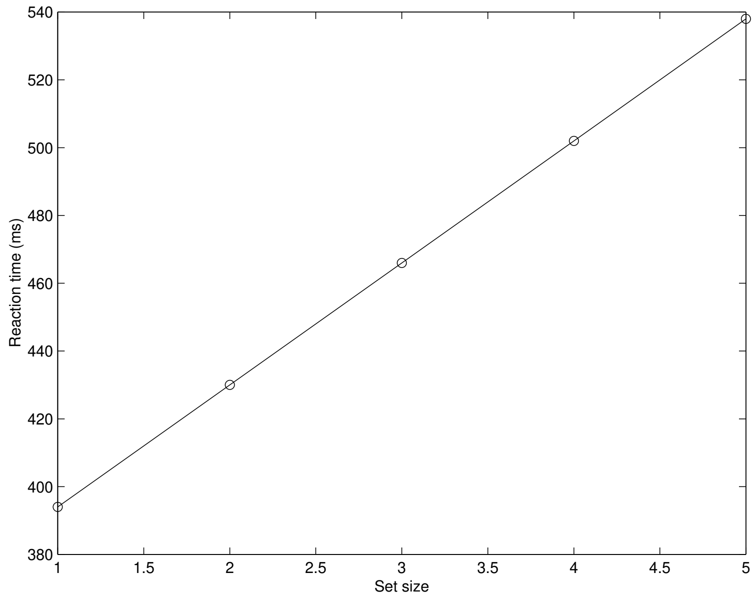
# Abstract

The linear increase of reaction time with memory set size in the Sternberg memory scanning paradigm has been taken to support serial scanning in working memory. We demonstrate a qualitative connectionist model using a Bayesian confidence propagation neural network with incremental learning exhibiting a similar behavior.

# 1 Introduction

- The Sternberg memory scanning task [1] consists of showing test subjects a set or list of items. After a brief delay a probe item that may or may not have been part of the original set is shown, and the subjects respond to whether it was part of the set or not.

- The main result is a linear increase in reaction time as a function of memory set size, with a slope that is the same both for positive and negative responses.



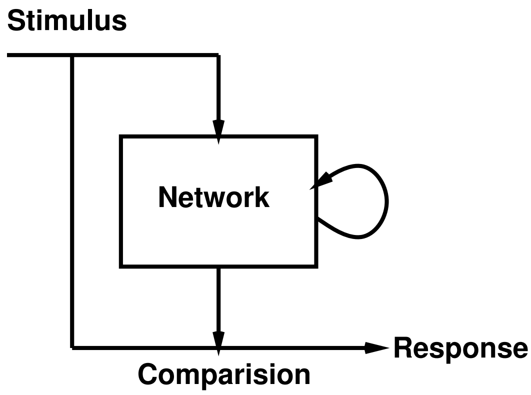

Simulated data for the Sternberg memory scanning task, based on the fit RT=36N+322 msec in [2].

- This observation has been used to support hypotheses of scanning processes underlying working memory, especially that working memory acts through an exhaustive serial search [3, 4, 2].

- Our results suggest that the same effect can be achieved in an attractor network with fast learning dynamics.

# 2 Method and Model

- We modeled a working memory using a Bayesian confidence propagation neural network.
- The network was trained with a number of random patterns that were shown sequentially to the network, and then tested with cued recall (with the learning dynamics turned off).
- Cued recall consisted of showing the network training patterns $\boldsymbol{\xi}^p$ with the active units of three hypercolumns randomly changed.
- The stopping criterion used was that the rate of change in unit activity was below a certain level $||d\boldsymbol{x}/dt||_1 < 0.05$.
- Retrieval quality after convergence was estimated using the overlap $\boldsymbol{\xi}^p \cdot \mathbf{x}/|\boldsymbol{\xi}^p||\mathbf{x}|$ between the activity $\mathbf{x}$ and the target $\boldsymbol{\xi}^p$.
- After convergence the activity pattern $\mathbf{x}$ was compared to the cue $\boldsymbol{\xi}^p$, a process assumed to take constant time. Only the network convergence time affects the total reaction time in a set-dependent manner in this model.



