MODULE 2

LIFE AS THE NEXT FRONTIER IN PHYSICS

Exploring the New Science of Astrobiology

World Science Scholars Sara Walker, PhD Arizona State University © 2019 World Science Foundation. All rights reserved.

MODULE 2:

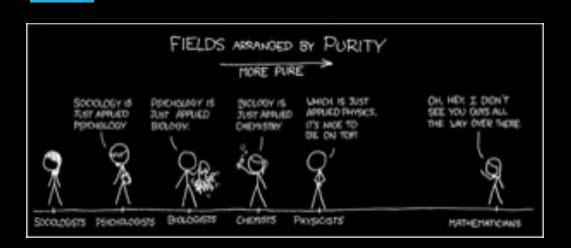
ARE THERE LAWS OF LIFE? WHAT WOULD THEY LOOK LIKE?



PART 1:

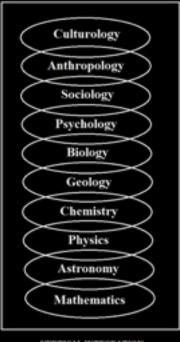
CELLULAR AUTOMATA

WHAT IS EMERGENCE? WHY IS IT INTERESTING?



"The ability to reduce everything to simple fundamental laws does not imply the ability to start from those laws and reconstruct the universe."

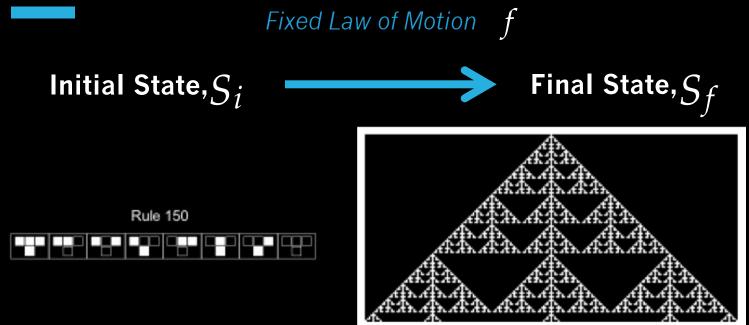
– Phil Andersen (Nobel laureate in Physics)



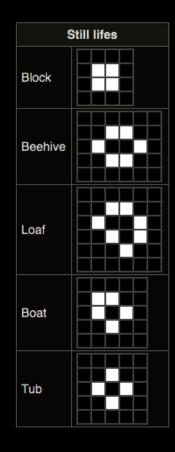


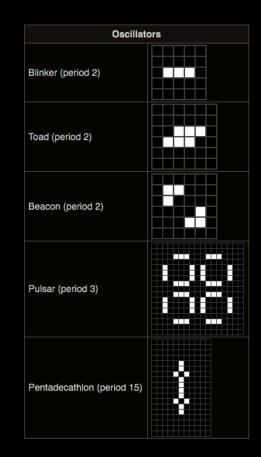
TRAFFIC JAM AS A MODEL FOR EMERGENT PROPERTIES

CELLULAR AUTOMATA AS MODELS OF PHYSICS: HOW GLOBAL PATTERNS EMERGE FROM SIMPLE, LOCAL RULES

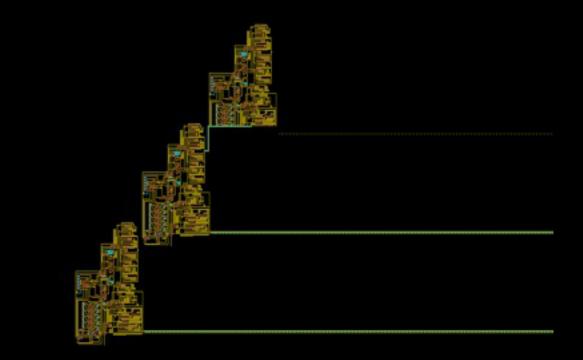


GAME OF LIFE: AN EXAMPLE OF MANY EMERGENT PROPERTIES FROM THE SIMPLE RULE SET





VON NEUMANN: SELF-REPRODUCING AUTOMATA



ARCHITECTURE OF SELF-REPRODUCING "MACHINES"

A SUPERVISORY UNIT enables replication of DNA The ribosome + assisting biomolecules act like a UNIVERSAL CONSTRUCTOR (well ... sort of) This is an instructional **TAPE**, i.e., a small part of a larger biological algorithm

J. von Neumann. Theory of Self-Reproducing Automata. University of Illinois, 1966. J. von Neumann. The Computer and the Brain. Yale University Press, 1958.

