Neuromorphic Computing for Temporal Scientific Data Classification

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Neuromorphic Computing Symposium

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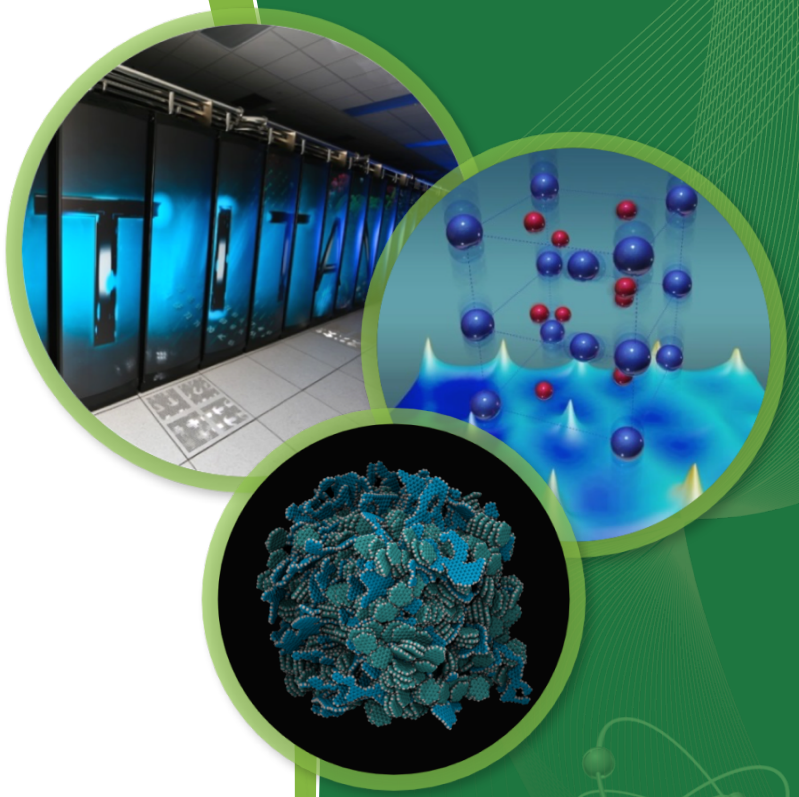

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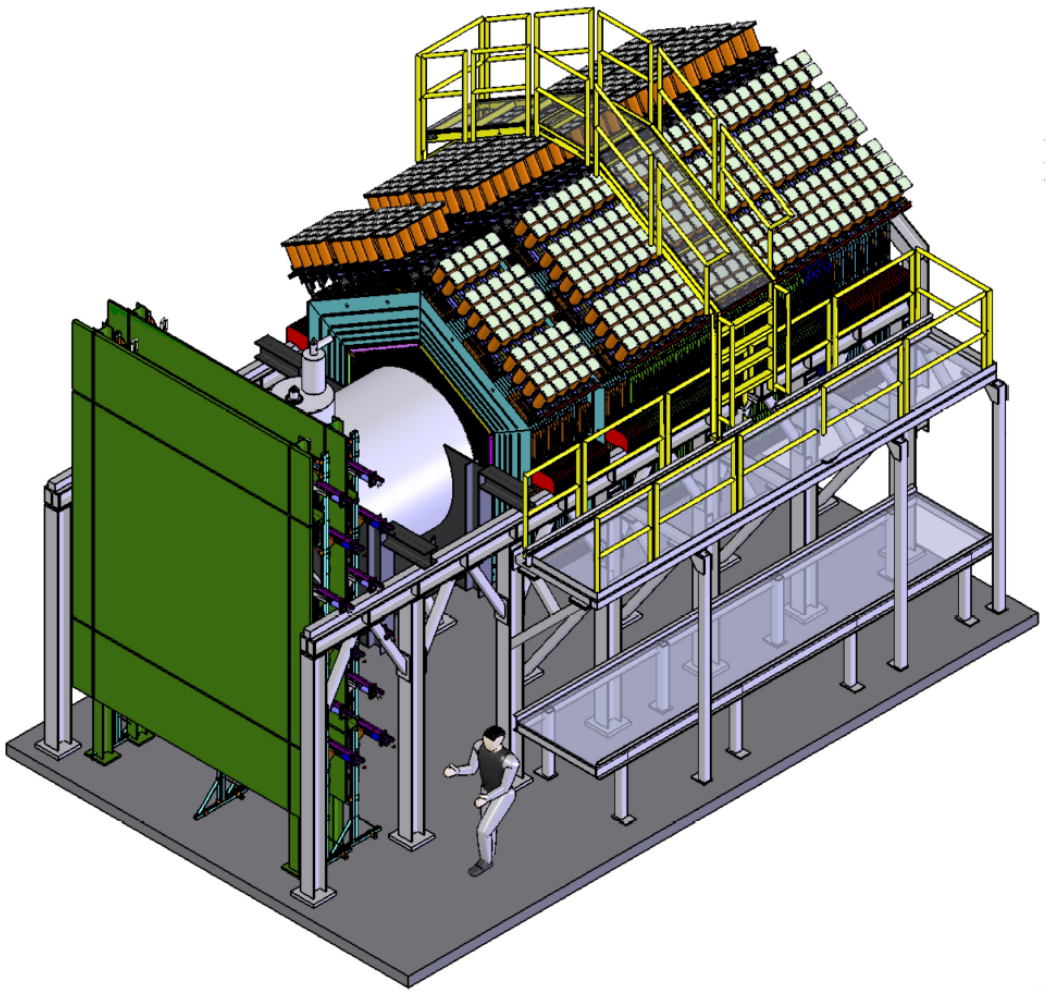
Introduction

- Spiking neural networks and spiking neuromorphic systems can be well-suited to processing temporal data.
  - Temporal data can be represented natively as spikes in the neuromorphic system.
- Some applications may have restricted power budgets or size/space restrictions.
  - Neuromorphic systems, especially those utilizing circuit components such as memristors, can achieve complex calculations with less energy.
- An application with those two characteristics:
  - Temporal scientific data collected at scientific instruments

Data from MINERvA (Main Injector Experiment for ν-A)

- Neutrino scattering experiment at Fermi National Accelerator Laboratory
- The detector is exposed to the NuMI (Neutrinos at the Main Injector) neutrino beam.
- Millions of simulated neutrino-nucleus scattering events were created.
- Classification task is to classify the horizontal region where the interaction originated.

