







EVALUATING THE IMPACT OF SPIKING NEURAL NETWORK TRAFFIC ON EXTREME-SCALE HYBRID SYSTEMS

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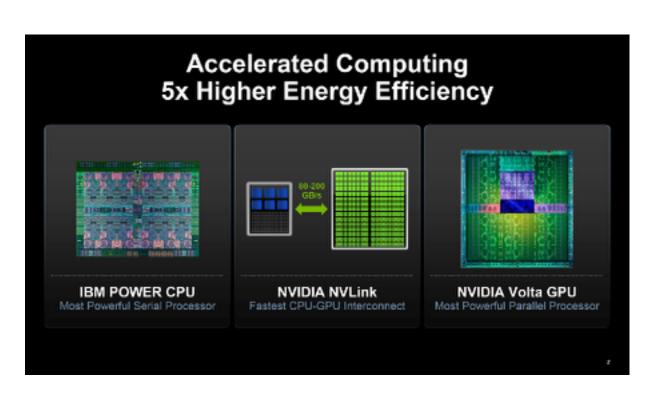
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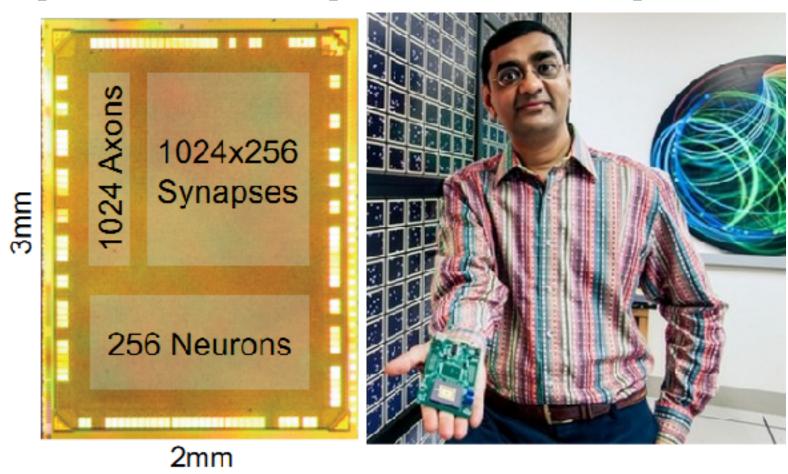
Animations: Caitlin Ross¹

November 12th, 2018

Hybrid Neuromorphic Supercomputer?







The question: how might a neuromorphic "accelerator" type processor be used to improve the HPC application performance, power consumption and overall system reliability of future exascale systems?

Driven by the recent DOE SEAB report on high-performance computing which highlights the neuromorphic architecture as one that "is an emergent area for exploitation".

Address using parallel systems simulation

Simulation Workflow

TrueNorth (Neuromorphic Design)

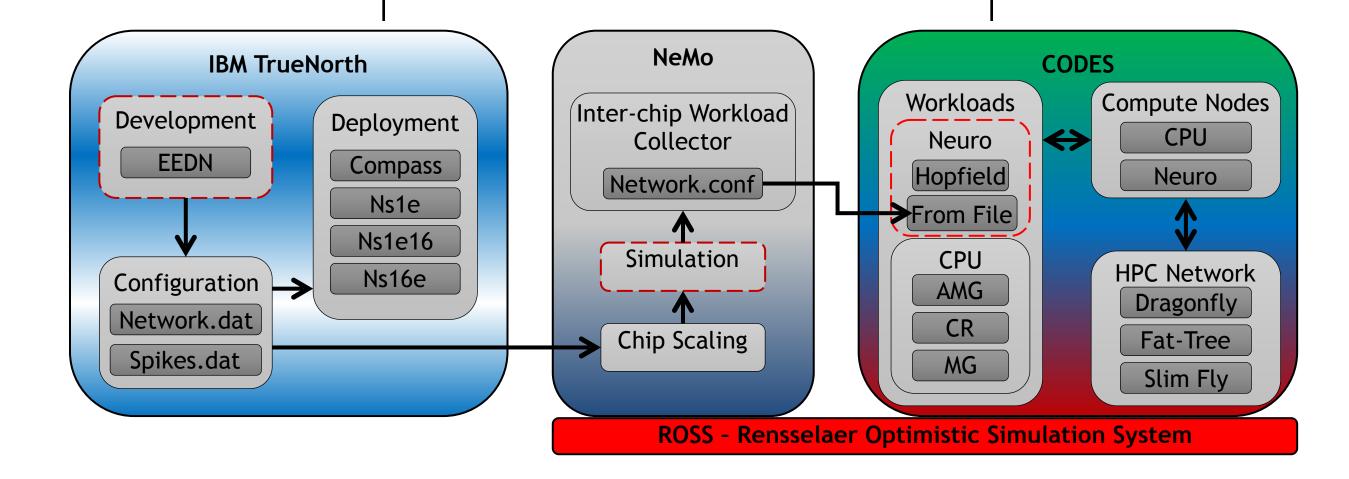
- Ecosystem for building real neural network applications for the IBM neuromorphic processor
- Spiking neuron based architecture with 4,096 neurosynaptic cores resulting in 1M neurons

