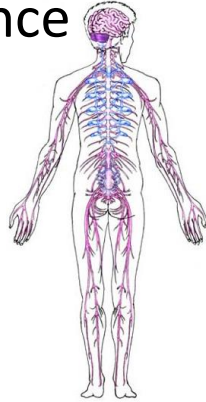
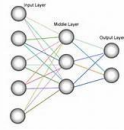


CISC 3250

Systems Neuroscience



Professor Daniel Leeds
 dleeds@fordham.edu
 JMH 328A

Systems 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



2

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

3

Recommended student background

Prerequisite:

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

Math

Some calculus

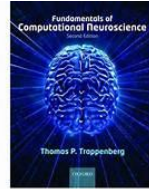
Computer
science

Some programming

4

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

5

Website

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

Go online for

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



6

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

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 330 and in LL 812

8

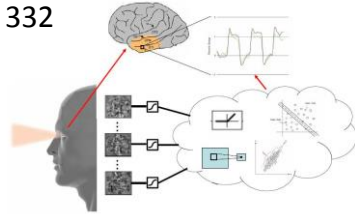
Your instructor

Prof. Daniel Leeds

E-mail: dleeds@fordham.edu

Office hours: Mon 11:30-12:30, Thurs 4:30-5:30

Office: JMH 332



computer science + psychology -> models of vision

9

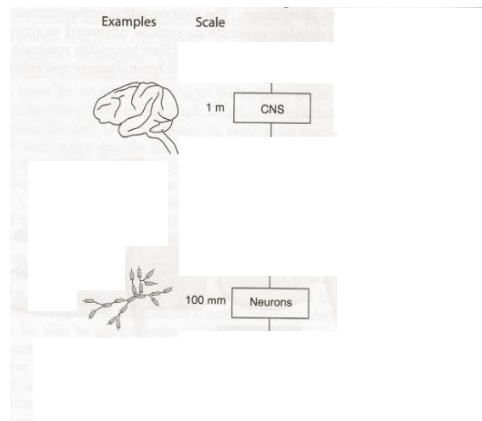
Introducing systems and computational neuroscience

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



11

Levels of organization



12

From a psychological perspective...

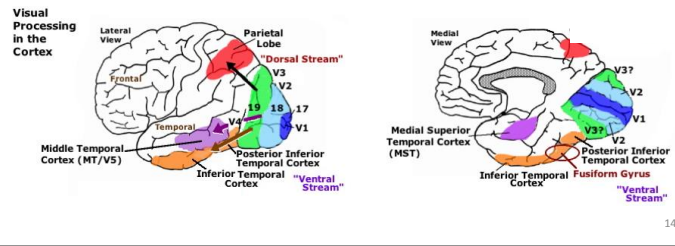
What are elements of cognition?

13

Systems neuroscience

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

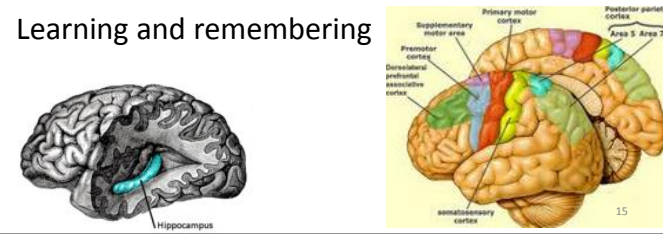
- Visual object recognition



Systems neuroscience

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

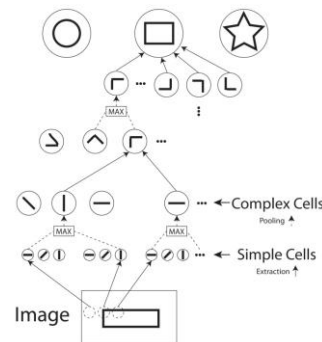
- Visual object recognition
- Motion planning and execution
- Learning and remembering



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):

