Beyond Simple Parallelism

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ZeRO-Infinity: Breaking the GPU Memory Wall for Extreme Scale Deep Learning

Motivation: Challenges Faced by Large Model Training

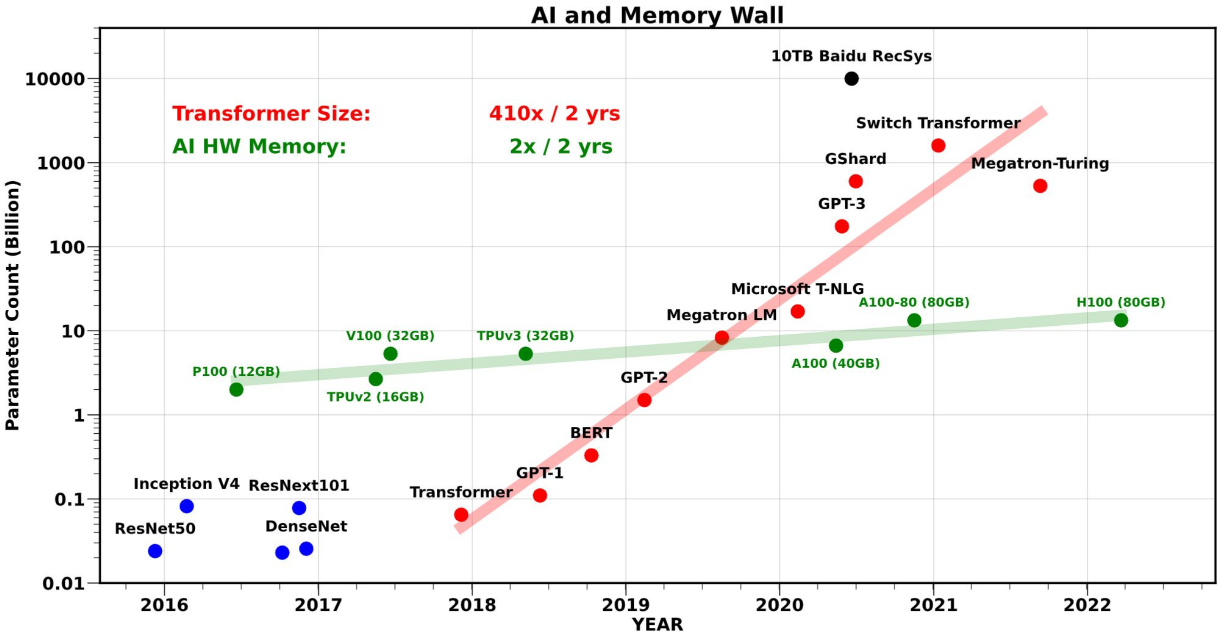
GPU Memory Wall

10T params: 8K V100 GPUs

Model size keeps growing

Model Code Refactoring

Need to rewrite the model using 3D parallelism

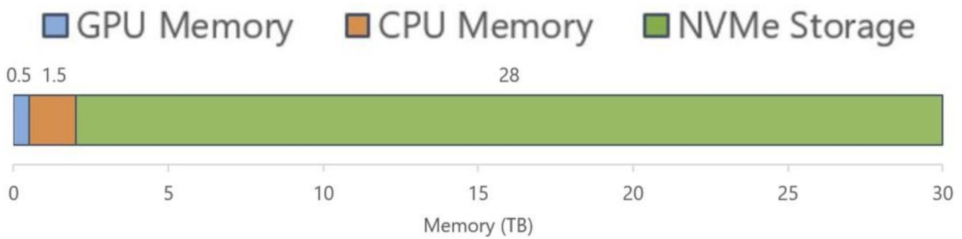


Possible Solution: Leverage Non-GPU Memory

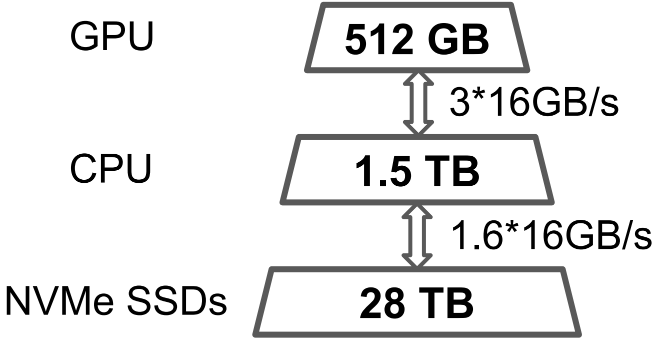
Modern clusters have heterogeneous memory systems.

GPU memory only comprises a small fraction

Leverages GPU/CPU/NVMe memory
- 1T params on a single node



Memory available on a Single DGX-2 Node



Memory Hierarchy of DGX-2/2H System (16V100 GPUs)

Possible Solution: Leverage Non-GPU Memory

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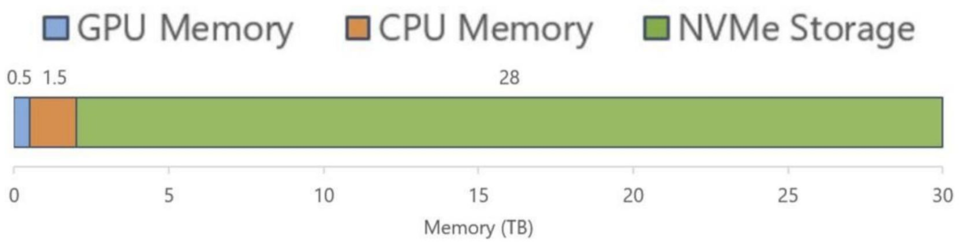
How to leverage non-GPU memory?



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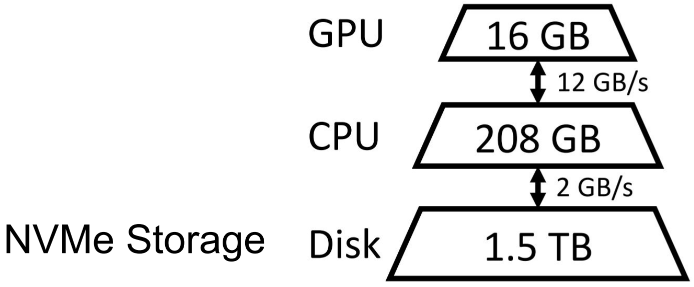


Memory Hierarchy of NVIDIA T4 GPU

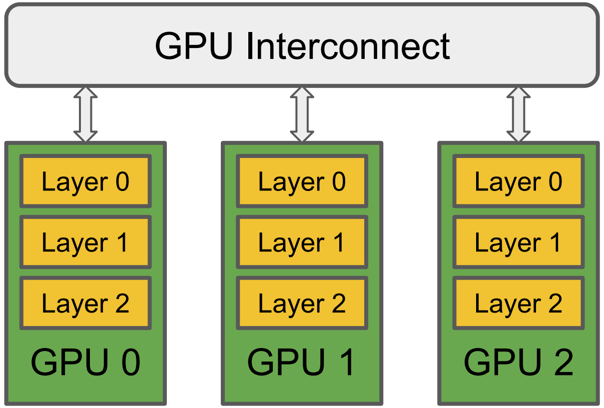
How to leverage non-GPU memory?

Directly applying existing parallel training technology?
Data Parallelism: Replication causes memory explosion
Tensor-Slicing: Does not scale beyond a single node
Pipeline-Parallelism: Requires significant code refactoring

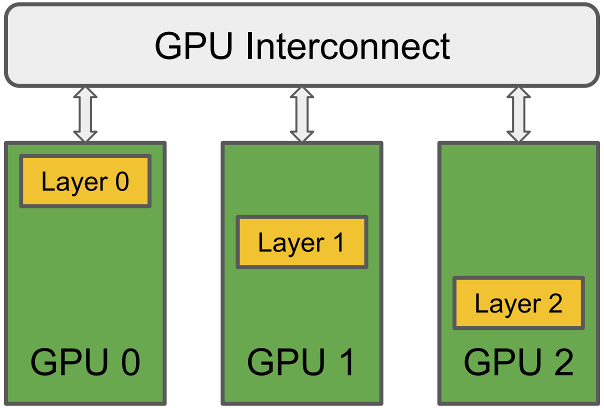
Zero Redundancy Optimizer (ZeRO)?
- Efficiently scale across nodes – trillions of parameters
- No model code refactoring necessary

Zero Redundancy Optimizer (ZeRO)

ZeRO is a memory efficient form of DP
Each GPU stores a mutually exclusive subset of the parameters
Broadcast parameters from owner to all the GPUs as needed



Original DP Training



ZeRO Training

ZeRO with CPU/NVMe Offloading

Offload model states to CPU/NVMe (store in CPU/NVMe and send to GPU when needed)
Broadcast and reduce as ZeRO
Efficiency analysis to deal with possible bandwidth issues.

$$\begin{cases} efficiency = \dfrac{compute\_time}{compute\_time + communication\_time} \\ compute\_time = \dfrac{total\_computation}{peak_{tp}} \text{ (Peak tput)} \\ \text{arithmetic intensity } ait = \dfrac{total\_computation}{total\_data\_movement} \\ communication\_time = \dfrac{total\_data\_movement}{bw} = \dfrac{total\_computation}{ait \times bw} \end{cases}$$

$$\Rightarrow \quad efficiency = \frac{ait \times bw}{ait \times bw + peak_{tp}}$$

Measuring the Training Efficiency

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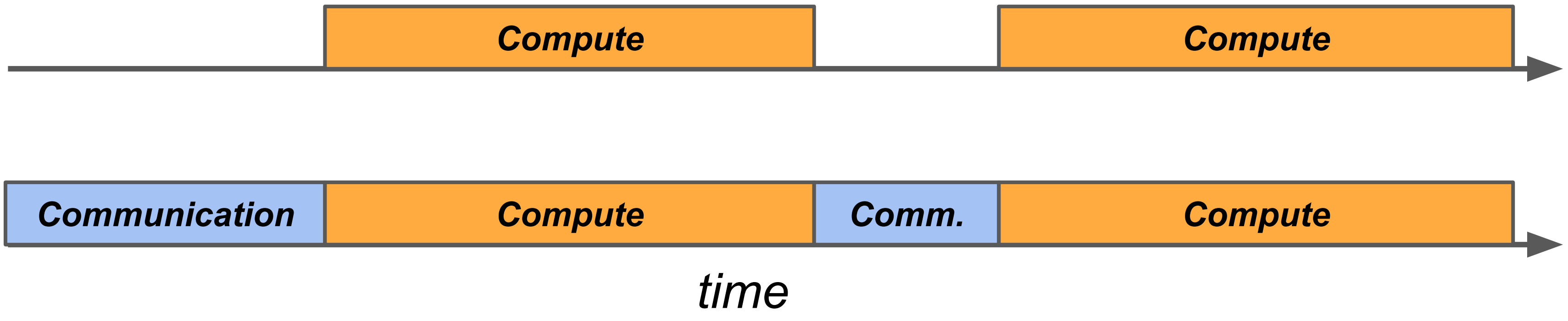
$$efficiency = \frac{compute\_time}{compute\_time + communication\_time}$$



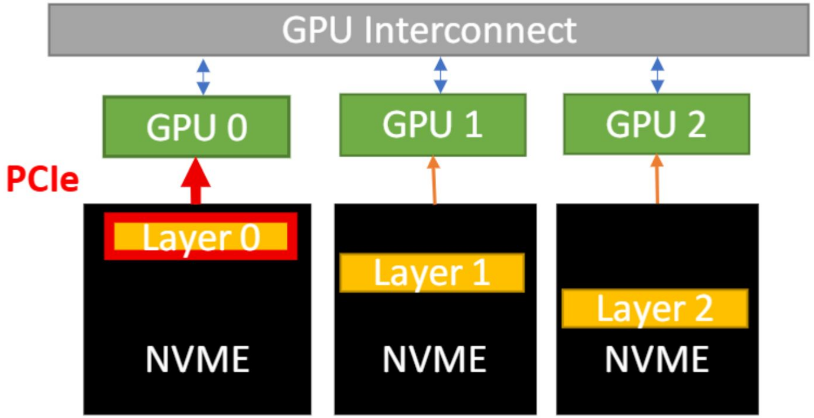
Bandwidth-Centric Partitioning

Broadcast

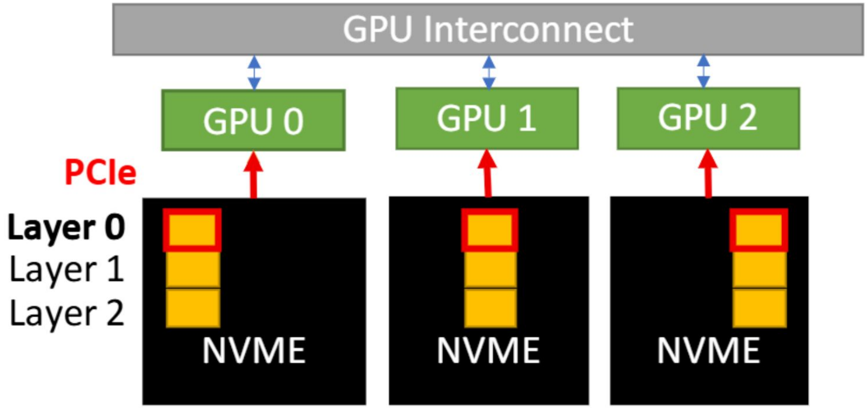
Each parameter is owned by a data parallel process, the parameter must be moved to the GPU memory before the broadcast. Only a single PCIe can be active for this process.

Partitioning + Allgather (ZeRO-Infinity)

All PCIe links are active in parallel, each bringing in a portion of the parameter.

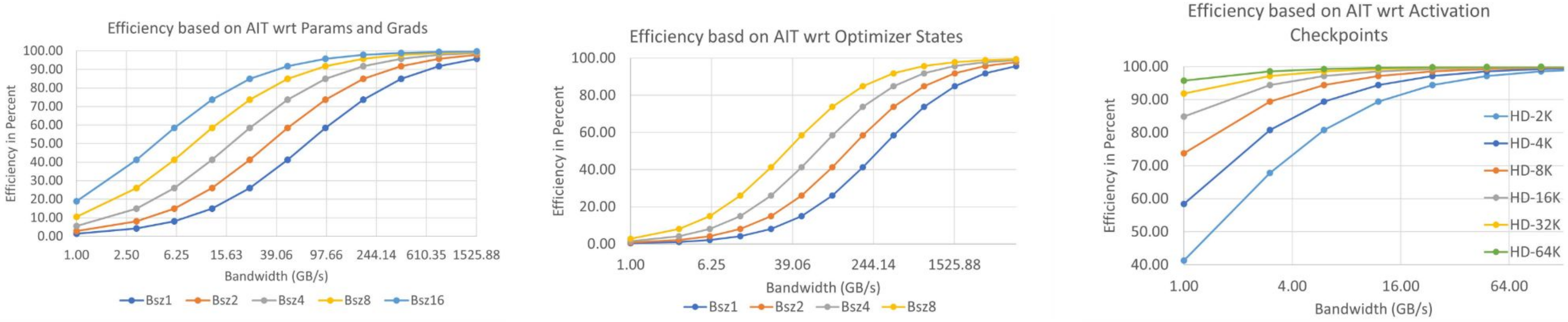


Broadcast



Partitioning + Allgather

ZeRO with CPU/NVMe Offloading



(a) Parameter and Gradient Bandwidth **(b) Optimizer States bandwidth** **(c) Activation Checkpoint Bandwidth**

Figure 3: Impact of bandwidth on efficiency assuming an accelerator with 70 TFlops of single GPU peak achievable throughput.

$$efficiency = \frac{ait \times bw}{ait \times bw + peak_{tp}}$$

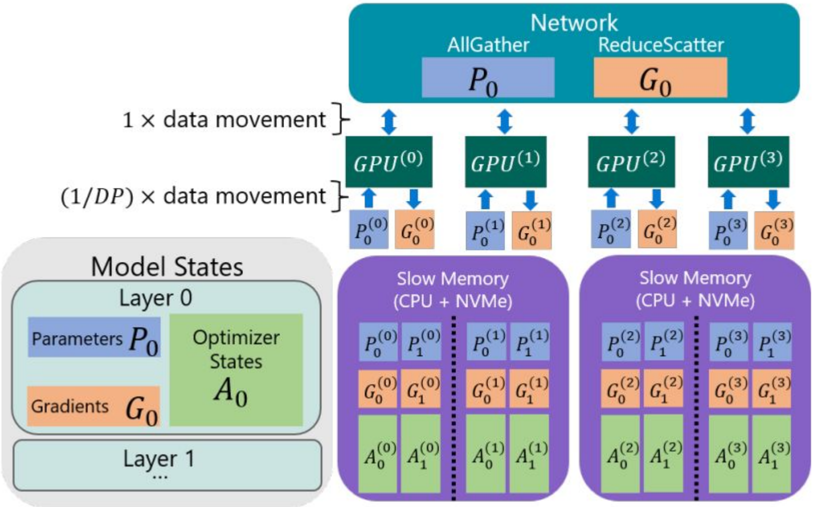
batch size (*bsz*) hidden dimension (*hd*)

Arithmetic intensity depends on the data types (e.g. parameters, gradients, optimizer states or activation checkpoints)

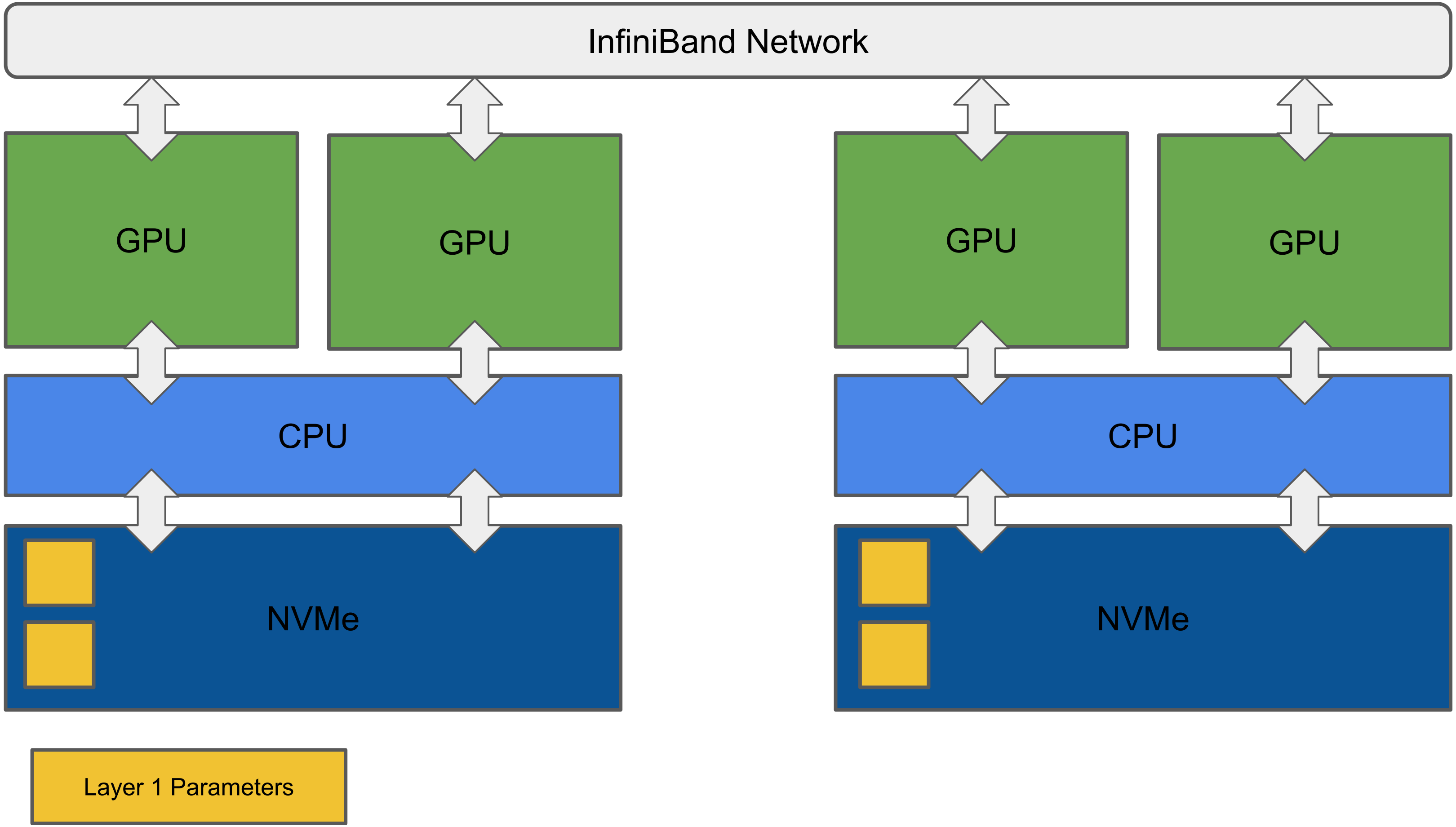
ZeRO-Infinity System Overview

A heterogeneous system that leverages GPU, CPU, and NVMe memory to allow for unprecedented model scale on limited resources without requiring model code refactoring

