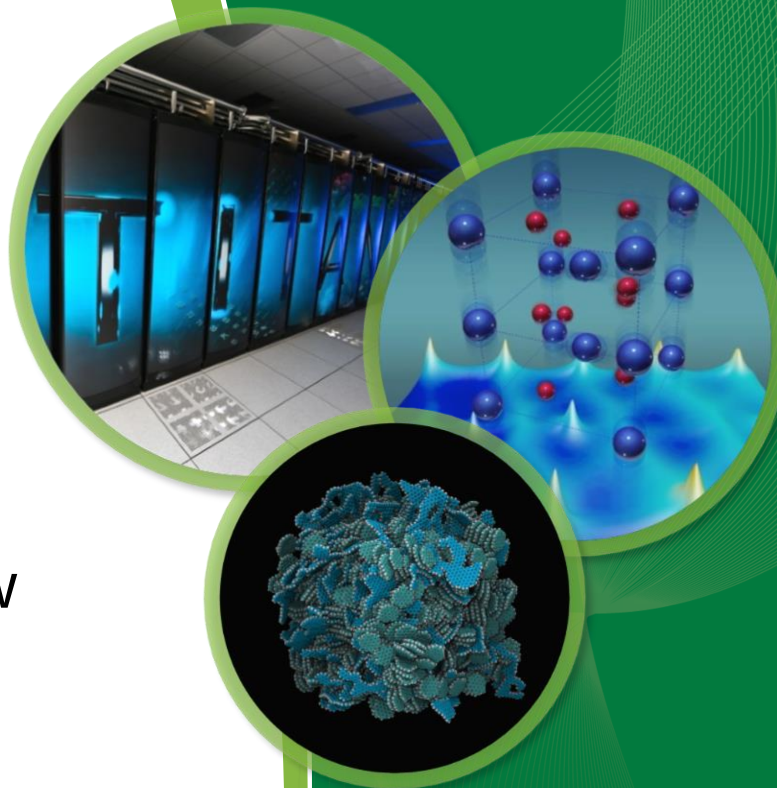
Parallel Evolutionary Optimization for Neuromorphic Network Training



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Computational Data Analytics

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Neuromorphic Computing

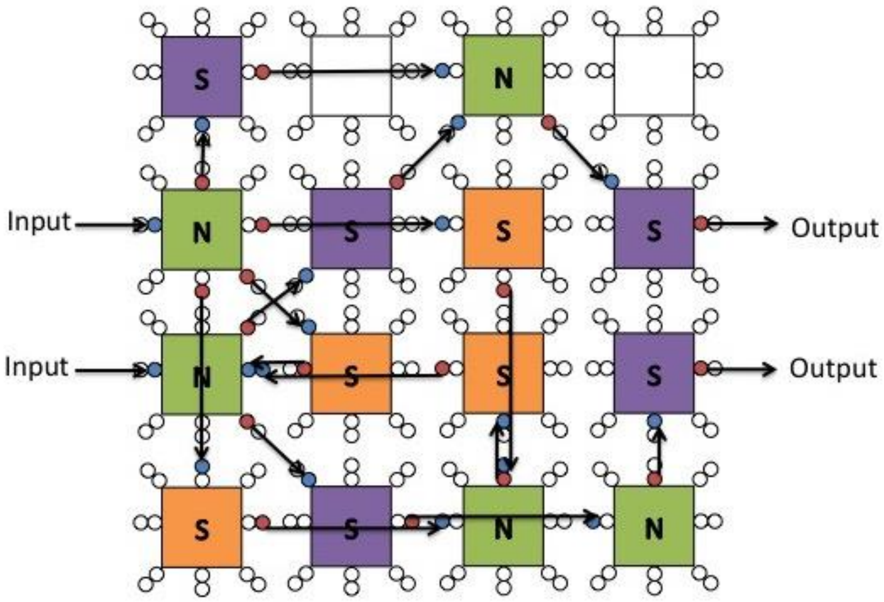
- Neuromorphic computing systems are software/hardware systems that are inspired by biological brains.
  - Neural networks in hardware.
- Goal is to capture important capabilities of the biological brain: real-time processing abilities, generalization of learned information, adaptability to changes in the environment, robustness.
- Neuromorphic hardware: improvements in power, size/portability, computation time, communication costs over neuromorphic simulations.

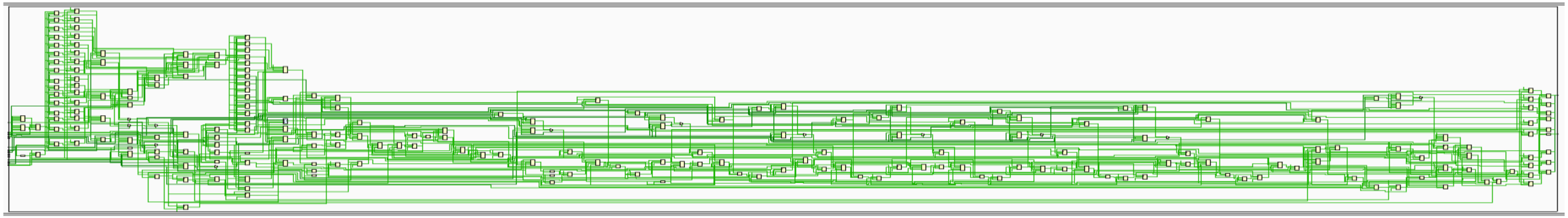
Neuromorphic Computing

- What characterizes a neuromorphic computer?
  - Many simple processor/memory structures (e.g., neurons and synapses).
  - Communication using simple messages (e.g., spikes).
  - Algorithms usually emphasize temporal interaction.
    - Messages have a time-stamp (implicit or explicit).
    - Operation is usually event-driven.

Dynamic Adaptive Neural Network Array (DANNA)

- Array of programmable neuromorphic elements.
- Elements can connect to to 16 neighbors.
- Current: FPGA.
- Future: VLSI, memristors





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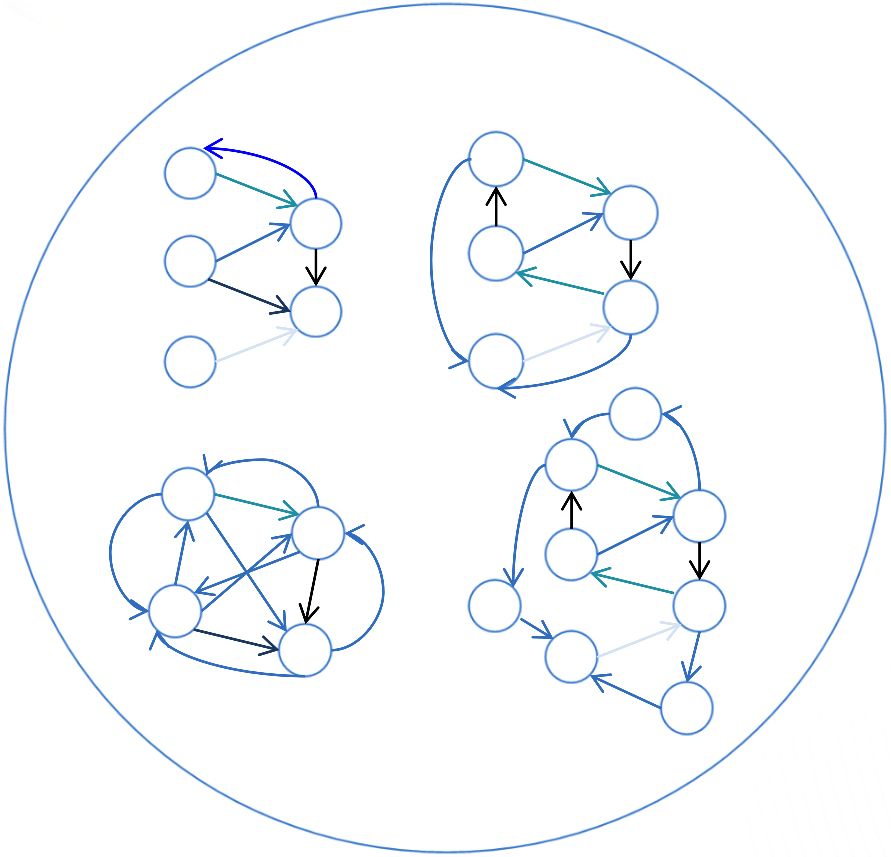
How do we program neuromorphic computers?

Example Training/Design: Evolutionary Optimization



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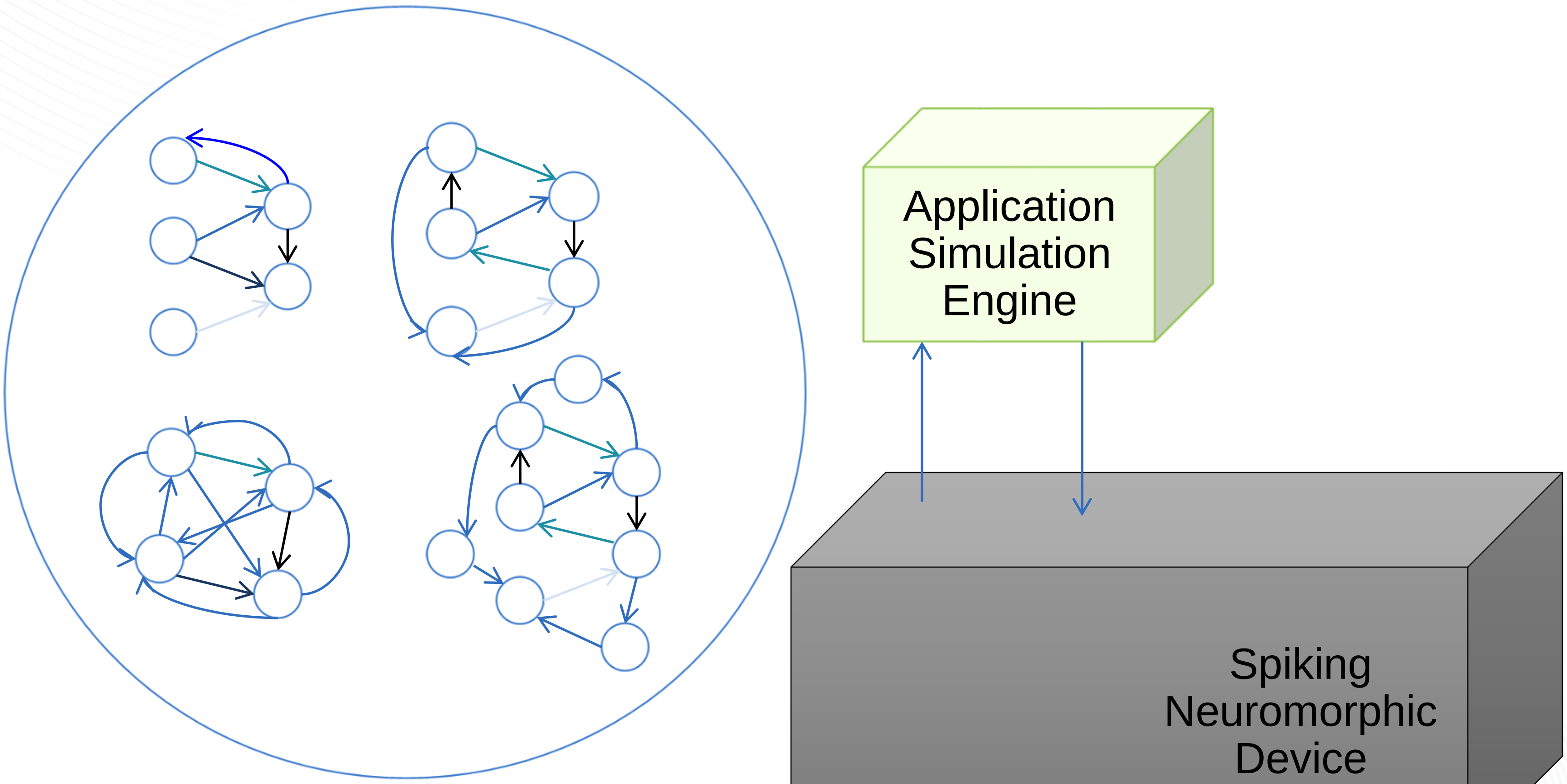

