CS 498: Machine Learning System
Spring 2025

Minjia Zhang

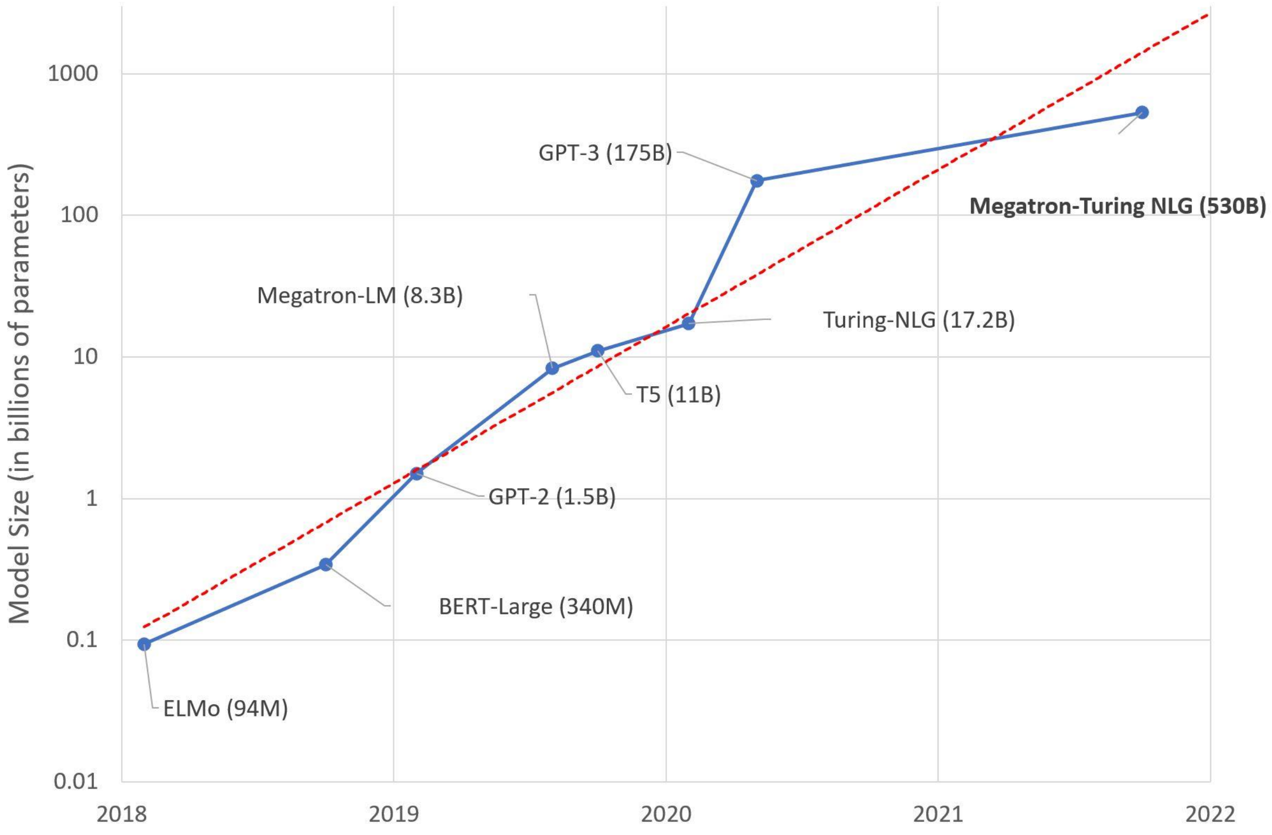
The Grainger College of Engineering

Today

ZeRO-Style Data Parallelism (Fully-Sharded Data Parallelism)

- Motivation
- ZeRO capability overview
- Understanding Memory Consumption
- ZeRO-DP: ZeRO powered data parallelism
- Evaluation

Why large model training?



Models are scaling in size, and larger models lead to better accuracy

More compute efficient to train larger models than smaller ones to same accuracy

State-of-art and its limitations

	Max Parameter (in billions)	Max Parallelism	Compute Efficiency	Usability (Model Rewrite)
Data Parallel (DP)	Approx. 1.2	>1000	Very Good	Great

*Mixed precision Adam on Cluster of DGX-2 with NVIDIA 32 GB V100 GPUs

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Democratization of large model training requires easy to use solutions that can support large model sizes and parallelism degree while remaining highly efficient

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Pipeline Parallel (PP)	Approx. 100	Approx. 128	Very Good	Needs Model Rewrite

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Motivation

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ZeRO	*> 1000*	*> 1000*	Very Good	Great

Outline

- Motivation
- ZeRO capability overview
- **Understanding Memory Consumption**
- ZeRO-DP: ZeRO powered data parallelism
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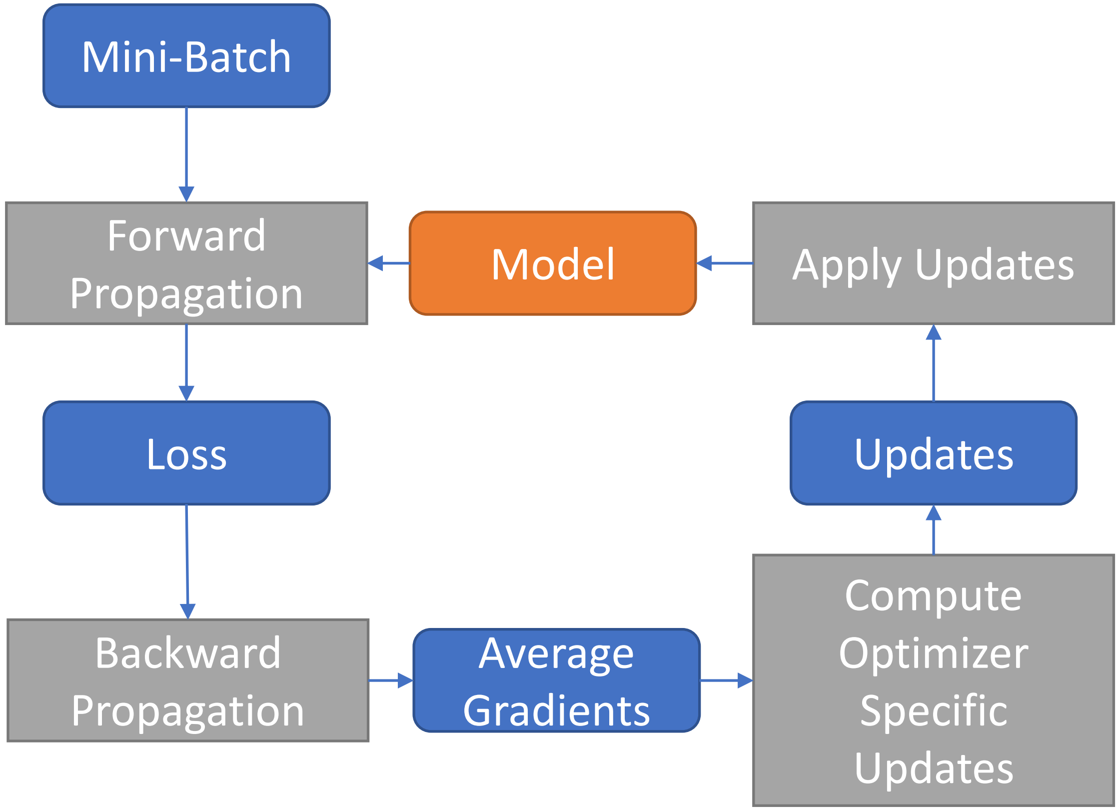
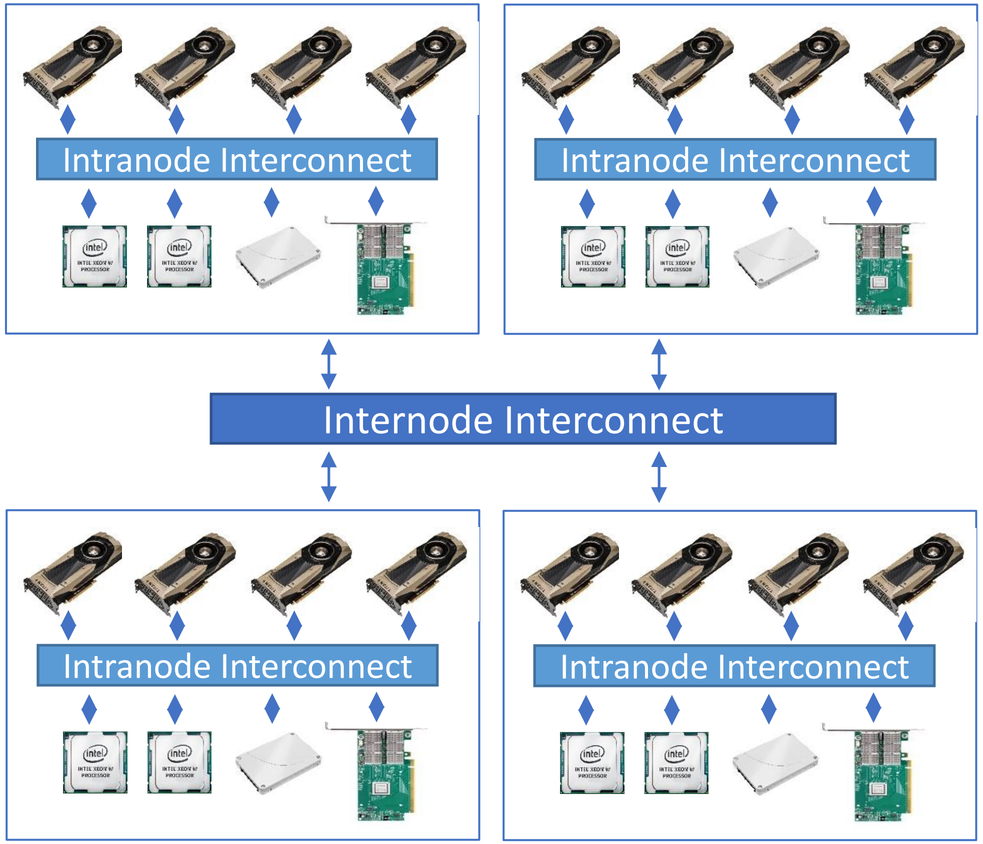
Distributed Data Parallel Training Overview