Based on Zero Redundancy Optimizer (ZeRO)



Training Demo: Forward: Parameters



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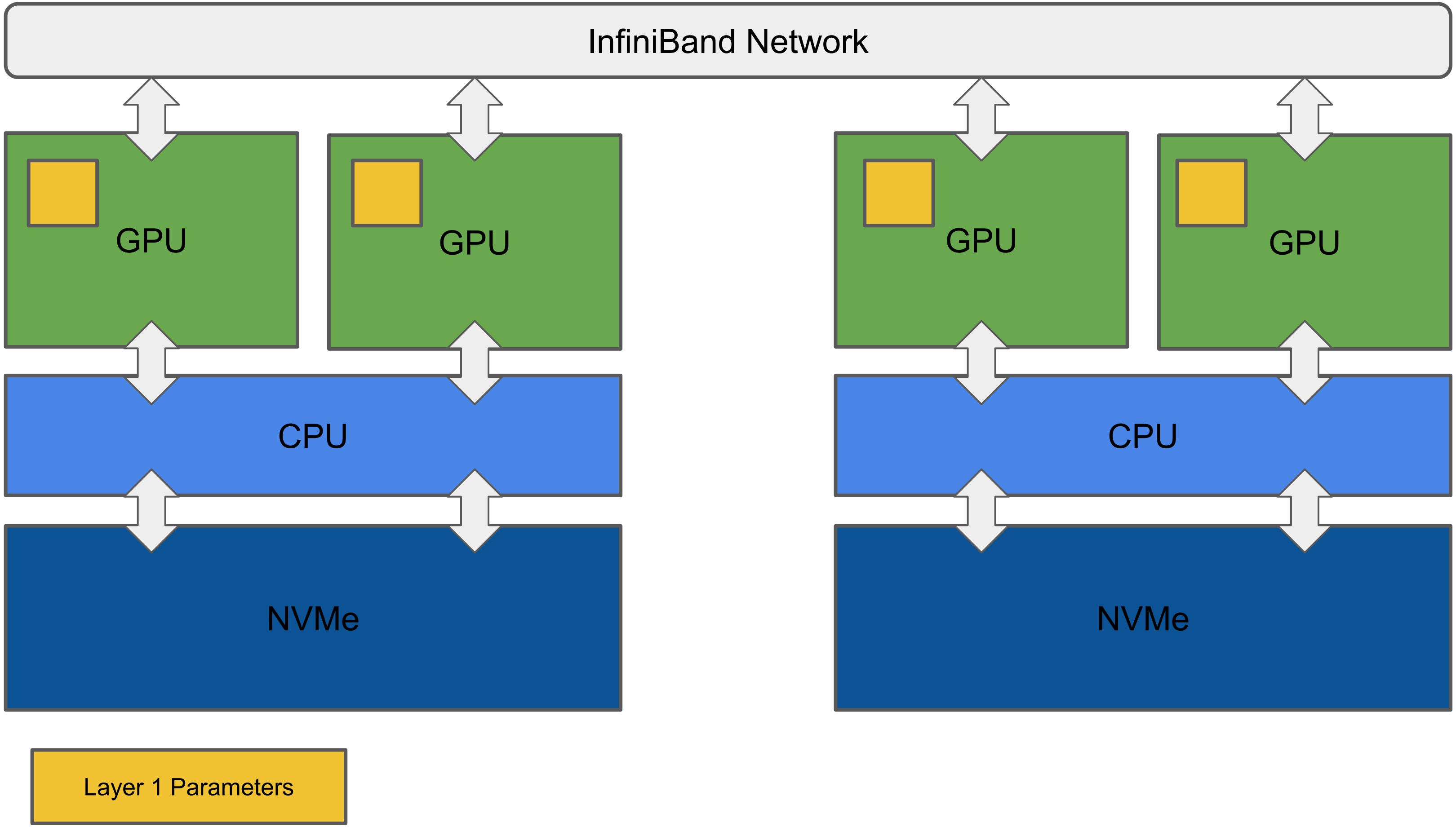
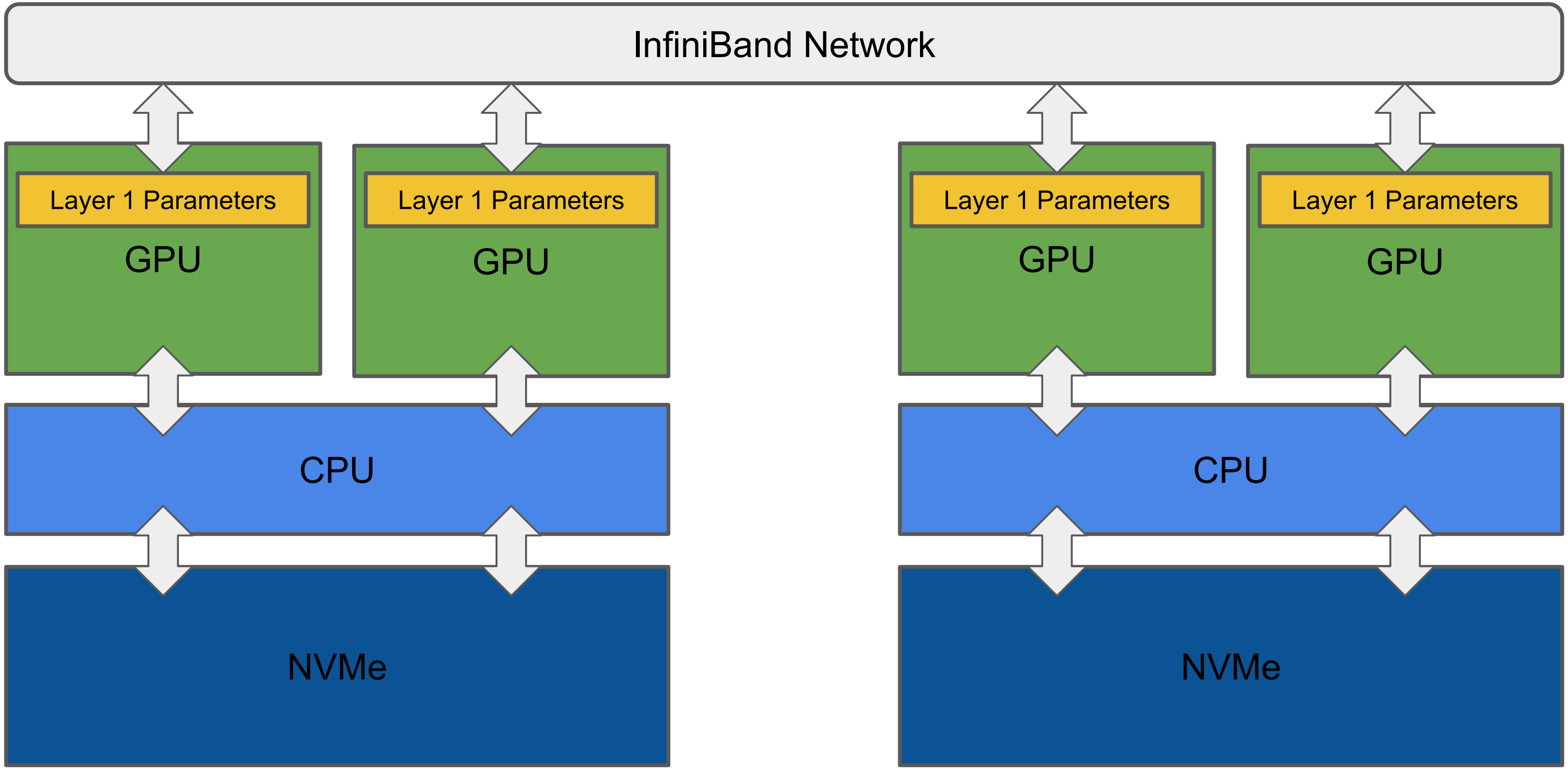


Training Demo: Forward: Allgather of Parameters



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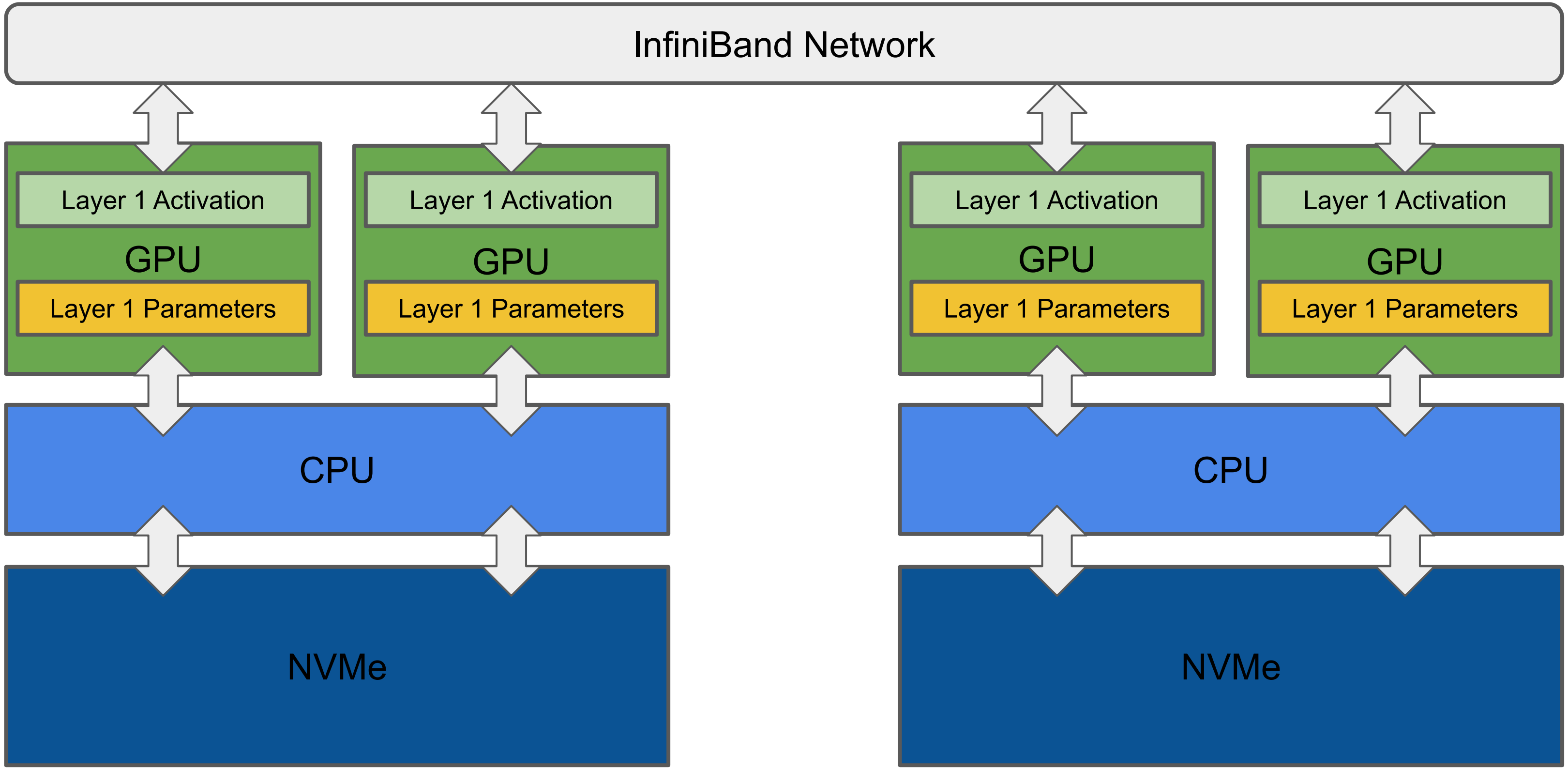

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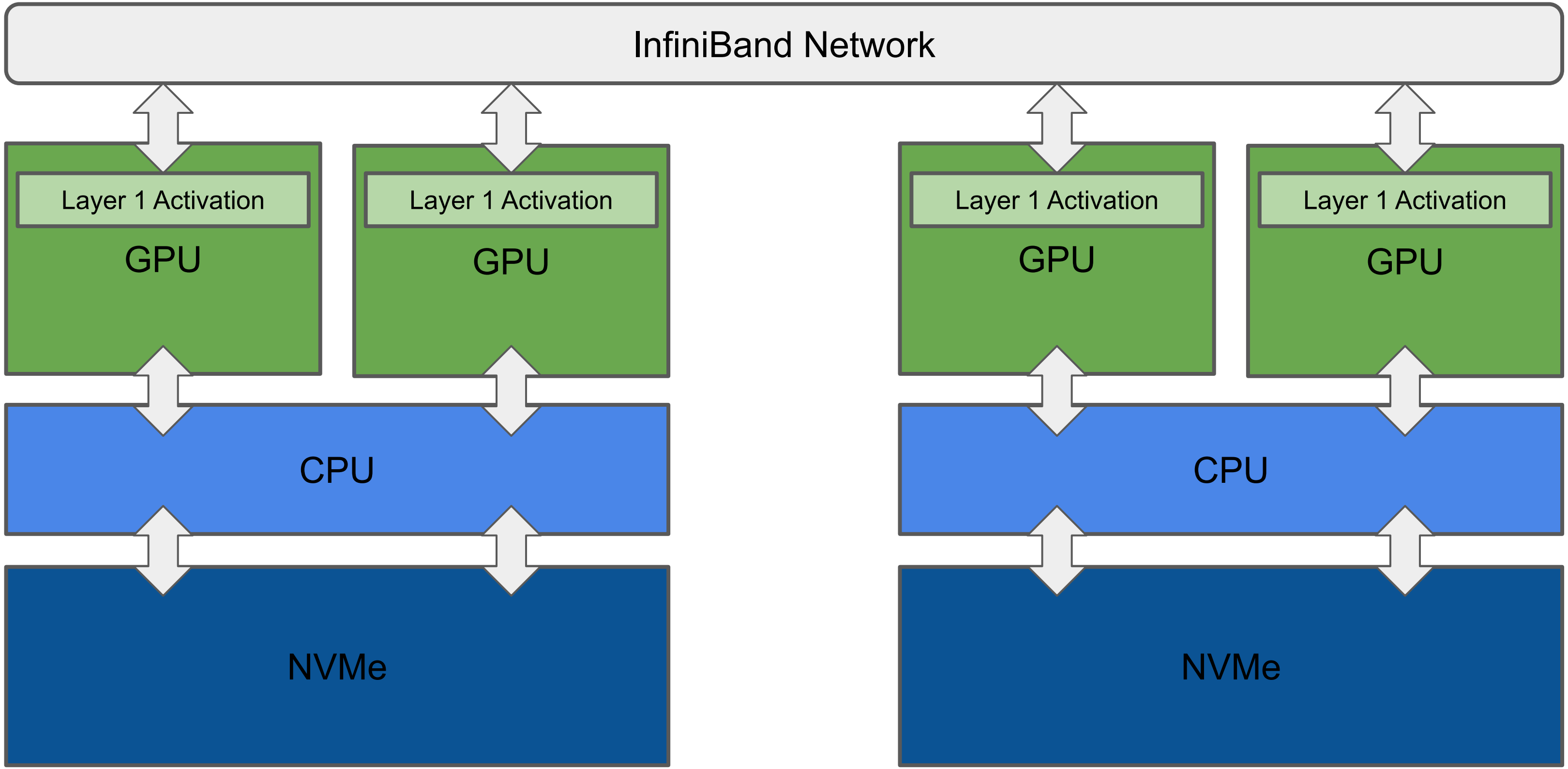

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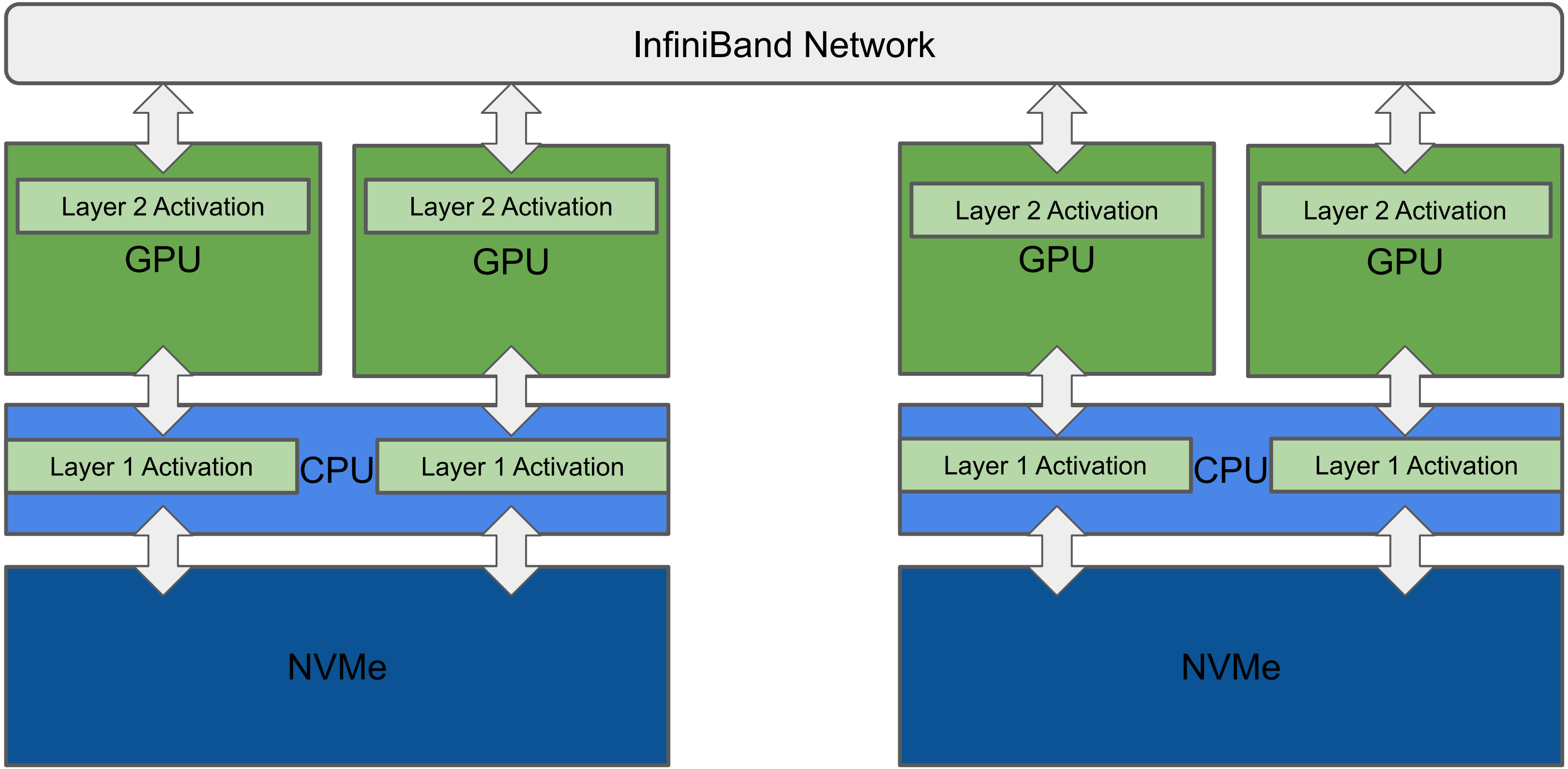

