Liquid Brains: searching the cognition space

Evolution of Complexity & Statistical Physics, Yerevan Workshop. June 30, 2022

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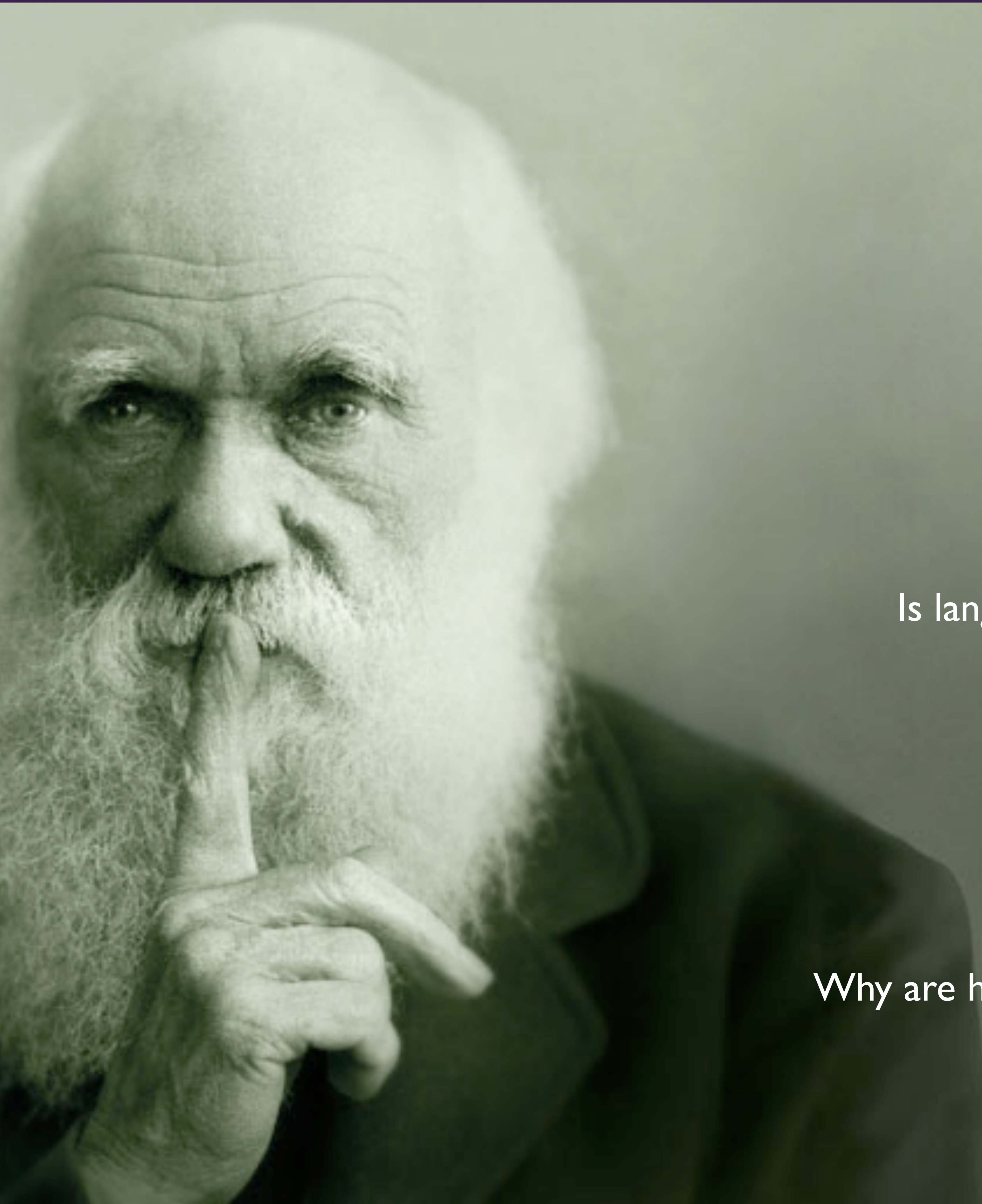
Cognitive transitions: complexity & Evolution



How does cognition emerge?

Why brains?

What kind of brains?

Are there other minds?

How intelligence arises in evolution?

Is language a pre-condition or a consequence?

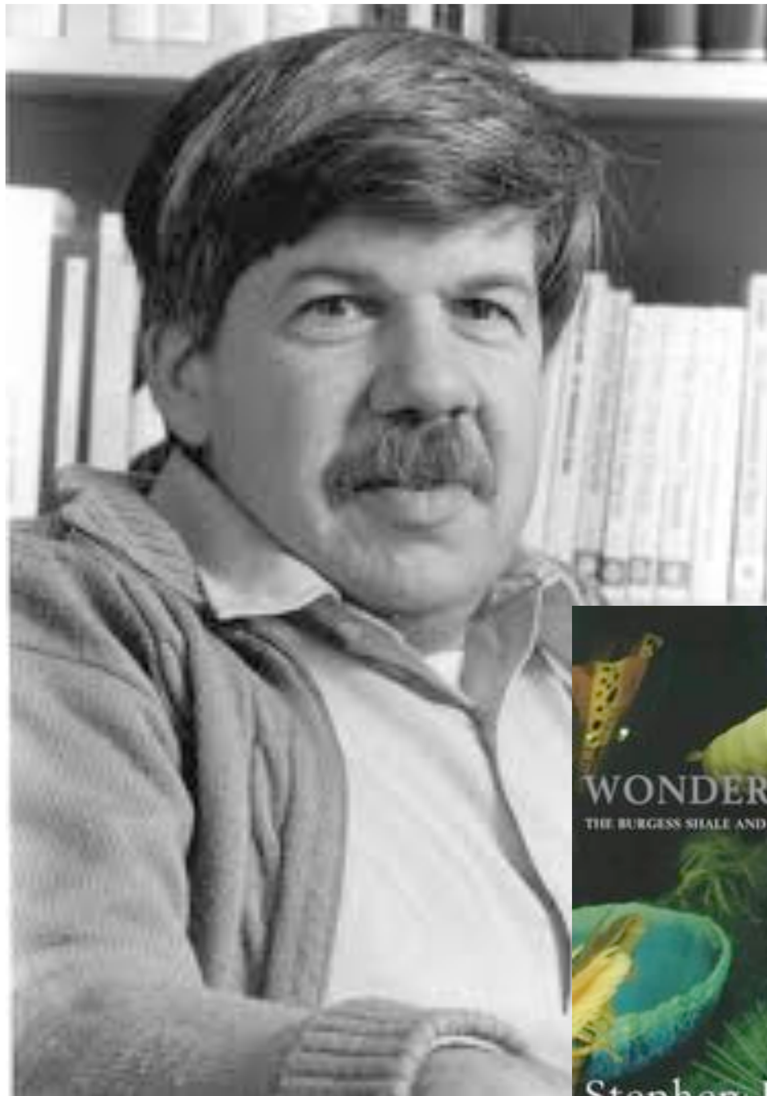
Is consciousness an emergent property?

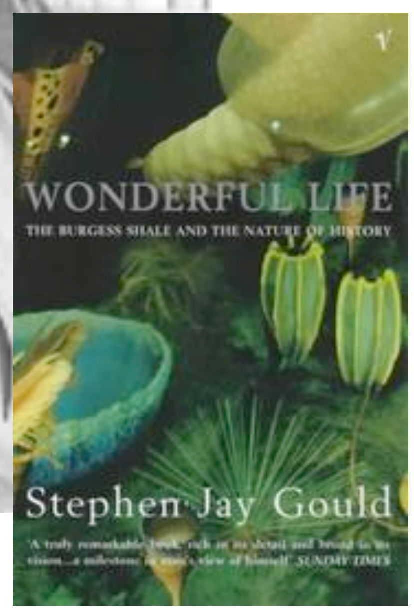
Is it possible to build an artificial mind?

How can we measure consciousness?

Why are humans so different (from other species)?

Contingency, constraints and universals





Geobios, mémoire spécial n° 12 p. 21-57, 19 fig., 2 pl. Lyon, 1989

THE LOGIC OF MONSTERS :
EVIDENCE FOR INTERNAL CONSTRAINT IN DEVELOPMENT AND EVOLUTION

Pere Alberch*

Abstract

One of the most outstanding properties of natural diversity is its discreteness and order. Species can be identified and classified because of this property. There are two philosophical approaches to interpret the orderliness of natural systems. These two conceptual positions, wich I refer to as ''externalist'' and ''internalist'', prescribe drastically distinct methodological approaches. Classical neo-Darwinism falls within the ''externalist'' tradition, with its emphasis in natural selection as the main ordering agent in evolution, this approach basically argues that the properties of the

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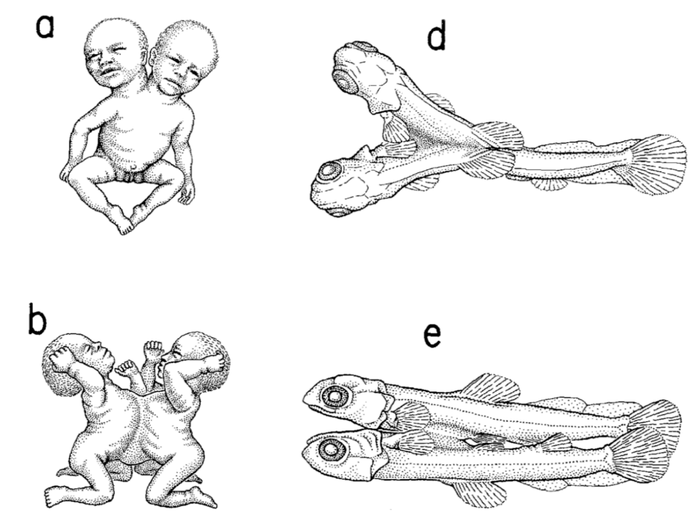
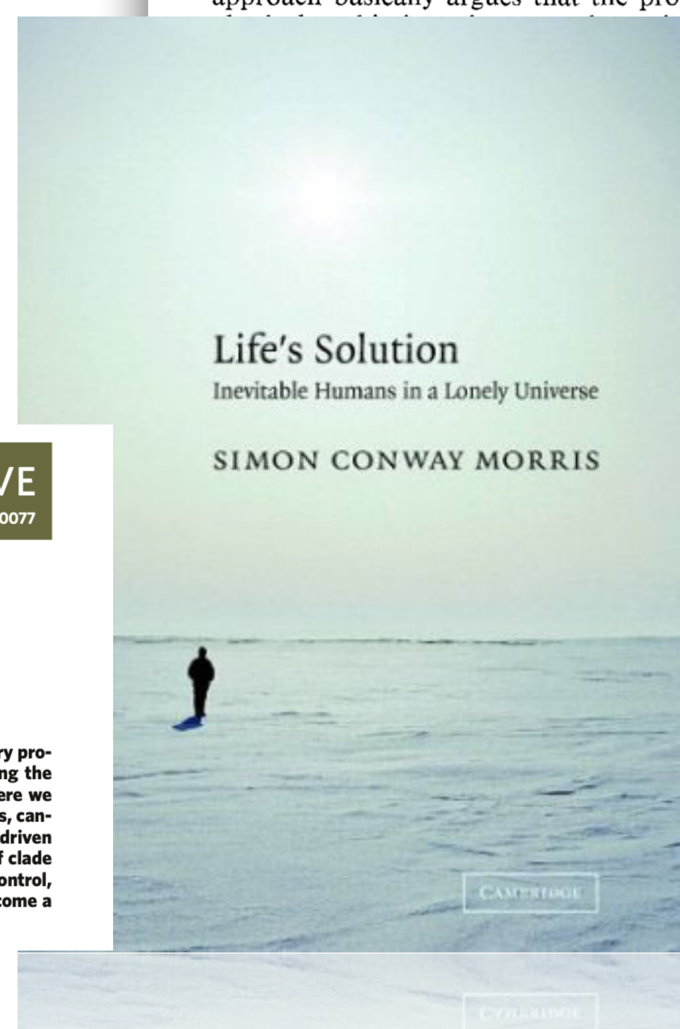
… The interna-





nature ecology & evolution PERSPECTIVE
PUBLISHED: 21 FEBRUARY 2017 | VOLUME: 1 | ARTICLE NUMBER: 0077

Predicting evolution

Michael Lässig[1]*, Ville Mustonen[2*†] and Aleksandra M. Walczak[3]*

The face of evolutionary biology is changing: from reconstructing and analysing the past to predicting future evolutionary processes. Recent developments include prediction of reproducible patterns in parallel evolution experiments, forecasting the future of individual populations using data from their past, and controlled manipulation of evolutionary dynamics. Here we undertake a synthesis of central concepts for evolutionary predictions, based on examples of microbial and viral systems, cancer cell populations, and immune receptor repertoires. These systems have strikingly similar evolutionary dynamics driven by the competition of clades within a population. These dynamics are the basis for models that predict the evolution of clade frequencies, as well as broad genetic and phenotypic changes. Moreover, there are strong links between prediction and control, which are important for interventions such as vaccine or therapy design. All of these are key elements of what may become a predictive theory of evolution.

The Major synthetic transitions

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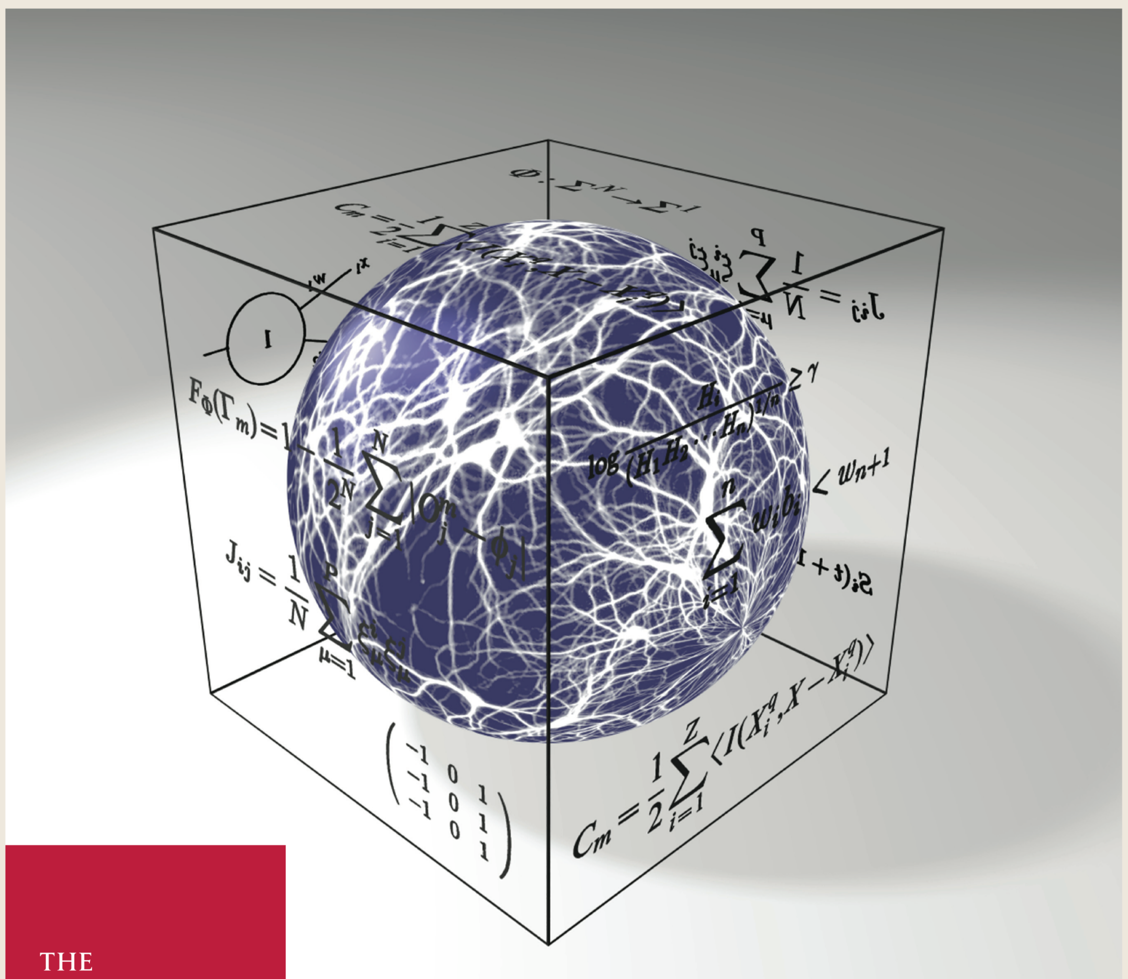
BIOLOGICAL SCIENCES

Phil. Trans. R. Soc. B | Volume 371 | Issue 1701 | 19 August 2016 The major synthetic evolutionary transitions

The major synthetic evolutionary transitions

Theme issue compiled and edited by Ricard Solé



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One contribution of 13 to a theme issue 'The major synthetic evolutionary transitions'.

Subject Areas:
systems biology, synthetic biology, theoretical biology, bioengineering, evolution

Keywords:
major transitions, artificial life, synthetic biology, evolutionary robotics, phase transitions

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Synthetic transitions: towards a new synthesis

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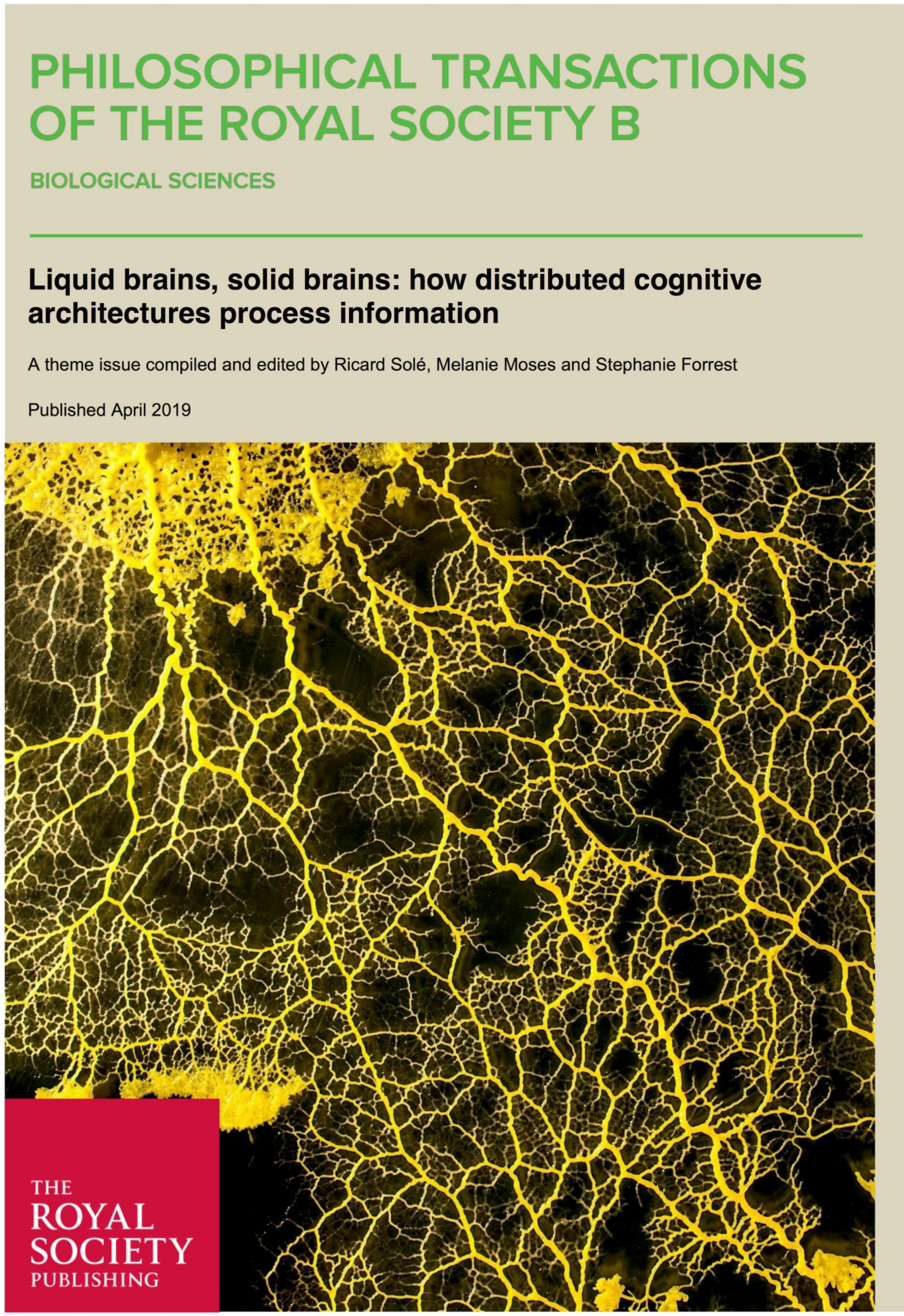
The evolution of life in our biosphere has been marked by several major innovations. Such major complexity shifts include the origin of cells, genetic codes or multicellularity to the emergence of non-genetic information, language or even consciousness. Understanding the nature and conditions for their rise and success is a major challenge for evolutionary biology. Along with data analysis, phylogenetic studies and dedicated experimental work, theoretical and computational studies are an essential part of this exploration. With the rise of synthetic biology, evolutionary robotics, artificial life and advanced simulations, novel perspectives to these problems have led to a rather interesting scenario, where not only the major transitions can be studied or even reproduced, but even new ones might be potentially identified. In both cases, transitions can be understood in terms of phase transitions, as defined in physics. Such mapping (if correct) would help in defining a general framework to establish a theory of major transitions, both natural and artificial. Here, we review some advances made at the crossroads between statistical physics, artificial life, synthetic biology and evolutionary robotics.

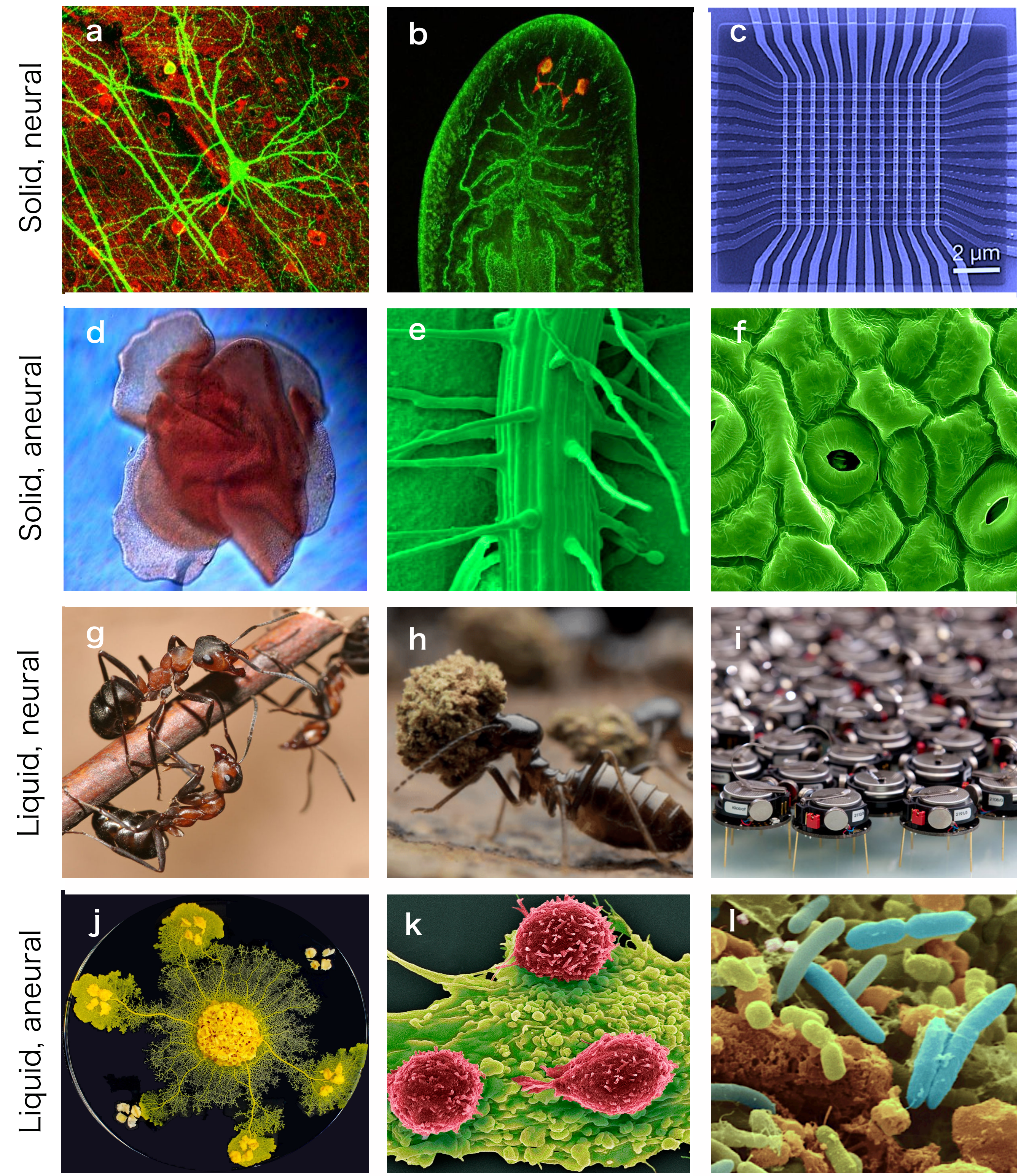
This article is part of the themed issue 'The major synthetic evolutionary transitions'.

1. Introduction: synthetic transitions

Looking backward to the unfolding of life on our planet, it is possible to identify several major qualitative changes that deeply marked evolutionary history. They have been labelled as the major evolutionary transitions (METs) owing to the fundamentally unique nature of the changes involved [1]. The emergence of life, the genetic code, complex cells, multicellular organisms and language are some of the best-known examples. They all involve a novel class of organization with high-order properties not reducible to the properties of the lower-scale units. The list of METs differs among authors [1–7], and in this paper we address a revised list of major transitions (MTs) incorporating different proposals. A first classification of METs would include (i) a loss of replicative potential by the units once belonging to a higher-order entity, (ii) a specialization of different units in different tasks, which requires a nonlinear mapping between genotype and phenotype, and (iii) changes in the ways information is processed and stored. But more importantly, we want to consider METs under the light of the theoretical, experimental and engineering perspectives involving the modelling, synthesis and imitation of living systems. For example, we can create a new multicellular system by engineering new cell–cell signals on single cells. Similarly, a proto-grammar can emerge in a group of interacting, evolvable robots. These are *synthetic transitions* that are not necessarily related to standard evolutionary paths, but they do involve ways to generate major innovations starting from simpler systems. We will use a general term to label this broad class of non-natural

Cognitive networks: what is the space of the possible?





Emergence of neurons, neural agents and brains

Available online at www.sciencedirect.com
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Journal of Theoretical Biology 239 (2006) 236–246
Journal of Theoretical Biology
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The evolution of information in the major transitions

Eva Jablonka[a,*], Marion J. Lamb[b]
[a] The Cohn Institute for the History and Philosophy of Science and Ideas, Tel-Aviv University, Tel Aviv 69978, Israel
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Available online 19 October 2005

"...with a high level of internal integration and the ability to make rapid adaptive responses. However, the emergence of the neural individual meant more than a change in the nature and speed of adaptation. Neural processing led to behaviour based on sensory perception, and this in turn led to a form of communication between individuals that did not require contact or the transmission of physical material from one to the other. This mode of information transmission had interesting consequences, one of which was the ability of animals to learn from others through perceiving their behaviour or the outcomes of their behaviour, i.e. it led to social learning.

Jablonka and Lamb (2006)

Why brains?
What kinds of brains?
What are the constrains?

Case studies

Building synthetic cognition

The moving hypothesis: brains as prediction machines

The moving hypothesis posits that active exploration of an organism’s spatial environment was a key step in the evolutionary trajectory that produced brains

R. Llinás, 1987

What is intelligence: a space of possibilities?