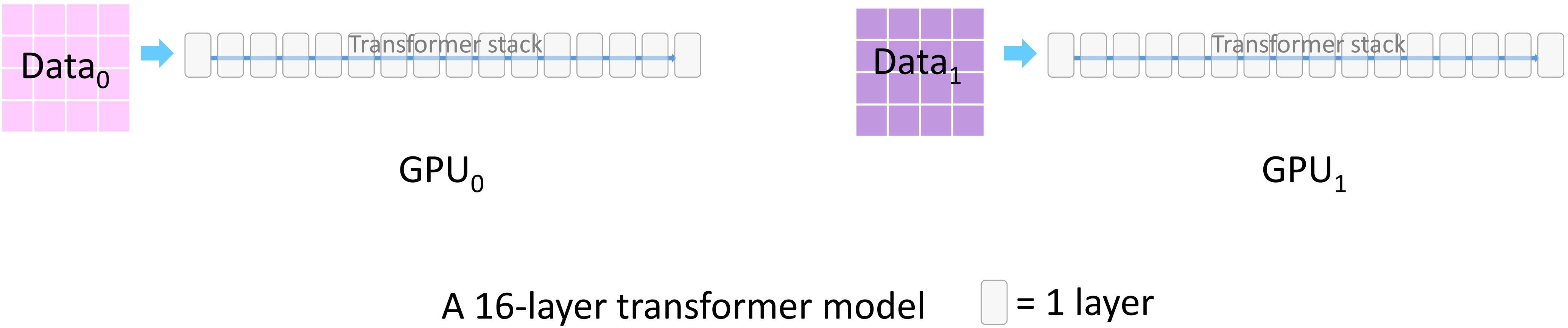


Data Parallel Training Loop



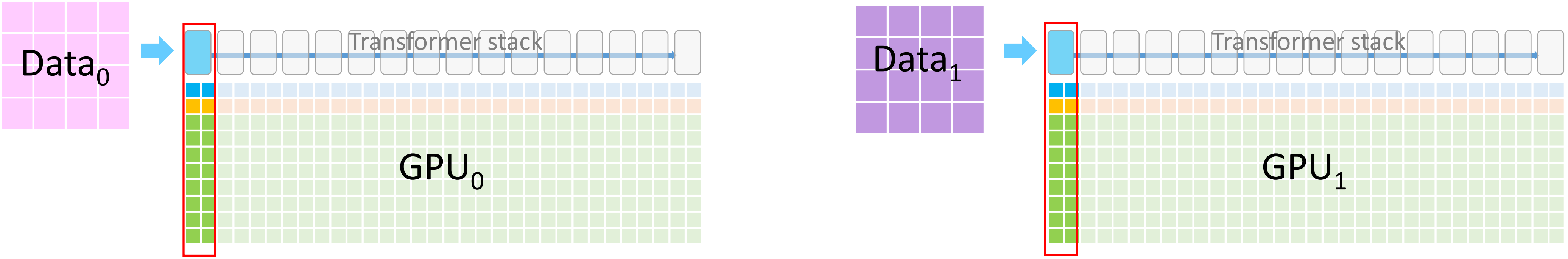
Distributed GPU Cluster

Understanding Memory Consumption



*[Mixed Precision Training](#) (ICLR '18) with Adam Optimizer

Understanding Memory Consumption



Each cell represents GPU memory used by its corresponding transformer layer

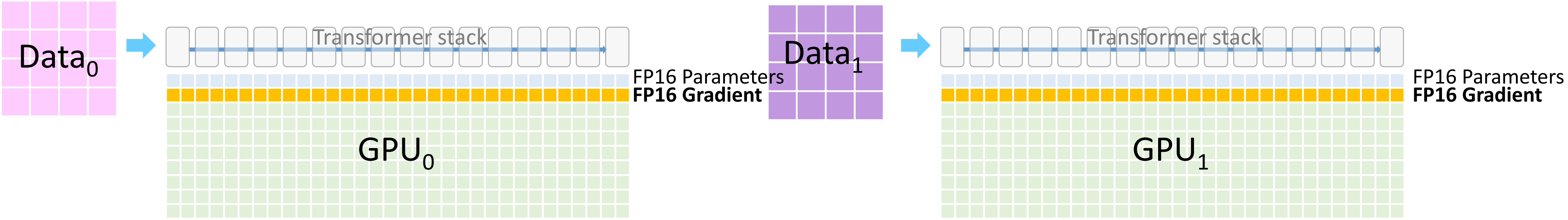
*Mixed Precision Training (ICLR '18) with Adam Optimizer

Understanding Memory Consumption

- FP16 parameter

*[Mixed Precision Training](#) (ICLR '18) with Adam Optimizer

Understanding Memory Consumption



- FP16 parameter
- FP16 Gradients

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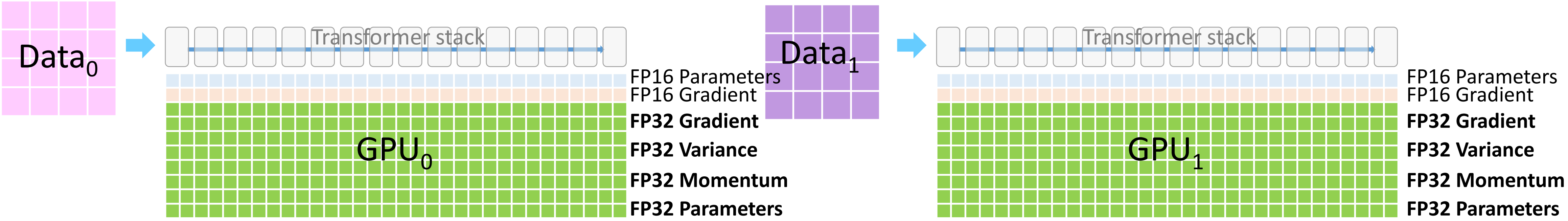

- FP16 parameter
- FP16 Gradients
- FP32 Optimizer States
  - Gradients, Variance, Momentum, Parameters

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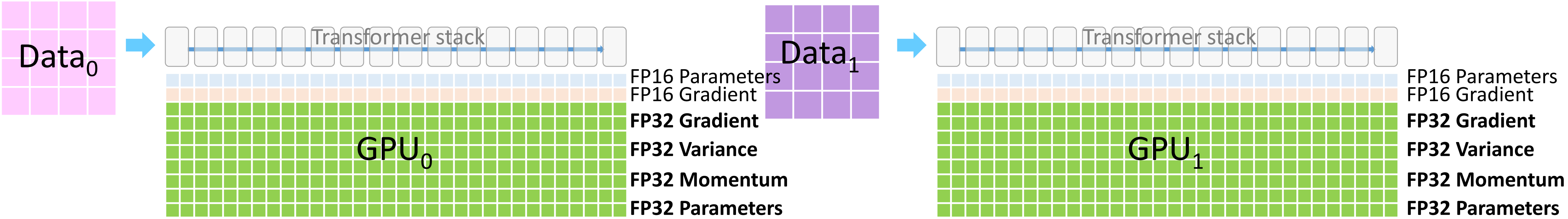
Understanding Memory Consumption



- FP16 parameter **: 2M bytes**
- FP16 Gradients **: 2M bytes**
- FP32 Optimizer States **: 16M bytes**
  - Gradients, Variance, Momentum, Parameters

M = number of parameters in the model

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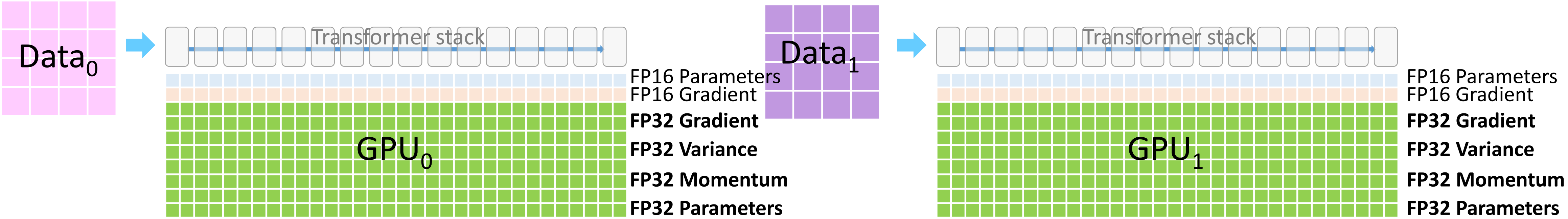
Understanding Memory Consumption



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Example 1B parameter model -> 20GB/GPU

Memory consumption doesn't include:

- Input batch + activations

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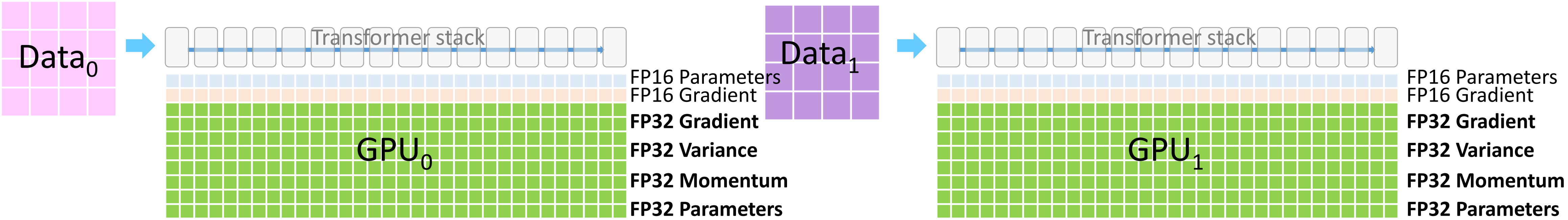

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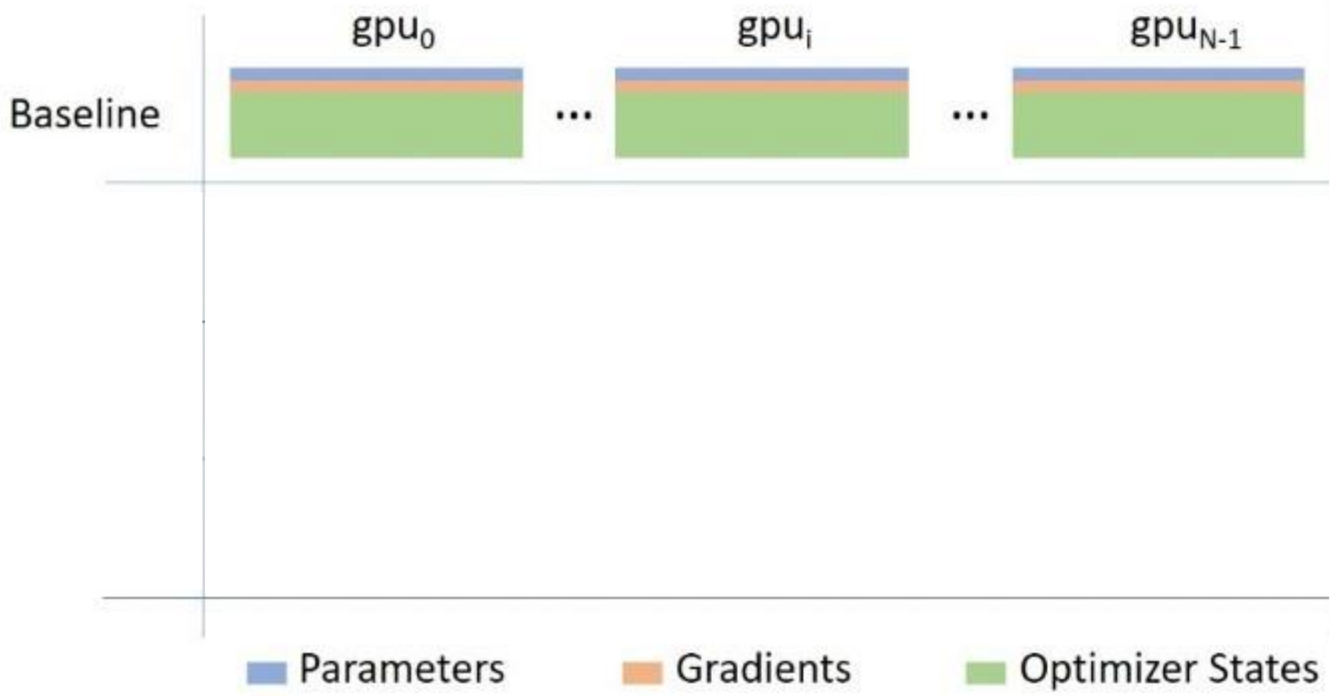
ZeRO-DP: ZeRO powered Data Parallelism

- ZeRO removes the redundancy across data parallel process
- Partitioning optimizer states, gradients and parameters (3 stages)



