Nascent Program in Computational Neuroscience

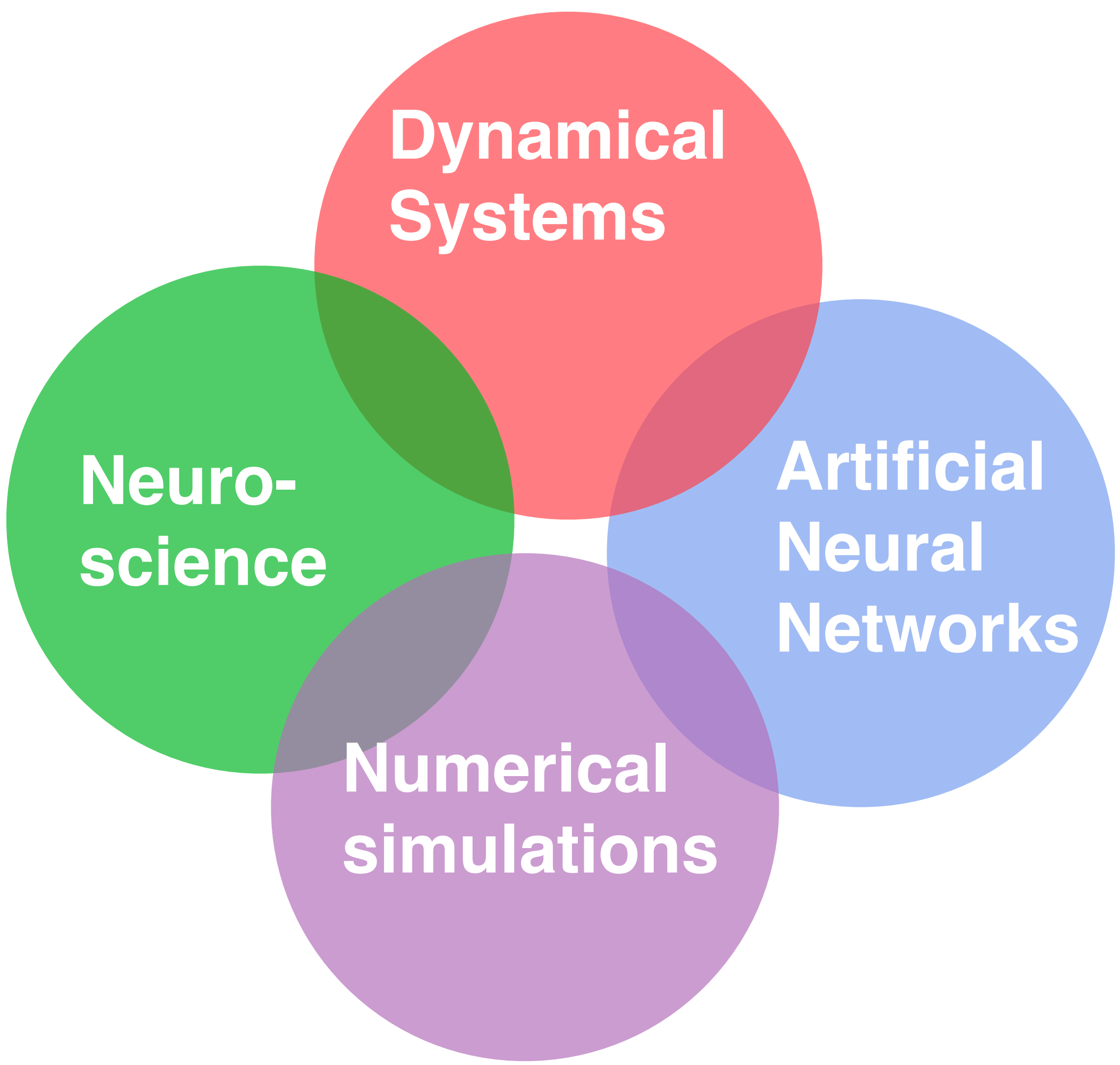
Gordon Erlebacher

Roadmap

June 2014 - April 2015

- How it all started
- Biology and modeling
- Artificial neural networks
- The learning process
- An algebra for polychrony
- New Collaboration
- Ending thoughts

Computational Neuroscience



Artificial Neural Networks
Biological networks

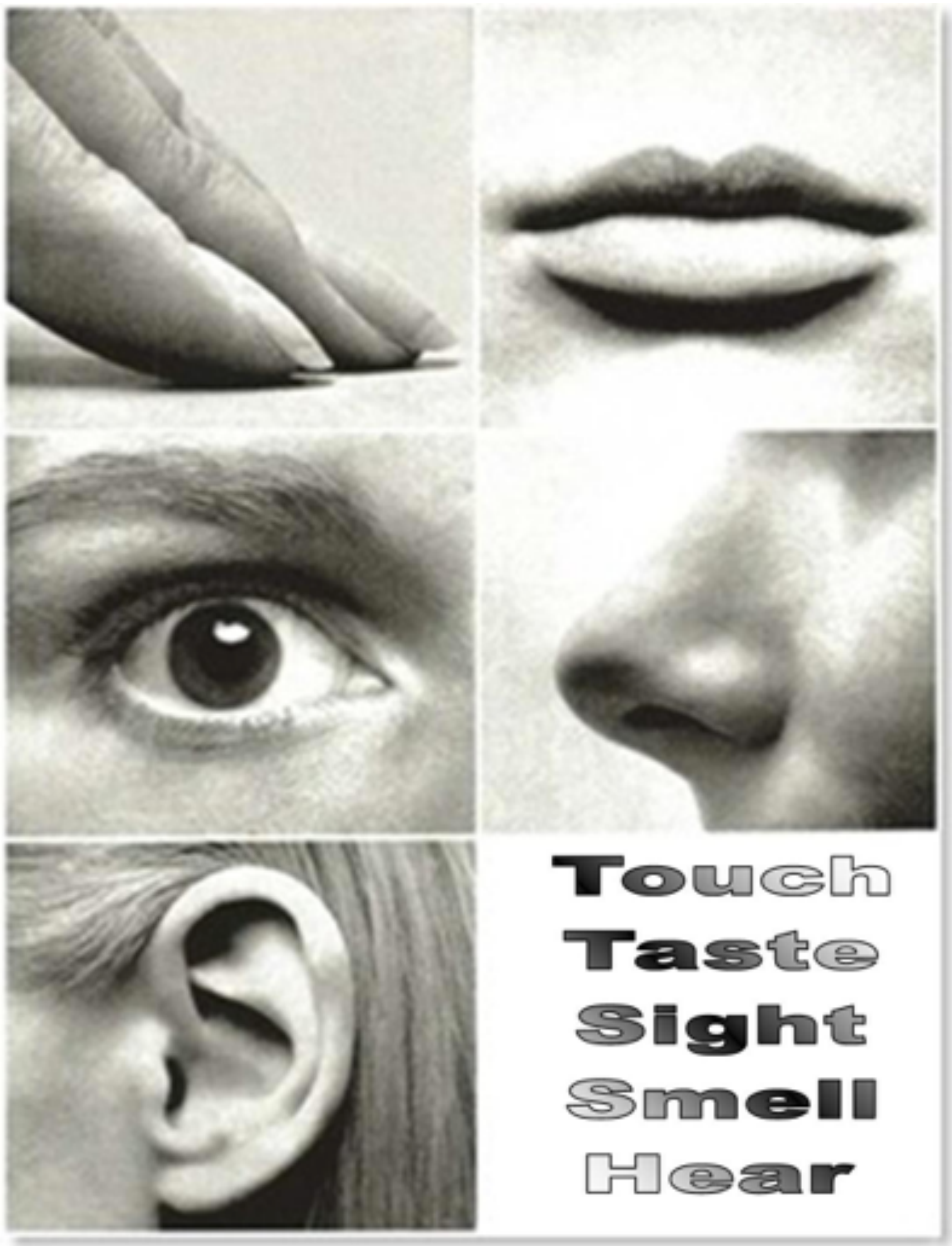
Reduced modeling of neurons
Population modeling

Dynamical systems
Mean field equations
Fokker Planck models
Stochastics, noise

Big question

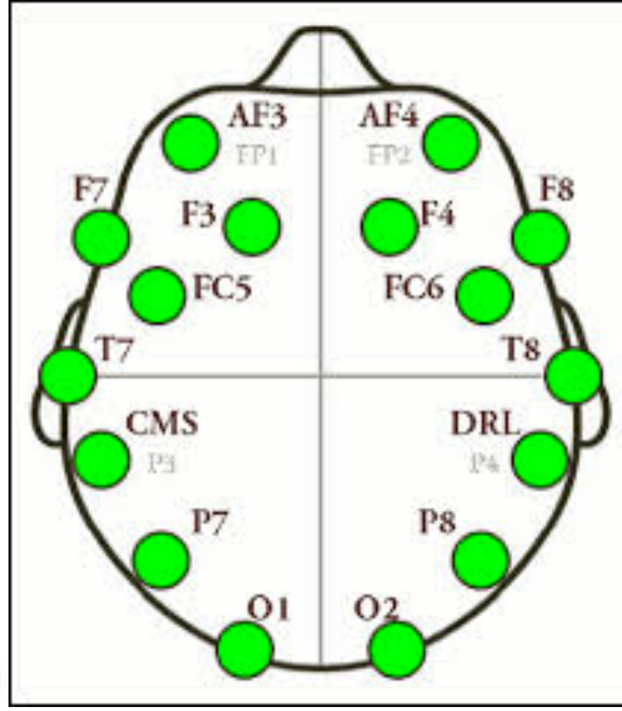
- How does the brain learn?
- If we understood the functioning of the brain, one might create an artificial construct, pose a problem it had not confronted before and it would provide a coherent answer

- We interact with the world through our senses
- Our brain emits and receives waves (EEG)

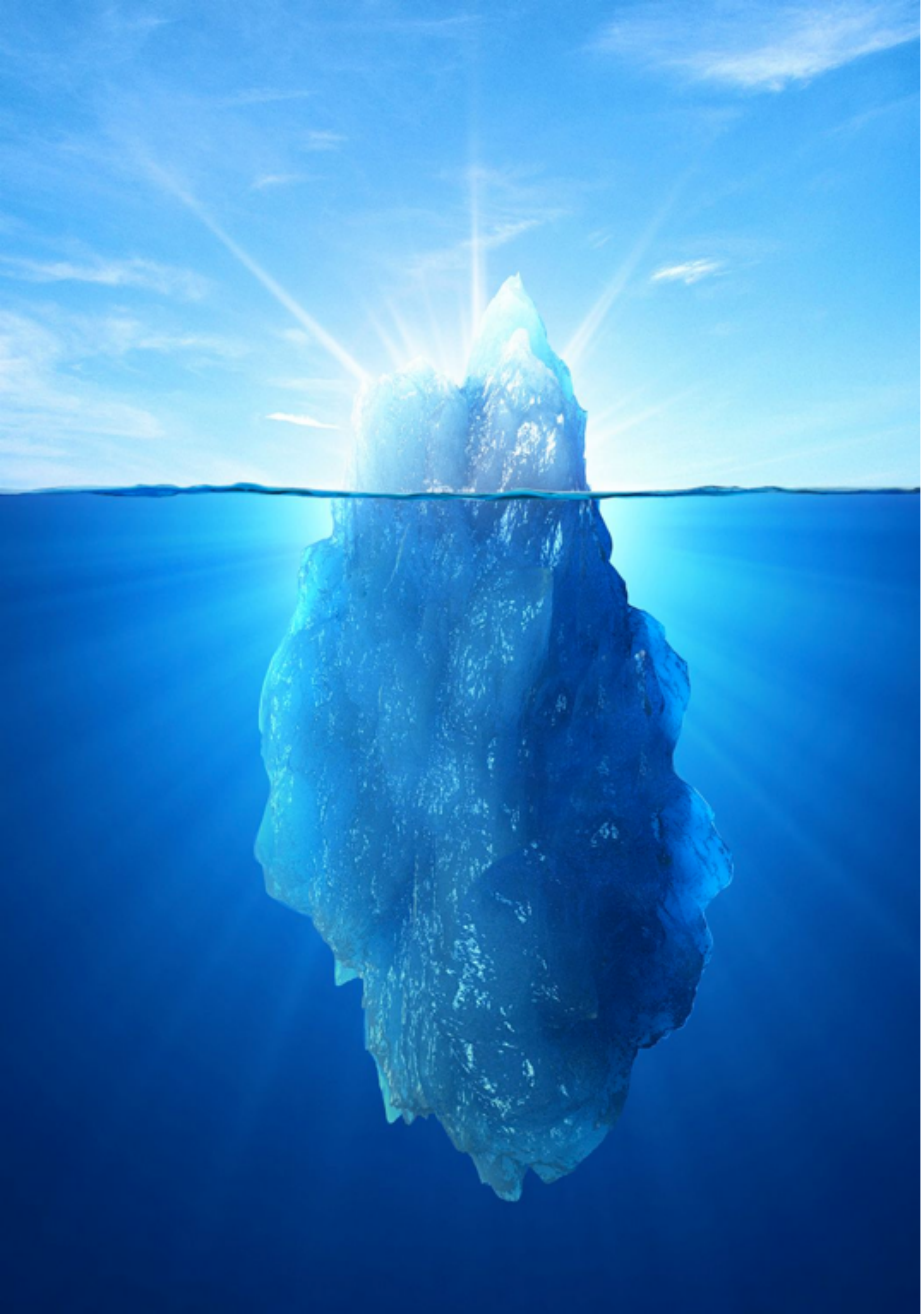


June-July 2014

- Start work with <u>three</u> Young Scholar Students
- Generated EEG waves with the Emotiv-Epoch
- Used Emotiv to control a simple game with the mind
- Experimented with the Hierarchical Temporal Memory of Jeff Hawkins (2007)


