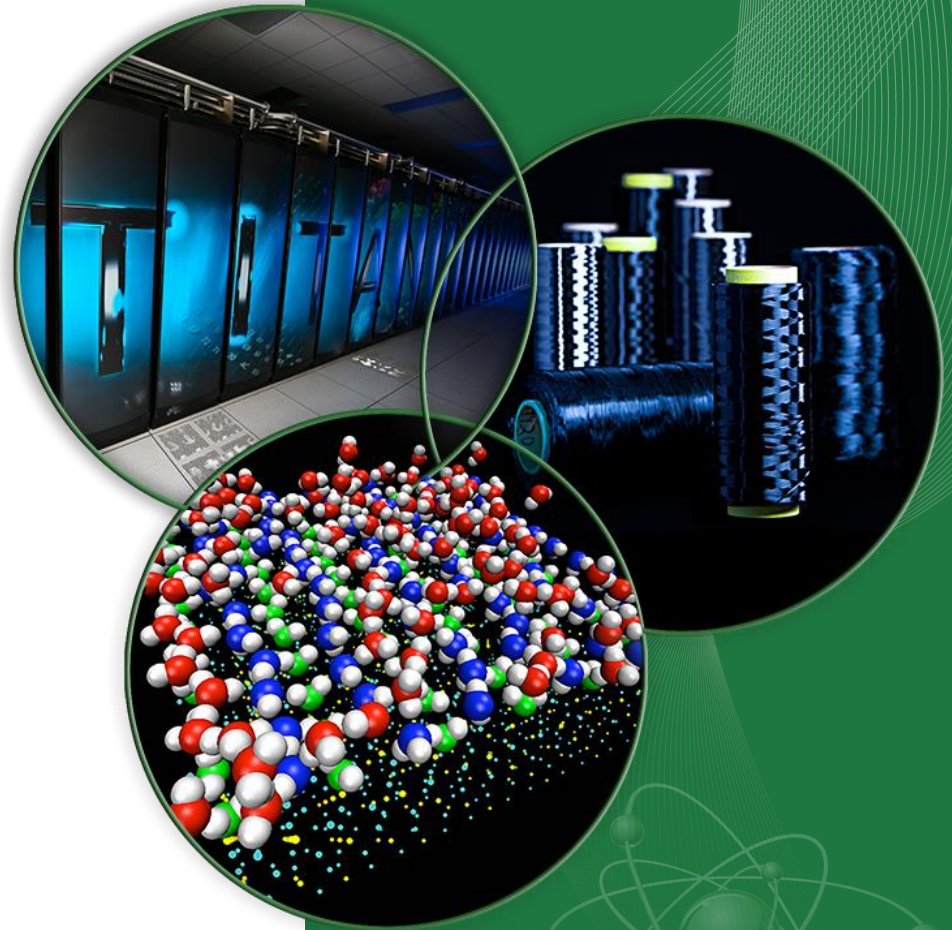


A Study of Complex Deep Learning Networks on High Performance, Neuromorphic, and Quantum Computers

Thomas E. Potok, Ph.D.

