A brief introduction to Computational Neuroscience

Sophie Deneve

Group for Neural Theory
Ecole normale supérieure Paris

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

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

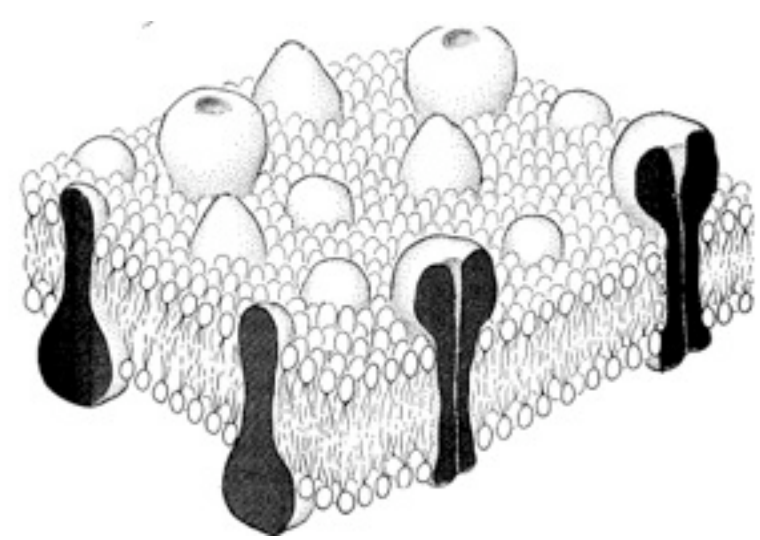
more complex brains generate a greater variety of behaviors

more complex brains can learn more behaviors

What's the brain made of?

Molecules

1 nm

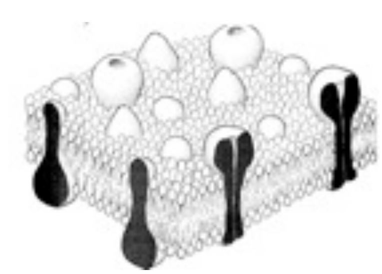


What's the brain made of?

Neurons — 100 µm

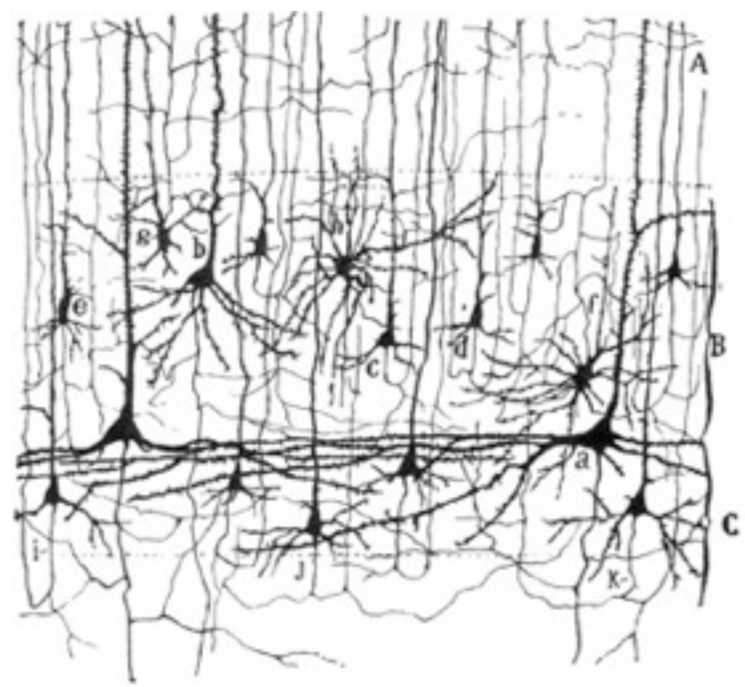
Synapses — 1 µm

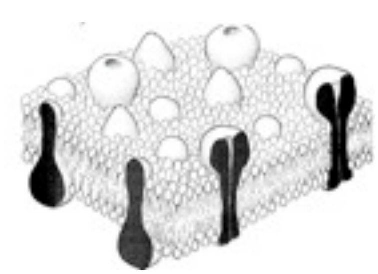
Molecules — 1 nm



What's the brain made of?

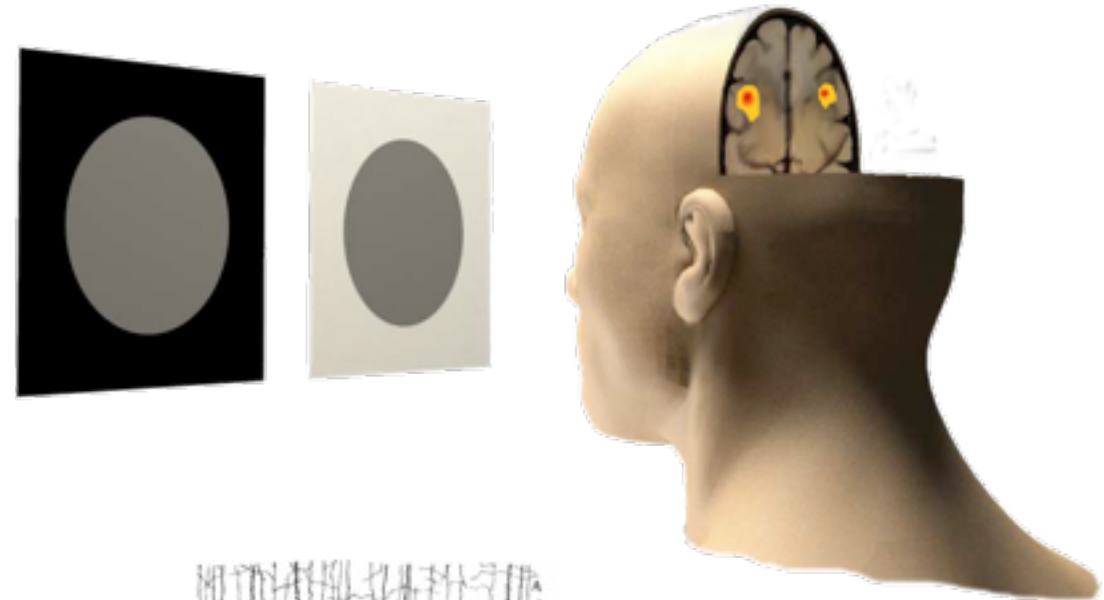
Maps	1 cm
Networks	1 mm
Neurons	100 µm
Synapses	1 µm
Molecules	1 nm

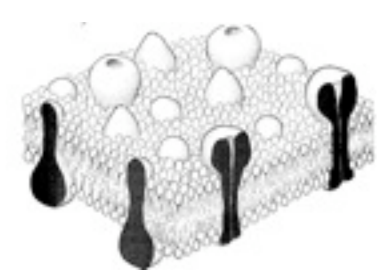




What's the brain made of?

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





How does the brain work?

A physics/engineering approach

Just rebuild the whole thing

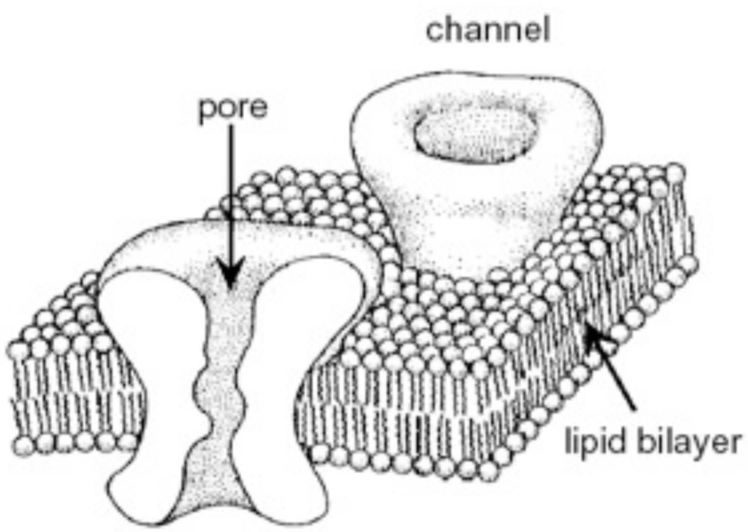
The quest for mechanisms: Constructing systems from parts

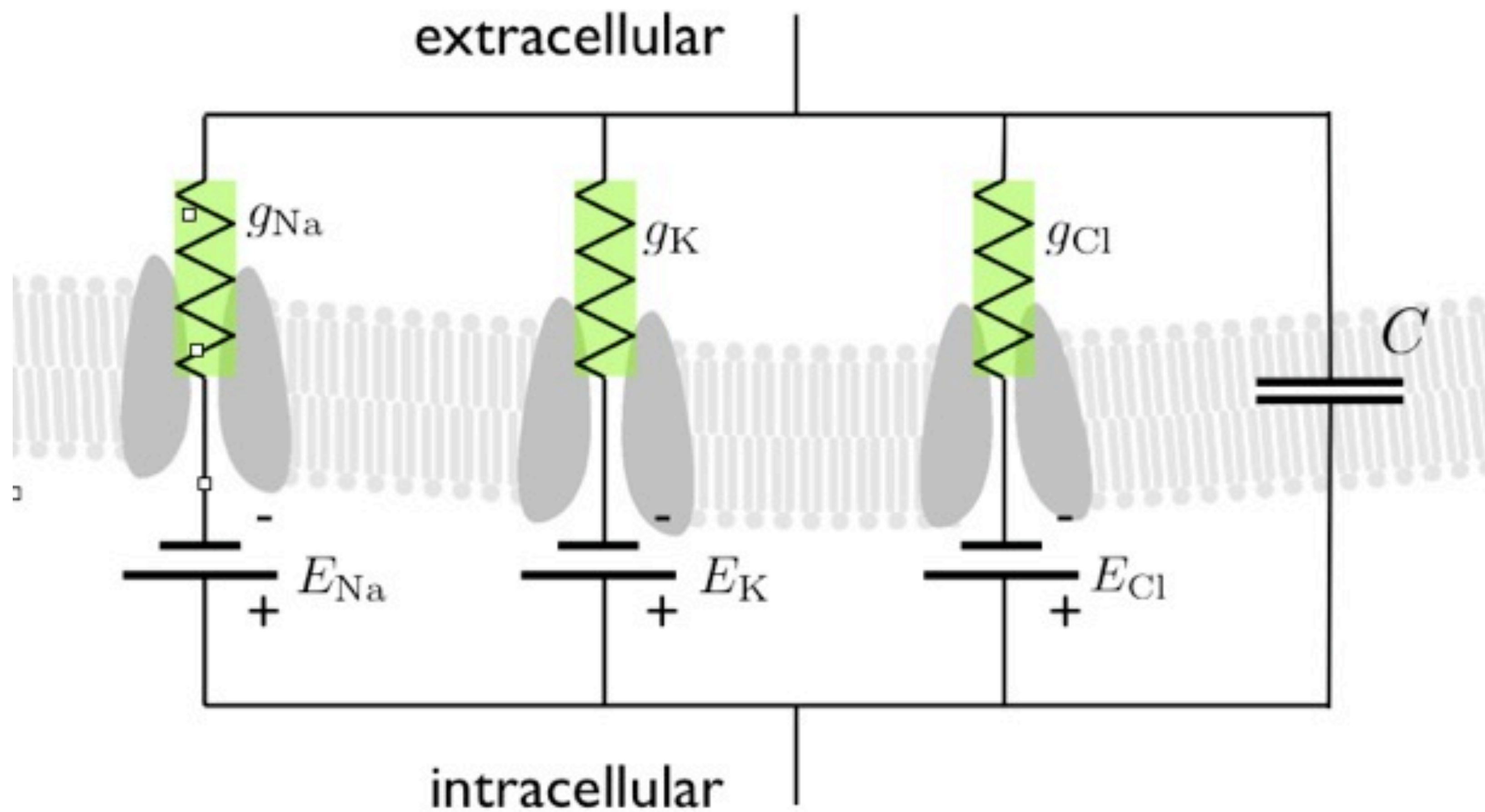
CNS	1 m
Systems	10 cm
Maps	1 cm
Networks	1 mm
Neurons	100 µm
Synapses	1 µm
Molecules	1 nm

