Artificial Neural Network with Complex Structures

Sara Kaviani Insoo Sohn

Division of Electronics & Electrical Engineering

Dongguk University

saraka1365@gmail.com isohn@dongguk.edu

Abstract

Due to the fully-connected complex structure of Artificial Neural Networks (ANNs), systems based on ANN may consume much computational time, energy and space. In this paper, the methodology and results of some recent papers are summarized and discussed in which the authors investigated the efficacy of random complex networks, on the performance of Hopfield associative memory and multi-layer ANNs compared with ANNs with small-world, scale-free and regular structures.

1. Introduction

Artificial Neural Networks (ANNs), inspired from biological brain networks, have obtained a fair amount of success in various domains such as speech and pattern recognition [1], climate forecasting [2] and disease diagnosis [3]. The first neural network model introduced by Hopfield [4] which has been used for associative memory, has produced significant results about improving their memory capacity and pattern stability and retrieval through extensive investigations [5]. Imitating the biological brain structure, another type of ANNs, called the Multi-layer perceptron was invented to understand the information flow through the neural network and the learning process.

In this paper, we review and explore articles which have studied the influence of topology on the performance of ANNs based on complex systems structures. We specifically concentrate on the effect of random structures which has been defined and used in complex systems theory. Applying various complex structures in Hopfield associative memory and multi-layer perceptron as two important types of ANNs and comparing the networks performance with each other, the random networks was shown to be the most efficient structures among fully-connected, small-world and scale-free networks.

2. Materials

In this section we review the methodology and the results of some recent articles in which the complex network topologies has been applied on ANNs.

2.1 Hopfield neural networks

Hopfield (HF) networks are recurrent neural networks made up of binary neurons that evolve based on spin glass models in physics in order to hit a local minimum of energy. These neural networks can be used as associative memory (i.e., also called Hopfield-type attractor neural network) in a sense that the Hopfield model can be assumed as a memory which can be addressed through its contents. In the Hopfield associative memory, the local minimums are called "stored patterns" [5]. An input pattern overlap with a stored pattern, even if it is perturbed by an amount of noise, is checked and the pattern will be recognized. The performance of these memories are evaluated by the stability of the stored patterns which increases as the induced noise to the pattern decrease, ability to recognize the stored patterns from an error-induced state and the networks storage capacity. After realizing that the Hopfield model [4] was a generalization of the infinite range spin glass [6] with the same theoretical background, researchers tried to investigate the model in its fully connected and randomly diluted structures .

The first attempts to apply random networks on ANNs was presented by McGraw et al. [8]. They studied the computational performance of Hopfield-type attractor neural networks with asynchronous updating in random [5] and Hebbian [9] connection strength with different types of topologies such as regular lattice, random, small-world, and scale-free networks. It was shown that the network with random structure outperforms other topologies with the same number of nodes and connections in storage, stability and retrieval of the patterns. On the other hand, while the regular lattice degrades more rapidly than the other topologies, the small-world network performance is between regular and random networks. The scale-free network degrades a little more rapidly than the random structure, but they are more efficient in pattern partial recognition due to their hubs.

In 2006, Lu et al. [10], explored the effects of topology on the associative memory as well. They also compared between different topologies with fixed number of nodes and connections but they added some new results about the scale-free potential to improve the performance. They obtained the same conclusions as [8]. The authors generally claimed that more random topologies with less locality (lower clustering coefficient), would improve the pattern stability and retrievability. Hence, adding some shortcuts to the network can largely enhance the network's performance.

2.2 Multi-layer neural netwroks

Inspired by the brain's neuronal structure, a specific type of artificial neural networks, multi-layer ANNs, consist of one input layer, one or more hidden layers and one output layer are designed. The signal propagates through the network and pass one layer to another in a way that the output of each layer will be the input for the next layer. The ANNs with multiple hidden layers are called "Deep neural networks" (DNNs) that are mostly used in image and voice recognition [11].

