

CSE 528

Lecture 5: Modeling Single Neurons
(Chapter 5)

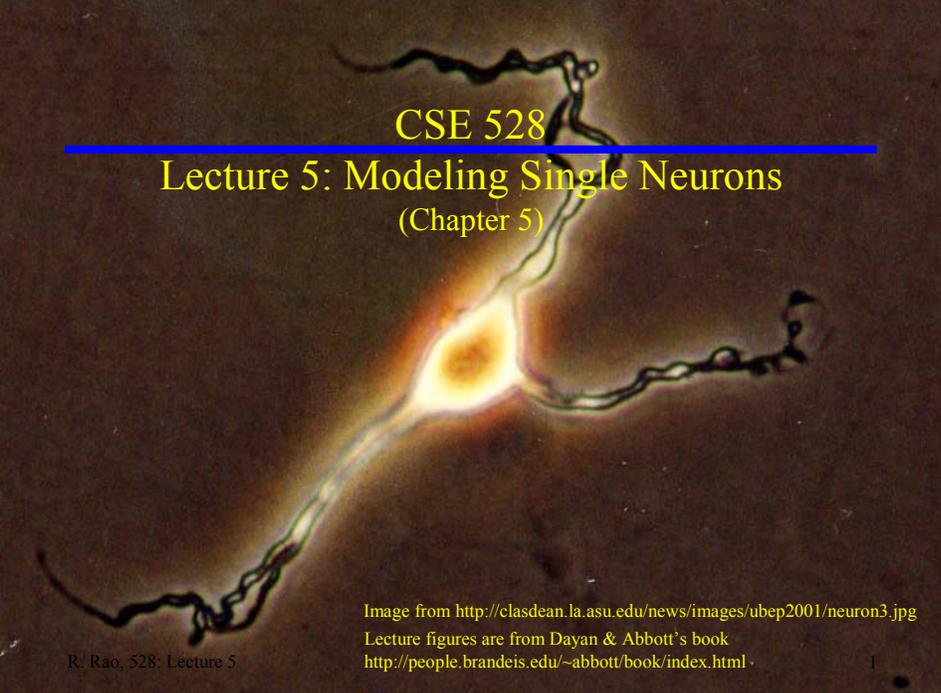
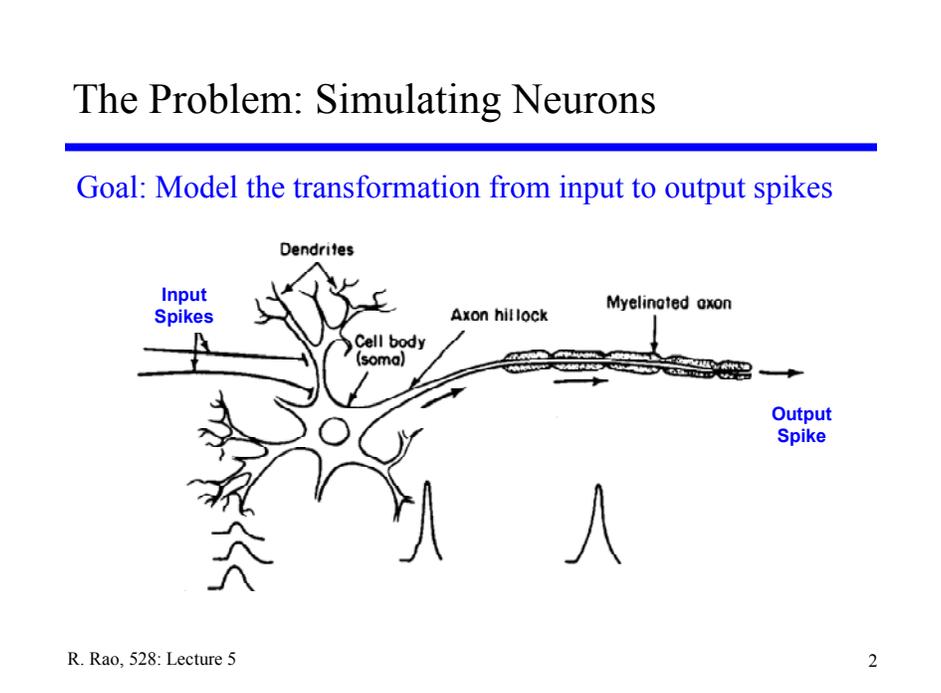


