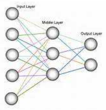
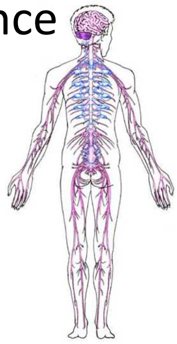
CISC 3250
Systems Neuroscience



Professor Daniel Leeds
dleeds@fordham.edu
JMH 328A

Systems Neuroscience

- How groups of neurons work together to achieve intelligence
- How the nervous system performs computations

- Requirement for the Integrative Neuroscience major
- Elective in Computer and Information Science

Objectives

To understand information processing in biological neural systems from computational and anatomical perspectives

- Understand the function of key components of the nervous system
- Understand how neurons interact with one another
- Understand how to use computational tools to examine neural data

Recommended student background

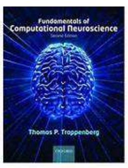
Prerequisite:

- Officially: CISC 2500 Data and Information Management
- Unofficially: CISC 2500, or Bioinformatics, or Data Mining or Computer Science I

Math	Computer science
Some calculus	Some programming

Textbook(s)

Fundamentals of Computational Neuroscience, Second Edition, by Trappenberg



- **Suggested**
- We will focus on the ideas and study a relatively *small set* of equations

Computational Cognitive Neuroscience, by O'Reilly et al.

- **Optional**, alternate perspective

Website

http://storm.cis.fordham.edu/leeds/cisc3250/

Go online for

- Lecture slides
- Assignments
- Course materials/handouts
- Announcements

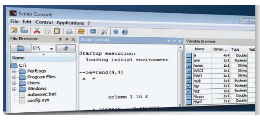
Requirements

- Attendance and participation
  - 1 unexcused absence allowed
  - Ask and answer questions in class
- Homework: Roughly 5 across the semester
- Exams
  - 2 midterms, in February and April
  - 1 final, in May
- Don't cheat
  - You may discuss homeworks with other students, but your submitted work must be your own

7

Software

We will use Scilab – an environment for numeric analyses and computational modeling.



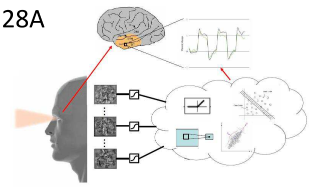
- Free
- Runs on all popular operating systems
- Similar to the very-popular Matlab®

http://www.scilab.org

8

Your instructor

- Prof. Daniel Leeds
- E-mail: dleeds@fordham.edu
- Office hours: Tuesday 2-3pm, Thurs 12-1pm
- Office: 328A



computer science + psychology -> brain models

9

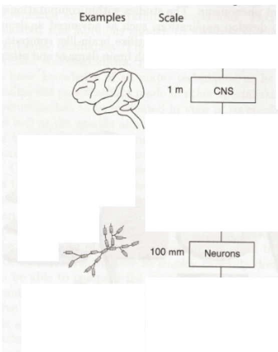
Introducing systems and computational neuroscience

- How groups of neurons work together to achieve intelligence

- How the nervous system performs computations

10

Levels of organization



11

From a psychological perspective…

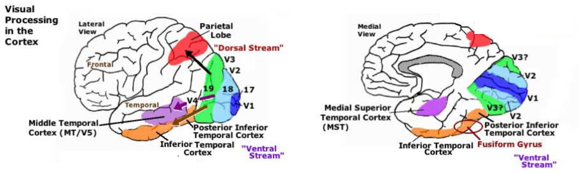
What are elements of cognition?

12

Systems neuroscience

Regions of the central nervous system associated with particular elements of cognition

- Visual object recognition

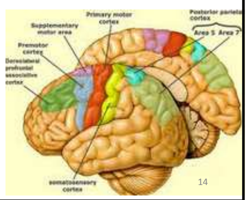


13

Systems neuroscience

Regions of the central nervous system associated with particular elements of cognition

- Visual object recognition
- Motion planning and execution
- Learning and remembering

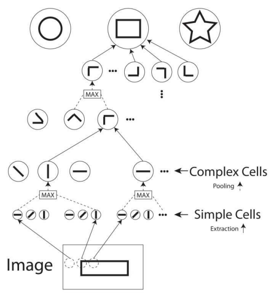


14

Computational neuroscience

Strategy used by the nervous system to solve problems

- Visual object perception through biological hierarchical model "HMAX"



15

Computational neuroscience as "theory of the brain"

David Marr's three levels of analysis (1982):

- **Computational theory:** What is the computational goal and the strategy to achieve it?
- **Representation and algorithm:** What are the input and output for the computation, and how do you mathematically convert input to output?
- **Hardware implementation:** How do the physical components perform the computation?

