

Architectures of Intelligence

Lecture 9
Neural Networks I:
Spiking Neurons

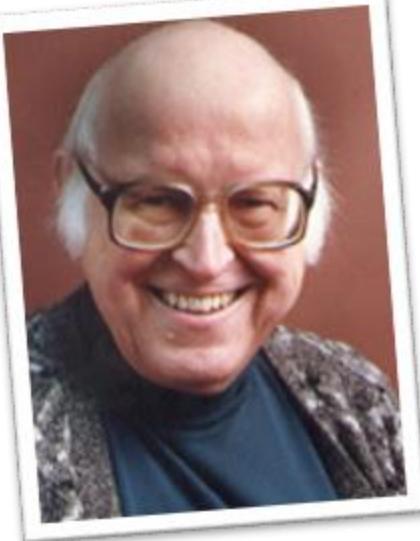
Jelmer Borst



university of
groningen



Allen Newell



1927-1992

Question:

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

Allen Newell



1927-1992

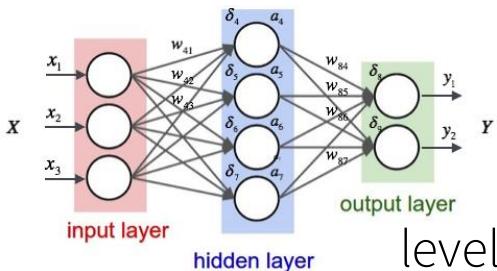
Question:

**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”.*

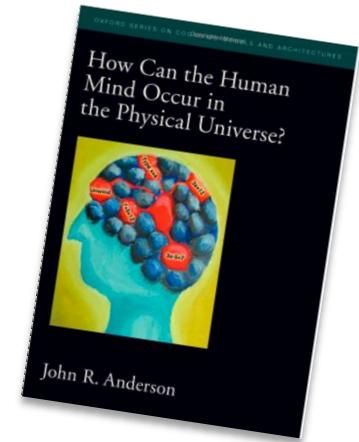
=> cognitive architecture

Different levels of abstraction



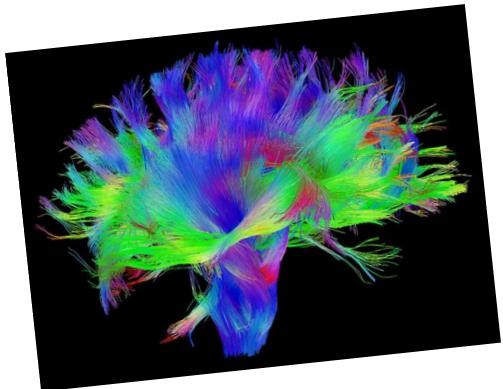
ACT-R

high level, requires symbols,
end-to-end functionality



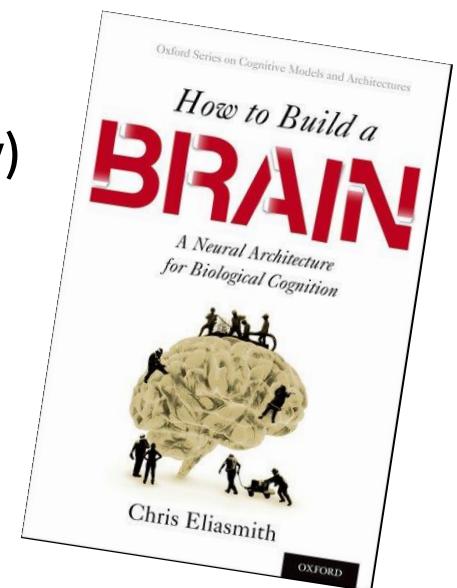
Traditional connectionists

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



Functional connectionists (Nengo, O'Reilly)

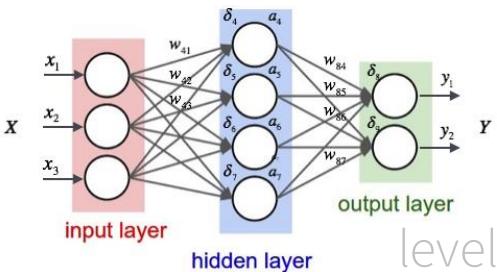
level of spiking neurons,
symbols, end-to-end functionality



Human brain project

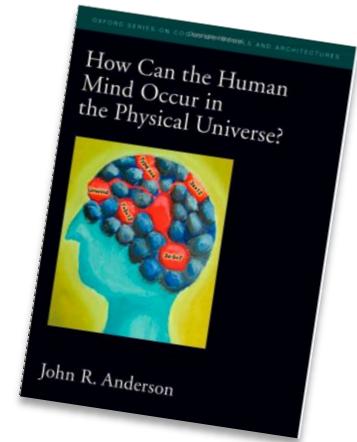
highly detailed neural level,
no symbols, emergent functionality

Different levels of abstraction



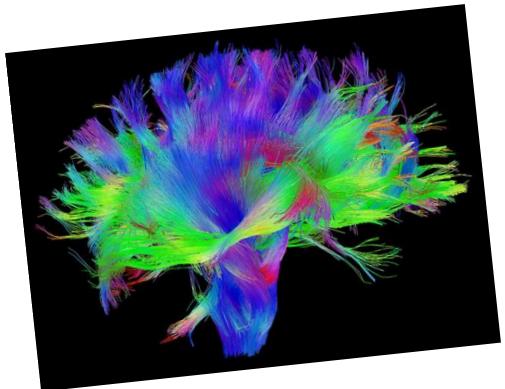
ACT-R

high level, requires symbols,
end-to-end functionality



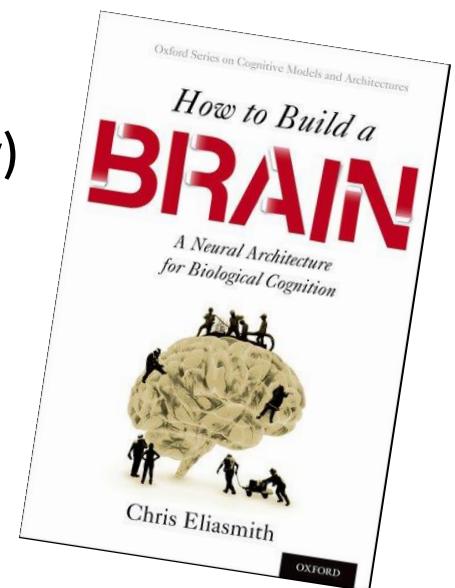
Traditional connectionists

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



Functional connectionists (Nengo, O'Reilly)

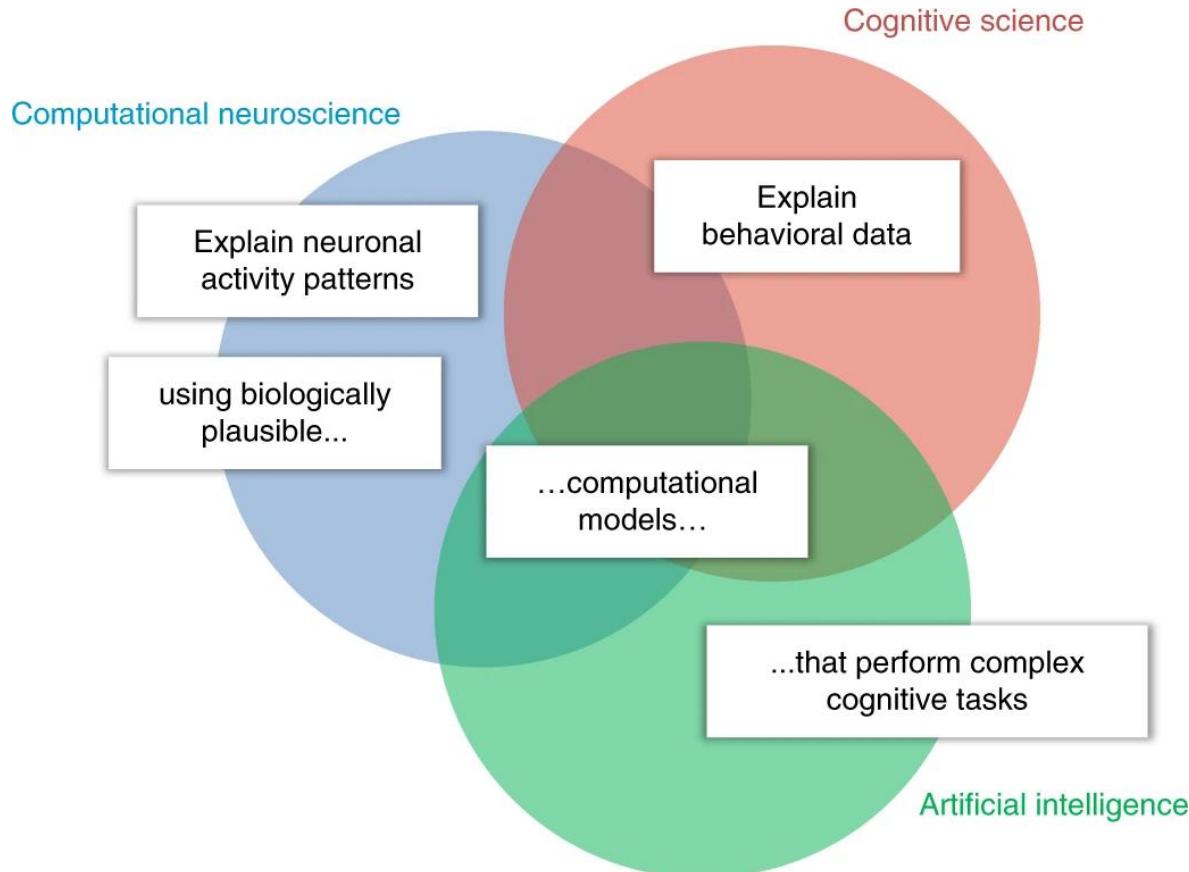
level of spiking neurons,
symbols, end-to-end functionality



Human brain project

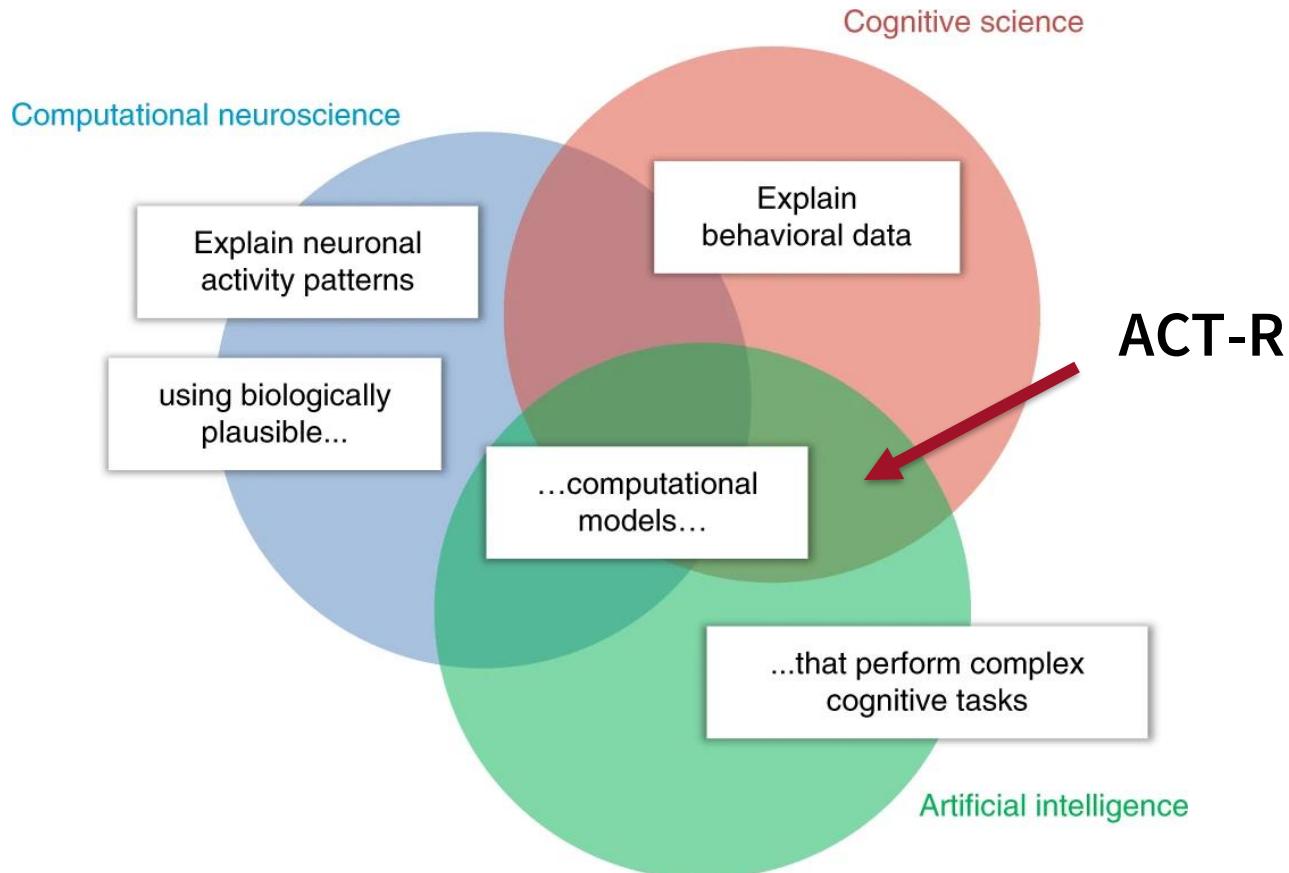
highly detailed neural level,
no symbols, emergent functionality

Cognitive Computational Neuroscience

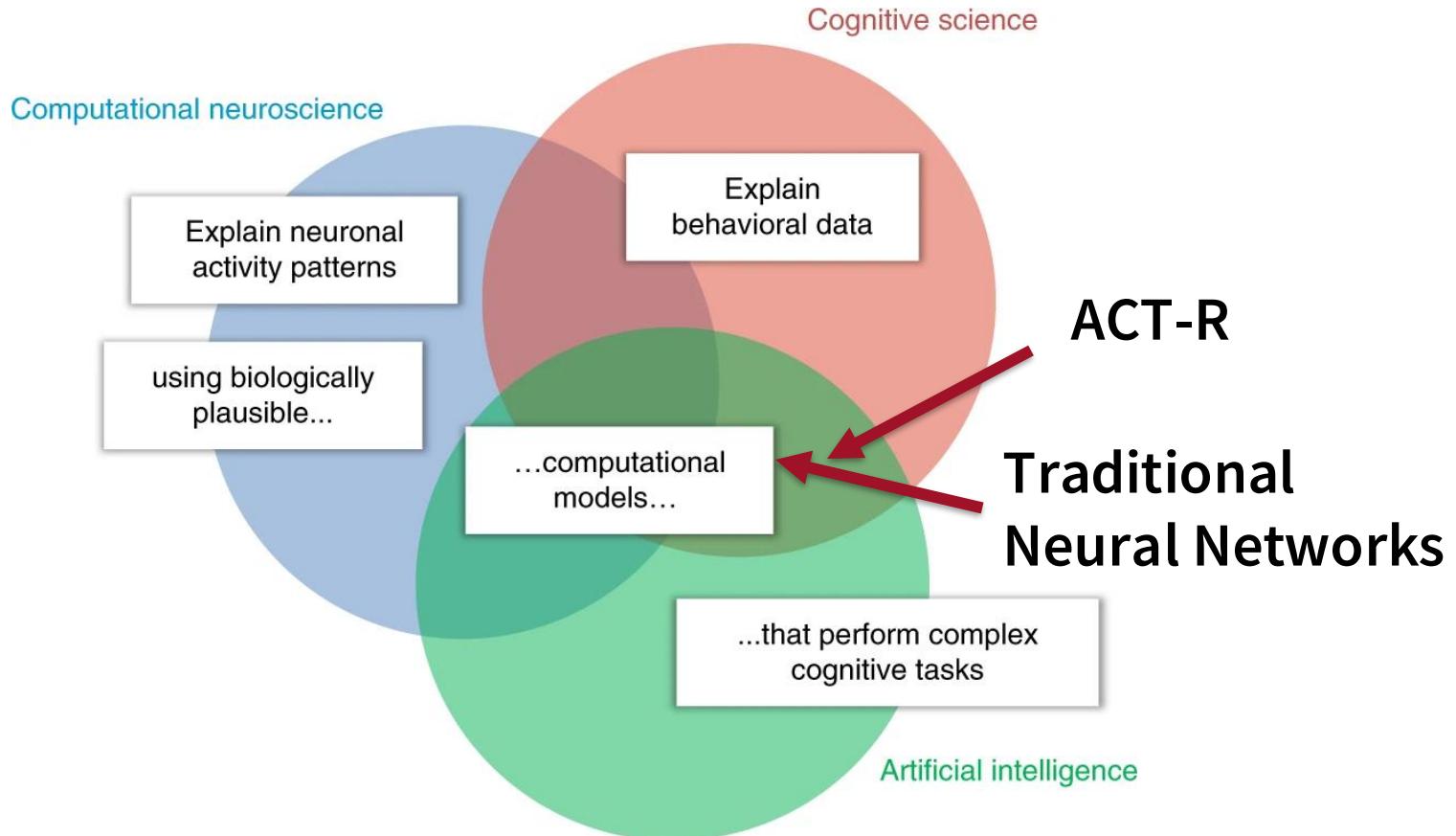


(Kriegeskorte & Douglas, *Nature*, 2018)

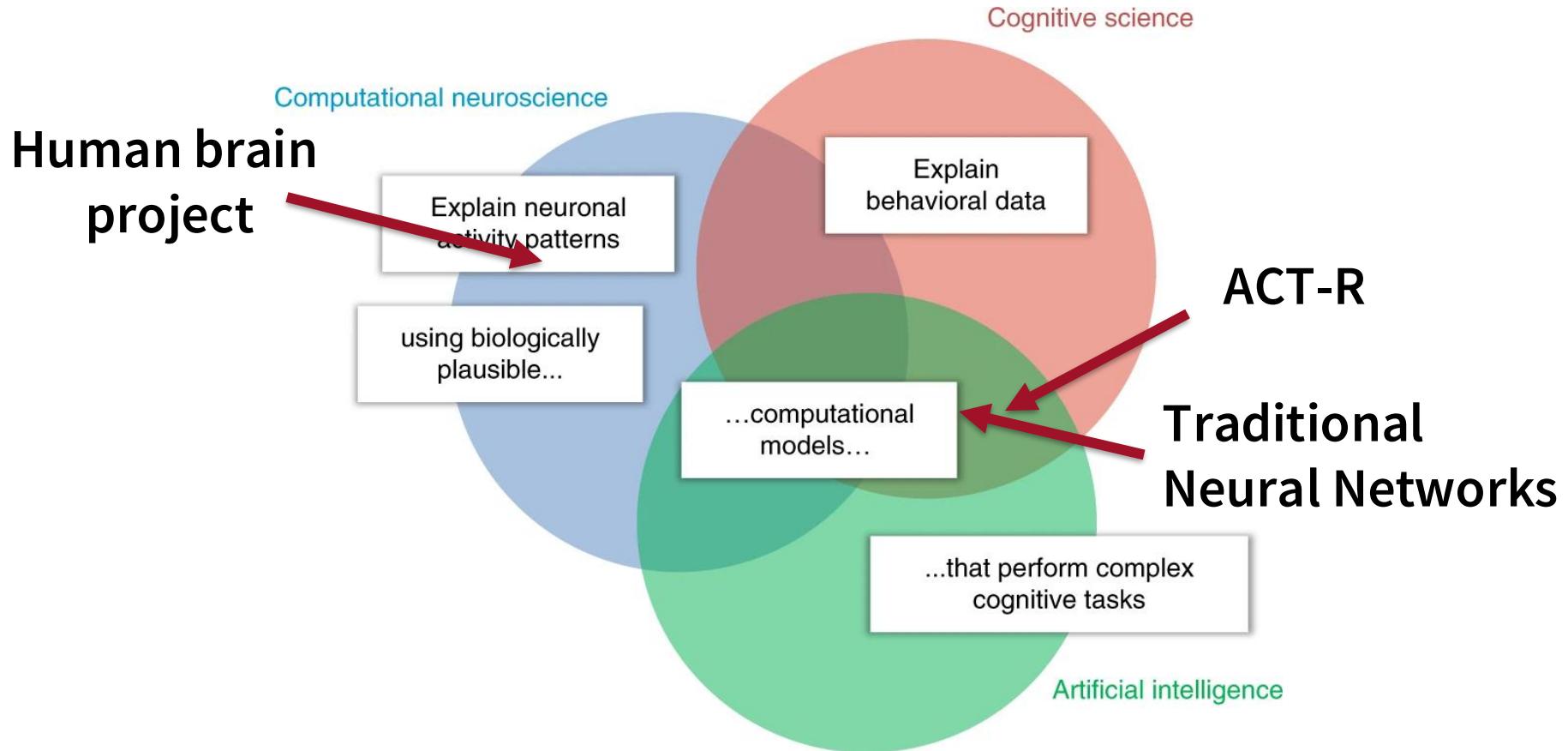
Cognitive Computational Neuroscience



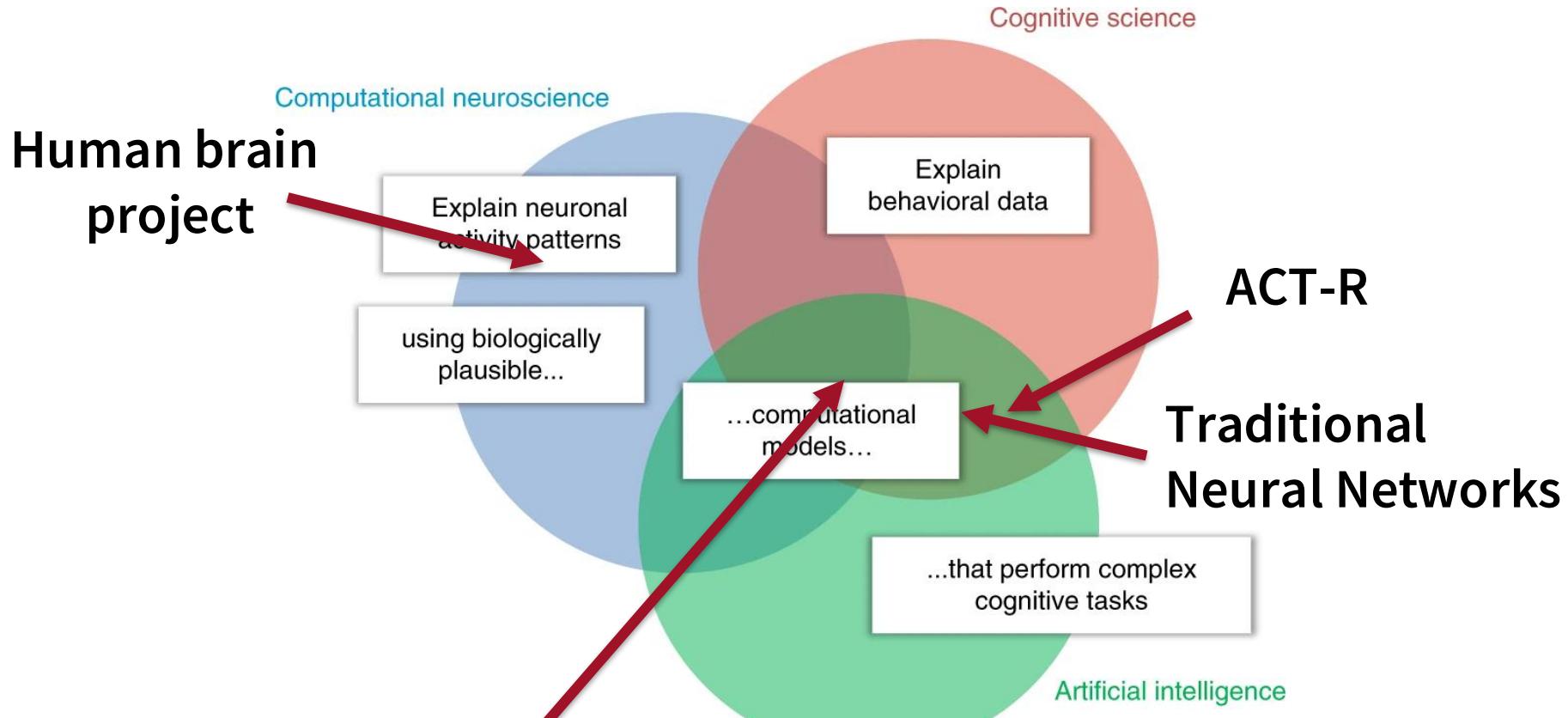
Cognitive Computational Neuroscience



Cognitive Computational Neuroscience



Cognitive Computational Neuroscience



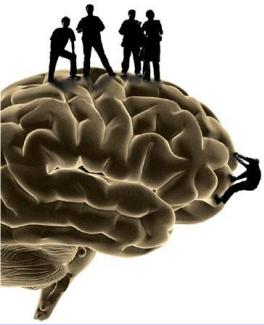
(Why) should we go to the neural level?

(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

(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

-



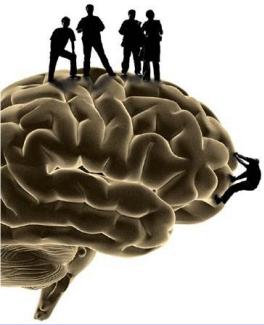
Advantage 1

More predictions

-



Terry Stewart



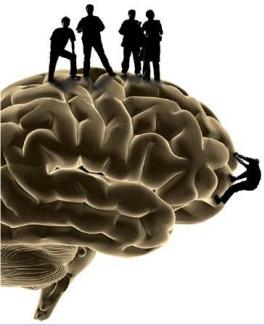
Advantage 1

More predictions

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



Terry Stewart



Advantage 1

More predictions

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



Terry Stewart

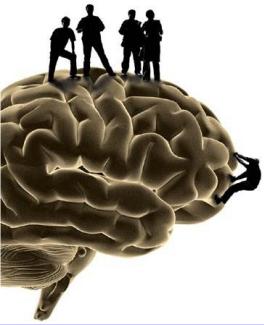
We can use those extra predictions to evaluate our models!



