Title: How to build a brain: A suggestion for how to unify the brain sciences

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Abstract: Theoretical neuroscience, like theoretical physics, attempts to discover and quantify the basic principles governing the systems it studies. Currently, however, there are very few attempts at unification across the levels of organization found in the brain. In this talk, I will describe the biological mechanisms of interest to neuroscientists, and describe a quantitative method for constructing sophisticated models of these mechanisms. Through a series of examples, I will show how the three principles that make up this method are general, allowing us to better understand a broad range of complex behaviour in a unified manner.

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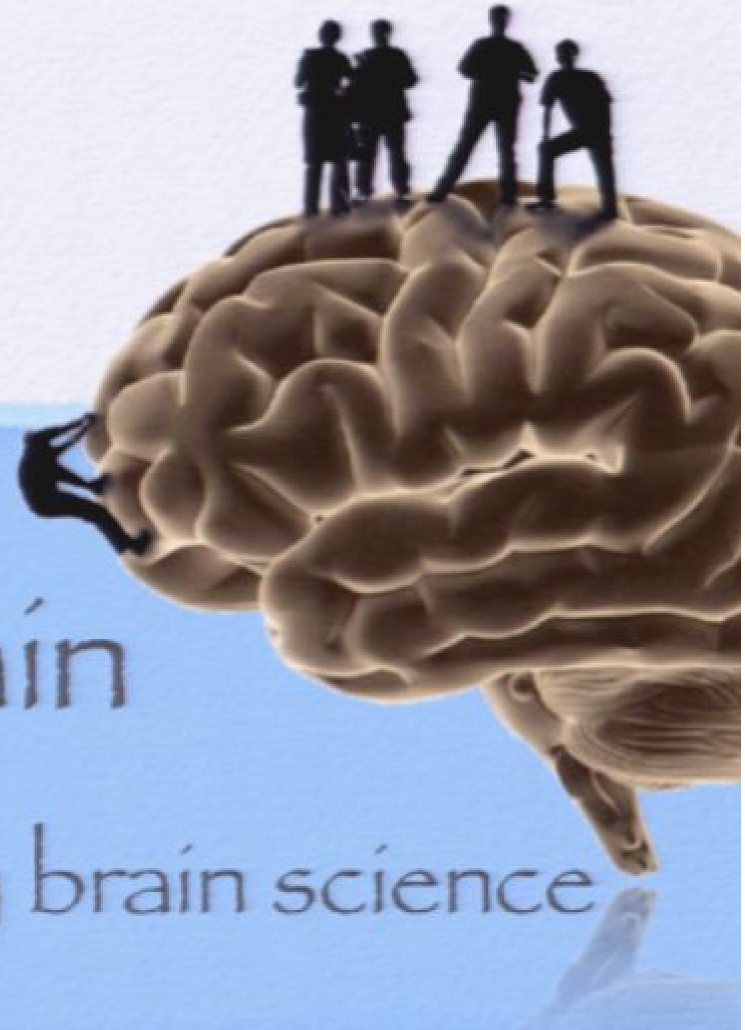

How to build a brain

A suggestion for how to unify brain science

Chris Eliasmith
Centre for Theoretical Neuroscience

CTN

CNRG
computational neuroscience
research group

A fertile analogy

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	Theoretical physics	Theoretical neuroscience

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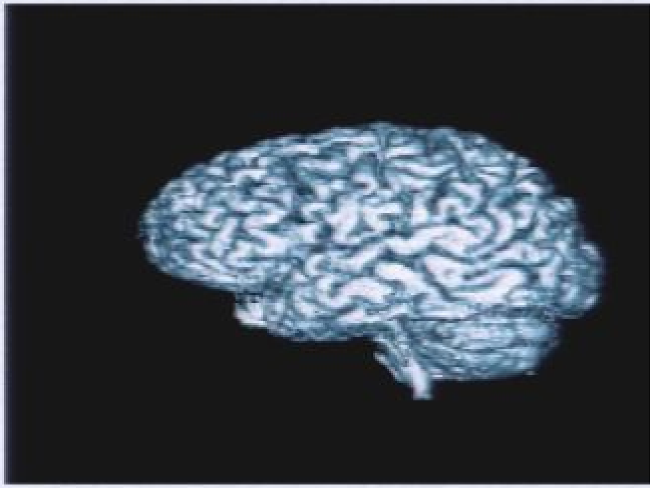
What there is

Who we are

Brains

Brains

- Mass: 1-2 kg (2% body weight)



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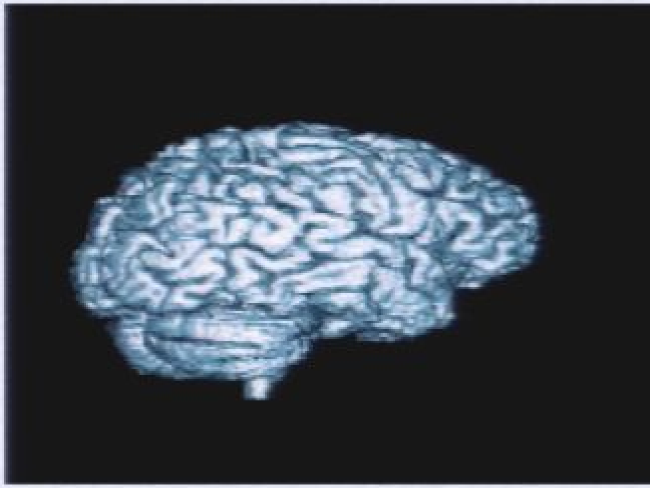

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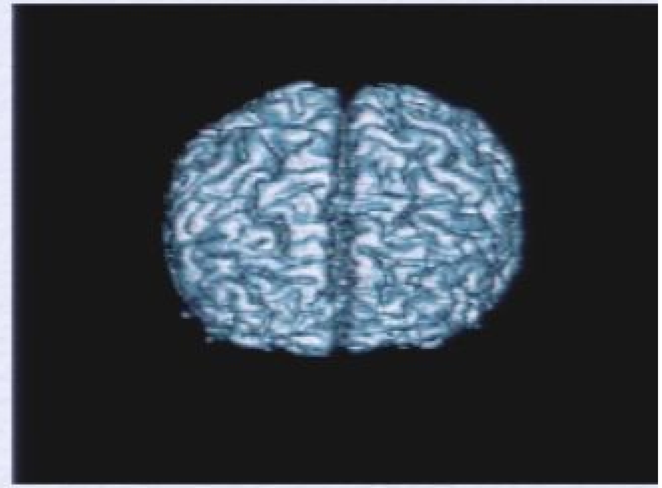
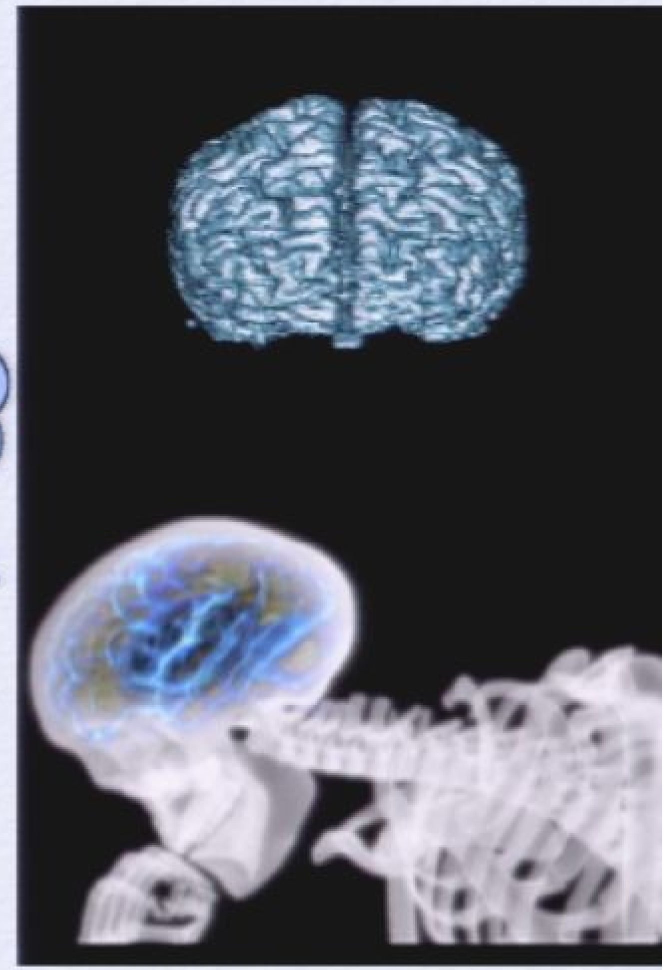


Brains

- Mass: 1-2 kg (2% body weight)
- 25% energy (glucose)
- Power: ~20 Watts



Brains

- Mass: 1-2 kg (2% body weight)
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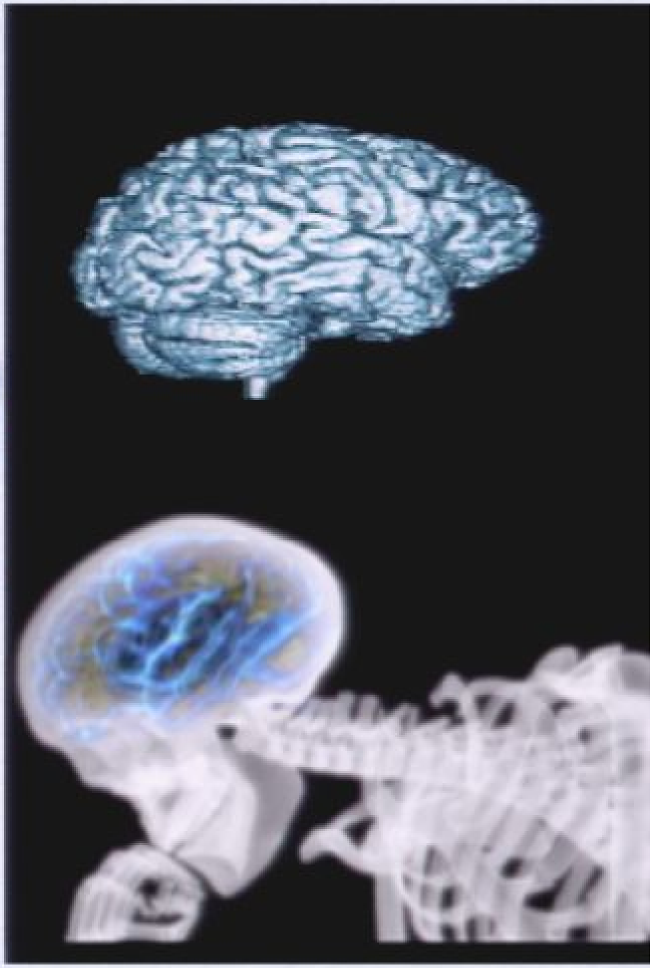
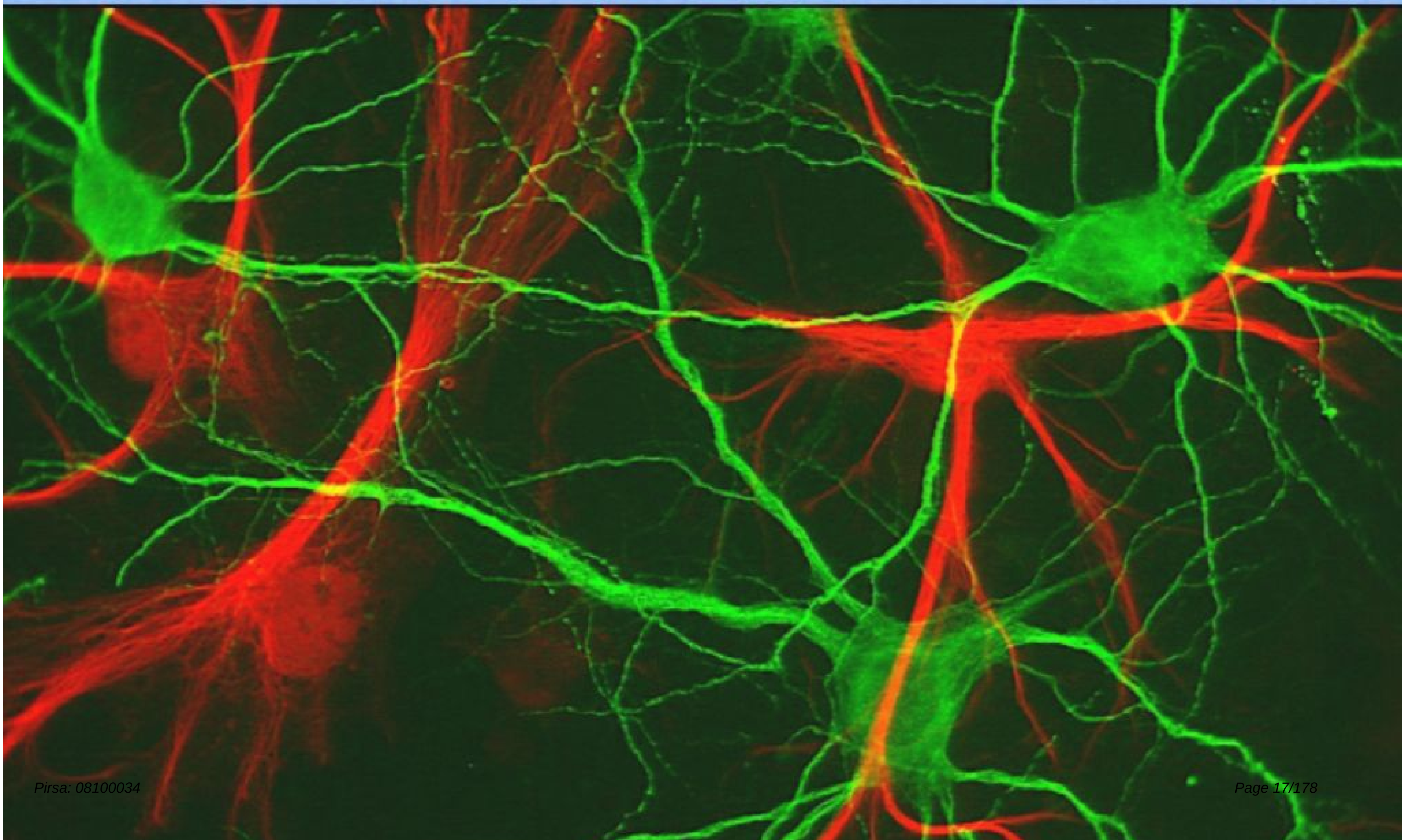
- Power: ~20 Watts
- Area: 4 sheets of paper
- Neurons: 100 billion



Neurons



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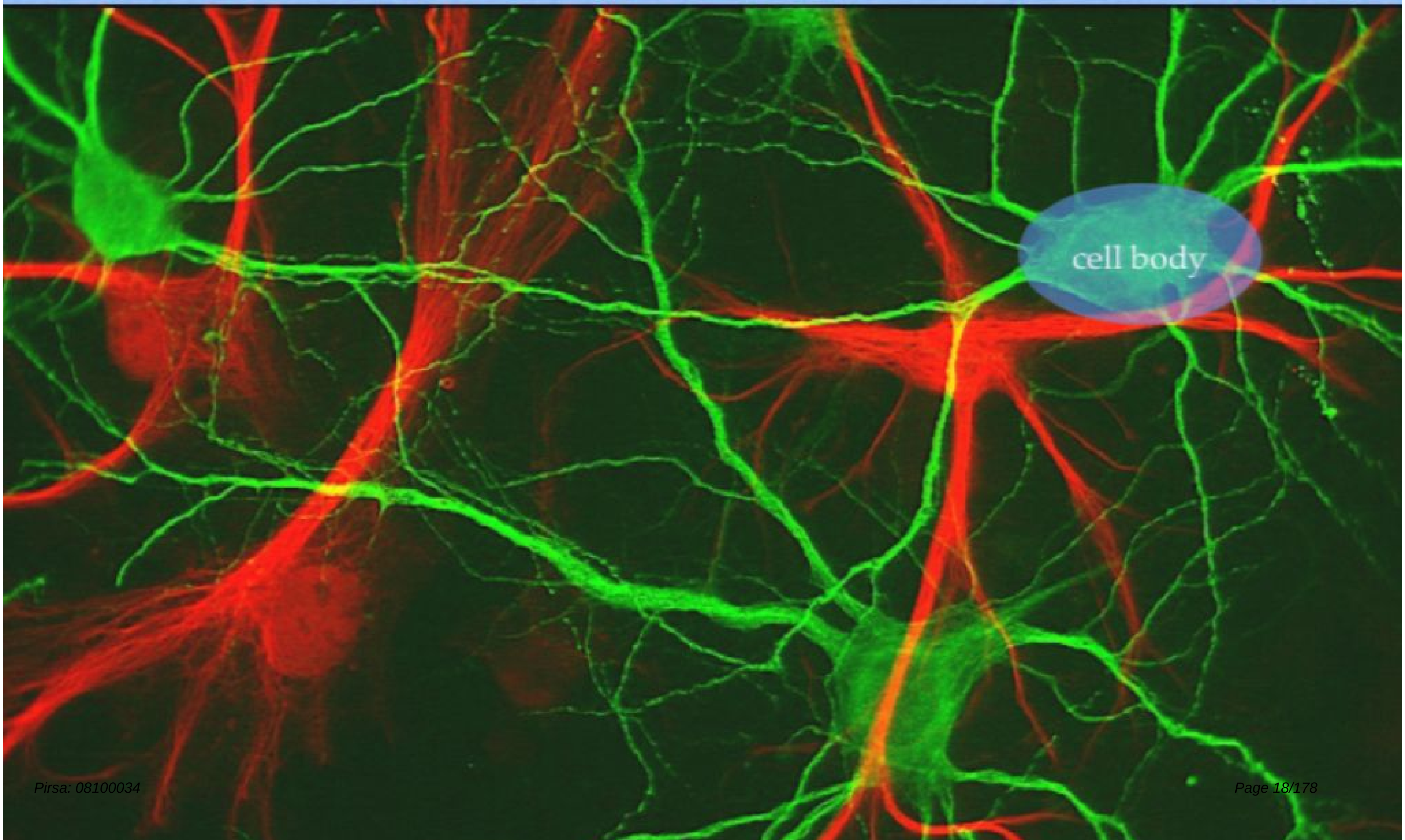

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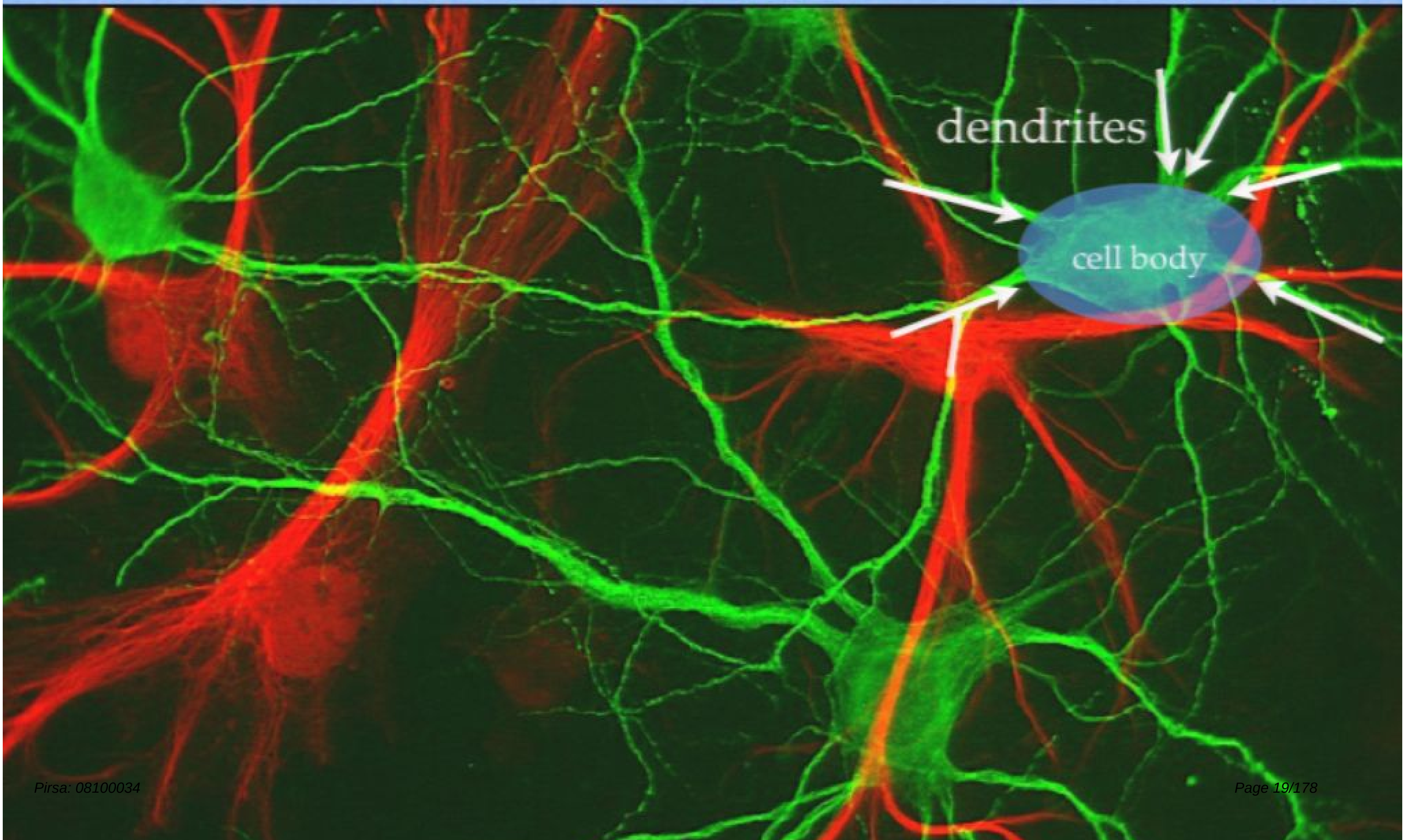

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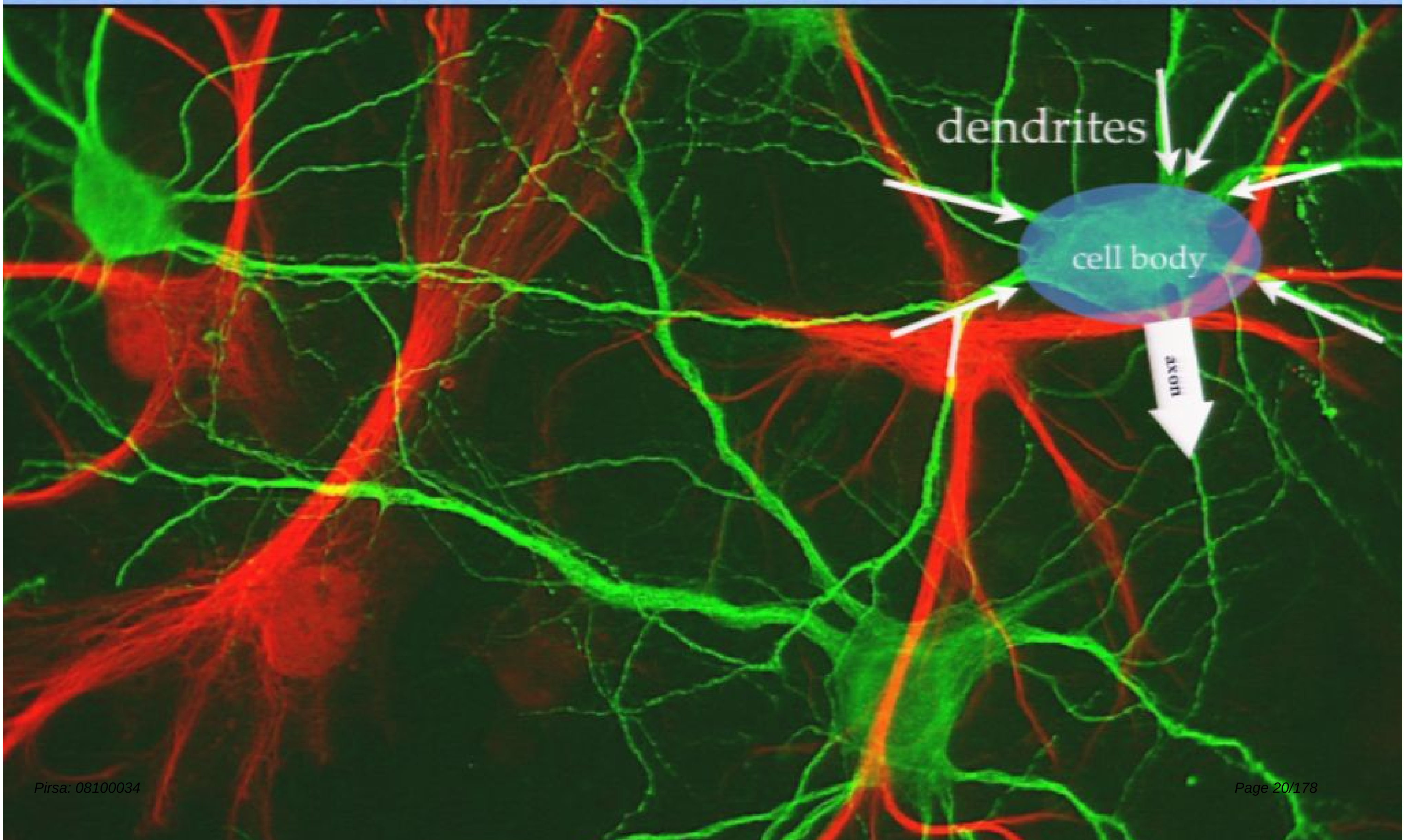

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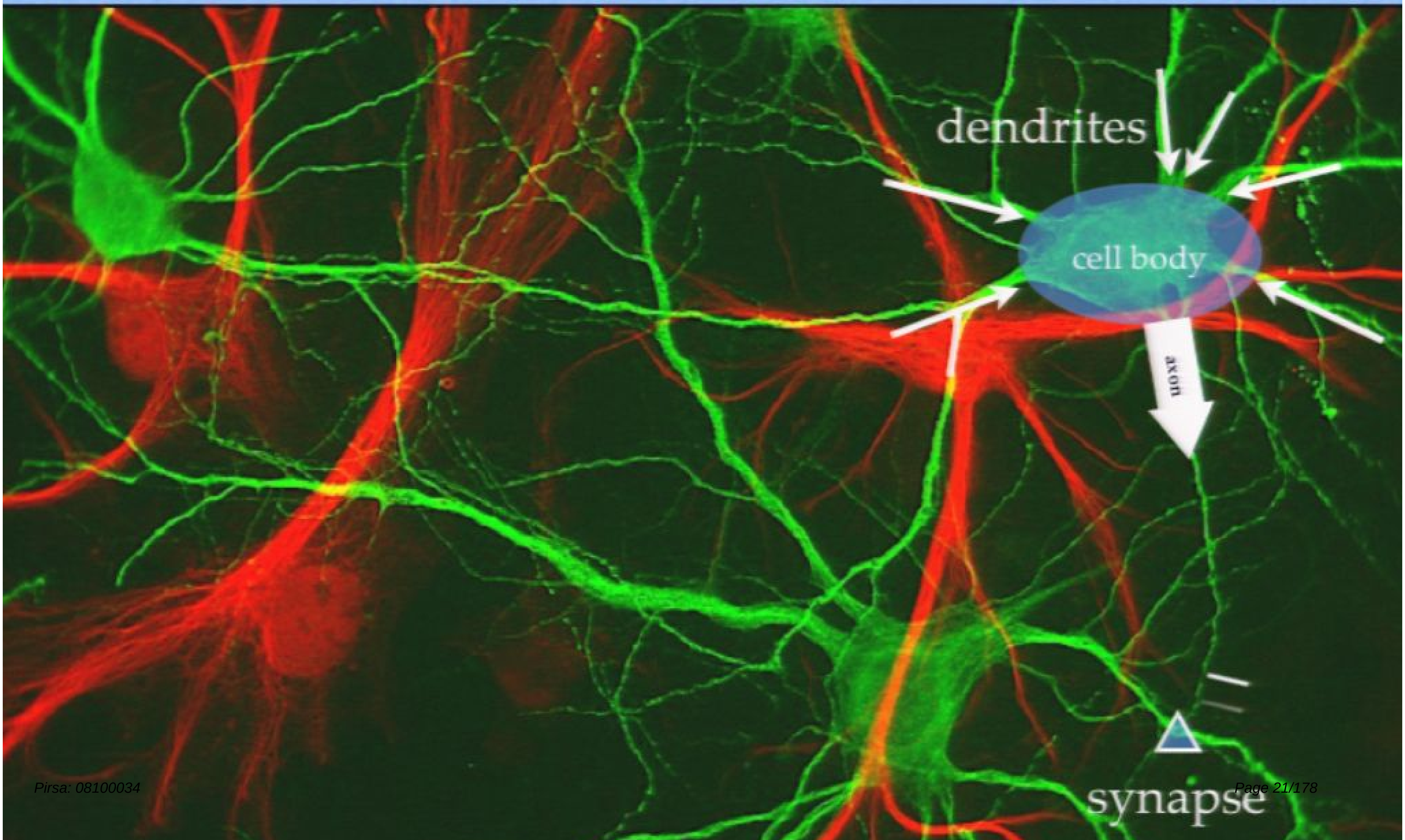

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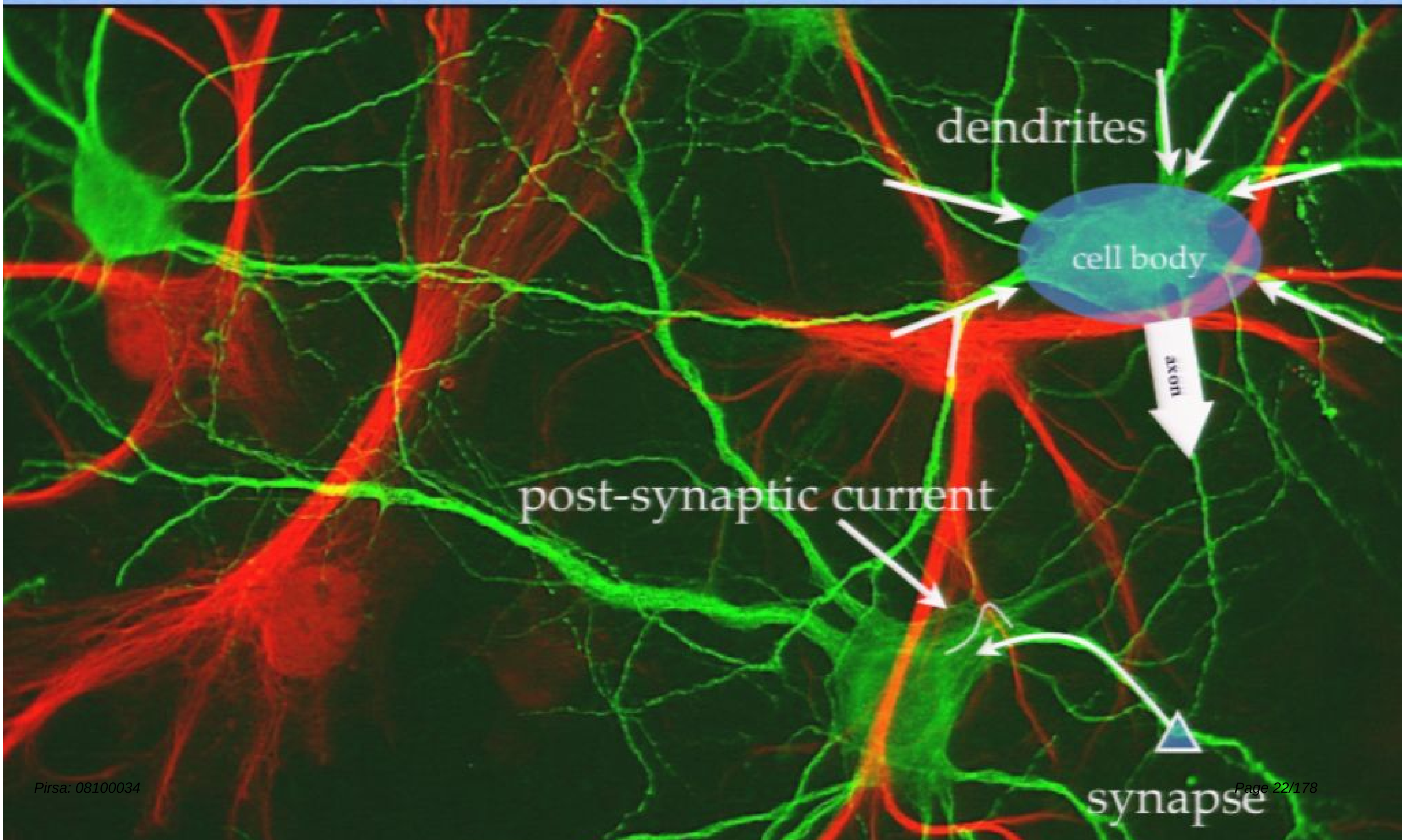

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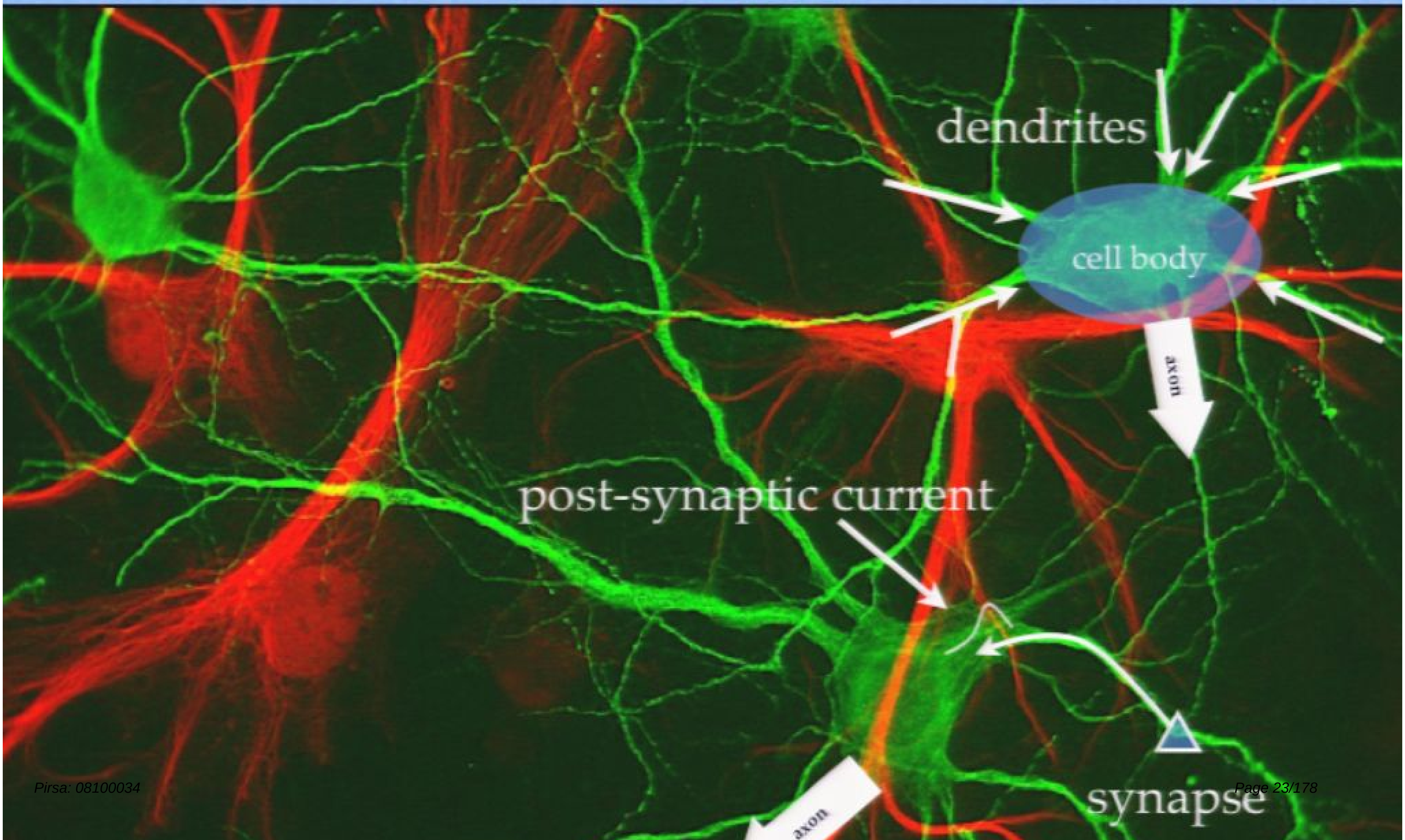
dendrites
cell body
axon
post-synaptic current
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Neurons


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Neurons

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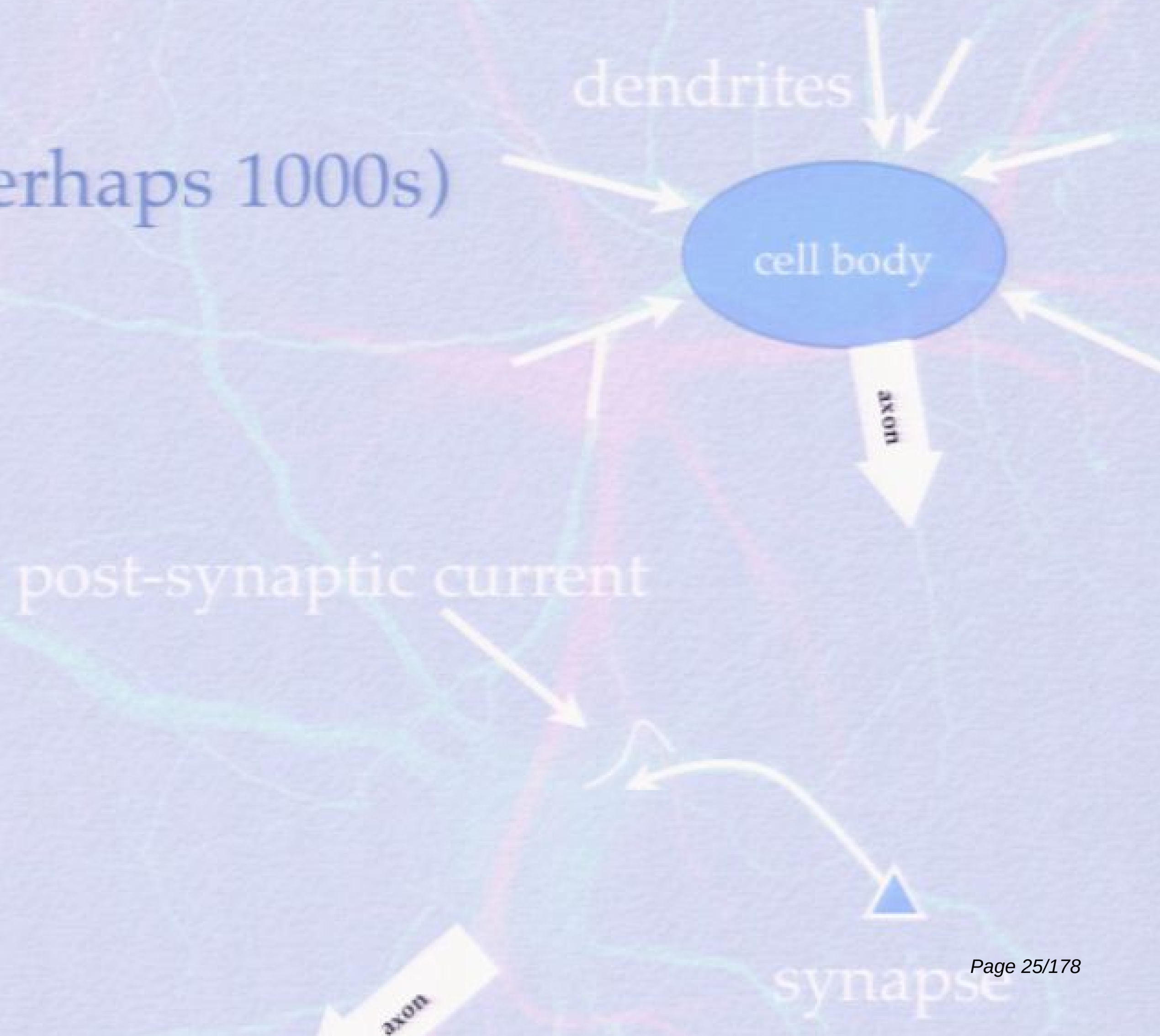

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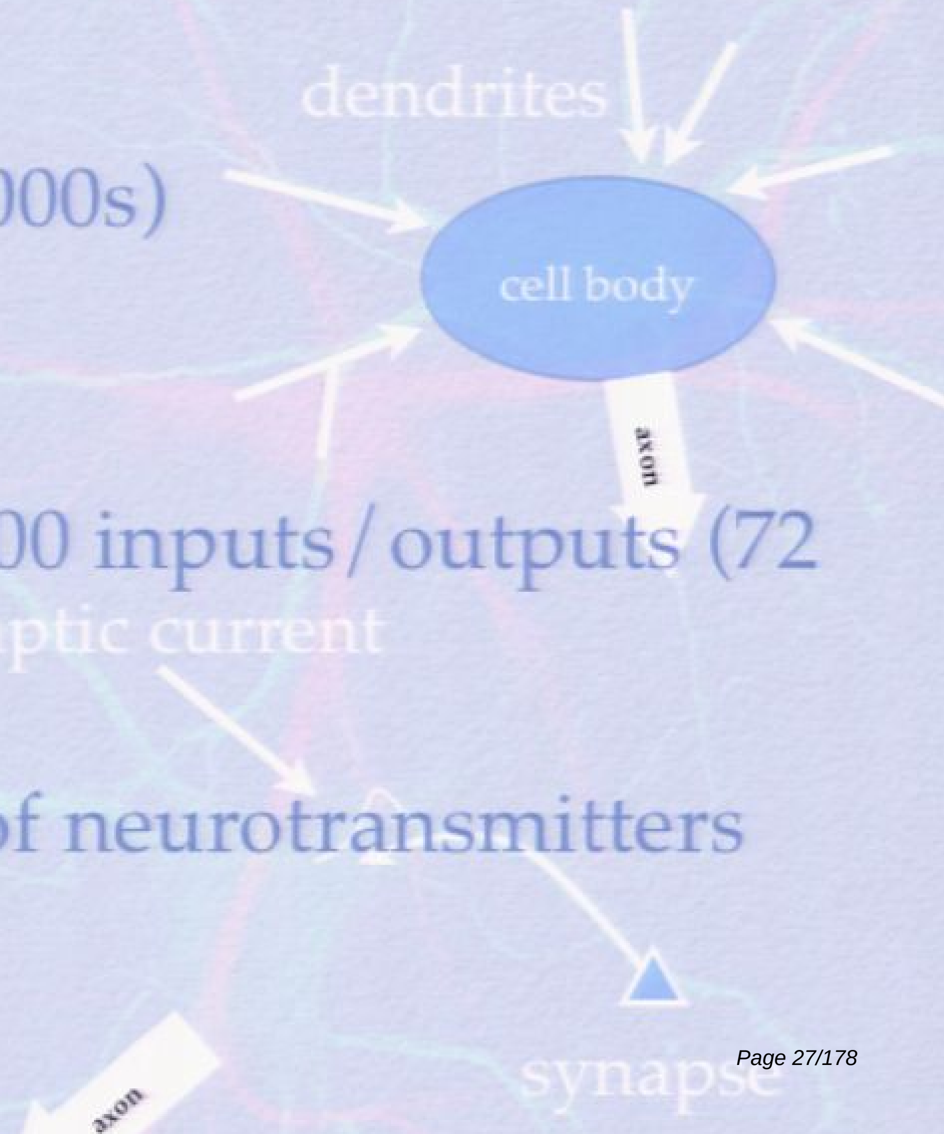