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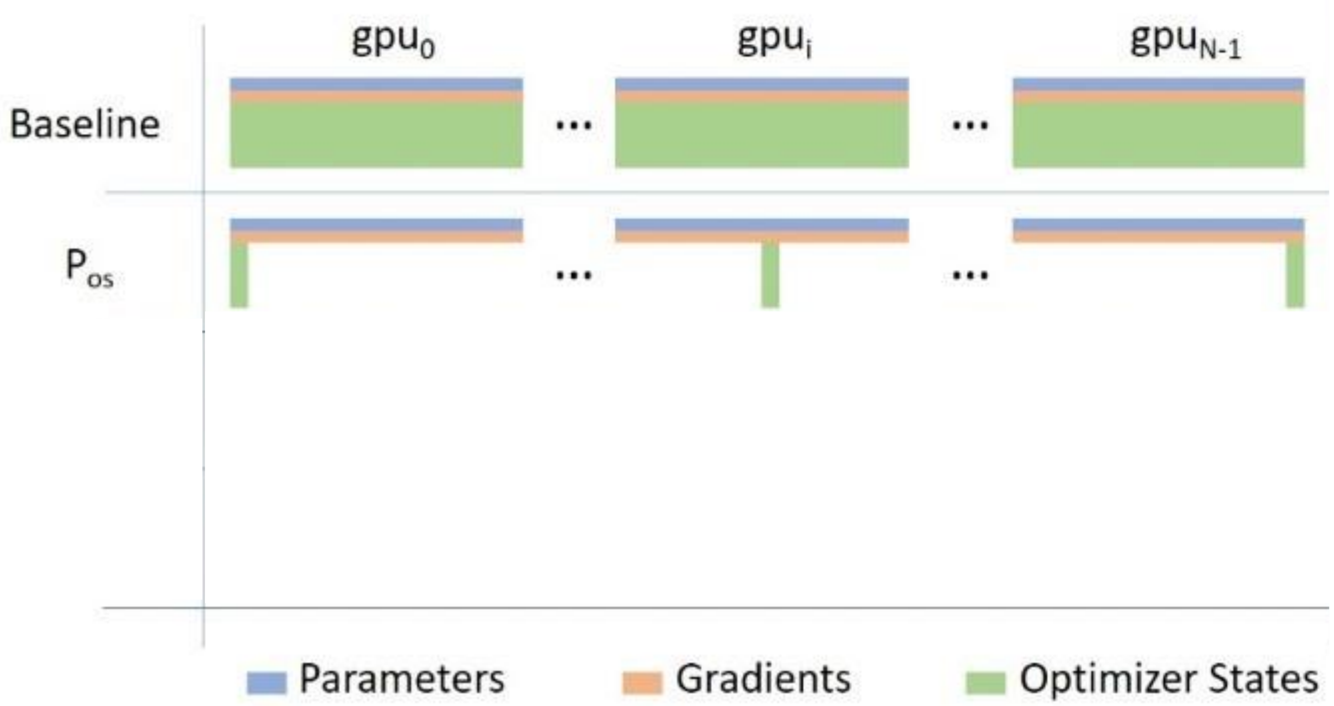

Stage 1 (P_{os})

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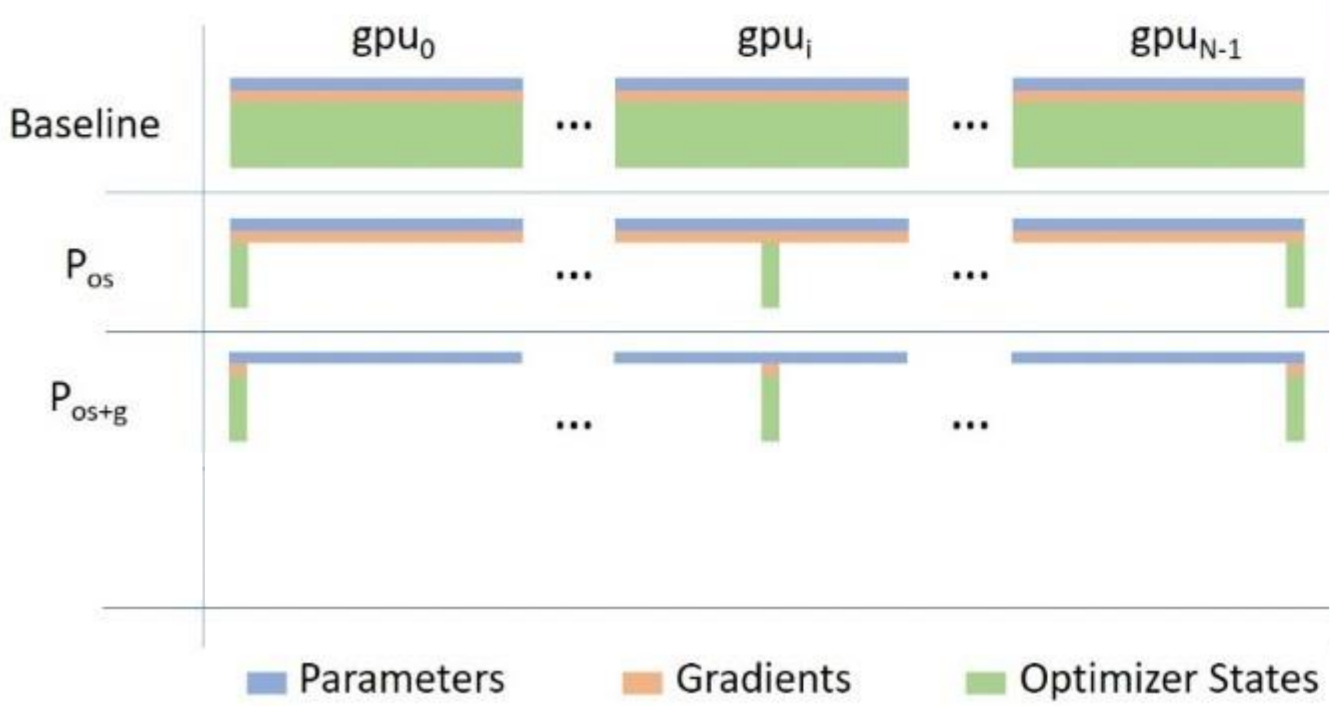

Stage 2 (P_{os+g})

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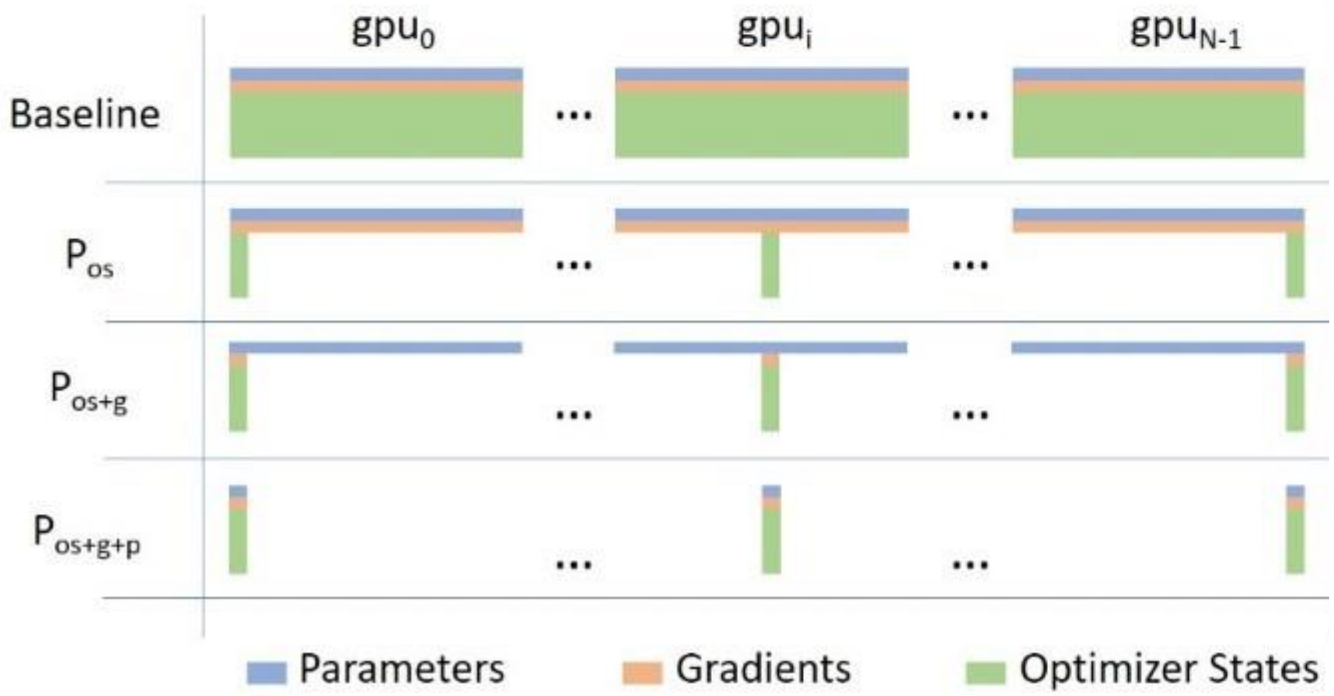

Stage 3 (P_{os+g+p})

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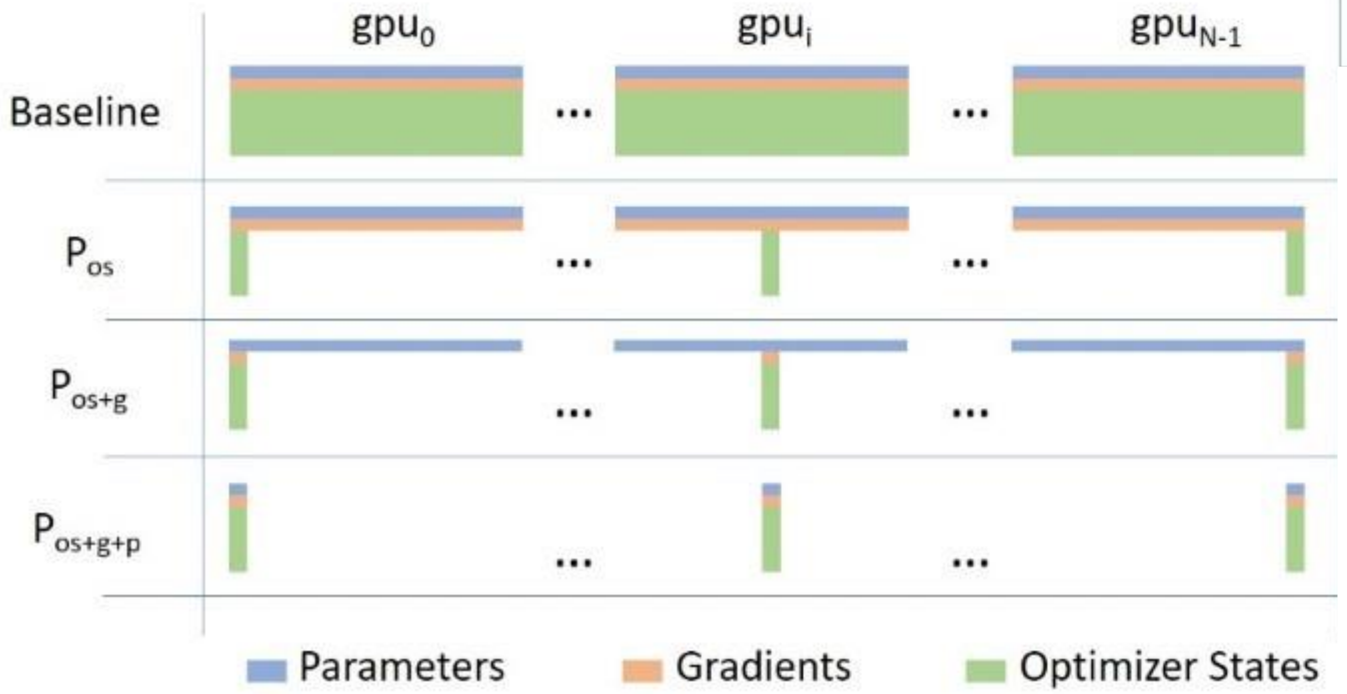

