Spiking neural network model of reinforcement learning in the honeybee implemented on the GPU

Esin Yavuz[1], Pascale Maul[2] and Thomas Nowotny[1]
[1]University of Sussex, Brighton, BN1 9RH, UK
[2]Institute of Cognitive Science, University of Osnabrück, 49069 Osnabrück, Germany

Pioneering research and skills

Abstract

Honeybees can learn and perform complex behavioral tasks despite their small brains that contain less than a million neurons. At the same time they are accessible to physiological experiments and the relatively small number of neurons in their brain lends itself to quite detailed numerical simulations. Bees therefore are a good model system for studying sensory cognition and reinforcement learning.

We have shown in earlier work (Nowotny et al. 2005) that the anatomy and known electrophysiological properties of the olfactory pathway of insects in combination with spike-timing dependent plasticity (STDP) and lateral inhibition lend themselves to an unsupervised self-organization of synaptic connections for the recognition of odors. Here we extend this model by adding a more realistic model of early olfactory system where the activity is modulated by mechanisms of reinforcement learning. We employ a three factor learning rule where plasticity is governed by pre-synaptic and post-synaptic activity and a global octopaminergic/dopaminergic reinforcement signal, triggered by a reward. We investigated the role of feed-forward and feedback mechanisms, as well as the role of the connectivity initially achieved by unsupervised STDP.

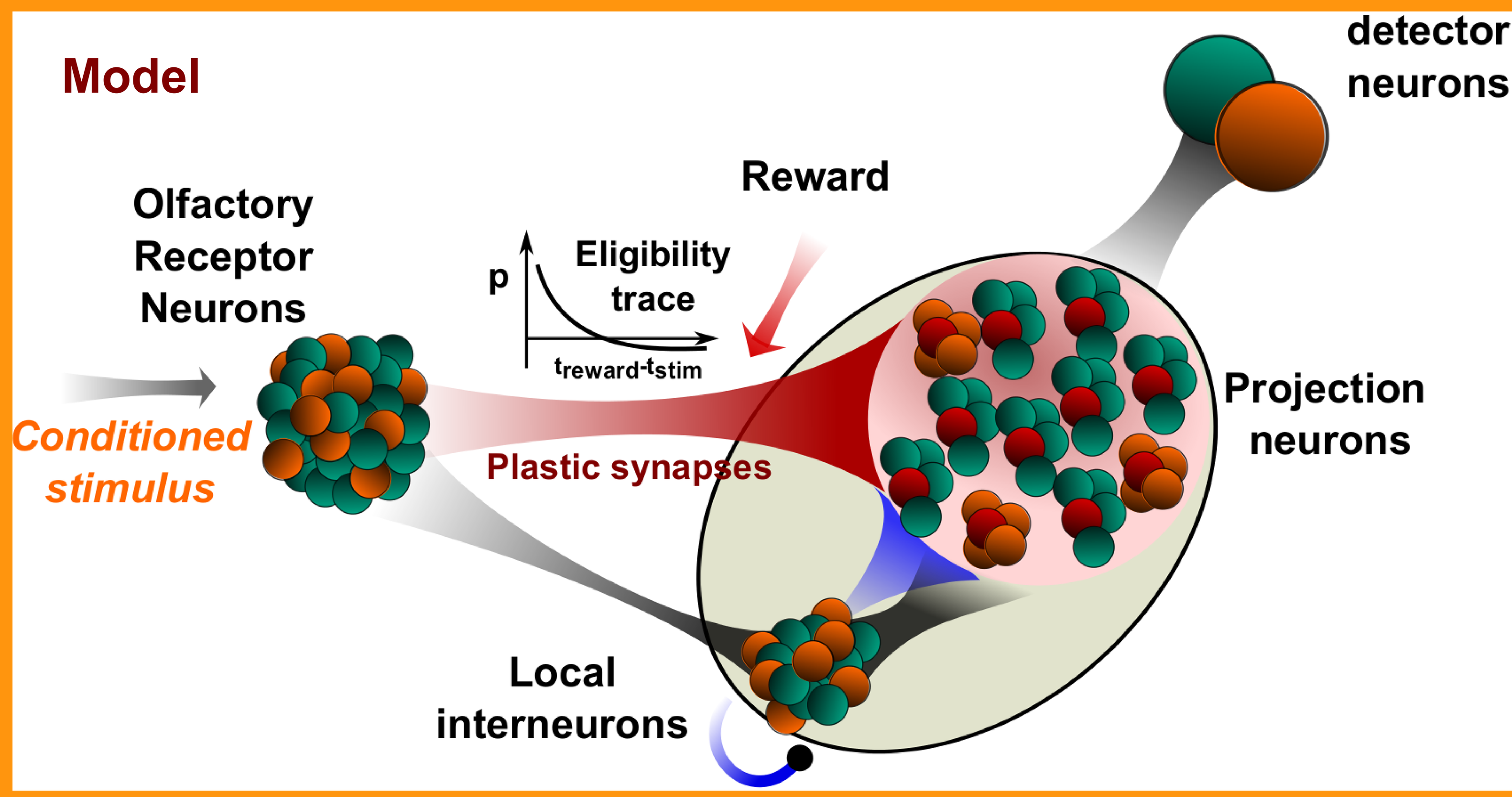
Our model is implemented in the GeNN framework, which facilitates the use of GPUs for spiking neural network simulations using a code generation framework. Because of the massive parallelism provided by GPUs, we can simulate tens of thousands of neurons in real time in the sparse firing regime relevant here. We investigated optimization strategies and neuron and synapse model choices for a better performance on the GPU. The model presented here is a stepping-stone to more sophisticated learning models and multi-sensory integration in the Green Brain Project, in which we aim to control a flying robot with a simulation of learning and decision making mechanisms in the honeybee related both to the olfactory and visual pathways.