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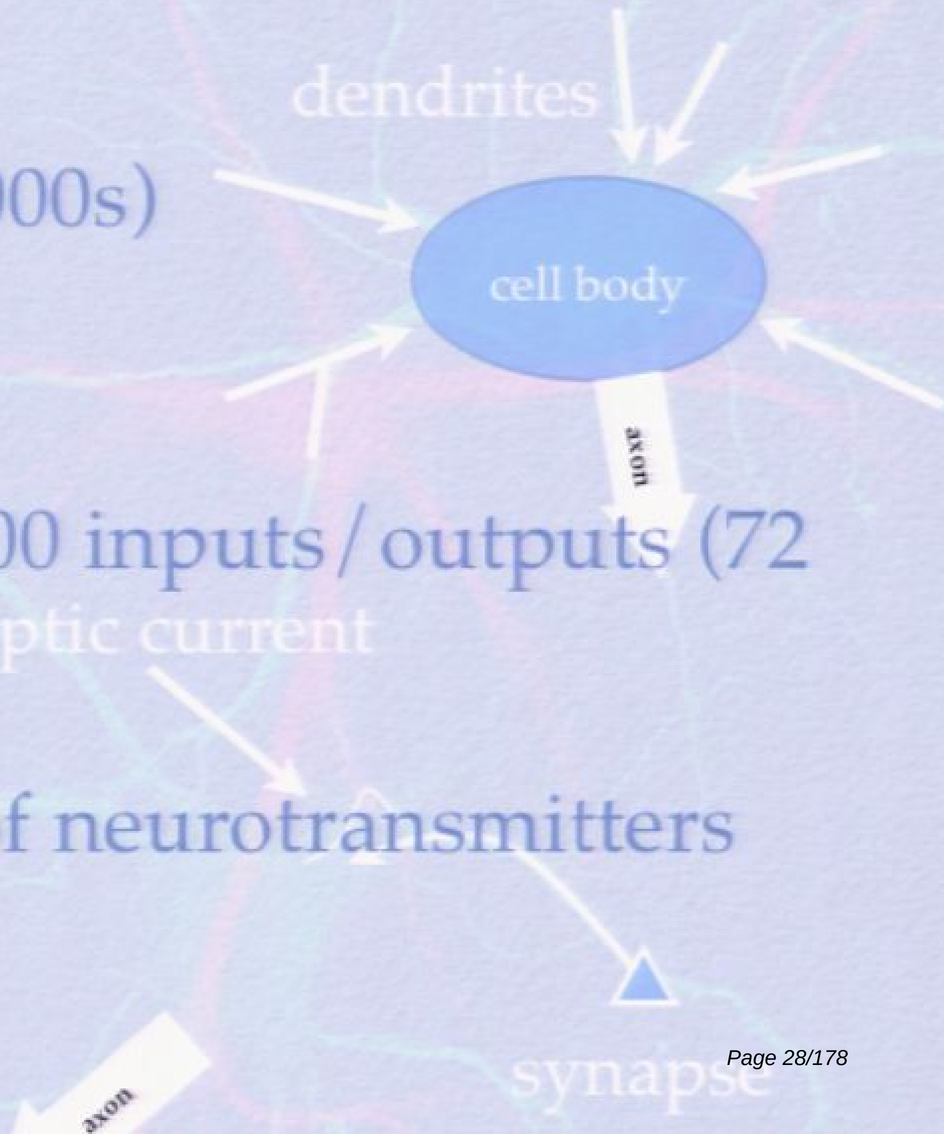
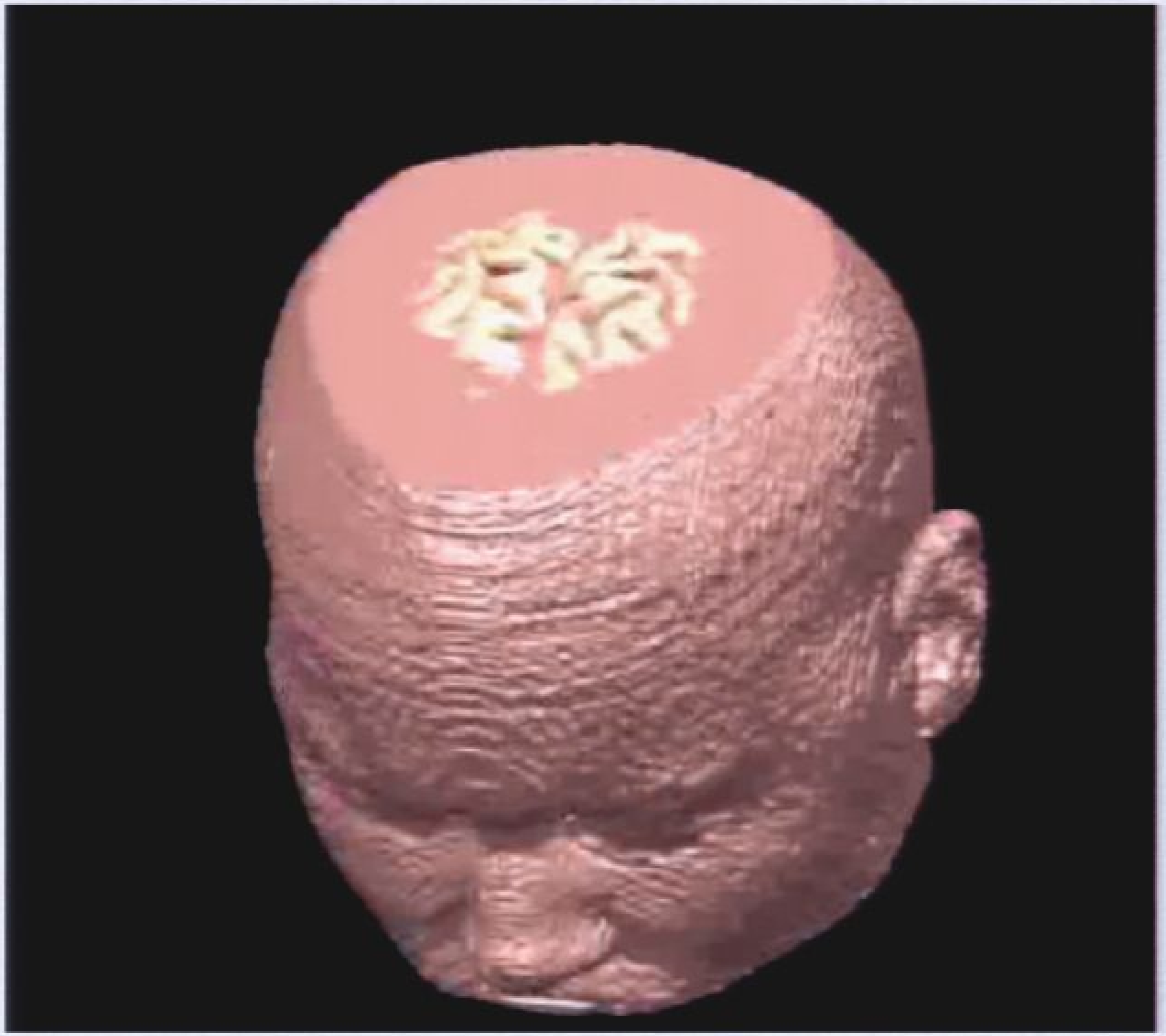


fMRI: Systems



Mothers and children

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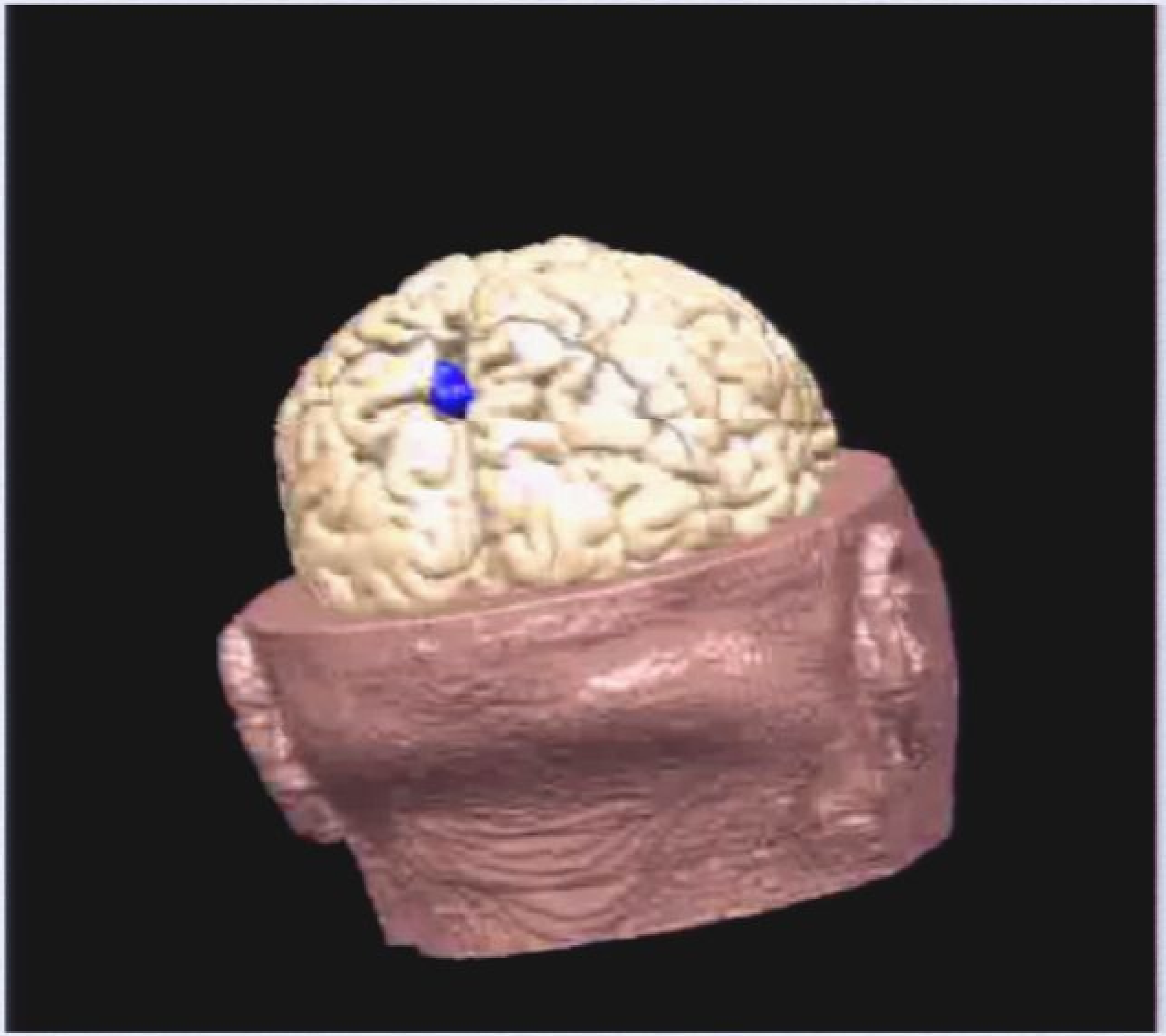

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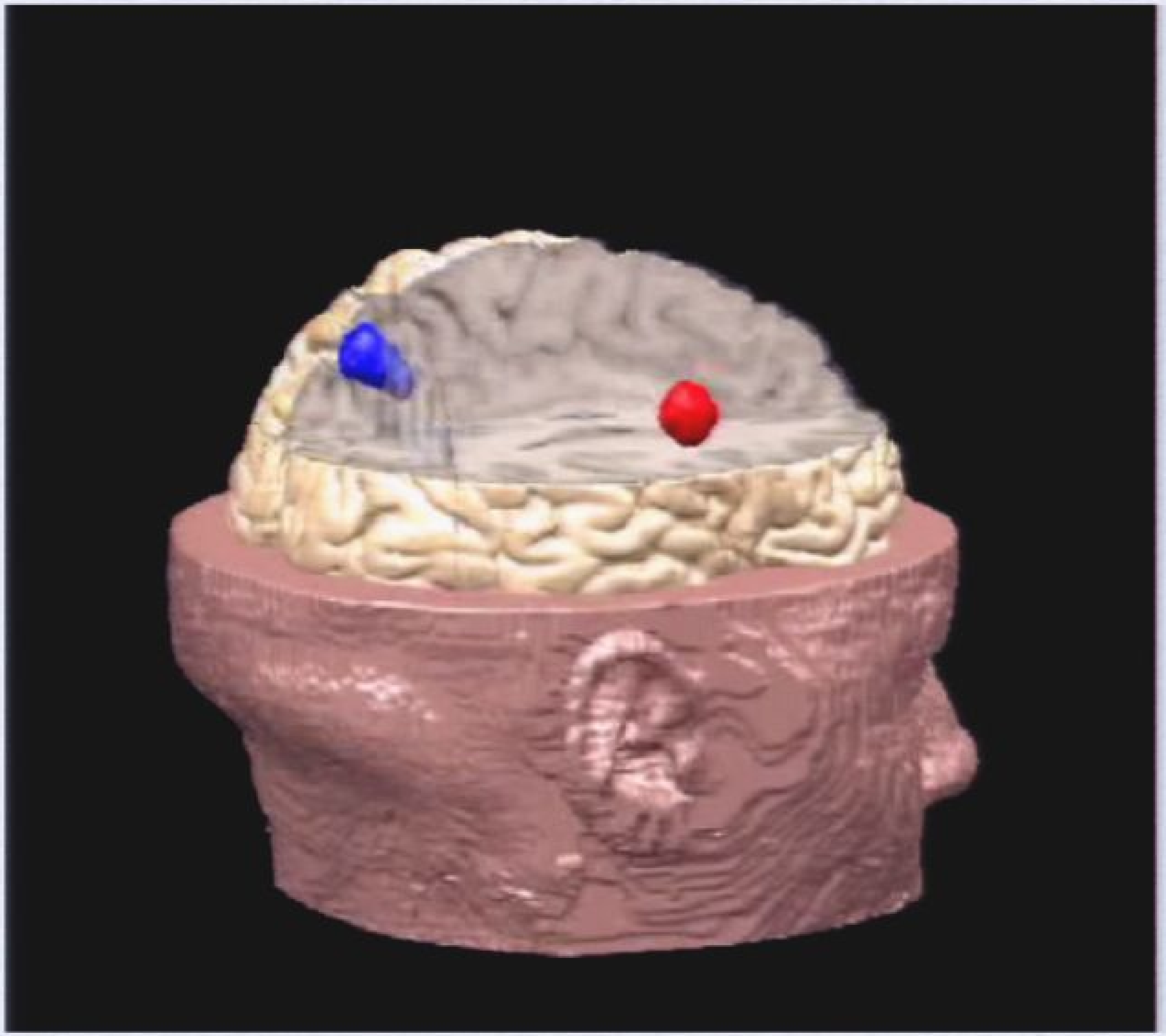
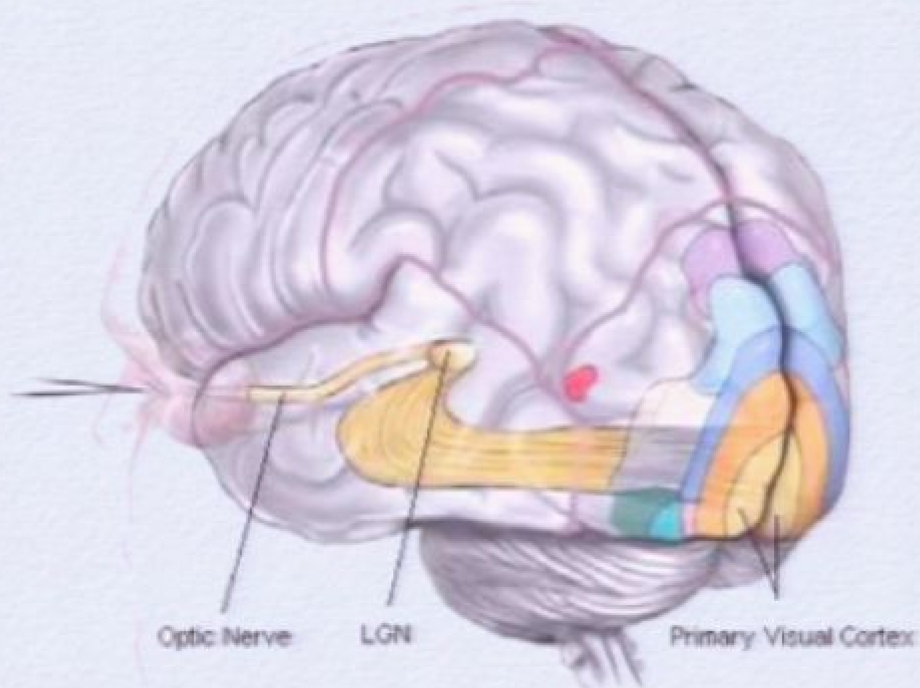


Mothers and children

Surface Imaging: Maps/Networks



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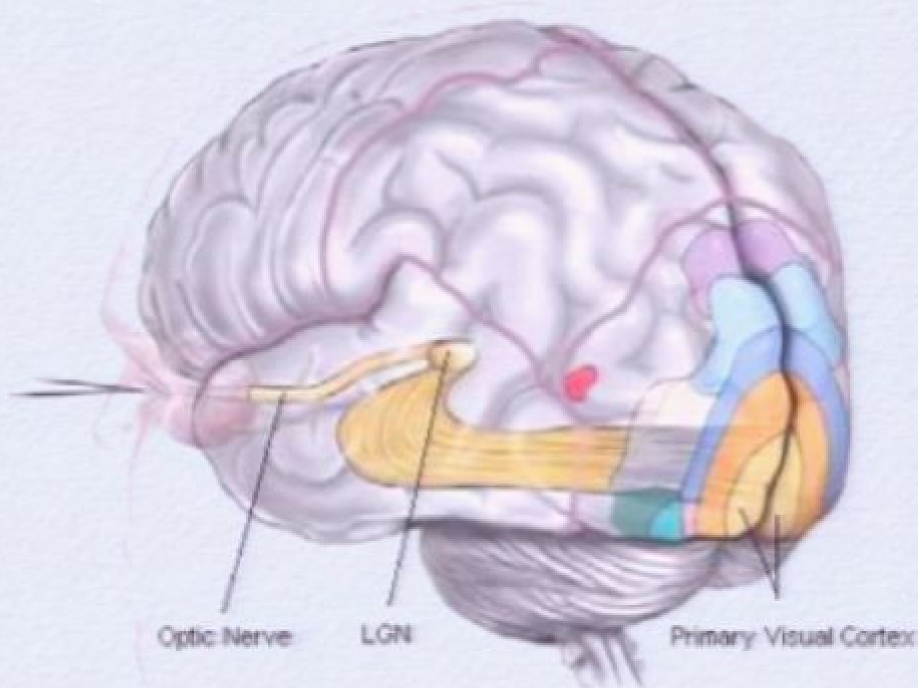

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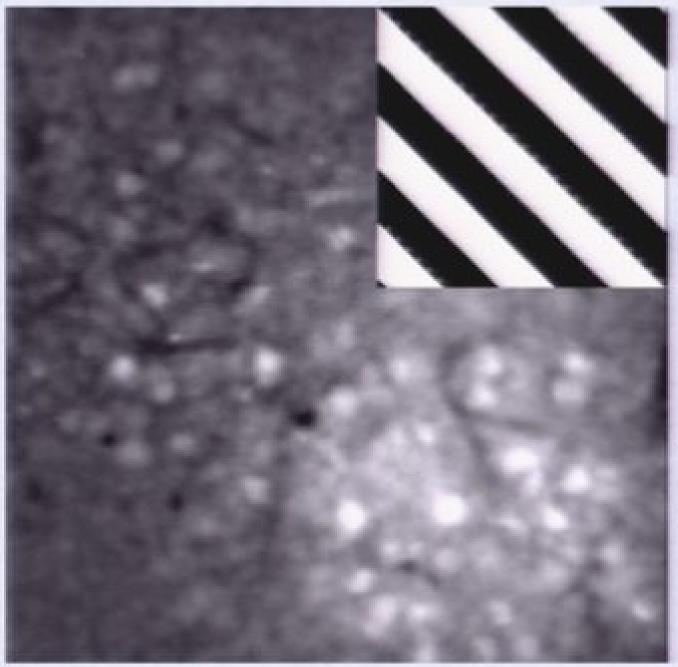
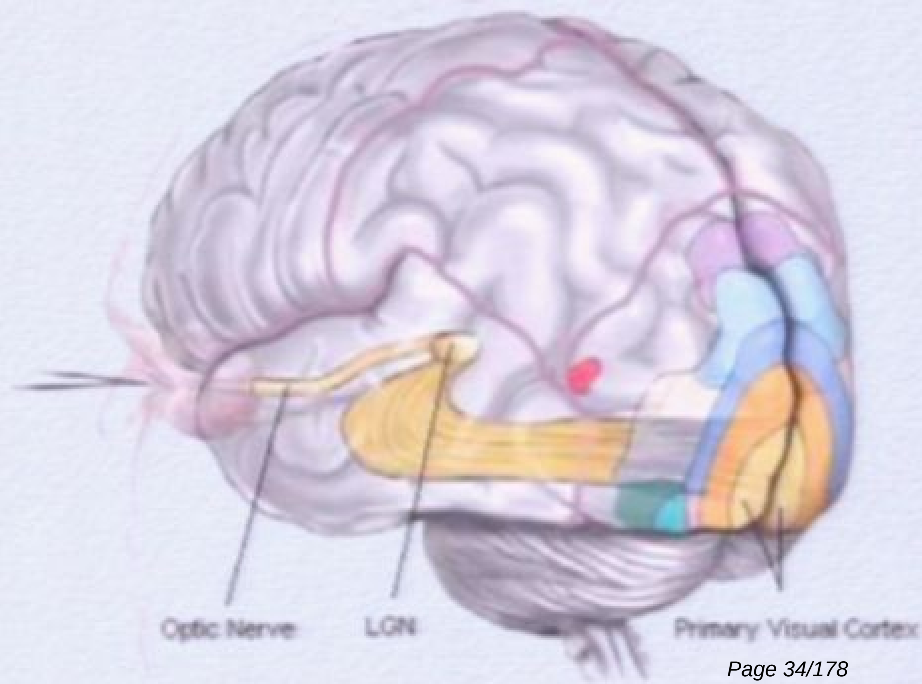


Response to gratings



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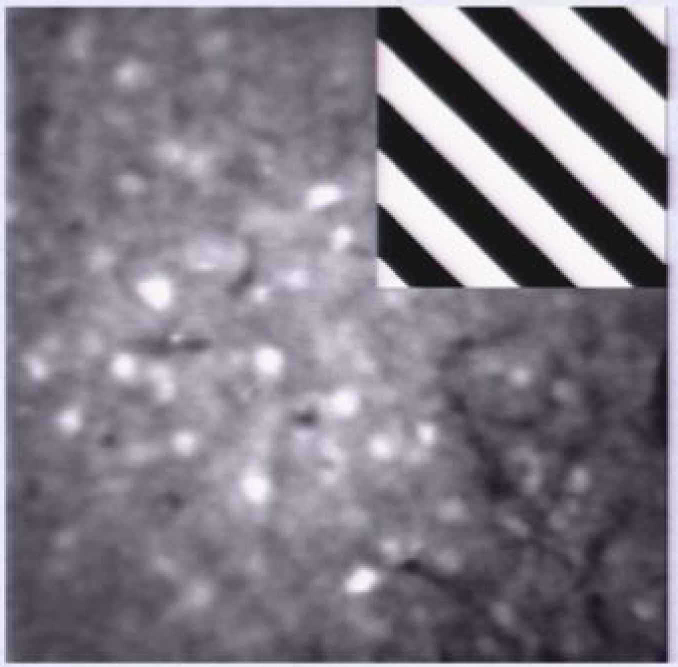

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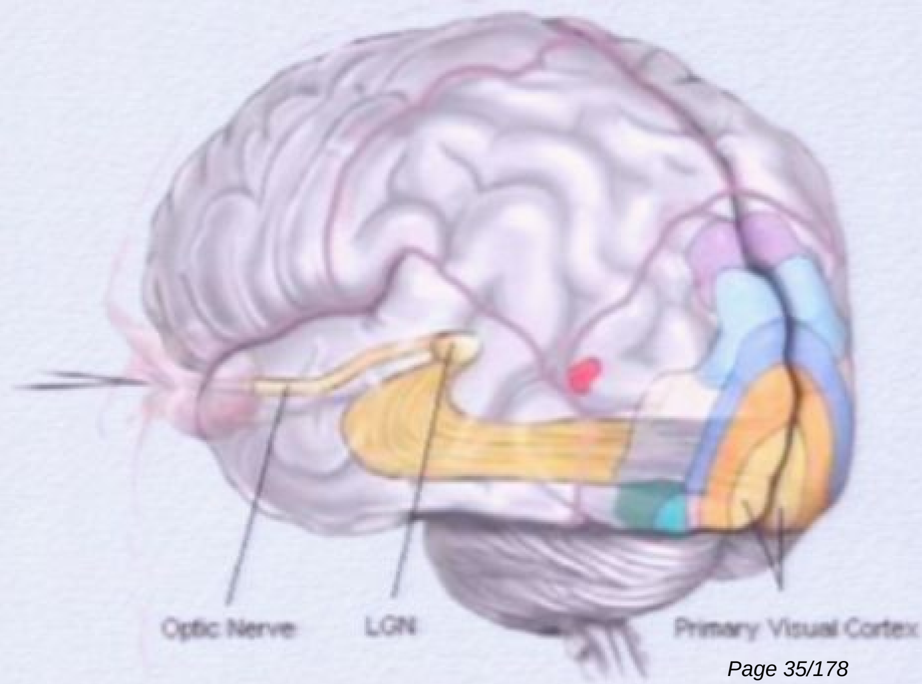

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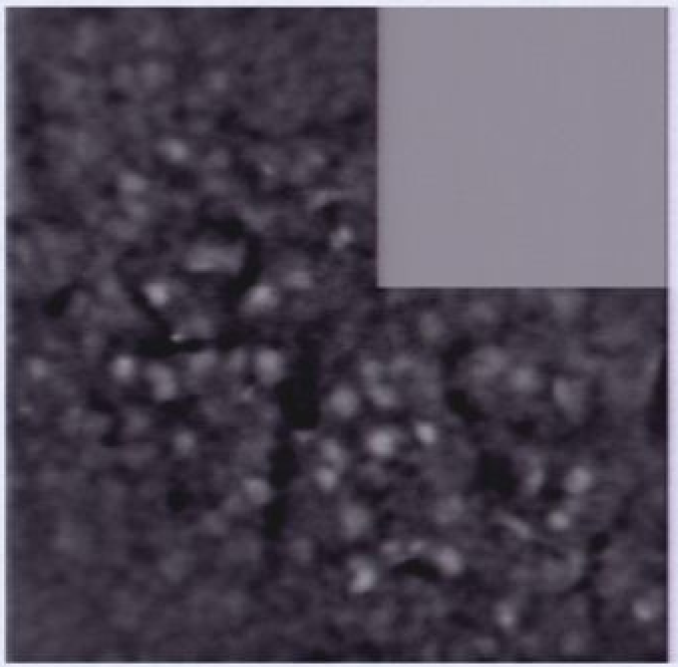

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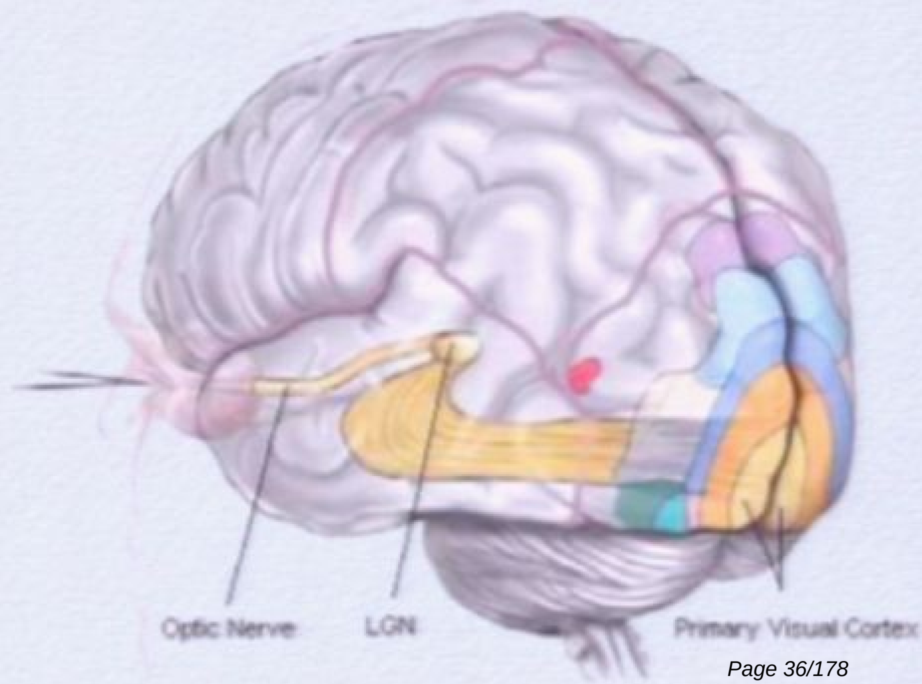
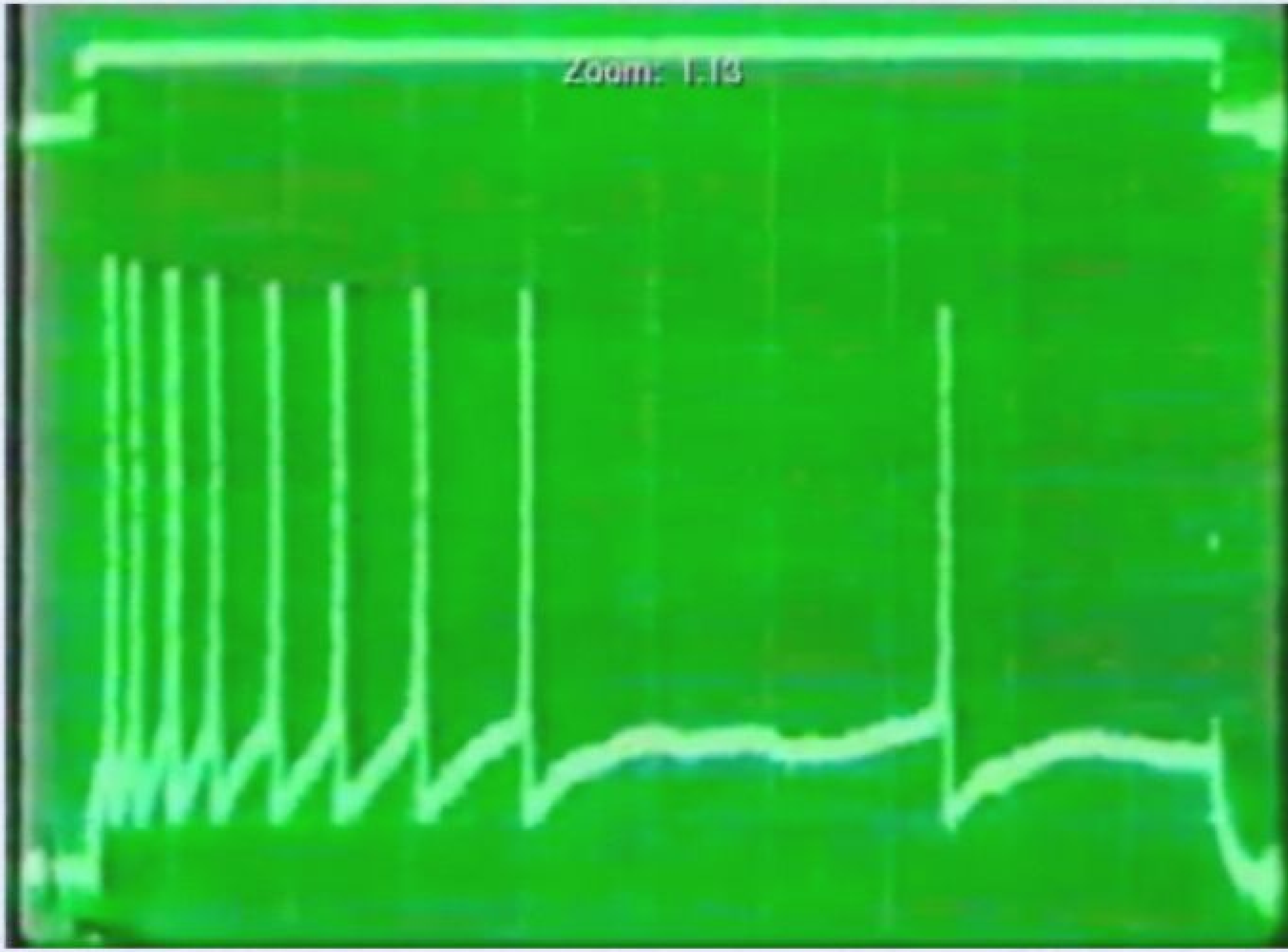


Single Cell Electrodes: Neurons

Current→

Cell Response



Cortical cell with injected current

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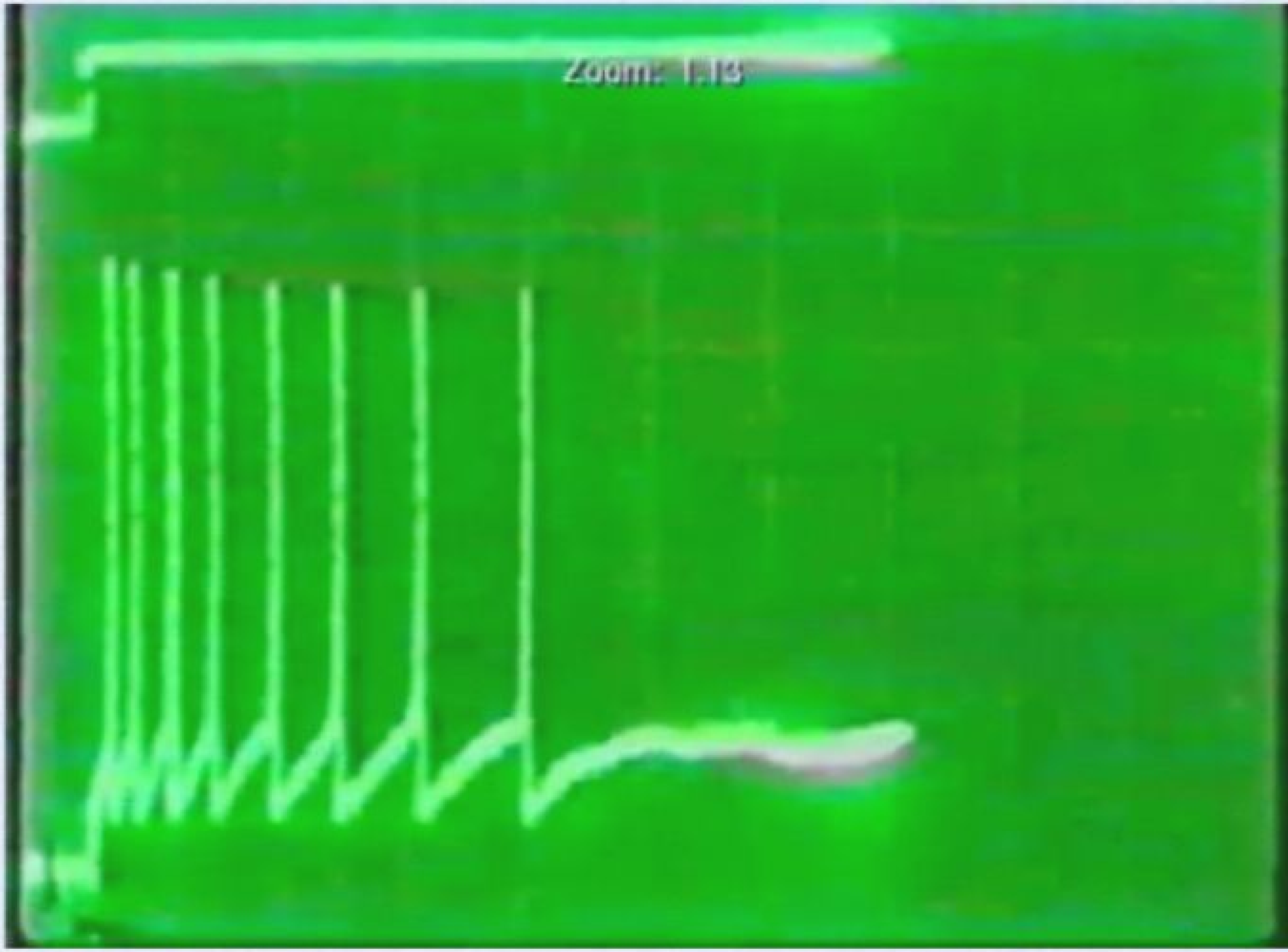

Cortical cell with injected current

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- Neuroscience is

  "Data rich and theory poor"

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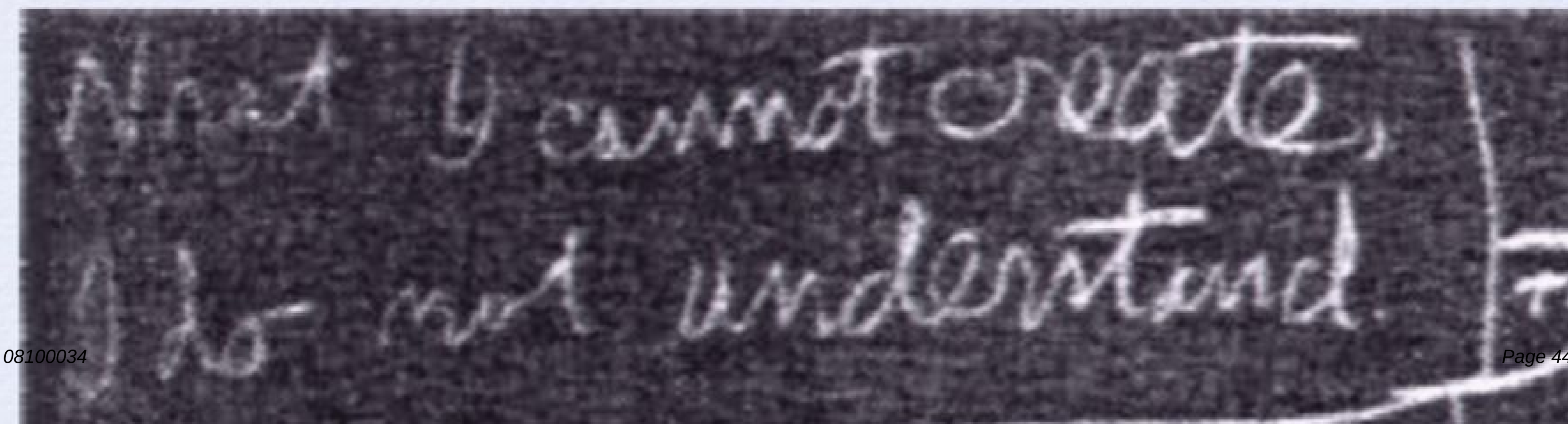

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  - Account for many nonlinearities

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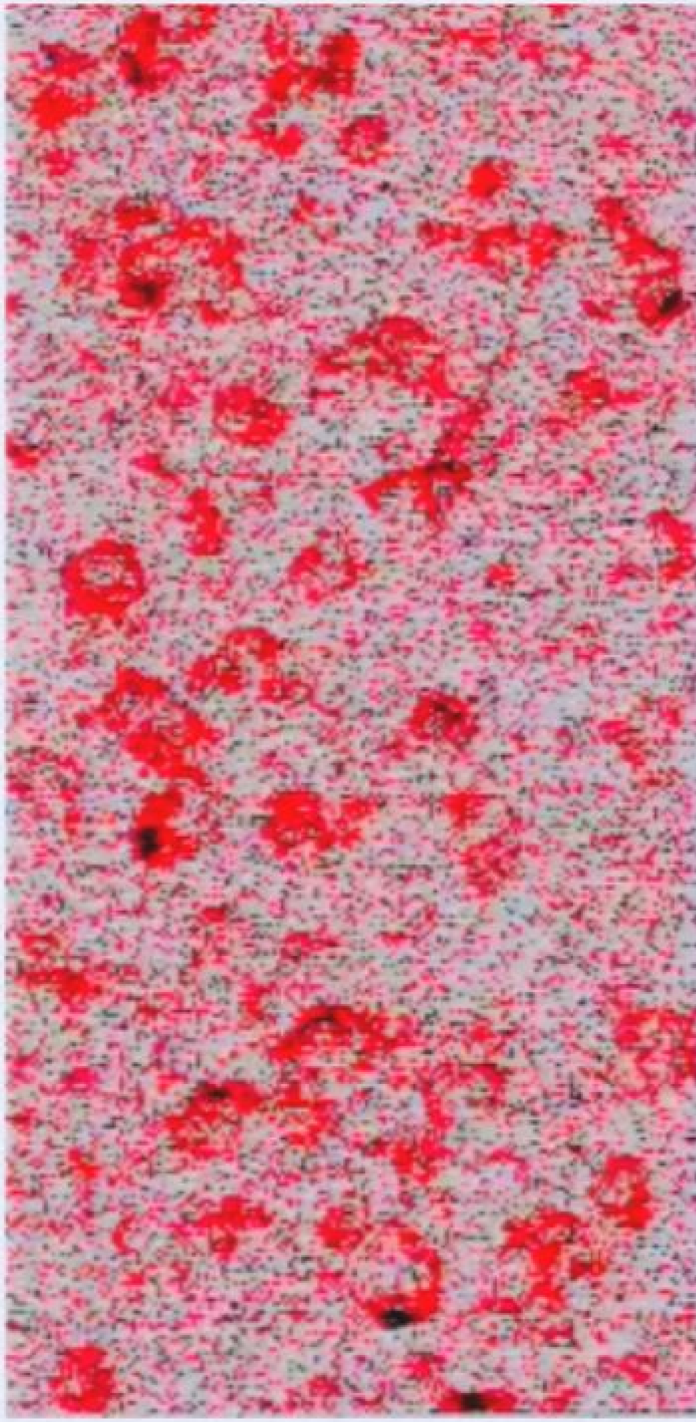
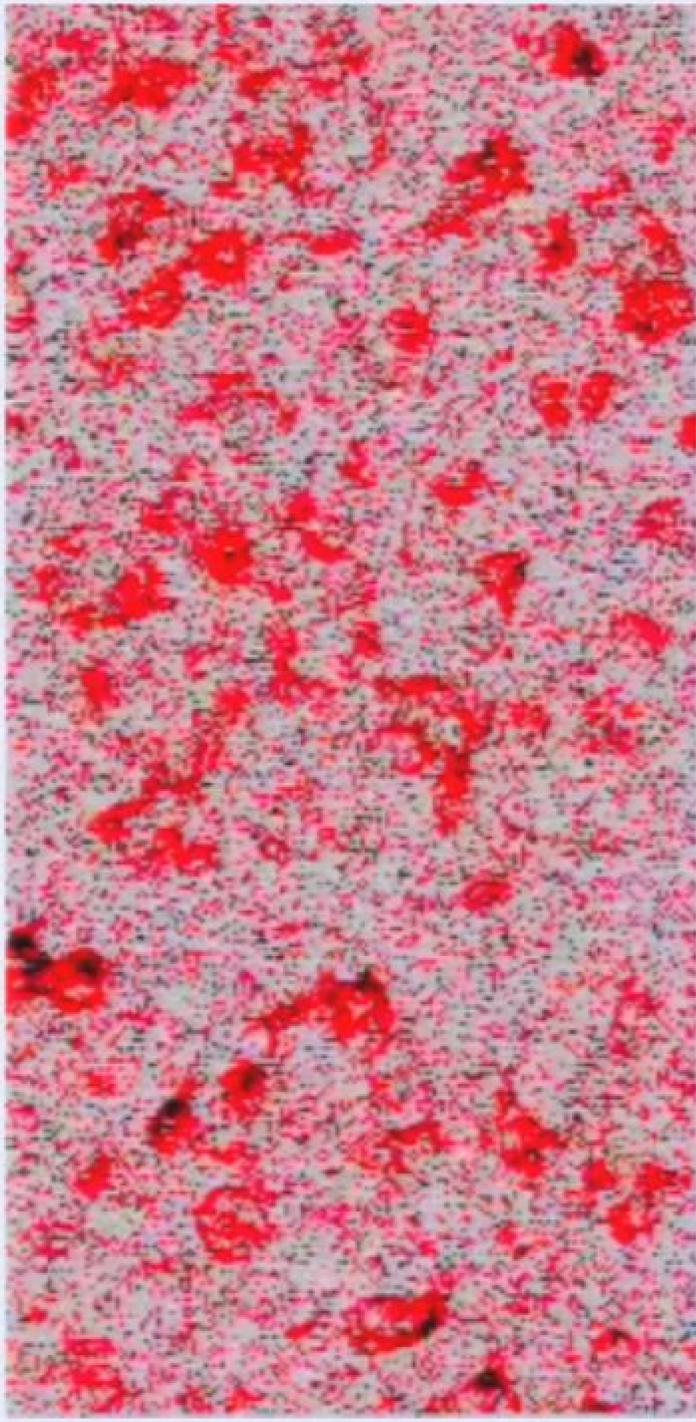
  - Learning (STDP, Hebbian, backprop, etc.)