NeMo (Neuromorphic Scaling)

- Framework for simulating general purpose neuromorphic processors
- Capable of generating partially synthetic multi-chip workloads from TrueNorth applications
- Built on ROSS

CODES (HPC)

- High-fidelity packet-level framework for exploring design of HPC interconnects and workloads
- Synthetic or application trace network workloads
- Built on ROSS



HPC Interconnection Networks

Fat-Tree

• Nodes: 3,240

• Routers: 468

• Links: 9,720

• Levels: 3

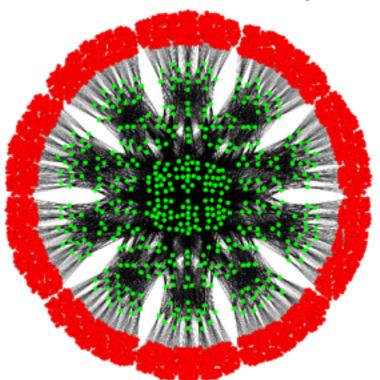
*Net Diameter: 4

Routing: Static

WC Hop Count: 6

• Inj. BW: 316 Tbps

Net BW: 648 Tbps



Dragonfly-2D

• Nodes: 3,072

• Routers: 768

• Links: 11,424

• Groups: 8

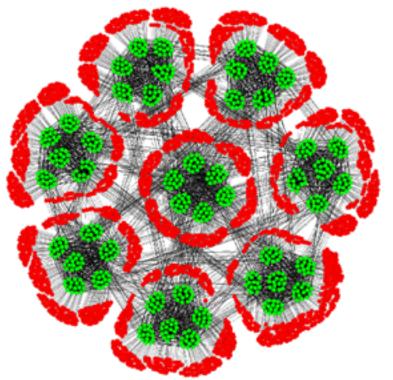
• *Net Diameter: 5

Routing: Adaptive

• WC Hop Count: 12

• Inj BW: 300 Tbps

Net BW: 835 Tbps



Dragonfly-1D

• Nodes: 3,200

• Routers: 400

• Links: 8,600

• Groups: 25

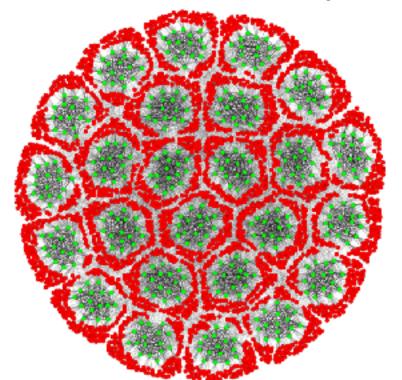
• *Net Diameter: 3

Routing: Adaptive

WC Hop Count: 7

• Inj BW: 313 Tbps

Net BW: 540 Tbps



Slim Fly

• Nodes: 3,042

• Routers: 338

• Links: 6,253

• Groups: 26

*Net Diameter: 2

Routing: Adaptive

WC Hop Count: 6

• Inj BW: 297 Tbps

Net BW: 321 Tbps



Simulation Parameters Dragonfly-2D Dragonfly-1D

Router Latency: 90ns

• NIC Latency: 1.5us

• MPI Latency: 2.5us

• Buffer Space per VC: 64KB

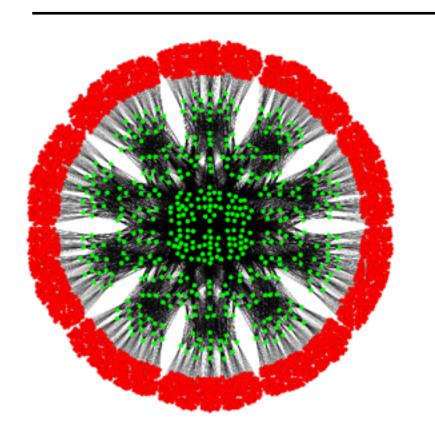
• Link Speed: 100Gbps

Job Mapping: Contiguous

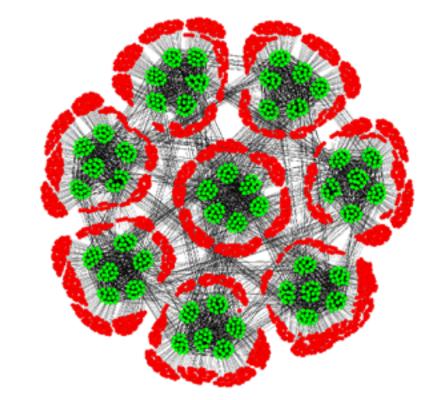
System Utilization:

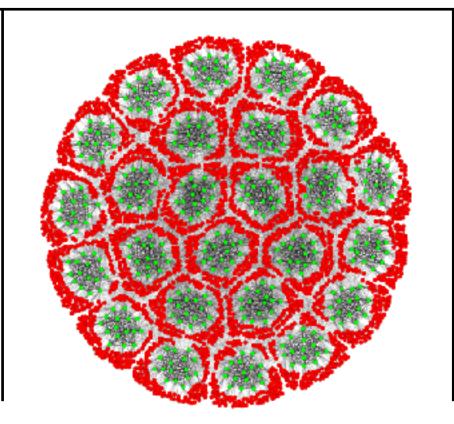
• Neuromorphic: 33%

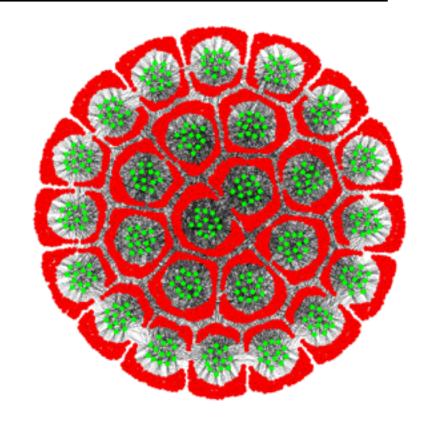
• CPU: 33-55%



Fat-Tree







Slim Fly

WC: worst-case, Inj: injection, BW: bandwidth, Net: network

Application Workloads

Neuromorphic Workloads

Workload	Chips	Connectivity	Spikes/Tick	MB/Tick	Waits
MNIST	1234	15 layers	577K	4.4MB	0
CIFAR	1024	15 layers	647K	4.9MB	0
Hopfield	1024	all-to-all	10.2M	80MB	0

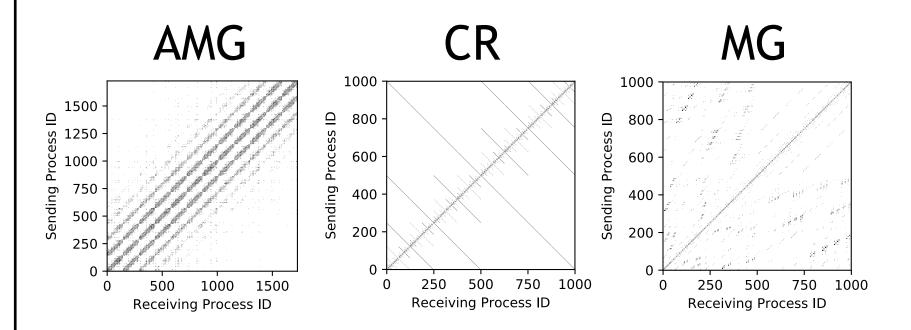
A tick is 1ms of simulated time.

CIFAR MNIST Hopfield 1000 1200 1000 1000 800 800 Sending Chip ID Sending Chip ID Sending Chip ID 800 600 400 200 200 200 0 · 0 -1000 1000 500 500 1000 Receiving Chip ID Receiving Chip ID Receiving Chip ID

CPU Workloads

Workload	Processes	End Time	Msgs	Msg Size	Waits
AMG	1,728	0.50ms	2.2M	0.79KB	101.1K
CR	1,000	258.48ms	39.9M	7.95KB	39.9M
MG	1,000	5.51ms	0.5M	9.30KB	248K

End time is the virtual time to replay the workload through the Fat-Tree configuration. Msg size is the average size of all messages transfered across all processes.