Expected behaviour

Here we investigate whether elemental learning can be achieved at the early olfactory system, as a result of the synaptic plasticity modulated by the interaction between the reward signal and expectancy defined by the eligibility trace.

	R <0	R >0
p <0	+ (recovery)	-(inactivation)
p >0	- (extinction)	+ (reinforcement)

Model



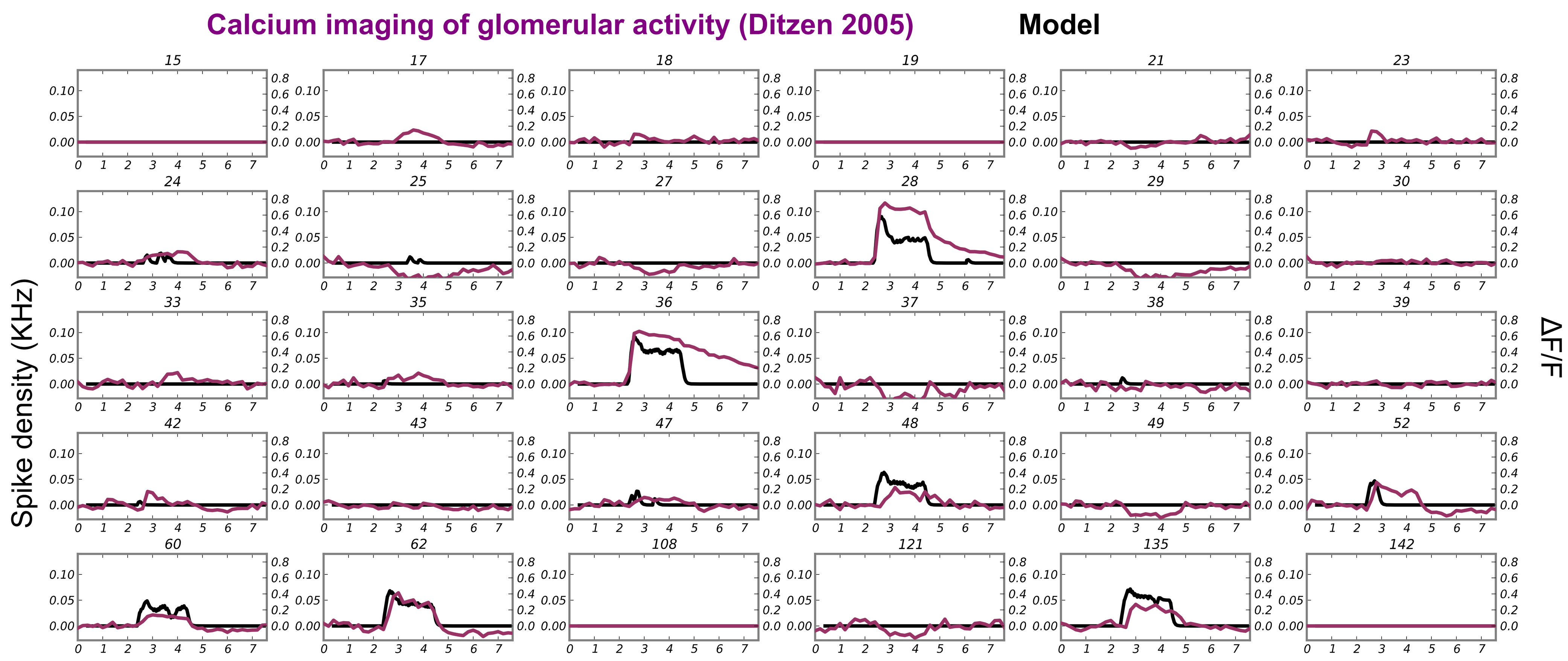
Model is based on a previous study (Nowotny et al 2013), where olfactory transduction in the olfactory receptor neurons (ORNs) is modelled as odourant binding and unbinding at olfactory receptors. The fraction of activated receptors are then translated into the spike rate of a Poisson process used to model ORNs.

