19th USENIX Conference on File and Storage Technologies (FAST '21)

Behemoth: A Flash-centric Training Accelerator for Extreme-scale DNNs

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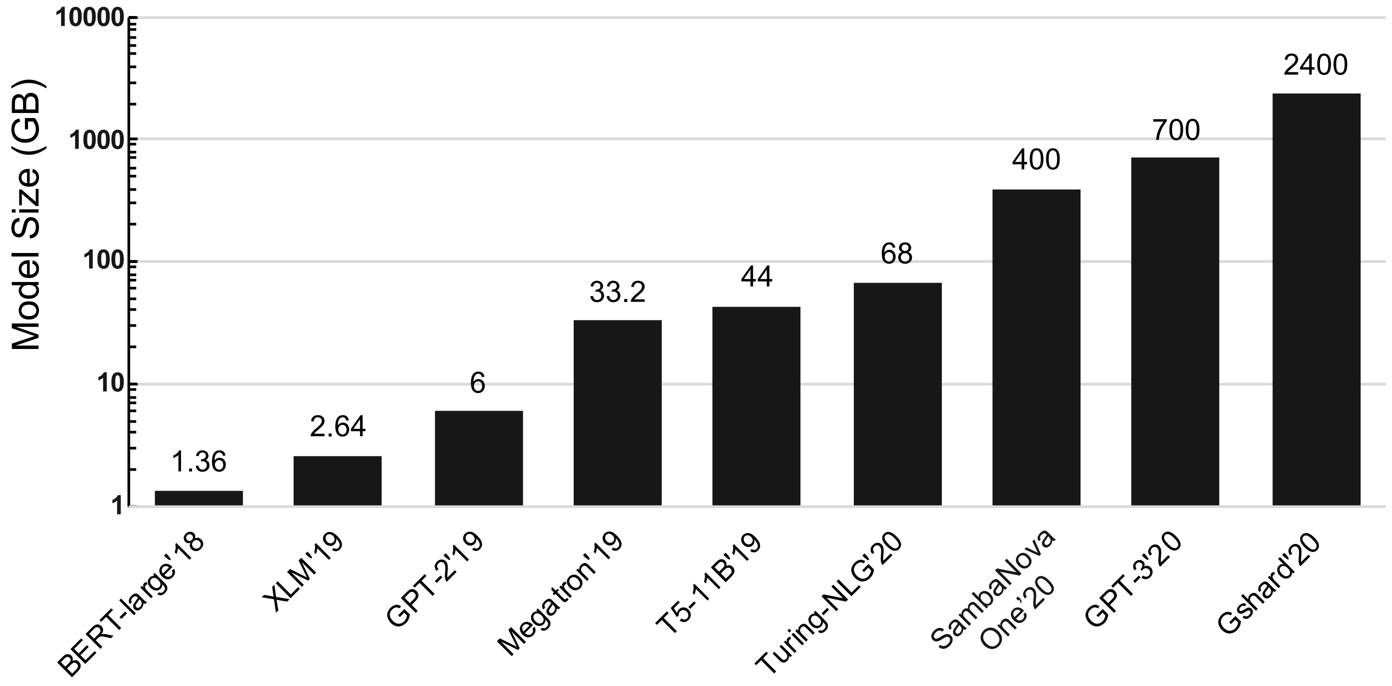
*Equal Contributions

Explosive expansion of DNNs

- Deep Neural Networks have become widespread in various application domains
  - Natural language processing, computer vision, recommendation, and so on
- Increasing the model size is crucial to improve accuracy of DNNs
  - Extreme-scale models demand a tremendous amount of computation and memory capacity



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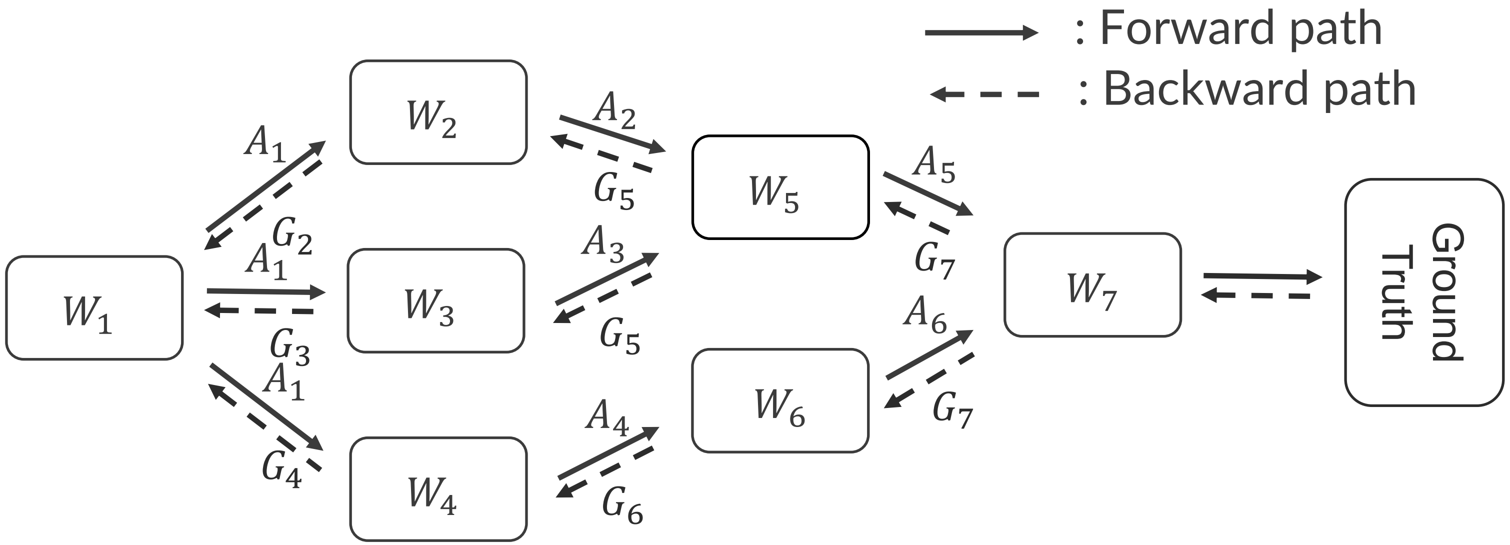
  - Forward path: multiply activation and weights to generate expected value
  - Calculate the difference (loss) between expected value and ground truth
  - Backward path: propagate the loss in backward order and update weights

A: Activation W: Weight G: Gradient



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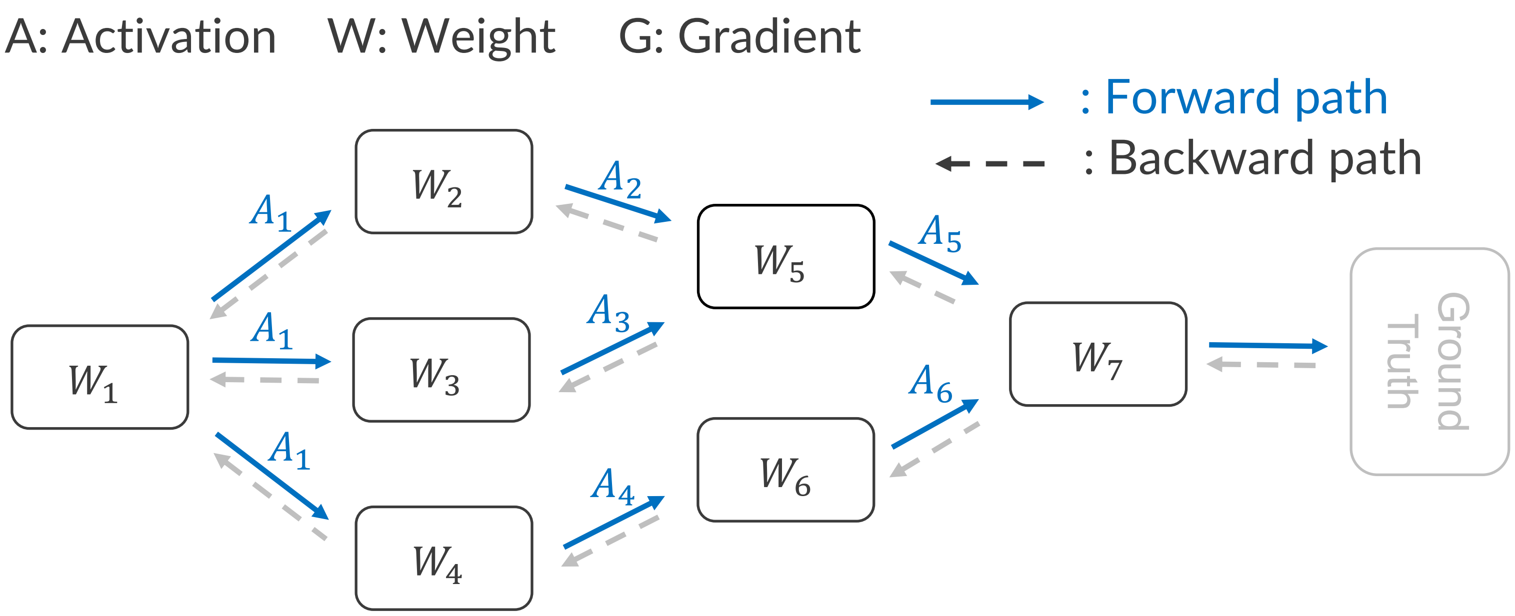

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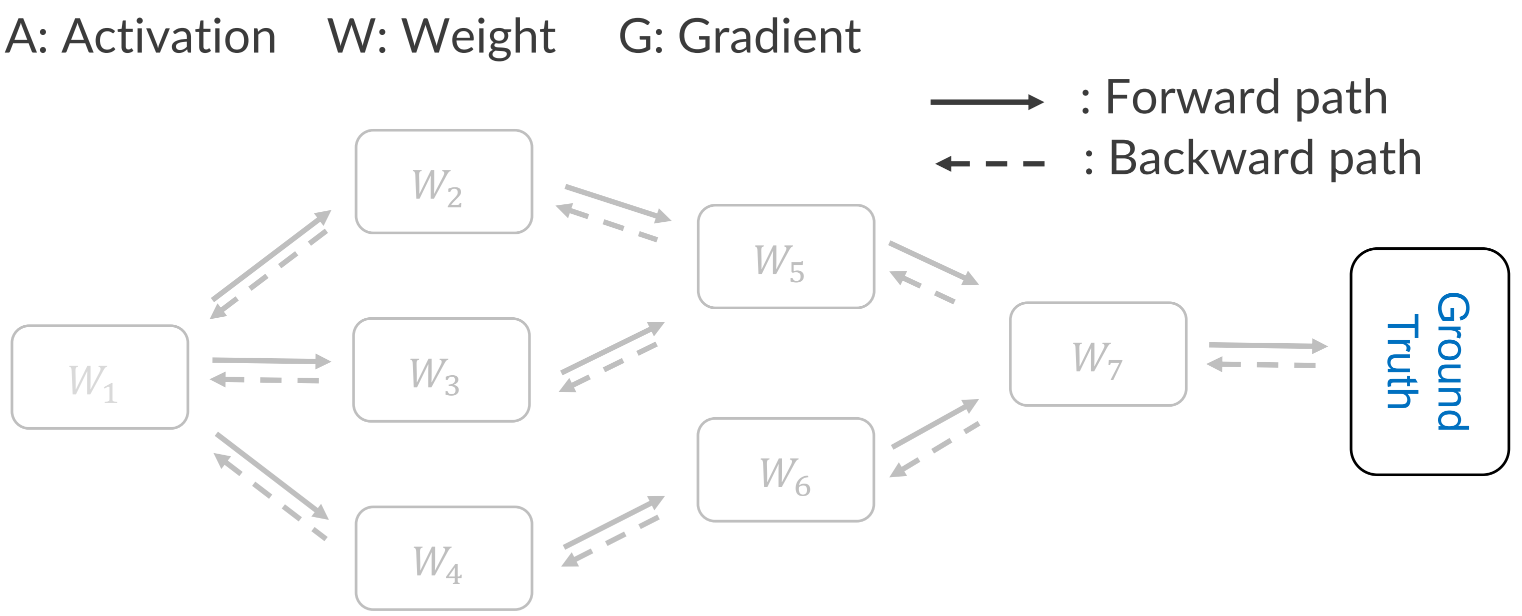

