Morphogenetic "Neuron-Flocking":

Dynamic Self-Organization of Neural Activity into Mental Shapes

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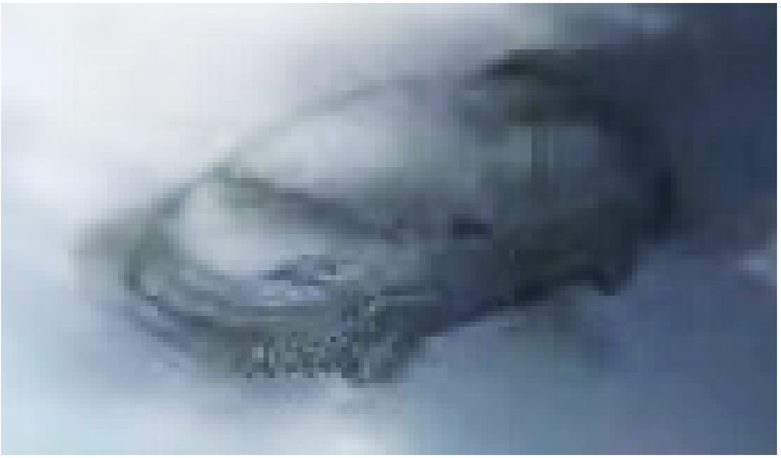
Abstract – My aim is to contribute to a new research focus on the theoretical modeling of the “shapes” of multiscale spatiotemporal phenomena in large neural populations. I wish to emphasize the “complex systems” view of the brain as a recurrent network chiefly occupied with its own intrinsic, emergent activity (sometimes also called “ongoing activity”, although this term is more evocative of a background nuisance than a core function). Traditionally, neural models have followed a rather naive paradigm of input/output signal processing, in which the system is considered passive and essentially stimulus-driven. We should now encourage a recent trend of computational neuroscience to move away from this linear reduction, in order to explore a dynamical paradigm of active self-organization. In this paradigm, stimuli only trigger or distort preexisting internal states, which have been molded and imprinted in synaptic connections during development and Hebbian-like learning. At one or several appropriate mesoscopic levels, the neocortex could be construed as a “pattern formation machine”, generating specific dynamical regimes made of myriads of bioelectrical neuronal signals – not unlike many other biological collective phenomena such as bird flocking, ant colonies or, closer to neurons, multicellular development. Dynamical “neuron flocking”, for its part, happens in phase space and across a complex network topology: What are the emergent mesoscopic objects of its dynamics? Can we characterize their fine spatiotemporal structure through experimental data and/or theoretical models? How are they are endogenously produced by the neuronal substrate – and exogenously evoked and perturbed by perceptual stimuli? How do they interact (bind and compose, breakup and compete) with each other and with motor action? I will present a few of my studies that have started to address these important questions of dynamical neural assembly and shape formation.

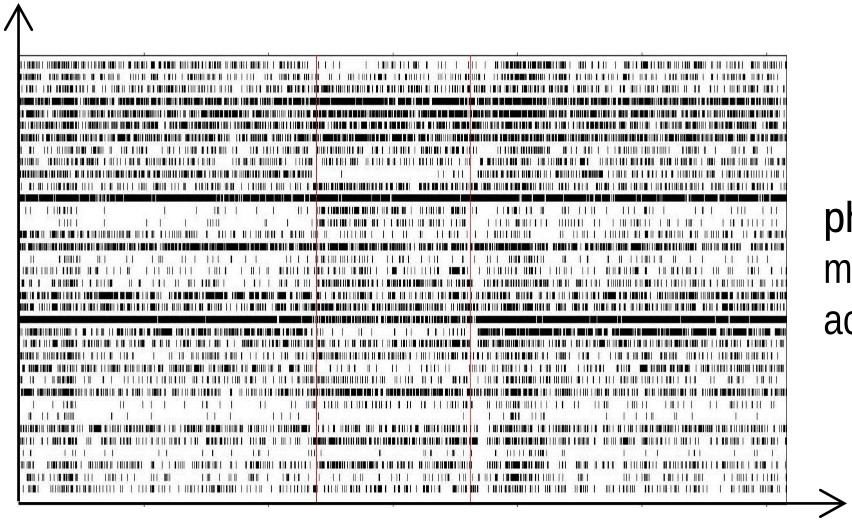
Morphogenetic "Neuron-Flocking"



phase space view:
complex spatiotemporal pattern =
mental shape

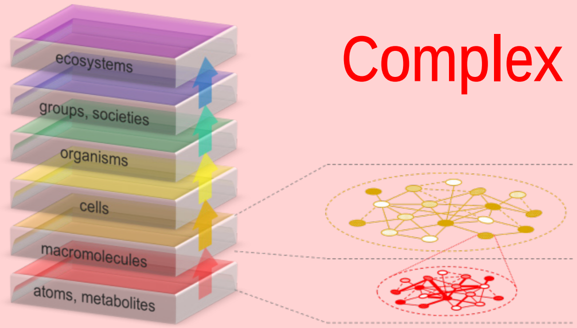
(dynamic) emergence? structure? properties?

(long-term) persistence? learning? storage? compositionality?



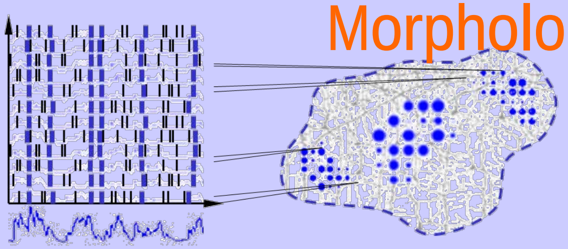
physical space view:
mega-MEA raster plot =
activity of 10^6-10^8 neurons

Morphogenetic "Neuron-Flocking"

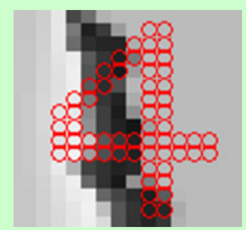


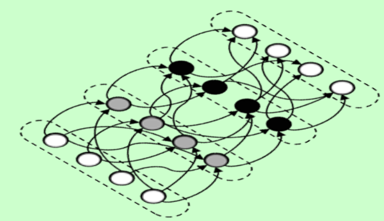
Complex Systems Levels

Temporal Code, Patterns, Morphology

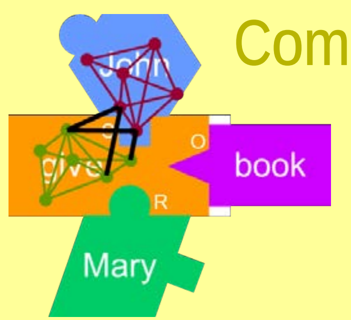


Waves, Chains, Phase Shapes

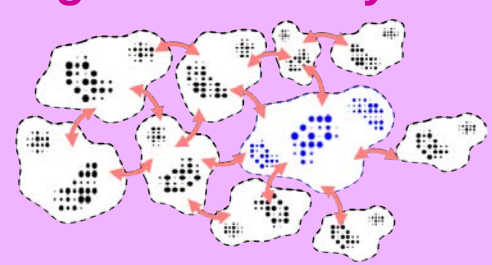




Compositionality



Emergent Neurodynamics



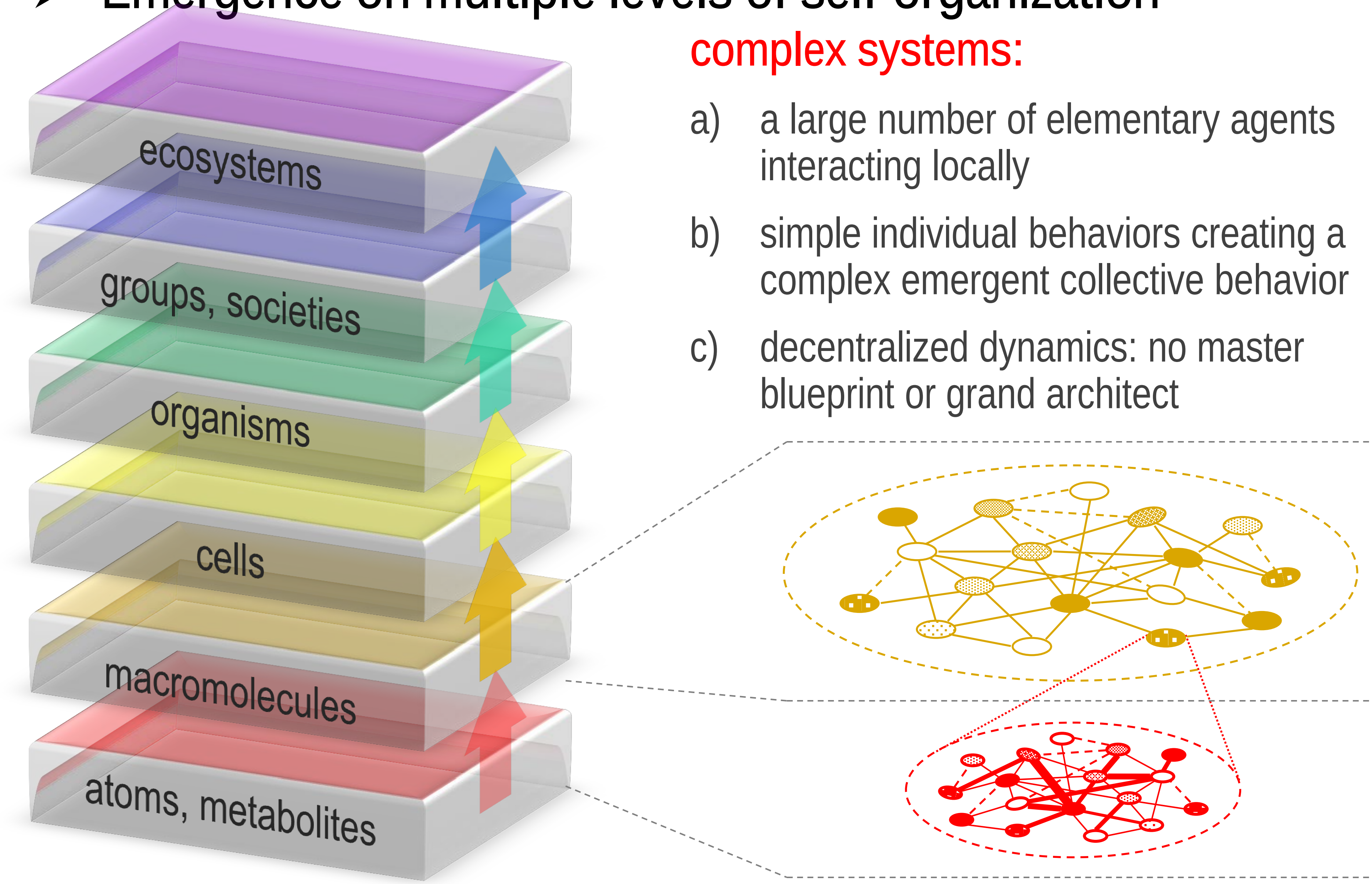
1. Cognitive Architectures in the Tower of Complex Systems

The emergence of neural/mind states on multiple levels of self-organization

- *From agents to collectives, via local interactions*
  - *From neurons to brain (anatomy)*
  - *From potentials to fMRI (physiology)*
  - *From connections to cognition (models)*

1. The Tower of Complex Systems

➢ Emergence on multiple levels of self-organization



complex systems:

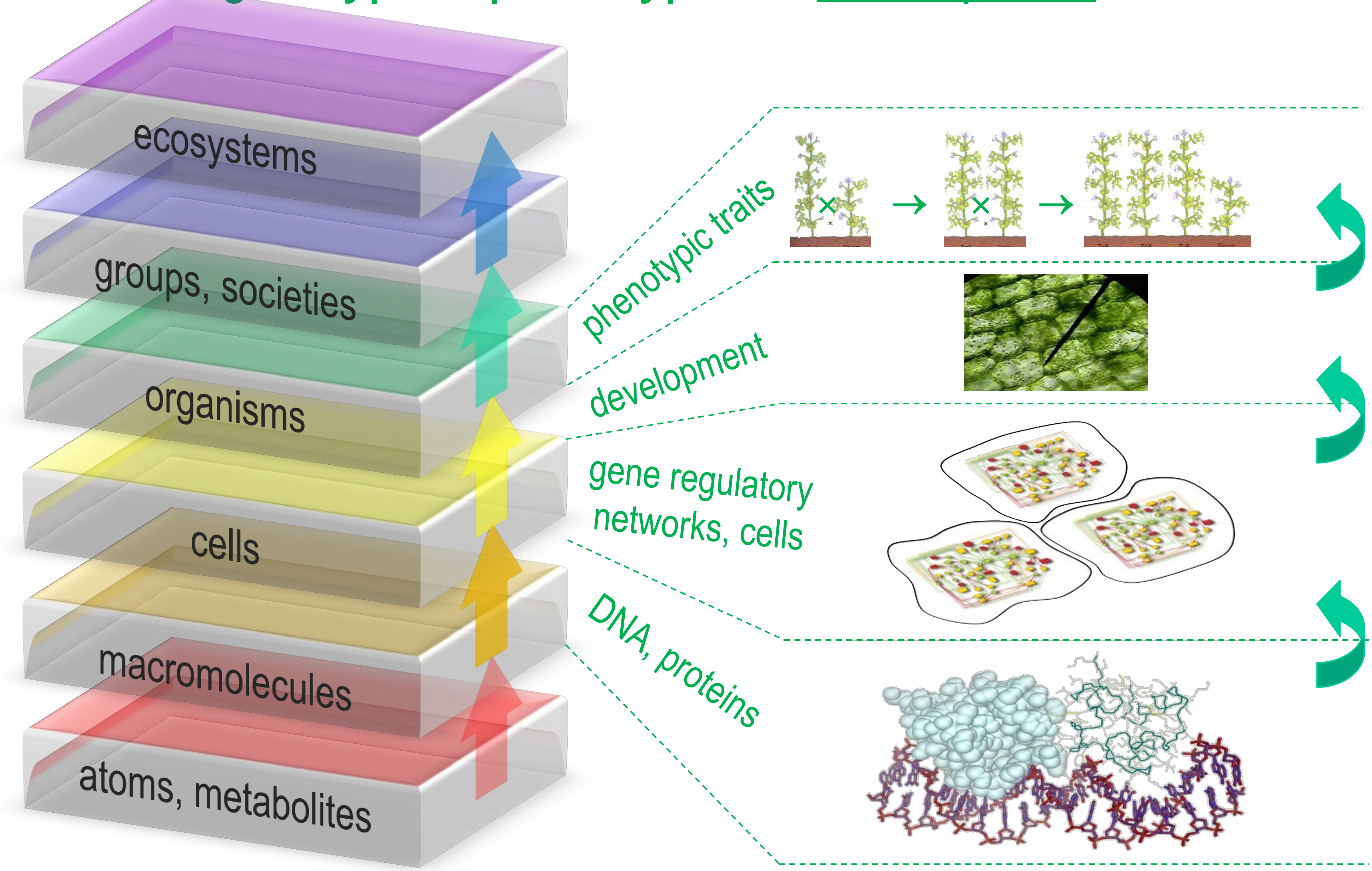
a) a large number of elementary agents interacting locally

b) simple individual behaviors creating a complex emergent collective behavior

c) decentralized dynamics: no master blueprint or grand architect

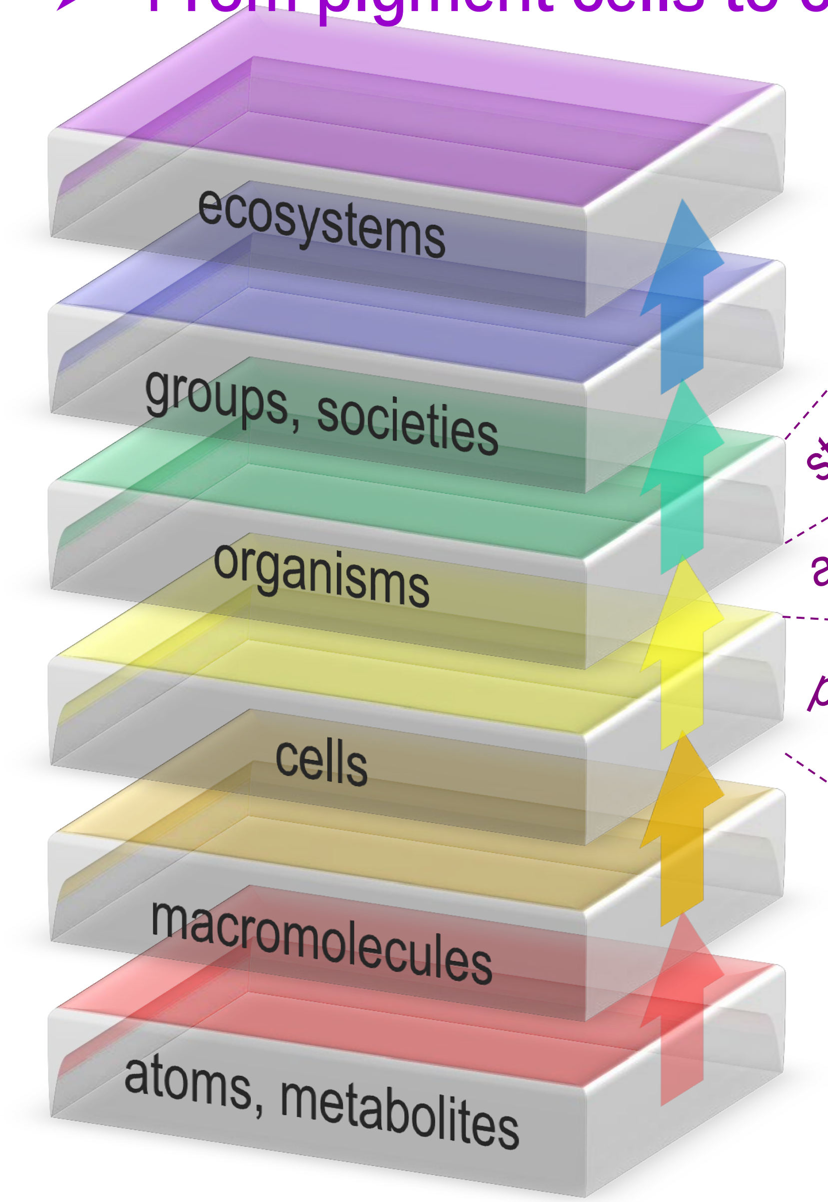
1. The Tower of Complex Systems

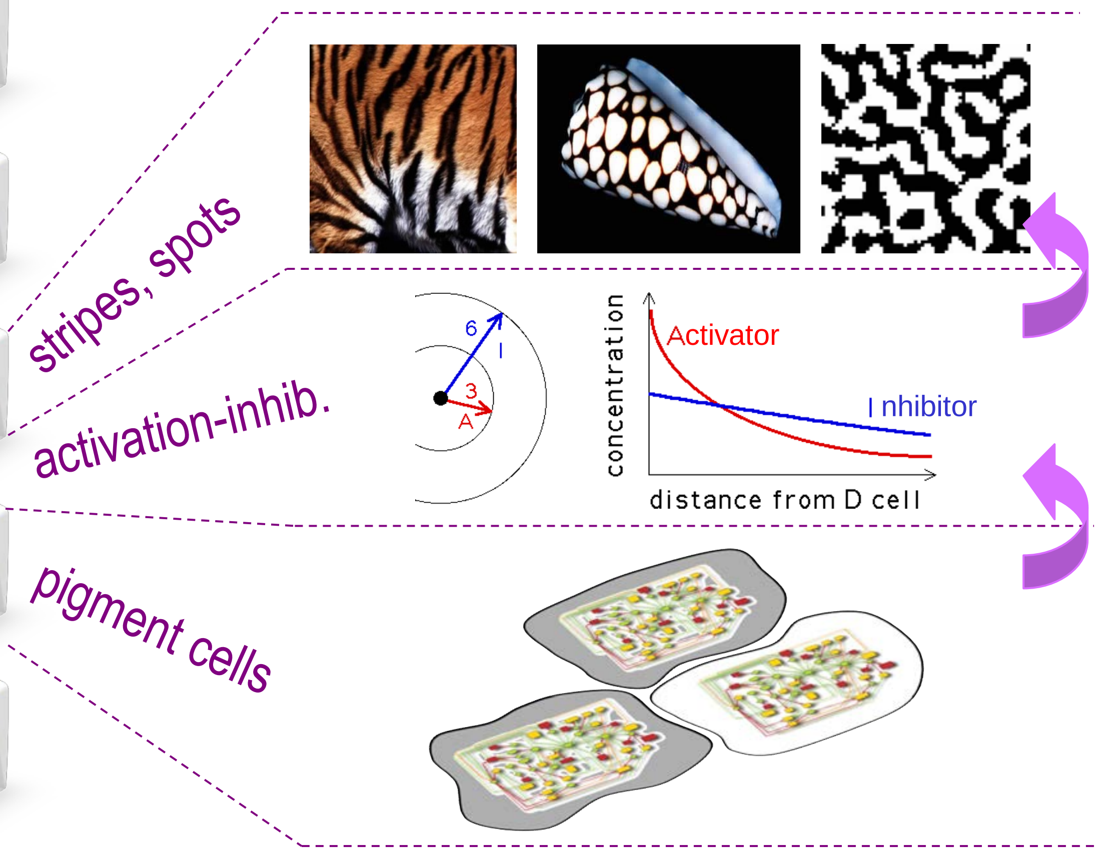
➢ From genotype to phenotype, via <u>development</u>



1. The Tower of Complex Systems

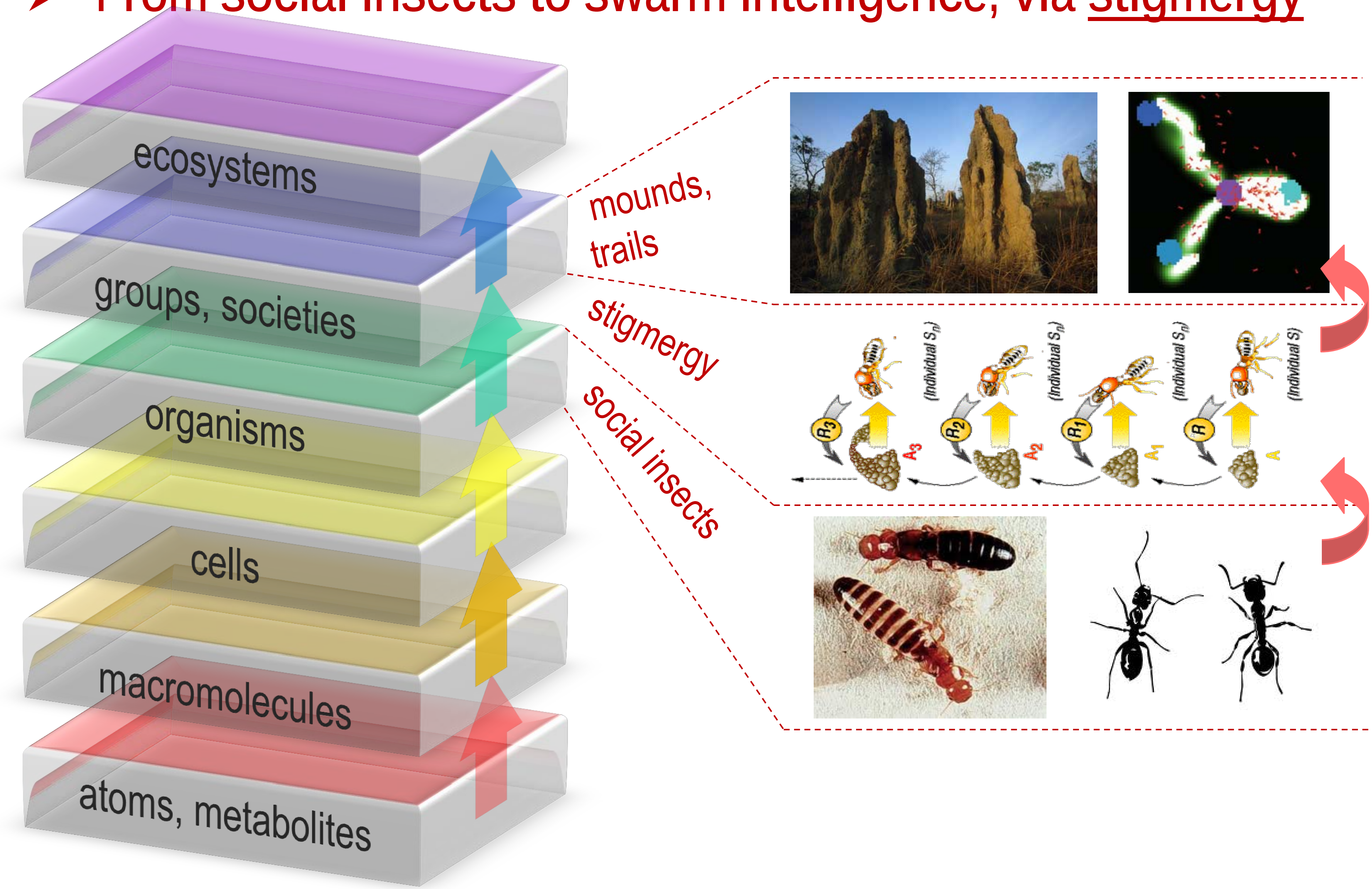
➤ From pigment cells to coat patterns, via reaction-diffusion





