Non-isomorphic Associative Memory

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Abstract. In this paper, we introduce a model of non-isomorphic associative memory. The learning rules of the non-isomorphic associative memory are inspired by constrained Hebbian rules and spike-timing dependent plasticity rules. Because the learning time depends linearly on the number of connections, the network learns very fast. With an appropriate way of feeding input patterns, non-isomorphic associative memory can be used to solve problems that require supervised models.

Keywords: Hebbian learning, associative memory, unsupervised learning

1 Introduction

In this paper, we propose a neural network model together with unsupervised learning rules that can simulate the ability to memorize concepts and associations between concepts. The learning rules are inspired by constrained Hebbian rules [2] and spike-timing dependent plasticity (STDP) rules [1]. The neural network is a feed-forward, randomly connected and weighted one which stores a pattern as a group of neurons that are activated only when the pattern but not any other pattern is given as the input. Rather than forcing the network to reproduce exactly the pattern as output after stored, the output of the network depends on its initial connections and weights. To use the network, the network output when a pattern is fed in is observed and taken as the recall of the pattern. The association of two patterns are stored when they are fed in to the network right after each other.

2 Non-isomorphic associative memory

For simplicity, in this paper, we focus on a non-isomorphic associative memory network with binary {0,1} neurons. The network is a feed-forward multi-layered network. Similar to the Perceptron neural network [3], we use a step activation function. Our unsupervised learning rules are inspired by constrained Hebbian rules [2] and spike-timing dependent plasticity (STDP) rules [1]. With these learning rules, the network can possess the two aforementioned properties: property 1 - the ability to store patterns, and property 2 - the ability to store links between patterns.

Pattern-storing learning rule In order to provide our neural networks with the sensitivity of each neuron to a single input, based on Lemma 1, we propose a modification of the Hebbian learning rule with constraints as follow:

$$\Delta w_i = \begin{cases} min(\eta y, T - w_i) & \text{if } x_i = 1 \text{ and } w_i \leq T \\ max(-\eta y, T - w_i) & \text{if } x_i = 1 \text{ and } w_i > T \\ -\eta y & \text{if } x_i = 0 \end{cases} \tag{1}$$

where T is the learning target with the relaxation factor ξ for each synapse weight:

$$T = \frac{\theta + \xi}{\sum_i x_i} \tag{2}$$

Association-storing learning rule Our association-storing learning rule is inspired by STDP rules. In addition to STDP rules reinforcing Hebbian learning rules, STDP rules explain in detail the relationship between timing of presynaptic spikes and postsynaptic spikes while Hebbian learning rules only mention the activation of two neurons together. Presynaptic spikes preceding postsynaptic spikes (known as pre-post spiking) and postsynaptic spikes preceding presynaptic spikes (known as post-pre spiking) can cause long-term potentiation (LTP) and long-term depression (LTD). Usually, pre-post spiking causes LTP, and post-pre spiking causes LTD. In this paper, we only concentrate on the pre-post spiking which causes LTP. We propose that when the activation of some pathways, even if they do not activate a neuron, is followed immediately by the activation of the neuron by some other pathways, then all activated pathways will benefit from the activation of the neuron. In addition, we propose an association training mode allowing two input patterns to be presented to the network immediately after each other, which results in the links between their related neurons being strengthened. The rule is described as follows. If a neuron is activated and there were pathways activated by the previous input pattern in association training mode, the weights of these pathways are also modified:

$$\Delta w_i = \begin{cases} min(\eta y, T - w_i) & \text{if } x_i^- = 1 \text{ and } w_i \leq T \\ max(-\eta y, T - w_i) & \text{if } x_i^- = 1 \text{ and } w_i > T \end{cases} \tag{3}$$

where x_i^- is the i-th input of the previous pattern in association training mode, and T is the learning target with the relaxation factor ξ for each synapse weight:

$$T = \frac{\theta + \xi}{\sum_i x_i^-} \tag{4}$$

3 Conclusion

In this paper, we proposed that in order to solve problems that require supervised models, we can use an "unsupervised learning" model with an appropriate way of presenting inputs. A non-isomorphic associative memory network that has the ability of storing information as well as storing the association between a pair of inputs was introduced. The new perspective on how associative memory stores and recalls information can be a starting point to simulate the brain better. The learning rules proposed in the paper can be extended for continuous valued or concurrent networks to solve more complex problems. The capacity and ability to recall information from heavily distorted inputs using our non-isomorphic associative memory also deserve more investigation.

References

1. H. Markram, J. Lubke, M. Frotscher, and B. Sakmann. Regulation of synaptic efficacy by coincidence of postsynaptic aps and epsps. *Science*, 275:213–215, 1997.
2. K. D. Miller and D. J. C. MacKay. The role of constraints in hebbian learning. *Neural Computation*, 6:100–126, 1994.
3. Frank Rosenblatt. The perceptron: A probabilistic model for information storage and organization in the brain. *Psychological Review*, 65(6):386–408, 1958.