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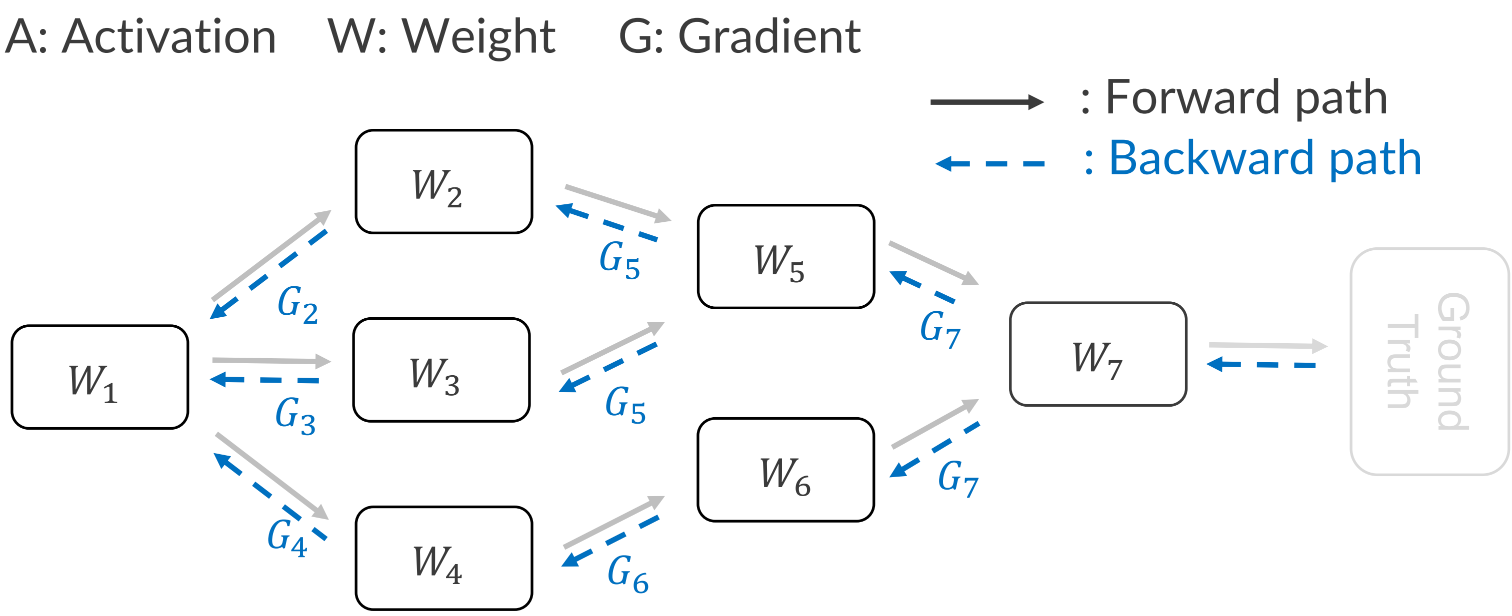
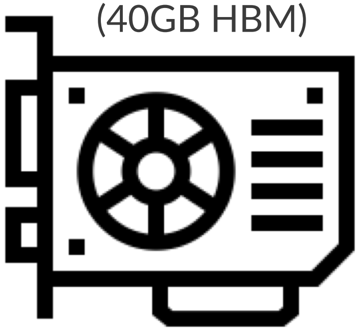


Challenges for Extreme-scale NLP Model Training

- Memory capacity wall
  - DNN model size exceeds memory capacity of a single GPU
  - Forces users to partition the model and distribute to HBM DRAM on GPU (Model Parallelism)

Split a model into layers

GPU A100
(40GB HBM)



X 18

700GB parameters

720GB memory (HBM)

*figure borrowed from http://jalammar.github.io/how-gpt3-works-visualizations-animations/

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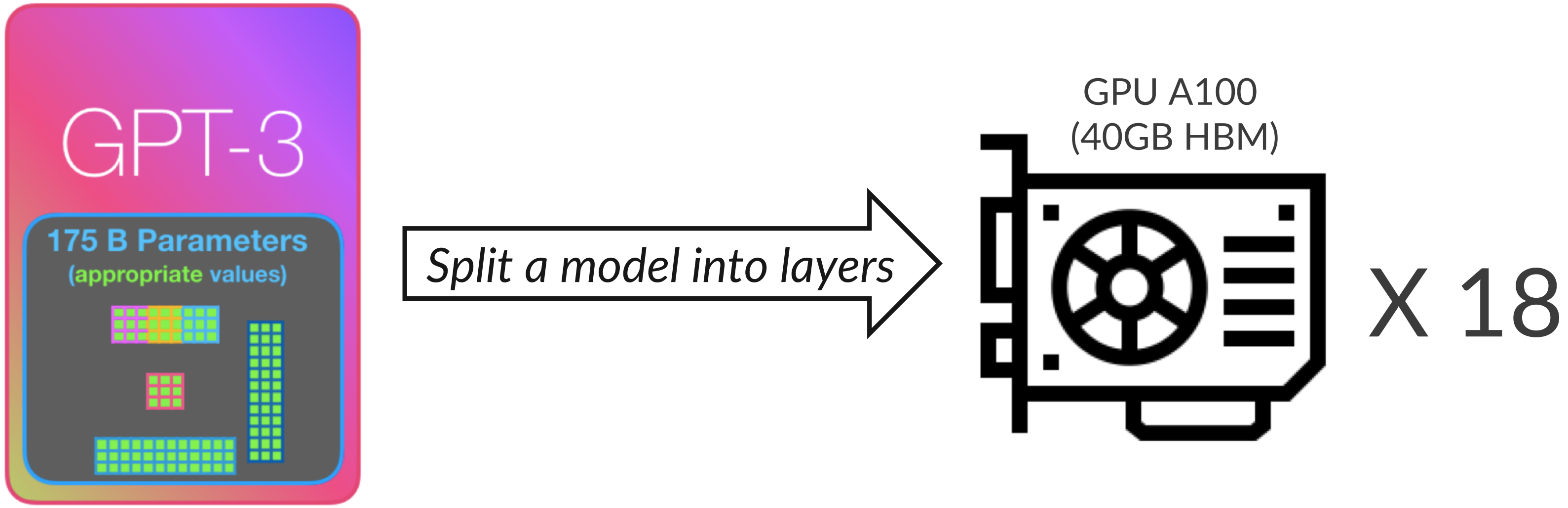
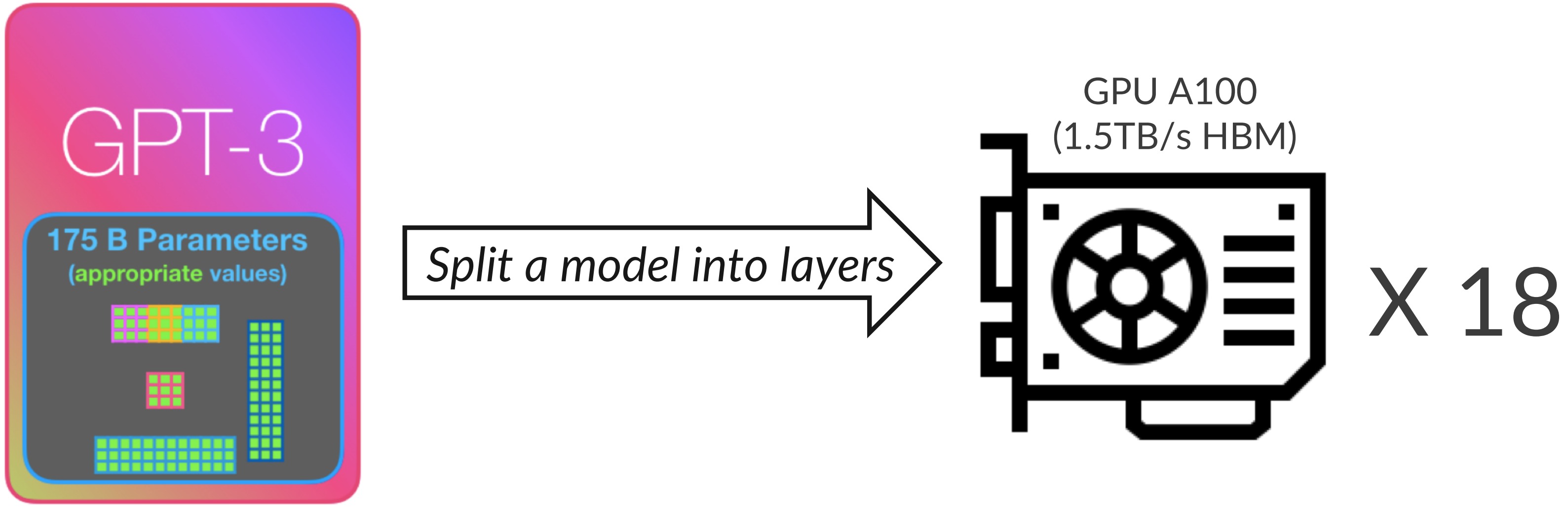


700GB parameters *720GB memory (HBM)*

Careful load balancing is required!