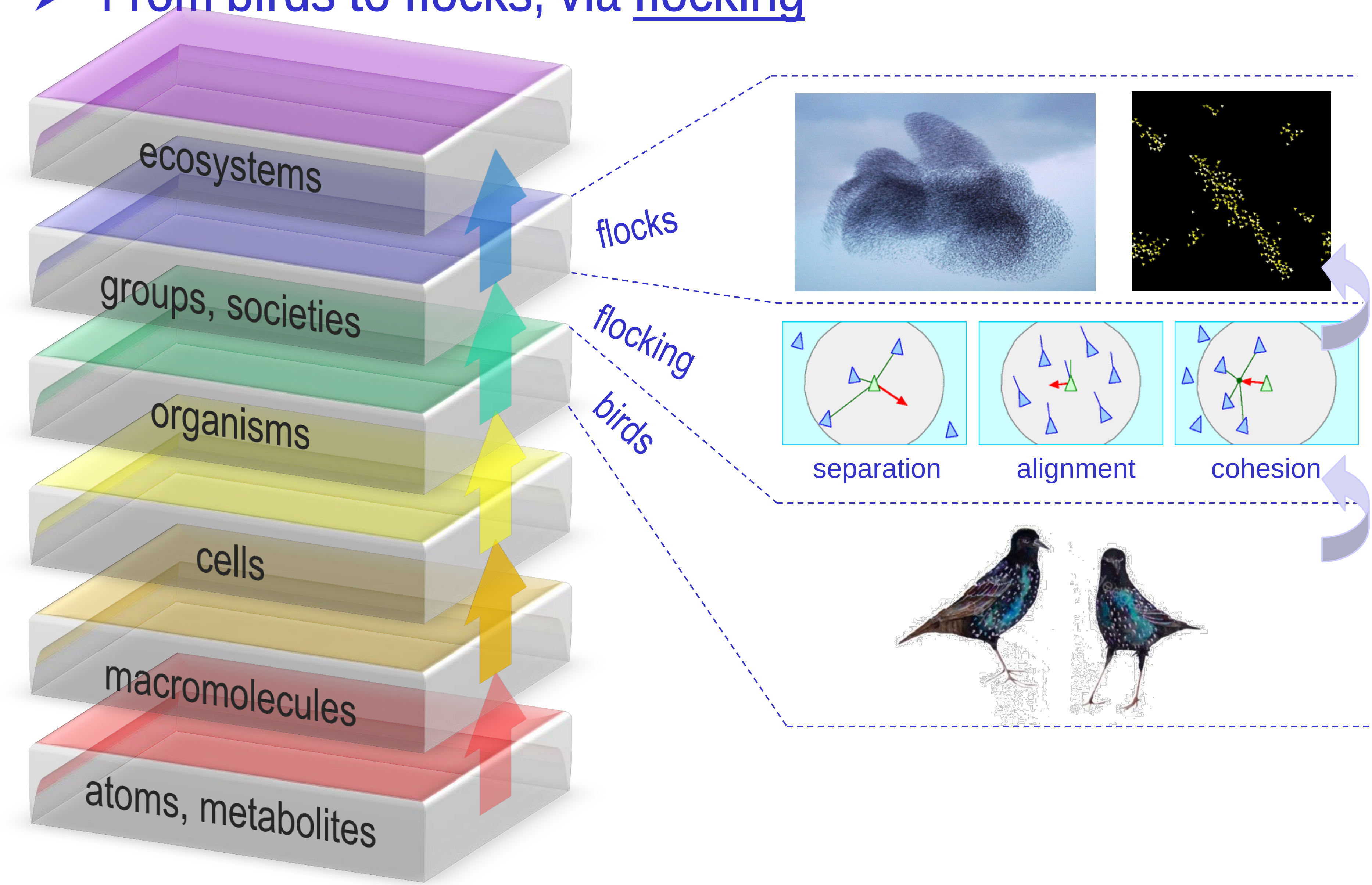
1. The Tower of Complex Systems

- From social insects to swarm intelligence, via <u>stigmergy</u>



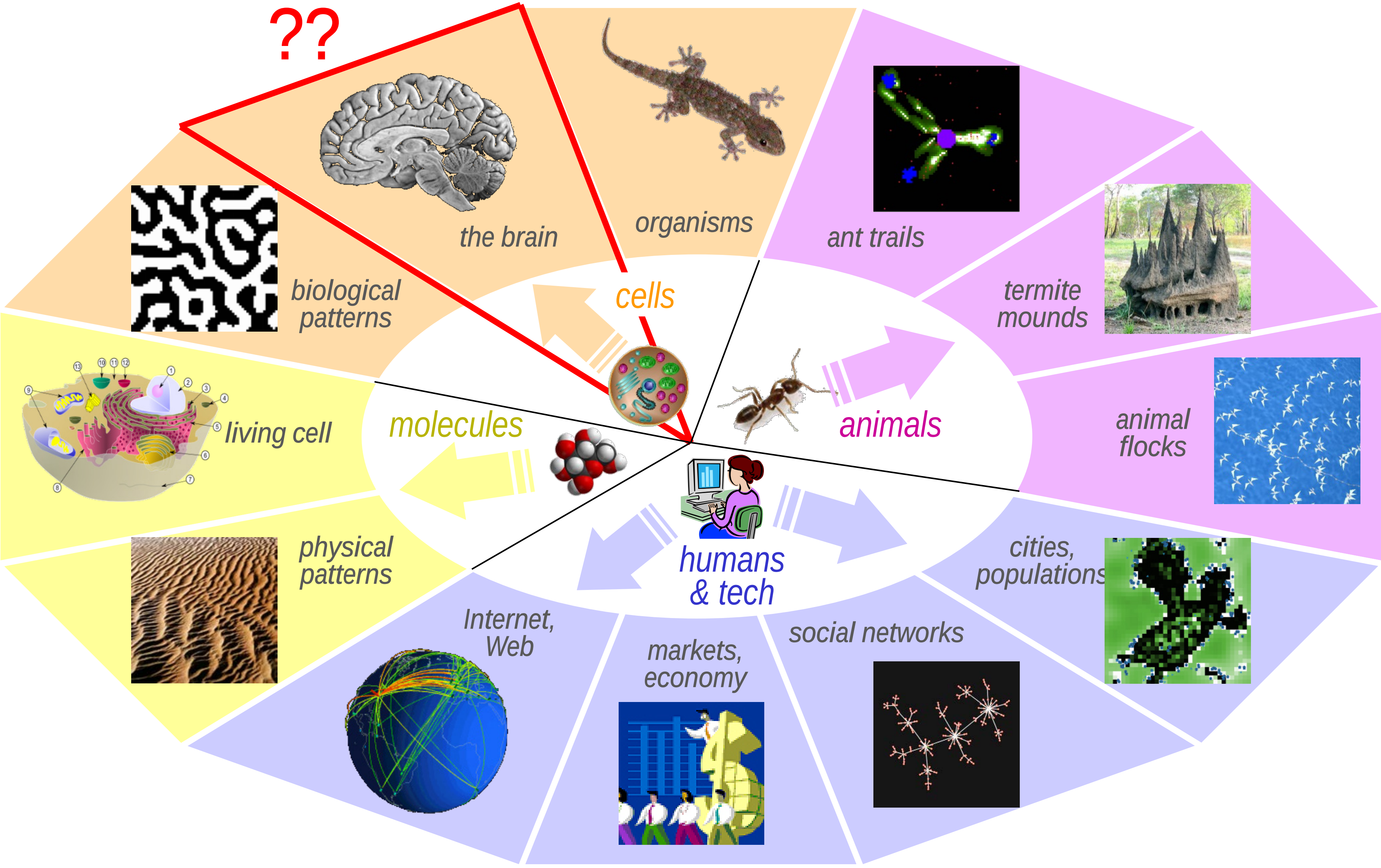
1. The Tower of Complex Systems

- From birds to flocks, via flocking



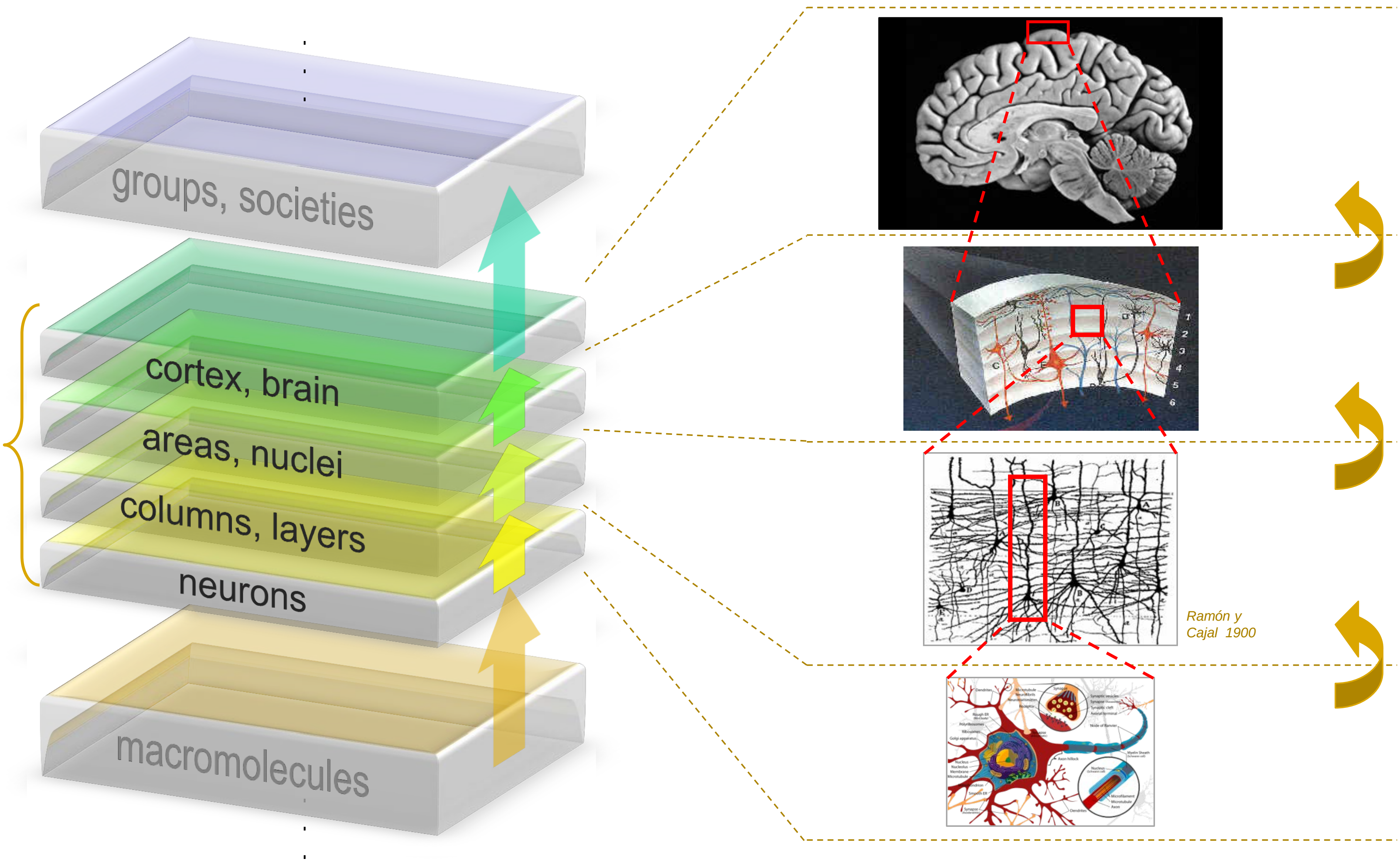
1. The Tower of Complex Systems

- All agent types: molecules, cells, animals, humans & tech



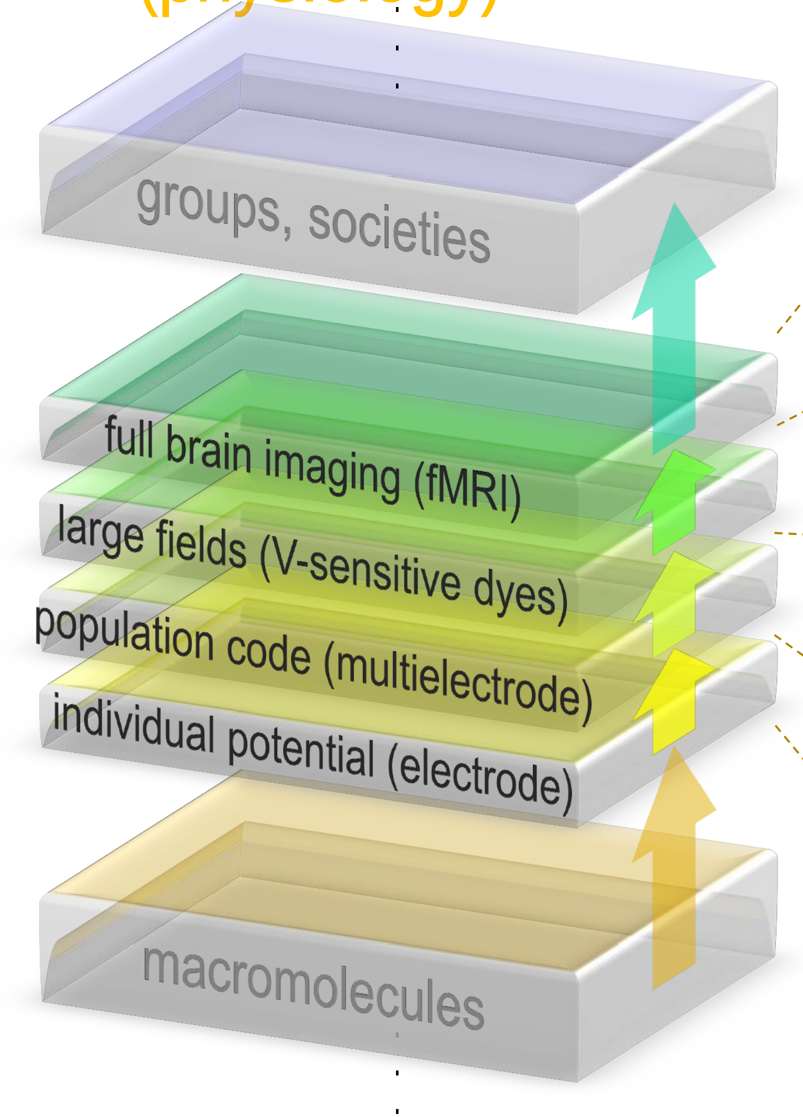
1. The Tower of Complex Systems

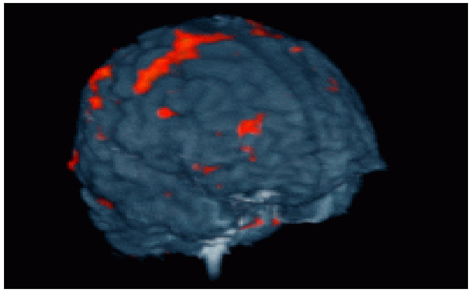
➢ From neurons to brain, via neural development (anatomy)



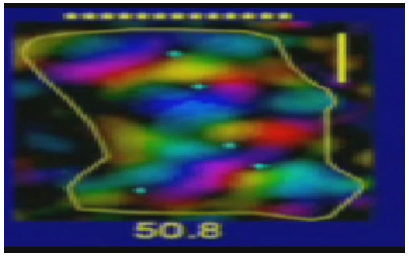
1. The Tower of Complex Systems

- From potentials to fMRI, via <u>synaptic transmission</u> (physiology)

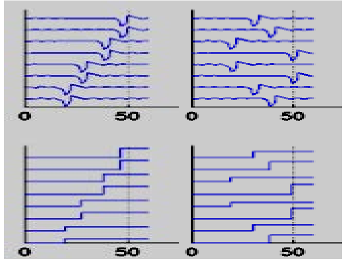




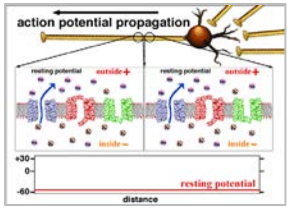
Animation of a functional MRI study (J. Ellermann, J. Strupp, K. Ugurbil, U Minnesota)



Dynamics of orientation tuning: polar movie Sharon and Grinvald, Science 2002

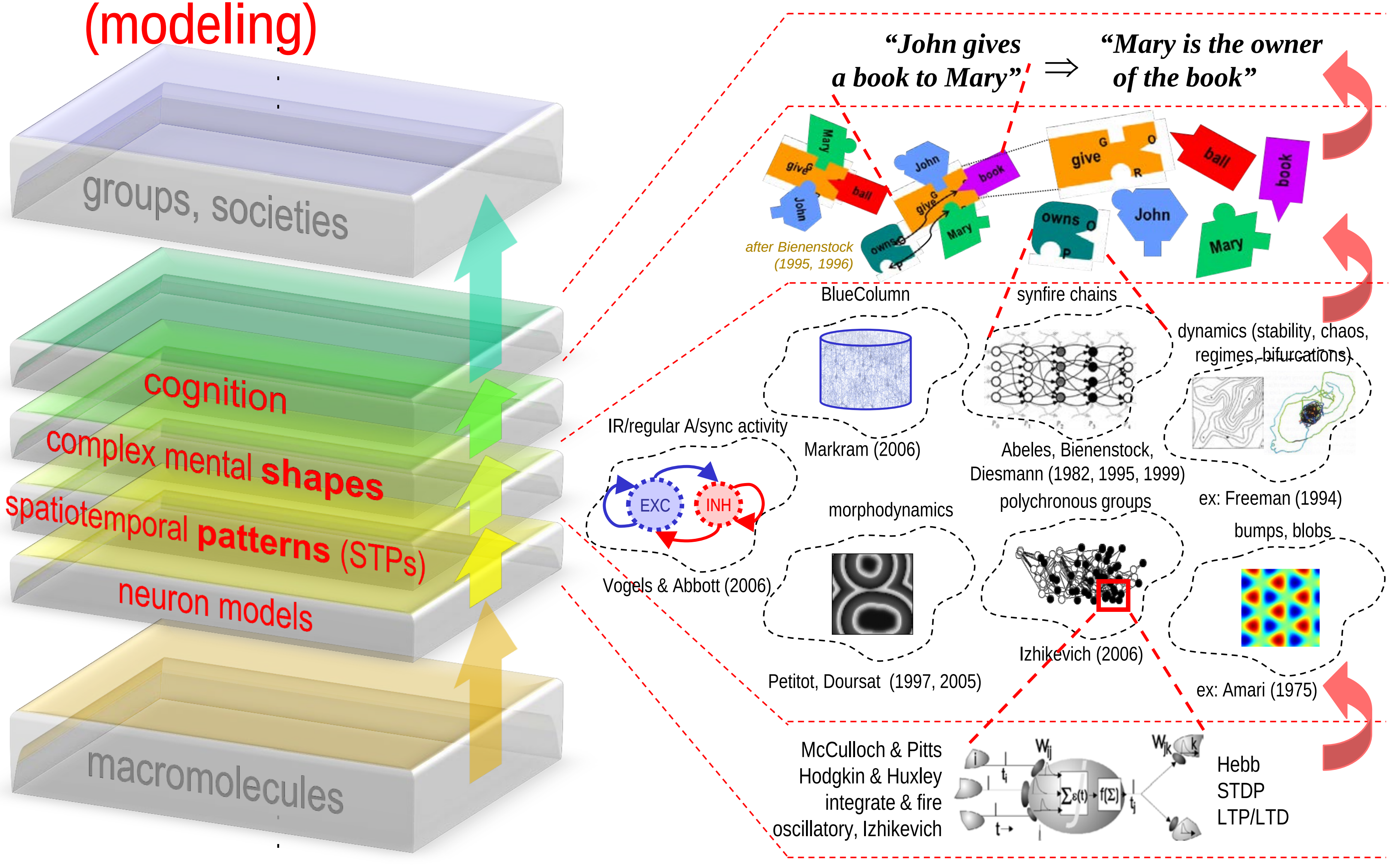


Raster plot of of a simulated synfire braid, Doursat et al. 2011



1. The Tower of Complex Systems

- From connections to cognition, via <u>correlations</u> (modeling)



1. Cognitive Architectures in the Tower of Complex Systems

The emergence of neural/mind states on multiple levels of self-organization

2. The Mind as a Pattern Formation Machine

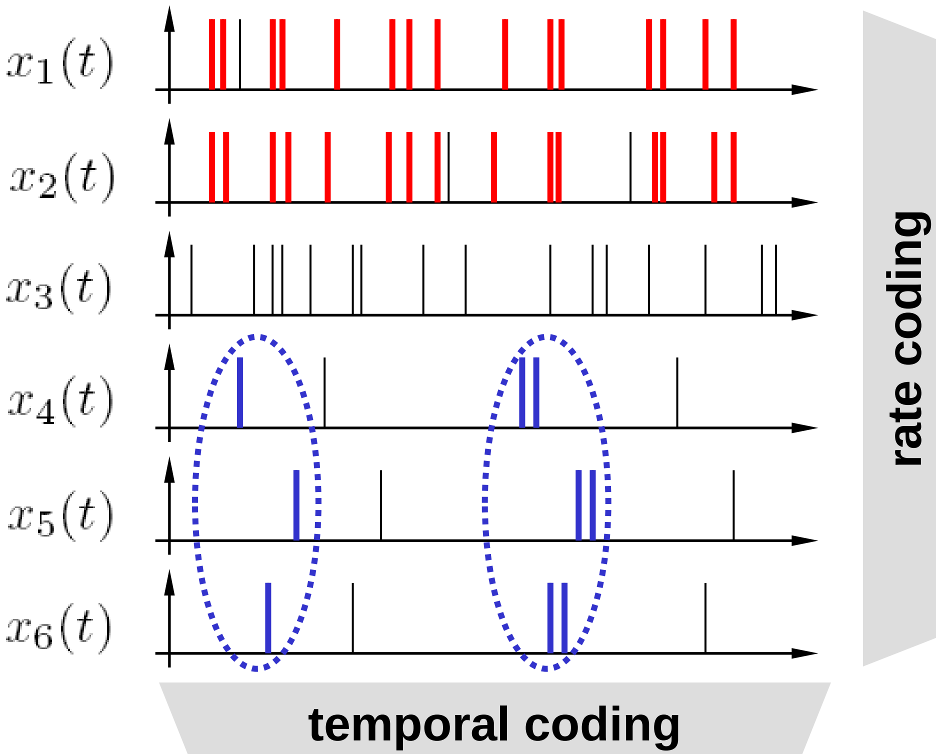
Neural correlations: The glue of spatiotemporal patterns (STPs)

- *The importance of temporal coding*
- *Pattern formation*
- *"Neuron flocking"*
- *Morphogenesis*

2. A Pattern Formation Machine

➢ The importance of temporal coding

✓ more than mean rates → *temporal correlations* among spikes



$\langle x_1(t) \rangle =$ ● high activity rate

$\langle x_2(t) \rangle =$ ● high activity rate

$\langle x_3(t) \rangle =$ ● high activity rate

$\langle x_4(t) \rangle =$ ○ low activity rate

$\langle x_5(t) \rangle =$ ○ low activity rate

$\langle x_6(t) \rangle =$ ○ low activity rate

after von der Malsburg (1981) and Abeles (1982)

$$\boxed{\langle x_1(t)\, x_2(t) \rangle \gg \langle x_1(t)\, x_3(t) \rangle}$$

➢ zero-delays: synchrony
(1 and 2 more in sync than 1 and 3)

$$\langle x_4(t)\, x_5(t-\tau_{4,5})\, x_6(t-\tau_{4,6}) \rangle$$

➢ nonzero delays: rhythms
(4, 5 and 6 correlated through delays)

2. A Pattern Formation Machine

Historical motivation for rate coding

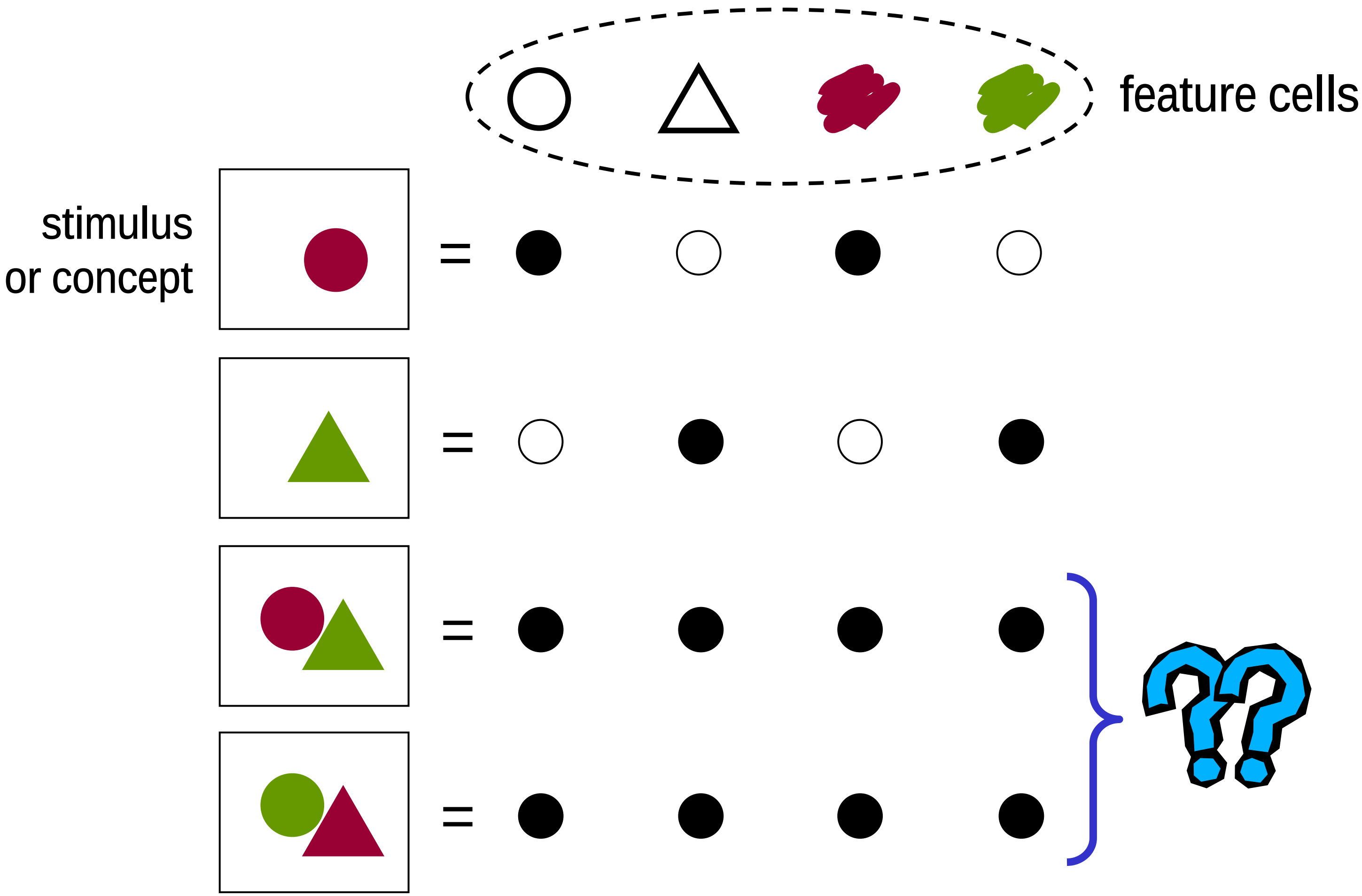
- Adrian (1926): *the firing rate of mechanoreceptor neurons in frog leg is proportional to the stretch applied*
- Hubel & Wiesel (1959): *selective response of visual cells; e.g., the firing rate is a function of edge orientation*

→ rate coding is confirmed in sensory system and primary cortical areas, however increasingly considered insufficient for integrating the information

Temporal coding pioneers of the 1980-90's

- von der Malsburg (1981): *theoretical proposal to consider correlations*
- Abeles (1982, 1991): *precise, reproducible spatiotemporal spike rhythms, named "synfire chains"*
- Gray & Singer (1989): *stimulus-dependent synchronization of oscillations in monkey visual cortex*
- O'Keefe & Recce (1993): *phase coding in rat hippocampus supporting spatial location information*
- Bialek & Rieke (1996, 1997): *in H1 neuron of fly, spike timing conveys information about time-dependent input*

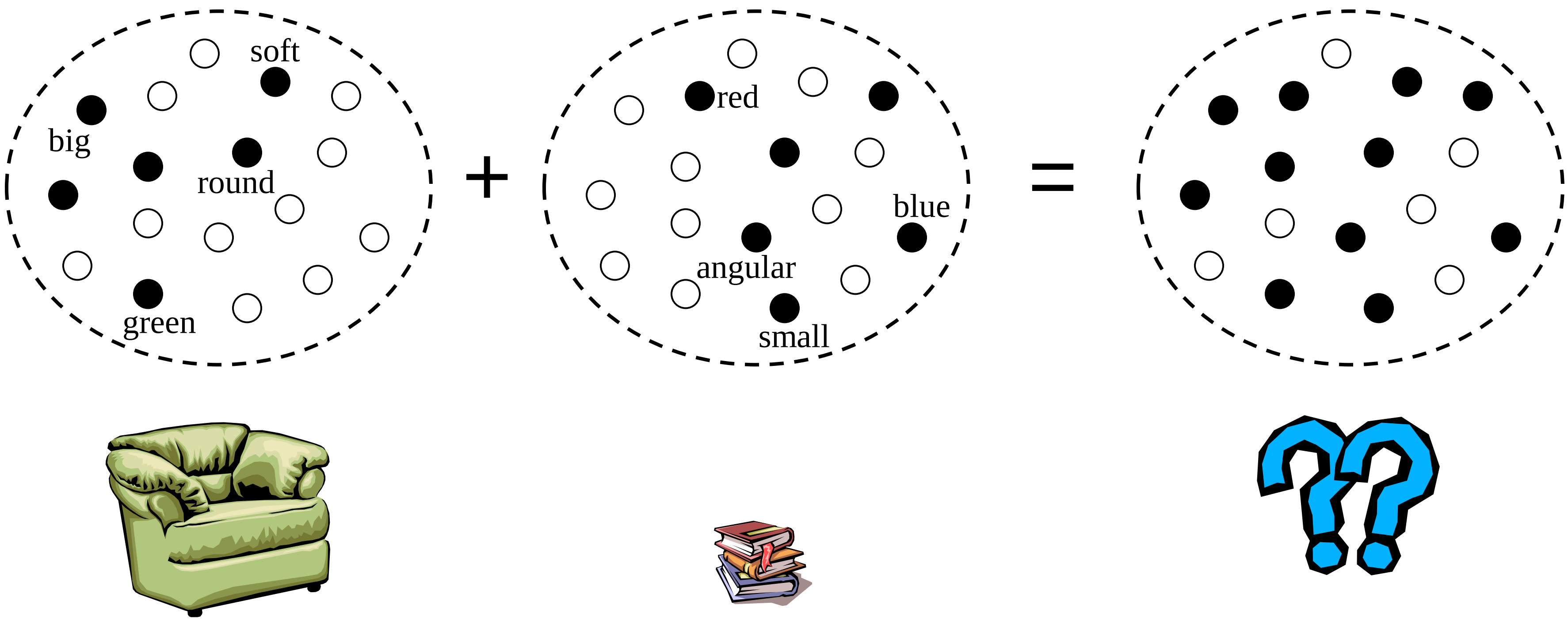
- The "binding problem": using temporal code
  - ✓ how to represent relationships?



2. A Pattern Formation Machine

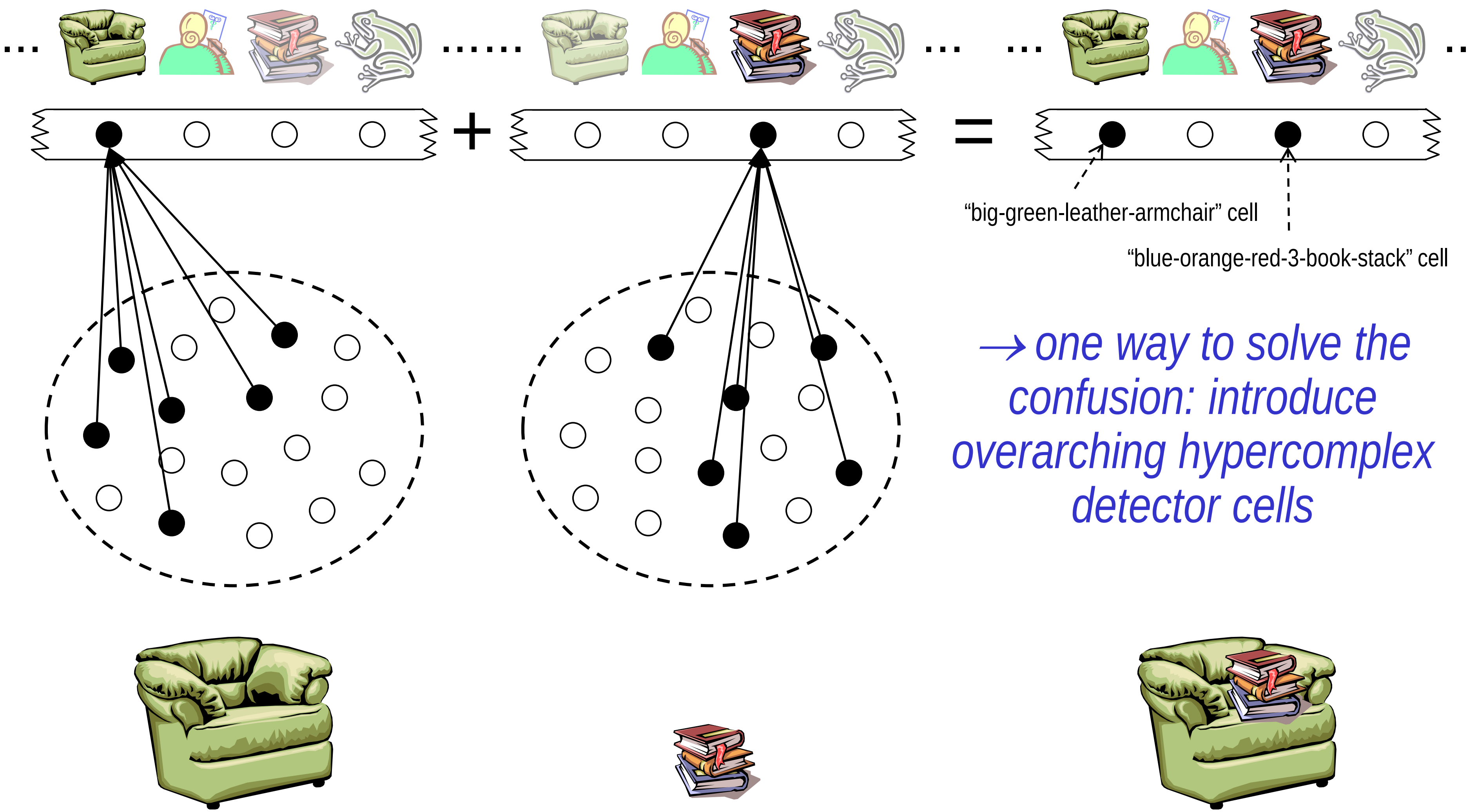
➢ More generallly: feature binding in cell assemblies

- ✓ unstructured lists or “sets” of features lead to the “superposition catastrophe”



2. A Pattern Formation Machine

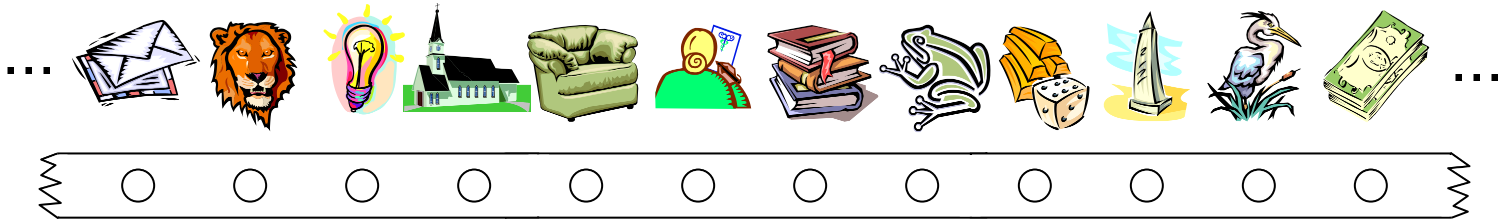
- ~~“Grandmother”~~ “Jennifer Aniston” cells... really?



→ *one way to solve the confusion: introduce overarching hypercomplex detector cells*

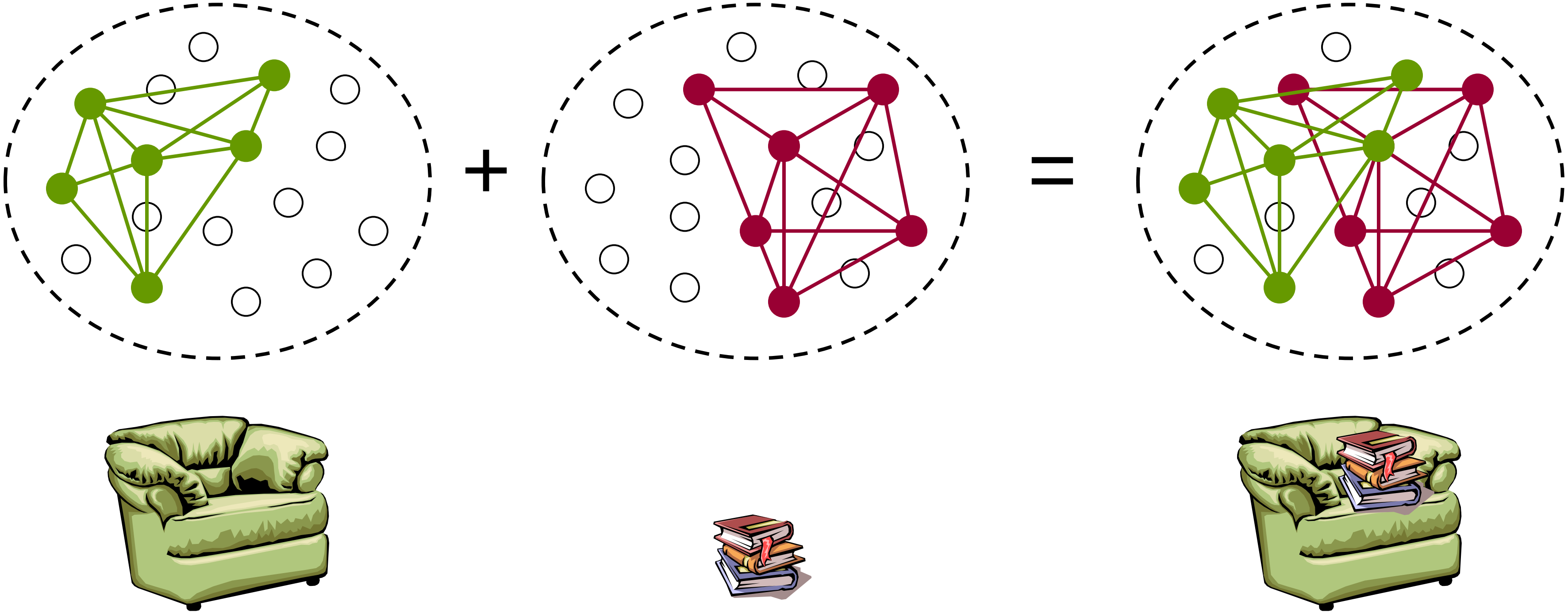
2. A Pattern Formation Machine

- ~~“Grandmother”~~ “Jennifer Aniston” cells... really?