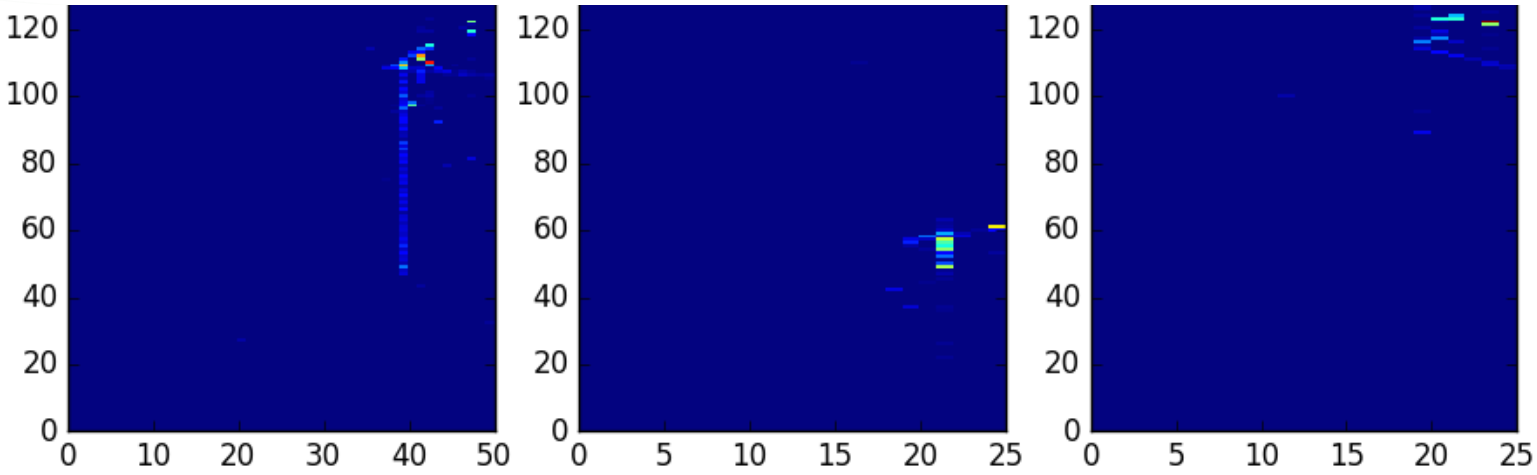


MINERvA Detector

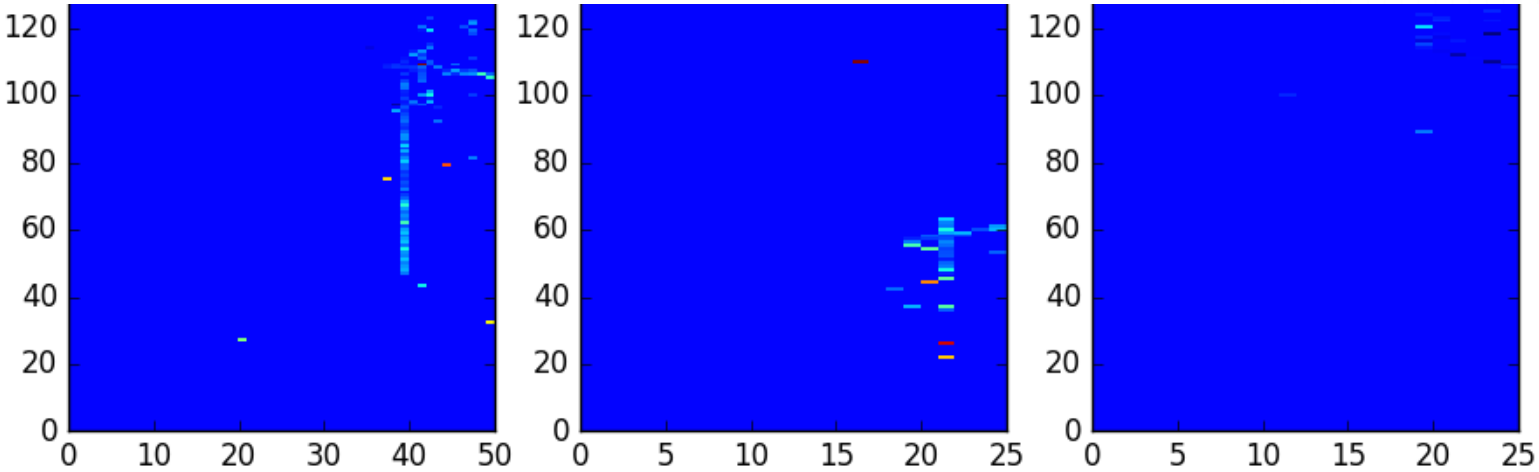
Source: A. Terwilliger, et al. Vertex Reconstruction of Neutrino Interactions using Deep Learning. IJCNN 2017.

Two Data Inputs Types (Three Views)

