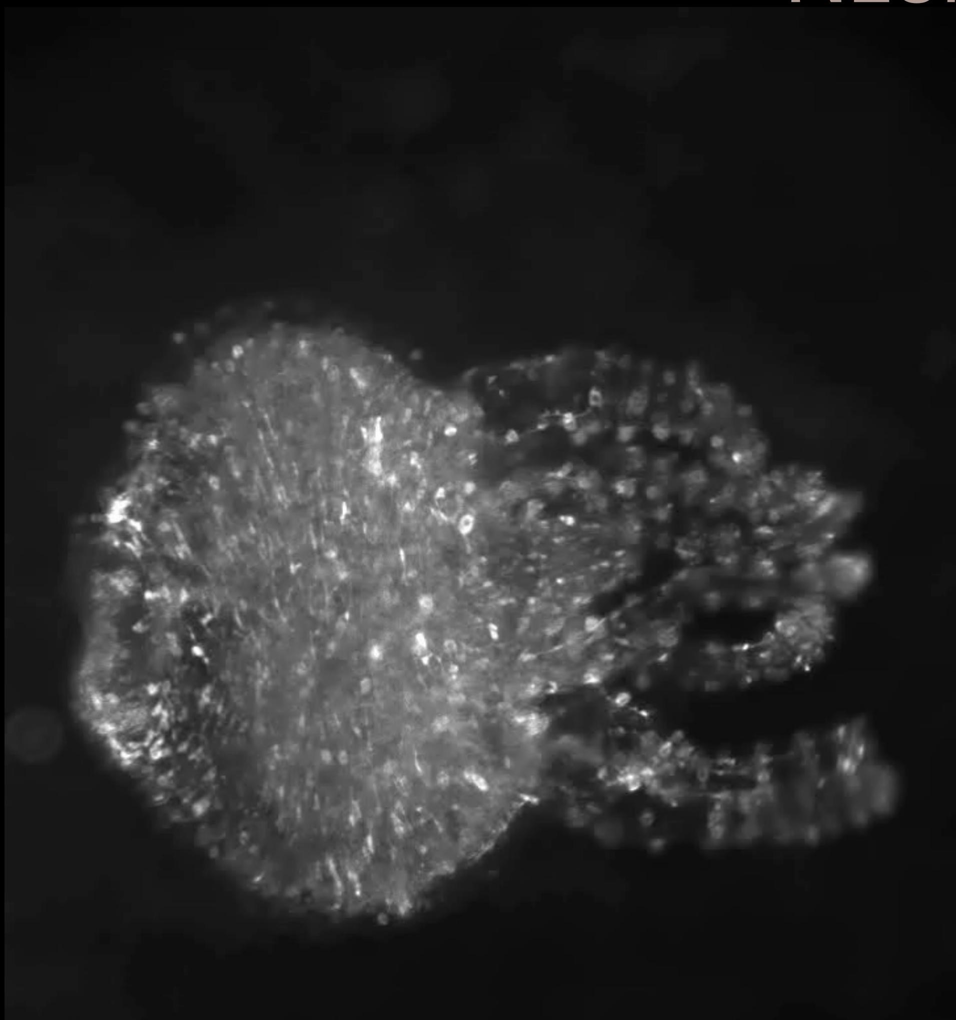
CS F441 Intro to Computational Neuroscience



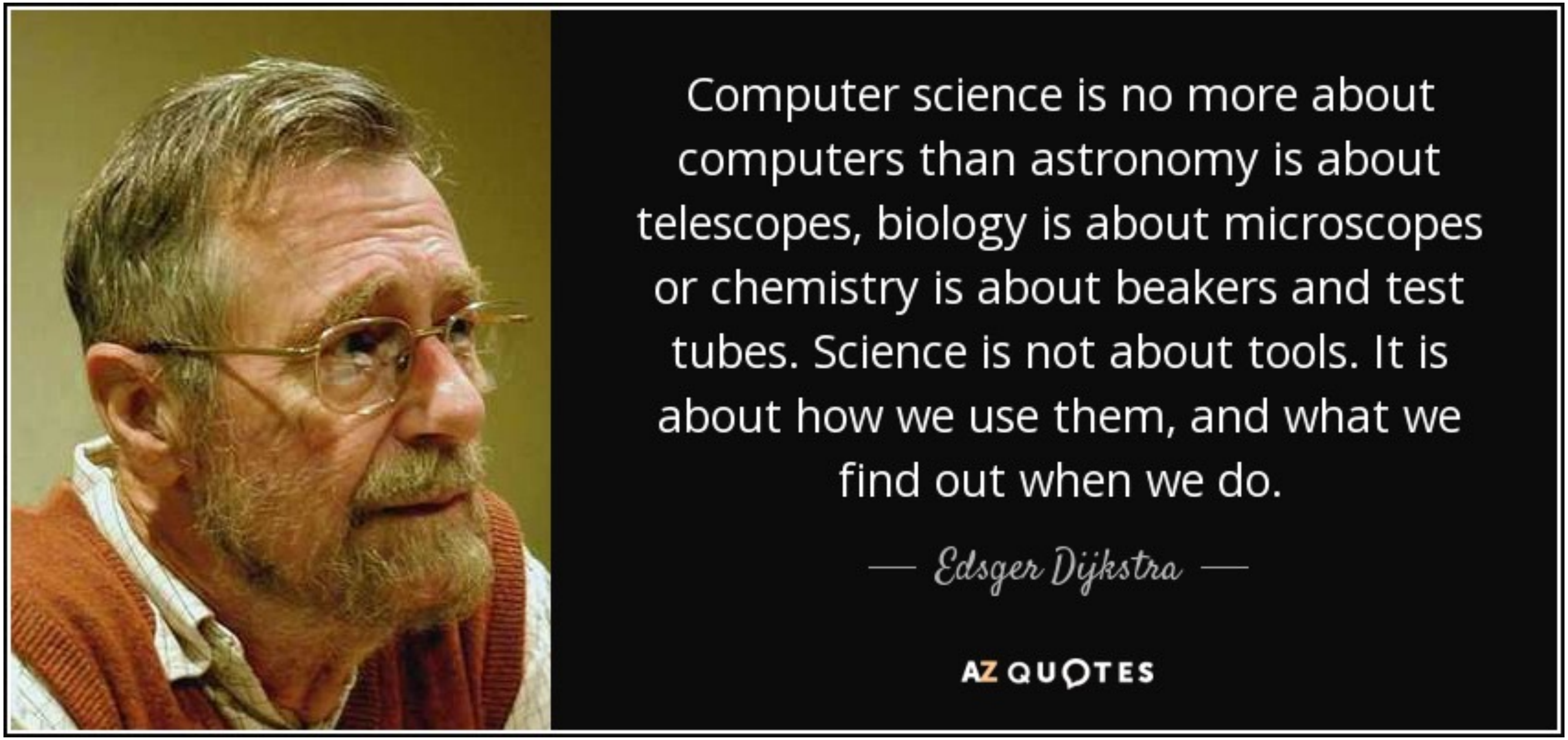
Venkat Ramaswamy

Birla Institute of Technology & Science

@VenkRamaswamy

Dupre C., Yuste R. (2017)
Non-overlapping Neural Networks in Hydra vulgaris.
Curr Biol. 2017 Apr 24; 27(8):1085-1097

WHY SHOULD CS CARE ABOUT NEUROSCIENCE?!



https://www.azquotes.com/quote/1034505

Neuroscience & Computer Science go back a long way !

First Draft of a Report
on the EDVAC

by

John von Neumann

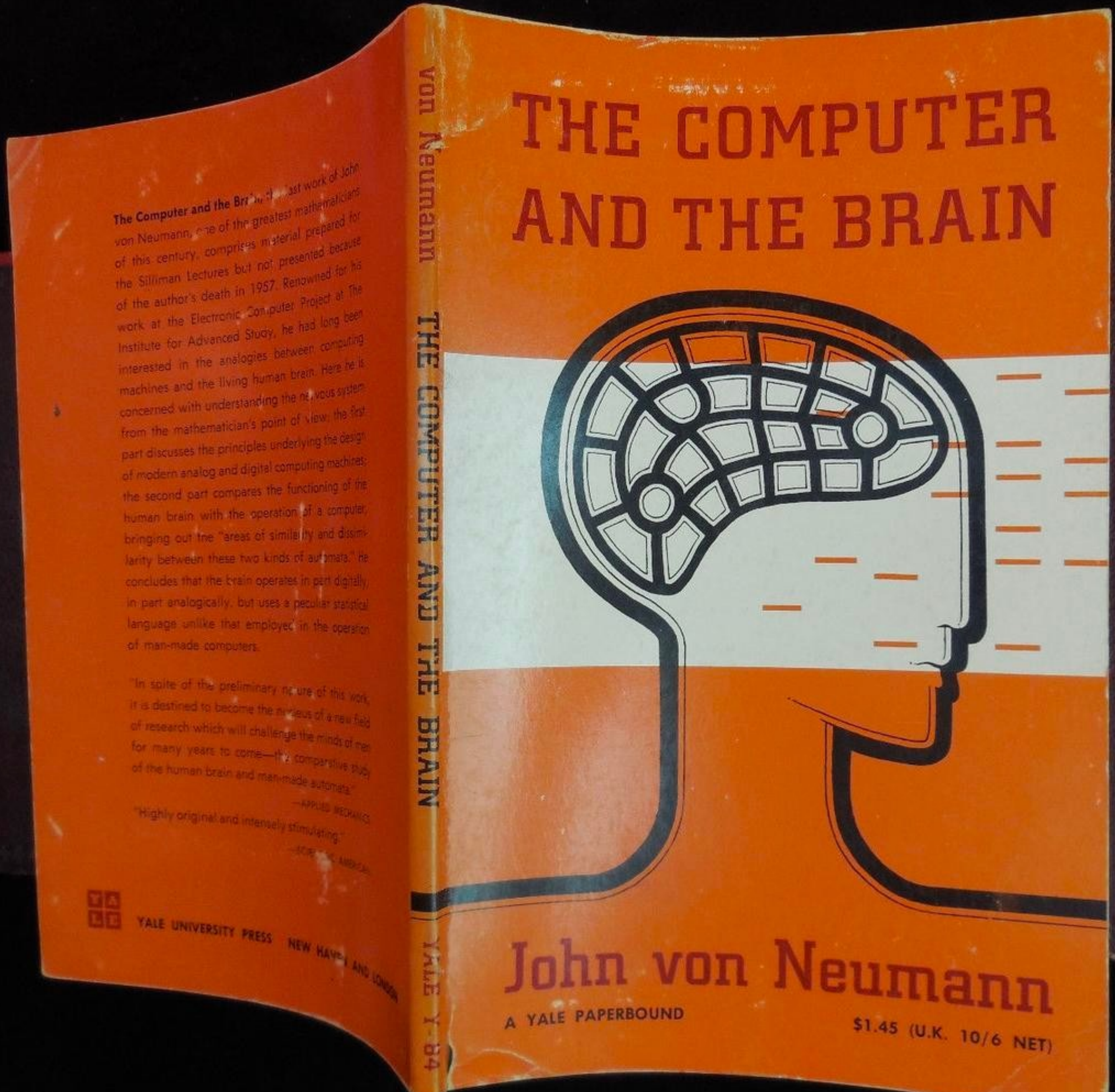
Moore School of Electrical Engineering
University of Pennsylvania

