Complex Systems Summer School

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Of Tapestries, Ponds and RAIN:

Toward a Fine-Grain Mesoscopic Neurodynamics

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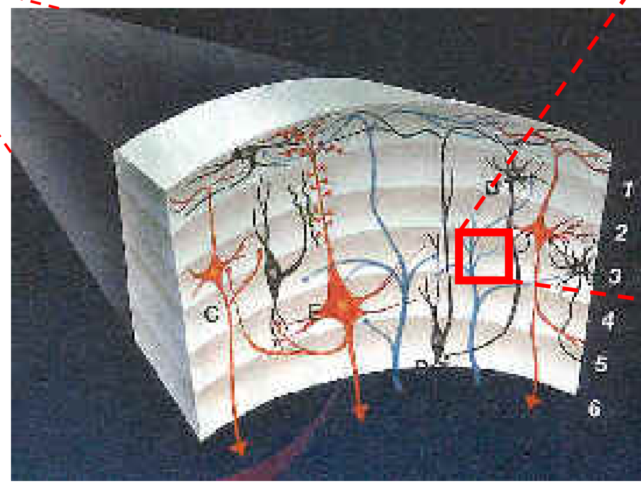
Toward a Fine-Grain Mesoscopic Neurodynamics

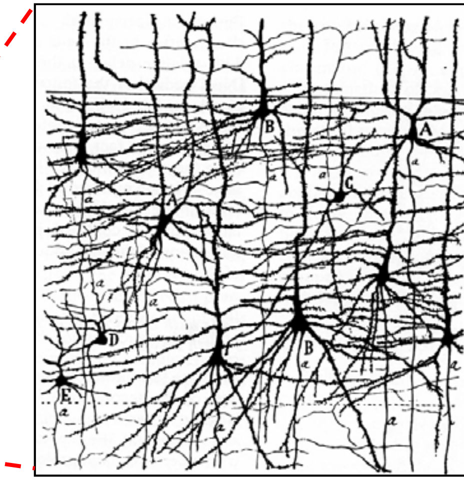
1. Cursory Review: Modeling Neural Networks
2. The Missing Mesoscopic Level of Cognition
3. The Importance of Binding with Temporal Code
4. Toward a Fine-Grain Mesoscopic Neurodynamics
    a. The self-made tapestry of synfire chains
    b. Waves in a morphodynamic pond
    c. Lock-and-key coherence in Recurrent Asynchronous Irregular Networks (RAIN)
5. A Multiscale Perspective on Neural Causality

1. Modeling Neural Networks

Medial surface of the brain
(Virtual Hospital, University of Iowa)

Cortical layers





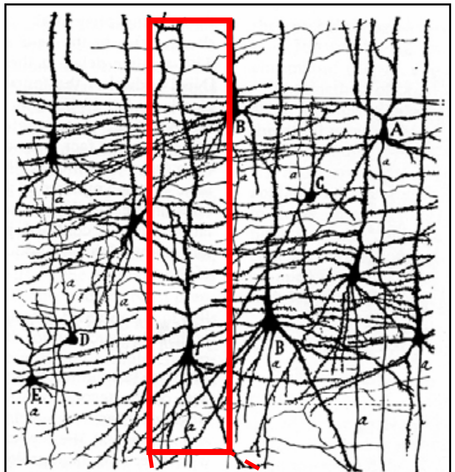
Pyramidal neurons and interneurons
(Ramón y Cajal 1900)

Phenomenon

- neurons together form... the brain! (and peripheral nervous system)
  - perception, cognition, action
  - emotions, consciousness
  - behavior, learning
  - autonomic regulation: organs, glands

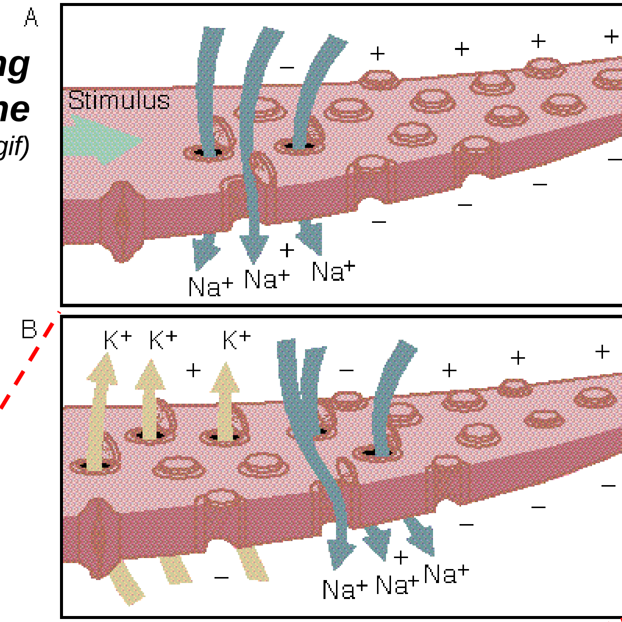
- ~10^{11} neurons in humans
- communicate with each other through (mostly) electrical potentials
- neural activity exhibits specific *patterns of spatial and temporal organization & coherence* ("neural code")

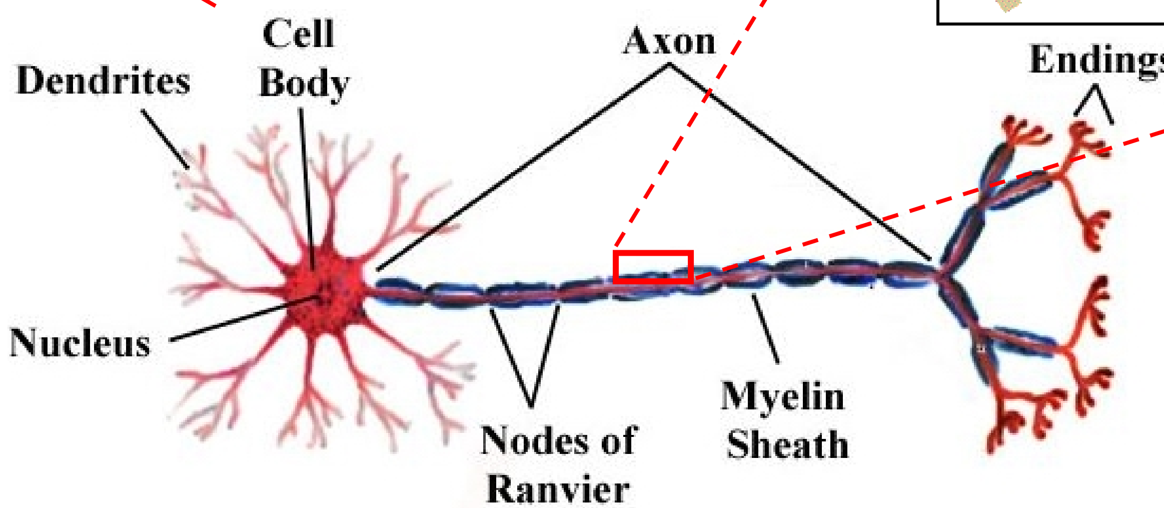
1. Modeling Neural Networks



Pyramidal neurons and interneurons
(Ramón y Cajal 1900)

Ionic channels opening and closing
→ depolarization of the membrane
(http://www.awa.com/norton/figures/fig0209.gif)

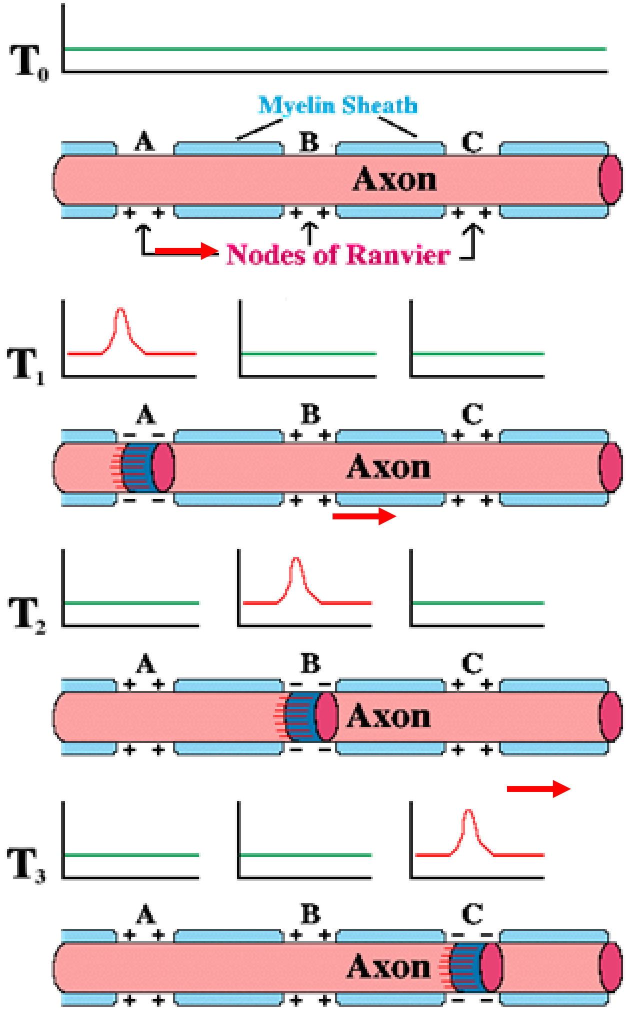


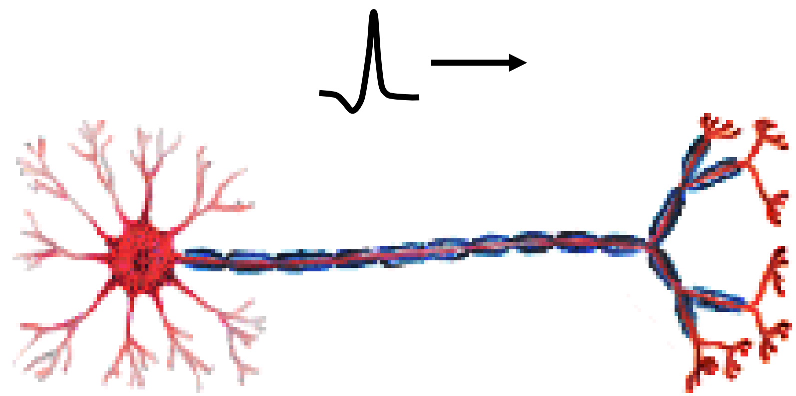


A typical neuron
(http://www.bio.brandeis.edu/biomath/mike/AP.html)

1. Modeling Neural Networks

➢ The propagation of bioelectrical potential



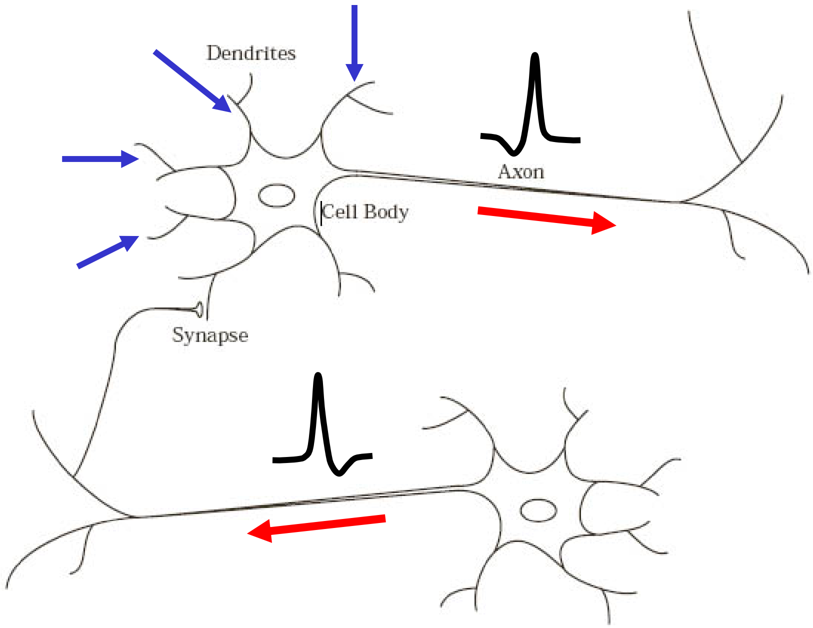


(http://www.bio.brandeis.edu/biomath/mike/AP.html)

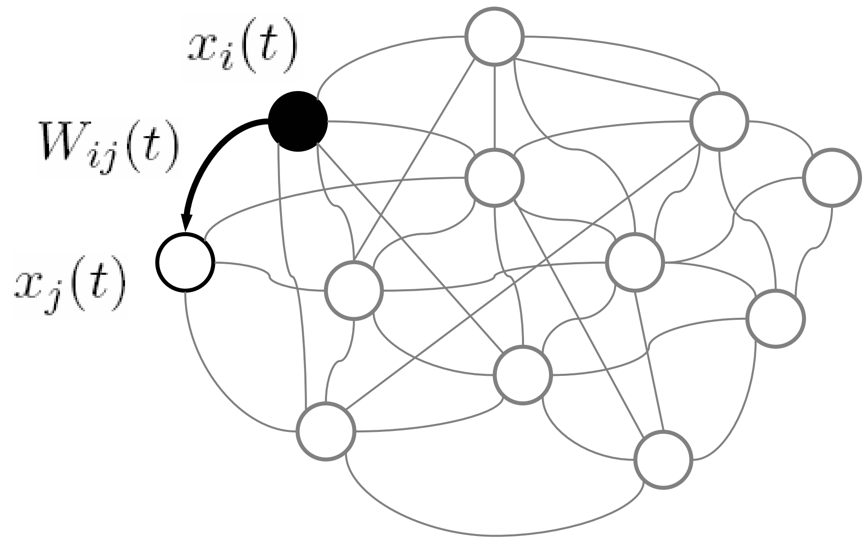
Cascade of channel openings and closings =
Propagation of the depolarization along the axon
→ called "action potential", or "spike"
(http://hypatia.ss.uci.edu/psych9a/lectures/lec4fig/n-action-potential.gif)

1. Modeling Neural Networks

➢ Schematic neural networks



Schematic neurons
(adapted from CS 791S "Neural Networks", Dr. George Bebis, UNR)



A neural network

Core dogma

- ➢ each neuron receives signals from many other neurons through its *dendrites*
- ➢ the signals converge to the *soma* (cell body) and are integrated
- ➢ if the integration exceeds a threshold, the neuron fires a <u>spike</u> on its *axon*

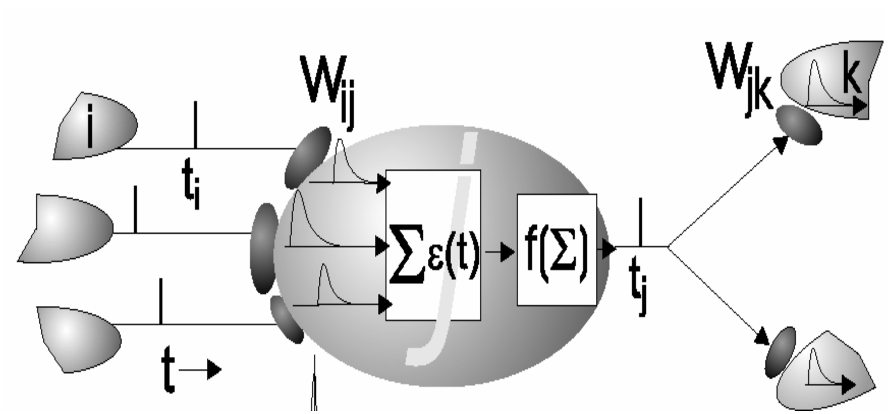
1. Modeling Neural Networks

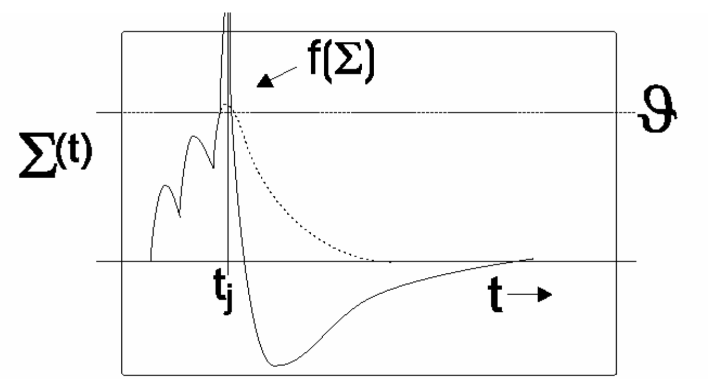
➢ Spiking neuron: levels of detail

more detailed

- ✓ binary threshold neuron
- ✓ integrate-and-fire
  - ▪ additive “bump” model
  - ▪ current-based differential equation
- ✓ Hodgkin-Huxley
  - ▪ conductance-based differential equation

more schematic

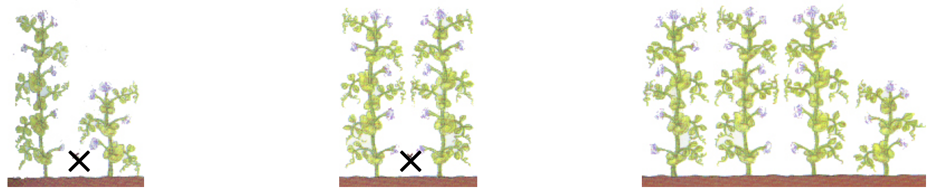




Toward a Fine-Grain Mesoscopic Neurodynamics

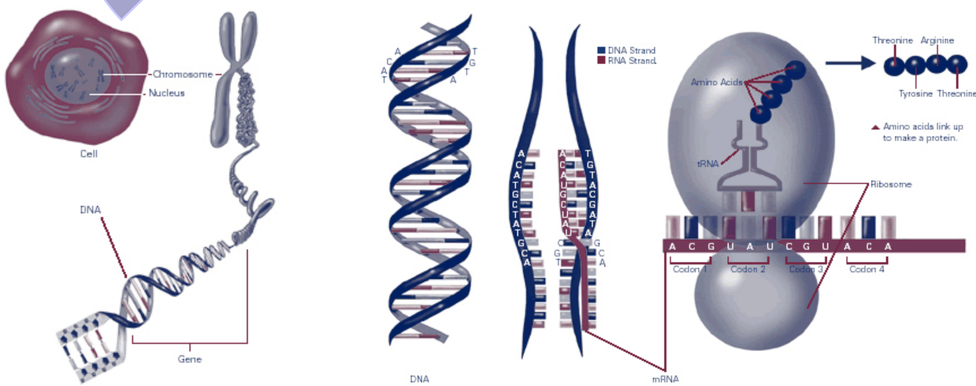
2. Mesoscopic Cognition

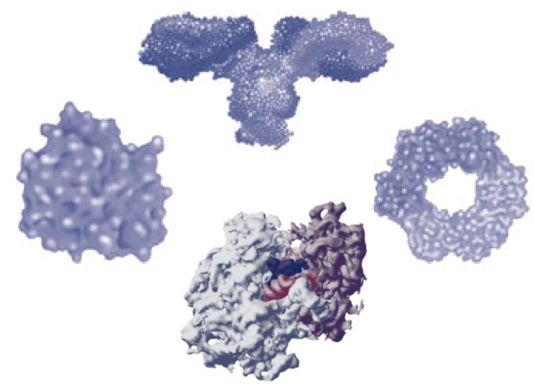
macrolevel:
genetics

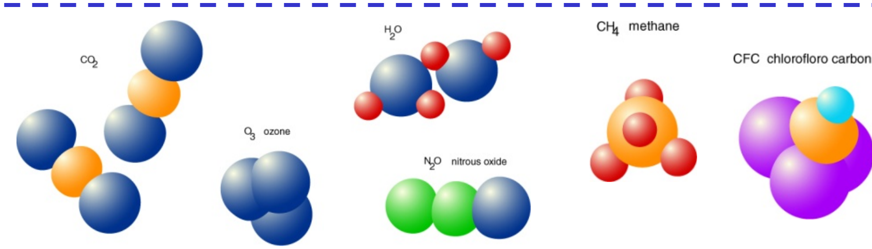


TT × Tt → Tt × Tt → TT, Tt, tT, tt

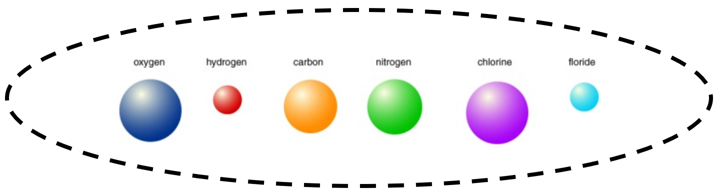
mesolevel:
molec. biology







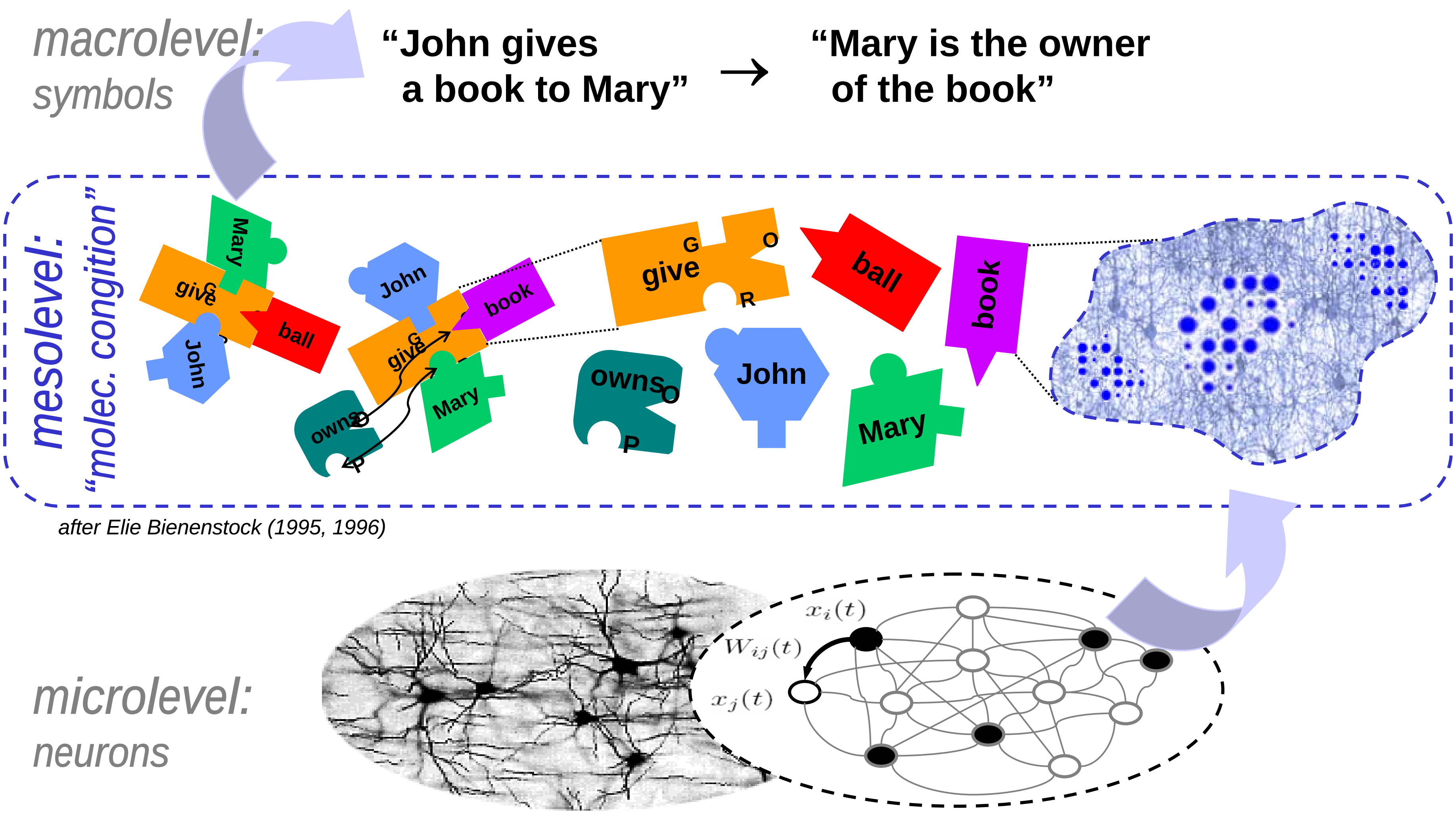
microlevel:
atoms



2. Mesoscopic Cognition

- Biology: cells, organisms → development, genetic rules
  - ✓ organisms contain cells that assemble in a generative way; species contain organisms that crossbreed and mutate
  - → *impossible to explain without the discovery of atoms, molecules, macromolecules, DNA, RNA, proteins and metabolic pathways*
- Physics, chemistry: particles, atoms → quantum rules
  - ✓ in physics, the foundational entities are elementary particles obeying string theory and quantum equations
  - → *conversely, the foundational laws and equations of physics cannot predict and describe the emergence of complex living systems*
- Missing link: biochemistry, molecular biology
  - ✓ organisms emerge as *complex systems* from the underlying biochemistry, via intermediary *macromolecular patterns*

2. Mesoscopic Cognition



after Elie Bienenstock (1995, 1996)

2. Mesoscopic Cognition

- AI: symbols, syntax → production rules
  - ✓ *logical systems* define high-level *symbols* that can be *composed* together in a generative way
  - → *they are lacking a "microstructure" needed to explain the fuzzy complexity of perception, categorization, motor control, learning*
- Missing link: "mesoscopic" level of description
  - ✓ cognitive phenomena emerge from the underlying *complex systems* neurodynamics, via intermediate *spatiotemporal patterns*
- Neural networks: neurons, links → activation rules
  - ✓ in neurally inspired *dynamical systems*, the *nodes* of a network *activate* each other by association
  - → *they are lacking a "macrostructure" needed to explain the systematic compositionality of language, reasoning, cognition*

2. Mesoscopic Cognition

- To explain macroscopic phenomena from microscopic elements, <u>mesoscopic</u> structures are needed

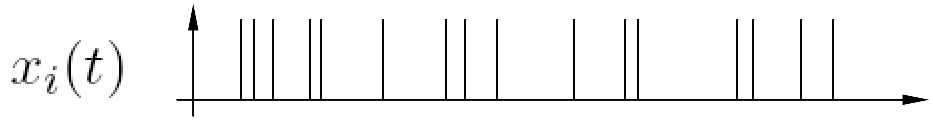
  - ✓ to explain and predict the symbolic rules of genetics from atoms, *molecular biology* is needed

  - ✓ similarly, to explain and predict the symbolic rules of perception and language (composition, hierarchy, inference) from neuronal activities, a new discipline of ***"molecular cognition"*** is needed

- What could therefore be the "macromolecules" of cognition?