Defining and measuring intelligence

Minds & Machines (2007) 17:391–444
DOI 10.1007/s11023-007-9079-x

Universal Intelligence: A Definition of Machine Intelligence

Shane Legg · Marcus Hutter

Received: 22 September 2006 / Accepted: 28 August 2007 / Published online: 10 November 2007

Abstract A fundamental problem in artificial intelligence is that nobody really knows what intelligence is. The problem is especially acute when we need to consider artificial systems which are significantly different to humans. In this paper we approach this problem in the following way: we take a number of well known informal definitions of human intelligence that have been given by experts, and extract their essential features. These are then mathematically formalised to produce a general measure of intelligence for arbitrary machines.
equation formally captures the concept of machine intelli
reasonable sense. We then show how this formal definition is
universal optimal learning agents. Finally, we survey the
definitions of intelligence that have been proposed for mach

Keywords AIXI · Complexity theory · Intelligence · Theo
Turing test · Intelligence tests · Measures · Definitions

$$\Upsilon(\pi) := \sum_{\mu \in E} 2^{-K(\mu)} V_{\mu}^{\pi}.$$

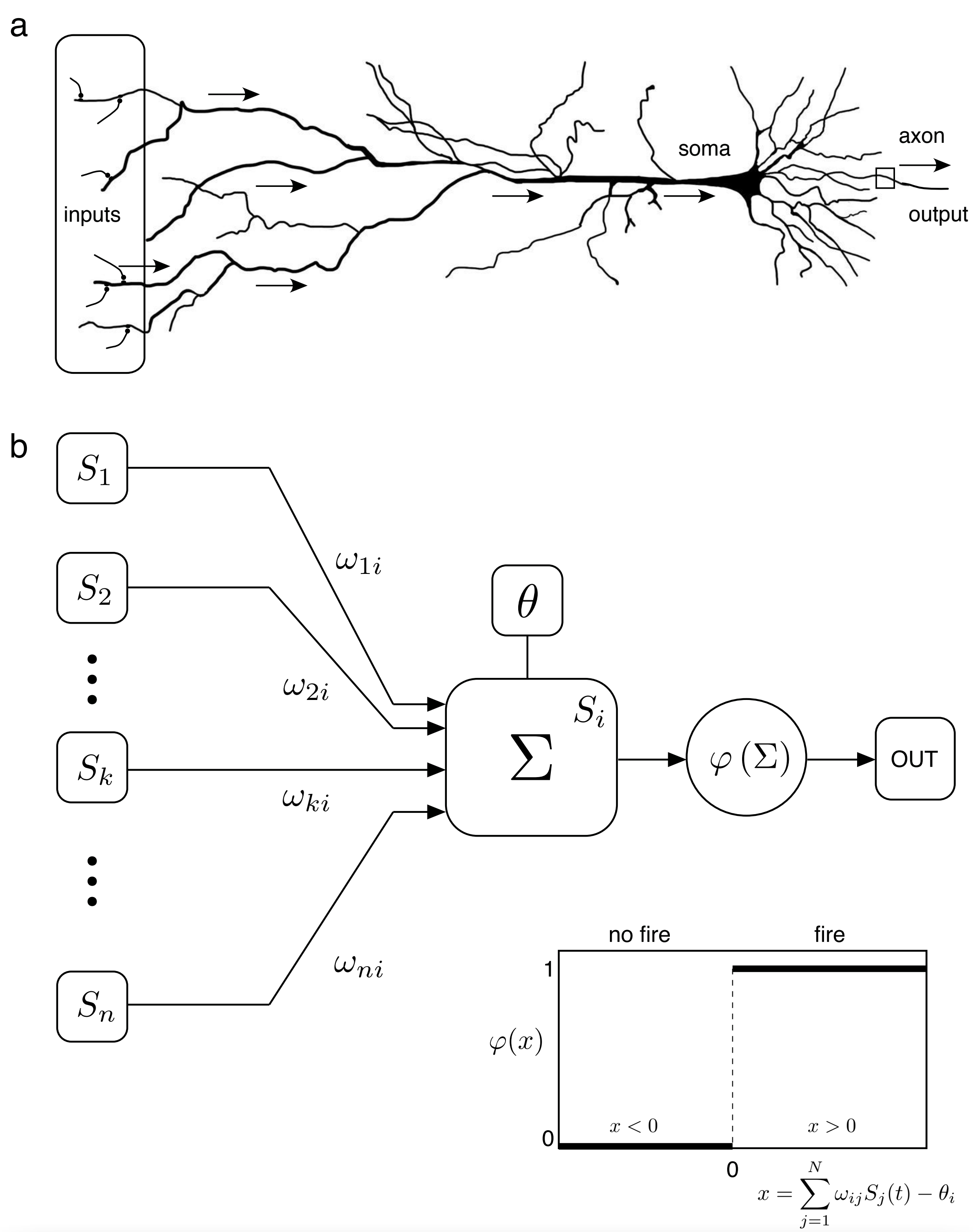
"Intelligence: the collection of sophisticated cognitive abilities, such as problem solving, complex social cognition, and future planning."

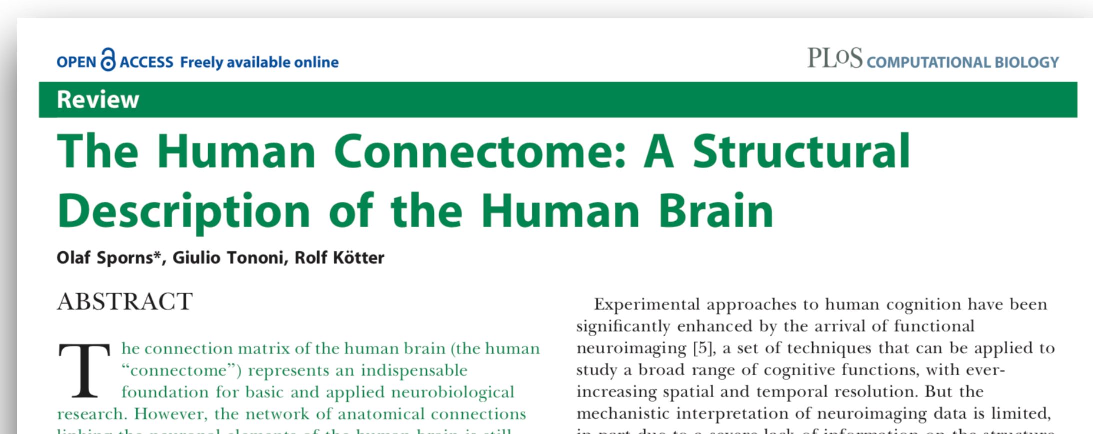
P. Amodio et al. TREE 2019

How can we model cognition?

Classical problem: “solid” neural networks

“Standard” brains / neural networks (solid brains)





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PLoS COMPUTATIONAL BIOLOGY

Review

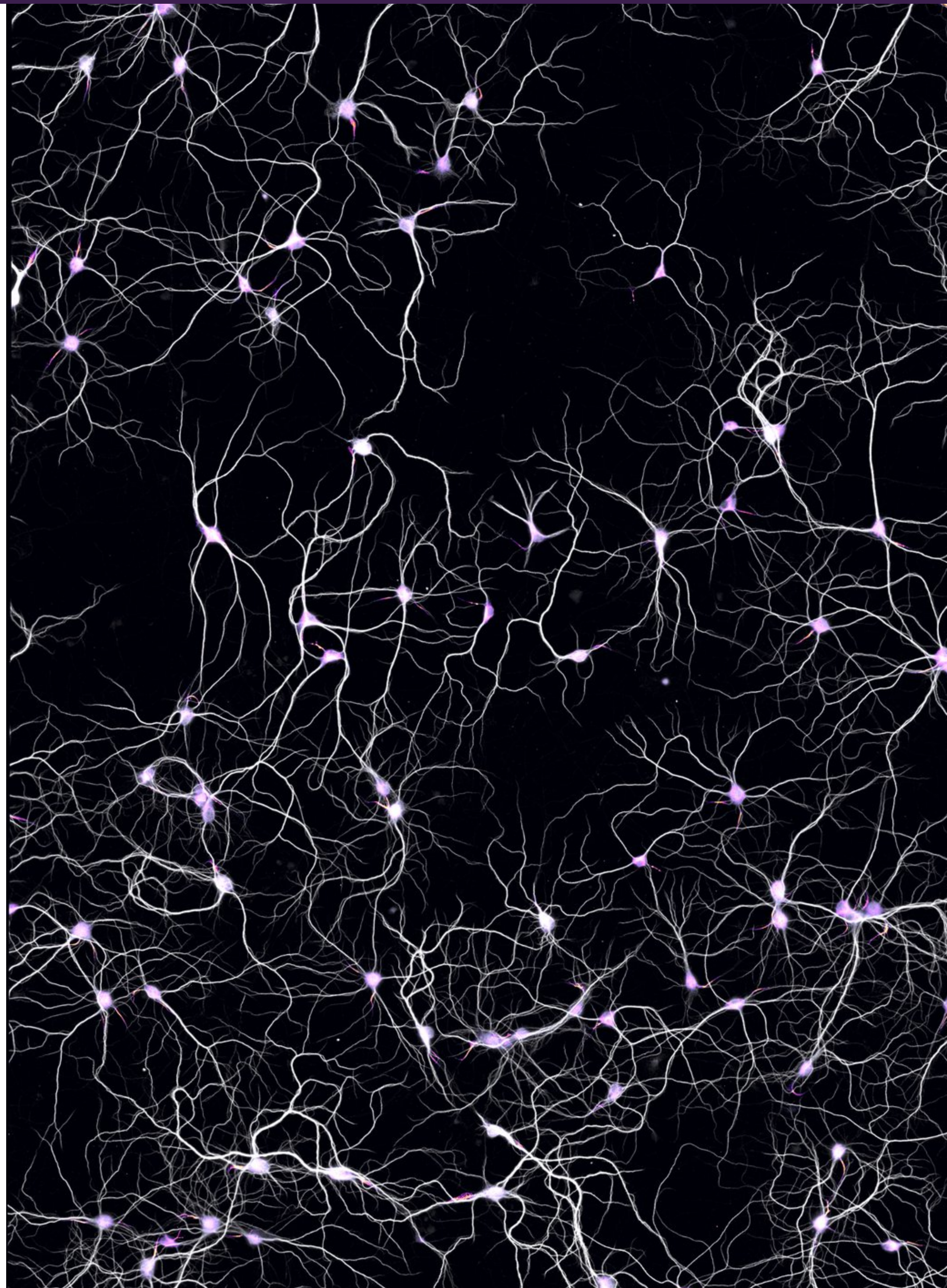
The Human Connectome: A Structural Description of the Human Brain

Olaf Sporns*, Giulio Tononi, Rolf Kötter

ABSTRACT

The connection matrix of the human brain (the human “connectome”) represents an indispensable foundation for basic and applied neurobiological research. However, the network of anatomical connections

Experimental approaches to human cognition have been significantly enhanced by the arrival of functional neuroimaging [5], a set of techniques that can be applied to study a broad range of cognitive functions, with ever-increasing spatial and temporal resolution. But the mechanistic interpretation of neuroimaging data is limited,



Neural and genetic network model(s)

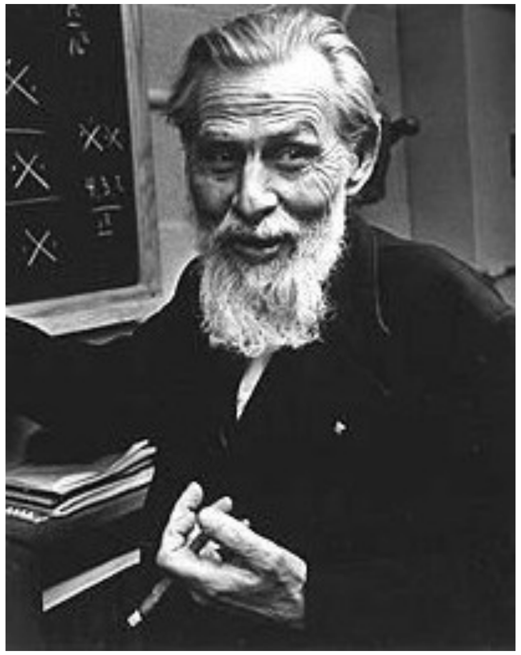
BULLETIN OF
MATHEMATICAL BIOPHYSICS
VOLUME 5, 1943

A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY

WARREN S. MCCULLOCH AND WALTER PITTS

FROM THE UNIVERSITY OF ILLINOIS, COLLEGE OF MEDICINE, DEPARTMENT OF PSYCHIATRY AT THE ILLINOIS NEUROPSYCHIATRIC INSTITUTE, AND THE UNIVERSITY OF CHICAGO

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.



Proc. Natl. Acad. Sci. USA
Vol. 81, pp. 3088–3092, May 1984
Biophysics

Neurons with graded response have collective computational properties like those of two-state neurons

(associative memory/neural network/stability/action potentials)

J. J. HOPFIELD

Divisions of Chemistry and Biology, California Institute of Technology, Pasadena, CA 91125; and Bell Laboratories, Murray Hill, NJ 07974

Contributed by J. J. Hopfield, February 13, 1984

ABSTRACT A model for a large network of "neurons" with a graded response (or sigmoid input–output relation) is studied. This deterministic system has collective properties in very close correspondence with the earlier stochastic model based on McCulloch–Pitts neurons. The content-addressable memory and other emergent collective properties of the original model also are present in the graded response model. The idea that such collective properties are used in biological systems is given added credence by the continued prese
properties for more nearly biological "neurons."
analog electrical circuits of the kind described wil
function. The collective states of the two models hav
correspondence. The original model will continue t
for simulations, because its connection to graded re
tems is established. Equations that include the effe
potentials in the graded response system are also d

of the original model (1) but built of operational amplifiers and resistors will function.

Form of the Original Model

The original model used two-state threshold "neurons" that followed a stochastic algorithm. Each model neuron i had two states, characterized by the output V_i of the neuron hav-

J. Theoret. Biol. (1969) **22,** 437–467

Metabolic Stability and Epigenesis in Randomly Constructed Genetic Nets

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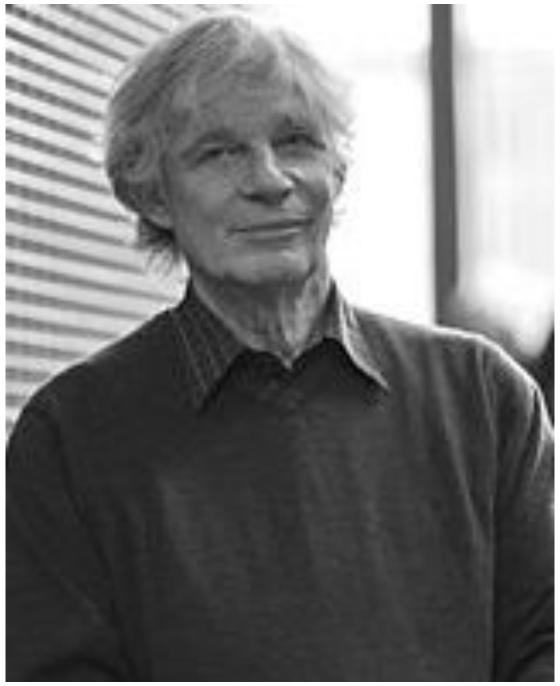
and

Research Laboratory of Electronics, Massachusetts Institute of Technology, Cambridge, Massachusetts, U.S.A.†

(*Received* 19 *March* 1968, *and in revised form* 8 *July* 1968)

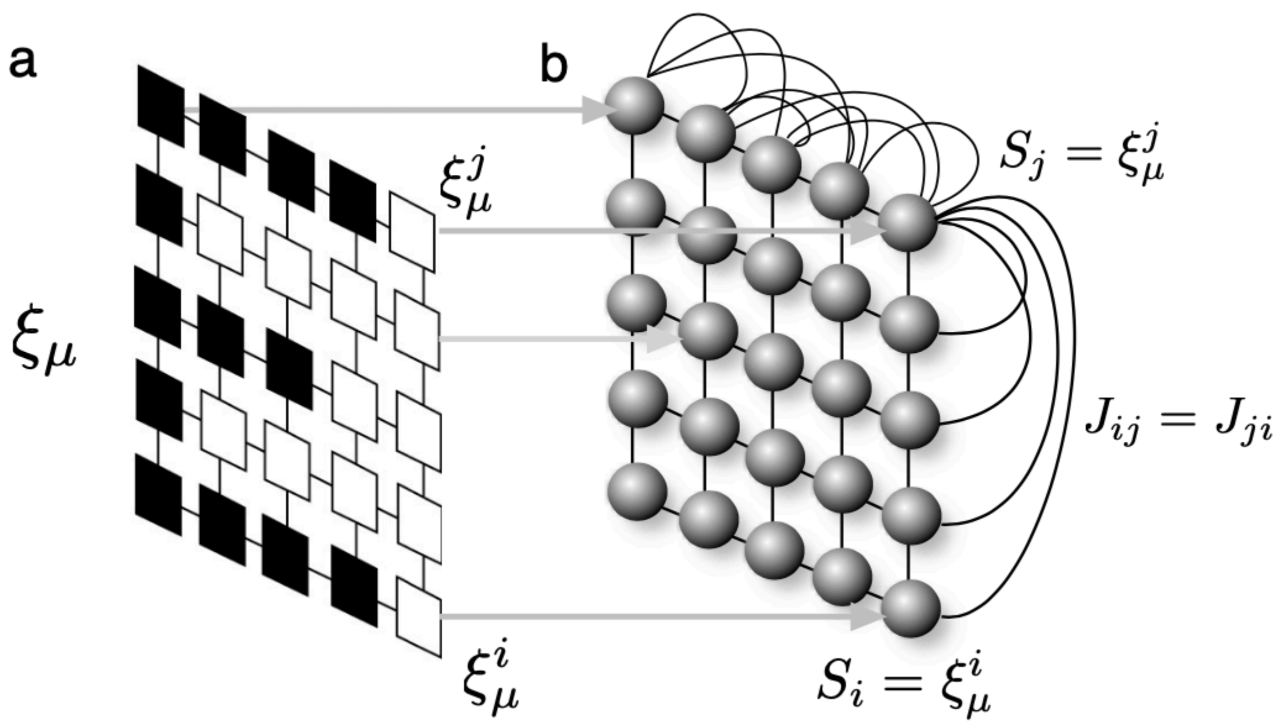
"The world is either the effect of cause or chance. If the latter, it is a world for all that, that is to say, it is a regular and beautiful structure."
Marcus Aurelius

Proto-organisms probably were randomly aggregated nets of chemical reactions. The hypothesis that contemporary organisms are also randomly



Attractor neural networks

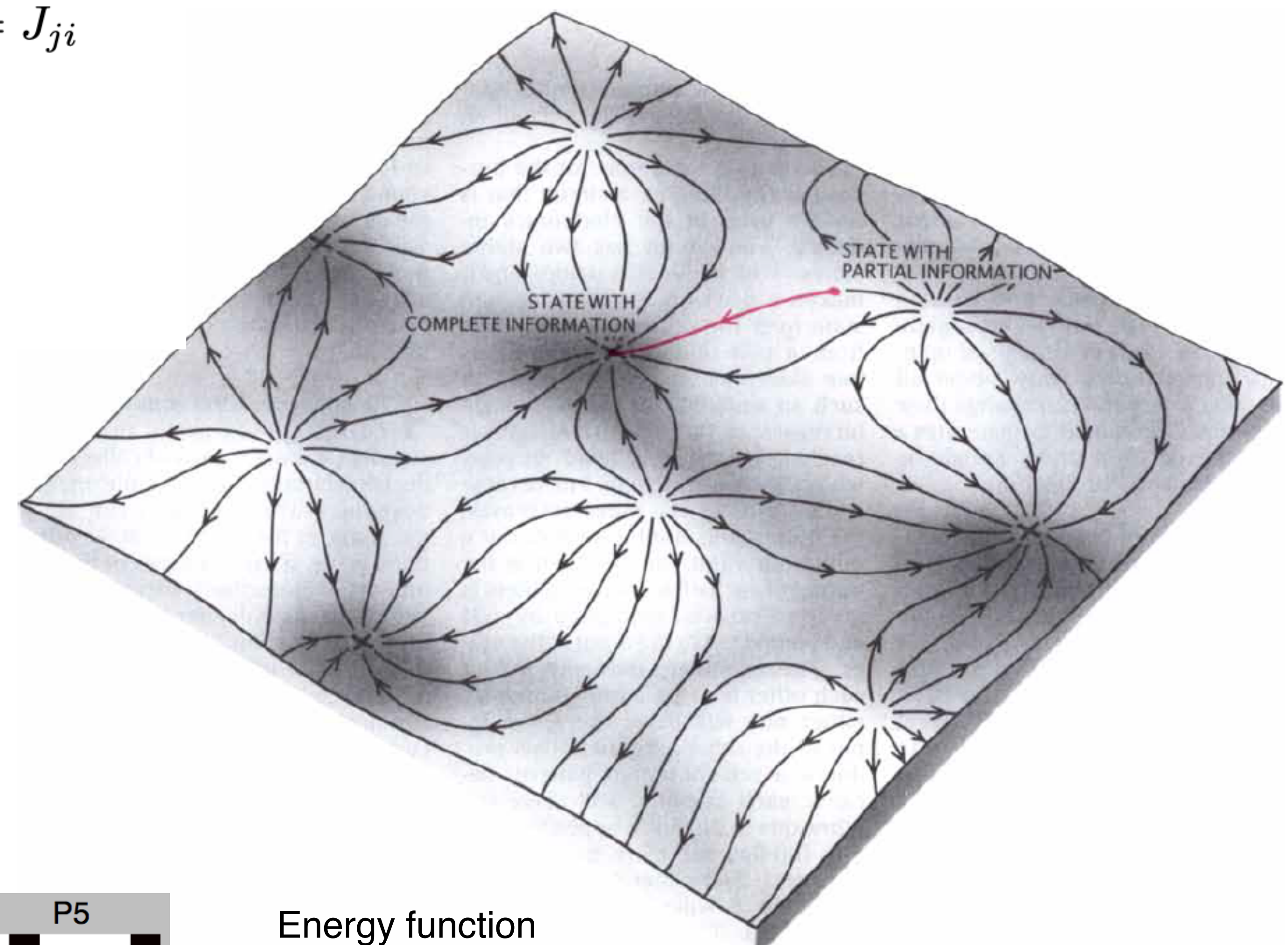
Network topology, connectivity matrix



$$S_i(t+1) = \phi\left(\sum_{\mu=1}^{N} \omega_{\mu i} S_\mu(t)\right)$$

$$\omega_{ij} = \omega_{ji}$$

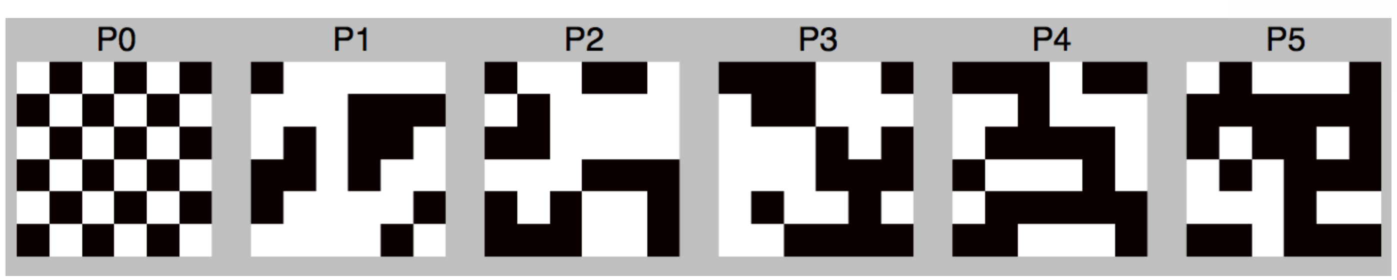
$$\omega_{ii} = 0$$



$s_i \in \{-1, +1\}$

$$\xi^\mu = \{\xi_1^\mu, ..., \xi_i^\mu, ..., \xi_N^\mu\}$$

$$\xi_i^\mu \in \{-1, +1\}$$



Energy function

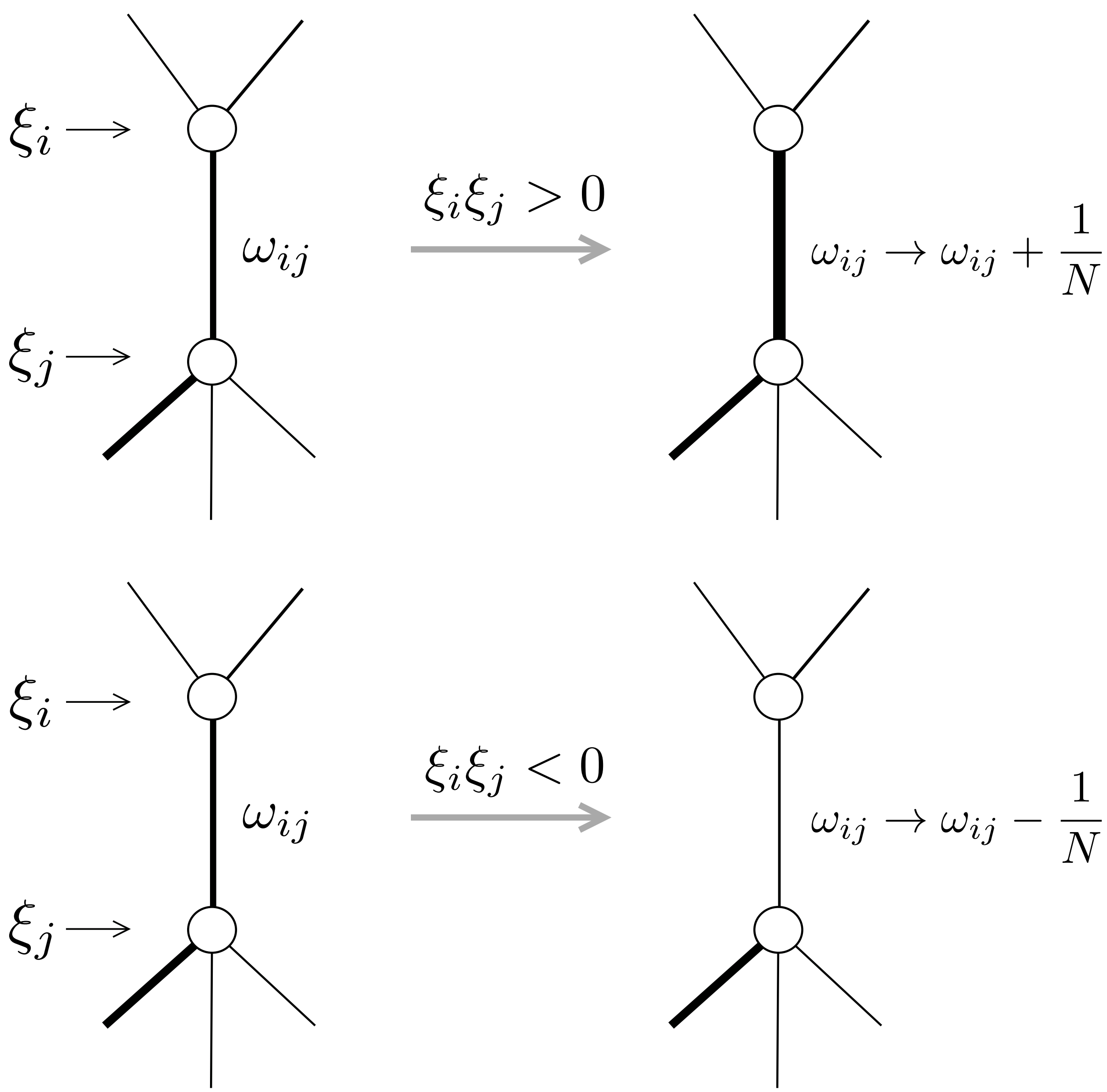
$$H = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \omega_{ij} S_i(t) S_j(t)$$

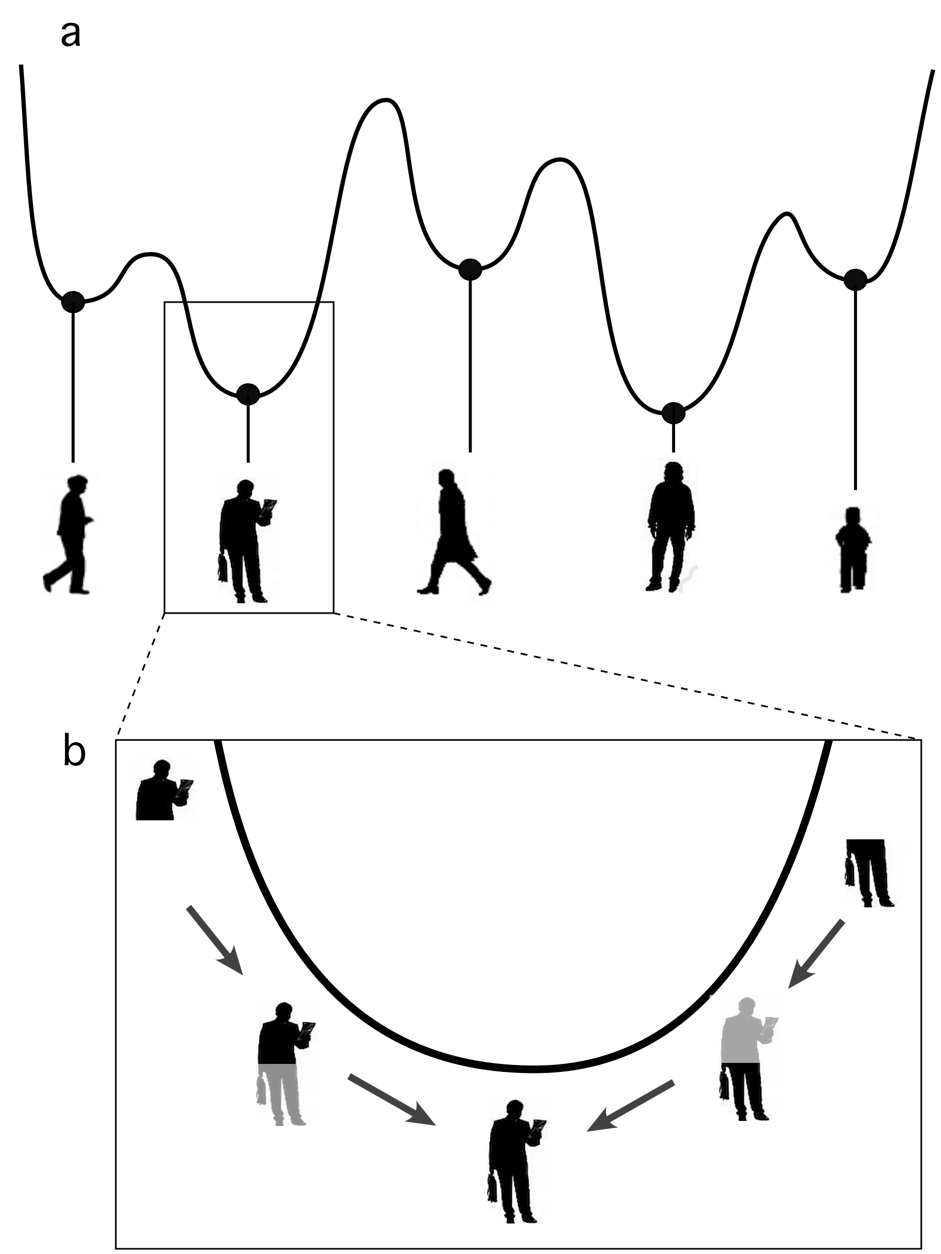
Formal Hebb's rule implementation

$$S_i(t+1) = \phi\left(\sum_{\mu=1}^{N} \omega_{\mu i} S_\mu(t)\right)$$

$$\omega_{ij} = \omega_{ji}$$

$$\omega_{ii} = 0$$



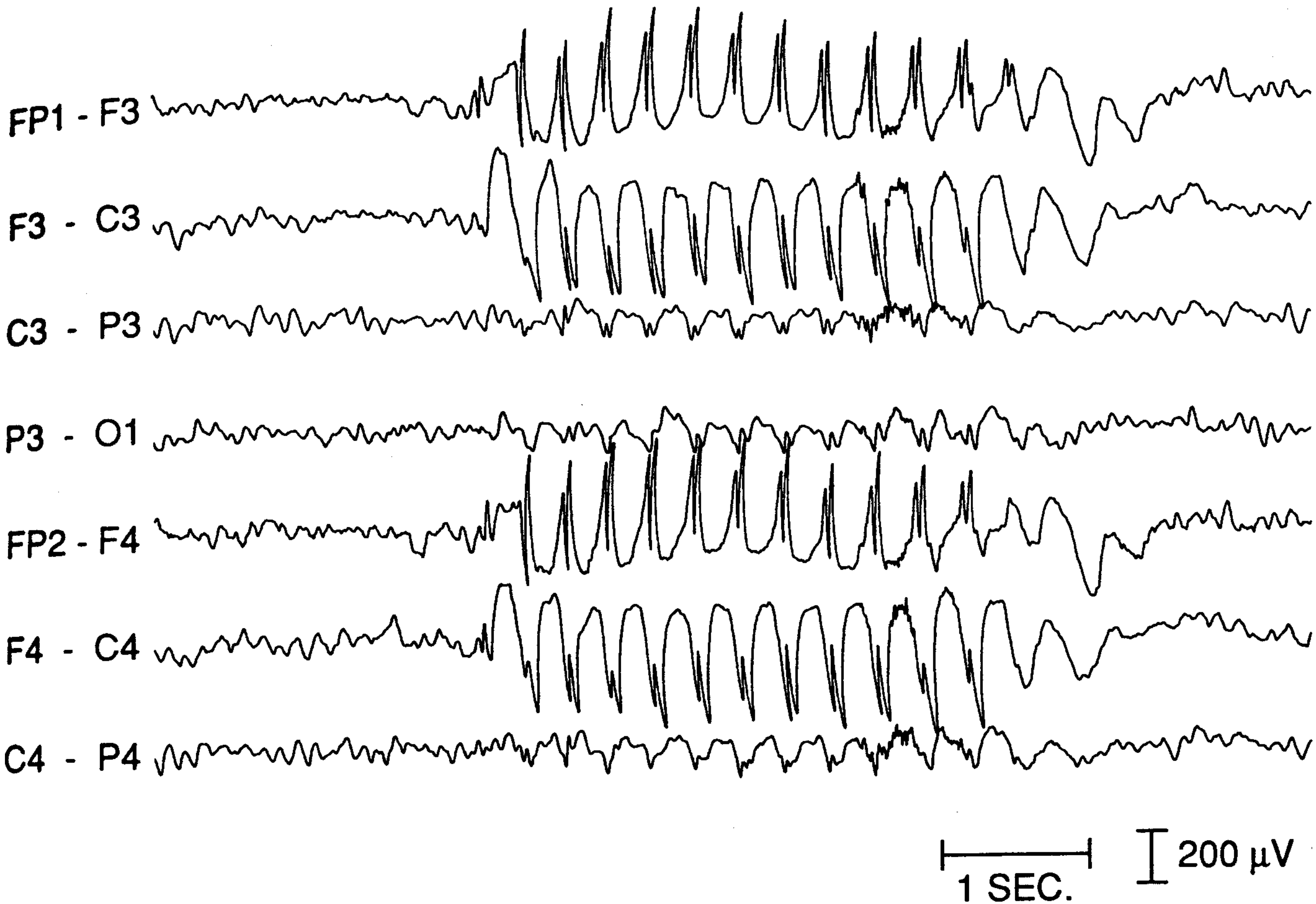


Memories as minima on H(s)

