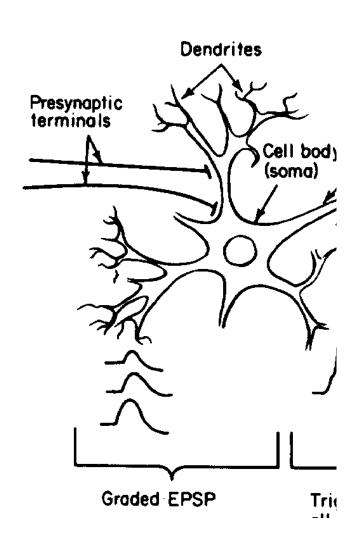
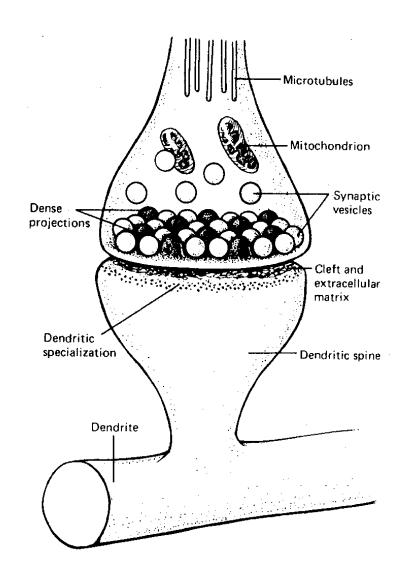
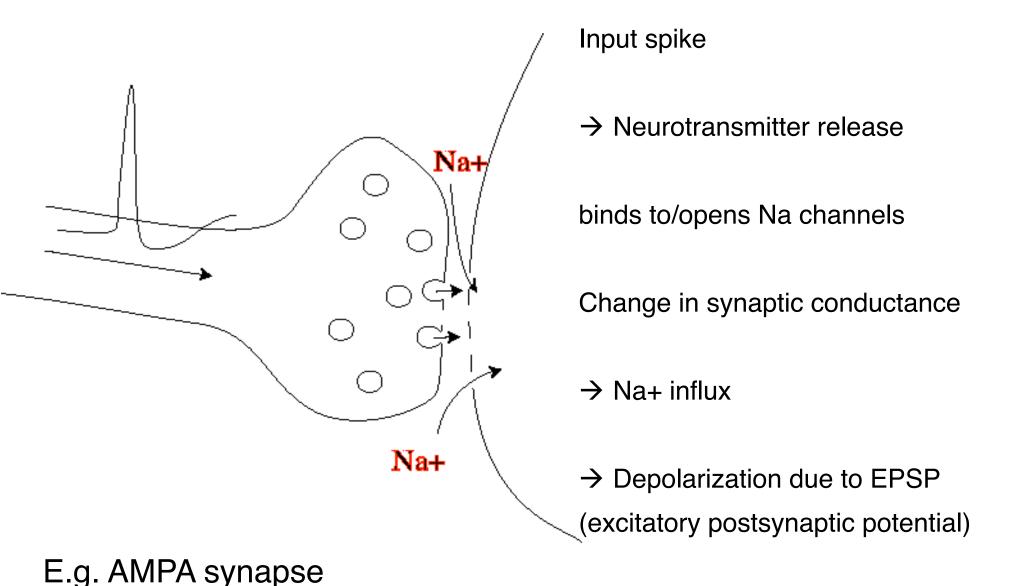


