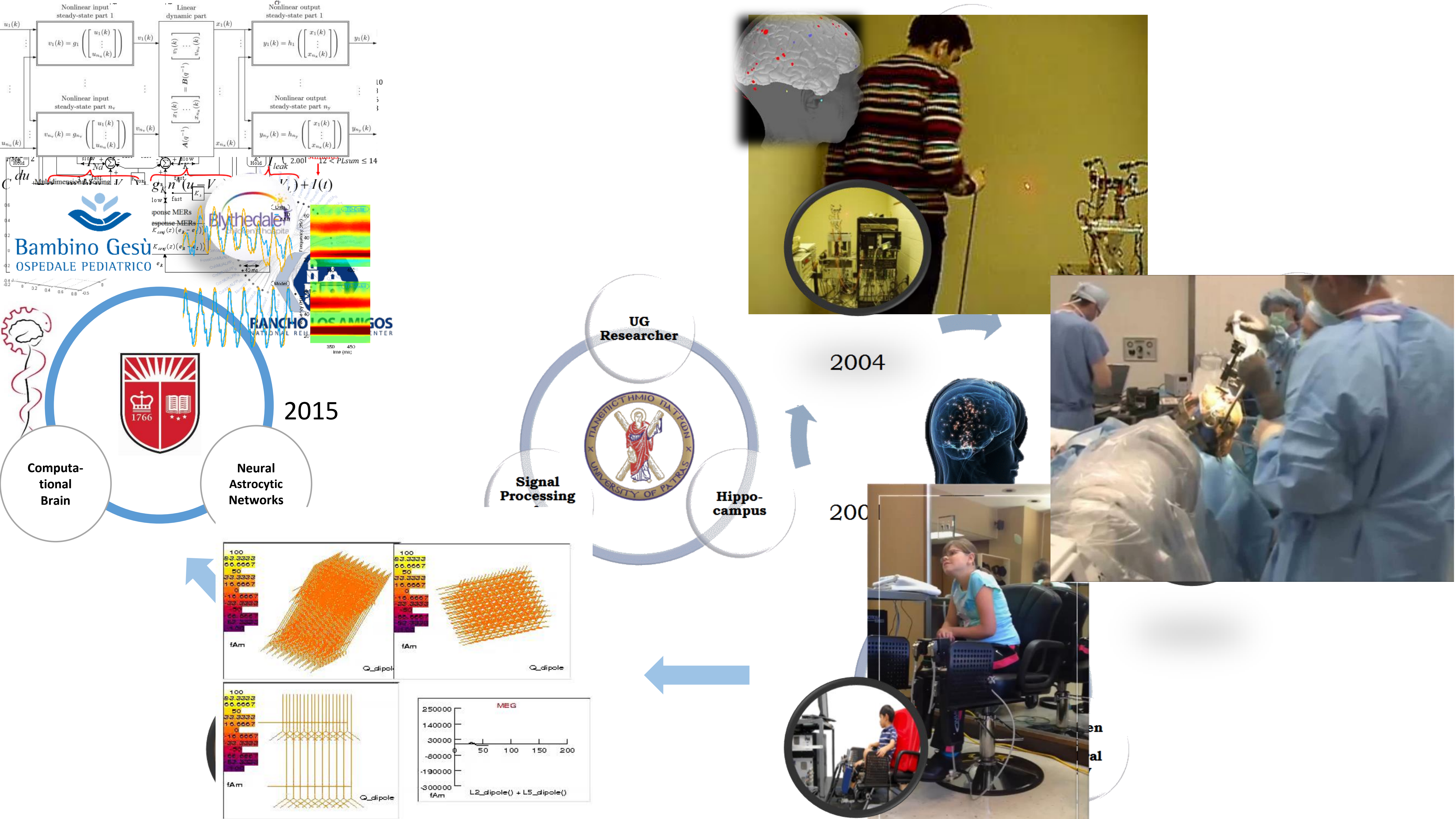
combra.cs.rutgers.edu

Brain-morphism: Astrocytes as Memory Units

Constantine Michmizos

Computational Brain Lab – Rutgers University

6th Neuro Inspired Computational Elements Workshop – Intel Hillsboro, OR



Nonlinear input steady-state part 1
Linear dynamic part
Nonlinear output steady-state part 1
Nonlinear input steady-state part n_y
Nonlinear output steady-state part n_y
Bambino Gesù
OSPEDALE PEDIATRICO
Blythedale
RANCHO LOS AMIGOS
1766
2015
Computa-
tional
Brain
Neural
Astrocytic
Networks
UG
Researcher
Signal
Processing
Hippo-
campus
2004
MEG
fAm
Q_dipole
L2_dipole() + L5_dipole()

ComBra Lab's goal

- To understand biological intelligence and translate our knowledge to artificial intelligence

Computa-tional Brain

Neural Astrocytic Networks

  - by developing **brain-morphic computational methods**

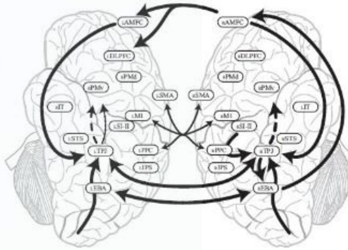
- that *integrate*† with the brain from the macro (behavioral) … ro (synaptic) scale

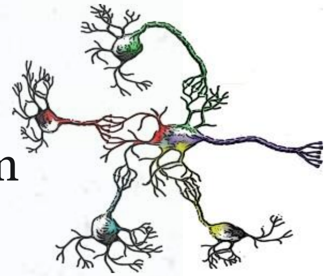
†mimic

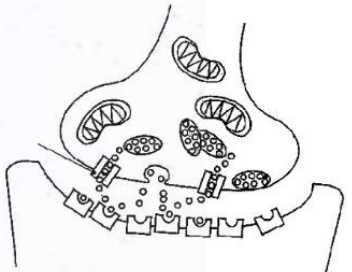
†restore

†understand

CNS	1 m
Systems	10 cm
Maps	1 cm
Networks	1 mm
Neurons	100 μm
Synapses	1 μm
Molecules	1 Å





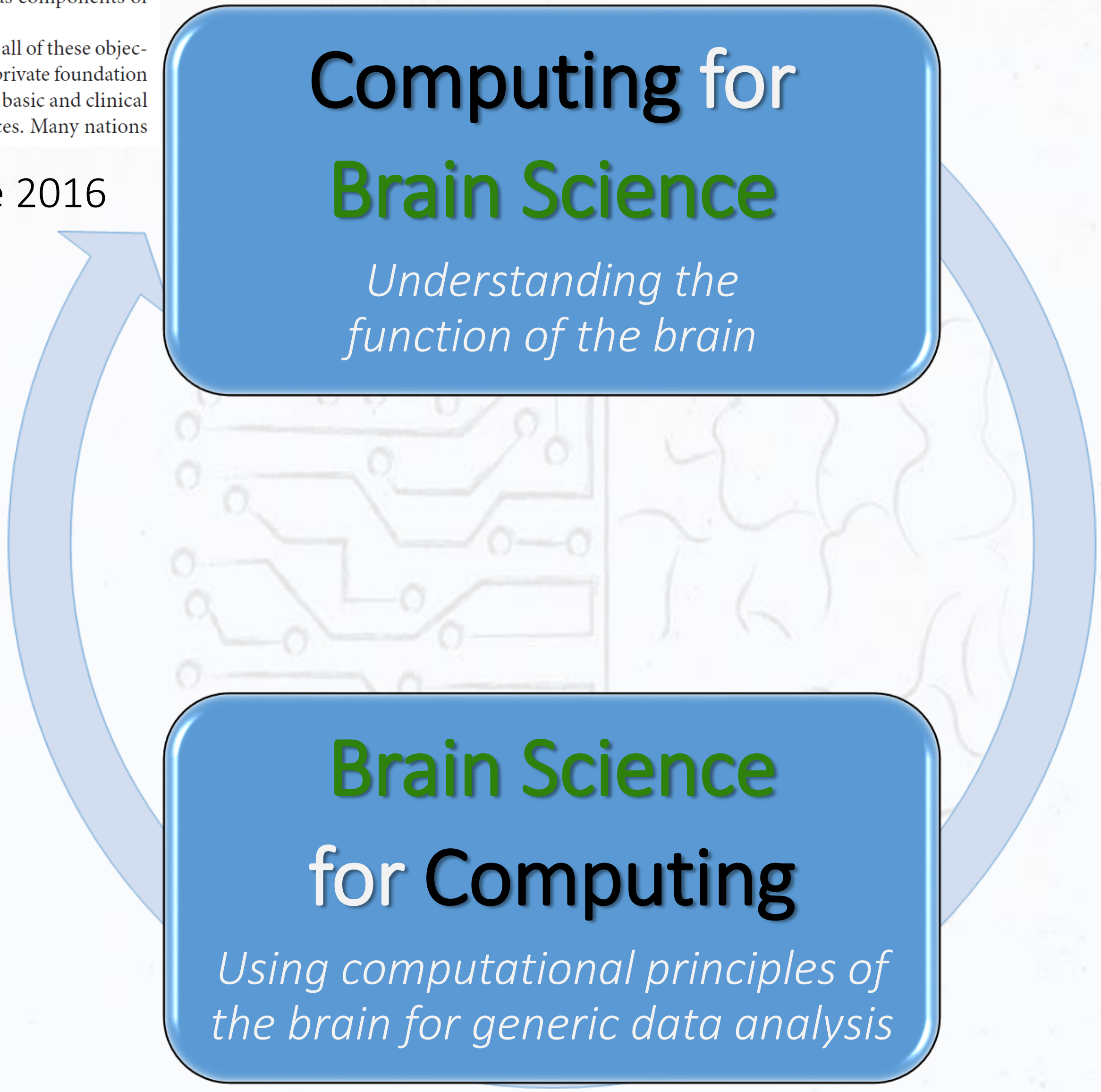


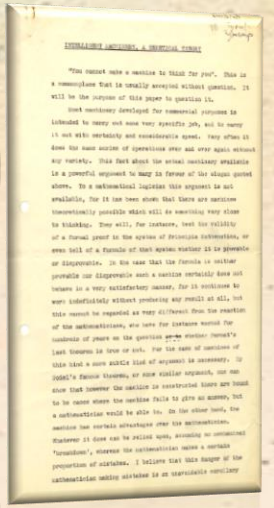
Adapted by Terry Sejnowski

In April 2016, the science academies of the G7 nations as well as seven additional academies issued a statement calling on world leaders to cultivate global brain resources and address the growing threat of brain disorders[1]. The statement proposed four objectives: (i) fundamental research with international collaboration; (ii) global programs for the diagnosis, prevention and treatment of brain disorders; (iii) theoretical modeling of the brain and the development of brain-based artificial intelligence; and (iv) integration of neuroscience with the social and behavioral sciences to improve education and life management as components of a brain-aware society.

Paramount to addressing all of these objectives is government and/or private foundation commitment to supporting basic and clinical research in the brain sciences. Many nations

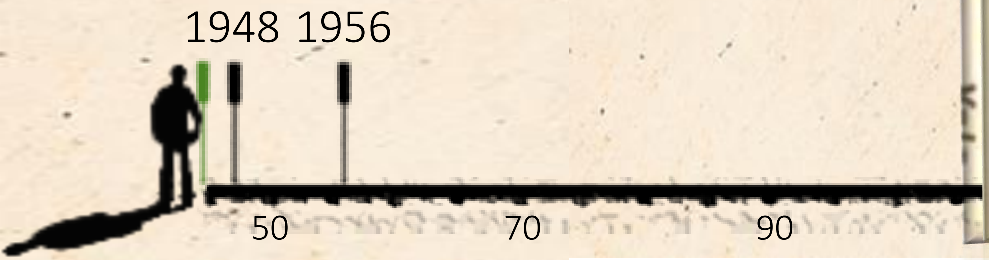
Grillner et al. Nature Neuroscience 2016

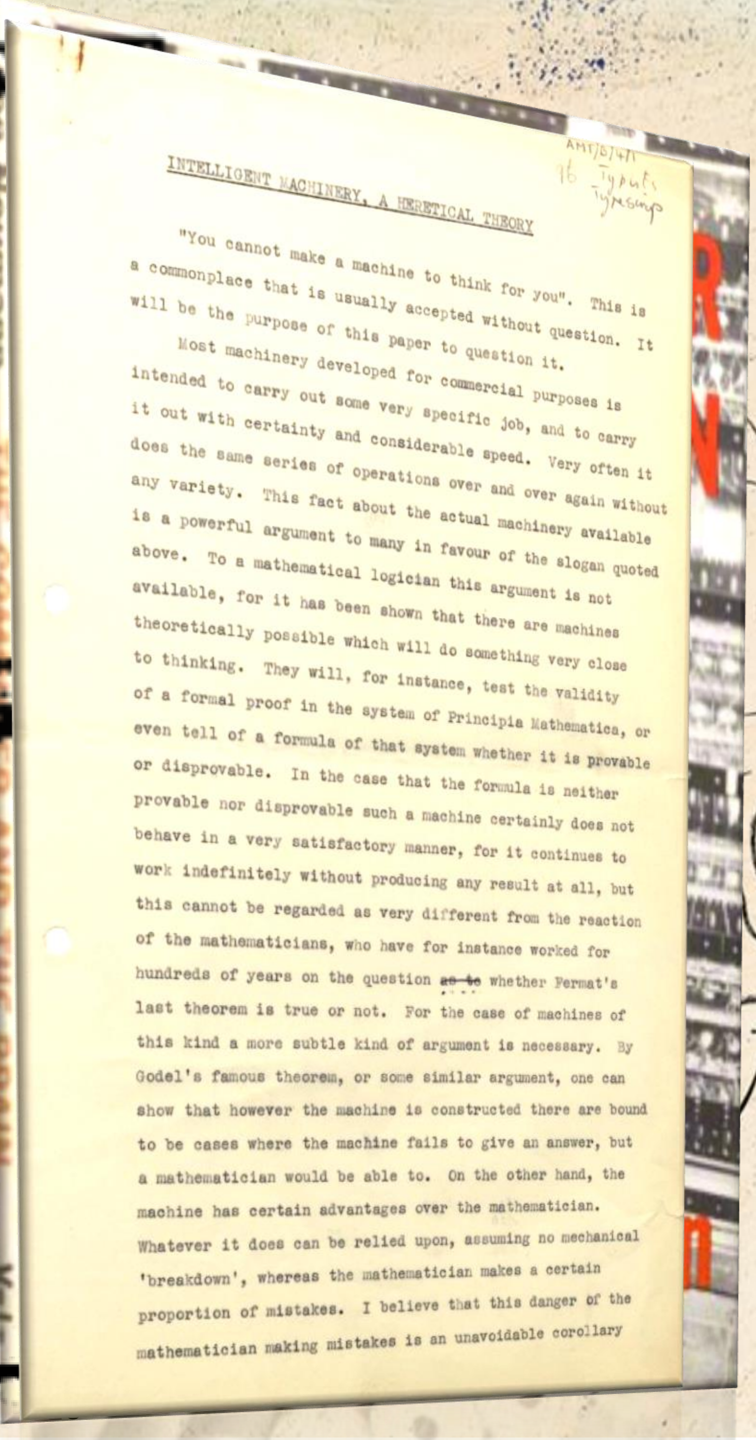




The Neuron as a Basic Information Processing Unit

McCulloch and Pitts (1943)





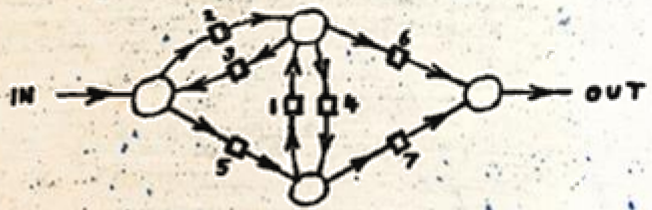
INTELLIGENT MACHINERY, A HERETICAL THEORY

"You cannot make a machine to think for you". This is a commonplace that is usually accepted without question. It will be the purpose of this paper to question it.

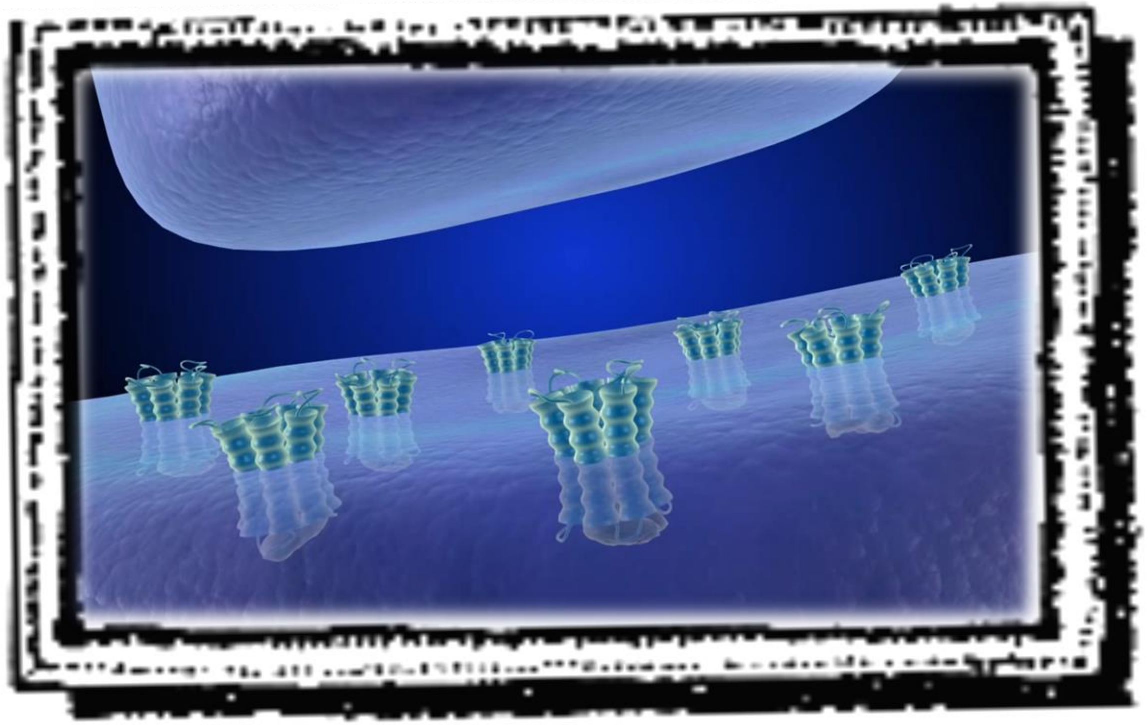
Most machinery developed for commercial purposes is intended to carry out some very specific job, and to carry it out with certainty and considerable speed. Very often it does the same series of operations over and over again without any variety. This fact about the actual machinery available is a powerful argument to many in favour of the slogan quoted above. To a mathematical logician this argument is not available, for it has been shown that there are machines theoretically possible which will do something very close to thinking. They will, for instance, test the validity of a formal proof in the system of Principia Mathematica, or even tell of a formula of that system whether it is provable or disprovable. In the case that the formula is neither provable nor disprovable such a machine certainly does not behave in a very satisfactory manner, for it continues to work indefinitely without producing any result at all, but this cannot be regarded as very different from the reaction of the mathematicians, who have for instance worked for hundreds of years on the question ~~as to~~ whether Fermat's last theorem is true or not. For the case of machines of this kind a more subtle kind of argument is necessary. By Godel's famous theorem, or some similar argument, one can show that however the machine is constructed there are bound to be cases where the machine fails to give an answer, but a mathematician would be able to. On the other hand, the machine has certain advantages over the mathematician. Whatever it does can be relied upon, assuming no mechanical 'breakdown', whereas the mathematician makes a certain proportion of mistakes. I believe that this danger of the mathematician making mistakes is an unavoidable corollary