2. Mesoscopic Cognition

- There is more to neural signals than mean activity rates



- ✓ rate coding: average spike frequency

$$\langle\, x_i(t)\,\rangle_T \;=\; \frac{1}{T}\int_0^T x_i(t)\,dt$$

- ✓ temporal coding: spike correlations
  - not necessarily oscillatory
  - possibly delayed

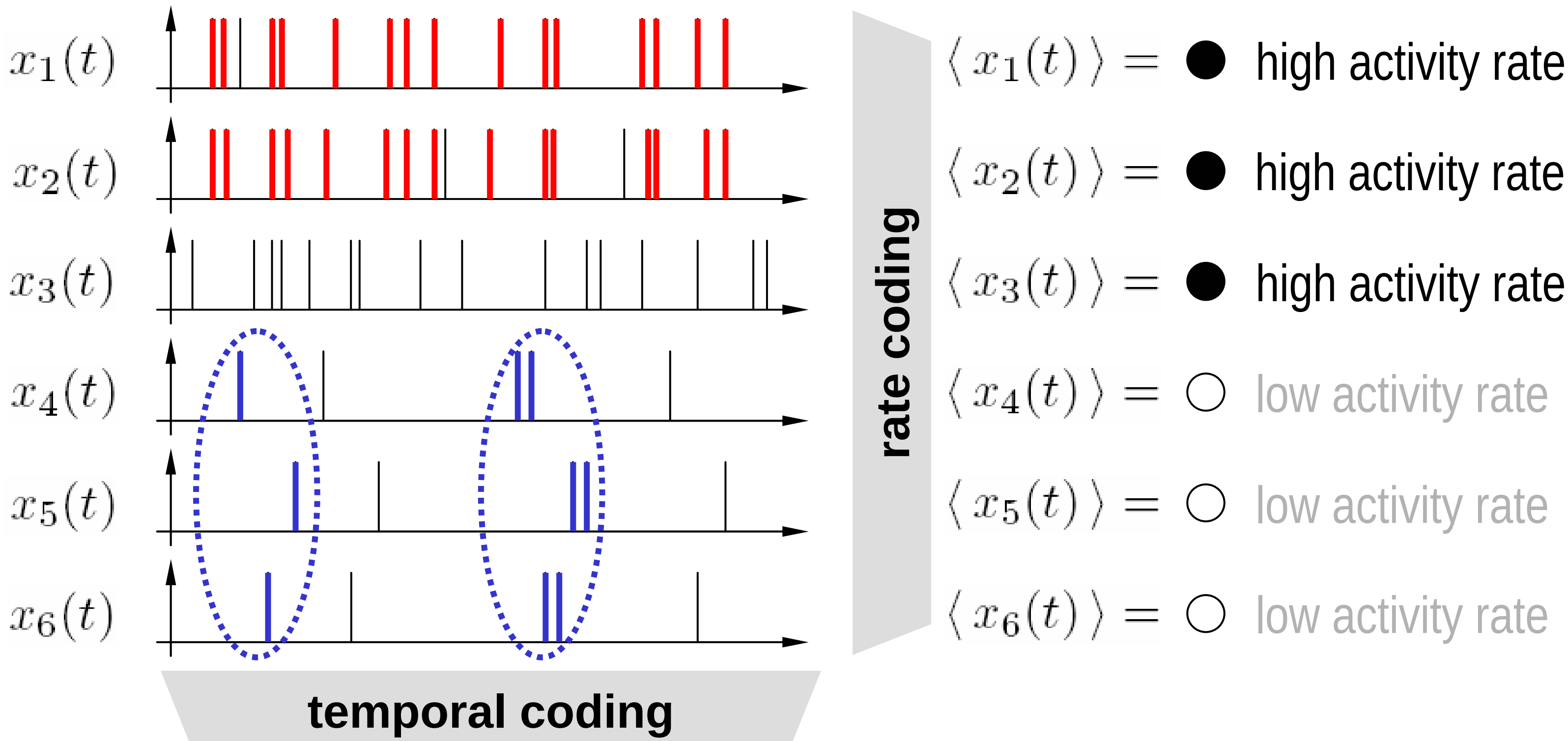
$$\langle\, x_i(t)\, x_j(t)\,\rangle$$

$$\langle\, x_i(t)\, x_j(t-\tau_{ij})\,\rangle$$

$$\langle\, x_1(t)\, x_2(t-\tau_{1,2})\,\ldots\, x_n(t-\tau_{1,n})\,\rangle$$

2. Mesoscopic Cognition

- **Below mean firing-rate coding: precise temporal coding**
  - ✓ more than mean rates → *temporal correlations* among spikes



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

- 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. Mesoscopic Cognition

➢ 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

➢ Recent temporal coding "boom": a few milestones

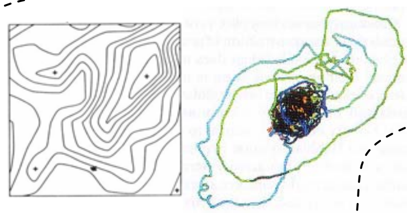
- von der Malsburg (1981): *theoretical proposal to consider <u>correlations</u>*
- Abeles (1982, 1991): *precise, <u>reproducible spatiotemporal spike rhythms</u>, named "synfire chains"*
- Gray & Singer (1989): *stimulus-dependent <u>synchronization of oscillations</u> in monkey visual cortex*
- O'Keefe & 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. Mesoscopic Cognition

➢ Populating the mesoscopic level: neural field models

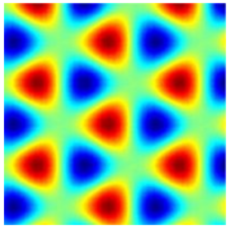
field mesolevel

spatial EEGs, chaotic attractors



Freeman (1994)

bumps, blobs, bubbles



Amari (1975, 1977)

✓ neural ensembles characterized by ***mean field variables***, continuous in time and space, e.g.

- local field potentials
- firing rates (spike densities)
- neurotransmitter densities, etc.

2. Mesoscopic Cognition

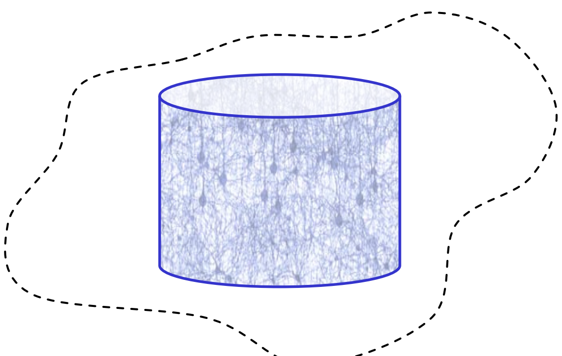
➢ Populating the mesoscopic level: spiking neural models

✓ large-scale, localized dynamic cell assemblies that display complex, ***reproducible*** digital-analog regimes of neuronal activity

→ fine-grain *spatiotemporal patterns* (STPs)

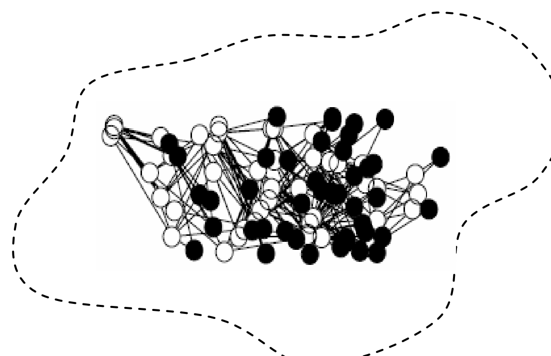
spiking mesolevel

BlueColumn



Markram (2006)

polychronous groups



Izhikevich (2006)

. . .

2. Mesoscopic Cognition

➢ Populating the mesoscopic level: spiking models (cont'd)

✓ large-scale, localized dynamic cell assemblies that display complex, *reproducible* digital-analog regimes of neuronal activity

→ fine-grain *spatiotemporal patterns* (STPs)


tapestries

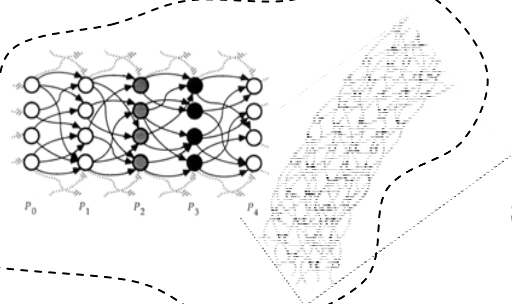

ponds


RAIN

spiking mesolevel

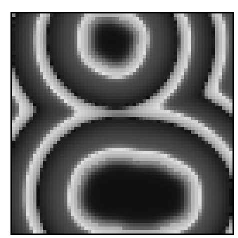
. . .

synfire chains & braids



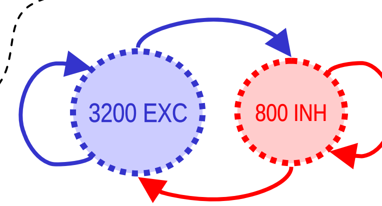
Abeles (1982),
Doursat (1991), Bienenstock (1995), D & B (2006)

morphodynamic waves



Doursat & Petitot (1997, 2005)

RAIN lock-&-key coherence



Vogels & Abbott (2006)
Doursat & Goodman (2006)

Toward a Fine-Grain Mesoscopic Neurodynamics

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3. **The Importance of Binding with Temporal Code**
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   a. The self-made tapestry of synfire chains
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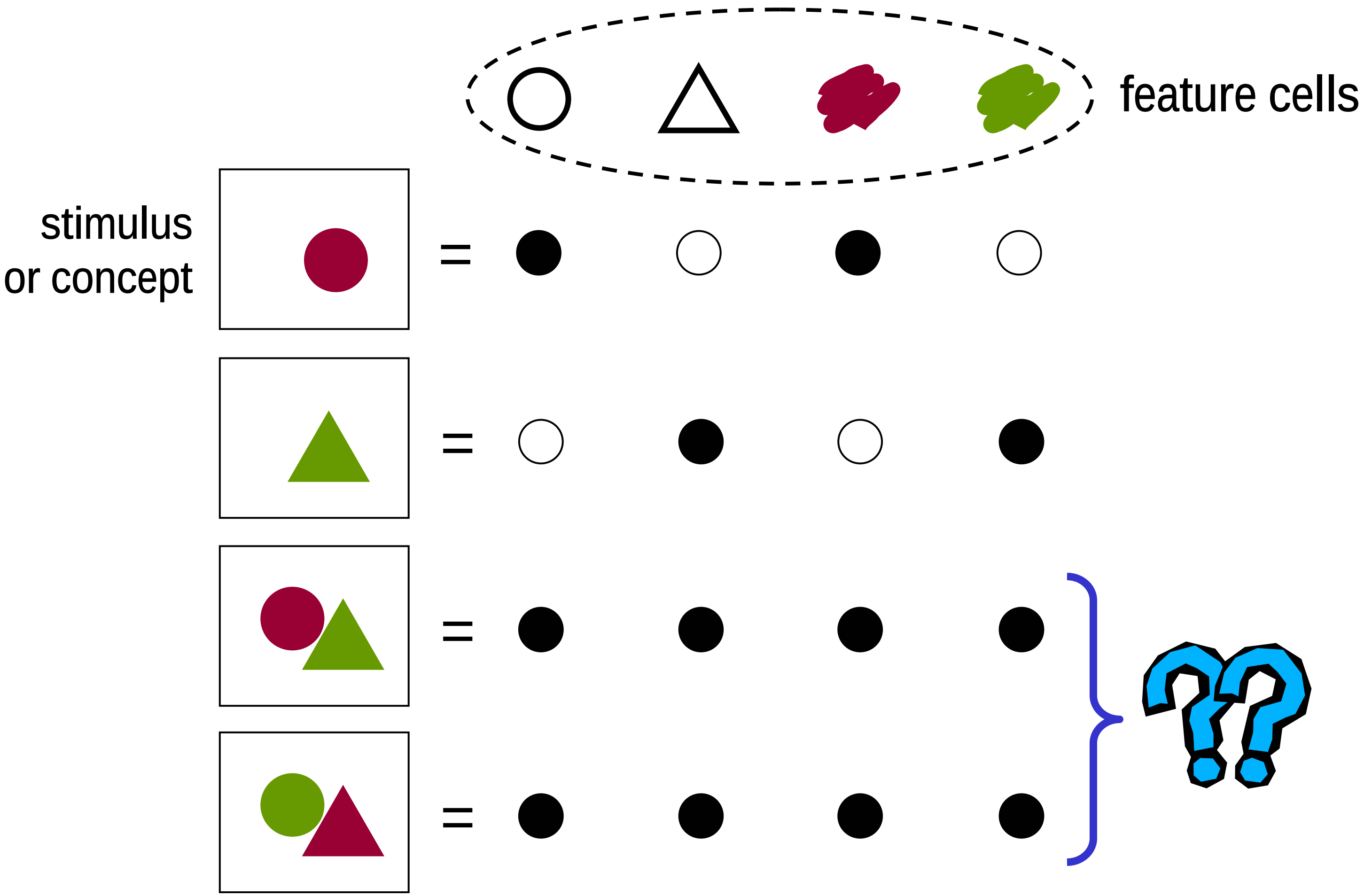
3. Binding with Temporal Code

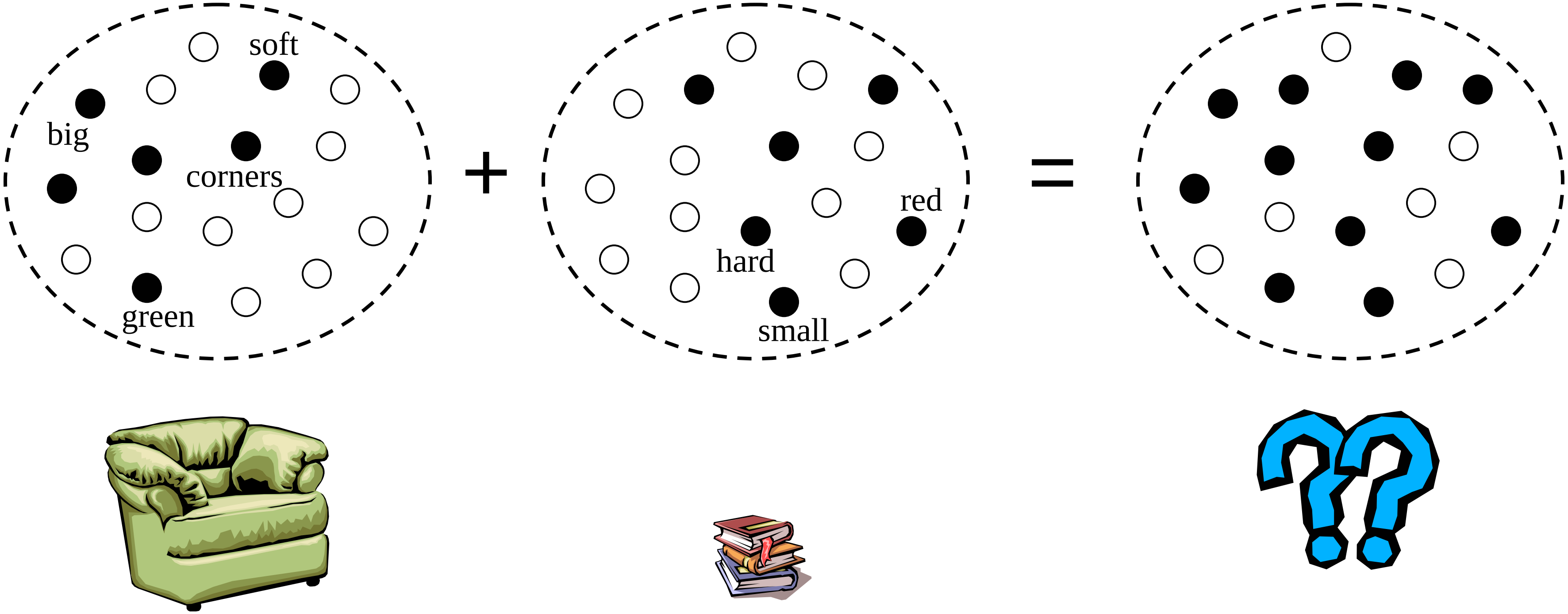
- The "binding problem"
  - ✓ how to represent relationships?



3. Binding with Temporal Code

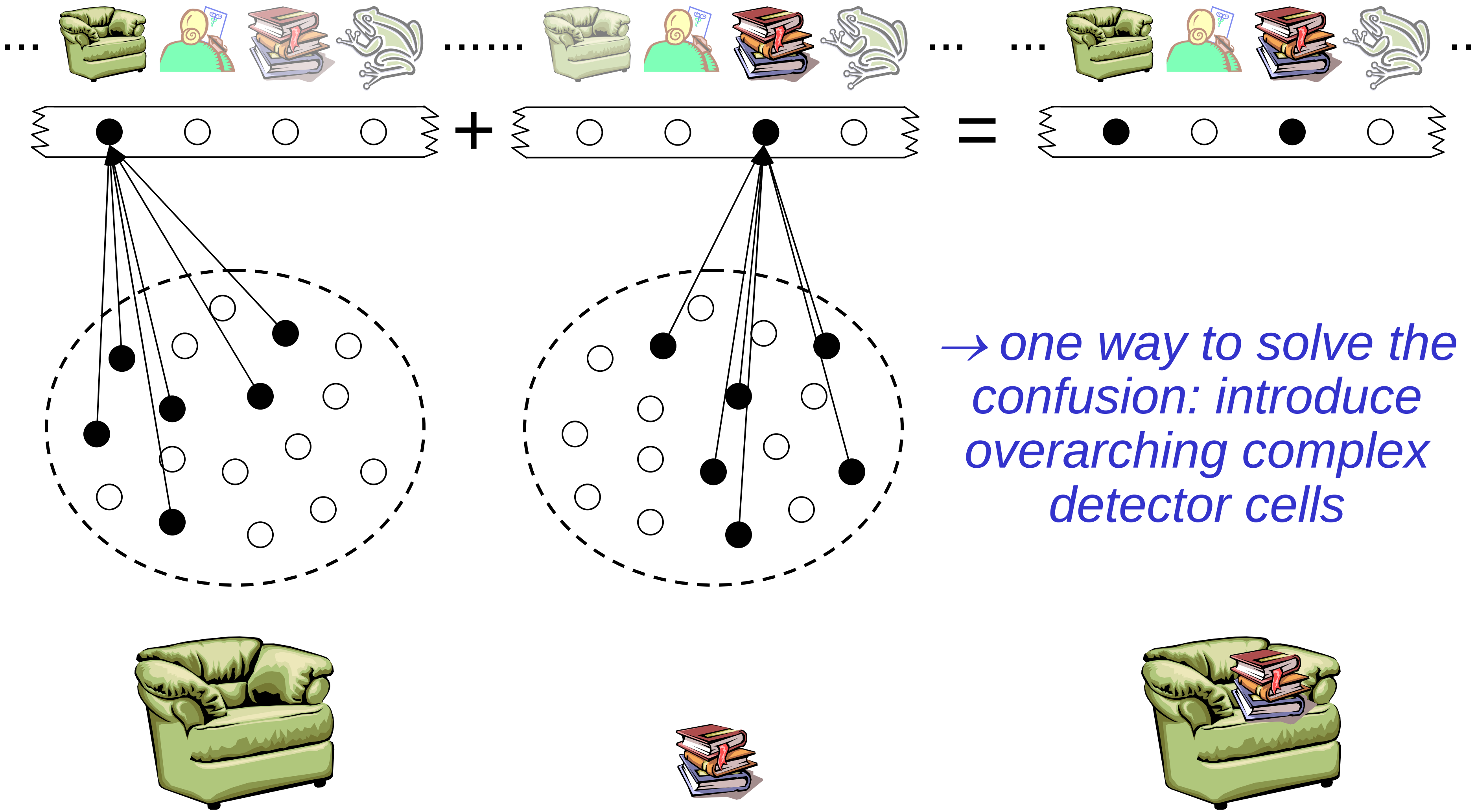
➢ More generallly: feature binding in cell assemblies

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



3. Binding with Temporal Code

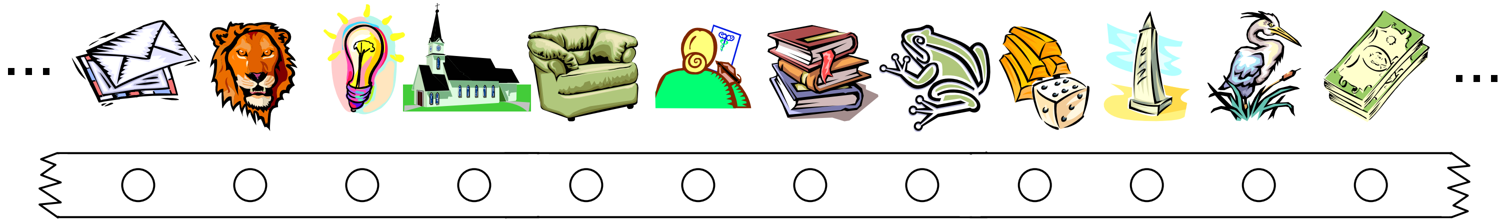
- "Grandmother" cells?