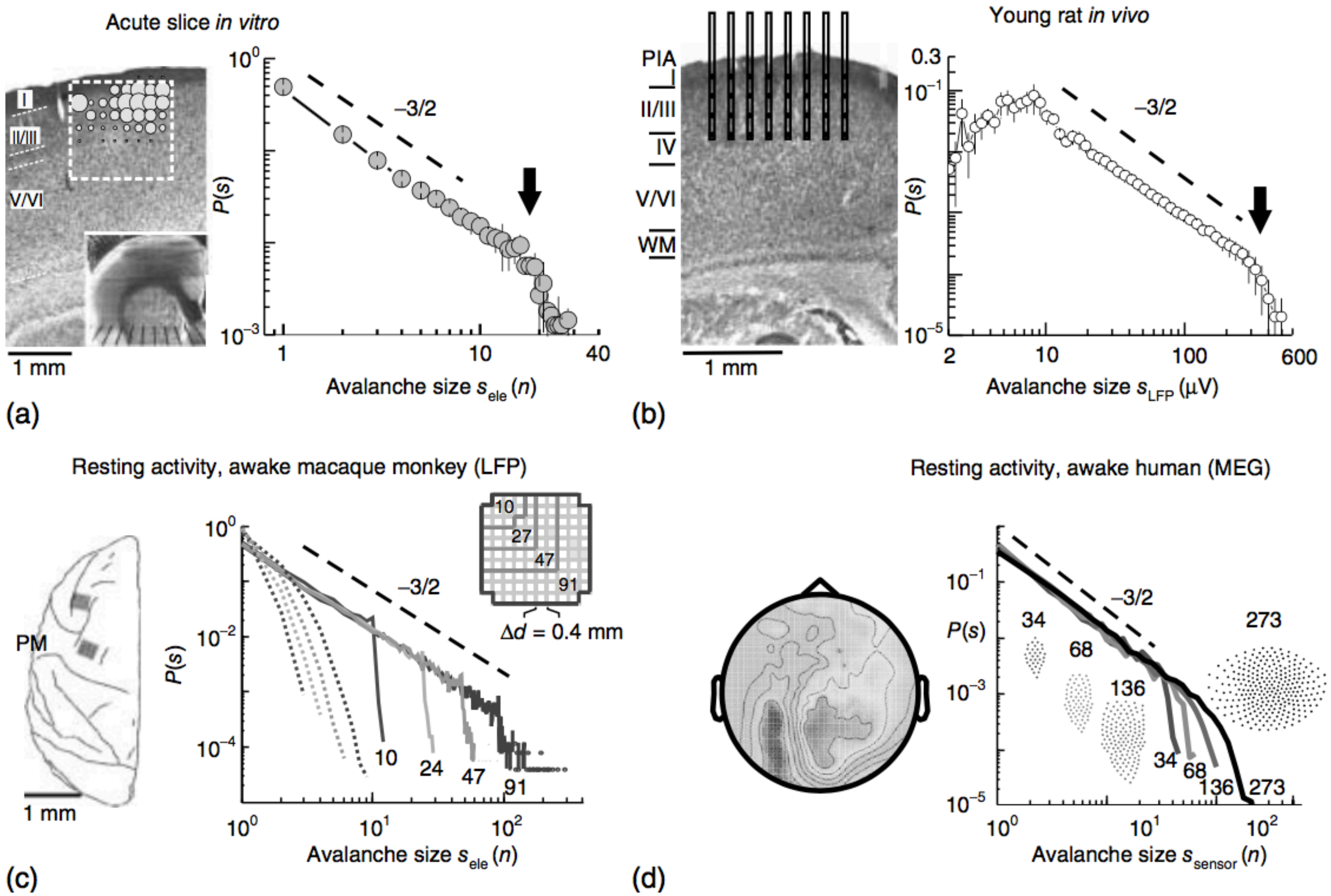
Synaptic weights at the end of the retrieval process:

$$\omega_{ij} = \frac{1}{N} \sum_{\mu=1}^{P} \xi_i^\mu \xi_j^\mu$$

Is the brain operating at the edge of chaos?



Neuronal avalanches are critical



REVIEW ARTICLES | INSIGHT
PUBLISHED ONLINE: 1 OCTOBER 2010 | DOI: 10.1038/NPHYS1803
nature physics

Emergent complex neural dynamics

Dante R. Chialvo[1,2]*

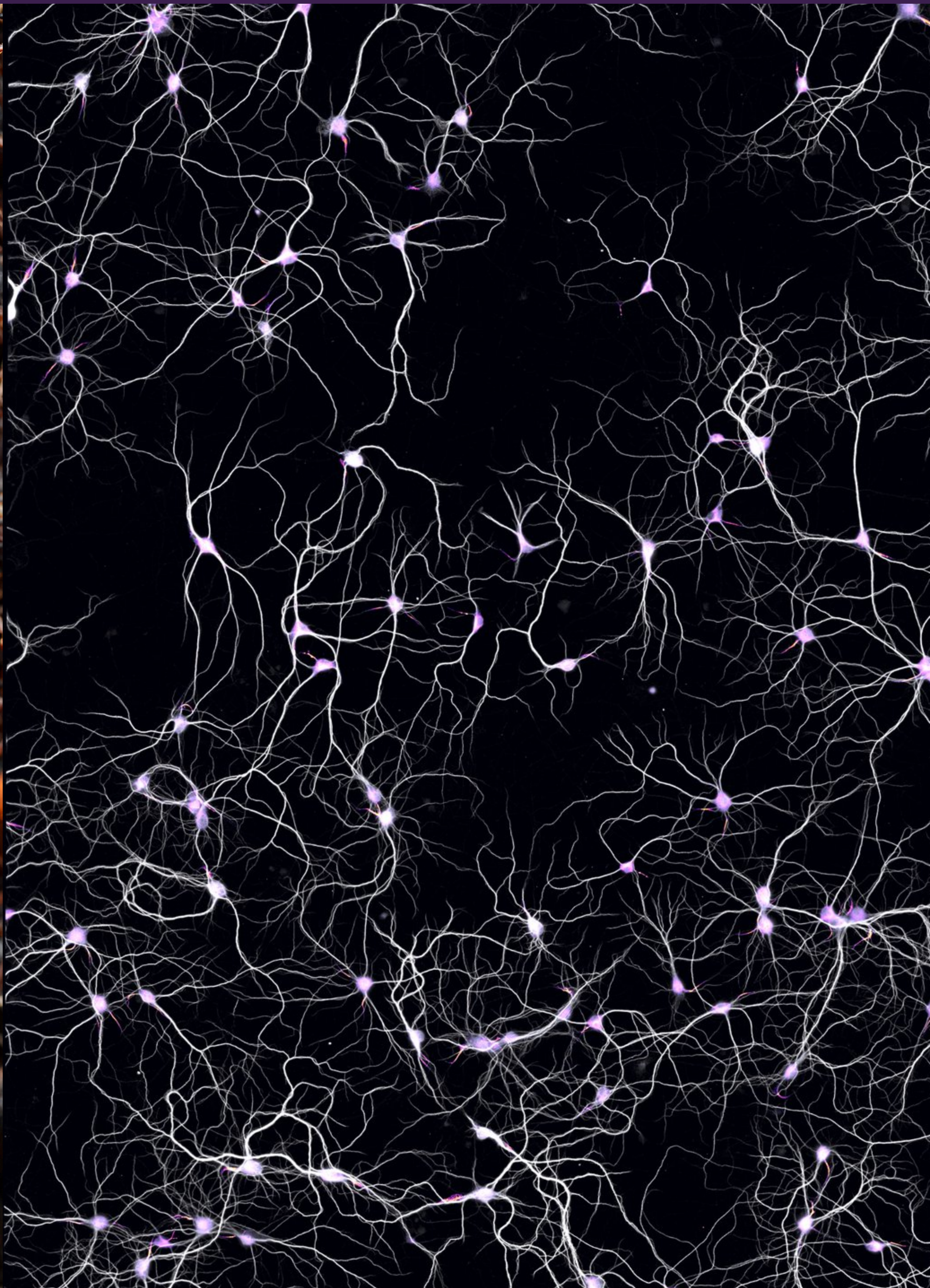
A large repertoire of spatiotemporal activity patterns in the brain is the basis for adaptive behaviour. Understanding the mechanism by which the brain's hundred billion neurons and hundred trillion synapses manage to produce such a range of

What happens if agents can move?

What kind of attractors?

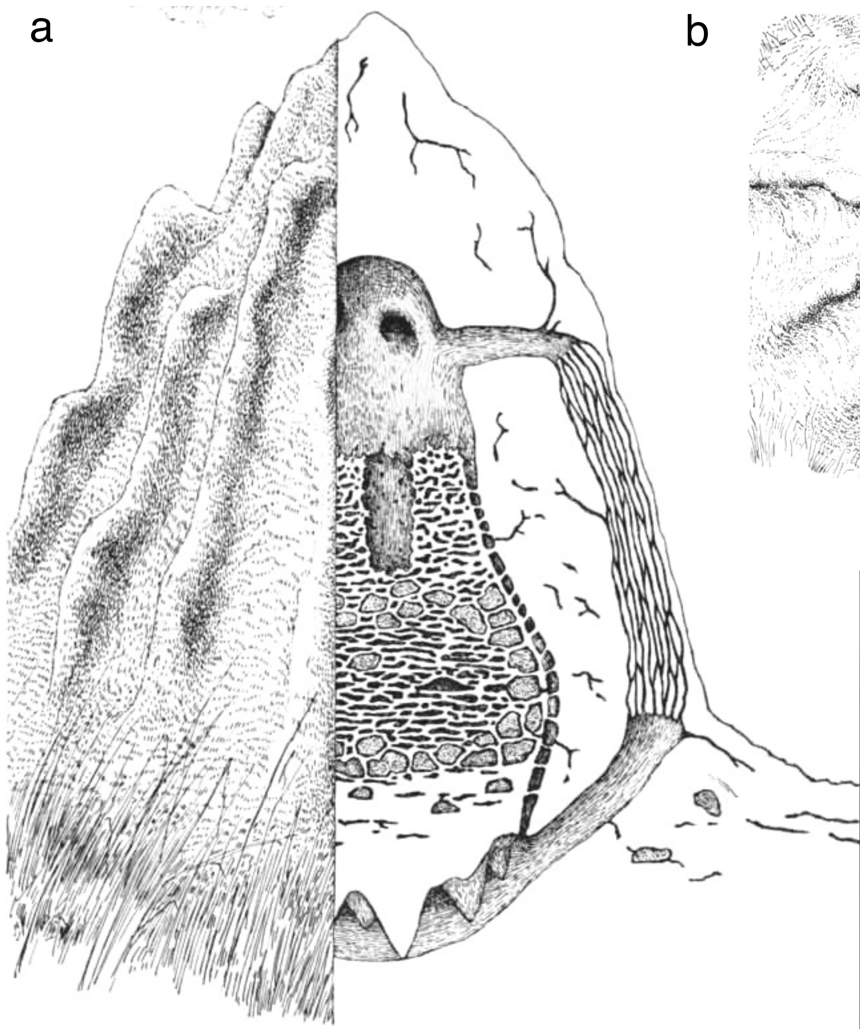
What kind of (collective) dynamical states?

Liquid versus solid “brains”



The collective mind: liquid + solid

a



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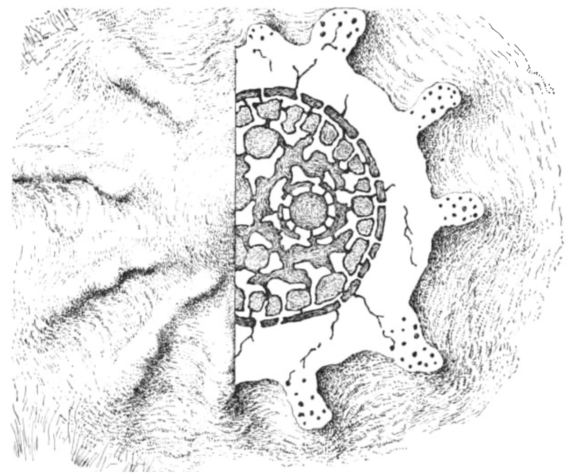


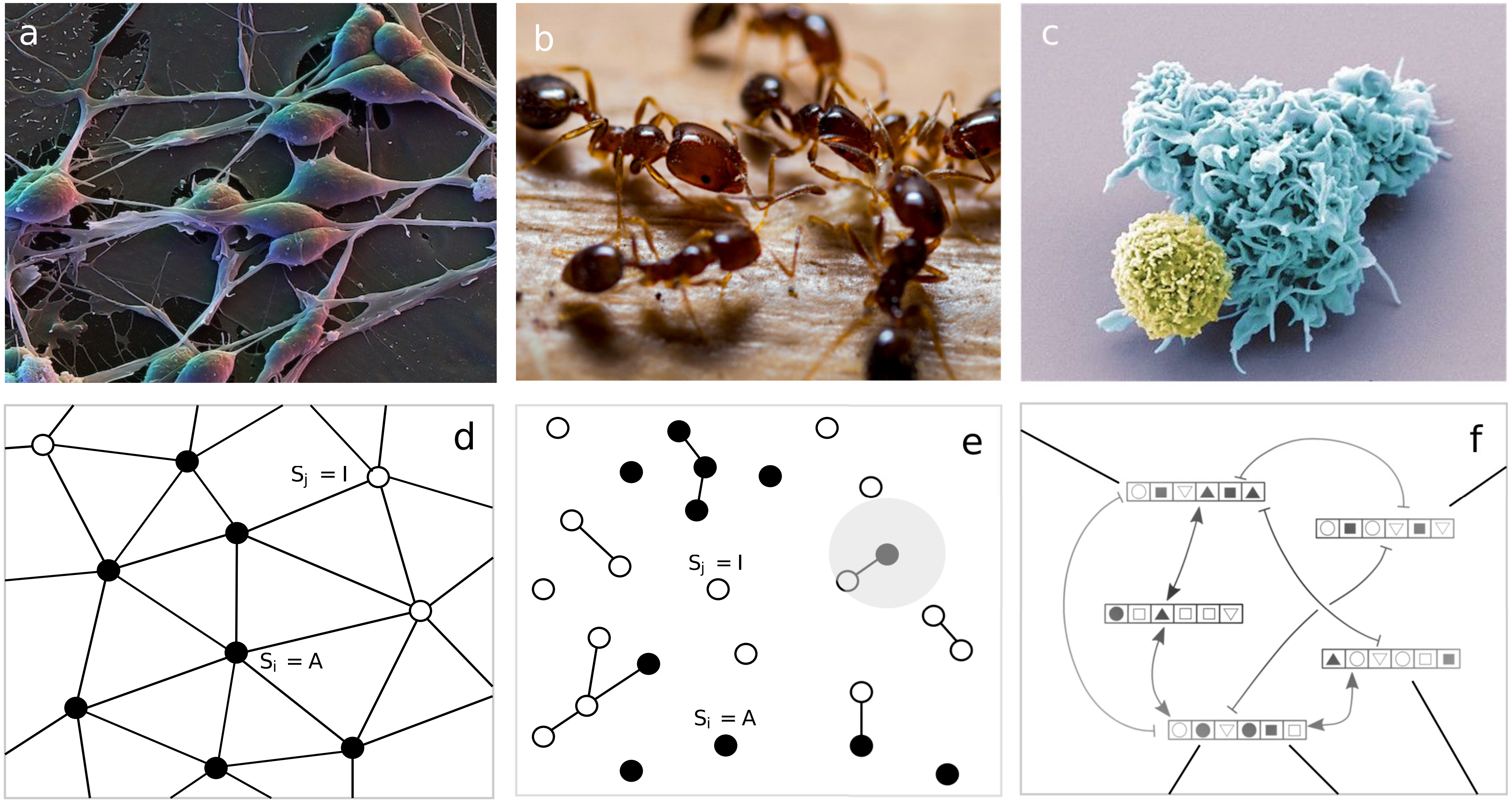
$$\frac{\partial H}{\partial t} = k_2 P - k_4 H + D_h \nabla^2 H$$

$$\frac{\partial C}{\partial t} = \phi - k_1 C + D_c \nabla^2 C - \gamma \nabla (C \nabla H)$$

$$\frac{\partial P}{\partial t} = k_1 C - k_2 P$$

Emergence of a super-structure with a two-way interaction loop

Fluid neural networks



PHILOSOPHICAL TRANSACTIONS B

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Review

Check for updates

Cite this article: Piñero J, Solé R. 2019 Statistical physics of liquid brains. *Phil. Trans. R. Soc. B* **374**: 20180376. http://dx.doi.org/10.1098/rstb.2018.0376

Statistical physics of liquid brains

Jordi Piñero[1,2] and Ricard Solé[1,2,3]

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[2]Institut de Biologia Evolutiva (CSIC-UPF), Psg Maritim Barceloneta, 37, 08003 Barcelona, Spain
[3]Santa Fe Institute, 1399 Hyde Park Road, Santa Fe, NM 87501, USA

JP, 0000-0002-4183-3733; RS, 0000-0001-6974-1008

Liquid neural networks (or 'liquid brains') are a widespread class of cognitive living networks characterized by a common feature: the agents (ants or immune cells, for example) move in space. Thus, no fixed, long-term agent-agent connections are maintained, in contrast with standard neural systems. How is this class of systems capable of displaying cognitive abilities, from learning to decision-making? In this paper, the collective dynamics, memory and

Neural networks as models of cellular networks

REVIEW ARTICLE

Protein molecules as computational elements in living cells

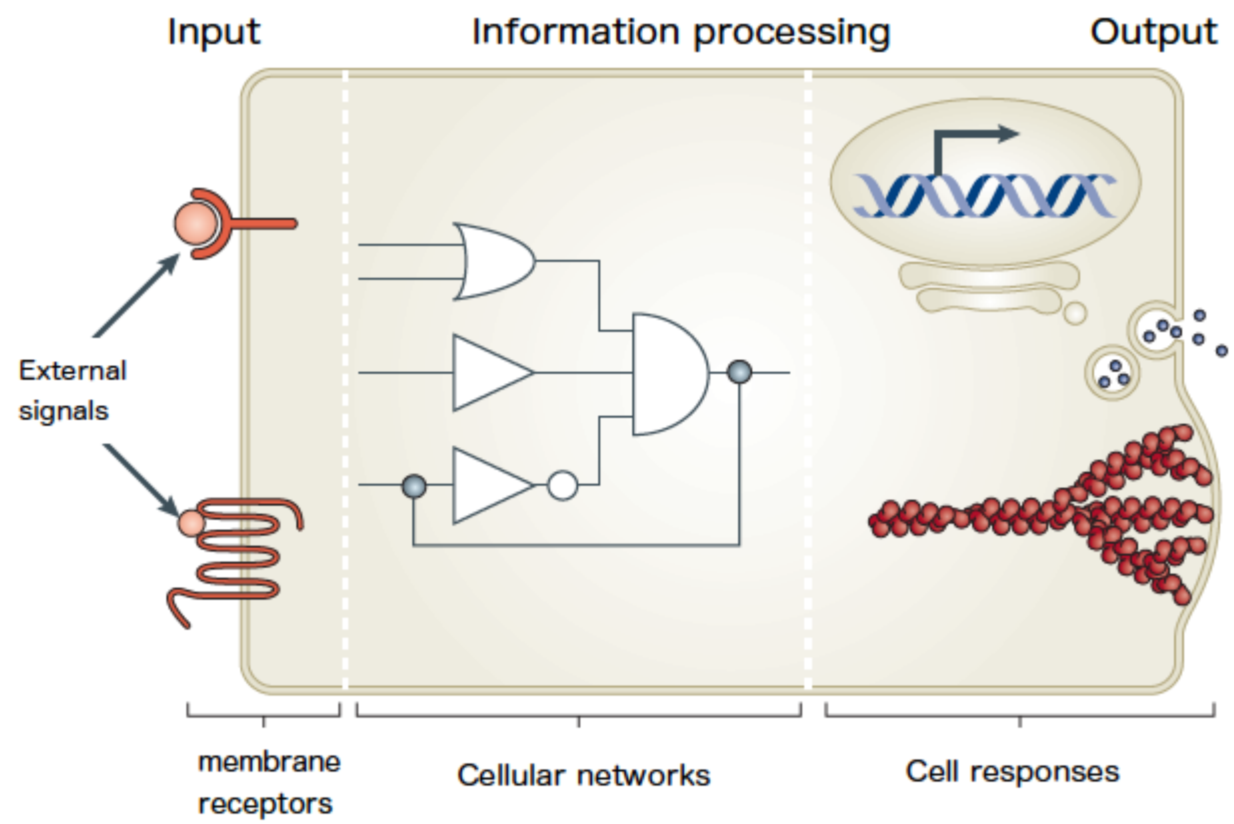
Dennis Bray

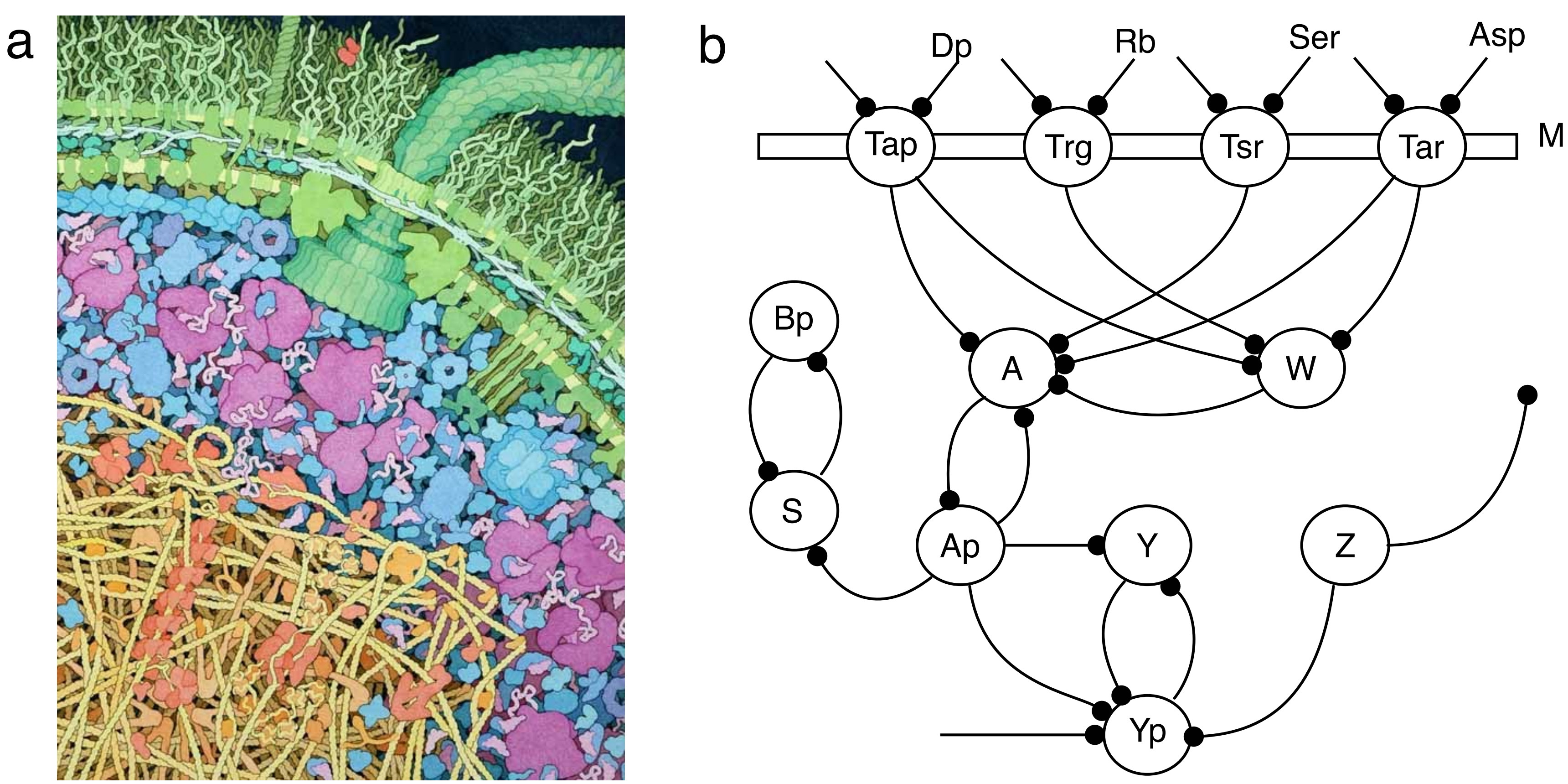
Many proteins in living cells appear to have as their primary function the transfer and processing of information, rather than the chemical transformation of metabolic intermediates or the building of cellular structures. Such proteins are functionally linked through allosteric or other mechanisms into biochemical 'circuits' that perform a variety of simple computational tasks including amplification, integration and information storage.