Deep Learning: Energy values as interpreted as pixels



Spiking: Time when energy deposition goes over a very low threshold

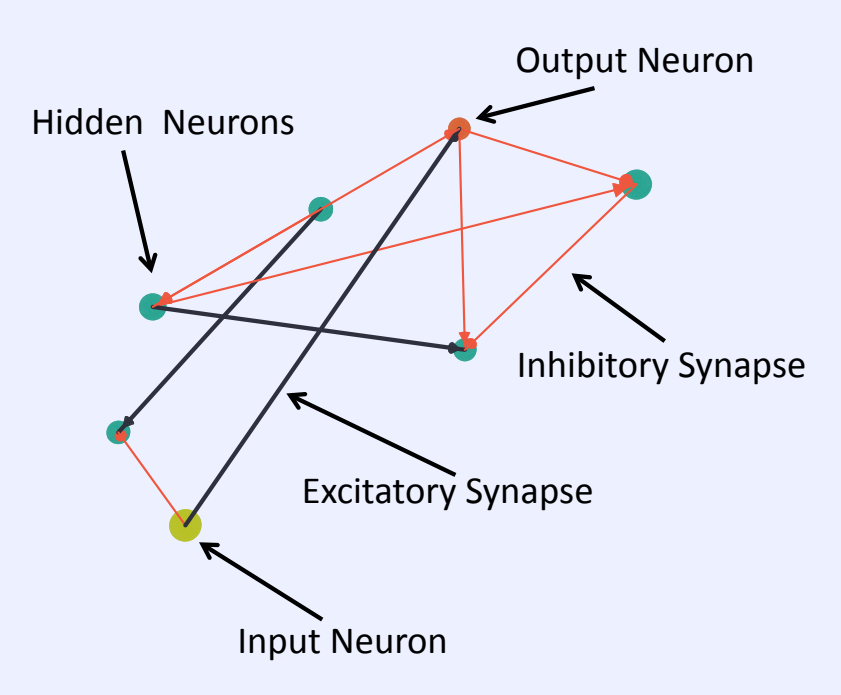


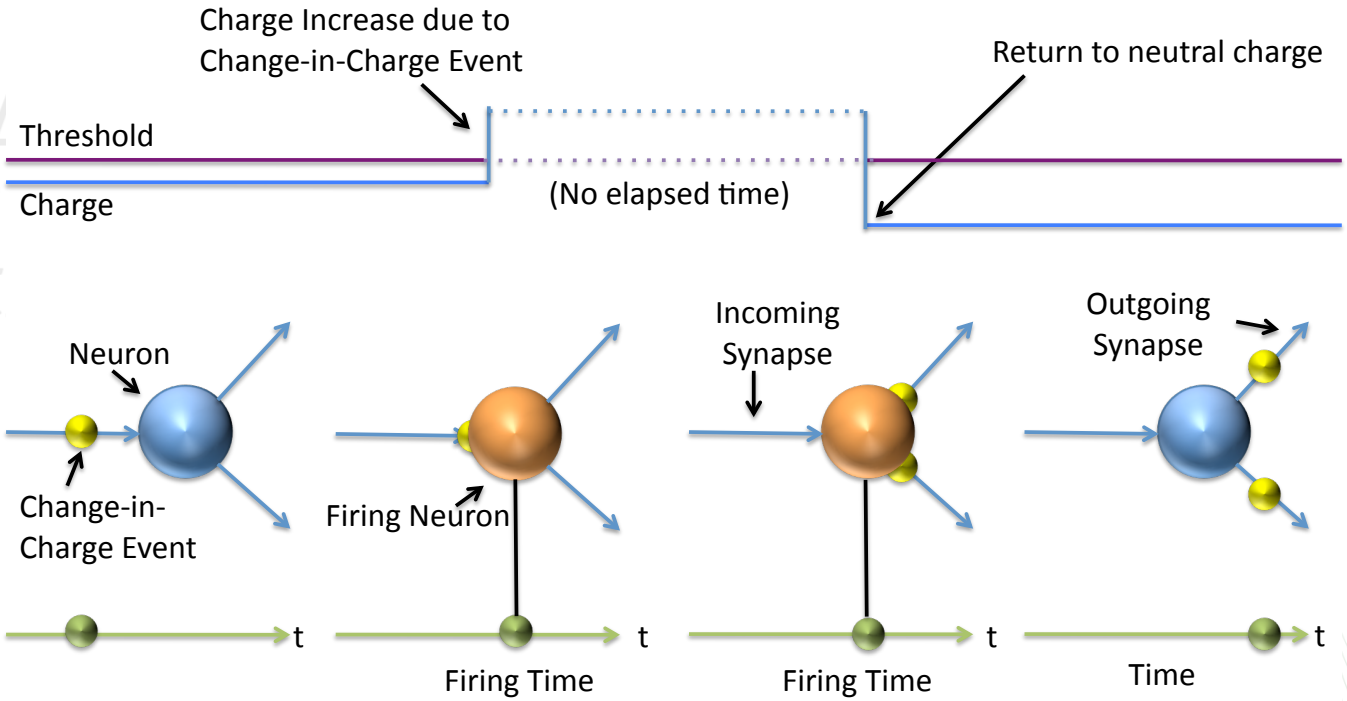
Two Approaches: Deep Learning and Spiking Neural Networks

	Deep Learning	Spiking
Training Method	Back-propagation	Not well established (here, genetic algorithms)
Native Input Types	Images/Arrays of values	Spikes
Network Size	Large (many layers, many neurons and synapses per layer)	Relatively small (fewer neurons and sparser synaptic connections)
Processing Abilities	Good for spatial	Good for temporal
Performance	Well understood and state-of-the-art	Not well understood

Neuroscience-Inspired Dynamic Architectures (NIDA)

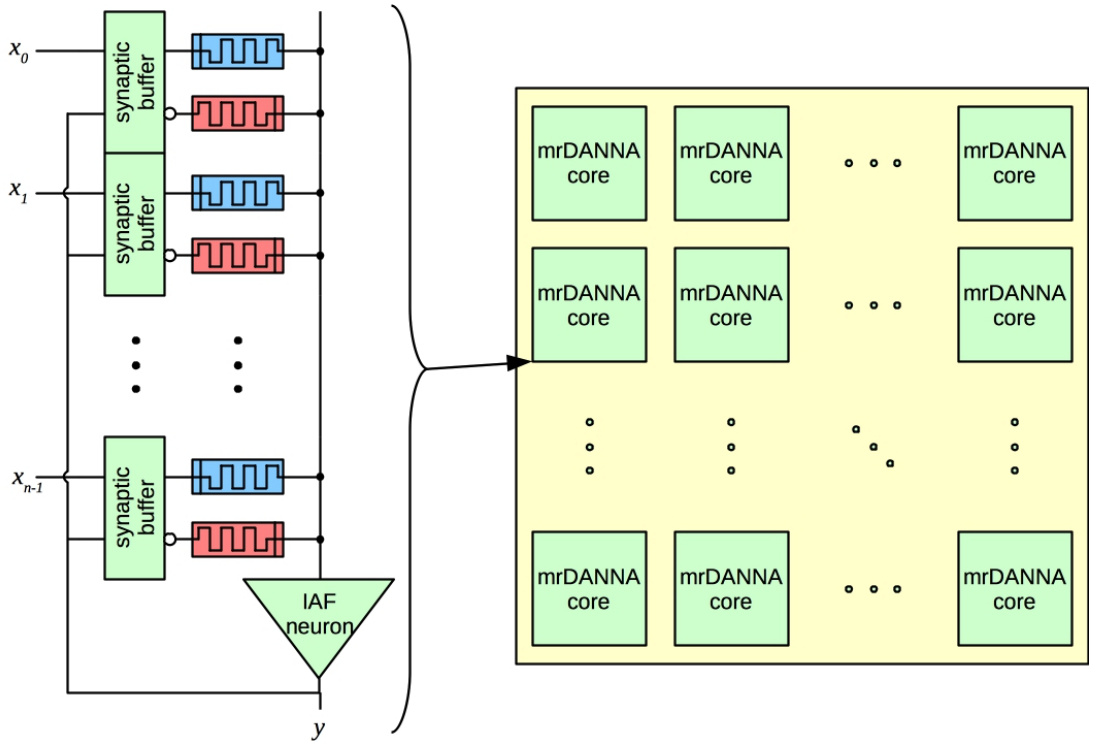
- Spiking neural network embedded in 3D space.
- Simple neuron and synapse implementation.
- Flexible structure.