# How do synapses transform inputs?



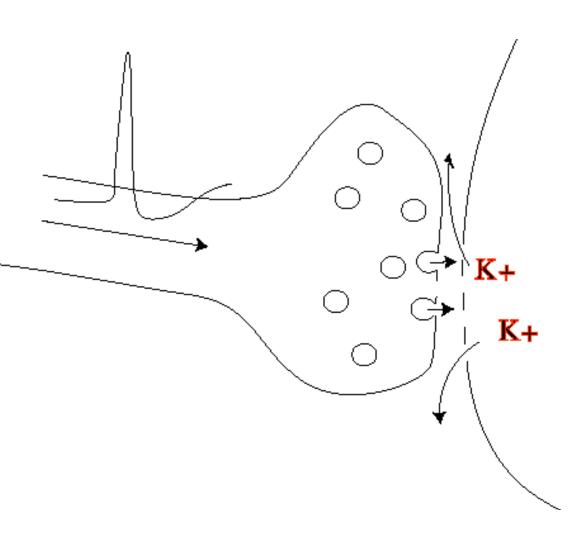


### **Excitatory** synapse



Vocab: Depolarization means make V less neg = more positive

### **Inhibitory** synapse



Input spike

→ Neurotransmitter release

binds to/opens K channels

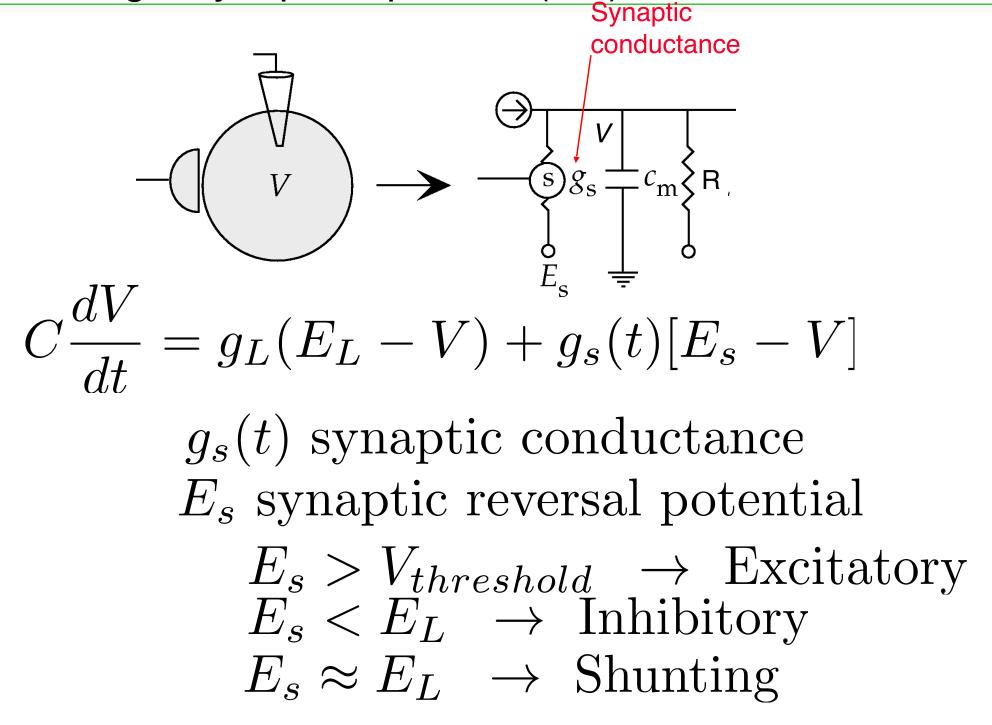
Change in synaptic conductance

K+ leaves cell

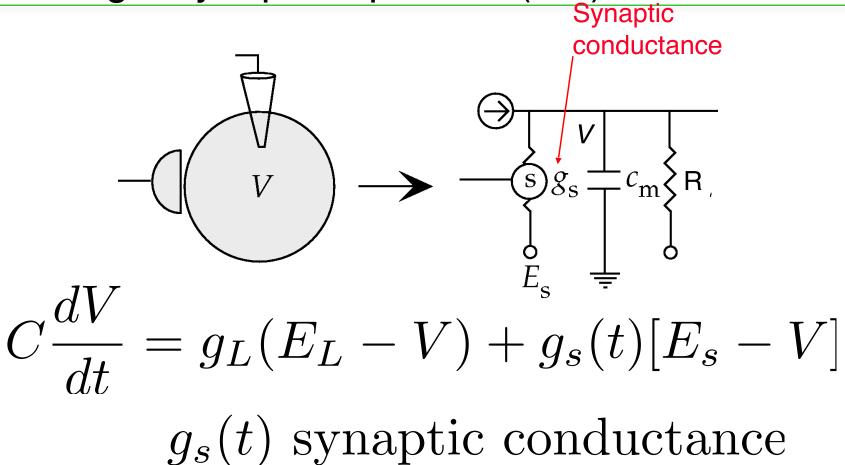
→ Hyperpolarization due to IPSP (inhibitory postsynaptic potential)

