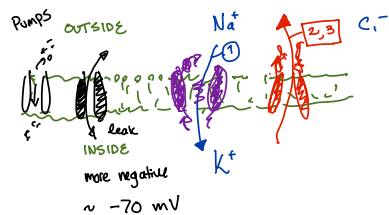
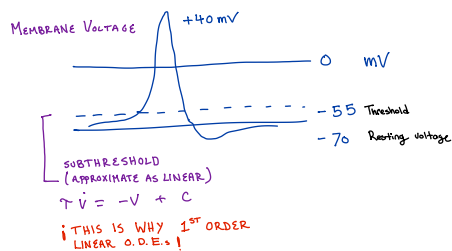
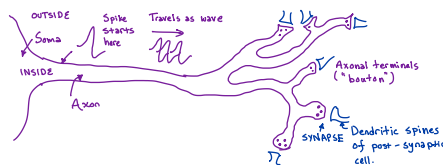


TODAY 15TH OCT. ①
 WHY WERE WE COVERING O.D.E.s, EULER'S METHOD, ETC.? ②
 Hippocampus, Hopfield, Delta Rule: REPRISÉ
 TABLED FOR TOMORROW
 ③ Exam review (continued tomorrow)

ACTION POTENTIAL



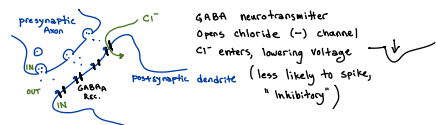
- 1: INITIATE: V goes above voltage-gated Na^+ channel threshold, usually $\approx -55 \text{ mV} \rightarrow$ runaway excitation
- 2: STOPS RISING: inward K^+ start opening $\approx -20 \text{ mV}$ Na^+ channels inactivate above $\approx 0 \text{ mV}$
- 3: REFRACTORY PERIOD: Open K^+ channels continue to conduct, hyperpolarize membrane. Na^+ channels stay inactive a bit, preventing spike.



DALE'S PRINCIPLE: (approx. truth)

Each neuron uses same chemical signals at all axonal terminals regardless of post-synaptic target.

EXAMPLE SYNAPSE: IONOTROPIC GABA



Glutamate
 AMPA $\rightarrow +V$ (excitatory)
 NMDA $\rightarrow \text{Ca}^{2+}$ (signal for learning)
 GABA
 GABA_A - ionotropic
 GABA_B - metabotropic (METABOTROPIC (Glu. 2. "HOLLA" not on exam))

LINEAR O.D.E.s \rightarrow membrane voltage

$x_0 \leftarrow \text{something}$
 for $t = 1 \dots 1000$
 $x \leftarrow f(x)$
 $\dot{V} = -V + f$
 $V \leftarrow \Delta t \cdot [f - V]$
 how to simulate membrane?
 in a loop integrate O.D.E. for example by forward Euler

$$\dot{V} = -V \quad V(t) = e^{-t} \cdot V(0)$$

$$\dot{V} = \underline{a} - V$$

$$V(t) = a + e^{-t} (V_0 - a)$$

$$\tau \dot{V} = -V \quad V(t) = e^{-t/\tau} \cdot V_0$$

$$\tau \dot{V} = -V + C$$

$$V(t) = C + e^{-t/\tau} (V - C)$$

$$\tau \dot{V} = \mathcal{E}_e - V + I \cdot R$$

linear 1st-order O.D.E. soln. (scalar, stable case)

- decay from where we start

- toward where we are driven ("equilibrium value")

- with time-constant τ "tau" (larger \rightarrow slower)

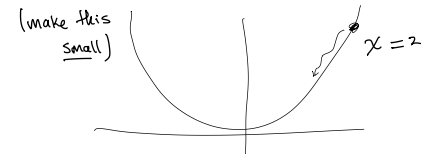
- generic form

- specific constants come from electronic properties of membrane, but we will cover this post-midterm.