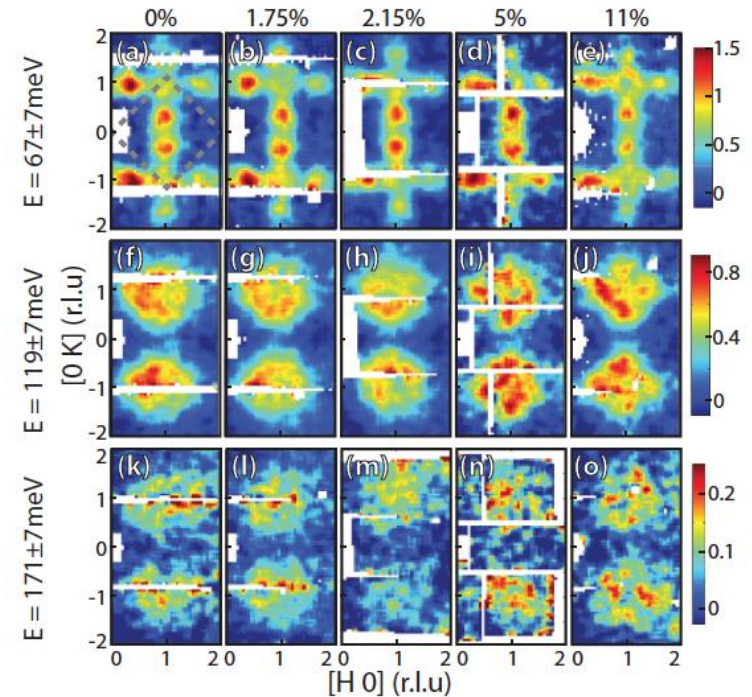
Computational Data Analytics Group

Oak Ridge National Laboratory



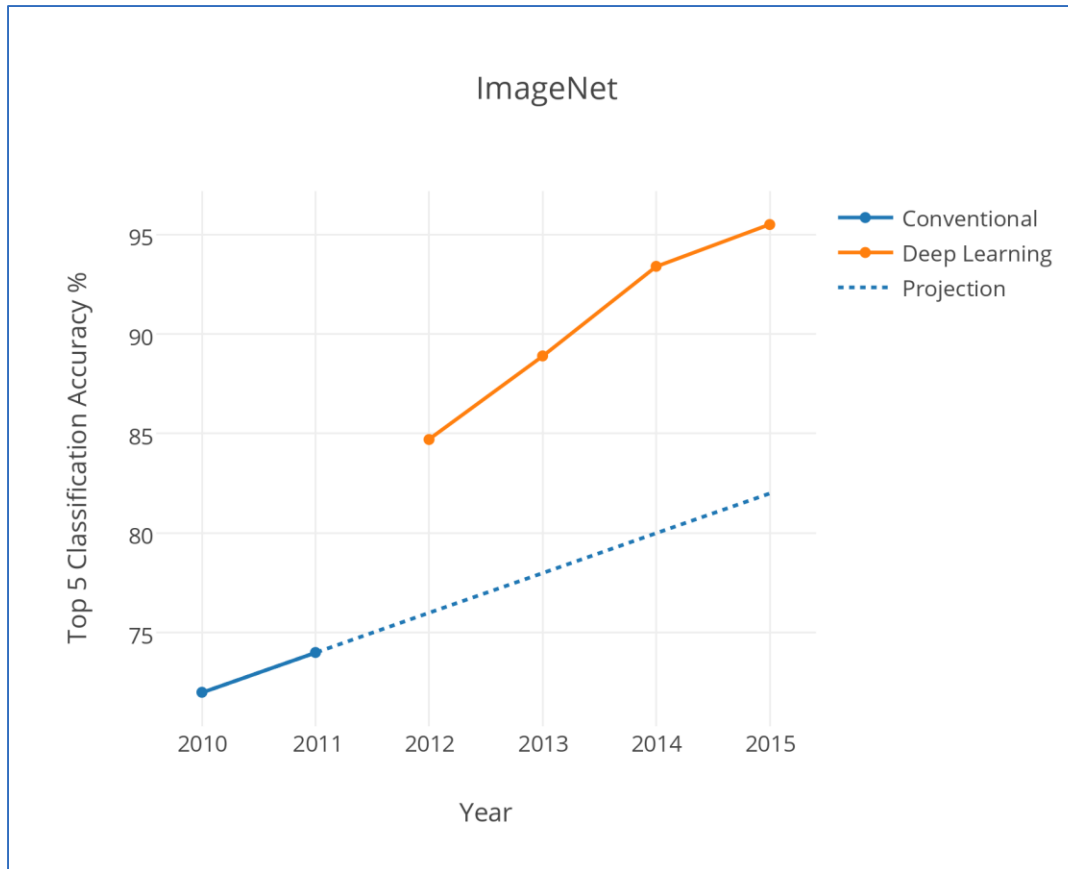
Motivation and Goals

- Scientific data is increasingly large and complex, making new discovery difficult
- Can deep learning and novel architectures provide a way of aiding scientific discovery?



Each pixel represents a 512x512 matrix of values from Spallation Neutron Source at ORNL

Deep Learning Performance



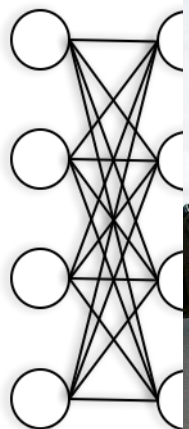
- What could you do with
 - HPC,
 - Quantum
 - Neuromorphic?