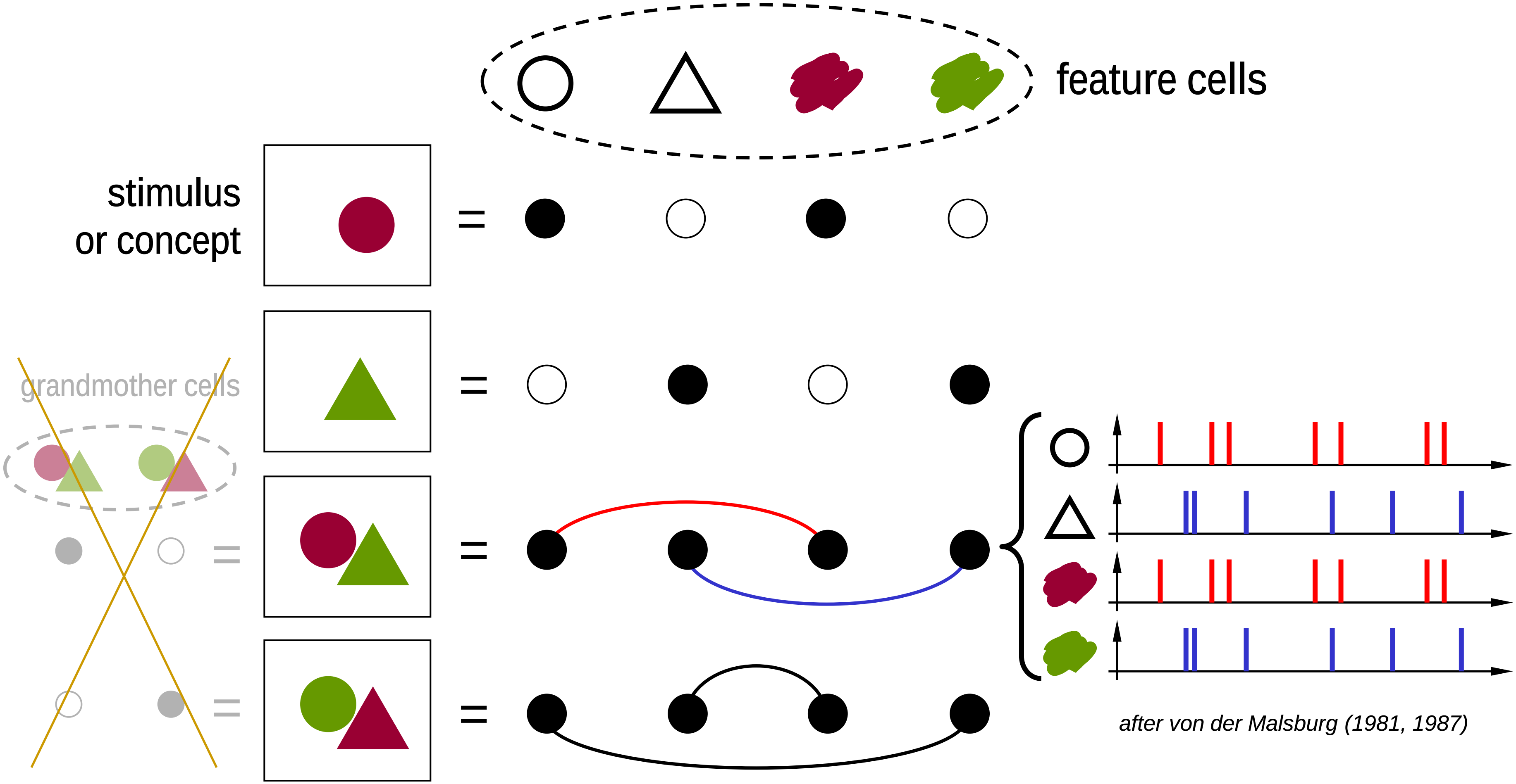
. . . however, this soon leads to
a combinatorial explosion

- Instead: relational representation → graph format
  - ✓ a better way to solve the confusion: represent relational information with *graphs*



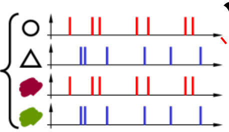
2. A Pattern Formation Machine

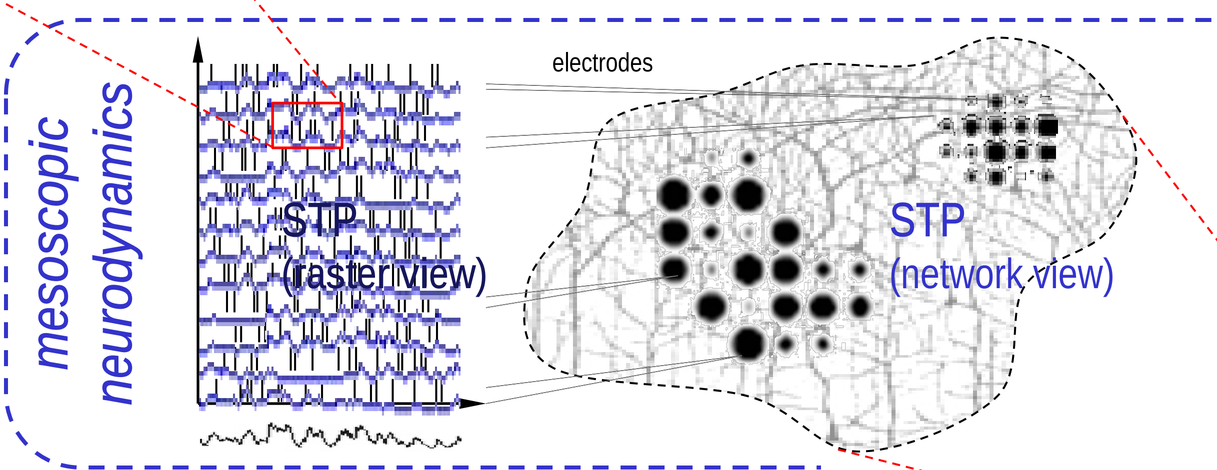
- Idea: relational information can be encoded *temporally*
  - ✓ back to the binding problem: a solution using temporal coding



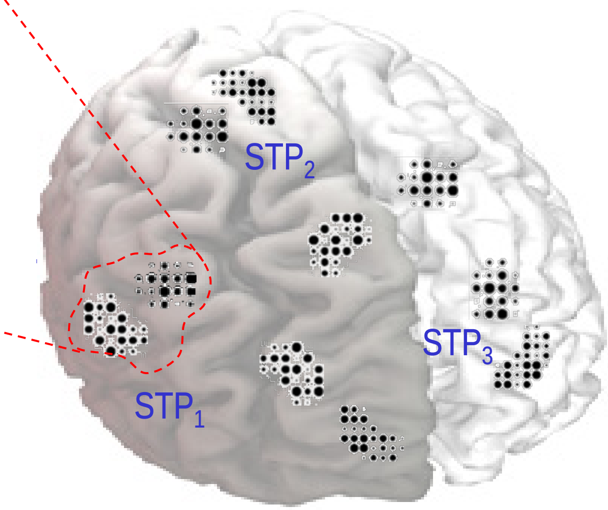
after von der Malsburg (1981, 1987)

- **Beyond small graphs → large *"spatiotemporal patterns"***
  - ✓ STPs: large-scale, localized dynamic cell assemblies that display complex, *reproducible* digital-analog regimes of neuronal activity
  - ✓ these regimes of activity are supported by specific, *ordered* patterns of recurrent synaptic connectivity





  - ✓ toward a "mesoscopic neurodynamics": construing the brain as a (spatio-temporal) *pattern formation machine*

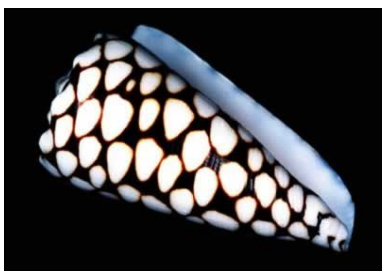
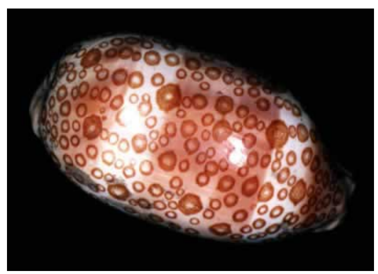


2. A Pattern Formation Machine

➢ Biological development is about pattern formation

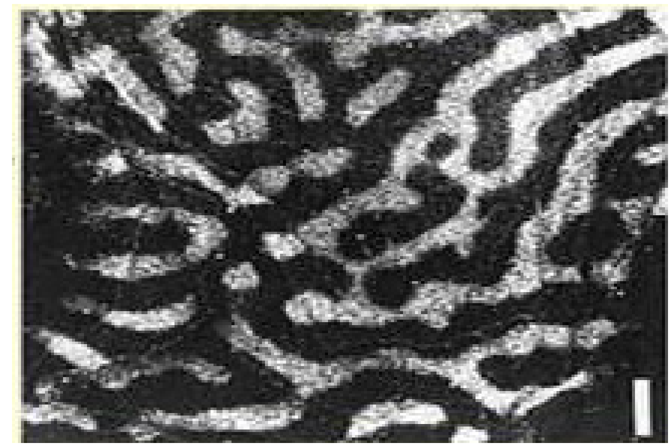
✓ multicellular patterning



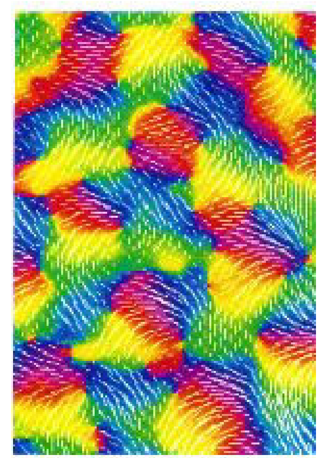



Scott Camazine, http://www.scottcamazine.com

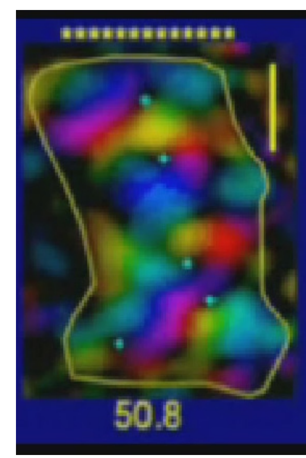
✓ ... the brain is no different



ocular dominance stripes Hubel & Wiesel, 1970



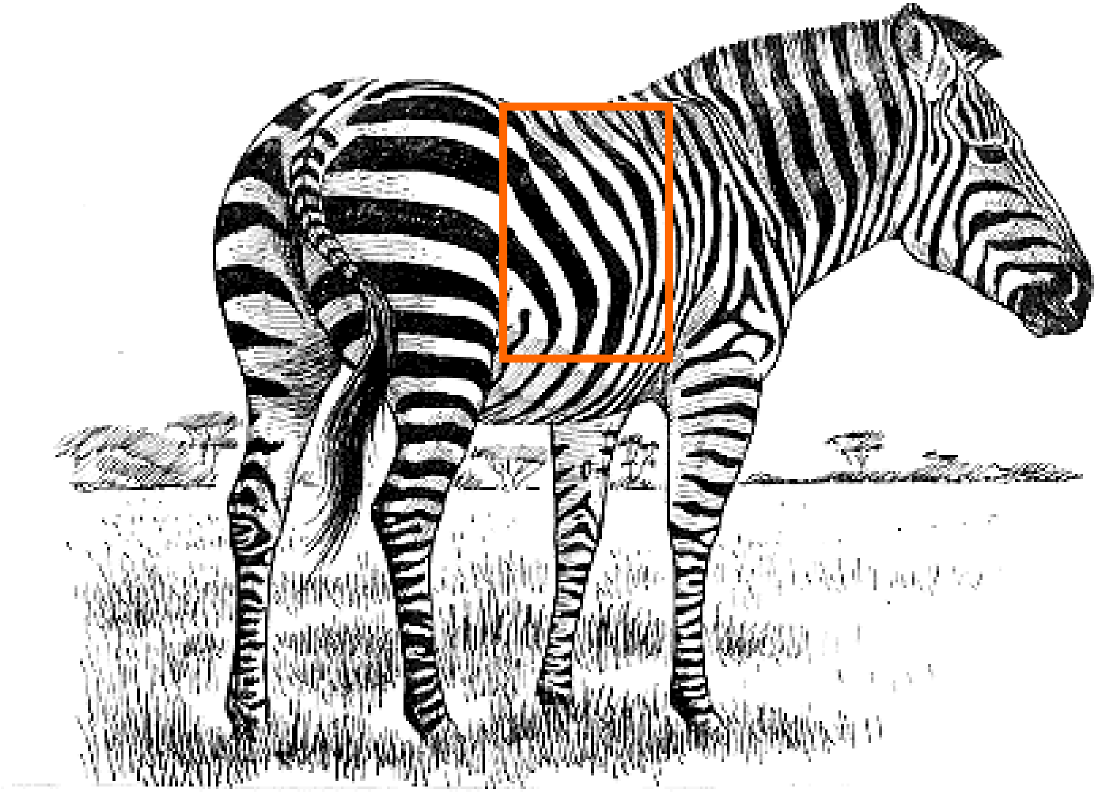
orientation column “pinwheels” Blasdel, 1992



Dynamics of orientation tuning: polar movie
Sharon and Grinvald, Science 2002

2. A Morphogenetic Machine

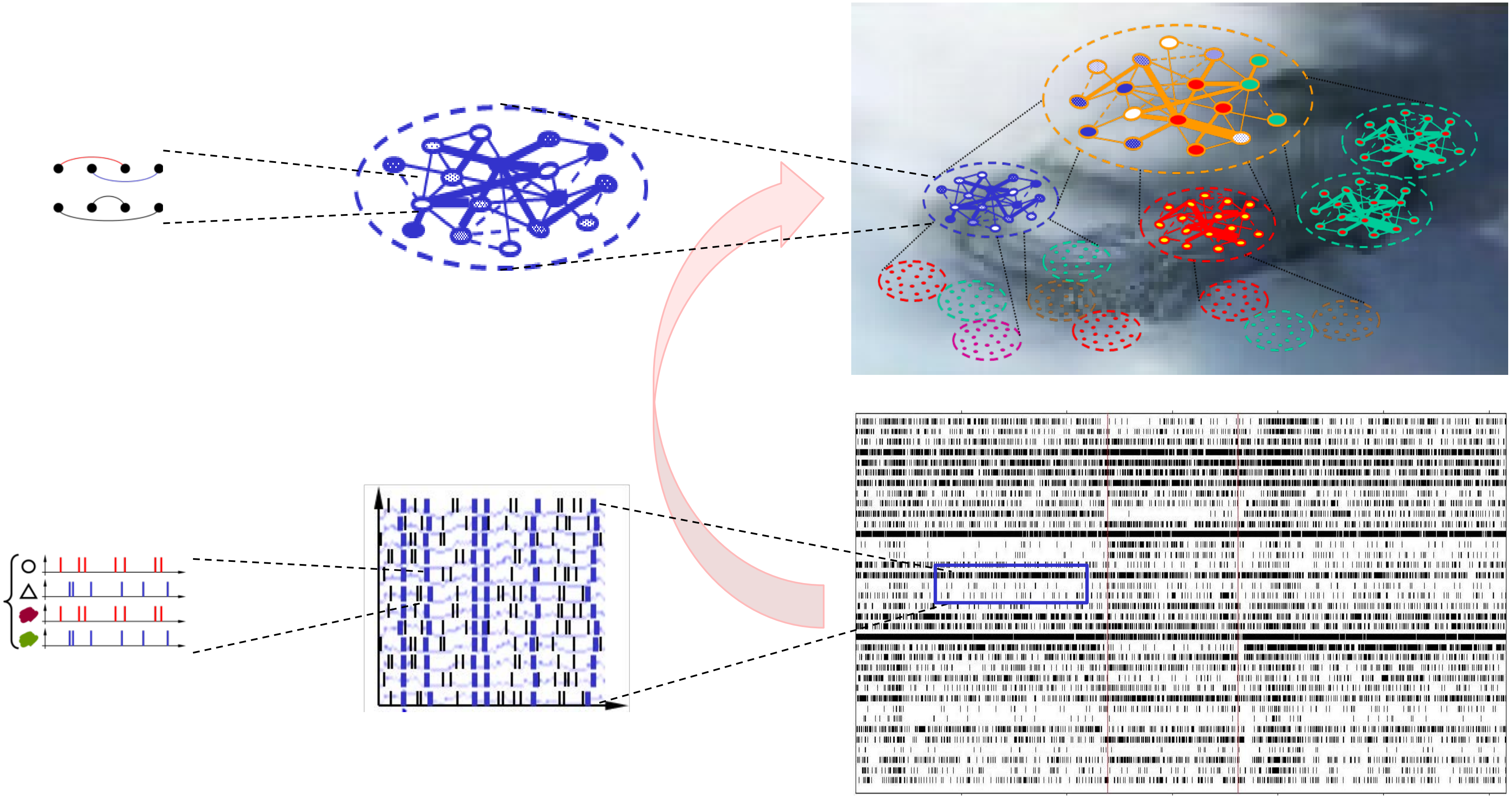
- ... but beyond pattern formation: complex morphogenesis
  - ✓ organisms are not just random, repetitive patterns but mostly complex, composite shapes endowed with a specific structure



"The stripes are easy, it's the horse part that troubles me"
—attributed to A. Turing, after his 1952 paper on the chemical basis of morphogenesis

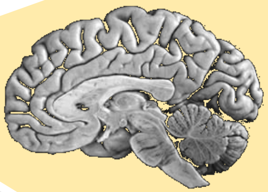
2. A Morphogenetic Machine

- ... but beyond pattern formation: complex morphogenesis
  - ✓ STPs are not just random, repetitive patterns but mostly *complex, composite shapes endowed with a specific structure*

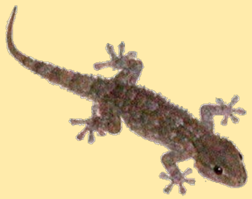


2. Architecture Without Architects

➢ "Simple"/random vs. **architectured** complex systems



the brain

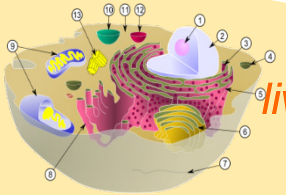


organisms

ant trails

termite mounds

biological patterns



living cell

animal flocks

physical patterns

➢ biology strikingly demonstrates the possibility of **combining** pure self-organization and elaborate architecture, i.e.:

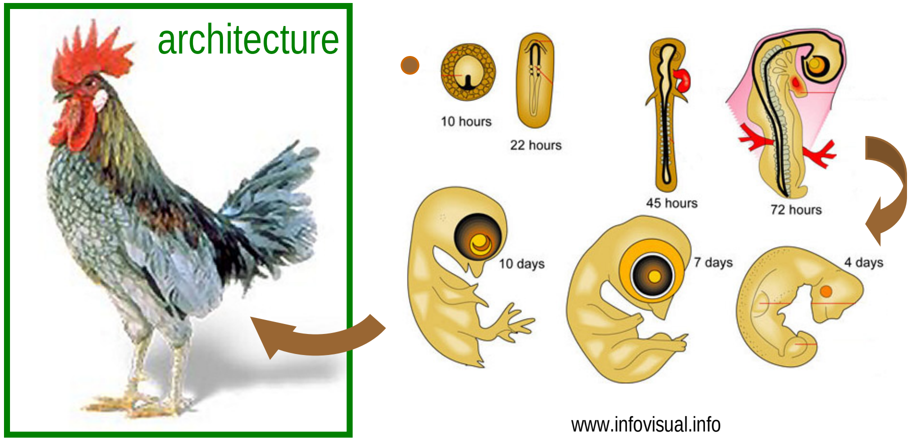
✓ a non-trivial, sophisticated morphology

- *hierarchical* (multi-scale): regions, parts, details
- *modular*: reuse of parts, quasi-repetition
- *heterogeneous*: differentiation, division of labor

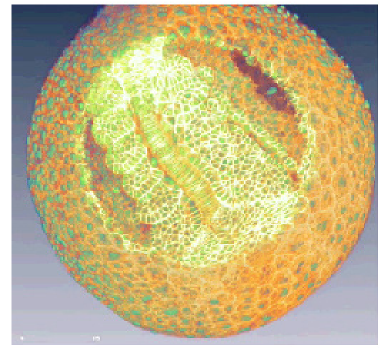
✓ *random* at agent level, *reproducible* at system level

2. Architecture Without Architects

➢ Ex: Morphogenesis – Biological development



www.infovisual.info

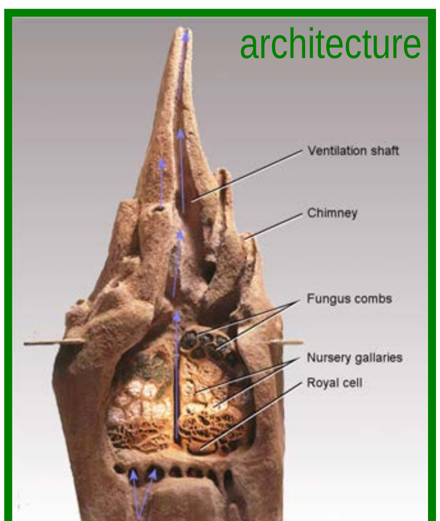


Nadine Peyriéras, Paul Bourgine et al.
(Embryomics & BioEmergences)

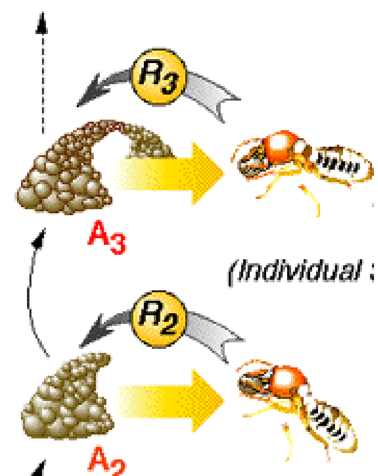
- cells build sophisticated organisms by division, genetic differentiation and biomechanical self-assembly

➢ Ex: Swarm intelligence – Termite mounds

Termite mound
(J. McLaughlin, Penn State University)



http://cas.bellarmine.edu/tietjen/ TermiteMound%20CS.gif



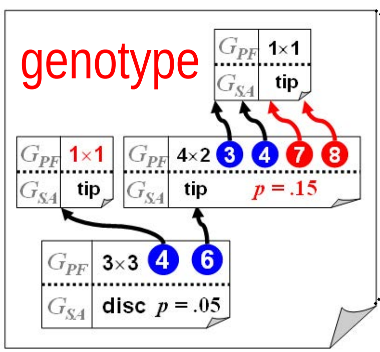
Termite stigmergy
(after Paul Grassé; from Solé and Goodwin, "Signs of Life", Perseus Books)

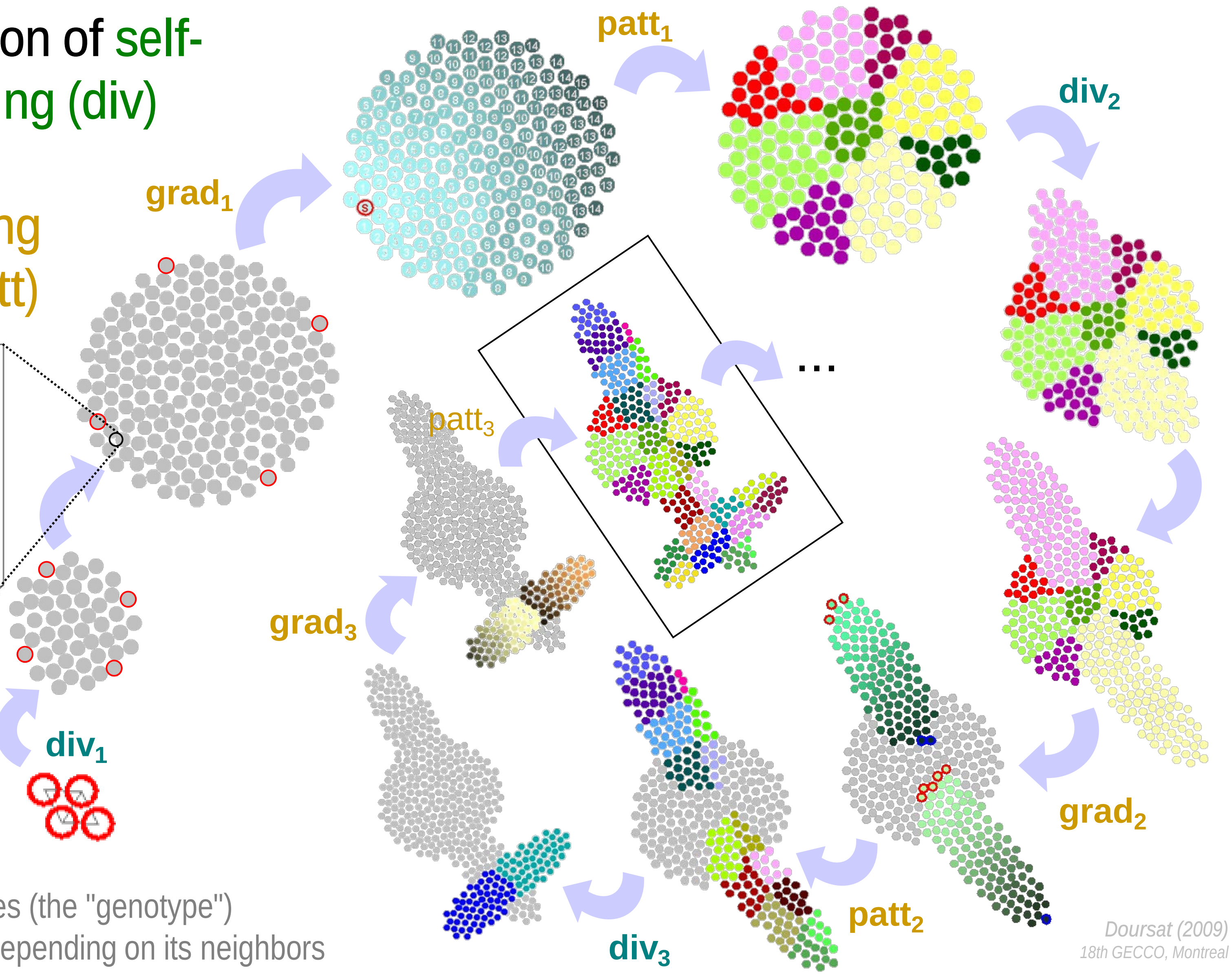
- termite colonies build sophisticated mounds by **"stigmergy"** = loop between modifying the environment and reacting differently to these modifications

2. Morphogenetic Engineering

An Artificial Life agent model capturing the essence of morphogenesis

- Alternation of self-positioning (div) and self-identifying (grad/patt)

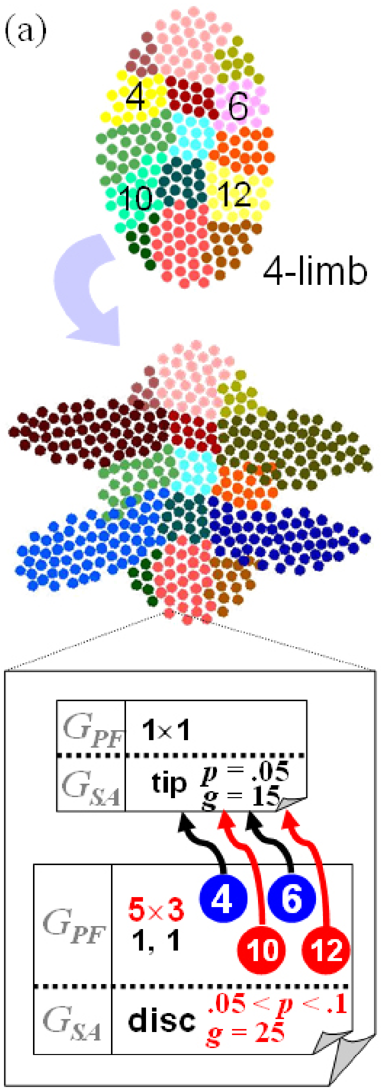


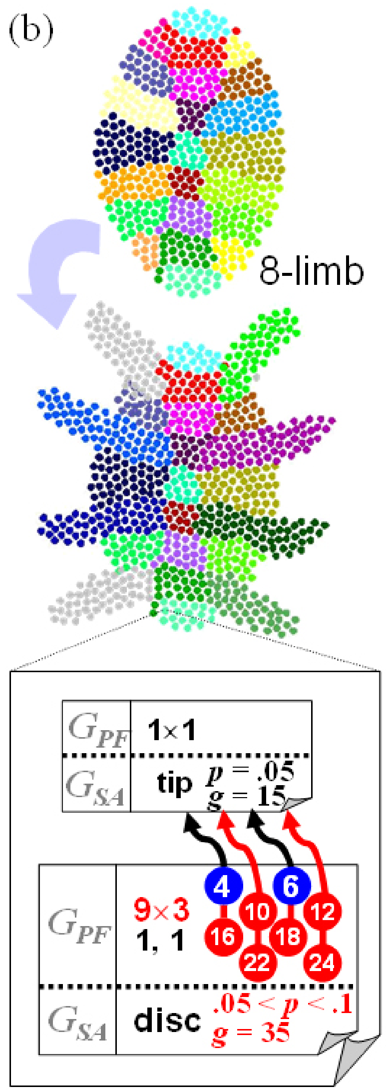


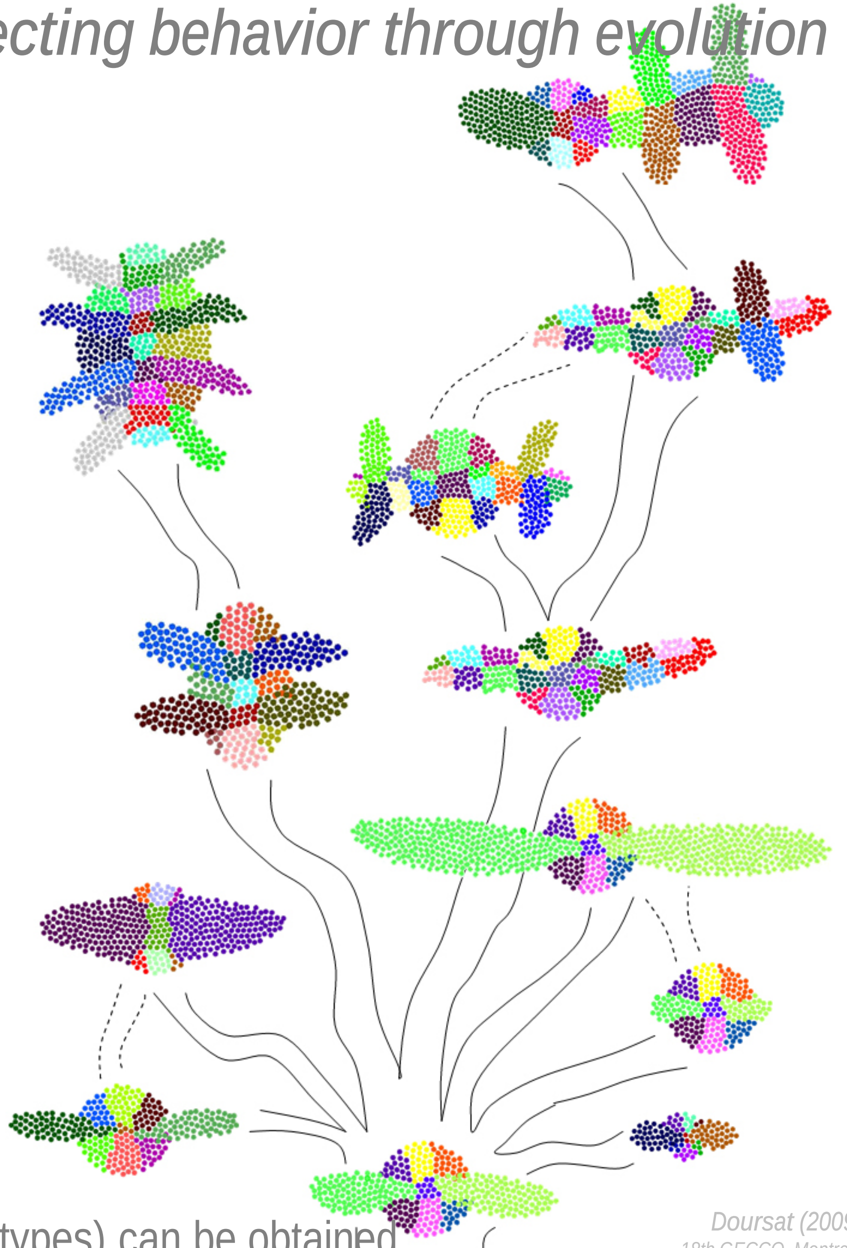
each agent
follows the same set
of self-architecting rules (the "genotype")
but reacts differently depending on its neighbors

2. Morphogenetic Engineering

... and changing the agents' self-architecting behavior through evolution







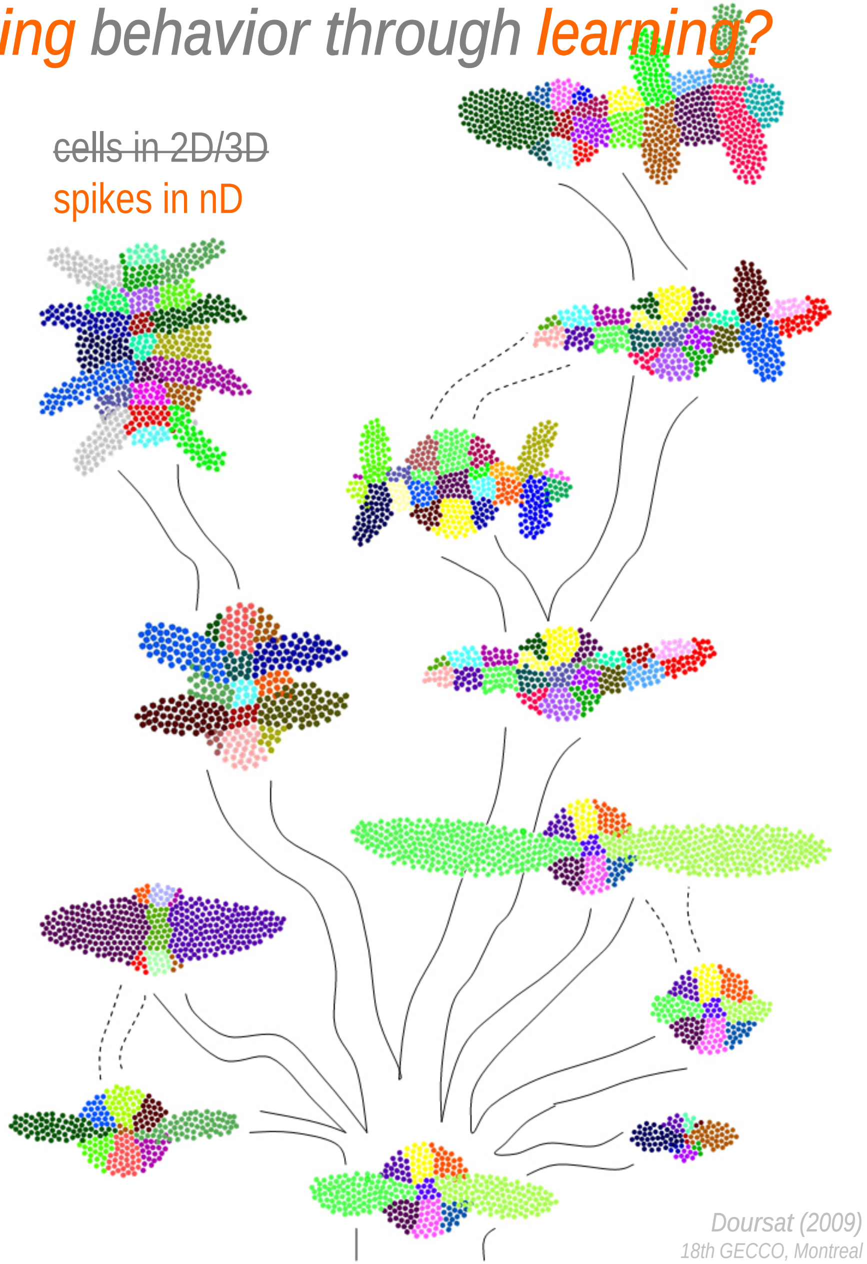
by tinkering with the genotype, new architectures (phenotypes) can be obtained

2. Morphogenetic Engineering

... and changing the *neurons' self-flocking* behavior through *learning?*

A metaphor for a "mental shape zoo"?
Neural morphogenesis extends beyond slow, 3-D physical development into fast, n-D spatio-temporal assemblies.