The quest for mechanisms: Constructing systems from parts

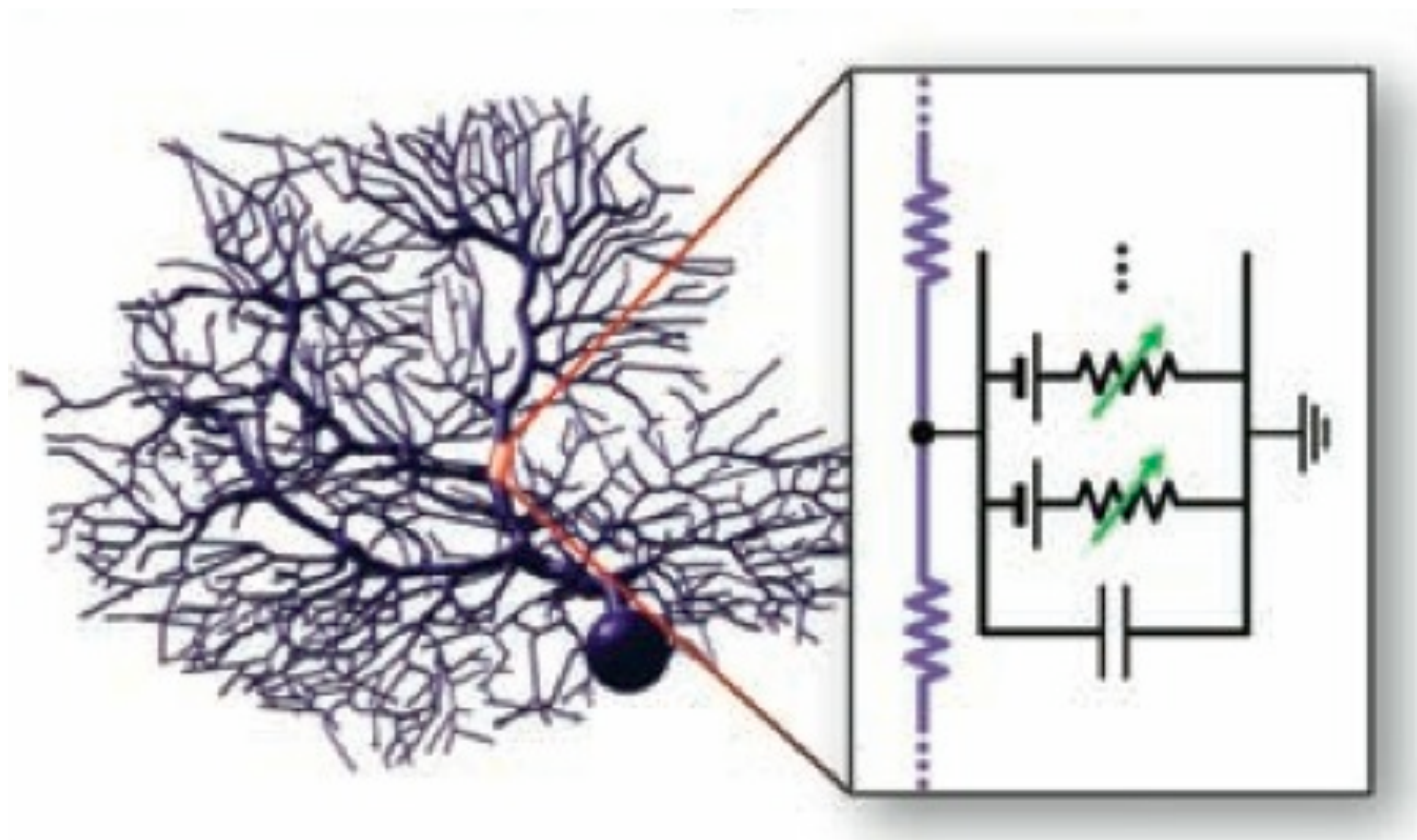
CNS	1 m
Systems	10 cm
Maps	1 cm
Networks	1 mm
Neurons	100 μm
Synapses	1 μm
Molecules	1 nm

Biophysics of the membrane voltage:
The Hodgkin-Huxley Model





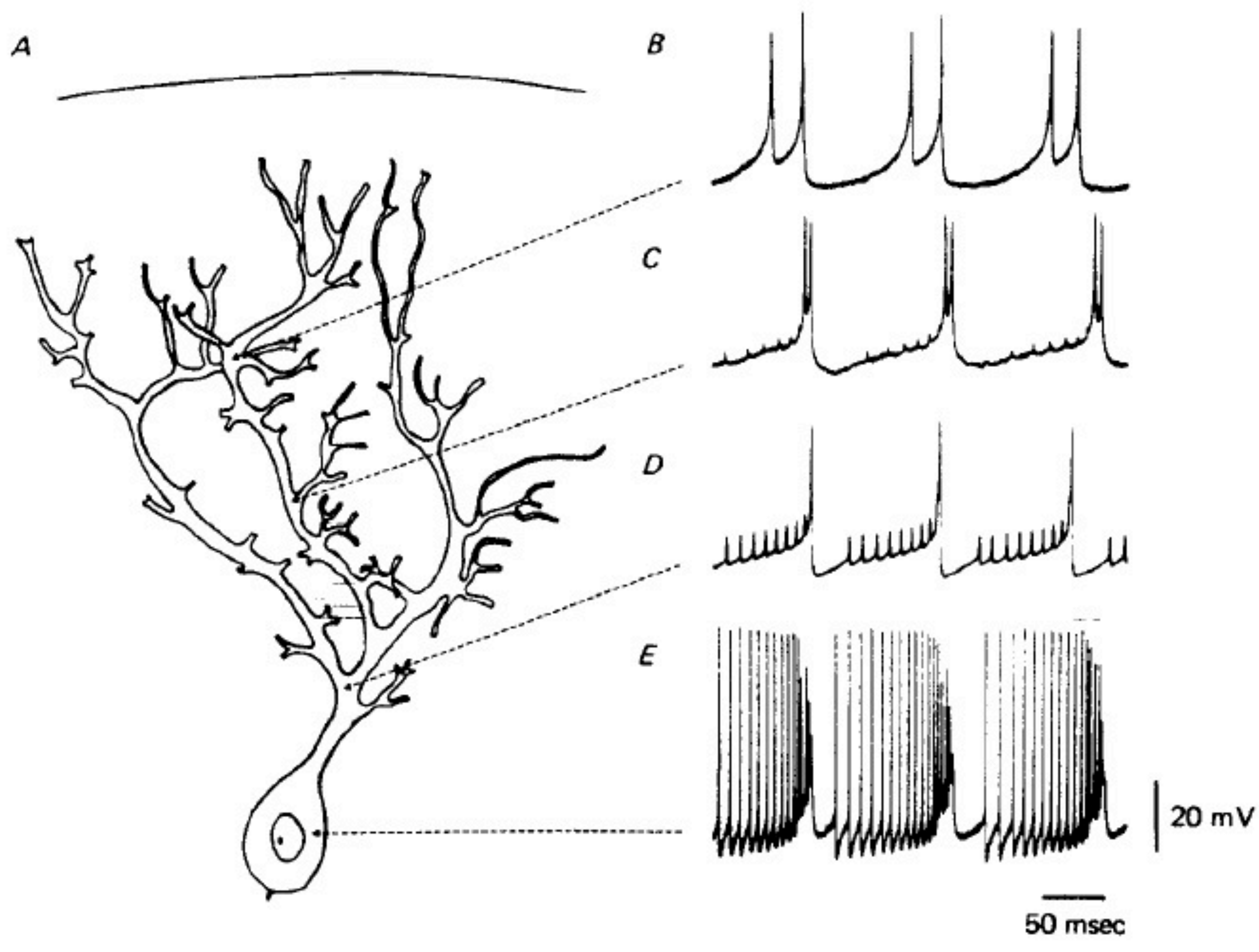
Reconstructing neurons:
Ralls' cable theory and compartmental modeling



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

Reconstructing neurons

Simulating the membrane potential



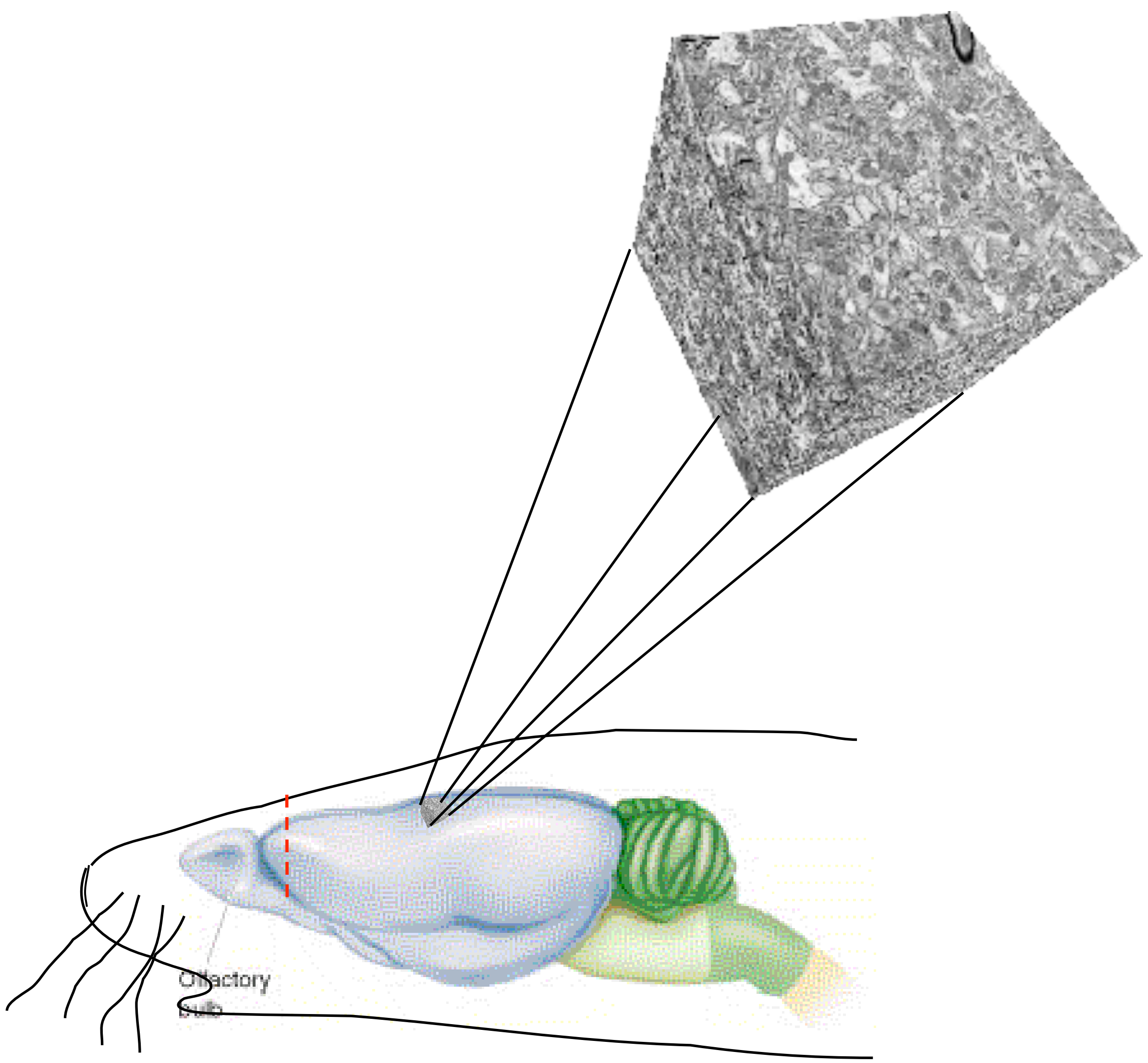
Llinas & Sugimori (1980)

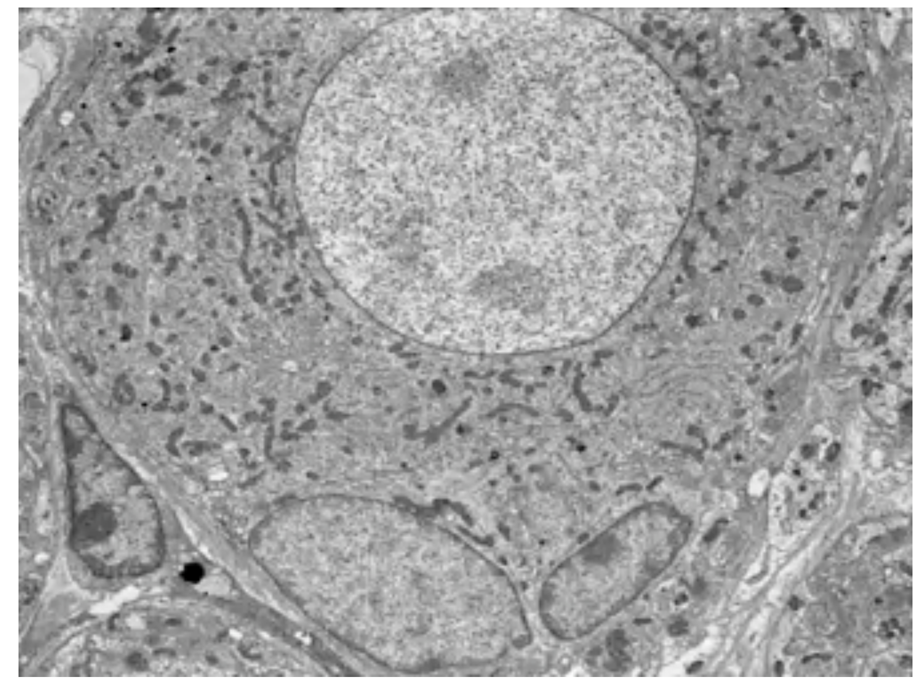
The quest for mechanisms: Constructing systems from parts

