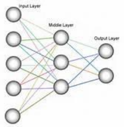
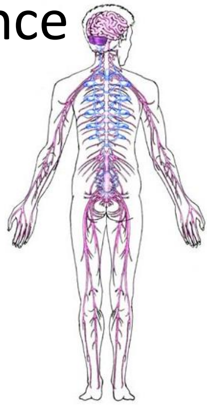
CISC 3250
Systems Neuroscience





Professor Daniel Leeds
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JMH 332

Systems (and Computational) Neuroscience

- How the nervous system performs computations
- How groups of neurons work together to achieve intelligence
- 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 to make mathematical models of cognition
- Understand how to use computational tools to examine neural data

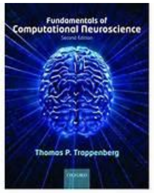
Recommended student background

Prerequisite:

- Officially: CISC 1800/1810 Intro to Programming
  or CISC 2500 Information and Data
  Management

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

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

Requirements

- Attendance and participation
  - 1 unexcused absence allowed
  - Ask and answer questions in class
- Homework: Roughly 5 across the semester
- Exams
  - 1 midterm and 1 final
  - 2 shorter quizzes
- Don't cheat
  - You may discuss course topics with other students, but you must answer homeworks yourself (and exams!) yourself

Matlab

Popular tool in scientific computing for:

- Finding patterns in data
- Plotting results
- Running simulations

Student license for $50 on Mathworks site

Available in computers at JMH 302 and LL 612

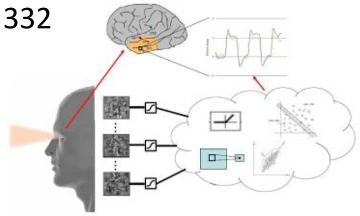
Your instructor

Prof. Daniel Leeds

E-mail: dleeds@fordham.edu

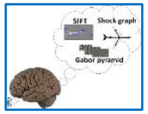
Office hours: **Mon 12-1, Thurs 2-3**

Office: JMH 332

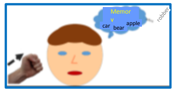


Prof. Leeds' Projects in Computational Neuroscience

- Computer vision models for cortical vision



- Effects of head trauma on cortical cognition

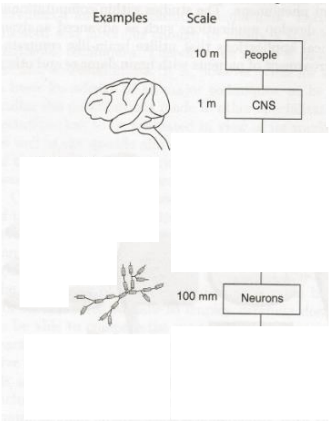


Introducing systems and computational neuroscience

- How groups of neurons work together to achieve intelligence

- How the nervous system performs computations

Levels of organization



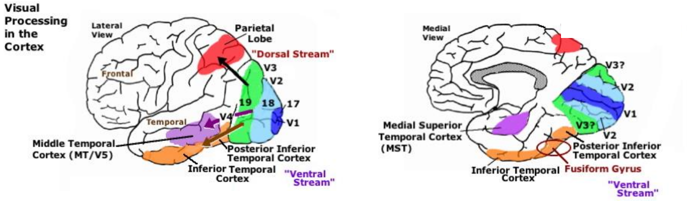
From a psychological perspective…

What are elements of cognition?

Systems neuroscience

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

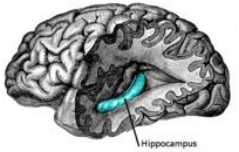
- Visual object recognition

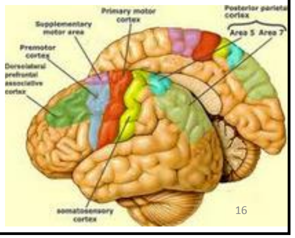


Systems neuroscience

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

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

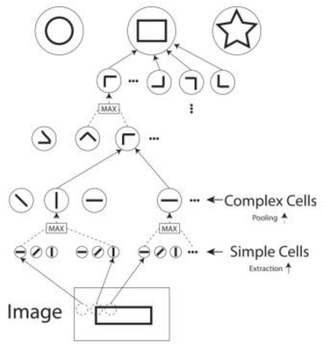




Computational neuroscience

Strategy used by the nervous system to solve problems

- Visual object perception through biological hierarchical model "HMAX"



Computational neuroscience as “theory of the brain”

