Neural Locks and Keys:
The Mesocircuits of Cognition

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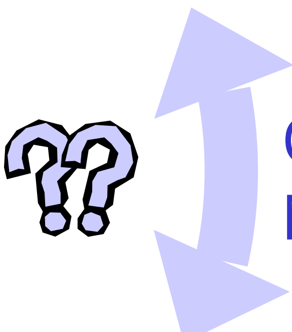
University of Nevada, Reno

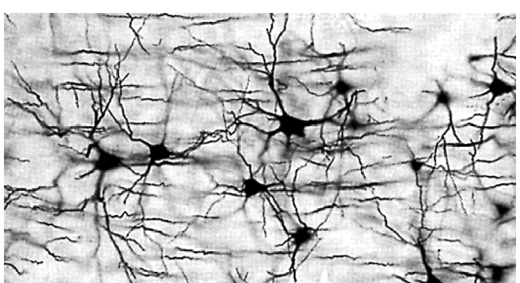
The Mesocircuits of Cognition

__macroscopic__

Artificial
Intelligence



Gap 1:
Modeling



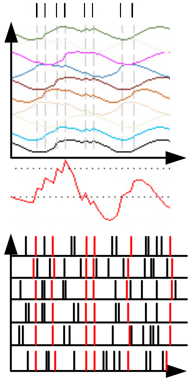
Neural
Networks

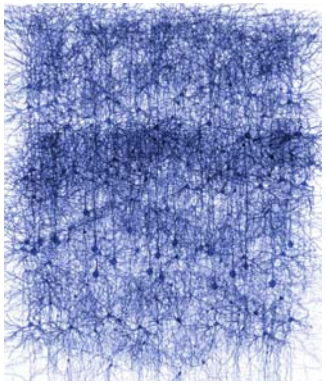
__microscopic__

The Mesocircuits of Cognition

macroscopic

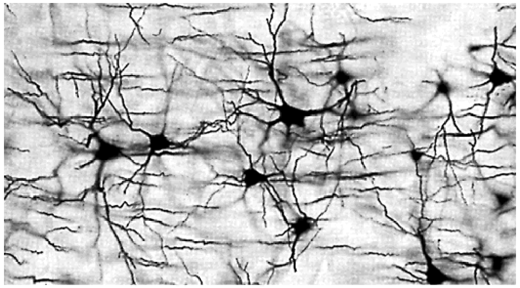
Artificial
Intelligence





mesoscopic

Complex
Neural
Computation



Neural
Networks

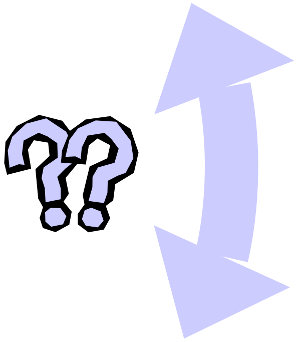
microscopic

The Mesocircuits of Cognition

macroscopic

Super
Computers

Gap 2:
Technology



Embedded
Devices

microscopic

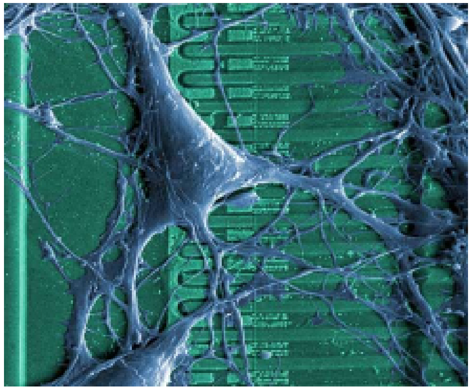
The Mesocircuits of Cognition

macroscopic

Super
Computers

mesoscopic

Analog
VLSI



Embedded
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microscopic

The Mesocircuits of Cognition

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Artificial
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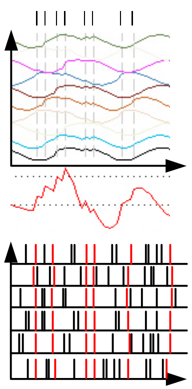
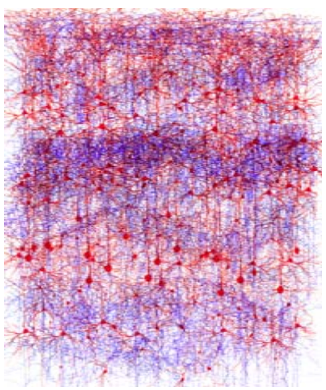
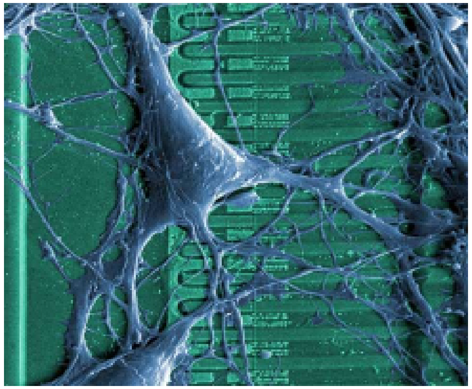


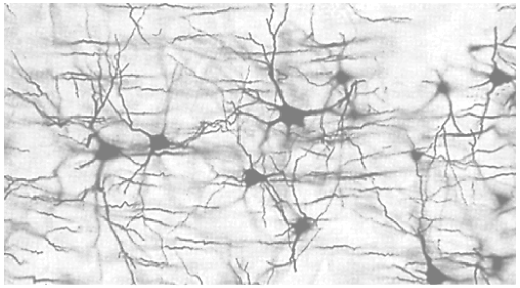


neuromorphic mesocircuits

Complex
Neural
Computation

Analog
VLSI





Neural
Networks

Embedded
Devices

microscopic

The Mesocircuits of Cognition

1. Reconciling Neurobiology & Cognition

   → *Complex Neural Systems*

2. Reconciling Complex Computation & Real-Time, Real-Space, Real-Power

   → *Neuromorphic Analog VLSI*

3. Complex Neural Computation in Analog VLSI

   → *Neuromorphic Mesocircuits*

The Mesocircuits of Cognition

1. Reconciling Neurobiology & Cognition
   a. The Lingering Gap Between AI and Neural Networks
   b. Temporal Coding and Spiking Networks
   c. A Mesoscopic Level of Complex Patterns
   d. Neural Locks and Keys
2. Reconciling Complex Computation & Real Time, Small Space, Low Power
3. Complex Neural Computation in Analog VLSI

1.a The Lingering Gap Between AI and Neural Nets

Brainless Mind vs. Mindless Brain

- 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*
- 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*
- The missing link is a "mesoscopic" level of description

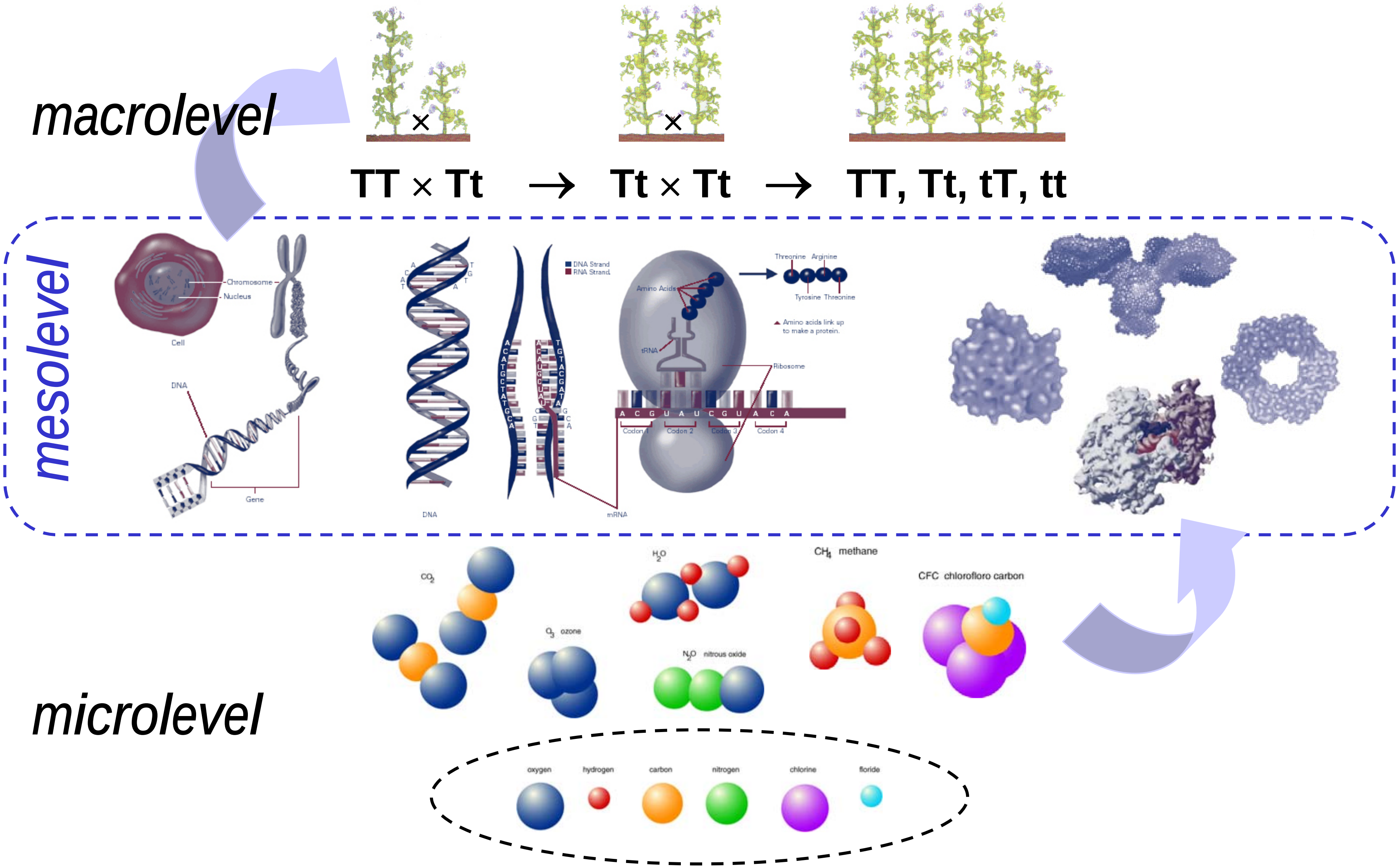
1.a The Lingering Gap Between AI and Neural Nets

Atomless Biology vs. Lifeless Physics

- **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: particles, atoms → quantum rules**
  - ✓ in physics, the foundational entities are elementary particles obeying string theory and quantum equations
  - → *the foundational laws and equations of physics cannot predict and describe the emergence of complex living systems*
- **The missing link is chemistry and molecular biology**

