# Architectures of Intelligence

Lecture 9

**Neural Networks I: Spiking Neurons**

Jelmer Borst

university of groningen

**Allen Newell**

1927-1992

*Question:*

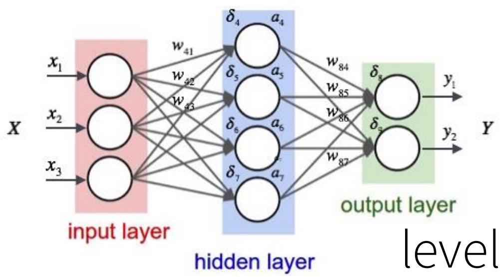
**How can the human mind occur in the physical universe?**

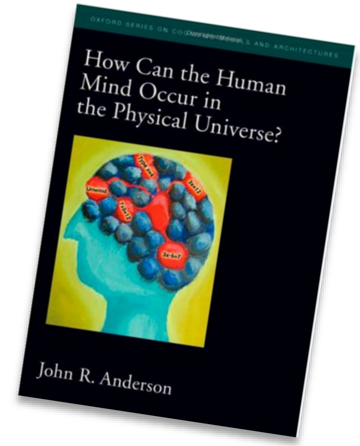
*The answer needs to have the details:*

"**I have got to know how the gears clank and how the pistons go**".

**=> *cognitive architecture***

# Different levels of abstraction

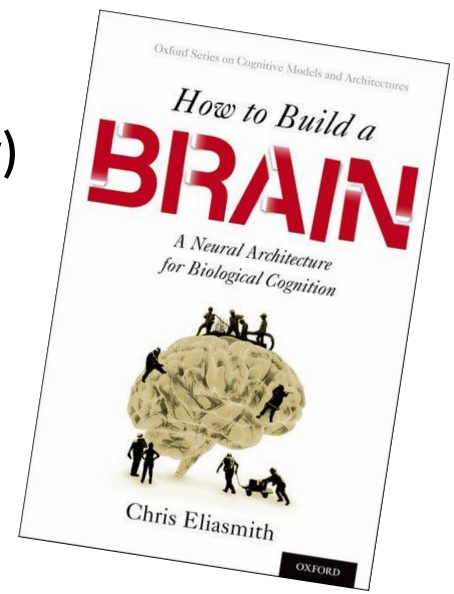


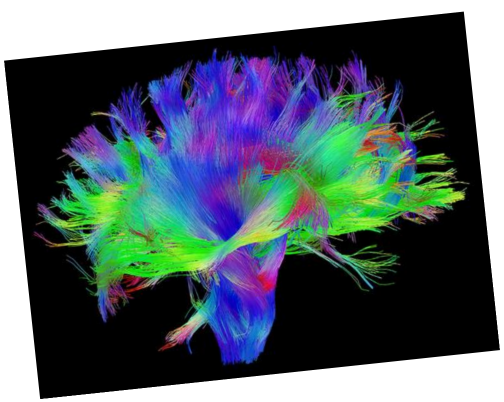

**ACT-R**
high level, requires symbols,
end-to-end functionality

**Traditional connectionists**
level of neurons (actually groups of neurons),
no symbols, some function

**Functional connectionists (Nengo, O'Reilly)**
level of spiking neurons,
symbols, end-to-end functionality

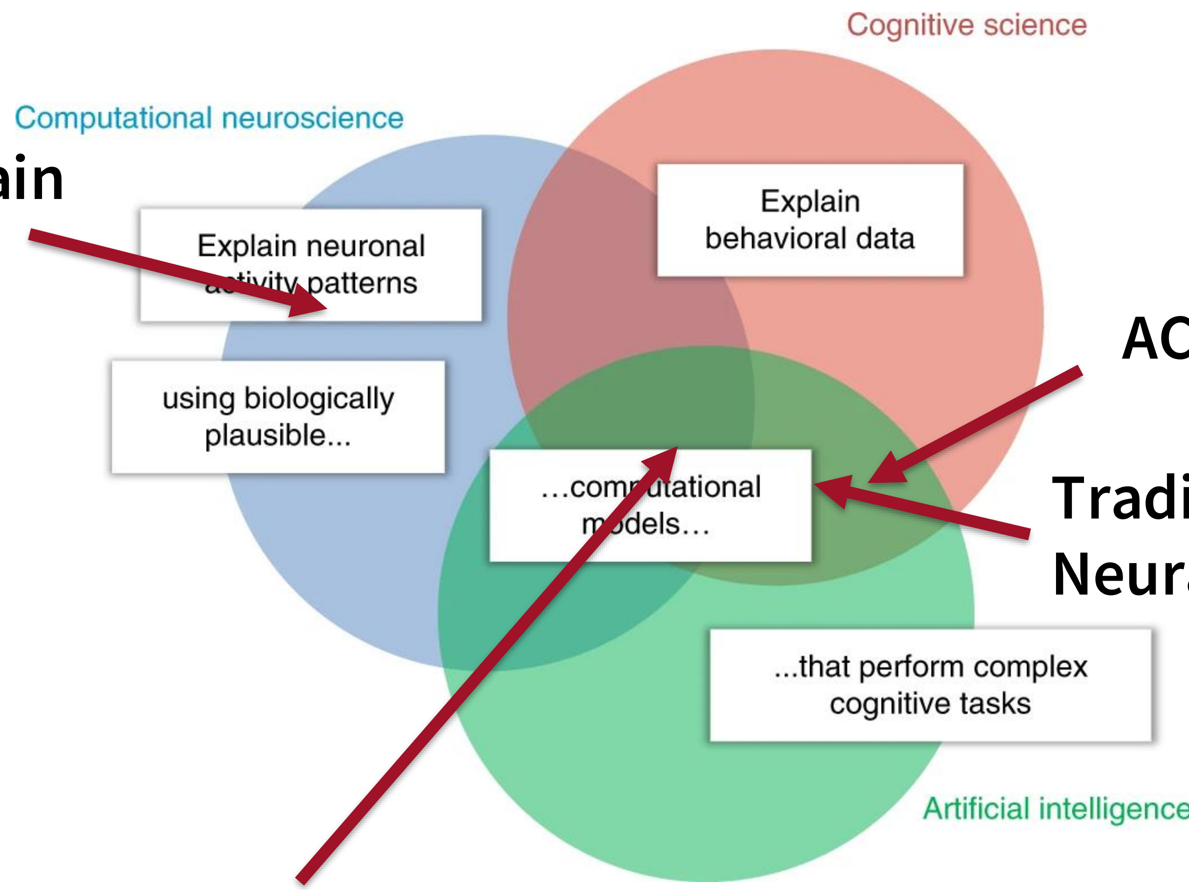



**Human brain project**
highly detailed neural level,
no symbols, emergent functionality



# Cognitive Computational Neuroscience

**Human brain project**




**ACT-R**

**Traditional Neural Networks**

**Functional connectionists / Nengo**

(Kriegeskorte & Douglas, *Nature*, 2018)

# (Why) should we go to the neural level?

- I would like to know how our cognitive system is based on the firing of (very simple) neurons
- Explain higher-level phenomena based on lower-level biological constraints (e.g., working memory limitations)

# Advantage 1
# More predictions


Terry Stewart

- A brain-based model will predict more than just overt behaviour
  - Connectivity
  - Firing patterns
  - Results of lesions
  - Timing
  - Effects of drugs

**We can use those extra predictions to evaluate our models!**

# Advantage 2
# Different algorithms

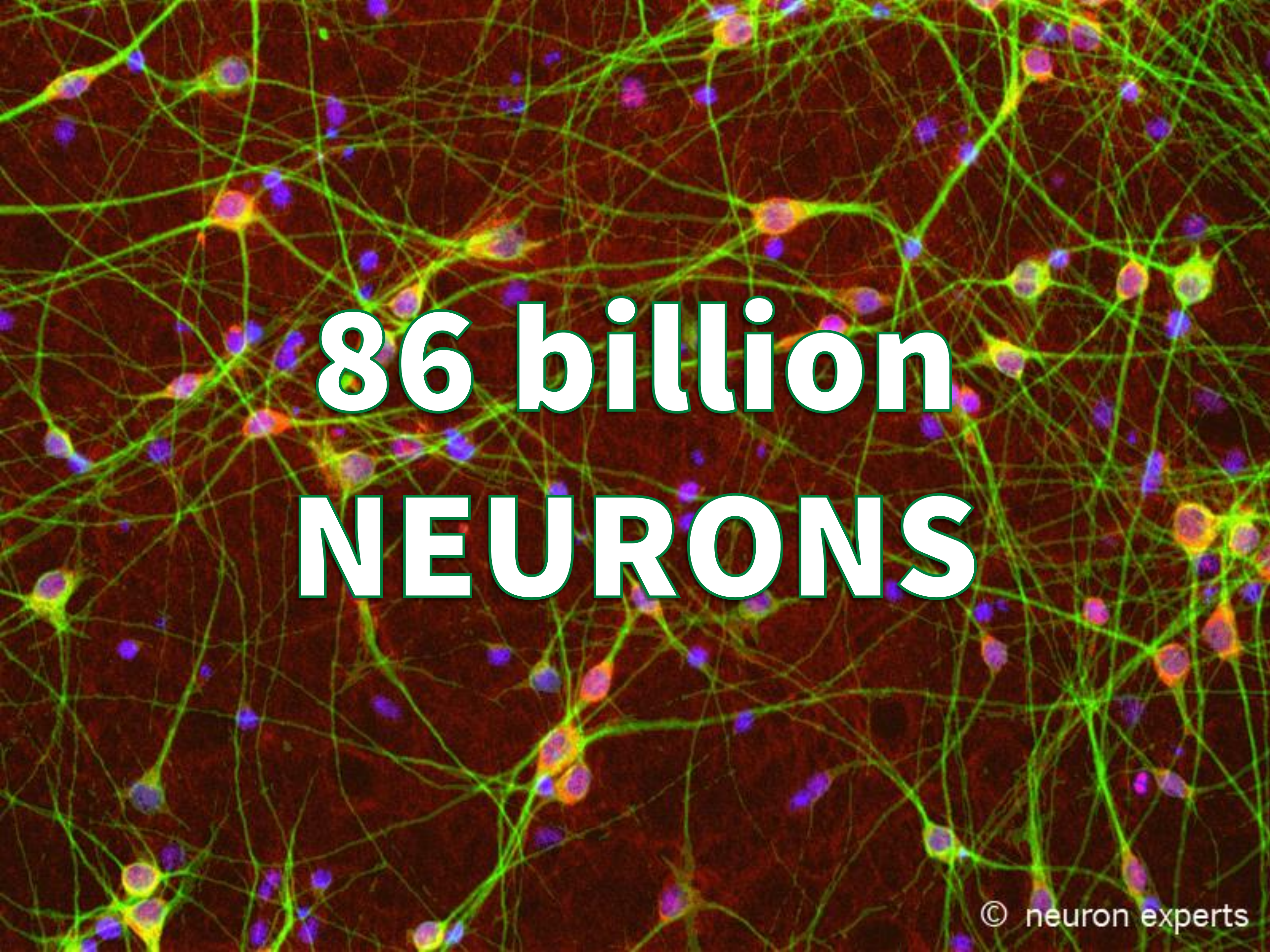
- Infinite numbers of algorithms to consider
- We implement algorithms on computers
  - So we are biased toward considering algorithms *that are easy to program*
- Instead, let's determine the types of algorithms that neurons would be good at implementing
  - Then make software tools to make those types of algorithms easy to program