Memory Consumption	
Formulation	Specific Example K=12 Ψ=7.5B N_d=64

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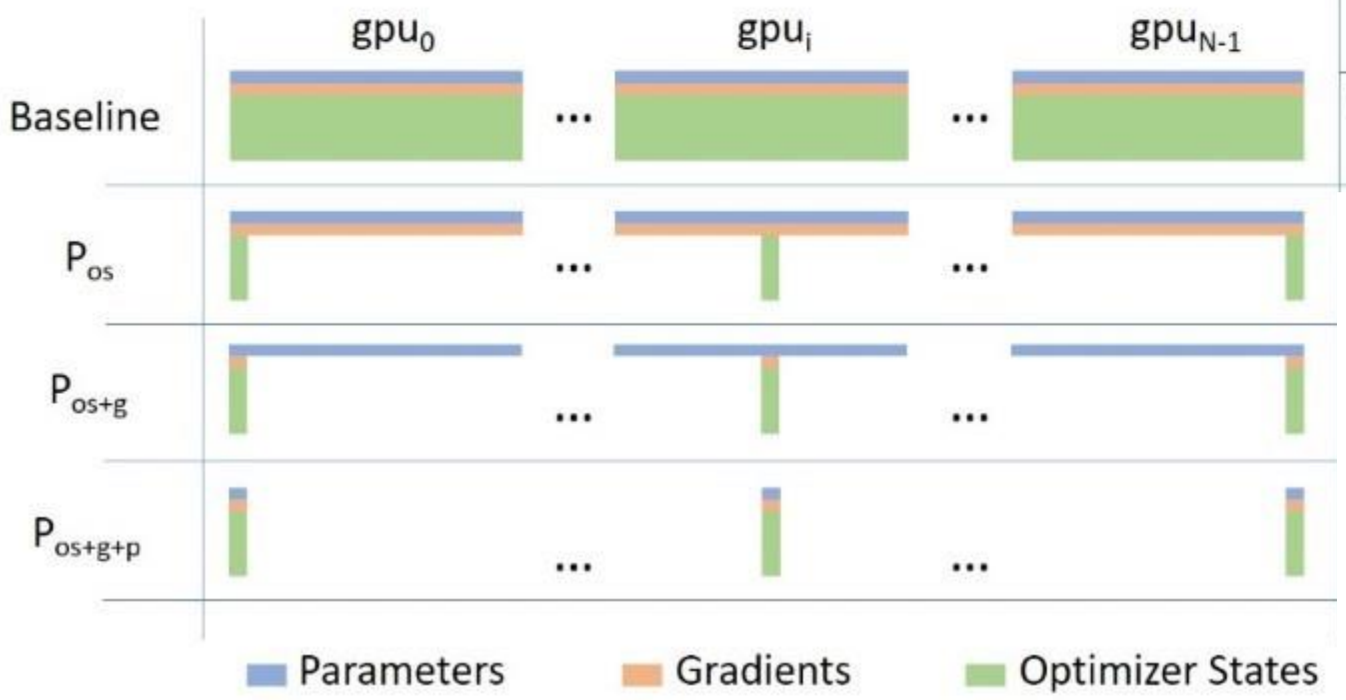

Memory Consumption	
Formulation	Specific Example $K=12$ $\Psi=7.5B$ $N_d=64$
$(2+2+K)*\Psi$	120GB

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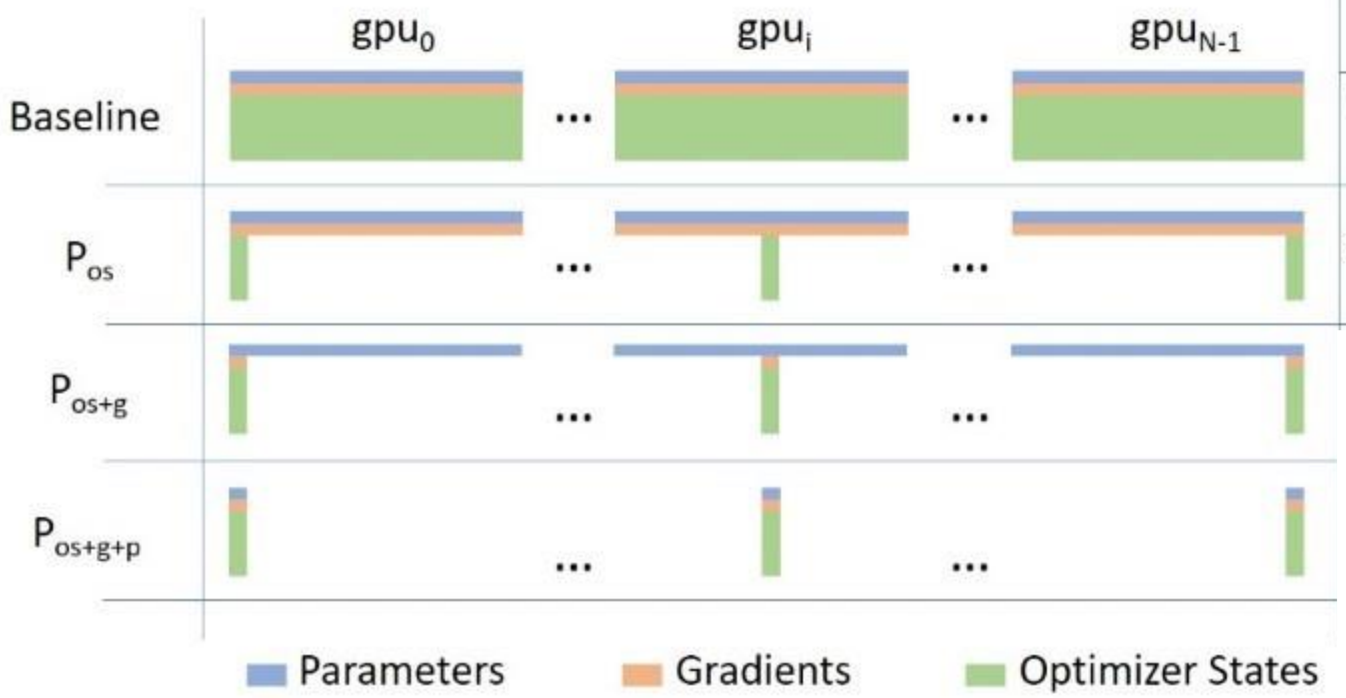

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$2\Psi+2\Psi+\frac{K*\Psi}{N_d}$	31.4GB

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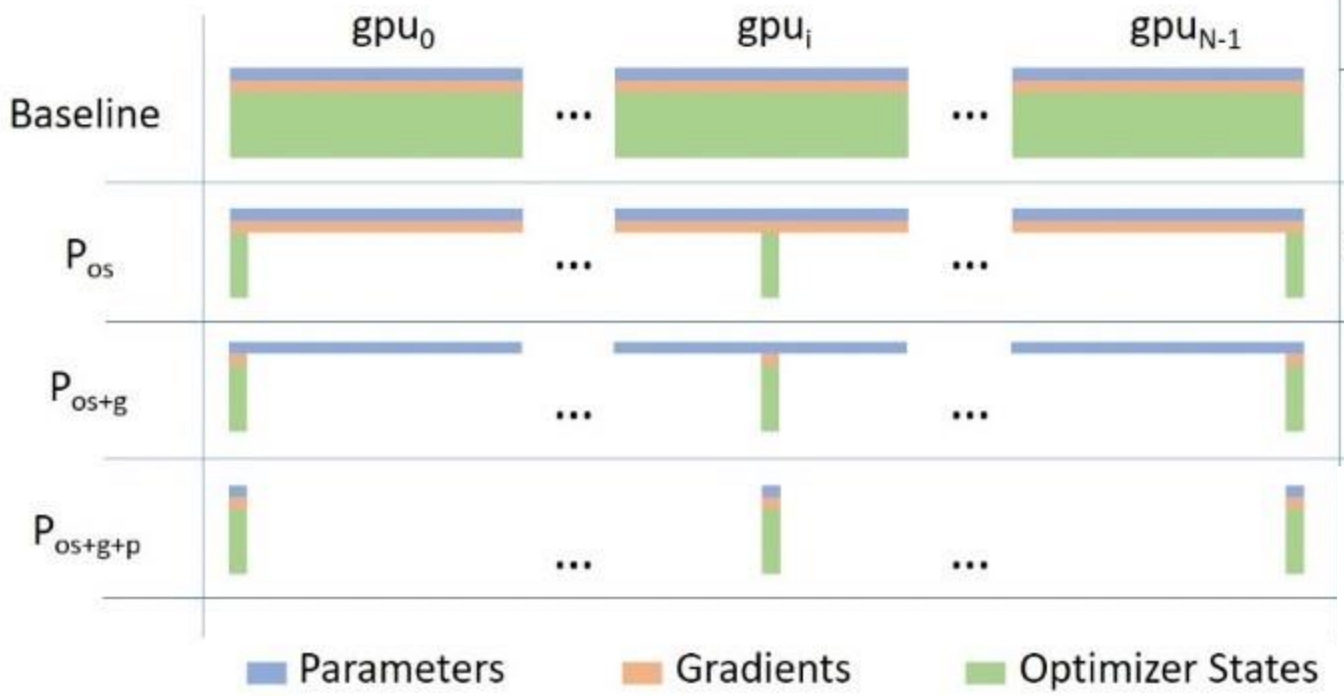

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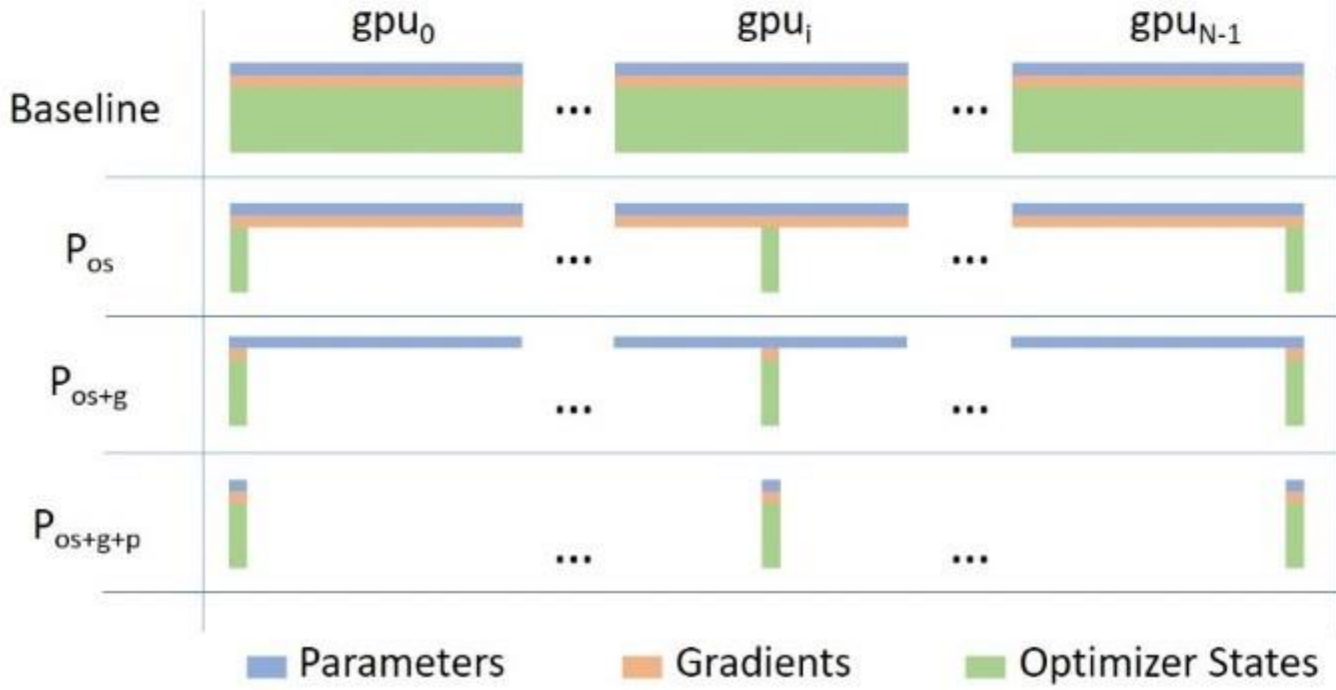

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P_{os+g}	$2\Psi+\frac{(2+K)*\Psi}{N_d}$	16.6GB
P_{os+g+p}	$\frac{(2+2+K)*\Psi}{N_d}$	1.9GB