Large-scale model

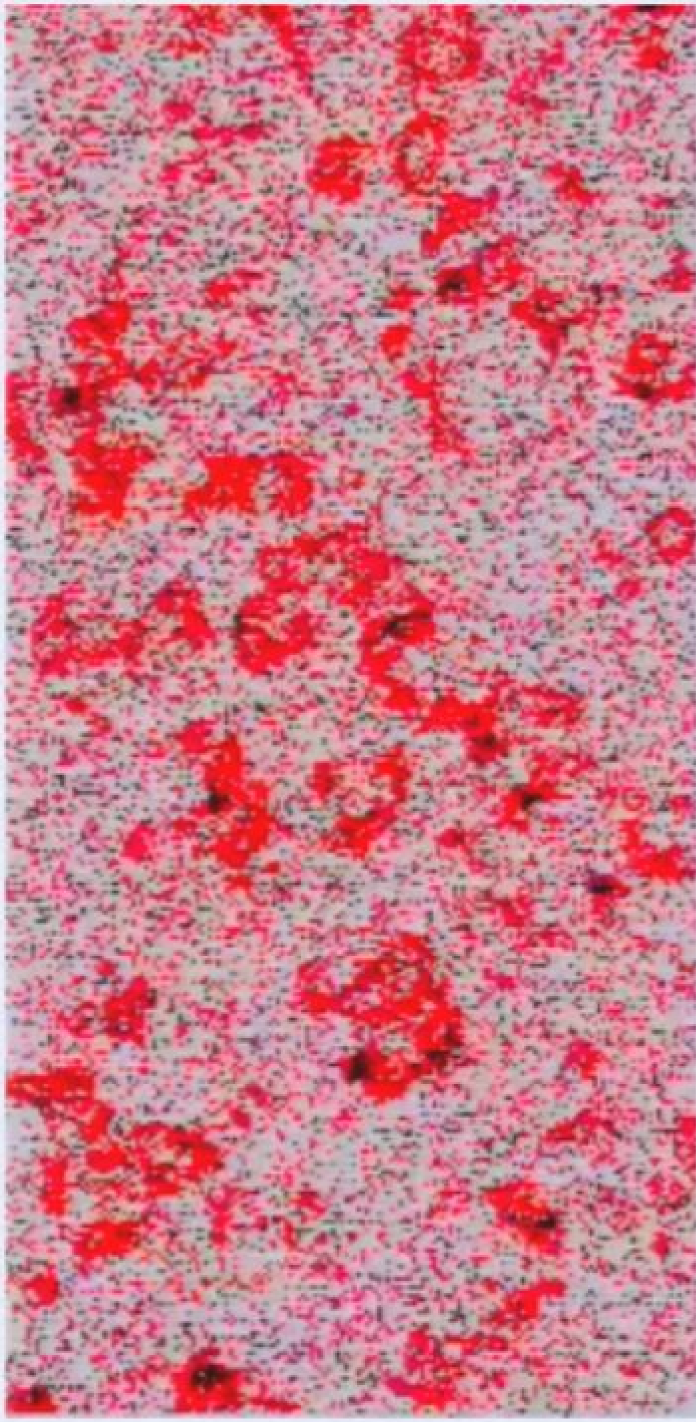


time: t = 152 ms

Large-scale model



time: t = 212 ms

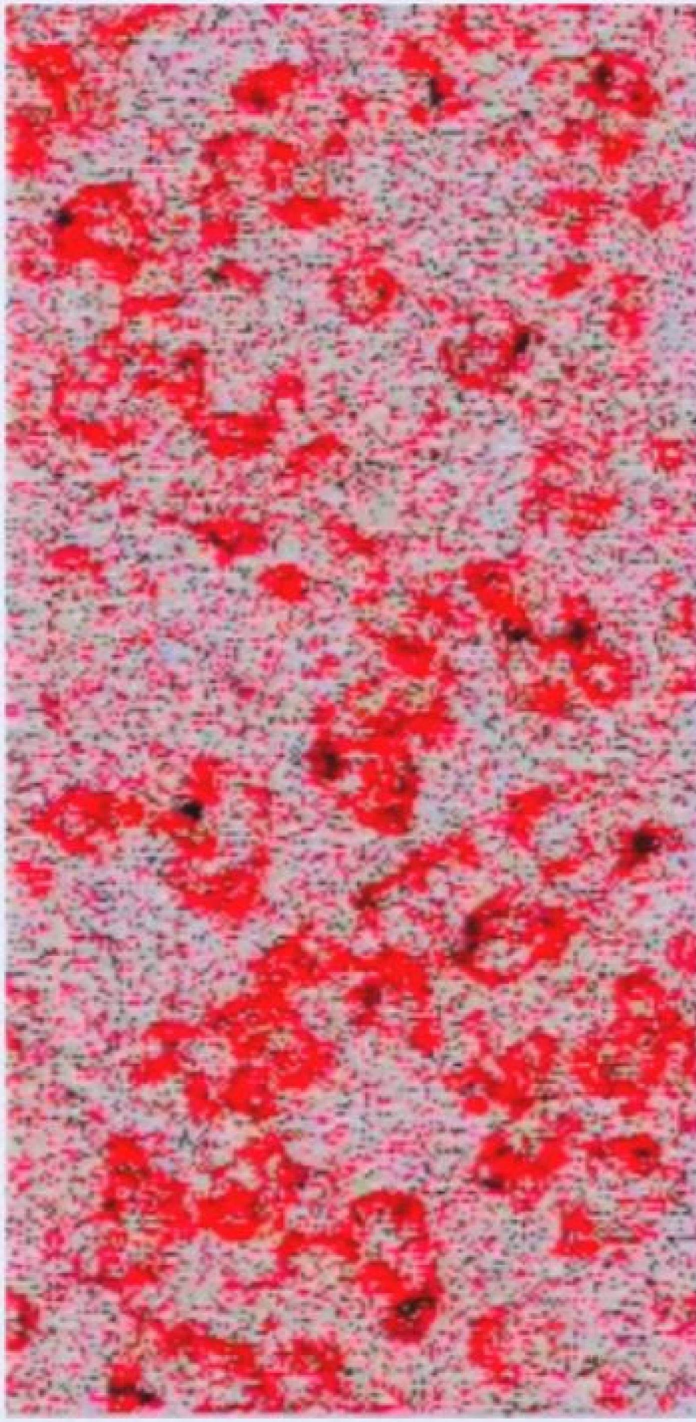


Large-scale model

100 billion simulated neurons

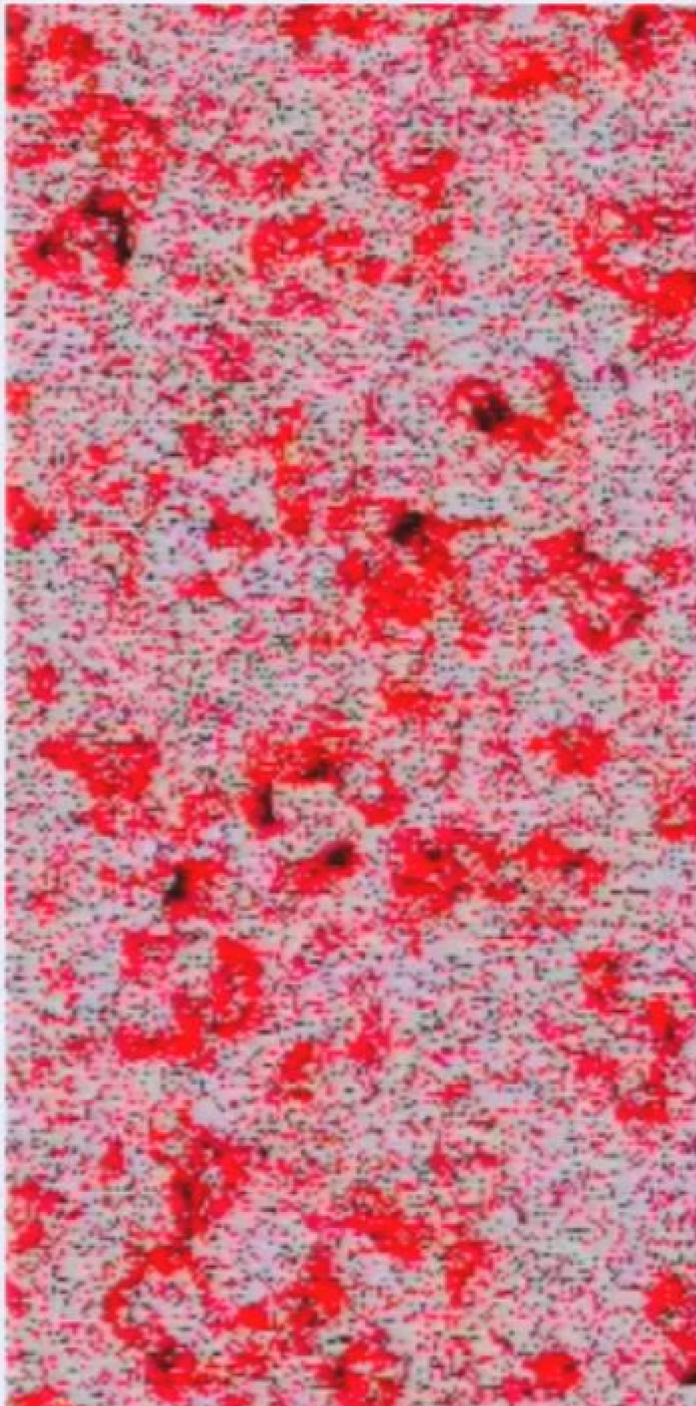
time: t = 411 ms

Large-scale model



100 billion simulated neurons

1 s of real time took 50 days on a supercomputer



Large-scale model

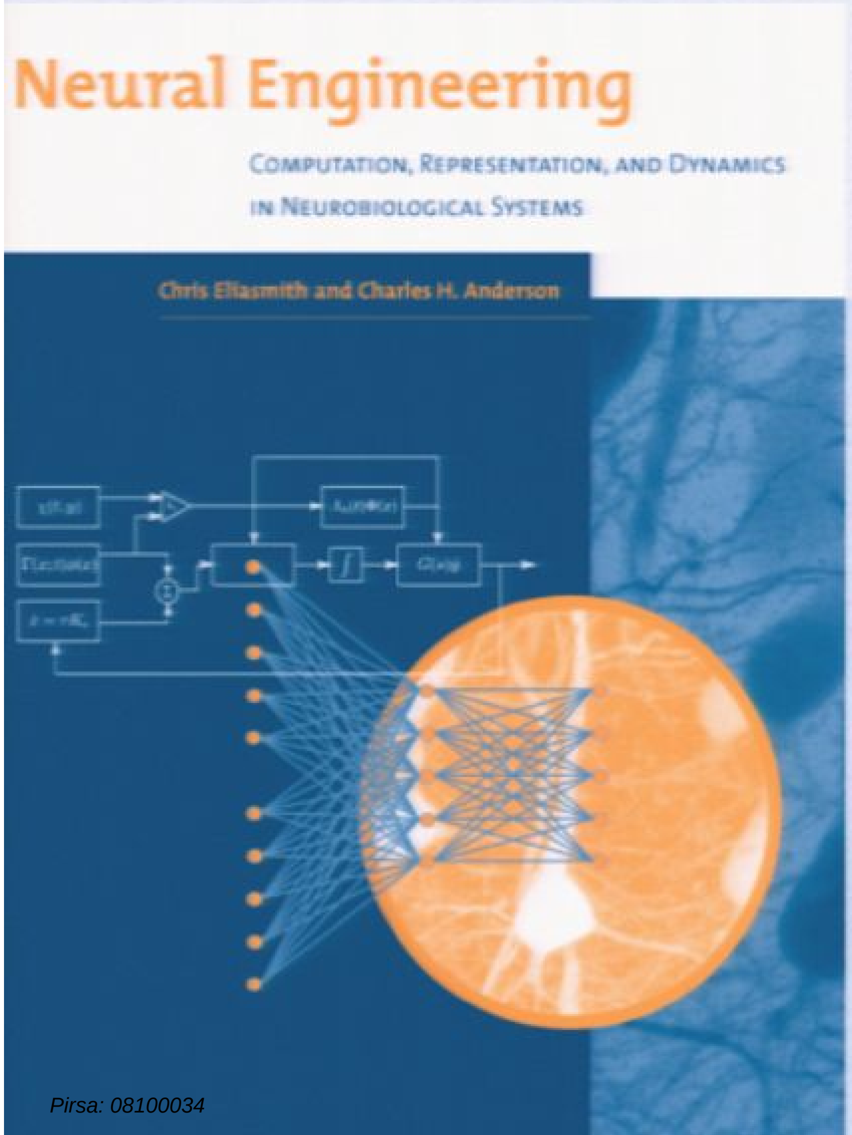
100 billion simulated neurons

1 s of real time took 50 days on a supercomputer

Randomly connected

time: t = 999 ms

Our work at the CNRG



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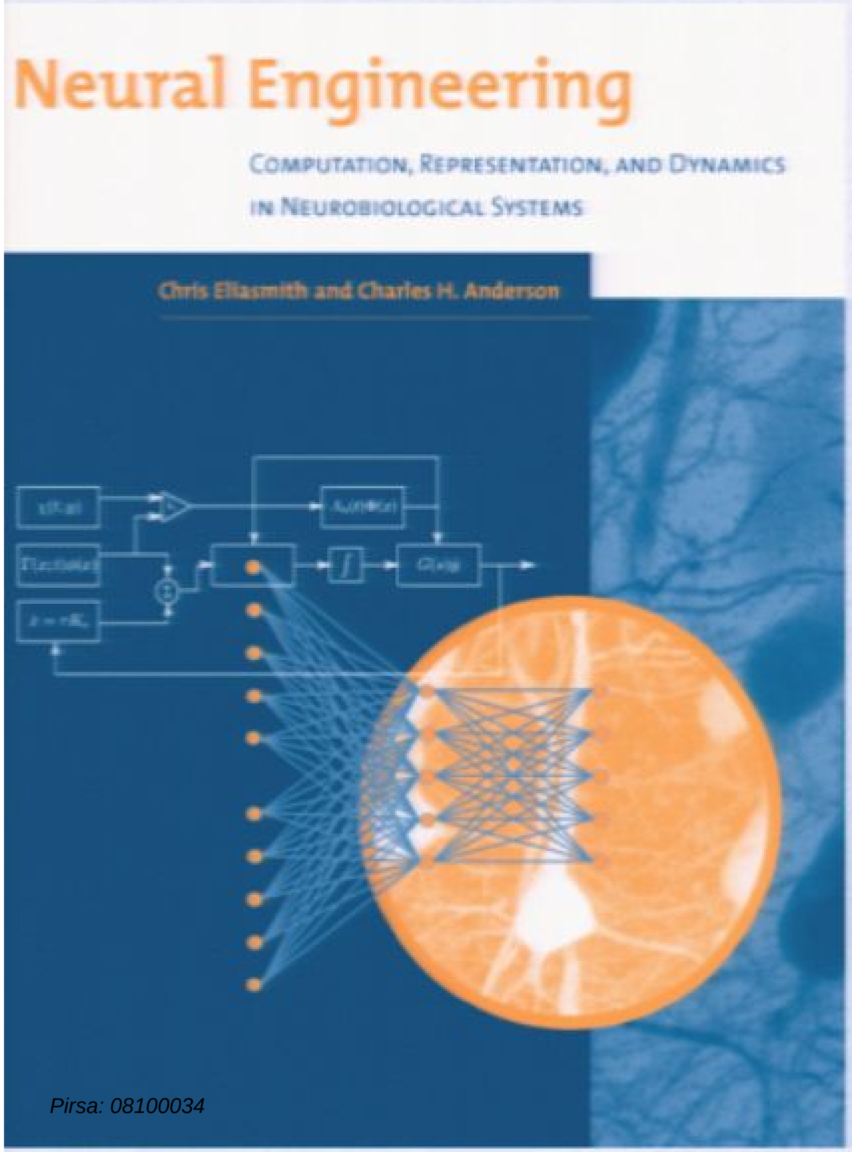

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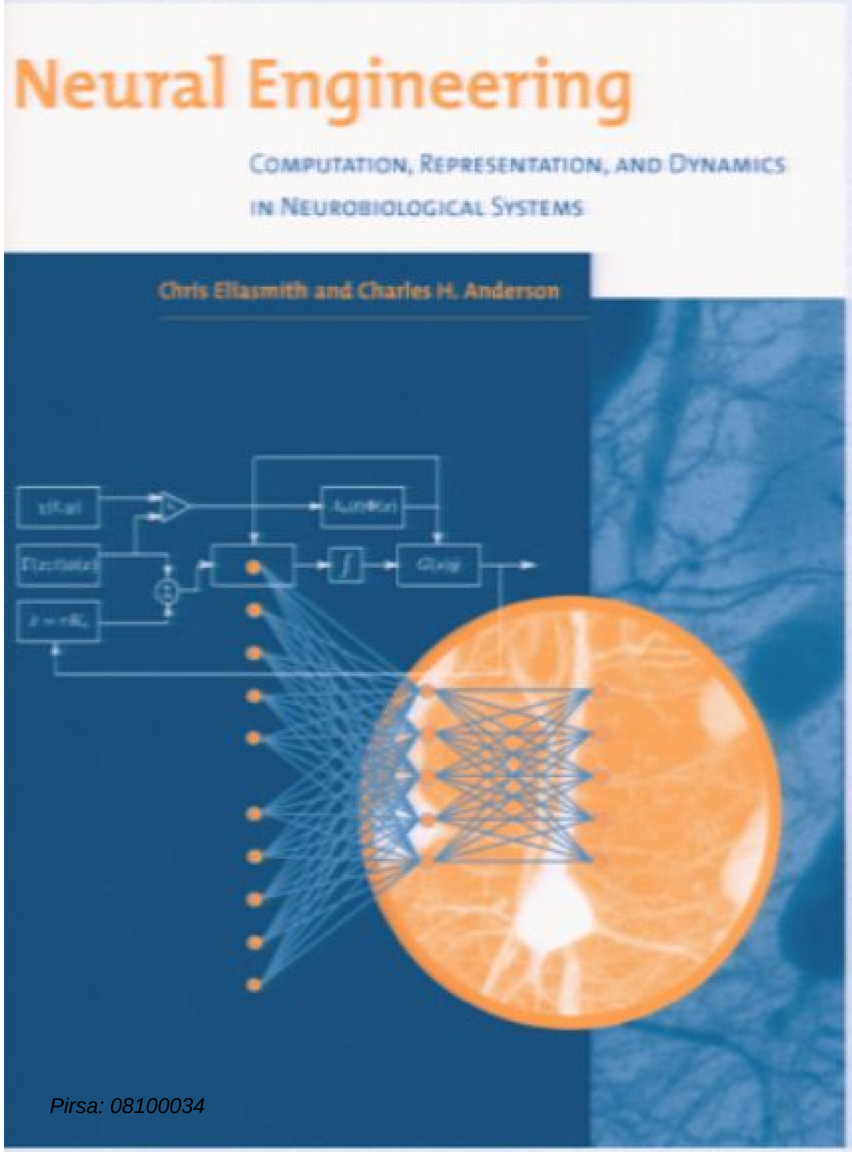
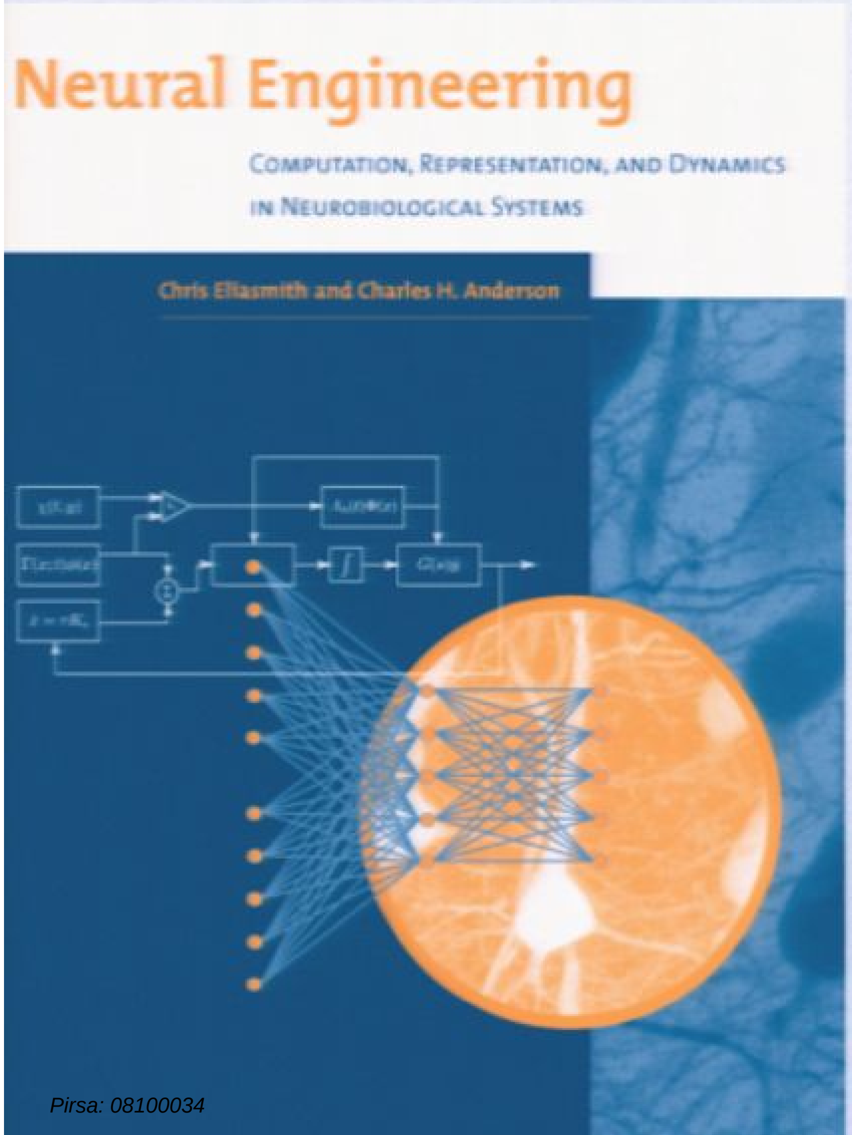


Neural Engineering Framework (NEF)

Our work at the CNRG



Neural Engineering Framework (NEF)

Given:

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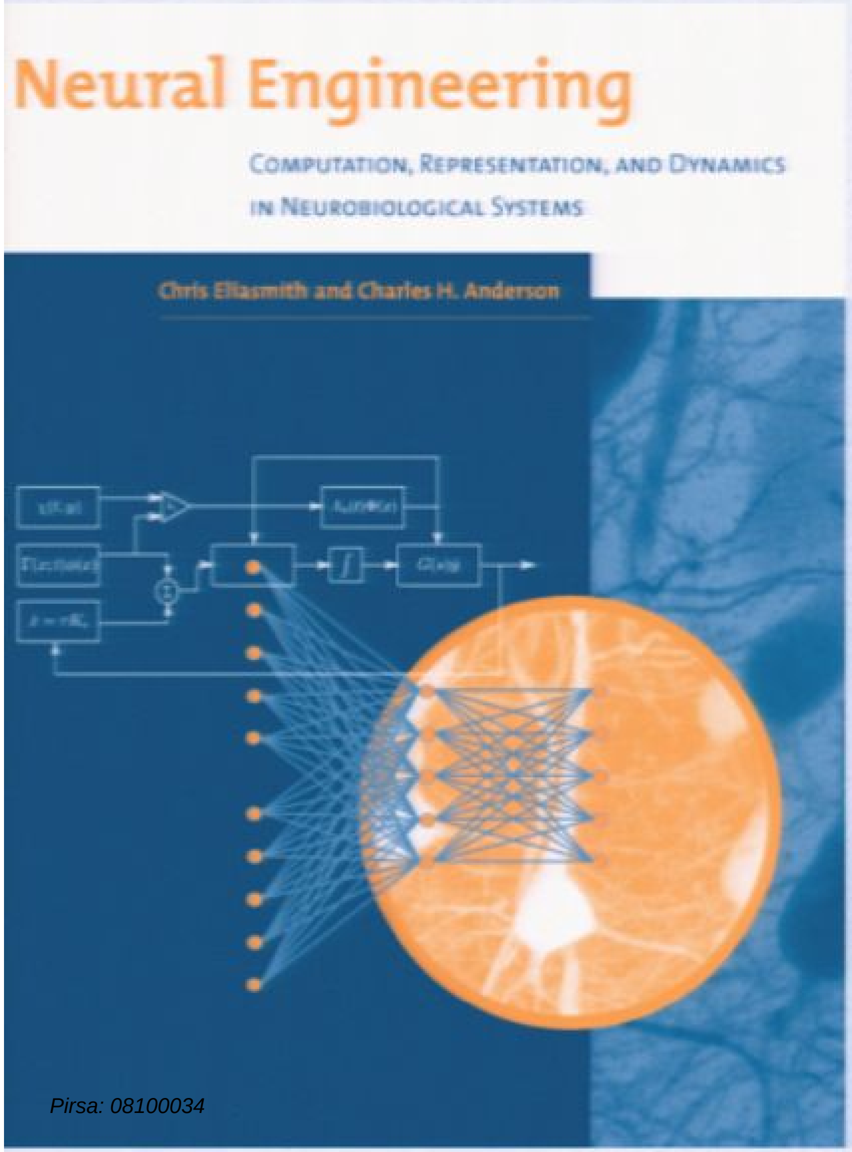

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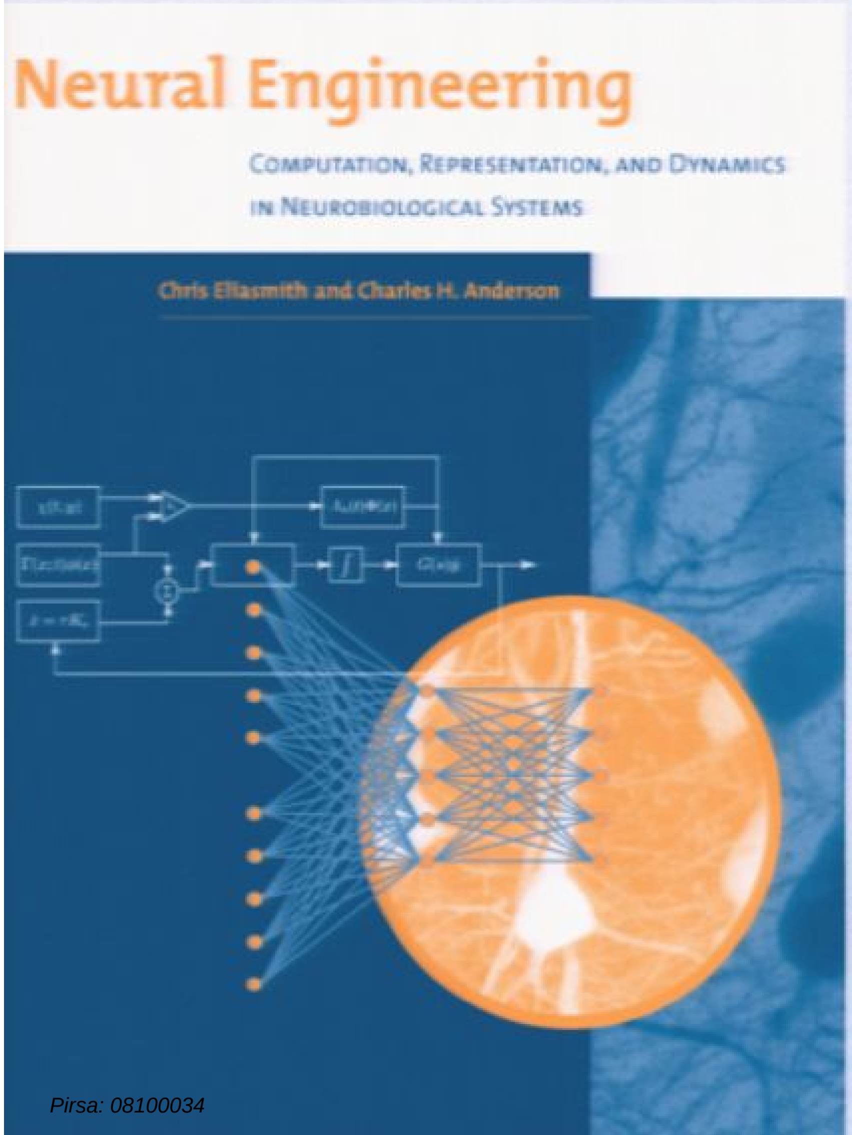

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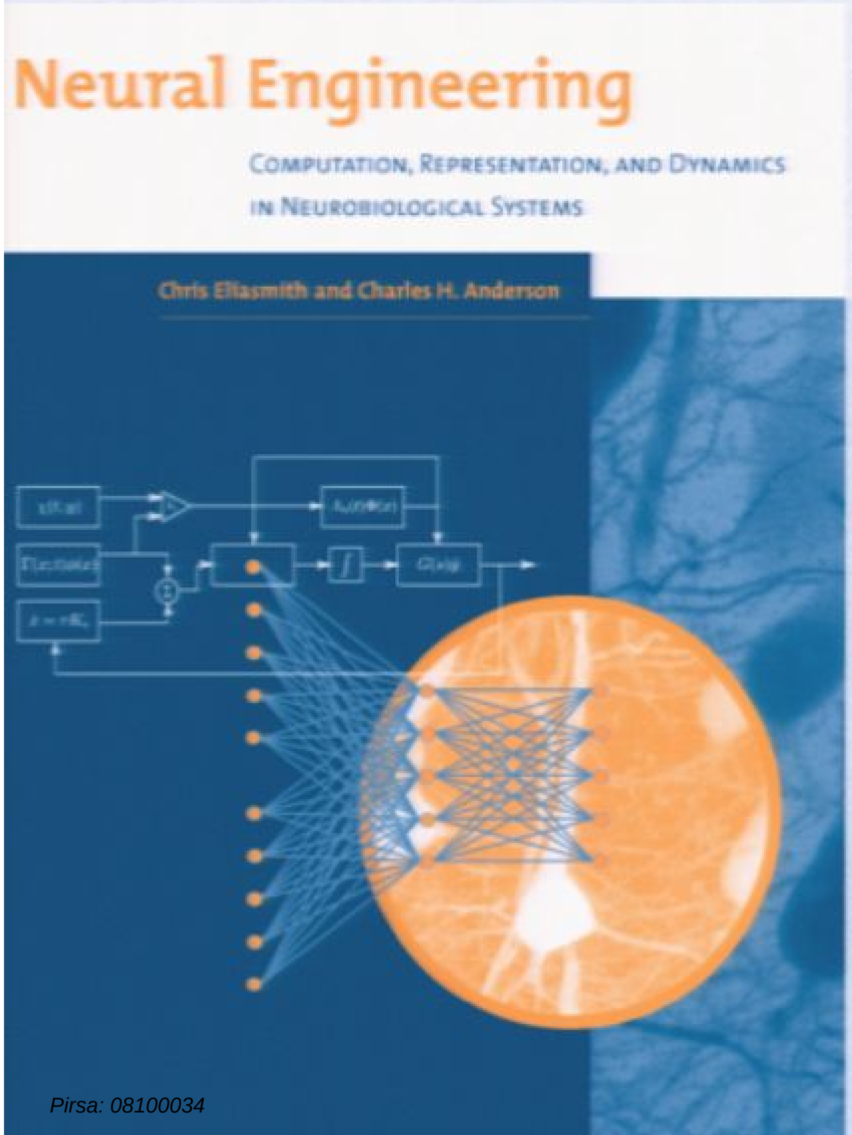

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Essentially a "neural compiler"

Returning to the analogy

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Not unlike Newton's theory:

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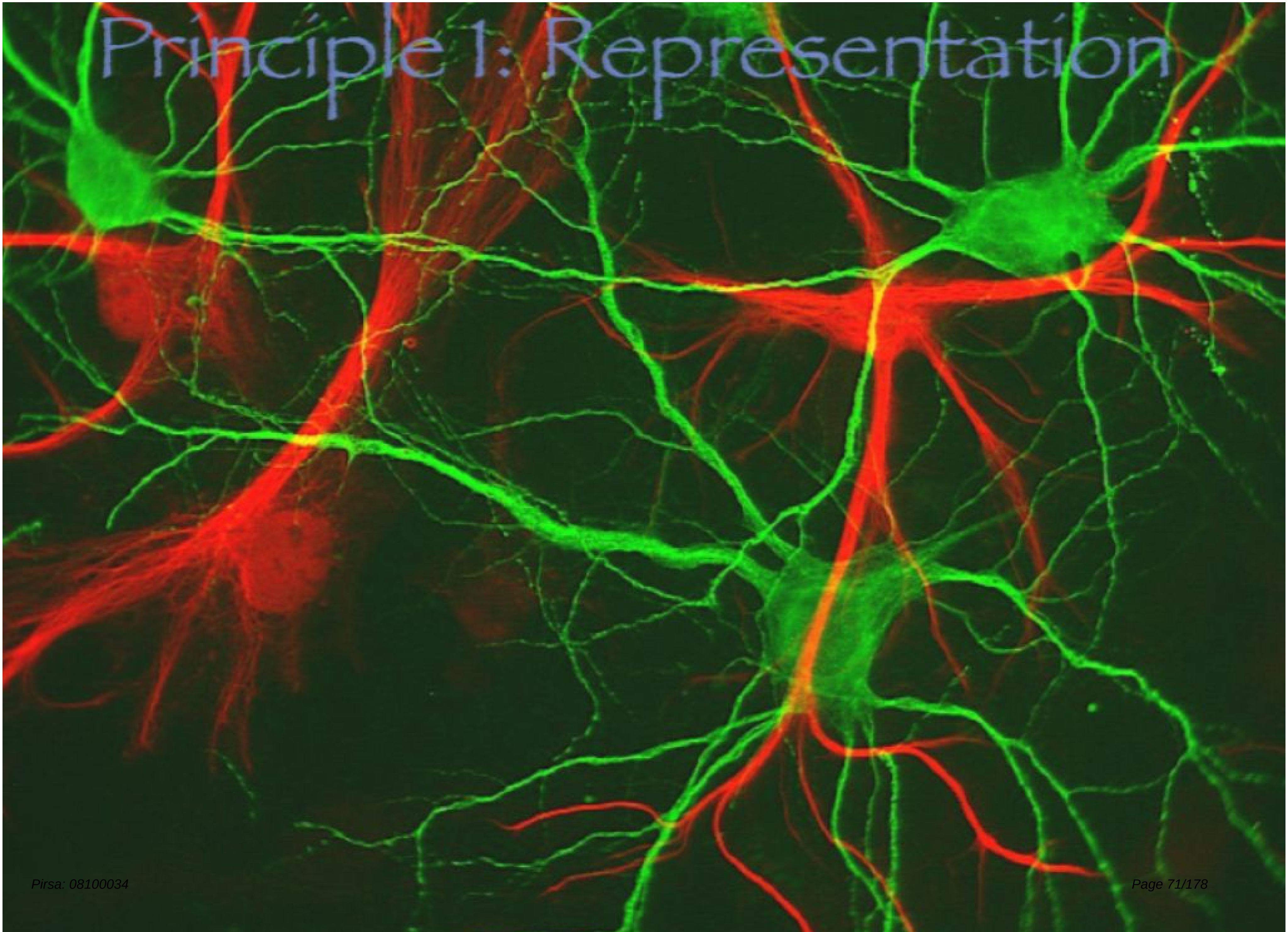
  - And a start

Principle 1: Representation



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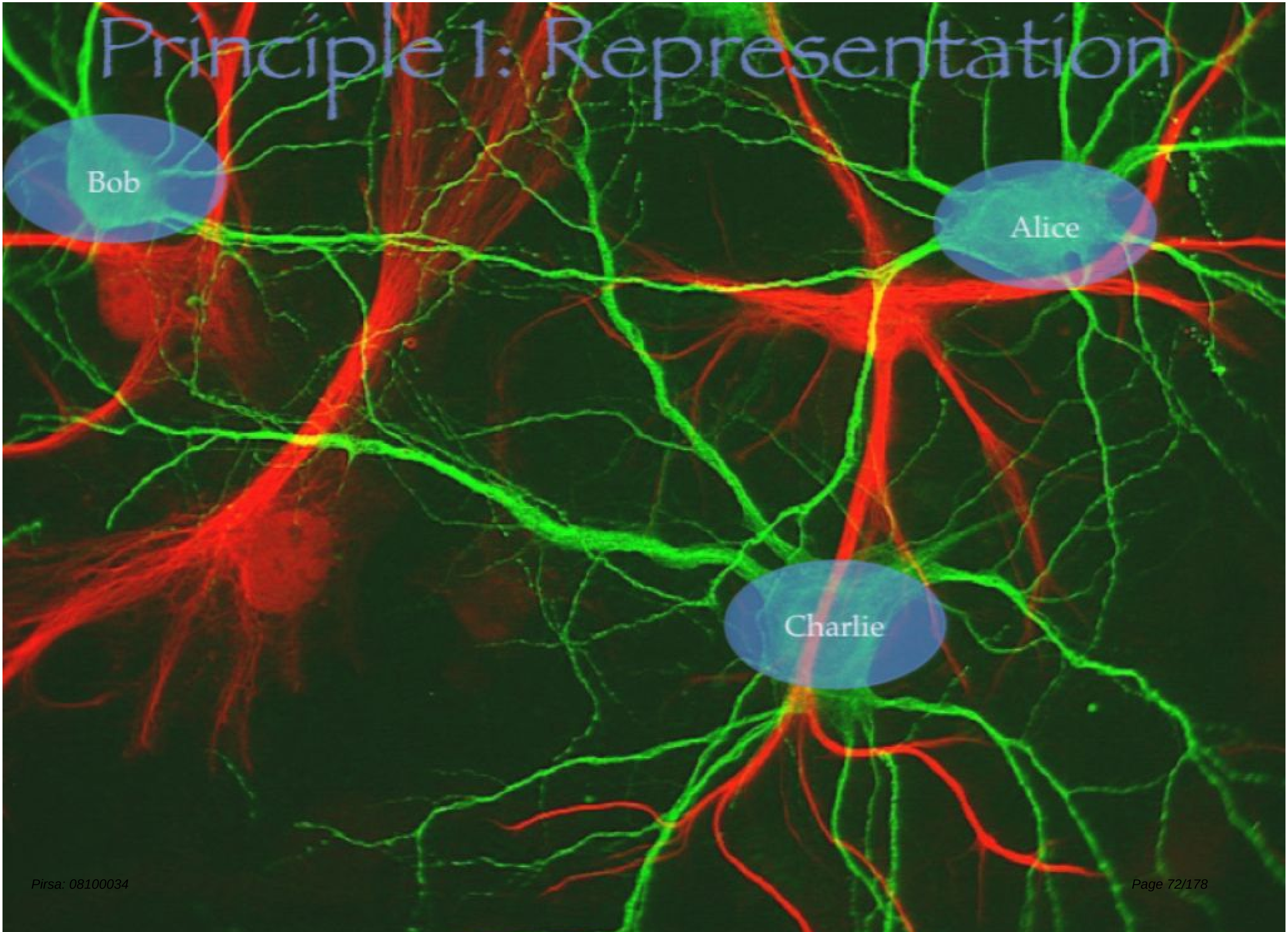

