Building Better Models in Cognitive Neuroscience: THEORY

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Better models help solve better problems

How to Build Better Cognitive Neuroscience Models

A) Why?

B) Ideals

C) Modeling

Why?

Increased Constraints

Find Unexpected Relationships

Make Novel Predictions

Better Model Testing


IDEALS

Neuroscience

1) Be consistent only known connections

2) Excitatory or Inhibitory Connections: Pick One

3) Predicted behavior consistent with known behavior

4) Predicted learning consistent with known learning


Simplicity

Set-in-Stone

Input

Black Box

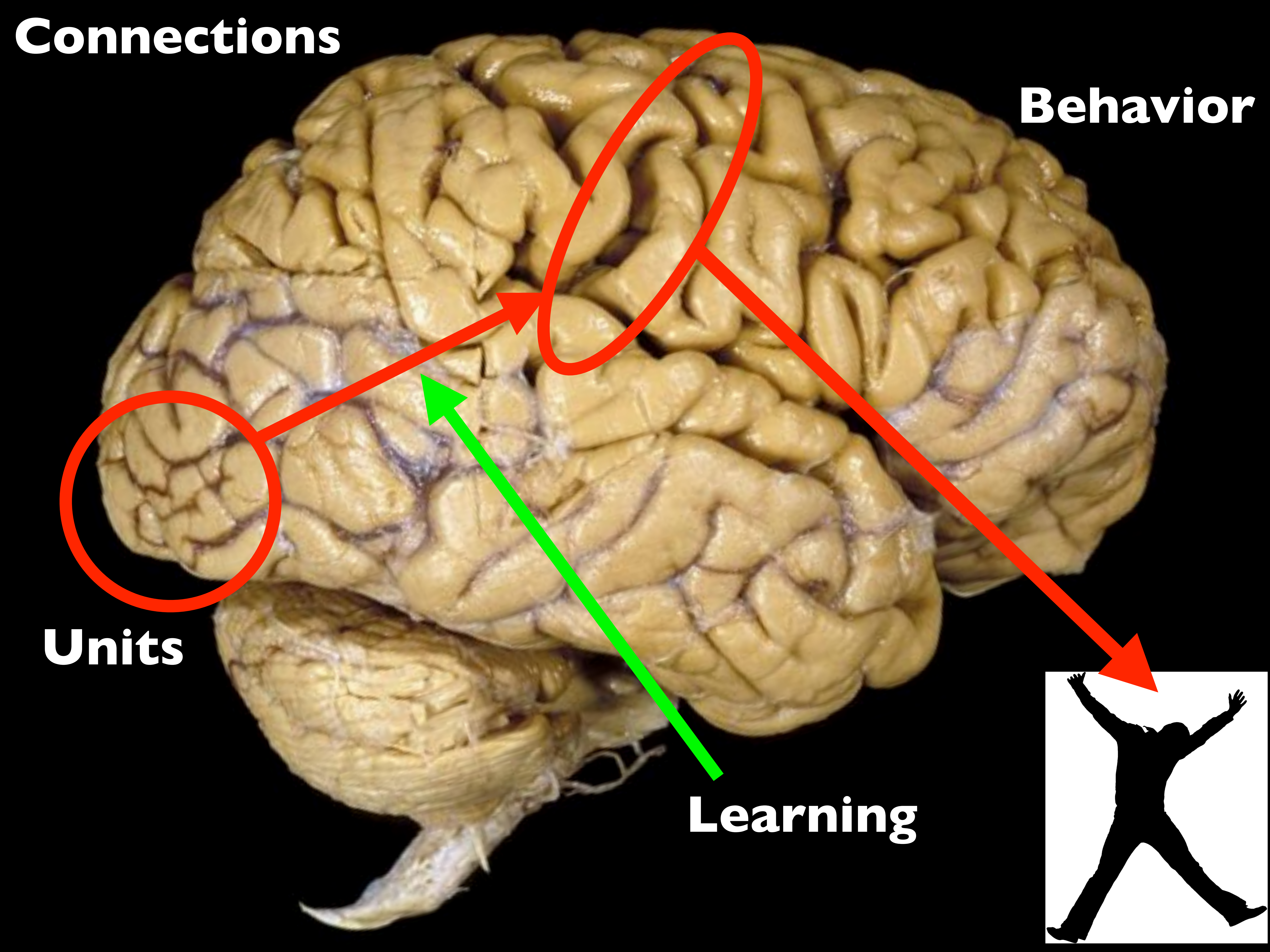
Output

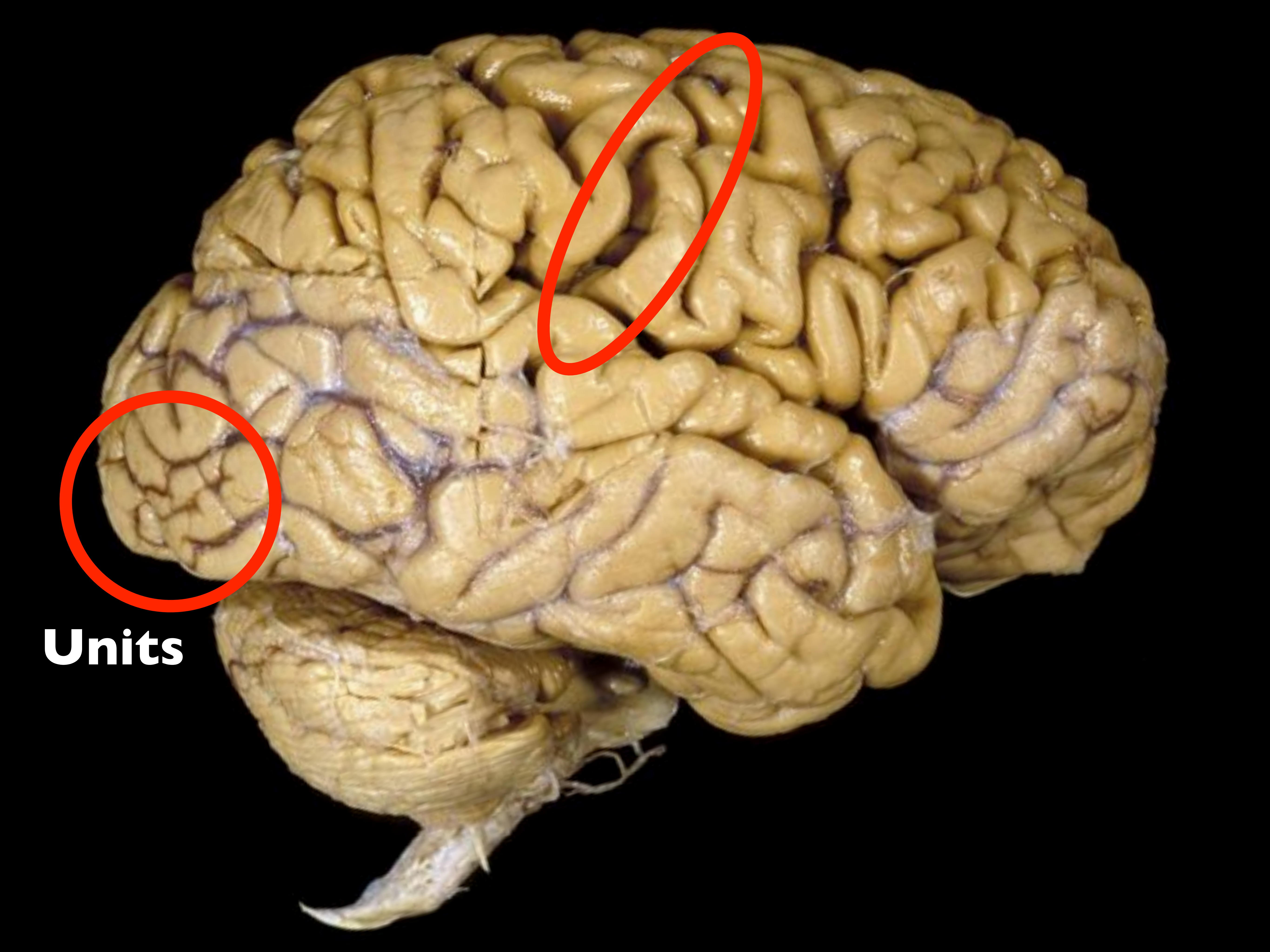
Goodness-of-Fit

Biological Simplicity

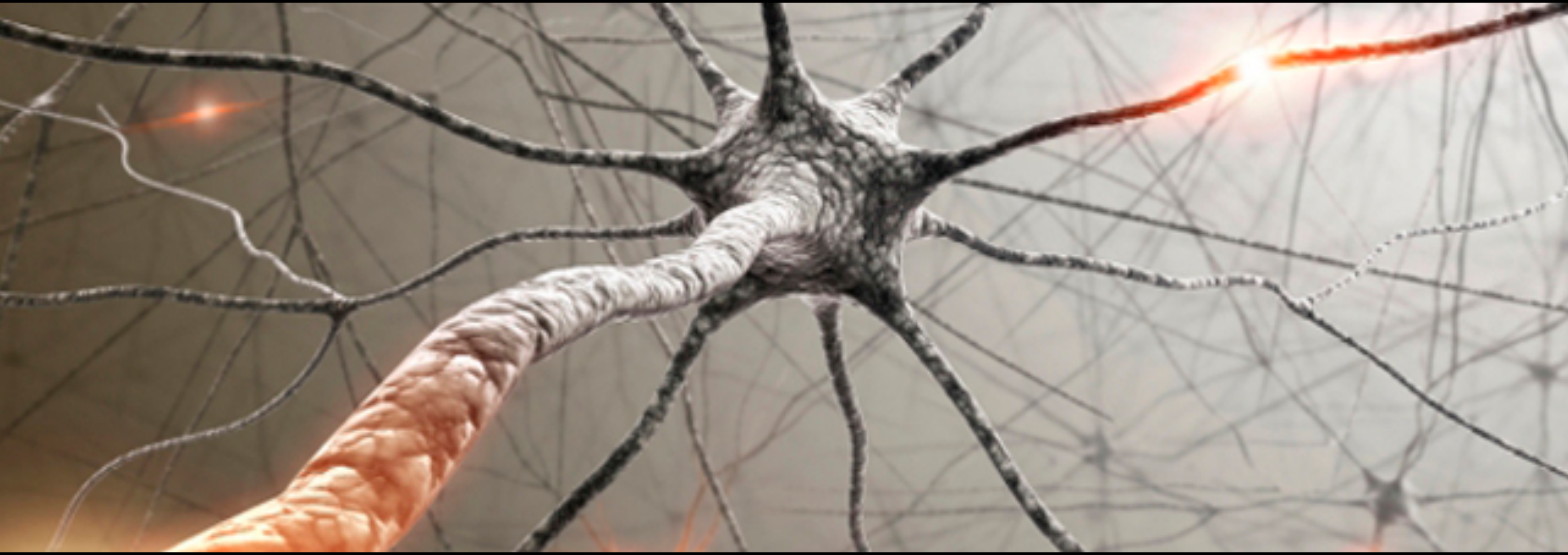
vs.

Scalability


Connections
Behavior
Units
Learning


Units

MODELING



UNITS

Leaky Integrate-and-fire Model

$$\frac{dV_B(t)}{dt} = \alpha f[V_A(t)] + \beta - \gamma V_B(t)$$

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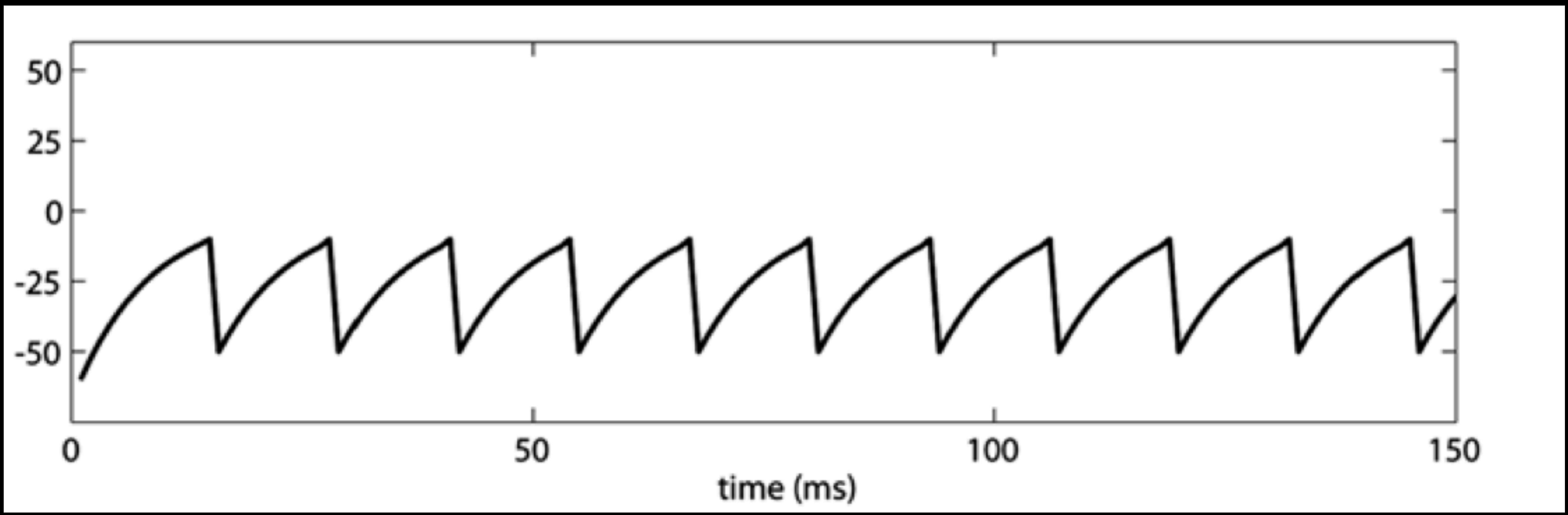
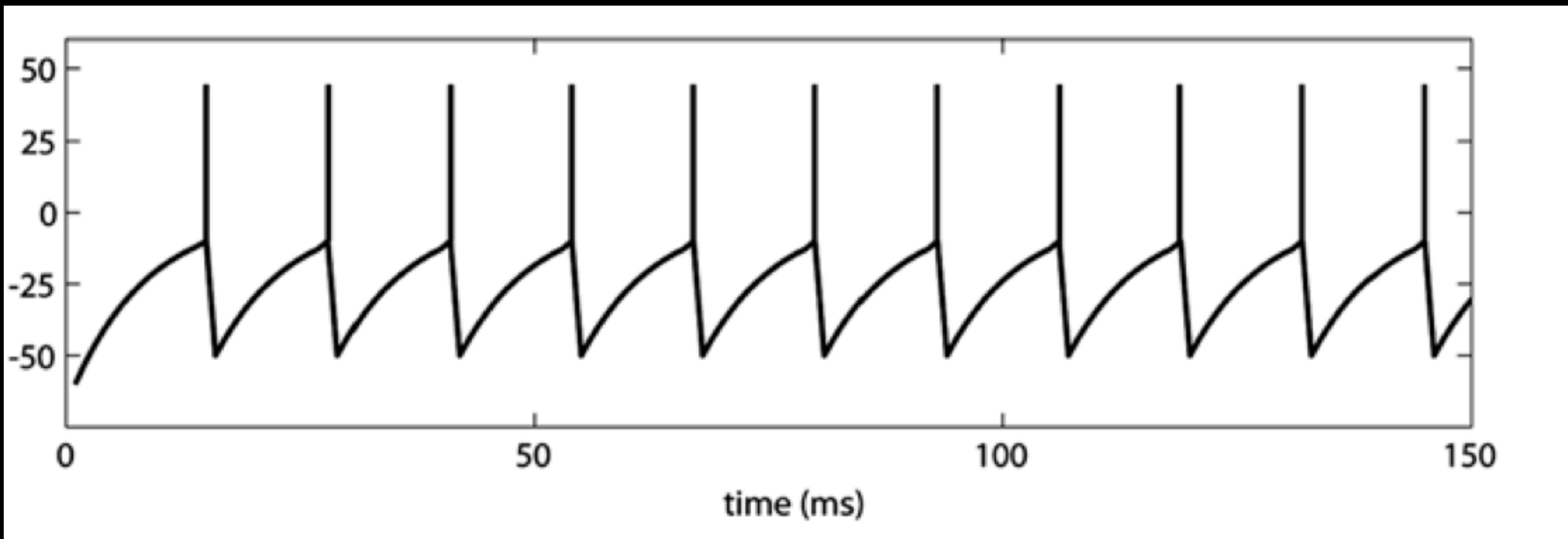
Activation