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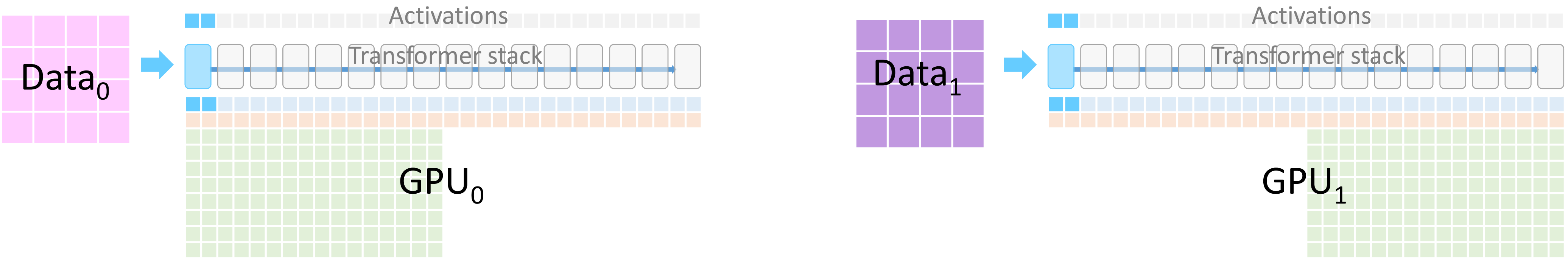

- ZeRO Stage 1
- Partitions optimizer states across GPUs
- Run Forward across the transformer blocks

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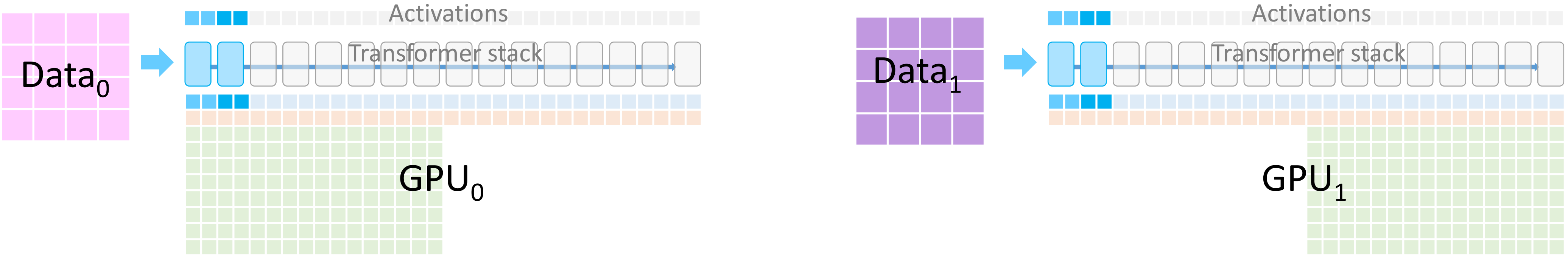

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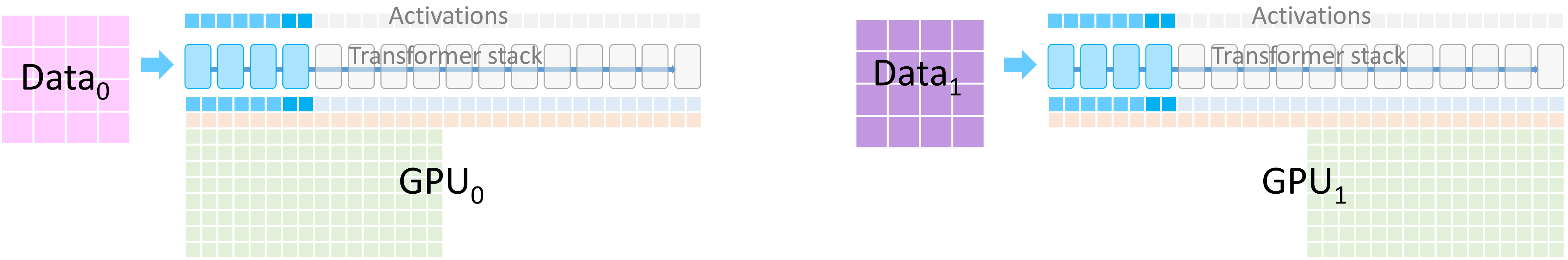

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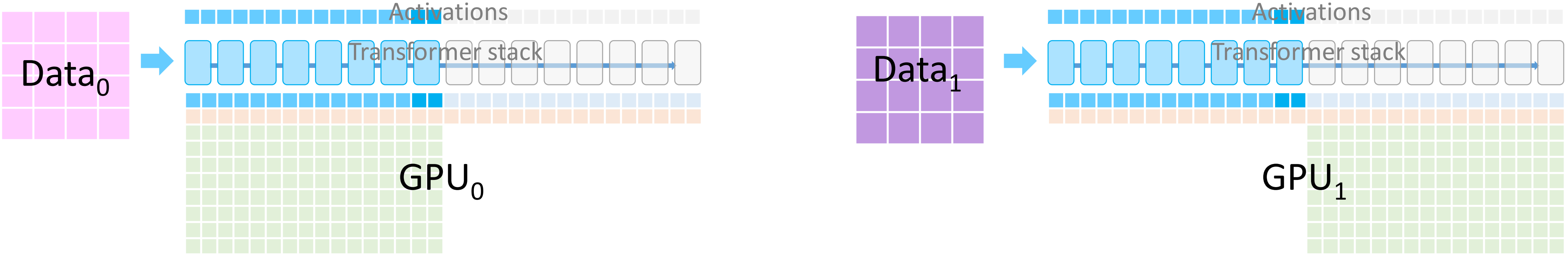

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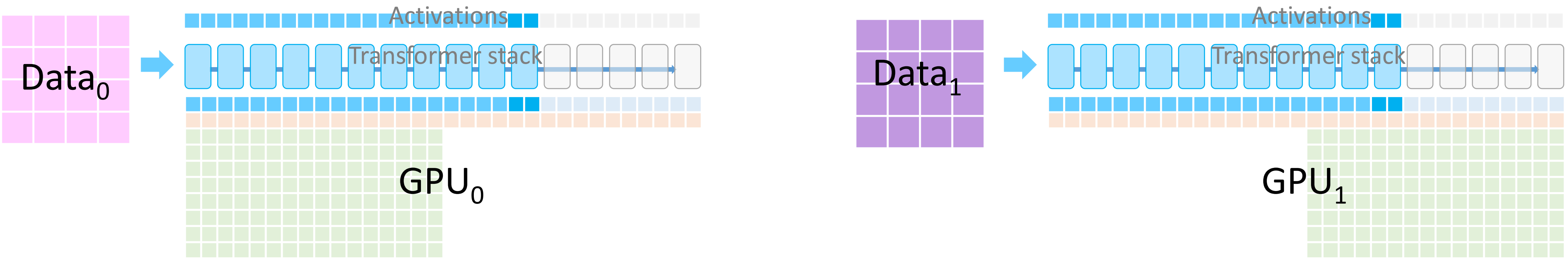

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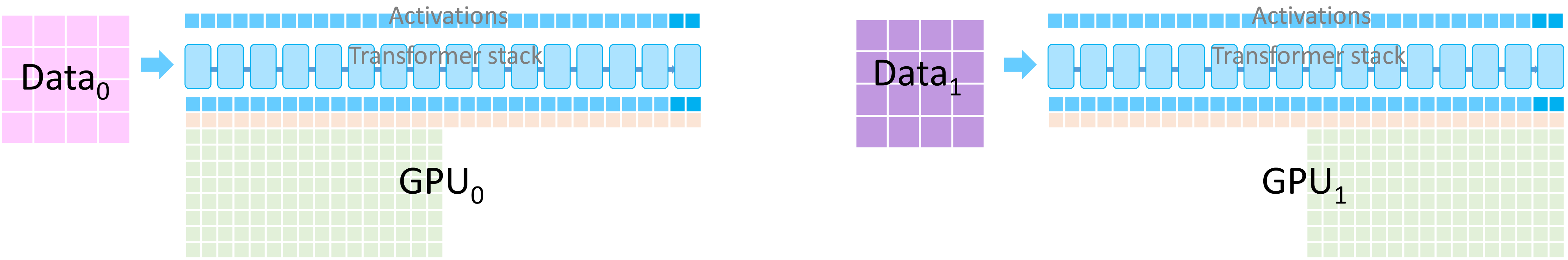

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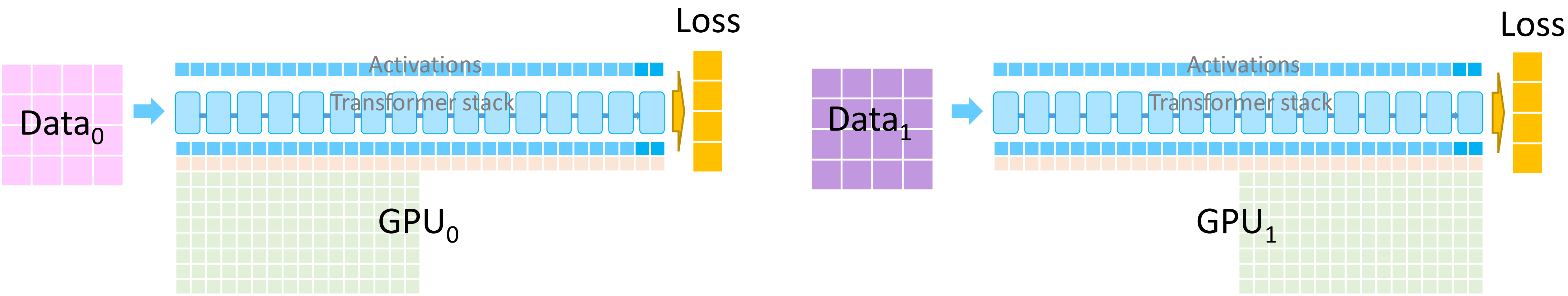

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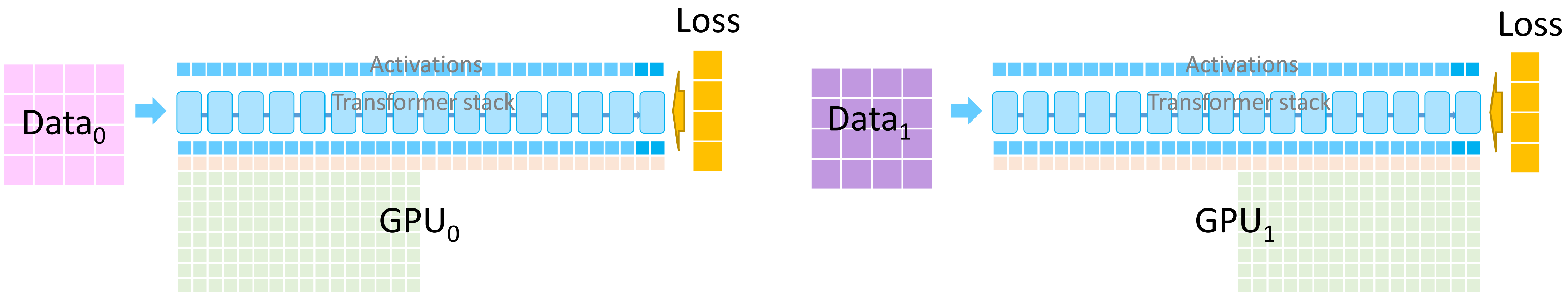

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- Backward propagation to generate FP16 gradients

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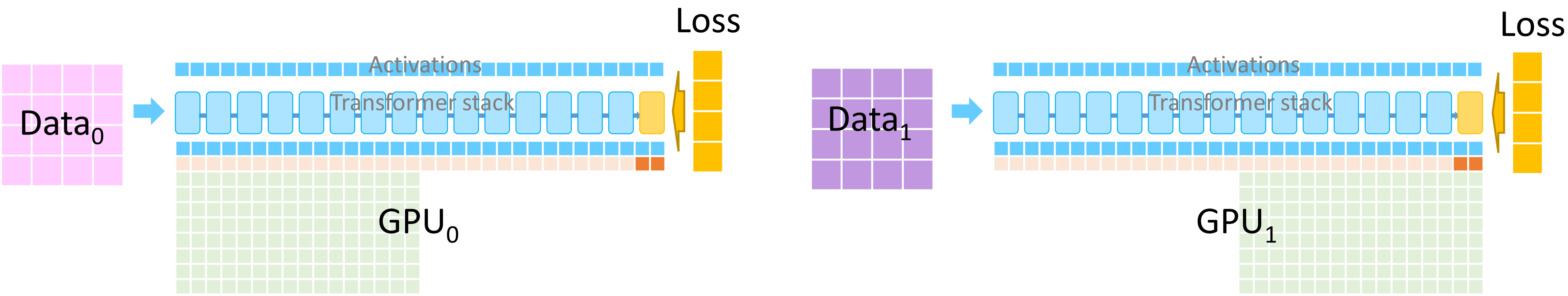

