15-442/15-642: Machine Learning Systems

Parallelization Part 1 (Data Parallelism and Zero Redundancy)

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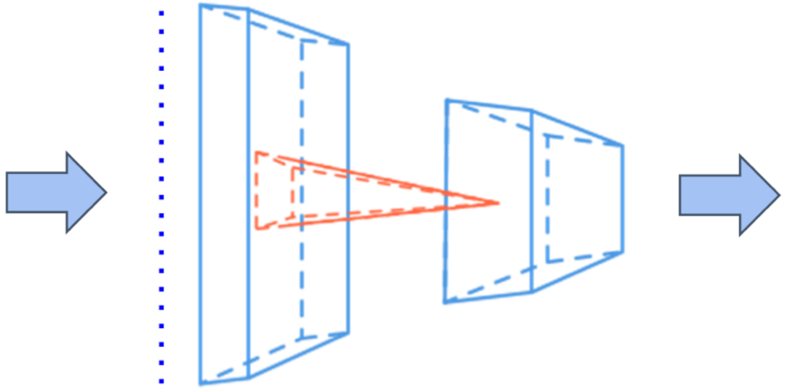
Recap: DNN Training Overview

layer1 extractor **layer2 extractor** **predictor**



$$\hat{y}_i = \frac{1}{1 + \exp\left(-w^T x_i\right)}$$

Objective

$$L(w) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \lambda \|w\|^2$$

Training

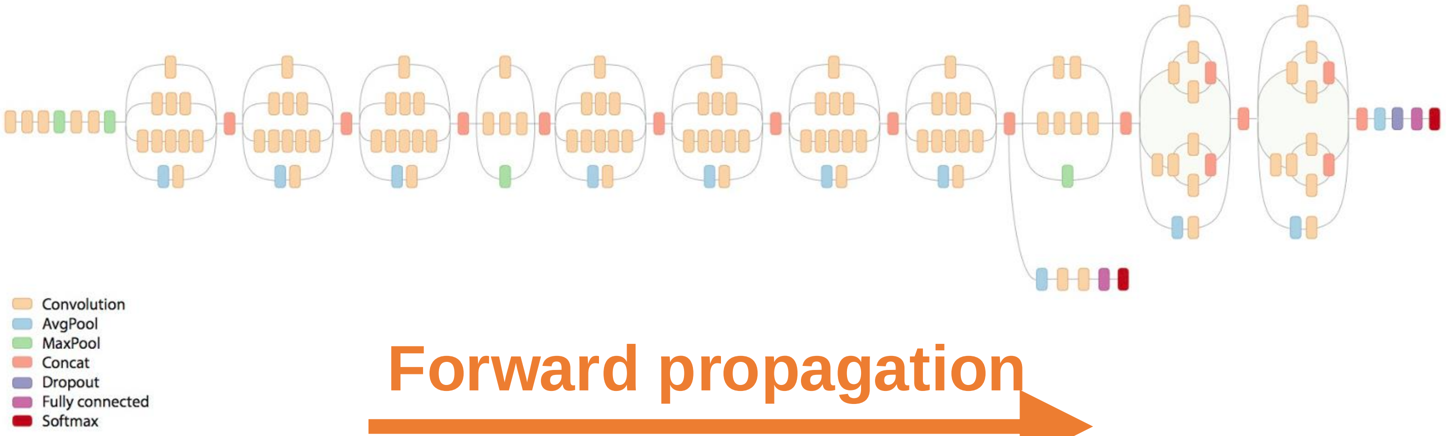
$$w \leftarrow w - \eta \nabla_w L(w)$$

DNN Training Process

Train ML models through many iterations of 3 stages

1. **Forward propagation**: apply model to a batch of input samples and run calculation through operators to produce a prediction
2. **Backward propagation**: run the model in reverse to produce error for each trainable weight
3. **Weight update**: use the loss value to update model weights

Model inputs



Model prediction

Forward propagation →

DNN Training Process

Train ML models through many iterations of 3 stages

1. **Forward propagation**: apply model to a batch of input samples and run calculation through operators to produce a prediction
2. **Backward propagation**: run the model in reverse to produce a gradient for each trainable weight
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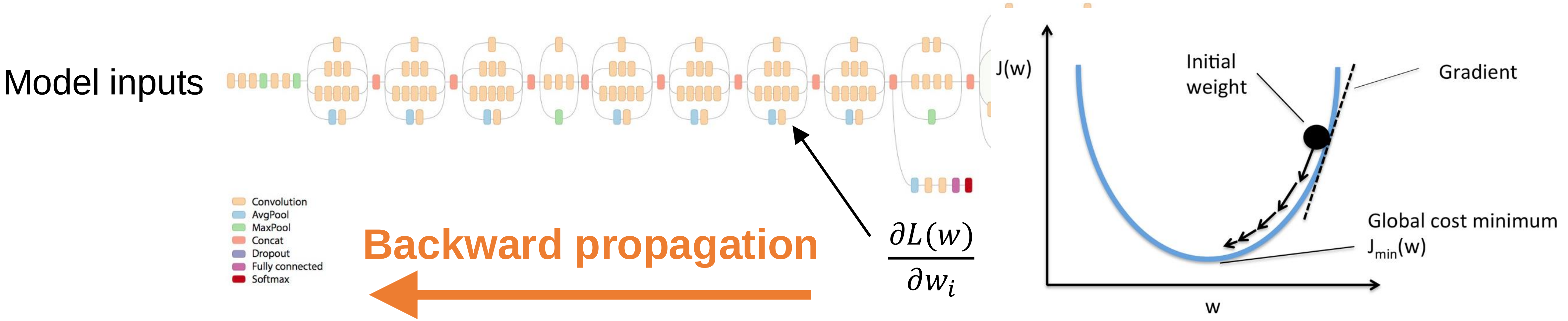


DNN Training Process

Train ML models through many iterations of 3 stages

1. **Forward propagation**: apply model to a batch of input samples and run calculation through operators to produce a prediction
2. **Backward propagation**: run the model in reverse to produce a gradient for each trainable weight
3. **Weight update**: use the gradients to update model weights

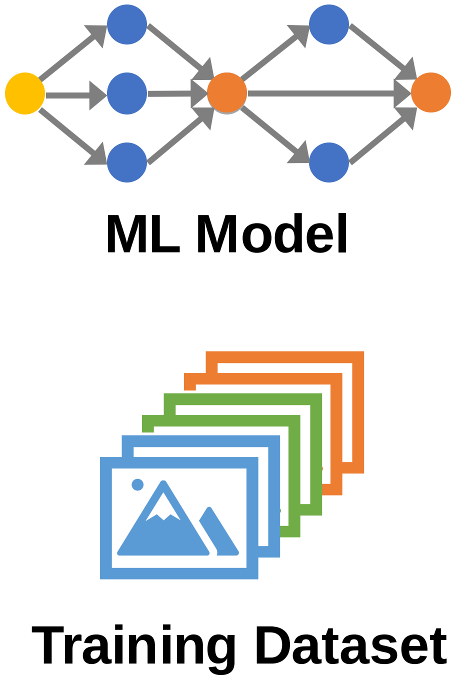
$$w_i \coloneqq w_i - \gamma \frac{\partial L(w)}{\partial w_i} = w_i - \frac{\gamma}{n} \sum_{j=1}^{n} \boxed{\frac{\partial l_i(w)}{\partial w_i}}$$