ARTICLE

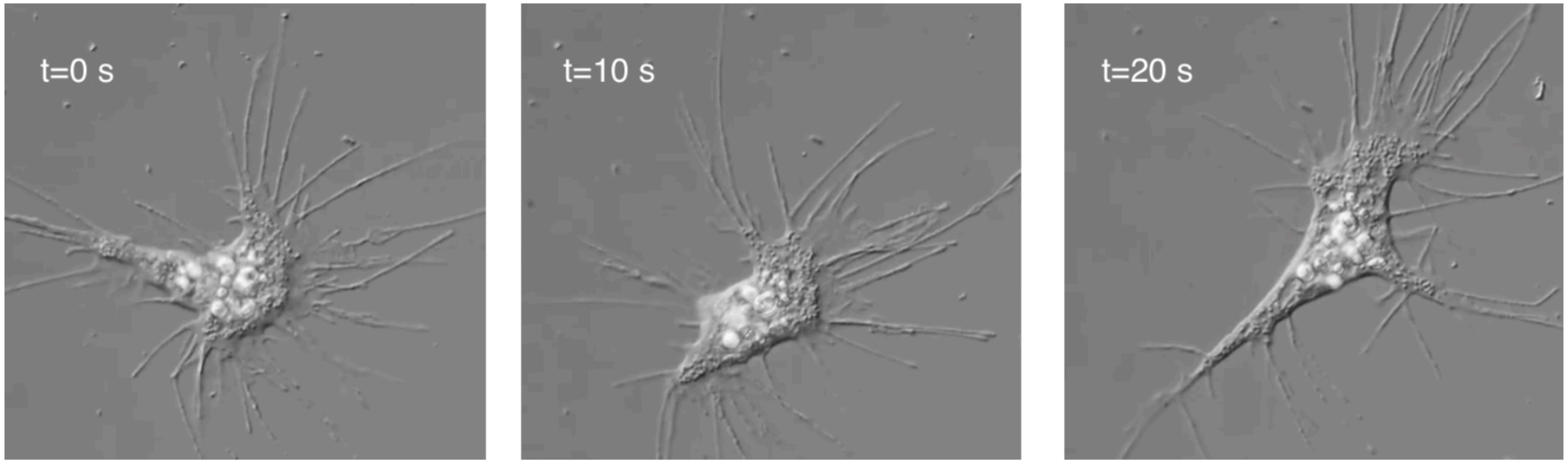
Circuit Simulation of Genetic Networks

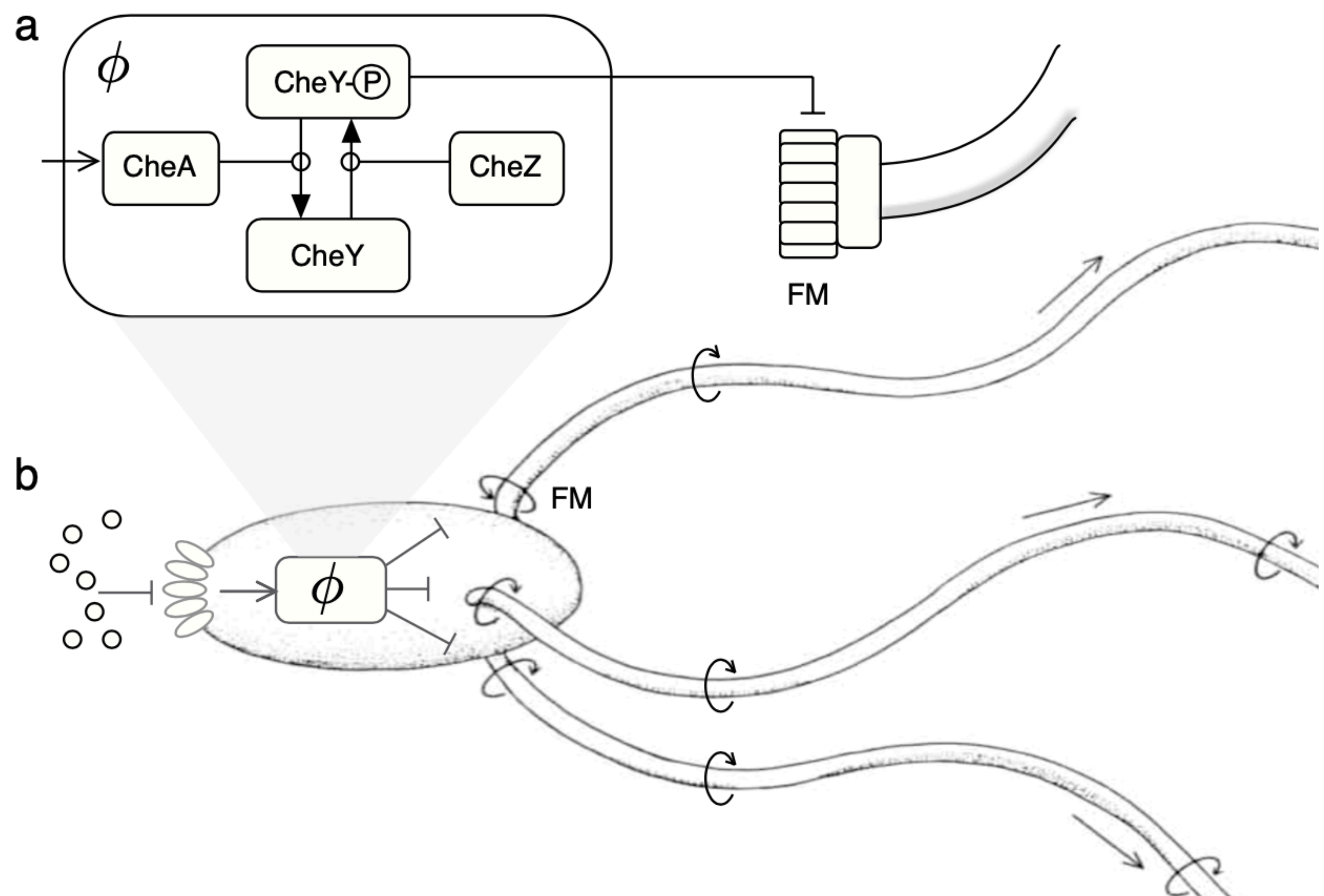
Harley H. McAdams and Lucy Shapiro



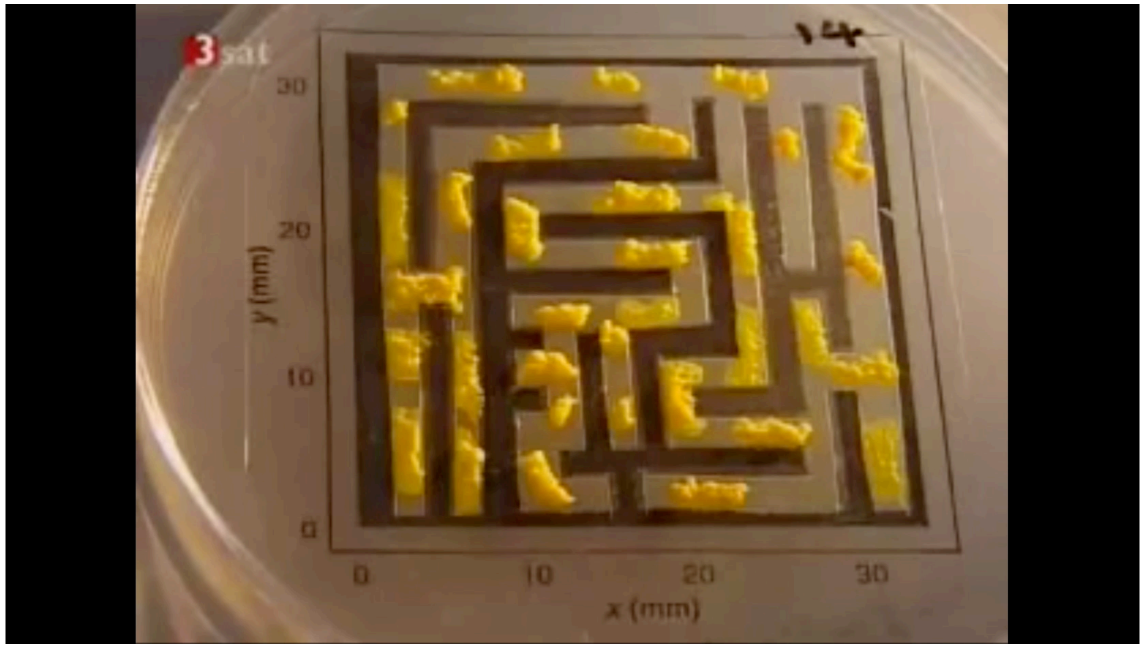


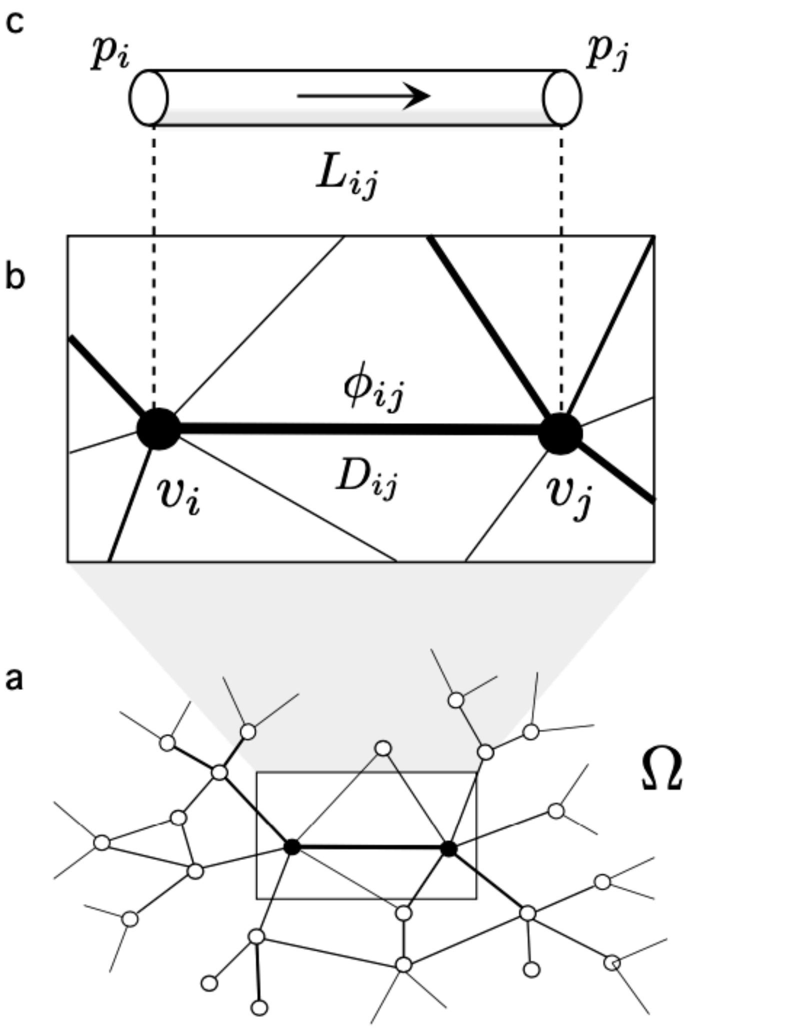
Single cells also move and search: a cellular brain?





Physarum machines: shortest path with brainless agents





$$\frac{dD_{ij}}{dt} = (1-\mu)\frac{|\phi|^n}{1+\mu|\phi|^n} - \delta D_{ij}$$

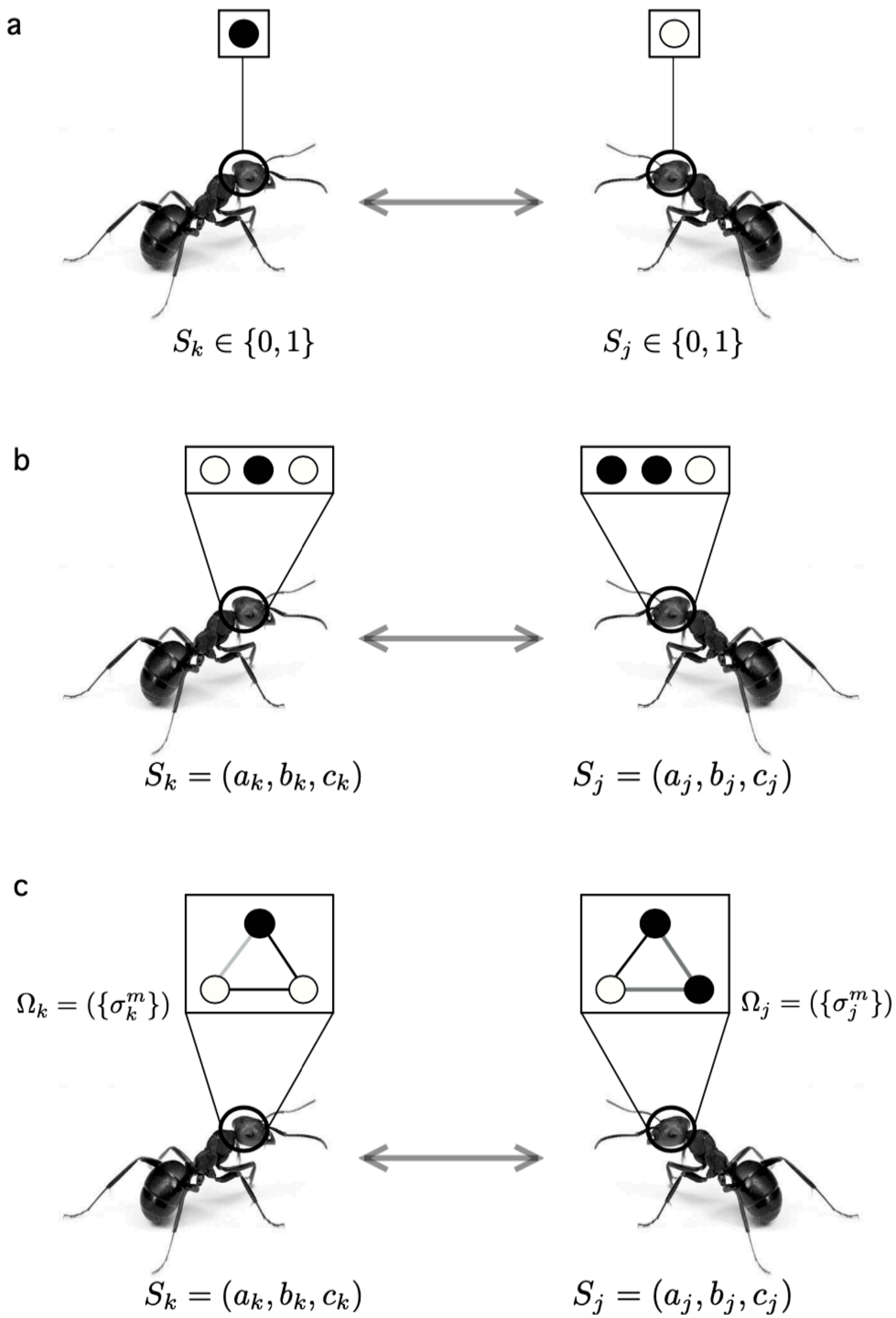
$$\frac{dD_1}{dt} = \left(\frac{D_1/L1}{D_1/L1 + D_2/L2}\right)^{\mu} - D_1$$

$$\frac{dD_2}{dt} = \left(\frac{D_2/L2}{D_1/L1 + D_2/L2}\right)^{\mu} - D_2$$

If ant colonies are like liquid brains,
what kind of attractors are there?

What are the constraints to cognition?

Ant colonies as liquid cognitive networks

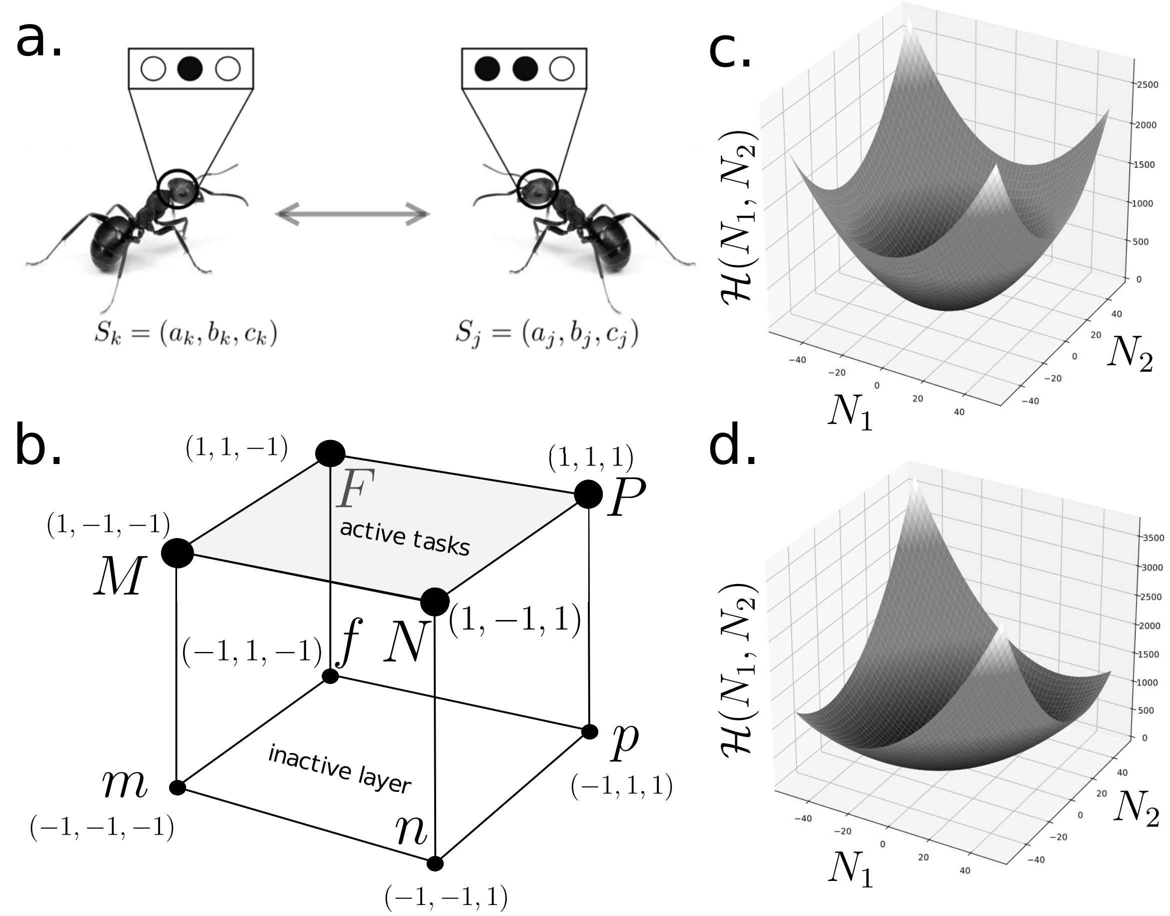


Each individual is a "neural agent"

Ant colonies as liquid cognitive networks

$$S_j^\mu(t+1) = \Theta\left(h_j^\mu(t)\right) = \Theta\left(\sum_k J_{jk}^\mu S_k^\mu(t)\right)$$

$$\mathcal{H}(\{S_k^\mu, J_{ij}^\mu\}) = -\frac{1}{2}\sum_\mu \sum_{i,j} J_{ij}^\mu S_i^\mu S_j^\mu \, .$$



$$\mathcal{H}(N_1, N_2) = -\frac{1}{2}\left(\sum_{S_i=+1} S_i h_i + \sum_{S_j=-1} S_j h_j\right)$$
$$= -\frac{1}{2}\left(\alpha N_1^2 + \alpha N_2^2 - 2\beta N_1 N_2\right) \, ,$$

The attractor is defined in terms of a population vector: is this a general result?

Colony attractors are highly degenerate. What about brain of brains?

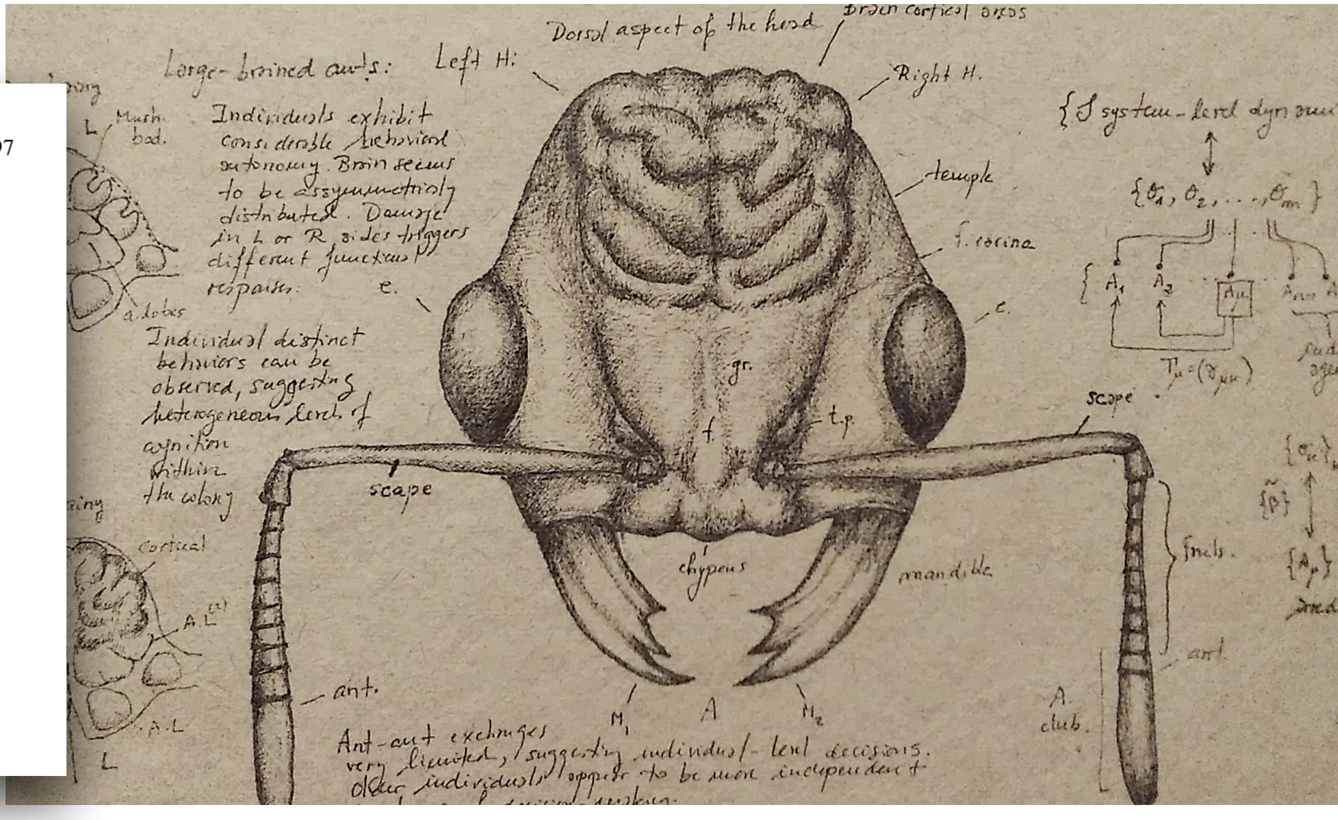
PHYSICAL REVIEW E VOLUME 55, NUMBER 3 MARCH 1997

Collective-induced computation

Jordi Delgado[1,2,3] and Ricard V. Solé[2,3]
[1]Departament de Llenguatges i Sistemes Informatics, Universitat Politecnica de Catalunya, Pau Gargallo 5, 08028 Barcelona, Spain
[2]Complex Systems Research Group, Departament de Física i Enginyeria Nuclear, Universitat Politècnica de Catalunya, Sor Eulàlia d'Anzizu s/n, Campus Nord, Mòdul B4, 08034 Barcelona, Spain
[3]Santa Fe Institute, 1399 Hyde Park Road, Santa Fe, New Mexico 87501
(Received 26 August 1996)

Many natural systems, such as social insects, perform complex computations collectively. In these groups, large numbers of individuals communicate in a local way and send information to its nearest neighbors. Interestingly, a general observation of these societies reveals that the cognitive capabilities of individuals are fairly limited, suggesting that the complex dynamics observed inside the collective is induced by the interactions among elements and is not defined at the individual level. In this paper we use globally coupled maps, as a generic theoretical model of a distributed system, and Crutchfield's statistical complexity, as our theoretical definition of complexity, to study the relation between the complexity the collective is able to induce on the individual and the complexity of the latter. It is conjectured that the observed patterns could be a generic property of complex dynamical nonlinear networks. [S1063-651X(97)00203-1]

PACS number(s): 05.45.+b



Evolution, 56(3), 2002, pp. 441–452

A COMPLEXITY DRAIN ON CELLS IN THE EVOLUTION OF MULTICELLULARITY

DANIEL W. MCSHEA
Department of Biology, Duke University, Durham, North Carolina 27708-0338
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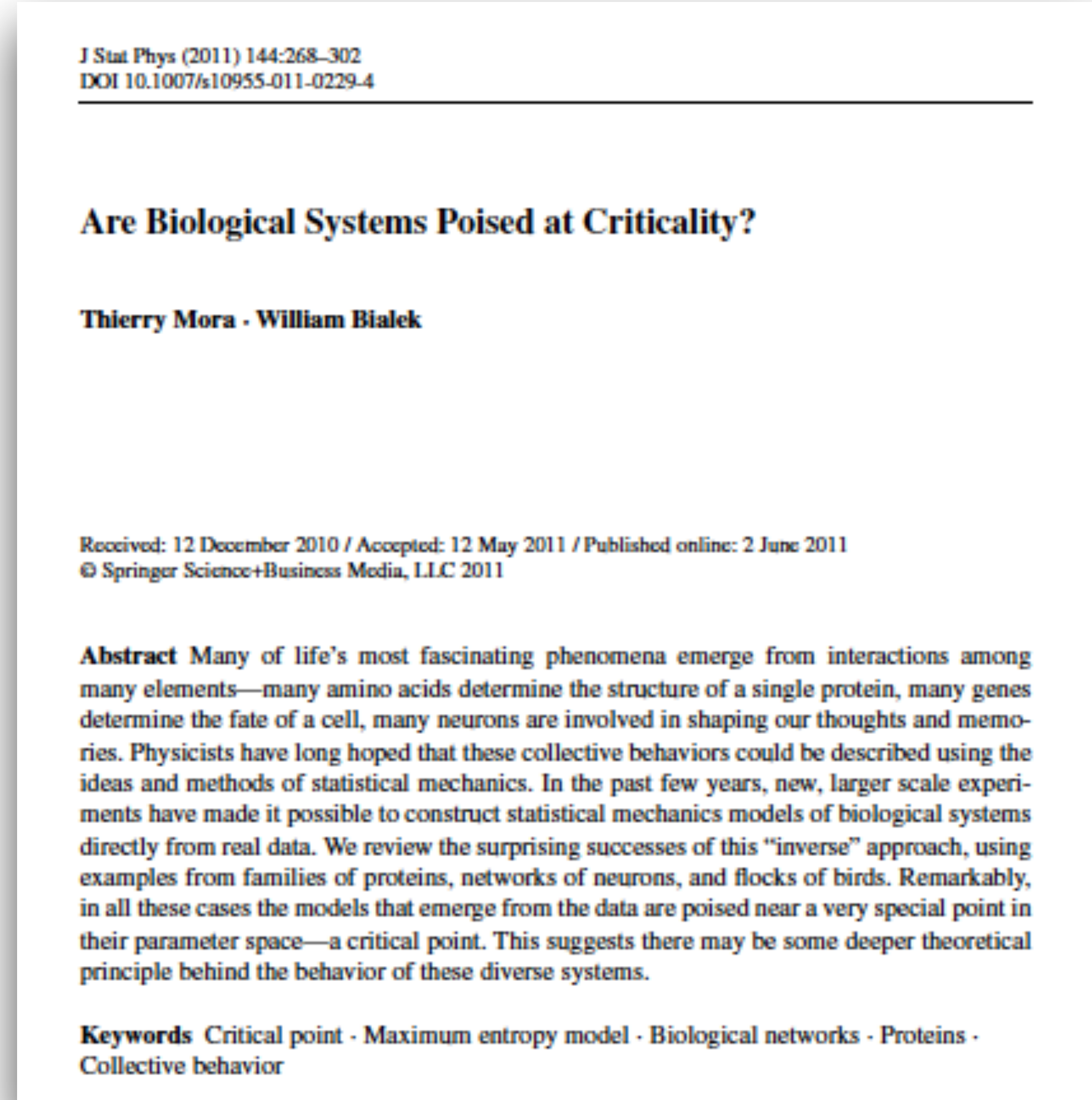
Abstract.—A hypothesis has been advanced recently predicting that, in evolution, as higher-level entities arise from associations of lower-level organisms, and as these entities acquire the ability to feed, reproduce, defend themselves, and so on, the lower-level organisms will tend to lose much of their internal complexity (McShea 2001a). In other words, in hierarchical transitions, there is a drain on numbers of part types at the lower level. One possible rationale is that the transfer of functional demands to the higher level renders many part types at the lower level useless, and thus their loss in evolution is favored by selection for economy. Here, a test is conducted at the cell level, comparing numbers of part types in free-living eukaryotic cells (protists) and the cells of metazoans and land plants. Differences are significant and consistent with the hypothesis, suggesting that tests at other hierarchical levels may be worthwhile.

Key words.—Complexity, evolutionary trends, hierarchy, parts.

Received June 18, 2001. Accepted October 15, 2001.

Is criticality relevant to liquid cognition too?

Criticality in swarms: collective behavior at criticality



J Stat Phys (2011) 144:268–302
DOI 10.1007/s10955-011-0229-4

Are Biological Systems Poised at Criticality?

Thierry Mora · William Bialek

Received: 12 December 2010 / Accepted: 12 May 2011 / Published online: 2 June 2011

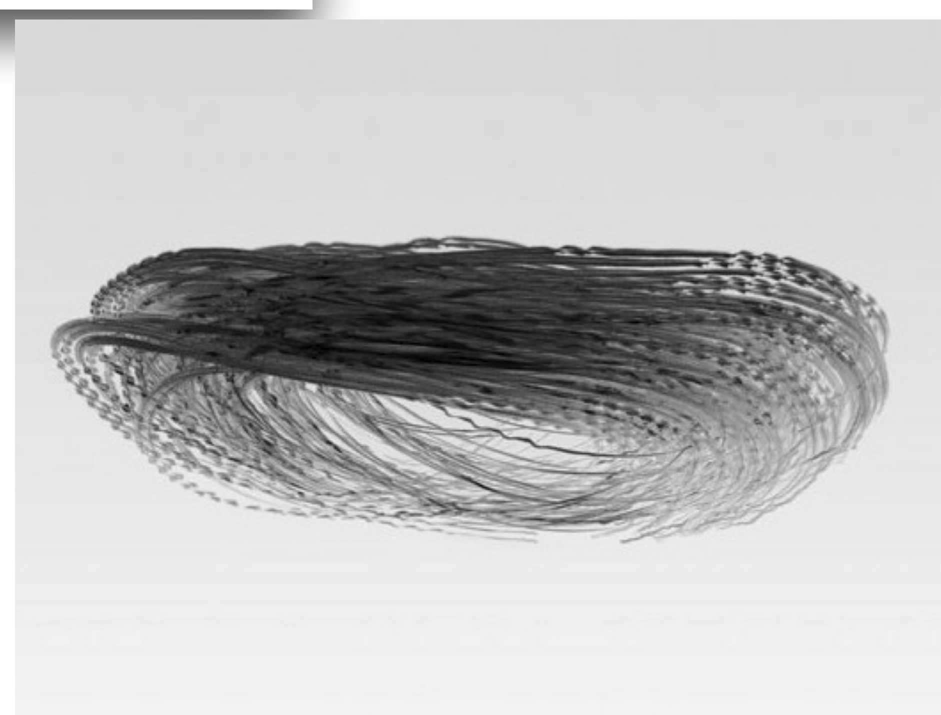
Abstract Many of life's most fascinating phenomena emerge from interactions among many elements—many amino acids determine the structure of a single protein, many genes determine the fate of a cell, many neurons are involved in shaping our thoughts and memories. Physicists have long hoped that these collective behaviors could be described using the ideas and methods of statistical mechanics. In the past few years, new, larger scale experiments have made it possible to construct statistical mechanics models of biological systems directly from real data. We review the surprising successes of this "inverse" approach, using examples from families of proteins, networks of neurons, and flocks of birds. Remarkably, in all these cases the models that emerge from the data are poised near a very special point in their parameter space—a critical point. This suggests there may be some deeper theoretical principle behind the behavior of these diverse systems.