Advantage 2

Different algorithms

-
-
-



Advantage 2

Different algorithms

- Infinite numbers of algorithms to consider
-
-



Advantage 2

Different algorithms

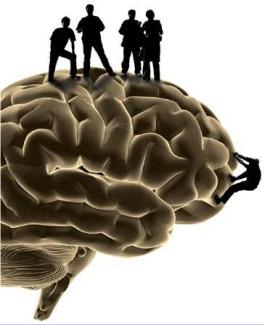
- Infinite numbers of algorithms to consider
- We implement algorithms on computers
-



Advantage 2

Different algorithms

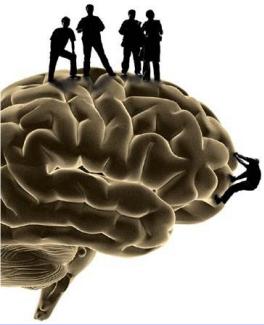
- Infinite numbers of algorithms to consider
- We implement algorithms on computers
 - So we are biased toward considering algorithms
that are easy to program
-



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



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)

(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

(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

(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:

Today

- Neural Networks I:
 - Spiking Neurons

Today

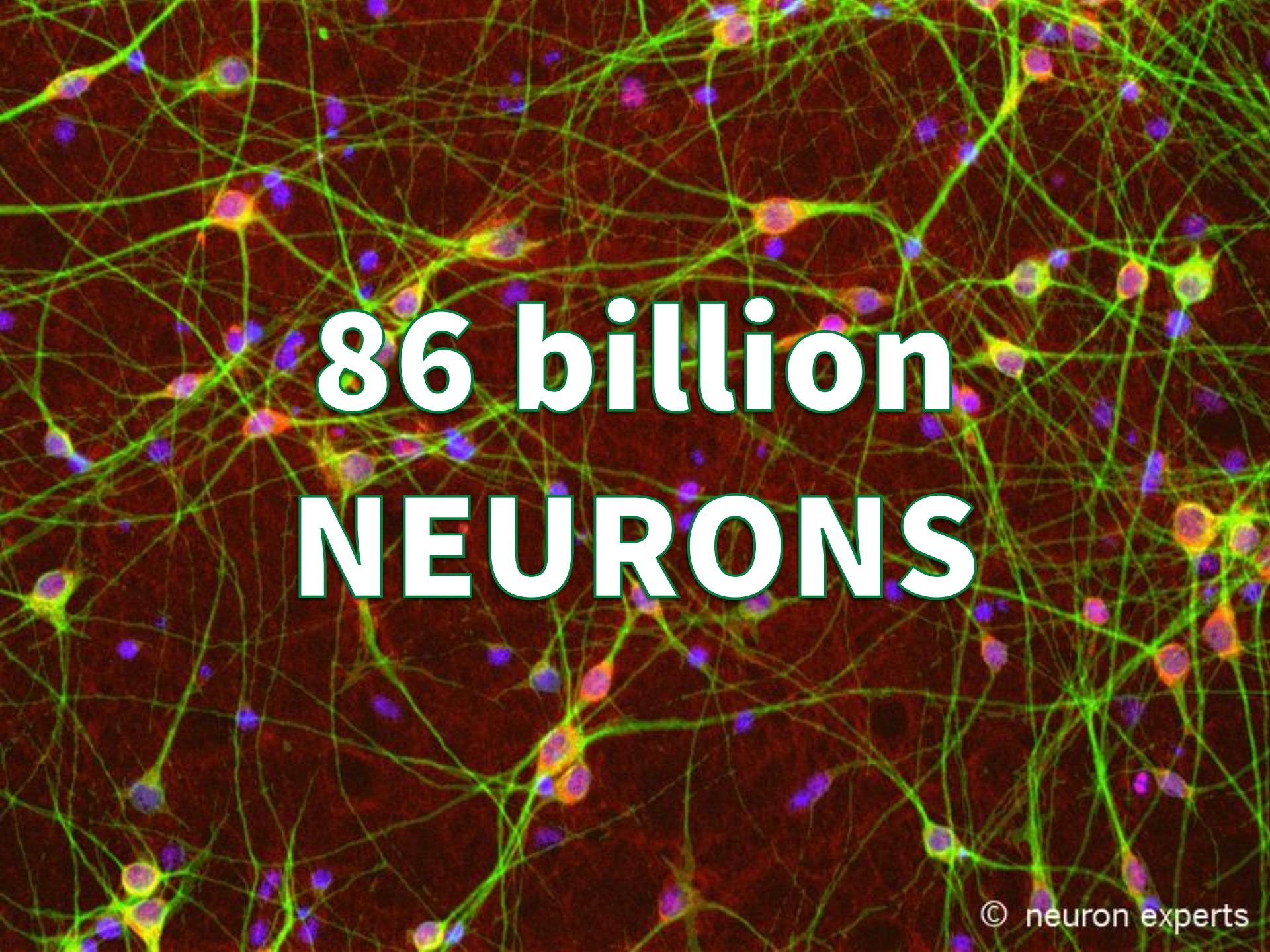
- Neural Networks I:
 - Spiking Neurons
 - How to build a brain: Nengo
 - Basics: representing values with spiking neurons

Today

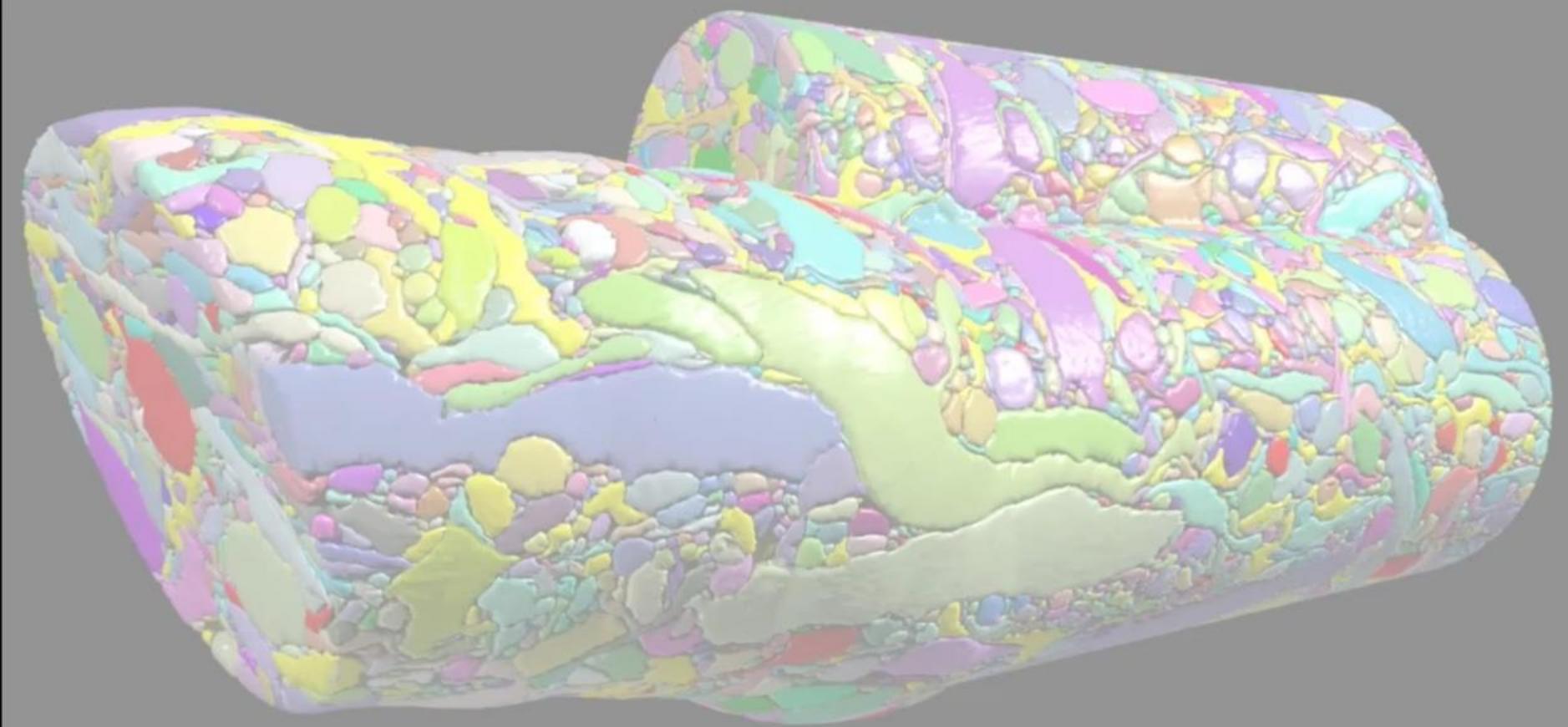
- Neural Networks I:
 - Spiking Neurons
 - How to build a brain: Nengo
 - Basics: representing values with spiking neurons
 - Spaun

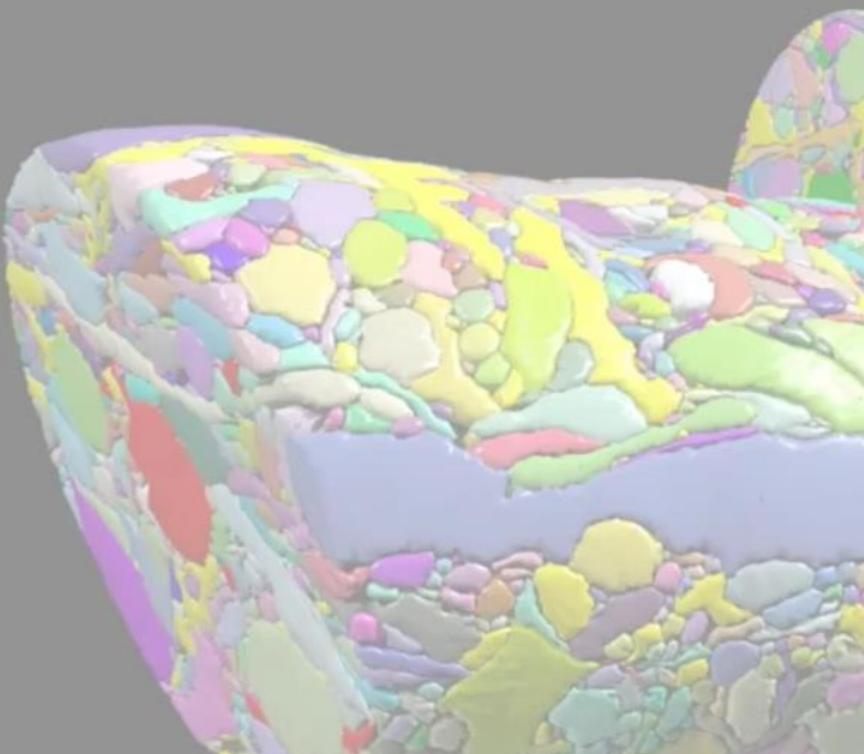


abp

A dense network of neurons, likely hippocampal neurons, stained with various markers. The cell bodies are primarily stained with a purple marker, while their long, branching processes are highlighted in bright green. Some neurons also exhibit orange staining, particularly in their soma or along their processes. The overall effect is a complex web of glowing green lines against a dark background.

**86 billion
NEURONS**





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,^{5,12} William Gray Roncal,^{3,13} Joshua Tzvi Vogelstein,^{7,14} Randal Burns,³ Daniel Lewis Sussman,⁴ Carey Elin Priebe,⁵ Hanspeter Pfister,³ and Jeff William Lichtman^{1,*}

¹Department of Molecular and Cellular Biology and Center for Brain Science, Harvard University, Cambridge, MA 02138, USA

²School of Engineering and Applied Sciences, Harvard University, Cambridge, MA 02138, USA

³Department of Computer Science, Johns Hopkins University, Baltimore, MD 21218-2128, USA

⁴Department of Statistics, Harvard University, Cambridge, MA 02138, USA

⁵Department of Applied Mathematics and Statistics, Johns Hopkins University, Baltimore, MD 21218-2682, USA

⁶Department of Brain and Cognitive Sciences, Massachusetts Institute of Technology, Cambridge, MA 02139, USA

⁷Department of Statistical Science and Neurobiology, Duke University, Durham, NC 27708, USA

⁸Present address: Department of Anatomy and Neurobiology, Boston University School of Medicine, Boston, MA 02118, USA

⁹Present address: Janeil Farm Research Campus, Ashburn, VA 20147, USA

¹⁰Present address: Department of Computer Science, Stanford University, Stanford, CA 94305, USA

¹¹Present address: Department of Neuroscience, Columbia University, New York, NY 10032, USA

¹²Present address: Princeton Neuroscience Institute and Department of Computer Science, Princeton University, Princeton, NJ 08544, USA

¹³Present address: Johns Hopkins University Applied Physics Laboratory, Laurel, MD 20723, USA

¹⁴Present address: Department of Biomedical Engineering and the Institute for Computational Medicine, Johns Hopkins University, Baltimore, MD 21218-2682, USA

*Correspondence: bobby.kasthuri@gmail.com (N.K.), jeff@mcb.harvard.edu (J.W.L.)

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 apparatus, 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). The database provides general access to the complexity of the neocortex for data-driven inquiries.

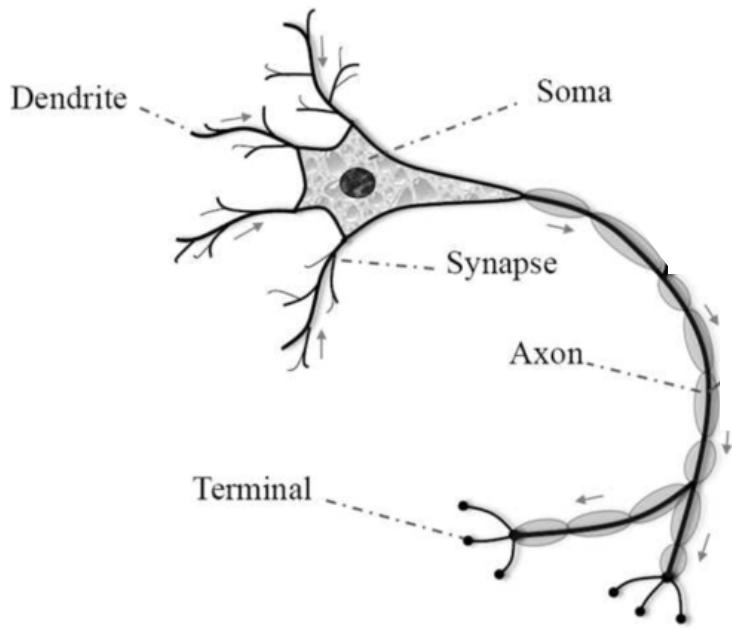
brain's many cellular components are not known. Several laboratories are now beginning to generate such data in mammals using electron microscopy (EM). This work has provided new insights into the visual system (Anderson et al., 2011; Helmstaedter et al., 2011; Kim et al., 2014; Briggman et al., 2011; 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 ($1,500 \mu\text{m}^3$) 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.

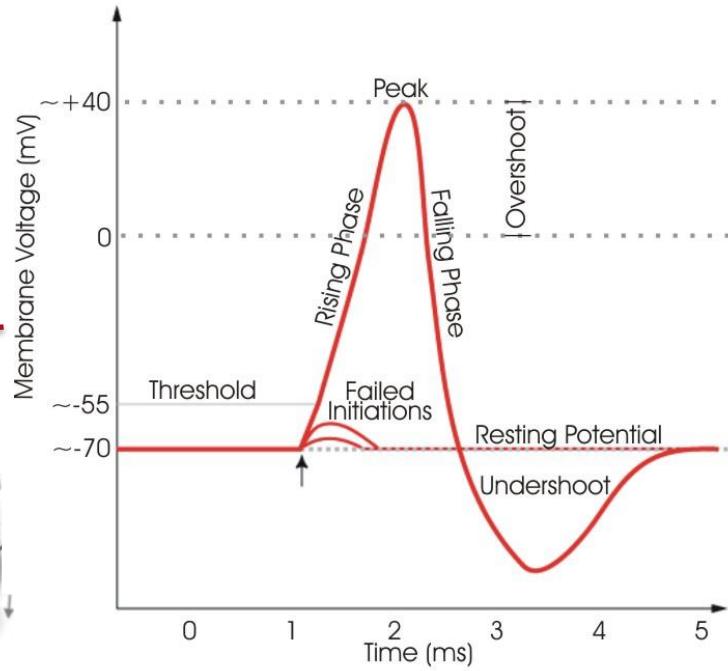
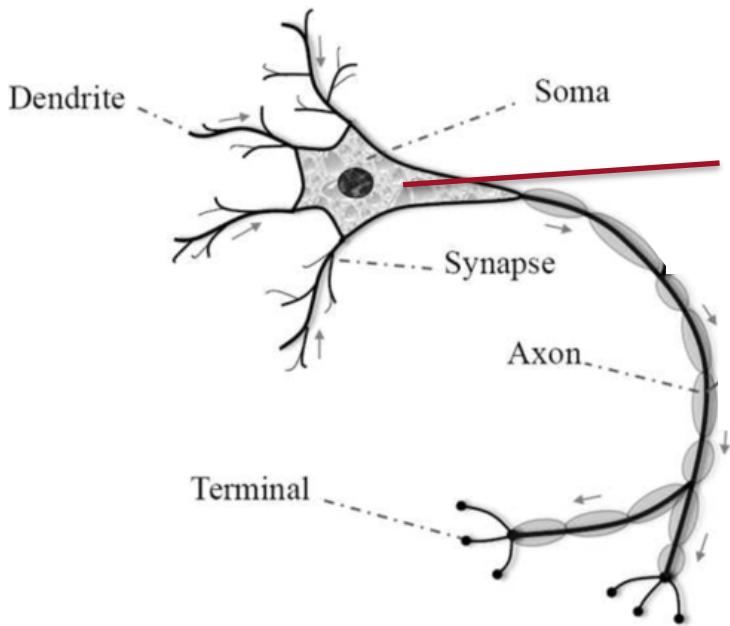
Previous connectomic studies of retina and hippocampus concluded that connectivity was not entirely predictable from the proximity of presynaptic elements to postsynaptic targets (Briggman et al., 2011; Mishchenko et al., 2010; Helmstaedter

a 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

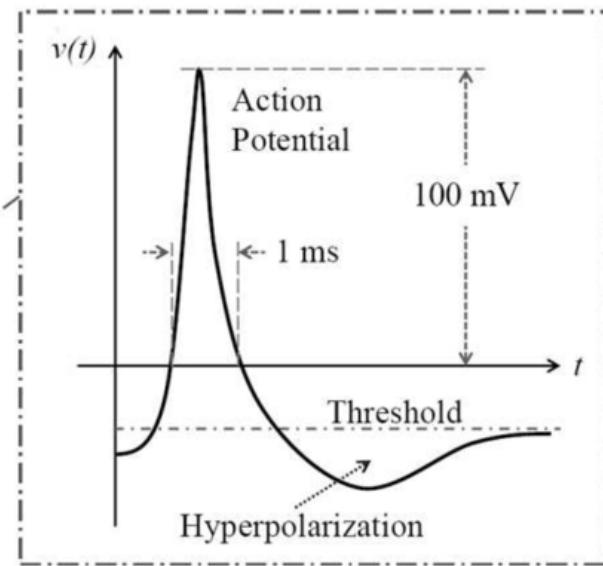
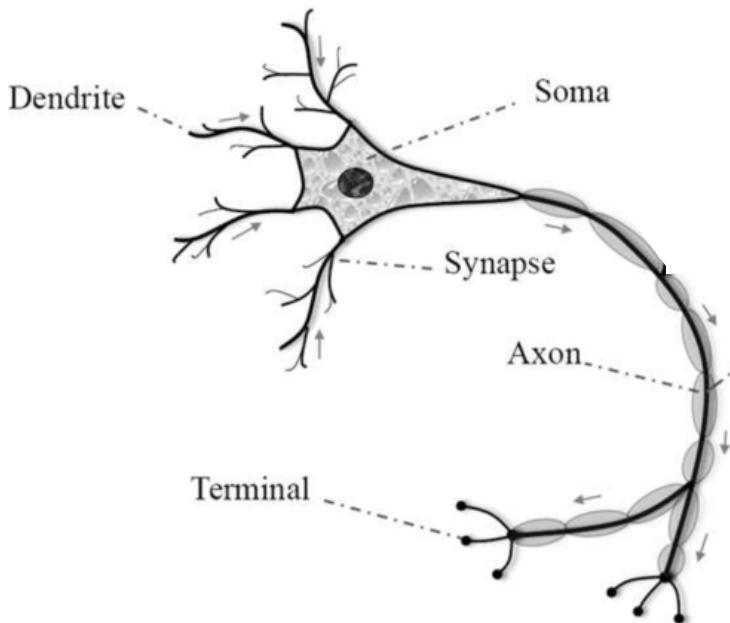
Spiking Neurons



Spiking Neurons

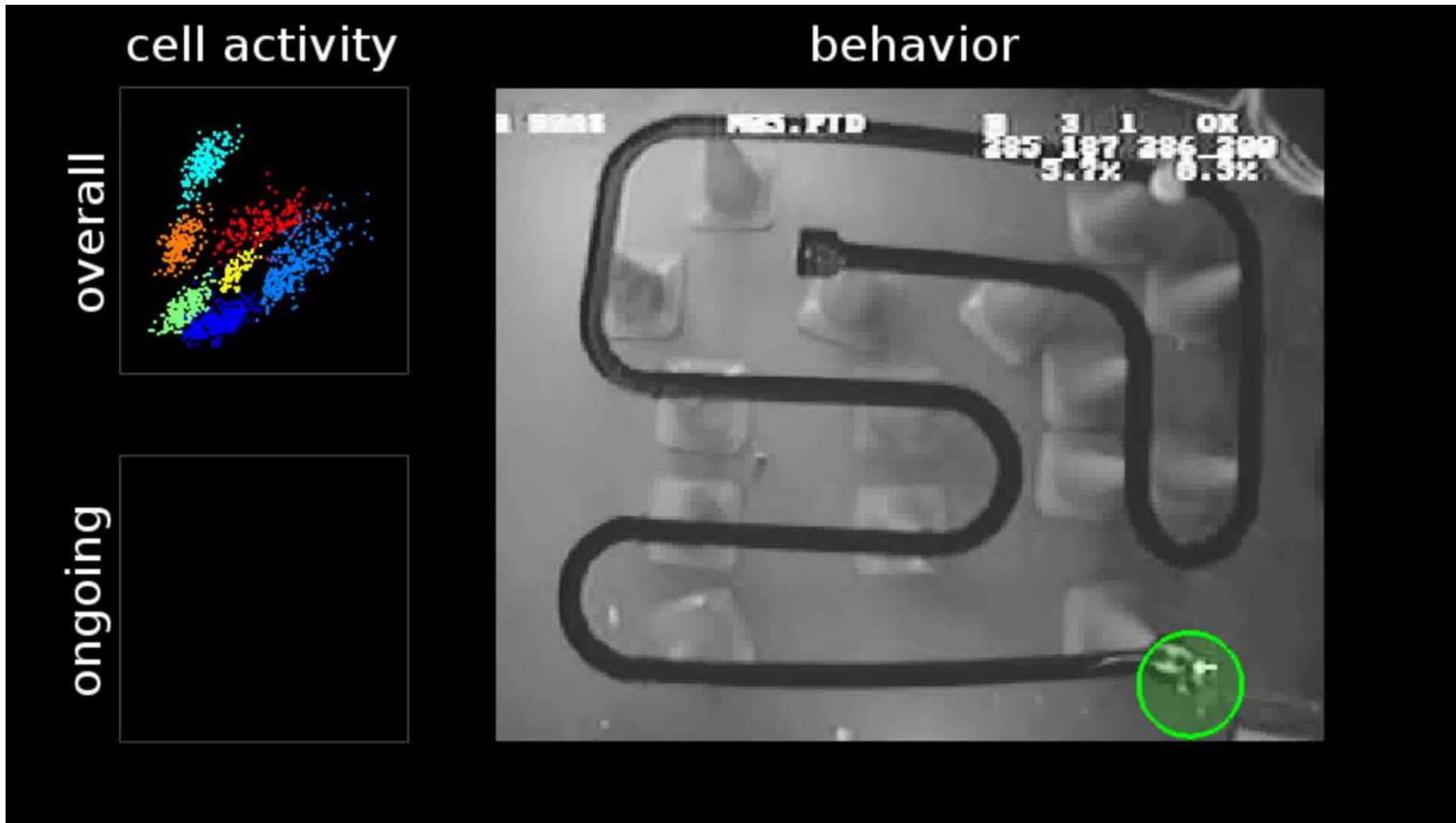


Spiking Neurons

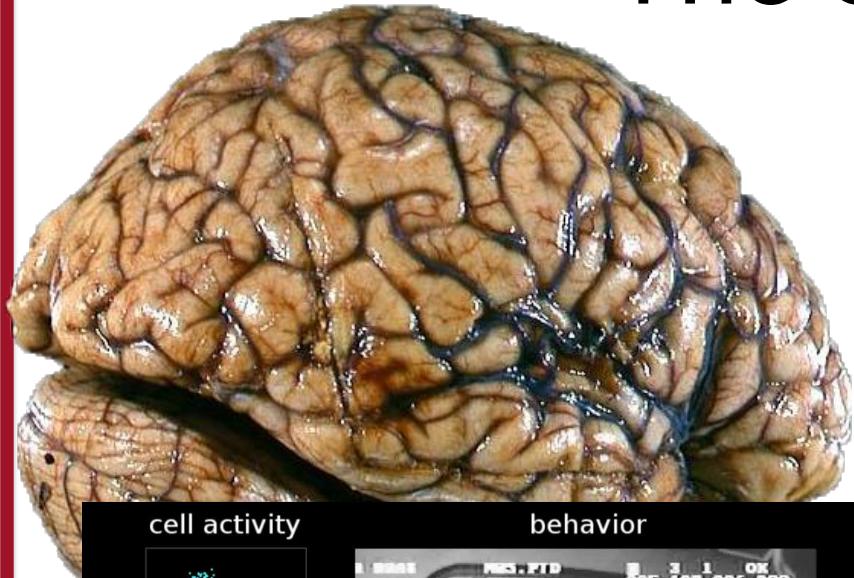


Spiking Neurons

Spiking Neurons

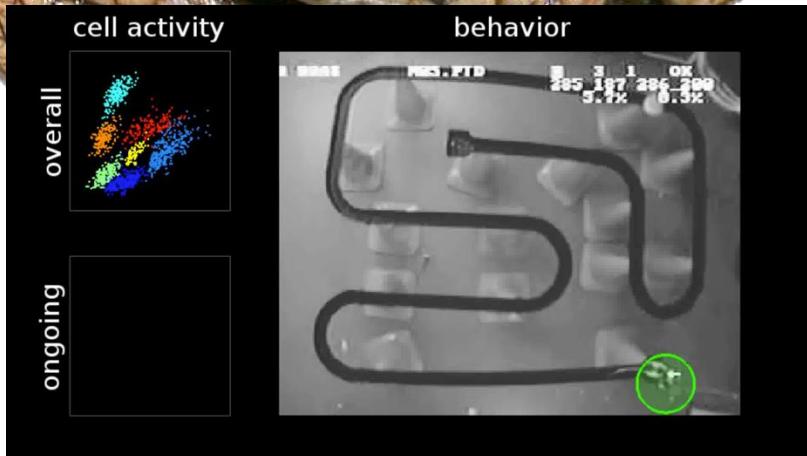
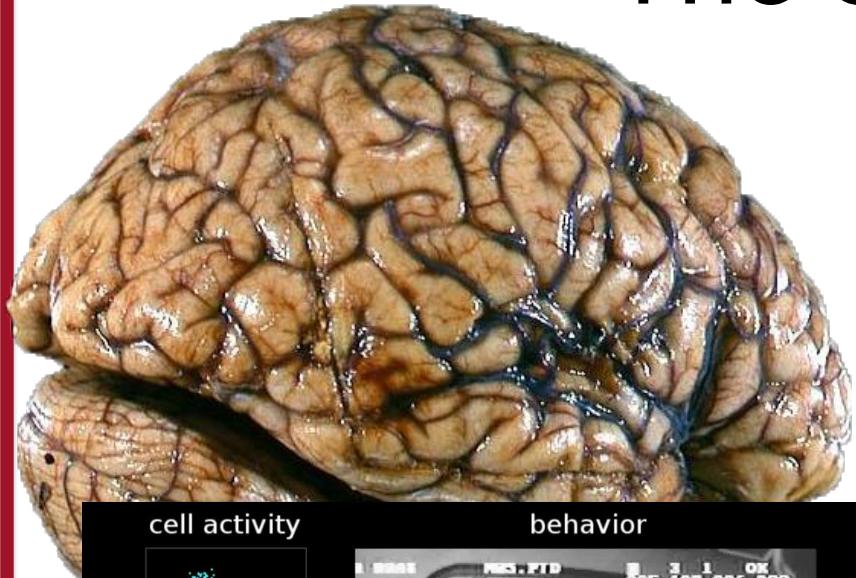


