Workshop on Mathematical Models of Cognitive Architectures

December 5-9, 2011, CIRM, Marseille

Morphogenetic "Neuron-Flocking": Dynamic Self-Organization of Neural Activity into Mental Shapes

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BrainModes marseille december 2011

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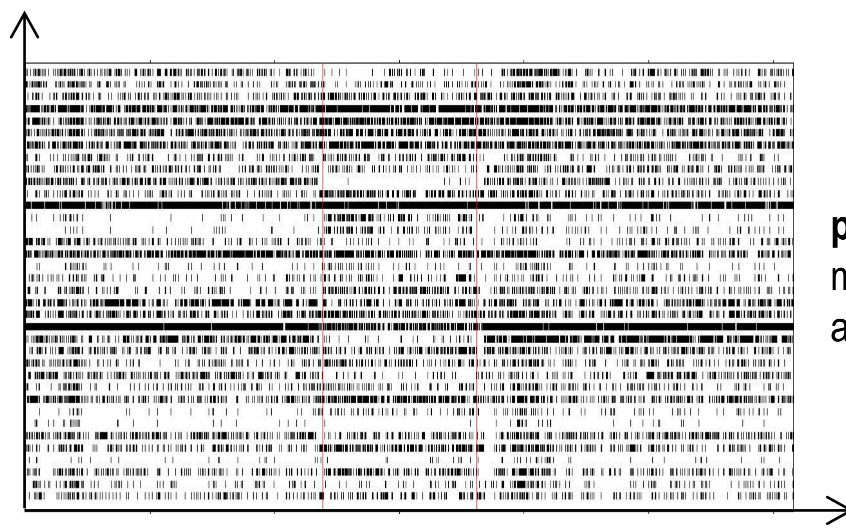
grupo de estudios en biomimética

MORPHOGENETIC "NEURON-FLOCKING"

phase space view:
complex spatiotemporal pattern =
mental shape

emergence?
structure?
properties?

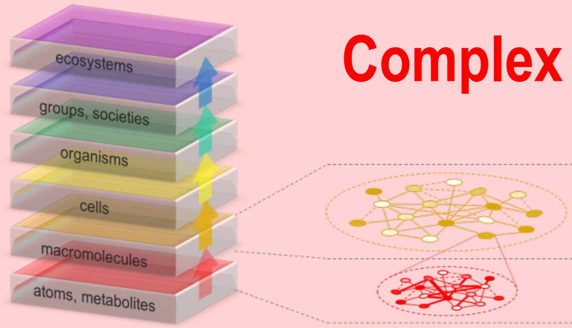
persistence? learning? storage? compositionality?



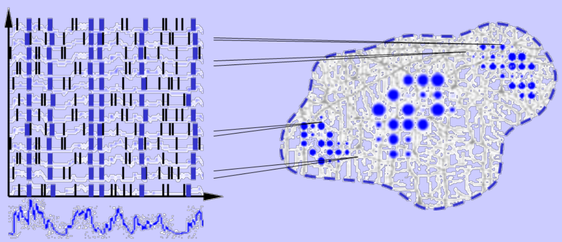
physical space view:
mega-MEA raster plot =
activity of 10^6-10^8 neurons

MORPHOGENETIC "NEURON-FLOCKING"

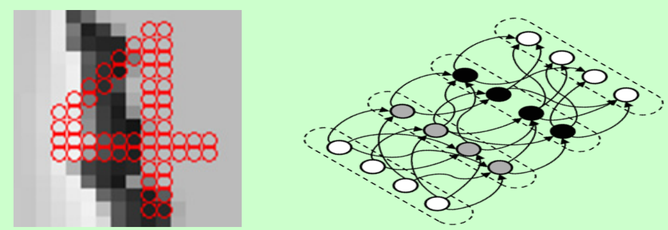
Complex Systems Levels



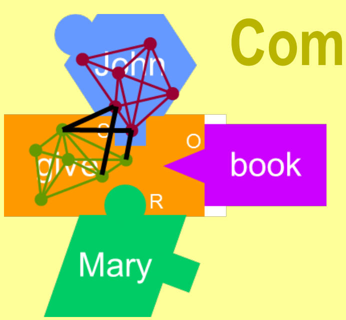
Temporal Code, Patterns



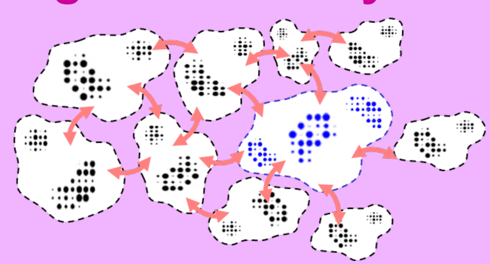
Waves, Chains, Phase Shapes



Compositionality



Emergent Neurodynamics



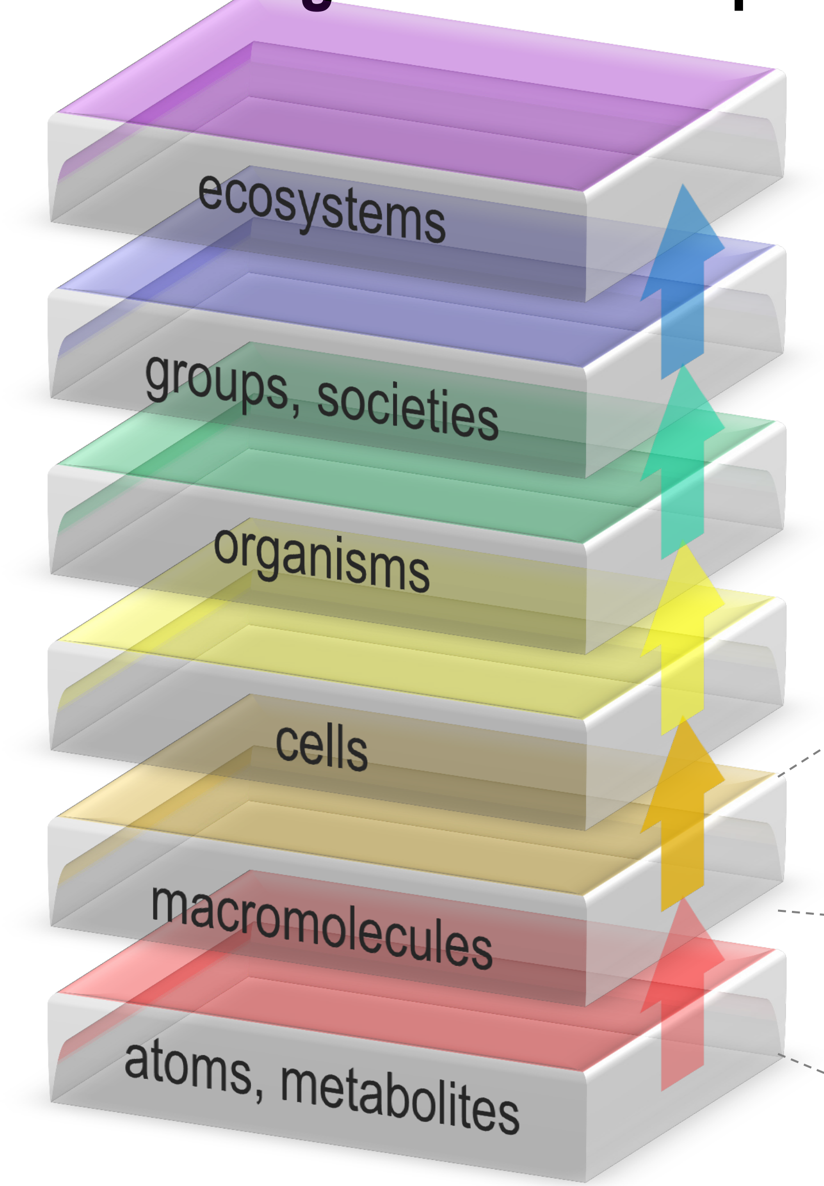
1. Cognitive Architectures in the Tower of Complex Systems

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**

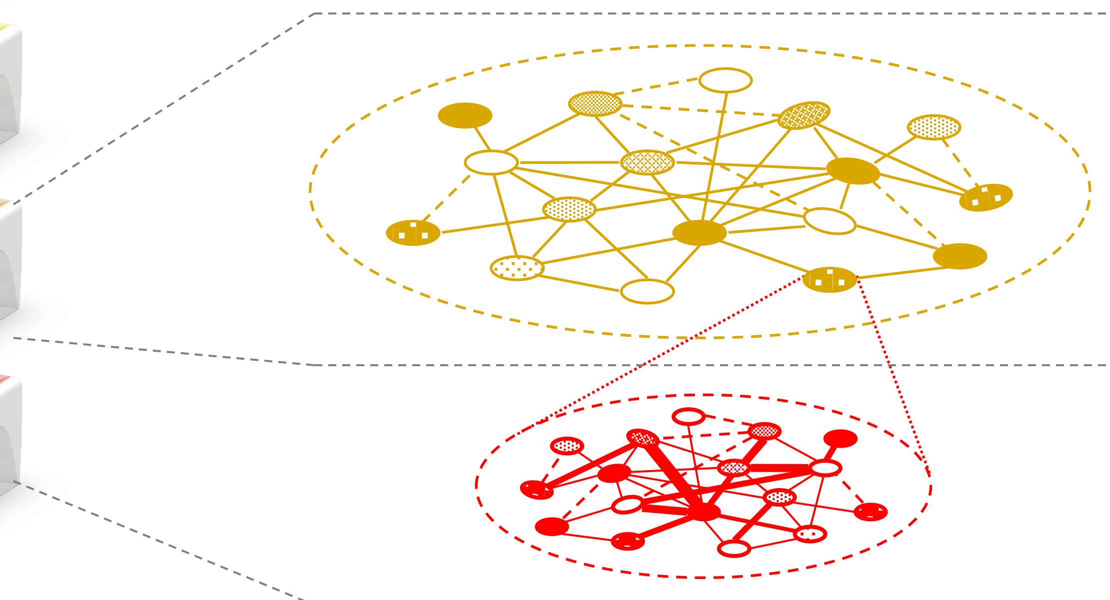


complex systems:

a) a large number of elementary agents interacting locally

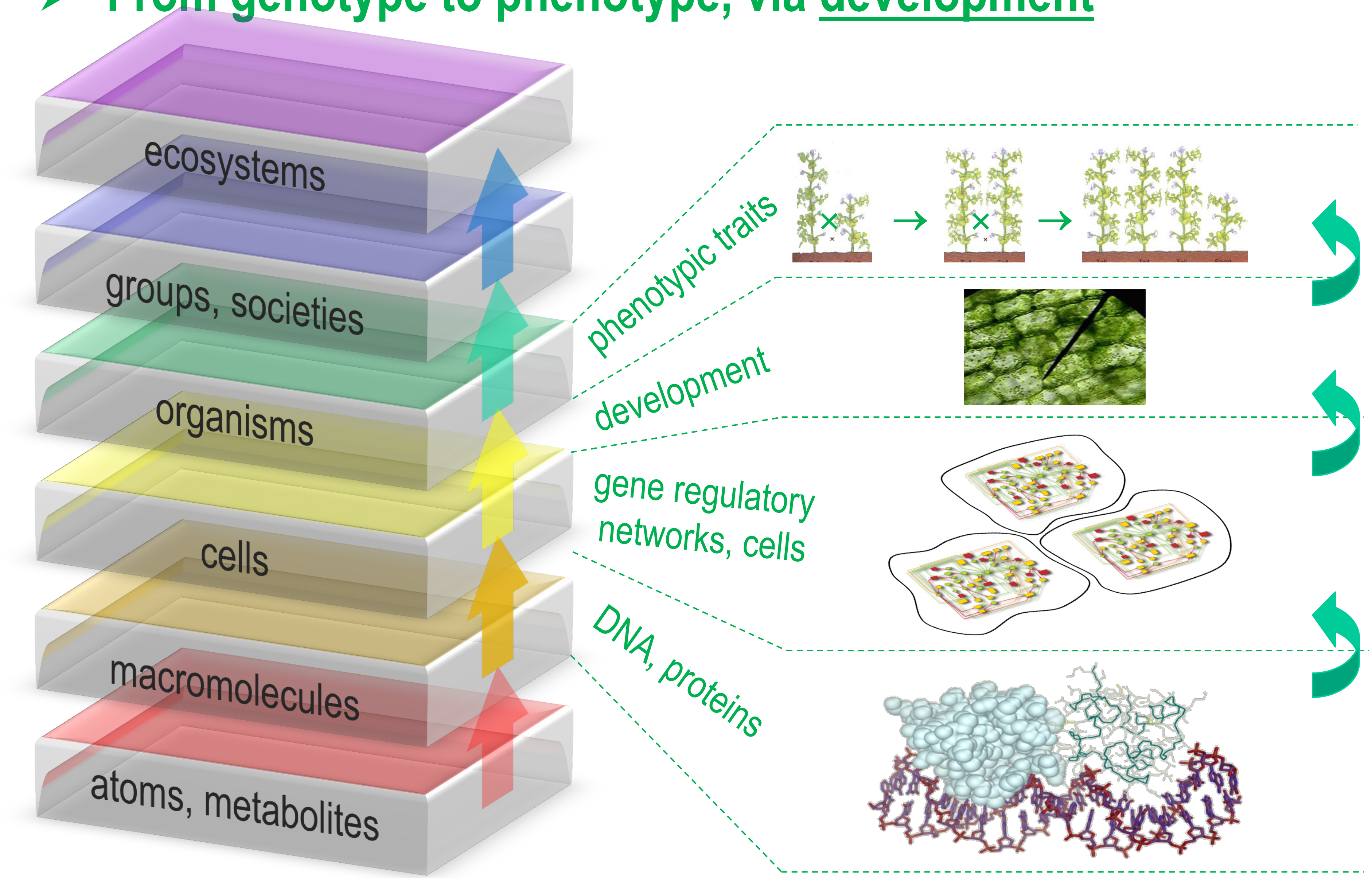
b) simple individual behaviors creating a complex emergent collective behavior