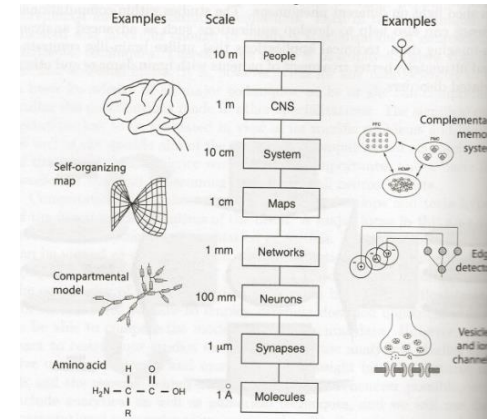
- **Computational theory:** What is the computational goal and the strategy to achieve it?
- **Representation and algorithm:** What are the input and output for the computation, and how do you mathematically convert input to output?
- **Hardware implementation:** How do the physical components perform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

18

Levels of organization



19

Course outline

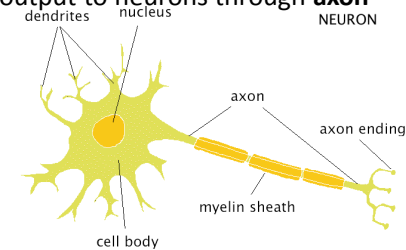
- Philosophy of neural modeling
- The neuron – biology and input/output behavior
- Learning in the neuron
- Neural systems and neuroanatomy
- Representations in the brain
- Perception
- Memory/learning
- Motor control

Plus: Matlab programming

20

The neuron

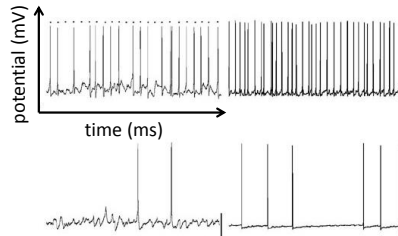
- Building block of all the systems we will study
- Cell with special properties
 - **Soma** (cell body) can have 5-100 μm diameter, but **axon** can stretch over 10-1000 cm in length
 - Receives input from neurons through **dendrites**
 - Sends output to neurons through **axon**



21

Neuron membrane voltage

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

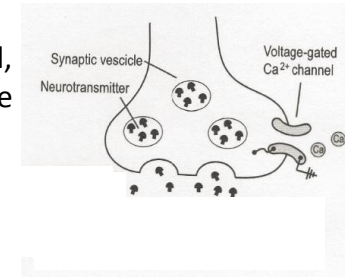


Example neural signals

22

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



23

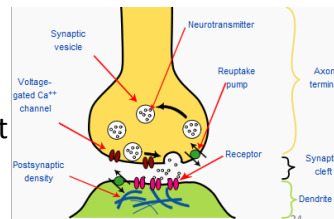
Inter-neuron communication

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



24

More on neuron membrane voltage

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

Inputs:

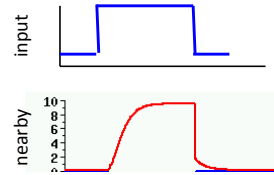
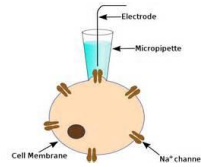
- Excitation temporarily increases potential
- Inhibition temporarily decreases potential

Continual drive to remain at rest

25

Patch clamp experiment

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

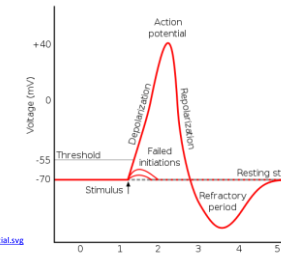


*Simplification of
neurophysiology
experiment*

26

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

27

Modeling voltage over time

Equations focusing on **change** in voltage v

Components:

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

$$\tau \frac{dv(t)}{dt} = \underbrace{-(v(t) - E_L)}_{\text{change towards resting state}} + \underbrace{RI(t)}_{\text{incorporate new input information}}$$

change towards
resting state

incorporate new
input information

28

Simulation

- Initial voltage
- Time interval for update
- Input at each time
- Apply rule to compute new voltage at each time