After cells have positioned themselves and established contacts, they continue "moving" and "assembling / disassembling" in virtual, phase space.



MORPHOGENETIC "NEURON-FLOCKING"

1. Cognitive Architectures in the Tower of Complex Systems

The emergence of neural/mind states on multiple levels of self-organization

2. The Mind as a Pattern Formation Machine

Neural correlations: The glue of spatiotemporal patterns (STPs)

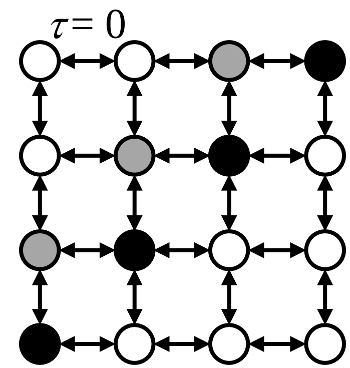
3. Example Model: Wave-Based Shape-Matching

Coding coordinates by phases, and shapes by waves

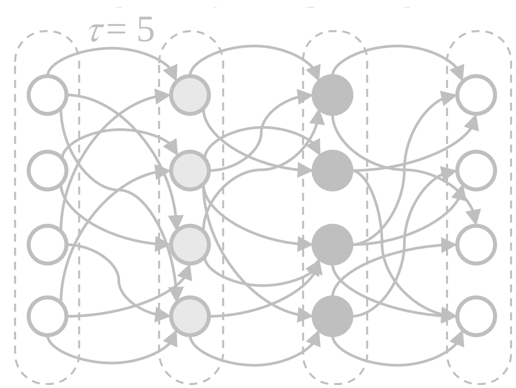
- *Lattices: group sync, waves, 2D shapes*
- *Synfire chains: wave storage, retrieval*
- *Synfire braids: shape storage, matching*

3. Wave-Based Shape-Matching

- Wave-based pattern retrieval and matching
  - ✓ Lattices of coupled oscillators (zero delays)
    - group synchronization
    - traveling waves
    - 2D wave shapes
    - shape metric deformation



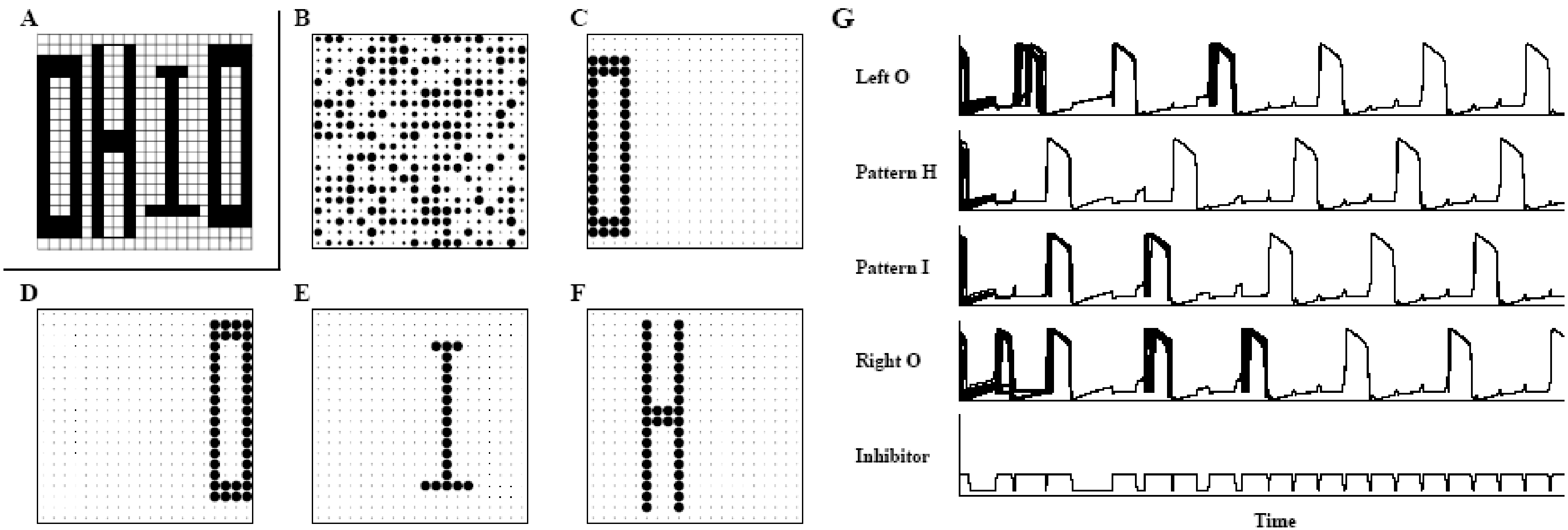
  - ✓ Synfire chains (uniform delays)
    - wave propagation
    - chain growth
    - pattern storage and retrieval



  - ✓ Synfire braids (transitive delays)
    - shape storage and retrieval
    - 2D wave-matching

3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators *– group sync, phase-tagging*
  - ✓ the base of many perceptual segmentation models in the 1990's
    - auditory: von der Malsburg & Schneider (1986), "cocktail party" processor
    - visual, after Gray & Singer (1989): Kurrer & Schulten (1990), König & Schillen (1991), DL Wang & Terman (1995), Campbell & DL Wang (1996), etc.
      - o oscillatory or excitable units as an abstraction of excit↔inhib columnar activity
      - o 2D lattice coupling as an abstraction of topographically organized visual cortex



(w/ relaxation oscillators similar to FitzHugh-Nagumo/Morris-Lecar + global inhibition)

Wang D.L. and Terman D. (1997): Image segmentation based on oscillatory correlation. *Neural Computation*, vol. 9, 805-836

3. Wave-Based Shape-Matching

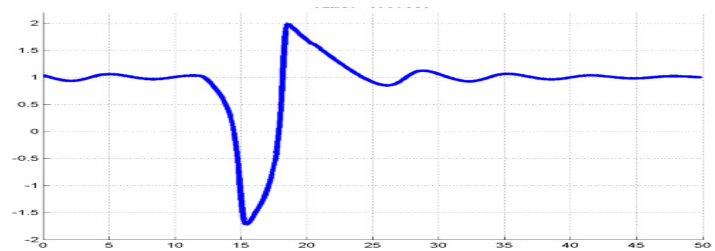
- Stochastic excitable units
  - ✓ ex: Bonhoeffer-van der Pol (BvP) oscillator's two main regimes:

$$\begin{cases} \dfrac{du_i}{dt} = c\left(u_i - \dfrac{u_i^3}{3} + v_i + z\right) + \eta \\ \dfrac{dv_i}{dt} = \dfrac{1}{c}\left(a - u_i - bv_i\right) + \eta \end{cases}$$

$z > z_c$ a) sparse, stochastic → ***excitable***

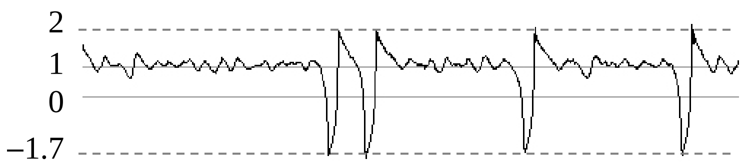
$z_c = -0.3465$

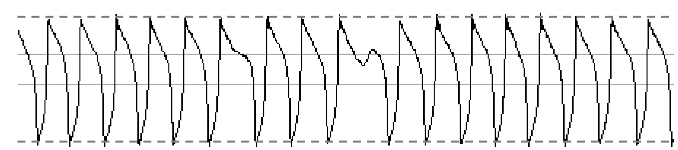
$z < z_c$ b) quasi-periodic → ***oscillatory***



$a = 0.7$
$b = 0.8$
$c = 3$

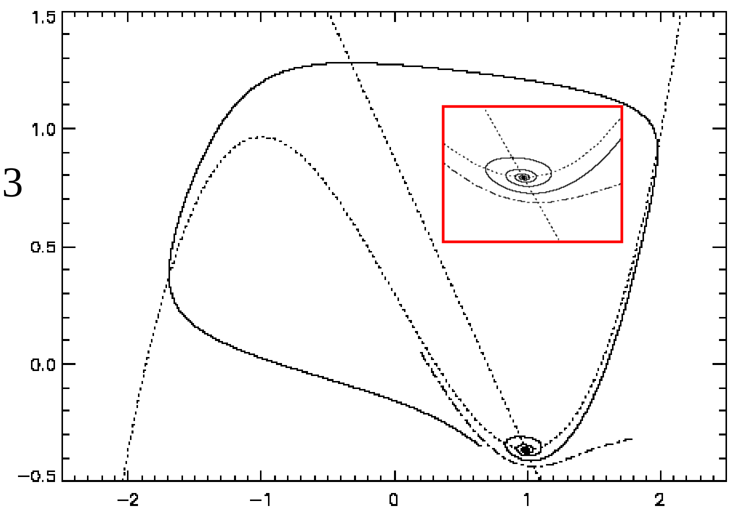
(a)

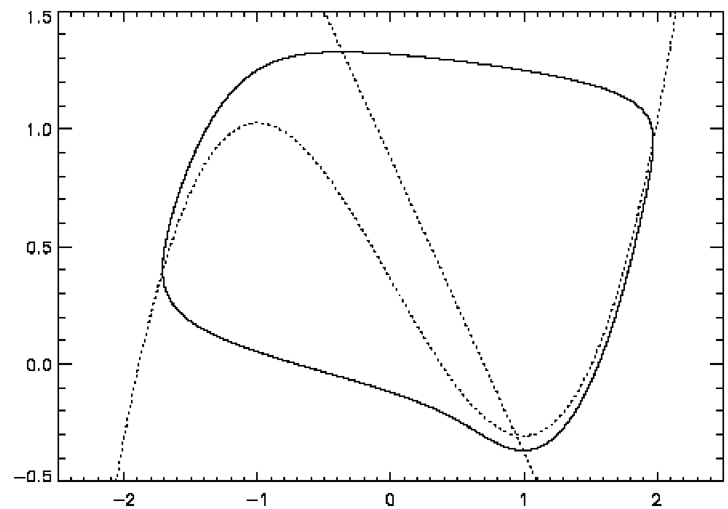




(b)

$z = -0.3$





$z = -0.36$

3. Wave-Based Shape-Matching – Lattice

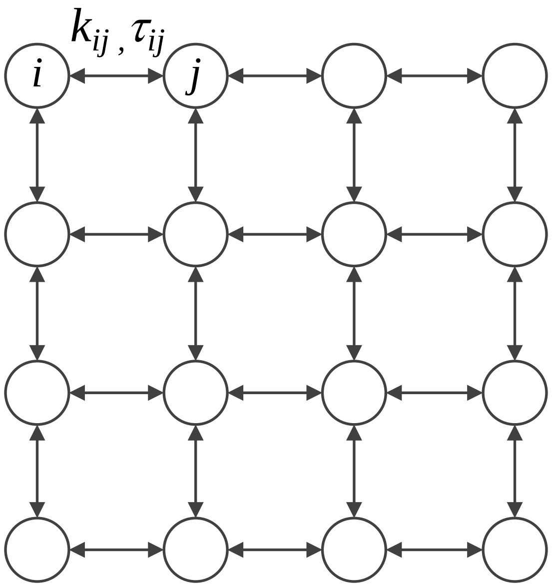
- Lattice of coupled oscillators
  - ✓ $i \leftarrow j$ coupling features
    - isotropic
    - proportional to the u signal difference
      - o only in spiking domain $u < 0$
    - positive connection weight k_{ij}
    - possible transmission delay τ_{ij}
      - o here zero delays $\tau_{ij} = 0$

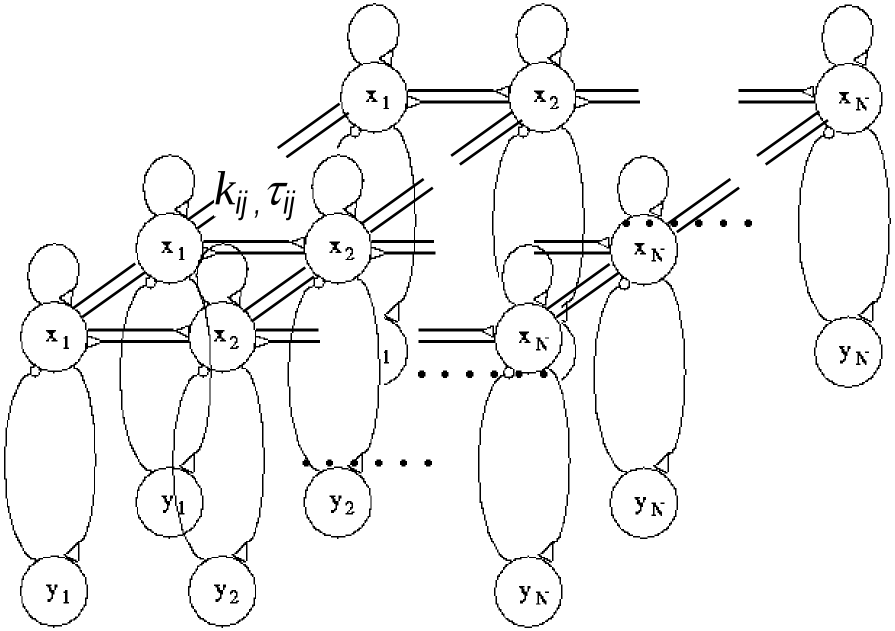
$$\begin{cases} \dfrac{du_i}{dt} = c(u_i - \dfrac{u_i^3}{3} + v_i + z) + \eta + K_i + I_i \\ \dfrac{dv_i}{dt} = \dfrac{1}{c}(a - u_i - bv_i) + \eta \end{cases}$$

coupling term

input term

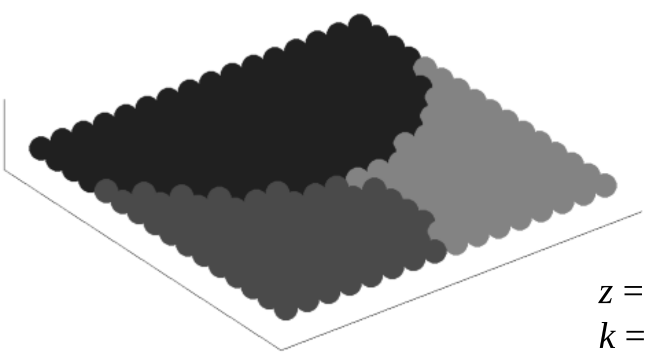
$$\boxed{K_i(t) = \sum_{\substack{j=1 \\ u_j(t-\tau_{ij})<0}}^{N} k_{ij}\big(u_j(t-\tau_{ij}) - u_i(t)\big)}$$





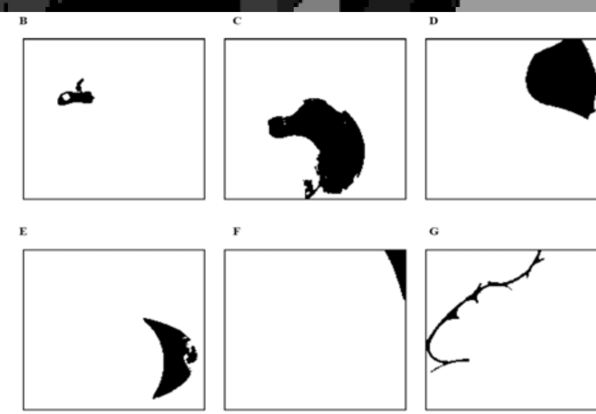
3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators *– group sync, phase-tagging*



$z = -0.336$
$k = 0.10$
$I = -2.34$

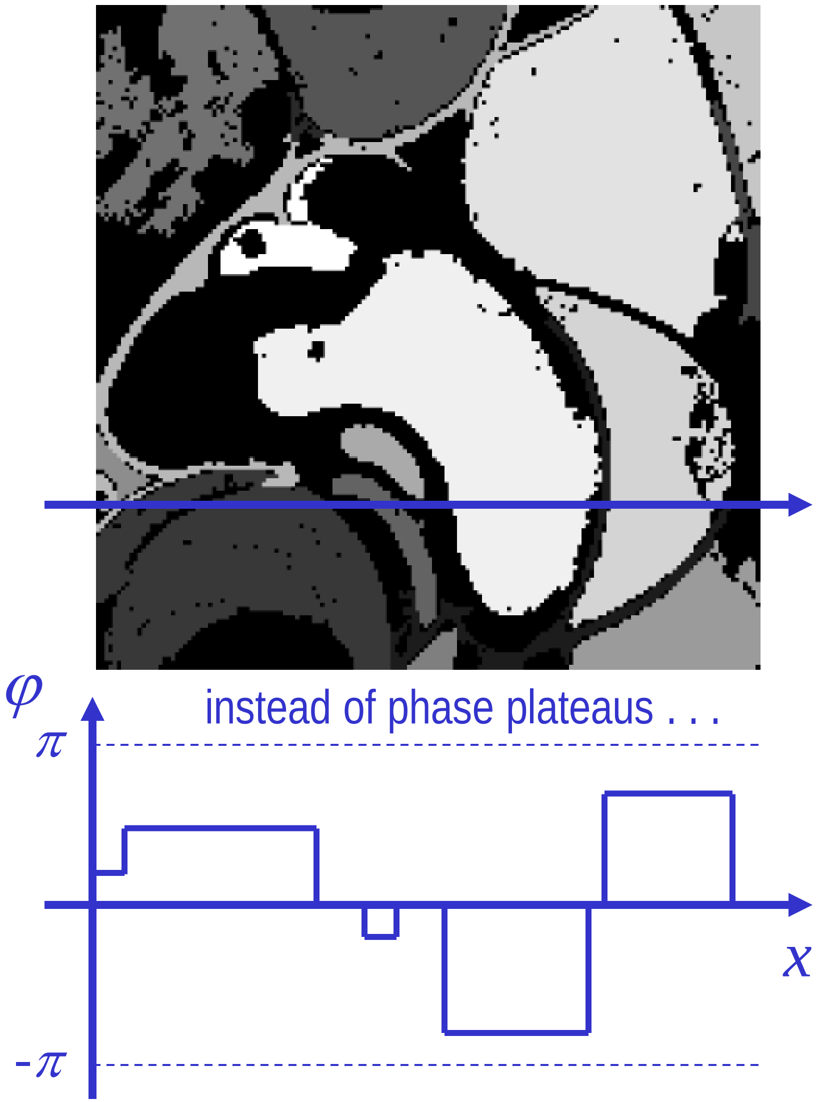
(illustration by Doursat & Sanchez 2011)



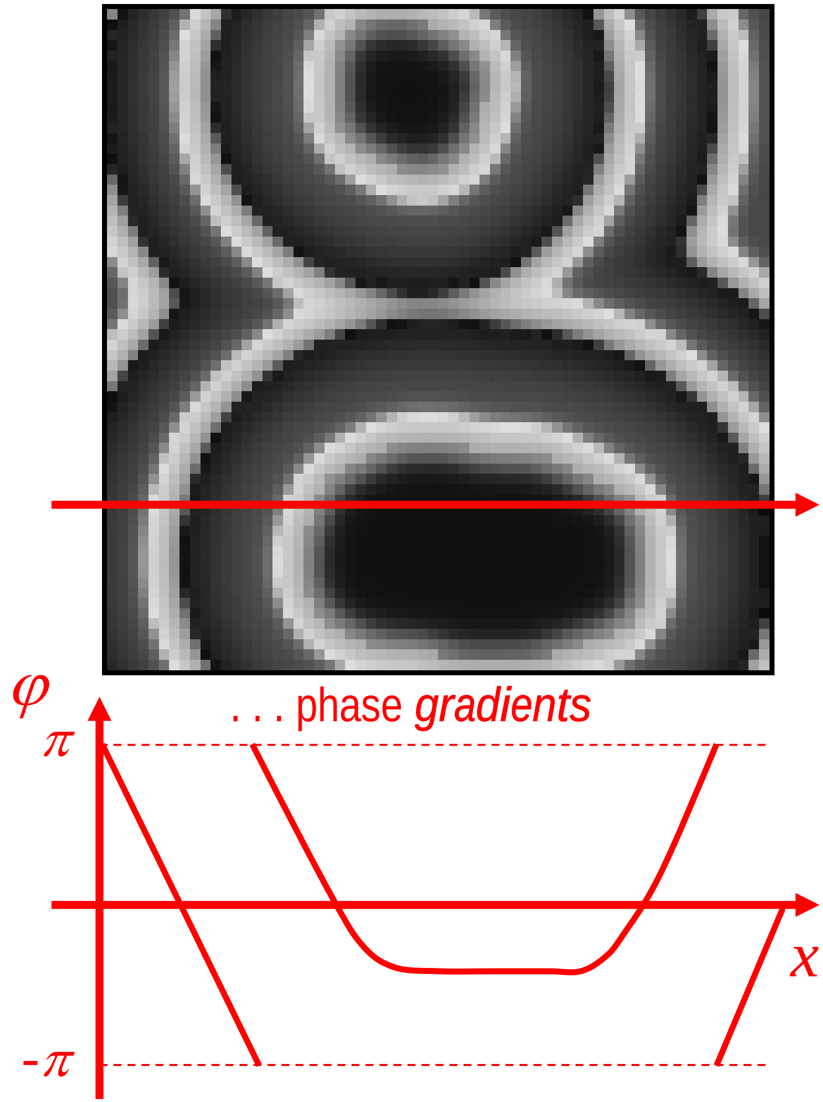
Wang D.L. and Terman D. (1997): Image segmentation based on oscillatory correlation. *Neural Computation*, vol. 9, 805-836

3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators – *traveling waves*



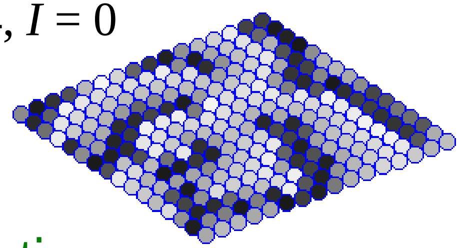
Wang D.L. and Terman D. (1997): Image segmentation based on oscillatory correlation. *Neural Computation*, vol. 9, 805-836



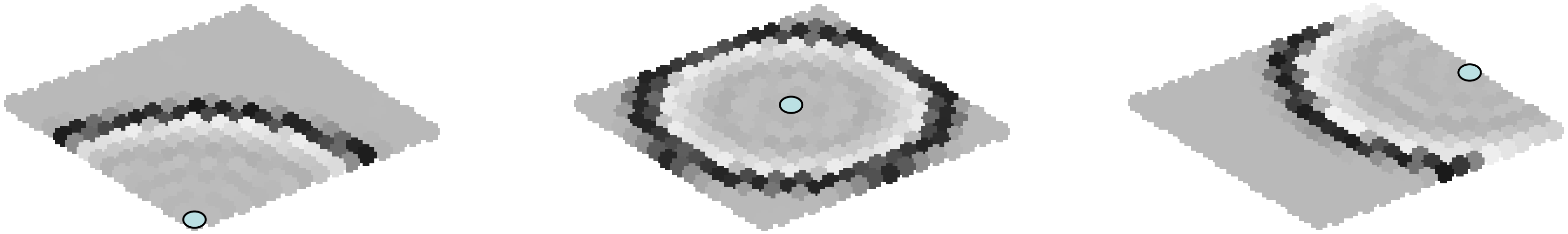
Doursat,, R. & Petitot, J. (2005) Dynamical systems and cognitive linguistics: Toward an active morphodynamical semantics. *Neural Networks* 18: 628-638.