c) decentralized dynamics: no master blueprint or grand architect



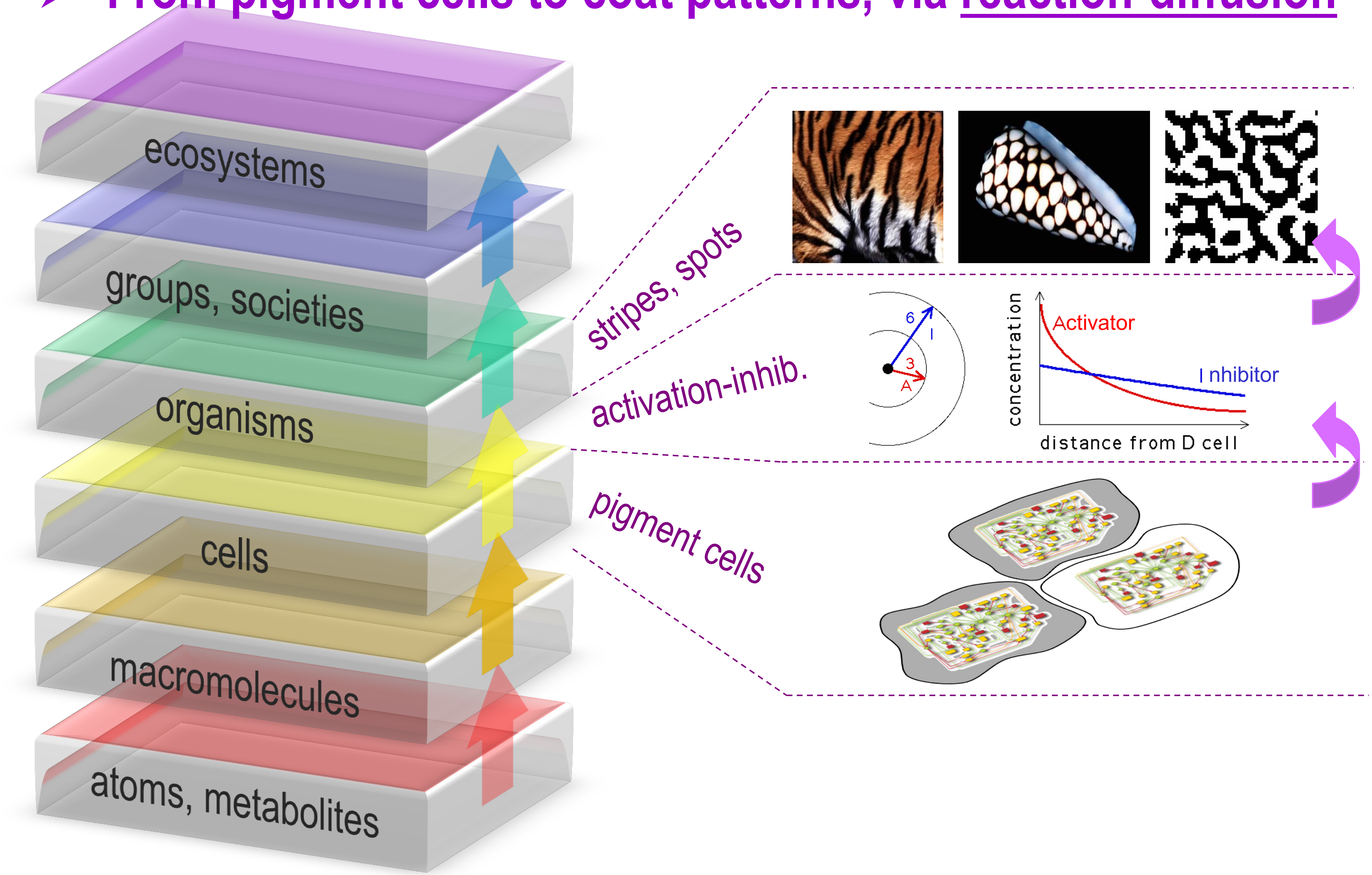
1. The Tower of Complex Systems

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



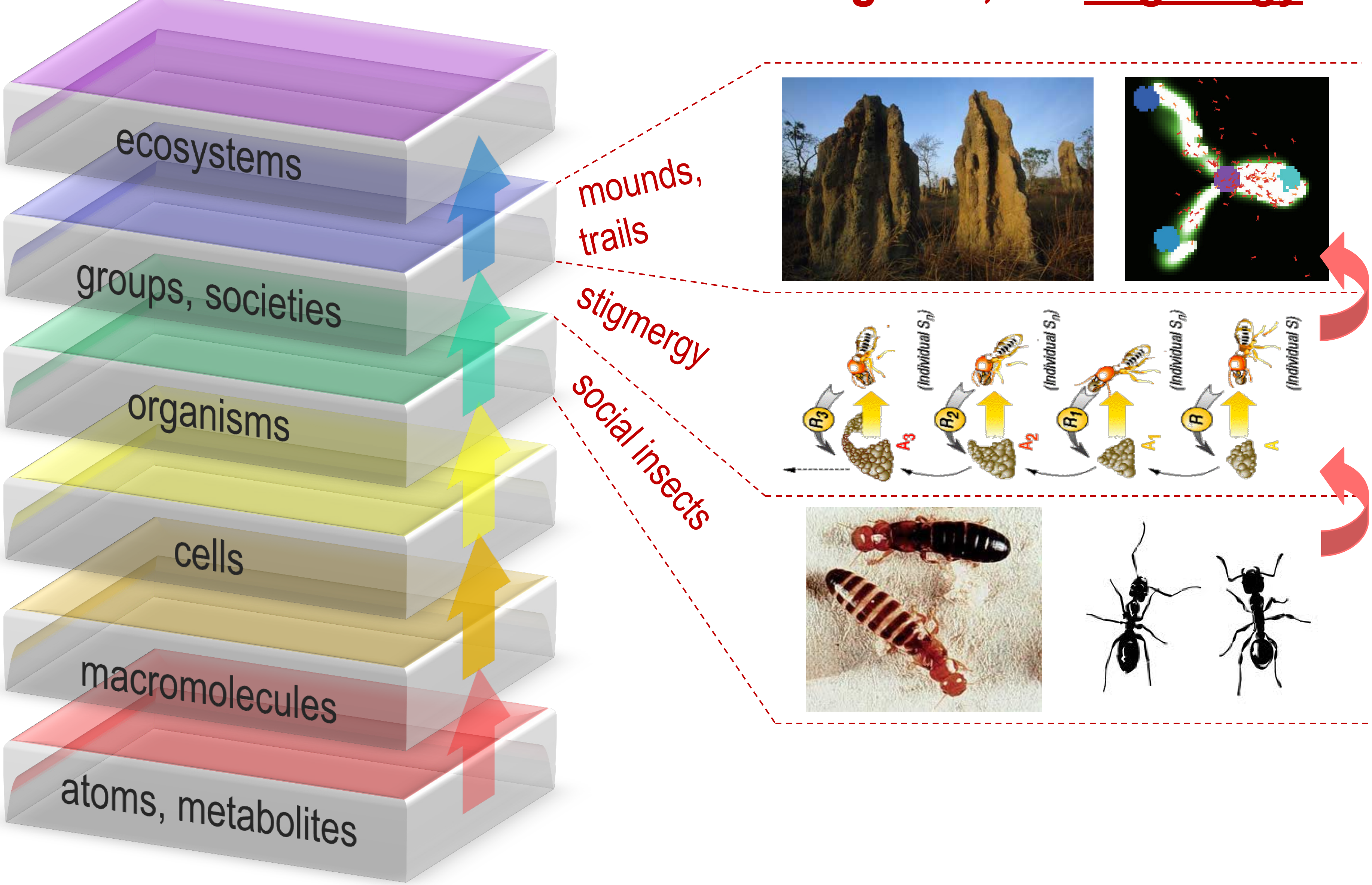
1. The Tower of Complex Systems

➢ **From pigment cells to coat patterns, via <u>reaction-diffusion</u>**



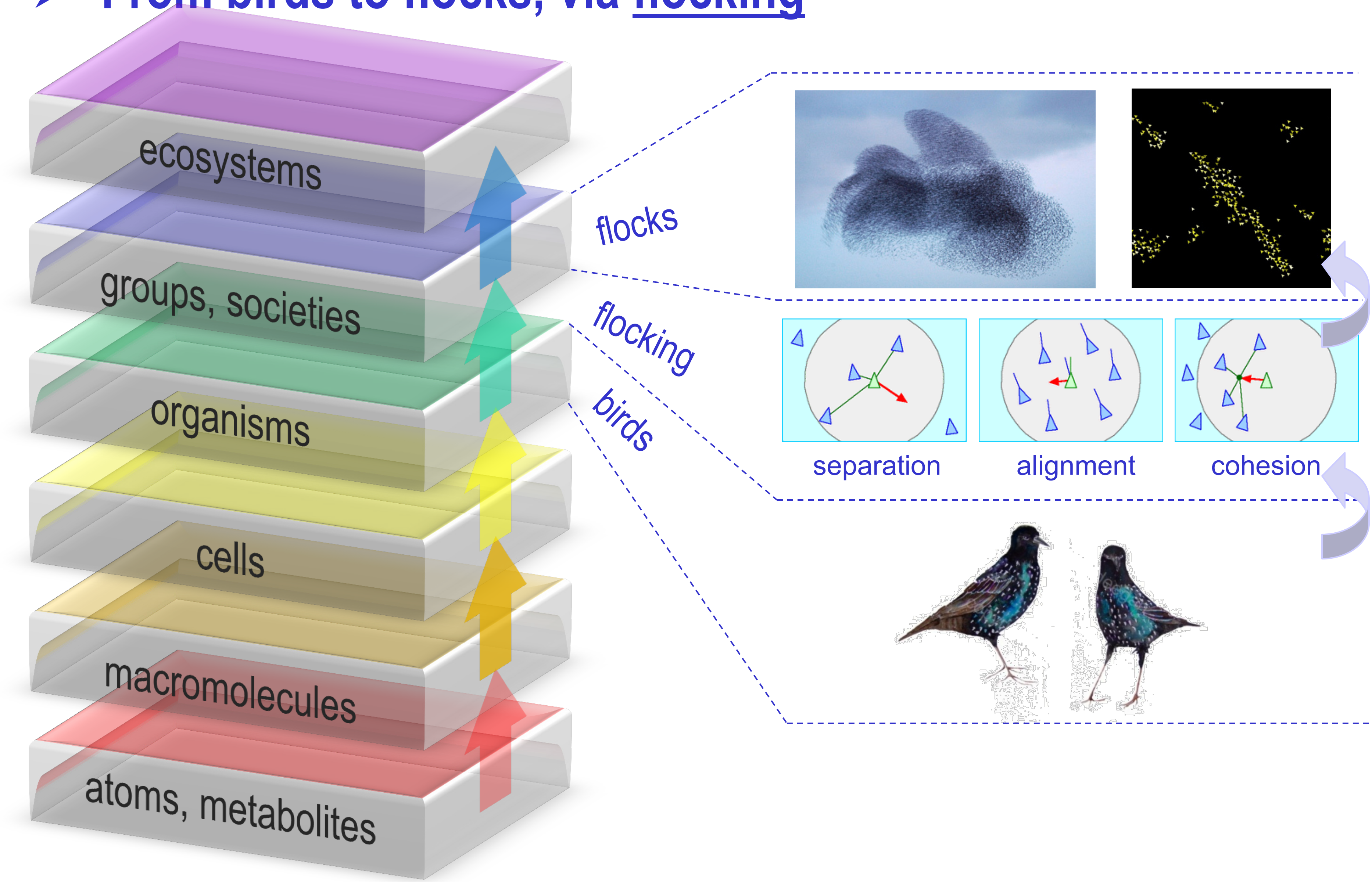
1. The Tower of Complex Systems

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



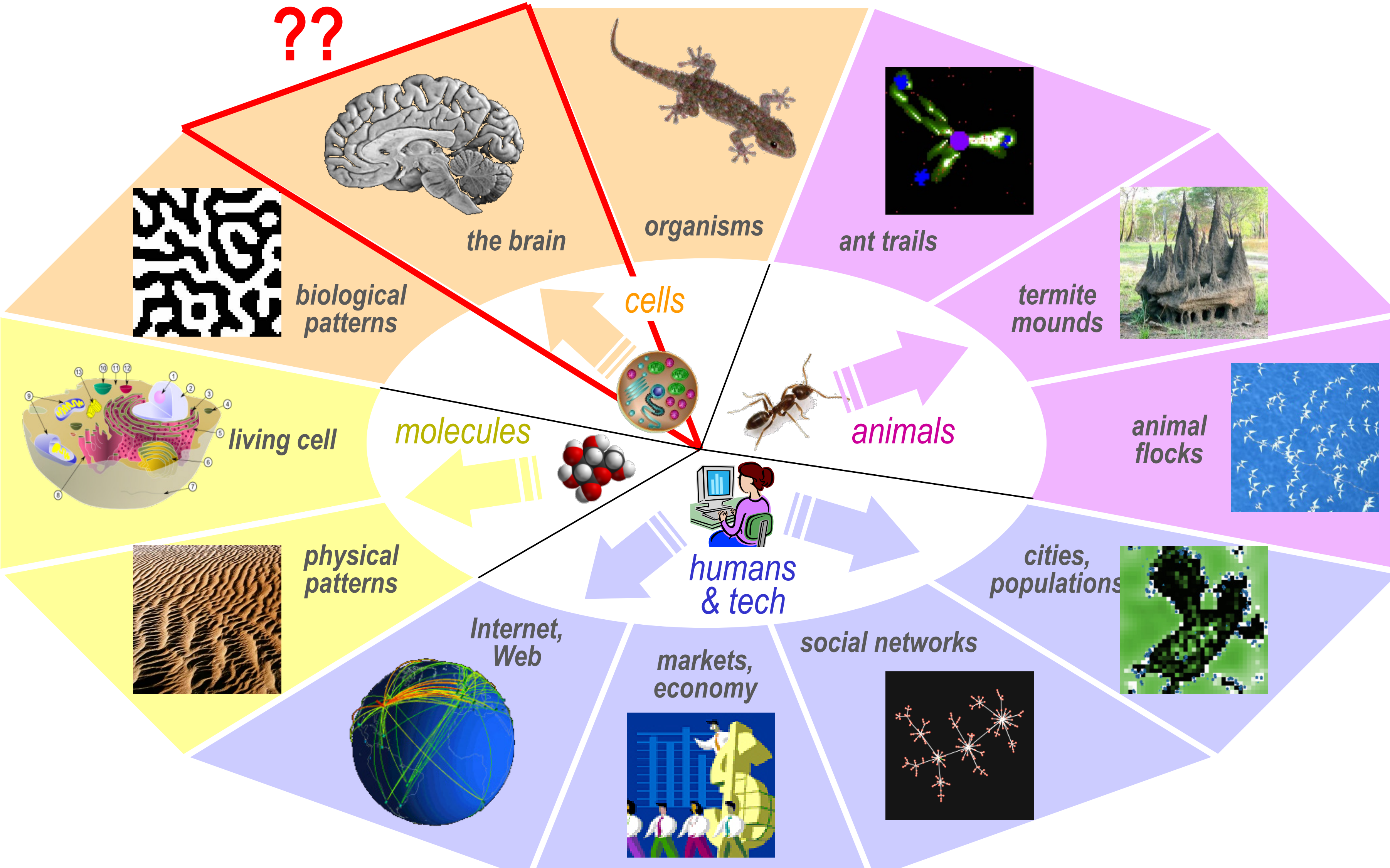
1. The Tower of Complex Systems

➢ From birds to flocks, via flocking



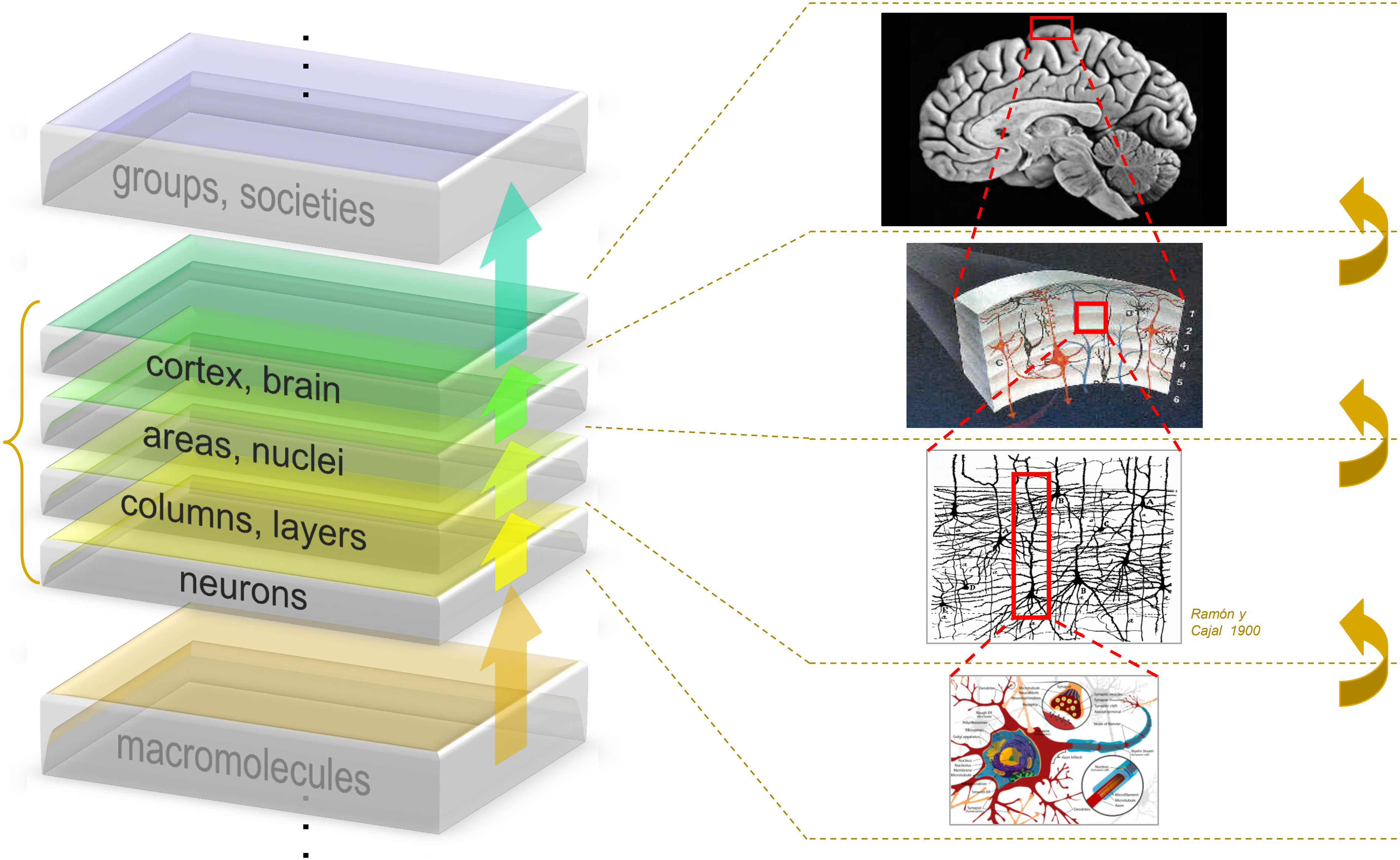
1. The Tower of Complex Systems

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



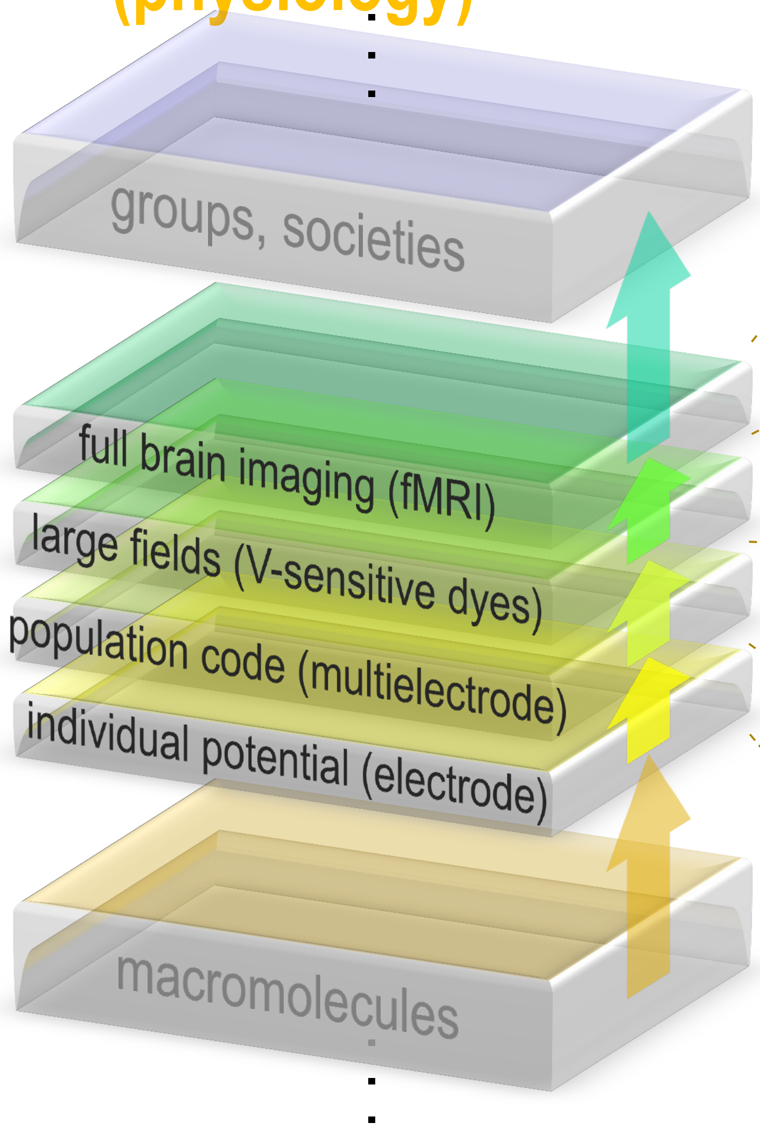
1. The Tower of Complex Systems

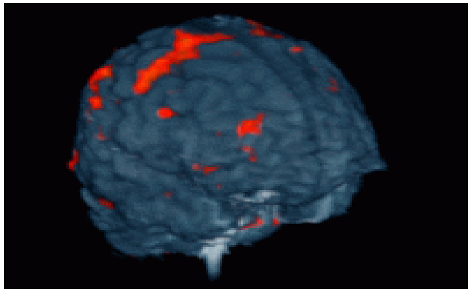
➢ From neurons to brain, via neural development (anatomy)



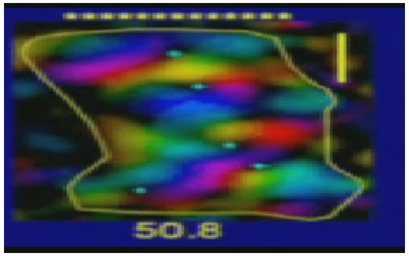
1. The Tower of Complex Systems

➢ From potentials to fMRI, via synaptic transmission (physiology)

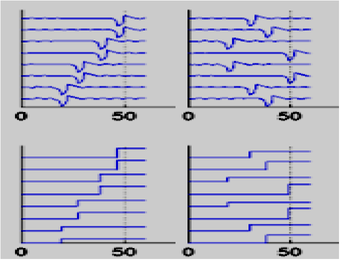




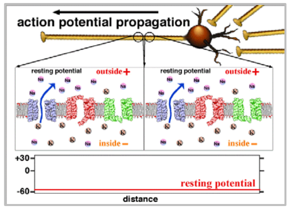
Animation of a functional MRI study (J. Ellermann, J. Strupp, K. Ugurbil, U Minnesota)



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

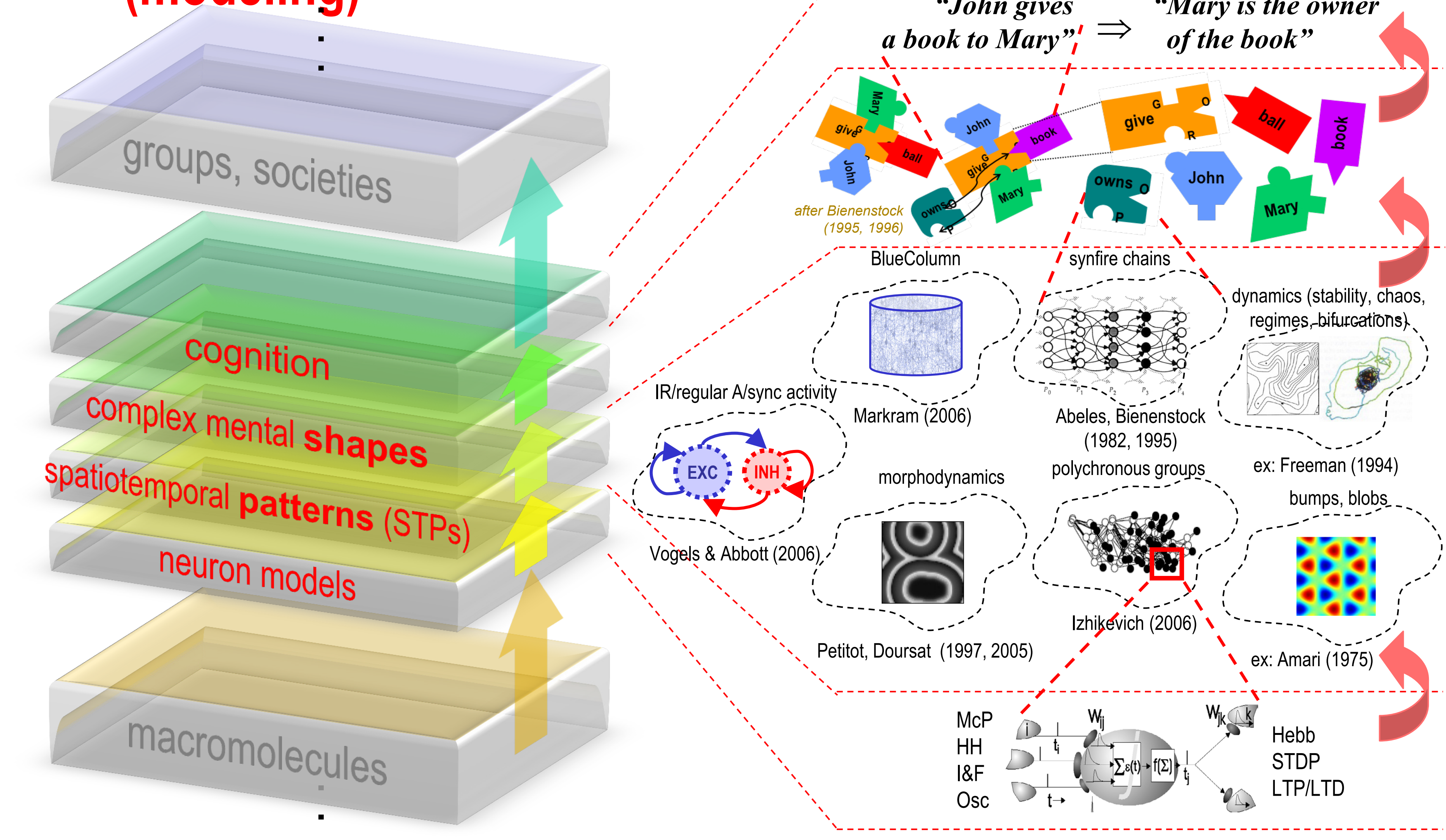


Raster plot of of a simulated synfire braid, Doursat et al. 2011



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

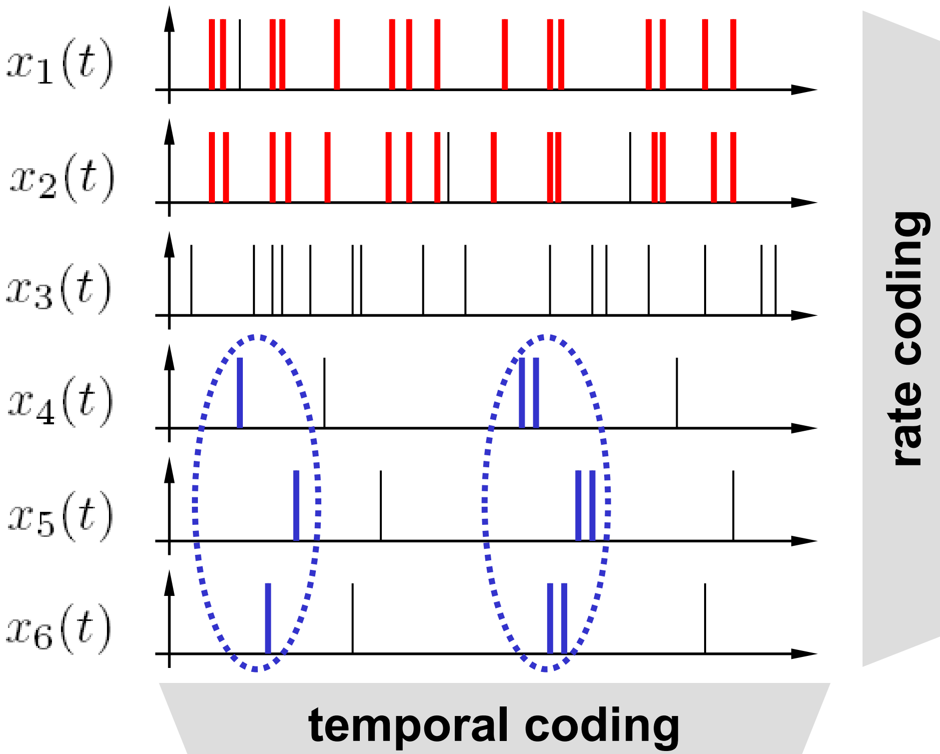
Neural correlations: The glue of spatiotemporal patterns (STPs)

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

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)

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

➢ 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 <u>integrating</u> the information

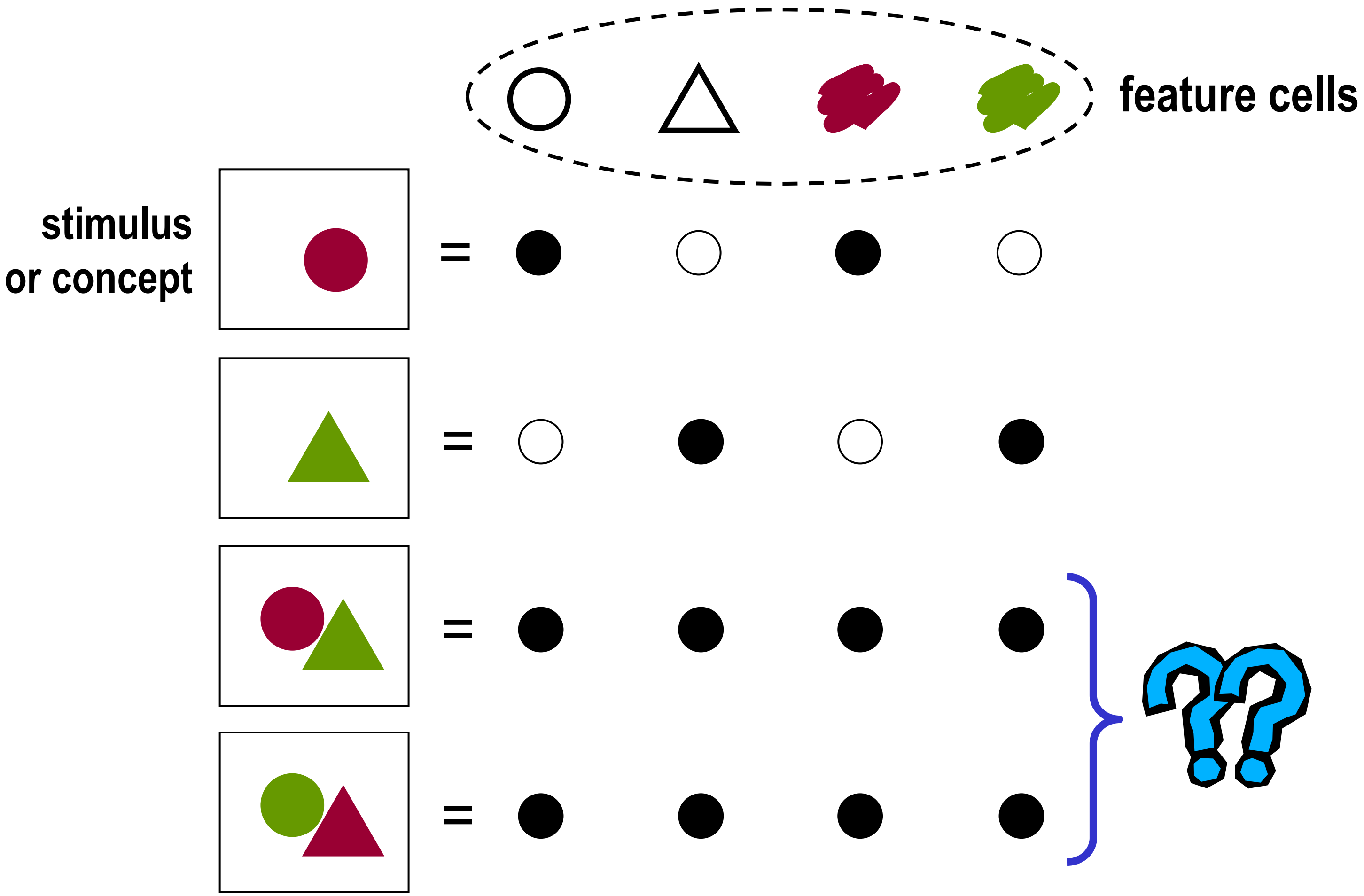
➢ Temporal coding pioneers of the 1980-90's

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

2. A Pattern Formation Machine

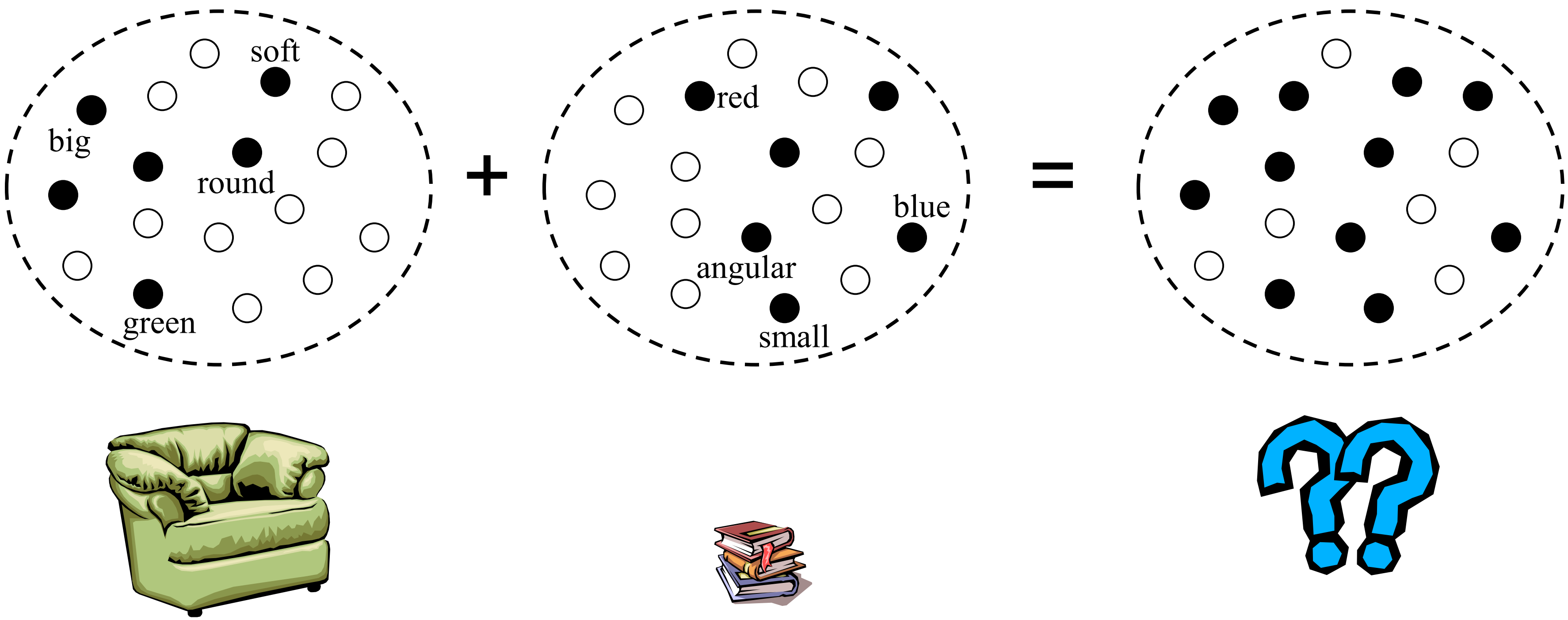
The "binding problem": using temporal code

- ✓ how to represent relationships?



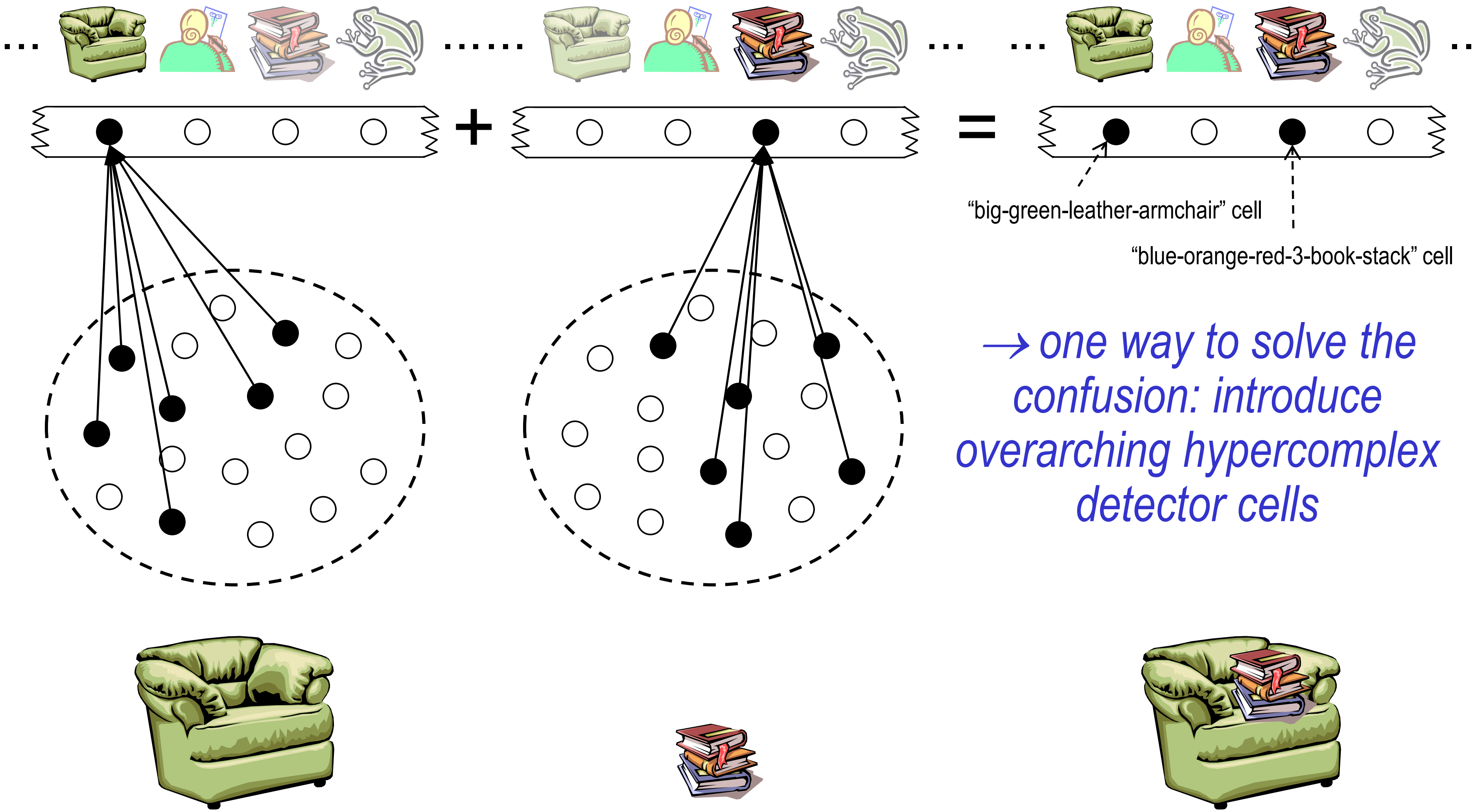
2. A Pattern Formation Machine

- **More generallly: feature binding in cell assemblies**
  - ✓ unstructured lists or "sets" of features lead to the "superposition catastrophe"



2. A Pattern Formation Machine

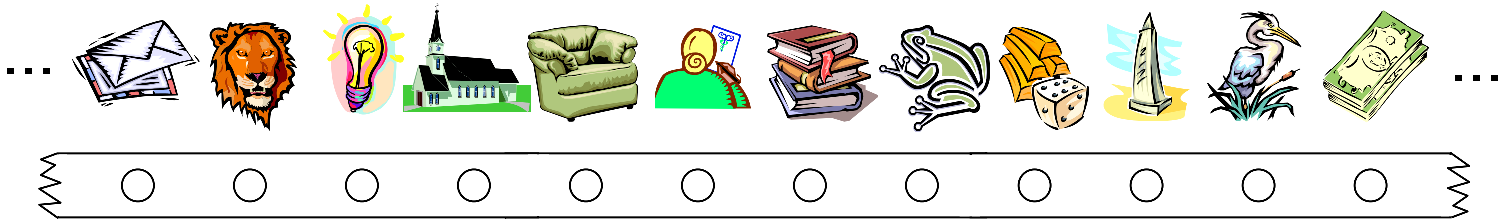
- ~~“Grandmother”~~ “Jennifer Aniston” cells... really?