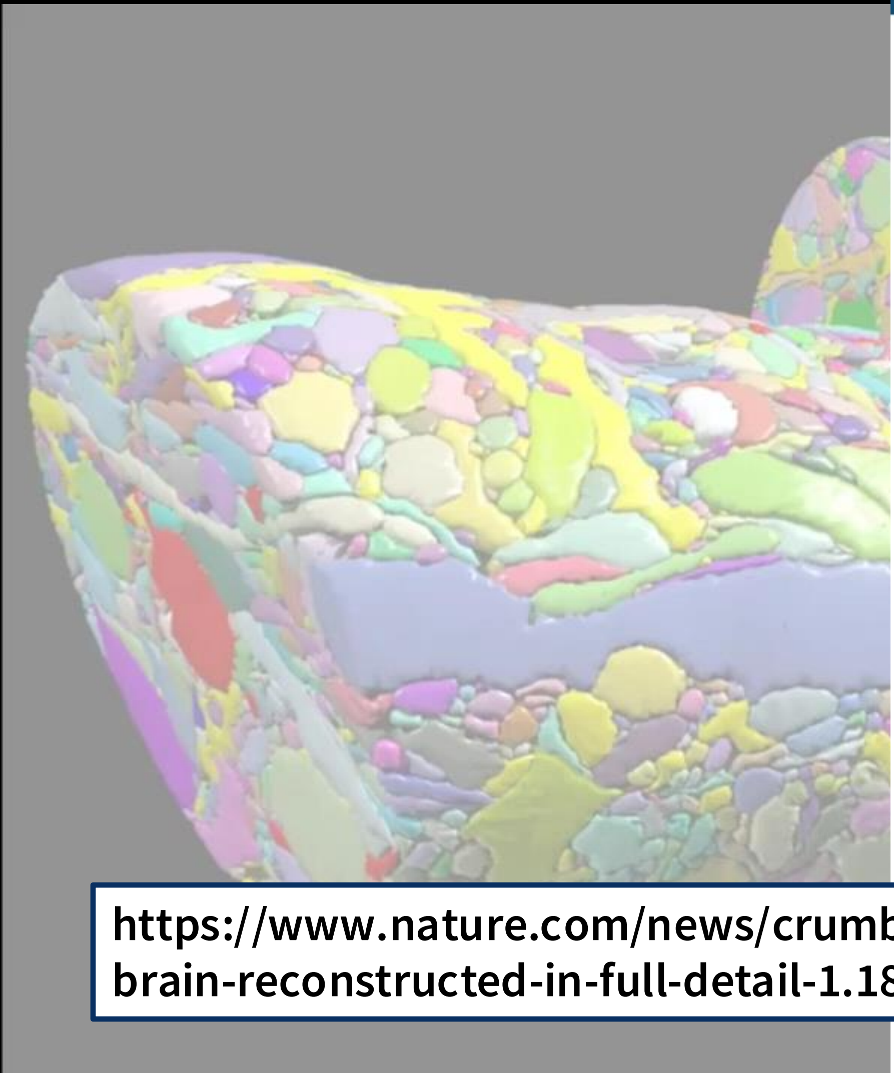
# (Why) should we go to the neural level?

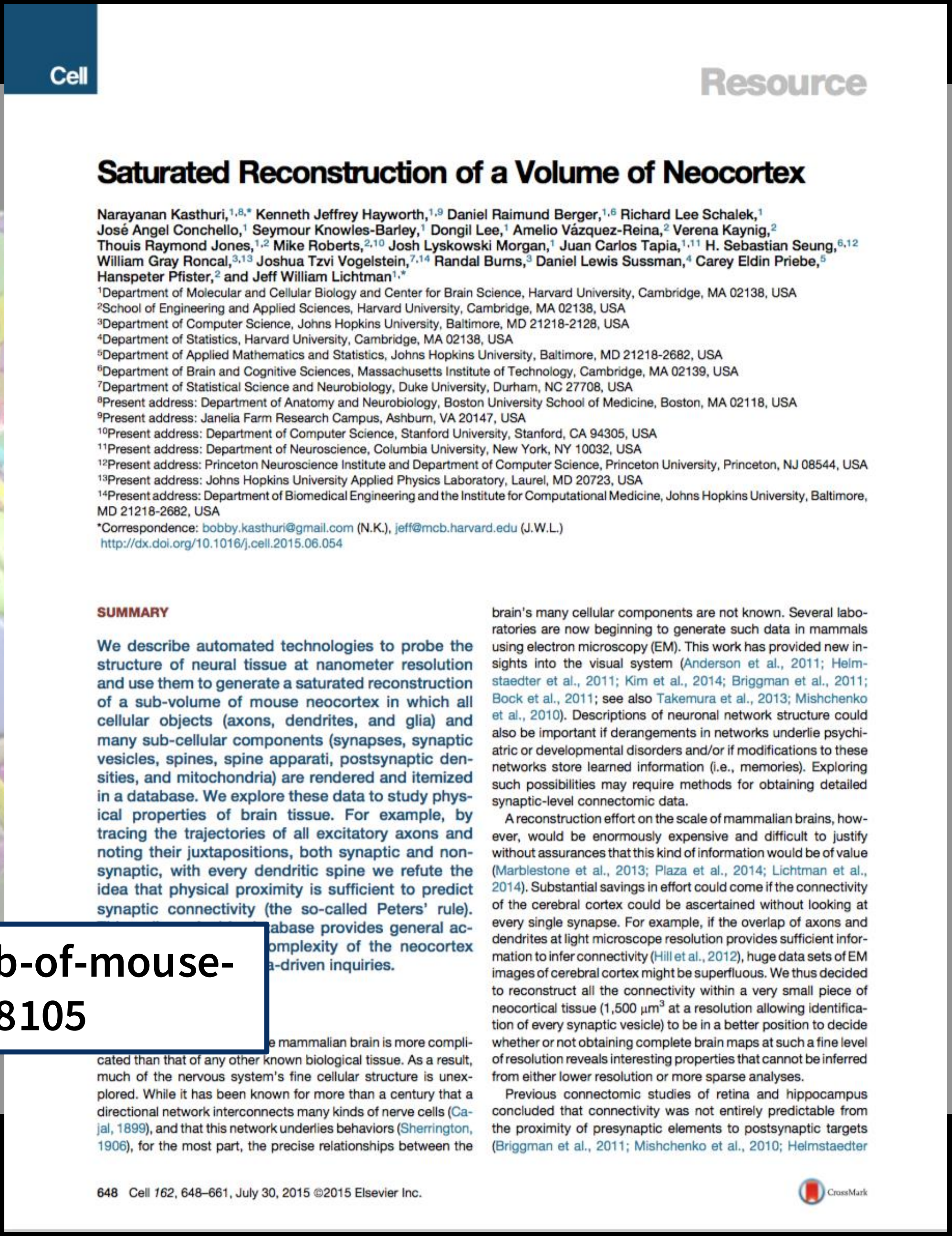
- Explains how our cognitive system is based on the firing of (very simple) neurons
- Explain higher-level phenomena based on lower-level biological constraints (e.g., working memory limitations)
- More constraints: firing patterns, precise timing, effect of drugs
- Might force/inspire us to use algorithms that neurons are good at, and cognition might be based on
- Inspiration for neural chips/neuromorphic hardware

# Today

- Neural Networks I:
  - Spiking Neurons
  - How to build a brain: Nengo
    - Basics: representing values with spiking neurons
  - Spaun


86 billion
NEURONS
© neuron experts





Cell

Resource

# Saturated Reconstruction of a Volume of Neocortex

Narayanan Kasthuri,[1,8,*] Kenneth Jeffrey Hayworth,[1,9] Daniel Raimund Berger,[1,6] Richard Lee Schalek,[1] José Angel Conchello,[1] Seymour Knowles-Barley,[1] Dongil Lee,[1] Amelio Vázquez-Reina,[2] Verena Kaynig,[2] Thouis Raymond Jones,[1,2] Mike Roberts,[2,10] Josh Lyskowski Morgan,[1] Juan Carlos Tapia,[1,11] H. Sebastian Seung,[6,12] William Gray Roncal,[3,13] Joshua Tzvi Vogelstein,[7,14] Randal Burns,[3] Daniel Lewis Sussman,[4] Carey Eldin Priebe,[5] Hanspeter Pfister,[2] and Jeff William Lichtman[1,*]
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http://dx.doi.org/10.1016/j.cell.2015.06.054

**SUMMARY**

We describe automated technologies to probe the structure of neural tissue at nanometer resolution and use them to generate a saturated reconstruction of a sub-volume of mouse neocortex in which all cellular objects (axons, dendrites, and glia) and many sub-cellular components (synapses, synaptic vesicles, spines, spine apparati, postsynaptic densities, and mitochondria) are rendered and itemized in a database. We explore these data to study physical properties of brain tissue. For example, by tracing the trajectories of all excitatory axons and noting their juxtapositions, both synaptic and non-synaptic, with every dendritic spine we refute the idea that physical proximity is sufficient to predict synaptic connectivity (the so-called Peters' rule). ... abase provides general ac- ... omplexity of the neocortex ... a-driven inquiries.

