

Exact sequence recall in a model of CA3

Nicola van Rijsbergen

David Willshaw

Institute for Adaptive and Neural Computation

University of Edinburgh

njvr@anc.ed.ac.uk

February 8, 2002

Abstract

Sequence learning has been proposed as CA3's contribution to hippocampal memory. We describe a one trial sequence learning recurrent heteroassociative network with modifications, closely related to the architecture proposed by Levy (1996), but that recalls correlated sequences more accurately, but remains a plausible model of CA3.

Sequence learning in the hippocampus

Levy (1996) proposes that the hippocampus can learn to recall sequences of events, especially those that have overlapping or correlated parts. In this paper we address the problem of how best to learn such sequences. We propose that a sequence recall strategy (recalling a long sequence from an initial pattern) is particularly useful for events that have been learned over a single trial, where the object of recall is merely to recall the order in which events occurred, and not any higher order relationship about the frequencies of their occurrence. Levy's model uses an asymmetric postsynaptic learning rule, which sets the weights according to $\delta W_{ij} = Post * (Pre - W_{ij})$. This rule should be useful for classification of input. However evidence (discussed below) from comparable models suggests it may not be the best rule for simple sequence recall.

The heteroassociative network is the simplest plausible model of hippocampal CA3 and is directly comparable to Levy's original model. The condition for successful sequence learning to occur in a recurrent heteroassociative architecture is just that recurrent feedback is silent during learning (Willshaw, 1971). The best nonlinear rule rules for storing binary pattern under sparse, orthogonal conditions is considered to be the clipped [1,0] Hebb-type rule (Dayan and Willshaw, 1991). Minai (1997) shows

Postsynaptic rule		
% Connectivity	performance	recall limit
100	.9 \pm .1	560 \pm 40
50	.8 \pm .24	132 \pm 23
Presynaptic rule		
% connectivity	performance	recall limit
100	.9 \pm .1	507 \pm 50
50	.7 \pm .15	68 \pm 13

Figure 1: Tables comparing fully connected and partially connected models trained on sequences with $N = 10$ with approximate competitive inhibition as described in Levy (1996)

that amongst the real valued rules a presynaptic covariance rule produces the best performance in a feedforward architecture, on correlated data, but his study did not train weights incrementally. The post synaptic rule used by Levy is comparable to the presynaptic rule (see below) but the two have not been compared in a sequence learning task.

We also consider the problem of how to set a threshold for recall. Graham and Willshaw (1995) show that for noise free data, a normalised *N-winner-takes-all*, is close to optimal for feedforward architectures. We therefore use this method to compare the learning rules.

Experiments

Firstly, we ran a preliminary experiment on five 1000×1000 models constructed as according to Amarasingham and Levy (1997) with 50% and 100% connectivity. We compared the number of patterns that could be recalled in sequence of uncorrelated binary patterns with $N = 10$, if they were stored with the presynaptic rule:

$$\delta W_{ij} = Pre * (Post - W_{ij}),$$

and the postsynaptic rule, using the inhibition scheme in Levy's original architecture. Performance was measured by average cosine between the desired patterns and the sequence of recalled patterns. Recall limit is defined as the average number of patterns that could be stored before the sequence failed.

We then constructed five 1000 by 1000 fully connected recurrent heteroassociative networks, and stored patterns compared the presynaptic rule with a Linear Hebb rule :

$$\delta W_{ij} = Pre * Post,$$

and the clipped rule :

$$W_{ij} = 1, \text{ if } Pre_i = 1 \text{ and } Post_j = 1, \text{ and zero otherwise,}$$

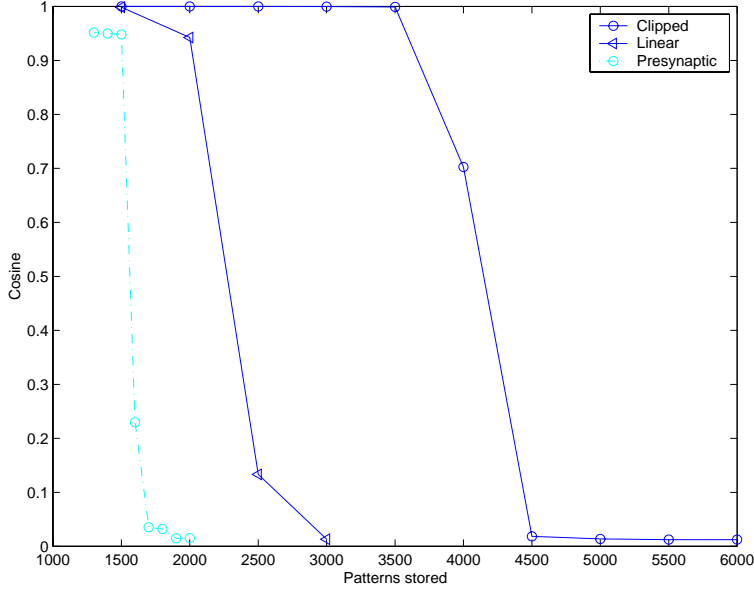


Figure 2: Averaged performance comparison of clipped, unclipped and presynaptic rules with N-WTA thresholding, using a sequence recall strategy. $N = 10$

in a fully connected situation using a *N-Winner-takes-all* threshold with $N = \text{ten}$ neurons, close to the optimal for the clipped rule. As expected the clipped rule performed much better than either the linear rule or the postsynaptic rule.

