In neural network models:
- input normalization commonly used e.g. for contrast invariance
- weight normalization needed to stabilize Hebbian learning

In neural circuits:
- input normalization implemented through feedforward inhibition [1]
- weight normalization by homeostatic synaptic scaling [2]

Questions:
- could they be more closely related than the separate investigations suggest?
- what functional purpose may this relation have?

In neural network models:
- scaling could generally facilitate learning in neural circuits
- simplified learning on constraint space → input normalization and synaptic scaling mirrors the normalization of input patterns

Neural network model:
- 2-layer neural network
- \[ s_c = \frac{\exp(L_c)}{\sum_{c'} \exp(L_{c'})}, \quad I_c = \sum_d W_{cd} y_d \text{ softmax} \]
- \[ \Delta W_{cd} = \epsilon (s_c y_d - s_c W_{cd}) \text{ learning rule} \]
- \[ y_d = (A - D) \frac{y_d}{\sum_c y_c} + 1 \text{ input normalization} \]

Network properties:
- functionality: clustering
- lateral competition (softmax)

Mixture model with Poisson noise:
- E-step: \[ p(c | y^{(n)}, W) = \frac{\exp(I_c)}{\sum_{c'} \exp(I_{c'})} \quad \text{where} \quad I_c = \sum_{d} y_c \ln(W_{cd}) \]
- M-step: \[ W_{cd} = A \sum_{n} \sum_{d} p(c | y^{(n)}, W^{(cd)}) y_d^{(n)} \]

Classification details:
- Interpreted as a graphical model:
  \[ B_{ck} = \frac{1}{M} \sum_{m=1}^{M} p(c | \tilde{y}^{(m)}, \Theta) \quad \text{where} \quad \tilde{y}^{(m)} \text{ is sampled from} \quad \tilde{y}^{(m)} = \frac{\sum_{c} B_{ck} p(k | c, \tilde{y}^{(m)}, \Theta)}{\sum_{c'} \sum_{k'} B_{c'k'} p(k | c', \Theta)} \]
- Data point \( k \) is generated by cause \( c \)
- cause \( c \) is generated by label \( j \)

Artificial data:
- Examples of generated artificial data with strong Poisson noise (for small A)

MNIST digits:
- Examples of handwritten digits from MNIST database

Results of numerical simulations:
- Data
- Neural network: learned weights
- Mixture model: learned generative fields
- Likelihood comparison
- Causes

Discussion:
- neural network with homeostatic synaptic scaling and feedforward inhibition learns optimal parameters in mixture model
- synaptic scaling mirrors the normalization of input patterns (the weights „follow“ the input)
- simplified learning on constraint space → input normalization and synaptic scaling could generally facilitate learning in neural circuits

References:
[1] Pouille at al., Input normalization by global feedforward inhibition expands cortical dynamic range, Nat. Neurosci. 12, 2009