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

2. A Pattern Formation Machine

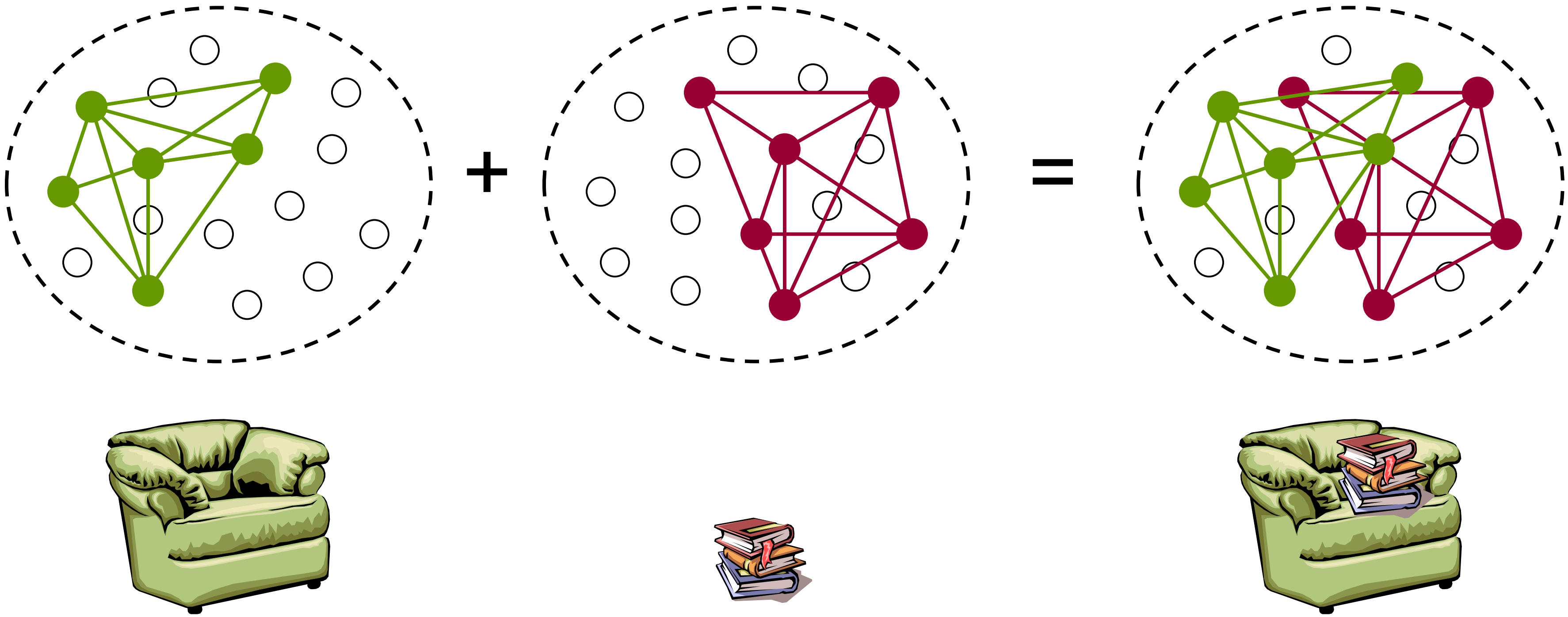
- ~~“Grandmother”~~ “Jennifer Aniston” cells... really?



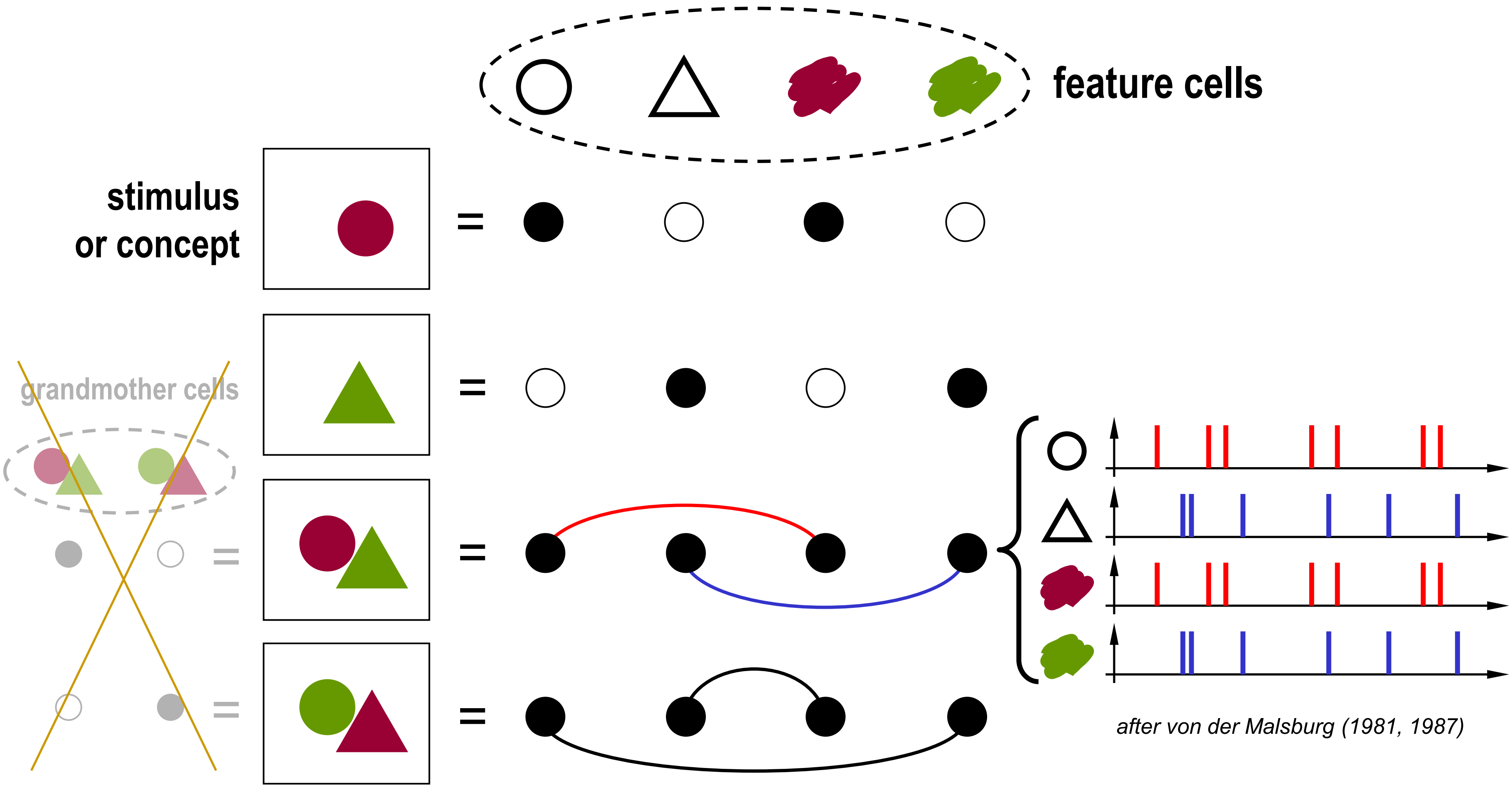
. . . however, this soon leads to
a combinatorial explosion

2. A Pattern Formation Machine

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



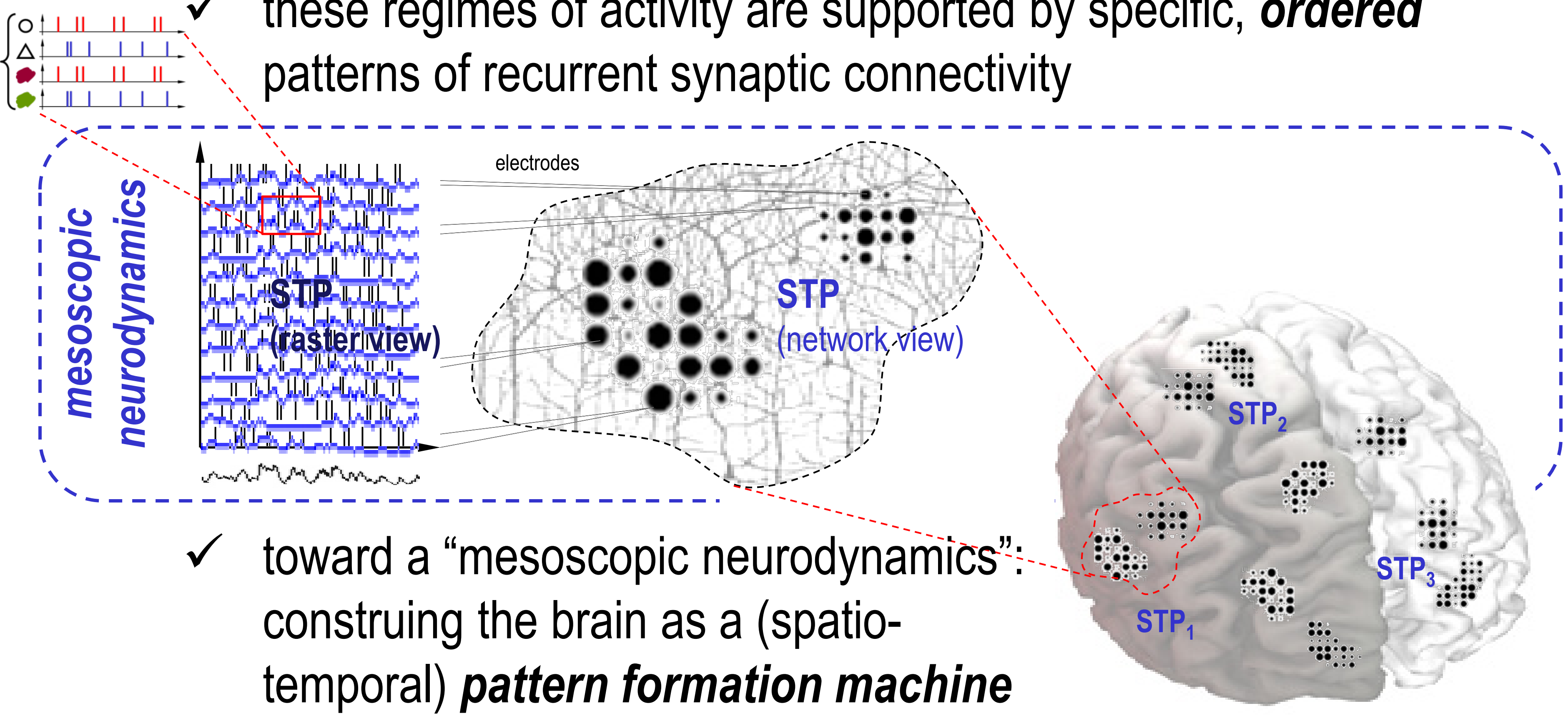
- **Idea: relational information can be encoded *temporally***
  - ✓ back to the binding problem: a solution using temporal coding



after von der Malsburg (1981, 1987)

2. A Pattern Formation Machine

- **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



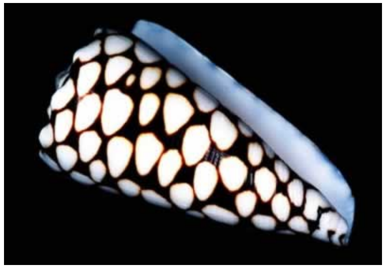
  - ✓ toward a "mesoscopic neurodynamics": construing the brain as a (spatio-temporal) ***pattern formation machine***

2. A Pattern Formation Machine

➢ Biological development is about pattern formation

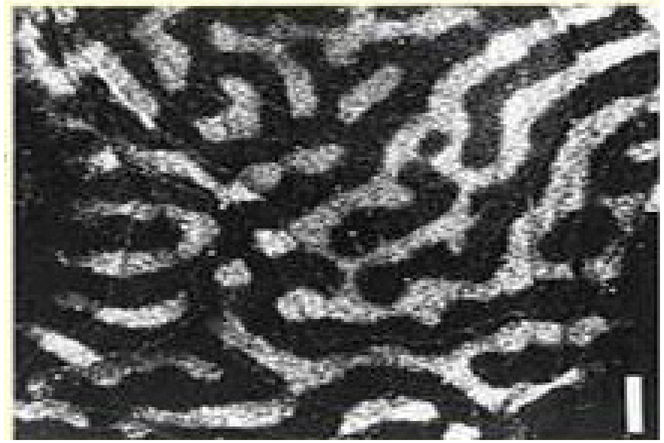
✓ multicellular patterning



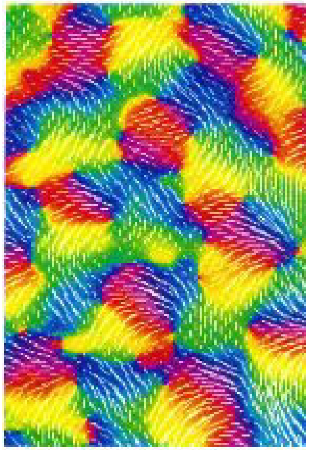



Scott Camazine, http://www.scottcamazine.com

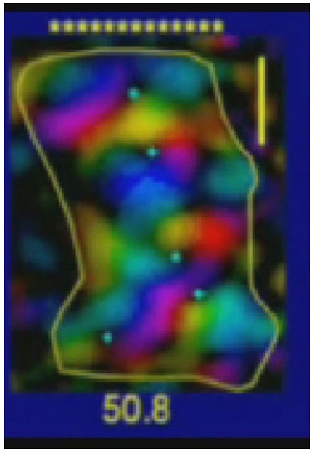
✓ ... the brain is no different



ocular dominance stripes Hubel & Wiesel, 1970



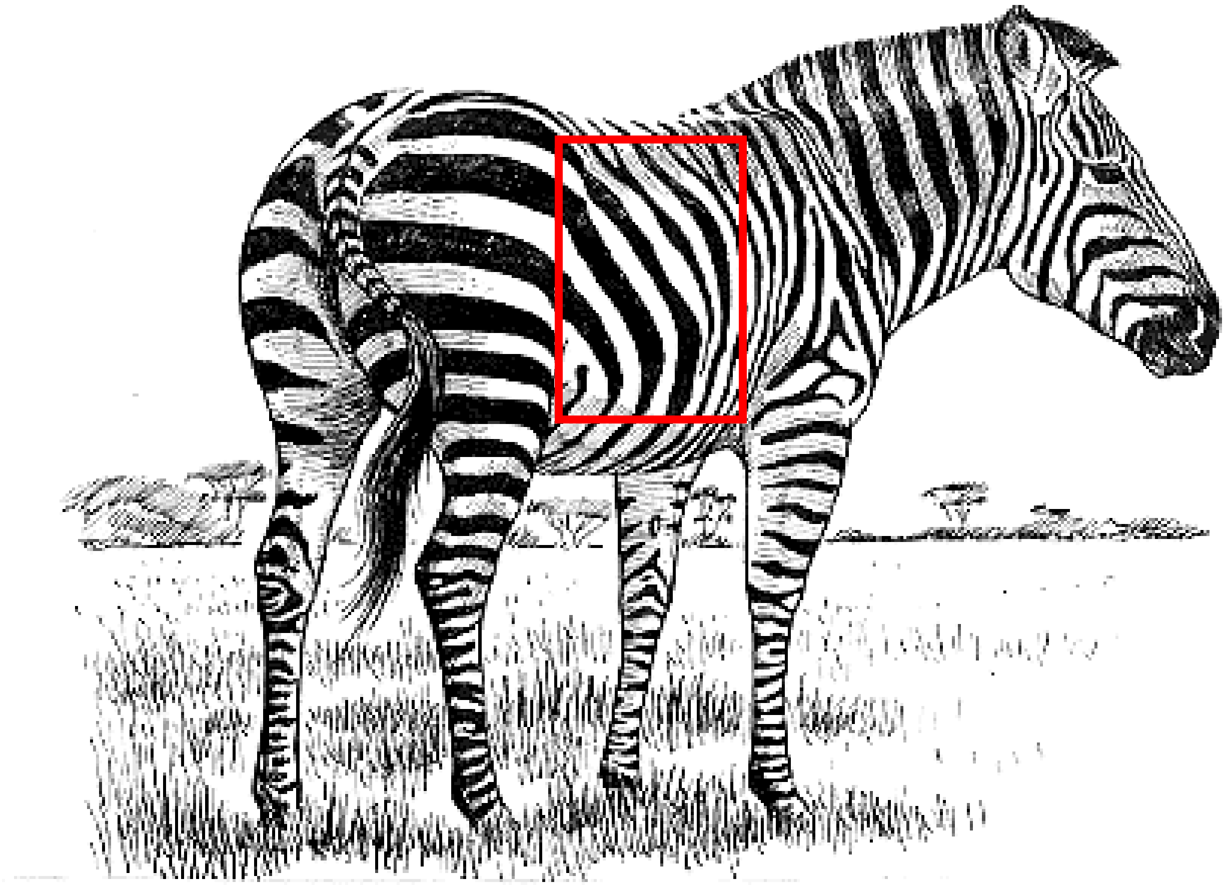
orientation column "pinwheels" Blasdel, 1992



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

2. A Morphogenetic Machine

- ... but beyond pattern formation: complex **morphogenesis**



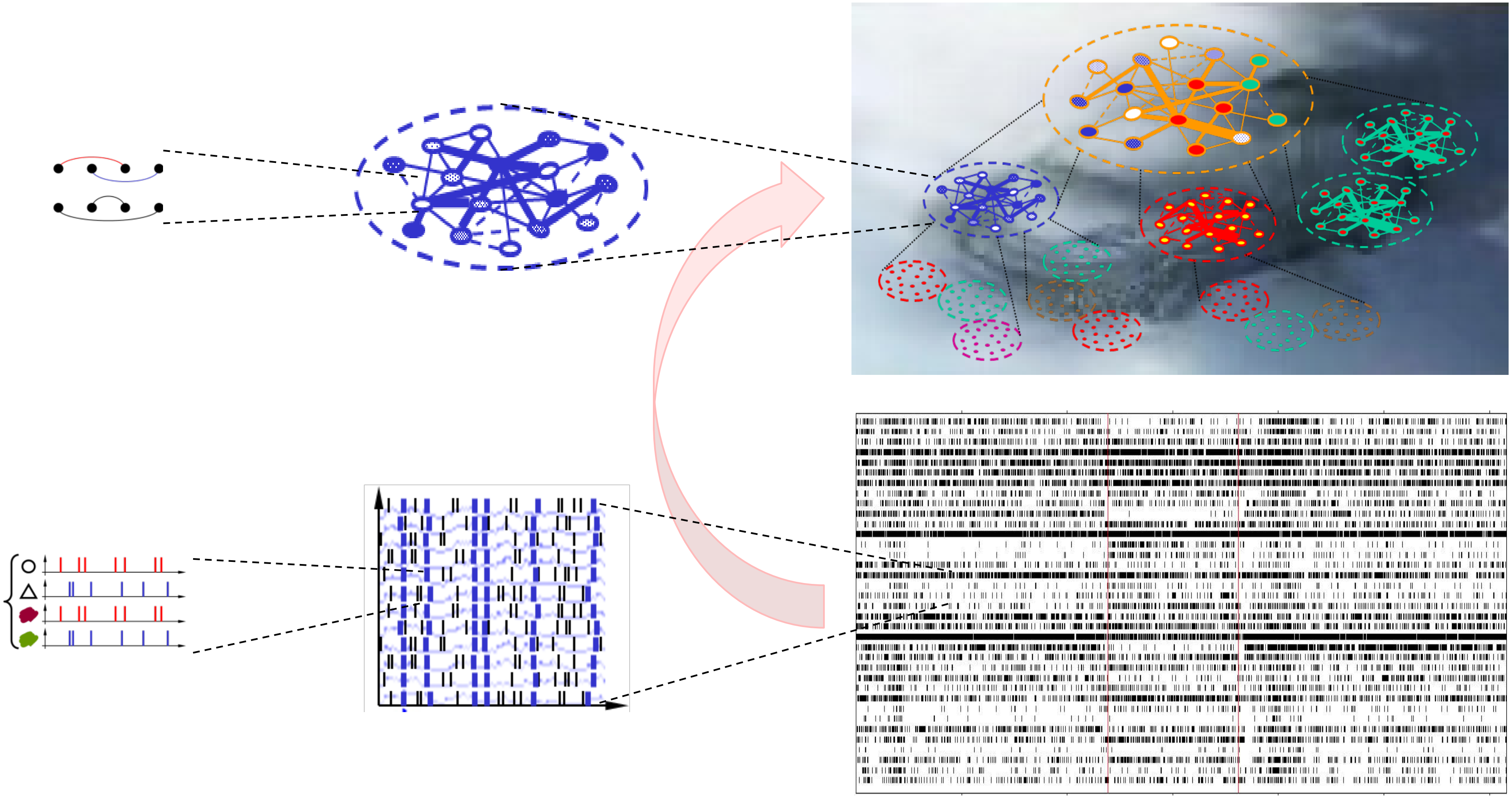
"I have the stripes, but where is the zebra?" OR

"The stripes are easy, it's the horse part that troubles me"

—attributed to A. Turing, after his 1952 paper on 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*



MORPHOGENETIC "NEURON-FLOCKING"

1. Cognitive Architectures in the Tower of Complex Systems

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Neural correlations: The glue of spatiotemporal patterns (STPs)

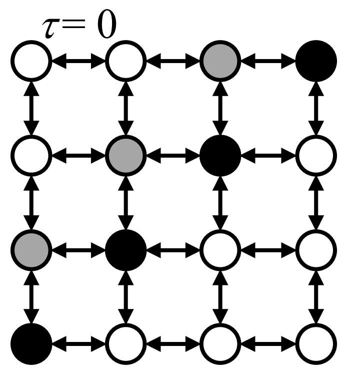
3. Example Model: Wave-Based Shape-Matching

Coding coordinates by phases, and shapes by waves

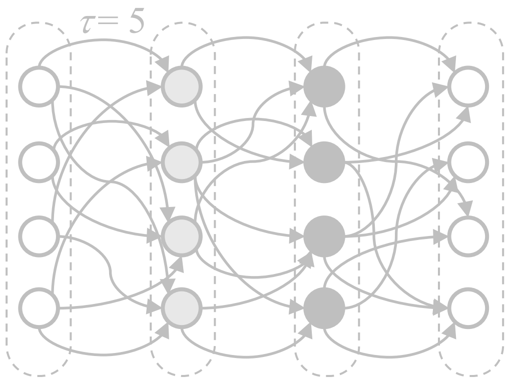
- *Lattices: group sync, waves, 2D shapes*
- *Synfire chains: wave storage, retrieval*
- *Synfire braids: shape storage, matching*

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



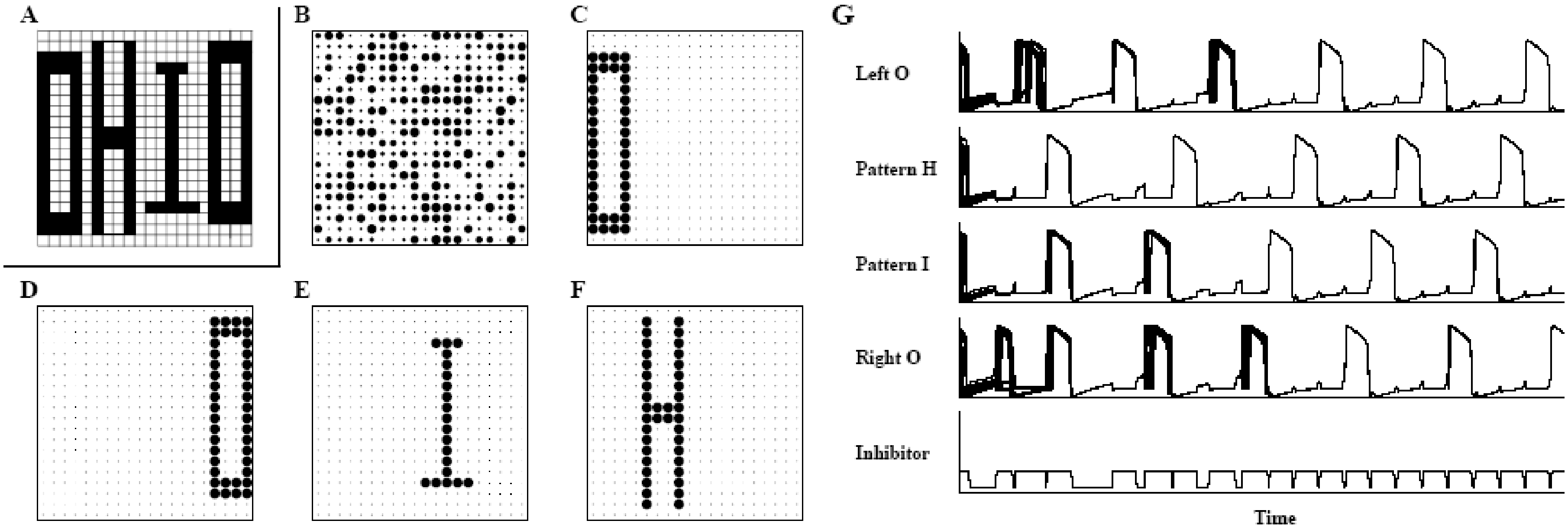
  - ✓ **Synfire chains** (uniform delays)
    - wave propagation
    - chain growth
    - pattern storage and retrieval



  - ✓ **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.
      - **oscillatory or excitable units** as an abstraction of excit↔inhib columnar activity
      - **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

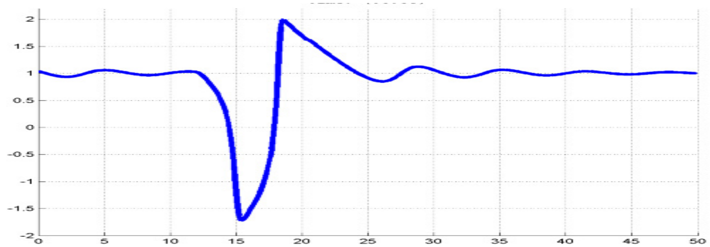
- **Stochastic excitable units**
  - ✓ ex: Bonhoeffer-van der Pol (BvP) oscillator's two main regimes:

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

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

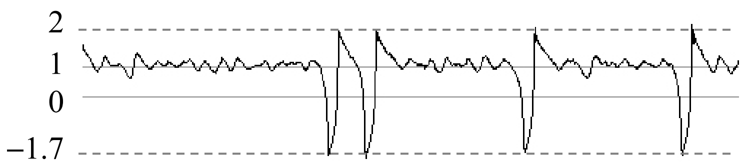
$z_c = -0.3465$

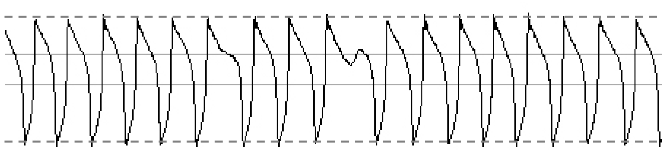
$z < z_c$ b) quasi-periodic → ***oscillatory***



