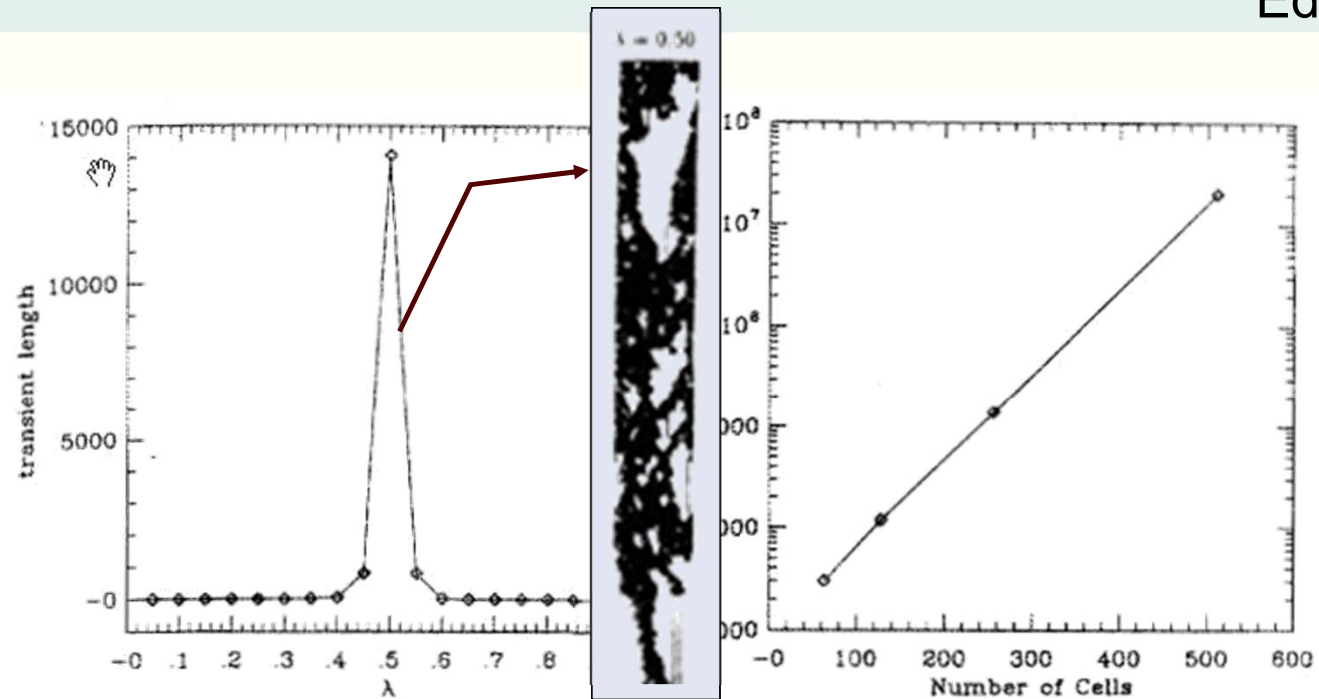


←
Approximate
time
when
density is
within 1%
of long-
term
behavior

$\lambda = 0.75$



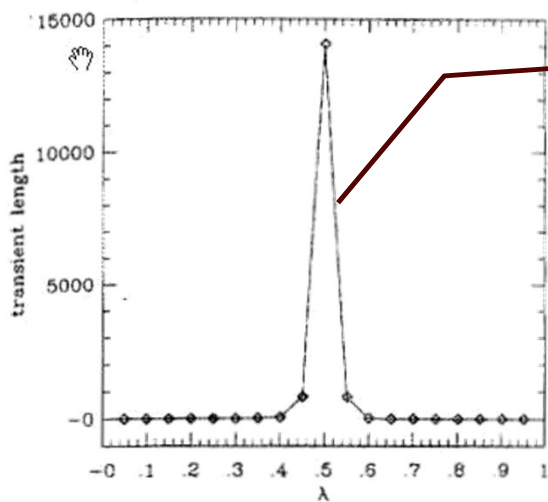
A phase transition?



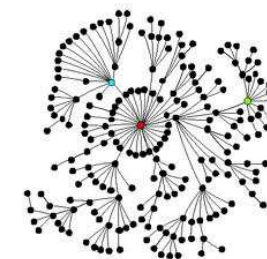
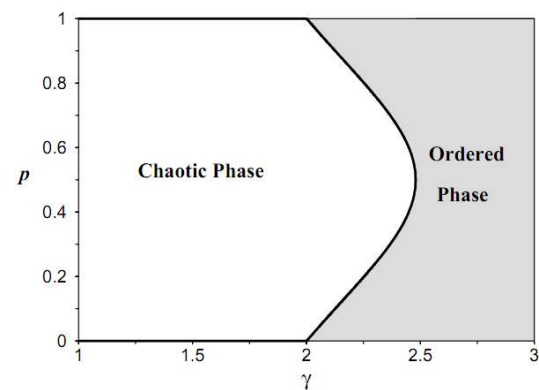
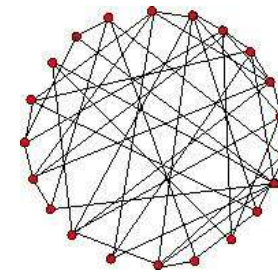
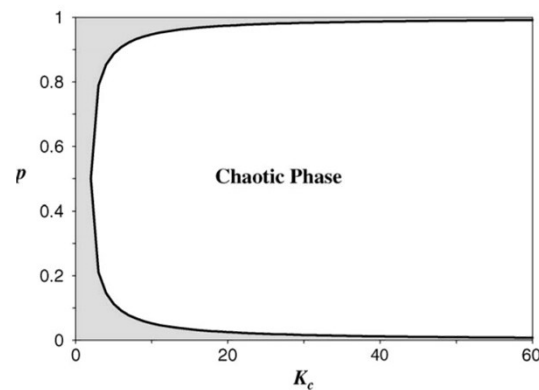
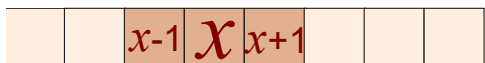
- Transient growth in the vicinity of phase transitions
 - Length of CA lattice only relevant around phase transition ($\lambda=0.5$)
- Conclusion: more complicated behavior found in the phase transition between order and chaos
 - Patterns that move across the lattice

- **Transition region**
 - Supports both static and propagating structures
 - $\lambda = 0.4+$
 - Propagating waves (“signals”?) across the CA lattice
 - Necessary for computation?
 - Signals and storage?
- **Computation**
 - Requires storage and transmission of information
 - Any dynamical system supporting computation must exhibit long-range signals in space and time
- **Wolfram’s CA classes**
 - I: homogeneous state
 - Steady-state
 - II: periodic state
 - Limit cycles
 - III: chaotic
 - IV: complex patterns of localized structures
 - Long transients
 - Capable of universal computation

Bias and lambda parameter



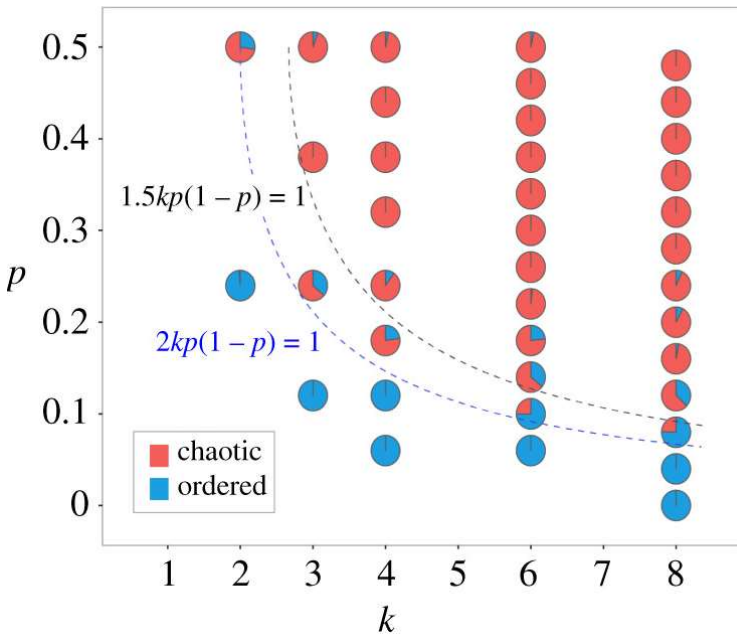
Cellular Automata



Boolean Networks

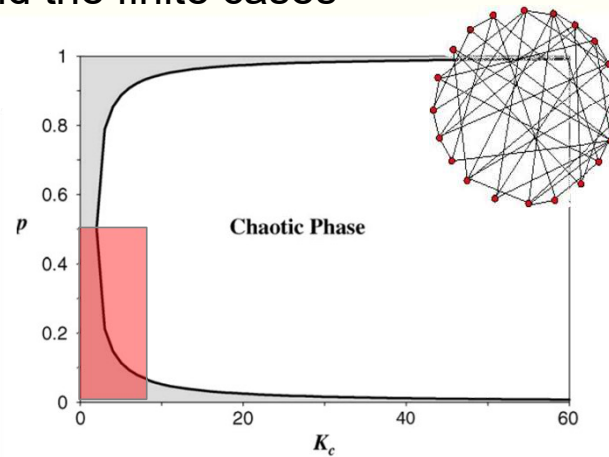
current theory for random networks and the finite cases

homogeneous networks

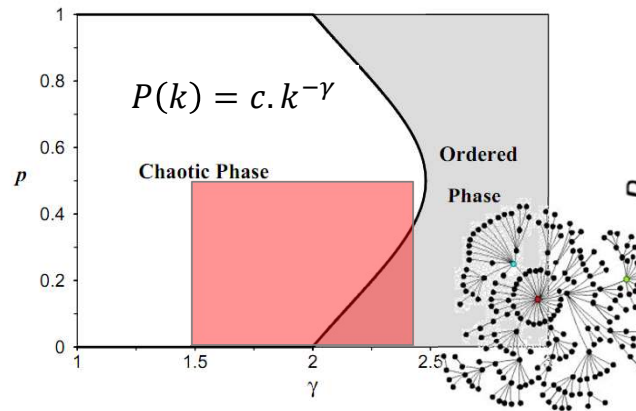


$$2 \cdot k \cdot p(1 - p) = 1$$

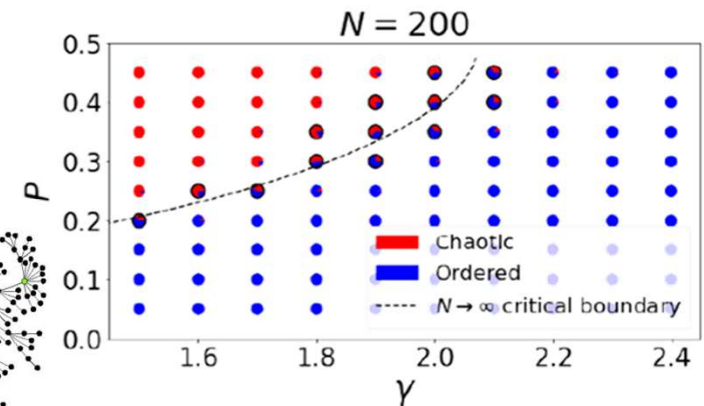
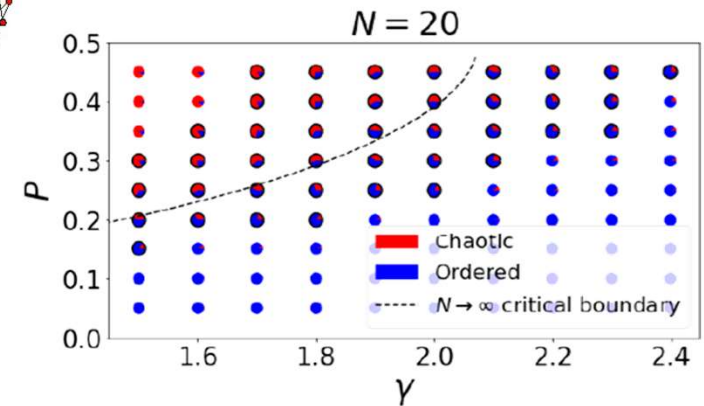
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Aldana, M. [2003]. *Physica D*. **185**: 45–66

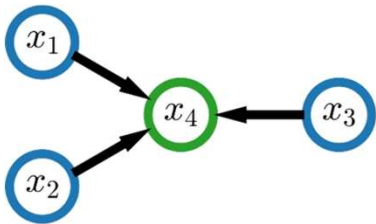


heterogeneous networks



redundancy in causal logic of automata (canalization)

effective graph: nonlinear measure of effective connectivity



look-up-table (LUT)

$F(x_4)$	x_1	x_2	x_3	x_4
f_1	0	0	0	0
f_2	0	0	1	0
f_3	0	1	0	0
f_4	0	1	1	0
f_5	1	0	0	0
f_6	1	0	1	0
f_7	1	1	0	1
f_8	1	1	1	1

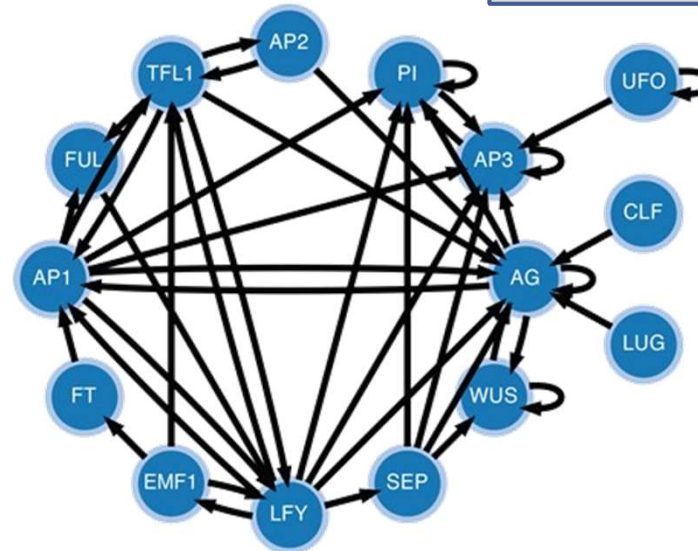
LUT entry/input condition →

↖ on/off state

Measuring dynamical **redundancy** and its dual **effectiveness**

$$p(x) = 2/8 = 0.25$$

p : bias, ratio of "1's" in output



Correia, Gates, Wang & Rocha [2018]. *Frontiers in Physiology* **9**: 1046.

Gates, Correia, Wang & Rocha [2021]. *PNAS*. **118** (12): e2022598118.

Marques-Pita & Rocha, [2013]. *PLoS ONE*, **8**(3): e55946.

Chaos et al [2006]. *J. of Plant*

Growth Regulation. **25**(4): 278-289.