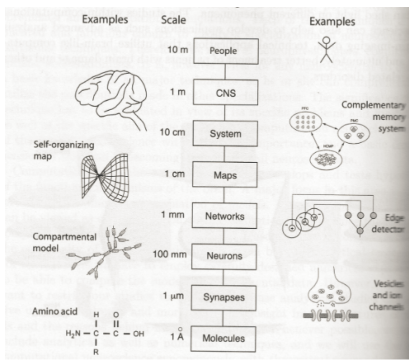
16

Marr's three levels for "HMAX" vision

- **Computational theory:** Goal is to recognize objects
- **Representation and algorithm:**
  - **Input:** Pixels of light and color
  - **Output:** Label of object identity
  - **Conversion:** Through combining local visual properties
- **Hardware implementation:**
  - Visual properties "computed" by networks of firing neurons in object recognition pathway

17

Levels of organization



18

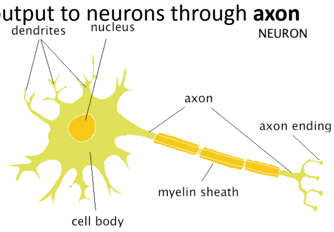
Course outline

- Philosophy of neural modeling
- The neuron – biology and input/output behavior
- Learning in the neuron
- Neural systems and neuroanatomy
- Representations in the brain
- Perception
- Memory/learning
- Motor control

19

The neuron

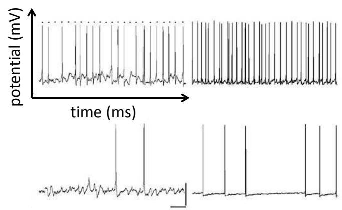
- Building block of all the systems we will study
- Cell with special properties
  - **Soma** (cell body) can have 5-100 µm diameter, but **axon** can stretch over 10-1000 cm in length
  - Receives input from neurons through **dendrites**
  - Sends output to neurons through **axon**



20

Neuron membrane voltage

- Voltage difference across cell membrane
  - **Resting potential**: ~-65 mV
  - **Action potential**: quick positive **spike** in voltage

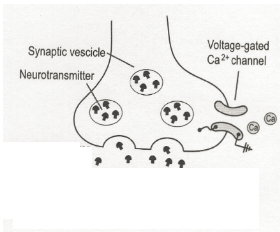


Example neural signals

21

The action potential

- Action potential begins at axon hillock and travels down axon
- At each axon terminal, spike results in release of **neurotransmitters**
- **Neurotransmitters (NTs)** attach to dendrite of another neuron, causing voltage change in this second neuron



22

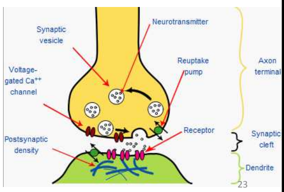
Inter-neuron communication

Neuron receives input from 1000s of other neurons

- **Excitatory** input can increase spiking
- **Inhibitory** input can decrease spiking

A **synapse** links neuron A with neuron B

- Neuron A is **pre-synaptic**: axon terminal outputs NTs
- Neuron B is **post-synaptic**: dendrite takes NTs as input



23

More on neuron membrane voltage

- Given no input, membrane stays at resting potential (~ -65 mV)

Inputs:

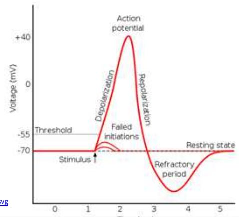
- Excitation temporarily increases potential
- Inhibition temporarily decreases potential