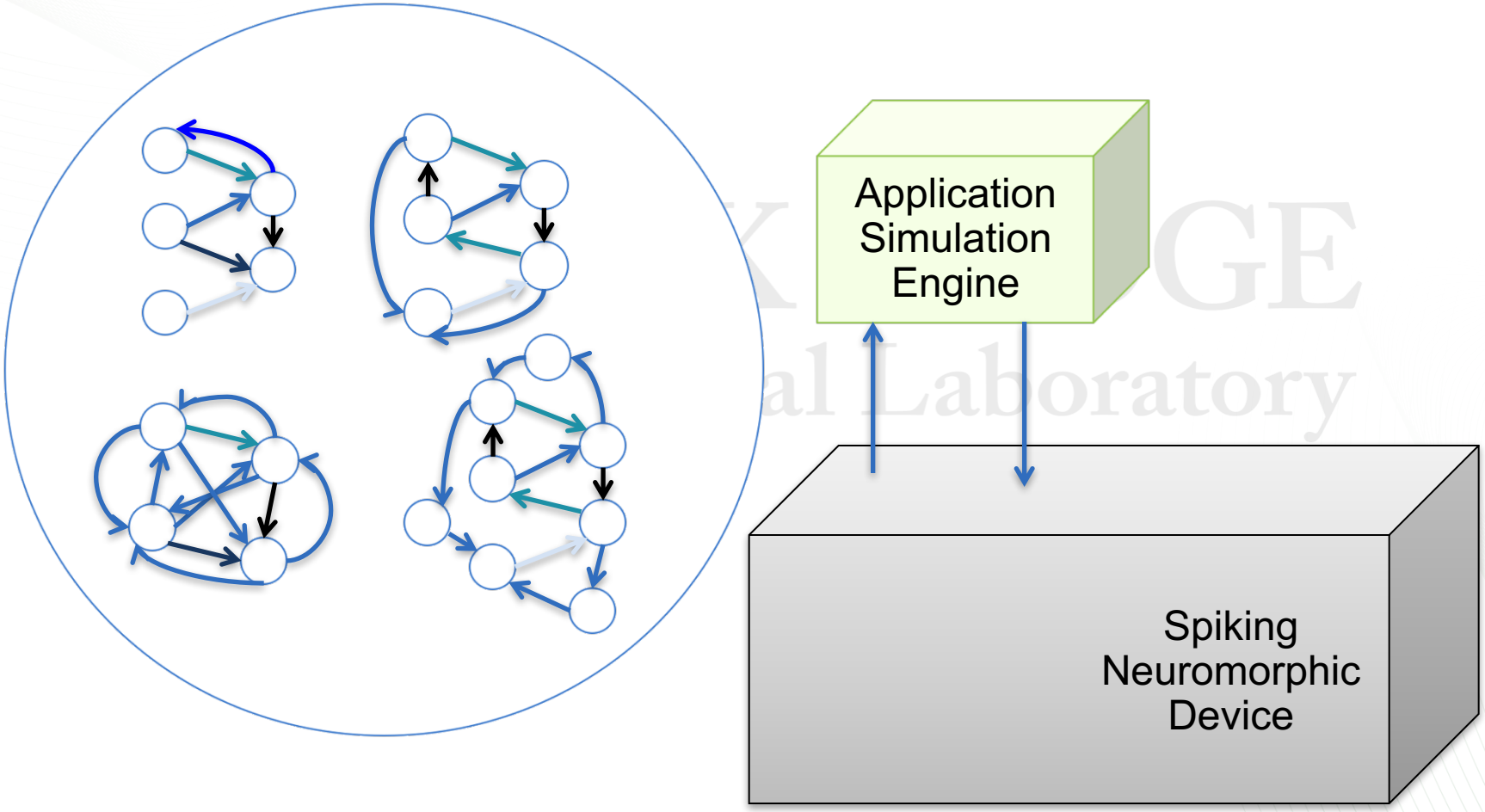


Memristive DANNA (mrDANNA)

- Mixed analog/digital implementation.
  - Mixed signal analog neurons.
  - Each synaptic weight is implemented with two memristors.
- More restrictive in terms of achievable weights than DANNA.
- Lower energy, better scaling than digital implementations.



