

# Neural Net Track Reconstruction for GLAST

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## What are we after?

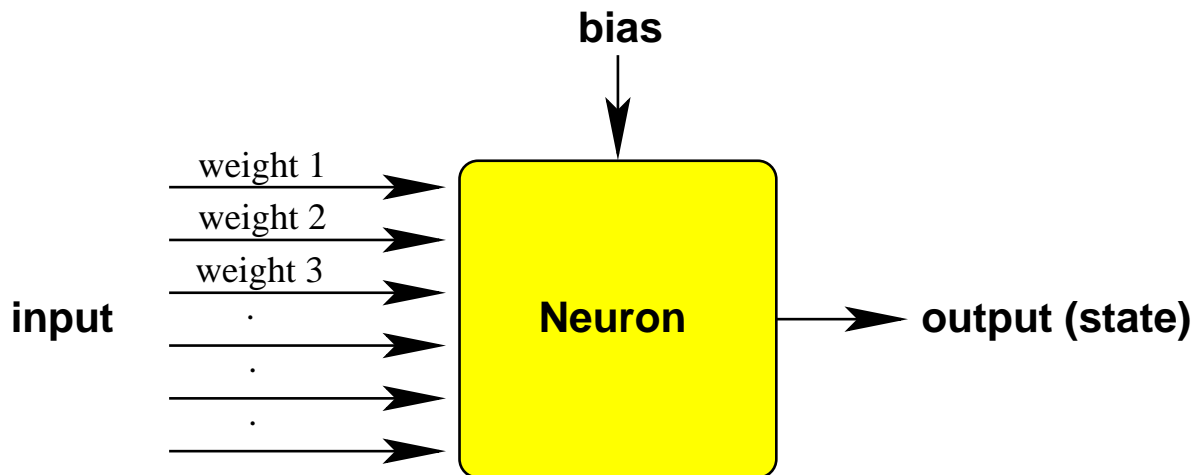
- We are after **findable tracks**, defined as:
  - Must have at least one degree of freedom.
    - N points to fit parameters.
    - at least 1 more to test hypothesis.
  - Must have 3 hits in consecutive layers in a single tower.
    - Defines a minimum pitch angle.
  - Must have a sagitta (bend) less than that set by detection limits.

## What are the requirements?

- Miss less than 1 of  $10^3$  findable tracks.
- Should be intrinsically 3-dimensional.
- Must apply **Globally** to the event.

# What is a Neural Net?

A Neural Network consists of processing units, called neurons, and connections between them.



- The state of a neuron depends on the input neurons state and the strength (weight) of these connections.
- The dynamics of a neural net is given by:

$$S_i = \text{sign} \left( \sum_j T_{ij} S_j + \text{Bias} \right) \quad (1)$$

where  $T_{ij}$  is the weight and  $S_j$  is the state of the input.

# Neural Network Abstract

- A neural network is very similar to a spin glass, where the state of a spin is either 1 (spin up) or  $-1$  (spin down).
- A neuron has two states as well active (1) and inactive (0).
- In both cases interactions can be long range.
- The dynamics (eq. 1) or local update rule evolves the system to a local minimum of the energy:

$$E(S) = -\frac{1}{2} \sum_{ij} T_{ij} S_i S_j \quad (2)$$

- Functionally there are two ways to evolve the system: (both are possible using our code)
- The **Simulated Annealing** approach where the neurons take on states of 0 or 1.
- The **Mean Field Theory** approach where the neurons take on states in the range (0,1).

