SUMMARY

Neural networks and forest fires

The dynamics of large networks of spiking neurons resembles closely that of forest fires. During such an event forests contain burned, green, or burning trees. Models of forest fires have recently been shown to exhibit self-organized criticality. Green trees can be ignited by a burning neighbor or by lightning. Let p be the probability that a burned tree becomes green, and f the probability that a green tree is hit by lightning. It was conjectured by Bak, Chen & Tang (1990) and elaborated by Drossel & Schwabl (1992) that if f is much smaller than p, but much greater than p^2, then the forest fire dynamics becomes critical and clusters of burning trees develop. Such clusters vary in size from a small number of trees to an appreciable fraction of trees in the forest. Simulations show that if s is the number of trees per cluster, the cluster size distribution P(s) is approximately 1/s; and the average density of green trees approaches the value 0.408. Figure 1 shows such a simulation.

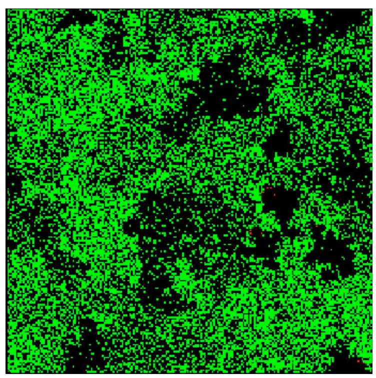

Figure 1. Simulation of a critical forest fire.

Such a distribution was conjectured by Bak (1996) to be universal and to be found in earthquakes, traffic flows, financial markets, evolution and extinction events, and in forest fires.

Neural networks have similar properties. There is a close correspondence between green, burned and burning trees and sensitive, refractory and activated neurons. Thus if 1/p is now interpreted to be the mean time it takes for a refractory neuron to recover sensitivity and 1/f the mean time between spontaneous activations of a neuron (produced, for example, by noise), then under certain conditions neural networks generate similar fluctuations and correlations of activity.

However neural networks are more complex than forests of trees. In particular sensitive neurons require excitation from several activated neighbors before they will activate. Thus the propagation of clusters of neural activity in neural network

models differs from that of clusters of burning trees in forest fire models. In spite of this difference both models have similar critical dynamics and also exhibit a phase transition to a much more organized state characterized by the initiation and propagation of waves and spirals of burning trees or activated neurons. Such a state can be produced by stochastic resonance in a number of differing ways. Figure 2 shows an example of such a state generated by tuning the variance of threshold fluctuations.

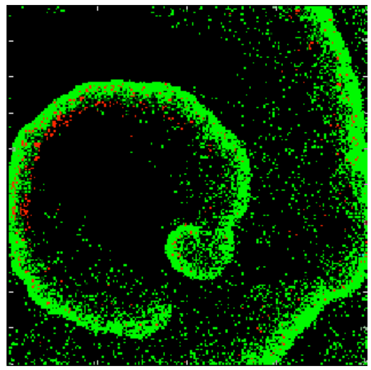

Figure 2. Spiral wave fronts in a network of neurons

A phase transition to such a state occurs in the limit when f is much smaller than p, but p is greater than 1/▯. In such a case the average density of green trees or sensitive neurons approaches 0.592.

In addition there are two types of neurons-excitatory and inhibitory. About 25% of all neurons in the cortex of the brain are inhibitory-they act to prevent other neurons from activating; the other 75% are excitatory. In terms of the forest fire analogy inhibitory neurons act like sprinklers making it more difficult for fires to burn trees and to propagate. There is also some evidence that the spatial extent of inhibition differs from that of excitation. This has profound consequences for the dynamics of neural activation. The spread of activity in a network of randomly connected neurons in which proximal neighbor connections tend to be excitatory and more distal ones tend to be inhibitory now consists of localized clusters of activated and refractory neurons which move around and avoid each other as if they were atoms in a box. Figure 3 shows a snapshot of the activity in such a network at one moment.

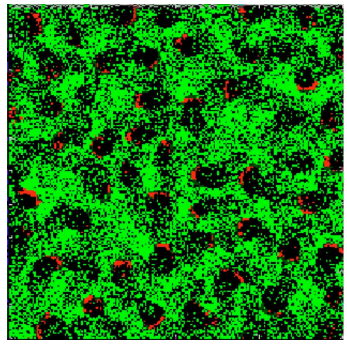

Figure 3. Activity in a network of neurons with lateral inhibition.

Some implications of this as a way to think about the dynamics of large-scale brain activity will be discussed.

Network activity modeled via integrate and fire neurons is based on the work of Davidsen and Schuster (2002) in that each neuron has a noisy threshold which follows a Brownian motion within reflecting boundaries. This threshold value does not reset after the neuron fires, rather the membrane voltage is reset into an absolute refractory state. Additionally, the system can be driven by an external input modeled independently for each cell as a Poisson process of excitatory pulses. In this model as well as in a model following pure forest fire dynamics we study a variety of neuronal connectivity such as excitatory coupling that decays exponentially with distance (as in Chu, Milton and Cowan, 1993, and Jung and Mayer-Kress, 1995) and center surround excitatory and inhibitory connections chosen from Gaussian probability distributions (as in Usher and Stemmler, 1995).

References:

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