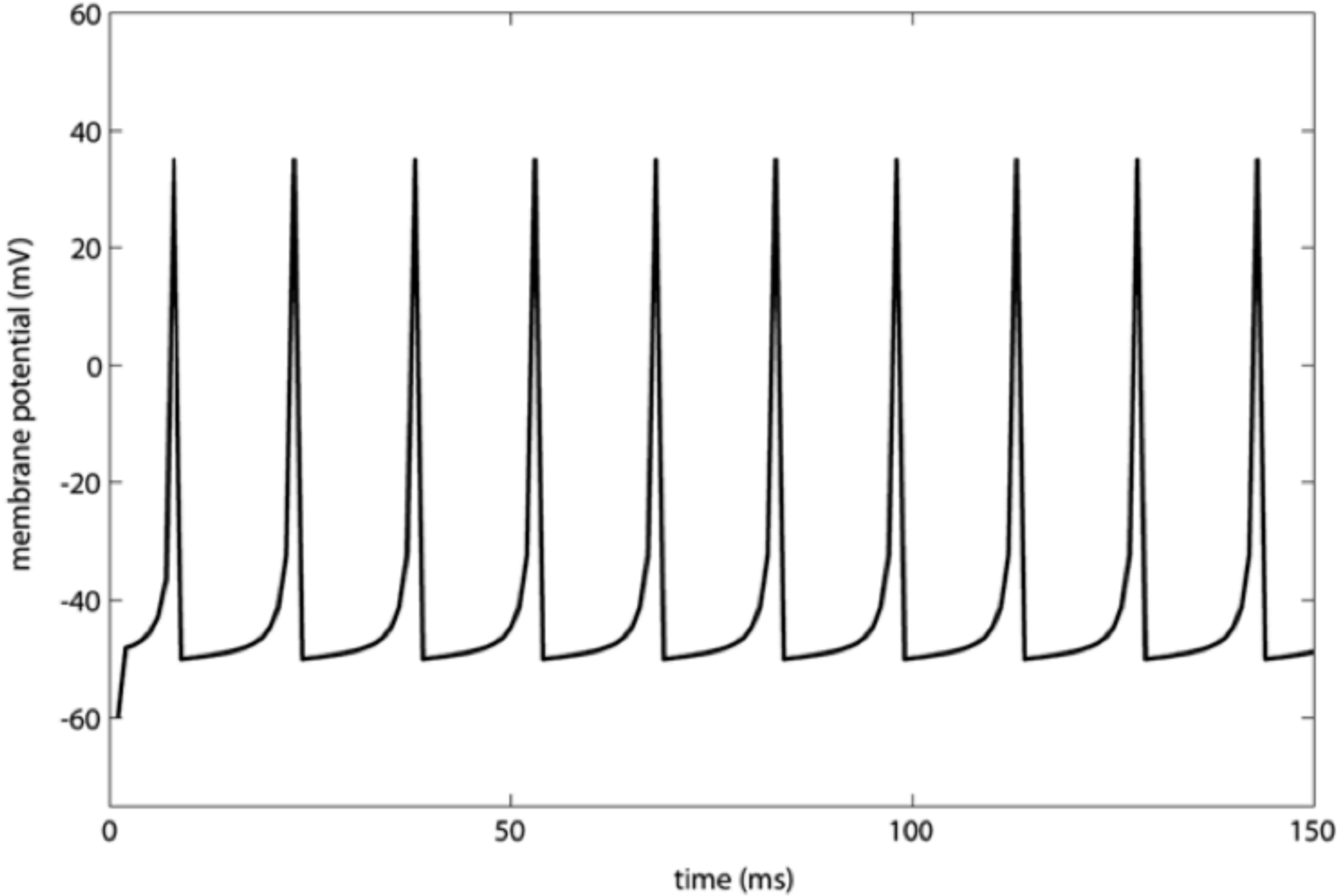
Set spiking threshold, V_{peak}, on $V_B(t)$


50
25
0
-25
-50
0
50
100
150
time (ms)

Leaky Integrate-and-fire Model

with quadratic polynomial

$$\frac{dV_B(t)}{dt} = \alpha f[V_A(t)] + \beta + \gamma[V_B(t) - V_r][V_B(t) - V_\mathrm{t}]$$



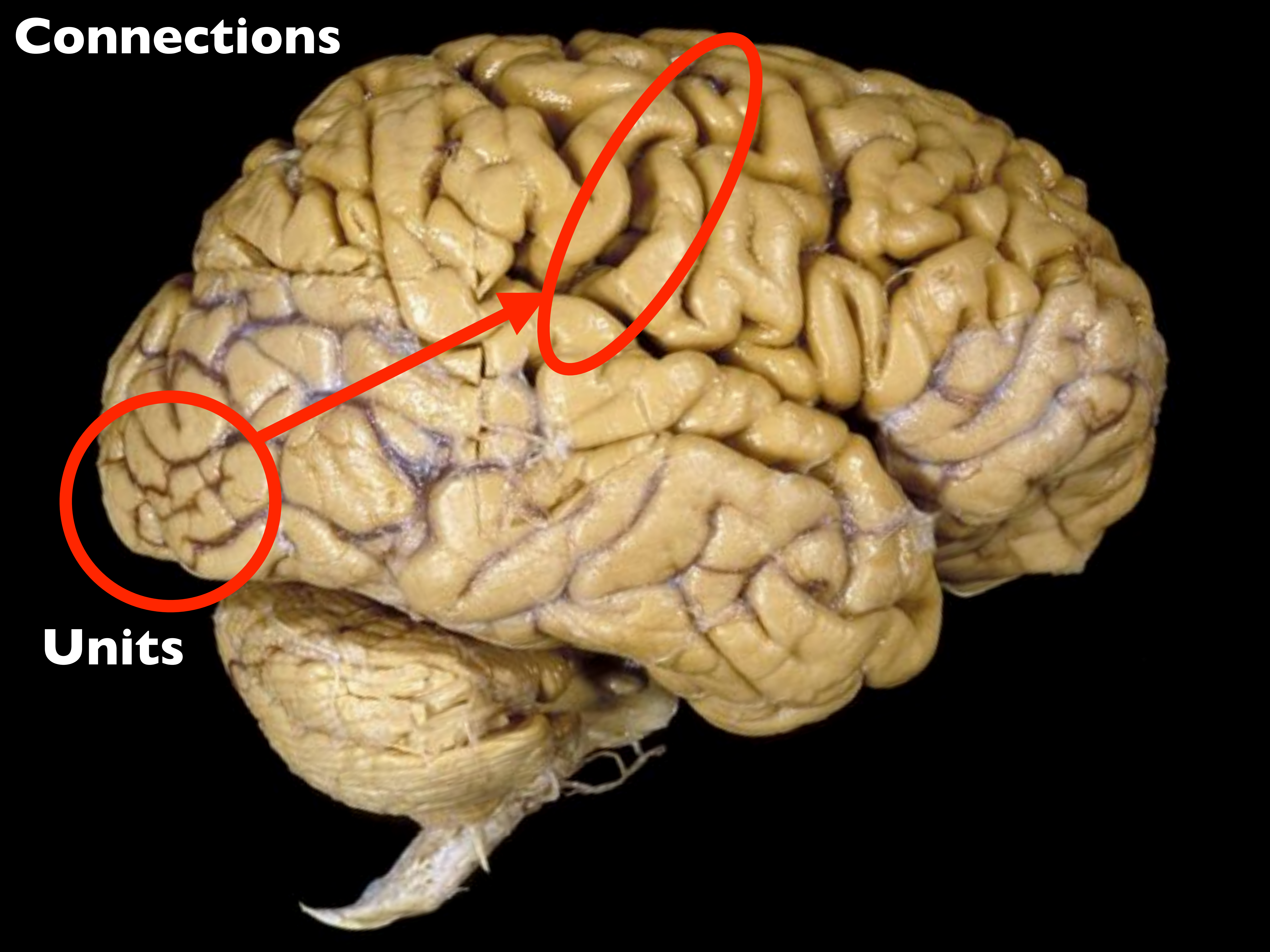
60
40
20
0
-20
-40
-60
membrane potential (mV)
0
50
100
150
time (ms)