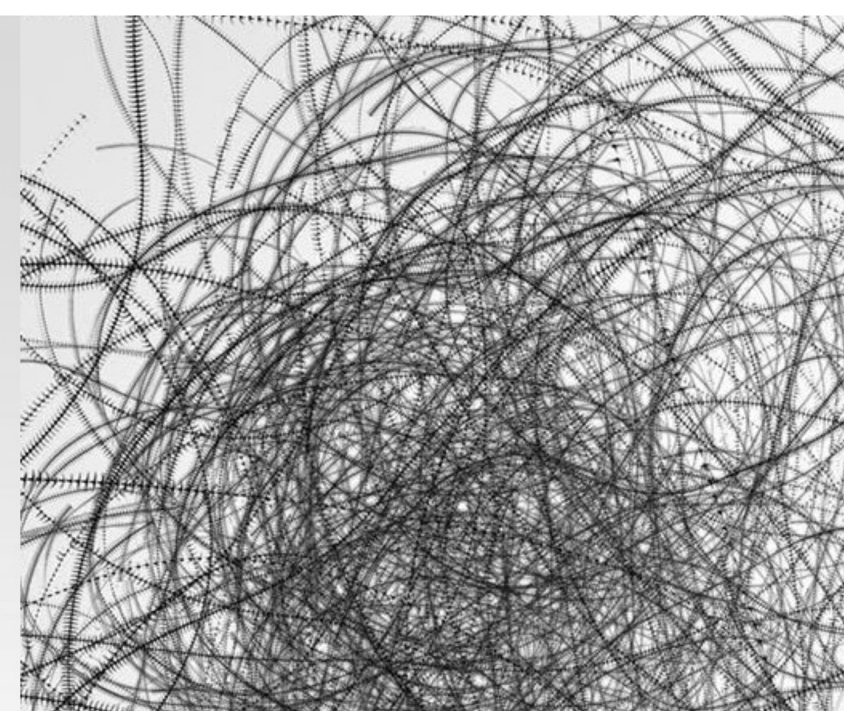
Keywords Critical point · Maximum entropy model · Biological networks · Proteins · Collective behavior

$$P(\{\vec{s}_i\}) = \frac{1}{Z(\{J_{ij}\})} \exp\left[\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} J_{ij}\vec{s}_i \cdot \vec{s}_j\right],$$

Statistical mechanics for natural flocks of birds

Bialek et al, PNAS 2012



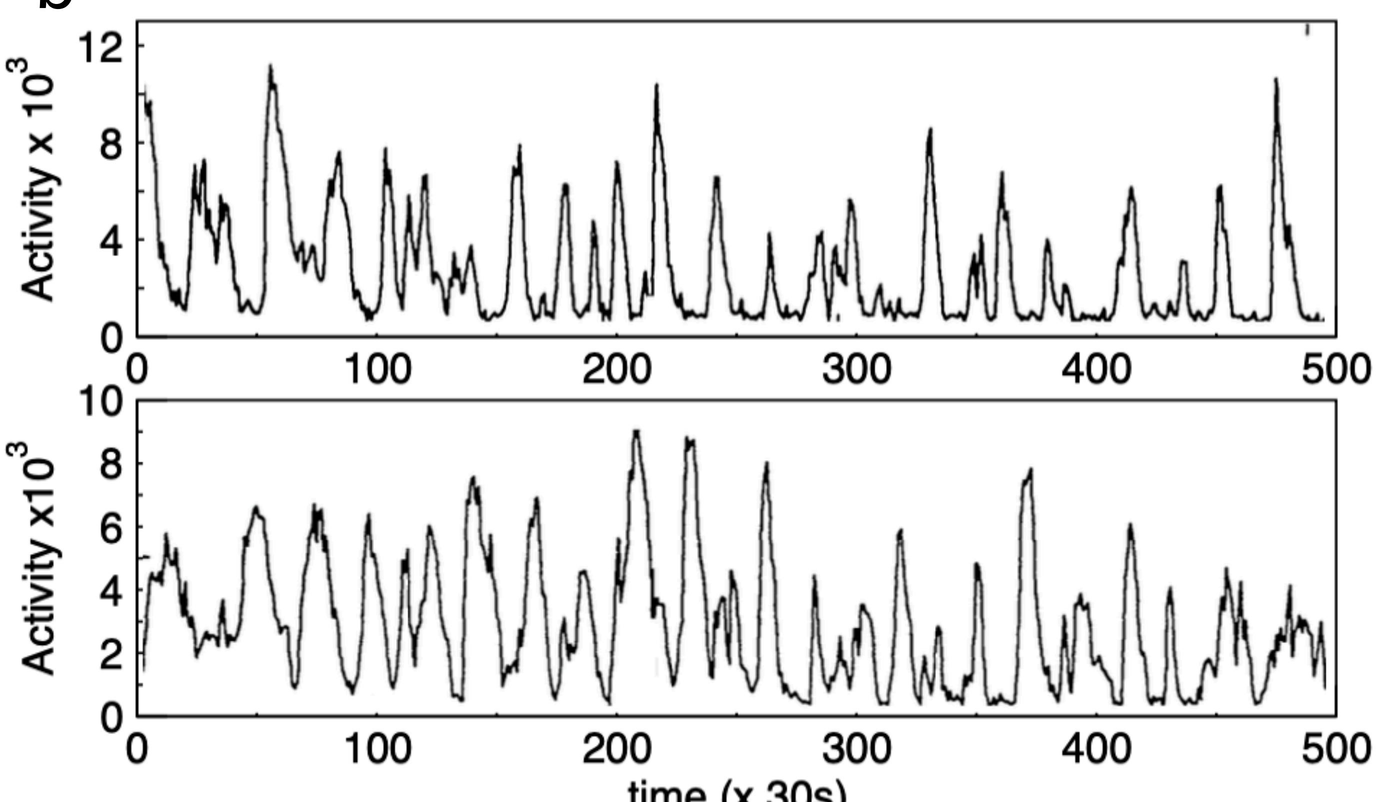


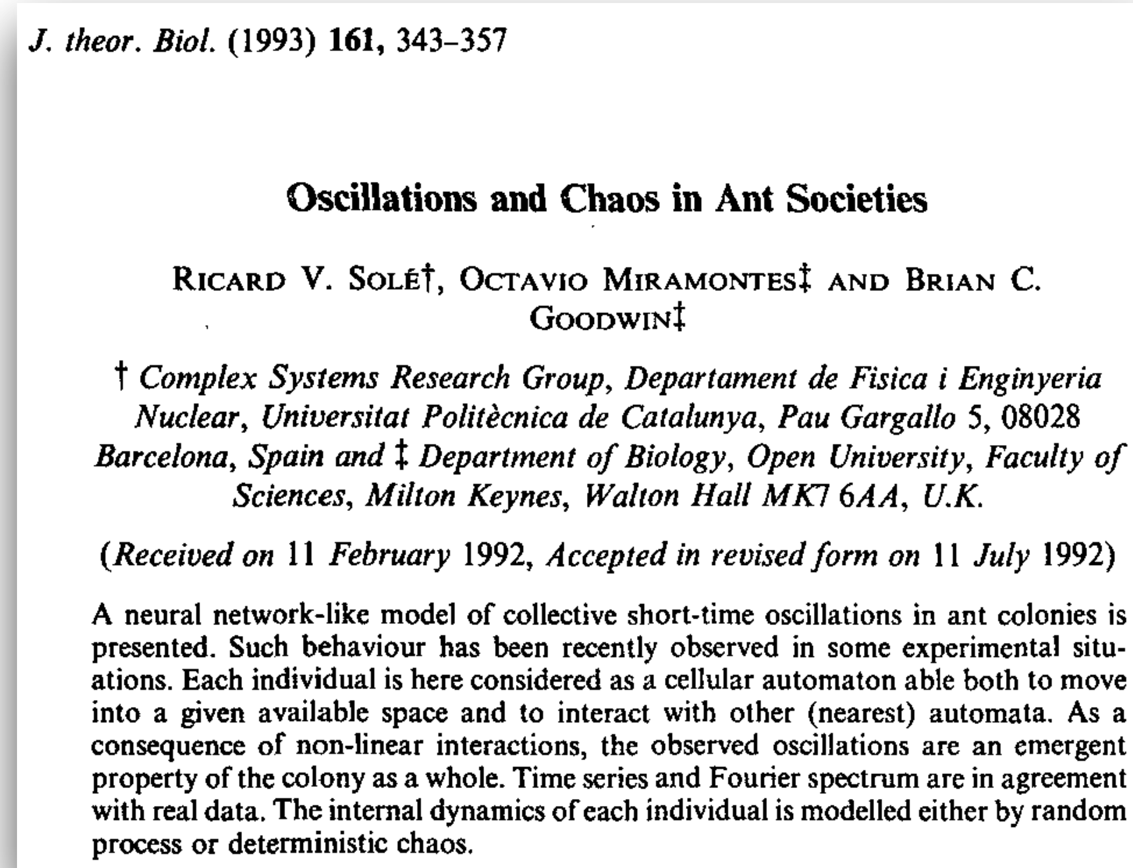
http://www.xavibou.com

Collective synchronisation of non-periodic agents

a

b





J. theor. Biol. (1993) **161,** 343–357

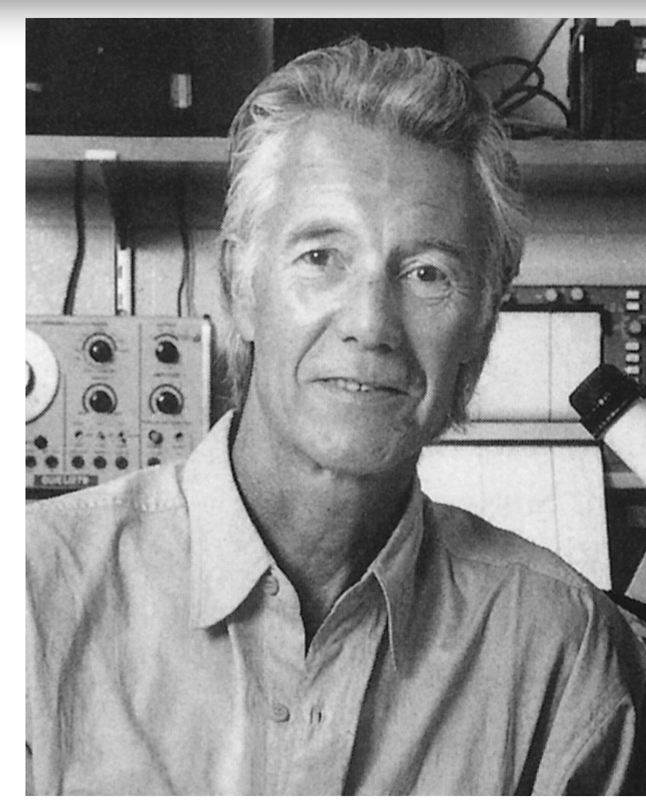
Oscillations and Chaos in Ant Societies

Ricard V. Solé†, Octavio Miramontes‡ and Brian C. Goodwin‡

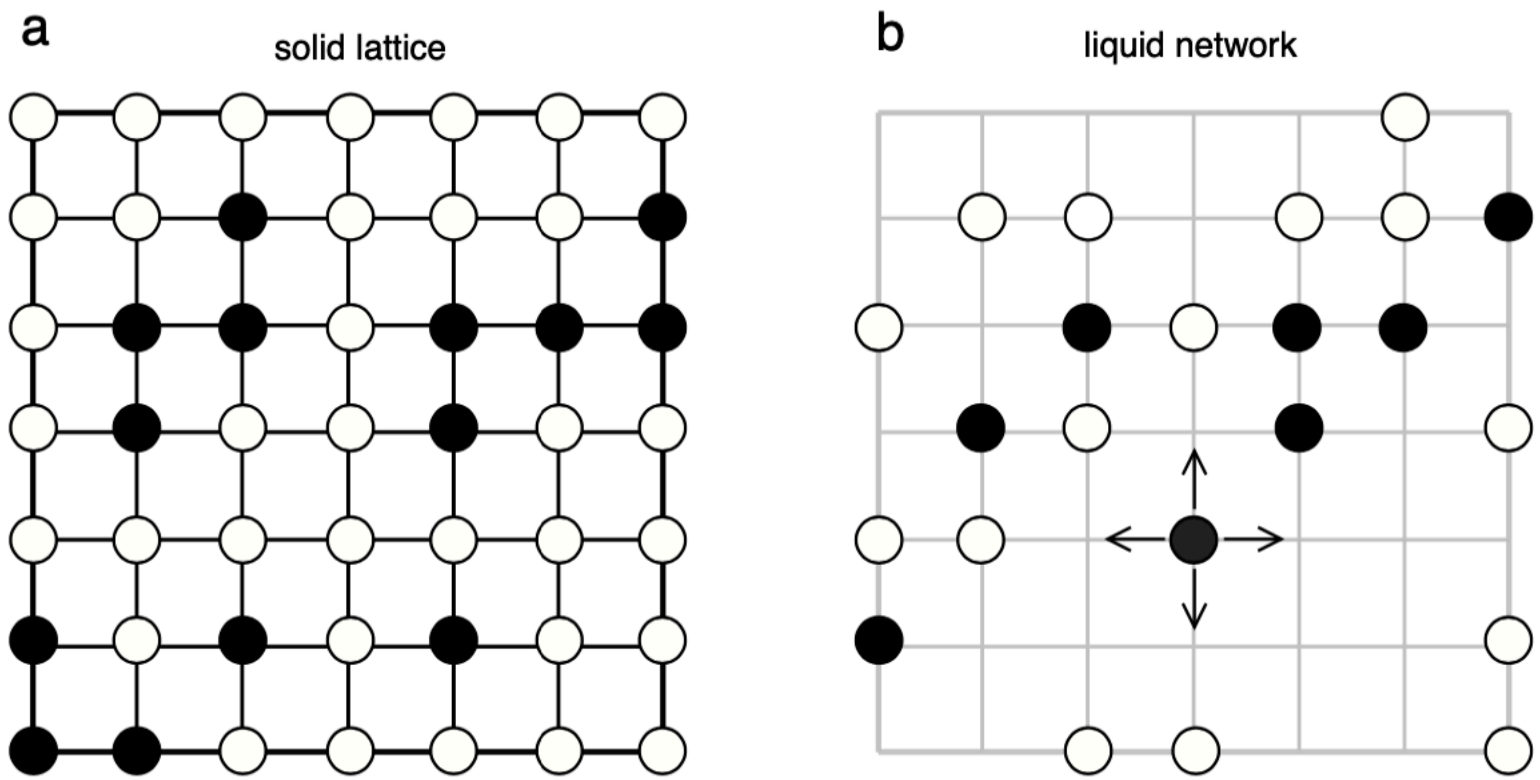
† *Complex Systems Research Group, Departament de Fisica i Enginyeria Nuclear, Universitat Politècnica de Catalunya, Pau Gargallo 5, 08028 Barcelona, Spain and* ‡ *Department of Biology, Open University, Faculty of Sciences, Milton Keynes, Walton Hall MK7 6AA, U.K.*

(*Received on* 11 *February* 1992, *Accepted in revised form on* 11 *July* 1992)

A neural network-like model of collective short-time oscillations in ant colonies is presented. Such behaviour has been recently observed in some experimental situations. Each individual is here considered as a cellular automaton able both to move into a given available space and to interact with other (nearest) automata. As a consequence of non-linear interactions, the observed oscillations are an emergent property of the colony as a whole. Time series and Fourier spectrum are in agreement with real data. The internal dynamics of each individual is modelled either by random process or deterministic chaos.



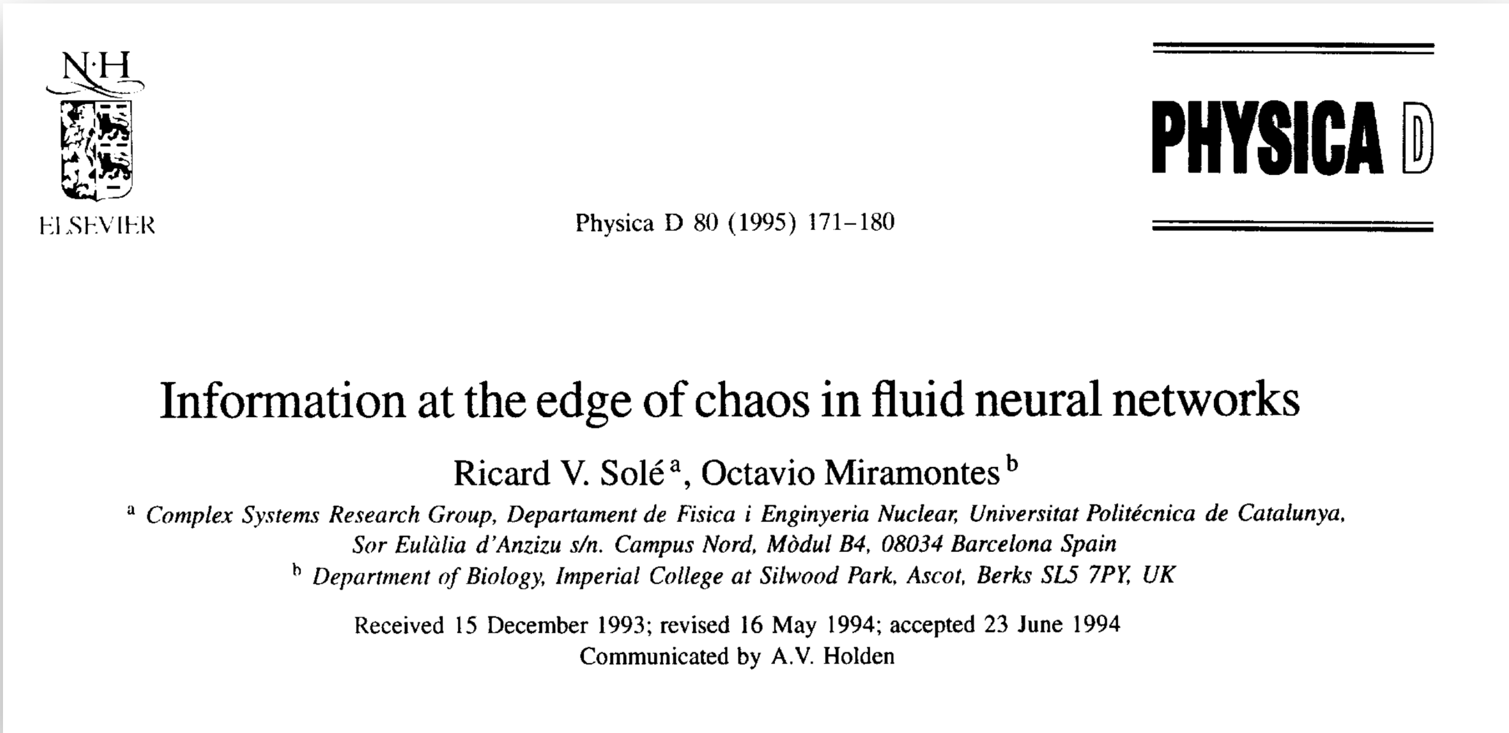
Collective synchronisation



$$[J(\eta_j, \eta_i)] = \begin{bmatrix} J_{00} & J_{01} \\ J_{10} & J_{11} \end{bmatrix}$$

$$S_i(t+1) = \Theta\left(\sum_{j \in \Gamma_i} J(\eta_j(t), \eta_i(t)) S_j(t)\right)$$

At criticality



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Physica D 80 (1995) 171–180

PHYSICA D

Information at the edge of chaos in fluid neural networks

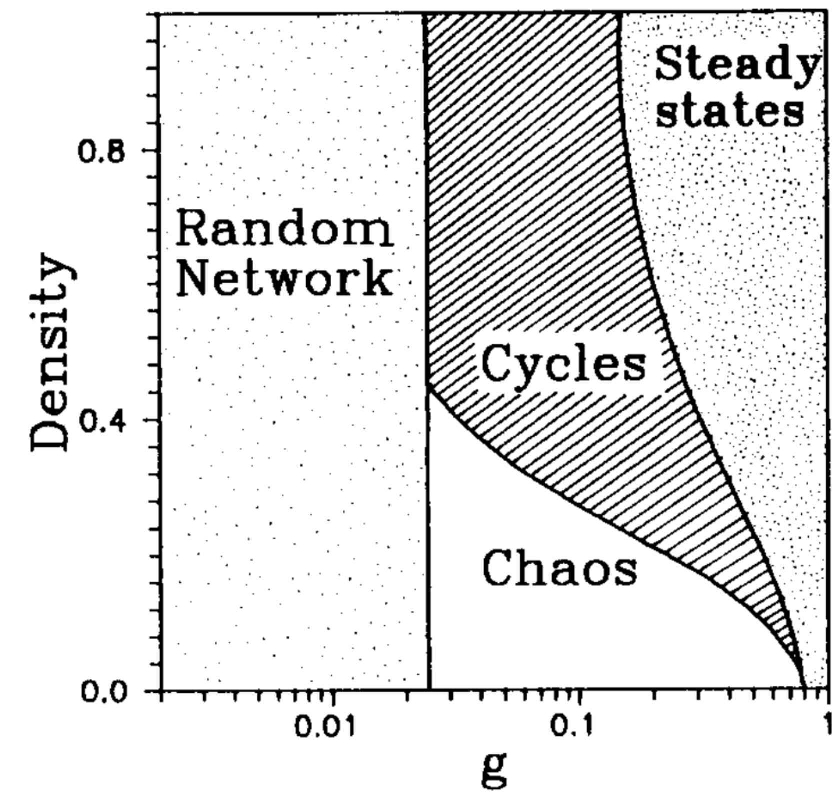
Ricard V. Solé [a], Octavio Miramontes [b]

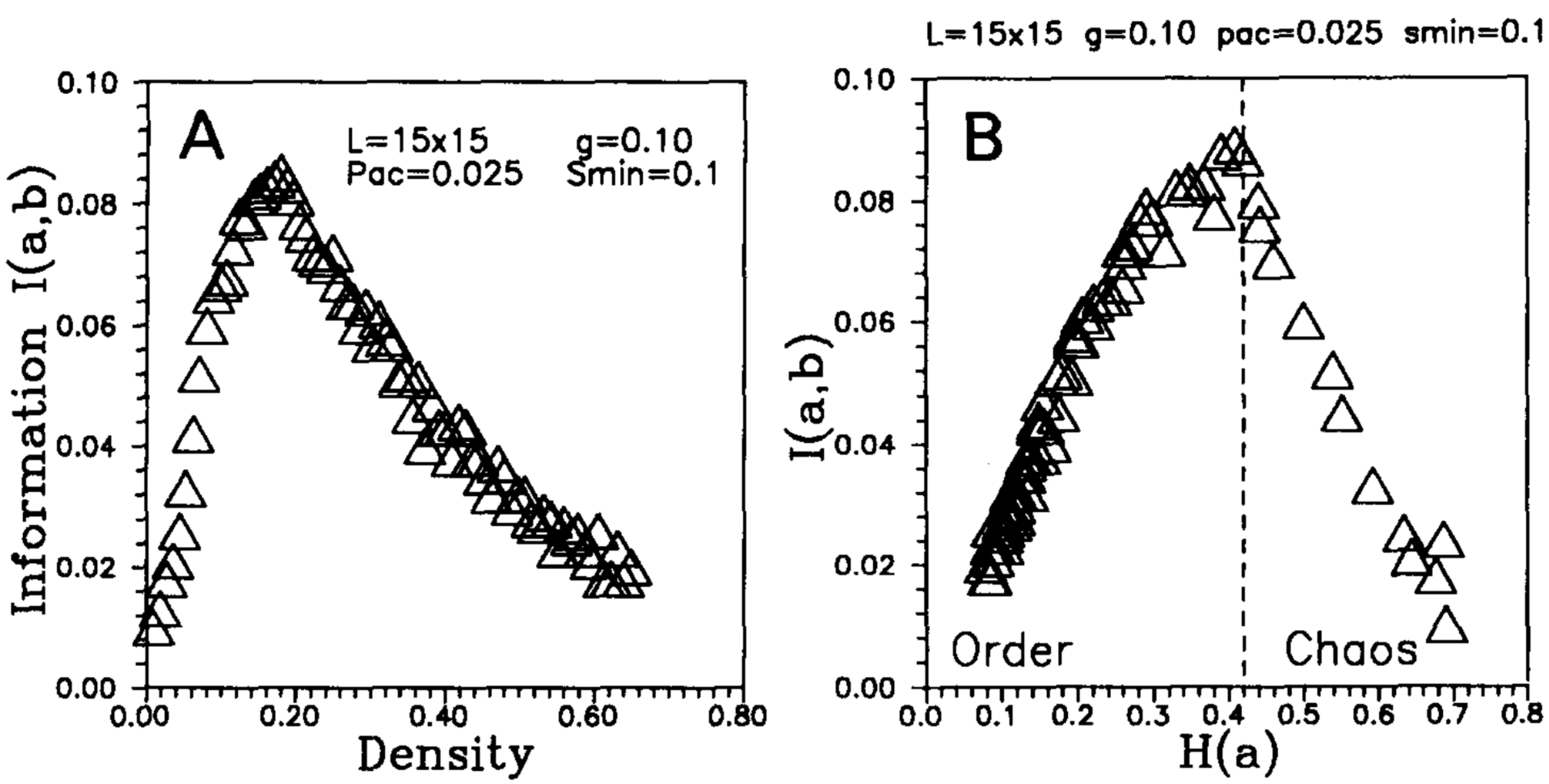
[a] Complex Systems Research Group, Departament de Fisica i Enginyeria Nuclear, Universitat Politécnica de Catalunya, Sor Eulàlia d'Anzizu s/n. Campus Nord, Mòdul B4, 08034 Barcelona Spain

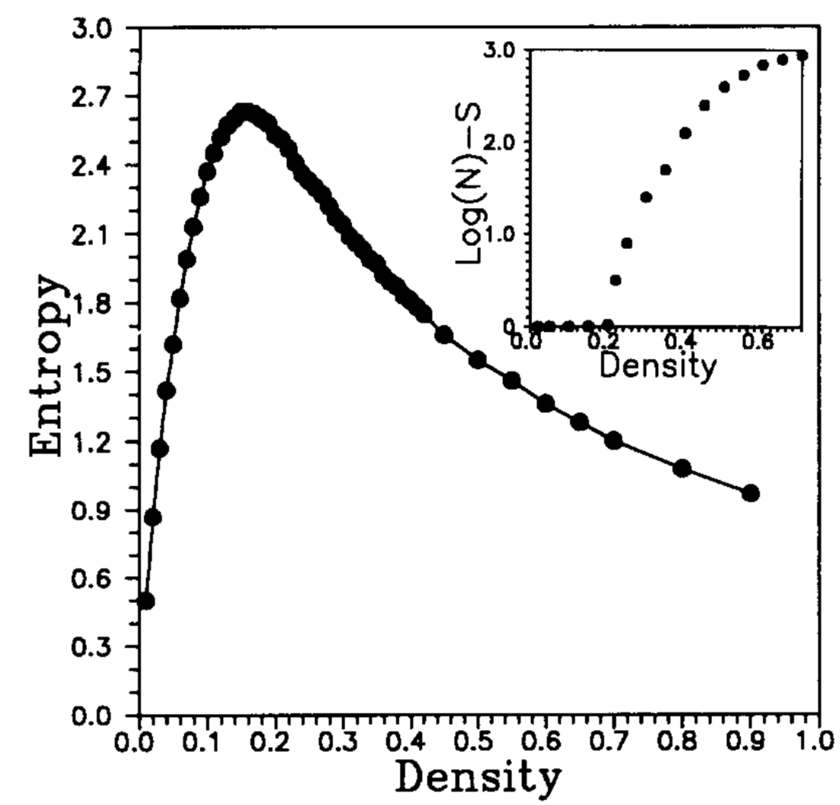
[b] Department of Biology, Imperial College at Silwood Park, Ascot, Berks SL5 7PY, UK