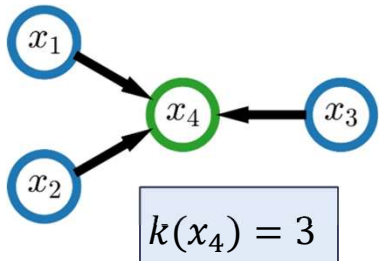


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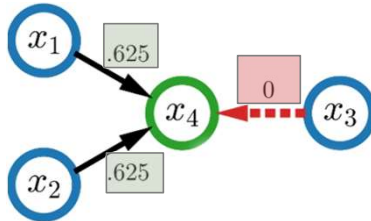
redundancy in causal logic of automata (canalization)

effective graph: nonlinear measure of effective connectivity



$x_4 = x_1 \wedge x_2$

$k_e(x_4) = 1.25$



look-up-table (LUT)

$F(x_4)$	x_1	x_2	x_3	x_4
f_1	0	0	0	0
f_2	0	0	1	0
f_3	0	1	0	0
f_4	0	1	1	0
f_5	1	0	0	0
f_6	1	0	1	0
f_7	1	1	0	1
f_8	1	1	1	1

LUT entry/input condition →

prime implicant →

$F'(x_4)$	x_1	x_2	x_3	x_4
f'_1	#	0	#	0
f'_2	0	#	#	0
f'_3	1	1	#	1

on/off state variable ↗
wildcard symbol ↖

Prime Implicants (Quine-McCluskey)

github.com/CASCI-lab/CANA

Measuring dynamical **redundancy** and its dual **effectiveness**

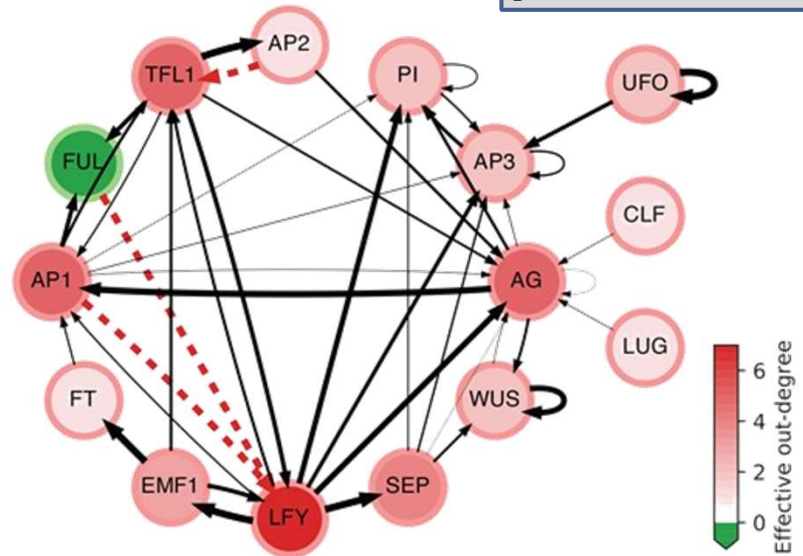
input redundancy:
 $k_r(x) = \text{mean number of " \# " in LUT}$

$k_r(x_4) = 1.75$

effective connectivity:
 $k_e(x) = k(x) - k_r(x)$

$p(x) = 2/8 = 0.25$

p : bias, ratio of "1"s in output



Effective out-degree

Correia, Gates, Wang & Rocha [2018]. *Frontiers in Physiology* 9: 1046.

Gates, Correia, Wang & Rocha [2021]. *PNAS*. 118 (12): e2022598118.

Marques-Pita & Rocha, [2013]. *PLoS ONE*, 8(3): e55946.

Chaos et al [2006]. *J. of Plant Growth Regulation*. 25(4): 278-289.



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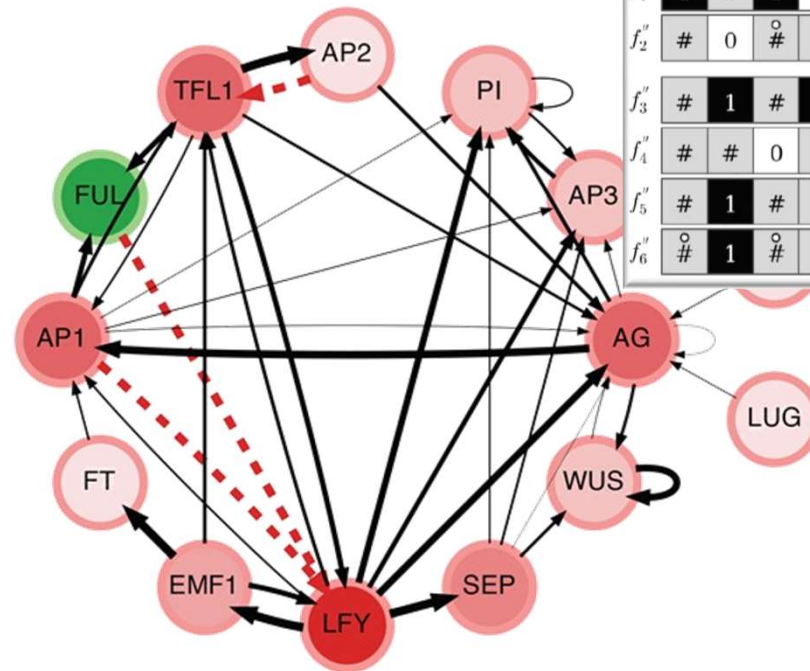
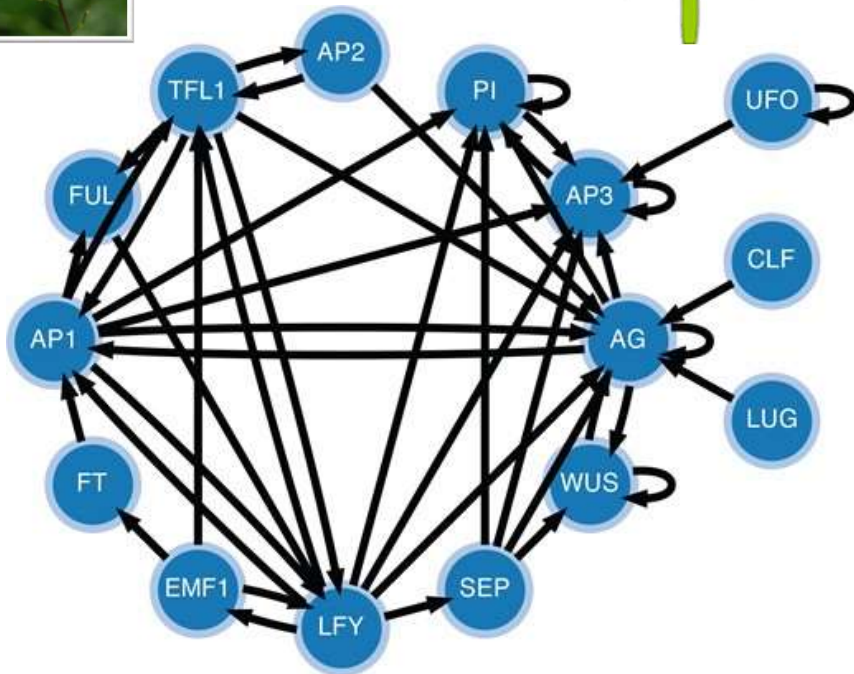
arabidopsis thaliana network



Chaos et al [2006]. *J. of Plant Growth Regulation*. **25**(4): 278-289.

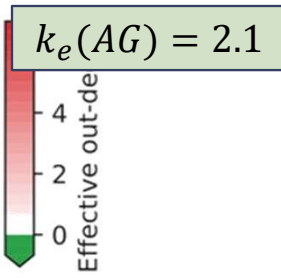


redundant variables and more effective control pathways revealed



	AP1	LFY	AP2	WUS	AG	LUG	CLF	TFL1	SEP	AG
f_1'	1	#	1	0	0	1	1	#	#	: 0
f_2'	#	0	#	#	#	#	#	1	#	: 0
f_3'	#	1	#	1	#	#	#	#	#	: 1
f_4'	#	#	0	#	#	#	#	0	#	: 1
f_5'	#	1	#	#	1	#	#	#	1	: 1
f_6'	#	1	#	#	#	#	0	#	#	: 1

$k(AG) = 9$



Gates, Correia, Wang & Rocha [2021]. *PNAS*. **118** (12): e2022598118.

Gates & Rocha [2016]. *Scientific Reports* **6**, 24456.

Marques-Pita & Rocha, [2013]. *PLoS ONE*, **8**(3): e55946.

github.com/CASCI-lab/CANA



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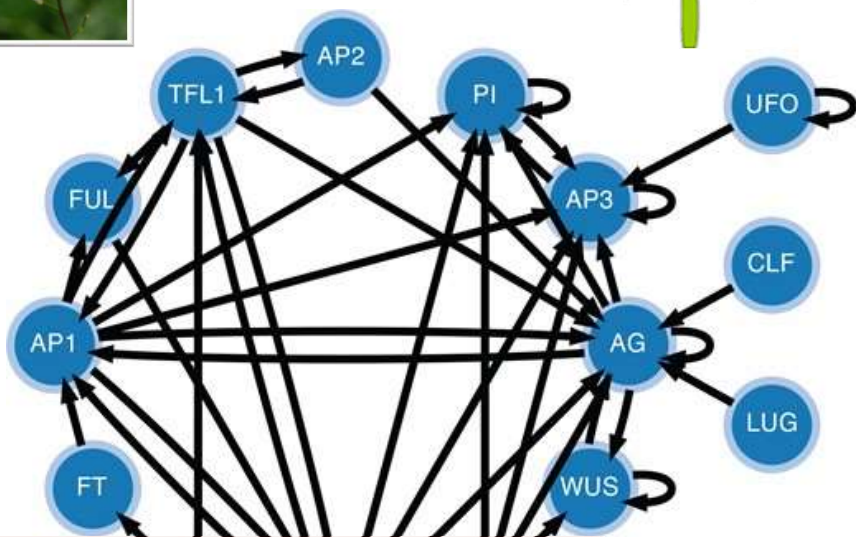
arabidopsis thaliana network



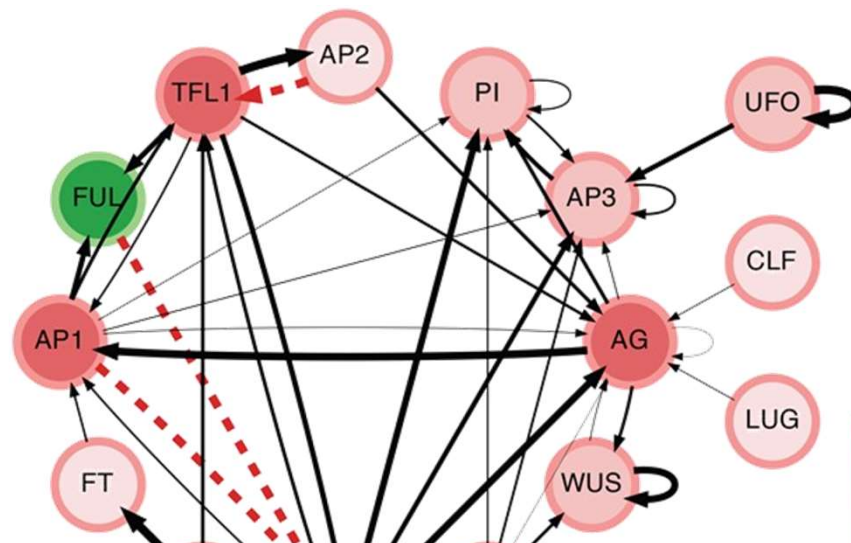
Chaos et al [2006]. *J. of Plant Growth Regulation*. **25**(4): 278-289.



redundant variables and more effective control pathways revealed



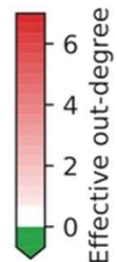
Interaction graph obtained from pairwise estimation of interaction. No dynamics represented in graph; many dynamics fit same structure.



Effective graph redundancy in (nonlinear) dynamics is integrated probabilistically (not estimated). Provides **causal explanation** of how **likely** dynamical perturbation and control signals propagate in biochemical pathways.

$k(AG) = 9$

$k_e(AG) = 2.1$



github.com/CASCI-lab/CANA

Gates, Correia, Wang & Rocha [2021]. *PNAS*. **118** (12): e2022598118.

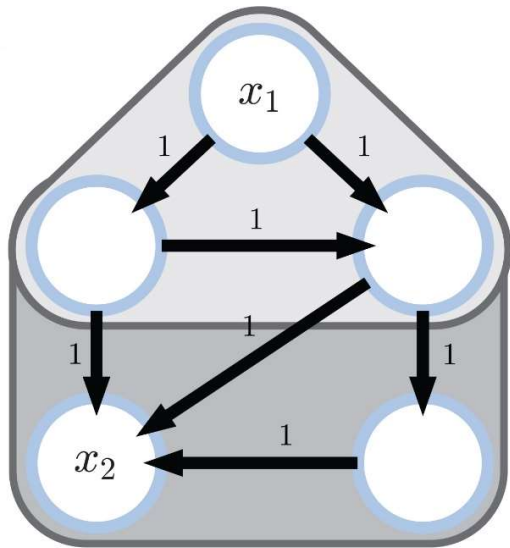
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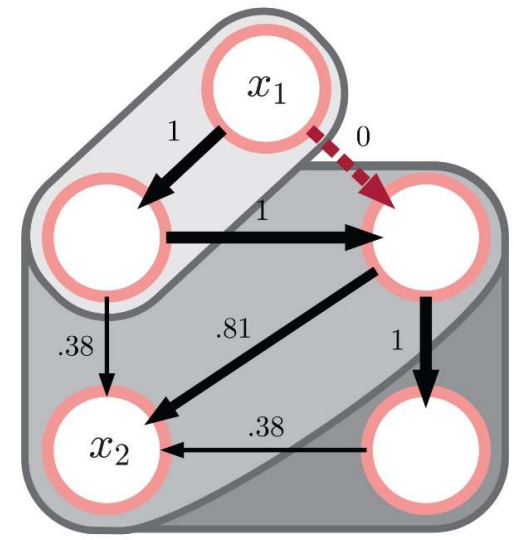
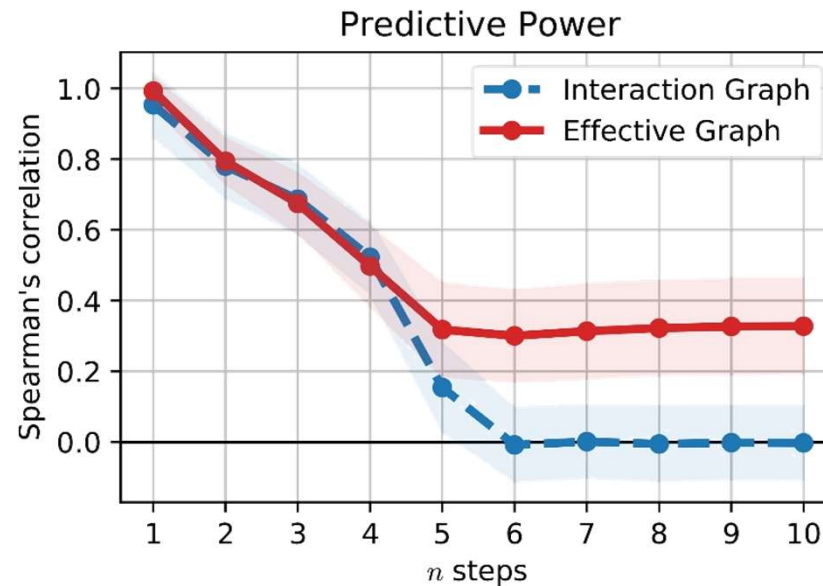


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probabilistic and precise characterization of causal (nonlinear) dynamics



$$p_3(x_1, x_2) = 1 \times 1 = 1$$



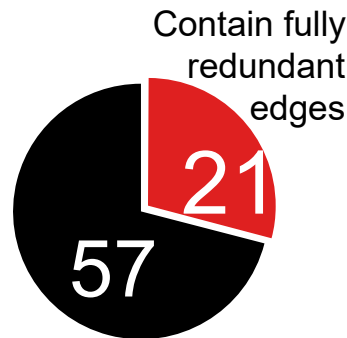
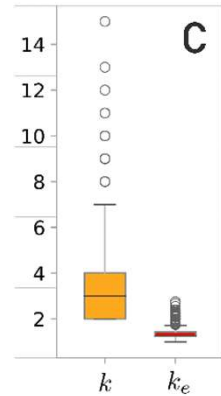
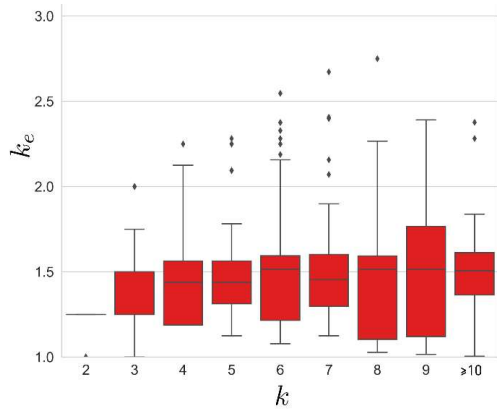
$$p_3(x_1, x_2) = 1 \times 1 \times 0.81 = 0.81$$

Interaction graph typically obtained from (qualitative) pairwise estimation of interaction. No dynamics represented in graph; many dynamics fit same structure.

