

SMLab  
Weekly Presentation  
15th Jan 2025

# Spiking Neural Network

An Introduction

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Neuromorphic Computing

Bio-plausiblility

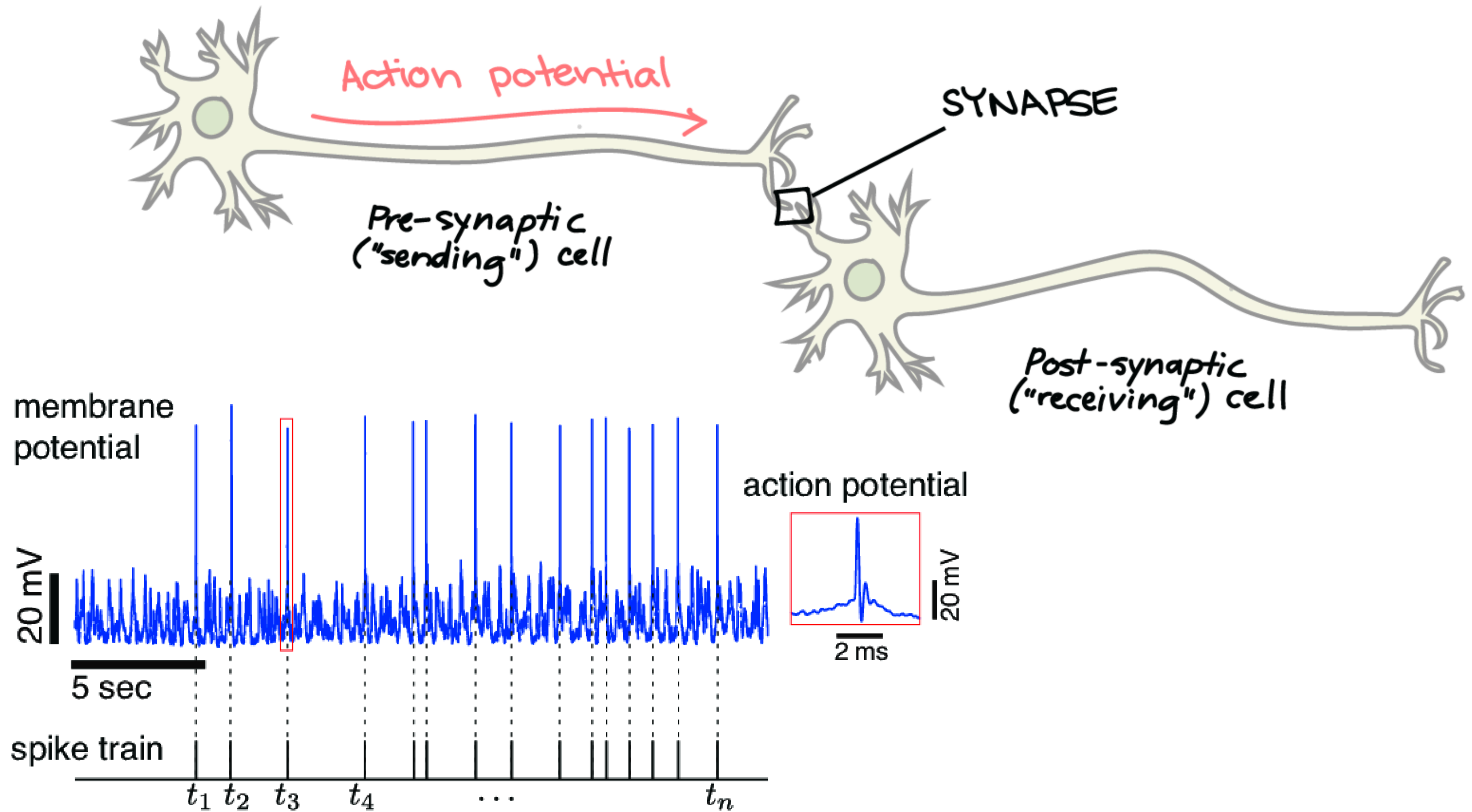
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Spiking Neural Networks

We take cues from how brain works?