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

3. Binding with Temporal Code

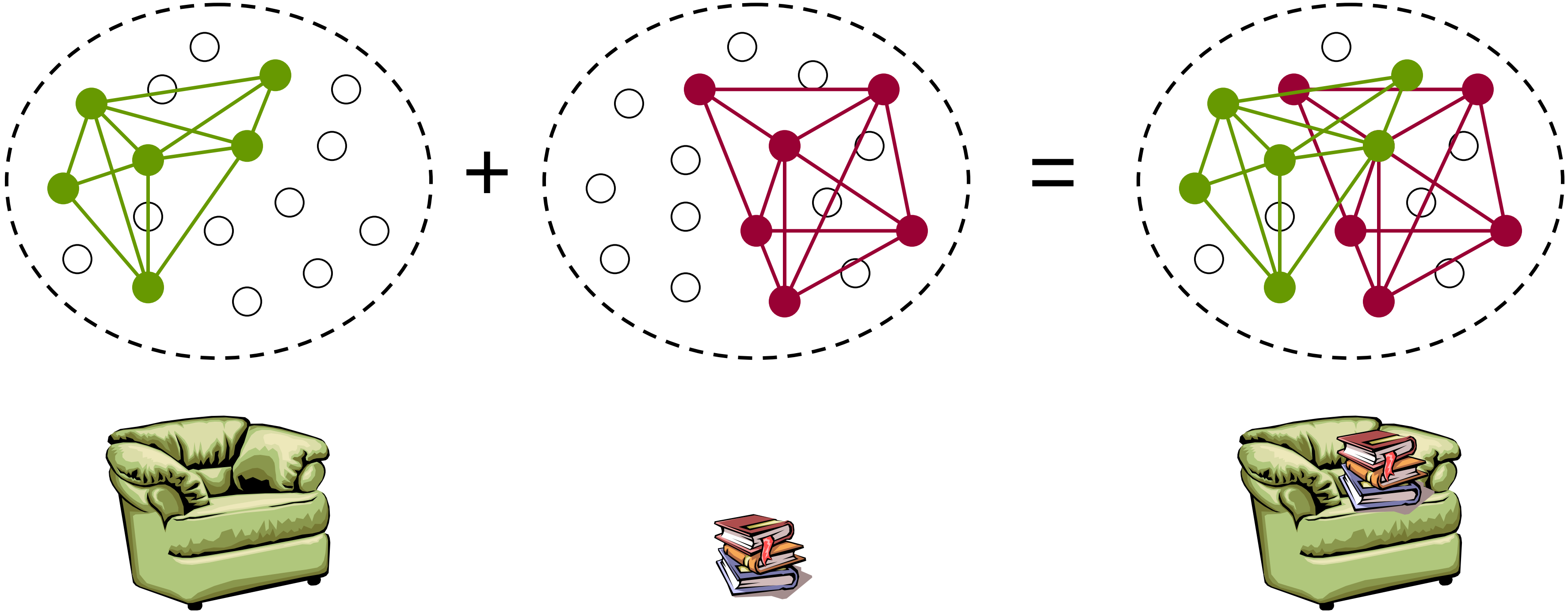
- “Grandmother” cells?



. . . however, this soon leads to an unacceptable combinatorial explosion!

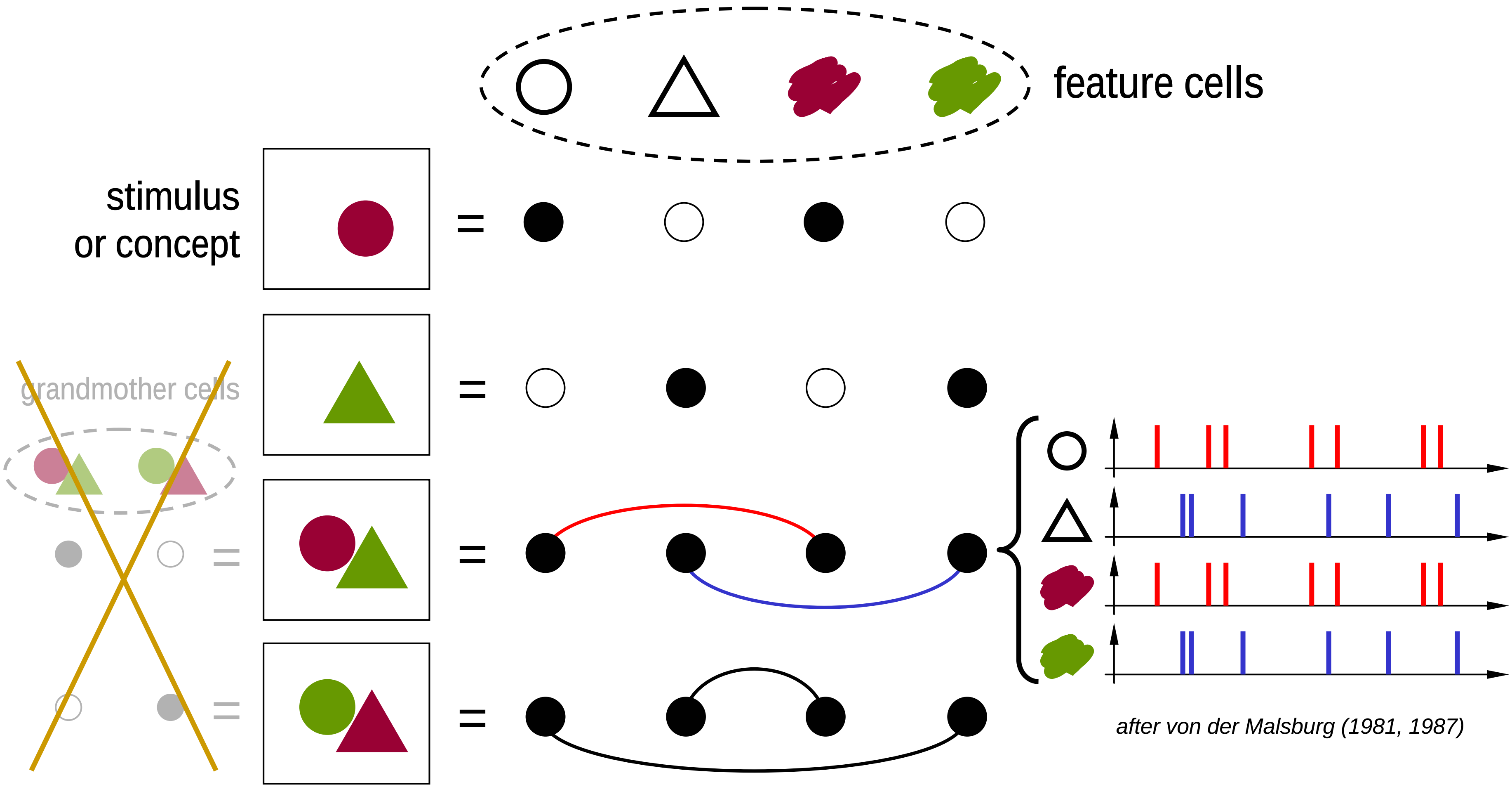
3. Binding with Temporal Code

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



3. Binding with Temporal Code

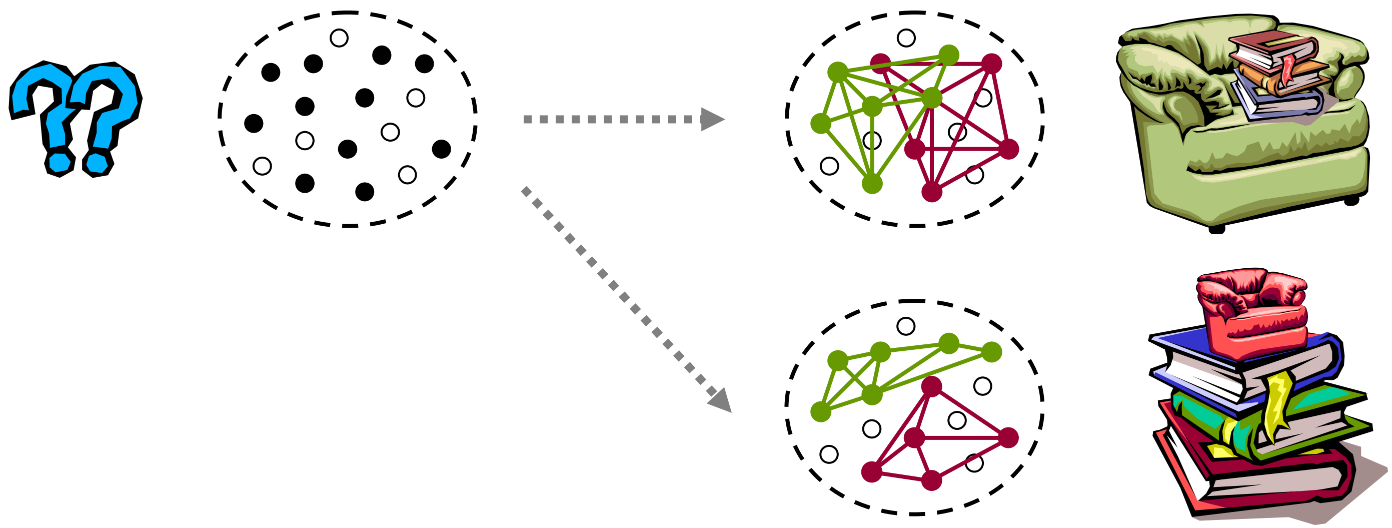
- Idea: relational information can be encoded *temporally!*
  - ✓ back to the binding problem: a solution using temporal coding



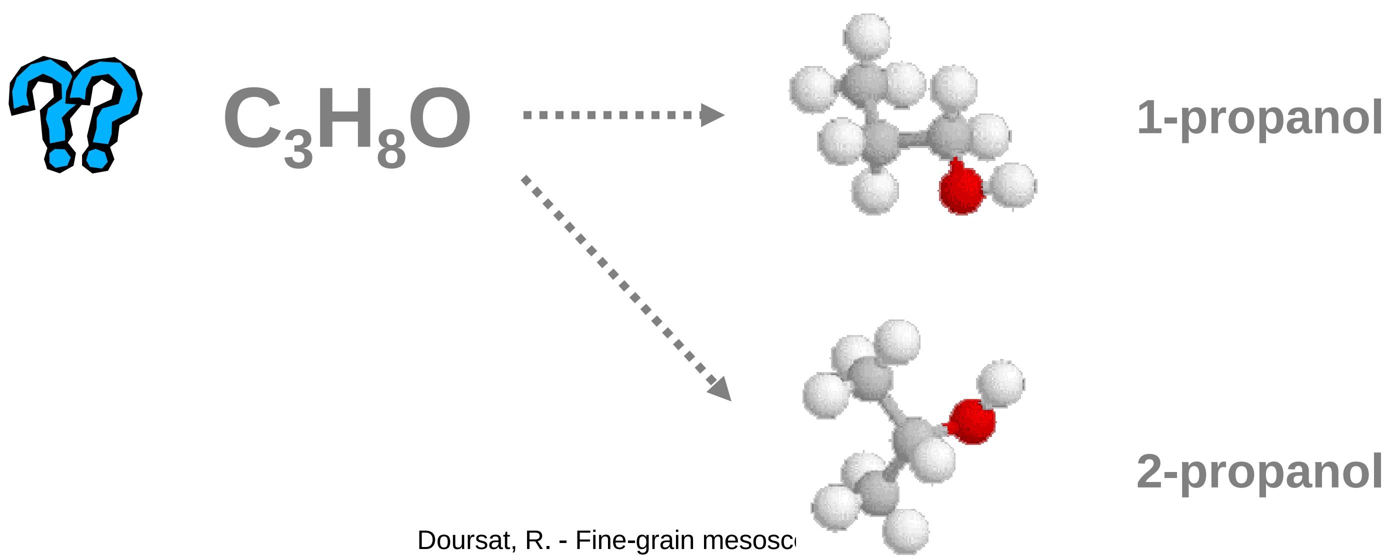
after von der Malsburg (1981, 1987)

3. Binding with Temporal Code

- Molecular metaphor: spatiotemporal patterns



“cognitive isomers” made of the same atomic features



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   a. The self-made tapestry of synfire chains

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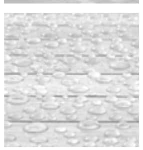


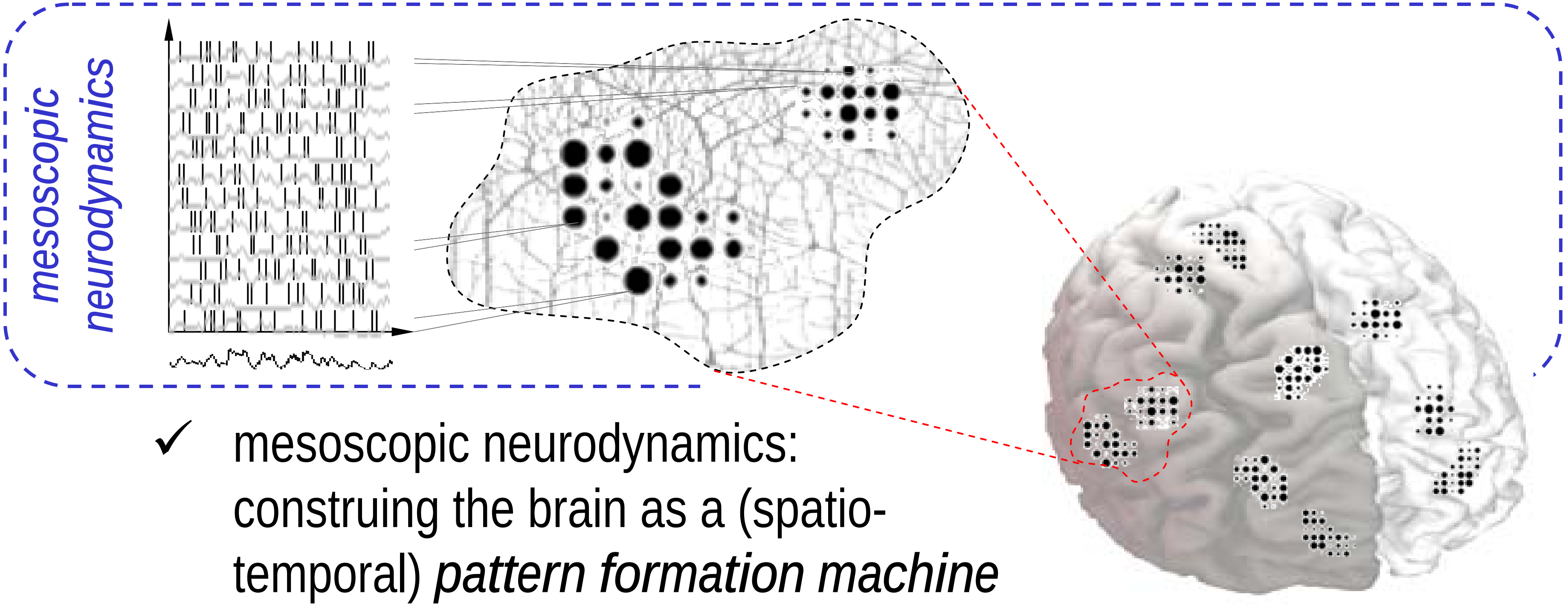
   c. Lock-and-key coherence in Recurrent Asynchronous Irregular Networks (RAIN)

5. A Multiscale Perspective on Neural Causality

4. Mesoscopic Neurodynamics

➢ The dynamic richness of 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



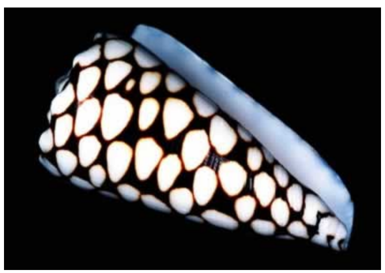
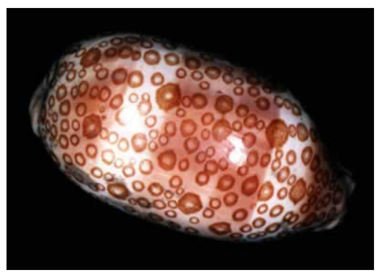
- ✓ mesoscopic neurodynamics: construing the brain as a (spatio-temporal) *pattern formation machine*

4. Mesoscopic Neurodynamics

- **Biological development is all about pattern formation**

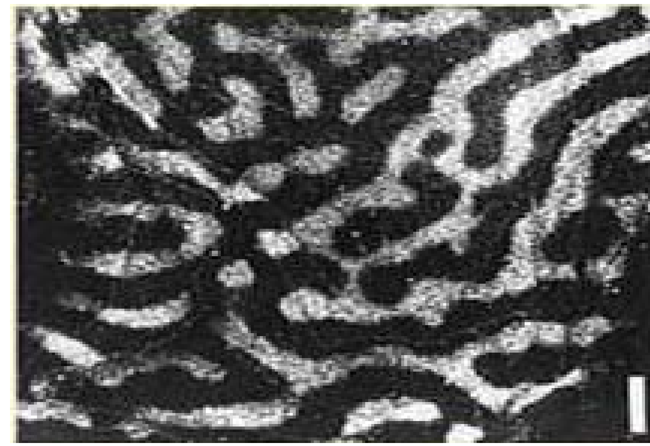
✓ static, structural patterning



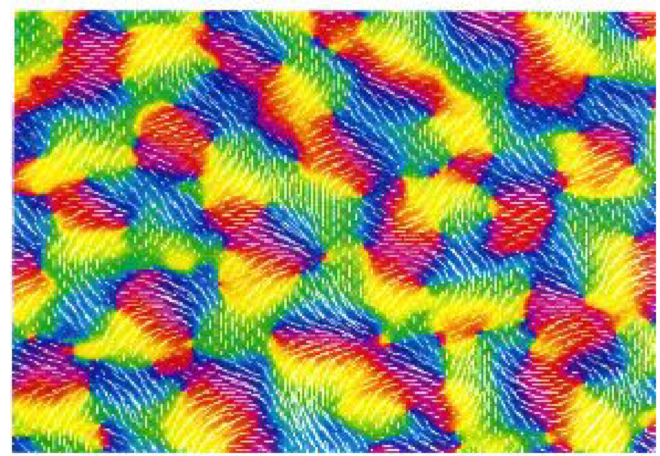



Scott Camazine, http://www.scottcamazine.com

✓ why would the brain be different?



ocular dominance stripes Hubel & Wiesel, 1970



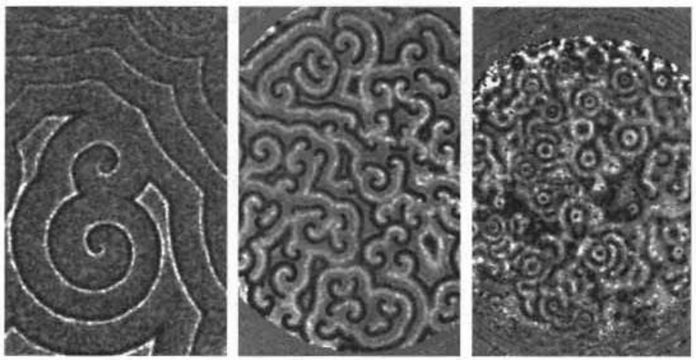
orientation column "pinwheels" Blasdel, 1992

4. Mesoscopic Neurodynamics

➢ Tissue physiology is also about pattern formation

✓ dynamic, functional pattng

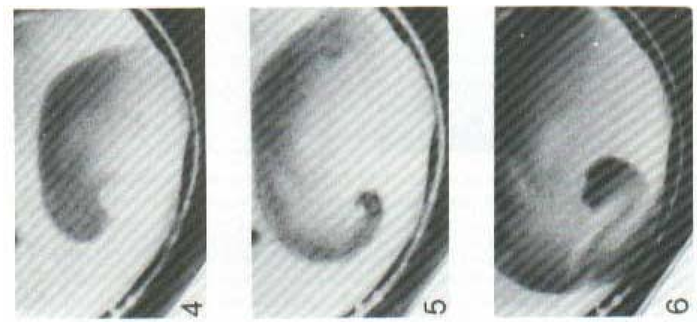
Aggregating slime mold
B. Goodwin, Schumacher College, UK



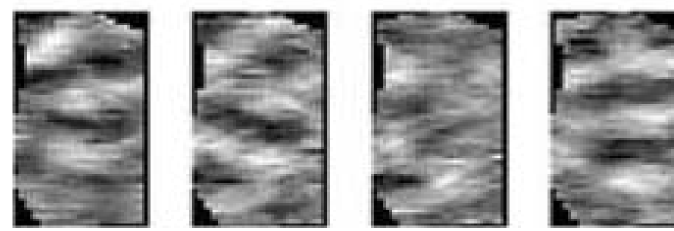
Model of dog heart
J. Keener, University of Utah

✓ why would the brain be different?

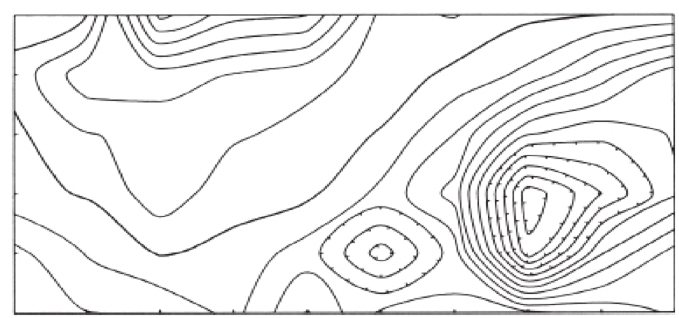
Chicken retina waves
Gorelova & Bures, 1983



Spontaneous VC activity Grinvald



Olfactory bulb phase pattern W. Freeman



4. Mesoscopic 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,

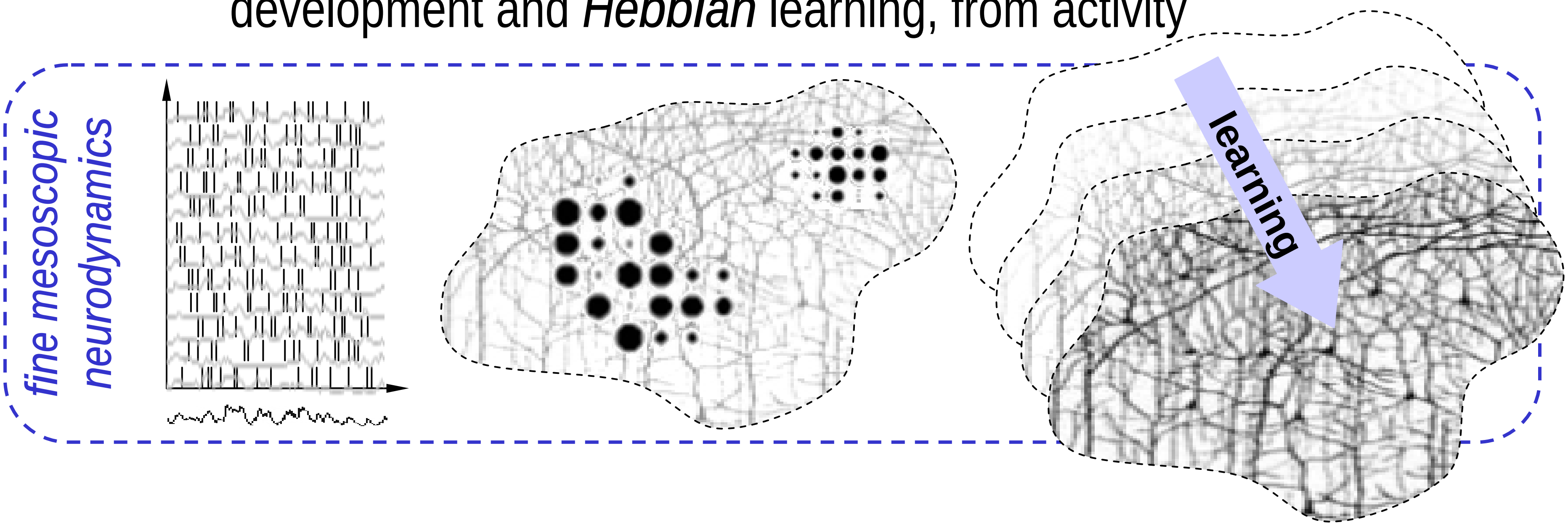
  b) exogenously evoked & perturbed under the influence of stimuli,

  c) interactively binding to each other in competitive or cooperative ways.