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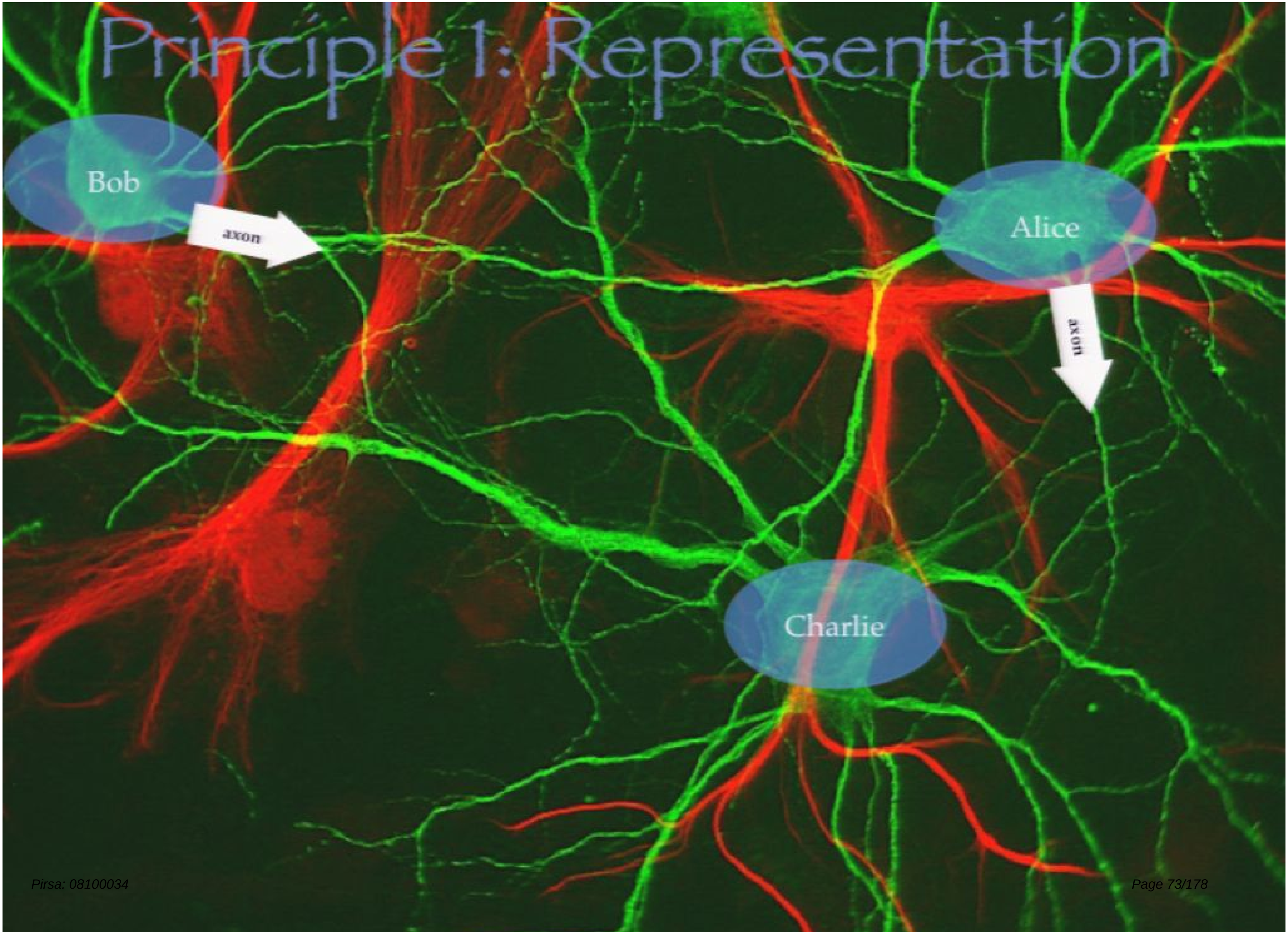

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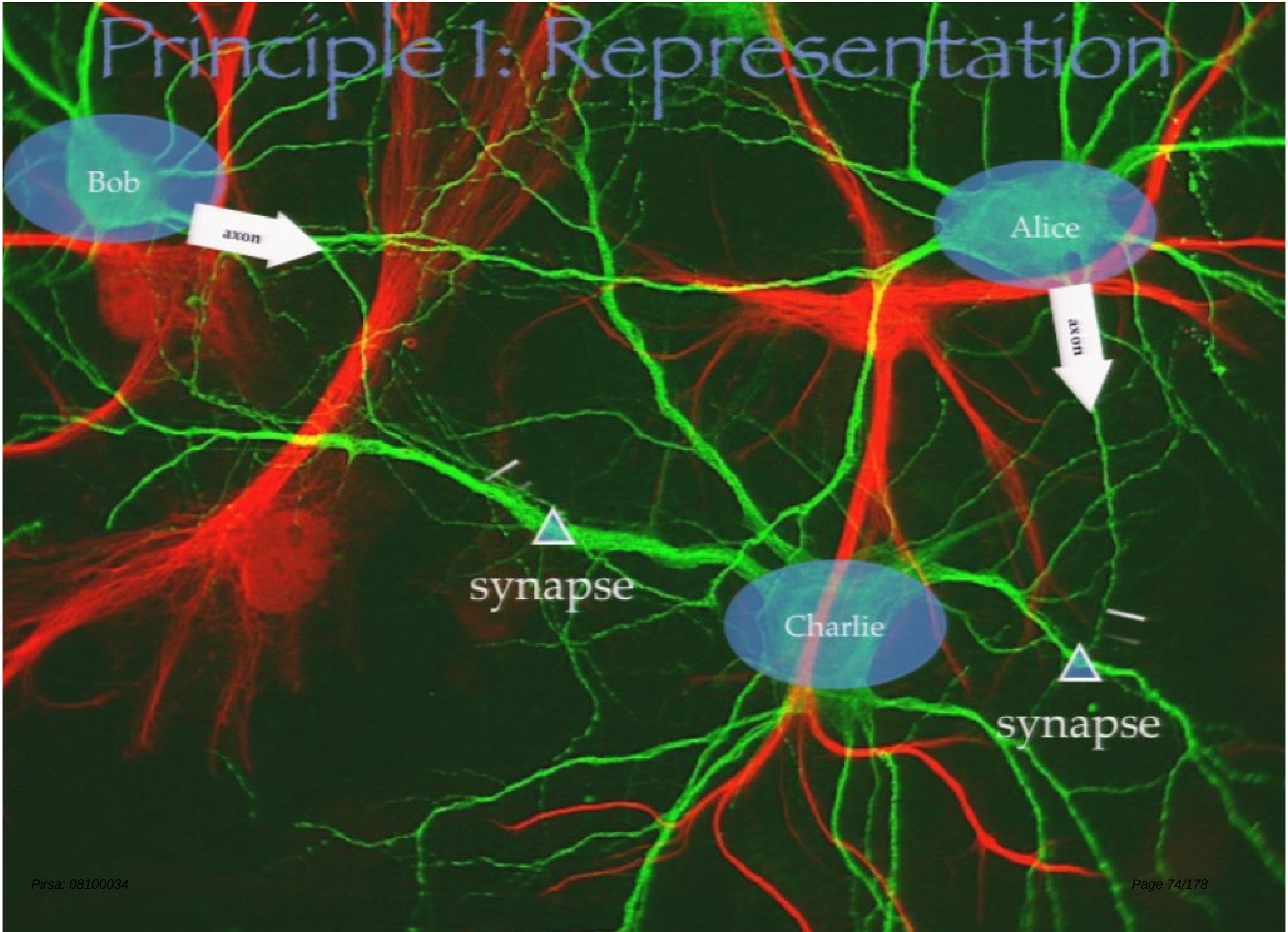

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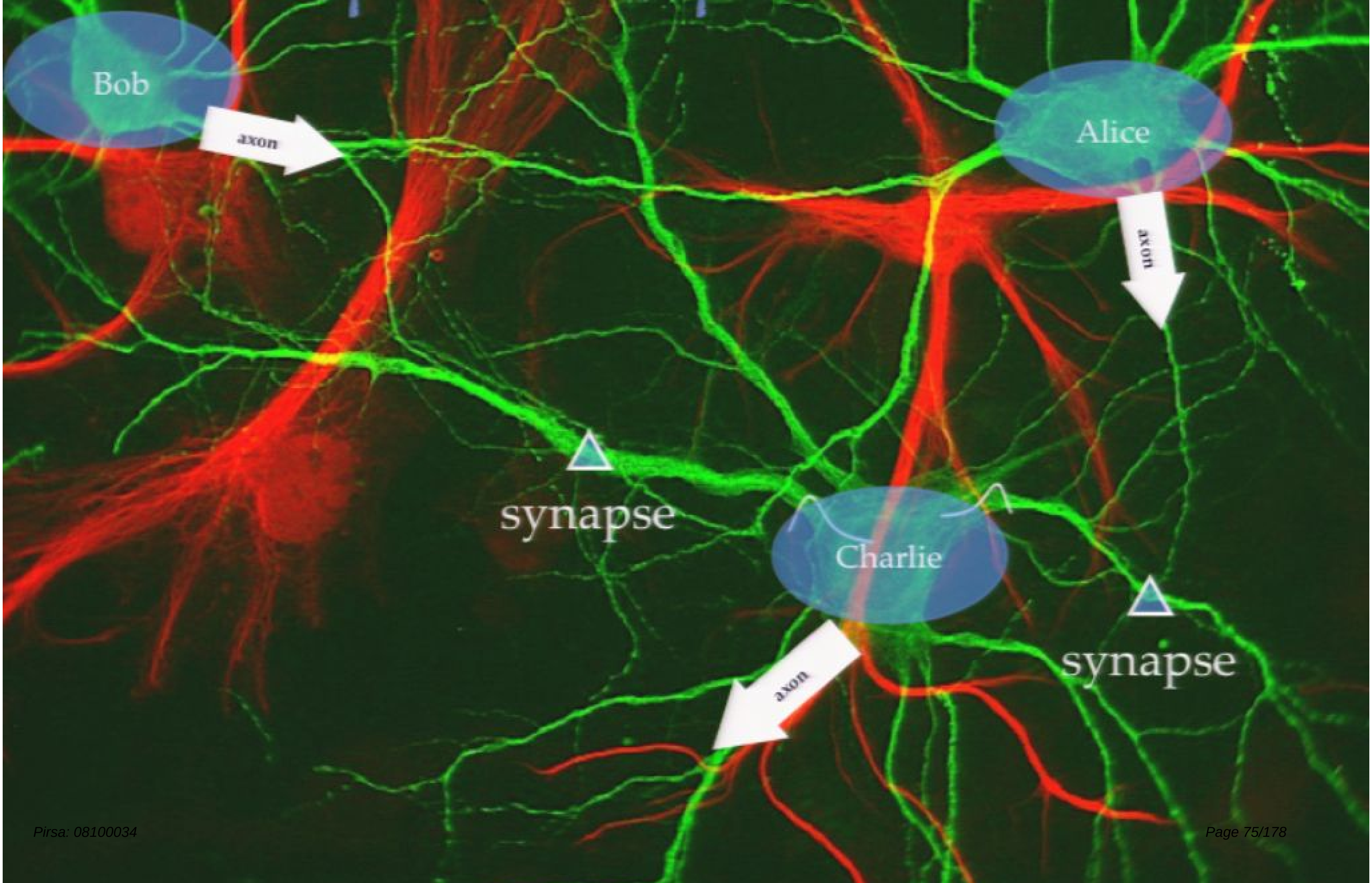

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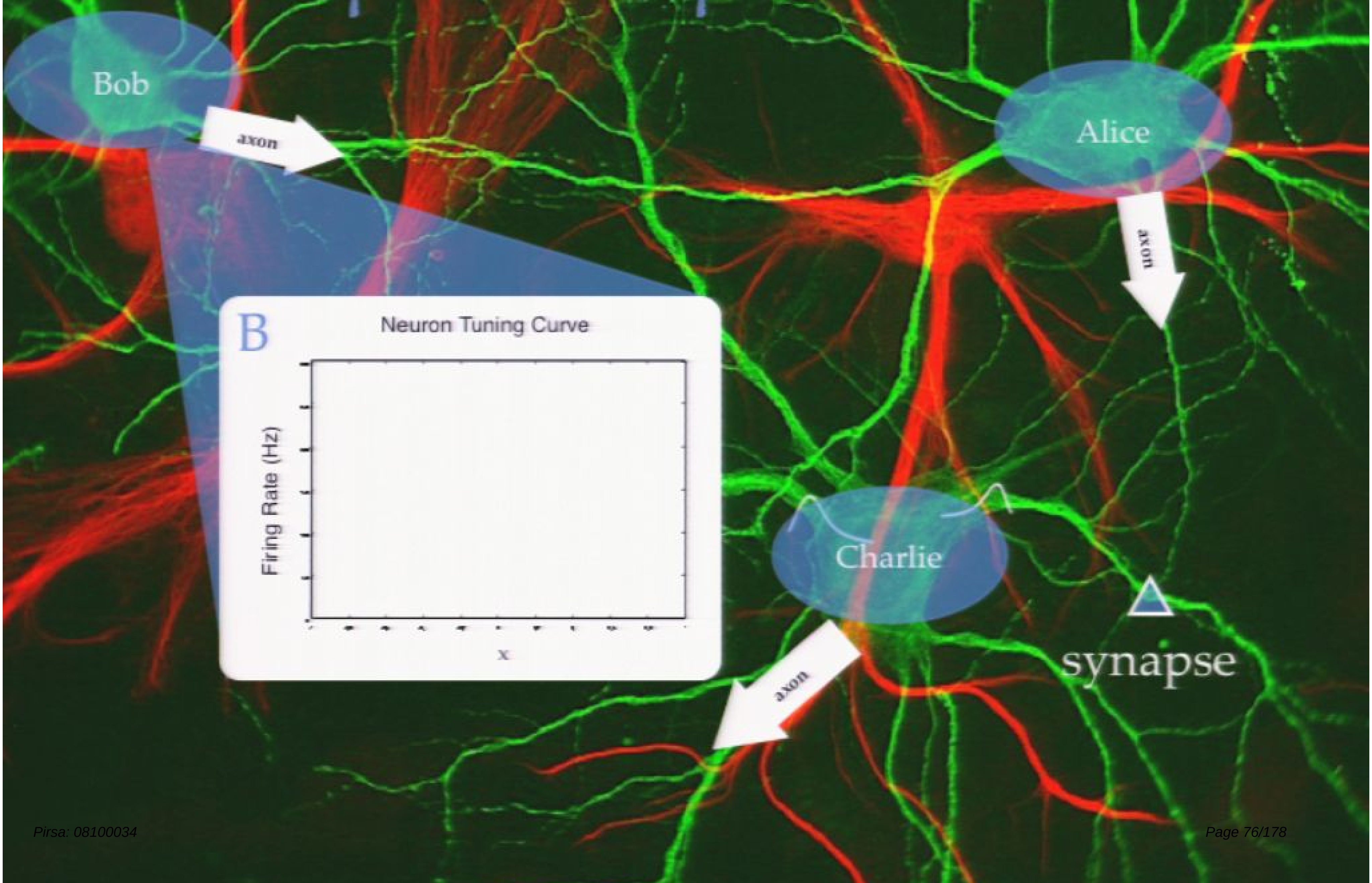

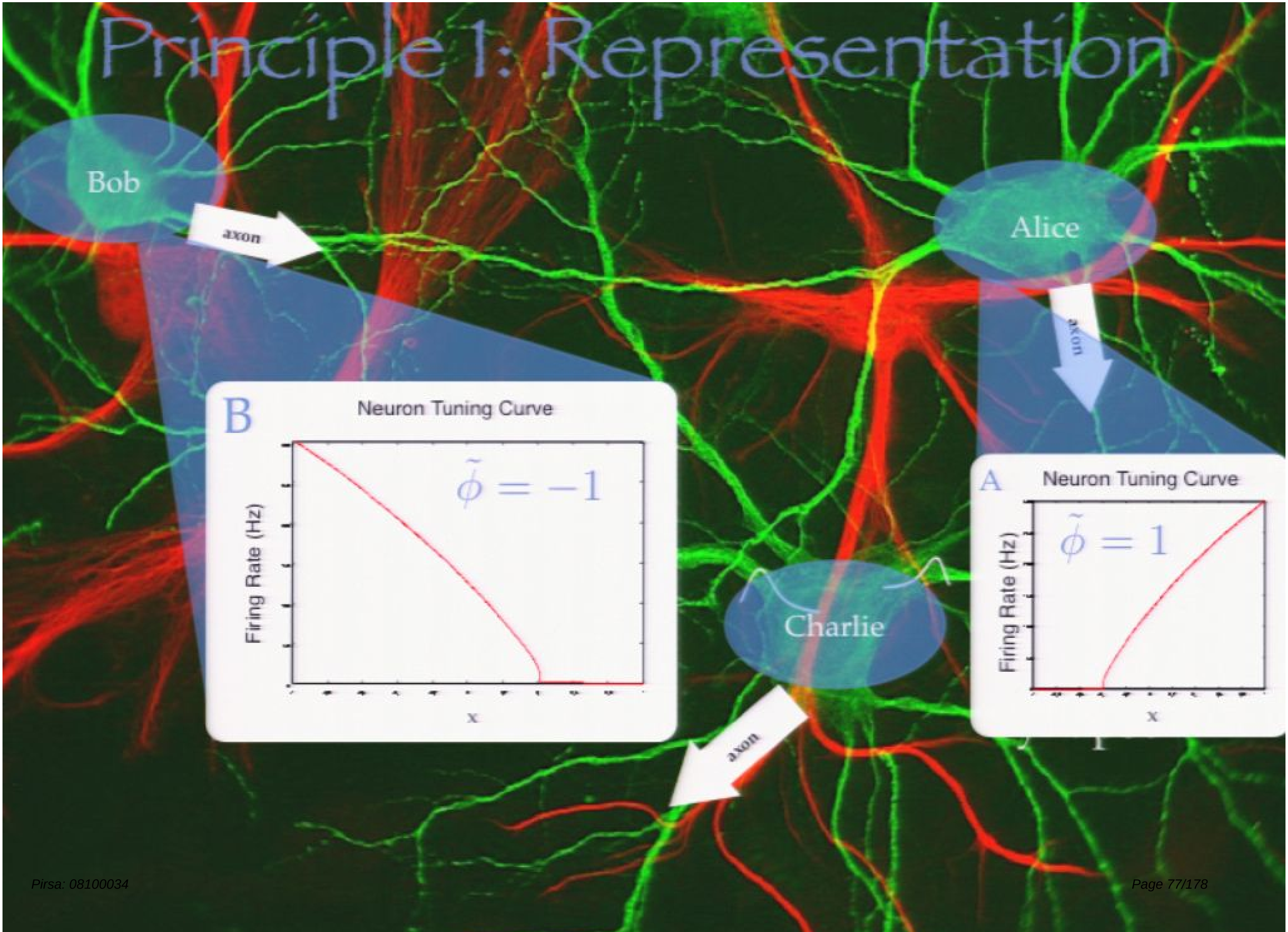
Principle 1: Representation
Bob
axon
Alice
axon
B
Neuron Tuning Curve
$\tilde{\phi} = -1$
Firing Rate (Hz)
x
A
Neuron Tuning Curve
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Firing Rate (Hz)
x
Charlie
axon

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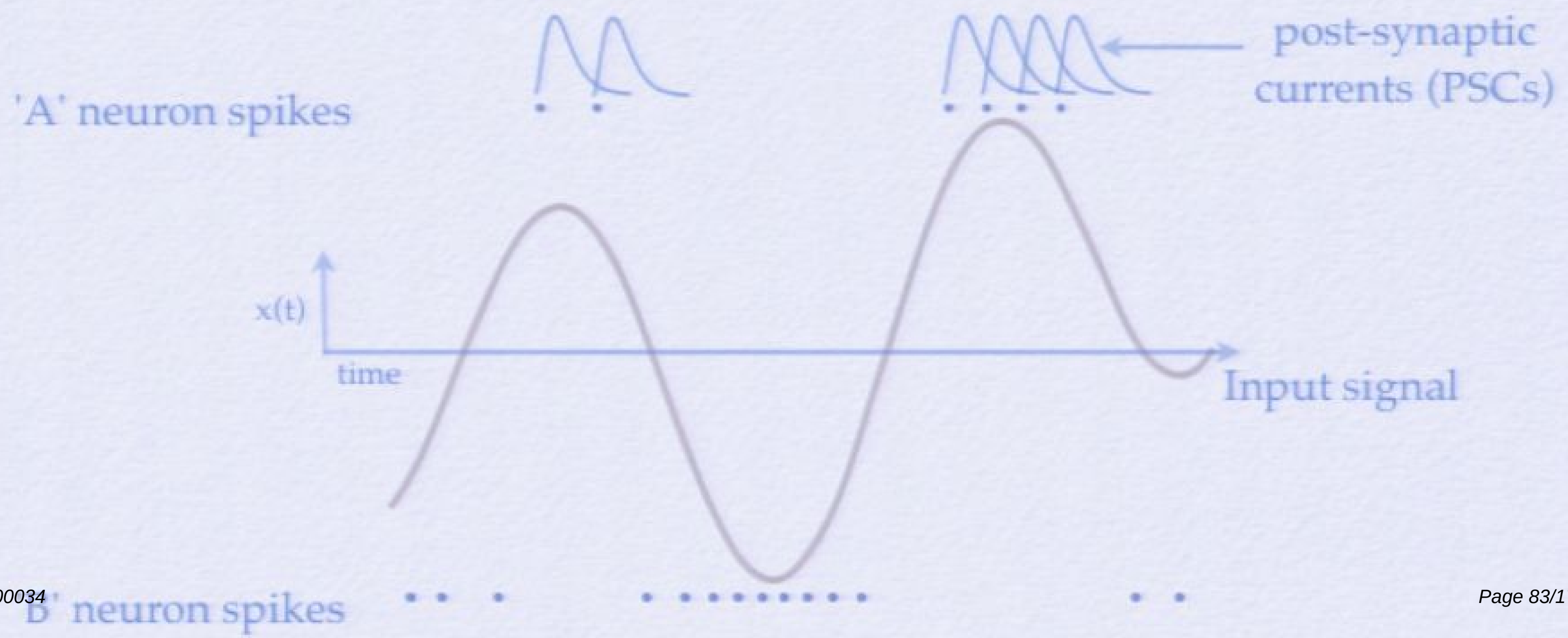

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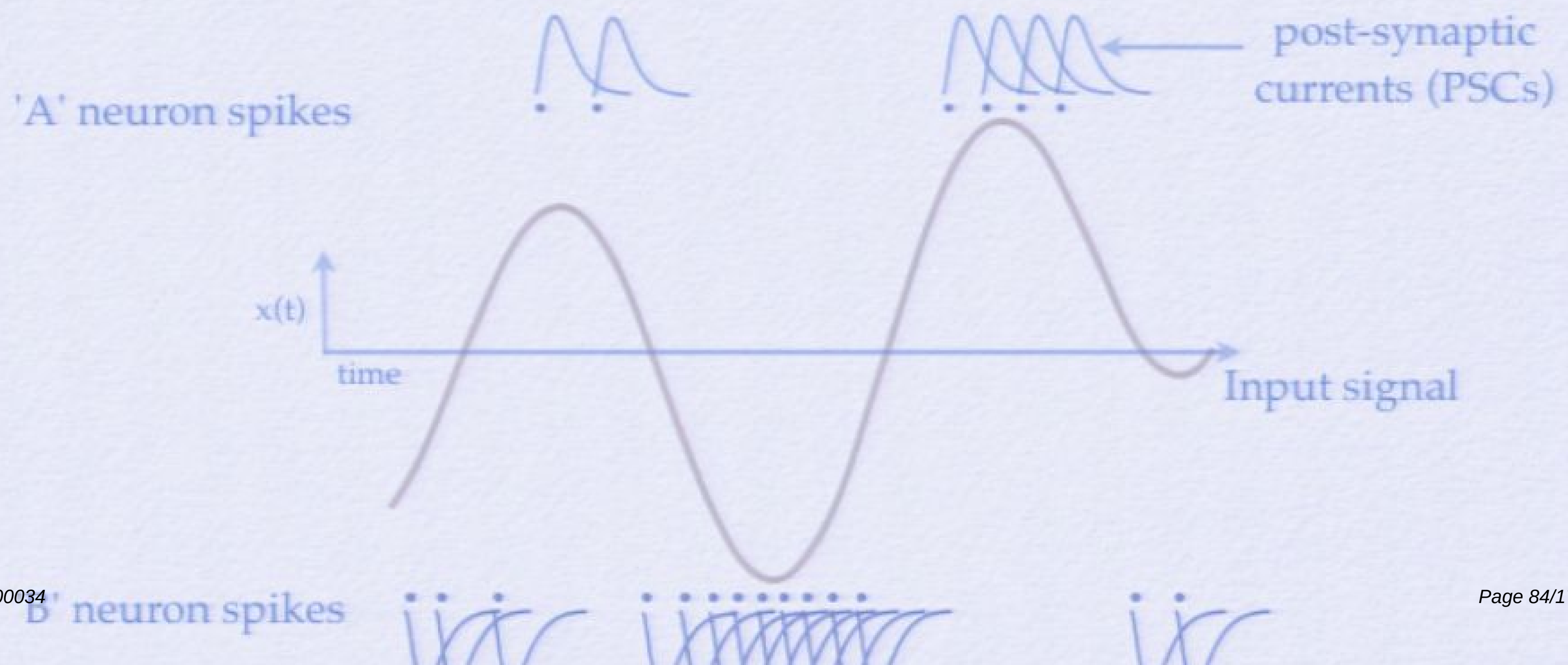

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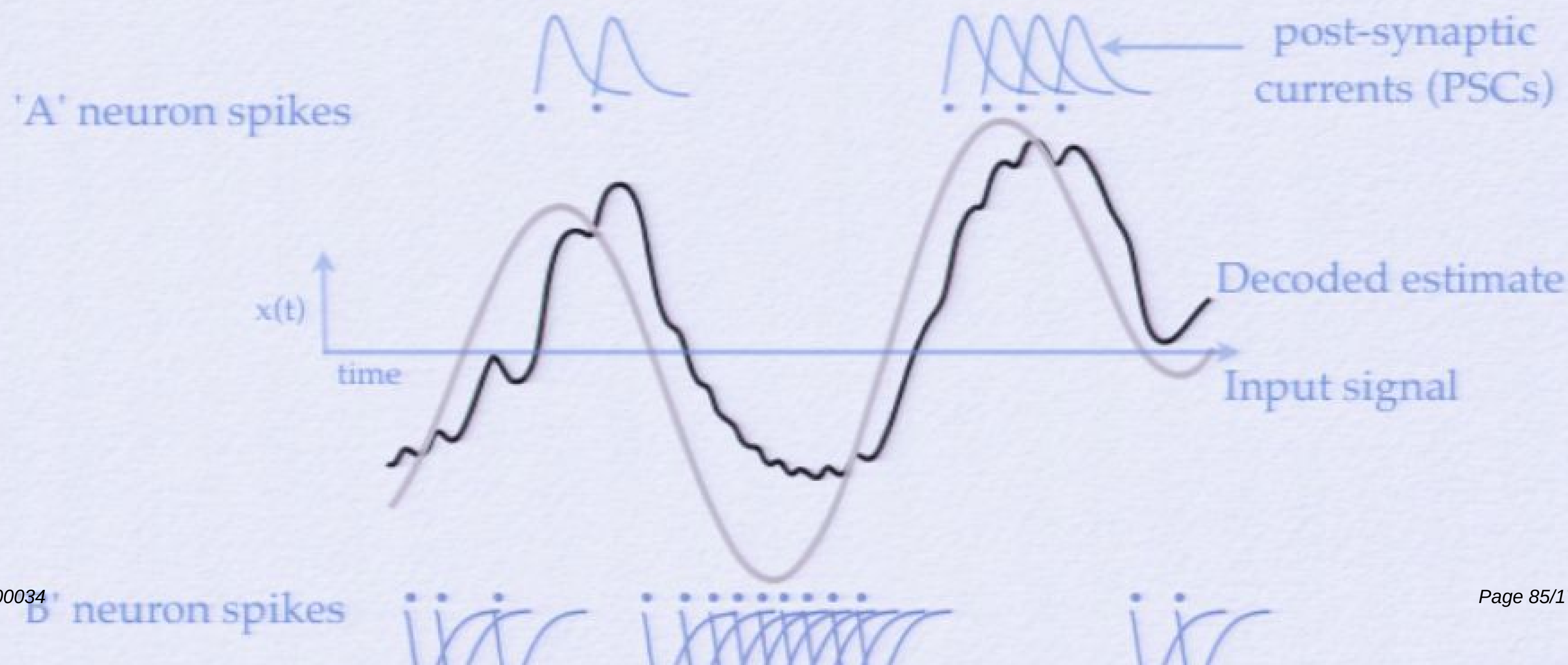

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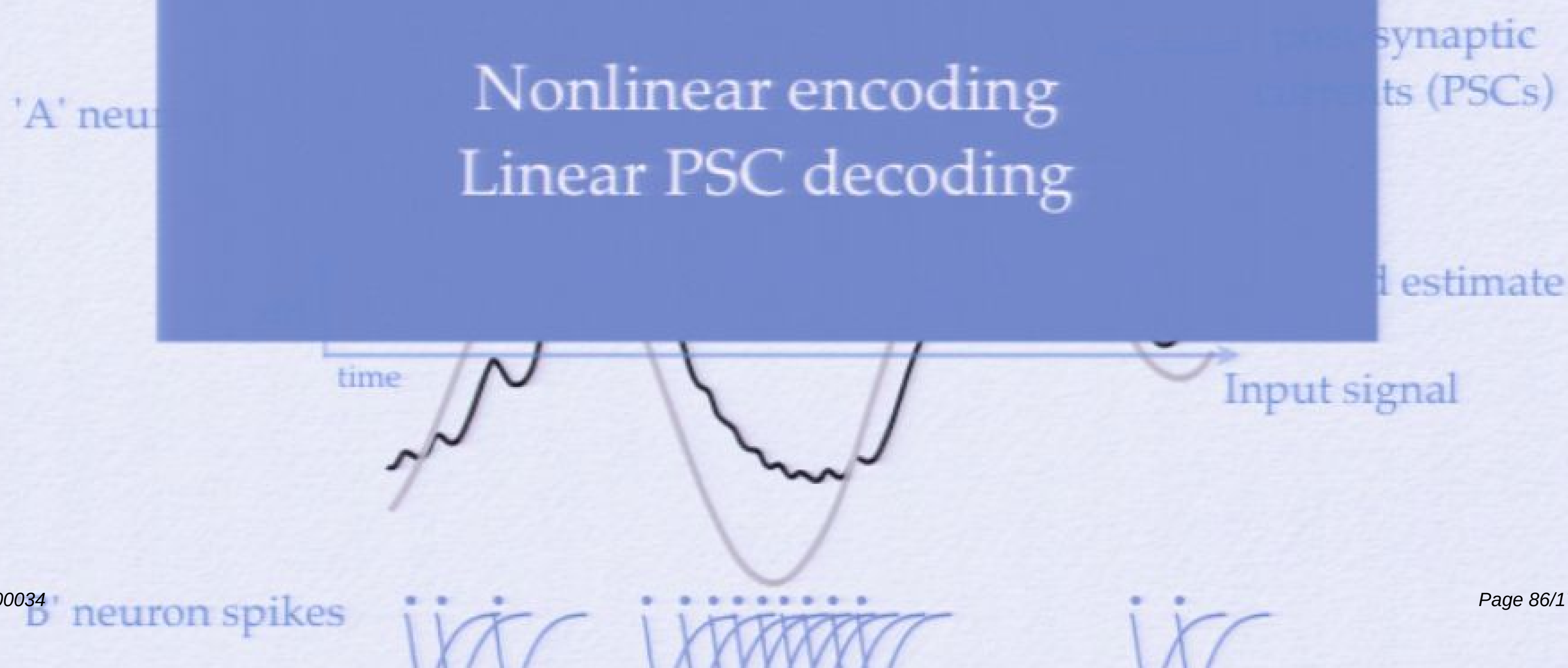
Nonlinear encoding
Linear PSC decoding



Principle 2: Transformation

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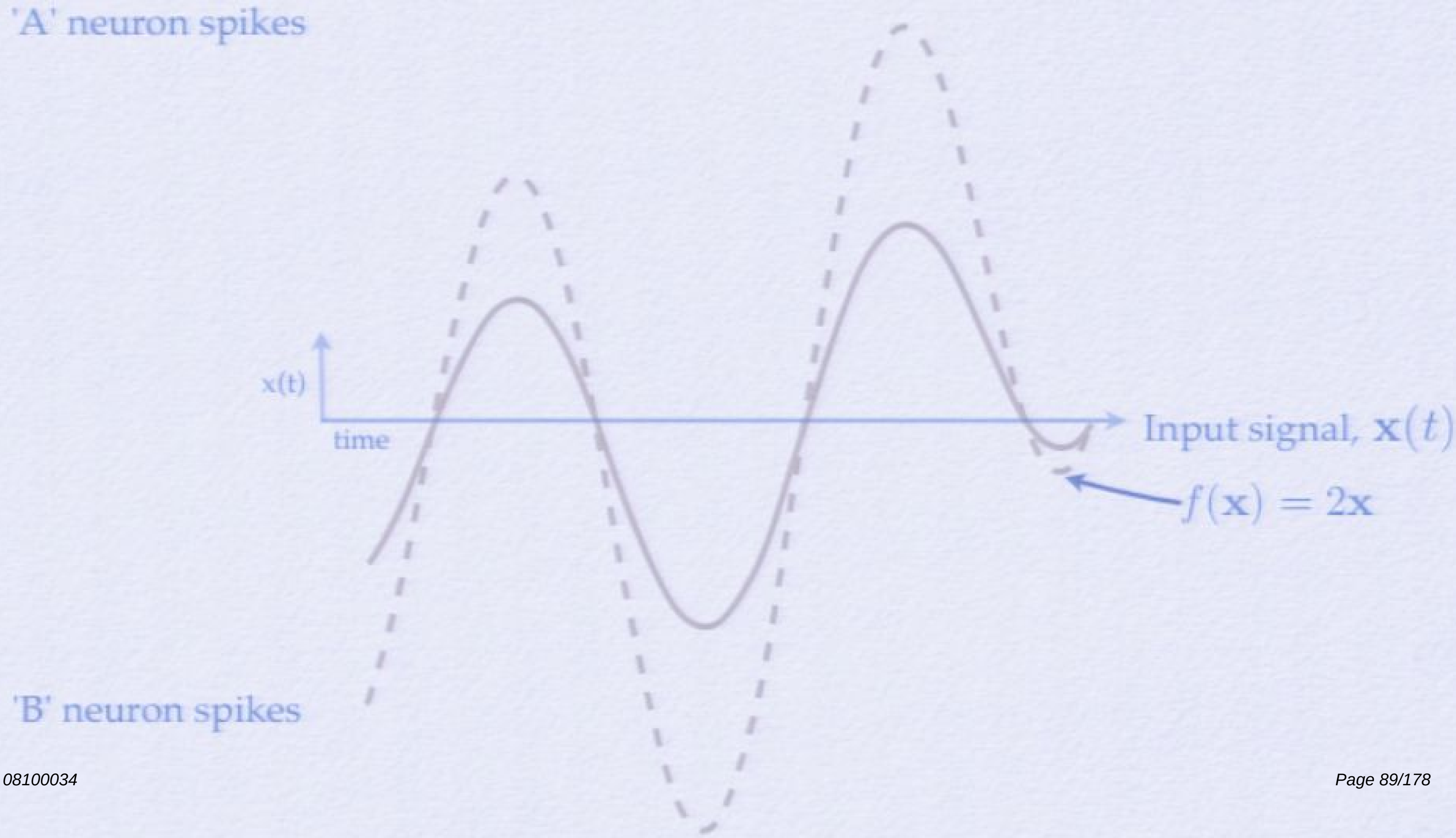
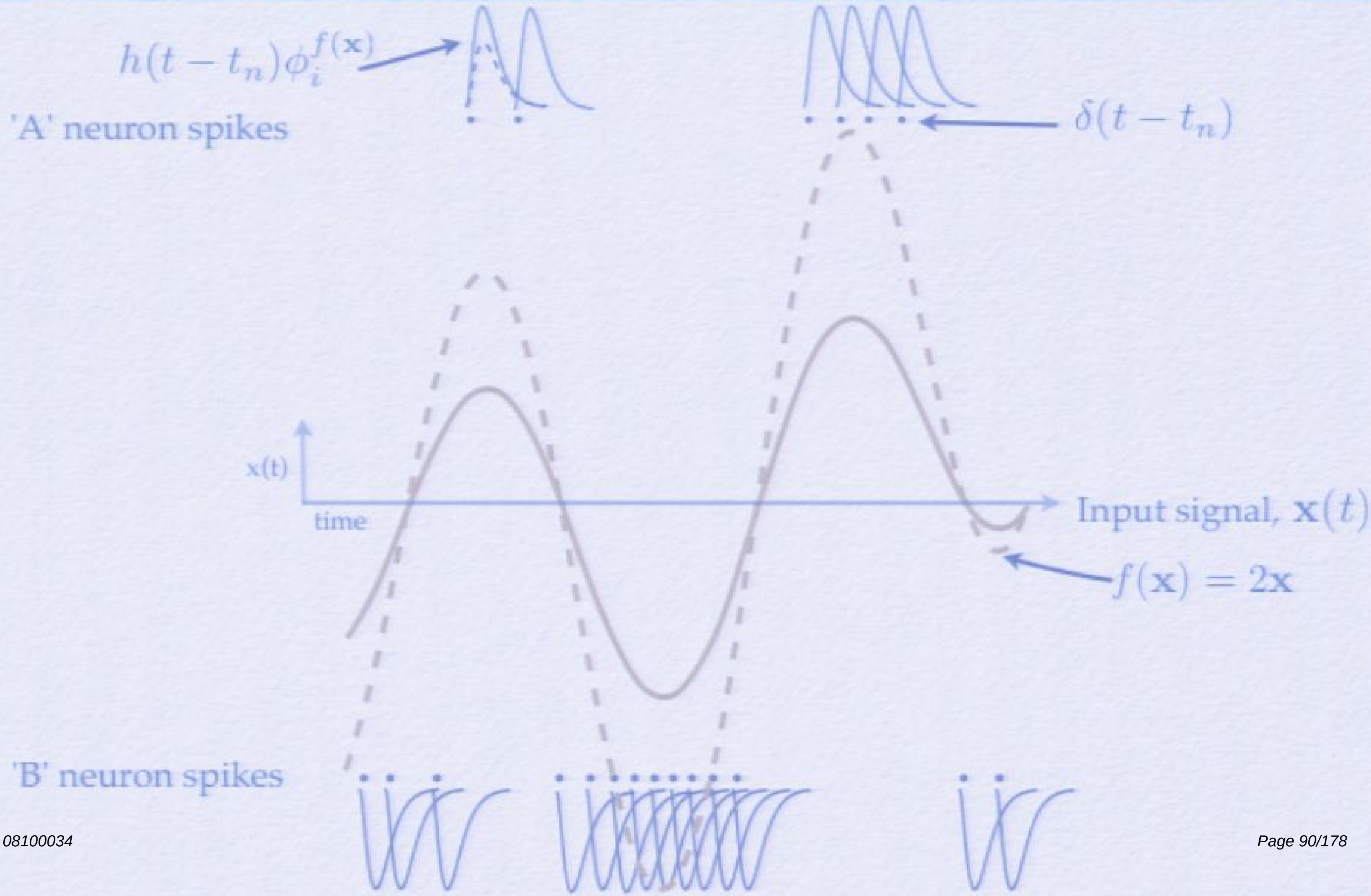


Principle 2: Transformation



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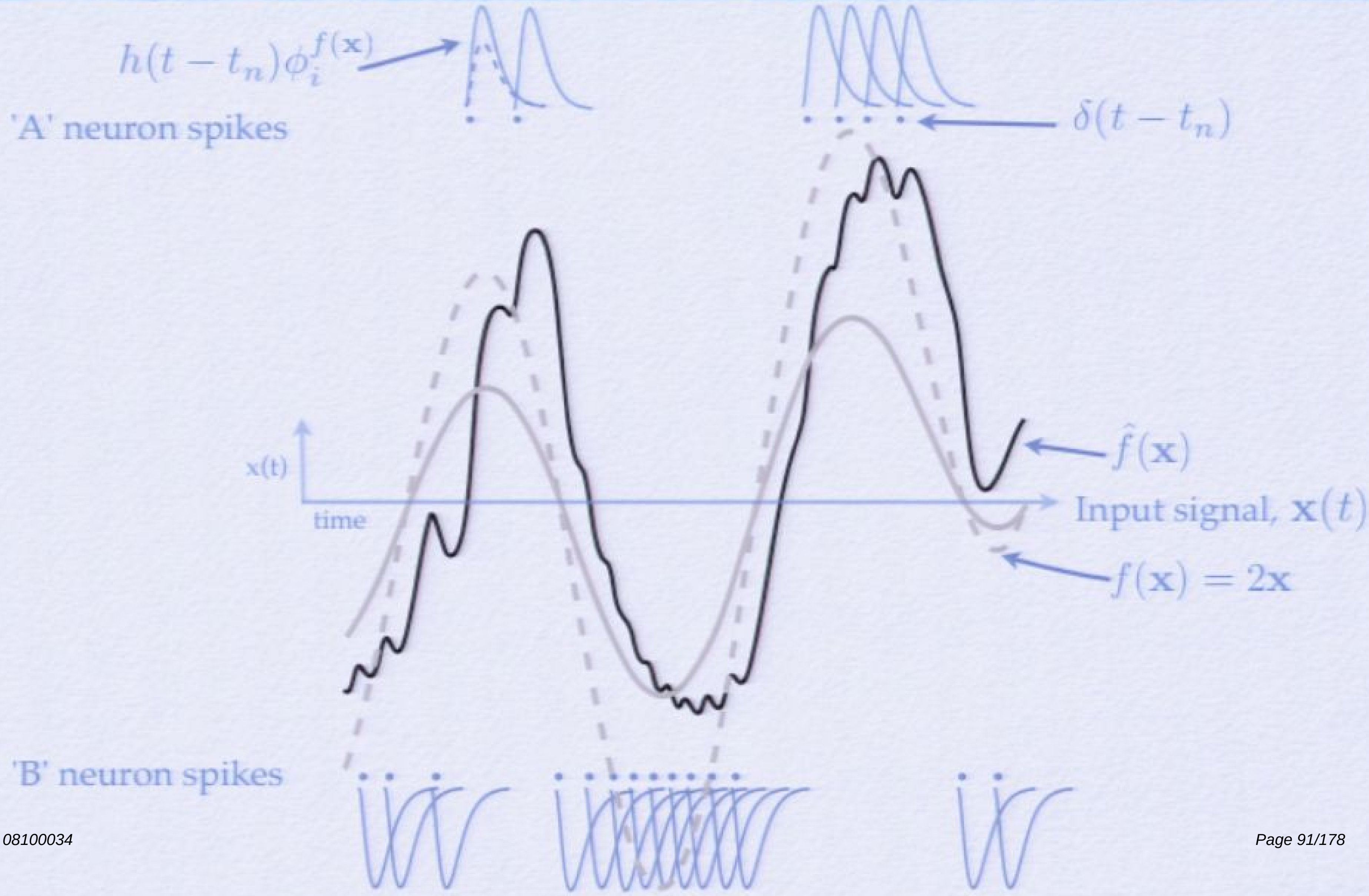

