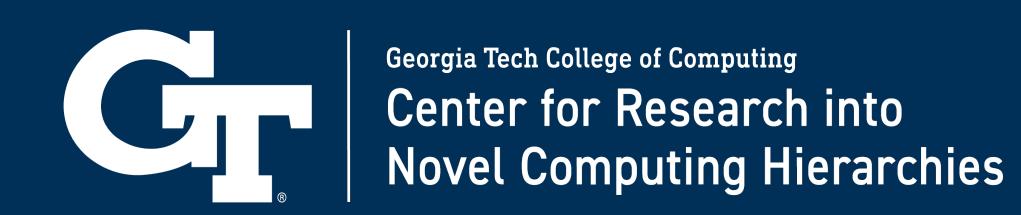


Themis: A Network Bandwidth-Aware Collective Scheduling Policy for Distributed Training of DL Models



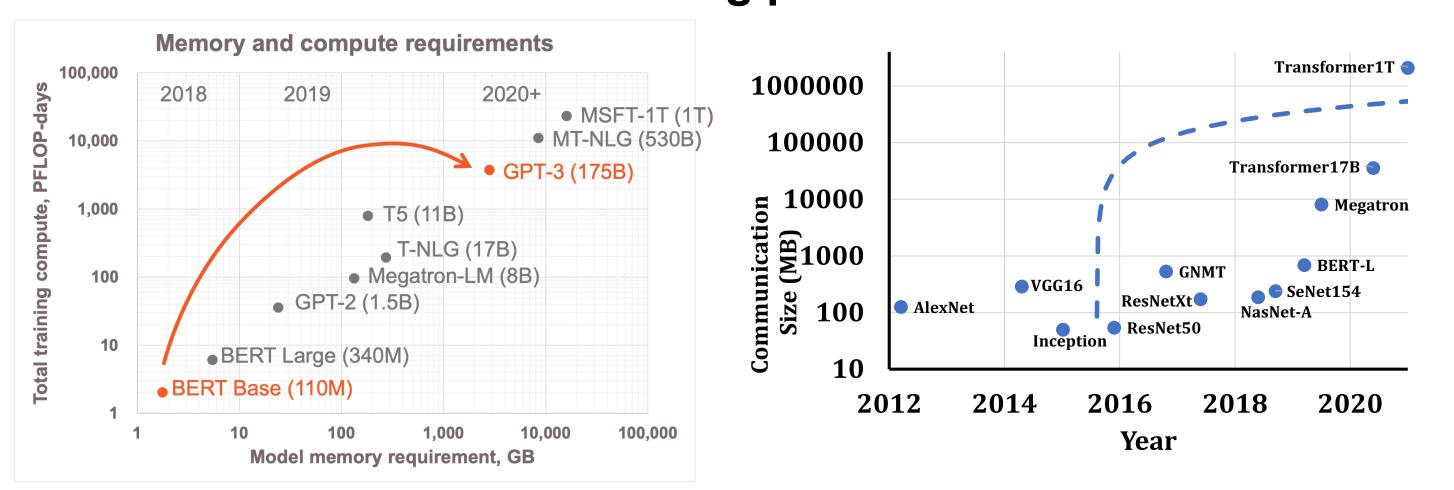


In Proceedings of the 49th International Symposium on Computer Architecture (ISCA), Jun 2022 Saeed Rashidi¹, William Won¹, Sudarshan Srinivasan², Srinivas Sridharan³, and Tushar Krishna¹

Georgia Institute of Technology, ²Intel, ³Meta

Large Al Models

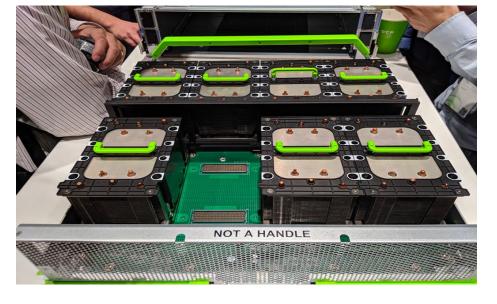
- Deep Learning: **Model size is increasing** (2× / 3.4 months)
 - GPT-3: 355 GPU years to train
- Necessitates distributed training platforms