Projection neurons and local interneurons are modelled as Hodgkin-Huxley neurons. Spikes are transmitted at every 0.02 ms and neurons are updated at every 0.002 ms.

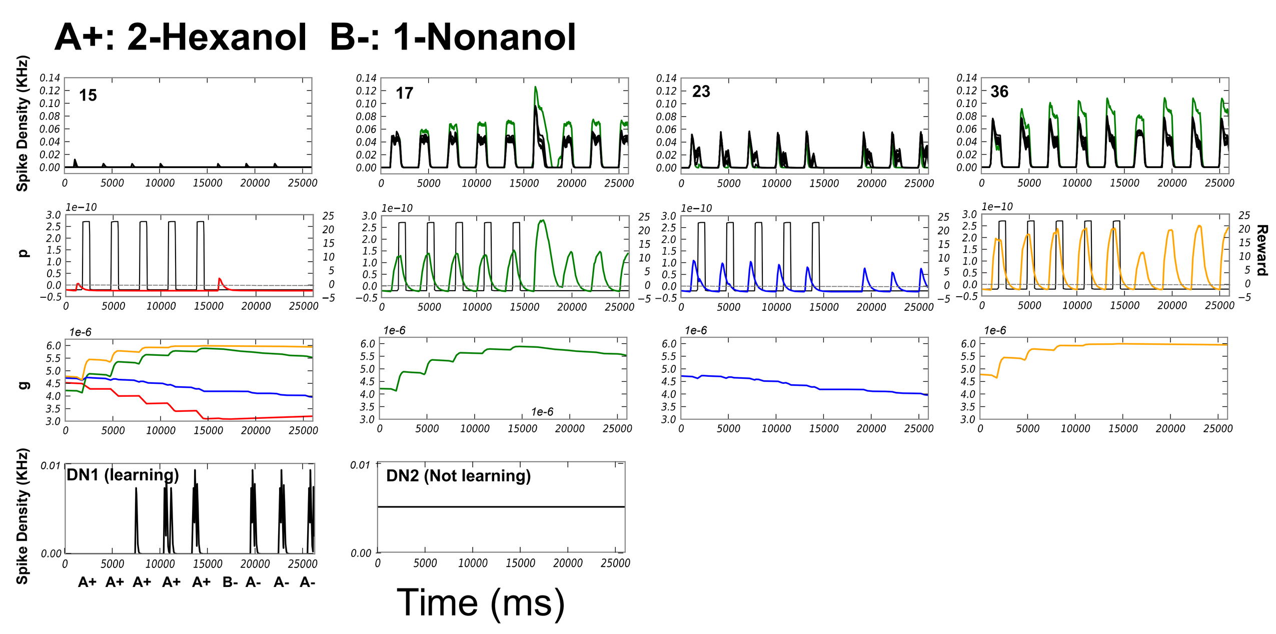
There is an "eligibility trace **p** which is updated for each pre- or post-synaptic spike according to **p** → **p** + FSTDP(Δtspike), where the STDP function is defined as a function of Δt = tpost − tpre as an exponential decay (τ+ = 120 ms, τ- = 60 ms).
Synaptic conductance **g** is then updated as Δ**g = R · p**