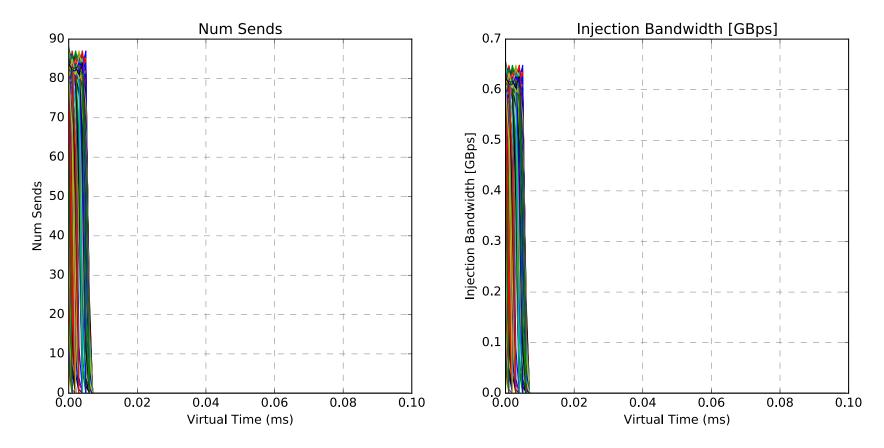


Application Workloads

MNIST

(Neuromorphic)

- **Description:** Convolutional neural network for handwritten digit classification
- Communication Pattern: Periodic injection of 8B messages between 15 interconnected layers of neurons
- Trace Size: 1,234 neuromorphic chips



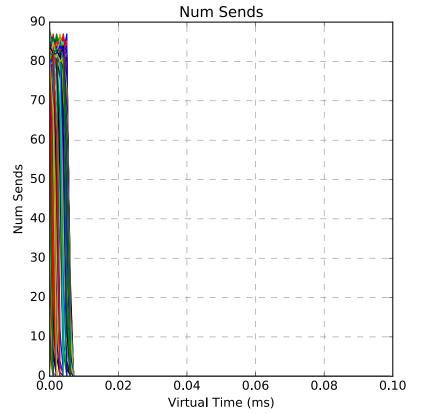
MNIST 1234 NEUROMORPHIC CHIP WORKLOAD SLIMFLY NETWORK

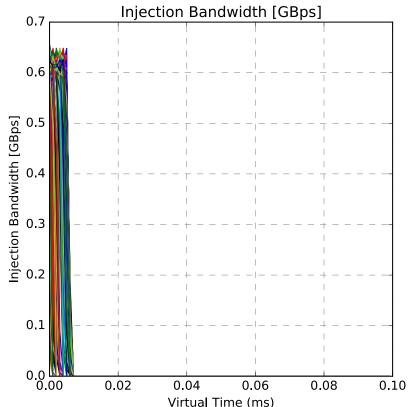
Application Workloads

MNIST

(Neuromorphic)