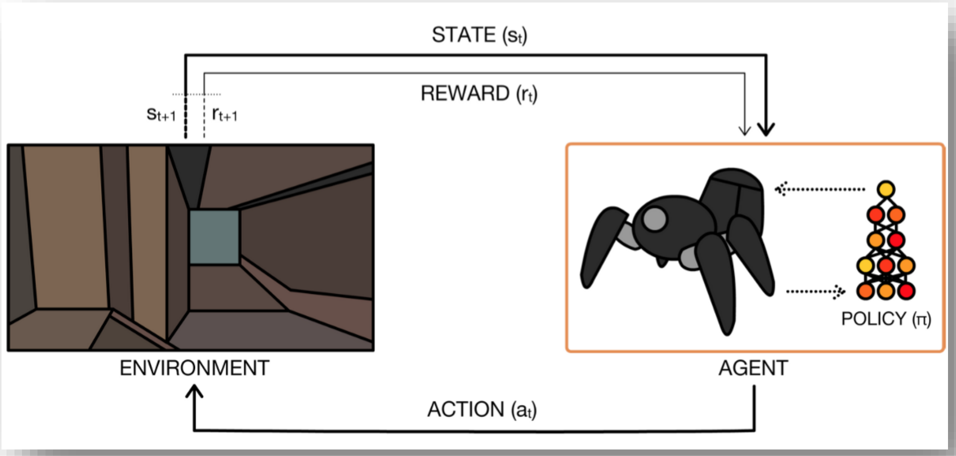
Alan Turing, 1948

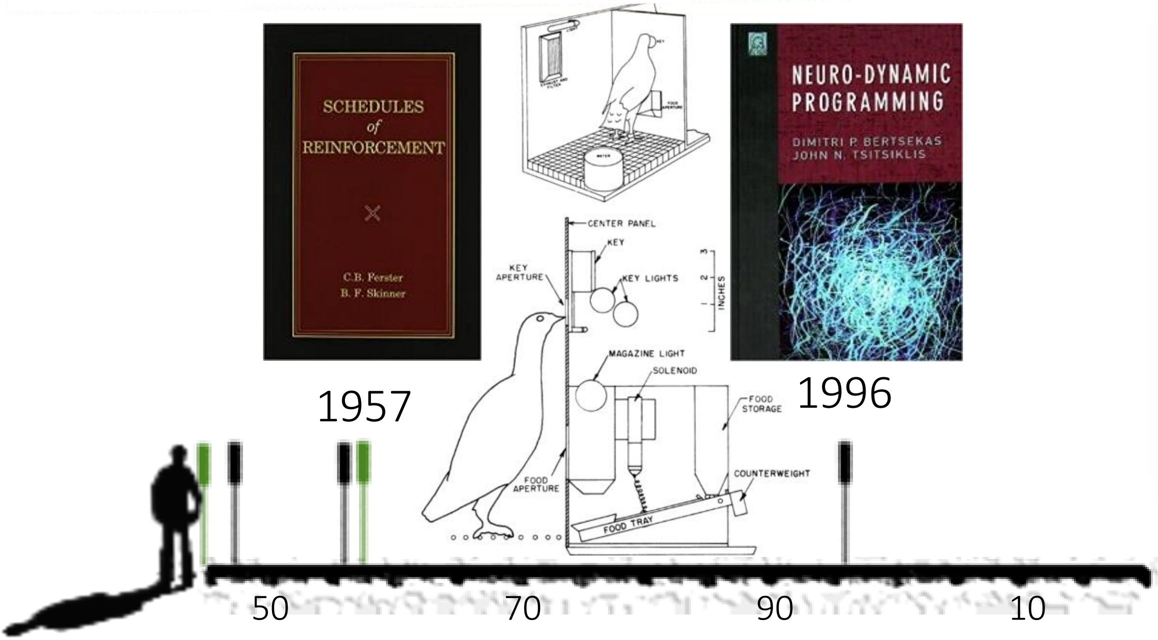
- A fascinating prelude to today's AI
- Proposed connectionist models that would today be called neural networks

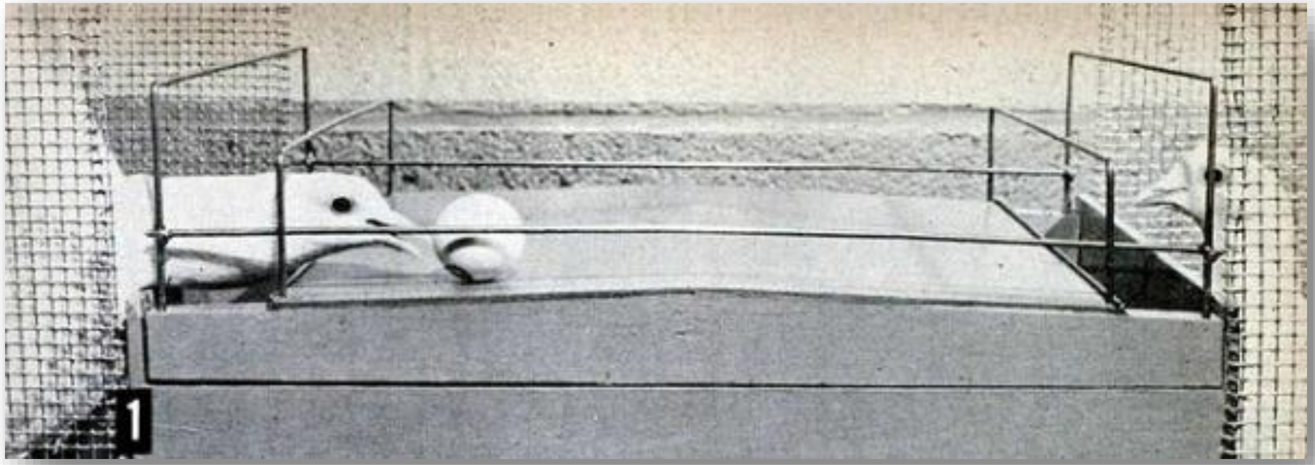


- Randomly connected networks of artificial neurons
- Training via reinforcing successful and useful links and cutting useless ones
- The proposed learning rule was inspired by the infant's brain









pigeons playing ping-pong - Skinner 1950

574

J. Physiol. (1959) 148, 574-591

RECEPTIVE FIELDS OF SINGLE NEURONES IN THE CAT'S STRIATE CORTEX

By D. H. HUBEL* and T. N. WIESEL*

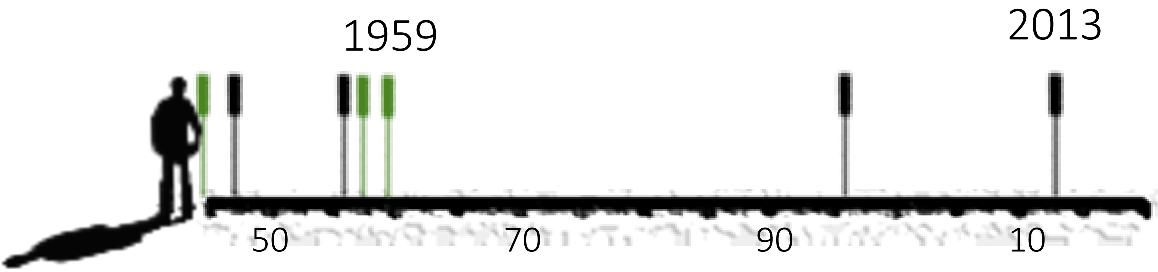
From the Wilmer Institute, The Johns Hopkins Hospital and University, Baltimore, Maryland, U.S.A.

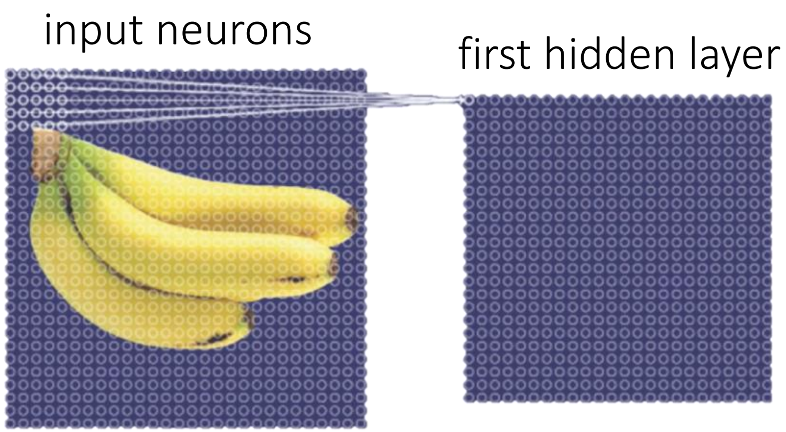
(Received 22 April 1959)

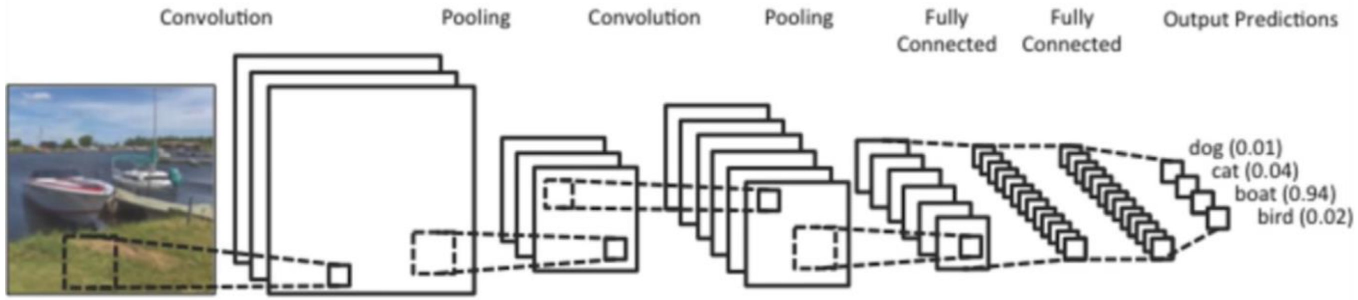
Gradient-Based Learning Applied to Document Recognition

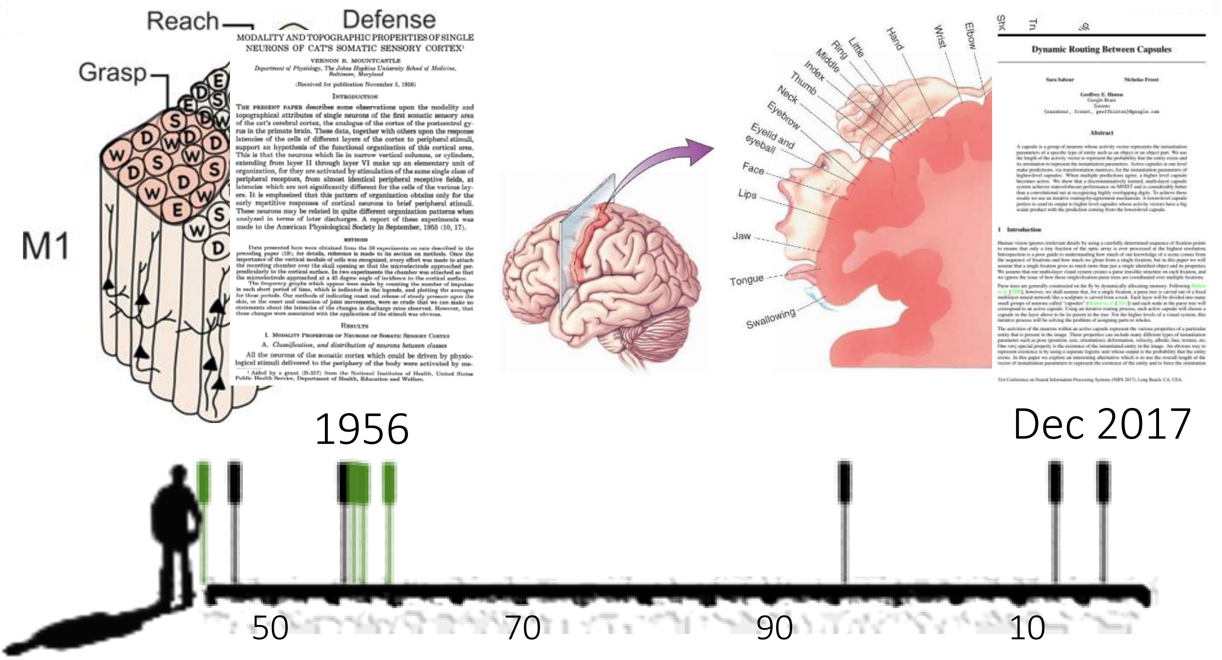
Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner

I. Introduction





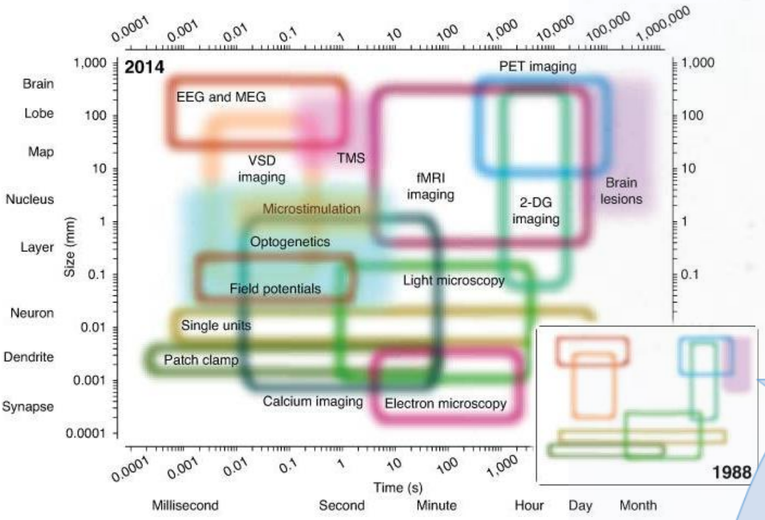




A capsule is a subset of neurons within a layer that outputs:

1. an instantiation parameter: is an entity present within a limited domain?
2. a vector of pose parameters: the pose of the entity relative to a canonical version

A capsule replaces max pooling



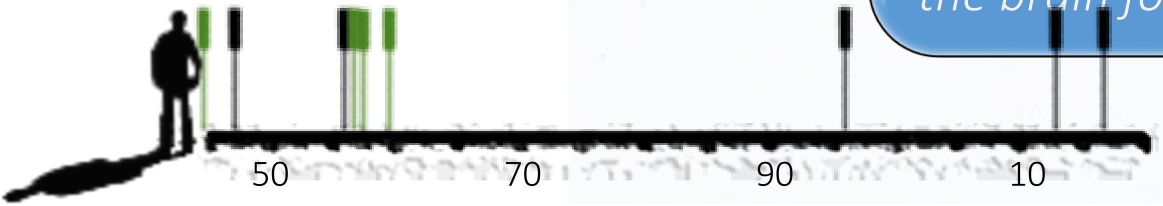
Sejnowski et al.
Putting big data to good use in neuroscience
Nature Neuroscience 2014

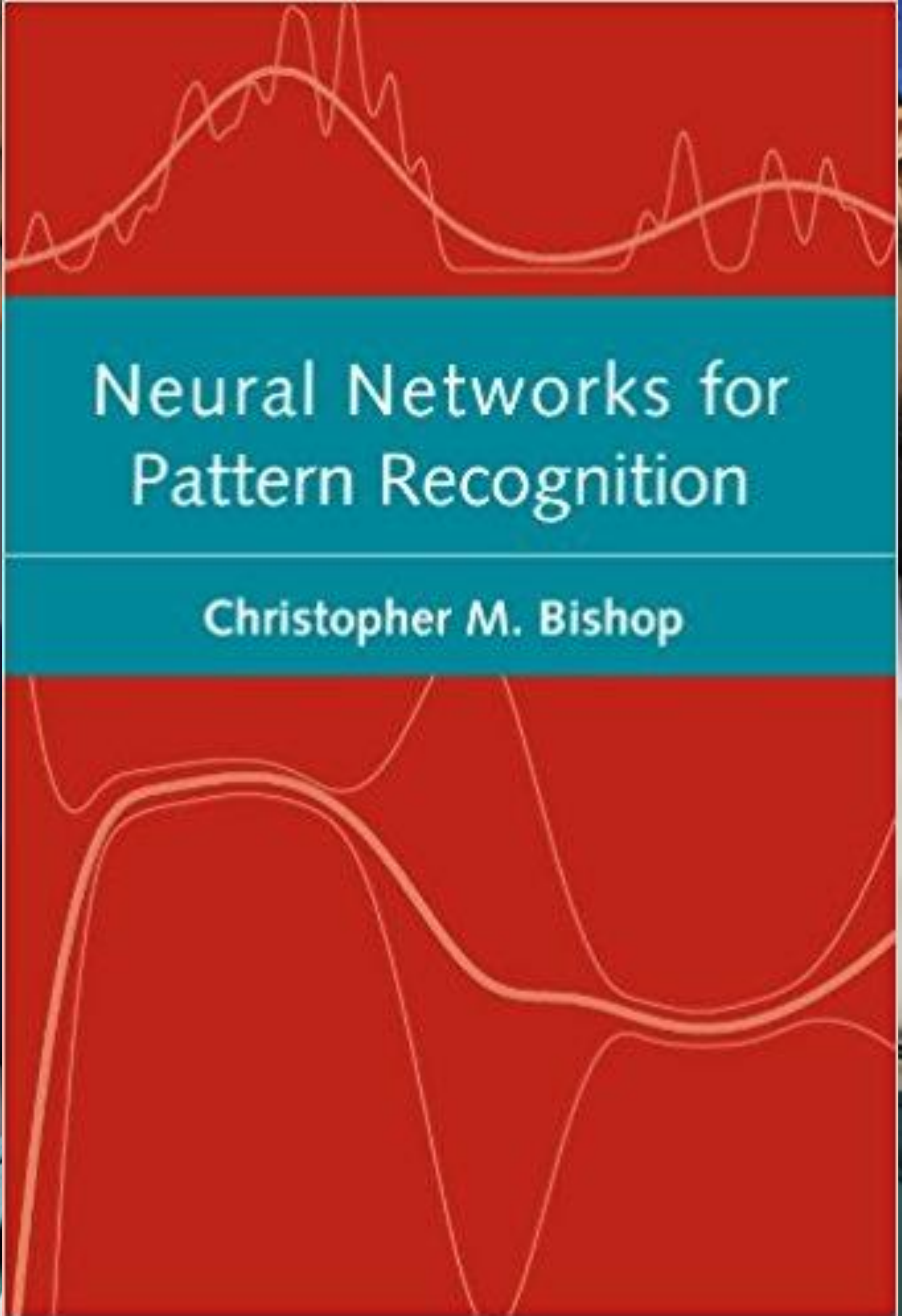
Computing for Brain Science

Understanding the function of the brain

Brain Science for Computing

Using computational principles of the brain for generic data analysis



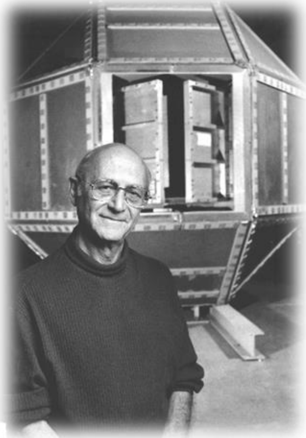


Neural Networks for
Pattern Recognition
Christopher M. Bishop

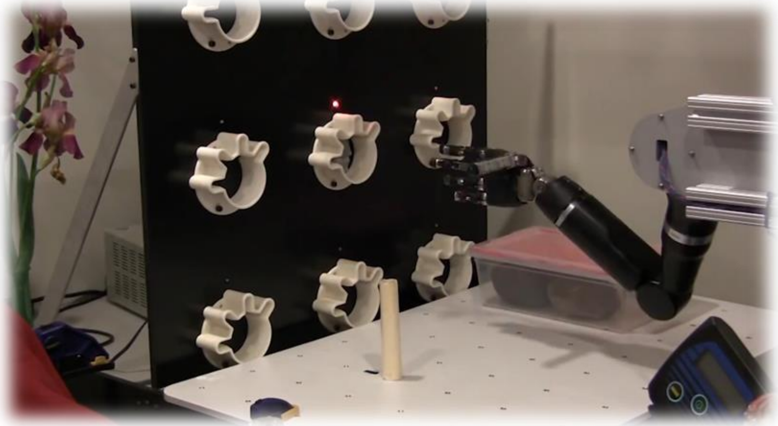
Shabbar F. Danish, M.D.
Division of Neurosurgery

Record

1932. Edgar Adrian, Nobel Prize
Single-Neuron Recordings



1971. David Cohen, MIT
Magnetoencephalography



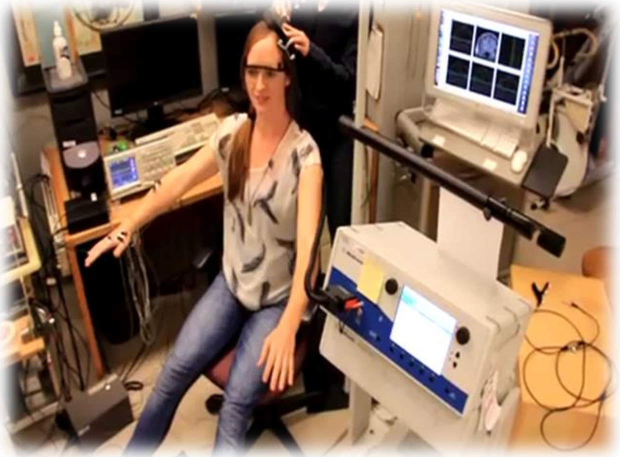
2013. Motor neurons control a robotic arm for paraplegic patients (BrainGate)