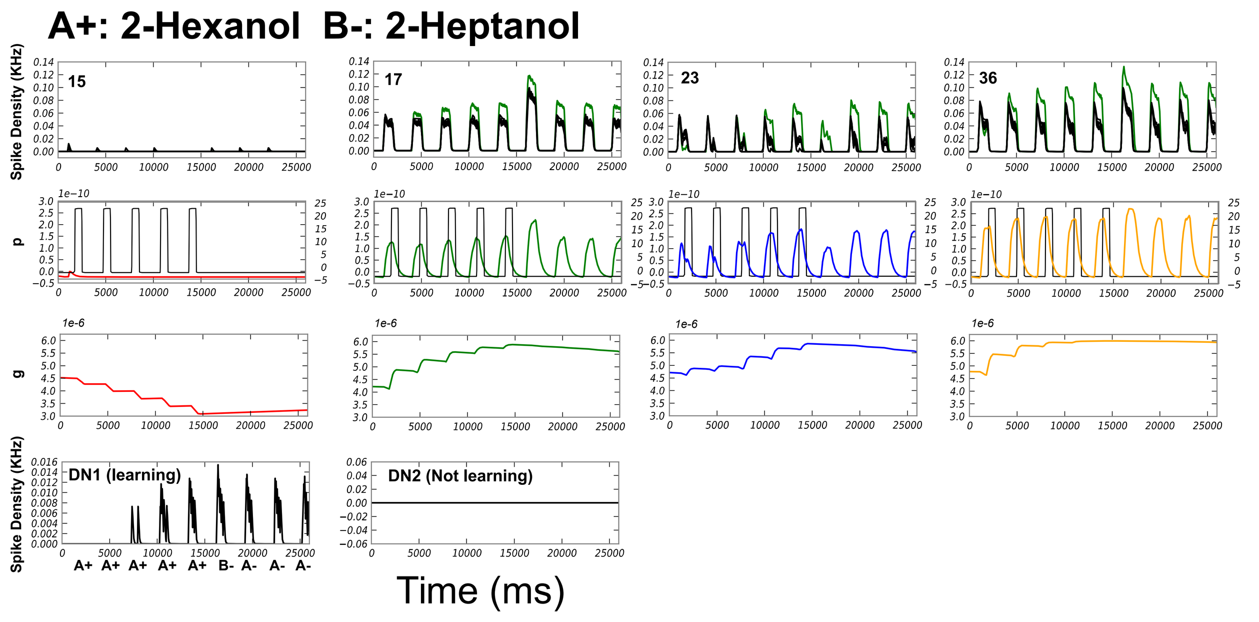
Results

1: PN activity is in coherence with calcium imaging data



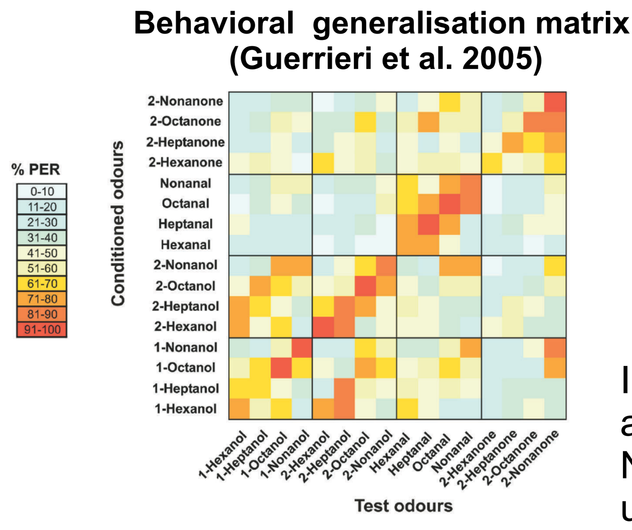
2: Model learns to discriminate A+ from B- if odours are not similar



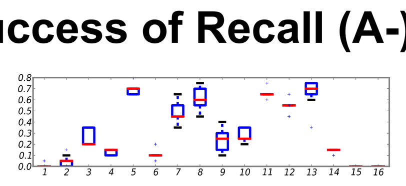


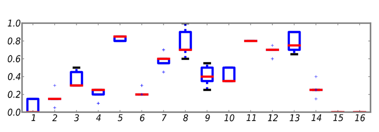
3: Learning and discrimination depends on the odour identity

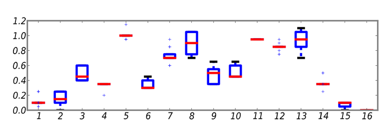
We simulated the model in the absolute conditioning protocol for pairs of 16 odours that were used by Guerrieri et al. 2005 and Ditzen 2005. We calculated the sum of spike density during the first A- stimulation to see