The Challenge



86 billion spiking
neurons

The Challenge



Higher-level
cognitive functions

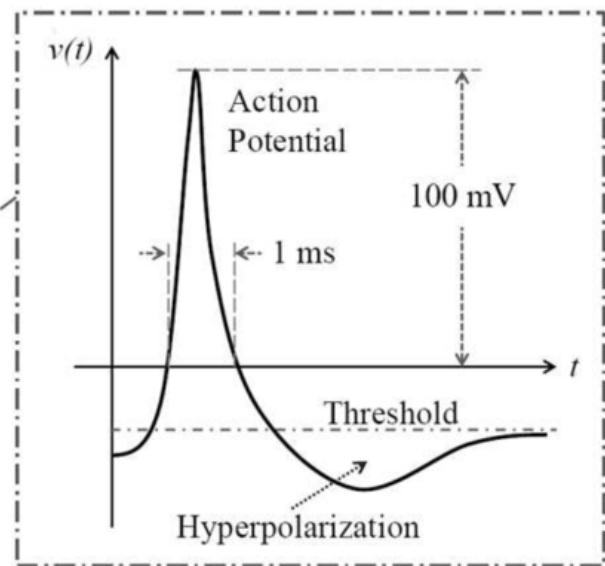
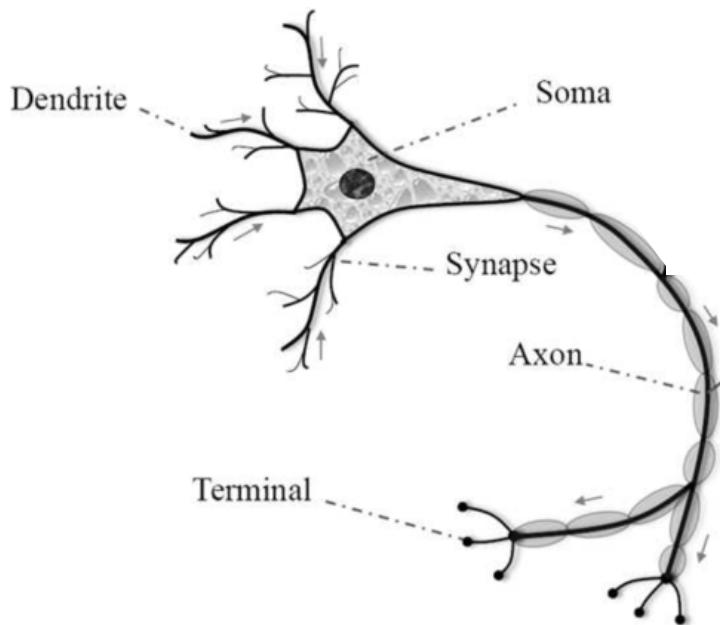
A handwritten mathematical equation on a grid-lined notebook page. The equation is:

$$\frac{(x-1)}{6} = \frac{(x+5)}{5} = -50$$

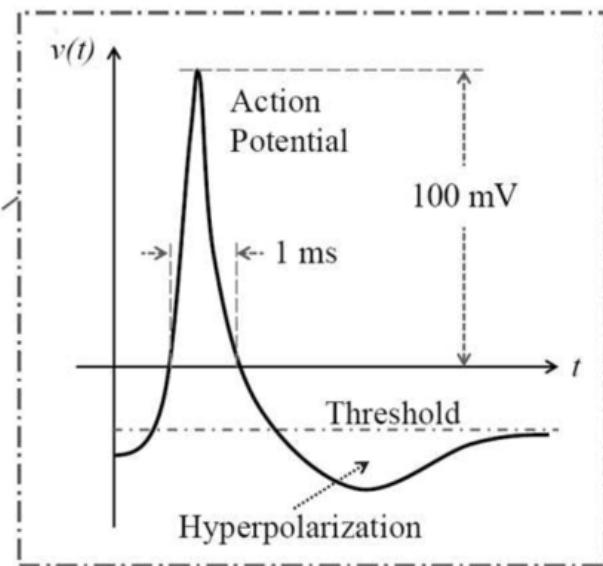
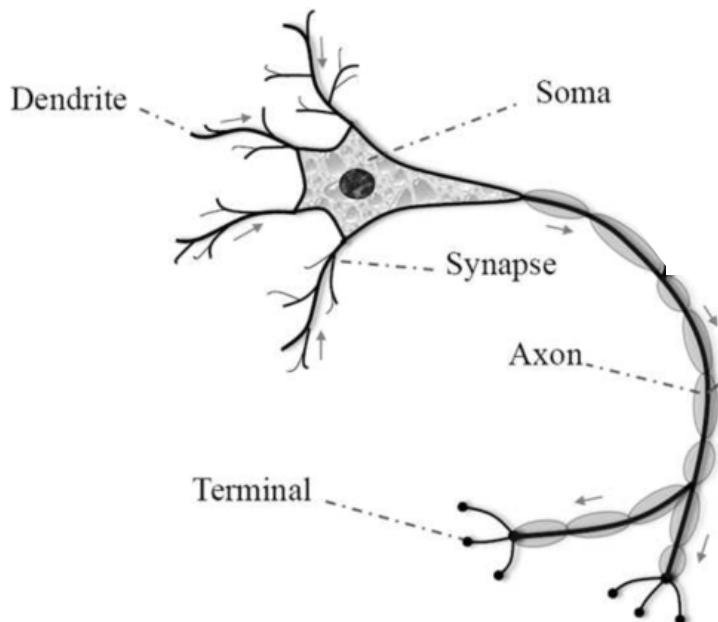
Below the equation, there is additional handwritten text: $+32 = 0$.

86 billion spiking
neurons

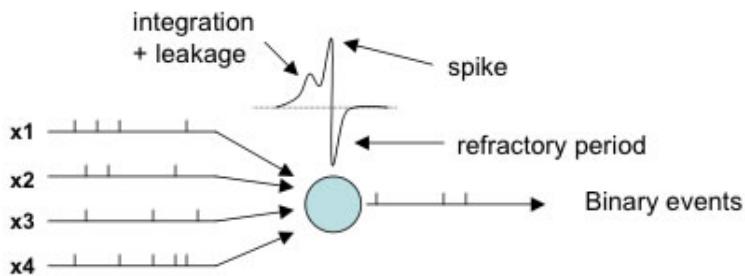
Spiking Neurons



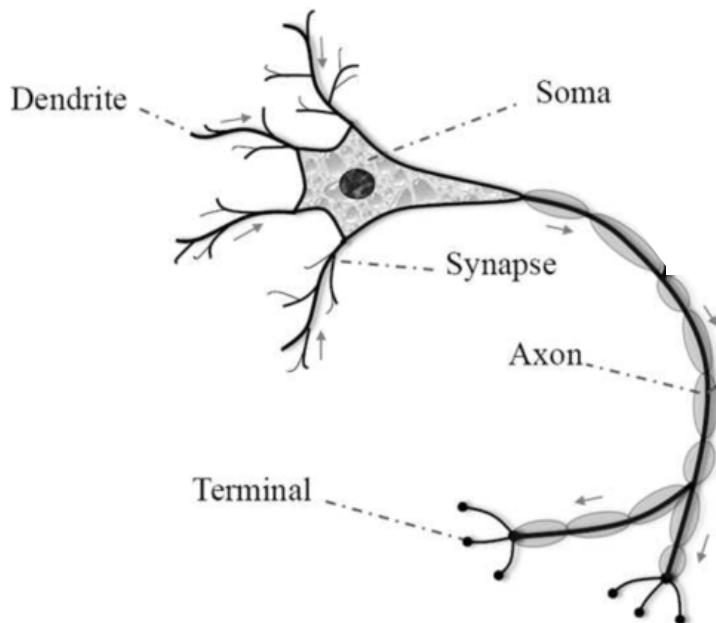
Spiking Neurons



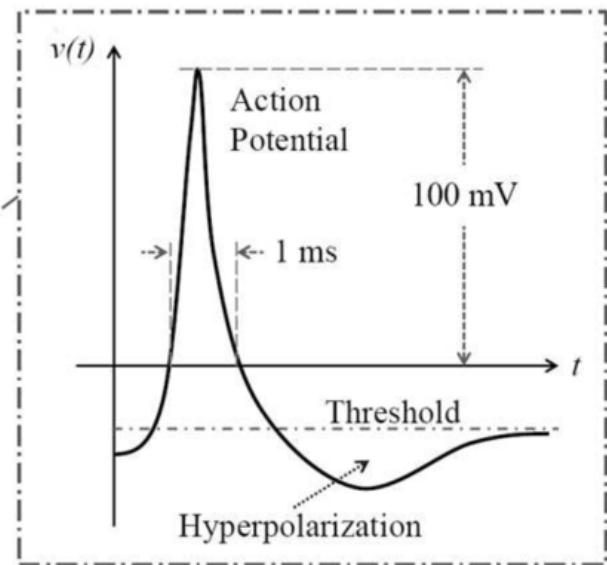
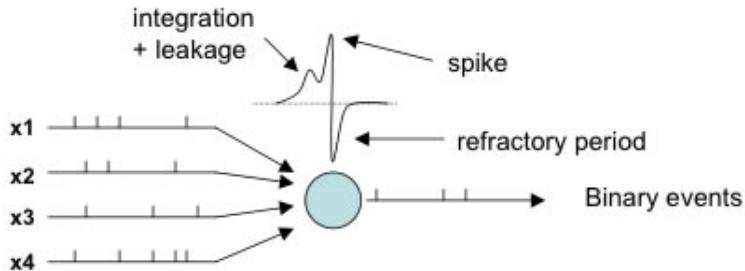
Spiking artificial neurons



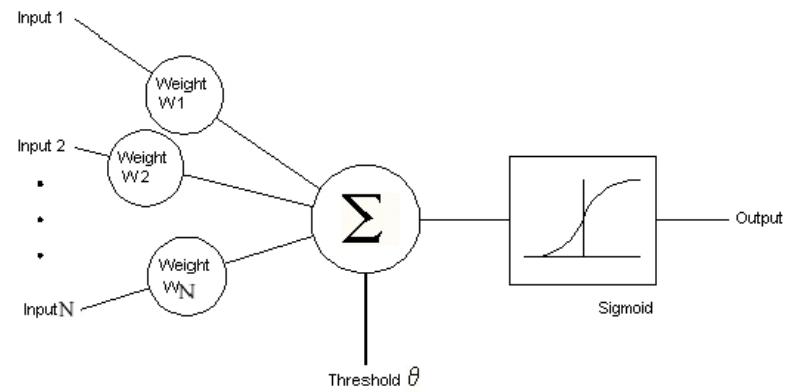
Spiking Neurons



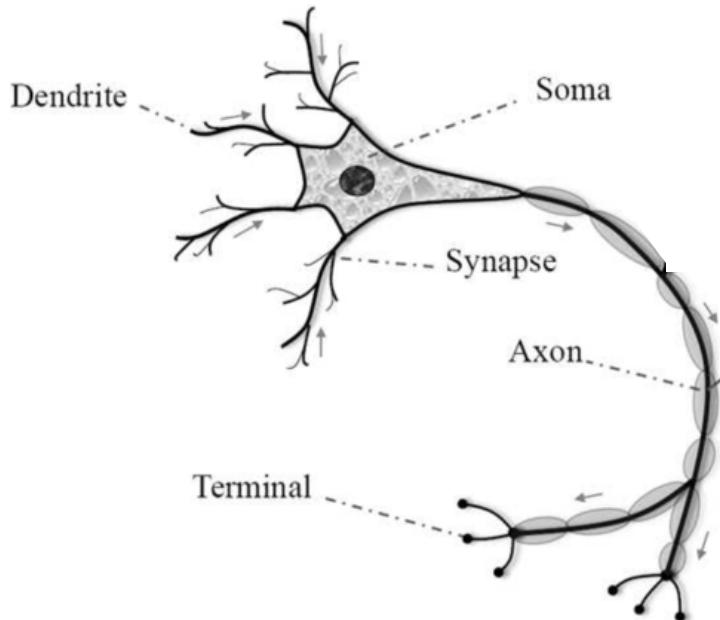
Spiking artificial neurons



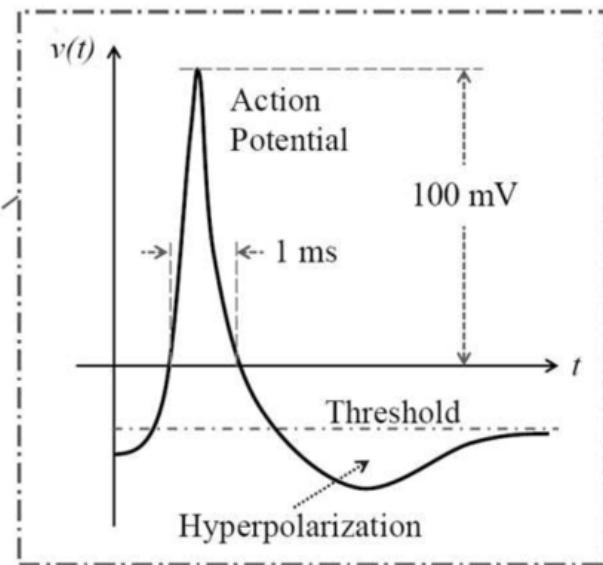
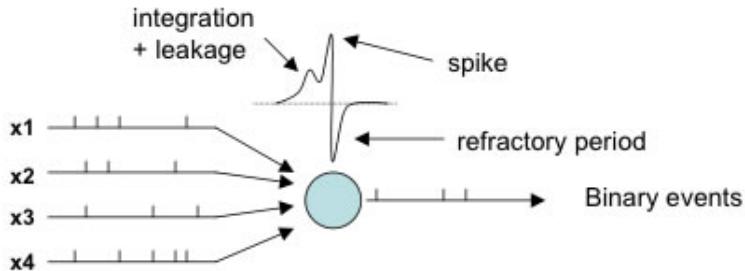
Traditional artificial neurons



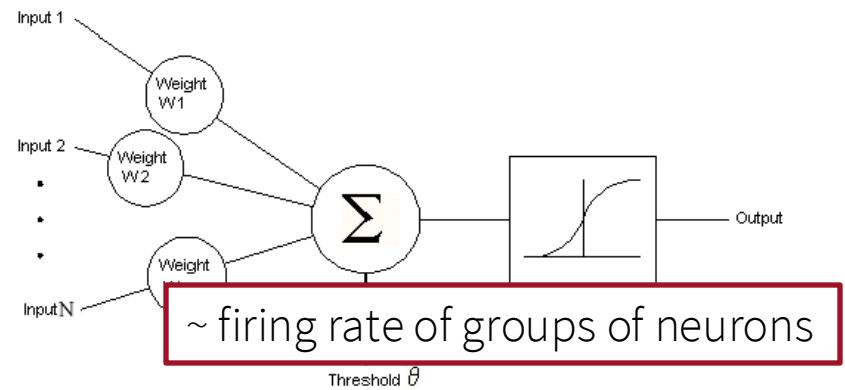
Spiking Neurons



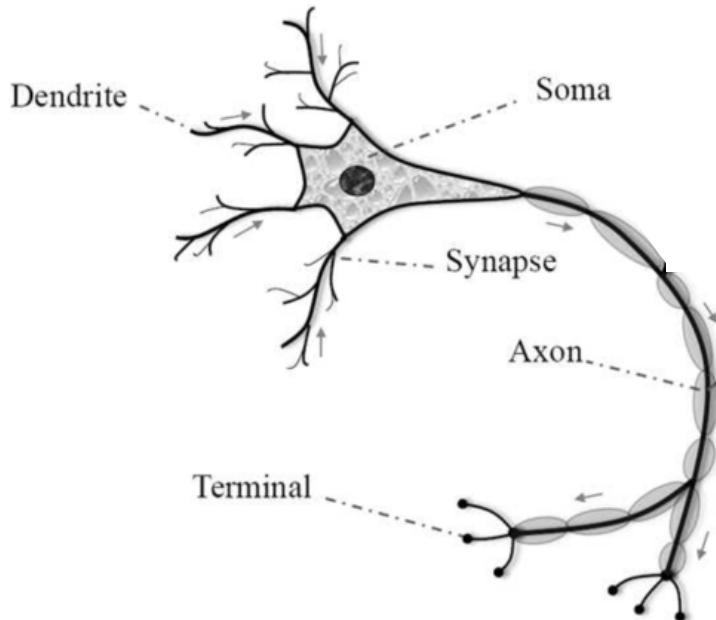
Spiking artificial neurons



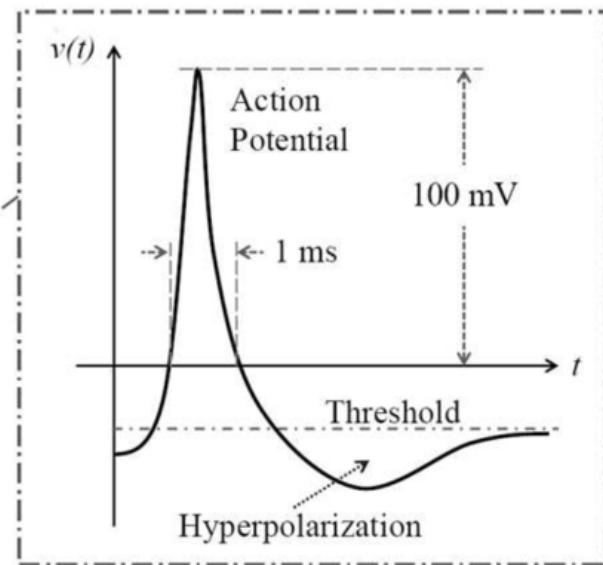
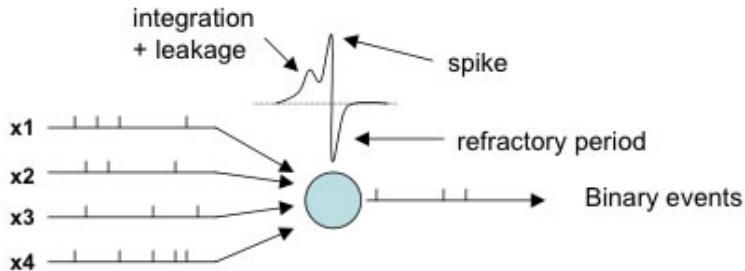
Traditional artificial neurons



Spiking Neurons



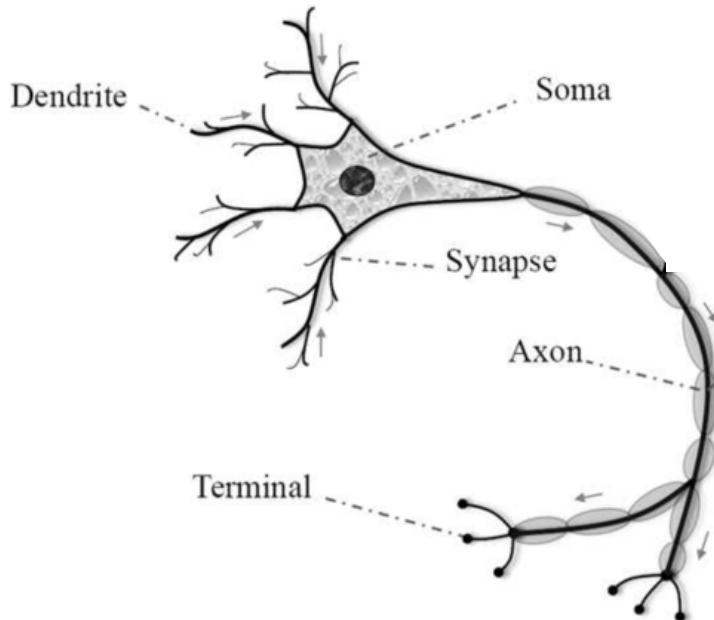
Spiking artificial neurons



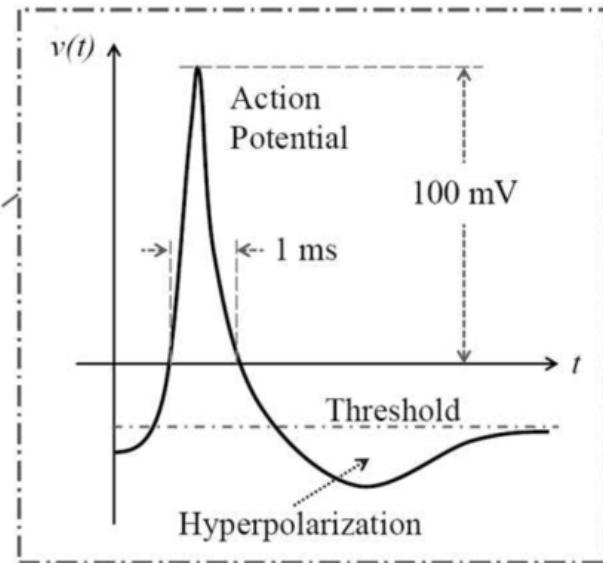
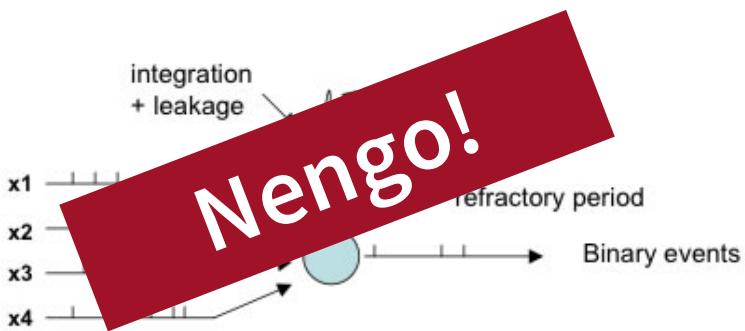
Traditional artificial neurons



Spiking Neurons



Spiking artificial neurons



Traditional artificial neurons



Challenges for (Spiking) Neurons

Challenges for (Spiking) Neurons

- How to represent values (information)?

Challenges for (Spiking) Neurons

- How to represent values (information)?
- How to communicate values?

Challenges for (Spiking) Neurons

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

Challenges for (Spiking) Neurons

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

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?

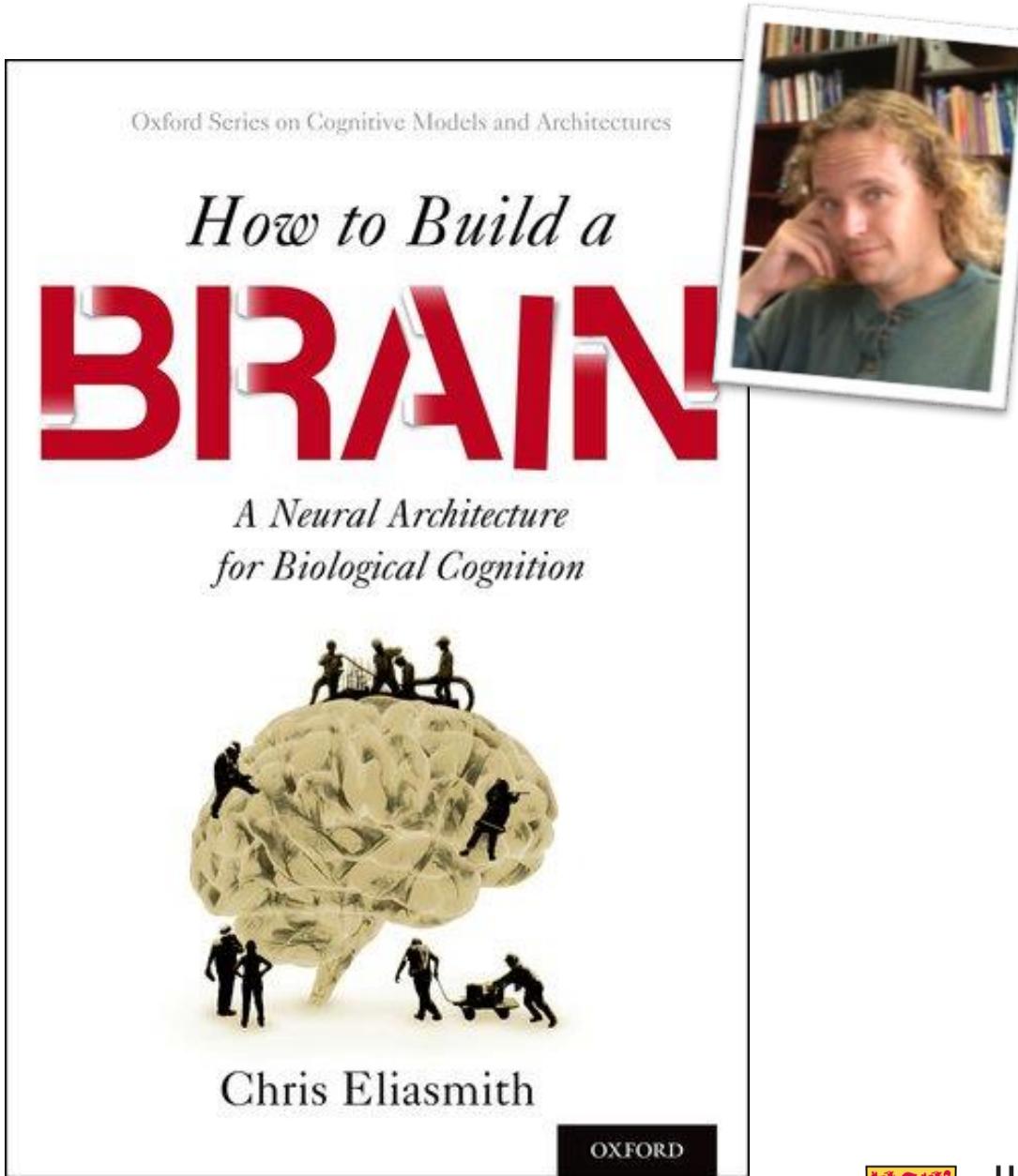
Challenges for (Spiking) Neurons

- 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?