Information =
f (electrical activity)

neurons

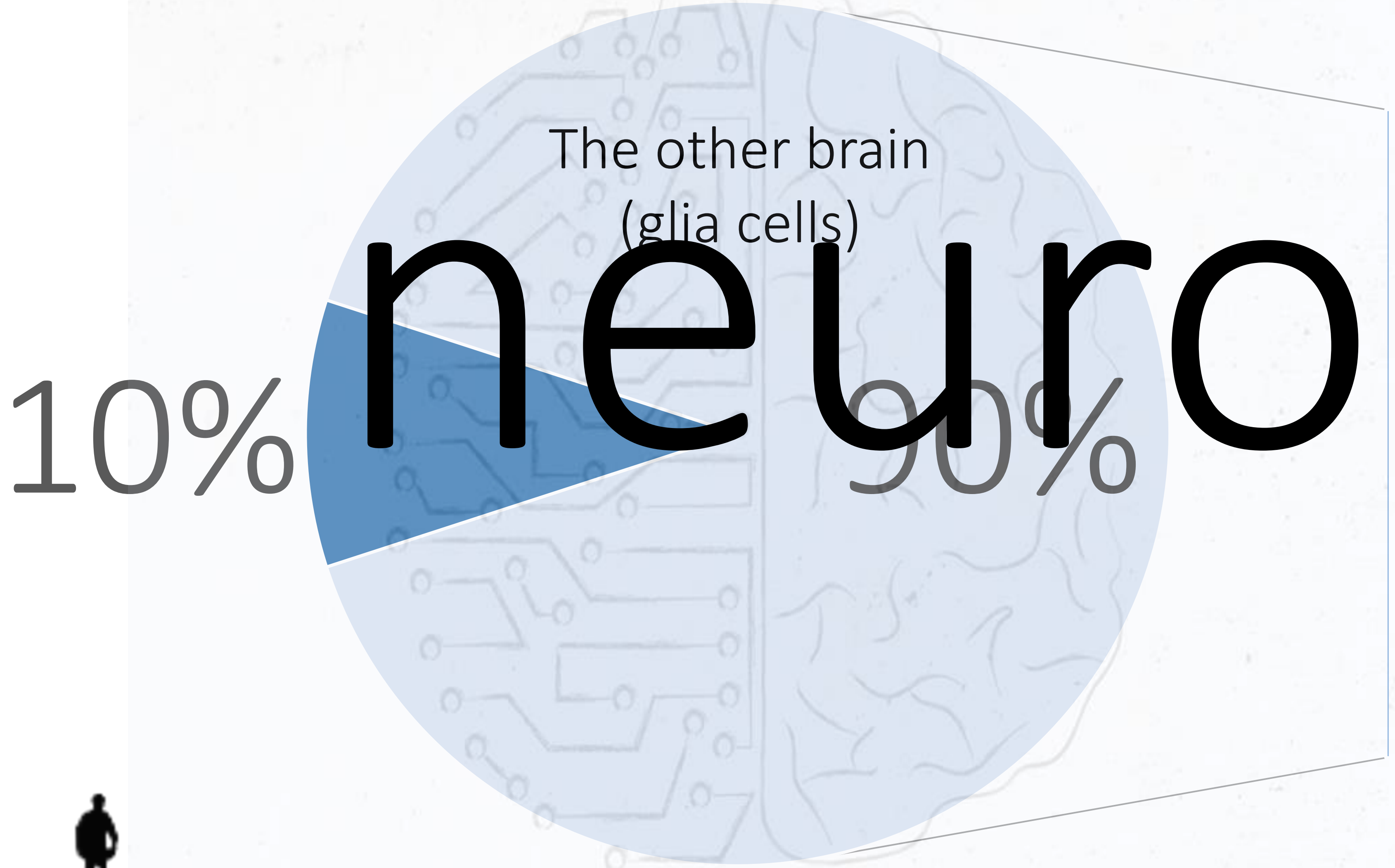
Manipulate

1997. Deep Brain Stimulation for alleviating Parkinson's disease

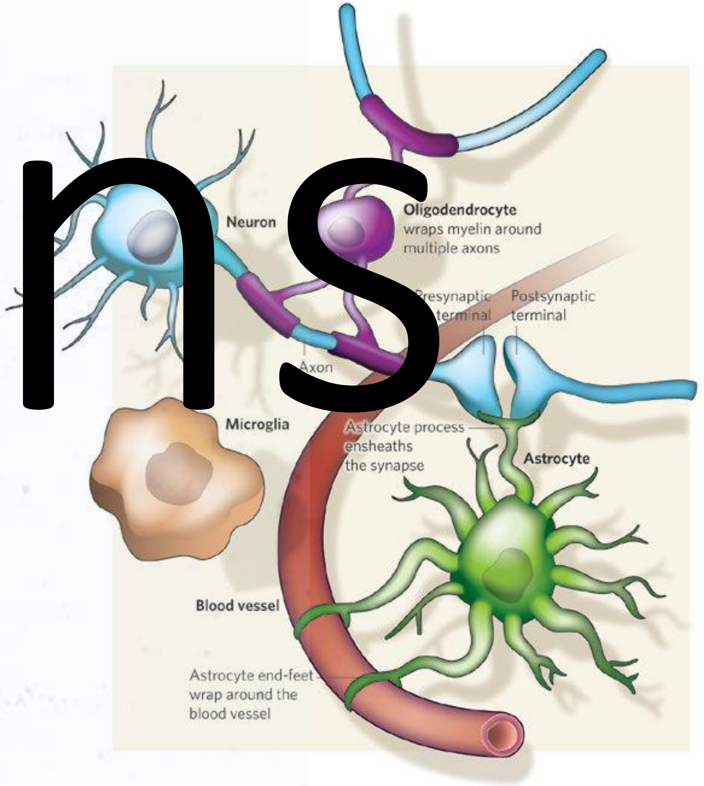


2013. TMS applied to the motor cortex induces hand movement

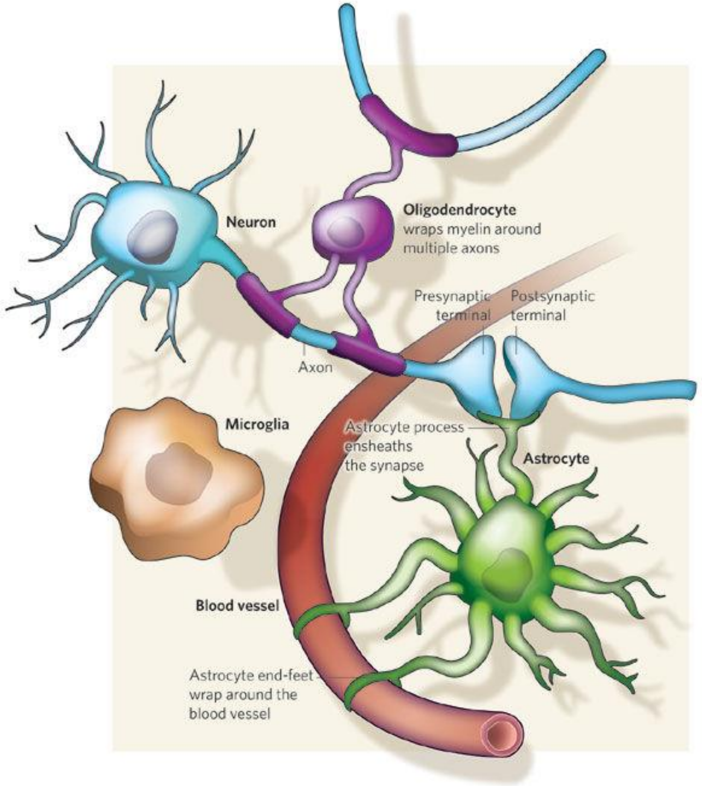
Non-neuronal brain cells
are electrically silent



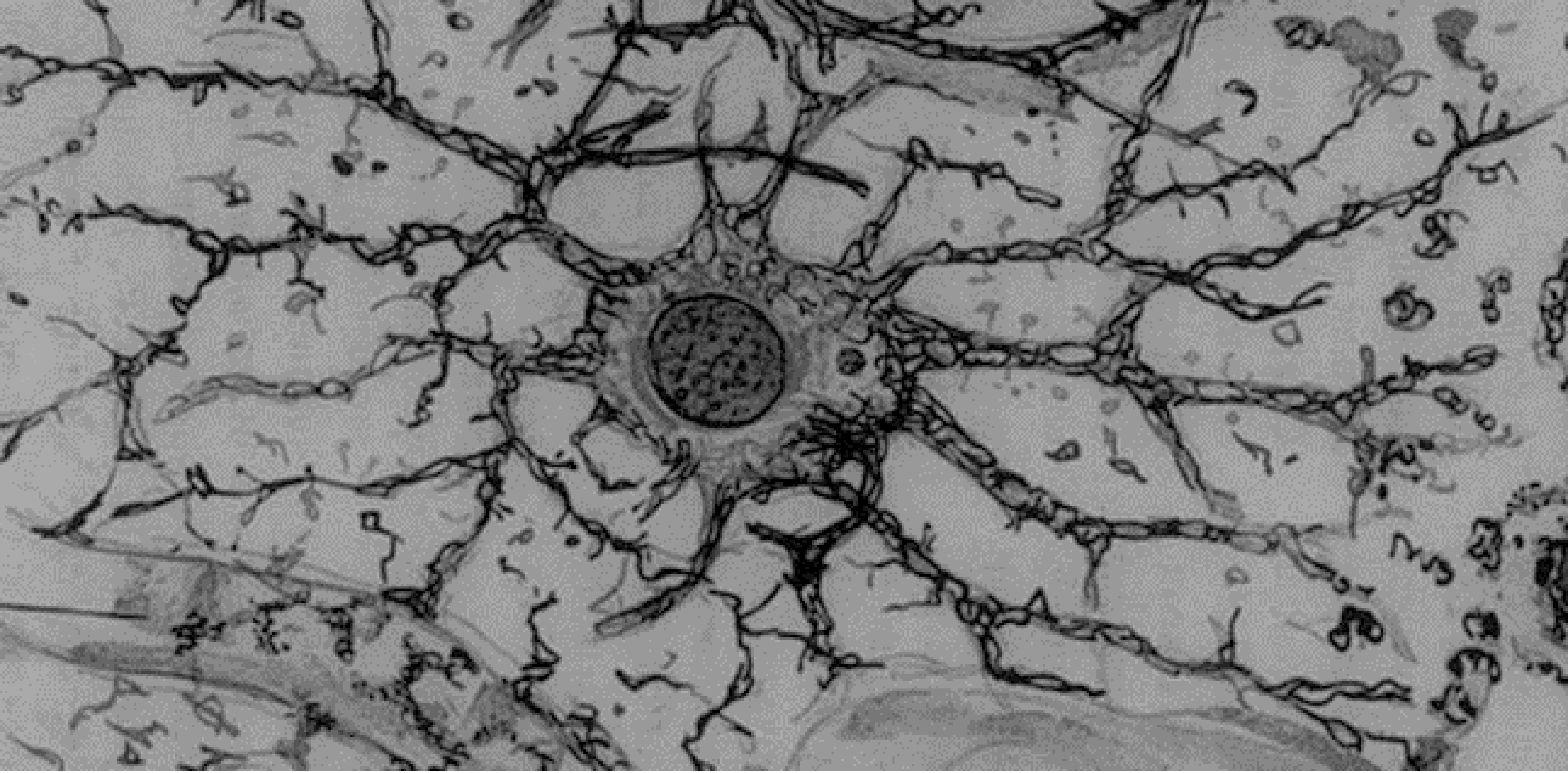
neurons



Non-neuronal brain cells
are electrically silent

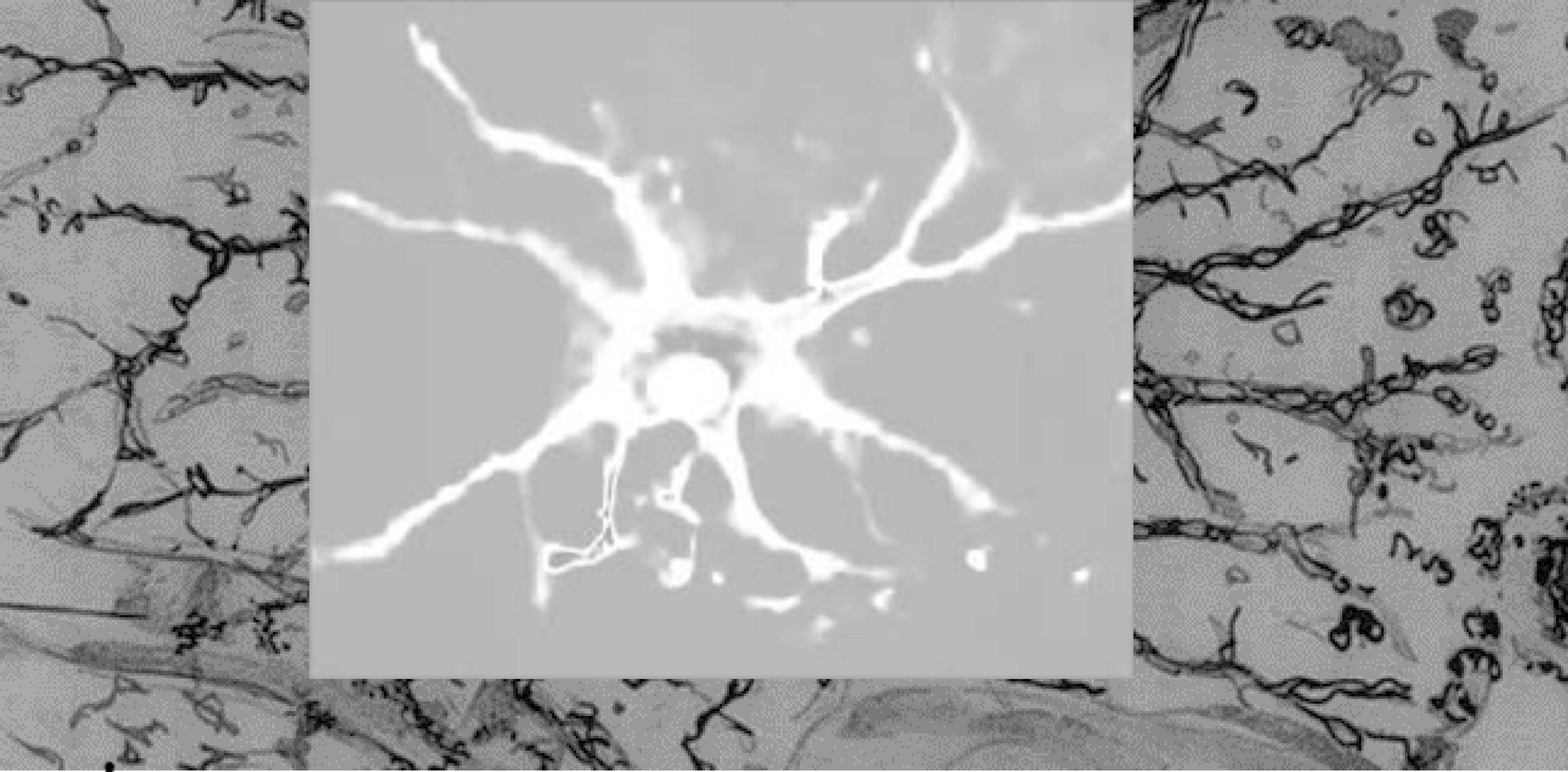


2000's. Calcium Imaging allows studies of calcium signaling in hundreds of neurons and glial cells, within neuronal circuits .

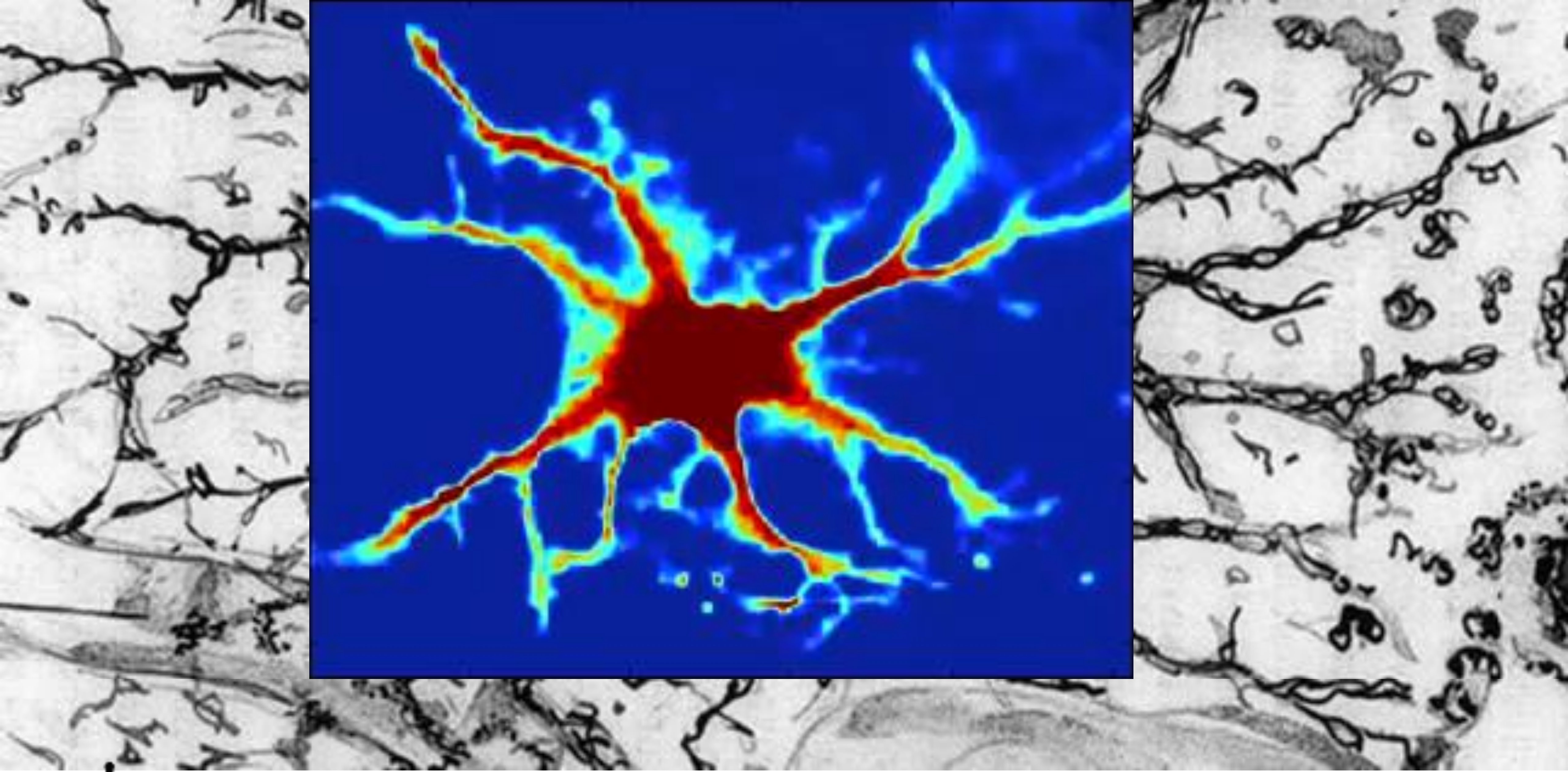


Santiago Ramón y Cajal's drawing of an astrocyte

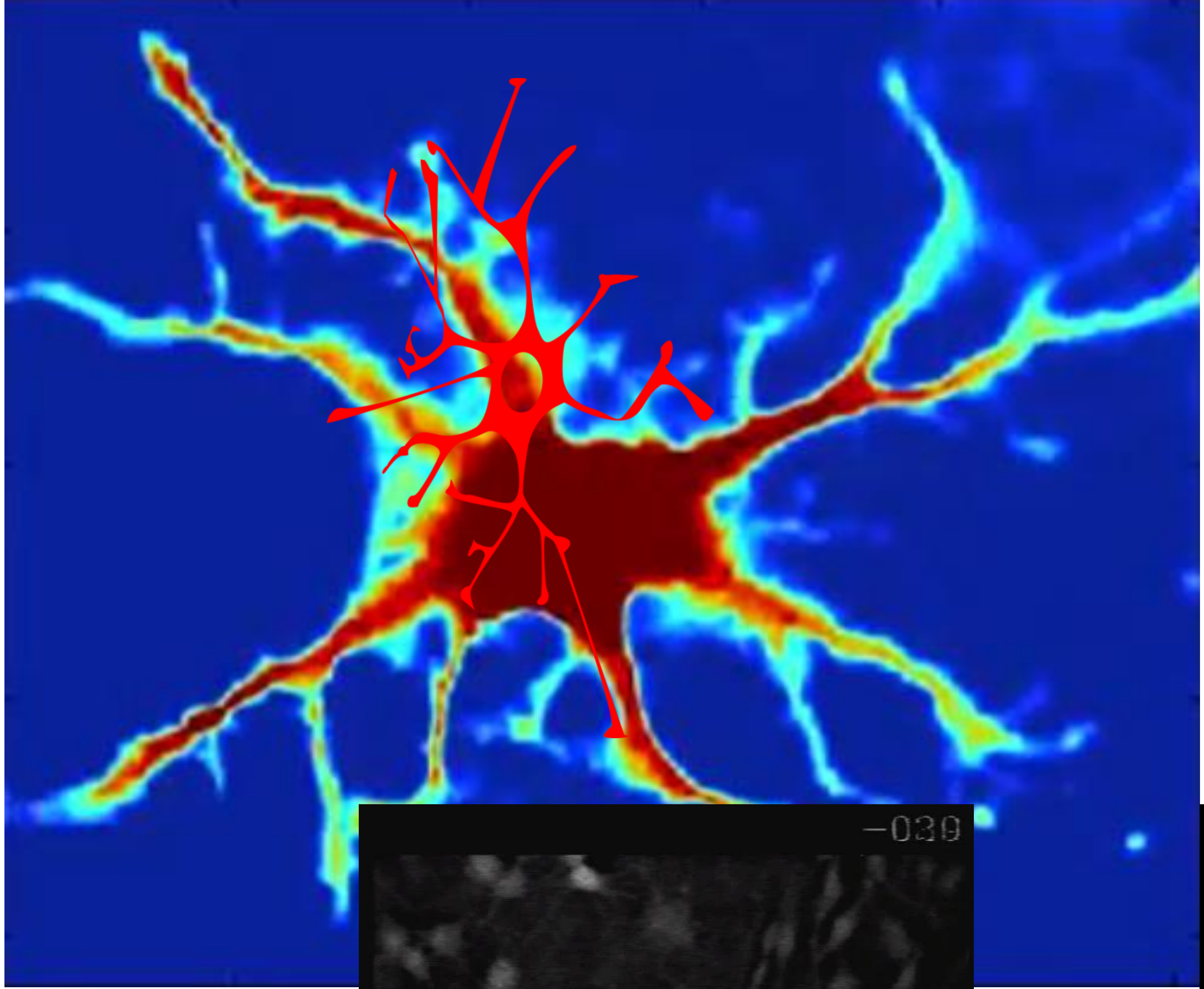
Ramón y Cajal S. Something about the physiological significance of neuroglia. *Revista Trimestral Micrografía* 1, 3–47, 1897