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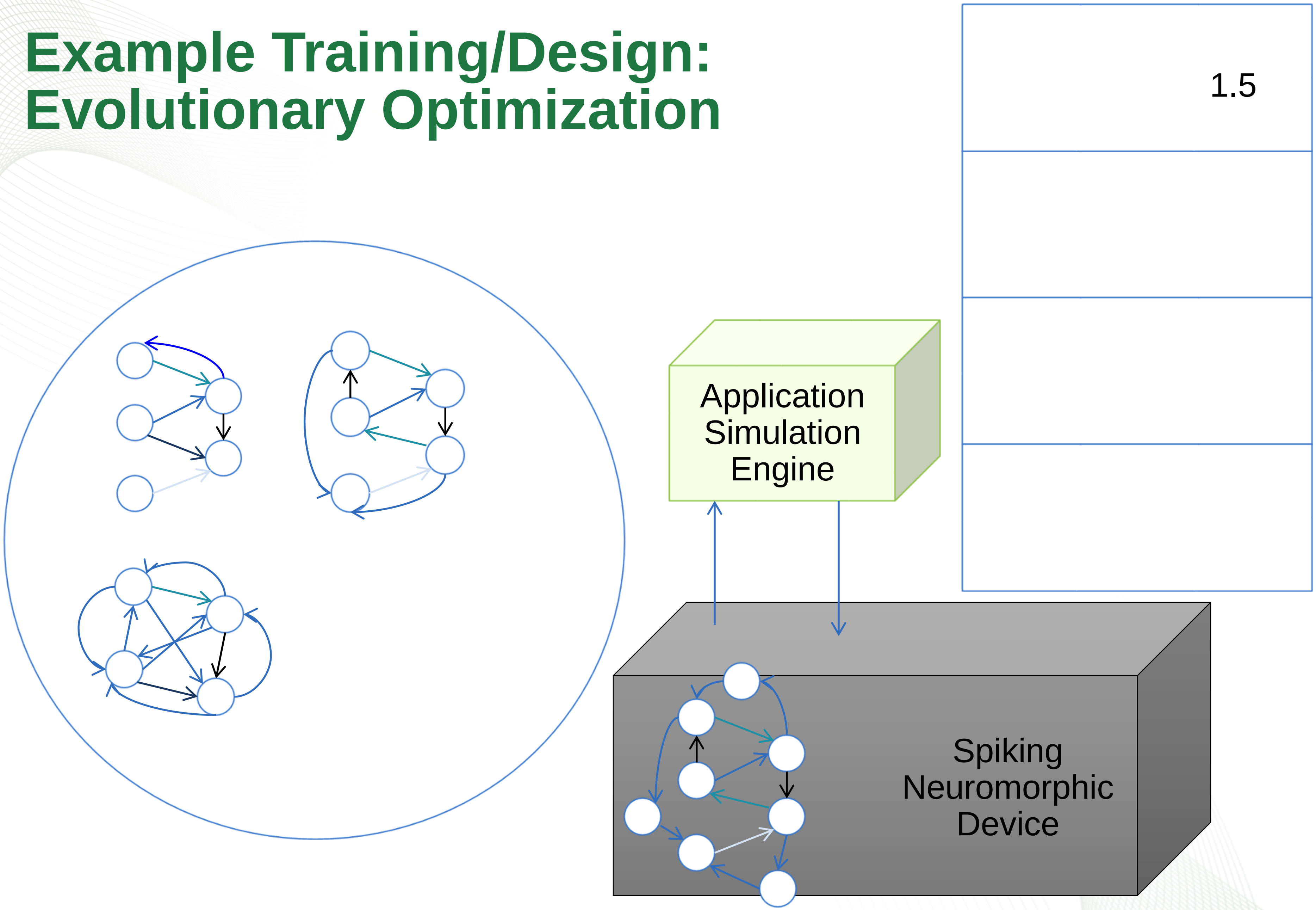

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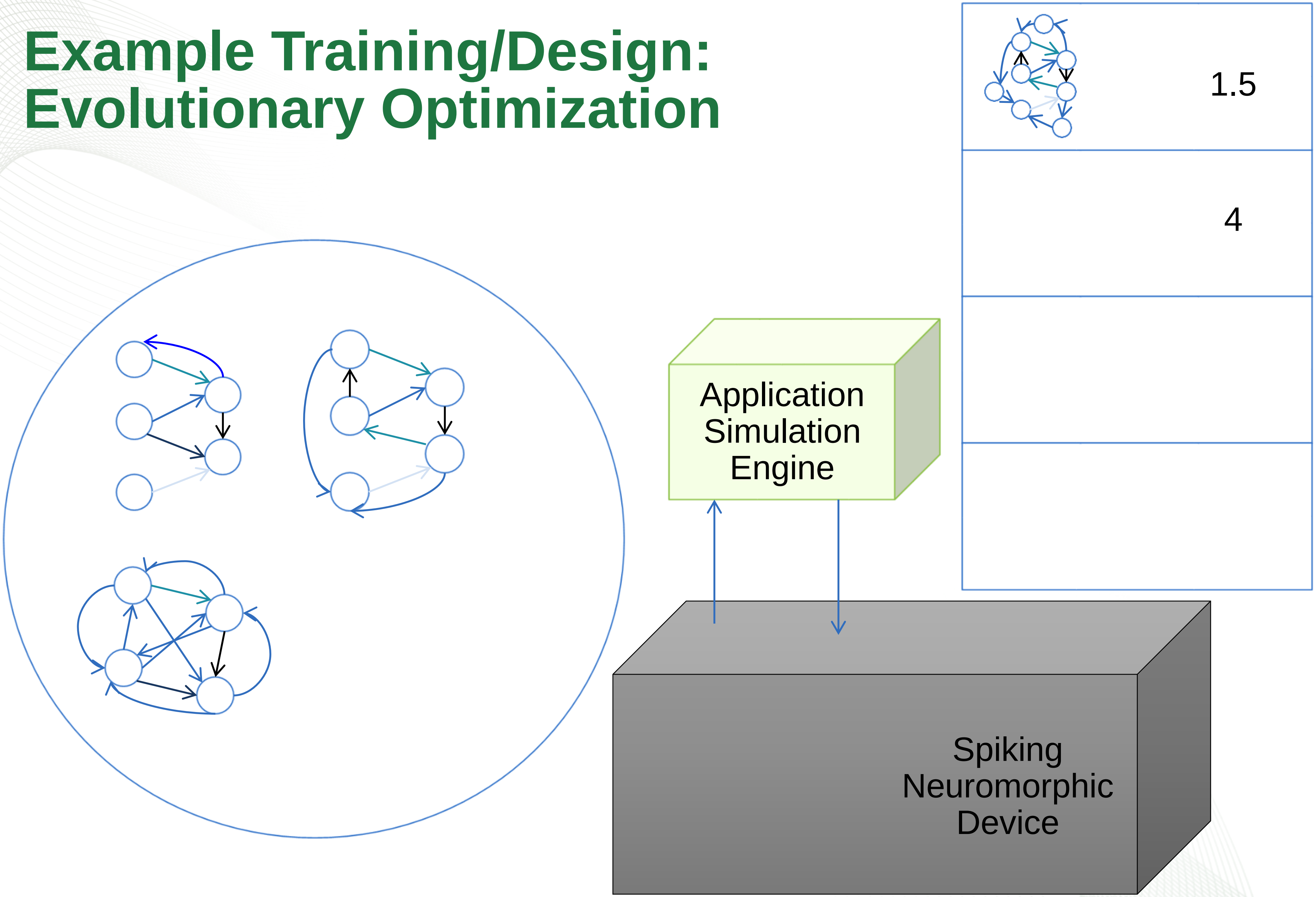

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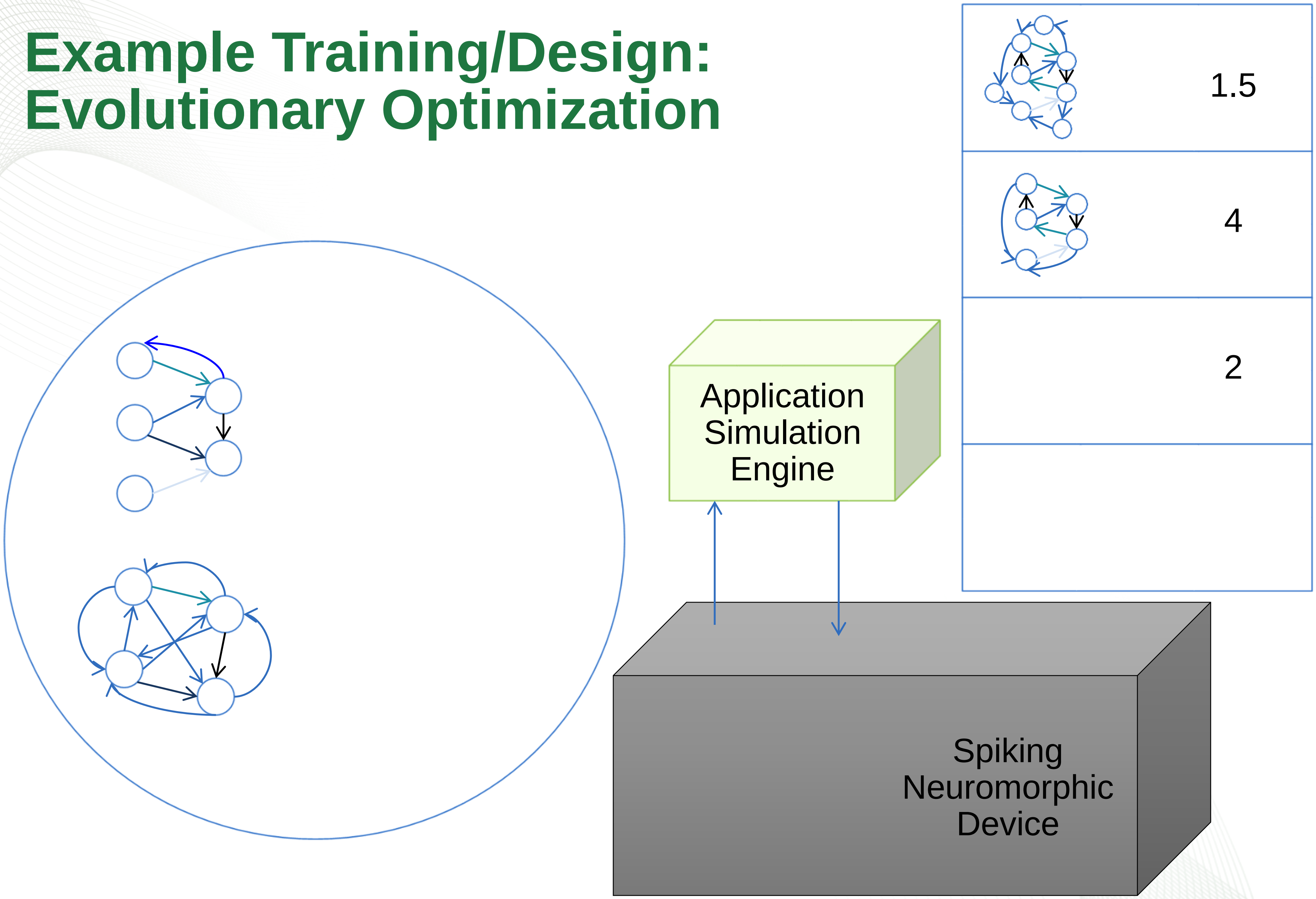

