Abstract for Minischool and Workshop on
MULTIPLE TIME SCALES IN THE DYNAMICS OF THE NERVOUS SYSTEM

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Memory in biological neural systems is believed to be stored in the synaptic weights. Computational models of such memory systems have been constructed in order to investigate, for example, optimal learning rules and storage capacity. Commonly, a synaptic weight in such models is represented by an unbounded, continuous real number. However, in biology, synaptic weights should take values between certain bounds. Furthermore, physiology experiments suggest that synaptic weight changes may occur in steps. For example, putative single synapse experiments show that a switch-like increment or reduction to the excitatory post-synaptic current can be induced by pairing brief pre-synaptic stimulation with some appropriate post-synaptic depolarisation [Petersen et al., 1998, O'Connor et al., 2005].

In networks with bounded synapses, old memories decay automatically as they are overwritten by new ones [Parisi 1986]. This is in contrast to networks with continuous, unbounded synapses, which can typically only be presented with a finite number of patterns to learn, all of which get stored equally well (or badly). The automatic forgetting of discrete, bounded synapses allows us to study learning in a realistic equilibrium context, in which there can be continual storage of new patterns.

Previous signal-to-noise ratio (SNR) analysis of the performance of discrete, bounded synapses has resulted in ambiguous conclusions [Fusi & Abbott 2007]. This is because altering parameters typically results in either 1) a decrease in initial SNR but a slower decay of the SNR (i.e. an increase in memory lifetime), or 2) an increase in initial SNR but a decrease in memory lifetime. Here we show how to resolve this ambiguity by analyzing the capacity of bounded, discrete synapses in terms of Shannon information. We then use our framework to find optimal learning rules.

We model a single neuron, and investigate how information capacity depends on the number of synapses and the number of synaptic states, both for dense and sparse coding. We find that below a critical number of synapses, total capacity is linear in the number of synapses, while for more synapses the capacity grows only as the square root of the number of synapses. This critical number is dependent on the sparseness of the patterns stored, as well as on the number of synaptic states. Furthermore, when increasing the number of synaptic states, we find that for small numbers, the information initially grows linearly, before levelling off and then saturating for many states.

Interestingly, for biologically realistic parameters, capacity is close to critical, suggesting that the number of synapses per cell is limited to prevent suboptimal learning. Moreover, for these parameters, capacity is comparable to that of unbounded, continuous synapses. Thus, discretization of synapses does not necessarily substantially reduce storage capacity.