Izhikevich model

$$\frac{dV_B(t)}{dt} = \alpha f[V_A(t)] + \beta + \gamma[V_B(t) - V_{\mathrm{r}}][V_B(t) - V_{\mathrm{t}}] - U_B(t)$$

$$\frac{dU_B(t)}{dt} = \lambda[V_B(t) - V_r] - \omega U_B(t),$$

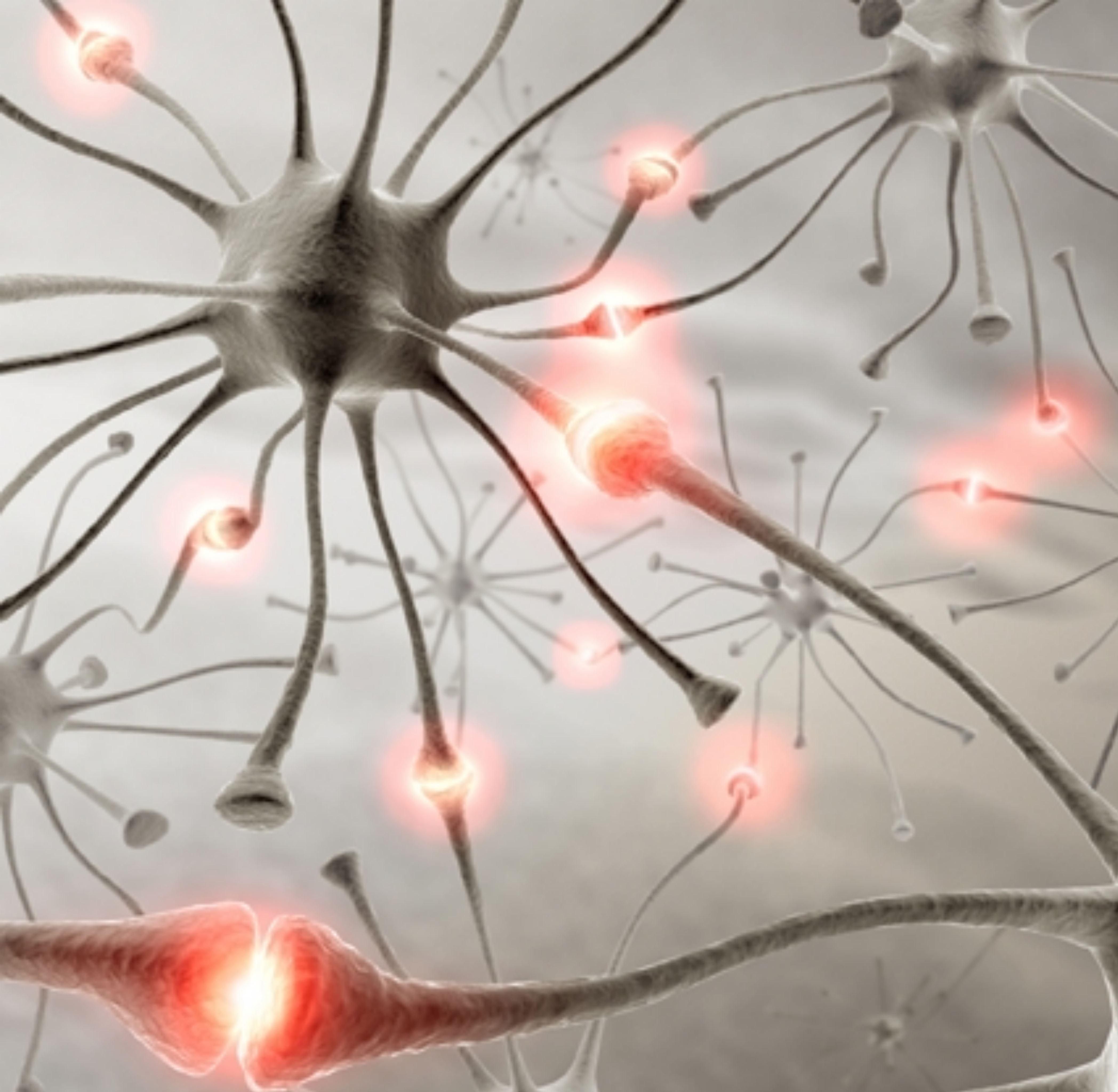
See Figure 3 in Paper


Connections
Units

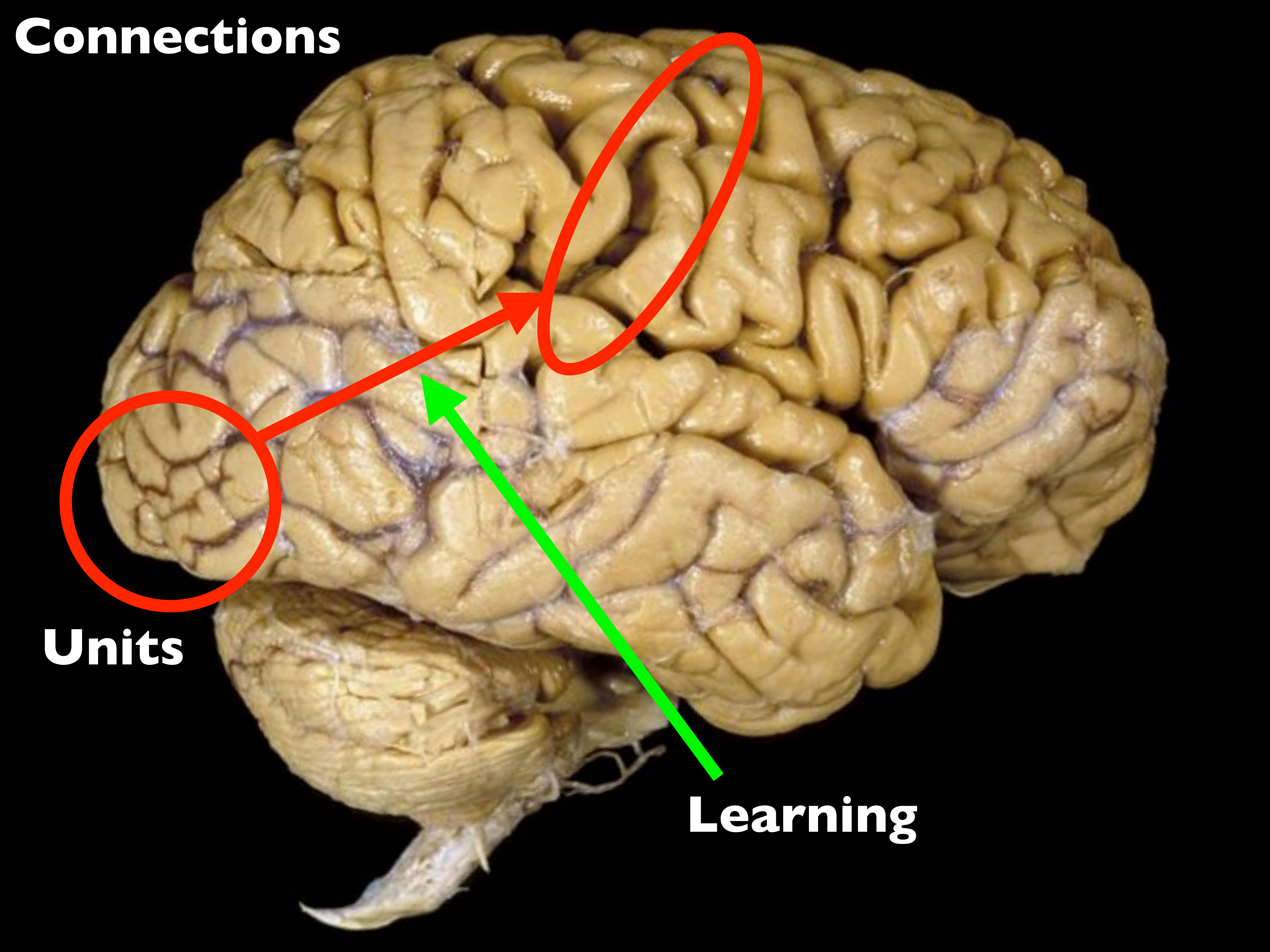
Axon & Synaptic Delays

$$f(t) = \frac{t}{\lambda} \exp\left(\frac{\lambda - t}{\lambda}\right).$$

Break



LEARNING


Connections
Units
Learning

Long-Term Potentiation
(LTP)