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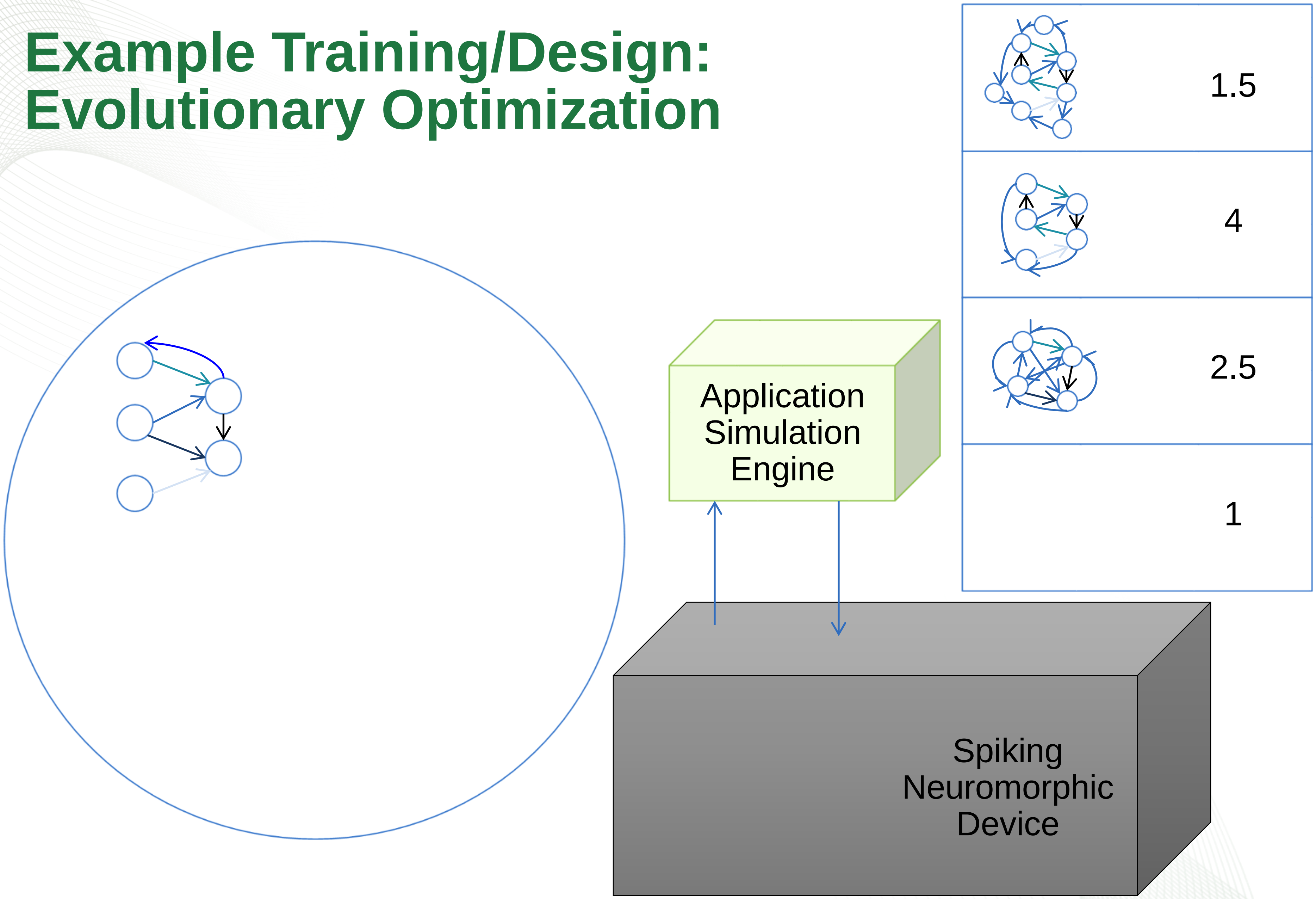

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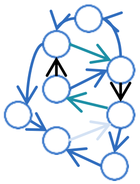
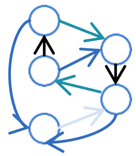
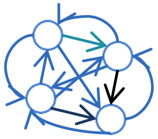
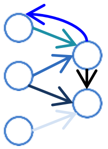
	1.5
	4
	2.5
	1

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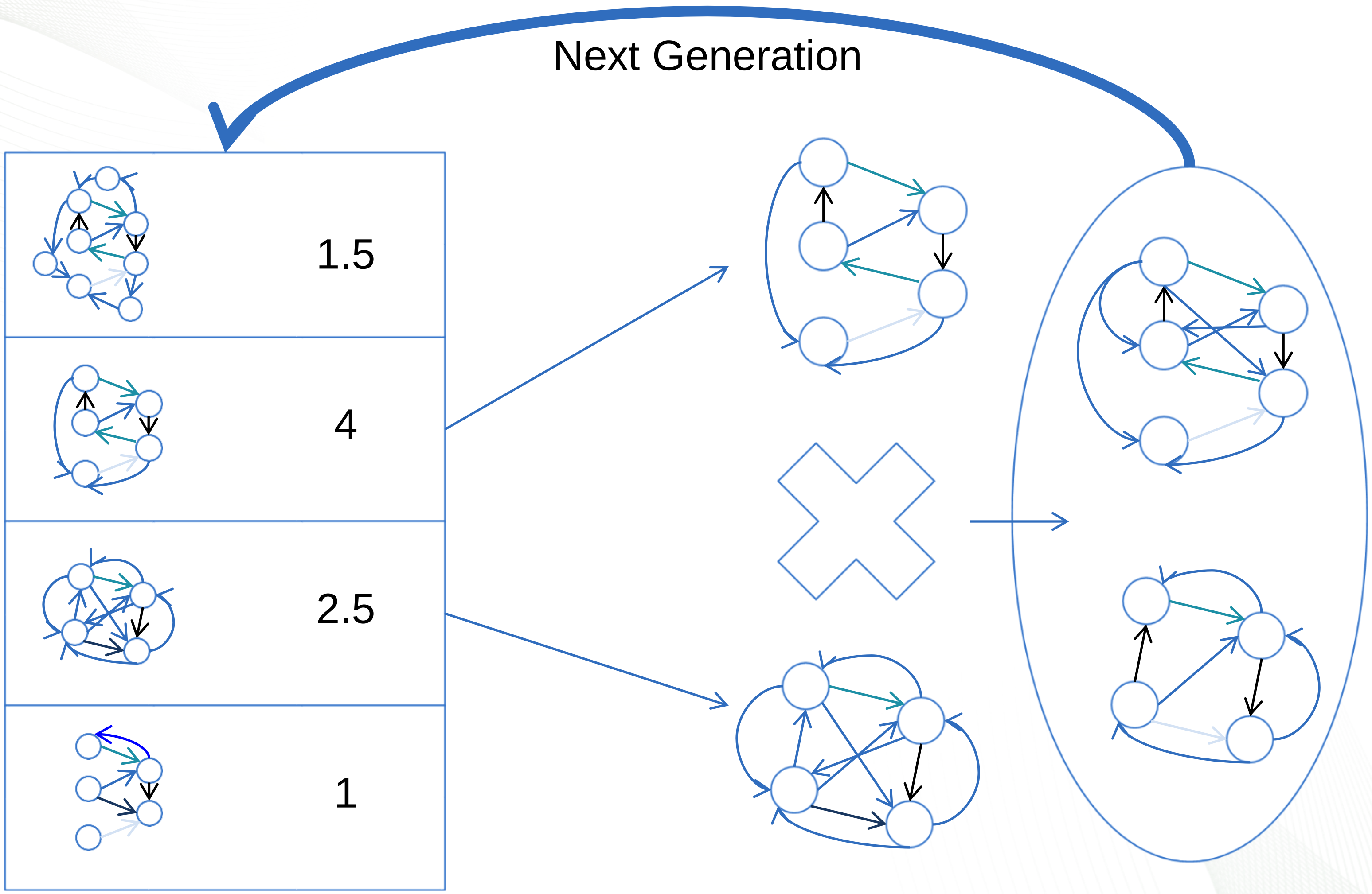
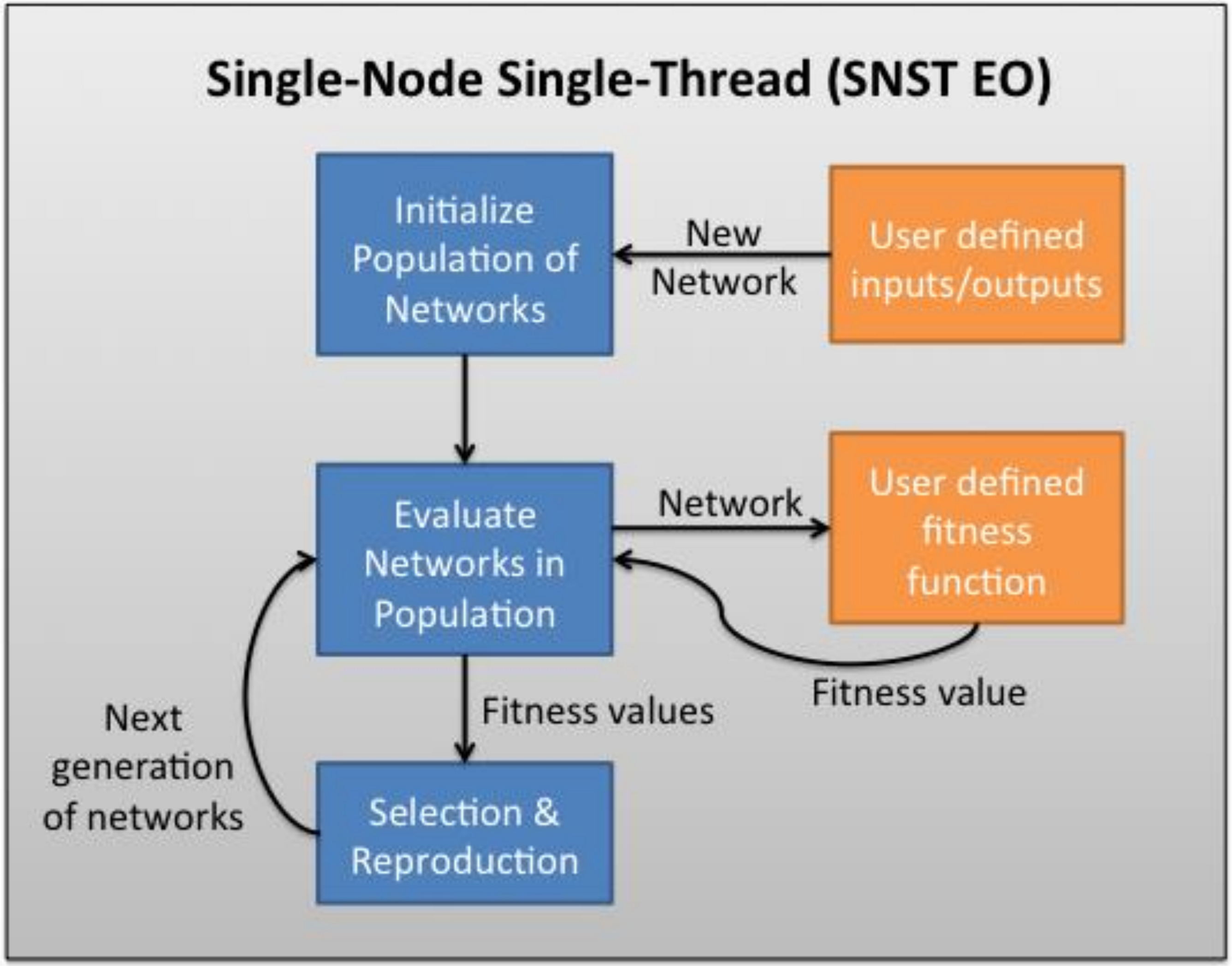


