Neuroscience for machine learners

Neuro4ML

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Synapse models

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https://neural-reckoning.org

Level of abstraction

Q: Are these changes fast enough to ignore?

Neurotransmitter release and binding

changes

Conductance

$g_{syn}(t)$

changes $\quad I_{syn}(t) = g_{syn}(t)(\,V(t) - E_{syn}\,)$

Current

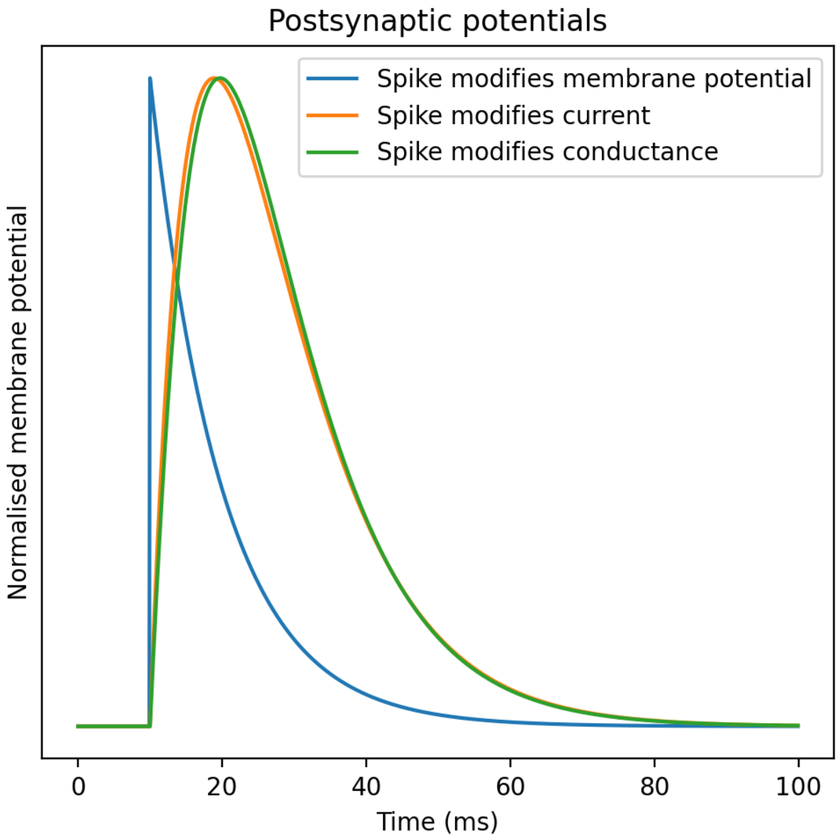
$I_{syn}(t)$

changes $\quad CV'(t) = I_{syn}(t) - V(t) + \cdots$

Membrane potential

$V(t)$

Q: Are we modelling this level of detail?