Training: Evolutionary Optimization



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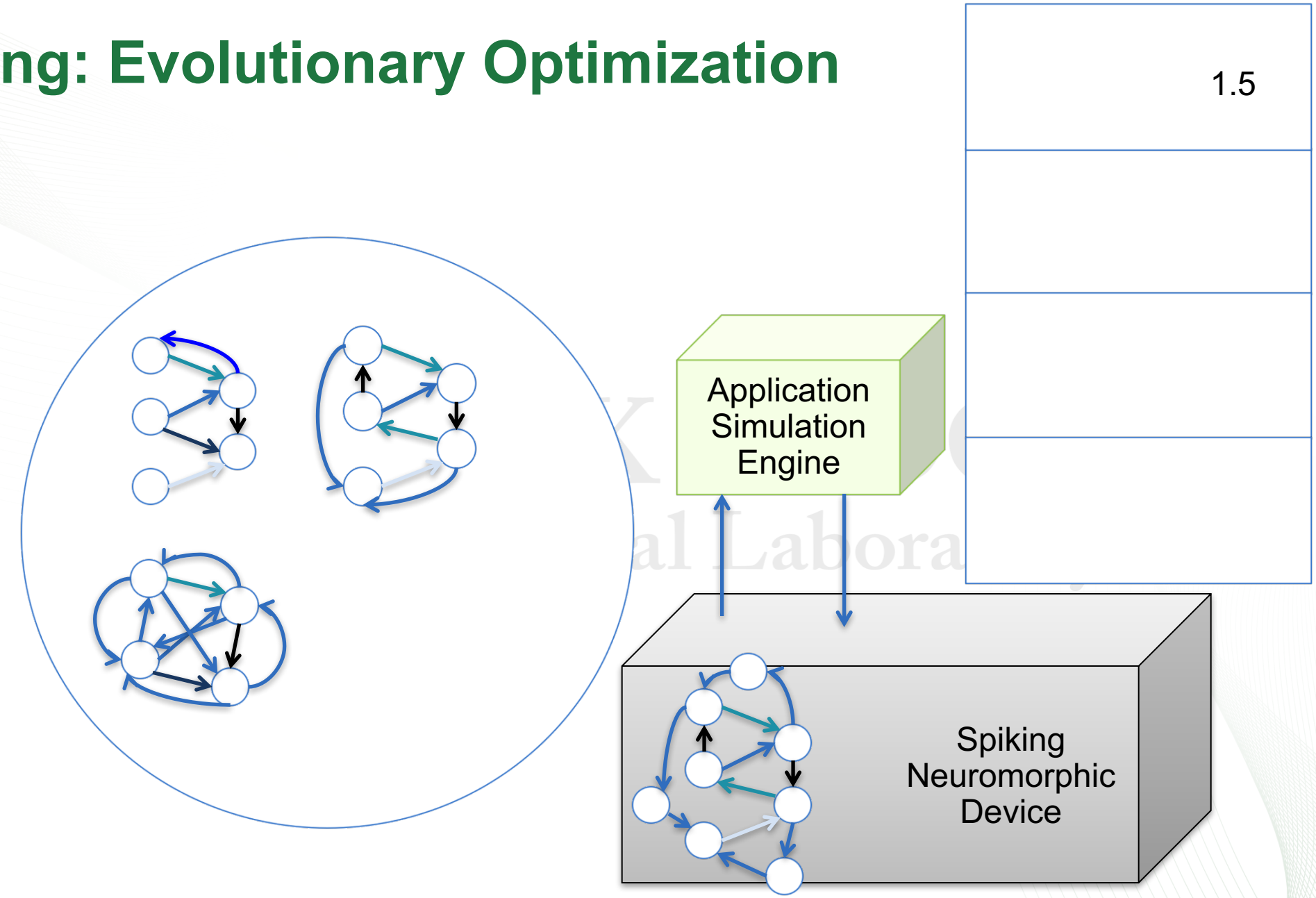

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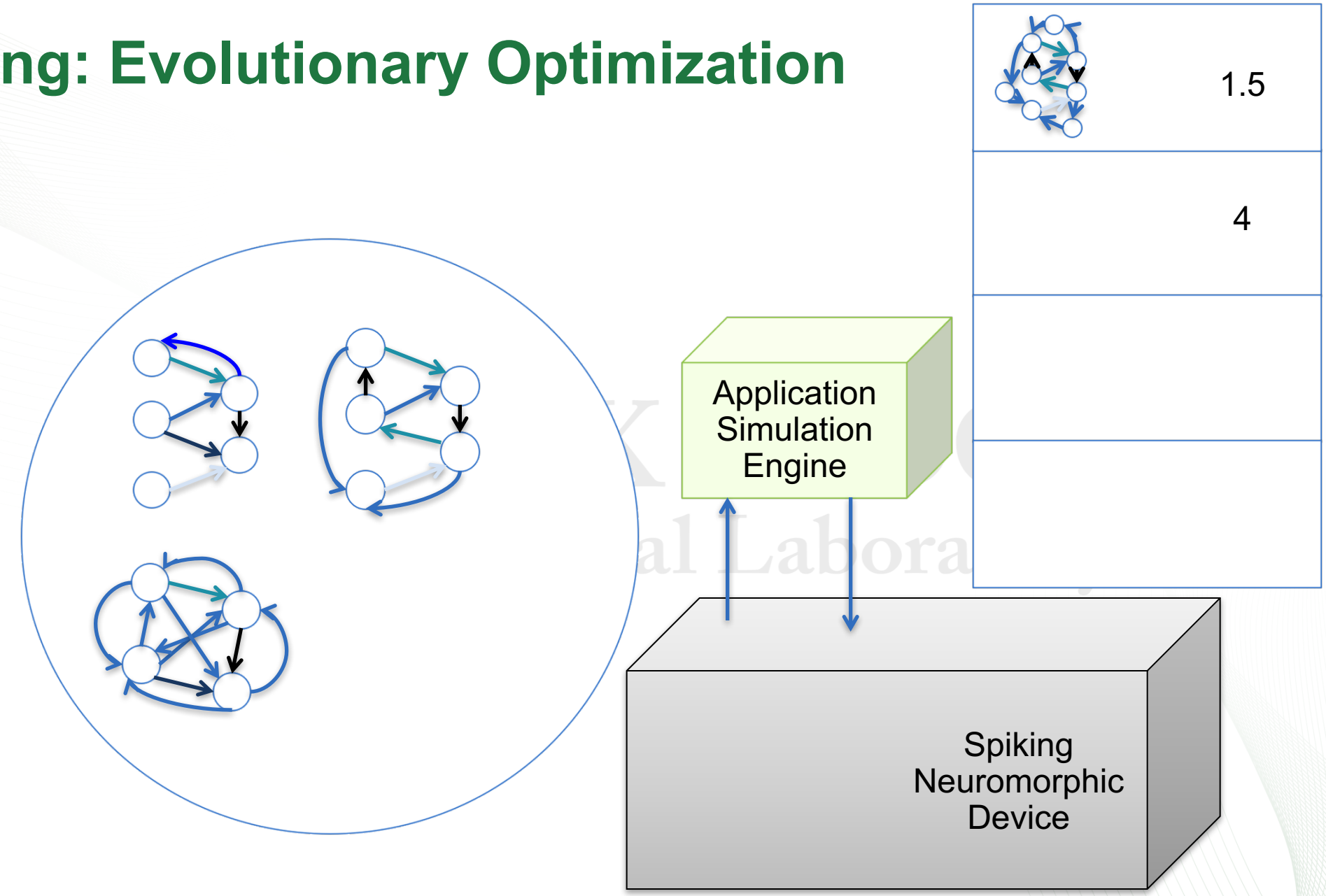

