

Computational Neuroscience Introduction Day

- 14.00 Introduction
- 14.30 Computational Neuroscience Groups in Paris
- 15.00 Discussion of papers in groups: Questions
- 15.45 Break
- 16.00 Discussion of papers in groups: Answers
- 16.45 Presentation of Answers
- 17.30 Concluding comments

A brief introduction to Computational Neuroscience

Christian Machens
Group for Neural Theory
Ecole normale supérieure Paris



What's the brain good for?



Tree
no neurons

What's the brain good for?



Tree
no neurons



C. elegans
302 neurons

brains generate motion
(= behavior)

What's the brain good for?



Tree
no neurons



C. elegans
302 neurons



Fly
1 000 000

more complex brains
generate a greater
variety of behaviors

What's the brain good for?



Tree
no neurons



C. elegans
302 neurons



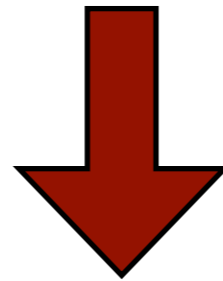
Fly
1 000 000



Rat
1 000 000 000



Human
100 000 000 000



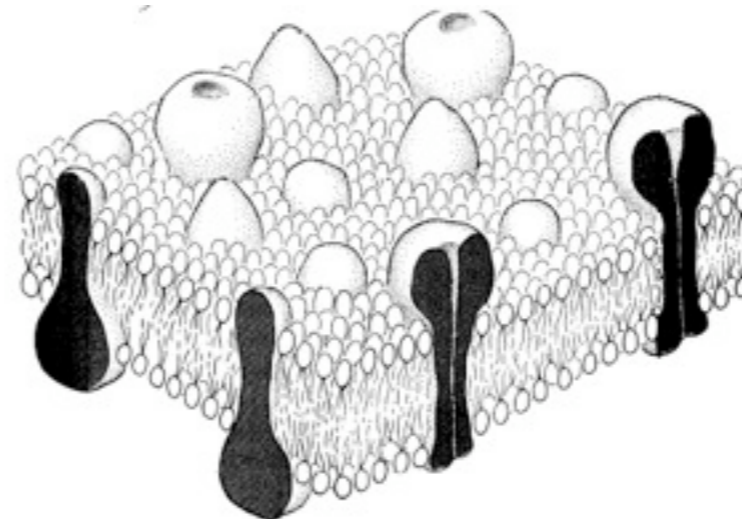
more complex brains
generate a greater
variety of behaviors

more complex brains
can learn more
behaviors

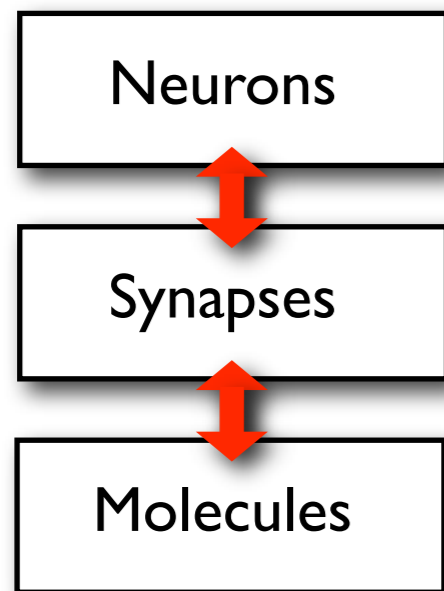
What's the brain made of?

Molecules

1 nm



What's the brain made of?



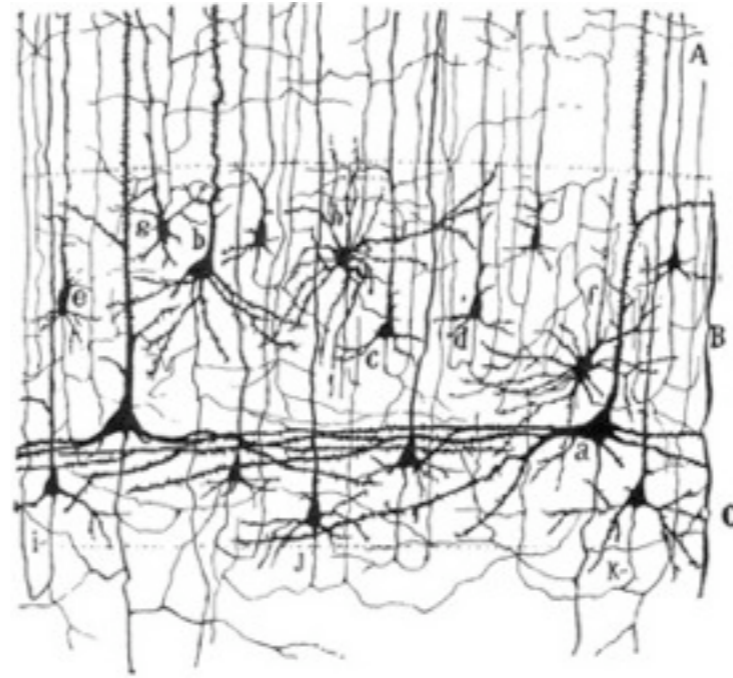
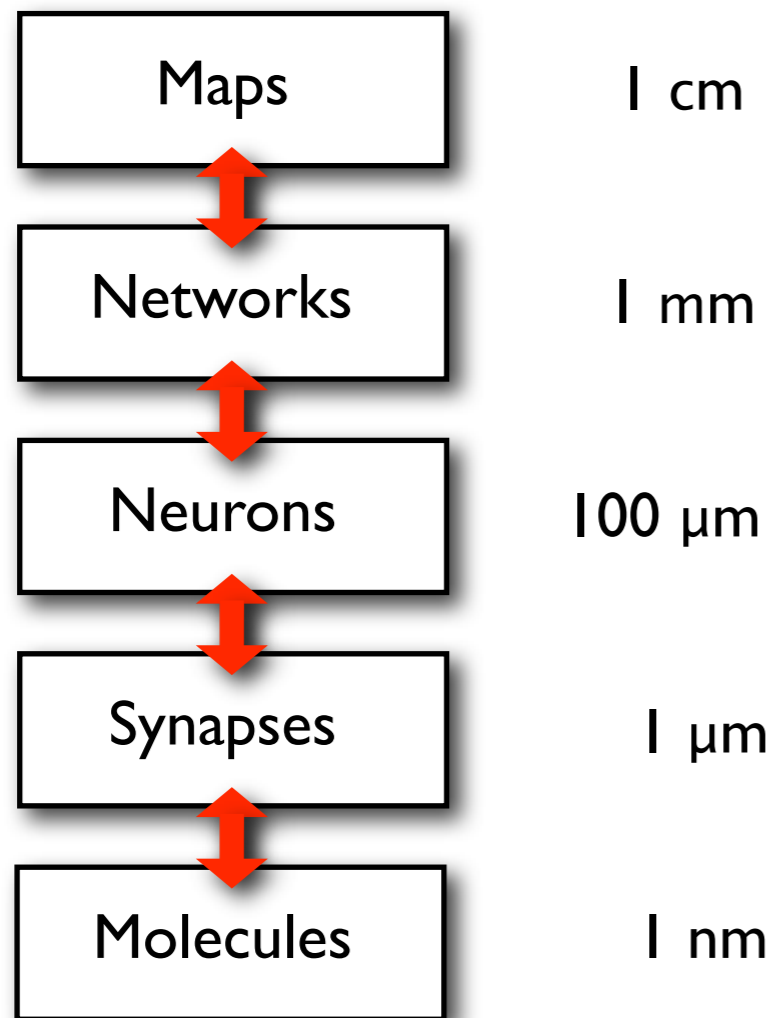
100 μm

1 μm

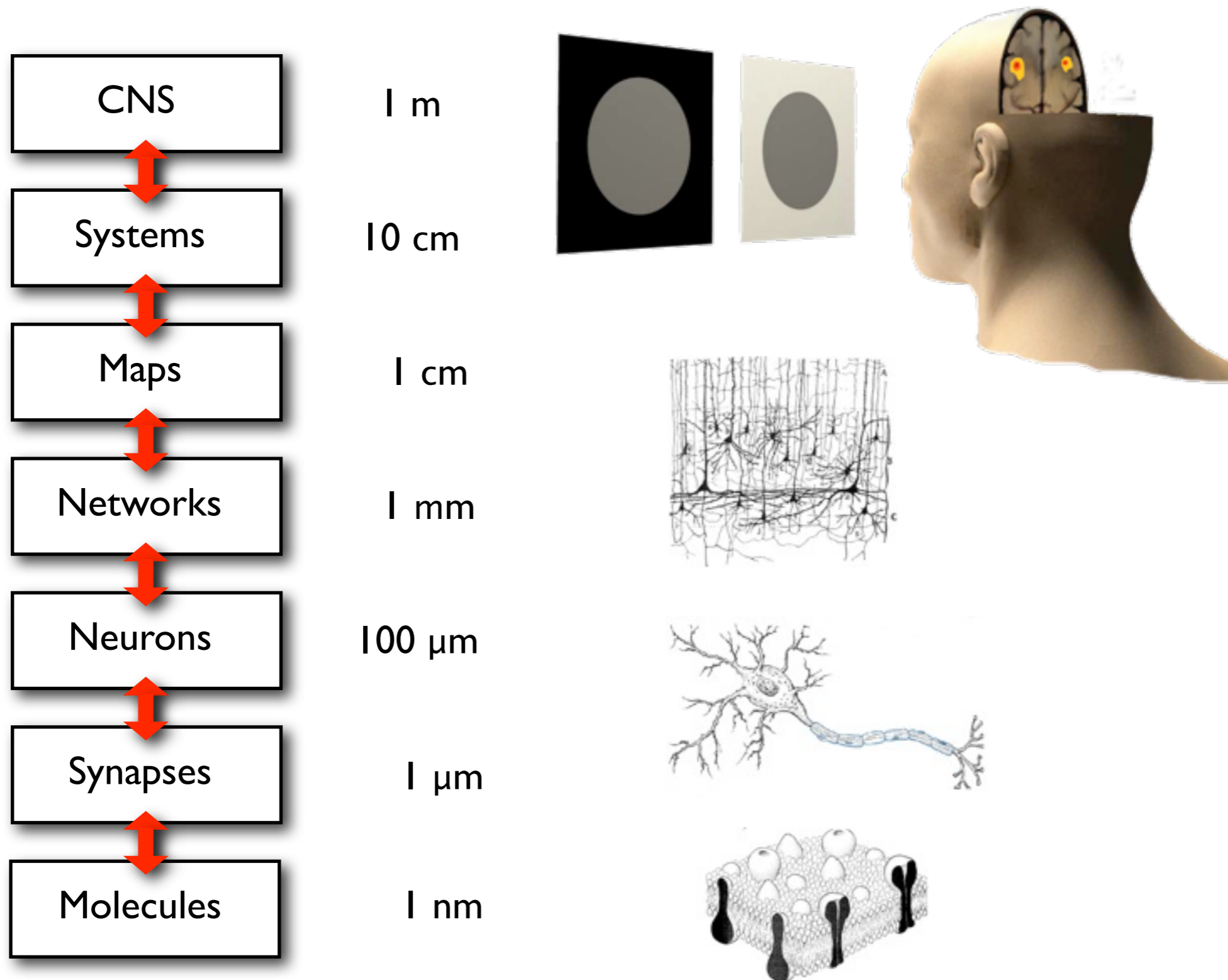
1 nm



What's the brain made of?



What's the brain made of?