DL Training Platforms

- Futuristic training networks: multi-dimension + heterogeneous BW
- Ring, Switch (SW), FullyConnected (FC)
- NVIDIA HGX-H100: SW_SW_SW
- Facebook Zion: FC_SW
- Google TPUv4: Ring_Ring_Ring







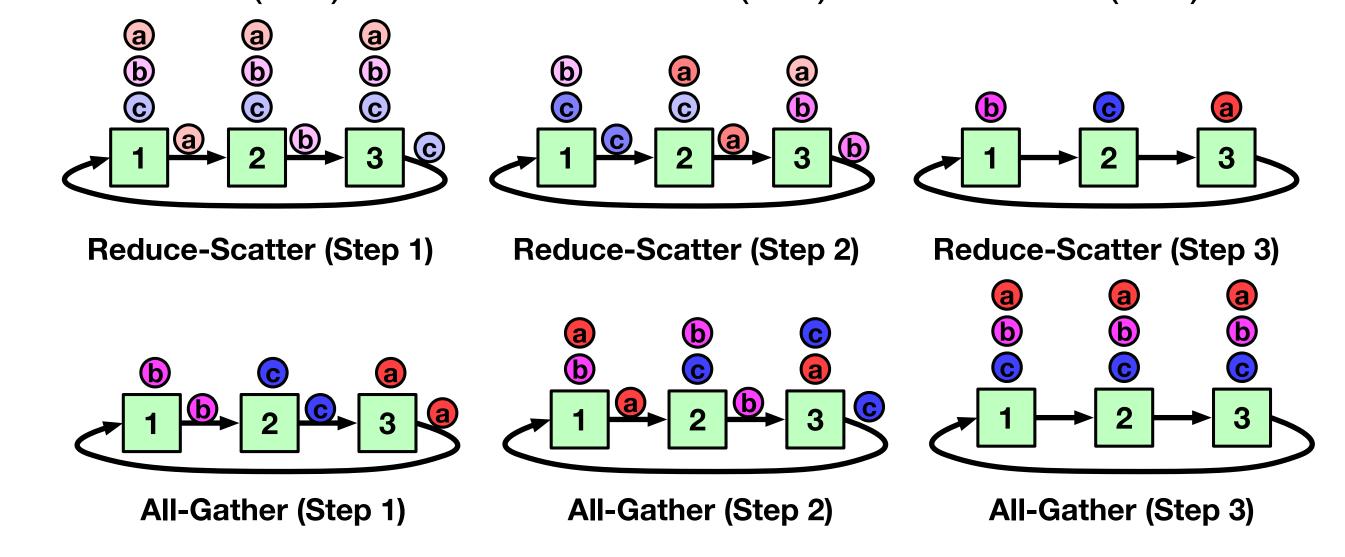
NVIDIA HGX-H100

Facebook Zion

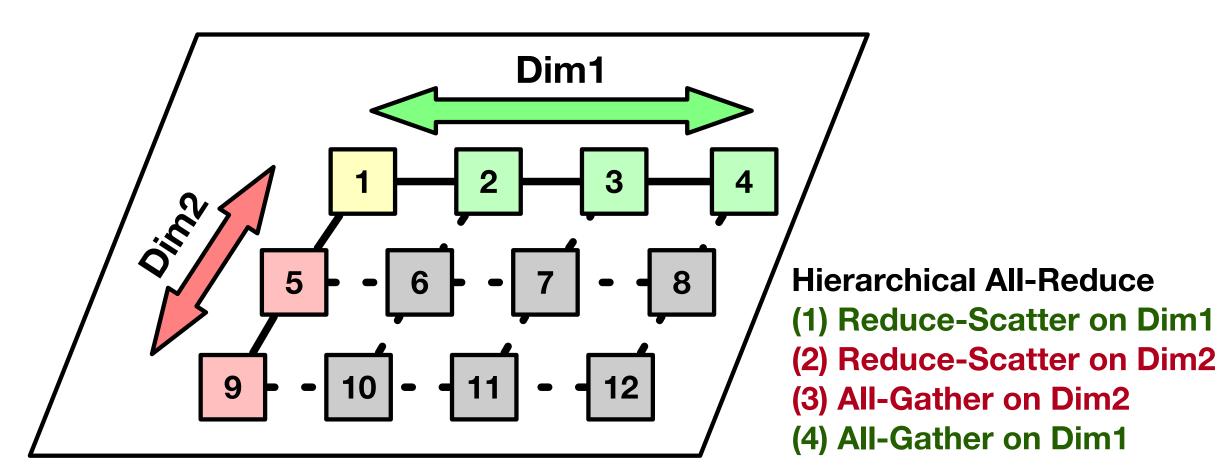
Google TPUv4

All-Reduce Algorithm

All-Reduce (AR) = Reduce-Scatter (RS) + All-Gather (AG)