June 30, 1945

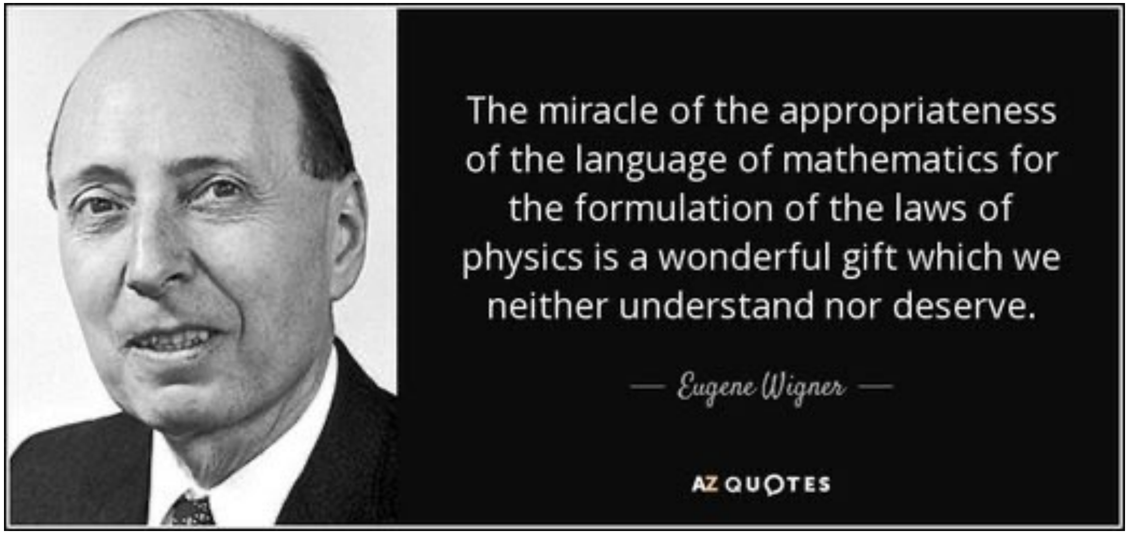
4.0 ELEMENTS, SYNCHRONISM NEURON ANALOGY

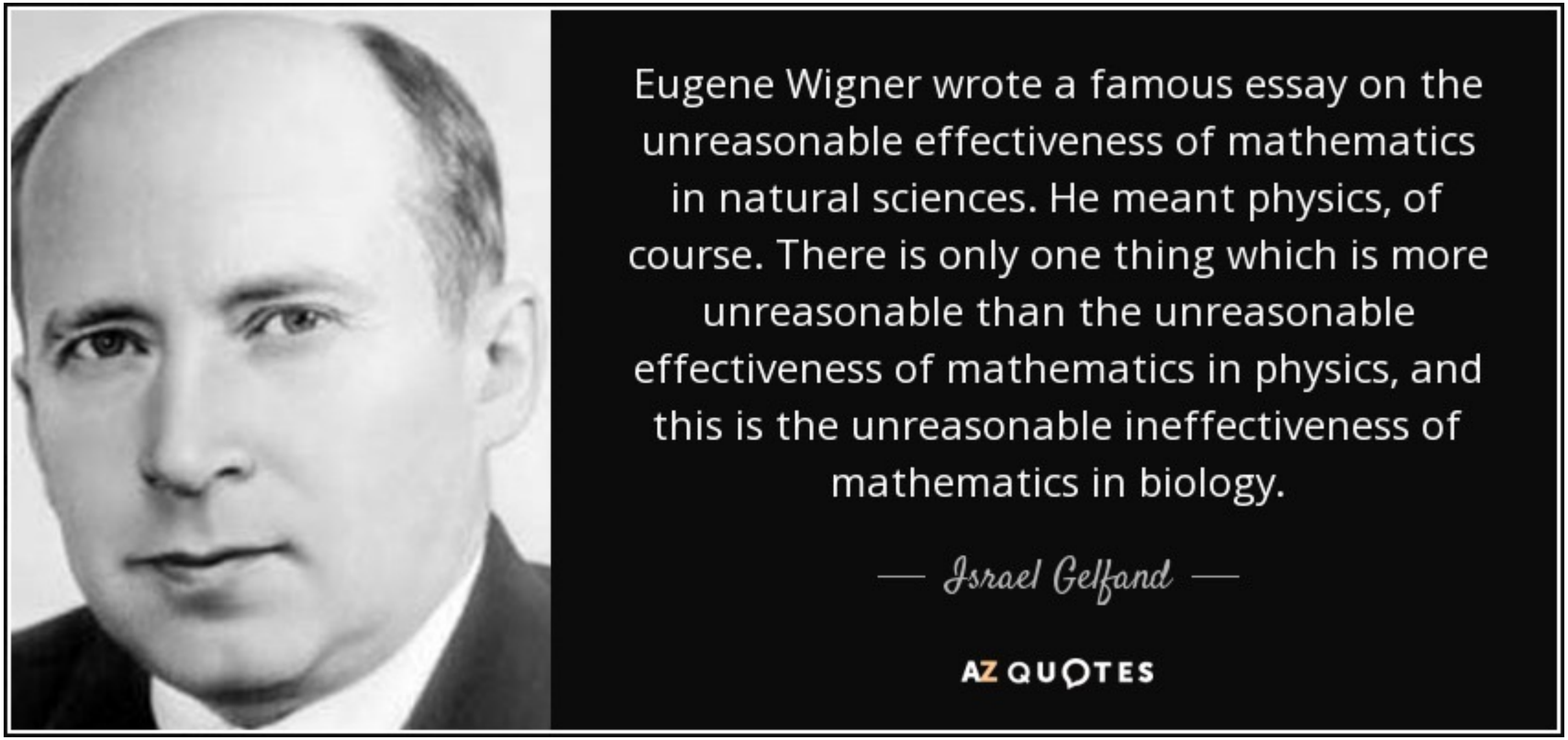
4.2 It is worth mentioning, that the neurons of the higher animals are definitely elements in the above sense. They have all-or-none character, that is two states: Quiescent and excited. They fulfill the requirements of 4.1 with an interesting variant: An excited neuron emits the standard stimulus along many lines (axons). Such a line can, however, be connected in two different ways to the next neuron: First: In an excitatory synapsis, so that the stimulus causes the excitation of that neuron. Second: In an inhibitory synapsis, so that the stimulus absolutely prevents the excitation of that neuron by any stimulus on any other (excitatory) synapsis. The neuron also has a definite reaction time, between the reception of a stimulus and the emission of the stimuli caused by it, the synaptic delay.

physics, Vol. 5 (1943), pp 115-133) we ignore the more complicated aspects of neuron functioning: Thresholds, temporal summation, relative inhibition, changes of the threshold by after effects of stimulation beyond the synaptic delay, etc. It is, however, convenient to consider occasion-



THE COMPUTER AND THE BRAIN
John von Neumann
A YALE PAPERBOUND
$1.45 (U.K. 10/6 NET)
von Neumann
THE COMPUTER AND THE BRAIN
YALE Y-84
The Computer and the Brain
von Neumann,
of the greatest mathematicians
of this century, comprises material prepared for
the Silliman Lectures but not presented because
of the author's death in 1957. Renowned for his
work at the Electronic Computer Project at The
Institute for Advanced Study, he had long been
interested in the analogies between computing
machines and the living human brain. Here he is
concerned with understanding the nervous system
from the mathematician's point of view; the first
part discusses the principles underlying the design
of modern analog and digital computing machines;
the second part compares the functioning of the
human brain with the operation of a computer,
bringing out the "areas of similarity and dissimi-
larity between these two kinds of automata." He
concludes that the brain operates in part digitally,
in part analogically, but uses a peculiar statistical
language unlike that employed in the operation
of man-made computers.
"In spite of the preliminary nature of this work,
it is destined to become the
of a new field
of research which will challenge the minds of men
for many years to come—
comparative study
of the human brain and man-made automata."
—APPLIED MECHANICS
"Highly original and intensely stimulating."
YALE UNIVERSITY PRESS NEW HAVEN AND LONDON