# Mean Field Theory

- In mean field theory, one uses the thermal average of  $S_i$ .

$$V_i \equiv \langle S_i \rangle_T = \left[ \frac{1}{2} + \tanh \left( -\frac{1}{T} \frac{\partial E}{\partial V_i} \right) \right] \quad (3)$$

and the energy becomes equivalently,

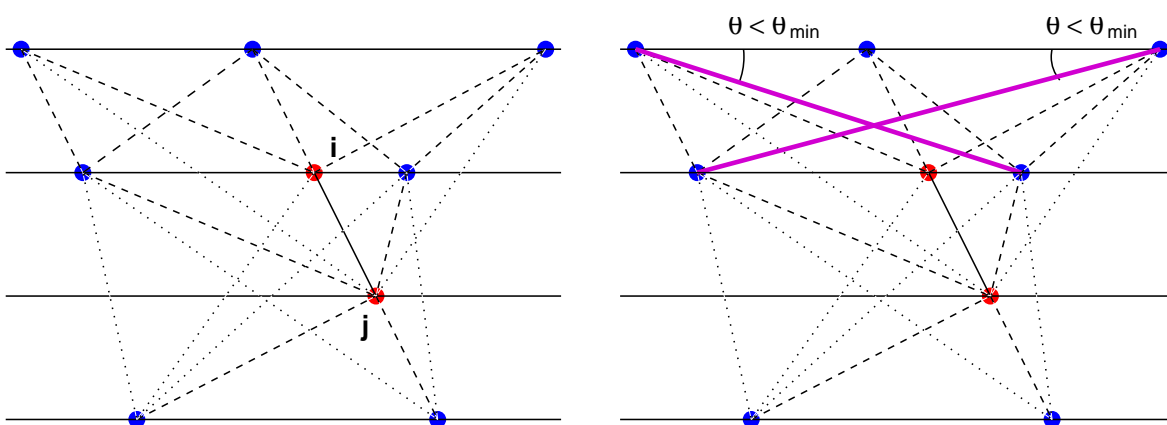
$$E = -\frac{1}{2} \sum_{ij} T_{ij} V_i V_j \quad (4)$$

- $V_i$  can take on any value between 0 and 1.
- $T$  is the temperature of the system.
  - The higher  $T$ , the more likely it is to escape local minima.
  - The higher  $T$ , the slower the system converges.
- Using this approximation, the process of finding the minimum energy is much faster than in the discrete case (active/not-active).

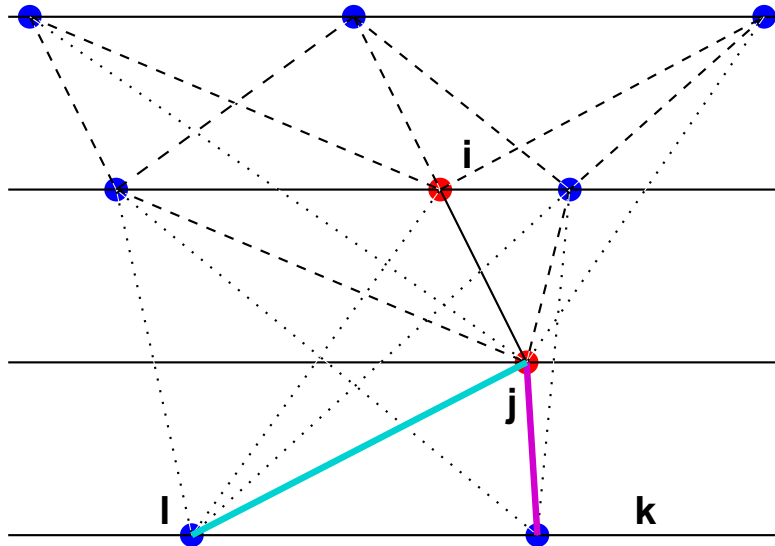
# Neuron Construction

Neurons are constructed of two hits and therefore denoted by 2 indices.

- The total number of all pairs is **HUGE**. We therefore must reduce the number of neurons (track segments).
- This done using criteria from the definition of a findable track.
- Neurons are only connected if:
  - The layer separation of the hits is less than a **Max Layer Separation**.
  - The neuron forms an angle of greater than  $\theta_{min}$  with the horizontal plane.