Vocab: hyperpolarization means make V more negative

## Modeling a synaptic input to a (RC) neuron



### Modeling a synaptic input to a (RC) neuron



$$g_s = g_{s,max} P_{rel} P_s$$
 — Probability of postsynaptic channel opening (= fraction of channels opened)

Probability of transmitter release given an input spike

### Basic synapse model

Assume  $P_{rel} = 1$  (for now)

What does a single spike input do to P<sub>s</sub>?

Kinetic model:

$$closed \xrightarrow{\alpha_s} open$$

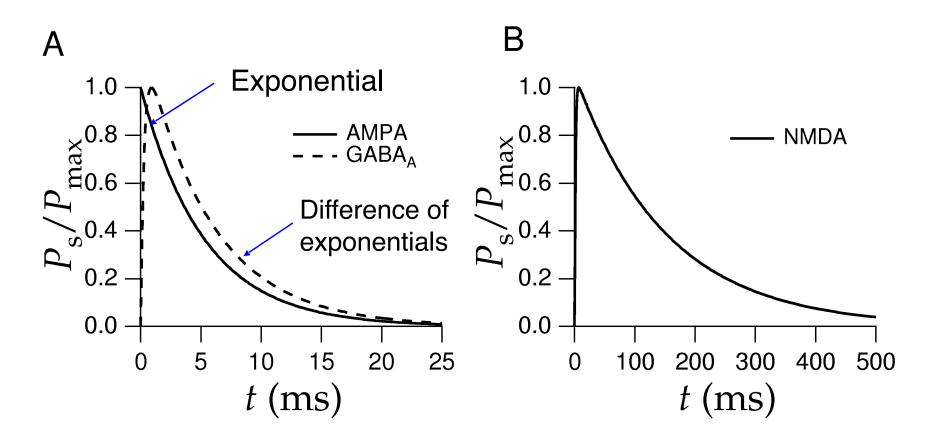
open 
$$\xrightarrow{\beta_s}$$
 closed

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

Fraction of channels closed

Where:  $lpha_s(V(t),Ca(t),...)$   $eta_s(V(t),Ca(t),...)$ 

# Synaptic filters

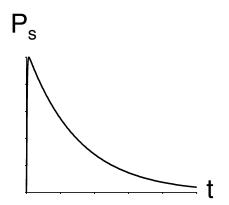


A difference of exponentials model better fits biological data for GABA, NMDA synapse types