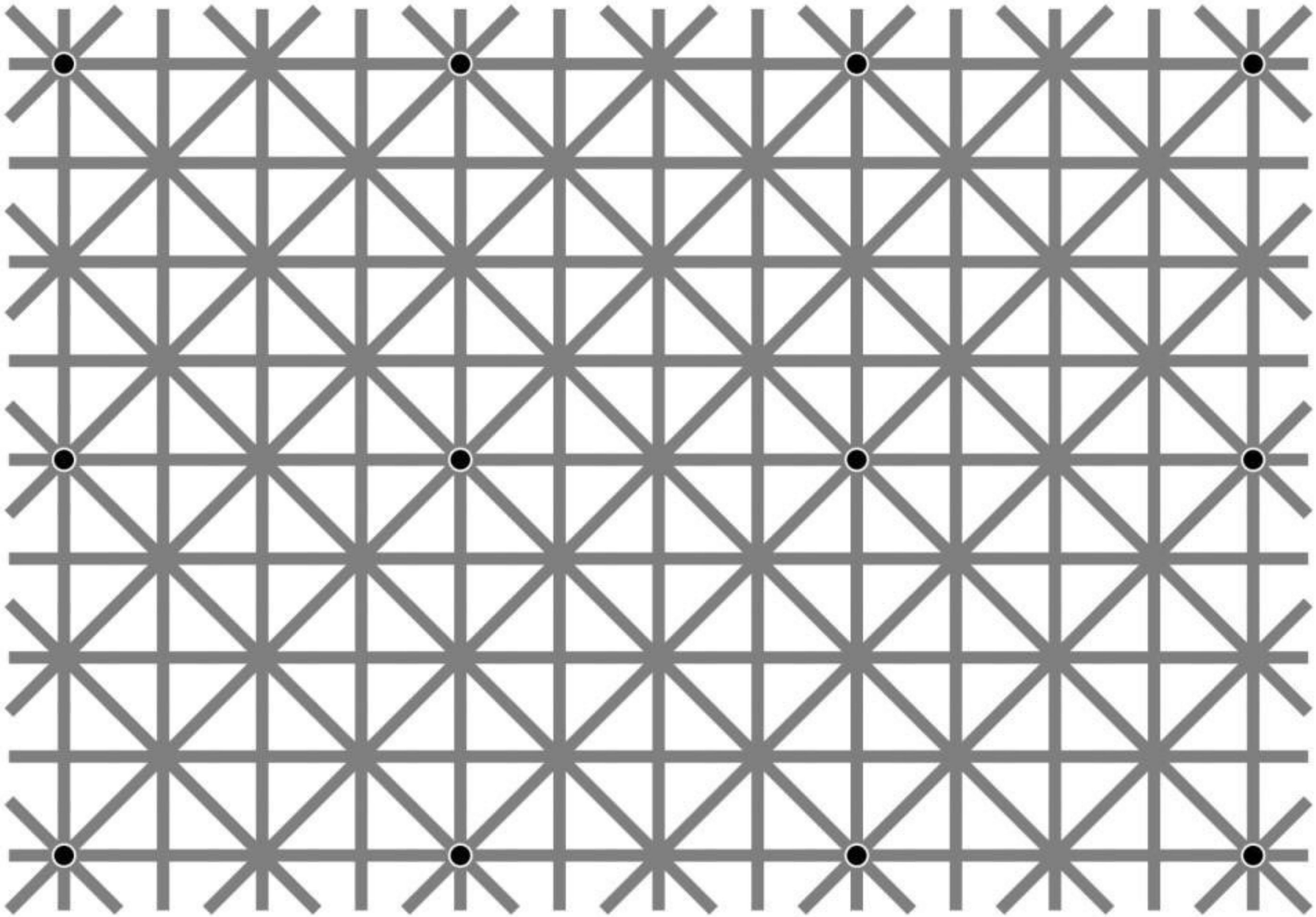

The miracle of the appropriateness of the language of mathematics for the formulation of the laws of physics is a wonderful gift which we neither understand nor deserve.
— Eugene Wigner —
AZ QUOTES


Eugene Wigner wrote a famous essay on the unreasonable effectiveness of mathematics in natural sciences. He meant physics, of course. There is only one thing which is more unreasonable than the unreasonable effectiveness of mathematics in physics, and this is the unreasonable ineffectiveness of mathematics in biology.
— Israel Gelfand —
AZ QUOTES

CHANGE BLINDNESS

Selective Attention

Optical Illusion (12 black dots)




BBC

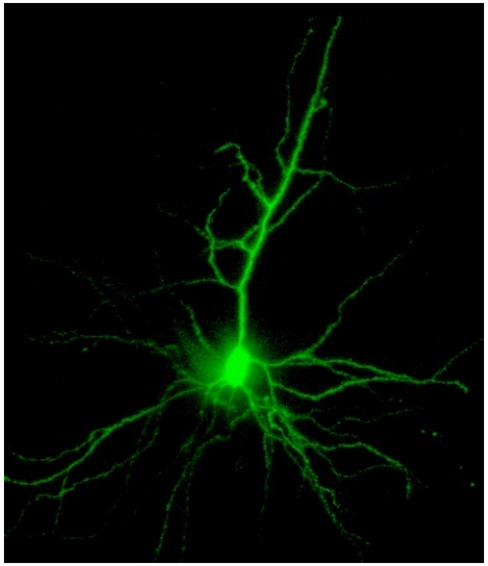
Hyperbolic Discounting

- *Hyperbolic discounting* is our inclination to choose immediate rewards over rewards that come later in the future, even when these immediate rewards are smaller.

- Milton Glaser

The Brain

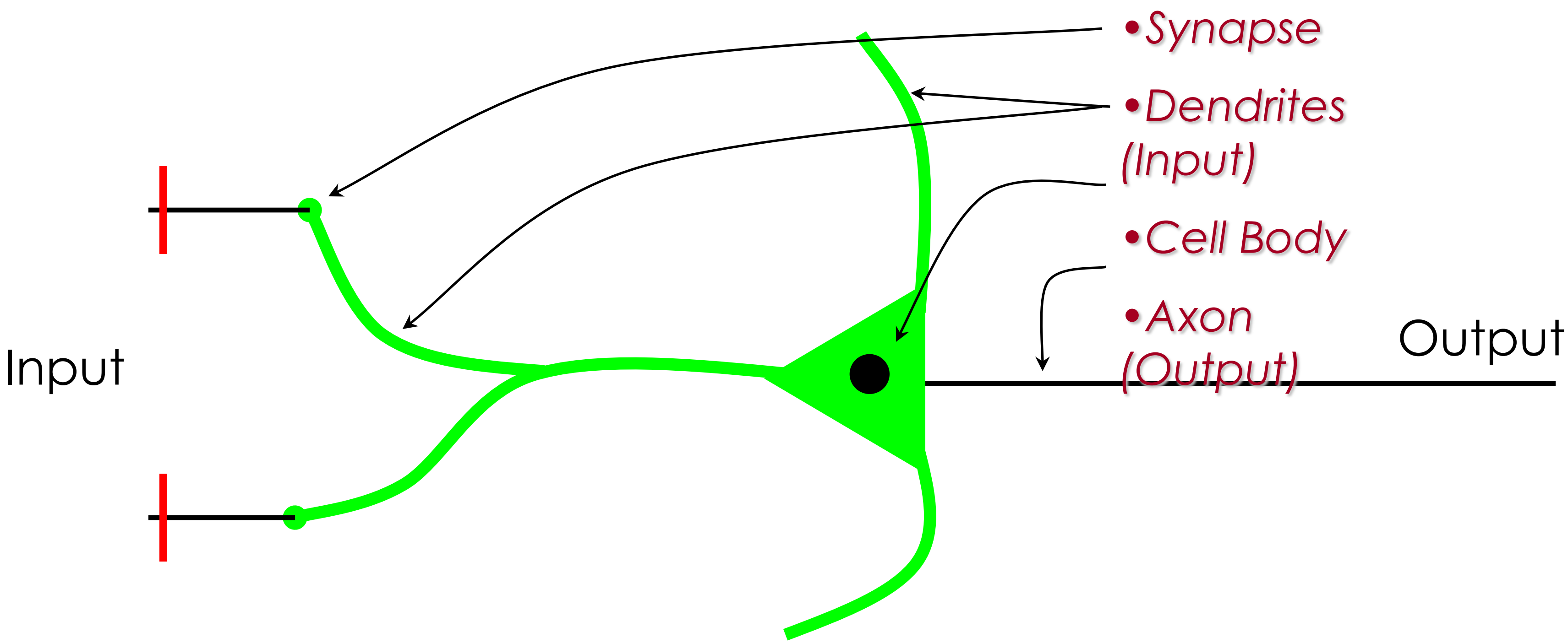
(From *http://www.brainhealthandpuzzles.com*)

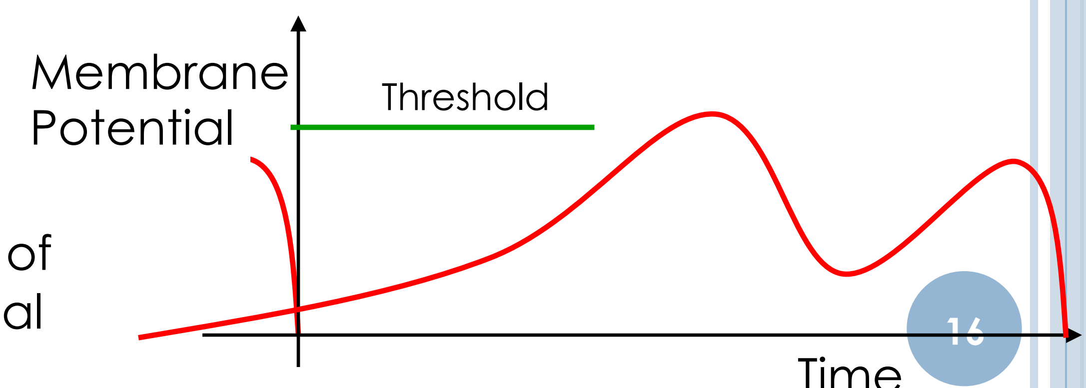


(From *http://www.wadsworth.org*)

- Neurons, Glial cells.
- 100 billion neurons.
- 100 trillion connections (synapses).