AF3
FP1
AF4
FP2
F7
F3
F4
F8
FC5
FC6
T7
T8
CMS
P3
DRL
P4
P7
P8
O1
O2


EPOC



Hierarchical Temporal Memory

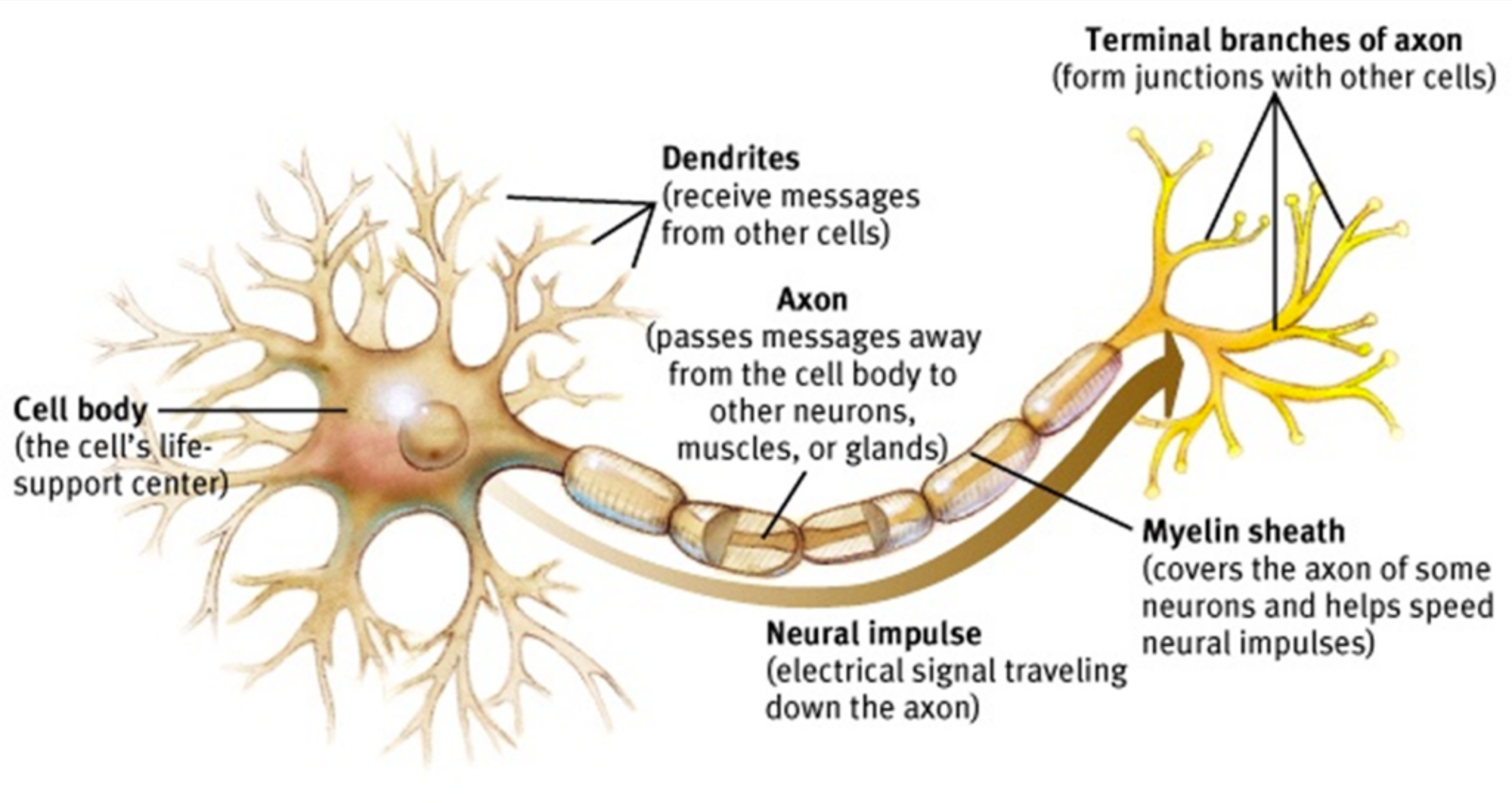
Convolution networks
Reservoir networks
Spiking networks

Hodgkin-Huxley model
Spatial models
Stochastic models
Reduced models
Spiking models

Spiking networks
Population theory
Mean equations

Some Biology

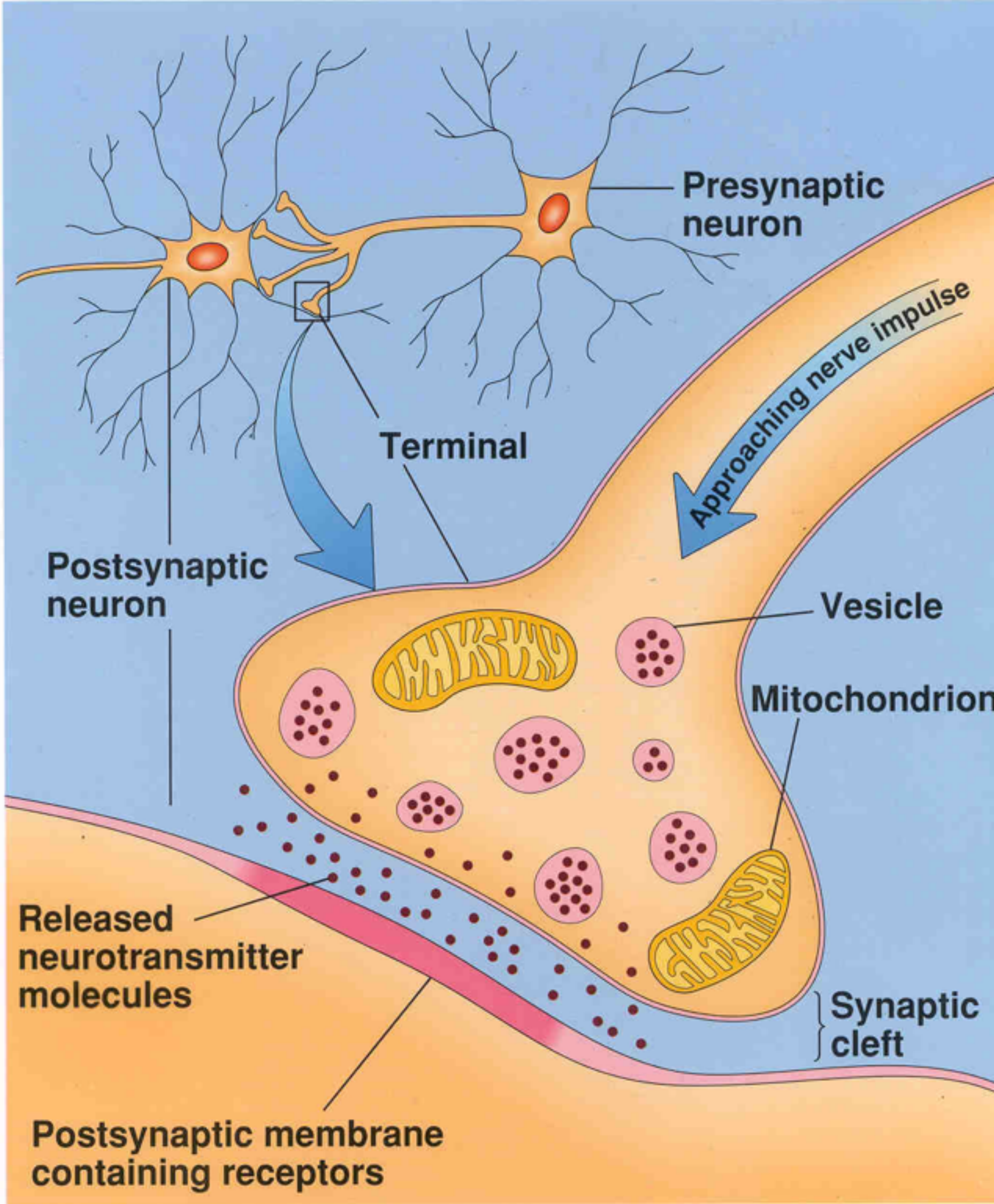
- Neurons
- Synapses
- Astrocytes


Terminal branches of axon
(form junctions with other cells)
Dendrites
(receive messages
from other cells)
Axon
(passes messages away
from the cell body to
other neurons,
muscles, or glands)
Cell body
(the cell's life-
support center)
Myelin sheath
(covers the axon of some
neurons and helps speed
neural impulses)
Neural impulse
(electrical signal traveling
down the axon)