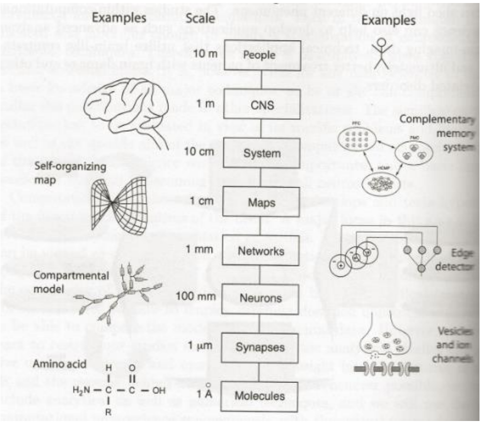
David Marr’s three levels of analysis (1982):

- **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?

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

Levels of organization



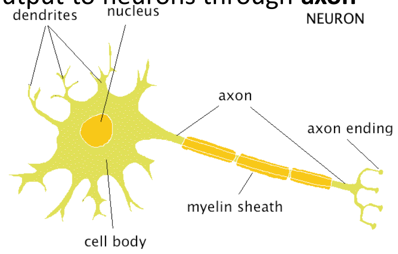
Course outline

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

Plus: Matlab programming

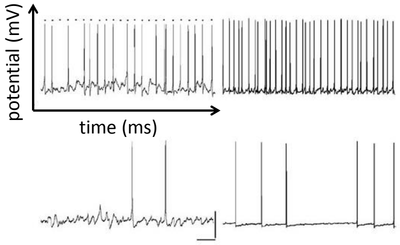
The neuron

- 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**



Neuron membrane voltage

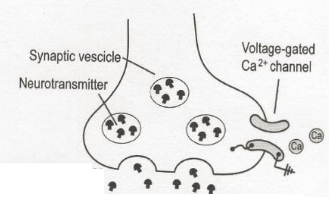
- Voltage difference across cell membrane
  - **Resting potential**: ~-65 mV
  - **Action potential**: quick upward **spike** in voltage



Example neural signals

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



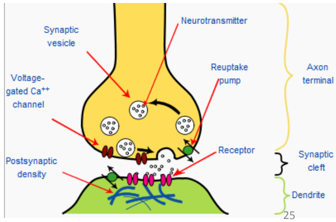
Inter-neuron communication

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



More on neuron membrane voltage

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

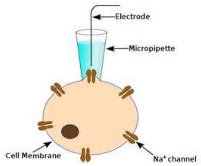
Inputs:

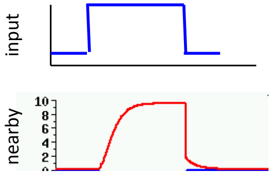
- Excitation temporarily increases potential
- Inhibition temporarily decreases potential

Continual drive to remain at rest

Patch clamp experiment

- Attach electrode to neuron
- Raise/drop voltage on electrode
- Measure nearby voltage (with another electrode)

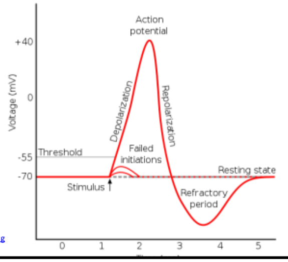




Simplification of neurophysiology experiment

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*

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

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

Applying dv/dt step-by-step

E_L=-65mV v(0ms)=-65mV τ=1
RI(t)=20mV (from t=0ms to 1000ms)
time step: 10ms

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

- v(10ms) = v(0ms) + $\frac{dv(0\text{ms})}{dt}x\frac{10}{1000}$
  = -65 + **[-(-65- -65) + 20]** x $\frac{10}{1000}$
  = -65 + **20** x $\frac{10}{1000}$
  = **-64.8**
- v(20ms) = v(10ms) + $\frac{dv(10\text{ms})}{dt}x\frac{10}{1000}$
  = -64.8 + **[-(-64.8- -65) + 20]** x $\frac{10}{1000}$
  = -64.8 + **-0.2+20** x $\frac{10}{1000}$
  = -64.8 + **19.8** x $\frac{10}{1000}$
  = **-64.602**

Applying dv/dt step-by-step

E_L=-65mV v(0ms)=-65mV τ=1
RI(t)=20mV (from t=0ms to 1000ms)
time step: 10ms

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

- v(30ms) = v(20ms) + $\frac{dv(0\text{ms})}{dt}x\frac{10}{1000}$
  = -64.602 + **[-(-64.602- -65) + 20]** x $\frac{10}{1000}$
  = -64.602 + **19.602** x $\frac{10}{1000}$
  = **-64.40598**