Schematic view of a neuron



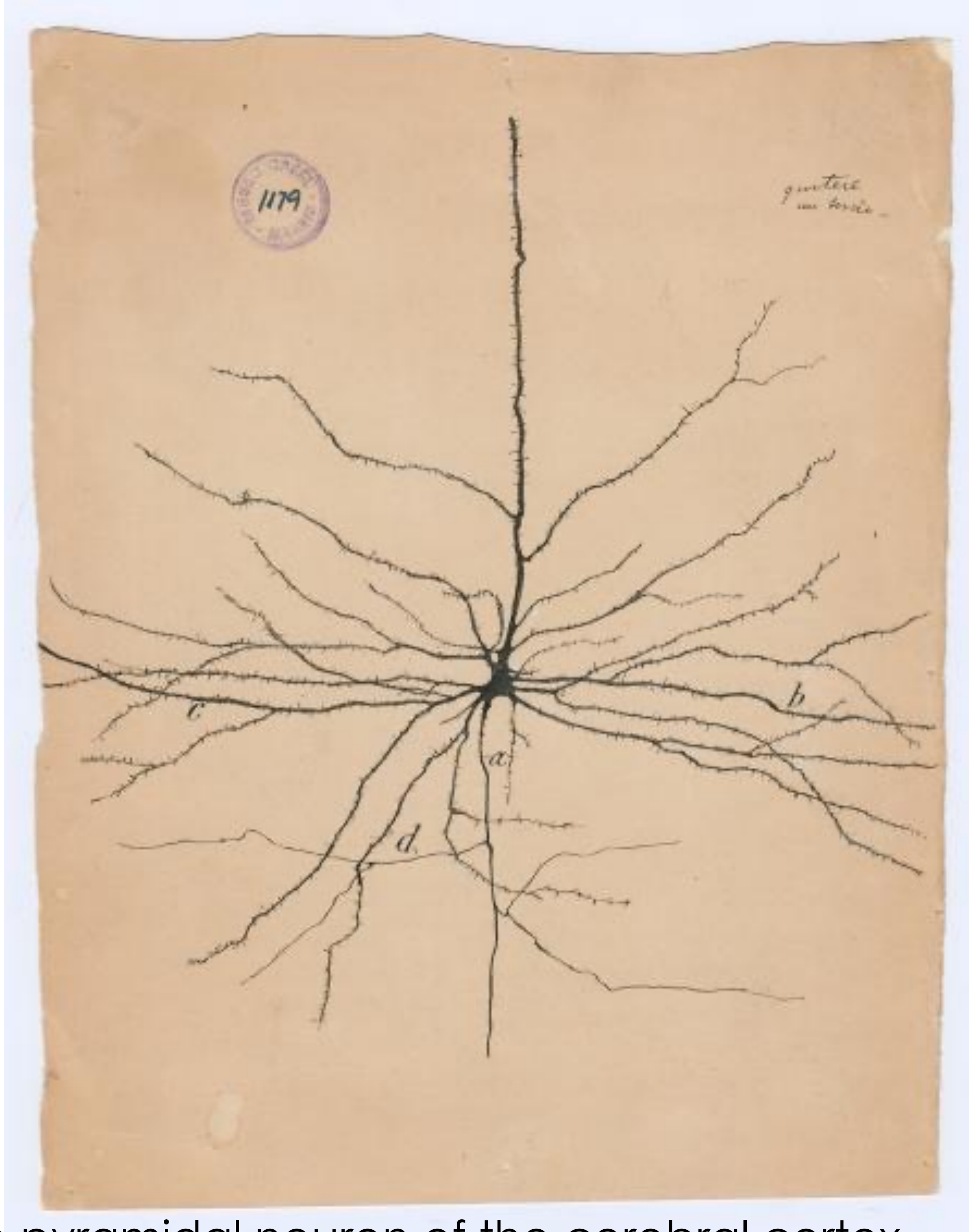


- *Absolute Refractory Period*
- *Exponential Decay* of effect of a spike on membrane potential

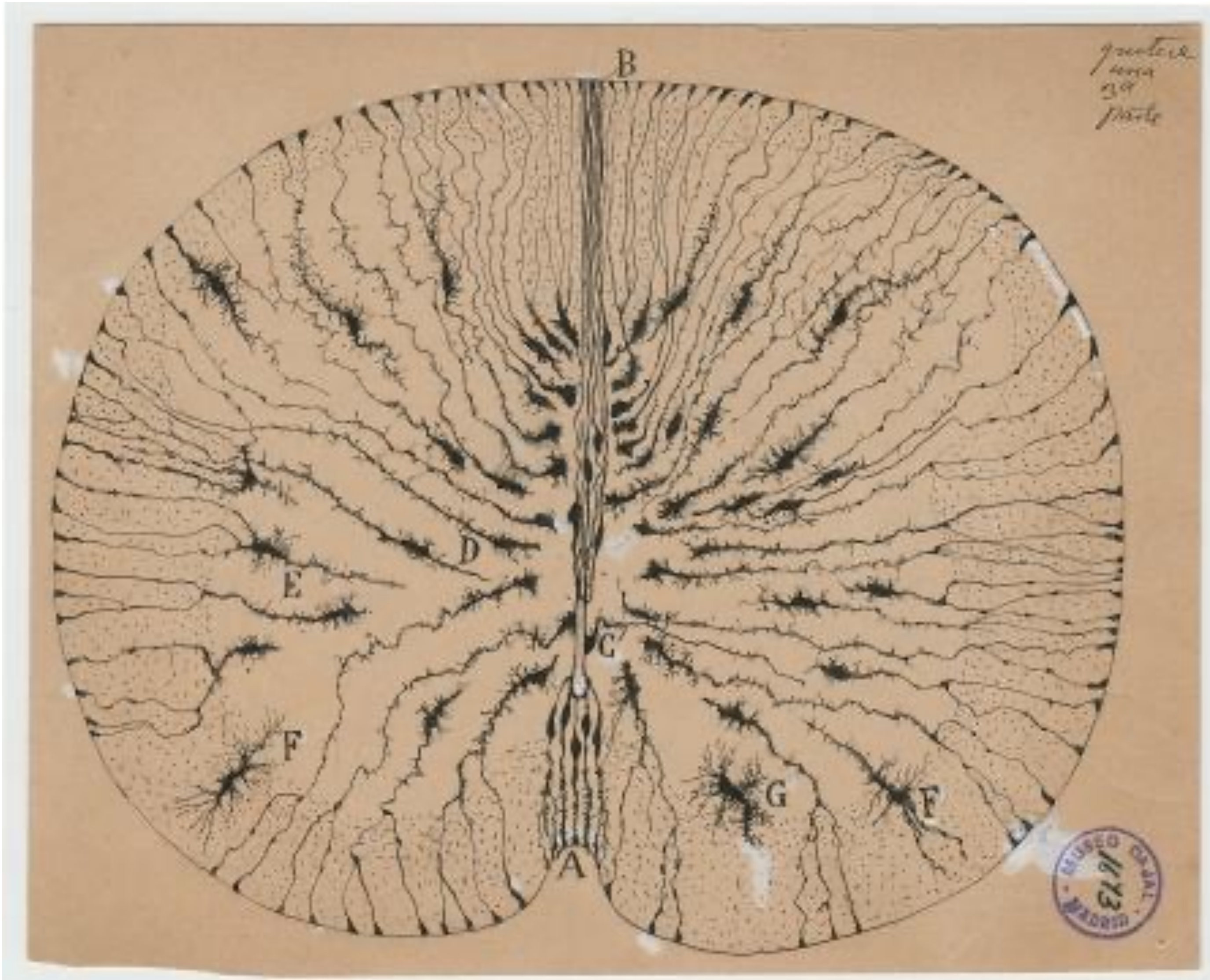
Neuroscience's Greatest Hits (A Selection)


Prof.r Camillo Golgi

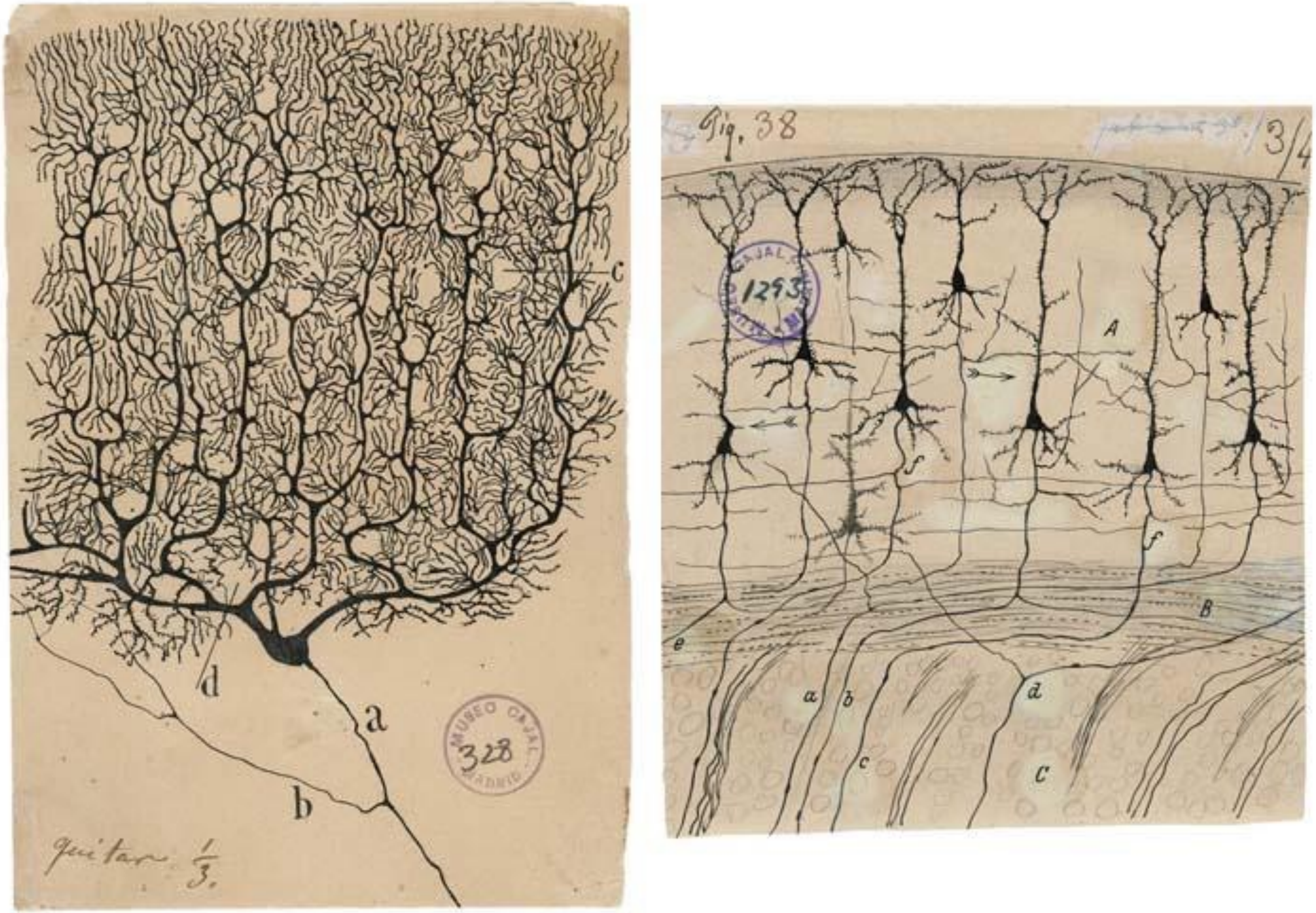
Santiago Ramón y Cajal



The pyramidal neuron of the cerebral cortex,
drawn by Cajal in 1904, using ink and pencil on paper.