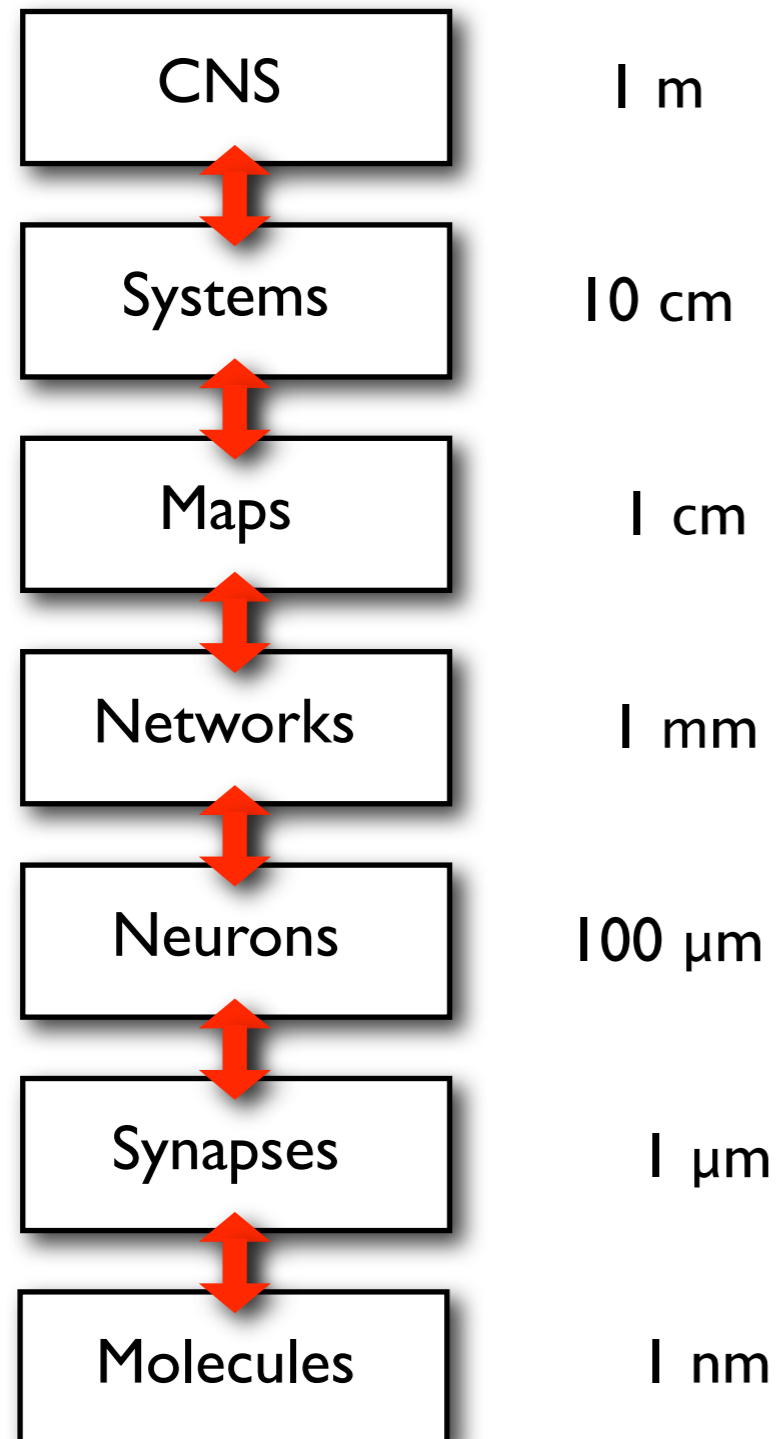


**How does the brain
work?**

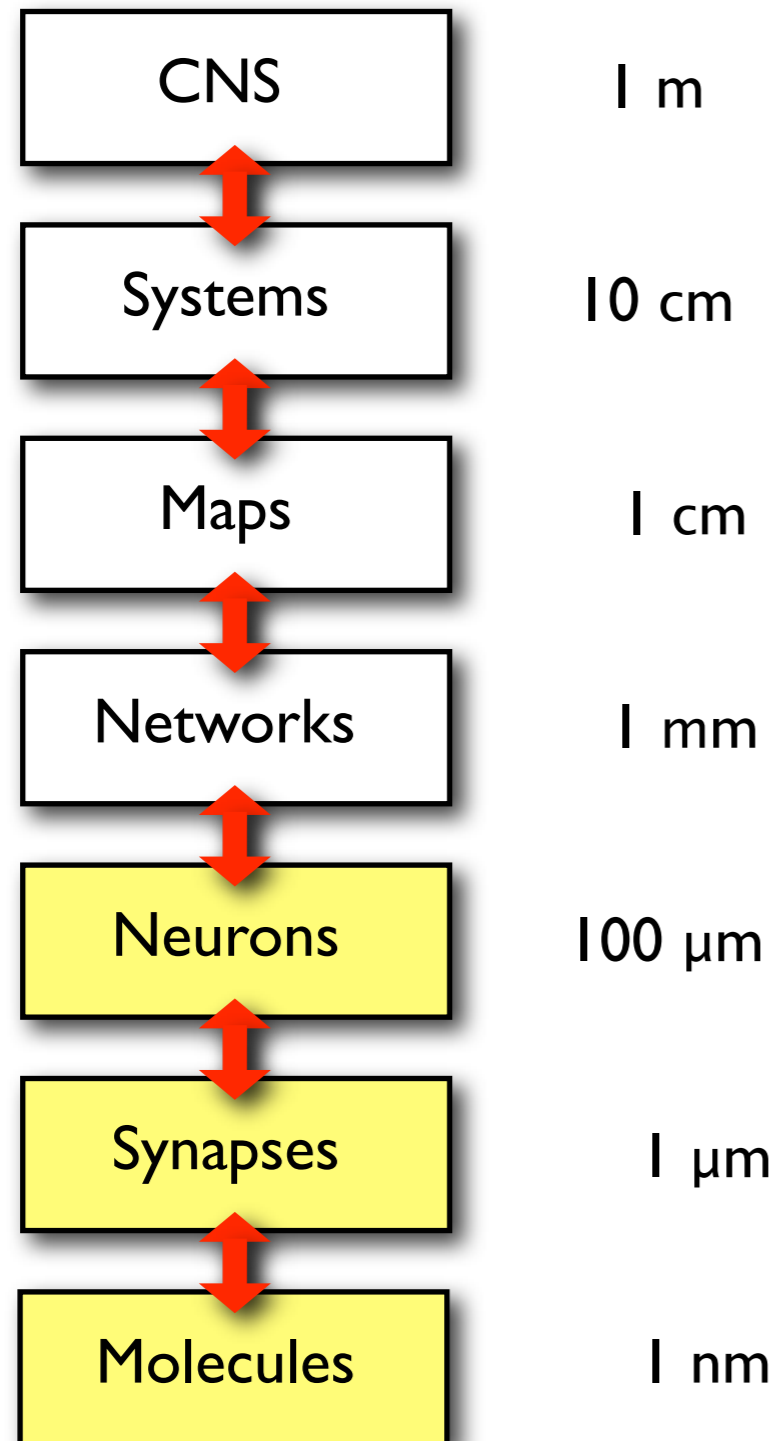
A physics/engineering approach

Just rebuild the whole thing

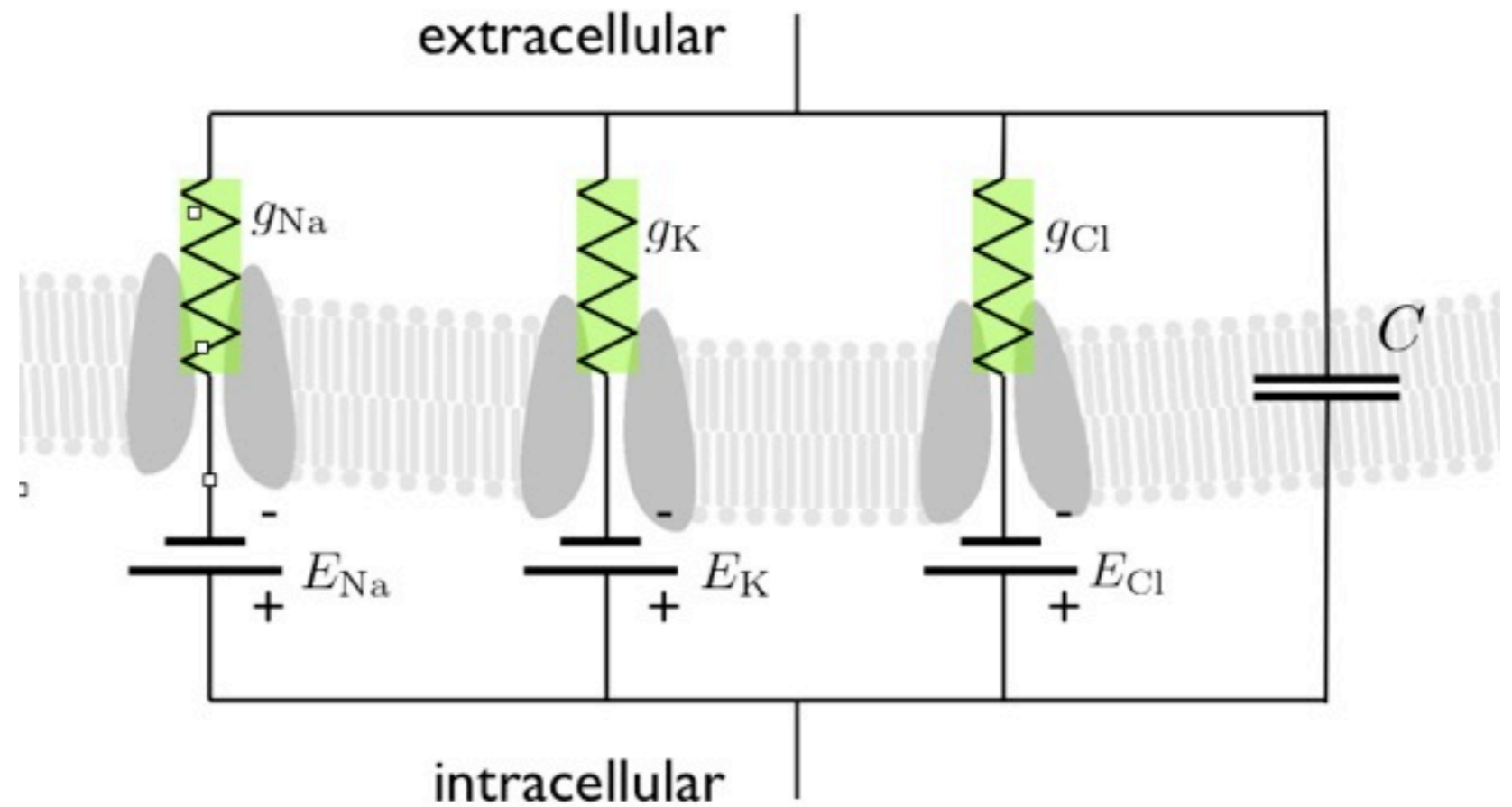
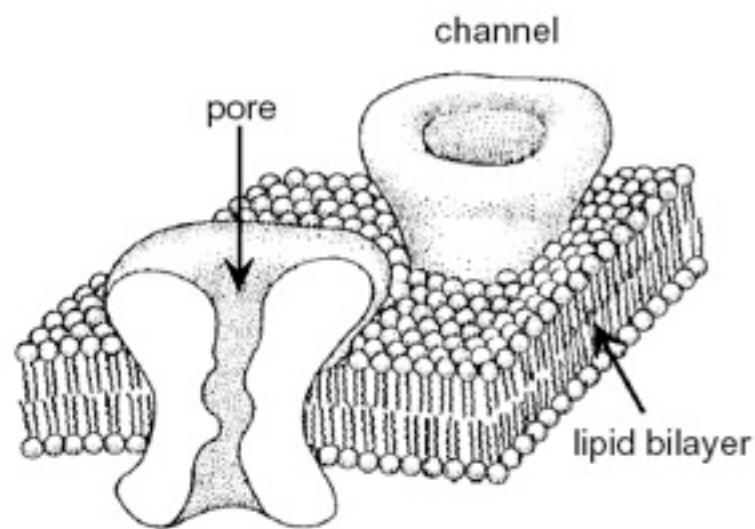
The quest for mechanisms: Constructing systems from parts



The quest for mechanisms: Constructing systems from parts



Biophysics of the membrane voltage: The Hodgkin-Huxley Model



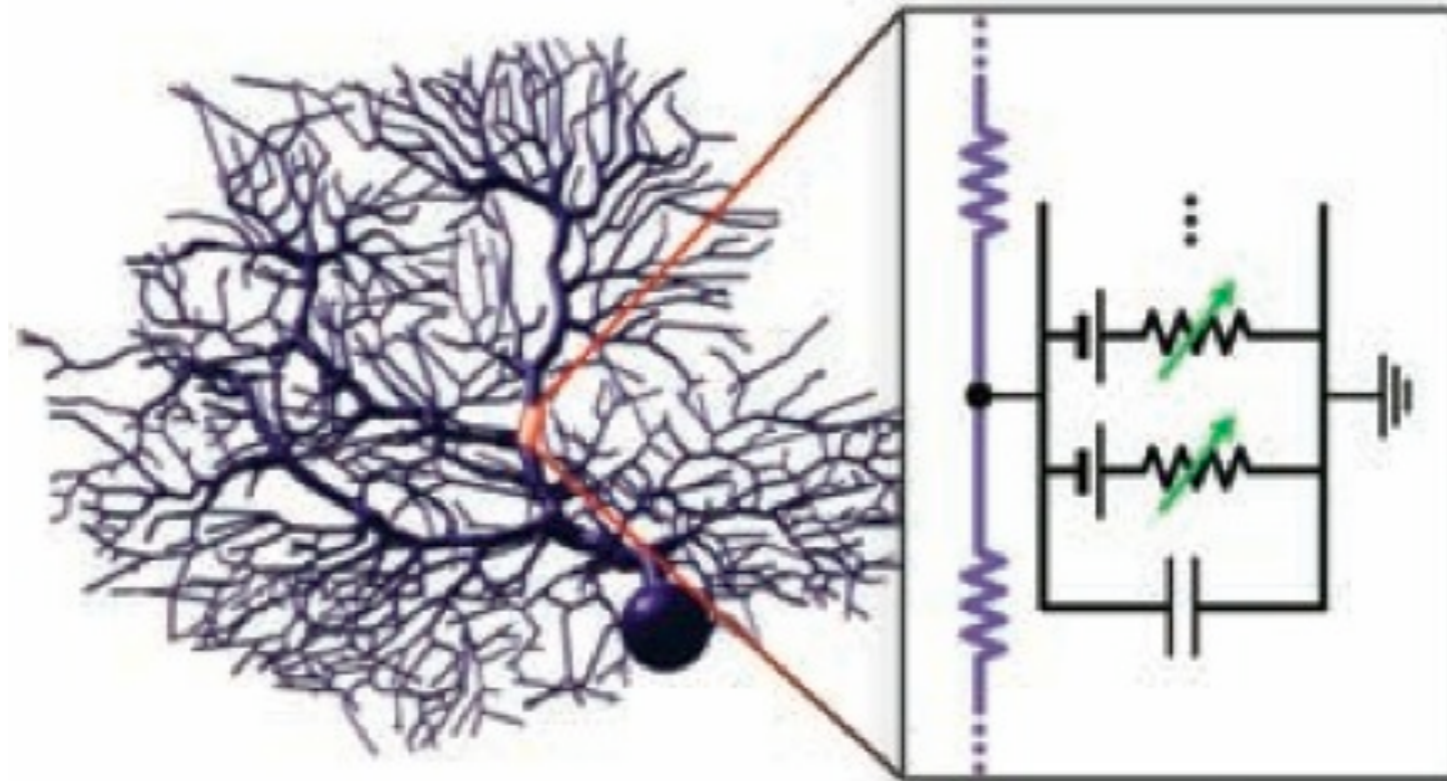
↑ voltage



time →

Reconstructing neurons:

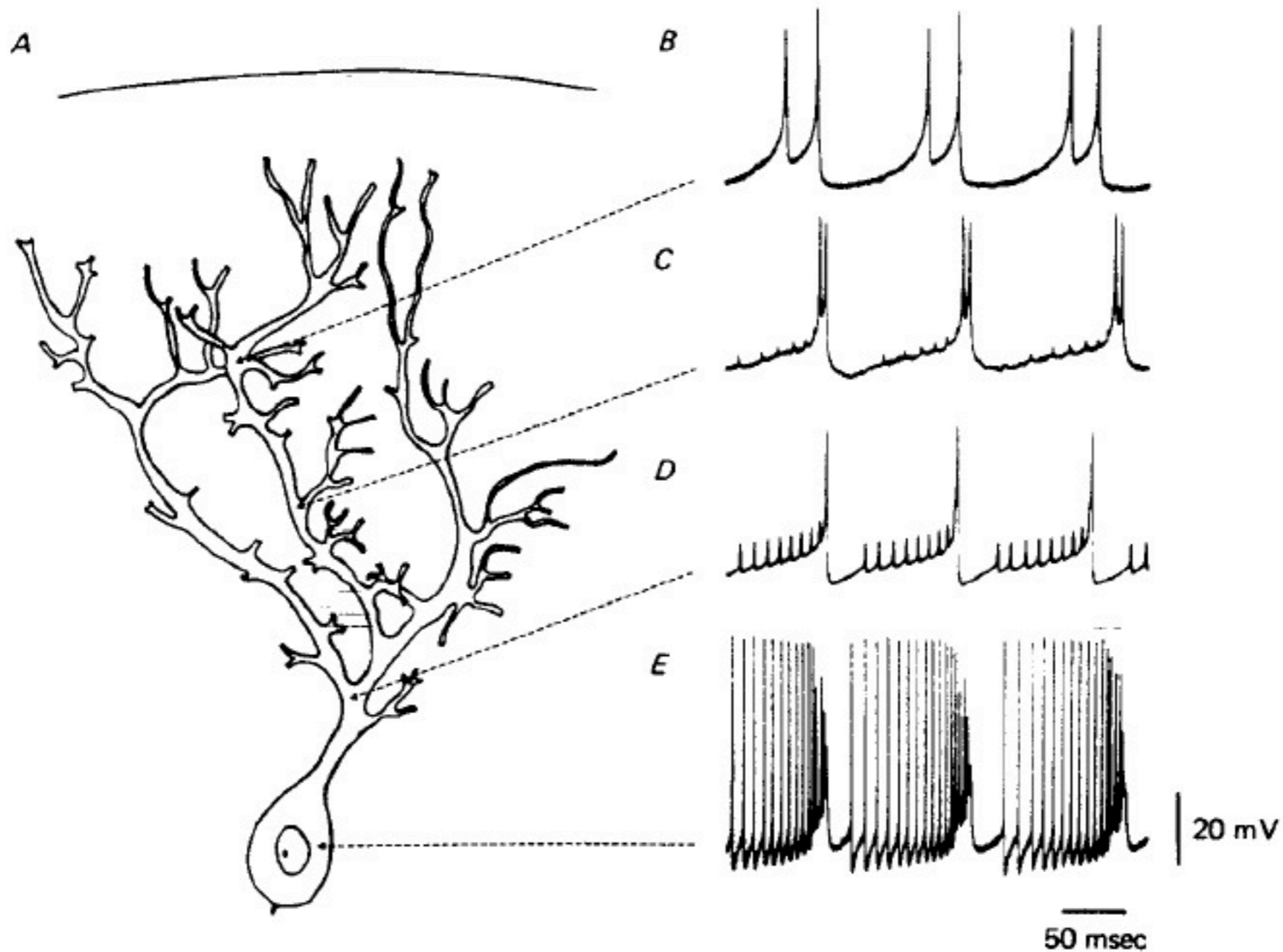
Ralls' cable theory and compartmental modeling



Detailed compartmental models of single neurons:
Large-scale differential equation models

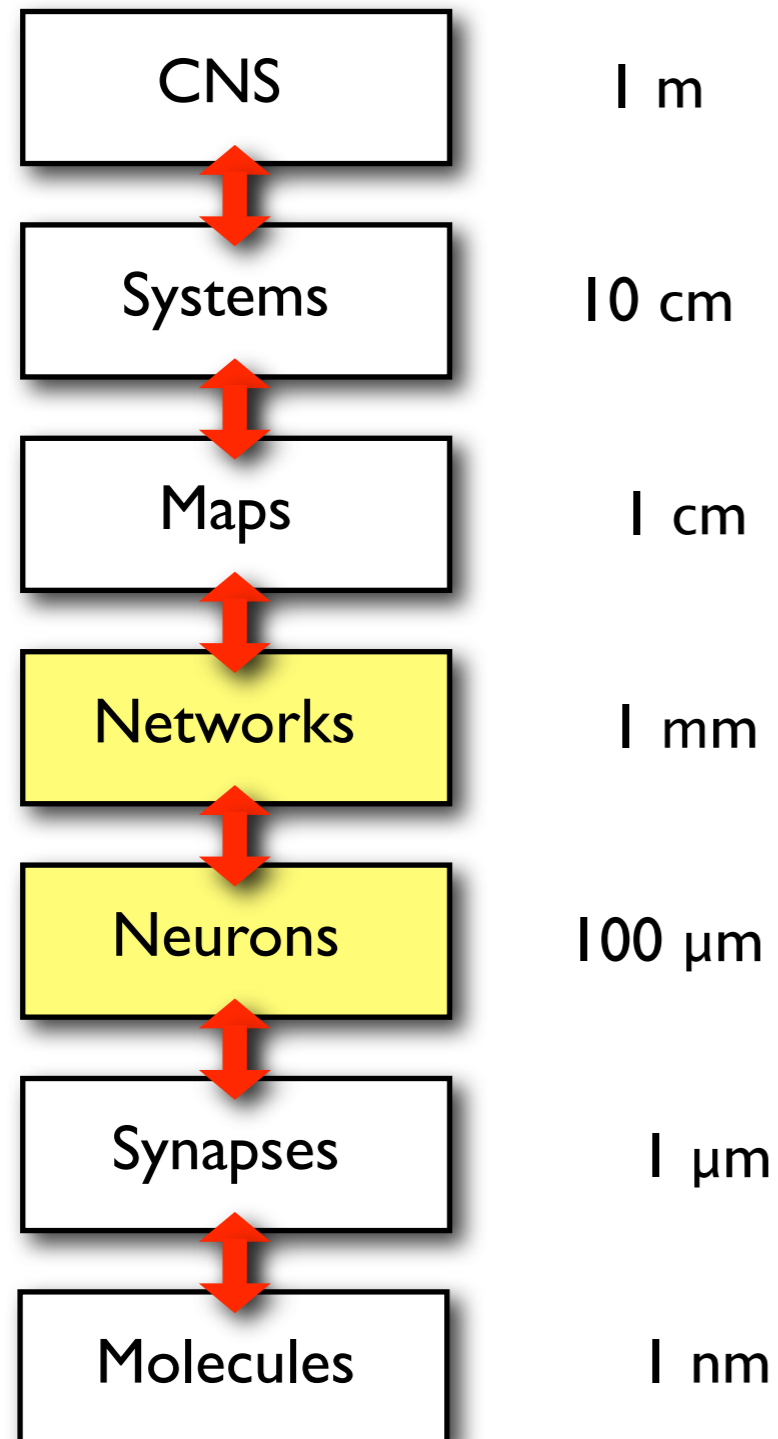
Reconstructing neurons

Simulating the membrane potential



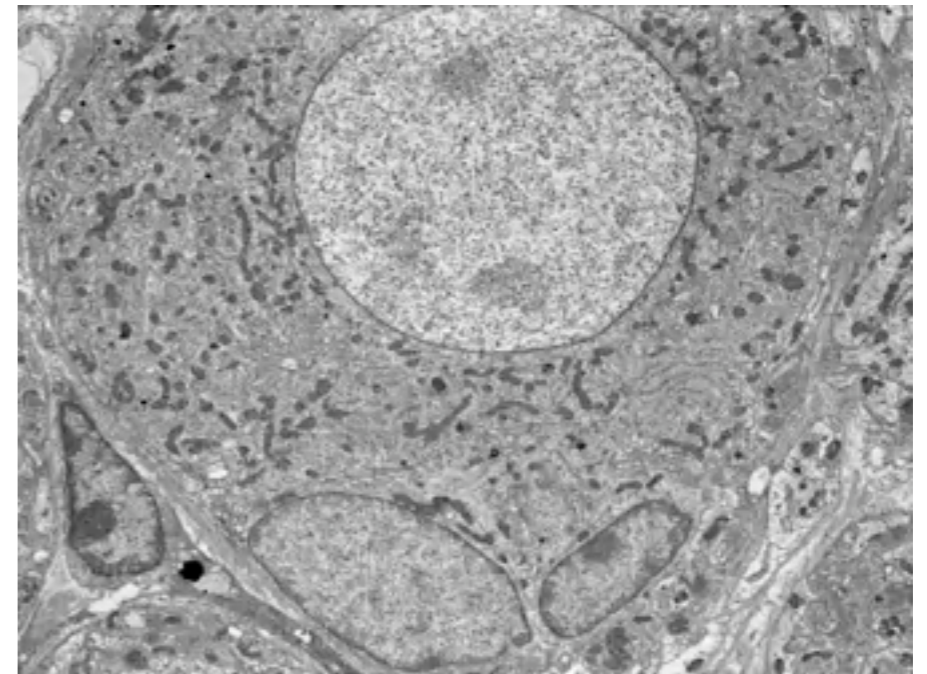
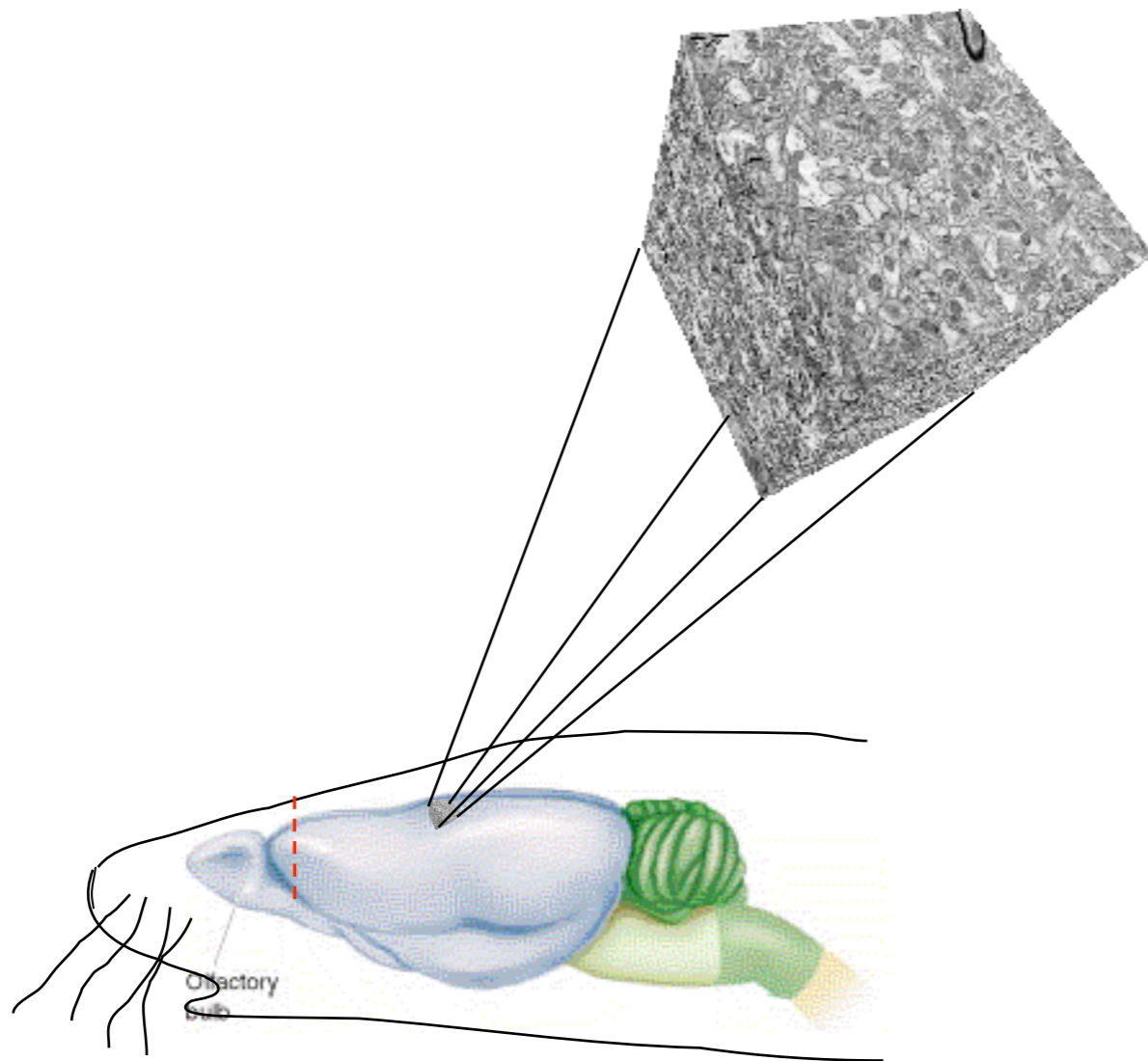
Llinas & Sugimori (1980)