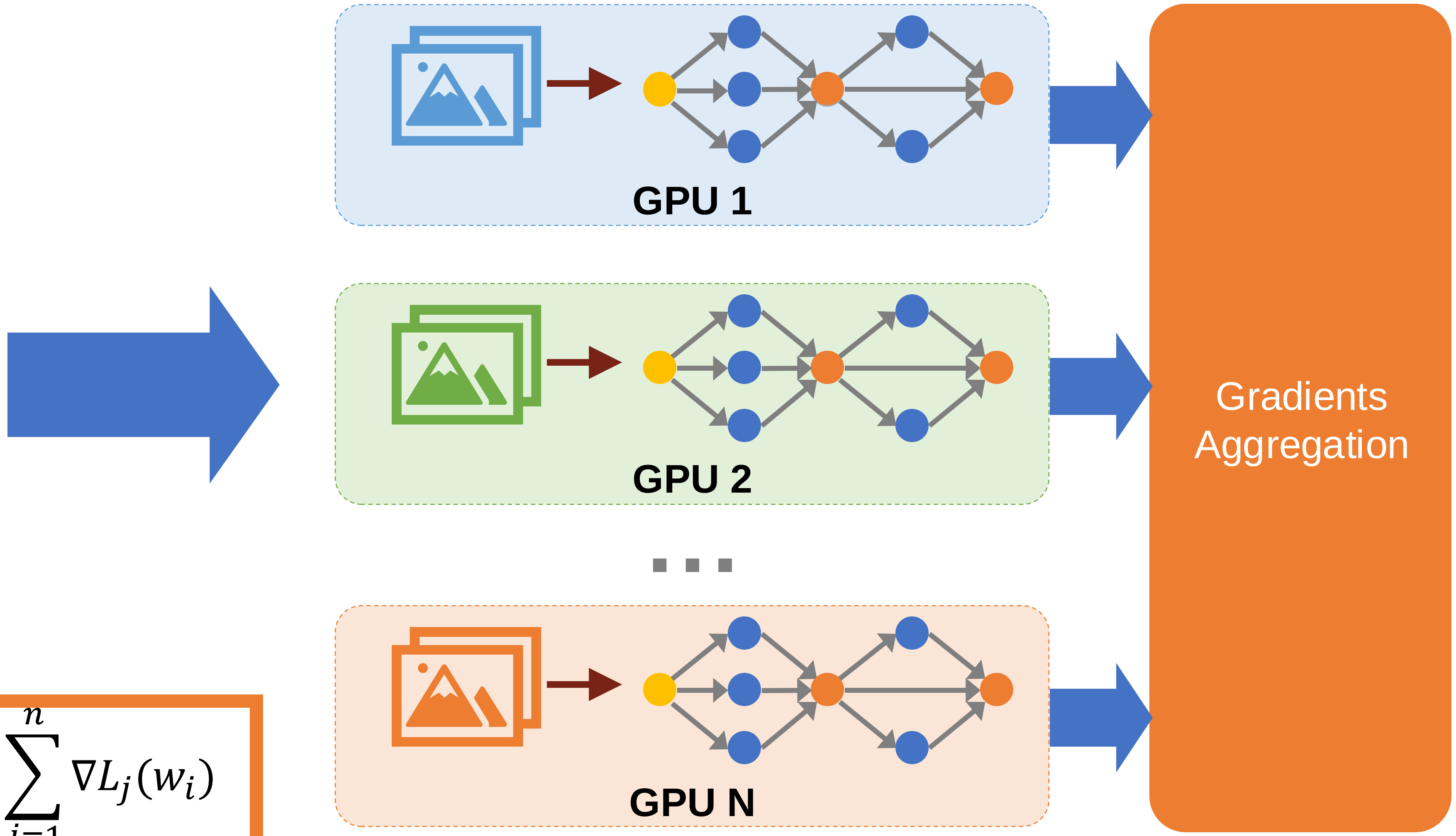
Gradients of individual samples

How can we parallelize DNN training?

$$w_i := w_i - \gamma \nabla L(w_i) = w_i - \frac{\gamma}{n} \sum_{j=1}^{n} \nabla L_j(w_i)$$

Data Parallelism





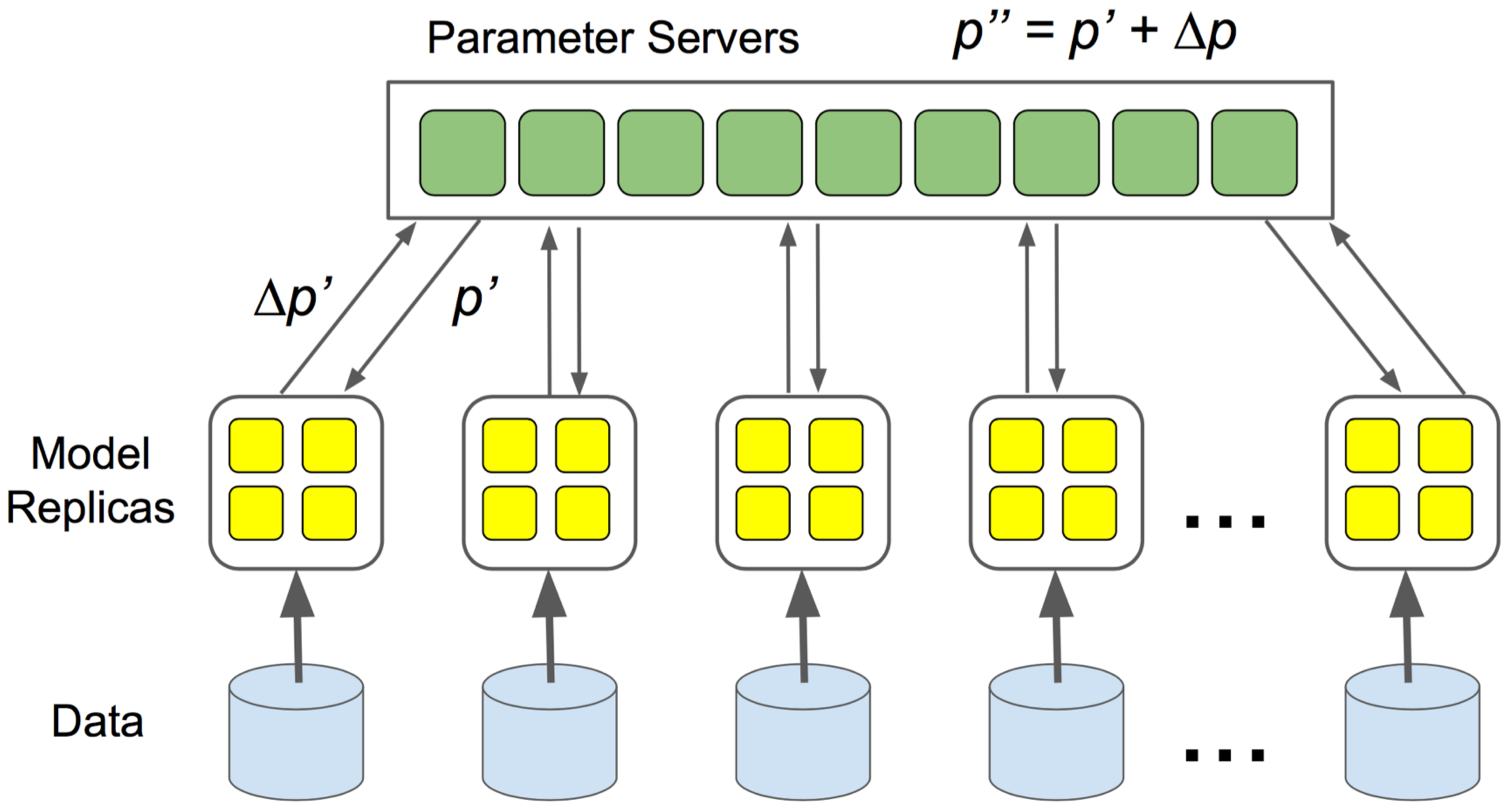
$$w_i := w_i - \gamma \nabla L(w_i) = w_i - \frac{\gamma}{n} \sum_{j=1}^{n} \nabla L_j(w_i)$$

1. Partition training data into batches

2. Compute the gradients of each batch on a GPU

3. Aggregate gradients across GPUs

Data Parallelism: Parameter Server

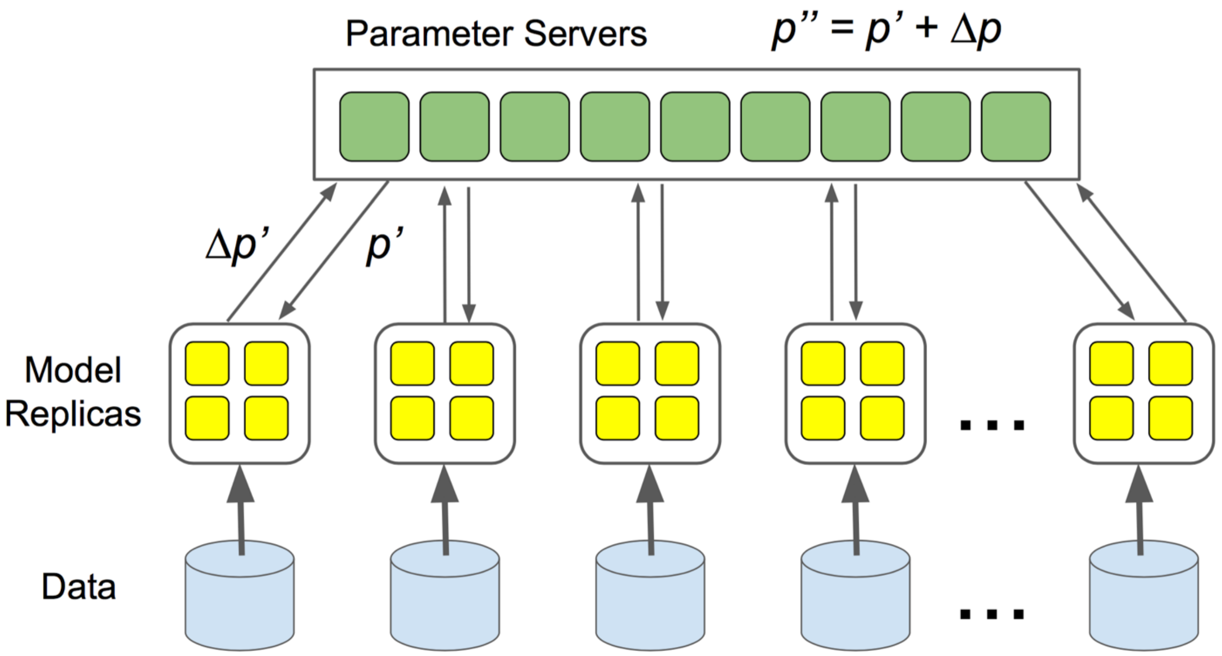


Workers push gradients to parameter servers and pull updated parameters back

Inefficiency of Parameter Server

- **Centralized communication**: all workers communicate with parameter servers for weights update; cannot scale to large numbers of workers

- How can we decentralize communication in DNN training?

