THEORETICAL NEUROSCIENCE

How to build a critical mind

The physics of phase transitions beautifully describes the collective behaviour of many populations of inanimate particles, from water molecules to magnetic spins. But could it also help in understanding ensembles of living neurons?

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In experiments with small networks of living neurons, bursts of activity are seen spreading in cascades through the network. The size distribution of these 'neuronal avalanches' can be approximated by a power law[1,2], a hint that the networks may be operating near the critical point, that is, in a regime, where, on average, one neuron activates exactly one other neuron — the overall activity doesn't increase or die out over time. Simulations of neural networks indicate that the critical point would be quite beneficial for information processing. Just as the correlation length and susceptibility are maximized in a ferromagnet at the critical point, the dynamic range[3], memory capacity[4] and computational power[5] are optimized in neural network simulations when they are tuned to the critical point. This tantalizing picture has been missing an important piece, though. Criticality depends on the tuning of network parameters, but it has been unclear how neural networks could reach the critical point. On page 857 of this issue, Anna Levina and colleagues[6] provide an interesting clue that may help to solve this puzzle. Through analysis and simulations, they show that a property known as synaptic depression — something commonly observed in synapses — can cause neural networks to robustly self-organize and operate at criticality.

To understand this important result, it may help to first summarize some properties of living neural networks. A typical excitatory neuron in the cerebral cortex makes and receives ~10^3 physical connections, called synapses, with other neurons, forming a highly parallel network. Excitatory neurons communicate by sending pulses through

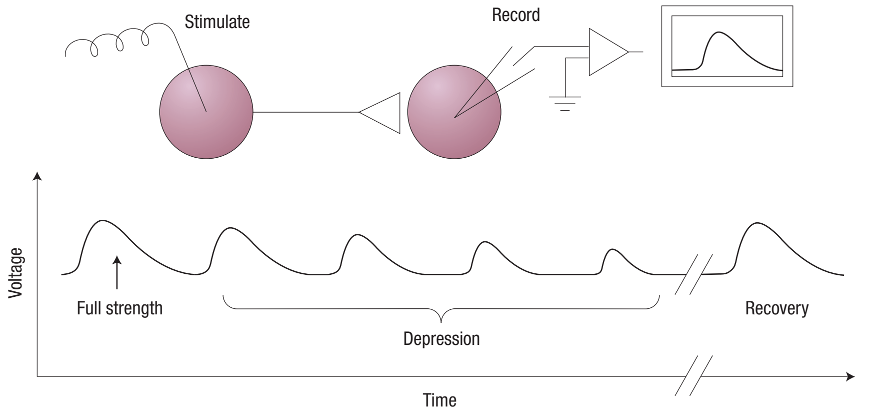

Figure 1 Driven into depression. Synaptic depression occurs when pulses are rapidly evoked from one neuron. At a recipient neuron, the first pulse is at full strength, but after many rapid stimulations, the synapse depresses and the received pulses become weaker and weaker. Pulse strength spontaneously recovers when the synapse is left unstimulated for several seconds.

these synapses, which increase the membrane potential of recipient neurons. Many pulses arriving within a time window of a few tens of milliseconds will drive the membrane potential of a recipient neuron over a threshold, when it will initiate a pulse of its own that will in turn be transmitted to thousands of other recipient neurons. There are also inhibitory neurons that transmit pulses that decrease membrane potential, but it is easy to show that above-threshold activity at one single neuron can initiate an avalanche of activity that spreads throughout a network.

So what keeps these networks from becoming continually over-excited? It's here where synaptic depression comes into play. Synaptic pulses between neurons are not constant, but vary in strength with frequency of use. When a synapse that has been inactive for several seconds is newly activated, it will produce a pulse at full strength (see Fig. 1). But if this synapse is called upon to transmit tens of times within one second, the strength of its pulses will rapidly diminish. This diminution is called synaptic depression, and is

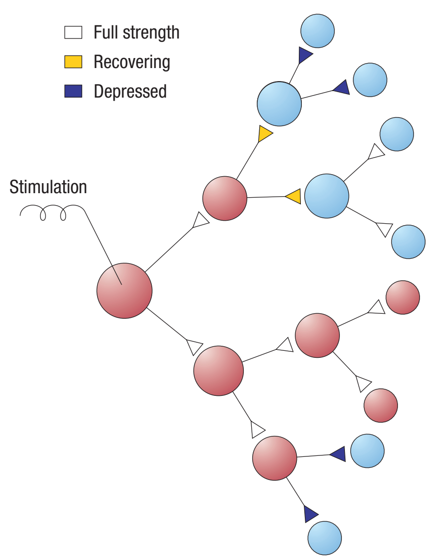

Figure 2 Setting off avalanches. One stimulated neuron in a highly connected network can initiate an avalanche of activity, indicated by red neurons. Some pathways are blocked as a consequence of previous avalanches. Over time, spontaneous recovery re-opens pathways. Antagonism between depression and recovery leads to a steady state where avalanches of all sizes occur.

observed at most connections between excitatory cortical neurons[7]. If the synapse is not activated again for many seconds, it will spontaneously recover to full strength.