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

Reconstructing circuits

Serial Blockface Scanning Electron Microscopy





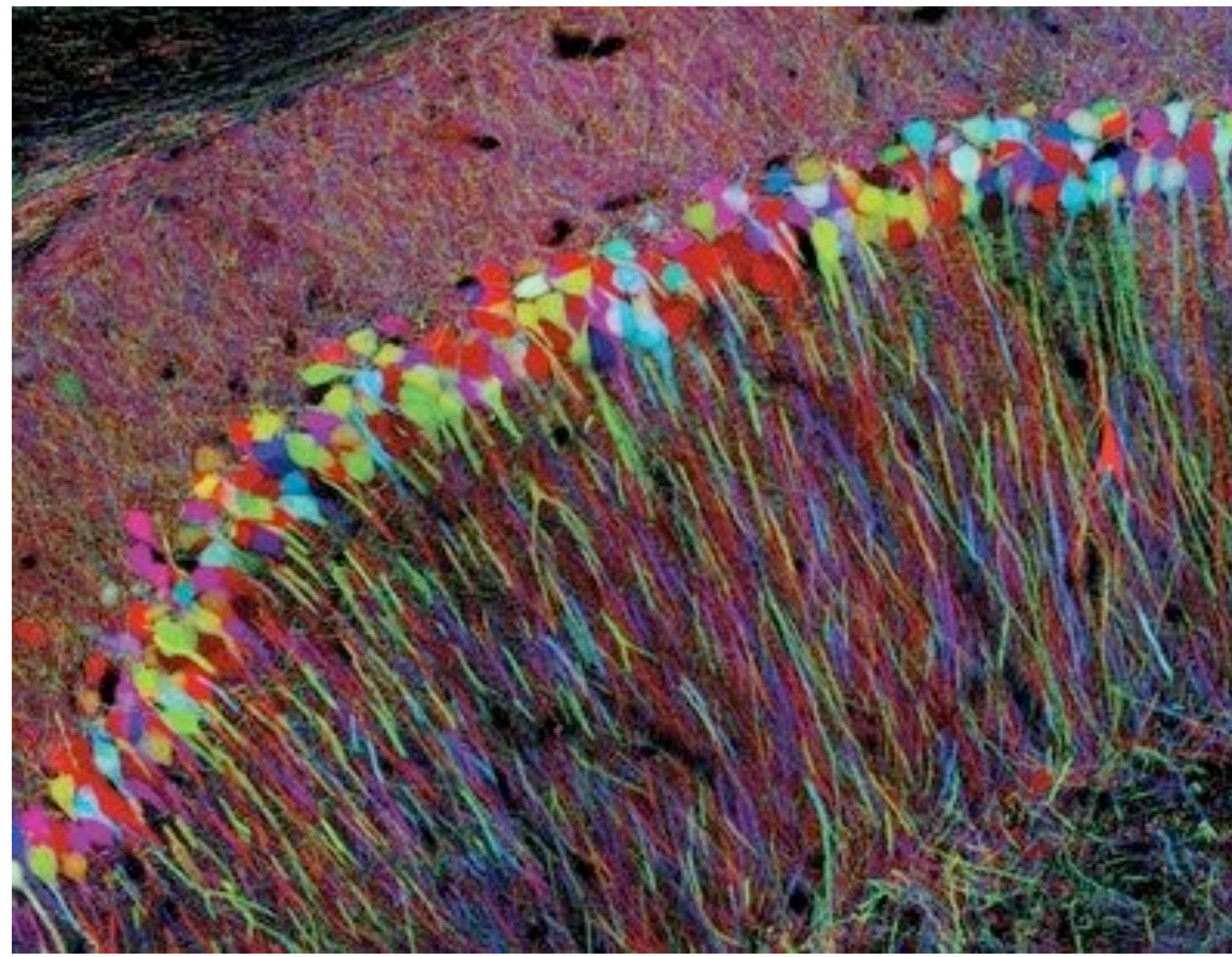
courtesy of W.Denk

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!

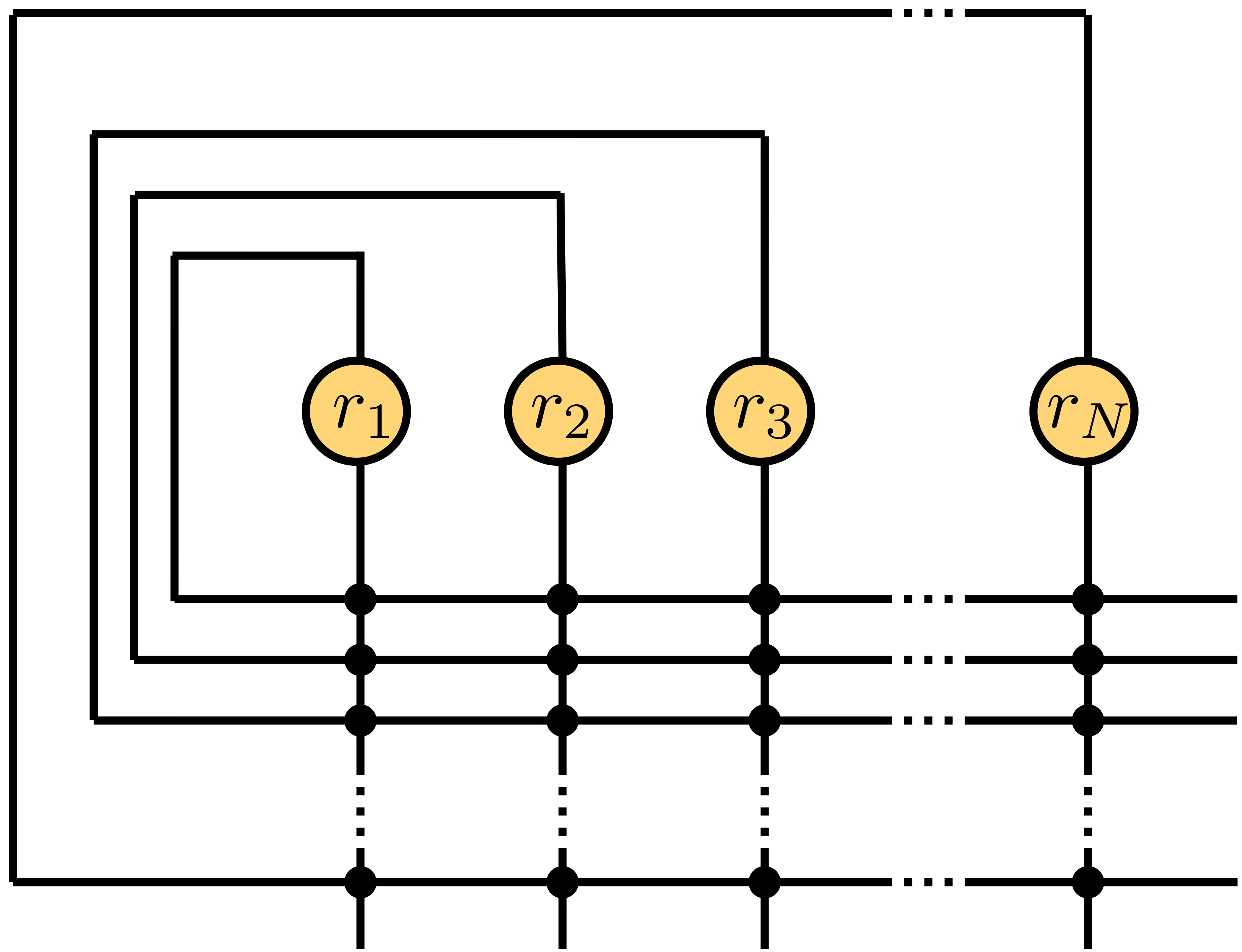


http://connectomes.org/

Theory of neural networks

Neurons, synapses ➡ network activity

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

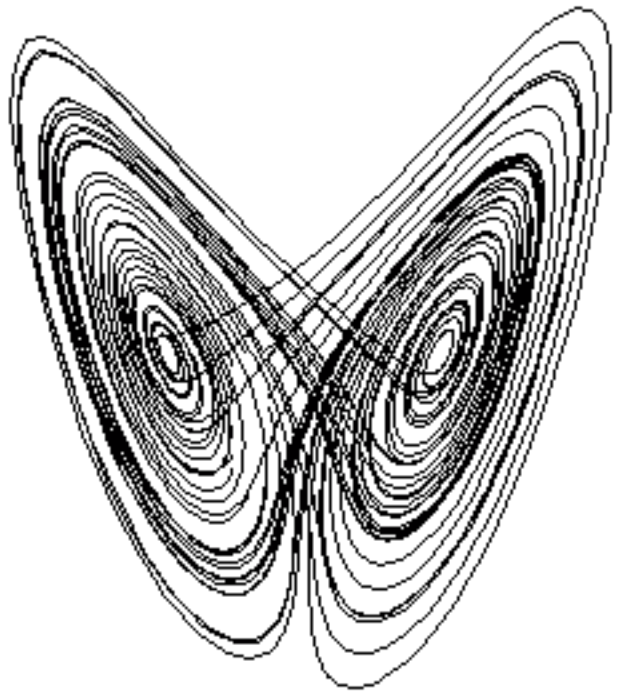


Network dynamics largely determined by connectivity

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

Possible dynamics:

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



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

For $N \rightarrow \infty$

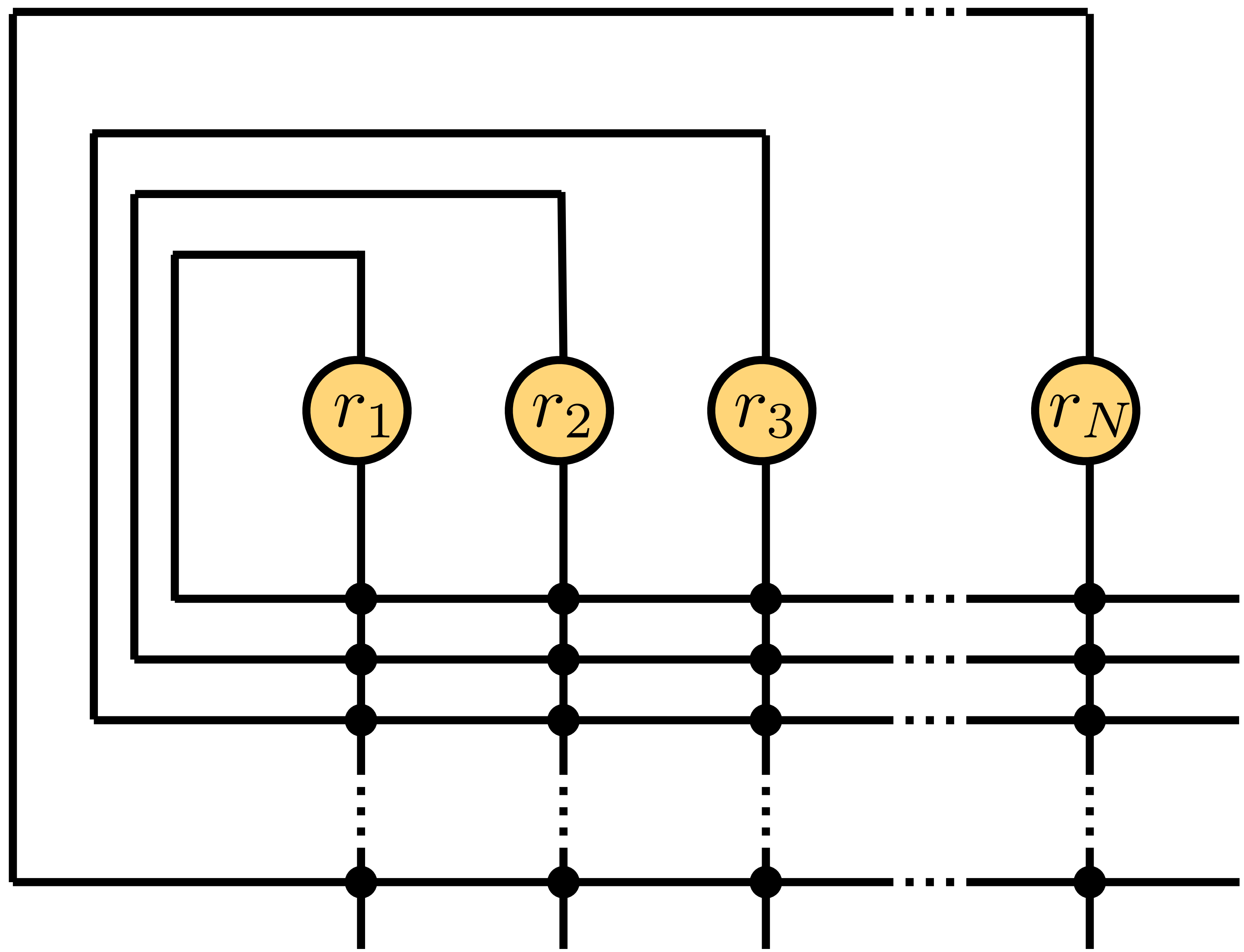
- neural networks can compute anything

(Statistical) theory of neural networks

Neurons, synapses → network activity

Under what conditions do you get

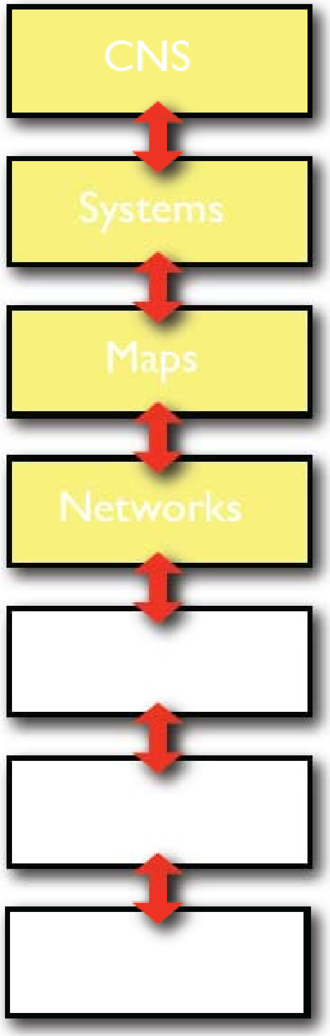
- only fixed points
- synchronous activity
- asynchronous activity
- Poisson spike trains
- oscillations
- spatial patterns
- ...



The quest for mechanisms: Constructing systems from parts

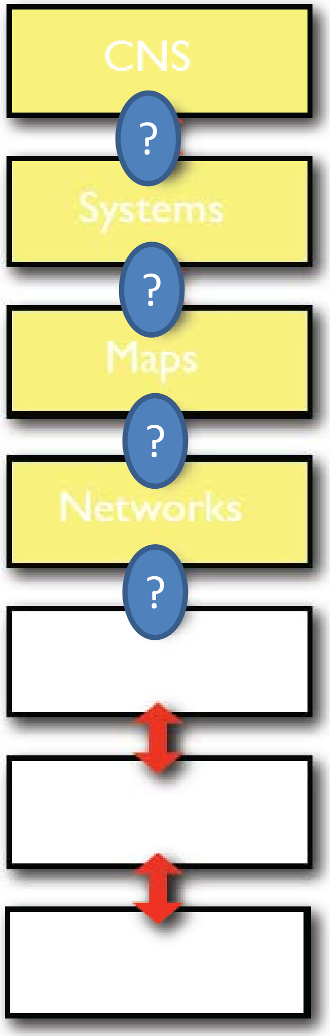
CNS	1 m
Systems	10 cm
Maps	1 cm
Networks	1 mm
Neurons	100 µm
Synapses	1 µm
Molecules	1 nm

The quest for mechanisms: Constructing systems from parts



Blue Brain project?

