

## Power laws, memory capacity, and self-tuned critical branching in an LIF model with binary synapses

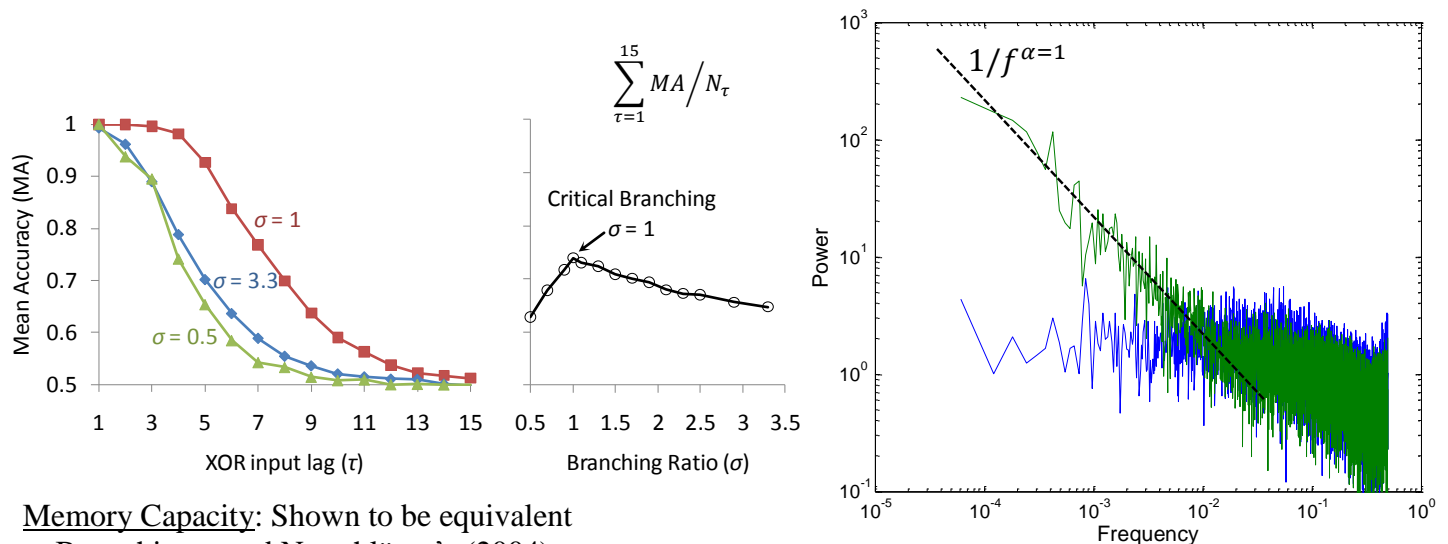
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**Summary:** Both fluctuations and distributions of spontaneous neural spiking activity have been observed to closely follow a variety of power laws. Multiple explanations have been offered for each observation, but few lead to mechanisms that encompass their widespread occurrence. Criticality is one theoretical principle that has the potential to encompass the generality of power laws in spiking activity. However, to apply it, a plausible mechanism is needed to maintain spike dynamics near a critical point. This mechanism should be generally adaptive to explain its apparent widespread occurrence.

A canonical, leaky integrate-and-fire model is presented in which a form of synaptic timing-dependent plasticity is used to maintain a state of *critical branching*. When a presynaptic neuron spikes, some number of spikes may occur afterwards over its postsynaptic connections. The critical branching point is a balance in the proportion of presynaptic to postsynaptic spikes such that  $\sigma = N_{post}/N_{pre} \sim 1$ . All neuronal and synaptic variables are updated in continuous time (using asynchronous, spike event-based simulation), using only current values of local variables. Postsynaptic spikes are weighted by a pre-post synaptic timing factor, and summed within each interspike interval. Each sum serves as a spatially and temporally local branching ratio estimate. For both excitatory and inhibitory units, critical branching is achieved by probabilistically potentiating post-synapses when a unit's branching ratio estimate is above unity, and de-potentiating when below unity.

Results showed that 1) the self-tuning algorithm maintained critical branching under a range of parameters; 2) power laws were obtained in spiking activity fluctuations ( $1/f$  scaling), size distributions of network bursts (neural avalanches), and temporal correlations in interspike intervals (Allan factor); 3) power laws disappeared once the self-tuning algorithm was disabled; and 4) critical branching was adaptive in that it maximized the network's memory capacity when assessed as a liquid state machine.

Membrane potentials were updated for each synaptic or external input  $I_j$  by  $V_i \leftarrow V_i e^{-\lambda_i(t-t')} + I_j$ , where  $t'$  was time of previous update. If  $V_i > \theta_i$ , then  $V_i \leftarrow 0$ , and  $I_k = w_k$  for all post-synaptic connections  $k$  at delay times  $t + \tau_k$ . For each first post-synaptic spike after a given pre-synaptic spike on unit  $i$ ,  $N_{post,i}$  was incremented by  $e^{-\lambda_i(t-t')}$ . For each ISI, update  $w_k$  if  $N_{post,i} \neq 1$  with probability  $\eta f(s_i) |N_{post,i} - 1| / U$ , where  $\eta$  is a tuning rate,  $U$  is the number of synapses available for (de)potentiation, and  $f(s_i)$  is a function of time since last spike.



**Memory Capacity:** Shown to be equivalent to Bertschinger and Natschläger's (2004) liquid state results at critical branching, where memory and separation of inputs was tested using delayed XOR test functions and linear classification.

**Example power law:** Spectral analysis of fluctuations in number of spikes per unit time interval, with self-tuned critical branching algorithm on (green) versus off (blue). Analogous results were obtained for neural avalanches and interspike intervals.