The quest for mechanisms: Constructing systems from parts



Reconstructing circuits

Serial Blockface Scanning Electron Microscopy



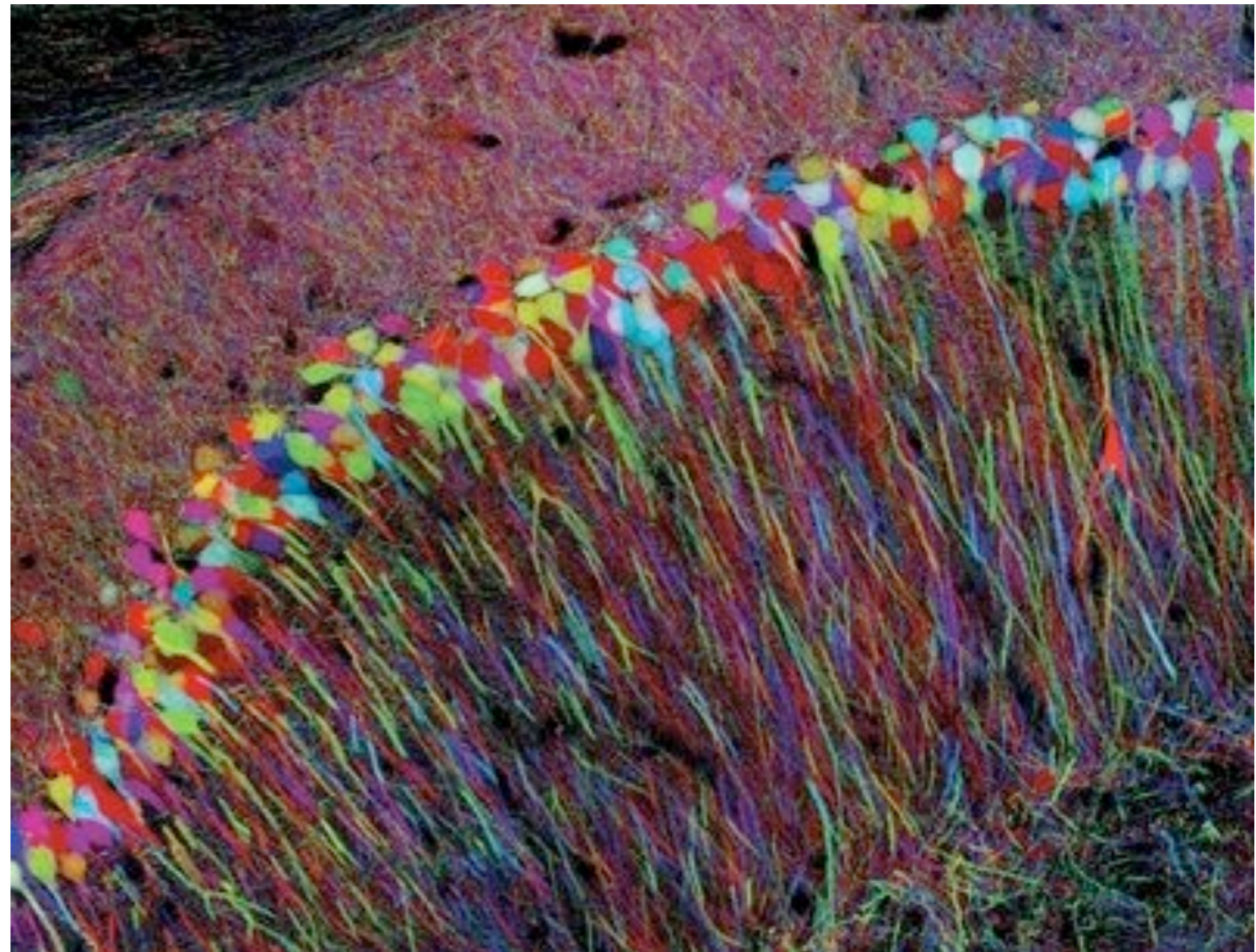
courtesy of W.Denk

Reconstructing circuits

The connectome

Scan brain slices and
reconstruct the circuit...

but: the devil is in the
details and when it comes
to connectivity, details
matter!

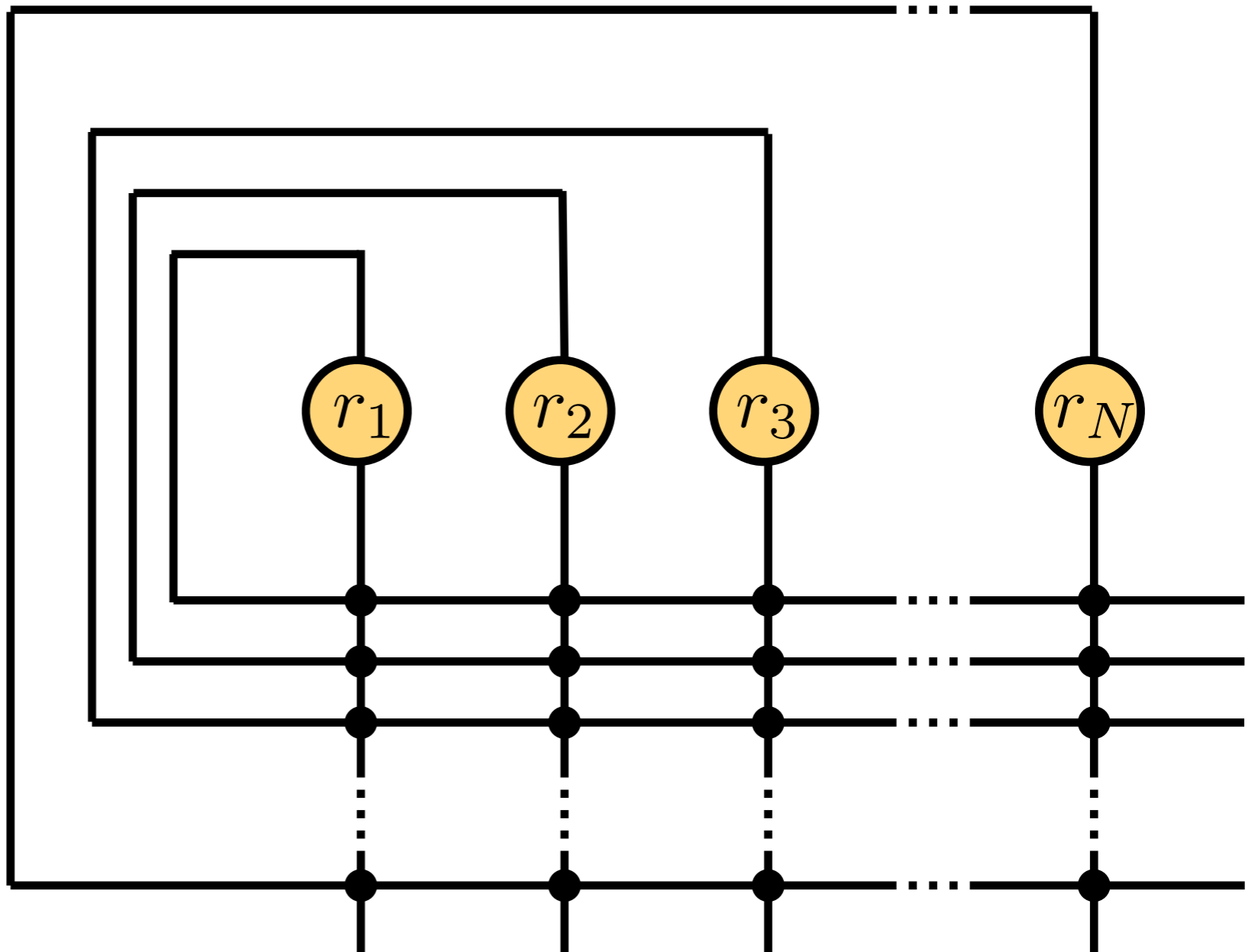


<http://connectomes.org/>

Theory of neural networks

Neurons, synapses  network activity

$$\dot{r}_i = -r_i + f\left(\sum_{j=1}^N w_{ij}r_j + I_i\right)$$



Network dynamics largely determined by connectivity

$$\dot{r}_i = -r_i + f\left(\sum_{j=1}^N w_{ij} r_j + I_i\right)$$

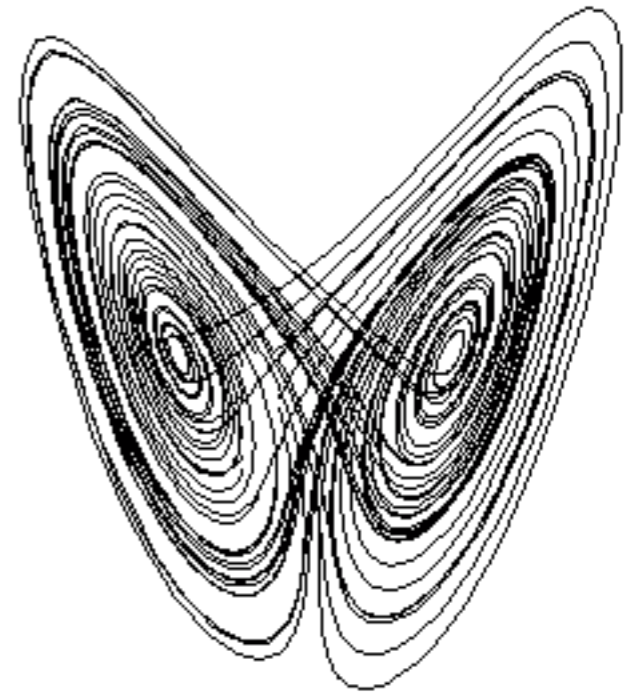
Possible dynamics:

- stable/ unstable fixed points
- limit cycles
- chaotic attractors

Note: different attractors can co-exist in different parts of the state space!

