Correlations strike back (again): the case of autoassociative memory recall
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This work was supported by the Wellcome Trust (CS, ML) and the Gatsby Charitable Foundation (PD).

**THE CASE OF AUTOASSOCIATIVE MEMORY RECALL**

- binary patterns
- recall cue = noisy version of original pattern
- recurrent network of excitatory neurons
- all-to-all connectivity (can be relaxed)

Optimal recall: inferring the distribution over the patterns to be retrieved, given information in the weights and recall cue (Sommer Dayan 1998; Lengyel et al 2005)

\[
P(\mathbf{x}|\mathbf{W}, \tilde{x}) \propto P(\mathbf{W}|\mathbf{x}) \cdot P(\tilde{x}|\mathbf{x}) \cdot P(\mathbf{x})
\]

Fundamentally a decoding problem:
- synaptic plasticity = encoding process
- recall dynamics = corresponding decoding algorithm

The neural dynamics at recall realize samples from the posterior distribution over possible patterns (Savin et al, 2011).

**Q1:** Where do synaptic correlations come from?

- easy to construct optimal decoder when
  - considering correlations
  - stimulus identity from the activity of a neuron population

\[
W_{ij} = \sum_{l} R(x_i, x_j)^{1/2} \Omega (x_i, x_j) = (x_i - \mu)(x_j - \beta)
\]

Assuming enough stored patterns, evidence from the weights is multivariate normal:

\[
P(\mathbf{W}|\mathbf{x}, t) = \frac{1}{(2\pi)^{N/2}|\Sigma|^{1/2}} \exp \left( -\frac{1}{2} (\mathbf{W} - \mu(\mathbf{x}, t))^T \Sigma^{-1} (\mathbf{W} - \mu(\mathbf{x}, t)) \right)
\]

**Q2:** How to recall in the face of synaptic correlations?

**A. ADDITIVE LEARNING RULES**

**B. BOUNDED SYNAPSES**

**EXPERIMENT**

- cascade model (Fusi, 2005)

- Post. gated
- Presyn. gated
- Control

**MODEL**

- Predicts nonlinear dendritic integration:

**CONCLUSIONS**

Synaptic correlations are a natural consequence of local learning.

Correlations in synaptic efficacies matter for retrieval, for a range of biologically relevant plasticity rules.

The model predicts a tight coupling between storage (synaptic correlation patterns) and retrieval (circuit dynamics)

**SYN. PLASTICITY RULE**

- additive
- cascade

**EXACT DYNAMICS**

- storage
- retrieval
- cascade
- presyn. gated
- postsyn. gated

**NEURAL IMPLEMENTATION**

- linear feedback inh.
- nonlinear feedback inh.
- nonlinear feedback inh.
- simple Hebbian
- strictly local
- nonlocal
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- linear dendritic inte.
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