The quest for mechanisms: Constructing systems from parts

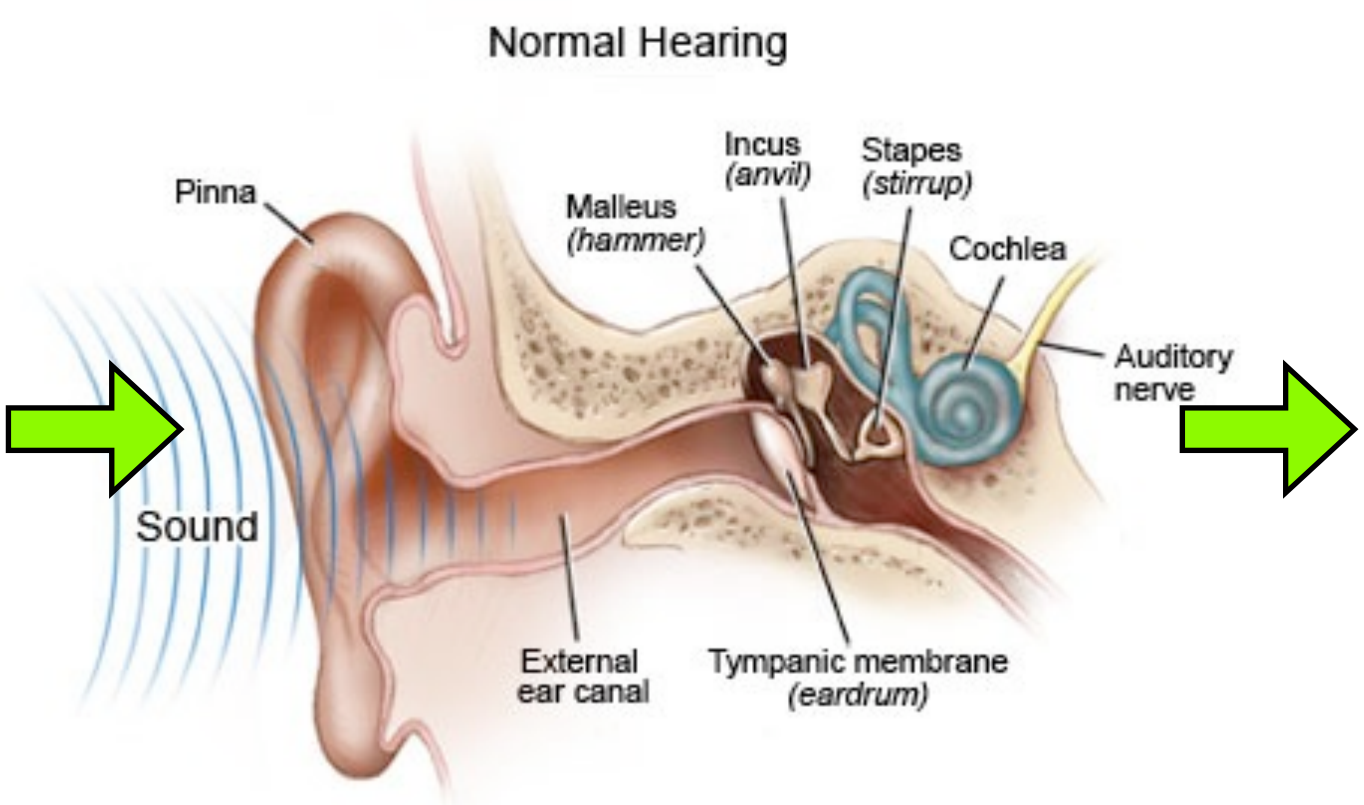


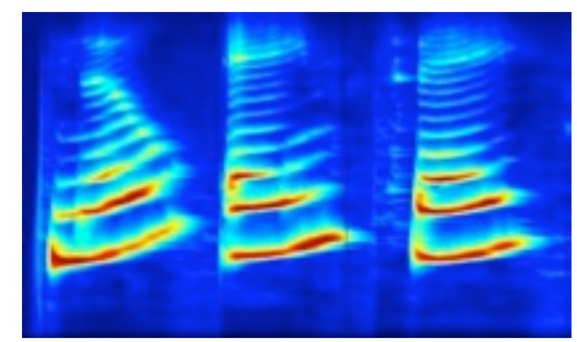
A computer science approach

Study the computational problems

Computation: manipulating information

sound pressure wave





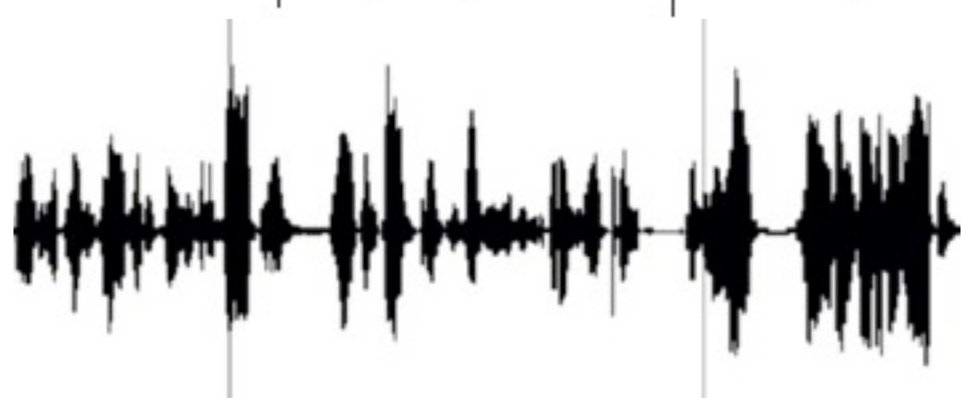
cochleogram
(time-frequency
representation of sound)

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`	Roman System
`23`	Decimal System
`00010111`	Binary System

Representations allow for easier algorithms

Example numbers:

`XXIII`	in ...?
`23`	in multiples of 10
`00010111`	in multiples of 2

Can you add these numbers?

```
   29        00011101        XXIX
 + 33      + 00100001    + 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        00011101       XXIX
 + 33      + 00100001   + XXXIII
 ----      ----------   --------
   62
```

Representations allow for easier algorithms

Example numbers:

```
XXIII       in ...?
23          in multiples of 10
00010111    in multiples of 2
```

Can you add these numbers?

```
   29       00011101      XXIX
 + 33     + 00100001  + XXXIII
 ----     ----------  --------
   62       00111110
```

Representations can ease certain computations

Example numbers:

```
XXIII        in ...?
23           in multiples of 10
00010111     in multiples of 2
```

Can you add these numbers?

```
   29        00011101        XXIX
 + 33      + 00100001    + XXXIII
 ----      ----------    --------
   62        00111110
```

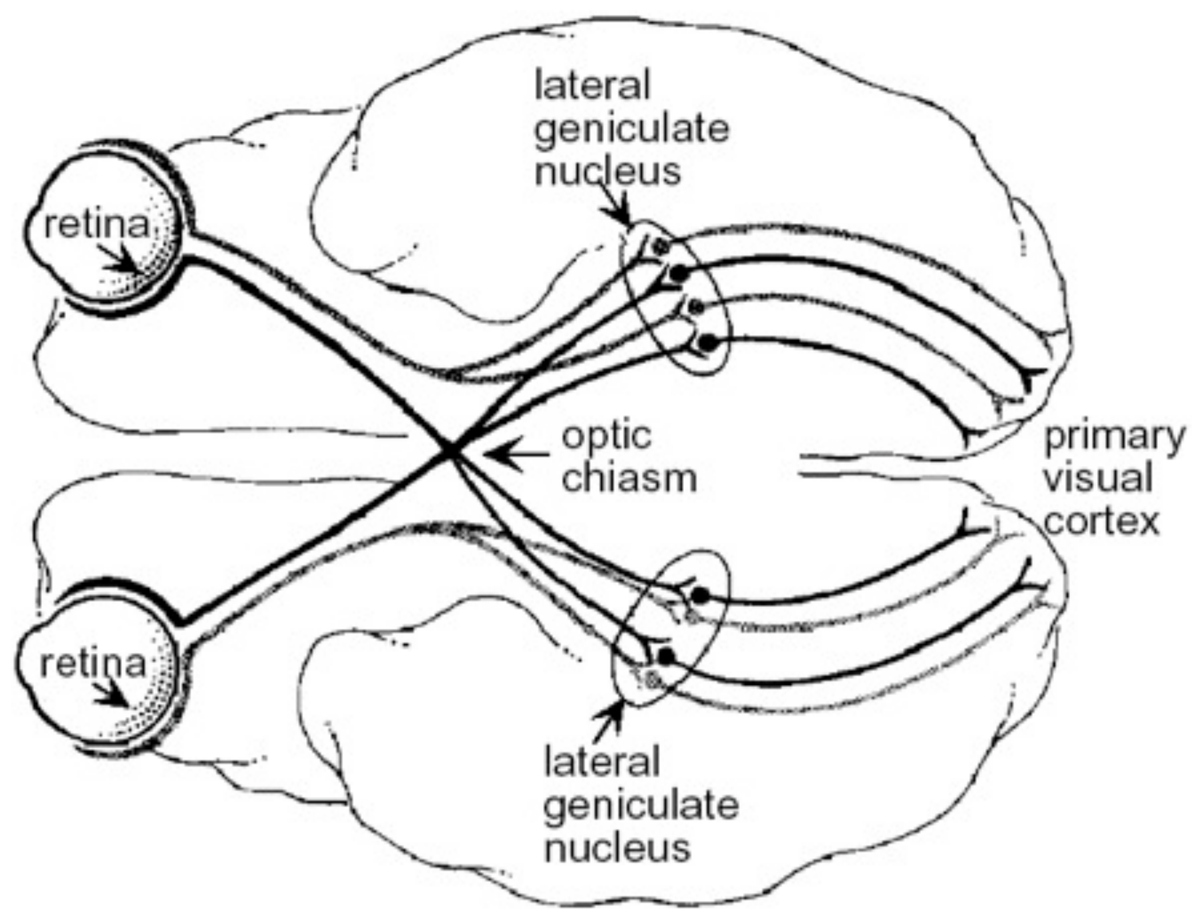
easy

easy

difficult

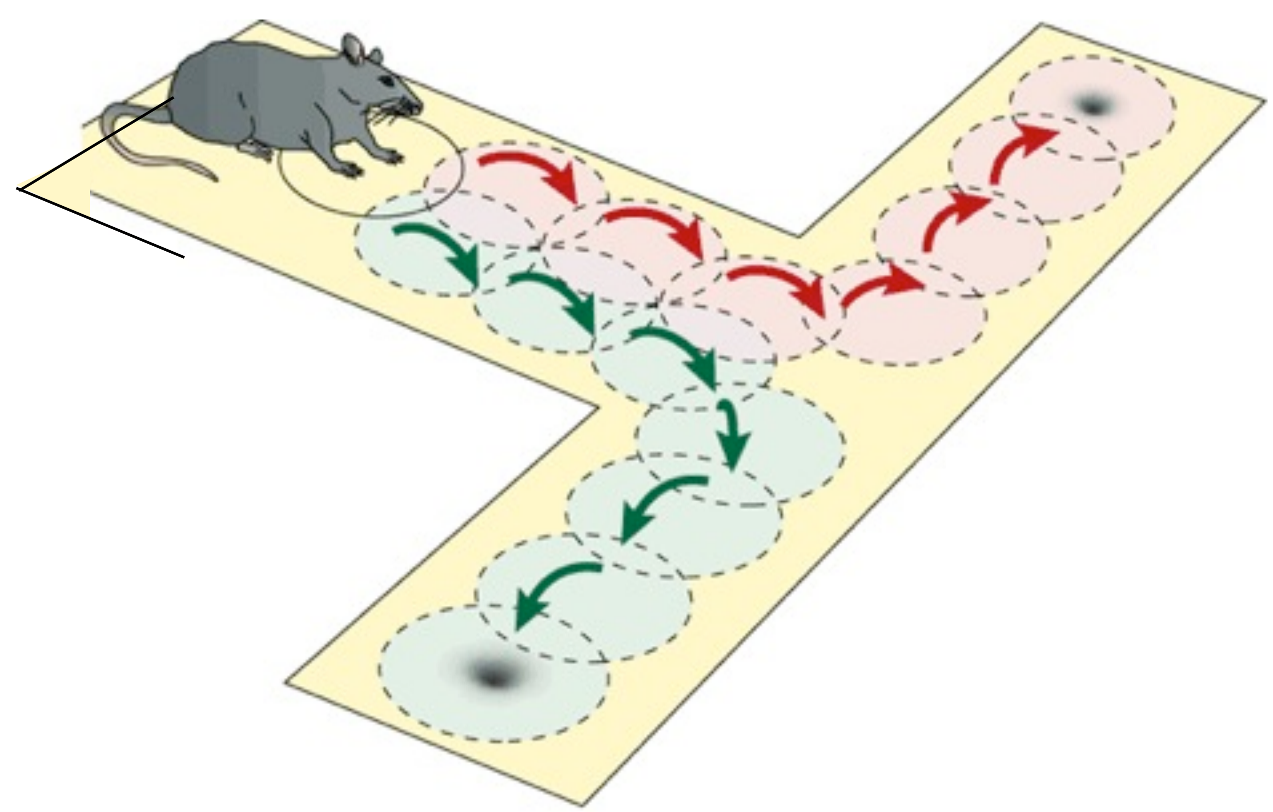
Most famous example: “edge detectors” in visual system