In 2012, in their neuroscience paper, Hill et al. [12] after accumulating various data from living brain of Wistar rats, confirmed that local neural microcircuits can be remarkably modeled by random synaptic formations. In 2016, Shafiee et al. [13], highly motivated by the findings of Hill et al. , introduced the concept of StochasticNet, in which the connectivity between neurons in DNNs is defined to be stochastic. This stochastic synaptic connections, taking advantage of Kovalenko random graph model, seem to be more efficient for some specific tasks. Results showed that with less than half (39%) the number of neural connections of a conventional DNN, comparable accuracy in CIFAR-10, MNIST, and SHVN datasets can be obtained.

In 2019, for the first time Adjodah et al. [14], explored how to optimize the topology of communication between agents in deep reinforcement learning (DRL) (i.e., a DNN which learns by trial and error), built upon evolution strategies (ES) algorithm, to obtain better performance. They introduced a networked decentralized variant of ES, as NetES and investigated the influence of changing the topology of the neural network to complex networks while running ES on DRL. The authors claimed that ER random networks not only outperforms all other structures but also performs better than the fully-connected networks by only 1/3 number of neurons in the fully-connected network.

3. Conclusion

Based on the recent research works, generally we can conclude that ANNs with alternative complex topologies rather than being fully-connected show high performance with less complexity and reduced computational time and energy.

According to their investigations, randomly connected H opfield networks perform better than regular and fully c onnected networks in general.

Moreover, it has been perceived that adding a certain number of shortcuts to a regular network, in order to see small-world behavior in the network, would enhance the pattern stability and retrievability. On the other hand, implementing scale-free topology in an associative memory network demonstrated that it can perform as well as random networks. Scale-free ANNs have been found to perform significantly better in partial image retrieval and are very efficient in improving storage capacity because of their highly connected hubs.

Acknowledgments

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRFK) funded by the Ministry of Education (2018R1D1A1B07041981).

References

[1] G. E. Dahl, D. Yu, L. Deng, A. Acero, Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition, IEEE Transactions on audio, speech, and language processing 20, no. 1 (2011): 30-42.

[2] M. C. V. Ramirez, H.F. de Campos Velho, N.J. Ferreira. Artificial neural network technique for rainfall forecasting applied to the Sao Paulo region, Journal of hydrology 301, no. 1-4 (2005): 146-162.

[3] O. Erkaymaz, O. Mahmut, M. Perc, Performance of small-world feedforward neural networks for the diagnosis of diabetes, Applied Mathematics and Computation 311 (2017): 22-28.

[4] J. J. Hopfield, Neural networks and physical systems with emergent collective computational abilities, Proceedings of the national academy of sciences 79, no. 8 (1982): 2554-2558.

[5] D. J. Amit, Modeling brain function: The world of attractor neural networks, Cambridge university press, 1992.

[6] D. Sherrington, S. Kirkpatrick, Solvable model of a spin-glass, Phys. rev. lett. 35, no. 26 (1975): 1792.

[7] P. N. McGraw, M. Menzinger, Topology and computational performance of attractor neural networks, Phys. Rev. E 68, no. 4 (2003): 047102.

[8] D. O. Hebb, The organization of behavior, Vol. 65. New York: Wiley, (1949). Cambridge university pres s, 1992.

[9] J. Lu, J. He, J. Cao, Z. Gao, Topology influences performance in the associative memory neural networks, Phys. Lett. A 354, no. 5-6 (2006): 335-343.

[10] J. Schmidhuber, Deep Learning in Neural Networks: An Overview, Neural Networks. 61: 85–117. arXiv:1404.7828 (2015).

[11] S. L. Hill, Y. Wang, I. Riachi, F. Schürmann, H. Markram, Statistical connectivity provides a sufficient foundation for specific functional connectivity in neocortical neural microcircuits, Proceedings of the National Academy of Sciences 109, no. 42 (2012).

[12] M. J. Shafiee, P. Siva, A. Wong, Stochasticnet: Forming deep neural networks via stochastic connectivity, IEEE Access 4 (2016): 1915-1924.

[13] D. Adjodah, D. Calacci, A. Dubey, A. Goyal, P. Krafft, E. Moro, A. Pentland, Communication Topologies Between Learning Agents in Deep Reinforcement Learning, (2019). arXiv preprint arXiv:1902.06740.

[14] J. Lu, J. He, J. Cao, Z. Gao, Topology influences performance in the associative memory neural networks, Phys. Lett. A 354, no. 5-6 (2006): 335-343.