Today

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

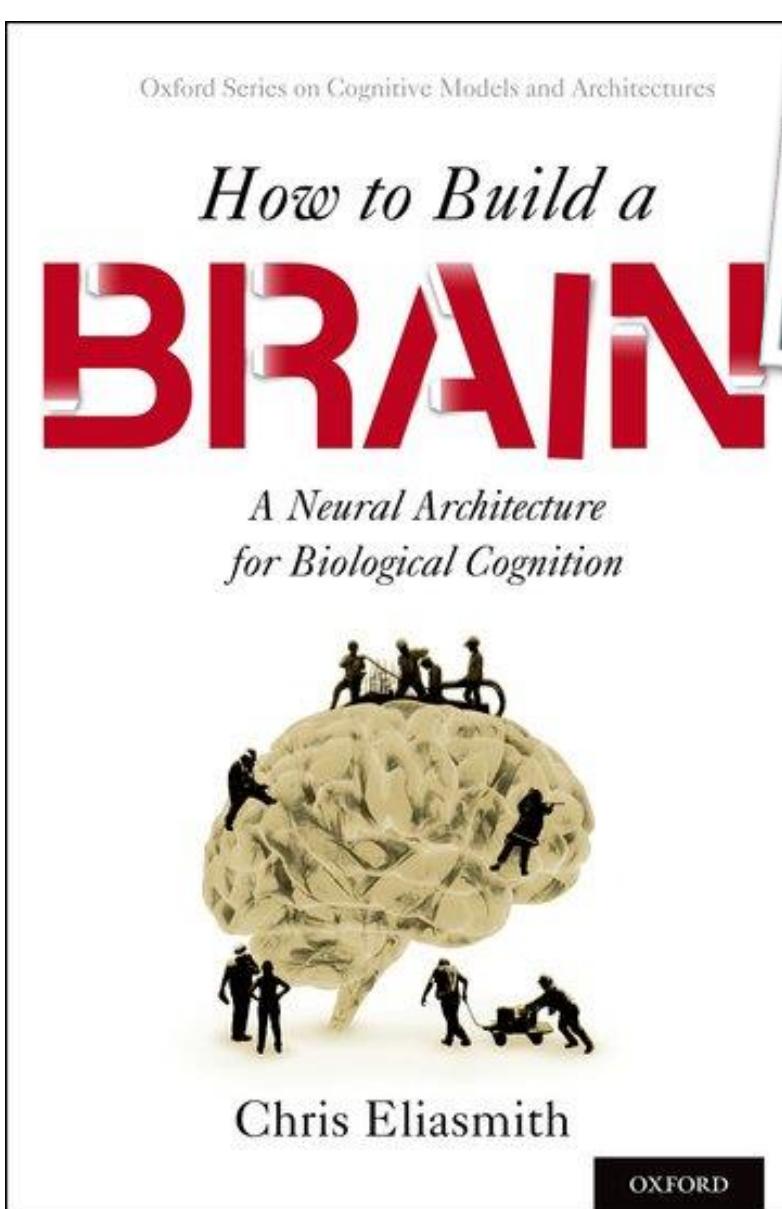
Nengo Architecture



<https://www.nengo.ai>



Nengo Architecture



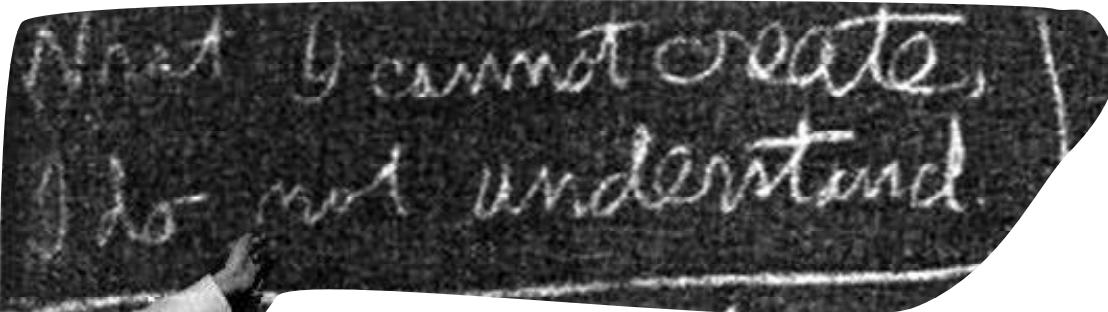
<https://www.nengo.ai>



Terry Stewart



UNIVERSITY OF
WATERLOO



large-scale
complete behaviour

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

Challenges for (Spiking) Neurons

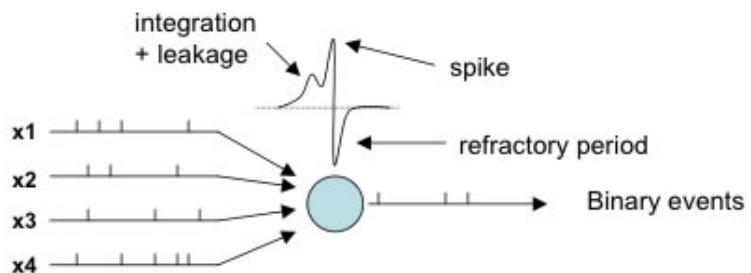
- How to represent values?
- How to communicate values?
- How can we store values?

Challenges for (Spiking) Neurons

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

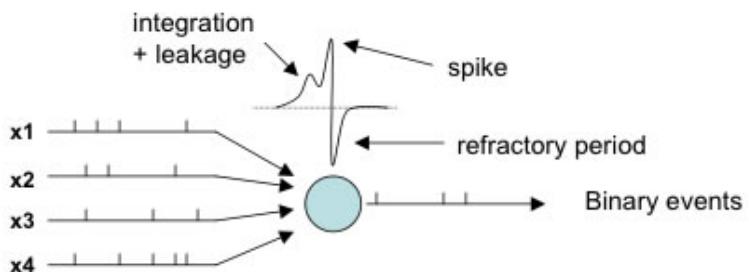
How can we represent values?

Leaky Integrate-and-Fire Neuron



How can we represent values?

Leaky Integrate-and-Fire Neuron

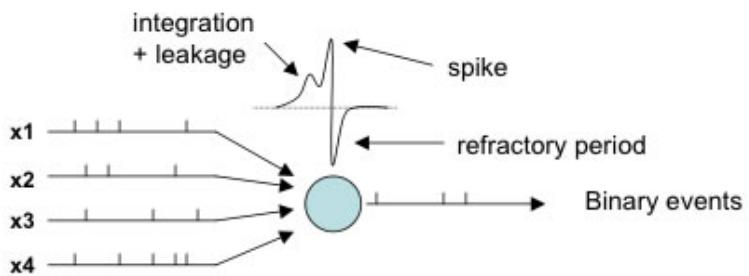


Other (more complex) options:

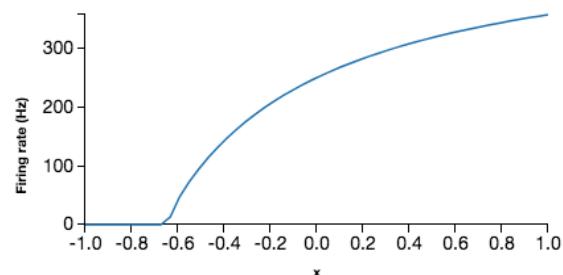
- Adaptive LIF
- Izhikevich
- Hodgkin-Huxley
(not in default nengo)

How can we represent values?

Leaky Integrate-and-Fire Neuron



Tuning Curve

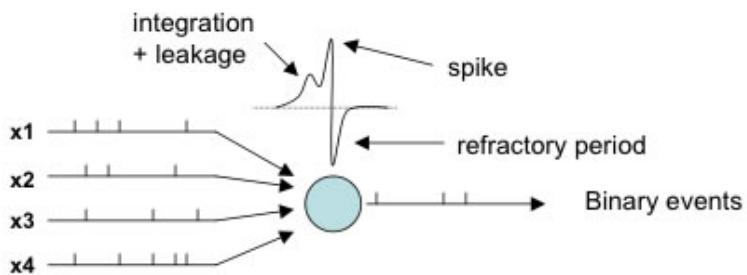


Other (more complex) options:

- Adaptive LIF
- Izhikevich
- Hodgkin-Huxley
(not in default nengo)

How can we represent values?

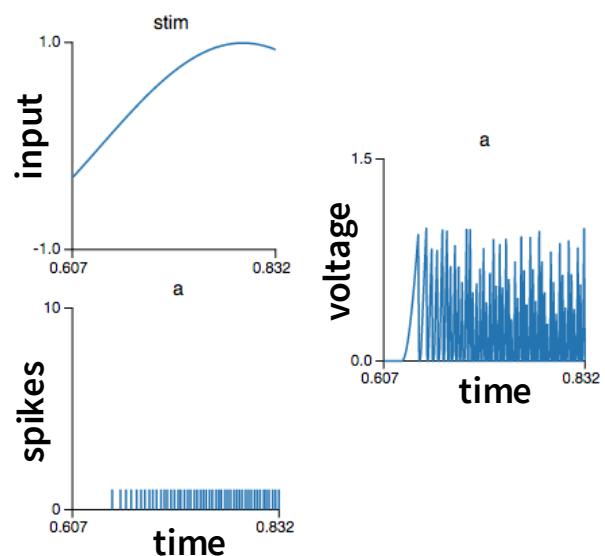
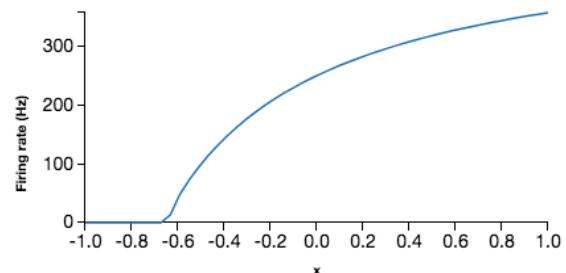
Leaky Integrate-and-Fire Neuron



Other (more complex) options:

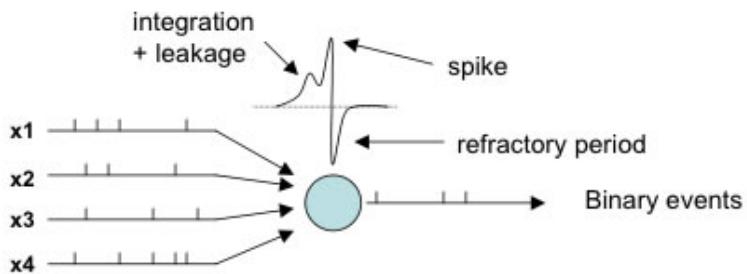
- Adaptive LIF
- Izhikevich
- Hodgkin-Huxley
(not in default nengo)

Tuning Curve



How can we represent values?

Leaky Integrate-and-Fire Neuron

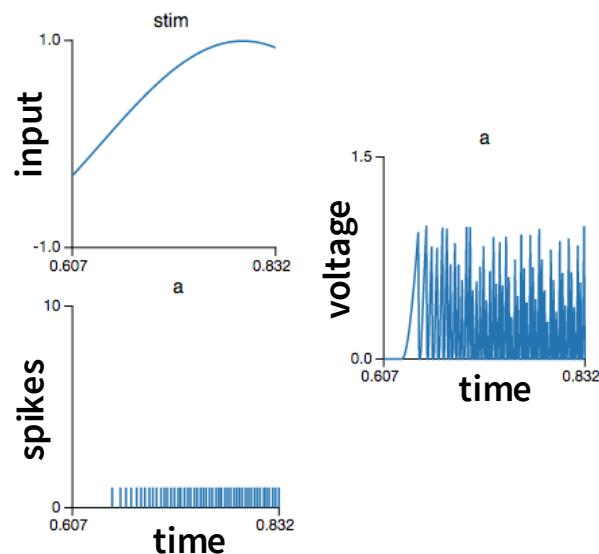
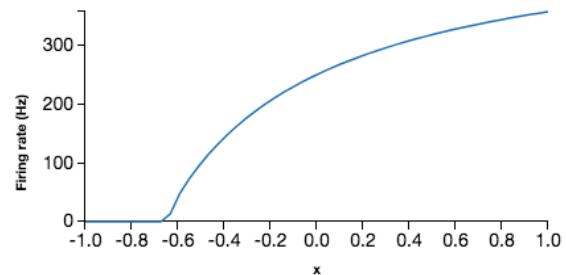


Other (more complex) options:

- Adaptive LIF
- Izhikevich
- Hodgkin-Huxley
(not in default nengo)

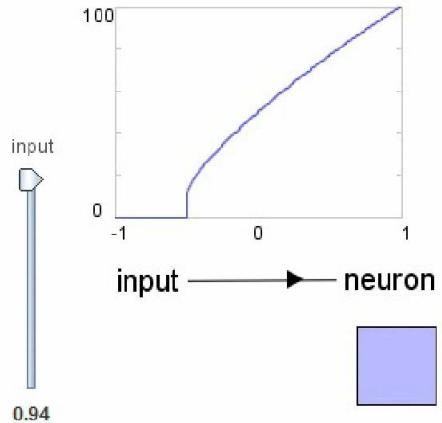
What is the problem of representing an input value this way?

Tuning Curve

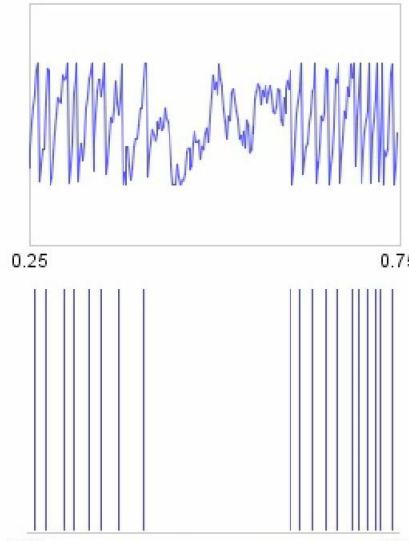
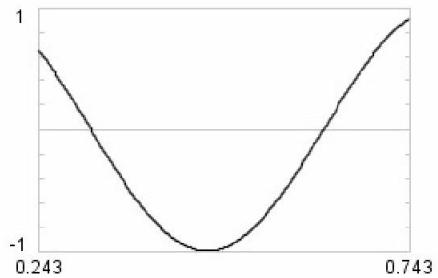


Single Neuron

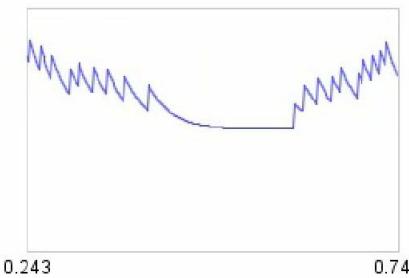
Tuning Curve



input



internal
membrane
voltage

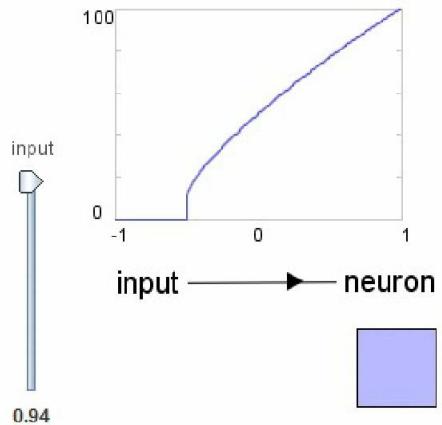


post-synaptic
current

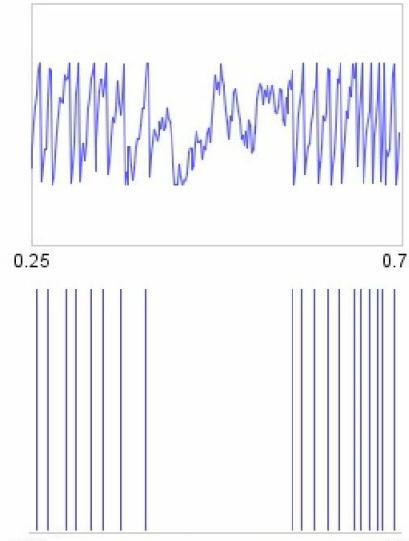
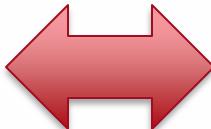
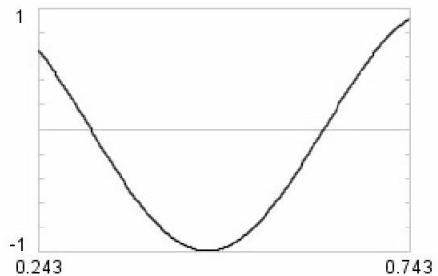
↑
Output