SELF-REPRODUCING AUTOMATA AS PHYSICAL SYSTEMS: PHYSICAL UNIVERSALITY

"physical" universality: the ability to implement any transformation whatsoever on any finite region

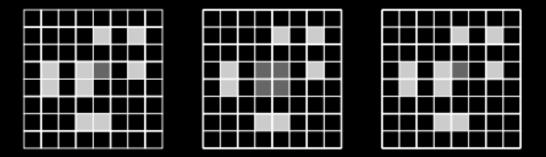
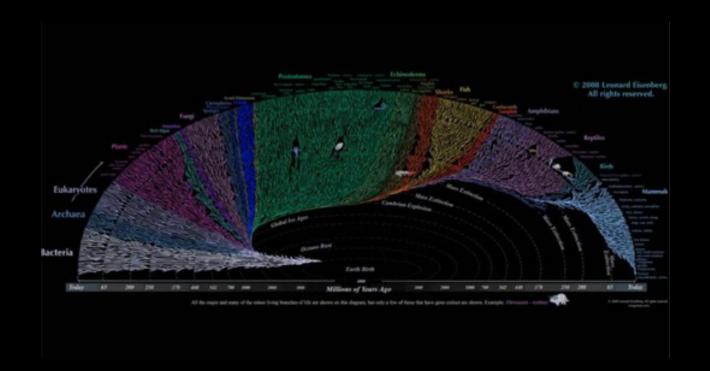
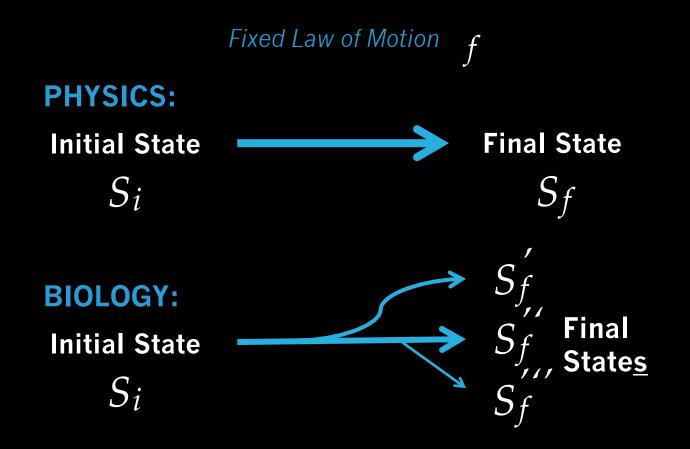


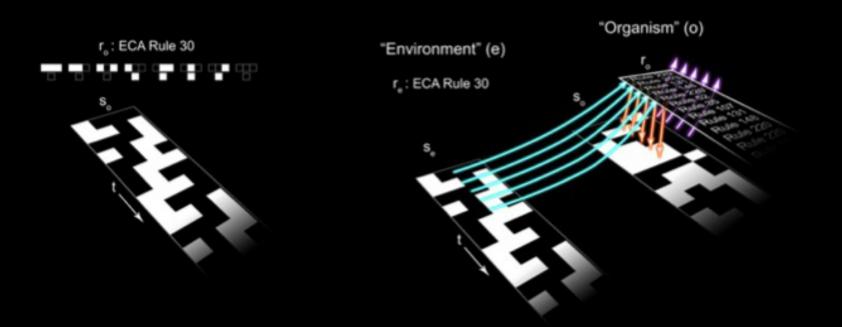
Figure 3: An example of a configuration (left) such that after only three timesteps, the abstract evolution (middle) differs from the minimal consistent configuration (right).

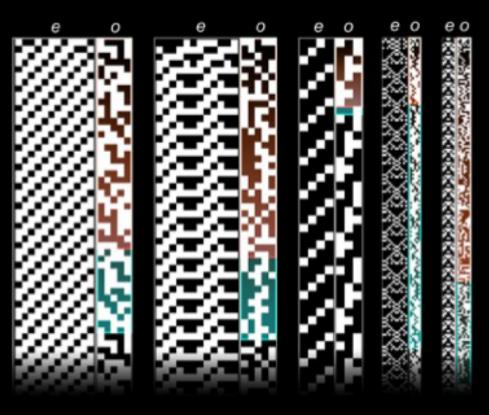
EVOLUTION AND THE DIVERSIFICATION OF LIFE





CELLULAR AUTOMATA WITH STATE-DEPENDENT "LAWS"





Examples of Case I CA exhibiting OEE. In each panel the environment e is shown on the left, and organism o on the right. For each o, the Poincare recurrence rate for an isolated system is highlighted in blue, and the recurrence time of the states is highlighted in red. (Adams et al (2017), Situation awareness and the cognitive management of complex systems.)

PART 2:

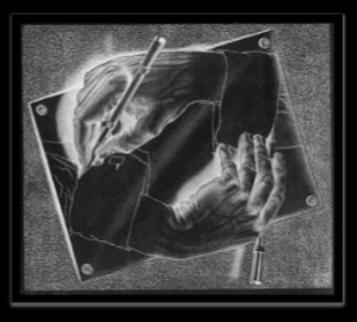
BOOLEAN NETWORKS TO MODEL BIOLOGICAL FUNCTION

SELF-REFERENTIAL DYNAMICS "DYNAMICAL LAWS CHANGING WITH STATES"

"[In biology] we encounter a situation where the rules must be selfreferential: The update rules change during the time evolution of the system, and the way in which they change is a function of the state and thus the history of the system."