Single Node, Single Thread (SNST EO)



Improving EO Performance

- Fitness evaluation is a bottleneck:
  - Optimize neuromorphic simulator.
  - Parallelize fitness evaluation.
- Solution space for network solutions is large for complex problems:
  - Larger population sizes can allow for better exploration of the search space, leading to solutions more quickly.
  - Subpopulations with communication allow for diversity, but also knowledge sharing.

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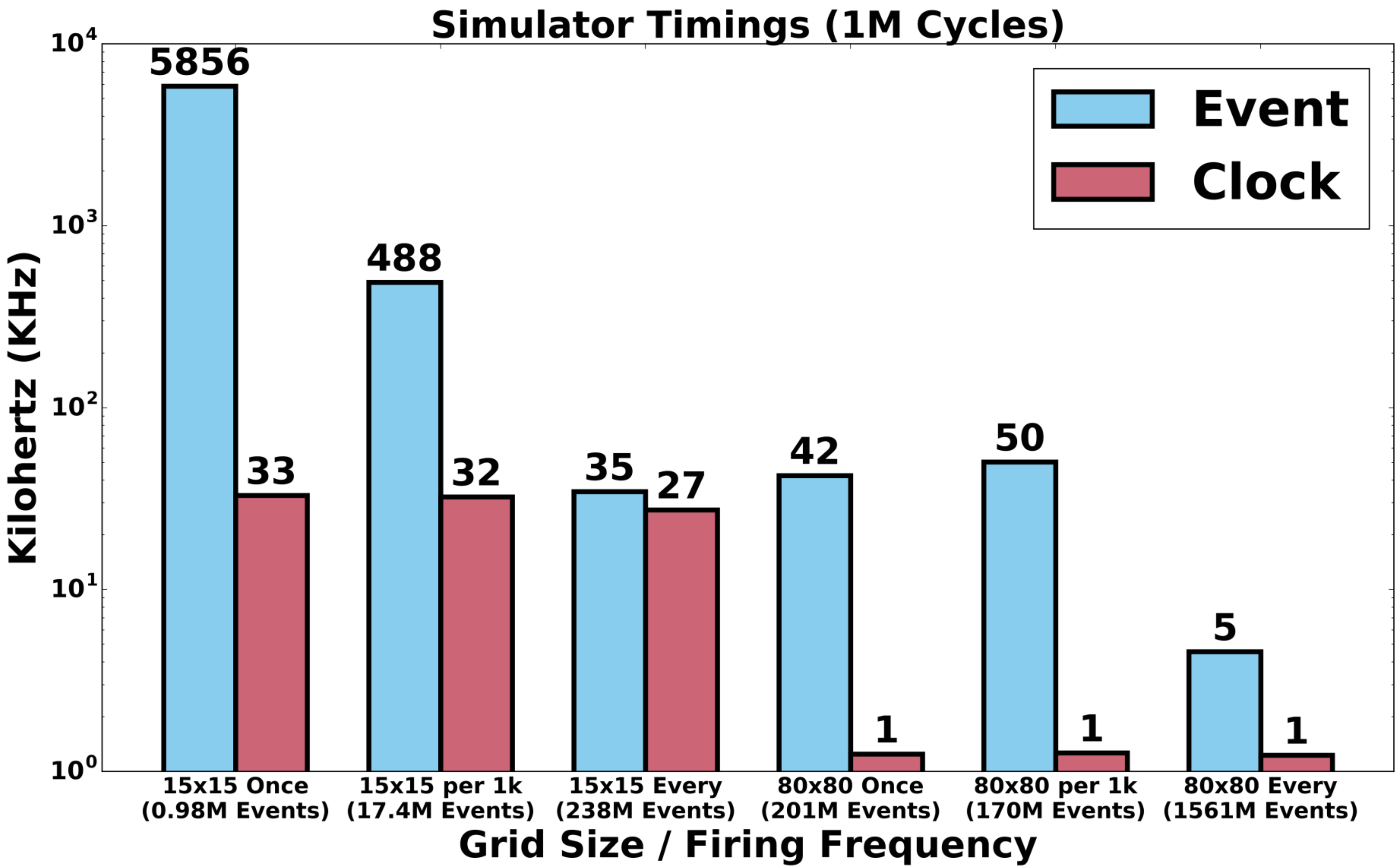
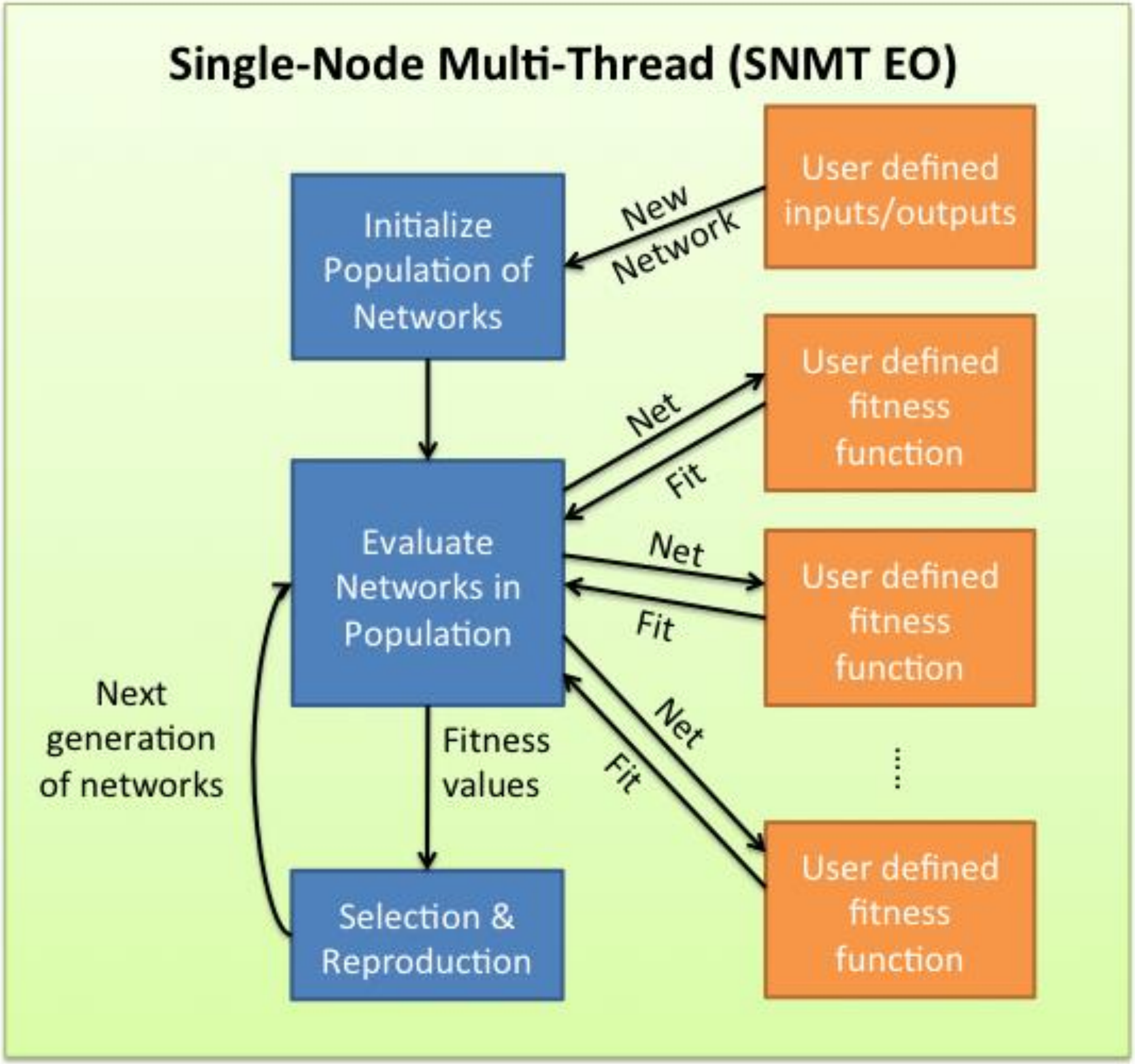
Simulator Performance



Single-Node Multi-Thread (SNMT EO)