Motivations for novel architectures

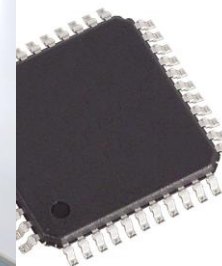
- Deep Learning network topologies are layered due to computability
 - Does a complex topology offer better results?
- Deep Learning Hyper-parameters are hard to tune
 - Can a CNN be quickly tuned for a new scientific datasets?
- Deep Learning Trained models are hard to deploy
 - Can models be deployed on or near scientific instruments?

Hypothesis

Scientific Data



Complex
Topology



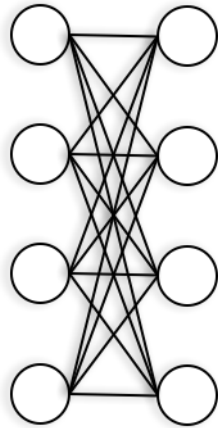
Hardware
Implementation

Scientific Instrument

Auto Tuned Hyper
Parameters

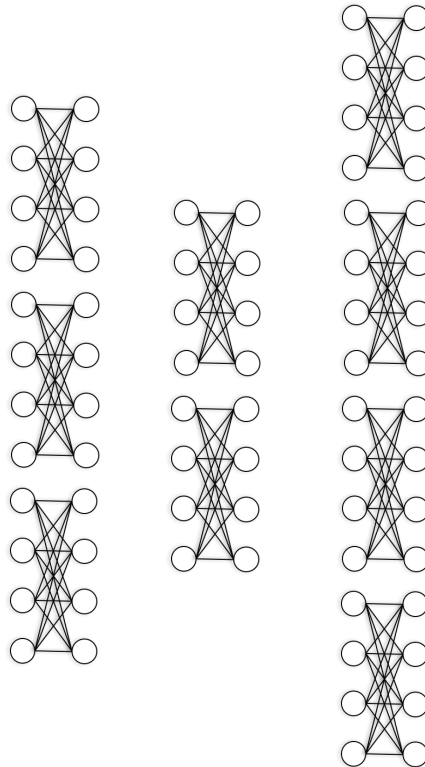
Methods

Quantum



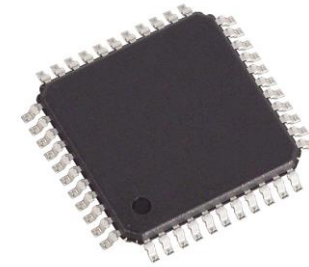
Complex
Topology

HPC



Auto Tuned Hyper
Parameters

Neuromorphic



Hardware
Implementation

Scientific Data

Scientific Instrument

Rational

Quantum

- Hints at speed up of certain hard problems

HPC

- Computational parallelization

Neuromorphic

- Native neural networks, very low power

Experimental Goals

Quantum

- Test feasibility of complex topologies (intra-layer connections)
- USC Lockheed Martin Quantum Computation Center D-Wave