# Weight Matrix



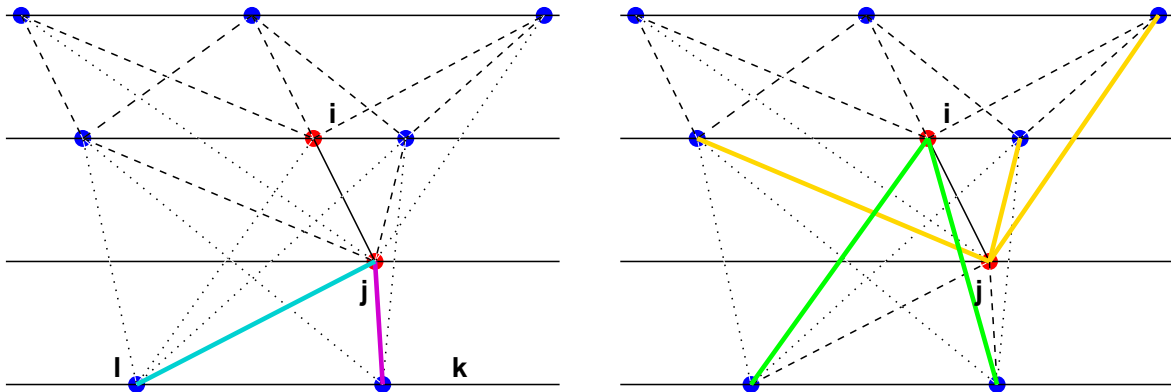
- Definition of weight matrix:

$$T_{ijk} = \frac{\cos^\lambda \psi_{ijk}}{d_{ij}^\mu + d_{jk}^\mu} \quad (5)$$

- This weight will favor straighter tracks.
- The parameter  $\lambda$  will be a function of the registered calorimeter energy. Higher energy  $\rightarrow$  Straighter track.
- $d$  is defined as the layer separation of the two hits (i and j). Biased against neurons which skip layers.

## Expanded Update Rule

$$V_{ij} = \frac{1}{2} \left[ 1 + \tanh \left( \frac{c}{T} \sum_k T_{ijk} V_{jk} - \frac{\alpha}{T} \left( \sum_{(k \neq j)} V_{ik} + \sum_{(l \neq i)} V_{lj} \right) - \frac{\beta}{T} \left( \sum_{kl} V_{kl} - N_a \right) \right) \right] \quad (6)$$



- Using the parameters  $c$ ,  $\alpha$  and  $\beta$  we can adjust the relative importance of the three terms.
- The  $c$  term is the previously defined weight matrix.
- The  $\alpha$  term is shown graphically on the right. It has the opposite sign of the weight matrix, and biases against too many active neurons connected to one hit.
- The  $\beta$  term is a stimulation term. The stimulation comes from the fact that  $\beta$  contribution is positive if  $N_a < \sum V_{kl}$ .

## New Energy Function

- The energy function also becomes:

$$E = -\frac{1}{2} \left[ c \sum_{ijk} T_{ijk} V_{ij} V_{jk} - \alpha \left( \sum_{ijk(k \neq j)} V_{ij} V_{ik} + \sum_{ijl(l \neq i)} V_{ij} V_{lj} \right) - \beta \left( \sum_{kl} V_{kl} - N_a \right)^2 \right] \quad (7)$$

## Updating Neurons

- In practice we have replaced the  $\beta$  term with a bias (knob) on each neuron.
- Near the end of the relaxation, the bias of neurons no longer enforced by their neighbors can be turned down, thus quickening convergence.
- We randomly queue the neurons and update each neuron at every timestep following the queue allowing the update to have an immediate.
- Convergence is determined using:

$$\frac{1}{N} \sum_{ij} \left| V_{ij}^I - V_{ij}^{I+1} \right| \leq \textit{criterion} \quad (8)$$

where  $I$  is the iteration number.

- Once a minimum is found,  $T$  can be lowered and the system can be relaxed again in order to test the current best state of the system.
- Finally we make a cut in activation level (ie  $V_i > 0.9$ ). The neurons which are above this cut become the hypothesis for the track fitting routine.

## NN applied to Aleph

This Neural Network track finding algorithm was applied to simulations of the Aleph detector in 1990.

- They found it to be more accurate than other track recon algorithms
- They found that the behavior of the network did not depend strongly on the parameters.
- They report that it converged very quickly in most cases (6 iterations).
- They also found that the neuron setup was the largest fraction of the algorithms running time.

# Implimentation