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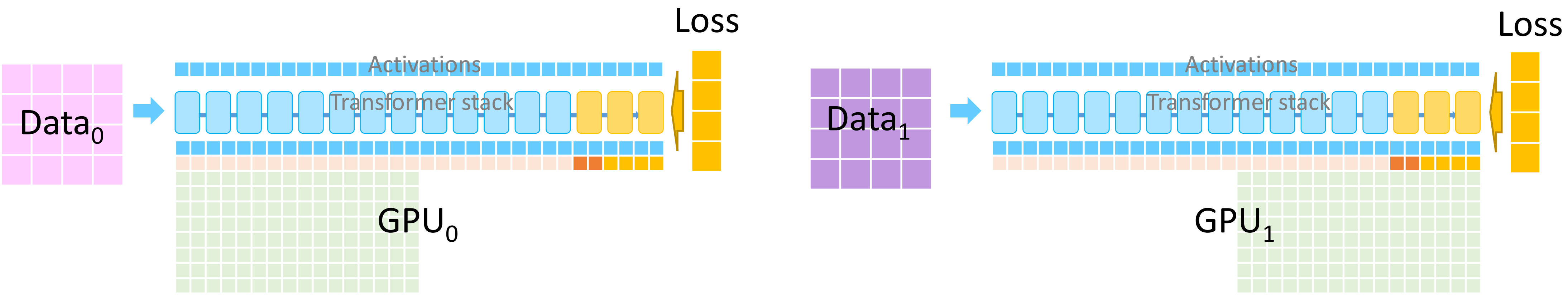

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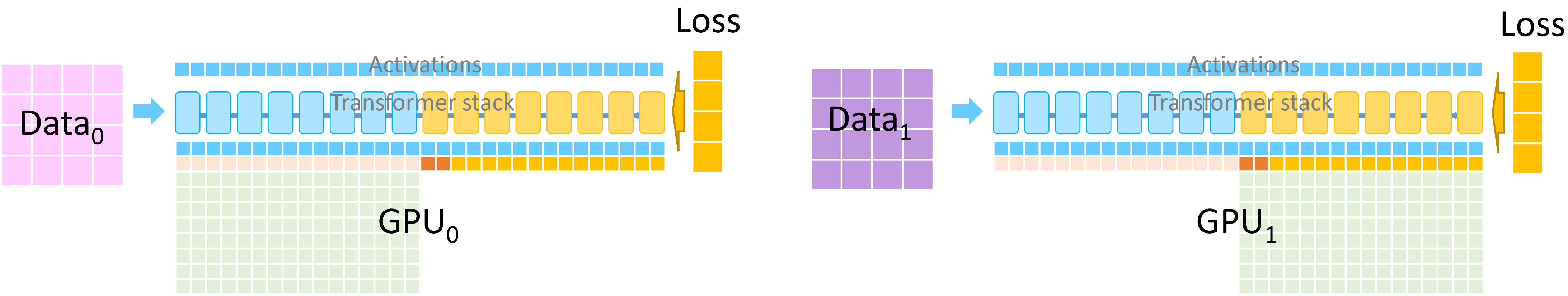

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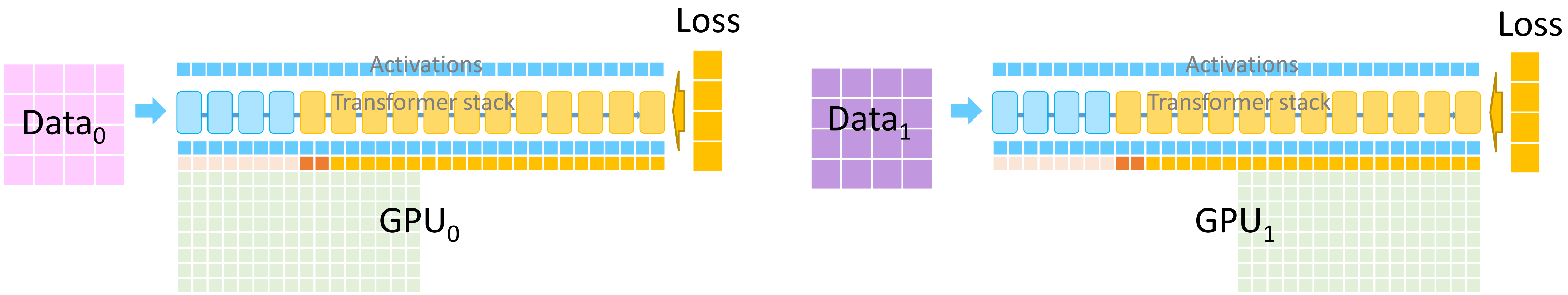

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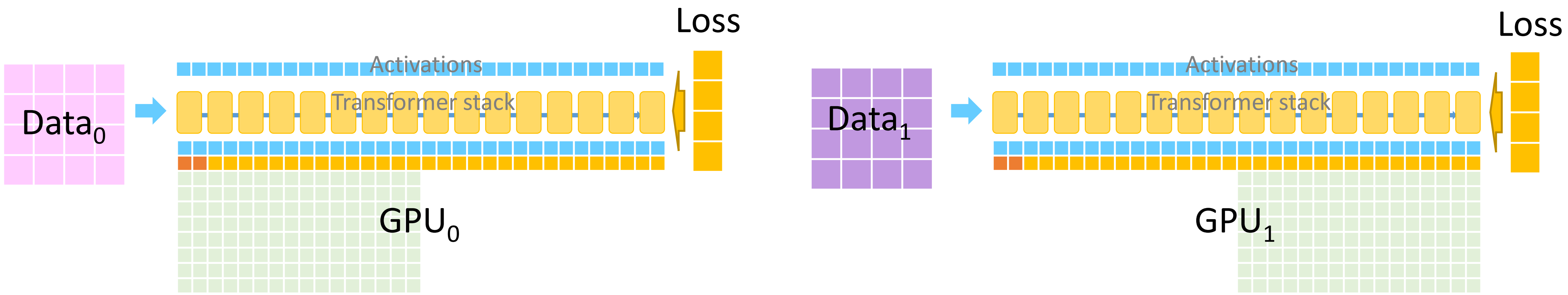

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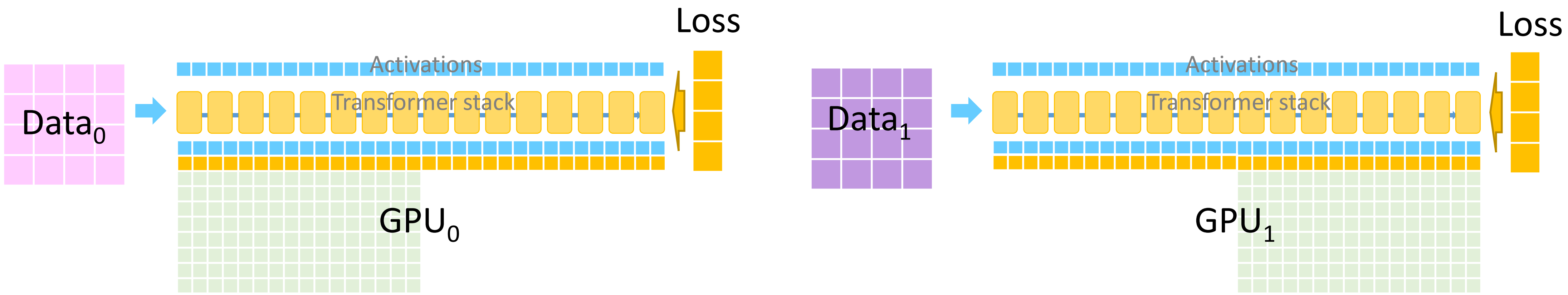

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- Partitions optimizer states across GPUs
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- Backward propagation to generate FP16 gradients and reduce scatter to average

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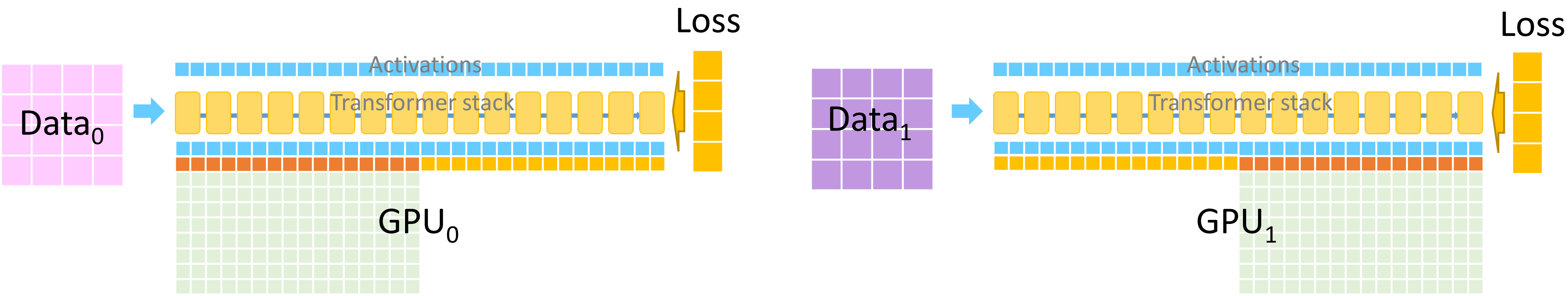

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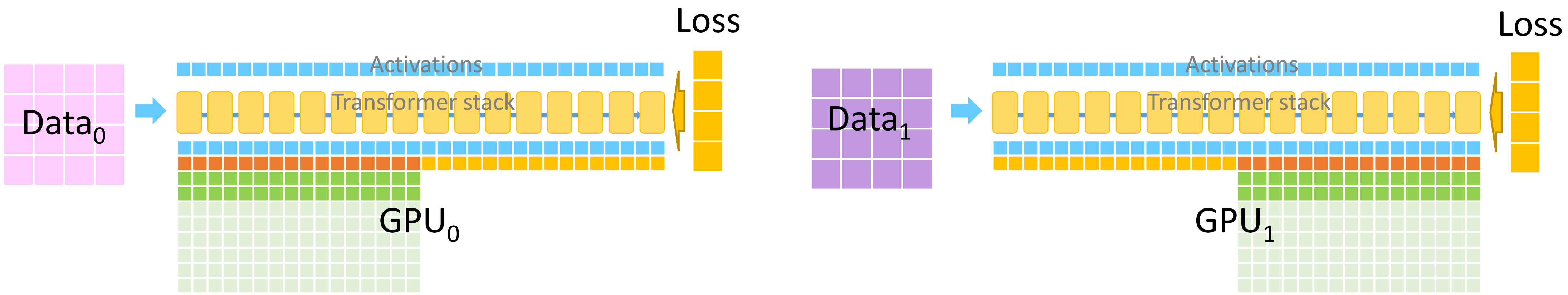