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

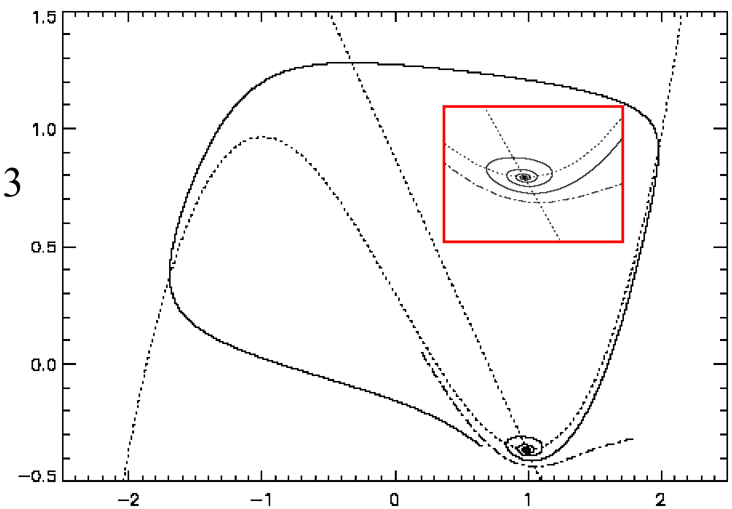
(a)

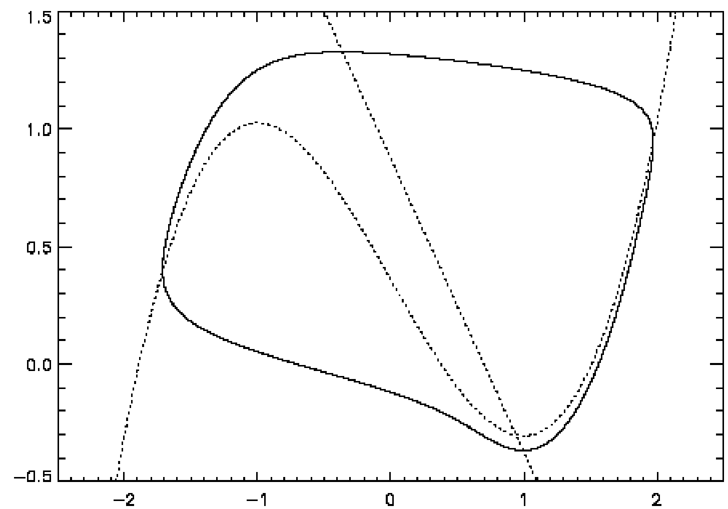




(b)

$z = -0.3$





$z = -0.36$

3. Wave-Based Shape-Matching – Lattice

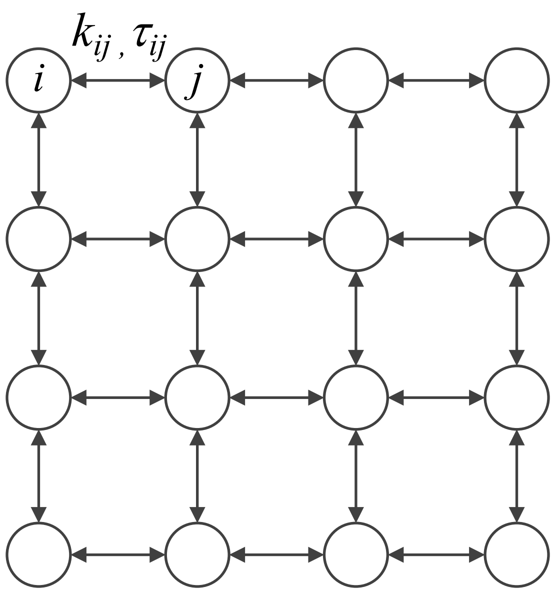
- **Lattice of coupled oscillators**
  - ✓ $i \leftarrow j$ coupling features
    - isotropic
    - proportional to the u signal difference
      - only in spiking domain $u < 0$
    - positive connection weight k_{ij}
    - possible transmission delay τ_{ij}
      - here zero delays $\tau_{ij} = 0$

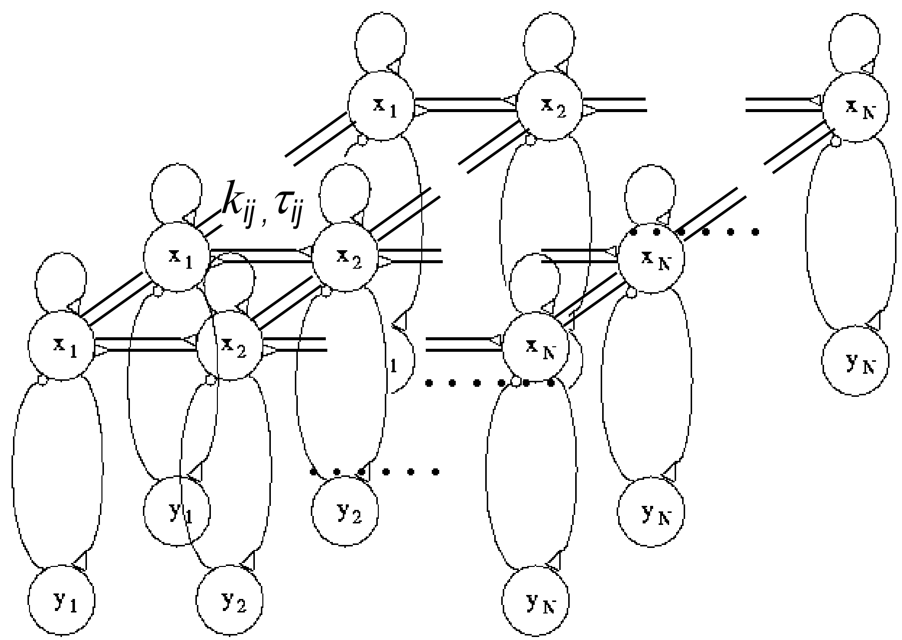
$$\begin{cases} \dfrac{du_i}{dt} = c\left(u_i - \dfrac{u_i^3}{3} + v_i + z\right) + \eta + K_i + I_i \\ \dfrac{dv_i}{dt} = \dfrac{1}{c}(a - u_i - bv_i) + \eta \end{cases}$$

coupling term

input term

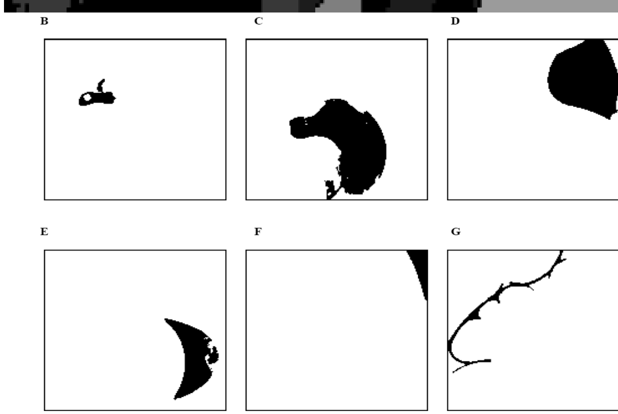
$$\boxed{K_i(t) = \sum_{\substack{j=1 \\ u_j(t-\tau_{ij})<0}}^{N} k_{ij}\Big(u_j(t-\tau_{ij}) - u_i(t)\Big)}$$



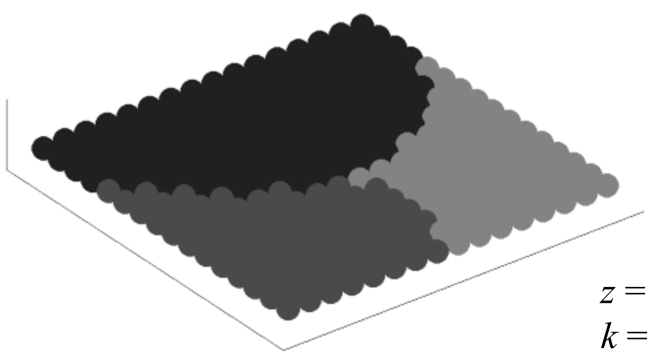


3. Wave-Based Shape-Matching – Lattice

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



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

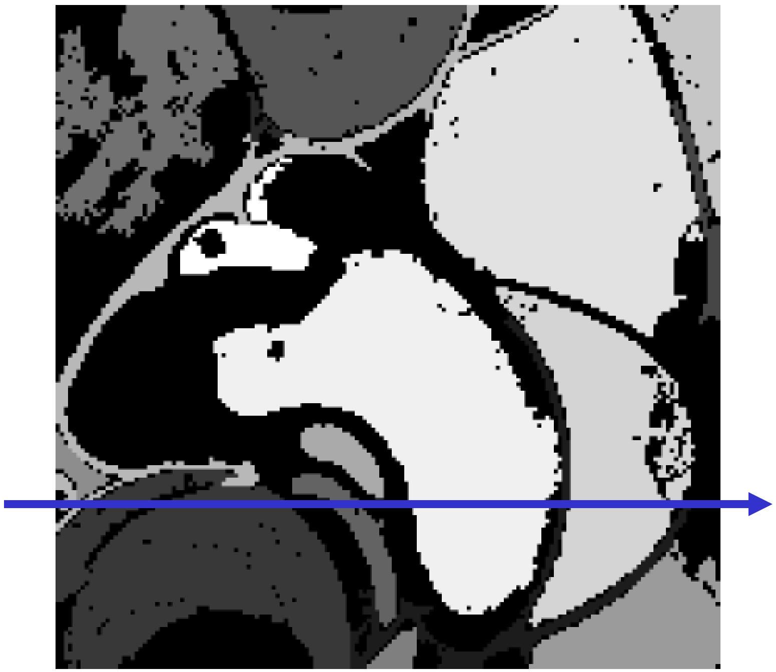


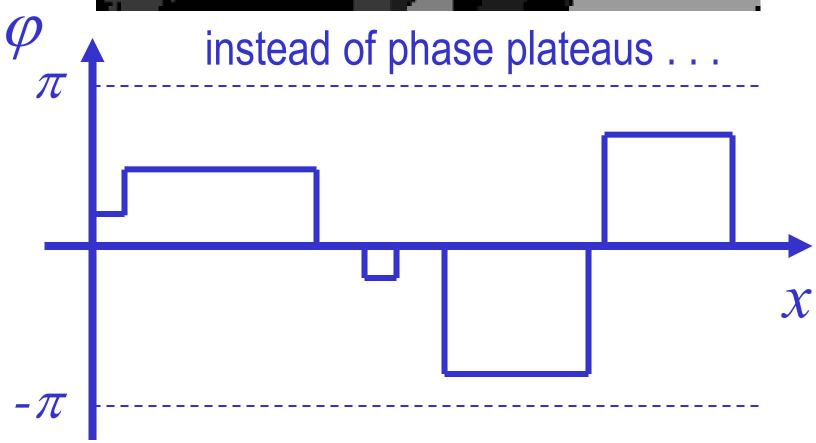
$z = -0.336$
$k = 0.10$
$I = -2.34$

(illustration by Doursat & Sanchez 2011)

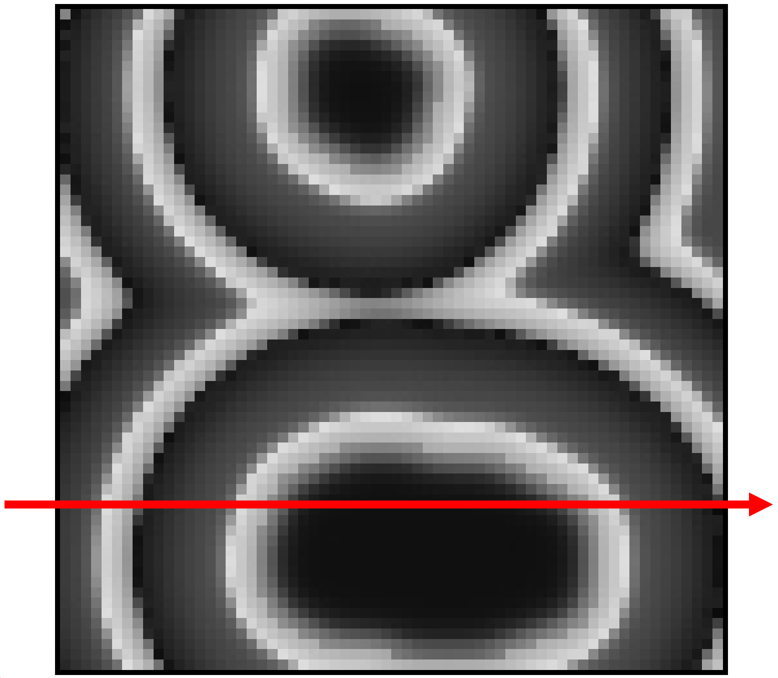
3. Wave-Based Shape-Matching – Lattice

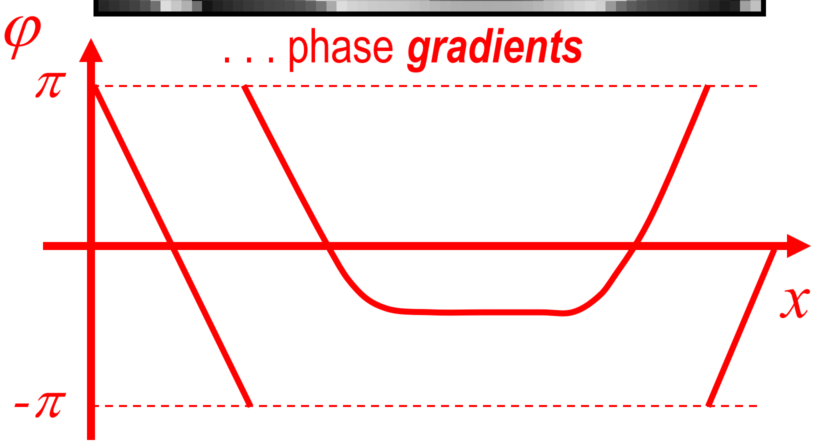
➢ **Lattice of coupled oscillators – *traveling waves***





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

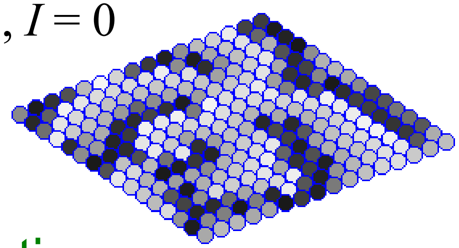




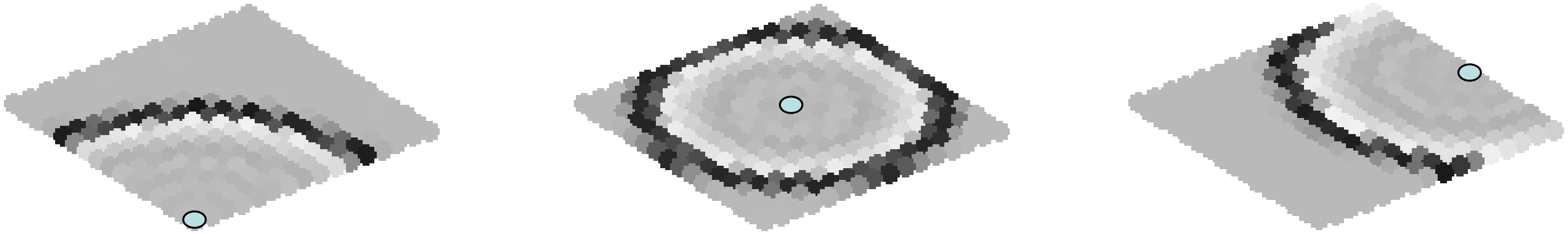
Doursat,, R. & Petitot, J. (2005) Dynamical systems and cognitive linguistics: Toward an active morphodynamical semantics. *Neural Networks* **18**: 628-638.

3. Wave-Based Shape-Matching – Lattice

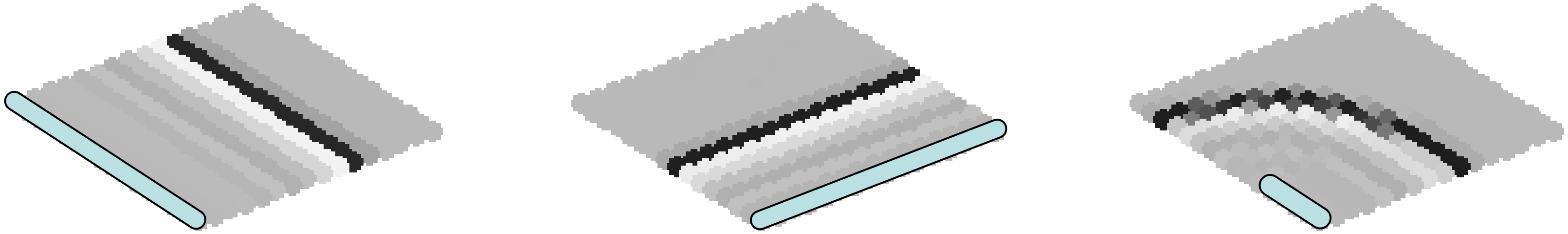
- **Lattice of coupled oscillators** – ***traveling waves***
  - ✓ Random propagation
    - $z = –0.346, k = 0.04, I = 0$



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

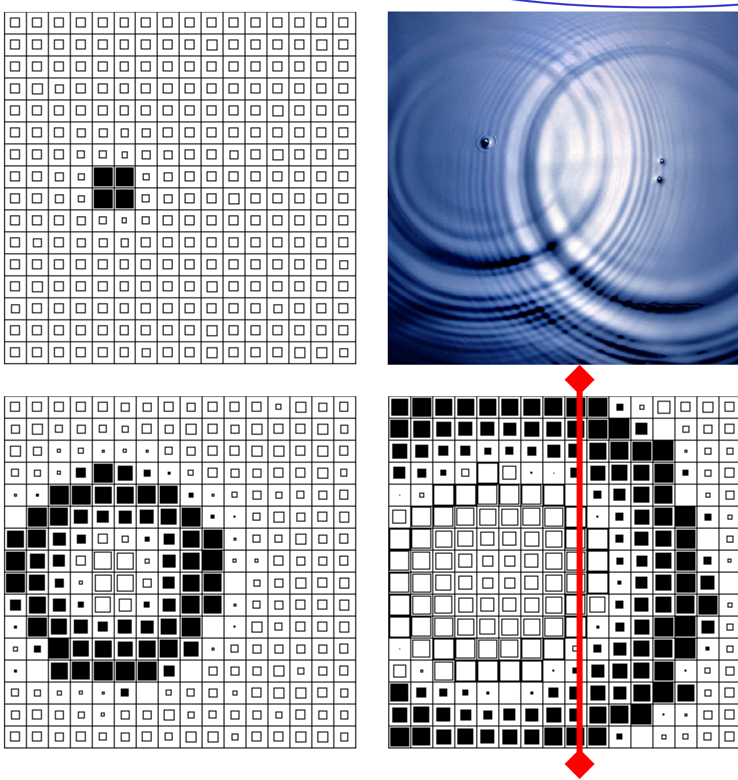


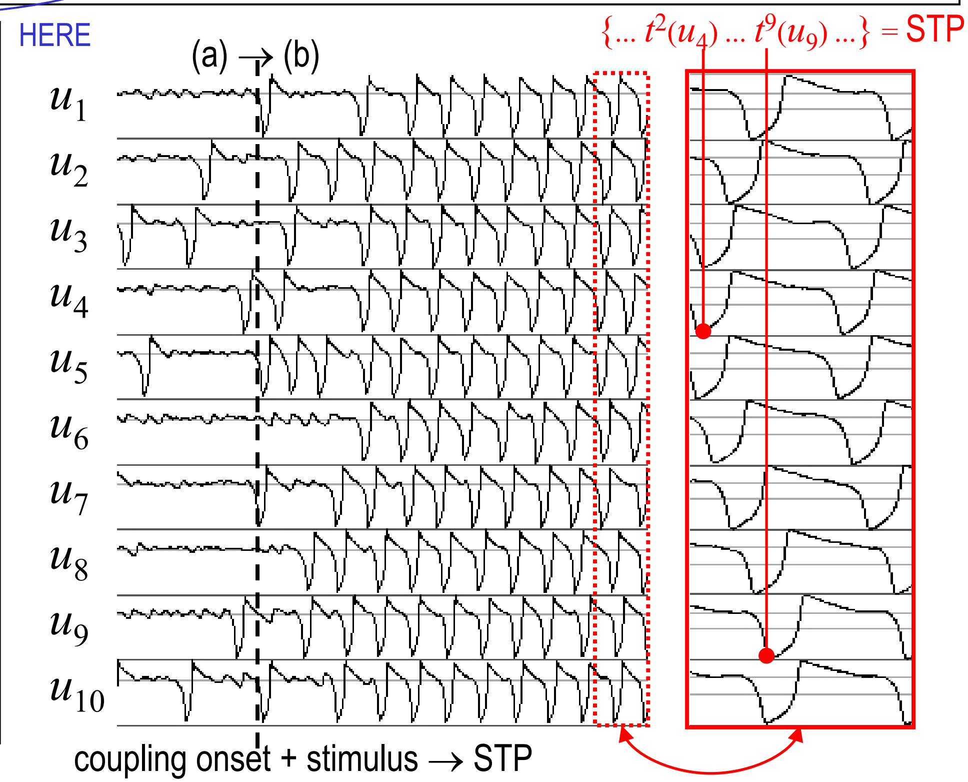
  - ✓ Planar & mixed wave generation
    - $z = –0.29, k = 0.10, I = –0.44$ (bar stimulus ▭)



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)



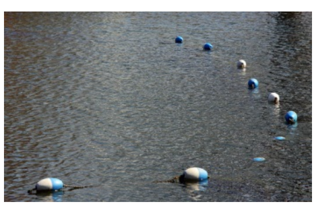


3. Wave-Based Shape-Matching – Lattice

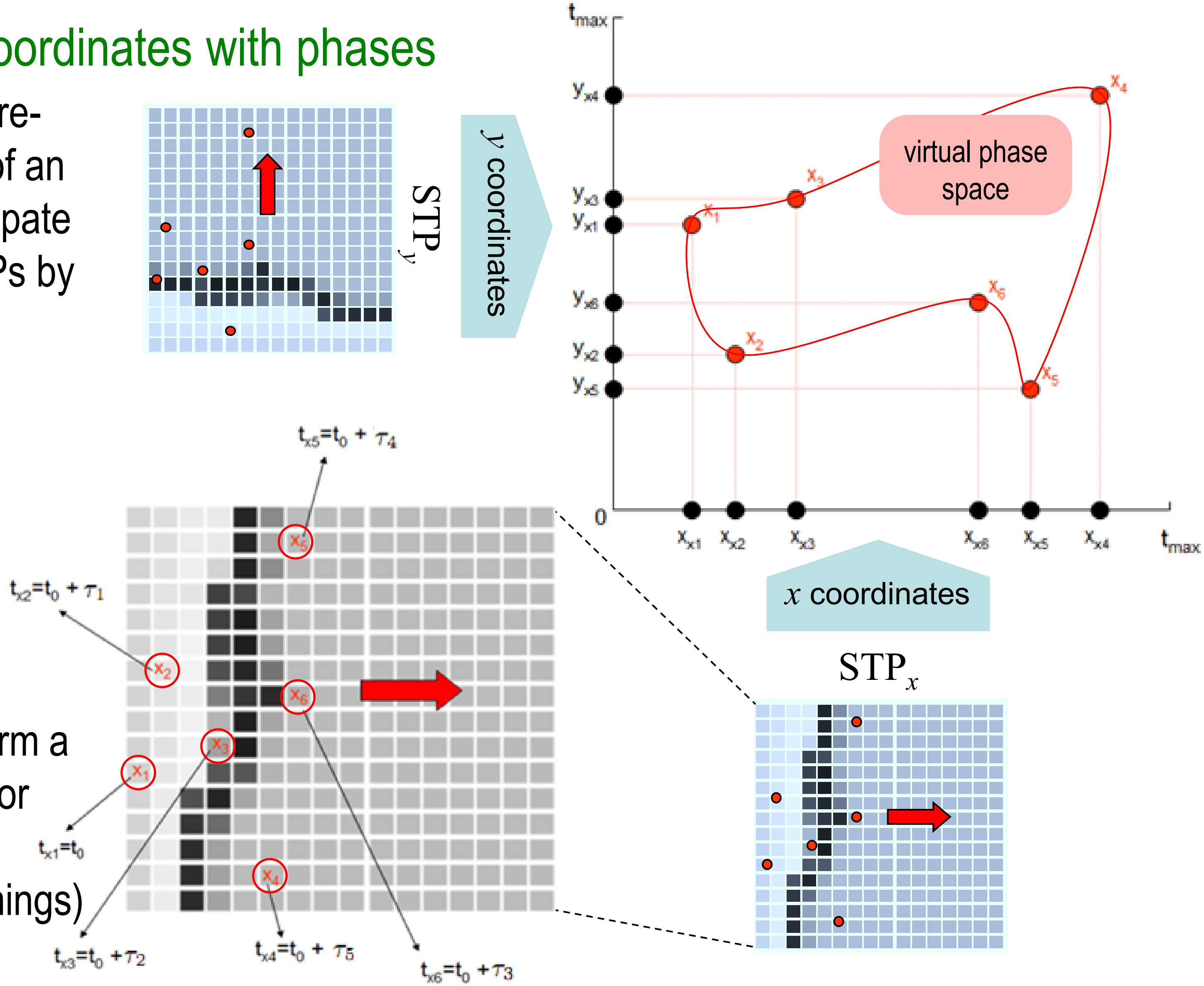
➢ Lattice of coupled oscillators – *2D wave shapes*

✓ 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)

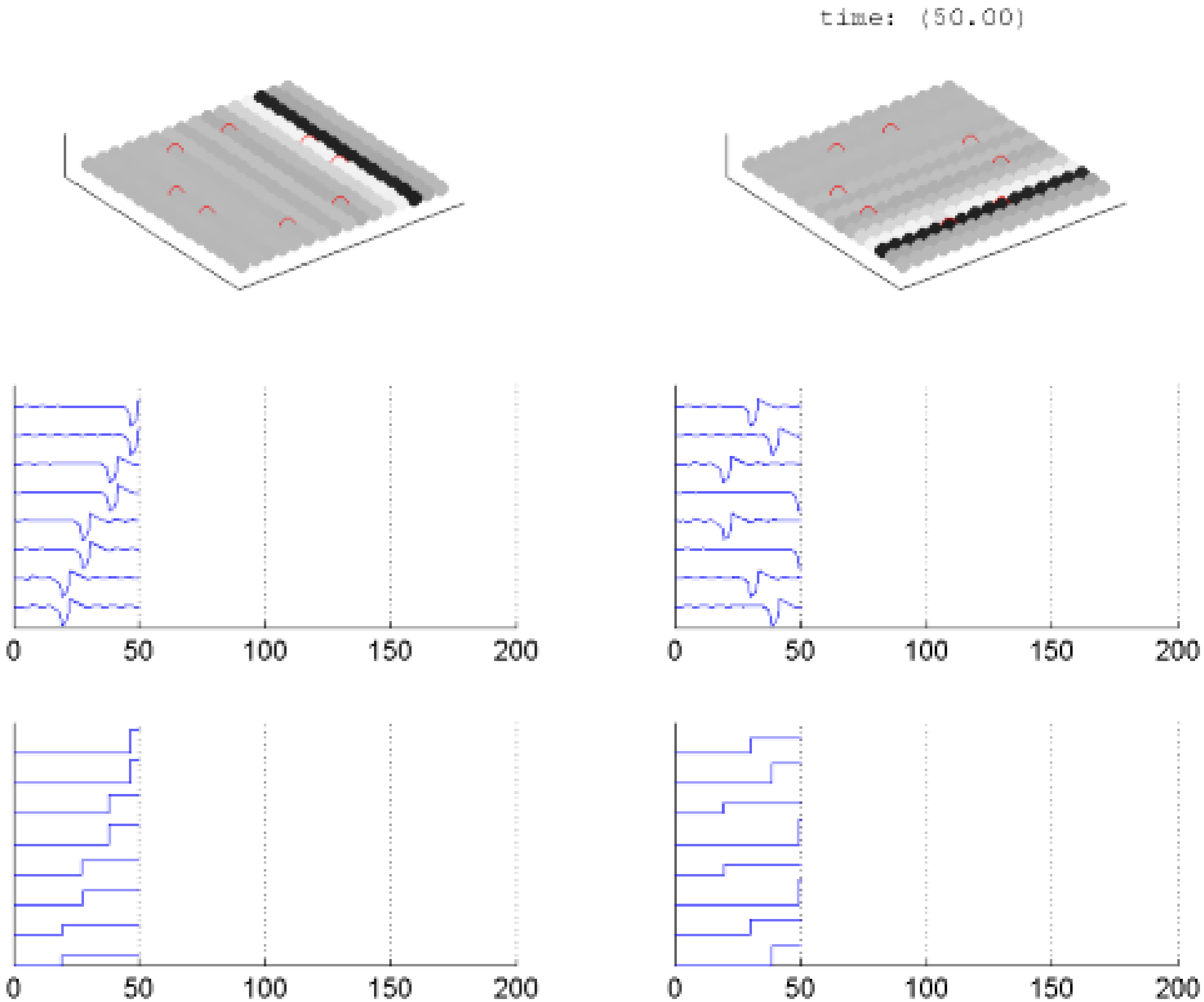


➢ Lattice of coupled oscillators – *2D wave shapes*

✓ coding coordinates with phases

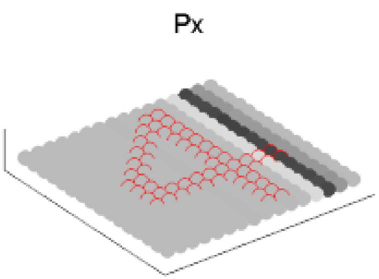
- the salient “feature-detecting” units of an object can participate in 2 different STPs by propagation of 2 different waves
- similar to buoys floating on water