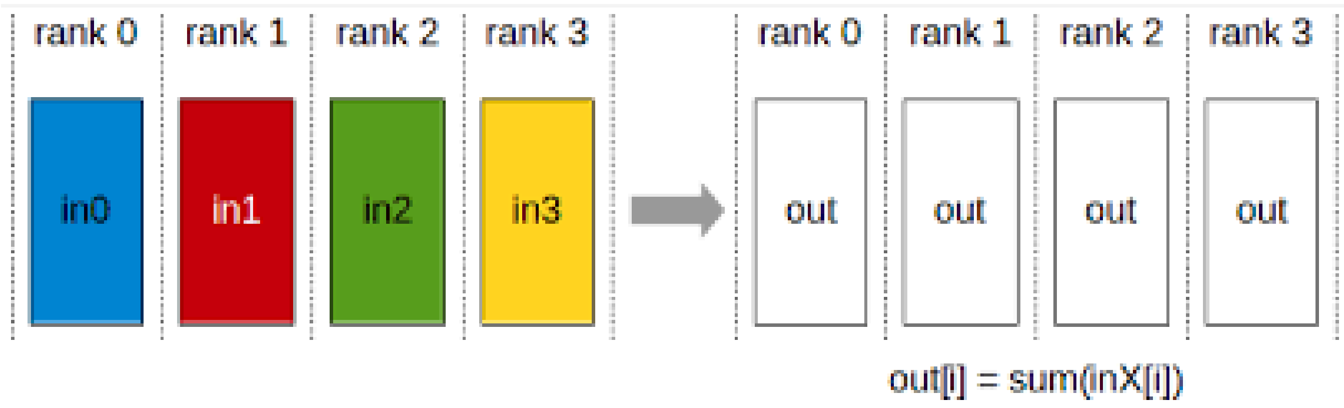


Inefficiency of Parameter Server

- **Centralized communication**: all workers communicate with parameter servers for weights update; cannot scale to large numbers of workers

- How can we decentralize communication in DNN training?

- **AllReduce**: perform element-wise reduction across multiple devices

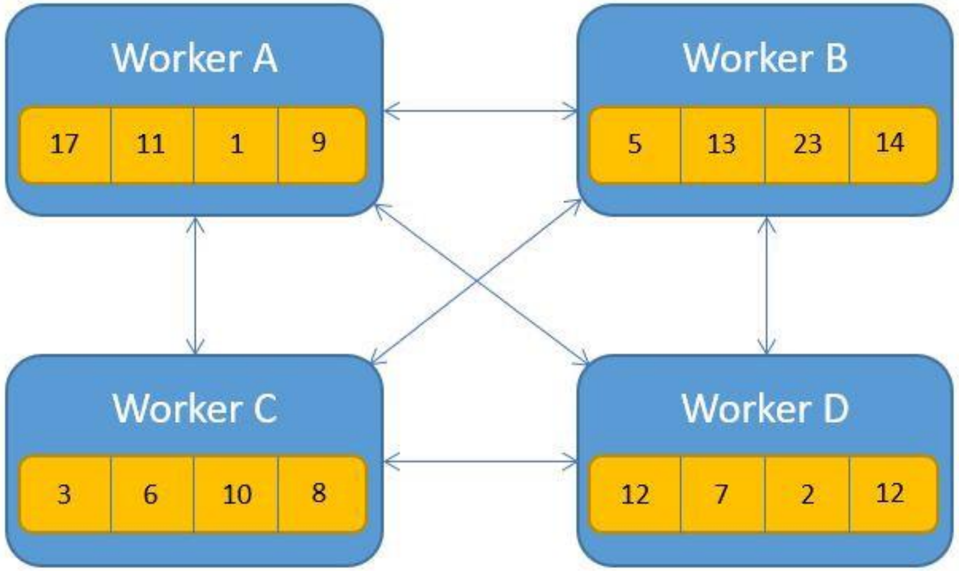


Different Ways to Perform AllReduce

- Naïve AllReduce
- Ring AllReduce
- Tree AllReduce
- Butterfly AllReduce

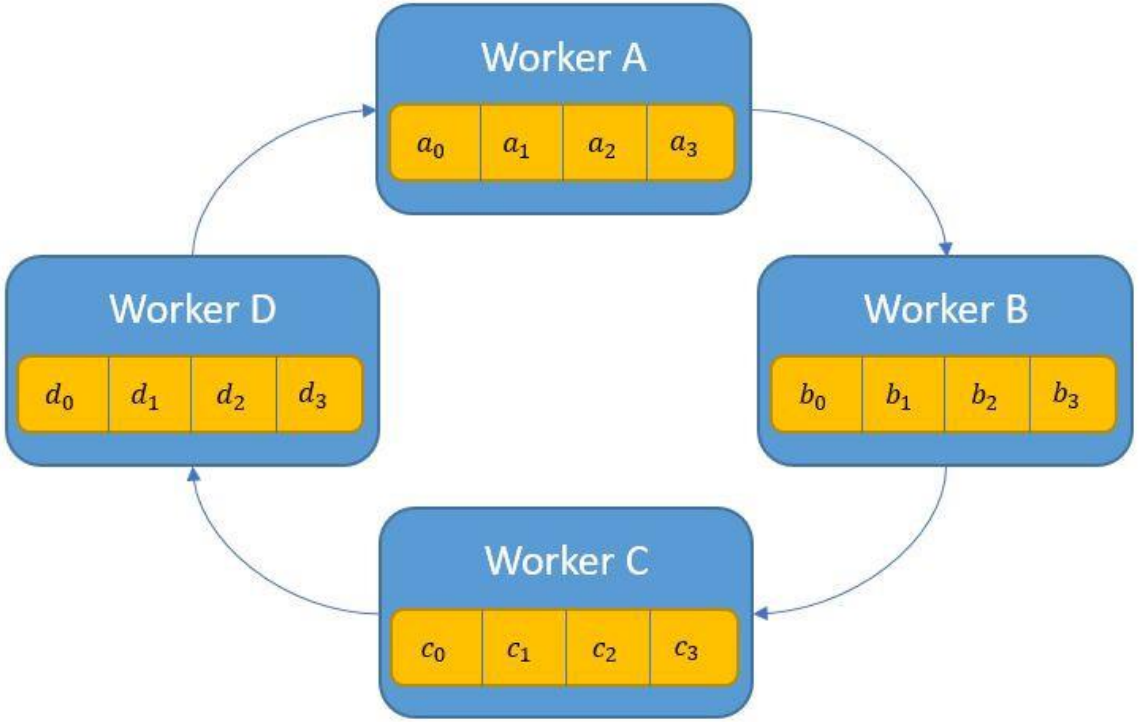
Naïve AllReduce

- Each worker can send its local gradients to all other workers
- If we have N workers and each worker contains M parameters
- Overall communication: N * (N-1) * M parameters
- **Issue**: each worker communicates with all other workers; same scalability issue as parameter server



Ring AllReduce

- Construct a ring of N workers, divide M parameters into N slices
- Step 1 (Aggregation): each worker send one slice (M/N parameters) to the next worker on the ring; repeat N times