29

Applying dv/dt step-by-step

$$E_L = -65\text{mV} \quad v(0\text{ms}) = -65\text{mV} \quad \tau = 1$$

$$RI(t) = 20\text{mV} \text{ (from } t=0\text{ms to } 1000\text{ms)}$$

time step: 10ms

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

31

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

32

Voltage over time: reset

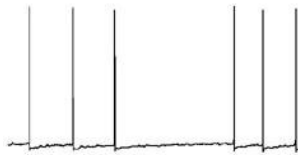
$$\tau \frac{dv(t)}{dt} = -(v(t) - E_L) + RI(t)$$

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

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

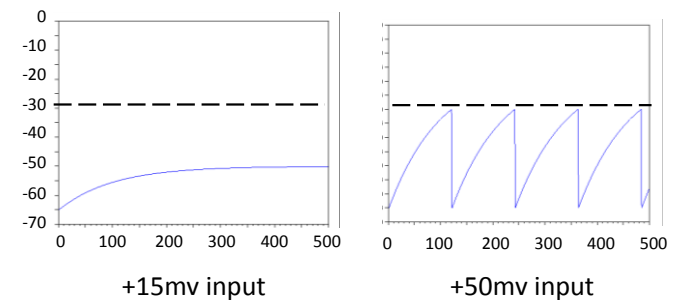
$$v(t^f + \delta) = v_{res}$$

δ is small positive number close to 0



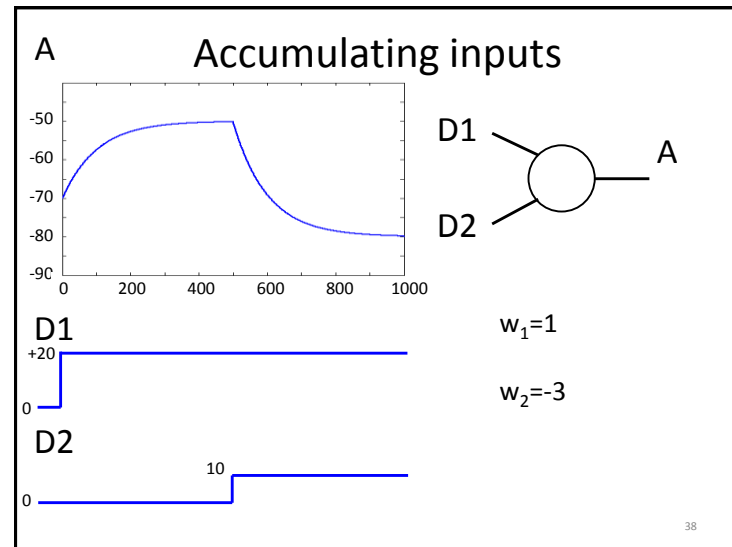
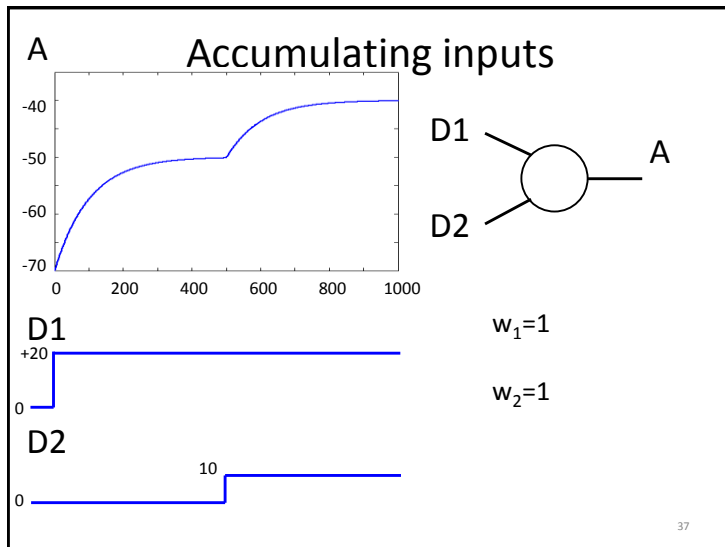
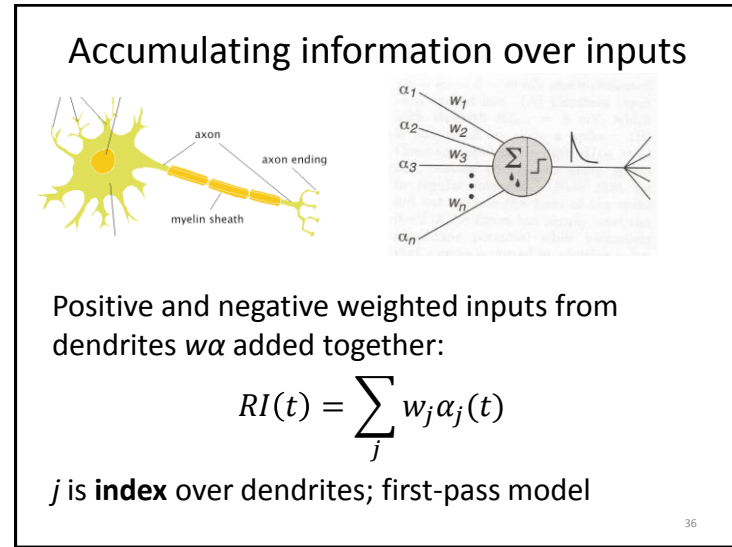
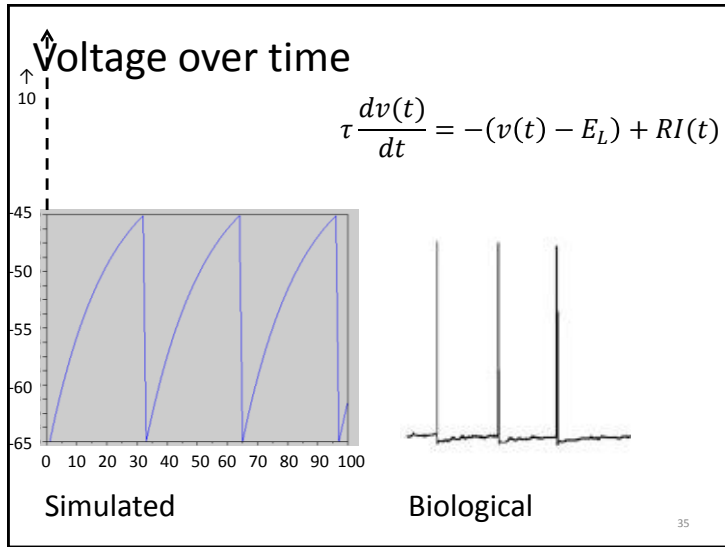
33