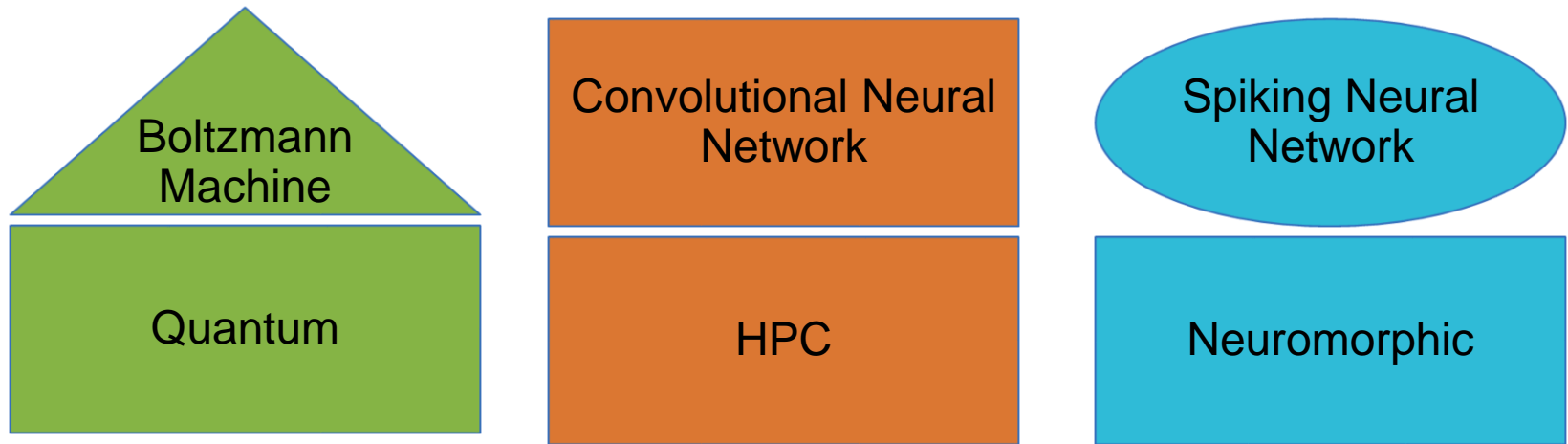
HPC

- Test evolutionary algorithms to auto-tune hyper-parameters
- ORNL's Titan

Neuromorphic

- Test the ability to represent neural network models in low power hardware
- UTK Memristive Nida System

How do we compare the architectures?

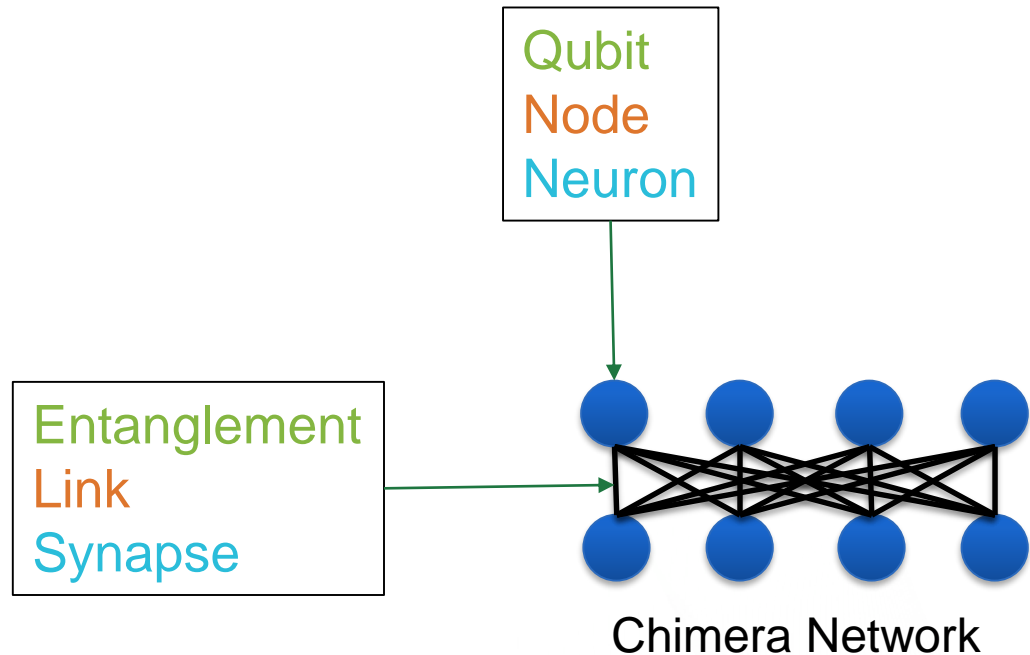


- The MNIST database contains 60,000 training images and 10,000 testing images
- Very small images size, 28x28
- <http://yann.lecun.com/exdb/mnist/>