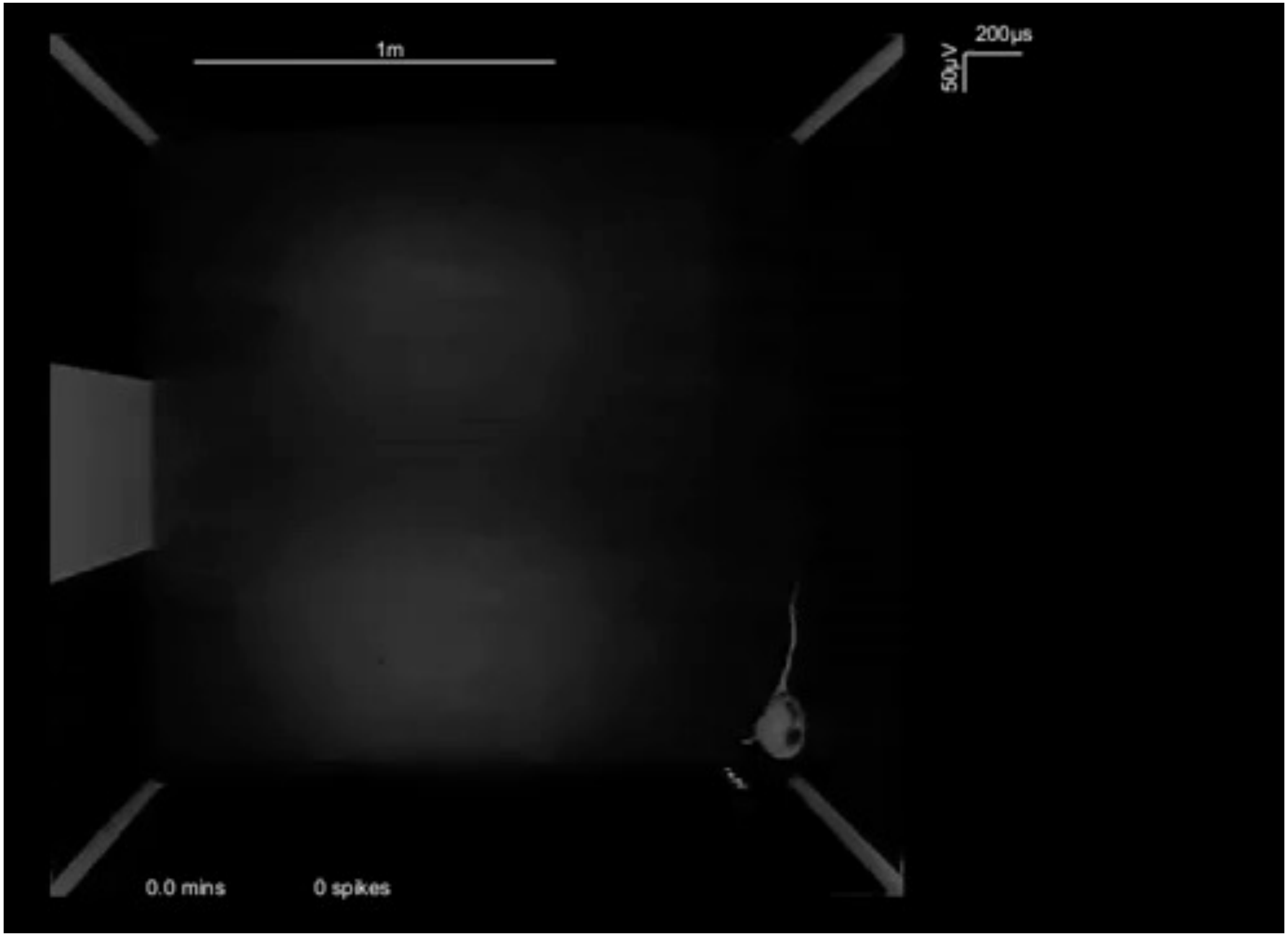


Glial cells of the mouse spinal cord, 1899.

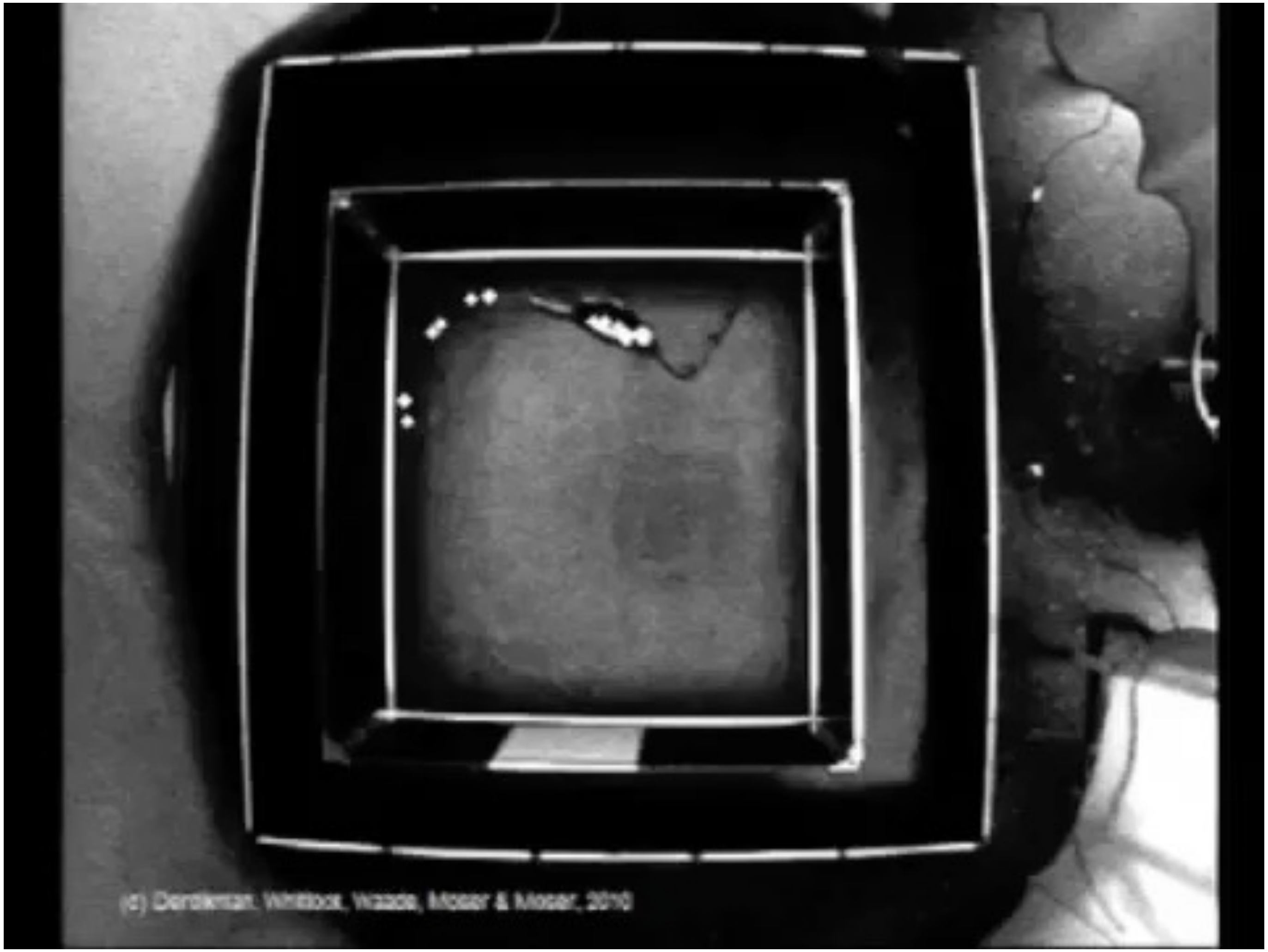


Purkinje cell (left), Pyramidal neurons in the cerebral cortex (right

PLACE CELLS


1m
200µs
50µV
0.0 mins
0 spikes

Grid Cells



Other Cell Types with correlated activity

- Mirror Neurons https://www.pbslearningmedia.org/resource/hew06.sci.life.reg.mirrorneurons/mirror-neurons/

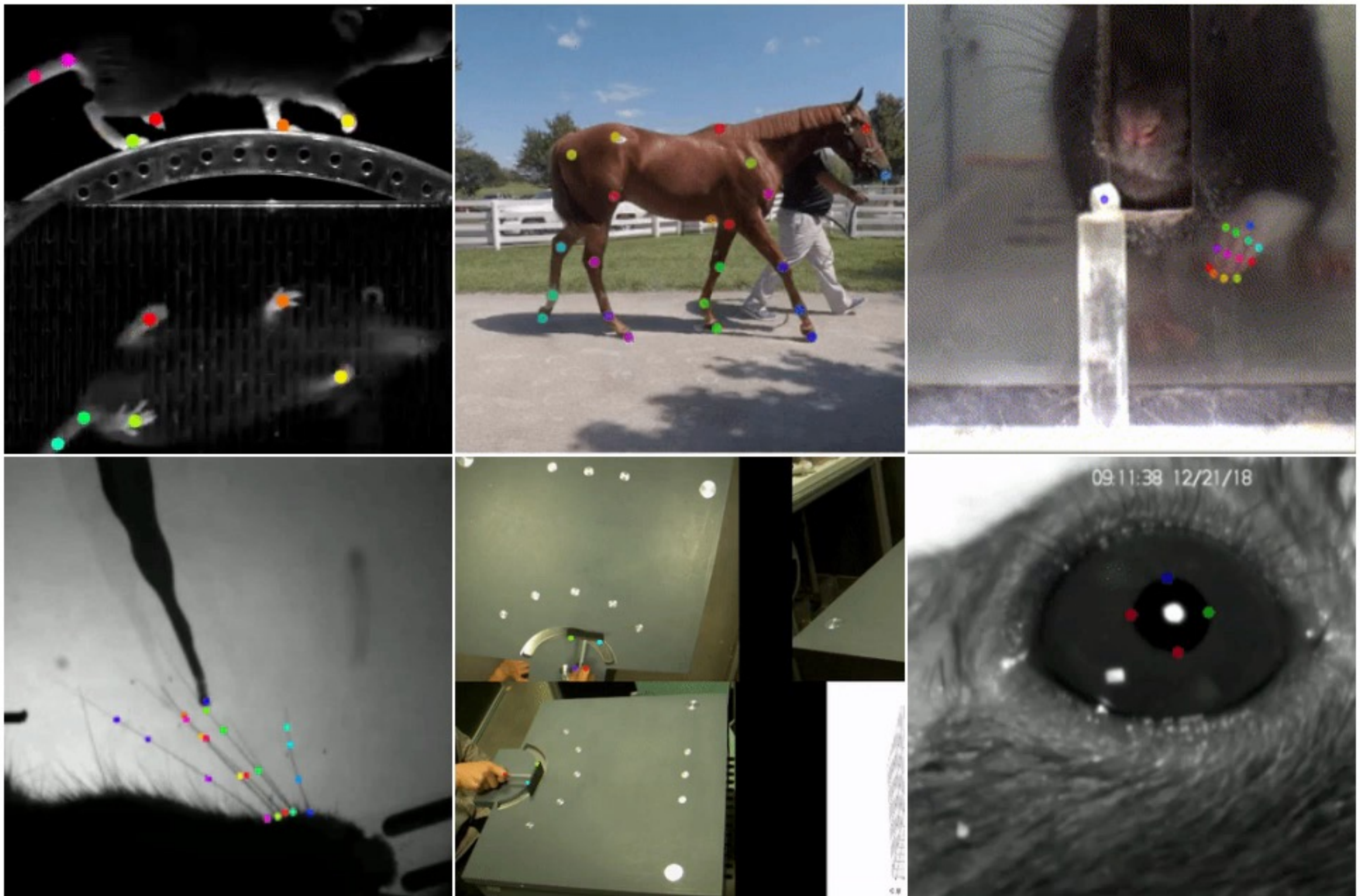
- Concept cells or "Jennifer Aniston neurons".