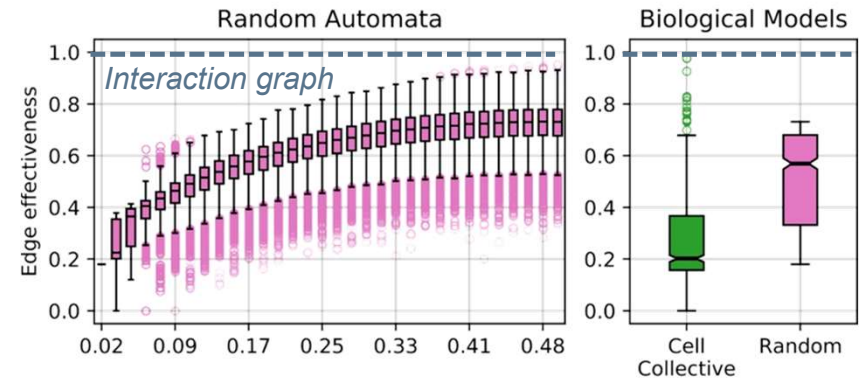
Effective graph redundancy in dynamics is integrated probabilistically (not estimated). Reveals network of nonlinear interactions that escapes pairwise estimation. Provides **causal explanation** of how dynamical perturbation and control signals propagate in biochemical pathways.

redundant pathways are ubiquitous in biochemical regulation

node-level



edge-level



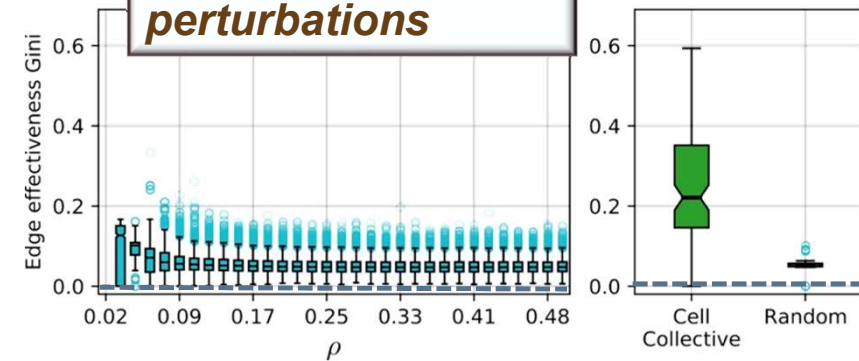
dynamical redundancy is pervasive in systems biology models of regulation and signaling: biochemical variables are controlled by substantially fewer inputs than interaction graph suggests.

effectiveness is heterogenous: only few inputs are very effective, most are ineffective or redundant.



8,220 interactions (of over 3K automata) in 78 models

robustness to most perturbations



Gates & Rocha [2016]. *Scientific Reports* 6, 24456.

Manicka, Marques-Pita, & Rocha, [2021]. *J. Royal Society Interface*. 19(186):20210659.

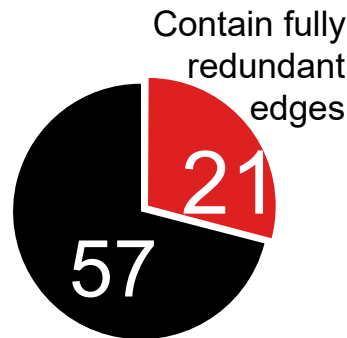
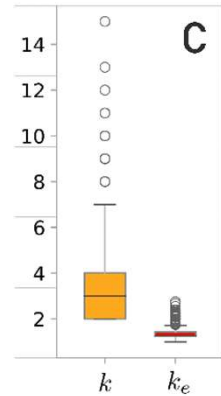
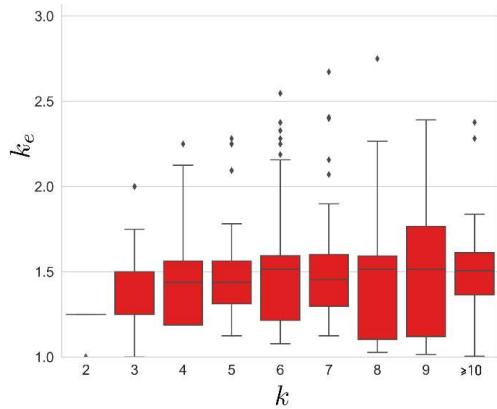
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redundant pathways are ubiquitous in biochemical regulation

node-level

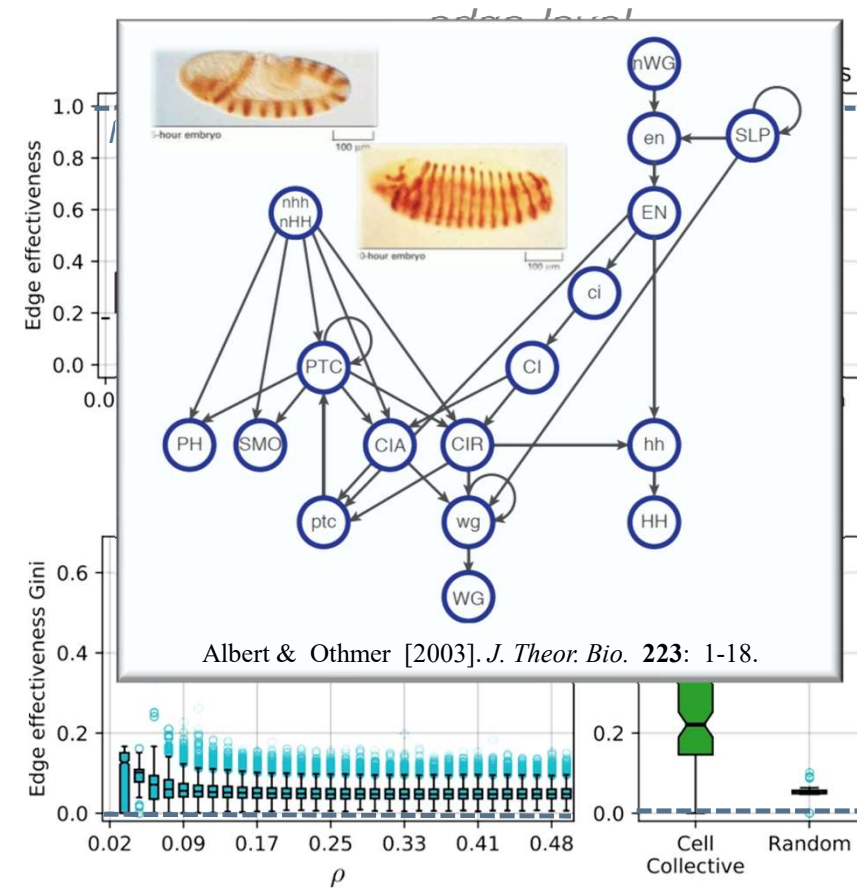


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8,220 interactions (of over 3K automata) in 78 models



Albert & Othmer [2003]. *J. Theor. Bio.* **223**: 1-18.

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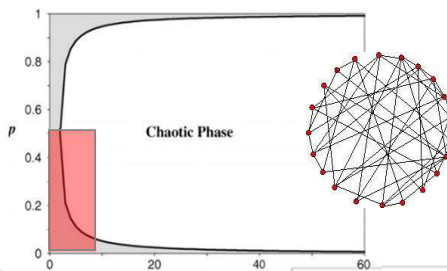
criticality in the presence of canalization/redundancy

effective connectivity enables greater robustness (random ensembles)

Derrida & Pomeau. [1986] *EPL* . **1.2**: 45.

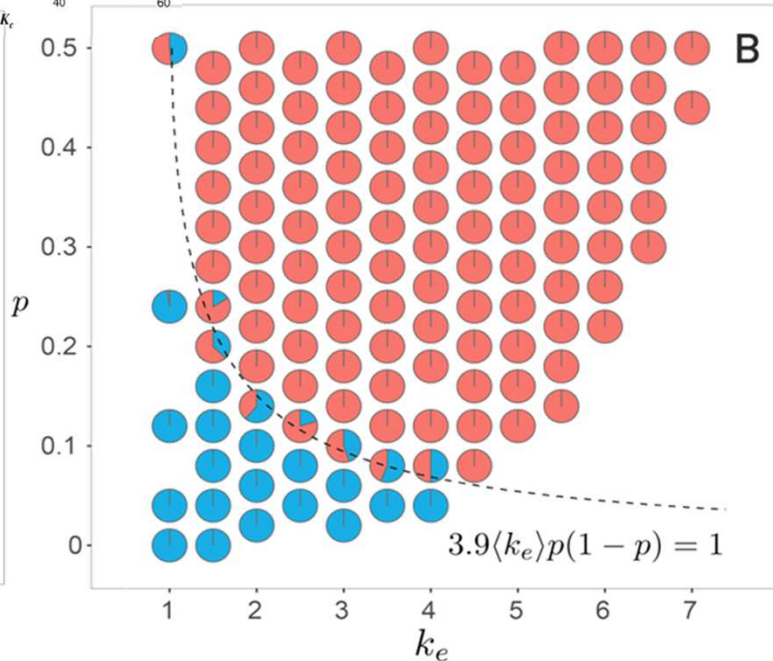
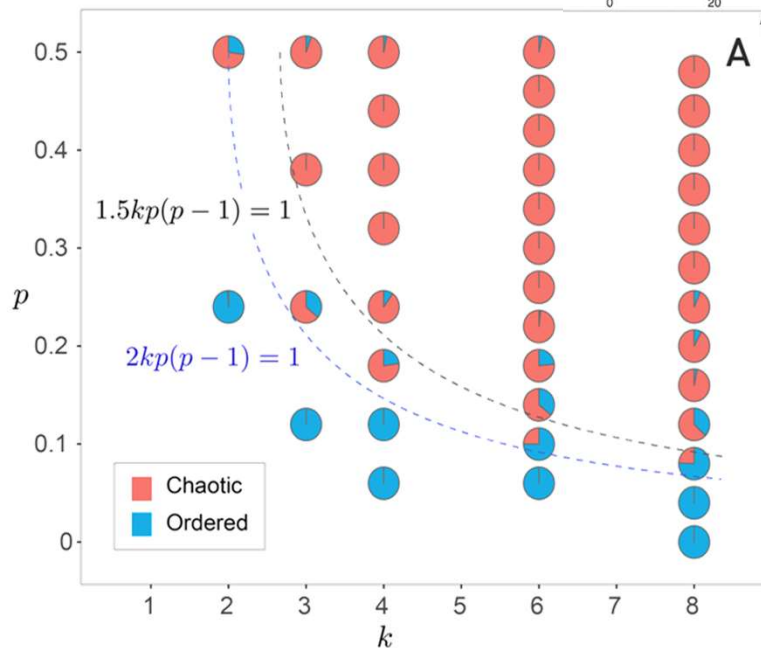
Aldana, M. [2003]. *Physica D*. **185**: 45–66

$$c. k \cdot p(1 - p) = 1$$



$$k_e(x) = k(x) - k_r(x)$$

$$c. k_e \cdot p(1 - p) = 1$$



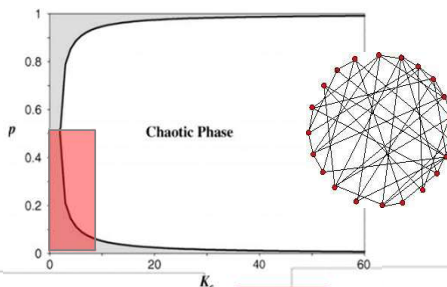
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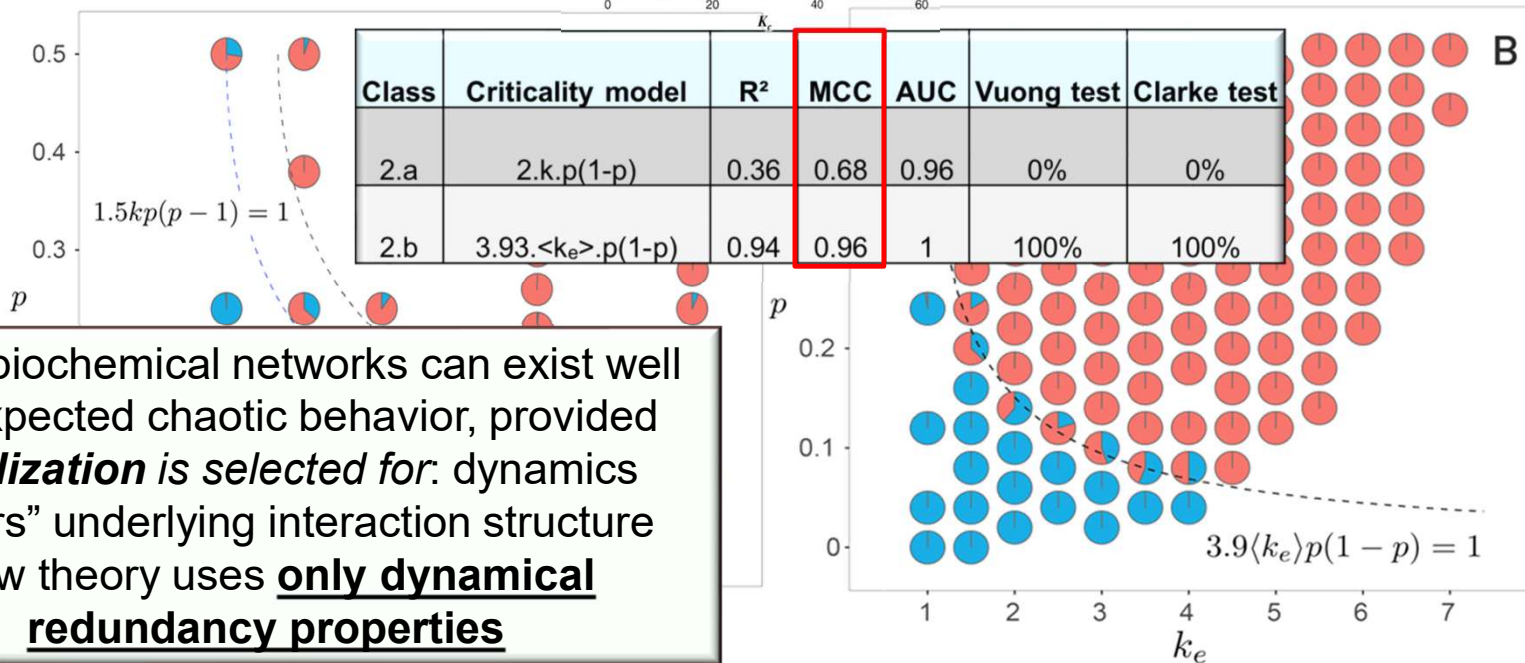
Aldana, M. [2003]. *Physica D*. **185**: 45–66

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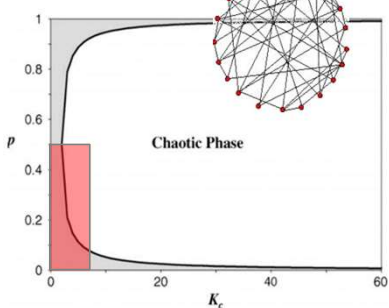
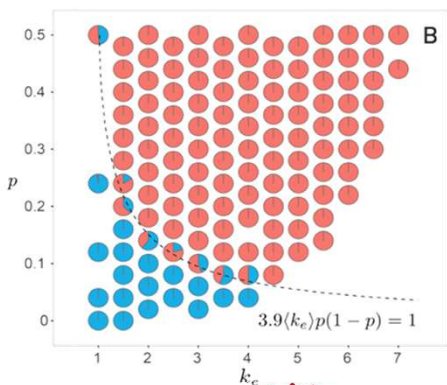