Stimulus:
black bar

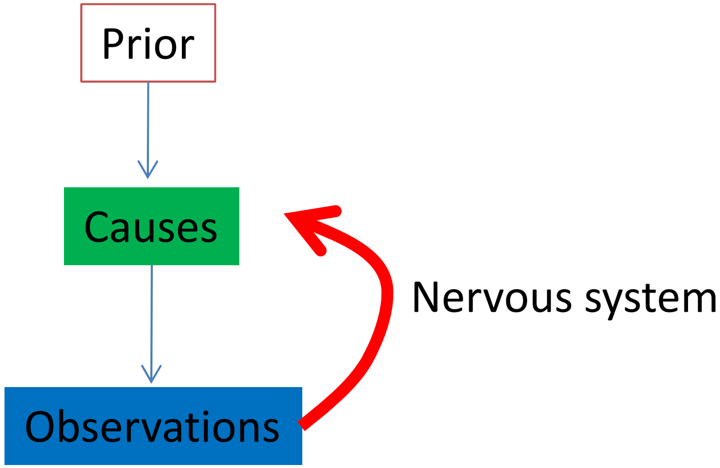


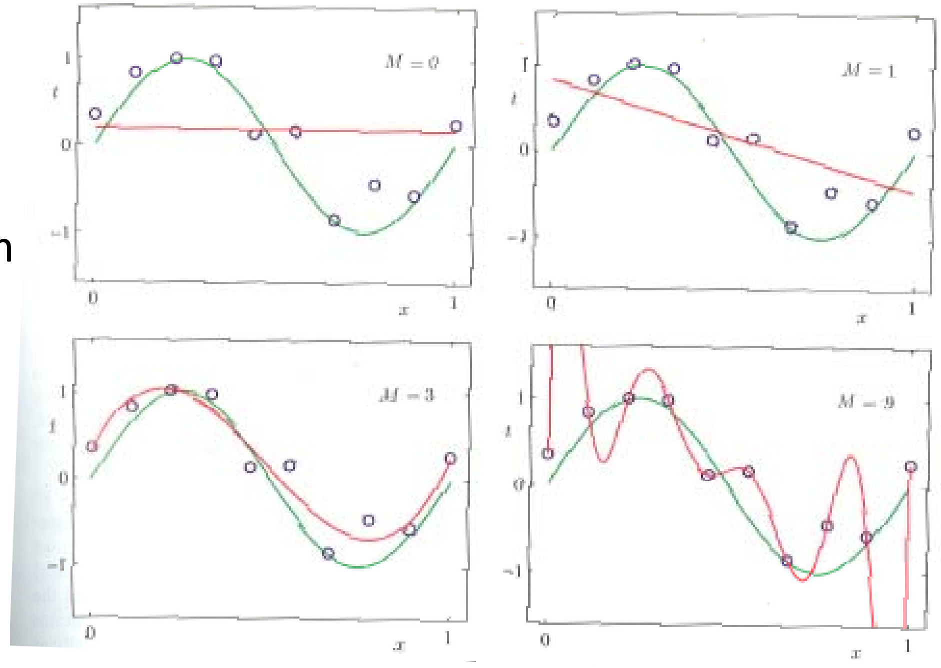
Activity of
a neuron in V1

Another famous example: Place cells in the hippocampus



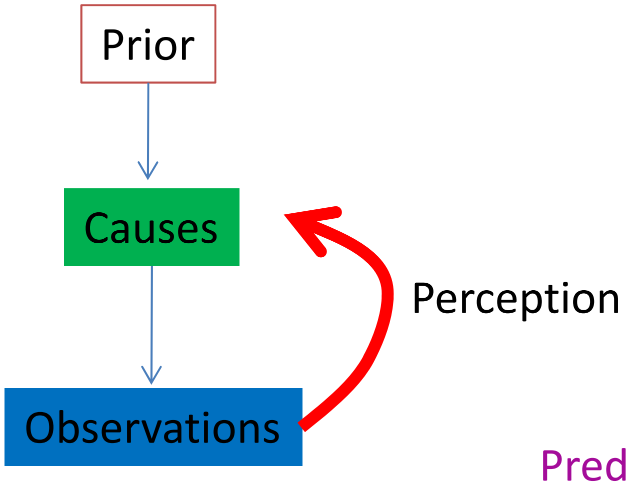
Understanding cognition. What is the problem?

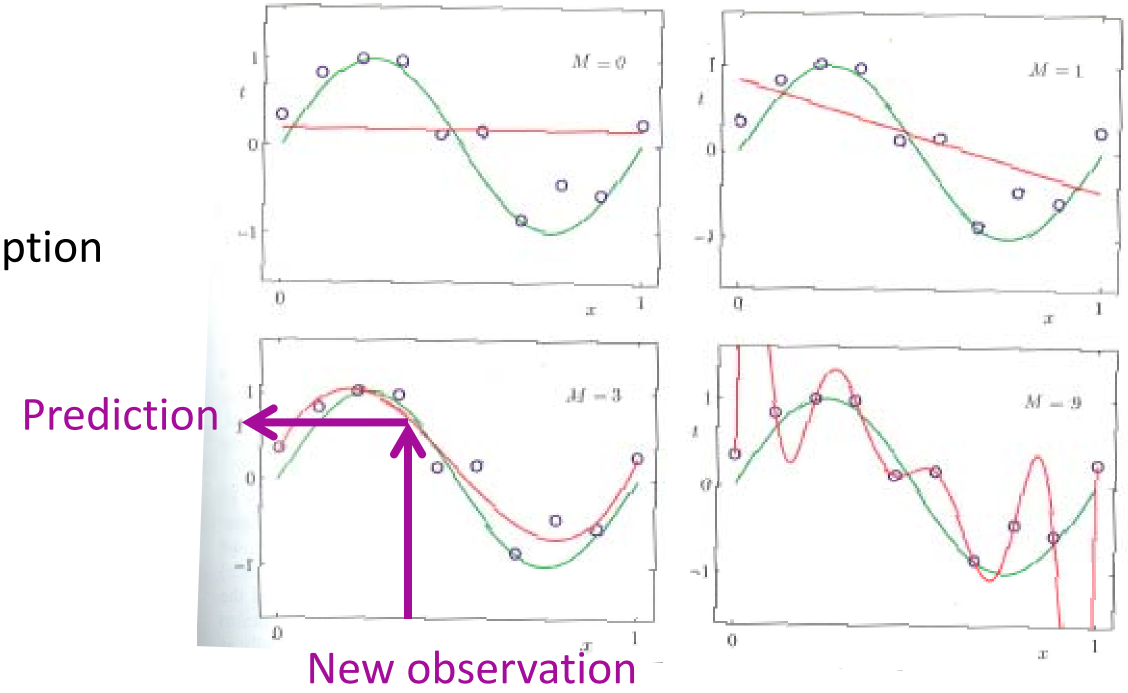




Machine learning

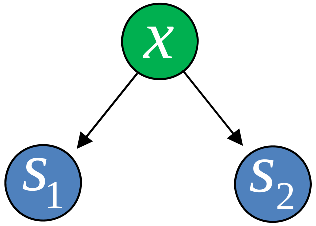
Understanding cognition. What is the problem?





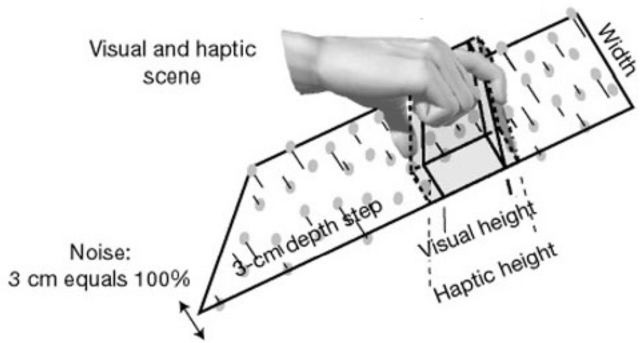
Machine learning

Example: integrating information from multiple sources



Kording and Wolpert, 2004.

Van Beers, Sittig and Gon, 1999, Ernst and Banks 2002



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

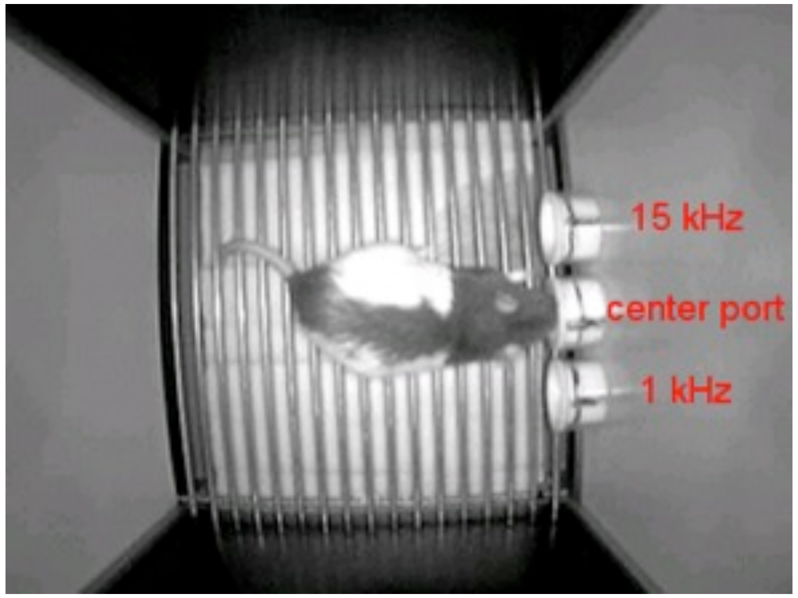
What we understand now

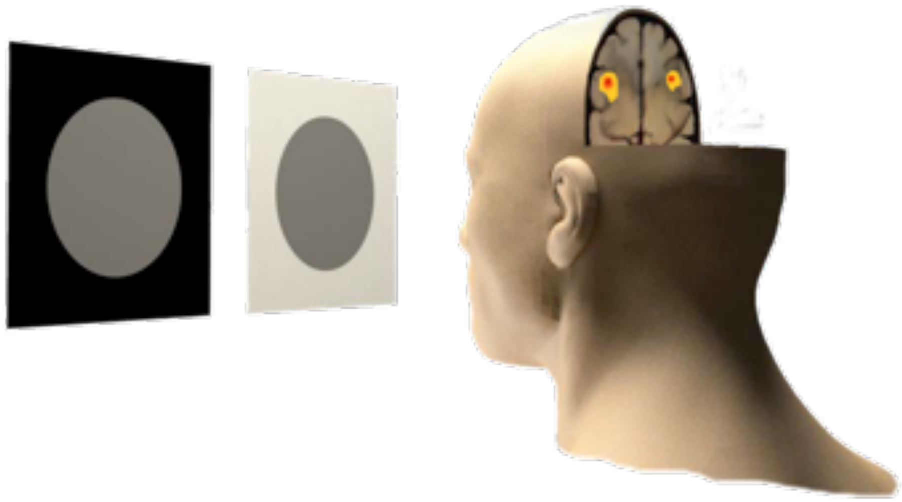
very little

What we need

- biologists
- psychologists

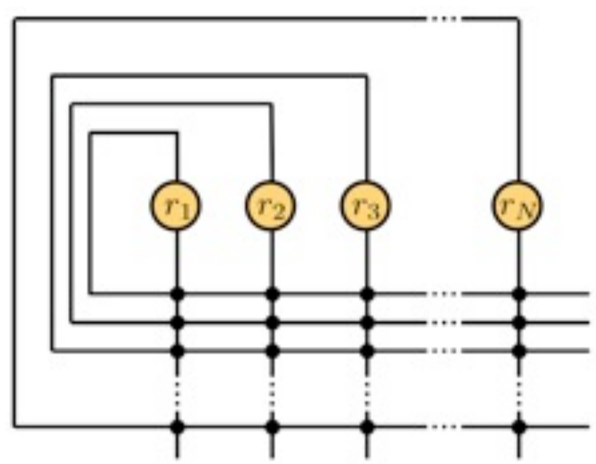




- to probe the brains of animals and humans
- to design and carry out clever experiments
- to investigate and quantify human and animal behavior

What we need

- physicists, computer scientists, engineers, etc.



$$\dot{r}_1 = -r_1 + f\Big(\sum_{j=1}^{N} w_{1j} r_j + E_1\Big)$$

$$\dot{r}_2 = -r_2 + f\Big(\sum_{j=1}^{N} w_{2j} r_j + E_2\Big)$$

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

Teaching in the Cogmaster

Computational Neuroscience

Core classes

- AT2: Atelier Comput. Neuroscience- V Benichoux. S2
- CO6: Introduction to Comput. Neuroscience – R Brette, B Gutkin, S Deneve. S2
- CA6(a): Theoretical Neuroscience- JP Nadal, N Brunel, R Brette, G Mongillo. S1
- CA6(b): Seminar in Quantitative Neuroscience- S Deneve, B Gutkin. S1
- CA6(c): Machine learning applied to cognition- F Bach, S Deneve. S2

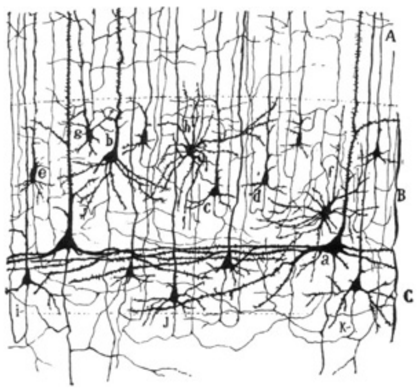
Many more classes available!!

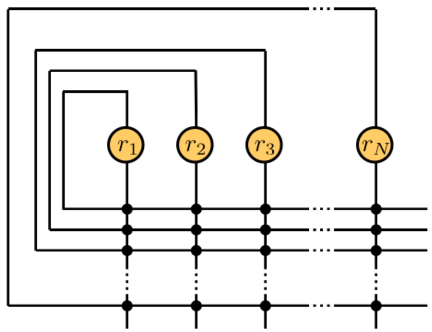
see cogmaster website!!
contact us!!