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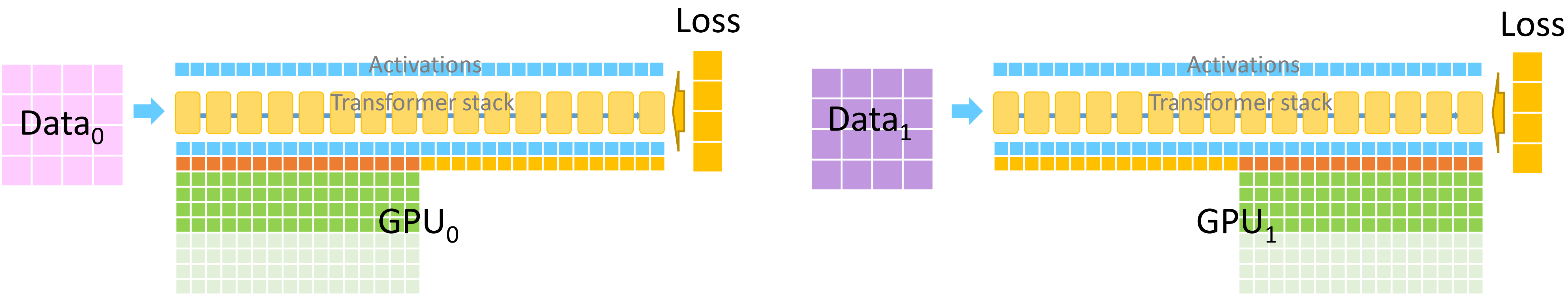

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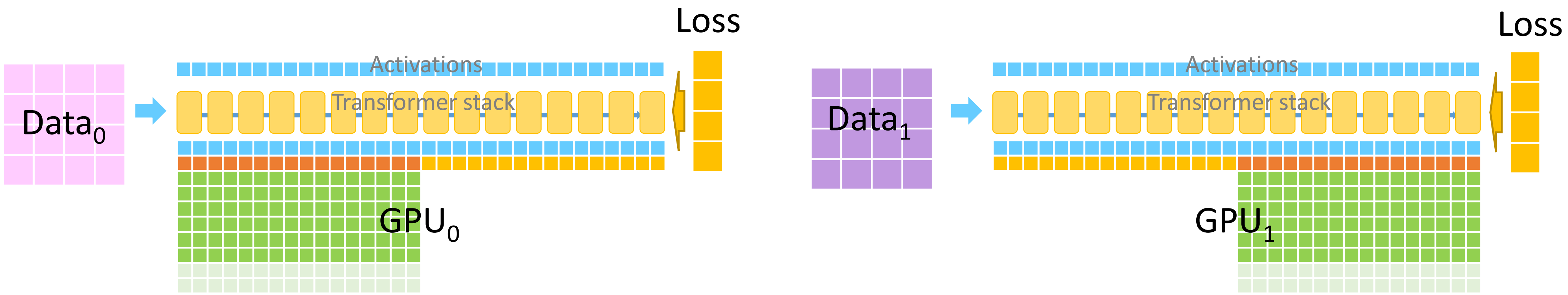

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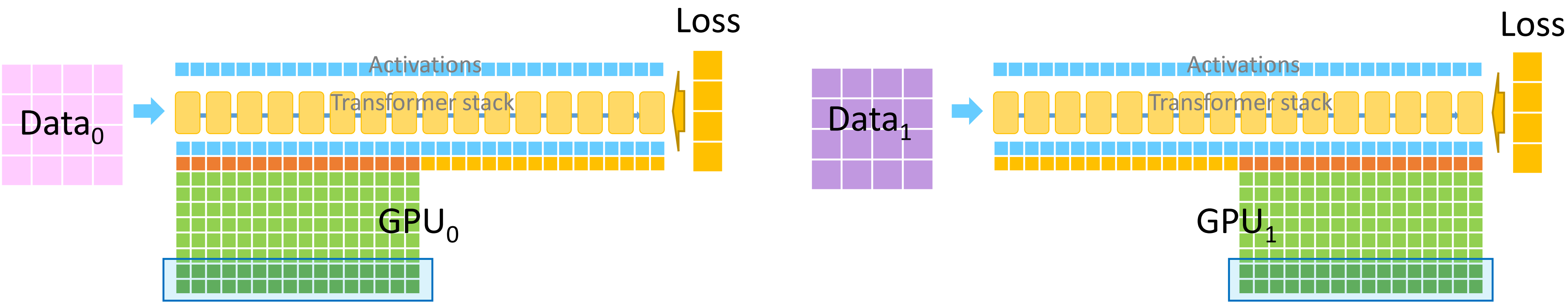

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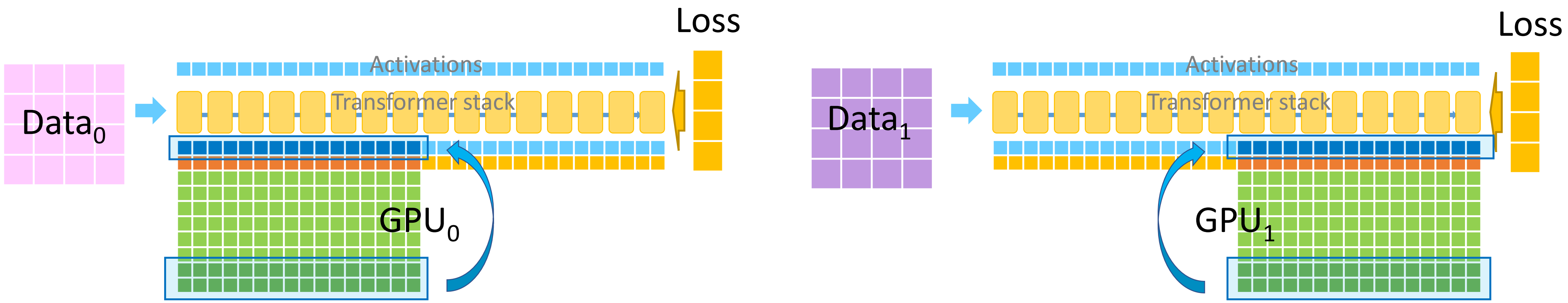

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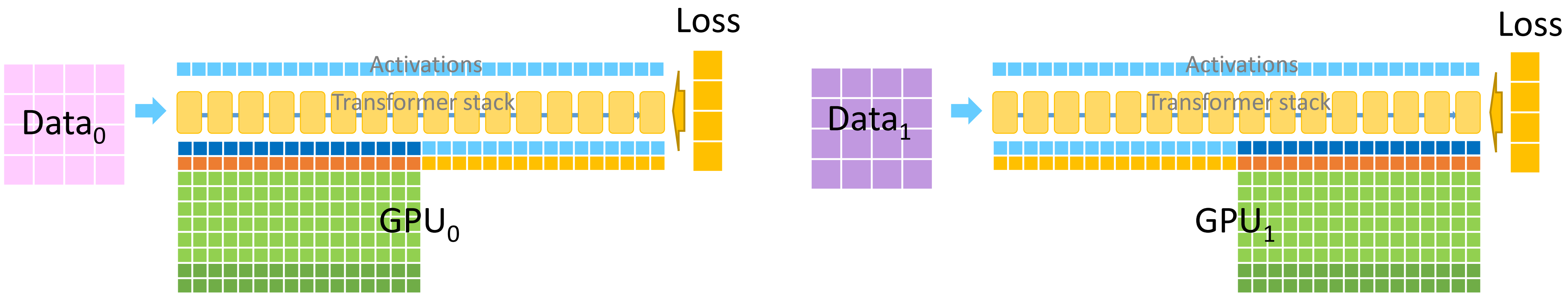

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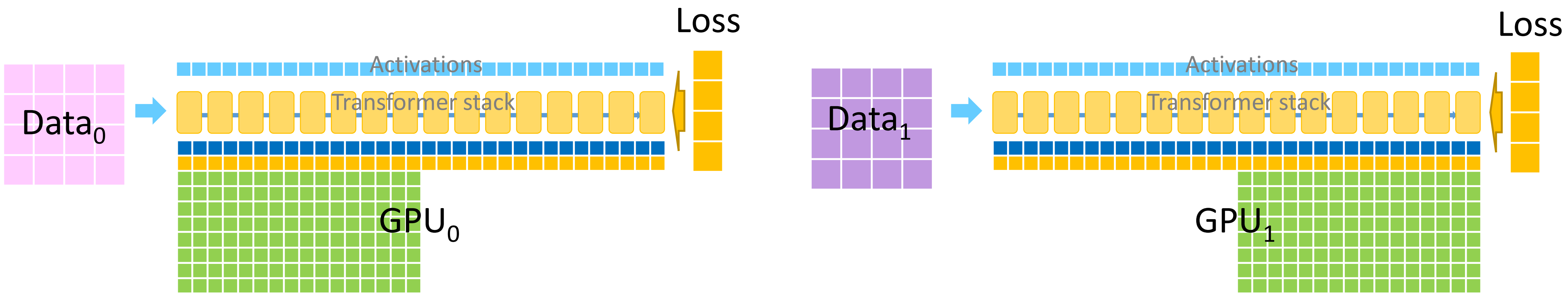
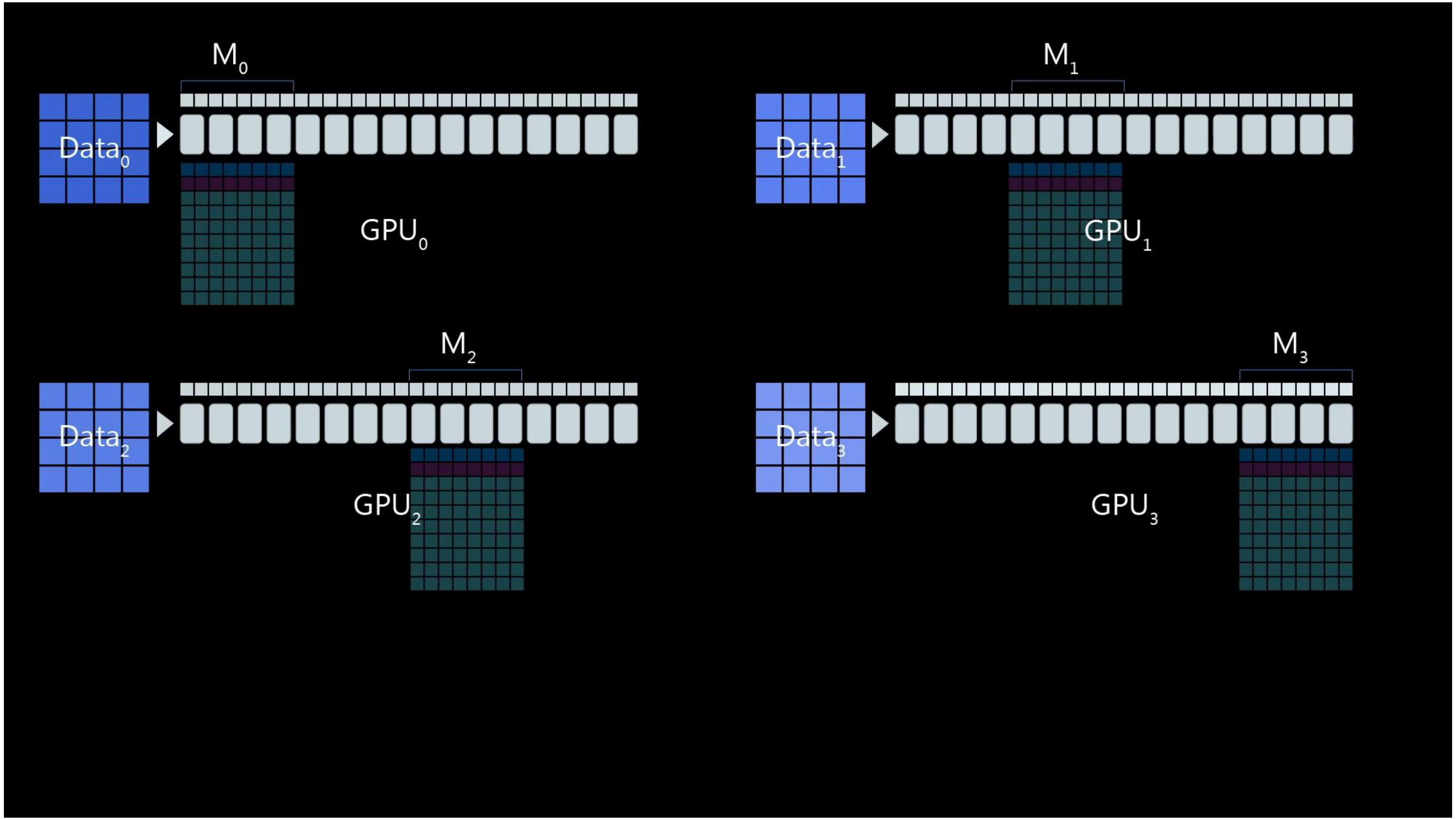
- Update the FP32 weights with ADAM optimizer
- Update the FP16 weights
- All Gather the FP16 weights to complete the iteration