3. Wave-Based Shape-Matching – Lattice

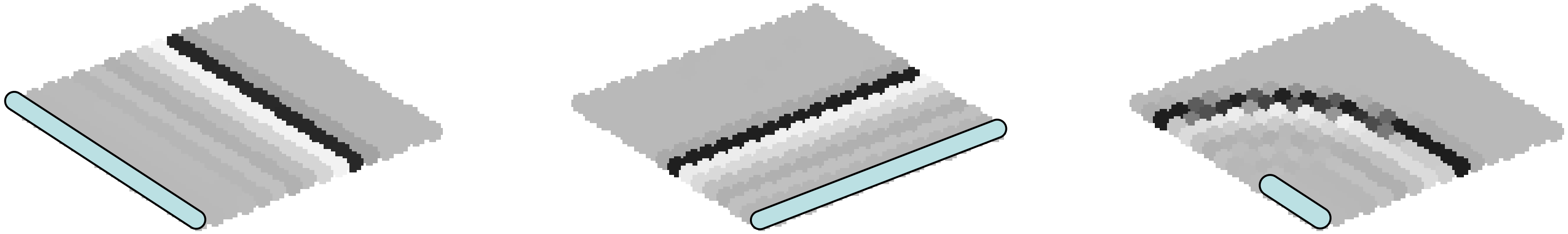
- Lattice of coupled oscillators – *traveling waves*
  - ✓ Random propagation
    - $z = -0.346$, $k = 0.04$, $I = 0$



  - ✓ Circular wave generation
    - $z = -0.29$, $k = 0.10$, $I = -0.44$ (point stimulus)



  - ✓ Planar & mixed wave generation
    - $z = -0.29$, $k = 0.10$, $I = -0.44$ (bar stimulus)



3. Wave-Based Shape-Matching – Lattice

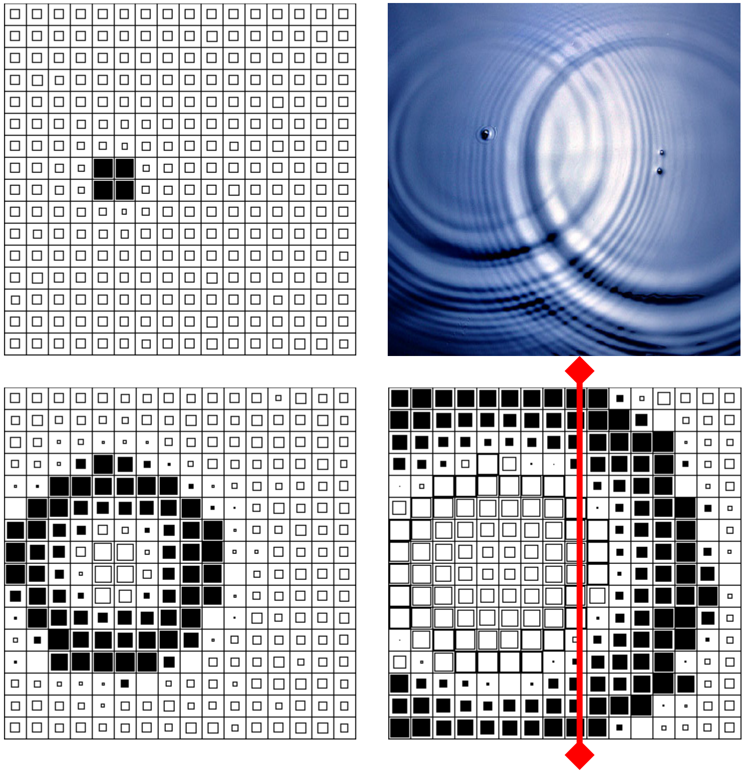
➢ The "morphodynamic pond": a neural medium at criticality

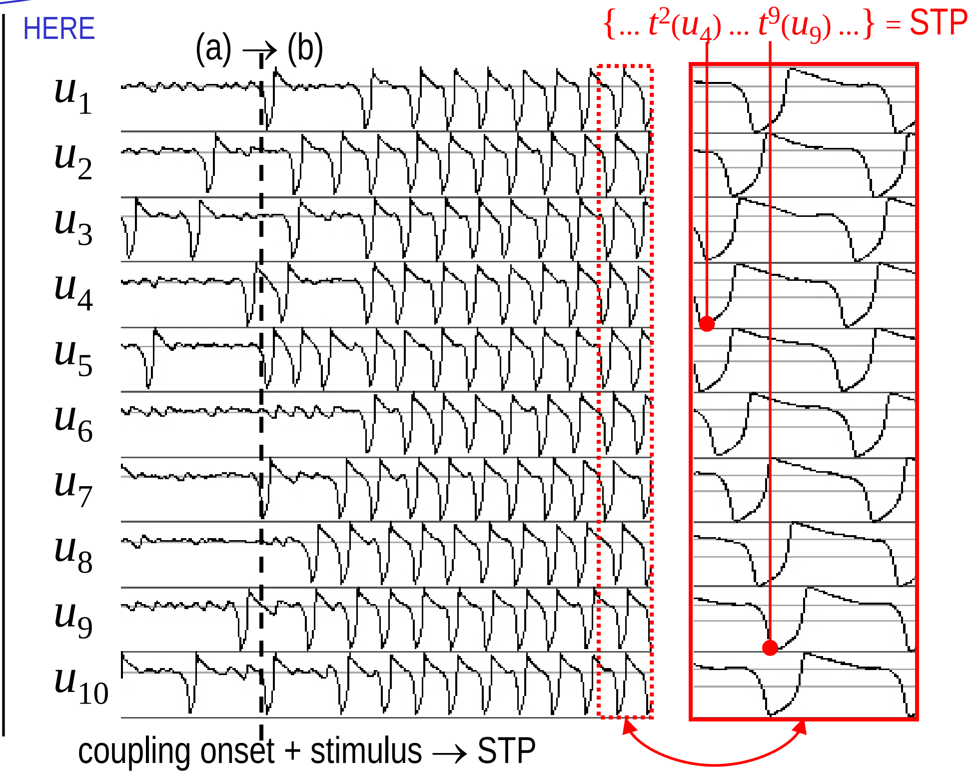
✓ upon coupling onset and/or stimulation → emergence of a wave

- quick transition to ordered regime (STP): reproducible succession of spike events ($t^1, t^2, \ldots$)

✓ the structure of the STP is a trade-off between

- endogenous factors: *connectivity* (structural bias), *attractors* (preferred activation modes)
- exogenous factors: *stimulus* (perturbation), *binding* (composition with other STPs)

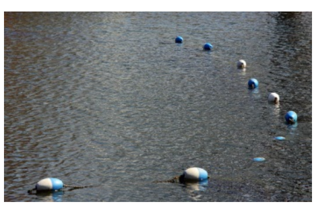




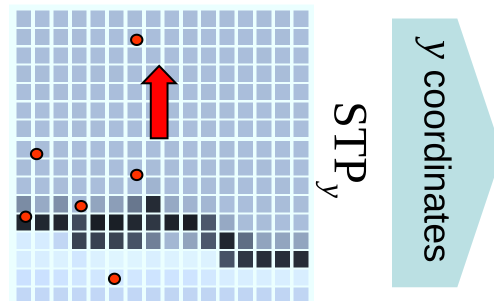
➢ Lattice of coupled oscillators – *2D wave shapes*

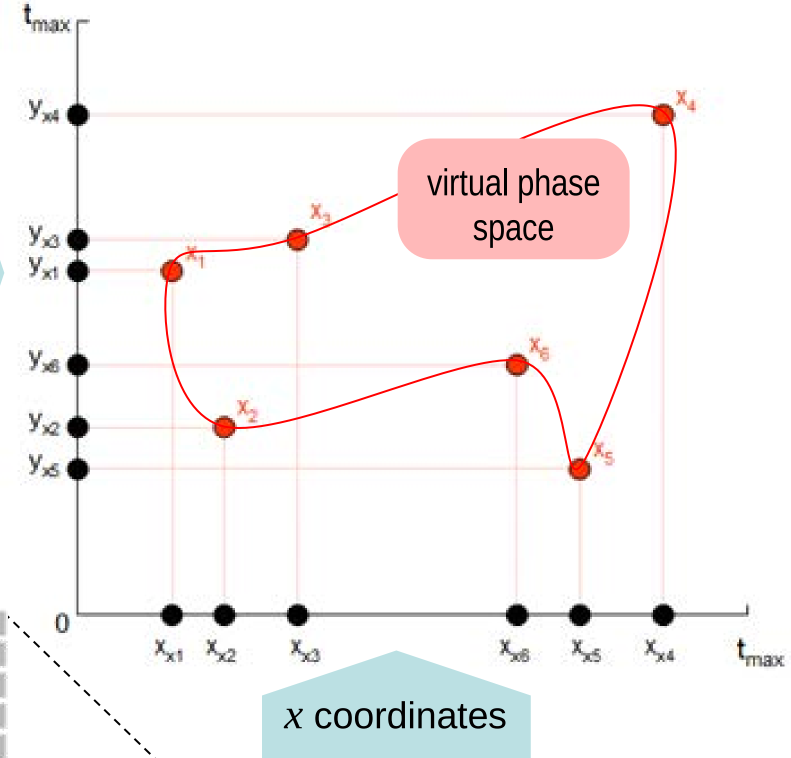
✓ coding coordinates with phases

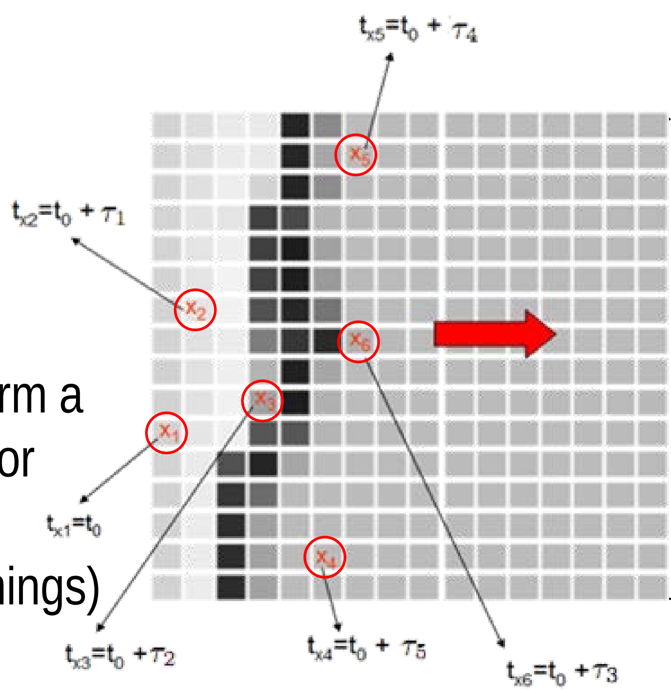
- the salient "feature-detecting" units of an object can participate in 2 different STPs by propagation of 2 different waves
- similar to buoys floating on water

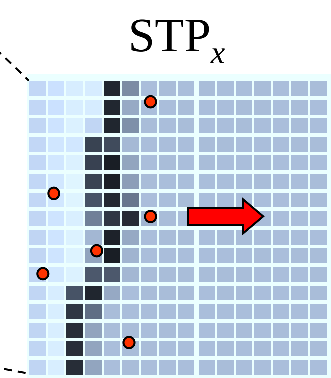


- these 2 STPs form a 2D constellation or "shape" in virtual phase space (timings)









➢ Lattice of coupled oscillators *– 2D wave shapes*

✓ coding coordinates with phases

- the salient "feature-detecting" units of an object can participate in 2 different STPs by propagation of 2 different waves
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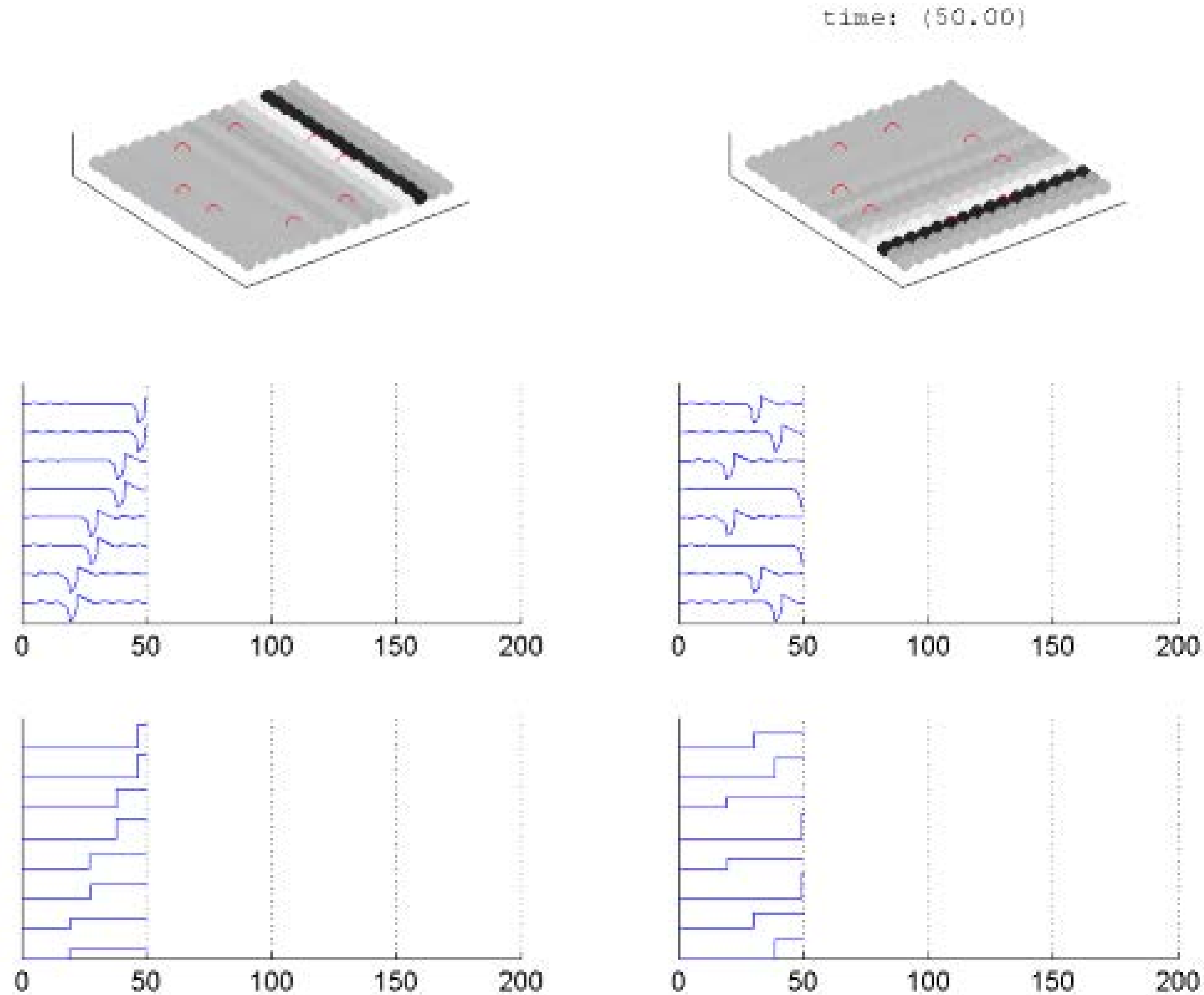
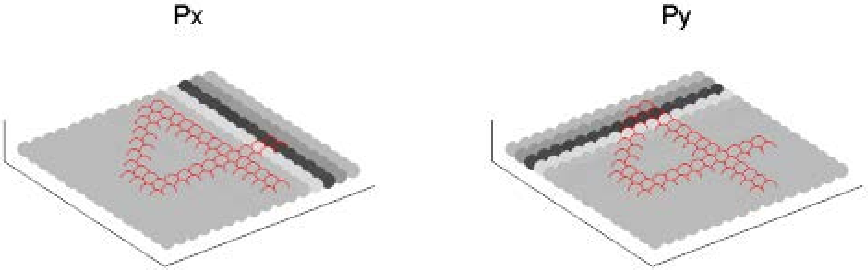
- these 2 STPs form a 2D constellation or "shape" in virtual phase space (timings)

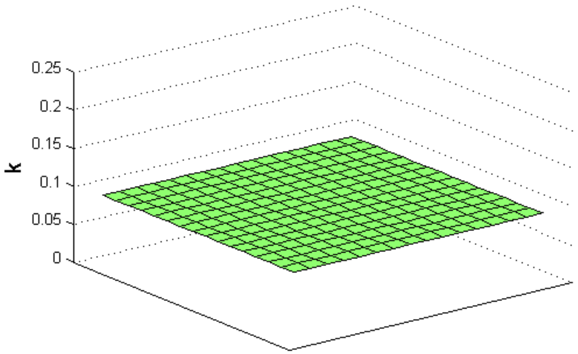


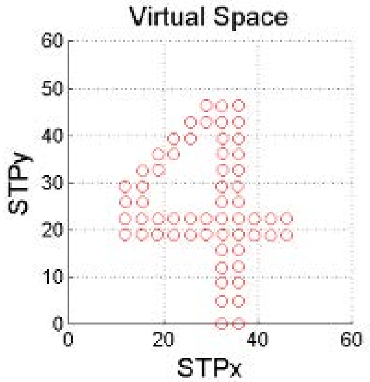
3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators *– 2D wave shapes*
  - ✓ the final shape in virtual phase space depends on
    - the physical position of the feature units on the lattice
    - the form and direction of the two waves, itself depending on:
      - o endogenous factors: connectivity and weight distribution
      - o exogenous factors: stimulus domains
  - ✓ ex: no deformation
    - planar & orthogonal waves
      - o uniform weights on P_X and P_Y
      - o orthogonal full-bar stimuli
    - → *shape = physical positions*



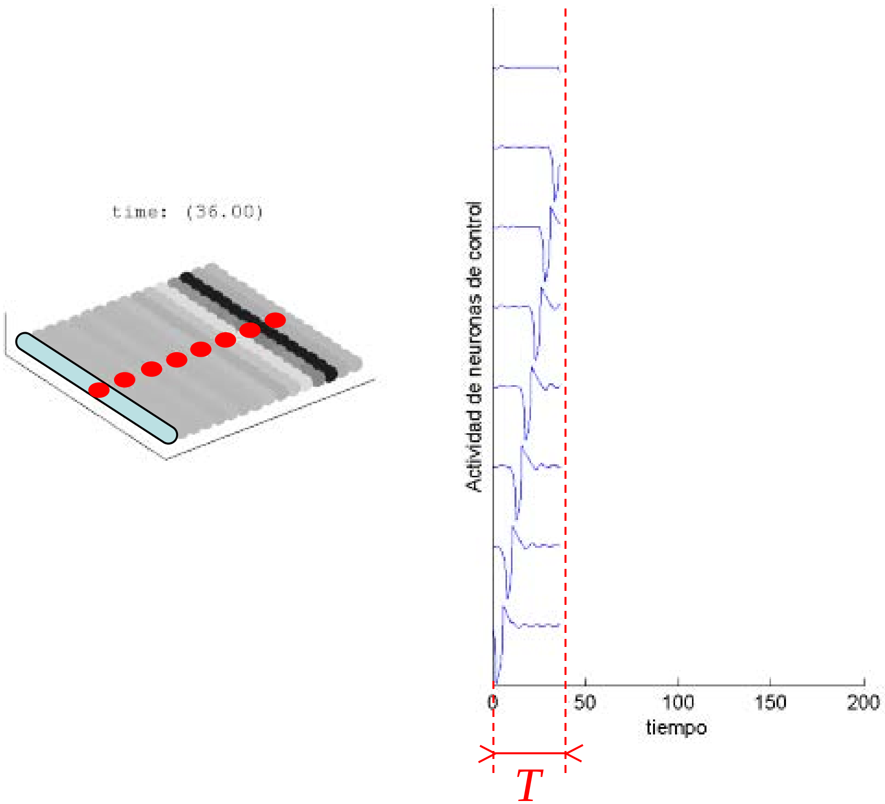
uniform weight distribution: $k = 0.09$

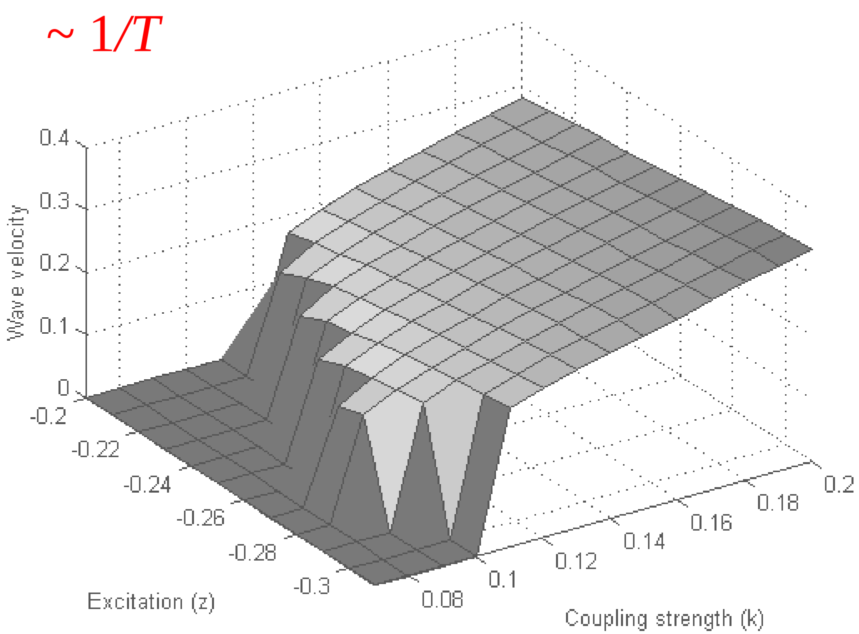




3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators – *shape metric deformation*
  - ✓ wave detection and velocity measure based on control units
    - the probability of wave generation increases with $z\searrow$ and $k\nearrow$
    - the velocity of the generated wave increases with $z\searrow$ and $k\nearrow$

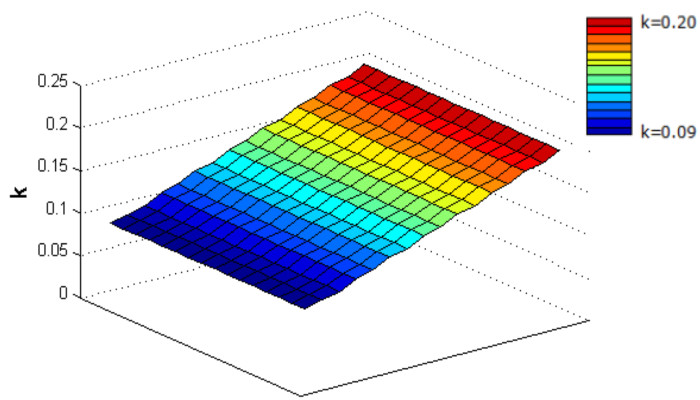


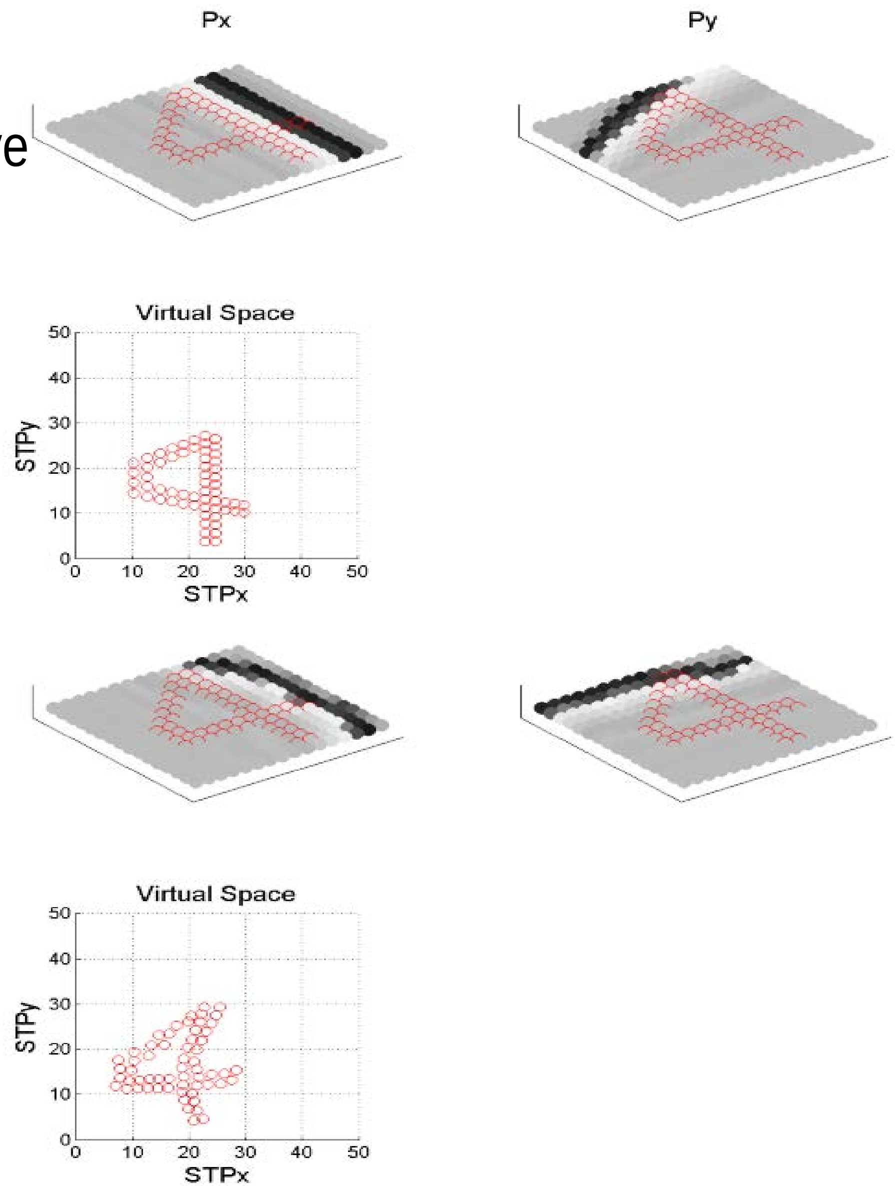


3. Wave-Based Shape-Matching – Lattice

- Lattice of coupled oscillators *– shape metric deformation*
  - ✓ ex: "shear stress" deformation
    - ▪ vertical wave + horizontal wave
      - o Y-gradient of weights on P_Y
      - o orthogonal full-bar stimuli

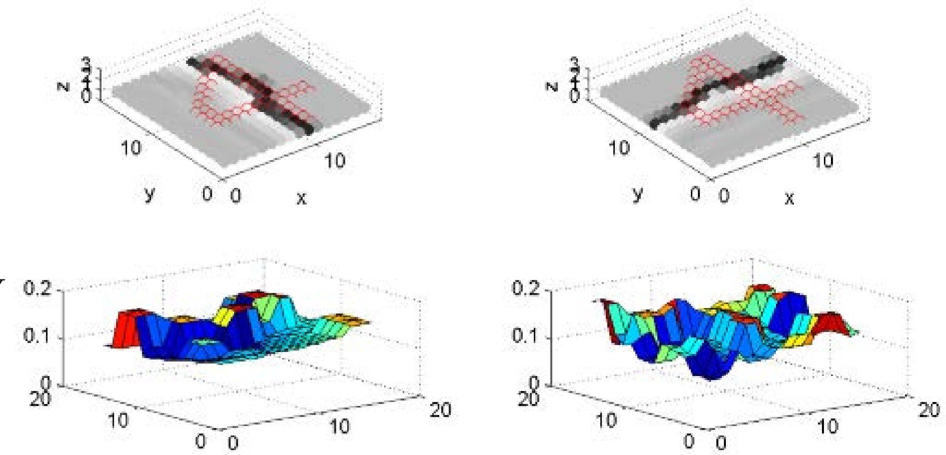
gradient weight landscape:
$k \in [0.09, 0.20]$

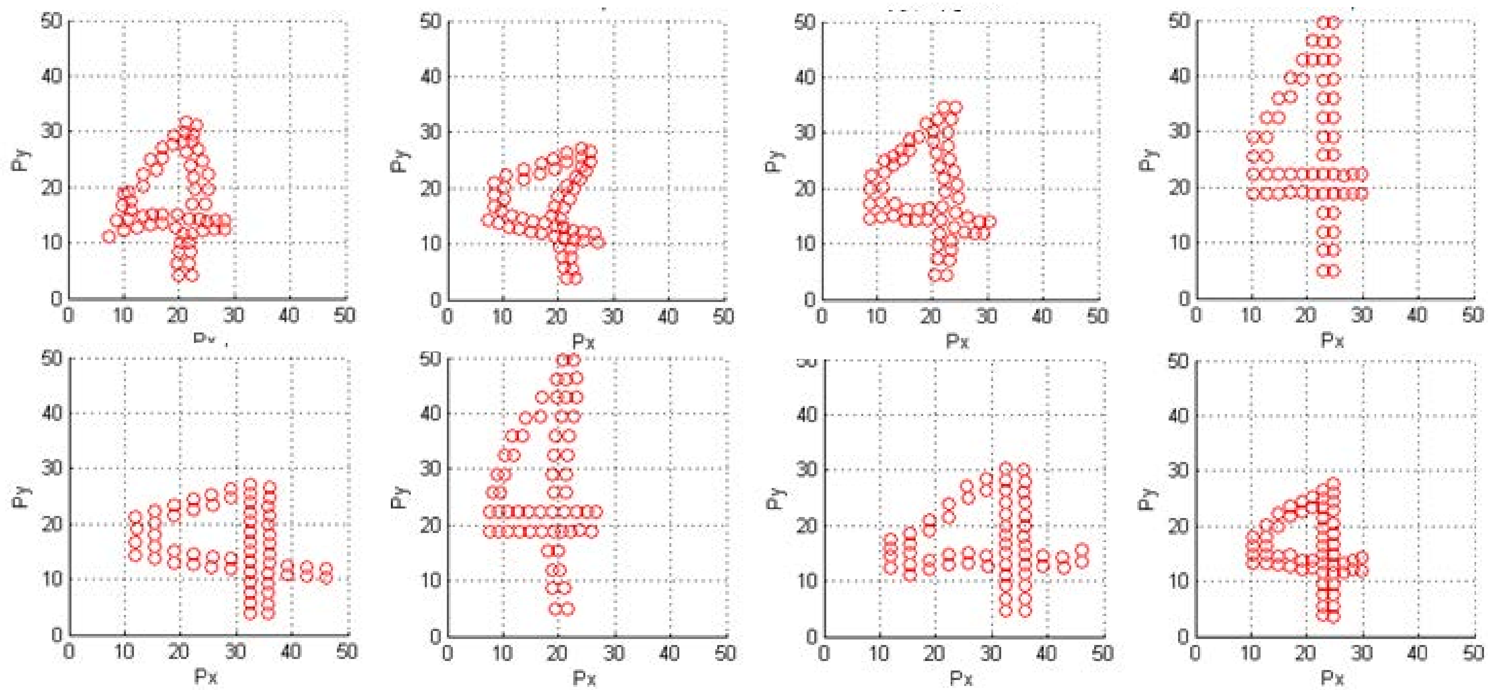




  - ✓ ex: "laminar flow" deformation
    - ▪ laminar wave + vertical wave
      - o Y-gradient of weights on P_X
      - o orthogonal full-bar stimuli

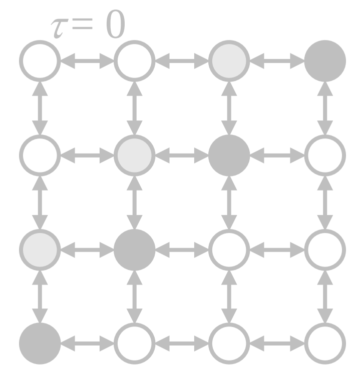
- Lattice of coupled oscillators – *shape metric deformation*
  - ✓ ex: irregular deformation
    - heterogeneous waves
      - o random weight distribution (bumps & dips) on P_X and P_Y
      - o orthogonal full-bar stimuli
  - ✓ various weight combinations



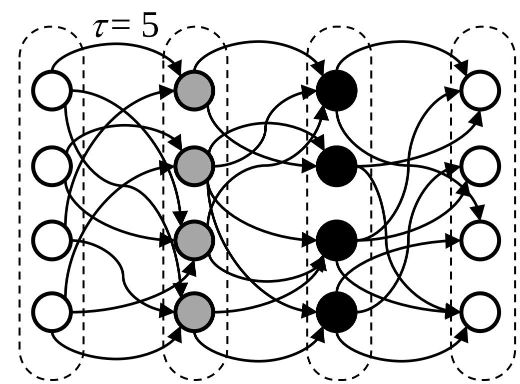


3. Wave-Based Shape-Matching

- Wave-based pattern retrieval and matching
  - ✓ Lattices of coupled oscillators (zero delays)
    - group synchronization
    - traveling waves
    - 2D wave shapes
    - shape metric deformation



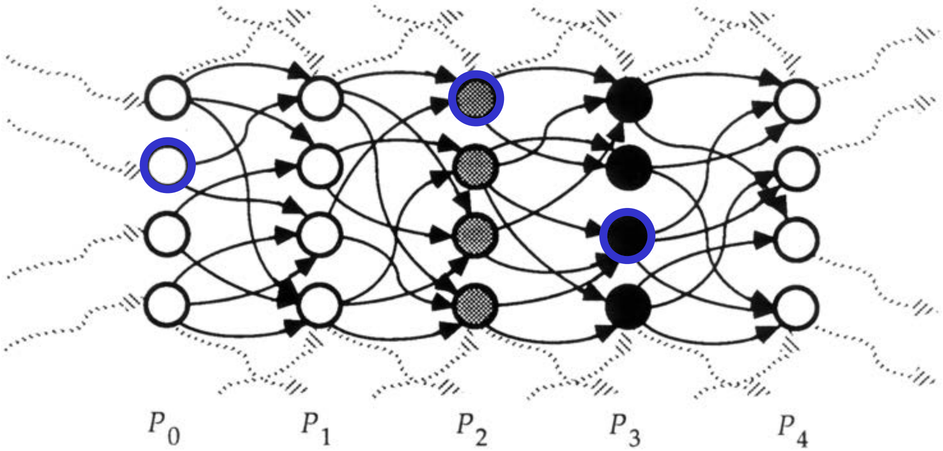
  - ✓ Synfire chains (uniform delays)
    - wave propagation
    - chain growth
    - pattern storage and retrieval

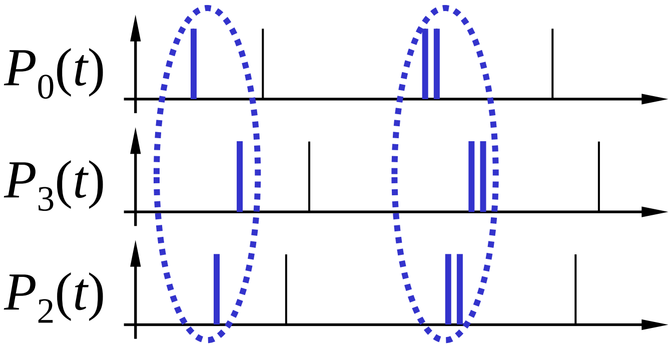


  - ✓ Synfire braids (transitive delays)
    - shape storage and retrieval
    - 2D wave-matching

➢ Synfire chains – *definition*

- ✓ a synfire chain (Abeles 1982) is a sequence of synchronous neuron groups $P_0 \rightarrow P_1 \rightarrow P_2$ ... linked by feedfoward connections that can support the propagation of waves of activity (action potentials)



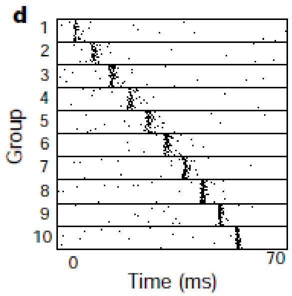


- ✓ synfire chains have been hypothesized to explain neurophysiological recordings containing statistically significant delayed correlations
- ✓ the redundant divergent/convergent connectivity of synfire chains can preserve accurately synchronized action potentials, even under noise

3. Wave-Based Shape-Matching – Chains

➢ Synfire chains – *typical example studies*

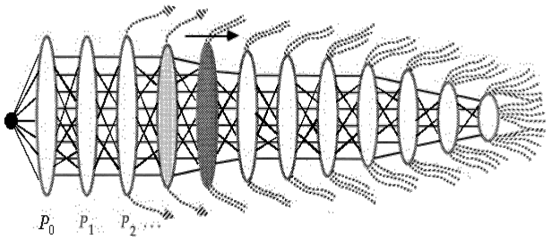
✓ 1-chain propagation viability



mental shape *stability*

- Diesmann, Gewaltig & Aertsen (1999) *Stable propagation of synchronous spiking in cortical neural networks*

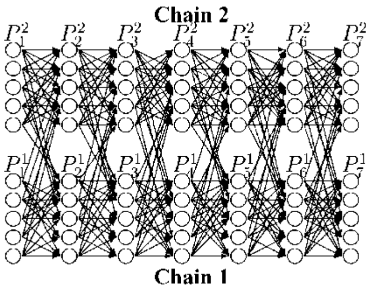
✓ 1-chain self-organized growth



mental shape *learning*

- Doursat & Bienenstock (1991, 2006) *Neocortical self-structuration as a basis for learning*