Received 15 December 1993; revised 16 May 1994; accepted 23 June 1994

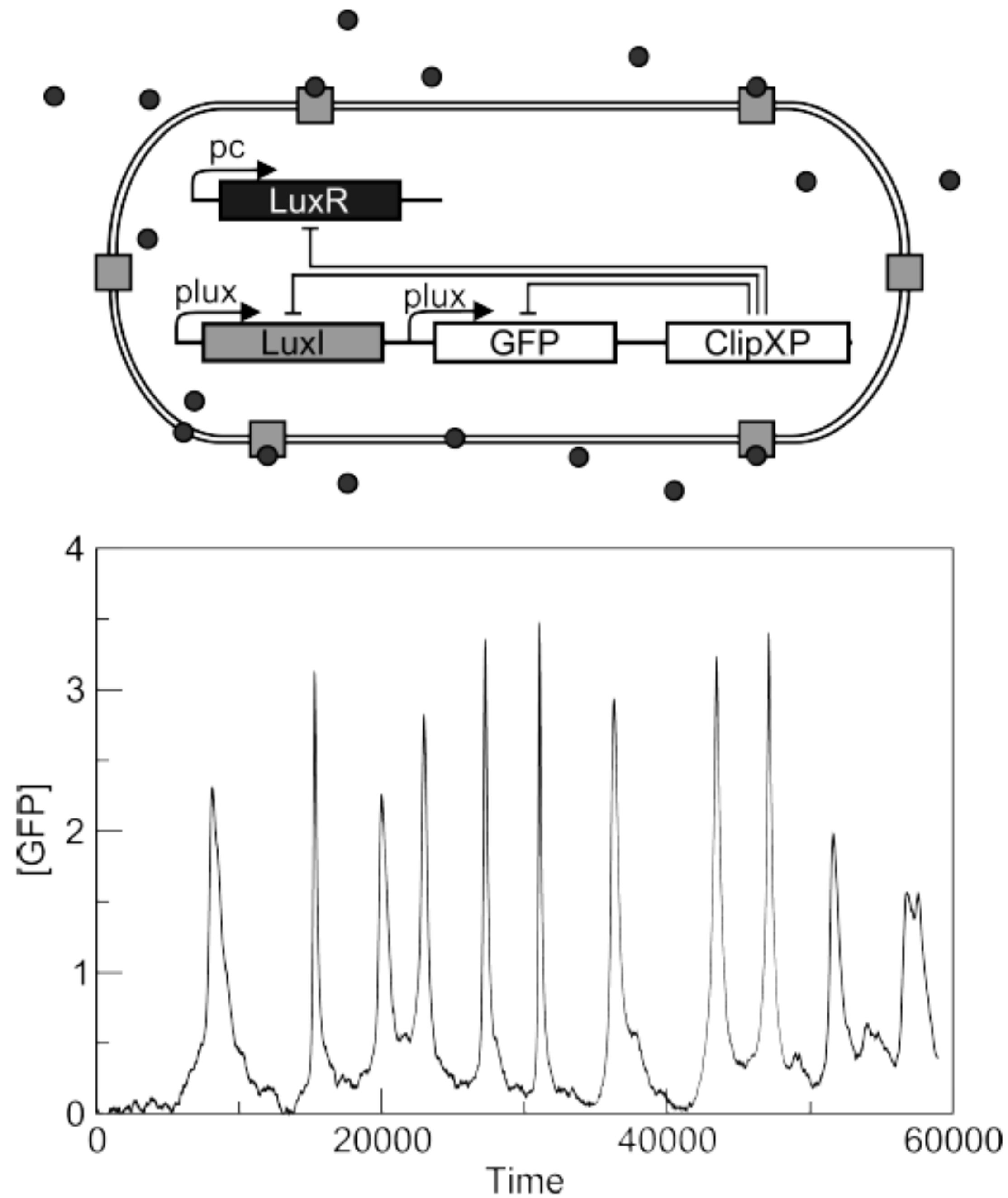
Communicated by A.V. Holden

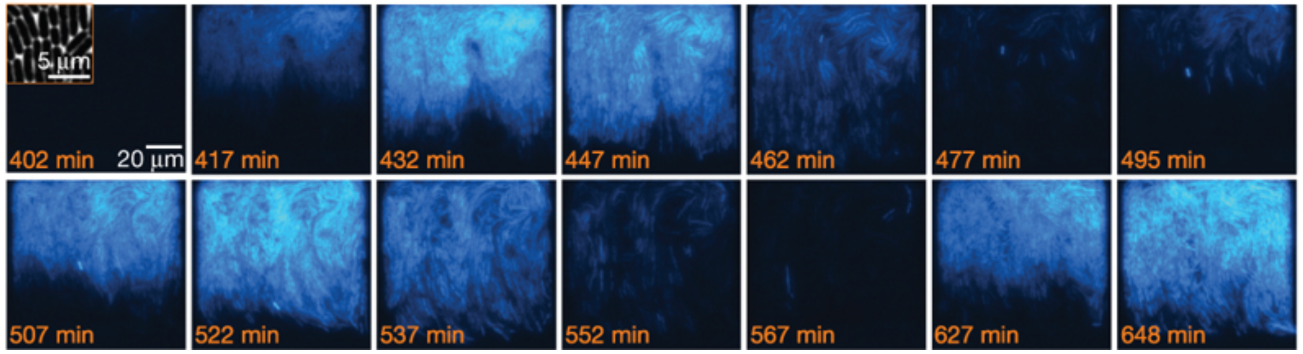


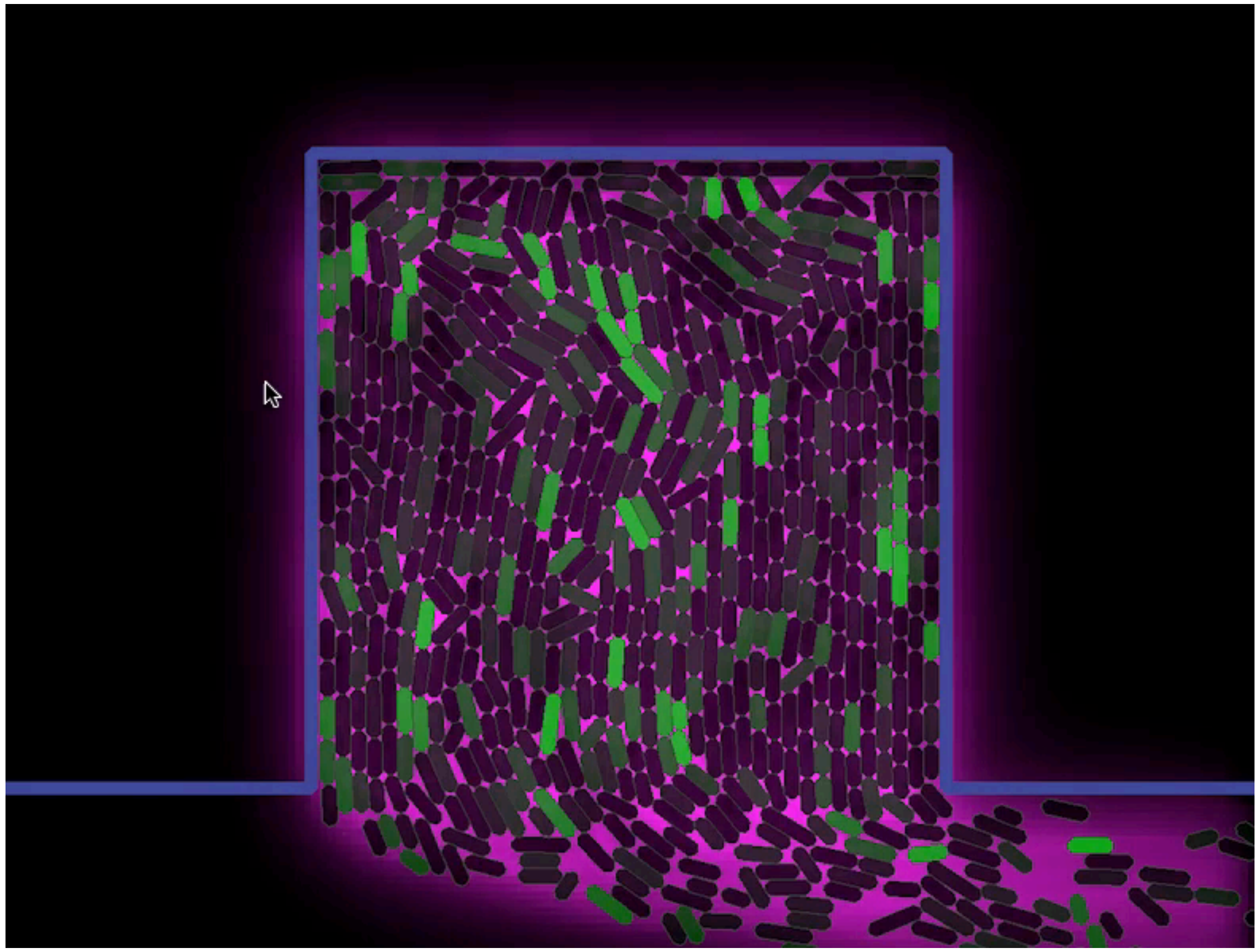




Collective synchronisation: making synthetic ants







Criticality in cells

PNAS PNAS PNAS PNAS

Gene expression dynamics in the macrophage exhibit criticality

Matti Nykter*†, Nathan D. Price†, Maximino Aldana‡, Stephen A. Ramsey†, Stuart A. Kauffman§, Leroy E. Hood†¶, Olli Yli-Harja*, and Ilya Shmulevich†¶

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Contributed by Leroy E. Hood, December 14, 2007 (sent for review October 20, 2007)

Cells are dynamical systems of biomolecular interactions that process information from their environment to mount diverse yet specific responses. A key property of many self-organized systems is that of criticality: a state of a system in which, on average, perturbations are neither dampened nor amplified, but are propagated over long temporal or spatial scales. Criticality enables the coordination of complex macroscopic behaviors that strike an optimal balance between stability and adaptability. It has long been hypothesized that biological systems are critical. Here, we address this hypothesis experimentally for system-wide gene expression dynamics in the macrophage. To this end, we have developed a method, based on algorithmic information theory, to assess macrophage criticality, and we have validated the method on networks with known properties. Using global gene expression data from macrophages stimulated with a variety of Toll-like receptor agonists, we found that macrophage dynan critical, providing the most compelling evidence tc general principle of dynamics in biological systems

complex systems | normalized compression distance | infor

exposure to certain stimuli. Therein lies a delicate balance between stability and adaptability. Too much stability—a characteristic of ordered behavior—and the system cannot respond to changes, rendering it inflexible. Too much sensitivity—a feature of chaotic behavior—and the system loses its ability to maintain one or more stable steady states necessary for executing orderly cellular functions.

Such exquisite molecular decision-making is exemplified by the macrophage, a cornerstone cell type of the innate immune system and a key regulator of the inflammatory response. Batteries of cell surface receptors, such as the Toll-like receptors (TLRs), recognize different pathogen-associated molecular patterns and propagate that information through intracellular molecular networks (15). By combining the information associated with each of these molecular patterns, the macrophage triggers

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Journal of Theoretical Biology 246 (2007) 449–460

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Why a simple model of genetic regulatory networks describes the distribution of avalanches in gene expression data

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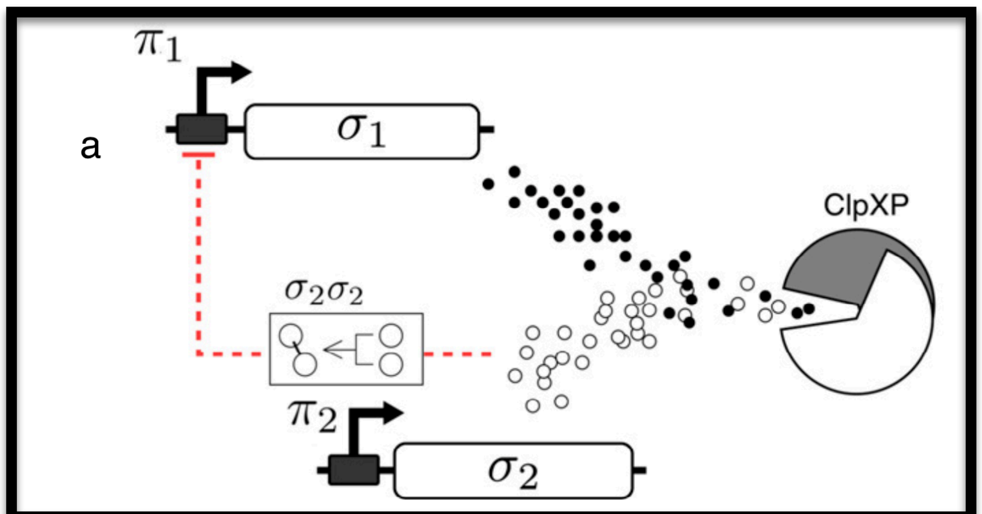
Available online 24 January 2007

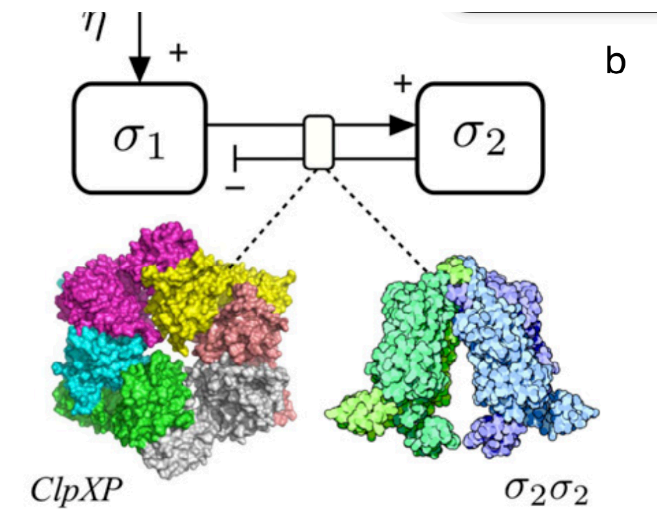
Engineering synthetic criticality in cells

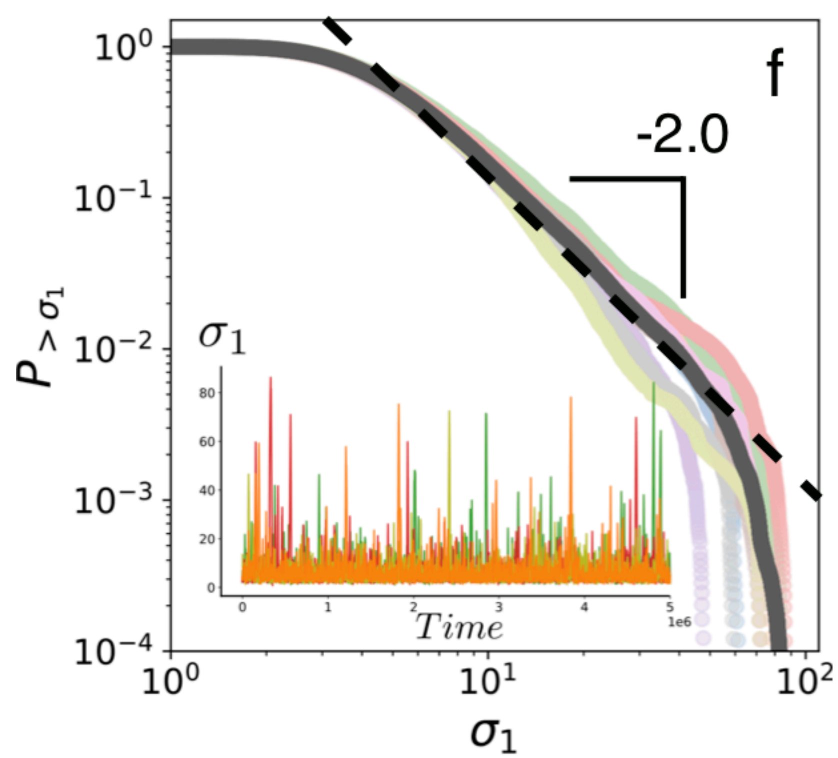
$$\begin{cases} \dfrac{d\sigma_1}{dt} = f(\sigma_2) - \delta_1\,\sigma_1 - \sigma_1\Gamma(\sigma_1,\sigma_2), \\ \\ \dfrac{d\sigma_2}{dt} = \eta_2 - \delta_2\,\sigma_2 - \sigma_2\Gamma(\sigma_1,\sigma_2). \end{cases}$$

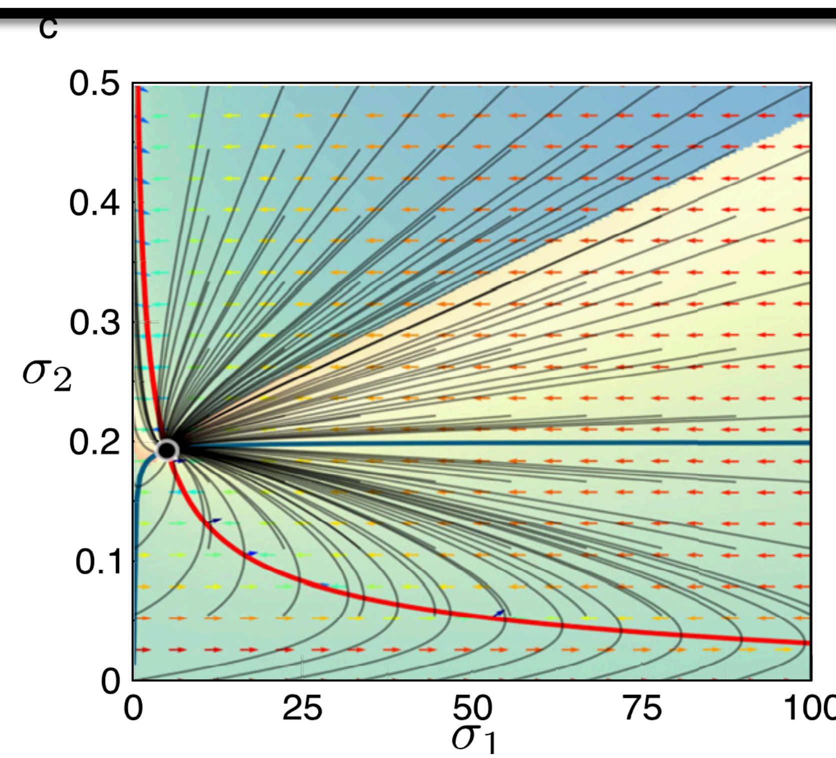
$$\Gamma(\sigma_1,\sigma_2) = \frac{\delta_c C}{K + \sigma_1 + \sigma_2}$$

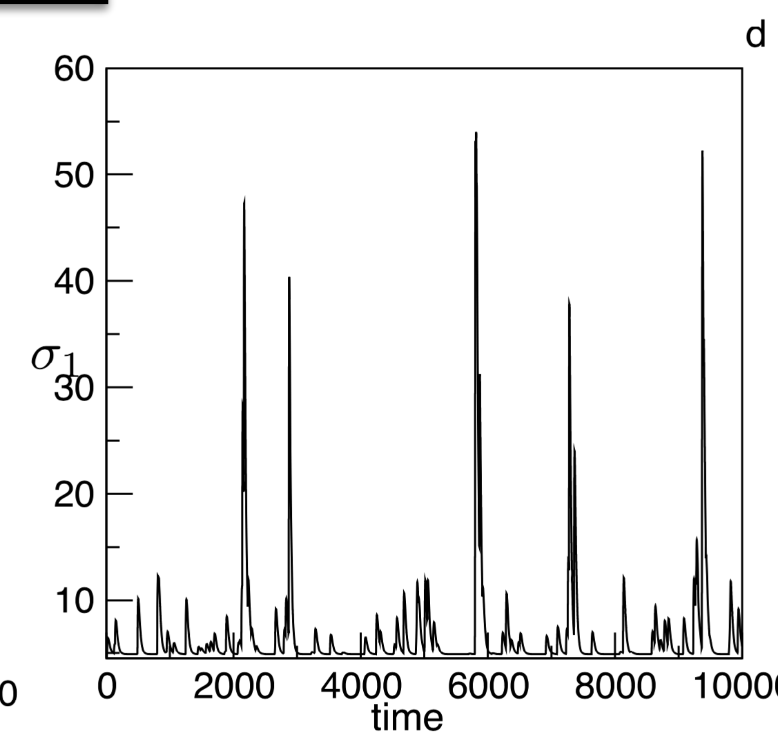
$$f(\sigma_2) = \frac{\eta_1}{\theta + \mu^2\,\sigma_2^2}.$$





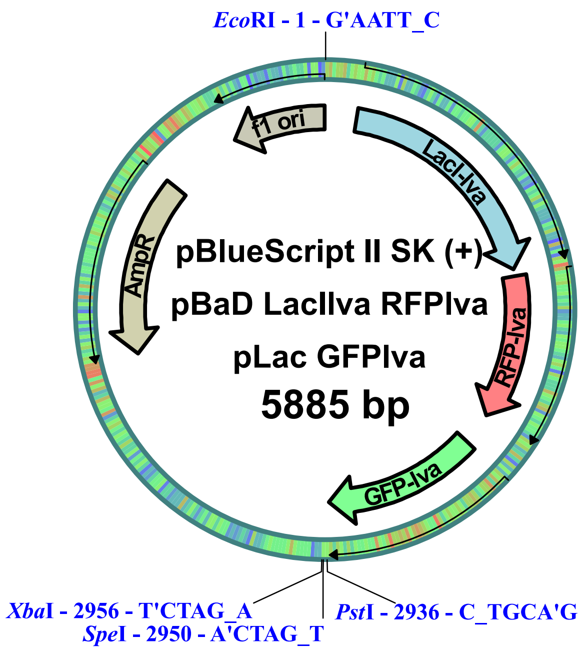


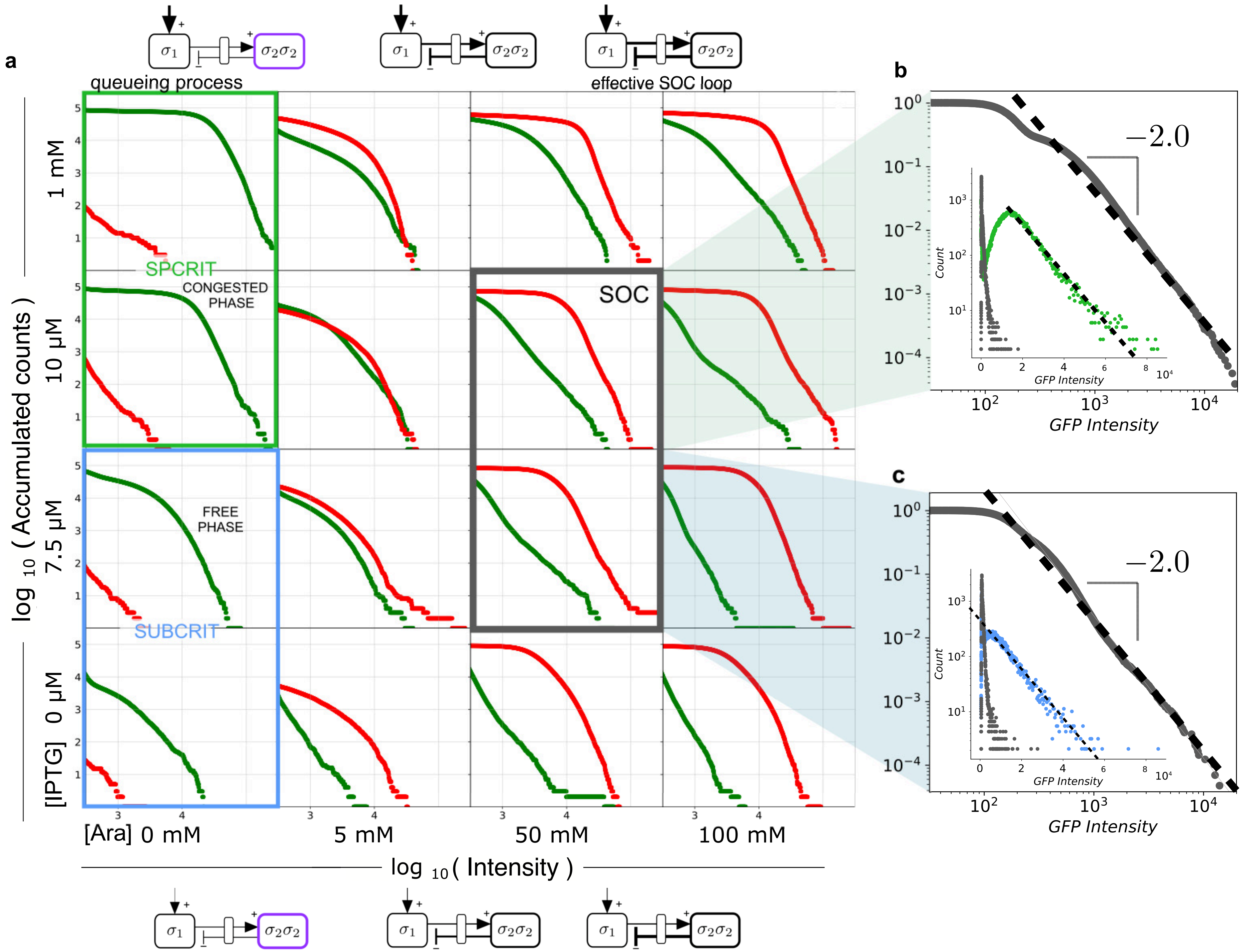




Vidiella, B. Et al. 2021. **Engineering self-organized criticality in living cells.** Nature Comm.12:4415

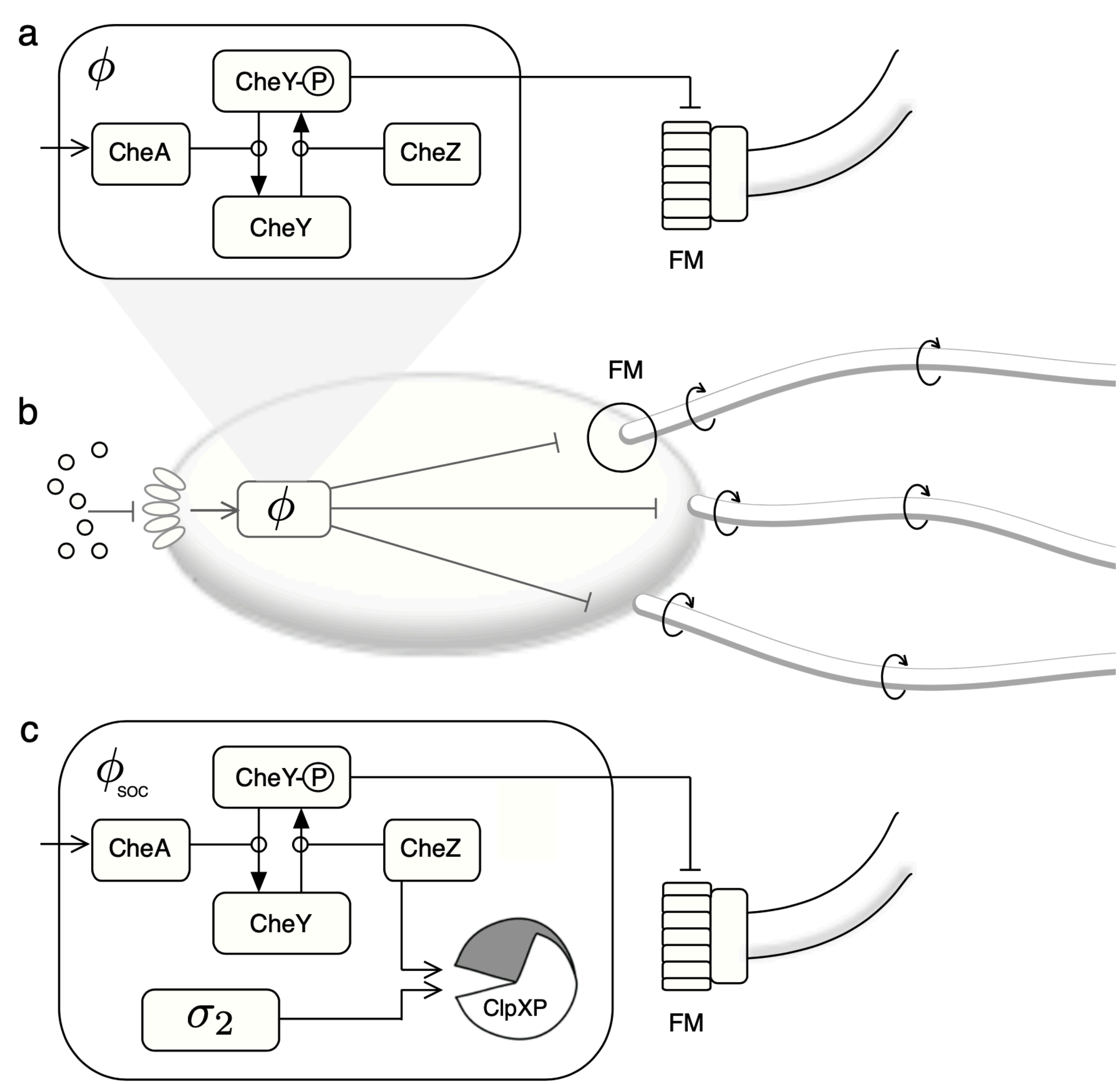
Engineering synthetic criticality in cells



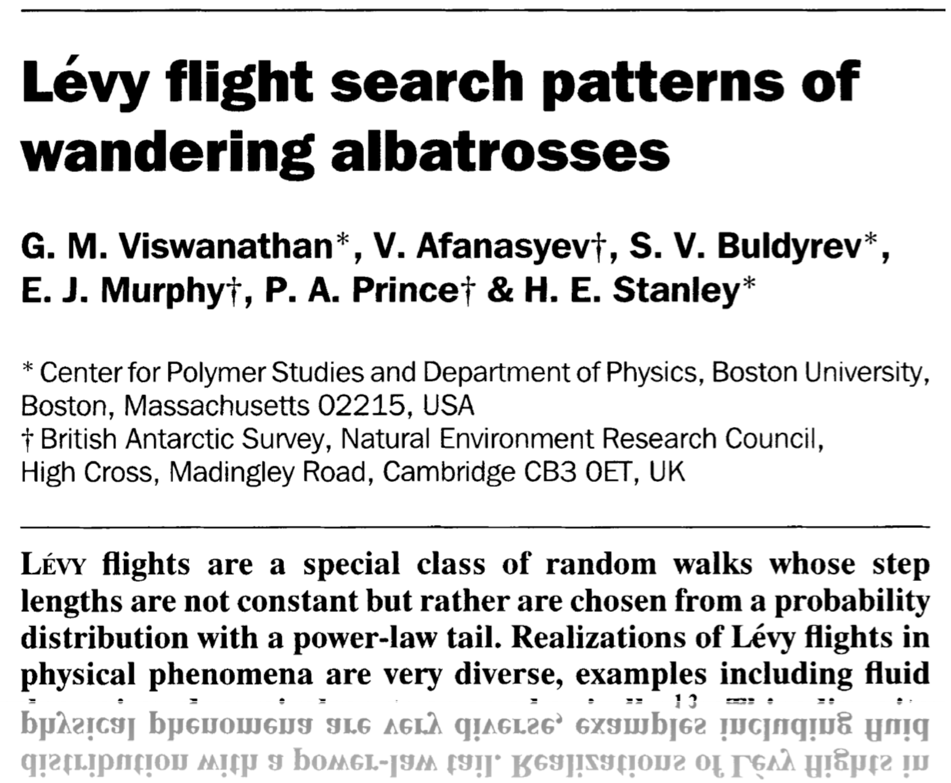


Vidiella, B. Et al. 2021. **Engineering self-organized criticality in living cells.** Nature Comm.12:4415

Synthetic search patterns?