Continual drive to remain at rest

24

More on the action potential

1. Accumulated excitation passes certain level
2. Non-linear increase in membrane voltage
3. Rapid reset



http://commons.wikimedia.org/wiki/File:Action_potential.svg
CC User: Chris 73

Modeling voltage over time

Equations focusing on **change** in voltage *v*

Components:

- Resting state potential (voltage) E_L
- Input voltages *RI*
- Time *t*

$$\tau \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t)$$

change towards resting state — incorporate new input information

Simulation

- Initial voltage
- Time interval for update
- Input at each time

- Apply rule to compute new voltage at each time

Voltage over time: reset

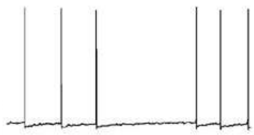
$$\tau \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t)$$

When voltage passes threshold v_{thresh}, voltage reset to v_{res}

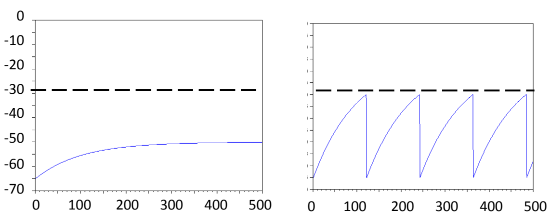
$$v(t^f)=v_{thresh}$$

$$v(t^f+\delta)=v_{res}$$

δ is small positive number close to 0



Below and above threshold

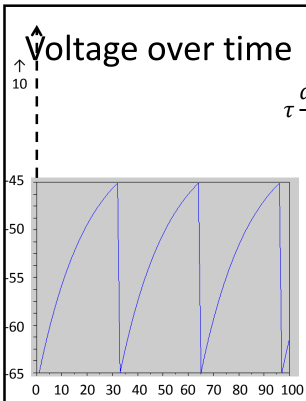


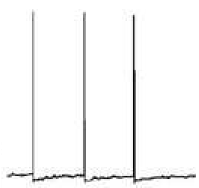
+15mv input — +50mv input

Time to spike: $t^f = -\tau_m \ln \frac{v_{thresh} - RI}{v_{res} - RI}$

Voltage over time

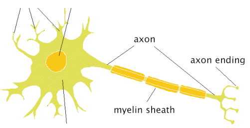
$$\tau \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t)$$

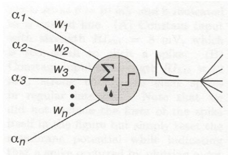




Simulated — Biological

Accumulating information over inputs





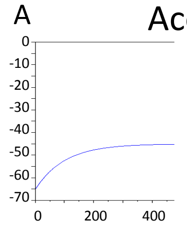
Positive and negative weighted inputs from dendrites *wα* added together:

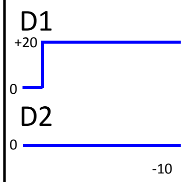
$$RI(t) = \sum_j w_j \alpha_j(t)$$

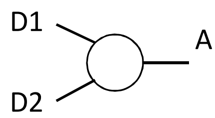
j is **index** over dendrites; first-pass model

32

Accumulating inputs

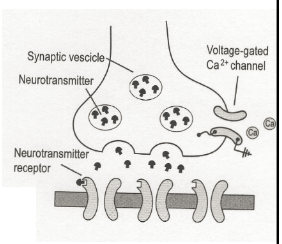






33

Chemical level: NT receptors



34

Form of dendrite input

$$\tau \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t)$$

Pre-synaptic neuron spikes

↓

Neurotransmitter (NT) released

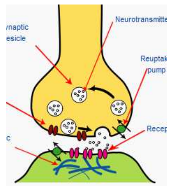
↓

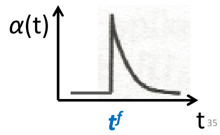
NT received by **post-synaptic** dendrite at time t^f