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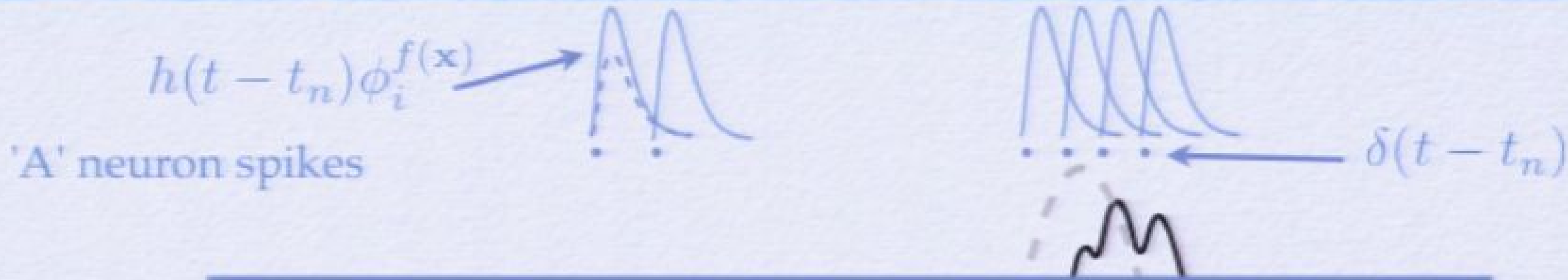


encoding $\sum_n \delta_i(t-t_n) = G_i(\tilde{\phi}_i \cdot \mathbf{x}(t))$

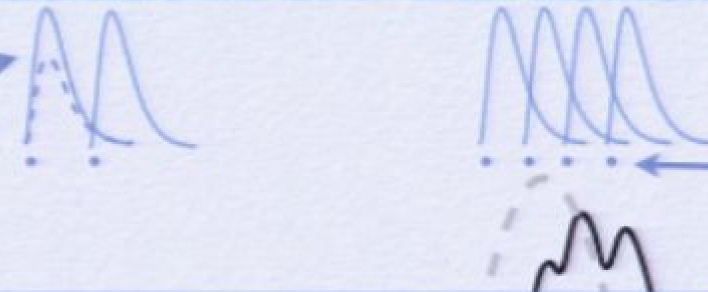
decoding $\hat{f}(\mathbf{x}) = \sum_{i,n} h_i(t-t_n)\phi_i^{f(\mathbf{x})}$

$\delta_i(t-t_n)$	spikes from neuron i at time t_n
G_i	neuron model generating spikes
$\tilde{\phi}_i$	preferred direction vector
$\mathbf{x}(t)$	stimulus signal
$\hat{f}(\mathbf{x})$	computed function of stimulus
$h_i(t-t_n)$	PSCs convolved with spikes
$\phi_i^{f(\mathbf{x})}$	optimal linear weights for $f(\mathbf{x})$

Principle 2: Transformation

$h(t - t_n)\phi_i^{f(\mathbf{x})}$

'A' neuron spikes



$\delta(t - t_n)$

Heterogeneity

encoding $\quad \sum_n \delta_i(t - t_n) = G_i(\tilde{\phi}_i \cdot \mathbf{x}(t))$

decoding $\quad \hat{f}(\mathbf{x}) = \sum_{i,n} h_i(t - t_n)\phi_i^{f(\mathbf{x})}$

$\delta_i(t - t_n)$	spikes from neuron i at time t_n
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$\hat{f}(\mathbf{x})$	computed function of stimulus
$h_i(t - t_n)$	PSCs convolved with spikes
$\phi_i^{f(\mathbf{x})}$	optimal linear weights for $f(\mathbf{x})$

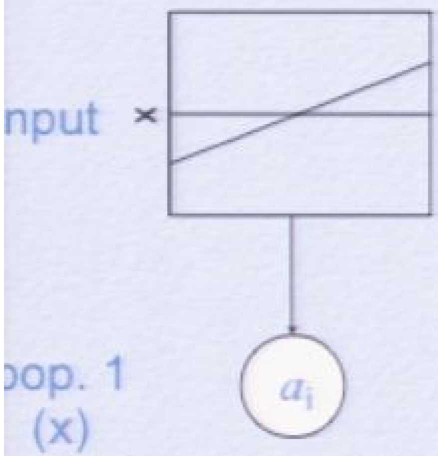
signal, $\mathbf{x}(t)$

$) = 2\mathbf{x}$

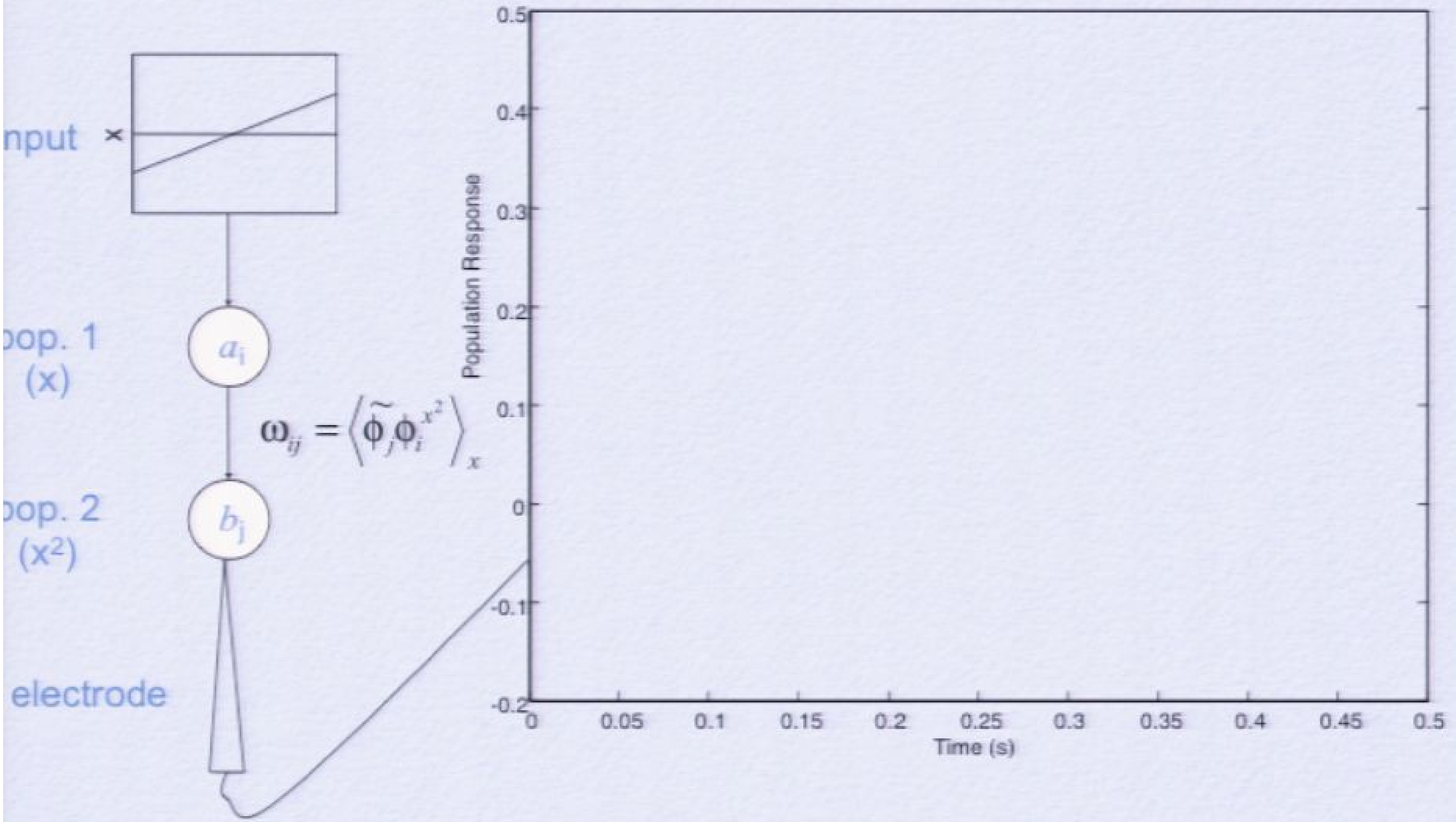
'B' neuron

Principle 2: Transformation

Principle 2: Transformation



Principle 2: Transformation



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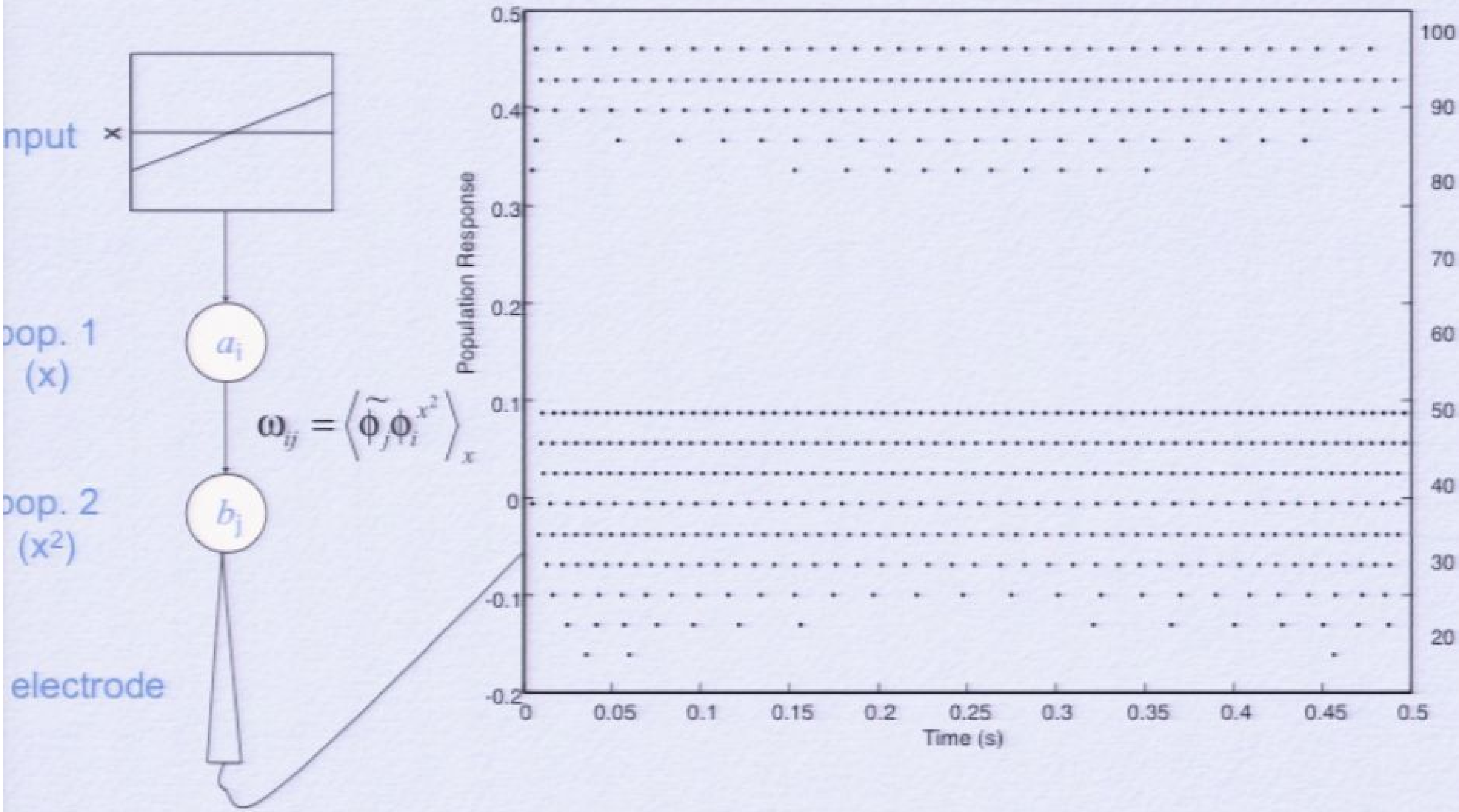
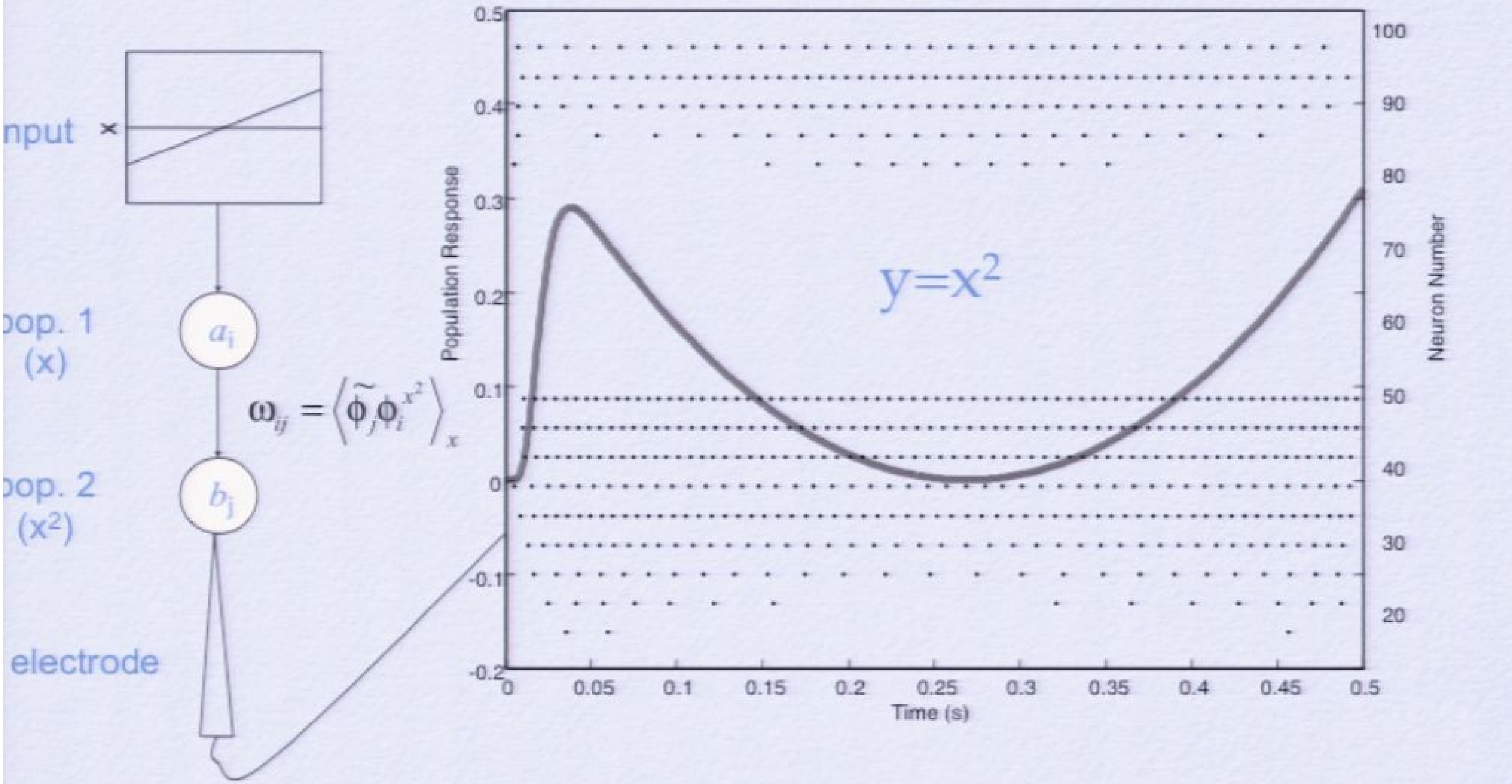
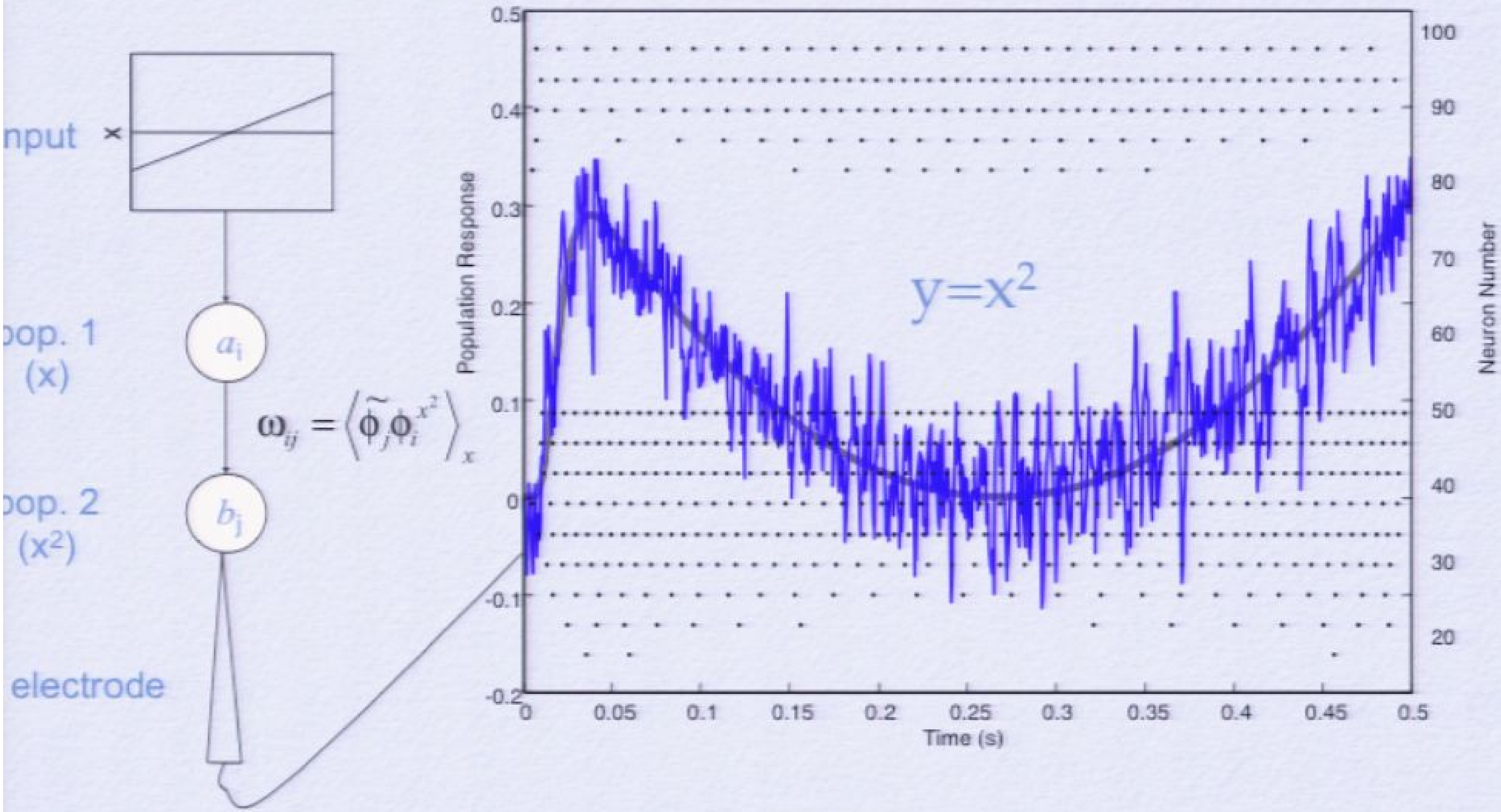


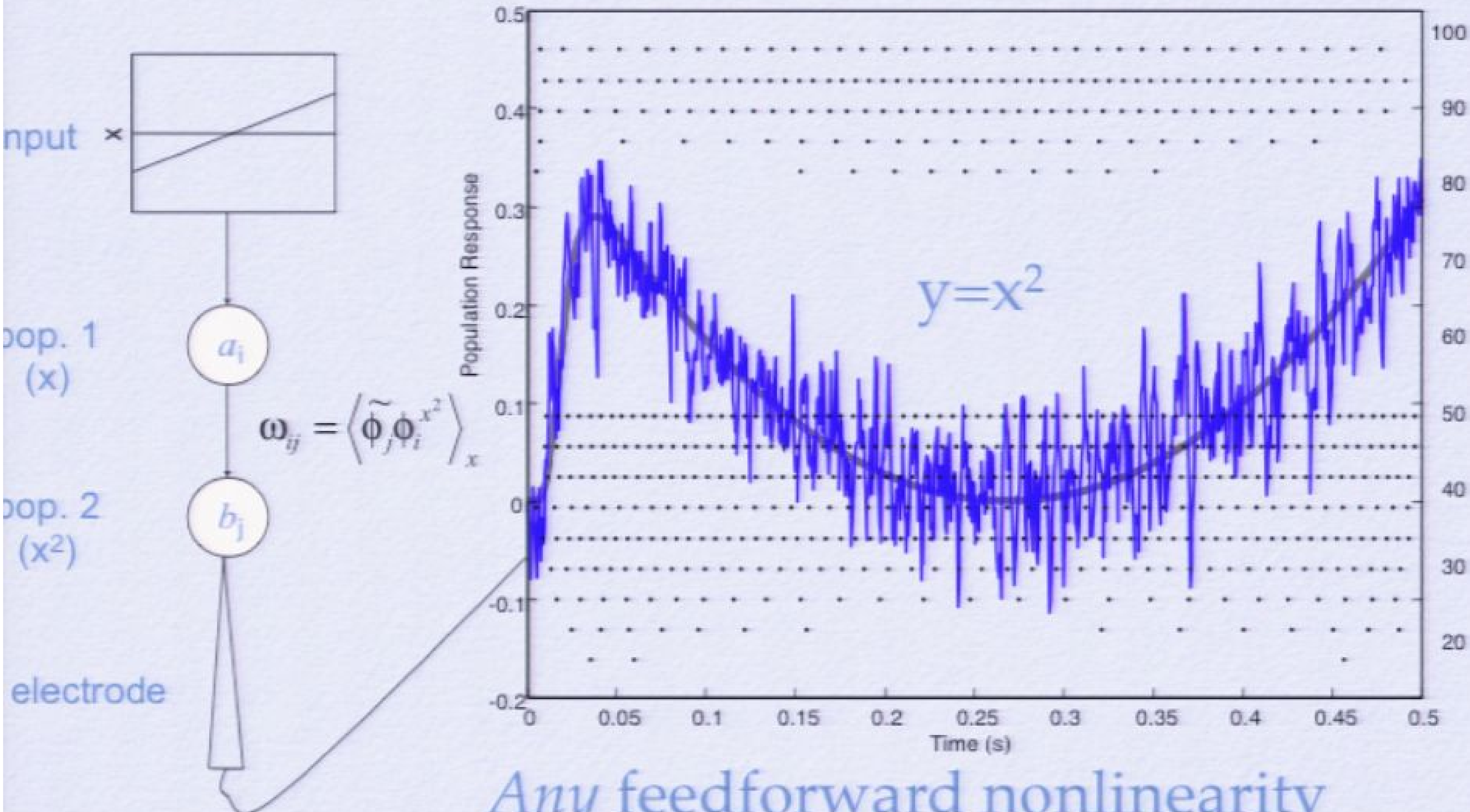
Principle 2: Transformation



Principle 2: Transformation



Principle 2: Transformation



$$\omega_{ij} = \left\langle \tilde{\phi}_j \phi_i^{x^2} \right\rangle_x$$

Any feedforward nonlinearity

Principle 3: Dynamics

- A new mapping of a standard representation of dynamics onto neural systems

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neural transformation

$$\dot{\mathbf{x}} = f(\mathbf{x}, t)$$

neural representation

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- A new mapping of a standard representation of dynamics onto neural systems

neural dynamics   neural transformation

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neural representation

Neural Control Theory

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- Adapt standard control theory to neurobiological systems

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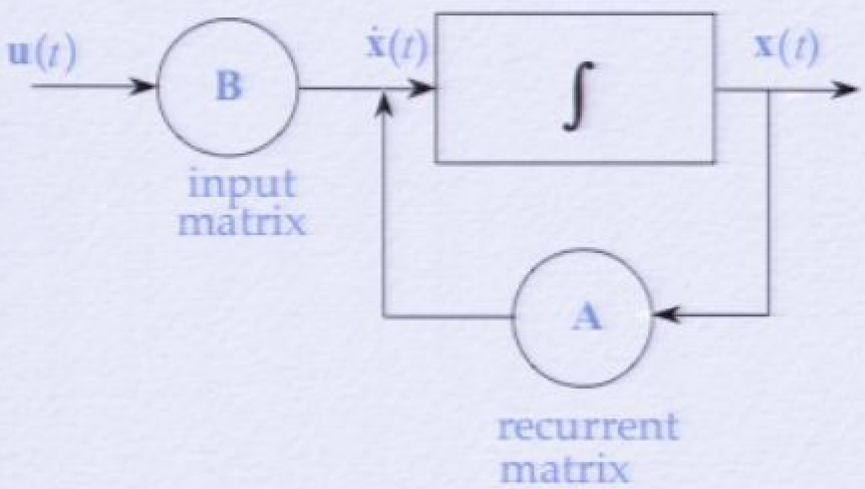
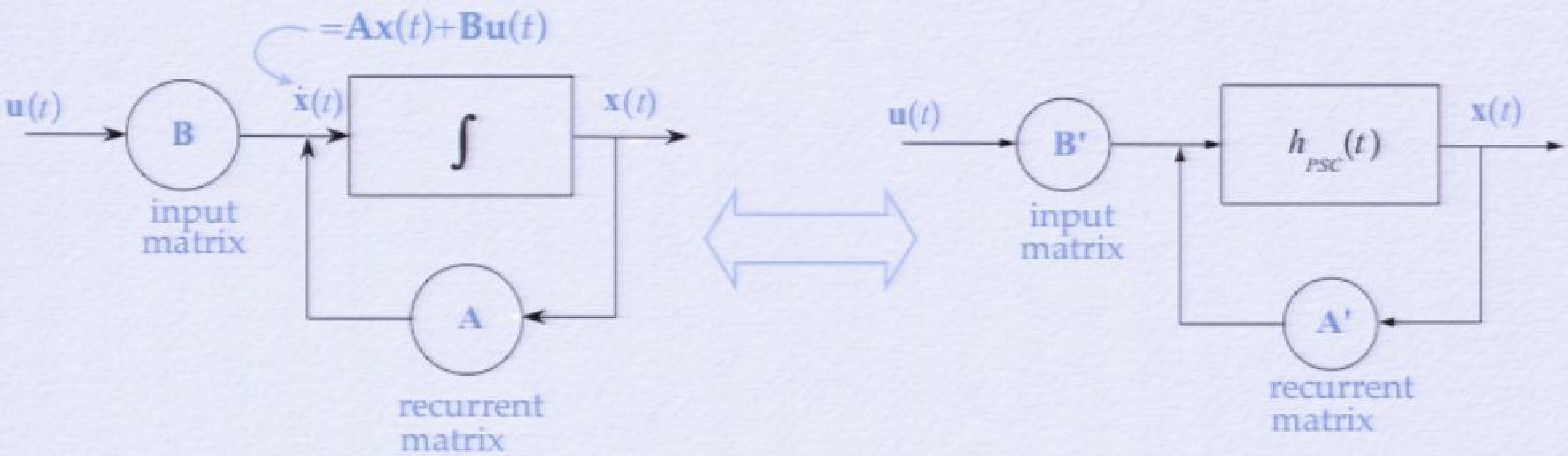


Neural Control Theory

- Adapt standard control theory to neurobiological systems



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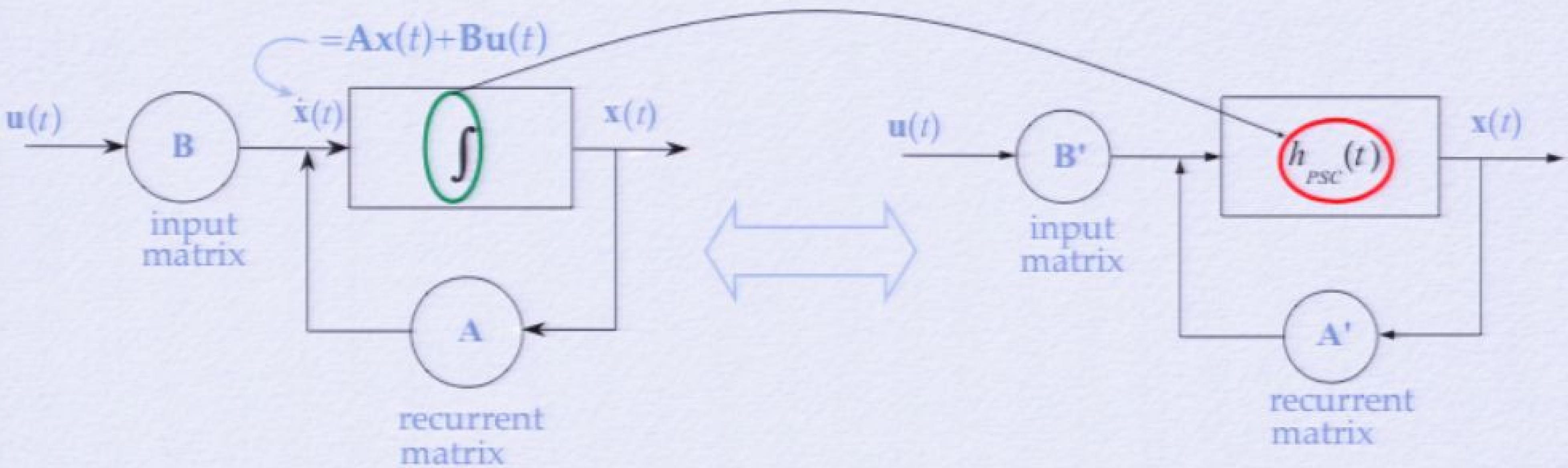

The NEF defines a *generic* neural subsystem

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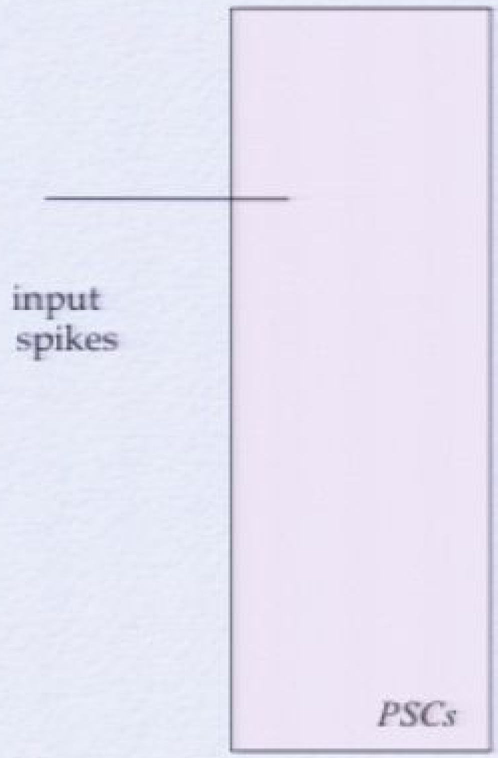

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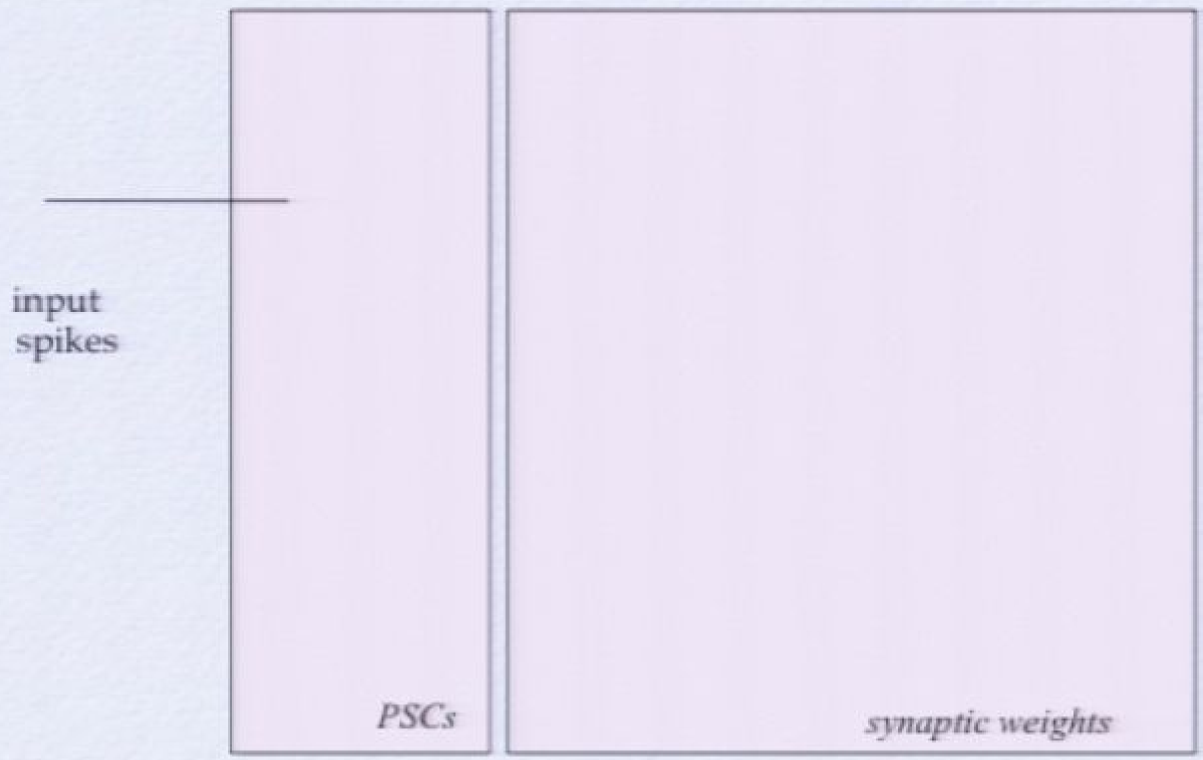

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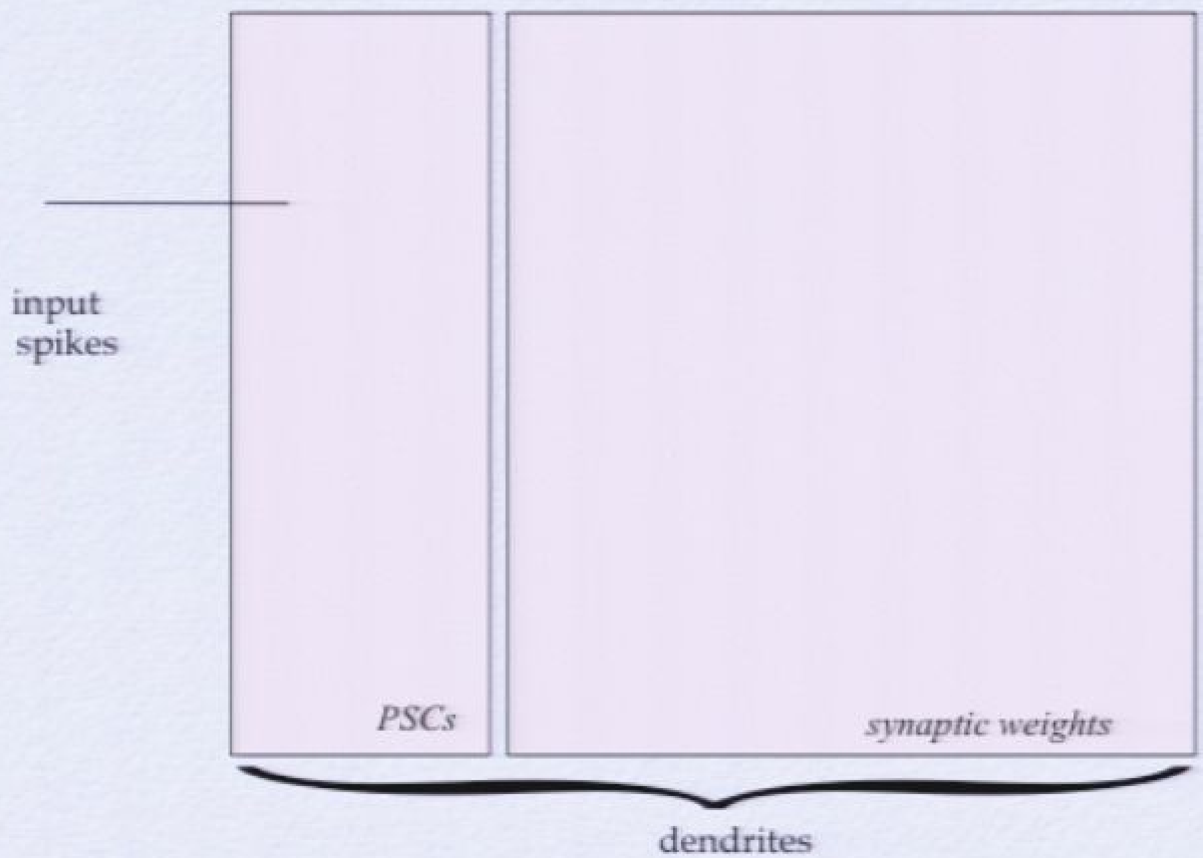

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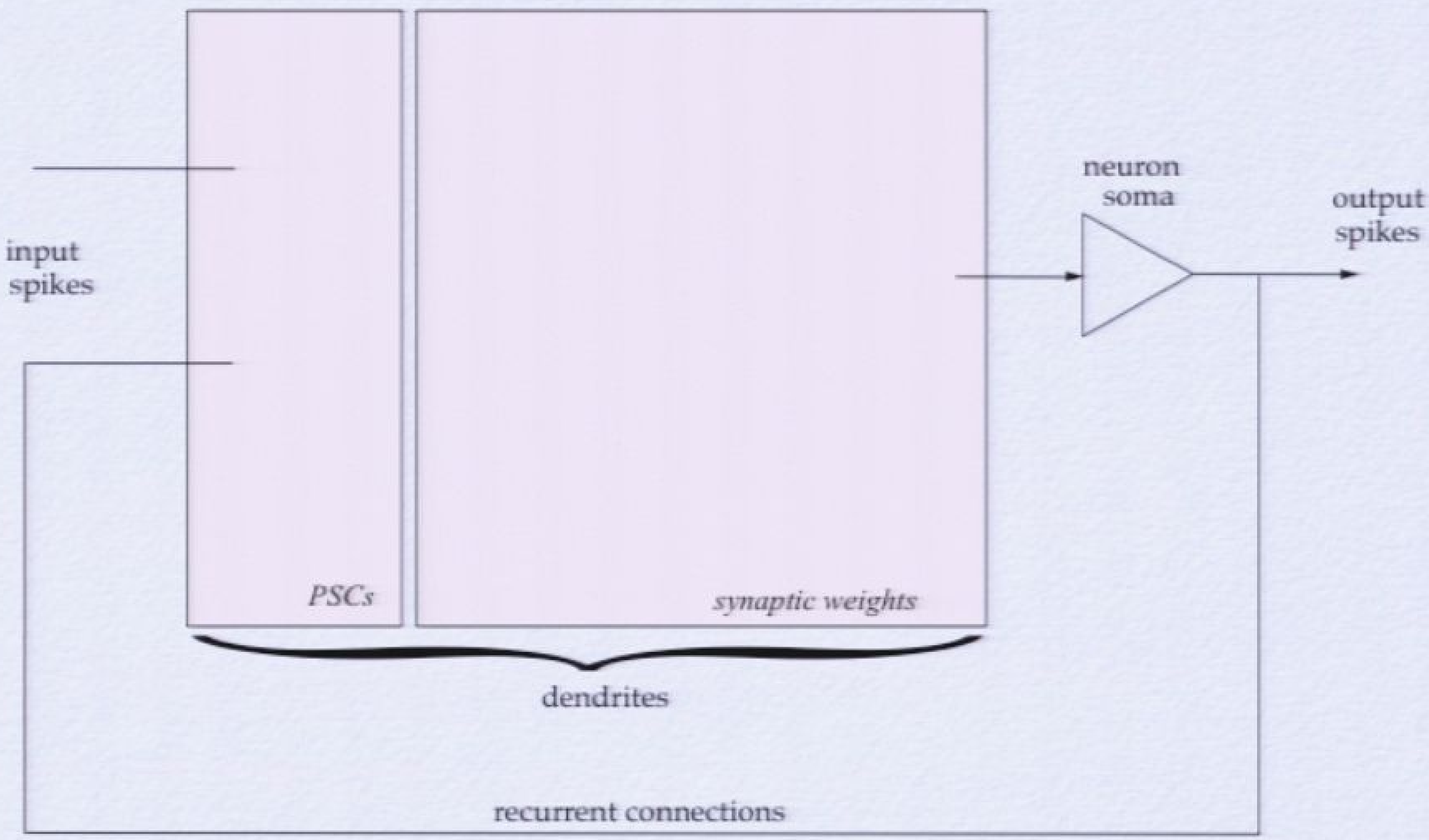

