



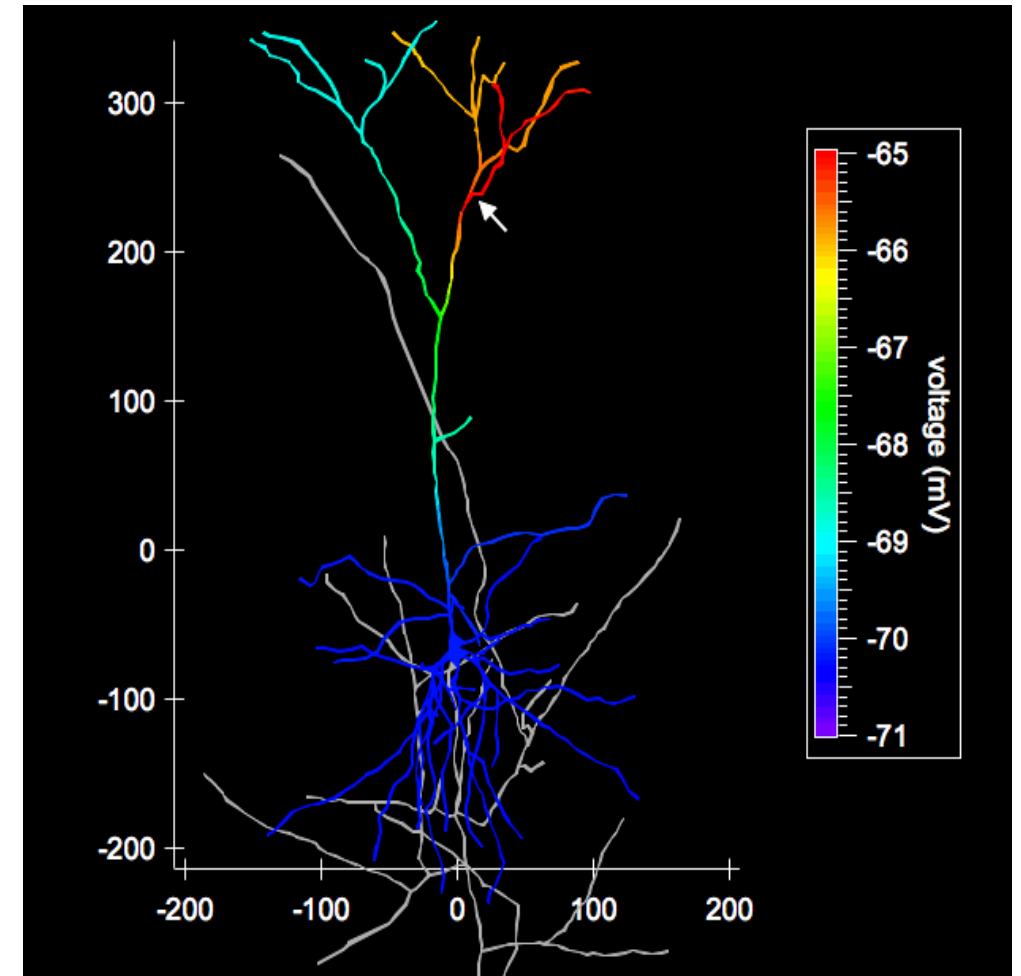
Reinforcement Learning in a Neurally Controlled Robot Using Dopamine Modulated STDP

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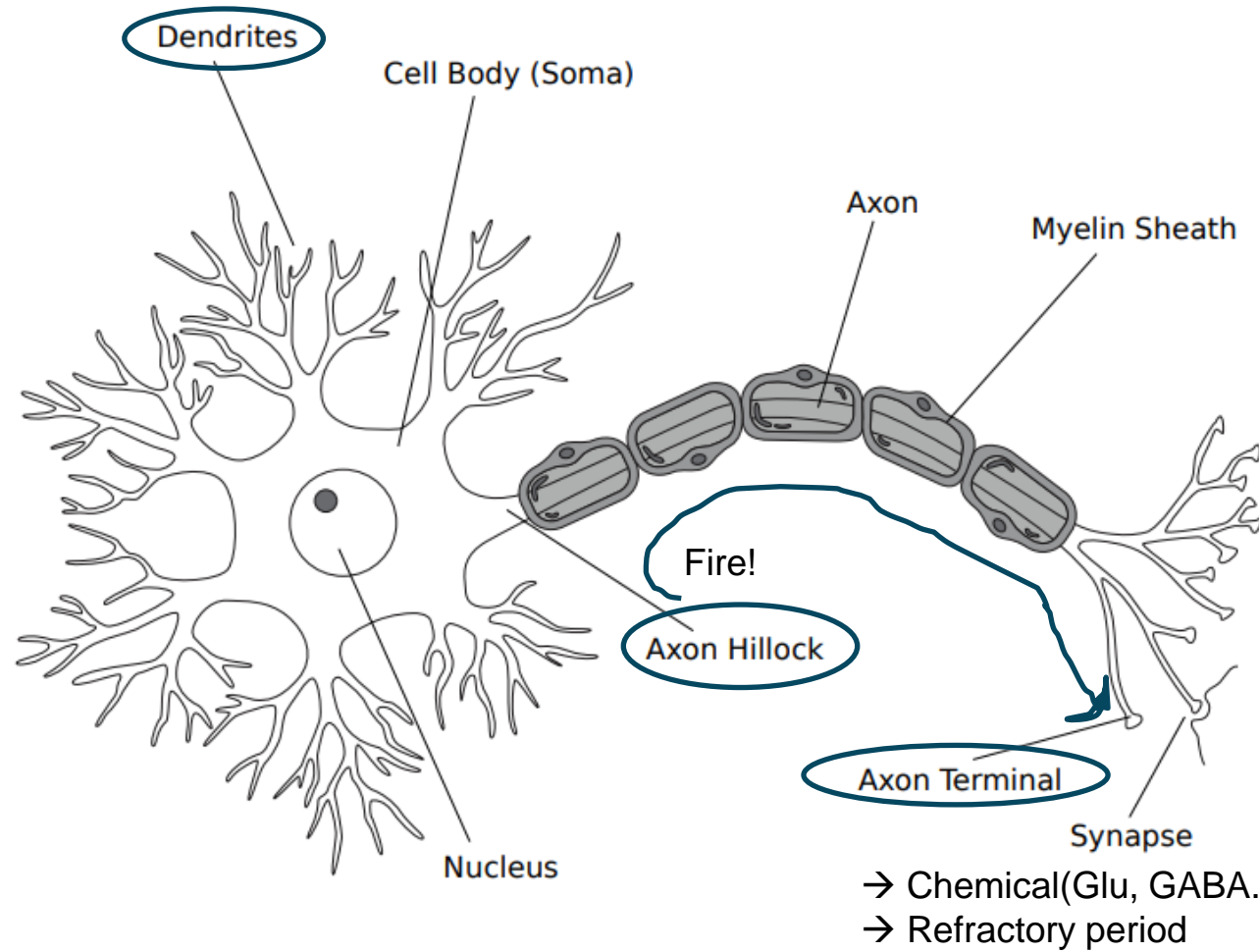
- Neurons
- RL in Brain
- SNN controlled robot
- Discussion