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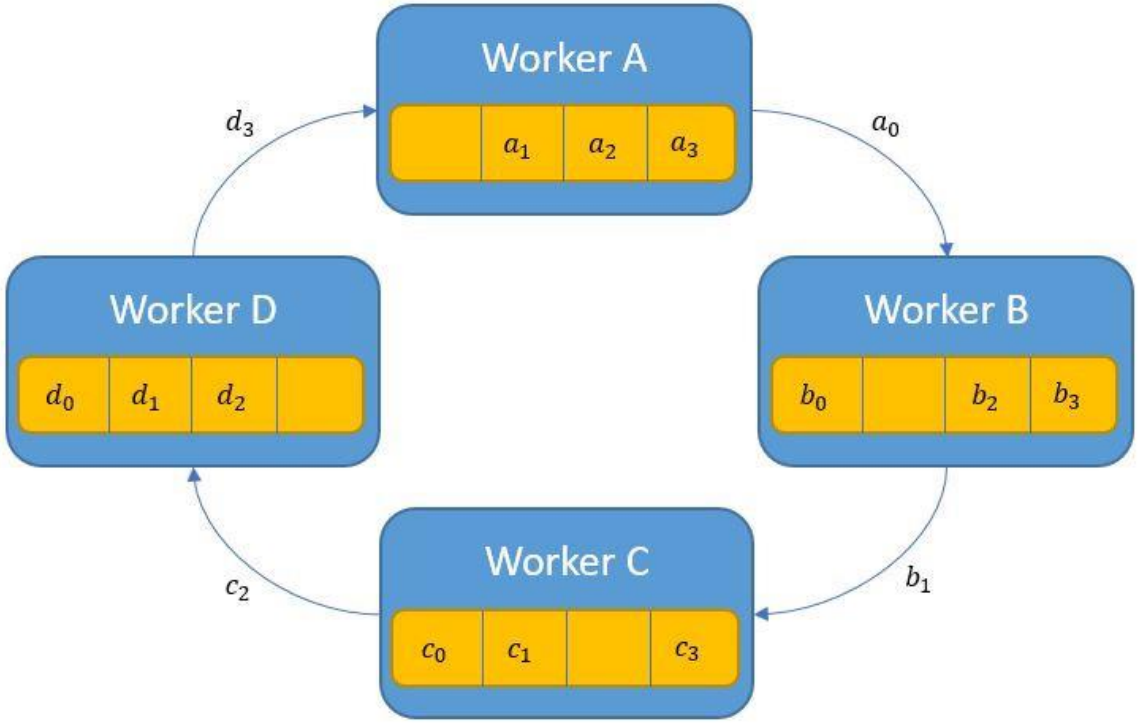

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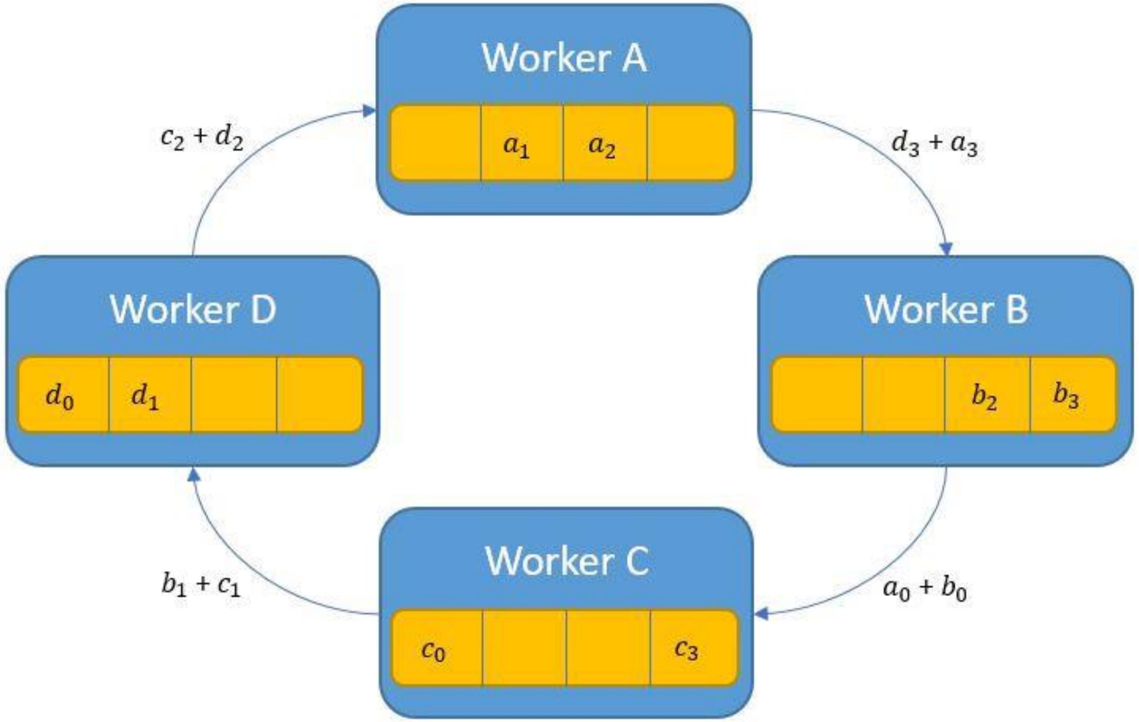
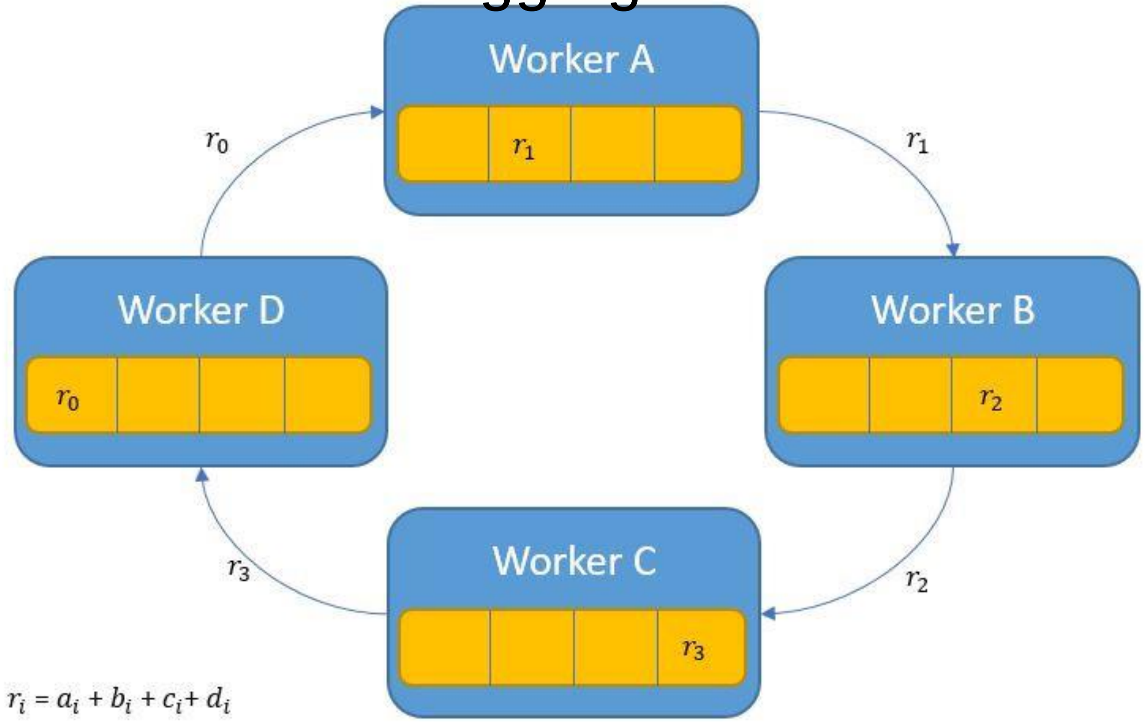