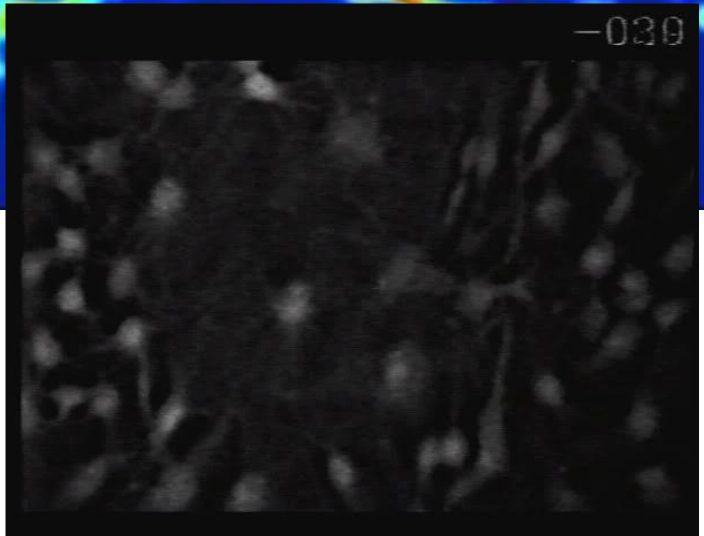


2015



2015

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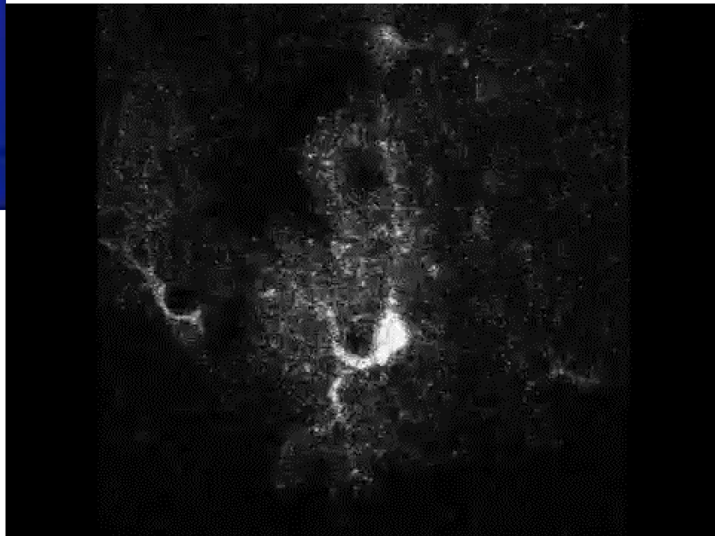
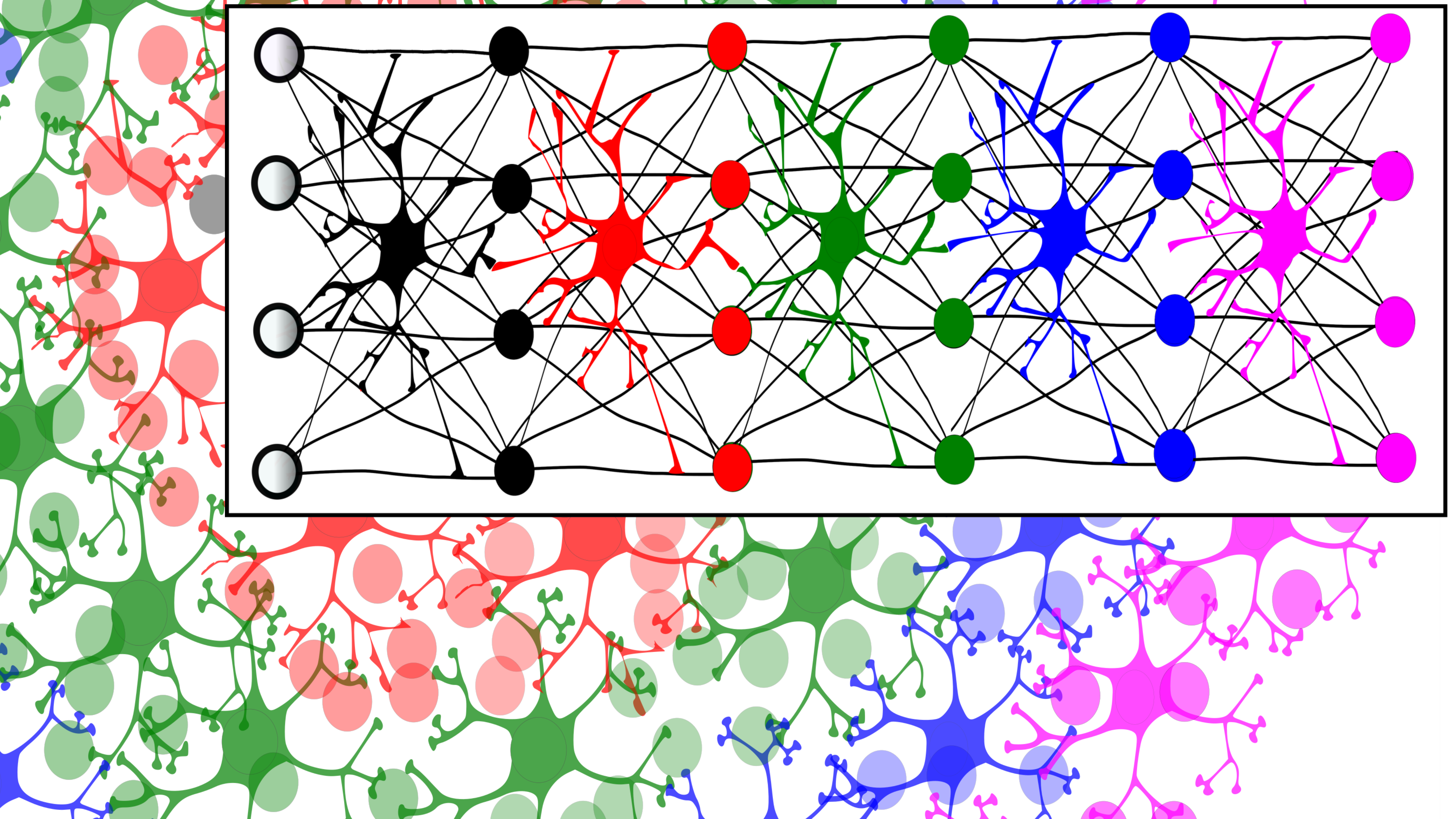
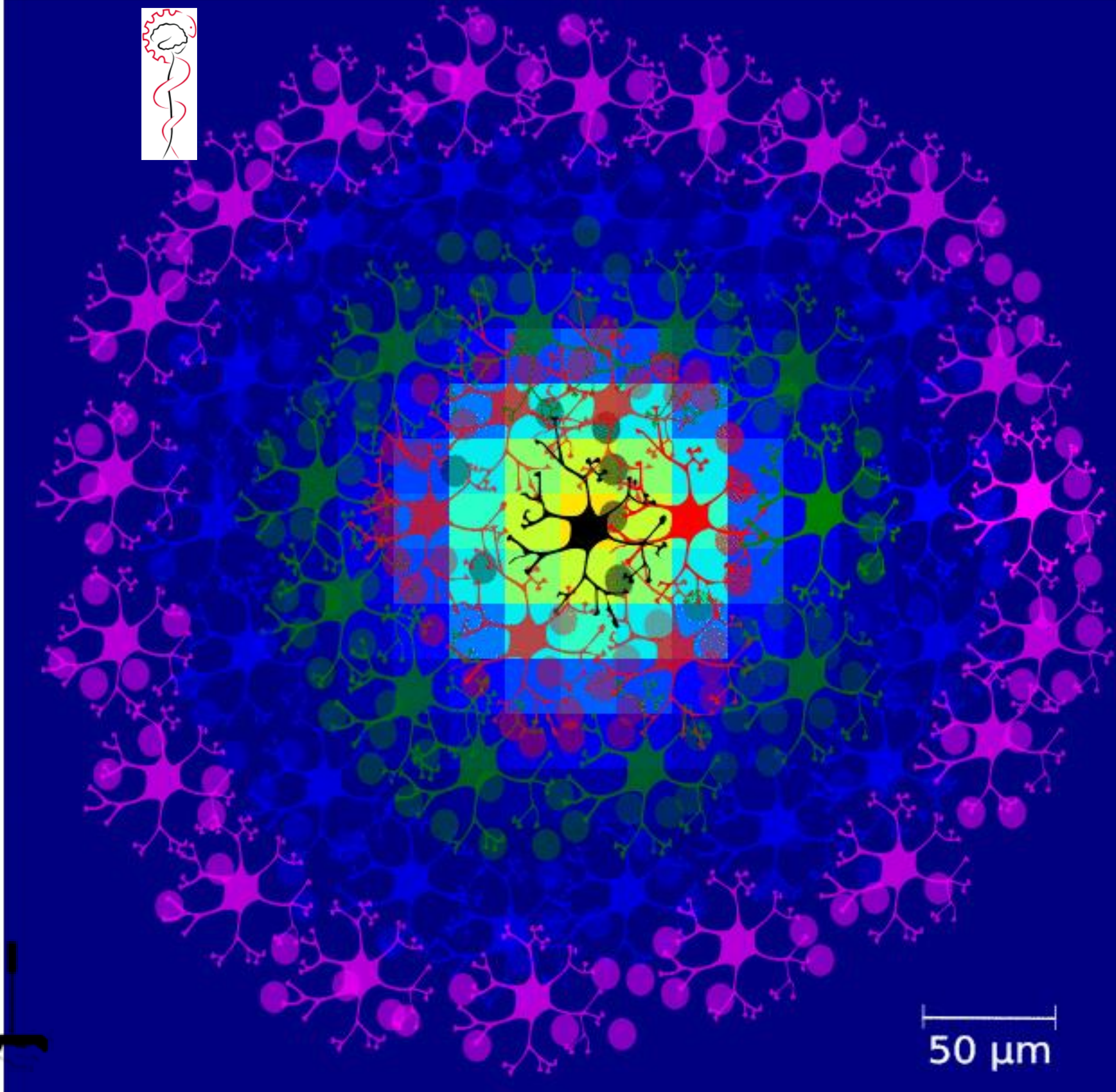




Astrocytes

Brain

A paradigm shift in Neuroscience

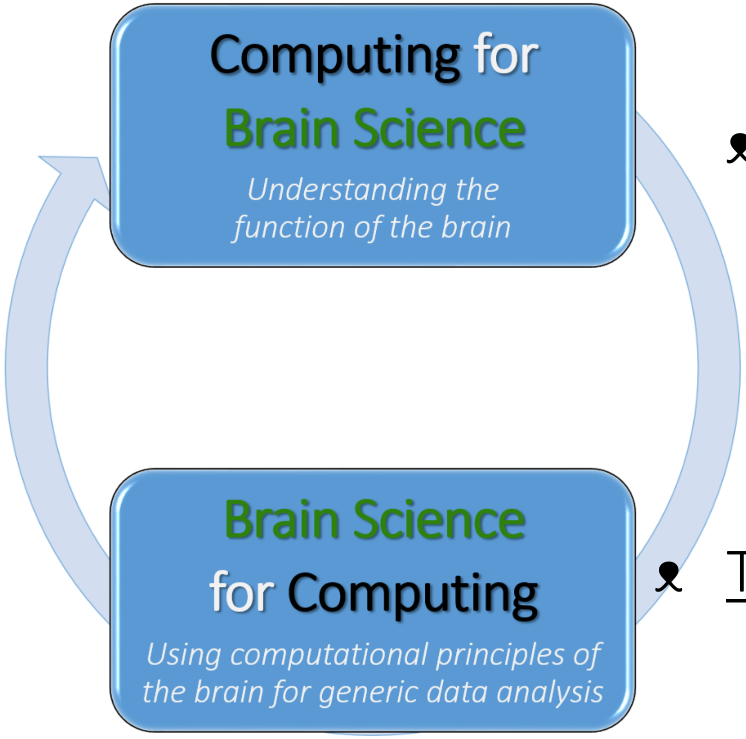


Astrocytes Astrocytes ence

Brain

A paradigm shift in Neuroscience

- Understanding astrocytes beyond by calcium imaging
  - Embed astrocytic mechanisms into NANs
  - Suggest functions for astrocytes at the network level and large time scales
    - where behavior and diseases emerge

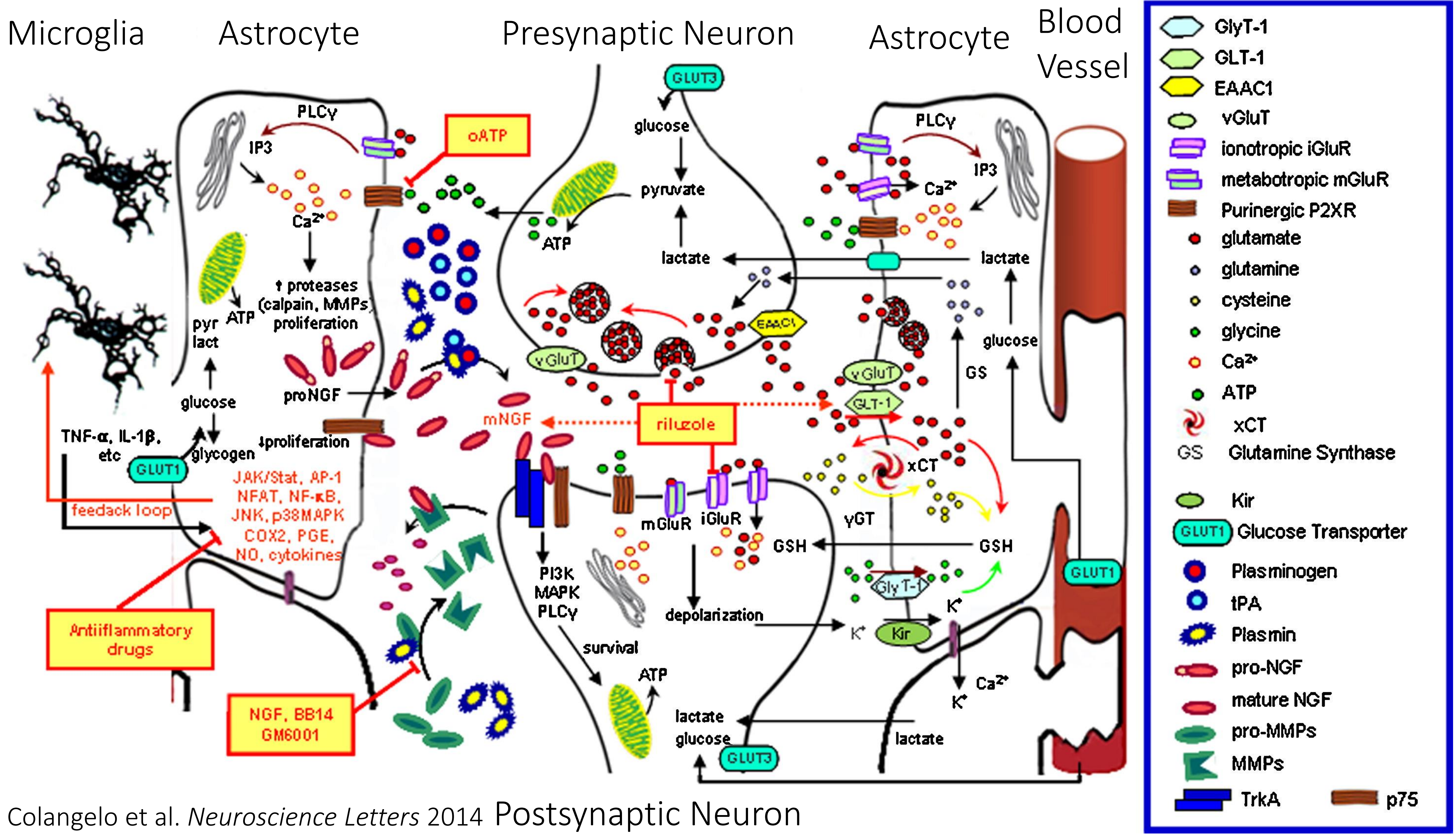


Brain

- Neuro-morphic Computing
  - Introducing astrocyte, a new computational unit into Neural Networks Neural-Astrocytic Networks

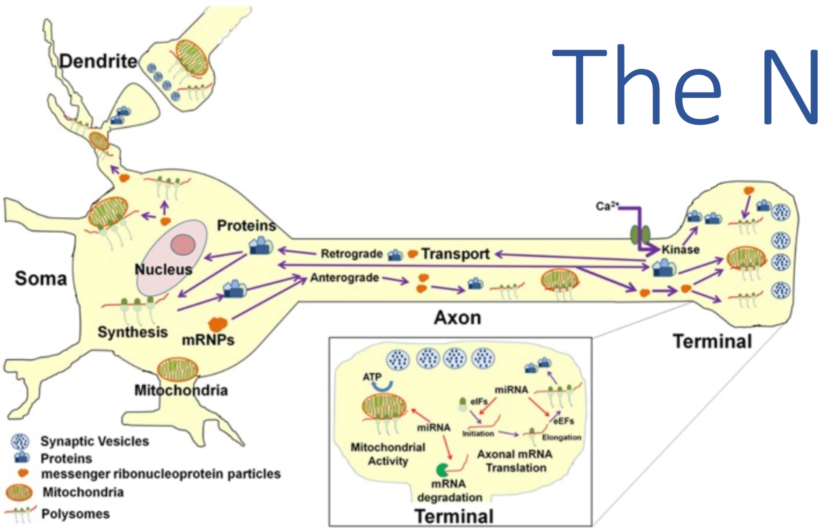
- Learning beyond by weight updating
  - The third part of the synapse introduces an orthogonal dimension to "neural" plasticity

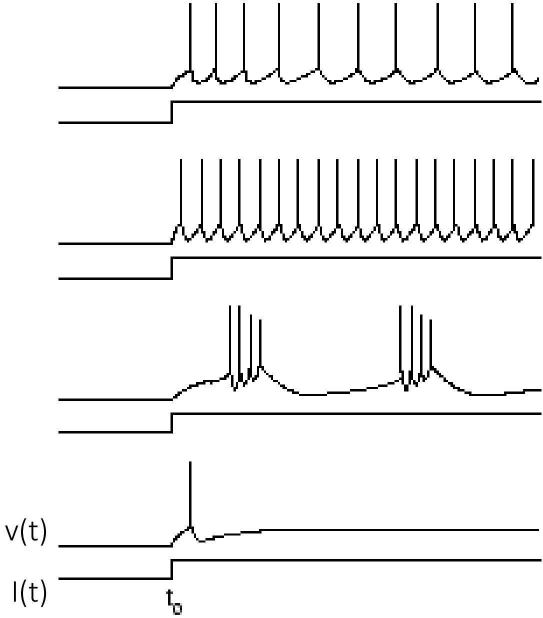
- Time beyond in discrete instances
  - Astrocytes respond dynamically and in larger time scales than neurons, mapping neural activity into the slower behavioral scales



Colangelo et al. *Neuroscience Letters* 2014

The Neural Modeling Paradigm





Physical Phenomenon

(e.g., neural firing)

Computing for Brain Science

Understanding the function of the brain

Brain Science for Computing

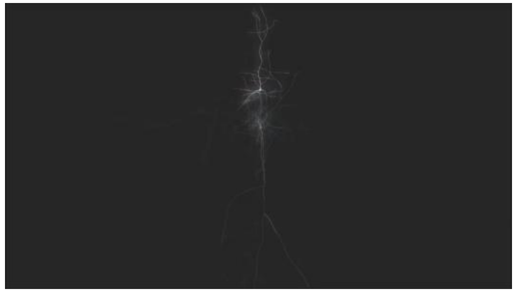
Using computational principles of the brain for generic data analysis

treat as emergent phenomenon

- Byophysics-based models
- Understand the principles of the underlying phenomena
- Data drives details

