Lattice Neural Networks with Spike Trains

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Overview

- Rationale for Lattice Based Dendritic Computing
- The lattice-based dendritic model
- Spike Trains
- The Spike Train Model
- Concluding remarks
- Questions

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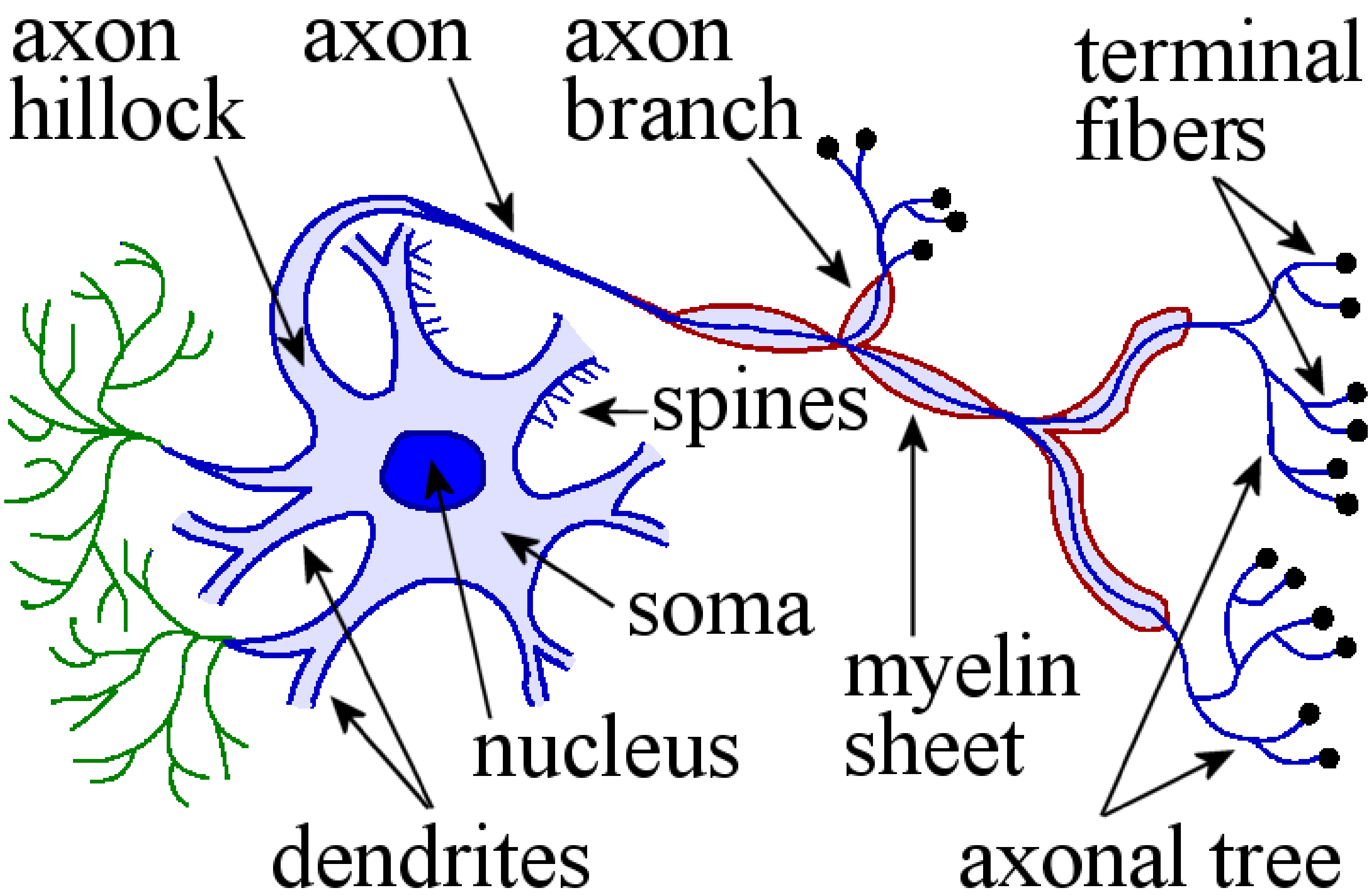
Rationale for the Proposed Model