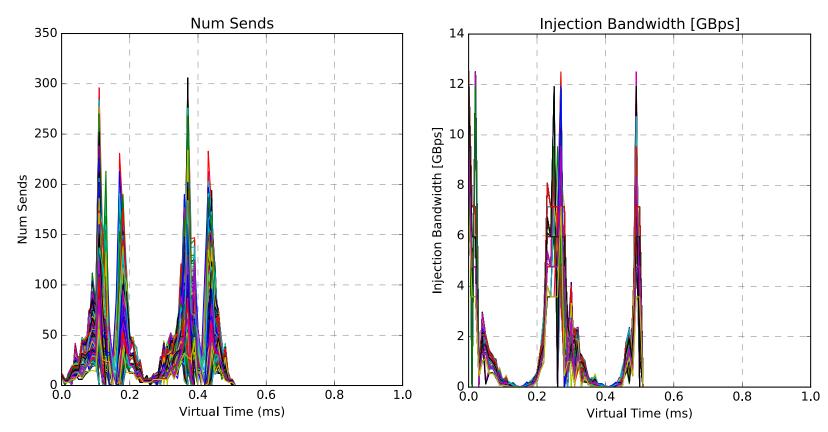
- Description: Convolutional neural network for handwritten digit classification
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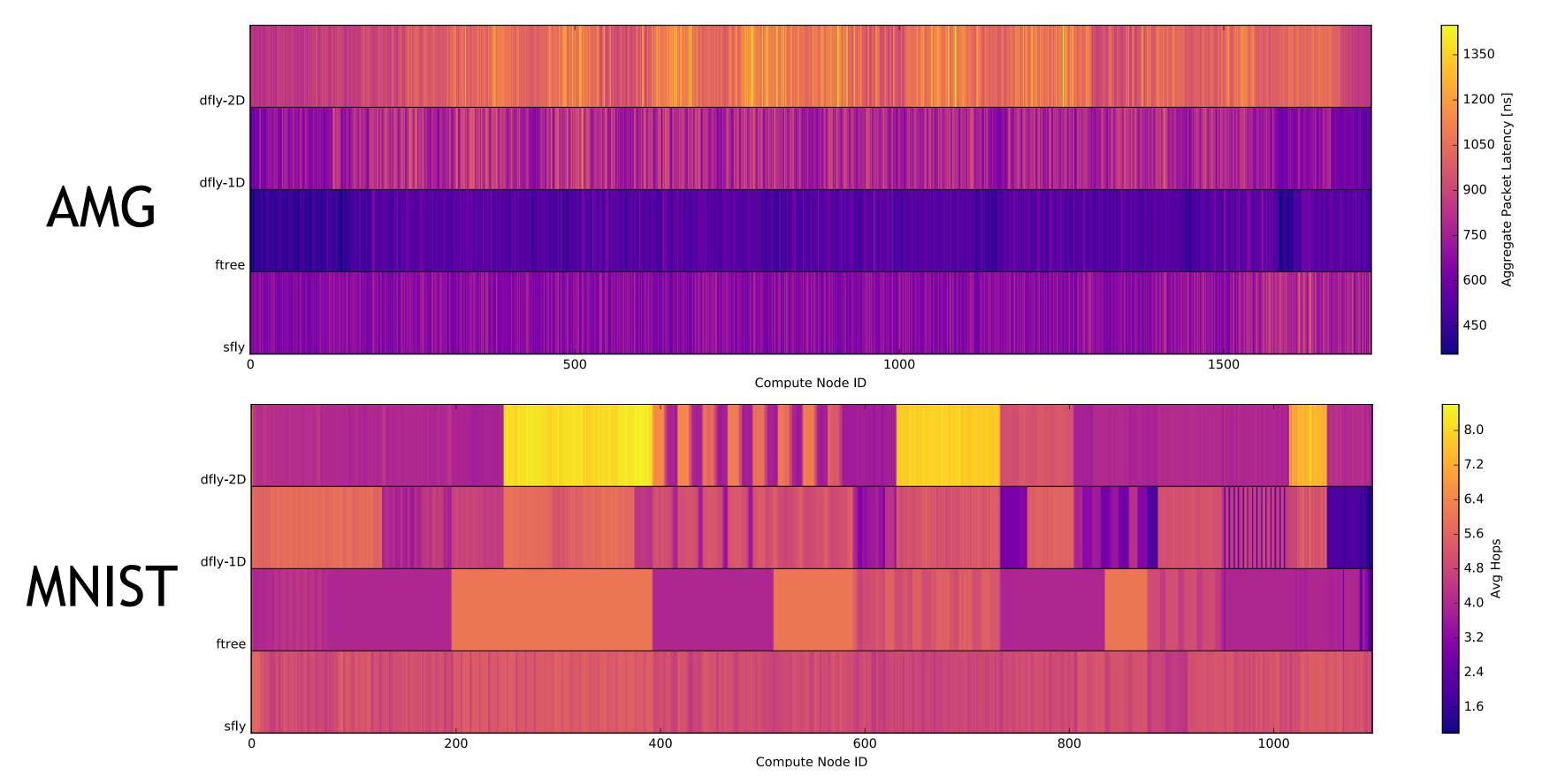
Algebraic Multigrid Solver (HPC)

- Description: Parallel Algebraic Multigrid Solver (AMG) used for unstructured grids developed at LLNL
- Communication Pattern: Bursty periods of ~1KB messages following 3D nearest neighbor
- Communication Time: 52.9% of runtime
- Trace Size: 1,728 CPU processes



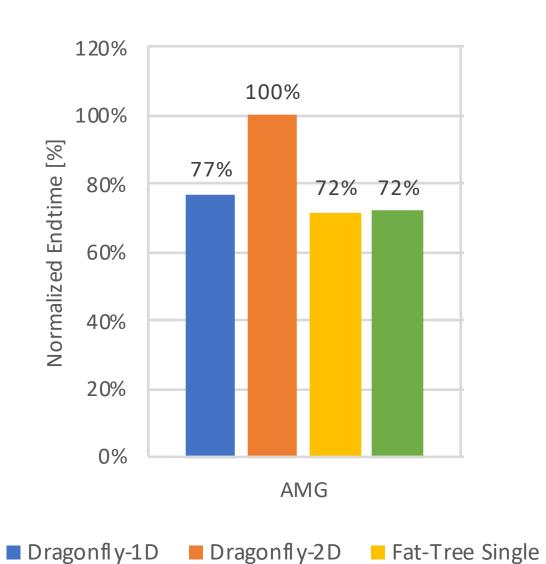
AMG 1728 MPI RANK WORKLOAD SLIMFLY NETWORK

Homogeneous Results



Homogeneous Results (AMG)