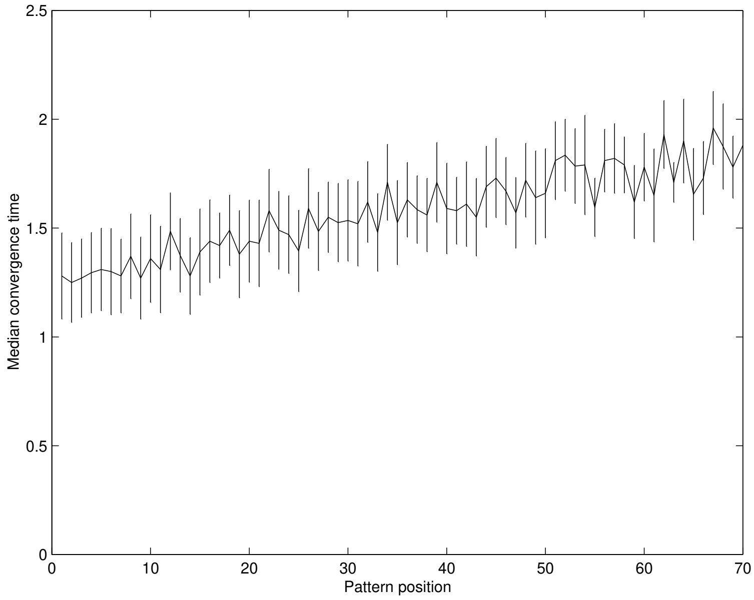
# 3 Bayesian Confidence Propagation Neural Networks

- The BCPNN is an autoassociative ANN with Hebbian learning informally derived from Bayes' Rule [5, 6, 7].
- The BCPNN is based on a probabilistic view of learning and retrieval, with unit activities roughly representing confidence in the presence of different features.
- Synaptic weights are set by soft counters estimating the probability of co-activation and mean activity.
- Units are organized into hypercolumns, representing mutually inhibitory feature detectors.

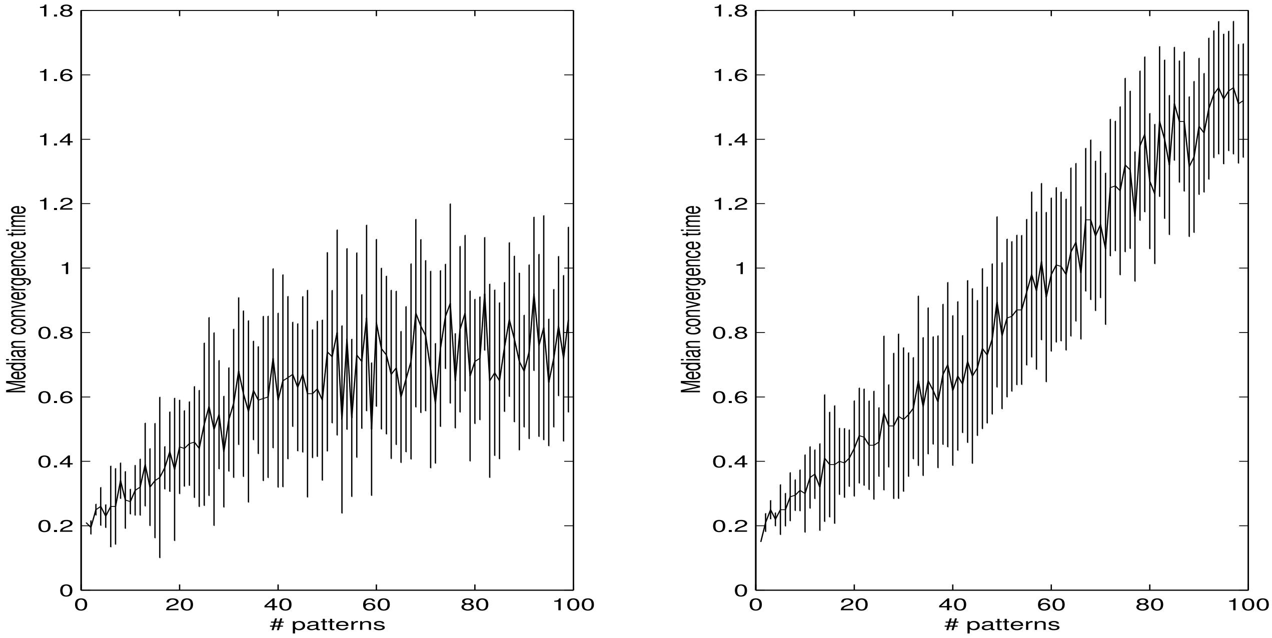
$$
\begin{aligned}
\frac{dh_{ii'}(t)}{dt} &= \beta_{ii'}(t) + \sum_{j}^{N} \log\left(\sum_{j'}^{M_i} w_{ii'jj'}(t) o_{jj'}(t)\right) - h_{ii'}(t) \\
o_{ii'}(t) &= \frac{e^{h_{ii'}}}{\sum_j e^{h_{ij}}} \\
\frac{d\Lambda_{ii'}(t)}{dt} &= \alpha([(1-\lambda_0)o_{ii'}(t) + \lambda_0] - \Lambda_{ii'}(t)) \\
\frac{d\Lambda_{ii'jj'}(t)}{dt} &= \alpha([(1-\lambda_0^2)o_{ii'}(t)o_{jj'}(t) + \lambda_0^2] - \Lambda_{ii'jj'}(t)) \\
\beta_{ii'}(t) &= \log(\Lambda_{ii'}(t)) \\
w_{ii'jj'}(t) &= \frac{\Lambda_{ii'jj'}(t)}{\Lambda_{ii'}(t)\Lambda_{jj'}(t)}
\end{aligned}
$$