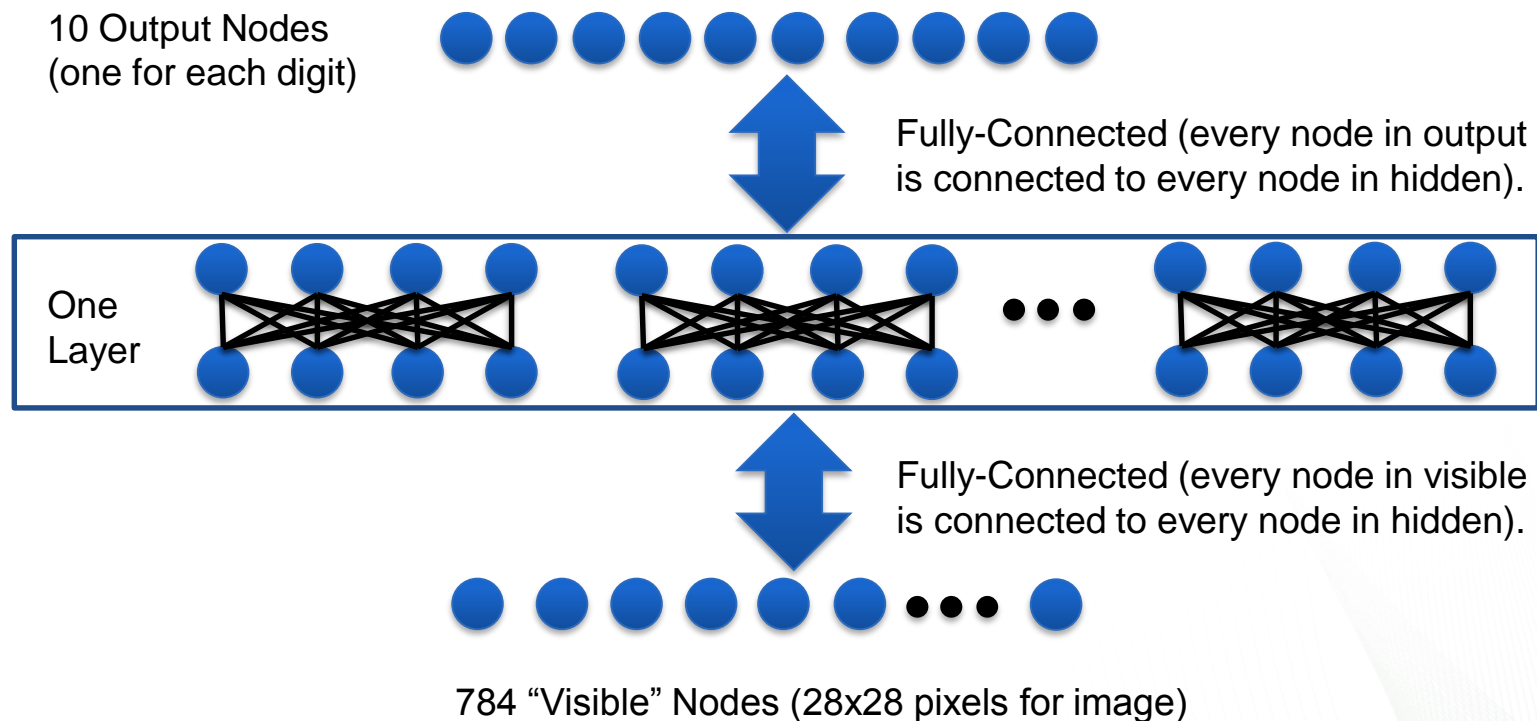


Common Ground

- Quantum Physics
- Computer Science
- Electrical Engineering
- Neuroscience



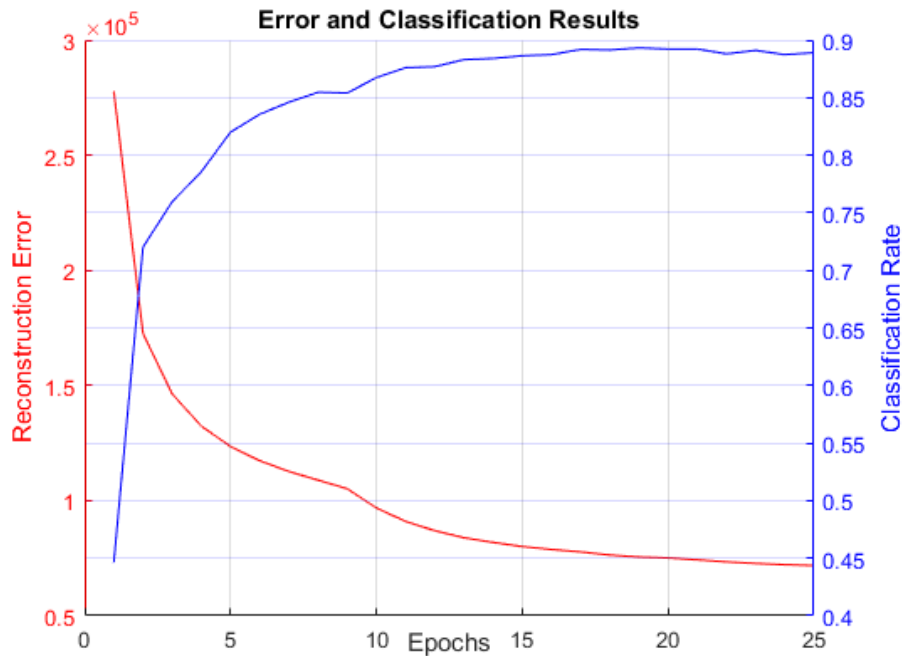
Limited Boltzmann Machine Network



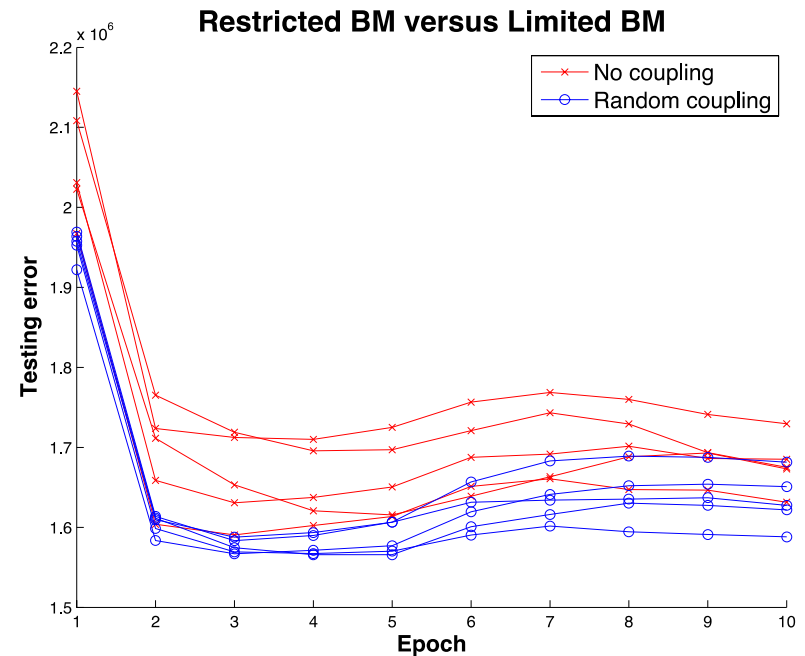