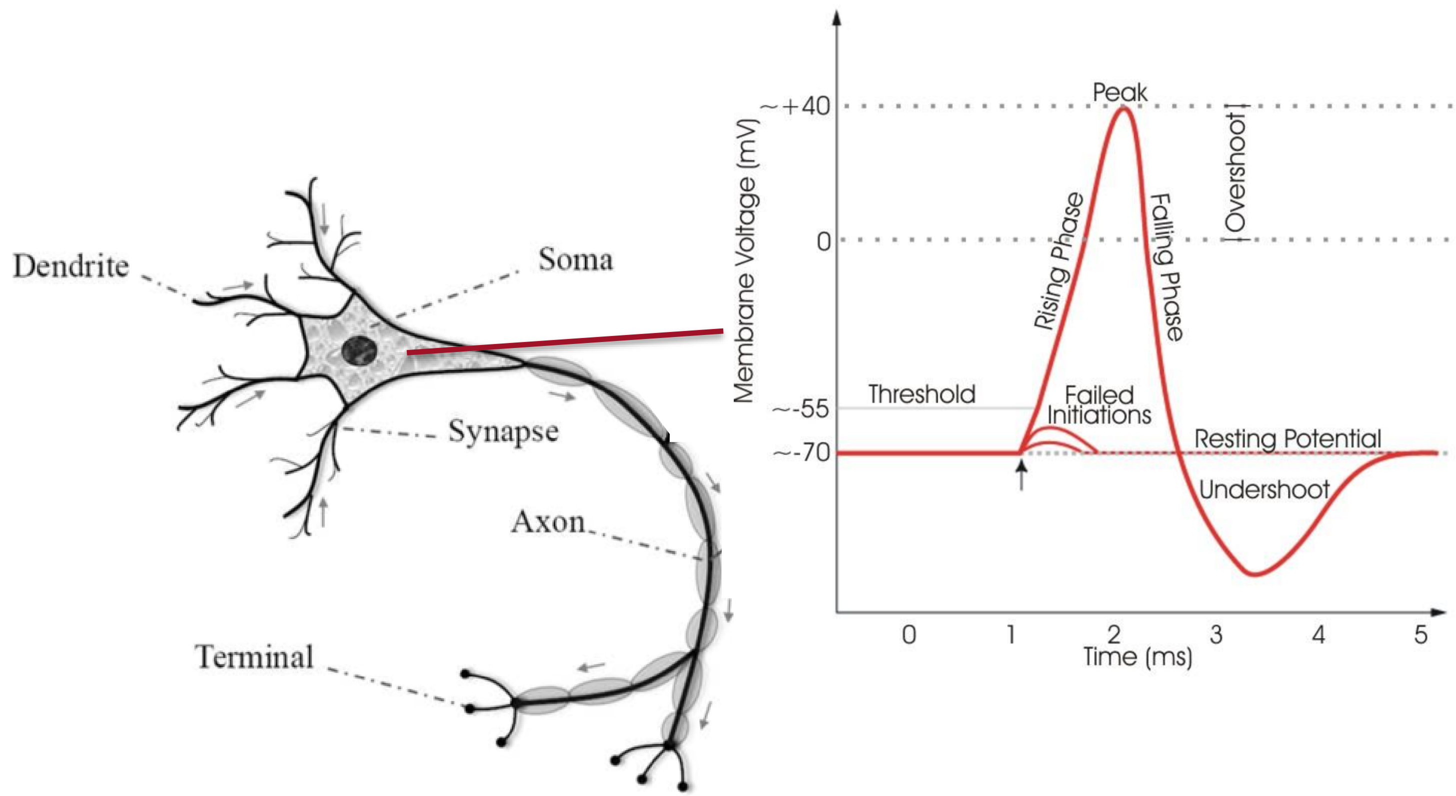
https://www.nature.com/news/crumb-of-mouse-brain-reconstructed-in-full-detail-1.18105

...e mammalian brain is more complicated than that of any other known biological tissue. As a result, much of the nervous system's fine cellular structure is unexplored. While it has been known for more than a century that a directional network interconnects many kinds of nerve cells (Cajal, 1899), and that this network underlies behaviors (Sherrington, 1906), for the most part, the precise relationships between the brain's many cellular components are not known. Several laboratories are now beginning to generate such data in mammals using electron microscopy (EM). This work has provided new insights into the visual system (Anderson et al., 2011; Helmstaedter et al., 2011; Kim et al., 2014; Briggman et al., 2011; Bock et al., 2011; see also Takemura et al., 2013; Mishchenko et al., 2010). Descriptions of neuronal network structure could also be important if derangements in networks underlie psychiatric or developmental disorders and/or if modifications to these networks store learned information (i.e., memories). Exploring such possibilities may require methods for obtaining detailed synaptic-level connectomic data.

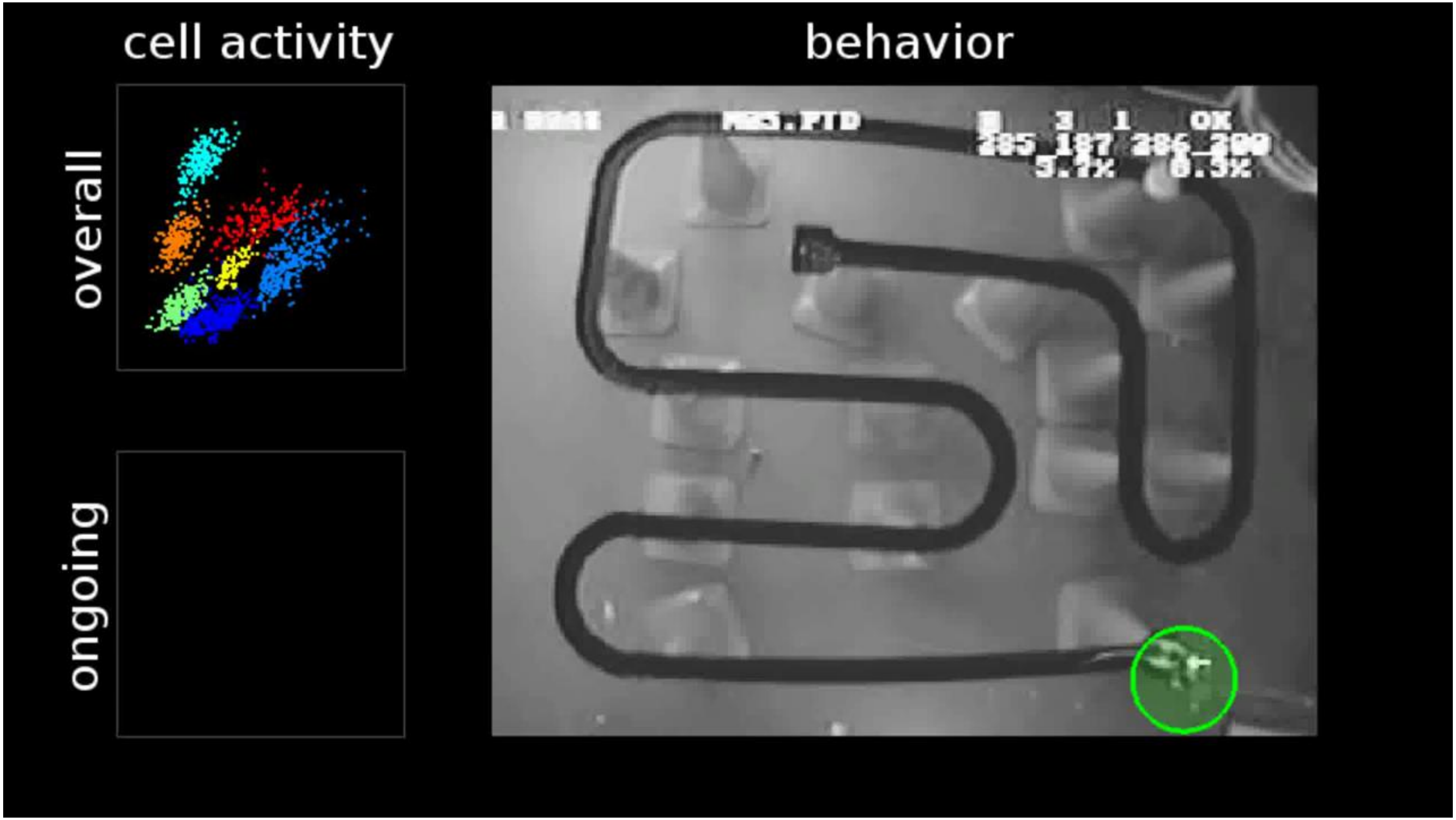
A reconstruction effort on the scale of mammalian brains, however, would be enormously expensive and difficult to justify without assurances that this kind of information would be of value (Marblestone et al., 2013; Plaza et al., 2014; Lichtman et al., 2014). Substantial savings in effort could come if the connectivity of the cerebral cortex could be ascertained without looking at every single synapse. For example, if the overlap of axons and dendrites at light microscope resolution provides sufficient information to infer connectivity (Hill et al., 2012), huge data sets of EM images of cerebral cortex might be superfluous. We thus decided to reconstruct all the connectivity within a very small piece of neocortical tissue (1,500 $\mu m^3$ at a resolution allowing identification of every synaptic vesicle) to be in a better position to decide whether or not obtaining complete brain maps at such a fine level of resolution reveals interesting properties that cannot be inferred from either lower resolution or more sparse analyses.

Previous connectomic studies of retina and hippocampus concluded that connectivity was not entirely predictable from the proximity of presynaptic elements to postsynaptic targets (Briggman et al., 2011; Mishchenko et al., 2010; Helmstaedter