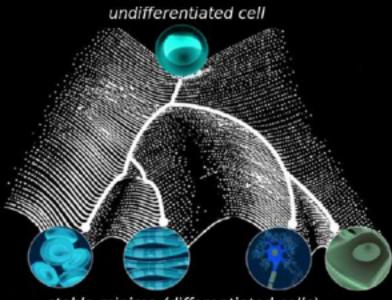
– Goldenfeld and Woese (2011)

Drawing Hands by M.C. Escher



N. Goldenfeld and C. Woese. Life is physics: evolution as a collective phenomenon far from equilibrium. *Ann. Rev. Condens. Matter Phys.* (2011) 2: 375–399. P. C. W. Davies. The epigenome and top-down causation. *J. R. Soc. Interface*, 2(1):42–48, 2012.

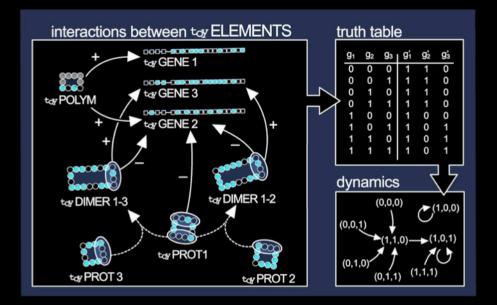
WADDINGTON EPIGENETIC LANDSCAPE – INTRODUCE IDEA OF ATTRACTOR STATES



stable minima (differentiated cells)

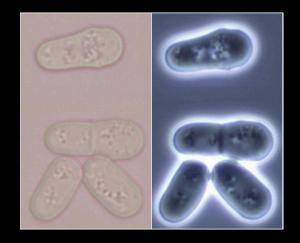
The image is pulled from: <u>https://www.researchgate.net/figure/Waddington-epigenetic-landscape-In-this-metaphor-the-undifferentiated-embryonic_fig2_276920795</u>

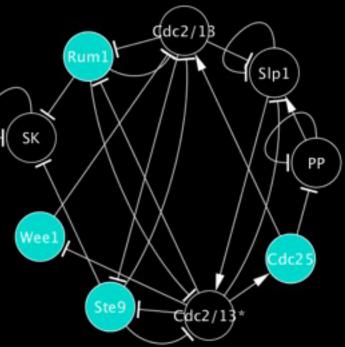
MODELING GENETIC "NETWORKS" AS BOOLEAN NETWORKS, ATTRACTOR LANDSCAPES



F. Arias, Clemente & Catalán, Pablo & Manrubia, Susanna & A. Cuesta, José. (2014). ToyLIFE: A computational framework to study the multi-level organisation of the genotype-phenotype map. Scientific reports. 4. 10.1038/srep07549.

THE FISSION YEAST CELL CYCLE REGULATORY NETWORK





Davidich, M. I., & Bornholdt, S. (2008). Boolean network model predicts cell cycle sequence of fission yeast. PLoS ONE, 3(2), e1672.

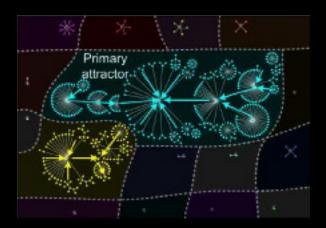
THE FISSION YEAST CELL CYCLE BOOLEAN NETWORK

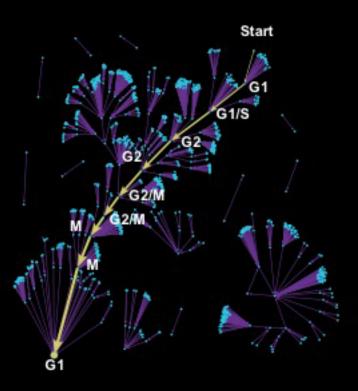
Time Start SK Cdc2 Ste9 Rum Slp1 Cdc2/ Wee Cdc2 PP Phase /Cdc Step Cdc1 1 5 4 13 3* Start 1 2 G1 G1/S 3 G2 4 5 G2 G2/M 6 G2/M 7 8 Μ М 9 10 G1

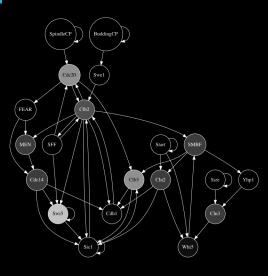
Davidich, M. I., & Bornholdt, S. (2008). Boolean network model predicts cell cycle sequence of fission yeast. PLoS ONE, 3(2), e1672.

CONTROL KERNEL

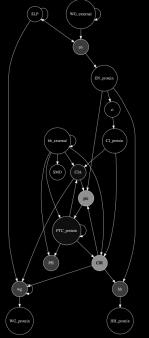
THE NETWORK STATE SPACE FOR THE FISSION YEAST CELL CYCLE



