Sequence memory with dynamical synapses
(This is a 1000 word summary)

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Abstract

A cortical attractor memory model capable of sequential recall is presented. The network is trained using a Hebbian learning rule that operates by redistribution of synaptic efficacy. The model performs free recall or sequential recall depending on parameters. Performance is compared to psychological data. Memory capacity scaling with network size is tested.

1 Introduction

Attractor neural networks as models for cortical memory range from purely abstract models, such as the Hopfield network, to models incorporating considerable biological detail [3, 5]. Several reports show that key characteristics are not dependent on level of detail, indicating that it is meaningful to study simplified models [2, 7].

In its simplest form such a memory stores static patterns, as fixpoint attractors. Without additional mechanisms, it will remain forever in the first recall state that it reaches. A more complete model of cortical memory should incorporate a mechanism to get out attractors, allowing the system to switch between memories in some random order (free recall) or in a learned order (sequential recall).

In the context of symbolic processing, ability to perform such temporal tasks should be built on top of an autoassociative memory. This means that the brain retains the ability to represent each of the memory states individually. Some models that do not have this ability are the heteroassociative Hopfield network and any pure feedforward network. The simple model presented here satisfies this constraint and is shown to reproduce free recall data from experimental psychology.

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2 Model

Our model is an n-winner-take-all network with synchronous updating; each time step the n units with greatest support value are selected as active. Units are a leaky integrators. Synapses are dynamical, depleting part of their resources each time they transmit a signal. Noise is Gaussian, independent between units and high frequency. The network equations read:

$$\begin{aligned}
h_i(t+1) &= (1-\mu_{mem})h_i(t) + \sum_j u_{ij} r_{ij}(t) s_j(t) \\
s_i(t) &= \begin{cases} 1 & \text{if } i \in \text{n-argmax}_j\left(h_j(t)+n_j(t)\right) \\ 0 & \text{otherwise} \end{cases} \\
n_i(t) &\in N(0,\sigma) \\
r_{ij}(t+1) &= \left(1-u_{ij}s_j(t)\right) r_{ij}(t) + \mu_{rec}(1-r_{ij}(t))
\end{aligned}$$

Here h_i is the support of the i:th unit; μ_{mem} corresponds to membrane integration time. s_i indicates whether a unit is active, n_i is noise. The synapse connecting the j:th unit to the i:th expends a fraction u_{ij} of its resources each time it is activated. The remaining synaptic resources r_{ij} recover at a rate μ_{rec} [10]. During training, the following equations are used:

$$\begin{aligned}
x_j(t+1) &= (1-\mu_{pre})x_j(t) + s_j(t) \\
y_i(t+1) &= (1-\mu_{post})y_i(t) + s_i(t) \\
c_{ij}(t+1) &= (1-\mu_{learn})c_{ij}(t) + y_i x_j \\
u_{ij}(t) &= \frac{c_{ij}(t)}{1+c_{ij}(t)}
\end{aligned}$$

x_j and y_i are pre- and postsynaptic activity traces, decaying as determined by μ_{pre} and μ_{post}. Coincidences are integrated by c_{ij}; optionally with a forgetting rate μ_{learn}. From this, $u_{ij} \in [0,1]$ is calculated, as defined above this is the fraction of available resources expended during one transmission event. Overall synaptic efficacy is not modified by training; it is just redistributed.

3 Results

3.1 Network behavior

The trained network is principally autoassociative, with a heteroassociative component due to temporal integration in synapses. Started from a random state, it quickly converges to one of the learned patterns. After some time the pattern destabilizes due to synaptic depression and another pattern becomes active (figure 1). Transitions are sharp, as have been found in cortical recordings from animals performing sequence tasks [9]. Heteroassociation will compete with noise in selecting the next pattern as shown schematically in figure 2.