Single Neuron

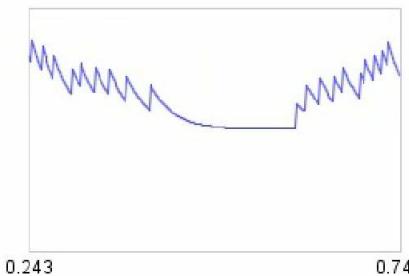
Tuning Curve



input



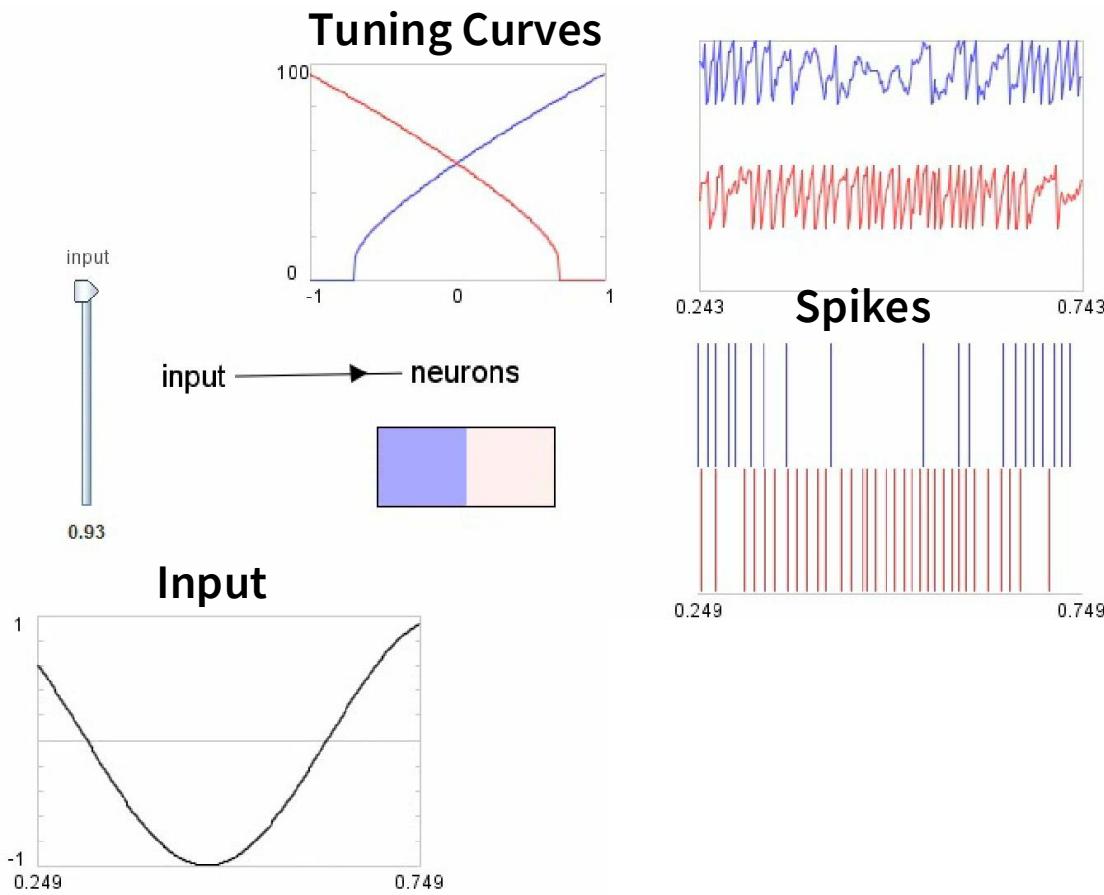
internal
membrane
voltage



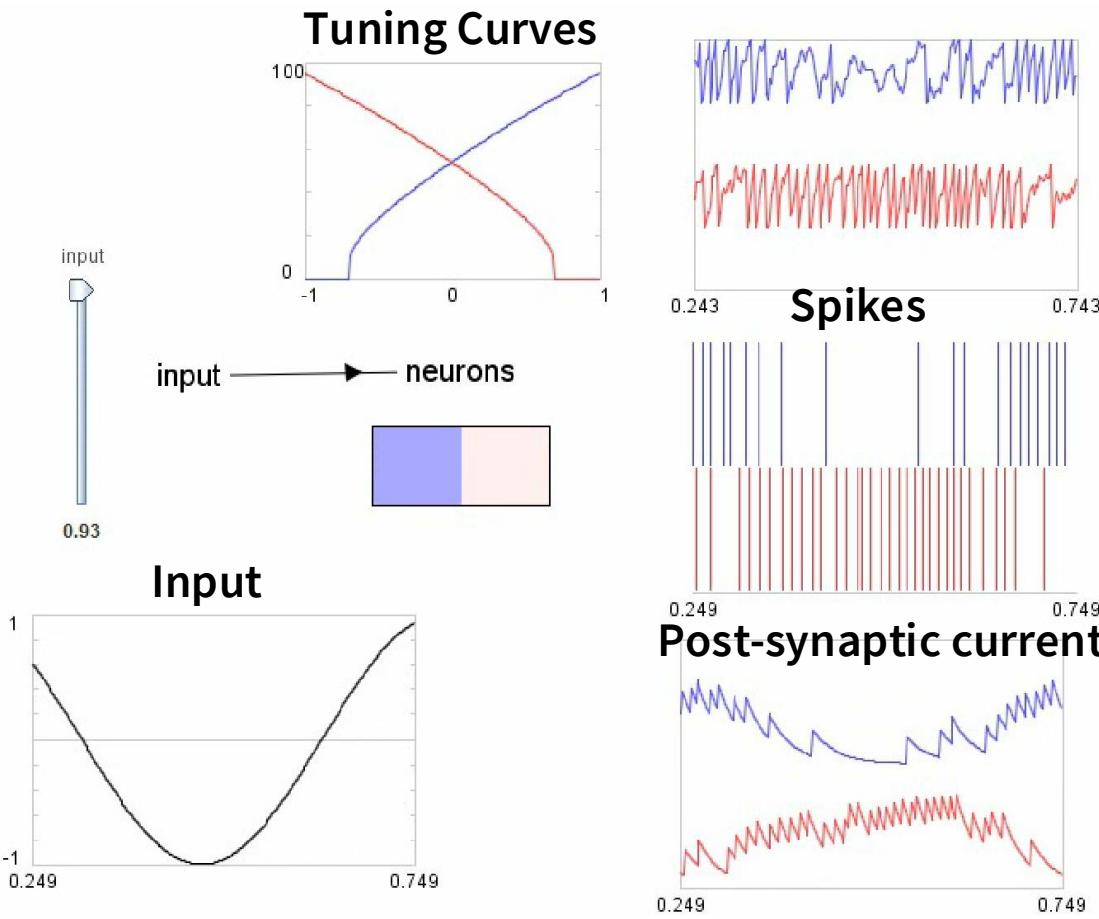
spike
output

Output

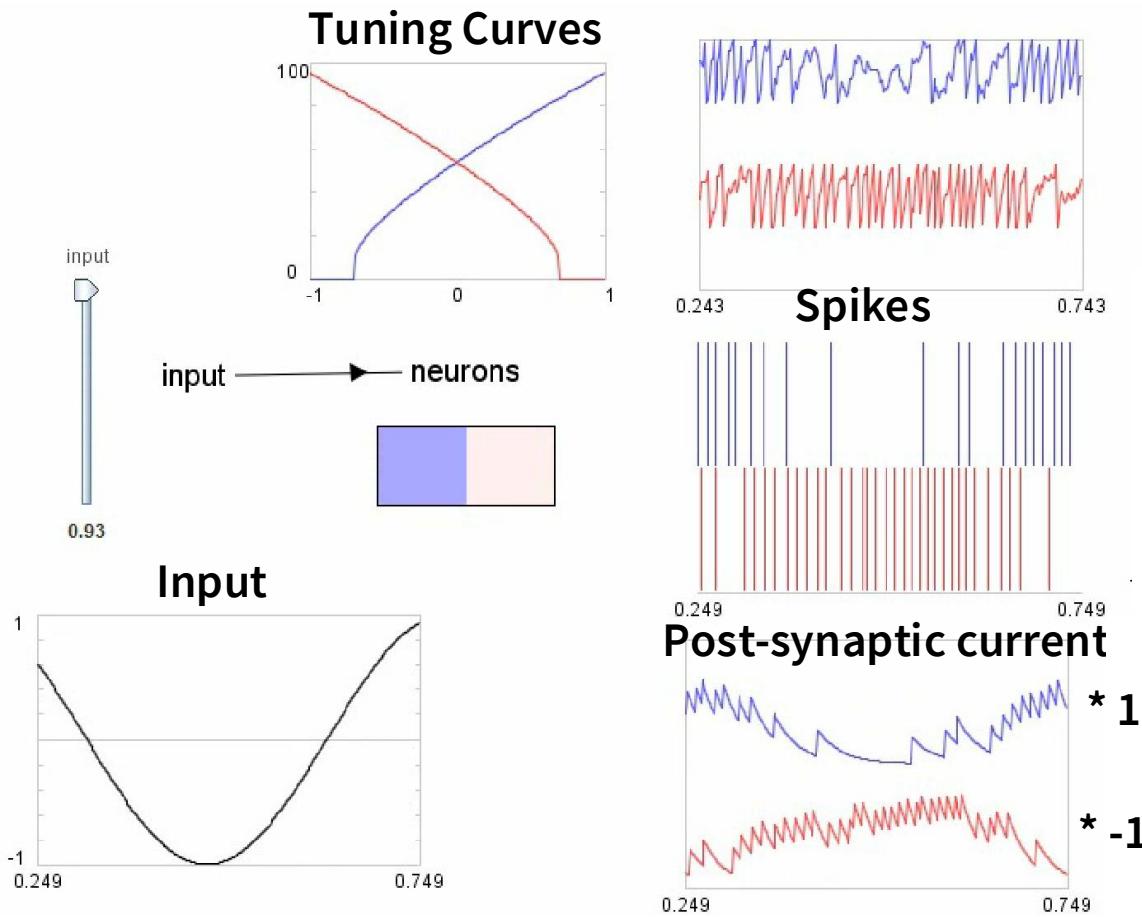
Two Neurons



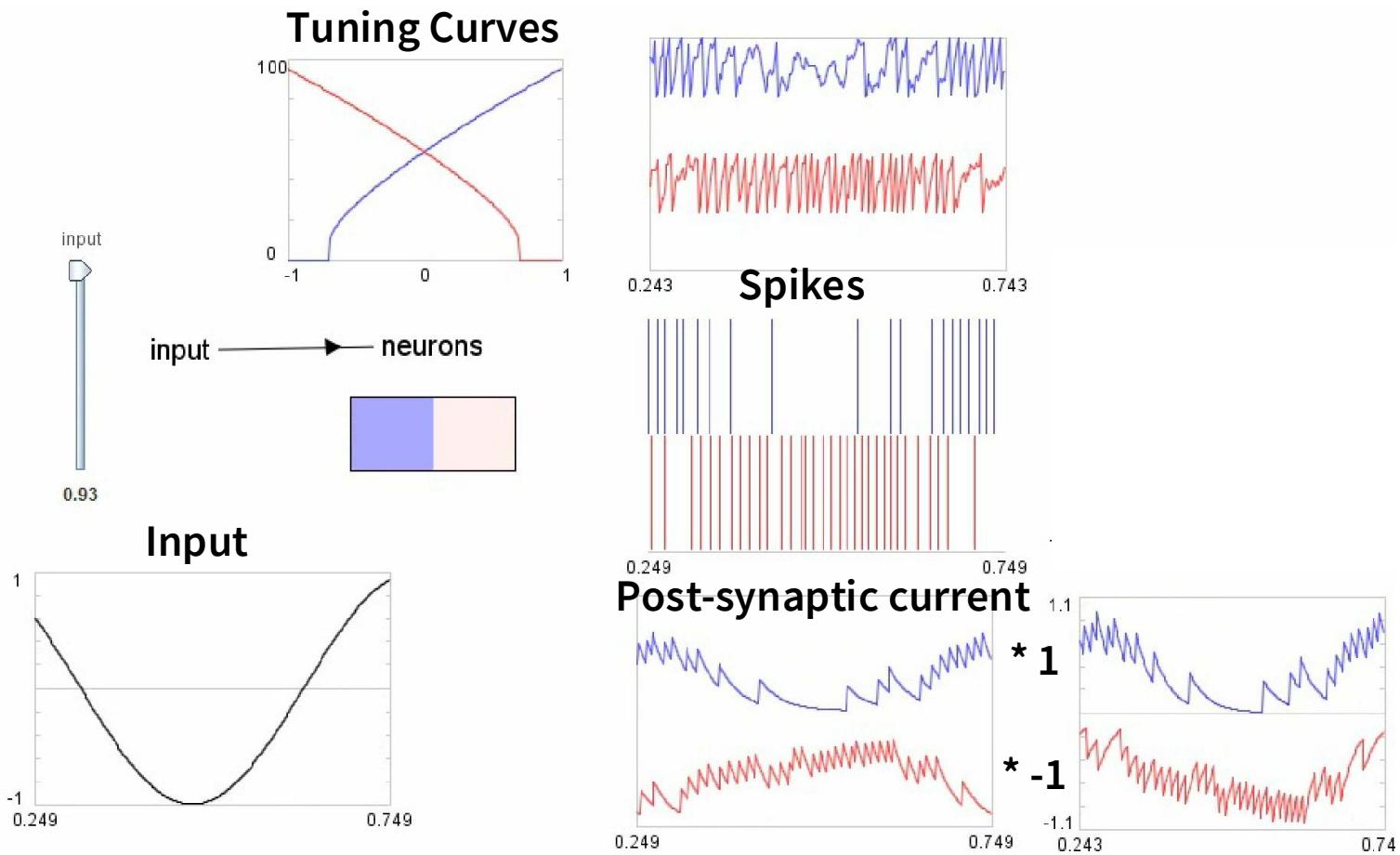
Two Neurons



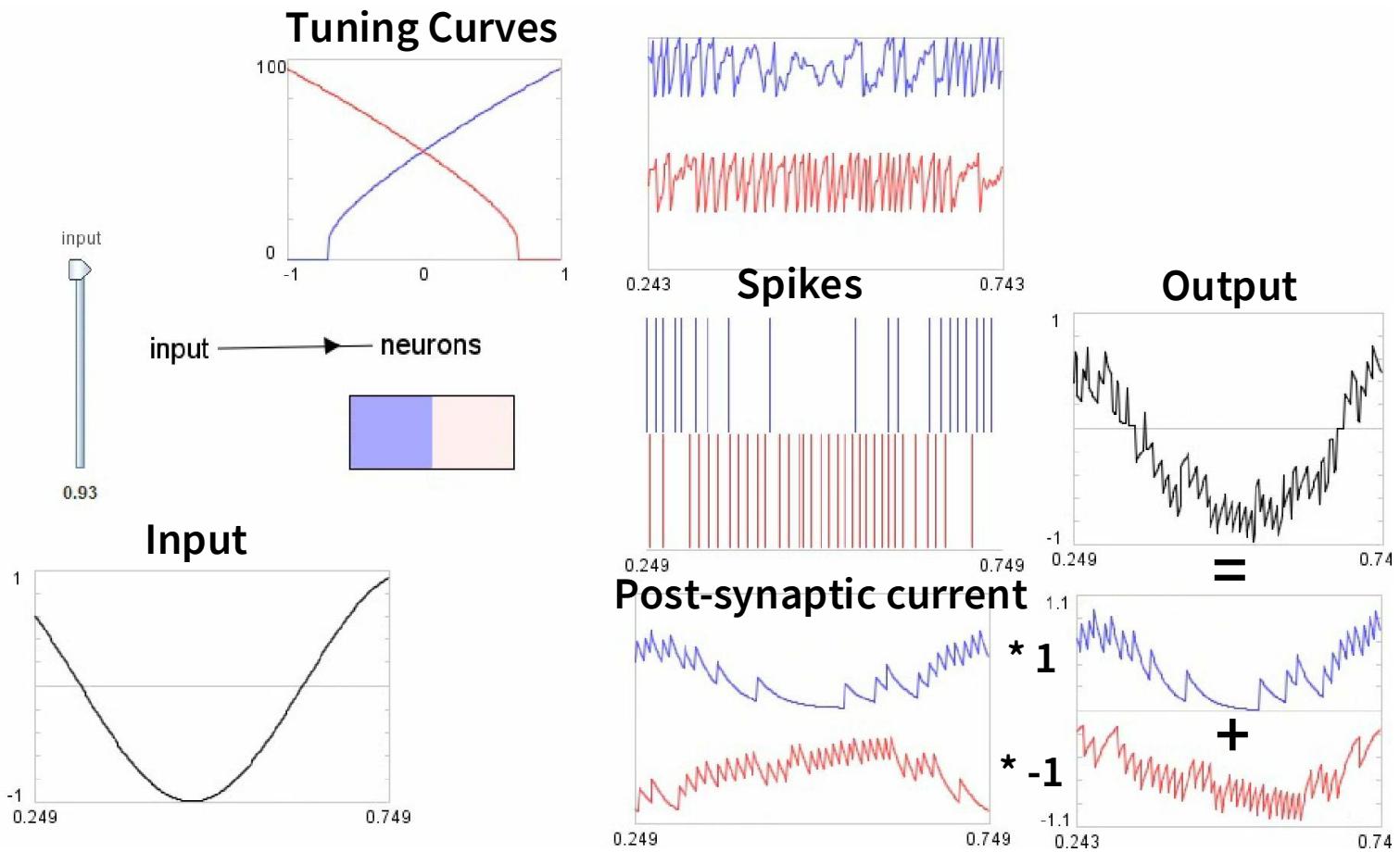
Two Neurons



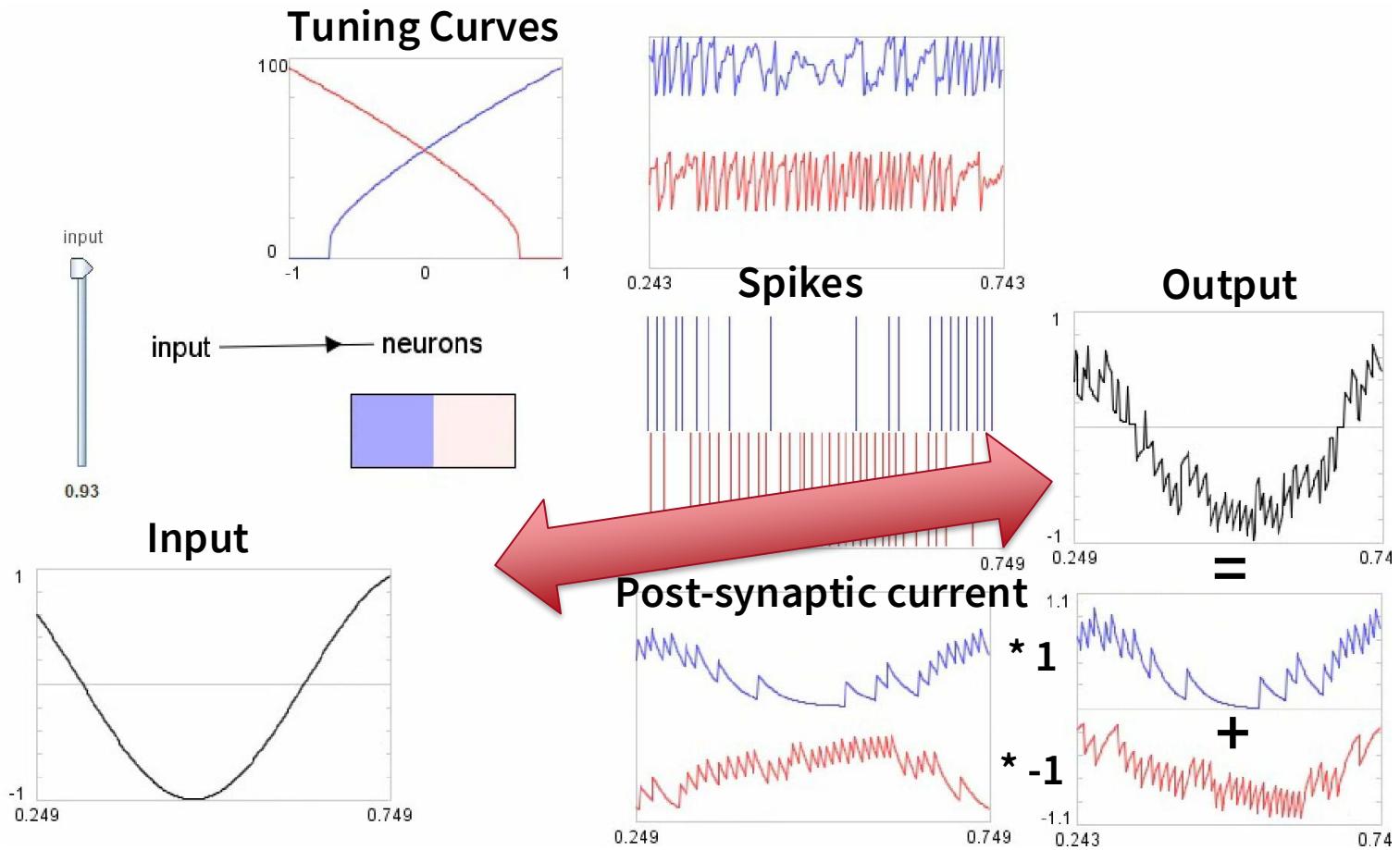
Two Neurons



Two Neurons

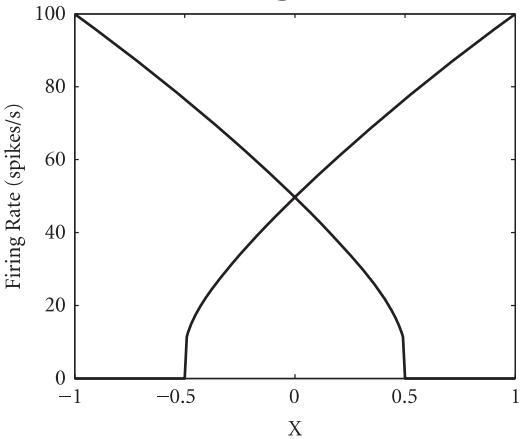


Two Neurons

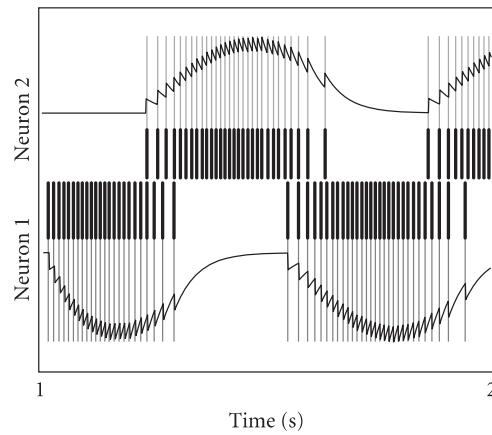


Two Neurons

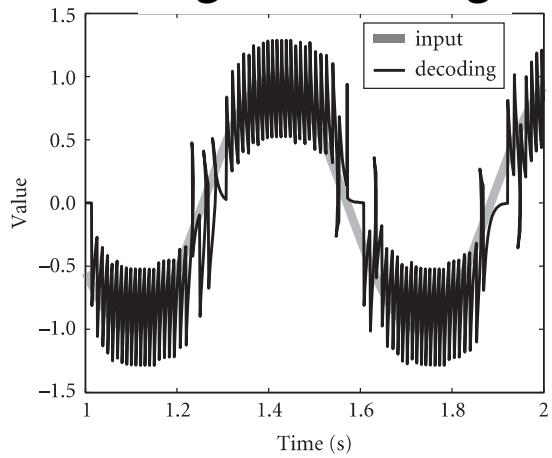
Tuning Curves



Spike Raster

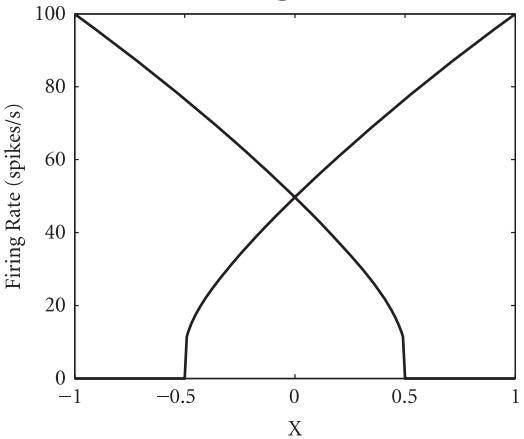


Signal Decoding

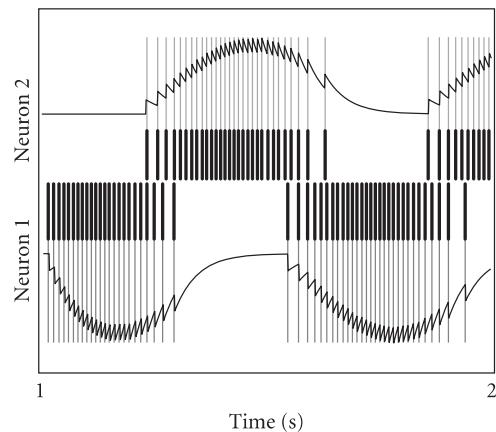


Two Neurons

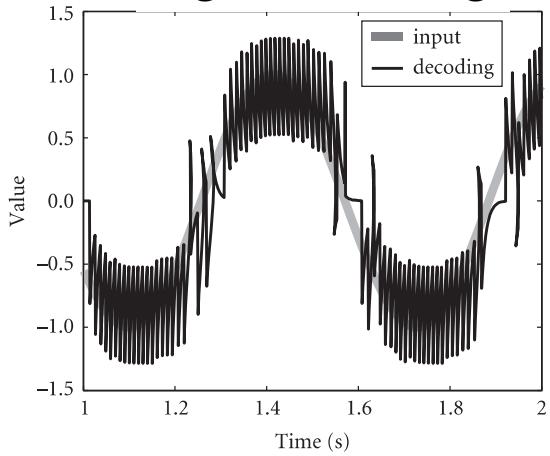
Tuning Curves



Spike Raster

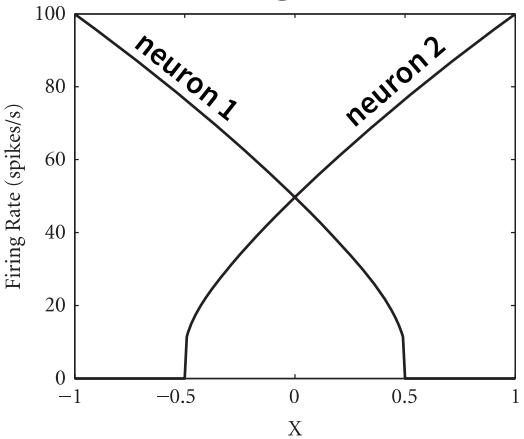


Signal Decoding

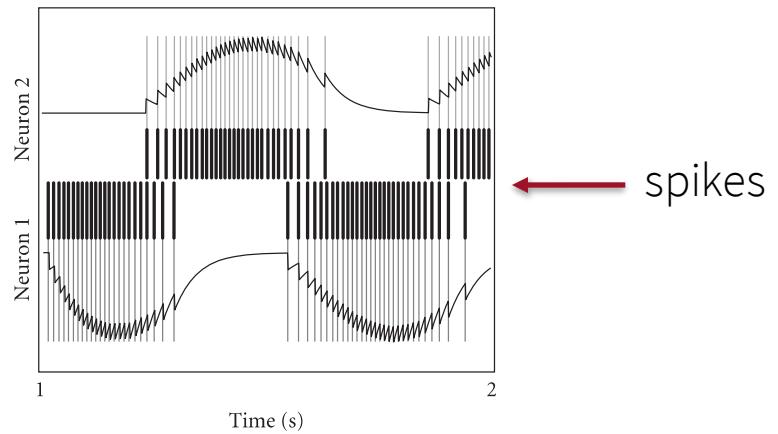


Two Neurons

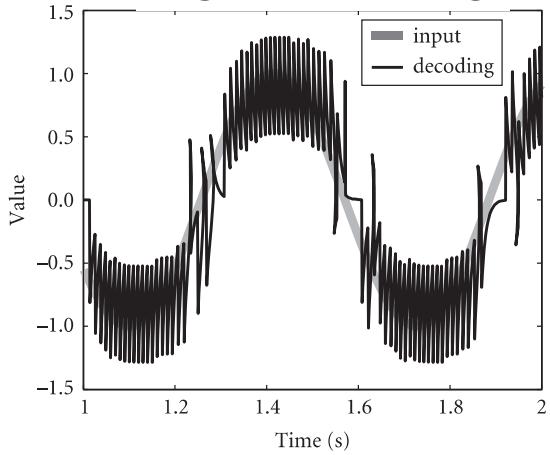
Tuning Curves



Spike Raster

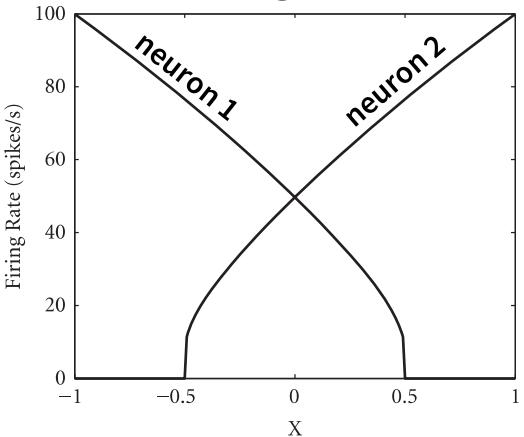