# A simple model: the leaky integrate-and-fire (LIF) neuron

Membrane potential  $V$  evolves according to a differential equation

$$\tau \frac{dV}{dt} = -V$$

Leak

When a neuron receives a spike,  $V$  increases by synaptic weight  $w$ :

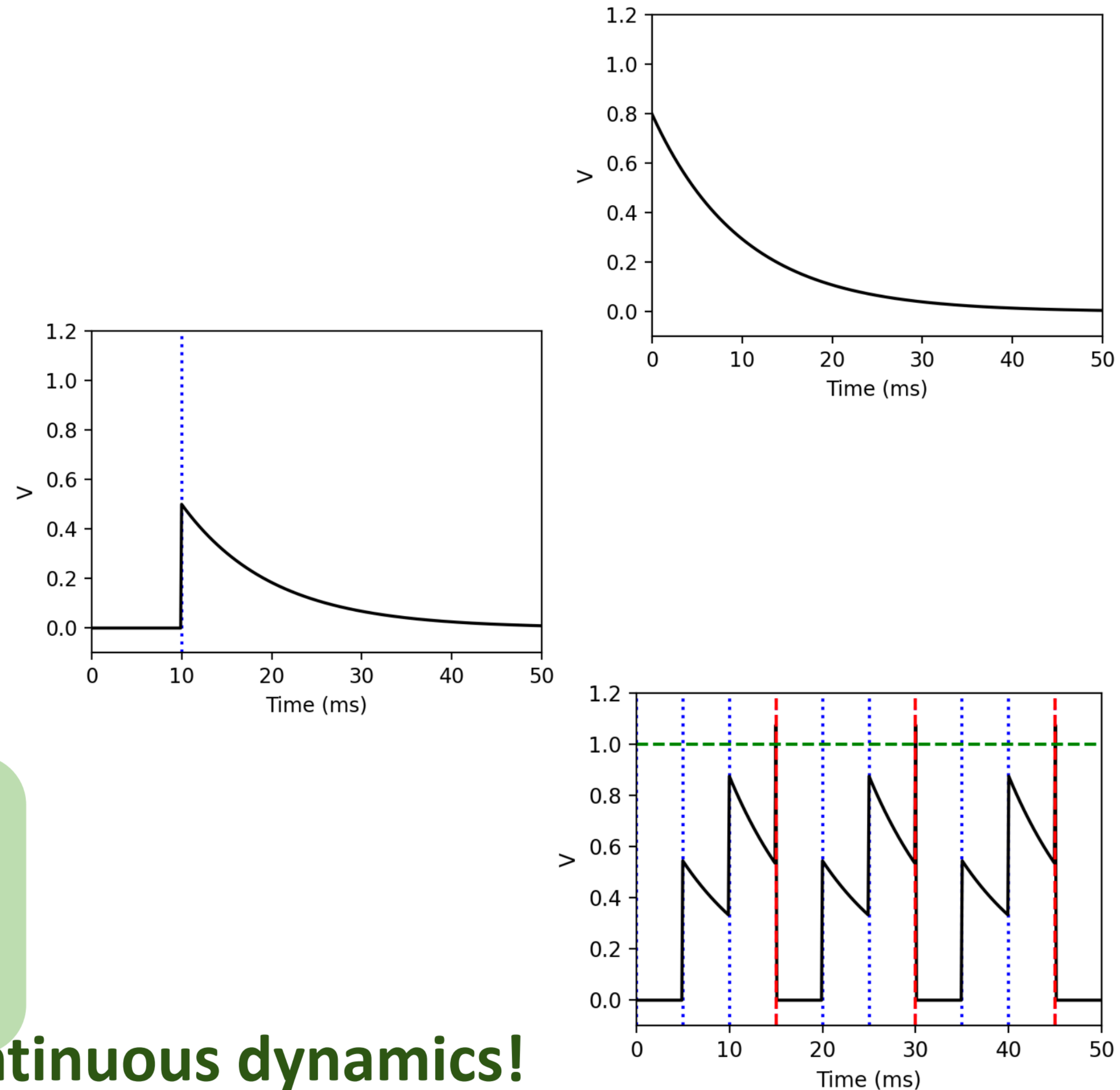
$$V \leftarrow V + w$$

Integrate

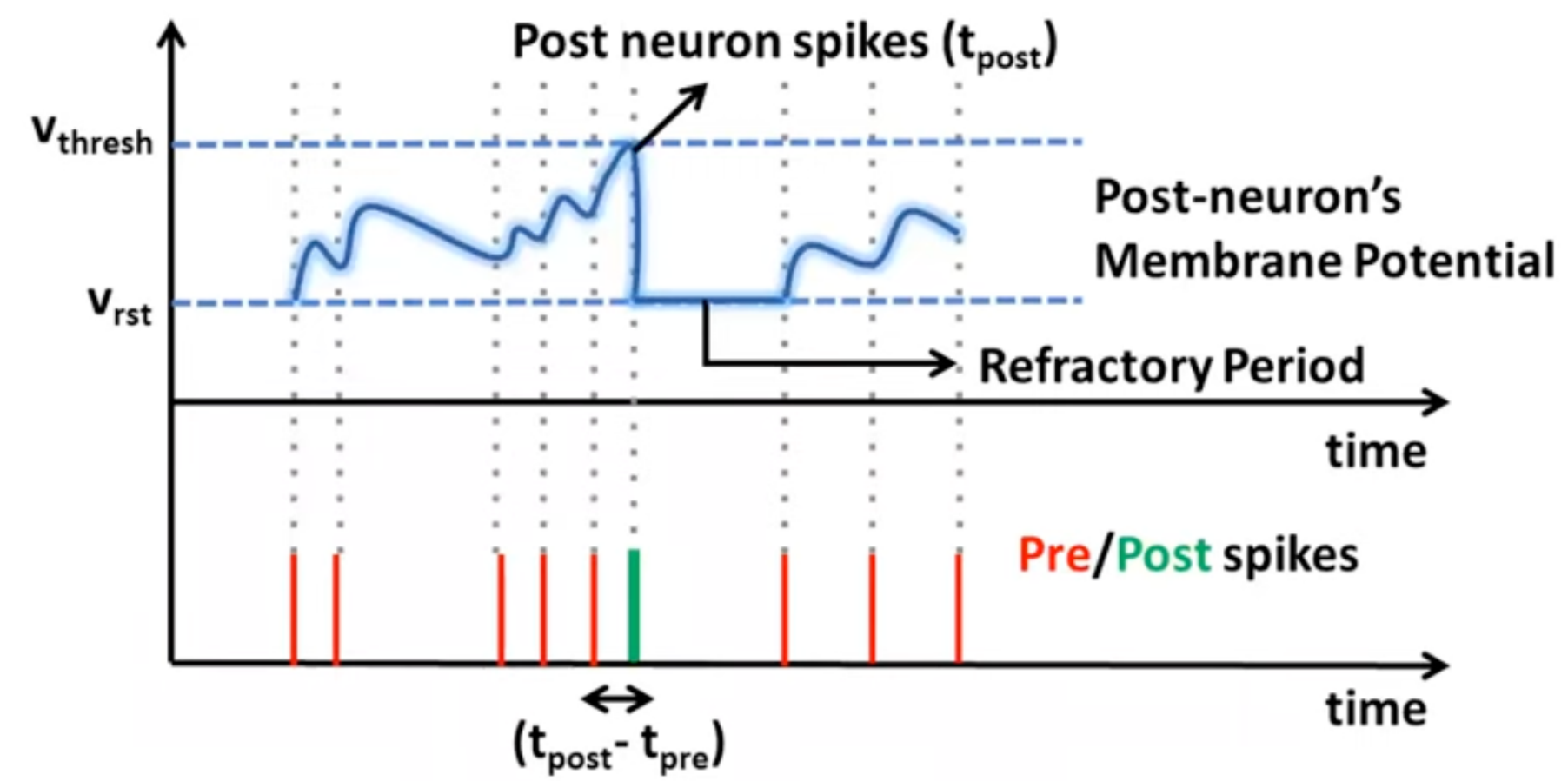
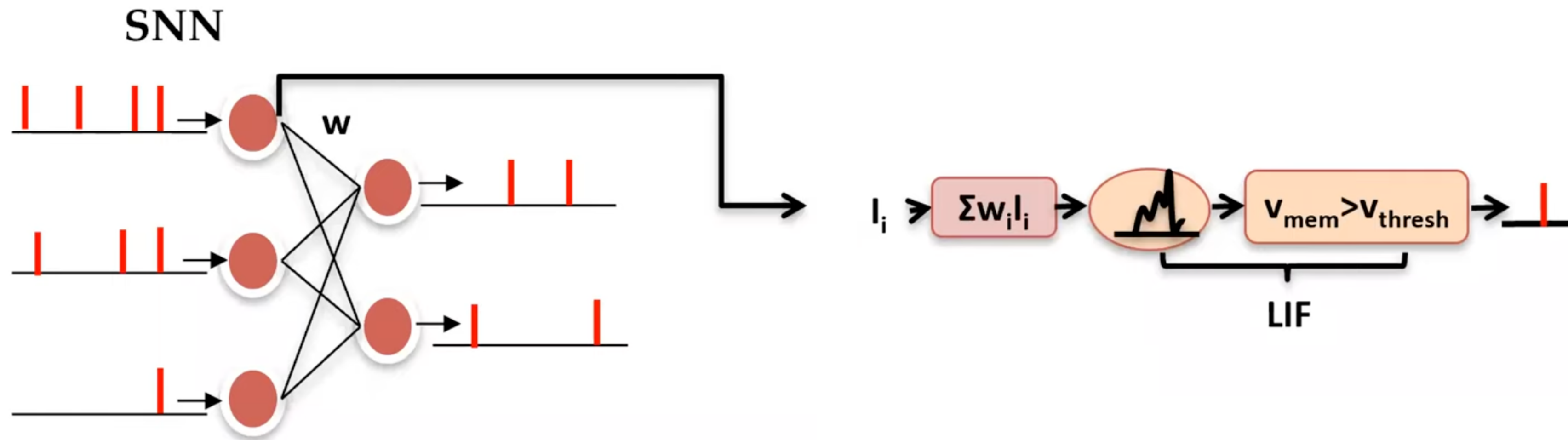
When  $V > V_t$  the neuron “fires a spike” and resets:

$$V \leftarrow 0$$

**Nonlinear, discontinuous dynamics!**

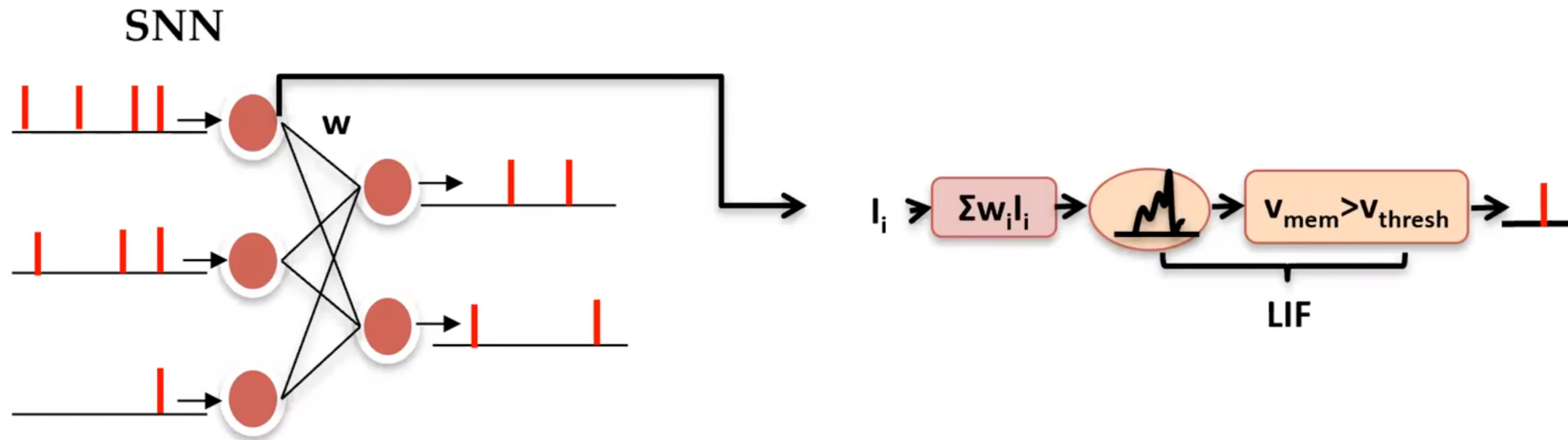