Neuron

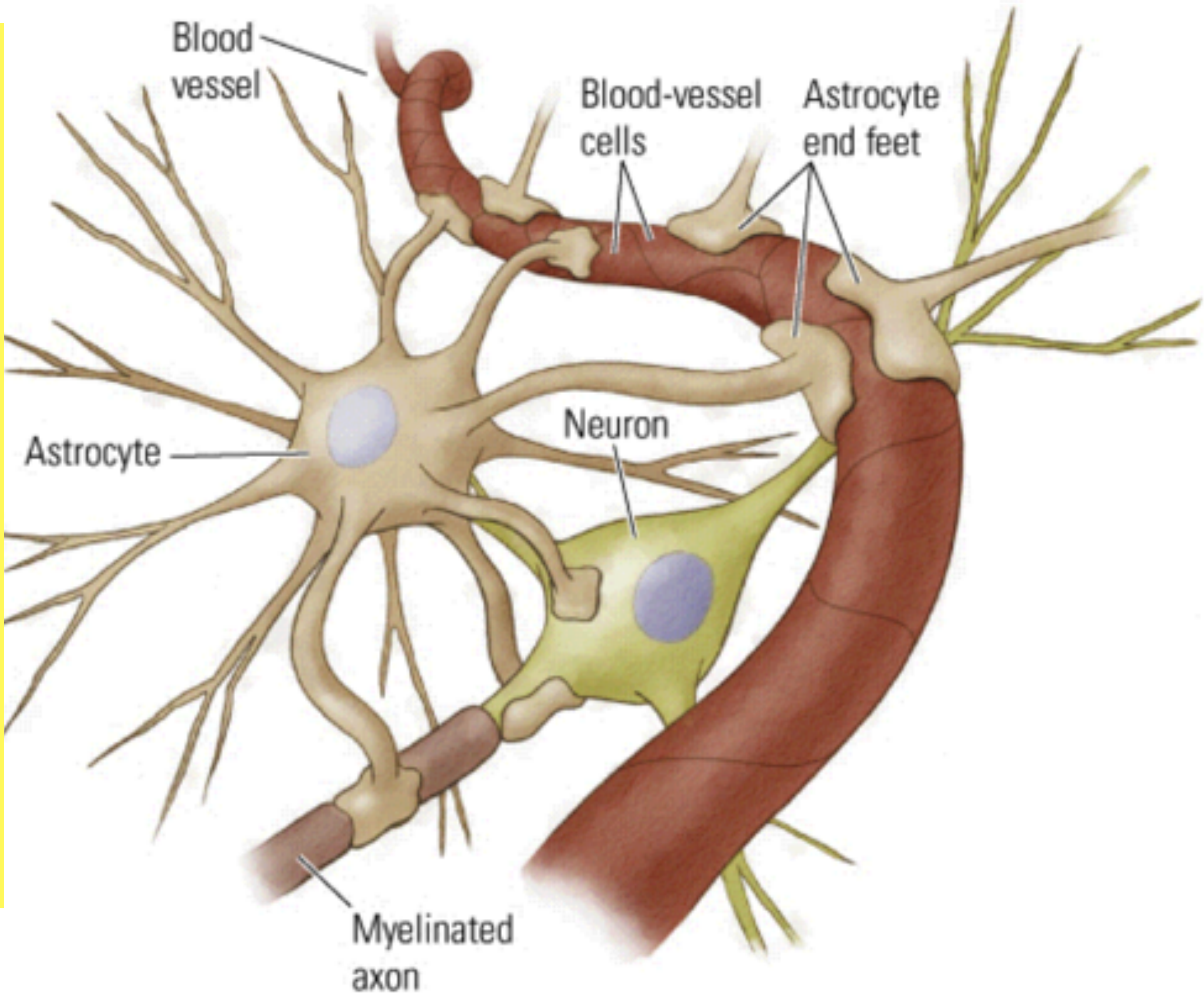
The Synapse

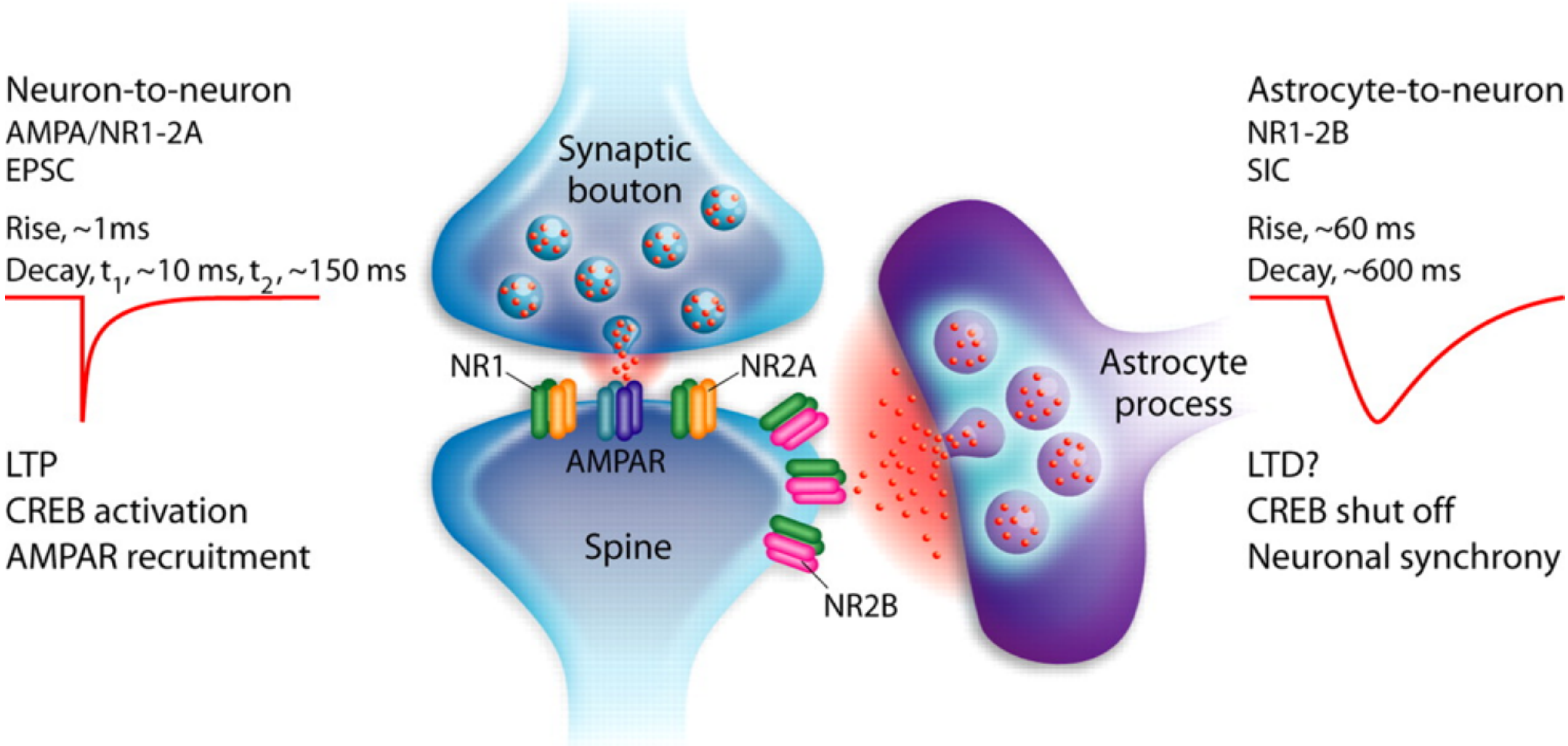
Dendrite-Axon Junction



Astrocytes

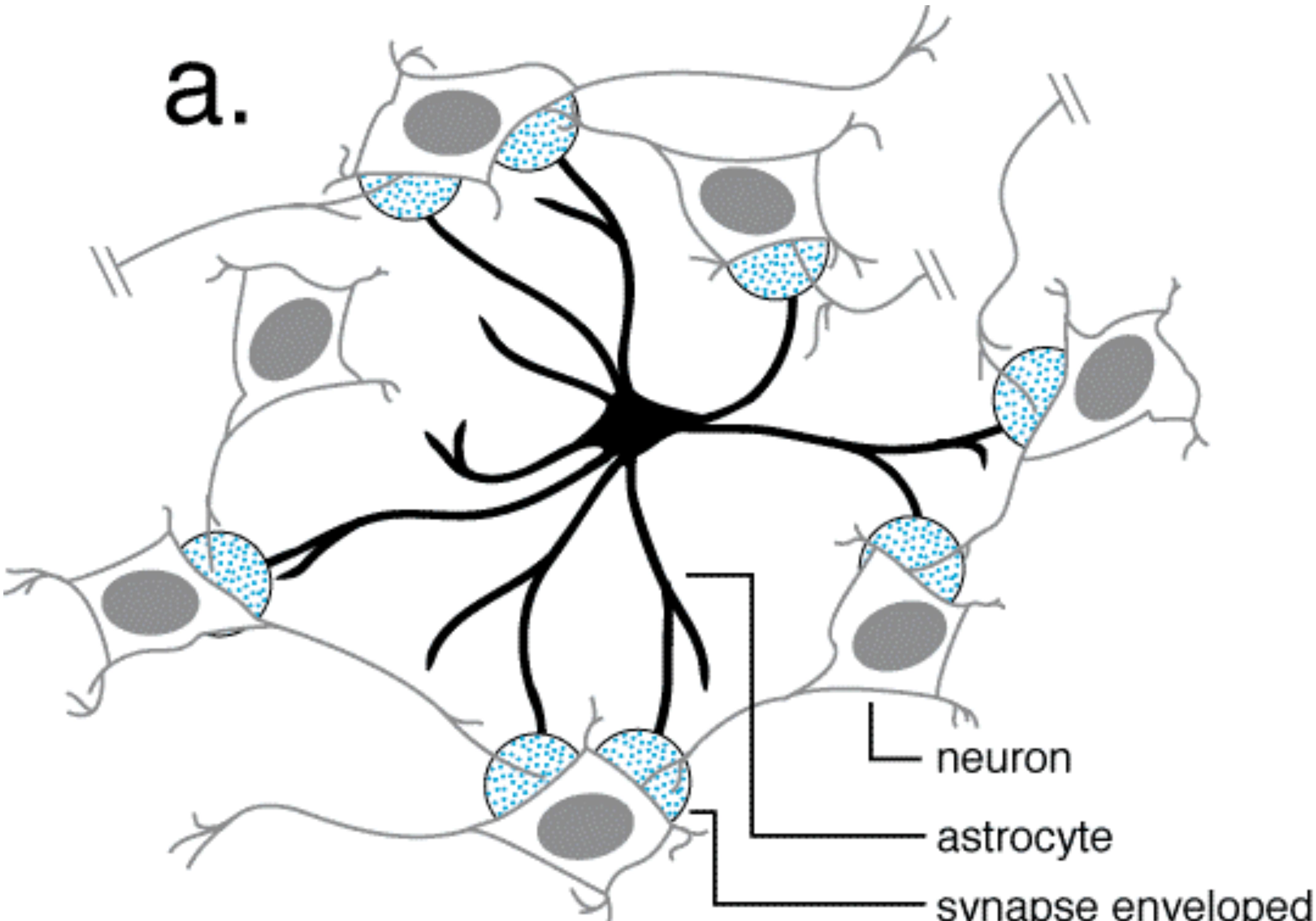
- Astrocytes have many functions
  - provide nutrients to neurons
  - regulate calcium flow
  - play a role in various medical disorders (e.g. epilepsy)
  - modulate synaptic strength of neurons





Tripartate Configuration
Astrocyte + Synapse (pre- + post- neuron)

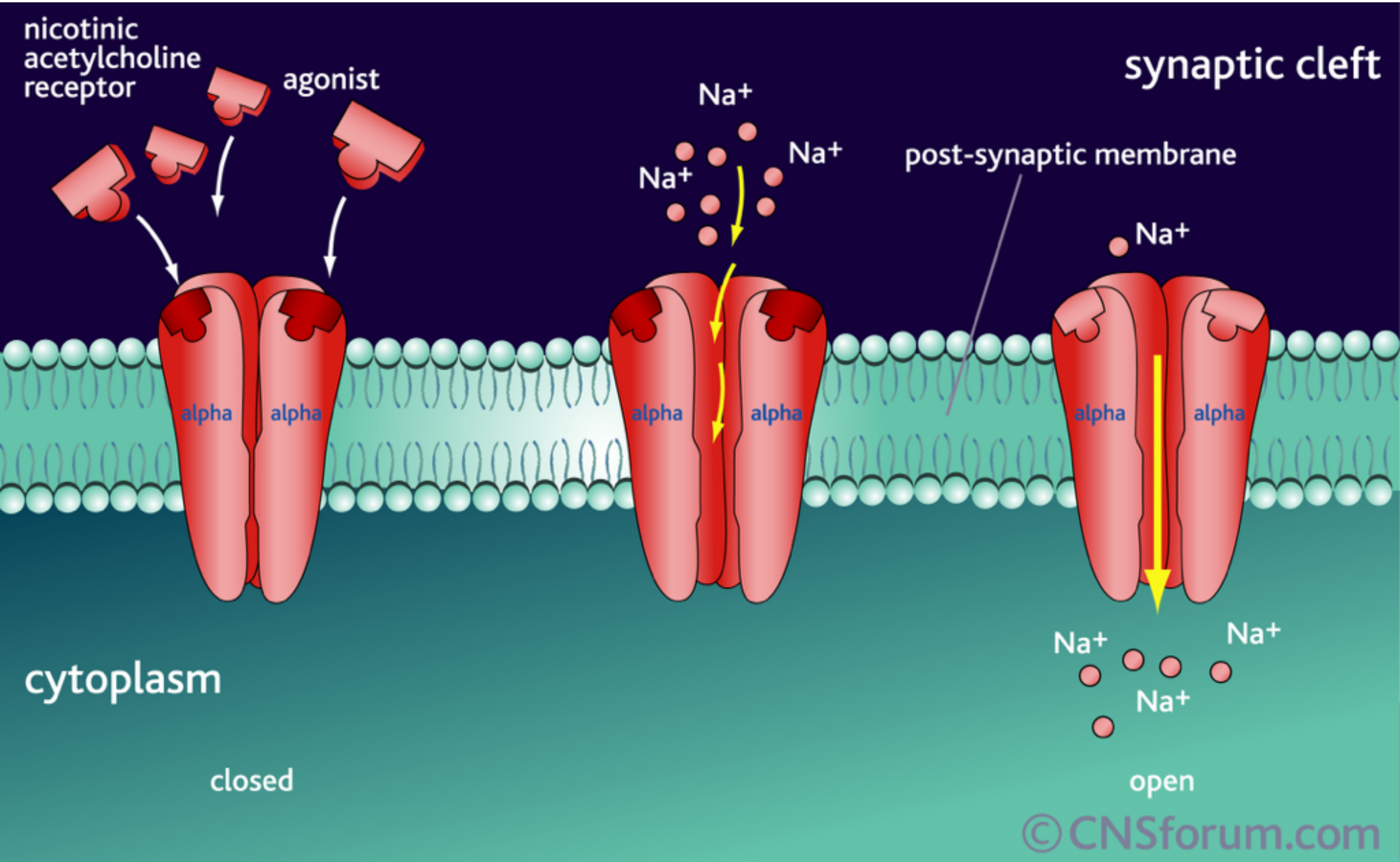
http://physrev.physiology.org/content/physrev/86/3/1009/F2.large.jpg


a.
neuron
astrocyte
synapse enveloped
by astrocyte

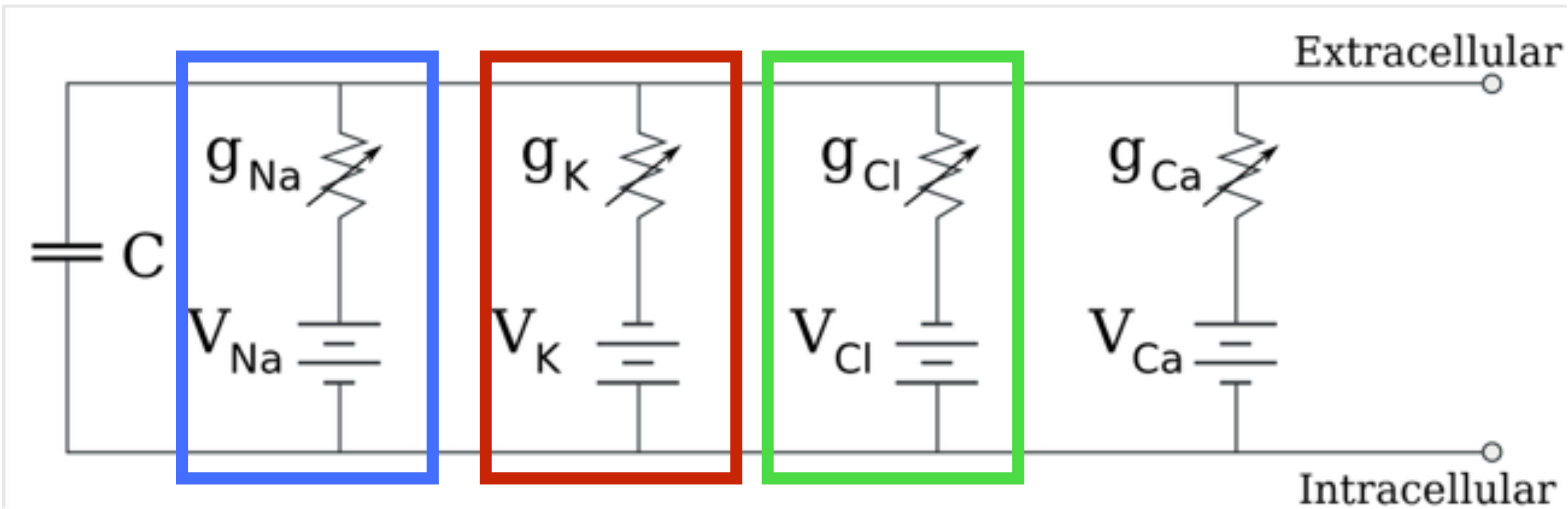
Prototypical Models

- Hodgkins-Huxley (HH)
  - single compartment
  - modeling of the neuron via electric circuitry
- Multi-compartment models
  - model spatial extent of axon and dendrites

Ion Channels



Point Neuron



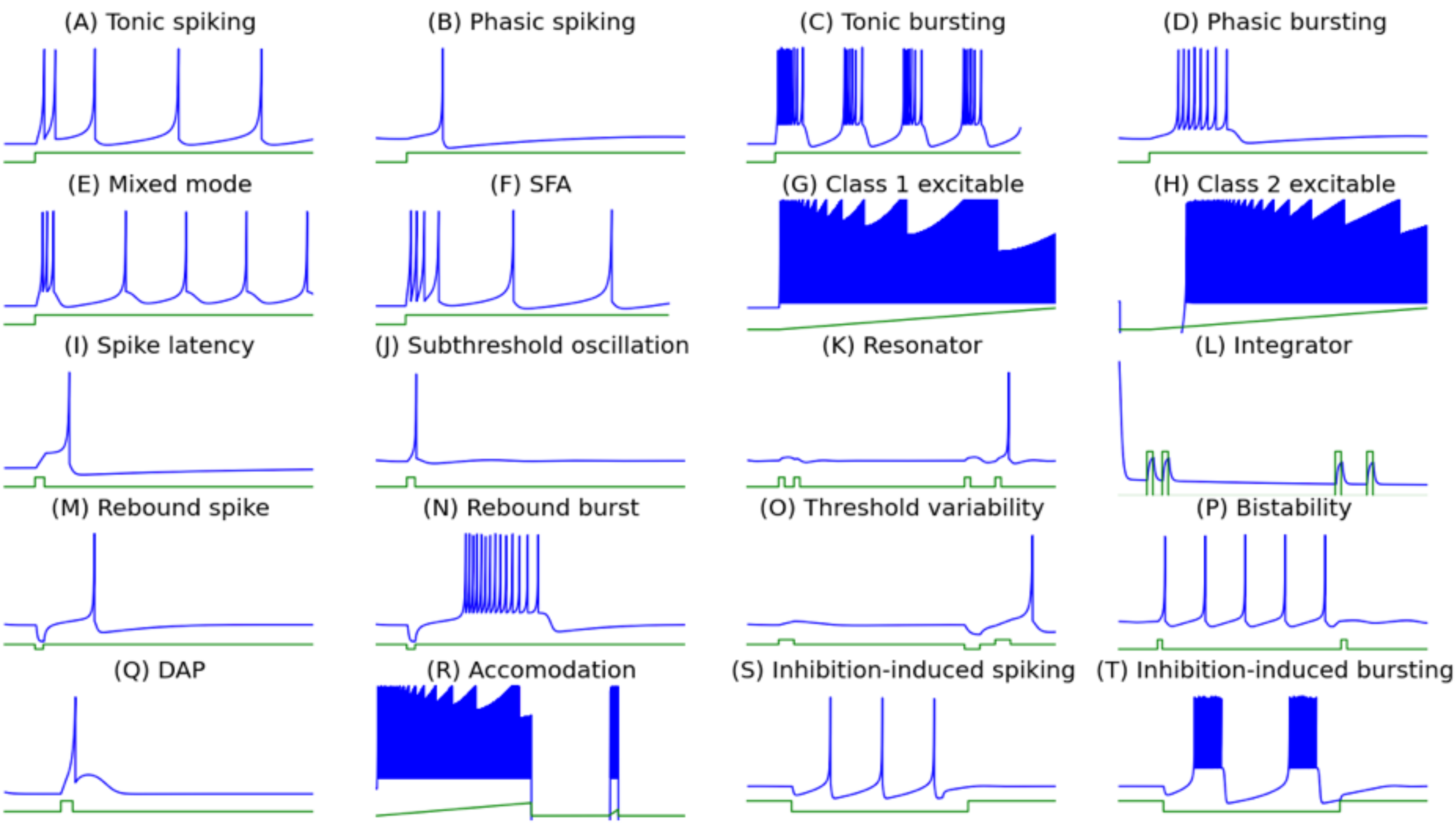
Equivalent electric circuit

$$I = C_m \frac{dV_m}{dt} + \boxed{g_K(V_m - V_K)} + \boxed{g_{Na}(V_m - V_{Na})} + \boxed{g_l(V_m - V_l)}$$

Potassium current **Sodium current** **Leak current**

conductances g_K, g_{Na} and g_l are functions of voltage and ion channel properties

Zoo of voltage spiking behavior



Simplified Models

	biophysically meaningful	tonic spiking	phasic spiking	tonic bursting	phasic bursting	mixed mode	spike frequency adaptation	class 1 excitable	class 2 excitable	spike latency	subthreshold oscillations	resonator	integrator	rebound spike	rebound burst	threshold variability	bistability	DAP	accommodation	inhibition-indiced spiking	inhibition-induced bursting	cha	Flops
integrate-and-fire	-	+	-	-	-	-	-	+	-	-	-	-	+	-	-	-	-	-	-	-	-	-	5
integrate-and-fire with adapt.	-	+	-	-	-	-	+	+	-	-	-	-	+	-	-	-	-	+	-	-	-	-	10
integrate-and-fire-or-burst	-	+	+		+	-	+	+	-	-	-	-	+	+	+	-	+	+	-	-	-		13
resonate-and-fire	-	+	+	-	-	-	-	+	+	-	+	+	+	+	-	-	+	+	+	-	-	+	10
quadratic integrate-and-fire	-	+	-	-	-	-	-	+	-	+	-	-	+	-	-	+	+	-	-	-	-	-	7
Izhikevich (2003)	-	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	13
FitzHugh-Nagumo	-	+	+	-		-	-	+	-	+	+	+	-	+	-	+	+	-	+	+	-	-	72
Hindmarsh-Rose	-	+	+	+			+	+	+	+	+	+	+	+	+	+	+	+	+	+		+	120
Morris-Lecar	+	+	+	-		-	-	+	+	+	+	+	+	+		+	+	-	+	+	-	-	600
Wilson	-	+	+	+			+	+	+	+	+	+	+	+	+	+		+	+				180
Hodgkin-Huxley	+	+	+	+			+	+	+	+	+	+	+	+	+	+	+	+	+	+		+	1200