Signal Decoding

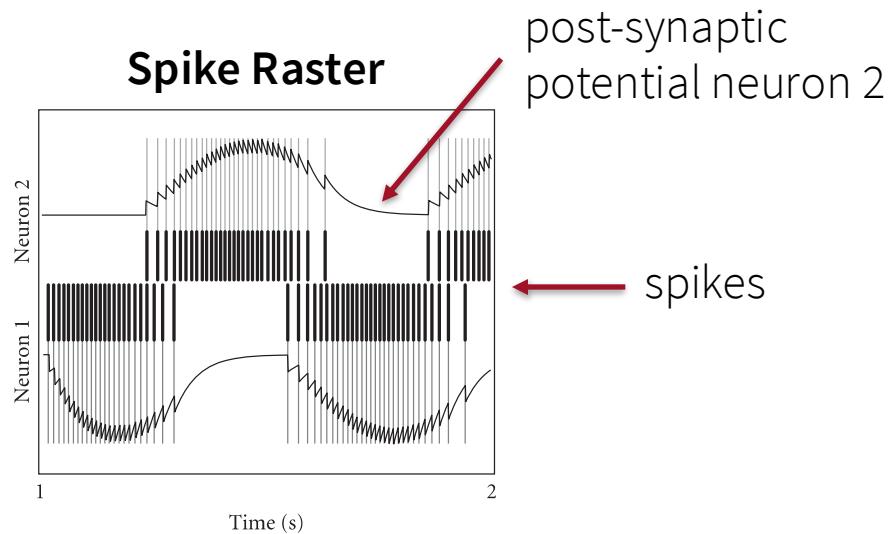


Two Neurons

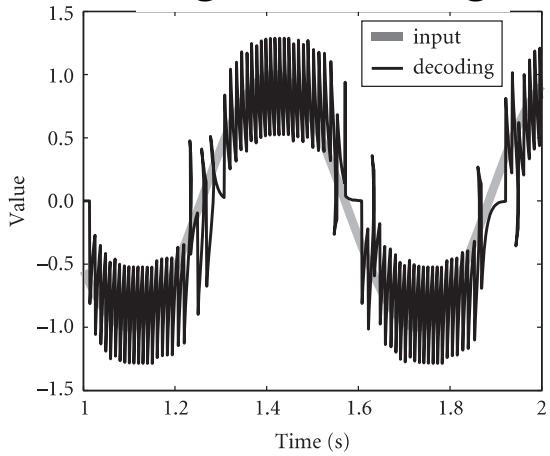
Tuning Curves



Spike Raster

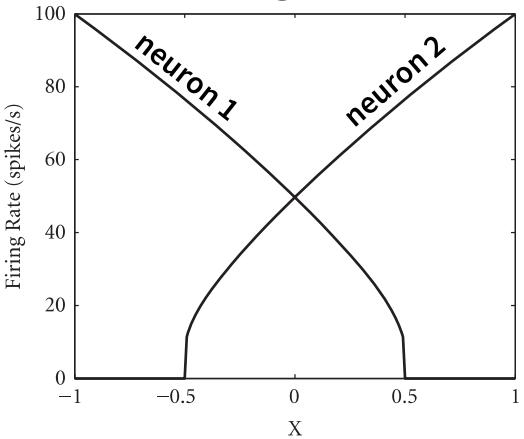


Signal Decoding

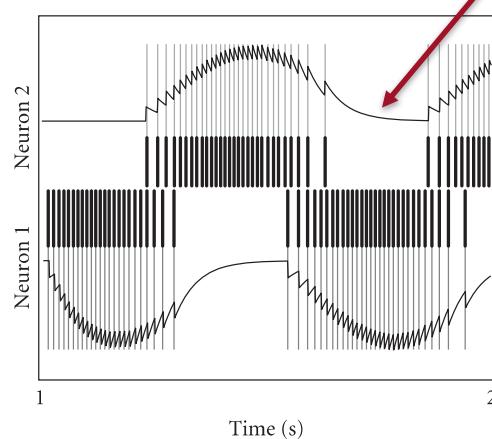


Two Neurons

Tuning Curves



Spike Raster

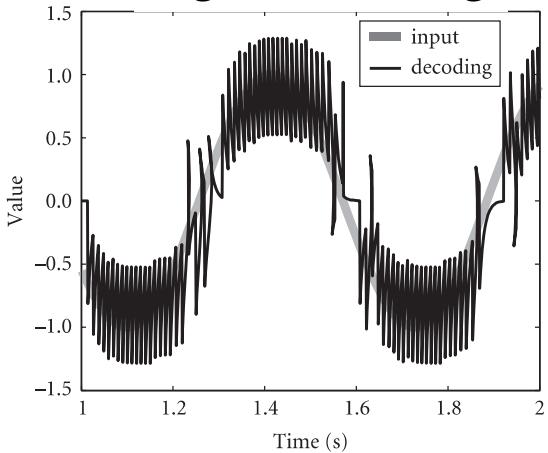


post-synaptic potential neuron 2

spikes

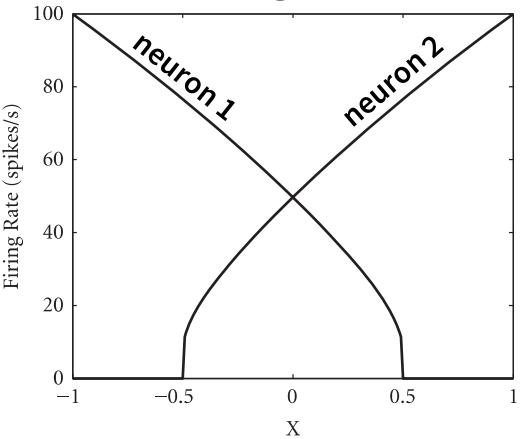
-1 * post-synaptic potential neuron 1

Signal Decoding

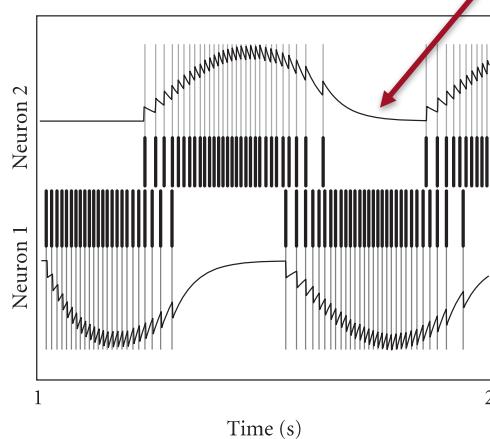


Two Neurons

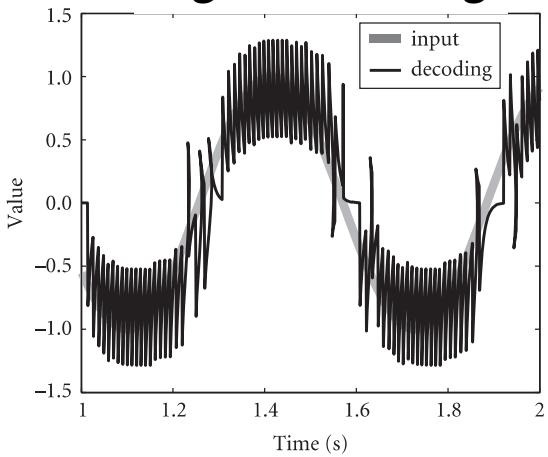
Tuning Curves



Spike Raster



Signal Decoding

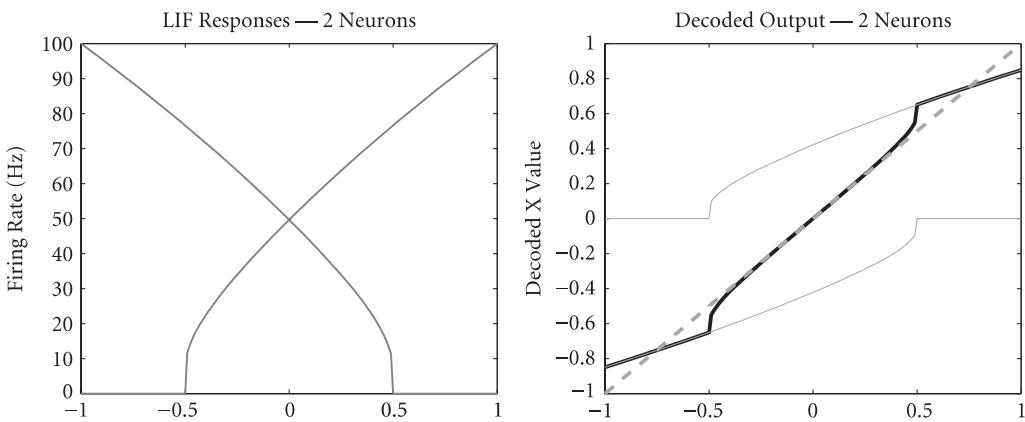


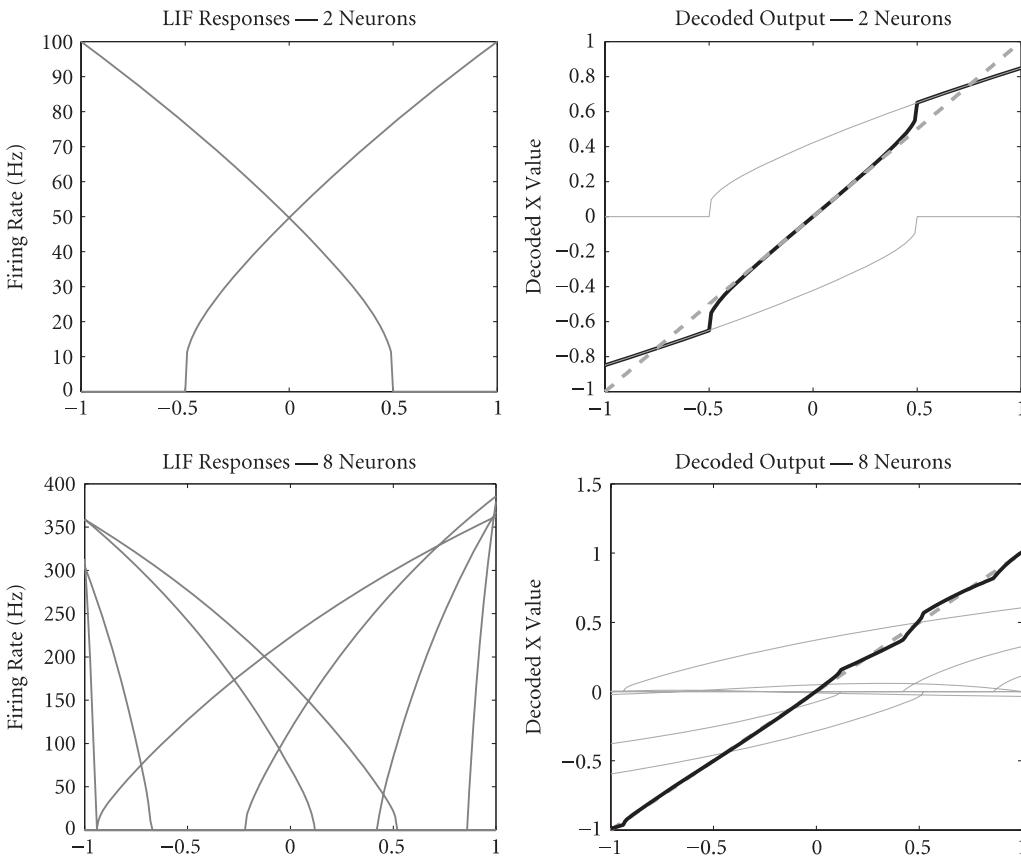
post-synaptic
potential neuron 2

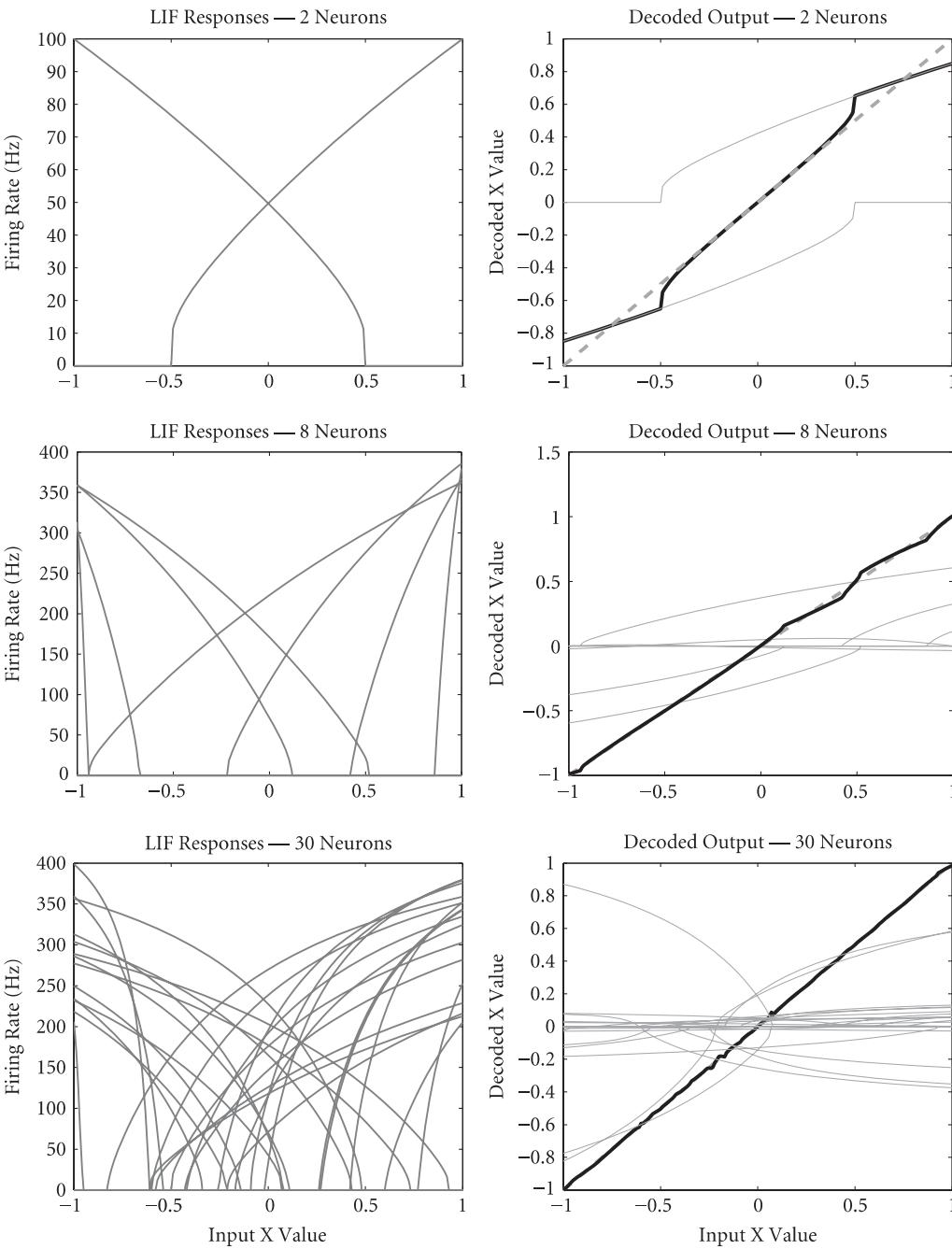
spikes

-1 * post-synaptic
potential neuron 1

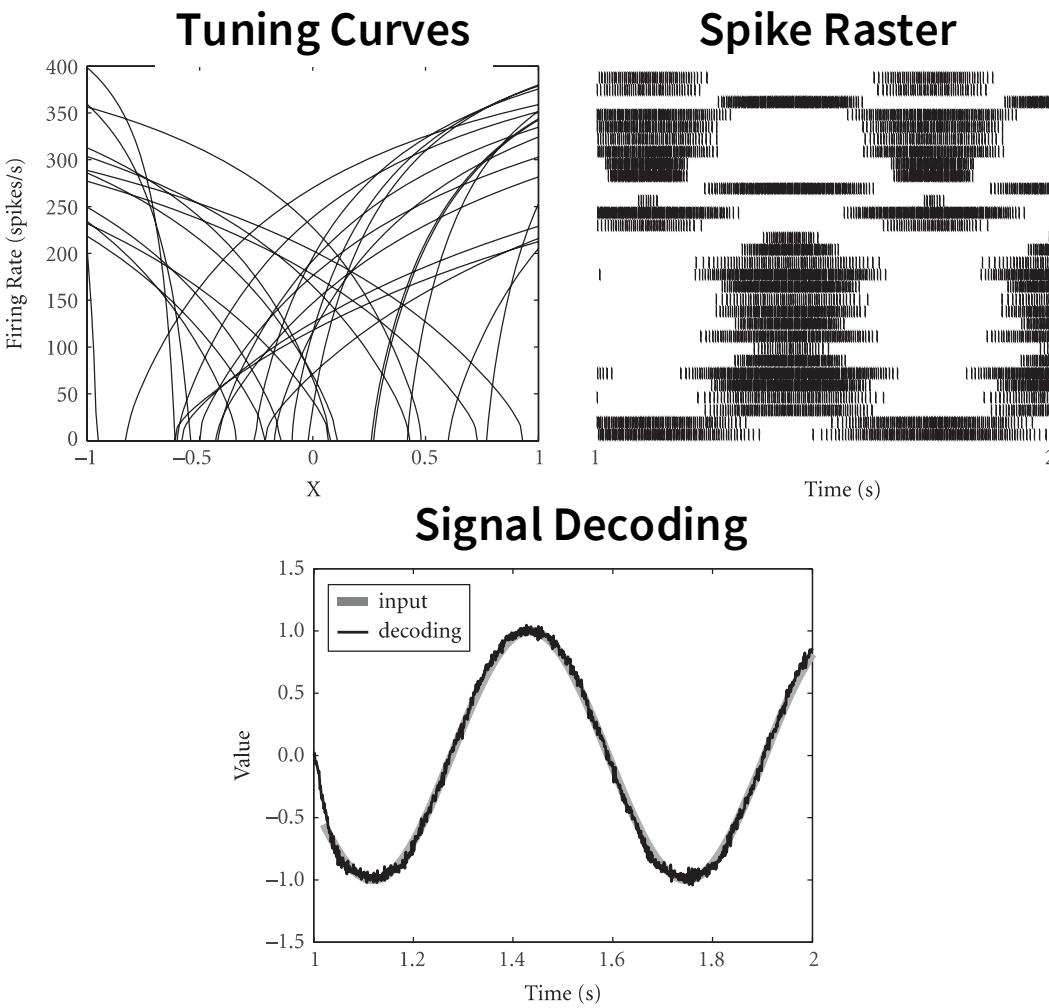
= weighted sum of psp's



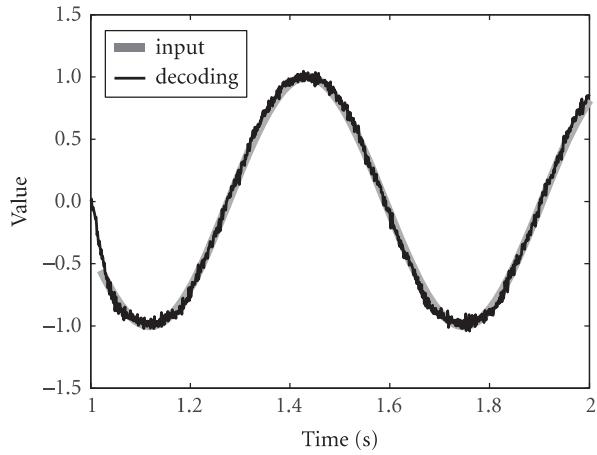
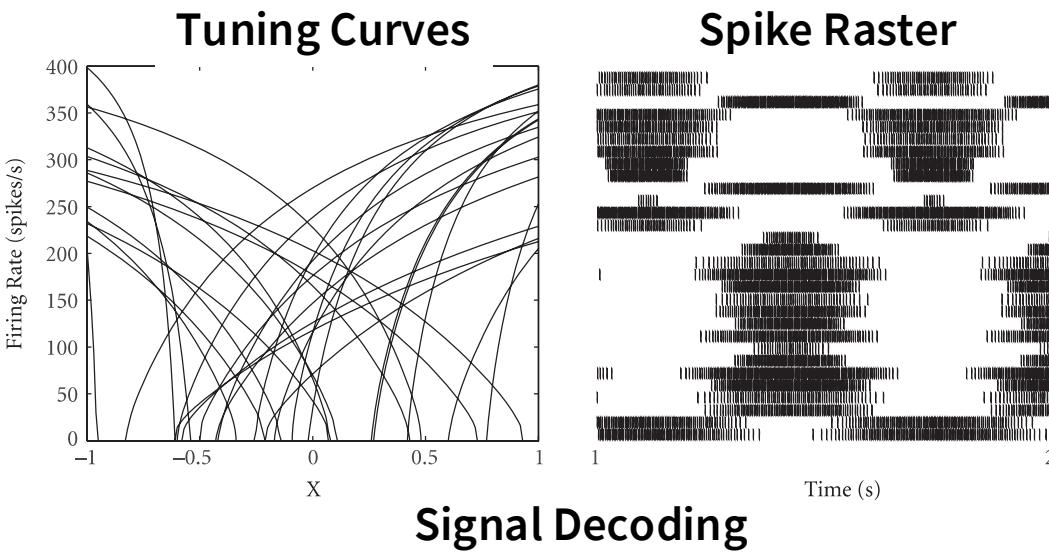




Thirty Neurons



Thirty Neurons

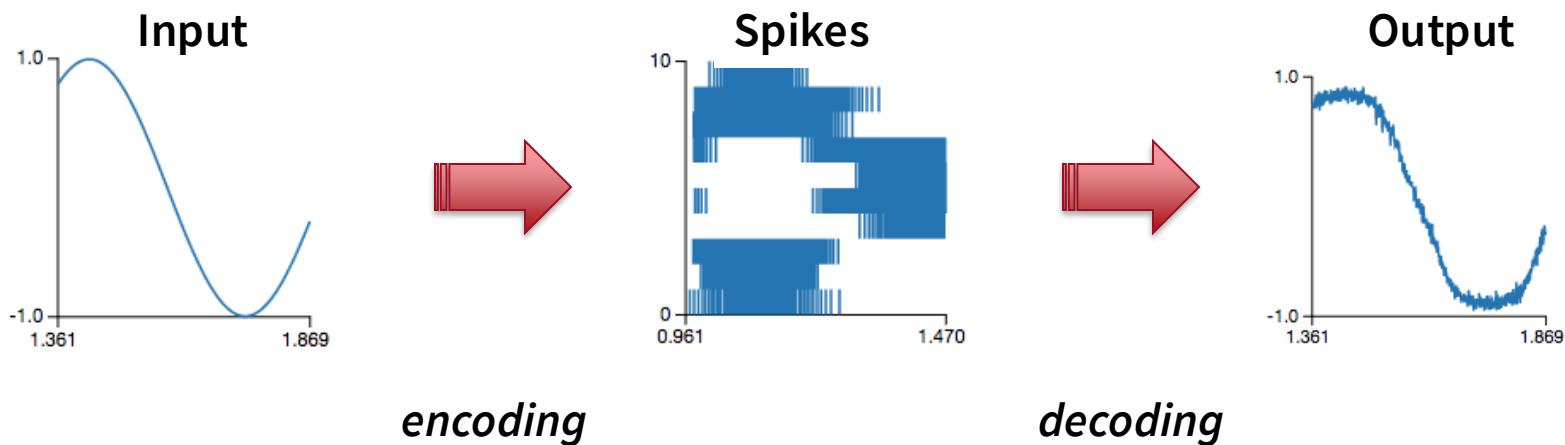


Demo!