Challenges for Extreme-scale NLP Model Training

- Memory B/W underutilization
  - As a DNN model (matrix) size increased, each value in the matrix is reused more often
  - The memory B/W requirement does not increase as the computation amount increases



50GB/s[1] (required B/W) ***Total 28TB/s (HBM B/W)***

1) *Training with batch size of 16 on 840 TFLOPs compute core*

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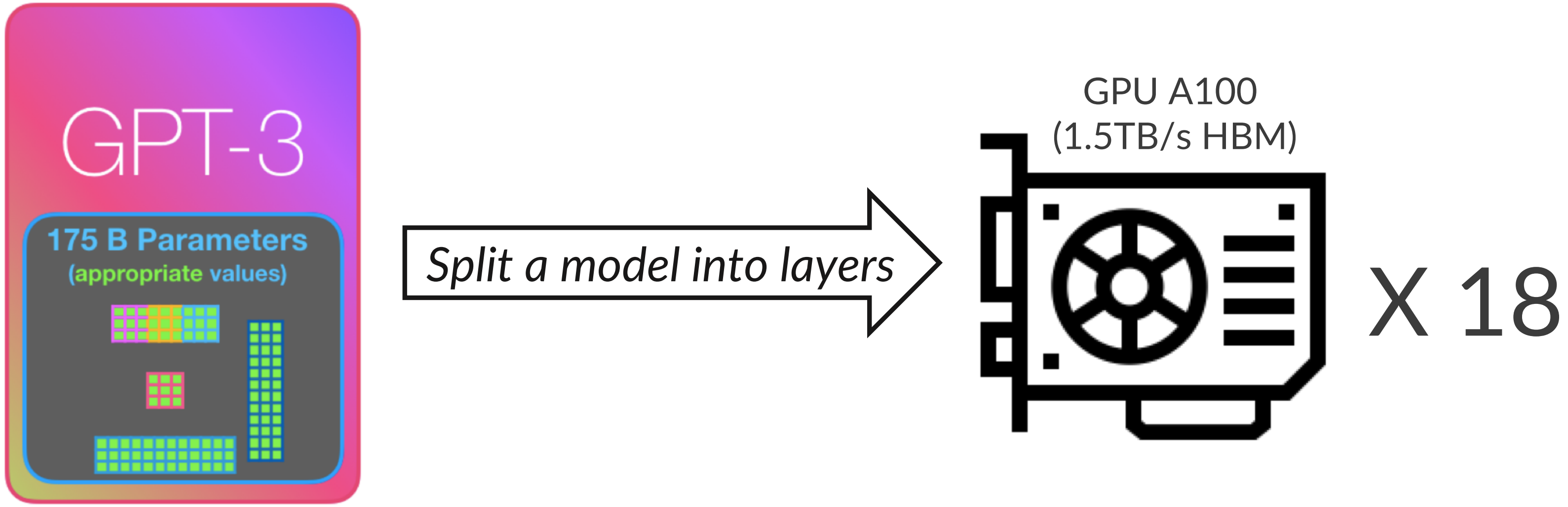


50GB/s[1] (required B/W) *Total 28TB/s (HBM B/W)*

Significant memory B/W underutilization occurs!

1) *Training with batch size of 16 on 840 TFLOPs compute core*

Challenges for Extreme-scale NLP Model Training

Scaling of DNNs necessitates

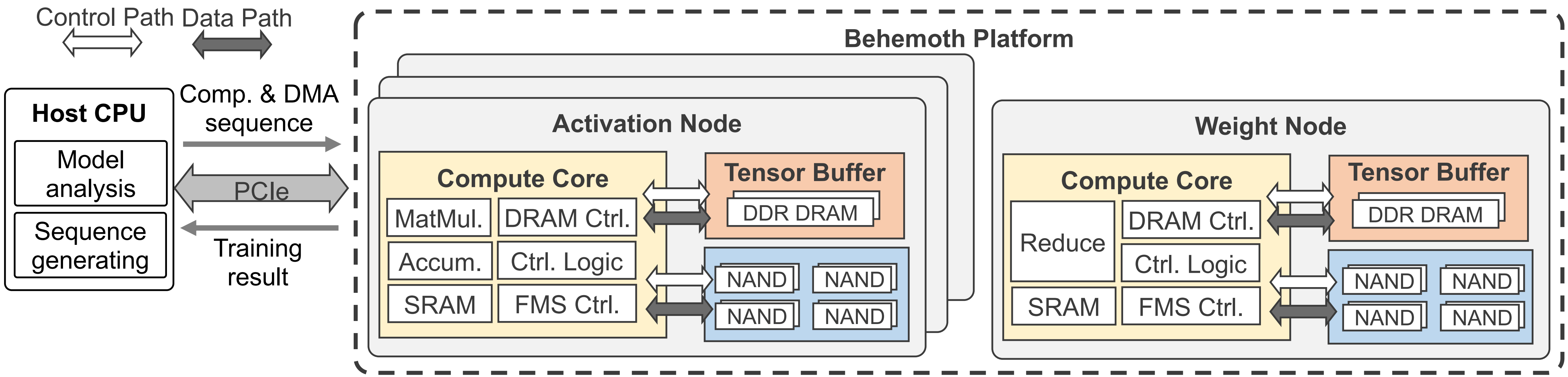
a new memory system with

high-capacity and low-cost

(replacing low-capacity, high-cost HBM)

System Overview

Behemoth holds the entire DNN model in a single node to enable **data-parallel** training



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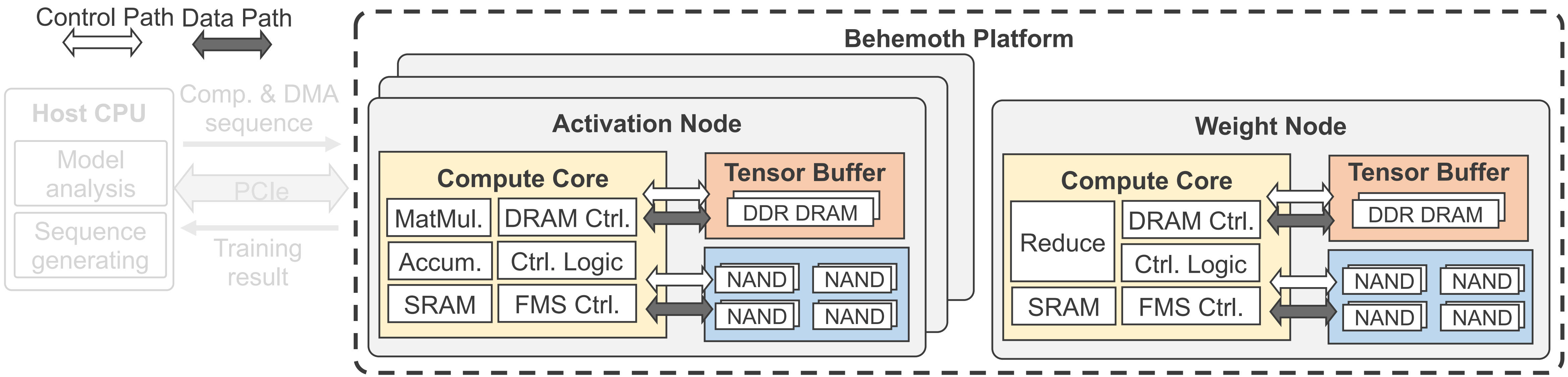

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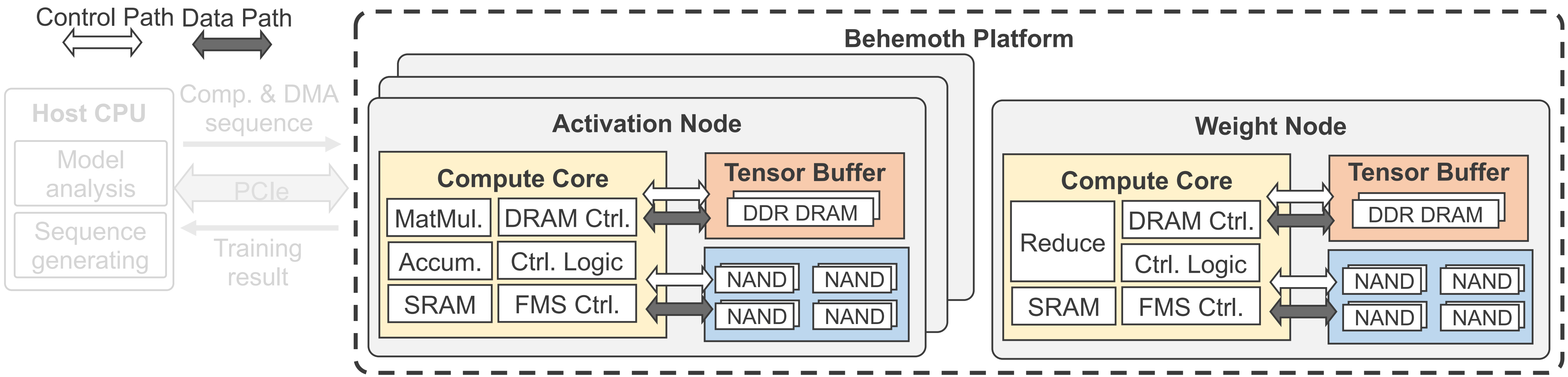

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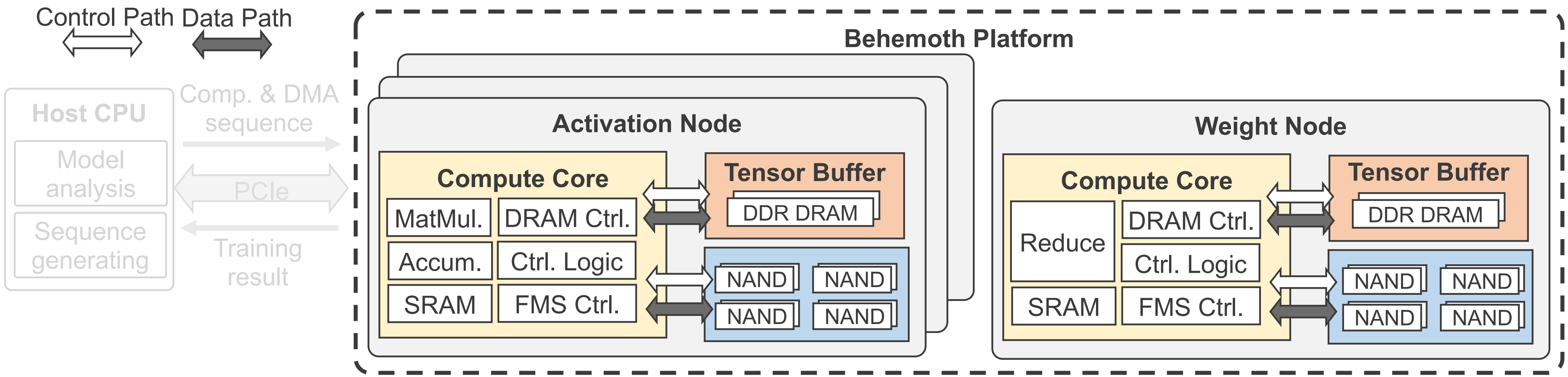