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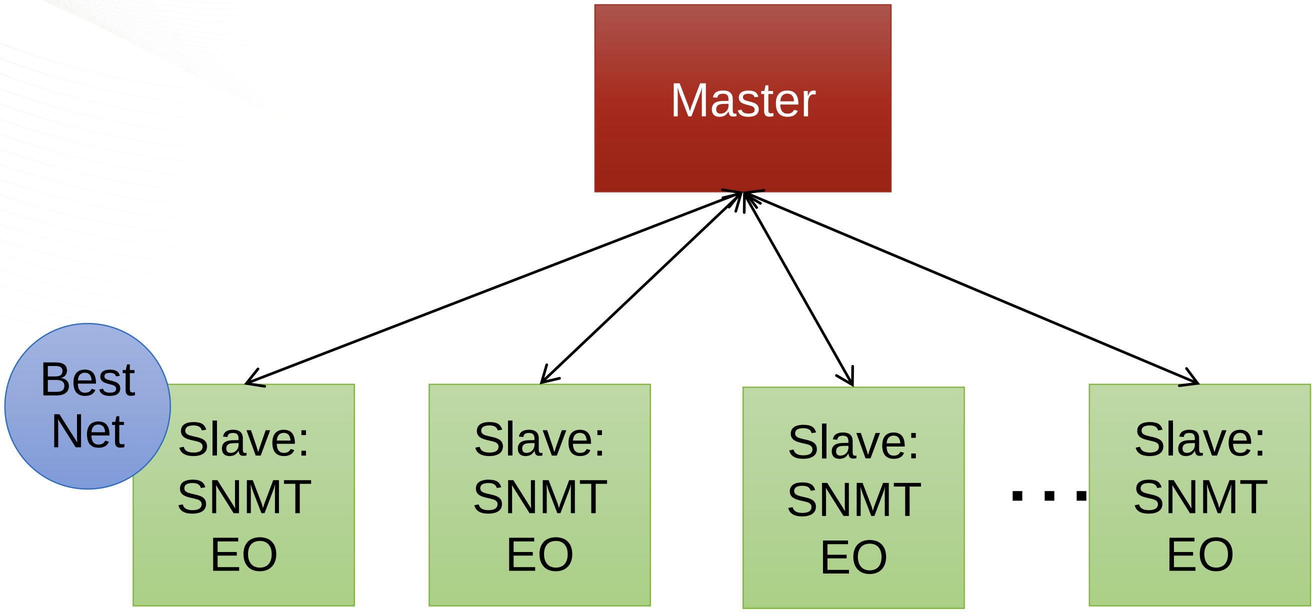
Multi-Node: Master-Slave



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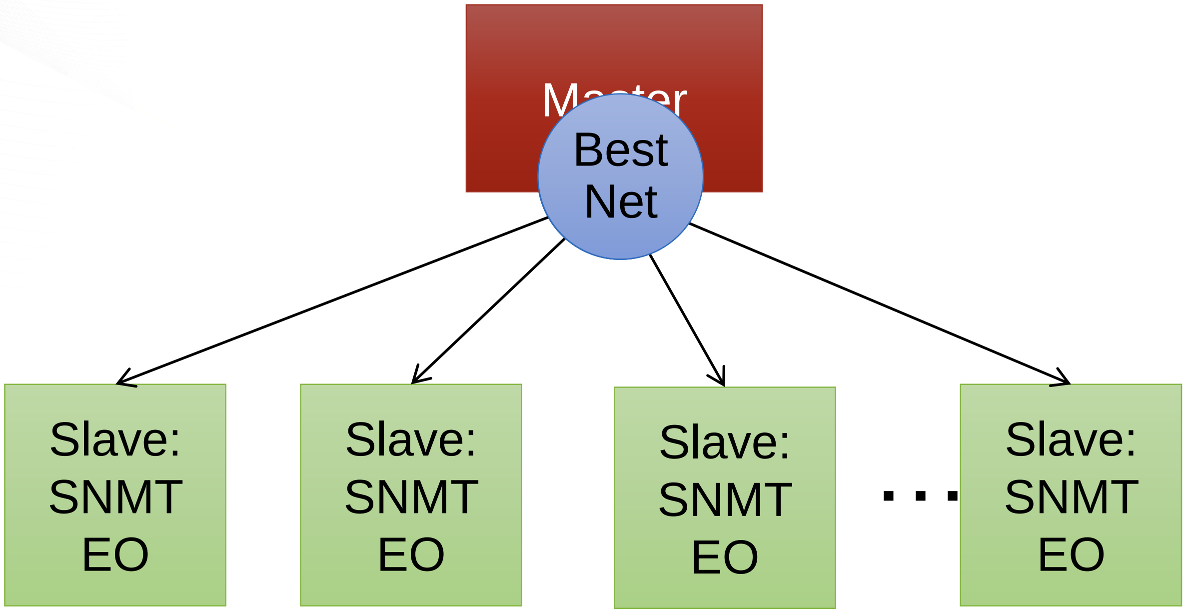
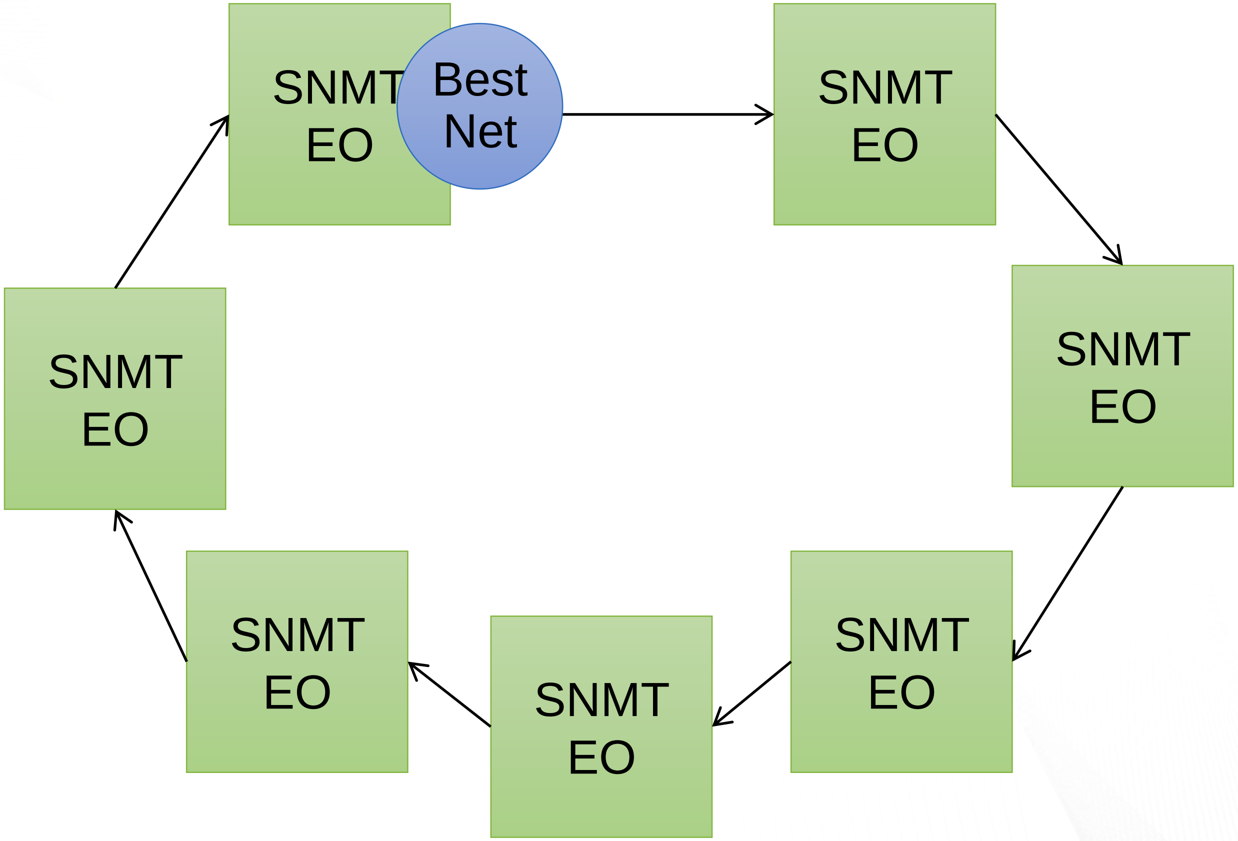


Direct Subpopulation to Subpopulation (SP2SP)



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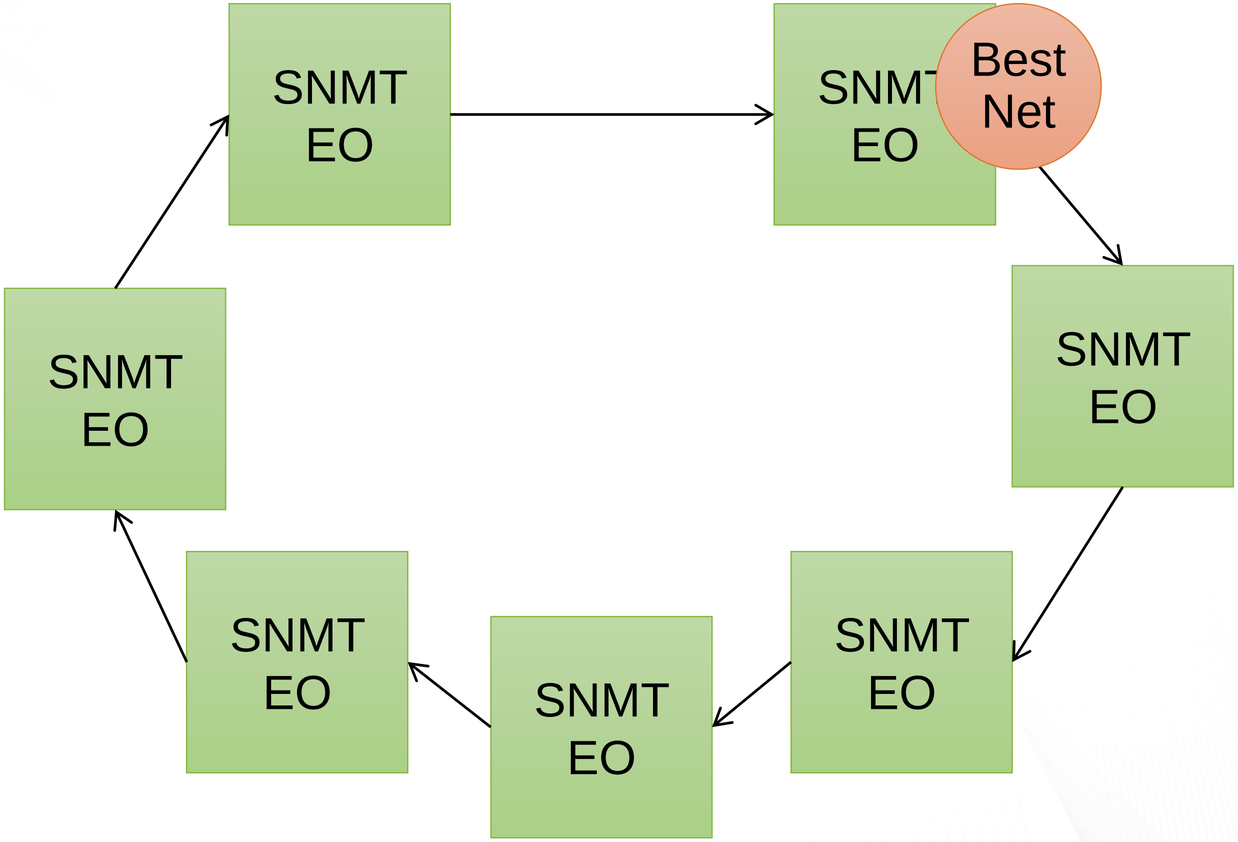