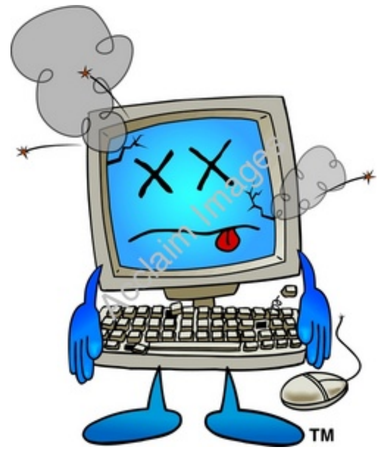
M1

AT2 Atelier théorique neuromodélisation

S2







What you need

- Basic math skills
  (ask if you are uncertain!)

What you get

- Education in an exciting field!
- 4 ECTS

Validation

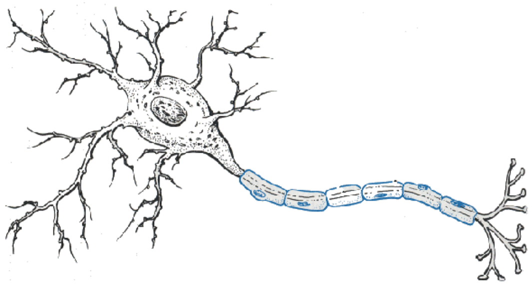
- 100% course exercises

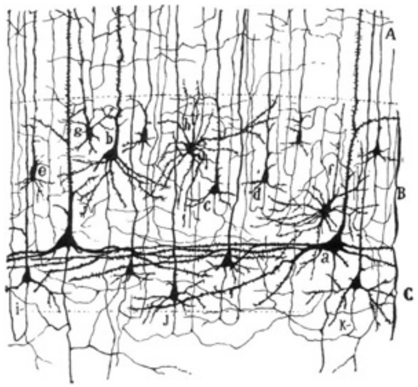
M1

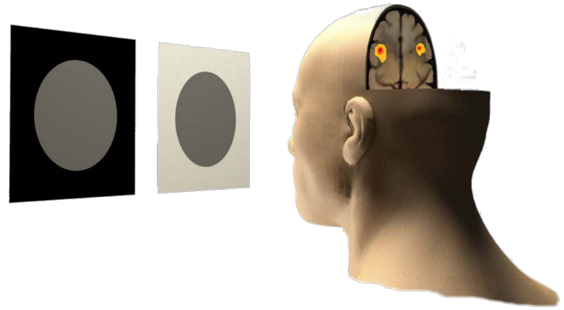
CO6 Introduction aux neurosciences computationnelles

S2

Boris Gutkin/Sophie Deneve/Romain Brette







Neurons

- Membrane voltage
- Action potentials
- Computations

Networks

- Attractors
- Associative memory
- Decision-making
- Sensory processing

Behavior

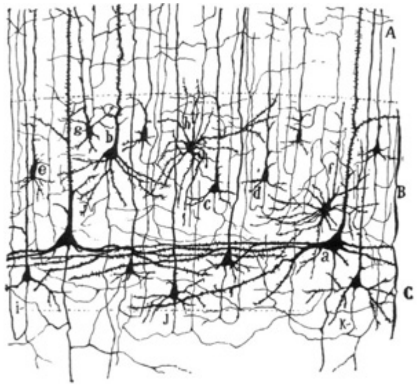
- Psychophysics
- Reinforcement Learning
- Neuroeconomics

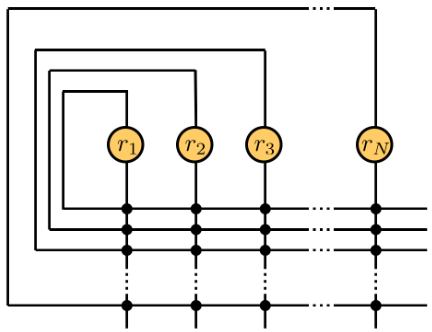
M1

CO6 Introduction aux neurosciences computationnelles

S2

Boris Gutkin/Sophie Deneve/Romain Brette





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

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

What you need

- Basic math skills
  (ask if you are uncertain!)

What you get

- Education in an exciting field!
- 6 ECTS

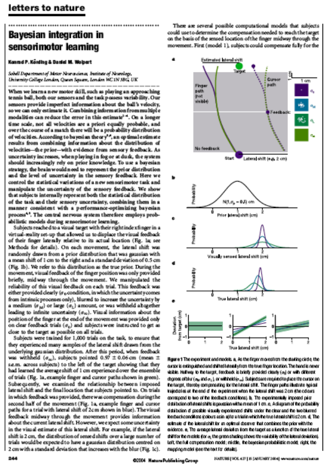
Validation

- 100% exam

M1-M2

CA6b Seminar / Journal Club
Quantitative Neuroscience

Boris Gutkin/Vincent Hakim/Sophie Deneve/Romain Brette


letters to nature

Bayesian integration in sensorimotor learning

What you need

- Basic math skills

  (ask if you are uncertain!)

What you get

- State-of-the-art science
- Learn how to give a talk
- 4 ECTS

Validation

- 50% talk
- 50 % course participation

Theoretical Neuroscience Course

Romain Brette, Nicolas Brunel, Gianluigi Mongillo, Jean-Pierre Nadal
TA: Alexis Dubreuil

1 Introduction

Lecture 1 (Sept 29) NB

2 Basic tools

2.1 Neurons

Lecture 2 (Oct 6) RB

- Spike trains: the Poisson process
- Neuronal electricity (electrodiffusion, equivalent electrical circuit, the membrane equation).
- The integrate-and-fire model (definition, firing rate, reliability of spike timing).
- The Hodgkin-Huxley model (voltage-gated channels, HH model, threshold in a 1D approximation, refractory period)
- Variations around the IF model (perfect integrator, quadratic, exponential, Izhikevich, adaptive exponential)
- Dendrites (linear cable theory, stationary response, Green function, cable equation on the dendritic tree)

2.2 Synapses

Lecture 3 (Oct 13) GM

- Basic physiological facts about chemical synaptic transmission.
  - Neurotransmitter release and post-synaptic receptor machinery.
  - The Katz synapse: quantal release, role of calcium, stochasticity.
  - The binomial model.
- Short-term synaptic plasticity
  - The Tsodyks-Markam (TM) model for STP
  - Quantal interpretation of the TM model
  - Stochastic STP model
  - Statistics of post-synaptic response as a function of pre-synaptic activity
  - Filtering properties of STP
- Long-term synaptic plasticity
  - Phenomenological models of STDP
  - Role of post-synaptic calcium in STDP
  - A simple phenomenological model of a bistable synapse

2.3 Learning

Lecture 4 (Oct 20) JPN

- Different types of learning : supervised, unsupervised, reinforcement learning
- Supervised learning : perceptron
- Hebbian unsupervised learning : the Oja model; link with neural coding

2.4 Coding

Lecture 5 (Oct 27) JPN

- Basic tools (Shannon information, Fisher information)
- Optimal tuning curve : Laughlin's fly
- Population coding
- Decoding, decision-making: reaction times

2.5 Networks

Lecture 6 (Nov 10) NB (Rate models, Network architectures)

- Large-scale anatomy
- Architecture of neuronal microcircuits
- Rate models

Lecture 7 (Nov 17) NB (Networks of spiking neurons)

- Local cortical networks: anatomy, physiology
- Low rate irregular activity
  - Asynchronous states in networks of spiking neurons
  - The balanced network model
  - Networks of LIF neurons
- Oscillations
  - Overview of oscillations in the nervous system
  - Overview of mechanisms
  - Oscillations in networks of LIF neurons

3 Models of specific systems

3.1 Retina

Lecture 8 (Nov 24)

3.2 Primary visual cortex

Lecture 9 (Dec 1)

3.3 Auditory system

Lecture 10 (Dec 15)

3.4 Association cortex

Lecture 10 (Dec 8)

3.5 Hippocampus

Lecture 11 (Jan 5)

3.6 Cerebellum

Lecture 13 (Jan 12)

CA6(c) Machine learning applied to cognition

Enseignants: Francis Bach, Sophie Deneve S2

1. **Probabilistic methods.**
   Prior, posterior, likelihood, Generative models, maximum likelihood.
   Application: Cue combination in behavior and cortical networks.

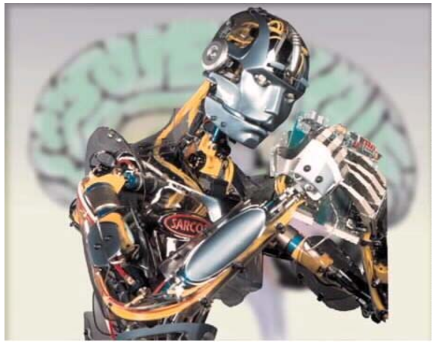
   2. Representational learning (unsupervised learning)
   Information maximization, Principle component analysis (PCA), Independent component analysis (ICA), sparse coding.
   Application: sensory receptive fields.
   Methods: PCA, ICA, CCA, sparse coding

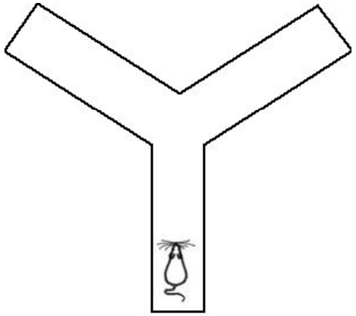
   3. Supervised learning (classification/regression).
   Linear classifiers, Gaussian mixtures, support vector machines (linear and non-linear).
   Applications: Reading out the mind. Object recognition.
   Methods: SVM, logistic, k-NN, Cart, neural networks

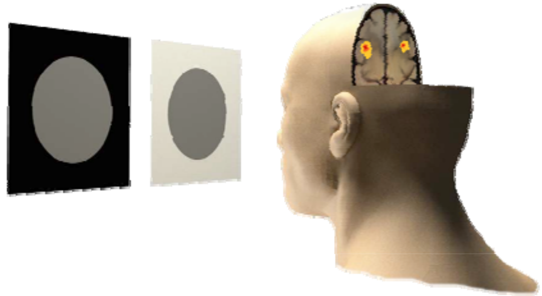
4. **Interpolation.**
   Gaussian processes, density estimation, Expectation/maximization.
   Application: Unsupervised learning in humans and animals.
   Methods: Parzen, k-means, GMM

M2 CA6(c) Machine learning applied to cognition

F Bach, G Obozinski, N le Roux, S Deneve







Learning in machine

- Bayesian networks
- Sparse coding
- SVM

Learning in Behavior

- Unsupervised
- Supervised
- Hierarchy
- Internal models

Neural implementation

- Receptive fields
- Sensory representation
- Neural code

Brain machine interface

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.)

Computational Neuroscience Groups, ENS

Group for Neural Theory, DEC

Boris Gutkin
Sophie Deneve
Srdjan Ostrojic

Neurocomputation, Equipe Audition, DEC

Romain Brette

Computational Neuroscience, LPS, Physics

Vincent Hakim
Jean-Pierre Nadal
Rava da Silveira

Frontal Lobe Function Group, LNC, DEC

Etienne Koechlin

Neuromathcomp, Dept of Computer Science, ENS

O Faugeras

Group for Neural Theory

- Boris Gutkin:
  - Dynamics of Neuronal Activity, Addiction Models, Oscillations in Speech Processing and Memory
- Sophie Deneve:
  - Bayesian Theory of Sensory Processing, Bayesian Theory of Neuronal Dynamics, Computational Psychiatry
- Srdjan Ostrojic:
  - Models of Oscillatory Dynamics, Models of Sequence learning and decision making

Neurocomputation, Equipe Audition

- Romain Brette
  - spike-based computation in the auditory system (especially sound localization and pitch perception).
  - spiking neuron models (including threshold dynamics)
  - simulation of spiking neural networks (in particular the Brian simulator)

Frontal Lobe Function Group, LNC, DEC

- Etienne Koechlin
  - Information value learning in human prefrontal cortex
  - executive and motivational control during decision making

Laboratoire de Physique Statistique (LPS)
Ecole Normale Supérieure
24, rue Lhomond – 75005 Paris

Neurosciences computationnelles, biophysique théorique

Computational neuroscience, theoretical biology

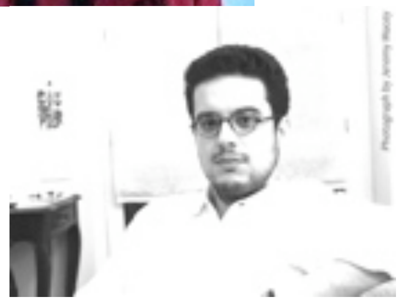
Rava da Silveira	*theoretical neuroscience*
Simona Cocco	*theoretical biophysics (DNA, neurons,...)*
Vincent Hakim	*theoretical biology, theoretical neuroscience*
Thierry Mora	*theoretical biophysics*
Jean-Pierre Nadal	*theoretical neuroscience, complex systems*
Jacques Ninio	*experimental psychophysics, theoretical biology*

Team **Complex networks and cognitive systems**
http://www.lps.ens.fr/~risc/rescomp/

Contacts:
nadal@lps.ens.fr
hakim@lps.ens.fr

Computational Neuroscience, LPS, Physics

- Vincent Hakim
  - Neuronal synchronization, dynamics of neural ensembles
  - Cerebellar processing
- Jean-Pierre Nadal
  - Information processing in biological systems
  - Complex systems in cognitive and social sciences
- Rava da Silveira
  - computation and adaptation in single neurons
  - coding of information in the brain
  - molecular machinery at synapses