Typically higher model complexity

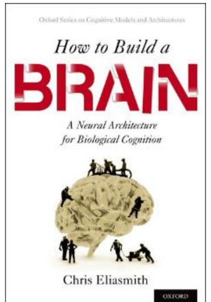
Blue Brain Project

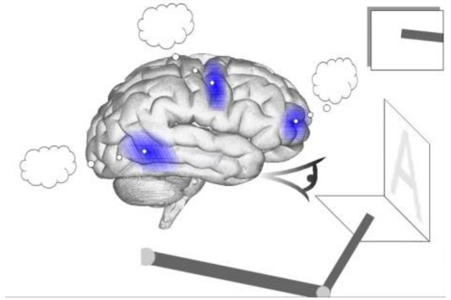


treat as target function

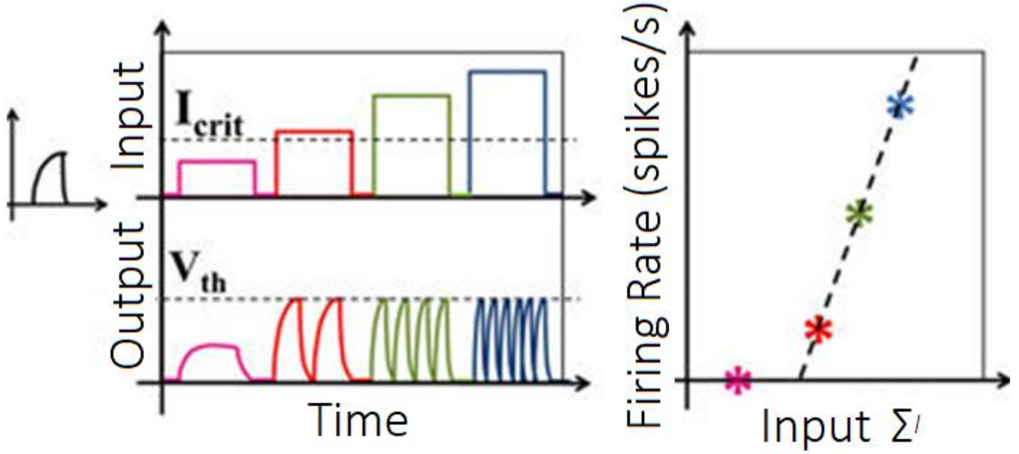
- Phenomenological models
- Occam's razor/KISS principle
- Level of detail is hypothesis/interest driven

Typically lower model complexity





Adapted by Karlheinz Meier



Neurons encode information in spike rate

Spiking

Neural Network

To capture the dynamics of the interaction between the neuronal and the astrocytic component of the networks

Step 1. Input as Spike timing

$$V_j(t) = \sum_i \delta(t - t_i)$$

Step 2. Synaptic current response

$$I_j(t, t_i) = \begin{cases} w_j\left(e^{-\frac{t-t_i}{\tau}} - e^{-\frac{t-t_i}{4\tau}}\right), & if\ t > t_i \\ 0, & if\ t \leq t_i \end{cases}$$

Step 3. Integration of synaptic current

$$I(t) = \sum_j I_j(t)$$

Step 4. Output spike

$$V_o(t) = \mathrm{LIF}\,\{I(t)\}$$

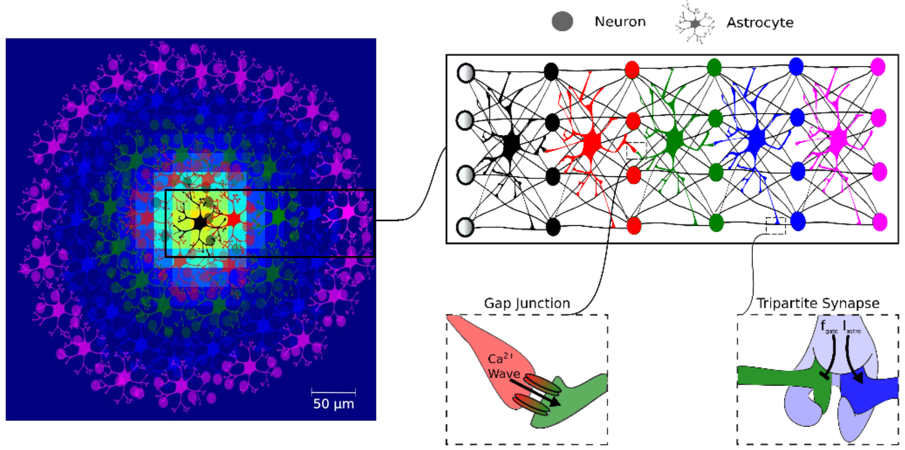
Mapping function between input-output

Leaky Integrate-and-Fire (LIF) Neuron

$$\tau \frac{dv}{dt} = v_{reset} - v(t) + RI(t)$$

LIF

$$if\ v(t) \geq V_{\mathrm{th}}$$
$$then\ v(t+1) \leftarrow v_{reset}$$



Inter-cellular Ca^{2+} wave propagation in space and time

$$a_i = a_0 * n * \exp\left(-\frac{i}{\tau_d}\right)$$

amplitude

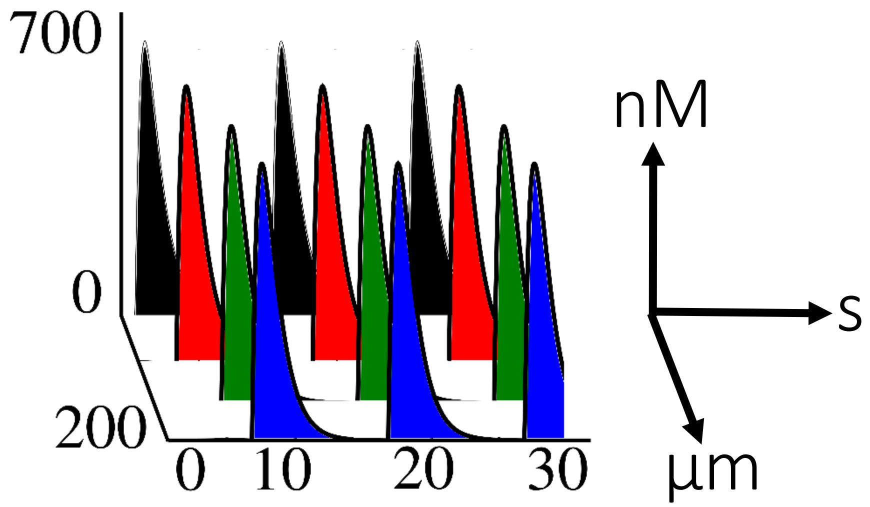
$$c_i(r_i, t) = a_i \cdot g_i(r_i, t)$$

shape

$$g_i(r_i, t) = exp\left(-\frac{r_i - \mu \cdot v \cdot t}{\tau_{decay}}\right) - exp\left(-\frac{r_i - \mu \cdot v \cdot t}{\tau_{rise}}\right)$$

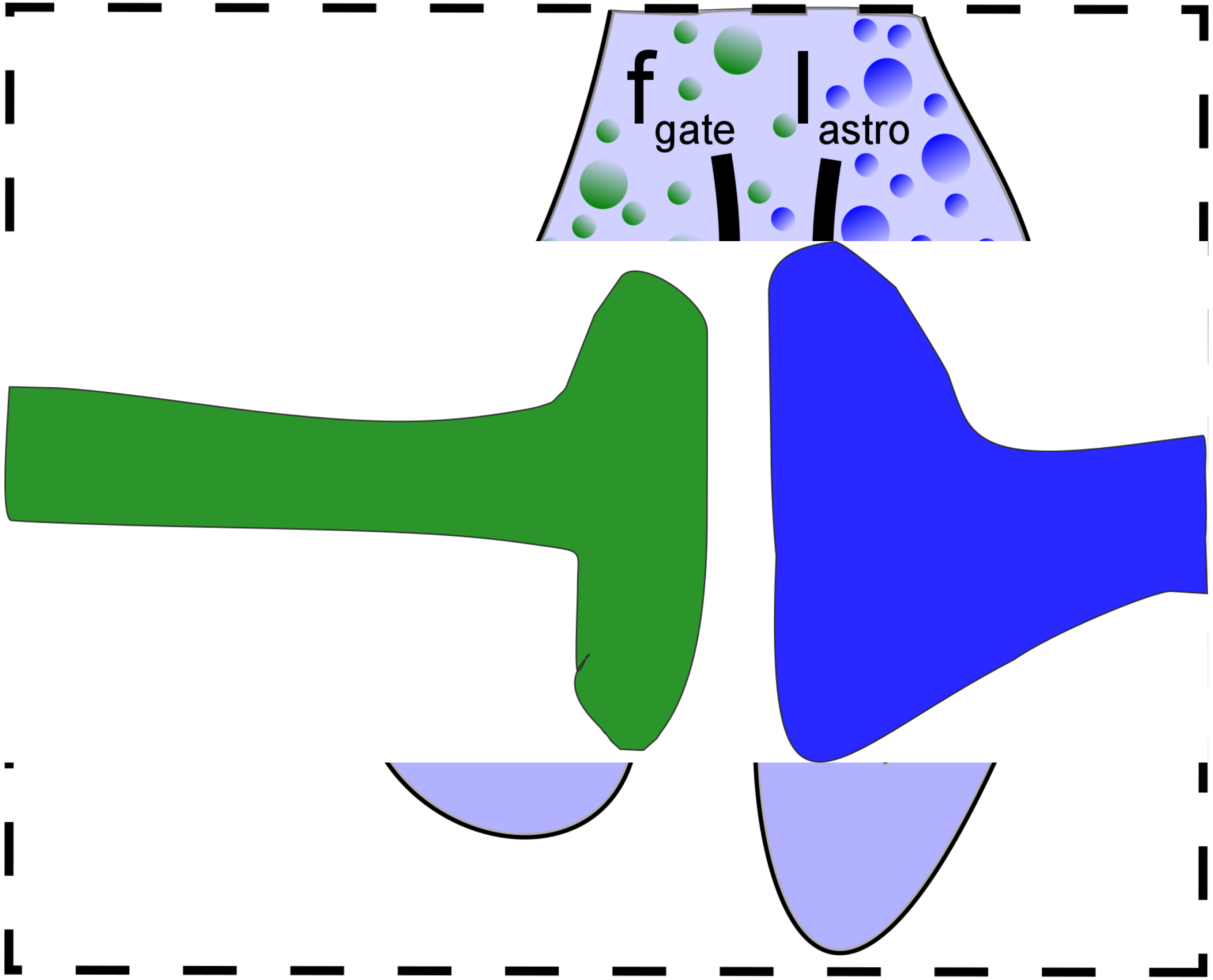
the distance of astrocyte i from the origination site ($r_0 \equiv 0$)

intracellular Ca^{2+} level in astrocyte i at time t

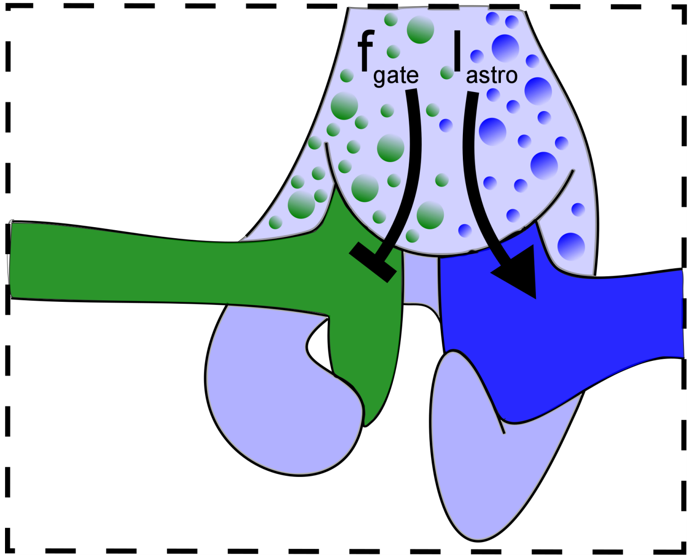


- $\tau_{decay}, \tau_{rise}$ control the fall and rise time of the Ca^{2+} wave
- τ_d controls the magnitude of the amplitude fall-off between astrocytes
- μ captures the permeability of the cells through which the wave propagates with speed v - lumping together all the sub-mechanisms of gap-junctional and extracellular communication
- n is the normalization constant for biexponential function, which is a function of the rise and decay parameter

Tripartite Synapse



Tripartite Synapse



$$\frac{dx}{dt} = \frac{z}{\tau_{rec}} - u \cdot x \cdot \delta(t - t_{sp})$$

$$\frac{dy}{dt} = -\frac{y}{\tau_{in}} + u \cdot x \cdot \delta(t - t_{sp})$$

$$\frac{dz}{dt} = \frac{y}{\tau_{in}} - \frac{z}{\tau_{rec}}$$

M. Tsodyks, A. Uziel, and H. Markram
Synchrony generation in recurrent networks with frequency-dependent synapses *J. Neurosci.* 2000

synaptic current | synaptic strength

$$I_{syn} = A \cdot y(t)$$

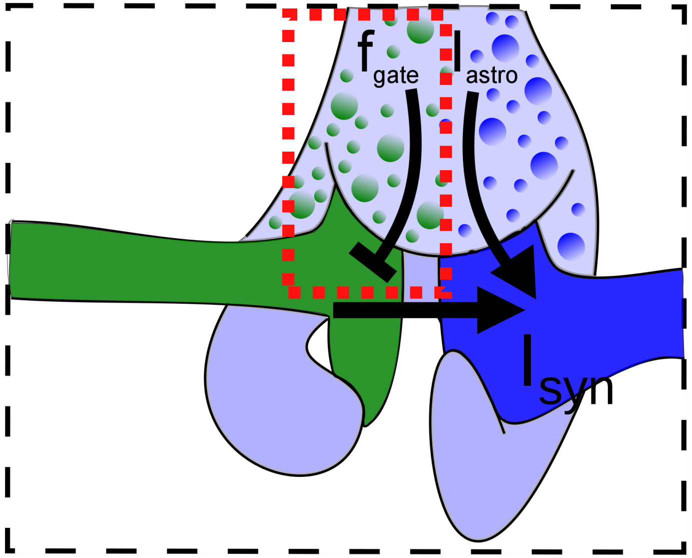
τ_{in} is the characteristic time of postsynaptic currents (PSCs) decay

τ_{rec} is the recovery time from synaptic depression

$x + y + z = 1$ are the fractions of synaptic resources in a recovered, active, inactive state

u is the fraction of x released when a spike arrives at the synapse at time t_{sp}

Tripartite Synapse



$$\mathrm{I_{syn}} = \mathrm{A} \cdot y(\mathrm{t})$$

$$\frac{dx}{dt} = \frac{z}{\tau_{rec}} - (1 - f) \cdot u \cdot x \cdot \delta(t - t_{sp})$$

$$\frac{dy}{dt} = -\frac{y}{\tau_{in}} + (1 - f) \cdot u \cdot x \cdot \delta(t - t_{sp})$$

$$\frac{dz}{dt} = \frac{y}{\tau_{in}} - \frac{z}{\tau_{rec}}$$

$$\frac{df}{dt} = \left(-\frac{f}{\tau_{Ca}}\right) + (1 - f) \cdot \kappa \cdot \Theta(c_i(r_i, t) - c_{thresh})$$

τ_{Ca} is the decay constant of f

κ controls the rise time of f

τ_{in} is the characteristic time of postsynaptic currents (PSCs) decay

τ_{rec} is the recovery time from synaptic depression

$\Theta(x)$ Heaviside function

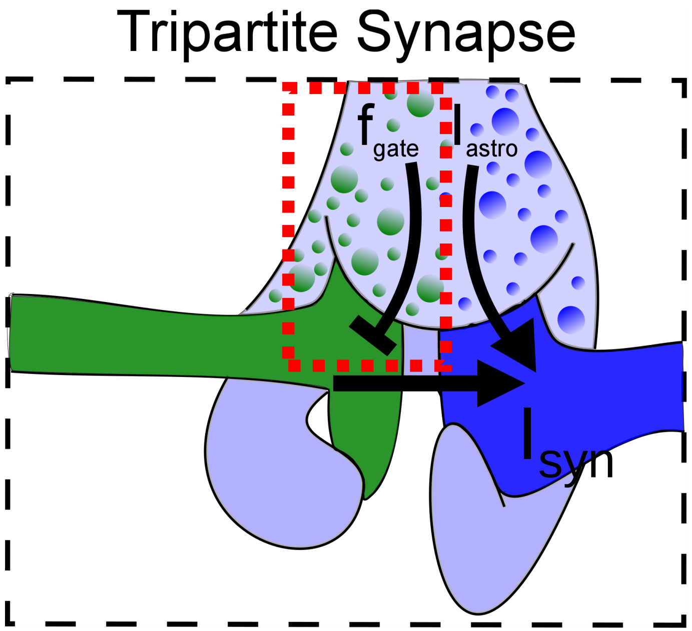
c_{thresh} is [intracellular Ca^{2+}] needed to activate f

f is the **gating variable**

It models Ca^{2+}-dependent presynaptic inhibition

$x + y + z = 1$ are the fractions of synaptic resources in a recovered, active, inactive state

u is the fraction of x released when a spike arrives at the synapse at time t_{sp}



Astrocytes inject into the post-synaptic neuron a slow-injected current (SICs)

Upon reaching a Ca^{2+} peak, an astrocyte releases glio-transmitters that lead to NMDAR-mediated SICs, with the SIC amplitude being logarithmically proportional to the Ca^{2+} wave amplitude.

SICs

- are well fit to bi-exponential distributions
- have a rapid rise time (on the order of tens of ms)
- have a comparatively larger decay time (on the order of hundreds of ms)
- are correlated with Ca^{2+} wave peaks in both time and amplitude

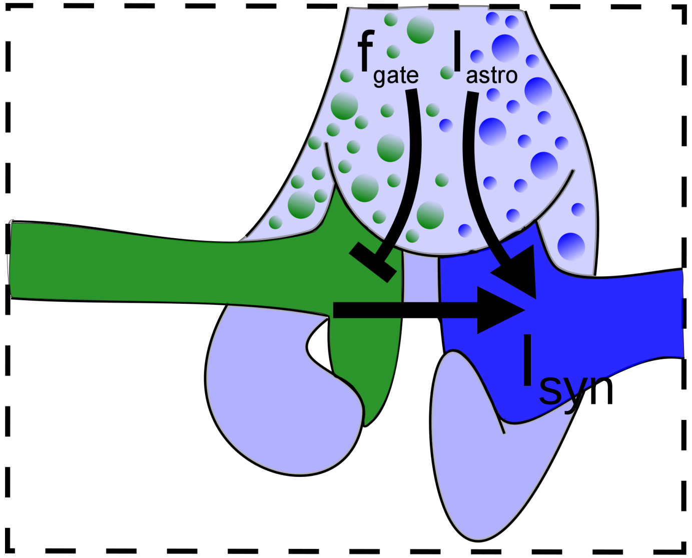
$$\mathrm{I}_{\mathrm{astro}} = 2.11 \cdot \frac{\mu A}{cm^2} \cdot ln(w) \cdot \Theta\big(ln(w)\big)$$

$$w = c_i\,(r_i, t)/n\,M - 196.69$$

$$\mathrm{I}_{\mathrm{SIC}}(t) = \mathrm{I}_{\mathrm{astro}}\big(c_i(r_i, t) = \mathrm{c}_{\mathrm{peak}}\big)\left(exp\left(-\frac{t}{\tau_{decay}^{SIC}}\right) - exp\left(-\frac{t}{\tau_{rise}^{SIC}}\right)\right)$$

Tripartite Synapse

Neural Network | Astrocytic Network | Tripartite Synapse



$$\mathrm{I}_{syn} = A \cdot y(t)$$

$$\frac{dx}{dt} = \frac{z}{\tau_{rec}} - (1 - f) \cdot u \cdot x \cdot \delta(t - t_{sp})$$

$$\frac{dy}{dt} = -\frac{y}{\tau_{in}} + (1 - f) \cdot u \cdot x \cdot \delta(t - t_{sp})$$

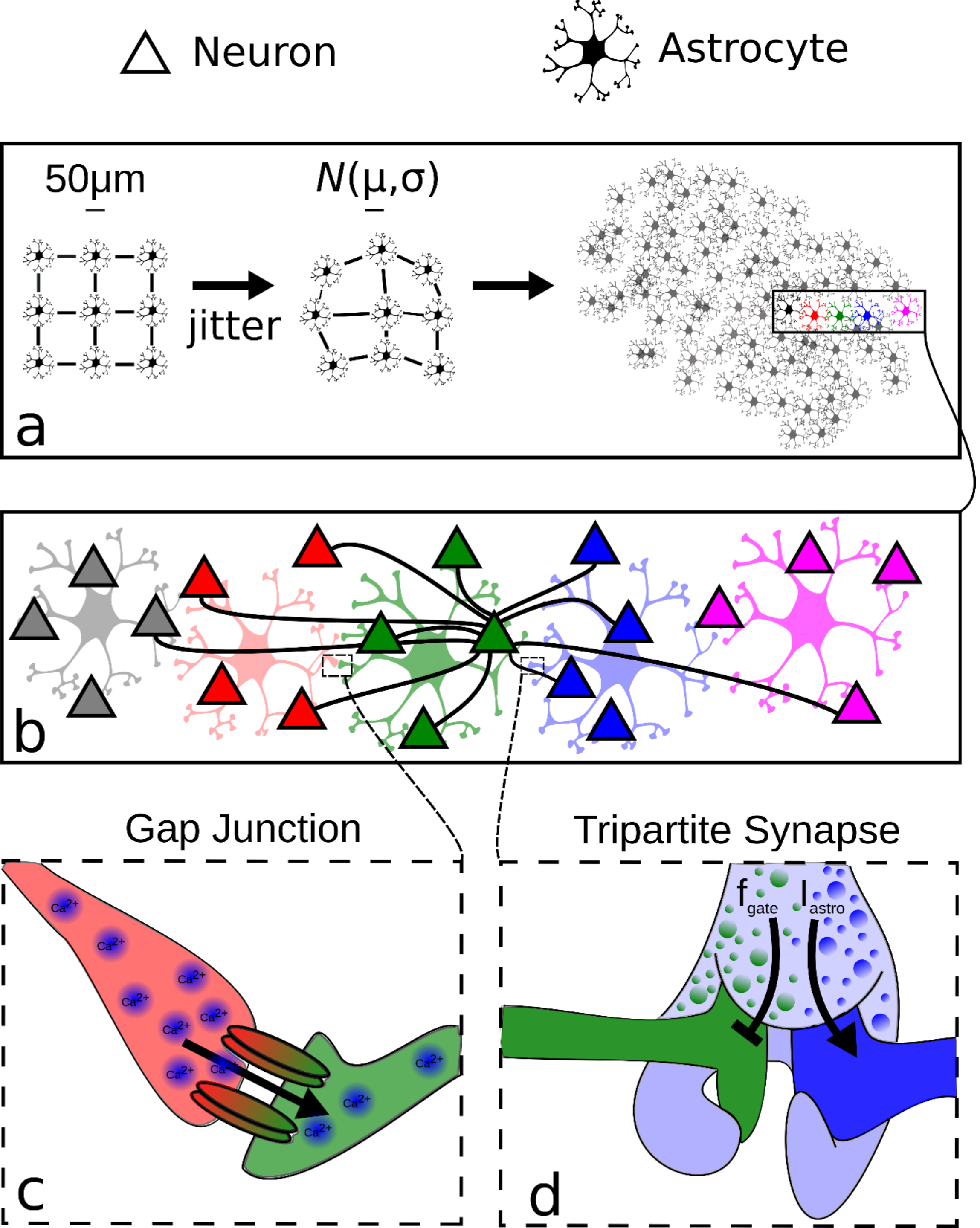
$$\frac{dz}{dt} = \frac{y}{\tau_{in}} - \frac{z}{\tau_{rec}}$$

$$\frac{df}{dt} = \left(-\frac{f}{\tau_{Ca}}\right) + (1 - f) \cdot \kappa \cdot \Theta(c_i(r_i, t) - c_{thresh})$$