Neurons

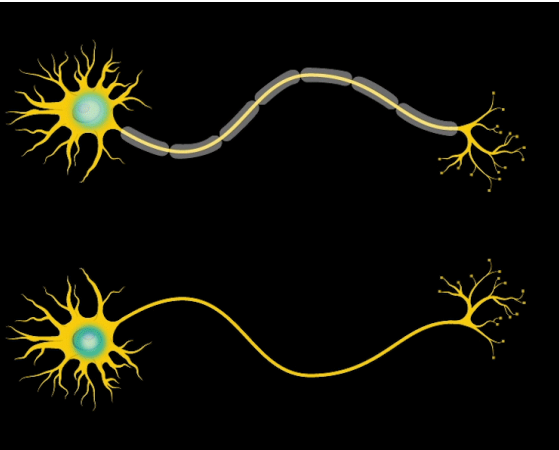
■ General architecture

Input from several
Pre-synaptic neurons

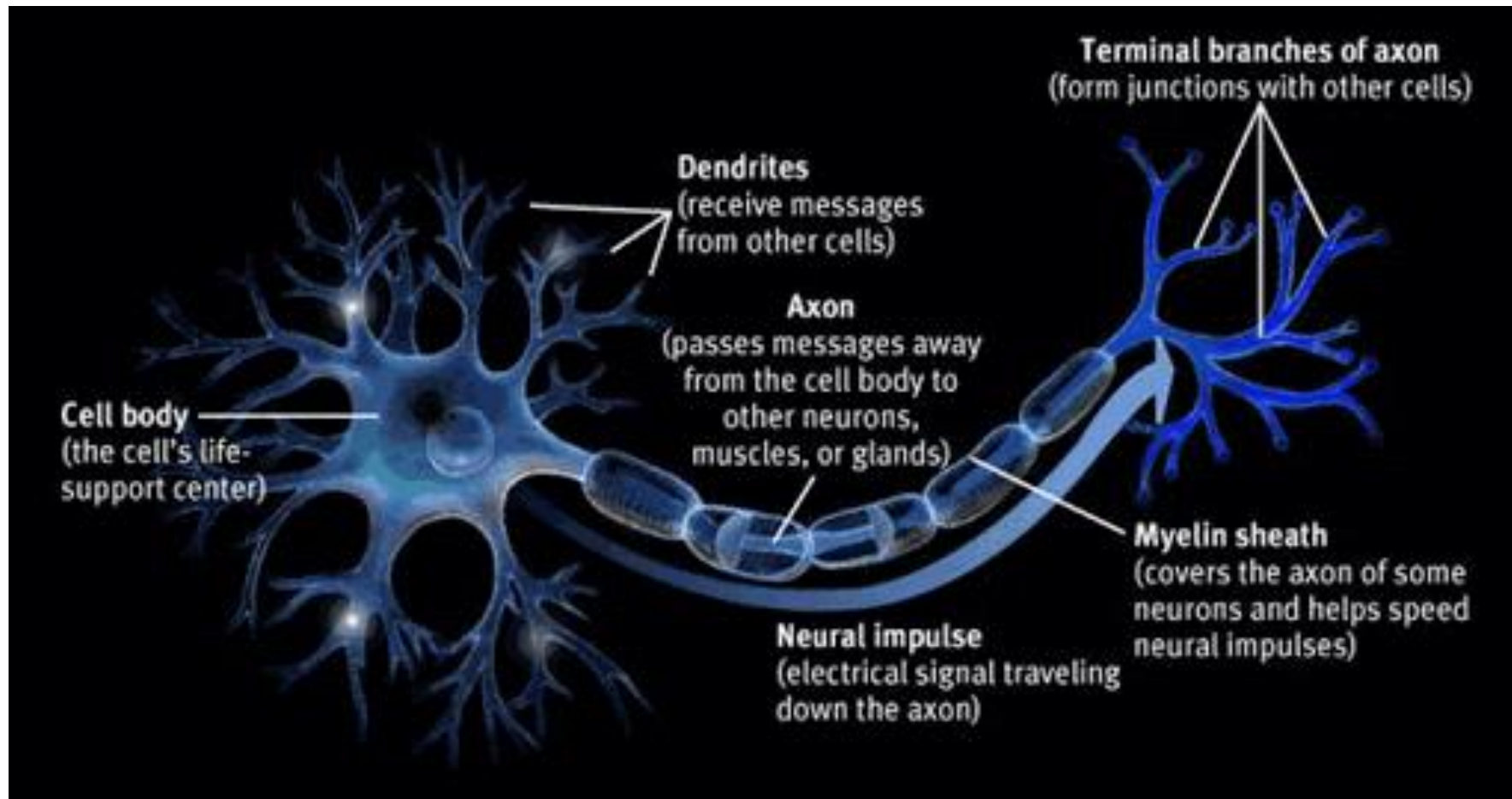


Excitatory
or
Inhibitory

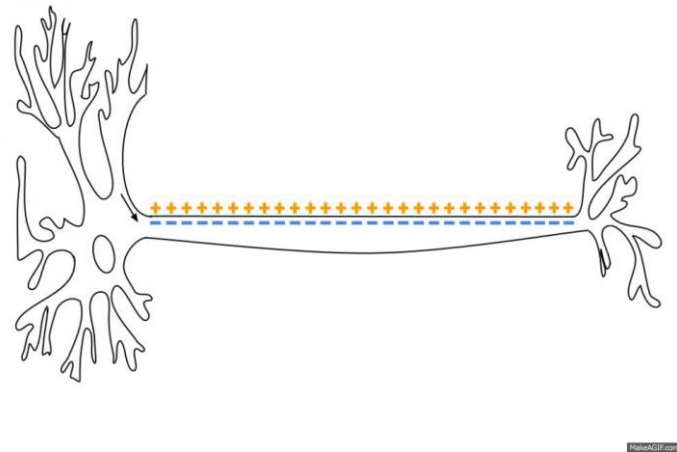
Figure 2.1: The structure of a neuron.