Laboratory of Neurophysics and Physiology

CNRS - Université Paris Descartes

45 rue des Saints Pères, 75006 Paris

People

Carl van Vreeswijk 

Claude Meunier 

David Hansel 

Gianluigi Mongillo 

Nicolas Brunel 

Research interests

- Single neuron dynamics: C. van Vreeswijk, N.Brunel, C.Meunier
- Network dynamics: C. van Vreeswijk, N.Brunel, D.Hansel, G.Mongillo
- Models of specific systems:
  - Spinal cord (C.Meunier, collaboration with experimental group of D.Zytnicki)
  - Visual cortex (D.Hansel and C.van Vreeswijk, collaboration with experimental group of L.Nowak (Toulouse); N.Brunel, collaboration with experimental group of N.Logothetis (Tubingen))
  - Motor cortex (C.van Vreeswijk, collaboration with experimental group of C.Capaday (Copenhagen))
  - Cerebellum (N Brunel, collaboration with V Hakim, JP Nadal, and experimental groups of B Barbour, S Dieudonné, C Léna (ENS)
  - Basal ganglia (D Hansel, collaboration with experimental groups of T Boraud (Bordeaux) and H Bergman (Jerusalem))

Laboratory for Computational Neuroscience

Unit de Neurosciences, Information and Complexit (UNIC)

CNRS

91198 Gif-sur-Yvette

People

Alain Destexhe

Michelle Rudolph

The articles you have read:

Neural coding

WT Newsome, KH Britten, JA Movshon
Neuronal correlates of a perceptual decision

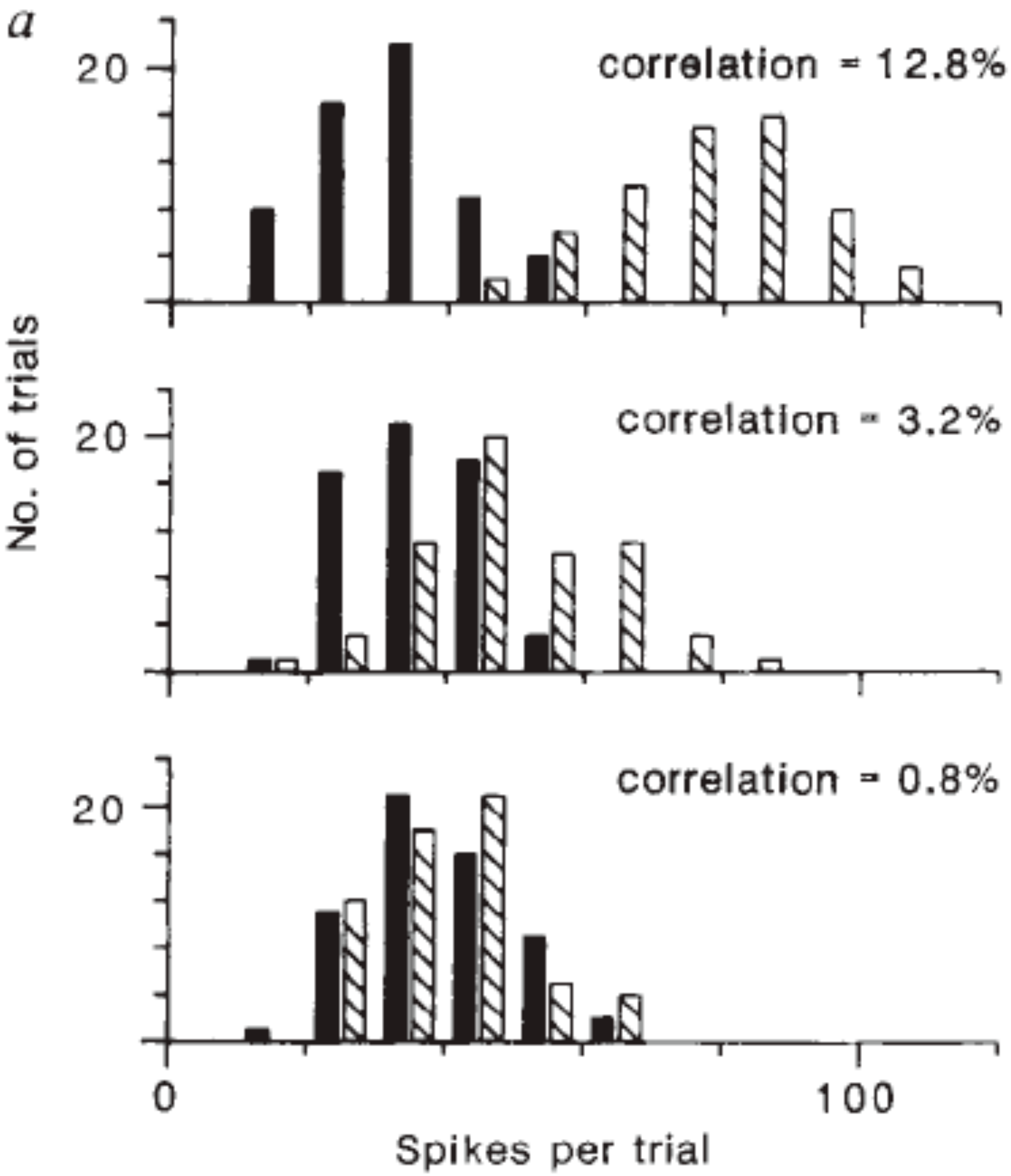
Reinforcement Learning

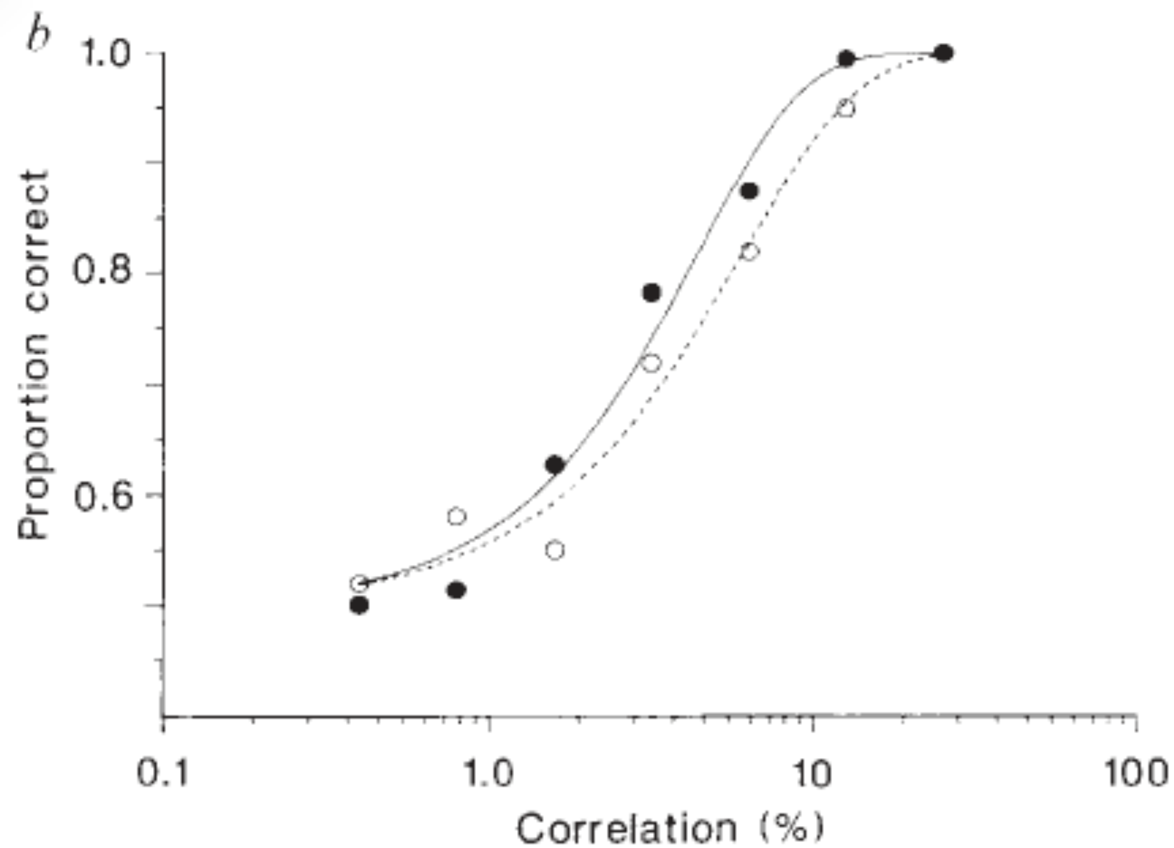
W Schultz, P Dayan, PR Montague
A neural substrate of prediction and reward

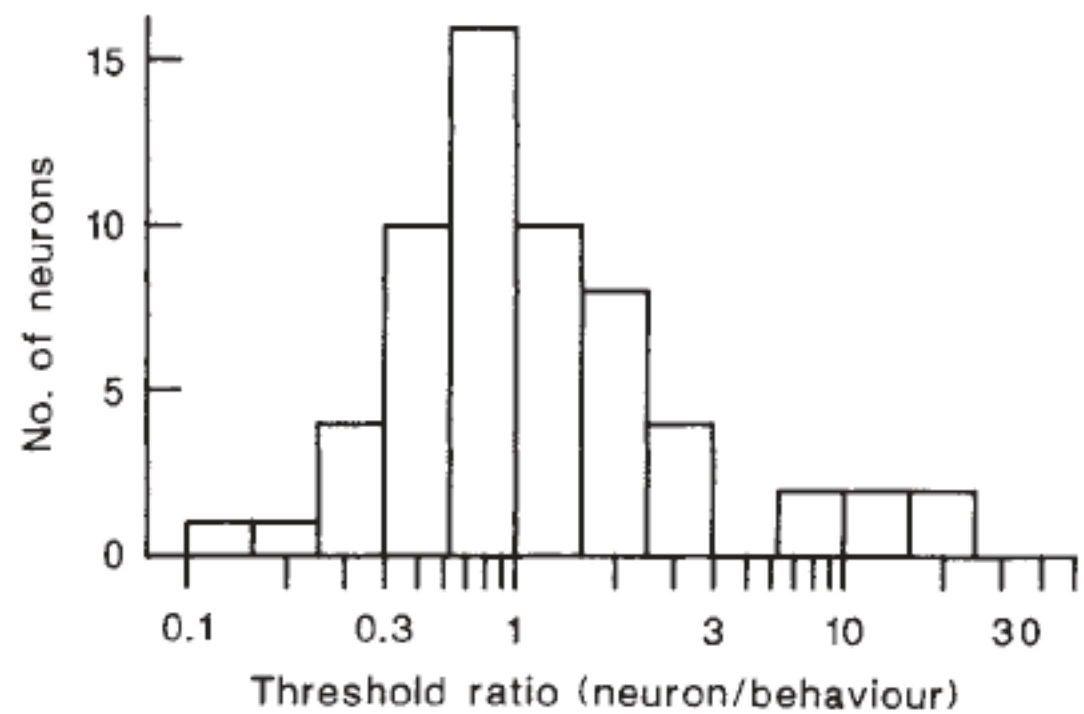
Neuronal correlates of a perceptual decision