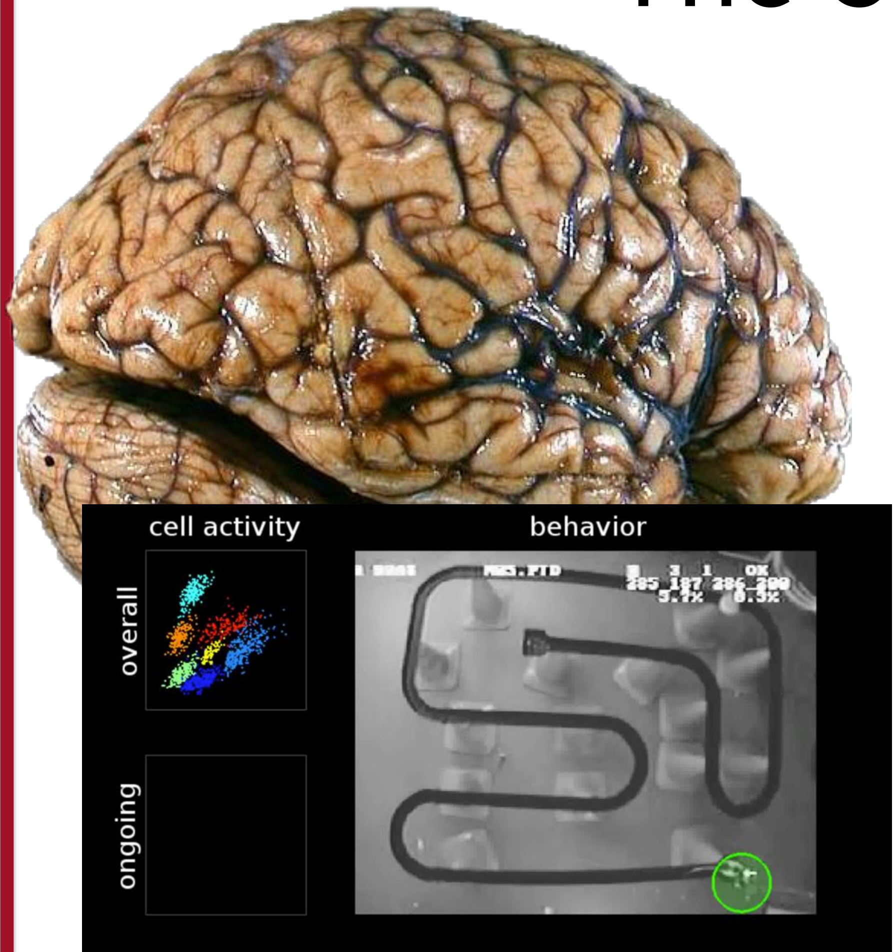
# Spiking Neurons



# Spiking Neurons

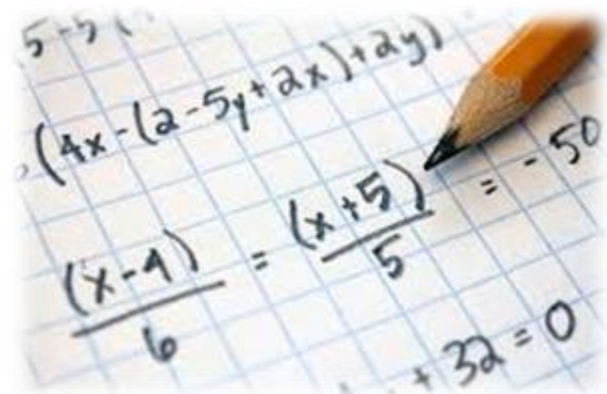


# The Challenge

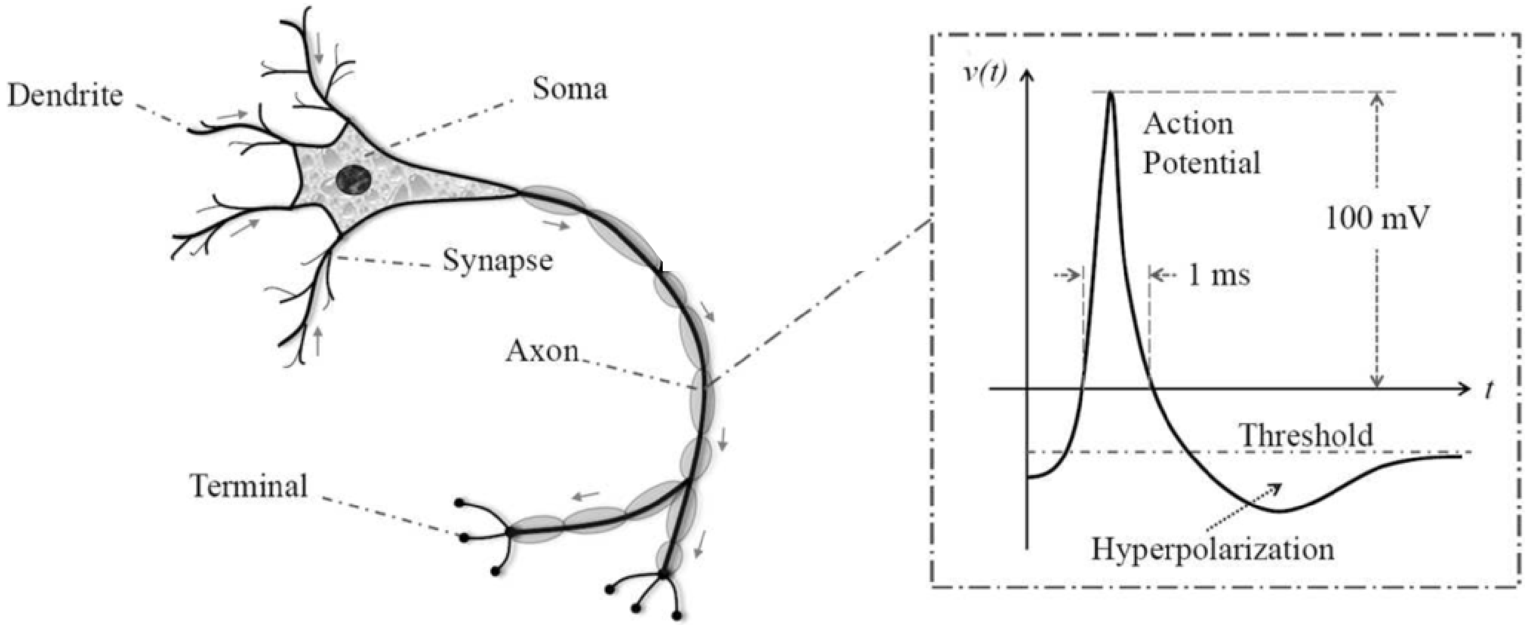



86 billion spiking neurons

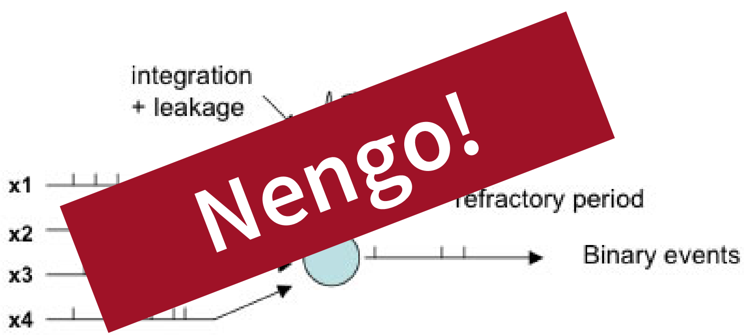
Higher-level cognitive functions



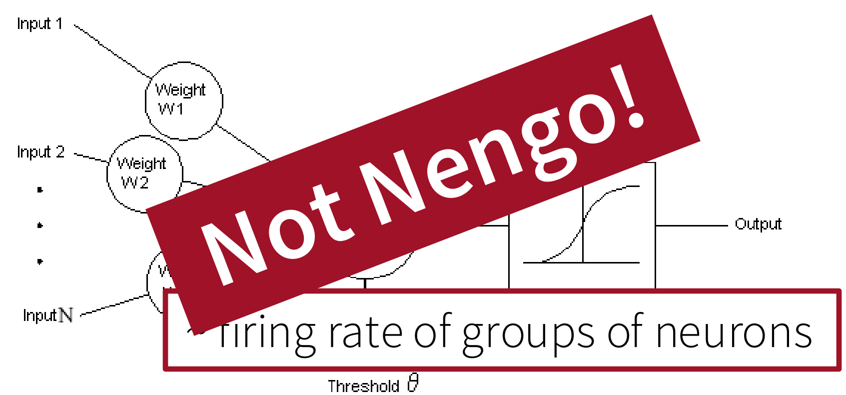
# Spiking Neurons




**Spiking artificial neurons**




**Traditional artificial neurons**



# Challenges for (Spiking) Neurons

- How to represent values (information)?
- How to communicate values?
- How can we store values?

- How to represent symbols?
- How to ground symbols in the world?

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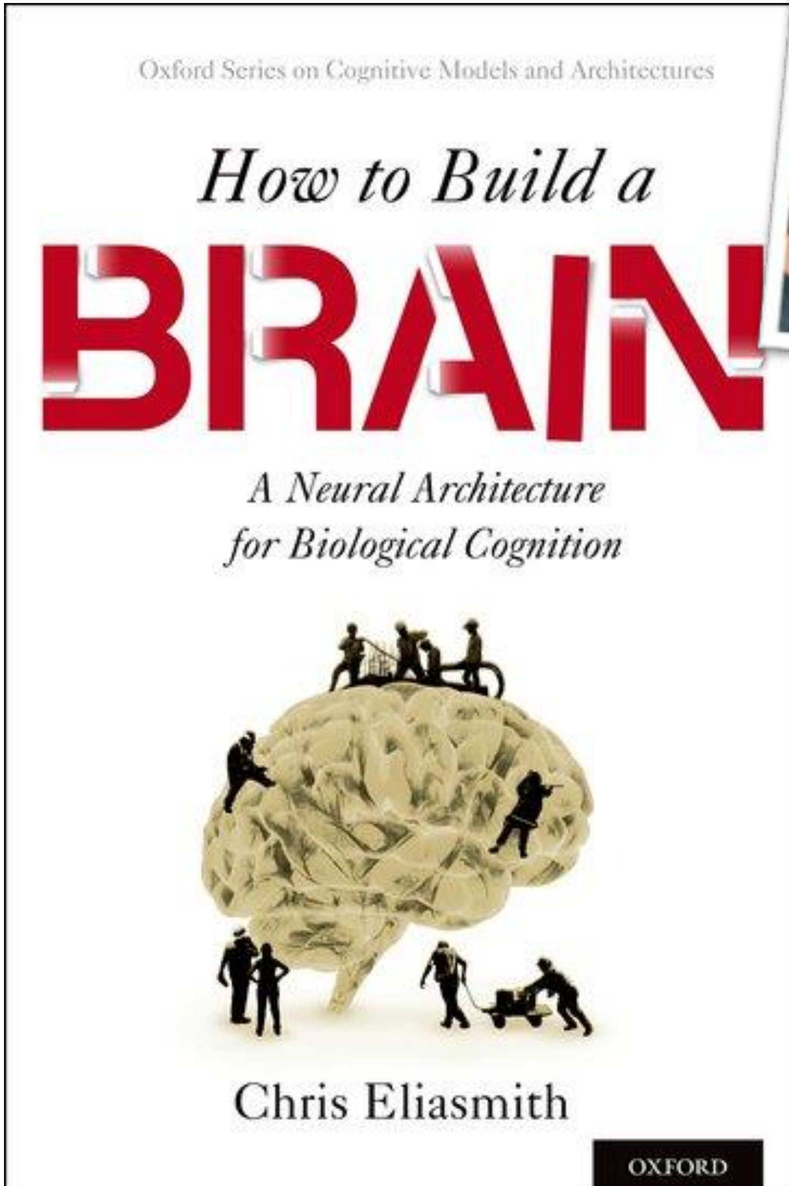
# Today

- Neural Networks I:
  - Spiking Neurons
  - How to build a brain: Nengo
    - Basics: representing values with spiking neurons
  - Spaun