For $N \rightarrow \infty$

- neural networks can compute anything

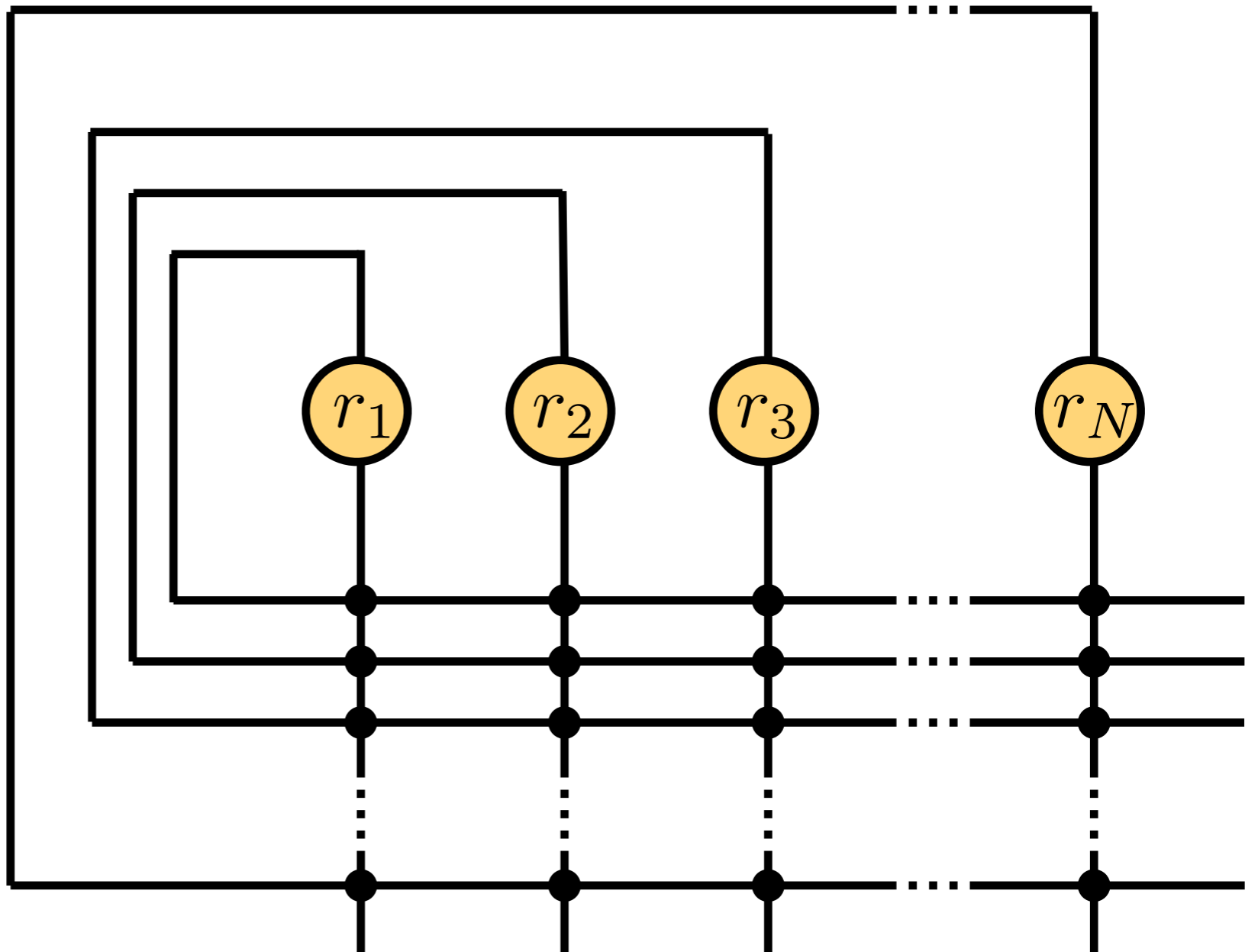


(Statistical) theory of neural networks

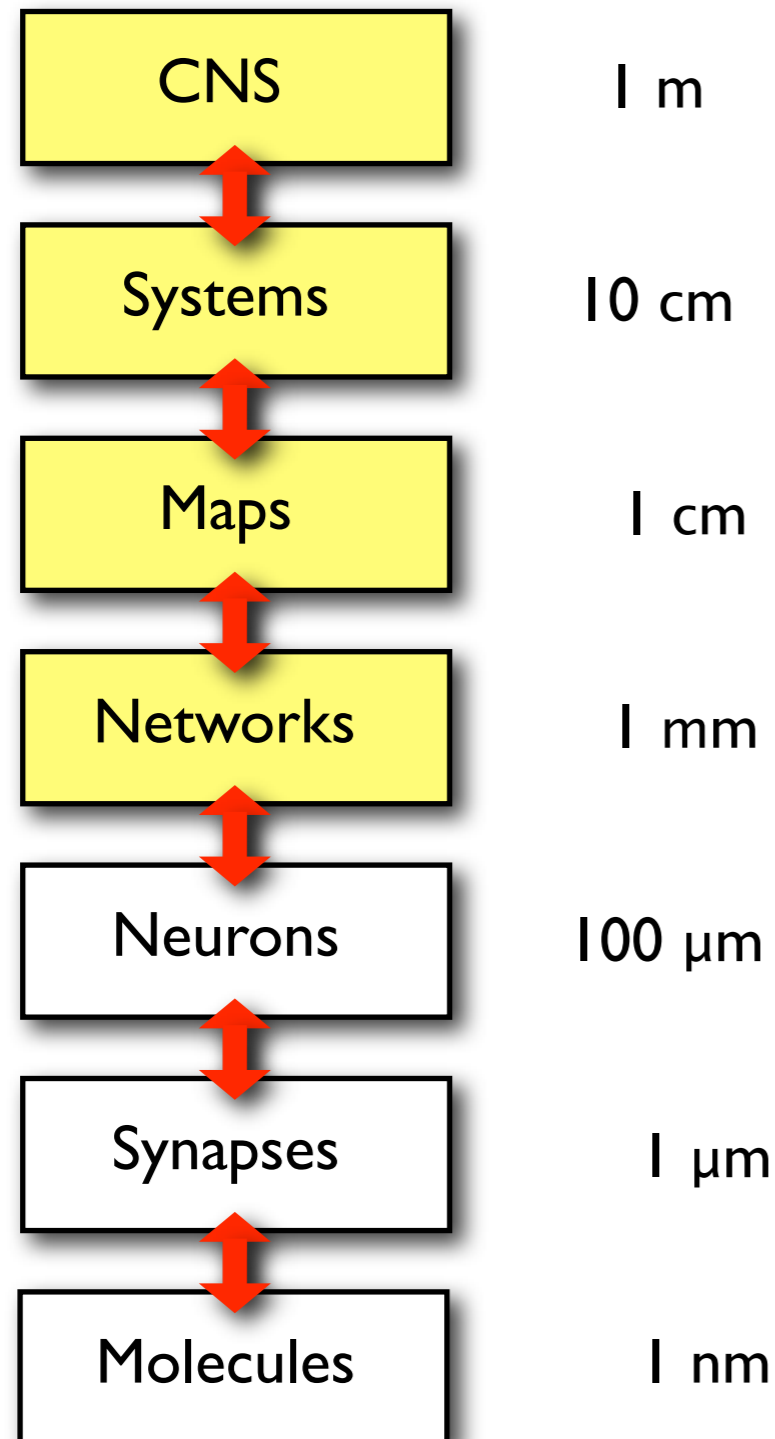
Neurons, synapses  network activity

Under what conditions do you get

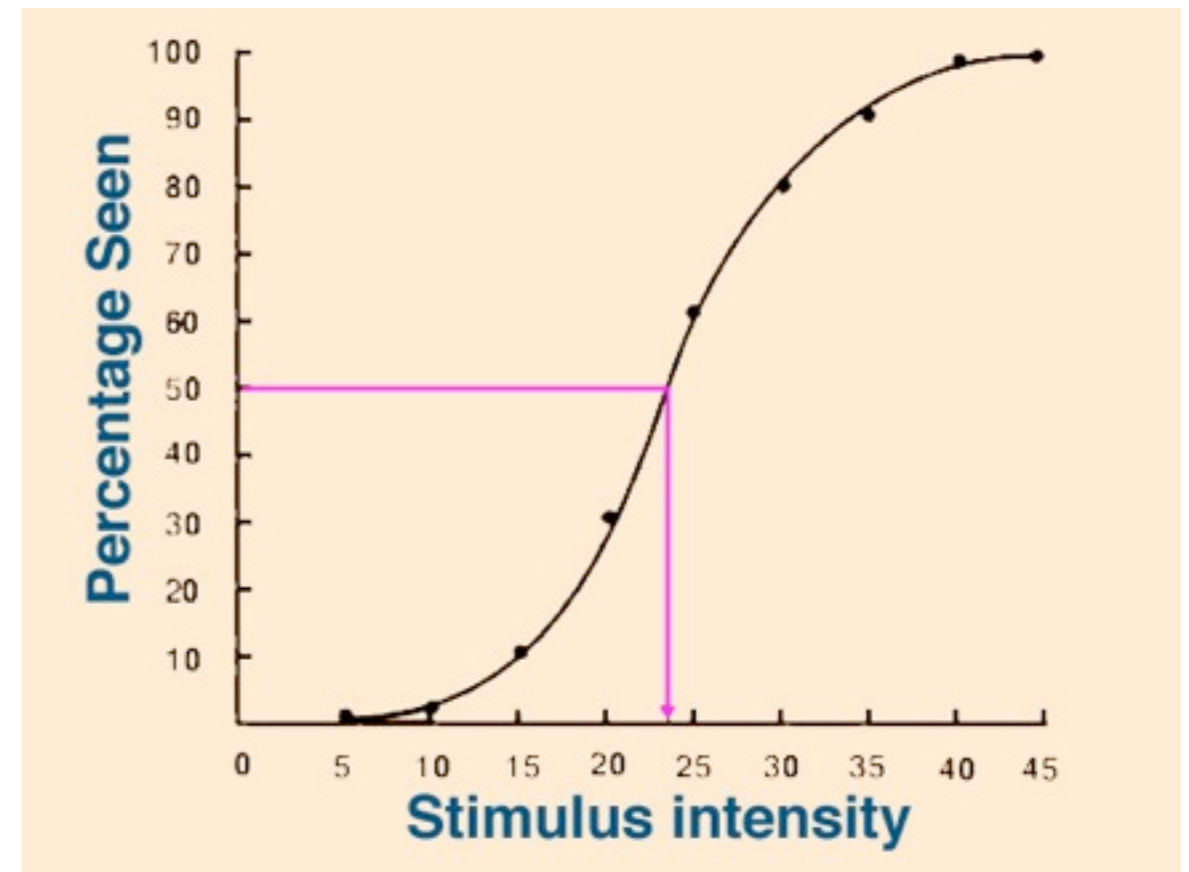
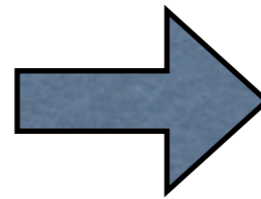
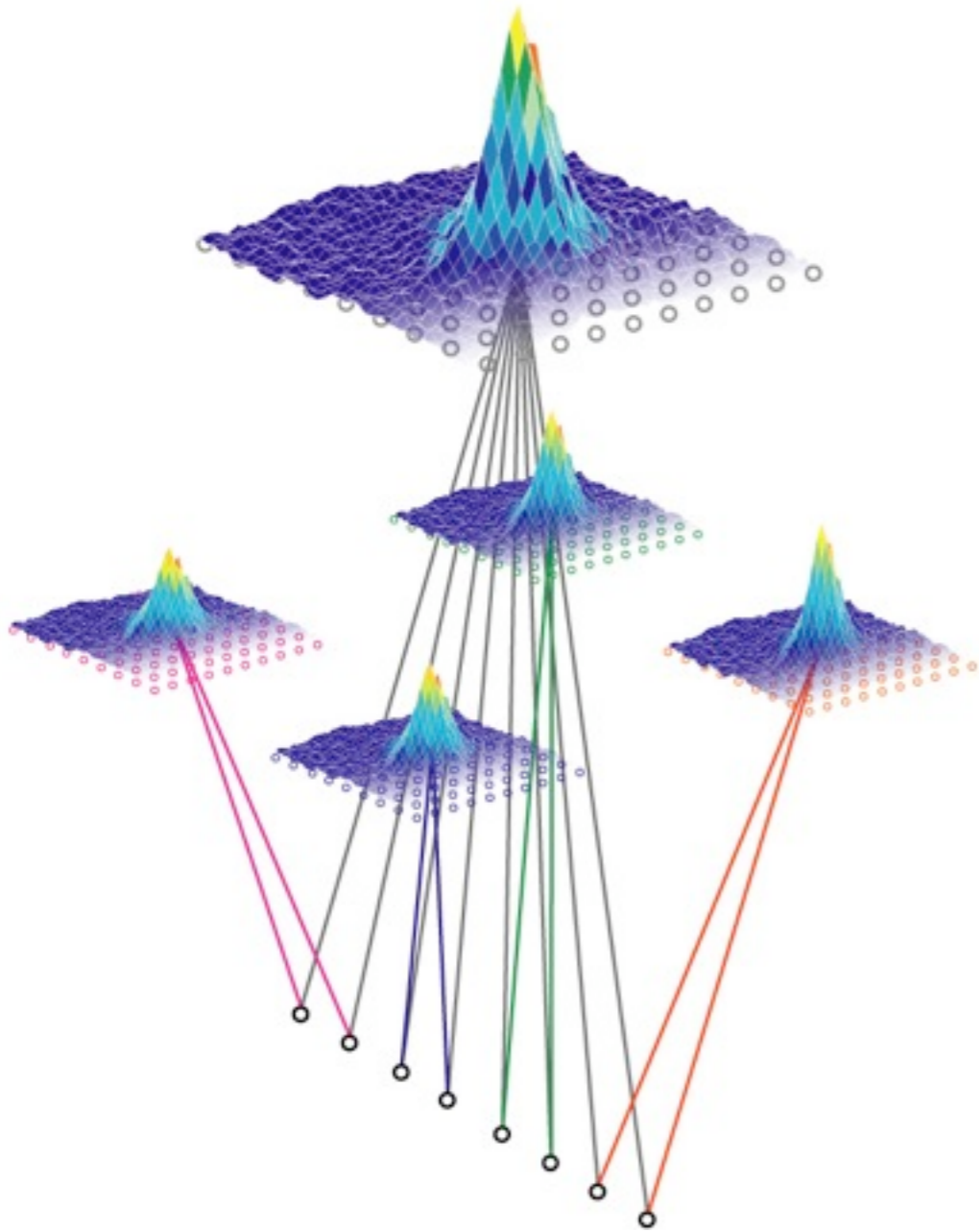
- only fixed points
- synchronous activity
- asynchronous activity
- Poisson spike trains
- oscillations
- spatial patterns
- ...



The quest for mechanisms: Constructing systems from parts



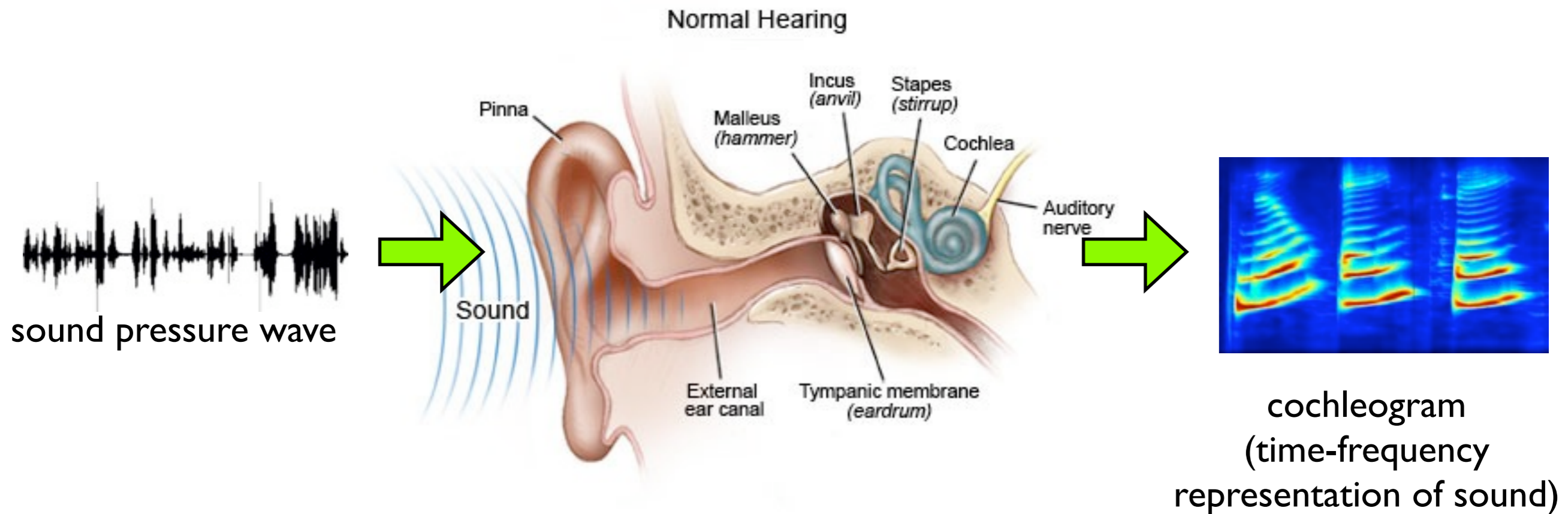
Connectionist models: From networks to behavior



A computer science approach

Study the computational problems

Computation: manipulating information



Representation of information, more or less lossy

Example music:

sheet notes



Sound



CD



Language

The other day, I heard this cool jazz CD with this drummer...

Why represent information differently?

Example numbers:

XXIII

23

00010111

Roman System

Decimal System

Binary System

Representations allow for easier algorithms

Example numbers:

XXIII

23

00010111

in ...?

in multiples of 10

in multiples of 2

Can you add these numbers?

29
+ 33

00011101
+ 00100001

XXIX
+ XXXIII

Representations allow for easier algorithms

Example numbers:

XXIII

23

00010111

in ...?

in multiples of 10

in multiples of 2

Can you add these numbers?

29
+ 33

62

00011101
+ 00100001

XXIX
+ XXXIII

Representations allow for easier algorithms

Example numbers:

XXIII

23

00010111

in ...?

in multiples of 10

in multiples of 2

Can you add these numbers?