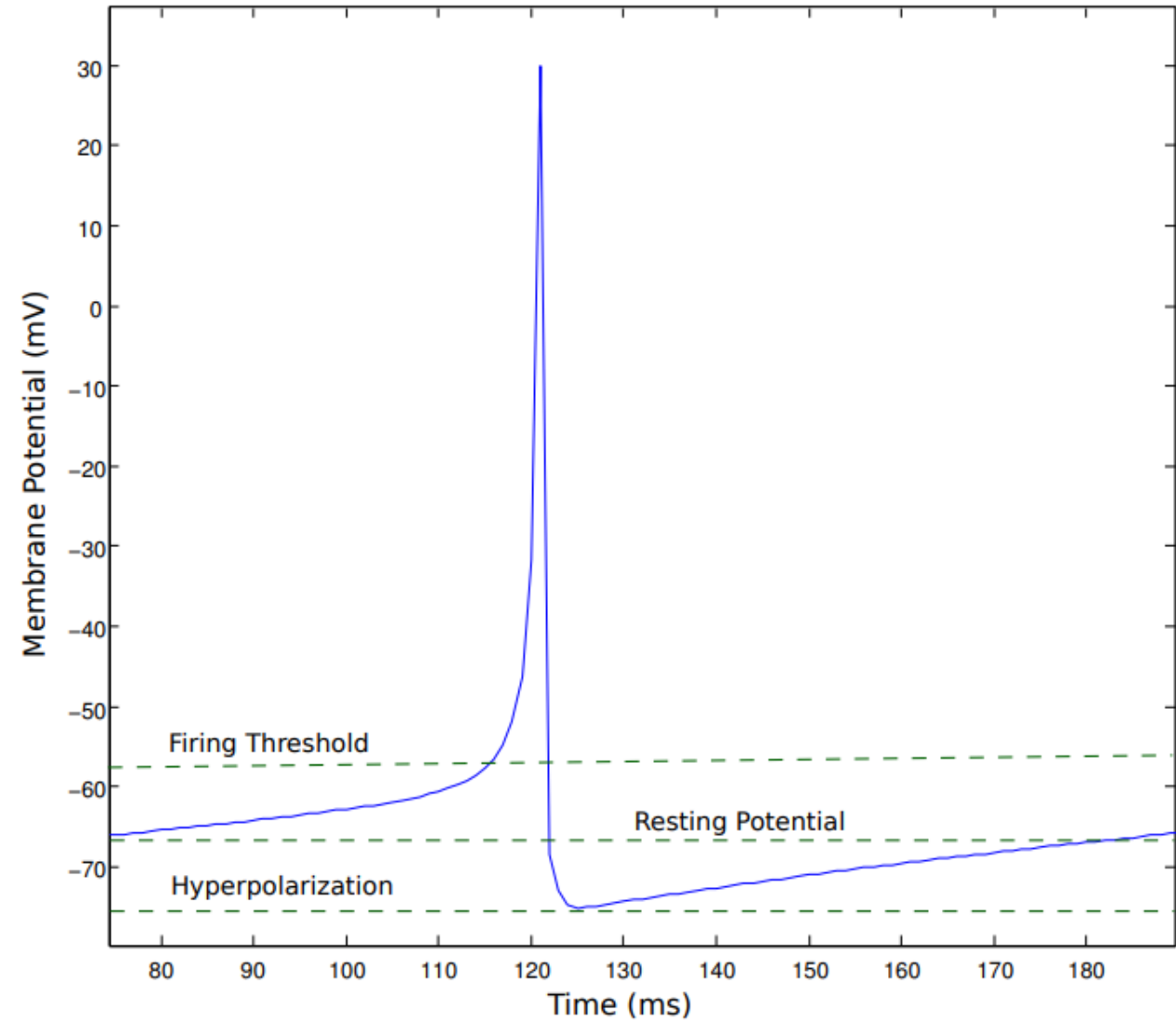
Neurons



Neurons

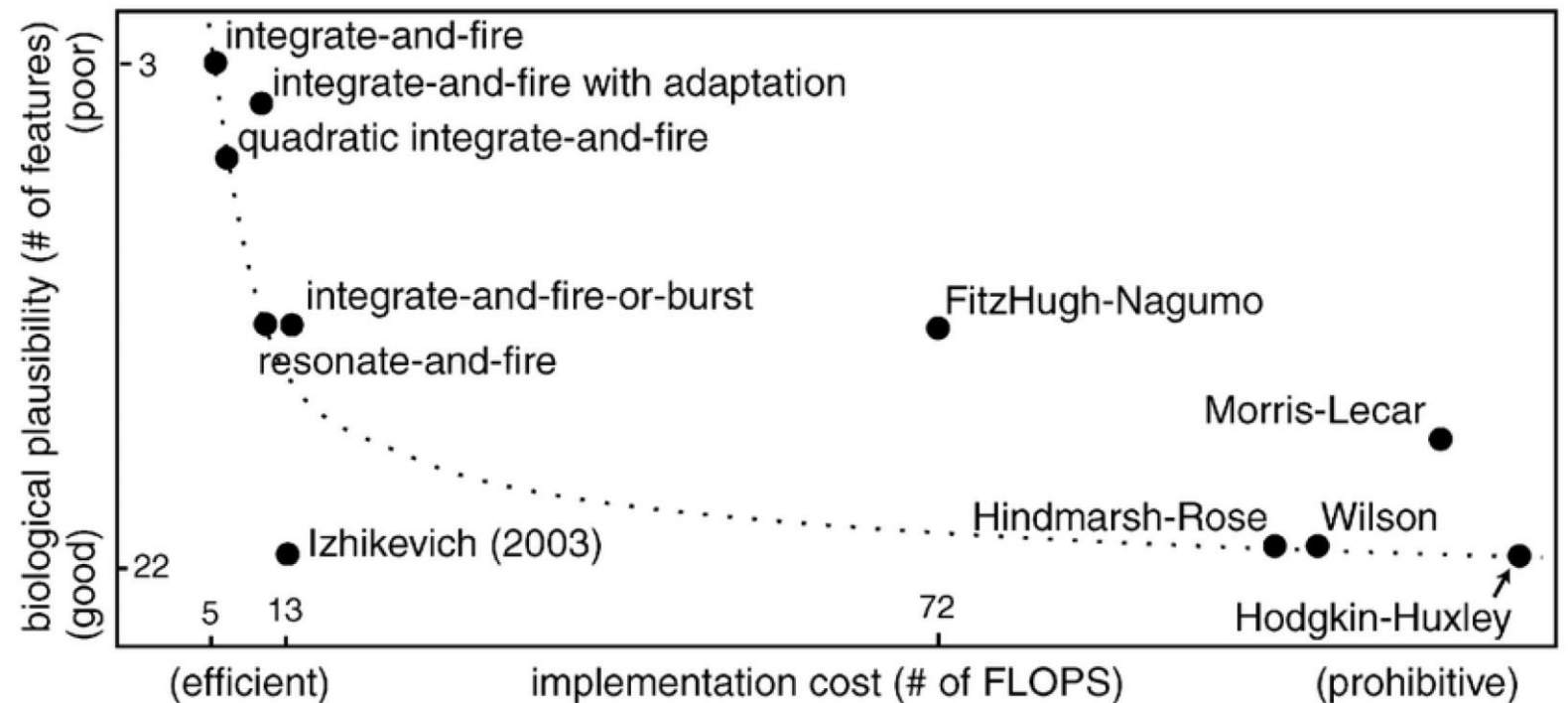


Membrane Potential of a Single Neuron Over Time



Neurons

- Hodgkin-Huxley Model
- Izhikevich Model
- LIF Model



Neurons

- Hodgkin-Huxley Model

$$C \frac{dv}{dt} = - \sum_k I_k + I$$

where

C = The capacitance of the neuron,

v = The membrane potential of the neuron,

I_k = The various ionic currents that pass through the cell,

I = The external current coming from pre-synaptic neurons,

t = Time.



Neurons

- Izhikevich Model

$$\frac{dv}{dt} = 0.04v^2 + 5v + 140 - u + I \quad (2.2)$$

u is the recovery variable that determines the refractory period