# Simplified synaptic models

### Difference of exponentials:

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

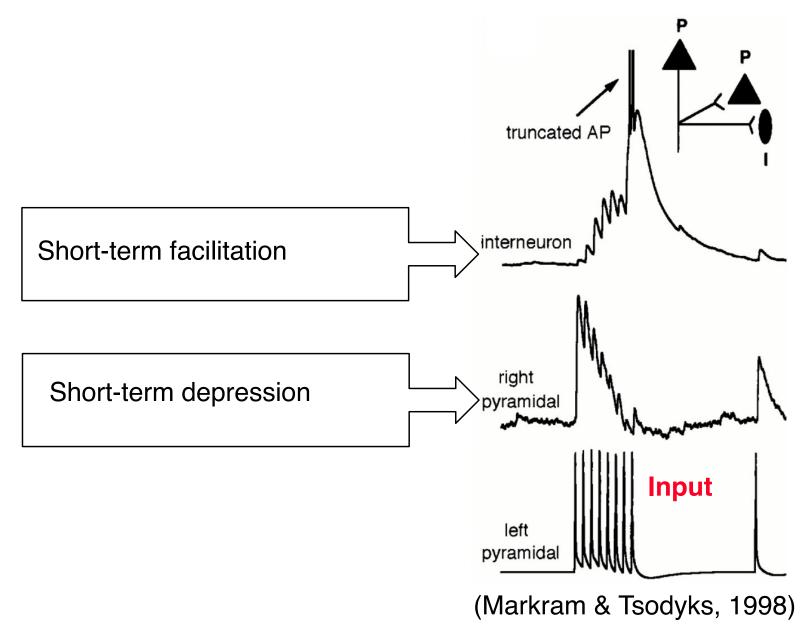


### Alpha function:

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

### What happens with a sequence of input spikes?

Biological synapses are dynamic!



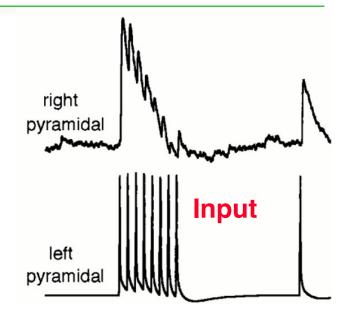
### Short-term synaptic plasticity: describe this via P\_rel

Recall definition of synaptic conductance:

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

Idea: Specify how P<sub>rel</sub> 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  $P_0$ 

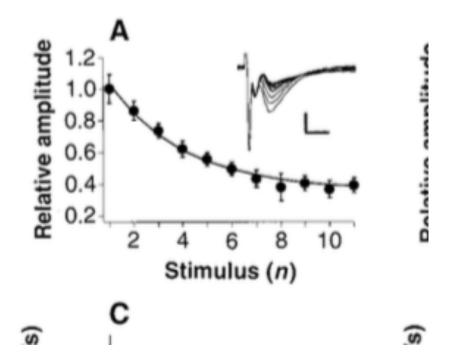
If input spike:

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

depression: decrement P<sub>rel</sub>

Fig. 1. Experimental results and fits of the model for synaptic depression.

(A) Depression of synaptic responses during repetitive stimulation. Filled circles indicate normalized average field potential amplitudes evoked by 11 consecutive stimuli at 20 Hz. Error bars are stan-



#### Lab exercise:

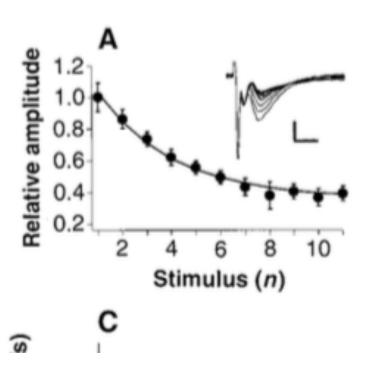
Write a code that implements the Abbott et al mechanism for synaptic depression.

Drive the synapse with spikes occurring regularly at 20 Hz, as in Fig. 1A of Abbott et al '97. Can you reproduce that figure?

Hint: this should be a few lines of code.

Fig. 1. Experimental results and fits of the model for synaptic depression.

(A) Depression of synaptic responses during repetitive stimulation. Filled circles indicate normalized average field potential amplitudes evoked by 11 consecutive stimuli at 20 Hz. Error bars are stan-



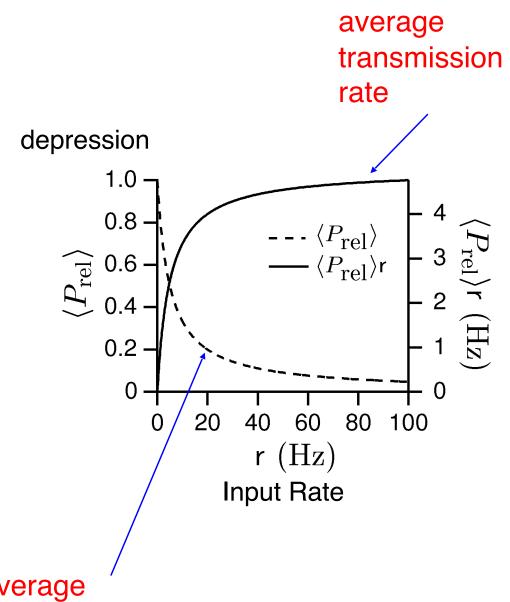
# Impact of synaptic depression

Key result (a few lines of calculation, see (7) in paper [ESB notes]):