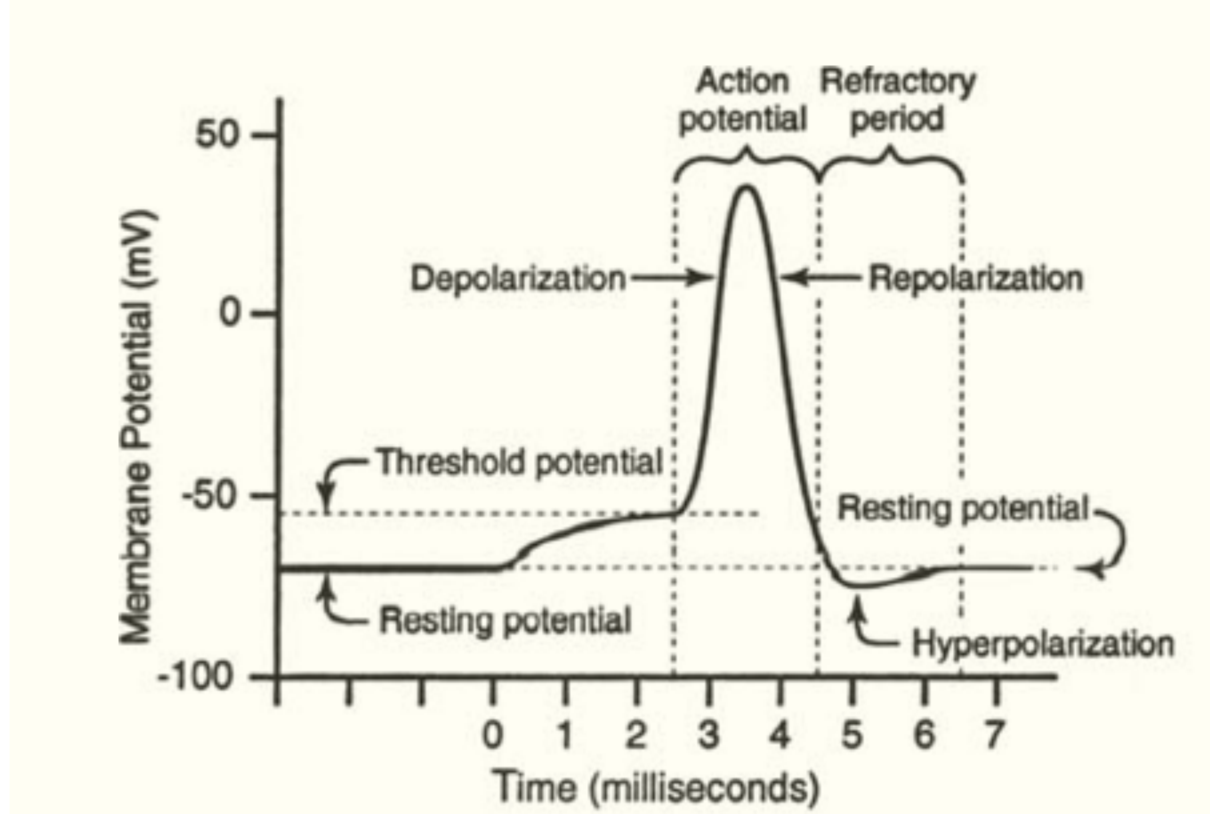
Izhikevich 2003

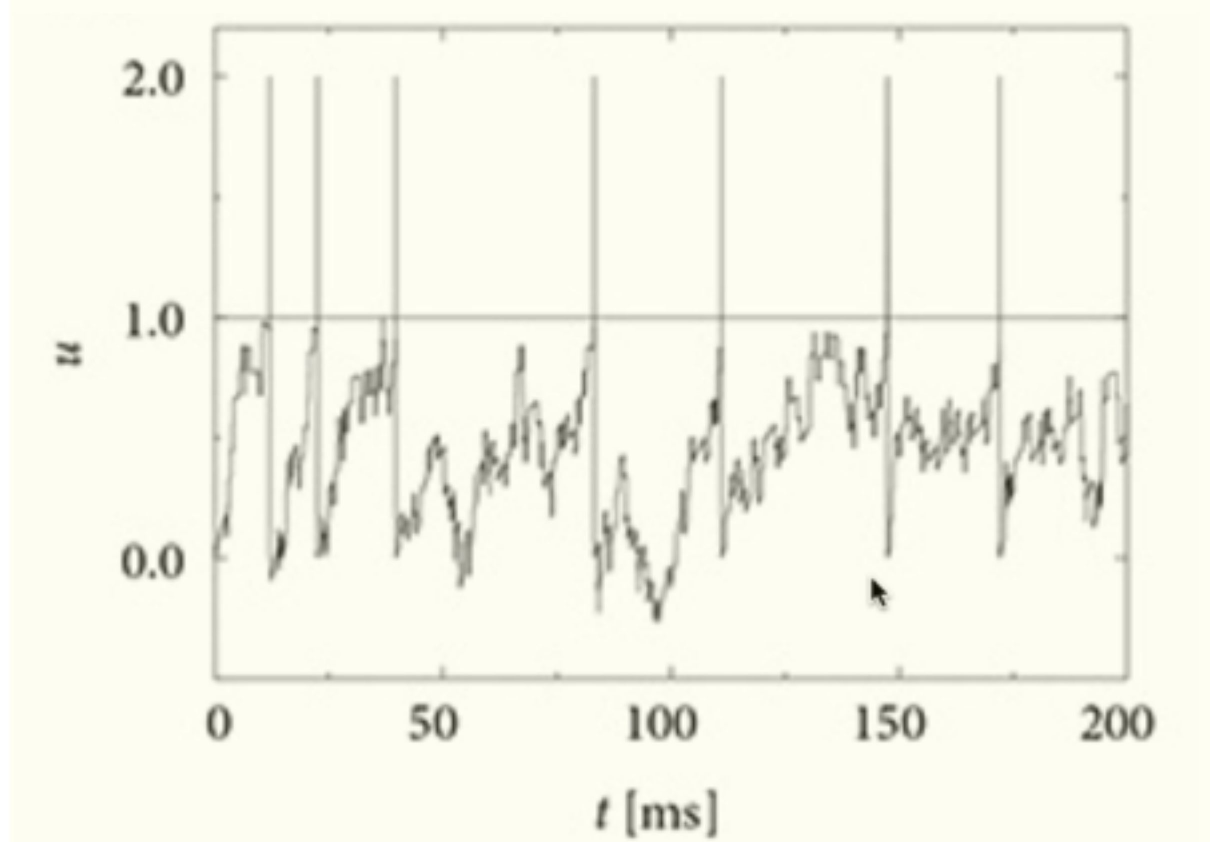
Integrate & Fire

$$\frac{dV}{dt} = cV^2 + dV - u + I$$

$$\frac{du}{dt} = a(bV - u)$$

if $V == V_{peak}$
then $v \leftarrow V_{reset}$, $u = u_0$





http://www.izhikevich.org/

Some important concepts

- **Spiking dynamics**
  - how does spiking relate to information content, memory, etc.
- **Propagation speed**
  - how long does a single spike take to propagate from neuron to neuron
- **Plasticity**
  - change in the synaptic efficacy

How we Learned

- Online courses
- FSU courses (most notably from R. Bertram in math)
- Several hundred downloaded papers
- Weekly group meetings (open to all)
  - talks and free-flowing conversation
- Question everything
- Coding up interactive demos
- Networking

Interactive Demo

$$\epsilon \frac{dw}{dt} = (v - v^3/3 - w)$$

$$\frac{dw}{dt} = (v + 1.05 - I)$$

python FN.py

http://i.huffpost.com/gen/1530991/thumbs/o-HEALTHY-BRAIN-faceb

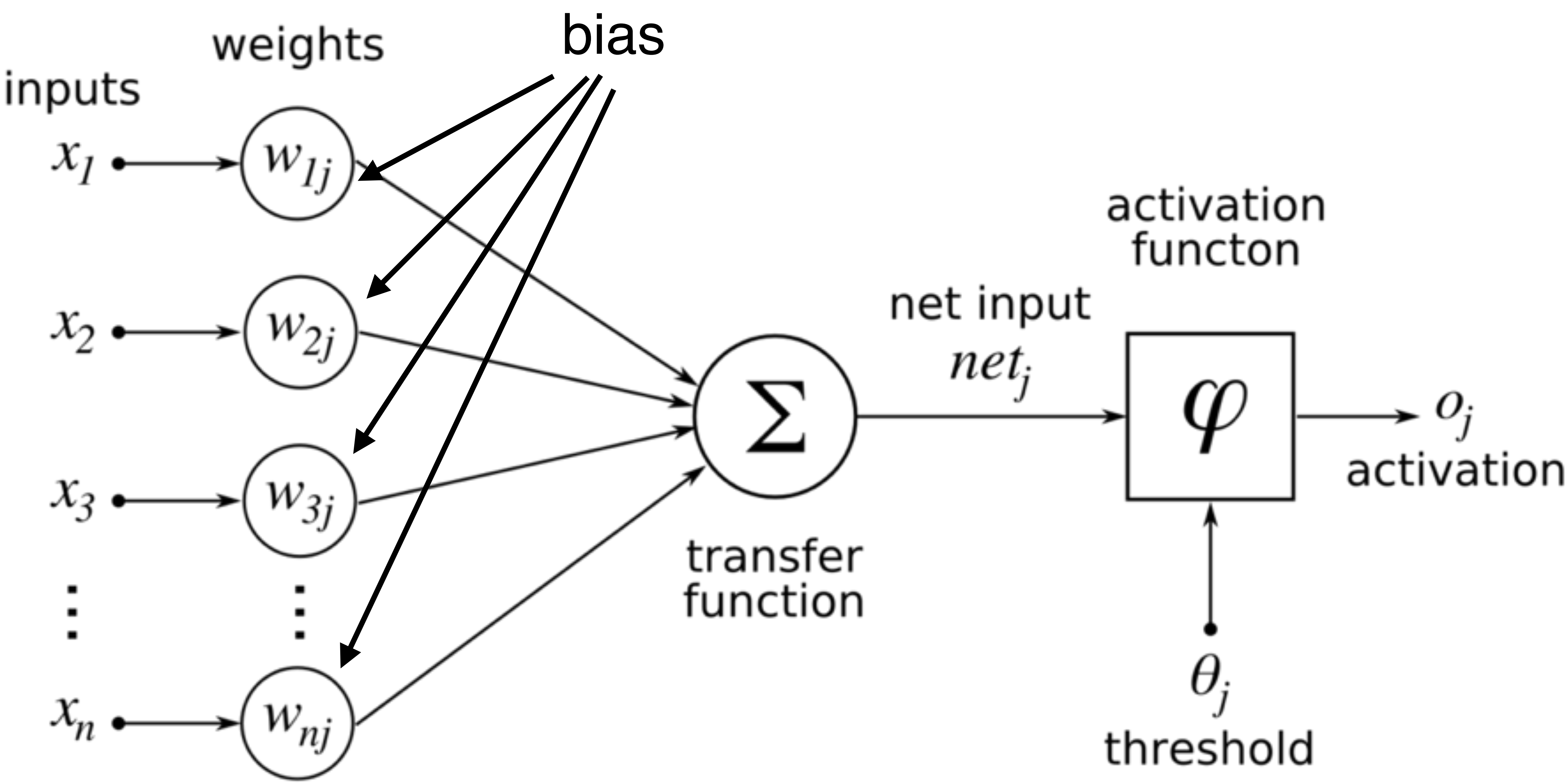
Reality

Goal

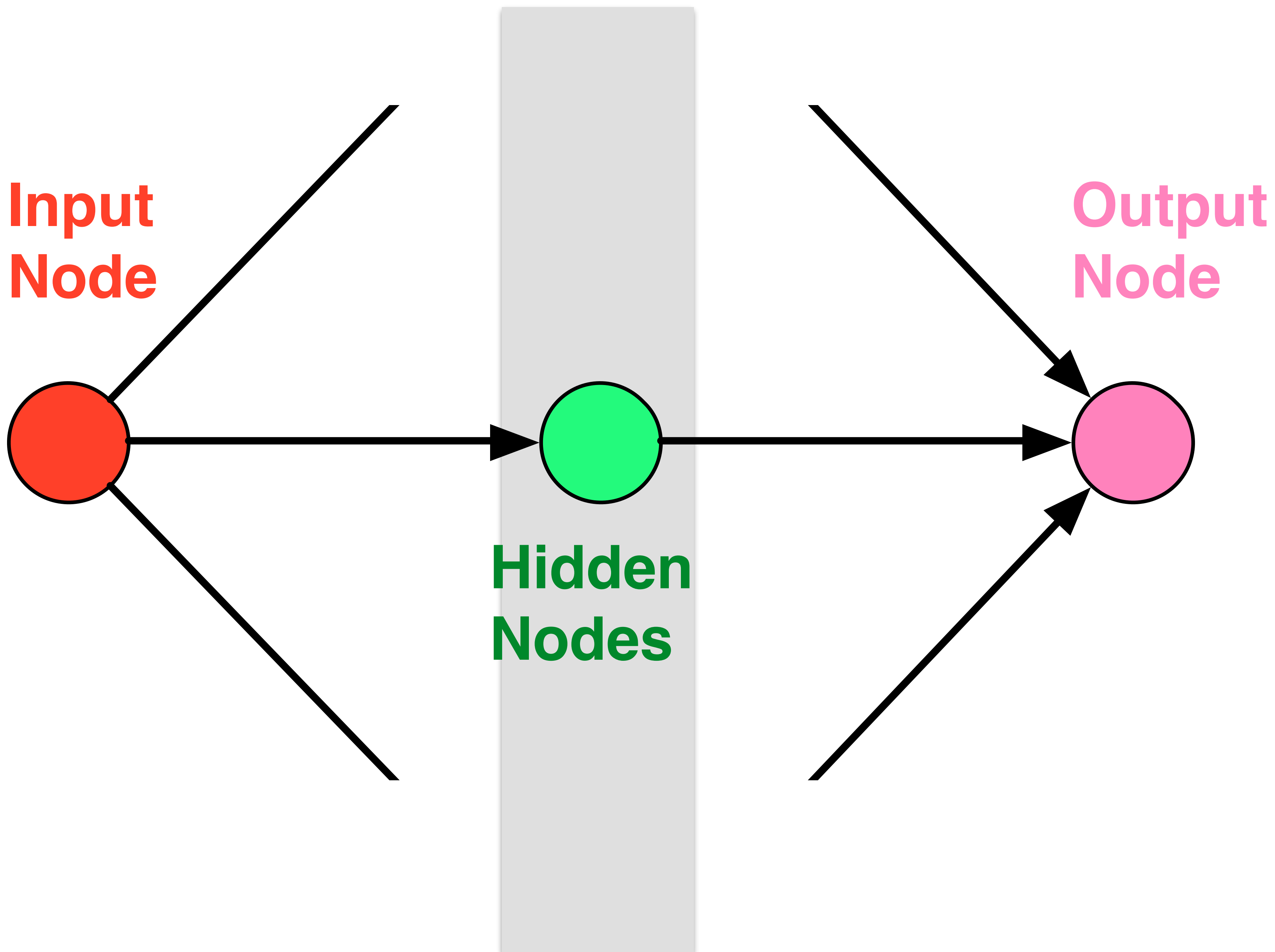
Most Algorithms (including the Brain)