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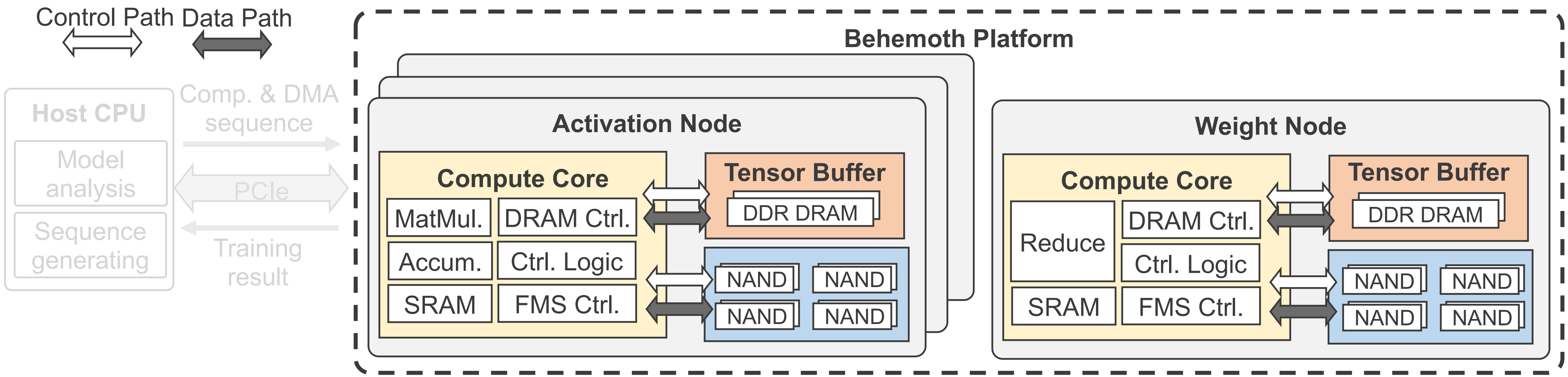

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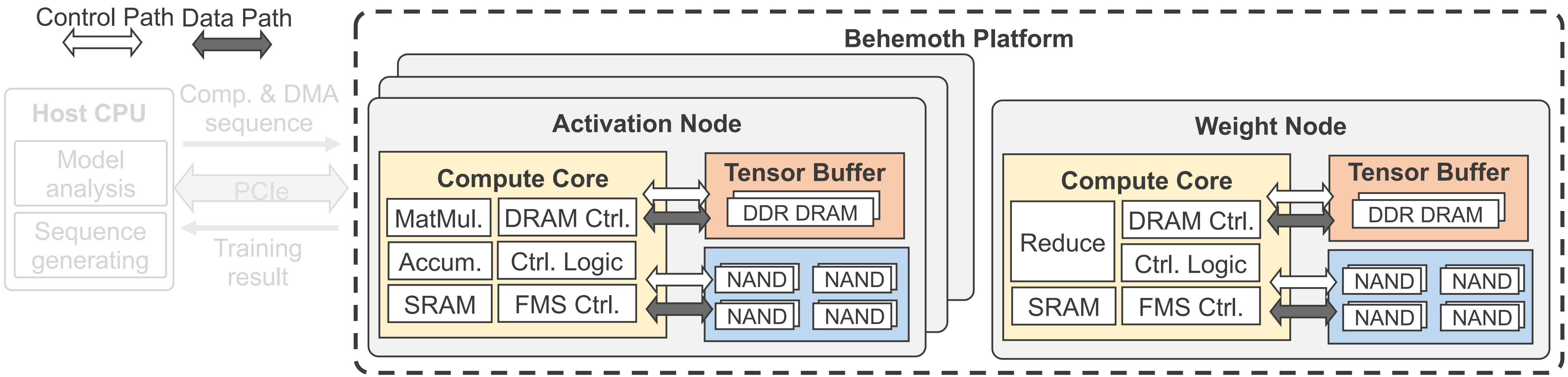
Behemoth adopts a **two-level** memory architecture using DDR DRAM and NAND flash to reduce the DNN training cost



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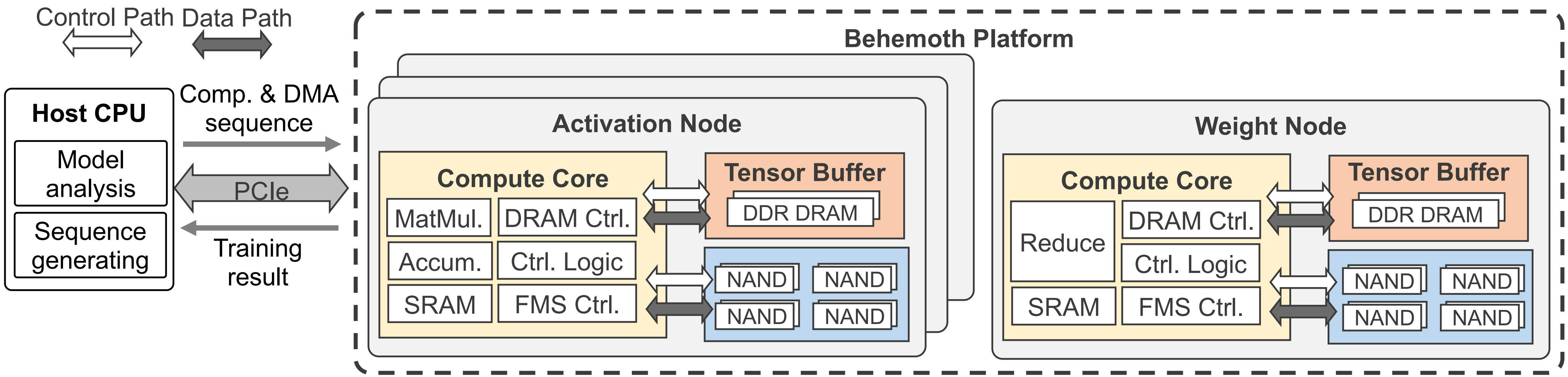
Behemoth platform consist of multiple Activation Nodes and a single Weight Node enabling data-parallel training



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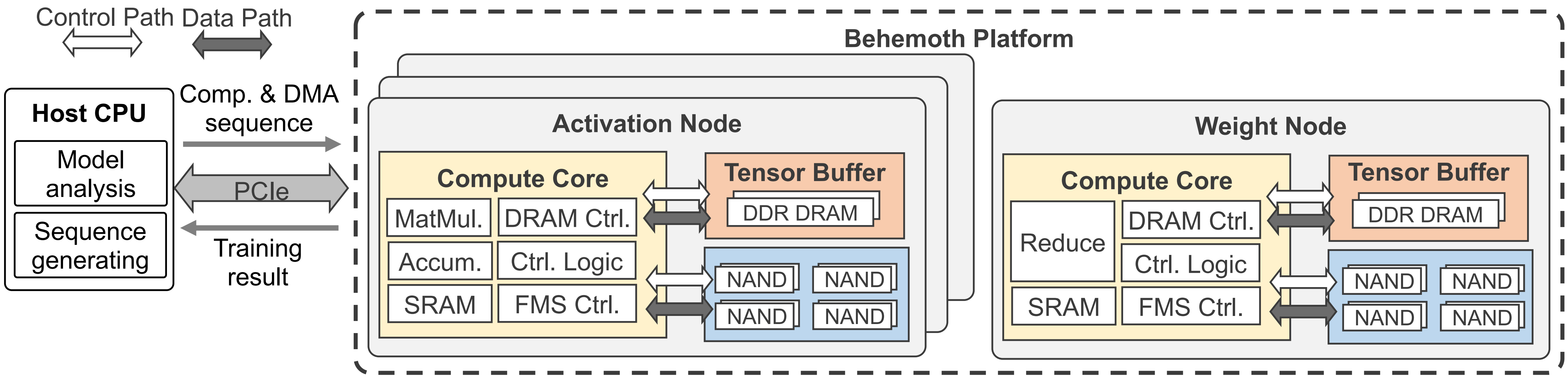

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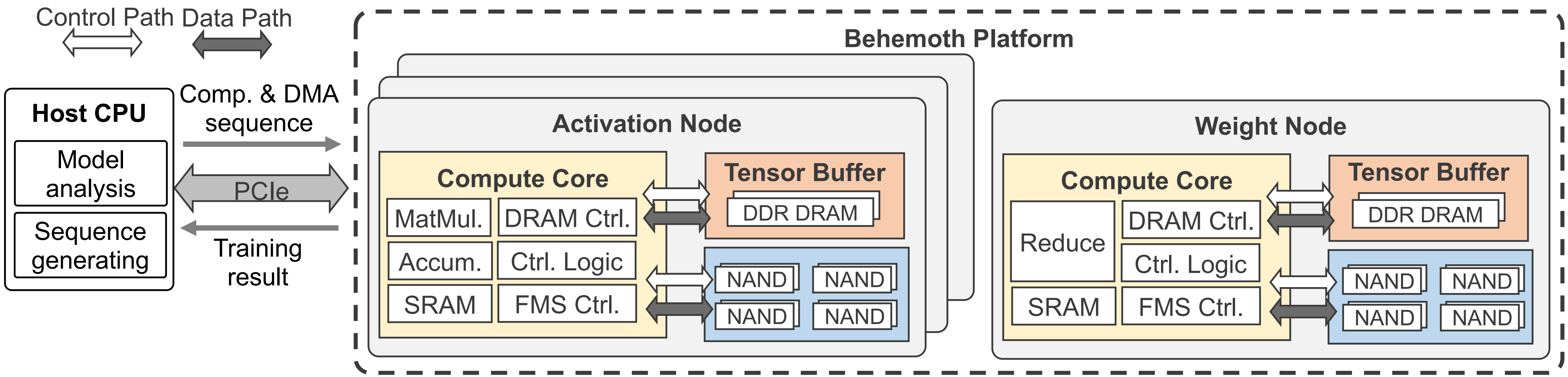

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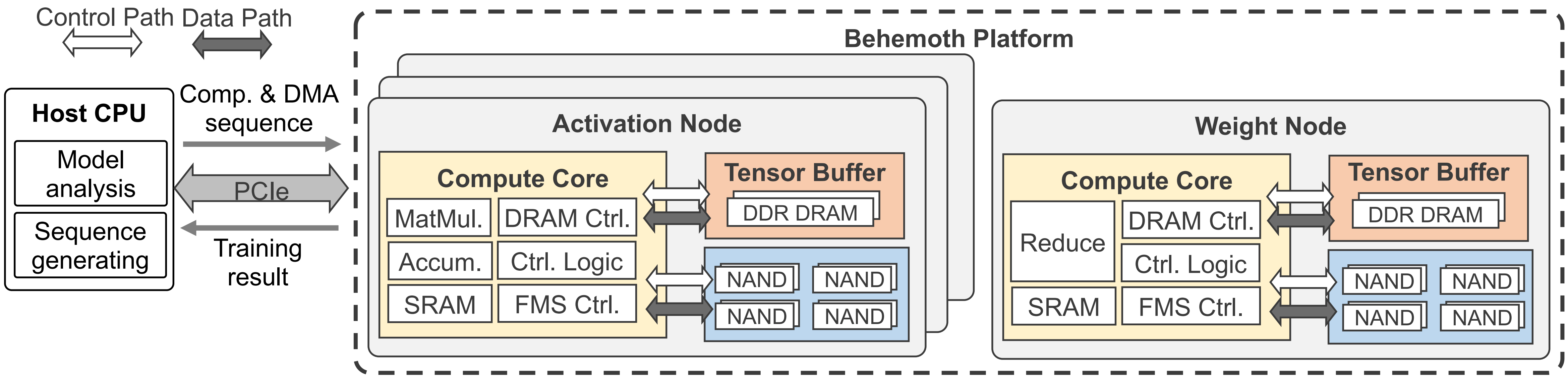