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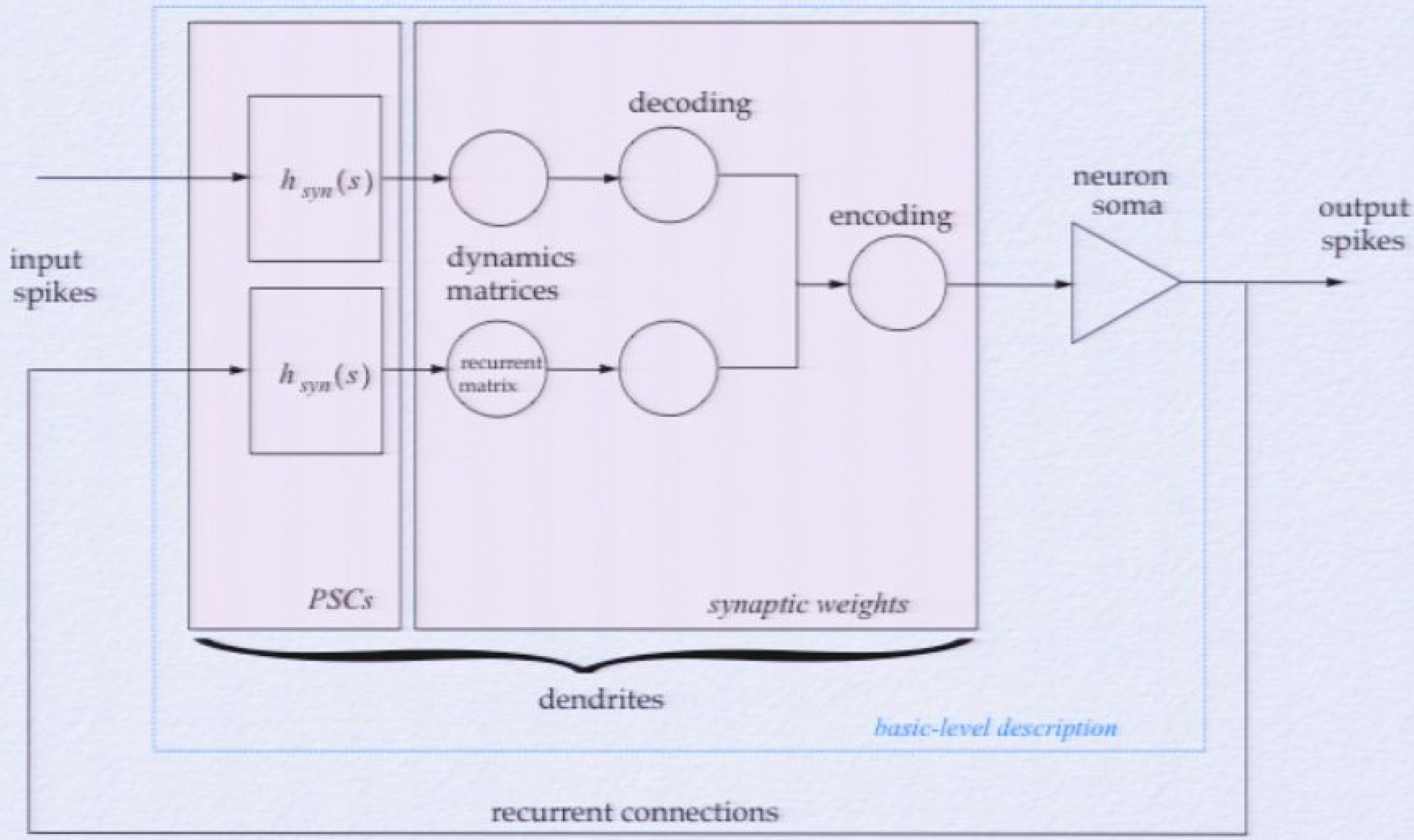

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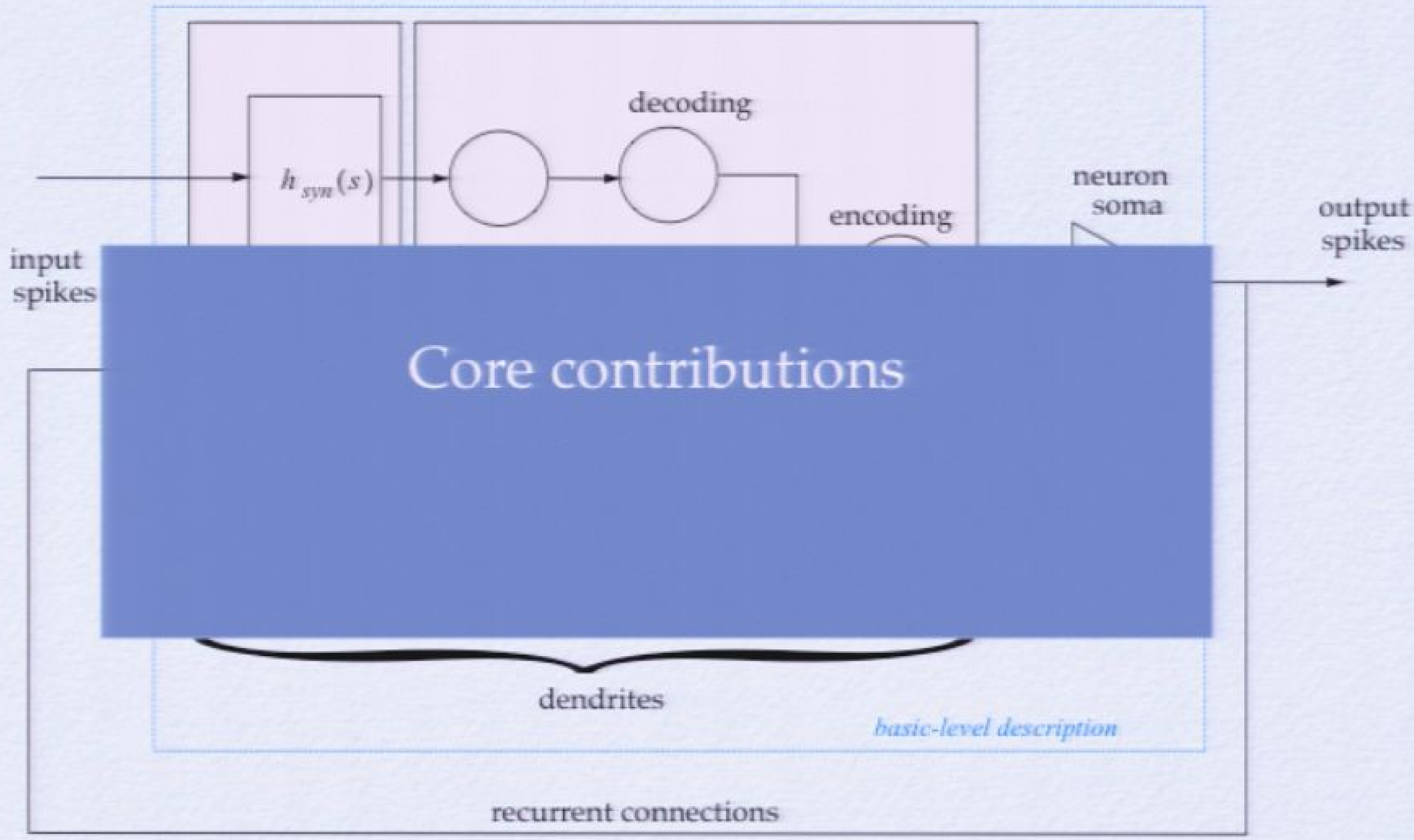
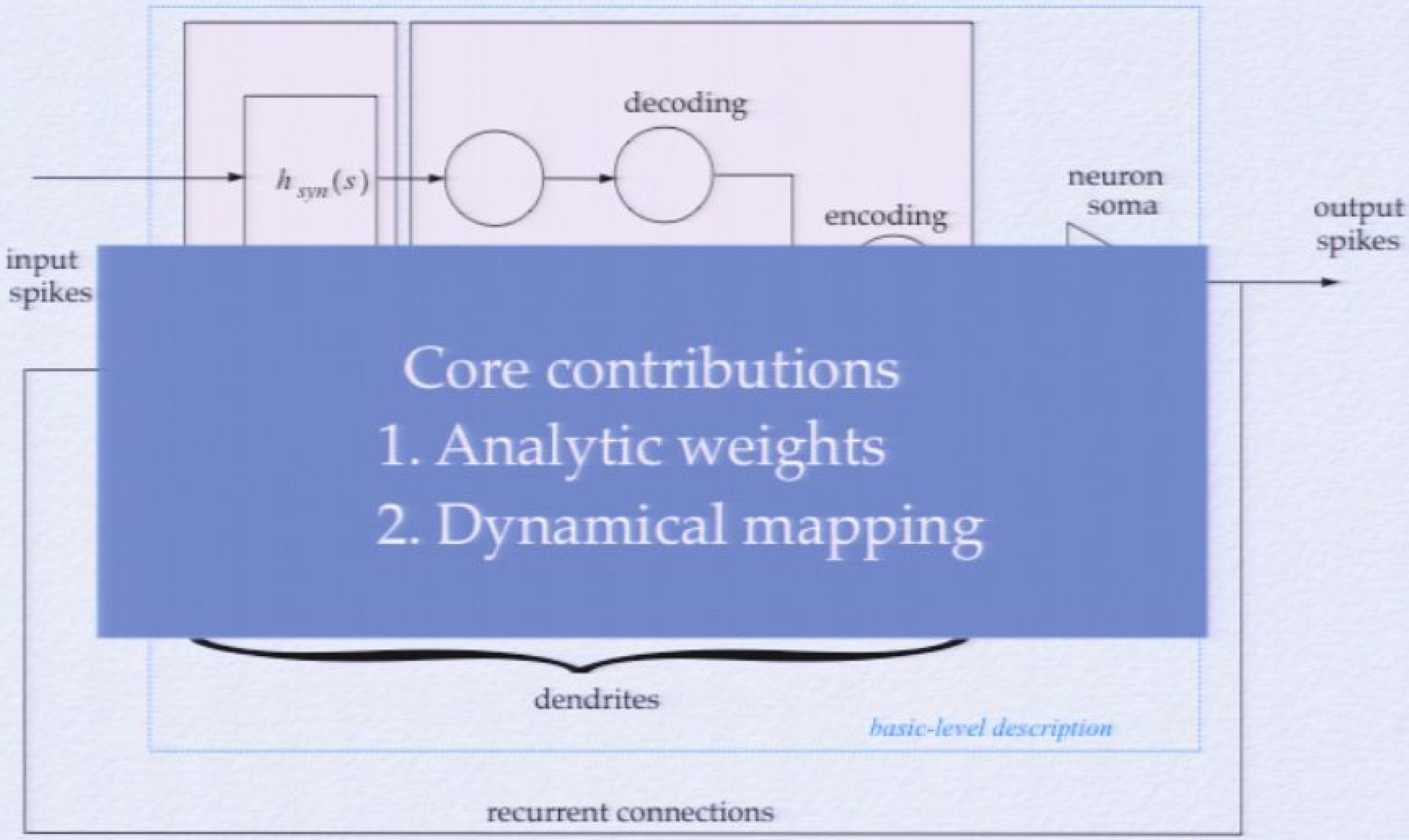


Core contributions

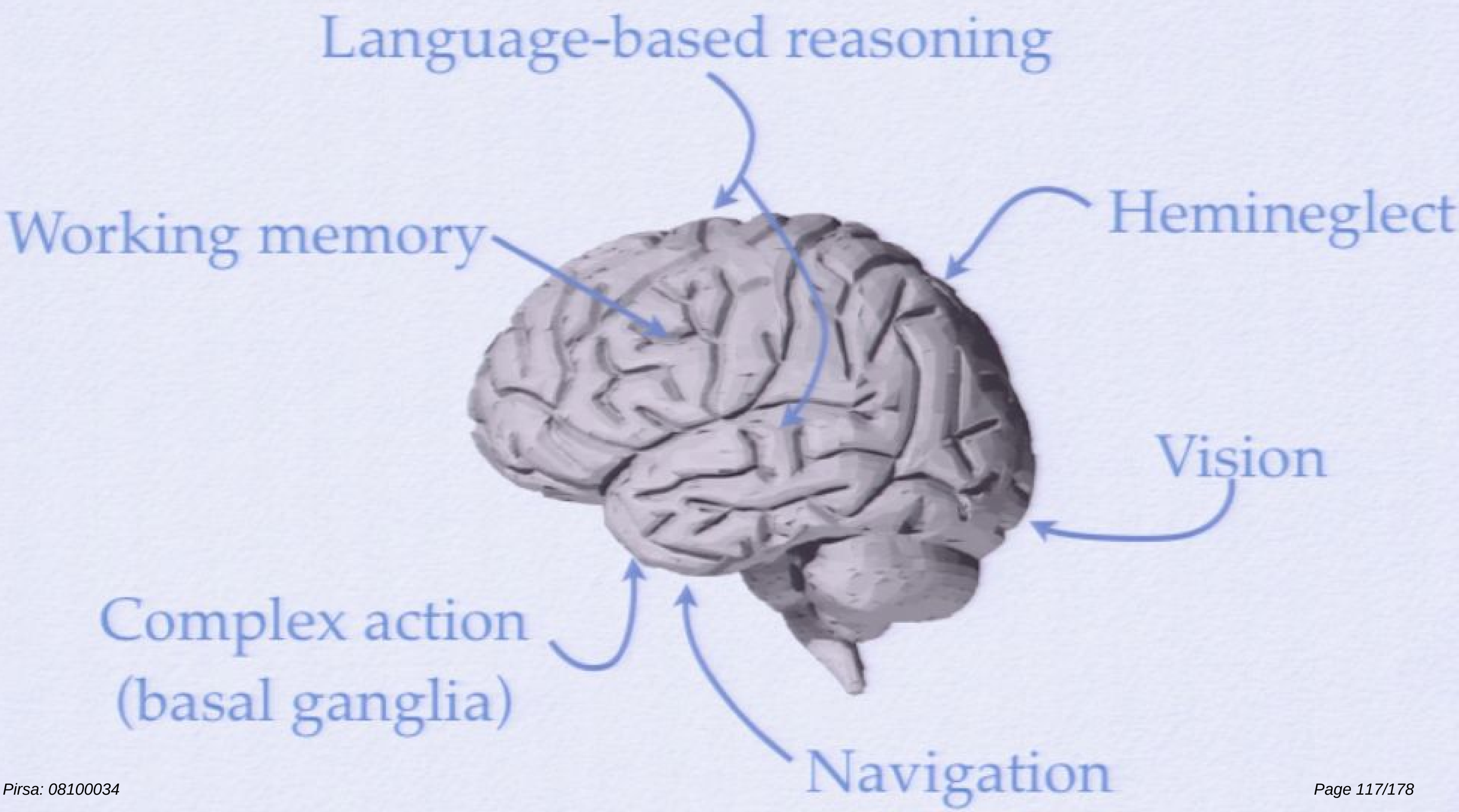
The NEF defines a *generic* neural subsystem



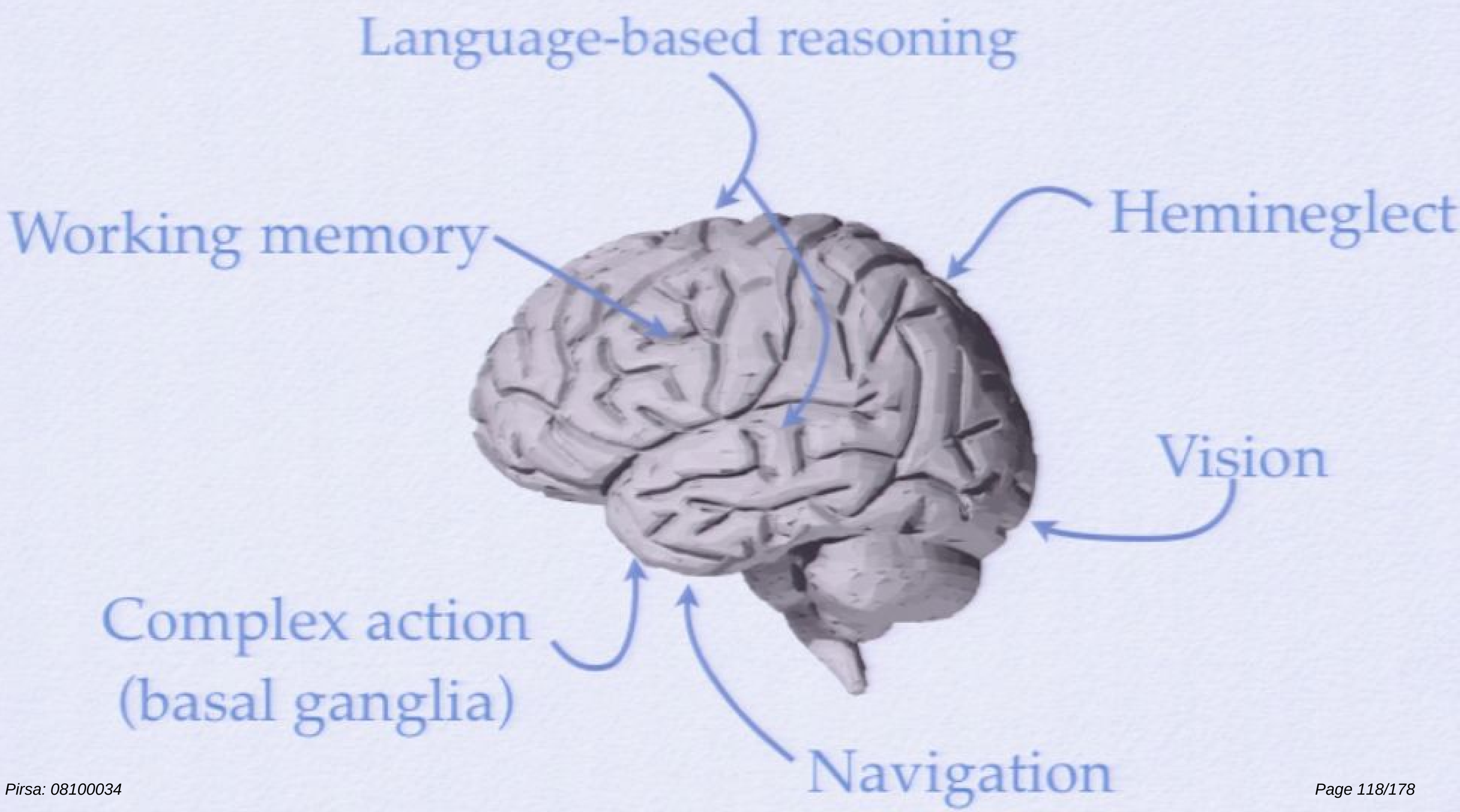
Core contributions

1. Analytic weights
2. Dynamical mapping

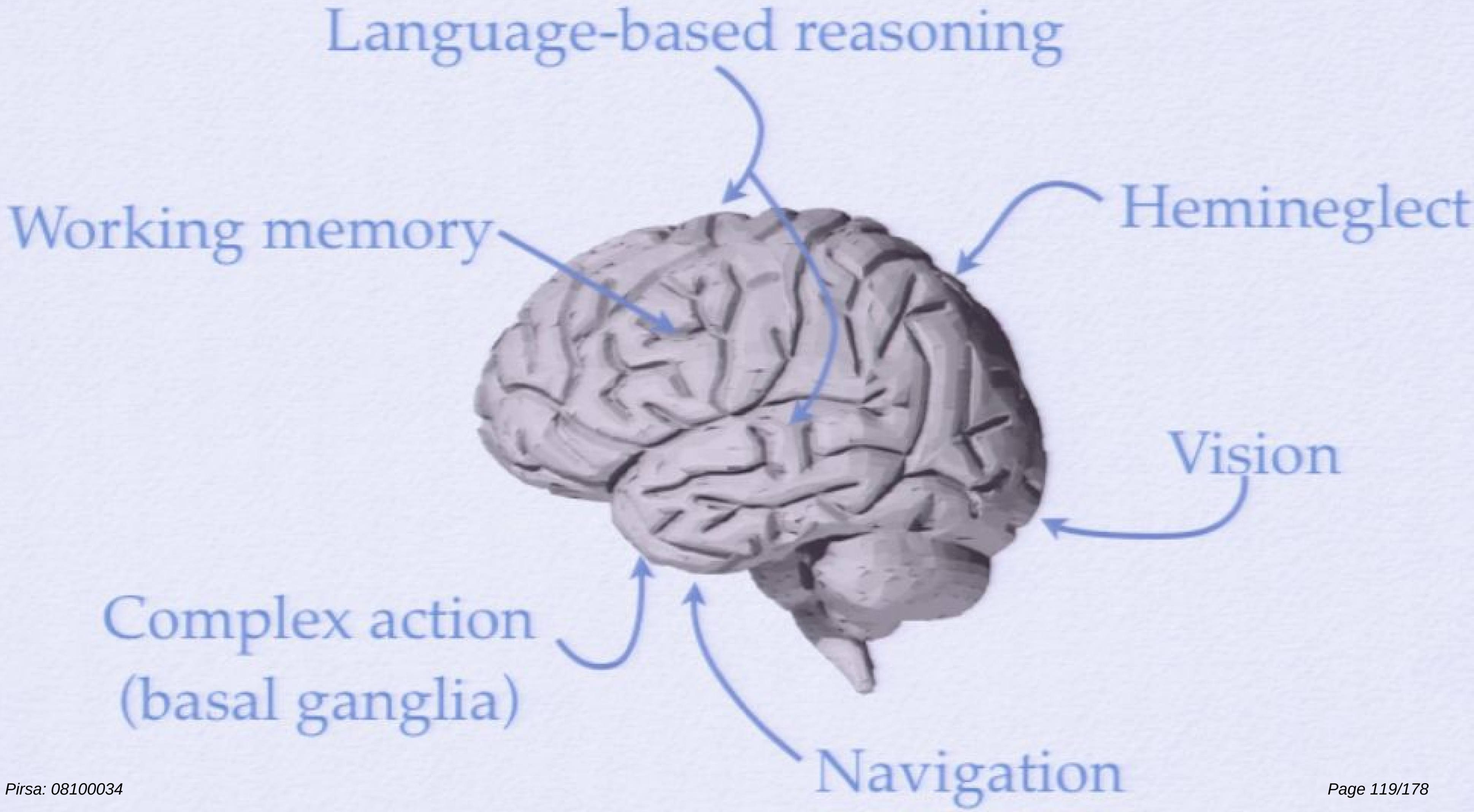
Applications



Applications



Applications



Path Integration

Conklin and Eliasmith (2005) A controlled attractor model of path integration
in the rat. J. Comp. Neuro. 18: 183-203

Path Integration

- Sharp (1997) data: tuning curve width, spike rate distribution

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Path Integration

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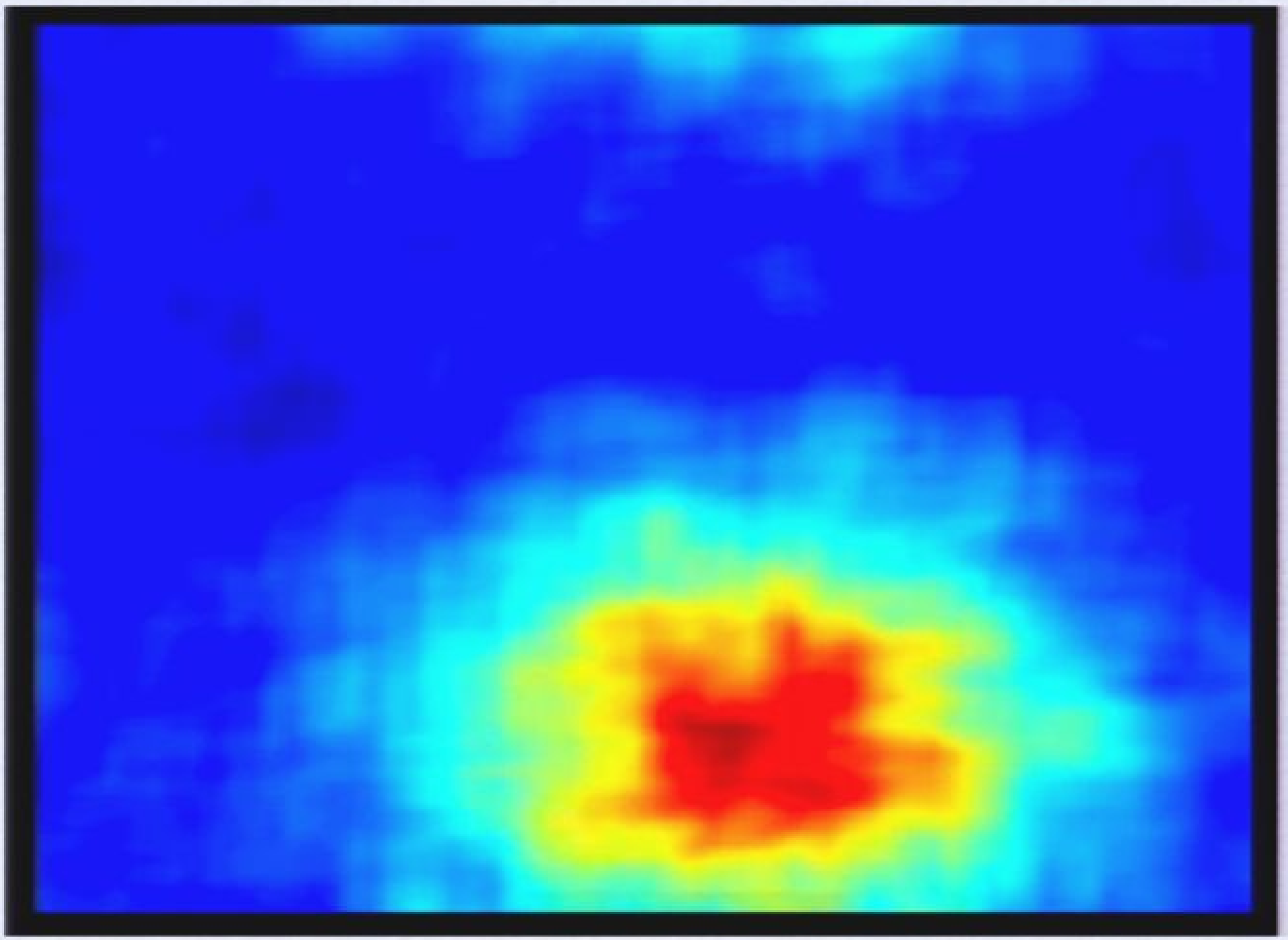
- Coupling weights from NEF

Conklin and Eliasmith (2005) A controlled attractor model of path integration in the rat. J. Comp. Neuro. 18: 183-203

- Biologically realistic model that *explains behaviour*



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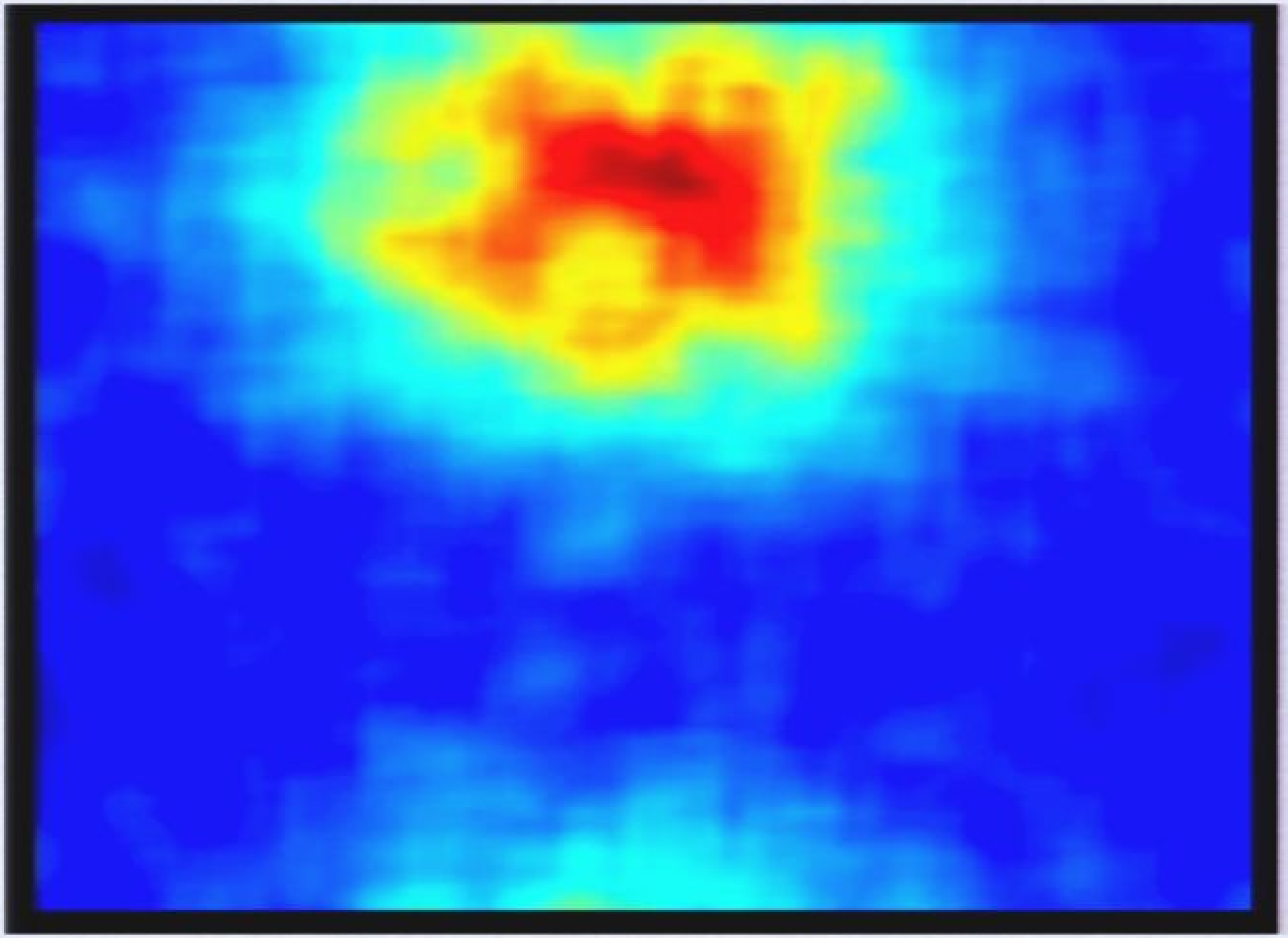
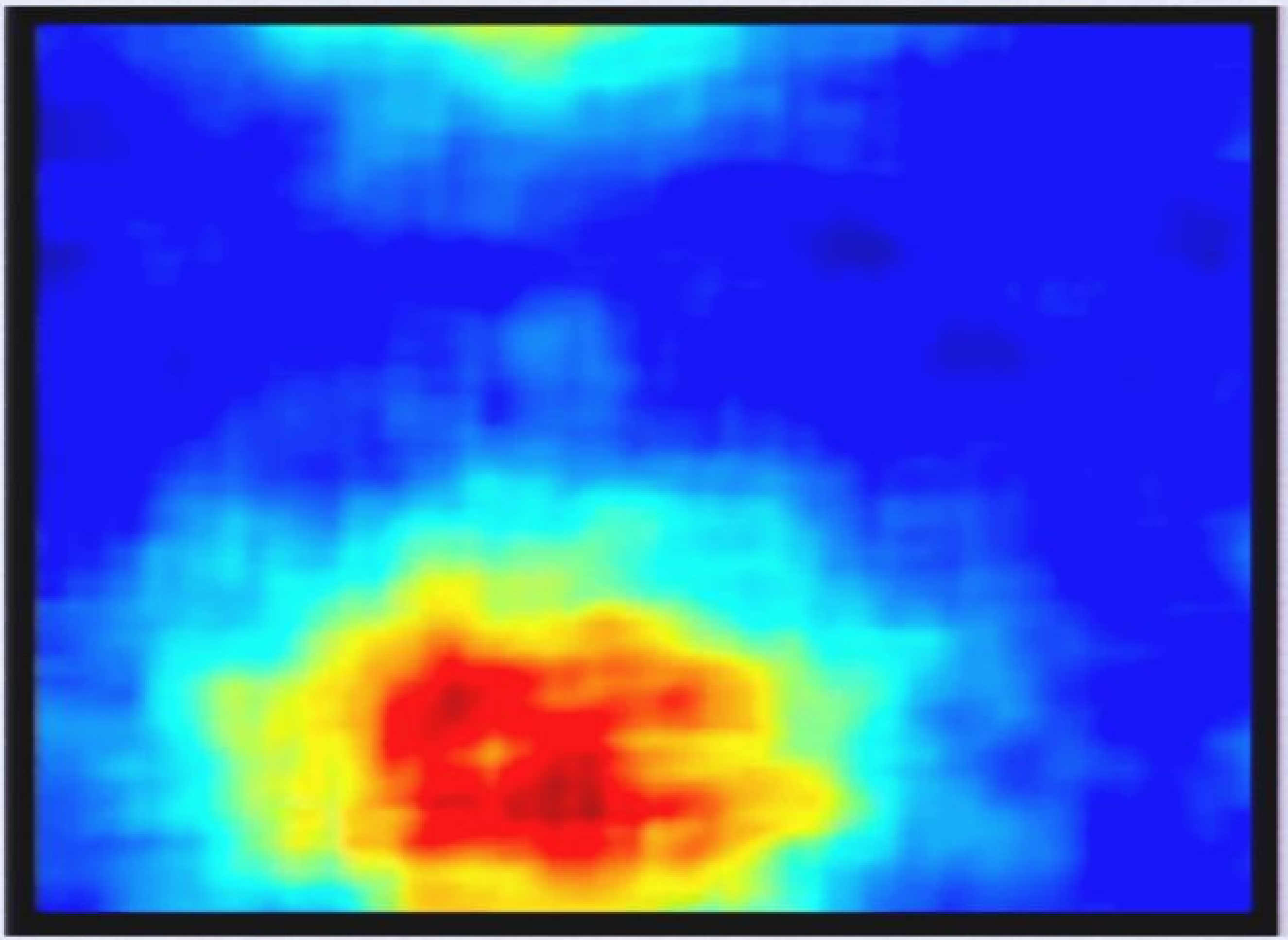


- Biologically realistic model that *explains behaviour*



- this model: 11% error with 4000 cells
- best previous model: 100% error with 300 000 cells

Model accounts for:

Model accounts for:

- Tuning curves in different environments

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- Velocity sensitivity of neuron tuning
- Theta dependent phase precession and amplitude

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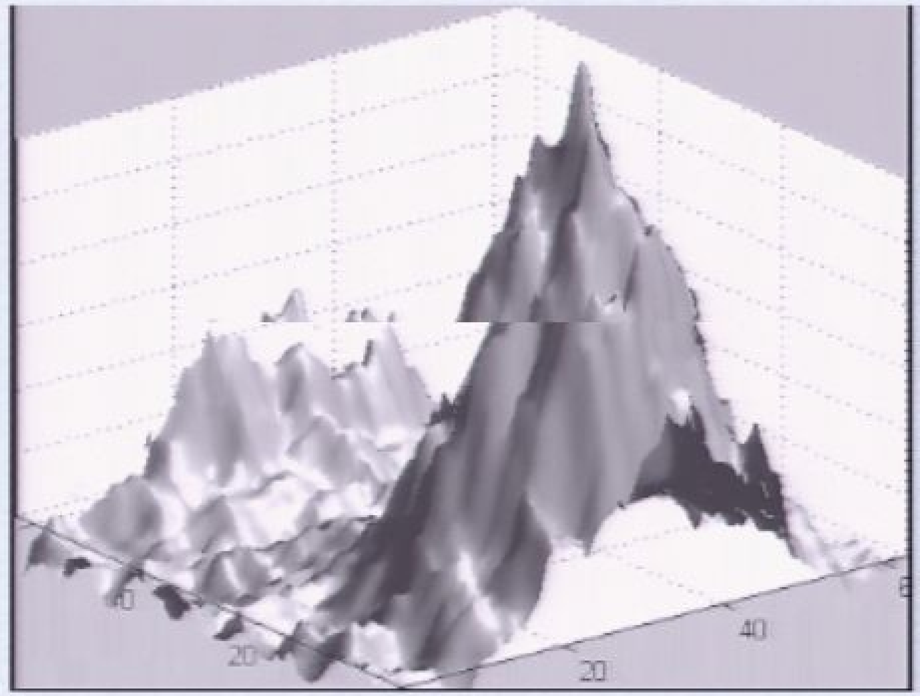

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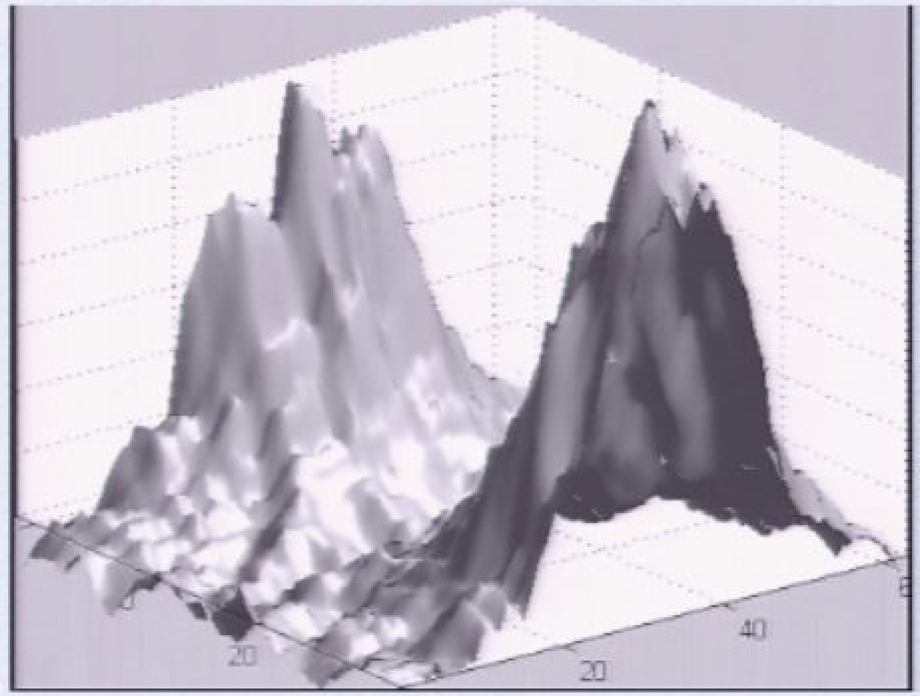

Model accounts for:

- Tuning curves in different environments
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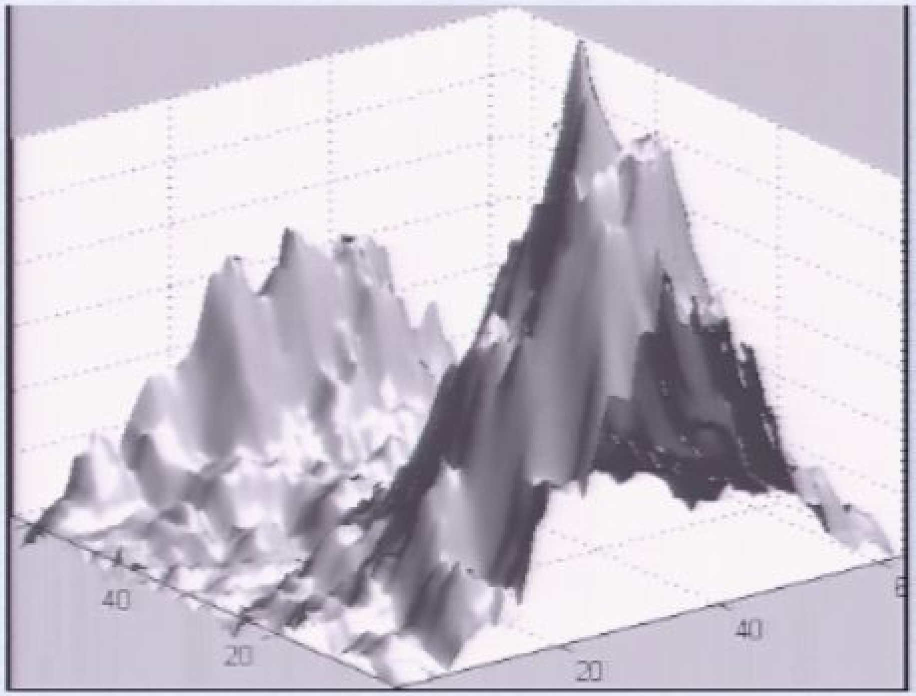
- Weak visual input gives smooth acceleration



Model accounts for:

- Tuning curves in different environments
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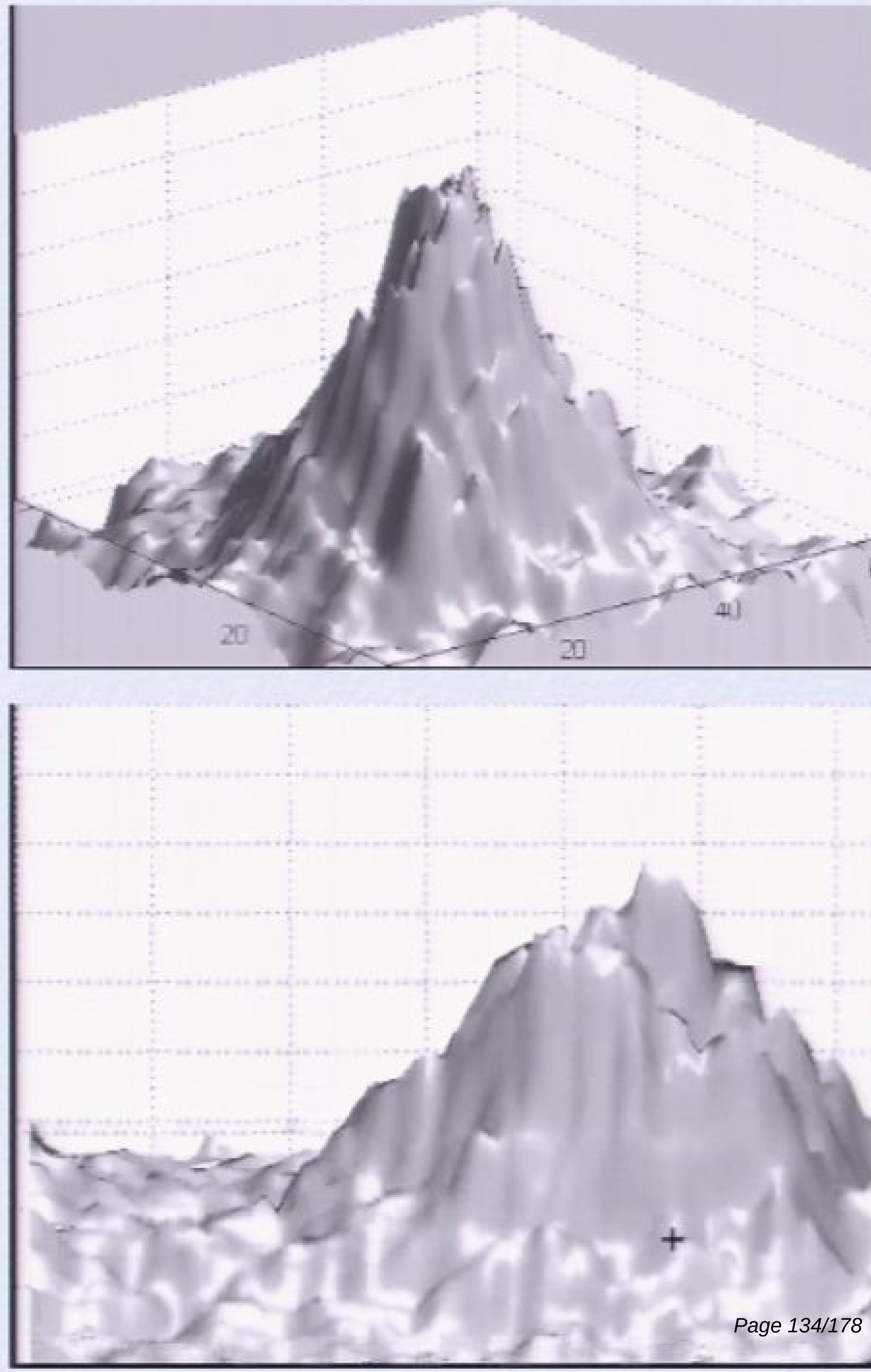
- Theta dependent phase precession and amplitude
- Weak visual input gives smooth acceleration
- Strong visual input gives rapid displacement