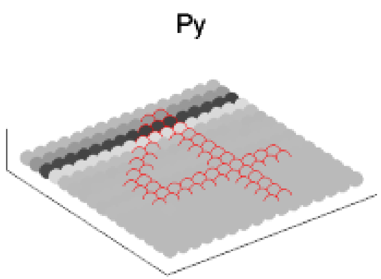
- these 2 STPs form a 2D constellation or “shape” in virtual phase space (timings)

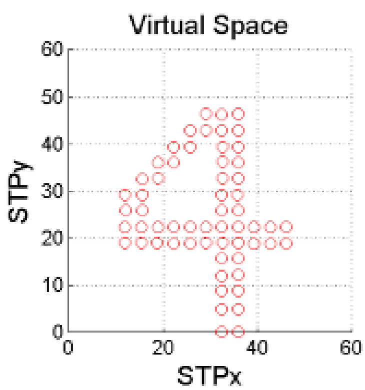


3. Wave-Based Shape-Matching – Lattice

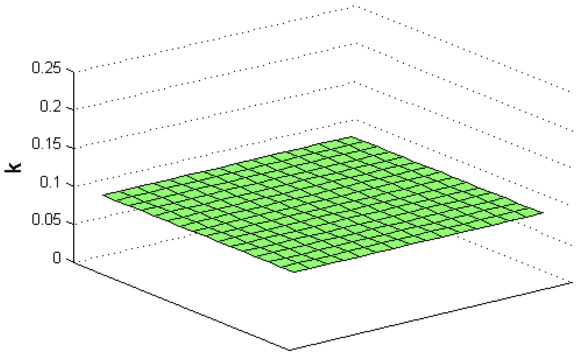
- **Lattice of coupled oscillators** *– 2D wave shapes*
  - ✓ the final shape in virtual phase space depends on
    - ▪ the physical position of the feature units on the lattice
    - ▪ the form and direction of the two waves, itself depending on:
      - ○ endogenous factors: connectivity and weight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





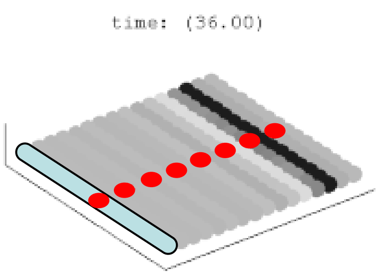


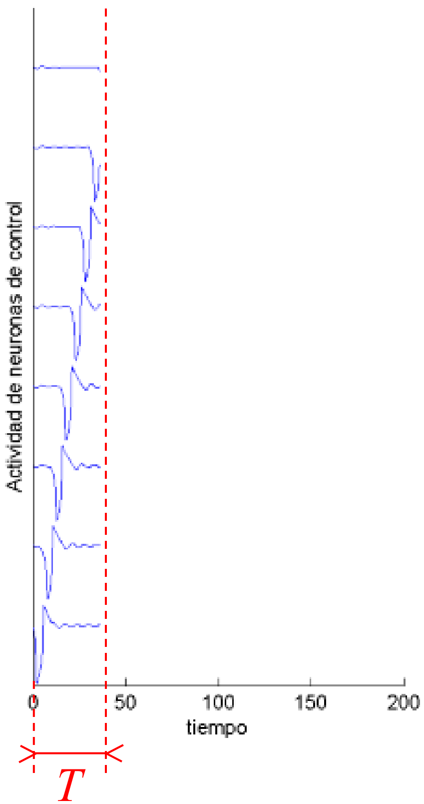
uniform weight distribution: $k = 0.09$

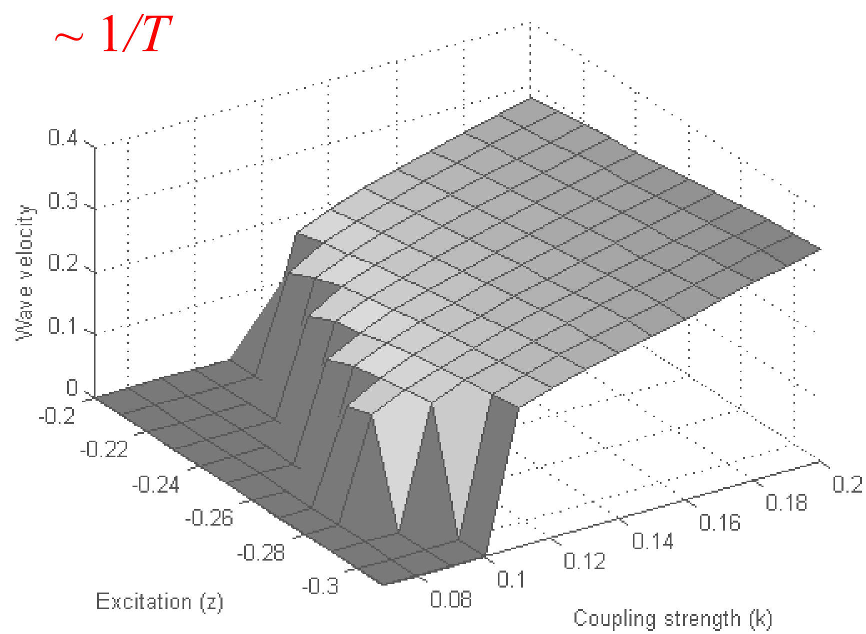


3. Wave-Based Shape-Matching – Lattice

- **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 $k\nearrow$





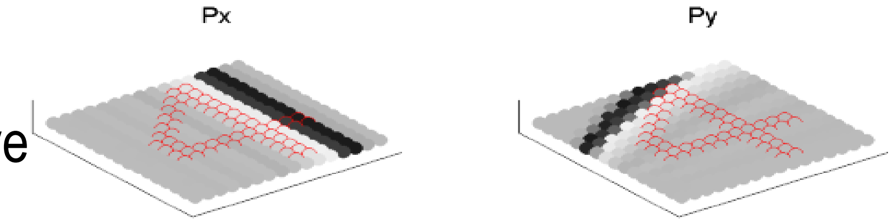


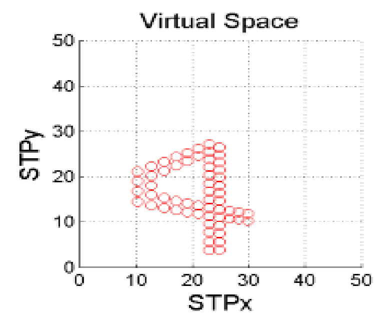
3. Wave-Based Shape-Matching – Lattice

➢ **Lattice of coupled oscillators** *– shape metric deformation*

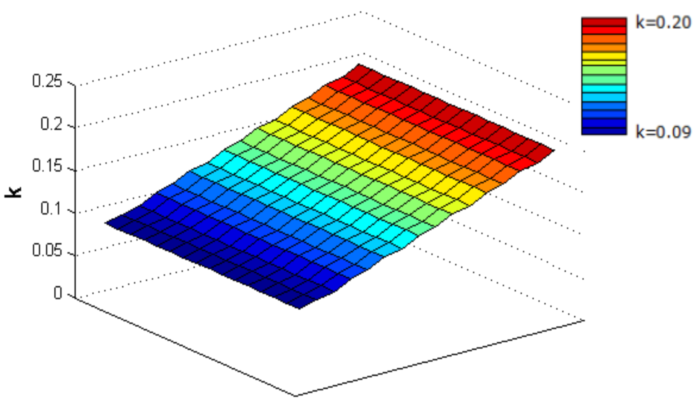
✓ ex: "shear stress" deformation

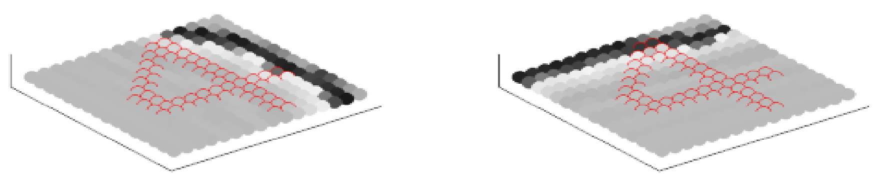
- vertical wave + horizontal wave
  - ○ Y-gradient of weights on P_Y
  - ○ orthogonal full-bar stimuli





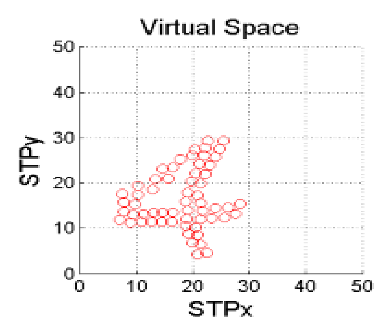
gradient weight landscape:
$k \in [0.09, 0.20]$





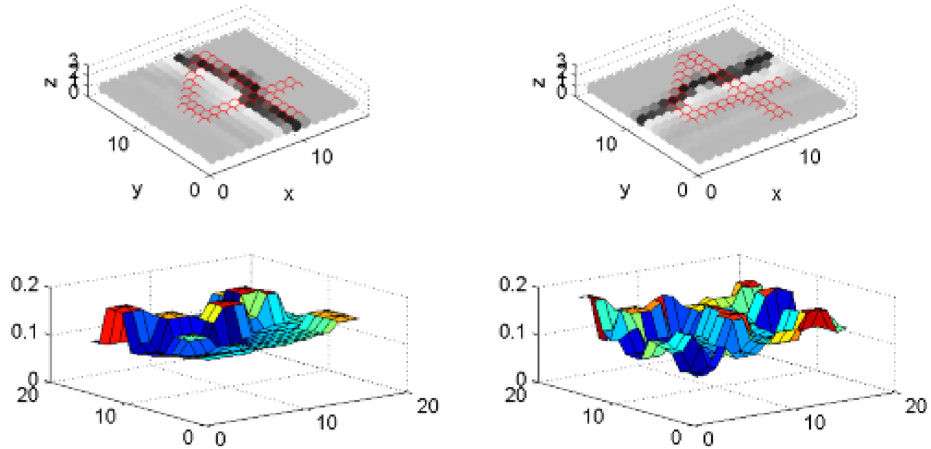
✓ ex: "laminar flow" deformation

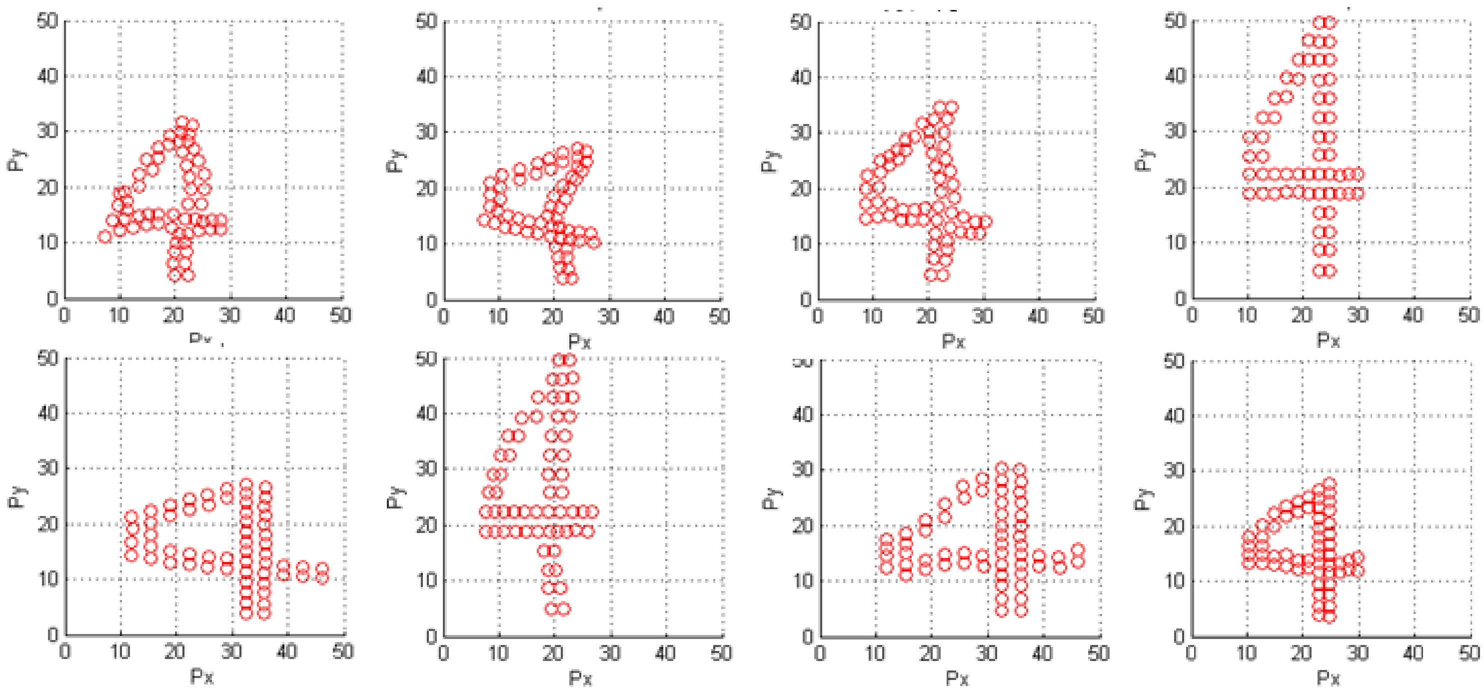
- laminar wave + vertical wave
  - ○ Y-gradient of weights on P_X
  - ○ orthogonal full-bar stimuli



3. Wave-Based Shape-Matching – Lattice

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

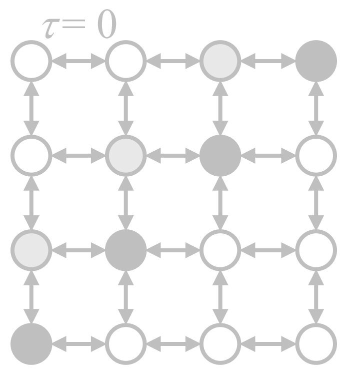




➢ Wave-based pattern retrieval and matching

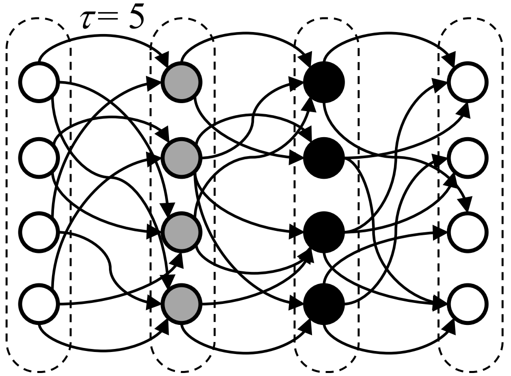
✓ Lattices of coupled oscillators (zero delays)

- group synchronization
- traveling waves
- 2D wave shapes
- shape metric deformation



✓ Synfire chains (uniform delays)

- wave propagation
- chain growth
- pattern storage and retrieval

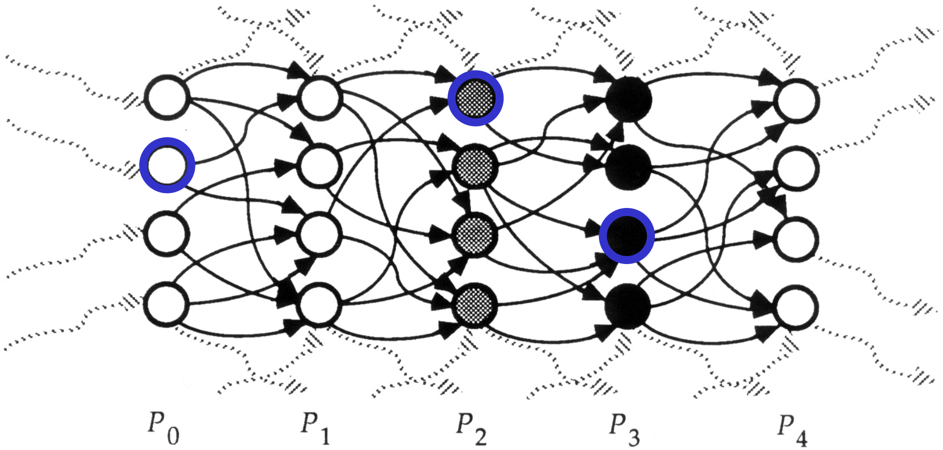


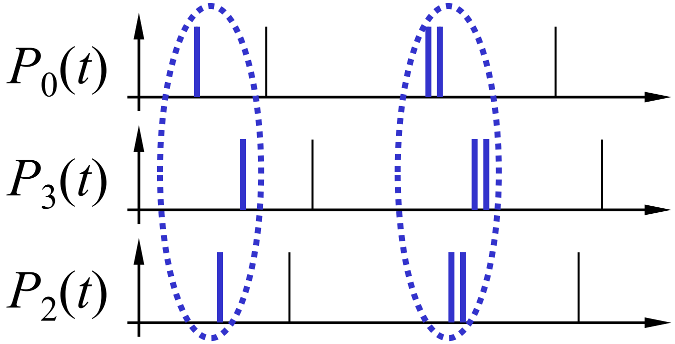
✓ Synfire braids (transitive delays)

- shape storage and retrieval
- 2D wave-matching

3. Wave-Based Shape-Matching – Chains

- **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)

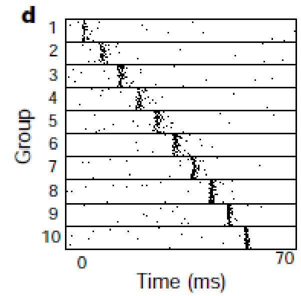




  - ✓ synfire chains have been hypothesized to explain neurophysiological recordings containing statistically significant delayed correlations
  - ✓ the redundant divergent/convergent connectivity of synfire chains can preserve accurately synchronized action potentials, even under noise

3. Wave-Based Shape-Matching – Chains

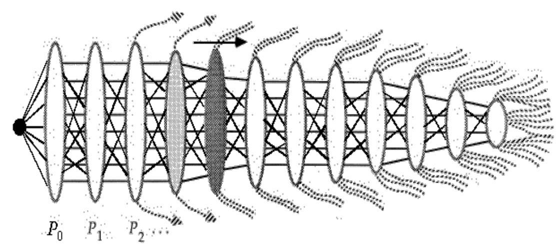
➢ Synfire chains – *typical example studies*



✓ 1-chain propagation viability

mental shape **stability**

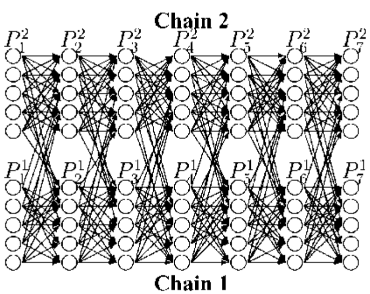
- Diesmann, Gewaltig & Aertsen (1999) *Stable propagation of synchronous spiking in cortical neural networks*



✓ 1-chain self-organized growth

mental shape **learning**

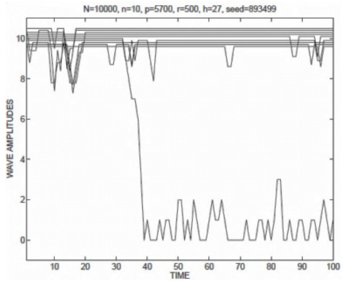
- Doursat & Bienenstock (1991, 2006) *Neocortical self-structuration as a basis for learning*



✓ 2-chain binding ($\rightarrow$ 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

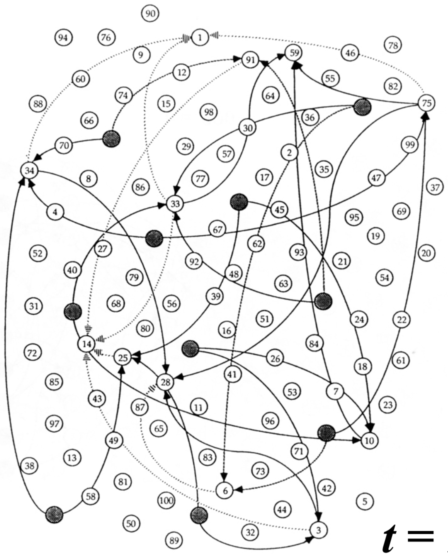
➢ Synfire chains – *self-organized growth*

1. Hebbian rule

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

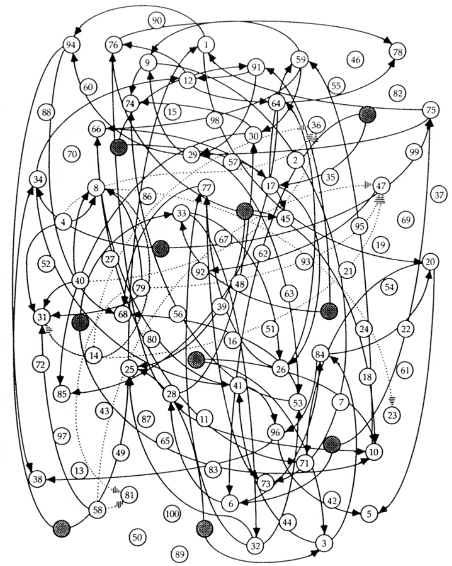
$$\sum \Delta W_{ij} \sim 0$$

2. sum rule



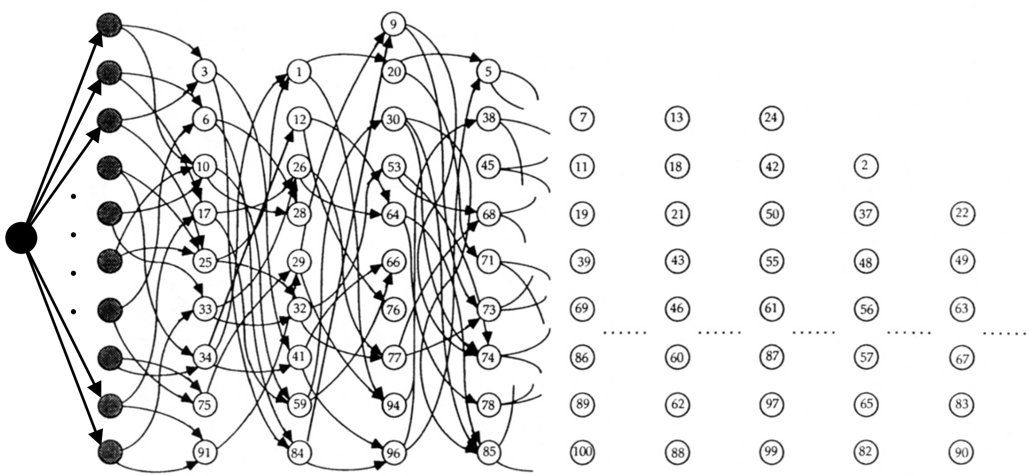
$t = 200$

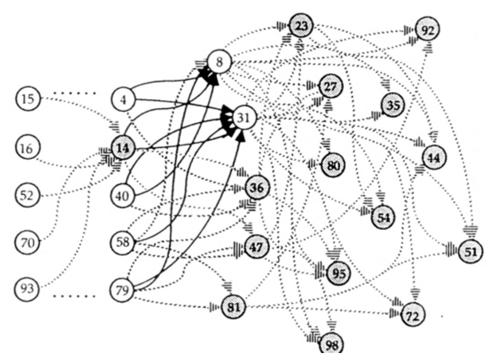
network **structuration** by accretive synfire growth



$t = 4000$

spatially rearranged view





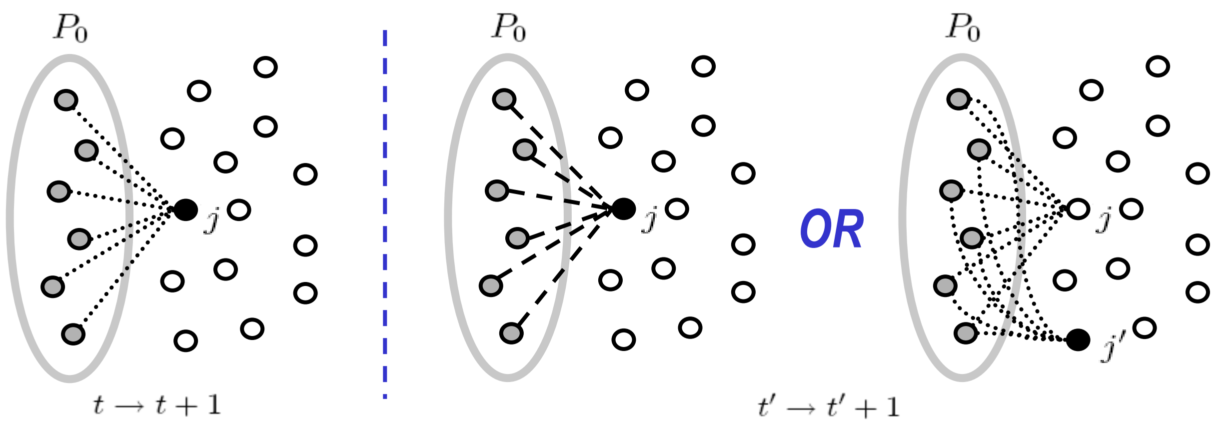
Doursat, R. (1991), Doursat & Bienenstock, E. (2006) Neocortical self-structuration as a basis for learning. *5th International Conference on Development and Learning (ICDL 2006)*, May 31-June 3, 2006, Indiana University, Bloomington, IN. IU, ISBN 0-9786456-0-X.