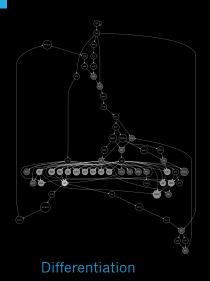


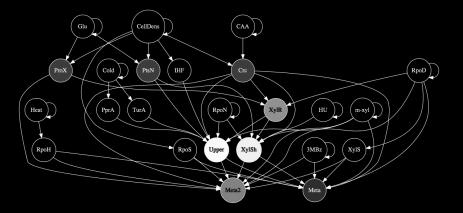


Cell Cycle

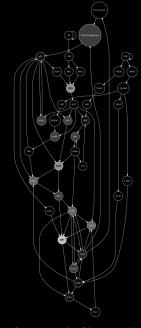


Body Segmentation

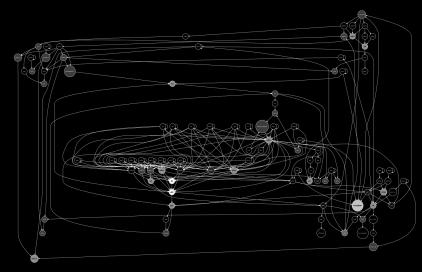




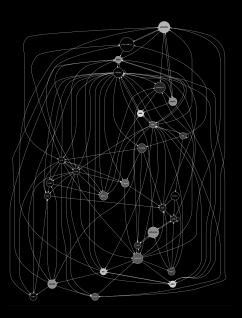
Toll Regulatory Network



Apoptosis Network



Egfr and Erbb Signaling



FA BRCA Pathway



T Cell Signaling

INFORMATION STRUCTURES MATTER IN LIVING SYSTEMS

Vol 454|24 July 2008

HORIZONS

Life, logic and information

Paul Nurse

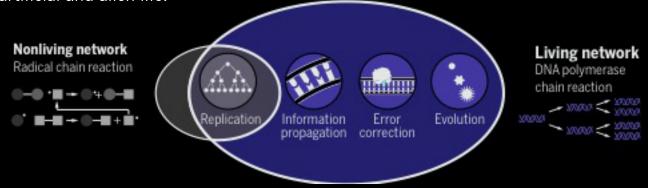
nature

Focusing on information flow will help us to understand better how cells and organisms work.



ORIGIN OF LIFE CORRESPONDS TO A TRANSITION IN HOW INFORMATION IS STORED, PROPAGATED, AND USED

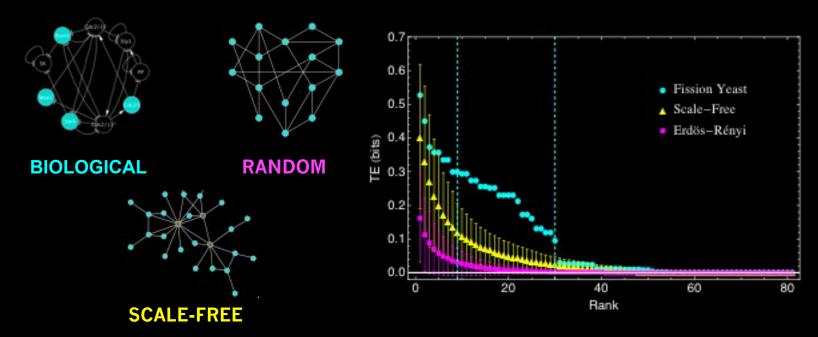
"Focusing on information... may perhaps provide our best shot at uncovering universal laws of life that work not just for biological systems with known chemistry but also for putative artificial and alien life."



LIFE GENERATES HIGHLY IMPROBABLE STRUCTURES



INFORMATIONAL STRUCTURE AS A BIOSIGNATURE

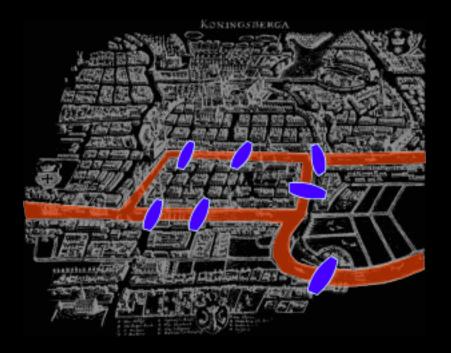


H. Kim, P.C.W. Davies and S.I. Walker (2015) New Scaling Relation for Information Transfer in Biological Networks. J. Roy. Soc. Interface 2015; Davies, P.C. and Walker, S.I., 2016. The hidden simplicity of biology. *Reports on Progress in Physics*, 79(10), p.102601.

PART 3:

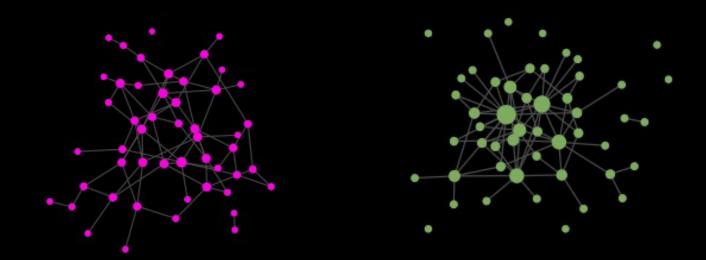
NETWORKS

BRIDGES OF KONIGSBERG



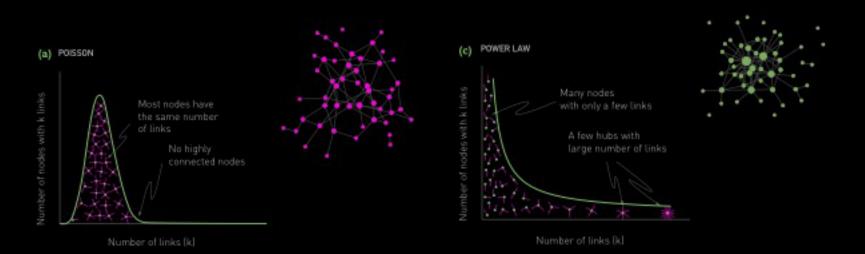
Source: https://en.wikipedia.org/wiki/Seven_Bridges_of_K%C3%B6nigsberg

WHAT IS A NETWORK?