29
+ 33

62

00011101
+ 00100001

00111110

XXIX
+ XXXIII

Representations can ease certain computations

Example numbers:

XXIII

23

00010111

in ...?

in multiples of 10

in multiples of 2

Can you add these numbers?

$$\begin{array}{r} 29 \\ + 33 \\ \hline 62 \end{array}$$

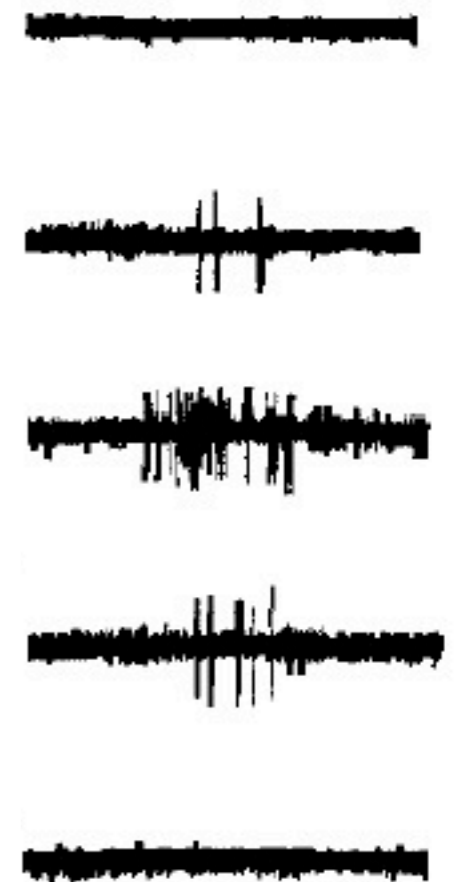
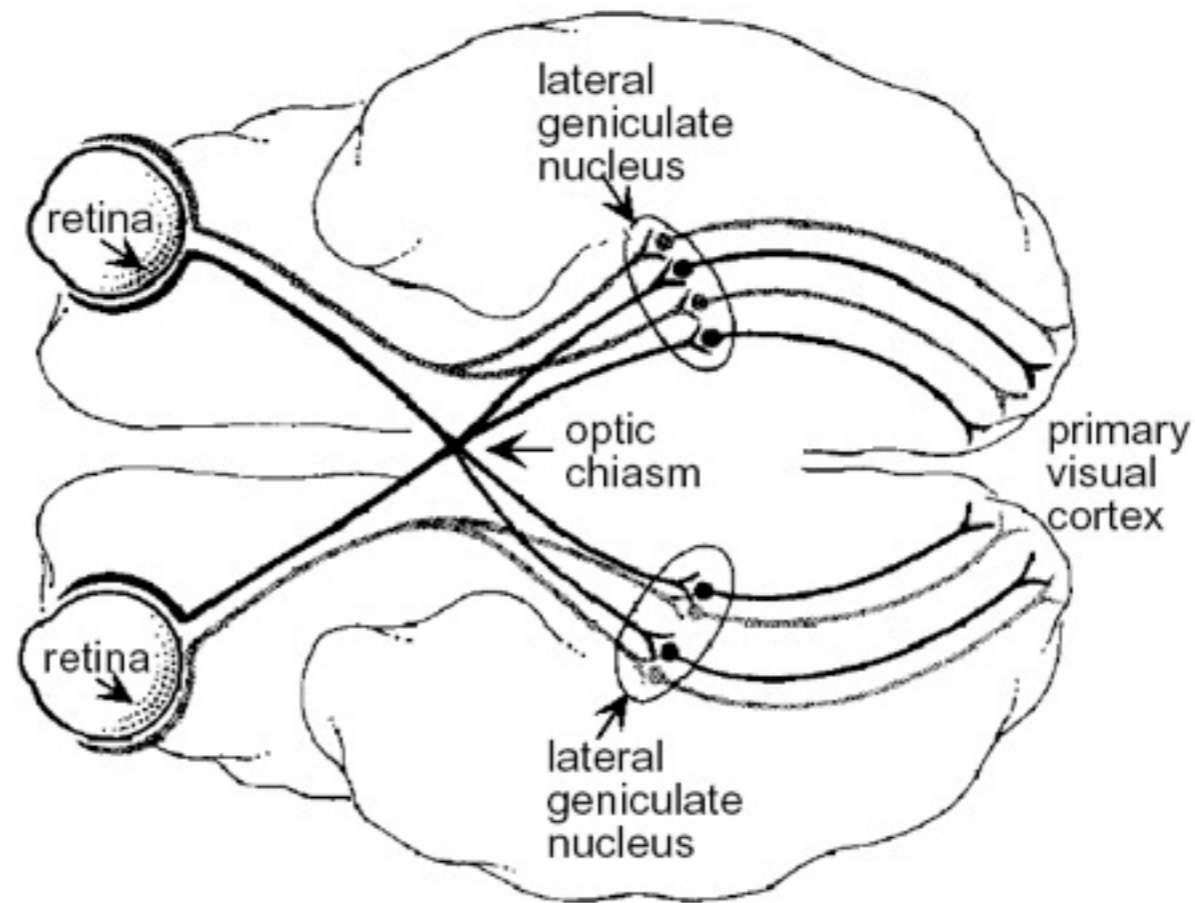
$$\begin{array}{r} 00011101 \\ + 00100001 \\ \hline 00111110 \end{array}$$

$$\begin{array}{r} XXIX \\ + XXXIII \\ \hline \end{array}$$

Most famous example: “edge detectors” in visual system

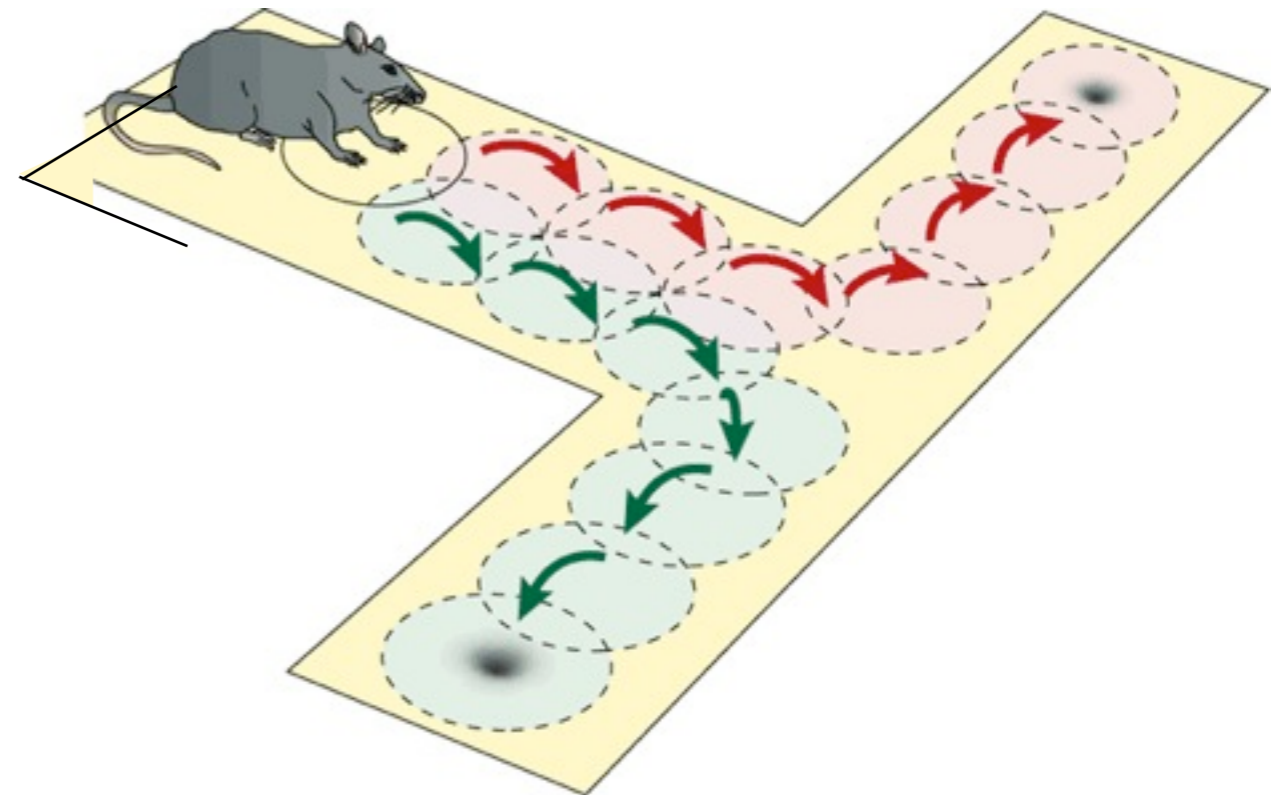


Stimulus:
black bar



Activity of
a neuron in V1

Another famous example: Place cells in the hippocampus



Studying representations in the brain

Experimental work

- perceptual representations:
vision, audition, olfaction, etc.
- representation of motor variables
- “higher-order” representations:
decisions
short-term memory
rewards
dreams
uncertainty
... you name it ...

Theoretical work

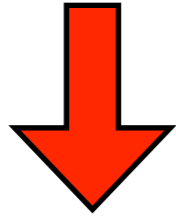
- Quantifying information content
quest for the neural code,
information theory, discriminability, ...
- Understanding the computational
problems: object recognition, sound
recognition, reward maximization

What we understand now

very little

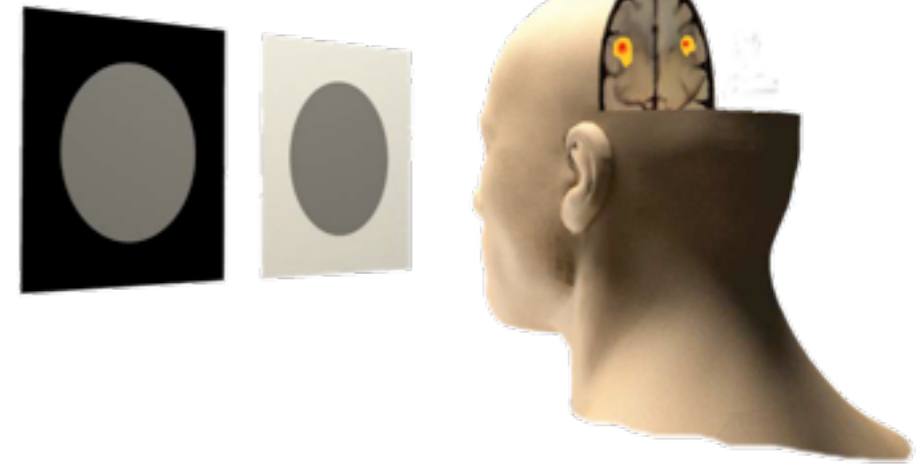
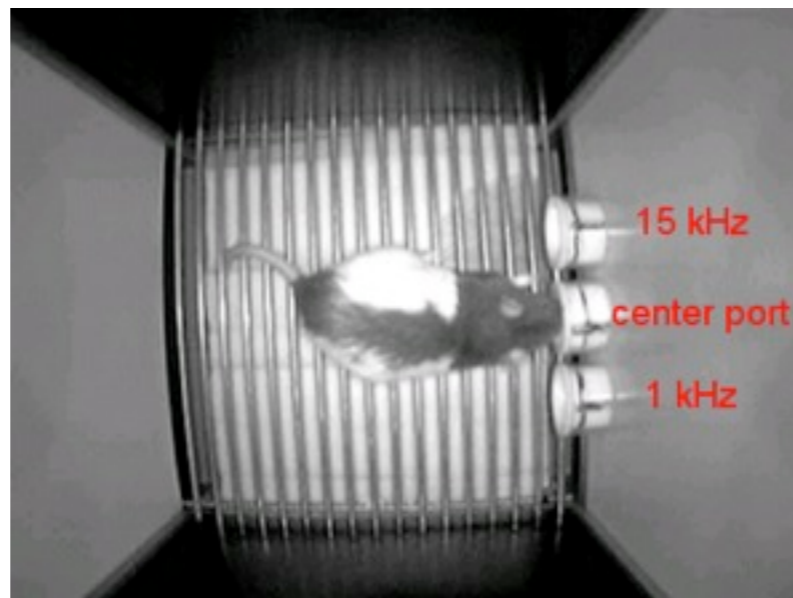
What we understand now

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What we need

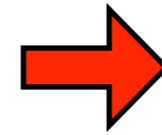
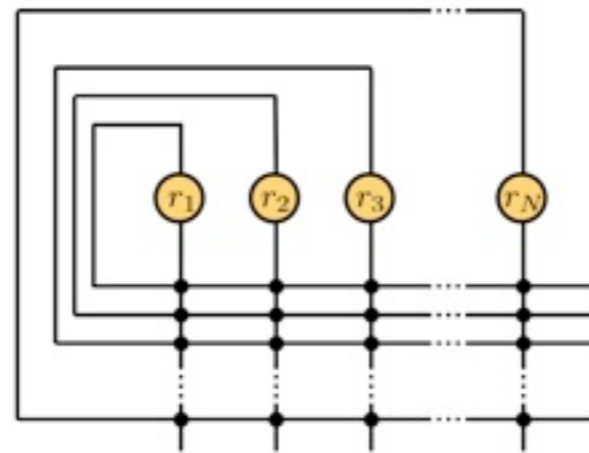
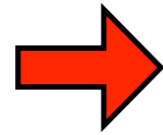
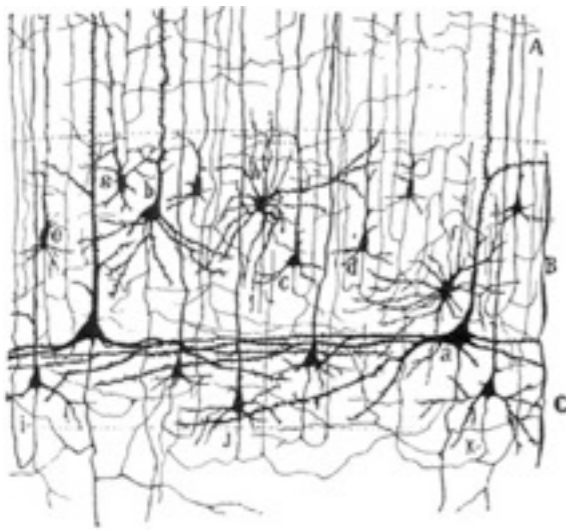
- biologists
- psychologists



- to probe the brains of animals and humans
- to design and carry out clever experiments
- to investigate and quantify human and animal behavior

What we need

- physicists, computer scientists, engineers, etc.



$$\dot{r}_1 = -r_1 + f\left(\sum_{j=1}^N w_{1j}r_j + E_1\right)$$
$$\dot{r}_2 = -r_2 + f\left(\sum_{j=1}^N w_{2j}r_j + E_2\right)$$

- to formulate mathematical theories of information processing
- to create biophysical models of neural networks

Teaching in the Cogmaster

Computational Neuroscience

Core Classes

S I

CA6(a) Theoretical Neuroscience

JP Nadal, N Brunel, R Brette, G Mongillo
Thursday, 14-17, ???,

START:

CA6(b) Seminar in Quantitative Neuroscience

R Brette, R da Silveira, S Deneve, B Gutkin, V Hakim, C Machens
Tuesday, 17-18.30, Salle Seminaire DEC (29, rue d'Ulm, RdC)

START: 5 Oct

S2

CO6 Introduction to Comput. Neuroscience

V Benichoux, R Brette, C Machens
Tuesday, 17-19

AT2 Atelier Comput. Neuroscience

C Machens
Monday, 10-12

Many more classes available!!

see cogmaster website!!

contact us!!