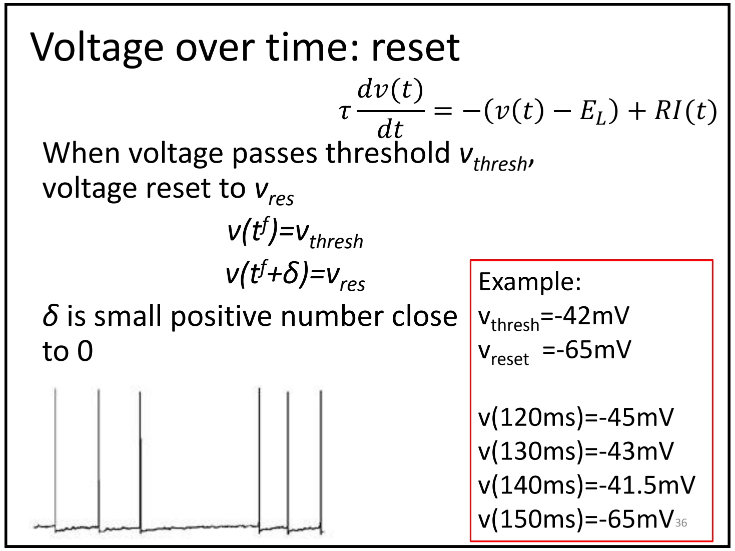
Changing model terms

τ has inverse effect

- increase τ decreases update speed
- decrease τ increases update speed

RI(t) has linear effect

- increase RI(t) increases update speed
- decrease RI(t) decreases update speed



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}

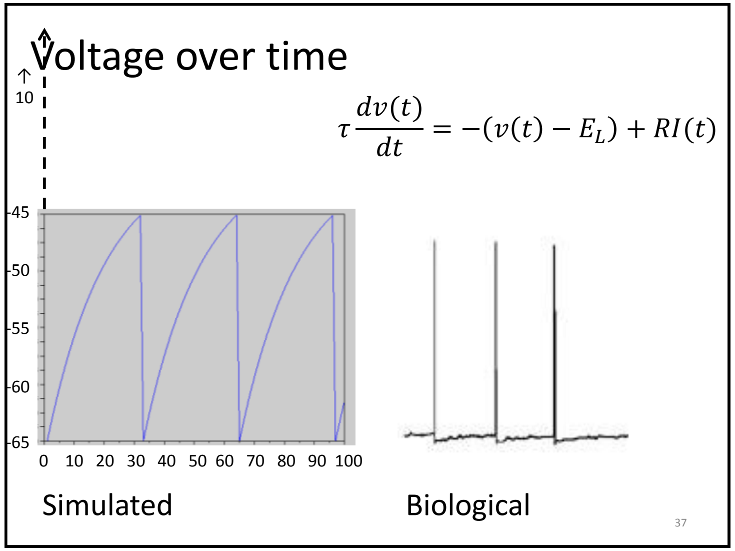
$$v(t^f)=v_{thresh}$$

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

δ is small positive number close to 0

Example:
v_{thresh}=-42mV
v_{reset} =-65mV

v(120ms)=-45mV
v(130ms)=-43mV
v(140ms)=-41.5mV
v(150ms)=-65mV

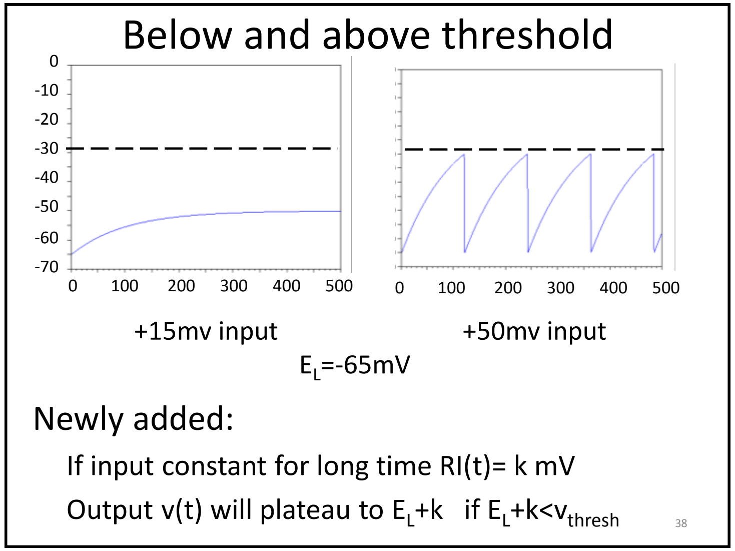


Voltage over time

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

Simulated

Biological



Below and above threshold

+15mv input

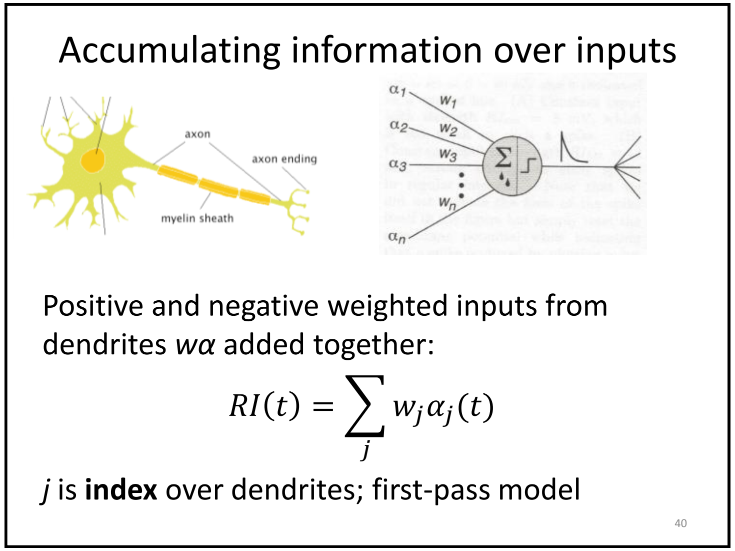
+50mv input

E_L=-65mV

Newly added:

If input constant for long time RI(t)= k mV

Output v(t) will plateau to E_L+k if E_L+k<v_{thresh}

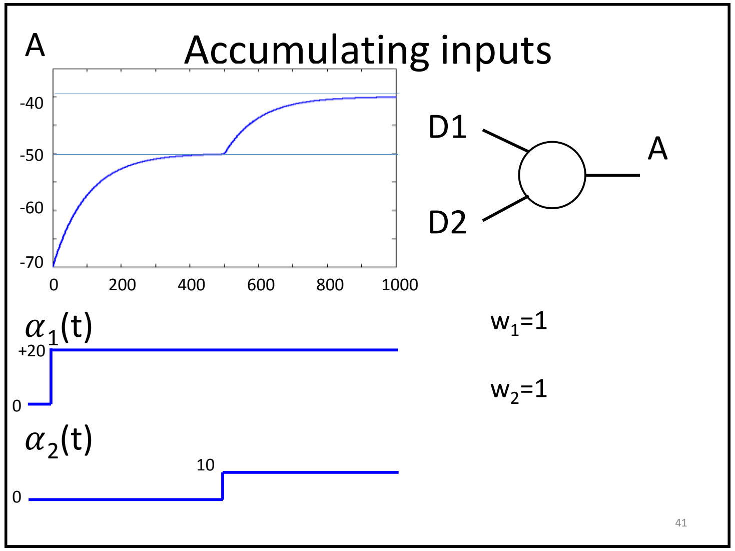


Accumulating information over inputs

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

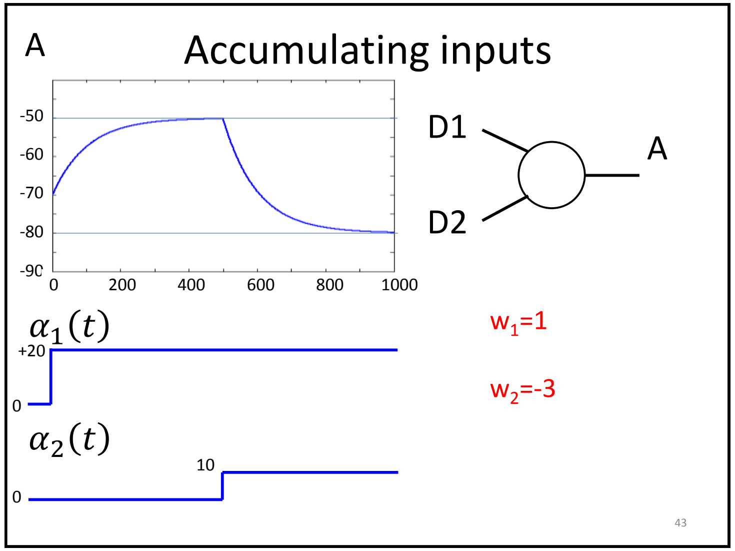


Accumulating inputs

w_1=1

w_2=1

41

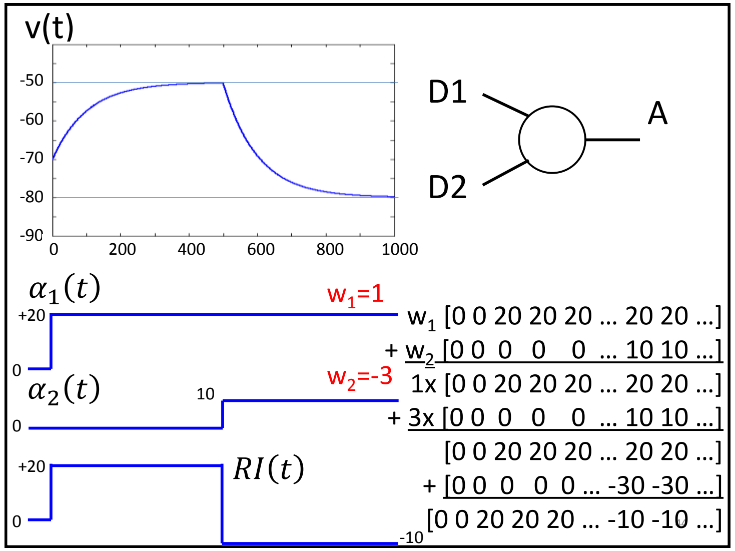