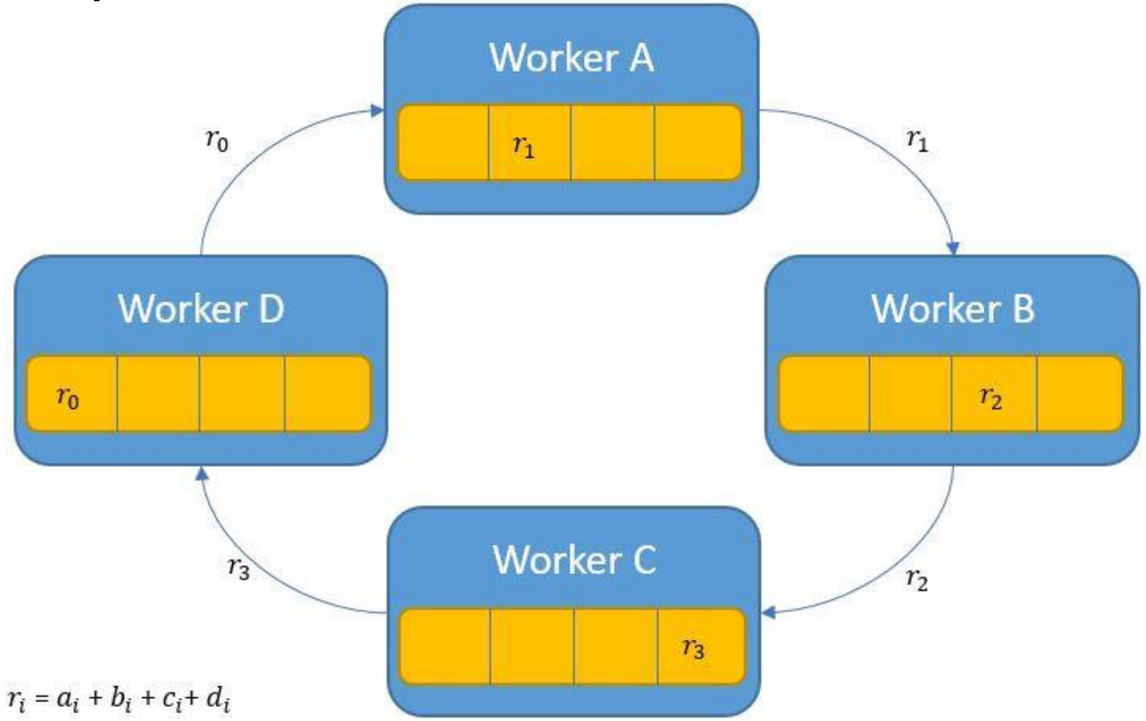
Ring AllReduce

- Construct a ring of N workers, divide M parameters into N slices
- Step 1 (Aggregation): each worker send one slice (M/N parameters) to the next worker on the ring; repeat N times
- After step 1, each worker has the aggregated version of M/N parameters



Ring AllReduce

- Construct a ring of N workers, divide M parameters into N slices
- Step 1 (Aggregation): each worker send one slice (M/N parameters) to the next worker on the ring; repeat N times
- Step 2 (Broadcast): each worker send one slice of aggregated parameters to the next worker; repeat N times



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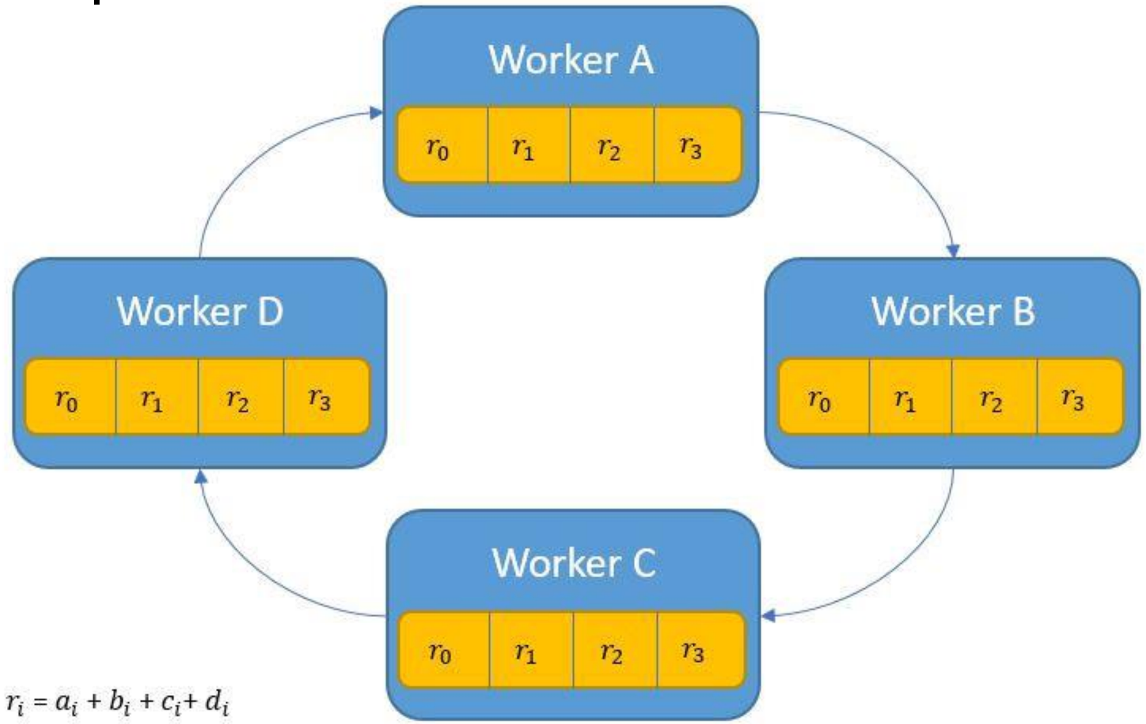
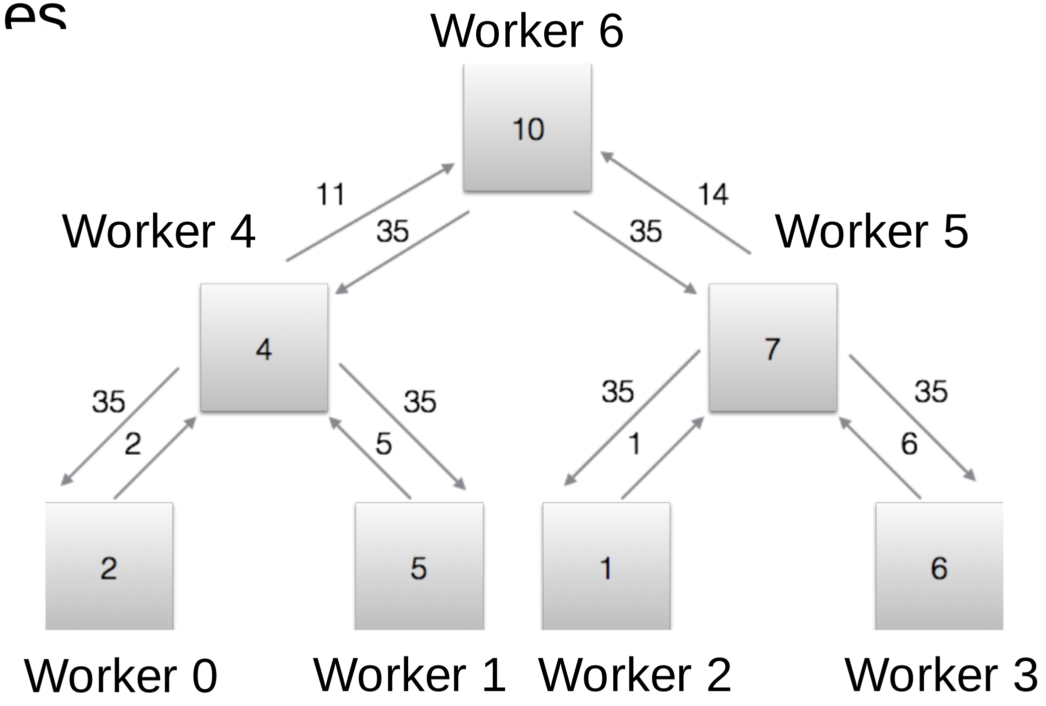


Ring AllReduce

- Construct a ring of N workers, divide M parameters into N slices
- Step 1 (Aggregation): each worker send one slice (M/N parameters) to the next worker on the ring; repeat N times
- Step 2 (Broadcast): each worker send one slice of aggregated parameters to the next worker; repeat N times
- Overall communication: 2 * M * N parameters
  - Aggregation: M * N parameters
  - Broadcast: M * N parameters

Tree AllReduce

- Construct a tree of N workers;
- Step 1 (Aggregation): each worker sends M parameters to its parent; repeat log(N) times
- Step 2 (Broadcast): each worker sends M parameters to its children; repeat log(N) times