$$\frac{du}{dt} = a(bv - u) \quad (2.3)$$

$$\text{if } v \geq 30 \text{ then } \begin{cases} v \leftarrow c \\ u \leftarrow u + d \end{cases} \quad (2.4)$$

Neurons

Izhikevich Model

$$\frac{du}{dt} = a(bv - u)$$

$$\geq 30 \text{ then } \begin{cases} v \leftarrow c \\ u \leftarrow u + d \end{cases}$$

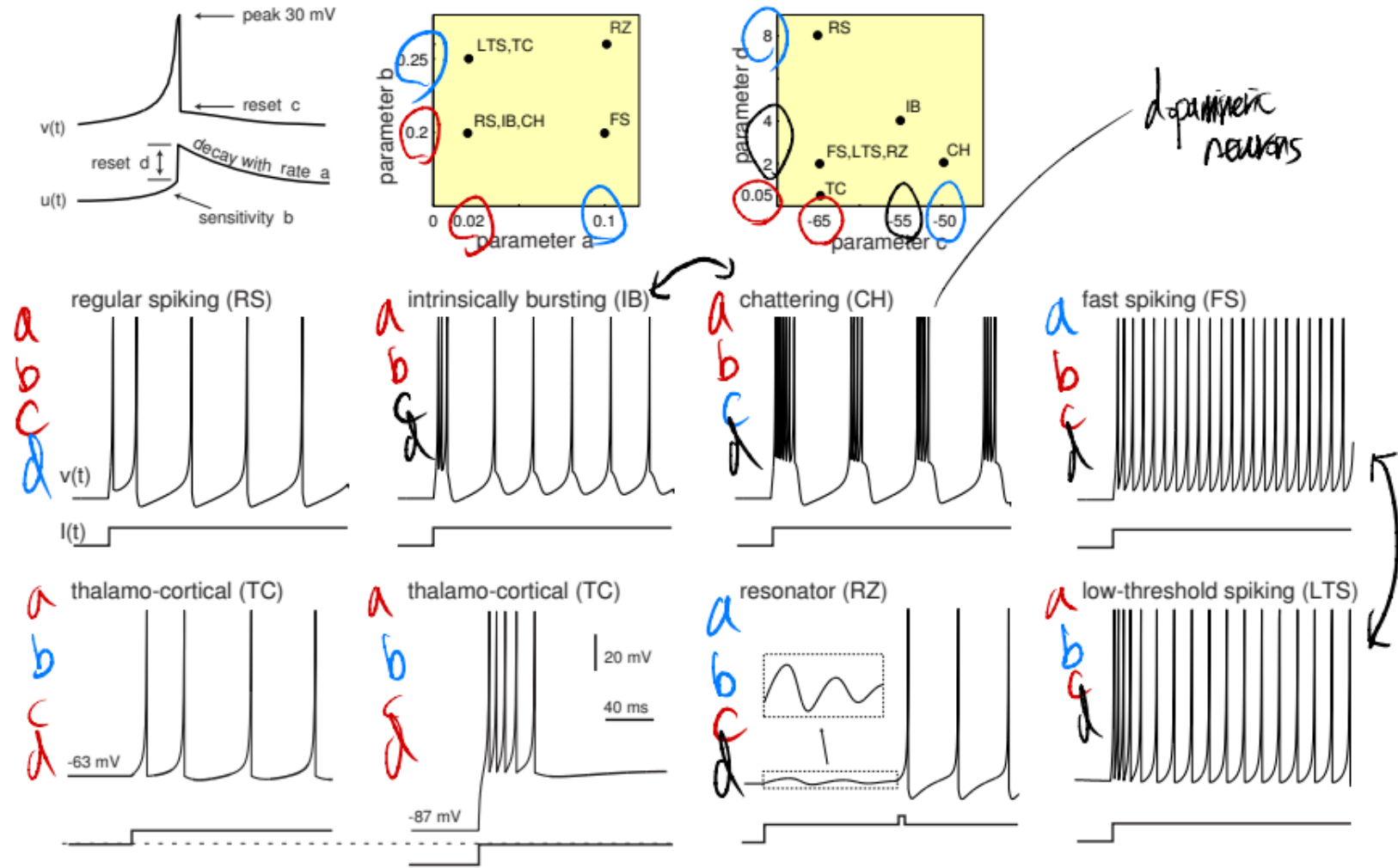


Figure 2.3: An overview of some types of neurons that can be modelled with the Izhikevich model^[1]

Reinforcement Learning

- Markov property
- Q-function
- Sarsa
- Q-Learning

$$Q^\pi(s, a) = E\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \mid \pi, s_t = s, a_t = a\right]$$