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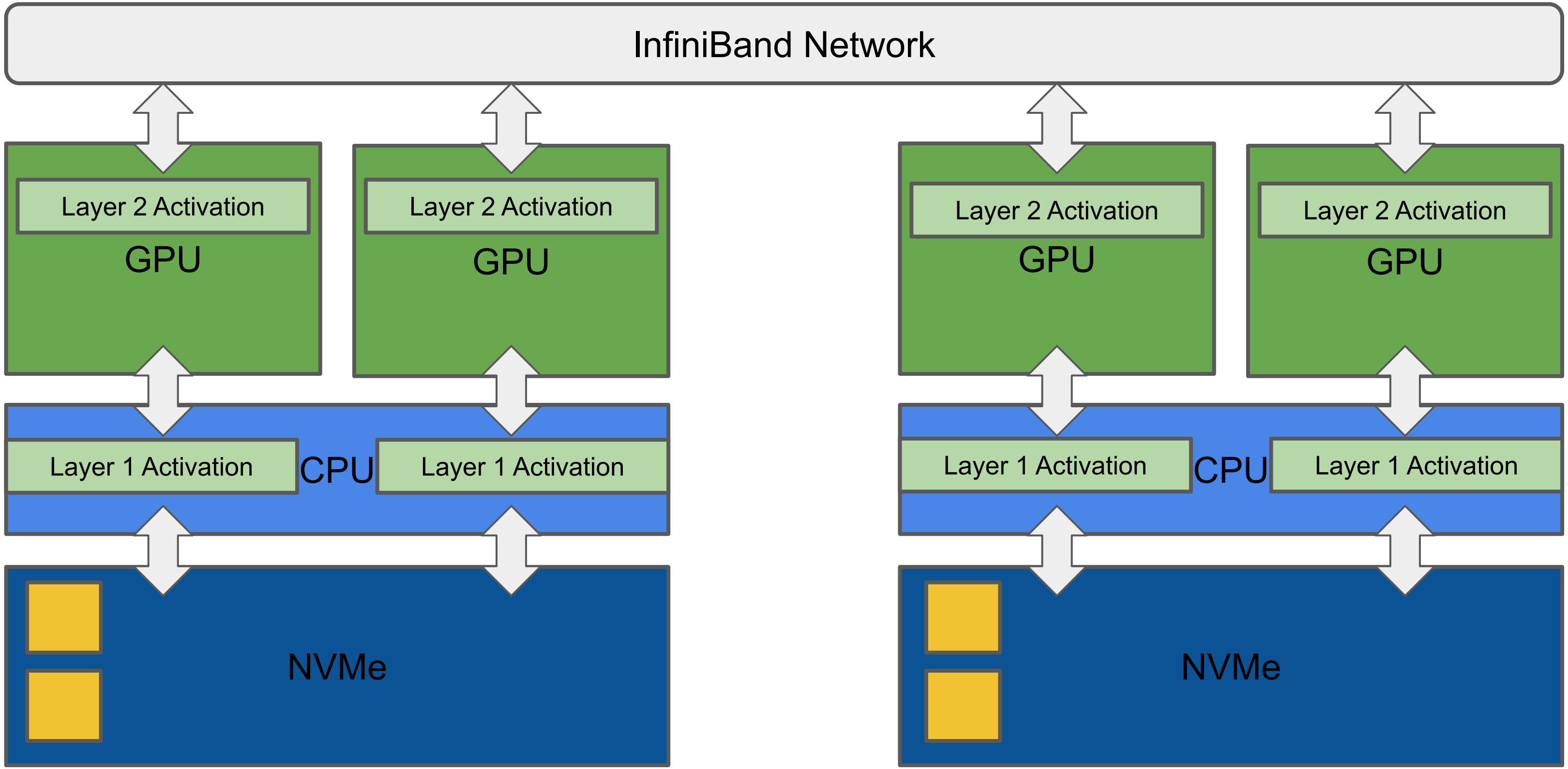

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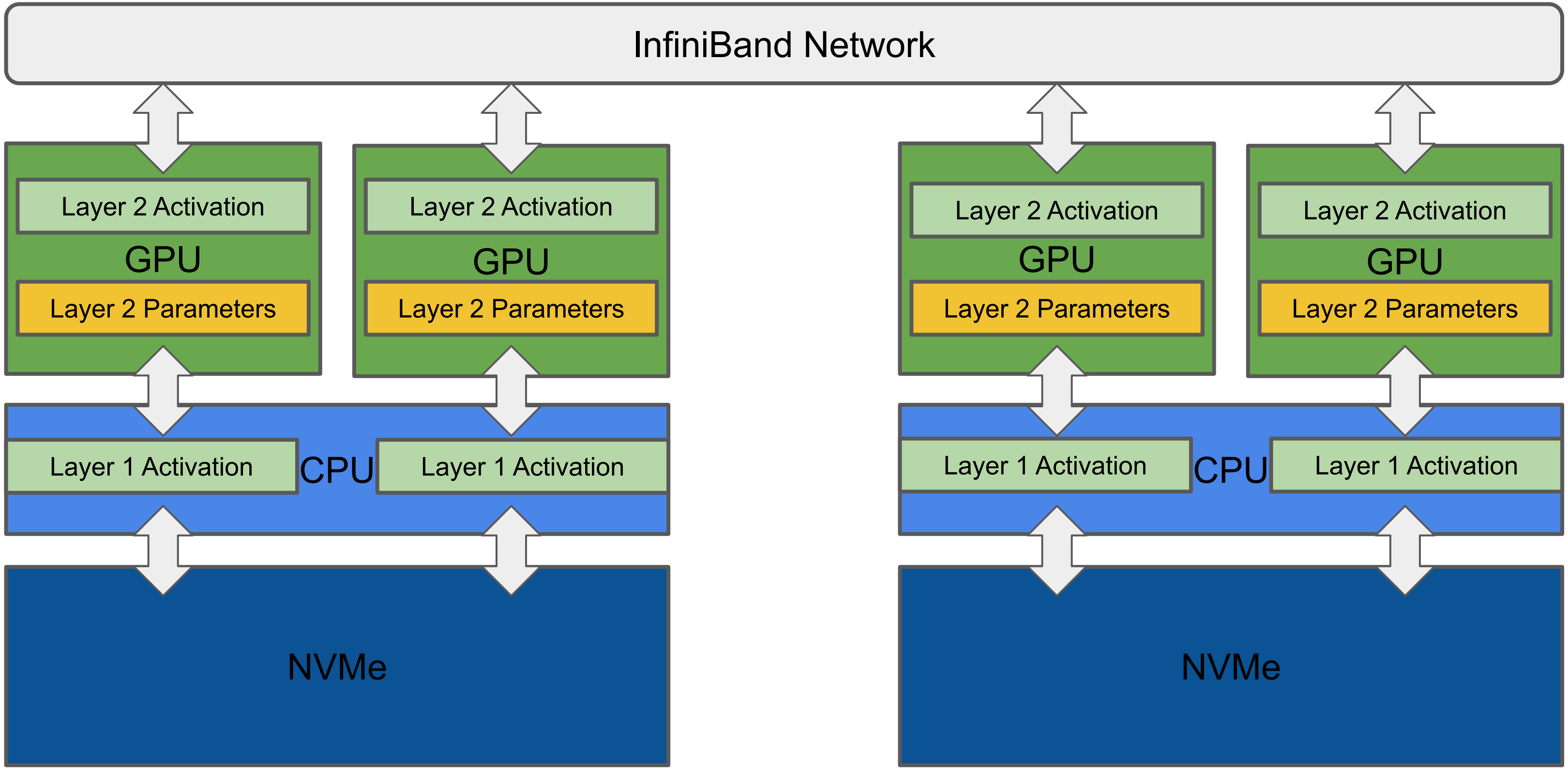

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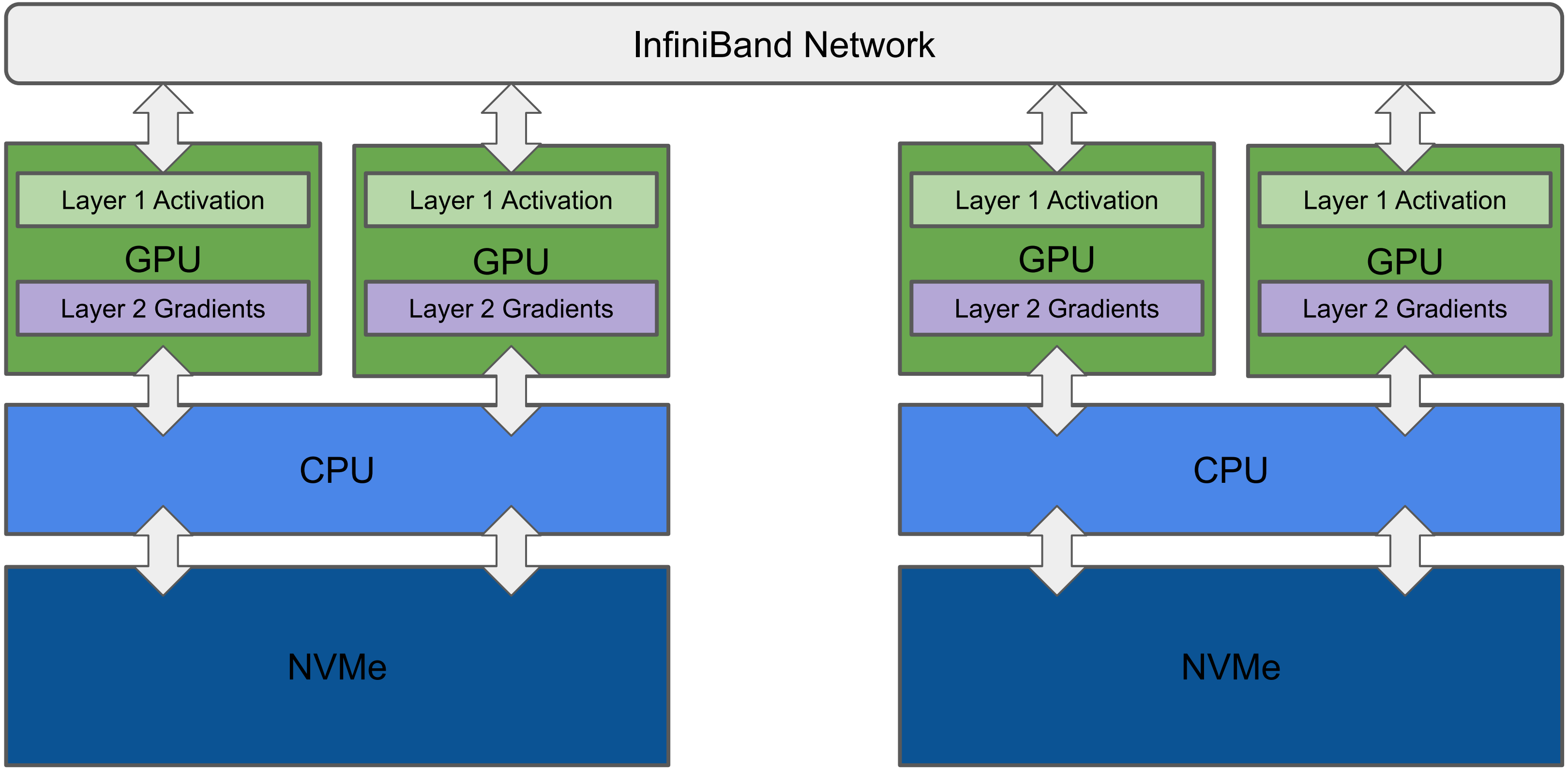

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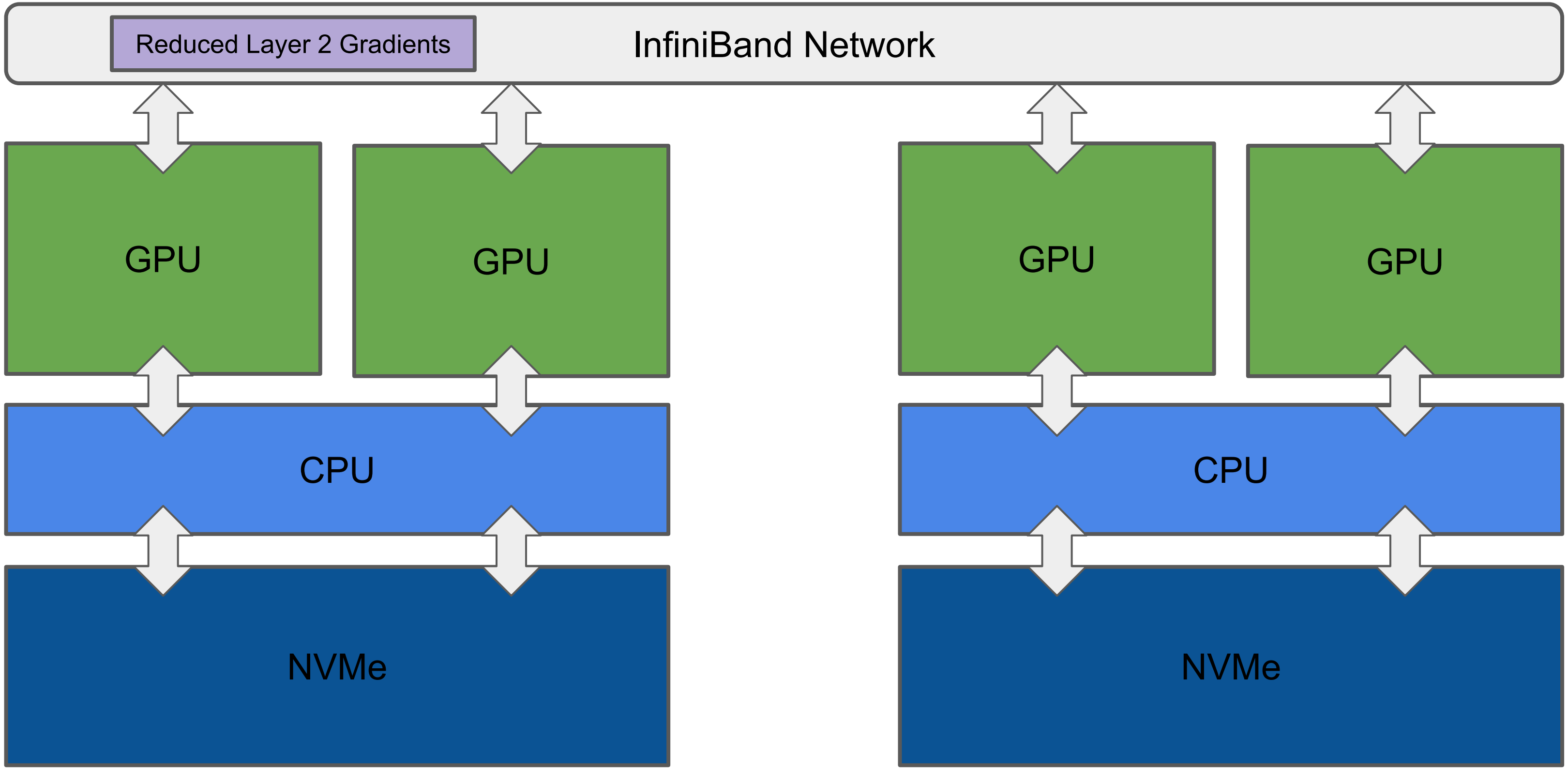

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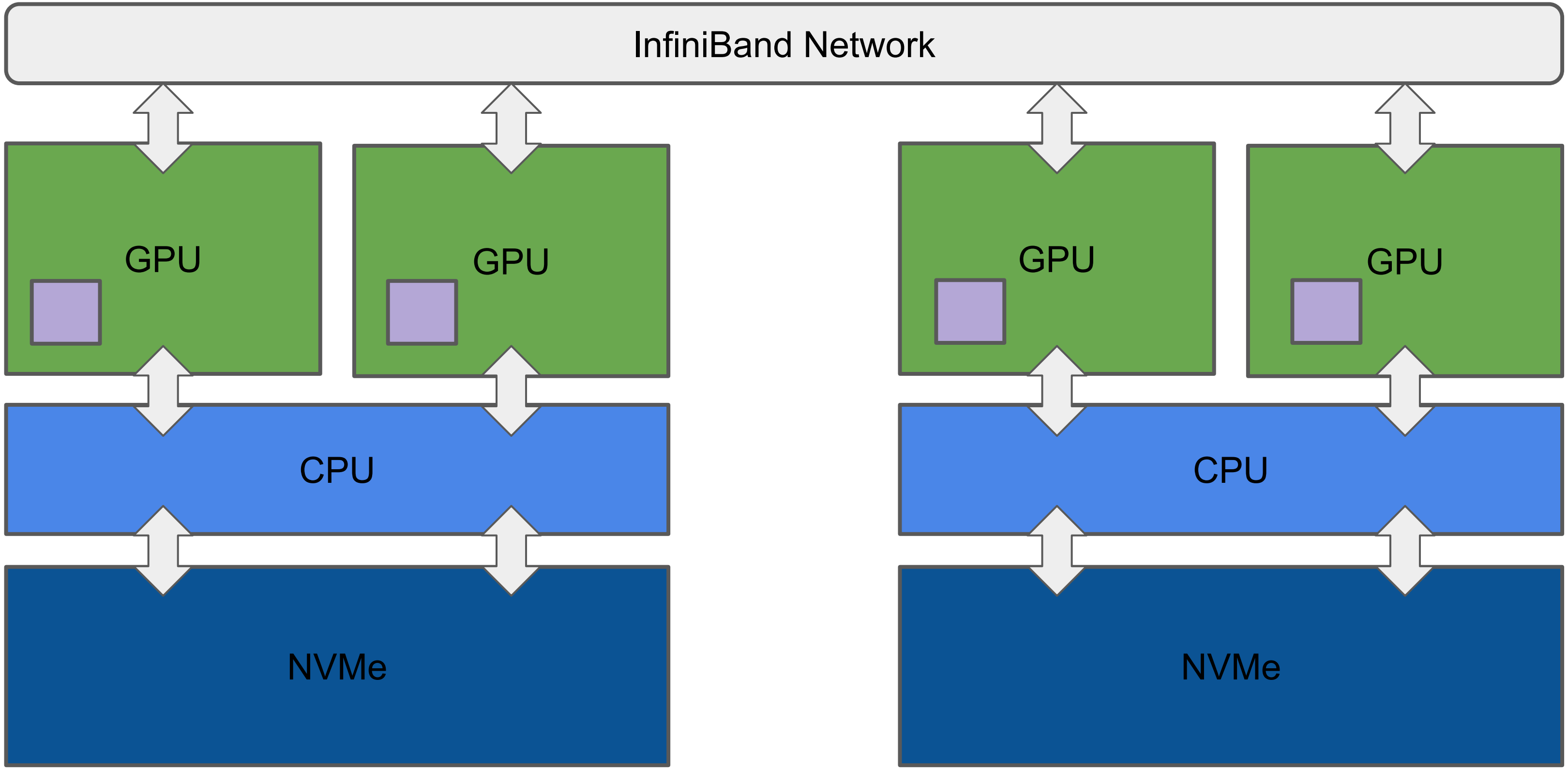

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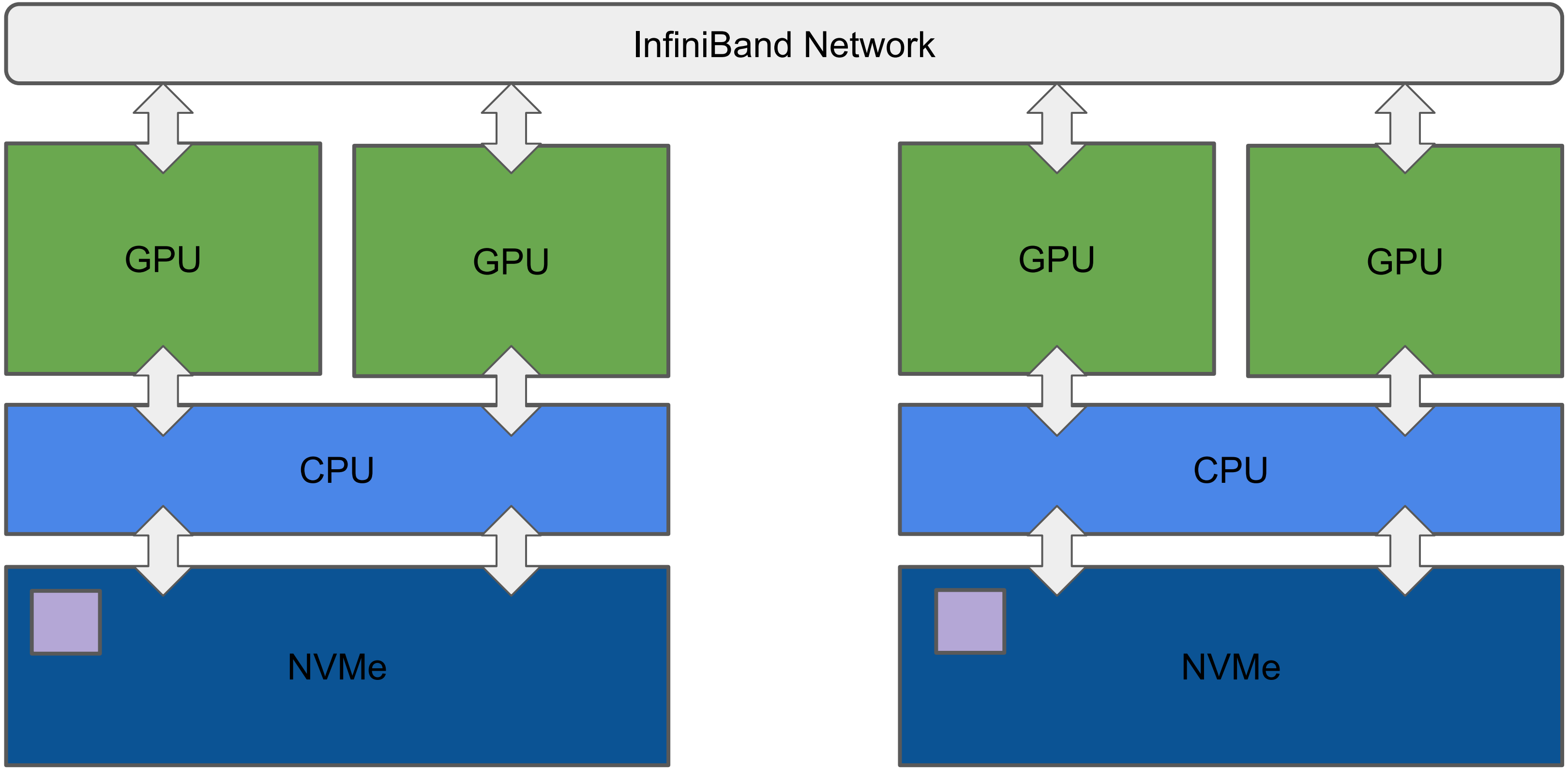