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Quantum Results – USC/ISI D-Wave

Complex topology learns and provides better results than no intra-layer connection



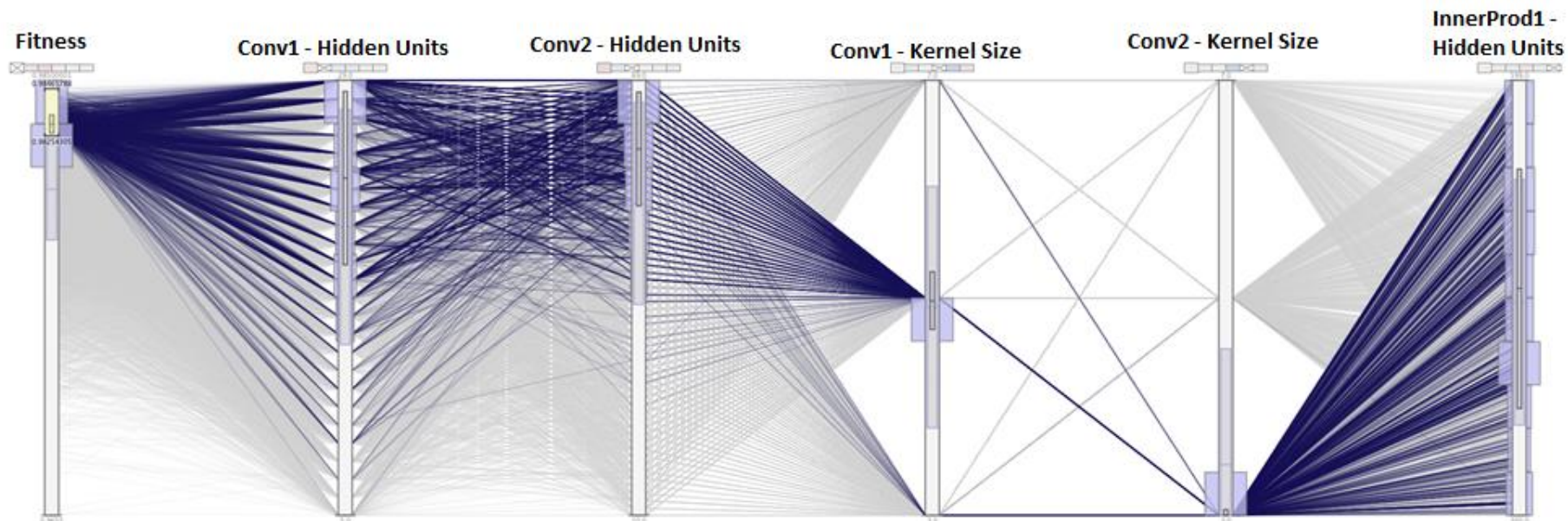
Limited Boltzmann
Machine learning from
training examples



