Stochastic Physical Neural Networks

E. Sigler[1], G. Sasikumar[1], S. Kumara[1], T. Dou[1], P.Girdhar[1,2], D. Petty[1], G. J. Milburn[3], J. Plested[4], and M. J. Woolley[1]

[1]School of Engineering and Technology, UNSW Canberra, Australia
[2] Department of Engineering Science, University of Oxford, United Kingdom
[3] Department of Physics and Astronomy, University of Sussex, United Kingdom
[4] School of Systems and Computing, UNSW Canberra, Australia

Machine learning algorithms have demonstrated a significant and growing technological impact. A learning machine, by contrast with a machine learning algorithm, is an analogue physical system that learns. The study of physical learning machines may provide insight into the dynamics and thermodynamics of learning, while also suggesting pathways to energy-efficient implementations of learning. One type of learning machine developed recently is a so-called *physical neural network*, a machine in which the weights, inputs, and neurons of the network are physical rather than digital.

We consider learning in physical neural networks where the neurons are implemented as *stochastic switches*; that is, *stochastic physical neural networks*. The dynamics of the neuron weights and biases are described in both discrete-time and continuous-time via stochastic difference equations and differential equations, respectively. The learning (that is, weight and bias update) is implemented by feeding back the labelled training data and physical stochastic switch output onto the drift term in the weight and bias dynamics. This provides both an elementary framework for incorporating noise into a physical neural network model and a plausible model of physical implementations. Possible quantum photonic implementations of stochastic switches as elements of stochastic physical neural networks are given.

Physics-aware training of a stochastic physical neural network is studied analytically and numerically, working through canonical problems: learning the NOT and XOR gates, vowel classification, and handwritten digit recognition trained with the MNIST dataset. Backpropagation-free training of a stochastic physical neural network is also studied. Physics-aware training of a stochastic physical neural network with a classification accuracy above 90% for more than five trials on the MNIST-trained model was achieved.

This performance demonstrates the potential capability of intrinsically noisy and quantum-limited physical systems to complement current implementations of deep neural networks on conventional digital computers.