where $h_{ii'}$ the potential of the $i'$th unit in hypercolumn $i$, $o_{ii'}$ the output of the unit, $\beta$ the bias, $w$ the weights, $\Lambda$ rate estimates, $\lambda_0$ a low background activity (set to $10^{-4}$ throughout this poster), $N$ the number of hypercolumns, $M_i$ the number of neurons in hypercolumn $i$ and $\alpha$ the inverse of the learning time constant.

# 4 Convergence Speed

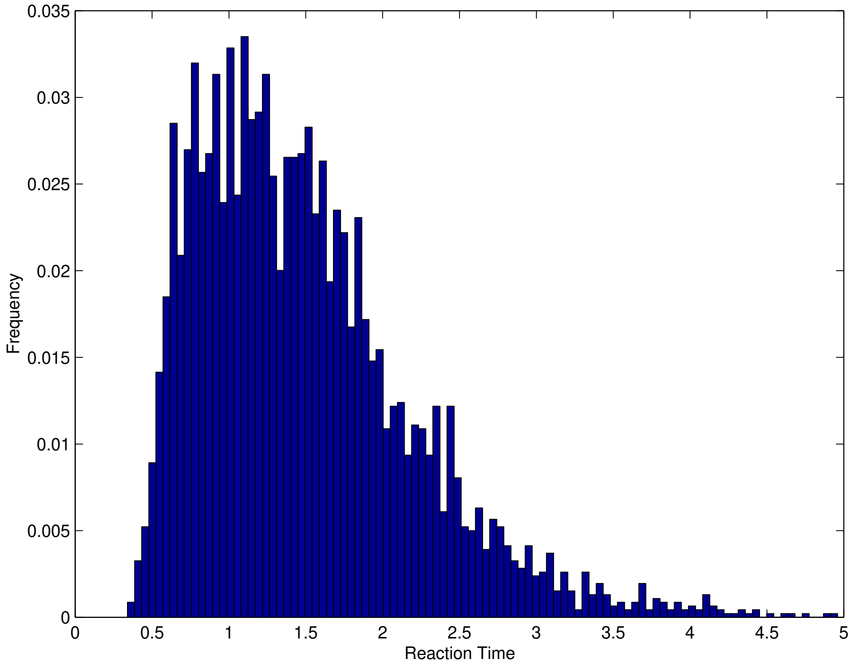



Median convergence time and standard deviation for retrieval of stored patterns from a disturbed input, as a function of position in the training set. Pattern 1 is the most recently learned pattern. Only retrieval of correct patterns was counted, and since this was sparser beyond pattern 70 only the first 70 patterns are shown. $\alpha = 0.01$, the network was trained with 100 patterns.