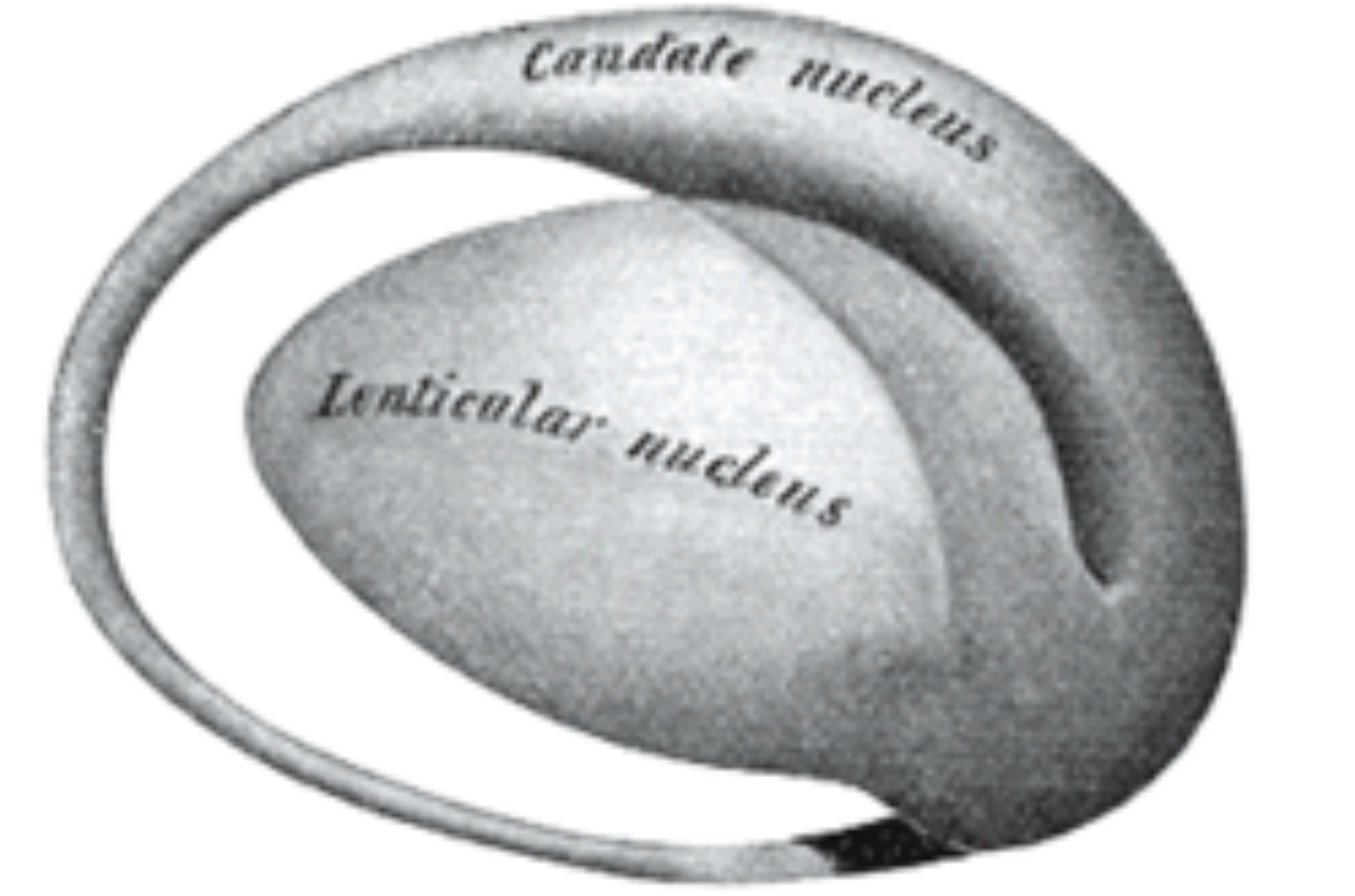
Long lasting **increase** in the efficacy of a synapse

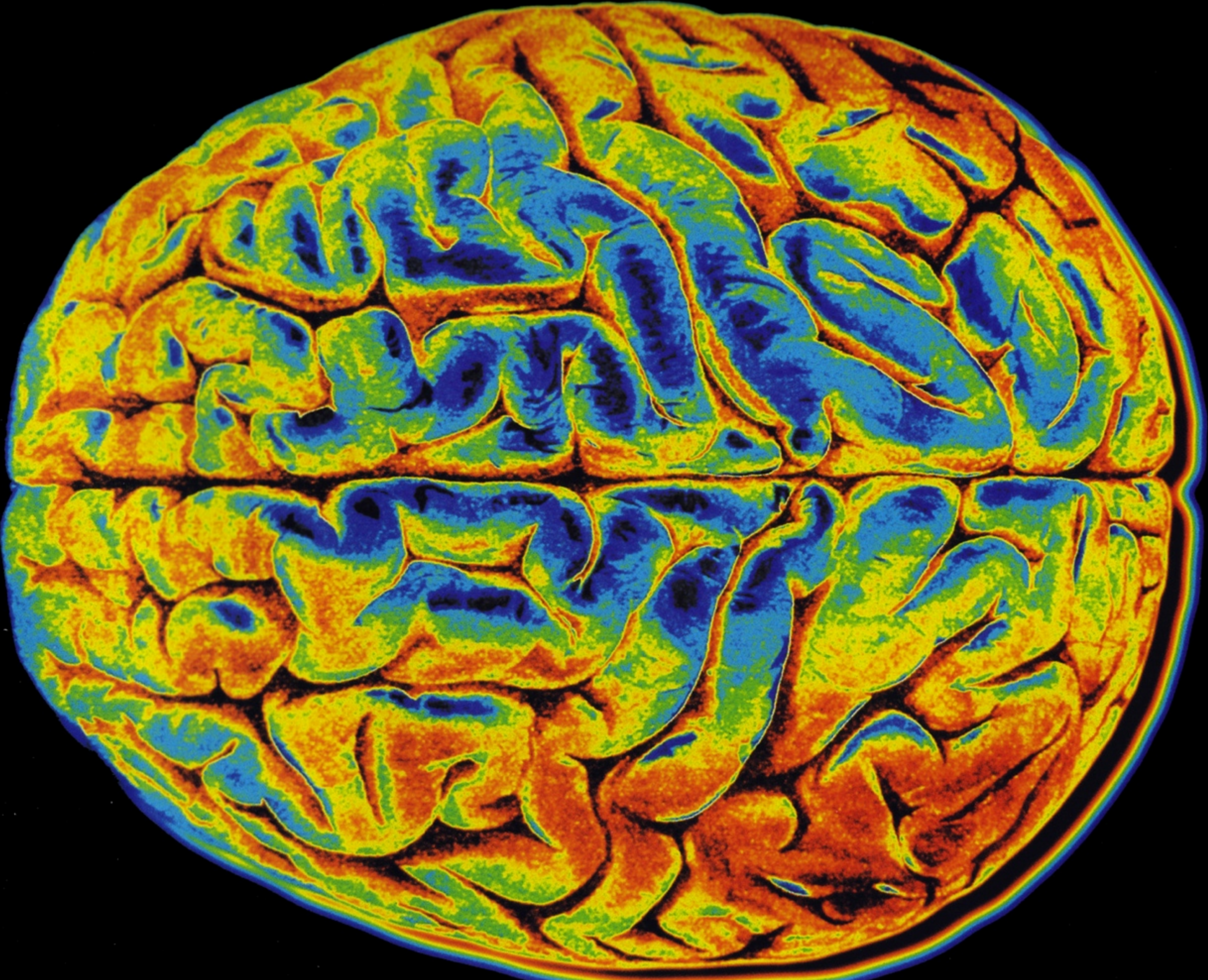
Long-Term Depression (LTD)