4. Mesoscopic 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

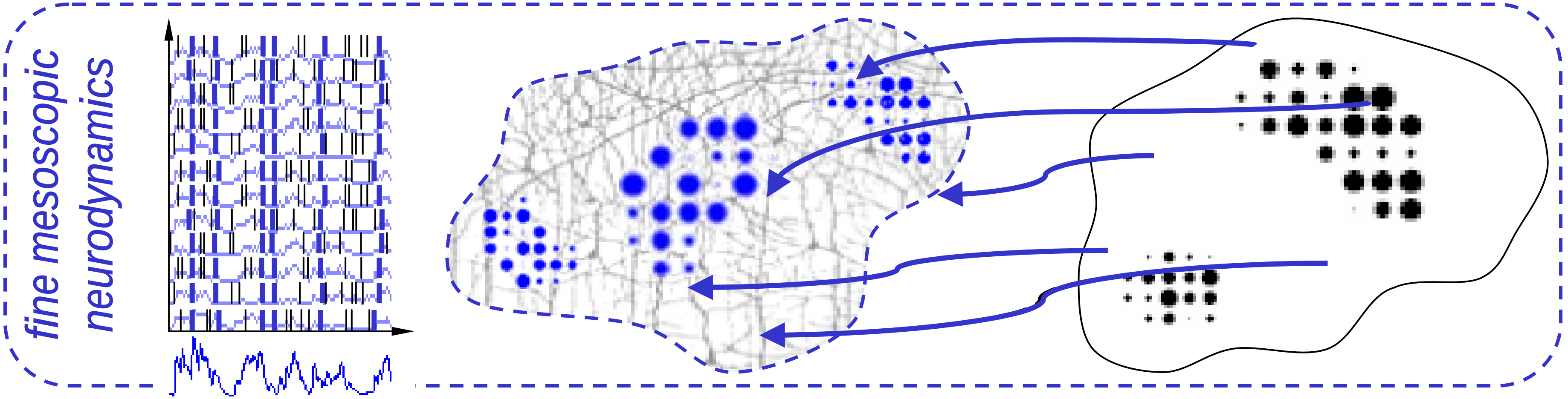


→ *the identity, specificity or stimulus-selectiveness of a mesoscopic entity is largely determined by its internal pattern of connections*

4. Mesoscopic 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

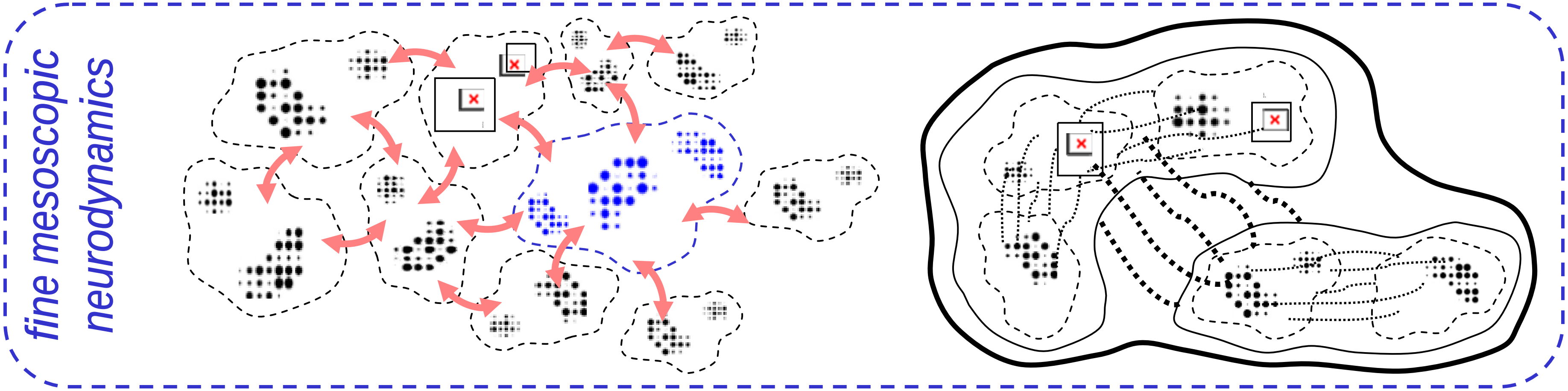


- ✓ mesoscopic entities may have stimulus-specific ***recognition or "representation"*** abilities, without being "templates" or "attractors" (no resemblance to stimulus)

4. Mesoscopic 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

Toward a Fine-Grain Mesoscopic Neurodynamics

1. Cursory Review: Modeling Neural Networks
2. The Missing Mesoscopic Level of Cognition
3. The Importance of Binding with Temporal Code
4. Toward a Fine-Grain Mesoscopic Neurodynamics

a. The self-made tapestry of synfire chains

b. Waves in a morphodynamic pond

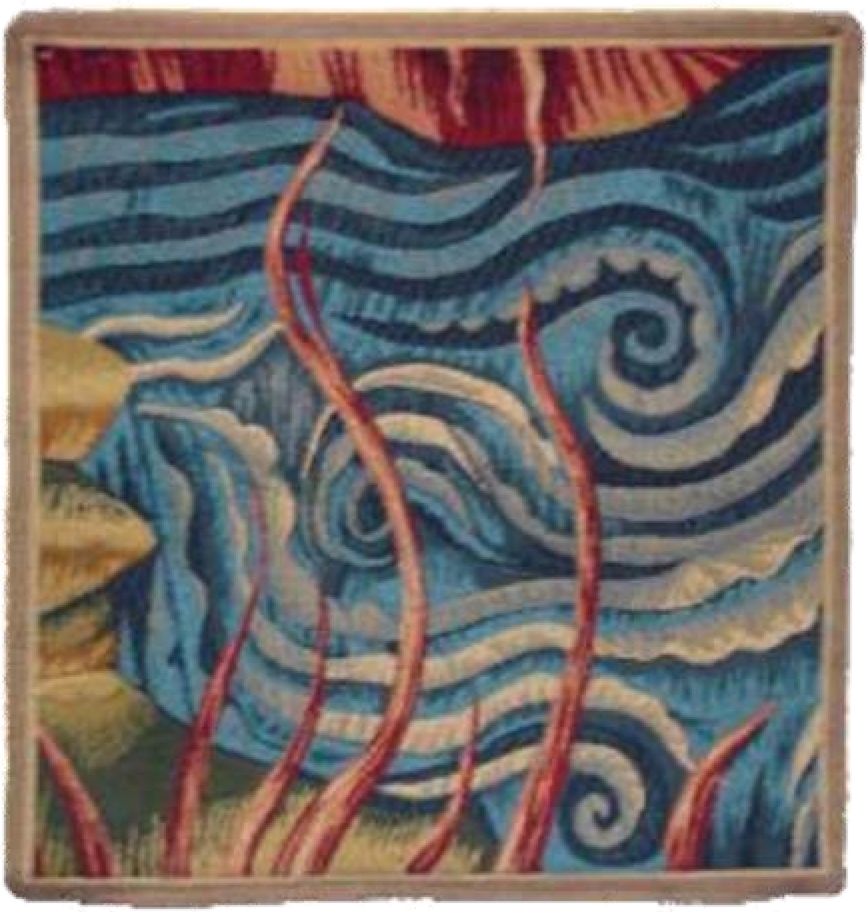
c. Lock-and-key coherence in Recurrent Asynchronous Irregular Networks (RAIN)

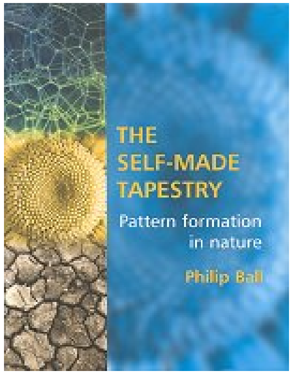
5. A Multiscale Perspective on Neural Causality

4. Mesoscopic Neurodynamics

a) The self-made tapestry of synfire chains

→ *constructing the architecture of STPs*



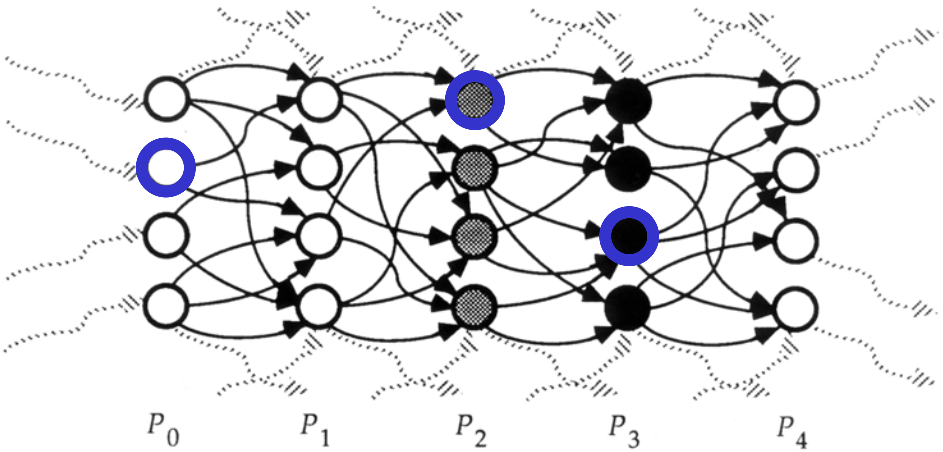


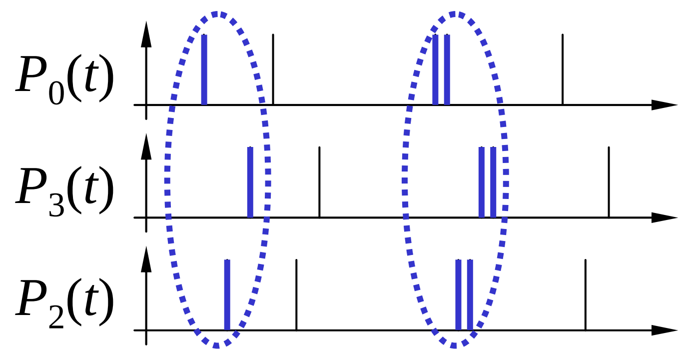
Doursat (1991), Bienenstock (1995), Doursat & Bienenstock (2005)

4.a Synfire Chains

➢ What is a synfire chain?

- ✓ 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)



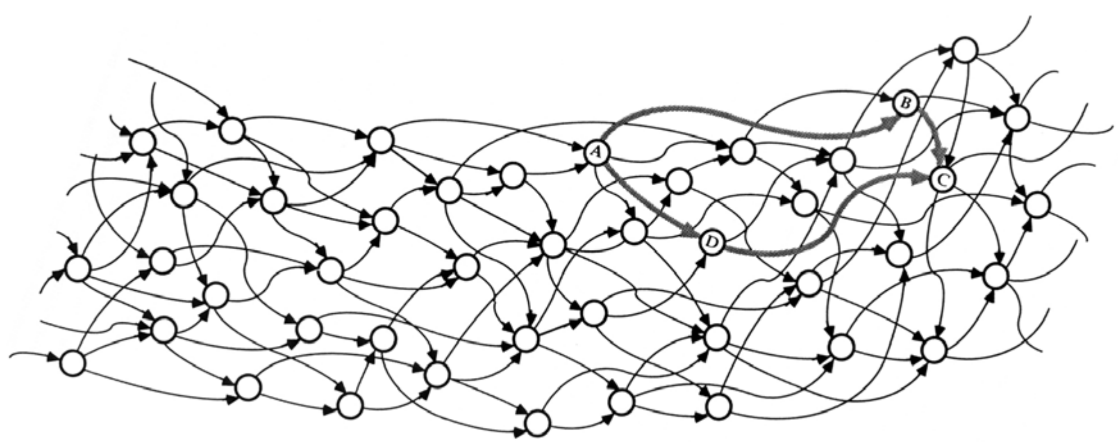


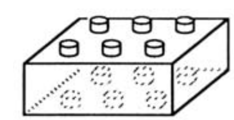
- ✓ synfire chains have been hypothesized to explain neurophysiological recordings containing statistically significant delayed correlations
- ✓ the redundant divergent/convergent connectivity of synfire chains can preserve accurately synchronized action potentials, even under noise

4.a Synfire Chains

➢ What is a synfire braid?

- ✓ synfire braids are more general structures with longer delays among nonconsecutive neurons, but no identifiable synchronous groups
- ✓ they were rediscovered as "polychronous groups" (Izhikevich, 2006)

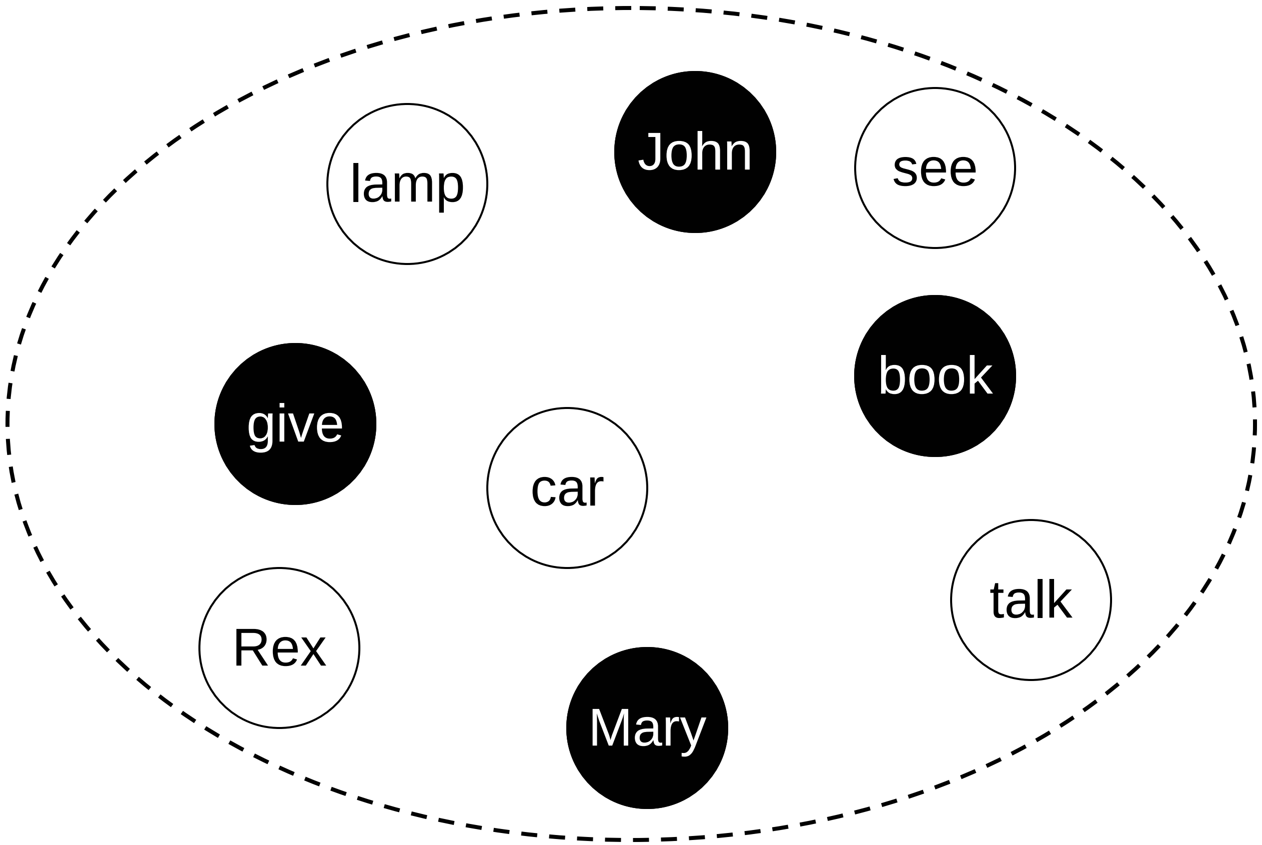




- ✓ in a synfire braid, ***delay transitivity*** $\tau_{AB} + \tau_{BC} = \tau_{AD} + \tau_{DC}$ favors strong spike coincidences, hence a stable propagation of activity

4.a Synfire Chains

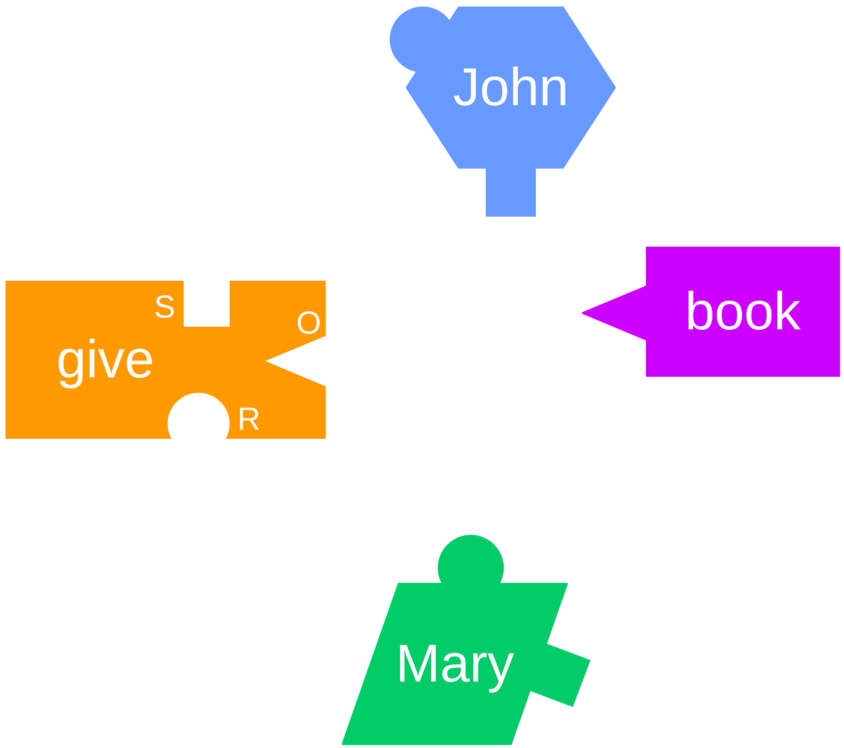
- Problems of compositionality again—in language



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

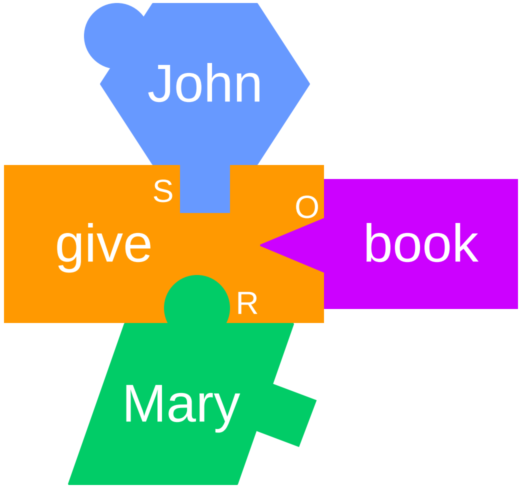
4.a Synfire Chains

- Problems of compositionality again—in language



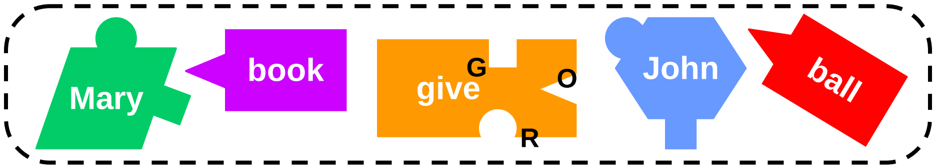
4.a Synfire Chains

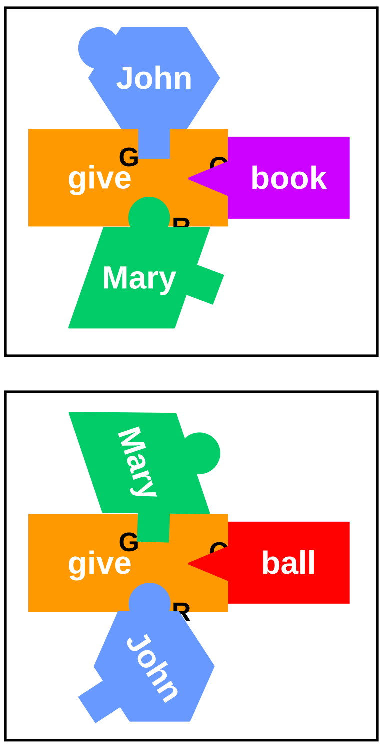
- Problems of compositionality again—in language
  - ✓ language is a "building blocks" construction game



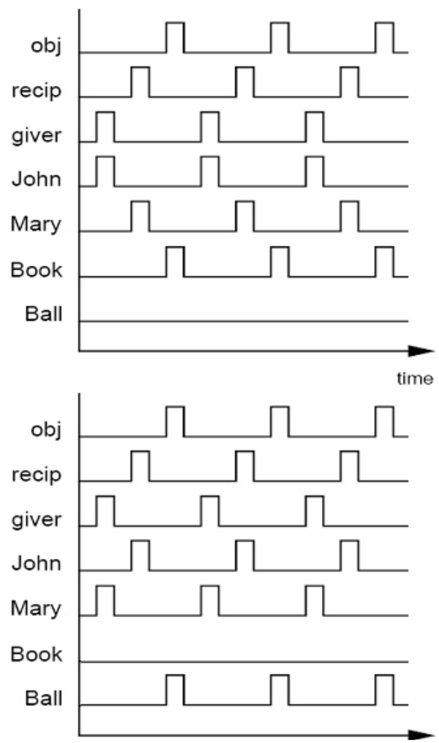
4.a Synfire Chains

➢ A building-block game of language





after Bienenstock (1995)

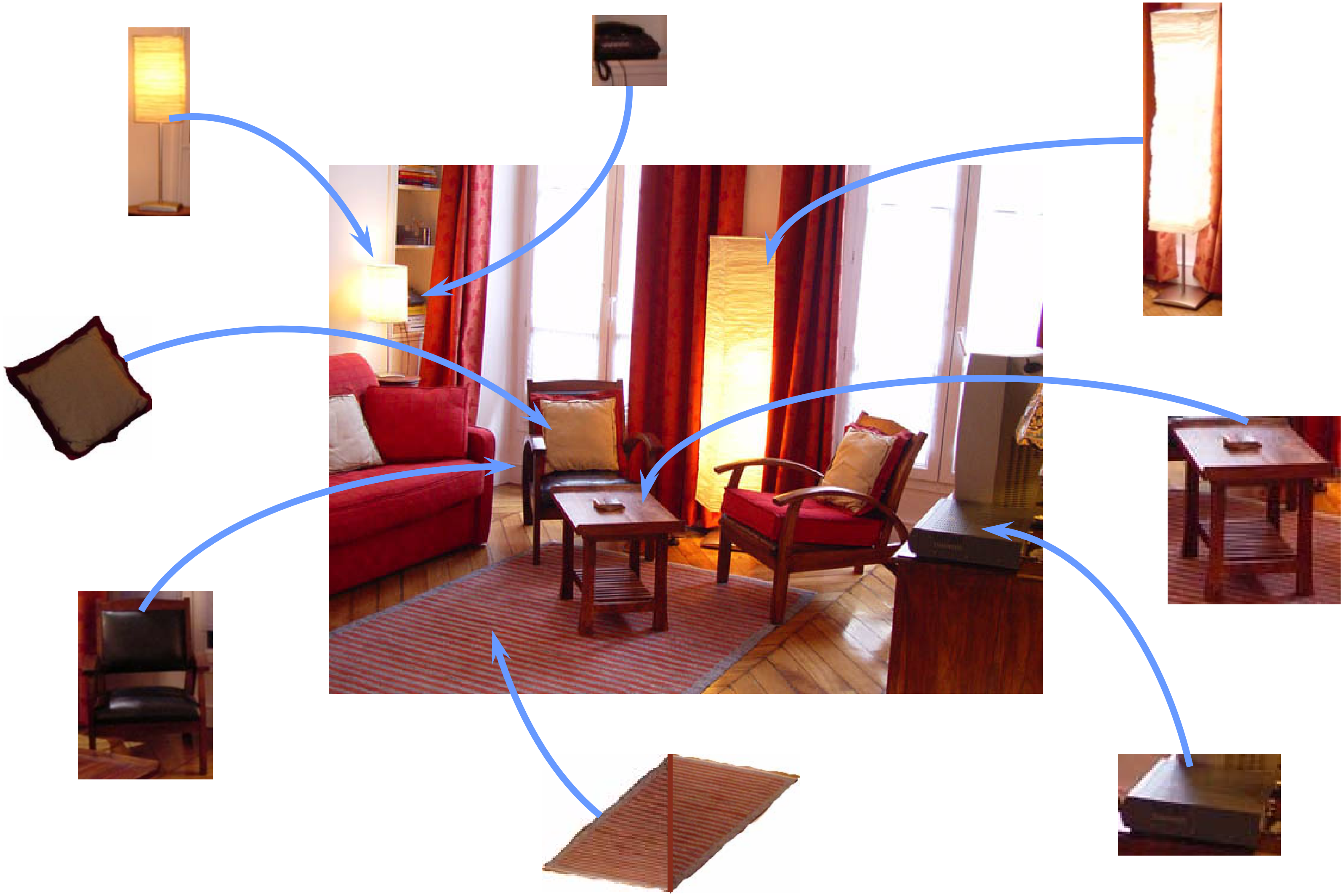


after Shastri & Ajjanagadde (1993)