3. Wave-Based Shape-Matching – Chains

➢ Synfire chains – *self-organized growth*

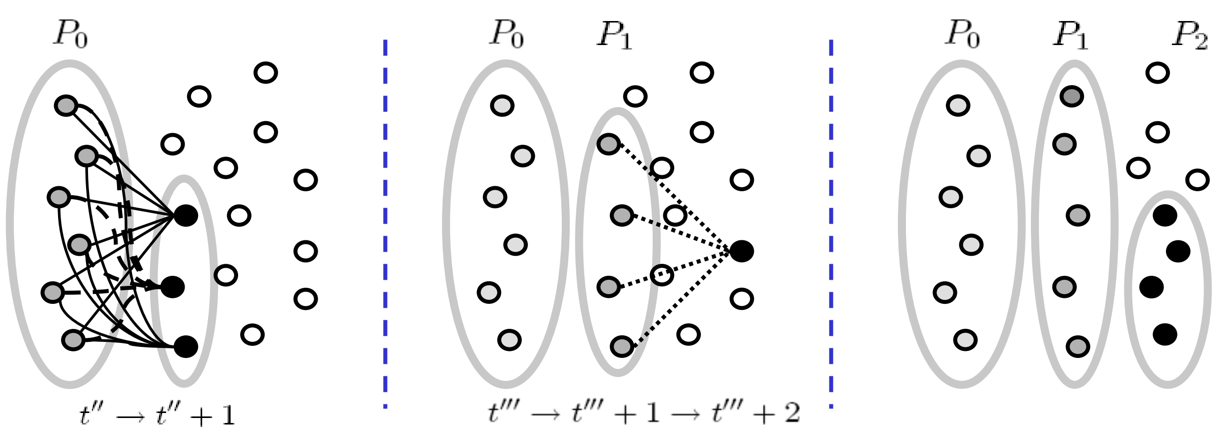
✓ a special group of n_0 synchronous cells, P_0, is repeatedly (not necessarily periodically) activated and recruits neurons "downstream"

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)

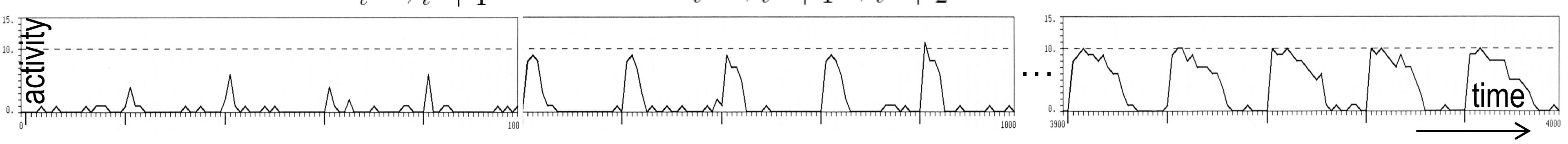


if j fires a 2[nd] time after P_0, j has now 50% chance of doing so a 3[rd] time; else it stays at 12% while another cell, j' reaches 12%

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

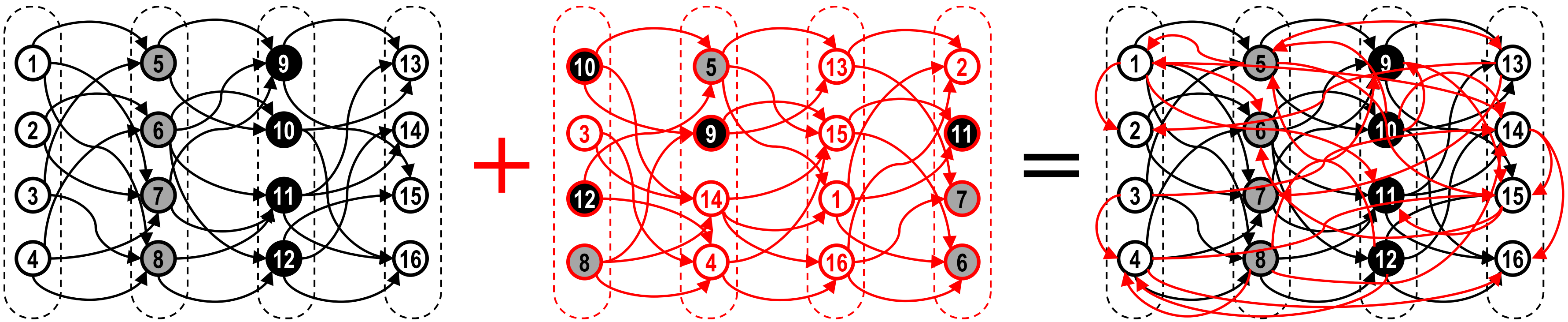


once it reaches a critical mass, P_1 also starts recruiting and forming a new group P_2, etc.



➢ 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

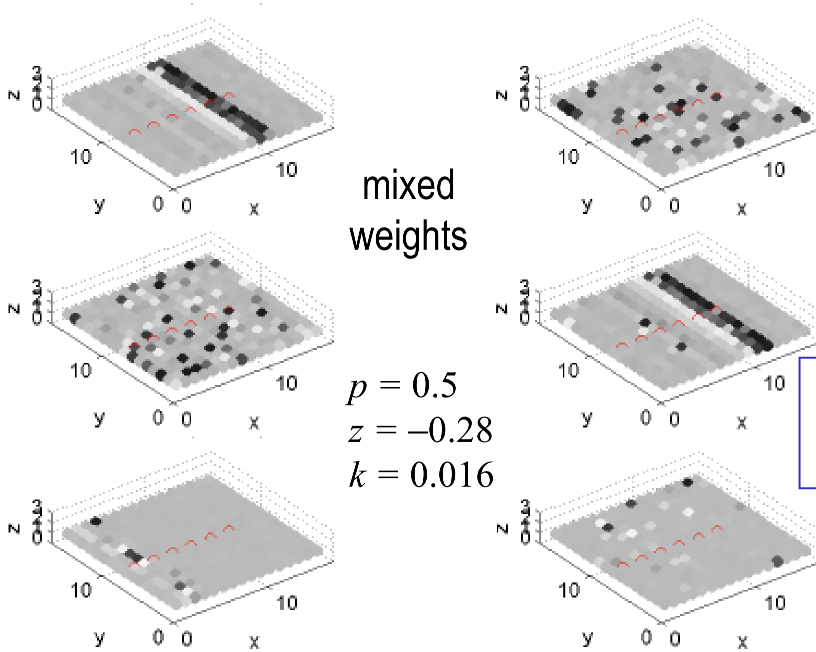
layout A w/ mixed weights A + weights B

---

layout A
$N_A = 13$

layout B
$N_B = 13$

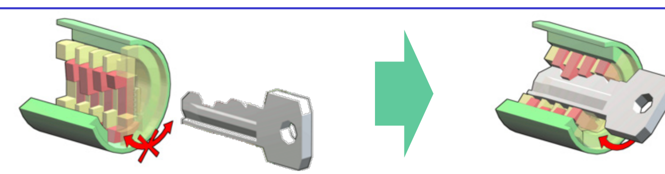
layout A
$N_A = 8$
→ no wave



✓ high specificity of synfire stimulus

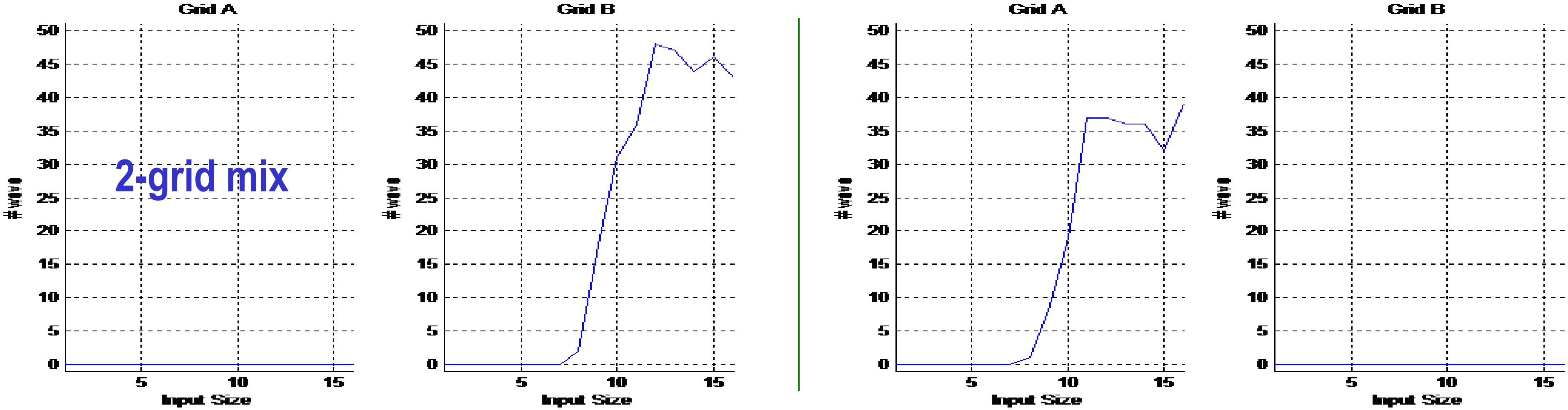
- unlike the "sensitive" isotropic lattice, not any input pattern will trigger a wave
- a synfire chain needs a "critical seed" of N stimulated neurons at the right place

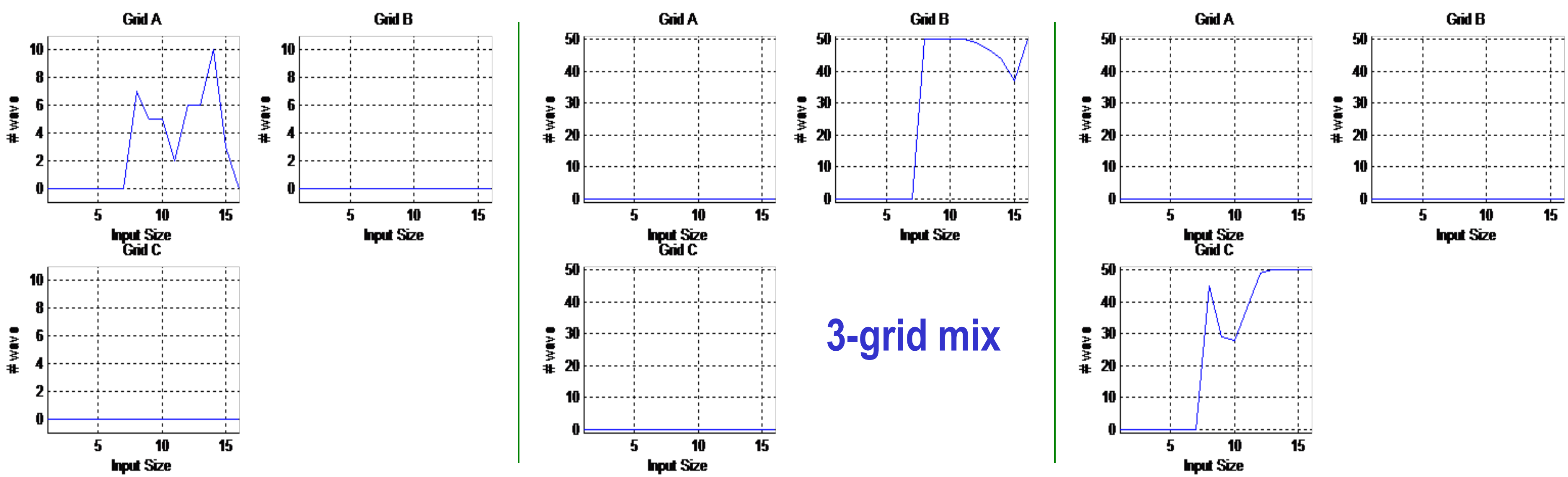
- **endo:** *connectivity, attractors* HERE
- **exo:** *stimulus, binding*



3. Wave-Based Shape-Matching – Chains

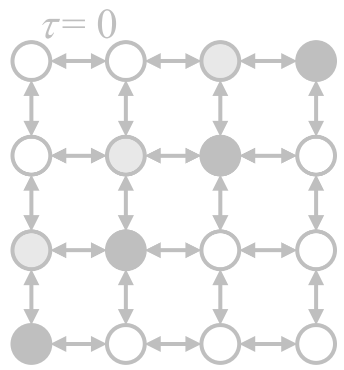
- **Synfire chains** – *pattern mix and selective retrieval*
  - ✓ statistics of selective retrieval depending on input size (in first pool)

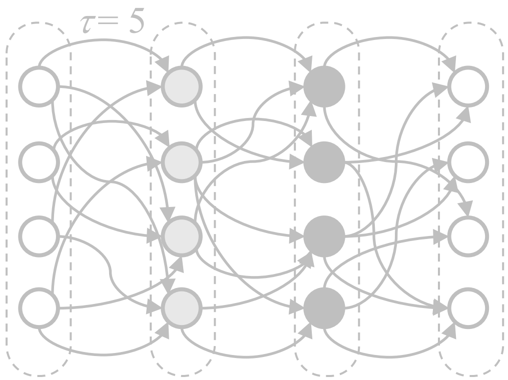




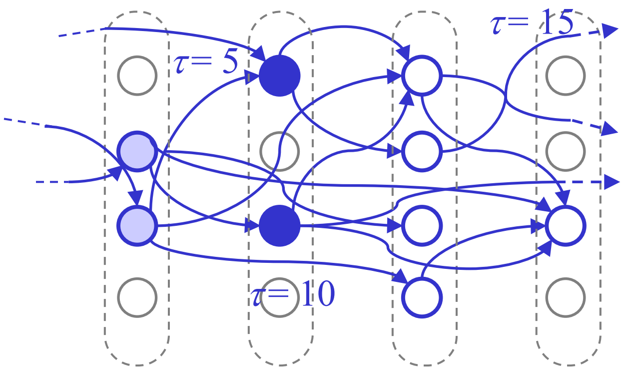
3. Wave-Based Shape-Matching

- **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

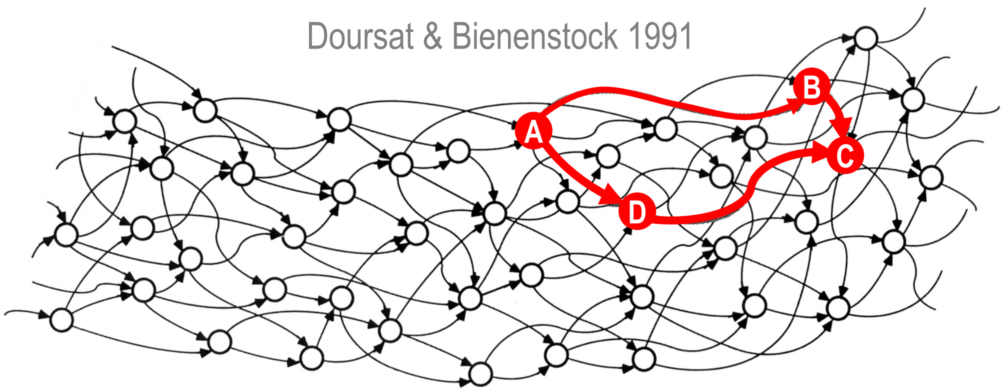


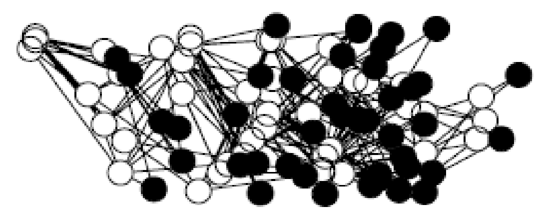
3. Wave-Based Shape-Matching – Braids

➢ 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)

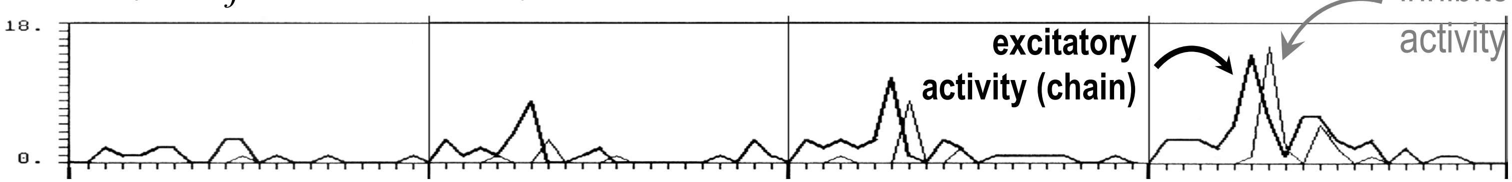
Doursat & Bienenstock 1991





Izhikevich 2006

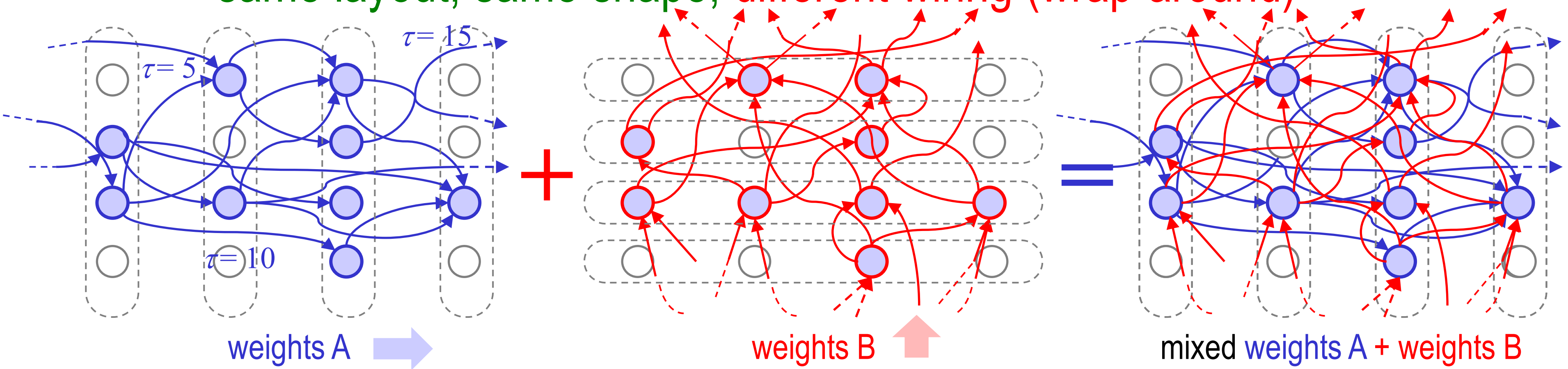
- ✓ in a synfire braid, delay transitivity $\tau_{AB} + \tau_{BC} = \tau_{AD} + \tau_{DC}$ supports incoming spike coincidences, hence stable propagation of activity
- ✓ synfire braids can also grow in a network with nonuniform integer-valued delays τ_{ij} and inhibitory neurons



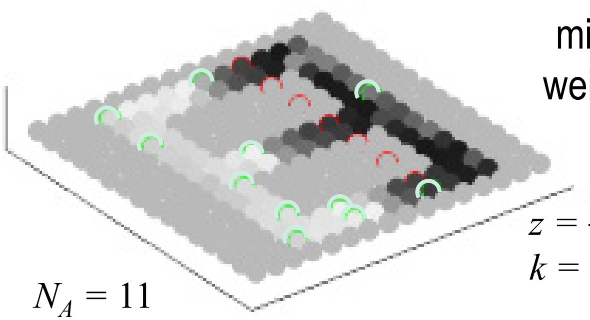
Doursat & Bienenstock 1991

3. Wave-Based Shape-Matching – Braids

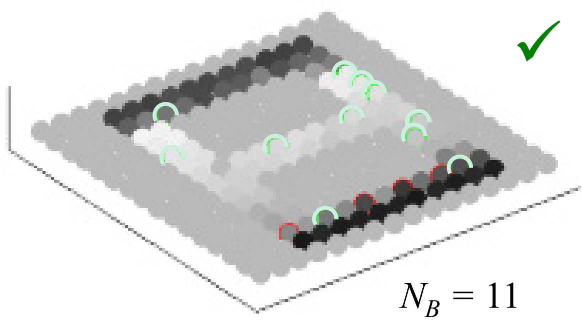
- **Synfire braids** – ***pattern mix and selective retrieval***
  - ✓ same layout, same shape, different wiring (wrap-around)



mixed weights

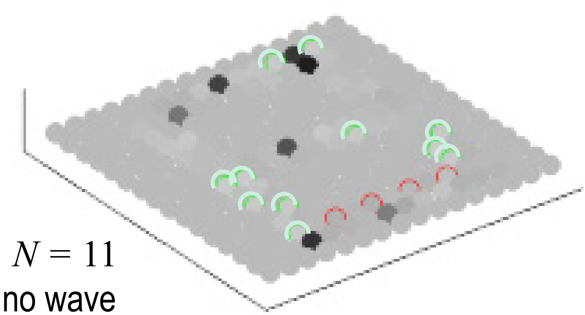


$z = -0.28$
$k = 0.016$



$N_A = 11$
in ‘A’ sequence

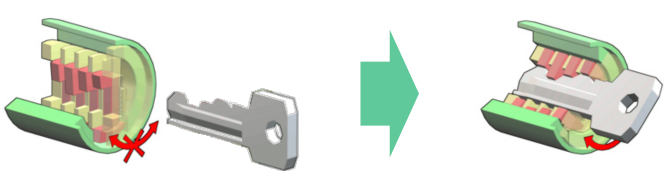
$N_B = 11$
in ‘B’ sequence



$N = 11$
simultaneously → no wave

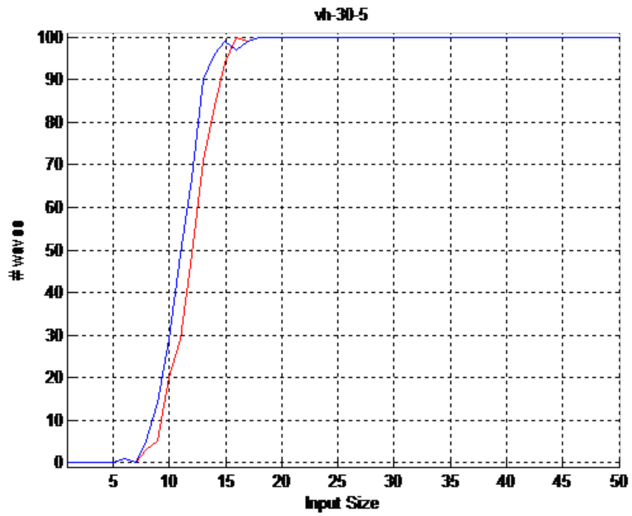
✓ high stimulus specificity

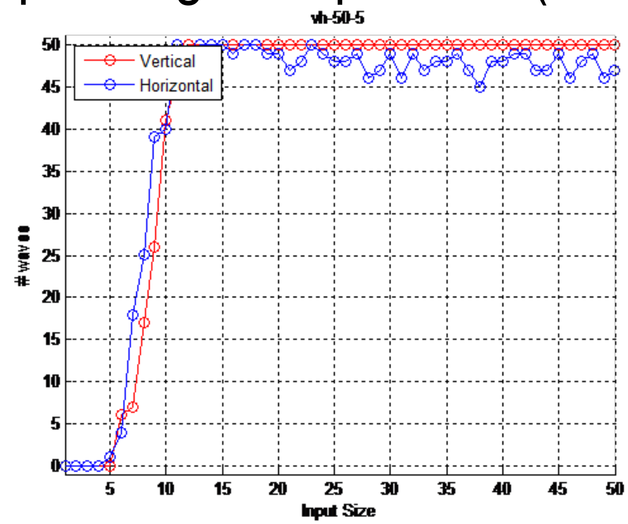
- to generate a wave, a synfire braid needs a minimum of N neurons stimulated in a *sequence (“sub-STP”) compatible with the delays*



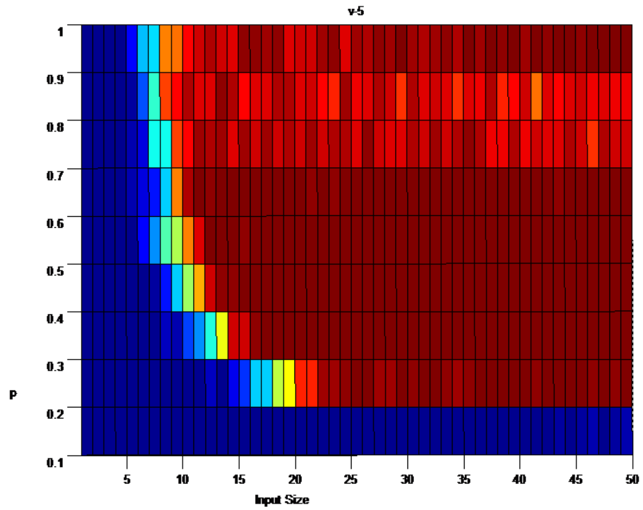
3. Wave-Based Shape-Matching – Braids

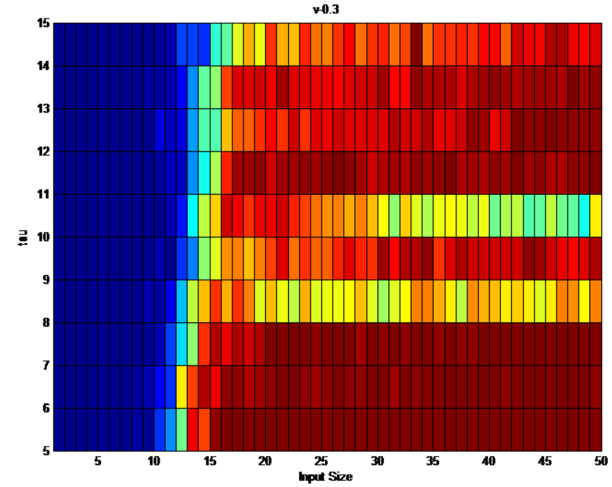
- **Synfire braids** – ***pattern mix and selective retrieval***
  - ✓ statistics of selective retrieval depending on input size (in sequence)





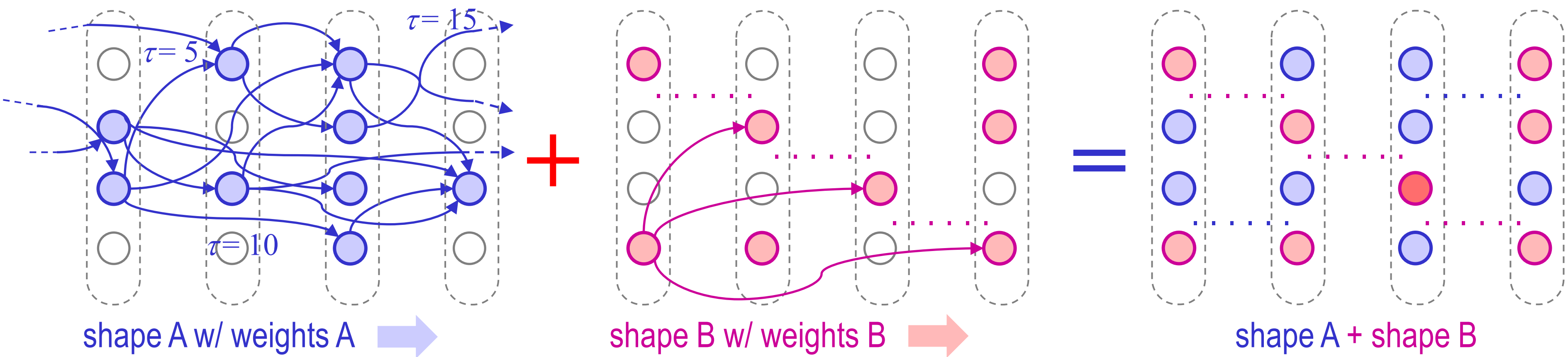
  - ✓ statistics of selective retrieval depending on input size and p or τ