Algorithm 1 Sarsa

```
Initialize  $Q(s, a)$  arbitrarily
Repeat (for each episode)
  Initialize  $s$ 
  Choose  $a$  from  $s$  using policy derived from  $Q$ 
  Repeat (for each step of episode):
    Take action  $a$ , observe  $r, s'$ 
    Choose  $a'$  from  $s'$  using policy derived from  $Q$ 
     $Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma Q(s', a') - Q(s, a)]$ 
     $s \leftarrow s'; a \leftarrow a'$ 
  until  $s$  is terminal
```

Algorithm 2 Q-Learning

```
Initialize  $Q(s, a)$  arbitrarily
Repeat (for each episode)
  Initialize  $s$ 
  Choose  $a$  from  $s$  using policy derived from  $Q$  with exploration
  Repeat (for each step of episode):
    Take action  $a$ , observe  $r, s'$ 
     $Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$ 
     $s \leftarrow s'$ 
  until  $s$  is terminal
```

Reinforcement Learning

■ Eligibility Traces

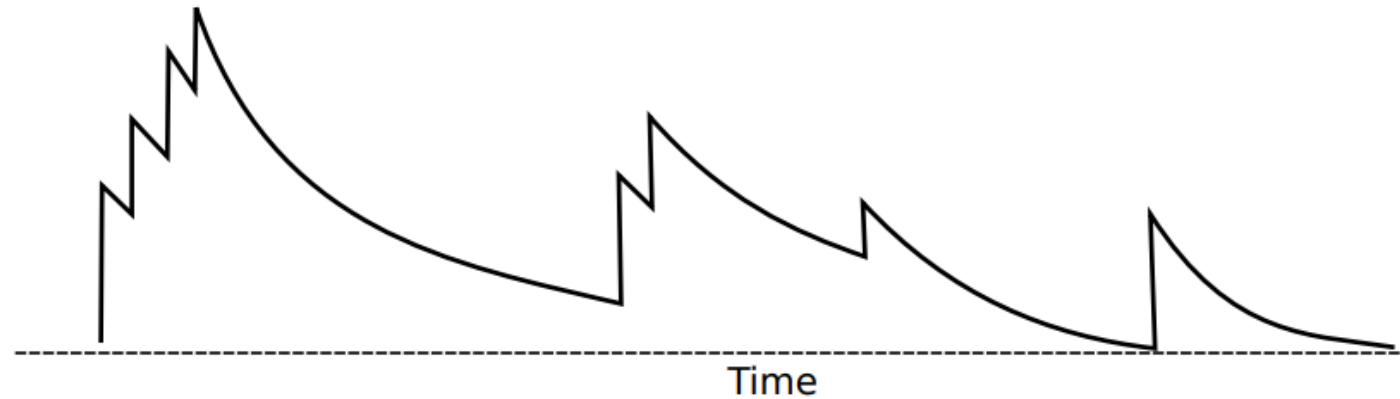


Figure 2.6: The eligibility trace for a state over time, as it is repeatedly visited.

We can incorporate the eligibility trace into the Sarsa algorithm (referred to as Sarsa(λ)), if we define $e(s, a)$ as the eligibility trace for the state s and action a then the Q-function update becomes:

$$Q(s, a) \leftarrow Q(s, a) + \alpha e(s, a)[r + \gamma Q(s', a') - Q(s, a)] \quad (2.6)$$

Reinforcement Learning

■ Eligibility Traces

Algorithm 3 Sarsa(λ)

Initialize $Q(s, a)$ arbitrarily and $e(s, a) = 0$, for all s, a

Repeat (for each episode)

Initialize s, a

Repeat (for each step of episode):

Take action a , observe r, s'

Choose a' from s' using policy derived from Q

$\delta \leftarrow r + \gamma Q(s', a') - Q(s, a)$

$e(s, a) \leftarrow e(s, a) + 1$

For all s, a :

$Q(s, a) \leftarrow Q(s, a) + \alpha \delta e(s, a)$

$e(s, a) \leftarrow \gamma \lambda e(s, a)$

$s \leftarrow s'; a \leftarrow a'$

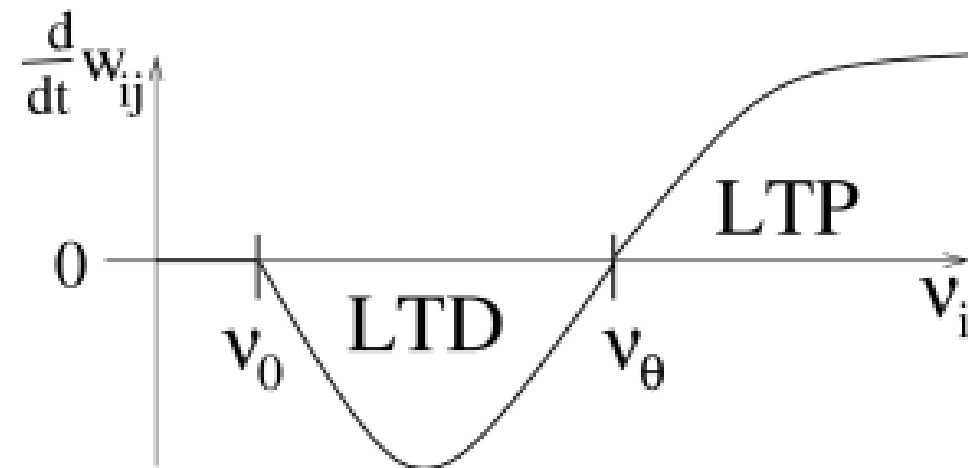
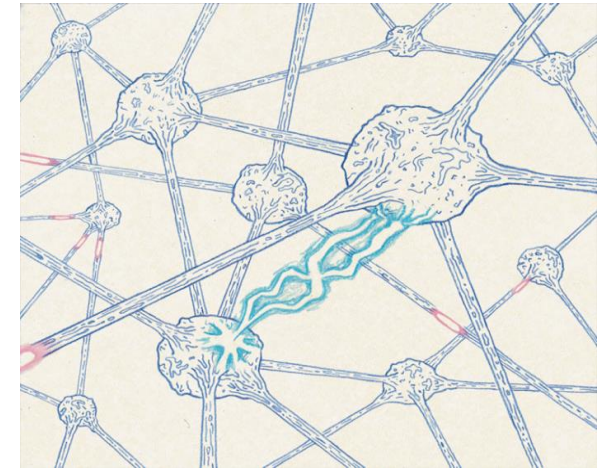
until s is terminal

RL in the Brain

- BCM Theory

Hebb : "Fire together, Wire together"
→ LTP (long term potentiation)

BCM (Bienenstock, Cooper, Munro)
→ LTD (long term depression)



RL in the Brain

- STDP (Spike-timing Dependent Plasticity)

$$\Delta w = \begin{cases} A^+ e^{-\Delta t / \tau^+} & \text{if } \Delta t \geq 0 \\ -A^- e^{\Delta t / \tau^-} & \text{if } \Delta t < 0 \end{cases}$$

Δw is the weight update

$$\Delta t = t_{post} - t_{pre}$$

A^+, A^-, τ^+ and τ^- are constants that define how STDP is applied over time.