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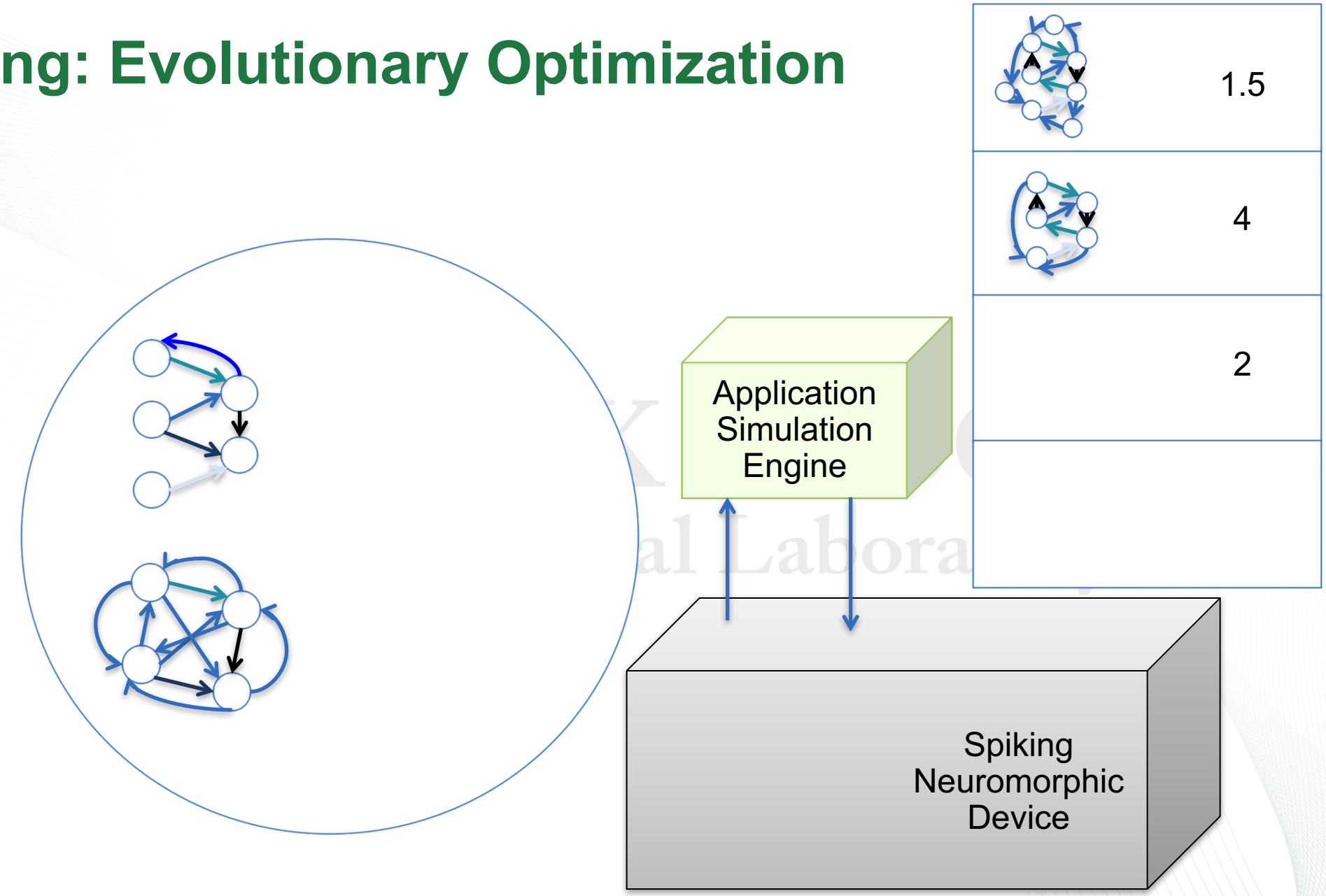

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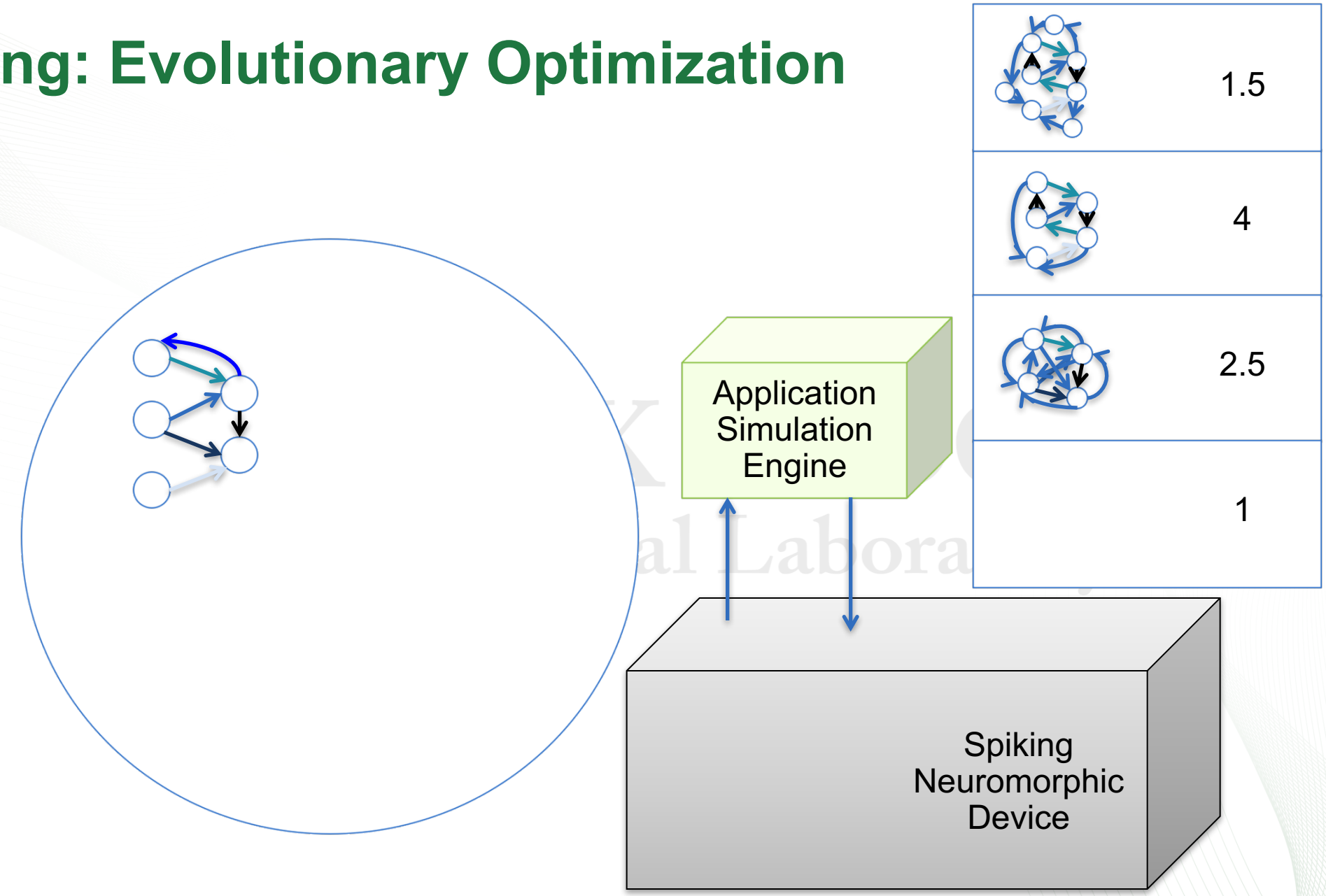