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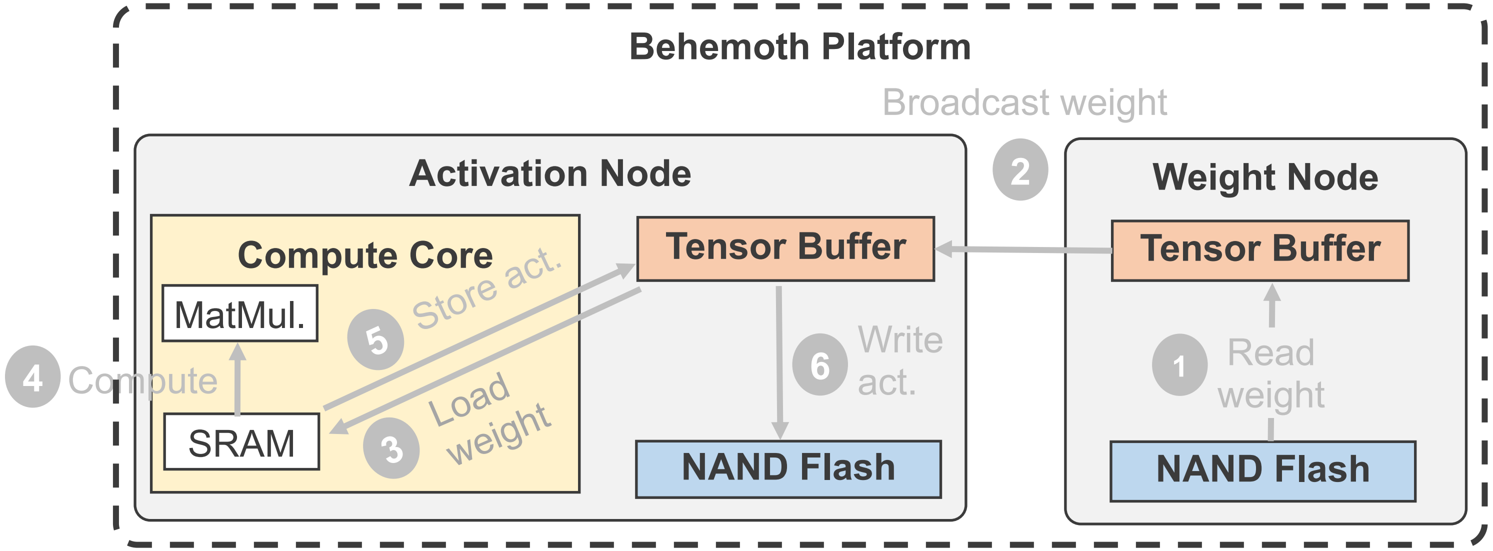
- Weight Node: update and store weights
- Host system: transfer training command sequence to Behemoth

Example Execution Walk-Through

DNN training is a repetitive process of *forward/backward* propagation



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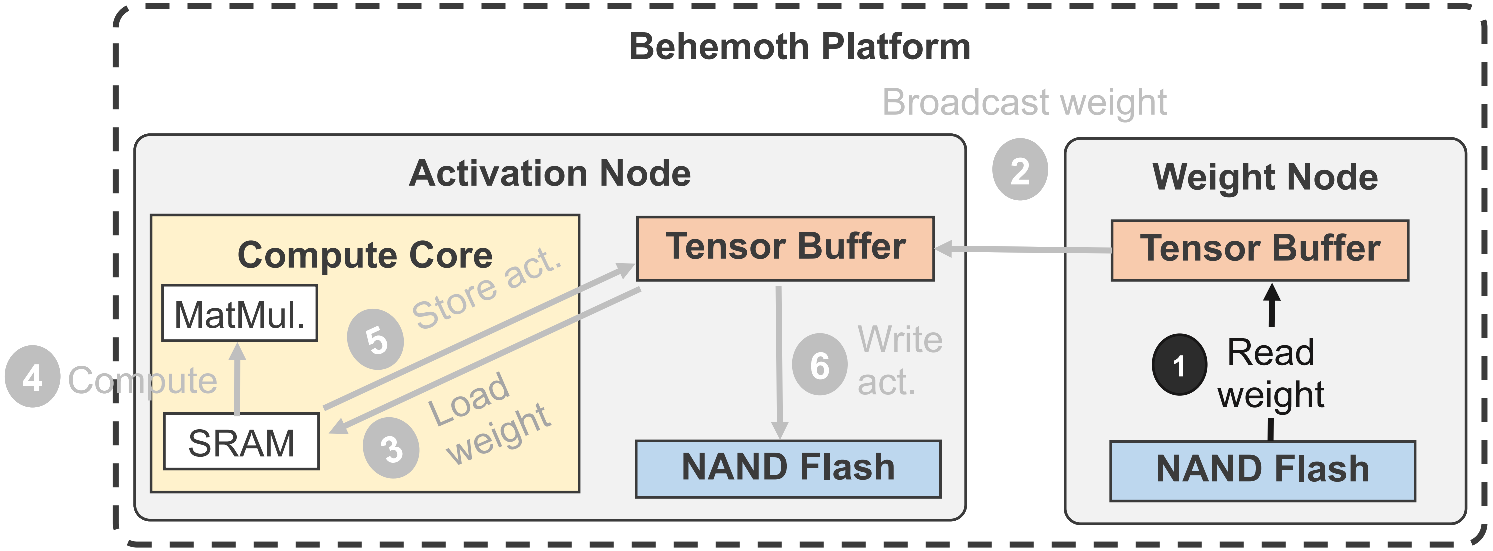

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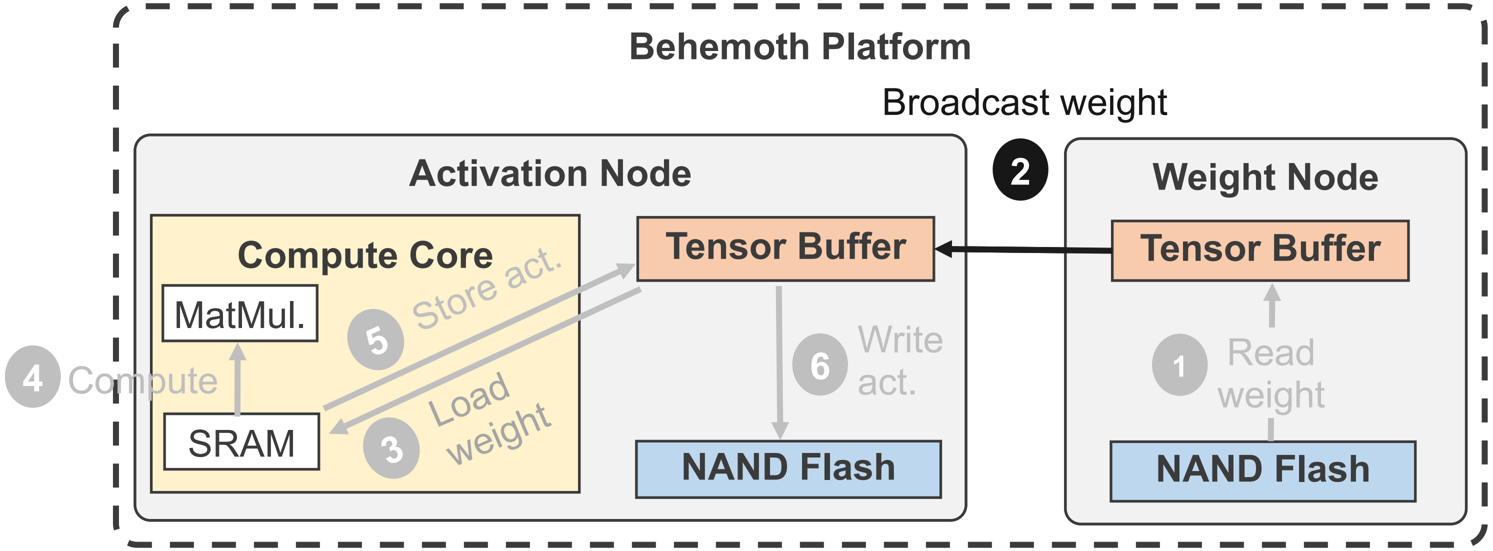

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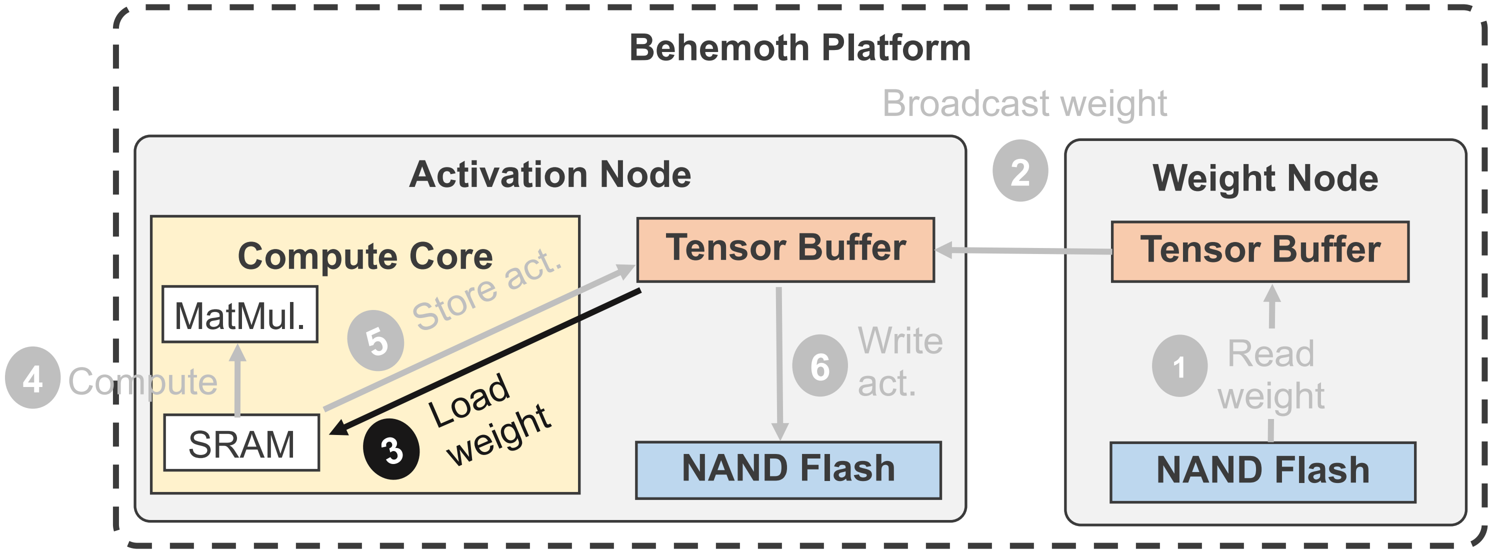