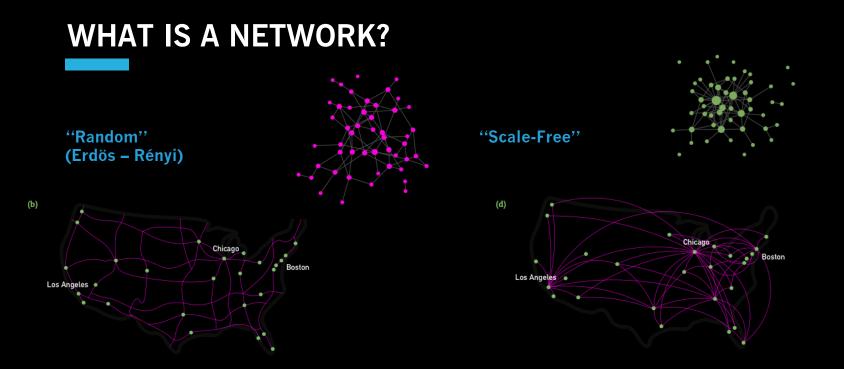
Network theory is a mathematical language for describing complex systems e.g., systems with interactions between many heterogeneous components

WHAT IS A NETWORK?



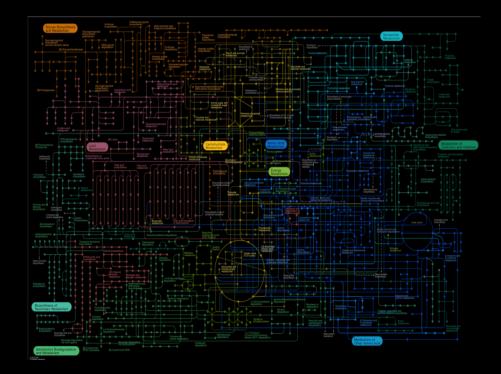
Network theory deals with the **statistics of interactions** among system components and their resultant dynamics

Albert, R., & Barabási, A. L. (2002). Statistical mechanics of complex networks. Reviews of modern physics, 74(1), 47.

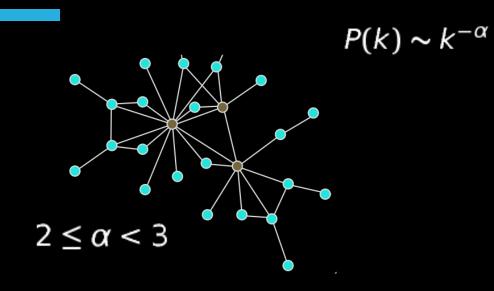


Solving the same problem, different networks can emerge due to different constraints

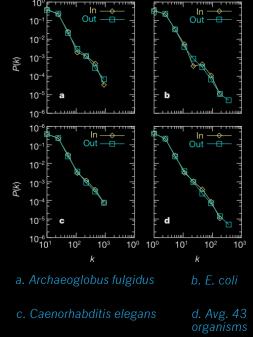
NETWORK THEORY AND BIOCHEMISTRY



BIOCHEMICAL NETWORKS SHARE COMMON PROPERTIES INDEPENDENT OF EVOLUTIONARY DOMAIN OR MAJOR METABOLISM



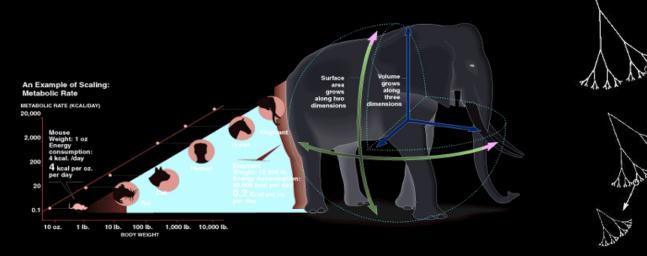
A universal signature of living organization?



Jeong *et al.* "The large-scale organization of metabolic networks" *Nature* (2000) 407: 651 – 654.

SCALING LAWS IN BIOLOGY

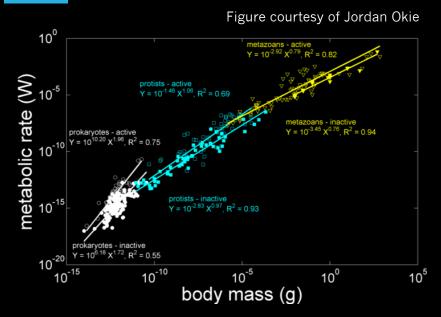
Scaling laws describe metabolic rate, body (cell size), number of organelles, lifespan, heartbeats per lifetime, global microbial diversity, the percentage of mass in predators and prey ...