Median convergence time and standard deviation for increasing memory load for $\alpha = 0.1$ (left) and $\alpha = 0.01$ (right). The network is trained with up to 100 patterns, but for $\alpha = 0.1$ has capacity for only around 20–30.

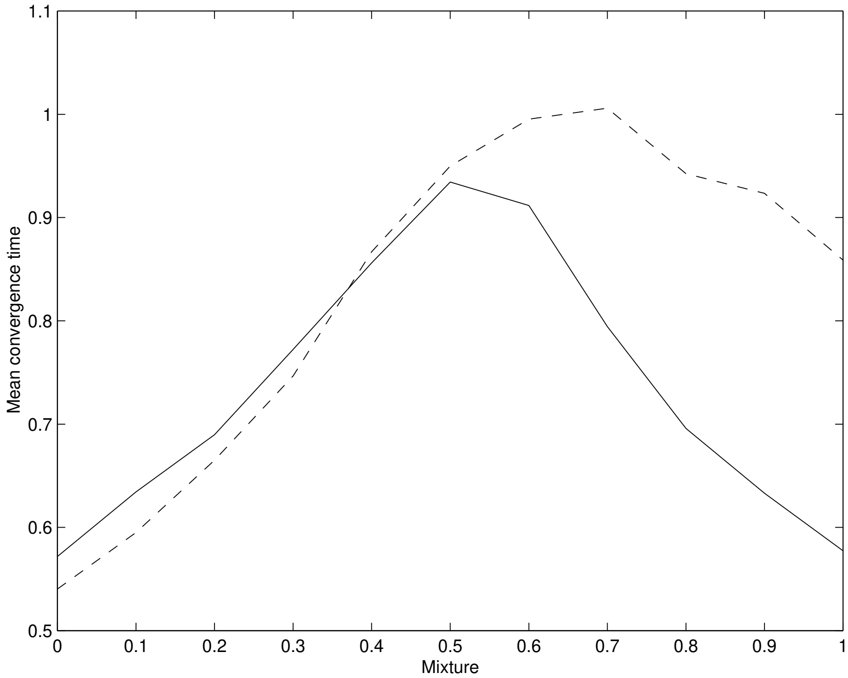
# 5 Reaction Time Distribution




Histogram of convergence time in cued recall. $\alpha = 0.01$, the network was trained with 100 patterns.

# 6 Decision making

The convergence of the network can be viewed as a decision-making process where an uncertain stimuli is classified into one of several learned categories.




Convergence time for mixed input patterns. The input to the network consists of 0–10 hypercolumns of one pattern and the rest from the other pattern. The solid curve represents interpolation between the latest and second latest pattern, the dashed curve interpolation between the latest and an old pattern (#10). 70% of pattern 10 was required to produce convergence to that pattern. The network was trained with $\alpha = 0.01$.

# 7 Summary and Comments

- The convergence time for recall increased linearly with the size of the memory set.
- Convergence time as a function of list position also increased roughly linearly, at least for the latest well-remembered patterns.
- The convergence time histogram shows a skewed distribution similar to experimental reports. Variance and skewness of the reaction time distribution increases with increasing load.
- For mixed patterns the convergence time shows the same slowing behavior at a decision boundary as reported in [8].
- These results demonstrate that attractor dynamics in a neural network can reproduce linear increases in reaction time similar to those observed in the Sternberg paradigm.

# 8 References

See also poster 41604.09: Anders Sandberg, Anders Lansner and Karl-Magnus Petersson, *Incremental Bayesian learning in a hypercolumn architecture: A palimpsest memory* for a more detailed treatment of the BCPNN model and its relevance.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