Endtime

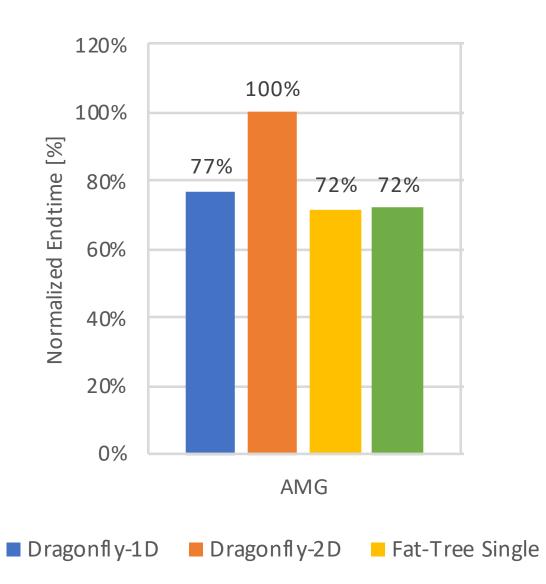


Dragonfly-1D 23% faster than Dragonfly-2D

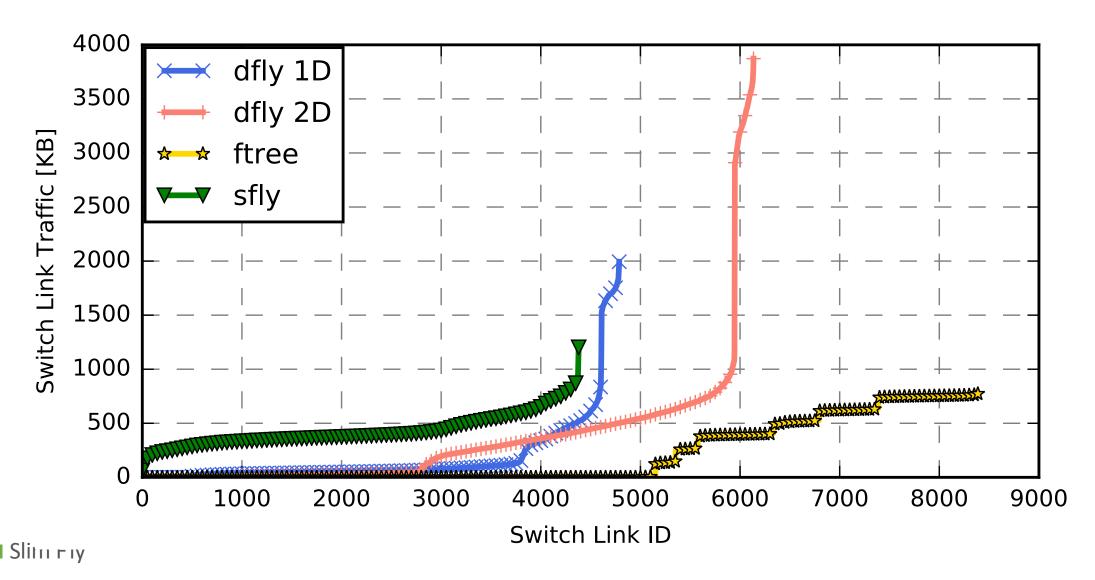
Slim Fly & Fat-Tree 28% faster than Dragonfly-2D

Homogeneous Results (AMG)



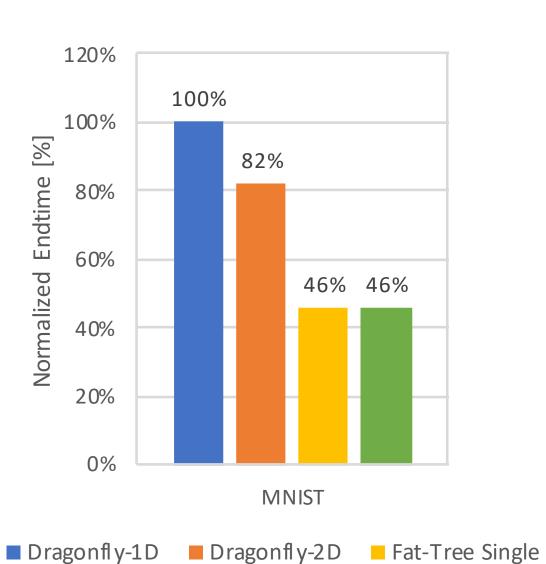


Link Traffic



Homogeneous Results (MNIST)