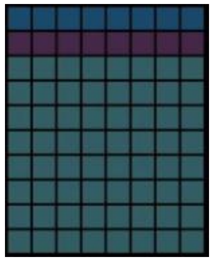
ZeRO-DP: ZeRO powered Data Parallelism



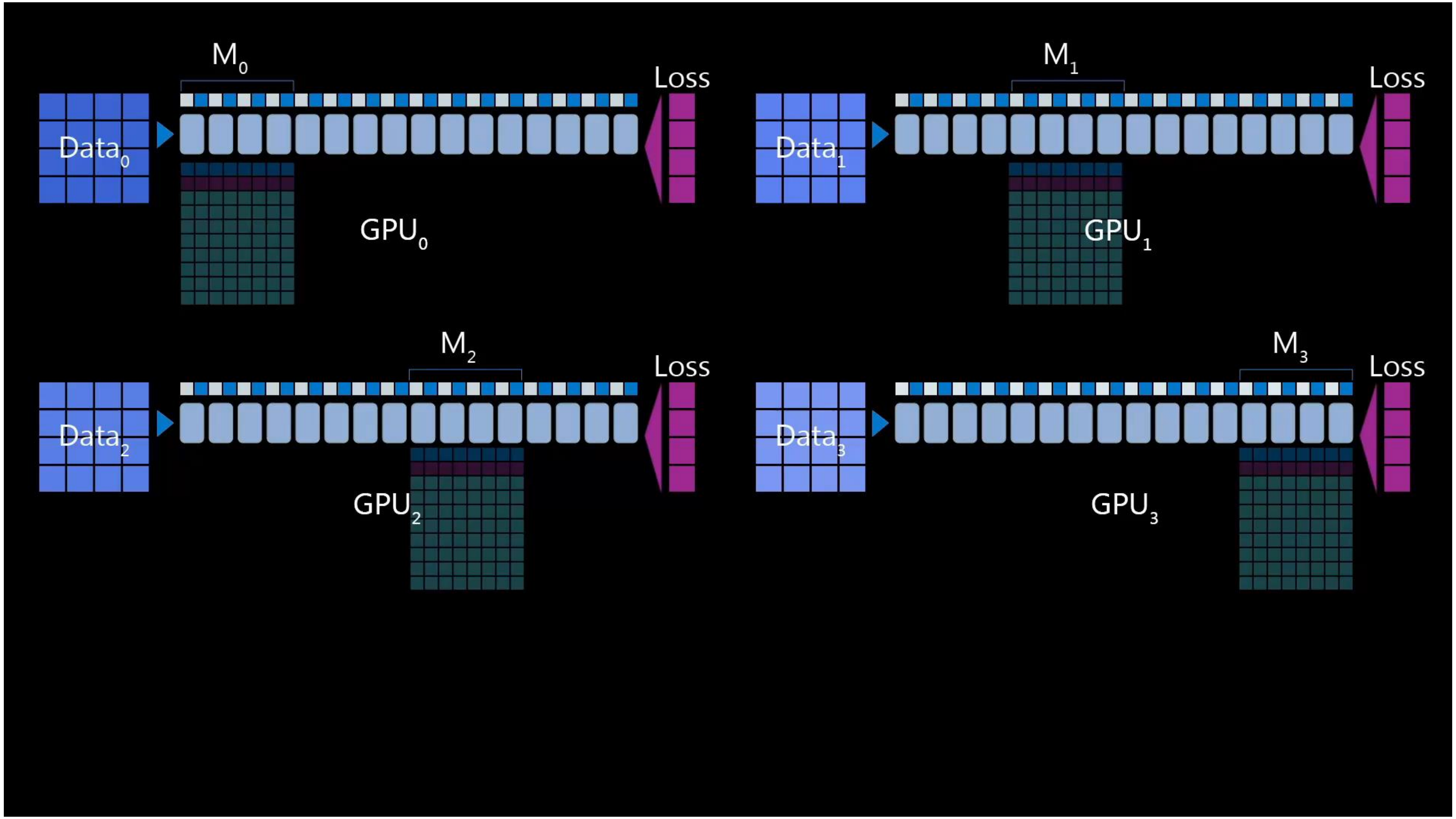
- ZeRO Stage 1
- Partitions optimizer states across GPUs
- Run Forward across the transformer blocks
- Backward propagation to generate FP16 gradients and reduce scatter to average
- Update the FP32 weights with ADAM optimizer
- Update the FP16 weights
- All Gather the FP16 weights to complete the iteration

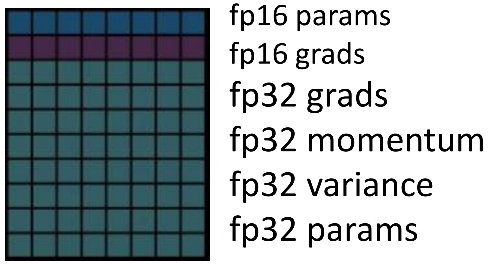
ZeRO-DP : Stage 3 Forward Propagation



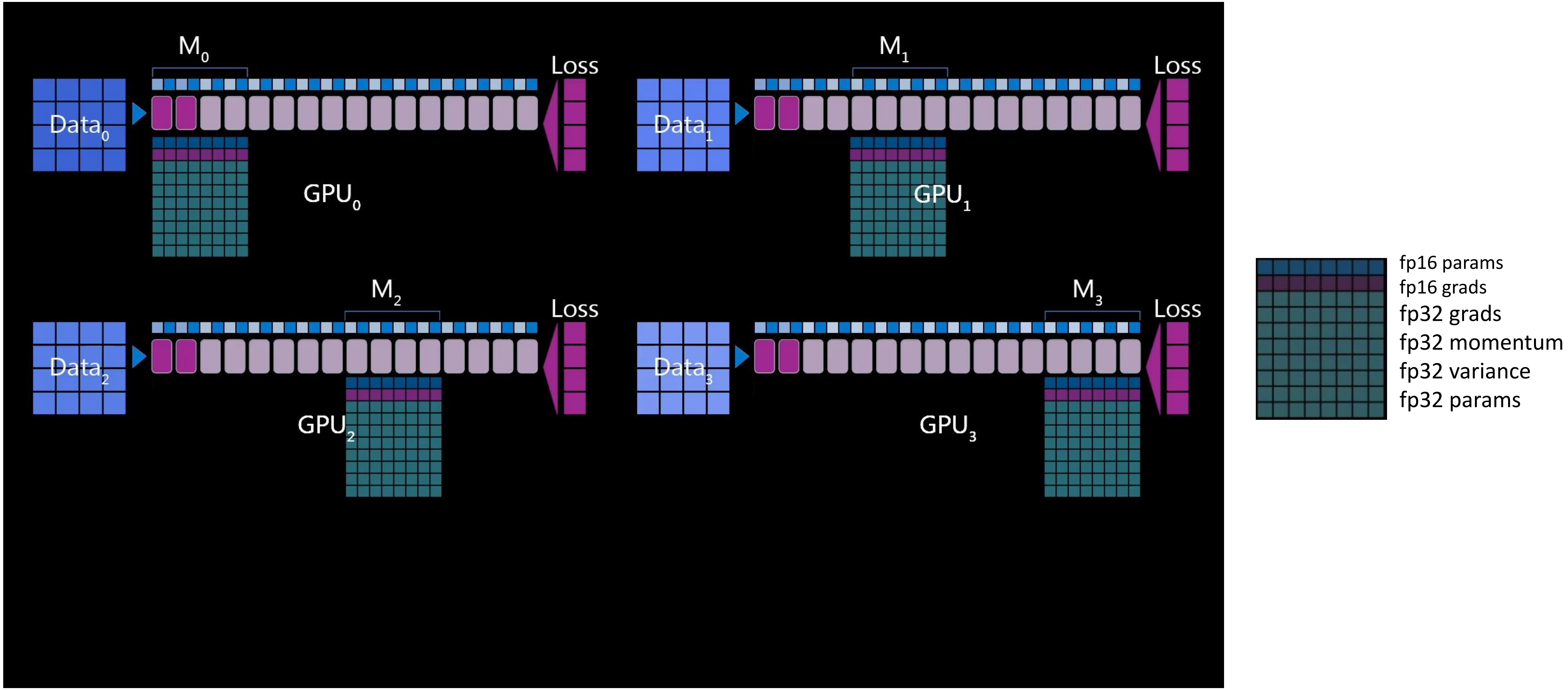


ZeRO-DP : Stage 3 Backward Propagation





ZeRO-DP : Stage 3 Optimizer Step



ZeRO-DP: Memory Savings

- Progressive memory savings and Communication Volume

	Memory Reduction with N GPUs
Data Parallel	1x
ZeRO Stage 1 (P_{os})	4x
ZeRO Stage 2 (P_{os+g})	8x
ZeRO Stage 3 (P_{os+g+p})	Nx

*Mixed precision Adam on Cluster of DGX-2 with NVIDIA 32 GB V100 GPUs

ZeRO-DP: Memory Savings

- Progressive memory savings and Communication Volume

	Memory Reduction with N GPUs	Max params with ZeRO only (in billions)
Data Parallel	1x	1.2
ZeRO Stage 1 (P_{os})	4x	6
ZeRO Stage 2 (P_{os+g})	8x	13
ZeRO Stage 3 (P_{os+g+p})	Nx	>1000

*Mixed precision Adam on Cluster of DGX-2 with NVIDIA 32 GB V100 GPUs

ZeRO-DP: Memory Savings

- Progressive memory savings and Communication Volume

	Memory Reduction with N GPUs	Max params with ZeRO only (in billions)	Max params with ZeRO and model parallelism (in billions)
Data Parallel	1x	1.2	20
ZeRO Stage 1 (P_{os})	4x	6	100
ZeRO Stage 2 (P_{os+g})	8x	13	200
ZeRO Stage 3 (P_{os+g+p})	Nx	>1000	>1000

*Mixed precision Adam on Cluster of DGX-2 with NVIDIA 32 GB V100 GPUs

ZeRO-DP: Communication Volume

- Progressive memory savings and Communication Volume

	Memory Reduction with N GPUs	Max params with ZeRO only (in billions)	Max params with ZeRO and model parallelism (in billions)	Comm Volume
Data Parallel	1x	1.2	20	1x
ZeRO Stage 1 (P_{os})	4x	6	100	1x
ZeRO Stage 2 (P_{os+g})	8x	13	200	1x
ZeRO Stage 3 (P_{os+g+p})	Nx	>1000	>1000	1.5x

*Mixed precision Adam on Cluster of DGX-2 with NVIDIA 32 GB V100 GPUs

DeepSpeed/ZeRO Usability

```python
# construct torch.nn.Module
model = MyModel()

# wrap w. DeepSpeed engine
engine, *_ = deepspeed.initialize(
    model=model,
    config=ds_config)

# training-loop w.r.t. engine
for batch in data_loader:
  loss = engine(batch)
  engine.backward(loss)
  engine.step()
```

```python
ds_config = {
  "optimizer": {
    "type": "Adam",
    "params": {"lr": 0.001}
  },
  "zero": {
    "stage": 3,
    "offload_optimizer": {
        "device": "[cpu|nvme]"
    },
    "offload_param": {
        "device": "[cpu|nvme]"
    }
  }
}
```

Logistics

The instructor was invited to serve as the LLM session chair at PPoPP 2025 next week

- March 4 (online, course project discussion)
- March 6 (online, course project discussion)

Two guest lectures from industry

- March 11, Microsoft, Masahiro Tanaka (online)
- March 13, Google, Yanqi Zhou (online)

Questions?