↓

Post-synaptic voltage rises and then fades, *α(t)*

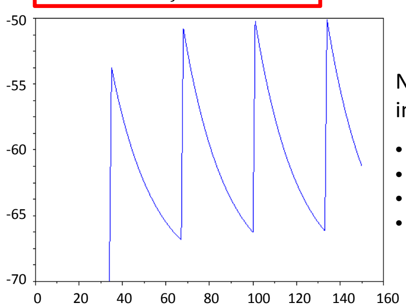
$$I(t) = \sum_j w_j \alpha_j(t)$$





35

$$RI(t) = \sum_j w_j \alpha_j(t)$$



New pre-synaptic inputs at

- 34 ms
- 68 ms
- 100 ms
- 135 ms

36

"Leaky integrate-and-fire" neuron

- Sum inputs from dendrites ("integral") $RI(t) = \sum_j w_j \alpha_j(t)$
- Decrease voltage towards resting state ("leak") $\tau \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t)$
- Reset after passing threshold ("fire") $v(t^f + \delta) = v_{res}$

37

Activation function

Often non-linear relation between dendrite input and axon output $\tau \frac{dv(t)}{dt} = -(v(t) - E_L) + g(RI(t))$

$RI(t) = \sum_j w_j \alpha_j(t)$ Sum inputs

↓

$g(RI(t))$ Apply (non-linear?) transformation to input

38

Activation function

Function type	Graphical represent.	Mathematical formula	MATLAB implementation
Linear		$g^{lin}(x) = x$	x
Step		$g^{step}(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{elsewhere} \end{cases}$	floor(0.5*(1+sign(x)))
Threshold-linear		$g^{theta}(x) = x\,\Theta(x)$	x.*floor(0.5*(1+sign(x)))
Sigmoid		$g^{sig}(x) = \frac{1}{1+\exp(-x)}$	1./(1+exp(-x))
Radial-basis		$g^{gauss}(x) = \exp(-x^2)$	exp(-x.^2)

39

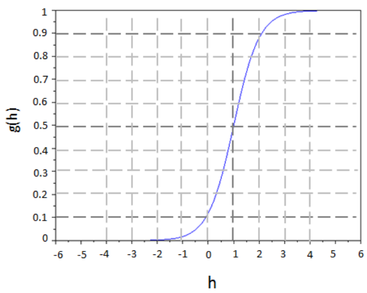
An example sigmoid

g(2)=

g(1)=

g(0)=

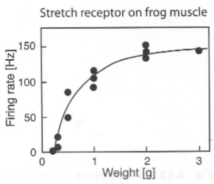
g(-4)=



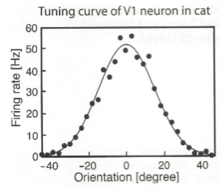
40

Tuning curves

Some single neurons fire in response to "perceiving" a quality in the world



Adrian, *J Physiol* 1926.



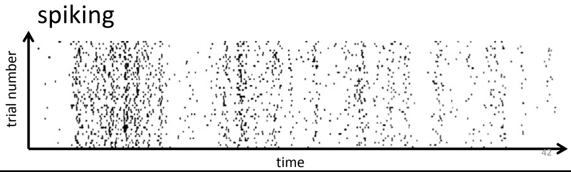
Henry et al., *J Neurophys* 1974.

41

Neural coding

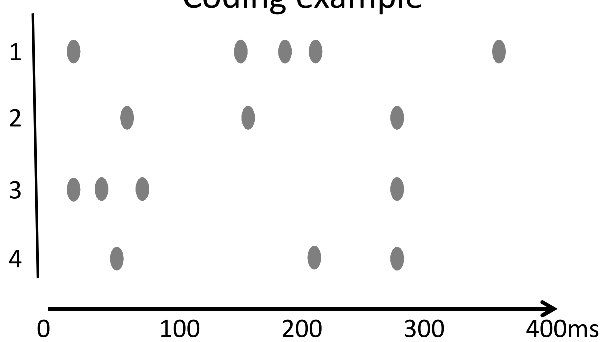
Perception, action, and other cognitive states represented by firing of neurons

- Coding by rate: high rate of pre-synaptic spiking causes post-synaptic spiking
- Coding by spike timing: multiple pre-synaptic neurons spiking together causes post-synaptic spiking



42

Coding example



43

Computing spike rate

- Add spikes over a period of time

$$v(t) = \frac{num\ spikes\ in\ \Delta T}{\Delta T}$$

- Average spikes over a set of neurons

$$A(t) = \lim_{\Delta T \to 0} \frac{1}{\Delta T} \frac{num\ spikes\ in\ N\ neurons}{N}$$

44