Computational Neuroscience Research in the Cogmaster and Beyond

ENS: [Group for Neural Theory](#)

(Sophie Deneve, Boris Gutkin, Christian Machens, ...)

ENS: [Equipe Audition](#)

(Romain Brette, Victor Benichoux, ...)

ENS: [Laboratoire de Physique Statistique](#)

(Jean-Pierre Nadal, Vincent Hakim, ...)

Paris V: [Laboratoire de Neurophysique et Physiologie](#)

(Nicolas Brunel, David Hansel, ...)

you can find more labs under:

<http://cogmaster.net>

<http://neurocomp.risc.cnrs.fr>

for internship / stages / Master's thesis: contact the faculty! (email etc.)

The articles you have read:

Neural coding

[WT Newsome, KH Britten, JA Movshon](#)
[Neuronal correlates of a perceptual decision](#)

Reinforcement Learning

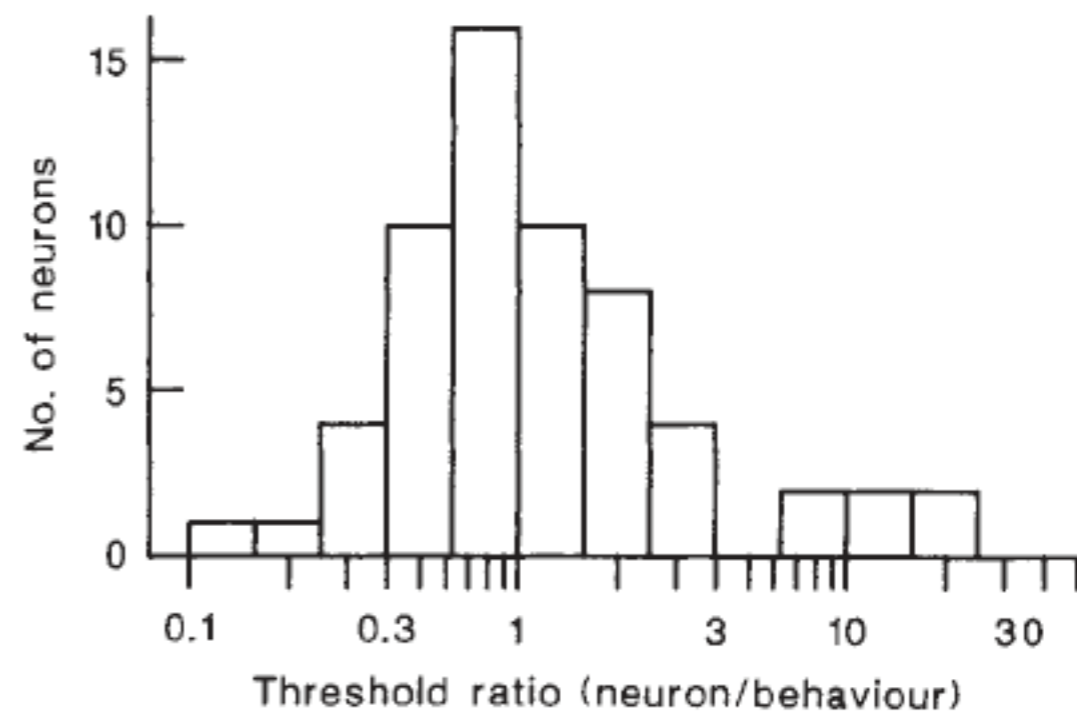
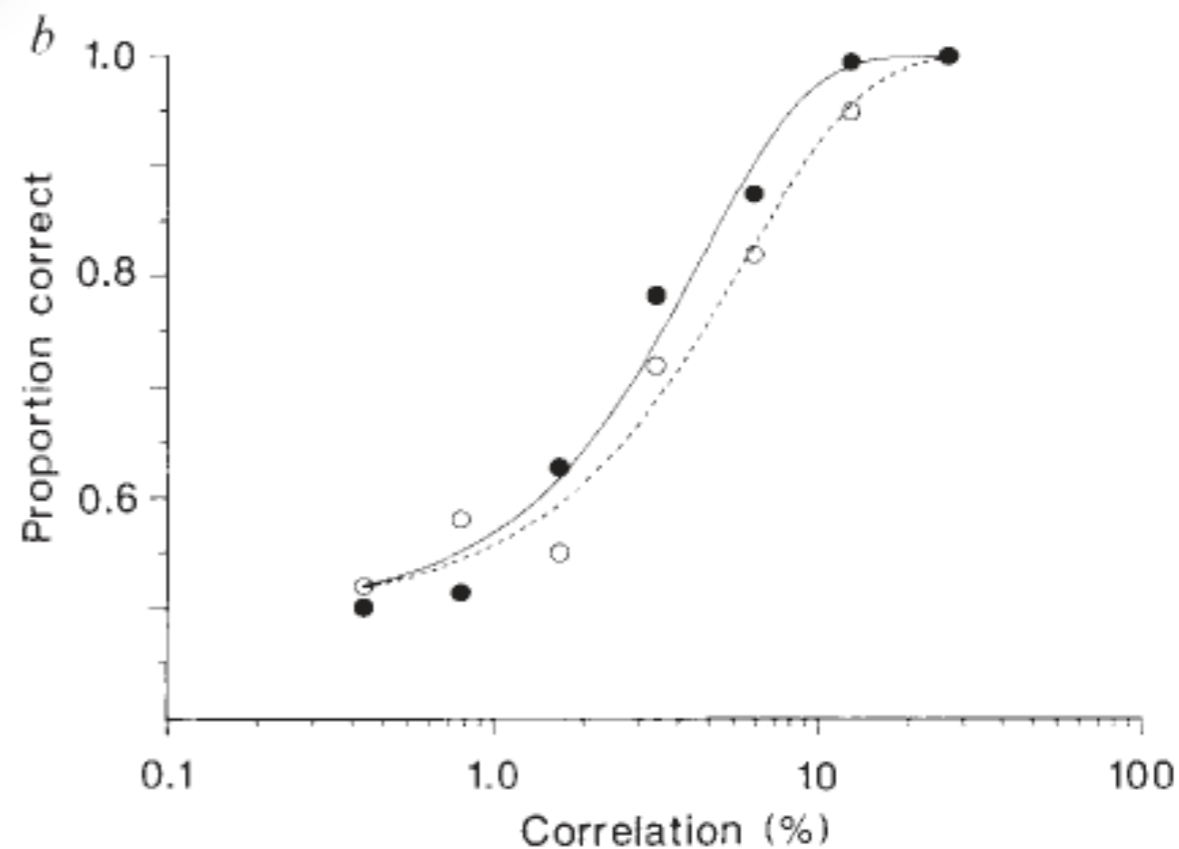
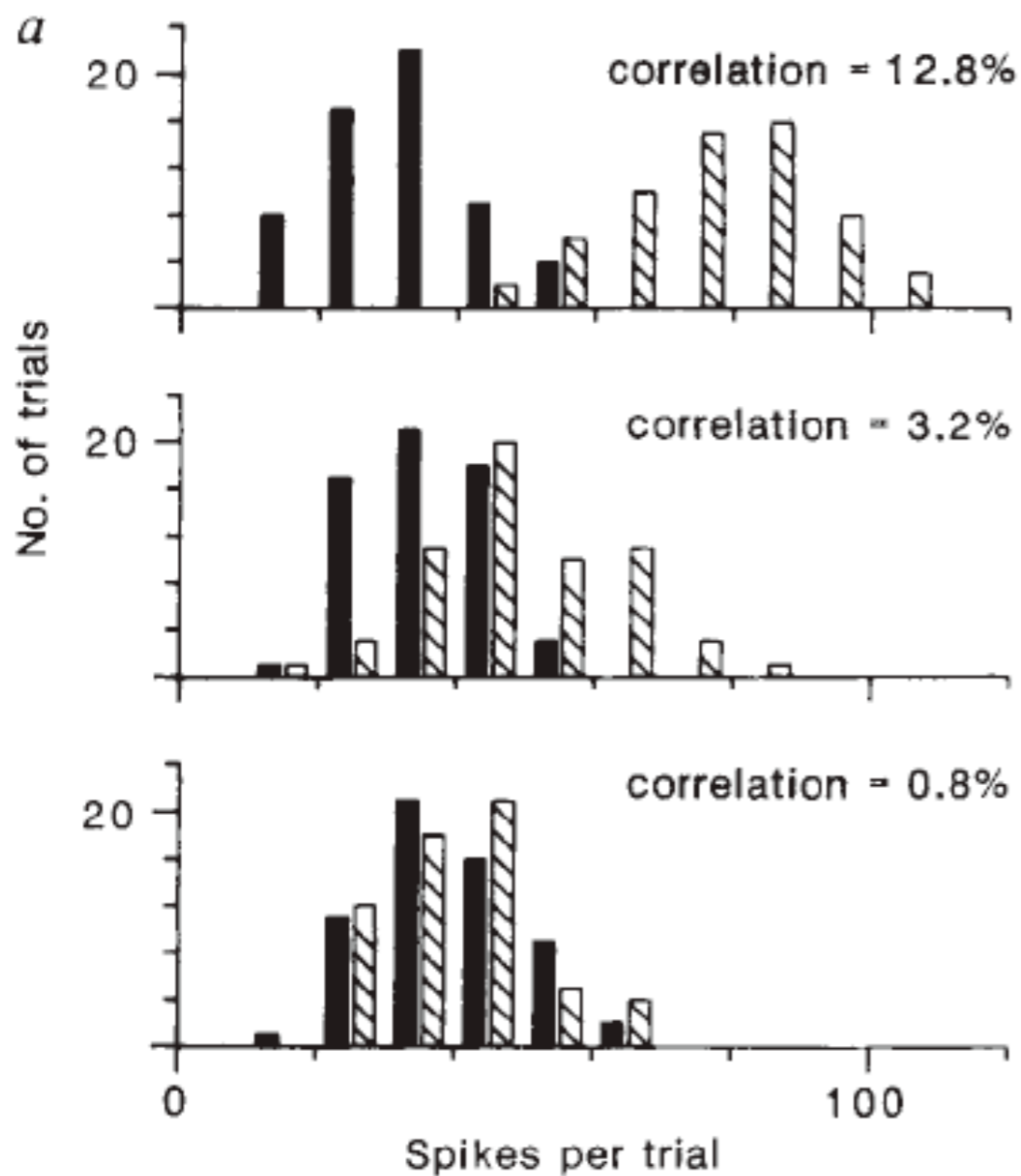
[W Schultz, P Dayan, PR Montague](#)
[A neural substrate of prediction and reward](#)

Neuronal correlates of a perceptual decision

William T. Newsome*†, Kenneth H. Britten*†
& J. Anthony Movshon‡

* Department of Neurobiology and Behavior, State University of New York,
Stony Brook, New York 11794, USA

‡ Department of Psychology and Center for Neural Science,
New York University, New York 10003, USA

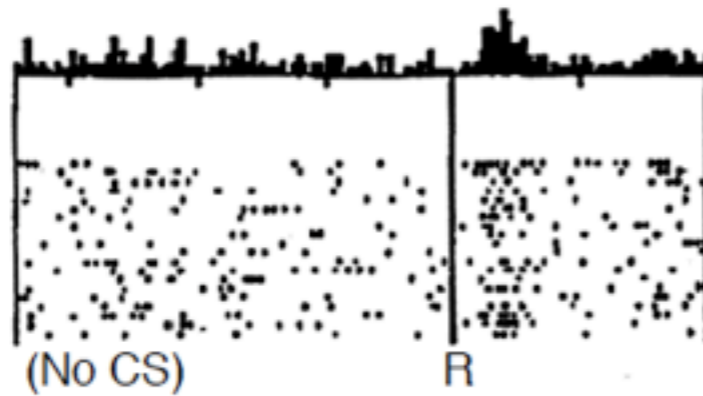


A Neural Substrate of Prediction and Reward

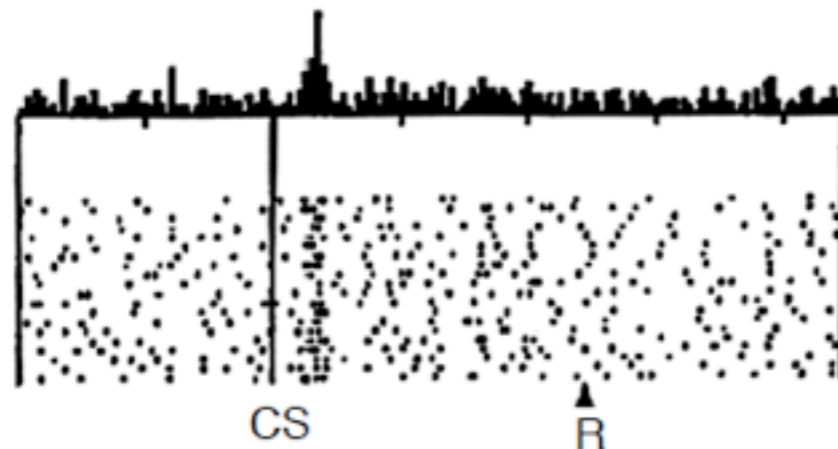
Wolfram Schultz, Peter Dayan, P. Read Montague*

Do dopamine neurons report an error in the prediction of reward?