Tree AllReduce

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- Step 2 (Broadcast): each worker sends M parameters to its children; repeat log(N) times
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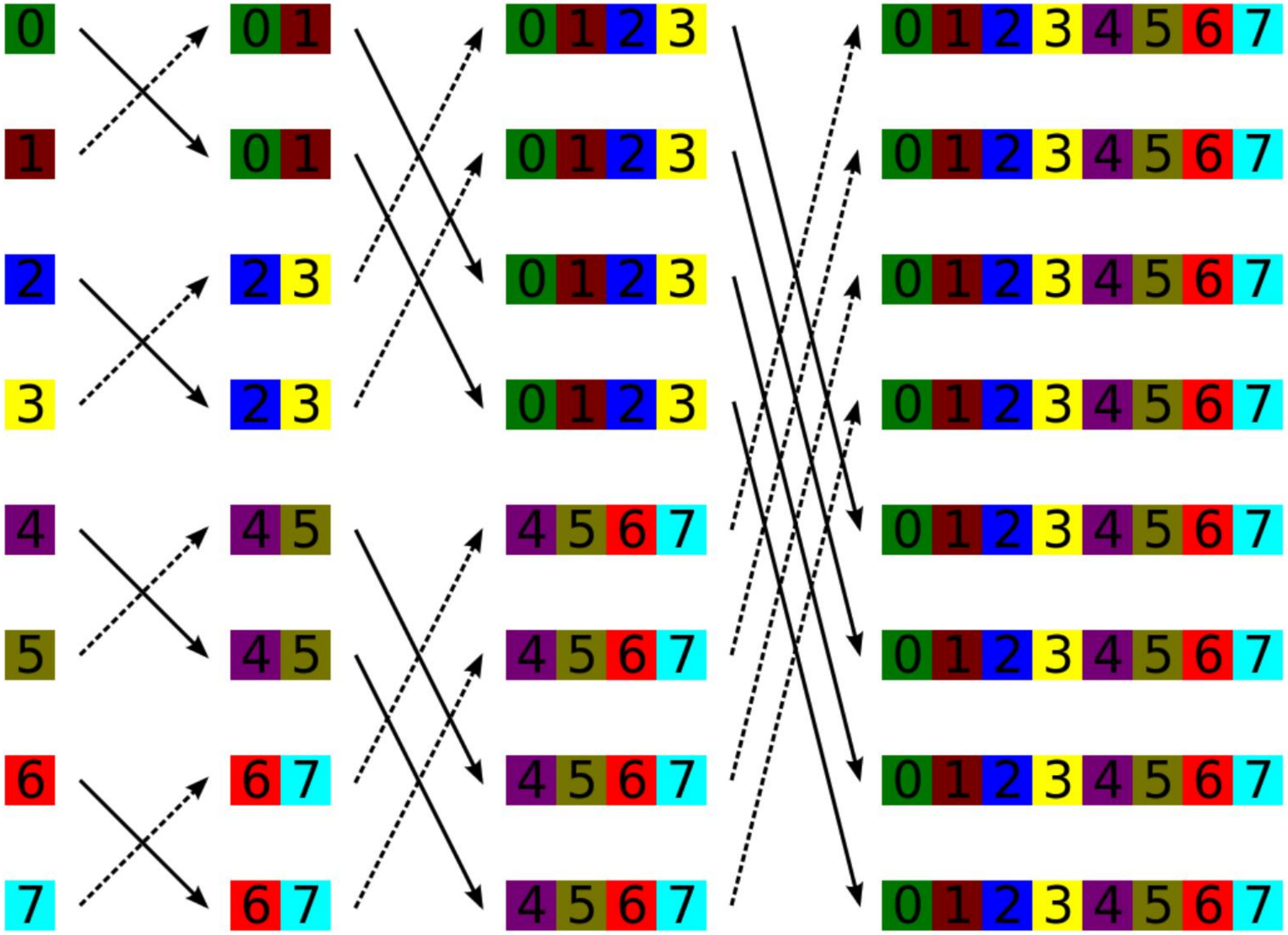
  - Aggregation: M * N parameters
  - Broadcast: M * N parameters

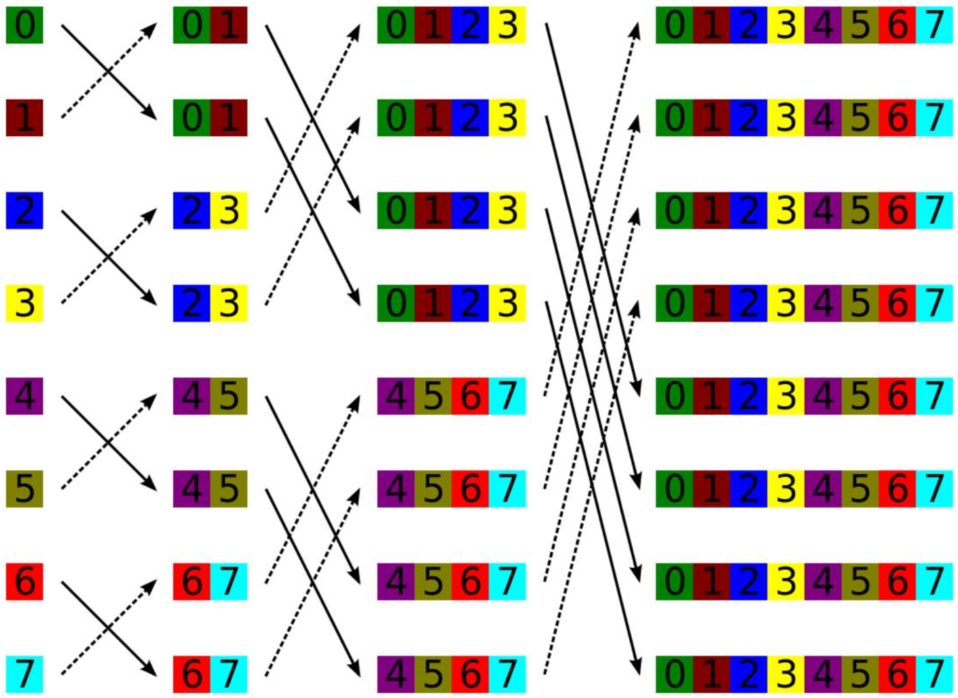
Butterfly Network



Butterfly AllReduce

- Repeat log(N) times:
  1. Each worker sends M parameters to its target node in the butterfly network
  2. Each worker aggregates gradients locally

- Overall communication: N * M * log(N) parameters



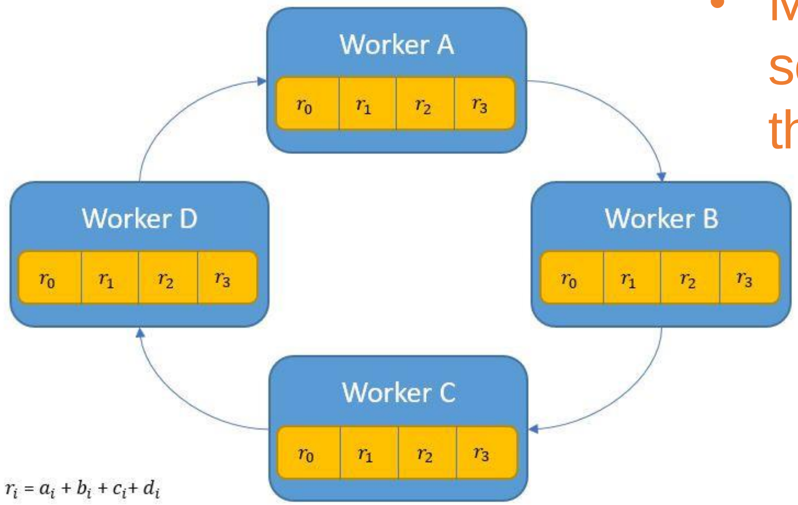
Comparing different AllReduce Methods

	Parameter Server	Naïve AllReduce	Ring AllReduce	Tree AllReduce	Butterfly AllReduce
Overall communication	$2 \times N \times M$	$N^2 \times M$	$2 \times N \times M$	$2 \times N \times M$	$N \times M \times \log N$

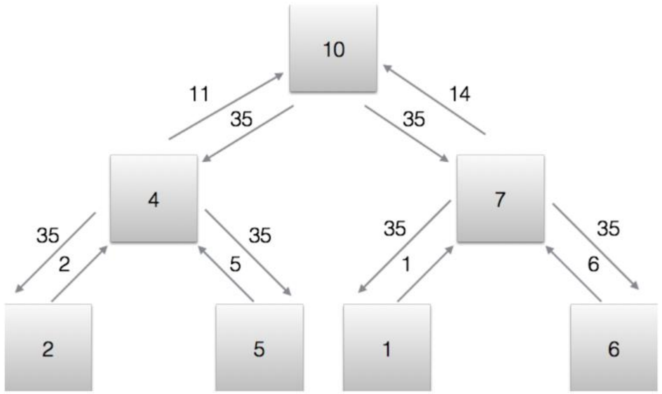
Question: Ring AllReduce is more efficient and scalable then Tree AllReduce and Parameter Server, why?