if the model can respond to the conditioned odour without presence of reward (success of recall), and during B- stimulation to obtain the generalisation matrices. This is not a direct measure of response probability, but a high spike density indicates that the response is very strong and the model is likely to respond in other trials as well.
Odour identities are in the same order as in the behavioral generalisation matrix shown on the right.



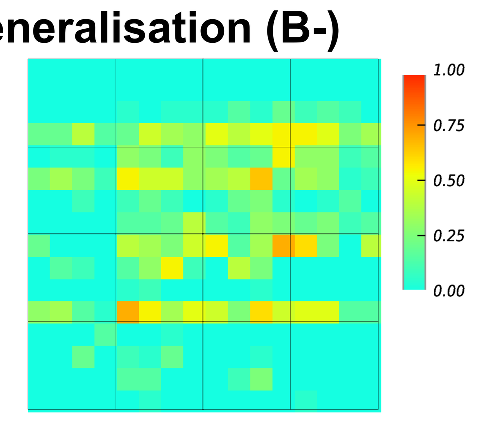
Success of Recall (A-)



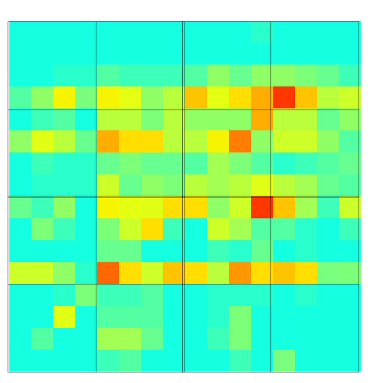




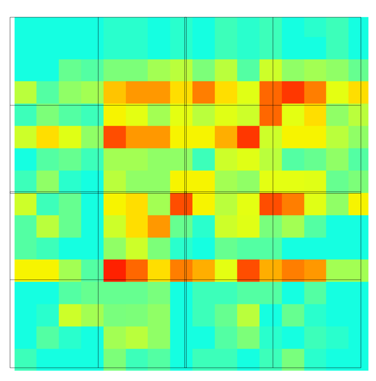
Generalisation (B-)