Image from <http://clasdean.la.asu.edu/news/images/ubep2001/neuron3.jpg>
Lecture figures are from Dayan & Abbott's book
<http://people.brandeis.edu/~abbott/book/index.html>

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The Problem: Simulating Neurons

Goal: Model the transformation from input to output spikes



The diagram illustrates the structure and function of a neuron. On the left, **Input Spikes** are shown entering the **Dendrites**. These signals travel to the **Cell body (soma)**, where they are integrated. The resulting signal then passes through the **Axon hillock**, a region where the signal is amplified. This leads to the **Myelinated axon**, which carries the signal away from the cell body. Finally, an **Output Spike** is generated at the end of the axon. Below the main diagram, two smaller diagrams show the shape of the action potential (spike) at different stages: one at the axon hillock and one at the end of the axon.

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Sub-Problems and Solutions

- ◆ Model how the membrane potential changes with inputs
 - ⇒ Passive “RC” membrane model
- ◆ Model the entire neuron as one component
 - ⇒ Integrate-and-Fire Model
- ◆ Model the effects of inputs from synapses
- ◆ Model active membranes
 - ⇒ Hodgkin-Huxley model
- ◆ Model the structure of neurons
 - ⇒ Dendrites, cell body, axon
- ◆ Chapters 5 & 6 in text

Conductance-based
Compartmental
Models
(next class)

Today's Agenda

- ◆ Single Neuron Models
 1. Just the bare essentials: Connectionist Model
 2. Modeling membranes: The RC model
 3. Keeping it simple: 1-Compartment Model
 4. Producing spikes: Integrate-and-Fire Model
 5. Modeling inputs: Synapse models
 6. Example applications
- ◆ Next time: Active membranes and multi-compartment models
 1. Modeling spike generation: Hodgkin-Huxley Model
 2. Modeling it all (almost): Multi-Compartment Models

Connectionist Model of a Neuron

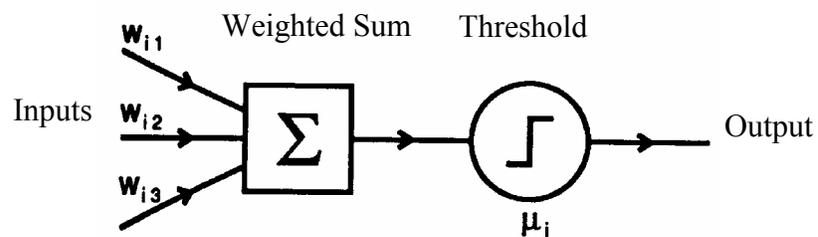
◆ Attributes of artificial neuron:

⇨ m binary inputs and 1 output (0 or 1)

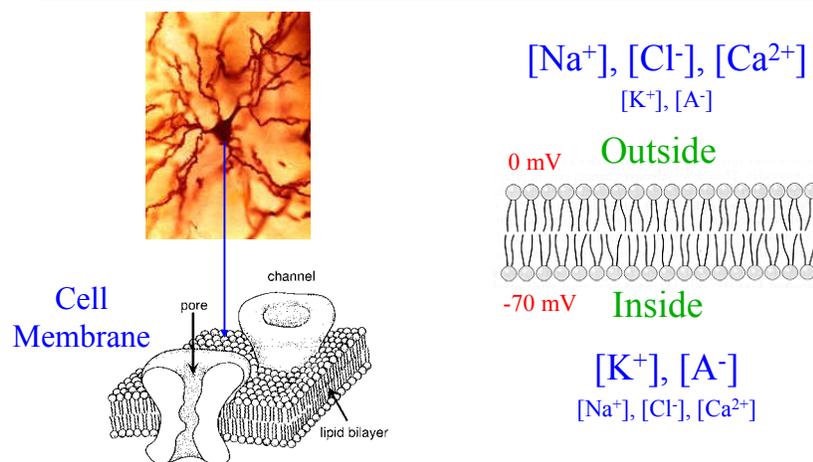
⇨ Synaptic weights w_{ij}

⇨ Threshold μ_i

$$out_i = \begin{cases} 1 & \text{if } \sum_j w_{ij} in_j \geq \mu_i \\ 0 & \text{otherwise} \end{cases}$$

