Developing neural networks with neurons competing for survival

Zhen Peng
Max Planck Institute for Biological Cybernetics,
Max Planck Institute for Intelligent Systems,
IMPRS for Cognitive and Systems Neuroscience,
Tübingen, Germany
Email: zhen.peng@tuebingen.mpg.de

Daniel A. Braun
Max Planck Institute for Biological Cybernetics,
Max Planck Institute for Intelligent Systems,
Tübingen, Germany
Email: daniel.braun@tuebingen.mpg.de

I. INTRODUCTION

We study developmental growth in a feedforward neural network model inspired by the survival principle in nature. Each neuron has to select its incoming connections in a way that allow it to fire, as neurons that are not able to fire over a period of time degenerate and die. In order to survive, neurons have to find reoccurring patterns in the activity of the neurons in the preceding layer, because each neuron requires more than one active input at any one time to have enough activation for firing. The sensory input at the lowest layer therefore provides the maximum amount of activation that all neurons compete for. The whole network grows dynamically over time depending on how many patterns can be found and how many neurons can maintain themselves accordingly. If a neuron has found a stable firing pattern, a new neuron is created in the same layer. It is also made sure that there is always at least one neuron in each activated layer that is searching for novel patterns. If a layer stops growing for a certain amount of time, a new layer is created starting with a single neuron.

The survival principle works both on the level of neurons and on the level of synapses. In our model we therefore introduce variables that measure the well-being of neurons and synapses. The well-being of a neuron is increased whenever the neuron fires. Moreover, the well-being of all neurons is decreased over time such that neurons that do not fire will eventually die because their well-being has fallen below a certain threshold. The well-being of a synapse is increased whenever it was active and the neuron fired. The well-being of a synapse is actively decreased whenever it was inactive and the neuron fired. Moreover, the well-being of all synapses is decreased over time such that synapses die when their well-being falls below a certain threshold. When a synapse dies, its synaptic strength is randomly re-allocated to another synapse of the same neuron.

A. Algorithm

The i-th neuron in layer k has index \( N_i^{(k)} \) and is characterized by two parameters: the activation \( f_i^{(k)} \in \mathbb{R}_0^+ \) and the well-being \( p_i^{(k)} \in \mathbb{N}_0 \). The synapse \( s_{ij}^{(k)} \) connects neuron \( N_i^{(k-1)} \) to neuron \( N_j^{(k)} \) and has three important parameters: the activity \( a_{ij}^{(k)} \in \mathbb{R}_0^+ \), the synaptic weight \( \omega_{ij}^{(k)} \in \mathbb{N}_0 \) and the well-being \( h_{ij}^{(k)} \in \mathbb{N}_0 \). Signal propagation starts at the sensory layer and all variables are updated layerwise by running Algorithm 1.

Algorithm 1 UPDATE_NEURON

Ensure: neuron \( N_i^{(k)} \) is alive
1: \( f_i^{(k)} = \sum_j a_{ij}^{(k)} \)
2: if \( f_i^{(k)} \geq f^* \) then
3: \( p_i^{(k)} \leftarrow p_i^{(k)} + P^+ \) \{firing increases neural well-being\}
4: \( \forall j \mid \omega_{ij}^{(k+1)} > 0 : a_{ij}^{(k+1)} \leftarrow A \cdot \frac{\omega_{ij}^{(k+1)}}{\sum_j \omega_{ij}^{(k+1)}} \)
5: else
6: \( N_j^{(k+1)} \leftarrow 0 \)
7: end if
8: UPDATE_SYNAPSE
9: \( p_i^{(k)} \leftarrow p_i^{(k)} - 1 \) \{neuron ages\}
10: if \( p_i^{(k)} = 0 \) then
11: \( \forall j : h_{ji}^{(k)} \leftarrow 0, \omega_{ji}^{(k)} \leftarrow 0 \) \{neuron dies\}
12: end if
13: if \( p_i^{(k)} \geq P^* \) and NotReproducedYet then
14: \{activate new neuron\}
15: end if
16: \( f_i^{(k)} \leftarrow 0 \)