Accumulating inputs

w_1=1

w_2=-3

43



w_1=1

w_2=-3

w_1 [0 0 20 20 20 … 20 20 …]

+ $\underline{w_2\ [0\ 0\ 0\ 0\ 0\ …\ 10\ 10\ …]}$

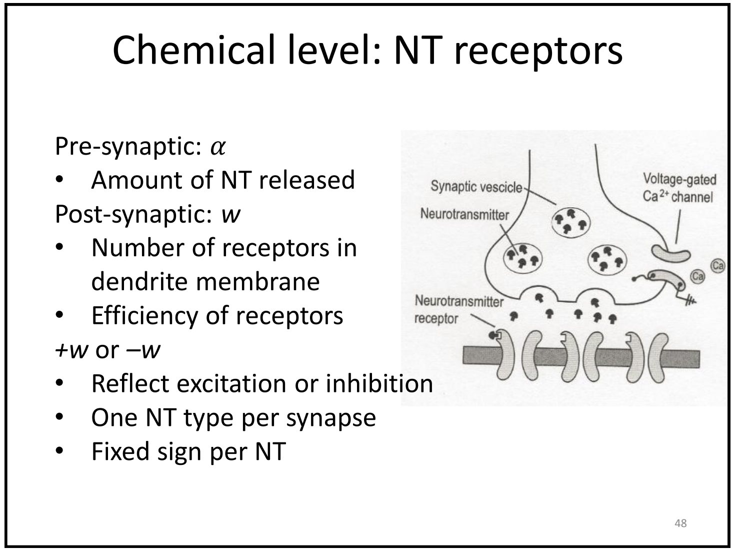
1x [0 0 20 20 20 … 20 20 …]

+ $\underline{3x\ [0\ 0\ 0\ 0\ 0\ …\ 10\ 10\ …]}$

[0 0 20 20 20 … 20 20 …]

+ $\underline{[0\ 0\ 0\ 0\ 0\ …\ -30\ -30\ …]}$

[0 0 20 20 20 … -10 -10 …]