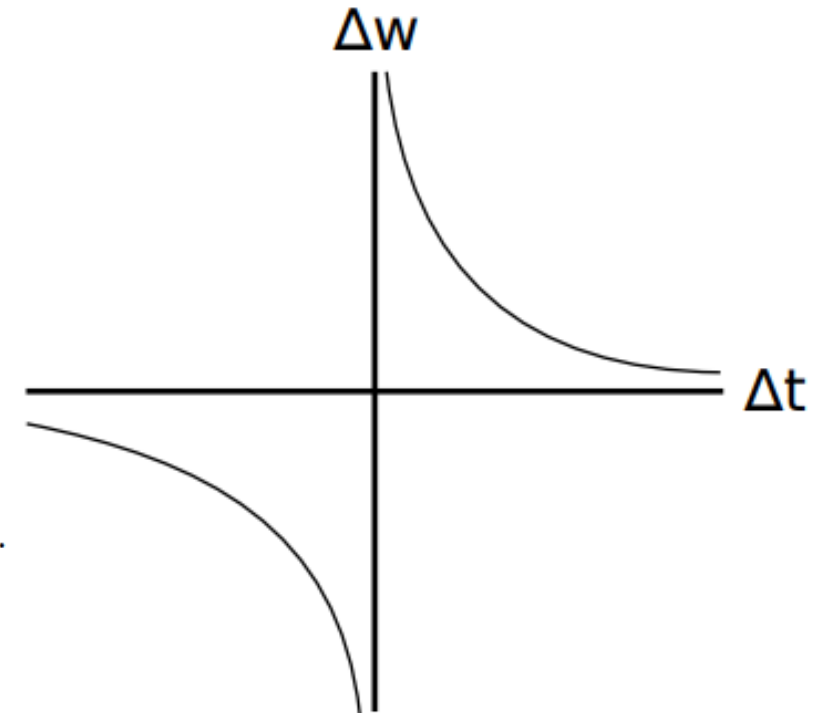
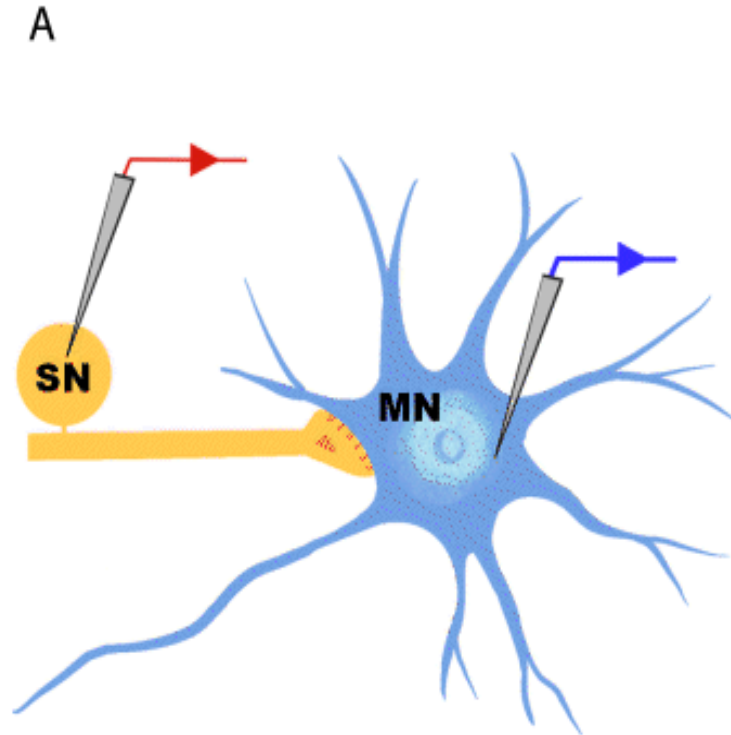


Figure 2.7: Graph showing how the weight update Δw relates to the $\Delta t = t_{post} - t_{pre}$ parameter.

RL in the Brain

■ STDP



B

MN

SN

C

MN

SN

Synaptic Depression

Synaptic Facilitation

RL in the Brain

■ Dopamine Modulated STDP

This is the pathway of the dopamine!