- Basic Goal: A return of ANNs to its Roots in Neurobiology and Neurophysics
- Radial Basis Function NNs, SVM, Boltzmann Machines, etc., bear little resemblance to biological neural networks
- Dendrites make up more than 50% of a neuron's membrane
- Dendrites make up the largest component in both surface area and volume of the brain
- Thus, when attempting to model artificial brain networks, one cannot ignore dendrites

Rationale for the Proposed Model

- Dendrites and dendritic spines are major postsynaptic targets of presynaptic inputs
- The number of synapses on a single neuron ranges between 500 and 200,000
- The number of synapses in the human brain ranges between 60 trillion and 240 trillion (240×10^{12})
- These synapses reside on 10 to 20 billion neurons

Biological Neurons and Their Processes

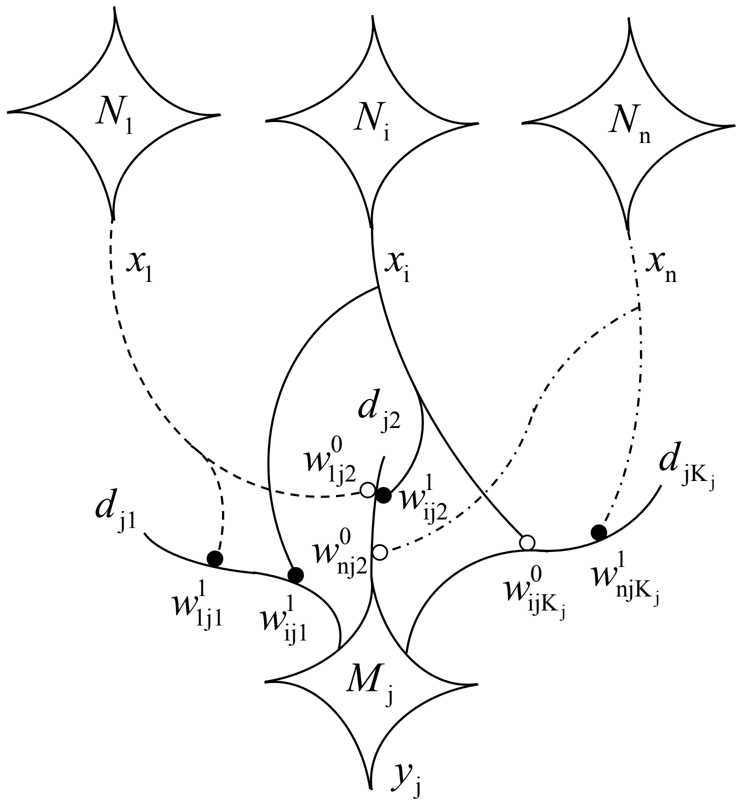


Dendritic LNNs have their roots in biological neurons and their processes.

Dendritic Computation: Assumptions

- A postsynaptic neuron M_j receives input from n presynaptic neurons $N_1, \ldots, N_n$.
- Each input neuron N_i has axonal branches that terminate at various synaptic regions of M_j.
- The synaptic regions are distributed along a finite number of dendrites $d_1, \ldots, d_{K(j)}$.
- Incoming information from axonal branches is transformed in the synaptic interaction
- The transformed data will result in either an *excitatory* postsynaptic response or an *inhibitory* postsynaptic response in the dendrites membrane.

An SLLP with dendritic structures



Terminal branches of axonal fibers originating from the presynaptic neurons make contact with synaptic sites on dendritic branches of M_j