Stable biochemical networks can exist well into expected chaotic behavior, provided **canalization** is selected for: dynamics “buffers” underlying interaction structure
New theory uses only dynamical redundancy properties

criticality in the presence of canalization/redundancy

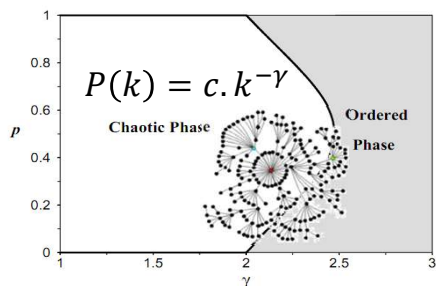
effective connectivity enables greater robustness (random ensembles)

homogeneous networks

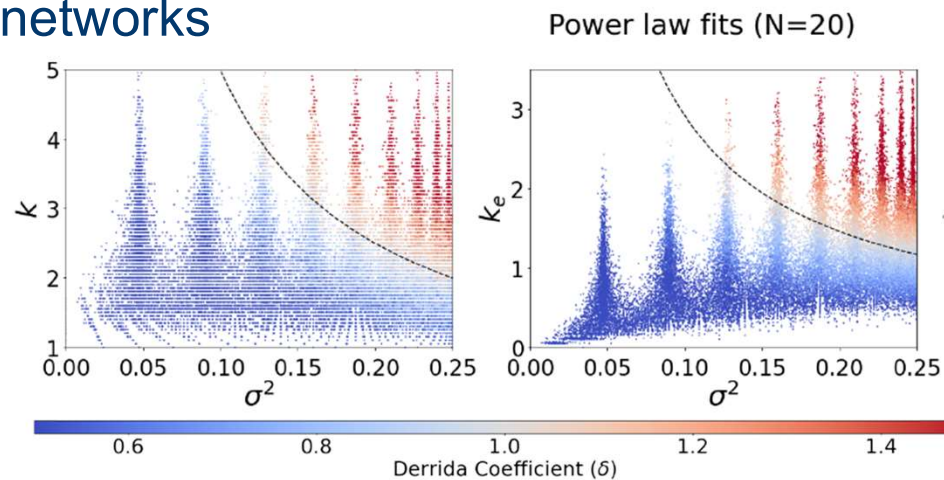


$$c \cdot k_e \cdot p(1 - p) = 1$$

heterogeneous networks



Stable biochemical networks can exist well into expected chaotic behavior, provided **canalization is selected for**: dynamics “buffers” underlying interaction structure



$$\sigma^2 = p(1 - p)$$

N	20	50	100	200
$\sigma^2 k$	93.83	95.04	95.88	96.71
$\sigma^2 k_e$	96.09	96.35	96.53	96.8

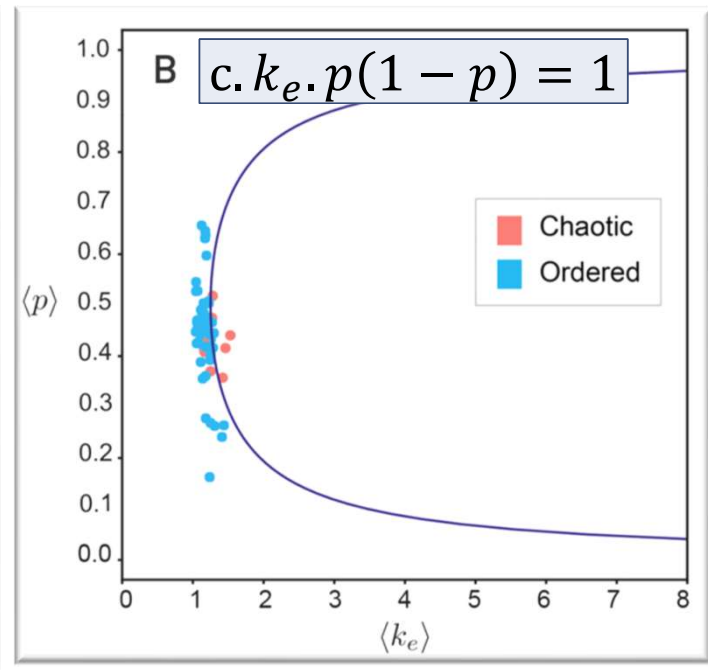
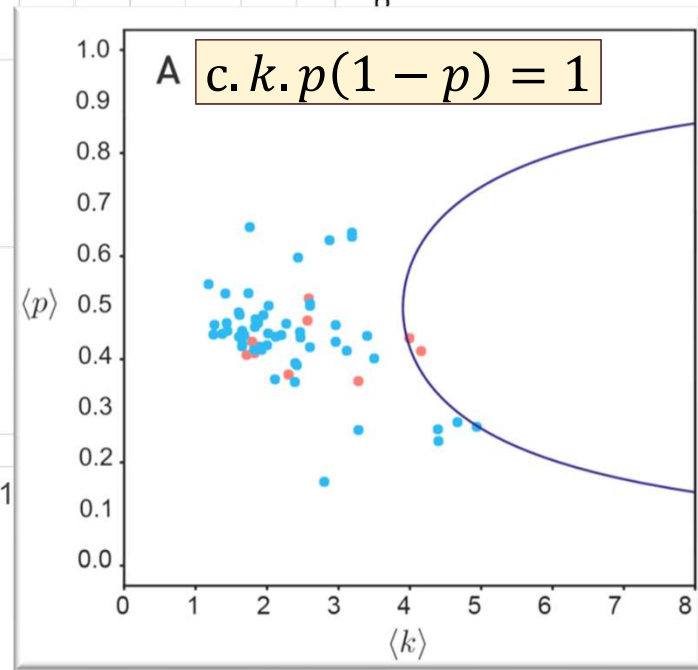
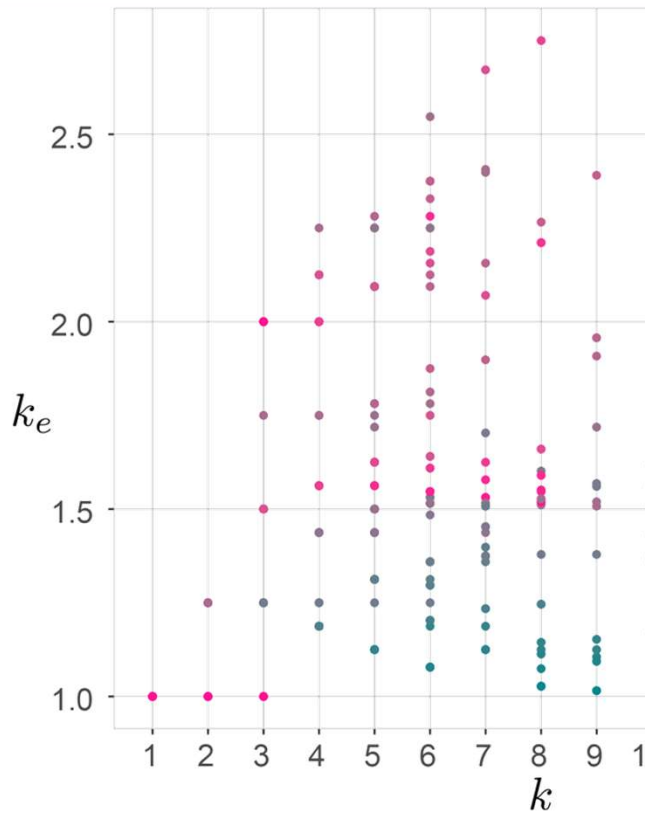
Costa, Rozum, Marcus, & Rocha[2023]. *Entropy*. **25**(2):374.

Manicka, Marques-Pita, & Rocha, [2021]. *J. Royal Society Interface*. **19**(186):20210659.

ubiquitous canalization in (experimentally-validated) systems biology models

low effective connectivity leads networks closer to “edge of chaos”

63 Biochemical regulation models with very low effective connectivity despite high connectivity. In new theory networks are near criticality

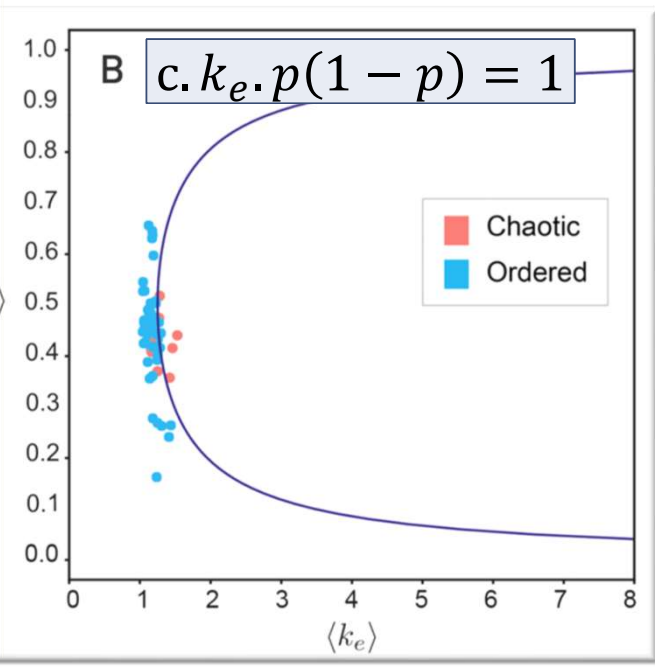
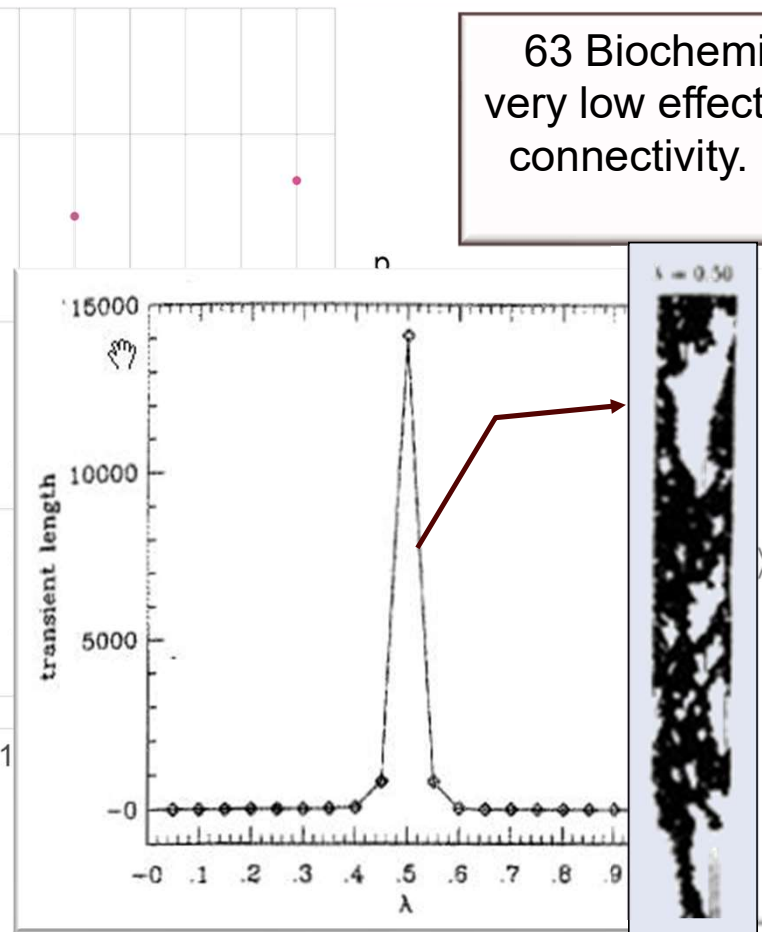
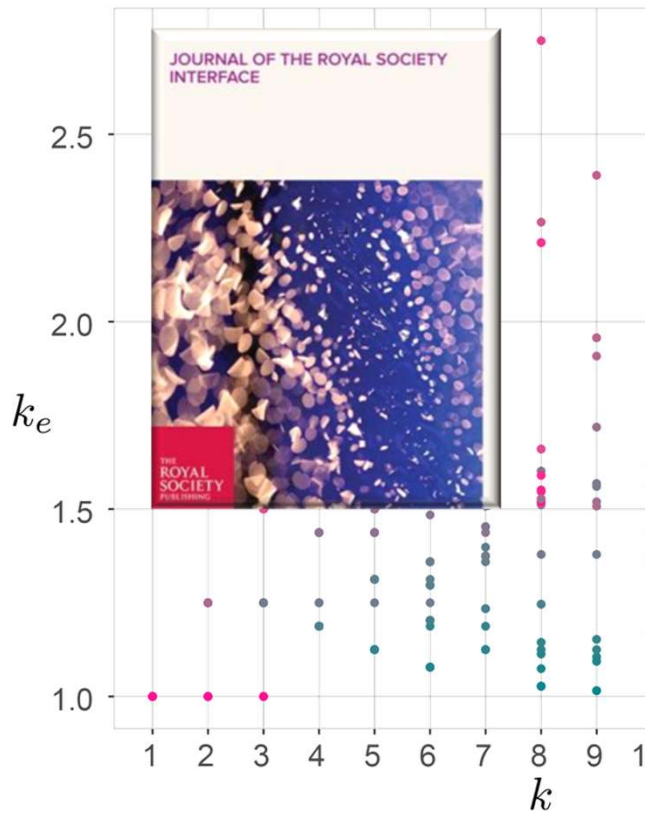


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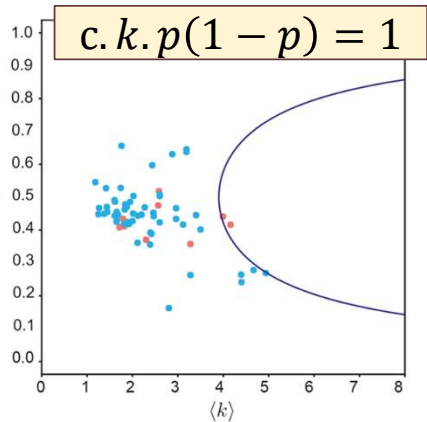


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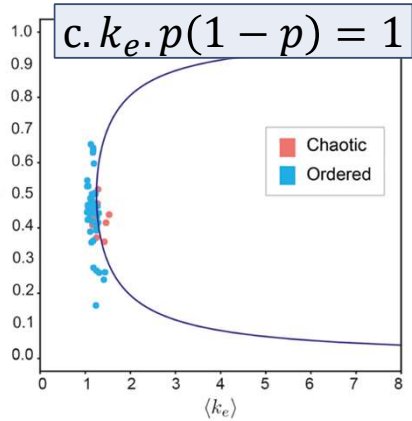
ubiquitous canalization in (experimentally-validated) systems biology models

effective connectivity better predicts critical transition

homogeneous networks



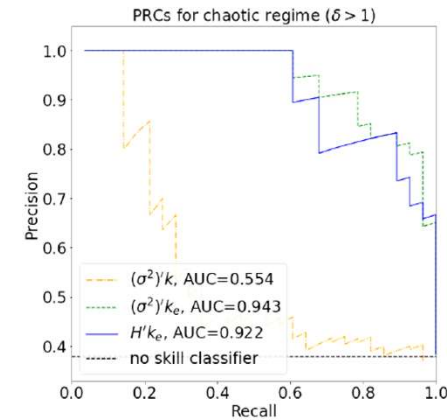
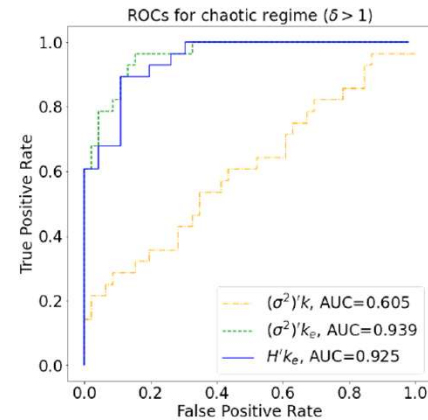
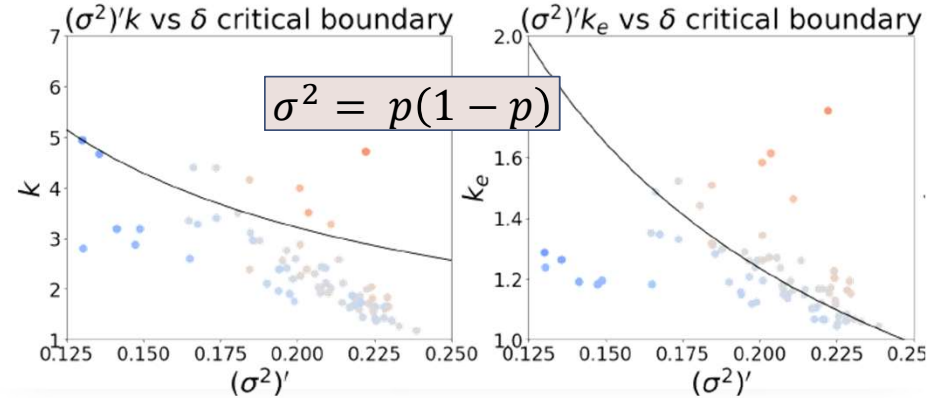
Biochemical regulation models have very low effective connectivity despite high connectivity. Accounting for heterogeneity and canalization better predicts dynamical regime



Optimal criticality predictions in the Cell Collective

$\delta \leq 1$	45	1	39	7
$\delta > 1$	22	6	1	27
	$(\sigma^2)'k \leq 0.64$	$(\sigma^2)'k > 0.64$	$(\sigma^2)'k_e \leq 0.25$	$(\sigma^2)'k_e > 0.25$

heterogeneous networks



Costa, Rozum, Marcus, & Rocha[2023]. *Entropy*. 25(2):374.
 Manicka, Marques-Pita, & Rocha, [2021]. *J. Royal Society Interface*. 19(186):20210659.

