Input normalization and synaptic scaling – two sides of the same coin

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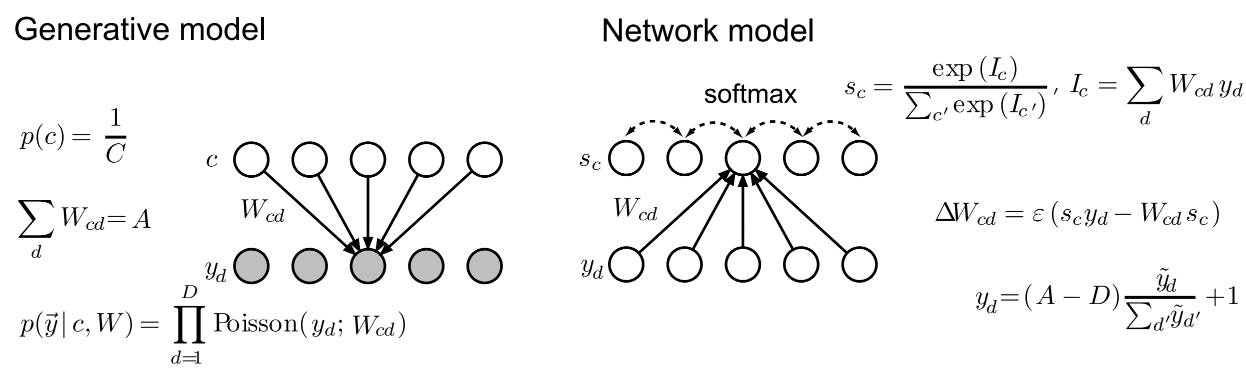
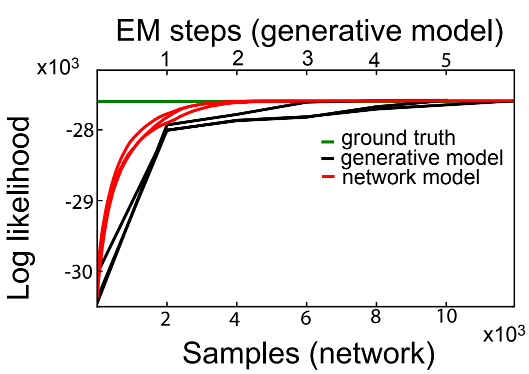
To maintain sensitivity to a range of stimulus intensities, neurons adapt their input gain through multiple mechanisms. On the one hand, global feedforward inhibition normalizes the input to neurons on a fast timescale (Poille et al 2009). On the other, homeostatic mechanisms such as synaptic scaling regulate the strength of synapses to maintain a certain total incoming drive (Turrigiano & Nelson 2004). Although often studied in isolation, these mechanisms have been observed to co-occur in various cells (e.g., CA1 pyramidal neurons), suggesting there may be some computational advantage in combining input normalization and synaptic scaling. What this advantage could be, however, remains unclear.

Using a probabilistic approach, we show here that input normalization and synaptic scaling interact synergistically during unsupervised learning. We consider a neural network with soft winner-take-all dynamics receiving normalized inputs from an input layer. To study learning in such a network we model the input using a generative model with Poisson noise, treating the normalization as an explicit input constraint. We demonstrate analytically and numerically that the optimal maximum likelihood solutions for the generative model can be recovered by simple Hebbian plasticity and synaptic scaling in the network. Notably, we find that synaptic scaling mirrors the normalization of neural input patterns, autonomously adjusting the norm of the weights to that of the input.

Our results suggest a close connection between input normalization and synaptic scaling, which could be relevant for cortical processing. We show that, beyond its conventional use as a mechanism to remove undesired pattern variations (e.g., stimulus intensities), input normalization makes standard neural processing and learning optimal on the constraint stimulus space. Moreover, as learning tends to be easier in this space, it is tempting to consider the interplay between normalization and synaptic scaling as a general strategy to facilitate learning in neural circuits.





Methods. To compare the network and the generative model, we derived parameter update rules for the generative model using constraint optimization based on EM. We have shown that the maximum likelihood solutions are equivalent to the steady-state solutions of neural learning dynamics, in the limit of infinitely many data points. The softmax activation is typical for mixture models, while the standard forms for postsynaptic input I_c and synaptic plasticity ΔW_{cd} are a consequence of the input constraint. We confirmed our analytical results using numerical simulations for artificial (generated) data and for real data (MNIST digits).