

# Network Induced Multi-Neuronal Spike Train Pseudometric

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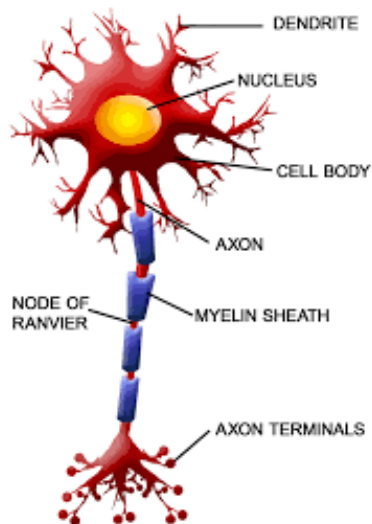
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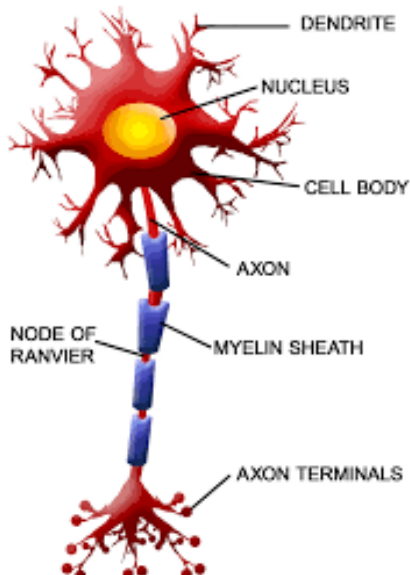
# Introduction

- Looking at behavior of subnetworks in spiking neural networks under various learning algorithms.
- Current metrics for multiple neurons treat each neuron as independent of one another.
- Wanted to create a metric which would take the network structure into account.
- Looked then at signal propagation rather than signal generation.

# Definitions

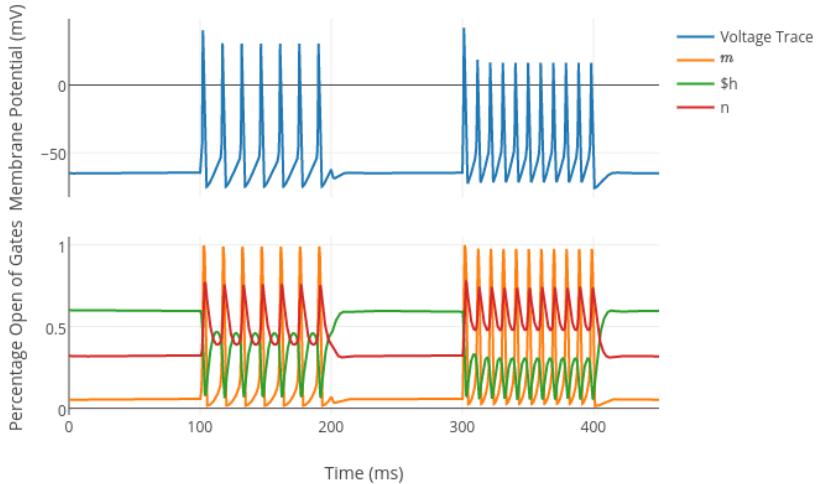


# Definitions

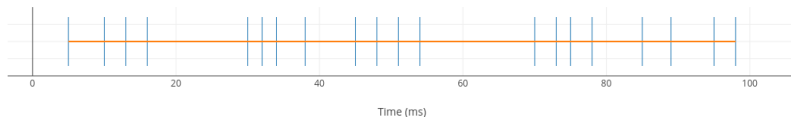


- Receives input generally through the dendrites.
- Soma (Cell Body) integrates incoming signals and then potentially generates action potential, or *spike*.
- Spike travels down axon, activating synapses on the axon terminals as it goes.
- Action potential is a short sharp increase in membrane potential, followed by a fast decrease.

## Hodgkin-Huxley Example



# Spike Train



A *spike train* is a listing of times that one particular neuron has fired, either during an experiment or a numerical simulation. We will denote a spike train by  $S$  and numerate the spike times in  $S$  by  $t_i^f$ .