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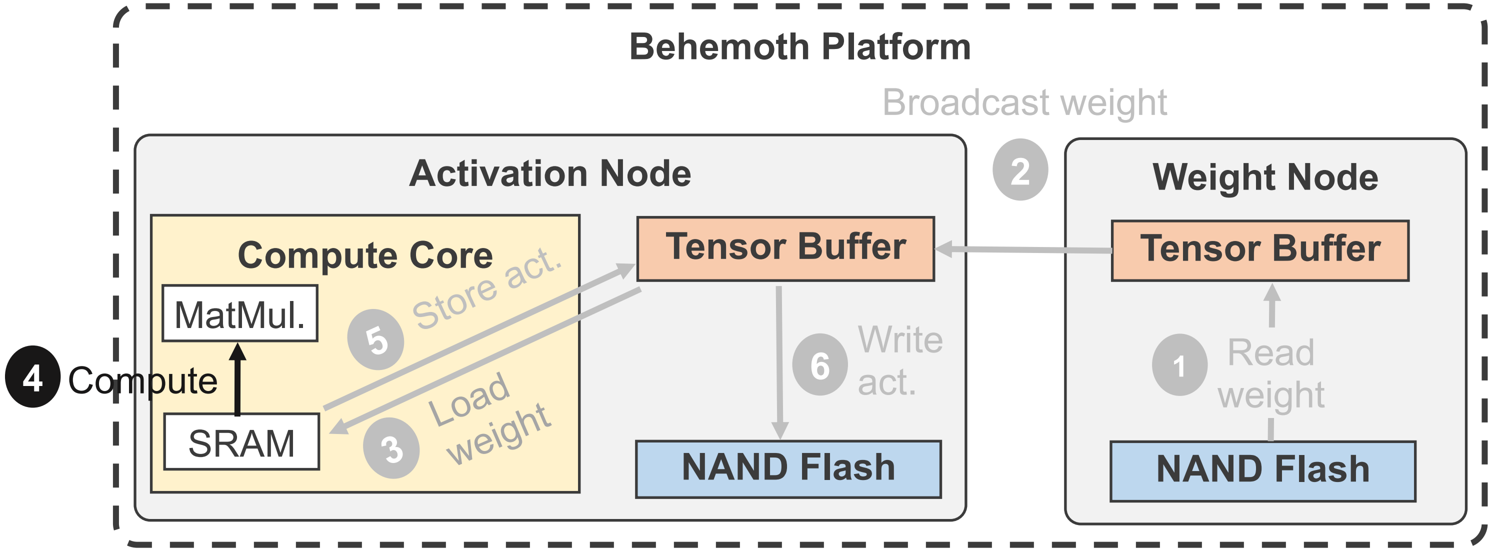

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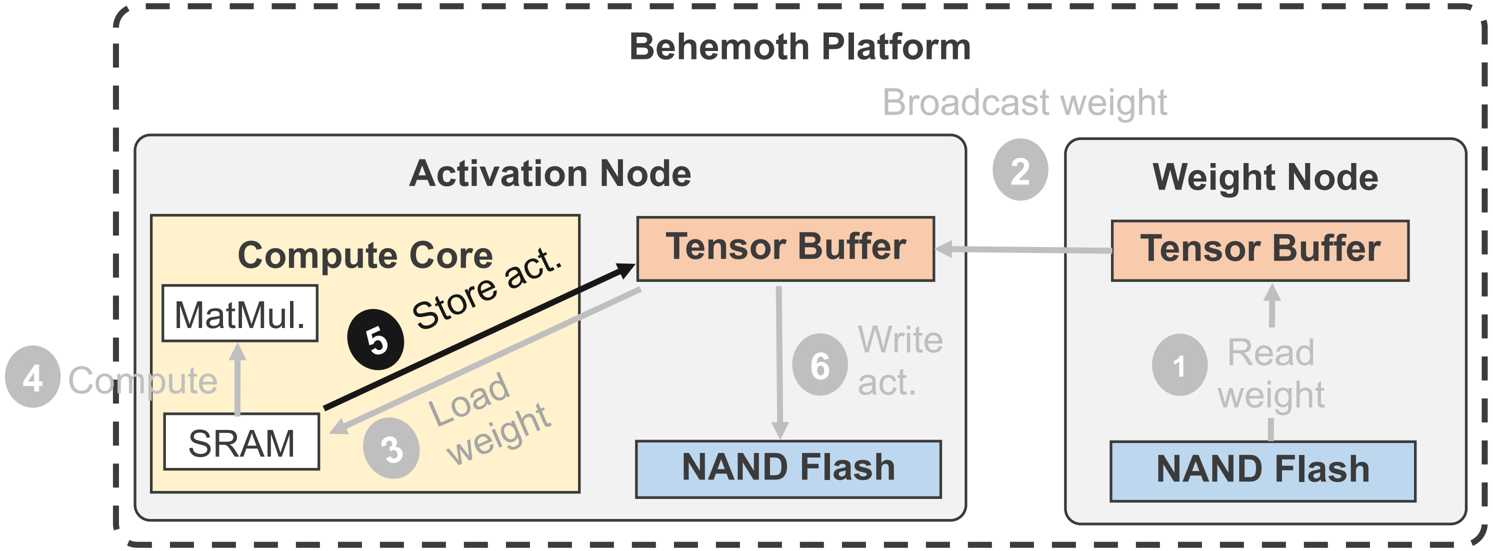

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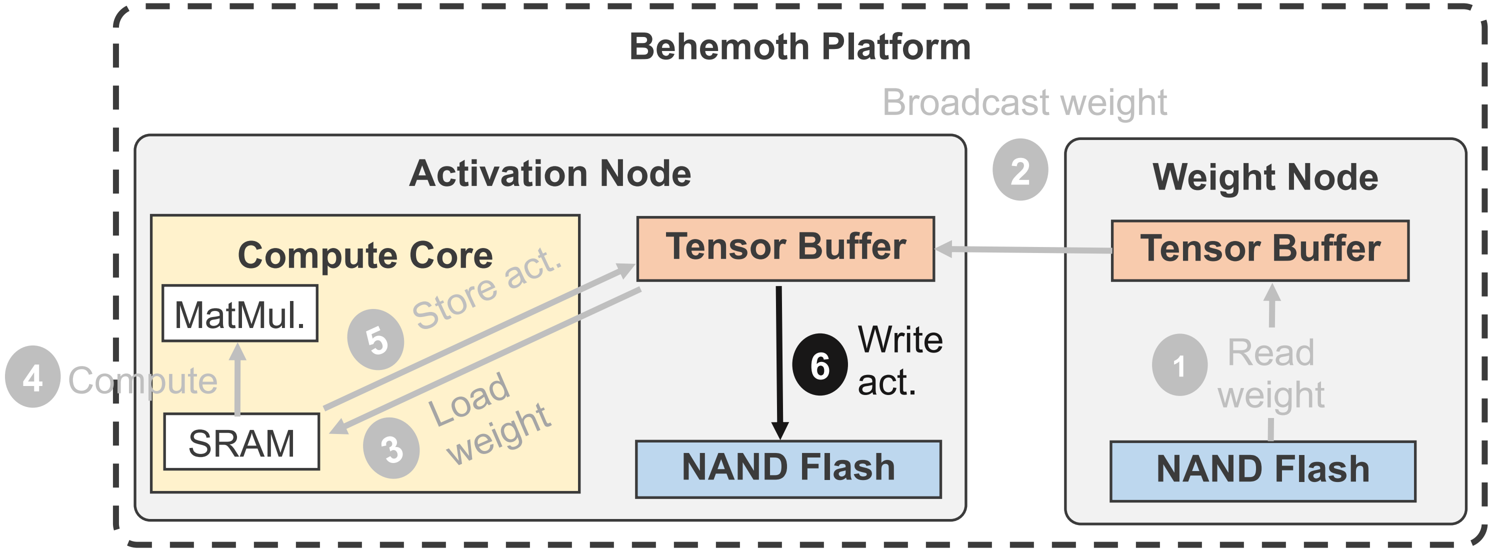

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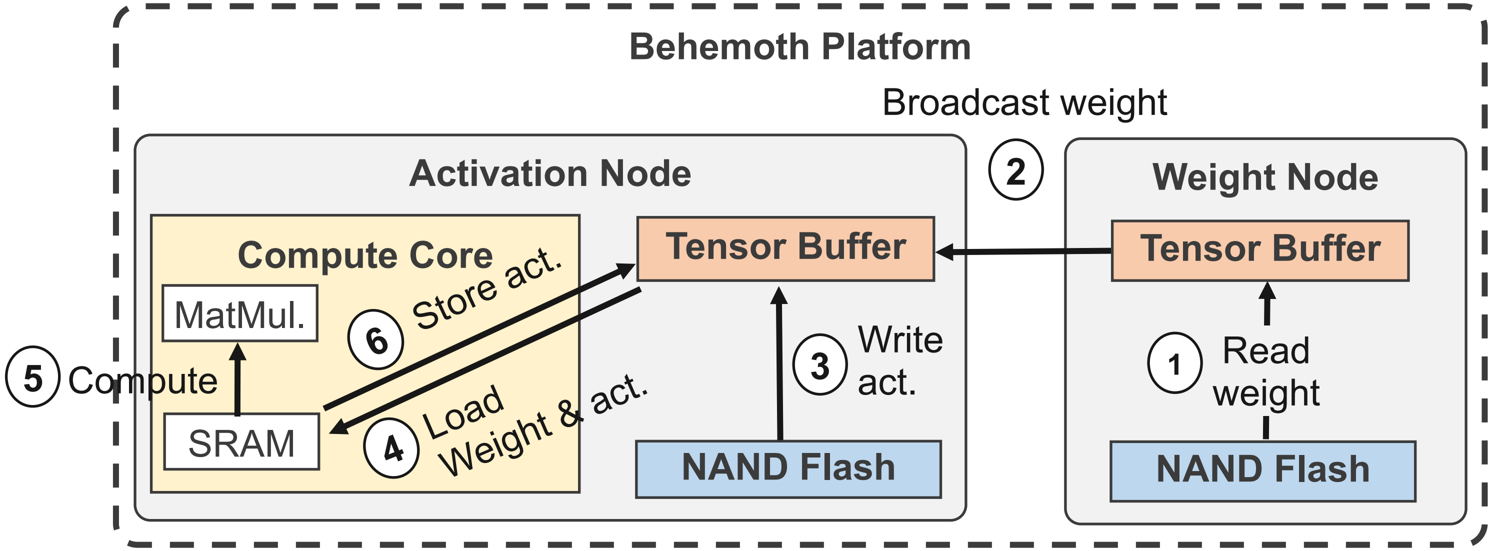

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Architecting Specialized FMS for DNN Training