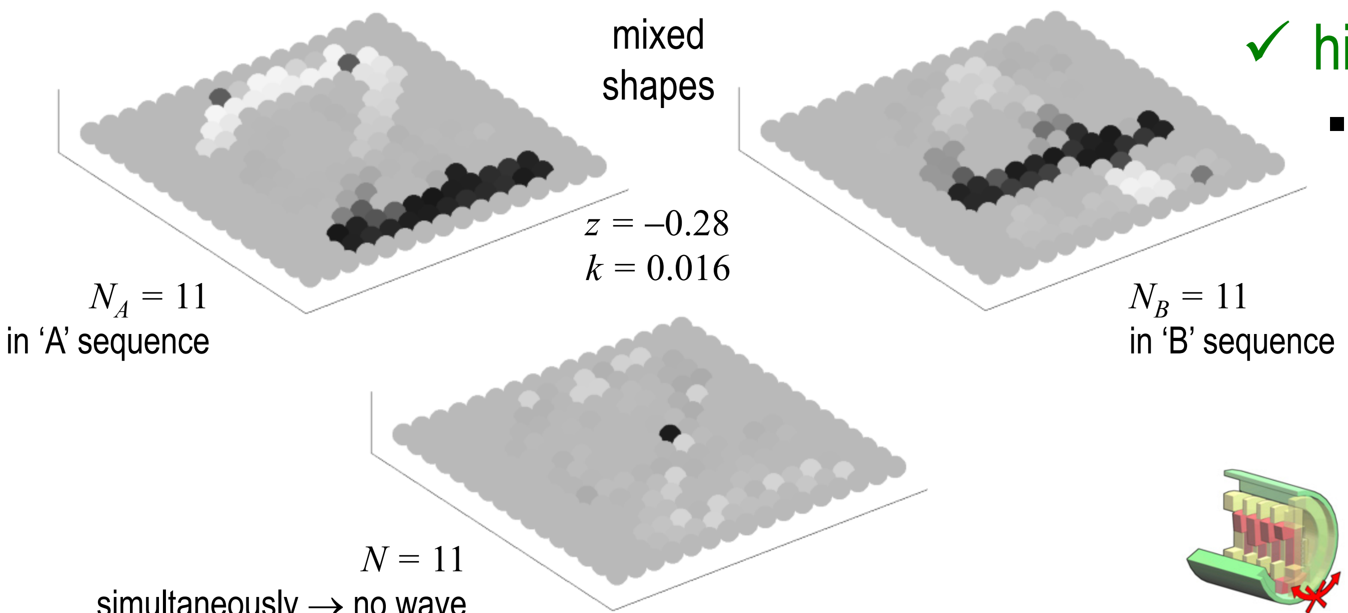




3. Wave-Based Shape-Matching – Braids

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





✓ high stimulus specificity

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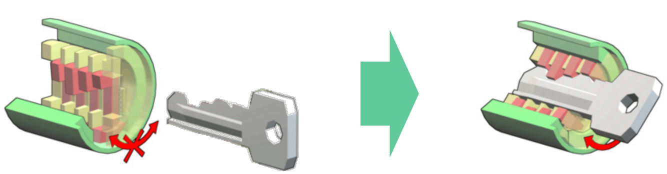


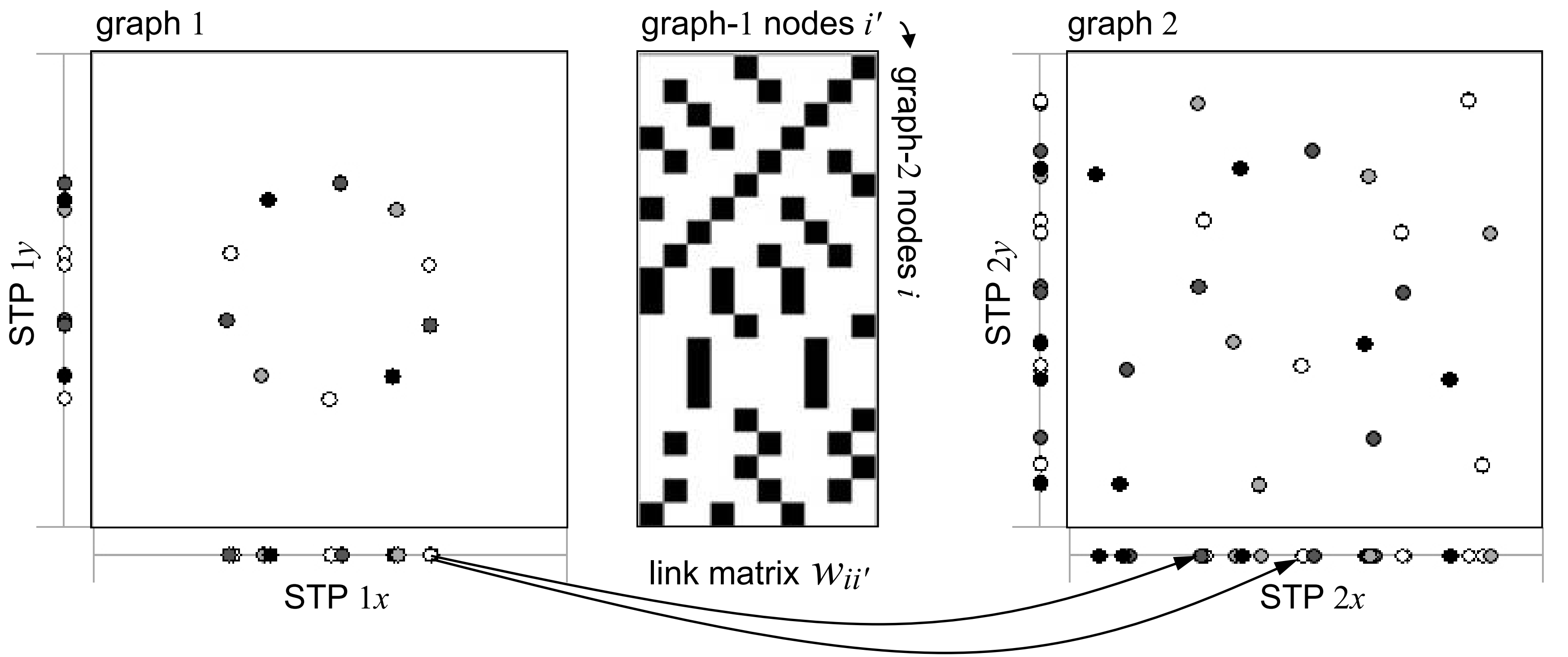
3. Wave-Based Shape-Matching – Braids

➢ Synfire braids – *wave-matching*

✓ graph-matching implemented as dynamical link matching between two pairs of STPs

$$\begin{cases} \dfrac{du_i}{dt} = c\left(u_i - \dfrac{u_i^3}{3} + v_i + z\right) + \eta + K_i + W_i \\[2ex] \dfrac{dv_i}{dt} = \dfrac{1}{c}(a - u_i - bv_i) + \eta \end{cases}$$

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



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

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

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

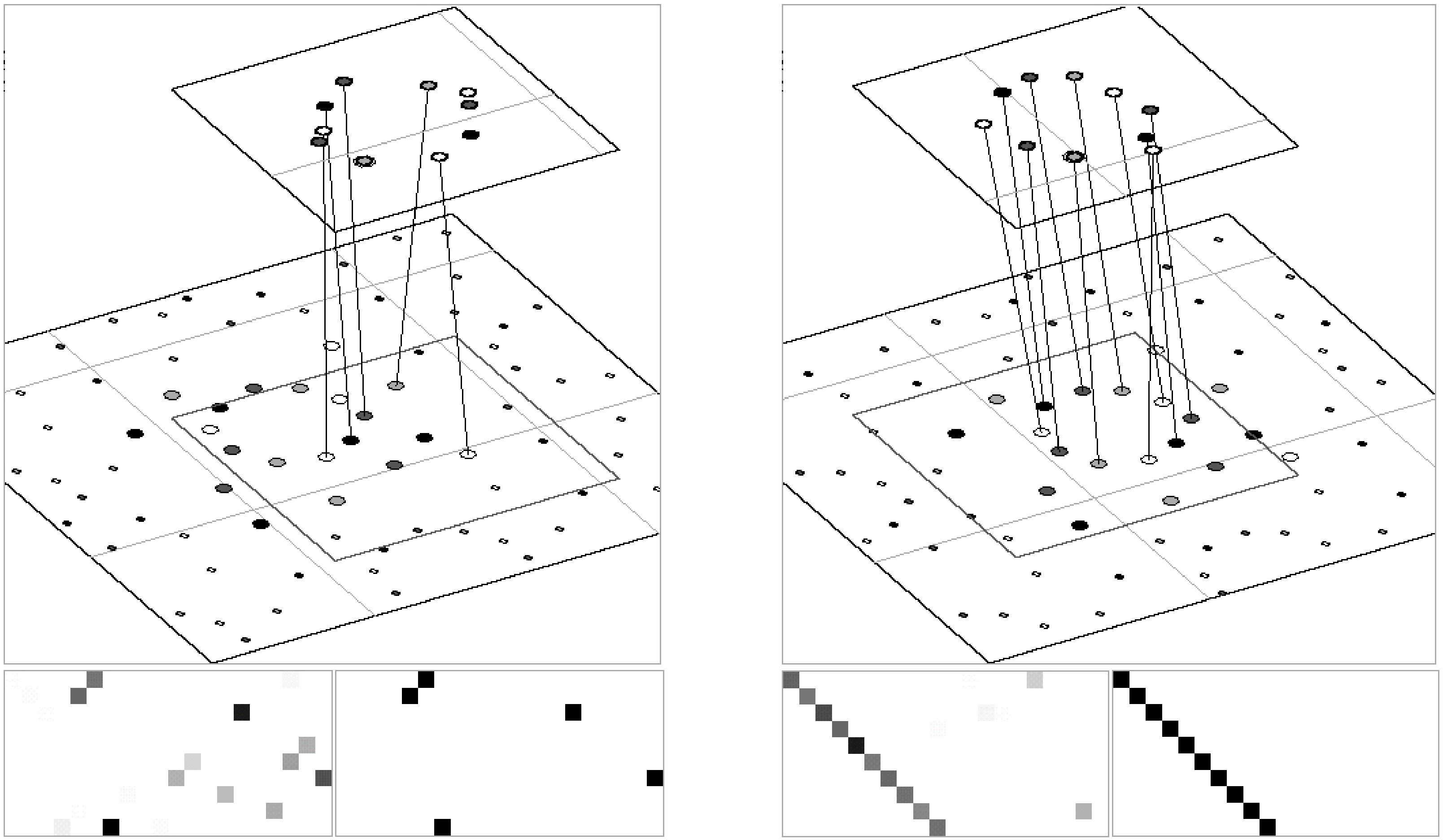
2. competition: renormalize efferent links

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

3. label-matching constraint

3. Wave-Based Shape-Matching – Braids

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



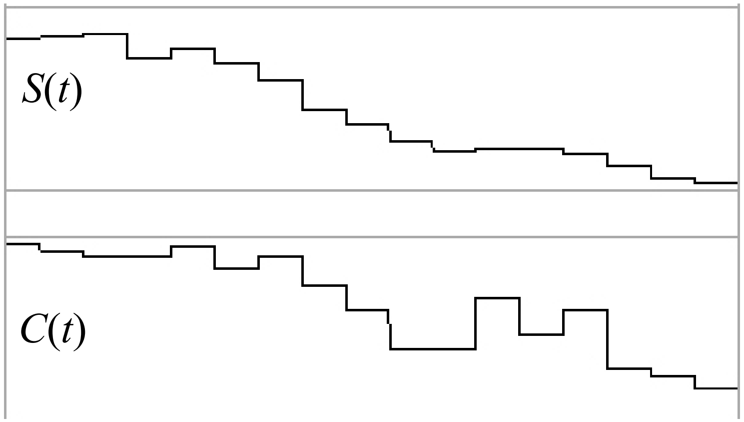
- **Synfire braids** – ***2D wave-matching***
  - ✓ to drive the system to the best match (global minimum), internal coupling k in graph-2 layer is regularly lowered and increased again
    - if match is weak, this will perturb STP 2 and undo matching links
    - if match is strong, this will not perturb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

global "correlation" order parameter S:

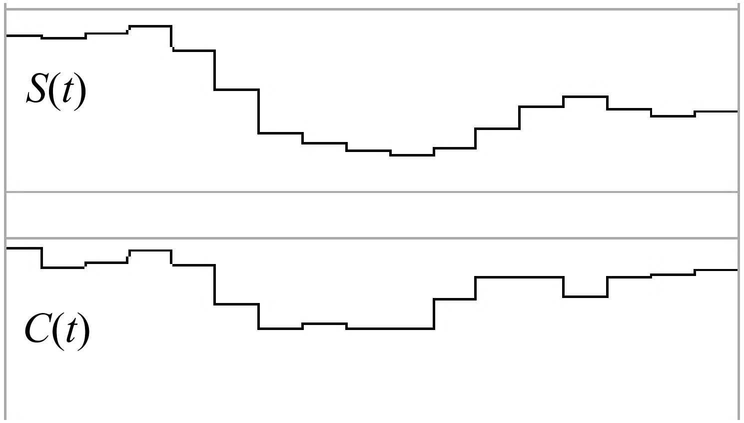
$$S(t) = \frac{1}{N(N-1)} \sum_{i \neq j} \langle u_i(t')\ u_j(t' - \tau_{ij}) \rangle_{t-T_s}^{t}$$

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 $\rightarrow$ undone by uncoupling



strong match $\rightarrow$ resistant to uncoupling

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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

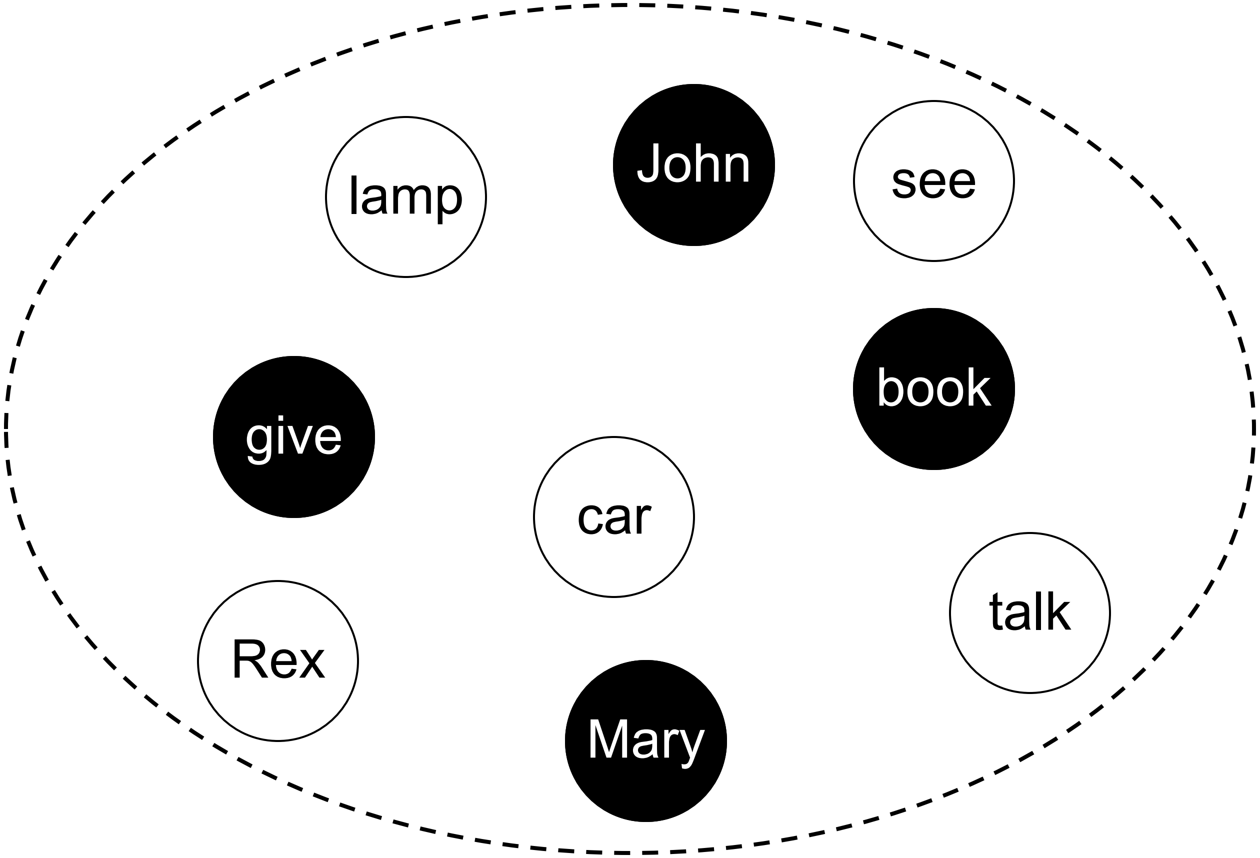
Coding coordinates by phases, and shapes by waves

4. Shape-Based Compositionality

STPs: The building blocks of mental shapes

4. Shape-Based Compositionality

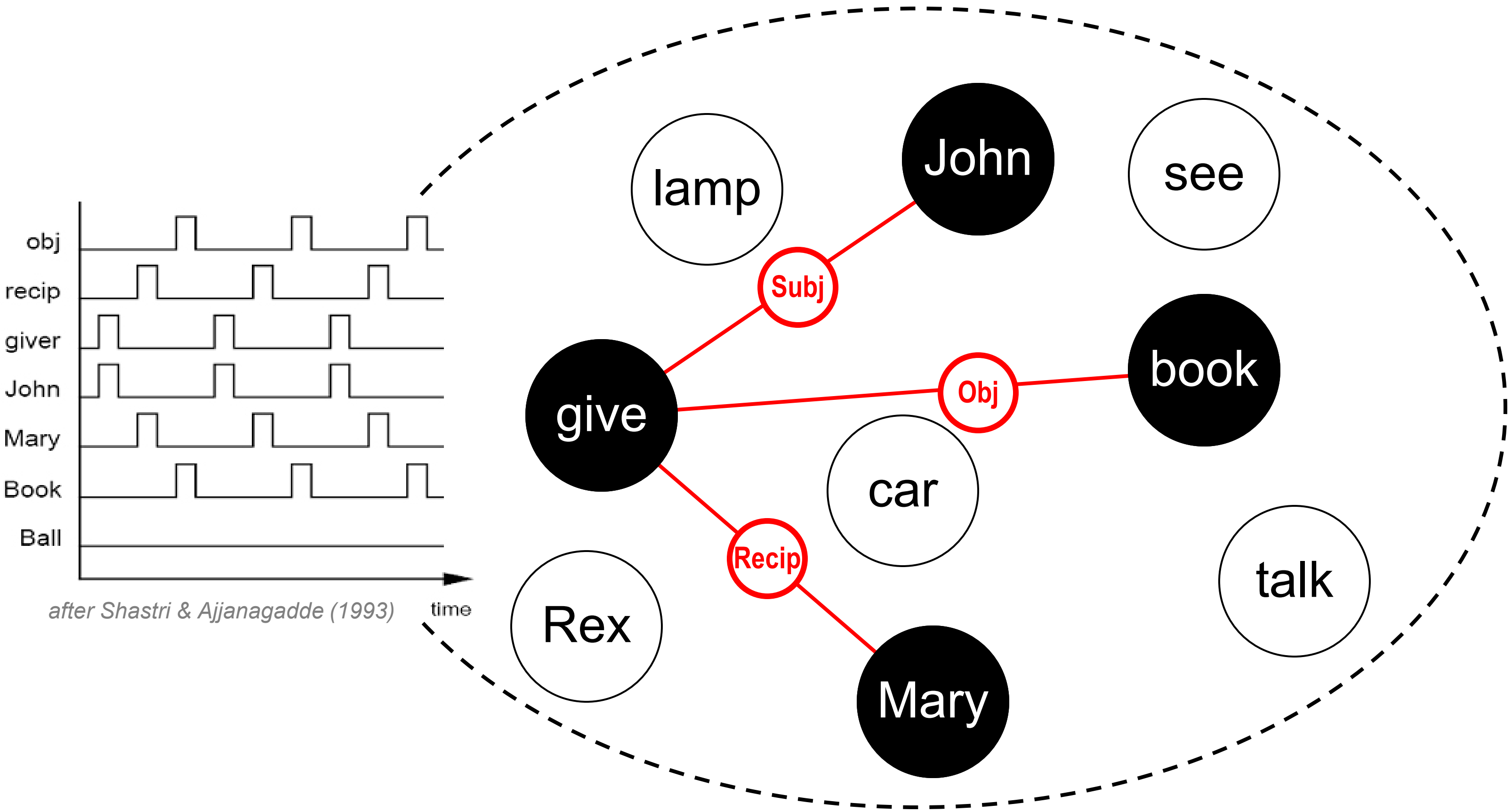
➢ **From temporal binding to shape-based composition**



(a) John gives a book to Mary.
(b) Mary gives a book to John.
(c) Book John Mary give.*

??

➢ From temporal binding to shape-based composition

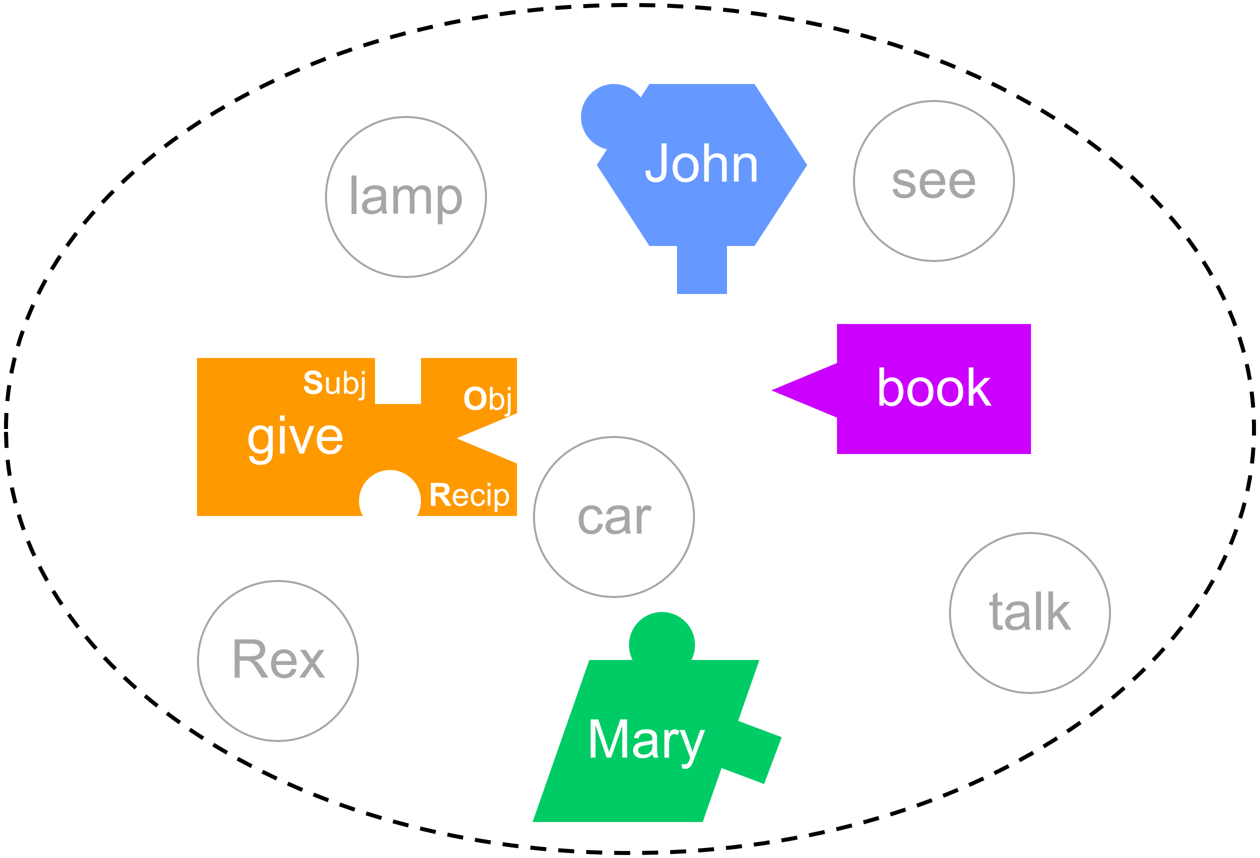


(a) John gives a book to Mary.