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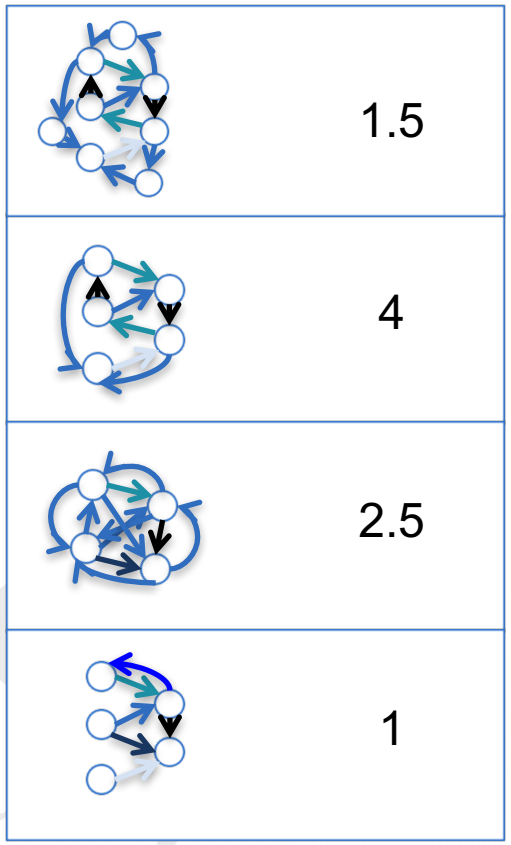

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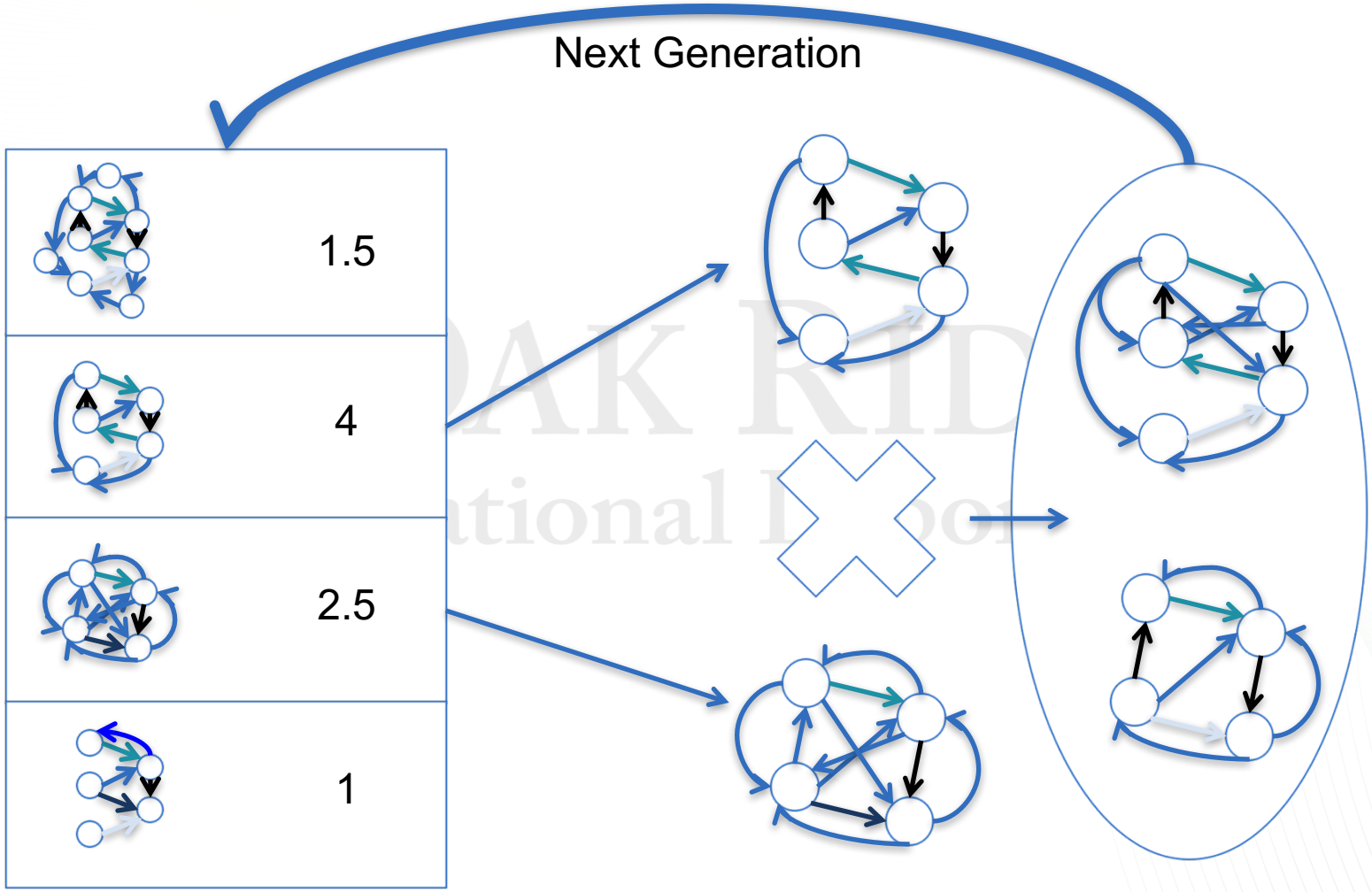
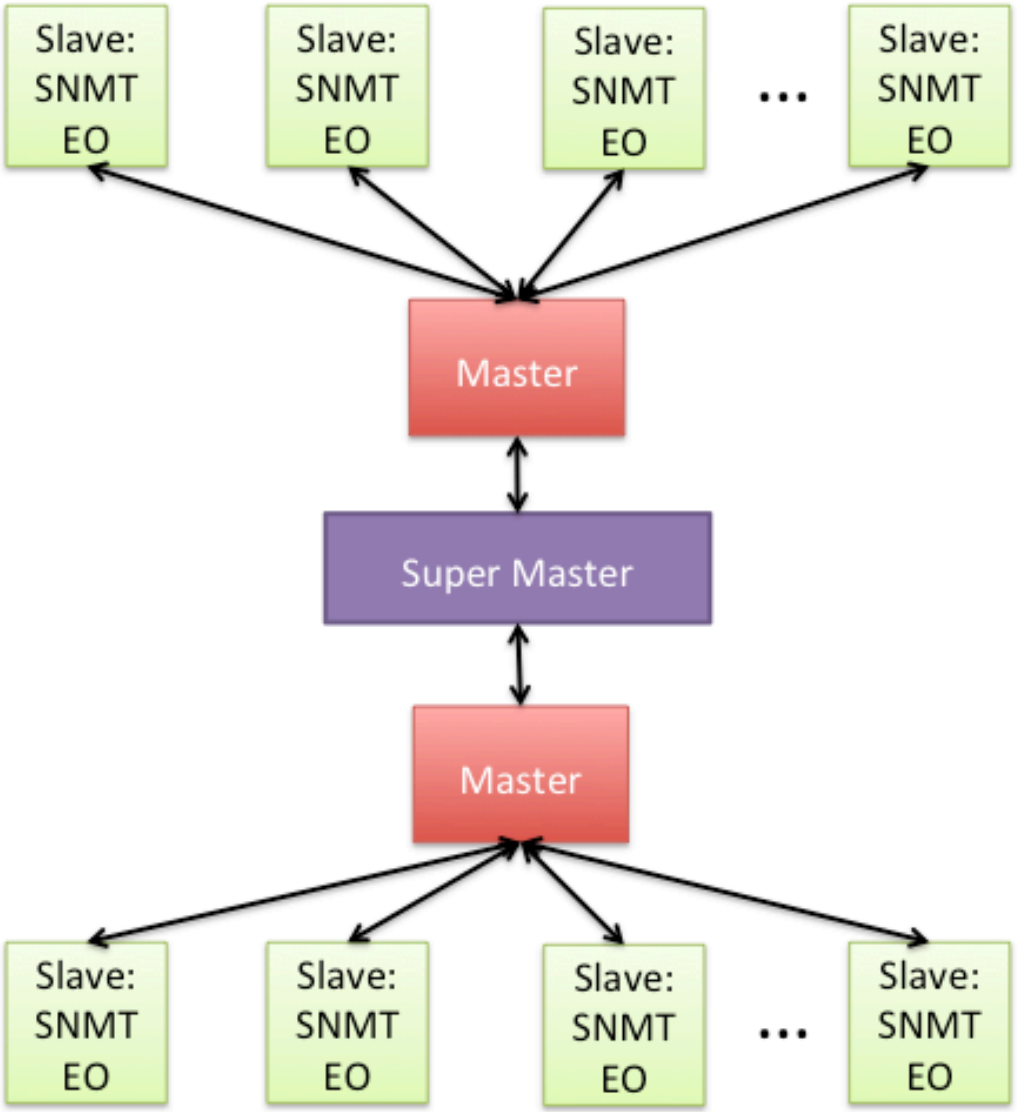