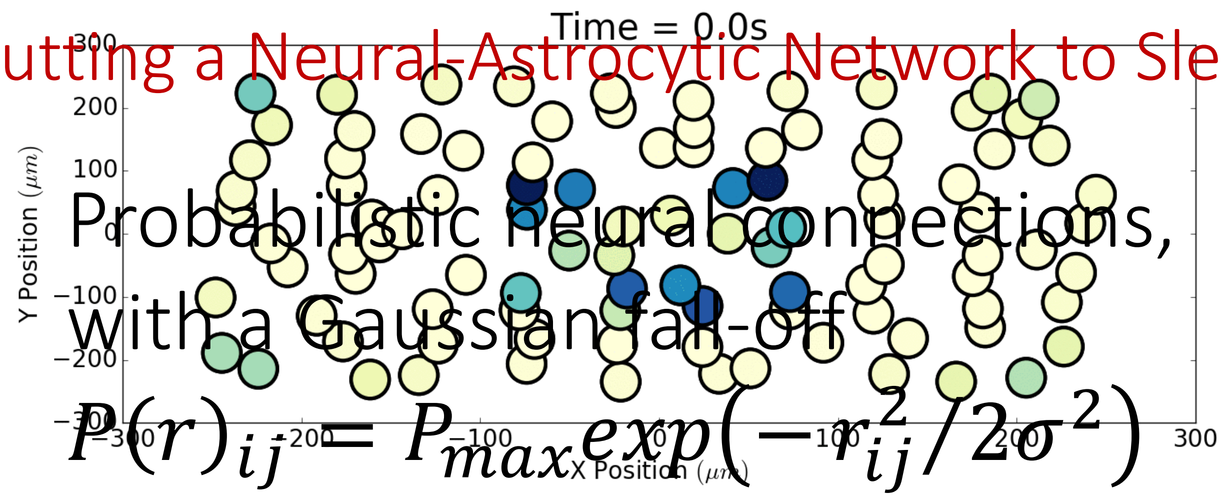
$$\mathrm{I}_{astro} = 2.11 \cdot \frac{\mu A}{cm^2} \cdot ln(w) \cdot \Theta(ln(w))$$

$$w = c_i\,(r_i, t)/n\,M - 196.69$$

$$\mathrm{I}_{SIC}(t) = \mathrm{I}_{astro}(c_i(r_i, t) = \mathrm{c}_{peak})\left(exp\left(-\frac{t}{\tau_{decay}^{SIC}}\right) - exp\left(-\frac{t}{\tau_{rise}^{SIC}}\right)\right)$$

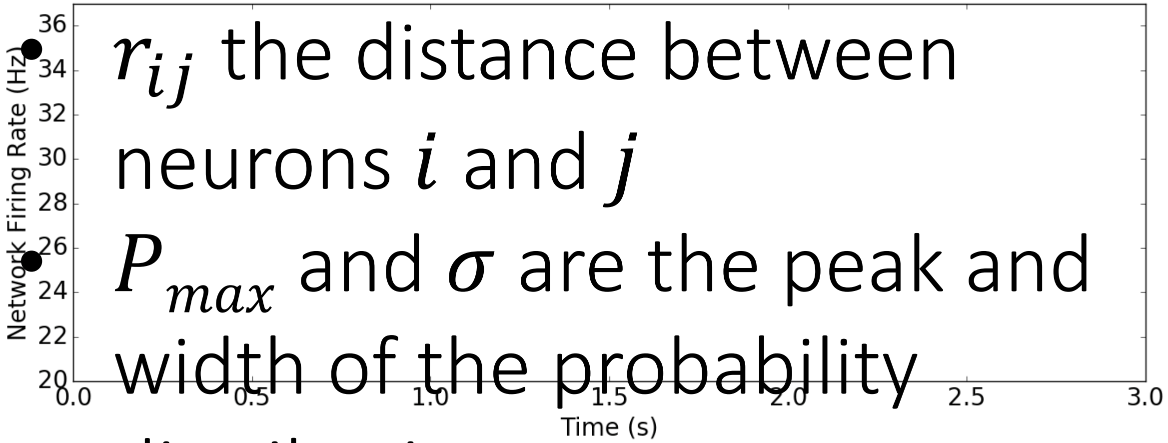


Putting a Neural-Astrocytic Network to Sleep



- Probabilistic neural connections, with a Gaussian fall-off

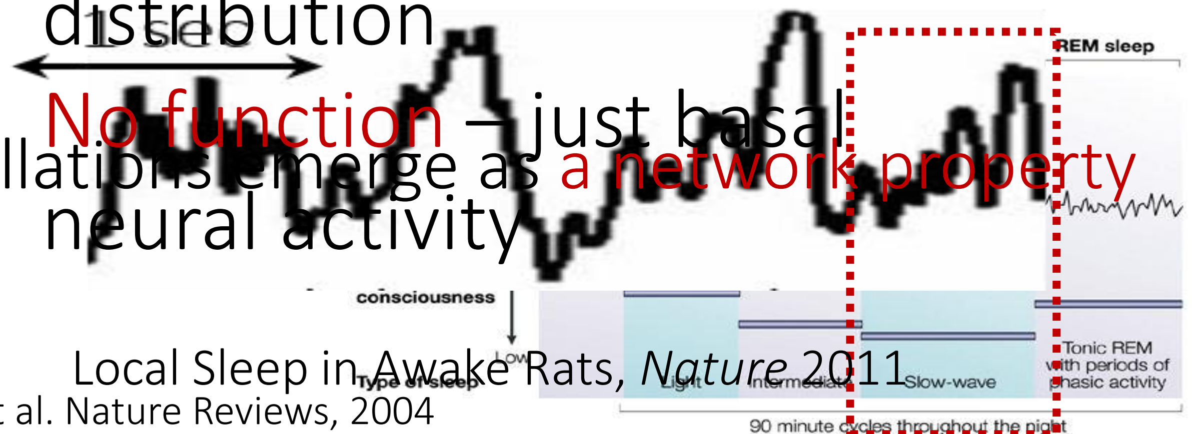
$$P(r)_{ij} = P_{max} exp\left(-r_{ij}^2/2\sigma^2\right)$$



- r_{ij} the distance between neurons i and j
- P_{max} and σ are the peak and width of the probability distribution

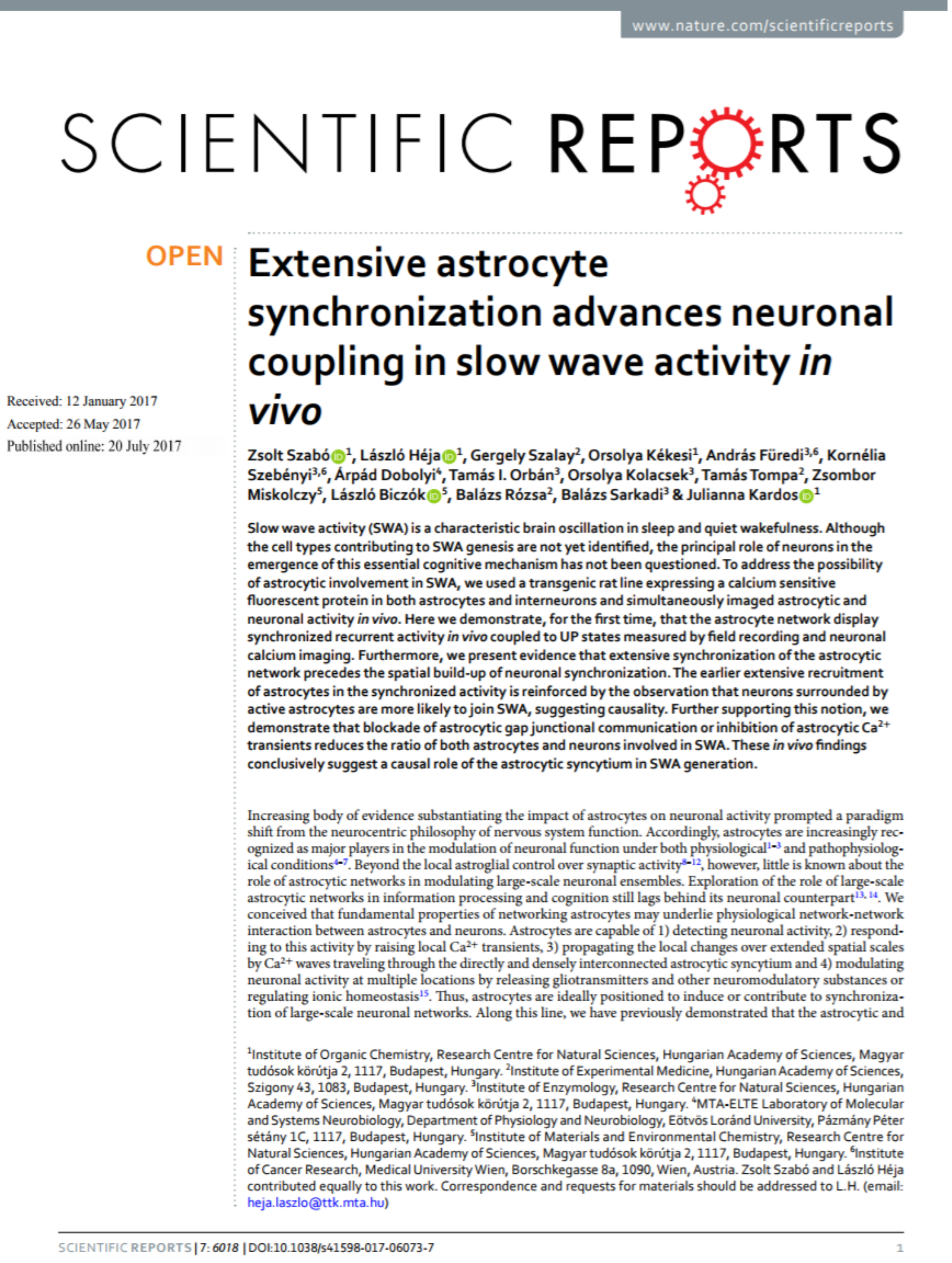
- No function – just basal neural activity

Oscillations emerge as a network property



Local Sleep in Awake Rats, *Nature* 2011

Bryant et al. Nature Reviews, 2004



SCIENTIFIC REPORTS

OPEN

Extensive astrocyte synchronization advances neuronal coupling in slow wave activity *in vivo*

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Slow wave activity (SWA) is a characteristic brain oscillation in sleep and quiet wakefulness. Although the cell types contributing to SWA genesis are not yet identified, the principal role of neurons in the emergence of this essential cognitive mechanism has not been questioned. To address the possibility of astrocytic involvement in SWA, we used a transgenic rat line expressing a calcium sensitive fluorescent protein in both astrocytes and interneurons and simultaneously imaged astrocytic and neuronal activity *in vivo*. Here we demonstrate, for the first time, that the astrocyte network display synchronized recurrent activity *in vivo* coupled to UP states measured by field recording and neuronal calcium imaging. Furthermore, we present evidence that extensive synchronization of the astrocytic network precedes the spatial build-up of neuronal synchronization. The earlier extensive recruitment of astrocytes in the synchronized activity is reinforced by the observation that neurons surrounded by active astrocytes are more likely to join SWA, suggesting causality. Further supporting this notion, we demonstrate that blockade of astrocytic gap junctional communication or inhibition of astrocytic Ca^{2+} transients reduces the ratio of both astrocytes and neurons involved in SWA. These *in vivo* findings conclusively suggest a causal role of the astrocytic syncytium in SWA generation.

Increasing body of evidence substantiating the impact of astrocytes on neuronal activity prompted a paradigm shift from the neurocentric philosophy of nervous system function. Accordingly, astrocytes are increasingly recognized as major players in the modulation of neuronal function under both physiological[1–3] and pathophysiological conditions[4–7]. Beyond the local astroglial control over synaptic activity[8–12], however, little is known about the role of astrocytic networks in modulating large-scale neuronal ensembles. Exploration of the role of large-scale astrocytic networks in information processing and cognition still lags behind its neuronal counterpart[13,14]. We conceived that fundamental properties of networking astrocytes may underlie physiological network-network interaction between astrocytes and neurons. Astrocytes are capable of 1) detecting neuronal activity, 2) responding to this activity by raising local Ca^{2+} transients, 3) propagating the local changes over extended spatial scales by Ca^{2+} waves traveling through the directly and densely interconnected astrocytic syncytium and 4) modulating neuronal activity at multiple locations by releasing gliotransmitters and other neuromodulatory substances or regulating ionic homeostasis[15]. Thus, astrocytes are ideally positioned to induce or contribute to synchronization of large-scale neuronal networks. Along this line, we have previously demonstrated that the astrocytic and

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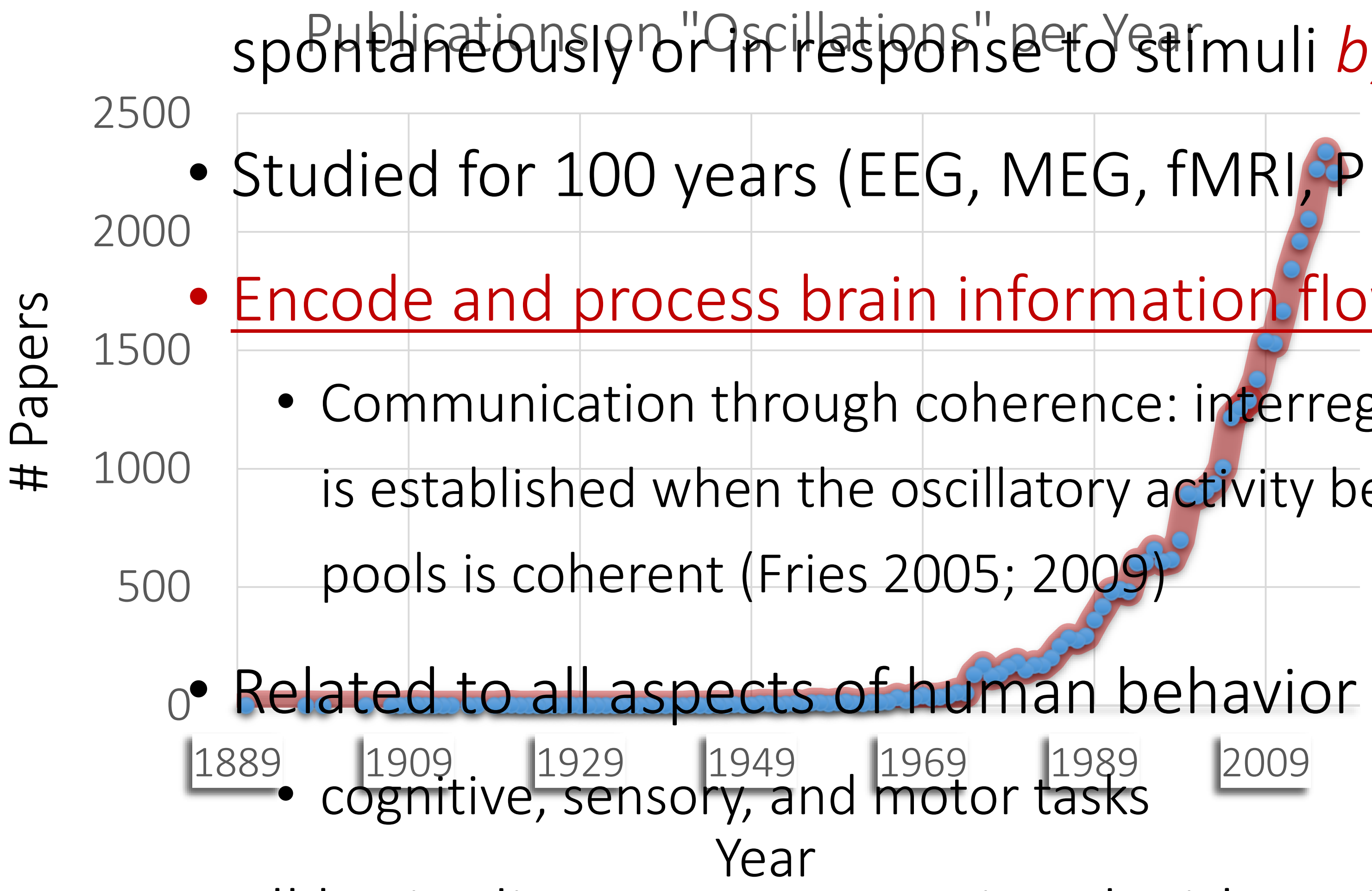
"This hypothesis was reinforced by a recent modelling study showing that intercellular Ca2+ signaling potentially can introduce slow oscillation in neurons [our Ref]. Our experimental data strongly supports this hypothesis by demonstrating that increasing astrocytic influence on neurons indeed drives them to join the oscillatory activity (Fig. 5C). In this context it is also important to note, that the ratio of astrocytes involved in the SWA was found to start decreasing right after virtually all neurons joined the simultaneous activity (Figs 4 and 5). This observation further supports the view that astrocytic activity corresponds to the generation or maintenance, rather than termination of SWA."

brain oscillations are still lacking a mechanistic origin

- Rhythmic or repetitive *electrical* activity generated spontaneously or in response to stimuli *by the neurons*
- Studied for 100 years (EEG, MEG, fMRI, PET, MER)
- Encode and process brain information flow
  - Communication through coherence: interregional communication is established when the oscillatory activity between neuronal pools is coherent (Fries 2005; 2009)
- Related to all aspects of human behavior
  - cognitive, sensory, and motor tasks
- All brain diseases are associated with oscillatory imbalances

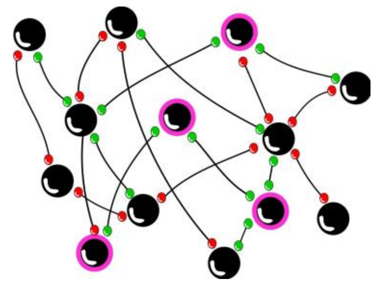


Source: PubMed

Introducing *function* into a Neural-Astrocytic Network

NAN Hopfield Nets

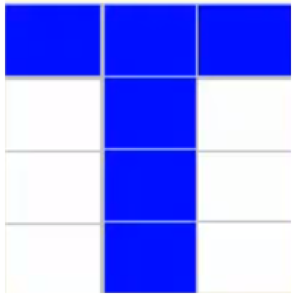
- The idea of *memories as energy minima* was proposed by I.A. Richards in 1924 in "Principles of Literary Criticism"
- Hopfield (1982) proposed that *memories could be energy minima of a neural net*
- Using energy minima to represent memories gives a content-addressable memory
- Memories are stored in ~~the~~ tripartite synapses

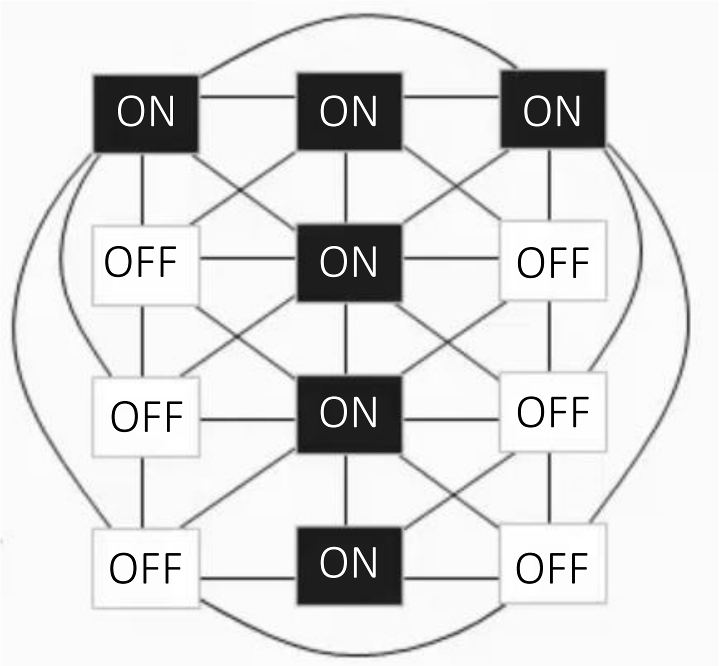


With 19,000 citations, Hopfield nets are the precursors of Boltzman Machines (BM), Restricted BM and Deep Belief Networks