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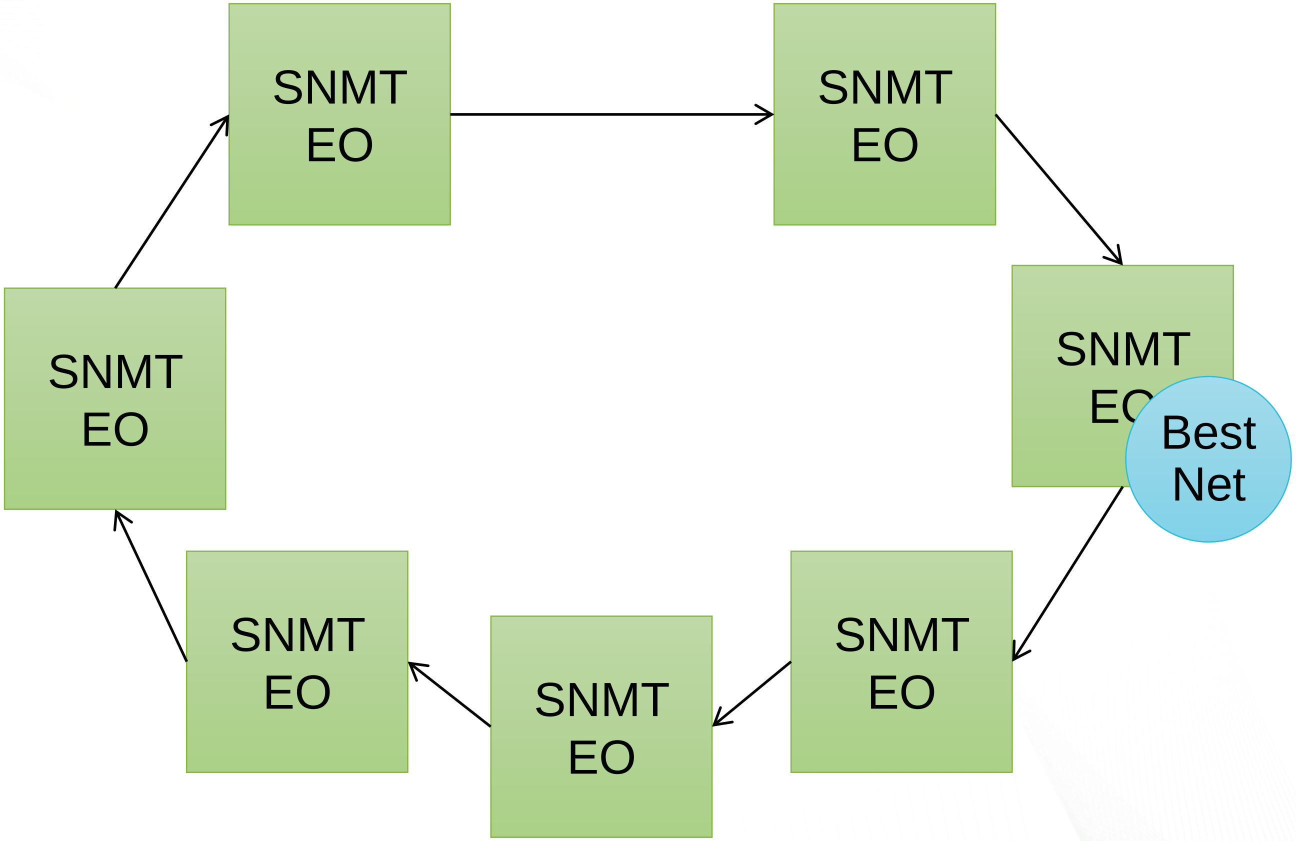

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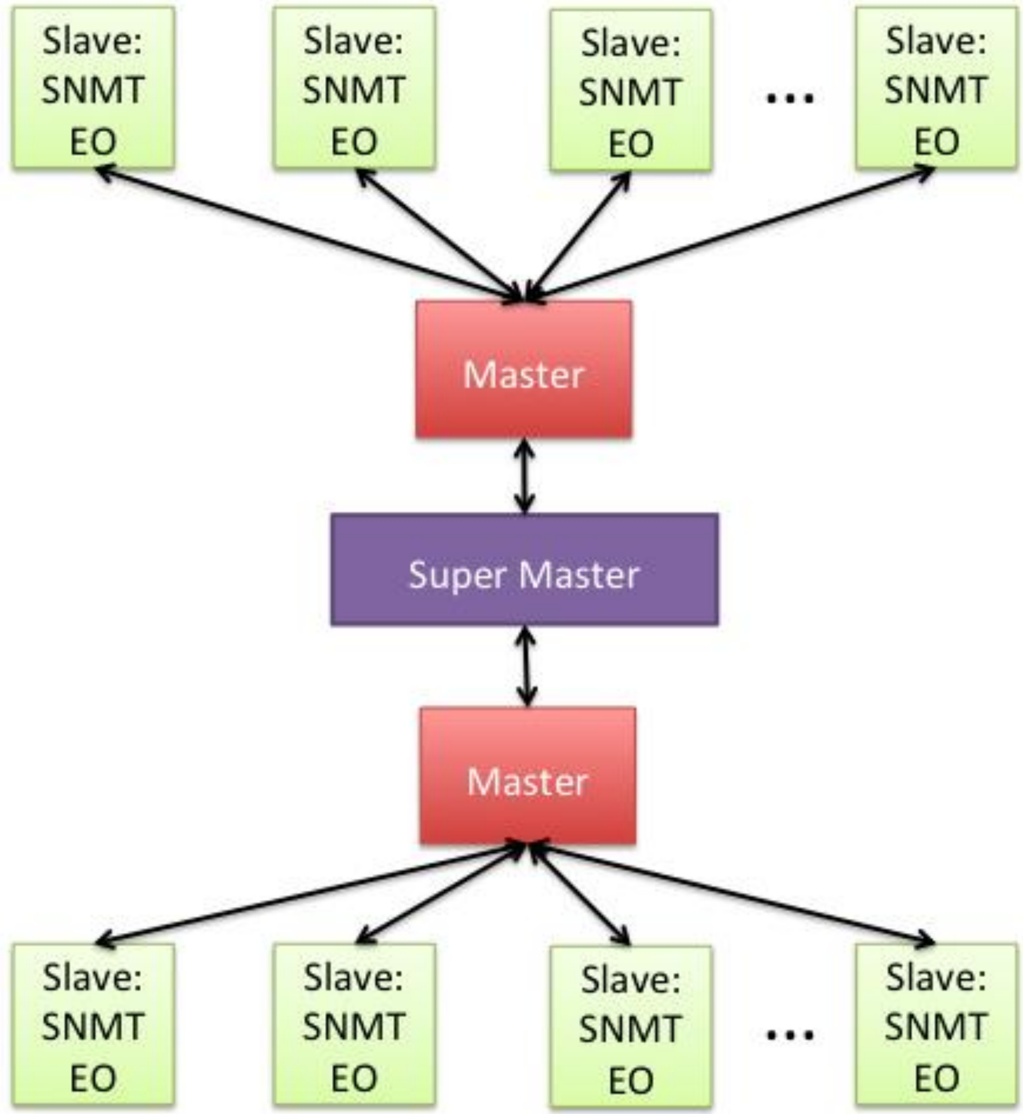
Super Master – Master-Slave



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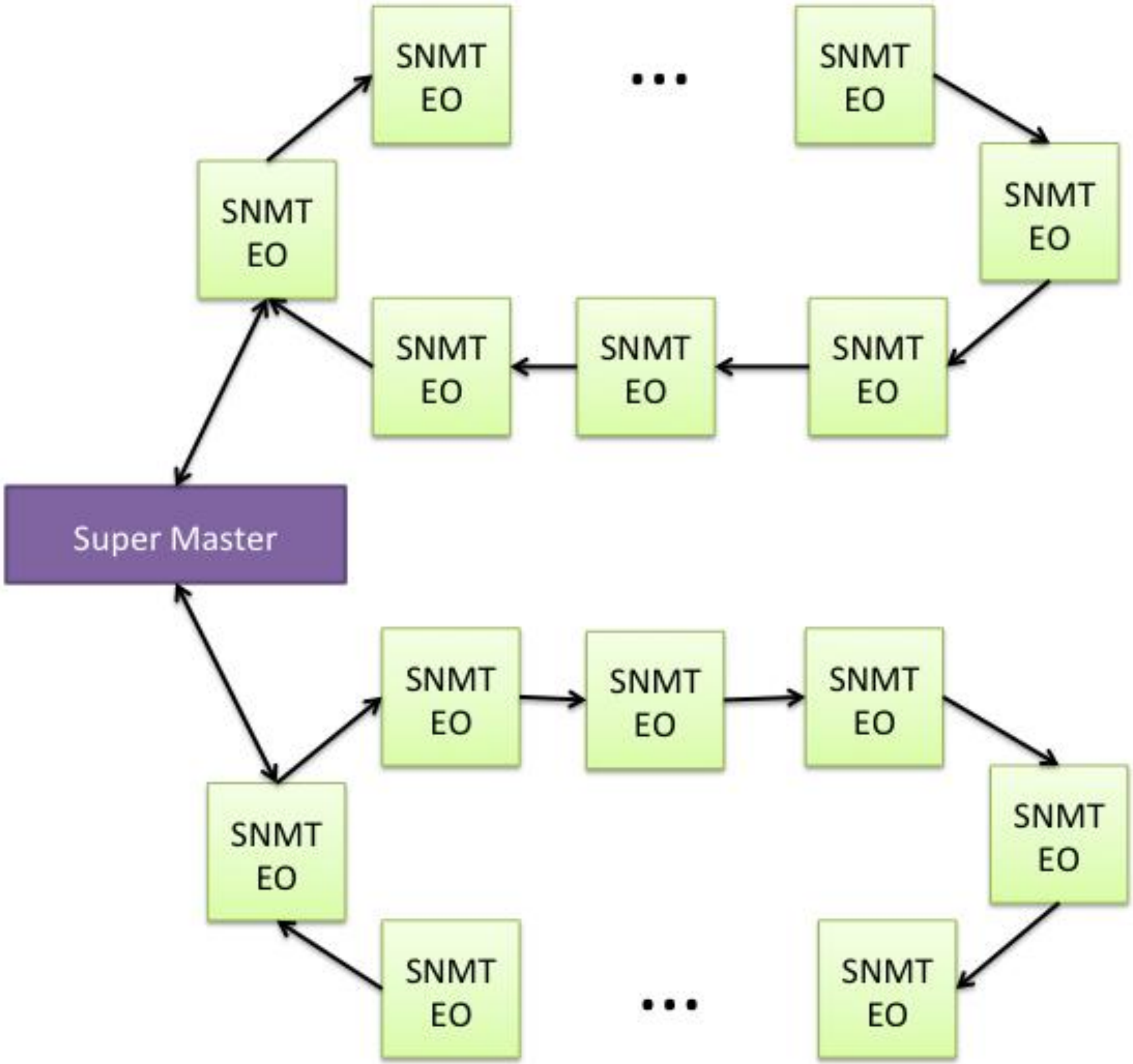
Super-Master – SP2SP



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Titan

- 18,688 compute nodes – 16 core AMD processors on each node (along with an NVIDIA Kepler GPU).
- 3rd on the Top 500 Supercomputers List in June 2016.

