M2 INTERNSHIP PROPOSAL

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Unsupervised learning of spike patterns in the cortex

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In order to make sense of the outside world, the brain needs to perform unsupervised learning on sensory stimuli to discover structures that can subsequently be recognized as objects or events. Despite immense progress in machine learning, how this is implemented in the brain is still not fully understood. Because it remains very hard to measure synaptic weights and their evolution in biological networks, the interaction of spontaneous and evoked neural activity with ongoing plasticity has received increasing attention in the computational literature using models of recurrent spiking networks. Previous studies have mostly focused on the formation and stability of neural assemblies in response to rate patterns (i.e. transiently increased input rates) or correlated input spike trains [1,2] (Fig. 1a). The response to arbitrary repeated spatio-temporal input spike patterns has received considerably less attention and will be the focus of the proposed internship. Some early studies investigated how neurons can become efficient pattern detectors based on spike-timing dependent plasticity (STDP), both for isolated neurons [3] and in networks [4] (Fig. 1b), but whether the plasticity of recurrent connections can shape the network's response has not been addressed. Using computational models, we plan to investigate how cortical networks acquire representations of repeated sensory stimuli for different generic [5] and biophysically grounded [6] synaptic plasticity rules. We also hope by doing so to shed more light on the phenomenon of 'representational drift', that describes the change of network responses to stimuli on long times. Recently, experiments established that the representational drift is much smaller than previously thought when the precise spike-timing relationships among neurons are considered [7,8] (Fig. 1c); we thus expect that spike-timing based plasticity plays a key role in controlling the robustness of such network responses. Eventually, predictions of our model may be tested on publicly available data sets of large-scale recordings e.g. in mice [9].

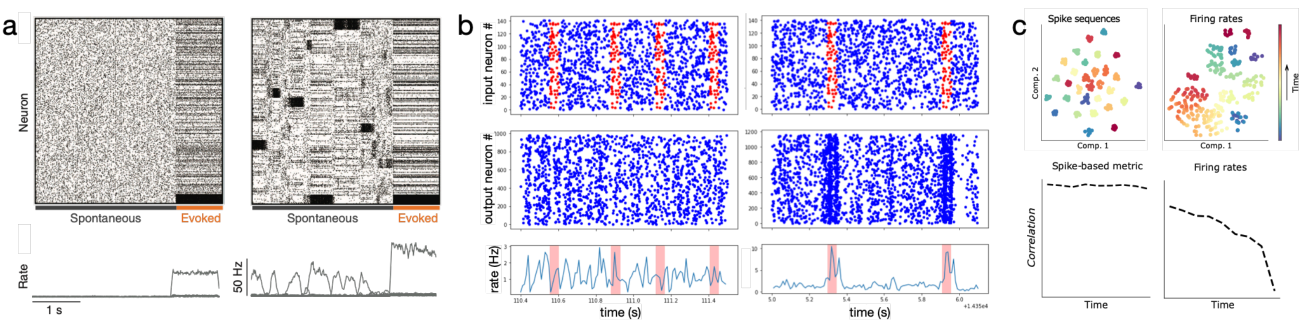

Figure 1: **(a)** STDP-mediated formation of assemblies of co-active neurons in response to increased inputs (evoked response), [1]. **(b)** Sketch of spike-pattern recognition by a network of neurons. Top panels: Input spike trains, with repeated spike patterns shown in red. Middle panels: Network neuron raster plots. After learning, neurons respond by stronger firing. **(a,b)** Bottom plots: average firing rates; left panels before, right panels after learning. **(c)** The responses in mouse visual cortex to repeated identical stimuli are more similar when analyzed in terms of relative spike timings (left) than in terms of firing rates (right), [7]. Upper panels: Principal components of responses; lower panels: correlation of responses over time.

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