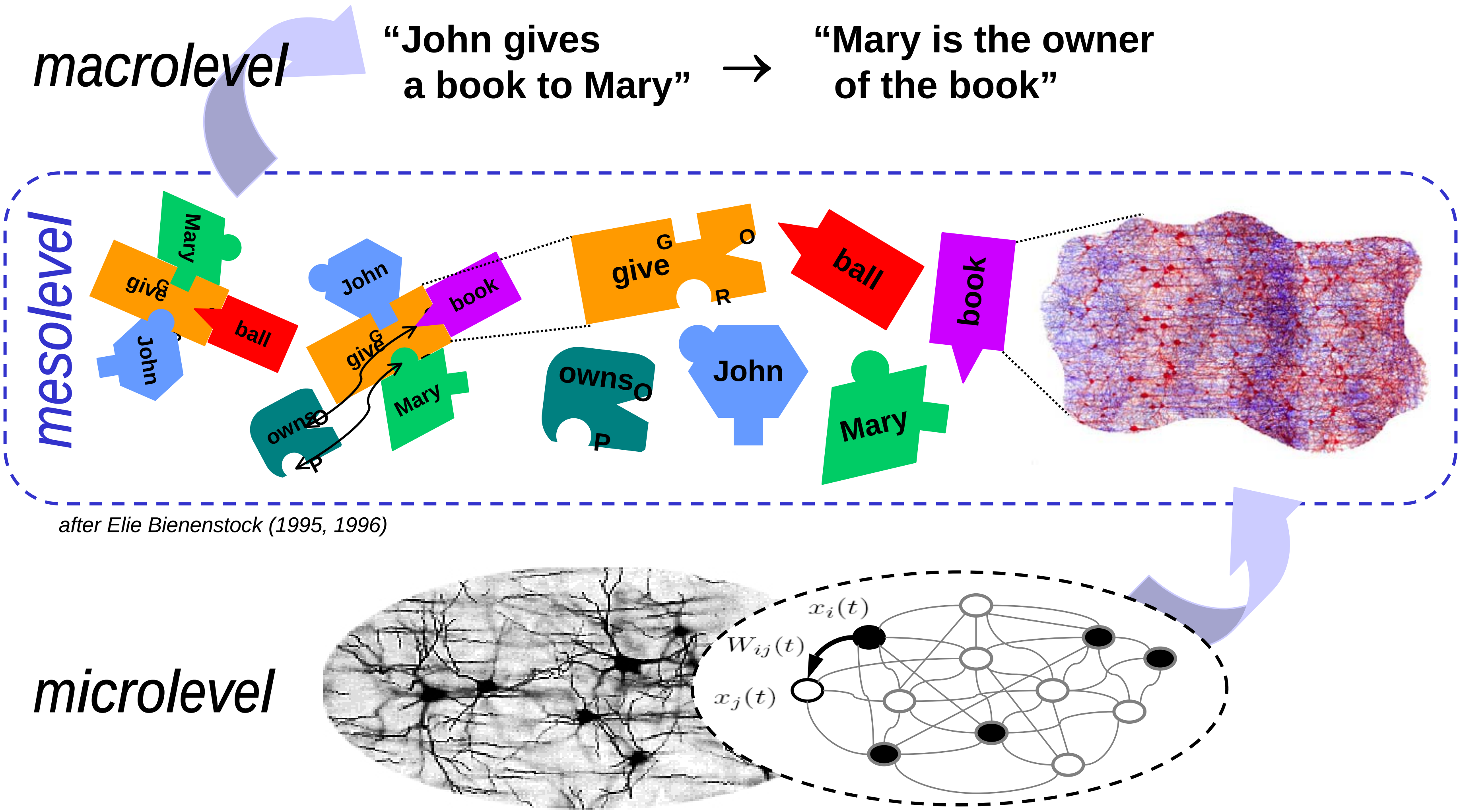
1.a The Lingering Gap Between AI and Neural Nets

Atomless Biology vs. Lifeless Physics



1.a The Lingering Gap Between AI and Neural Nets

Brainless Mind vs. Mindless Brain



after Elie Bienenstock (1995, 1996)

1.a The Lingering Gap Between AI and Neural Nets

Brainless Mind vs. Mindless Brain

- 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

  - ✓ 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 (after Elie Bienenstock, 1995, 1996)

- What could be the “macromolecules” of cognition?

1.b Temporal Coding and Spiking Networks

Symbolic Networks and the Binding Problem

macrolevel

"John gives a book to Mary" → **"Mary is the owner of the book"**

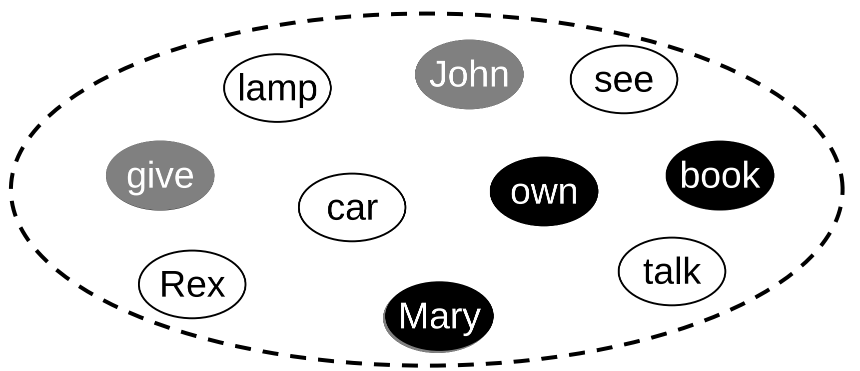
mesolevel

Symbolic networks bypass the mesoscopic level

✓ symbols are directly encoded by the nodes and "activated"

→ *conflation of levels comparable to genetic traits stored in atoms!*

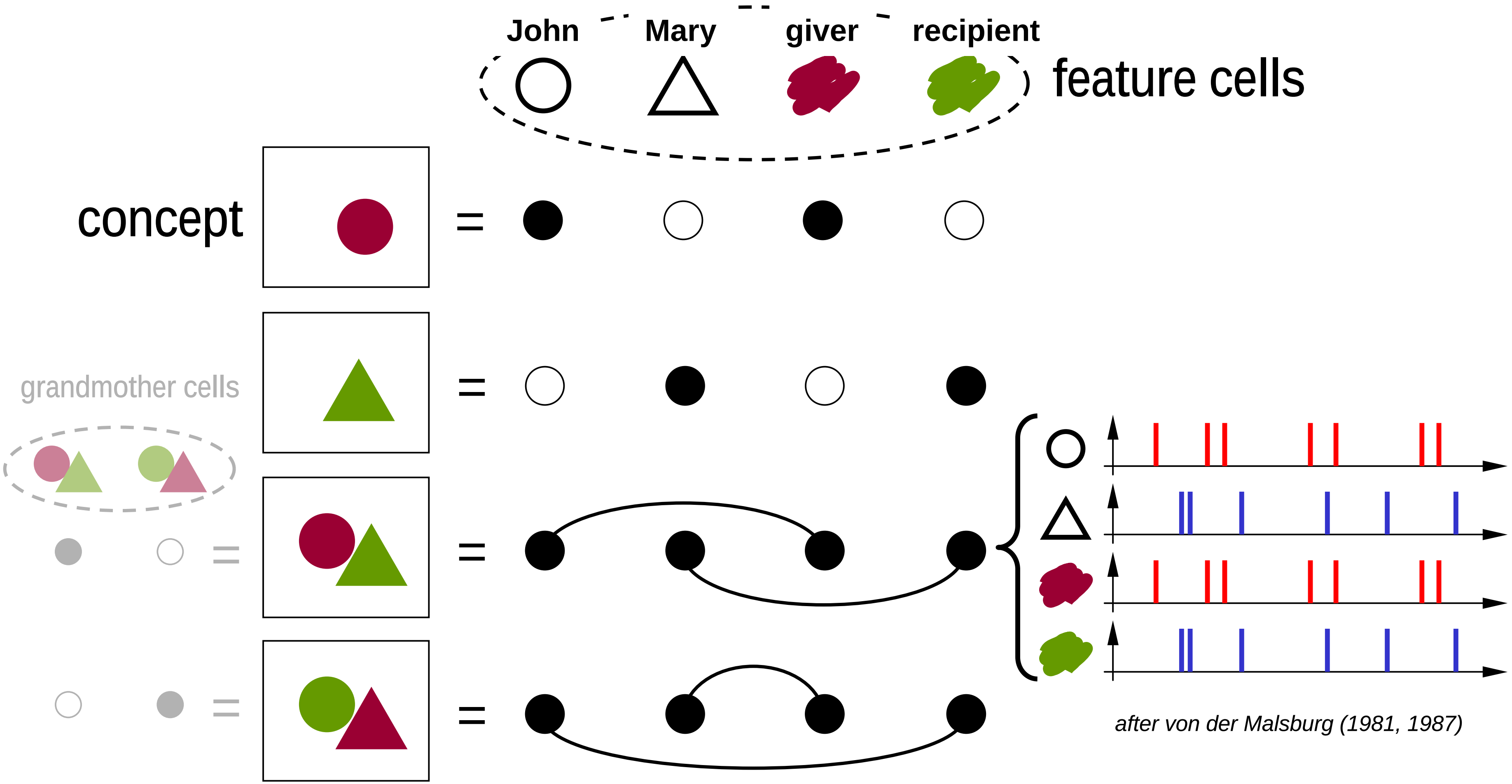
→ *this format of representation also leads to confusions: is it (a) John gives a book to Mary? or (b) Mary gives a book to John? etc.*



microlevel

1.b Temporal Coding and Spiking Networks
Symbolic Networks and the Binding Problem

➢ Relational information can be encoded *temporally*



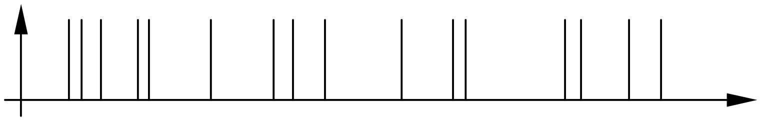
after von der Malsburg (1981, 1987)