Long lasting **decrease** in the efficacy of a synapse

Dopamine

Important function
but depends on location


Caudate nucleus
Lenticular nucleus



Discrete-Time
vs.
Continuous-Time

Discrete Time & Slow DA Reuptake

$$w_{A,B}(n+1) = w_{A,B}(n)$$
$$+\alpha_w \int f[V_A(t)]dt \left[\int [V_B(t)]^+ dt - \theta_{NMDA}\right]^+ [w_{\max} - w_{A,B}(n)]$$
$$-\beta_w \int f[V_A(t)]dt \left\{\left[\theta_{NMDA} - \int [V_B(t)]^+ dt\right]^+ - \theta_{AMPA}\right\}^+ w_{A,B}(n)$$

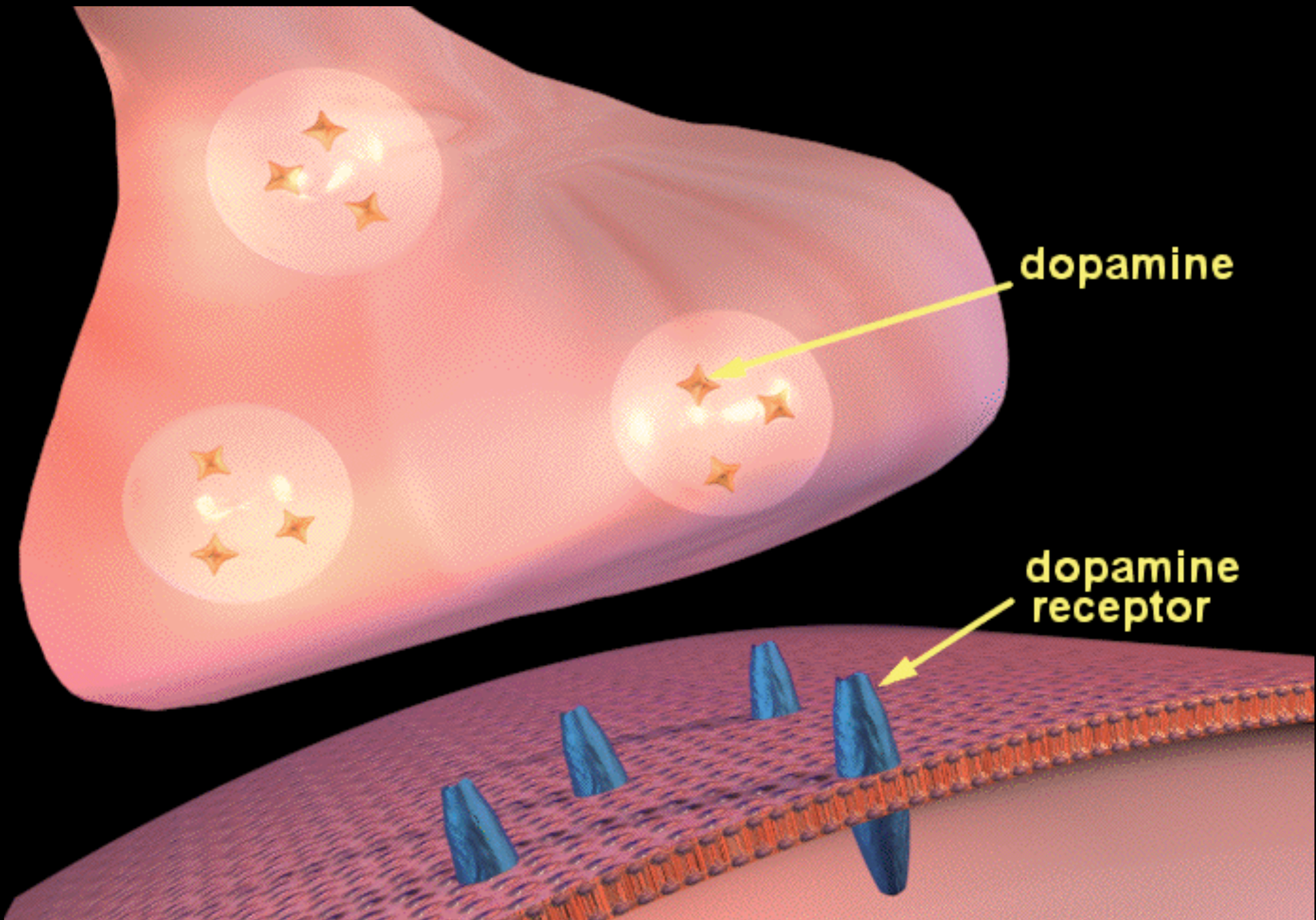
Discrete Time & Slow DA Reuptake

$$w_{A,B}(n+1) = w_{A,B}(n)$$
$$+\alpha_w \int f[V_A(t)]dt \left[\int [V_B(t)]^+ dt - \theta_{NMDA}\right]^+ [w_{\max} - w_{A,B}(n)]$$
$$-\beta_w \int f[V_A(t)]dt \left\{\left[\theta_{NMDA} - \int [V_B(t)]^+ dt\right]^+ - \theta_{AMPA}\right\}^+ w_{A,B}(n)$$

Discrete Time & Fast DA Reuptake

$$
\begin{aligned}
w_{A,B}(n+1) = w_{A,B}(n) &+ \alpha_w \int f[V_A(t)]dt \left[\int [V_B(t)]^+ dt - \theta_{\mathrm{NMDA}} \right]^+ [D(n) - D_{base}]^+ [w_{max} - w_{A,B}(n)] \\
&- \beta_w \int f[V_A(t)]dt \left[\int [V_B(t)]^+ dt - \theta_{\mathrm{NMDA}} \right]^+ [D_{base} - D(n)]^+ w_{A,B}(n) \\
&- \gamma_w \int f\,[V_A(t)]\,dt \left\{ \left[\theta_{\mathrm{NMDA}} - \int [V_B(t)]^+ dt \right]^+ - \theta_{\mathrm{AMPA}} \right\}^+ w_{A,B}(n)
\end{aligned}
$$

Modeling Dopamine Release



Input

Black Box

Output

$$\text{Reward Prediction Error (RPE)} = \text{Obtained Reward} - \text{Predicted Reward}$$

Obtained Reward (Simple)