Parallel EO Approach



Preliminary Results

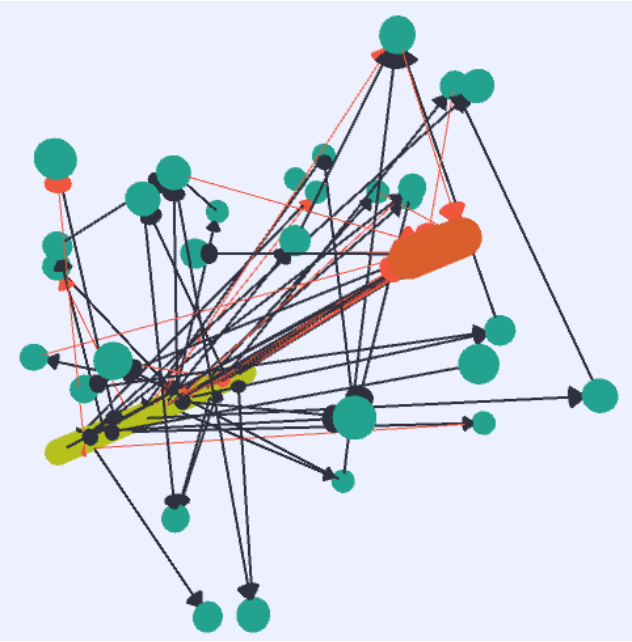
Number of Nodes	Maximum Classification Accuracy after One Hour
100	70.82%
1000	72.6%
10000	79.11%

This research used resources of the Oak Ridge Leadership Computing Facility, which is a DOE Office of Science User Facility supported under Contract DE-AC05-00OR22725.

Best Results: Single View

x-view (127x50)	conv1 (8x3)	pool1 (2x1)	conv2 (7x3)	pool2 (2x1)	conv3 (6x3)	pool3 (2x1)	conv4 (6x3)	pool4 (2x1)	fc1 (196)	drop out	fc2 (98)	drop out	fc3 (11)	classification

Convolutional Neural Network Result: ~80.42%



- 90 neurons, 86 synapses
- Estimated energy for a single classification for mrDANNA implementation: 1.66 μJ

Spiking Neural Network Result: ~80.63%

Source for CNN results: A. Terwilliger, et al. Vertex Reconstruction of Neutrino Interactions using Deep Learning. IJCNN 2017.

Future Work

- Incorporate three views of Fermilab data:
  - Preliminary results on u-view and v-view
- Train specifically for mrDANNA and DANNA (fully digital neuromorphic implementation for FPGA) on Titan.
- Combine deep learning and neuromorphic results.
- Coordinate with domain scientists on applying spiking neuromorphic systems to other temporal scientific data sets.

Conclusion

- An important use case for spiking neuromorphic systems can be processing temporal scientific data.
  - We have achieved classification results that are comparable with convolutional neural network results on the same task.
  - The domain scientists have expressed interested in low-power in situ classifiers to be used on or near their detectors.
- DOE is well-positioned to tackle these issues:
  - Data/Application: High energy physics, materials science, advanced manufacturing, etc.
  - Computing resources for training: OLCF, ALCF, etc.
  - Exciting work in building and using new neuromorphic systems

Collaborators

THE UNIVERSITY OF TENNESSEE KNOXVILLE

TENN LAB NEUROMORPHIC ARCHITECTURES. LEARNING. APPLICATIONS.

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