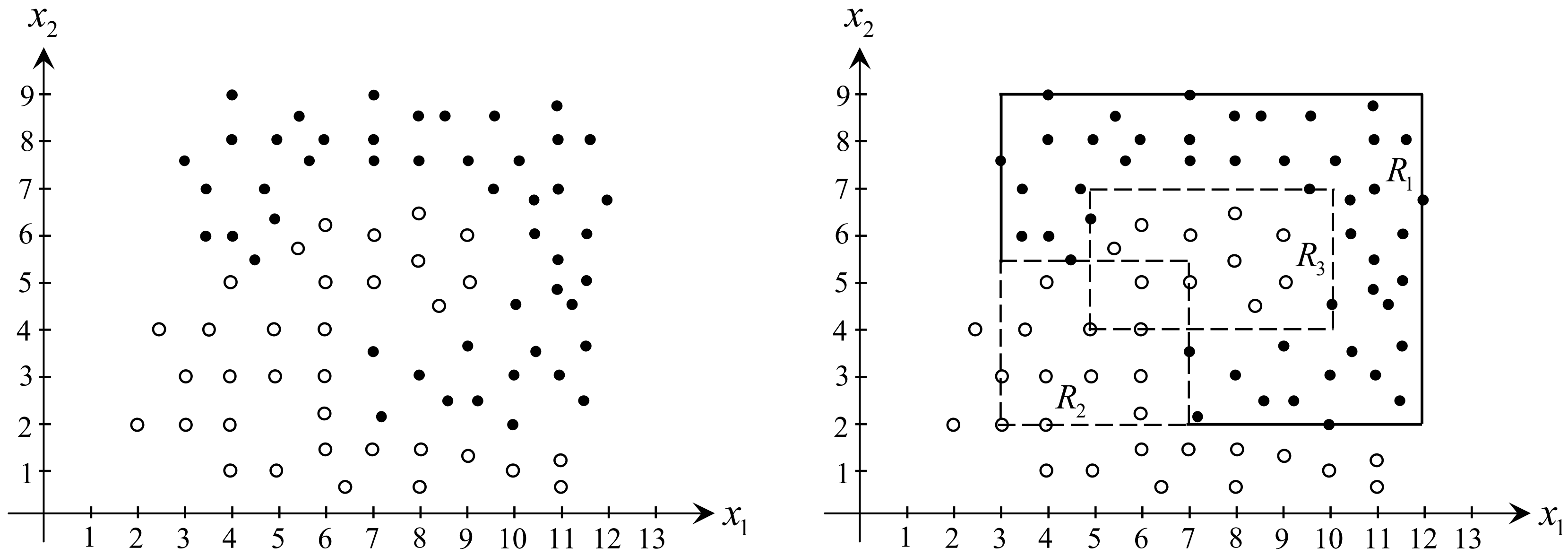
Dendritic Computation: Mathematical Model

The computation performed by the kth dendrite for input $\mathbf{x} = (x_1, \ldots, x_n)' \in \mathbb{R}^n$ is given by

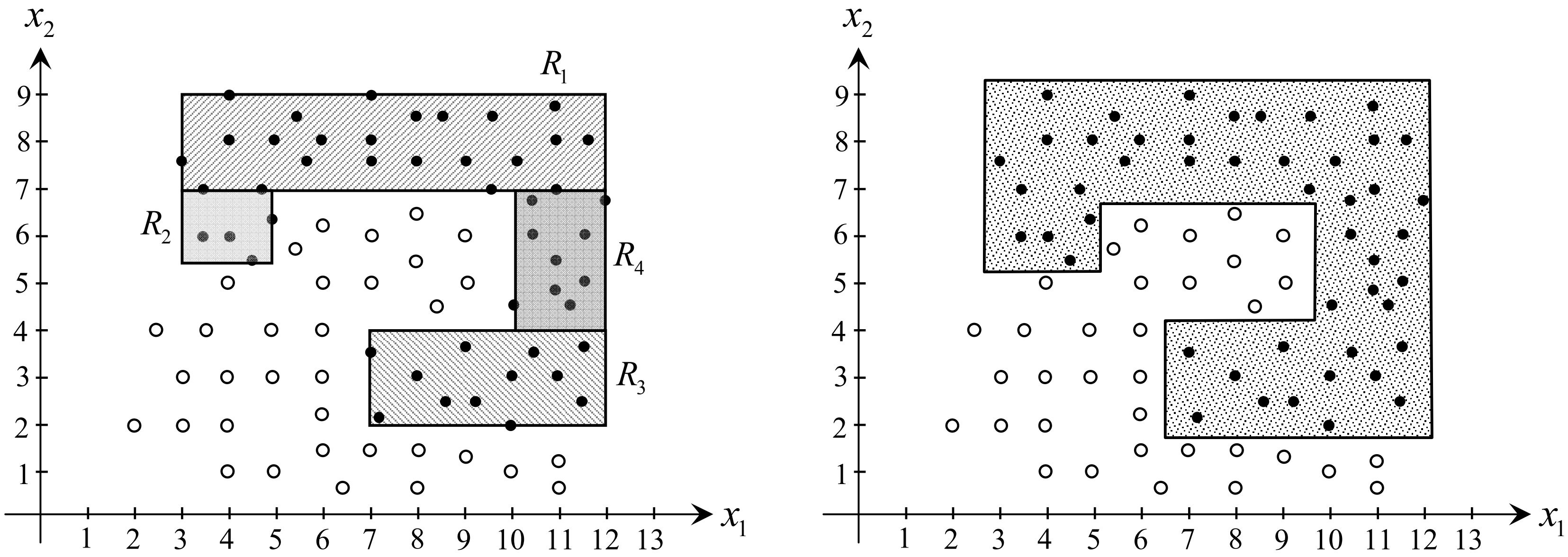
$$\tau_k^j(\mathbf{x}) = p_{jk} \bigwedge_{i \in I(k)} \bigwedge_{\ell \in L(i)} (-1)^{1-\ell} \left(x_i + w_{ijk}^{\ell}\right) \ ,$$