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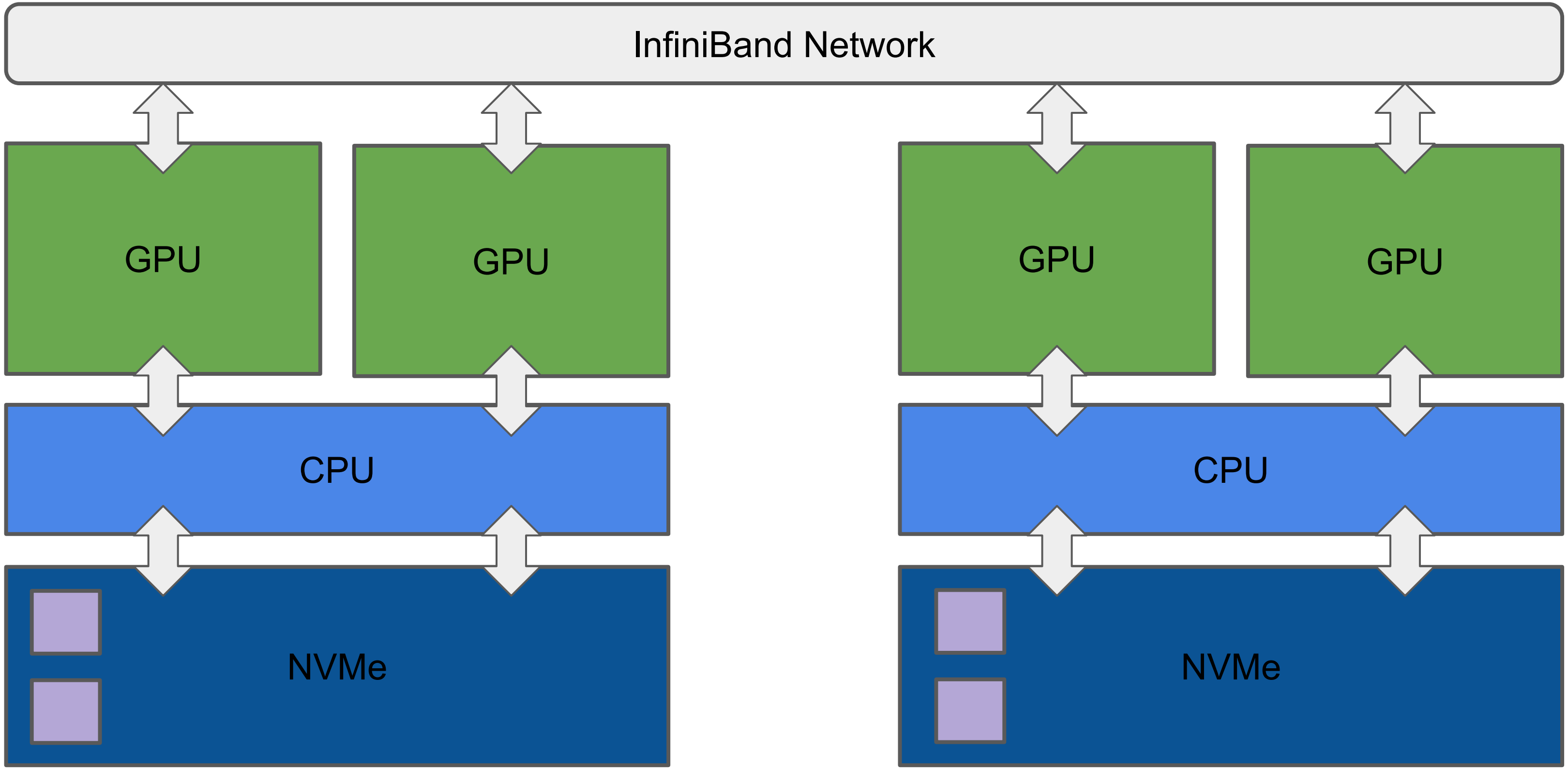
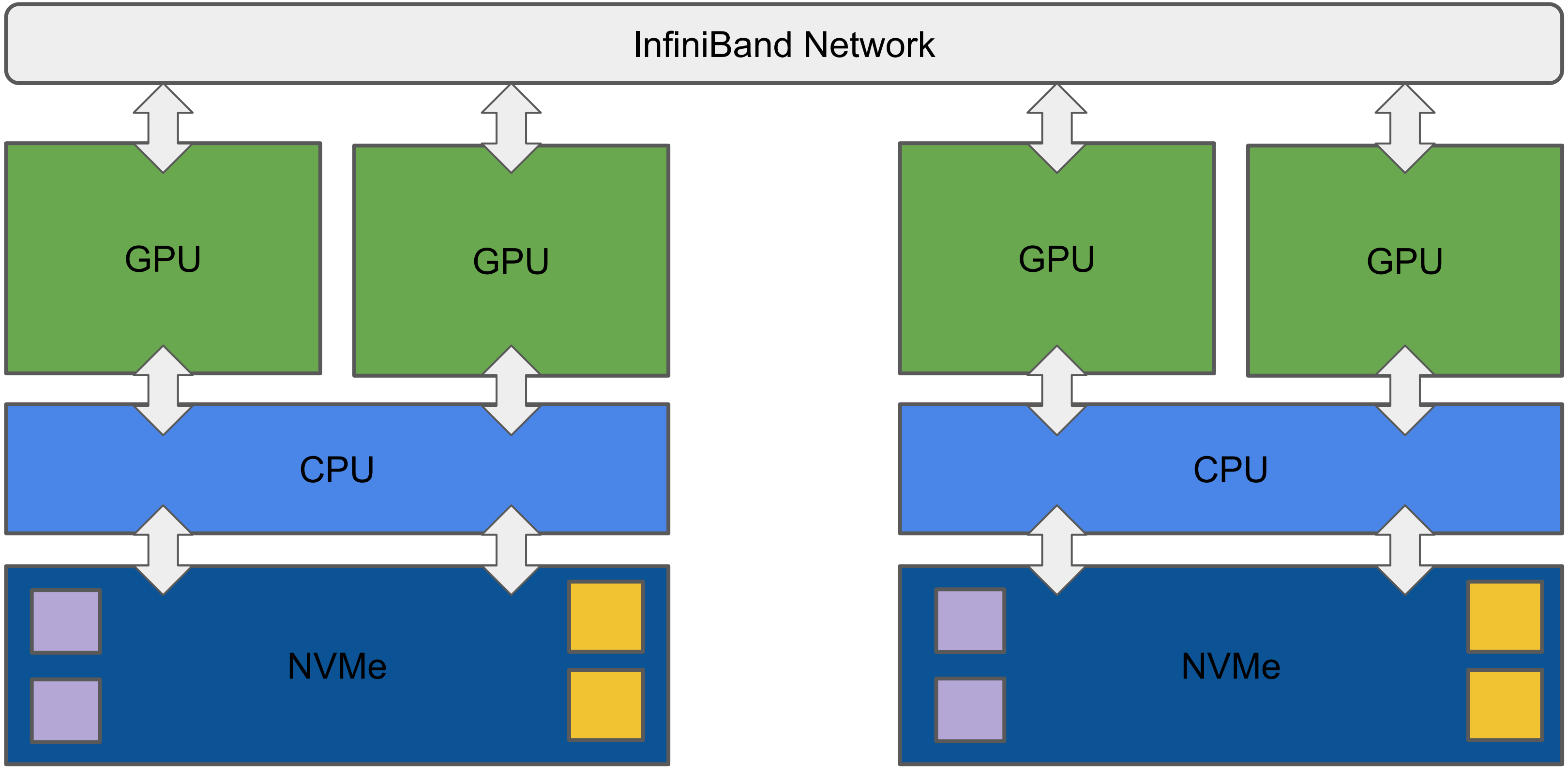


Training Demo: Optimizer Step: Params & Gradients to CPU



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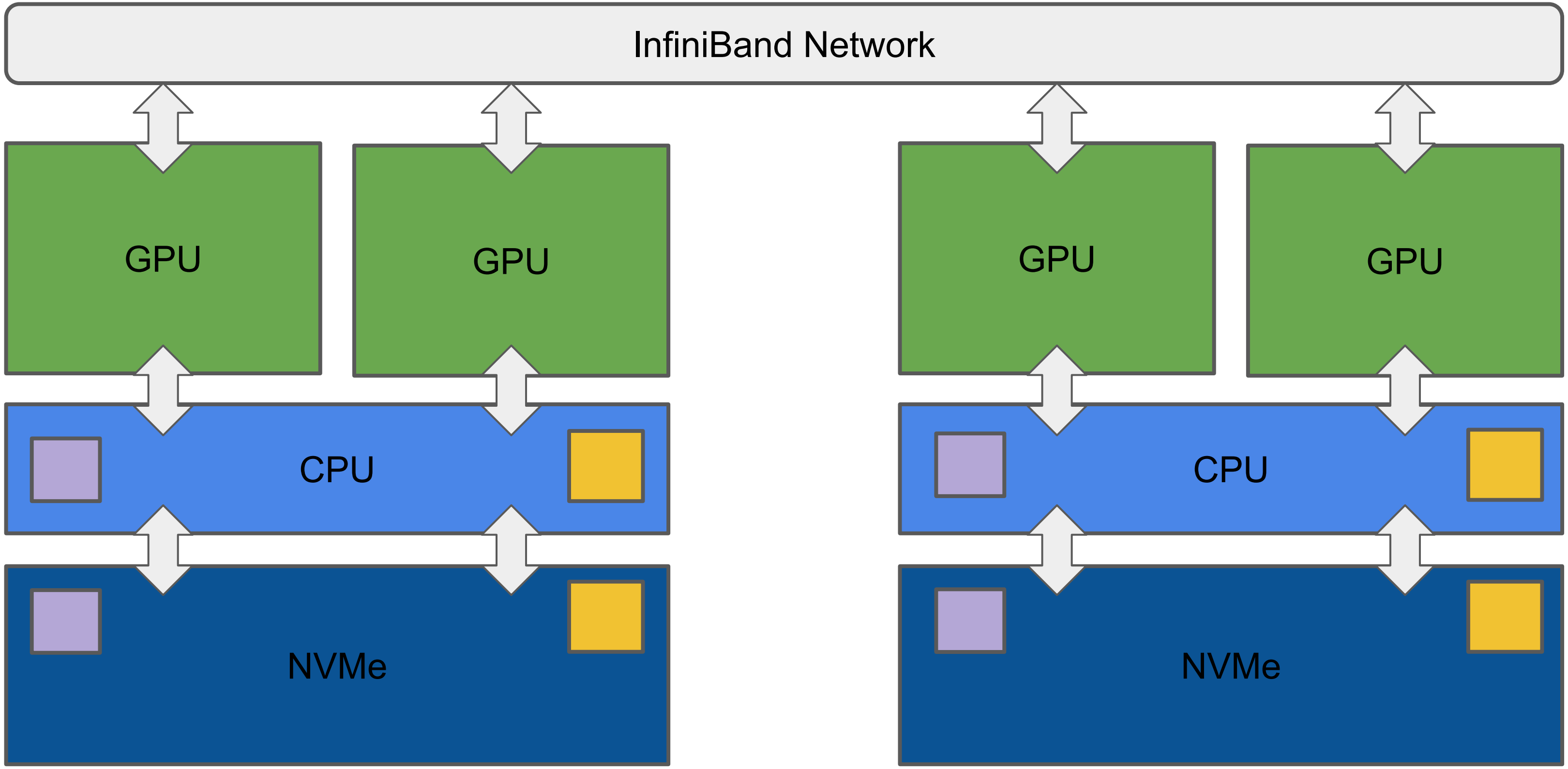
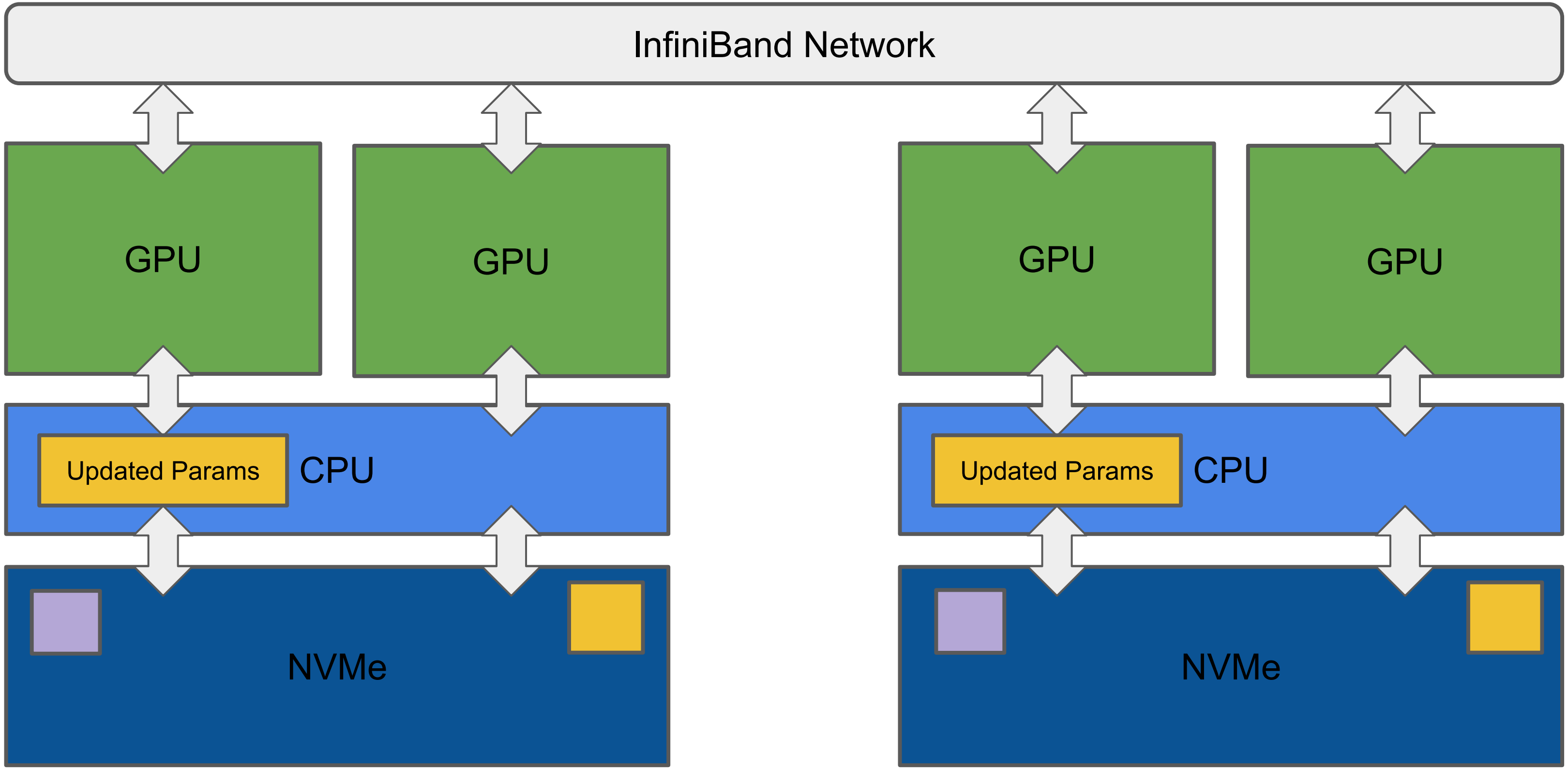
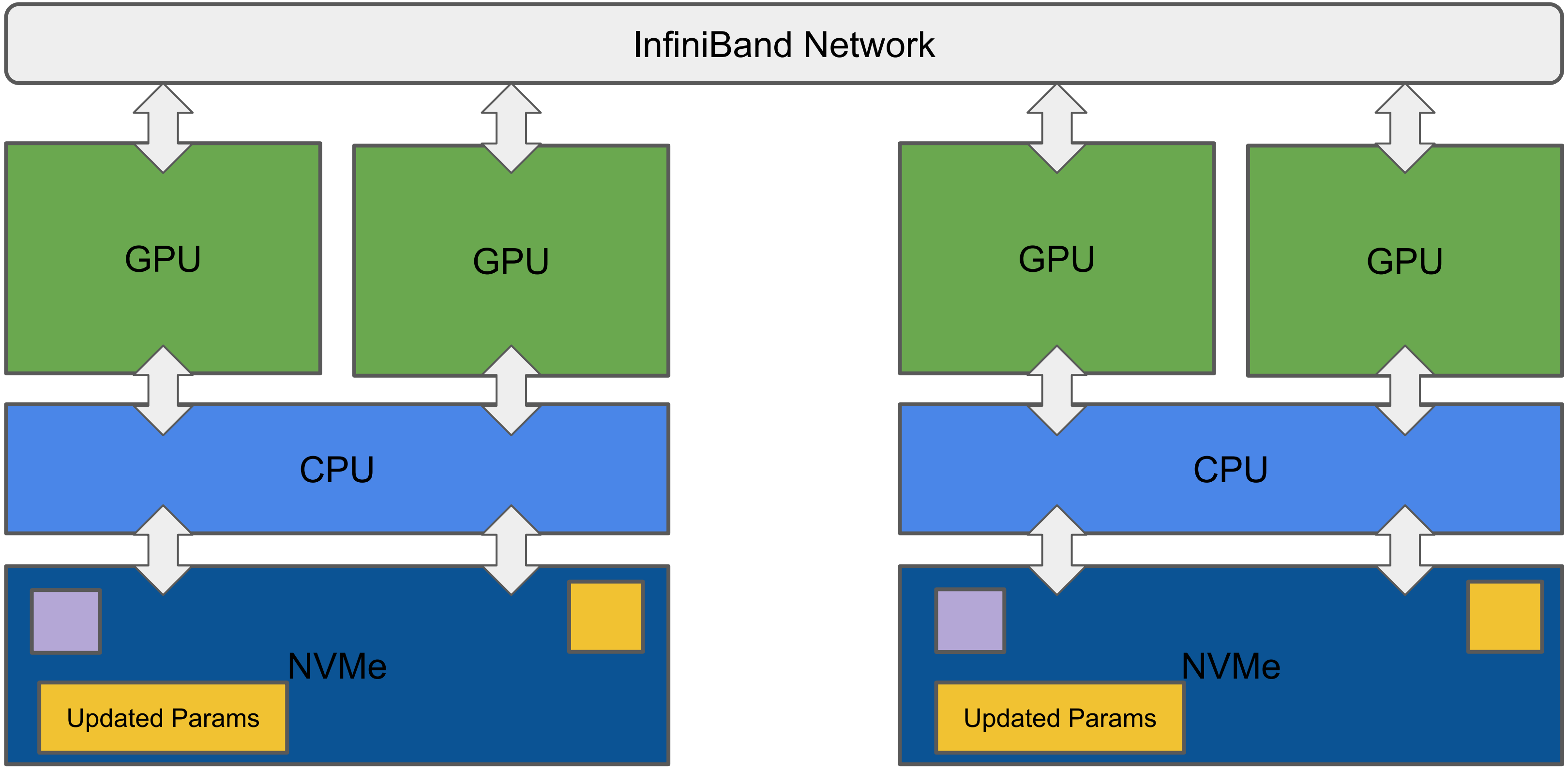