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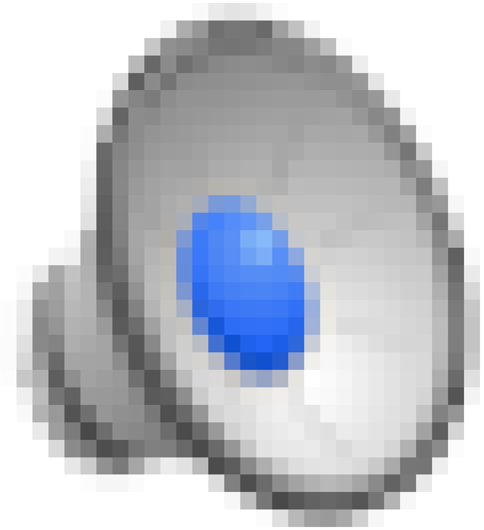
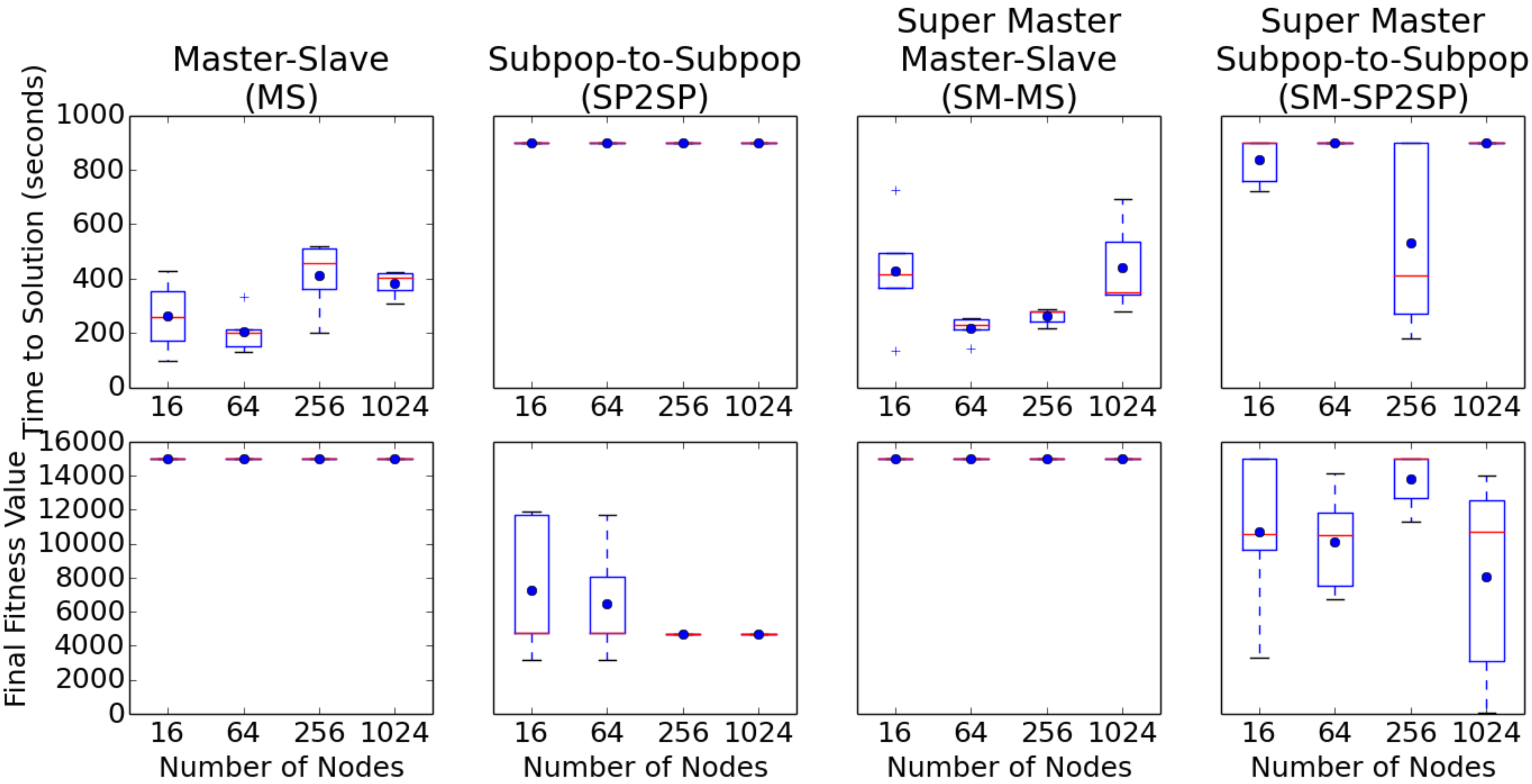
Application: Pole Balancing



Pole Balancing Results - Titan



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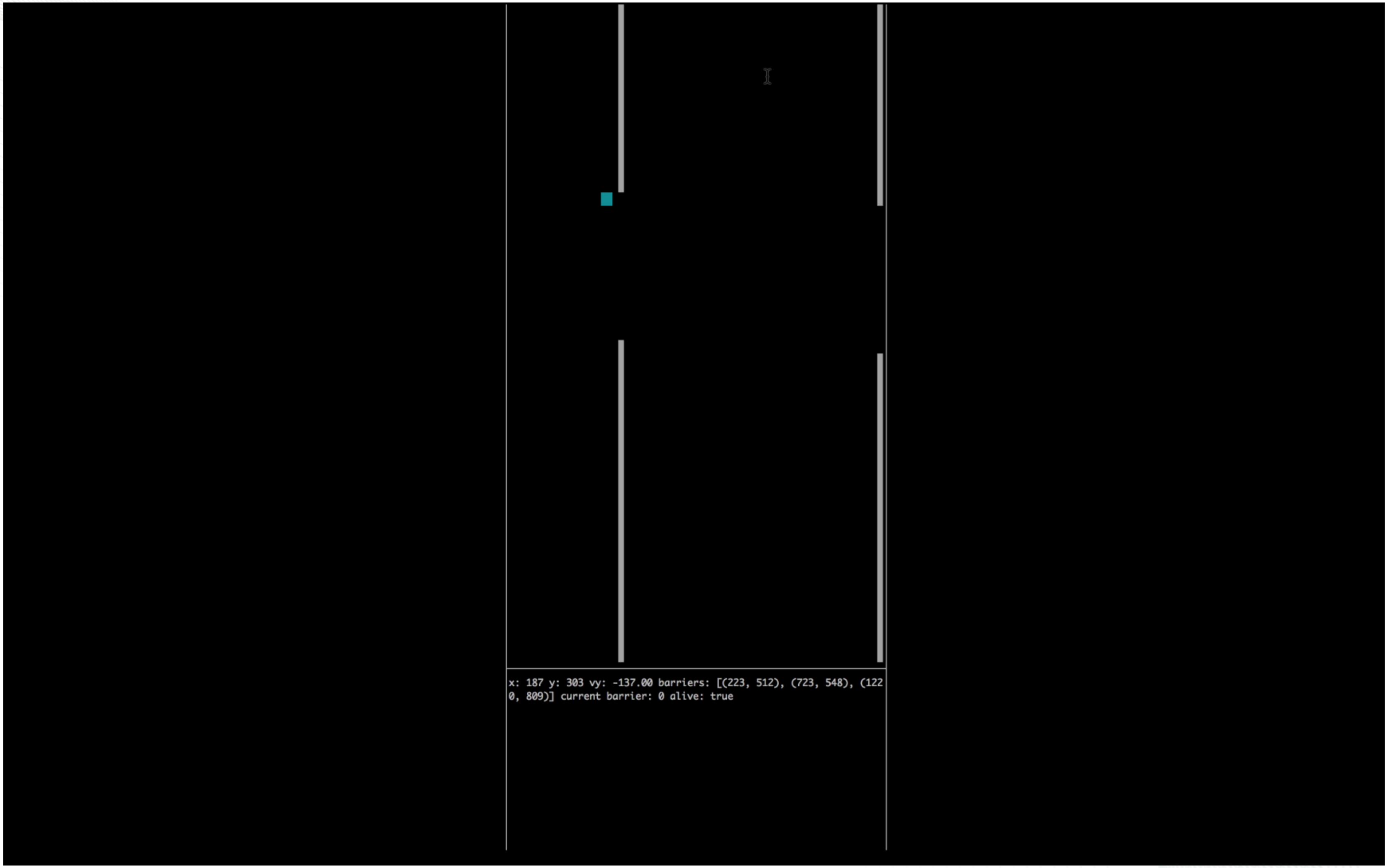
Application: One Dimensional Navigation



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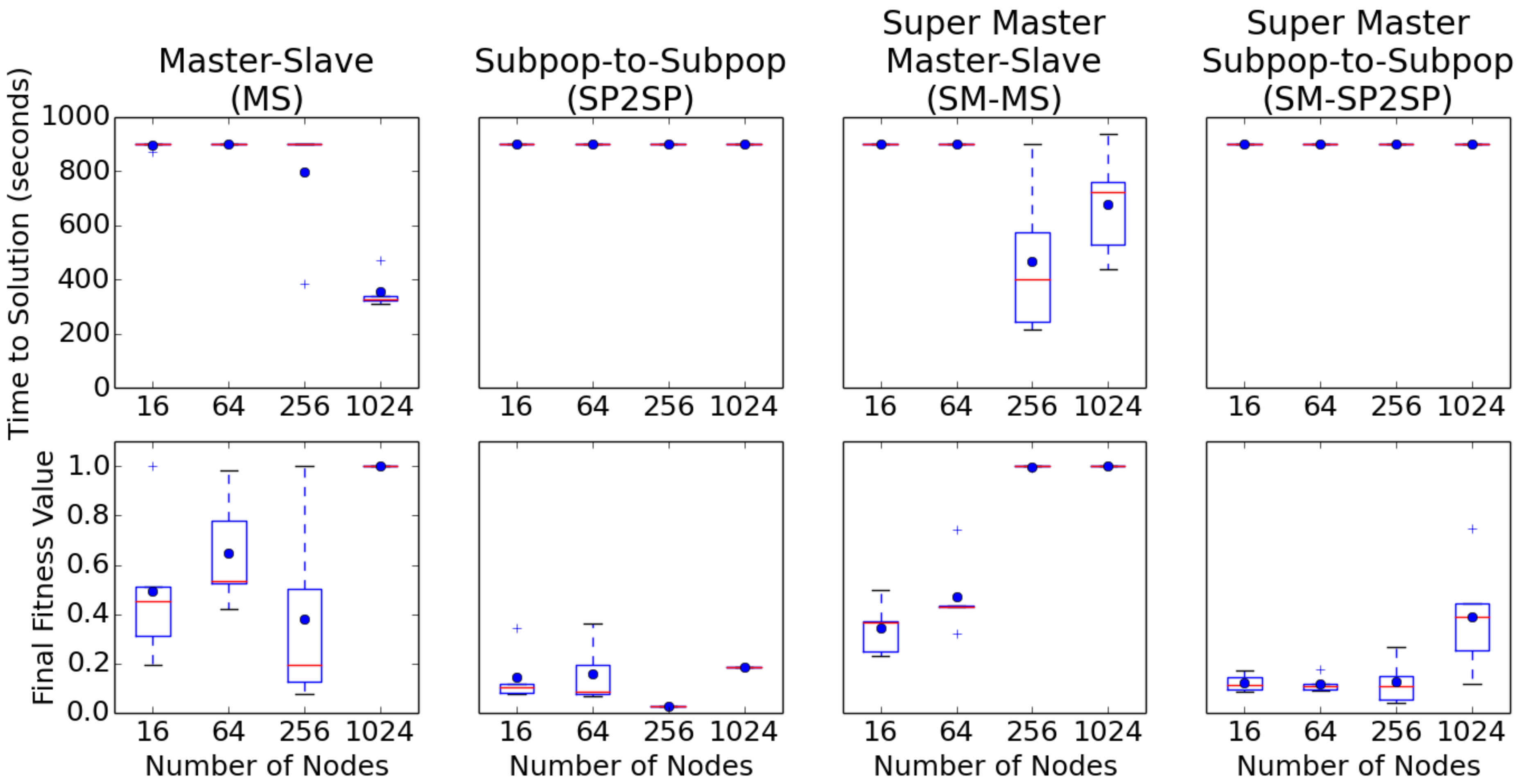
Flappy Bird Results - Titan