1.b Temporal Coding and Spiking Networks

Rate Coding vs. Temporal Coding

- There is more to neural signals than mean activity rates

$x_i(t)$



- ✓ 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

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

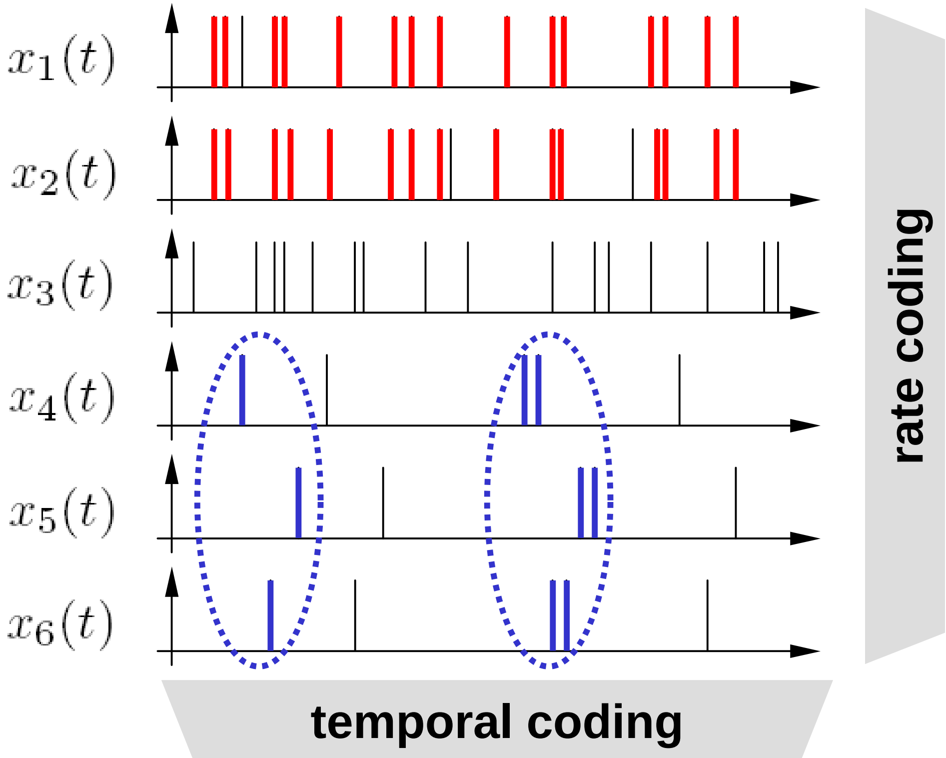
$$\langle\, x_i(t)\, x_j(t-\tau_{ij})\,\rangle$$

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

1.b Temporal Coding and Spiking Networks

Rate Coding vs. Temporal Coding

- There is more to neural signals than mean activity rates



$\langle x_1(t) \rangle =$ ● 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

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

- 1 and 2 more in sync than 1 and 3

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

- 4, 5 and 6 correlated through delays

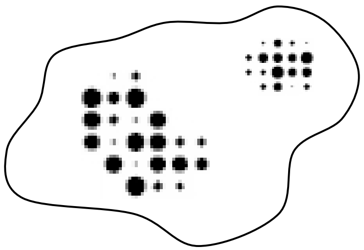
1.c A Mesoscopic Level of Complex Patterns

The "Chemistry" of Cognition

- What could be the “macromolecules” of cognition?
  - ✓ “macromolecules” could be dynamic cell assemblies supported by ordered connectivity: *spatiotemporal patterns (STPs)*, e.g.,

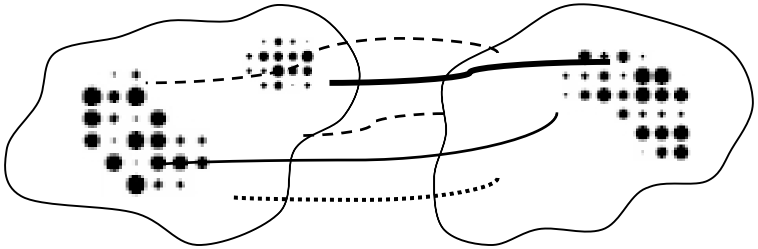
mesolevel

- synfire chains & braids
- polychronous groups
- cortical columns
- analog locks & keys, etc.



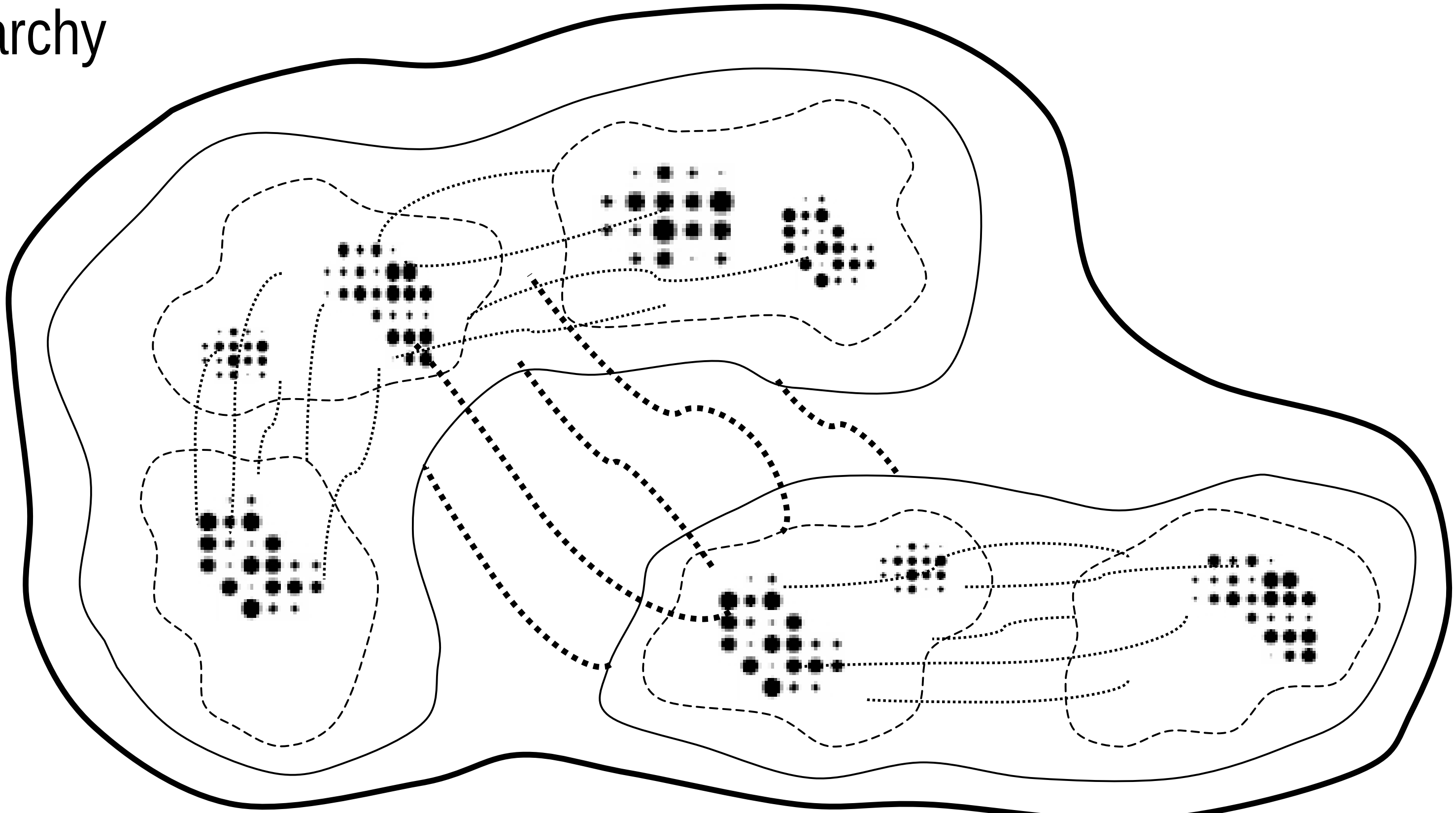
  - ✓ “covalent, ionic, or hydrogen bonds” in and between molecules could be *temporal binding* and fast synaptic plasticity, e.g.,

- synchronization
- delayed correlations & waves
- induction, resonance, etc.



1.c A Mesoscopic Level of Complex Patterns
The "Chemistry" of Cognition

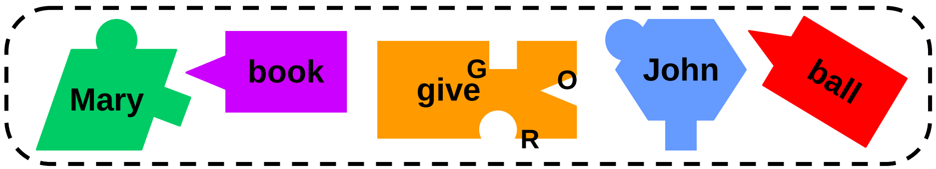
- A building-block game of mental representations
  - ✓ like proteins, STPs can *interact* and *assemble* at several levels, forming complex structures from simpler ones in a hierarchy

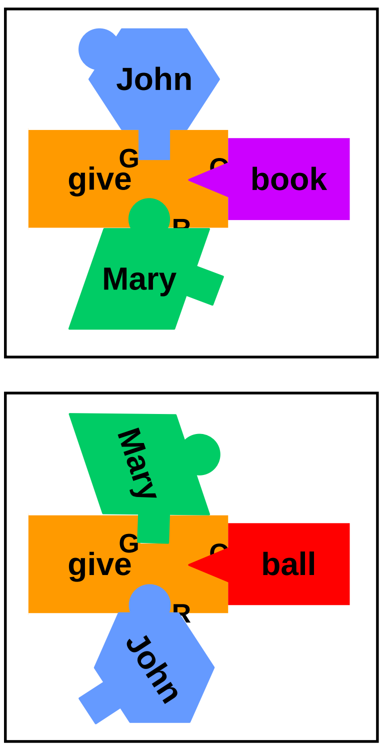


1.c A Mesoscopic Level of Complex Patterns

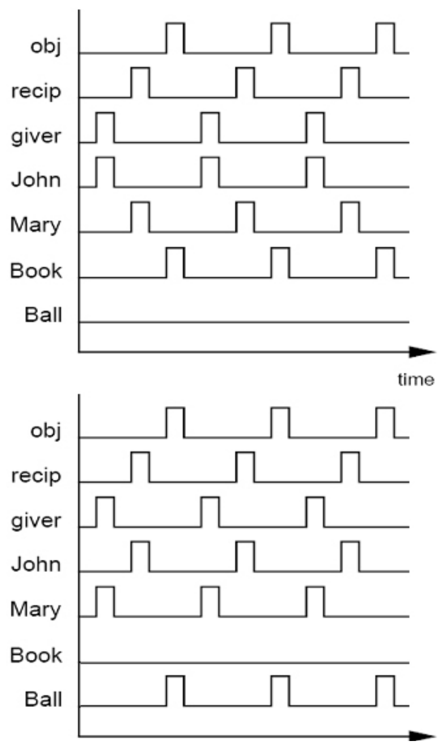
The "Chemistry" of Cognition

- A building-block game of language





after Bienenstock (1995)



after Shastri & Ajjanagadde (1993)

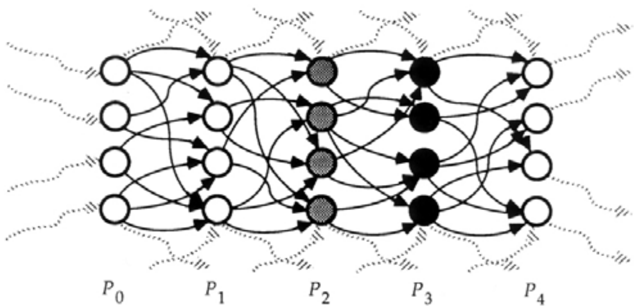
✓ the “blocks” are elementary representations (linguistic, perceptive, motor) that ***assemble dynamically*** via temporal binding