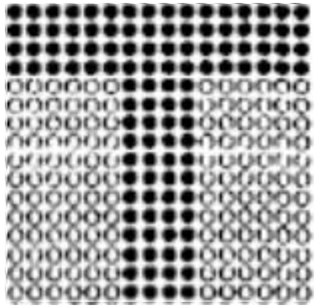
- A Hopfield net is composed of binary threshold units with recurrent connections between them
- Recurrent nets of non-linear units are generally hard to analyze. They can:

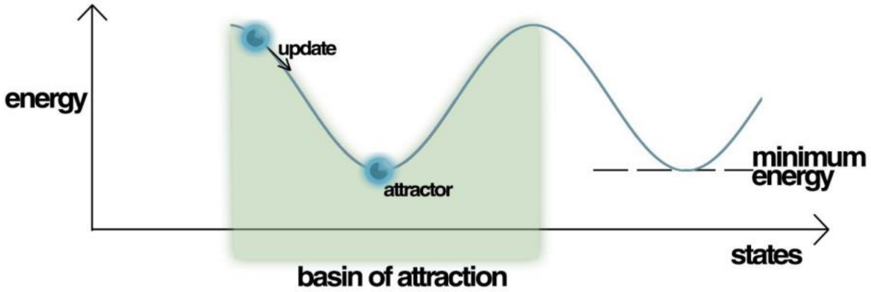
Settle to a stable state | Oscillate | Follow chaotic trajectories that cannot be predicted far into the features



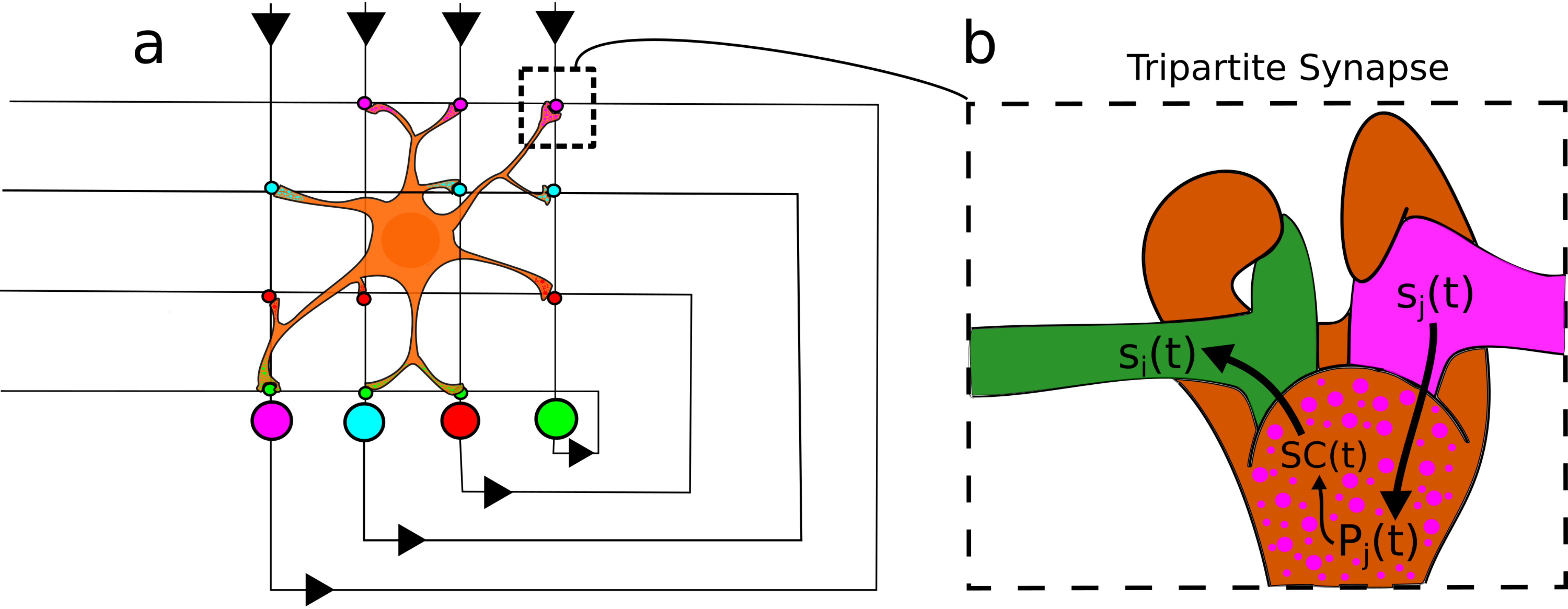


Fully connected (not shown)





- Hopfield (and others) realized that if the connections are symmetric, there is a global energy function
  - Each binary configuration of the whole network has an energy
  - The binary threshold decision rule causes the network to settle to a minimum of this energy function



Goal: To generate a sequence of patterns

- by going through a predetermined (by the astrocytes) sequence, in a closed limit cycle
- Sequences of patterns occur widely in biological sequences (e.g., walking, learning a task, rehab)

Network

N neurons with values $x_i = \pm 1, i = 1, \dots, N$

Fully connected neurons, i.e., every neuron is connected to every other neuron

Connectivity weight $w_{ij} = w_{ji}, w_{ii} = 0$

Neuron

Aligns with the local field, h_i:

$$s_i(t+1) = sng(h_i(t))$$

$$h_i(t) = h_i(t)^{neural} + h_i(t)^{astro}$$

$$J_{ij} = \frac{1}{N}\sum_{\mu}^{m}(2\xi_i^{\mu} - 1)\left(2\xi_j^{\mu} - 1\right), i \neq j$$

$$h_i(t)^{neural} = \sum_{j=1}^{N} J_{ij} s_j(t)$$

stabilizing symmetric matrix (short-time connections)

$$T_{ij} = \frac{\lambda}{N}\sum_{\mu}^{q}(2\xi_i^{\mu+1} - 1)\left(2\xi_j^{\mu} - 1\right), i \neq j$$

$$h_i(t)^{astro} = \sum_{j=1}^{N} T_{ij} SC_j(t)$$

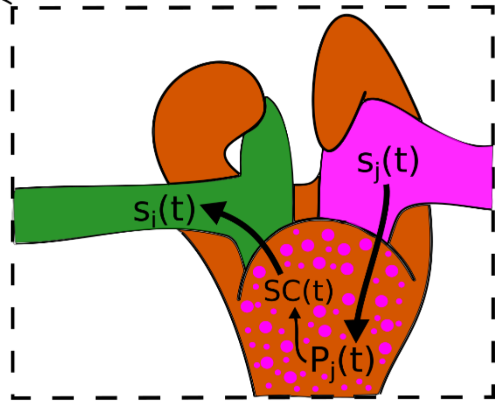
$$SC = e^{\frac{t-\delta_{cal}}{\tau_{SC}}}$$

matrix of amplitudes for the SICs (long-time connections)

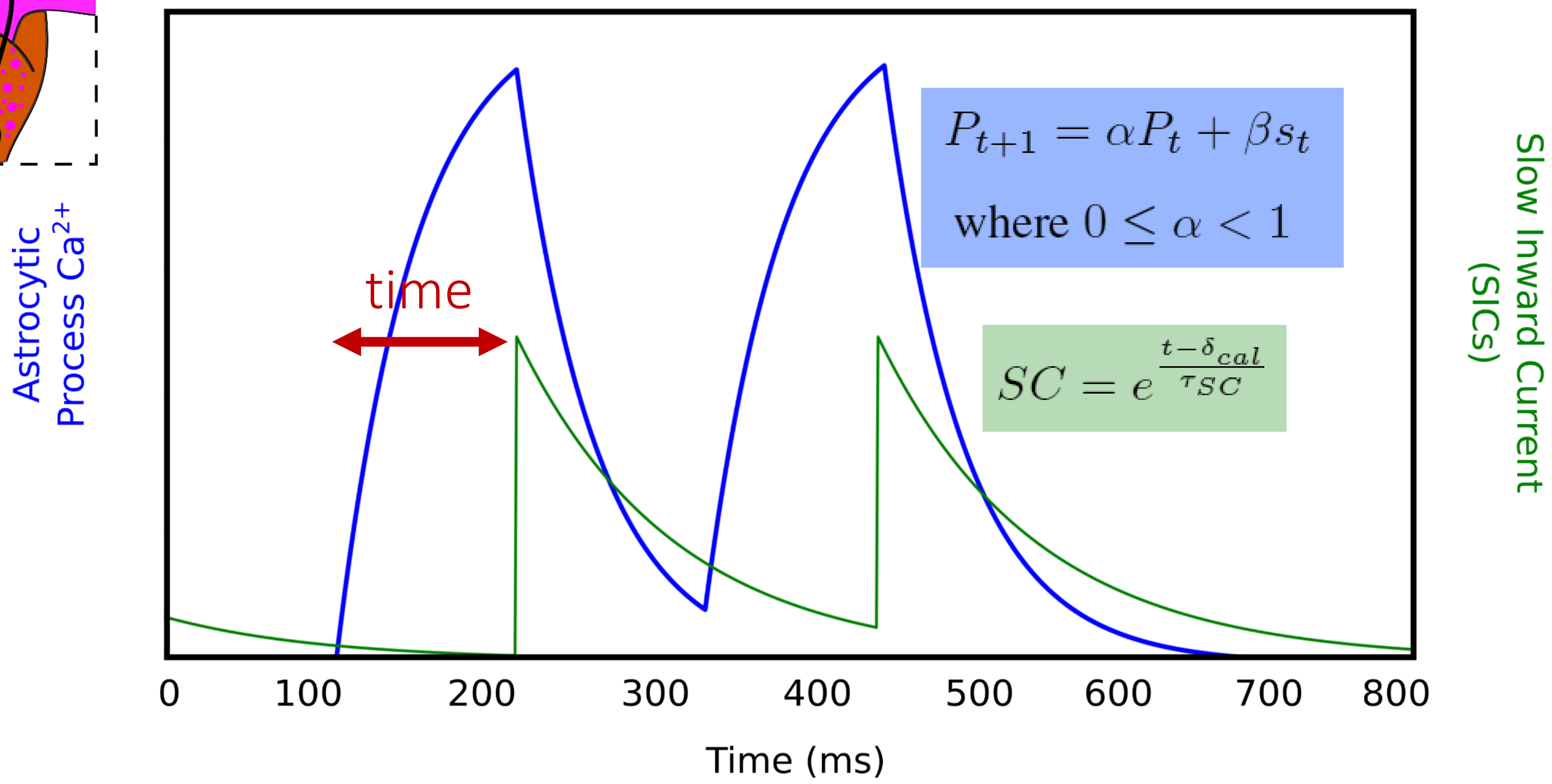
Memories

$$\vec{\xi} = (x_1, \dots, x_i, \dots, x_N) \in \{-1,1\}^N$$

m memories $\vec{\xi}^p, p = 1, \dots, m$

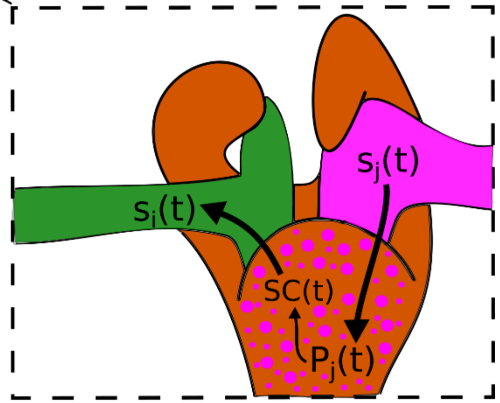


Single Astrocyte Process Ca^{2+} & SICs



The dynamics of the two signals of interest in an astrocytic process: Local Ca^{2+} wave which rises in response to the presynaptic activity and the related SIC injected into the postsynaptic neuron.

δ_{cal} the time at which the astrocyte Ca^{2+} reached c_{thresh}



Derive time spent in each memory τ

$$P_{t+1} = \alpha P_t + \beta s_t$$

$$\text{where } 0 \leq \alpha < 1$$

Define the linear operator $\hat{L}$:

- $\hat{L} P_t \equiv P_{t-1}$
- $\hat{L}^2 P_t \equiv P_{t-2}$

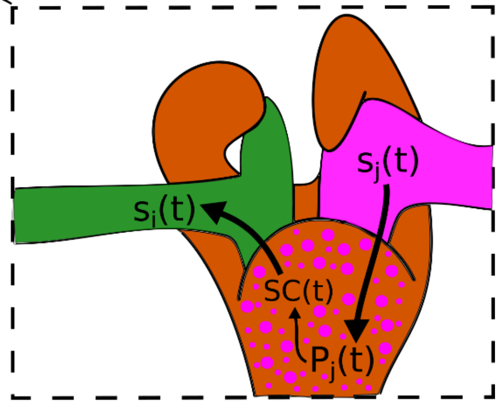
We can solve for P_t:

Taylor series of $\frac{1}{1-x}$

$$P_t = \frac{\beta s_t}{1 - \alpha \hat{L}} = \beta \sum_{t'=0}^{\infty} (\alpha \hat{L})^{t'} s_t = \beta \sum_{t'=0}^{\infty} \alpha^{t'} s_{t-t'}$$

For $P_t = c_{thresh}$ in the continuous limit: $\frac{c_{thresh}}{\beta} = \int_0^{\tau} \alpha^{\tau - t'} dt'$

with the general solution $\tau = \dfrac{\ln(\frac{c_{thresh}}{\beta} \ln(\alpha) + 1)}{\ln(\alpha)}$



Derive time spent in each memory τ

$$P_{t+1} = \alpha P_t + \beta s_t$$

where $0 \leq \alpha < 1$

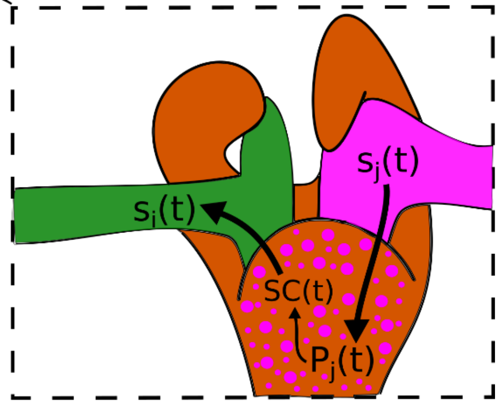
$$\int_0^{\tau} \beta \alpha^t dt = 1$$

$$\beta = \ln\left(\frac{1}{a}\right)$$

$$\tau = \frac{\ln(1 - c_{thresh})}{\ln(\alpha)}$$

Biological consideration. The more the astrocyte depends on its own Ca^{2+} level in the previous time-step (α), the less it depends on the presynaptic neural activity (β).

$$\tau = \frac{\ln(\frac{c_{thresh}}{\beta}\ln(\alpha) + 1)}{\ln(\alpha)}$$



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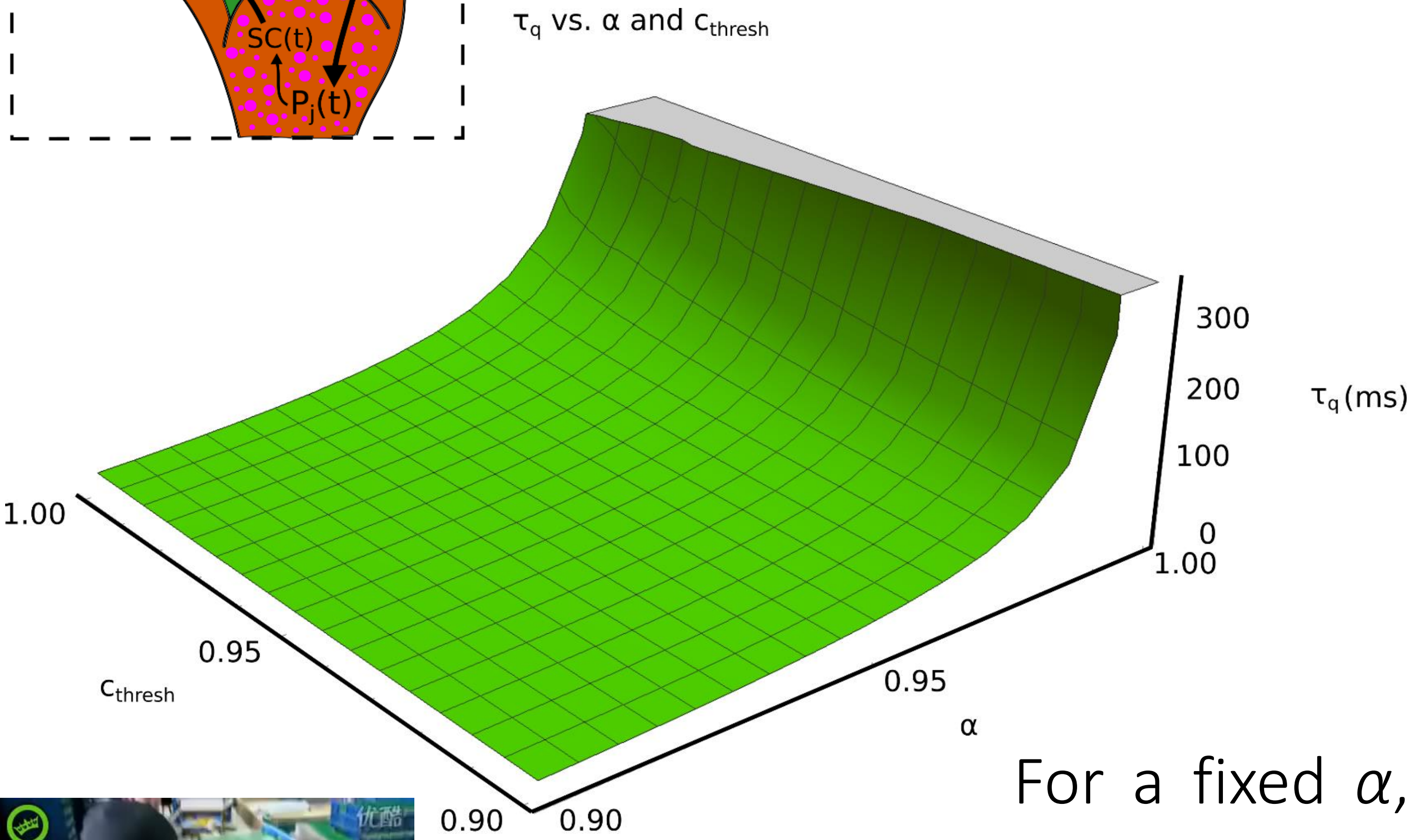
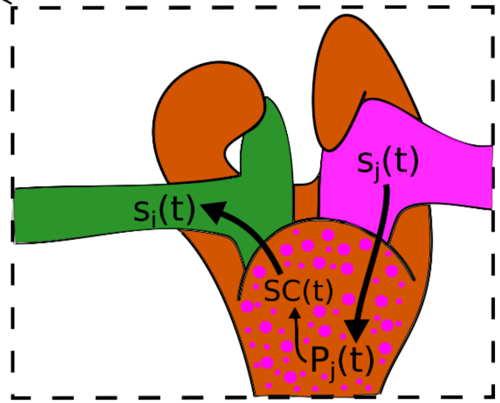