Training Demo: Optimizer Step: Update Params



Training Demo: Optimizer Step: Params to NVMe



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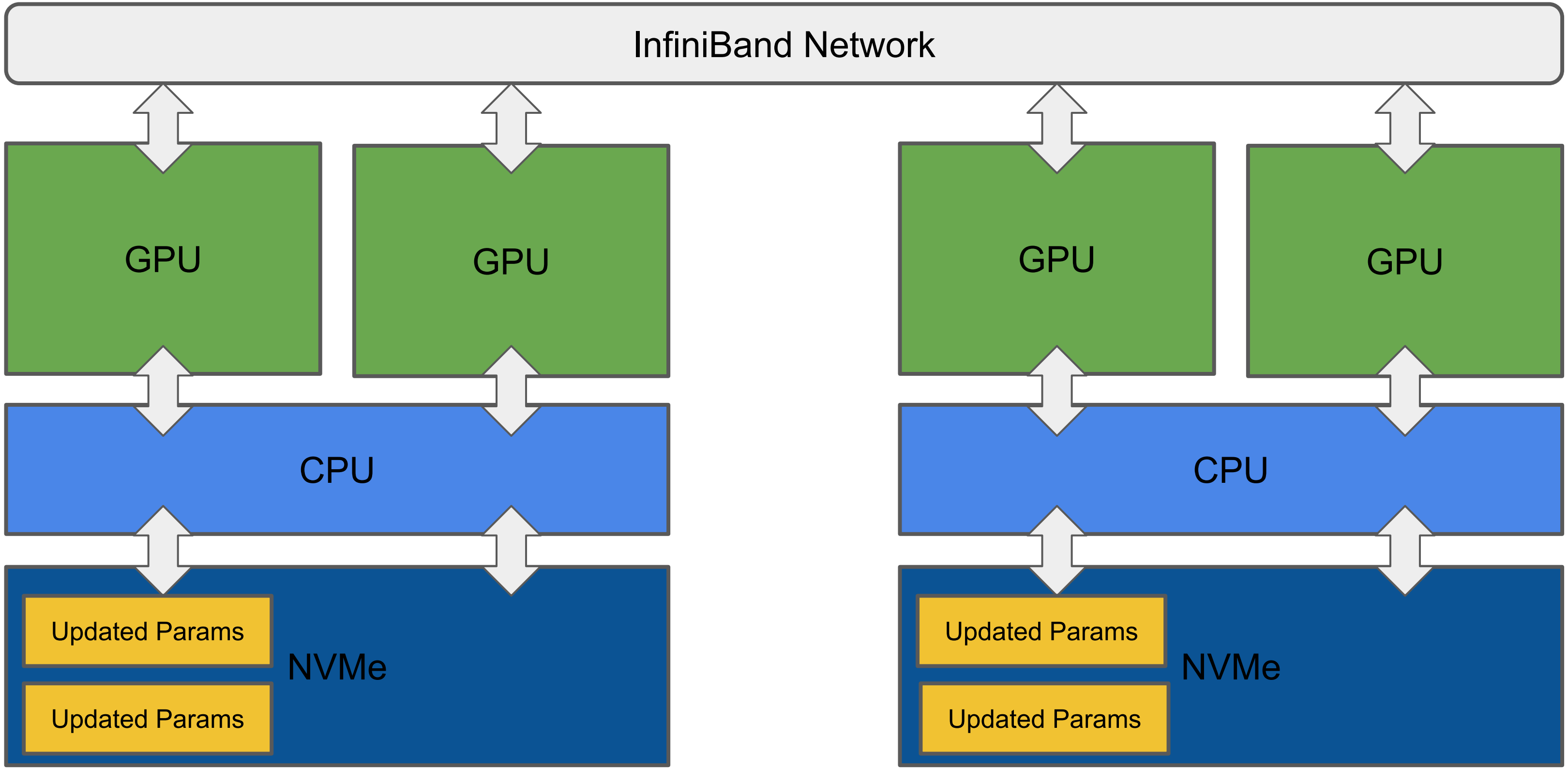

Design for Unprecedented Scale

ZeRO with Simple CPU/NVMe Offloading
Optimizer states to NVMe
Activation memory to CPU memory
Parameters and gradients stay in GPU memory

ZeRO-Infinity
Infinity Offload Engine for Model States
The infinity offload engine can offload all of the partitioned model states to CPU or NVMe memory, or keep them on the GPU based on the memory requirements.

CPU Offload for Activations
Offload activation memory (activation checkpoints) to CPU memory when necessary.

Memory-centric Tiling for Working Memory
Represent the large linear operator as a mathematically equivalent sequence of smaller linear operators consisting of tiles of parameters from the original operator, and executes them sequentially.

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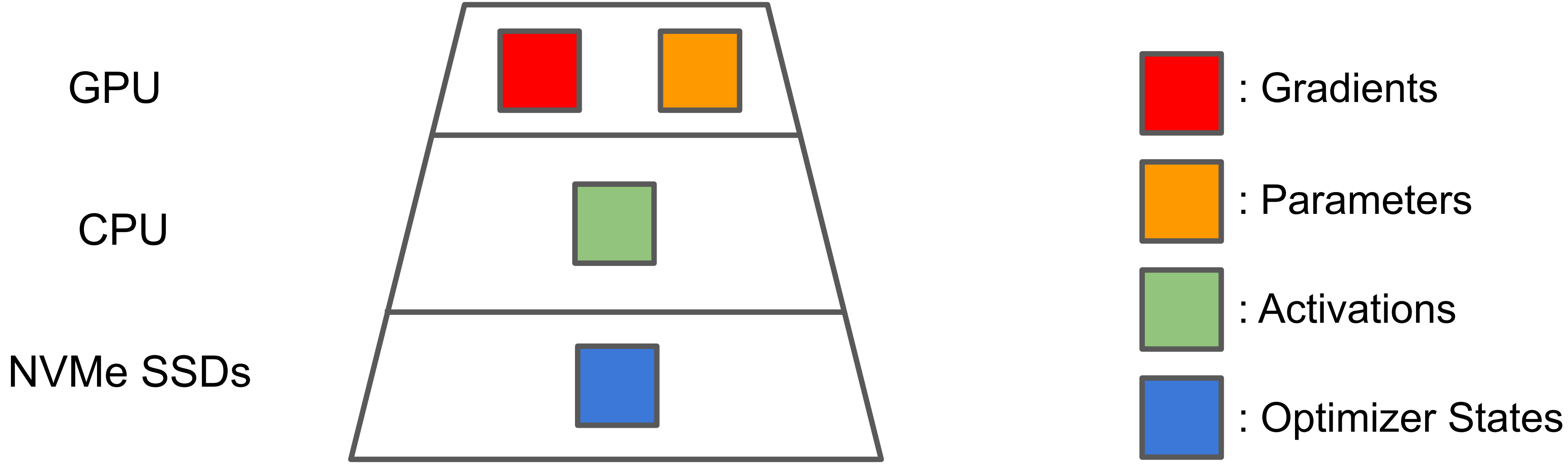

ZeRO Offloading Memory Hierarchy

Design for Unprecedented Scale

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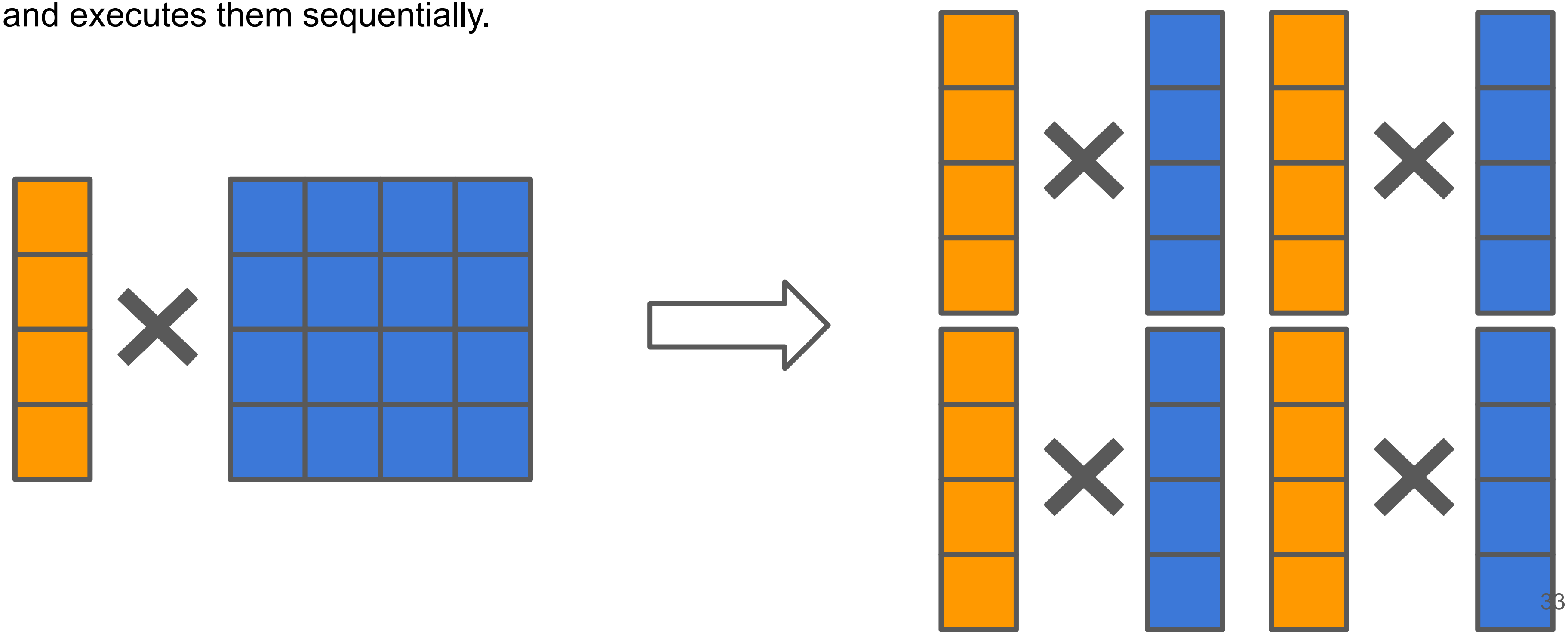
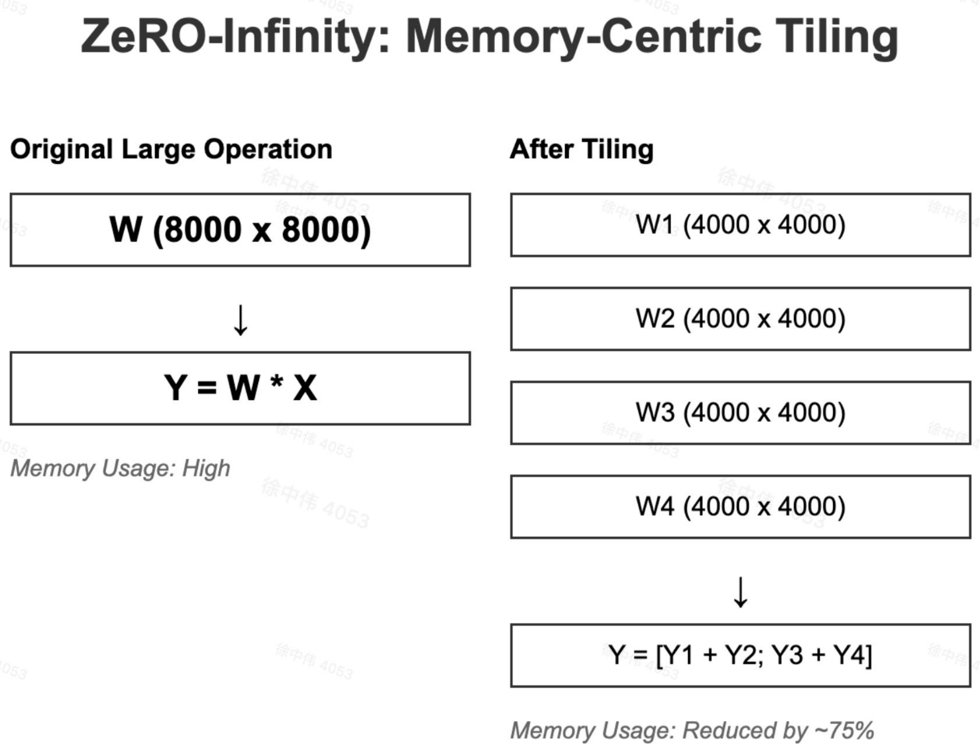


Memory-centric tiling

This method works by:

- Breaking down large operators into smaller, sequential tiles.
- Executing these tiles one at a time.
- Leveraging ZeRO-3's data fetch and release pattern.



Bandwidth Centric Partitioning

This method works by:

- Single parameter partitioned across all data-parallel processes, uses allgather
- Bandwidth scales linearly with number of nodes
- Provides heterogeneous memory bandwidth far exceeding training efficiency needs
- Each link brings in 1/dp of the parameter at one time

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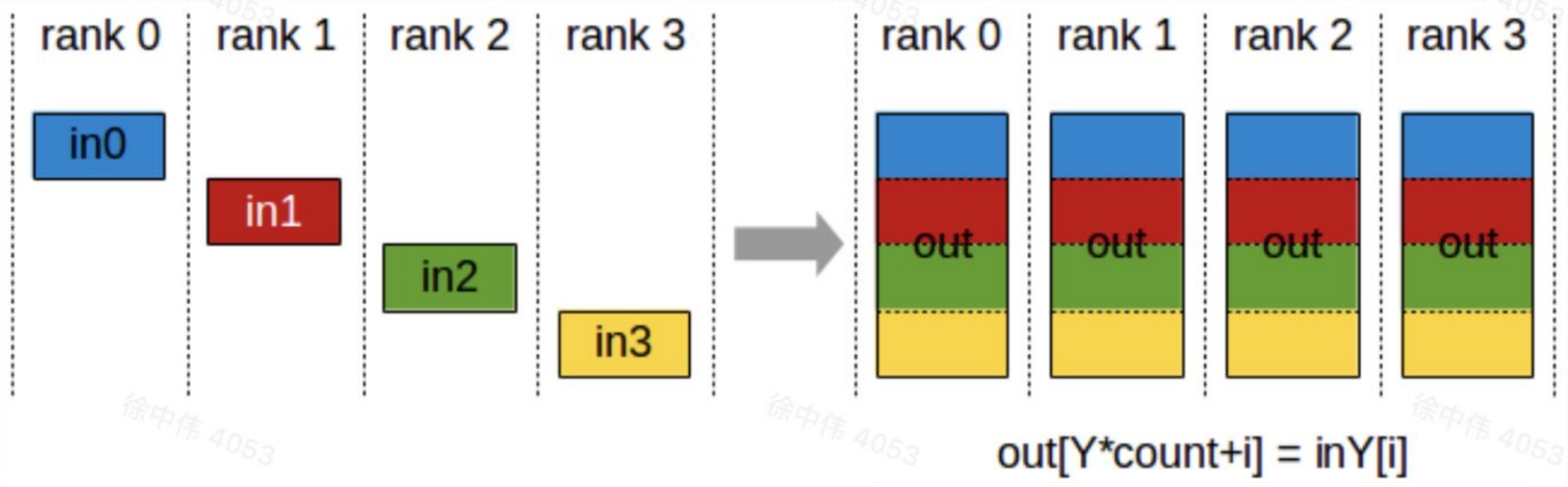

AllGather operation: each rank receives the aggregation of data from all ranks in the order of the ranks.

Overlapping Centric

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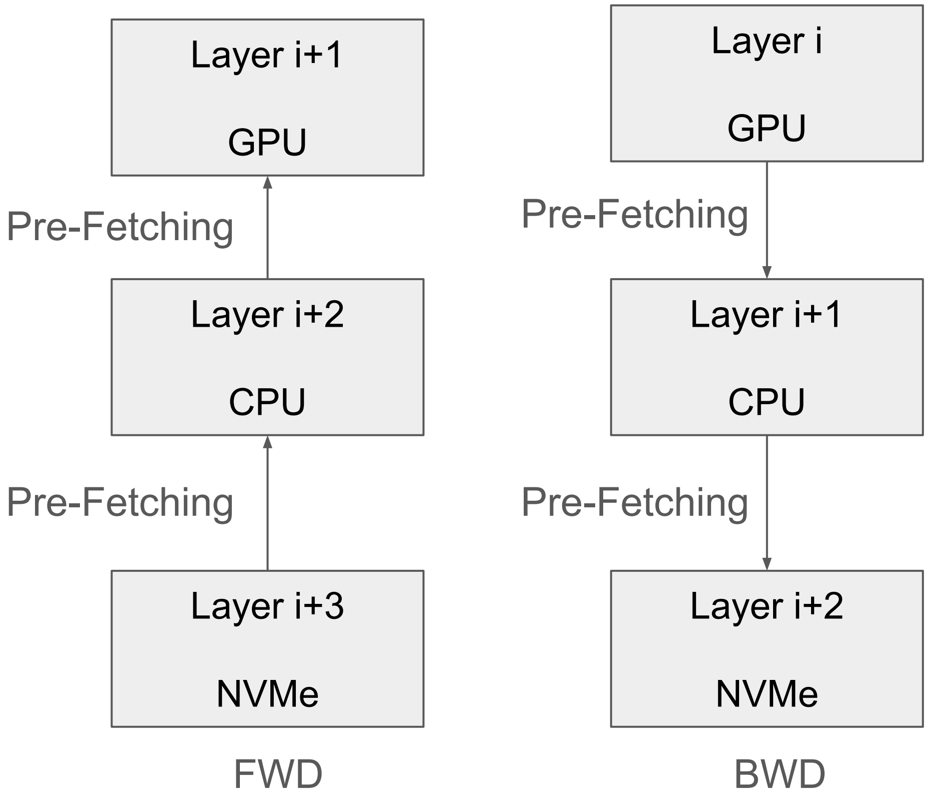


Ease Of Use

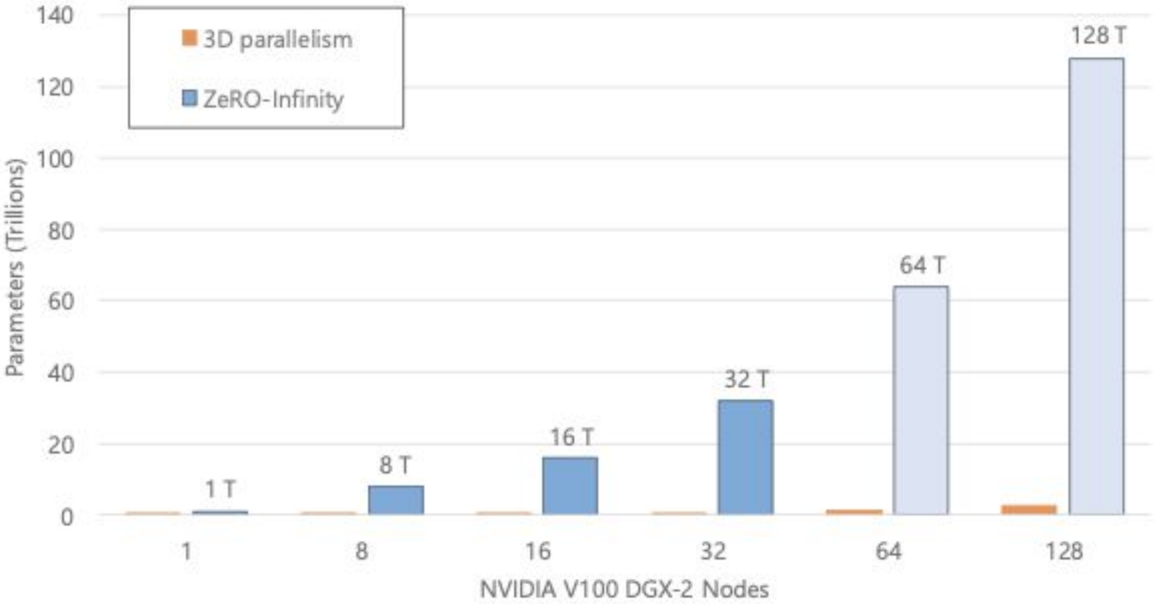
- Automated data movement: The system automatically gathers necessary parameters before they are needed for use.

- Automated parameter partitioning: When certain parameters are no longer needed, the system automatically partitions them and may offload them to CPU or NVMe.