Chemical level: NT receptors

Pre-synaptic: α

- Amount of NT released

Post-synaptic: *w*

- Number of receptors in dendrite membrane
- Efficiency of receptors

+w or *–w*

- Reflect excitation or inhibition
- One NT type per synapse
- Fixed sign per NT

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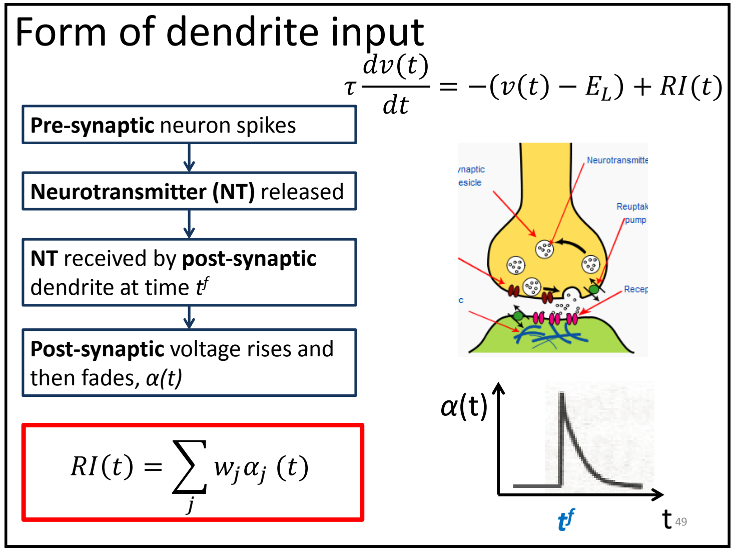

Form of dendrite input

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

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)*

$$\boxed{RI(t) = \sum_j w_j \alpha_j\ (t)}$$

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α(t)
t^f
t

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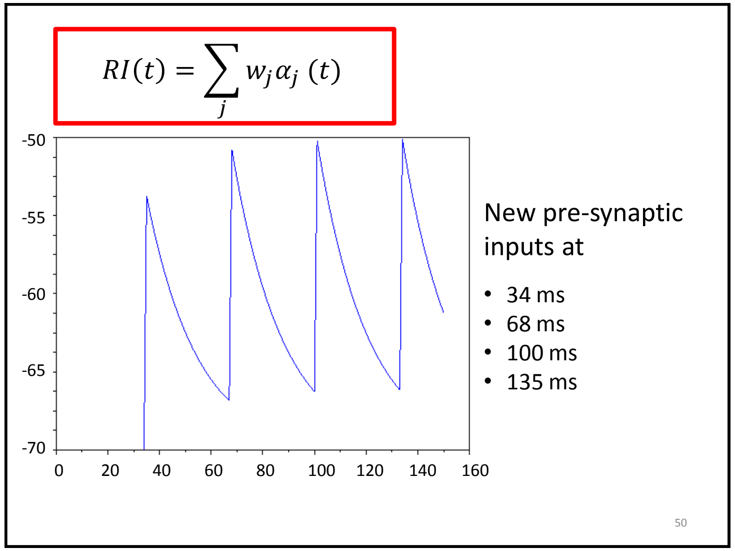
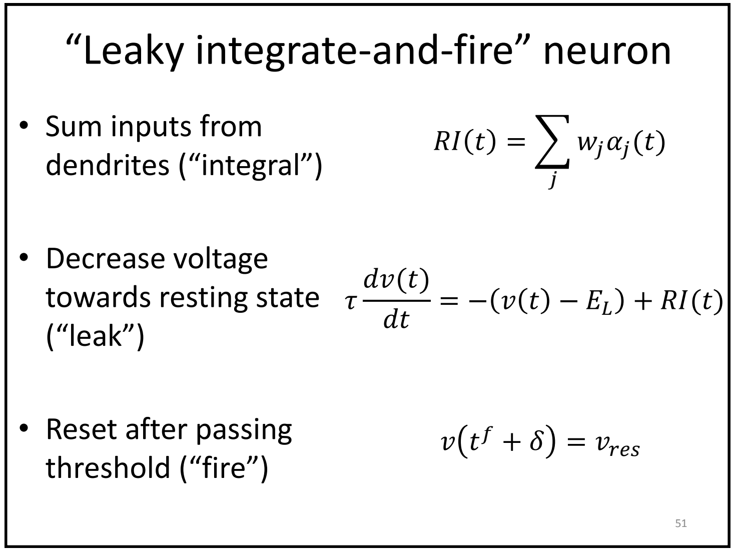


$$\boxed{RI(t) = \sum_j w_j \alpha_j\ (t)}$$

New pre-synaptic inputs at

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

50



“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”)