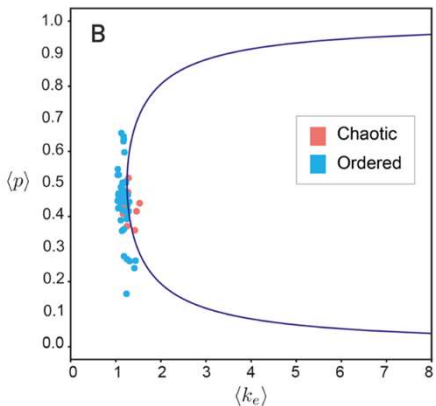


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ubiquitous canalization in (experimentally-validated) systems biology models

but is there an edge of chaos boundary?

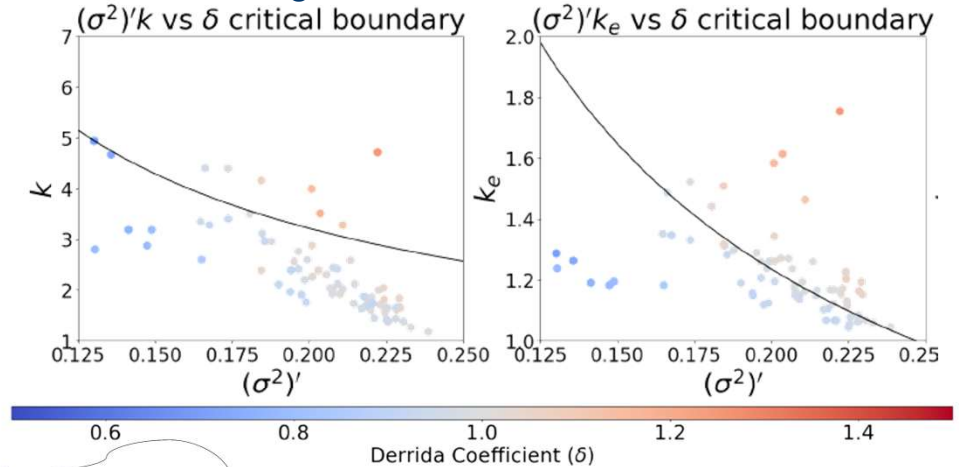
homogeneous networks



Once canalization (dynamical redundancy) is considered optimal critical region very small and dynamical range is better predicted.



heterogeneous networks



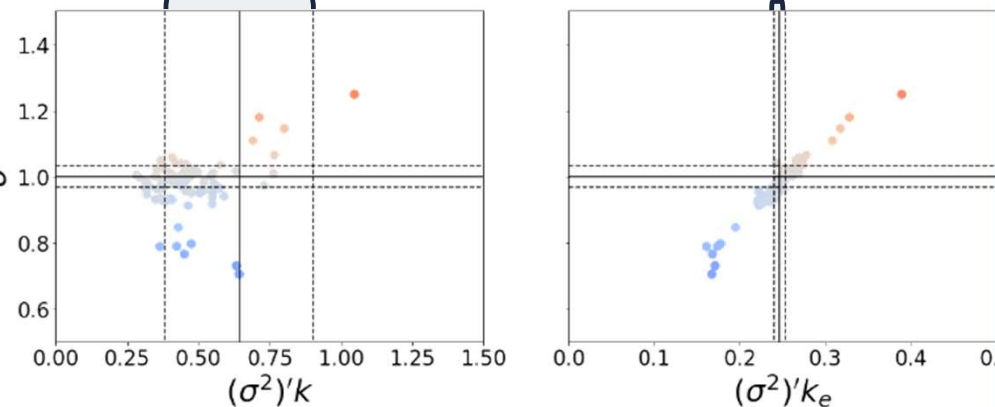
Optimal classification thresholds

Optimal criticality predictions in the Cell Collective

Dynamical regime from δ Region Width = 0.06	Region Width = 0.52			Region Width = 0.01		
	Ordered	Critical	Chaotic	Ordered	Critical	Chaotic
Ordered	11	20	0	26	5	0
Critical	8	23	0	0	21	10
Chaotic	2	9	1	0	1	11
	Ordered	Critical	Chaotic	Ordered	Critical	Chaotic

Dynamical regime from $(\sigma^2)'k$ Dynamical regime from $(\sigma^2)'k_e$

IQR Of Derrida



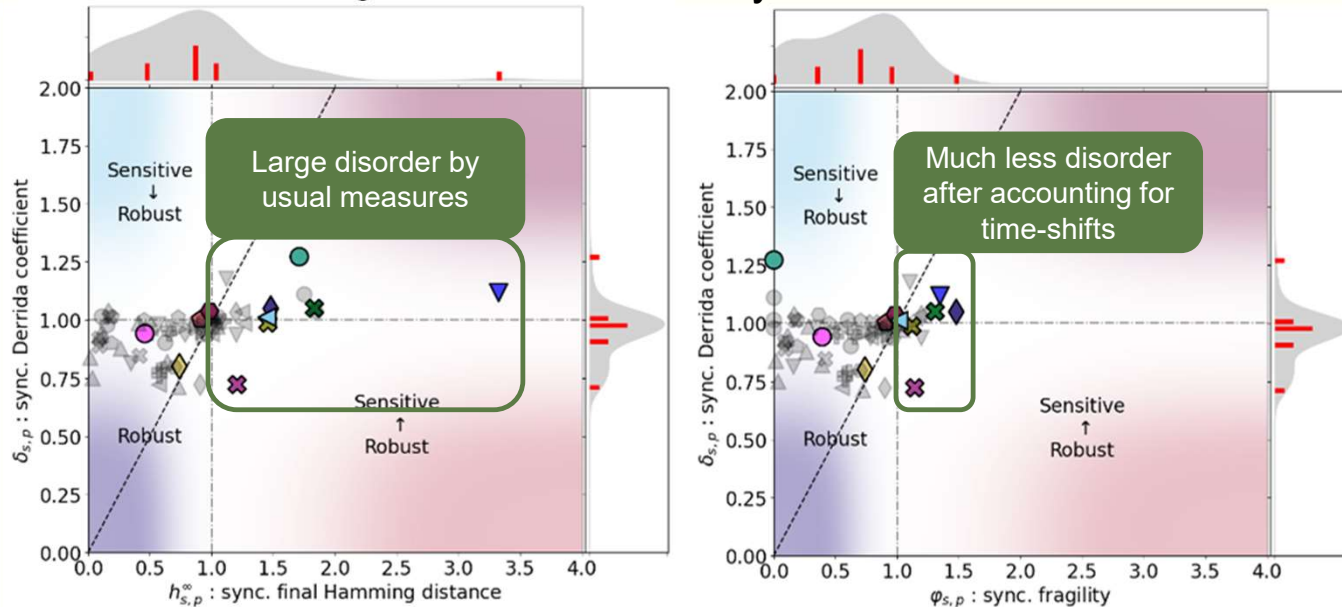
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ubiquitous canalization in (experimentally-validated) systems biology models

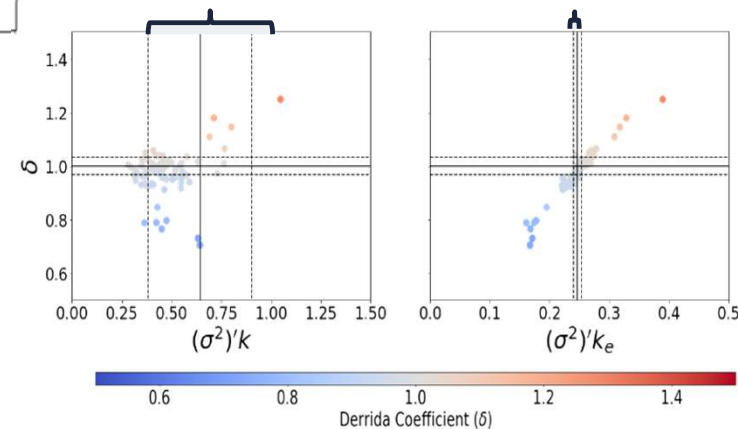
but is there an edge of chaos boundary?



Criticality might arise from interactions of amongst largely stable modules



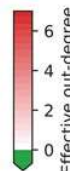
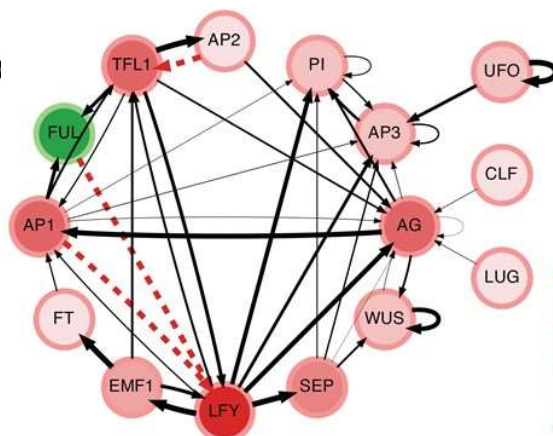
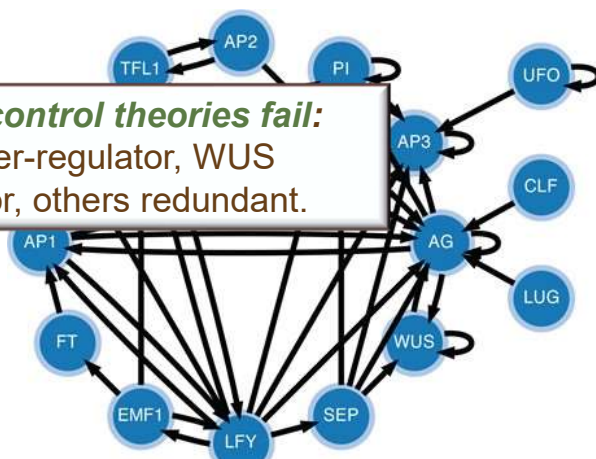
More accurate measures of dynamical regime show that experimentally-validated systems biology are far from the edge of chaos



Park, Costa, Rocha, Albert, & Rozum [2023]. *PRX Life*. **1**, 023009.
 Costa, Rozum, Marcus, & Rocha [2023]. *Entropy*. **25**(2):374.
 Manicka, Marques-Pita, & Rocha, [2021]. *J. Royal Society Interface*. **19**(186):20210659.

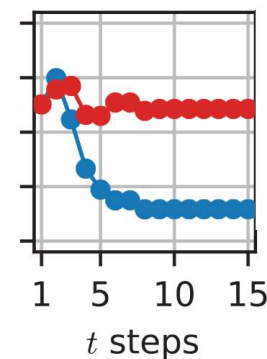
Thaliana control pathways (using structure and dynamics information)

Structural control theories fail:
LFY is master-regulator, WUS
autoregulator, others redundant.

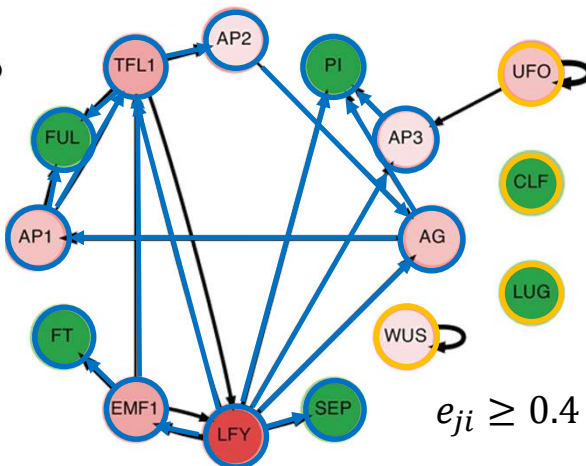
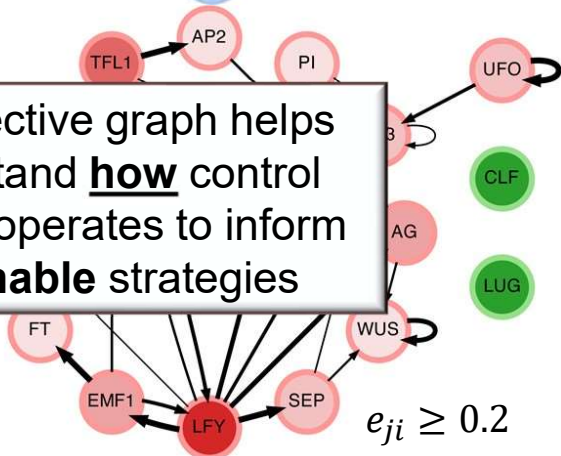


Interaction graph Effective graph

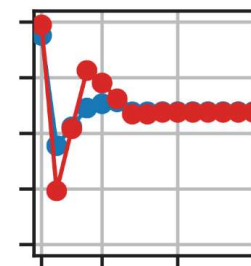
WUS



The effective graph helps
understand **how** control
actually operates to inform
actionable strategies



LFY

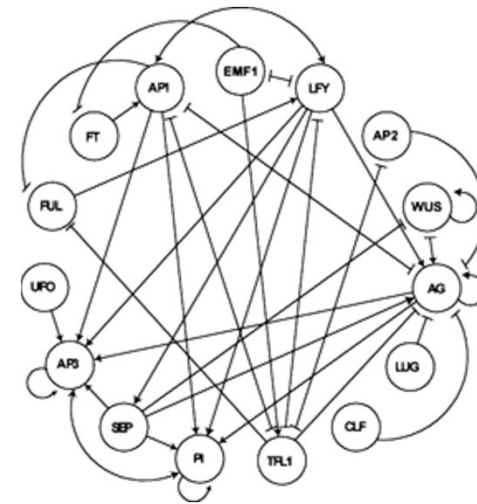
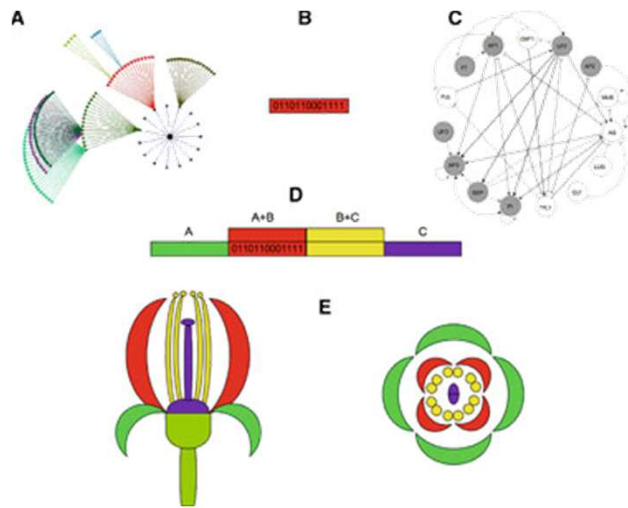


Chaos et al [2006]. *J. of Plant Growth Regulation*. **25**(4): 278-289.

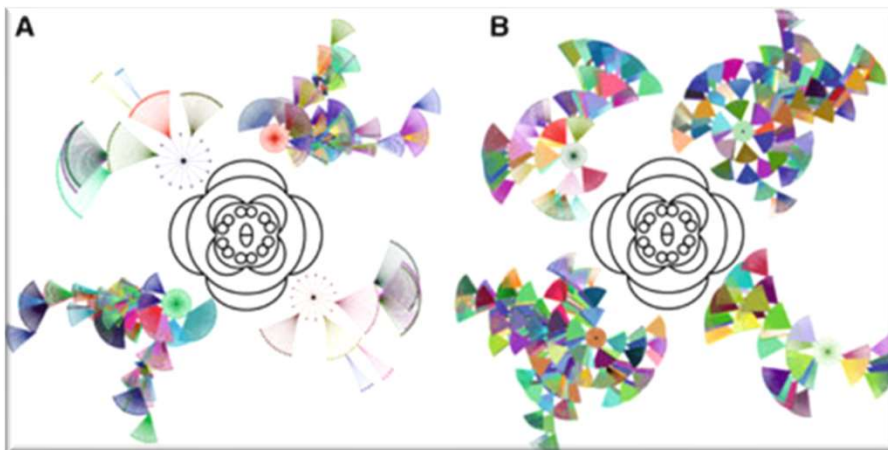
Gates & Rocha [2016]. *Sci. Rep.* **6**, 24456.