Solé, R. et al.. 2021. **Synthetic criticality in cellular brains.** J. Phys. Complexity 2, 041001

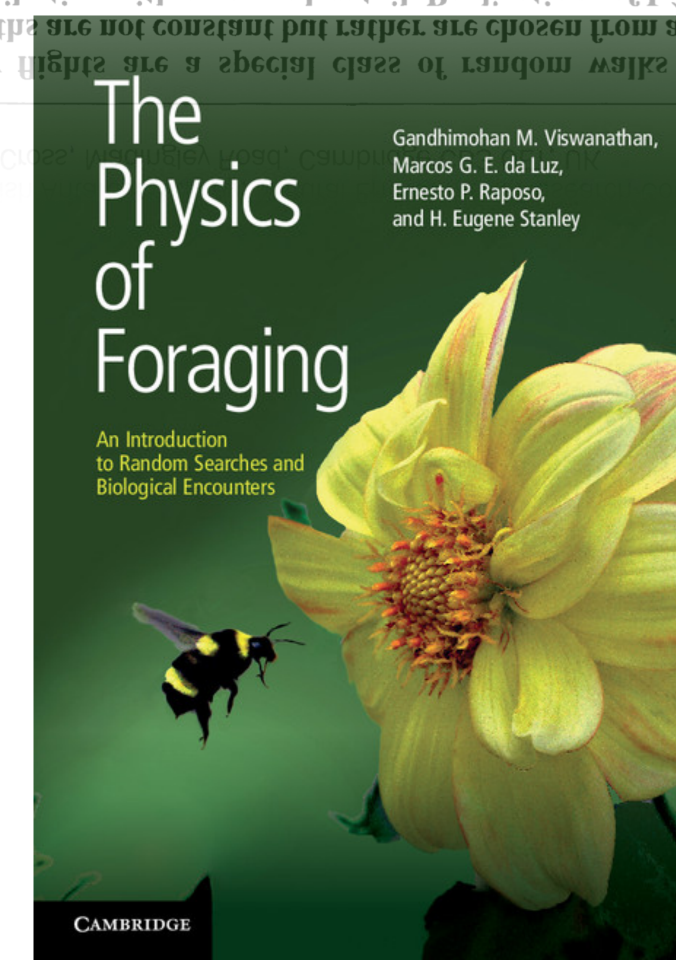


Lévy flight search patterns of wandering albatrosses

G. M. Viswanathan*, V. Afanasyev†, S. V. Buldyrev*, E. J. Murphy†, P. A. Prince† & H. E. Stanley*

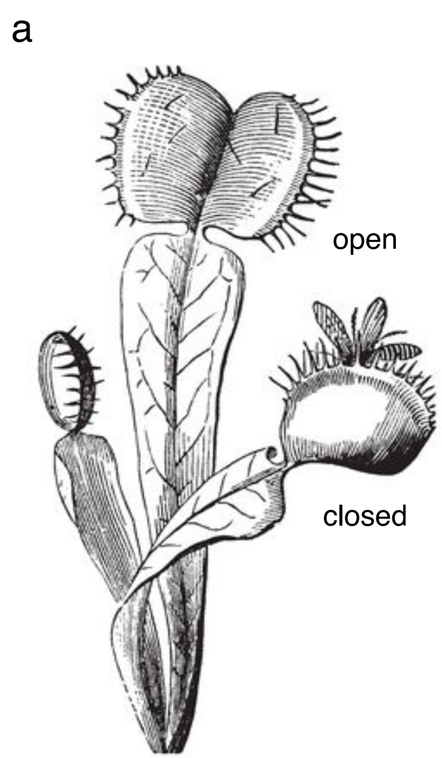
* Center for Polymer Studies and Department of Physics, Boston University, Boston, Massachusetts 02215, USA
† British Antarctic Survey, Natural Environment Research Council, High Cross, Madingley Road, Cambridge CB3 0ET, UK

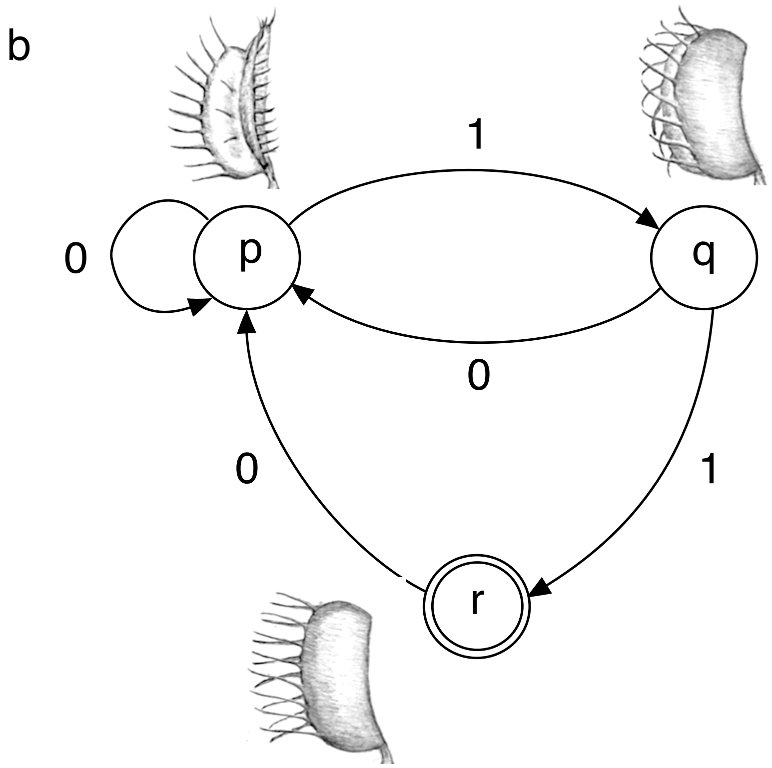
Lévy flights are a special class of random walks whose step lengths are not constant but rather are chosen from a probability distribution with a power-law tail. Realizations of Lévy flights in physical phenomena are very diverse, examples including fluid



What about plants?

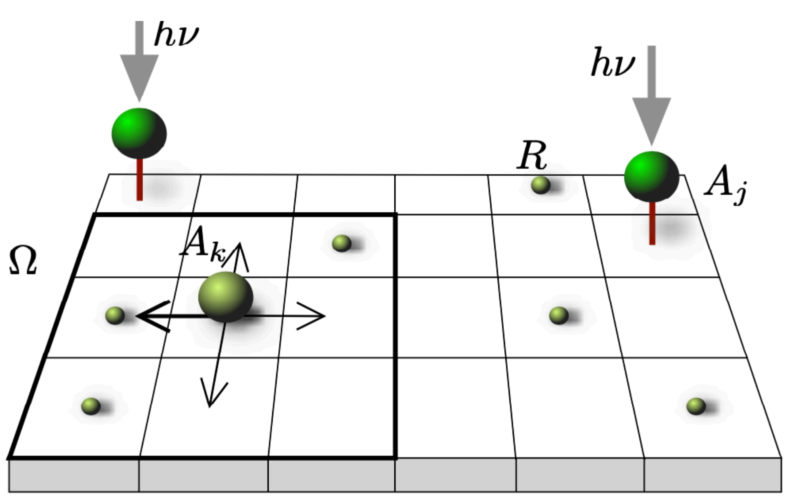
Plant intelligence? No movement, no cognition?

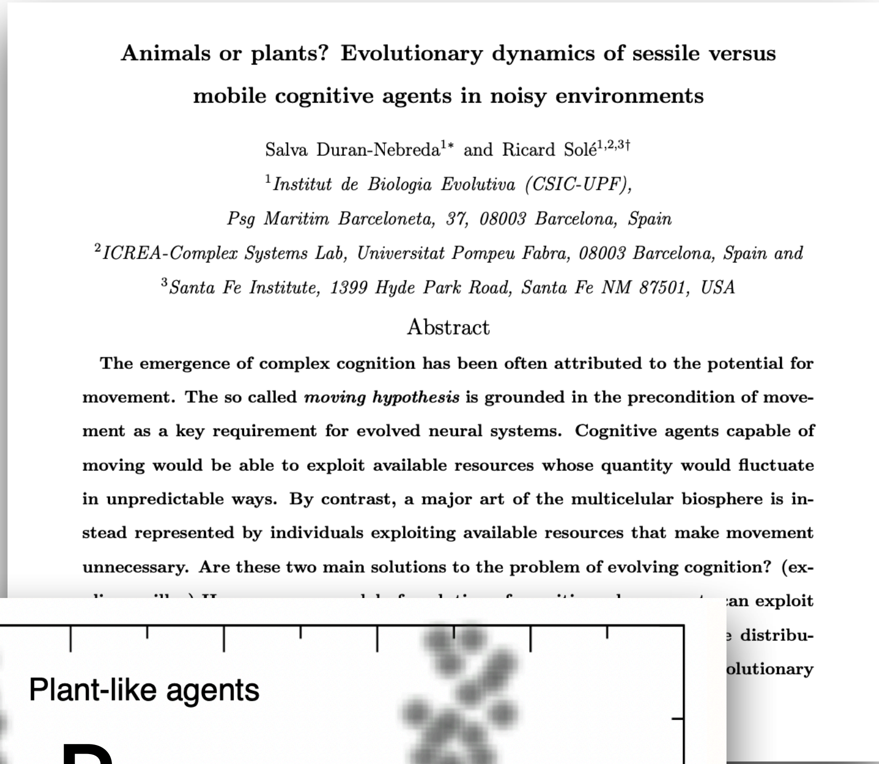




$$U_{plant}(A_\mu(j,k)) = u_L \mathcal{L}(j',k')$$

$$U_{animal}(A_\mu(j,k),\mathcal{V}_\mu) = \sum_{(j',k')\in\Gamma_\mu(j,k)} u_R P(j',k') u_R \mathcal{R}(j',k')$$



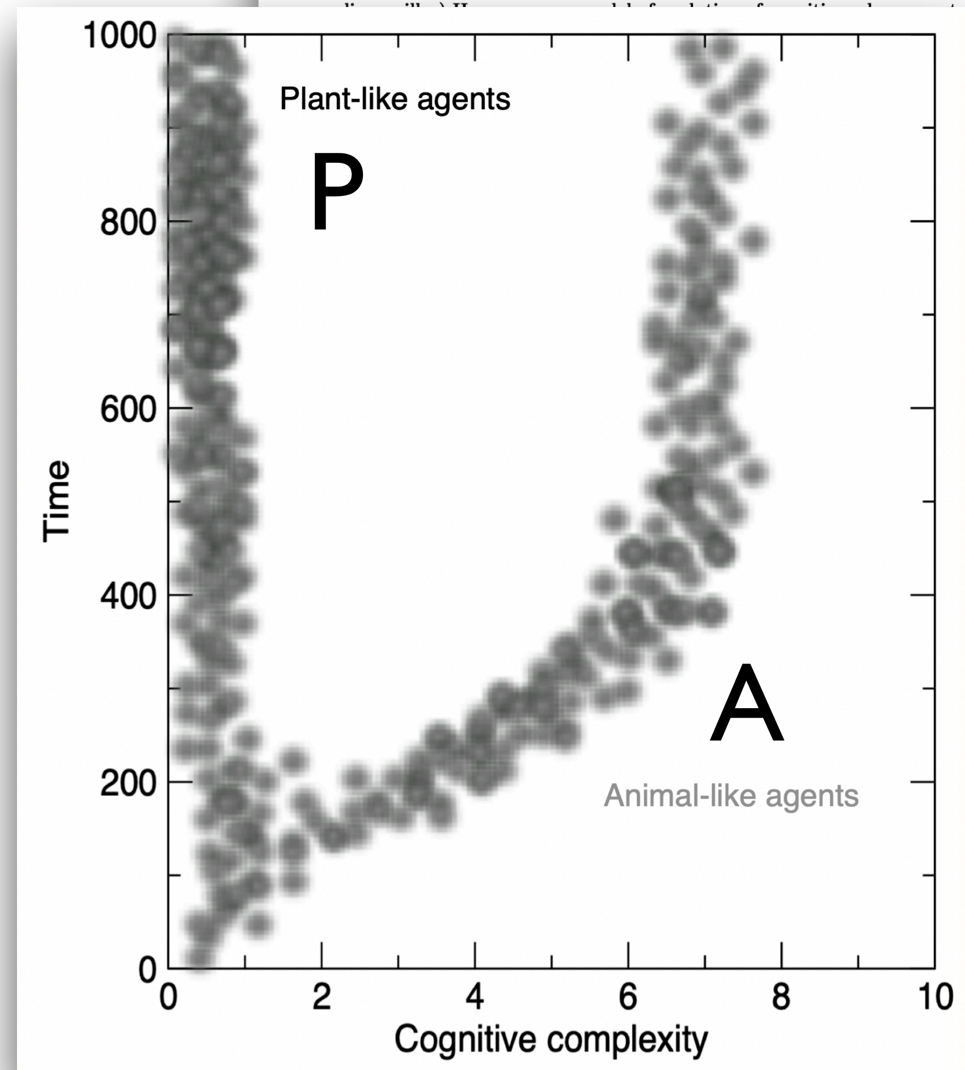


Animals or plants? Evolutionary dynamics of sessile versus mobile cognitive agents in noisy environments

Salva Duran-Nebreda[1*] and Ricard Solé[1,2,3†]
[1] *Institut de Biologia Evolutiva (CSIC-UPF), Psg Maritim Barceloneta, 37, 08003 Barcelona, Spain*
[2] *ICREA-Complex Systems Lab, Universitat Pompeu Fabra, 08003 Barcelona, Spain and*
[3] *Santa Fe Institute, 1399 Hyde Park Road, Santa Fe NM 87501, USA*

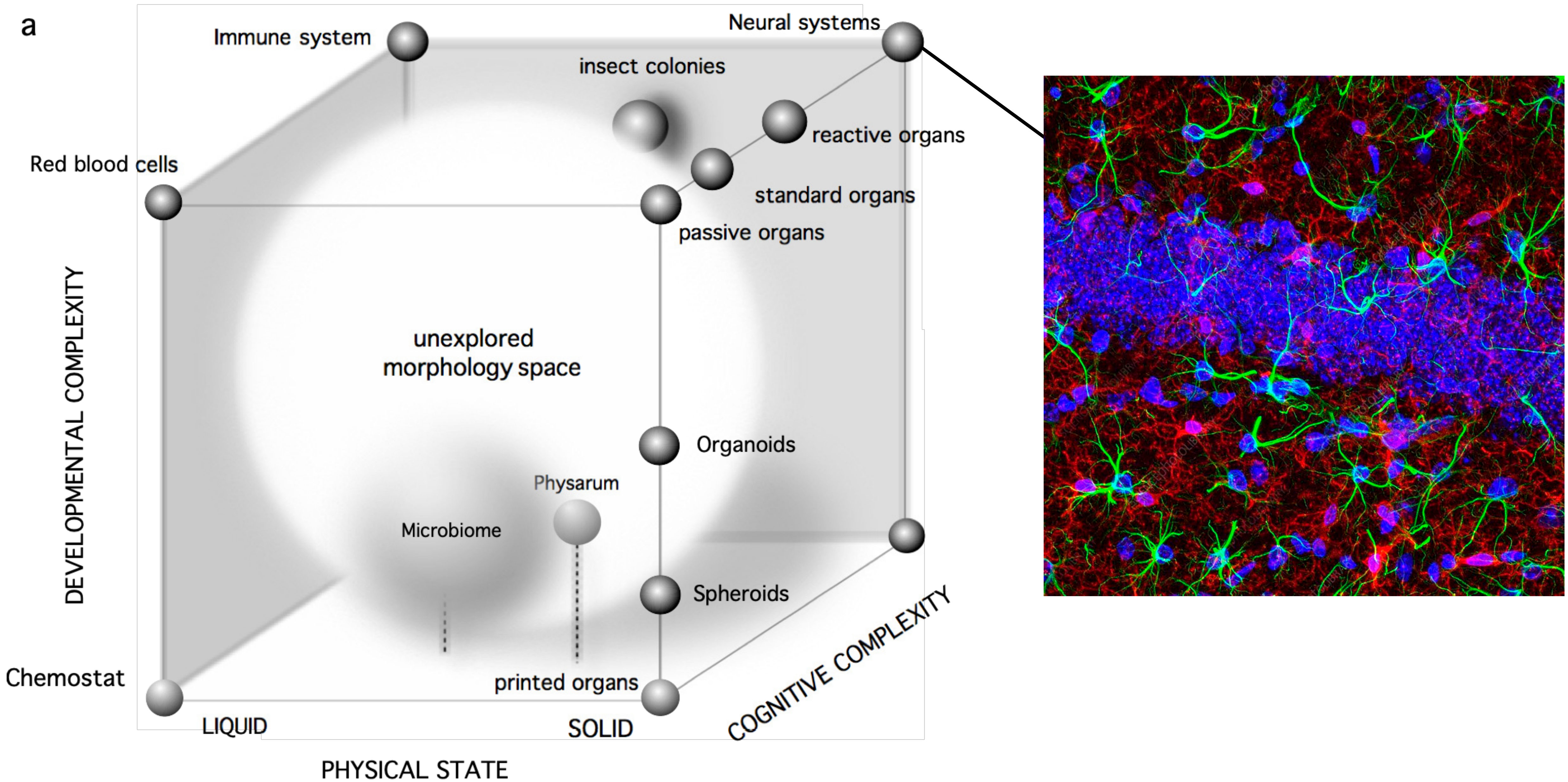
Abstract

The emergence of complex cognition has been often attributed to the potential for movement. The so called *moving hypothesis* is grounded in the precondition of movement as a key requirement for evolved neural systems. Cognitive agents capable of moving would be able to exploit available resources whose quantity would fluctuate in unpredictable ways. By contrast, a major art of the multicelular biosphere is instead represented by individuals exploiting available resources that make movement unnecessary. Are these two main solutions to the problem of evolving cognition? (ex- ... an exploit ... distribu- ... olutionary



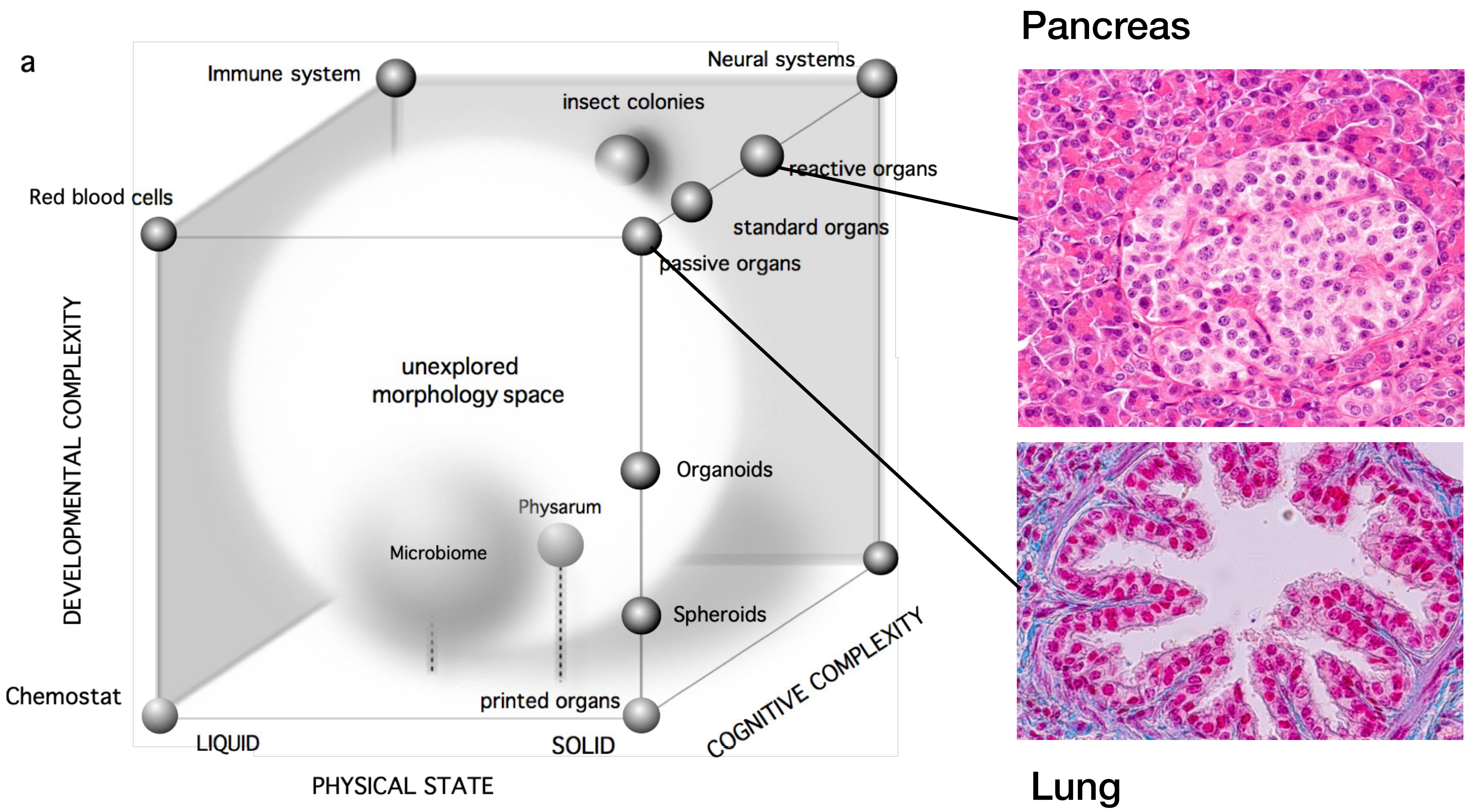
How to define a cognition space?
Can it be described as a phase space?

A morphospace of embodied cognition



Ollé-Vila, A. et al. (2016). *A morphospace for synthetic organs and organoids: the possible and the actual.* Integrative Biology, 8, 485-503.

A morphospace of embodied cognition



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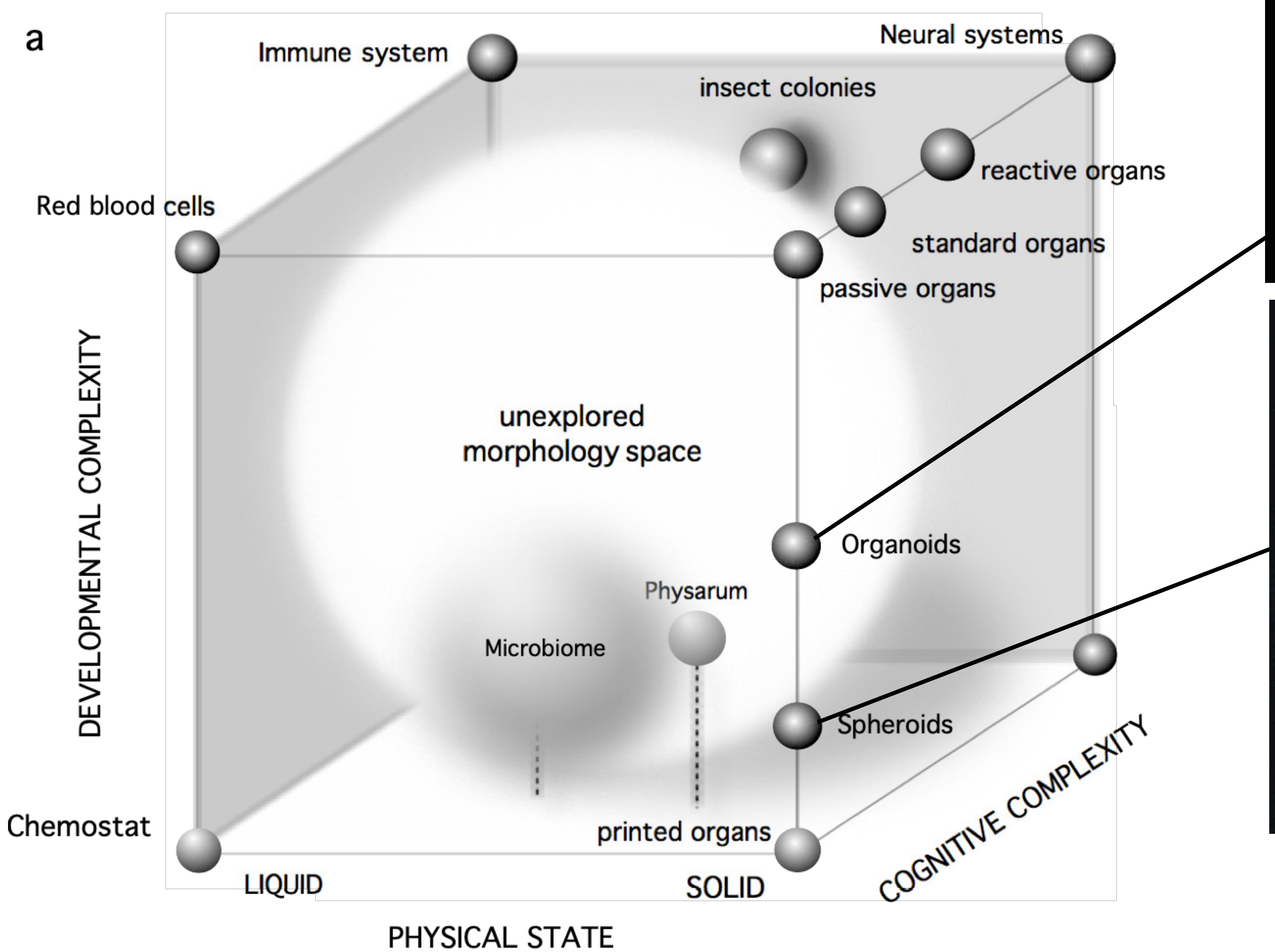
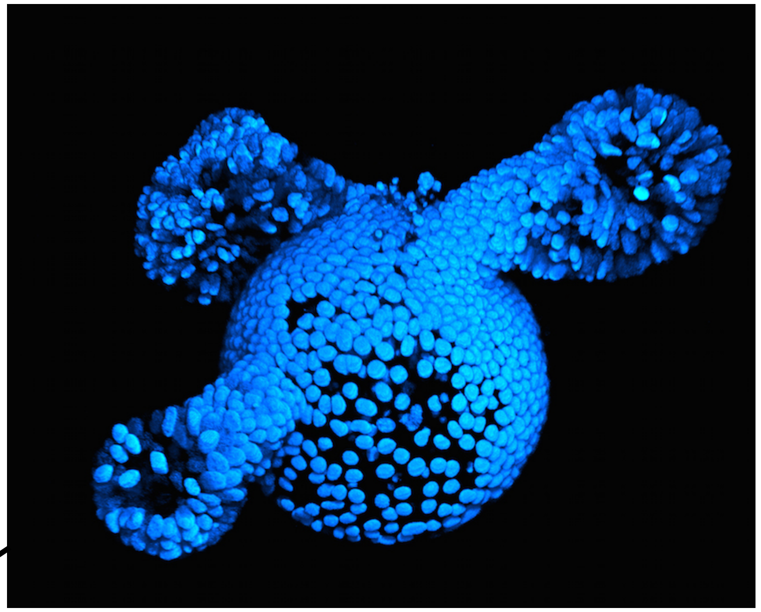
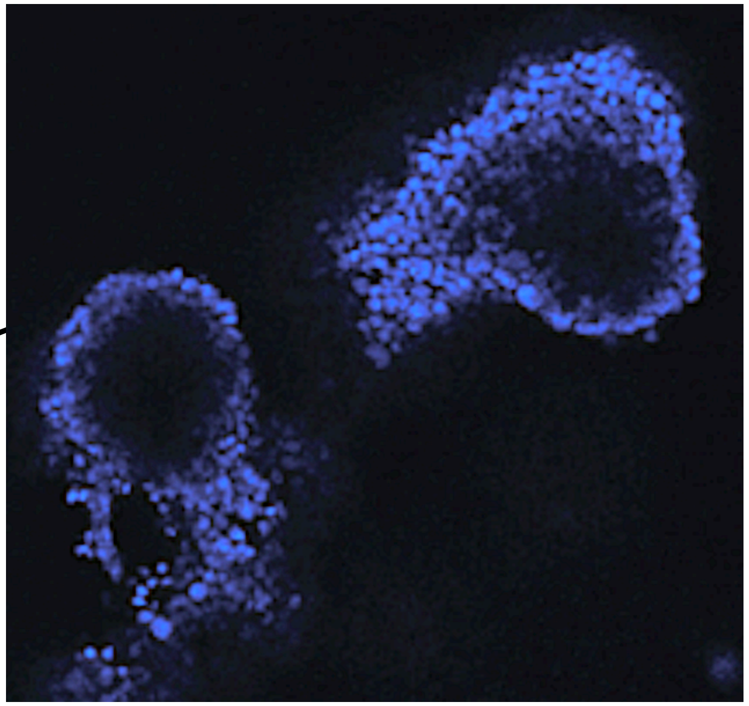
A morphospace of embodied cognition