where

- x_i – value of neuron N_i;
- $I(k) \subseteq \{1, \ldots, n\}$ – set of all input neurons with terminal fibers that synapse on dendrite d_{jk};
- $L(i) \subseteq \{0, 1\}$ – set of terminal fibers of N_i that synapse on dendrite d_{jk};
- $p_{jk} \in \{-1, 1\}$ – inhibitory/excitatory response.

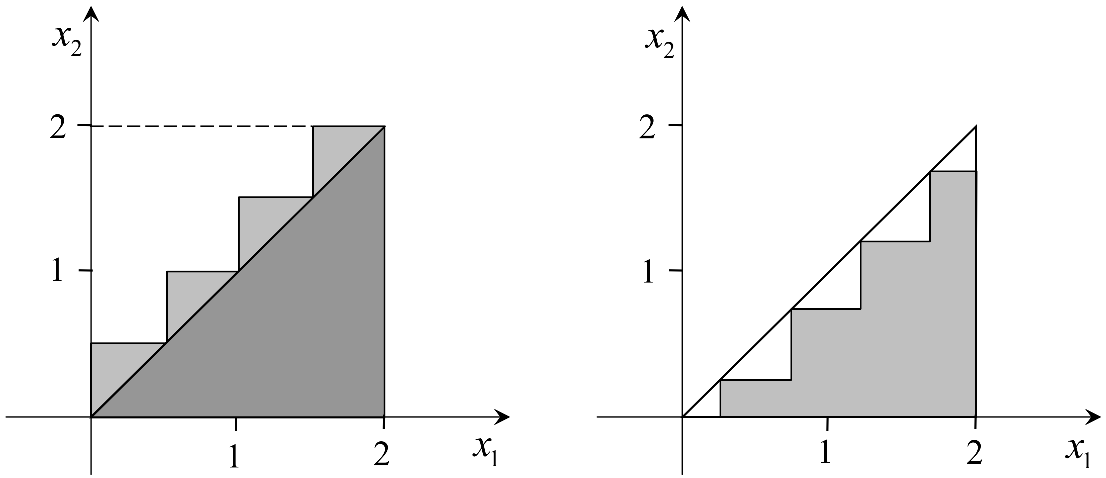


Left: Two class data set. Right: The elimination method.



Left: The merging method. Right: Boundary readjustment.

Problems with the Hyperbnox Approach



The triangular data can never be modeled *exactly* using either elimination or merging.

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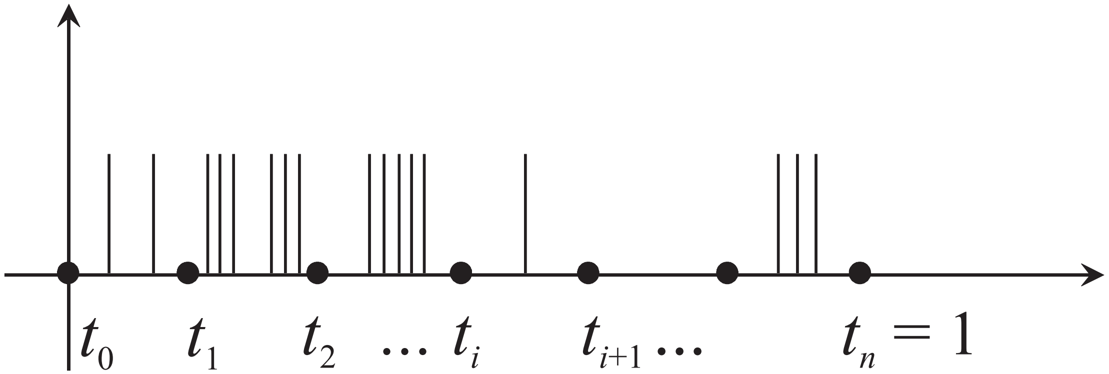
A Possible Solution: Spike trains