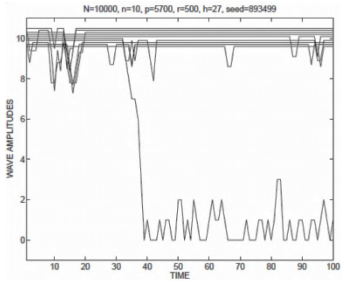
✓ 2-chain binding (→ see Section 4.)



mental shape *composition*

- Abeles, Hayon & Lehmann (2004) *Modeling Compositionality by Dynamic Binding of Synfire Chains*

✓ N-chain storage capacity



mental shape *memory*

- Bienenstock (1995) *A model of neocortex*
- Trengove (2007) *Storage capacity of a superposition of synfire chains using conductance-based I&F neurons*

synfire chains potential fill all the requirements for a mesoscopic world of mental shapes

3. Wave-Based Shape-Matching – Chains

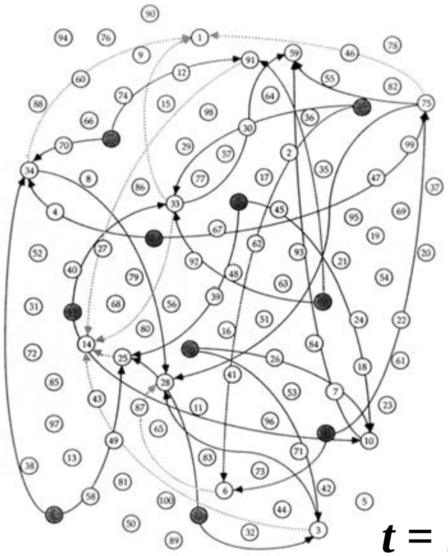
➢ Synfire chains – *self-organized growth*

1. Hebbian rule

$$\Delta W_{ij} \sim x_i x_j$$

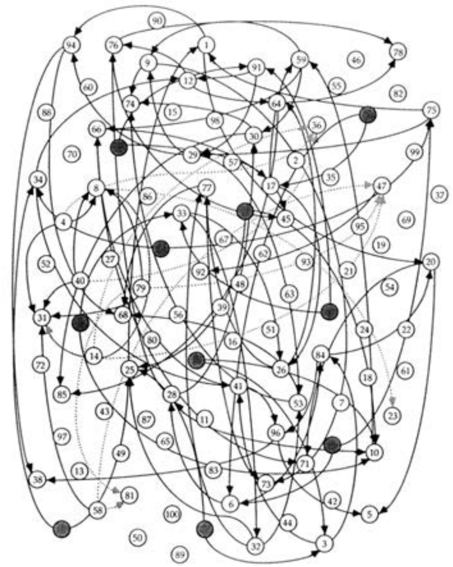
$$\sum \Delta W_{ij} \sim 0$$

2. sum rule

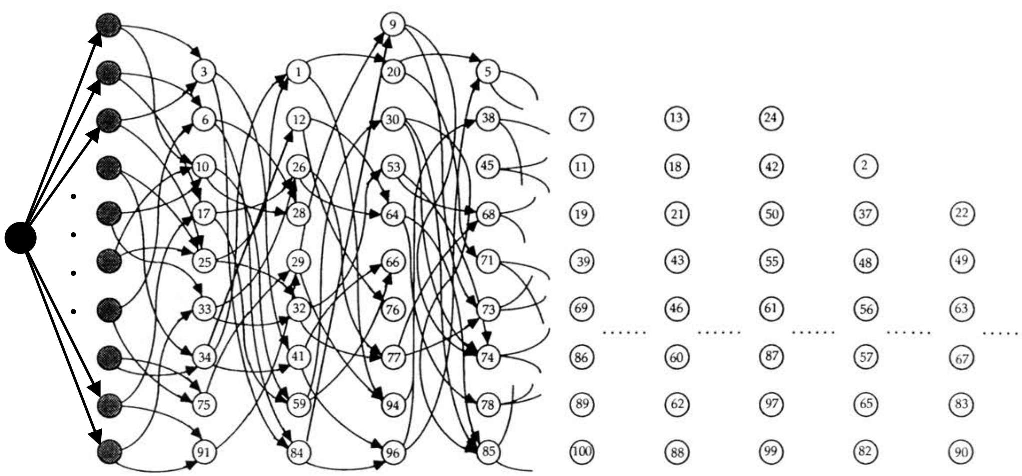


t = 200

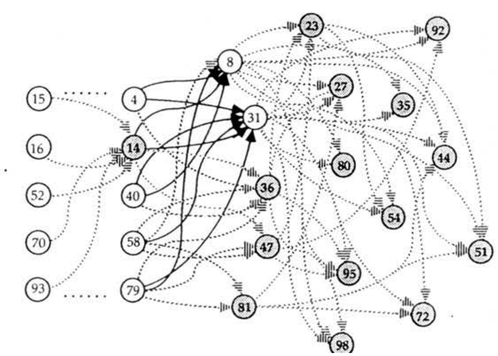
network structuration by accretive synfire growth



t = 4000



spatially rearranged view



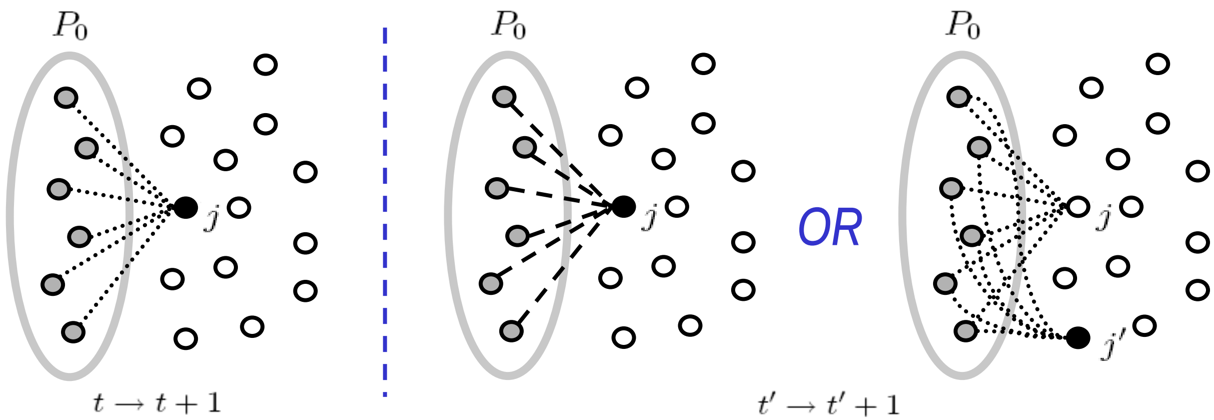
Doursat, R. (1991), Doursat & Bienenstock, E. (2006) Neocortical self-structuration as a basis for learning. *5th International Conference on Development and Learning (ICDL 2006)*, May 31-June 3, 2006, Indiana University, Bloomington, IN. IU, ISBN 0-9786456-0-X.

3. Wave-Based Shape-Matching – Chains

➢ Synfire chains – *self-organized growth*

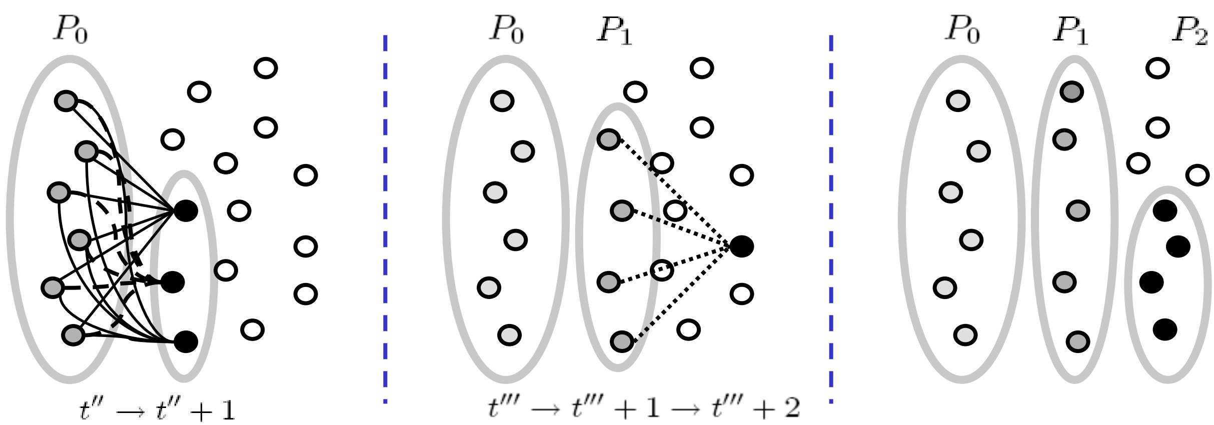
✓ a special group of n_0 synchronous cells, P_0, is repeatedly (not necessarily periodically) activated and recruits neurons "downstream"

if j fires once after P_0, its weights increase and give it a 12% chance of doing so again (vs. 1.8% for the others)

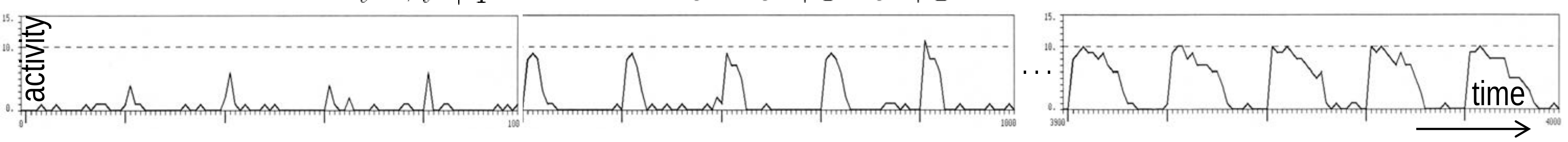


if j fires a 2nd time after P_0, j has now 50% chance of doing so a 3rd time; else it stays at 12% while another cell, j' reaches 12%

the number of post-P_0 cells (cells with larger weights from P_0) increases and forms the next group P_1

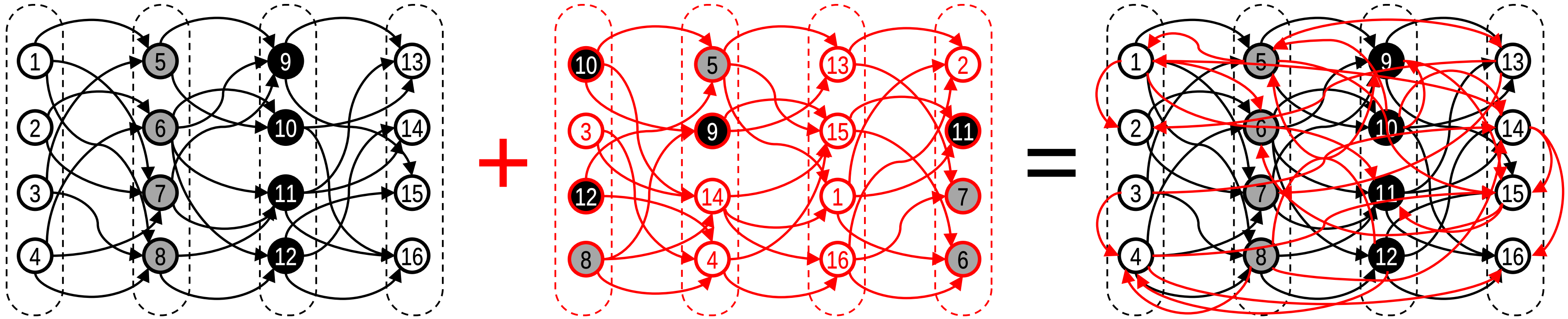


once it reaches a critical mass, P_1 also starts recruiting and forming a new group P_2, etc.



3. Wave-Based Shape-Matching – Chains

- **Synfire chains** – *pattern mix and selective retrieval*
  - ✓ random renumbering and uniform rewiring (column→column probability p)

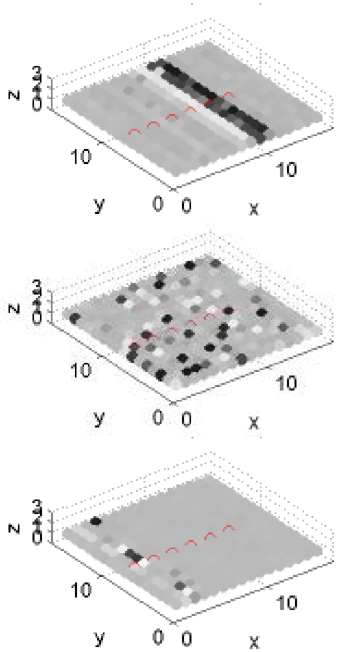


layout A w/ weights A | layout B w/ weights B | layout A w/ mixed weights A + weights B

layout A
$N_A = 13$

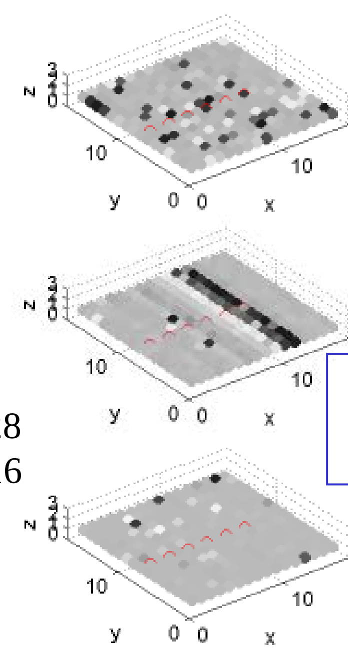
layout B
$N_B = 13$

layout A
$N_A = 8$
→ no wave



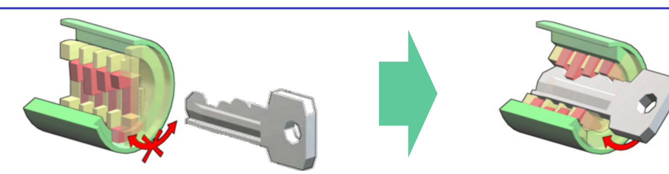
mixed weights

$p = 0.5$
$z = -0.28$
$k = 0.016$



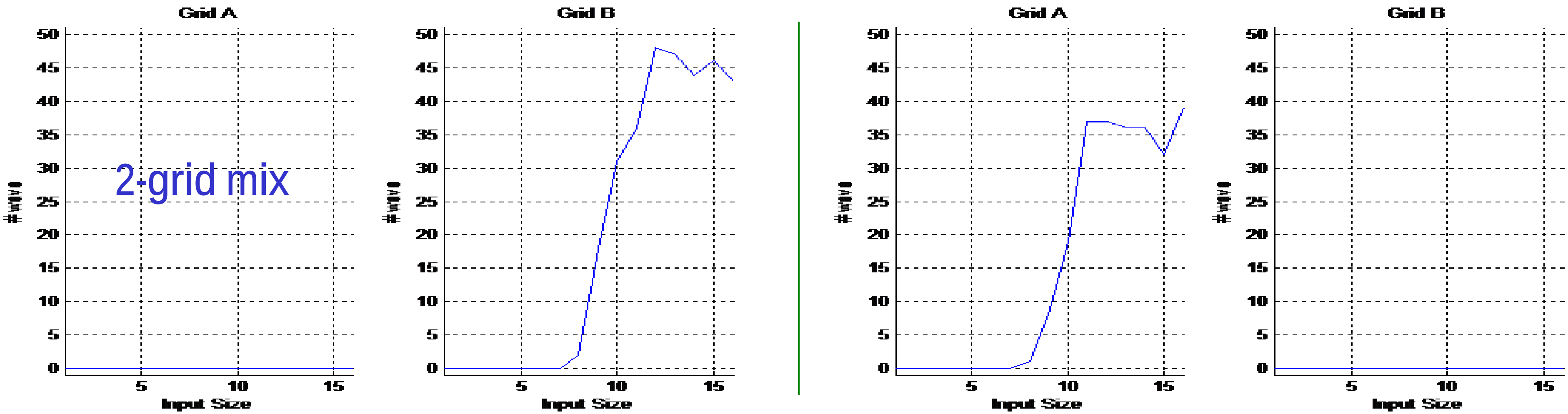
- ✓ high specificity of synfire stimulus
  - unlike the "sensitive" isotropic lattice, not any input pattern will trigger a wave
  - a synfire chain needs a "critical seed" of N stimulated neurons at the right place

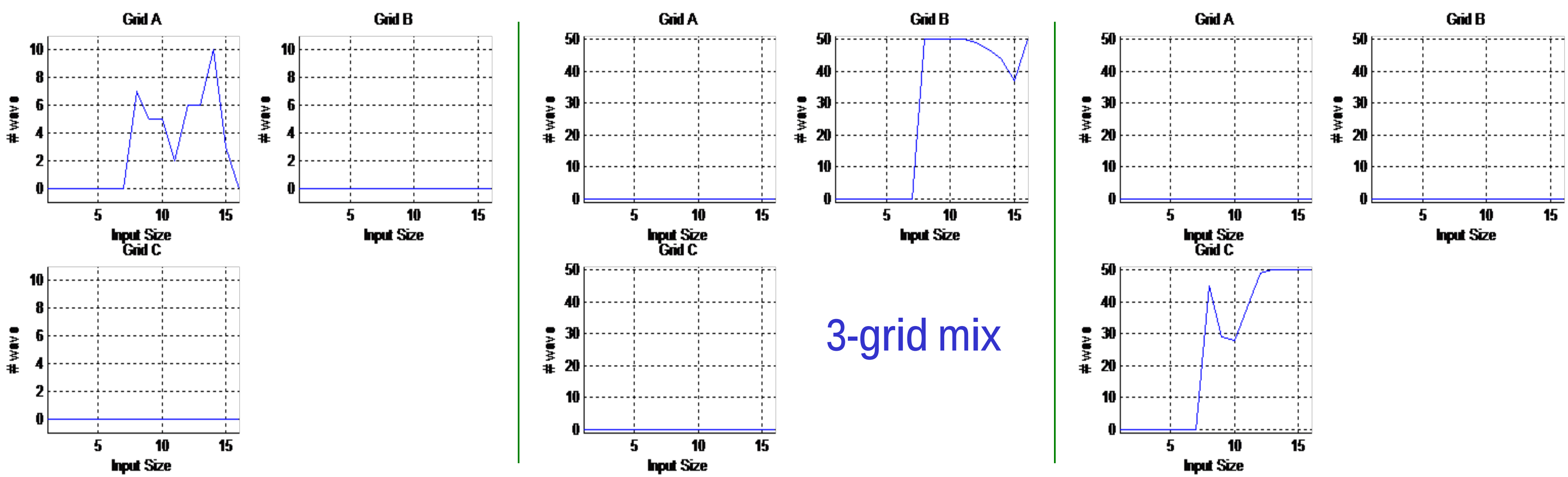
- endo: *connectivity*, *attractors* HERE
- exo: *stimulus*, *binding*



3. Wave-Based Shape-Matching – Chains

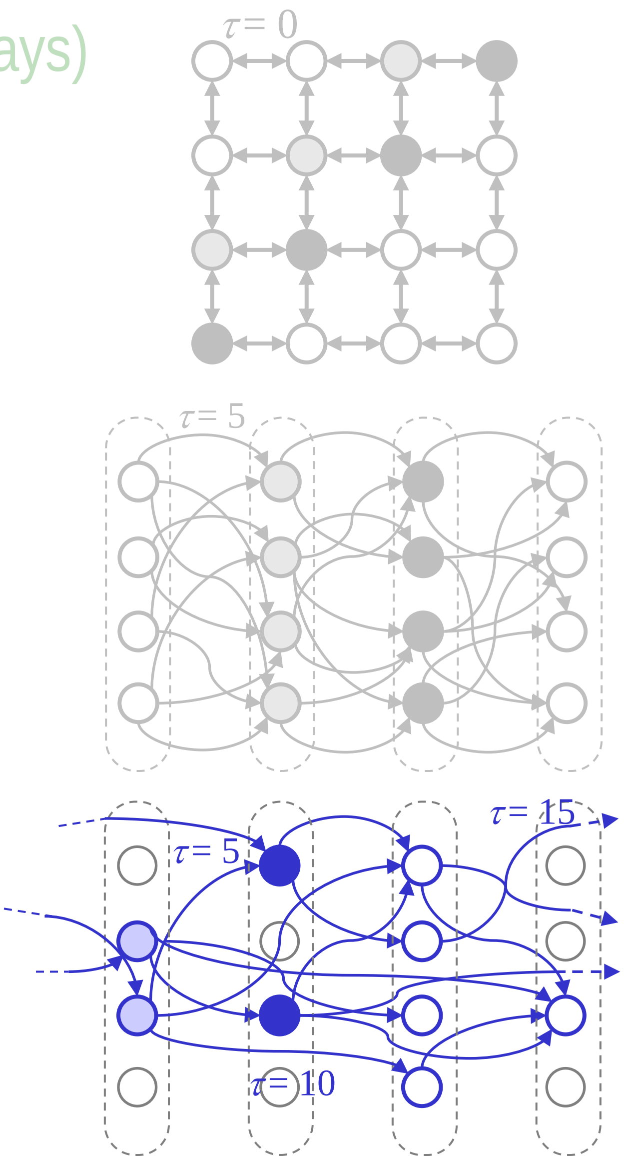
- Synfire chains – *pattern mix and selective retrieval*
  - ✓ statistics of selective retrieval depending on input size (in first pool)





3. Wave-Based Shape-Matching

- Wave-based pattern retrieval and matching
  - ✓ Lattices of coupled oscillators (zero delays)
    - group synchronization
    - traveling waves
    - 2D wave shapes
    - shape metric deformation
  - ✓ Synfire chains (uniform delays)
    - wave propagation
    - chain growth
    - pattern storage and retrieval
  - ✓ Synfire braids (transitive delays)
    - shape storage and retrieval
    - 2D wave-matching

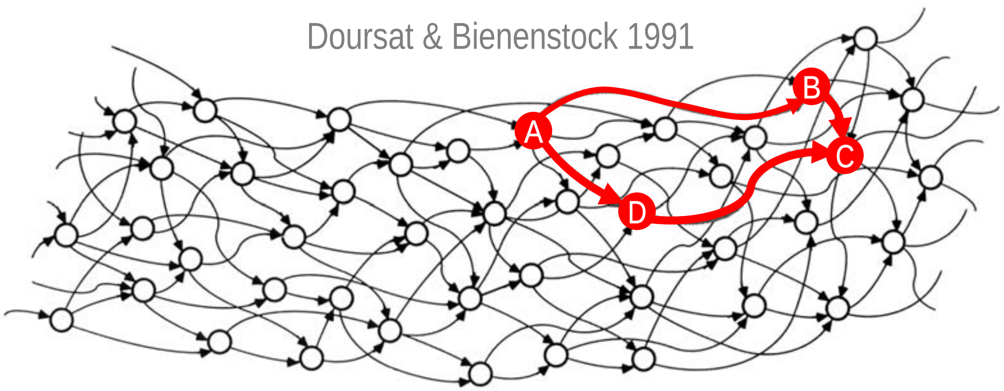


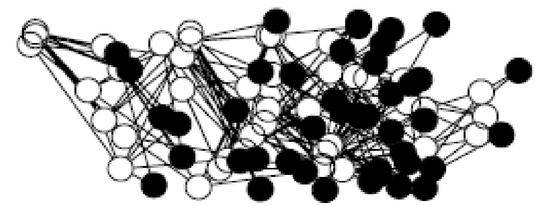
3. Wave-Based Shape-Matching – Braids

➢ Synfire braids – *definition*

- ✓ synfire braids (Bienenstock 1991, 1995) are generalized STPs with longer delays among nonconsecutive neurons, without distinct synchronous groups
- ✓ they were rediscovered later as “polychronous groups” (Izhikevich 2006)

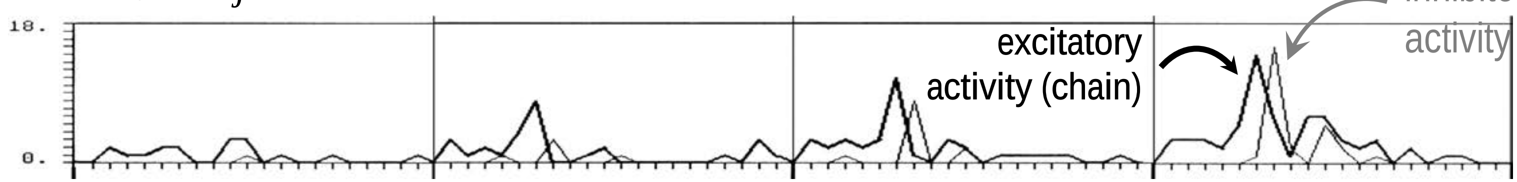
Doursat & Bienenstock 1991





Izhikevich 2006

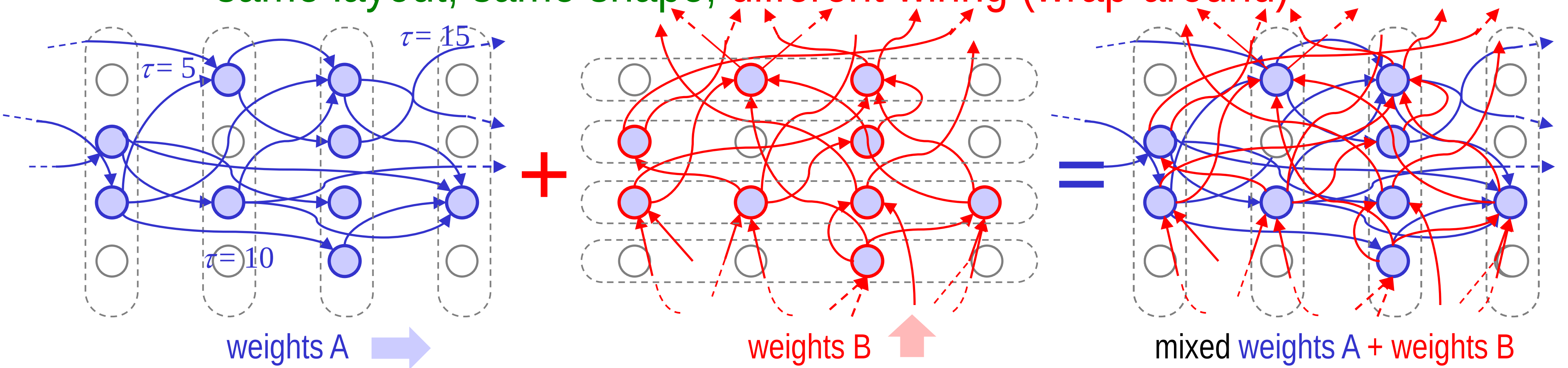
- ✓ in a synfire braid, delay transitivity $\tau_{AB} + \tau_{BC} = \tau_{AD} + \tau_{DC}$ supports incoming spike coincidences, hence stable propagation of activity
- ✓ synfire braids can also grow in a network with nonuniform integer-valued delays τ_{ij} and inhibitory neurons

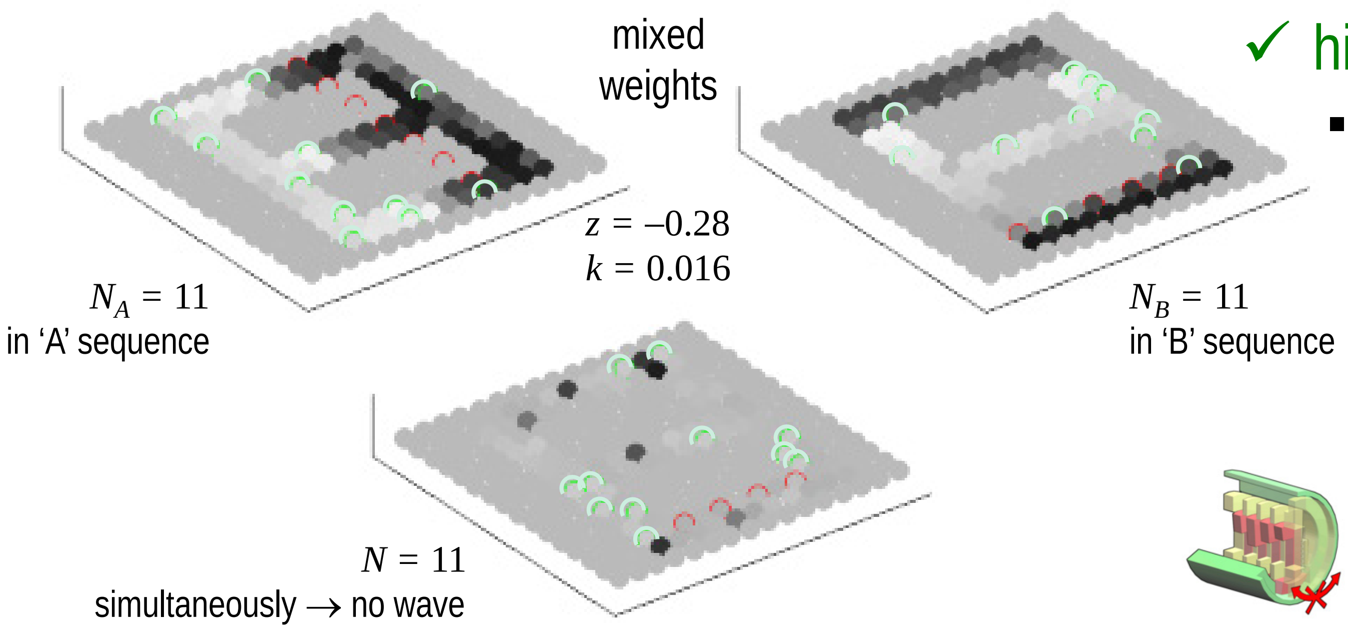


Doursat & Bienenstock 1991

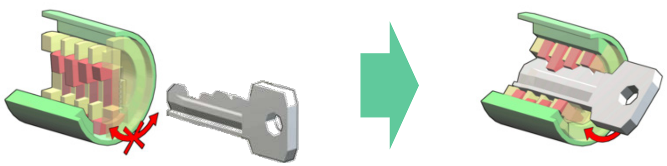
3. Wave-Based Shape-Matching – Braids

- Synfire braids – *pattern mix and selective retrieval*
  - ✓ same layout, same shape, different wiring (wrap-around)



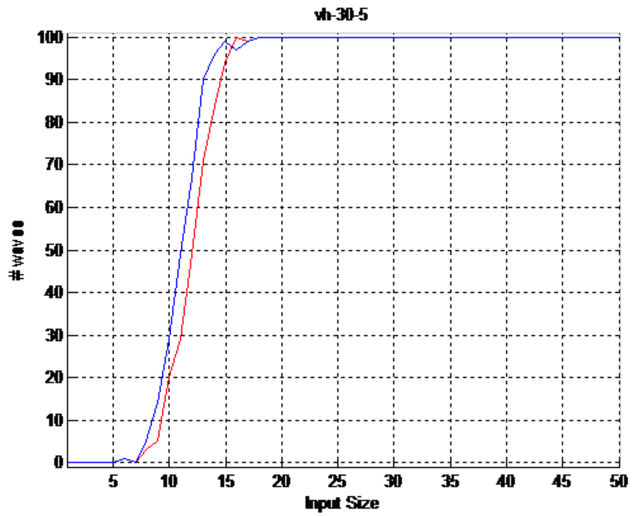


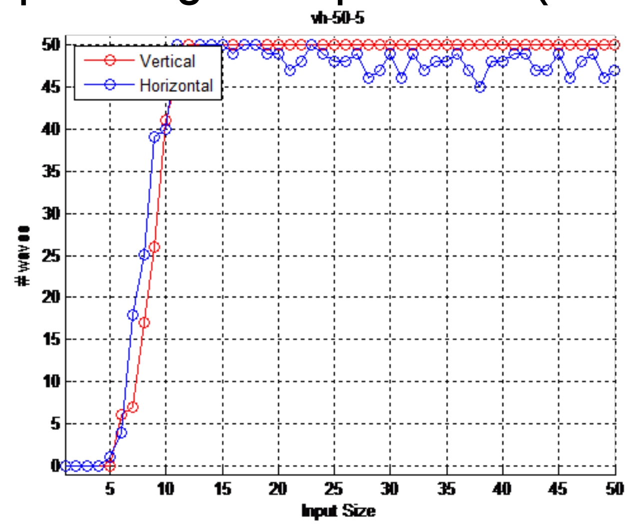
- ✓ high stimulus specificity
  - to generate a wave, a synfire braid needs a minimum of N neurons stimulated in a *sequence ("sub-STP") compatible with the delays*