Below and above threshold



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

34



Chemical level: NT receptors

Pre-synaptic: α

- Amount of NT released

Post-synaptic: w

- Number of receptors in dendrite membrane
- Efficiency of receptors

$\pm w$ or $-w$

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

41

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, $\alpha(t)$

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

42

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

New pre-synaptic inputs at

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

43

“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”)

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

44

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

45

Activation function

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

46

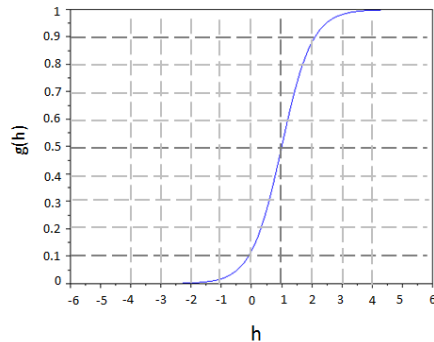
An example sigmoid

$$g(2) = 0.9$$

$$g(1) = 0.5$$

$$g(0) = 0.1$$

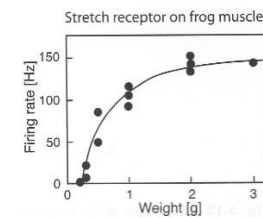
$$g(-4) = 0$$



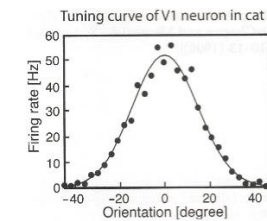
47

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.