**Where the most of
dopaminergic neurons are!
(VTA)**

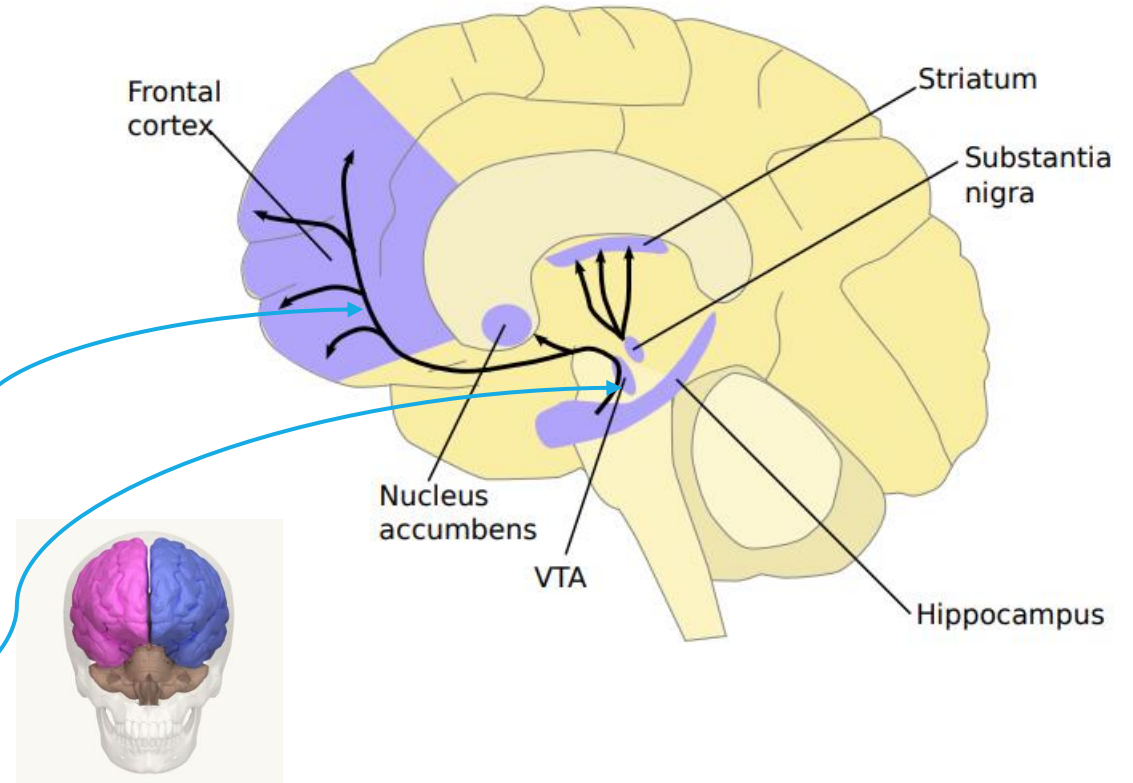


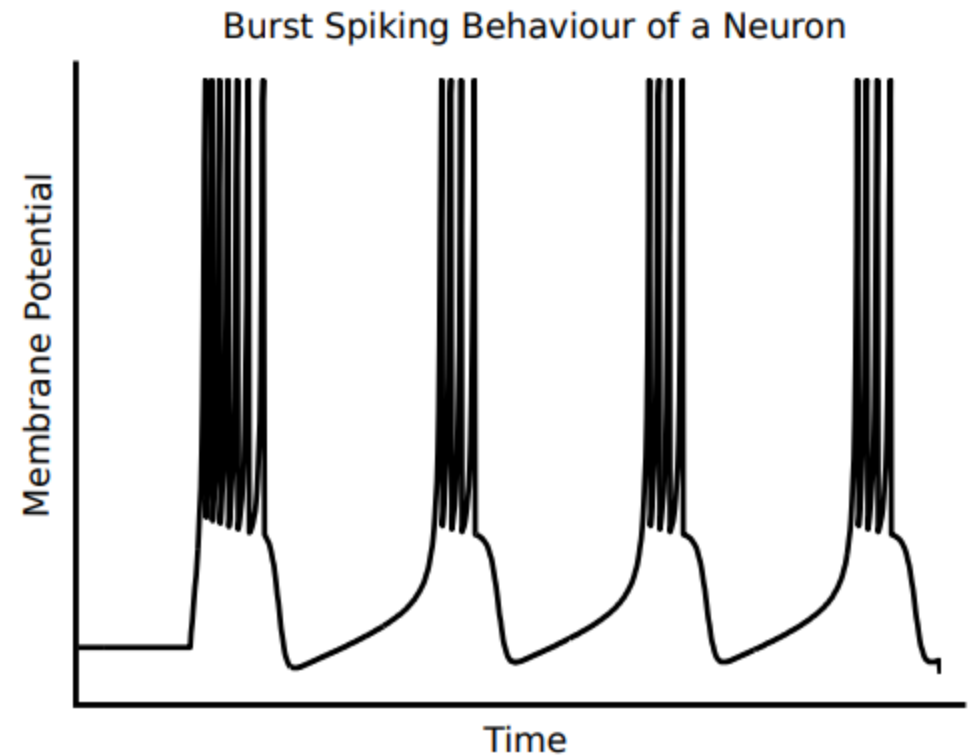
Figure 2.8: The main dopamine pathways in the human brain.

RL in the Brain

■ Dopamine Modulated STDP

Two different firing pattern(dopaminergic neurons)

