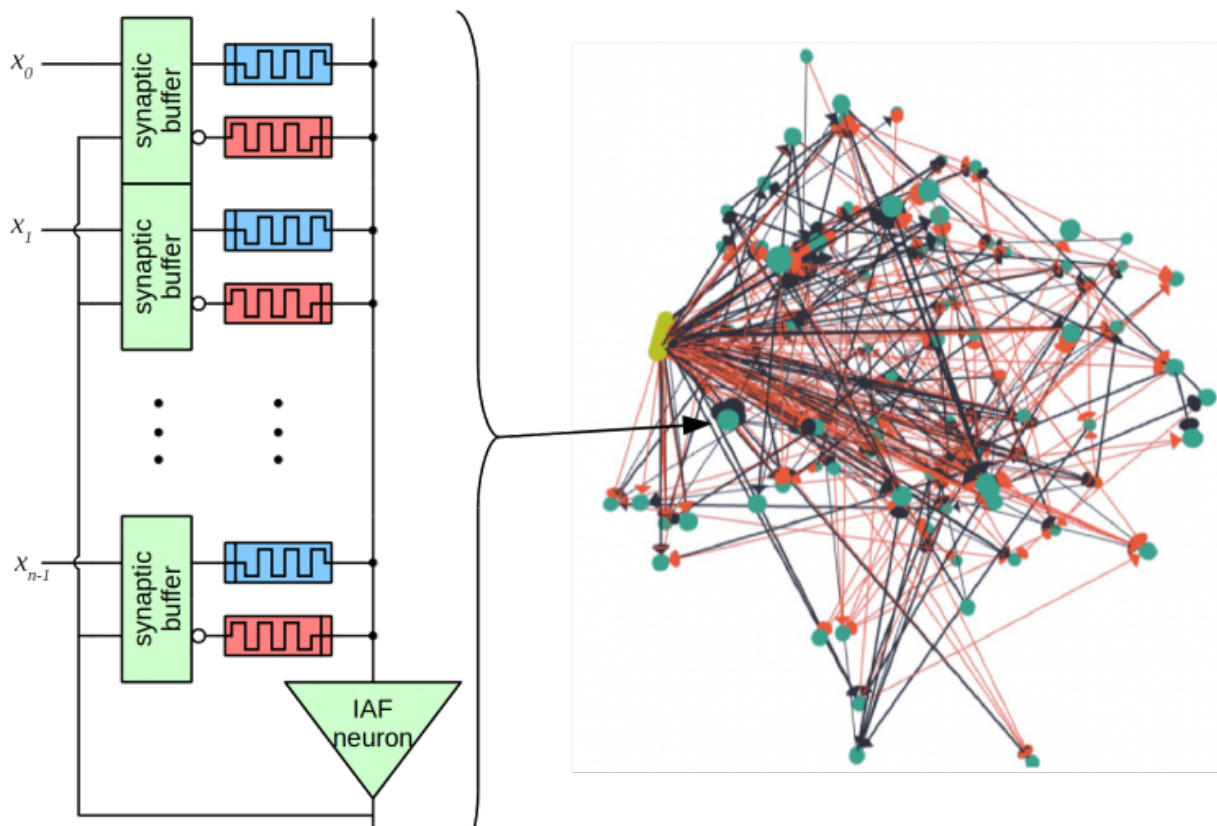


Computing—quantum deep

April 3 2017, by Sara Shoemaker



This neuromorphic circuit simulation is part of a tri-fold experiment, led by Oak Ridge National Laboratory, that brings together quantum, high-performance and neuromorphic architectures to resolve complex issues in intelligence computing. Credit: Oak Ridge National Laboratory

In a first for deep learning, an Oak Ridge National Laboratory-led team is bringing together quantum, high-performance and neuromorphic