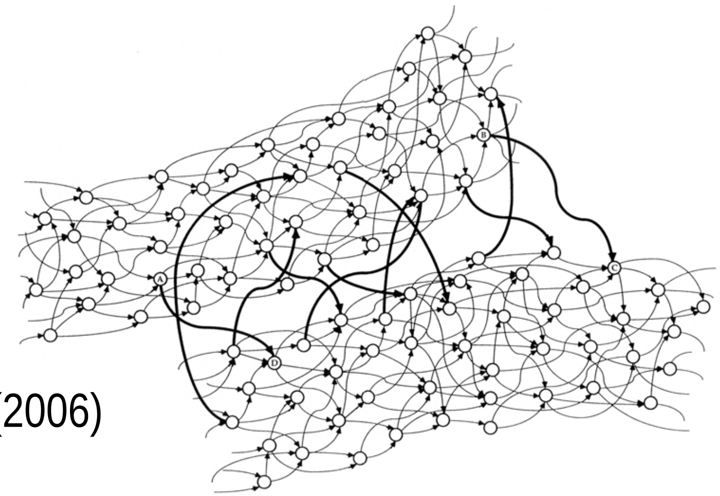
✓ representations possess an internal spatiotemporal structure at all levels

1.c A Mesoscopic Level of Complex Patterns

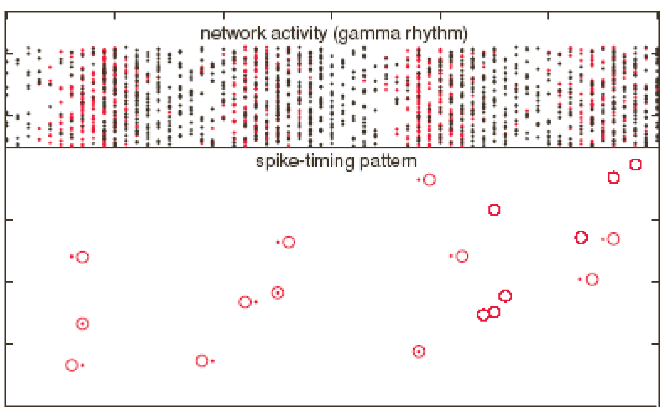
The "Macromolecules" Are Dynamic Cell Assemblies

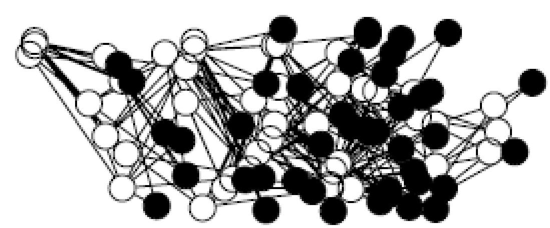
- Theories populating the mesolevel: a zoology of STPs
  - ✓ synfire chains & braids – Abeles (1982), Bienenstock (1995), Doursat (1991)





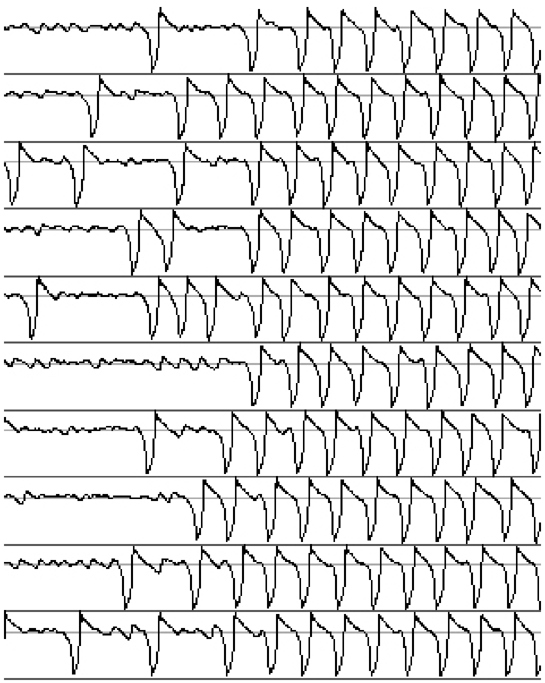
  - ✓ polychronous groups – Izhikevich (2006)

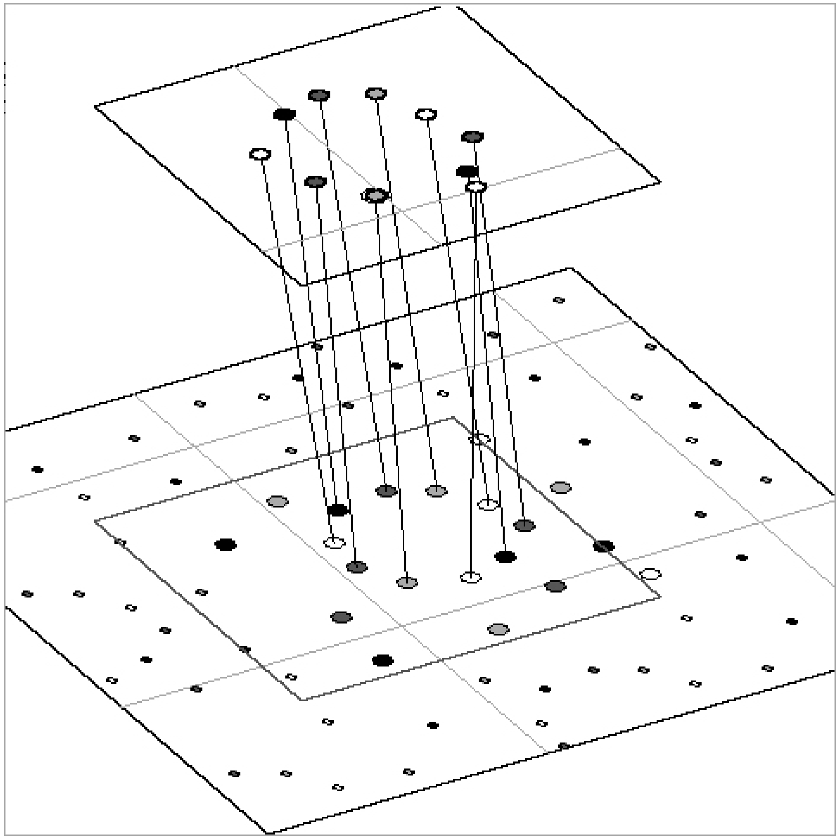




1.c A Mesoscopic Level of Complex Patterns
The "Macromolecules" Are Dynamic Cell Assemblies

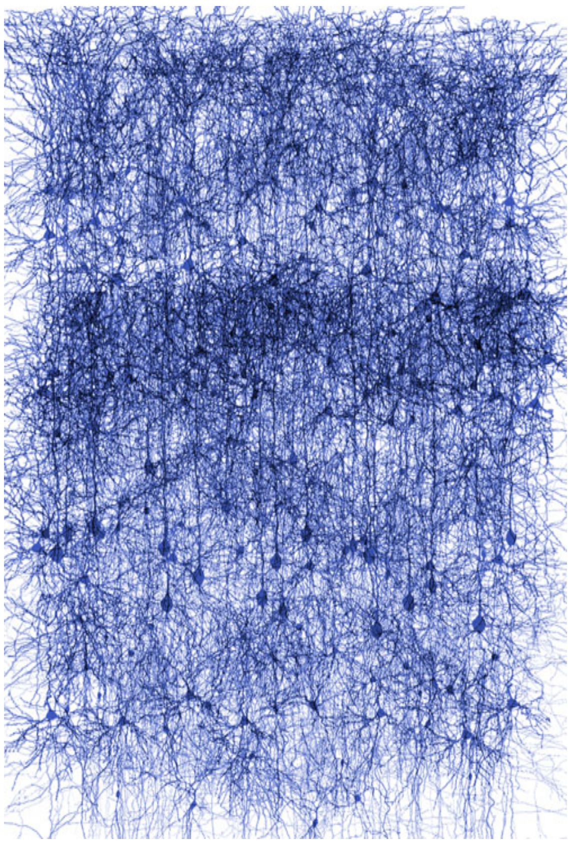
- Theories populating the mesolevel: a zoology of STPs
  - ✓ wave matching – Doursat, von der Malsburg & Bienenstock (1995)

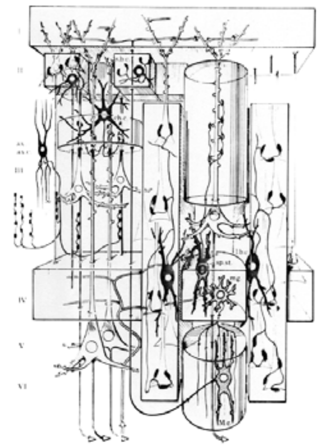




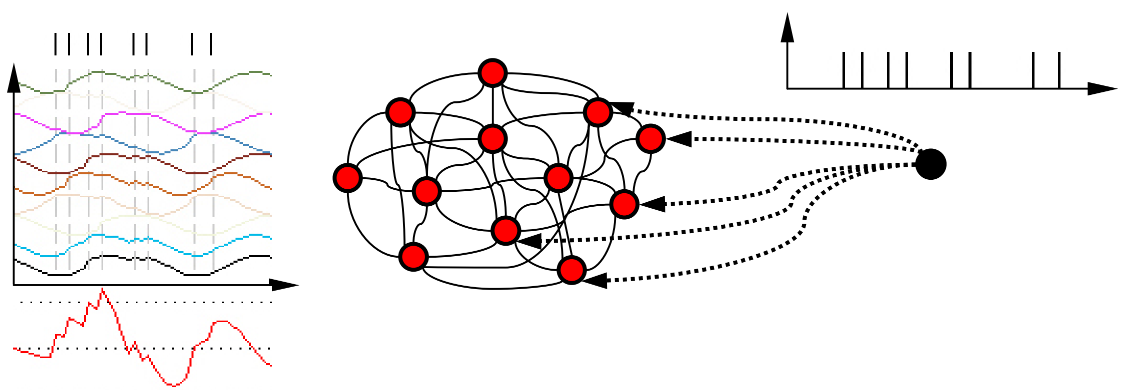
1.c A Mesoscopic Level of Complex Patterns
The “Macromolecules” Are Dynamic Cell Assemblies

- Theories populating the mesolevel: a zoology of STPs
  - ✓ BlueColumn – Markram (2006)