# Nengo Architecture

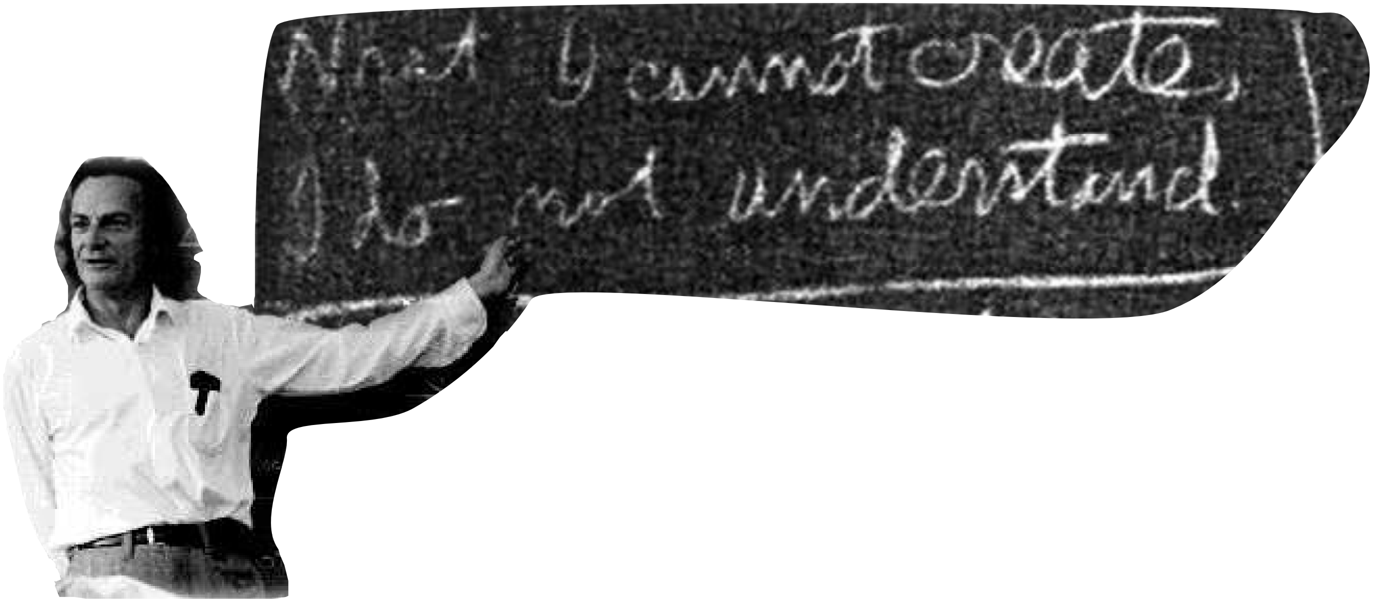



Terry Stewart

https://www.nengo.ai

UNIVERSITY OF WATERLOO

# Chris Eliasmith:




Richard Feynman

large-scale

complete behaviour

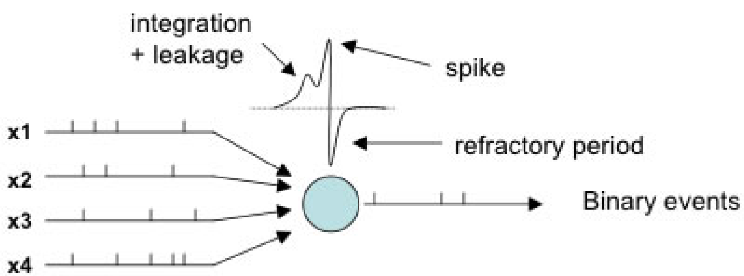
A *more* synthetic approach to neuroscience (to *complement* the analytic approach)

# Challenges for (Spiking) Neurons

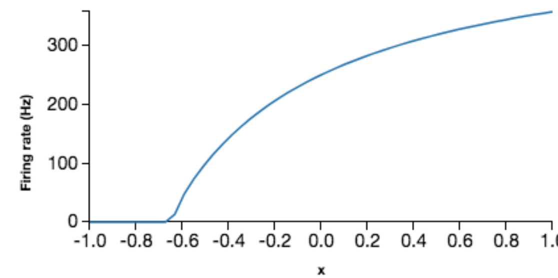
- How to represent values?
- How to communicate values?
- How can we store values?

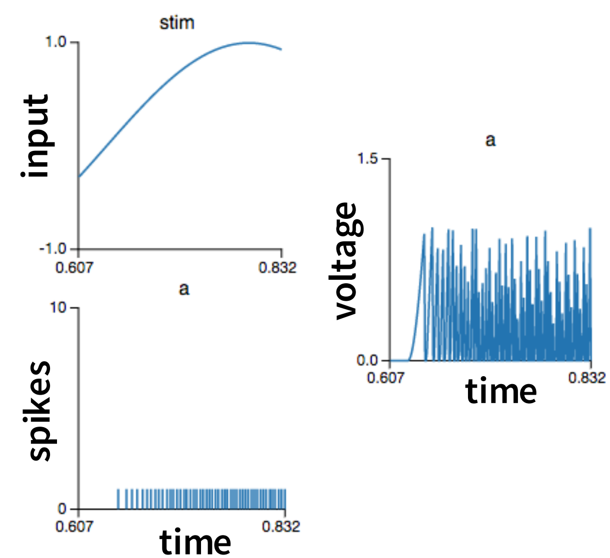
# How can we represent values?