Self-Similar Structure (Fractal)

> Fractal networks can describe the flow of energy/ nutrients in living system (e.g., circulatory networks), yielding predictions consistent with observed scaling trends

EXAMPLE: SHIFTS IN METABOLIC RATE SCALING ACROSS THE MAJOR EVOLUTIONARY TRANSITIONS OF LIFE



Empirically observed scaling laws for metabolic rate as a function of body-mass exhibits three major regimes, associated with prokaryotes, protists, and metazoans.

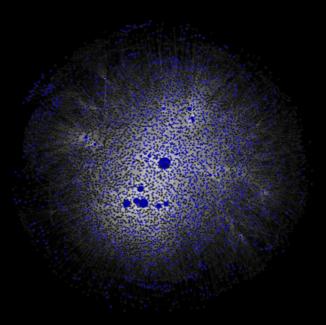
DeLong, John P., et al. "Shifts in metabolic scaling, production, and efficiency across major evolutionary transitions of life." *Proceedings of the National Academy of Sciences* 107.29 (2010): 12941-12945.

SCALING LAWS CAN HELP US UNDERSTAND PLANETARY-SCALE ORGANIZATION OF LIFE



SCALING LAWS CAN HELP US UNDERSTAND PLANETARY-SCALE ORGANIZATION OF LIFE



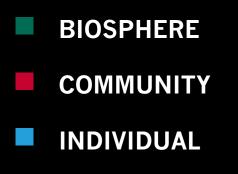


Network representation of the global inventory of enzymatically catalyzed biochemical reactions

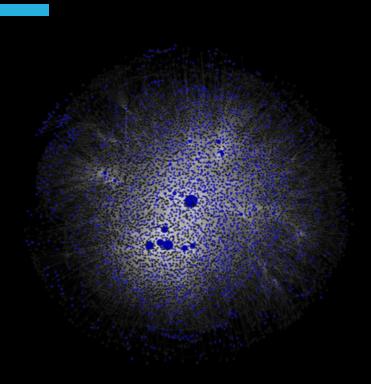
"LEVELS" OF ORGANIZATION

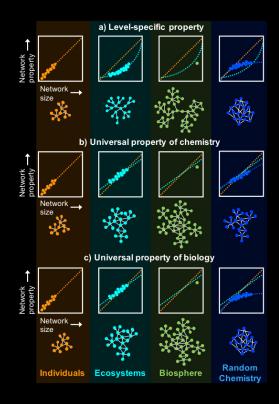


"Having a biosphere is a definite 'state' for the earth, which is positively favored over alternative states devoid of life ..." *—Eric Smith* [JTB 252 (2008) 185-19)]



SCALING LAWS ACROSS BIOCHEMICAL NETWORKS

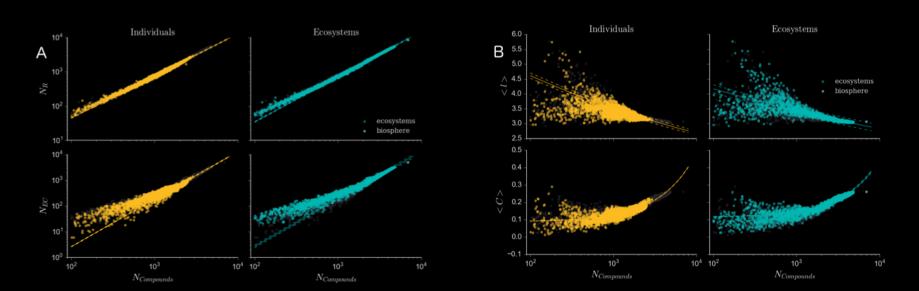




UNIVERSAL SCALING LAWS DESCRIBE BIOCHEMICAL NETWORKS OF INDIVIDUALS AND ECOSYSTEMS

NETWORK TOPOLOGY

CATALYTIC DIVERSITY

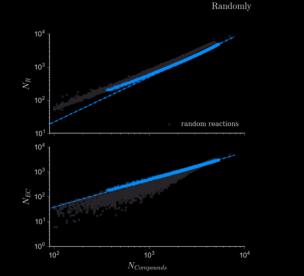


Kim, Hyunju, Harrison Smith, Cole Mathis, Jason Raymond, and Sara Walker. "Universal Scaling Across Biochemical Networks on Earth" bioRxiv (2017): 212118.

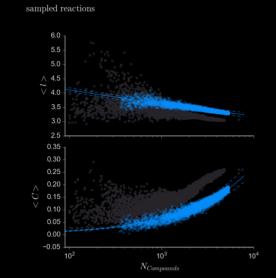
SCALING LAWS FOR REAL BIOCHEMICAL NETWORKS DIFFERS FROM RANDOM

(even with same global inventory of chemical reactions)

CATALYTIC DIVERSITY



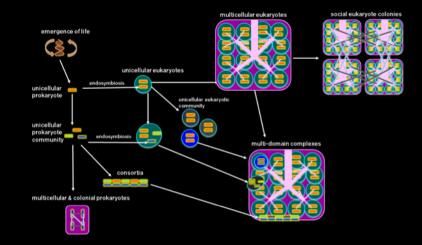
NETWORK TOPOLOGY



Kim, Hyunju, Harrison Smith, Cole Mathis, Jason Raymond, and Sara Walker. "Universal Scaling Across Biochemical Networks on Earth" bioRxiv (2017): 212118.