Artificial Neural Network

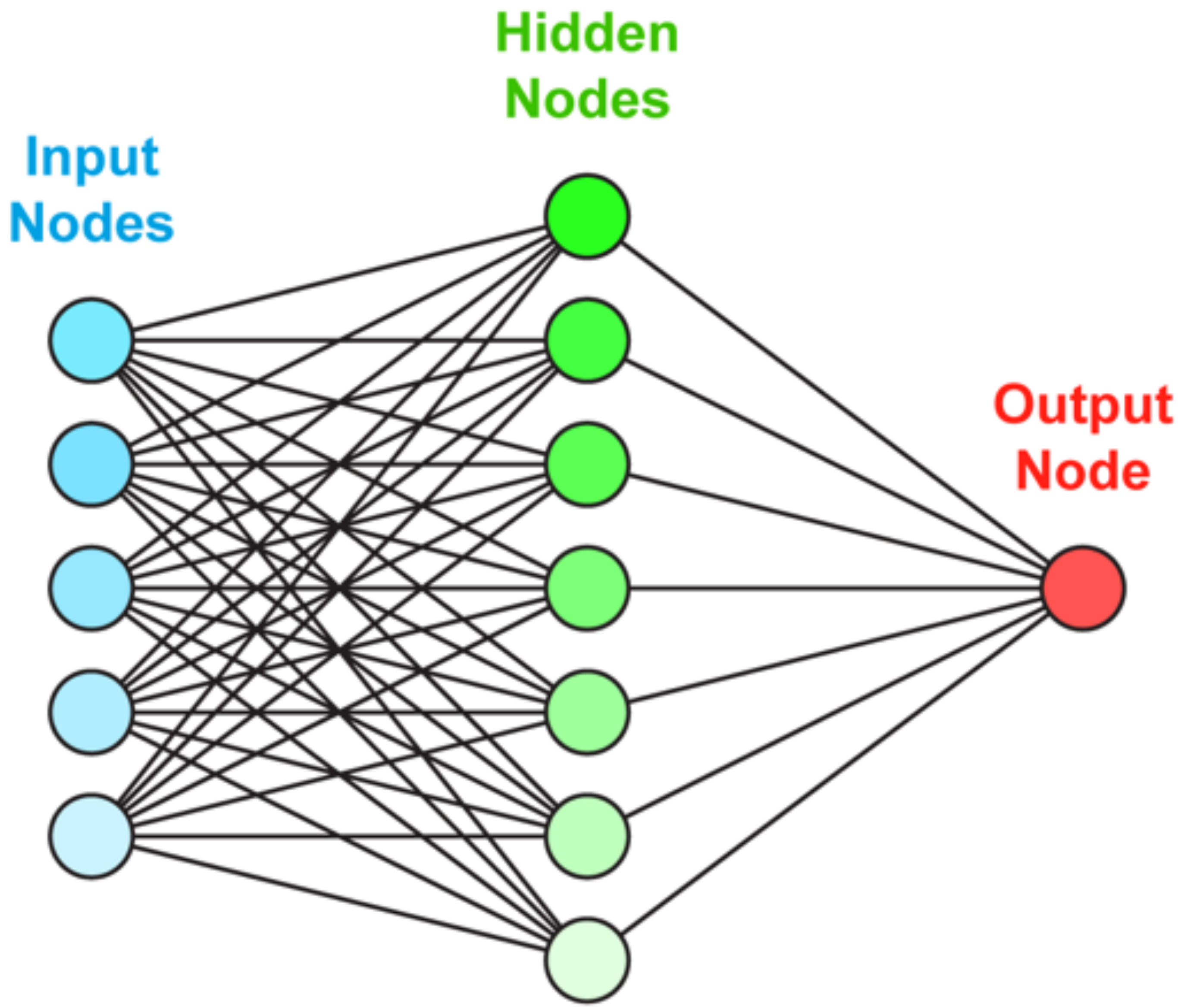
Basic computational unit



http://en.wikibooks.org/wiki/Artificial_Neural_Networks/Activation_Functions

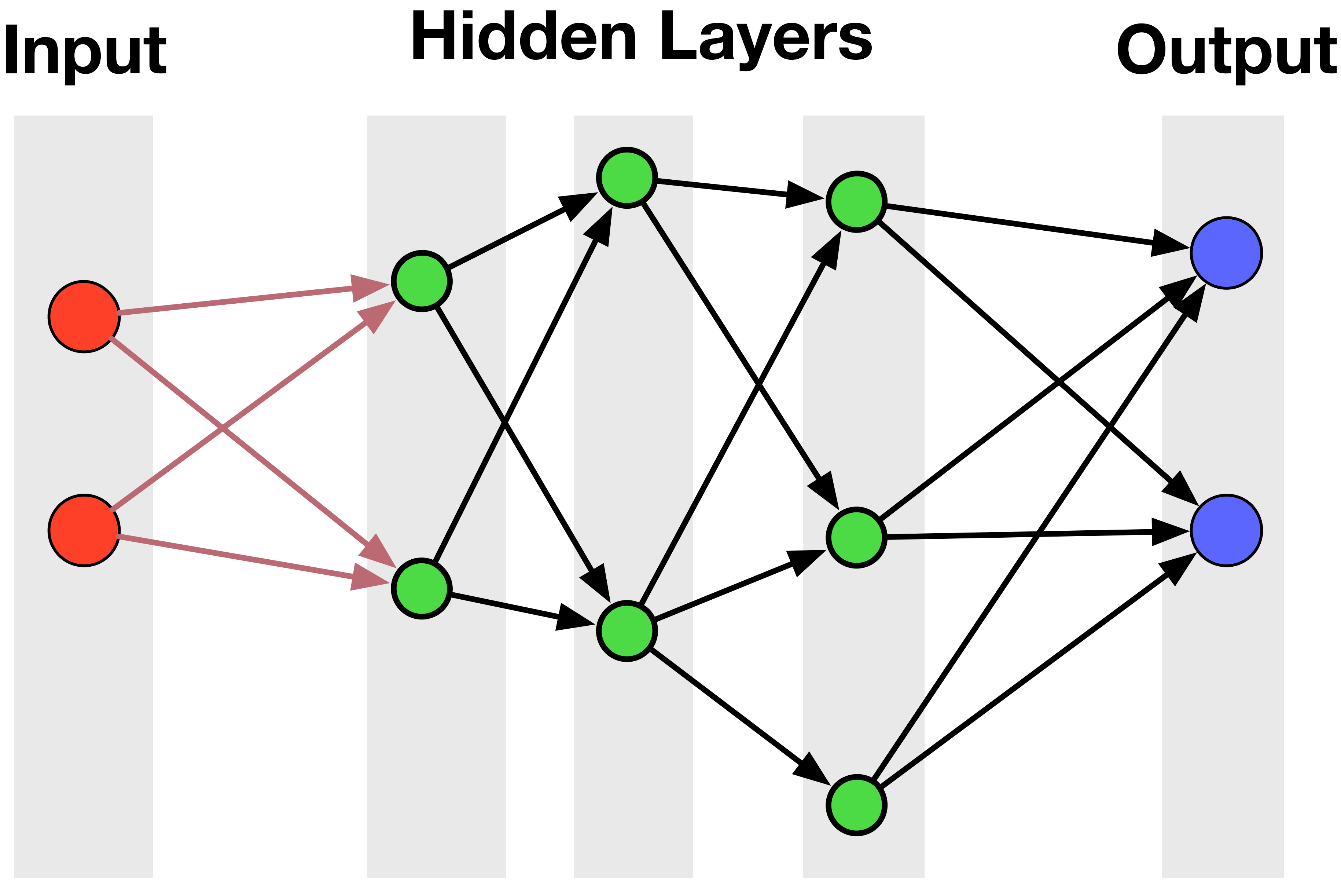


Single Hidden Layer



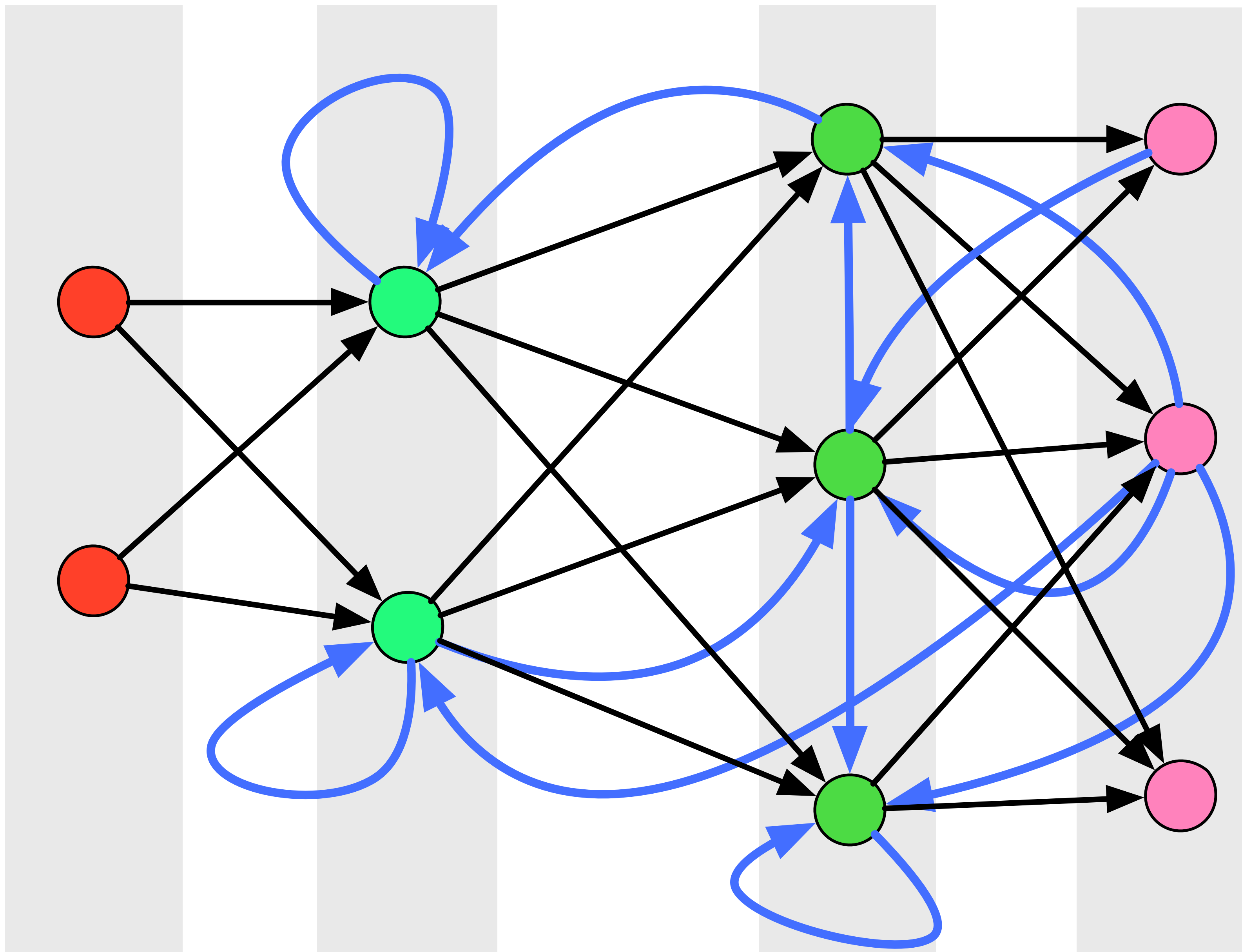
Can approximate any function if there are a sufficient number of nodes in the hidden layer

Multilayer, Feedforward



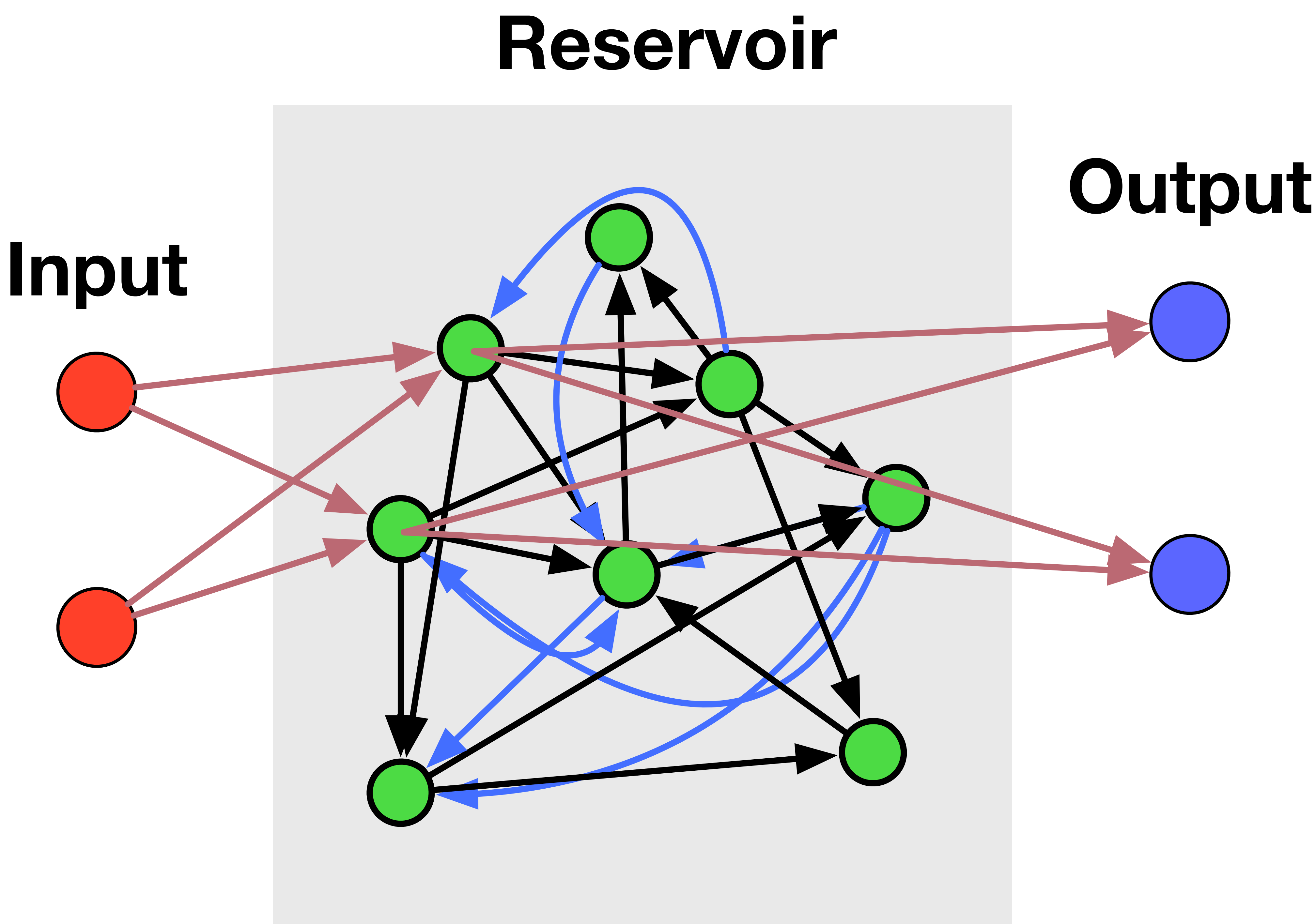
Deep Learning

Multilayer, Recursive



Can model all systems of ODEs
(i.e., dynamical systems)

Reservoir Networks



Reservoir Networks

- Have the potential to store information
- Recursion in networks often translates to the use of past information
- It is possible to control the length of time information is maintained in the network
- Thus, there is the hope of building in memory effects (short, medium, long term) into these reservoirs
- **The average neuron in the brain has 1000 to 10000 recurrent connections**

Some Remarks

- In all the preceeding networks
  - no propagation speed
  - no spiking
  - weights are the solution to a large system of nonlinear equations (one per node), combined with the minimization of some cost function (supervised learning)

Biologically-Enhanced Artificial Neural Networks

- All the previous networks can be enhanced to add
  - spiking
  - propagations between nodes
  - weight changes via plasticity