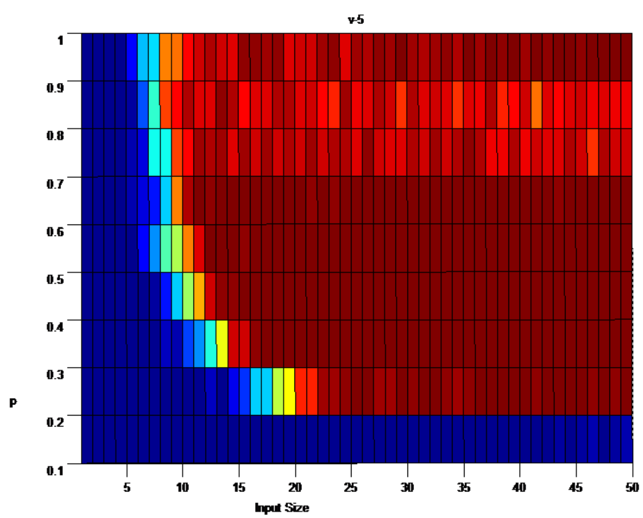
3. Wave-Based Shape-Matching – Braids

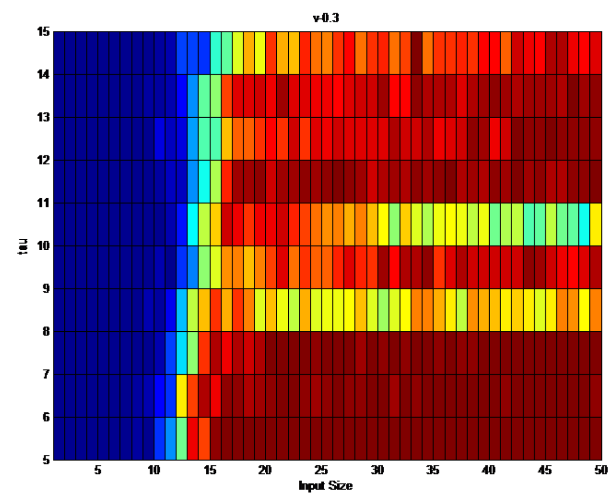
- Synfire braids – *pattern mix and selective retrieval*
  - ✓ statistics of selective retrieval depending on input size (in sequence)





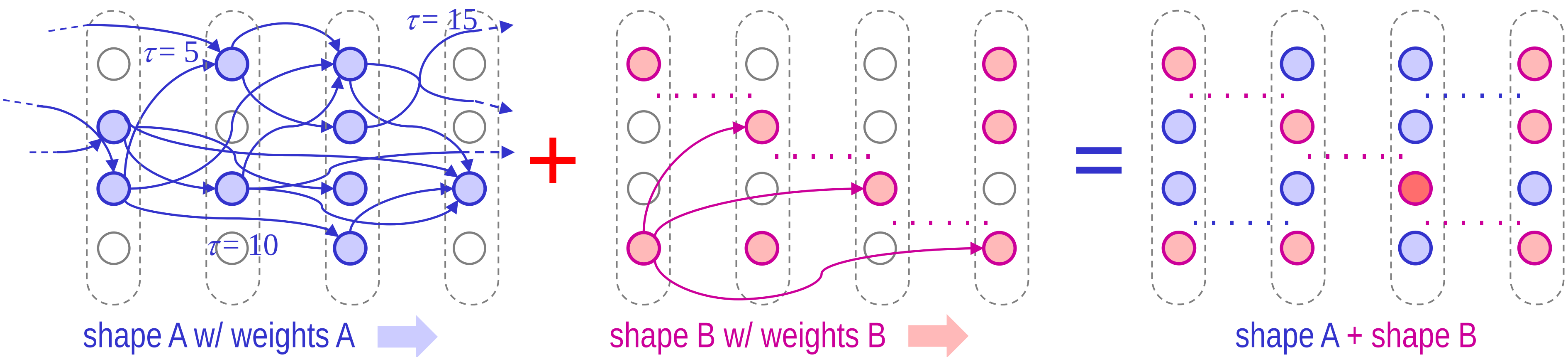
  - ✓ statistics of selective retrieval depending on input size and p or τ

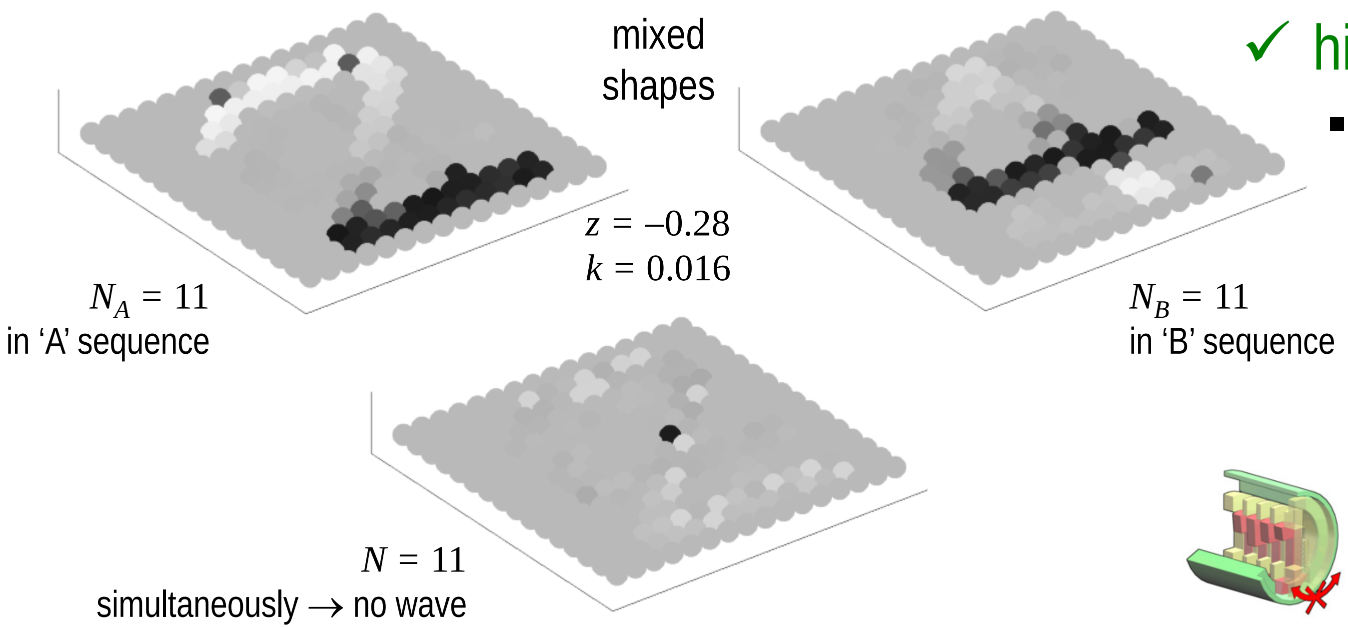




3. Wave-Based Shape-Matching – Braids

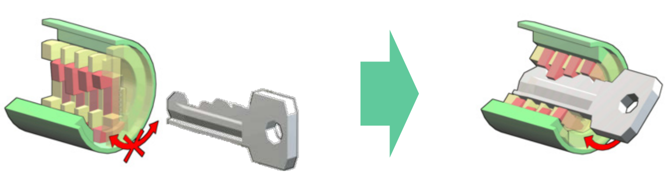
- Synfire braids – *shape mix and selective retrieval*
  - ✓ same layout, different shape





✓ high stimulus specificity

- to generate a wave, a synfire braid needs a minimum of N neurons stimulated in a *sequence (“sub-STP”) compatible with the delays*

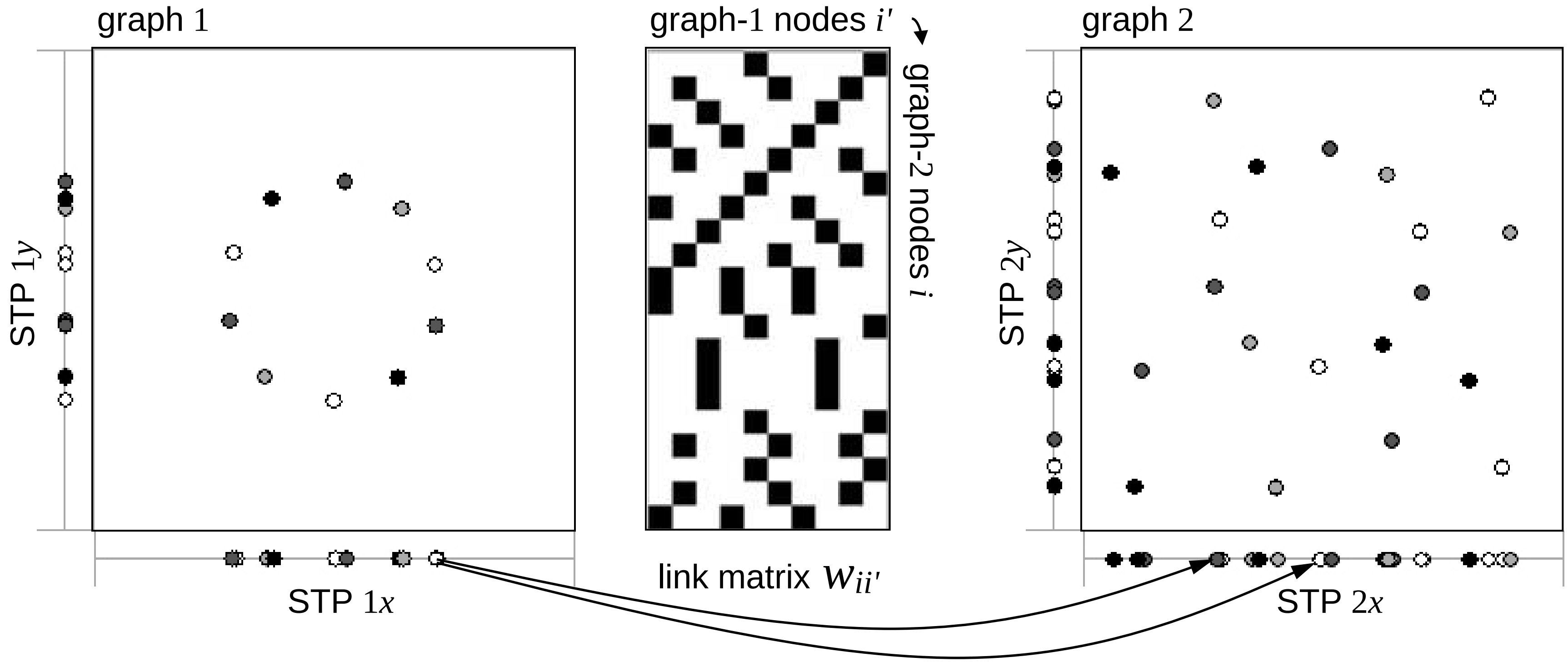


3. Wave-Based Shape-Matching – Braids

- Synfire braids – *wave-matching*
  - ✓ graph-matching implemented as dynamical link matching between two pairs of STPs

$$\left\{ \begin{aligned} \frac{du_i}{dt} &= c\left(u_i - \frac{u_i^3}{3} + v_i + z\right) + \eta + K_i + W_i \\ \frac{dv_i}{dt} &= \frac{1}{c}(a - u_i - bv_i) + \eta \end{aligned} \right.$$

$$\boxed{W_i = \sum w_{ii'}\,(u_{i'} - u_i)}$$



3. Wave-Based Shape-Matching – Braids

- Synfire braids – *wave-matching*
  - ✓ additional coupling term: $$W_i^{Xx}(t) = \sum_{\substack{j=1 \\ u_{i'}^{x}(t)<0}}^{N} w_{ii'}(t)\Big(u_{i'}^{x}(t) - u_i^{X}(t)\Big)$$
  - ✓ where $w_{ii'}$ varies according to

1. Hebbian-type synaptic plasticity based on temporal correlations

$$\Delta w_{ii'}(t) = \alpha\Big(- w_{ii'}(t) + w_0 f(s_{ii'}^{Xx}(0))\Big) \quad \text{with}$$

$$s_{ii'}^{Xx}(0) = \langle u_i^X(t')\ u_{i'}^x(t')\rangle_{t-T_s}^{t} \quad \text{and} \quad f(s) = (1 + e^{-\lambda(s-s_0)})^{-1}$$

2. competition: renormalize efferent links

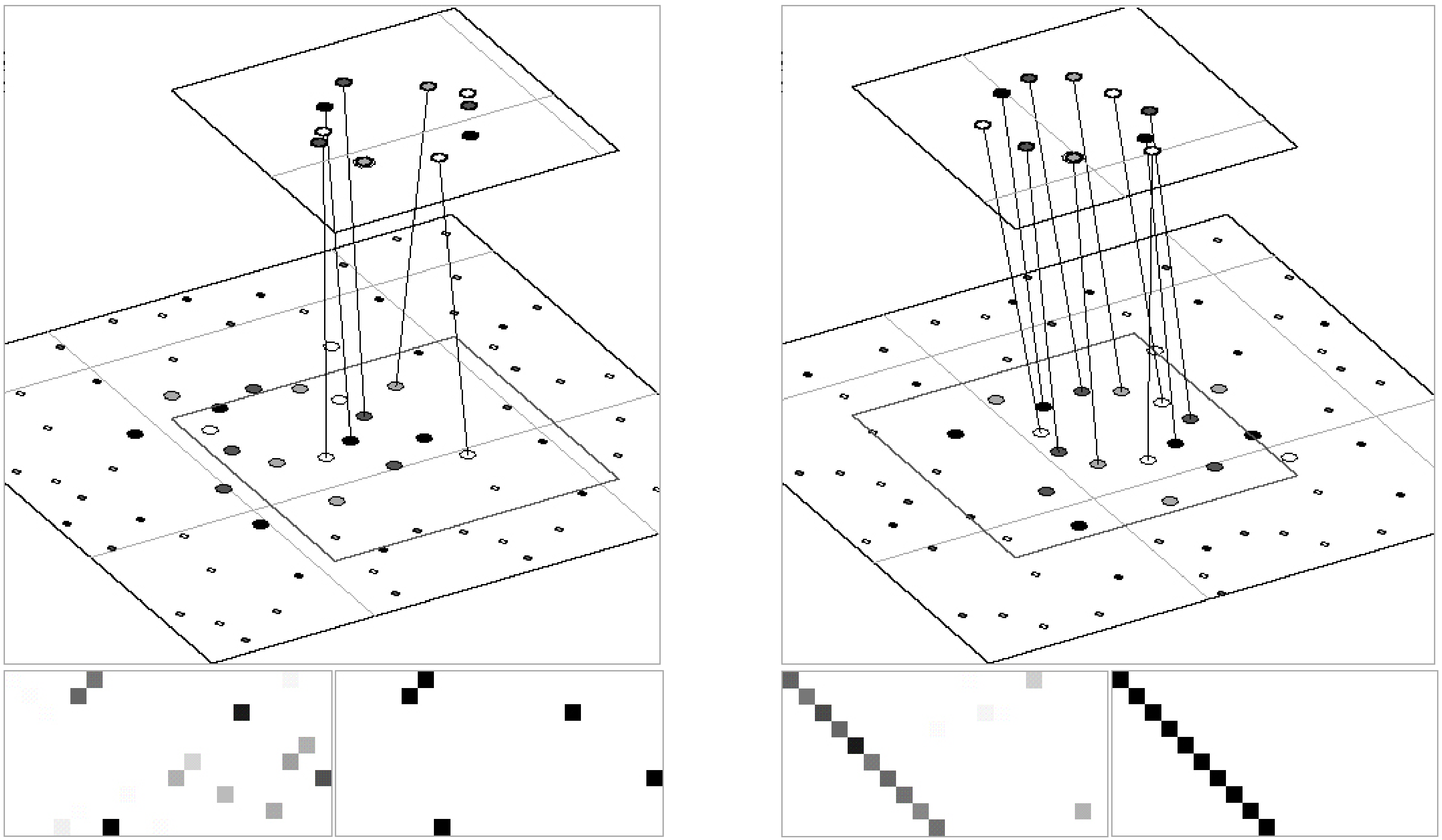
$$w_{ii'} \;\rightarrow\; w_{ii'} / \textstyle\sum_j w_{ji'}$$

3. label-matching constraint

3. Wave-Based Shape-Matching – Braids

- Synfire braids – *2D wave-matching*
  - ✓ Hebbian rule in 2D: $$\Delta w_{ii'}(t) = \alpha\Big(-\,w_{ii'}(t) + w_0 f\Big(\sqrt{s_{ii'}^{Xx}(0)\,s_{ii'}^{Yy}(0)}\Big)\Big)$$

$$s_{ii'}^{Xx}(0) = \langle u_i^X(t')\;\, u_{i'}^x(t')\rangle_{t-T_s}^{t} \qquad f(s) = \left(1 + e^{-\lambda(s-s_0)}\right)^{-1}$$



3. Wave-Based Shape-Matching – Braids

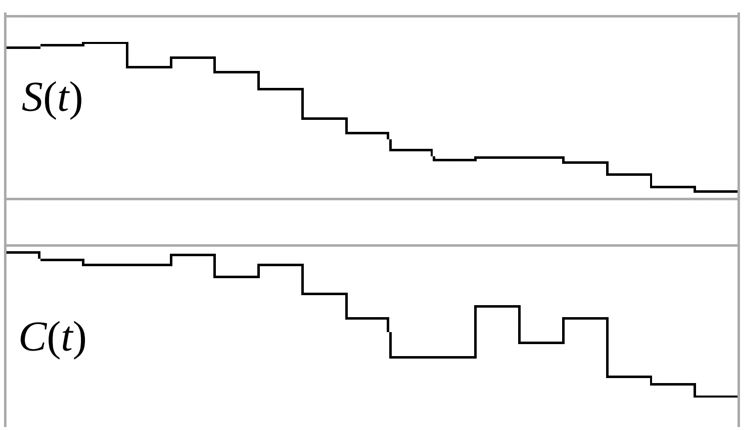
- Synfire braids – *2D wave-matching*
  - ✓ to drive the system to the best match (global minimum), internal coupling k in graph-2 layer is regularly lowered and increased again
    - if match is weak, this will perturb STP 2 and undo matching links
    - if match is strong, this will not perturb STP 2 because it will be sustained by matching links → *resonance* between links and STPs

global "correlation" order parameter S:

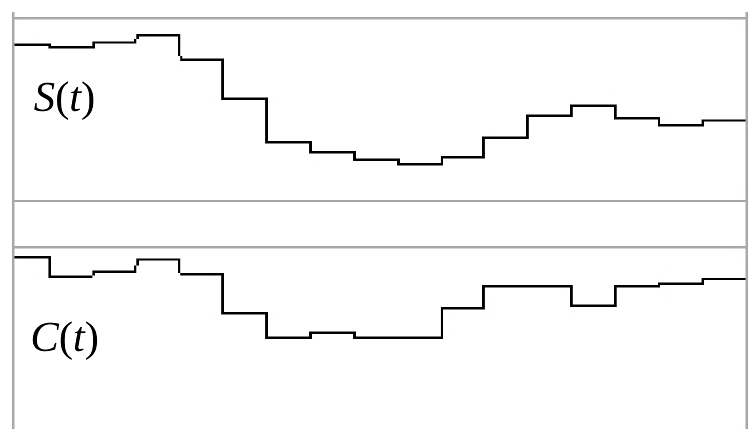
$$S(t) = \frac{1}{N(N-1)} \sum_{i \neq j} \langle u_i(t')\ u_j(t' - \tau_{ij}) \rangle_{t-T_s}^{t}$$

global "synchronicity" order parameter C:

$$C(t) = \frac{1}{N(N-1)} \sum_{i \neq j} \cos\left(\frac{2\pi}{T}(t_i(t) - t_j(t) - \tau_{ij})\right)$$



weak (mis)match → undone by uncoupling



strong match → resistant to uncoupling

Morphogenetic "Neuron-Flocking"

1. Cognitive Architectures in the Tower of Complex Systems

The emergence of neural/mind states on multiple levels of self-organization

2. The Mind as a Pattern Formation Machine

Neural correlations: The glue of spatiotemporal patterns (STPs)

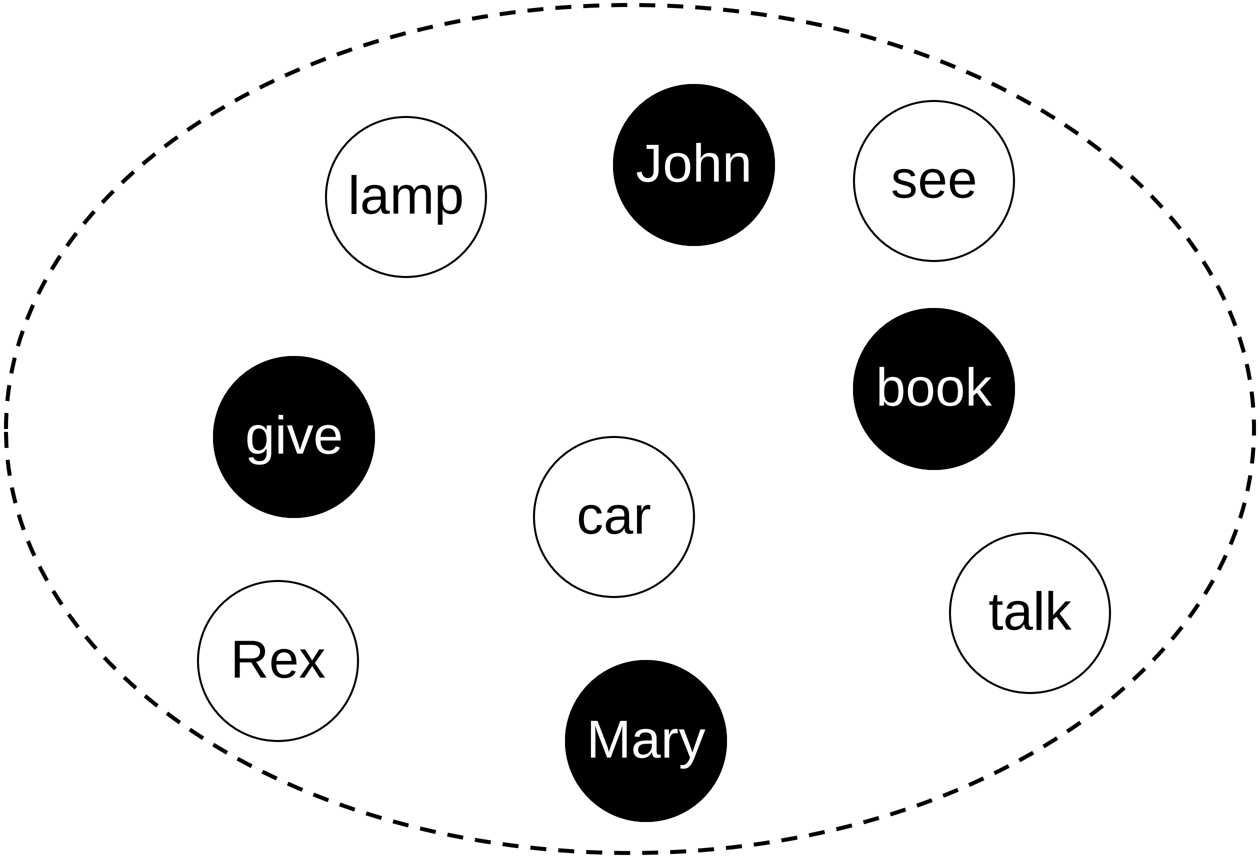
3. Example Model: Wave-Based Shape-Matching

Coding coordinates by phases, and shapes by waves

4. Shape-Based Compositionality

STPs: The building blocks of mental shapes

- From temporal binding to shape-based composition



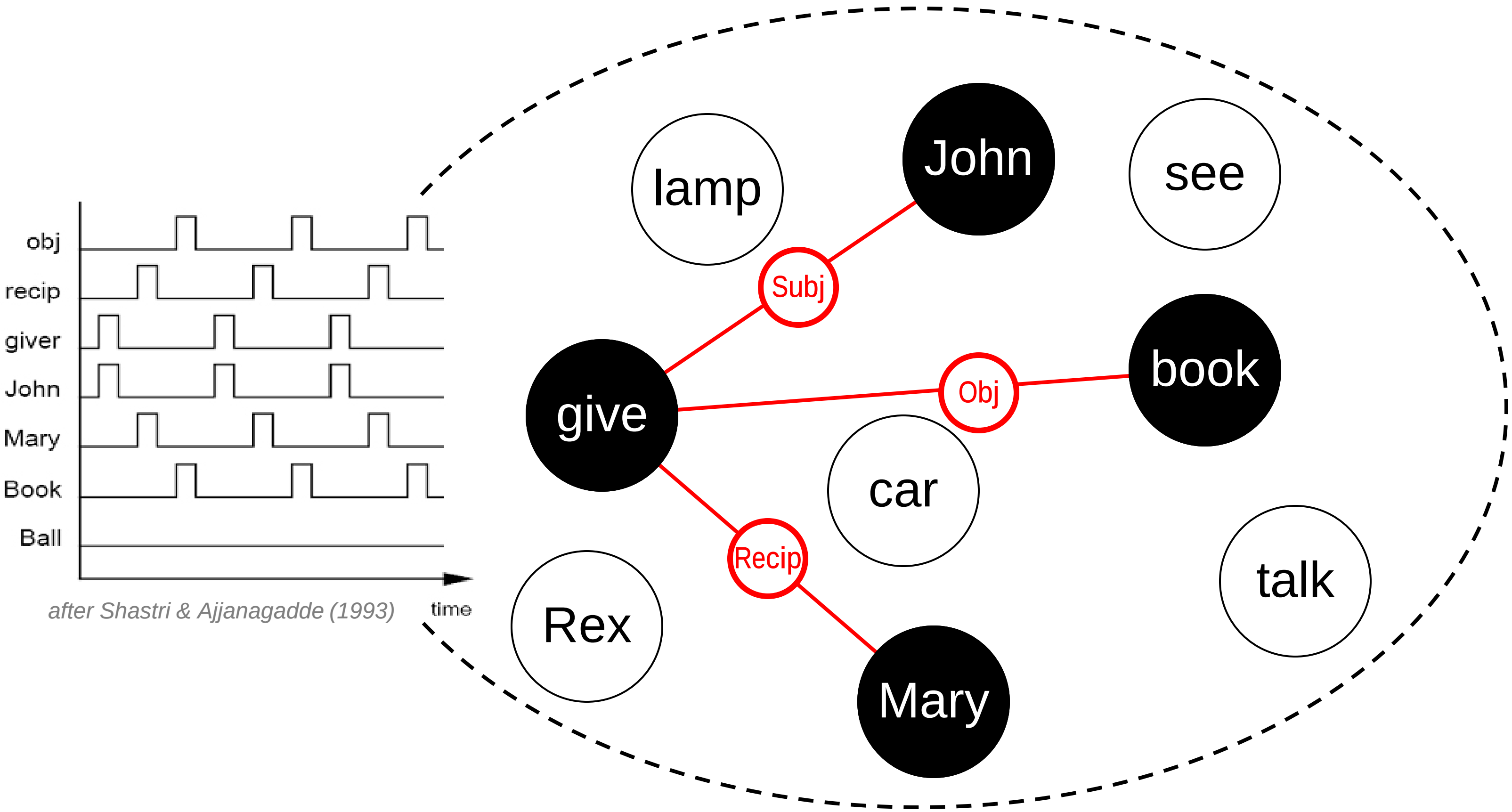
(a) John gives a book to Mary.

(b) Mary gives a book to John.

(c) Book John Mary give.*

4. Shape-Based Compositionality

➢ From temporal binding to shape-based composition



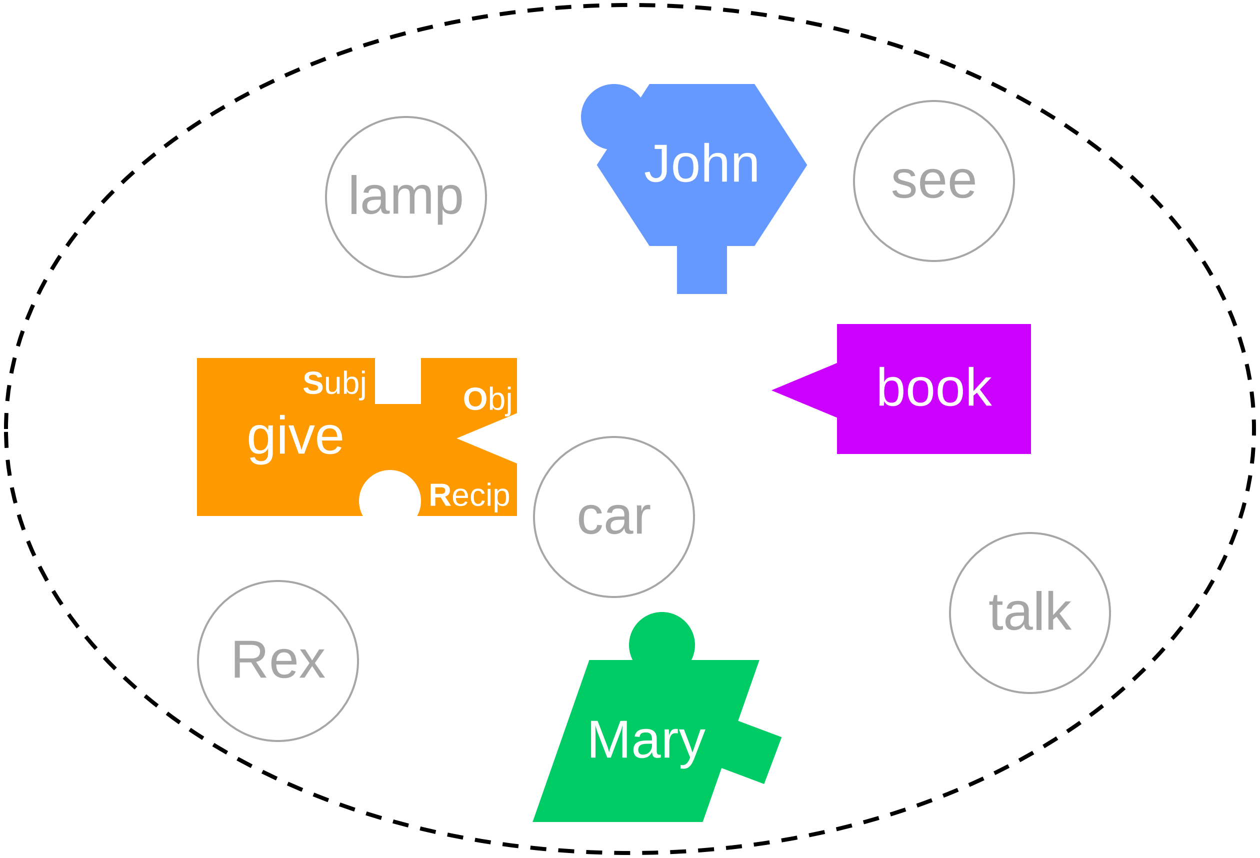
(a) John gives a book to Mary.