Algorithm 2 UPDATE_SYNAPSE

1: for \( \forall j \mid \omega_{ij}^{(k)} > 0 \) do
2: if \( f_i^{(k)} \geq f^* \) and \( a_{ij}^{(k)} > 0 \) then
3: \( h_{ji}^{(k)} \leftarrow h_{ji}^{(k)} + H^+ \) \{increase the well-being of contributing synapse\}
4: else if \( f_i^{(k)} \geq f^* \) and \( a_{ij}^{(k)} = 0 \) then
5: \( h_{ji}^{(k)} \leftarrow h_{ji}^{(k)} - H^- \) \{decrease the well-being of noncontributing synapse\}
6: end if
7: \( h_{ji}^{(k)} \leftarrow h_{ji}^{(k)} - 1 \) \{synapse ages\}
8: if \( h_{ji}^{(k)} \leq 0 \) then
9: \{synapse dies, reallocate its weight randomly to remaining synapses\}
10: end if
11: end for
B. Simulations

In our simulation, we used a two-dimensional sensory input layer (28 × 28 neurons) that is exposed to different visual stimuli. The input layer is divided into 16 perceptive fields of 7 × 7 neurons. Initially, there are 16 neurons in the first layer and each neuron is connected with all sensory neurons in one of the perceptive fields. When a stimulus occurs the corresponding sensory neurons are activated and fire and the activation spreads according to Algorithm 1. In the simulation we used the following parameter settings. The well-being of each neuron and each synapse was initialized as $\rho_{\text{init}} = 20$ and $h_{\text{init}} = 20$ respectively. All synaptic strengths were initialized as $w_{\text{init}} = 1$. We set the firing threshold $f^* = 200$ and the maximum output activation as $A = 190$. If a neuron fired, the well-being of the neuron was incremented by $P^* = 25$ and for contributing synapses the well-being was increased by $H^* = 100$, whereas for non-contributing synapses it was decreased by $H^- = 150$.

1) Unsupervised learning of patterns: Figure (a) illustrates the simulation process. As visual inputs we used the first twenty handwritten digits of the MNIST dataset [1]. In a first unsupervised learning regime, at each time step, one of the twenty images is provided as an input and the neural network activity is updated accordingly. Figure (b) shows the development of the neural network by indicating the number of neurons in each layer over time in one typical run of the simulation. Neural layers are activated one by one until the maximum number of layers (three in our simulation) is reached. The network reaches a stable final state.

2) Performance evaluation: In order to check whether the information in the last layer of the unsupervised network extracted useful information, we added an additional layer of associative neurons that received inputs both from the last unsupervised layer and a layer of label neurons as shown in Figure (a). The association layer also evolved according to algorithm 1. We compared this to a scenario where the association layer is directly coupled to the sensory layer. For the evaluation we tested all twenty training stimuli every 100 time steps and checked whether firing neurons in the layer preceding the association layer were connected to the correct label neurons. Figure (c) shows the average recognition rate over 10 simulations. The simulation results show that the four layer network only approximately 20% of correct labels can be recalled due to the massive ambiguity in the low level inputs, suggesting that the four layer network was able to extract useful information.

II. Conclusion

We have proposed a novel developing neural network model by introducing a variable for the well-being of neurons that struggle for survival. The network grows to a size that can be supported by the incoming sensory activation patterns, but not larger, as neurons that cannot find any patterns cannot support themselves and die eventually. We show in simulations that this naturally leads to abstractions in higher layers that emerge in a unsupervised fashion. When evaluating the network in a supervised learning paradigm, it is clear that our network is not competitive—compare for example the performance of linear feed-forward networks [2]. What is interesting though is that this performance was achieved by neurons that simply struggle for survival and do not know about performance error. In contrast to most studies on neural evolution [3], [4] that rely on a network-wide fitness function, our goal was to show that learning behaviour can appear in a system without being driven by any specific utility function or reward signal.

Acknowledgment

This study was supported by the DFG, Emmy Noether grant BR4164/1-1.

References