+1 if correct

-1 if error

Predicted Reward (Simple)

$$P_{n+1} = P_n + \eta(R_n - P_n)$$

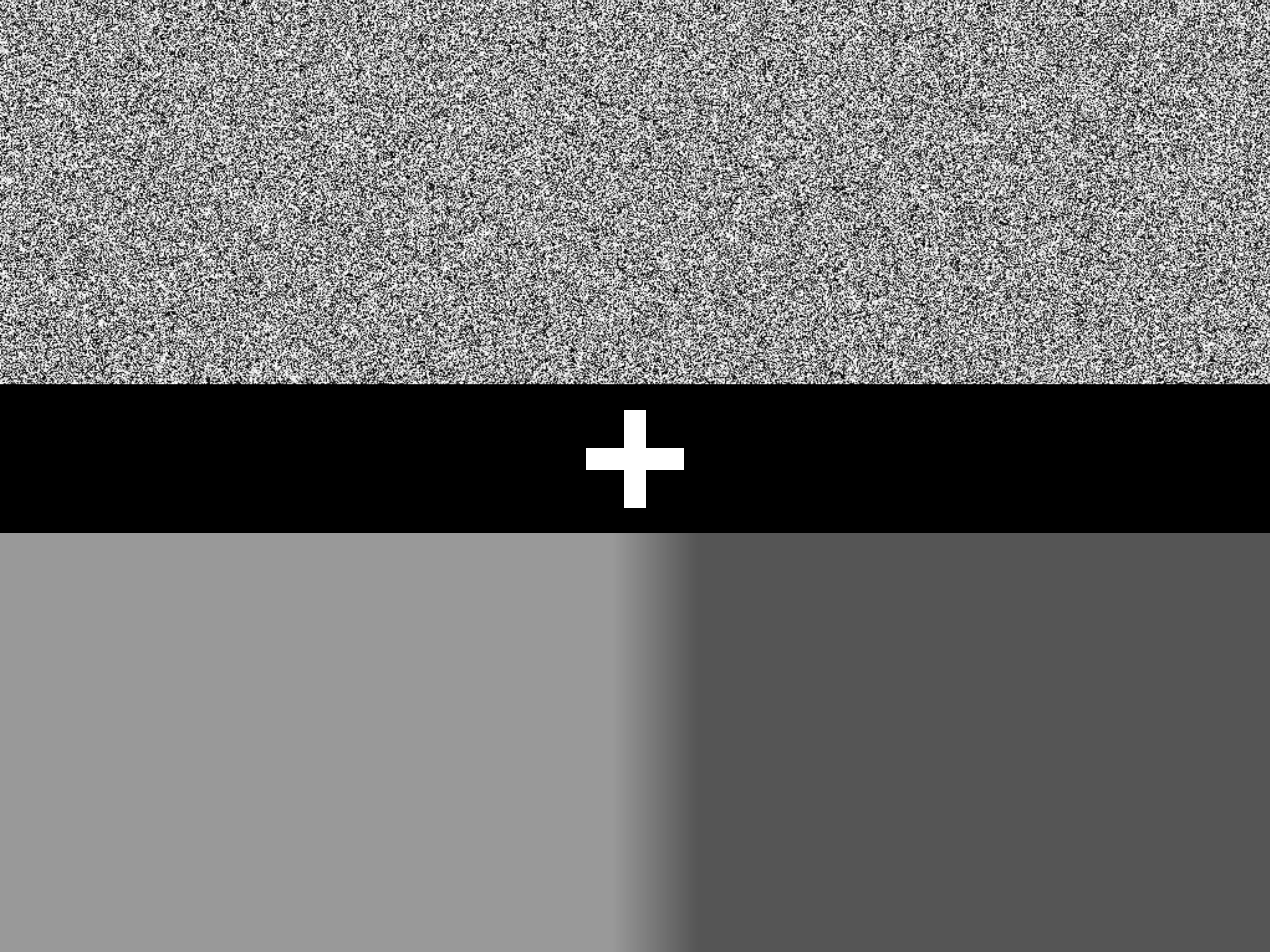
Dopamine & Reward Prediction Error

$$D(n) = \begin{cases} 1 & \text{if RPE} > 1 \\ .8\,\text{RPE} + .2 & \text{if } -.25 \le \text{RPE} \le 1 \\ 0 & \text{if RPE} < -.25. \end{cases}$$

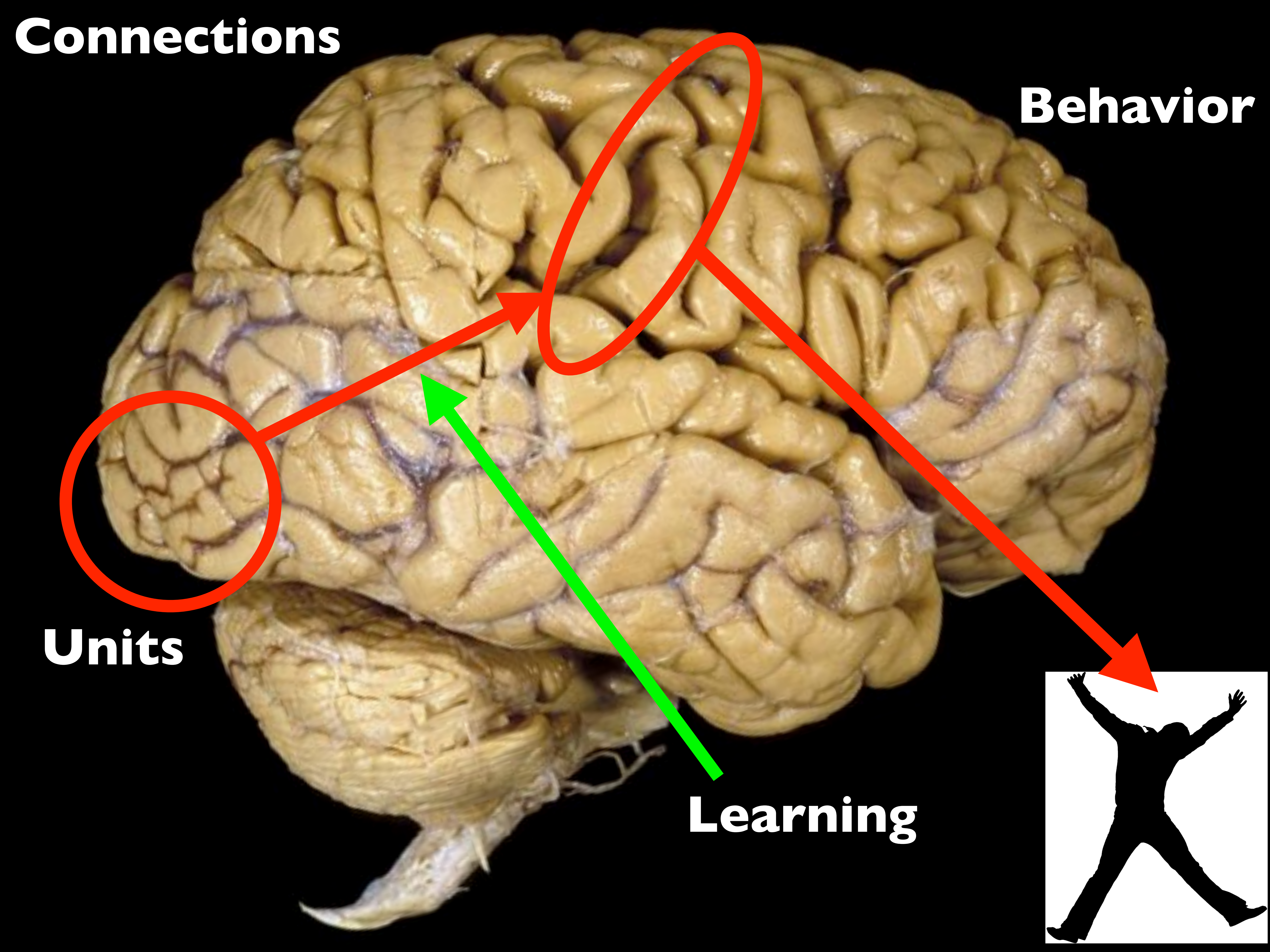
Continuous-time models of learning

$$\Delta = \begin{cases} e^{-(T_{\text{post}}-T_{\text{pre}})/\text{TM}_{+}} & \text{if } T_{\text{post}} - T_{\text{pre}} > 0 \\ -e^{(T_{\text{post}}-T_{\text{pre}})/\text{TM}_{-}} & \text{if } T_{\text{post}} - T_{\text{pre}} < 0 \end{cases}$$