Gates, Correia, Wang & Rocha [2021]. *PNAS*. **118** (12): e2022598118.

Boolean networks, control, sound, art, and education

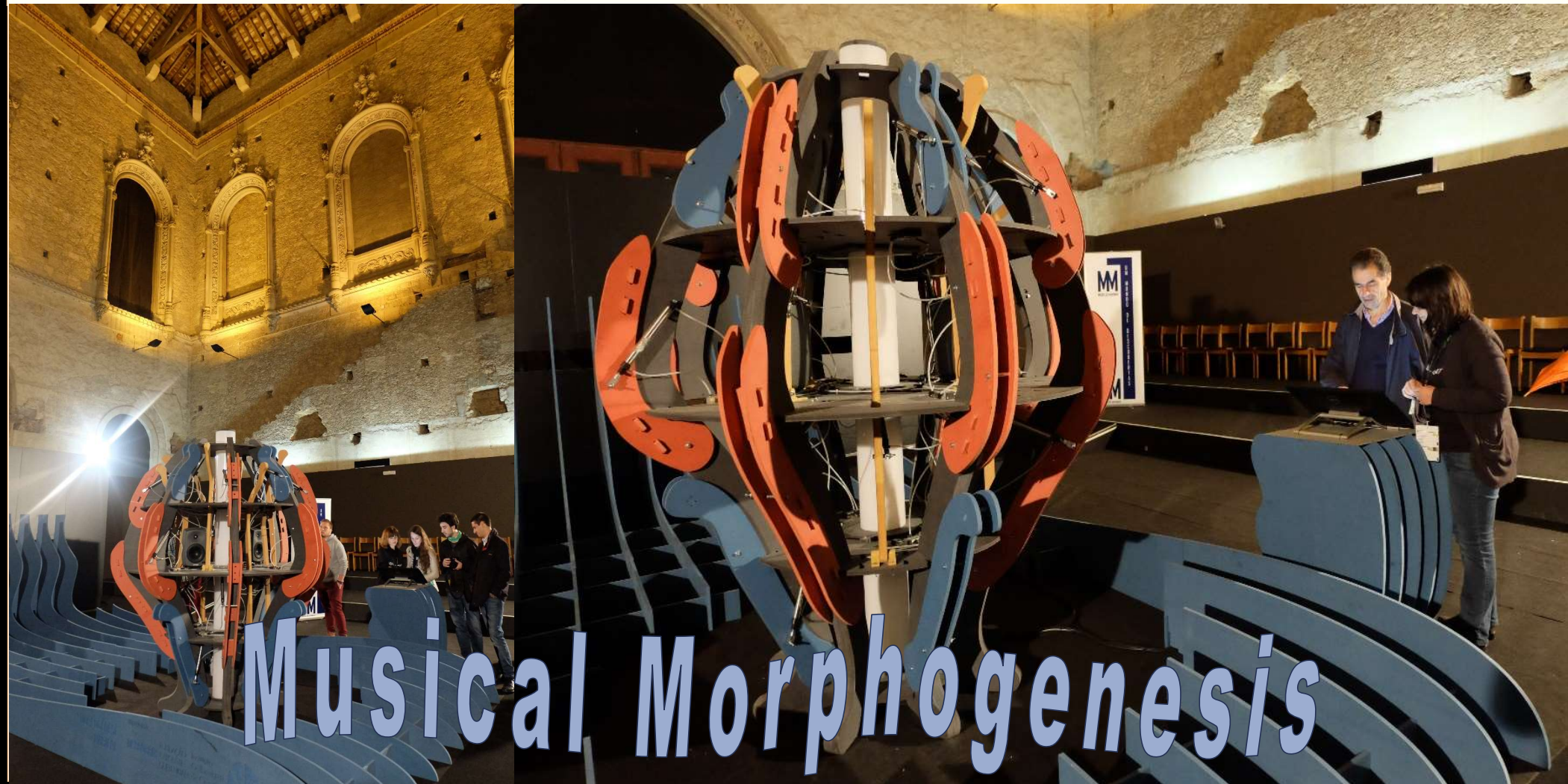


Chaos et al [2006]. "From Genes to Flower Patterns and Evolution: Dynamic Models of Gene Regulatory Networks". *Journal of Plant Growth Regulation*. **25**(4): 278-289.



control and the cybernetics of life

Boolean networks, control, sound, art, and education



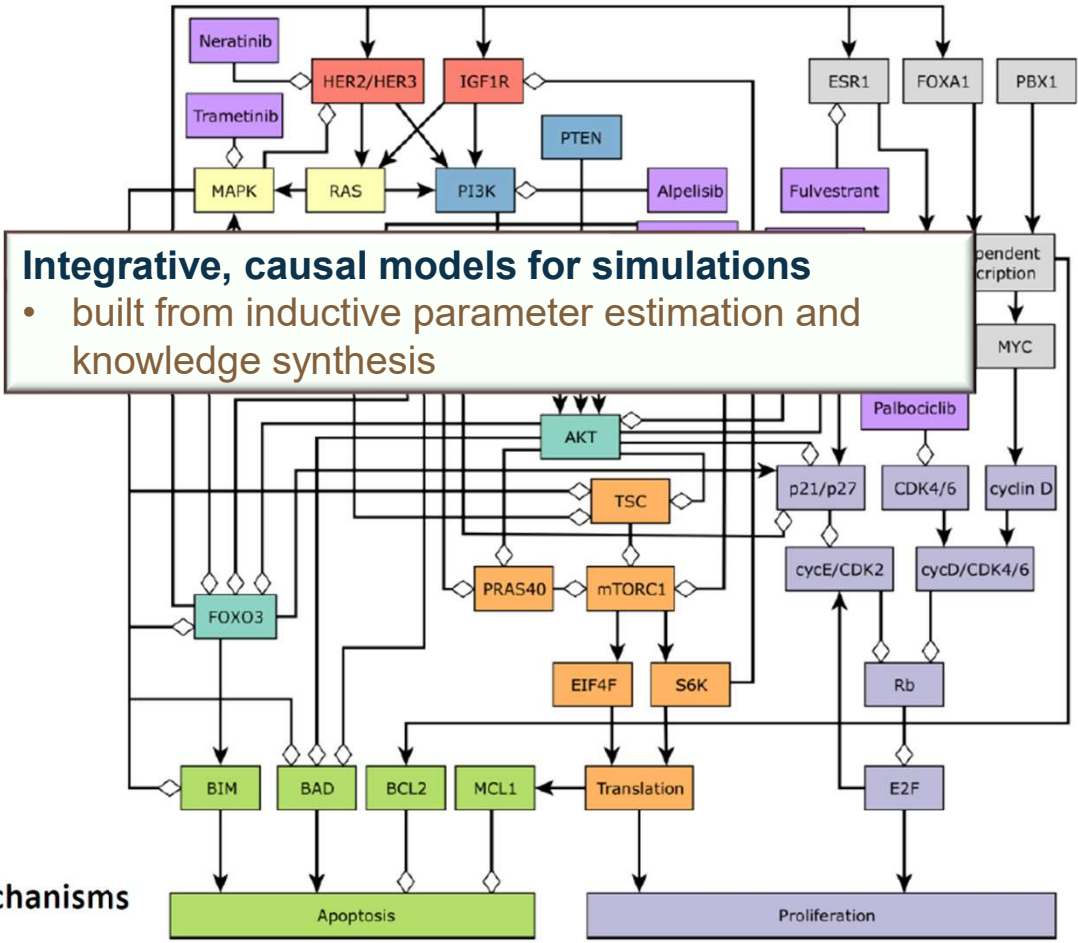
control and the cybernetics of life

Boolean networks, control, sound, art, and education



predicting drug and therapy targets in causal models

discrete modeling of within-cell **oncogenic signal transduction**, recapitulates known resistance PI3K inhibitors. Suggests novel combinatorial interventions.



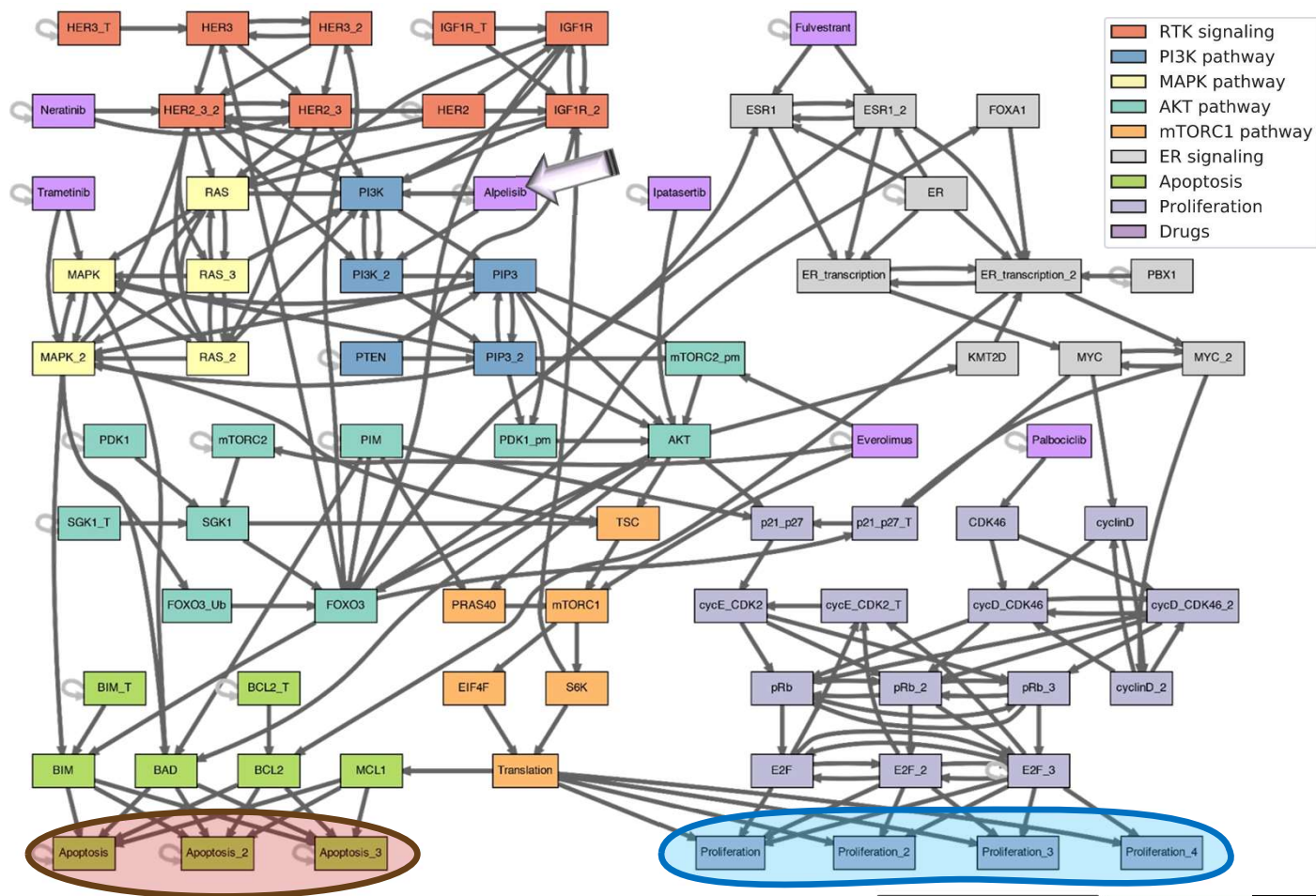
A network modeling approach to elucidate drug resistance mechanisms and predict combinatorial drug treatments in breast cancer

