A brief introduction to Computational Neuroscience

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

Tuesday, September 14, 2010
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?
What’s the brain made of?

- Neurons
- Synapses
- Molecules

Dimensions:
- 100 μm
- 1 μm
- 1 nm
What’s the brain made of?

Maps
Networks
Neurons
Synapses
Molecules

1 cm
1 mm
100 μm
1 μm
1 nm
What’s the brain made of?

- CNS
- Systems
- Maps
- Networks
- Neurons
- Synapses
- Molecules

Dimensions:
- 1 m
- 10 cm
- 1 cm
- 1 mm
- 100 μm
- 1 μm
- 1 nm

Tuesday, September 14, 2010
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
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
- Systems
- Maps
- Networks
- Neurons
- Synapses
- Molecules

1 nm
1 μm
100 μm
1 nm
1 μm
1 cm
10 cm
1 m

Tuesday, September 14, 2010
Reconstructing circuits
Serial Blockface Scanning Electron Microscopy

courtesy of W. Denk

Tuesday, September 14, 2010
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/
The theory of neural networks

Neurons, synapses $\rightarrow$ 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 \( N \to \infty \)
- 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
- ...

Tuesday, September 14, 2010
The quest for mechanisms:
Constructing systems from parts

- CNS
- Systems
- Maps
- Networks
- Neurons
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- Molecules

1 m
10 cm
1 cm
1 mm
100 μm
1 μm
1 nm
The quest for mechanisms: Constructing systems from parts
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

Tuesday, September 14, 2010
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  
+ 0011110

XXIX  
+ XXXIX  
------

-------

62  
00111110
Representations can ease certain computations

Example numbers:

XXIII
23
00010111

in ...?
in multiples of 10
in multiples of 2

Can you add these numbers?

29
+ 35
---
62
easy

00011101
+ 00100001
----------
00111110
easy

XXIX
+ XXXIII
--------
difficult

000111110
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?

Prior

Causes

Nervous system

Observations

Machine learning
Understanding cognition.

What is the problem?

Prior Causes

Perception

Prediction

Observations

New observation

Machine learning
Example:

Integrating information from multiple sources


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.

- to formulate mathematical theories of information processing
- to create biophysical models of neural networks
Teaching in the Cogmaster
Computational Neuroscience
Core classes

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\text{Comput.}

Neurosc

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V

Benichoux.

\text{• CO6: Introduction to Comput. Neuroscience} – Brette, Gutkin, S.

\text{• CA6 (a): Theoretical Neuroscience} – Nadal, Brunel, R., Brette, G., Mongillo.

\text{• CA6 (b): Seminar in Quantitative Neuroscience} – S.

\text{• CA6 (c): Machine learning applied to cognition} – Bach, S.

\text{• CA6 (d):}
Many more classes available!!

see cogmaster website!!
contact us!!
Atelier théorique
neuromodélisation

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
Introduction aux neurosciences computationnelles

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
What you need

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

What you get

- Education in an exciting field!
  - 6 ECTS

Validation

- 100% exam

\[
\begin{align*}
\dot{r}_1 &= -r_1 + f \left( \sum_{j=1}^{N} w_{1j} r_j + E_1 \right) \\
\dot{r}_2 &= -r_2 + f \left( \sum_{j=1}^{N} w_{2j} r_j + E_2 \right)
\end{align*}
\]
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

1. Probabilistic methods.

2. Representational learning


   - Interpolation.
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
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.)
Group for Neural Theory, DEC

Neurocomputation, Equipe Audition, DEC

Computational Neuroscience, LPS, Physics

Frontal Lobe Function Group, LNC, DEC

Neuromathcomp, Dept of Computer Science, ENS
• Boris Gutkin: – Dynamics of Neuronal Activity, Addicton 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
Neurocomputations, Equipe Audion • Romain Breve – 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
  - LNC,
  - DEC

- Ennen
  - Informa
  - value
  - learning
  - in
  - human
  - prefrontal cortex
  - executive
  - and
  - motor 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
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))
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

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(a) correlation = 12.8%

(b) Proportion correct vs. Correlation (%)
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?

---

A

M1

M2

D

\( \dot{V}(t) \)

\( r(t) \)

\( \delta(t) \)

Action selection

Internal states

---

B

\( X_0 W_0 \)

\( X_1 W_1 \)

\( X_2 W_2 \)

\( \vdots \)

\( X_n W_n \)

\( r(t) \)

\( \dot{V}(t) \)

\( \delta(t) \)
The Quest for the Neural Code

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

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

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

Psychology of Animal Learning

Edward Thorndike (1874-1949)

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Optimal Control Theory
Richard Bellman
(1920-1984)
How behaviors are learned

- Psychology of Animal Learning
  - Edward Thorndike (1874-1949)

- Optimal Control Theory
  - Richard Bellman (1920-1984)

- Artificial Intelligence (Machine Learning)
  - Marvin Minsky (1927-???)
  - Harry Klopf (1927-???)
How behaviors are learned

Psychology of Animal Learning

Optimal Control Theory

Reinforcement Learning

Artificial Intelligence (Machine Learning)

Edward Thorndike (1874-1949)

Marvin Minsky (1927-???)

Harry Klopf (1927-???)

Richard Bellman (1920-1984)

Richard Sutton (1956-???)

Andrew Barto (1948-???)

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