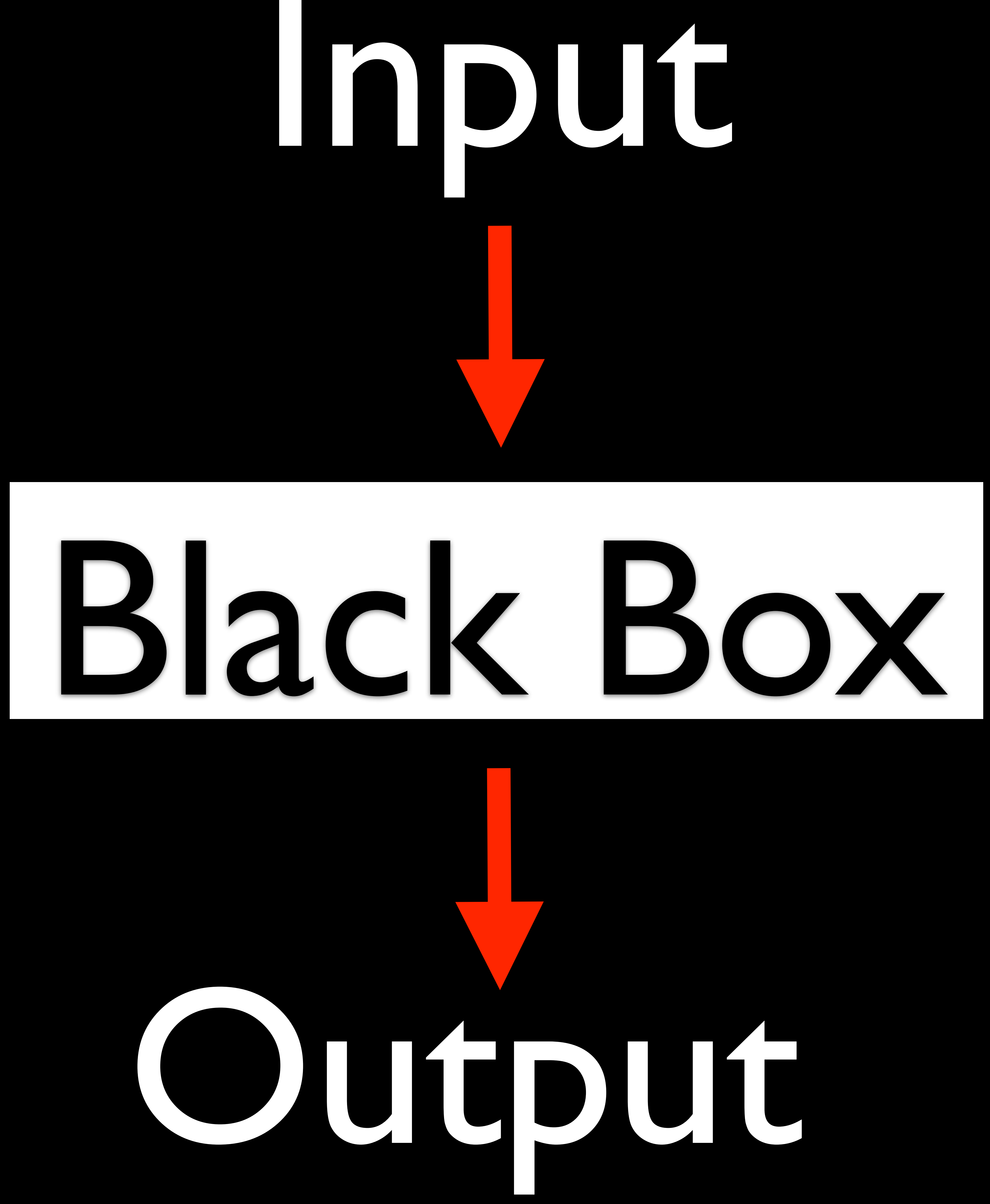
Learning Rules:
Local
vs.
Global



BEHAVIOR


Connections
Behavior
Units
Learning

1) Which brain regions controls behavior?


Input
Black Box
Output

2) What is the neural activity function that drives the decision?

1) Integrated neural activity
2) Spiking behavior
3) Integrated output alpha function

Integrated Output Alpha Function

$$\int_0^t f[V_B(t)]dt$$

3) How is response competition resolved?

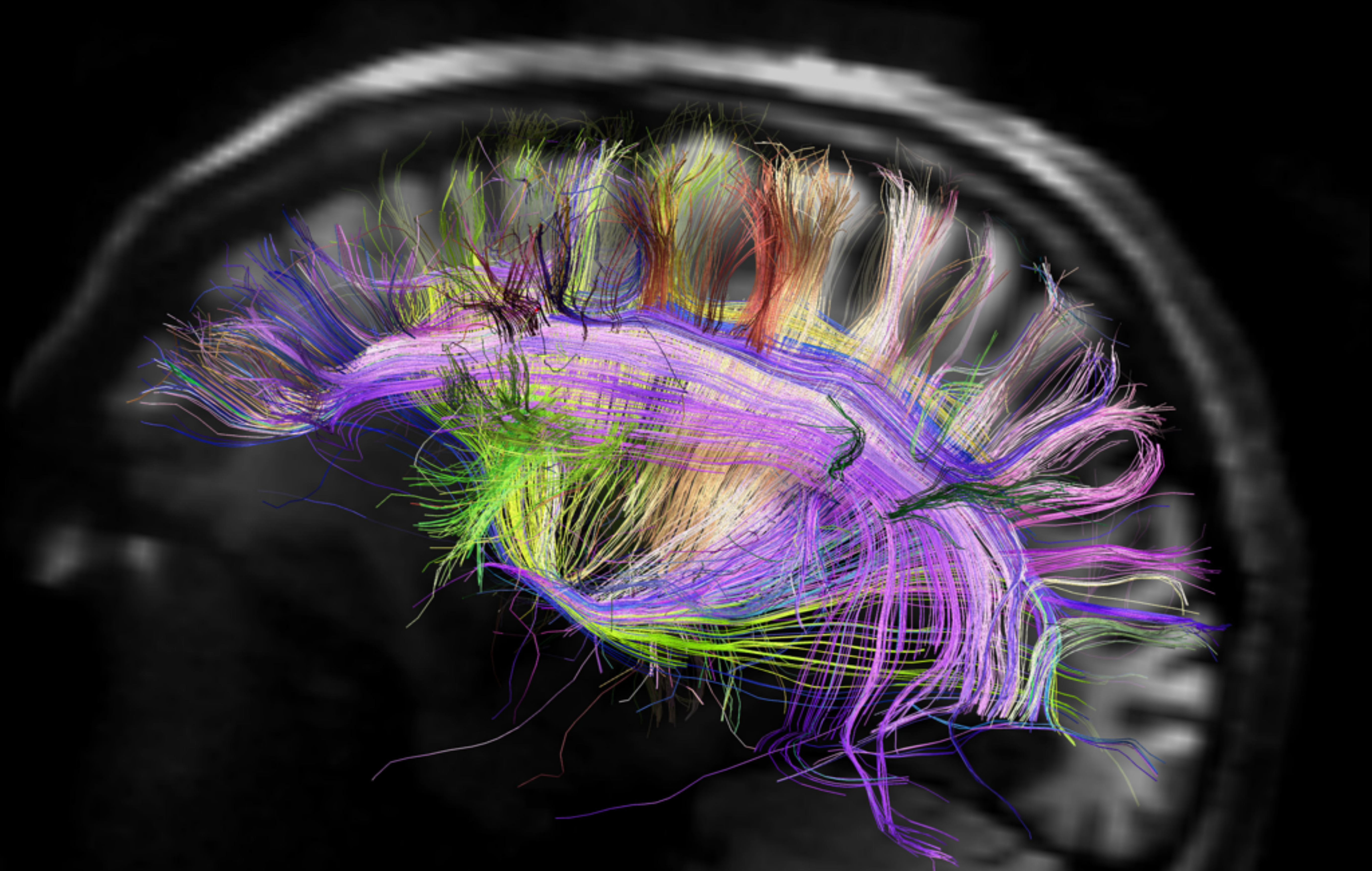
Two Choice Tasks

1) Diffusion Model
2) Accumulator/Race Model with Lateral Inhibition

>Two Choice Tasks

- Set criterion at each decision unit
- 1st unit that crosses threshold “wins”
- Add lateral inhibition

OVERCONNECTING



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A Neurobiological Theory of Automaticity in Perceptual Categorization

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Have a Happy