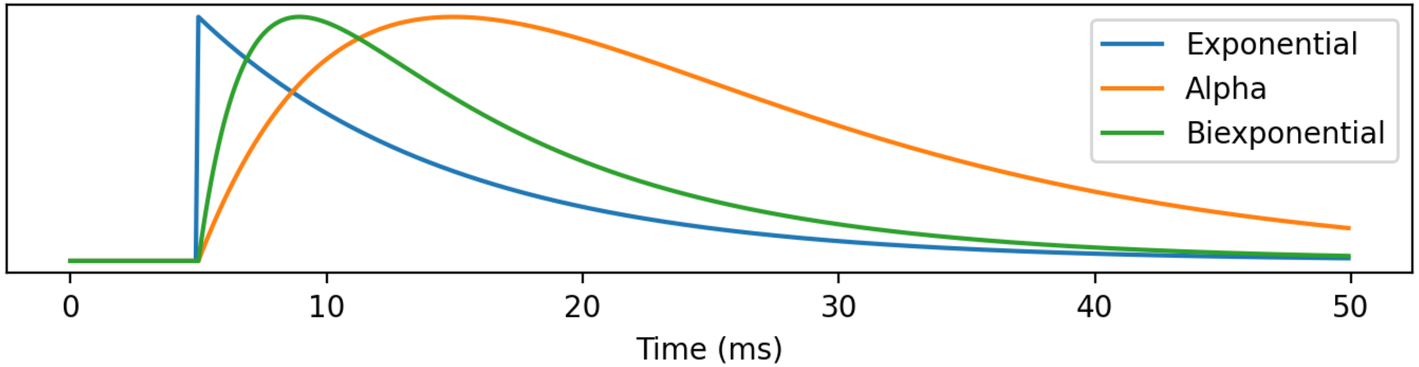
Synapse time course

Postsynaptic potential form	Differential equation form (ignoring constants)	Matrix form $\boldsymbol{y}' = M\boldsymbol{y}$
Exponential $v(t) = H(t)\, e^{-t/\tau}$	$\tau v' = -v$ $v(0) = 1$	$\boldsymbol{y} = (v)$ $M = (-1/\tau)$ Single eigenvalue $-1/\tau$
Alpha $v(t) = H(t)\, e^{-t/\tau}\, t/\tau$	$\tau v' = x - v$ $\tau x' = -x$ $x(0) = 1$	$\boldsymbol{y} = (v, x)$ $M = \begin{pmatrix} -1/\tau & 1 \\ 0 & -1/\tau \end{pmatrix}$ Repeated eigenvalue $-1/\tau$
Biexponential $v(t) = H(t)(e^{-t/\tau} - e^{-t/\tau_x})$ $\tau_x \neq \tau$	$\tau v' = x - v$ $\tau_x x' = -x$ $x(0) = 1$	$\boldsymbol{y} = (v, x)$ $M = \begin{pmatrix} -1/\tau & 1 \\ 0 & -1/\tau_x \end{pmatrix}$ Two eigenvalues $-1/\tau, -1/\tau_x$

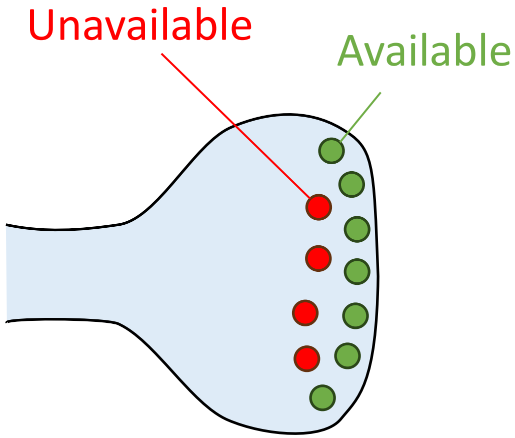
Differential equation
$\boldsymbol{y}' = M\boldsymbol{y}$

Has solutions
$\boldsymbol{y}(t) = \boldsymbol{y}^* e^{\lambda t}$
For eigenvalues λ
Eigenvectors $\boldsymbol{y}^*$

Repeated eigenvalues give
$\boldsymbol{y}(t) = \boldsymbol{y}^* t e^{\lambda t}, t^2 e^{\lambda t}, \ldots$