Jorge G. T. Zañudo^{1,2,3,*} and Réka Albert^{1,4,&}

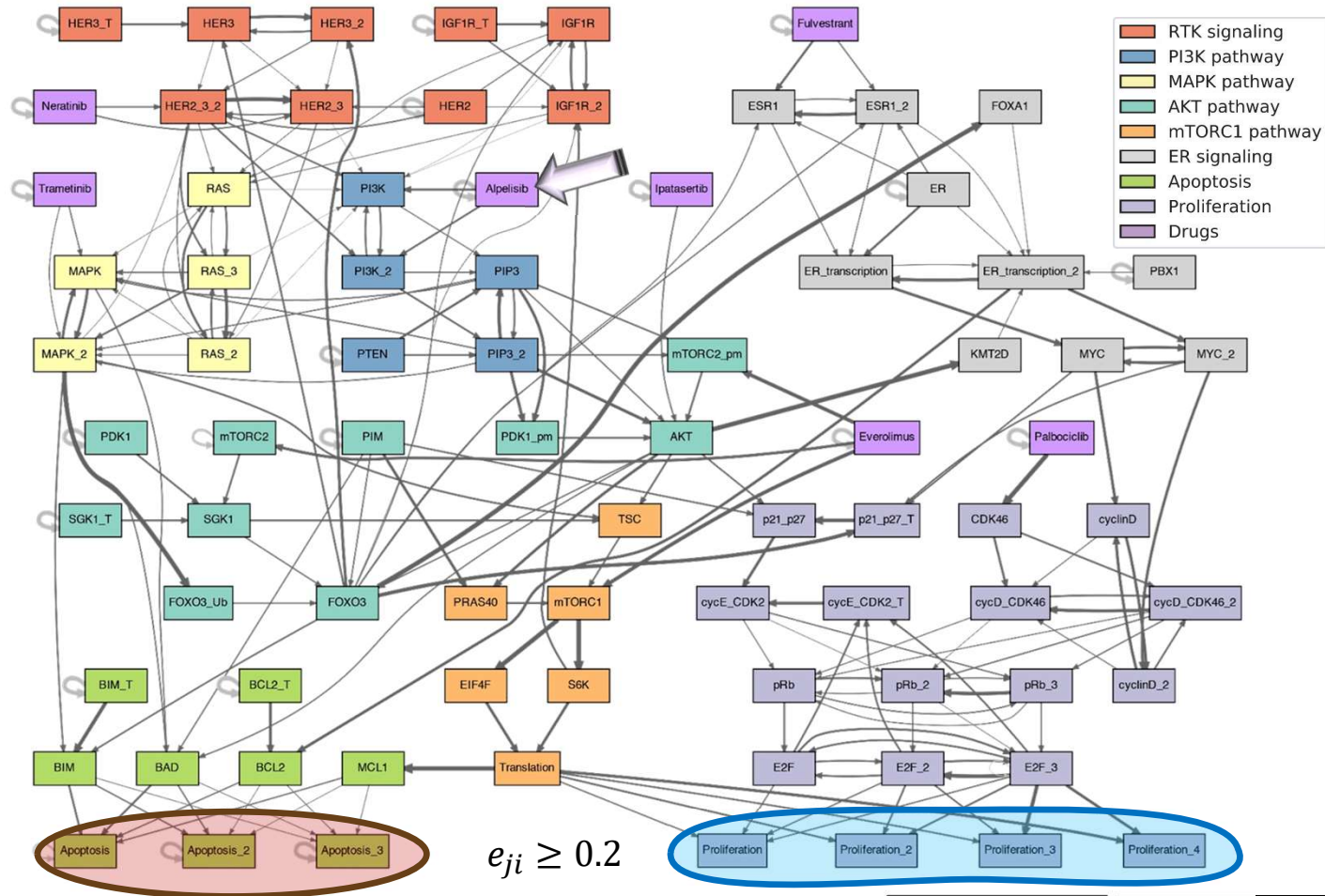


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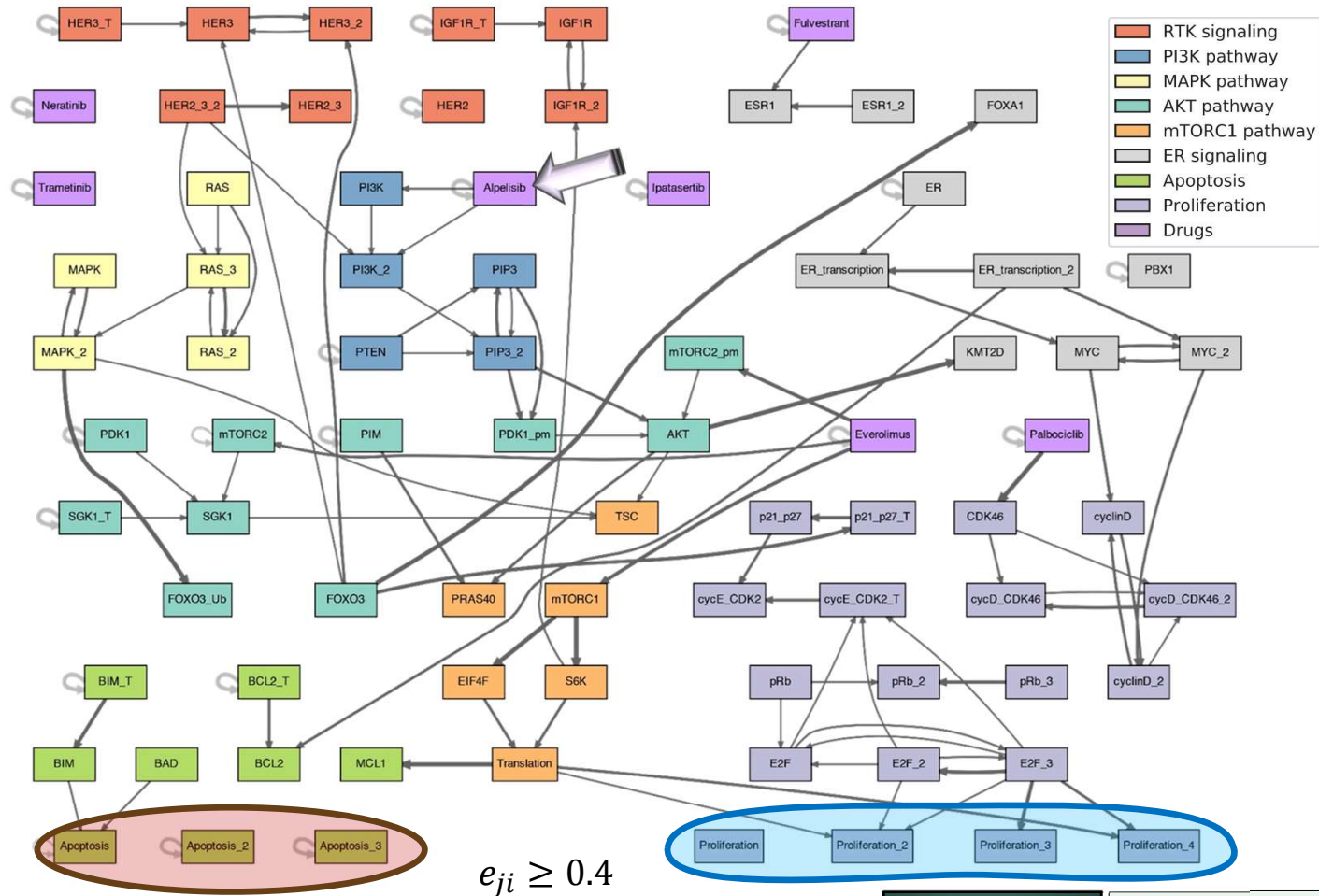
uncovering and characterizing control pathways for drug therapy



uncovering and characterizing control pathways for drug therapy



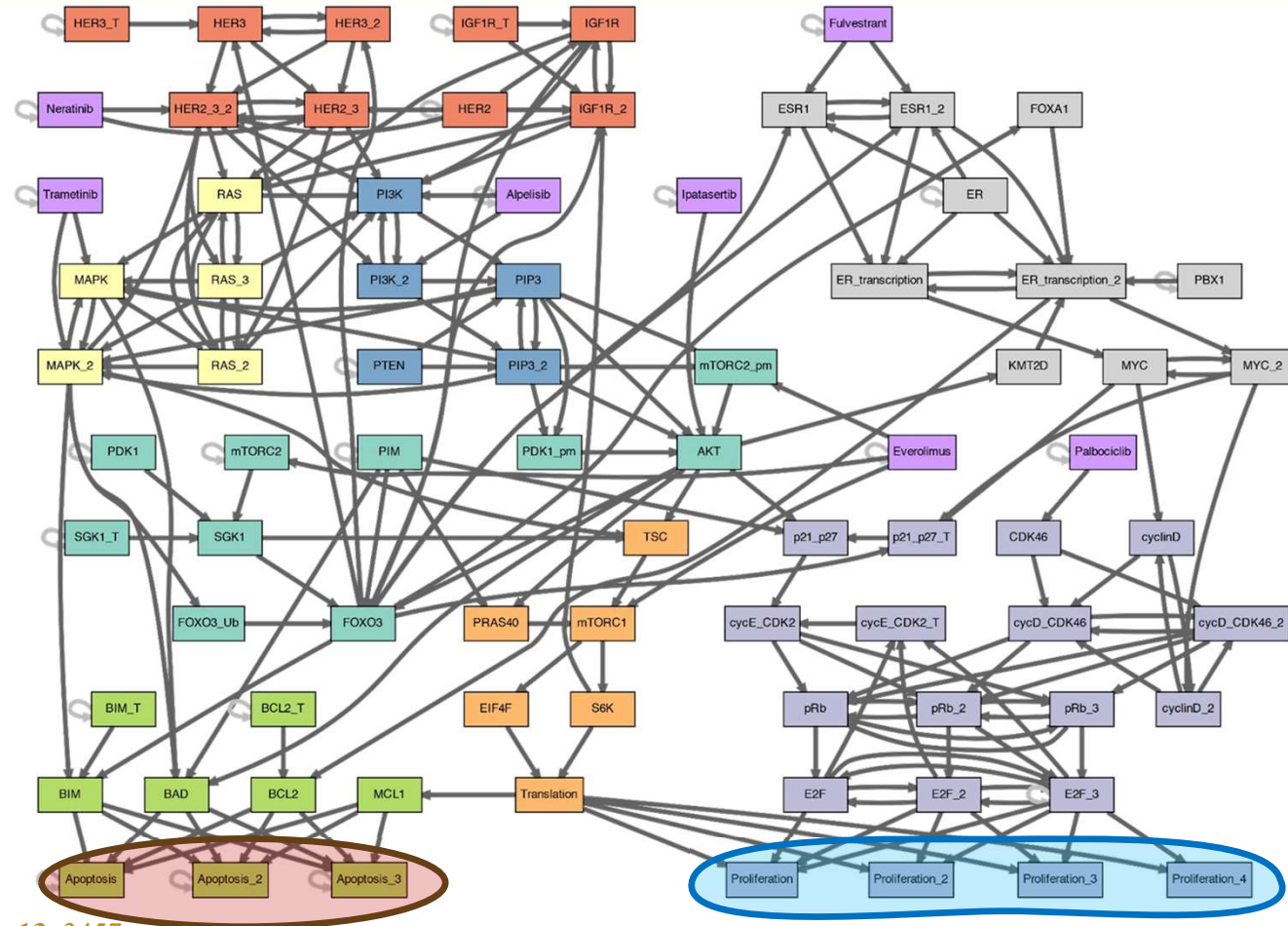
uncovering and characterizing control pathways for drug therapy



redundancy and control in biochemical regulation

causal (modular) dynamics via conditional effective connectivity

- RTK signaling
- PI3K pathway
- MAPK pathway
- AKT pathway
- mTORC1 pathway
- ER signaling
- Apoptosis
- Proliferation
- Drugs



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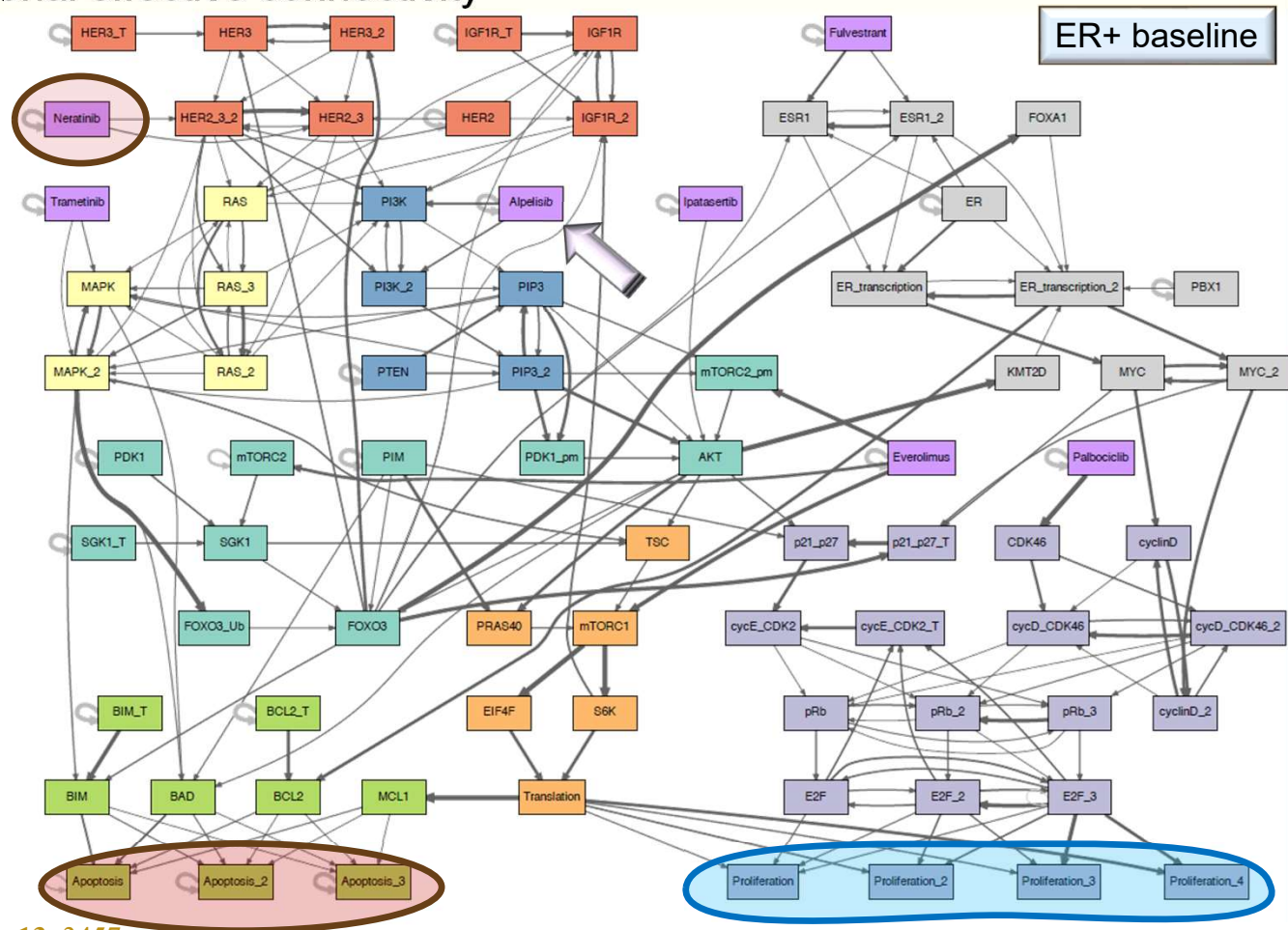


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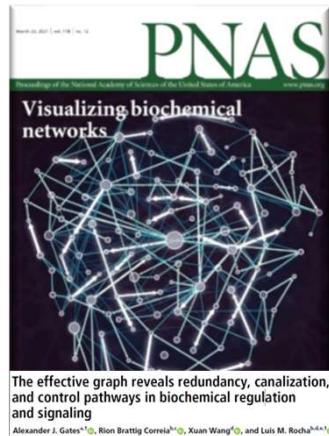
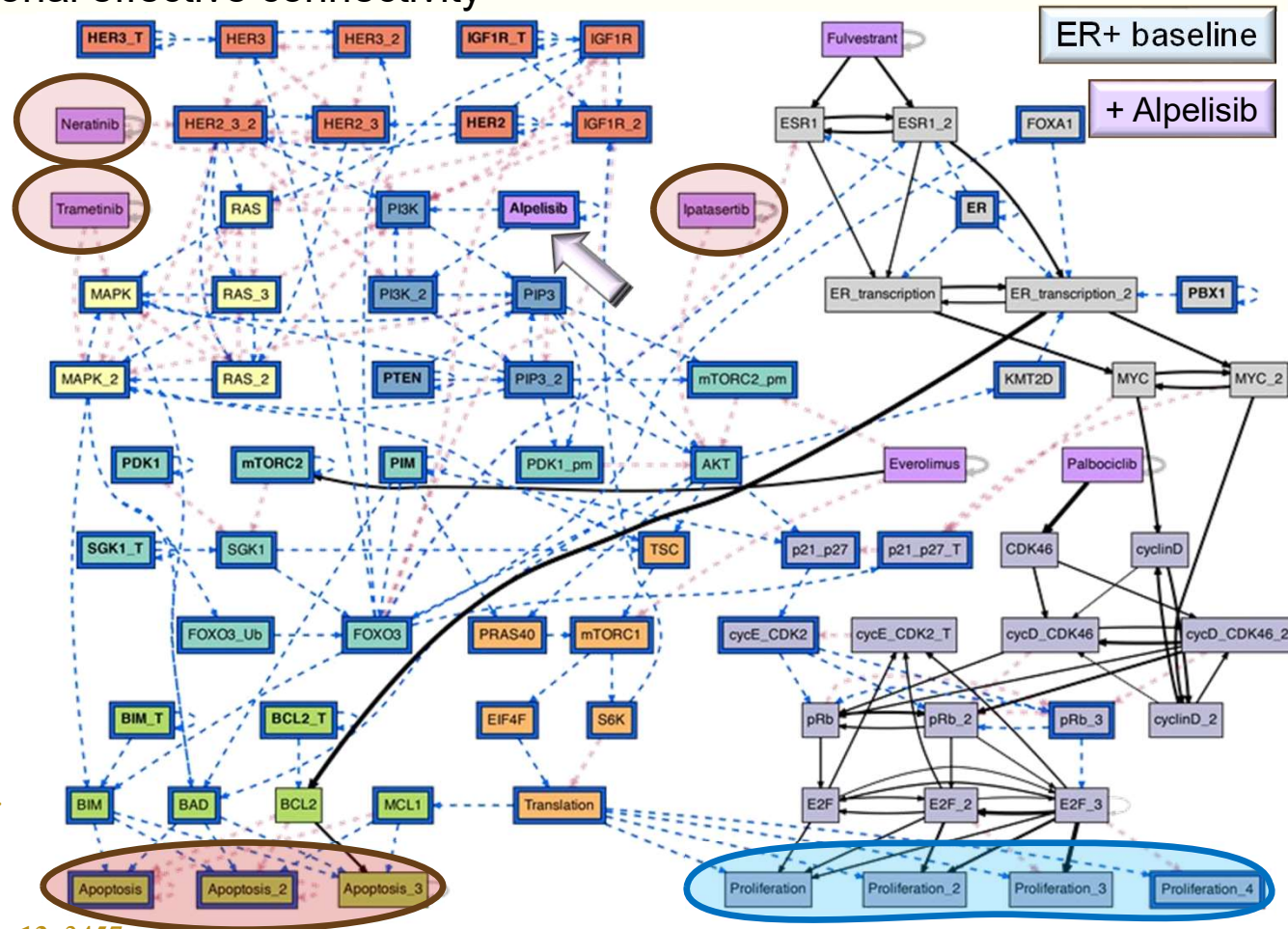
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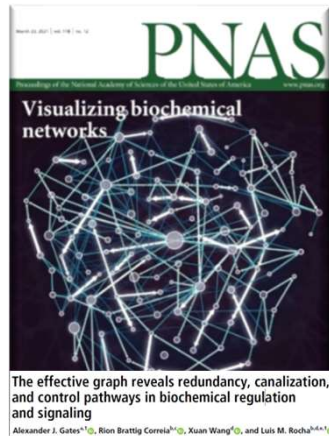
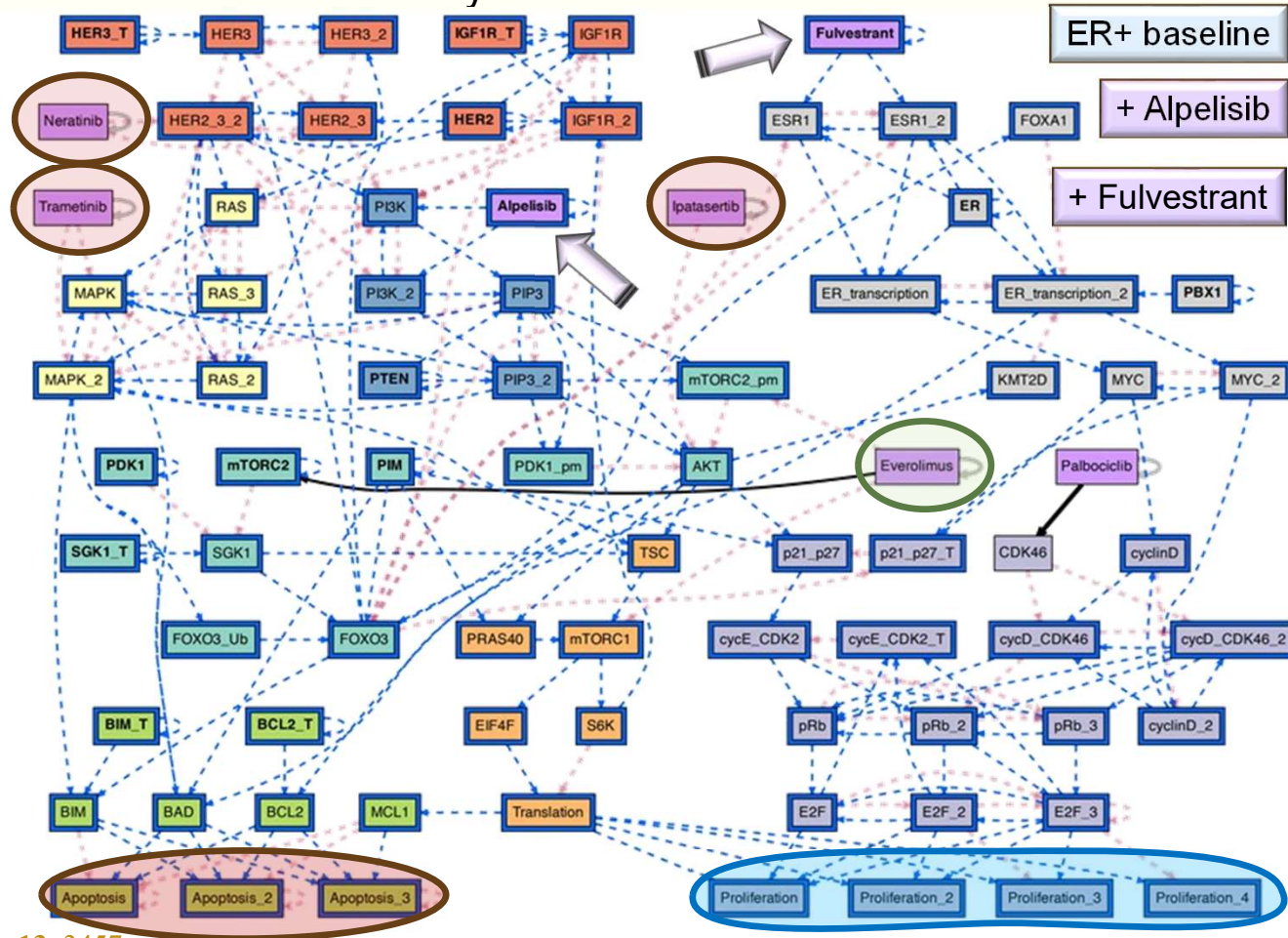