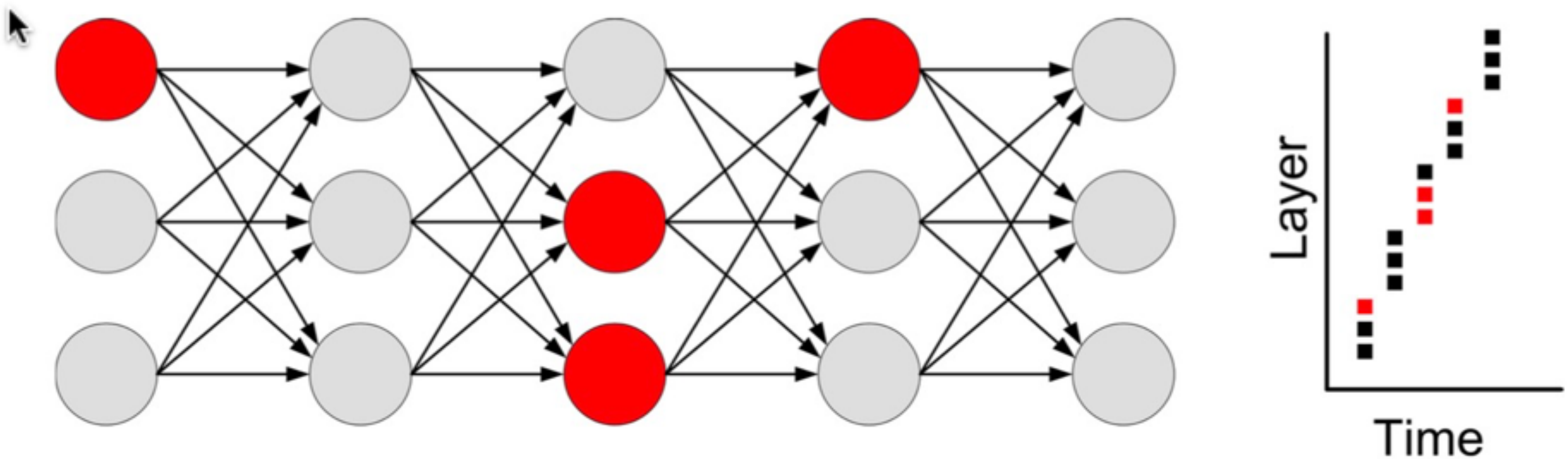
Important Biological Mechanisms

- Plasticity (multiple forms)
  - mechanisms that affect the strength of synapses
- Synchronization
  - propensity for multiple neurons to fire (i.e., spike) simultaneously
- Balance
  - some neurons excite and some inhibit (ratio of 5:1 excitatory:inhibitatory), downstream neurons
- Recursion
  - neuron networks are not feedforward

Synfire Chains

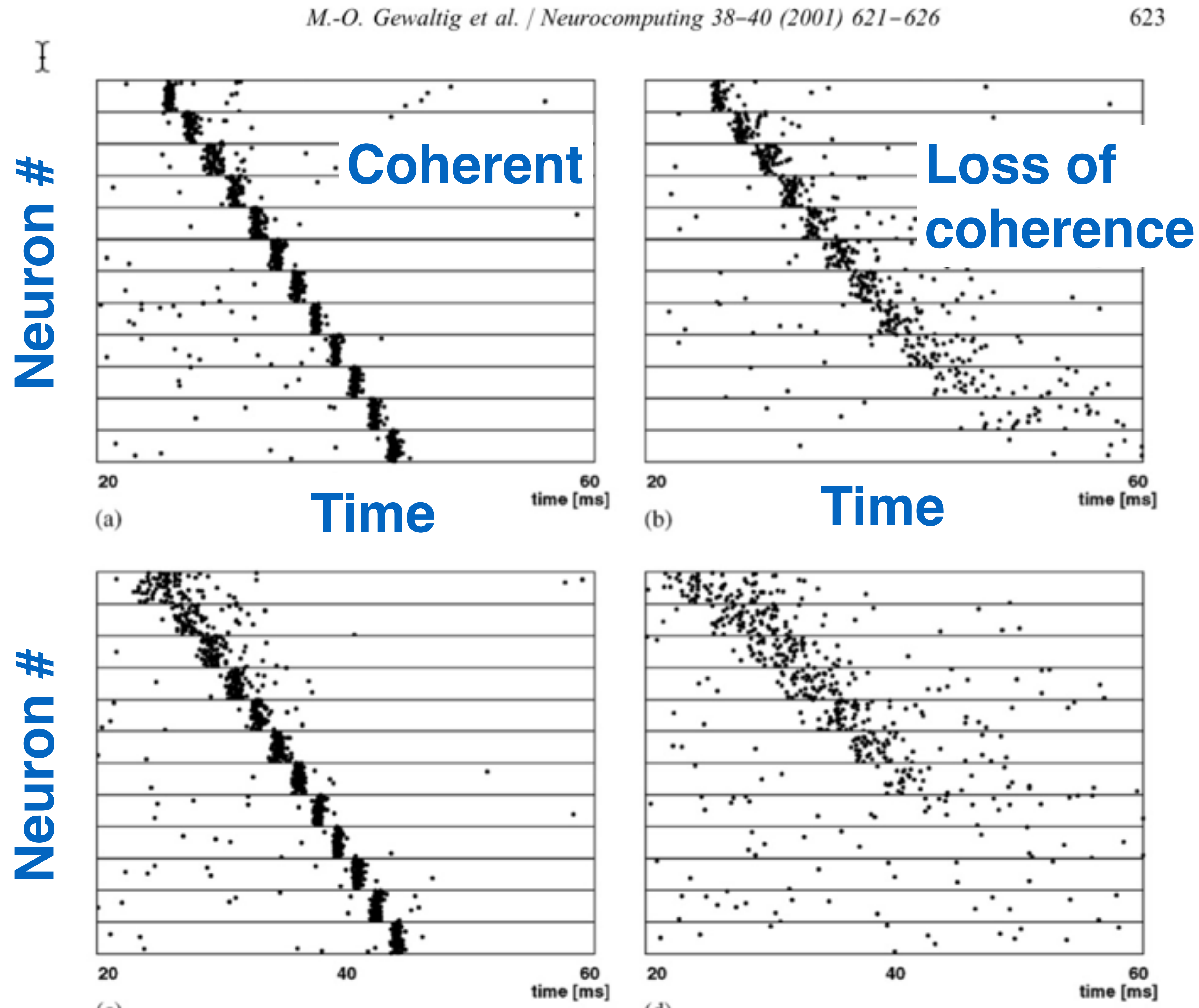
- Under certain conditions, neurons that fire together, will propagate together across a feedforward network
- Synfire chain theory assumes that spike delays are constant
- However, real neuron networks are
  - recursive
  - spike delays are in the range [1ms - 40ms]

Feedforward Architecture for Synfire Chains



- Neuronal Delays are constant
- Neurons in layer 1 spike within a small time interval
- These spikes propagate across the netowork, keeping their coherence

Synfire Chains



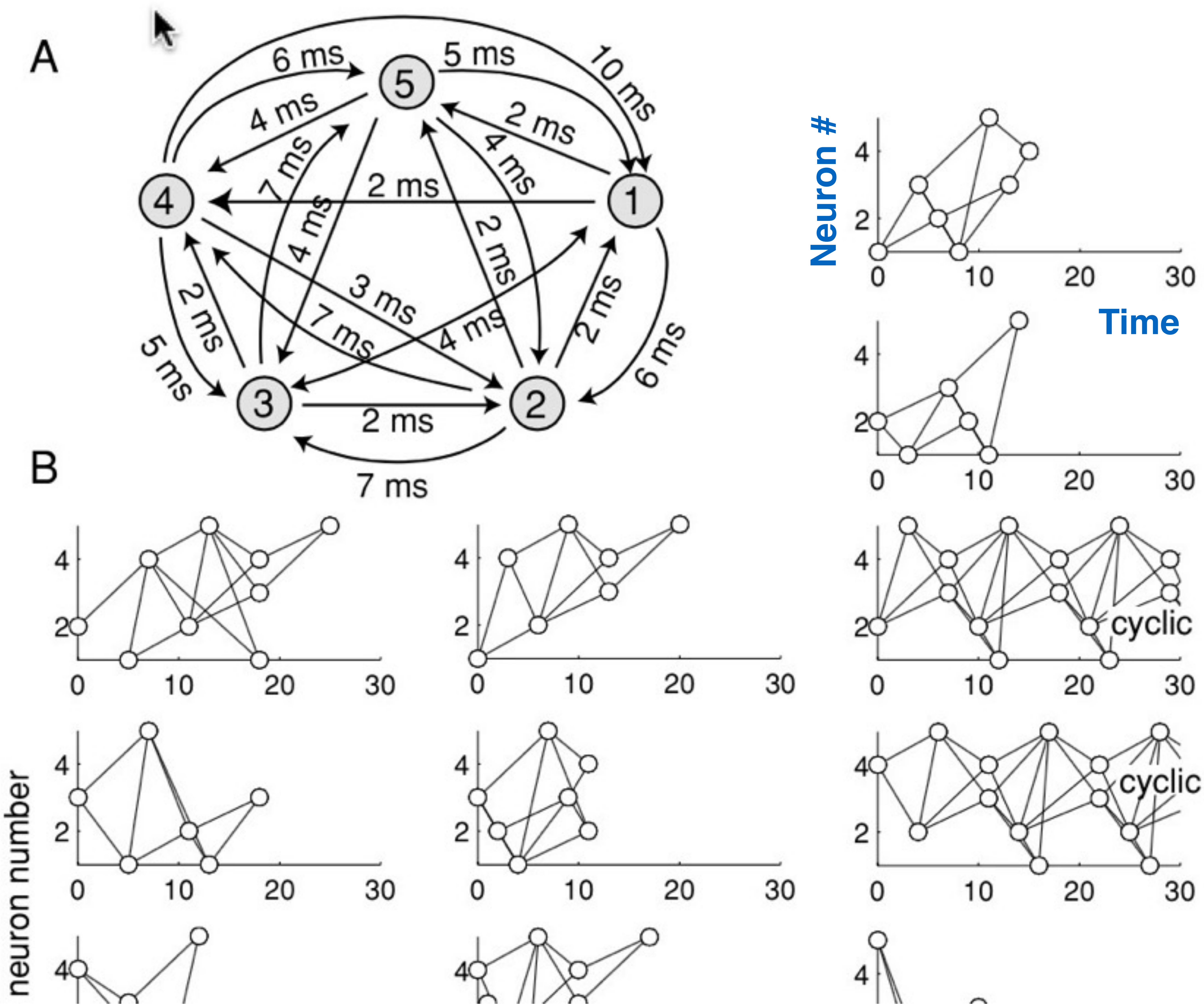
Non-constant delays

- Synfire chains transforms into a polychronous group
- What is a polychronous group?

A polychronous group is a subset of neurons that fire in a particular space-time sequence that is repeatable given the proper input

Why are we interested in Polychronous Groups?

Some researchers hypothesize that the sheer number of polychronous groups make them a candidate for the storage of memories


A
B
6 ms
5 ms
10 ms
4 ms
2 ms
7 ms
4 ms
2 ms
4 ms
2 ms
3 ms
7 ms
4 ms
2 ms
2 ms
5 ms
6 ms
2 ms
7 ms
Neuron #
Time
neuron number
cyclic
cyclic

Questions to answer

- What is the relationship between polychronous groups and synfire chains?
- What are the statistics associated with polychronous groups?
- How are polychronous groups affected by recursion, plasticity, and outside influence (i.e., astrocytes)

Some Questions

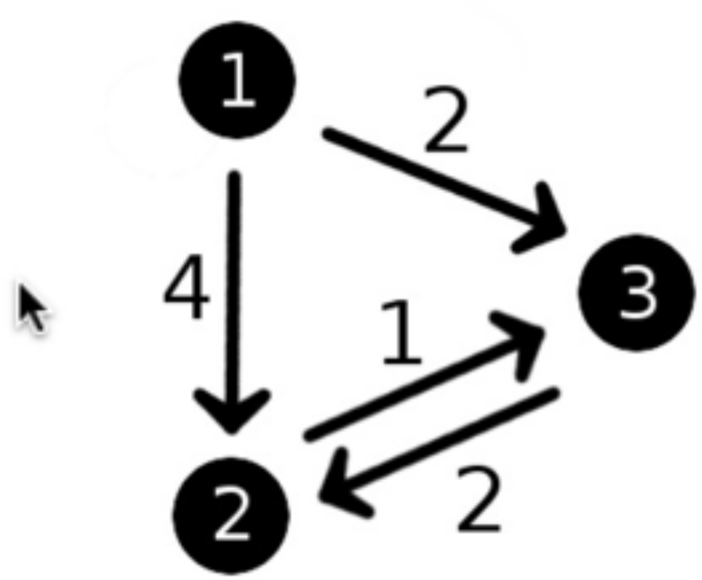
- Let G be the number of polychronous groups in a neuron network
- How does G(N) depend on the number **N**, the delay statistics, the number of neuronal connections?
- Dependence of G on the number of connections **m** required to fire?
- What is the affect of recursion on the properties of polychronous groups?
- How robust are polychronous groups to changes the effects of plasticity?
- How many polychronous groups contain a given neuron?

An Algebra

- Performing simulations to answer these questions is very expensive, even with the simplest models
- We'd like some theoretical results
- Try to create an algebra under very simple assumptions. Hopefully this will provide insight into more realistic situations
- Next: some initial ideas (by Nathan Crock)

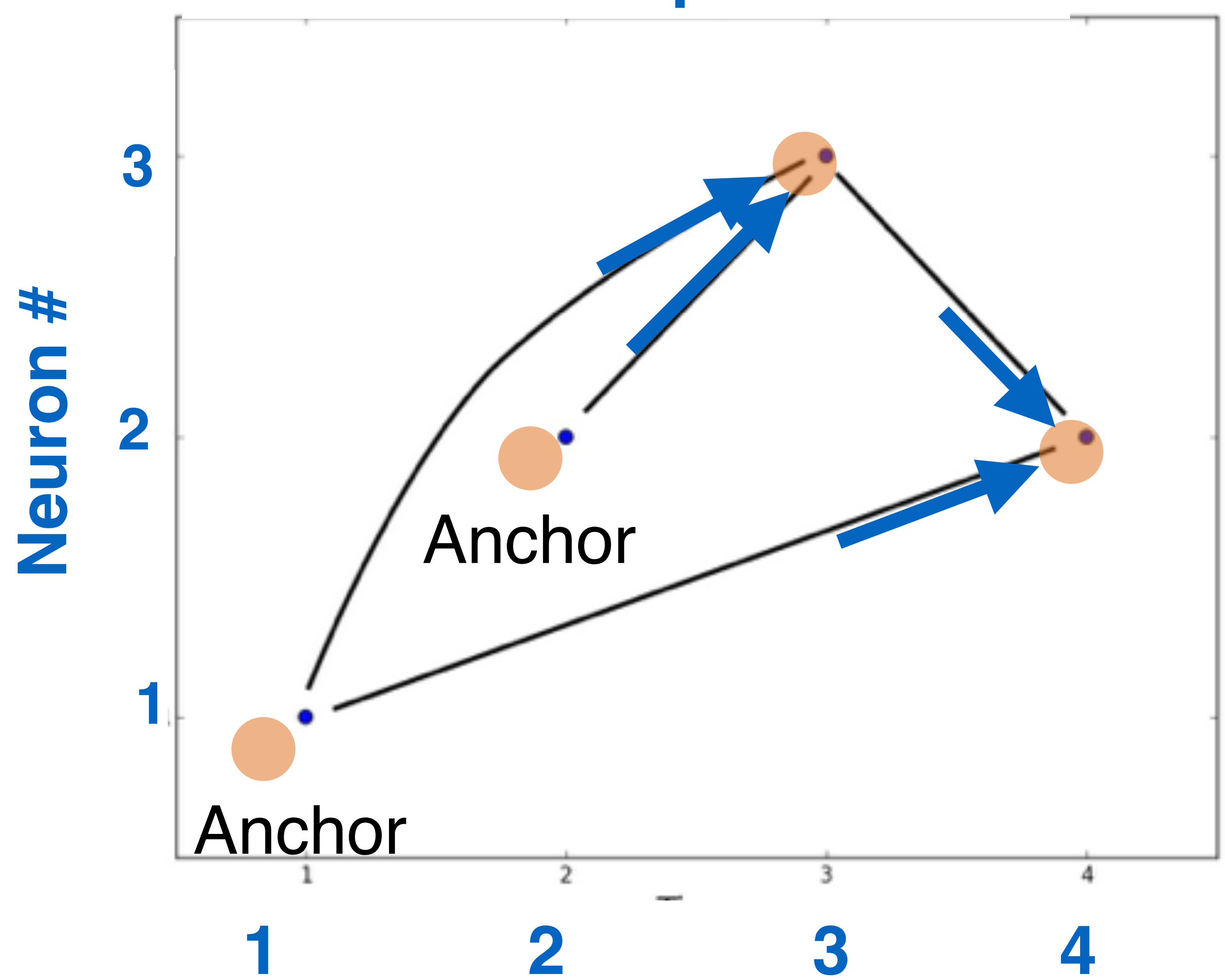
Each neuron requires two input spikes to be activated