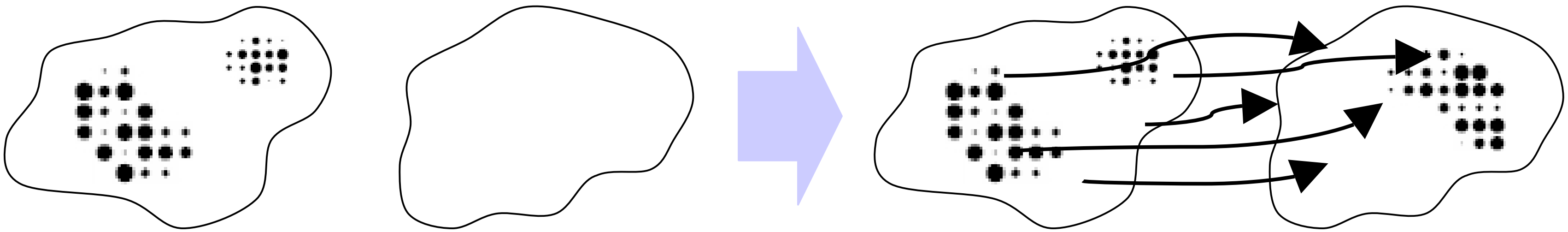
  - ✓ analog locks and keys – Doursat & Goodman (2006)



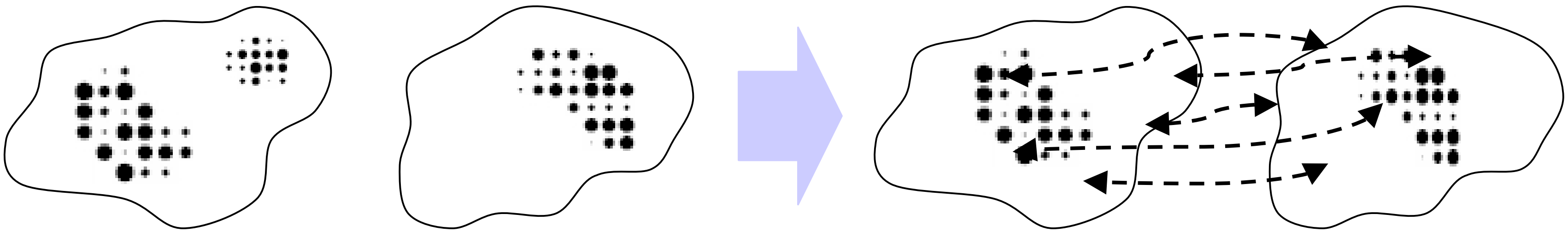
1.c A Mesoscopic Level of Complex Patterns

The "Chemical Bonds" Are Temporal Binding

- **New neural dynamics: perturbation by coupling**
  - ✓ old "input/output" paradigm — a lower area literally *activates* a higher area, initially silent



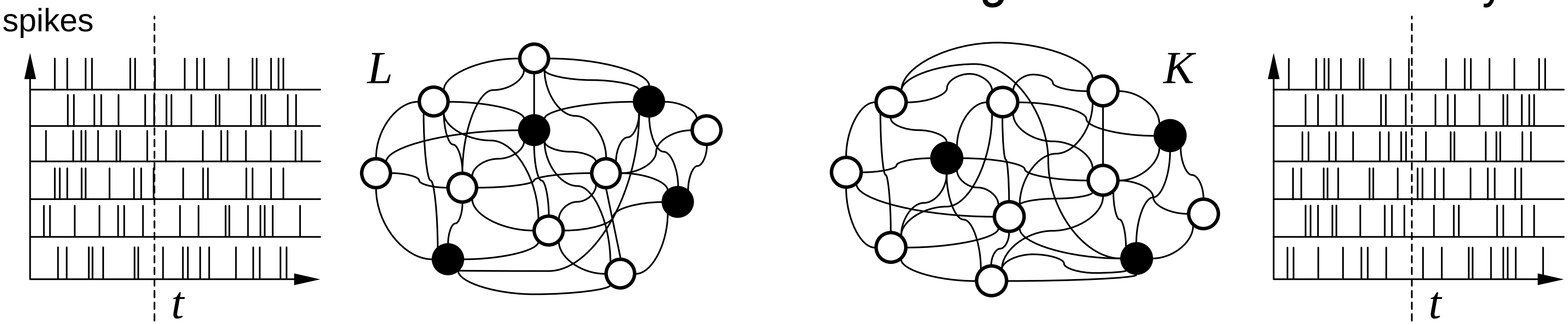
  - ✓ new "perturbation" paradigm — subnetworks already possess endogenous modes of activity, modified by coupling interactions



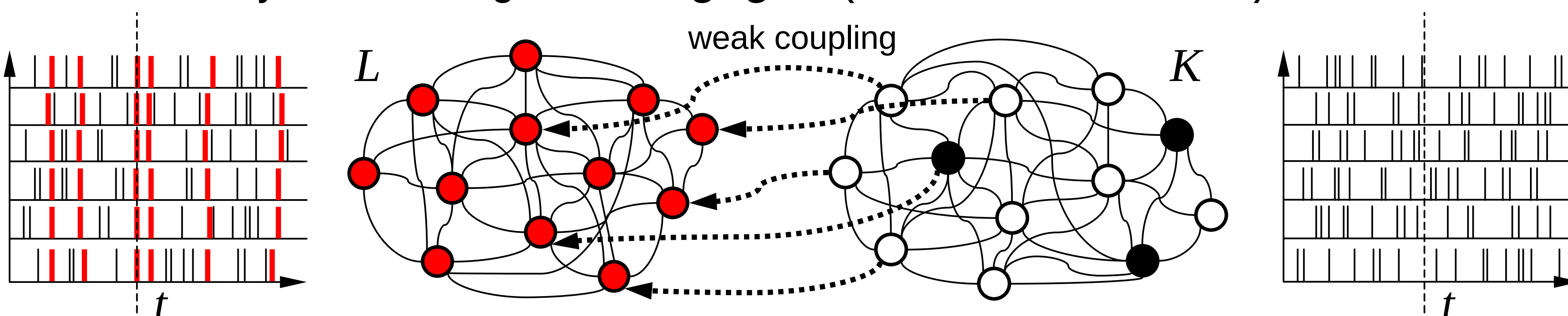
1.c Neural Locks and Keys

Coherence Induction Between Active Subnetworks

- **Pattern matching by spatiotemporal resonance**
  - ✓ a subnetwork alone has mixed *endogenous modes* of activity



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

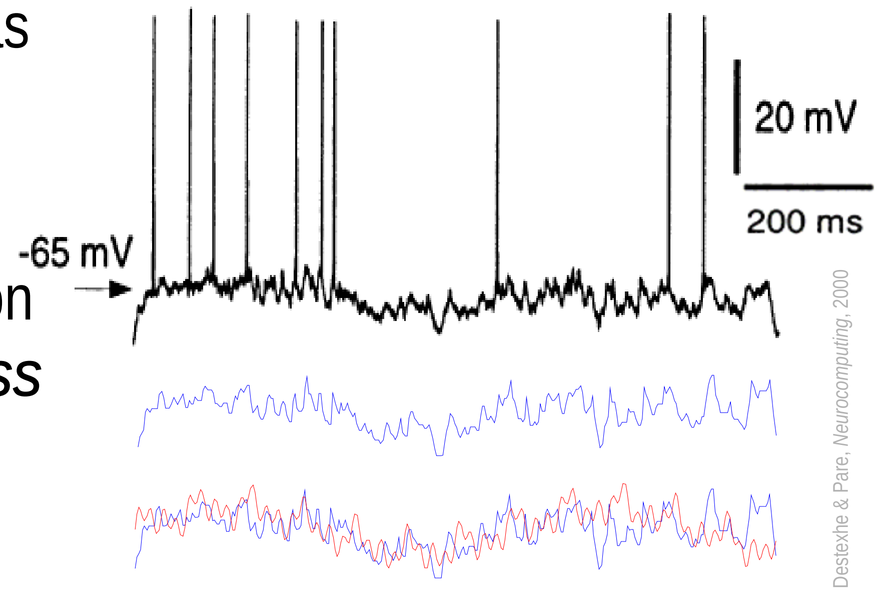


$\rightarrow$ the stimulation induces transient coherence

1.c Neural Locks and Keys

Coherence Induction Between Active Subnetworks

- **But spikes are only the tip of the iceberg**
  - ✓ just as rate coding lacks temporal information (spikes), spike coding lacks *current/voltage information* (membrane potential)
  - ✓ neurons receive a great amount of *background activity* from close or remote cortical areas
  - ✓ this activity is *irregular but somewhat rhythmic*
  - ✓ and has a critical influence on the neurons' *responsiveness*
  - → *analog binding*, instead of spike synchrony



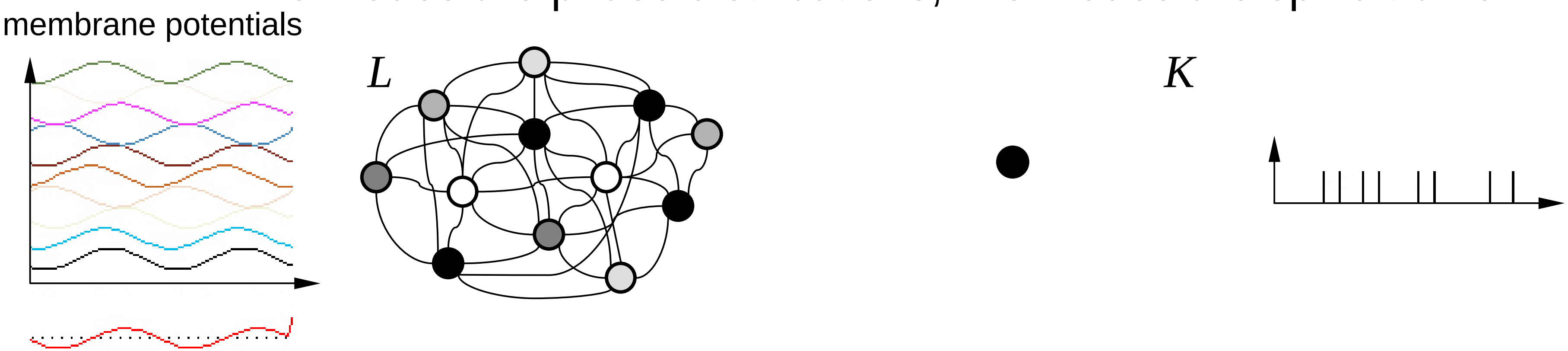
$$.55 \sin(1.7(2\pi t)) + .25 \sin(12.2(2\pi t)) + .2 \sin(24(2\pi t)) + .25 \sin(50(2\pi t))$$