1. Background firing (stimulus X)
2. Burst firing (stimulus O)



RL in the Brain

- Synaptic tag
→ For distal reward problem

$$\dot{c} = -c/\tau_c + STDP(\tau)\delta(t - t_{pre/post})$$

decay rate of
the eligibility trace

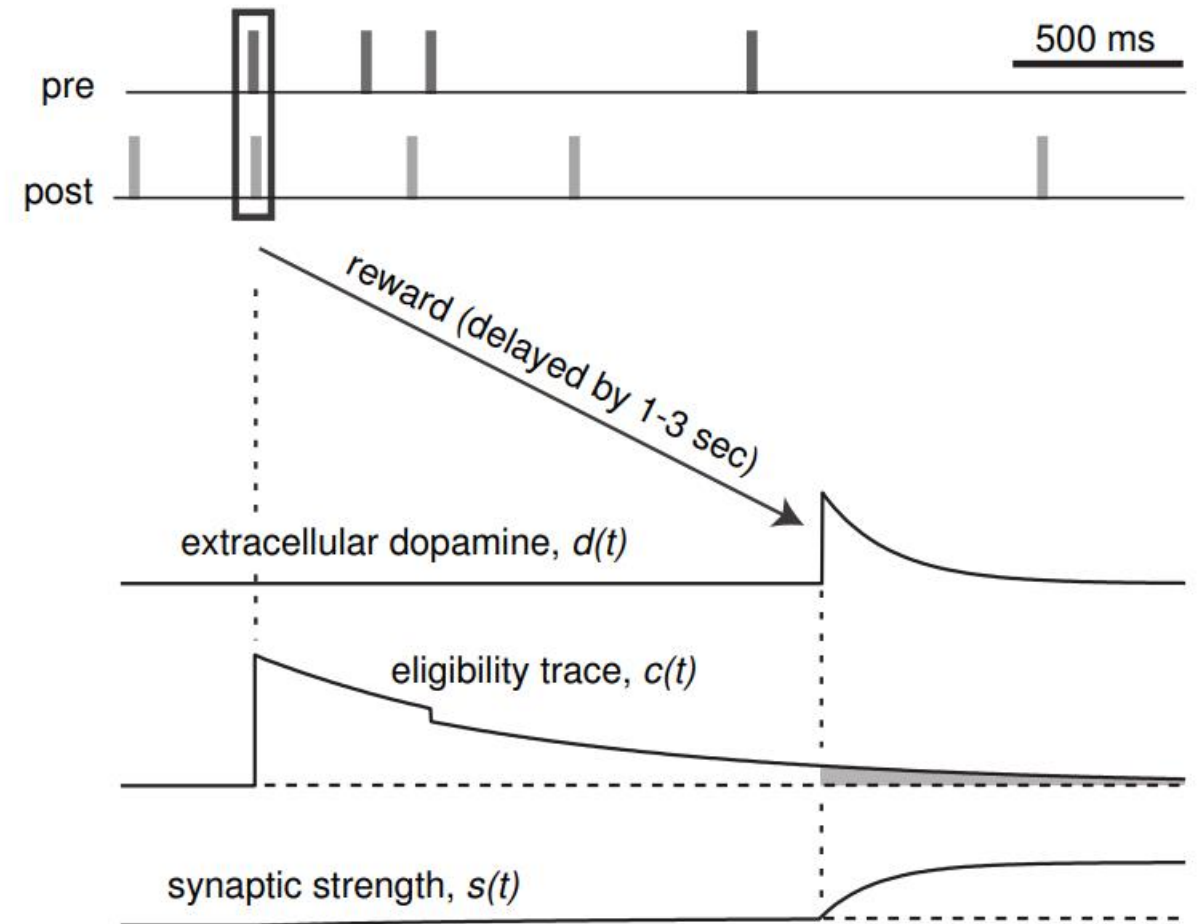
Dirac delta function

RL in the Brain

- Synaptic tag
→ For distal reward problem

$$\dot{s} = cd$$

Where s is the synapse strength
and d is the current level of dopamine.



RL in the Brain

■ Dual-path model

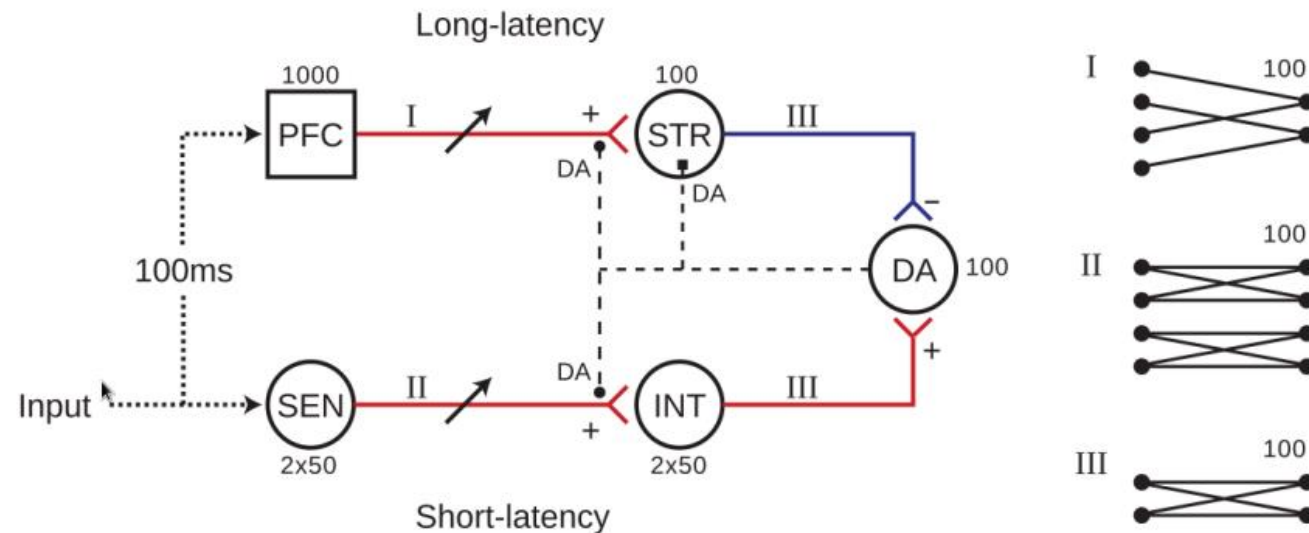


Figure 2.12: The network architecture used by Chorley & Seth [31], red lines represent excitatory connections and blue represent inhibitory connections. When neurons in the DA module fire then dopamine is released which causes STDP of the PFC→STR and SEN→INT pathways. The mean firing rate of the STR module is also modulated by the amount of dopamine.

RL in the Brain

■ Dual-path model

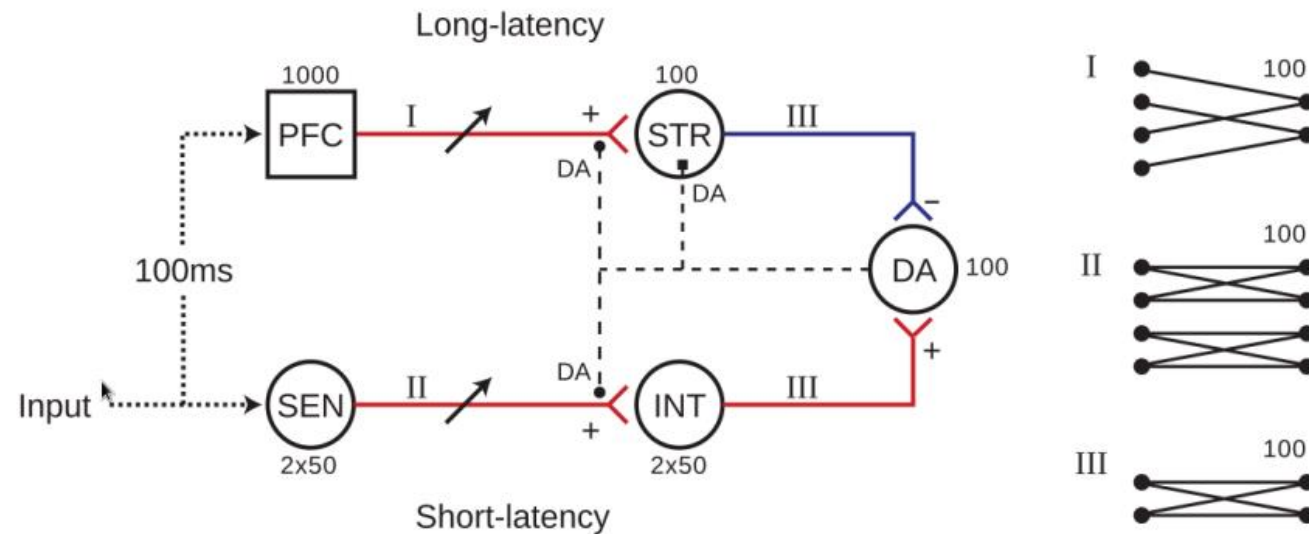


Figure 2.12: The network architecture used by Chorley & Seth [31], red lines represent excitatory connections and blue represent inhibitory connections. When neurons in the DA module fire then dopamine is released which causes STDP of the PFC→STR and SEN→INT pathways. The mean firing rate of the STR module is also modulated by the amount of dopamine.

Neural encoding

- Rate coding
- Population coding
- Temporal coding

Discussion

- Out of date(2015)
- bridge between RL and SNN