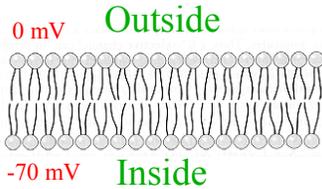


A Closer Look at a Neuron



Equilibrium Potential of Ions (Nernst Equation)

$[\text{Na}^+], [\text{Cl}^-], [\text{Ca}^{2+}]$
 $[\text{K}^+], [\text{A}^-]$



$[\text{K}^+], [\text{A}^-]$
 $[\text{Na}^+], [\text{Cl}^-], [\text{Ca}^{2+}]$

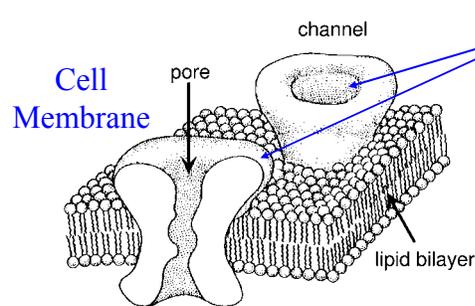
E = Membrane potential at which current flow due to diffusion of ions is balanced by electric forces

$$E = \frac{RT}{zF} \ln \left(\frac{[\textit{outside}]}{[\textit{inside}]} \right)$$

(T = temp, R & F = constants, z = valence of ion)

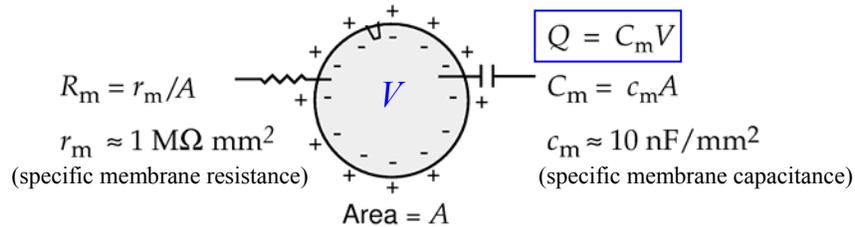
e.g. $E_{\text{Na}} = 50 \text{ mV}$, $E_{\text{K}} = -80 \text{ mV}$

Ionic Channels = Conductances



Ionic channels are modeled as conductances g_i (allow current to flow into or out of cell)

Modeling Neural Membranes



$$c_m \frac{dV}{dt} = \frac{dQ}{dt} = -i_m \quad \text{Membrane Current due to Ions ("Leak Current")}$$

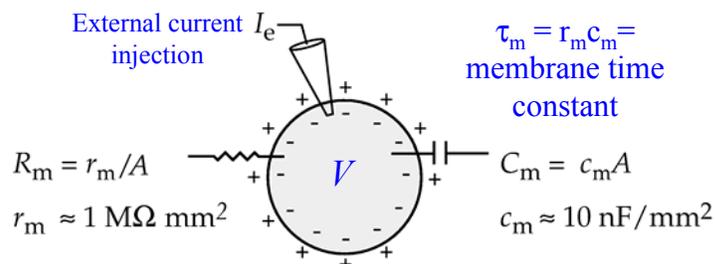
$$i_m = \sum_i g_i (V - E_i) = \bar{g}_L (V - E_L) = \frac{(V - E_L)}{r_m}$$

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Leak conductance

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Summary of 1-Compartment Membrane Model



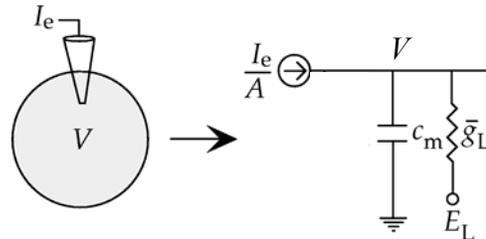
$$c_m \frac{dV}{dt} = -\frac{(V - E_L)}{r_m} + \frac{I_e}{A}, \text{ or equivalently}$$

$$\tau_m \frac{dV}{dt} = -(V - E_L) + I_e R_m$$

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Producing Spikes: Integrate-and-Fire Model