# Spiking Neural Networks

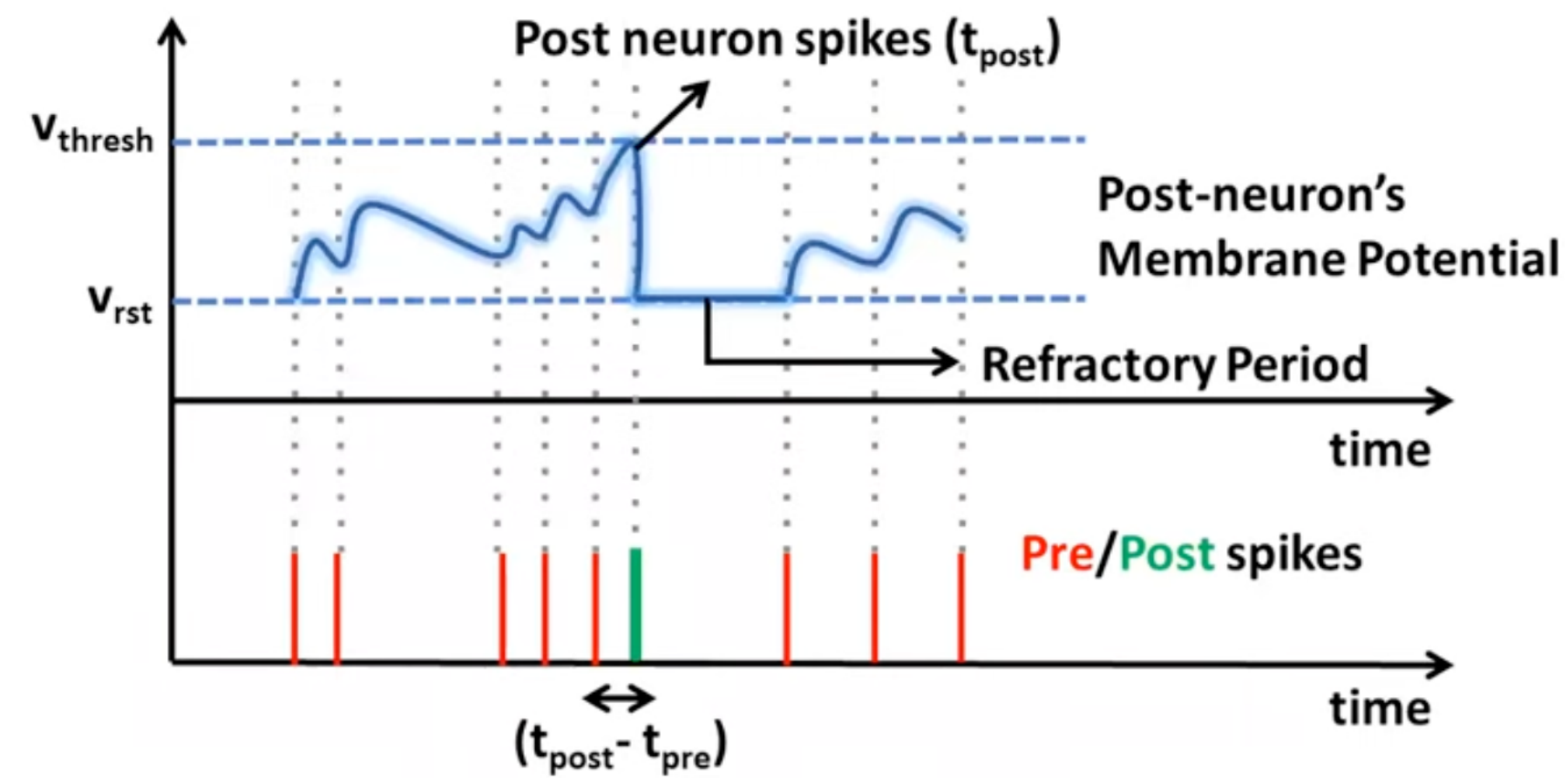




# Spiking Neural Networks