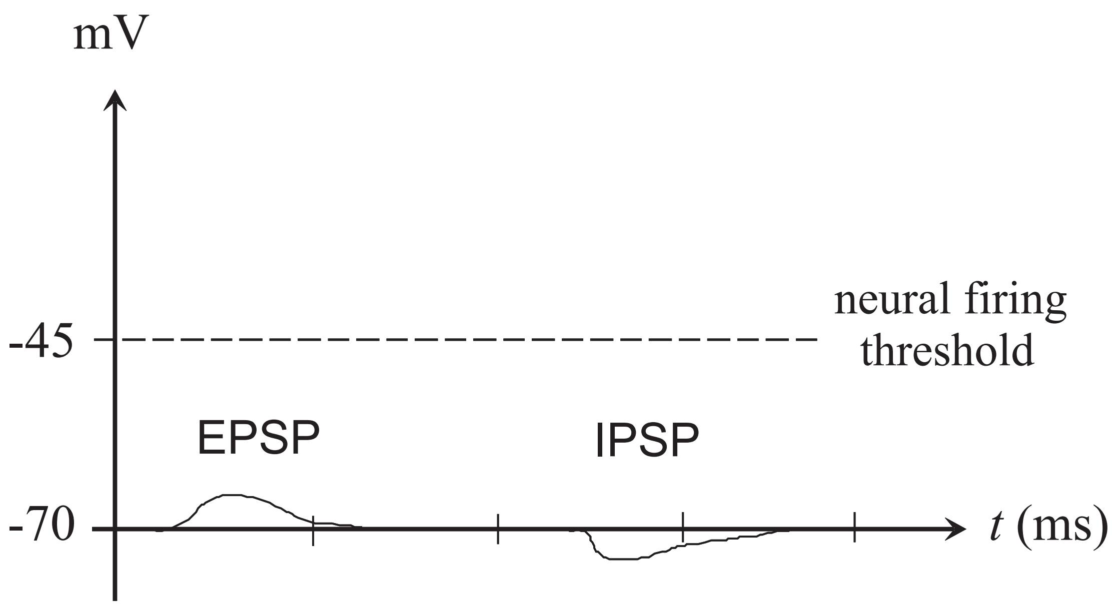
- *Spikes* are impulses that travel along the axon of a presynaptic neuron
- A spike automatically duplicates at each axonal branch
- A *Spike Train* is a time series of spikes
- The number of spikes within a time interval $\triangle t$ can be large
- The number of spikes and spike gaps in a train are key to information coding and decoding

Spike Trains



A one second spike train. The vertical line segments are just symbolic markers of action potentials

Post Synaptic Potentials



When the totality of the EPSPs and IPSPs exceeds the neuron's firing threshold, the neuron fires and sends a spike along its axon. Here t is in milliseconds and V in millivolts

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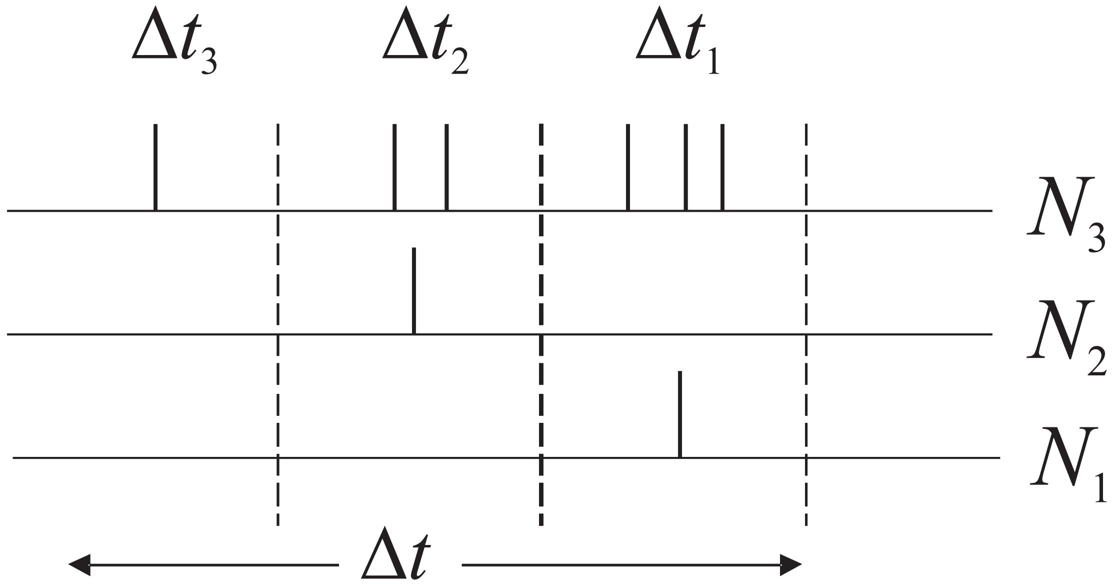
Spike Trains