$$\tau_m \frac{dV}{dt} = -(V - E_L) + I_e R_m$$

If $V > V_{\text{threshold}} \rightarrow$ Spike

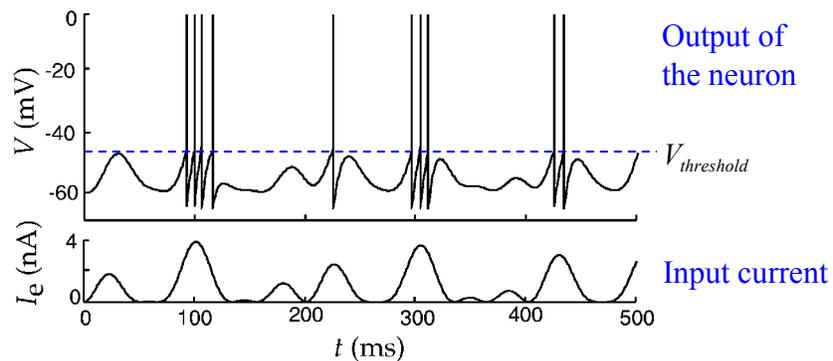
Then reset: $V = V_{\text{reset}}$

$E_L \approx -70$ mV
(resting potential)

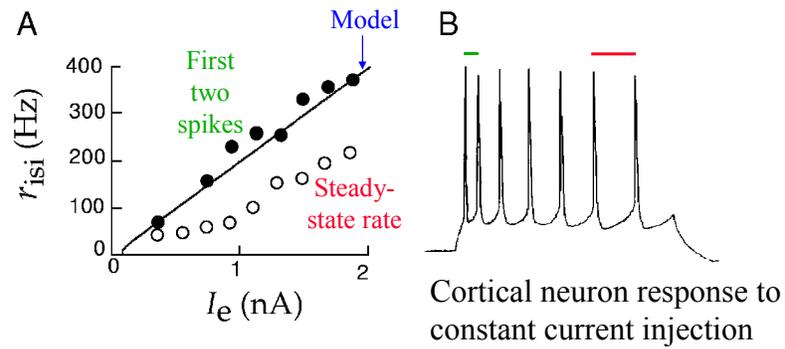
$V_{\text{threshold}} \approx -50$ mV

$V_{\text{reset}} \approx E_L$

The Integrate-and-Fire Model in Action



Comparison of I & F Model to Data



Real neuron exhibits spike-rate adaptation and refractoriness

Making the I & F model more realistic

$$\tau_m \frac{dV}{dt} = -(V - E_L) - r_m g_{sra} (V - E_K) + I_e R_m$$

$$\tau_{sra} \frac{dg_{sra}}{dt} = -g_{sra} \quad \leftarrow \text{Spike-rate adaptation}$$

If $V > V_{\text{threshold}} \rightarrow$
 Spike and set $g_{sra} = g_{sra} + \Delta g_{sra}$
 Reset: $V = V_{\text{reset}}$

(can also add refractoriness similarly)