FUTURE DIRECTIONS: UNIFYING SCALING LAWS

- Is there a unified theory that describes scaling across different dimensions of biological systems?
- Which scaling relations are universal, and which are contingent on the evolutionary history for life on Earth?

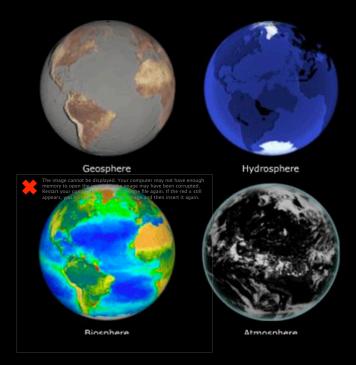


If scaling behavior is universal and can be derived from an underlying common theory, it will be an important step towards **predictive** theory for the properties of life on other worlds.

FUTURE DIRECTIONS: A PLANETARY-SCALE THEORY FOR THE ORGANIZATION OF LIVING WORLDS

Earth's systems can be represented as an interacting multi-layer network:

What can we learn about life as a planetary-scale process by studying these interacting networks?



PART 4:

COLLECTIVE BEHAVIOR



COLLECTIVE DECISION-MAKING IN *TEMNOTHORAX* ANT COLONIES

OVERVIEW

- Motivation: Looking for Laws of Life.
- Project Description: Determine where the information is stored (internal state vs external environment) during nest-site selection in Temnothorax rugatulus ant colonies.
- Previous Results: Behavior is heterogeneous, Brownian motion model
- Recent Progress: Quorum Sensing with Brownian Motion + Temporal Discounting. Nest Assessment Experiments.
- Next Steps: Tracking during nest assessment. Full dynamical model of collective decision.



MOTIVATION

- Looking for Laws of Life
- Living systems store information
- What information about the environment gets internalized and why?

CASE STUDY – NEST-SITE IN SELECTION IN TEMNOTHORAX RUGATULUS

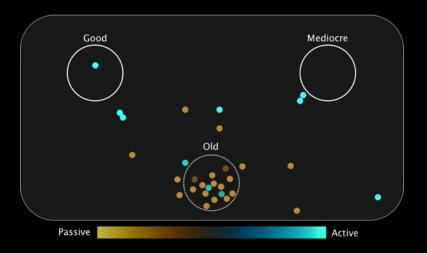
- House-hunting species of ant capable of robustly choosing the better of two candidate nests
- Well documented example of distributed computation with decentralized control
- What is the interplay between the internal state and external environment?
- Can we get a **predictive**, **mechanistic** account of dynamics?



REVIEW

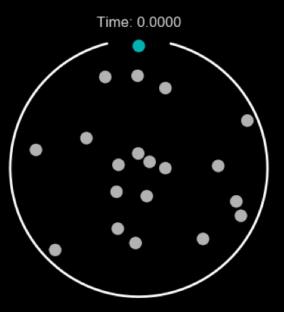
FOUR PHASES OF NEST-SITE SELECTION:

- Assessment Nest sites are discovered by active ants
- Tandem Runs Recruiters begin to lead other ants to the candidate nests via slow "tandem runs"
- Quorum Sensing A critical density is sensed at a candidate nest
- Transports Recruiters begin to carry their nest mates to the selected nest



BROWNIAN MOTION MODEL

- Null Hypothesis: Assume there is no dynamically relevant internal state
- Environment completely dictates the dynamics
- Ant motion is random (Brownian)
- Can this model account for any observations?

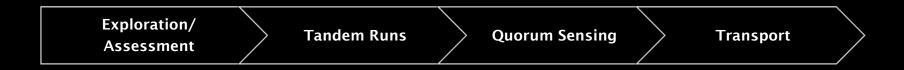


BROWNIAN MOTION MODEL

EXPERIMENT SIMULATION Time vs Encounter Rate (No Delay, Nest Pop = 20) 3000 800 200 Duration of Visit (sec) 2500 150 •• 2000 side 125 ü 1500 Time 100 75 1000 200 50 500 25 λ (enc/sec) 0.2 0.3 0.4 0.5 0.6 0.7 0 0.1 0.0 0.1 0.2 0.3 0.4 0.5 Encounter Rate **Encounter Rate During Visit**

Brownian motion appears to be able to account for critical slowing during quorum sensing

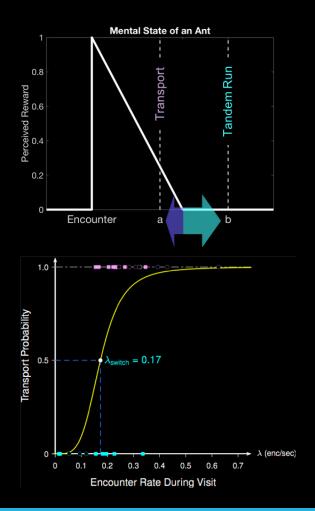
MISSING SOMETHING ...