E(gPN-DN) = 1.65



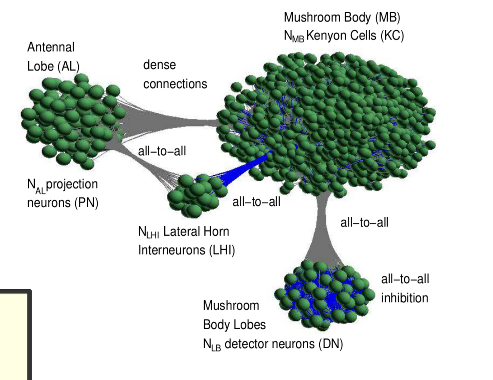
E(gPN-DN) = 1.8



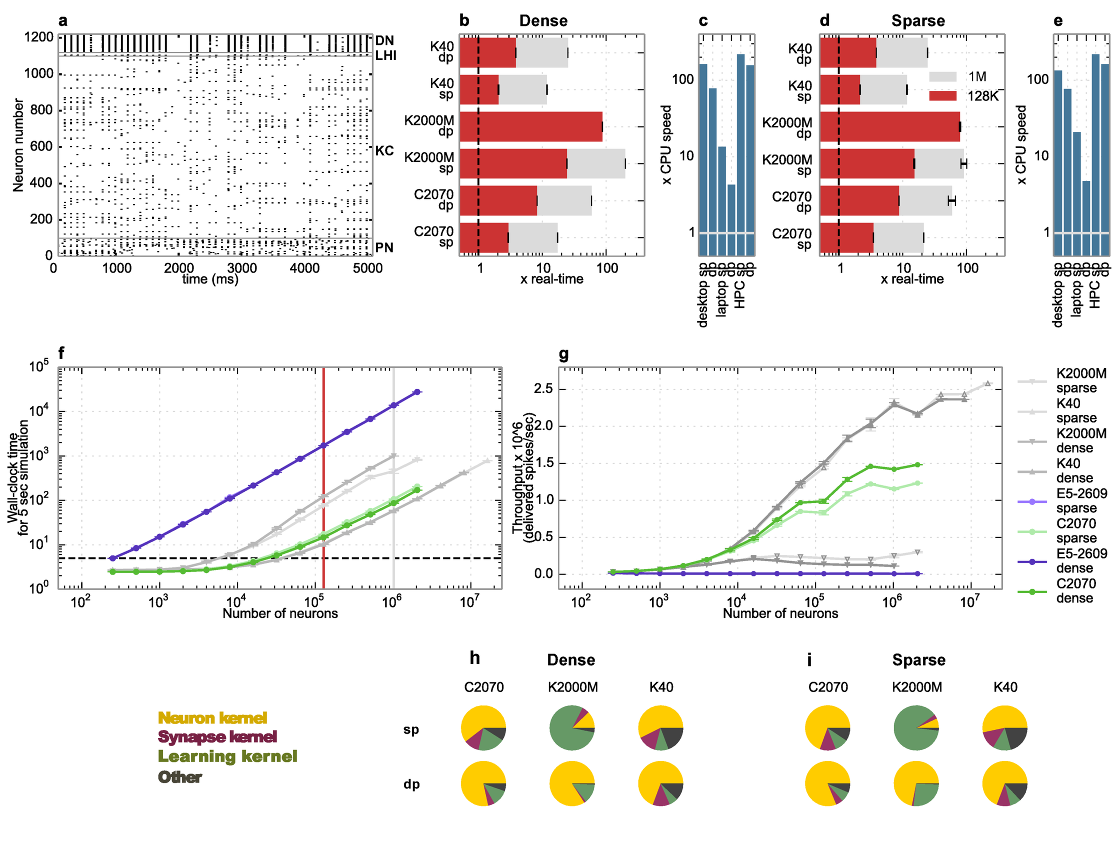
E(gPN-DN) = 1.95

4: Future direction: Mushroom body model on the GPU

In a parallel study, we implemented a model of mushroom body by Nowotny et al. 2005 on the GPU using the GeNN framework and tested different factors that play a role in GPU simulations of realistic biological spiking neuron network models (Yavuz et al., submitted). We will next combine both models to have a full model of honeybee olfactory system and its learning related pathways.



Model of mushroom body (Nowotny et al. 2005)



Yavuz et al., *submitted*

References

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Acknowledgements

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