### Leaky Integrate-and-Fire Neuron




### Tuning Curve

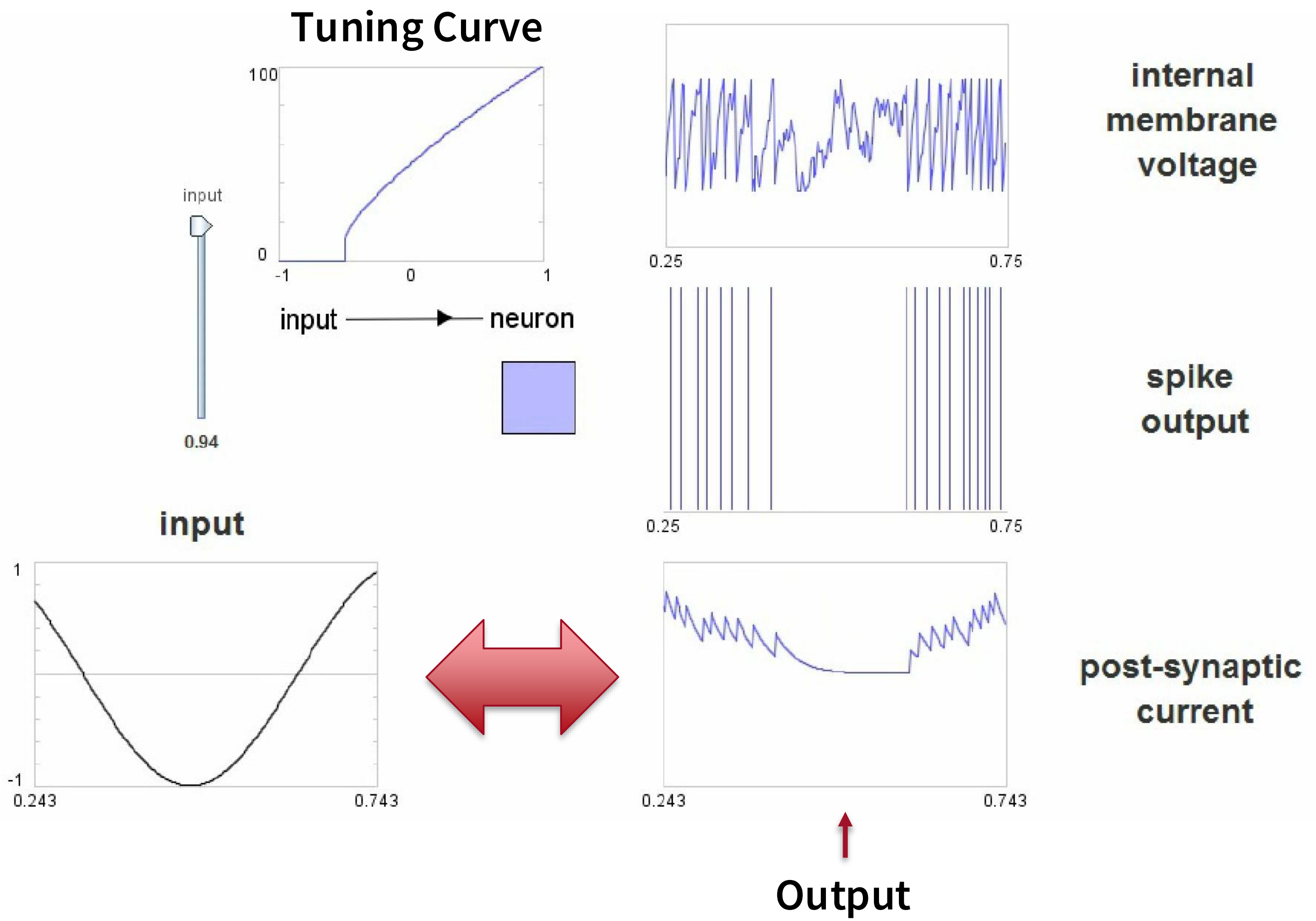


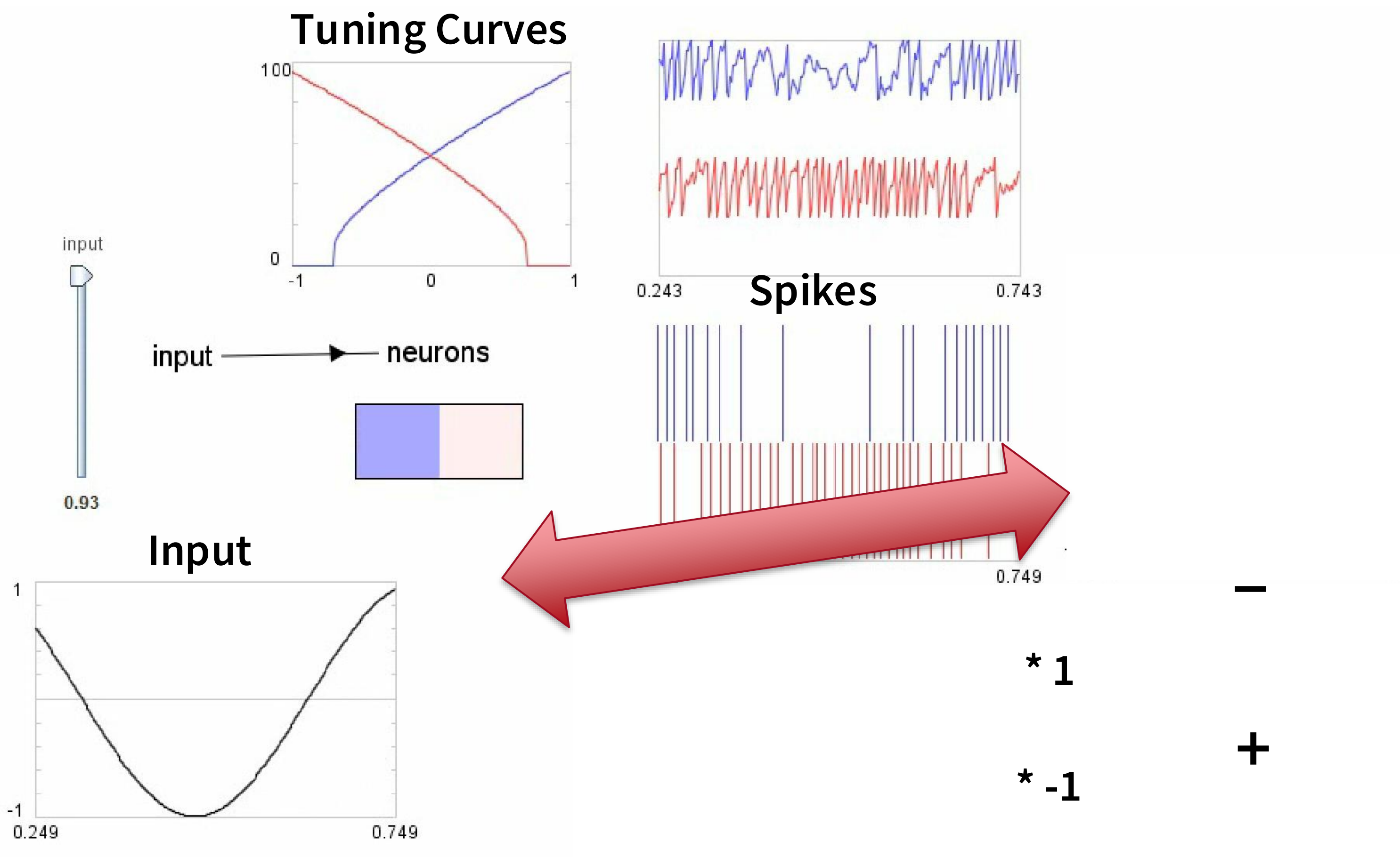

Other (more complex) options:
- Adaptive LIF
- Izhikevich
- Hodgkin-Huxley
  (not in default nengo)

**What is the problem of representing an input value this way?**

# Single Neuron



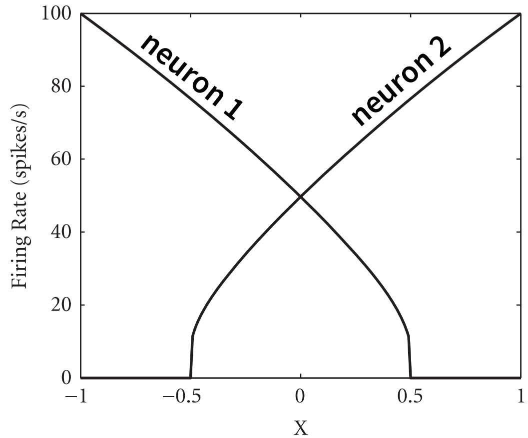
# Two Neurons



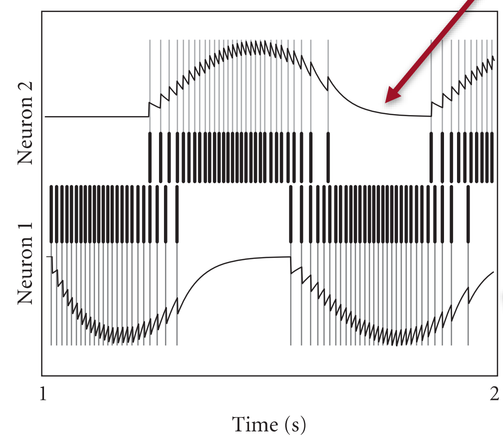
Tuning Curves
100
0
-1
0
1
input
0.93
input
neurons
0.243
Spikes
0.743
0.749
Input
1
-1
0.249
0.749
–
* 1
+
* -1
4

# Two Neurons

### Tuning Curves




### Spike Raster

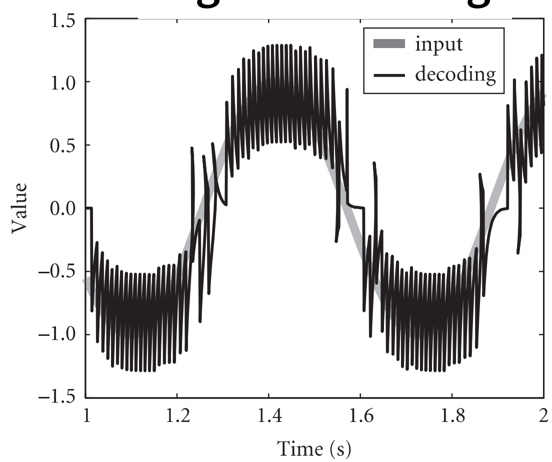



post-synaptic
potential neuron 2

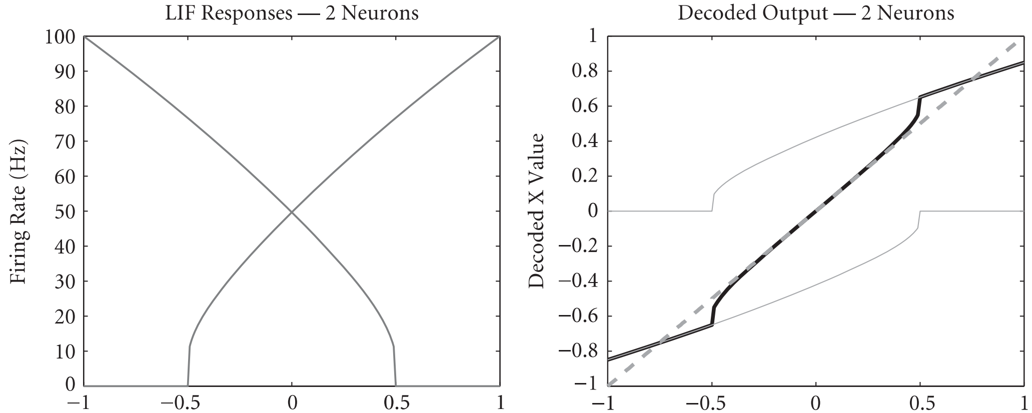
spikes

-1 * post-synaptic
potential neuron 1

### Signal Decoding



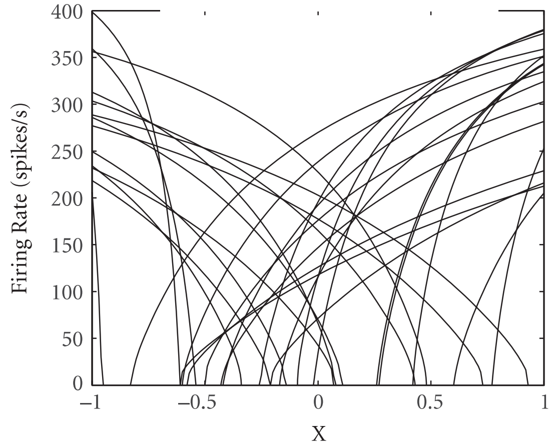

= weighted sum of psp's



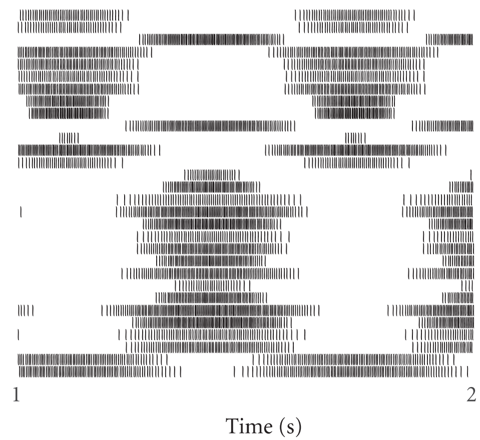
LIF Responses — 2 Neurons
Firing Rate (Hz)
100
90
80
70
60
50
40
30
20
10
0
−1
−0.5
0
0.5
1
Decoded Output — 2 Neurons
Decoded X Value
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
−0.8
−1
−1
−0.5
0
0.5
1