Values in Spiking Neurons

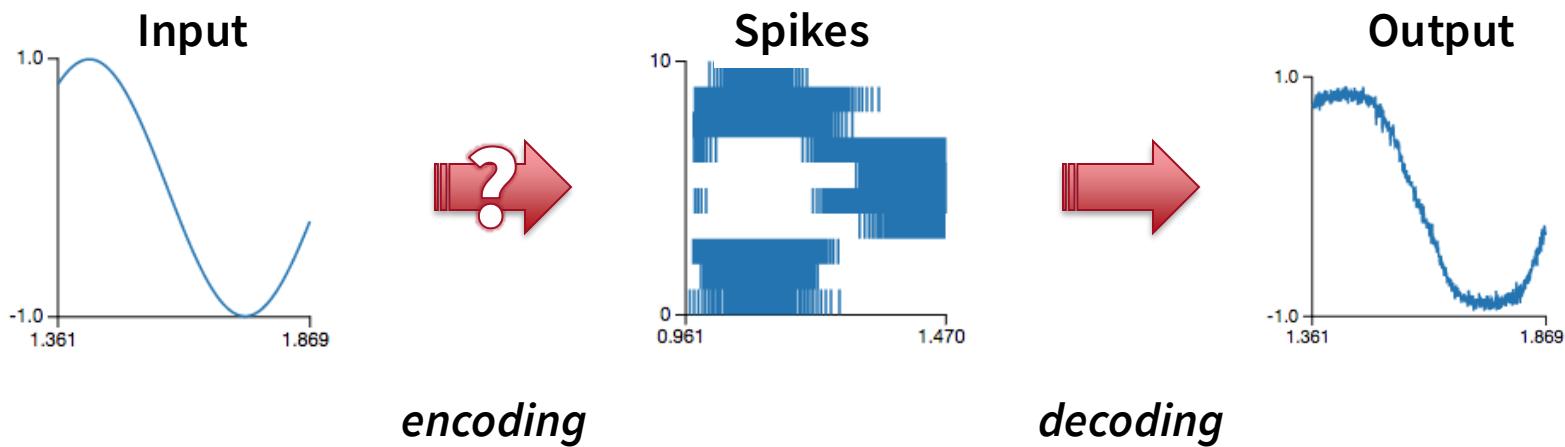
Values in Spiking Neurons

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



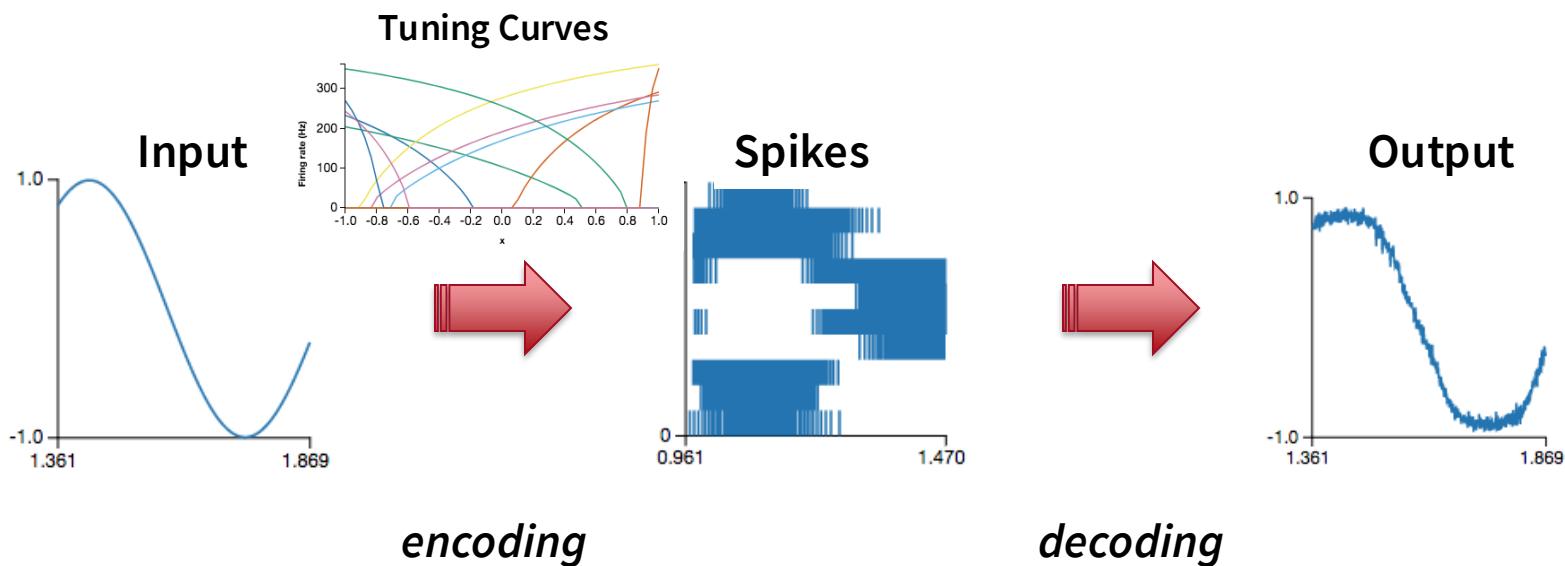
Values in Spiking Neurons

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



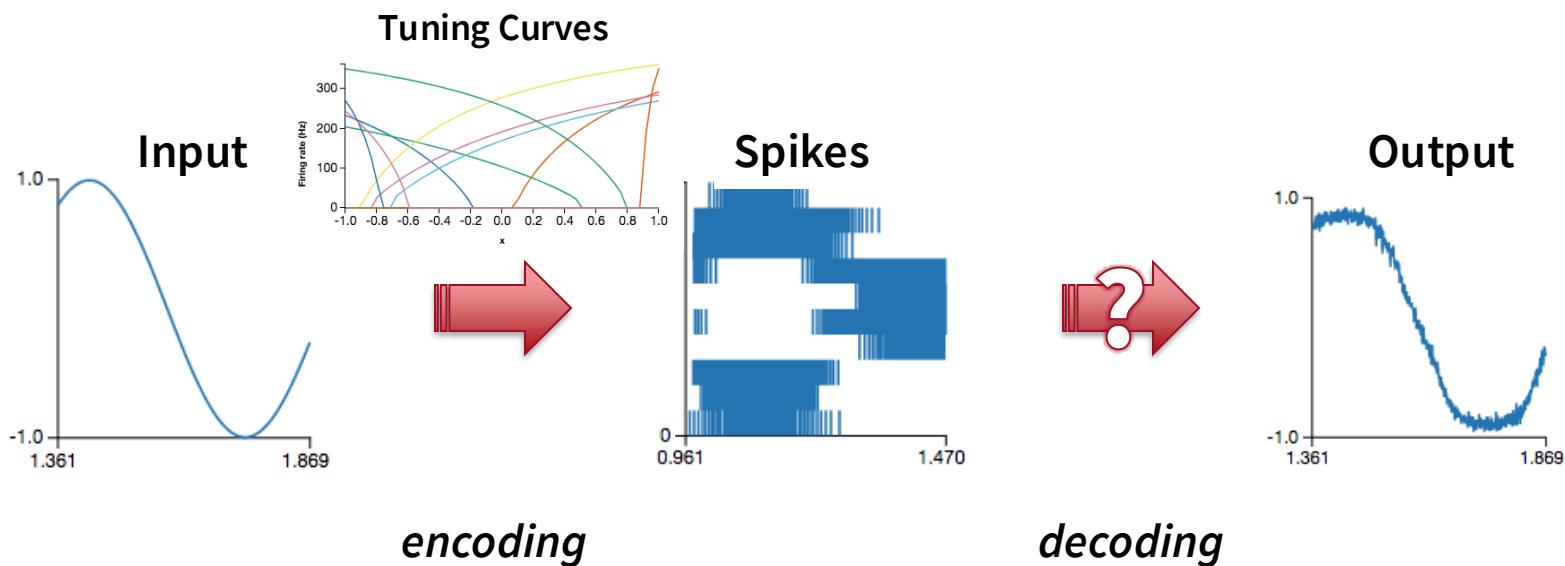
Values in Spiking Neurons

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



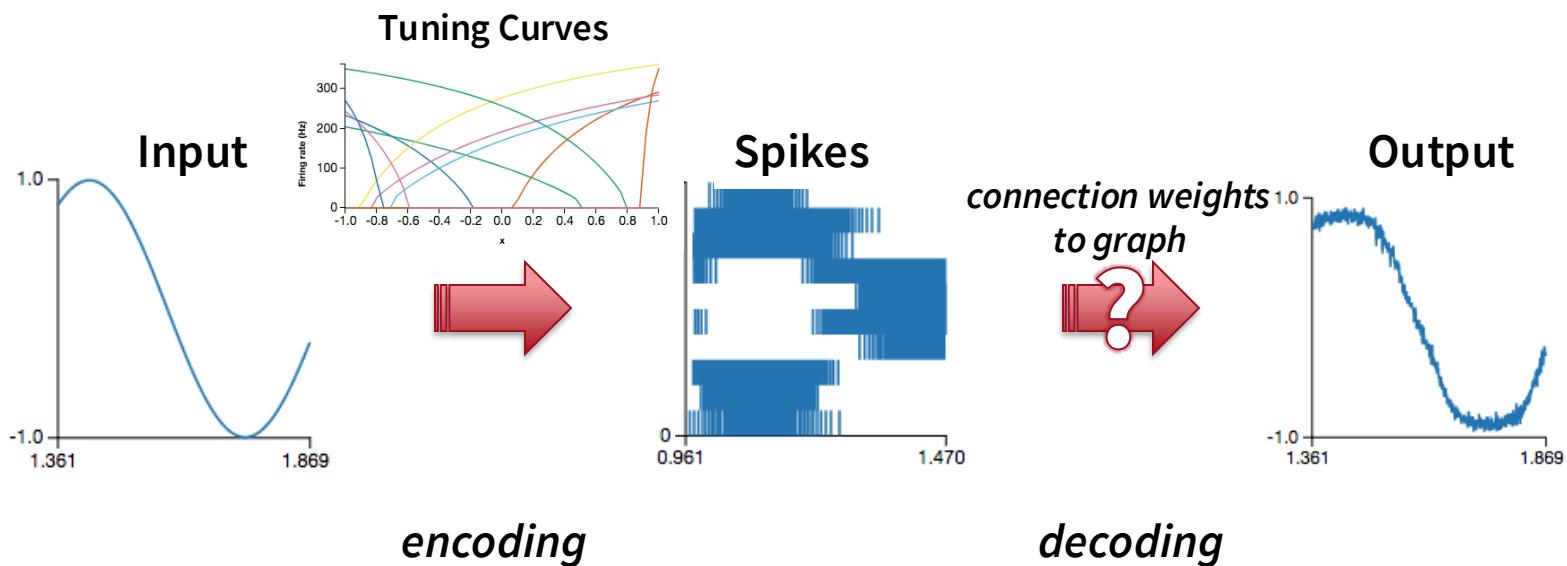
Values in Spiking Neurons

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



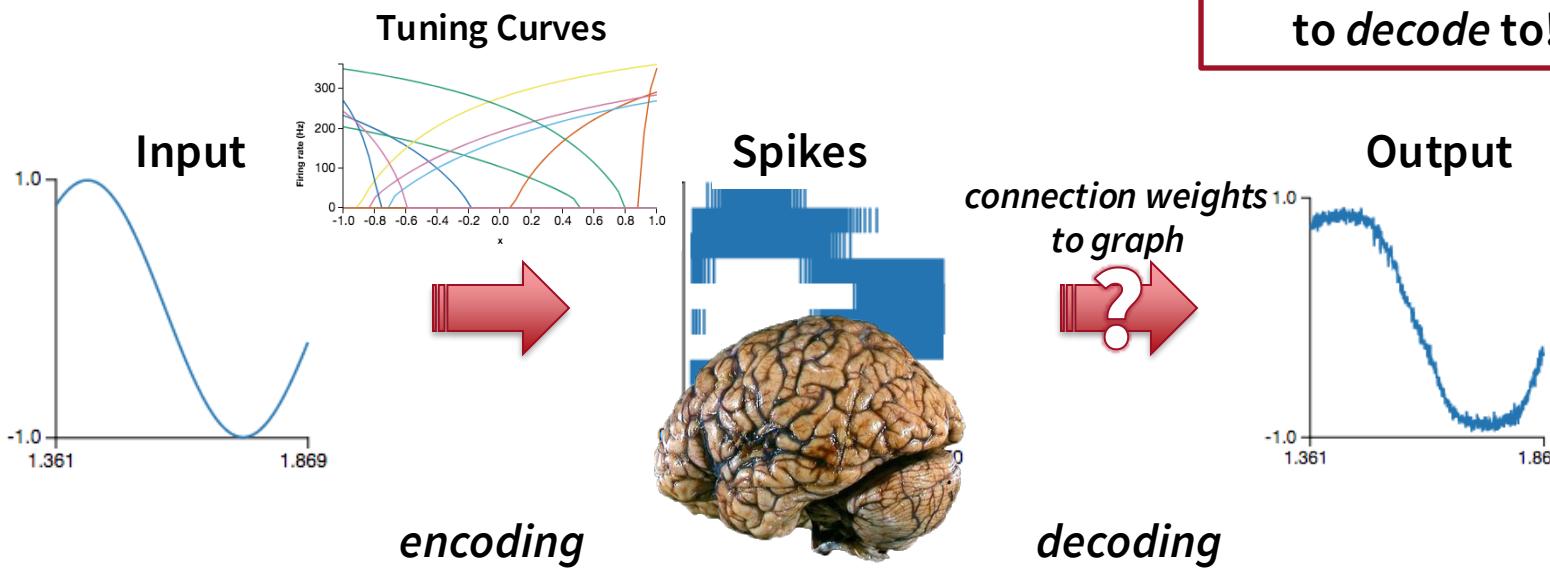
Values in Spiking Neurons

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



Values in Spiking Neurons

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



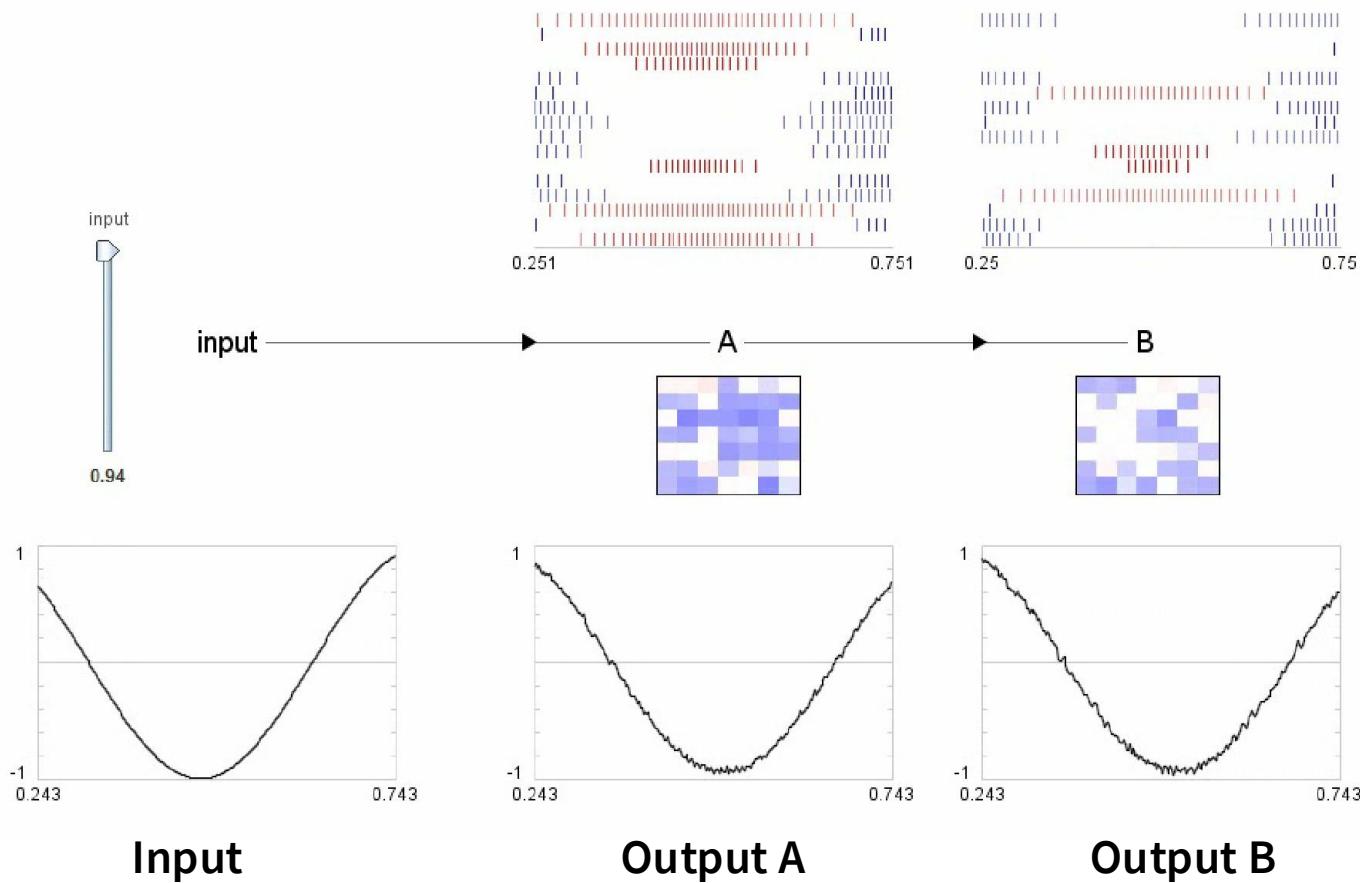
Challenges for (Spiking) Neurons

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

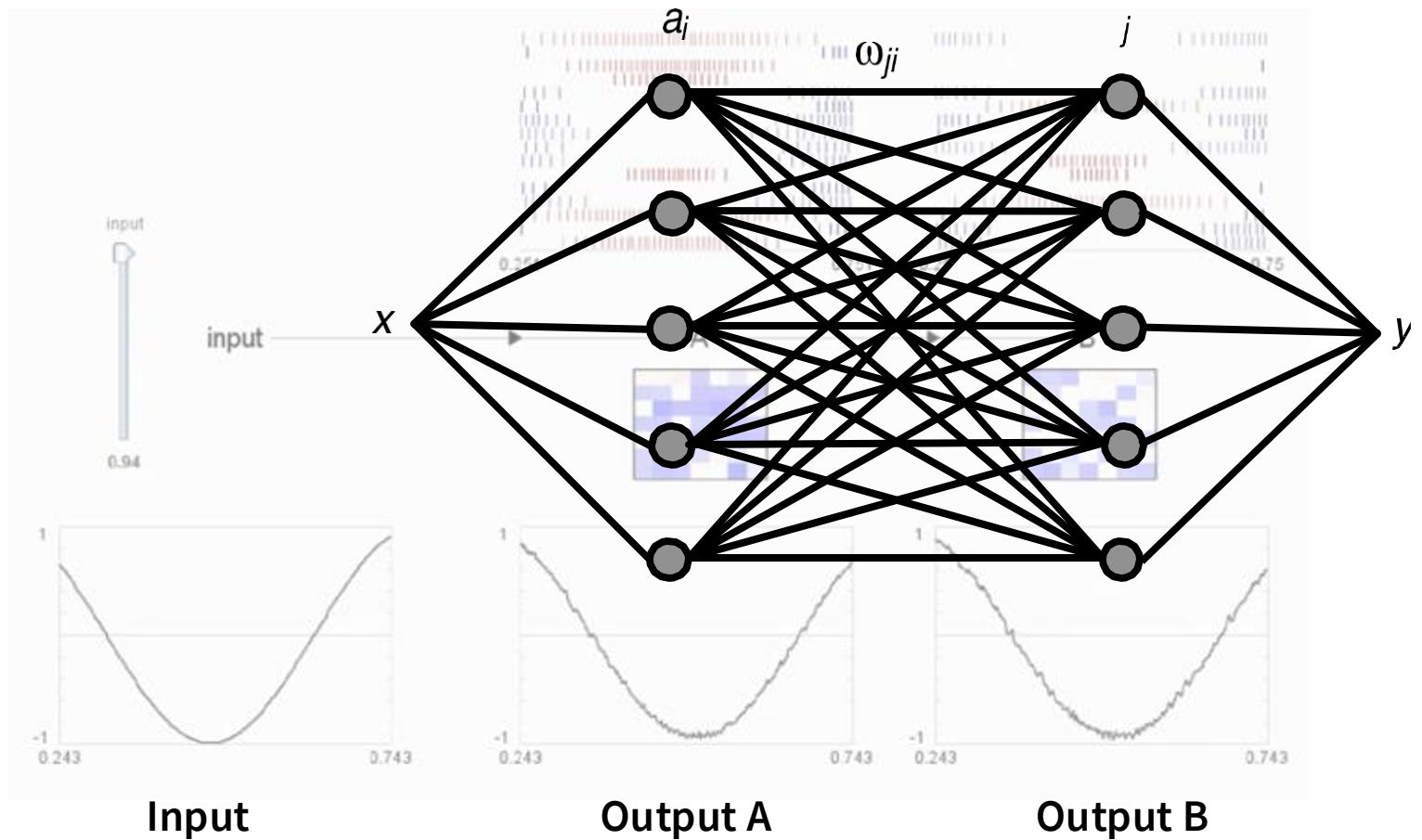
Challenges for (Spiking) Neurons

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

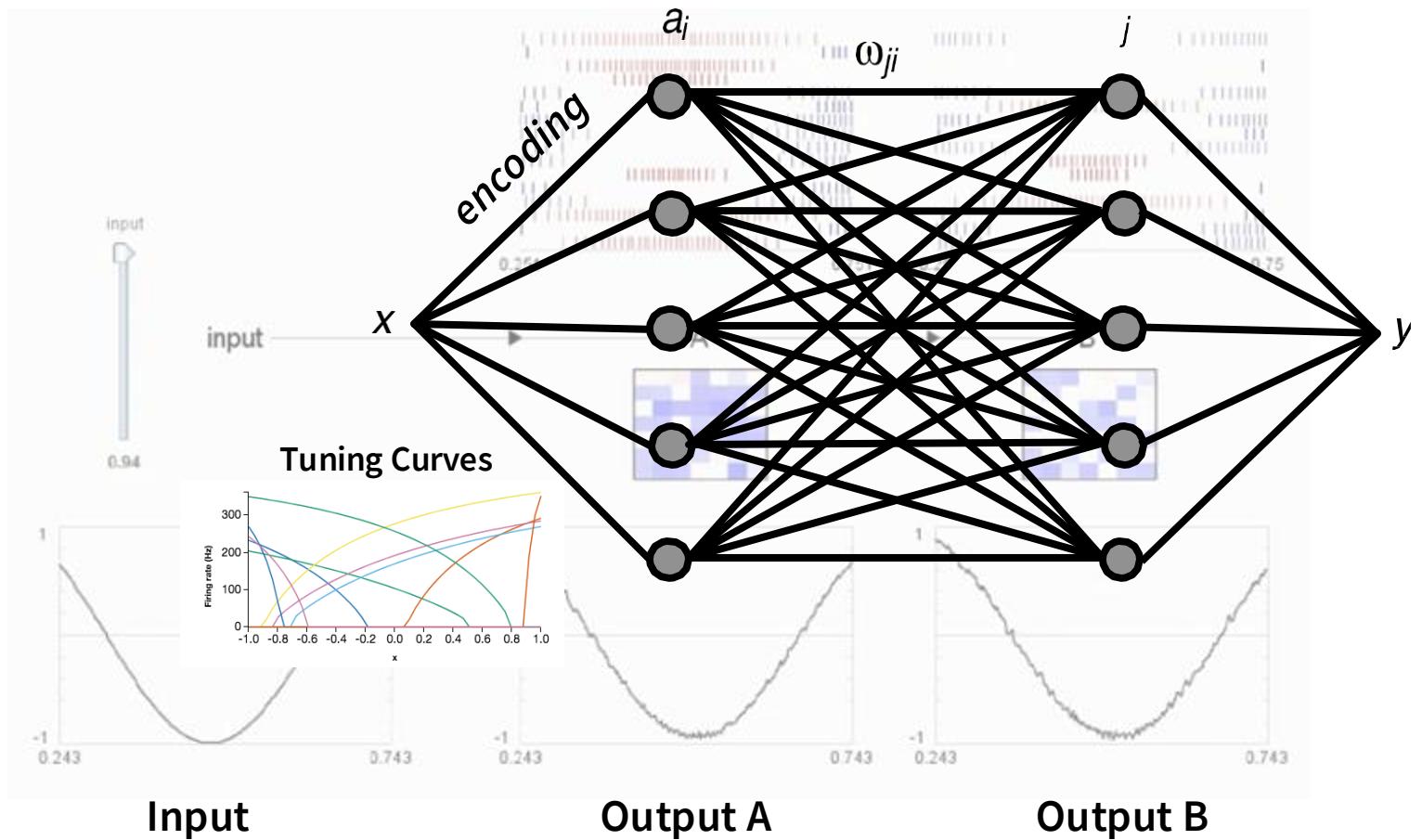
How to communicate values?



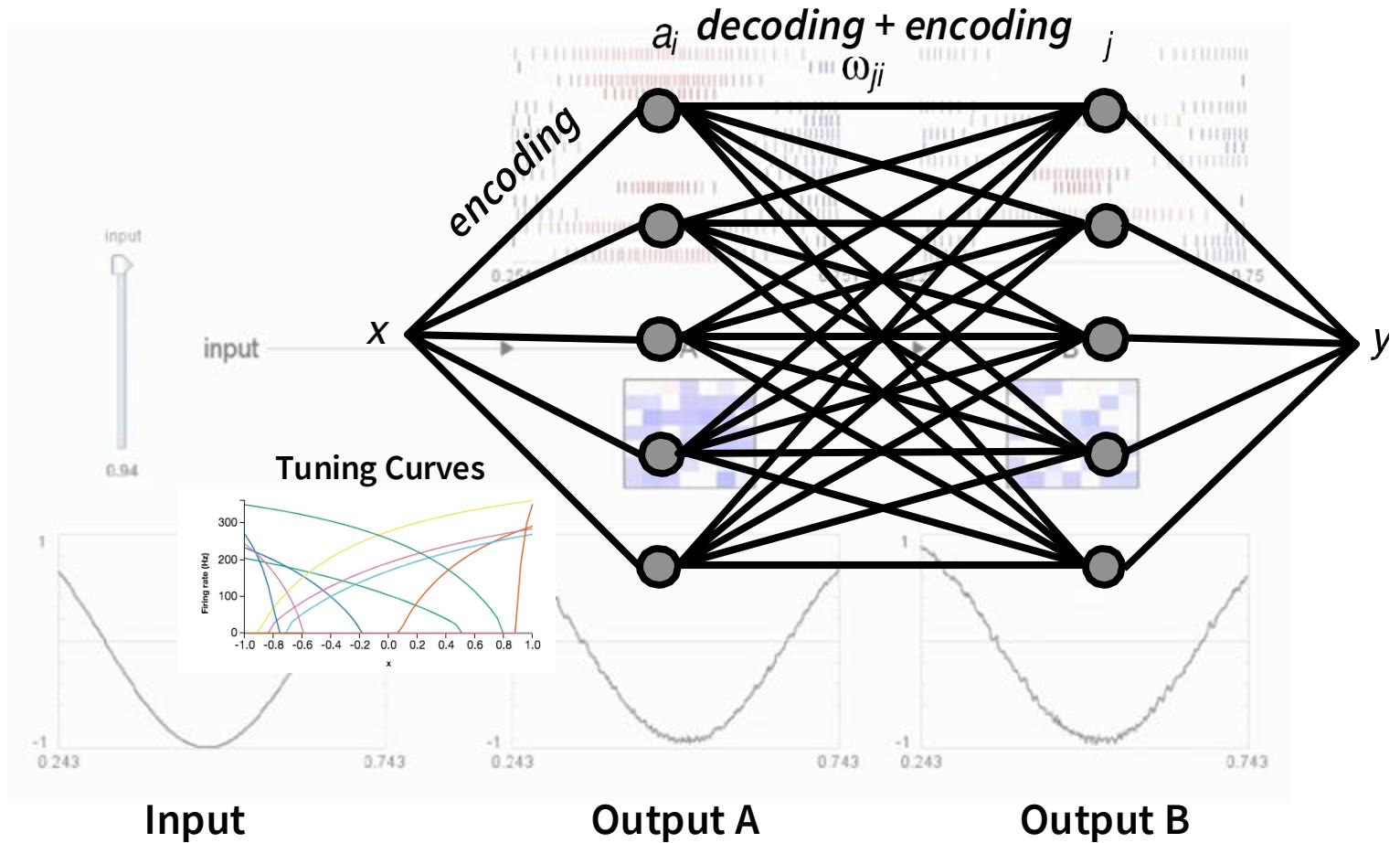
How to communicate values?



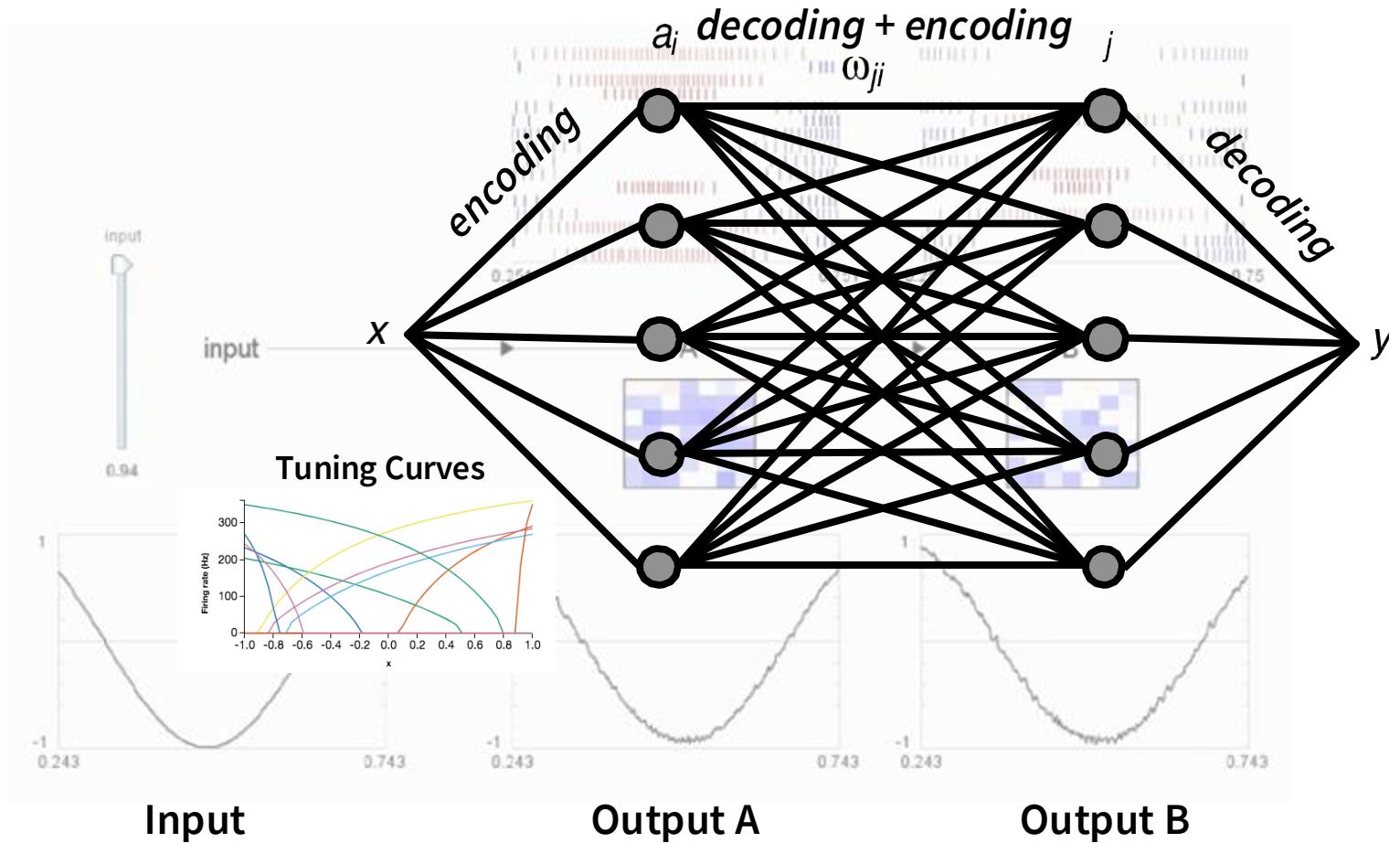
How to communicate values?



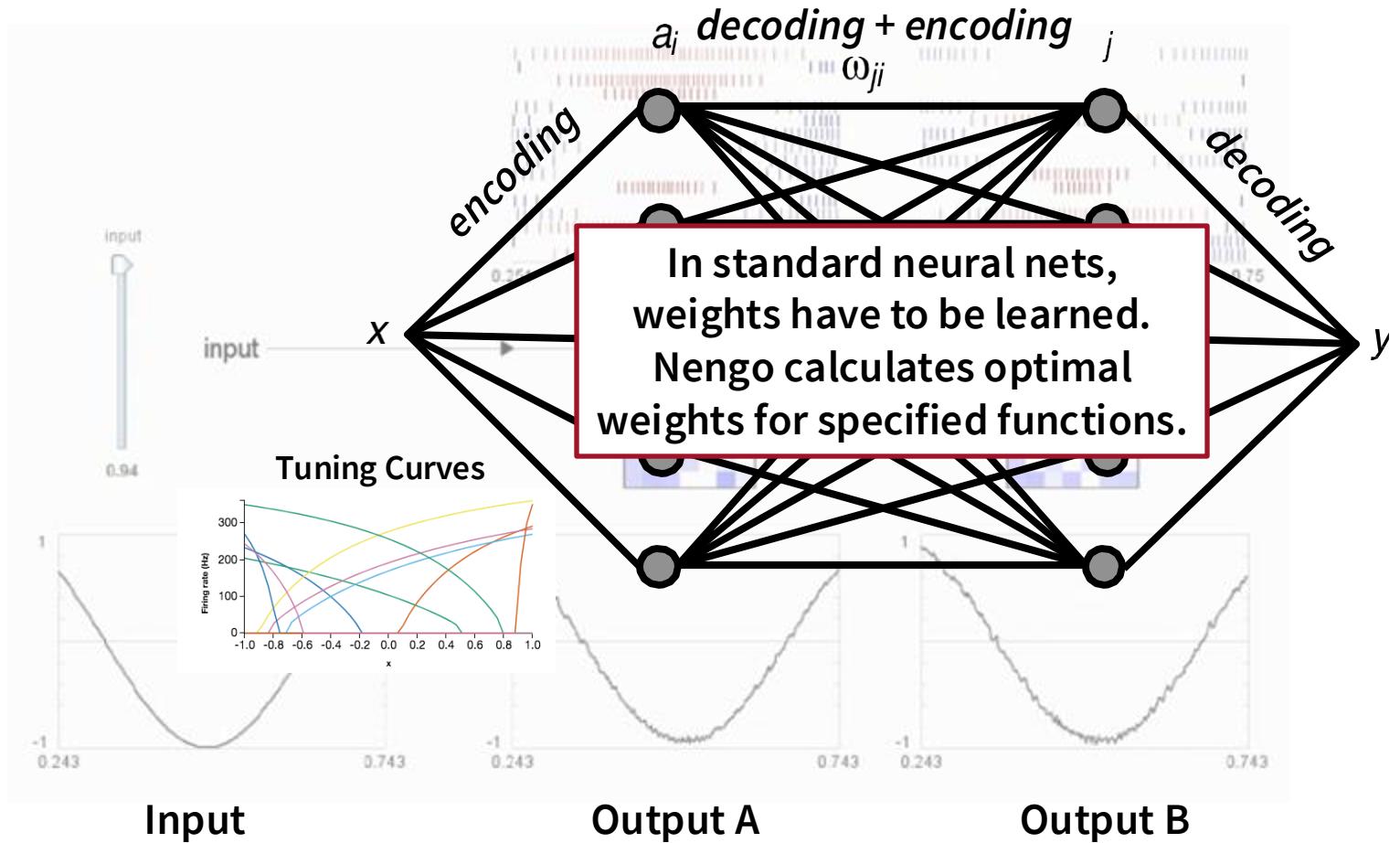
How to communicate values?



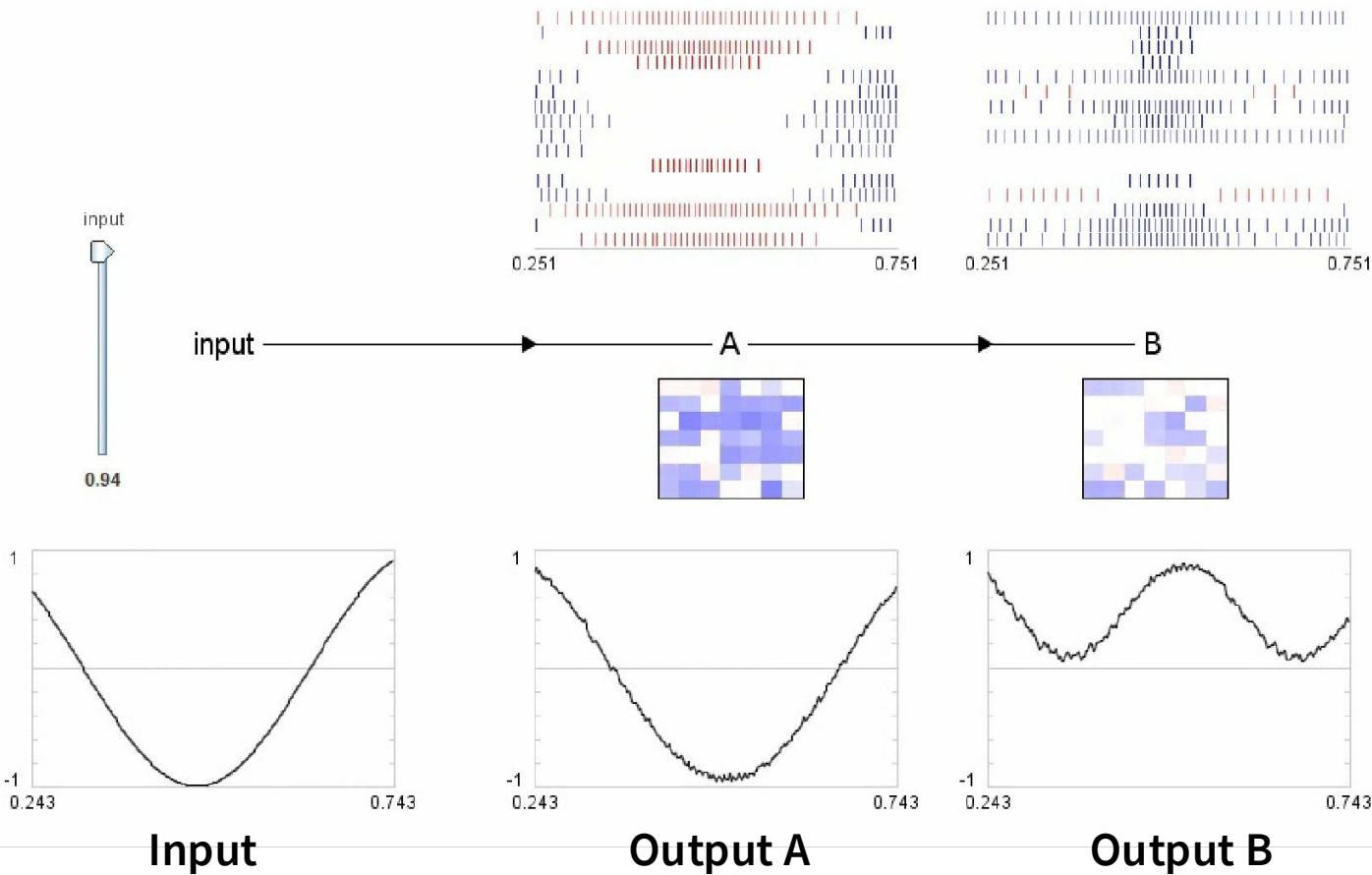
How to communicate values?