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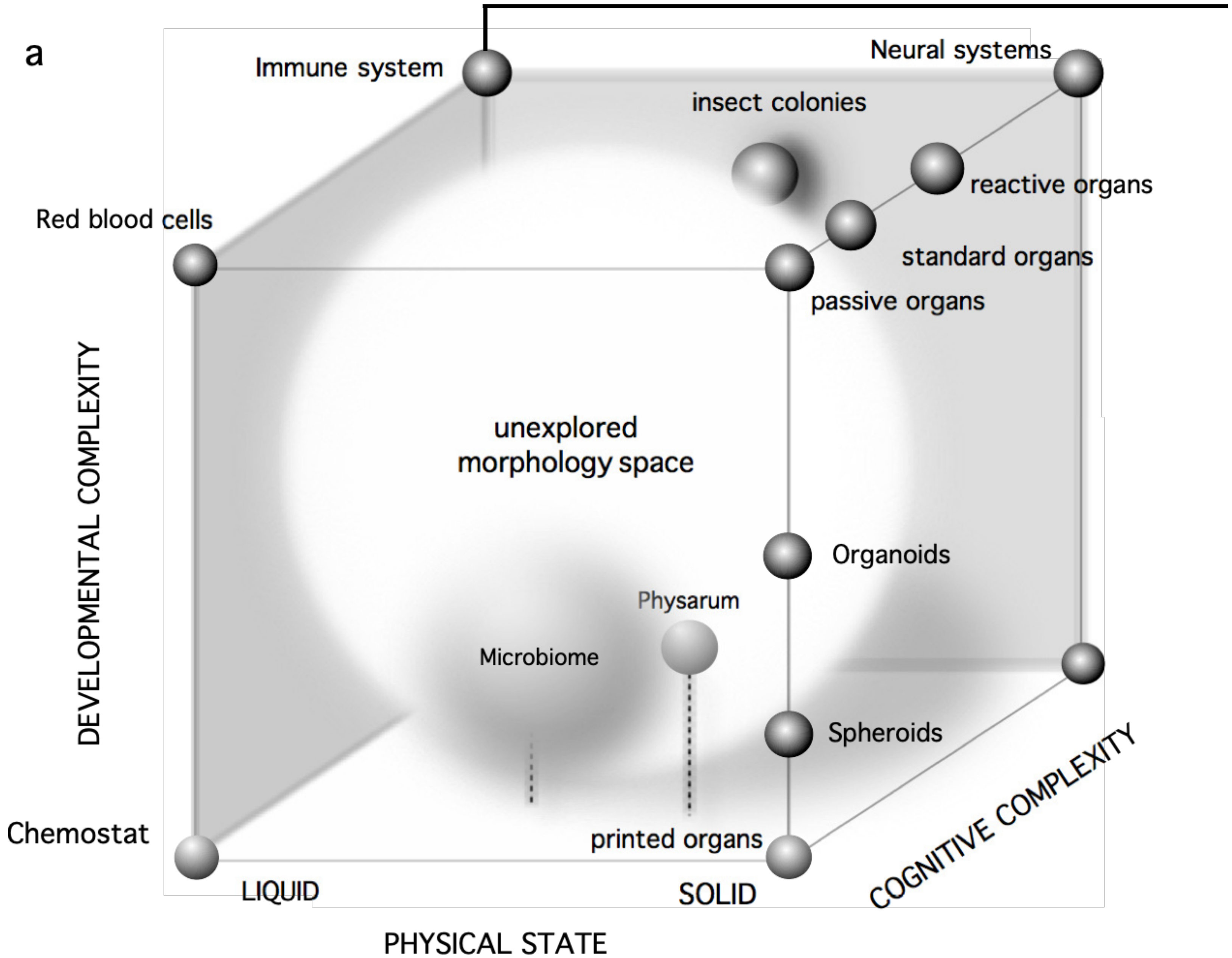
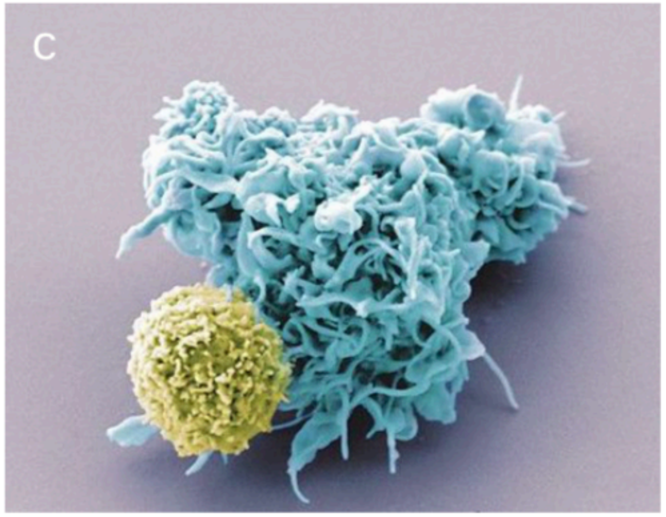
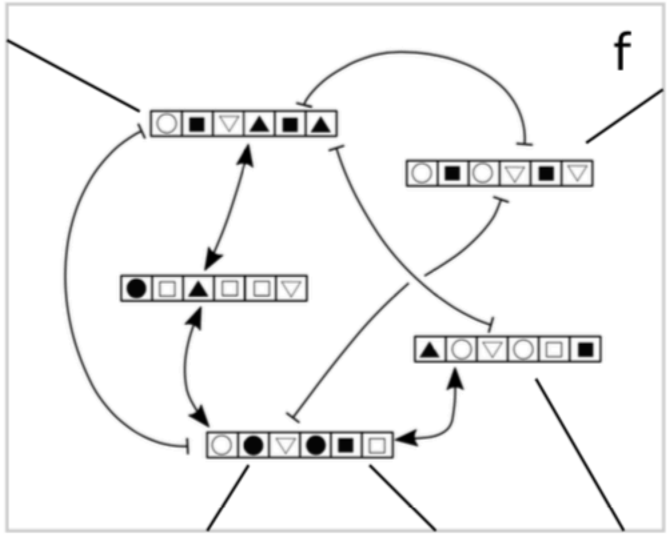
A morphospace of embodied cognition





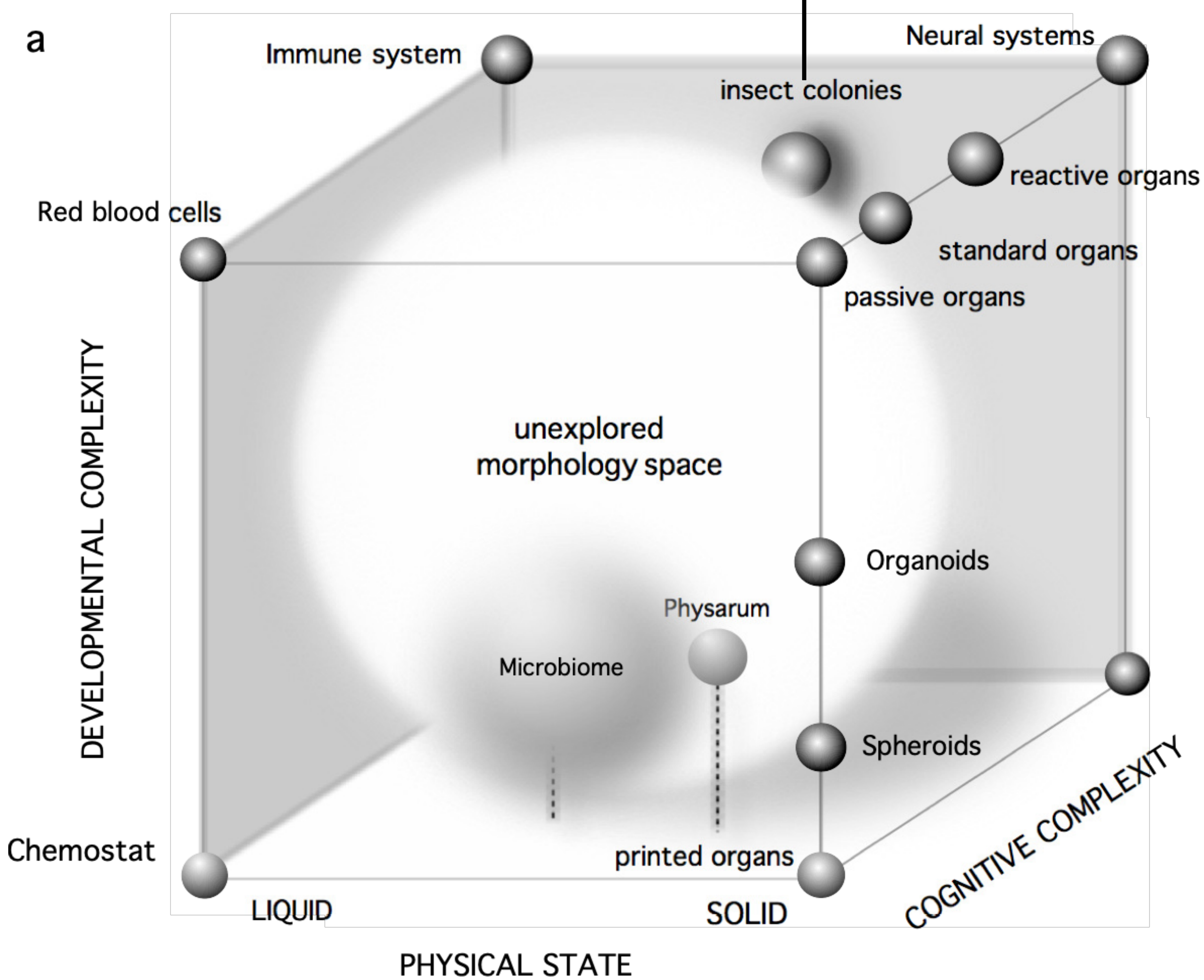


Very diverse
Liquid
Learning
Memory
Pattern matching

Ollé-Vila, A. et al. (2016). *A morphospace for synthetic organs and organoids: the possible and the actual.* Integrative Biology, 8, 485-503.

A morphospace of embodied cognition

a



Development
Liquid (ants) +Solid (nest)
Learning + Memory
(Super)organism

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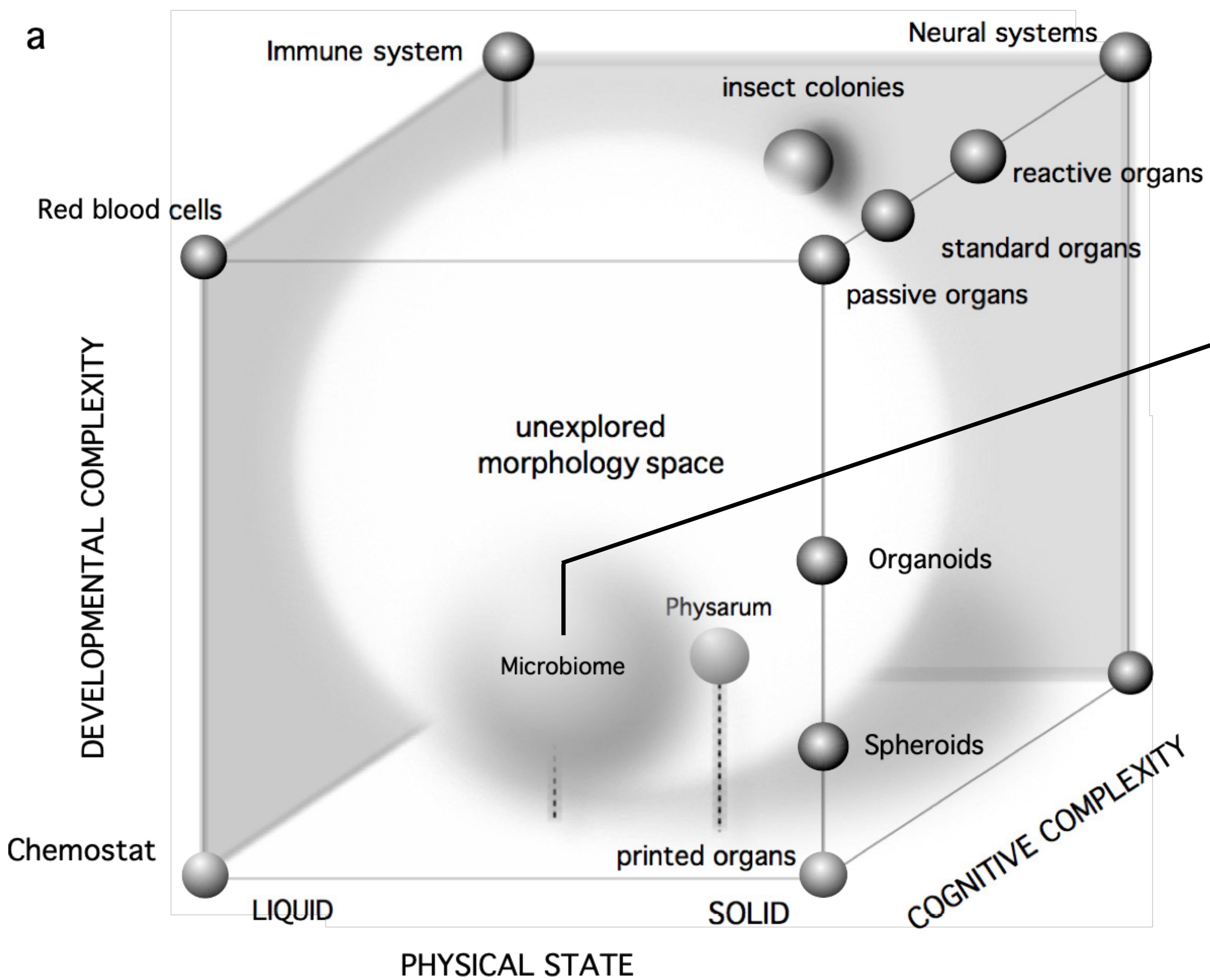
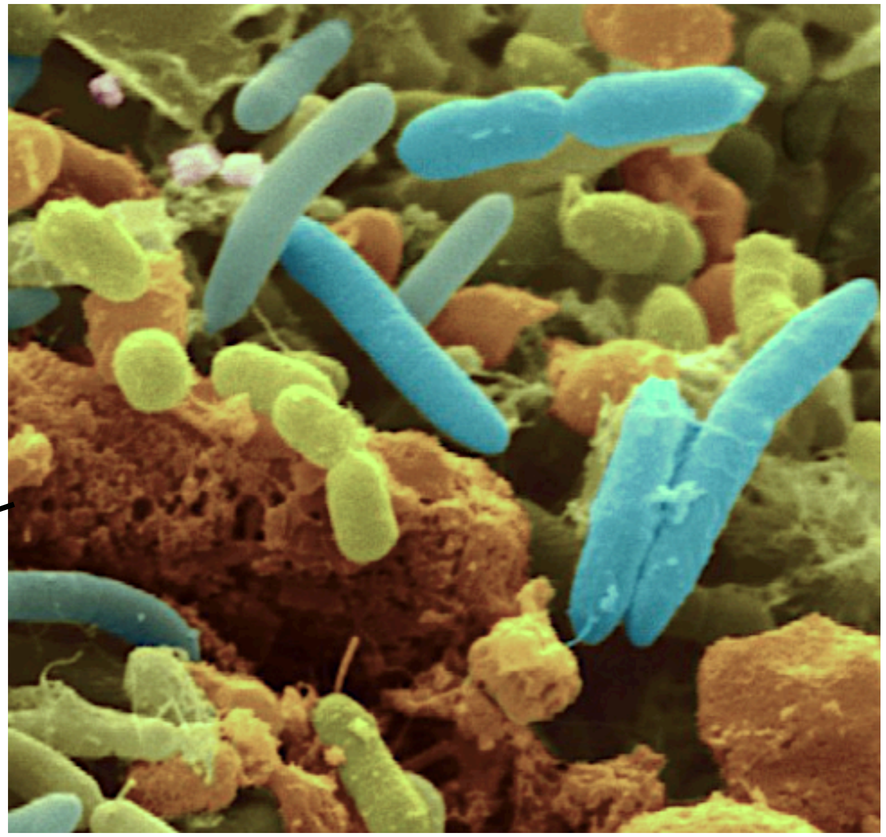
A morphospace of embodied cognition





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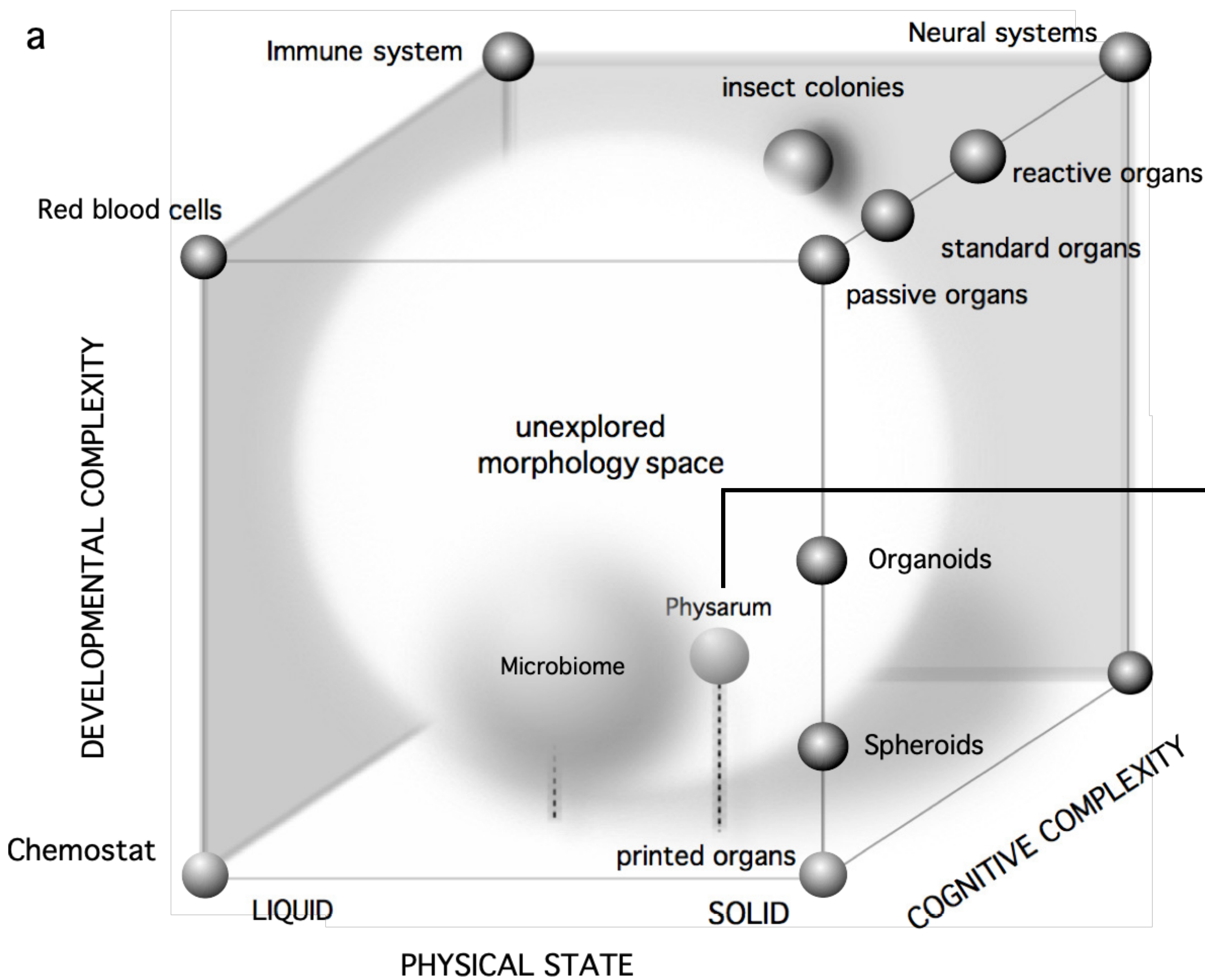
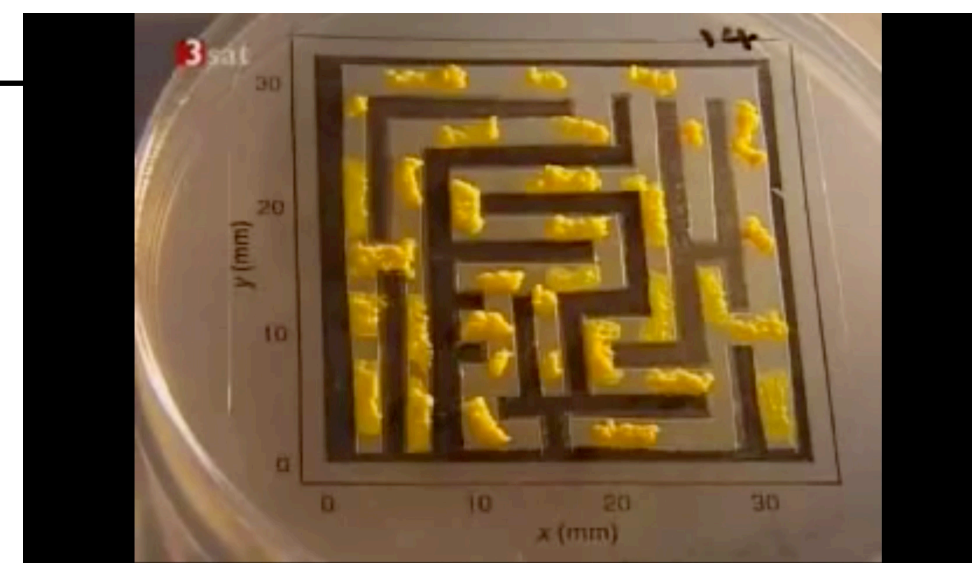
A morphospace of embodied cognition





Single-cell multinucleate
Liquid-solid
Learning+Memory
Shortest path, mazes

Ollé-Vila, A. et al. (2016). *A morphospace for synthetic organs and organoids: the possible and the actual.* Integrative Biology, 8, 485-503.

Solid artificial constructs: do they “explain” cognition?

entropy

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Perspective

Evolution of Brains and Computers: The Roads Not Taken

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Abstract: When computers started to become a dominant part of technology around the 1950s, fundamental questions about reliable designs and robustness were of great relevance. Their development gave rise to the exploration of new questions, such as what made brains reliable (since neurons can die) and how computers could get inspiration from neural systems. In parallel, the first artificial neural networks came to life. Since then, the comparative view between brains and computers has been developed in new, sometimes unexpected directions. With the rise of deep learning and the development of connectomics, an evolutionary look at how both hardware and neural complexity have evolved or designed is required. In this paper, we argue that important similarities have resulted both from convergent evolution (the inevitable outcome of architectural constraints) and inspiration of hardware and software principles guided by toy pictures of neurobiology. Moreover, dissimilarities and gaps originate from the lack of major innovations that have paved the way to biological computing (including brains) that are completely absent within the artificial domain. As it occurs within synthetic biocomputation, we can also ask whether alternative minds can emerge from A.I. designs. Here, we take an evolutionary view of the problem and discuss the remarkable convergences between living and artificial designs and what are the pre-conditions to achieve artificial intelligence.

Keywords: evolution; brains; deep learning; embodiment; neural networks; artificial intelligence; neurorobotics

check for updates

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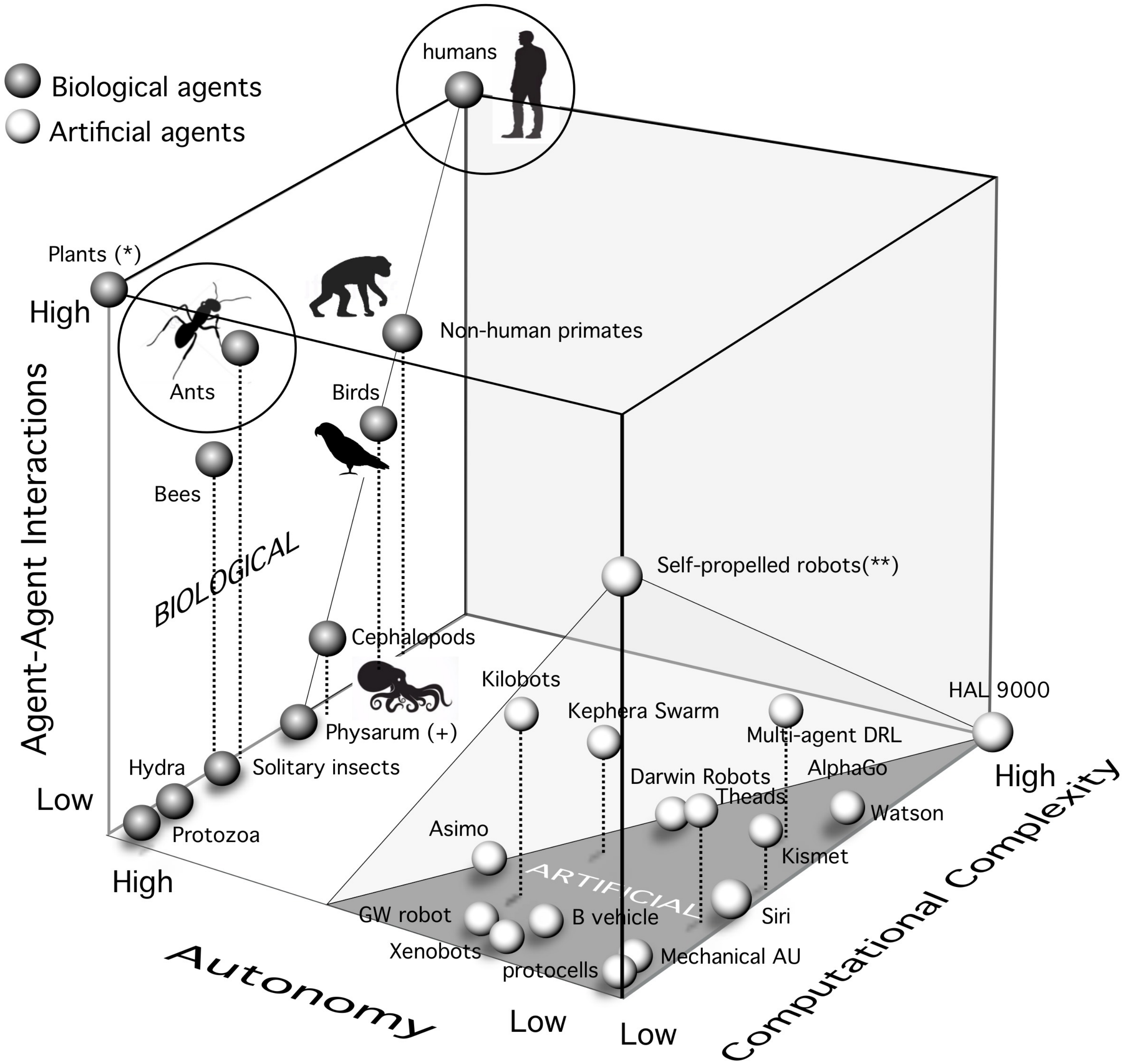
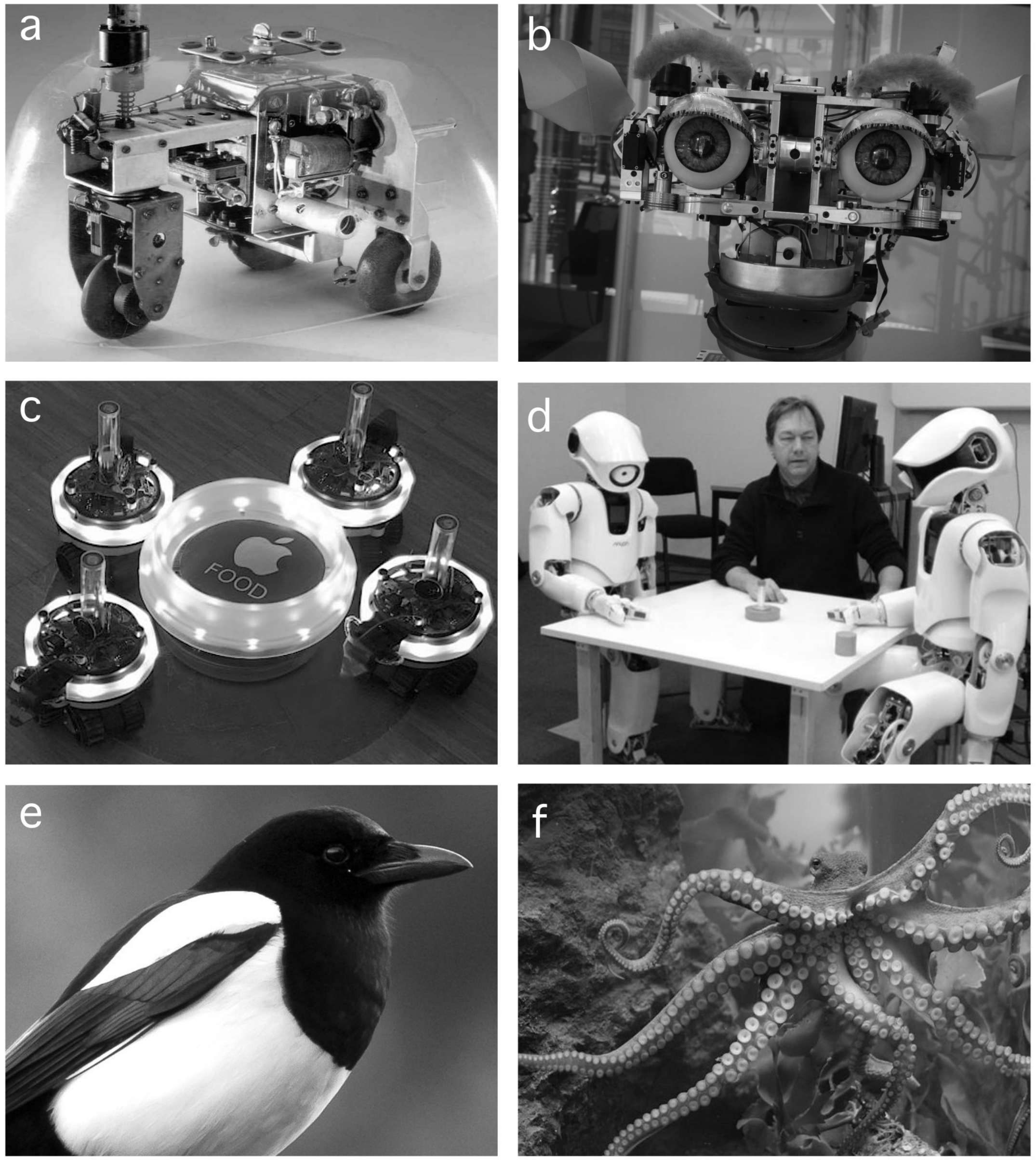
A(nother) morphospace of embodied cognition





THANK YOU

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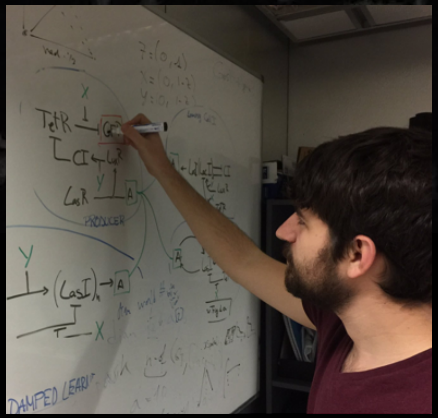
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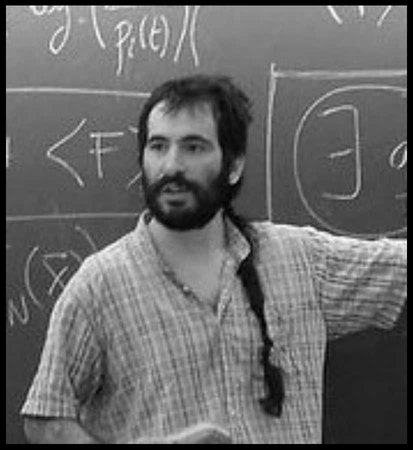
Gemma de las Cuevas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