Ring AllReduce v.s. Tree AllReduce v.s. Parameter Server

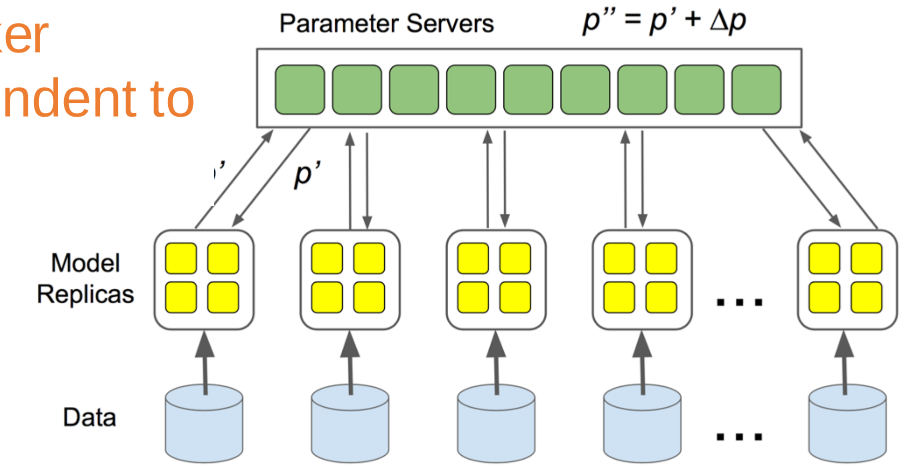
Ring AllReduce:
- Best latency
- Balanced workload across workers
- More scalable since each worker sends 2*M parameters (independent to the number of workers)



Each worker sends **M/N** parameters per iteration; repeat for **2*N** iterations
Latency: M/N * (2*N) / bandwidth



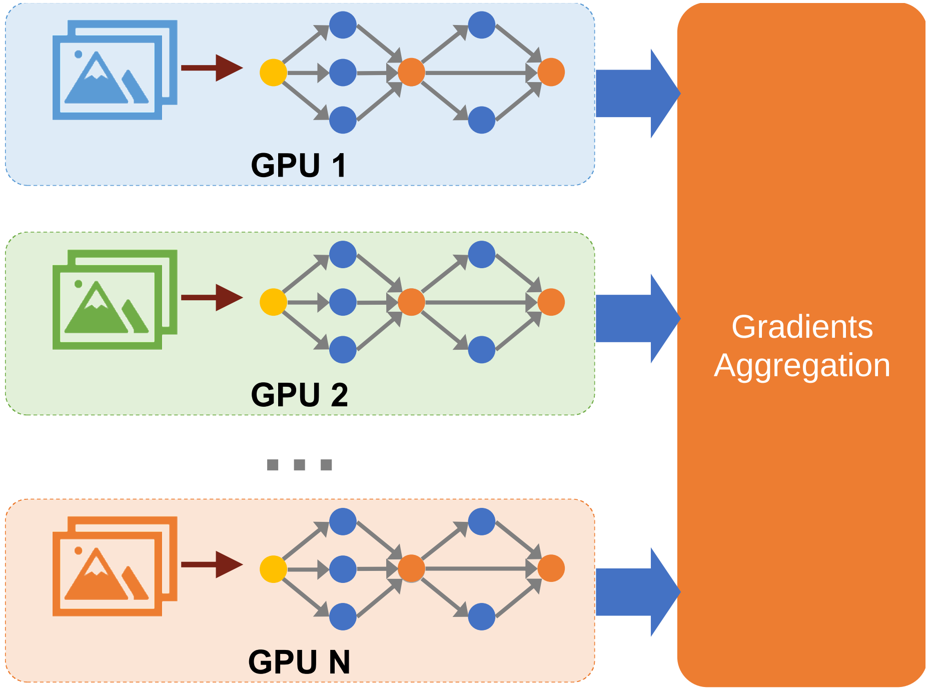
Each worker sends **M** parameters per iteration; repeat for **2*log(N)** iterations
Latency: M * 2 * log(N) / bandwidth



All workers send **M** parameters to parameter servers and receive **M** parameters from servers
Latency: M * N / bandwidth

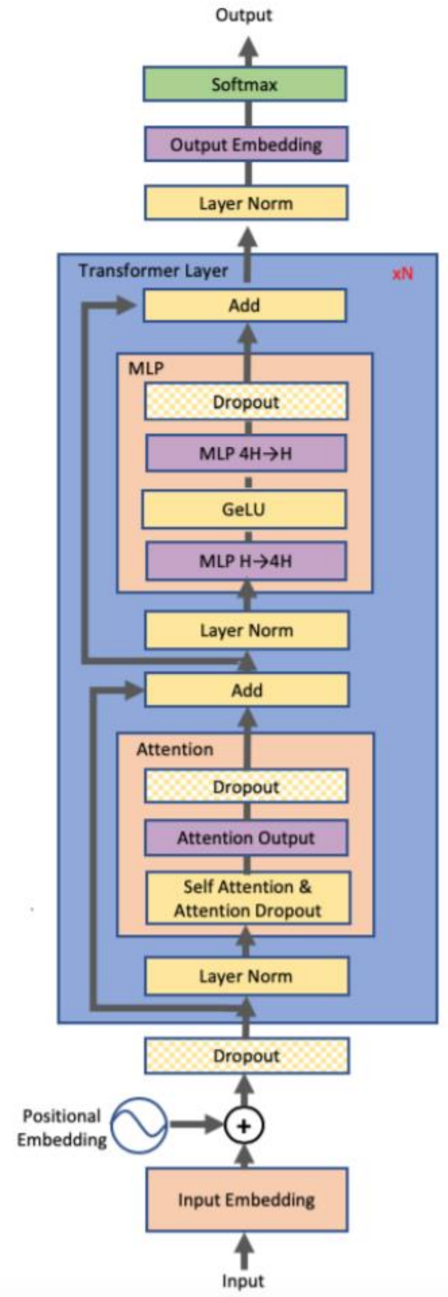
An Issue with Data Parallelism

- Each GPU saves a replica of the entire model
- Cannot train large models that exceed GPU device memory



Large Model Training Challenges

	Bert-Large	GPT-2	Turing 17.2 NLG	GPT-3
Parameters	0.32B	1.5B	17.2B	175B
Layers	24	48	78	96
Hidden Dimension	1024	1600	4256	12288
Relative Computation	1x	4.7x	**54x**	**547x**
Memory Footprint	5.12GB	24GB	**275GB**	**2800GB**



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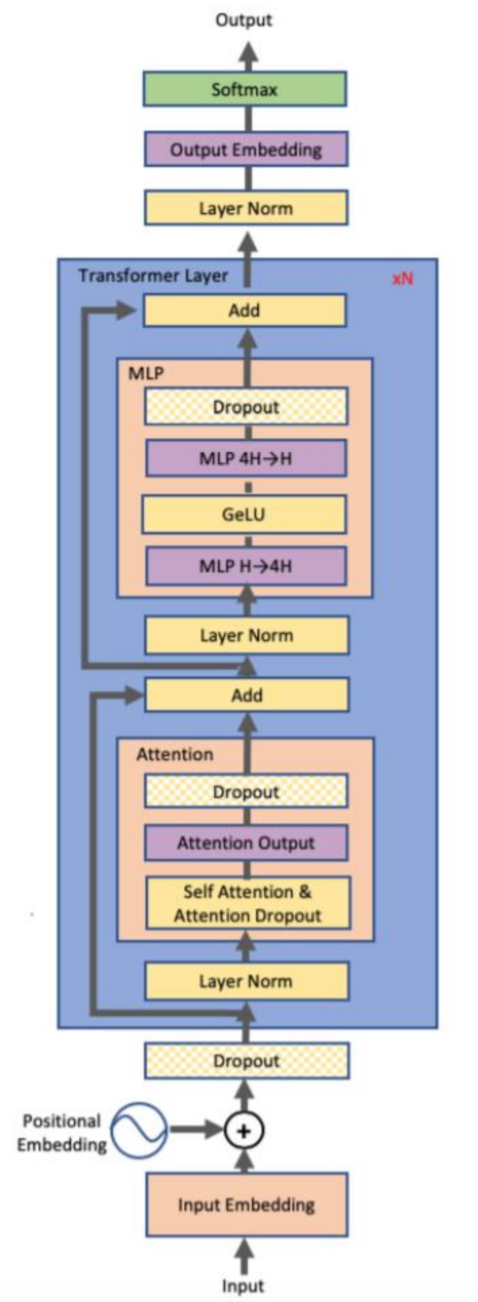
Out of Memory