Endtime

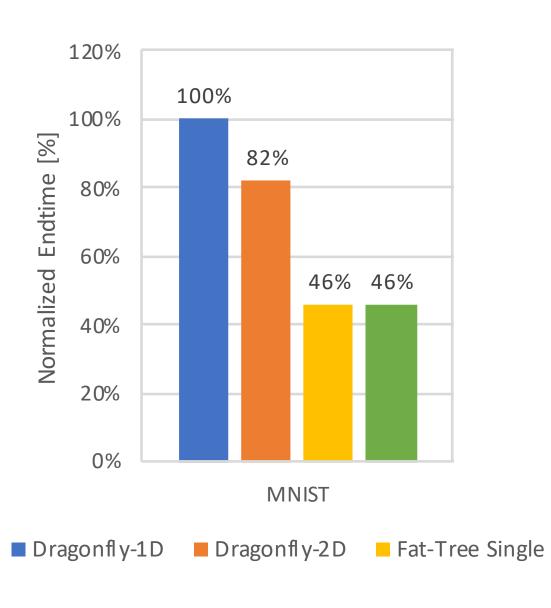


Dragonfly-2D 18% faster than Dragonfly-1D

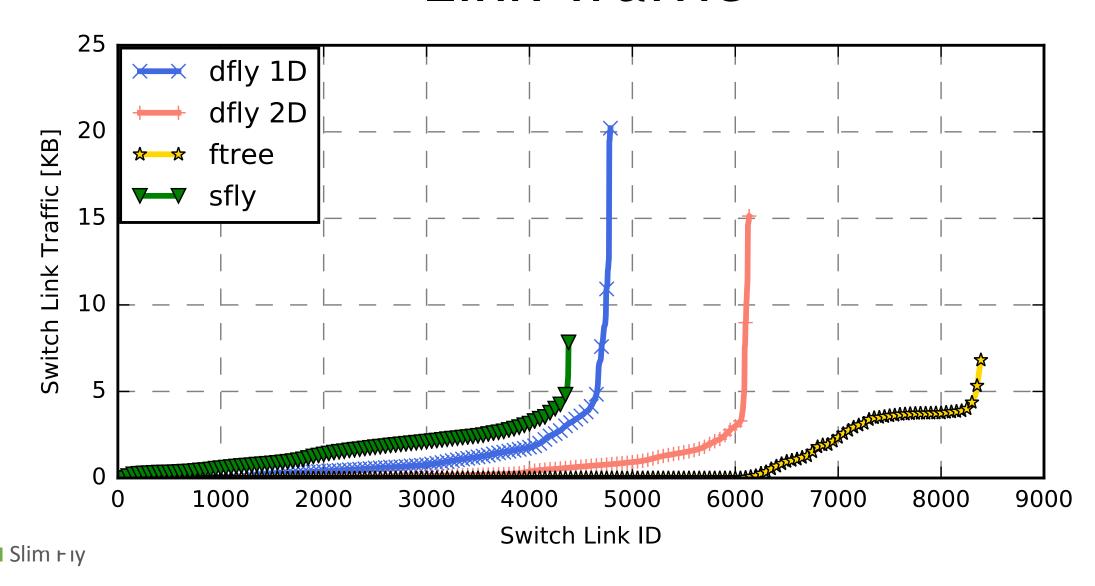
Fat-Tree & Slim Fly 54% faster than Dragonfly-1D

Homogeneous Results (MNIST)