# Thirty Neurons

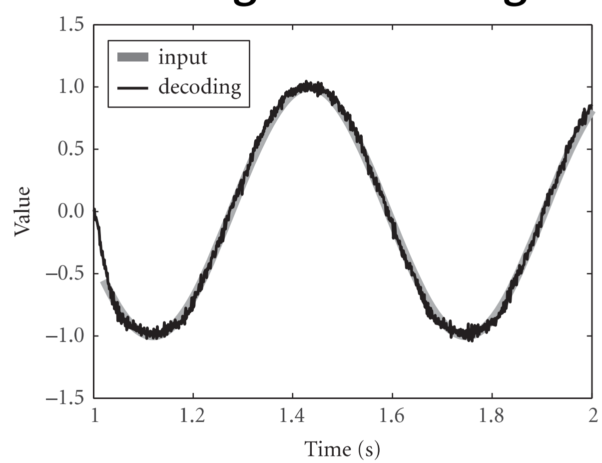
## Tuning Curves




## Spike Raster




## Signal Decoding

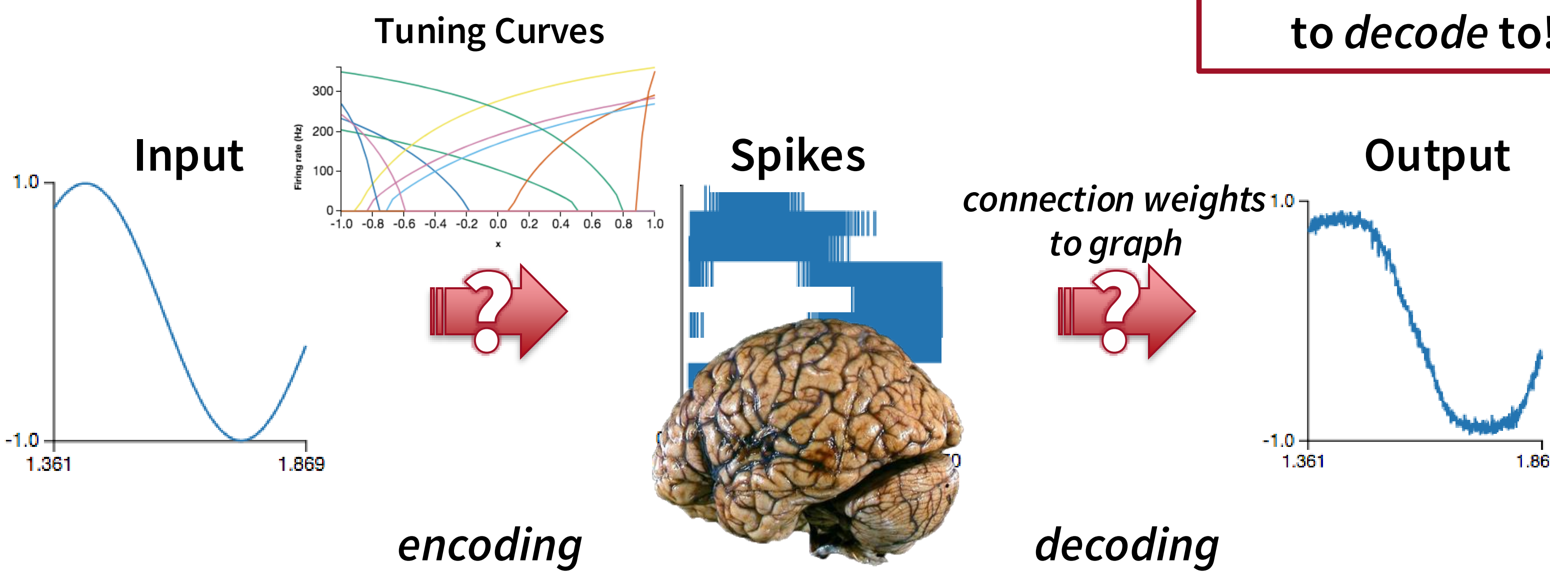



**Demo!**

# Values in Spiking Neurons

- Each neural ensemble can represent a value
  - Combination of spike rates of neurons
  - Encoding: value => spikes
  - Decoding: spikes => value

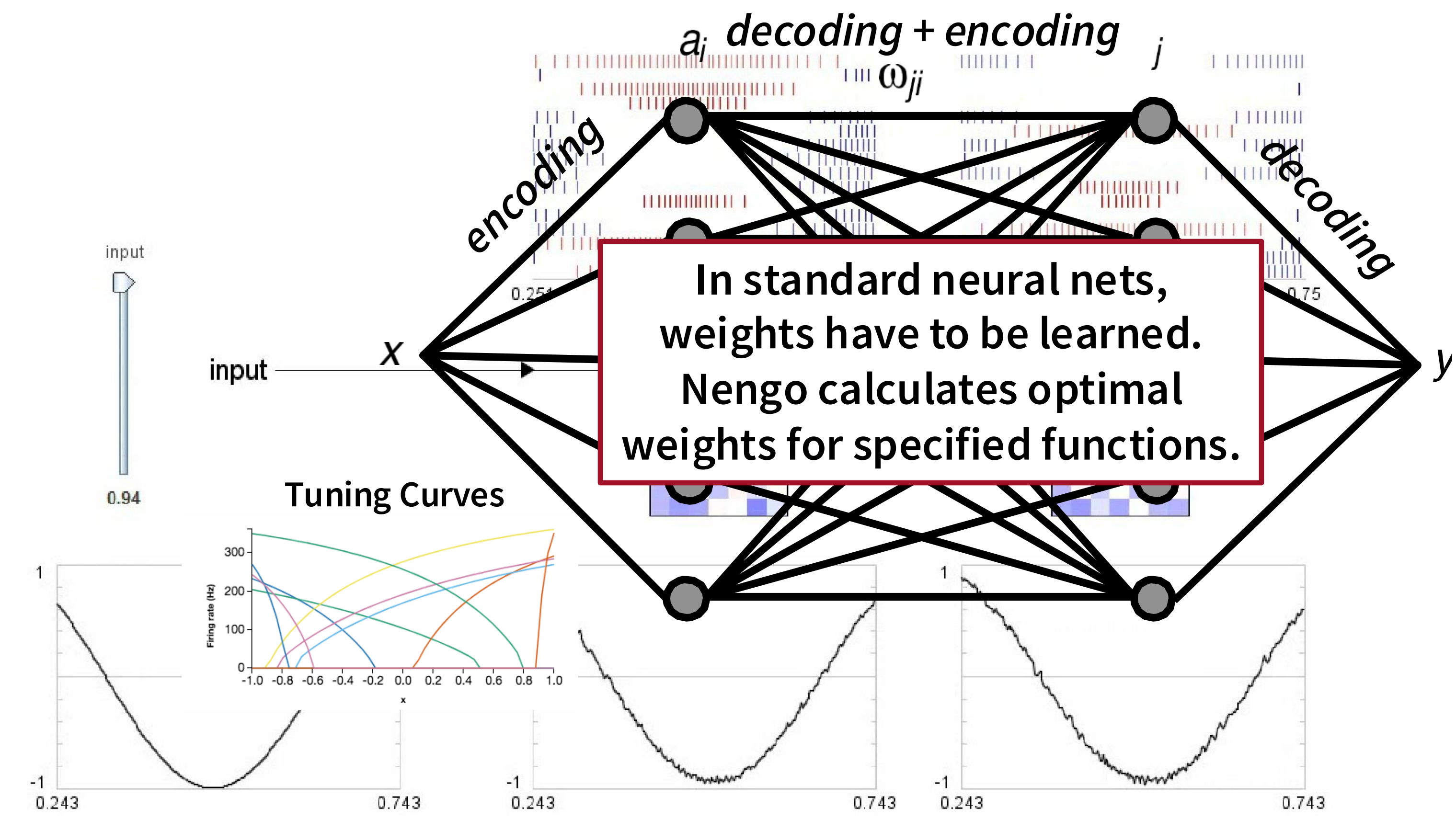
**We need something to *decode* to!**



# Challenges for (Spiking) Neurons

- How to represent values?
- How to communicate values?
- How can we store values?

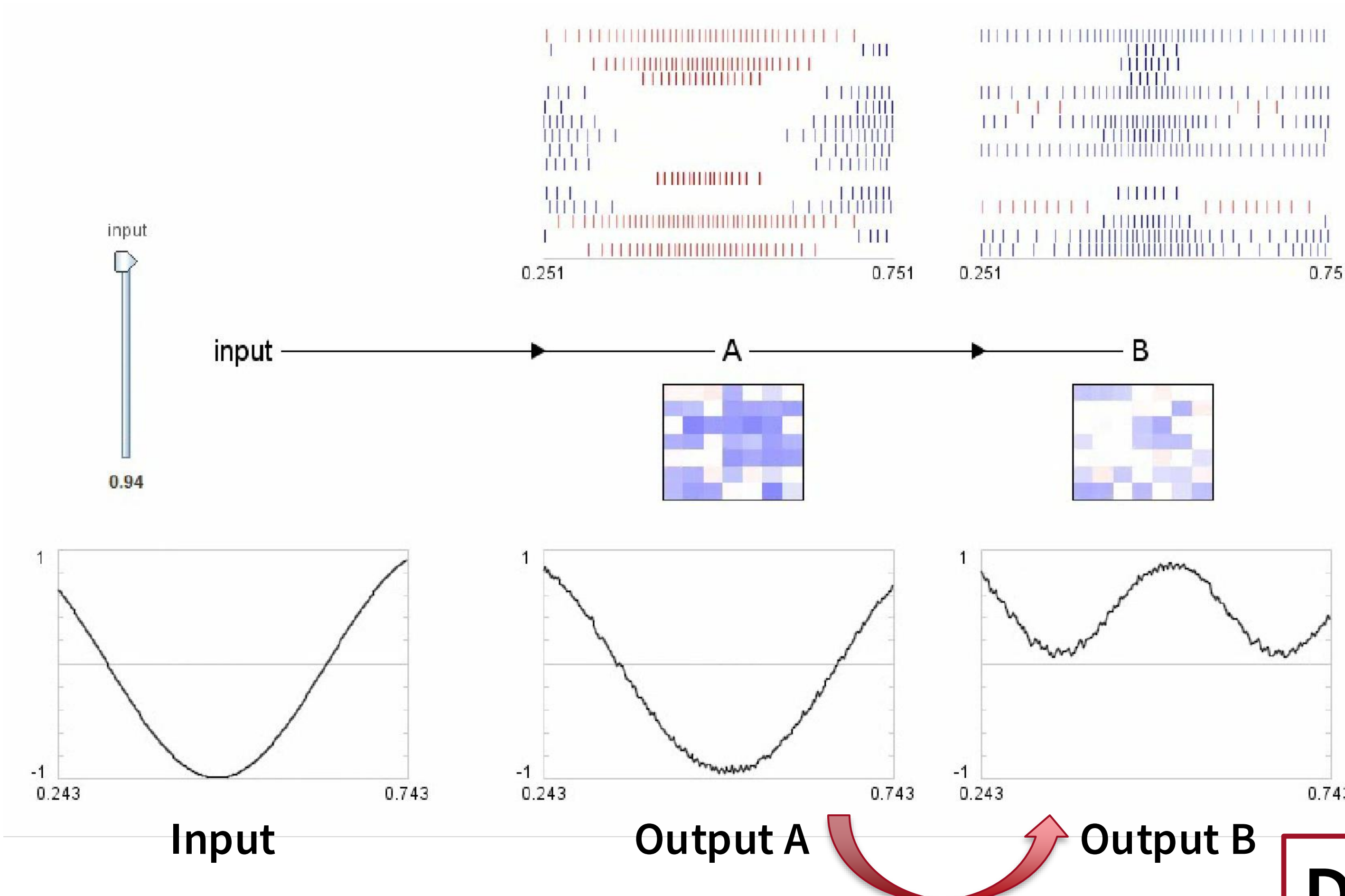
# How to communicate values?