The third experiment used %50 connectivity and stored patterns using the size $N = 30$, with degree of overlap between succeeding patterns $21/30$.

We then repeated the procedure for the presynaptic rule and the presynaptic covariance rule. The presynaptic covariance rule was implemented using dual weights, one trained by the presynaptic rule, and an inhibitory weight trained as proposed by Willshaw *et al.* (1996) using the θ_{max} rule

$$\delta\theta_j = \alpha(\text{Pre} * \theta_{max} - \theta).$$

Theta is a subtractive threshold proportional to output activity.

Under the conditions of correlated patterns, the presynaptic-covariance rule performed almost as well as the clipped rule. Normalisation of the dendritic sum by unit activity following Graham and Willshaw (1995) produced almost equivalent performance. Results are included in Figure 3.

Conclusions

The conclusions we draw from these simulations are twofold. Firstly the inhibition scheme that produces the best performance from the presynaptic rule differs from the approximate thresholding employed in Levy (1996); Smith and Levy (2000). This

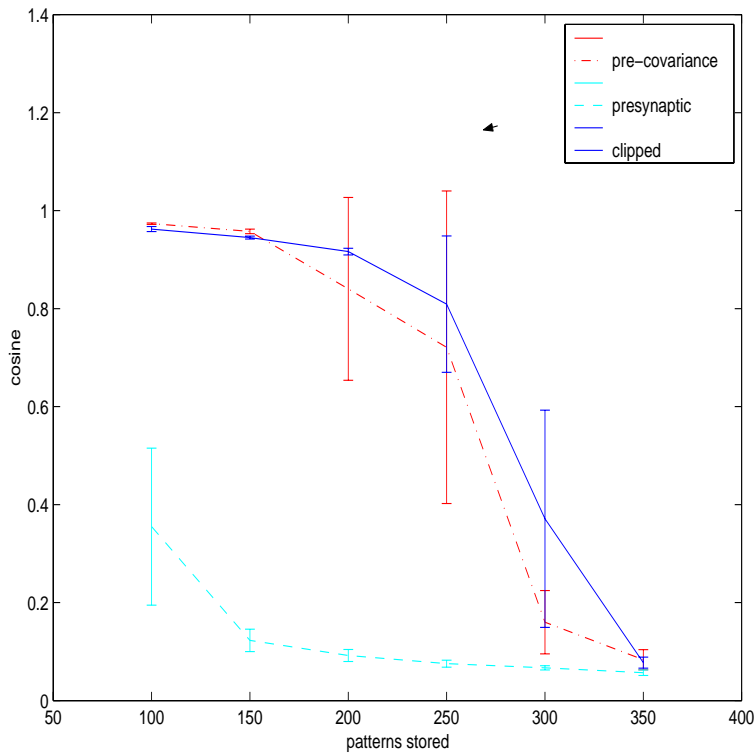


Figure 3: Average performance on correlated sequences, comparing the clipped, the presynaptic and the presynaptic covariance rules.

suggests that adapting their model correspondingly would substantially improve performance. Secondly, these results support the argument that if the aim is accurate sequence recall, variations in Epsp size of the kind utilised in the pre- and postsynaptic type rules make the problem harder than necessary. There is evidence that there may be different potentiation responses at an individual synapse with multiple active sites (Debanne *et al.*, 1999), some of which may be all or nothing (Petersen *et al.*, 1998). We therefore suggest that a one trial learning system such as the one we describe may exist along side a slower system.

References

- Amarasingham, A. and Levy, W. B. (1997). Predicting the distribution of synaptic strengths and cell firing correlations in a self organising, sequence prediction model. *Neural Computation*, **10**, 25–57.
- Dayan, P. and Willshaw, D. (1991). Optimising synaptic learning rules in linear associative memories. *Biological Cybernetics*, **65**, 253–265.
- Debanne, D., Gahawiler, B., and Thompson, S. (1999). Heterogeneity of synaptic

- plasticity at unitary CA3-CA1 and CA3-CA3 connections in rat hippocampal slice cultures. *Journal of Neuroscience*, **19**(24), 10664–10671.
- Graham, B. and Willshaw, D. (1995). Improving recall from an associative memory. *Biological Cybernetics*, **72**, 337–346.
- Levy, W. B. (1996). A sequence predicting CA3 is a flexible associator. *Hippocampus*, **6**, 579–590.
- Minai, A. (1997). Covariance learning of correlated data in neural networks. *Neural Computation*, **9**(3), 667–681.
- Petersen, C. C. H., Malenka, R. C., Nicoll, R. A., *et al.* (1998). All or nothing potentiation at CA3-CA1 synapses. *Proceedings of the National Accademy of Sciences USA*, **95**(8), 4732–4737.
- Smith, A. C. and Levy, W. B. (2000). Controlling activity fluctuations in a large, sparsely connected random network. *Network: Computation in Neural Systems*, **11**, 63–81.
- Willshaw, D. (1971). *Models of associative memory*. Ph.D. thesis, University of Edinburgh.
- Willshaw, D., Hallam, J., Gingell, S., and Lau, S. (1996). Marr’s theory of the neocortex. *Neural Computation*, **9**(4), 911–936.