1.c Neural Locks and Keys

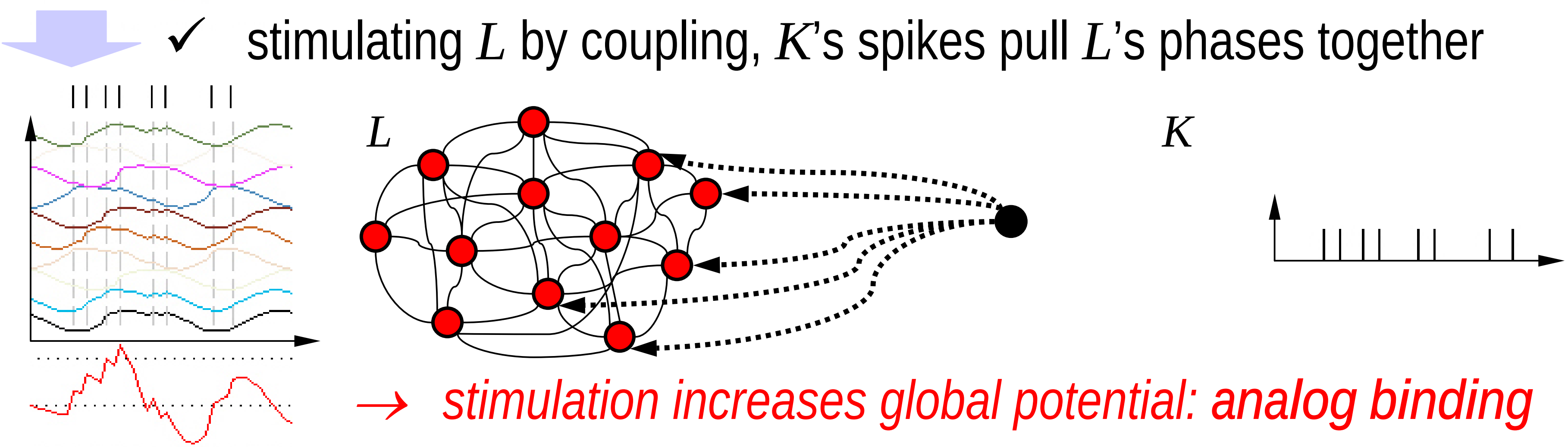
Coherence Induction Between Active Subnetworks

➢ Below spikes: subthreshold membrane potentials

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



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



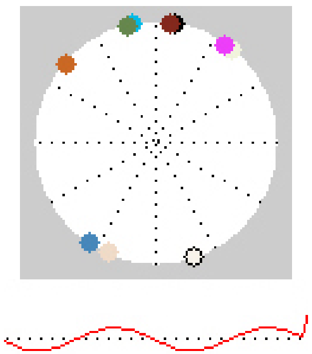
→ *stimulation increases global potential: analog binding*

1.c Neural Locks and Keys
Coherence Induction Between Active Subnetworks

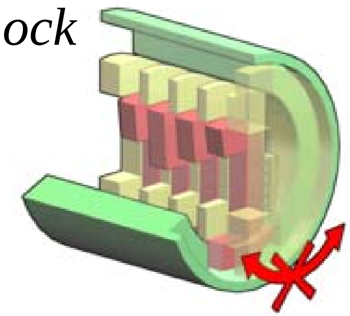
➢ Locksmithing analogy

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

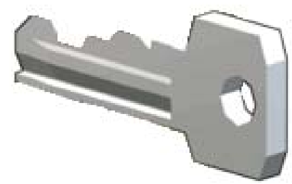
potential phases

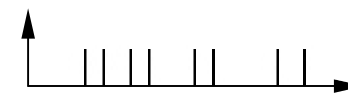


Lock

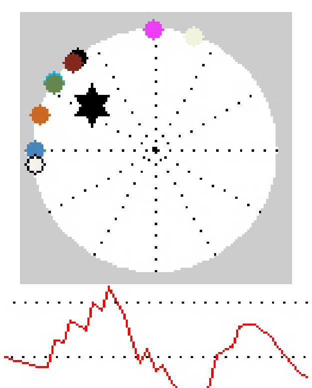


Key

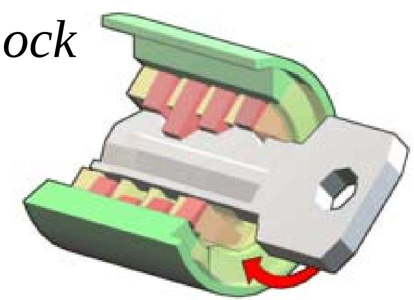




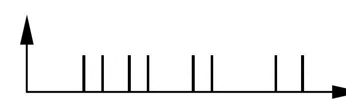
✓ *Key*’s notches raise *Lock*’s discs just enough to release them



Lock



Key



→ *the key opens the tumbler lock*

1.c Neural Locks and Keys

Coherence Induction Between Subnetworks

- Numerical simulations: phase space (Matlab)

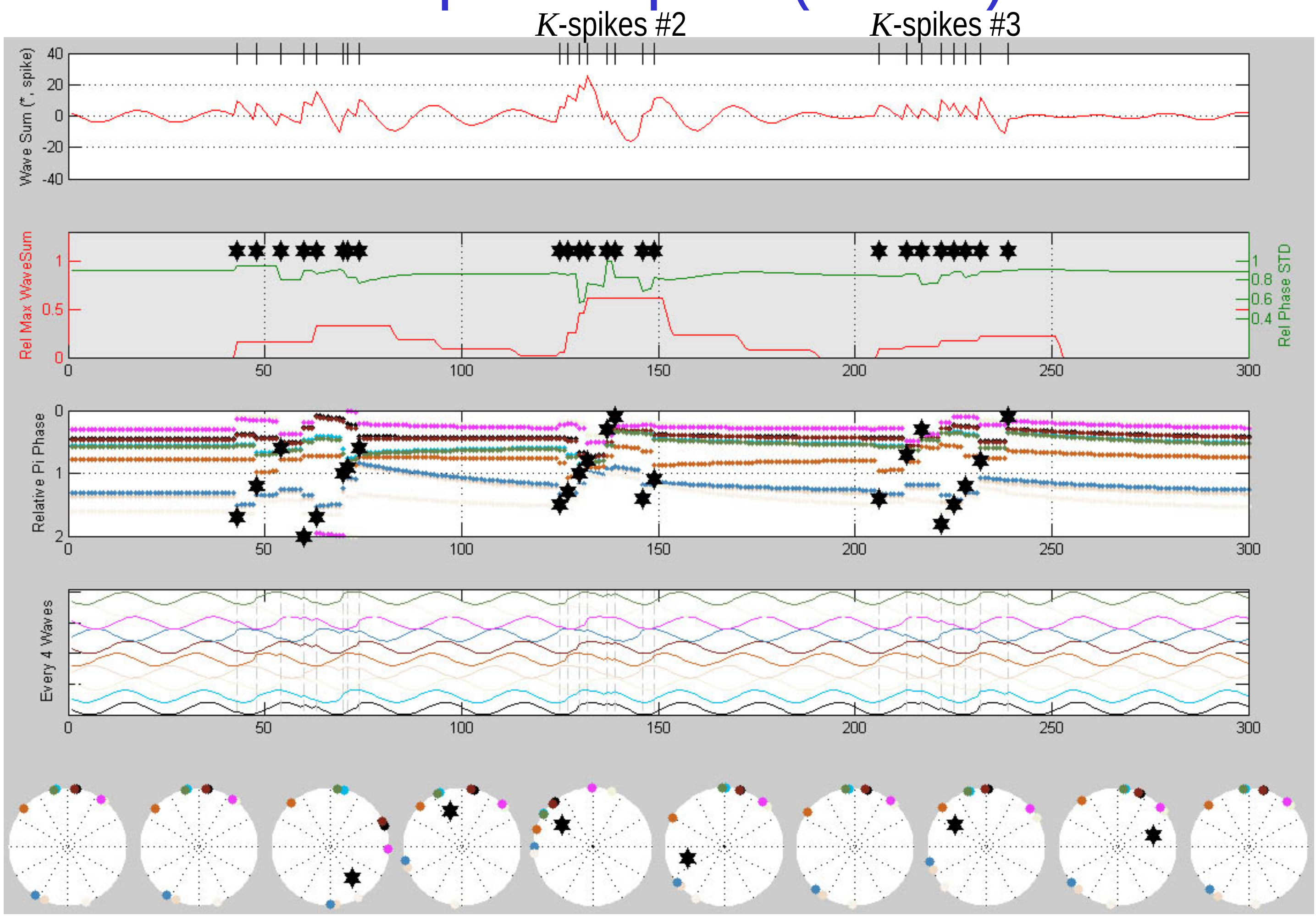
interference pattern (sum of L-signals)

local max of sum

individual L-phases

individual L-signals

individual L-phases in circle view

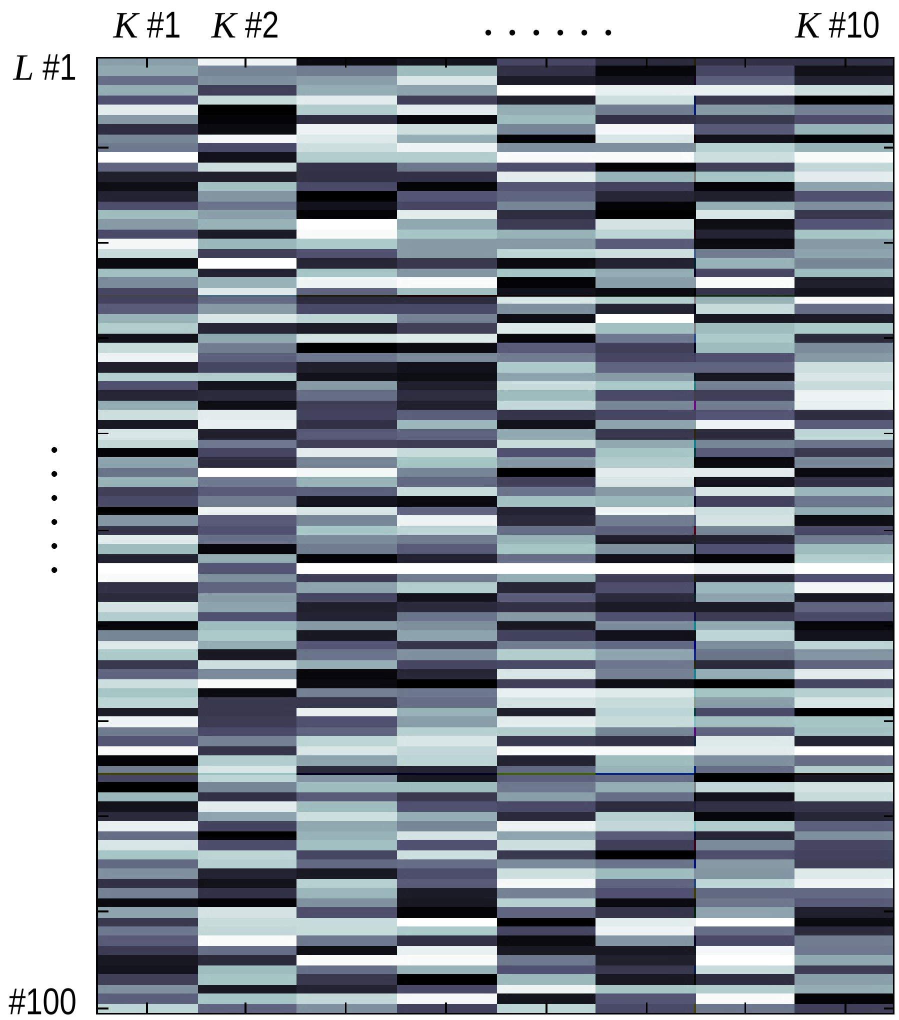


1.c Neural Locks and Keys

Coherence Induction Between Subnetworks

➢ Numerical simulations

- ✓ uniqueness of ***transient response*** of a specific phase distribution L to a specific incoming spike pattern K, despite identical mean rates
- ✓ reproducibility of this unique response
- ✓ sensitivity to variations in either pattern, K or L
- → *evidence for distinct "key and lock" engagement*