If synapse receives input spikes at rate r, then the steady state value of

$$P_{rel}(r) \sim 1/r$$

### Consequences of synaptic depression: steady state



At steady state,

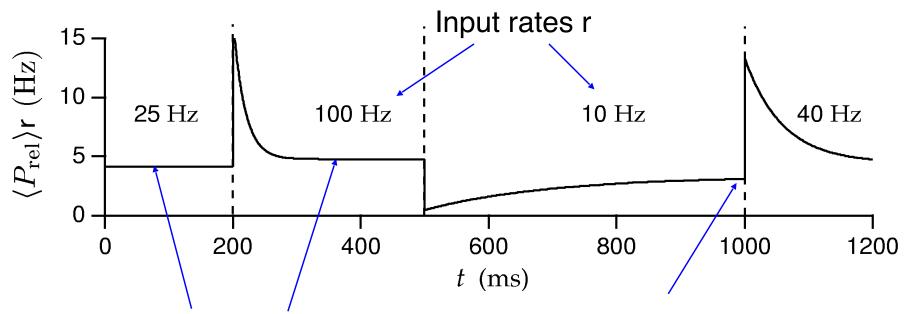
 $P_{rel}(r) \times r \approx \text{const for large } r$ 

Constant synaptic input for Wide range of inputs!

Steady-state gain control

average release probability

### Consequences of synaptic depression: dynamic response



Steady-state transmission rates are similar for different rates

Transient inputs are amplified relative to steady-state inputs

# <u>In fact: an equal-percent change from baseline gives an equal transient response.</u>

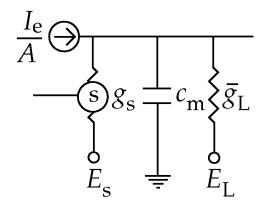
Who cares? Abbott et al 97: Neuron gets inputs from 1000's of upstream cells, each of which fires at 1-200 Hz. How can we be responsive to all?

Synaptic depression yields "gain control" to satisfy this. vs. Adaptation or inhibition, does so in an INPUT-SPECIFIC way!

### Extending the model to include facilitation

Recall definition of synaptic conductance:  $\frac{l_e}{\Delta}$ 

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



If input spike:

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

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

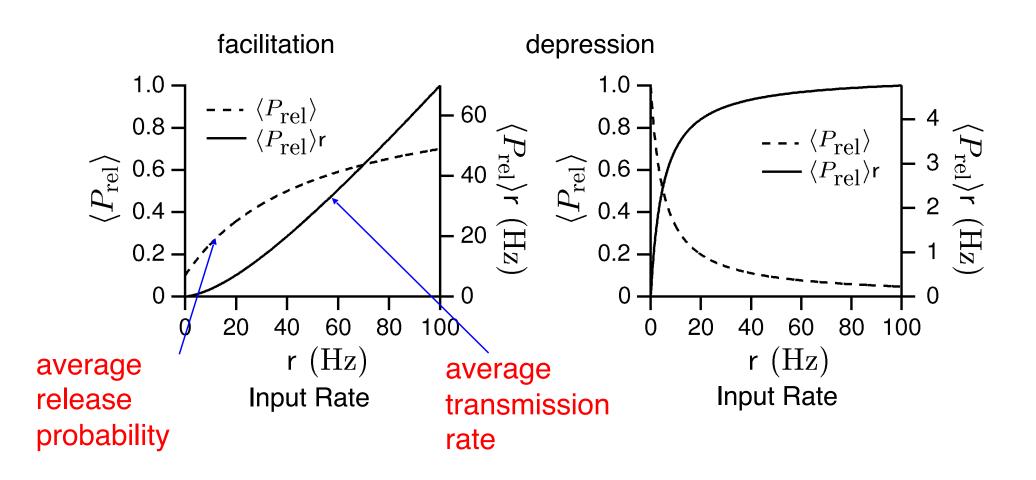
depression: decrement P<sub>rel</sub>

facilitation: increment P<sub>rel</sub>

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

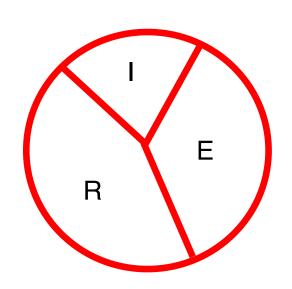
Abbott et al 1997

### Effects of synaptic facilitation & depression



### More detailed plasticity model

- Incoming spike activates a fraction of recovered resources R to become effective (E)
- Amount of effective resources E govern size of gs(t)
- Effective resources rapidly inactivate (msec)
- Inactivated recover (100s of msec)
- E(t) determines postsynaptic current

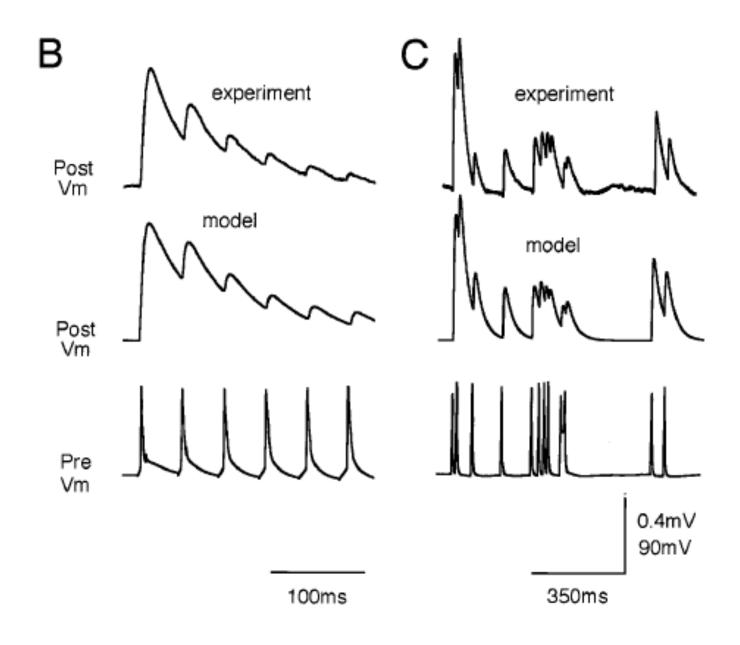


$$t_{AP}$$
: time of spike at all spike times  $\lim_{t \to \infty} R = \frac{I}{t_{rec}} - \frac{I}{U_{SE} \cdot R \cdot \delta(t - t_{AP})}$ 

$$\frac{dE}{dt} = -\frac{E}{\tau_{inact}} + \frac{U_{SE} \cdot R \cdot \delta(t - t_{AP})}{\text{similar meaning}}$$
 $I = 1 - R - E$ 

Markram and Tsodyks, PNAS 1997

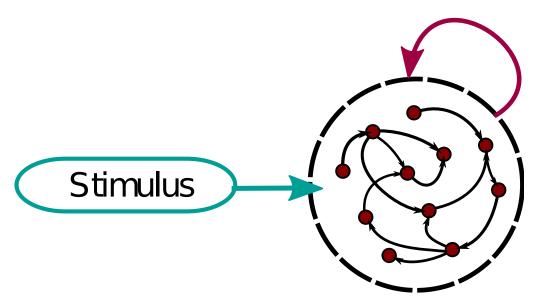
### Match between model and experiment



### Summary:

Synapses provide an additional layer of dynamics and computation, beyond that occurring in single neurons!

### Network computation via simplified "firing rate" models



W, connection weight matrix

W\_ij = weight from j to i

neuron (or neural population) i fires with rate  $\ r_i(t)$ 

neuron (or neural population) i receives input

$$input_i = stim_i(t) + \sum_j W_{ij}r_j(t)$$

**DYNAMICS:** rates approach steady states f(input)

$$\tau \frac{dr_i}{dt} = f(input_i) - r_i$$