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>50GB/s Read and Write Bandwidth

5-year Endurance

Improving Bandwidth of FMS

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- SSD firmware has become a bottleneck for scalable performance
- H/W implemented (automated) data-path can be a solution
- Complex functions of FTL make data-path automation difficult
  - Garbage Collection (GC), Wear-leveling (WL), Metadata management for persistency, and so on

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FMS separates data types and adopts lightweight FTL to implement H/W automated data path

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#: Stream name (Act. Node / Weight Node)	**Persistency**	**Retention**	**Access permission**	
			Host	**Behemoth**
1: NV-Stream (Training inputs / –)	Non-volatile	Years	Append-only seq. write	Read only
2: V-Stream (Activations / Interm. weights)	Volatile	Minutes	N/A	Read & Append-only seq. write
3: NV-Stream (– / Trained weights)	Non-volatile	Years	Read only	Read & Append-only seq. write

Multi-stream support for data seperation

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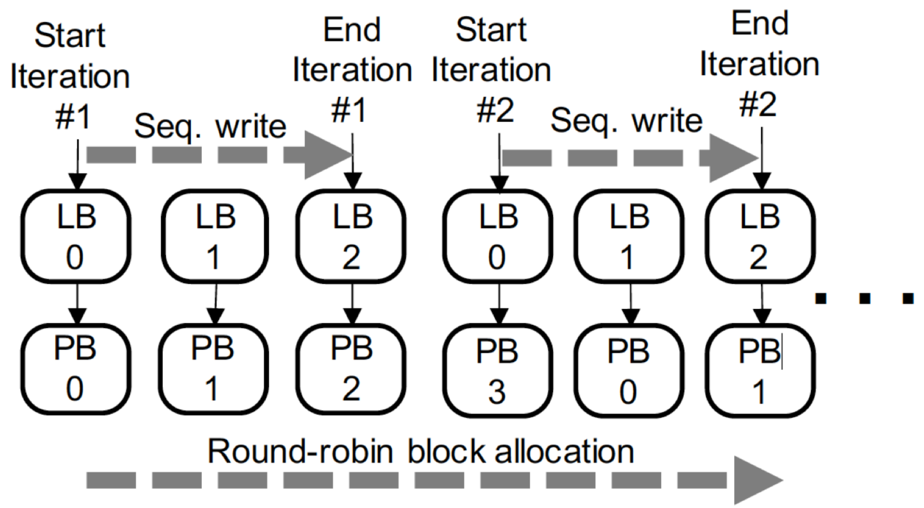
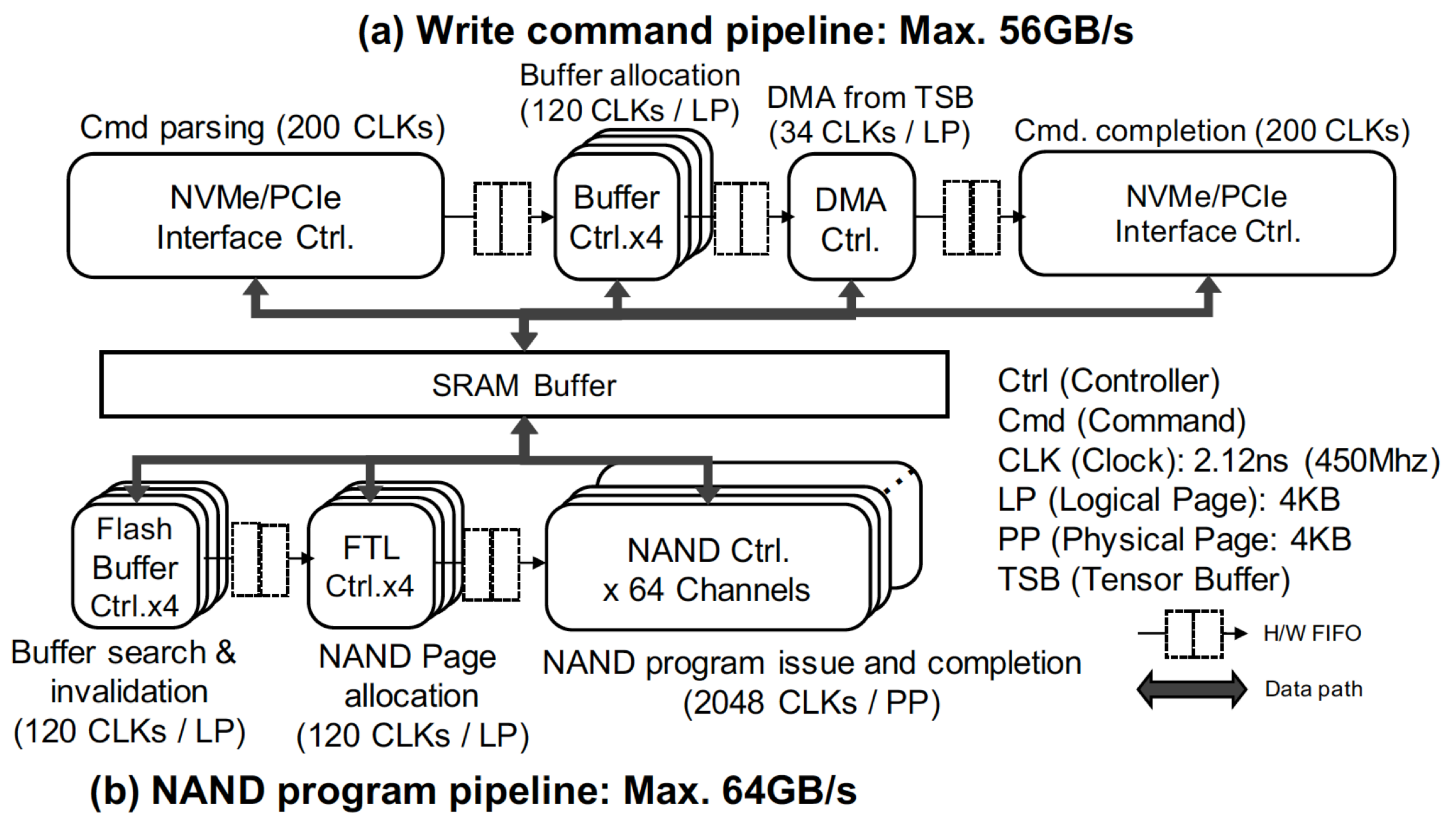


Strict append-only seq. write for lightweight FTL

Improving Bandwidth of FMS



H/W automated write data path of FMS

(a) write command pipeline: transfers data from TSB to an SRAM buffer in the FMS controller

(b) NAND program pipeline: programs data in the SRAM to NANDs

Improving Endurance of FMS

- Endurance of SSD relies on the Program/Erase (P/E) cycles for NAND block

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- DNN training workloads cause frequent P/E operation

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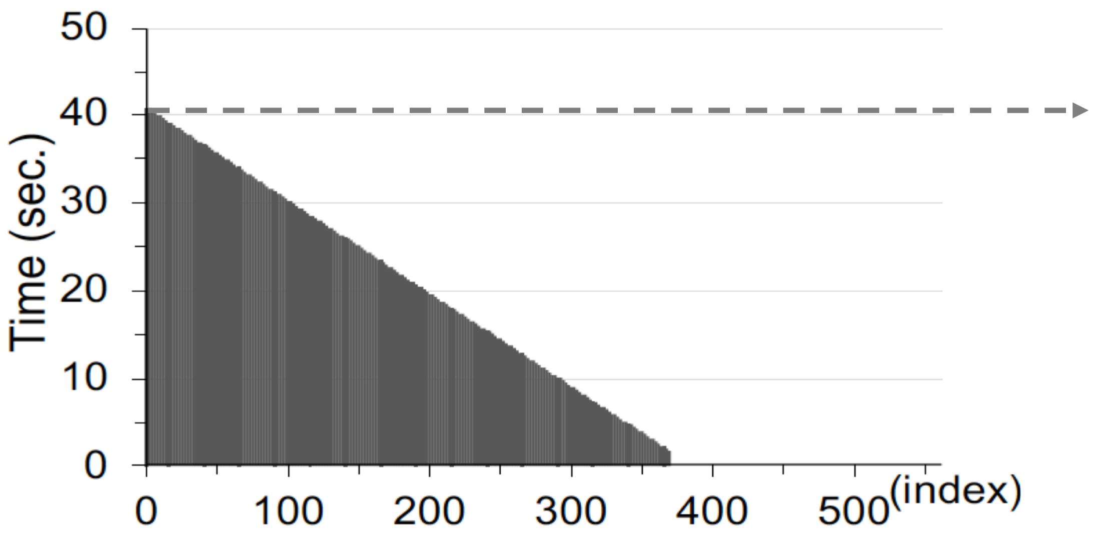

Tensor lifespan for a training iteration of GTP-3 on Behemoth

- Max. data lifespan: 41 sec.
- 1 year retention → 3 days
  - P/E cycle can be increased by at least 40x [1, 2]
  - e.g., 50K P/E cycle → 200K P/E cycle

1) *Yu cai et al*, *ICCD'12*, Flash correct-and-refresh: Retention-aware error management for increased flash memory lifetime
2) Ren-Shuo Liu *et al*, *FAST'12*, Optimizing NAND flash-based SSDs via retention relaxation

Improving Endurance of FMS

Behemoth reduces the data retention time
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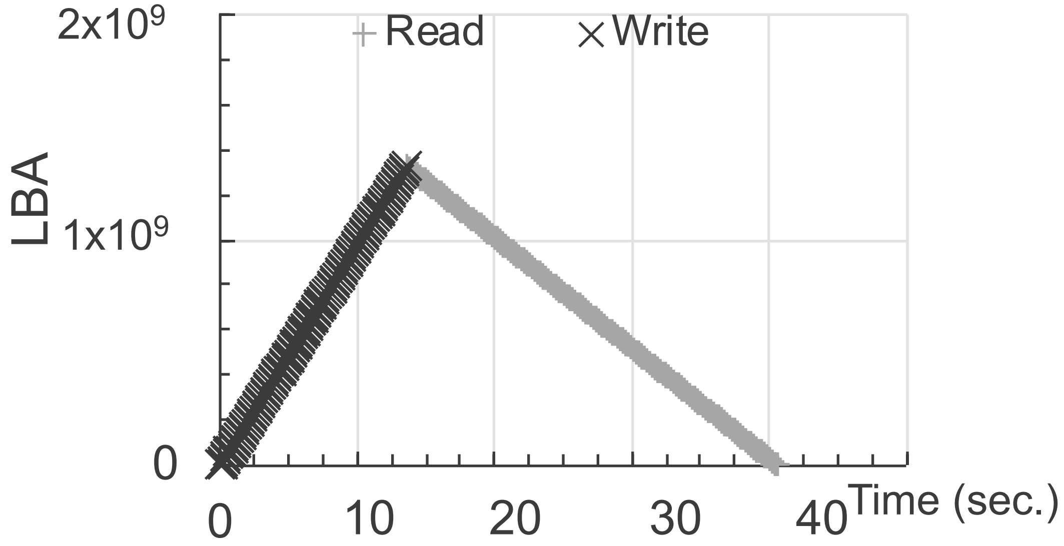
- Only performs monotonic sequential ***writes*** and *reads*
  - No garbage collection → WAF 1