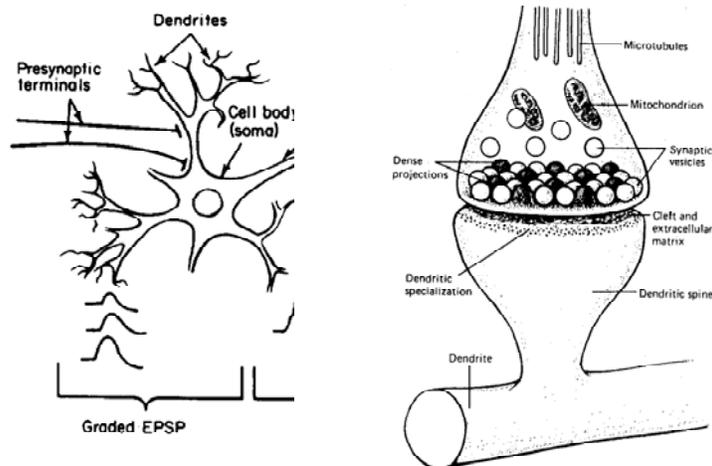
I & F Model with Spike-Rate Adaptation



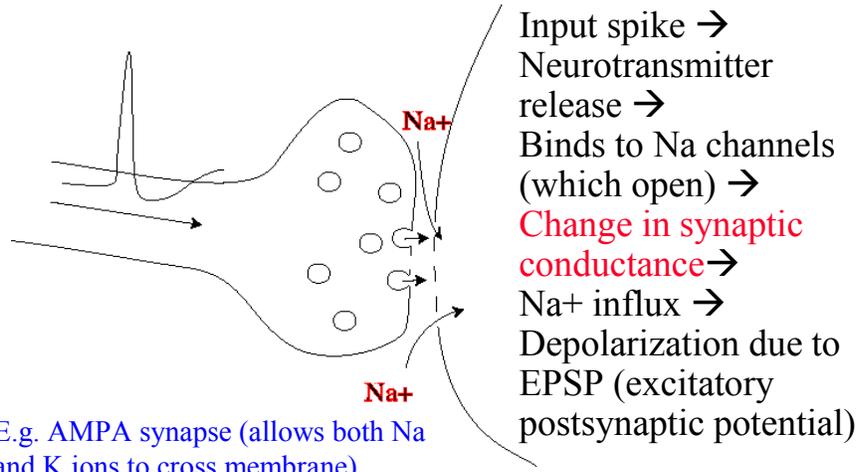
Cortical Neuron

Integrate-and-Fire Model
with Spike-Rate Adaptation

Synapses: Modeling the Inputs to a Neuron



Example of An Excitatory Synapse

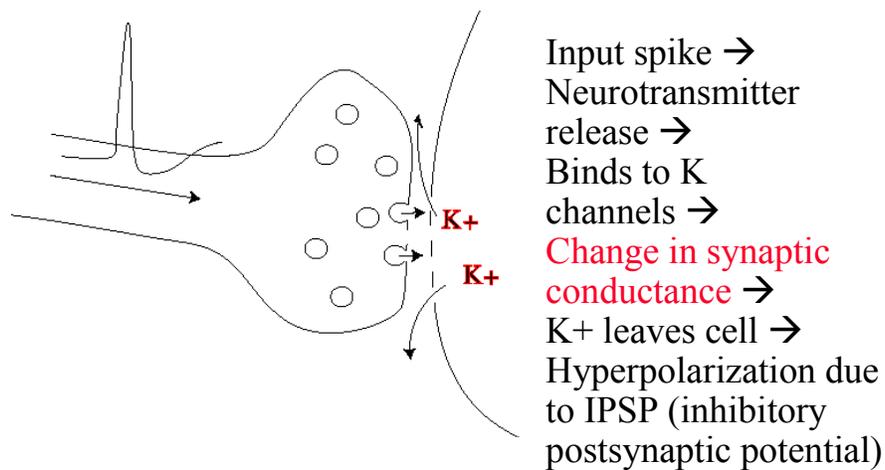


E.g. AMPA synapse (allows both Na and K ions to cross membrane)

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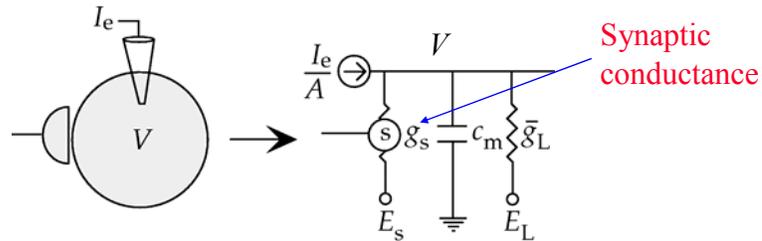
Example of An Inhibitory Synapse



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Modeling a Synaptic Input to a Neuron



$$\tau_m \frac{dV}{dt} = -(V - E_L) - r_m g_s (V - E_s) + I_e R_m$$

$$g_s = g_{s,\max} P_{rel} P_s$$

P_{rel} ← Probability of postsynaptic channel opening
 (= fraction of channels opened)
 P_s ← Probability of transmitter release given an input spike

Basic Synapse Model

- ◆ Assume $P_{rel} = 1$ (for now)
- ◆ Model the effect of a single spike input on P_s
- ◆ Kinetic Model: closed $\xrightarrow{\alpha_s}$ open

open $\xrightarrow{\beta_s}$ closed

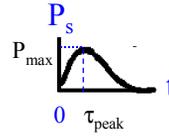
$$\frac{dP_s}{dt} = \alpha_s (1 - P_s) - \beta_s P_s$$

α_s → Opening rate
 β_s → Closing rate
 $(1 - P_s)$ → Fraction of channels closed
 P_s → Fraction of channels open

Simplified Synapse Models

◆ “Alpha Function” model:

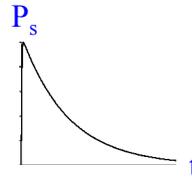
$$P_s(t) = \text{const} \cdot \frac{t}{\tau_{peak}} e^{-\frac{t}{\tau_{peak}}}$$



- ⇒ $\text{const} = e P_{\max}$ so that $P_s(\tau_{peak}) = P_{\max}$
- ⇒ Why Alpha? People used $\alpha = 1/\tau_{peak}$

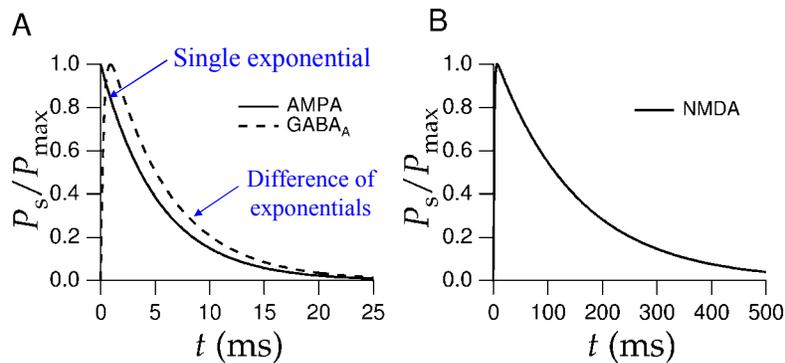
◆ Difference of Exponentials Model:

$$P_s(t) = \text{const} \cdot P_{\max} \left(e^{-\frac{t}{\tau_1}} - e^{-\frac{t}{\tau_2}} \right)$$



- ⇒ const chosen to make peak of $P_s = P_{\max}$

Comparison of Synapse Models to Data



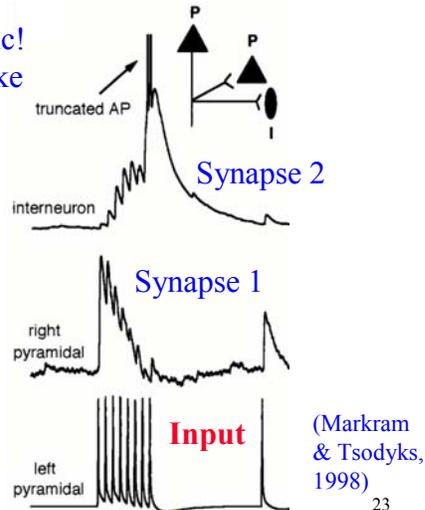
Difference of exponentials model was fit to biological data

What if there are multiple input spikes?

- Biological synapses are dynamic!
- Linear summation of single spike inputs not correct

Short-Term Facilitation

Short-Term Depression

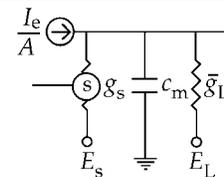


Modeling Dynamic Synapses

- ◆ Recall definition of synaptic conductance:

$$g_s = g_{s,\max} P_{rel} P_s$$

- ◆ Idea: Specify how P_{rel} changes as a function of consecutive input spikes



$$\tau_P \frac{dP_{rel}}{dt} = P_0 - P_{rel}$$

Between input spikes, P_{rel} decays exponentially back to P_0

If Input Spike:

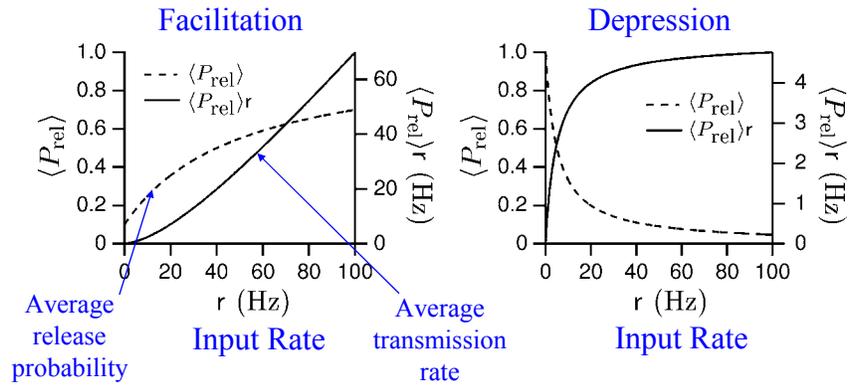
$$P_{rel} \rightarrow f_D P_{rel}$$

Depression: Decrement P_{rel}

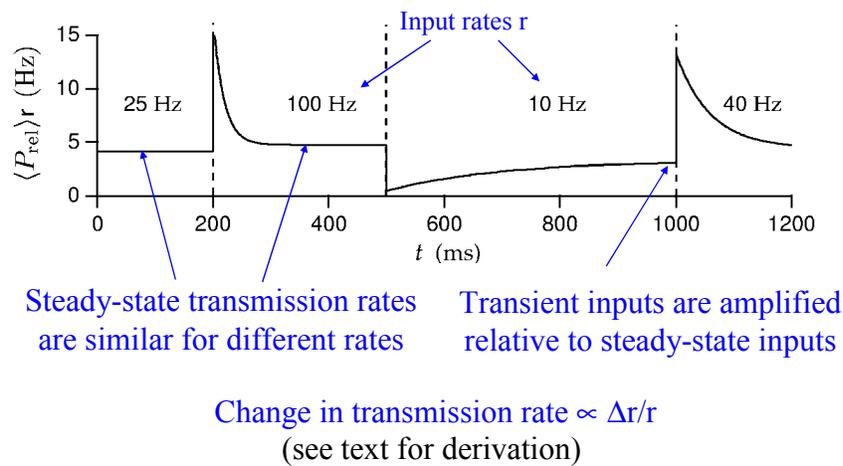
$$P_{rel} \rightarrow P_{rel} + f_F (1 - P_{rel})$$

Facilitation: Increment P_{rel}

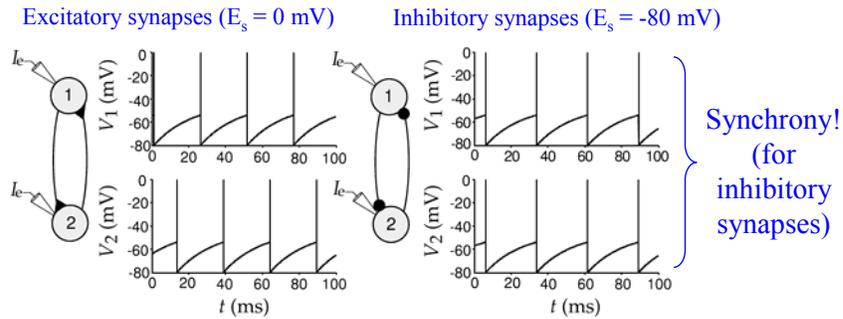
Effects of Synaptic Facilitation & Depression



Consequences of Synaptic Depression



Putting it all together: Network Examples



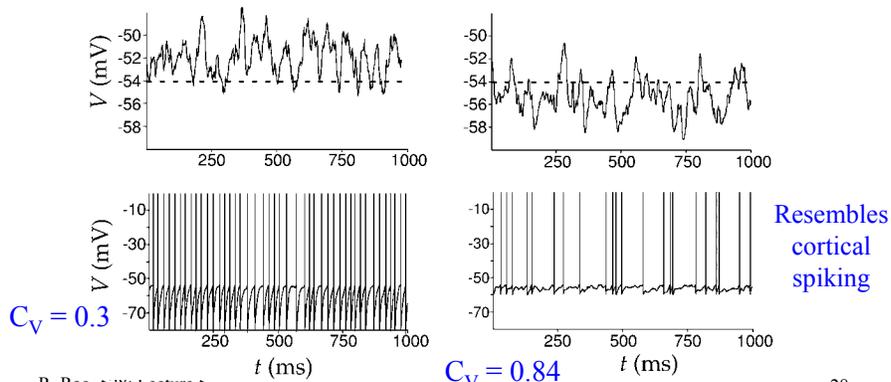
Each neuron:
$$\tau_m \frac{dV}{dt} = -(V - E_L) - r_m g_{s,\max} P_s (V - E_s) + I_e R_m$$

Synapses: Alpha function model for P_s

Explaining the Spiking Behavior of Cortical Neurons

- I & F Neuron with 1000 excitatory and 200 inhibitory Poisson inputs

More excitation than inhibition (Regular firing mode) Balanced excitation and inhibition (Irregular firing mode)



Next Class: Compartmental Models

◆ Things to do:

- ⇒ Finish Chapter 5 and Start Chapter 6
- ⇒ Matlab homework exercise #2 on web