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

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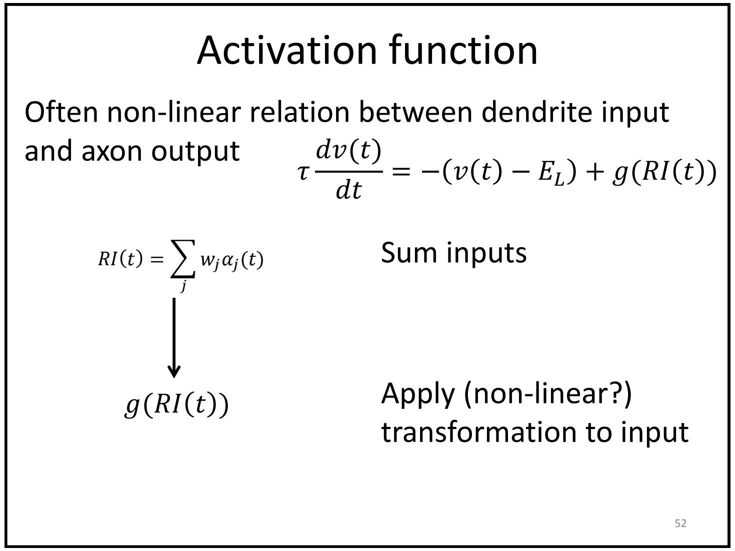

Activation function

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

$$\downarrow$$

$$g(RI(t))$$

Apply (non-linear?) transformation to input

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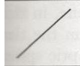
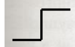
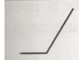
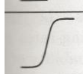
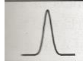
Activation function

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

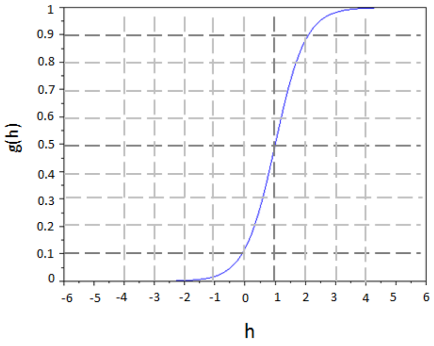
An example sigmoid

g(2)=

g(1)=

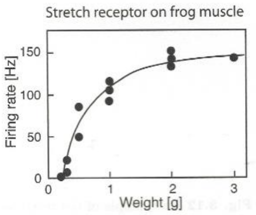
g(0)=

g(-4)=

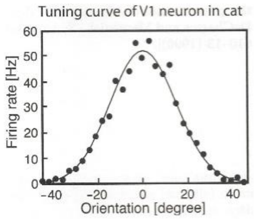


Tuning curves

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



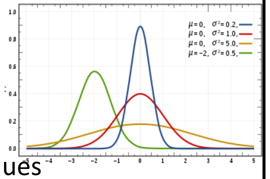
Adrian,
J Physiol 1926.

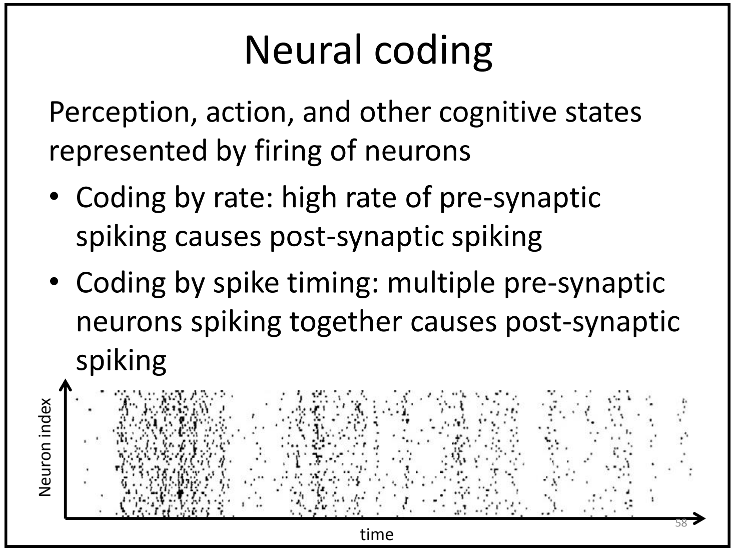


Henry et al.,
J Neurophys
1974.