# Network of Neurons

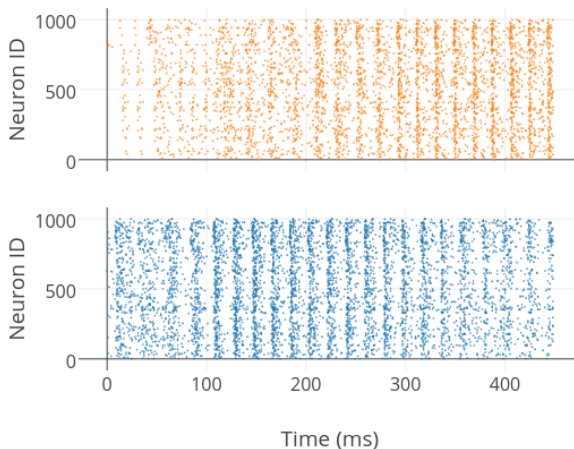
Let  $N = (V, E, \omega, \Delta)$  be a directed graph where the vertices represent neurons and with two weighing functions,

- $\omega : E \rightarrow [w_{I \max}, w_{E \max}]$ , defines the synaptic weight of the connection from one neuron to the next, and
- $\Delta : E \rightarrow (0, \Delta_{\max}]$ , defines the transmission delay from one neuron to the next.

As we simulate the network of neurons each neuron generates a spike train, and we denote the vector of spike trains, or *spike trainyard*, as  $\eta$ .

# Raster Plots

## Example Raster Plots





# Existing Metrics

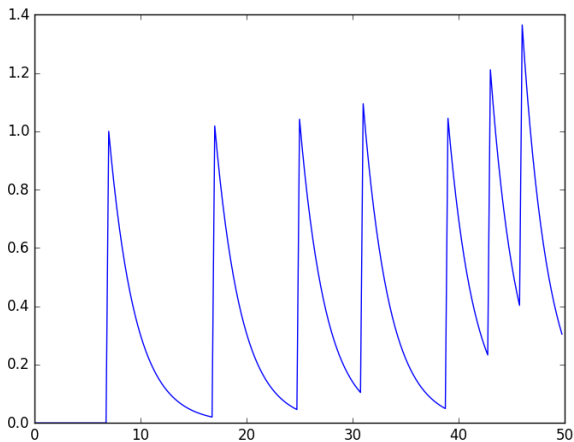
Let  $S$  be a spike train, then we define the profile operator,

$$F[S] = \sum_{t^f \in S} H(t - t^f) \exp \left[ -(t - t^f)/\delta_f \right] \quad (1)$$

then the distance between spike trains is the  $L^2$  distance between both the operator acting on both spike trains.

$$d(S_1, S_2) = \left[ \frac{1}{\tau_f} \int_X (F[S_1] - F[S_2])^2 dt \right]^{1/2} \quad (2)$$

# Profile Operator



# Population Extension

The metric can be extended out to a population of neurons as follows,

$$d(\eta_1, \eta_2) = \left[ \sum_{i=1}^N (d(\eta_1^i, \eta_2^i))^2 \right]^{1/2} \quad (3)$$

, This is a special case of the Population van Rossum metric for multiple spike trains.

# Where From Here?

- We see that the previous metric looks at the generation of spikes,
- Population van Rossum treats each neuron as independent, which is necessary due to potentially insufficient data in biological experiments.
- For synthetic networks, where all of the data can be known, can we construct a metric that incorporates the network structure in the calculation?

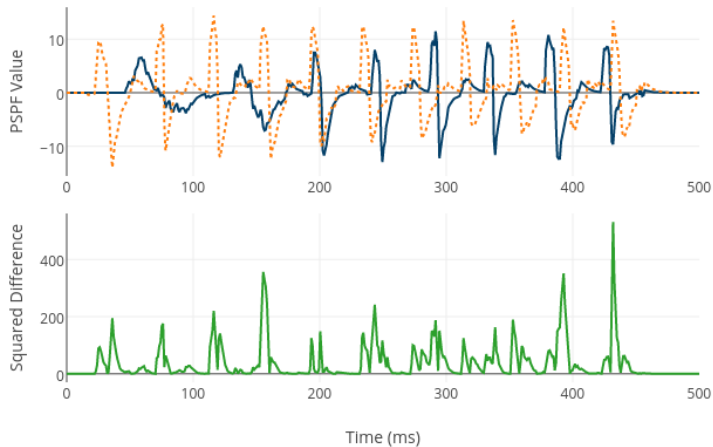
# Post-Synaptic Potential Function (PSPF)

Let  $N = (V, E, \omega, \Delta)$  be a network,  $F$  be a profile operator, and  $\eta$  be a spike train vector. Let  $\Delta_M = \max \{ \Delta(e) | e \in E \}$ , where  $\Delta_M \ll T$ . Then for  $t \in [\Delta_M, T]$  the PSPF for neuron  $j$  is given by

$$p_{N,F,j}(\eta, t) = \frac{1}{w_{\max}} \sum_{i=1}^{|V|} w_{i,j} F[\eta_i(t - \Delta_{i,j})] \quad (4)$$

We see that this function is measuring the input into neuron  $j$ .