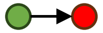


Short term plasticity



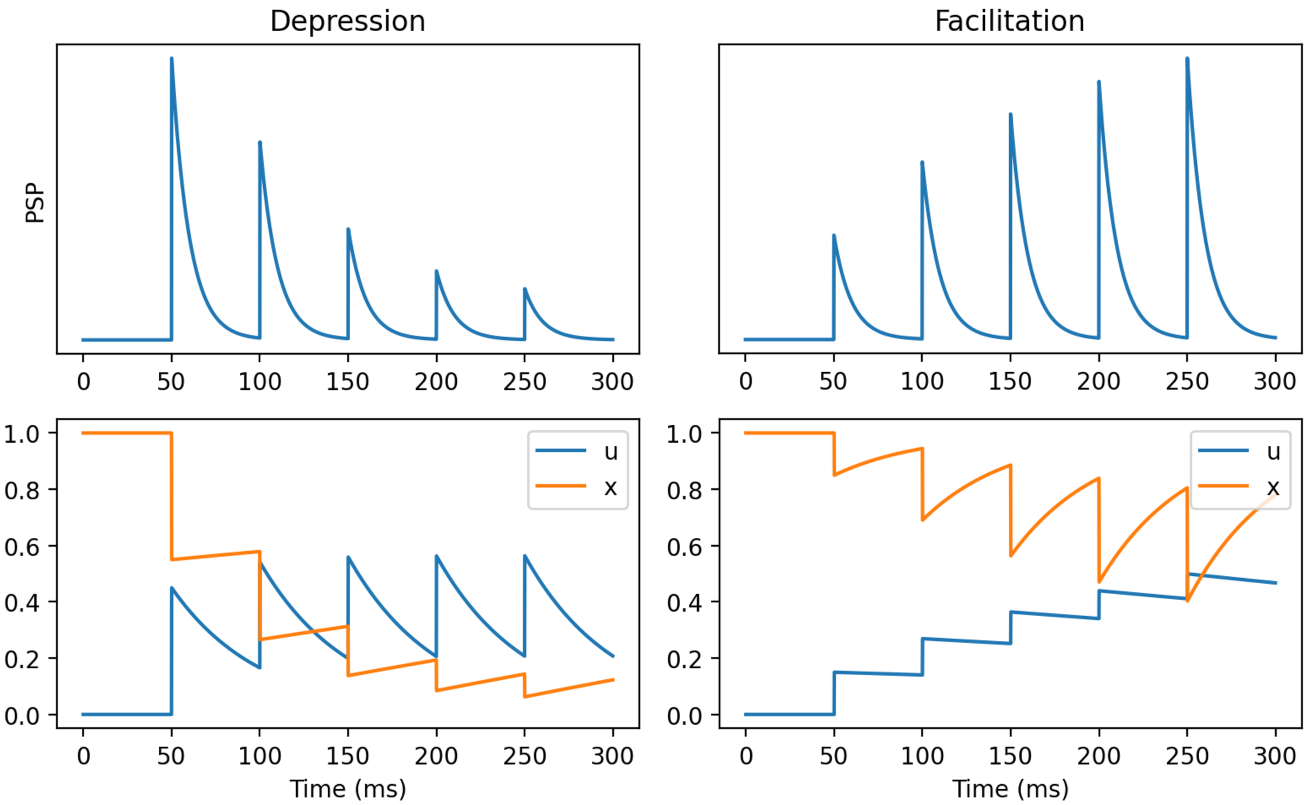
Fraction available $\boldsymbol{x}$

↘ Decreases after a spike



Probability of release $\boldsymbol{u}$

↗ Increases after a spike



Continuous evolution:

$$\tau_f u' = -u$$

$$\tau_d x' = 1 - x$$

When a spike arrives:

$$u \leftarrow u + U \cdot (1 - u)$$

$$v \leftarrow v + A \cdot u \cdot x$$

$$x \leftarrow x - u \cdot x$$

Order of operations matters!

Channel types: excitation and inhibition

Channel types include:

Inhibitory:

$GABA_A$ fast

$GABA_B$ slow

Excitatory:

AMPA fast

NMDA slow

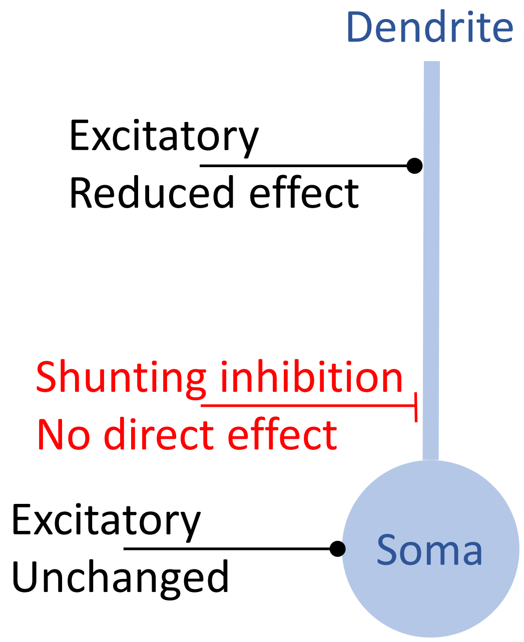
Shunting inhibition

Conductance increases locally

Reversal potential near resting potential

No effect on its own

Reduces effect of passing excitatory currents



Simplest model

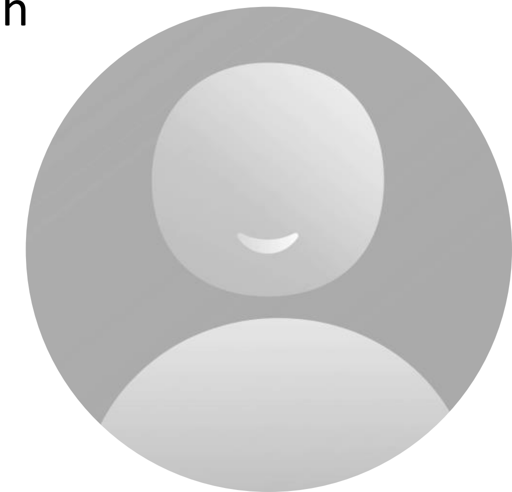
Excitation $v \leftarrow v + w$

Inhibition $v \leftarrow v - w$

NMDA

Highly nonlinear

Depends on postsynaptic membrane potential being high



Long term plasticity

Will come back to this in more detail in week 4

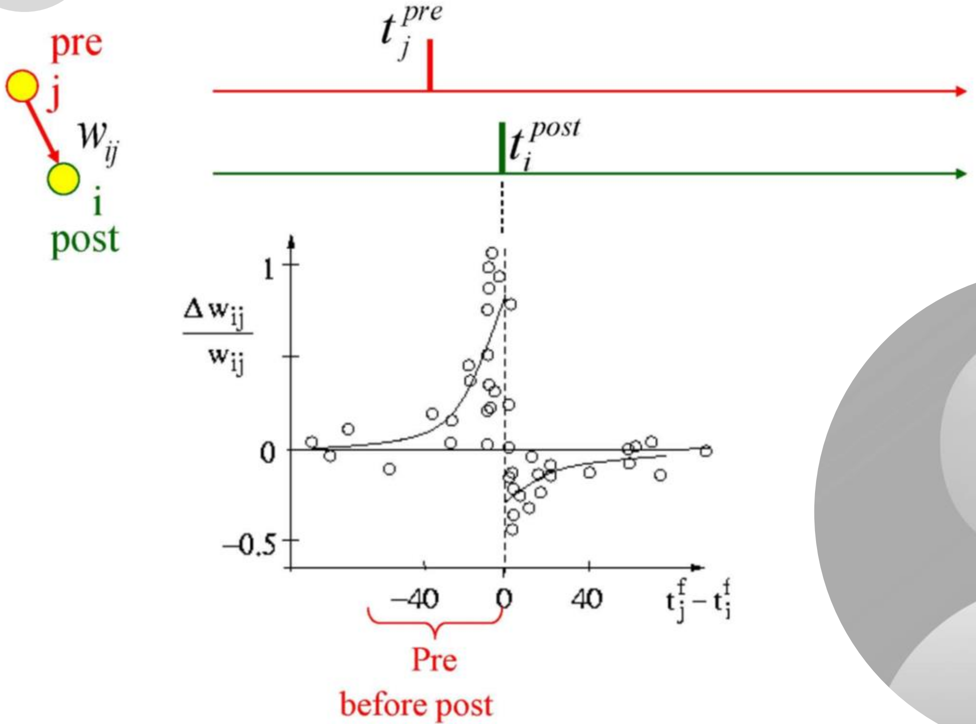
Hebbian rules can be modelled as:

$$\frac{\mathrm{d}w}{\mathrm{d}t} = \text{some function of } w \text{ and pre- and post-synaptic activity}$$

Spike timing-dependent plasticity (STDP):

$$\Delta w = \sum_{\substack{\text{presynaptic} \\ \text{spikes } t_j}} \sum_{\substack{\text{postsynaptic} \\ \text{spikes } t_i}} W(t_i - t_j)$$

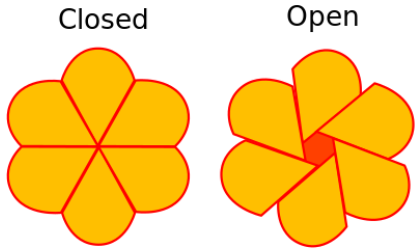
$$W(\delta t) = \begin{cases} A_+ \exp(-\delta t/\tau_+) & \text{for } \delta t > 0 \\ A_- \exp(-\delta t/\tau_-) & \text{for } \delta t < 0 \end{cases}$$