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

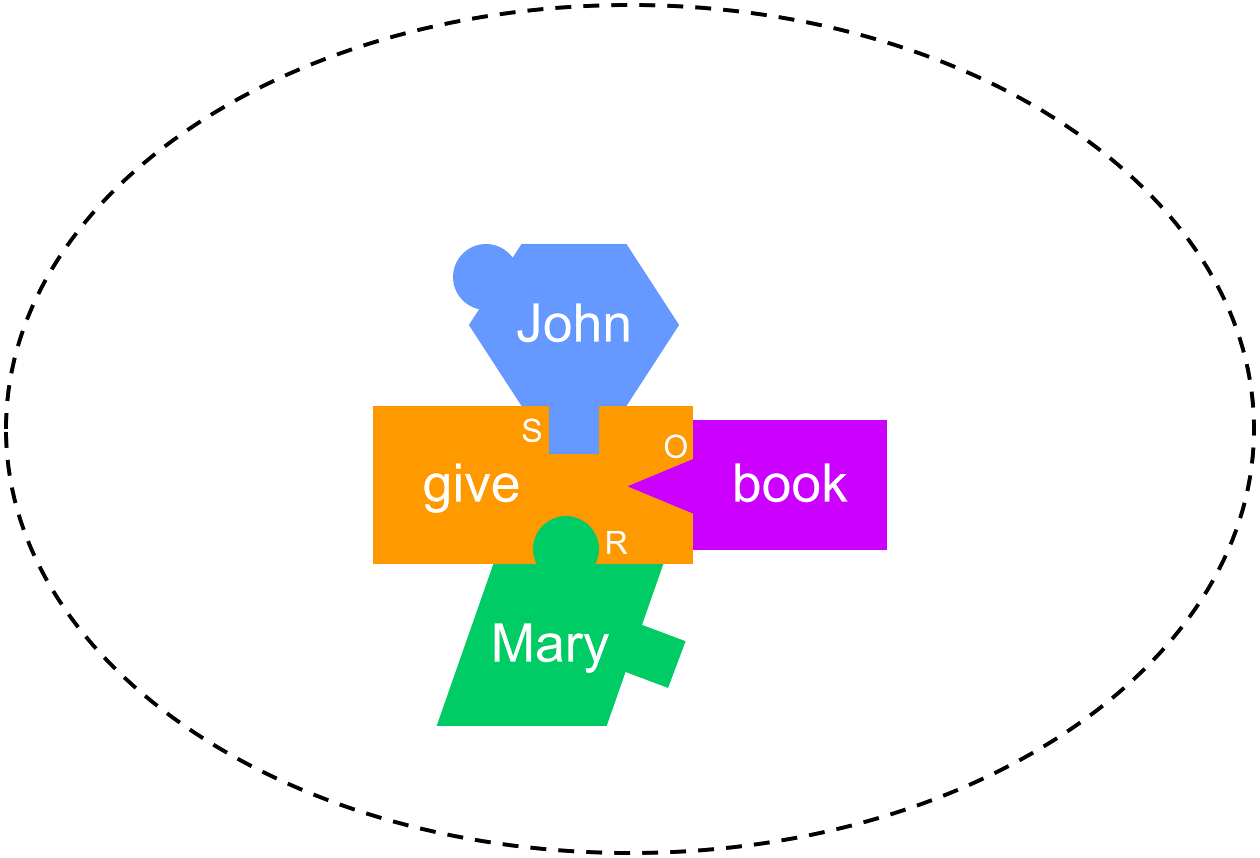
~~*(c)* Book John Mary give.*~~

- From temporal binding to shape-based composition



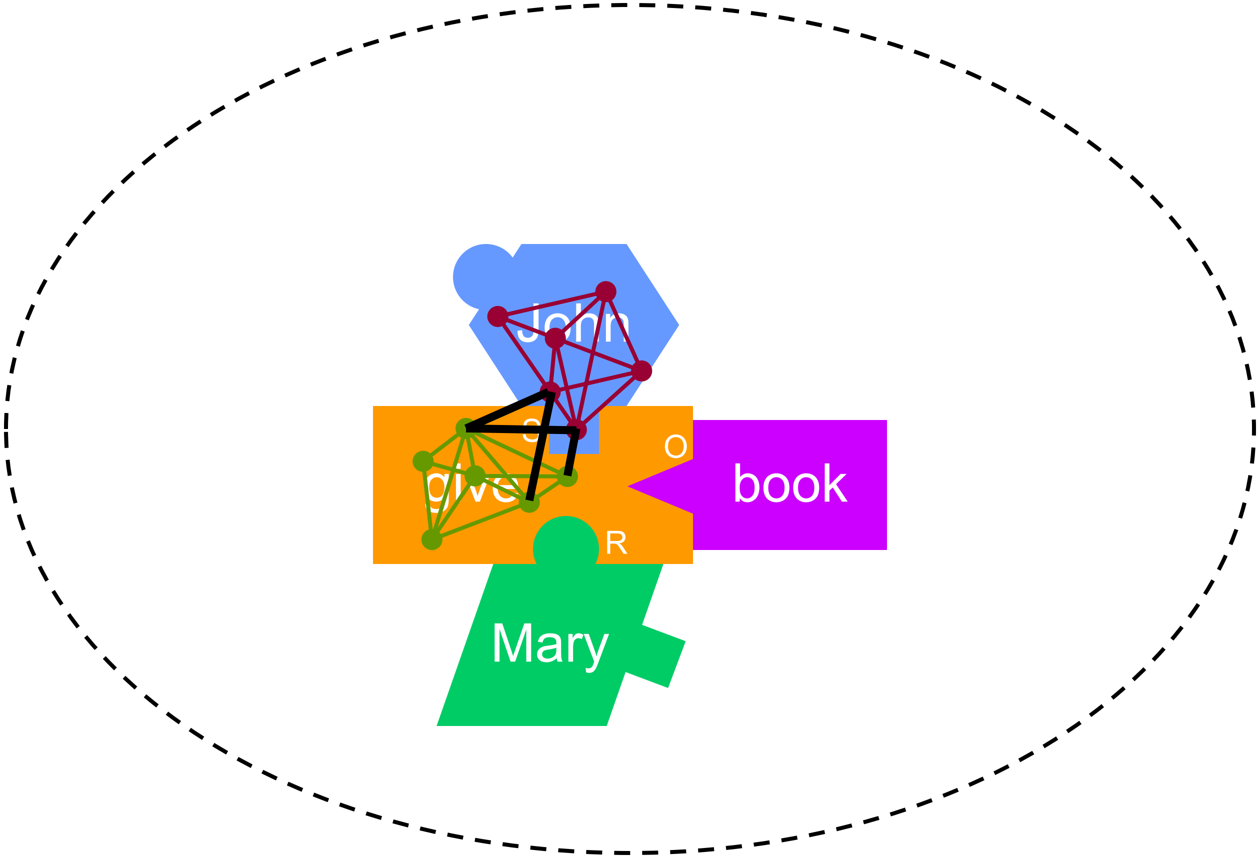
- ✓ language as a construction game of “building blocks”

➢ From temporal binding to shape-based composition



✓ language as a construction game of “building blocks”

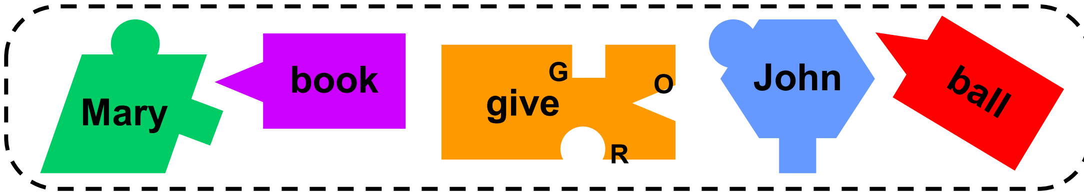
From temporal binding to shape-based composition

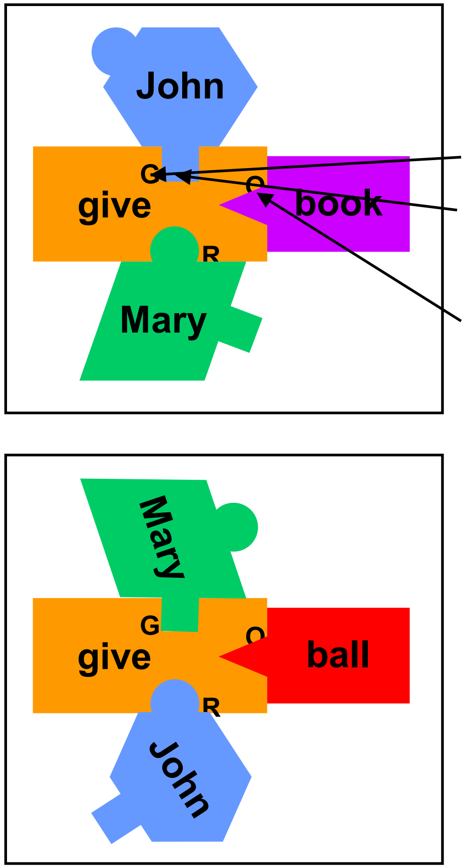


✓ language as a construction game of “building blocks”

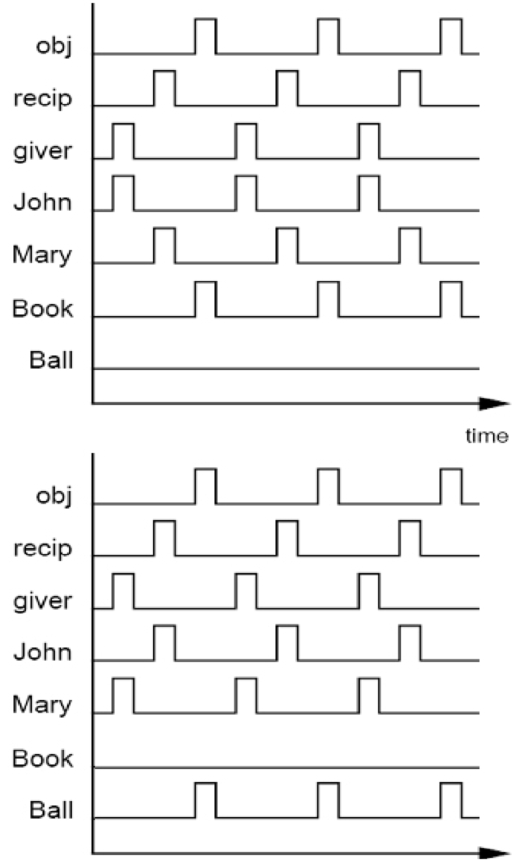
4. Shape-Based Compositionality

From temporal binding to shape-based composition





after Bienenstock (1995)



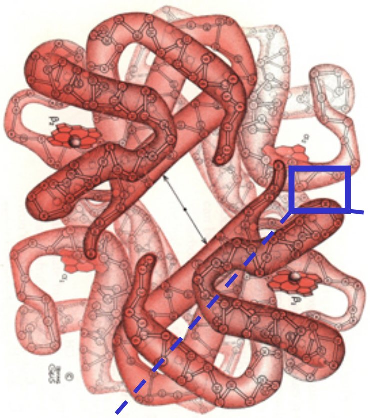
after Shastri & Ajjanagadde (1993)

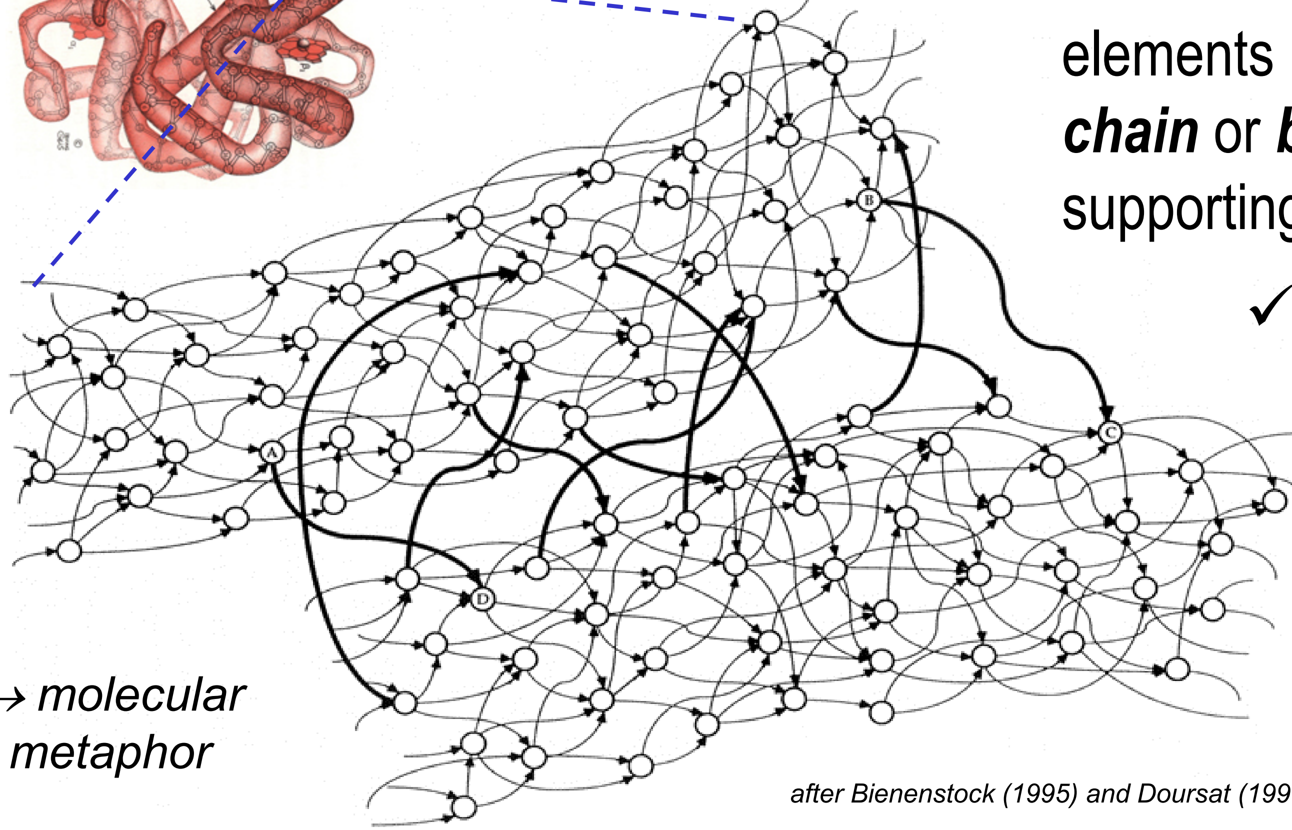
- ✓ language, perception, cognition are a game of ***building blocks***
- ✓ mental representations are internally ***structured***
- ✓ elementary components ***assemble dynamically*** via temporal binding

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***

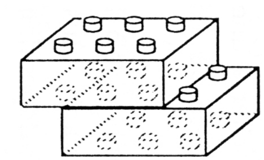
hemoglobin





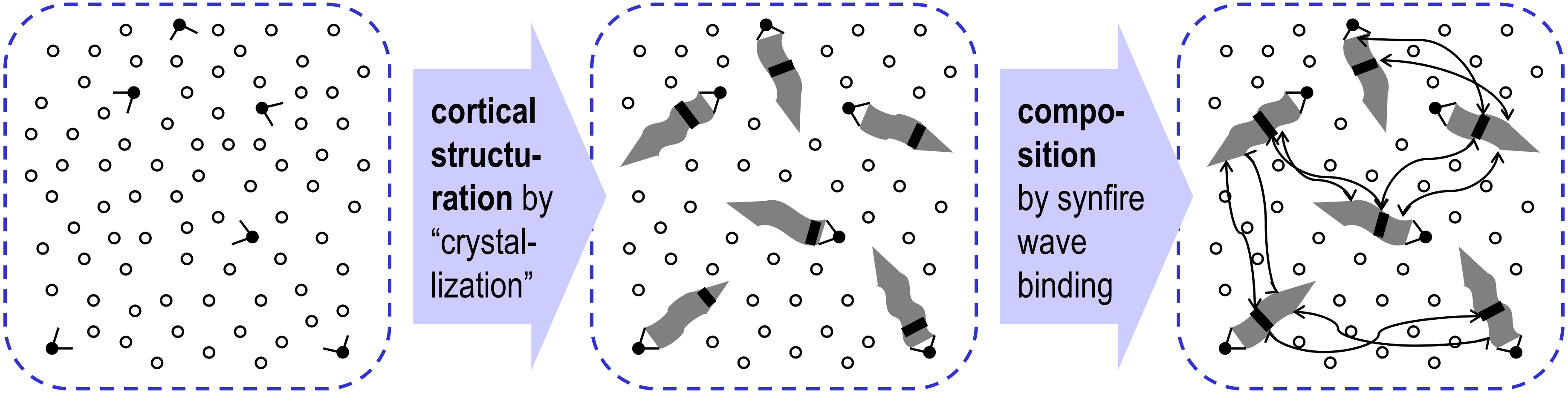
→ *molecular metaphor*

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

Morphogenetic "Neuron-Flocking"

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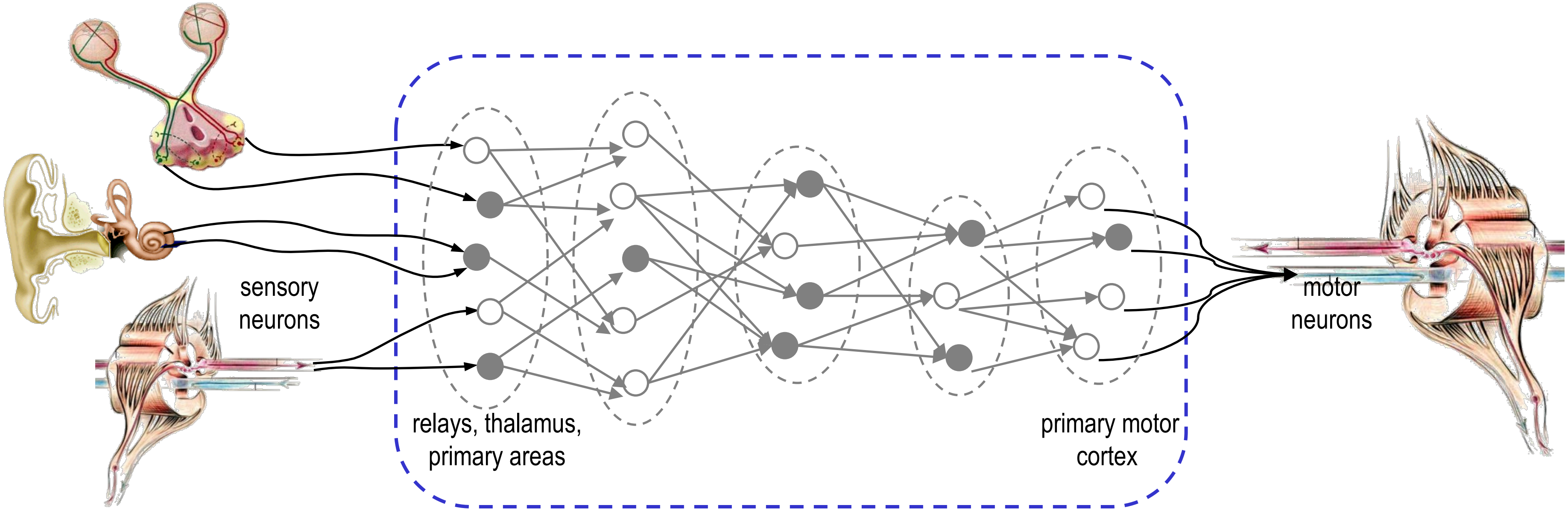
5. Toward Emergent Neurodynamics

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

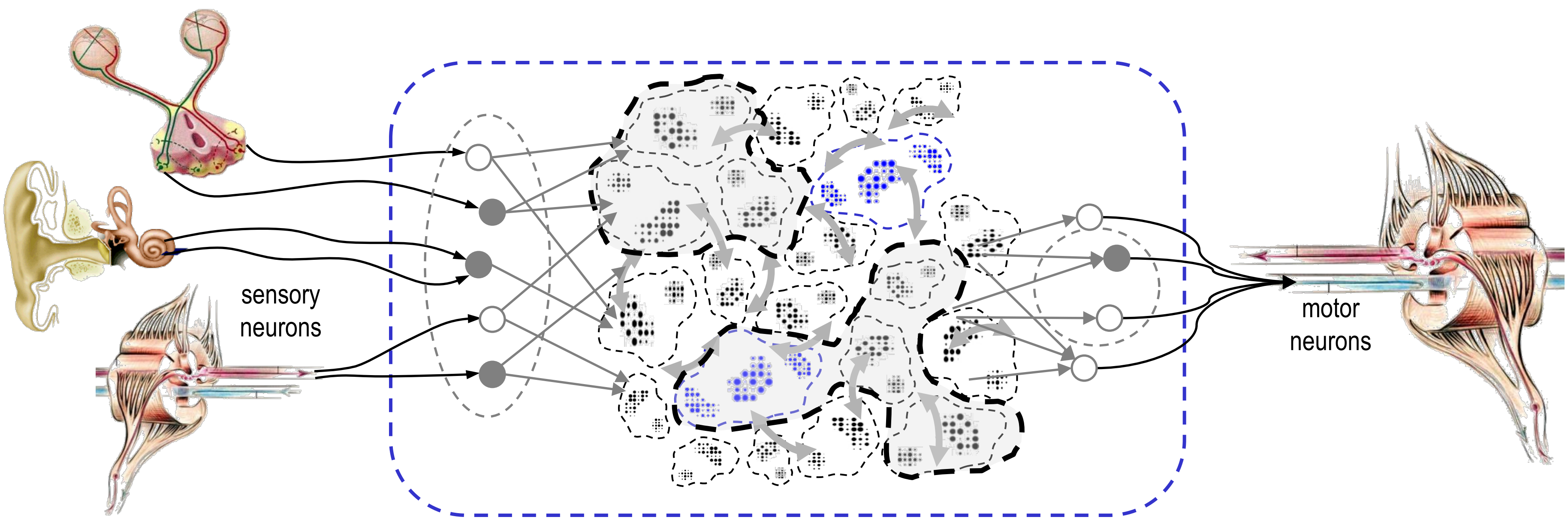
It is not because the brain is an intricate network of microscopic causal transmissions (neurons activating or inhibiting other neurons) that the appropriate description at the mesoscopic functional level should be "signal / information processing".

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

5. Toward Emergent Neurodynamics

➢ 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,

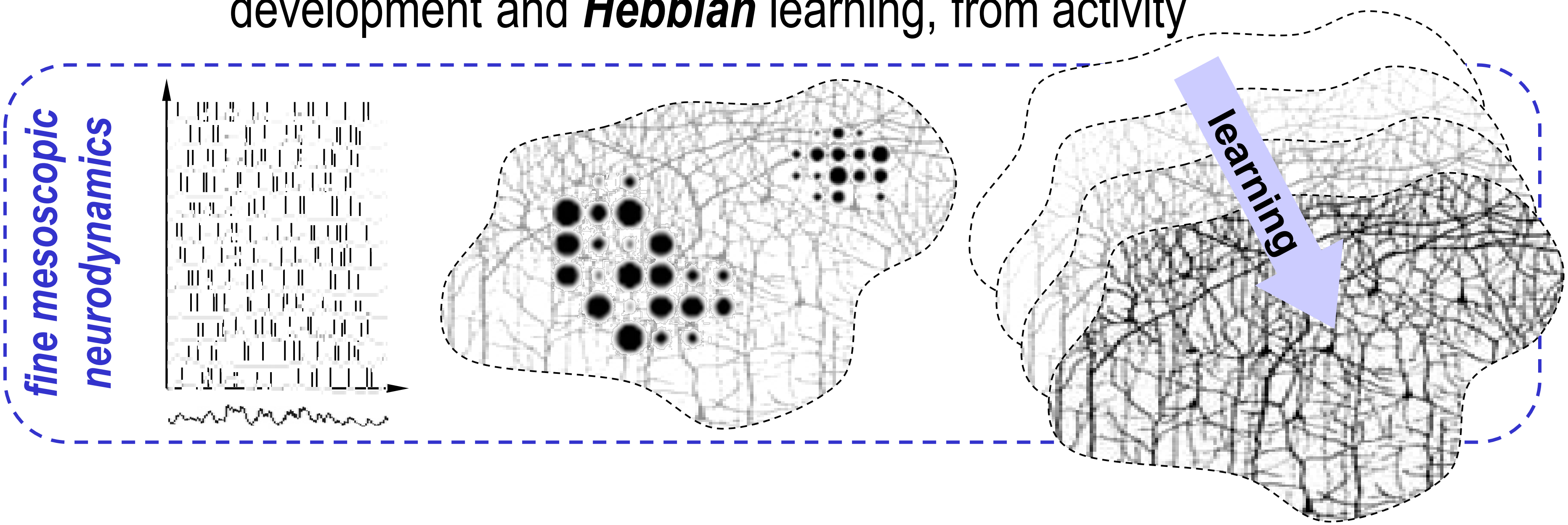
  b) exogenously evoked & perturbed under the influence of stimuli,

  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

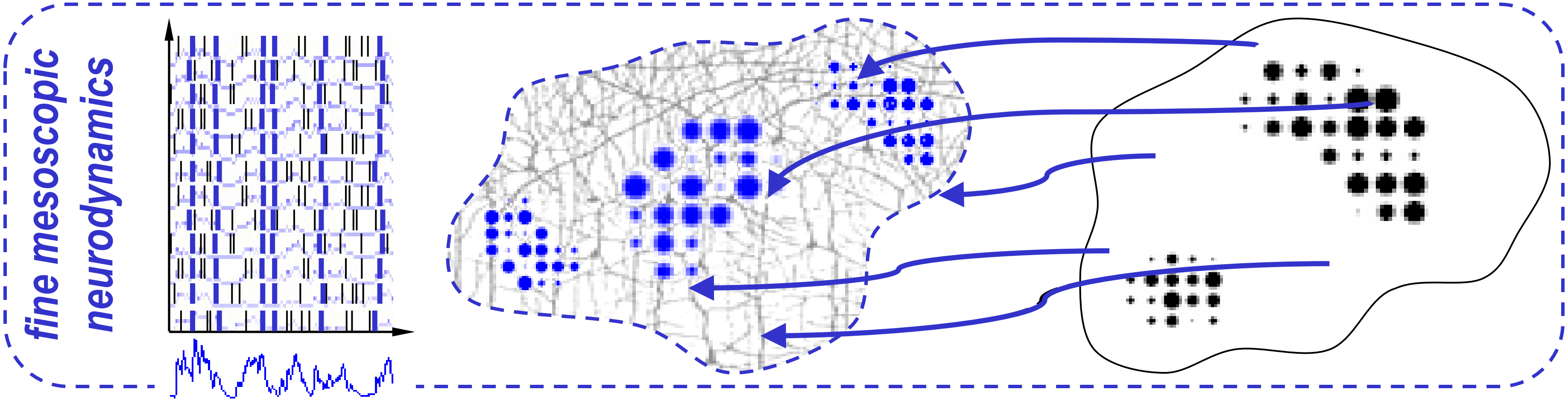


→ *the identity, specificity or stimulus-selectiveness of a mesoscopic entity is largely determined by its internal pattern of connections*

5. Toward Emergent Neurodynamics

b) Mesoscopic patterns are exogenously influenced

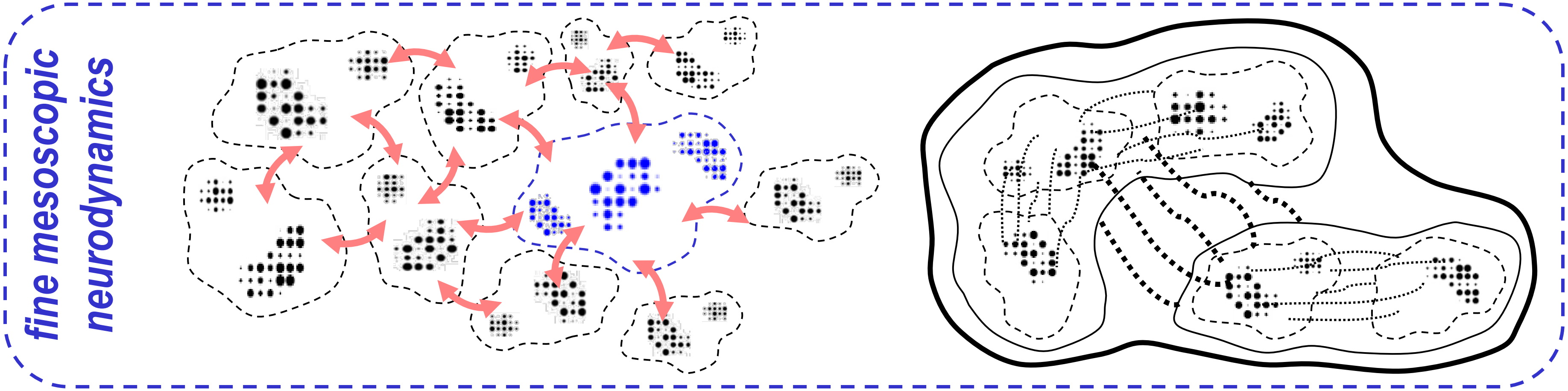
- ✓ external stimuli (via other patterns) may ***evoke & influence*** the pre-existing dynamical patterns of a mesoscopic assembly
- ✓ it is an indirect, ***perturbation*** mechanism; not a direct, activation mechanism



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

c) Mesoscopic patterns interact with each other

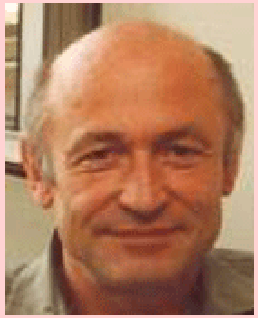
- ✓ populations of mesoscopic entities can ***compete & differentiate*** from each other to create specialized recognition units
- ✓ and/or they can ***bind*** to each other to create composed objects, via some form of temporal coherency (sync, fast plasticity, etc.)



evolutionary population paradigm

molecular compositionality paradigm

ACKNOWLEDGMENTS



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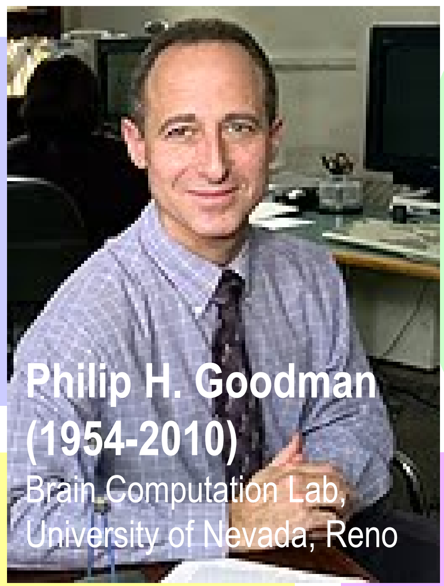
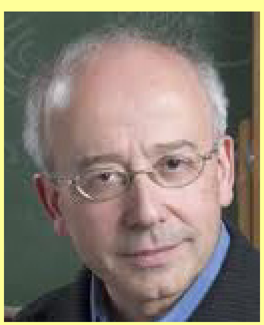


Philip H. Goodman (1954-2010)
Brain Computation Lab,
University of Nevada, Reno

Carlos Sánchez
lattice simulations

Francisco Vico, GEB,
U. de Málaga



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