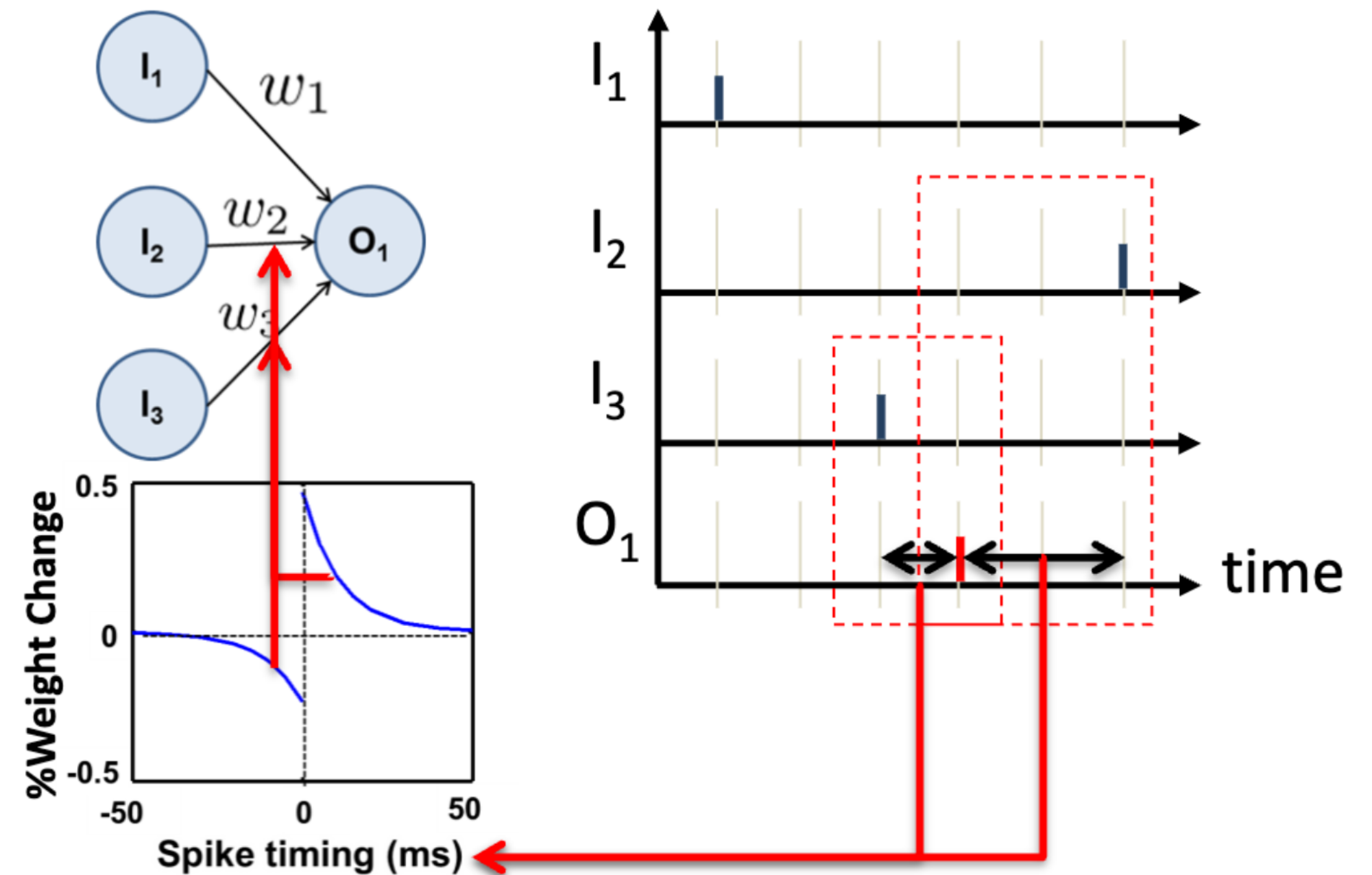
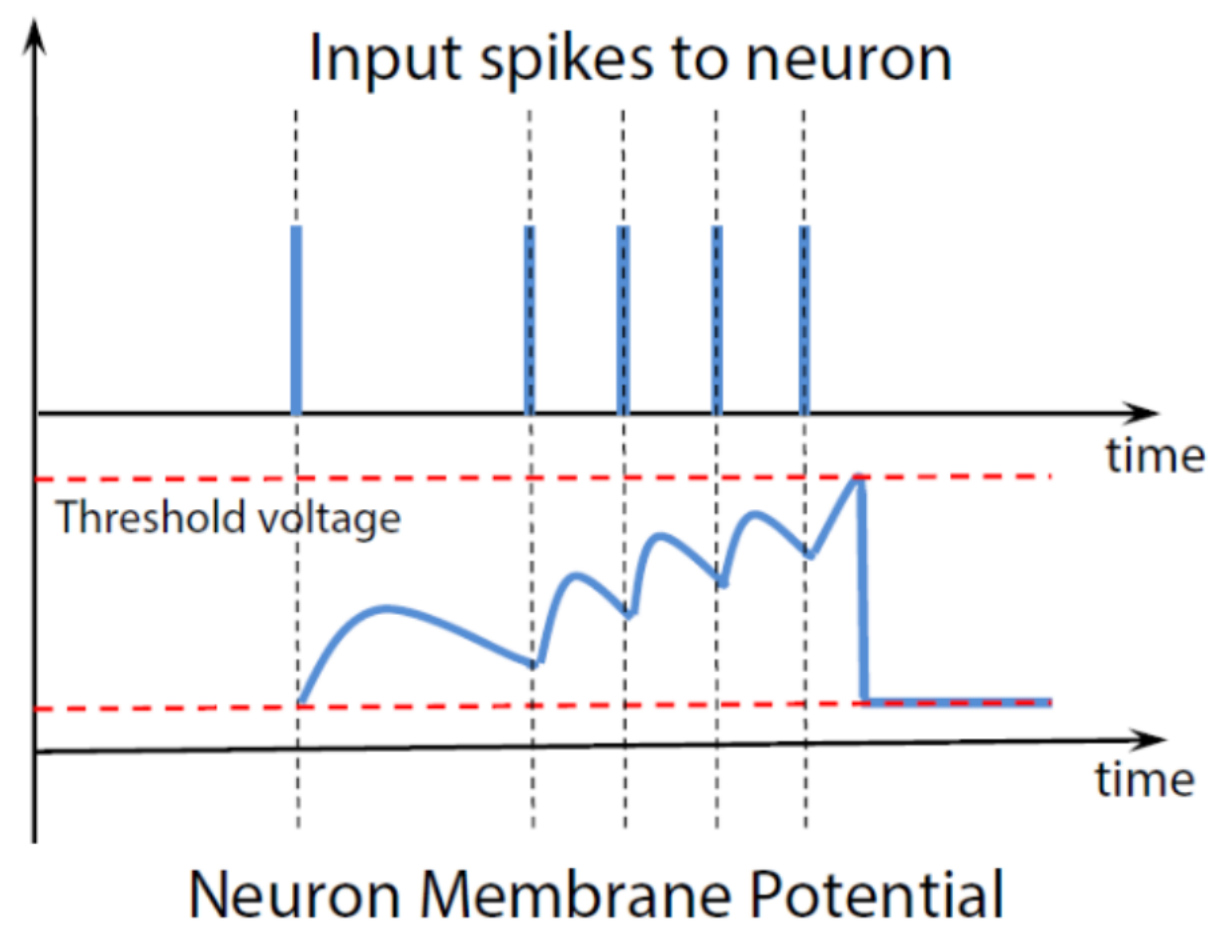
How to train it though? Backpropagation?