1.c Neural Locks and Keys

Coherence Induction Between Subnetworks

- Numerical simulations: spiking neural network (NCS)

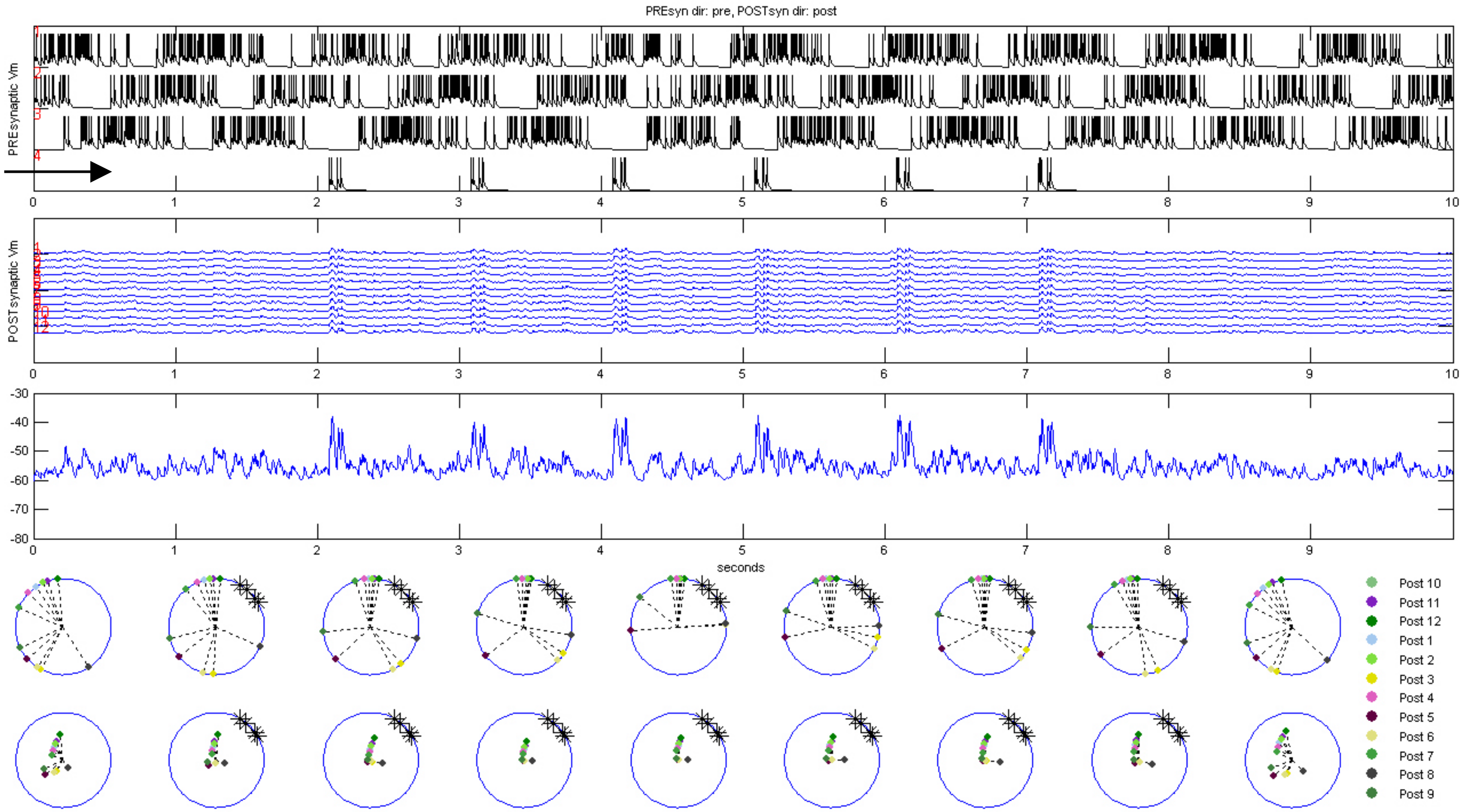
(background sources)

K-spikes

individual *L*-signals

interference sum of *L*-signals

individual *L*-phases in circle view



The Mesocircuits of Cognition

1. Reconciling Neurobiology & Cognition
2. Reconciling Complex Computation & Real Time, Small Space, Low Power
   a. Complex Neural Systems are Computationally Expensive
   b. Supercomputer Clusters Target Real-Time
   c. Embedded Systems Target Small-Space, Low-Power
   d. Neuromorphic Analog VLSI Targets All in One
3. Complex Neural Computation in Analog VLSI

2.a Complex Systems are Computationally Expensive

Toward an efficient complex computation

- **Massive, but structured, parallelism**
  - ✓ given that neurons are extremely slow components compared to transistors. . .
  - ✓ . . . how does the brain still perform perceptive and cognitive tasks better and faster than the most powerful digital processors?
  - ✓ . . . and is far more compact and millions of time more energy efficient than a typical personal computer?
  - → *the answer is in the way the brain's 10^{11} neurons are organized*
  - → *how can technology reproduce this organization?*
  - → *how can it function in real-time, low-power and small-space?*

2.a Complex Systems are Computationally Expensive

Complex Systems: The New Paradigm of the 21st Century

➢ The brain is one of many natural complex systems

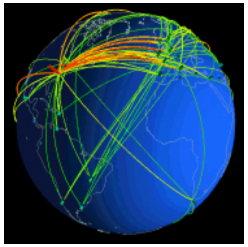
physical pattern formation

biological development

insect colonies

brain

Internet



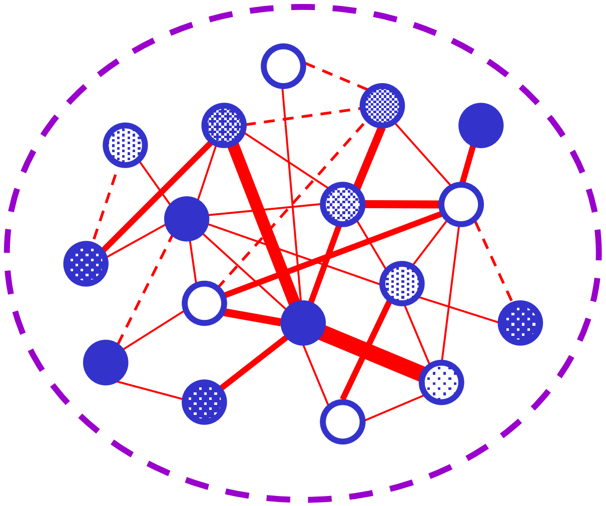
social networks

- ✓ large number of elements interacting locally
- ✓ simple individual behaviors create a complex emergent behavior
- ✓ decentralized dynamics: no master blueprint or external leader
- ✓ self-organization and evolution of order from randomness

2.a Complex Systems are Computationally Expensive

Software-Based Modeling and Simulation

➢ Complex networks are the backbone of complex systems



- agents = nodes: different states of activity, varying on a fast time-scale
- interactions = edges: different weight values, varying on a slow time-scale
- system = network: evolving structure

✓ complex behavior is difficult to describe or predict analytically

✓ complex networks are best investigated *computationally*

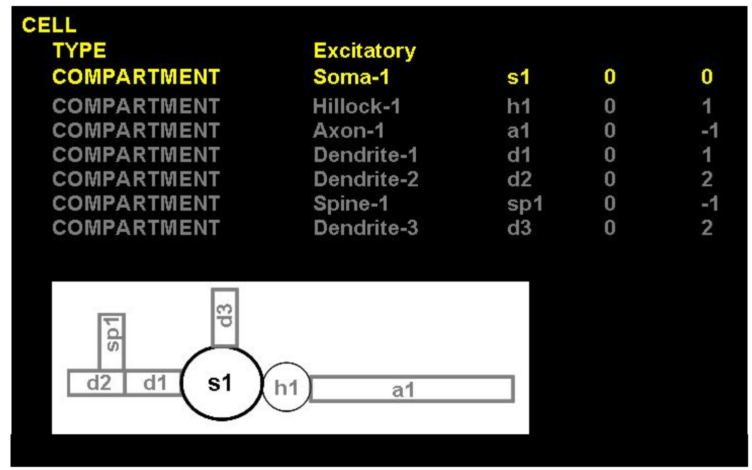
✓ thus, software-based modeling and simulation are crucial tools

✓ . . . but computationally expensive, as interactions ~ N^2 or ~ kN

2.b Supercomputer Clusters Target Real-Time

NeoCortical Simulator

- **Brain Computation Lab, University of Nevada, Reno**
  - ✓ 200-CPU cluster (Xeon/Opteron), Myrinet, 2 TB memory
  - ✓ C/C++ NeoCortical Simulator (NCS) software, MPI architecture



CELL				
TYPE	Excitatory			
COMPARTMENT	Soma-1	s1	0	0
COMPARTMENT	Hillock-1	h1	0	1
COMPARTMENT	Axon-1	a1	0	-1
COMPARTMENT	Dendrite-1	d1	0	1
COMPARTMENT	Dendrite-2	d2	0	2
COMPARTMENT	Spine-1	sp1	0	-1
COMPARTMENT	Dendrite-3	d3	0	2

