Emergent E/I tuning and balance during surrogate gradient learning

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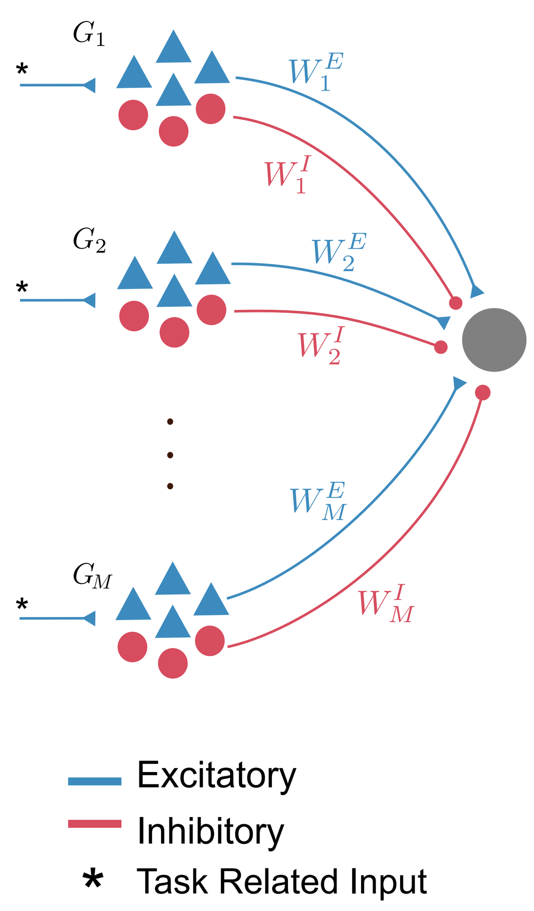
Take-home Messages

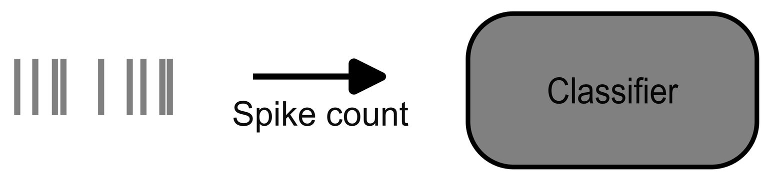
- Training spiking neural networks on simple discrimination tasks shapes the neural tuning curve of the upstream neuron.
- A simple selectivity task leads to E/I anti-tuning, and also to E/I balance if a constraint is put on the post-synaptic firing rate.
- A novelty selectivity task is much harder to train, but leads to E/I co-tuning.

Model Structure

The **feedforward** network consisted of 5 input neuron groups, each including 100 excitatory and 25 inhibitory neurons. These pre-synaptic neurons project onto a single current-based post-synaptic neuron. Excitatory inputs have faster time-scale than the inhibitory inputs.



$$L = \sum_{i=1}^{M} y_i \log(\tilde{y}_i) + \alpha \sum_{i=1}^{M} \Big[\sum_j \delta(t - t^j_{post})\Big]^2$$



$$C \cdot \frac{dv(t)}{dt} = -g_l.(v(t) - E_L) + I_E(t) - I_I(t)$$

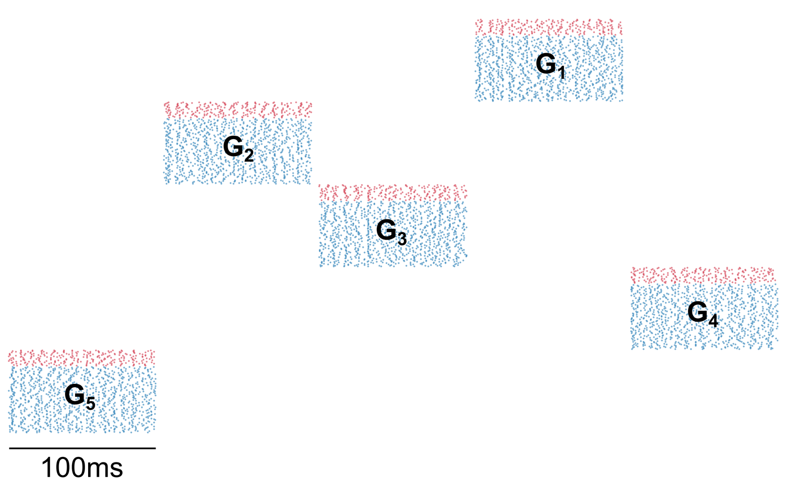
$$\frac{dI_E(t)}{dt} = \frac{-I_E(t)}{\tau_E} + \sum_n W^E_n \cdot \sum_j \delta(t - t^j_n)$$