- ✓ the "blocks" are elementary representations (linguistic, perceptive, motor) that ***assemble dynamically*** via temporal binding
- ✓ representations possess an internal spatiotemporal structure at all levels

4.a Synfire Chains

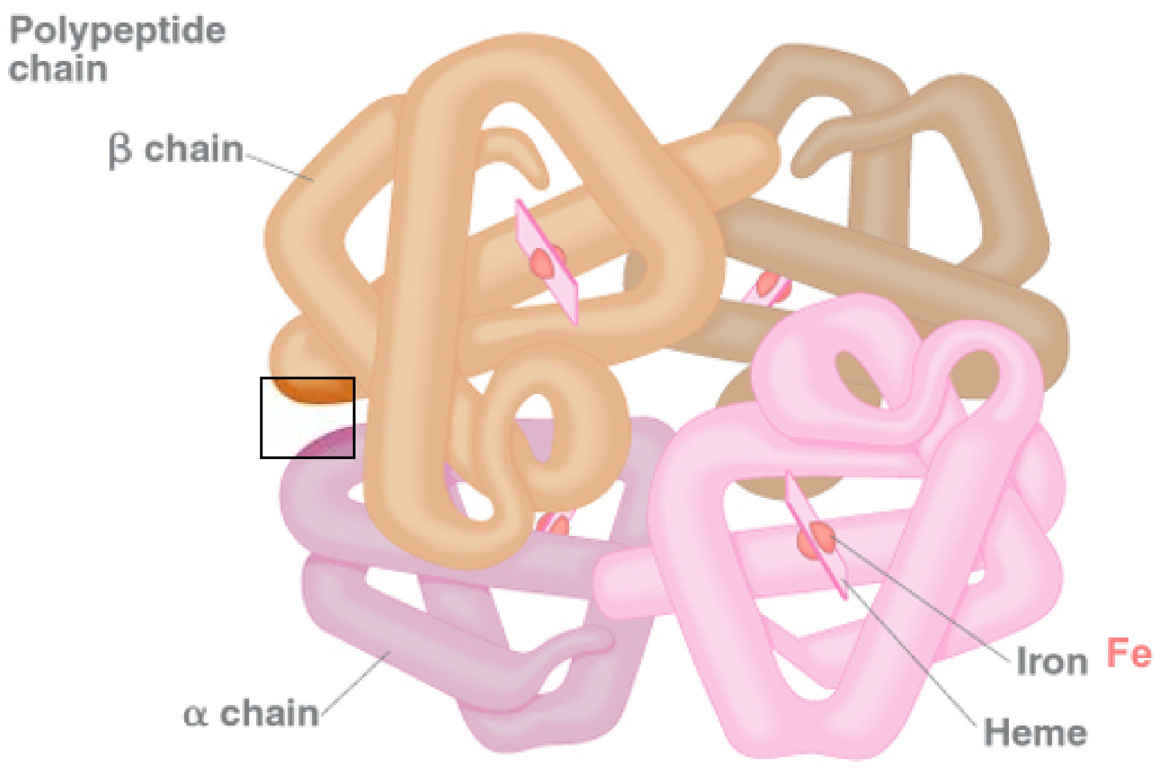
- Problems of compositionality again—in vision



4.a Synfire Chains

➢ Structural bonds

✓ protein structures provide a metaphor for the “mental objects” or “building blocks” of cognition

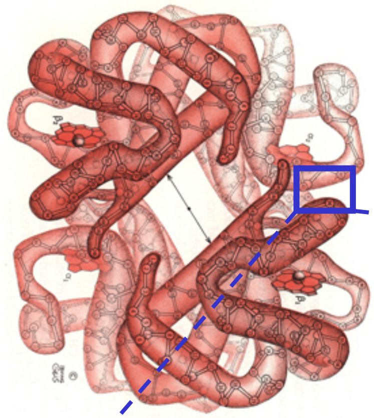


(b) Hemoglobin

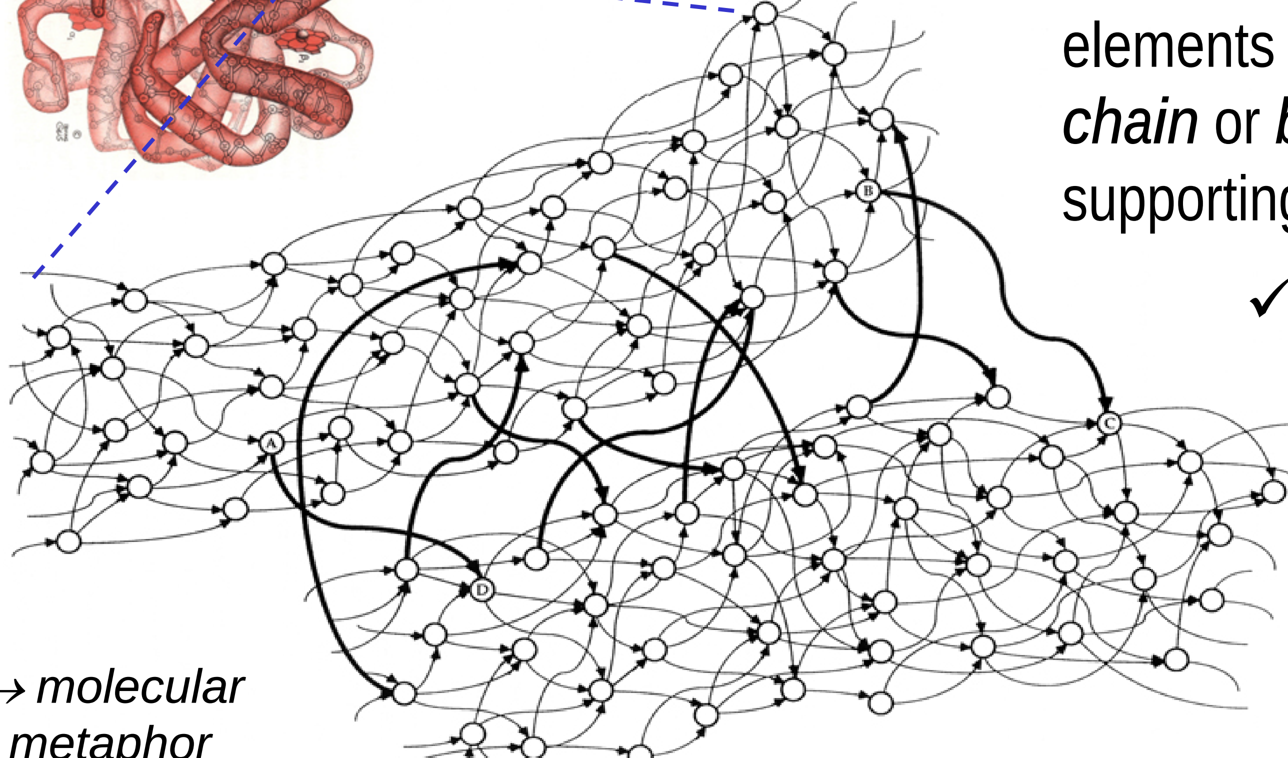
4.a Synfire Chains

➢ Synfire patterns can *bind*, thus support compositionality

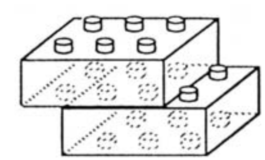
hemoglobin



- ✓ 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***



after Bienenstock (1995) and Doursat (1991)

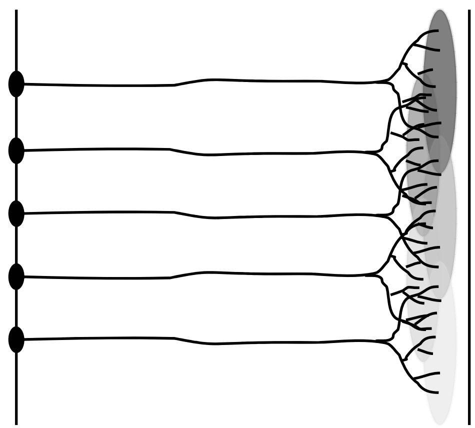


→ *molecular metaphor*

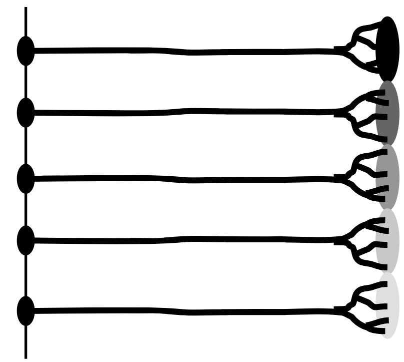
4.a Synfire Chains

➢ A model of synfire growth: tuning connectivity by activity

- ✓ development akin to the *epigenetic structuration* of cortical maps



focusing of innervation in the retinotopic projection



after Willshaw & von der Malsburg (1976)

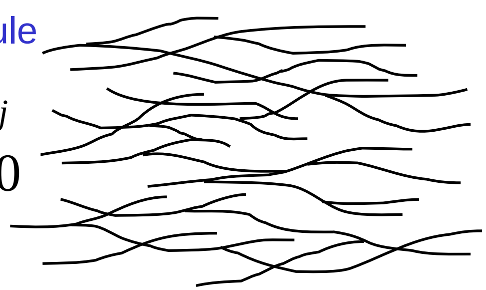
- ✓ in an initially broad and diffuse (immature) connectivity, some synaptic contacts are reinforced (selected) to the detriment of others

A. activation rule

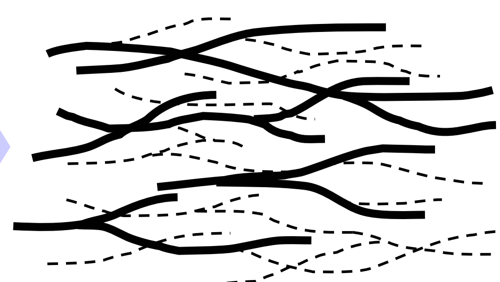
B. Hebbian rule

$$\begin{cases} \Delta W_{ij} \sim x_i x_j \\ \sum \Delta W_{ij} \sim 0 \end{cases}$$

C. sum rule



“selective stabilization” by activity/connectivity feedback



after Changeux & Danchin (1976)

4.a Synfire Chains

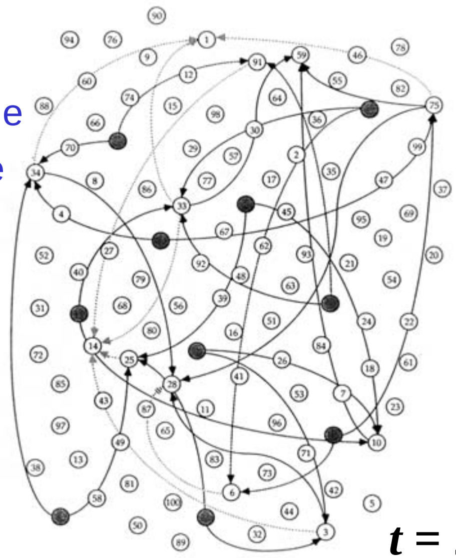
- Synfire chains develop recursively, adding groups 1 by 1

A. activation rule

B. Hebbian rule

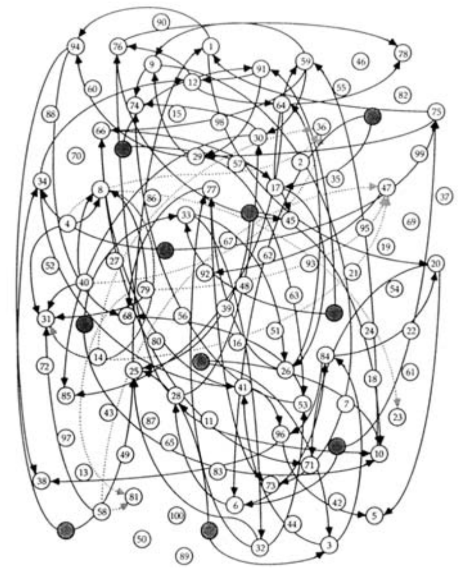
$$\begin{cases} \Delta W_{ij} \sim x_i x_j \\ \sum \Delta W_{ij} \sim 0 \end{cases}$$

C. sum rule



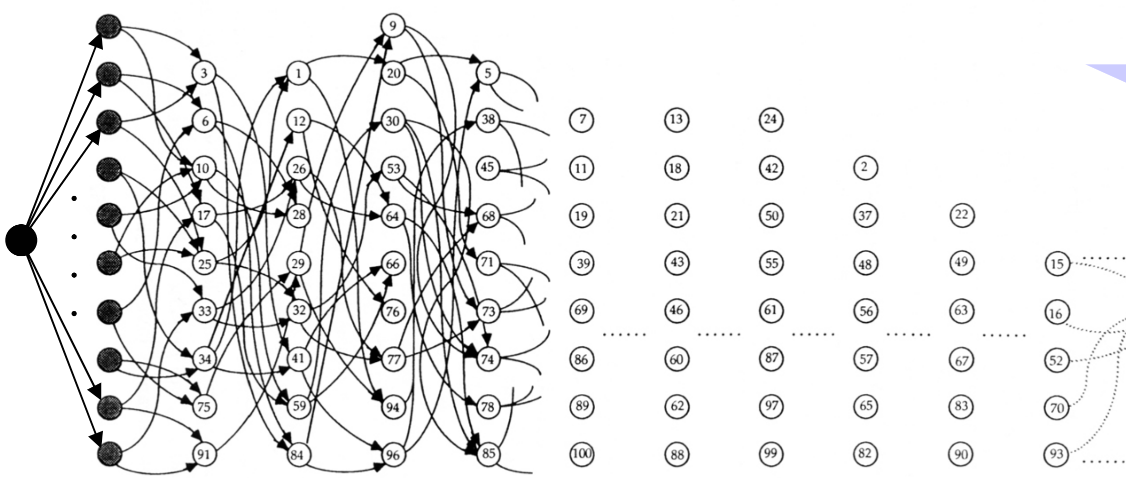
$t = 200$

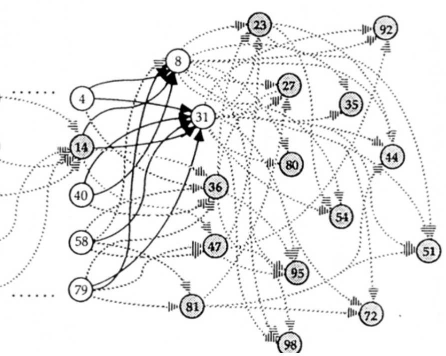
network **structuration** by accretive synfire growth



$t = 4000$

spatially rearranged view

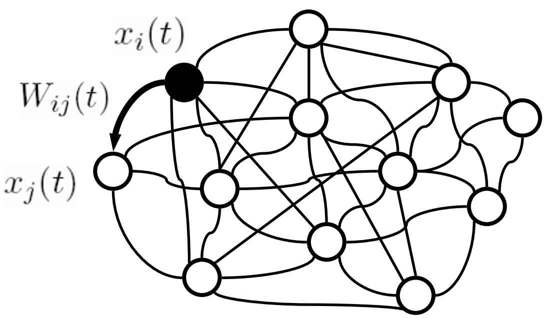




4.a Synfire Chains

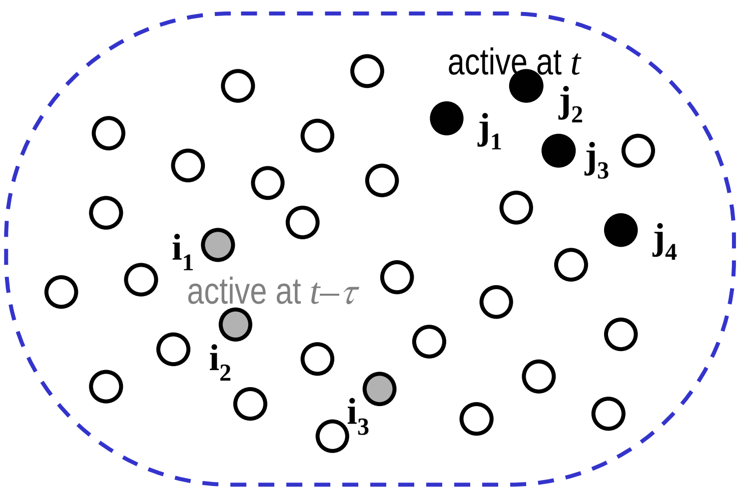
➢ Rule A: neuronal activation

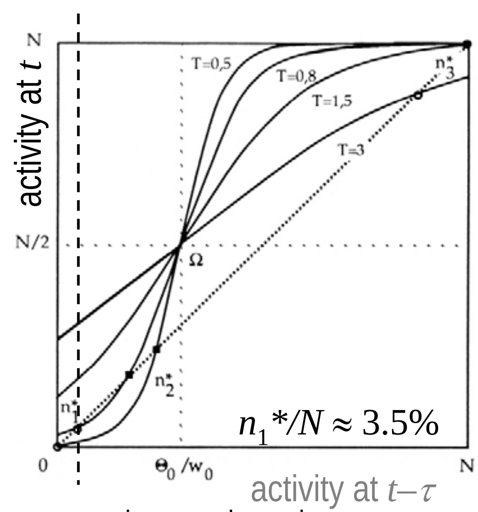
- ✓ we consider a network of simple binary units obeying a *LNP spiking dynamics* on the 1ms time scale (similar to “fast McCulloch & Pitts”)

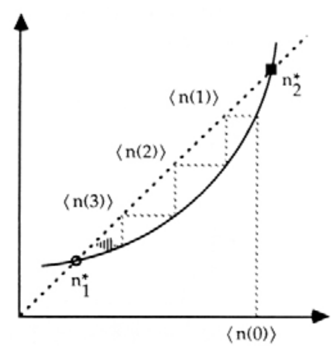


$$P[x_j(t) = 1] \;=\; \frac{1}{\underbrace{1 + e^{-(V_j(t) - \theta_j)/T}}_{V_j(t) \;=\; \sum_i W_{ij}(t)\, x_i(t - \tau_{ij})}}$$

- ✓ initial activity mode is stochastic at a low, stable average firing rate, e.g., $\langle n \rangle \,/\, N \approx$ 3.5% active neurons with $W = .1$, $\theta = 3$, $T = .8$







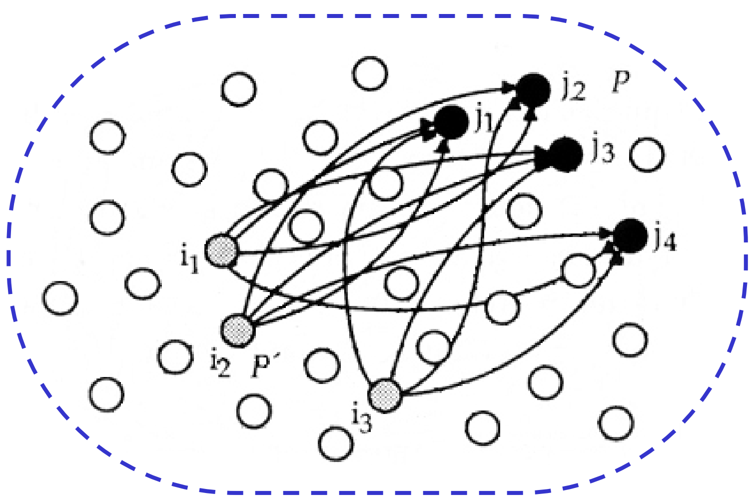
4.a Synfire Chains

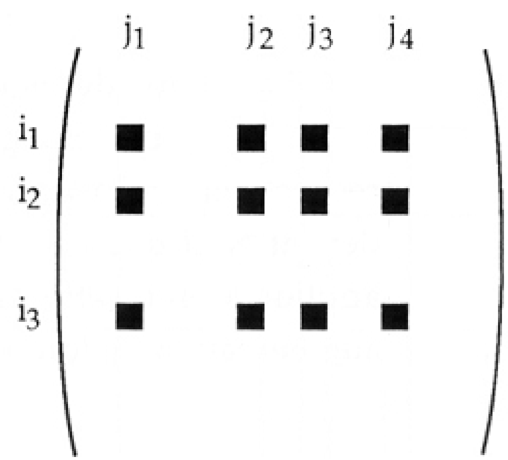
➢ Rule B: synaptic cooperation

- ✓ the weight variation depends on the *temporal correlation* between pre and post neurons, in a Hebbian or “binary STDP” fashion

$$W_{ij}(t) \;=\; W_{ij}(t-1) \;+\; B_{ij}(t) \;\begin{cases} x_i(t-\tau_{ij})=1,\; x_j(t)=1 & \Rightarrow \quad B_{ij}(t) \;=\; +\alpha \\ x_i(t-\tau_{ij})=1,\; x_j(t)=0 & \Rightarrow \quad B_{ij}(t) \;=\; -\beta \\ x_i(t-\tau_{ij})=0,\; x_j(t)=1 & \Rightarrow \quad B_{ij}(t) \;=\; -\beta \\ x_i(t-\tau_{ij})=0,\; x_j(t)=0 & \Rightarrow \quad B_{ij}(t) \;=\; 0 \end{cases}$$

- ✓ successful spike transmission events 1→1 are rewarded, thus connectivity “builds up” in the wake of the propagation of activity





B_{ij} matrix with $\beta = 0$

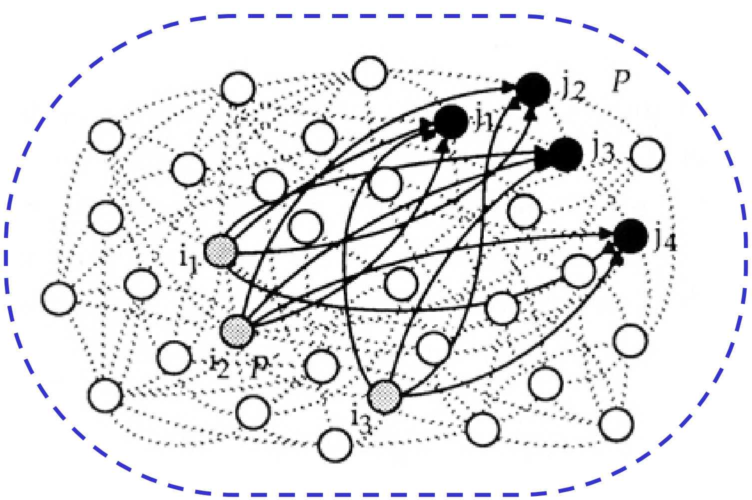
4.a Synfire Chains

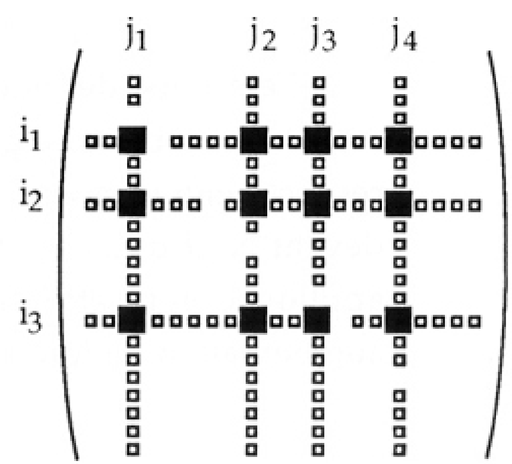
➢ Rule C: synaptic competition

- ✓ to offset the positive feedback between correlations and connections, a constraint *preserves weight sums* at s_0 (efferent) and s'_0 (afferent)

$$W_{ij}(t) = W_{ij}(t-1) + B_{ij}(t) + C_{ij}(t) \quad \left\{ \begin{aligned} C_{ij}(t) &= -\left(\frac{\partial H}{\partial W_{ij}}\right)_{\mathbf{W}(t-1)+\mathbf{B}(t)} \\ H(\mathbf{W}) &= \gamma \sum_i \Big(\sum_j W_{ij} - s_0\Big)^2 + \gamma' \sum_j \Big(\sum_i W_{ij} - s'_0\Big)^2 \end{aligned} \right.$$

- ✓ sum preservation ***redistributes*** synaptic contacts: a rewarded link slightly "depresses" other links sharing its pre- or postsynaptic cell