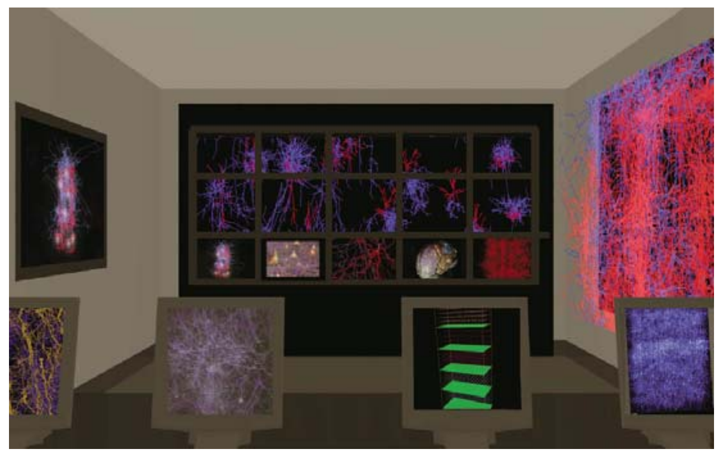
  - ✓ 100 columns x 10,000 cells = 1 million multicompartmental neurons, massively interconnected through 1 billion synapses

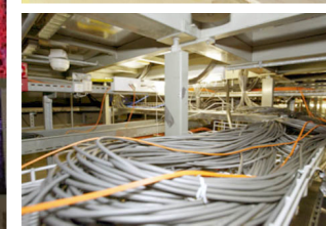
$\rightarrow$ *computing time on 100 nodes $\approx$ 30 mn. . . for 1 real-time second!*

2.b Supercomputer Clusters Target Real-Time

BlueBrain

- **Mind Brain Institute, EPFL, Lausanne, Switzerland**
  - ✓ IBM BlueGene: 8096-CPU cluster, 22 Trillion Flops
  - ✓ “BlueBrain”, running NCS and NEURON



  - ✓ 100,000 morphologically complex neurons in real time

→ *fantastic simulation and investigation tool. . . but completely impractical in field applications!*

2.c Embedded Systems Target Small-Space, -Power

- **Special-purpose devices vs. general-purpose computer**
  - ✓ house appliances, cellular phones, ATMs, car engines, etc.
  - ✓ perform predefined tasks with specific requirements
  - ✓ mostly controller chips, with limited computing capabilities



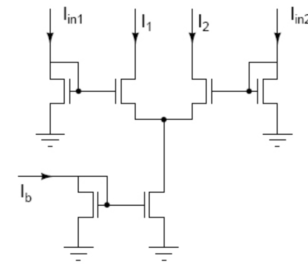

  - ✓ task-dedication allows to optimize design and implementation down to small-size, low-power and low-cost, then mass-produce

→ *but none have the required computational power*

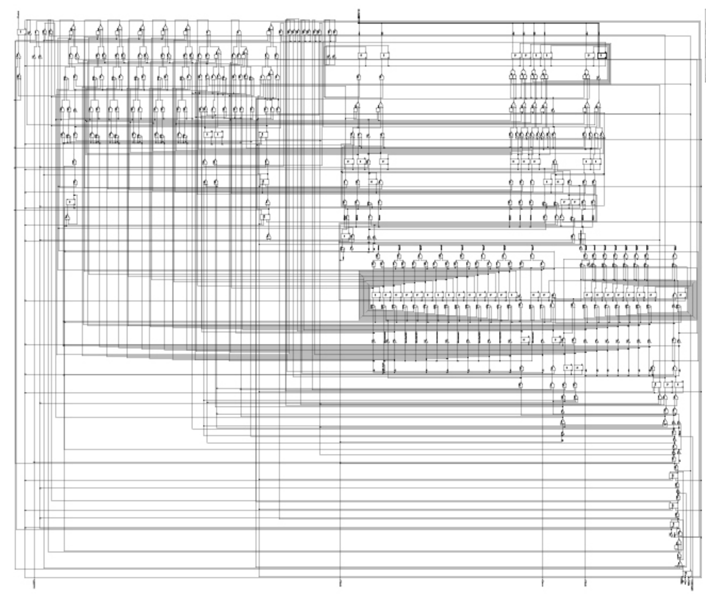
2.d Neuromorphic Analog VLSI Targets All in One

Analog vs. digital computing

- **Analog vs. digital computing**
  - ✓ *digital* computing
    - is robust against noise
    - supports logic
    - has computational universality (Turing completeness)
  - ✓ *analog* computing has
    - high speed
    - small silicon area
    - low power
    - interfacing without AD conversion
  - → *noise drowned in massive redundancy*
  - → *programming versatility not a goal*



Analog Multiplier

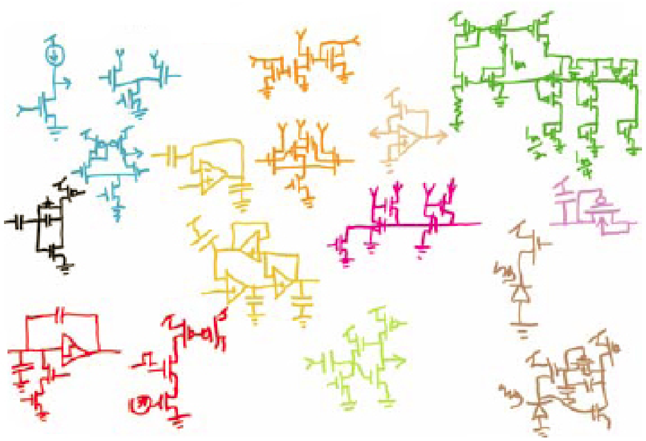


Digital Arithmetic Logic Unit

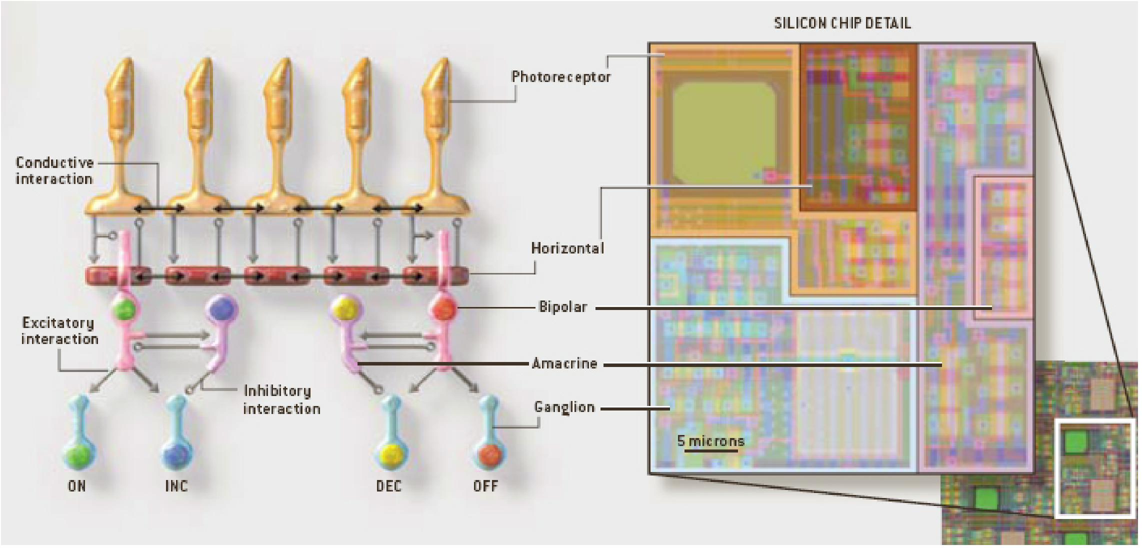
2.d Neuromorphic Analog VLSI Targets All in One

Neuromorphic Analog VLSI

- ➢ Carver Mead's pioneering work
  - ✓ MOSFET nonlinearities can be exploited in subthreshold mode
  - ✓ collection of elementary function-circuits that can be assembled, e.g., into a retina chip



Institut für Neuroinformatik, Uni Zürich, Winter 2005 course



Boahen, K. *Neuromorphic microchips*, Scientific American, May 2005

2.d Neuromorphic Analog VLSI Targets All in One

Sensor Chips

- aVLSI's focus is on peripheral sensors (retina, cochlea)
  - ✓ easily accessible, well-known structures, regular 1-D or 2-D repetitive layout, natural transduction of analog signals

NEUROMORPHIC ELECTRONICS RESEARCH GROUPS

Researchers seek to close the efficiency gap between electronic sensors and the body's neural networks with microchips that emulate the brain. This work focuses on small sensor systems that can be implanted in the body or installed in robots.

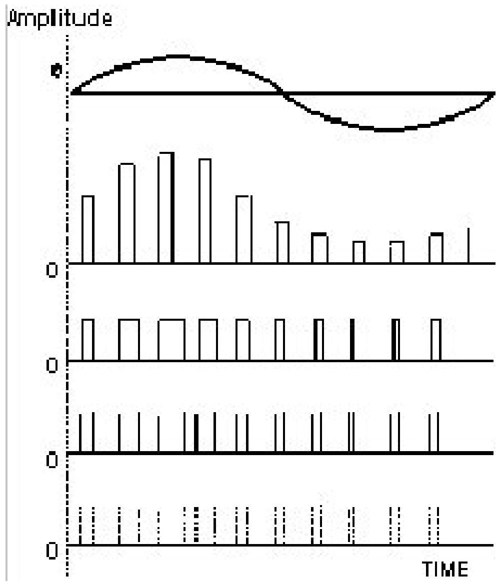
ORGANIZATION	INVESTIGATORS	PRINCIPAL OBJECTIVES
Johns Hopkins University	Andreas Andreou, Gert Cauwenberghs, Ralph Etienne-Cummings	Battery-powered speech recognizer, rhythm generator for locomotion and camera that extracts object features
ETH Zurich (University of Zurich)	Tobi Delbruck, Shi-Chii Liu, Giacomo Indiveri	Silicon retina and attention chip that automatically select salient regions in a scene
University of Edinburgh	Alan Murray, Alister Hamilton	Artificial noses and automatic odor recognition based on timing of signaling spikes
Georgia Institute of Technology	Steve DeWeerth, Paul Hasler	Coupled rhythm generators that coordinate a multisegmented robot
HKUST, Hong Kong	Bertram Shi	Binocular processor for depth perception and visual tracking
Massachusetts Institute of Technology	Rahul Sarpeshkar	Cochlea-based sound processor for implants for deaf patients
University of Maryland	Timothy Horiuchi	Sonar chip modeled on bat echolocation
University of Arizona	Charles Higgins	Motion-sensing chip based on fly vision

Boahen, K. *Neuromorphic microchips*, Scientific American, May 2005

2.d Neuromorphic Analog VLSI Targets All in One

Pulse-Based Computation Chips

- Communication bottleneck with analog signals
  - ✓ noise over long distances
  - ✓ difficulty of multiplexing
- Pulsed Neural Networks
  - ✓ idea: “communication circuits” can be designed independently from “computation circuits”
  - ✓ to transmit signals, use *pulses*, modulated in width, frequency or phase
  - ✓ pulses are natural equivalent of spikes
  - → *mixed analog/digital setup*



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Neuromorphic Mesocircuits

- Project

A. Develop the lock-and-key mesoscopic neural model

B. Investigate the state of the art in neuromorphic analog VLSI

C. Propose the first draft of a “neuromorphic mesocircuit” VLSI architecture