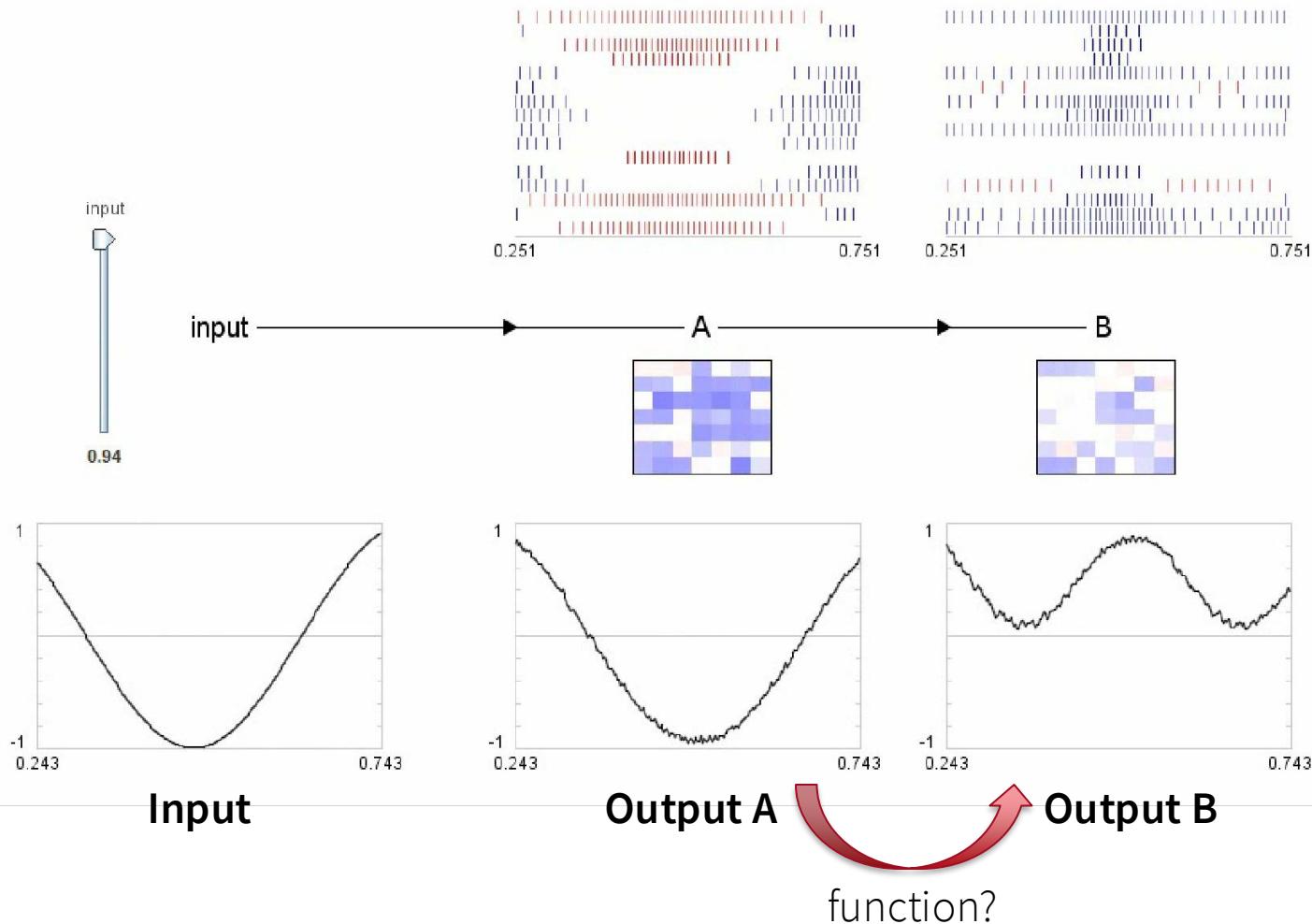
How to communicate values?



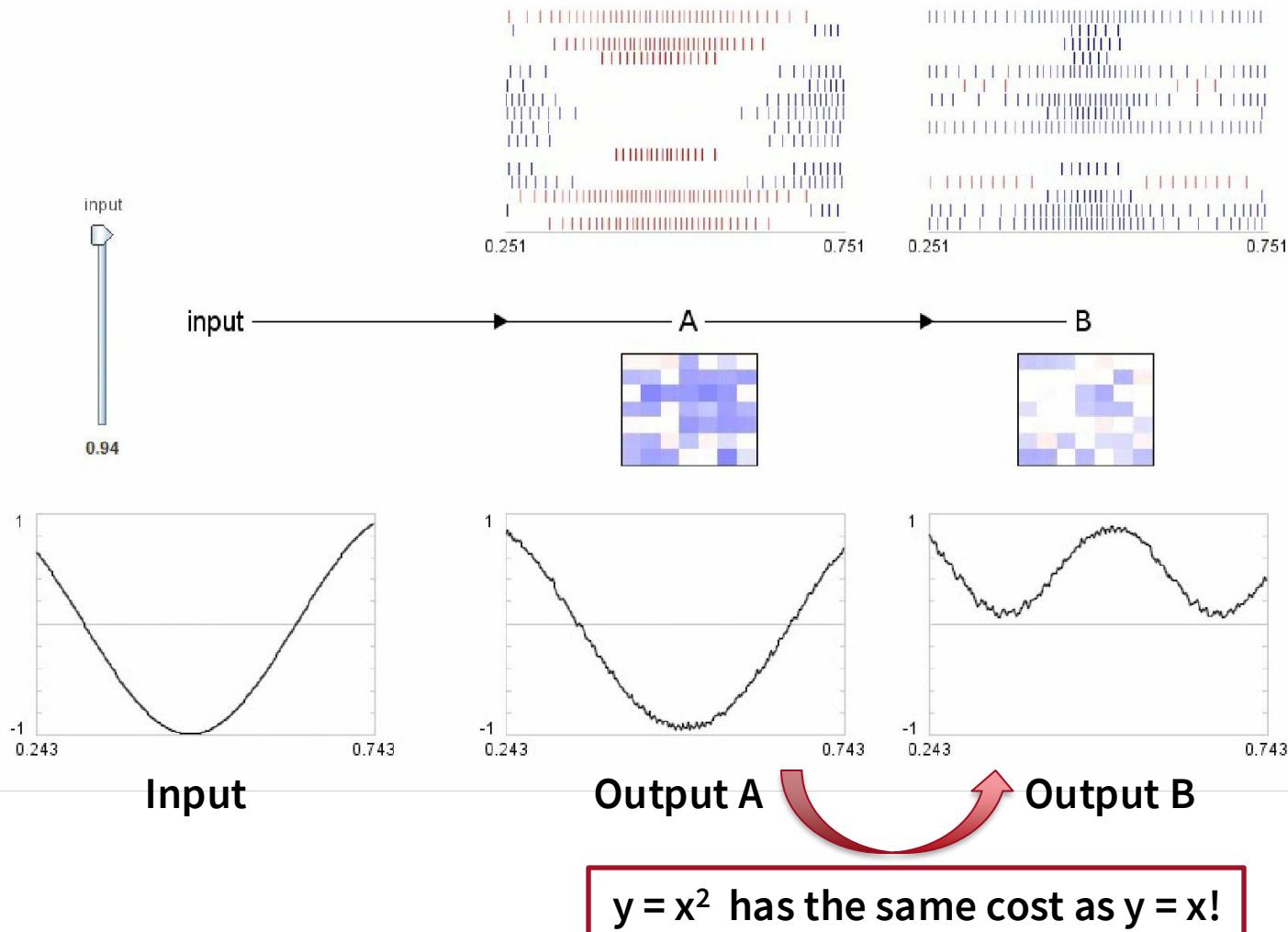
How to transform values?



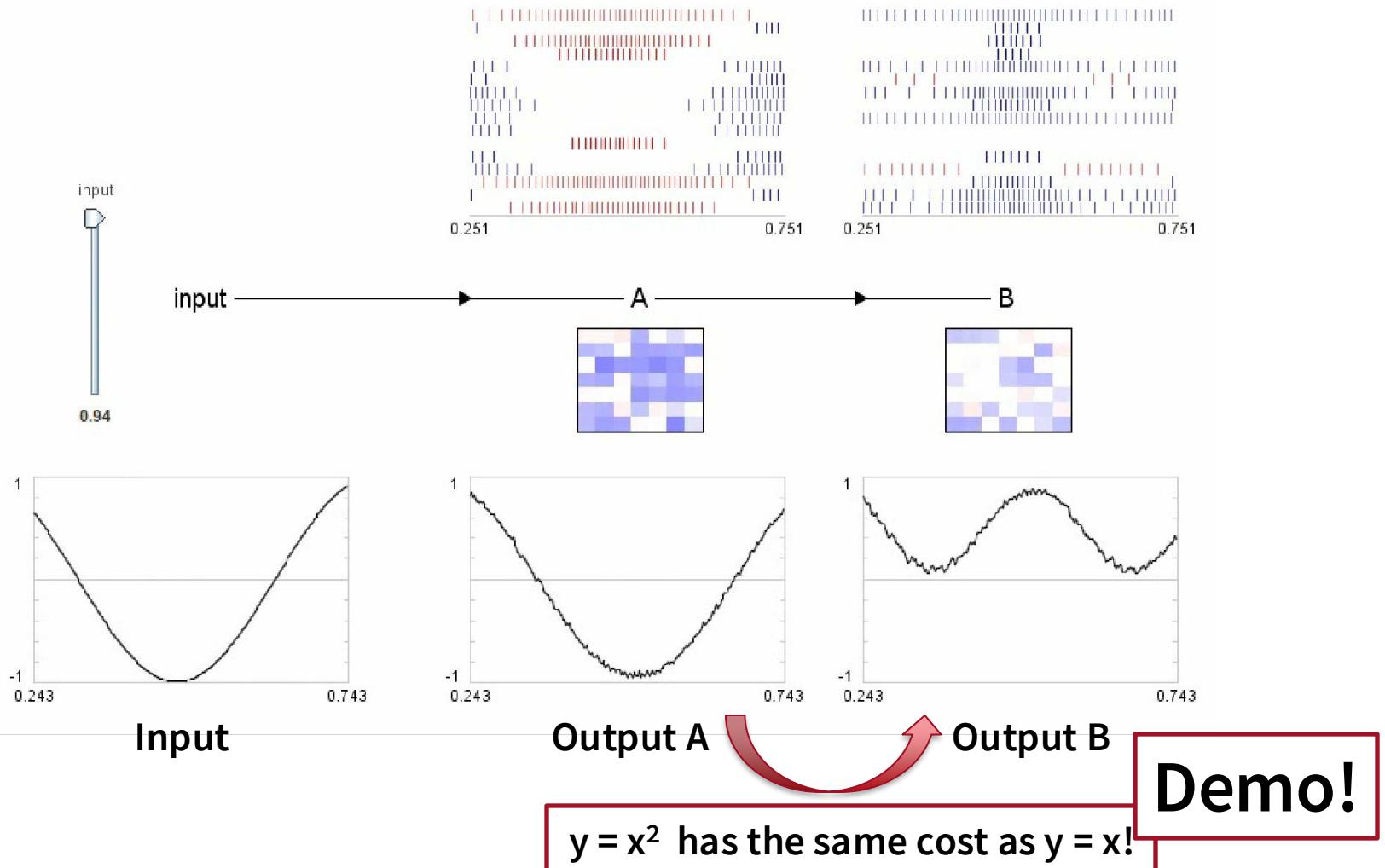
How to transform values?



How to transform values?



How to transform values?



Values in Spiking Neurons

- Each neural ensemble stores a value
 - Encoding: value => spikes
 - Decoding: spikes => value

Values in Spiking Neurons

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

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?

Challenges for (Spiking) Neurons

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

Challenges for (Spiking) Neurons

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

Demo!

Challenges for (Spiking) Neurons

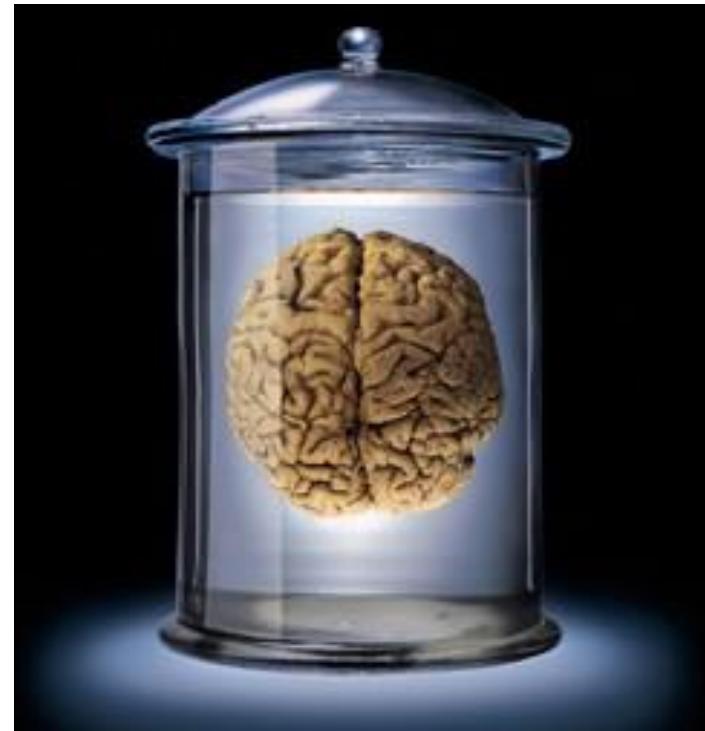
- How to represent values?
- How to communicate values?
- How can we store values?

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..

- 2012 - Spaun - (Eliasmith et al., Nov. 2012, *Science*)



The Story So Far..



- 2012 - Spaun - (Eliasmith et al., Nov. 2012, *Science*)
- 2013 - “It’s not a brain model...” (Henry Markram, *Science News*, 183(1):13, 2013)

The Story So Far..



- 2012 - Spaun - (Eliasmith et al., Nov. 2012, *Science*)
- 2013 - “It’s not a brain model...” (Henry Markram, *Science News*, 183(1):13, 2013)
- 2014 - “Yes it is” (Eliasmith+, *Curr Opin Neurobiol*. Apr;25:1-6)

The Story So Far..



- 2012 - Spaun - (Eliasmith et al., Nov. 2012, *Science*)
- 2013 - “It’s not a brain model...” (Henry Markram, *Science News*, 183(1):13, 2013)
- 2014 - “Yes it is” (Eliasmith+, *Curr Opin Neurobiol*. Apr;25:1-6)
- 2015 - “...this is” (Markram+, *Cell*. 2015 Oct 8;163(2):456-92)

The Story So Far..



- 2012 - Spaun - (Eliasmith et al., Nov. 2012, *Science*)
- 2013 - “It’s not a brain model...” (Henry Markram, *Science News*, 183(1):13, 2013)
- 2014 - “Yes it is” (Eliasmith+, *Curr Opin Neurobiol*. Apr;25:1-6)
- 2015 - “...this is” (Markram+, *Cell*. 2015 Oct 8;163(2):456-92)
- 2015 - “No, this is.” (*BioSpaun*, [arXiv:1602.05220](https://arxiv.org/abs/1602.05220))

The Story So Far..



- 2012 - Spaun - (Eliasmith et al., Nov. 2012, *Science*)
- 2013 - “It’s not a brain model...” (Henry Markram, *Science News*, 183(1):13, 2013)
- 2014 - “Yes it is” (Eliasmith+, *Curr Opin Neurobiol*. Apr;25:1-6)
- 2015 - “...this is” (Markram+, *Cell*. 2015 Oct 8;163(2):456-92)
- 2015 - “No, this is.” (*BioSpaun*, [arXiv:1602.05220](https://arxiv.org/abs/1602.05220))
- Now - “This is even better...” (unpublished)

The Story So Far..

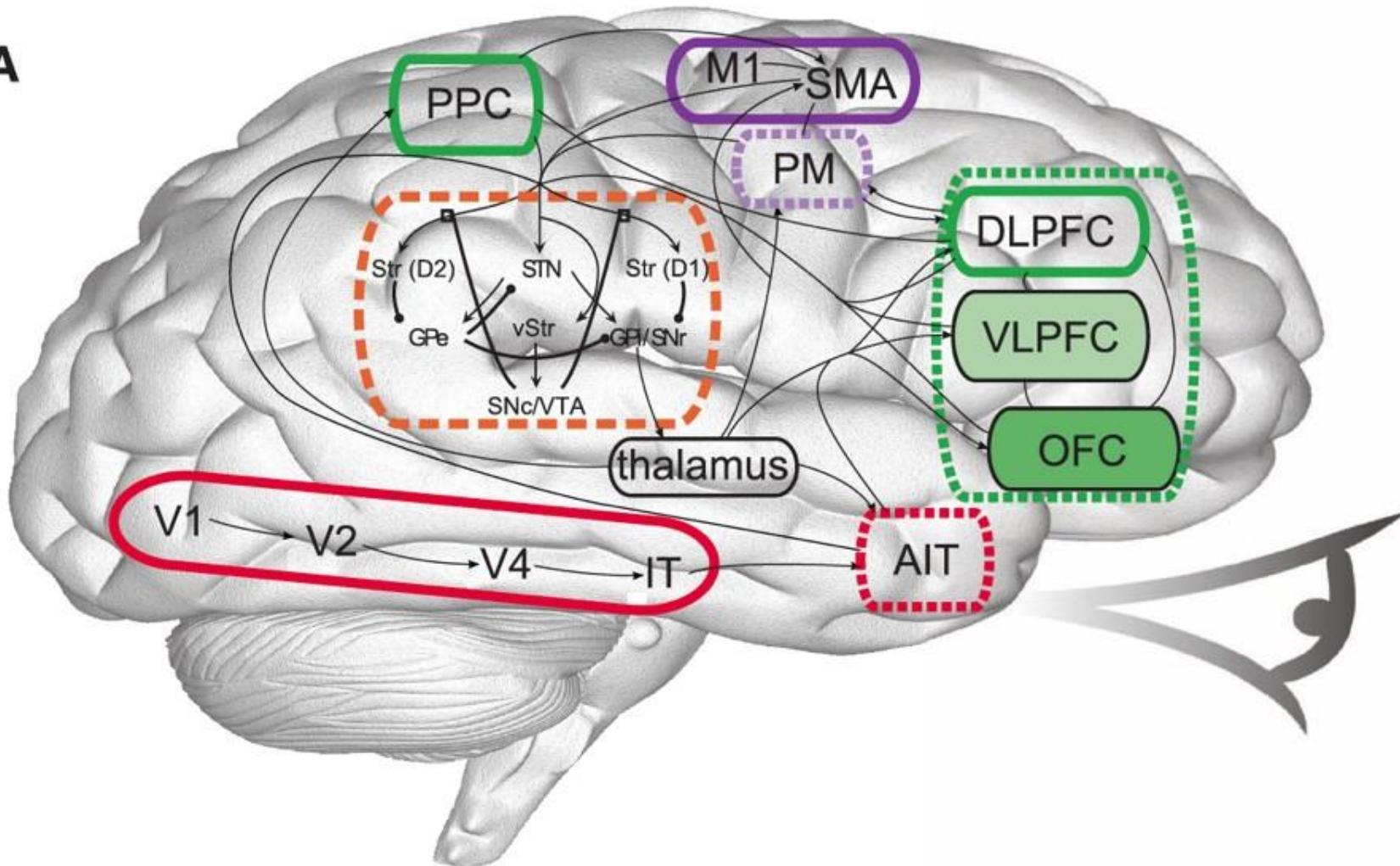


- 2012 - Spaun - (Eliasmith et al., Nov. 2012, *Science*)
- 2013 - “It’s not a brain model...” (Henry Markram, *Science News*, 183(1):13, 2013)
- 2014 - “Yes it is” (Eliasmith+, *Curr Opin Neurobiol*. Apr;25:1-6)
- 2015 - “...this is” (Markram+, *Cell*. 2015 Oct 8;163(2):456-92)
- 2015 - “No, this is.” (*BioSpaun*, [arXiv:1602.05220](https://arxiv.org/abs/1602.05220))
- Now - “This is even better...” (unpublished)

Bioplausibility vs *Function* (and bioplausibility)

Spaun: Anatomy

A



Tasks

Tasks

- Real input: 28x28 pixel images

Tasks

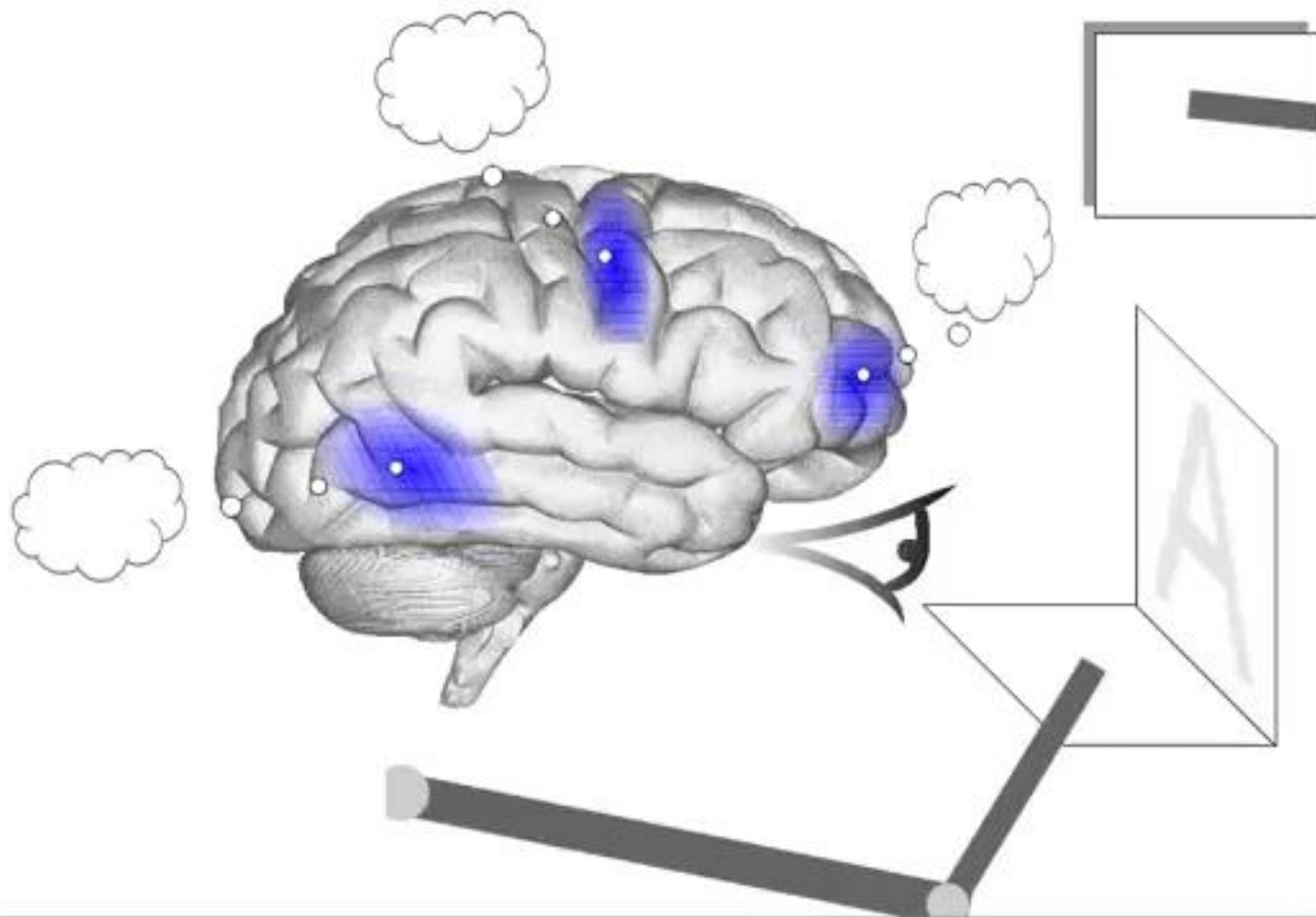
- Real input: 28x28 pixel images
- Output: physically modeled arm

Tasks

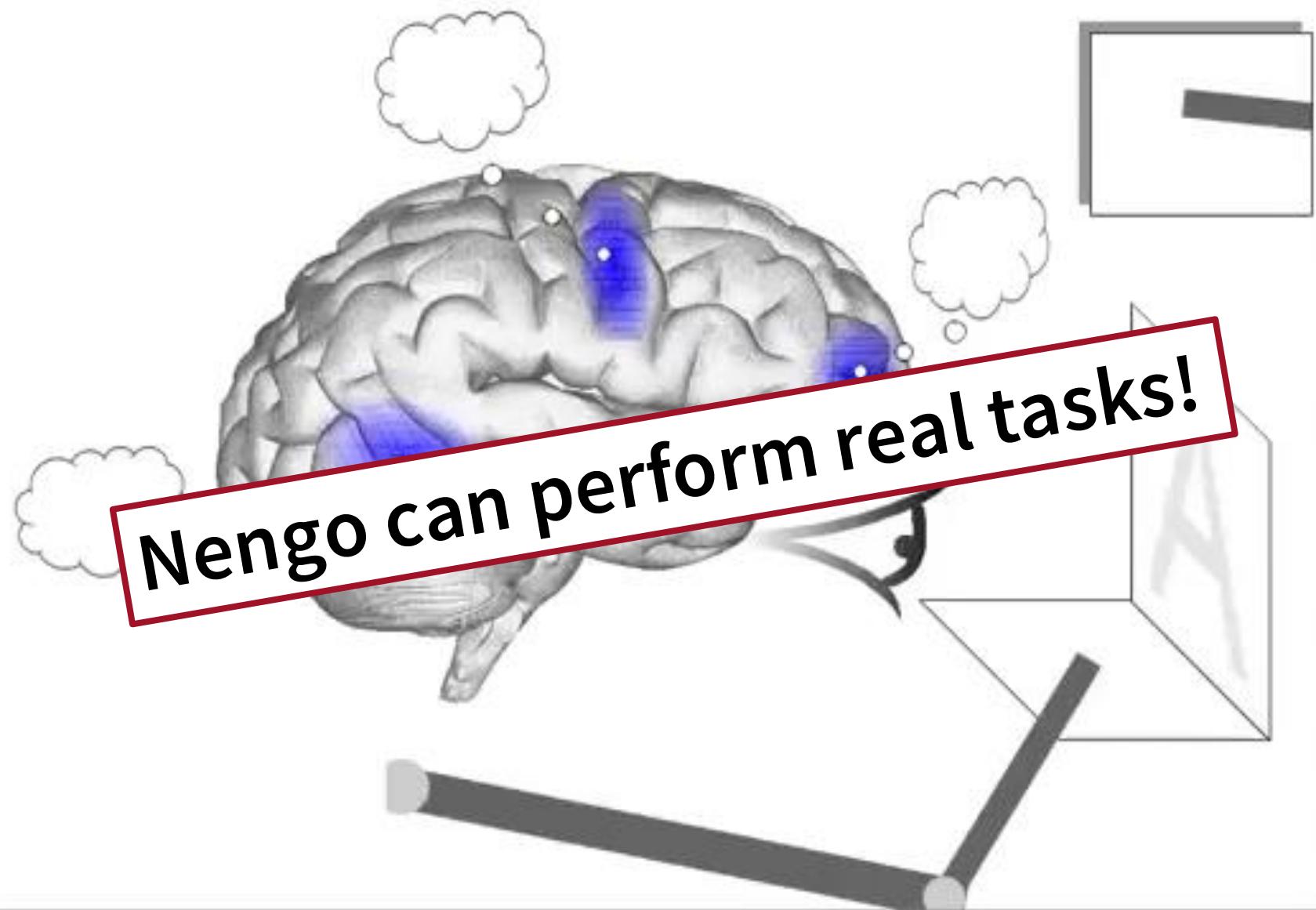
- Real input: 28x28 pixel images
- Output: physically modeled arm
- Tasks:
 - Copy drawing
 - Image recognition
 - Reinforcement learning
 - Serial Working Memory
 - Counting
 - Question Answering
 - Rapid variable creation
 - Raven's matrices



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



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



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

Summary

Summary

- Ensembles of neurons represent values

Summary

- Ensembles of neurons represent values
- These values can be communicated, transformed, and stored

Summary

- Ensembles of neurons represent values
- These values can be communicated, transformed, and stored
- Nengo calculates optimal encoders and decoders, allowing for large-scale models

Summary

- Ensembles of neurons represent values
- These values can be communicated, transformed, and stored
- Nengo calculates optimal encoders and decoders, allowing for large-scale models
- Spaun – a large-scale model – can do eight different task without having to be re-programmed

Summary

- Ensembles of neurons represent values
- These values can be communicated, transformed, and stored
- Nengo – a large-scale model
- **Next week: symbols, semantic pointers, memory, learning, behavior...**
- Nengo – a large-scale model – can do eight different task without having to be re-programmed

Summary

- Ensembles of neurons represent values
- These values can be communicated,
 → and stored
via pointers,
- **No lecture on Thursday!**
- **Next week:** memory, learning
- Brain – a large-scale model – can do eight different task without having to be re-programmed

**Good luck with
the assignment!**



university of
groningen