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

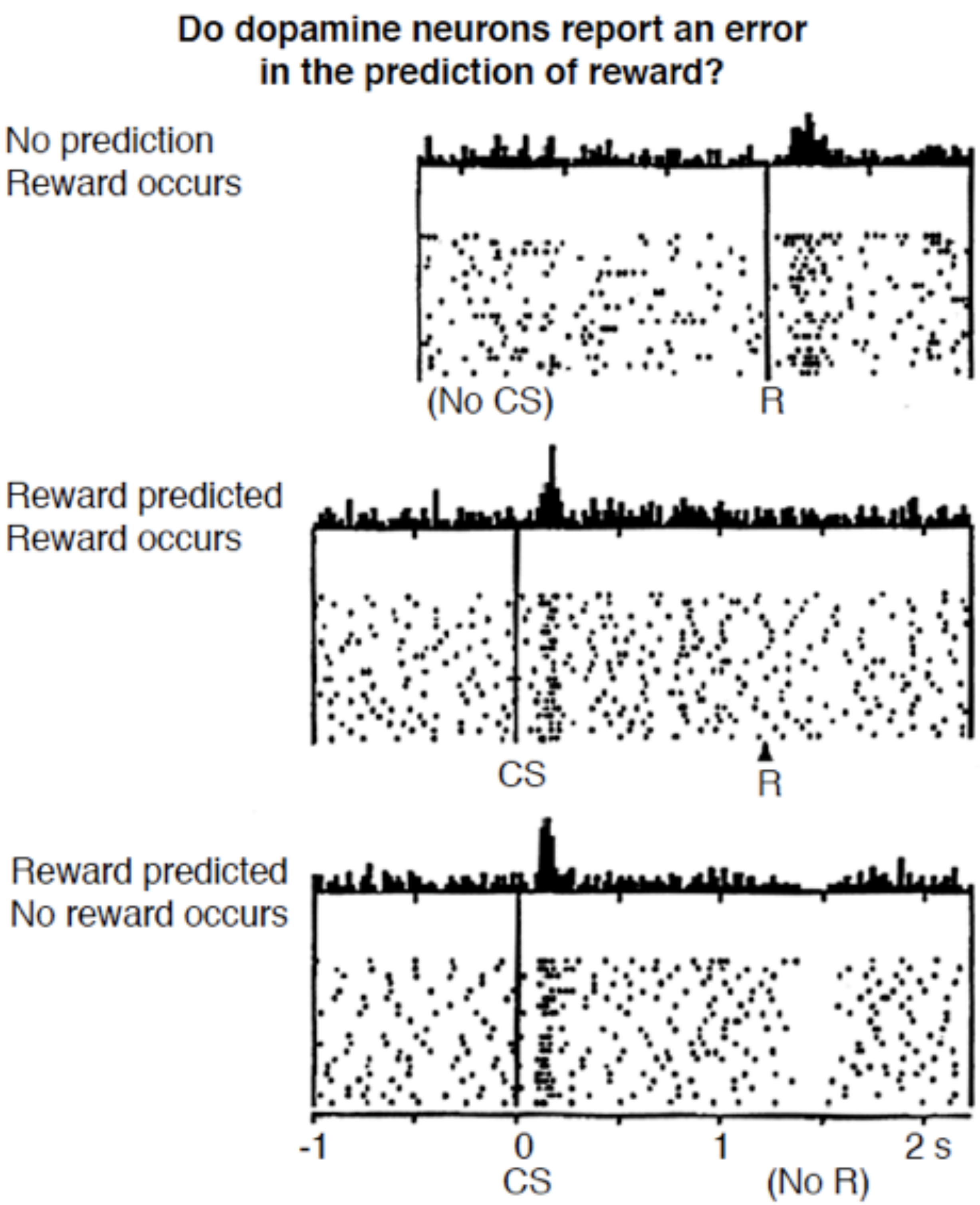


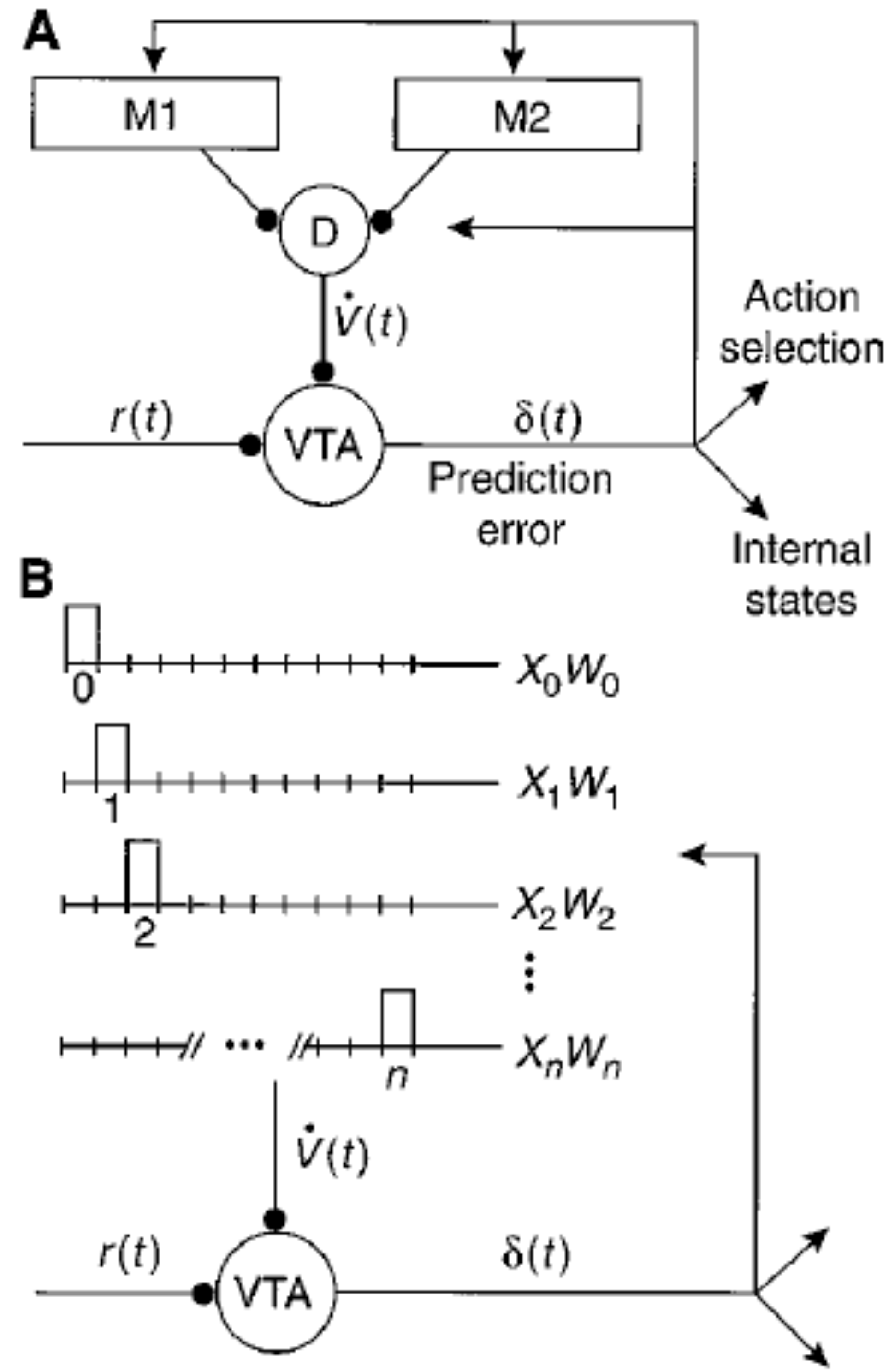




A Neural Substrate of Prediction and Reward

Wolfram Schultz, Peter Dayan, P. Read Montague*





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!

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!

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)

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!

how much information does the population contain?

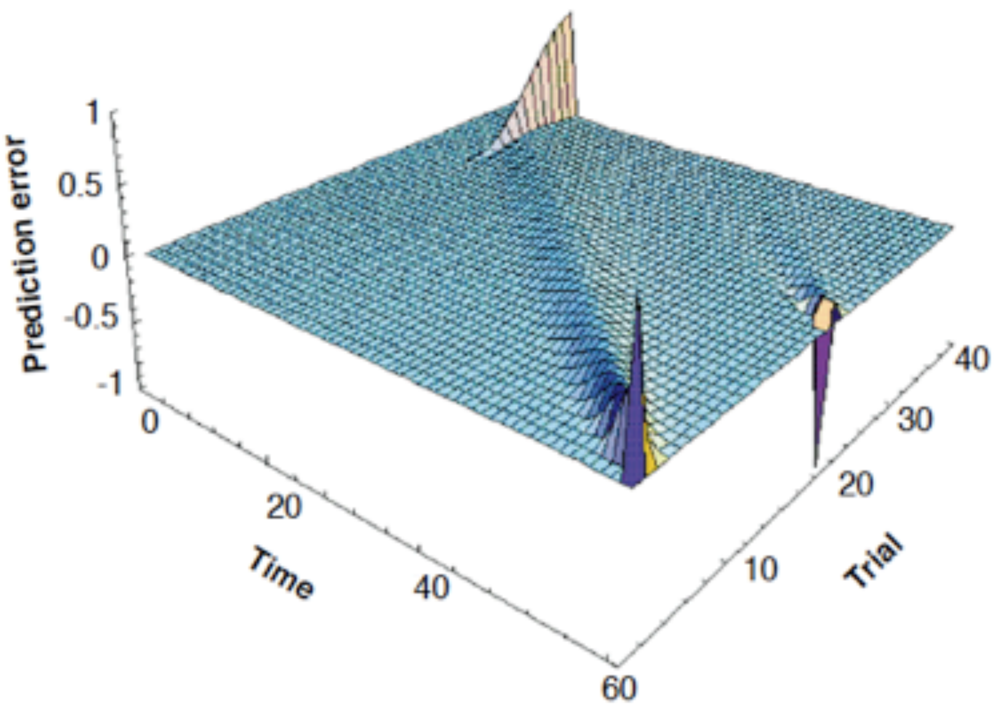
Population codes are complicated because you cannot just add the information from different neurons if these are correlated (if they carry redundant information)

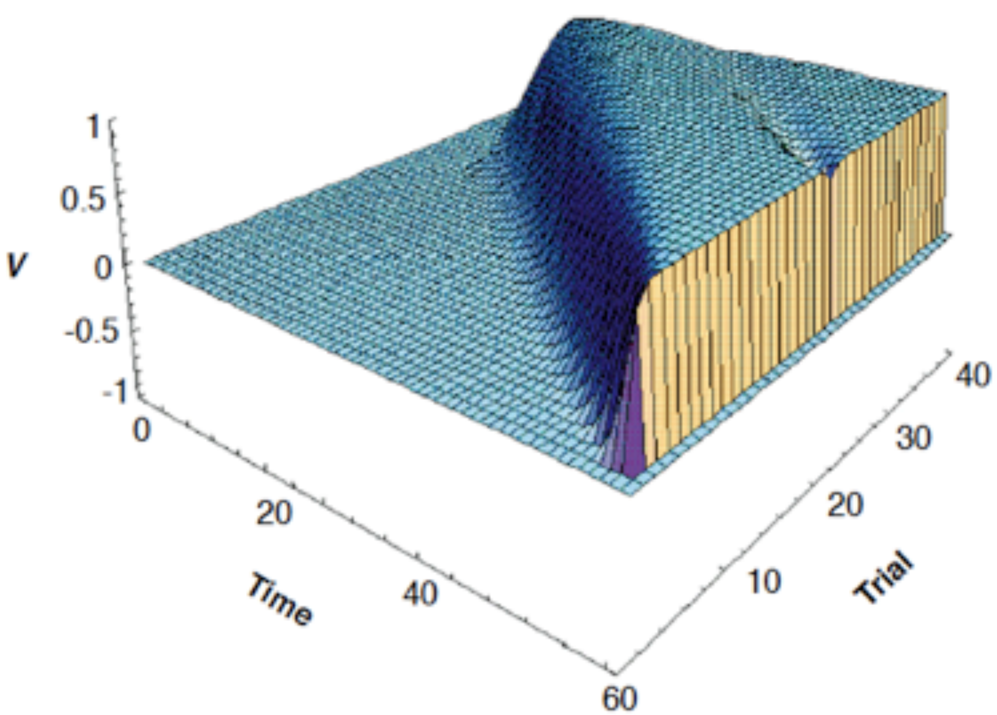
on what time scales is information represented?

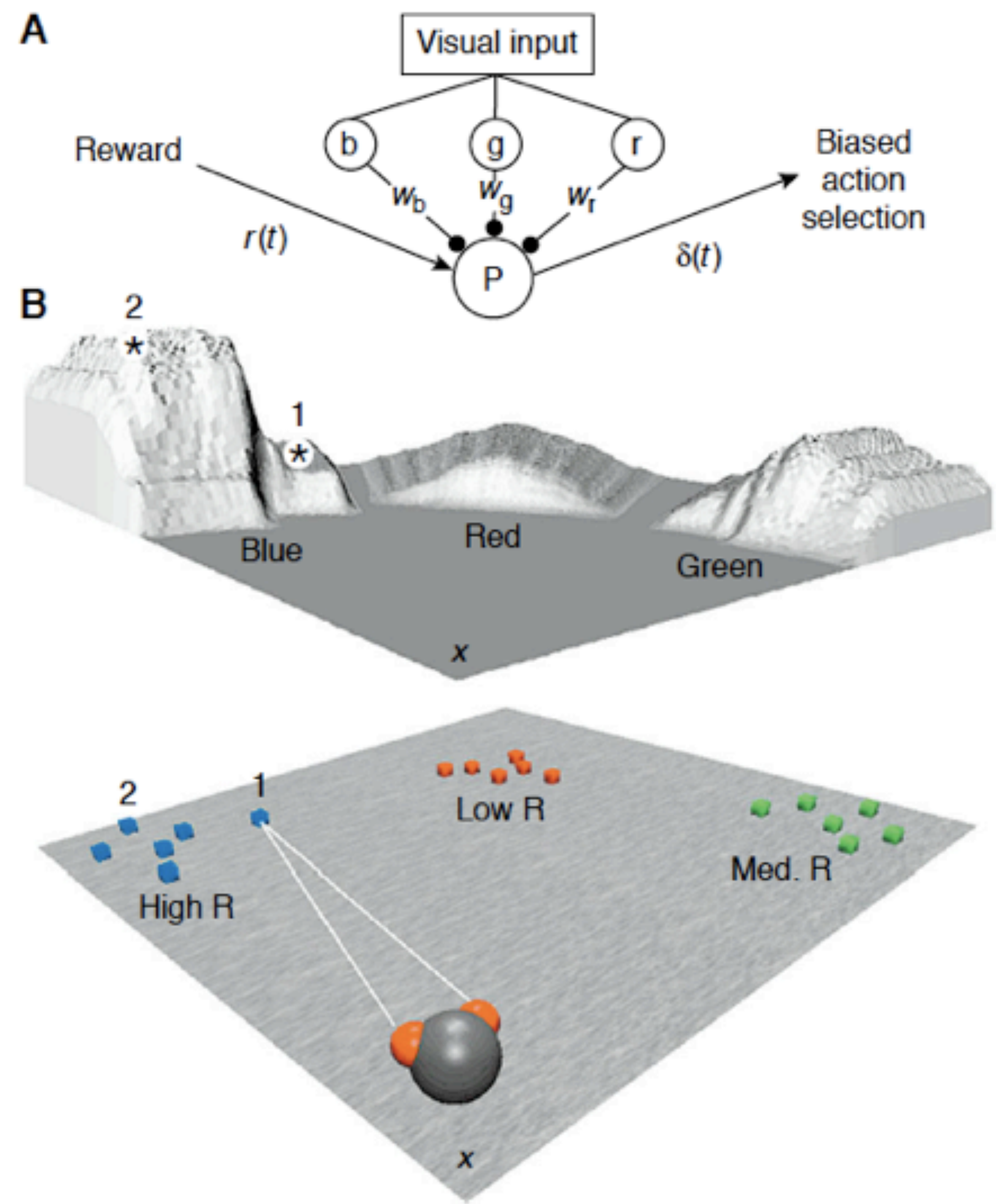
In the article, stimuli are 2 sec long! But monkeys (and humans) integrate motion over much shorter time scales (100s of millisec) - then each neuron contributes less info!

A Neural Substrate of Prediction and Reward

Wolfram Schultz, Peter Dayan, P. Read Montague*







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

Edward Thorndike
(1874-1949)

Psychology of Animal Learning

Optimal Control Theory

Richard Bellman
(1920-1984)

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-???)

Artificial Intelligence (Machine Learning)

Marvin Minsky
(1927-???)

Harry Klopf
(1927-???)