DELTA RULE

AN OPTIMIZATION PERSPECTIVE

Loss Function



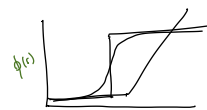
GRADIENT

$$\text{Loss} = \frac{1}{2} x^2 \rightarrow \frac{d\text{Loss}}{dx} = x$$

for epoch in $1 \dots 1000$

$x \leftarrow \eta(-x)$ gradient
 Learning Rate "descent"

$$\text{Loss}(\underbrace{w_1, w_2, \dots, w_n}_W; \underbrace{x_1, \dots, x_n}_X, y^*)$$



Activation function $\phi(\cdot)$
 - Many different monotonic operators depending on model.
 - clw used a hard threshold.

$$\text{minimize } \frac{1}{2} (\hat{y} - y^*)^2 \quad \hat{y} = \phi\left(\sum_i \omega_i x_i\right)$$

$$\frac{d}{d\omega_k} \text{Loss}(\dots) = (\hat{y} - y^*) \phi'(\dots) x_k$$

$$\Delta \omega_k = \eta \cdot (y^* - \hat{y}) x_k$$

learning rate $\eta = 0.001$ prediction error

$$\omega_k \leftarrow \omega_k + \Delta \omega_k$$

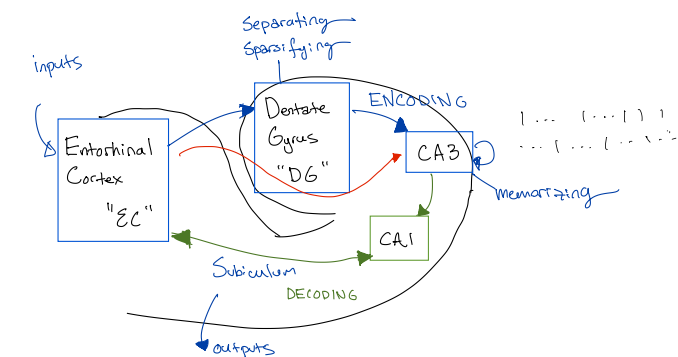
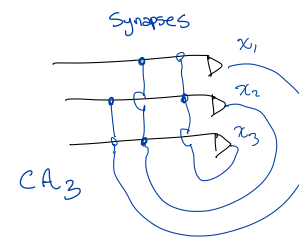
HIPPOCAMPAL FORMATION & HOPFIELD

Autoassociative:
 many axons recurrent in CA3

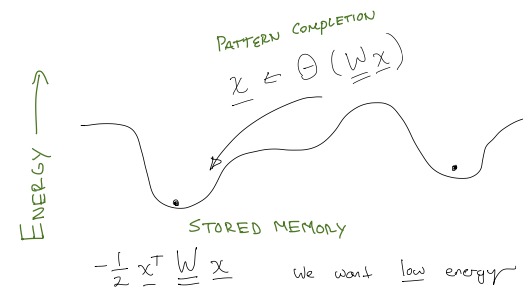
Weights for $\underline{x} = (1, -1, -1)$

$$\begin{aligned} x_1 &= 1 \\ x_2 &= -1 \\ x_3 &= -1 \end{aligned}$$

$$\Delta W = \begin{bmatrix} 0 & -1 & -1 \\ -1 & 0 & 1 \\ -1 & 1 & 0 \end{bmatrix}$$



$$\text{Hopfield-Net ENERGY} \quad -\frac{1}{2} \underline{x}^T \underline{W} \underline{x} = -\frac{1}{2} \sum_i x_i x_j \omega_{ij}$$



Want to remember

$$x_i = x_j$$

$$\omega_{ij} = +1$$

Pattern energy

$$x_i \cdot x_j \cdot \omega_{ij}$$

$$\begin{aligned} (-1) \cdot (-1) \cdot 1 &= 1 \\ 1 \cdot (-1) \cdot 1 &= -1 \end{aligned}$$

$$\begin{aligned} \mathcal{E} &= -1/2 \\ \mathcal{E} &= +1/2 \end{aligned} \quad \leftarrow \text{better}$$