Spike trains of three presynaptic neurons N_1, N_2, and N_3 for time interval $\triangle t = \sum_{i=1}^{3} \triangle t_i$

The Spike Train Model

The kth dendrite computes the value $\tau_k(\mathbf{x}, \triangle t)$

$$\tau_k(\mathbf{x}, \triangle t) = p_k \bigwedge_{h=1}^{m} \bigwedge_{r=1}^{r_k} \sum_{i \in I(k,r)} (-1)^{1-\ell(r,i)} s_i(\triangle t_h)(x_i + w_{ik}^r)$$

Where

- $s_i(\triangle t_h)$ equals the number of spikes generated by N_i during the time $\triangle t_h$.
- $\ell(r, i) \in \{0, 1\}$ depends on both r and i
- r denotes the rth spine of d_k

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The Spike Train Model

- The postsynaptic neuron collects the information generated by its dendrites over the time interval $\triangle t$ and computes the value

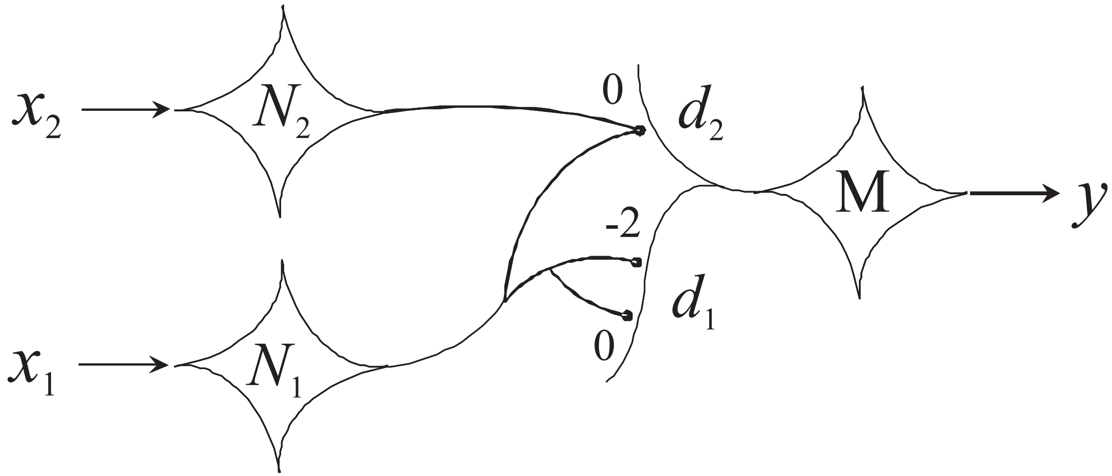
$$\tau(\vec{x}, \triangle t) = p \bigwedge_{k=1}^{K} \tau_k(\vec{x}, \triangle t),$$

  where $p = \pm 1$ is determined during training.
- Training is accoplished using the elimination algorithm combined with the Barmpoutis algorithm

An Example

- In the triangle problem the algorithm stops after Step 1 and $\triangle t_1 = \triangle t$
- During this time only one spike from each N_i is needed as each variable x_i is used only once in the step 1
- $r_1 = 2$, and $\tau_1(\triangle t_1) = (x_1 - 0) \wedge -(x_1 - 2)$
- $r_2 = 1$ and $\tau_2(\triangle t_1) = (x_1 - 0) + -(x_2 + 0) = x_1 - x_2$
- Hence $\tau(\vec{x}, \triangle t) \geq 0$ if and only if **x** is in the triangle

Graphical Representation of the Network



A LNN that solves the triangle problem. We assume that the two terminal fibers synapsing on d_2 have synapses on the same spine

Questions?

Thank you!