in a biological network, many spikes might be required



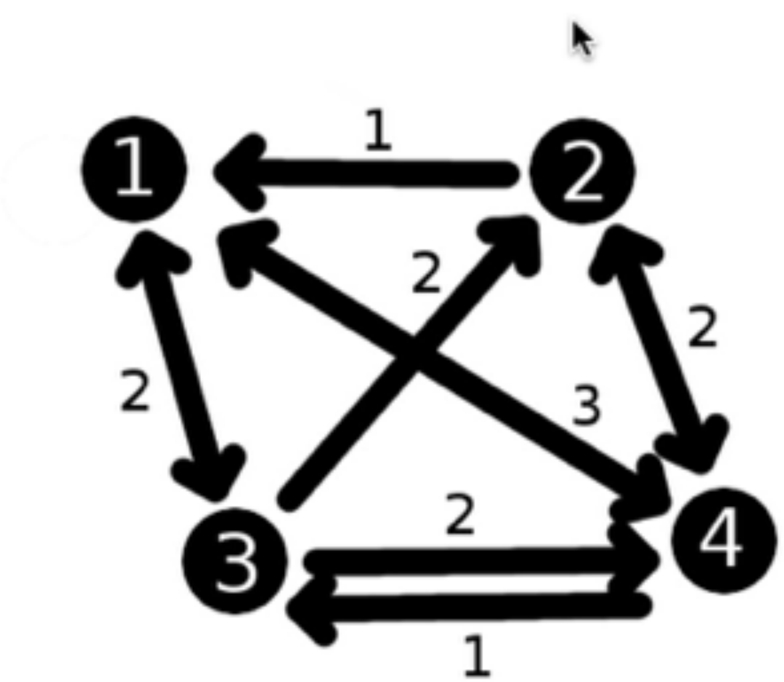
N=3
m=2

Neuronal Group Activation

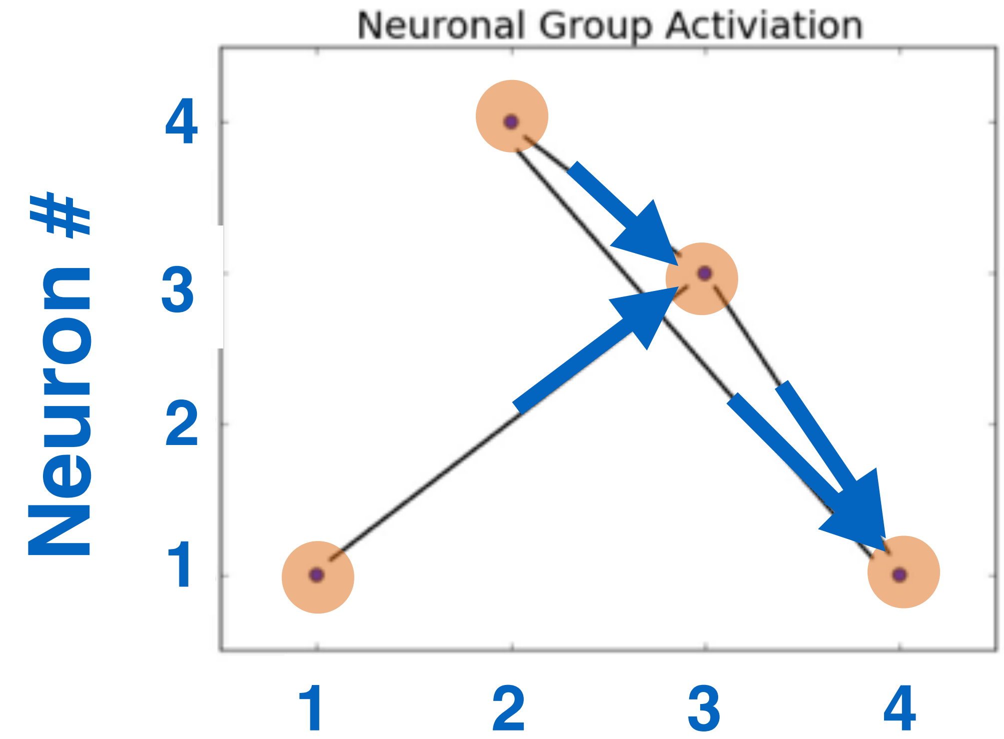


One polychronous group labelled by its anchors and time of emission

P1 = {(1,1), (2,1)}

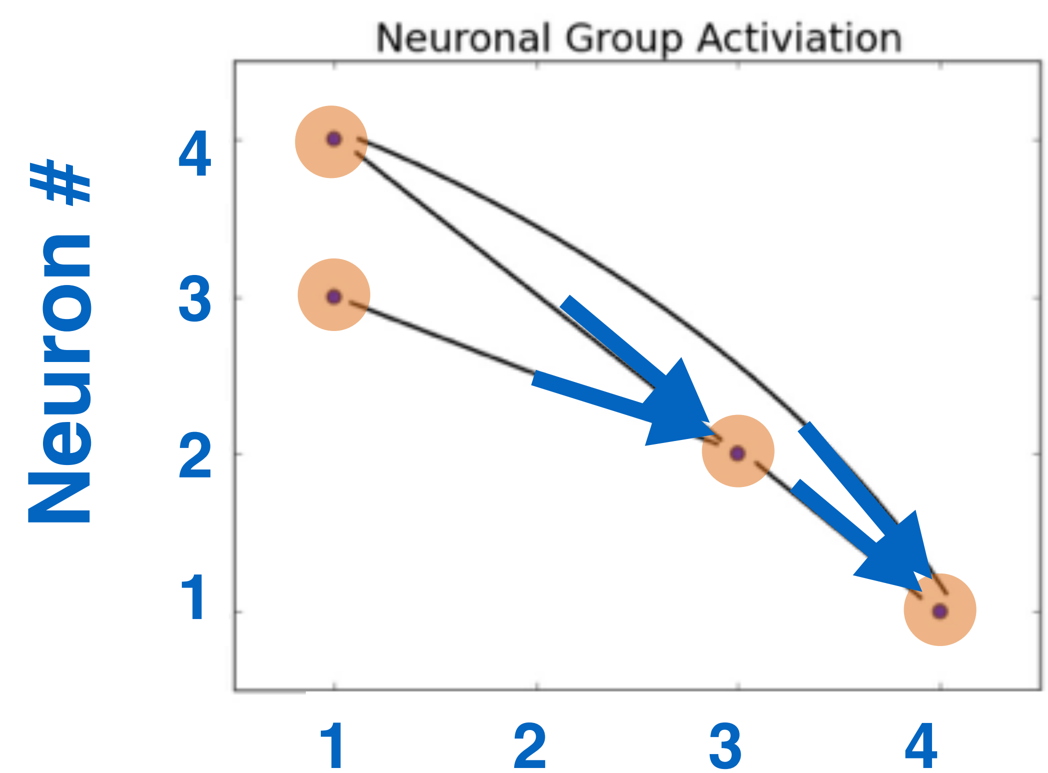


N=4
m=2



Two polychronous groups labelled by its anchors and its firing (spiking) time:

P1 = {(1,1), (4,2)}
P2 = {(3,1), (4,1)}



Initial properties

- Consider P1 = $\{(1,1), (4,2)\}$
- Assume the group is "activated" t_3 time units earlier
- Rewrite it as P1 = $\{(1,t_1), (4,t_2)\}$
- The following equality holds
  P1 = $\{(1,t_1-t_3), (4,t_2-t_3)\}$
- A polychronous group is said to exist independently of its time of "activation"

Network of

P1 = {(*1,1*), (*4,2*)}

Time shift invariance of polygroup

(<u>Recall</u>: a polygroup is represented by the neurons that activate it.)

Neuron #				
4	0	1	0	0
3	0	0	0	0
2	0	0	0	0
1	1	0	0	0
Time	1	2	3	4

Matrix-like object

The i^{th} Neuron

$$\mathbf{n}^{(i)} = \begin{pmatrix} d_1 \\ d_2 \\ \vdots \\ d_N \end{pmatrix}^{(i)}$$

Neuron index

Delay from neuron (i) to neuron 2

The “elements” of **n**(i) are the delays of its deferent (downstream) connections.

Summary

- Vector-like objects (neurons)
- Matrix-like objects (networks)
- Basis neurons (not shown)
- Time-shift operators
- Other operators (+, -)

Some Research Objectives

- Define notion of vector space for neurons and networks (metrics, norms)
- Define equivalence between networks
- Decompose a neuron or network into irreducible representations
- Construct more complex networks from simpler networks
- Pinpoint the notion of "polygroup complexity"
- Use these results as a first approximation of results when simulating more realistic biological configurations

Sunposium™ 2015: Neural circuits and sunshine

Please Note: You can watch the live stream of some of the talks here: http://www.maxplanckflorida.org/news-and-media/sunposium-live-stream/.

Max Planck Florida Institute for Neuroscience (MPFI) presents Sunposium™ 2015, the second biennial conference highlighting some of the most complex issues at the forefront of understanding neural circuits.

The two-day conference features world-renowned scientists from the Max Planck Society and research institutes and universities throughout the United S

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Attended by Nathan Crock and Joel Tabak

Richard Huganir

Na Ji

Yishi Jin

Erik Jorgensen

New Collaboration

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James Schummers, PhD

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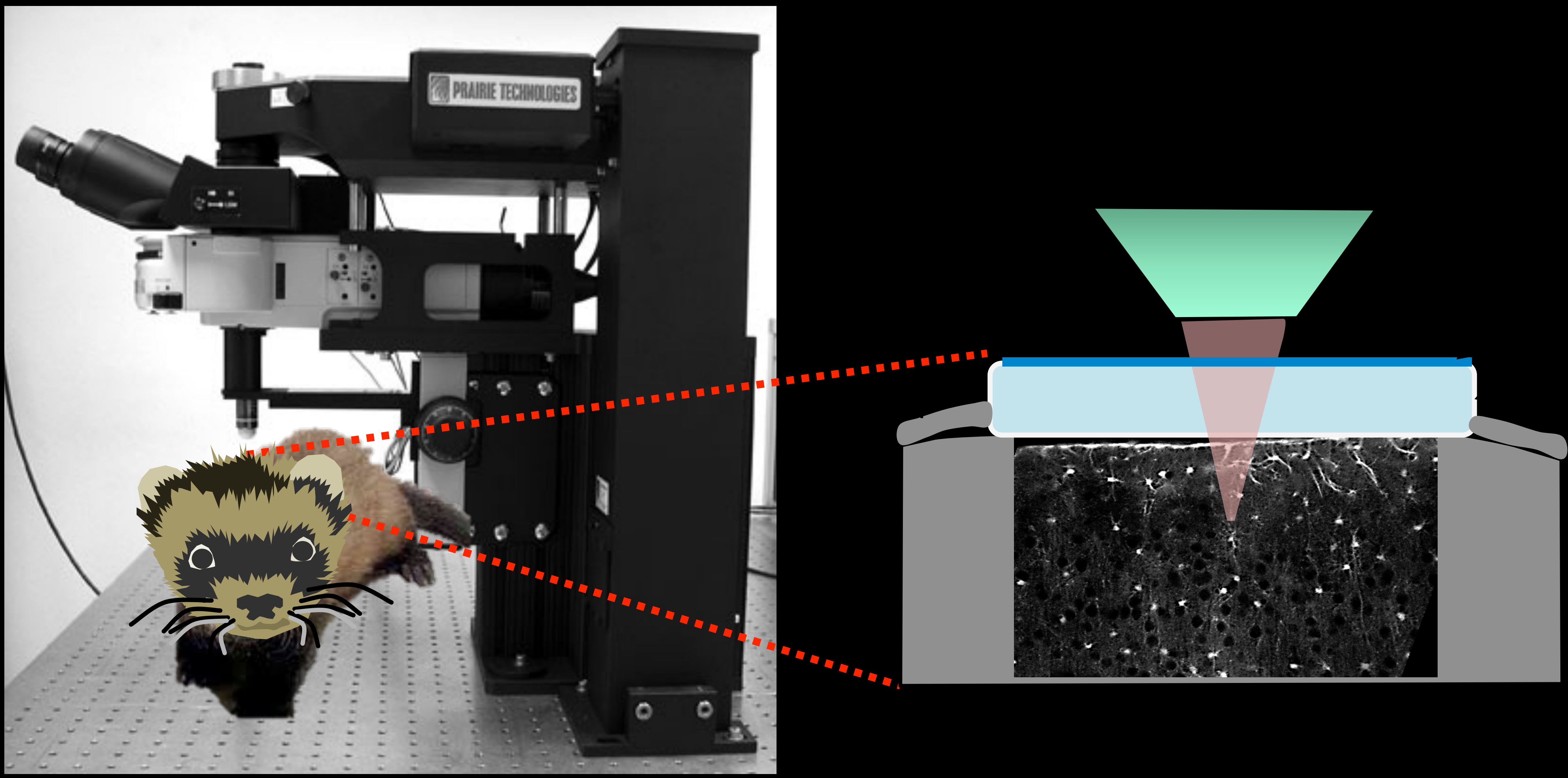
Researcher Bio