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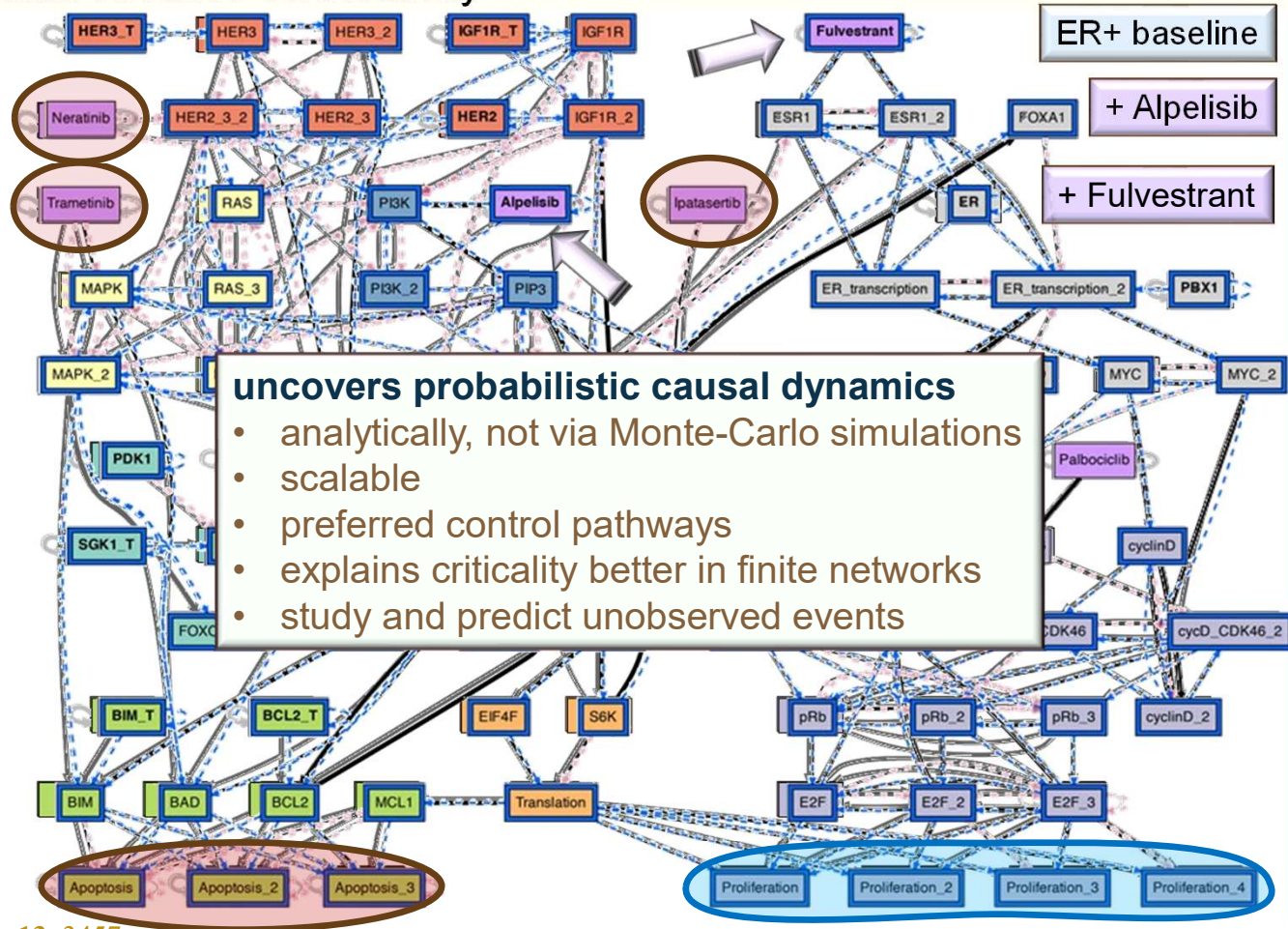
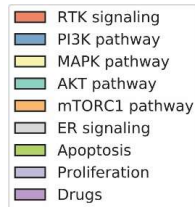
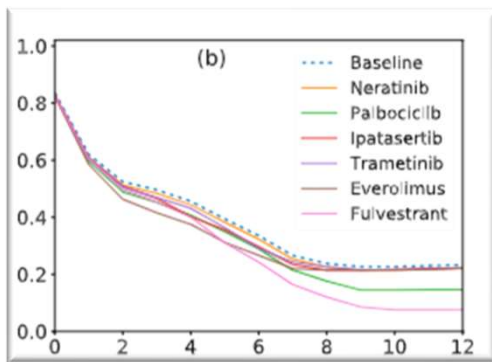
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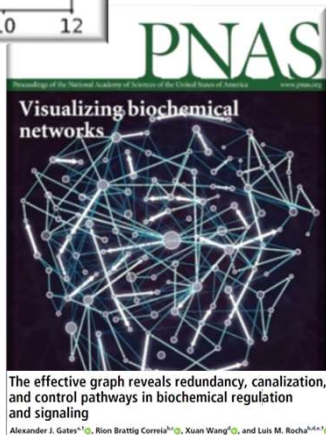
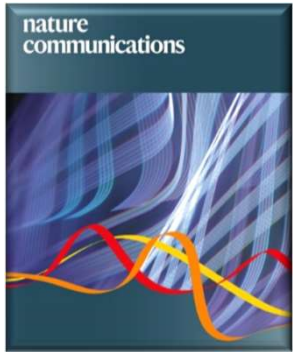
redundancy and control in biochemical regulation

causal (modular) dynamics via conditional effective connectivity



uncovers probabilistic causal dynamics

- analytically, not via Monte-Carlo simulations
- scalable
- preferred control pathways
- explains criticality better in finite networks
- study and predict unobserved events



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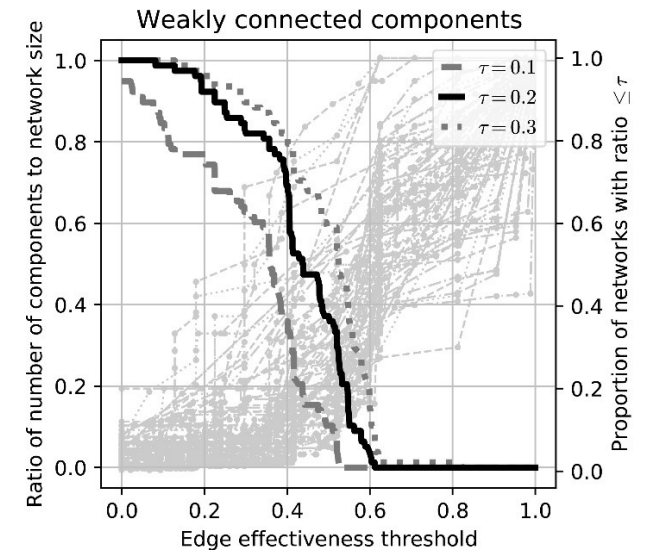
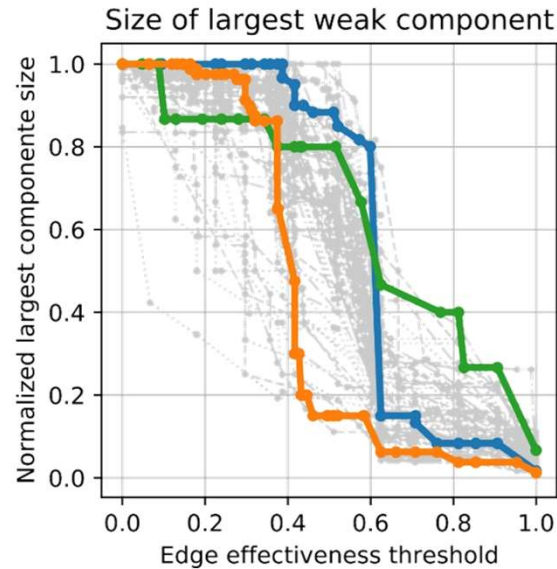
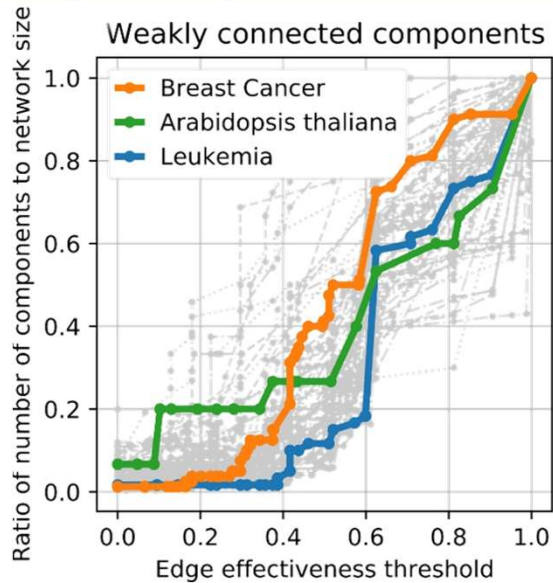
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dynamically-decoupled modules



Most networks preserve a large weakly connected component up to edge effectiveness ≤ 0.4 .



Allows comparisons between networks regarding the ability to effectively propagate signals.

But most break into dynamically-decoupled modules for edge effectiveness $> [0.4, 0.6]$.

Experimentally-validated models suggest biochemical regulation highly **modular** with low effectiveness interactions between modules granting robustness to perturbations.

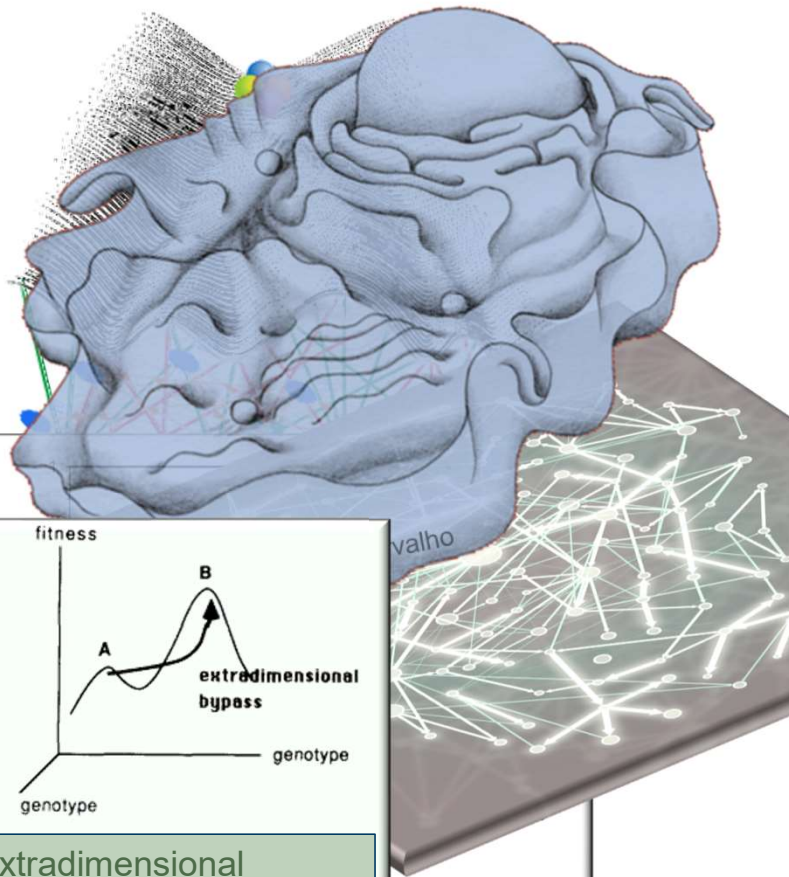
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canalization as a key mechanism for resilience

from evolutionary robustness to network and dynamical redundancy



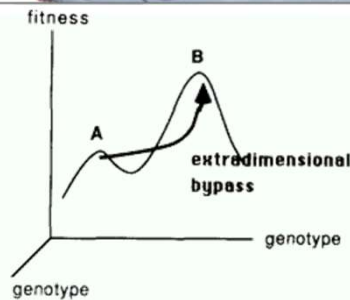
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Michael Conrad



Evolvability: extradimensional bypass, neutrality, redundancy, controllability and robustness tradeoff.

D. **185**: 45–66

robustness of phenotypes is the result of a **buffering** of developmental process.

dynamics of gene networks provides buffering (**self-organization**). But still easily chaotic.

Structure (**topological organization**), can provide larger stable or critical universe, but still easily chaotic.

canalized genetic control ignores some inputs (**redundancy**) to attain necessary resilience (tradeoff stability/evolvability)



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