48

Variations in activation functions

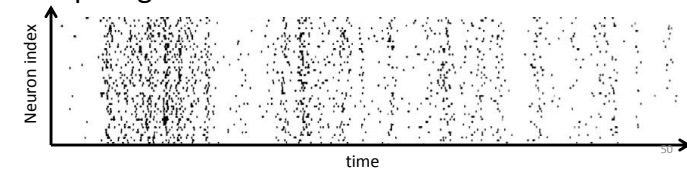
- Activation function has fixed shape
 - Sigmoid is S shape, Radial is Bell shape
- By default, transition between 0 and 1
- Some details of shape may vary
 - Smallest and lowest value
 - Location of transition between values

49

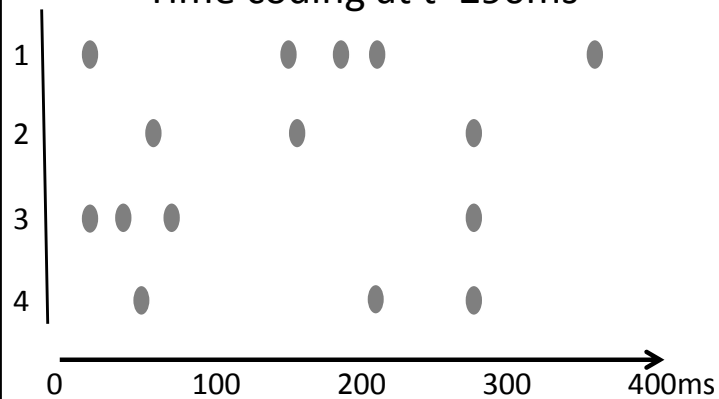
Neural coding

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

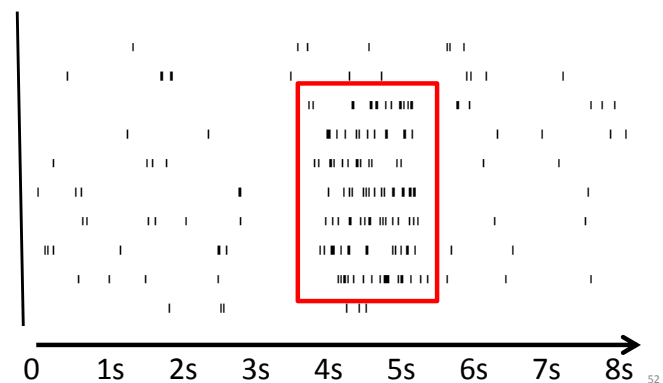


Time coding at t=290ms



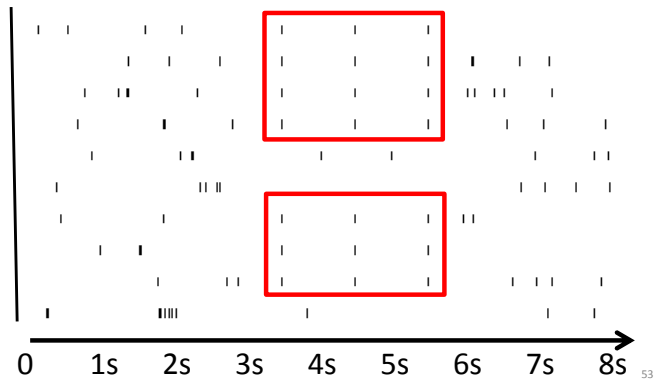
51

Rate coding: 3.5 – 5.5s



52

Spike time coding, 3-6s

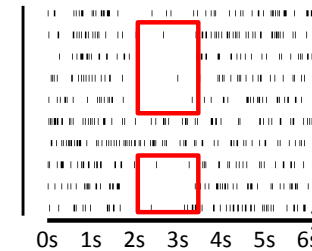


53

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

54

Computing spike rate

- Add spikes over a period of time

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

- Average spikes over a set of neurons

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

55