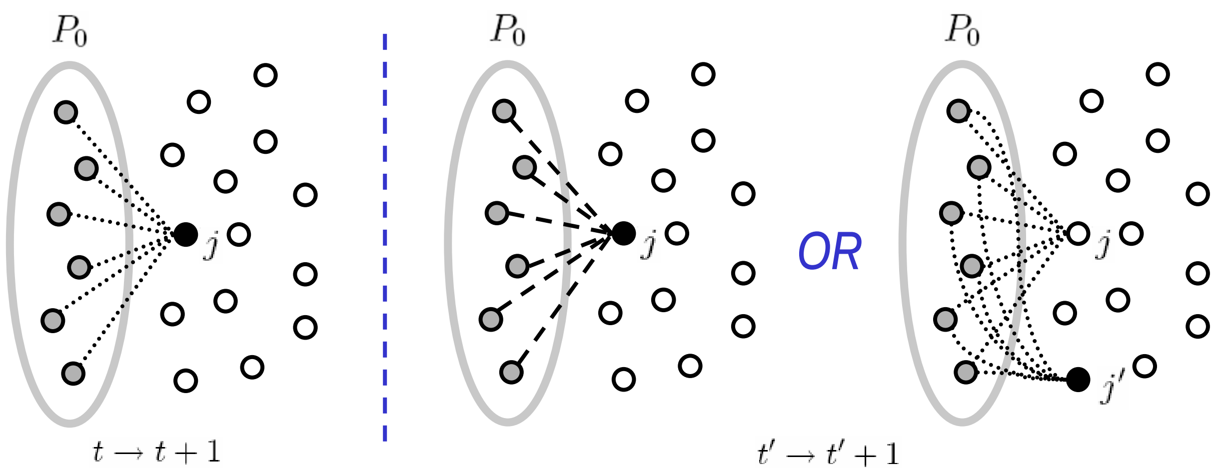
$B_{ij} + C_{ij}$ matrix

4.a Synfire Chains

➢ Development by aggregation

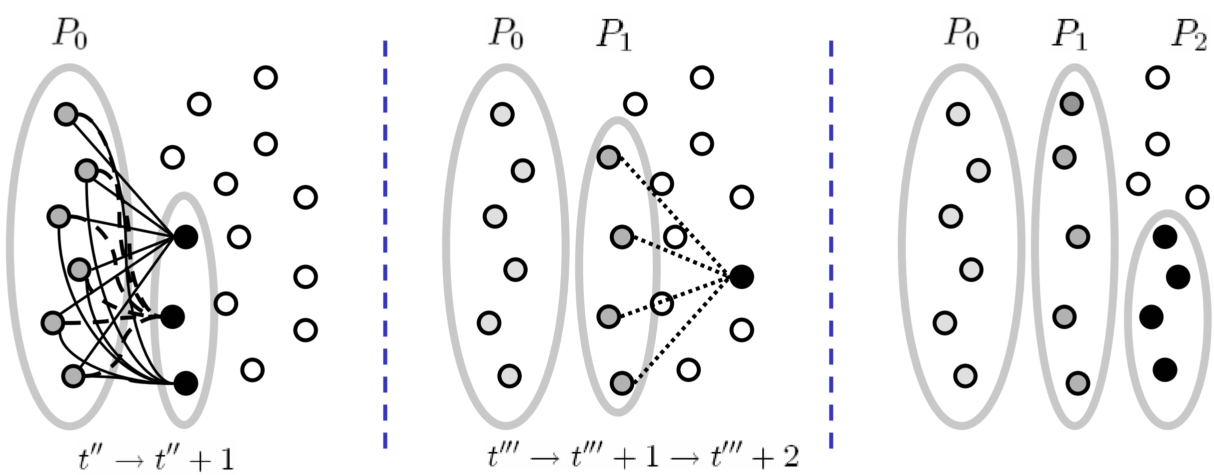
✓ a special group of n_0 *synchronous* cells, P_0, is ***repeatedly*** (yet not necessarily periodically) activated and recruits neurons "downstream"

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

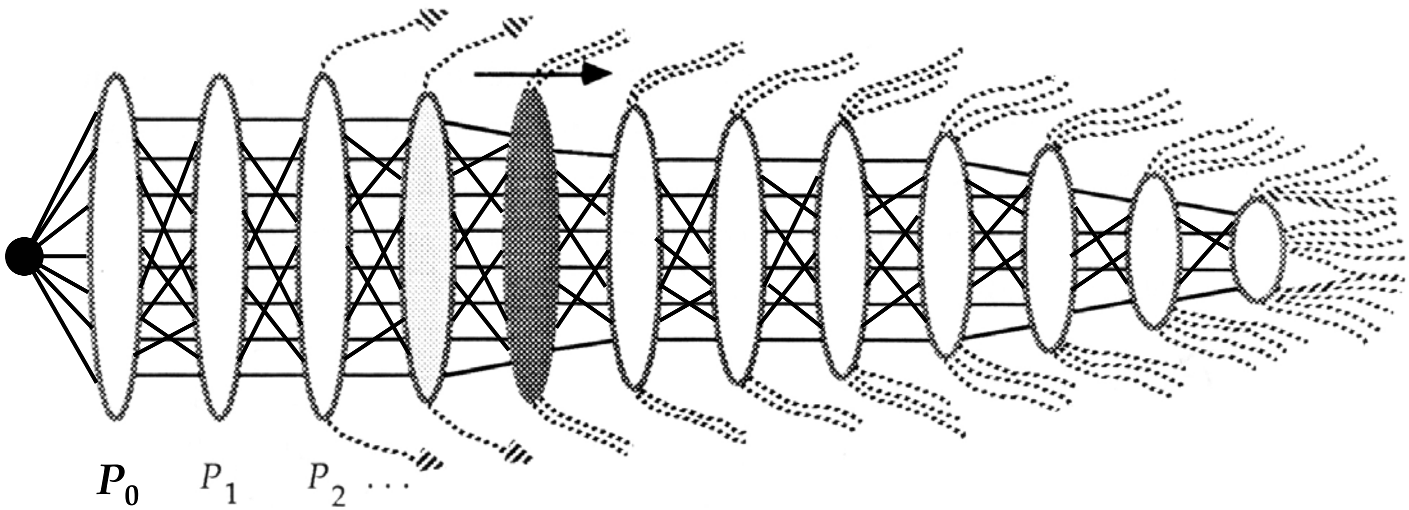


once it reaches a critical mass, P_1 also starts recruiting and forming a new group P_2, etc.

4.a Synfire Chains

➢ A chain grows like an "offshoot"

- ✓ P_0 becomes the root of a developing synfire chain P_0, P_1, P_2 ..., where P_0 itself might have been created by a ***seed neuron*** sending out strong connections and reliably triggering the same group of cells

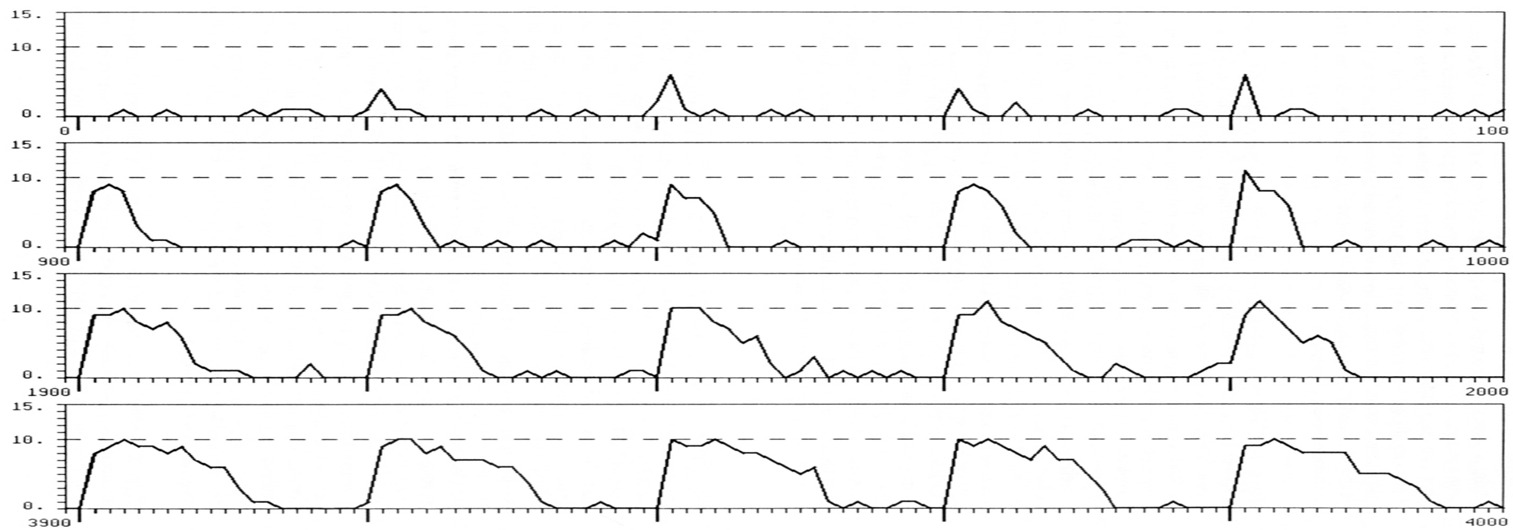


- ✓ the accretion process is not strictly iterative: groups form over broadly overlapping periods of time: as soon as group P_k reaches a critical mass, its activity is high enough to recruit the next group P_{k+1}
- ✓ thus, the ***chain typically lengthens before it widens*** and presents a "beveled head" of immature groups at the end of a mature trunk

4.a Synfire Chains

➢ Evolution of total activity

✓ global activity in the network, revealing the chain's *growing profile*



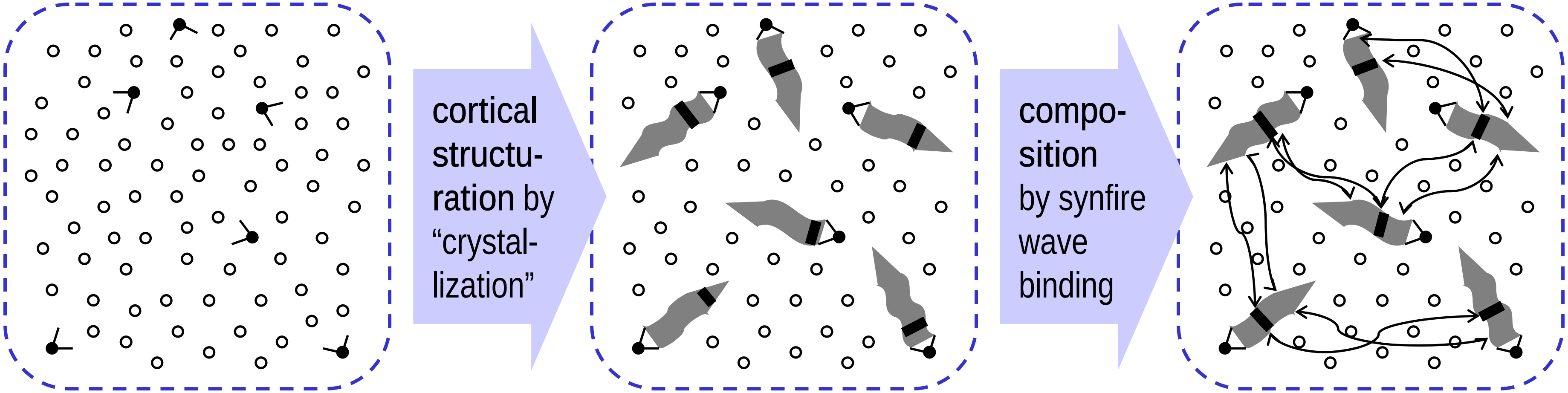
✓ *other examples* of chains (p: probability that connection $i \to j$ exists)

s_0	n_0	p	$n_0 \to n_1 \to n_2 \to n_3$ ...
7	5	1	(5) → 7 → 7 → 7 → 7 → 6 → 4 ...
7.5	4	1	(4) → 7 → 8 → 7 → 7 ...
10	15	1	(15) → 14 → 13 → 12 → 11 → 10 → 9 → 8 → 6 → 7 → 7 → 5 → 4 ...
7	15	1	(15) → 12 → 10 → 8 → 7 → 7 → 7 → 7 → 7 → 6 → 5 → 2 ...
8	12	1	(12) → 11 → 10 → 9 → 8 → 8 → 8 → 8 ...
8	10	.5	(10) → 14 → 13 → 13 → 13 → 11 → 5 ...
8	10	.8	(10) → 9 → 8 → 9 → 9 → 8 → 8 → 4 ...

4.a Synfire Chains

➢ 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

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

4.a Synfire Chains

Other synfire chain references

- A. Aertsen, Universität Freiburg
  - Diesmann et al. (1999): stable propagation of precisely synchronized APs happens despite noisy dynamics
- C. Koch, Caltech
  - Marsalek et al. (1997): preservation of highly accurate spike timing in cortical networks (macaque MT area), explained by analysis of output/input jitter in I&F model
- R. Yuste, Columbia University
  - Mao et al. (2001): recording of spontaneous activity with statistically significant delayed correlations in slices mouse visual cortex, using calcium imaging
  - Ikegaya et al. (2004): “cortical songs” in vitro and in vivo (mouse and cat visual cortex)
- E. Izhikevich, The Neurosciences Institute
  - Izhikevich, Gally and Edelman (2004): self-organization of spiking neurons in a biologically detailed “small-world” model of the cortex

Toward a Fine-Grain Mesoscopic Neurodynamics

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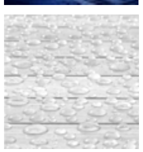
a. The self-made tapestry of synfire chains

b. Waves in a morphodynamic pond



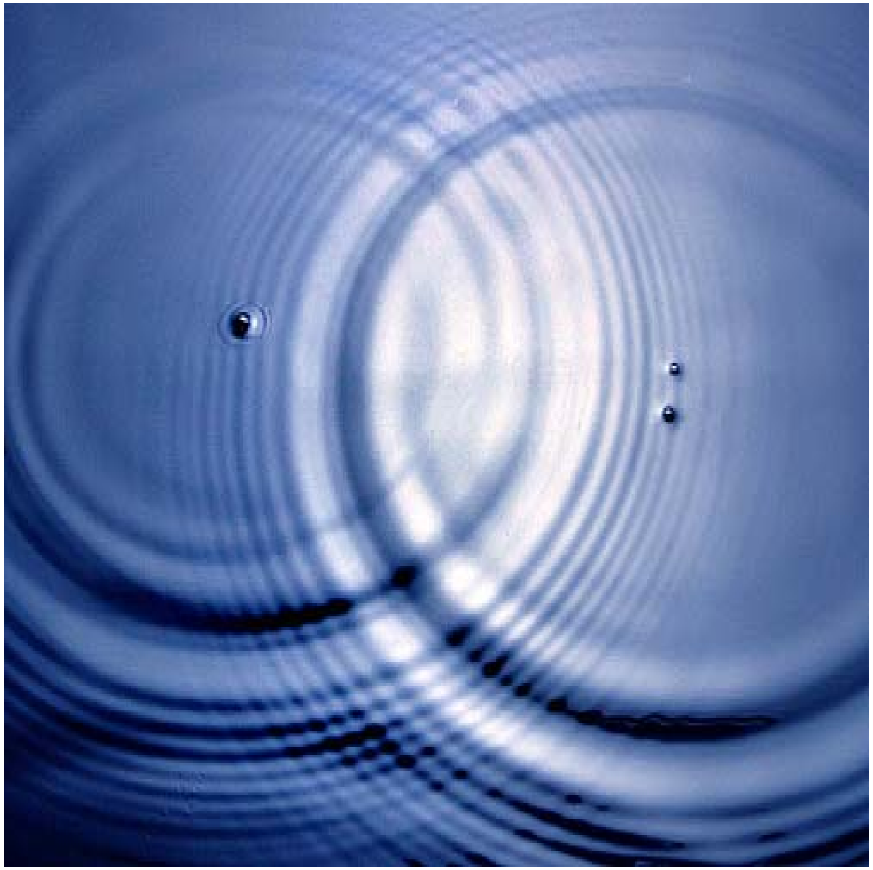
c. Lock-and-key coherence in Recurrent Asynchronous Irregular Networks (RAIN)

5. A Multiscale Perspective on Neural Causality

4. Mesoscopic Neurodynamics

b) Waves in a morphodynamic pond

→ *STPs envisionned as excitable media, at criticality*

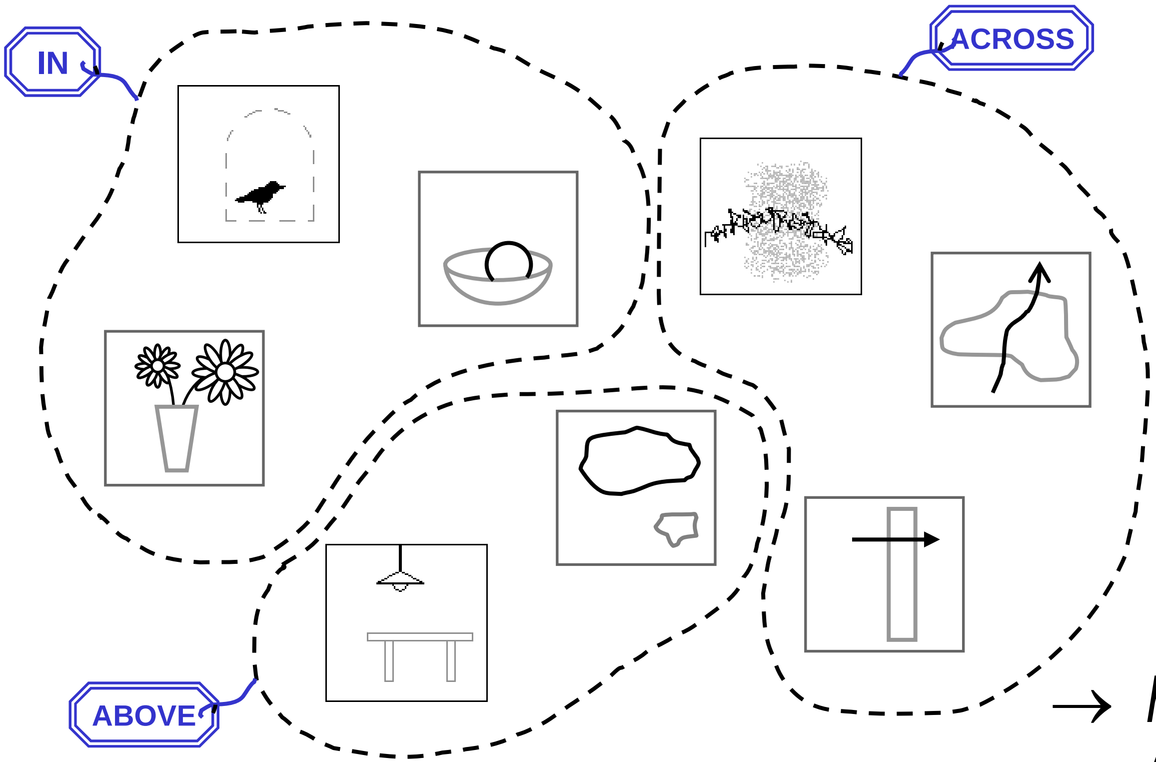


Doursat & Petitot (1997, 2005)

4.b Morphodynamic Waves

➢ Linguistic categories: the emergence of a symbolic level

✓ we can map an infinite continuum of scenes to a few spatial labels



perception → language
continuous → discrete
physical, dynamical → symbolic, logic

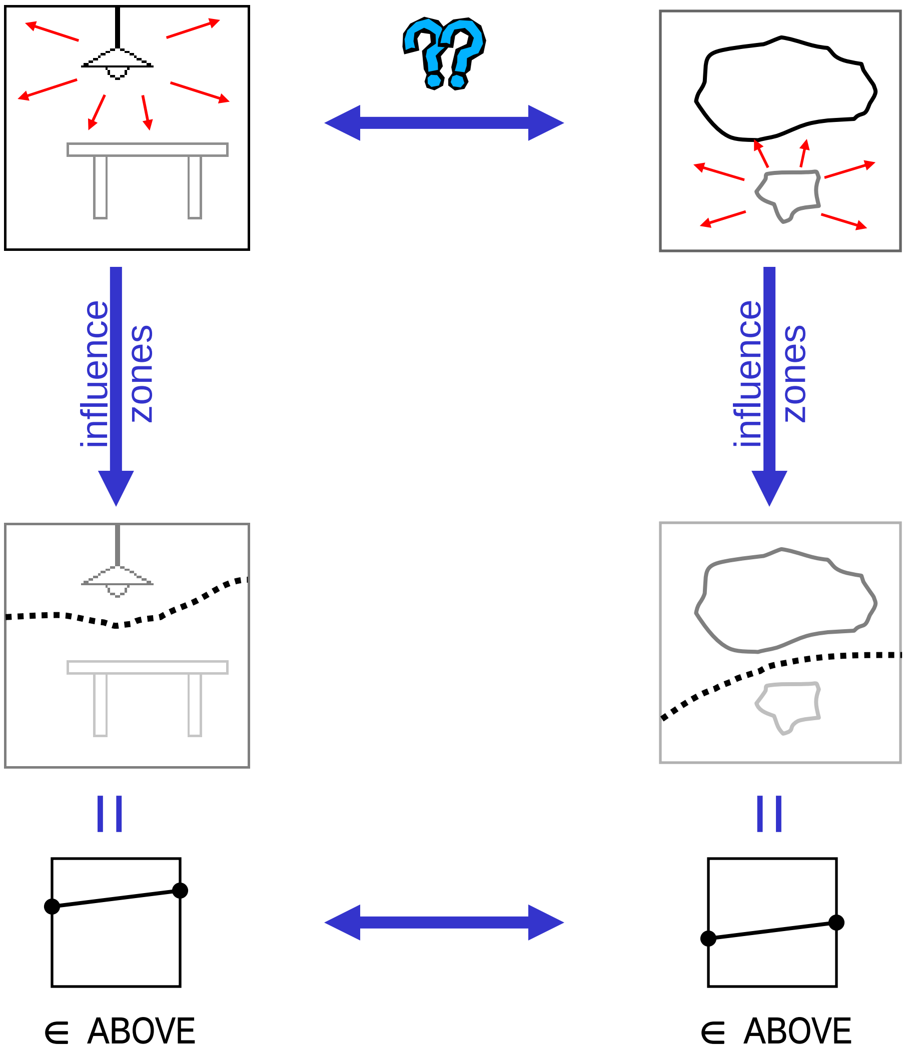
→ *how are these transforms accomplished by the brain?*

4.b Morphodynamic Waves

➢ The path to invariance: drastic morphological transforms

- ✓ scenes representing the same **spatial category** are not directly similar

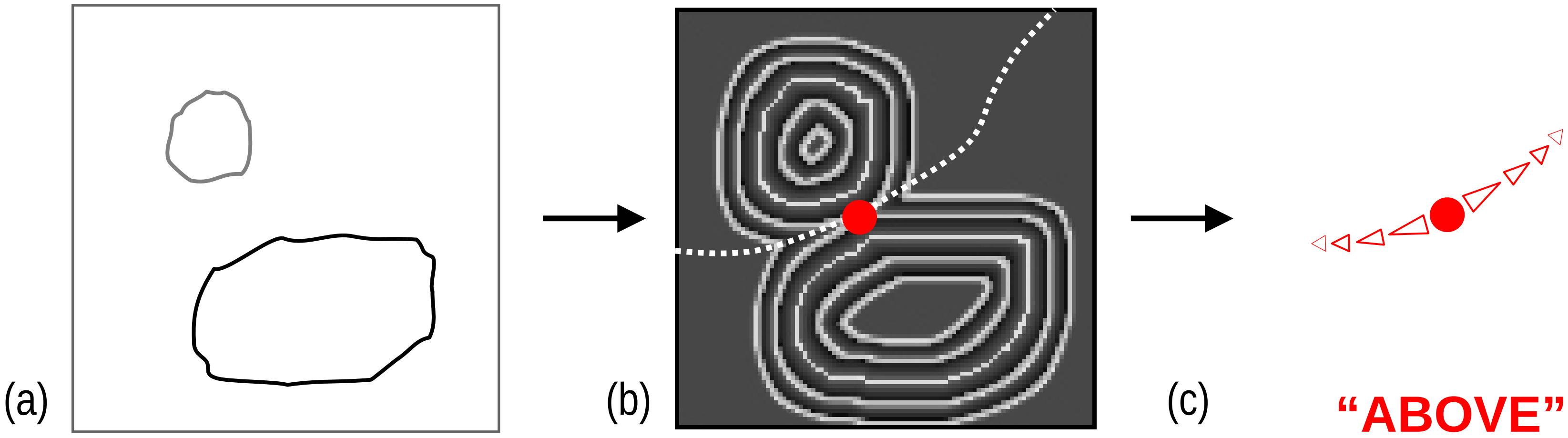
- ✓ what can be compared, however, are virtual structures generated by morphological transforms