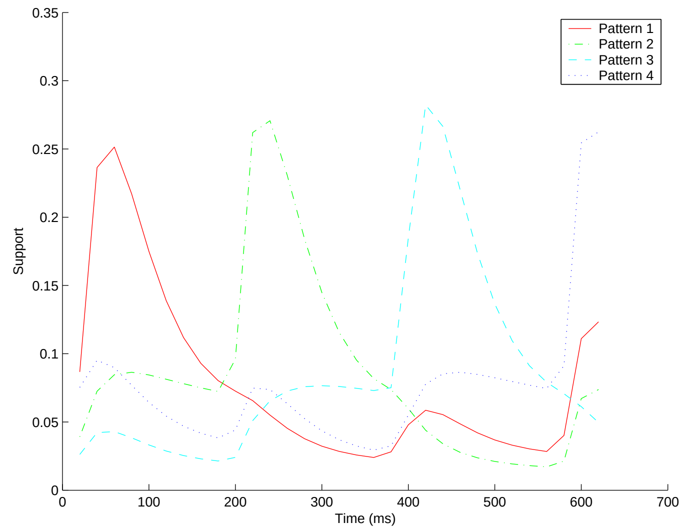

Figure 1: Pattern transitions. The support level of the active pattern declines due to synaptic depression, until it falls below the level of another pattern.

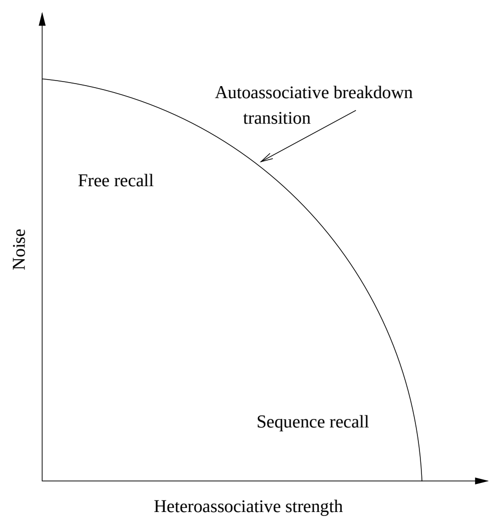

Figure 2: The relative strengths of noise and heteroassociation determine the randomness of pattern transitions. If their combined effects overwhelm the autoassociative signals that stabilize patterns, network performance breaks down.

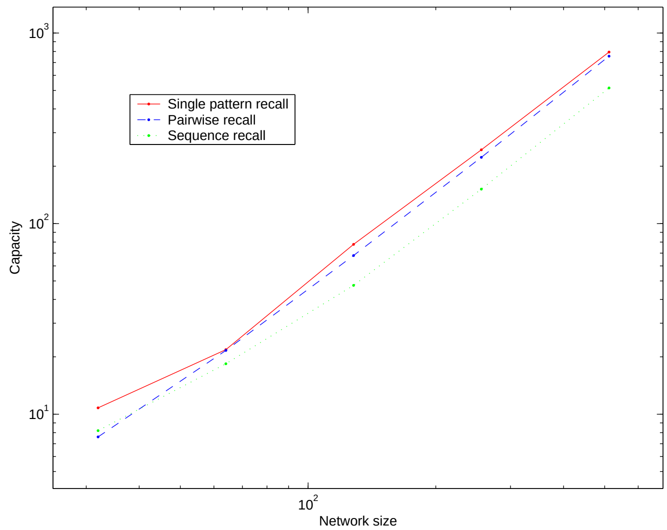

Figure 3: Memory capacities as defined in the text. Memory capacity was tested at high heteroassociative strength. Activity level was $n = \log_2 N$.

3.2 Memory capacity

The networks considered here are smaller than actual cortical networks. It is desirable for them to scale with regard to memory capacity. Three measures have been used. *Single pattern* capacity is the number of patterns that can be stored while at least half are reproduced during recall, *pairwise* capacity requires 50% of the pairwise associations to be intact, *sequence* capacity requires a continuous playback of half the sequence. All measures were found to scale with network size (figure 3).

3.3 Free recall

In a free recall task, a participant is asked to recall items from a previously presented list, in any order. One effect observed in such experiments is *lag-recency*; once an item has been recalled, a nearby item, as measured by list position, is likely to be recalled next. Another effect is repetition avoidance; an item that has been recalled is unlikely to be recalled again for some time [4].