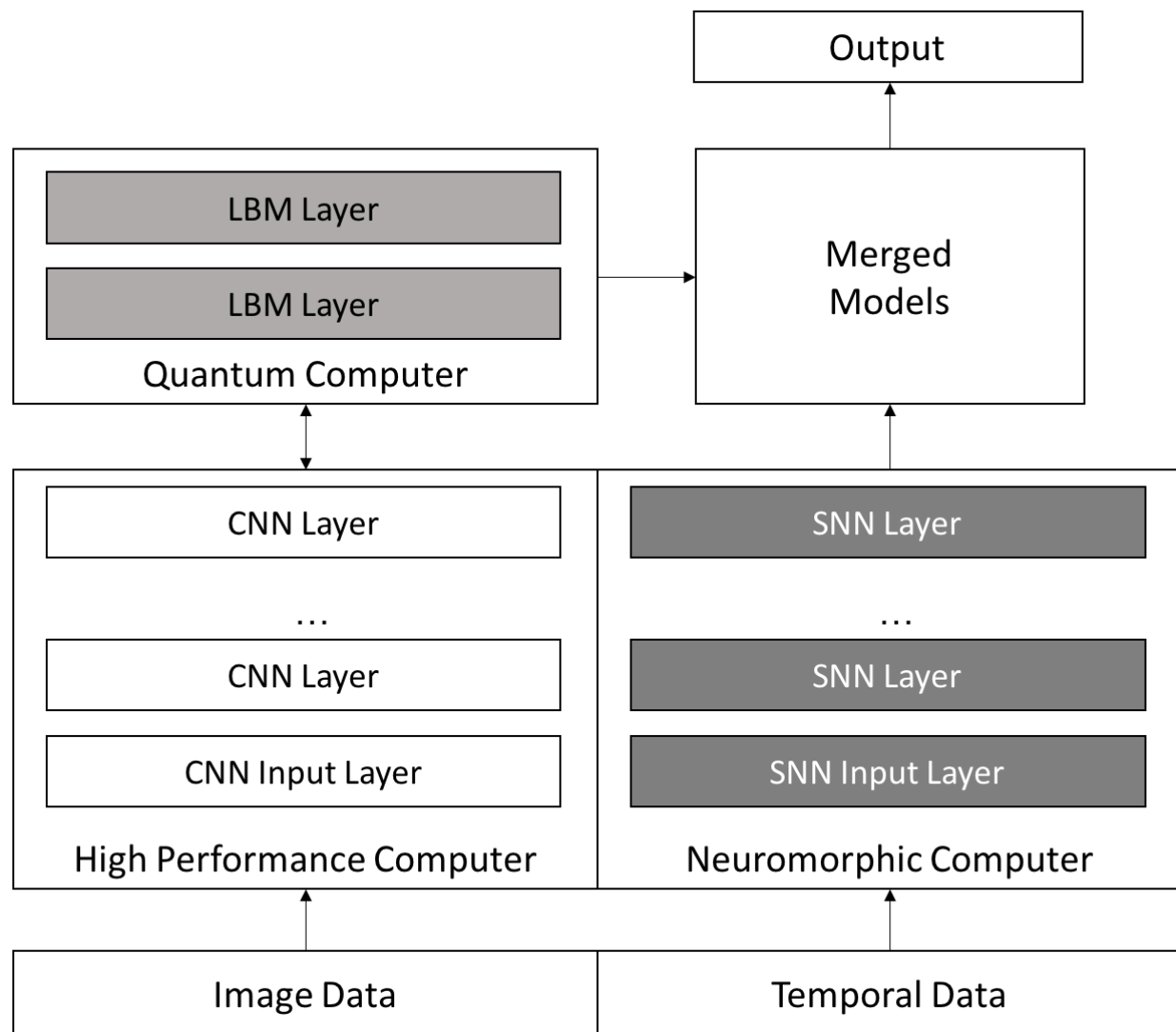
computing architectures to address complex issues that, if resolved, could clear the way for more flexible, efficient technologies in intelligent computing.

Deep learning refers to nature-inspired, computer-based technologies that push beyond the conventional binary code, advancing emerging fields such as facial and [speech recognition](#).

"Deep learning is transformative," ORNL's Thomas Potok said. "Our proposed approach can optimize and manage complexity in a low-power environment, resolving specific challenges when exploring complicated [scientific data](#)."

The team's tri-fold experiment demonstrates the feasibility of using the three architectures in tandem to overcome limitations and represents a new capability not currently available.

Details of the team's experiment are [available online](#).



This diagram represents the first proposed architecture that syncs quantum, high-performance and neuromorphic approaches that could be used to improve deep learning technologies. Credit: Oak Ridge National Laboratory

More information: A Study of Complex Deep Learning Networks on High Performance, Neuromorphic, and Quantum Computers, arXiv:1703.05364 [cs.NE] arxiv.org/abs/1703.05364

Abstract

Current Deep Learning approaches have been very successful using convolutional neural networks (CNN) trained on large graphical processing units (GPU)-based computers. Three limitations of this approach are: 1) they are based on a simple layered network topology, i.e., highly connected layers, without intra-layer connections; 2) the networks are manually configured to achieve optimal results, and 3) the implementation of neuron model is expensive in both cost and power. In this paper, we evaluate deep learning models using three different computing architectures to address these problems: quantum computing to train complex topologies, high performance computing (HPC) to automatically determine network topology, and neuromorphic computing for a low-power hardware implementation. We use the MNIST dataset for our experiment, due to input size limitations of current quantum computers. Our results show the feasibility of using the three architectures in tandem to address the above deep learning limitations. We show a quantum computer can find high quality values of intra-layer connections weights, in a tractable time as the complexity of the network increases; a high performance computer can find optimal layer-based topologies; and a neuromorphic computer can represent the complex topology and weights derived from the other architectures in low power memristive hardware.

Provided by Oak Ridge National Laboratory

Citation: Computing—quantum deep (2017, April 3) retrieved 10 April 2024 from <https://phys.org/news/2017-04-computingquantum-deep.html>

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