Variations in activation functions

- Activation function has fixed shape
  - Sigmoid is S shape, Radial is Bell shape
- By default, transition between 0 and 1
- Some details of shape may vary
  - Smallest and highest value
  - Location of transition between values





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

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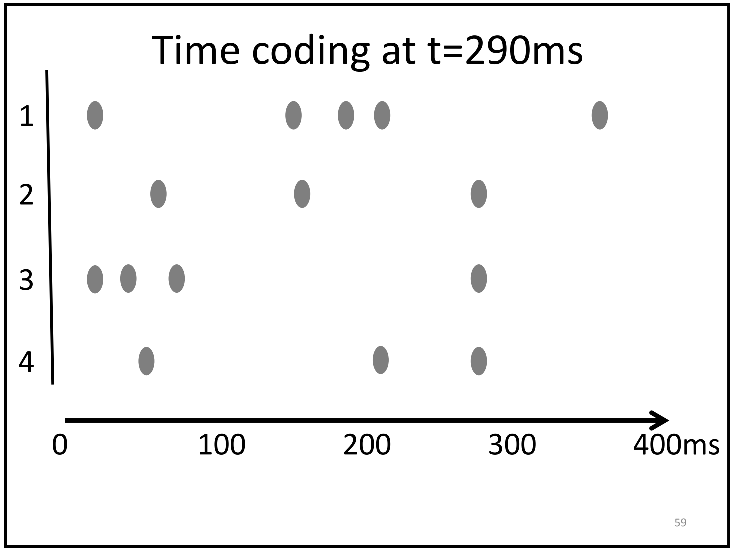
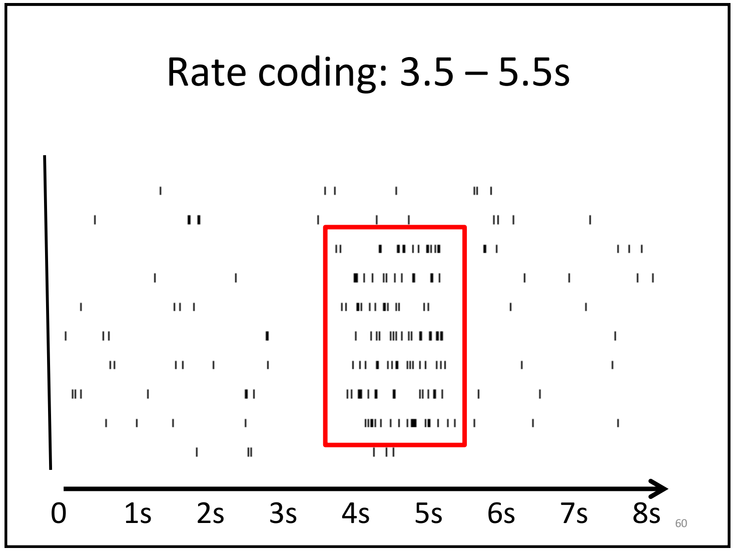


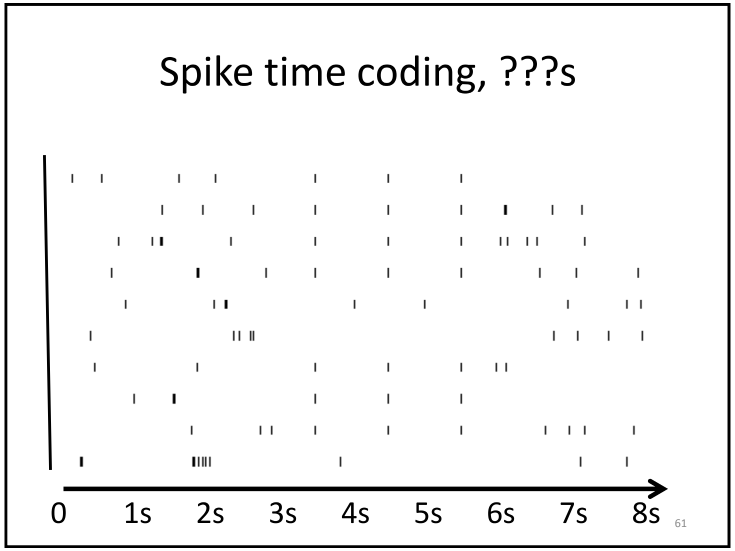
Time coding at t=290ms

59



Rate coding: 3.5 – 5.5s

60



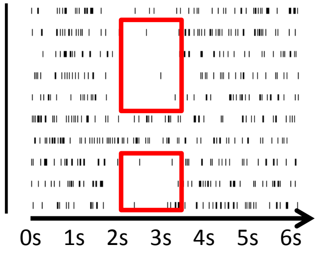
Spike time coding, ???s

61

Inhibition can be informative

Inputs of interest can produce

- Below-normal spike rate
- Decreased synchrony among neurons



Coding through rate inhibition, roughly in 2-3s interval

Take note of baseline. Rate and time coding are **deviations** from baseline

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

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