Model Predicts:



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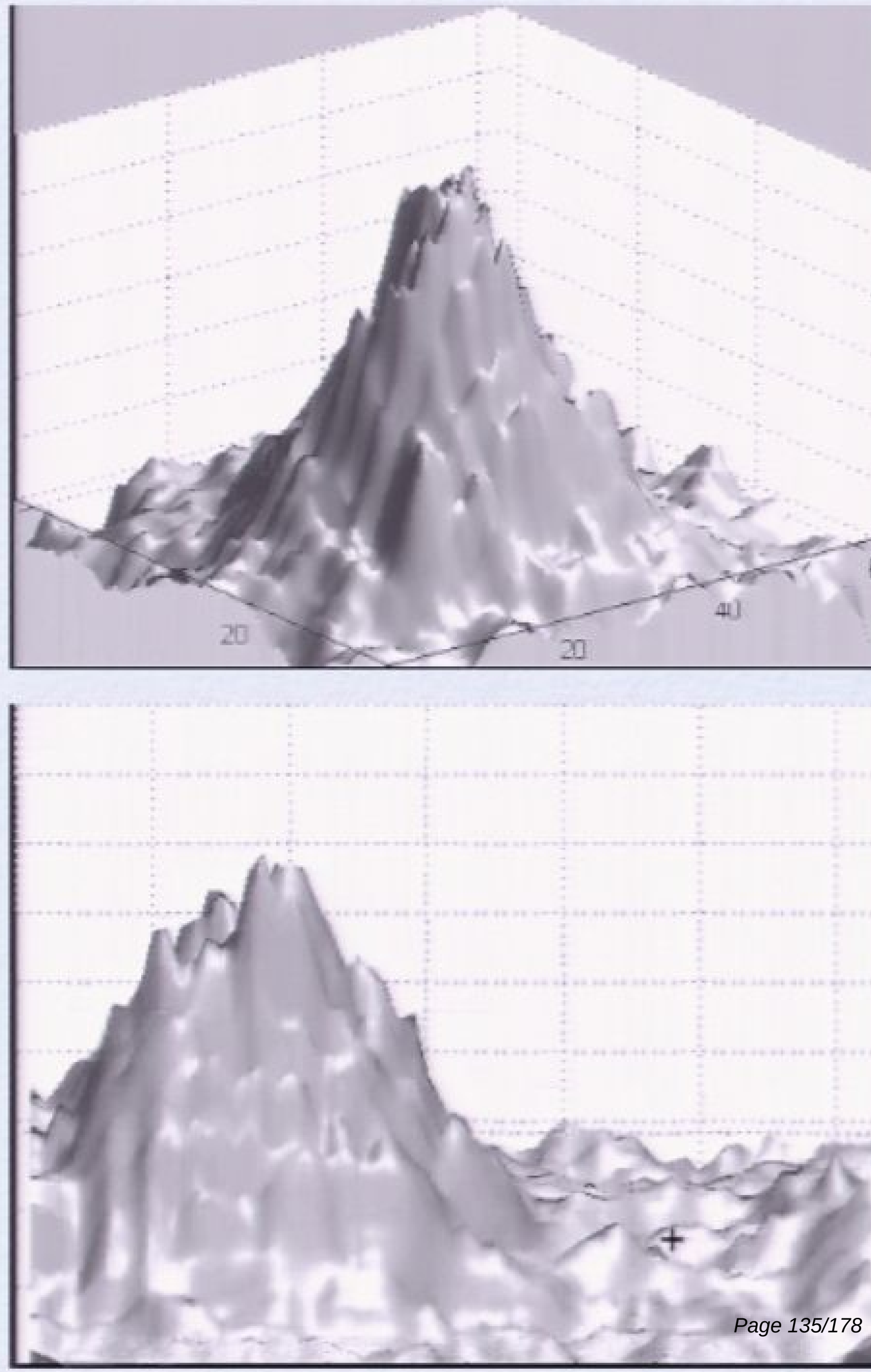
- Theta dependent phase precession and amplitude
- Weak visual input gives smooth acceleration
- Strong visual input gives rapid displacement

Model Predicts:

- Identically coupled velocity and direction sensitivity across environments



Model accounts for:

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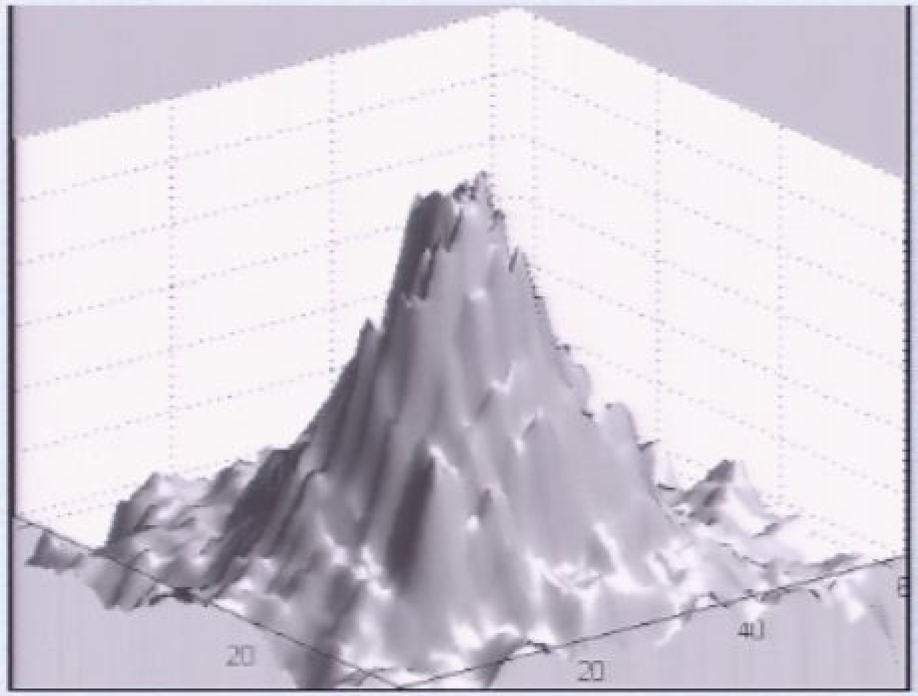
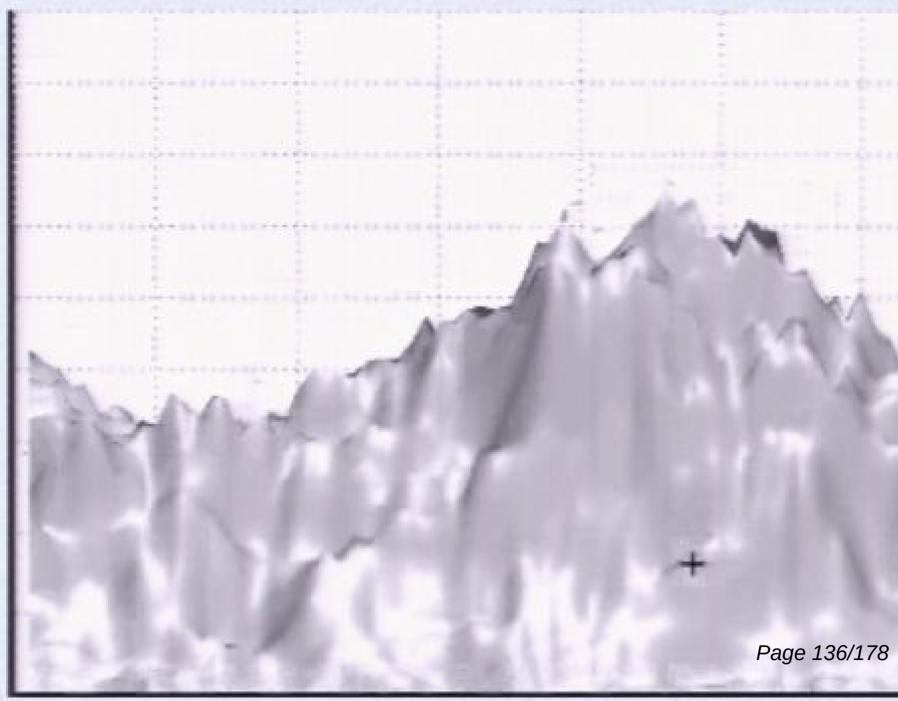
- Theta dependent phase precession and amplitude
- Weak visual input gives smooth acceleration
- Strong visual input gives rapid displacement

Model Predicts:

- Identically coupled velocity and direction sensitivity across environments
- Head-direction independent accuracy





- Abstract Rule
  - If there is a vowel on one side
    then there is an even number on the other.

A	B	2	3

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A B 2 3

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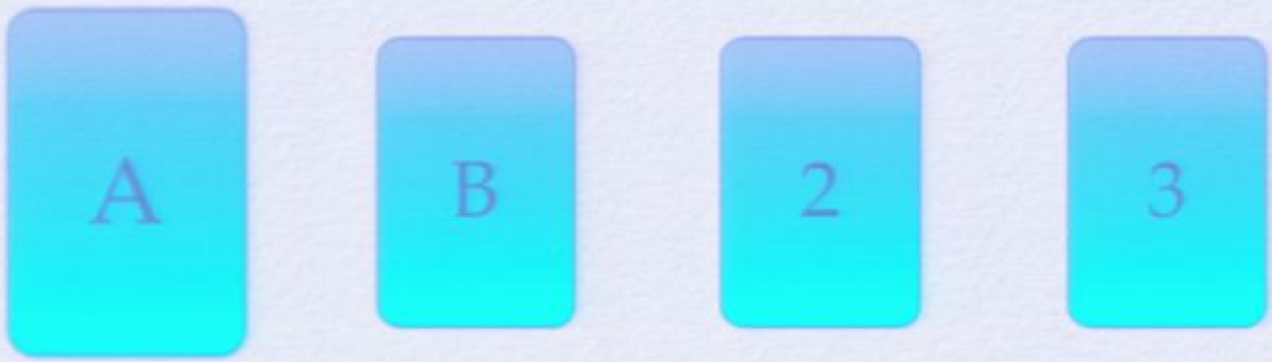

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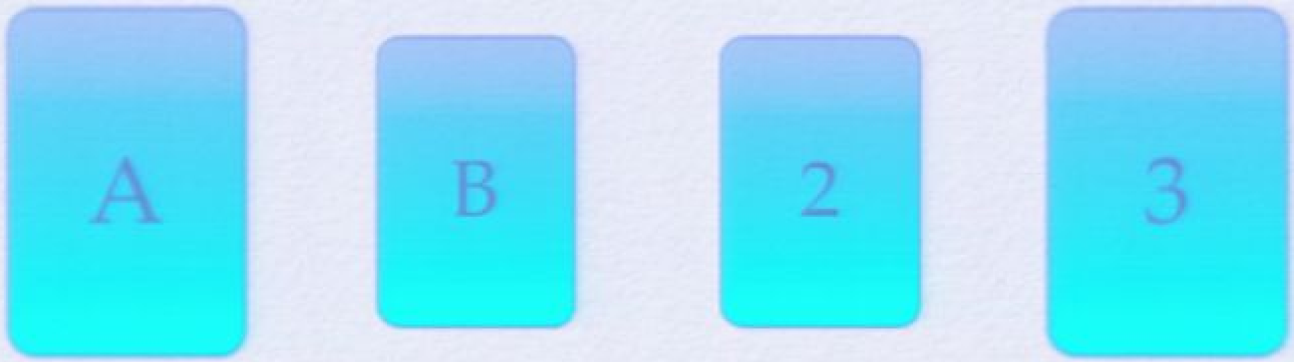

- Abstract Rule
  - If there is a vowel on one side
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A B 2 3 30%

- Abstract Rule
  - If there is a vowel on one side
    then there is an even number on the other.

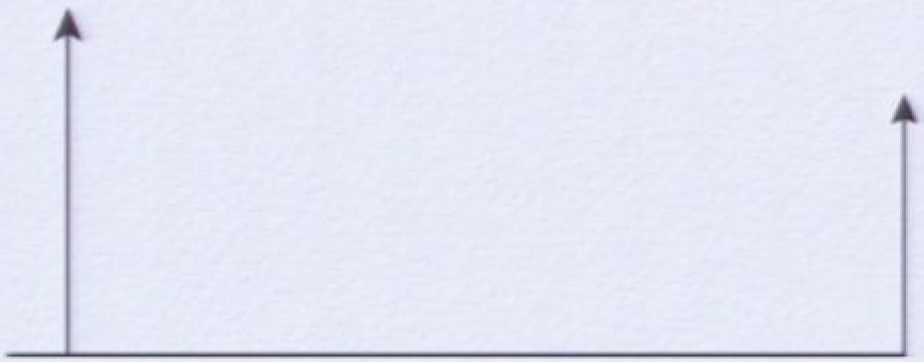
A	B	2	3	30%
Beer	Coke	22	16	

- Abstract Rule
  - If there is a vowel on one side
    then there is an even number on the other.

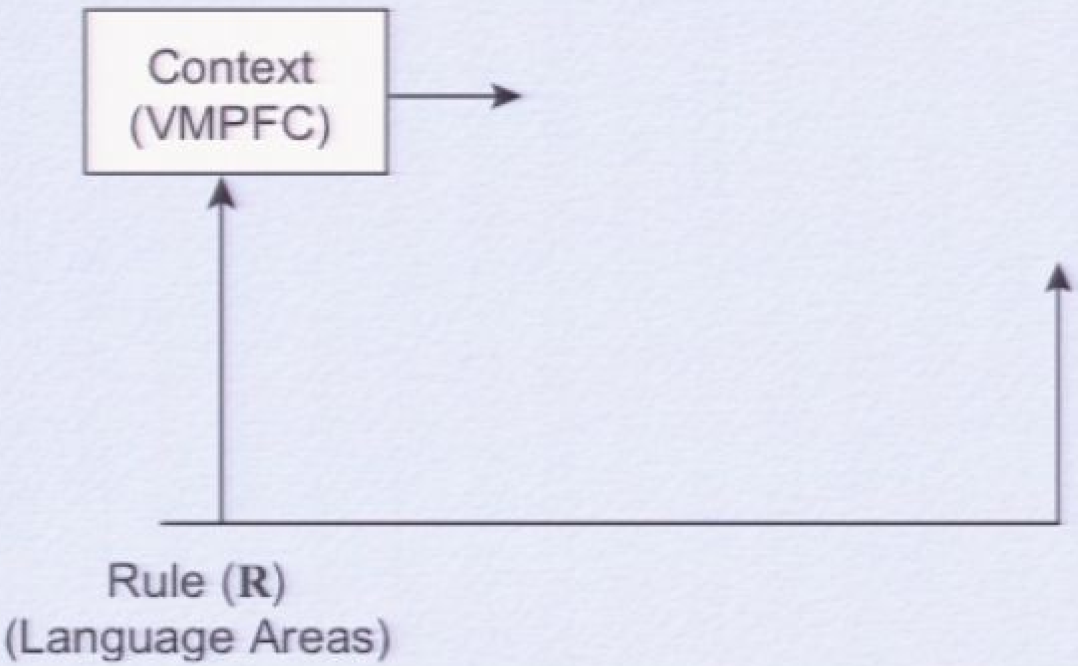
A	B	2	3	30%

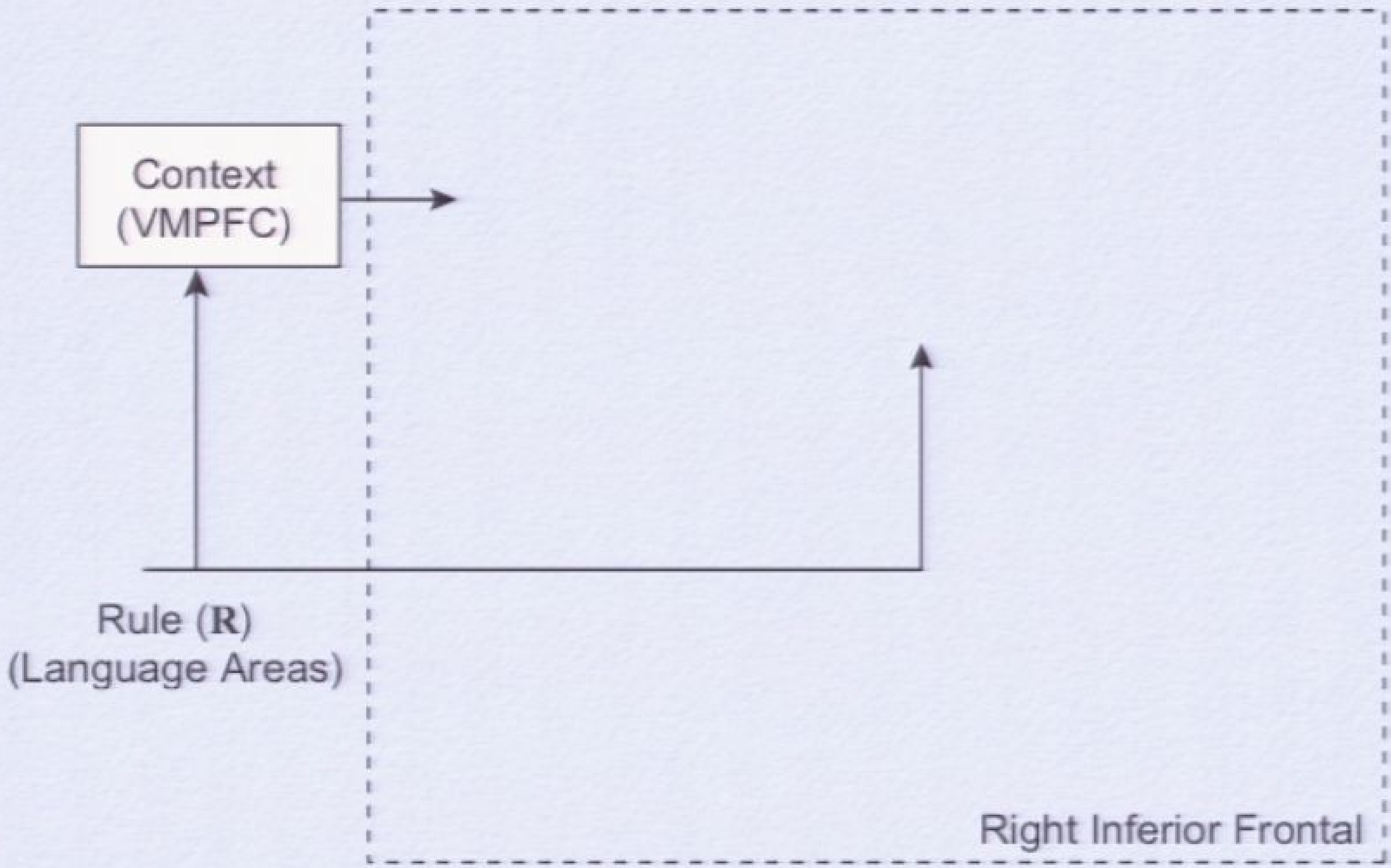
- Social Rule
  - If someone is drinking alcohol
    then they are over 21.

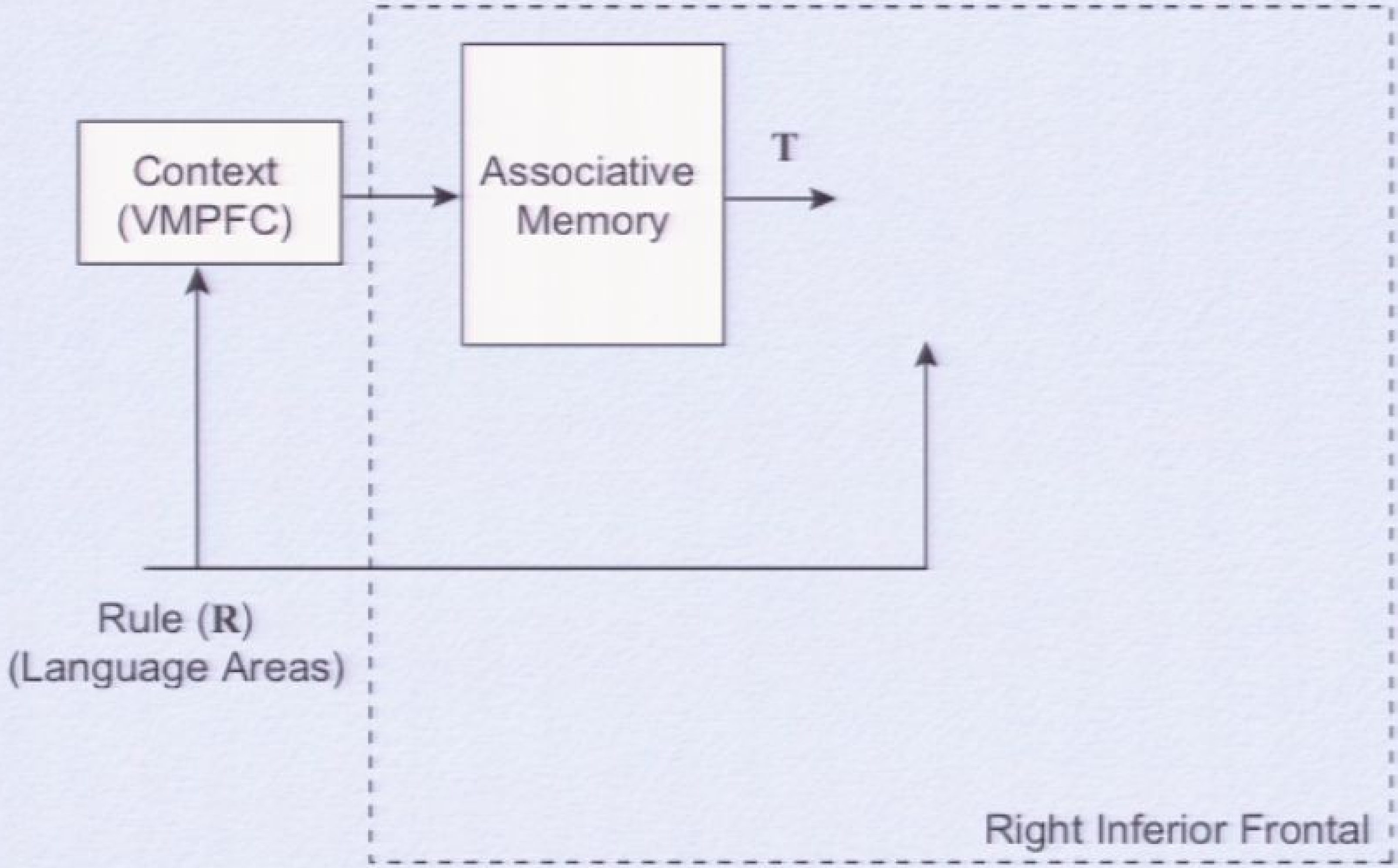
Beer	Coke	22	16

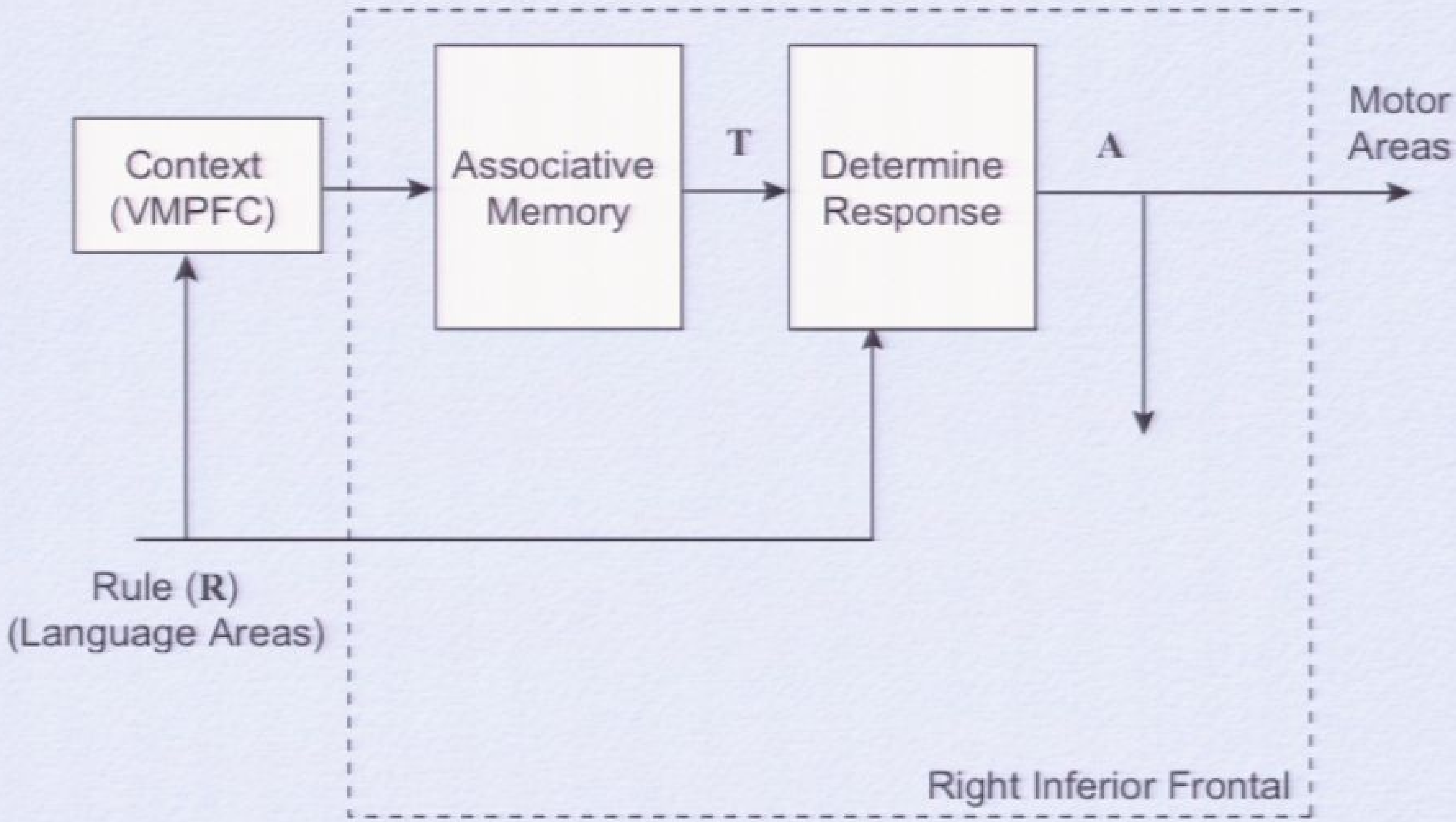


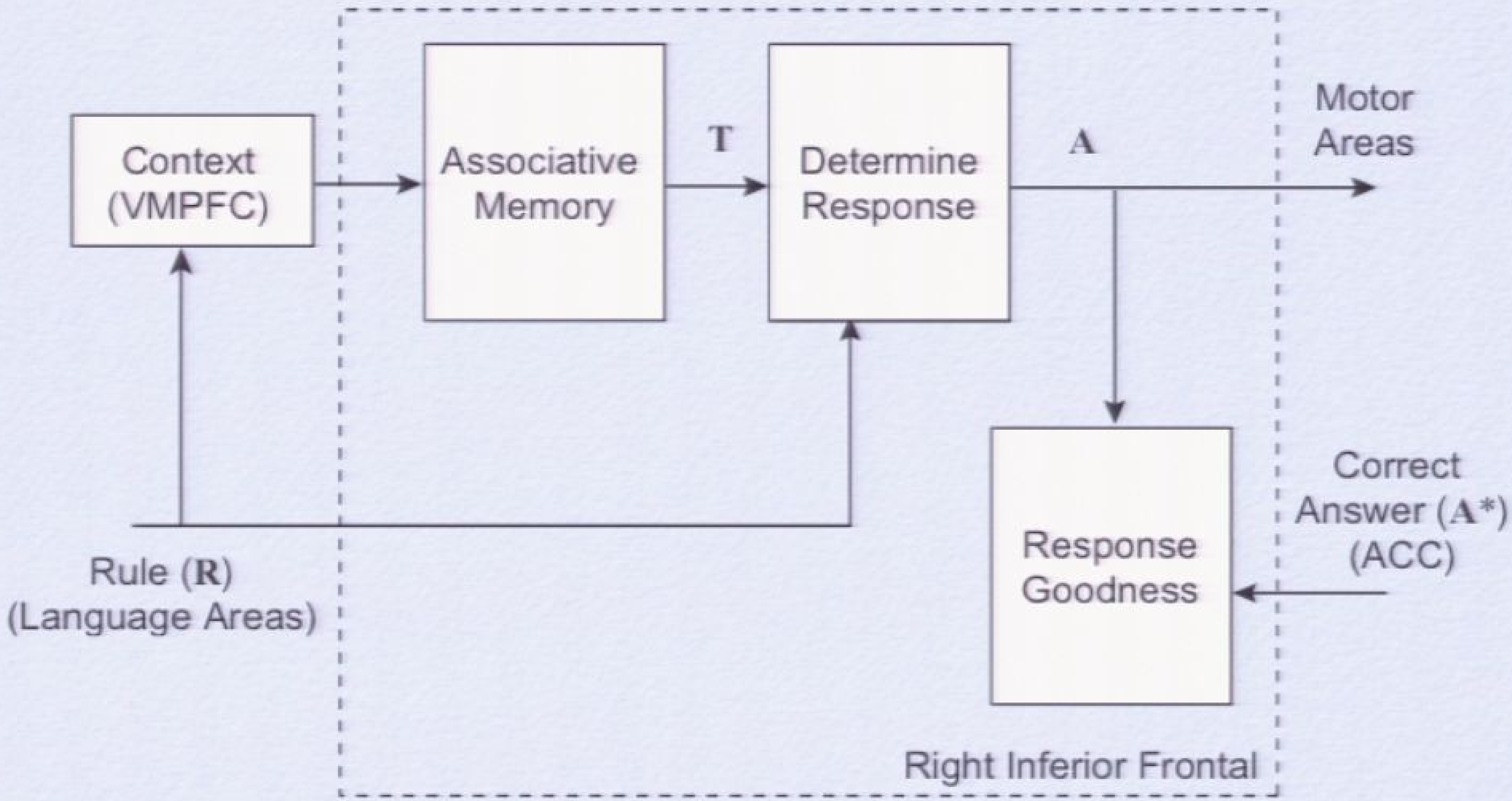
Rule (**R**)
(Language Areas)

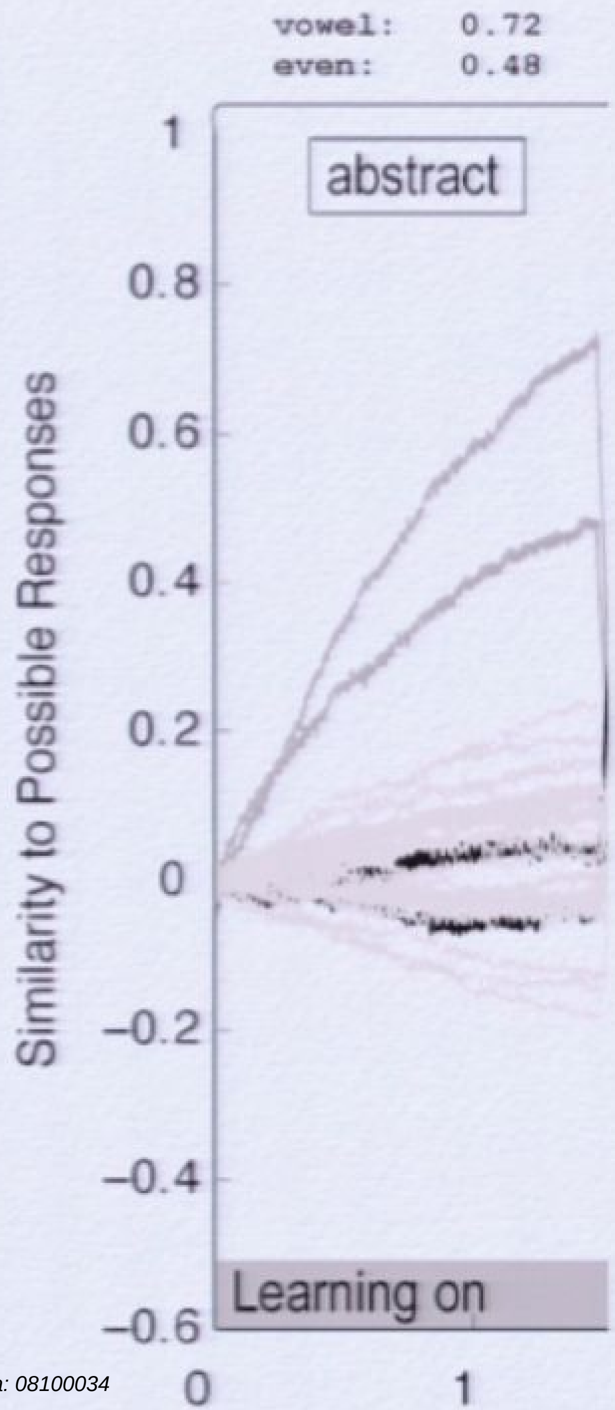

Context
(VMPFC)
Rule (R)
(Language Areas)

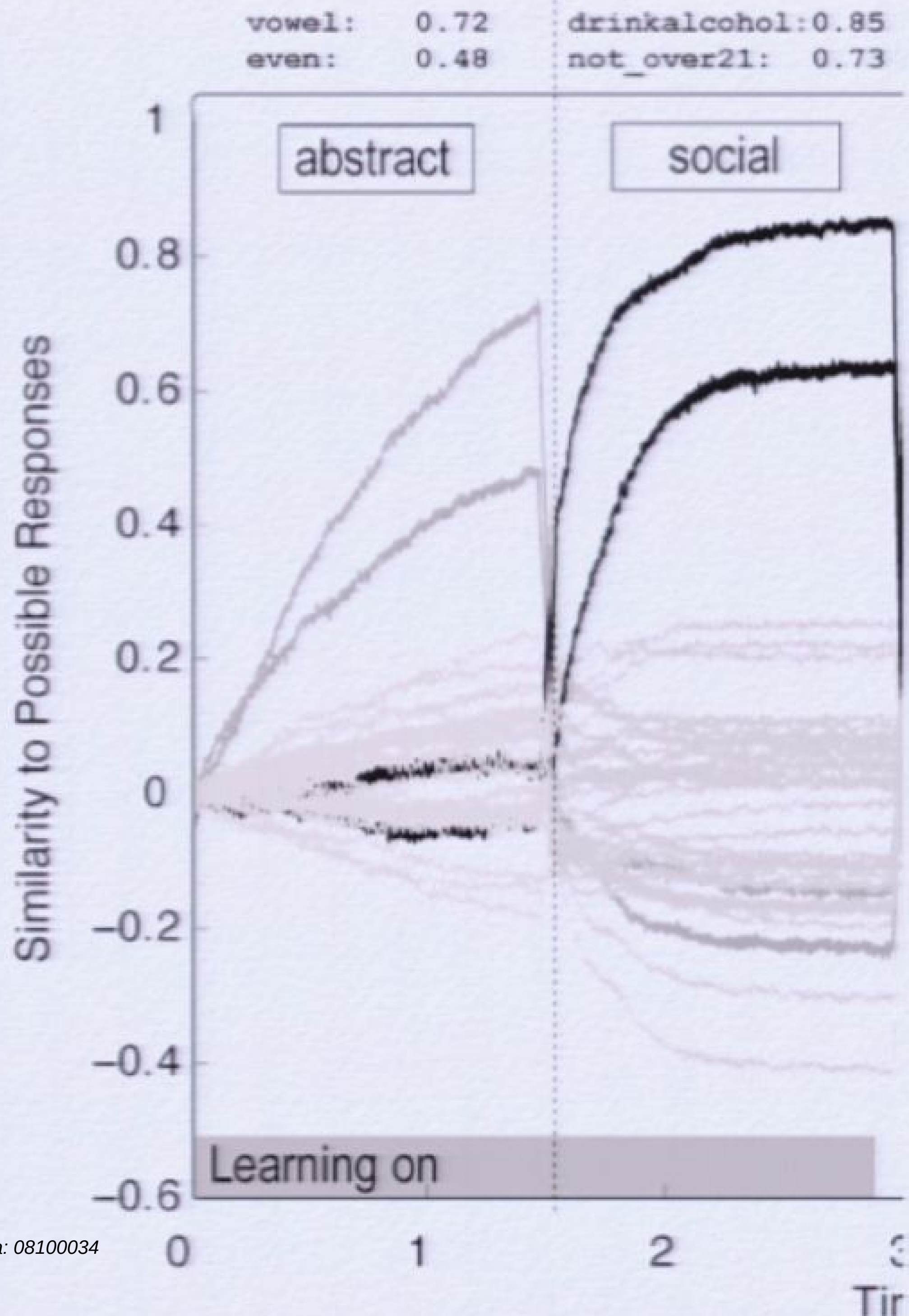

Context
(VMPFC)
Rule (R)
(Language Areas)
Right Inferior Frontal


Context
(VMPFC)
Associative
Memory
T
Rule (R)
(Language Areas)
Right Inferior Frontal

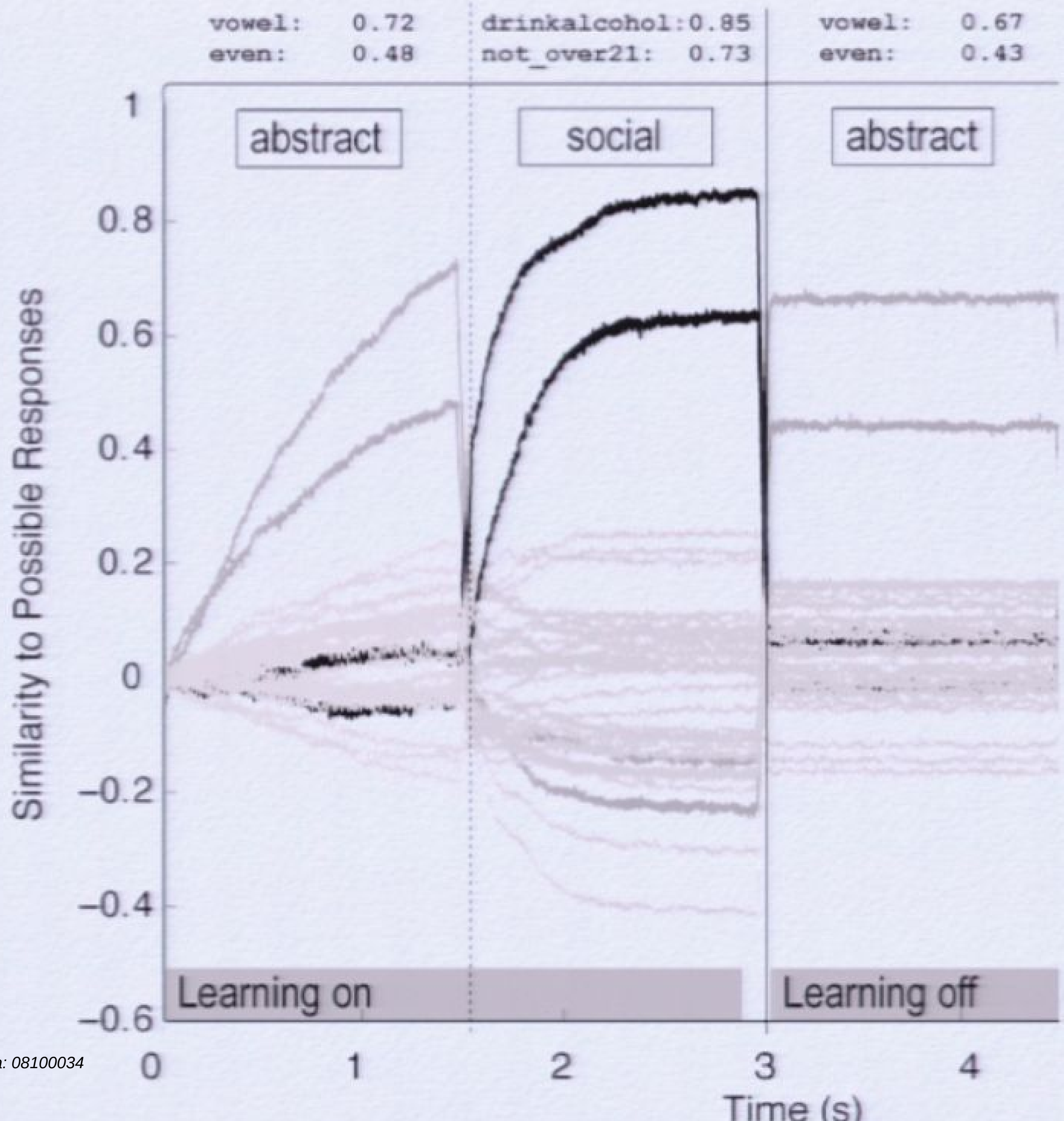

Context
(VMPFC)
Associative
Memory
T
Determine
Response
A
Motor
Areas
Rule (R)
(Language Areas)
Right Inferior Frontal