Levina and colleagues show that this frequency-dependent modulation of synaptic strength can play a crucial role in tuning a network towards criticality. In their model, when a single neuron is activated it will initiate an avalanche of activity that will spread until it encounters depressed synapses (Fig. 2). Depressed synapses will therefore limit avalanche sizes. But when the network consistently produces many small avalanches, then unused synapses will have time to recover strength, thus increasing the probability that large avalanches will occur later. In a similar manner, large avalanches will depress most synapses, causing the network to produce subsequently more small avalanches. This interplay between synaptic depression and spontaneous recovery pushes slowly driven neural networks to a steady state, poised between a phase where activity will be damped, and a phase where it will be amplified. At this critical point, avalanches of all sizes occur. When the probability of an avalanche is plotted against its size in log–log space, it produces a power law with an exponent of –3/2, matching what has been reported in experiments[1,2]. It is interesting to note that the dynamics in this model[6] bears a strong resemblance to what happens in forest fires, where freshly burned areas are less likely to ignite, and where recovery occurs when trees grow back. Forest fires have also been shown to obey a power law of event sizes[8].

Yet models must ultimately make predictions and influence experiments. Perhaps one prediction from the work of Levina and colleagues[6] would be that large avalanches should occur more often after long recovery times. Their model should generate a correlation between avalanche sizes and intervals between avalanches; this could be easily evaluated with existing data. Another issue concerns whether this picture really applies to the intact brain, as the experiments that motivated Levina *et al.* were all performed in isolated neural networks. If their model survives these tests, then perhaps we will have moved one step closer to a statistical mechanics not of particles, but of neurons.

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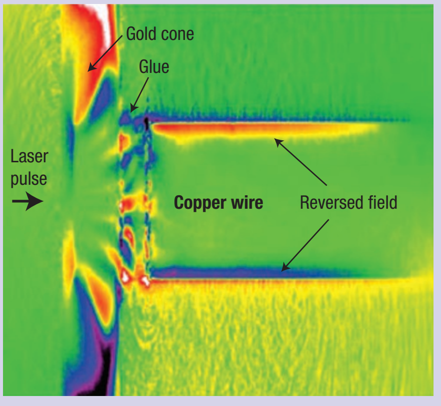
LASER–PLASMA INTERACTIONS

Fast electrons on a wire

The advent of ultra-high-intensity lasers has opened up the possibility of producing high-quality electron, proton, X-ray and ion beams in facilities that are much smaller and less costly than a typical particle accelerator or synchrotron radiation source. The ability to generate intense electron and ion beams in particular could hold the key to the so-called fast-ignition approach to laser-driven thermonuclear fusion (M. Tabak, *et al. Phys. Plasmas* **1,** 1626–1634; 1994), in which a target of hydrogen isotopes is first compressed by an array of laser beams, and then ignited by a single tightly focused higher-intensity beam that generates beams of fast electrons (or ions) within the resulting plasma. But when a laser is focused onto a simple planar target (with an intensity of around 10^{19} W cm^{-2} or higher), the MeV electrons produced emerge at a wide divergence angle of around 40°. This limits the ultimate intensity of the hotspot and is detrimental in most applications for which laser-driven beams are being developed.

A number of designs have been proposed to try and narrow this divergence of the electrons, but one of the most promising consists of a hollow gold cone with a thin (7 μm diameter) copper wire at its tip (R. Kodama *et al.*, *Nature* **432,** 1005–1008; 2004). The guiding of electrons by the large fields that is generated around a wire enables them to propagate for a distance of several millimetres within a diameter similar to that of the wire. This effectively increases their energy flux by an order of magnitude compared with a cone on its own, and by up to 30 times compared with a planar target. In addition, energy loss in the transverse direction (beam cooling) improves the beam emittance — a figure of merit that characterizes a beam's confinement and momentum spread — while electrons propagate along the wire. But the precise details of this process have proven elusive. In this issue J. S. Green and colleagues (*Nature Phys.* **3,** 853–856; 2007) present an exhaustive experimental and numerical study of the intricacies of the fast electron transport along a wire, and at laser irradiancies one order of magnitude higher than previously reported.



The authors' results demonstrate that when a petawatt laser pulse interacts with a cone-wire target, the heating of the plasma is maximized close to the wire surface.Moreover, their simulations show that the complex field structures that emerge from this interaction (see figure) involves a reversal of the magnetic field inside the wire, which enhances the return current within a thin layer beneath its surface. This finding substantially improves our understanding of the guiding mechanism, and should enable further improvements in the design of cone-wire targets for a host of applications in medicine, materials science, physics and biology in which laser-driven electrons beams are expected to be used.

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