- Marks the transition in recruitment behavior from slow tandem runs to fast transports
- Even if the motion is Brownian, **something must change internally** since recruiters change behavior
- What is being sensed to incite this change? That is, what information is internalized?
 - All we know is it is encounter rate dependent [Pratt, 2005]
- Proposed explanation
 - Brownian Motion + Temporal Discounting

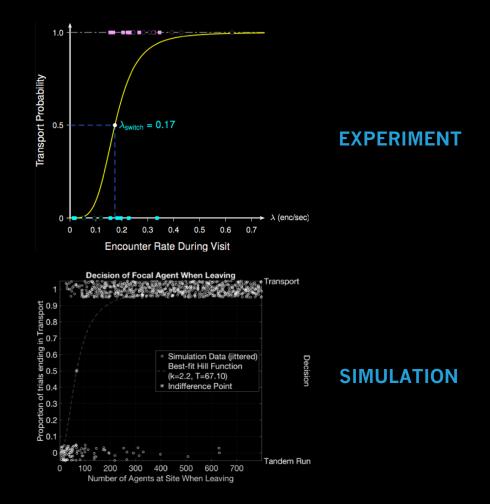
TEMPORAL DISCOUNTING MODEL

- Collisions stimulate recruiters from the ground state (tandem run) into an excited state (transport)
- The excited state decays back into the ground state with some time constant
- Ants move under Brownian motion so nest geometry still dictates the decision
- Model parameters can be tuned to select certain nest geometry

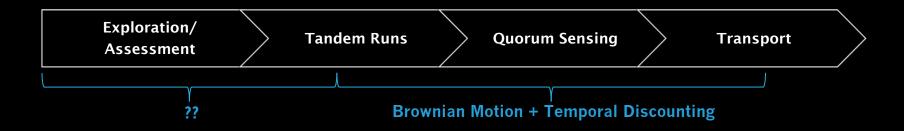


TEMPORAL DISCOUNTING MODEL

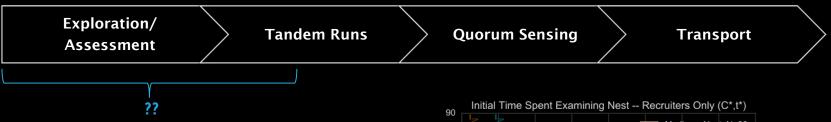
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IS THIS THE WHOLE STORY?



IS THIS THE WHOLE STORY?



- Experiments show preferential recruitment to the good nest [Mallon, 2001]
- Asymmetry in nest assessment
- Data shows recruiters spend significantly longer assessing the good nest
- Is this difference also a consequence of Brownian motion?



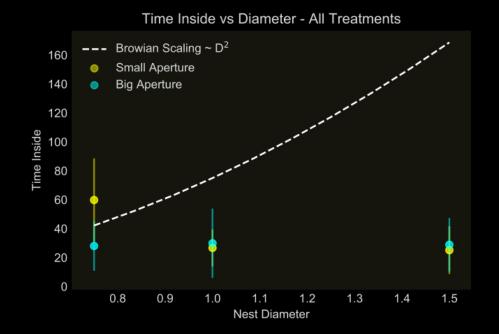
NEST AREA ASSESSMENTS (EXPERIMENTS)



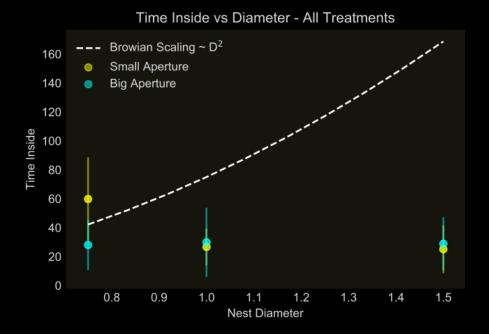


Determine whether ants use Brownian motion to assess nest geometry

NEST AREA ASSESSMENTS (RESULTS)



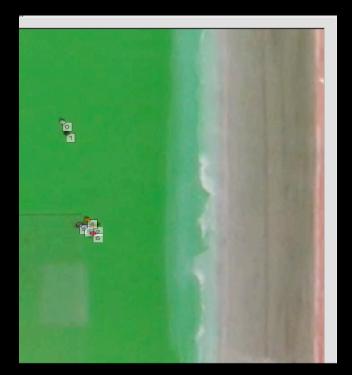
NEST AREA ASSESSMENTS (RESULTS)



Motion during assessment is not Brownian!!

NEST AREA ASSESSMENTS (TRACKING)

- If motion is not Brownian, how are nest area and aperture size assessed?
- What is being internalized?
- Are recruiters aware of these high-level concepts?
- Why is the recruitment asymmetric?



SUMMARY

- Life is an emergent phenomenon
- Not only are patterns emergent, but so are the rules
- Information is important for understanding these emergent properties
- Some emergent properties are universal to all life

MODULE 2

LIFE AS THE NEXT FRONTIER IN PHYSICS

Exploring the New Science of Astrobiology

World Science Scholars Sara Walker, PhD Arizona State University © 2019 World Science Foundation. All rights reserved.