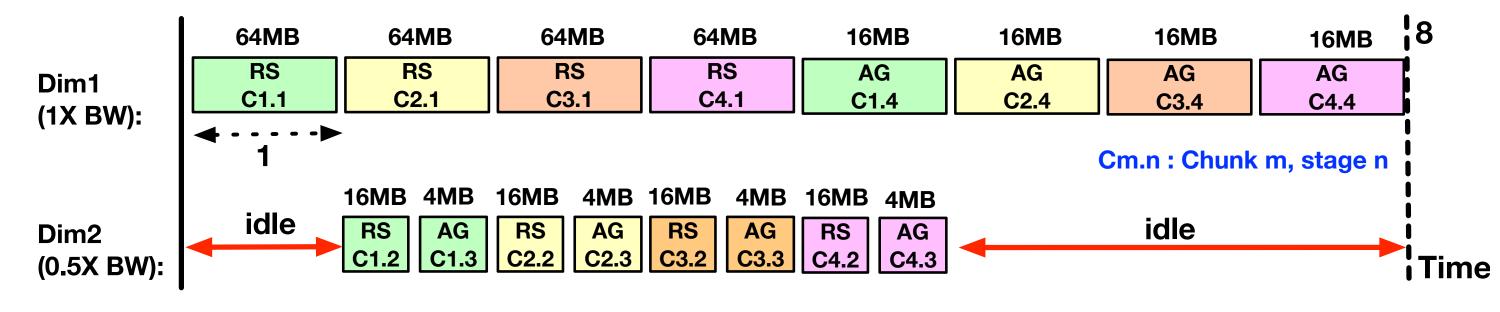


Hierarchical All-Reduce: Traverses dimensions in-order

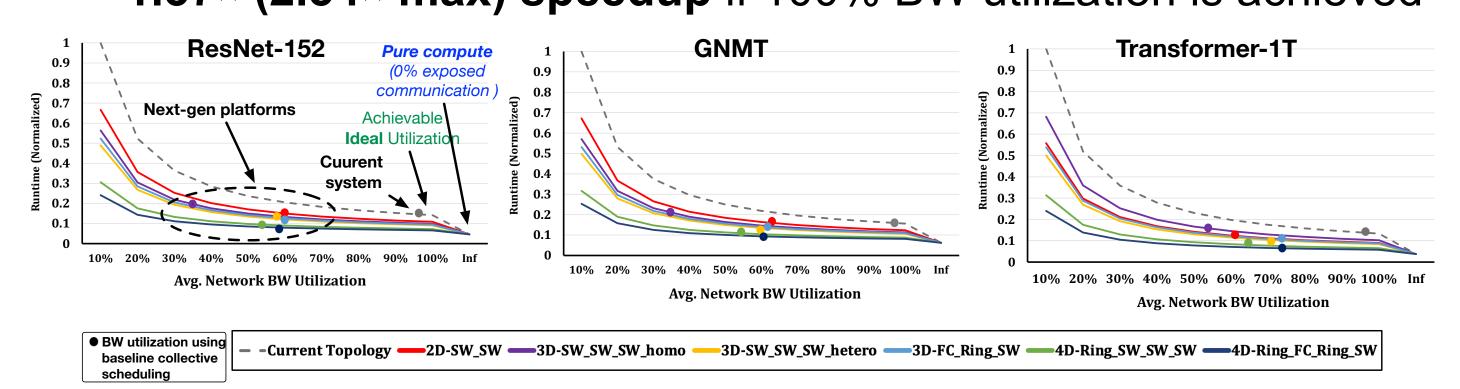


Motivation

- Message size decreases as traversing dimensions (Hierarchical AR)
- Each network dimension has different BW (Networking Technology)
- Network BW and chunk size mismatch across dimensions