A convergence of Neuroscience & Deep Learning?

Interface of Neuroscience & Deep Learning

- Use of Deep Learning techniques for analysis in Neuroscience.
- Deep Nets as models of biological neural systems?
- Deep Learning - inspiration from Biology?

Deep Learning for Data analysis in Neuroscience



Deep Nets as models of (Biological) Neural Systems

- Whole new genre of work that involves creating deep networks (w/ architectures often being similar to corresponding neural systems), which are then trained on tasks that the biological systems are known/thought to perform.
- Remarkably, such deep networks often end up having units that have responses that are similar to known cell types in the corresponding biological neuronal networks.

A Connectome Based Hexagonal Lattice Convolutional Network Model of the Drosophila Visual System

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Abstract

What can we learn from a connectome? We constructed a simplified model of the first two stages of the fly visual system, the lamina and medulla. The resulting hexagonal lattice convolutional network was trained using backpropagation through time to perform object tracking in natural scene videos. Networks initialized with weights from connectome reconstructions automatically discovered well-known orientation and direction selectivity properties in T4 neurons and their inputs, while networks initialized at random did not. Our work is the first demonstration, that knowledge of the connectome can enable in silico predictions of the functional properties of individual neurons in a circuit, leading to an understanding of circuit function from structure alone.

- A hexagonal-lattice convolutional network initialized with weights estimated from connectomic reconstructions from parts of the fly visual system.
- It was then trained (using backpropagation) to perform object tracking in natural scenes.
- Network recovered known orientation & direction-selectivity properties of fly T4 neurons & their inputs.

Convergent temperature representations in artificial and biological neural networks

Martin Haesemeyer*[1], Alexander F Schier[1,2,3,4,5] and Florian Engert†[1,2]

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[2]Center for Brain Science, Harvard University, Cambridge, MA 02138, USA
[3]Broad Institute of MIT and Harvard, Cambridge, MA 02142, USA
[4]Harvard Stem Cell Institute, Cambridge, MA 02138, USA
[5]Biozentrum, University of Basel, 4056 Basel, Switzerland

- A branched convolutional net was trained on a heat-gradient task that used larval zebrafish behavioral repertoire.
- The deep net recovered known ON and OFF type representations in the larval zebrafish brain.
- Indeed, analysis of the deep net for other unit-types led to the discovery of a new temperature-responsive cell-type in the zebrafish cerebellum.

Published as a conference paper at ICLR 2018

EMERGENCE OF GRID-LIKE REPRESENTATIONS BY TRAINING RECURRENT NEURAL NETWORKS TO PERFORM SPATIAL LOCALIZATION

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nature
International journal of science

Letter | Published: 09 May 2018

Vector-based navigation using grid-like representations in artificial agents

Andrea Banino, Caswell Barry, [...] Dharshan Kumaran

Nature **557**, 429–433 (2018) | Download Citation

- Deep Nets trained on spatial navigation tasks reproduce grid cells and other known cell-types in the mammalian entorhinal cortex.

Analysis of Deep Net Models of Brain Function

- Why do these similarities emerge?
- Do they represent profound underlying structure of the problems being solved?
- Or common principles underlying computation in biological and deep networks that arise from their connectionist underpinnings?
- Are these cell-types causally implicated in the ability of the Deep Net to perform said task?
- In practice, unlike nervous systems, deep networks can be manipulated at will.

Deep Learning – Inspiration from Biology

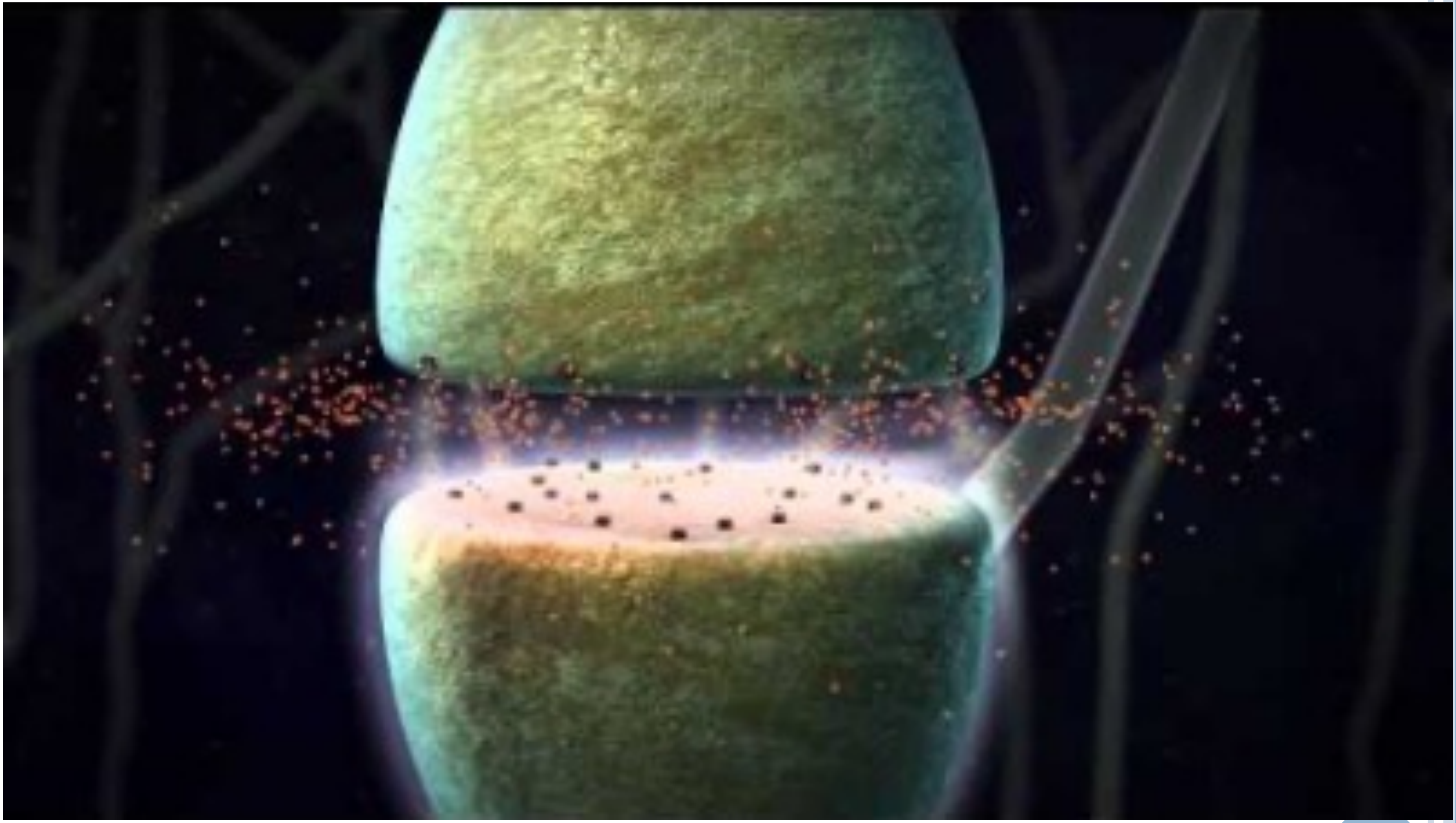
- Deep Nets & over-parameterization.
- Structures from Connectomics
  – Google, IARPA.
- Incorporating known features from Biology into next-generation Deep Learning.

Published as a conference paper at ICLR 2019

BACKPROPAMINE: TRAINING SELF-MODIFYING NEURAL NETWORKS WITH DIFFERENTIABLE NEUROMODULATED PLASTICITY

Thomas Miconi*, Aditya Rawal, Jeff Clune & Kenneth O. Stanley
Uber AI Labs
tmiconi|aditya.rawal|jeffclune|kstanley@uber.com

- Towards AGI?



Extraordinary Progress in (large scale) experimental techniques in Neuroscience

- Connectomics

CONNECTOMICS

they were both wrong.

These and other experiences led me to suspect models or theories that had been built when only some of the facts where known. So for dealing with models of how neurons might interact to produce behaviour, I invented a sceptic who would always ask: “How do you know there is not another wire that comes up the back of the animal and does something you have not accounted for?” Unlike in physics, where we might be able to deal with the ‘another wire’ sceptic on general principles, the only way to do so in biology is to be able to say that we know all the wires and therefore that there are no other wires. I use ‘wire’ in a general sense: good theories of molecular or cellular networks will need knowledge of all the connections.

