Xu et al #1115

Homeostatic Plasticity enhances robustness in spiking neural networks

* How does homeostatic synaptic plasticity impact the robustness of an SNN?
* This increases network robustness
* Improves accuracy of network
* Homeostatic plasticity has been ignored in ANNs, but is vital in biological neural networks to stabilize the network activity
* The authors argue that previous works have incorporated homeostatic plasticity in a biologocillaye implausible way

Method

* The connectivity in each synapse is upscaled or downscaled based on the firing rate of the neron

Results

* The model outperforms state of the art SNNs
* The weights and biases are more sparse – the majority of the weights seem to be 0

Comment clarity

* I am unsure about the final paragraph in the results section, I think the authors here modulate the strength of up- and downscaling, but I am not sure
* the authors mention an enhancement and a depression zone, these terms were not explicitly used before. I suspect they relate to the glutamatergic transmission changes and drop in somatic calcium, but it would help the reader if this could be clarified
* They also mention a parameter phi that was not introduced before
* I think the take-away is that in order for the adaptation to be effective, one needs both up- and downscaling..

Rating: great paper 8/10

Benefits of synchrony: Improving deep neural networks using complex values and Kuramoto synchronization

Muzellec

* Synchrony between complex-valued neurons in DNN
* The degree of synchrony/desynchrony between neurons was
* The model outperforms a CNN when presented with 2 inputs
* The ideas are based on the binding by synchrony model proposed by Singer et al
* Built a hierarchical model containing layers of complex operations (Deep Boltzmann Machines and Lowe for autoencoders)
* The authors add an intermediate layer to a CNN that synchronizes the phases within the Kuramoto model
* They use a multi\_MNIST data set
* The authors constrain the network to synchronize their activity based on their orientation selectivity

Zheng et al: Binding via combining spike synchrony and generative top-down attention

* SNN combines with ANN combined with denoising autoencoder to implement attention
* Spiking neurons as a model of v1 layer II
* And DAE is analogous to top-down control
* The starting point seems to be how temporal binding and feature integration can be integrated
* It is very exciting that the model seems to bind the single object, and reads them out phasically

Unclear

* In the abstract, it sounds a bit like an ANN is combined with an SNN (a combination of two models) that then receive input from a DAE, but in fact it is “just” an SNN with DAE
  + An SNN is also an ANN, I believe..
* What exactly does Fig1b show?
* The results in relation to Fig 3 could be a bit clearer. I think the colours represent responses to the same object?
* What is the unit of the time axis in a and d? Is it ms/iterations? If there are four peaks in 10 ms, then the resulting frequency would be 400Hz, which strictly speaking is not a gamma oscillations. I still think it is interesting that the authors find oscillations at all

Xu et al.: Enhancing Neural Network Expressivity and Learning Efficiency through the Integration of Dendrite Functionality in Spiking Networks: A study on pyramidal neurons

* Dendrite functionality integrated in spiking networks
* Model possesses better global property for convergence and superior representation capability: what does this mean?

Introduction

* Authors claim that ANNs fall short w.r.t. computational capabilities compared to biological neural networks – I am assuming this means “brains”? They argue that the main reason for that is that dendrites perform computations
  + There are no references to back this claim

Unclear

* The paper seems a bit rushed, equations are not numbered correctly, and the components of the first equation are not described in the text, it’s hard to follow
* It seems that the authors show that their model learns faster than other SNNs, is this due to them technically integrating another few units that can represent the data (the dendrites)?
* I don’t understand how the model can have the largest and smallest HE value at the same time, and the loss landscape is sharp and flat at the same time

Weidler et al: Synergizing Anatomy and Function: A Goal-driven Model of Frontoparietal Dexterous Object Manipulation

* Implementation of a fronto-parietal-inspired network -> macro-level structure
* A goal-driven model of the fronto-parietal and pericentral network that can manipulate objects
* More biological constraints than other DNNs
* The authors develop a large model consisting of smaller models mimicking several brain regions involved in motor control
* The model receives several inputs (goal, proprioception, touch, vision etc)
* It outperforms state-of-the-art models, learns faster
* Activations can decode neural activity in M1 and PMC

Hashim: Predictive Coding meets deep learning: learning by predicting representations

* Predictive coding DNN that predicts the activity of representation units
* In previous predictive coding models the layers do not predict the activity of their preceding layer, but of the error units, which is not in line with the predictive coding idea
* In this model, the upper layers predict the activity of the representations in the lower layers

Khosla: Privileged representational axes in biological and artificial neural networks

* Neurons seem to favour certain features in the environment
* Axes of neural representations are aligned across humans and macaques
* DCNNs also have privileged axes
* These asxes result in higher lifetime sparseness and lower wiring costs compared to an arbitrary basis (?????)