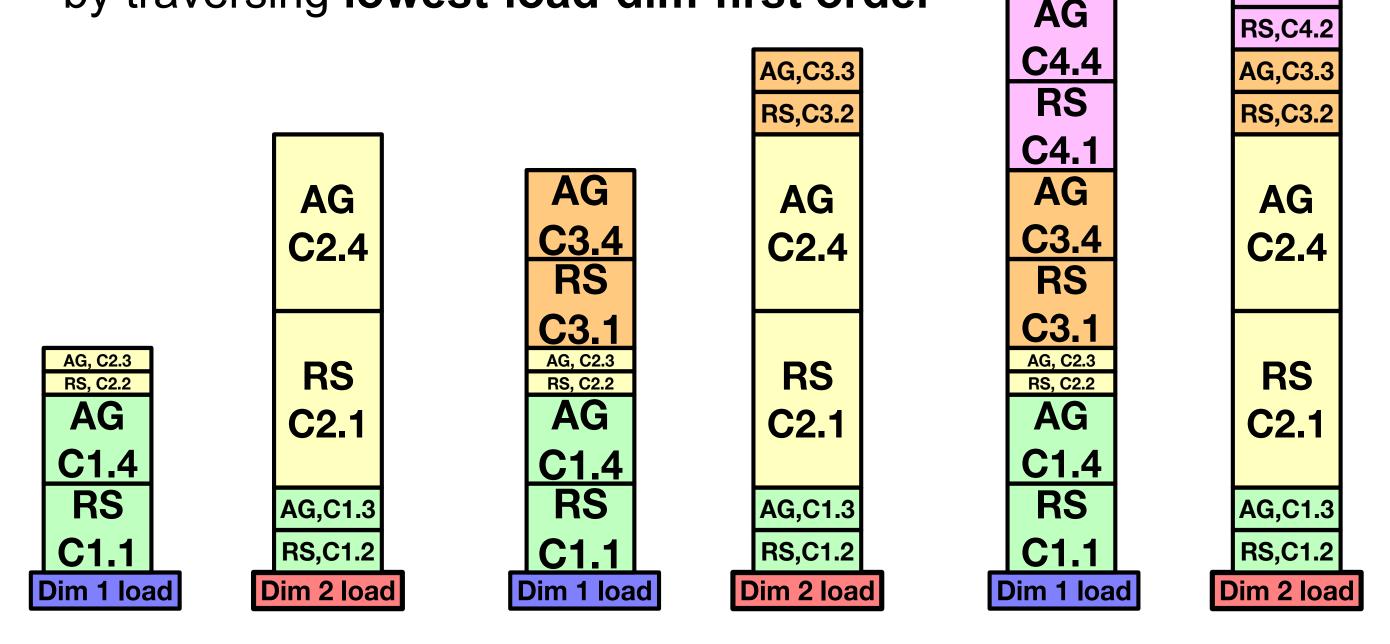


- Underutilization of Network BW Resource
 - Baseline: ~59.7% network BW utilization for next-gen topologies
 - ~1.37× (2.34× max) speedup if 100% BW utilization is achieved