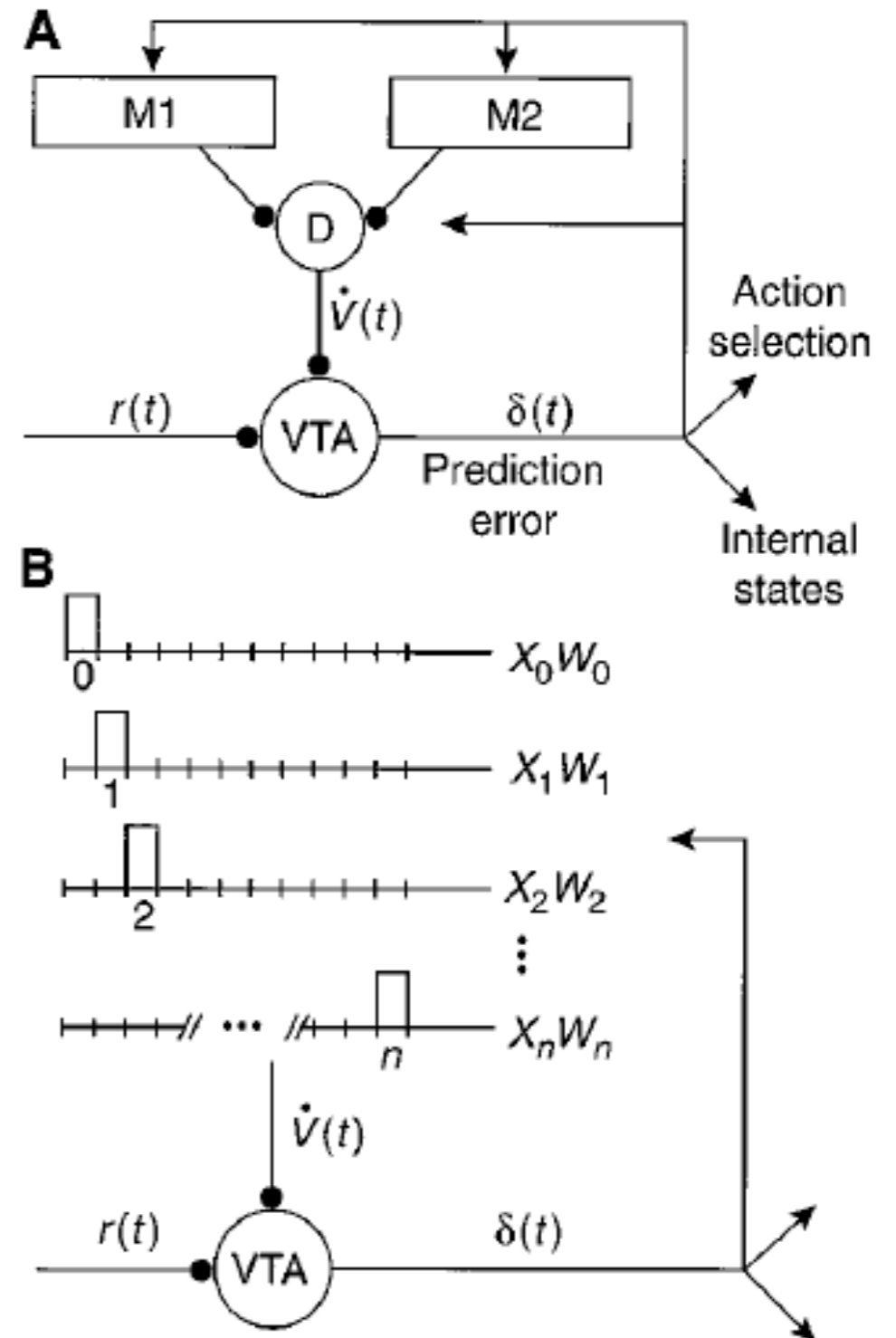
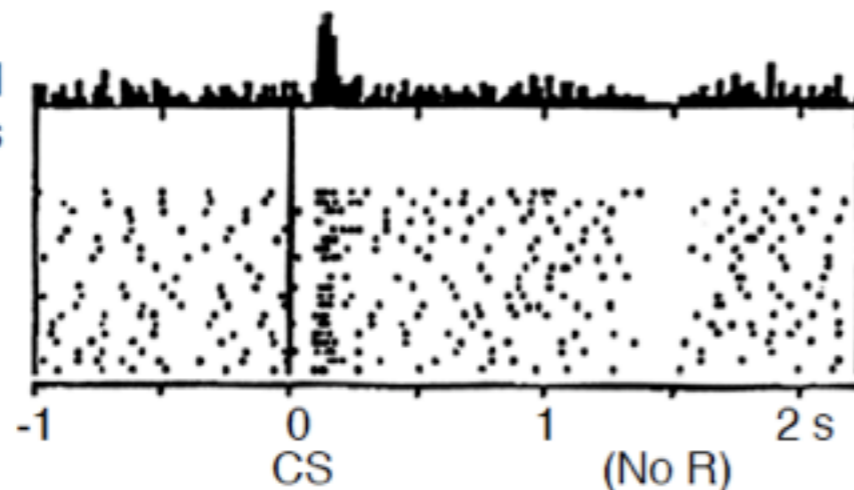
No prediction
Reward occurs



Reward predicted
Reward occurs

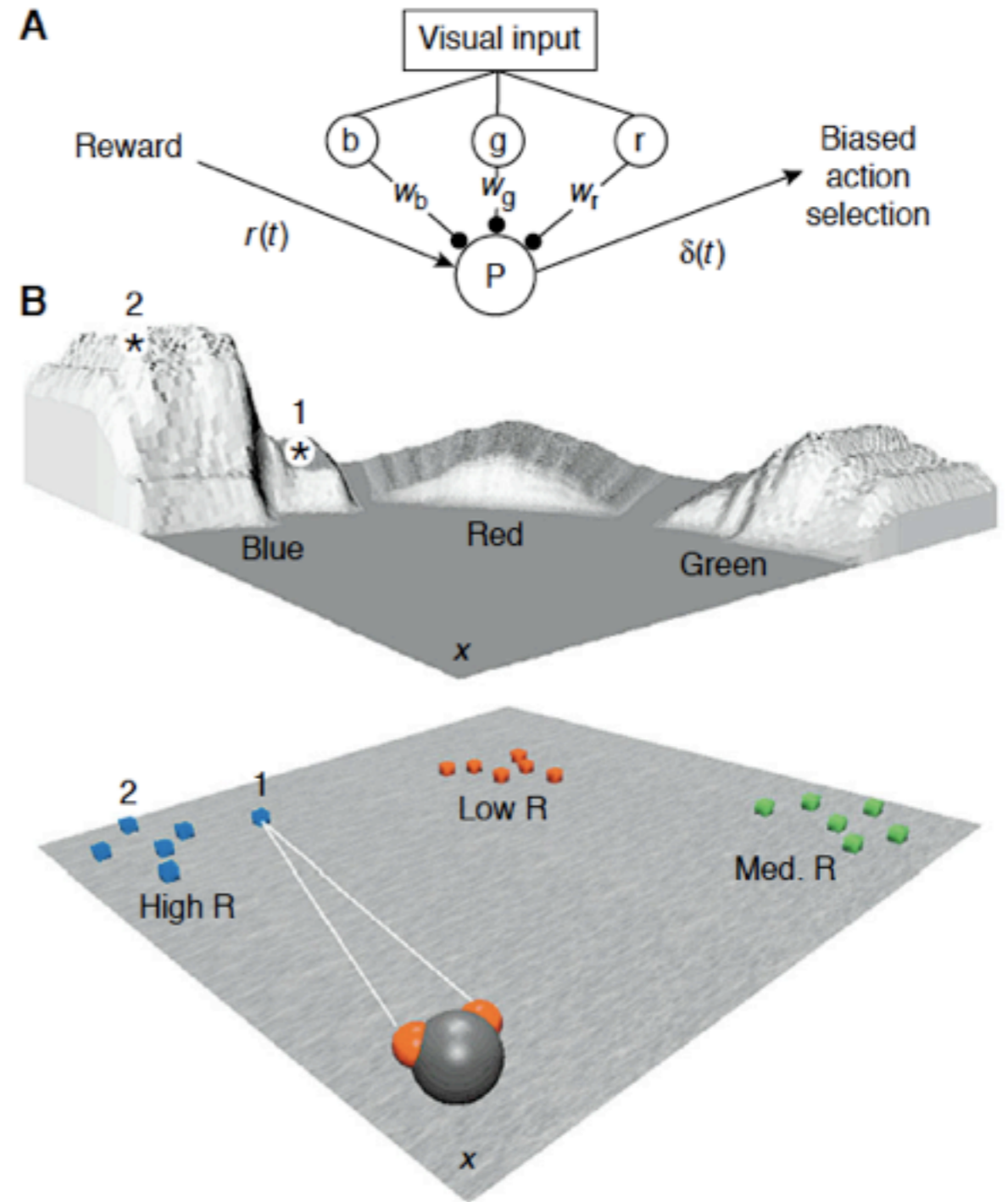
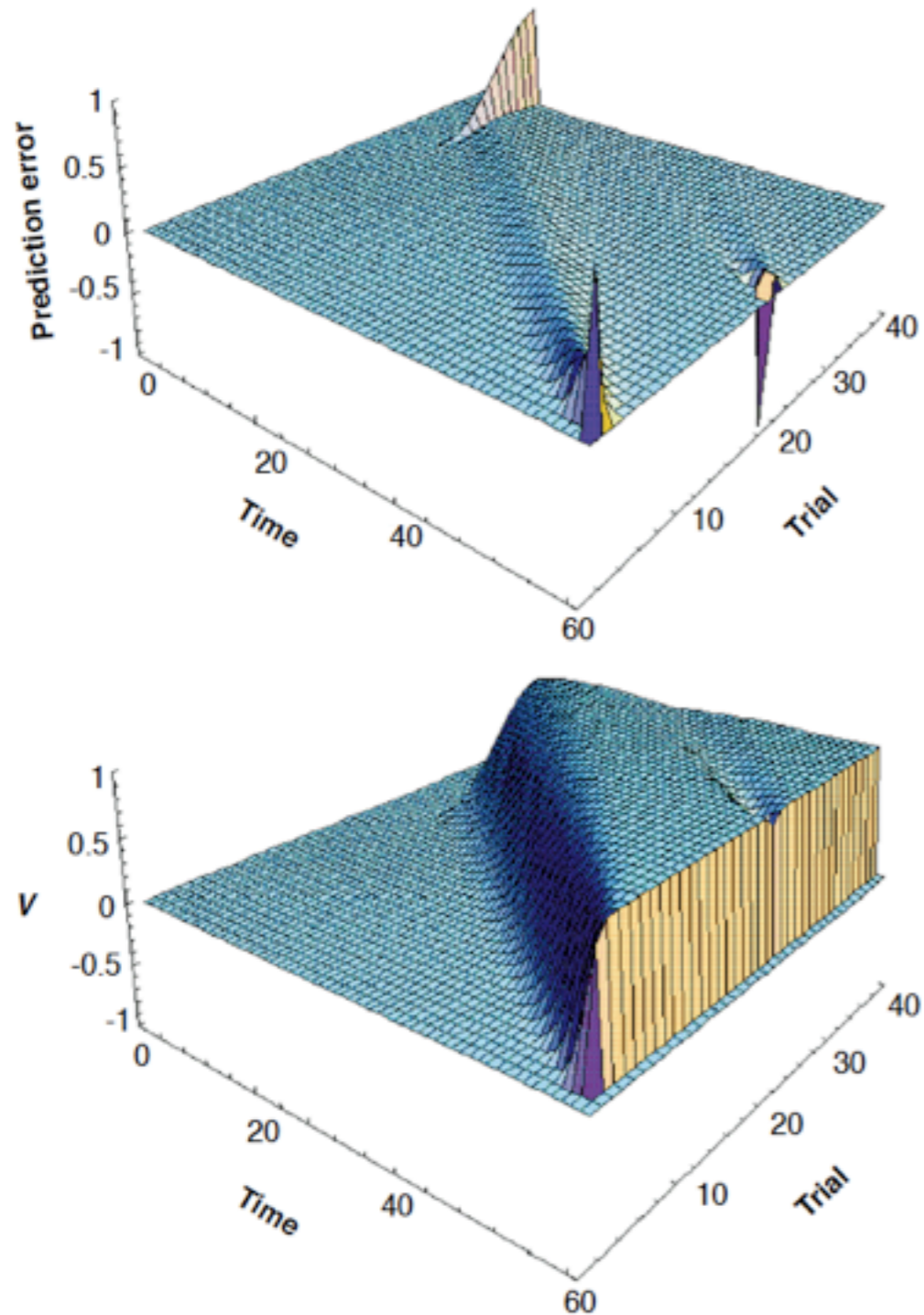


Reward predicted
No reward occurs



A Neural Substrate of Prediction and Reward

Wolfram Schultz, Peter Dayan, P. Read Montague*



The Quest for the Neural Code

Neuronal correlates of a perceptual decision

**William T. Newsome*†, Kenneth H. Britten*†
& J. Anthony Movshon‡**

* Department of Neurobiology and Behavior, State University of New York,
Stony Brook, New York 11794, USA
‡ Department of Psychology and Center for Neural Science,
New York University, New York 10003, USA

how is information represented in the brain?

Maybe it's the timing of spikes, rather than their average count (firing rate) that actually carries the information!

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how much information does the population contain?

Population codes are complicated because you cannot just add the information from different neurons if these are correlated (if they carry redundant information)

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Population codes are complicated because you cannot just add the information from different neurons if these are correlated (if they carry redundant information)

on what time scales is information represented?

In the article, stimuli are 2 sec long! But monkeys (and humans) integrate motion over much shorter time scales (100s of millisecc) - then each neuron contributes less info!

How behaviors are learned

**A Neural Substrate of
Prediction and Reward**

Wolfram Schultz, Peter Dayan, P. Read Montague*



Edward Thorndike
(1874-1949)

Psychology of
Animal Learning

How behaviors are learned



Edward Thorndike
(1874-1949)

Psychology of
Animal Learning

Optimal Control
Theory



Richard Bellman
(1920-1984)

How behaviors are learned



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Marvin Minsky
(1927-???)



Harry Klopf
(1927-???)

Artificial Intelligence
(Machine Learning)

How behaviors are learned



Edward Thorndike
(1874-1949)

Psychology of
Animal Learning

Optimal Control
Theory



Richard Bellman
(1920-1984)

Reinforcement
Learning



Richard Sutton
(1956-???)



Andrew Barto
(1948-???)



Marvin Minsky
(1927-???)



Harry Klopf
(1927-???)

Artificial Intelligence
(Machine Learning)

In case you are interested...

9th Computational Neuroscience Day, Wed

"Modeling Network Dynamics"

Salle Fessard
Institut de Neurobiologie Alfred Fessard
CNRS, Bat 33
1 Avenue de la Terrasse,
91190 Gif sur Yvette