GPT-3 training workloads running on FMS

Evaluation Methodology

- We evaluate our platform's effectiveness by
  1) Comparing the memory cost of Behemoth against the conventional TPU-based DNN training system
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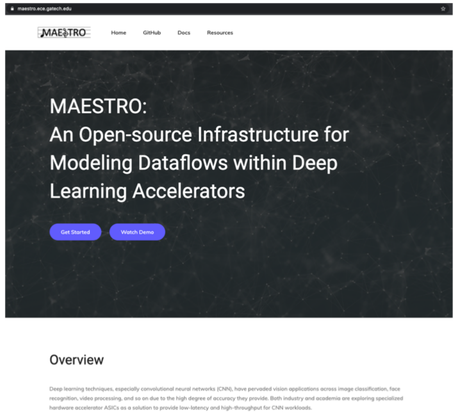
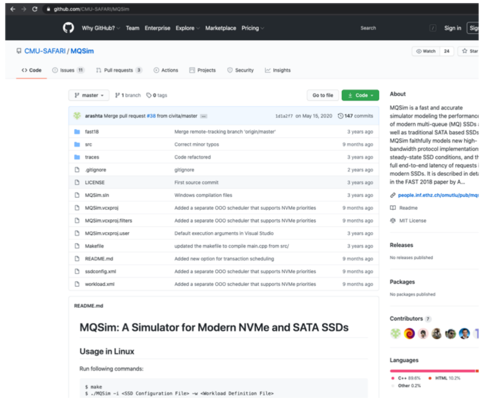


NPU Simulator:
MAESTRO[1)]



SSD Simulator:
MQ-Sim[2)]

1) https://maestro.ece.gatech.edu/
2) https://github.com/CMU-SAFARI/MQSim

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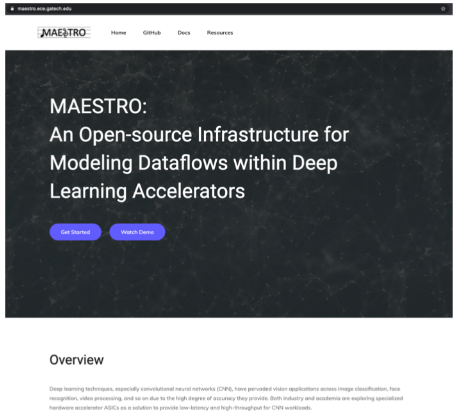

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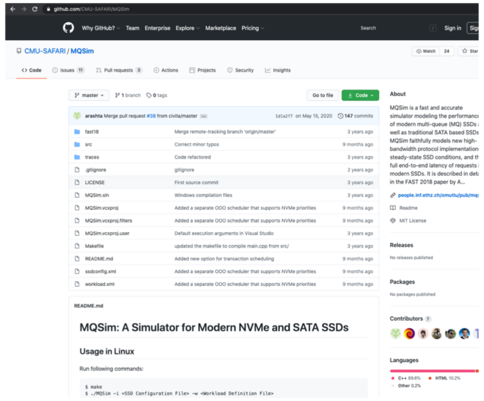

SSD Simulator: MQ-Sim[2)]

Model	Size	Total act. (GB)	Total weight (GB)	PFLOP
BERT/GPT3-like	1×1	44	350	2.15
	1×2	88	698	4.42
	1×4	175	1393	8.56
	2×1	88	1395	8.56
	2×2	175	2786	17.12
	2×4	349	5569	34.21
T5-like	1×1	40	305	0.62
	1×2	80	609	1.25
	1×4	160	1218	2.49
	2×1	80	1218	2.49
	2×2	160	2436	4.99
	2×4	319	4871	9.97

Evaluation workloads

1) *https://maestro.ece.gatech.edu/*
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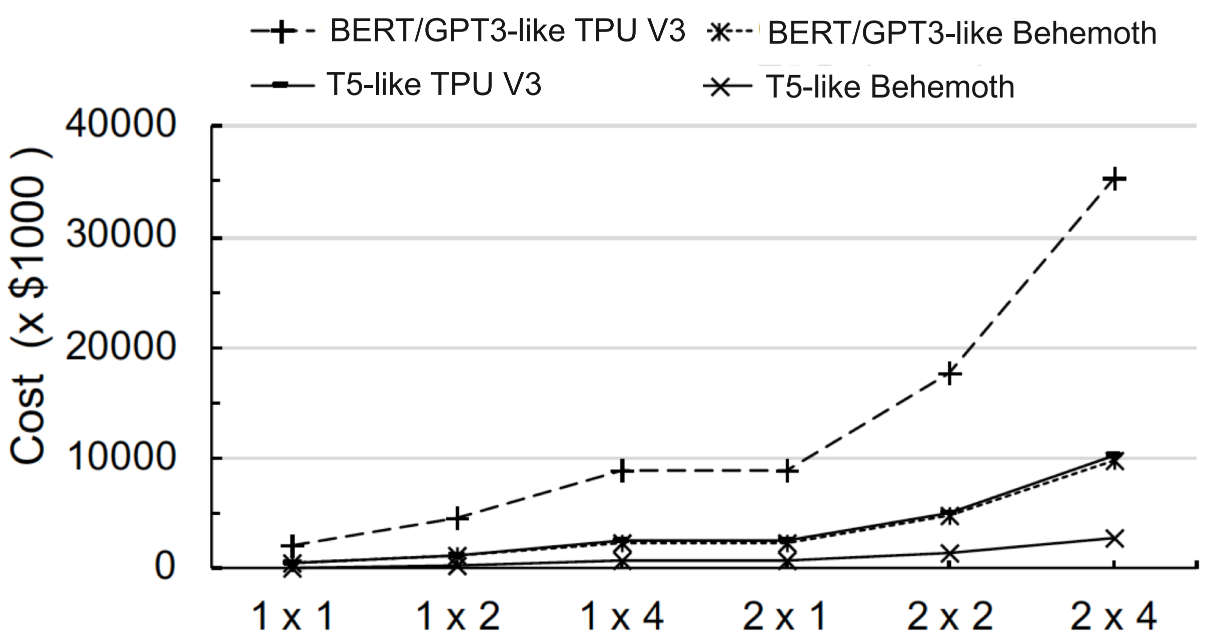
Memory Cost Evaluation

NPU Parameters		
Number of Cores	16 cores (52.5 TFLOPs per core)	
Number of PEs	524,288	
Peak throughput	840 TFLOPs	
Host I/F conf.	PCIe Gen4 x 32 lane	
Node and Memory Parameters		
	Resemble TPU	**Behemoth**
Number of Nodes	864	432
Buffer conf.	128GB HBM (16GB x 8ea)	16GB DDR4 DRAM + 2TB NAND flash
Peak bandwidth	4.8TB/s	50GB/s
Compute Parameters		
Parallel comp. method	Model parallelism	Data parallelism

Platform configurations for the cost comparison



Memory cost[1)] comparison between TPU V3 and Behemoth

- To maintain the same training throughput, TPUv3-like platform costs up to 3.65x the memory cost

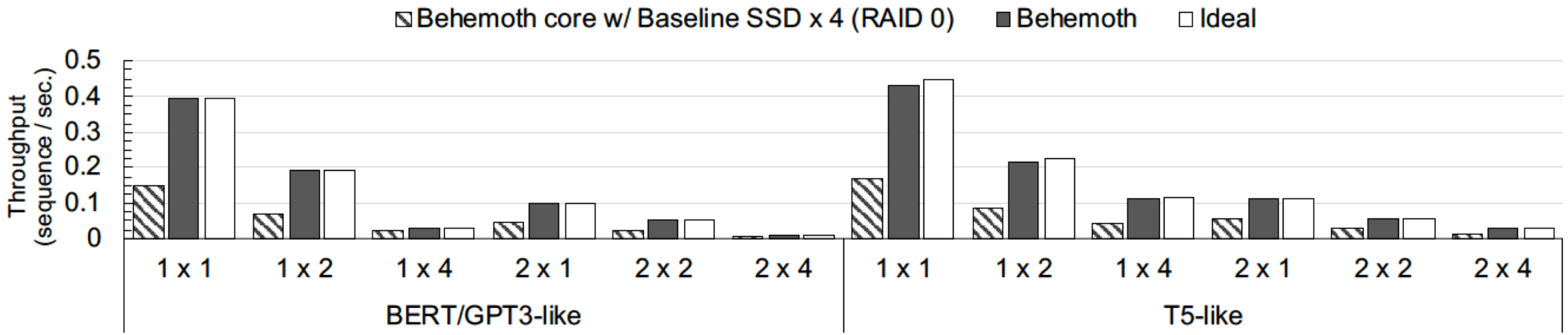
1) HBM: $20/GB, SLC NAND: $0.67/GB, DDR DRAM: $4/GB

Training Throughput Evaluation

- We compare Behemoth and baseline system utilizing the commodity SSDs
  - Behemoth with 2TB FMS
  - Behemoth core with 500GB of 4x SSDs (RAID 0)

Storage Parameters		
	Behemoth FMS	**Baseline SSD**
NAND Configurations	2TB, 64 channels, 2 chips/channel, 1 die/chip	500GB, 16 channels, 2 chips/channel, 1 die/chip
Channel Speed Rate	1200MT/s (MT/s: Mega Transfers per Second [20])	
NAND Structure	128Gb SLC / die: 8 planes / die, 683 blocks / plane, 768 pages / block, 4KB page	
NAND Latency	Read: 3μs, Program: 100μs, Block erase: 5ms	
Buffer Configurations	SRAM 16MB: 6MB for FTL metadata, 10MB for I/O buffer	DRAM 512GB: FTL metadata SRAM 8MB: I/O buffer, GC Buffer
FTL Schemes	Block mapping	Page mapping, Preemtible GC [38]
OP ratio	N/A	7%
Firmware Latency	N/A	Write: 1.45μs / a page (4KB)
Contoller Latency	Read: 1.93μs / an NVMe Cmd, Write: 1.18μs / an NVMe Cmd	Read: 1.93μs / an NVMe Cmd

Training Throughput Evaluation



- Behemoth is close to the ideal case
- Conventional SSDs show much lower training throughput (up-to 2.05x)
  - SSD firmware bottleneck is major cause for performance degradation

Summary

Behemoth enables efficient data-parallel training of extreme-scale DNN models

- Analyze the memory capacity problem for extreme-scale DNN model training
- Identify new opportunities to leverage NAND flash devices to hold those models
- Present a novel flash-centric DNN training accelerator
- Show 3.65x memory cost savings over TPUv3 and 2.05x training throughput impr ovement over conventional SSDs

Thank you !

Additional details in the paper:

- Analysis of Transformer: a key enabling primitive for extreme-scale DNNs
- Discussion of architectural decisions
- Coverage analysis for various DNN models
- Endurance evaluation