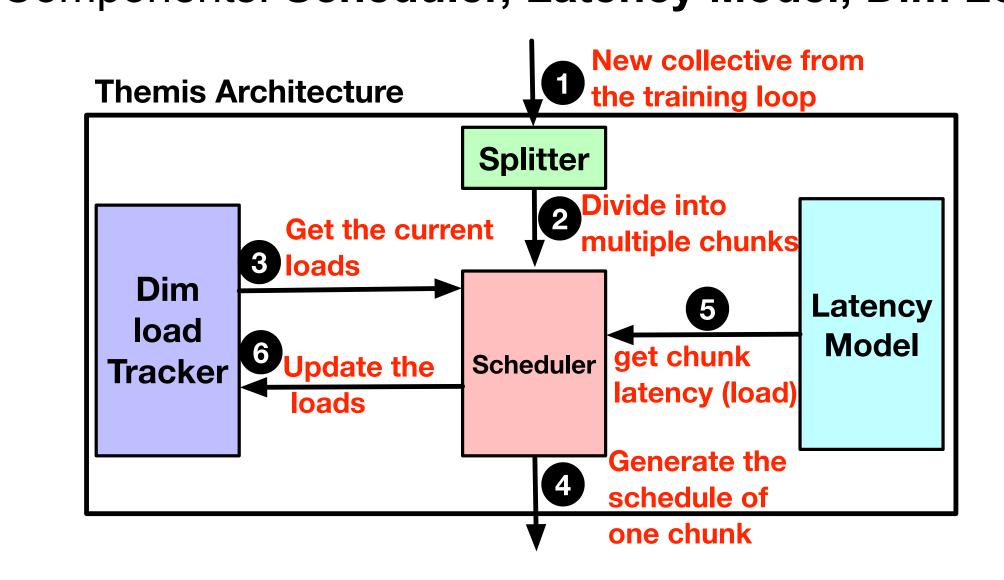
Themis

- Observations:
 - Each chunk can traverse network dimensions out-of-order
- Individual chunks can have separate scheduling policy
- **Themis**
- Track the current load of each dimension
- Dynamically balance the load gap of each dimension by traversing lowest-load-dim-first order



AG,C4.3

• Themis Components: Scheduler, Latency Model, Dim Load Tracker

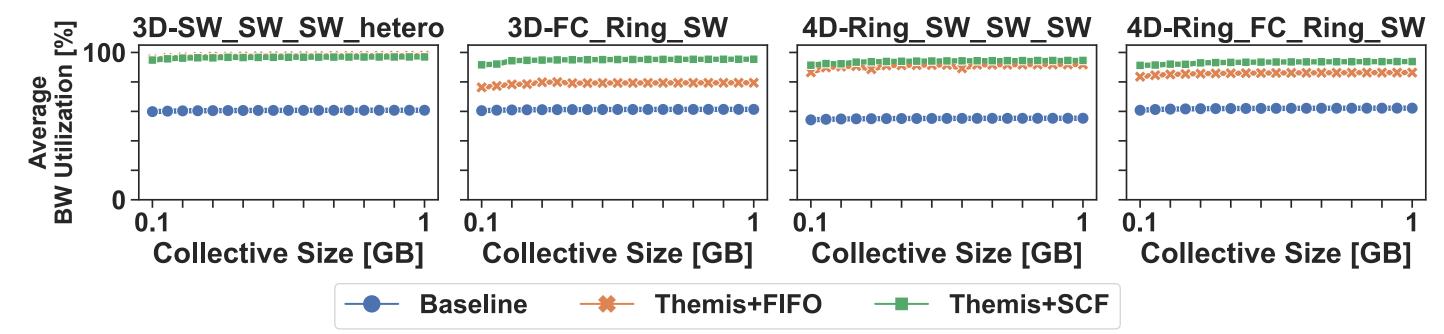


Results

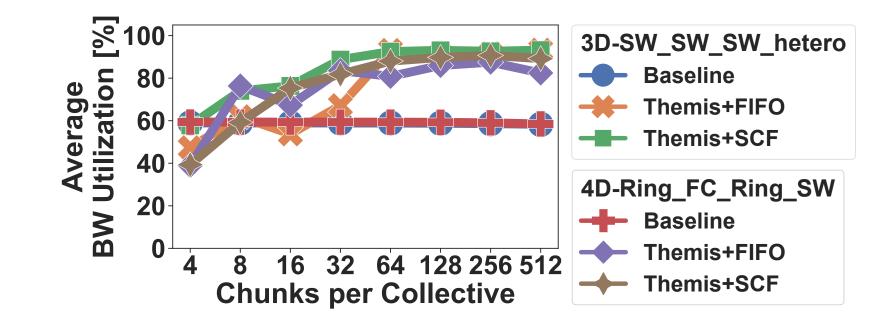
- Simulation Infrastructure: **ASTRA-sim**
- https://astra-sim.github.io

Name	Shape	BW (GB/s / Dim)	Latency (ns / Dim)
3D-SW_SW_SW_hetero	16 × 8 × 8	200, 100, 50	700, 1700
3D-FC_Ring_SW	8 × 16 × 8	175, 100, 50	700, 700, 1700
4D-Ring_SW_SW_SW	$4 \times 4 \times 8 \times 8$	250, 200, 100, 50	20, 700, 700, 1700
4D-Ring_FC_Ring_SW	$4 \times 8 \times 4 \times 8$	375, 175, 150, 100	20, 700, 700, 1700