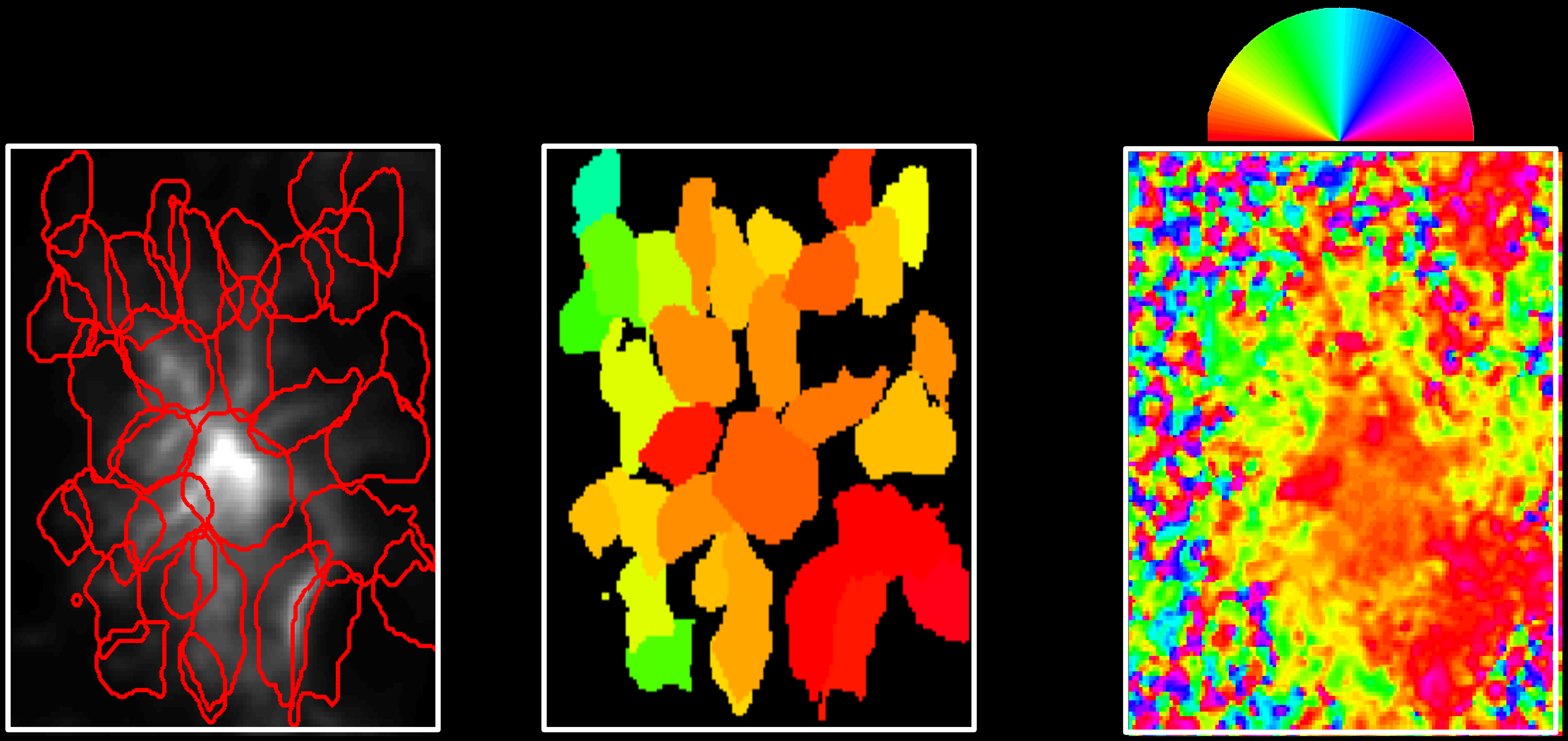
Dr. James Schummers was named an independent Research Group Leader at the Max Planck Florida Institute for Neuroscience in June 2010 and heads the Cellular Organization of Cortical Circuit Function research group. Dr. Schummers received his bachelor's degree in Neuroscience from Oberlin College in Oberlin, OH, where he studied the effects of the neurotransmitter neuropeptide-Y on long-term potentiation (LTP) in the hippocampus. He then moved to Denver CO, where he studied the effects of alcohol on LTP in the Department of Pharmacology at the University of Colorado Health Science Center. He received a PhD in Systems Neuroscience at the Massachusetts Institute of Technology with the support of a Howard Hughes Pre-Doctoral Fellowship. His thesis work combined intracellular and extracellular single neuron recordings with optical imaging approaches to study the integration of synaptic inputs in the context of visual processing. His postdoctoral work, also at MIT, focused on single-cell resolution imaging to study the response properties of different classes of cells, including both neurons and astrocytes, in the visual cortex.

In vivo 2-photon imaging in ferret visual cortex

- in vivo two photon imaging
- Lightly anesthetized (isoflurane)
- Adult ferrets

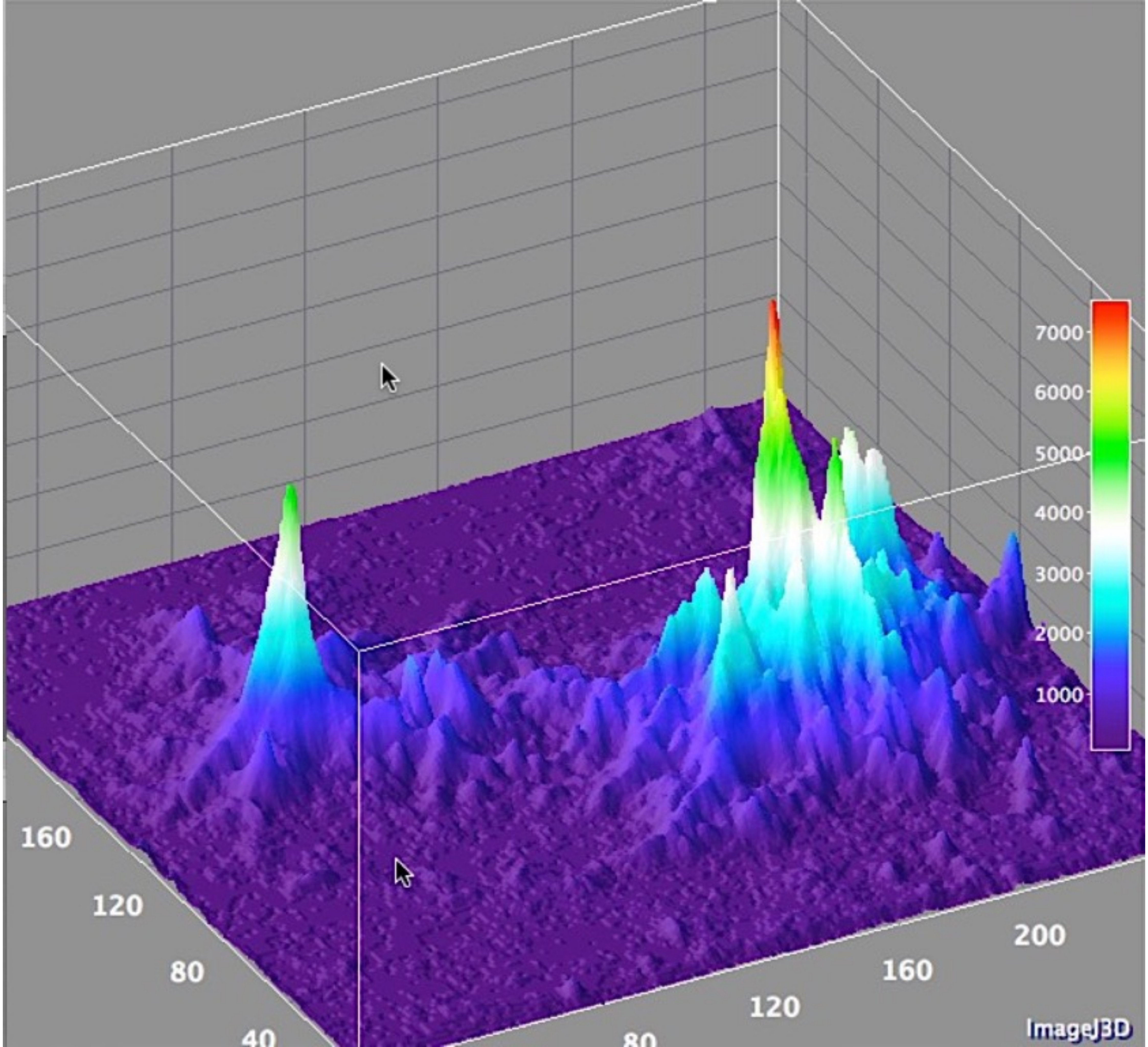


Orientation tuning in subcellular domains



Each sub-domain has similar orientation tuning, with quantitative differences

Does this suggest that they are responding to distinct neural activity?


7000
6000
5000
4000
3000
2000
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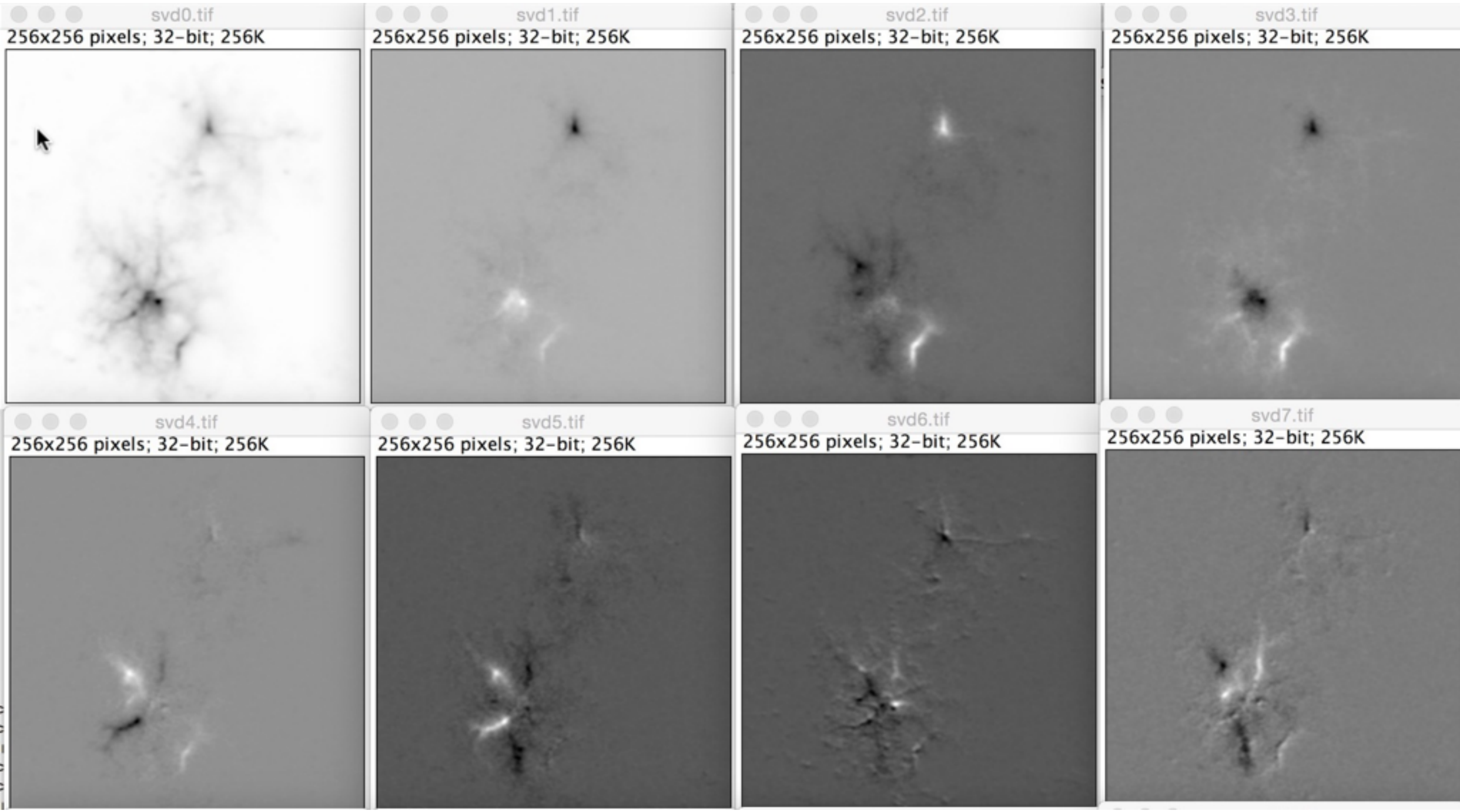
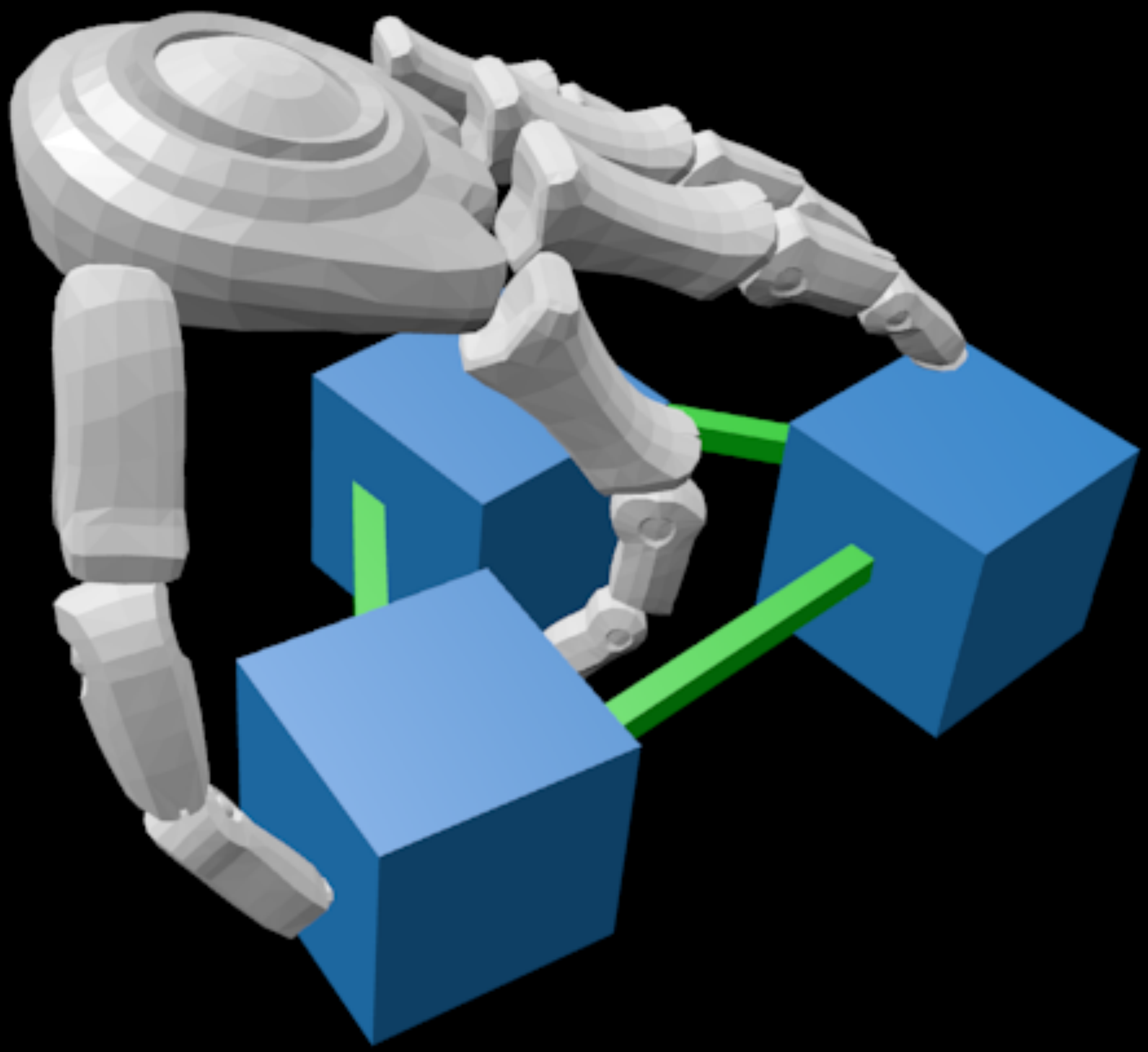
160
120
80
40
80
120
160
200
ImageJ3D

PCA, first 8 modes



Oculus Rift + Leap Motion



Leap + Oculus

- Work of Juan Llanos
- Objectives
  - construct and manipulate a neuron network in 3D space in a natural way
  - develop a backend, interaction computational engine
  - explore the results from this engine as

Research Group

- Gordon Erlebacher, Lead
- Joel Tabak, FSU Program in Neuroscience
- Nathan Crock (Ph.D.)
  - Astrocyte data analysis, polychrony
- Evan Cresswell (Ms)
  - Astrocyte modeling, plasticity
- Juan Llanos (Ms)
  - Interactive modeling software and visualization