~~*(b) Mary gives a book to John.*~~

~~*(c)* Book John Mary give.*~~

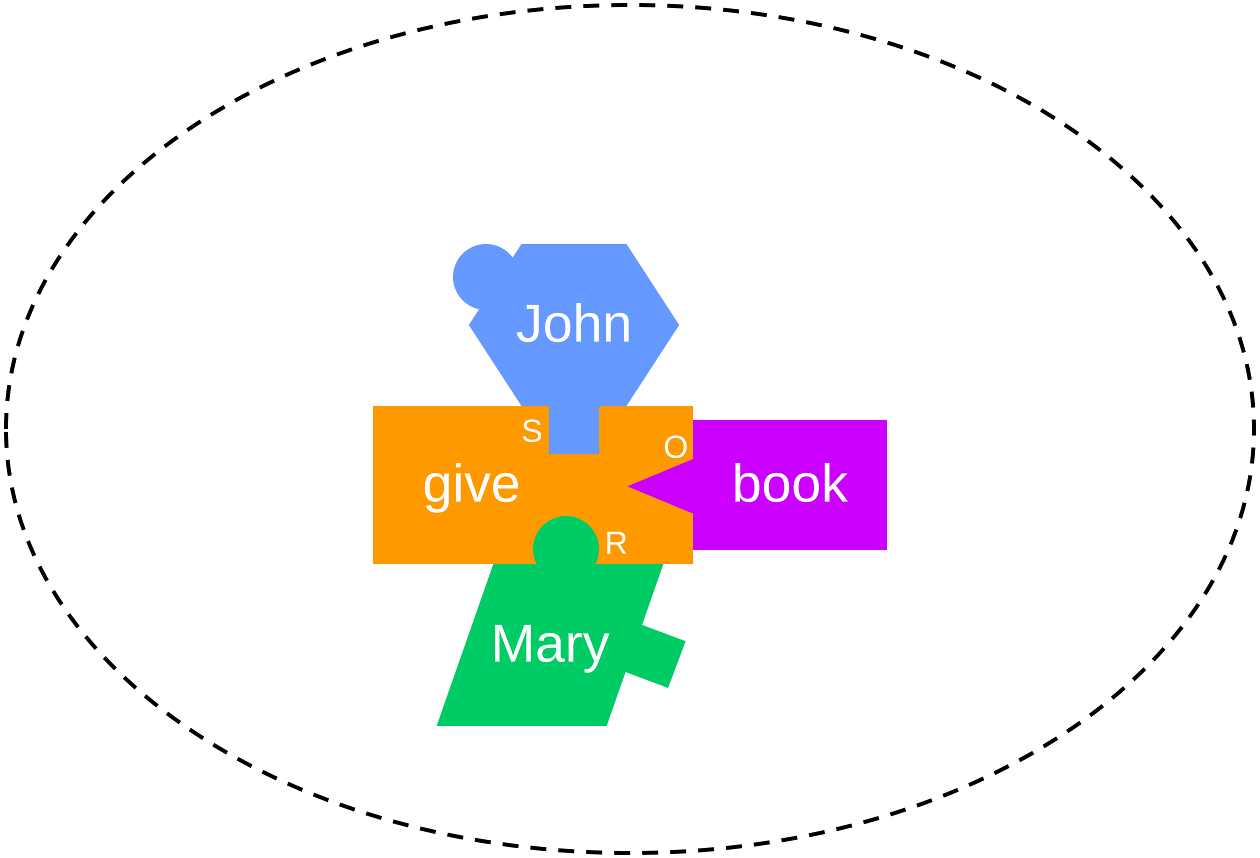
4. Shape-Based Compositionality

- From temporal binding to shape-based composition



✓ language as a construction game of "building blocks"

- From temporal binding to shape-based composition



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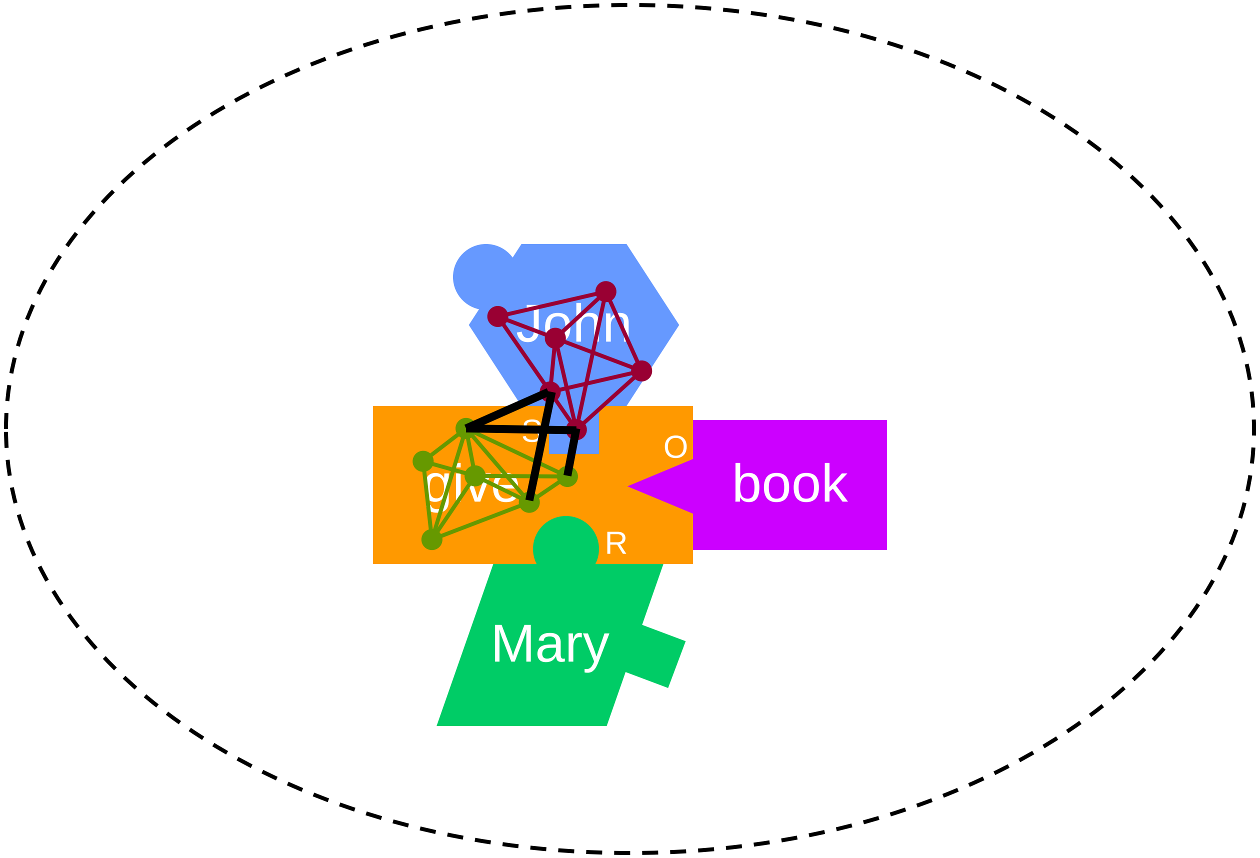

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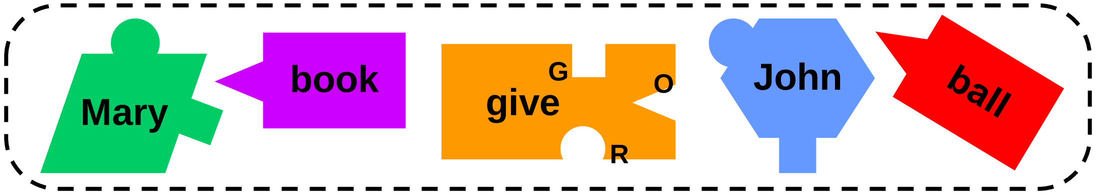
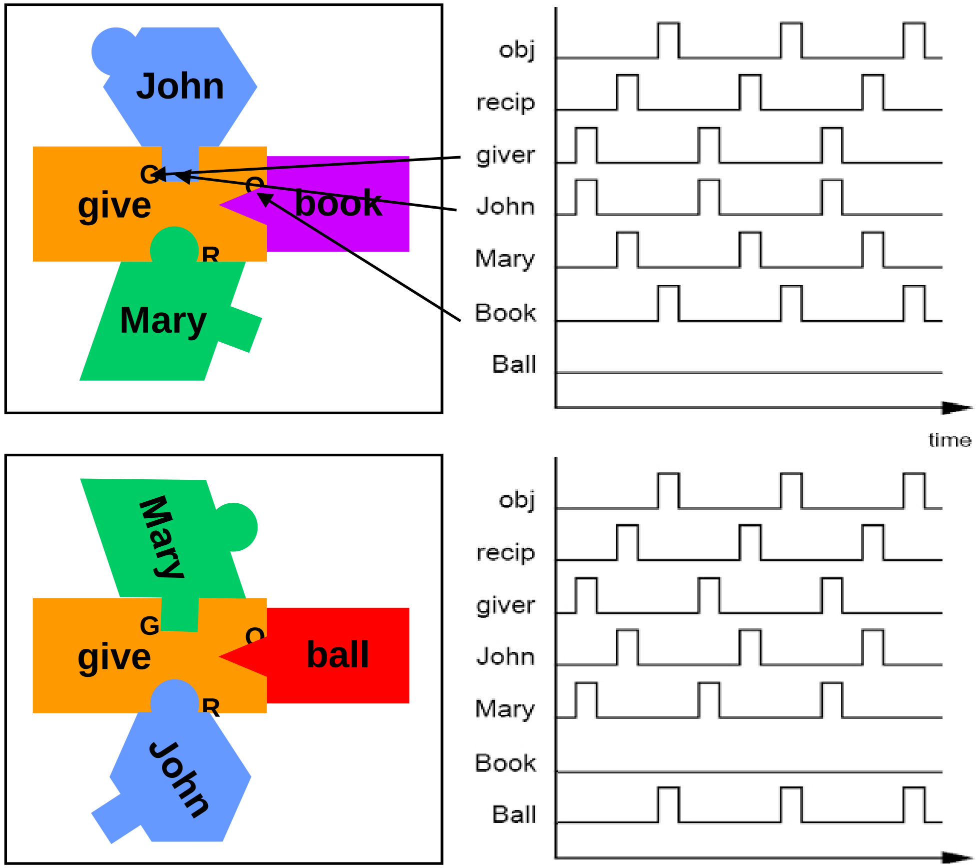




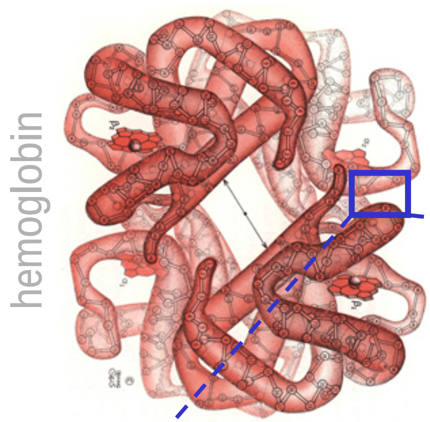
after Bienenstock (1995) *after Shastri & Ajjanagadde (1993)*

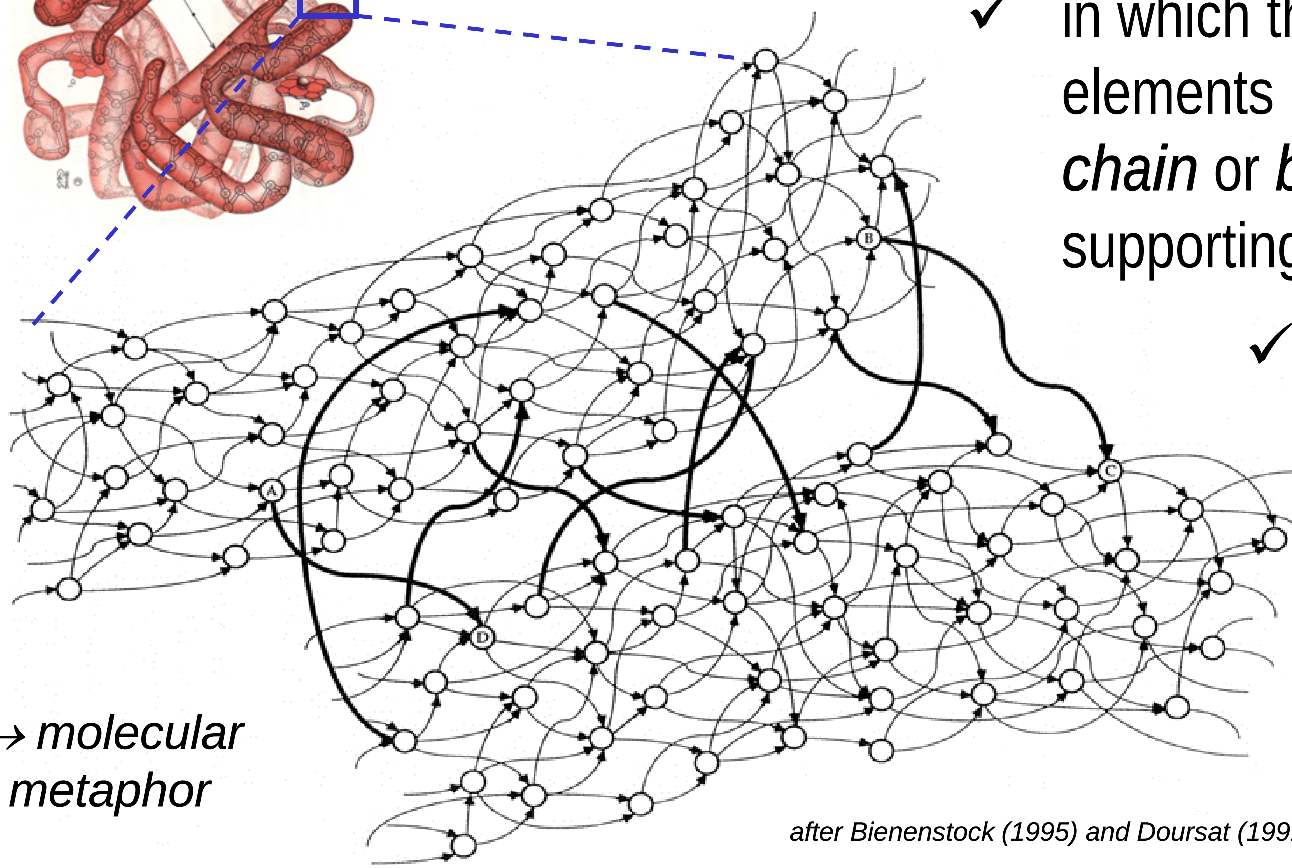
- ✓ language, perception, cognition are a game of *building blocks*
- ✓ mental representations are internally *structured*
- ✓ elementary components *assemble dynamically* via temporal binding

4. Shape-Based Compositionality

➢ Ex: synfire patterns can *bind*, i.e. support compositionality

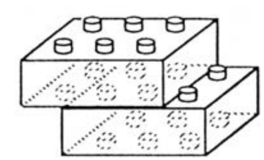
- ✓ cognitive compositions could be analogous to conformational interactions among proteins...
  - ✓ in which the basic “peptidic” elements could be ***synfire chain*** or ***braid*** structures supporting traveling waves
    - ✓ two synfires can bind by synchronization through ***coupling links***





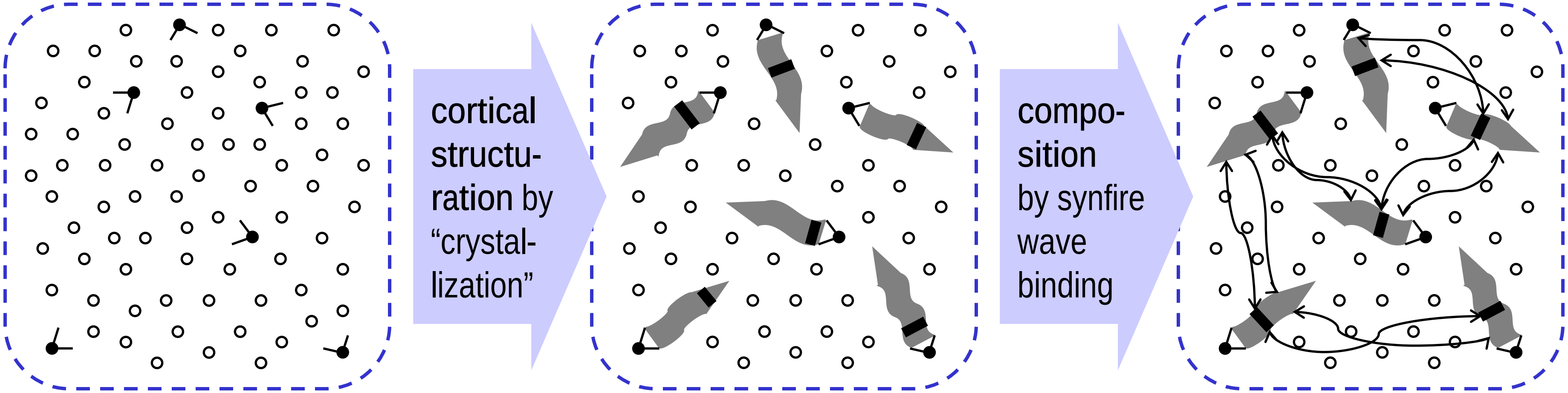
→ *molecular metaphor*

after Bienenstock (1995) and Doursat (1991)



➢ Sync & coalescence in a “self-woven tapestry” of chains

✓ multiple chains can “crystallize” from intrinsic “inhomogeneities” in the form of “seed” groups of synchronized neurons



see Bienenstock (1995), Abeles, Hayon & Lehmann (2004), Trengrove (2005)

✓ concurrent chain development defines a *mesoscopic scale of neural organization*, at a finer granularity than macroscopic AI symbols but higher complexity than microscopic neural potentials

✓ on this substrate, the dynamical binding & coalescence of multiple synfire waves provides the basis for compositionality and learning

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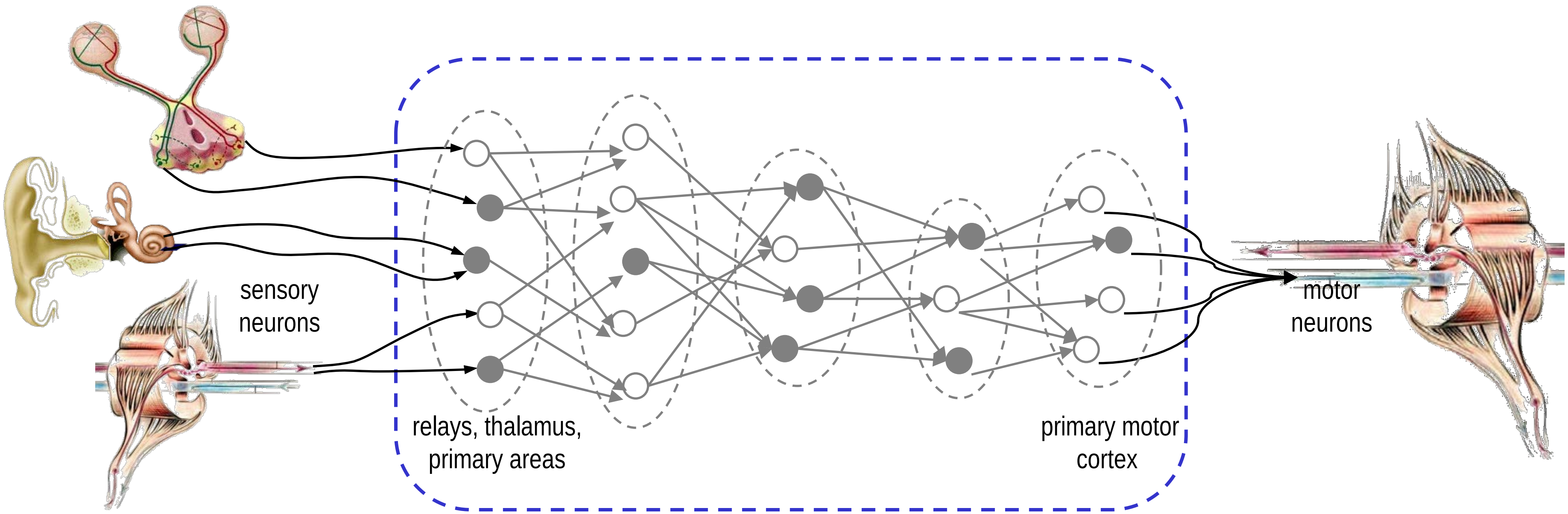
5. Toward Emergent Neurodynamics

Leaving "signal processing" for dynamic self-assembly

5. Toward Emergent Neurodynamics

- The naive engineering paradigm: “signal processing”
  - ✓ *feed-forward* structure – activity literally “moves” from one corner to another, from the input (problem) to the output (solution)
  - ✓ *activation* paradigm – neural layers are initially silent and are literally “activated” by potentials transmitted from external stimuli
  - ✓ *coarse-grain* scale – a few units in a few layers are already capable of performing complex “functions”



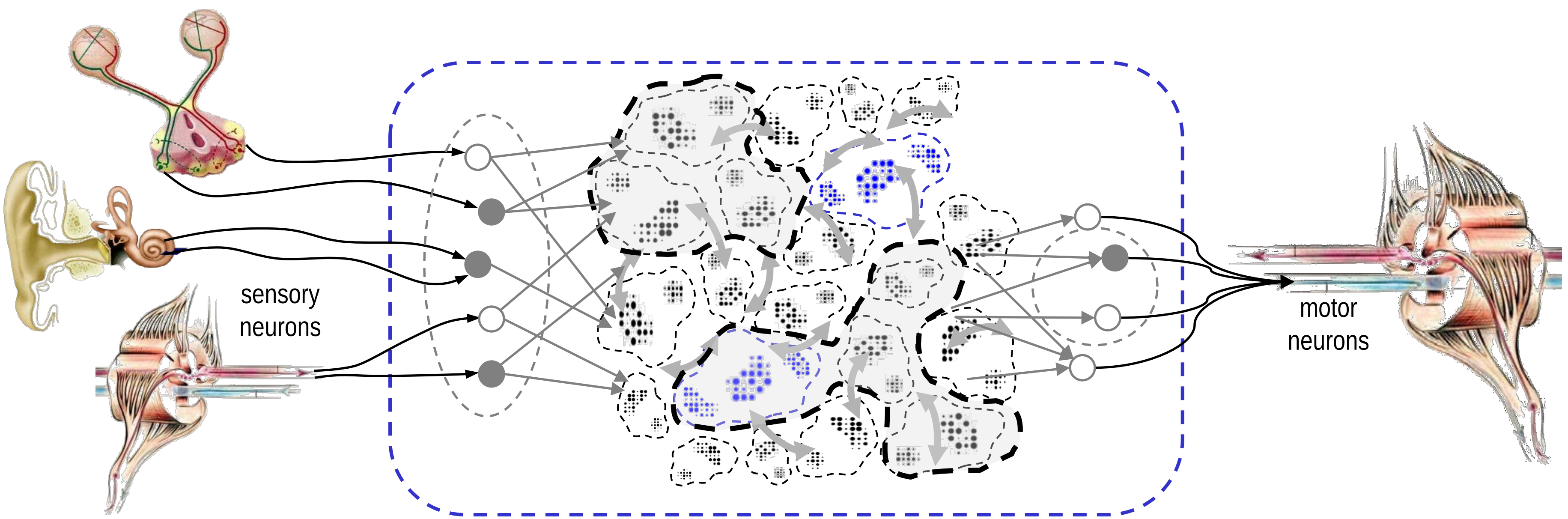
5. Toward Emergent Neurodynamics

It is not because the brain is an intricate network of microscopic causal transmissions (neurons activating or inhibiting other neurons) that the appropriate description at the mesoscopic functional level should be "signal / information processing".

This denotes a confusion of levels: mesoscopic dynamics is <u>emergent</u>, i.e., it creates mesoscopic objects that obey mesoscopic laws of interaction and assembly, qualitatively different from microscopic signal transmission

➢ The emergent dynamical paradigm: excitable media

- ✓ *recurrent* structure – activity can "flow" everywhere on a fast time scale, continuously forming new patterns; output is in the patterns
- ✓ *perturbation* paradigm – dynamical assemblies are already active and only "influenced" by external stimuli and by each other
- ✓ *fine-grain* scale – myriads of neurons form quasi-continuous media supporting structured pattern formation at multiple scales



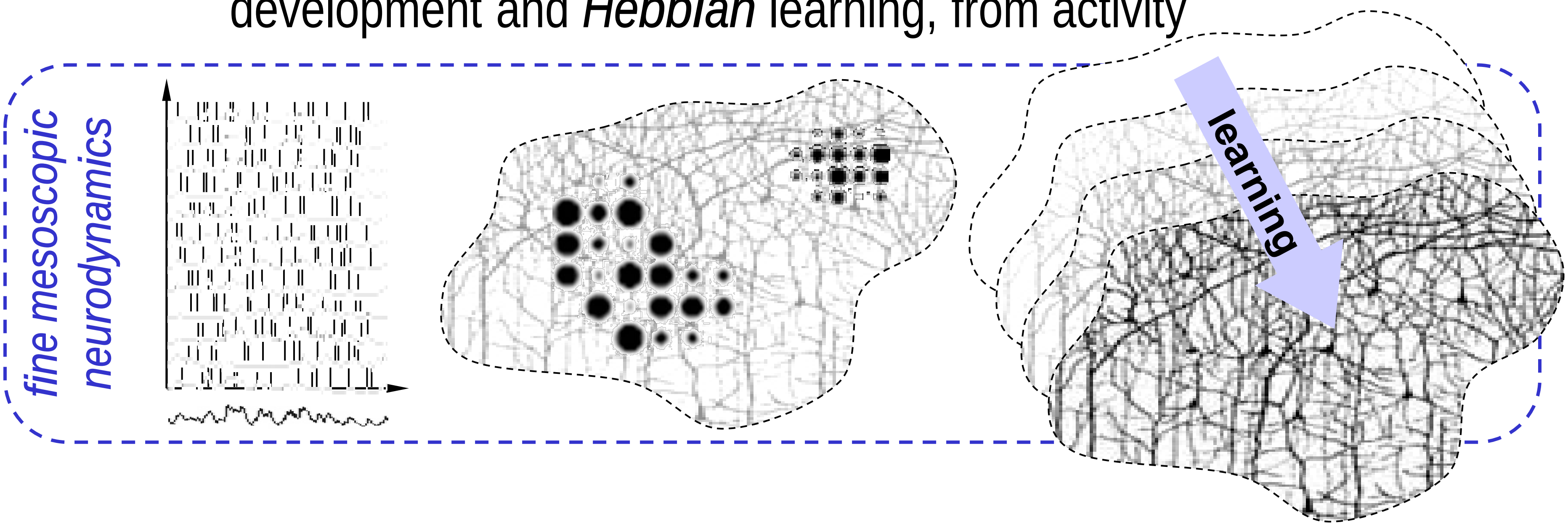
5. Toward Emergent Neurodynamics

- Tenet 1: mesoscopic neural pattern formation is of a fine spatiotemporal nature
- Tenet 2: mesoscopic STPs are individuated entities that are
  a) endogenously produced by the neuronal substrate,
  b) exogenously evoked & perturbed under the influence of stimuli,
  c) interactively binding to each other in competitive or cooperative ways.

5. Toward Emergent Neurodynamics

a) Mesoscopic patterns are endogenously produced

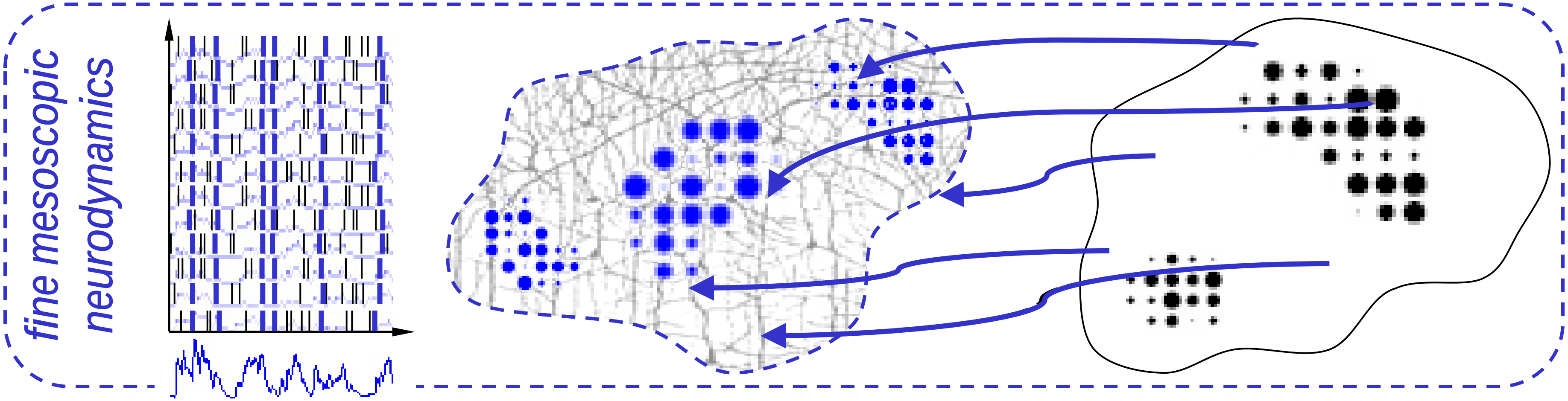
- ✓ given a certain connectivity pattern, cell assemblies exhibit various possible *dynamical regimes*, modes, patterns of ongoing activity
- ✓ the underlying connectivity is itself the product of *epigenetic* development and *Hebbian* learning, from activity



→ *the identity, specificity or stimulus-selectiveness of a mesoscopic entity is largely determined by its internal pattern of connections*

b) Mesoscopic patterns are exogenously influenced

- ✓ external stimuli (via other patterns) may *evoke & influence* the pre-existing dynamical patterns of a mesoscopic assembly
- ✓ it is an indirect, *perturbation* mechanism; not a direct, activation mechanism

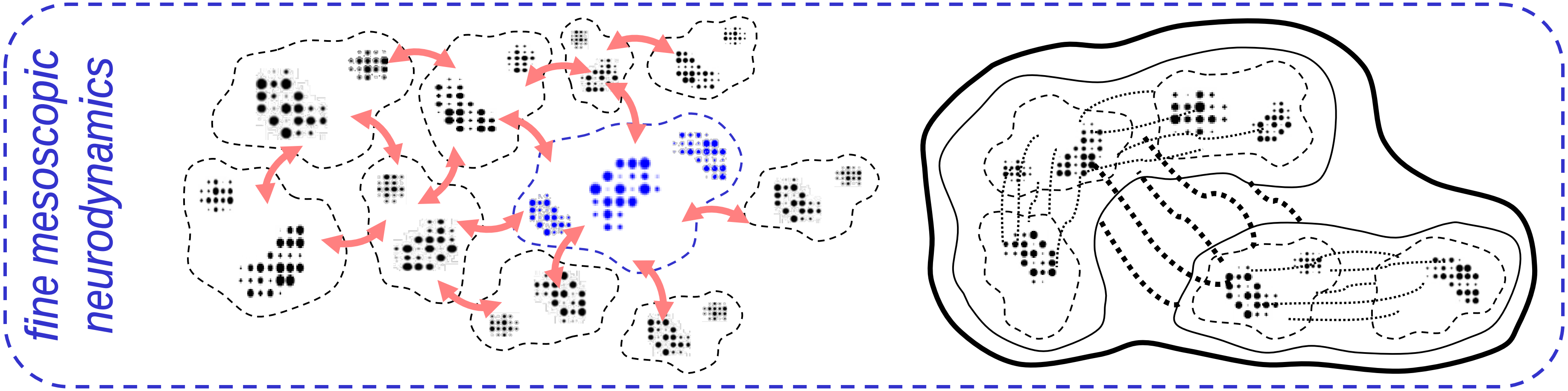


- ✓ mesoscopic entities may have stimulus-specific *recognition or "representation"* abilities, without being "templates" or "attractors" (no resemblance to stimulus)

5. Toward Emergent Neurodynamics

c) Mesoscopic patterns interact with each other

- ✓ populations of mesoscopic entities can *compete & differentiate* from each other to create specialized recognition units
- ✓ and/or they can *bind* to each other to create composed objects, via some form of temporal coherency (sync, fast plasticity, etc.)



evolutionary population paradigm

molecular compositionality paradigm

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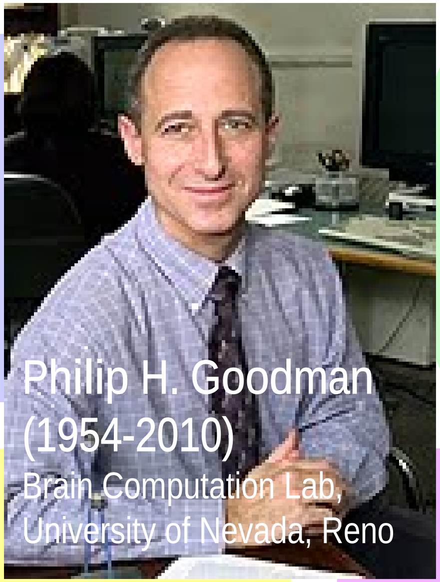
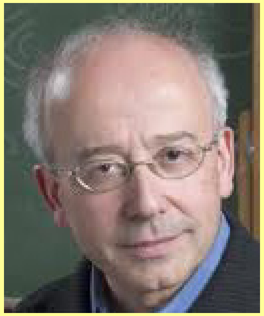


Philip H. Goodman (1954-2010)
Brain Computation Lab, University of Nevada, Reno

Carlos Sánchez
lattice simulations

Francisco Vico, GEB, U. de Málaga



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