The model reproduces both effects; the former by heteroassociation, the latter comes from synaptic depression. As can be seen in figure 4, however, the heteroassociation of the basic model raises recall probability only for immediate neighbors. To allow associations to span several presentation intervals, without breaking autoassociation, the forwards and backwards associations were separated out:

$$c_{ij}(t+1) = (1-\mu_l)c_{ij}(t) + \mathsf{f} \cdot s_i x_j + \mathsf{r} \cdot y_i s_j + (1 - \mathsf{f} - \mathsf{r}) s_i s_j$$

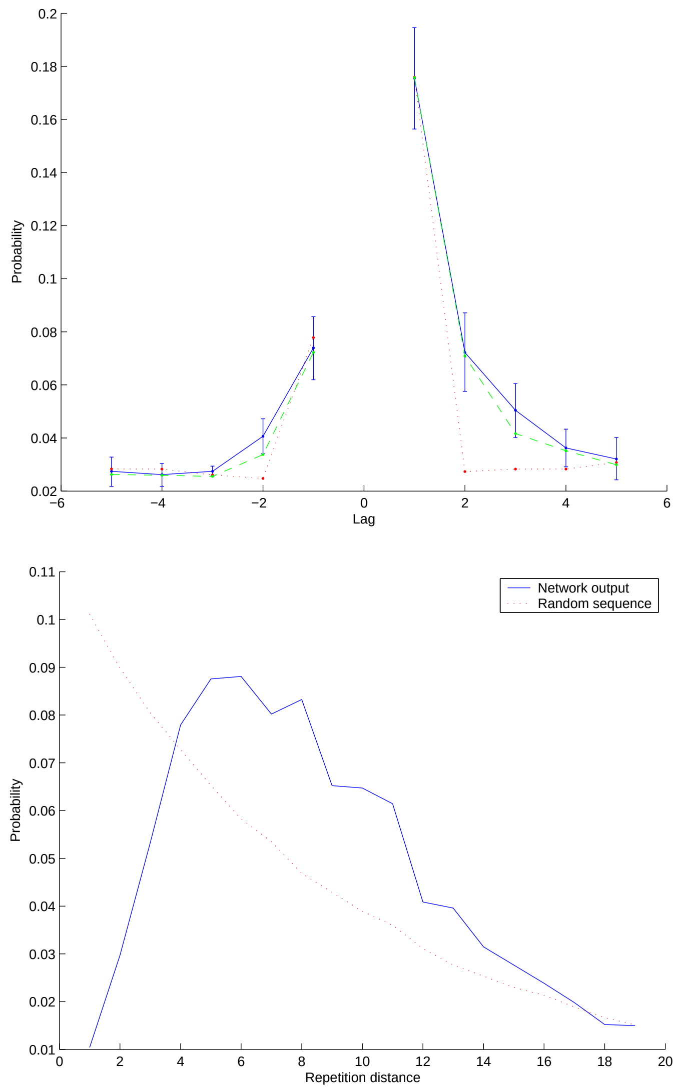

Figure 4: Free recall. *Top:* Lag-recency. Solid line is experimental data from [8]. Dotted line is response from the basic model. Dashed line is model response using separate hetero- and autoassociation. Synaptic plasticity parameters and noise level were manually tuned. Presentation interval is 1 second, list length is 30 items. *Bottom:* Repetition avoidance due to synaptic depression. Solid line is distribution of repetition intervals in model response, dotted line generated from a random sequence.

where f and r are constants determining the ratios of forward and backward chaining. This can be regarded as a phenomenological model for additional temporal integration mechanisms.

4 Discussion

The model presented here performs free and sequential recall. The core mechanisms are dynamical synapses and learning by redistribution of synaptic efficacy. Synaptic depression enables the system to move out of a pattern, something that would otherwise require a strong external signal.

The network reproduces experimental free recall data by simple means, though it is not intended to as a replacement for the more complex models used in this context [4]. Chaining of memories to accomplish sequence recall works well, though there are more stable models [6]. Through synaptic depression, the model also implements an approximate "fair scheduling" scheme. This is reminiscent of *competitive queuing*, a class of psychological models that have been put forward as an alternative to chaining mechanisms, though in this case the mechanism is too weak to produce accurate sequential recall [1].

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