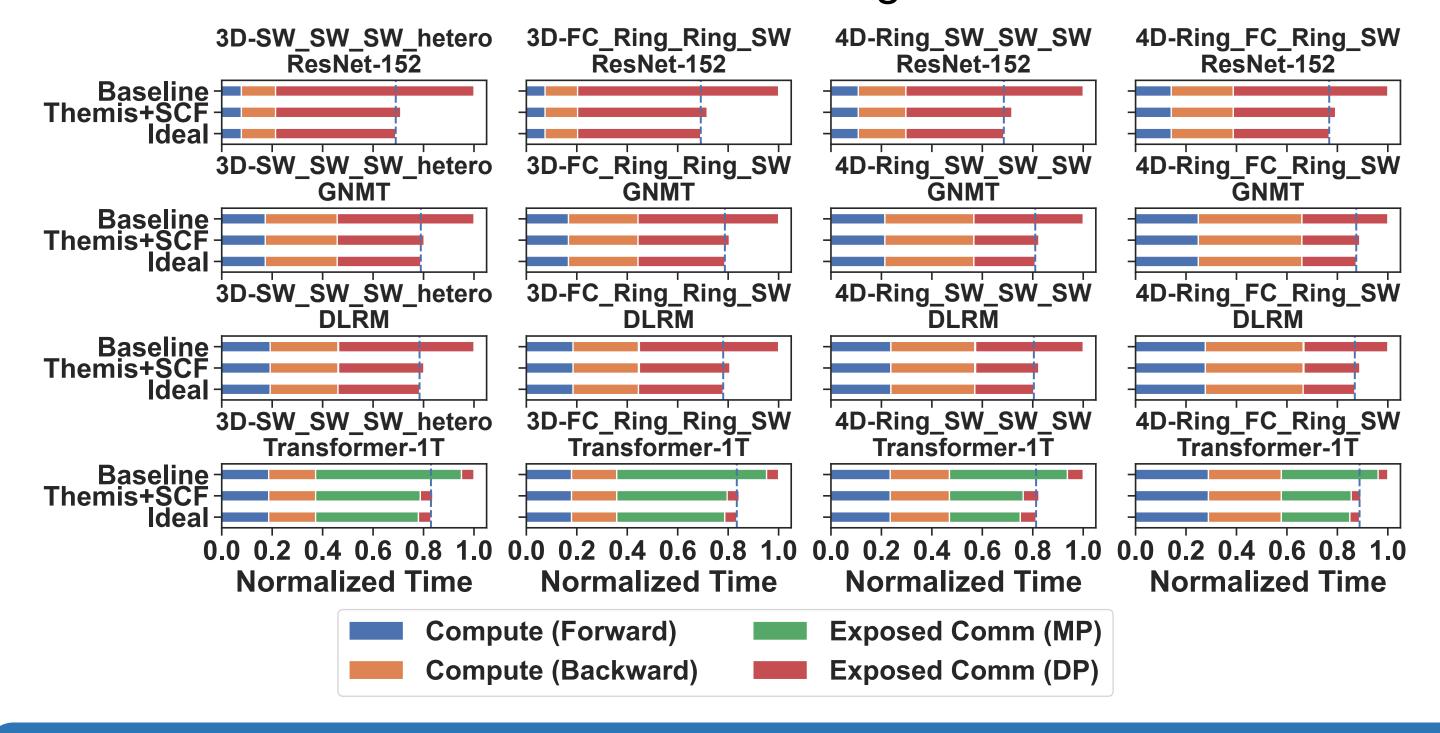
- Single All-Reduce: Themis achieves ~95.14% BW Utilization
 - Baseline: ~56.31% (1.72× speedup)



More #chunks = better load balancing capabilities



- Workloads: Themis reaches near-ideal training performance
 - ~1.49× (ResNet), ~1.30× (GNMT/DLRM), ~1.25× (T-1T) speedup over baseline hierarchical collective algorithm



Conclusion

- Understanding futuristic training platforms
 - Multi-dimensional network with heterogeneous BW
- Huge network BW underutilization is observed
- Due to chunk size and network BW mismatch across dimensions
- Themis: Dynamic chunk scheduler to improve BW utilization
 - By monitoring and balancing loads of each dimension
 - 95.14% network BW utilization (Single All-Reduce)
- 1.49× (ResNet-152), 1.25× (Transformer-1T) speedup