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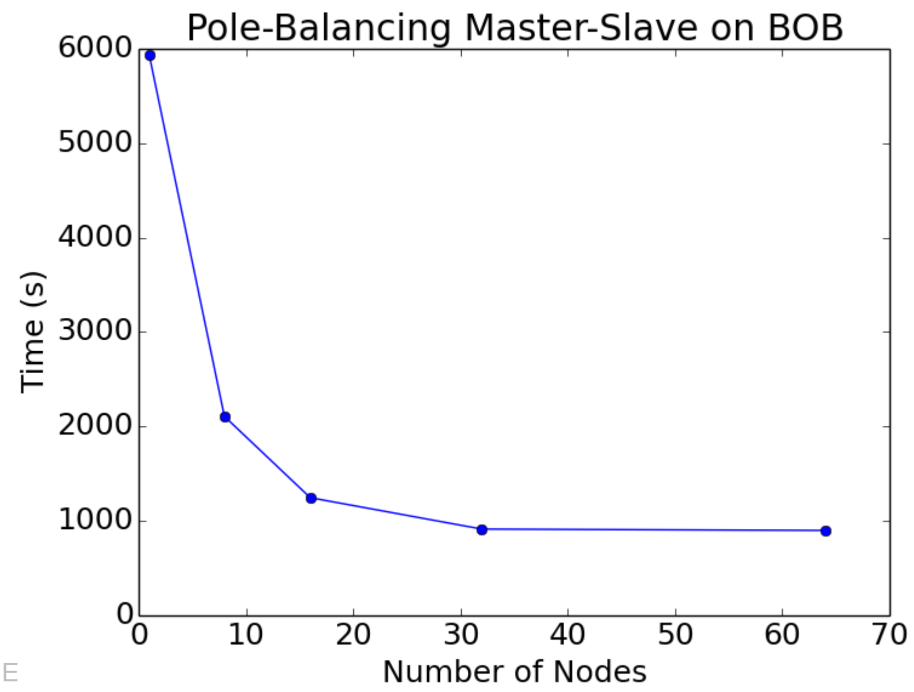
BOB – Raspberry Pi Cluster

- 64 Raspberry Pi 3 Cluster
  - 1.15 GHz quad core ARM Cortex A53 CPU
- Each set of 32 nodes is on a Gigabit Ethernet switch.
  - 32-node sets are connected by a single gigabit link.



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Network Structure Analysis

- EO has the by-product of producing lots of networks and their performance characteristics.
- We took 90,000 pole-balancing networks generated on Titan and analyzed input/output paths:

Input Neuron	Output Neuron	Est. Coeff.
(3, 0)	(6, 13)	1.552
(4, 0)	(6, 13)	1.417
(4, 0)	(7, 13)	1.409
(7, 0)	(6, 13)	1.621
(5, 0)	(7, 13)	1.596
(8, 0)	(6, 13)	2.486
(6, 0)	(7, 13)	2.885
(7, 0)	(7, 13)	1.886
(12, 0)	(6, 13)	1.655
(10, 0)	(7, 13)	2.074
(14, 0)	(6, 13)	1.569
(12, 0)	(7, 13)	1.386

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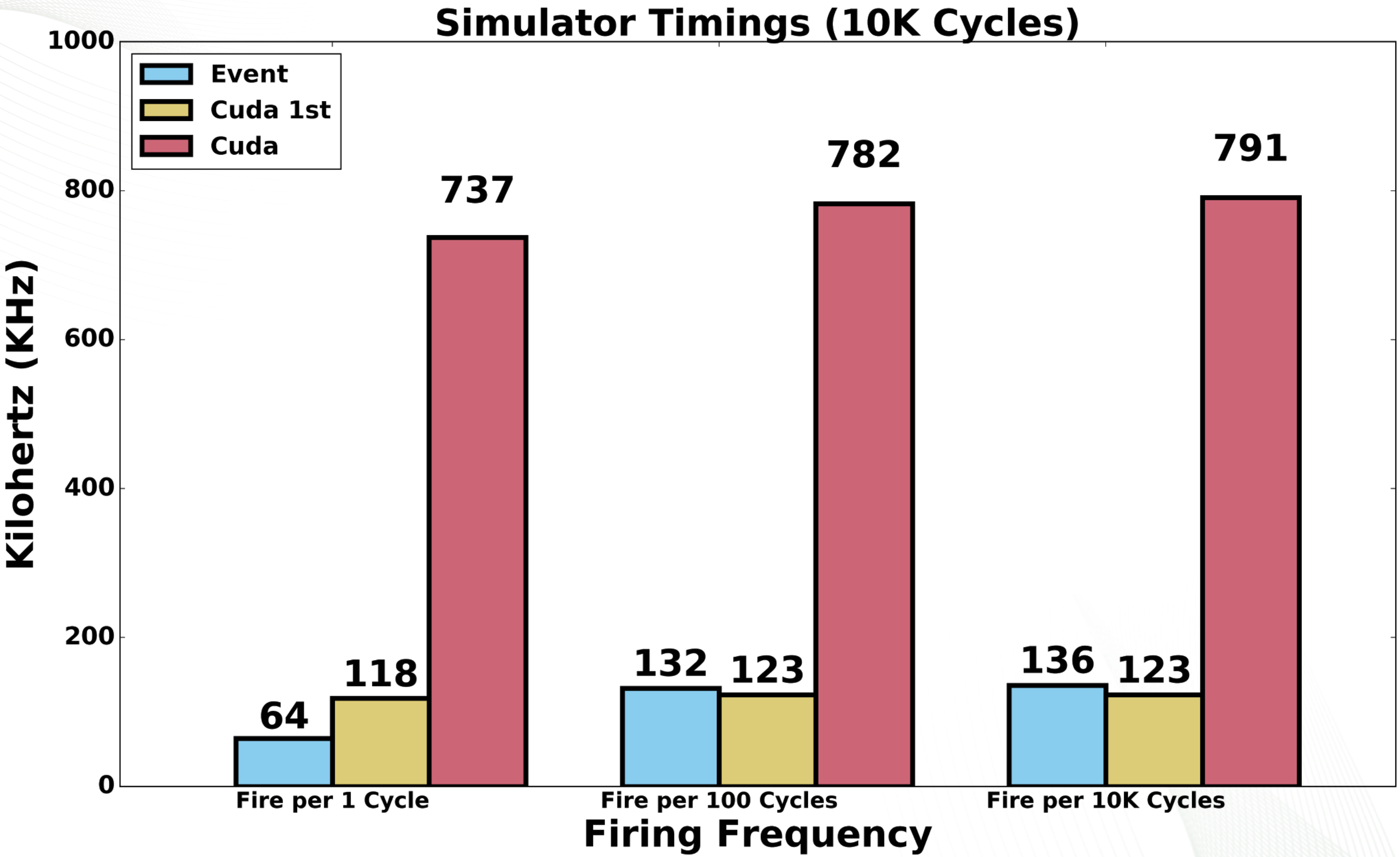
Future Work

- GPU simulator is in progress.
  - Can be used in combination with event-based simulator to take advantage of all computing resources to study neuromorphic systems.
- Profiling and optimizing existing implementations.
- Additional exploration of produced networks and their performance characteristics to understand the learning process.
  - What are the characteristics of “good” networks?
  - Can we embed learned information into the training process?

Preliminary GPU Implementation



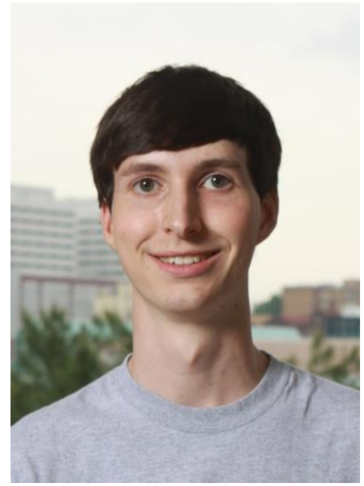
Conclusion

- Neuromorphic computing is clearly one architecture that will be present in the computing landscape of the future.
- There are still many unknowns about neuromorphic computing system, including the most efficient ways to train them.
- Evolutionary optimization (EO) is one way to train neuromorphic networks that is especially amenable for large-scale implementation.
- We implement, test, and demonstrate large-scale parallel EO methods on Titan and BOB.
- We demonstrate one way to utilize the produced results from large-scale EO implementations to study a neuromorphic architecture.

Acknowledgements

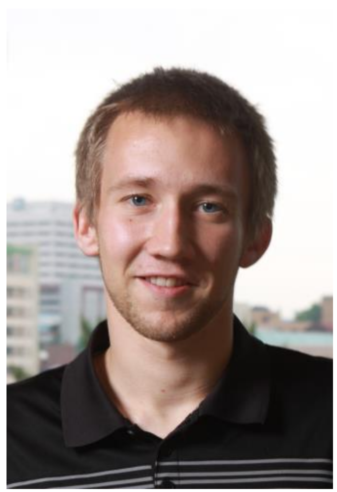
Adam Disney

Susheela Singh



Grant Bruer

Parker Mitchell



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AIR FORCE RESEARCH LABORATORY

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Thank You!

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Website: neuromorphic.eecs.utk.edu

GPU Improvements

- Batching of DANNA I/O packets
  - This reduces the number of kernel launches required
- Pinned memory for DANNA I/O packets
  - Allows transfers to be concurrent with simulation
- Load array in shared memory
  - Can’t really “block” simulation like a matrix multiply but current arrays are small enough to entirely fit in shared memory
  - In combination with Batching, only have to hit global memory at the beginning and end of the batch
- Neuron and Synapse list
  - To avoid divergence, divide the warps into Neuron warps and Synapse warps that run through their respective lists.