Endtime

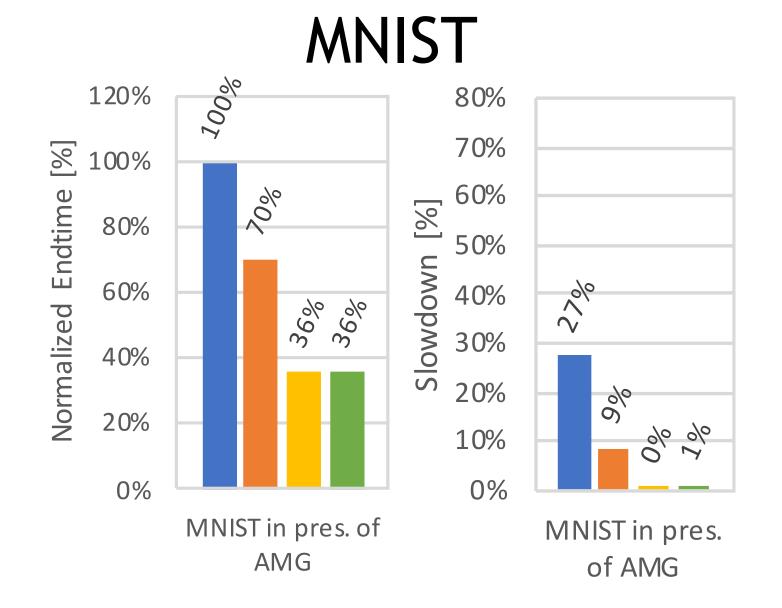


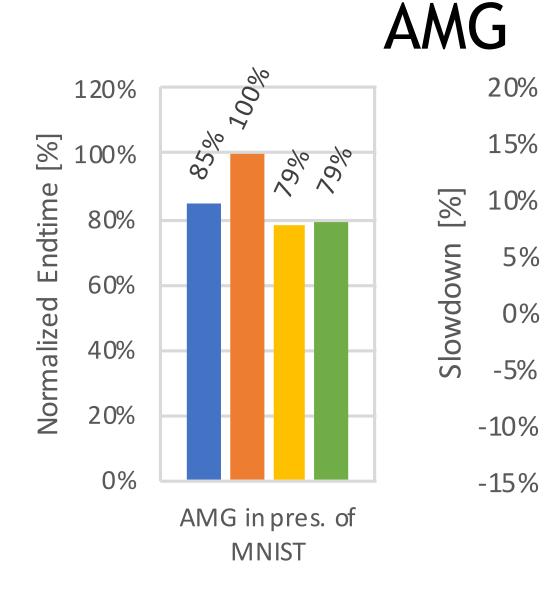
Link Traffic



Hybrid Results

(Endtime & Slowdown)





27% slowdown on Dragonfly-1D **9%** slowdown on Dragonfly-2D

9% improvement on Dragonfly-2D

0%

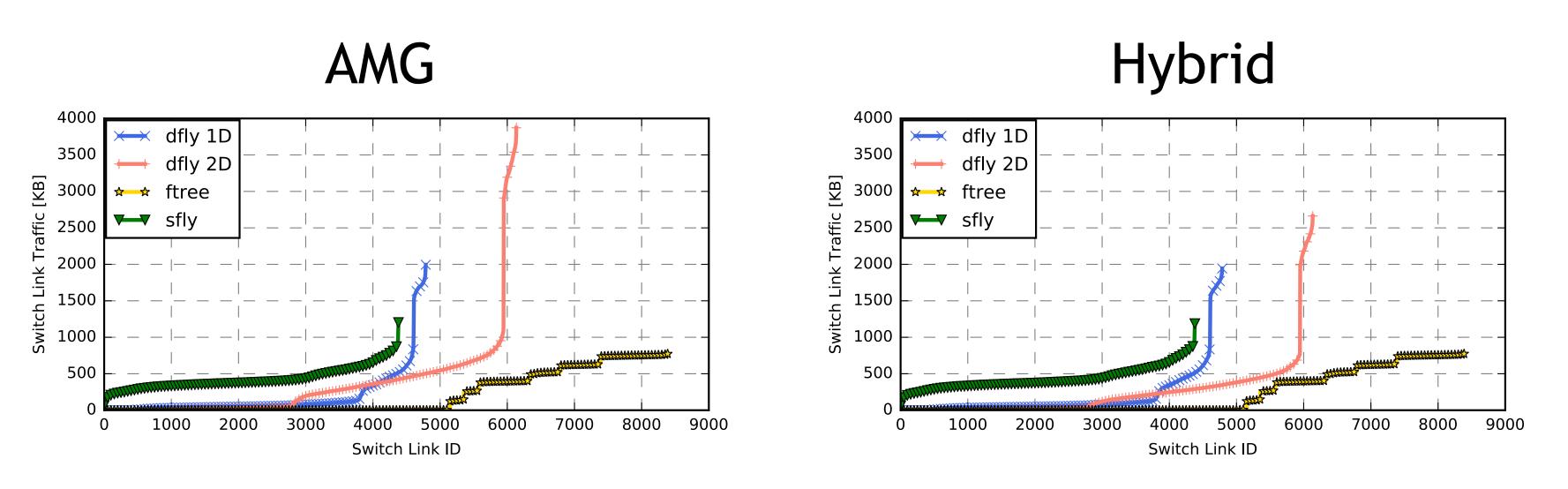
-9%

AMG in pres. of

MNIST

0% 1%

Hybrid Results (Link Traffic)



30% decrease in maximum link traffic for Dragonfly-2D

Summary

- Neuromorphic architectures such as IBM TrueNorth pose interesting design questions for future Extreme-Scale HPC systems.
- Using IBM TrueNorth, NeMo, CODES we can study network performance of real deep learning neuromorphic applications at scale in an HPC environment.
- Preliminary analysis shows Fat-Tree and Slim Fly HPC network topologies are better able to minimize interference between neuromorphic and traditional HPC applications than Dragonfly.
- Neuromorphic workloads representing convolutional neural network and Hopfield network applications pose little effect on traditional CPU applications when running in parallel in a multi-job hybrid HPC environment.
- Traditional CPU network workloads can significantly effect performance of Neuromorphic application workloads.

Future Work

- Investigating additional neuro workloads and approaches for workload scaling and chip mapping.
- Improving Dragonfly configuration performance by investigating minimal path bias, adaptive thresholds, and job allocations to compute nodes.
- Studying coexistence of multiple neuromorphic applications.