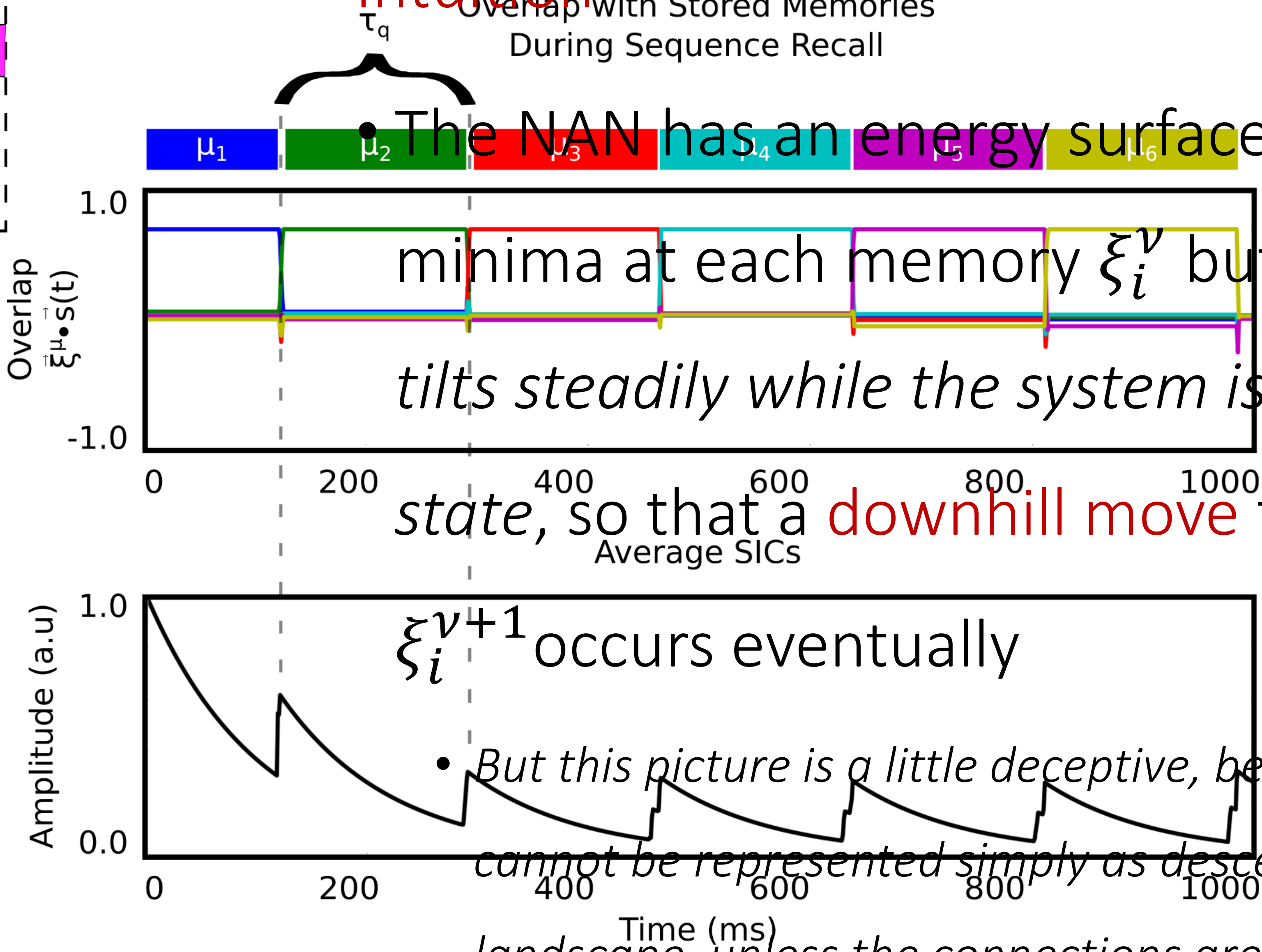
$$\tau = \frac{\ln(1 - c_{thresh})}{\ln(\alpha)}$$

For a fixed α, increasing c_{thresh} increases the time it takes for an astrocyte process to release an SC, thus increases τ_q

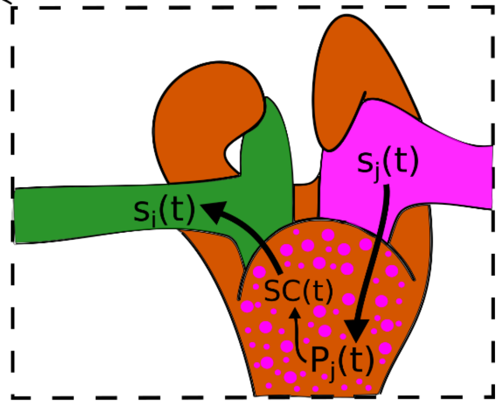
Intuition



- The NAN has an energy surface that has minima at each memory ξ_i^ν but which also *tilts steadily while the system is in a particular state*, so that a downhill move from ξ_i^ν to $\xi_i^{\nu+1}$ occurs eventually
  - *But this picture is a little deceptive, because the dynamics cannot be represented simply as descent on an energy landscape, unless the connections are symmetric*



The overlap of the neural network state with the stored memories. N = 500, p=7, q=6



Astrocytic Learning of Hebbian-type

Learning rate

Time btw. switching memories

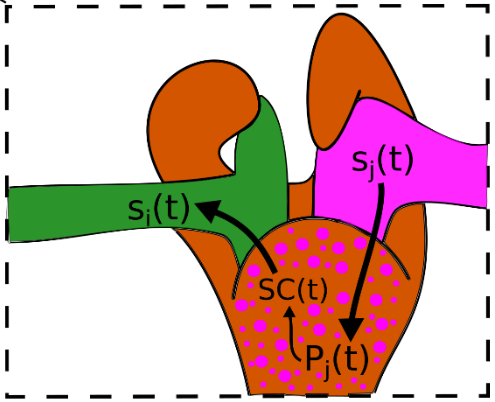
$$\Delta T_{ij} = \eta s_i(t_{switch}) P_j(t_{switch}) = \eta s_i(t_{switch}) s_j(0) = \eta \xi_i^{\mu+1} \xi_j^{\mu}$$

Postsynaptic state

Astrocytic state = Presynaptic State

for $t_{switch} \gg 0$

- At $t = t_{switch}$, the astrocyte correlates its current state with the state of the post-synaptic neuron and adjusts the levels of future gliotransmitter release accordingly—changing future SIC release
- *This mechanism requires retrograde signaling between the post-synaptic neuron and astrocyte process, known to occur through endocannabinoid mediated pathways (Fellin et al. Neuron 2004)*



What did we discover?

Kevin T. Feigelis, Physics Major, 2016

Now a PhD student at Stanford with Dan Yamins

NeuroAI Lab

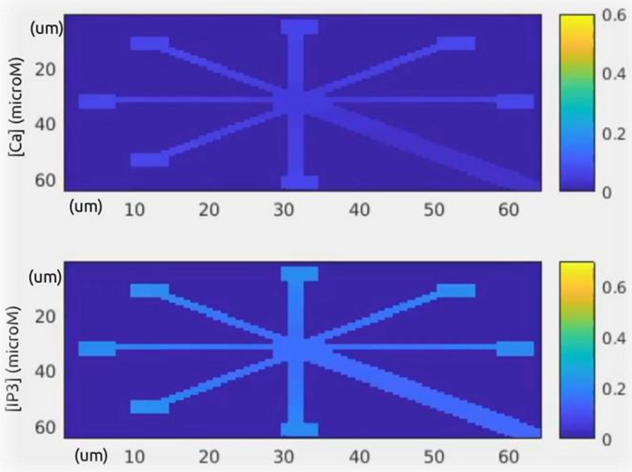
Leo Kozachkov, Physics/Math Major, 2016

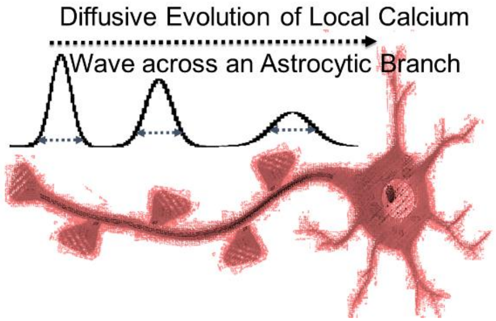
Now a PhD student at MIT with Earl K. Miller

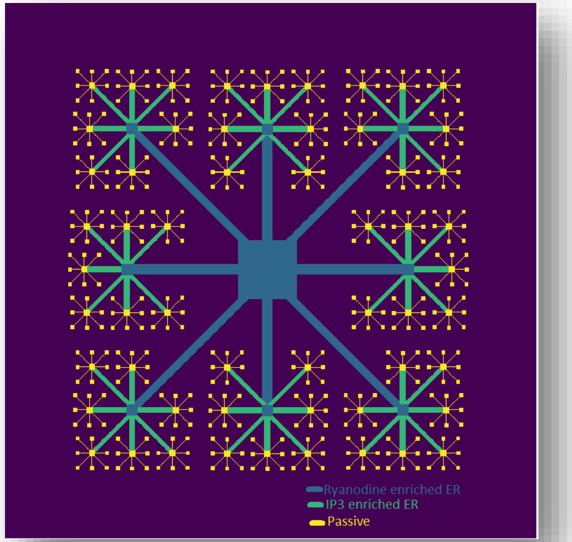
Brain & Cognitive Sciences Department

Giannis
Polykretis

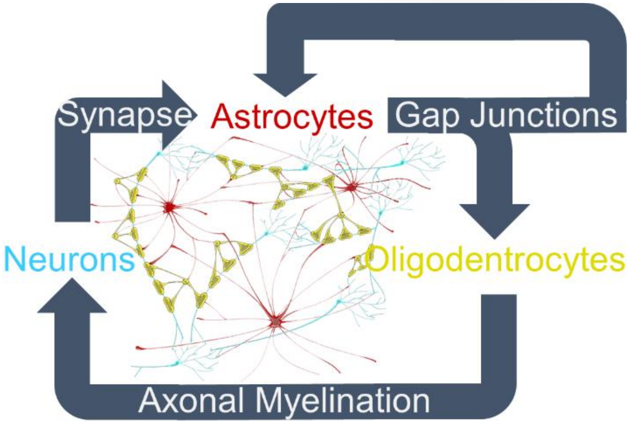
How astrocytes may encode information in Calcium waves

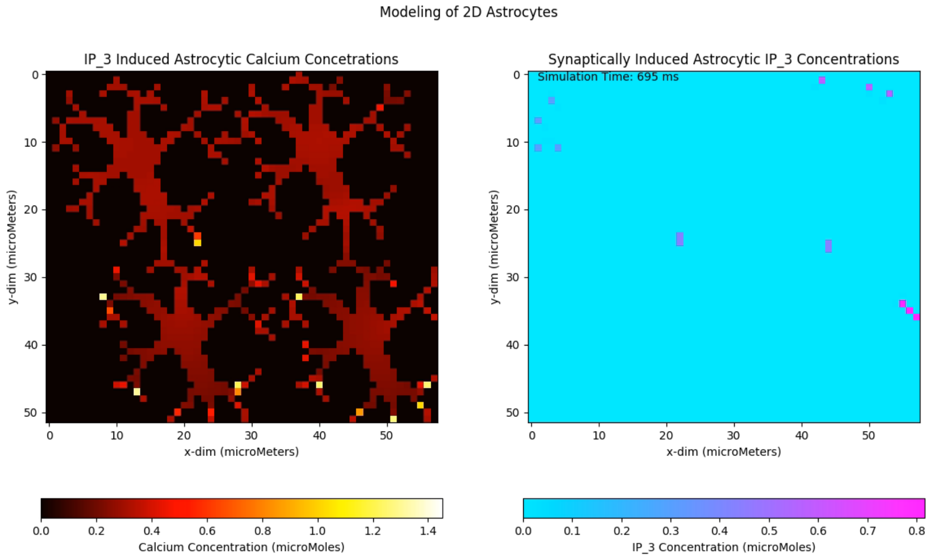




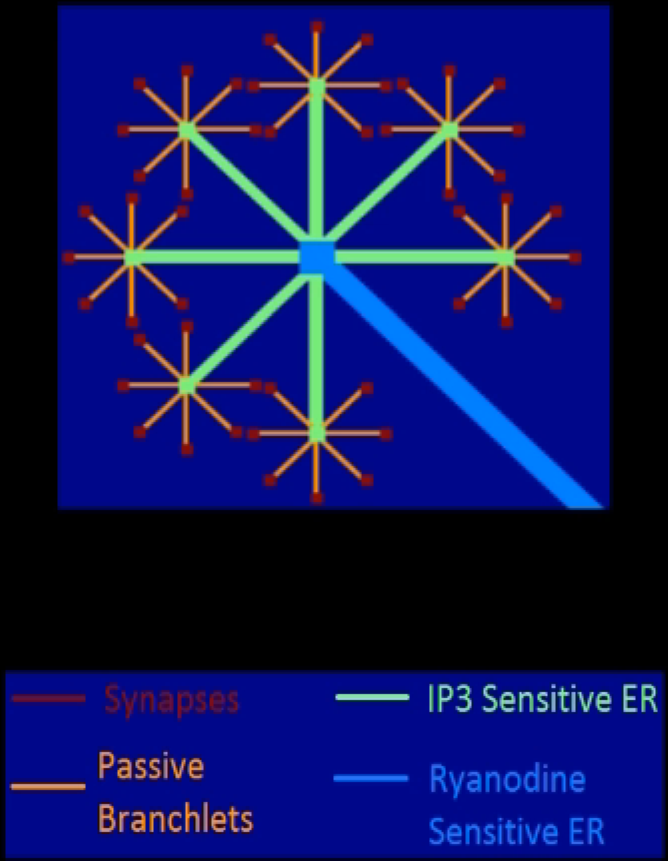


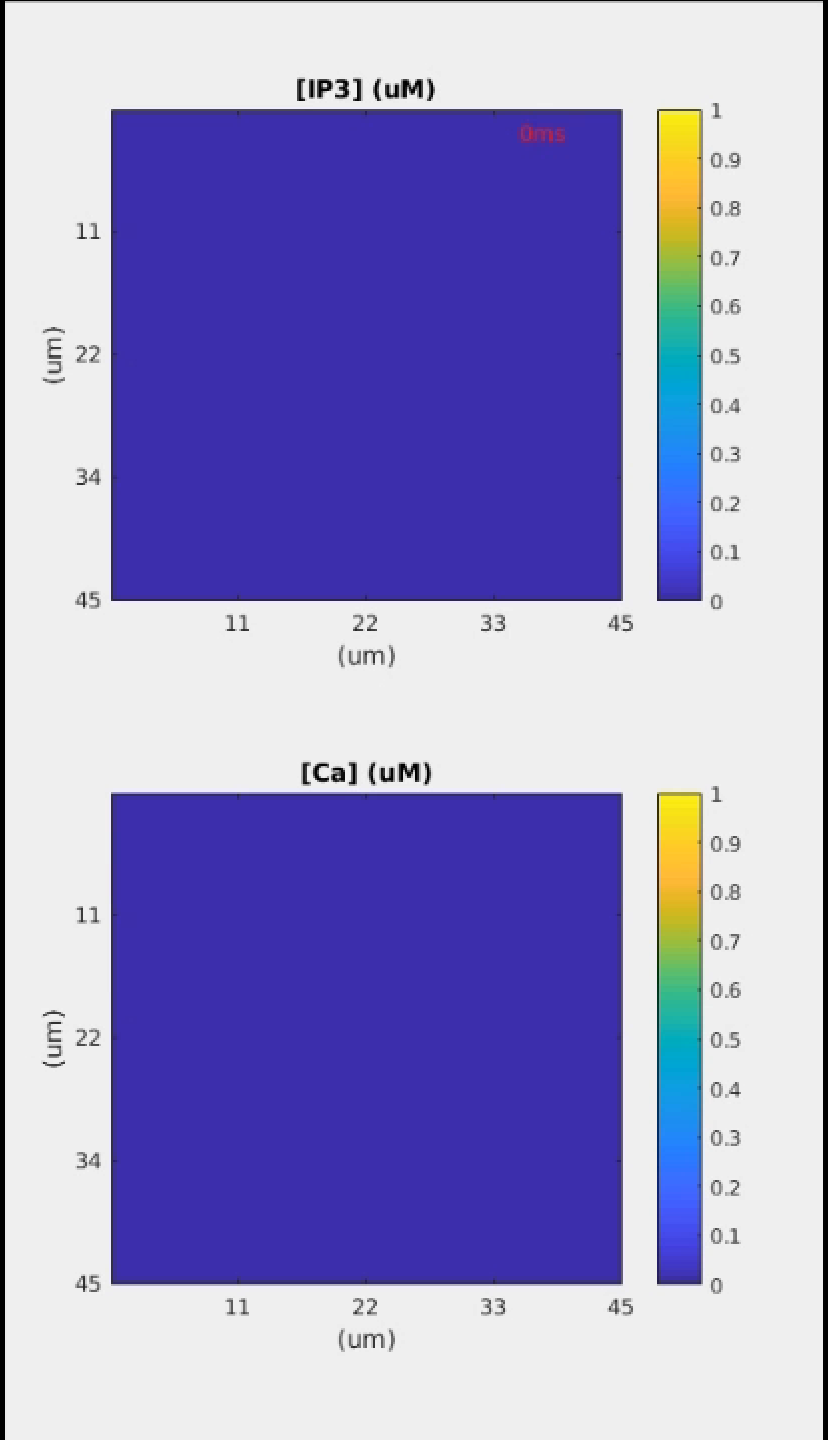
Vladimir
Ivanov





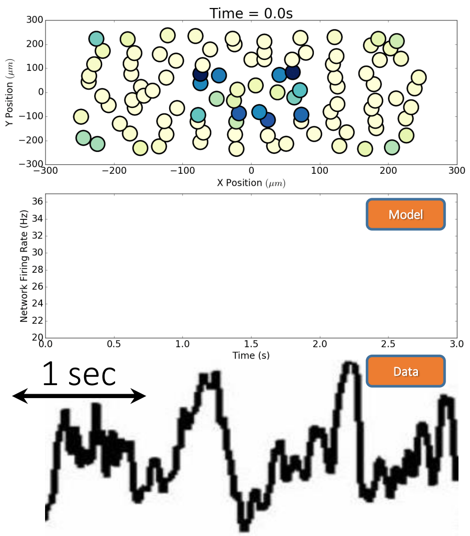
Towards
Mesochronous* Communication





** Thanks to Simon Knowles*

Astrocytes generate brain oscillations



Local sleep in awake rats
Nature 2011

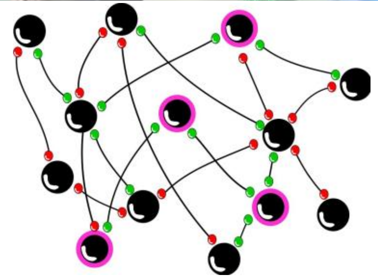
Neural – Astrocytic Networks

Biological Intelligence and NANs

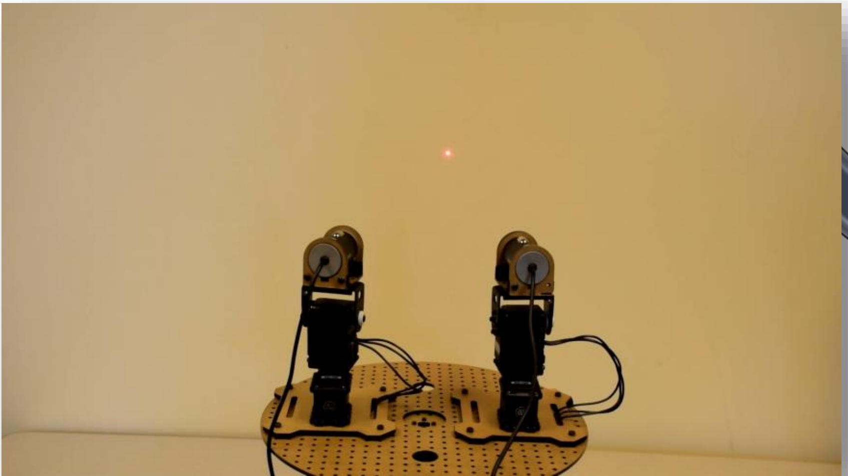
Artificial Intelligence and NANs

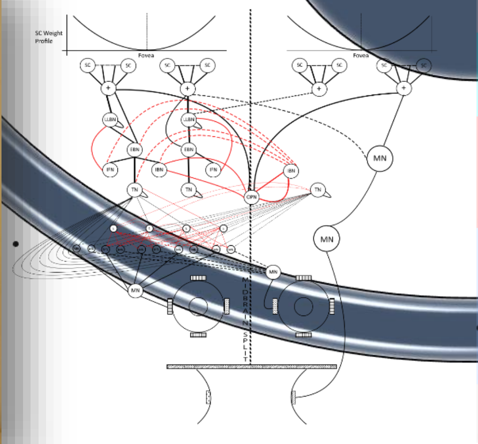
NAN Applications

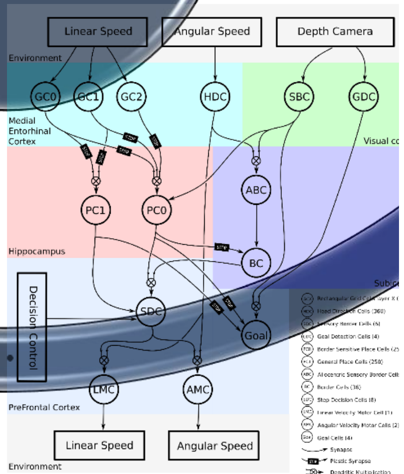
Astrocytes generate sequence learning



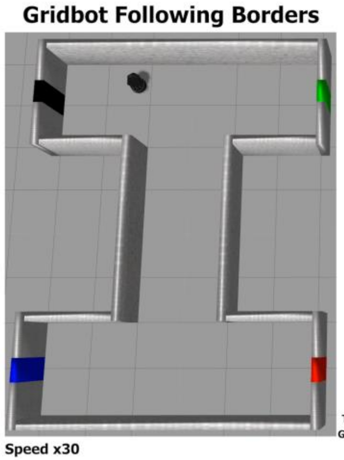
Brain ~~Neuro~~-mimetic Robotics

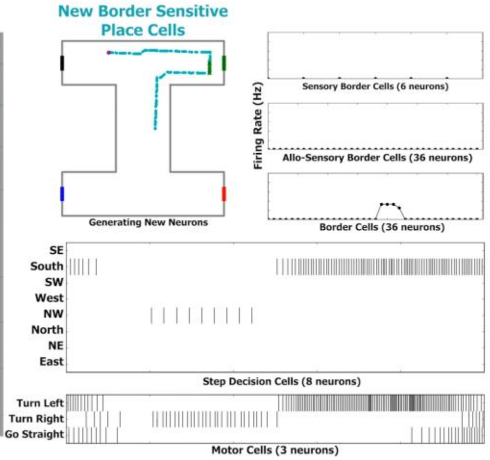






Brain ~~Neuro~~-morphic Computing





thank You

combra.cs.rutgers.edu

Brain-morphism: Astrocytes as Memory Units

Constantine Michmizos

Computational Brain Lab – Rutgers University