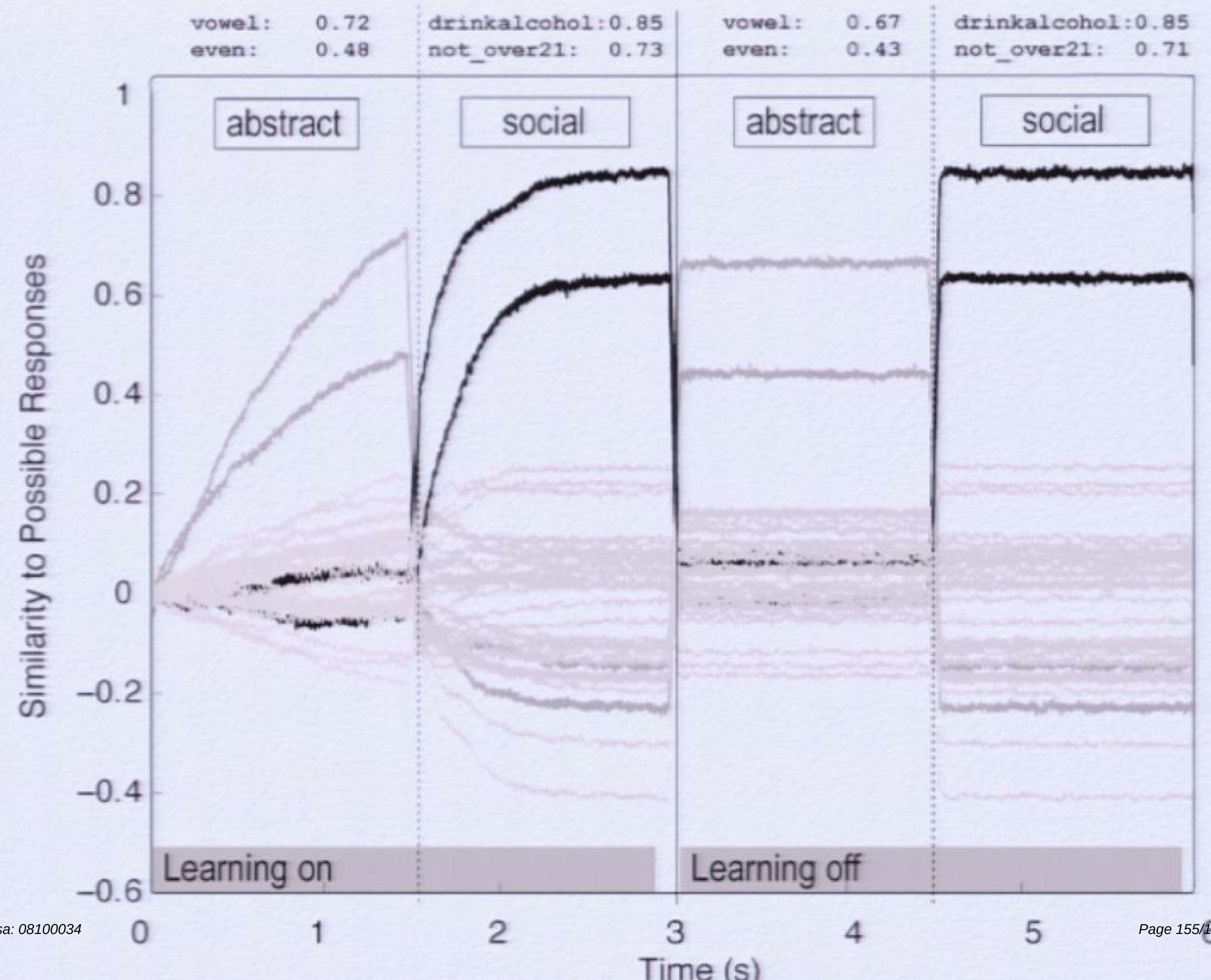

Context
(VMPFC)
Associative
Memory
T
Determine
Response
A
Motor
Areas
Response
Goodness
Correct
Answer (A*)
(ACC)
Rule (R)
(Language Areas)
Right Inferior Frontal

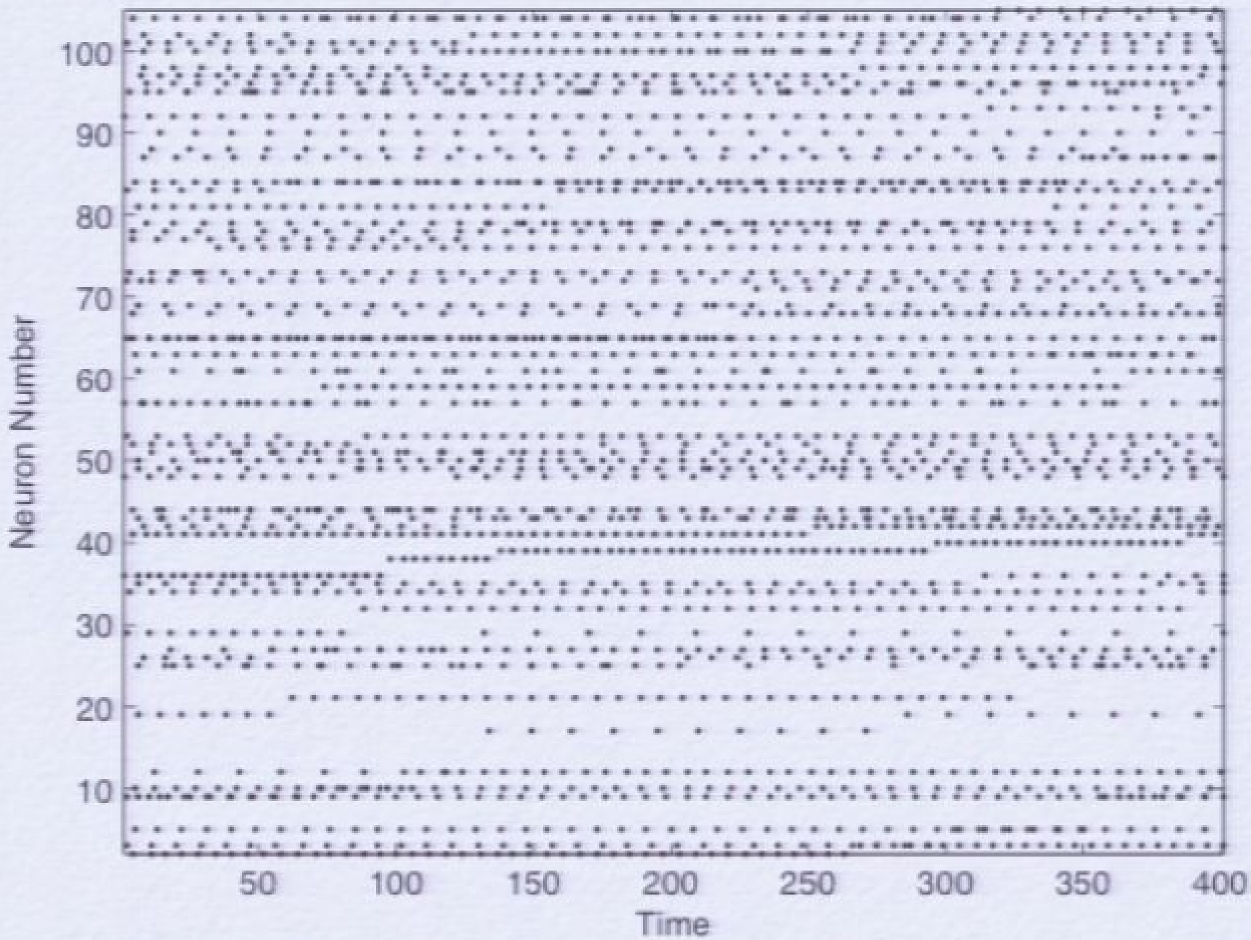

vowel: 0.72
even: 0.48
abstract
Learning on
Similarity to Possible Responses
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
0
1



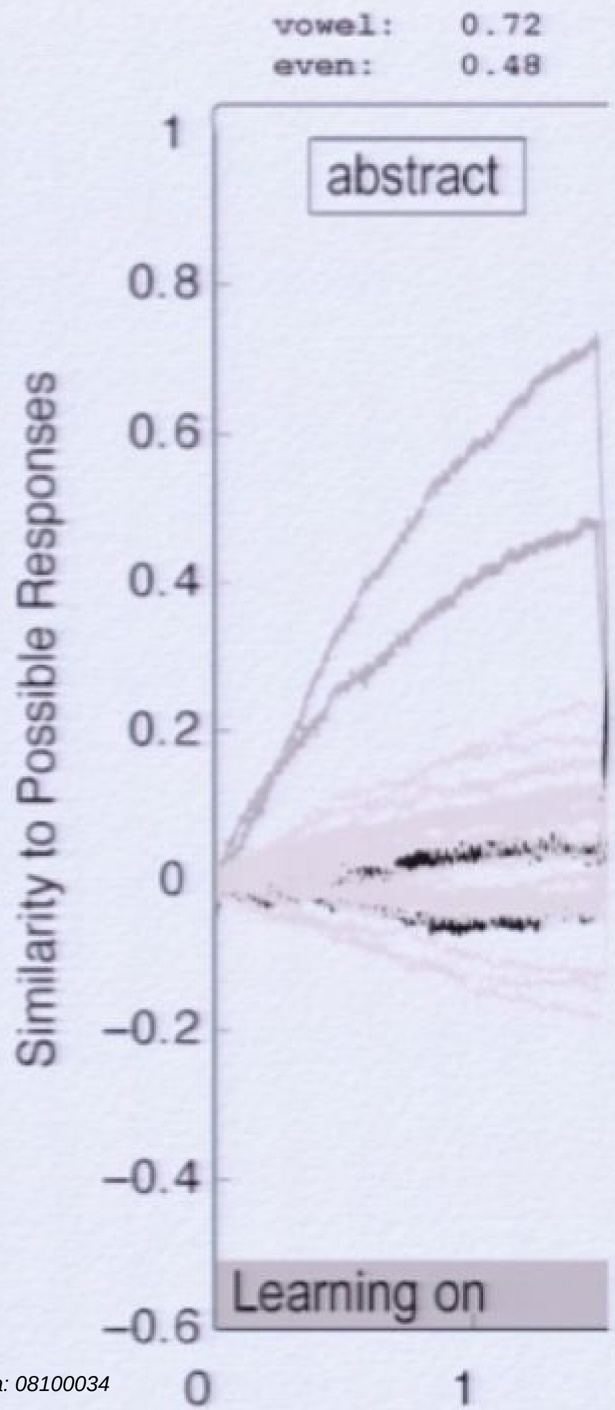
vowel: 0.72
even: 0.48
drinkalcohol:0.85
not_over21: 0.73
abstract
social
Similarity to Possible Responses
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
Learning on
0
1
2

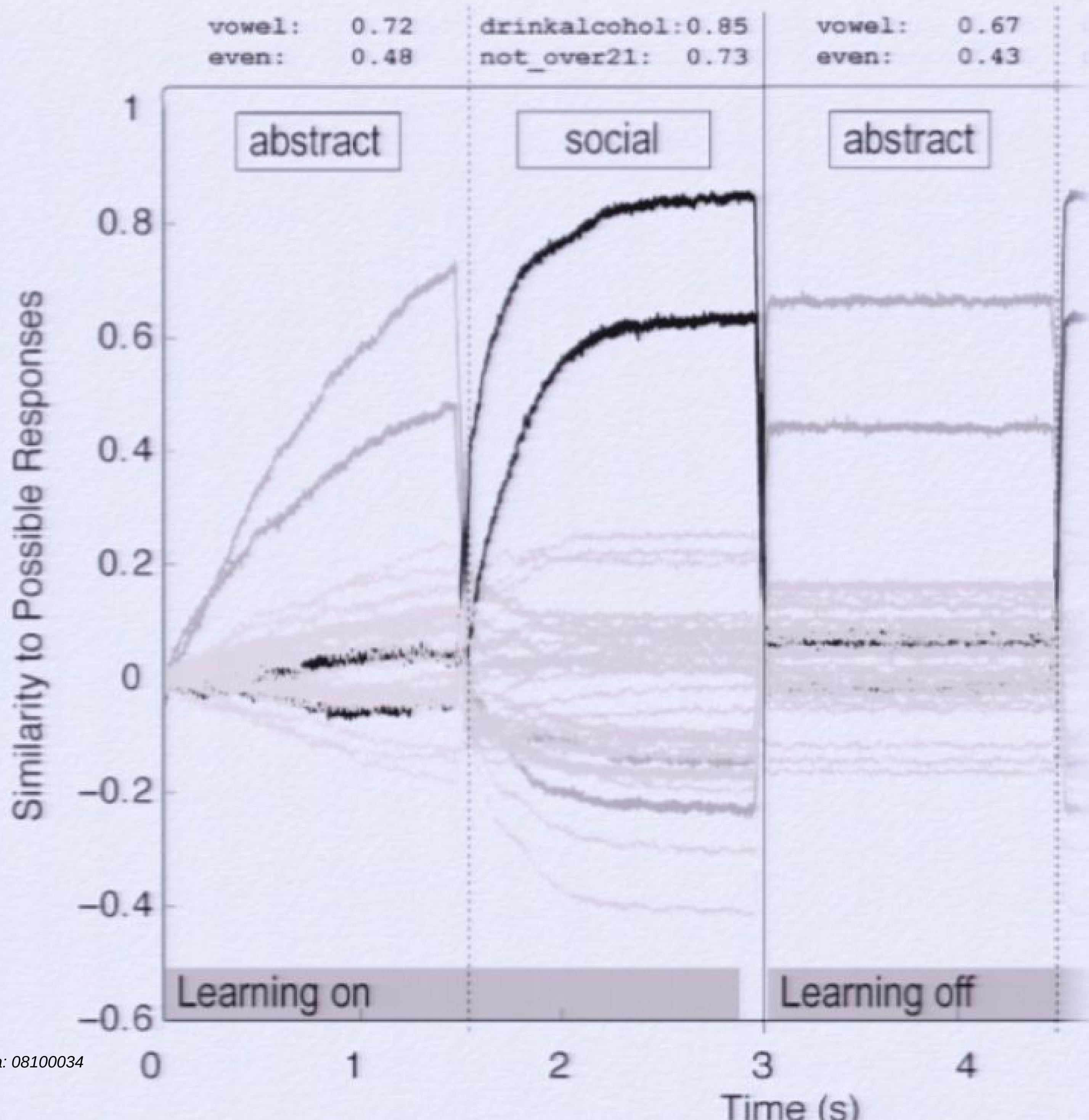

vowel: 0.72
even: 0.48
drinkalcohol:0.85
not_over21: 0.73
vowel: 0.67
even: 0.43
abstract
social
abstract
Learning on
Learning off
Similarity to Possible Responses
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
0
1
2
3
4
Time (s)


vowel: 0.72
even: 0.48
drinkalcohol:0.85
not_over21: 0.73
vowel: 0.67
even: 0.43
drinkalcohol:0.85
not_over21: 0.71
abstract
social
abstract
social
Learning on
Learning off
Similarity to Possible Responses
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
0
1
2
3
4
5
6
Time (s)



Neuron Number
Time
100
90
80
70
60
50
40
30
20
10
50
100
150
200
250
300
350
400


vowel: 0.72
even: 0.48
abstract
Similarity to Possible Responses
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
Learning on
0
1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vowel: 0.67
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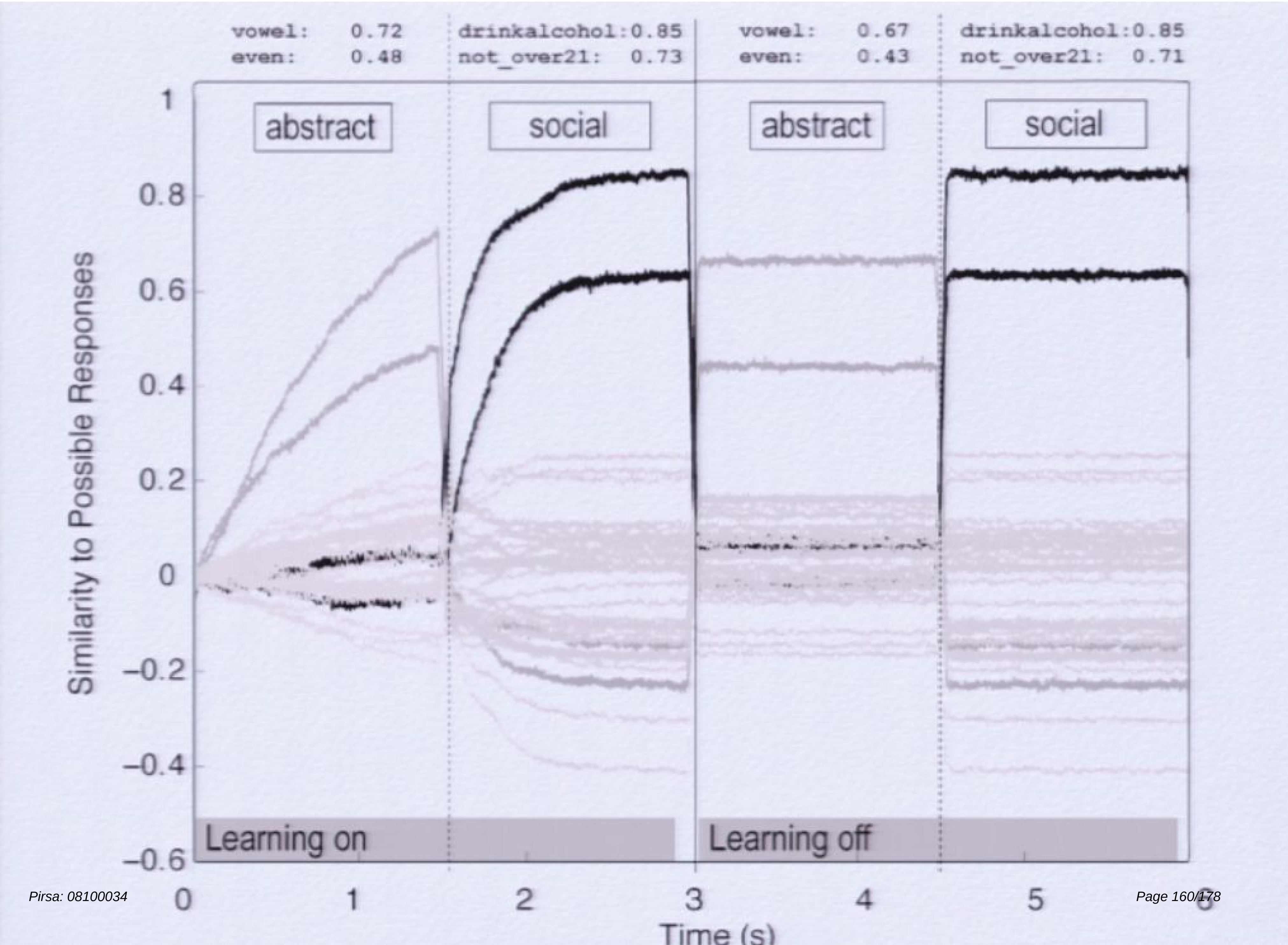
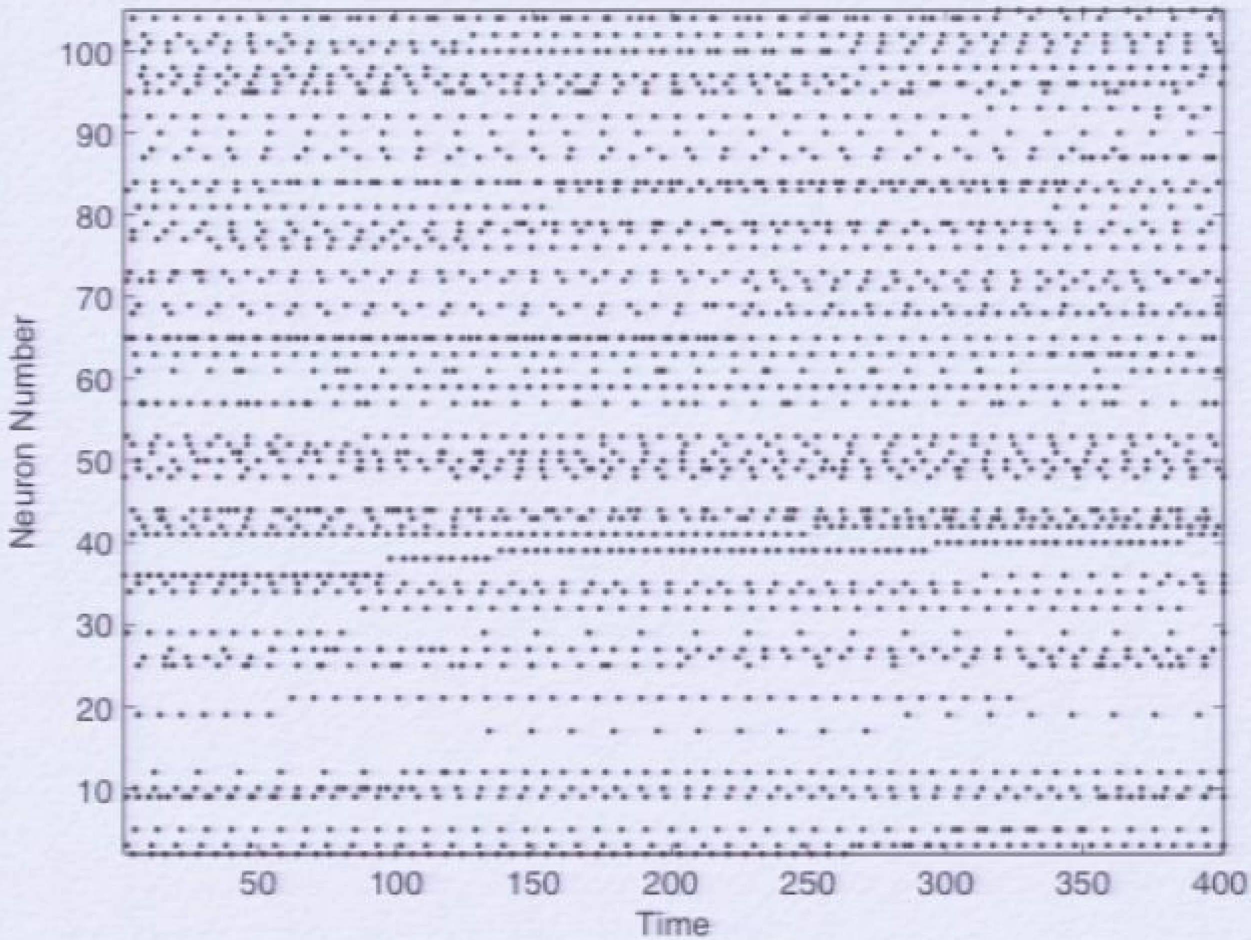
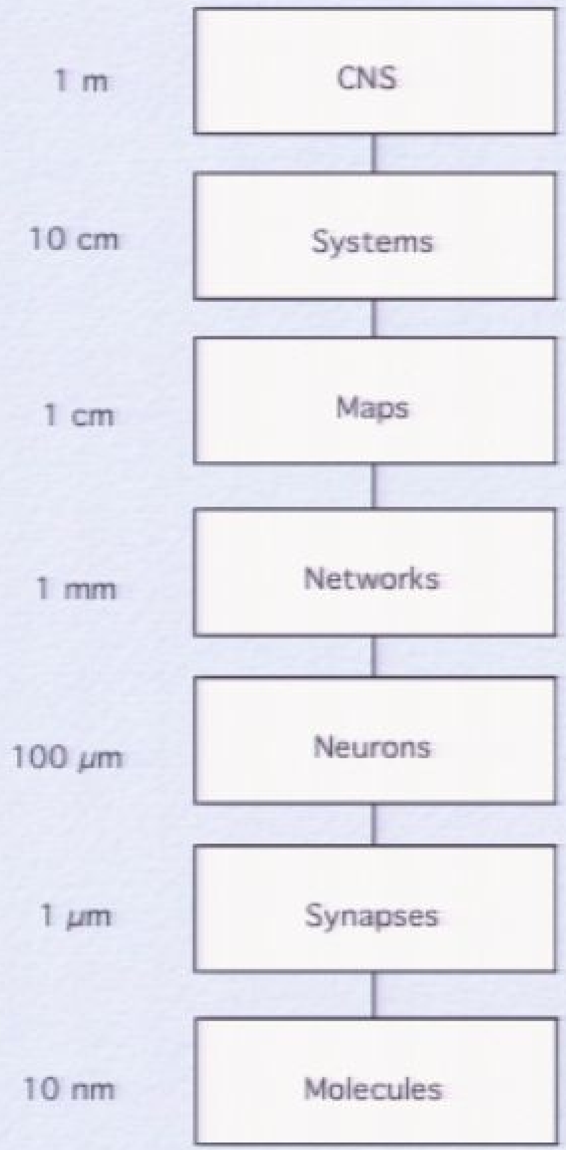
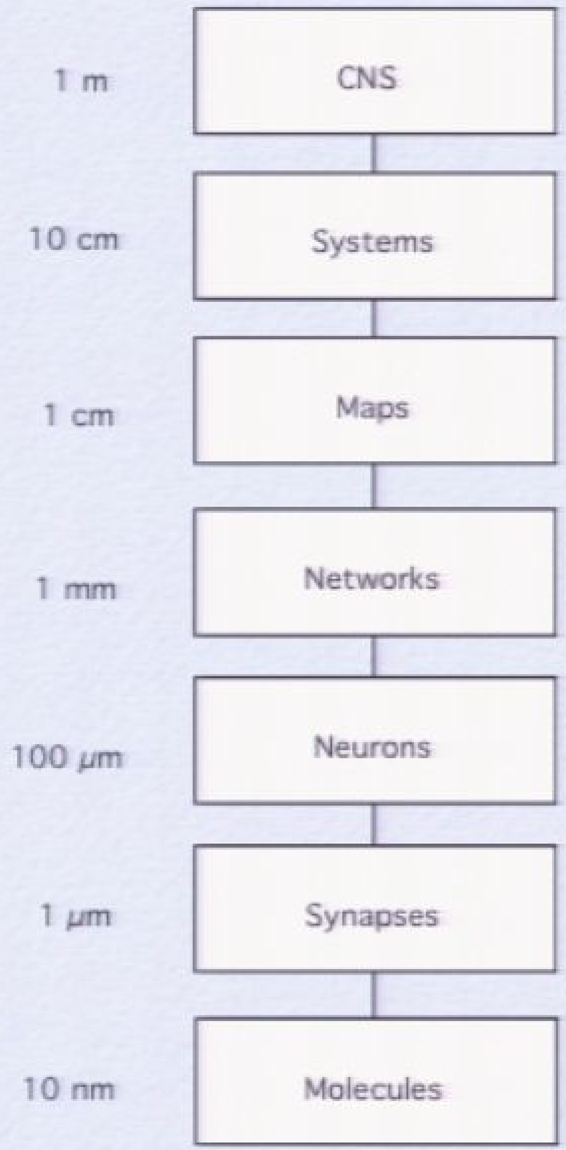
abstract
social
abstract
Learning on
Learning off
Similarity to Possible Responses
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
0
1
2
3
4
Time (s)


vowel: 0.72
even: 0.48
drinkalcohol:0.85
not_over21: 0.73
vowel: 0.67
even: 0.43
drinkalcohol:0.85
not_over21: 0.71
abstract
social
abstract
social
Learning on
Learning off
Similarity to Possible Responses
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
0
1
2
3
4
5
6
Time (s)


100
90
80
70
60
50
40
30
20
10
Neuron Number
50
100
150
200
250
300
350
400
Time


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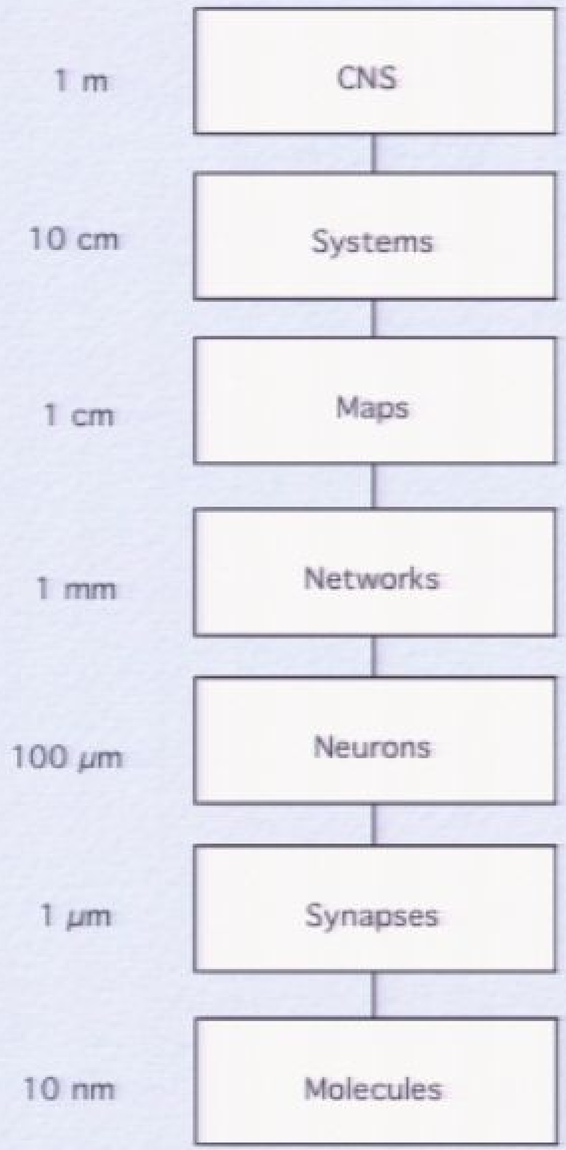
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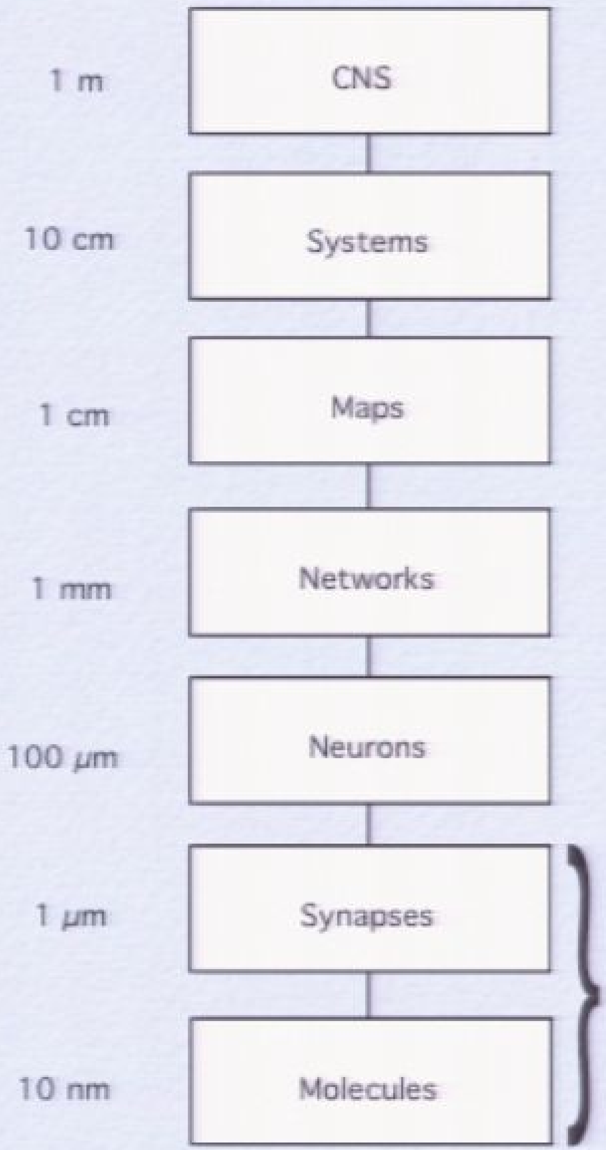
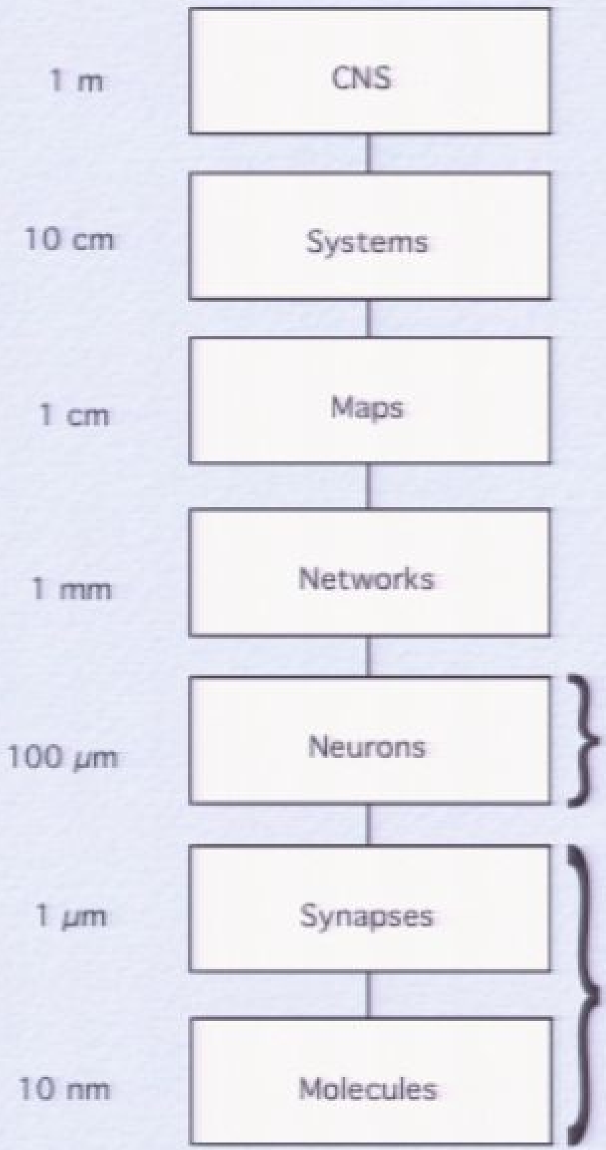
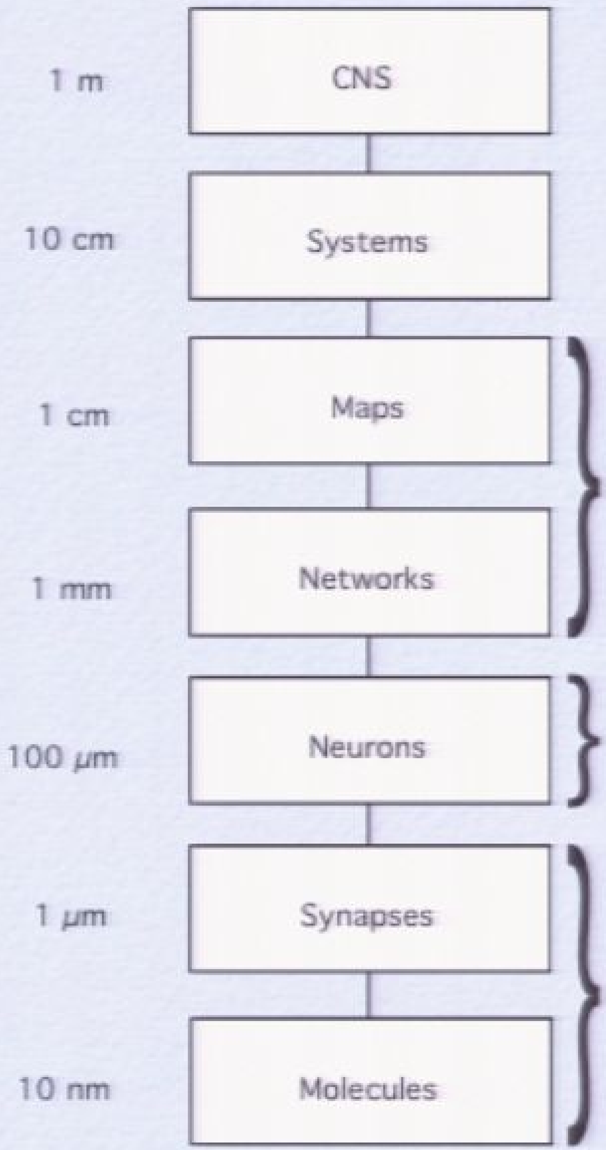


Fast-type receptors, most common in cortex



Spiking neurons

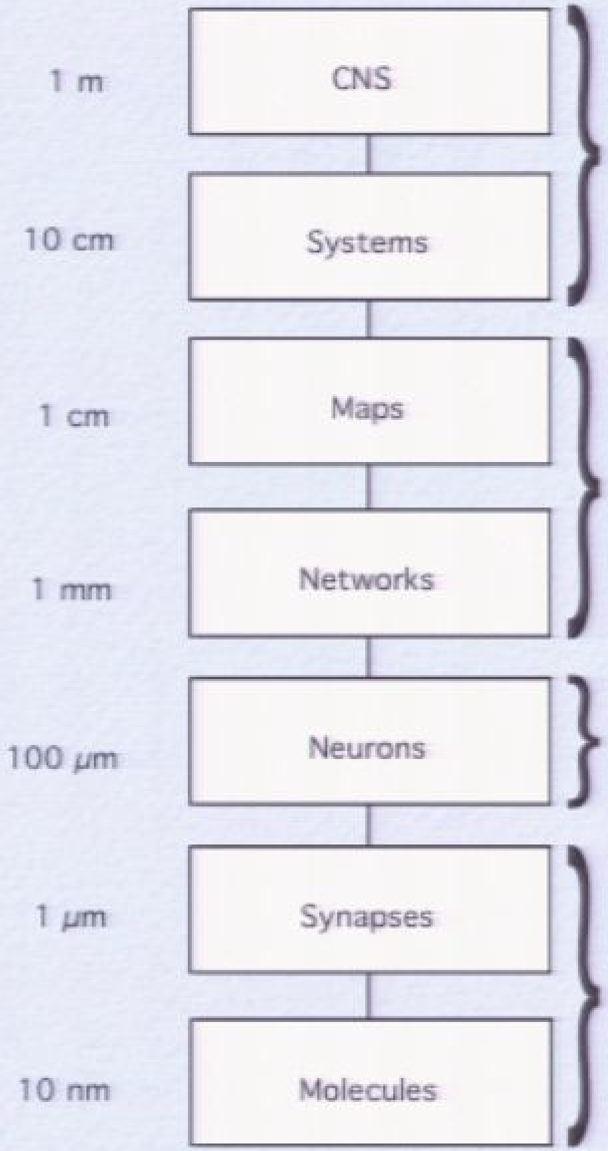
Fast-type receptors, most common in cortex



Maps of conceptual space,
20,000 neurons

Spiking neurons

Fast-type receptors, most
common in cortex



Frontal, left, cingulate cortex, reasoning systems

Maps of conceptual space, 20,000 neurons

Spiking neurons

Fast-type receptors, most common in cortex

Challenges

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- Incorporating more nonlinearities (single cell bursting, dendritic responses, dendritic structure, reverse-engineering networks, etc.)

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- Characterizing the relationship to learning

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- Characterizing the relationship to learning
- Figuring out what the brain does...

So, where are we?

So, where are we?

We are this person

So, where are we?

We are this person

At the very beginning of a long climb...

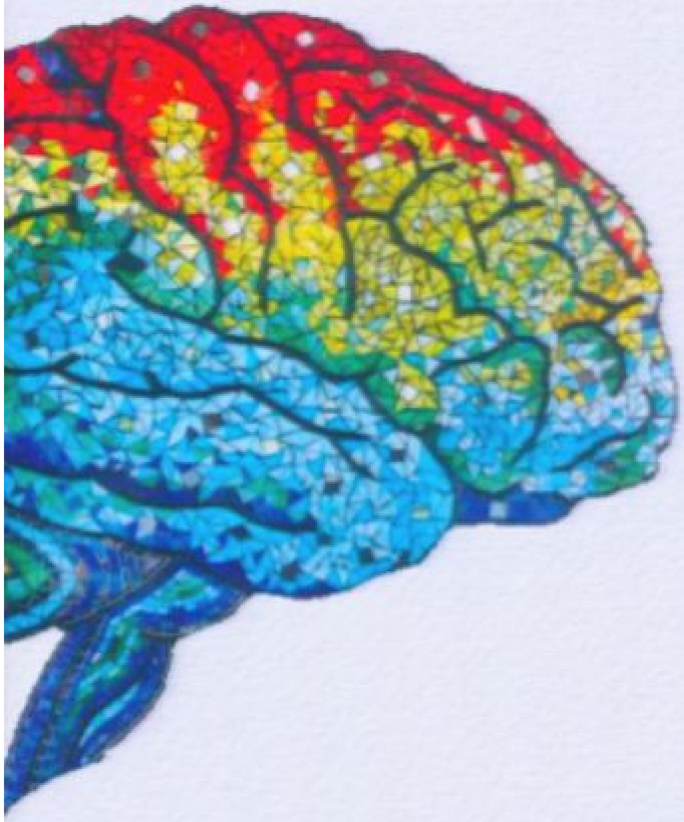
So, where are we?

We are this person

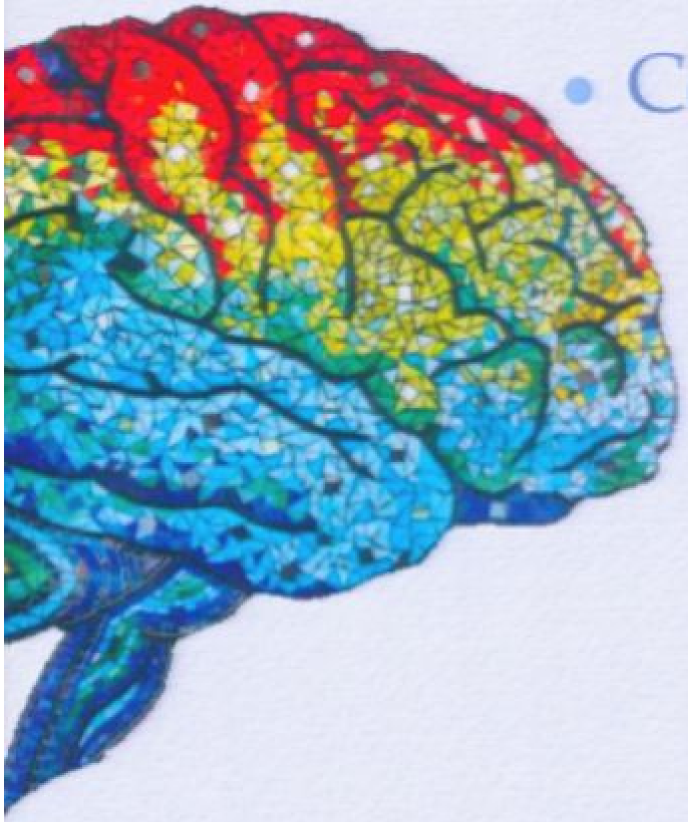
At the very beginning of a long climb...

...but hopefully the NEF provides some much needed footholds

More about brains...



More about brains...



- Centre for Theoretical Neuroscience
  - http://ctn.uwaterloo.ca
  - Mailing list for CTN seminars: celiasmith@uwaterloo.ca
  - Brain day April 6th, 2009