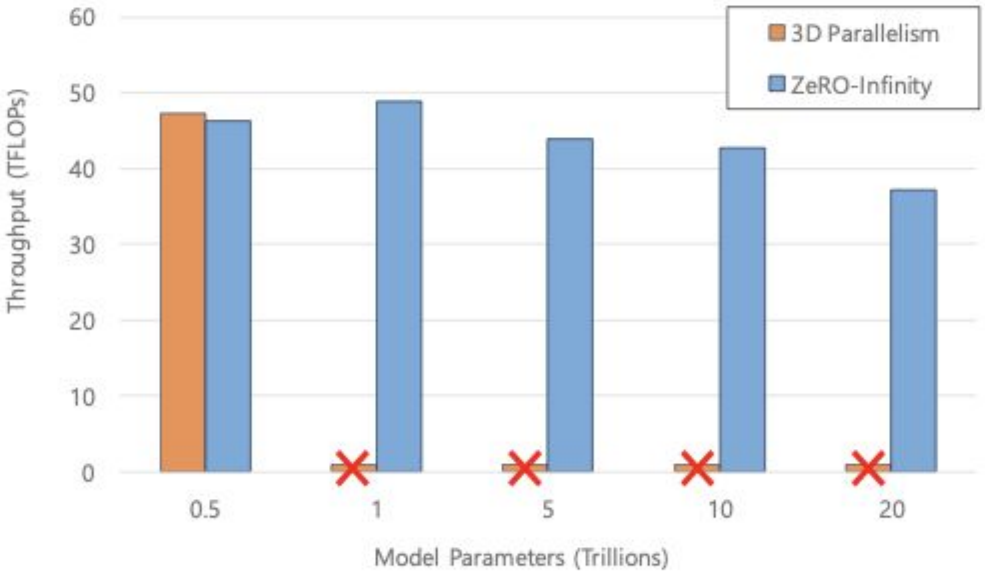
- Automated model partitioning during initialization: This allows for the initialization of large models, even if they cannot fit entirely into a single GPU or CPU memory.

Evaluation

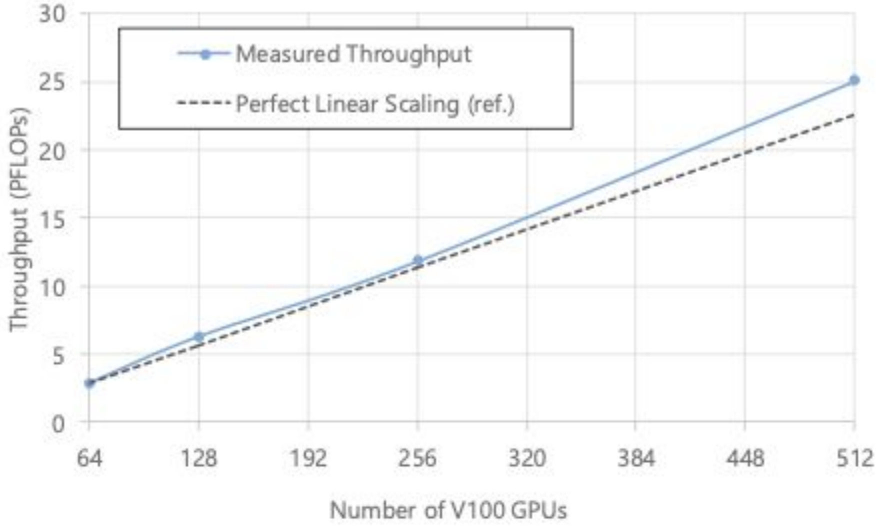
Massive model scale



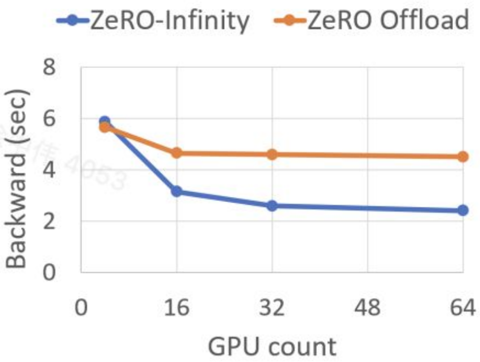
Excellent Efficiency



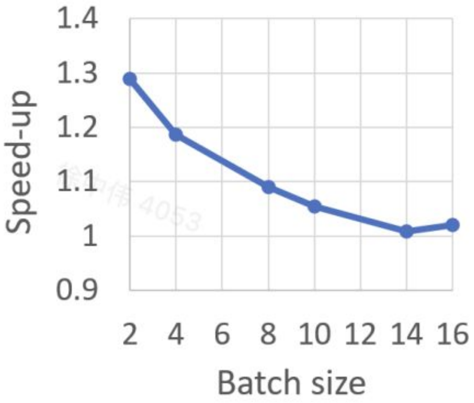
Super-linear Scalability



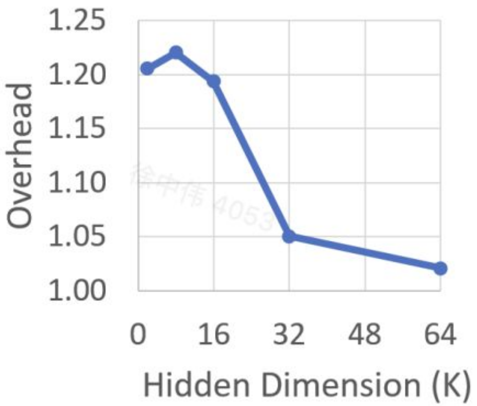
Impact of system features on model scale and performance



(c) ZeRO-Infinity vs ZeRO Offload

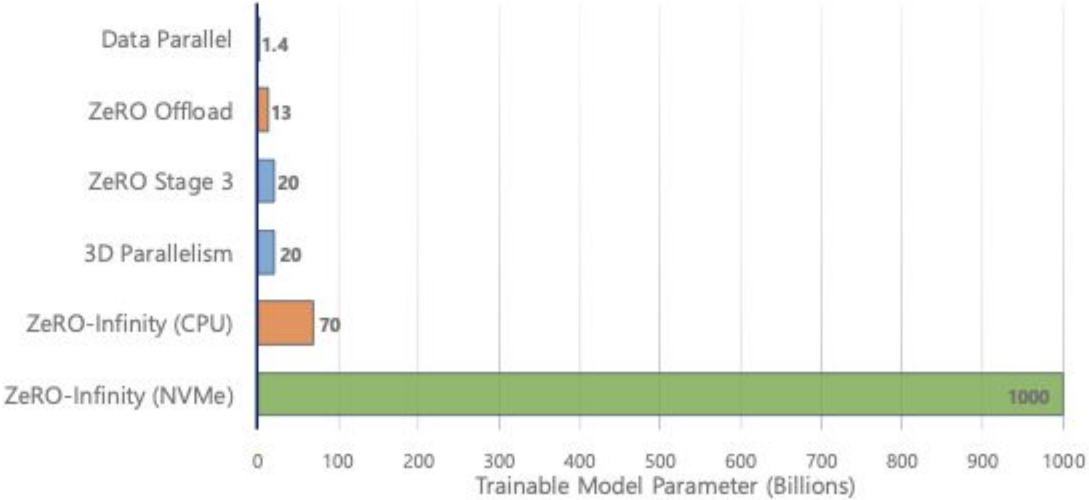


(d) Speedup from communication overlap.



(e) Overhead of offloading activation chkpt to CPU.

Democratizing Large Model Training

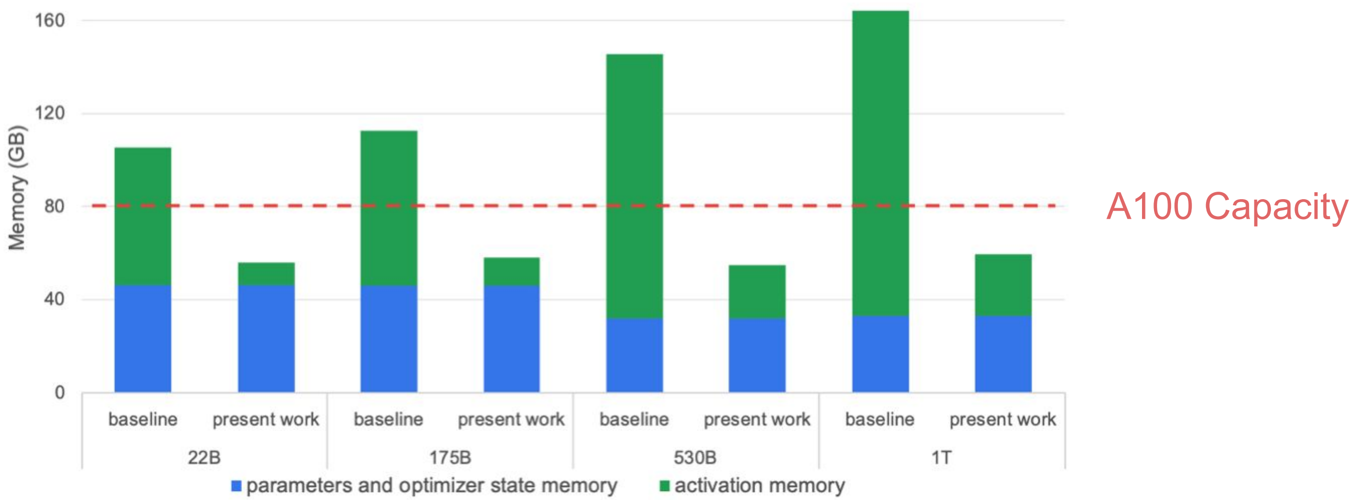


Reducing Activation Recomputation in Large Transformer Models

Activation Memory

Activations: “Intermediate results” of a layer after applying the activation functions

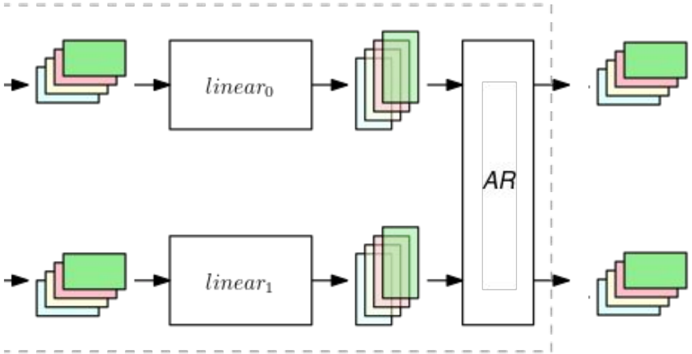
- Why do we want to keep them after the forward pass?
- For large models, they take up a lot of memory.



Required memory with tensor parallelism (n=8) + pipeline parallelism enabled

Potential solutions

- Increase tensor parallelism degree



- Using checkpointing + recomputing
  - Only store the activations of certain key layers (checkpoints).
  - Recompute the forward pass results during the backward pass.

- Disadvantages?

Key Contributions

1. Parallelizing the tensors better (sequence parallelism)
    - Enhanced **scalability**

2. Finding a good balance between re-computation and keeping the activations in memory
    - **Guidelines** for tradeoff

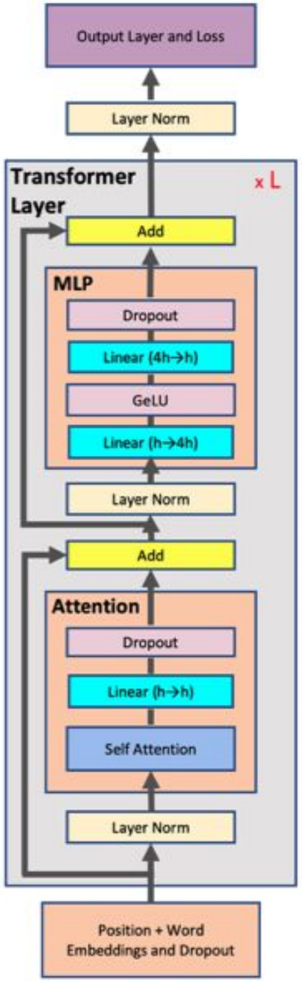
Recap: Transformers

- Each transformer unit has an attention block, a MLP block, and 2 layer-norm operators.
- Activation memory per layer = **sbh(34+5as/h)** bytes

$$11sbh + 5as^2b + 19sbh + 4sbh$$

Parameter	Description
s	Sequence Length
b	Micro-batch Size
h	Hidden Dimension Size
a	Number of Attention Heads
L	Number of Transformer Layers

Table 1: Model Parameters for Transformer-based Model



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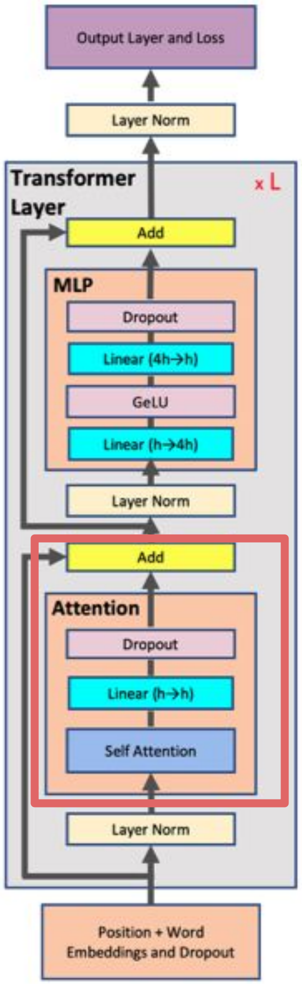

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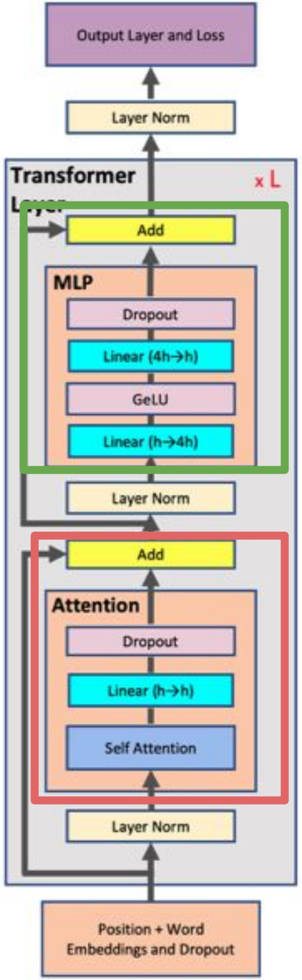

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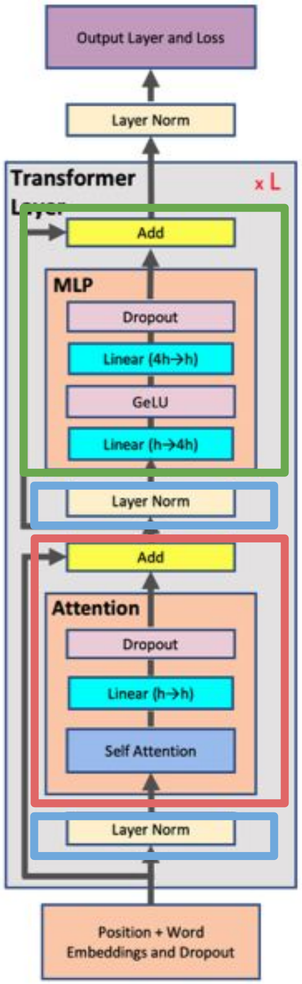
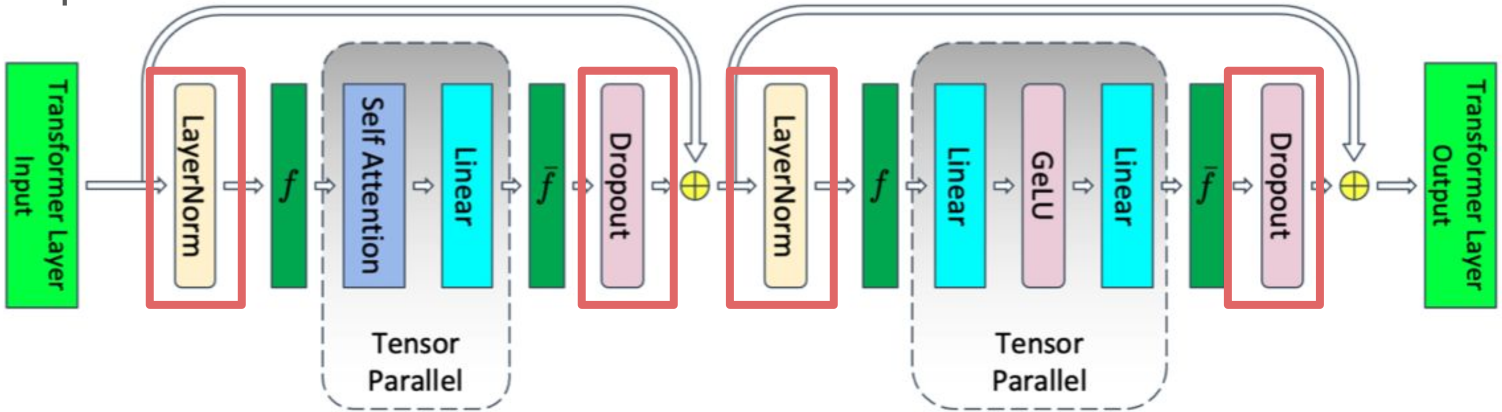


Transformers with Tensor Parallelism

- Not every layer is parallelized: passing through Layer Norm and Dropout require the entire activation matrix.



Communication Pattern

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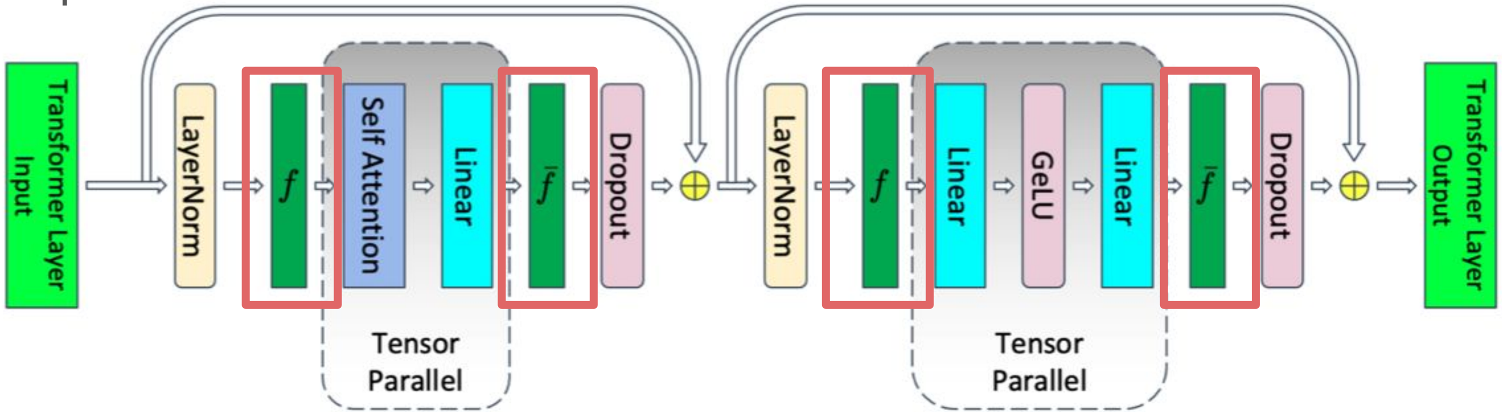
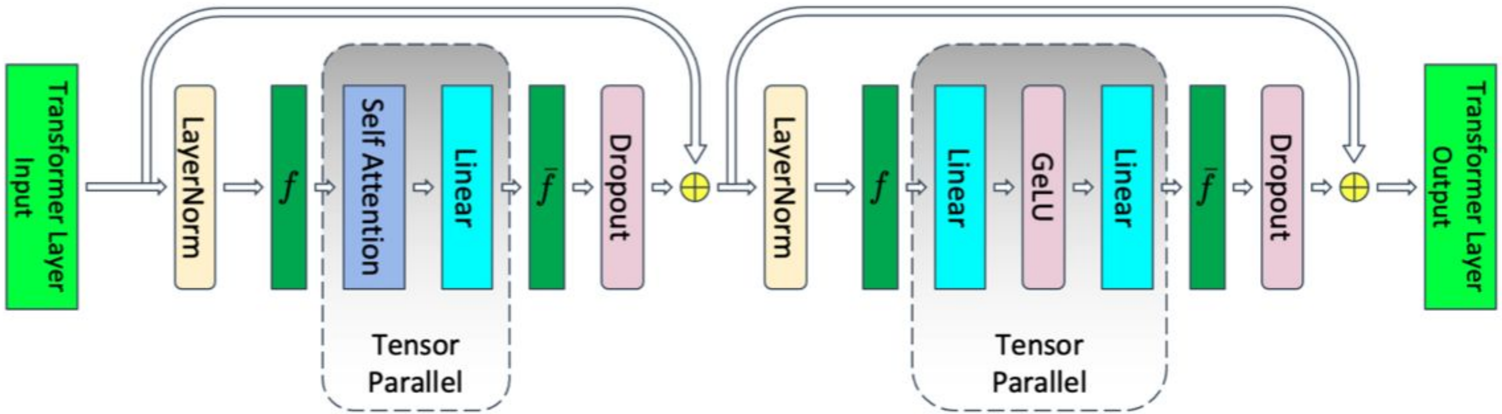


	forward	backward
f	No-op	All-reduce
$\bar{f}$	All-reduce	No-op

Memory Consumption Calculation

- Previously: $sbh(34 + \frac{5as}{h})$ bytes in total for each layer without parallelization.