Many of our discussions resorted

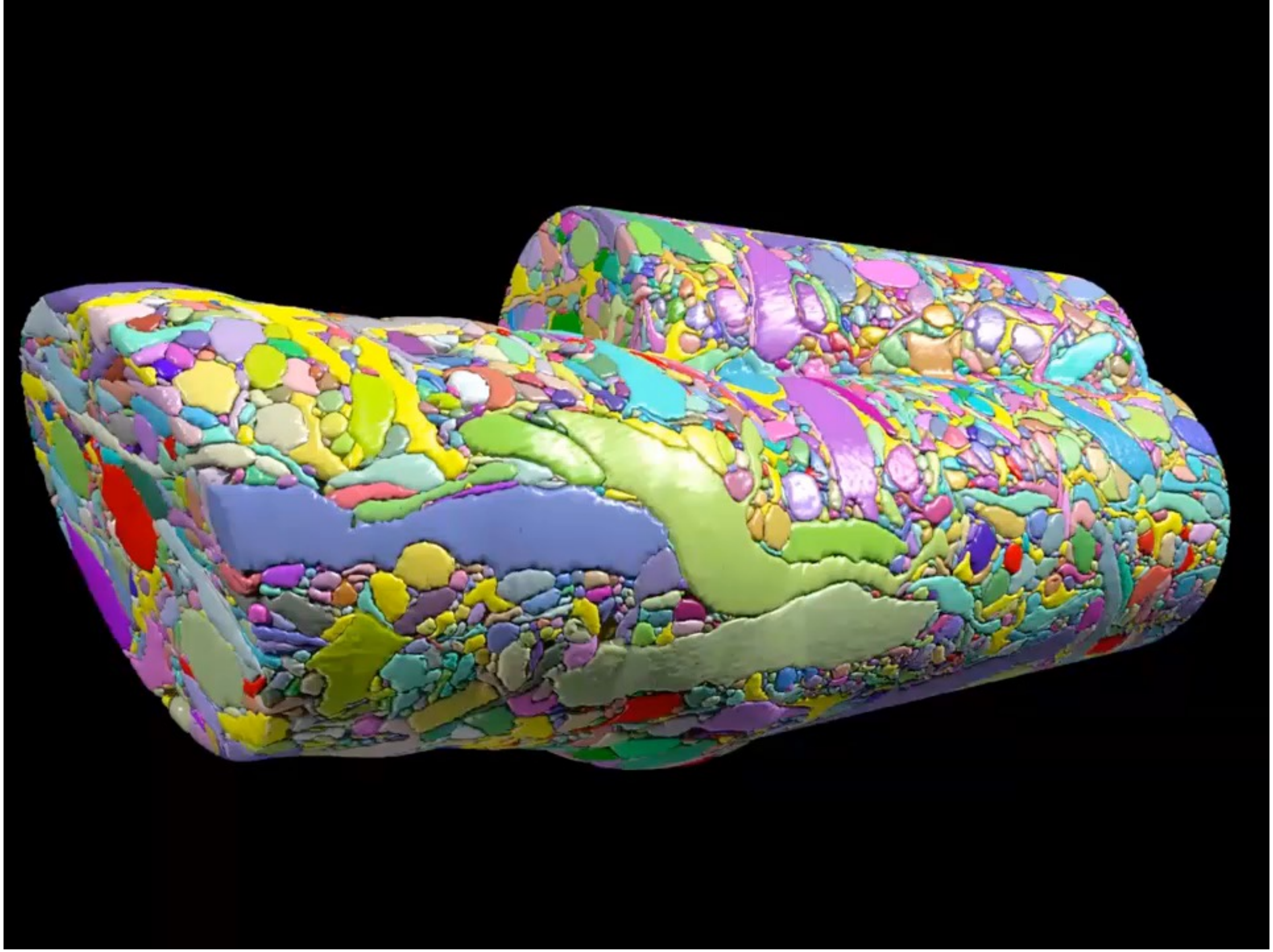
Loose ends

In theory
Sydney Brenner

Actually, the orgy of fact extraction in which everybody is currently engaged has, like most consumer economies, accumulated a vast debt. This is a debt of theory and some of us are soon going to have an exciting time paying it back — with interest, I hope.

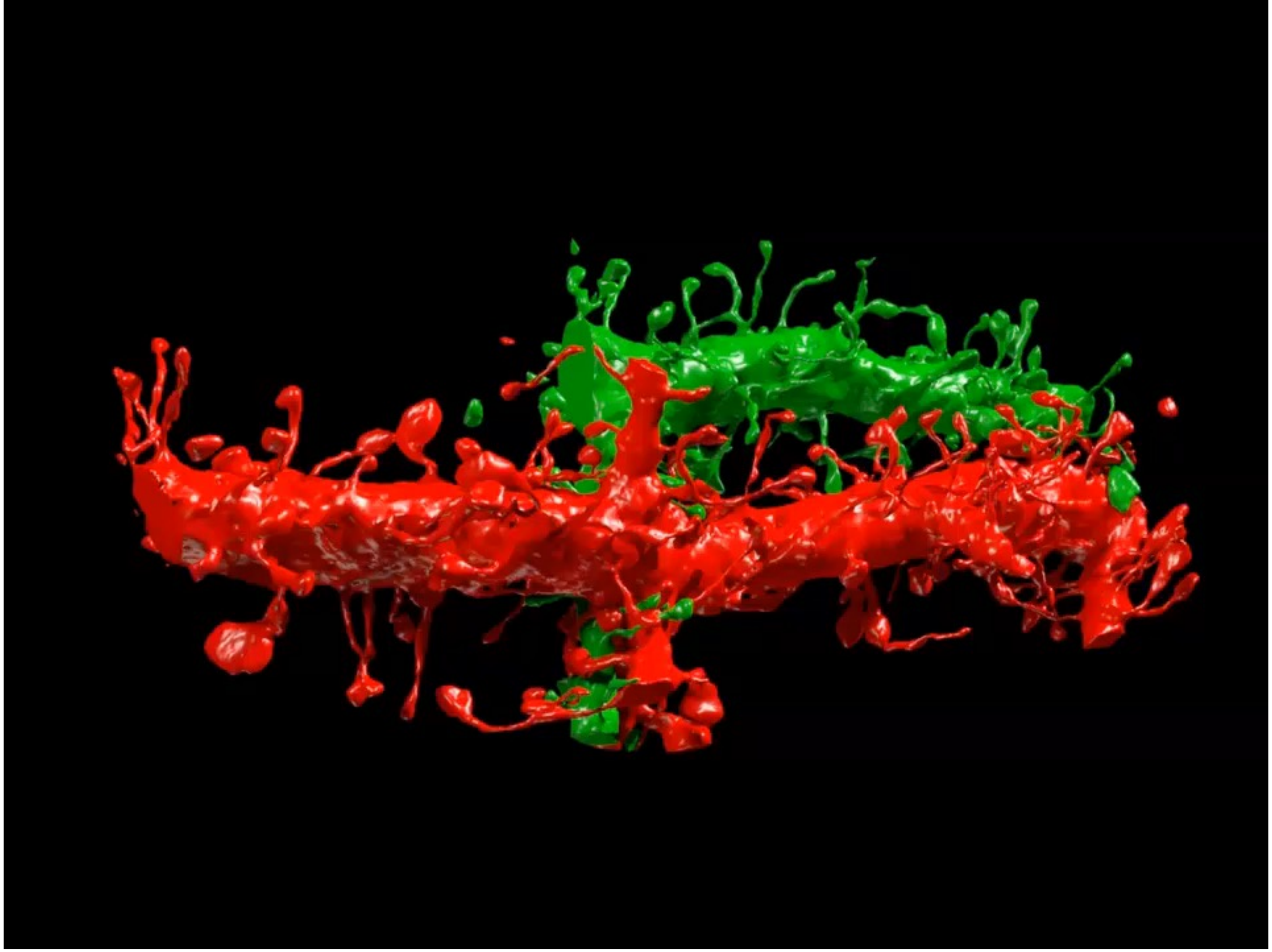
Connectomics – Background

- The connectome of an organism is the exact structure of the network(s) of neurons in its nervous system.
- *C. Elegans* connectome (302 neurons) was determined in 1986 after a ~15 year effort.
- Tadpole larval connectome of the sea squirt *Ciona intestinalis* (177 neurons) in 2016
- Recent remarkable experimental advances have brought the prospect of ascertaining the connectome of complex organisms closer to reality.
- Connectomics using Electron Microscopy
  - Brain tissue is prepared by staining it with heavy metals and is embedded in resin.
  - Sliced with a diamond knife.



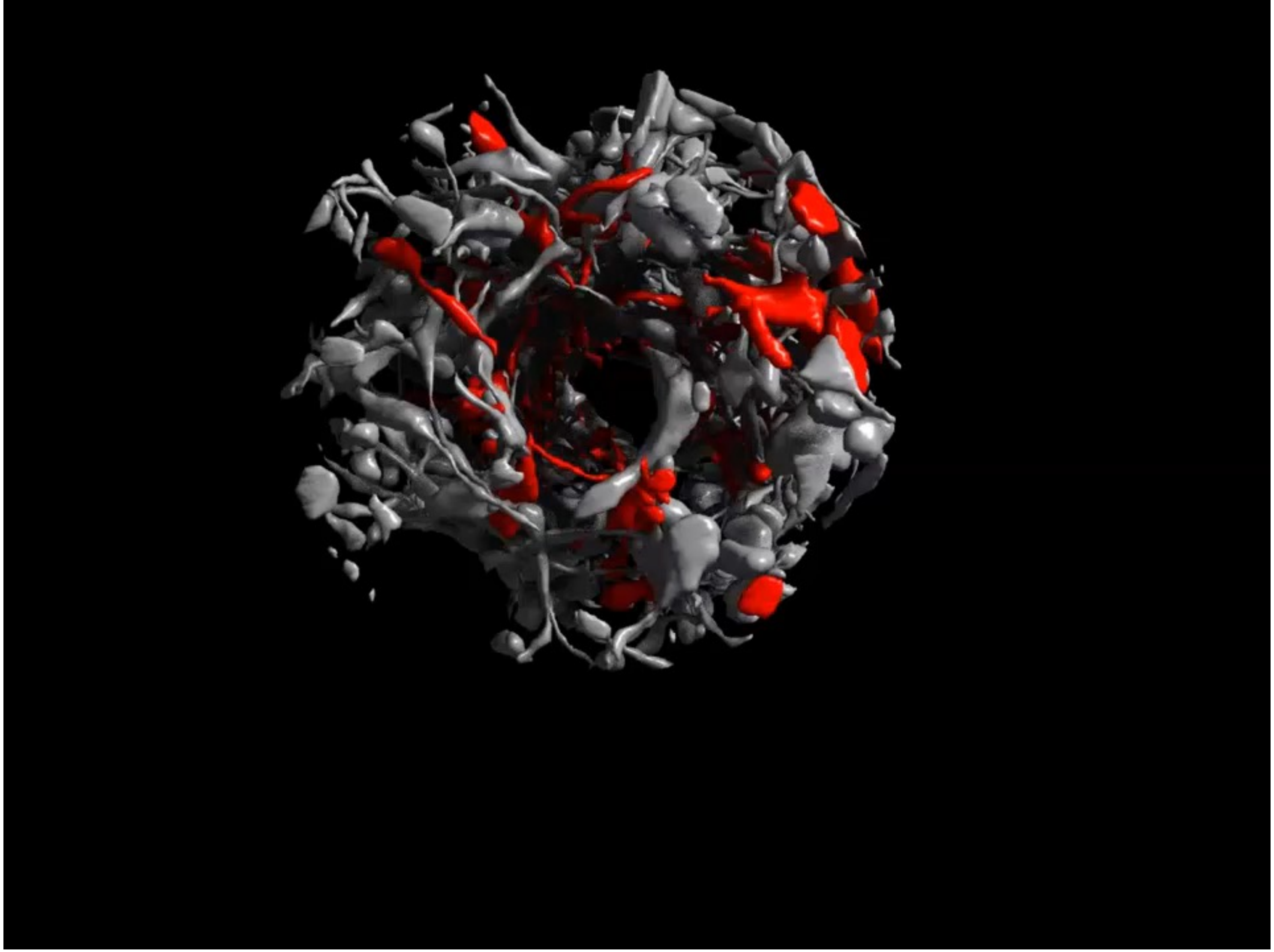
Movie S10. Three-Cylinder Parts List Explosion, Related to Figure 3.