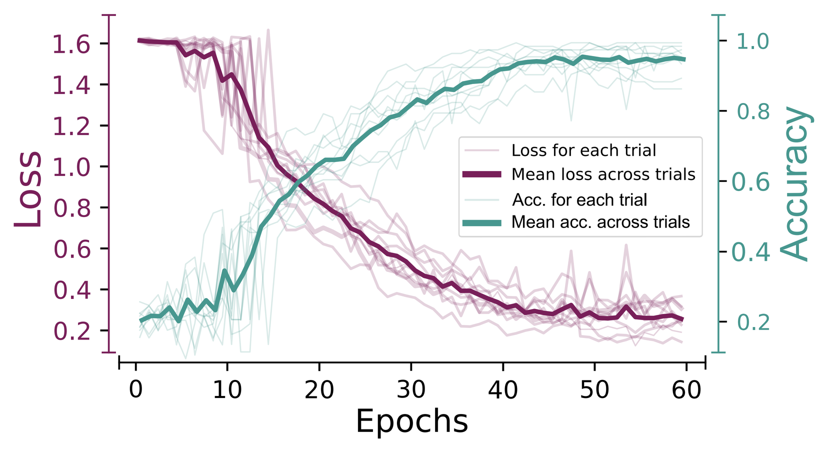
$$\frac{dI_I(t)}{dt} = \frac{-I_I(t)}{\tau_I} + \sum_n W^I_n \cdot \sum_j \delta(t - t^j_n)$$

An MLP classifier is given the spike counts of the post-synaptic neuron for different stimuli and is trained to identify the corresponding input group. The loss function is a sum of cross entropy and MSE, accounting for the classification loss and firing rate of the post-synaptic neuron. Feedforward connections are trained using via surrogate gradient learning [1].