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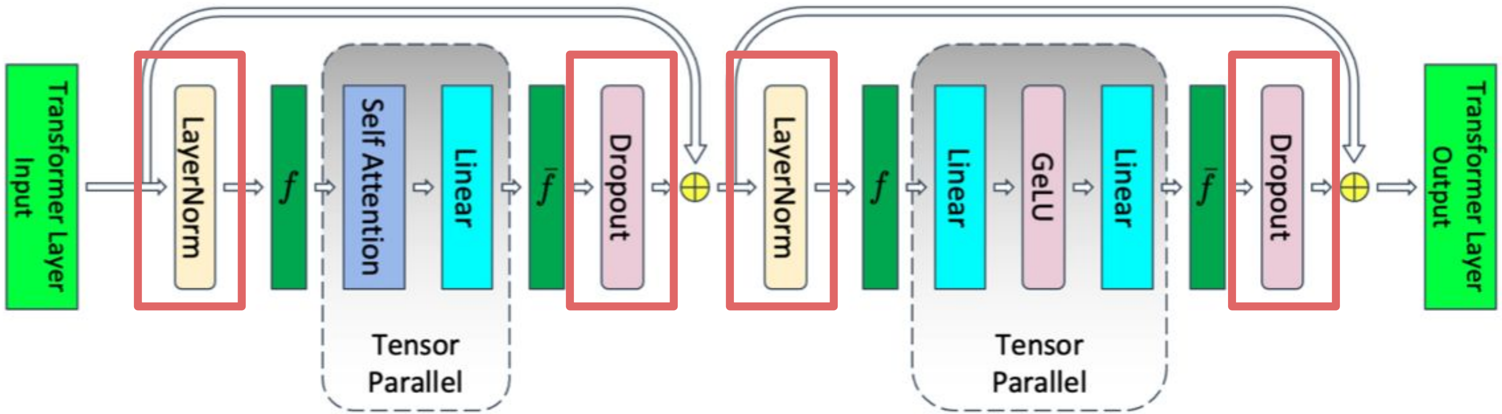
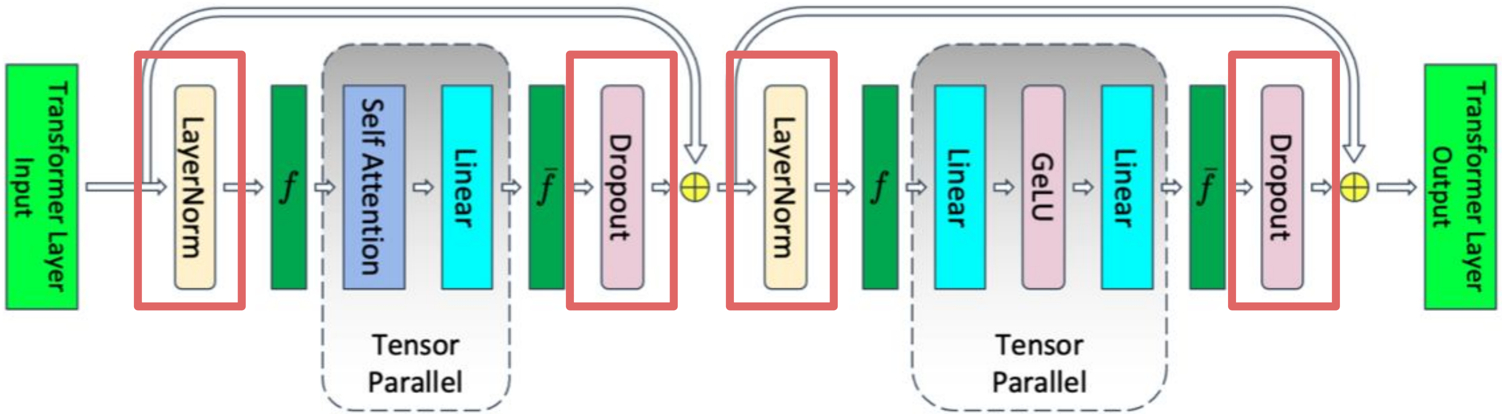


Memory Consumption Calculation

- Previously: $sbh(34 + \frac{5as}{h})$ bytes in total for each layer without parallelization.
- With t-way tensor parallelism: $sbh(\boxed{10} + \frac{24}{t} + \frac{5as}{ht})$ for each machine.

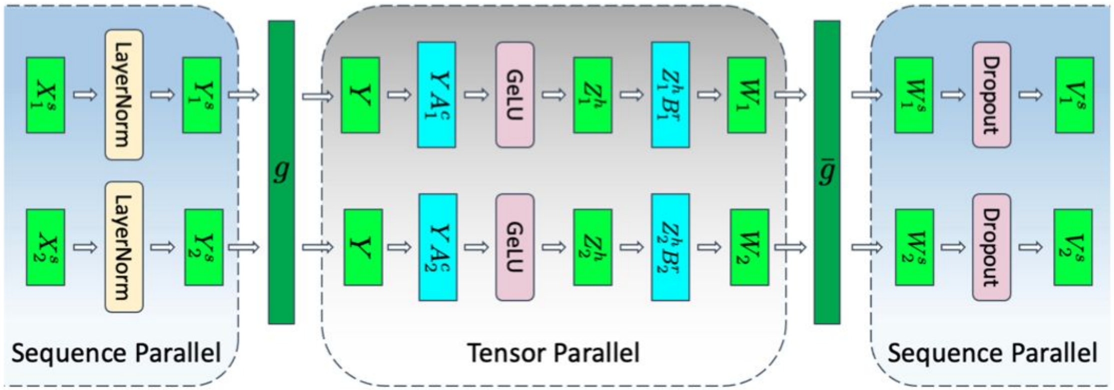


Idea: Sequence Parallel

- How do we parallelize the layer-norm + dropout operators?
  - Without incurring additional communication cost

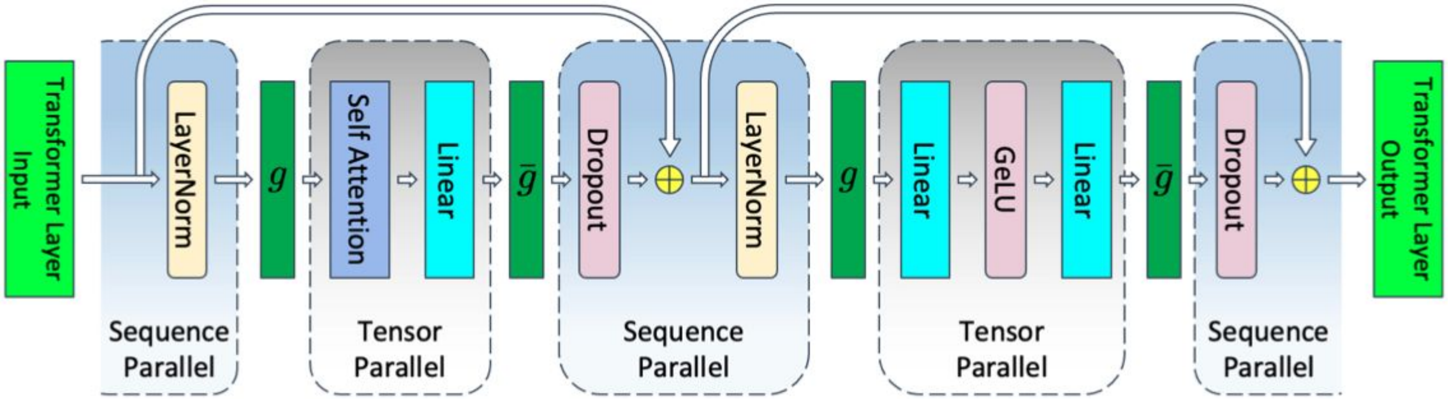
Idea: Sequence Parallel

- How do we parallelize the layer-norm + dropout operators?
  - Without incurring additional communication cost
- Split the matrices



Idea: Sequence Parallel

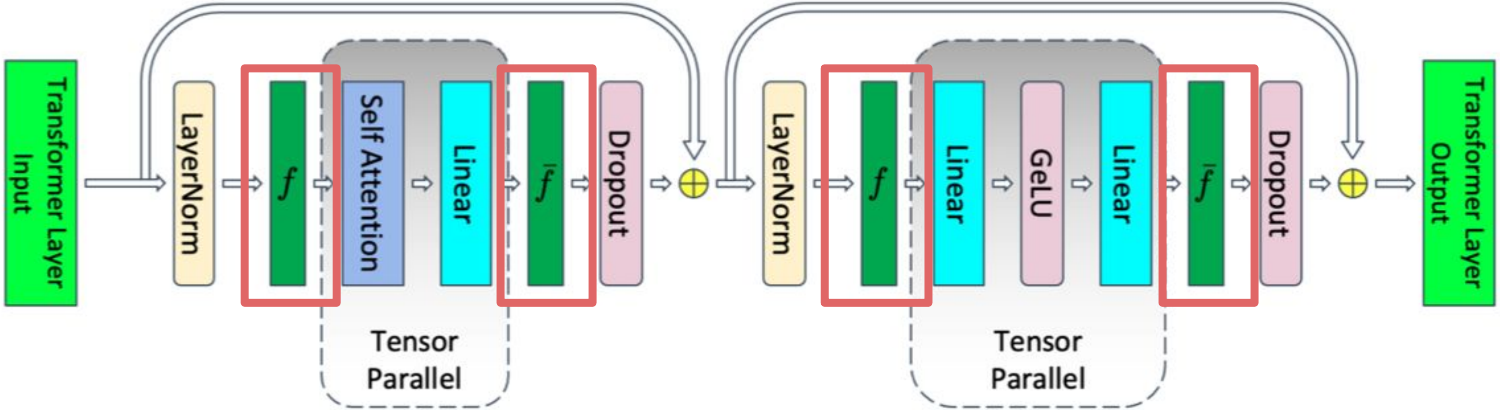
- The communication pattern needs to change
  - Are we doing more work?



	forward	backward
g	All-gather	Reduce-scatter
$\bar{g}$	Reduce-scatter	All-gather

Recall: Previous Communication Pattern

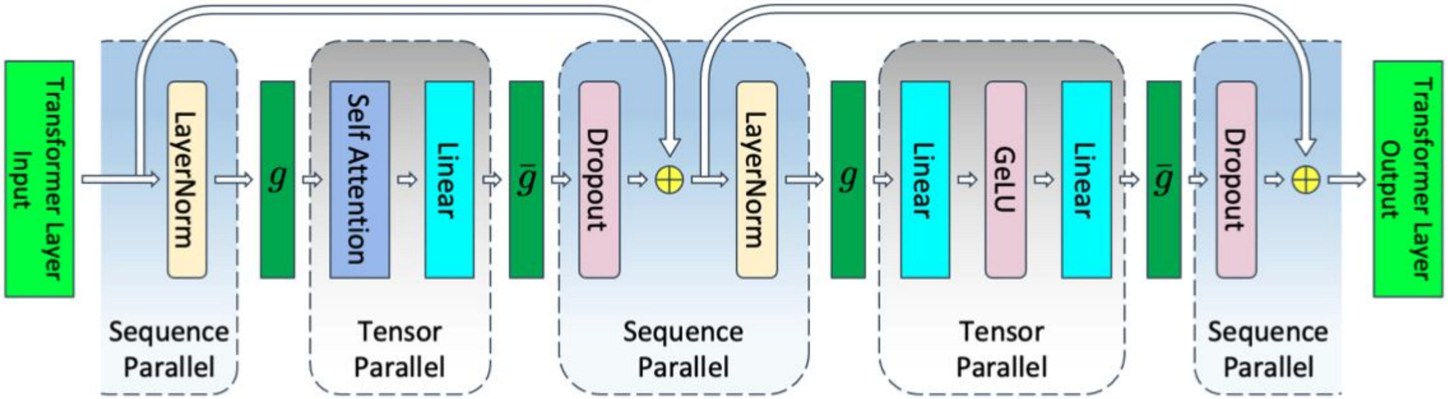
- Passing through Layer Norm and Dropout require the entire activation matrix across all model shards.



	forward	backward
f	No-op	All-reduce
$\bar{f}$	All-reduce	No-op

Idea: Sequence Parallel

- The communication pattern needs to change
  - Are we doing more work?



Recall: All-reduce = All-gather + Reduce Scatter!

	forward	backward
g	All-gather	Reduce-scatter
$\bar{g}$	Reduce-scatter	All-gather

Idea: Sequence Parallel

$$sbh(10 + \frac{24}{t} + \frac{5as}{ht})$$

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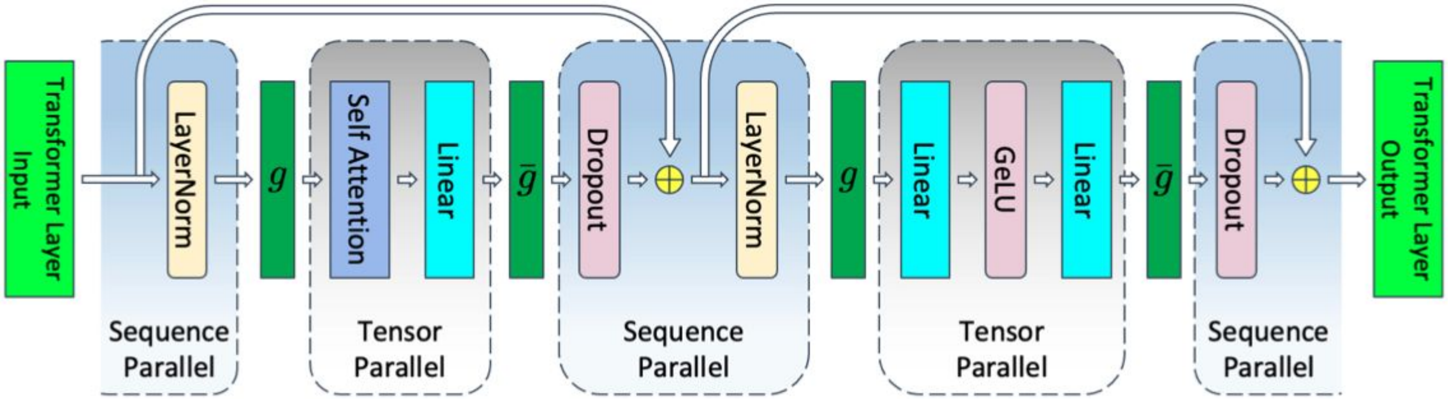

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	forward	backward
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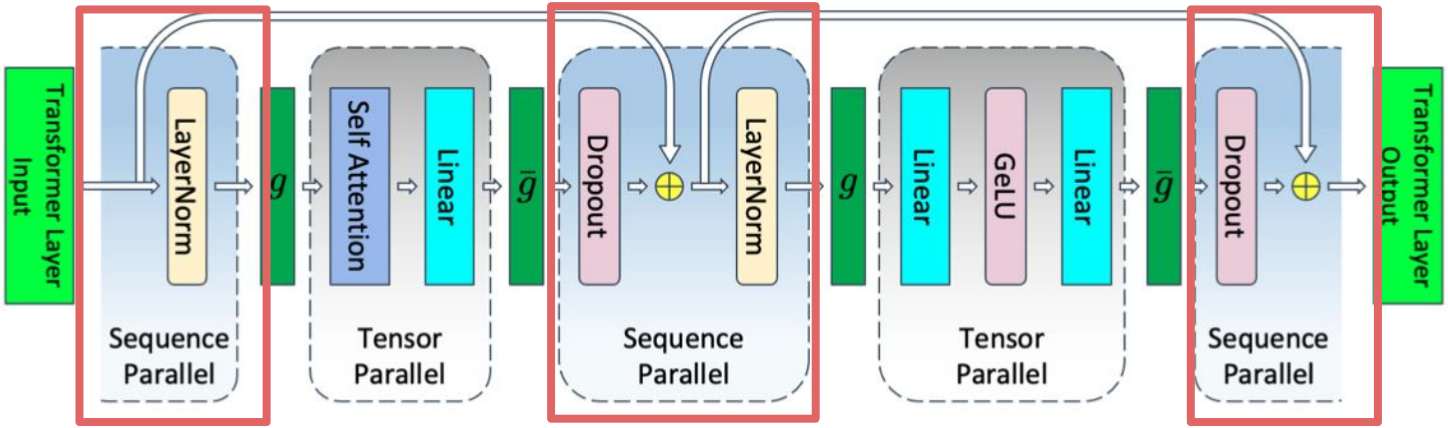
Idea: Sequence Parallel

$$sbh\left(\frac{10}{t} + \frac{24}{t} + \frac{5as}{ht}\right)$$

- The communication pattern needs to change
  - Are we doing more work?



Recall: All-reduce =
All-gather + Reduce Scatter!

	forward	backward
g	All-gather	Reduce-scatter
$\bar{g}$	Reduce-scatter	All-gather

Idea: Sequential Parallelization

- Same communication volume
  - And still parallelize the layer-norm + dropout

$$
\begin{aligned}
Y &= \text{LayerNorm}(X),\\
Z &= \text{GeLU}(YA),\\
W &= ZB,\\
V &= \text{Dropout}(W),
\end{aligned}
$$

$$\longrightarrow$$

$$
\begin{aligned}
[Y_1^s, Y_2^s] &= \text{LayerNorm}([X_1^s, X_2^s]),\\
Y &= g(Y_1^s, Y_2^s),\\
[Z_1^h, Z_2^h] &= [\text{GeLU}(YA_1^c),\ \text{GeLU}(YA_2^c)],\\
W_1 &= Z_1^h B_1^r \ \text{ and } \ W_2 = Z_2^h B_2^r,\\
[W_1^s, W_2^s] &= \bar{g}(W_1, W_2),\\
[V_1^s, V_2^s] &= [\text{Dropout}(W_1^s),\ \text{Dropout}(W_2^s)].
\end{aligned}
$$

Selective Activation Recomputation

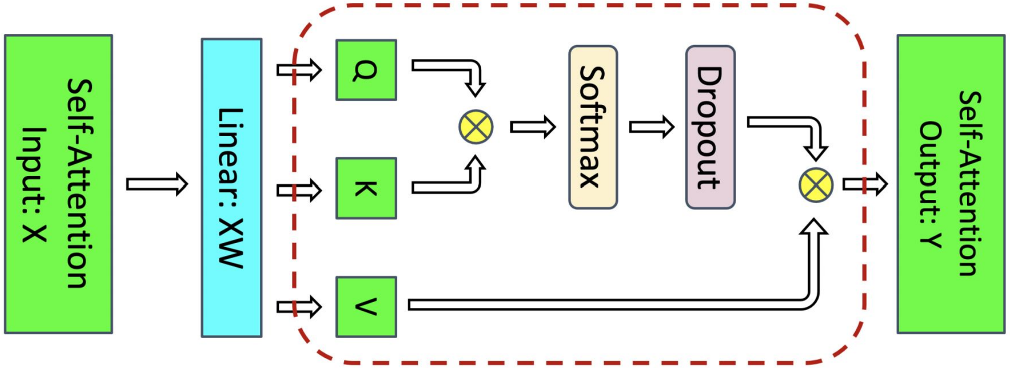
- Storing activations of all layers is memory-intensive.
- Use **checkpoints** to store output activations for **specific** layers.
- For **other** layers, **recompute** activations starting from the **nearest checkpoint**.

- We want to select the layers that takes up a lot of memory and not computationally expensive to recompute.

Selective Activation Recomputation

- Current memory overhead: sbh/t (34+5as/h) bytes
- For large models, 5as/h is larger than 34 and is the dominant factor.
- Activations corresponding to 5as/h are related to the attention operation, i.e., QK^T matrix multiply, softmax, softmax dropout,and attention over V

These operations are not flops heavy and recomputing them does not introduce much overhead for large models



Evaluations: setup

- Platform
  - All results are run with mixed precision on the Selene supercomputer
  - Each cluster node has 8 NVIDIA 80GB A100 GPUs connected to each other by NVLink and NVSwitch.
  - Each cluster node has 8 NVIDIA Mellanox 200Gbps HDR Infiniband Host Channel Adapters for application communication.