# Spike timing dependent plasticity (Local) Learning

## LIF Equation:

$$C \frac{dV}{dt} = -\frac{V}{R} + \sum_j w_j I_{post,j}$$



## Weight Update Equations

$$w_i^{new} = w_i^{old} + \Delta w(t_i) \times w_{max} \quad i = 1, 2, 3$$

Strength of the synapse should increase (decrease) as post and pre neurons appear to be temporally correlated (uncorrelated)



## Can we train deep SNNs efficiently?

### STDP Learning

**Pros:** Unsupervised local learning

**Cons:** Limited accuracy and shallow networks

Reference	MNIST Accuracy
Cook <i>et al.</i> Frontiers 2015 (ETH Zurich)	95.00%
Masquelier <i>et al.</i> Neural Networks 2017	98.40%
Lee <i>et al.</i> TCDS 2018	91.10%

### ANN-SNN Conv

**Pros:** Takes advantage of standard ANN training

**Cons:** Conversion limited by constraints

Reference	MNIST Accuracy
Pfeiffer <i>et al.</i> IJCNN 2015 (ETH Zurich)	99.10%
Eliasmith <i>et al.</i> arXiv 2016 (U Waterloo)	99.12%
Liu <i>et al.</i> Frontiers 2017 (ETH Zurich)	99.44%

### Backprop in SNN

**Pros:** Higher accuracy

**Cons:** Limited scalability, Discontinuous spike activities

Reference	MNIST Accuracy
Pfeiffer <i>et al.</i> Frontiers 2016 (ETH Zurich)	99.31%
Shi <i>et al.</i> Frontiers 2018 (Tsinghua)	99.42%
Zhang <i>et al.</i> arXiv 2018 (TAMU)	99.49%

### Stochastic STDP

**Pros:** Unsupervised local learning with binary synaptic weights

**Cons:** Limited accuracy

Reference	MNIST Accuracy
Gamrat <i>et al.</i> Proceedings of the IEEE '15	60.00%
Yousefzadeh <i>et al.</i> Frontiers 2018	95.70%
Roy <i>et al.</i> (Frontiers, 2019)	98.54%