An animation showing a 3D reconstruction of all the objects annotated in the three cylinders around two apical dendrites. The objects are initially shown in situ and then "exploded" to reveal the full collection of cellular objects.



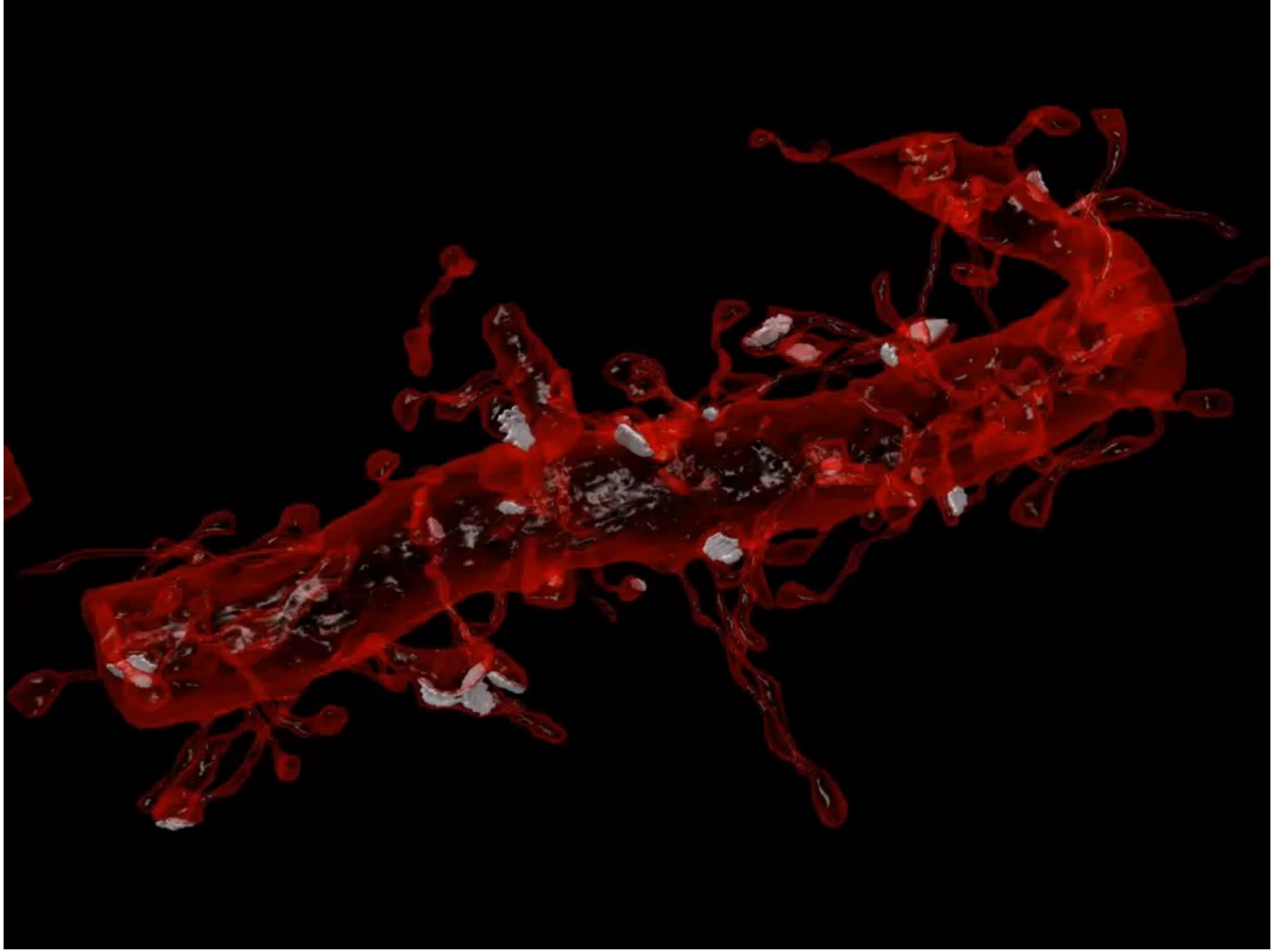
MOVIE S11. THREE-CYLINDER DECOMPOSITION BY TYPE, RELATED TO FIGURE 3.

AN ANIMATION SHOWING A 3D RECONSTRUCTION ALL OF THE OBJECTS ANNOTATED IN THE THREE CYLINDERS AROUND TWO APICAL DENDRITES. ALL THE OBJECTS ARE INITIALLY SHOWN IN SITU AND THEN SORTED BY CATEGORY—AXONAL, DENDRITIC, OR GLIAL—AND BY FUNCTIONAL TYPE (I.E., EXCITATORY OR INHIBITORY FOR AXONS AND DENDRITES AND WHEN POSSIBLE BY TYPE OF GLIAL CELL).



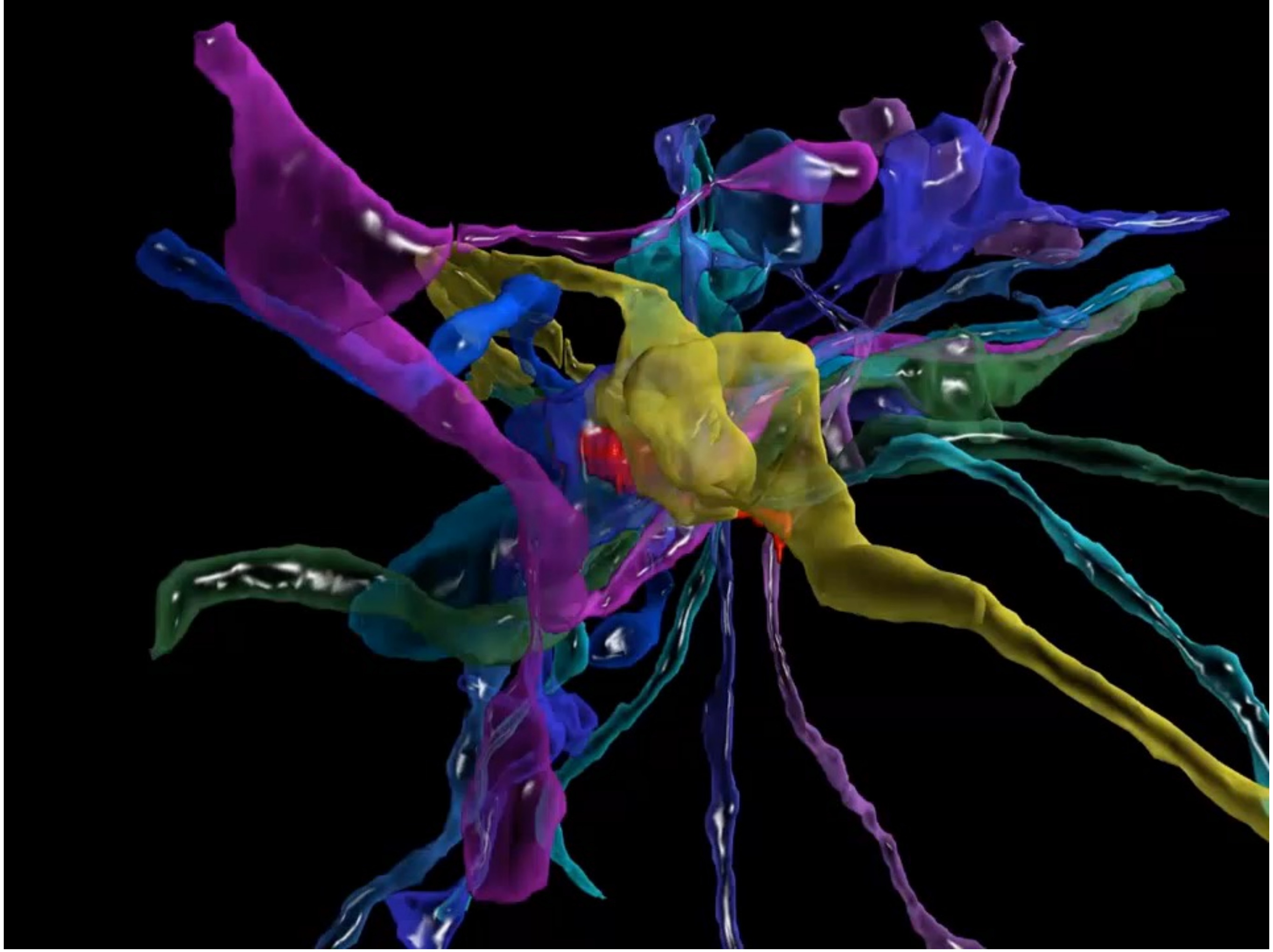
Movie S12. Reconstruction of the Central Dendrite's Spines and the Large Number of Other Dendritic Spines in Close Proximity to the Central Dendrite in Cylinder 1, Related to Figure 7.

An animation showing the spatial distribution of the spines originating from the central dendrite of cylinder 1 (red spines), along with spines originating from the other dendrites in cylinder 1 (gray spines).



Movie S13. Reconstruction of the Axons that Make Multiple Spine Connections with the Central Dendrite in Cylinder 1, Related to Figure 7.

An animation showing the central dendrite in cylinder 1 ("red dendrite") and serially displaying the 11 individual axons that make multiple synapses and the location of those onto spines of the central dendrite within the cylinder.



[Movie S14. Multiple Axons Are in Close Proximity to Individual Dendritic Spines, Related to Figure 7.]

An animation of the 3D reconstruction of the 13 axons that have membrane-to-membrane apposition with a single spine originating from the central dendrite of cylinder 1 (“red” spine; see Figure 7).

Central Neuroscience Question from the Lens of Computer Science

RESEARCH ARTICLE

Could a Neuroscientist Understand a Microprocessor?

Eric Jonas[1]*, Konrad Paul Kording[2,3]

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