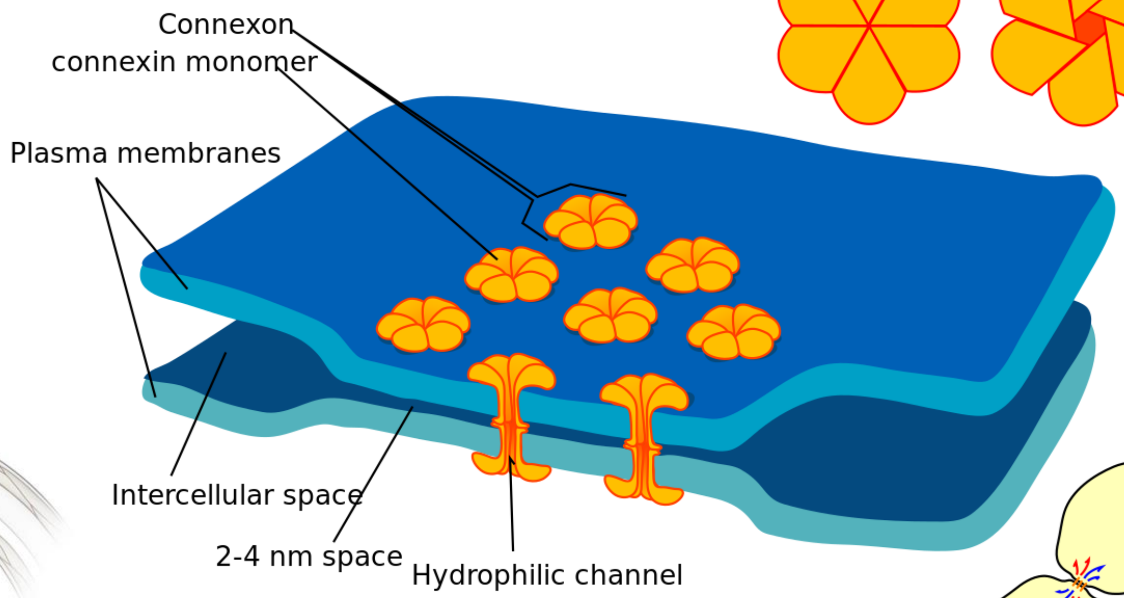


More synaptic fun

Synaptic failure

$v \leftarrow v + w$ (with probability p)



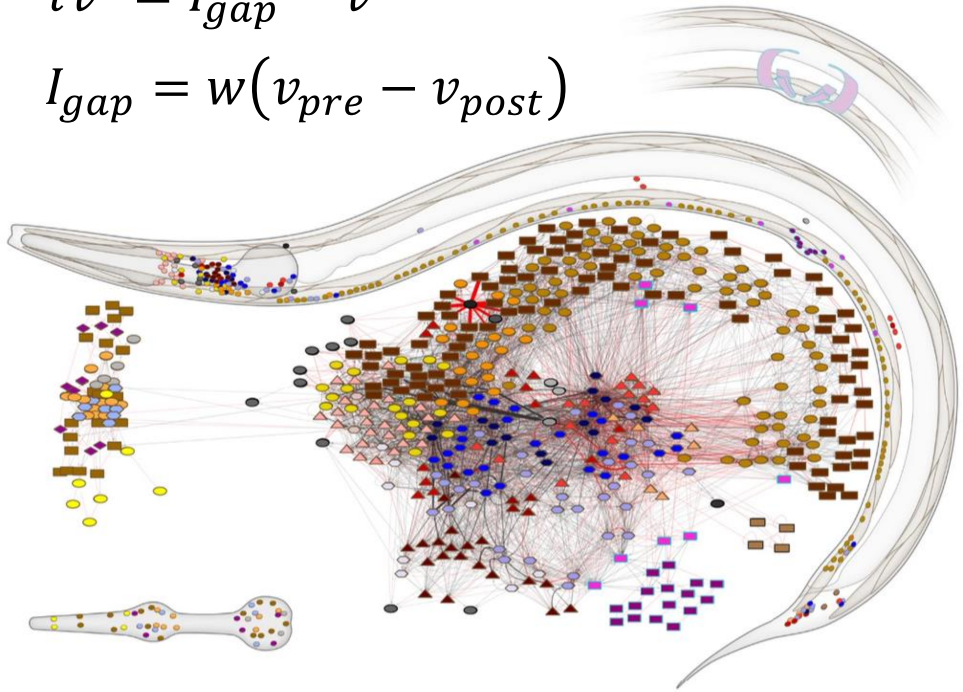


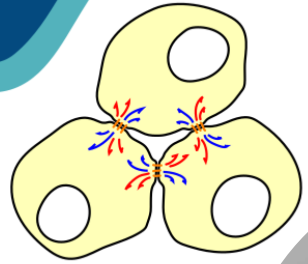
Gap junctions

For example…

$\tau v' = I_{gap} - v$

$I_{gap} = w(v_{pre} - v_{post})$





C. Elegans

Precisely 302 neurons

Always the same pattern

Mostly non-spiking, using gap junctions instead