# PSPFs and Squared Difference



# Network Induced Spike Train yard Pseudometric (NISTy)

Let  $N = (V, E, \omega, \Delta)$  and  $\eta^1, \eta^2$  be two spike train vectors of  $N$  on the interval  $[0, T]$ ,  $F$  be a profile operator,  $\tau_F$  be a time constant, and  $\Delta_M \ll T$ , then NISTy  $P_{N,F} : N \times N \rightarrow^{|V|} [0, \infty]$  is defined by

$$P_{N,F}(\eta^1, \eta^2) = \left[ \frac{1}{\tau_f} \sum_{j=1}^{|V|} \|p_{N,F,j}^1 - p_{N,F,j}^2\|_2^2 \right]^{1/2} \quad (5)$$

where the norm is taken over the time interval  $[\Delta_M, T]$ .

# Two Examples of Pseudometric

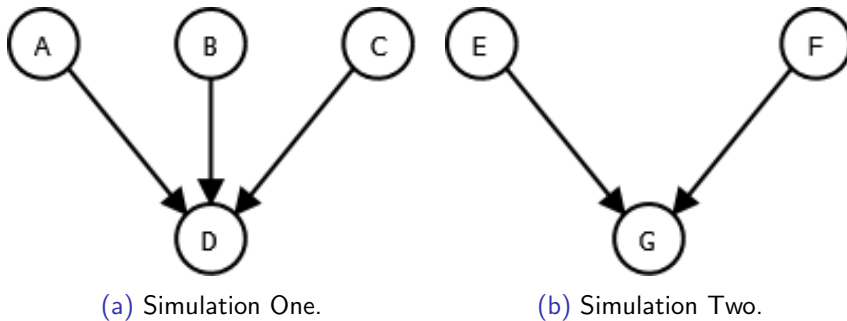


Figure: Network configurations for (a) simulation one, and (b) simulation two.



# Example One

For the network defined by Figure 2a let all edges have the same weight.

We set the delays as follows,  $\Delta_{D,A} = 5$ ,  $\Delta_{D,B} = 10$ ,  $\Delta_{D,C} = 15$ .

Let  $\eta^1$  be a vector of spike trains where  $A$  fires at time  $t = 15$  and  $B$  fires at time  $t = 10$ ,  $\eta^2$  have firing times for  $B$  at  $t = 10$  and  $C$  at  $t = 5$ .

Due to the equal weights and the temporal delays we get that  $P_{N,F}(\eta^1, \eta^2) = 0$ , while population van Rossum would show these as different vectors of spike trains. This is significant as NISTy can be used to successfully identify that output neuron  $D$  will behave identically under both  $\eta_1$  and  $\eta_2$ .

## Example Two

For the network defined by Figure 2b let all edges have the same temporal delay of  $\Delta = 5$ , with  $\omega_{G,E} = w > 0$  and  $\omega_{G,F} = -w$ .

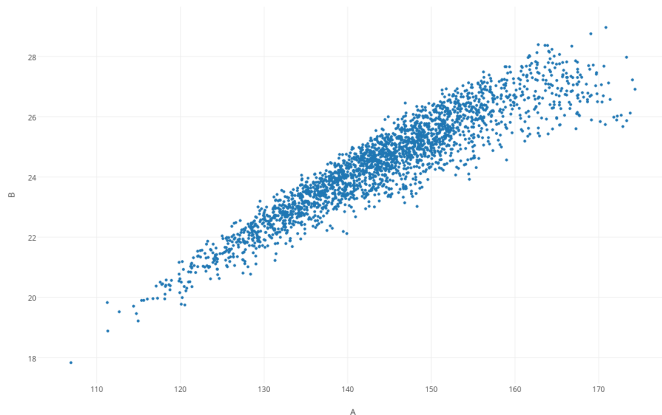
For  $\eta^1$  let  $E$  fire at  $t = 5$  and  $F$  fire at  $t = 5$ , and let  $\eta^2$  be an vector of empty spike trains, then  $P_{N,F}(\eta^1, \eta^2) = 0$ .

Once again, NISTy can be used to identify identical behavior on an output neuron.

# NISTy vs Population van Rossum

- We showed that NISTy displays different behavior from Population van Rossum.
- Due to investigating signal propagation rather than generation we see cases where different spike train vectors lead to equivalent inputs into neurons.
- How does the behavior of NISTy compare to Population van Rossum in general?

# Comparison with Existing Methods



**Figure:** Horizontal: NISTy, Vertical: Population van Rossum

# Conclusions

- Investigates signal propagation instead of generation,
- Suitable for synthetic systems as opposed to biological,
- With proper coding and foreknowledge doesn't significantly increase the computation time of simulations.

# Future Work and Applications

- Relationship Between Metric Spaces,
- Applications to studying learning algorithms, and
- Better understanding of the behavior of subnetworks.
- For subnetworks use NISTy for inputs and Population van Rossum for generation of activity.

Thank You.