**In standard neural nets, weights have to be learned. Nengo calculates optimal weights for specified functions.**

**Input** **Output A** **Output B**

# How to transform values?




**Demo!**

**$y = x^2$ has the same cost as $y = x$!**

# Values in Spiking Neurons

- Each neural ensemble stores a value
  - Encoding: value => spikes
  - Decoding: spikes => value
- Each connection
  - communicates
  - and potentially transforms the input
- Nengo calculates optimal encoders and decoders

# Challenges for (Spiking) Neurons

- How to represent values?
- How to communicate values?
- How can we store values? $\boxed{\textbf{Demo!}}$

# Challenges for (Spiking) Neurons

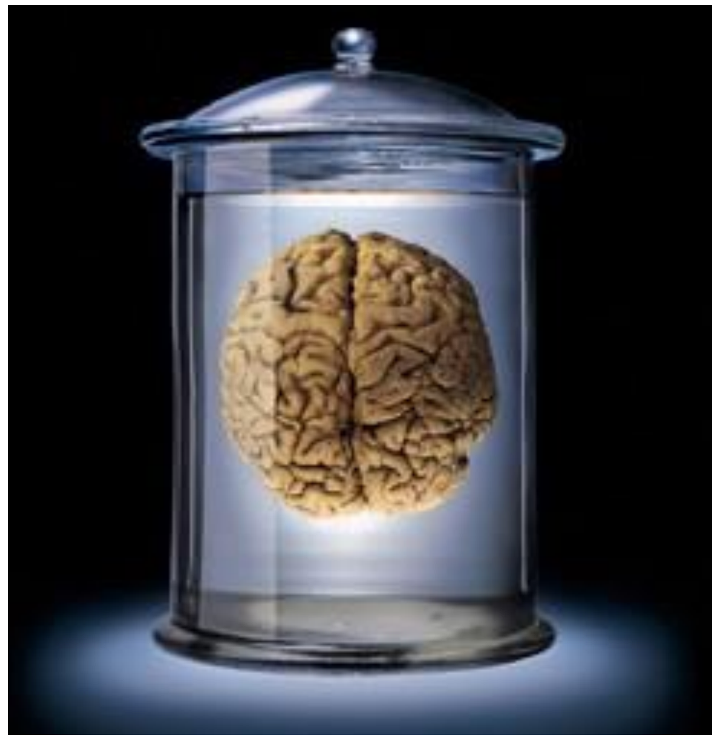
- How to represent values?
- How to communicate values?
- How can we store values?

**Can this actually do anything?**

# Today

- Neural Networks I:
  - Spiking Neurons
  - How to build a brain: Nengo
    - Basics: representing values with spiking neurons
  - Spaun

# The deeper problem



Complexity without function

# Spaun: 2.5 million neurons

REPORTS

## A Large-Scale Model of the Functioning Brain

Chris Eliasmith,* Terrence C. Stewart, Xuan Choo, Trevor Bekolay, Travis DeWolf, Yichuan Tang, Daniel Rasmussen

A central challenge for cognitive and systems neuroscience is to relate the incredibly complex behavior of animals to the equally complex activity of their brains. Recently described, large-scale neural models have not bridged this gap between neural activity and biological function. In this work, we present a 2.5-million-neuron model of the brain (called "Spaun") that bridges this gap by exhibiting many different behaviors. The model is presented only with visual image sequences, and it draws all of its responses with a physically modeled arm. Although simplified, the model captures many aspects of neuroanatomy, neurophysiology, and psychological behavior, which we demonstrate via eight diverse tasks.

Large-scale neural simulations are becoming increasingly common [see (*1*) for a review]. These include the ambitious Blue Brain Project (*2*), which has simulated about 1 million neurons in cortical columns and includes considerable biological detail, accurately reflecting spatial structure, connectivity statistics, and other neural properties. More recent work has simulated many more neurons, such as the 1 billion neurons simulated in the Cognitive Computation Project (*3*), which has been hailed as a cat-scale simulation. A human-scale simulation of 100 billion neurons has also been reported (*4*).

Although impressive scaling has been achieved, no previous large-scale spiking neuron models have demonstrated how such simulations connect to a variety of specific observable behaviors. The focus of this past work has been on scaling to larger numbers of neurons and more detailed neuron models. Unfortunately, simulating a complex brain alone does not address one of the central challenges for neuroscience: explaining how complex brain activity generates complex behavior. In contrast, we present here a spiking neuron model of 2.5 million neurons that is centrally directed to bridging the brain-neural network research and have not yet been demonstrated in spiking networks (e.g., counting, question answering, rapid variable creation, and fluid reasoning). The eight tasks (termed "A0" to "A7") that Spaun performs are: (A0) Copy drawing. Given a randomly chosen handwritten digit, Spaun should produce the same digit written in the same style as the handwriting (movie S1; all supplemental movies can be viewed at http://nengo.ca/build-a-brain/spaunvideos). (A1) Image recognition. Given a randomly chosen handwritten digit, Spaun should produce the same digit written in its default writing (movie S2). (A2) RL. Spaun should perform a three-armed bandit task, in which it must determine which of three possible choices generates the greatest stochastically generated reward. Reward contingencies can change from trial to trial (movie S3). (A3) Serial WM. Given a list of any length, Spaun should reproduce it (movie S4). (A4) Counting. Given a starting value and a count value, Spaun should write the final value (that is, the sum of the two values) (movie S5). (A5) Question answering. Given a list of numbers, Spaun should answer either one of two possible questions: (i) what is in a given position in the list? (a "P" question) or (ii)

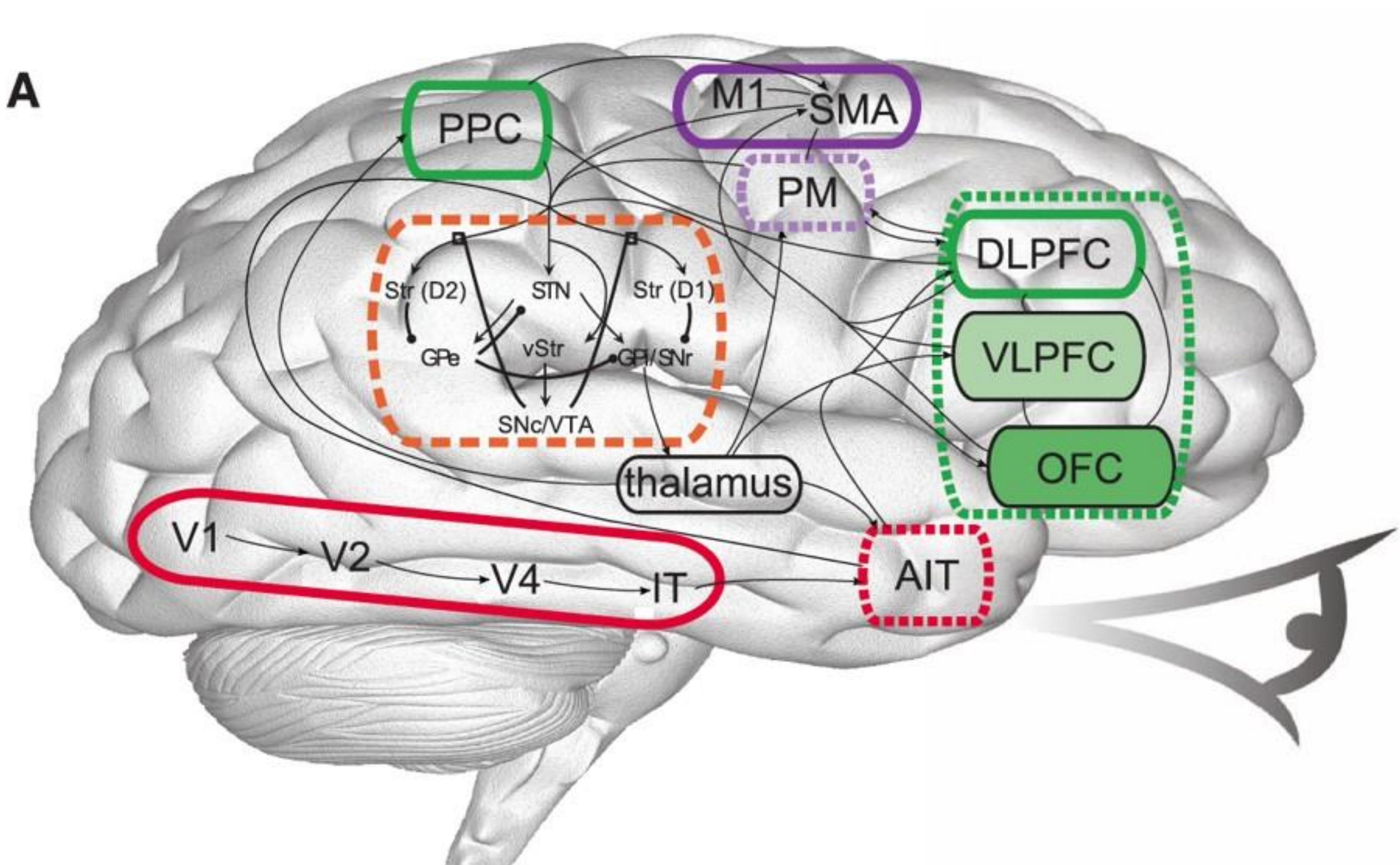
we modeled neuron and synaptic response properties on the electrophysiology literature for the relevant anatomical areas. For instance, the basal ganglia have largely GABAergic neurons, with dopamine modulating learning in the striatum, and the cortex has largely *N*-methyl-D-aspartate and AMPA synaptic connections (supplementary section S1.3). As a result, the dynamics in the model are tightly constrained by underlying neural properties (see supplementary section S2.4).

The functional architecture of the model is described in Fig. 1B. The network implementing the Spaun model consists of three compression hierarchies, an action-selection mechanism, and five subsystems. Components of the model communicate using spiking neurons that implement neural representations that we call "semantic pointers," using various firing patterns. Semantic pointers can be understood as being elements of a compressed neural vector space (supplementary sections S1.1 and S1.2). Compression is a natural way to understand much of neural processing. For instance, the number of cells in the visual hierarchy gradually decreases from the primary visual cortex (V1) to the inferior temporal cortex (IT) (*12*), meaning that the information has been compressed from a higher-dimensional (image-based) space into a lower-dimensional (feature) space (supplementary section S1.3). This same kind of operation maps well to the motor hierarchy (*13*), where lower-dimensional firing patterns are successively decompressed (for example, when a lower-dimensional motor representation in Euclidean space moves down the motor hierarchy to higher-dimensional muscle space).

Compression is functionally important because low-dimensional representations can be more efficiently manipulated for a variety of neural computations. Consequently, learning or defining different compression/decompression operations provides a means of generating neural representations that are well suited to a variety of neural computations.

# The Story So Far…

# Spaun: Anatomy



# Tasks

- Real input: 28x28 pixel images
- Output: physically modeled arm

- Tasks:
  - Copy drawing
  - Image recognition
  - Reinforcement learning
  - Serial Working Memory
  - Counting
  - Question Answering
  - Rapid variable creation
  - Raven's matrices

**Nengo can perform real tasks!**

https://xchoo.github.io/spaun2.0/videos.html

# Summary

- Ensembles of neurons represent values
- These values can be communicated, transformed, and stored
- Neng... large-scale models
- Spaun – a large-scale model – can do eight different task without having to be re-programmed

**Next week: symbols, semantic pointers, memory, learning, behavior…**

# Summary

- Ensembles of neurons represent values
- These values can be communicated, ... d stored
- ...
- Spaun – a large-scale model – can do eight different task without having to be re-programmed

Next ... tic pointers, memory, lea...

**No lecture on Thursday!**

# Good luck with the assignment!

university of groningen