PATTERN STORAGE IN A NEURAL NETWORK WITH CYCLIC ACTIVATION

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We present a model of a neural network with low firing rates. We introduce an alternative approach to pattern storage which assumes that patterns are stored as cycles of sparse activity. This yields low firing rates of neurons in stored patterns. The mean activity gets lower when the length of the cycle is lengthening. The model has a high capacity and operates under firing rates comparable to some physiological regimes in biological neural networks, for example in neocortex or in the CA3 part of hippocampus.

How are the patterns stored

The patterns are stored in cycles of the activity of a very small number of neurons. We call the whole cycles as patterns and the synchronous activity at the exact time frame in the cycle as sub-pattern. We define a relative activity as a ratio of active number of neurons to total number of neurons. We denote the sub-pattern activity as $a \in (0,1)$.(a is the probability that randomly chosen neuron of a sub-pattern is active.) We assume that a is constant number near 0 (In the example shown in Figure is $a < 10^{-4}$).

Let us denote the length of i-th pattern as $l(i)$, successive sub-patterns of the i-th pattern as ${}^{i}t^{1}, {}^{i}t^{2} \ldots {}^{i}t^{l(i)}$ and the activity of n neurons in j-th sub-pattern as ${}^{i}t_1^{j}, {}^{i}t_2^{j} \ldots {}^{i}t_n^{j}$, so the lower right index denotes the neuron number, upper left and upper right indices denote pattern and sub-pattern numbers respectively.

Now we have p patterns which we like the network to learn. In each k-th iteration of learning process the network learns the k-th pattern (a cycle of sub-patterns). Let us denote weights after k-th iteration as w_{ij}^{k}. In each iteration we modify weights according to the equation for the learning rule:

$$w_{ij}^{k} = \max\left(w_{ij}^{k-1}, \mathrm{H}\left({}^{k}t_i^{l(i)}\ {}^{k}t_j^{1} + \sum_{q=1}^{l(k)-1} {}^{k}t_i^{q}\ {}^{k}t_j^{q+1}\right)\right),$$

where H is the Heaviside step function. This gives values 0 or 1 to synaptic weights. If the value of the weight is 1, the corresponding synapse is called activated. The learning rule is a variant of the Hebbian rule, written with the aim to make each element of the cycle to evoke in next time step a network state, identical to the next cycle element.

Results and capacity of the network

Usually the capacity of a neural network model linearly depends on the number of neurons in the network. Our model does not have this property and even the function of capacity depending on the number of neurons has always finite limit for the number of neurons approaching infinity. However, for smaller number of neurons the capacity of the model could be large enough. In some cases, the model is capable of recognizing the same number of patterns as the number of neurons it has. This phenomenon can be commented by the statement that in biology it makes no sense to increase the number of neurons in the network while the relative activity remains the same. This property could give the optimum number of active neurons in the biological network.

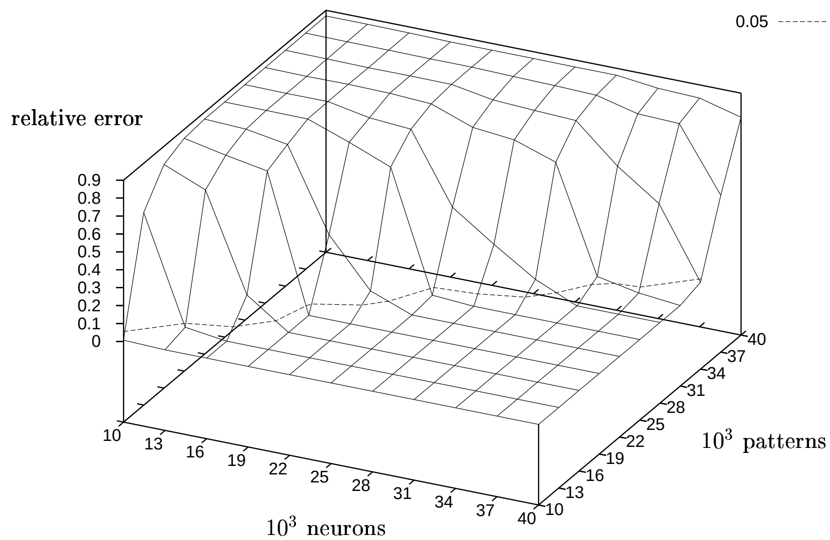

Figure 1: Relative error dependency of pattern recall process on the number of neurons and the number of patterns pattern at given pattern and sub-pattern activities. Only a part of the stored patterns were tested. Pattern activity 1.5%, sub-pattern activity 0.1%, 200 patterns tested.

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References

[1] D. Golomb, N. Rubin, and H. Sompolinsky. Willshaw model: Associative memory with sparse coding and low firing rates. *Phys Rev A.*, 41(4):1843–1854, Feb 1990.

[2] J. J. Hopfield. Neural networks and physical systems with emergent collective computational abilities. *Proc. Natl. Acad. Sci.*, 1982.

[3] J. P. Nadal and G. Toulouse. Information storage in sparsely coded memory nets. *Network*, 1:61–74, 1990.

[4] D. J. Willshaw, O. P. Buneman, and H. C. Longuet-Higgins. Non-holographic associative memory. *Nature*, (222):960–962, 1969.