Philip Tully. Dynamic phenomena in large networks (Anders Lansner, KTH; Matthias Henning, Univ. Edinburgh)

Although neuroscientific experimentalists and modelers alike have the tools at their disposal to generate anywhere from gigabytes to petabytes of spike time series data on only a few trials, the establishment of analysis methods required to understand the results of these simulations and recordings is of equal if not greater importance. After all, how is one to evaluate the predictive power of their model if there is no meaningful way to interpret and compare outputted information? Indeed, the advent of increasingly sophisticated neuronal recording technologies will potentially leave neurobiologists awash in an unconsolidated data deluge.

Measuring the occurrence of precisely timed spatiotemporal patterns (PTSPs) has been shown to have functional relevance in hippocampal and cortical regions. However, when applied to massively parallel spike train data, the existing methods have proven to be computationally tedious. One of my interests involves developing an algorithm that will efficiently detect PTSPs from datasets comprised of massively parallel spike trains. Formulating the task as an embarrassingly parallel problem, the algorithm will rely on the MapReduce paradigm. Just as a text document of words can be split up independently by line to sum the occurrence of each unique word and then totaled from there to get the overall word count for the document, so can the times of a spike train be split up by a maximum allowed pattern length to sum the occurrence of unique PTSPs. I expect a nontrivial speedup for this algorithm when executed on a large scale parallel shared memory machine housed at KTH, although memory considerations will need to be taken into account. With this tool at our disposal, the group will be able to begin to understand how spatiotemporal patterns evolve under different experimental conditions and how they are developed and maintained in artificial neuronal networks.

The functional architecture of the cerebral cortex is continuously modified throughout life. Despite these ongoing morphological changes, e.g. alteration of underlying ion channels and receptors, cortical networks and the cells comprising them are able to maintain functionality and complexity throughout development and in response to learning, loss of sensory input, and trauma. Moreover, consolidation of cortical circuitry persists although destabilizing Hebbian mechanisms alone (i.e. LTP or LDP) would seemingly propel network activity towards runaway excitation or quiescence. What stabilizing forces exist that act in opposition and that allow networks to organize patterns of connectivity to balance such learning with information processing? To this end, I am also extremely interested in developing large scale spiking neuronal network models that can account for these dynamics. I would like to implement a type of synaptic plasticity, the Bayesian Confidence Neural Network (BCPNN), that is originally derived from statistical mechanics and has been shown in abstract models to maximize e.g. storage capacity. A kind of Hebbian learning rule, BCPNN relies on synaptic traces at different temporal resolutions to characterize pre and post synaptic activity, and the weights are updated through classic Bayes' rule. I will analyze the dynamics that arise out of a network incorporating this plasticity, and compare against more standard types of STDP.

Lastly, cortical networks have been postulated to homeostatically regulate a critical state which enables a stable propagation of avalanche-like firing patterning. This criticality property in the coupling of neural circuits simultaneously tolerates the percolation of local events through the system in addition to the formation of more global events that engage many sites. The events, known as neuronal avalanches, are bursts of spontaneous activity indicating critical state dynamics because they are described by power law
distributions that can scale. Such a diversity in spontaneous neural
synchronization could optimize information transfer and memory retention in the
cortex. But what properties of a network can generate homeostatic behavior and can
tune its parameters toward a critical state? For example, do neurons have some
intrinsic knowledge of the number of other neurons they project to, and adjust the
strengths of their synapses accordingly? I have been interested in exploring this
phenomenon in spiking network models, and am especially keen on the idea of
cortical circuits entering up states that are critical (Millman et. al 2010).