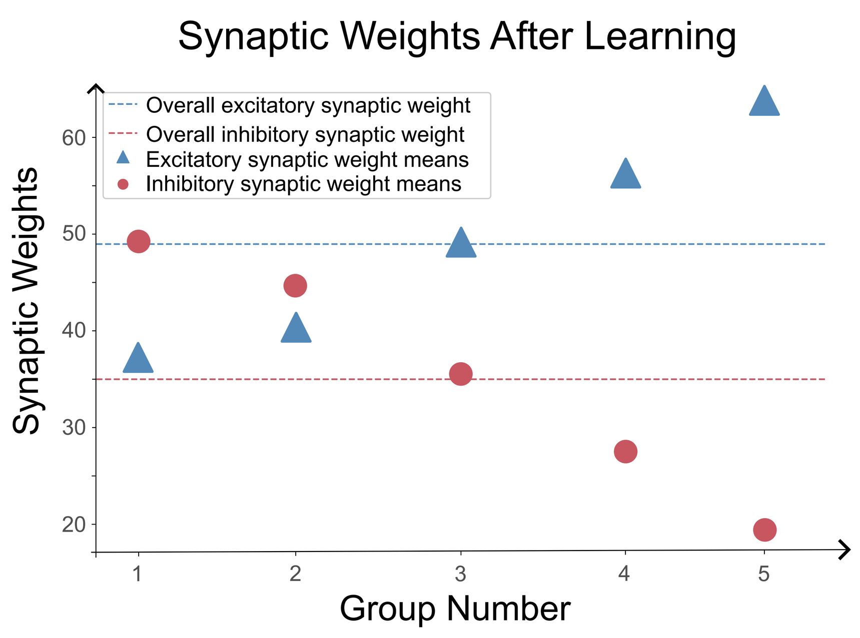
Simple Selectivity Task

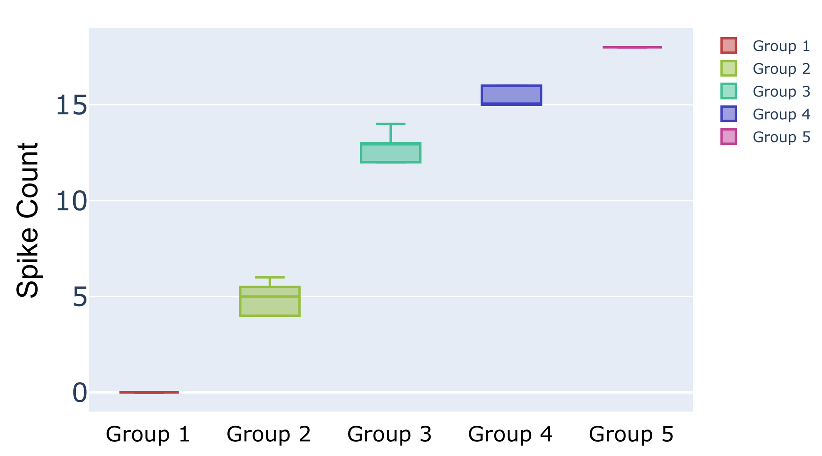
In this task only one of the input groups are active during any stimuli time-window, which is set at 100ms. The activity of the pre-synaptic neurons, and the accuracy-loss during the learning phase are shown below.





The classifier has to learn which one of the input groups was active during the corresponding time-window of the stimuli. It easily achieves that by adjusting the feedforward weights such that each input group causes different spike counts during their time-window. The networks prefers anti-tuning. This type of connectivity has been investigated in theoretical studies [2] and can emerge via synaptic plasticity mechanisms. Spike counts caused by input groups are distinct as shown below, and therefore the readout classifier is able to distinguish the different groups.

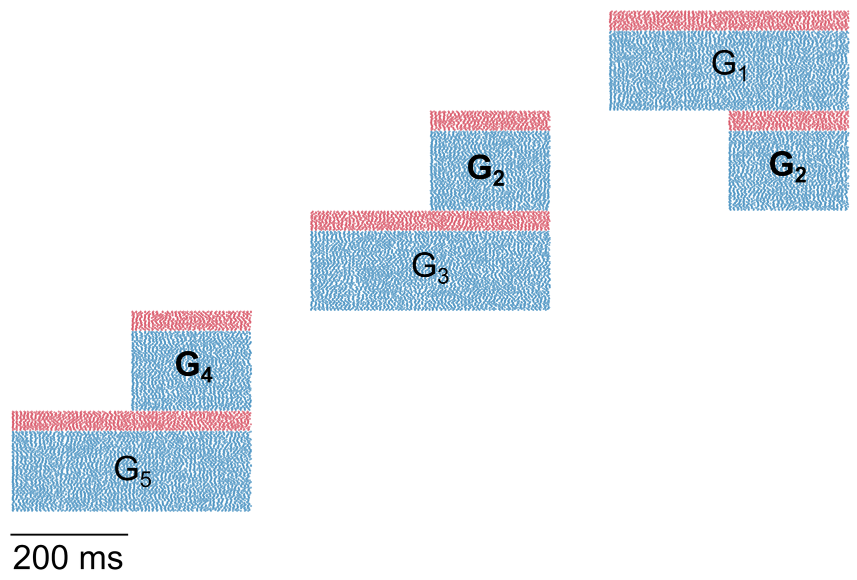


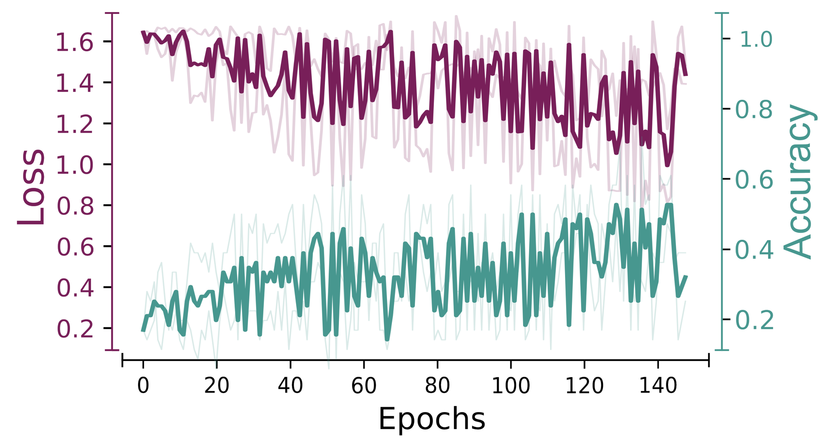


Increasing the constraint on the post-synaptic firing rate forces E/I balance, which is consistent with previous claims about efficient coding [3], but is detrimental to task accuracy if increased too much.