4.b Morphodynamic Waves

➢ Proposal: categorizing by morphological neurodynamics

- ✓ discrete *symbolic* information could *emerge* in the form of *singularities* created by pattern formation in a large-scale complex dynamical system (namely, the cortical substrate)

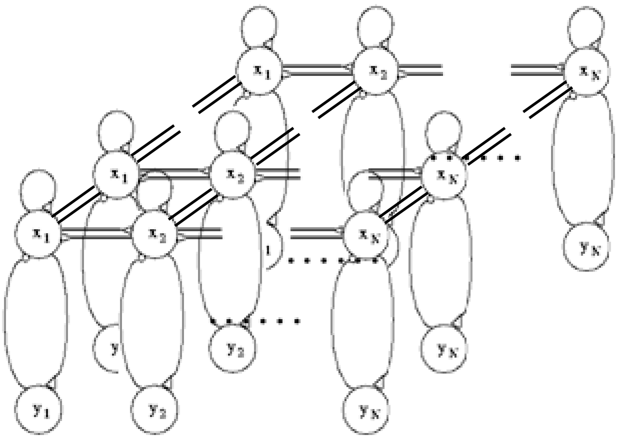


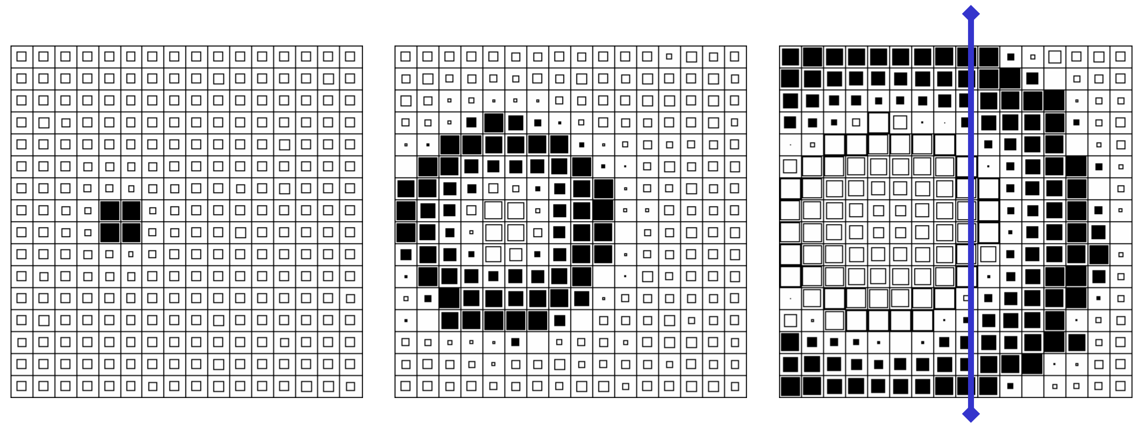
- ✓ for ex: in *traveling waves*, singularities are collision points
- ✓ (a) under the influence of an external input, (b) the internal dynamics of the system (c) spontaneously creates singularities that are characteristic of a symbolic category

4.b Morphodynamic Waves

➢ Spiking neural networks as excitable media

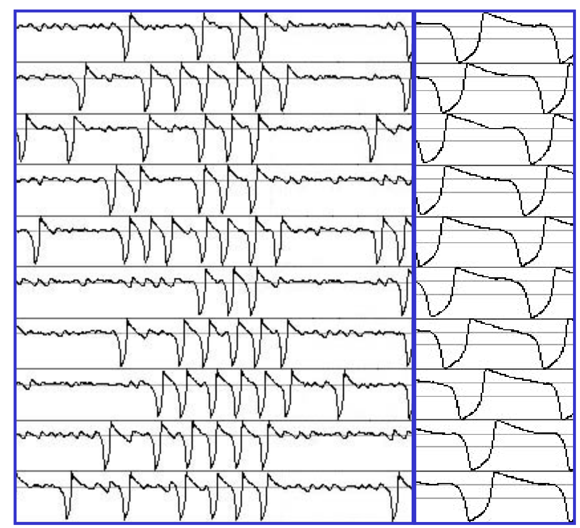
- ✓ ex: “grass-fire” wave on a lattice of Bonhoeffer-van der Pol units





- ✓ *criticality* in neural dynamics: when slightly perturbed by an input, the network quickly transitions into a new regime of spatiotemporal order

- ✓ the structure and singularities of this regime are *influenced* by the input



4.b Morphodynamic Waves

- Summary: key points of the morphodynamic hypothesis
  - ✓ input stimuli literally “boil down” to a handful of critical features through the intrinsic pattern formation dynamics of the system
  - ✓ these singularities reveal the characteristic “signature” of the stimulus’ category (e.g., the spatial relationship represented by the image)

  → *key idea: spatiotemporal singularities are able to encode a lot of the input’s information in an extremely compact and localized manner*

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a. The self-made tapestry of synfire chains

b. Waves in a morphodynamic pond

c. Lock-and-key coherence in Recurrent Asynchronous Irregular Networks (RAIN)

5. A Multiscale Perspective on Neural Causality

4. Mesoscopic Neurodynamics

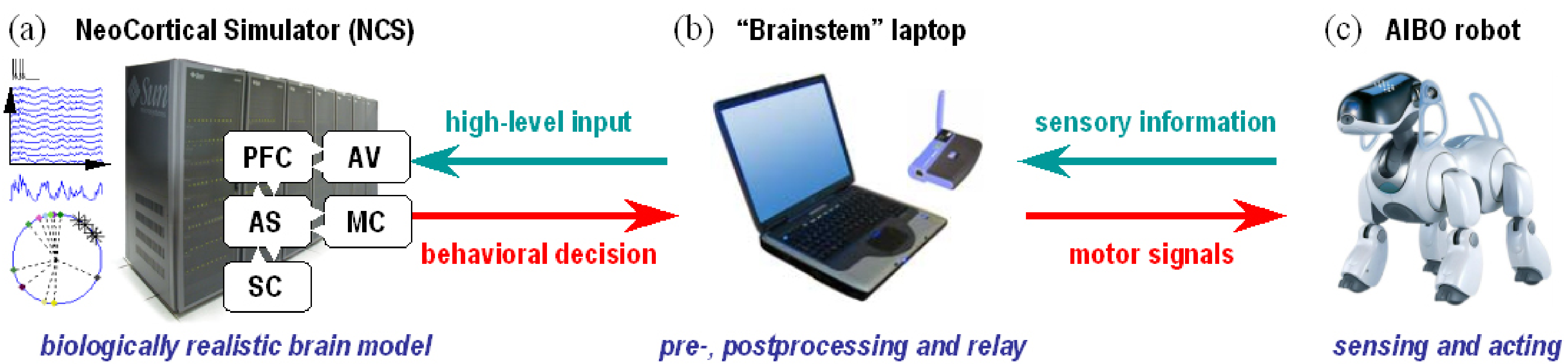
c) Lock-and-key coherence in RAIN Networks

→ *pattern recognition by specialized STPs*

Doursat & Goodman (2006), Goodman, Doursat, Zou et al. (2007)

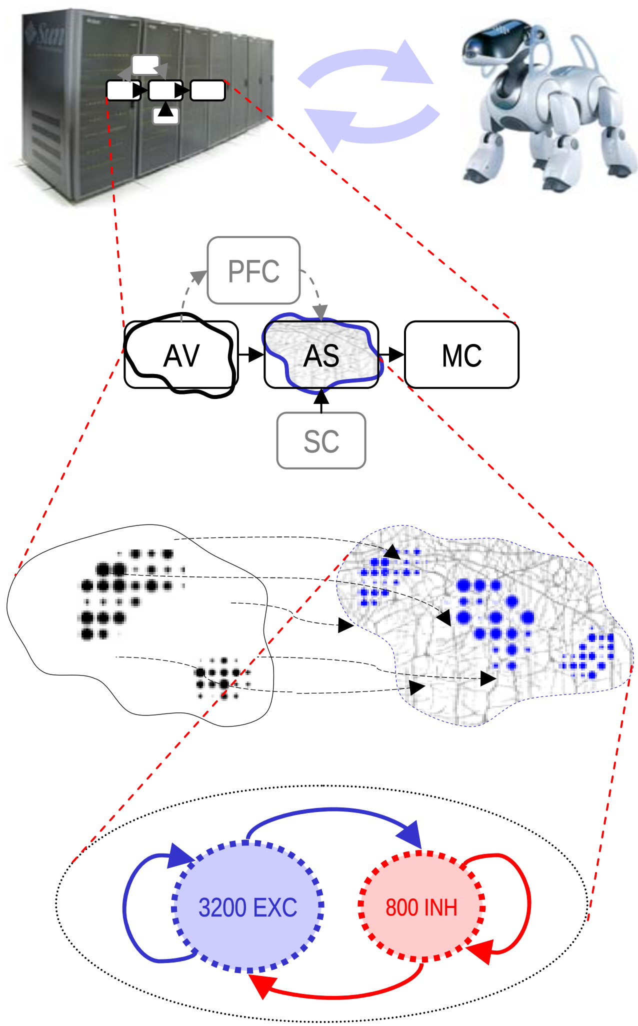
4.c RAIN Coherence

- ➢ Complete sensorimotor loop between cluster and robot
  - ✓ original attempt to implement a real-time, embedded neural robot
  - c) a robot (military sentry, industrial assistant, etc.) interacts with environment and humans via sensors & actuators
  - a) NeoCortical Simulator (NCS) software runs on computer cluster; contains the brain architecture for decision-making and learning
  - b) "brainstem" laptop brokers WiFi connection: transmits multimodal sensory signals to NCS; sends actuator commands to robot



4.c RAIN Coherence

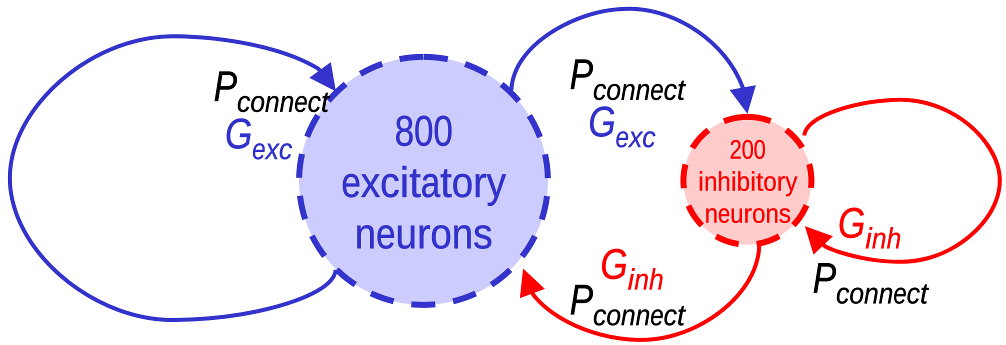
➢ Core of brain model: mesoscopic assemblies as RAINs

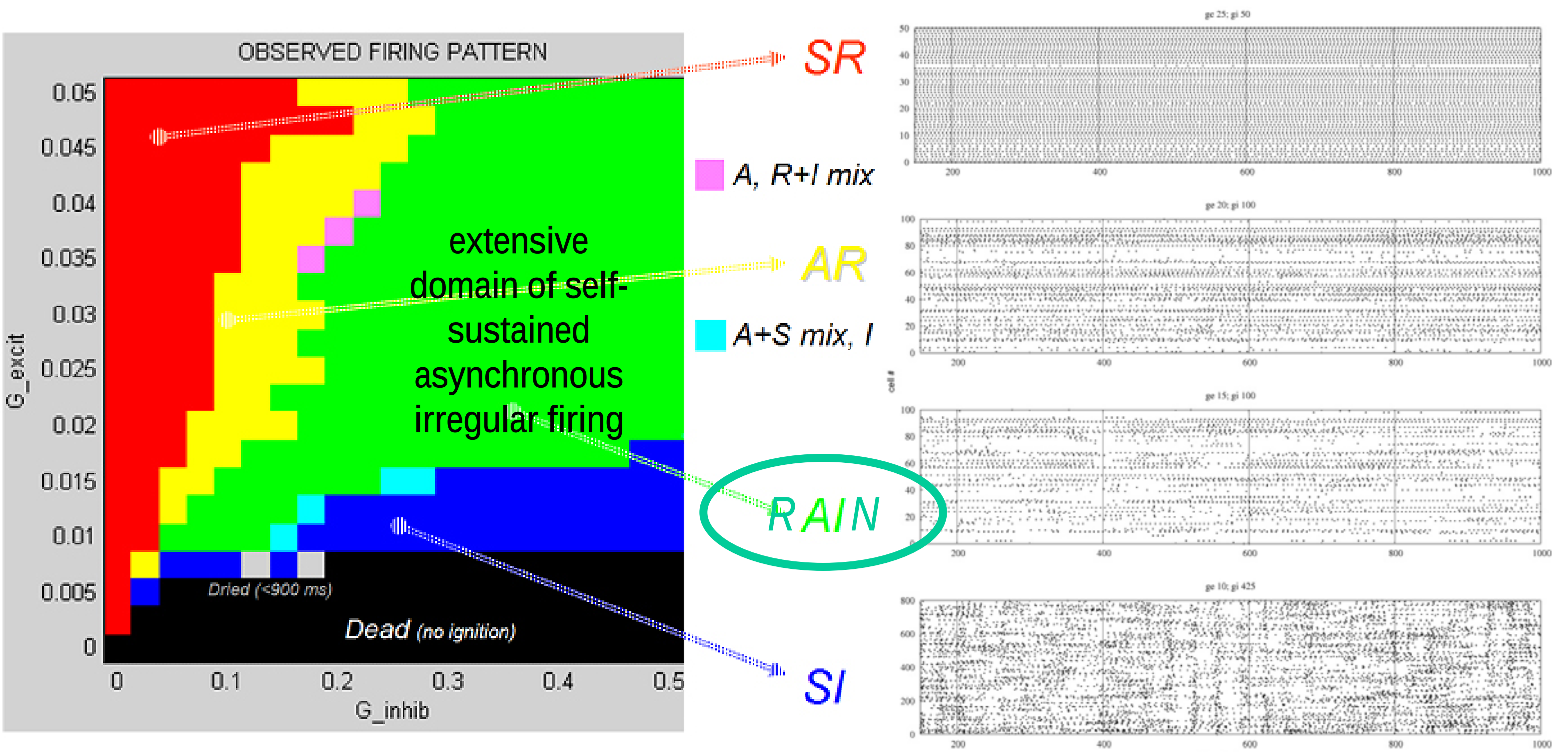


RAIN: Recurrent Asynchronous Irregular Network

4.c RAIN Coherence

- Recurrent Asynchronous Irregular Network (RAIN)

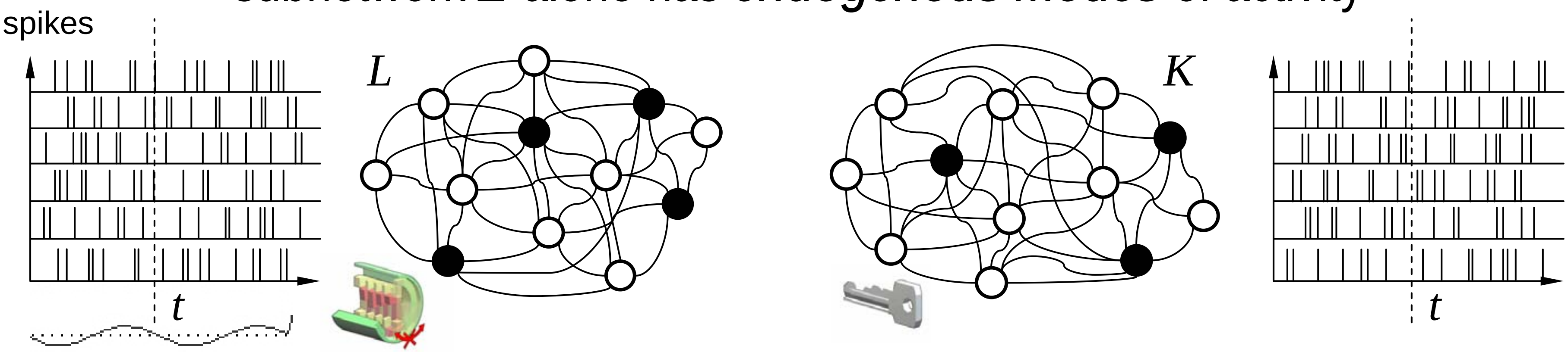




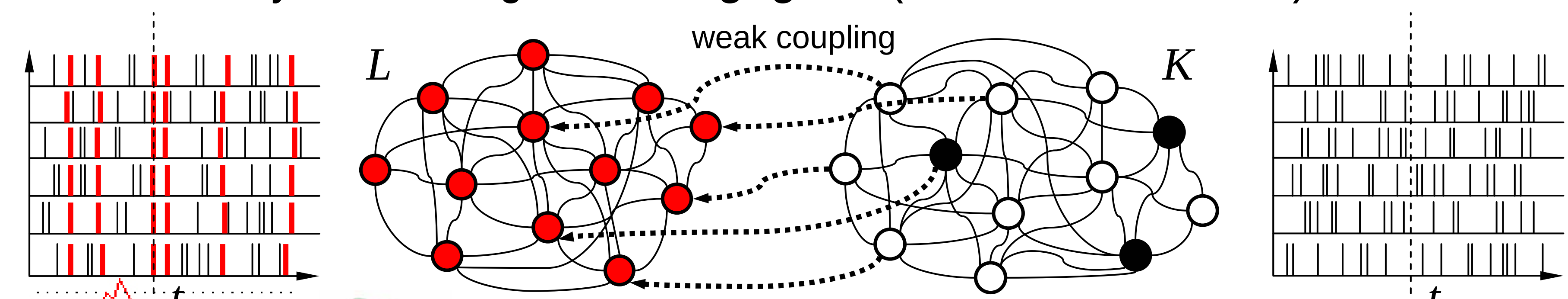
4.c RAIN Coherence

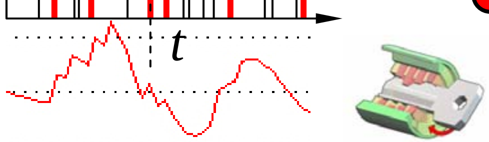
➢ Coherence induction among ongoing active STPs

✓ subnetwork L alone has ***endogenous modes*** of activity



✓ by stimulating L, K "***engages***" (but does not create) L's modes





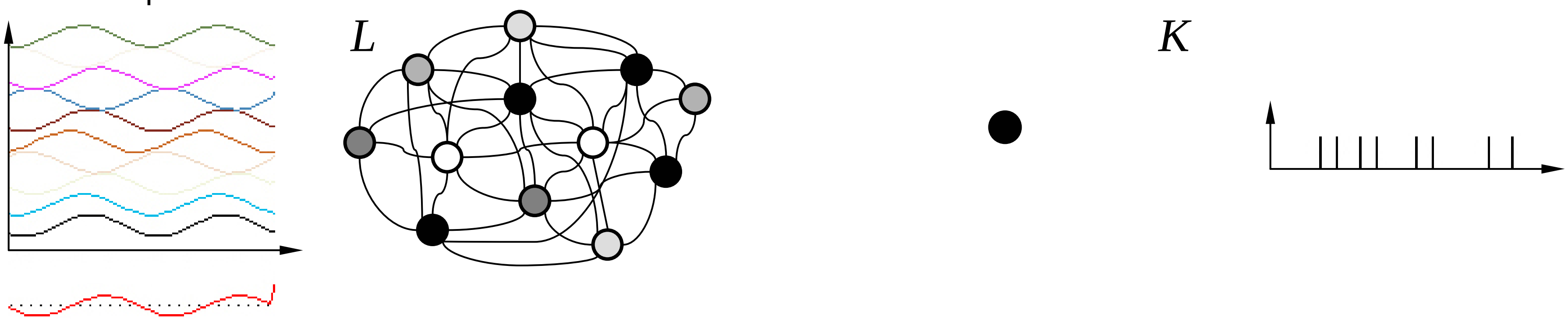
→ *the stimulation induces transient coherence & increased activity*

4.c RAIN Coherence

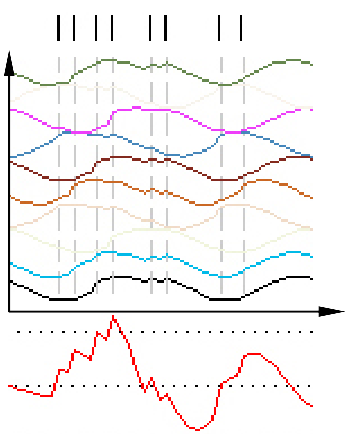
➢ Example 1: simple oscillatory membrane potentials

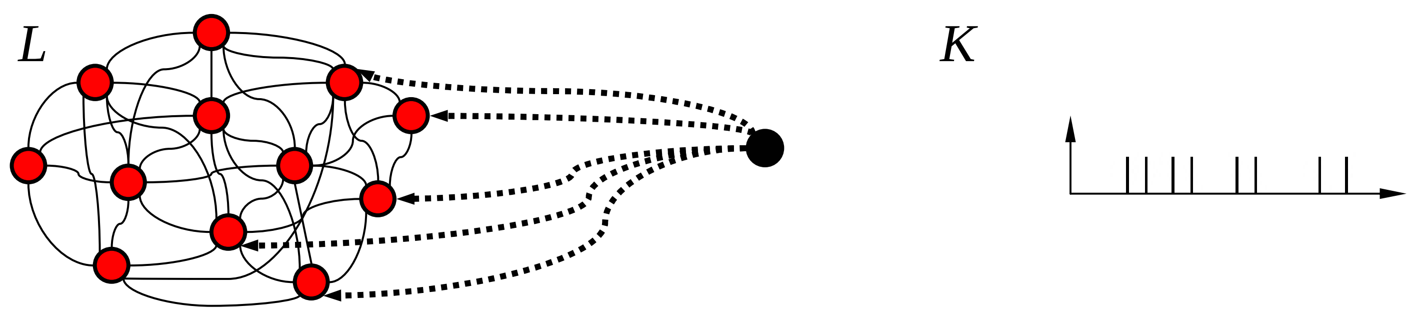
✓ L's modes are phase distributions; K's modes are spike trains

membrane potentials



✓ stimulating L by coupling, K's spikes pull L's phases together





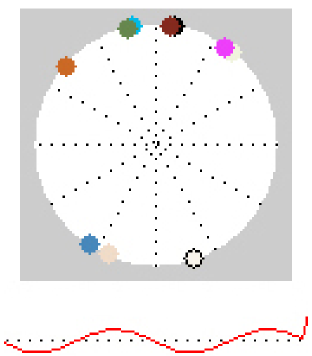
→ *stimulation increases global potential: analog binding*

4.c RAIN Coherence

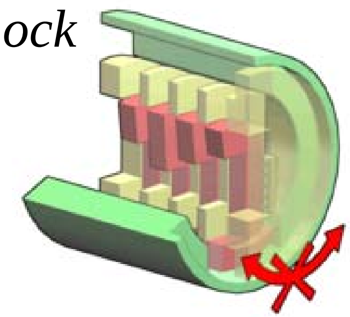
➢ Example 1: locksmithing analogy

✓ *Lock* is a set of discs at varying heights; *Key*, a series of notches

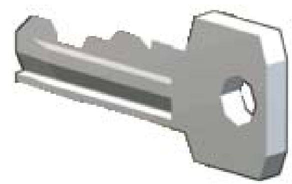
potential phases

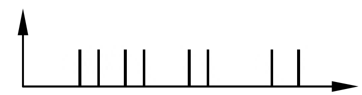


Lock

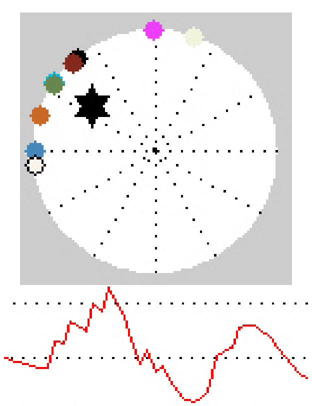


Key

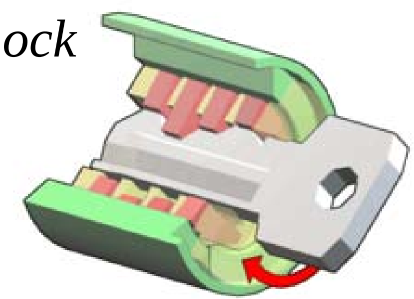




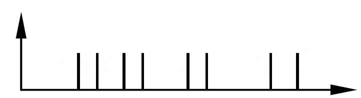
✓ *Key*'s notches raise *Lock*'s discs just enough to release them