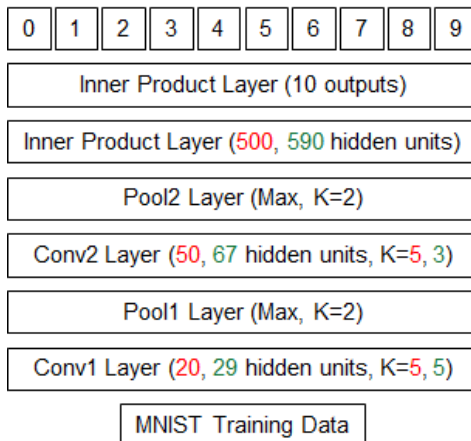
Limited Boltzmann
Machine more accurate
than restricted BM

HPC Results – 500 nodes on Titan

Demonstrates an effective way of auto tuning a CNN

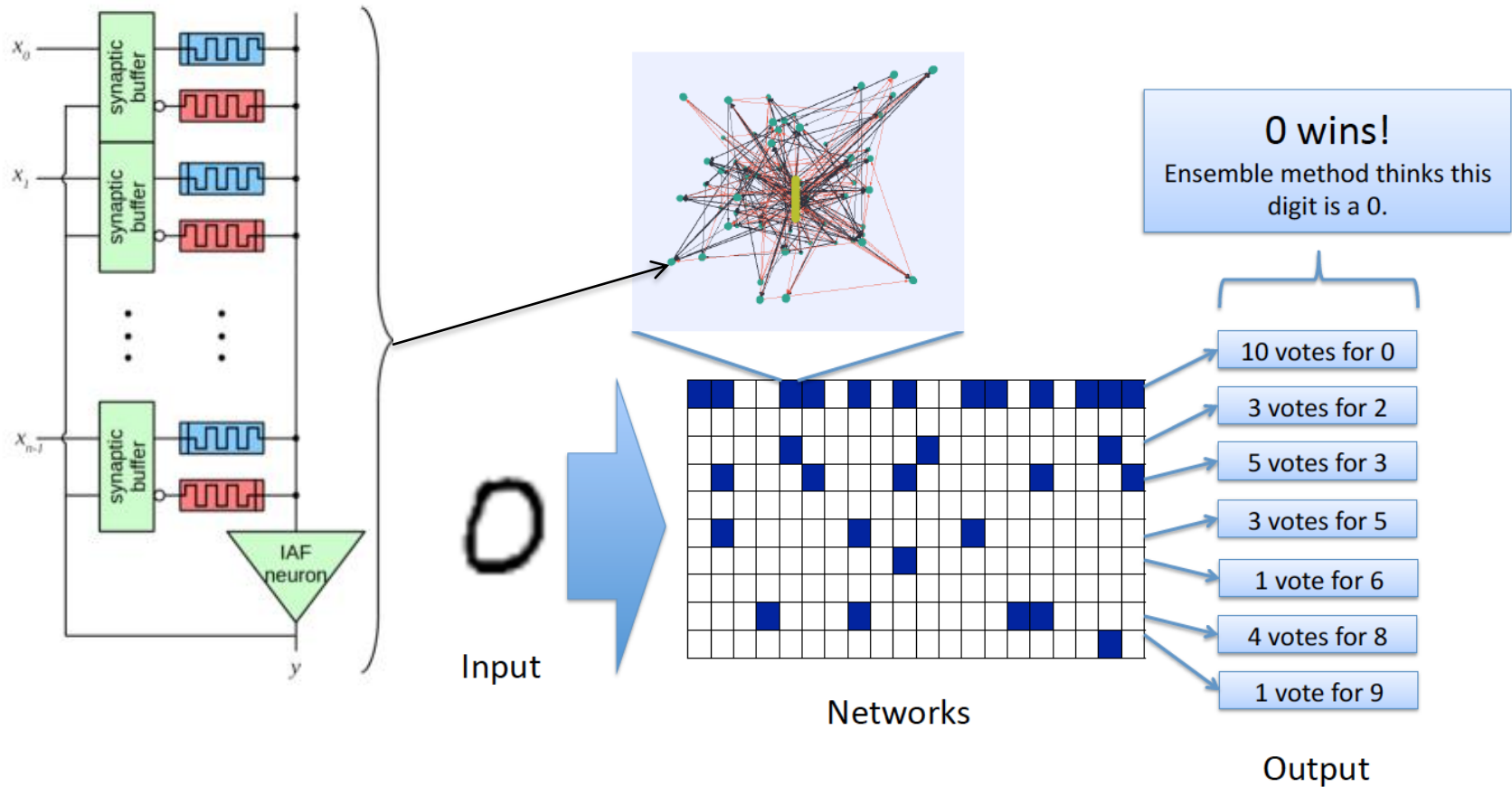


MNIST



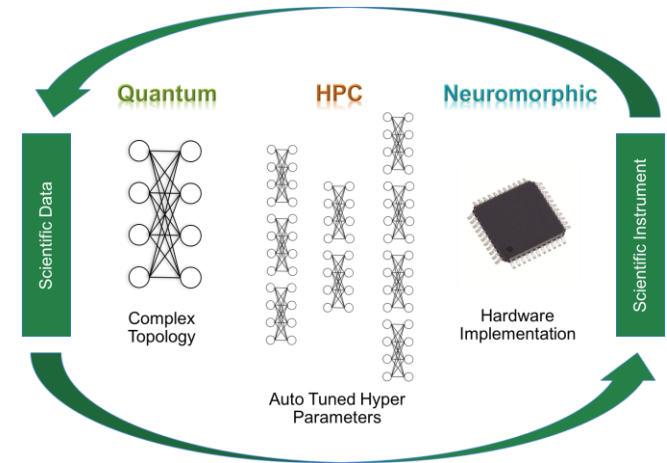
Neuromorphic – ORNL/UT NIDA network on Memristor

20X more energy-efficient than their CMOS counterparts



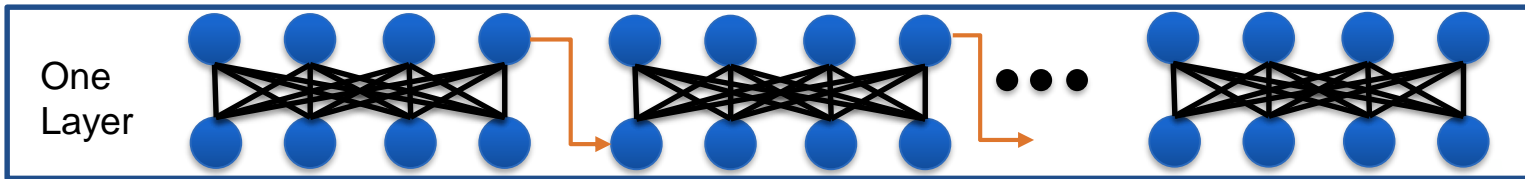
Conclusion

- Complex topologies with intra-layer connects have better classification performance than without connections
- HPC can be used to auto-tune CNN topologies
- Neuromorphic hardware has the potential to implement deep learning network in very low-power hardware
- A first step towards richer DL on novel architectures



Next Step

- Evaluate the strengths and weaknesses of each approach
- Quantum: Explore more complex networks



- HPC: Auto tune on Limited Boltzmann machines model
- Neuromorphic: Implement of Limited Boltzmann on FPGA version of neuromorphic hardware

Team

- Deep Learning/HPC
 - Robert Patton (ORNL)
 - Steven Young (ORNL)
 - Thomas Potok (PI/ORNL)
- Quantum Computing
 - Federico Spedalieri (USC/ISI)
 - Ke-Thia Yao(USC/ISI)
 - Bob Lucas (USC/ISI)
 - Jeremy Liu (USC)
- Neuromorphic Computing
 - Garrett Rose (UT)
 - Katie Schuman (ORNL)
 - Gangotree Chakma (UT)
- Program Manager
 - Robinson Pino (DOE ASCR)



Questions?