Evaluations: setup

- Workload
  - Sequence length is set to s = 2048 and vocabulary size is set to v = 51200.
  - No data parallelism is considered

Model Size	Attention Heads	Hidden Size	Layers	Tensor Parallel Size	Pipeline Parallel Size	Number of GPUs	Global Batch Size	Micro Batch Size
22B	64	6144	48	8	1	8	4	4
175B (GPT-3)	96	12288	96	8	8	64	64	1
530B (MT-NLG)	128	20480	105	8	35	280	280	1
1T	160	25600	128	8	64	512	512	1

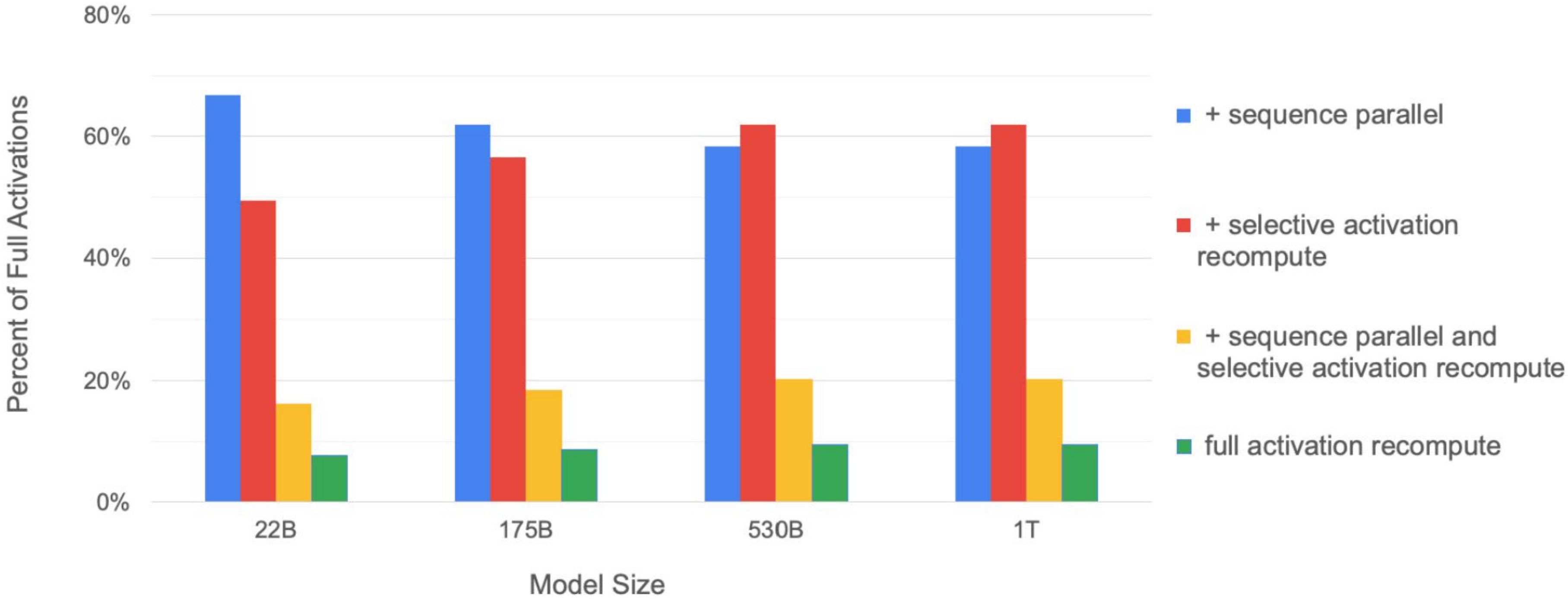
Evaluations: setup

- Questions to be answered
  - Memory usage
  - Execution Time

Evaluations: Memory usage

Configuration	Activations Memory (bytes)
no parallelism	$sbh\left(34 + 5\frac{as}{h}\right)$
tensor parallel (baseline)	$sbh\left(10 + \frac{24}{t} + 5\frac{as}{ht}\right)$
tensor + sequence parallel	$sbh\left(\frac{34}{t} + 5\frac{as}{ht}\right)$
tensor parallel + selective activation recomputation	$sbh\left(10 + \frac{24}{t}\right)$
tensor parallel + sequence parallel + selective activation recomputation	$sbh(\frac{34}{t})$
full activation recomputation	$sbh(2)$

Evaluations: Memory usage



Percentage of required memory compared to the tensor-level parallel baseline.

Individually, both techniques cut the memory requirement nearly in half, and combined bringing the memory requirements to under 20%.

Evaluations: Execution Time per Transformer Layer

Experiment	Forward (ms)	Backward (ms)	Combined (ms)	Overhead (%)
Baseline no recompute	7.7	11.9	19.6	–
Sequence Parallelism	7.2	11.8	19.0	–3%
Baseline with recompute	7.7	19.5	27.2	39%
Selective Recompute	7.7	13.2	20.9	7%
Selective + Sequence	7.2	13.1	20.3	4%

7.6

1.3

Time to complete the forward and backward pass of a single transformer layer of the 22B model.

- **Sequence Parallelism reduces the time to compute the forward pass**
- **Selective Recompute reduces the time to compute the backward pass**
- **Combining SP and SR, the overhead drops just 4%**

Evaluations: End-to-end iteration time

Model Size	Iteration Time (seconds)		Throughput Increase
	Full Recompute	Present Work	
22B	1.42	1.10	29.0%
175B	18.13	13.75	31.8%
530B	49.05	37.83	29.7%
1T	94.42	71.49	32.1%

End-to-end iteration time.

between 29.0% and 32.1% improvement in the throughput

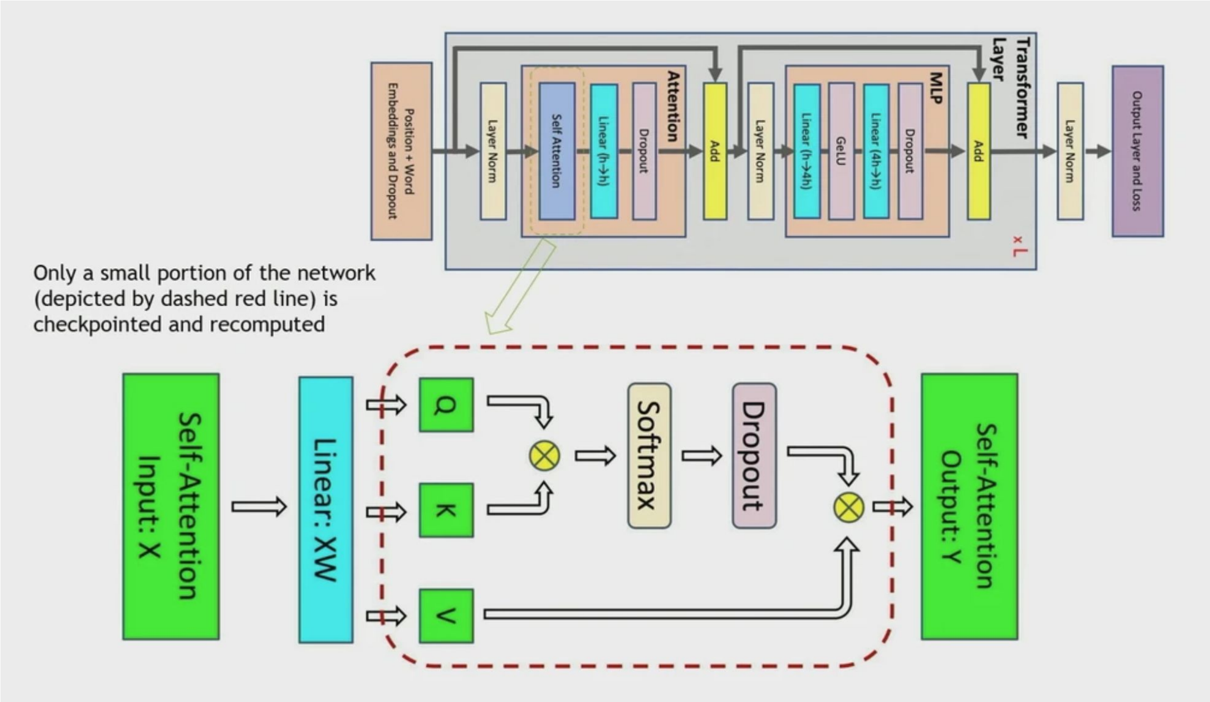
Thank you!

Selective Activation Recomputation

- Sequential parallelism reduces the activation memory per layer to: $sbh/t(34+5as/h)$ bytes
- For large models, $5as/h$ is larger than 34 and is the dominant factor.
- Examples:
  - $5as/h=80$ for GPT-3 ($a=96$, $h=12288$, $s=2048$)
  - $5as/h=64$ for Megatron-530B ($a=128$, $h=20480$, $s=2048$)

Selective Activation Recomputation

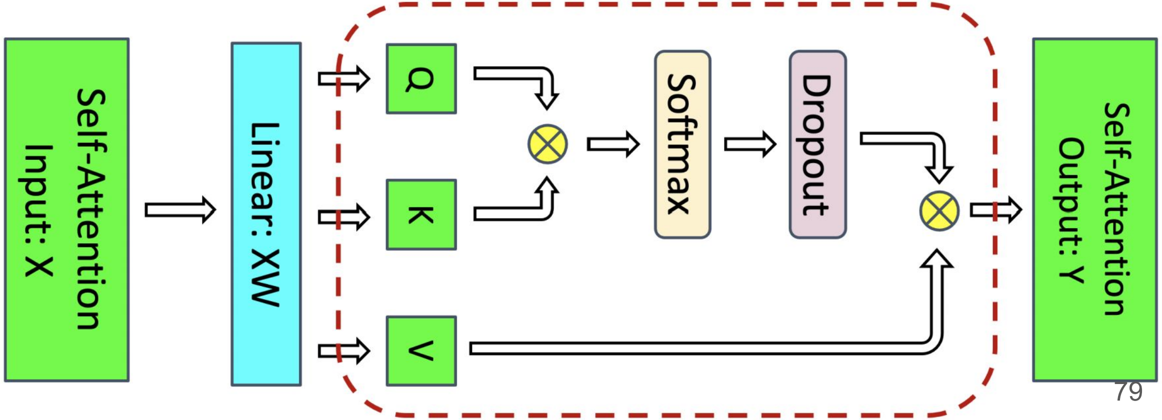
- Activations corresponding to **5as/h** are related to the attention operation, i.e., QK^T matrix multiply, softmax, softmax dropout,and attention over V



- Checkpointing these activations reduces memory per layer to: 34sbh/t bytes

Selective Activation Recomputation

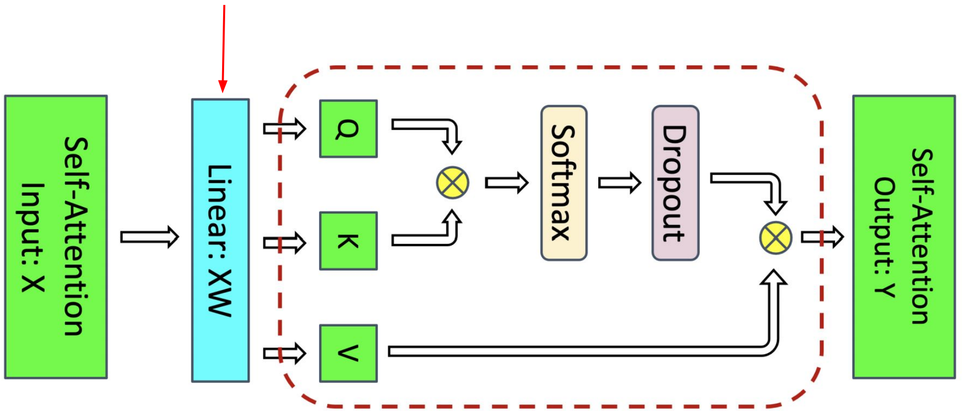
- These operations are not flops heavy and recomputing them does not introduce overhead for large models where h>> s.
- Computational complexity: $O(s^2h)$
  - QK^T matrix multiply: $O(s^2h)$
  - Softmax: $O(s^2)$
  - softmax dropout: $O(s^2)$
  - attention over V: $O(s^2h)$

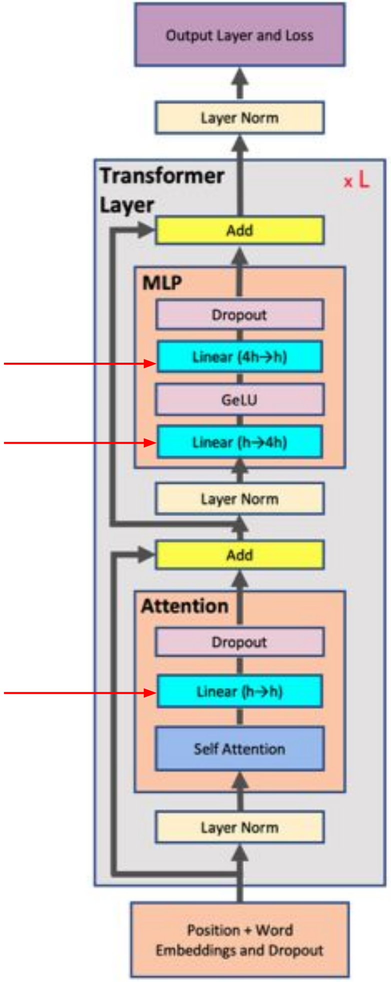


Selective Activation Recomputation

- Computational complexity of Linear layers: $O(sh^2)$
- $R^{s \times h} \times R^{h \times h}$

When h>>s, $O(sh^2) > O(s^2h)$



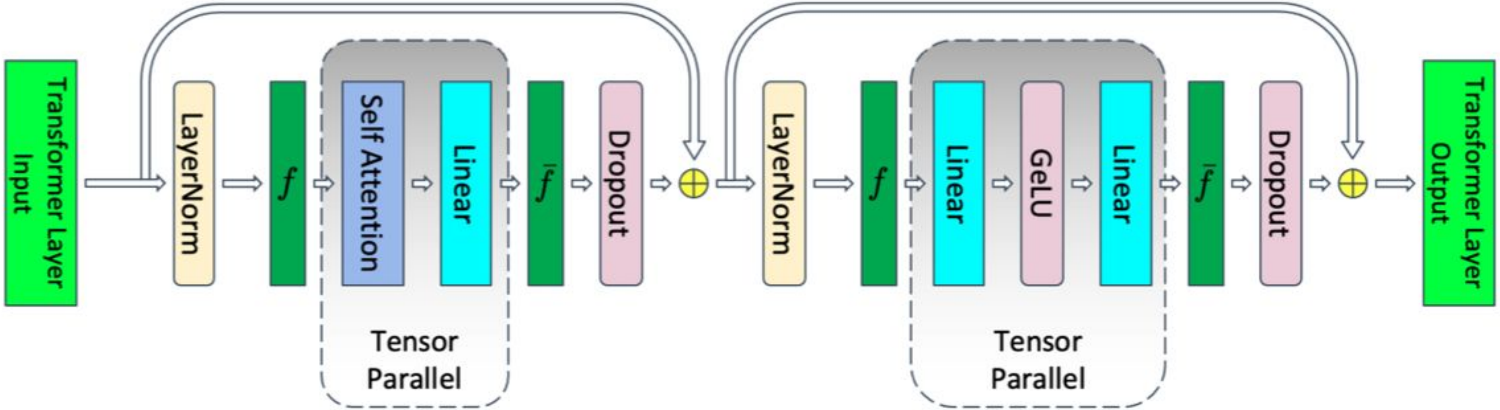


Recap: Transformers

- Activations require a substantial amount of memory for large models
  - If we consider attention, MLP, and the layer-norms
  - Activation memory per layer = sbh(34+5as/h) bytes

v	vocabulary size	b	micro batch size
s	sequence length	a	number of attention heads
h	hidden dimension size	L	number of transformer layers
t	tensor parallel size	p	pipeline parallel size

Table 1: Variable names



With Tensor Parallelism

- Activation memory per layer = sbh(10 + 24/t + 5as/ht) bytes

	forward	backward
f	No-op	All-reduce
$\bar{f}$	All-reduce	No-op

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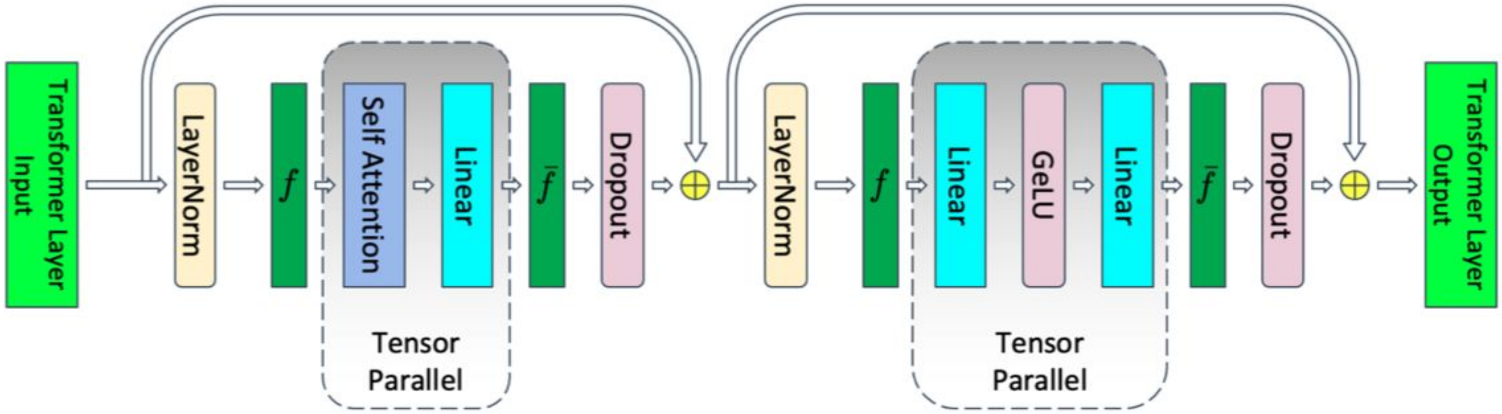

Idea: Sequential Parallelization

	forward	backward
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$\bar{g}$	Reduce-scatter	All-gather

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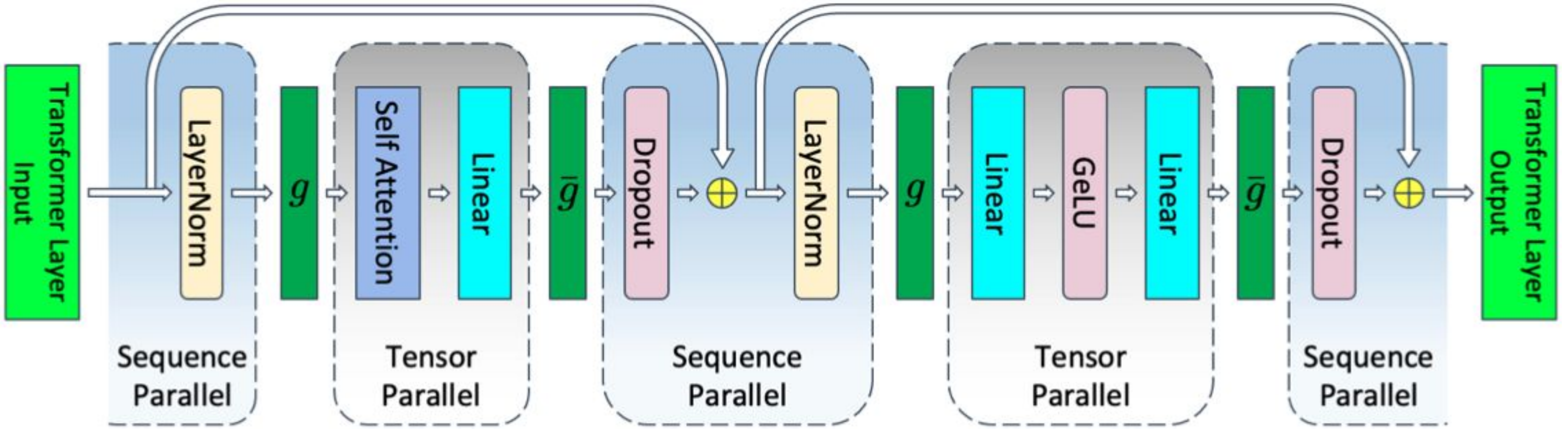

Memory: sbh(10/t + 24/t + 5as/ht)