Lock



Key

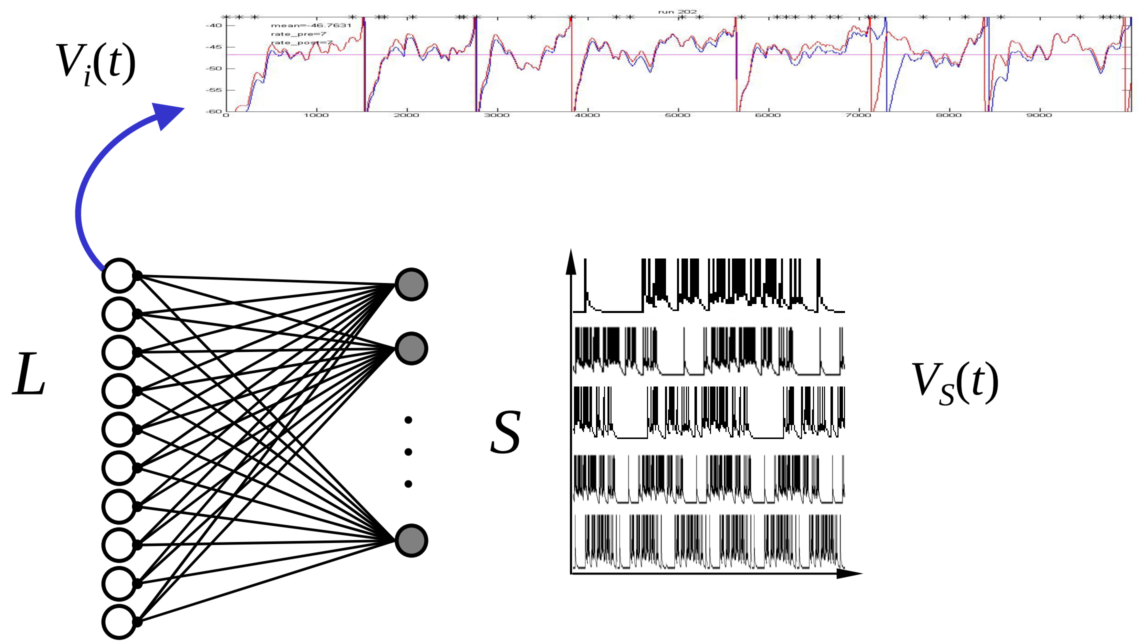


→ *the key opens the tumbler lock*

4.c RAIN Coherence

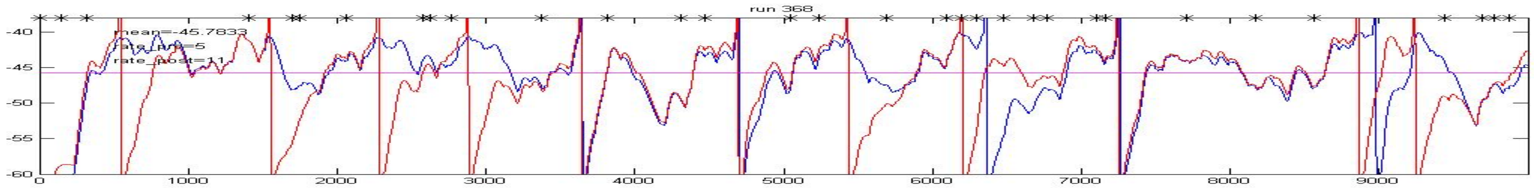
➢ Example 2: multifrequency lock

- ✓ here, background source cells with different bursting periods drive the lock assembly
- ✓ this creates in L-cells complex subthreshold potential landscapes, possibly with low frequency firing activity

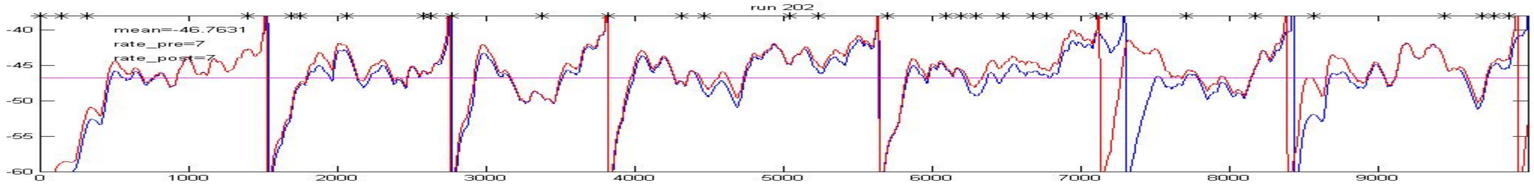


4.c RAIN Coherence

- Example 2: MF lock excited by train of spike
  - ✓ example of strongly resonant L-cell (6 more spikes when stimulated by K):

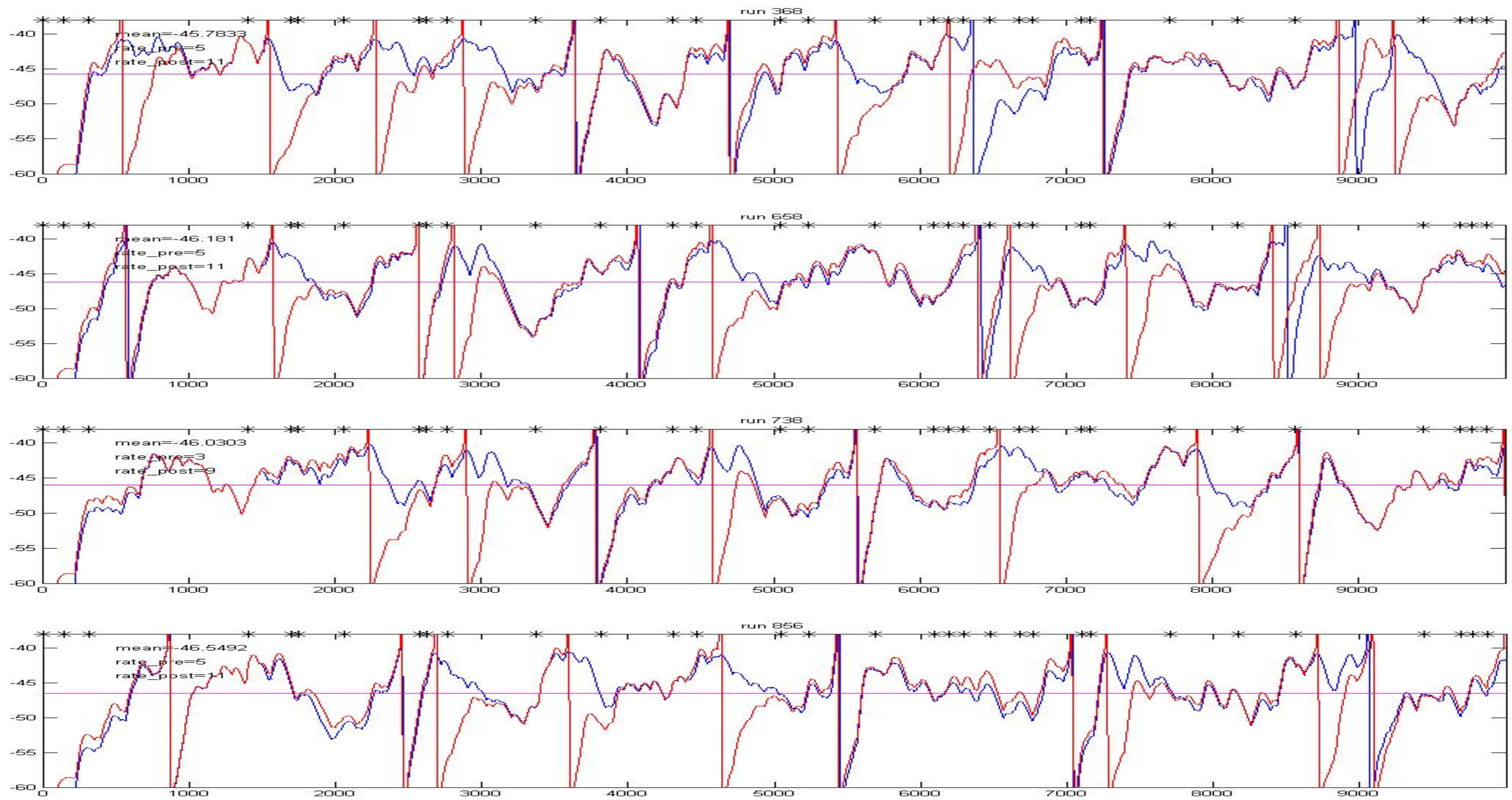


  - ✓ example of nonresonant L-cell (0 more spikes when stimulated by K):



4.c RAIN Coherence

- Example 2: MF lock excited by train of spike (cont'd)
  - ✓ other examples of L-cells strongly excited by the K spikes

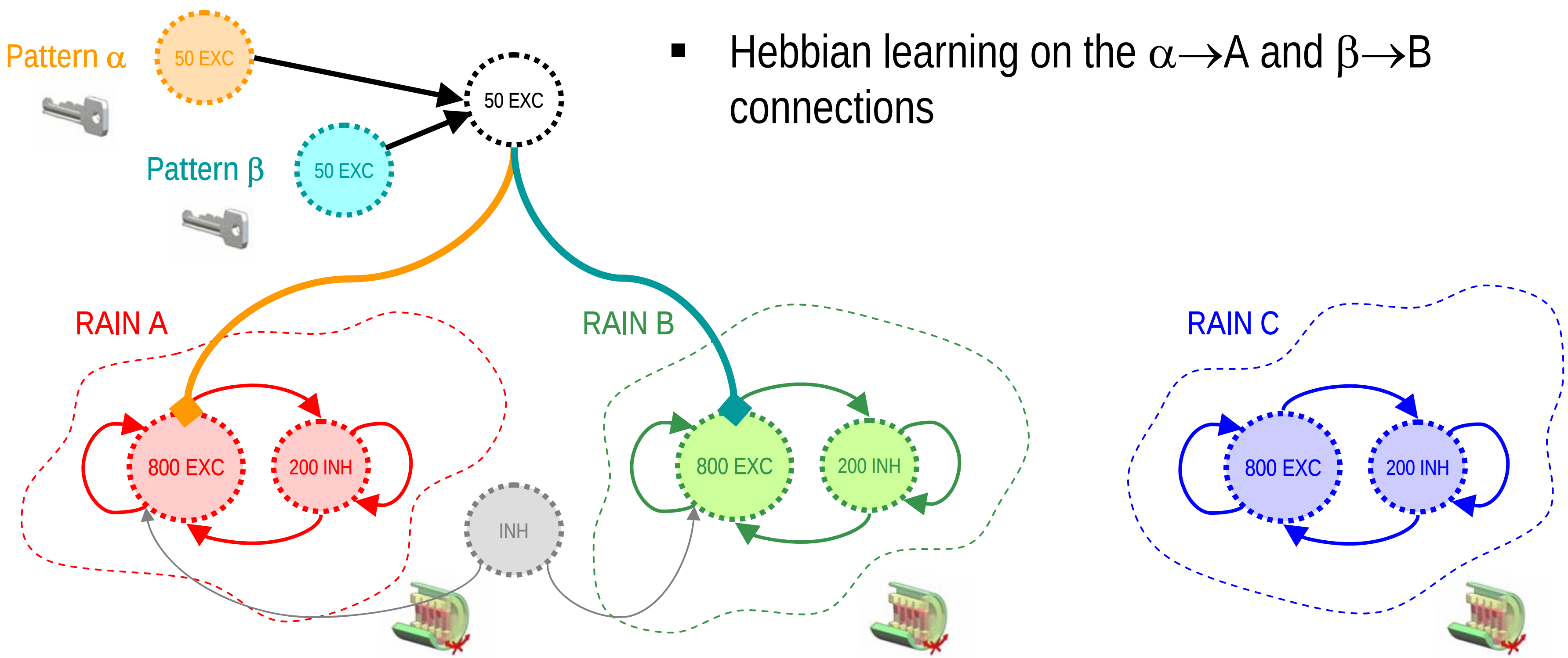


4.c RAIN Coherence

➢ Example 3: RAIN networks

✓ multi-RAIN discriminate Hebbian/STDP learning (setup)

- 2 RAINs, A and B stimulated by 2 patterns, α and β (RAIN extracts)
- 1 control RAIN, C (not stimulated) and 1 control pattern γ (not learned)
- 1 inhibitory pool common to A and B

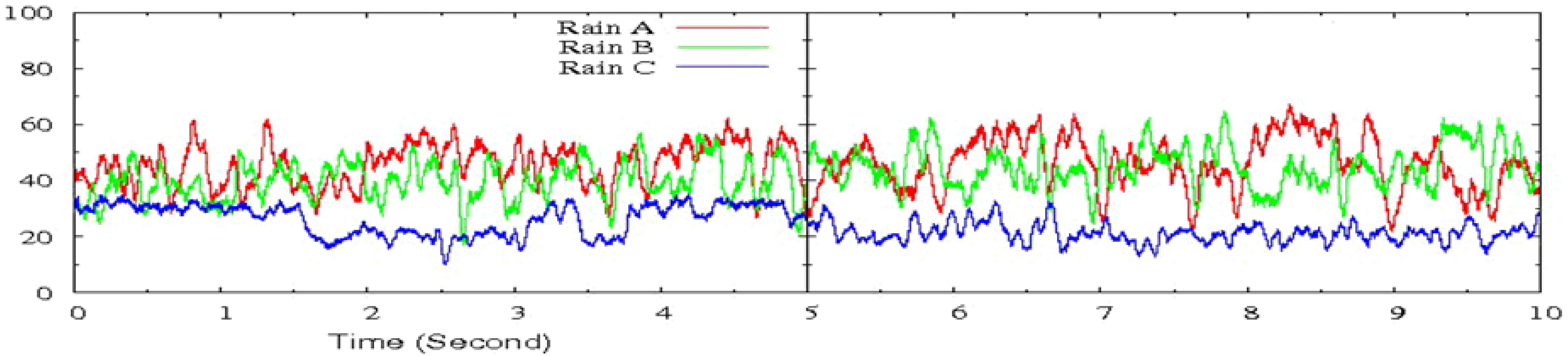


- Hebbian learning on the $\alpha \rightarrow A$ and $\beta \rightarrow B$ connections

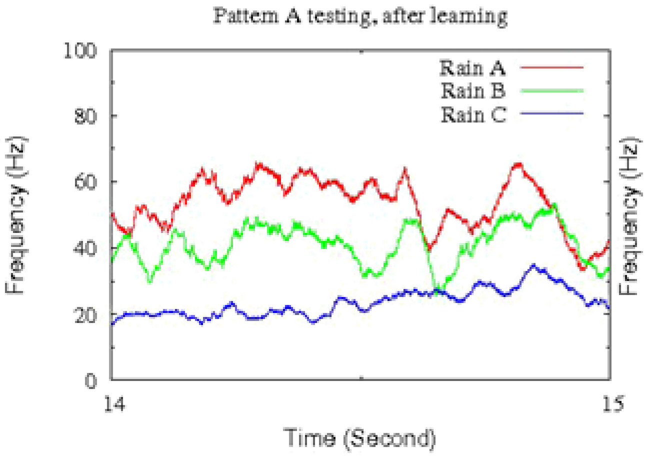
4.c RAIN Coherence

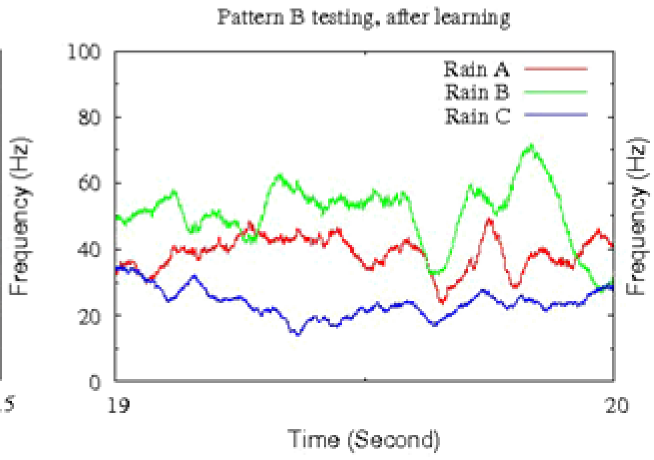
➢ Example 3: RAIN networks (results)

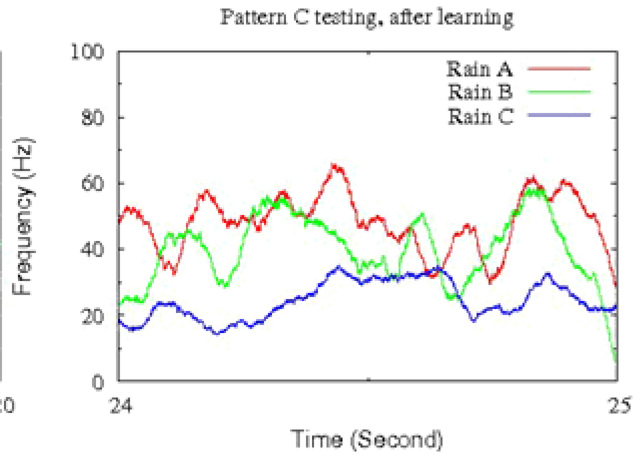
- ✓ training phase: alternating α-learning on A and β-learning on B



- ✓ testing phase: A's (rsp B's) response to α (rsp β) significantly higher







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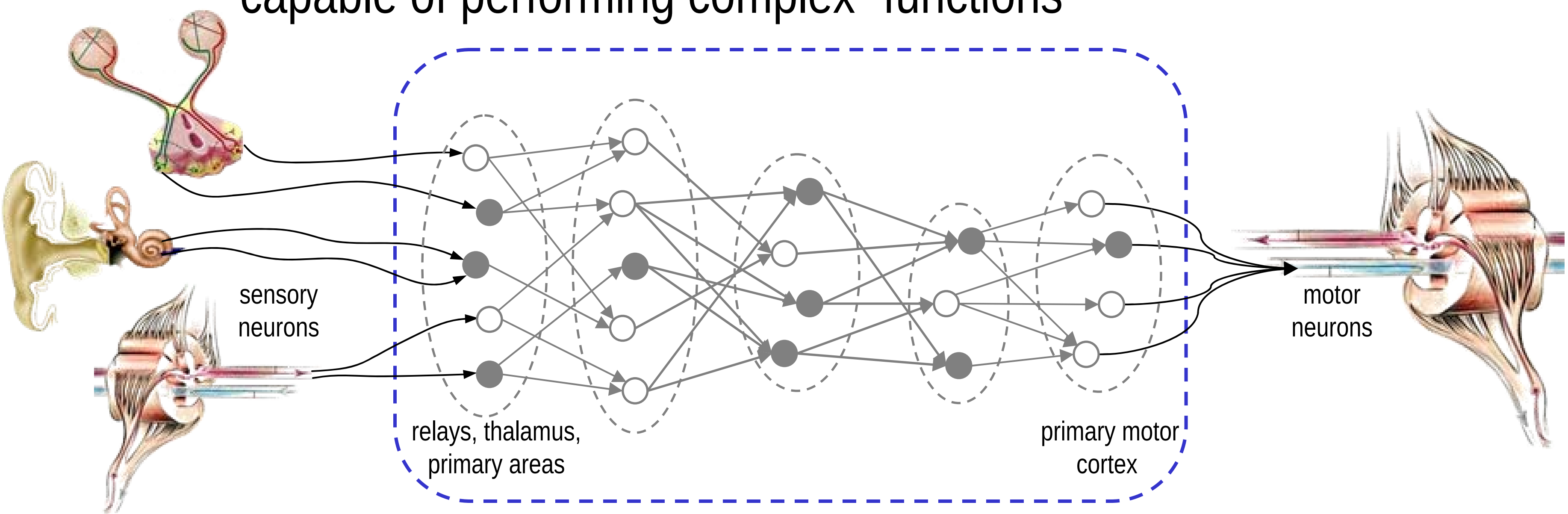
5. **A Multiscale Perspective on Neural Causality**

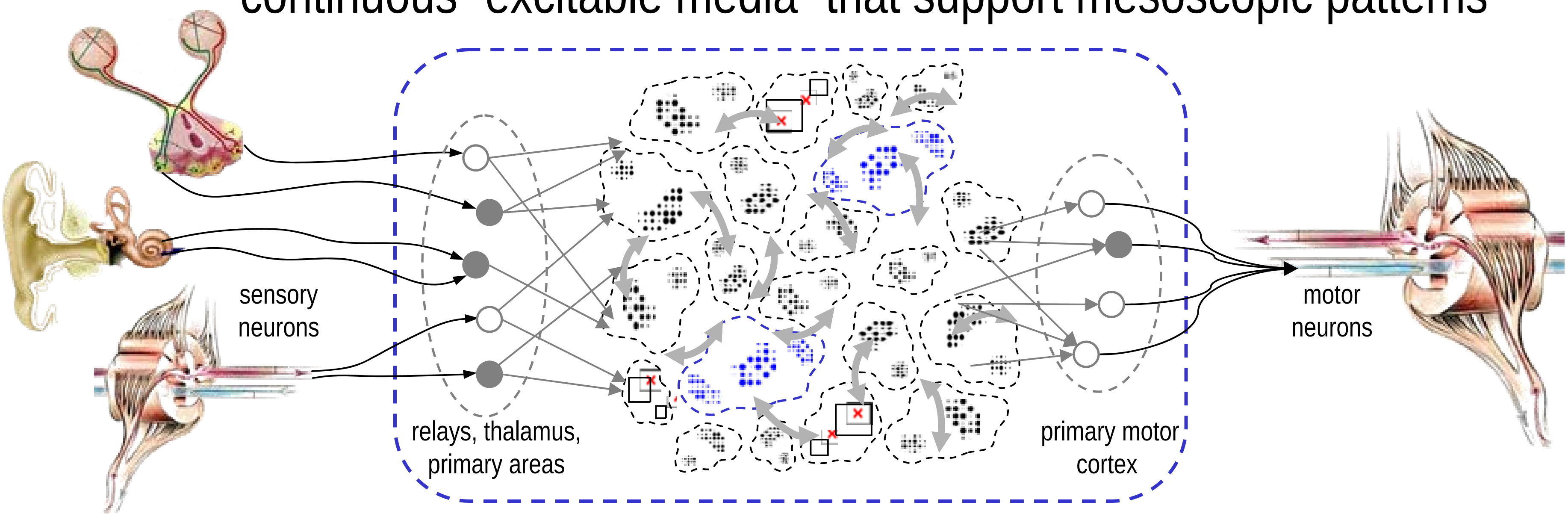
5. Neural Causality

- Old, unfit engineering metaphor: "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. Neural Causality

- New dynamical metaphor: mesoscopic 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 neuron are the substrate of quasi-continuous "excitable media" that support mesoscopic patterns



5. Neural Causality

- Cognitive neurodynamics
  - ✓ Springer journal: “CN is a trend to study cognition from a dynamic view that has emerged as a result of the rapid developments taking place in nonlinear dynamics and cognitive science.”
    - focus on the spatiotemporal dynamics of neural activity in describing brain function
    - contemporary theoretical neurobiology that integrates nonlinear dynamics, complex systems and statistical physics
    - often contrasted with computational and modular approaches of cognitive neuroscience

5. Neural Causality

➢ Field neurodynamics vs. spiking neurodynamics

- ✓ CN also distinguishes three levels of organization (W. Freeman):
  - microscopic – multiple spike activity (MSA)
  - “mesoscopic” – local field potentials (LFP), electrocorticograms (ECoG)
  - macroscopic – brain imaging; metabolic (PET, fMRI), spatiotemporal (EEG)
- ✓ here, the mesoscopic level is based on ***neural fields***:
  - continuum approximation of discrete neural activity by spatial and temporal integration of lower levels → loss of spatial and temporal resolution

→ *at a finer-grain mesoscopic level of description, details of spiking (and subthreshold) patterns are retained: what matters here are the spatiotemporal **“shapes”** of mesoscopic objects*

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