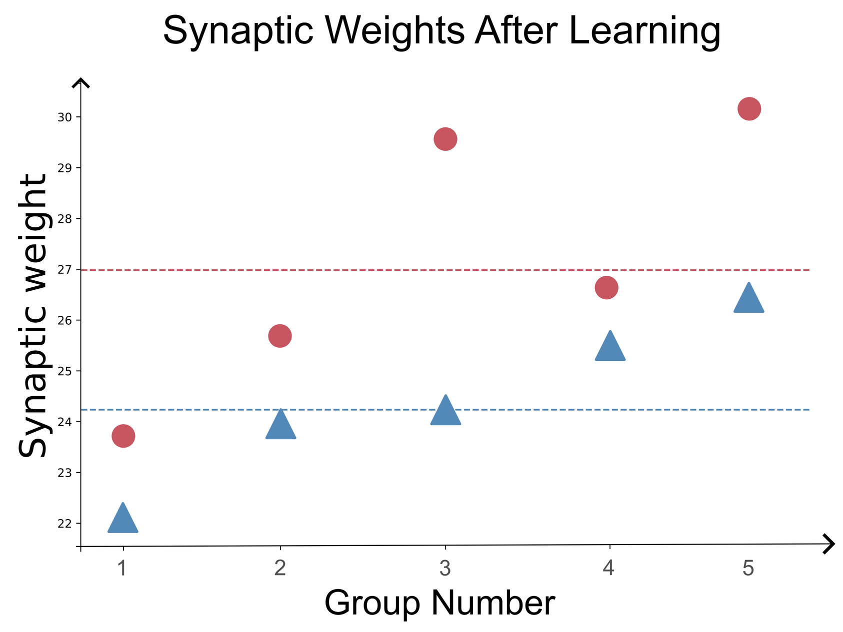
Novelty Selectivity Task

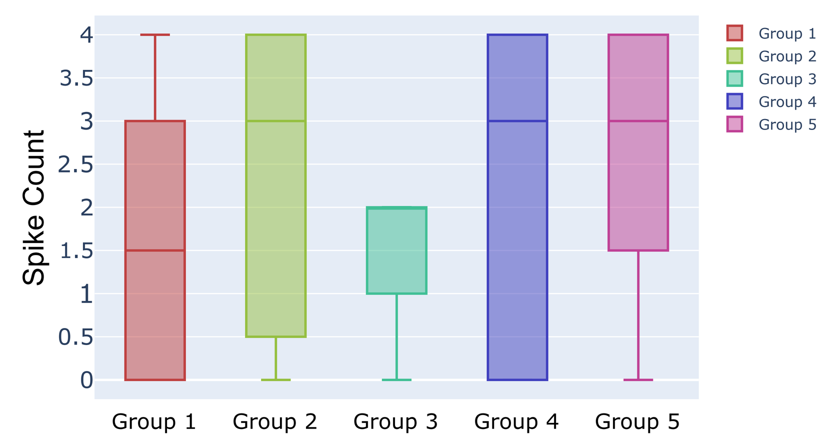
In this task, a novel input group becomes active at the middle of the previous input, shown on the figure with bold text. Novel input stays active for 200ms. Readout is only fed the post-synaptic spike counts during the novel stimuli.





In this case the post-synaptic neuron has to identify the input groups that was active during the corresponding time-window of the novel stimuli. This can only be done if the excitatory and inhibitory inputs cancel each other after some time, before the novel input arrives. E/I co-tuning is necessary to solve this problem [4].





In our experiments we did not observe consistent co-tuning and high accuracy, although we were able to find a parameter space that leads %100 accuracy with detailed balance setting, with each input group causing distinct spike counts. Here we show one of the examples of resulting co-tuning, which leads to relatively noisy post-synaptic responses.

Observations

- Training for distinguishing novel inputs in the continuous presence of other inputs is significantly harder than for individual inputs and leads to different connectivity patterns.
- Unlike the simple selectivity task which can be solved for a large range of initial conditions, the harder novelty selectivity task requires initializations within a narrower, biologically plausible range.
- While training for the simple selectivity task does not lead to E/I balance without a constraint on the firing rate, in the novelty task balance emerges organically, without additional constraints..

Future Work

- Improving accuracy on the novelty selectivity task and examining the implications of having multiple input groups given at any time. Also, the addition of noise on the post-synaptic neuron might change some of our results.
- We aim to investigate whether different plasticity rules that are known to produce E/I co-tuning and anti-tuning can result in near-optimal connectivities and identify the plasticity parameters that improve performance in such tasks.
- Finally, we plan to investigate how inputs from recurrent networks with different topologies can be distinguinshed by a post-synaptic neuron via different feedforward connectivity patterns.

References

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