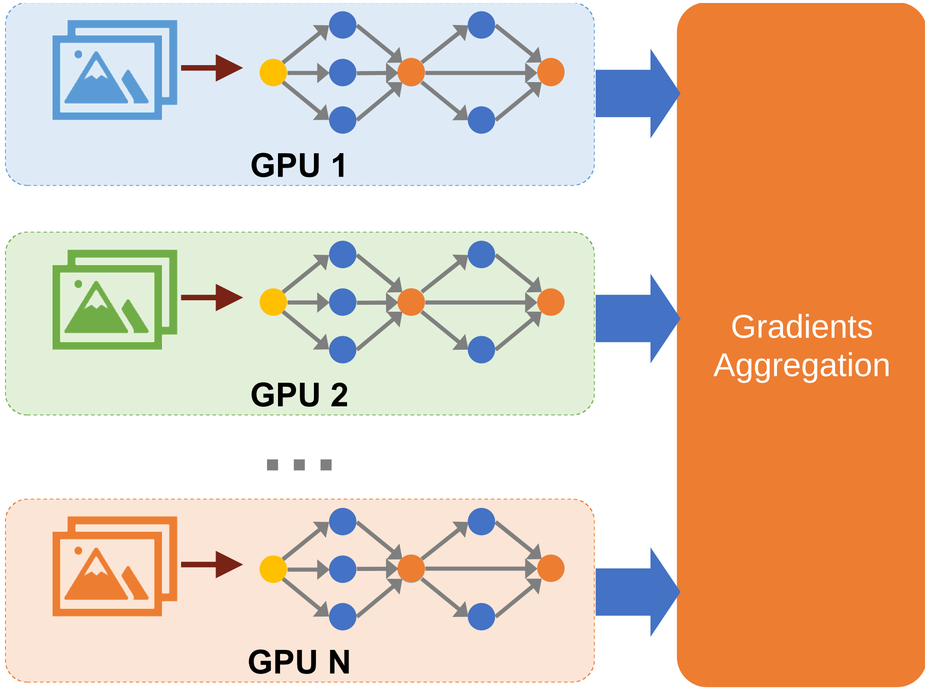
NVIDIA V100 GPU memory capacity: 16G/32G
NVIDIA A100 GPU memory capacity: 40G/80G



ZeRO: Zero Redundancy Optimizer

deepspeed

- Eliminating data redundancy in data parallel training
- A widely used technique for data parallel training of large models



Revisit: Stocastic Gradient Descent

Backward pass　　Forward pass

For t = 1 to T

$\Delta w = \eta \times \frac{1}{b} \sum_{i=1}^{b} \nabla \left(loss\left(f_w(x_i, y_i)\right)\right)$ // compute derivative and update

w -= Δw // apply update

End

Adapted from Minjia Zhang, DeepSpeed Presentation

Adaptive Learning Rates (Adam)

For t = 1 to T

g = $\frac{1}{b}\sum_{i=1}^{b} \nabla \left(loss\left(f_w(x_i, y_i)\right)\right)$

Δw = adam(g)

w -= Δw   // apply update

End

$$\nu_t = \beta_1 * \nu_{t-1} - (1-\beta_1) * g_t$$
$$s_t = \beta_2 * s_{t-1} - (1-\beta_2) * g_t^2$$
$$\Delta\omega_t = -\eta \frac{\nu_t}{\sqrt{s_t + \epsilon}} * g_t$$

g_t : *Gradient at time t along* ω^j

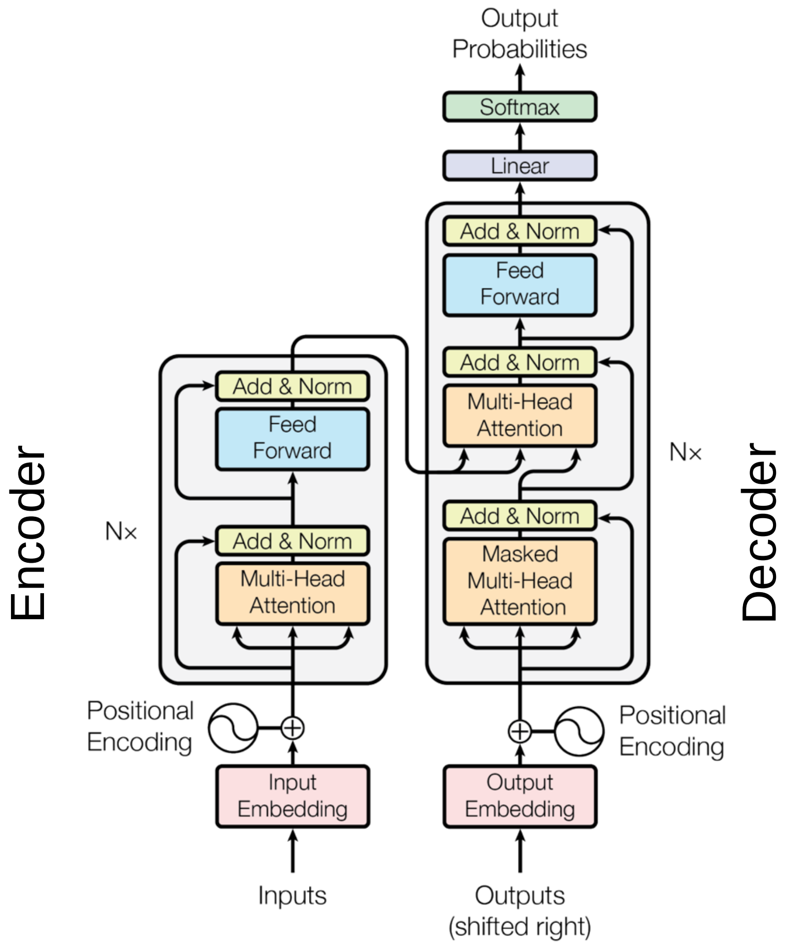
ν_t : *Exponential Average of gradients along* ω_j

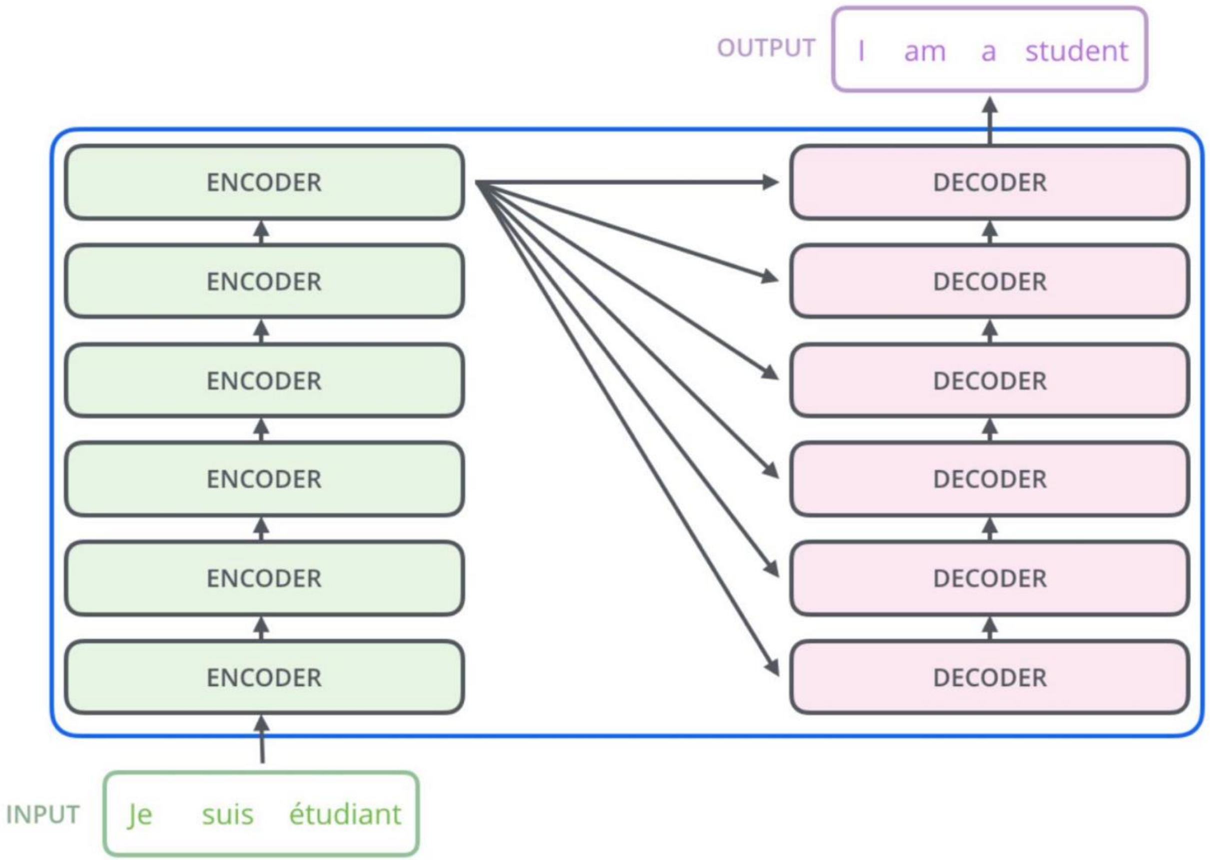
s_t : *Exponential Average of squares of gradients along* ω_j

β_1, β_2 : *Hyperparameters*

[1] Kingma and Ba, "Adam: A Method for Stochastic Optimization", 2014, https://arxiv.org/abs/1412.6980

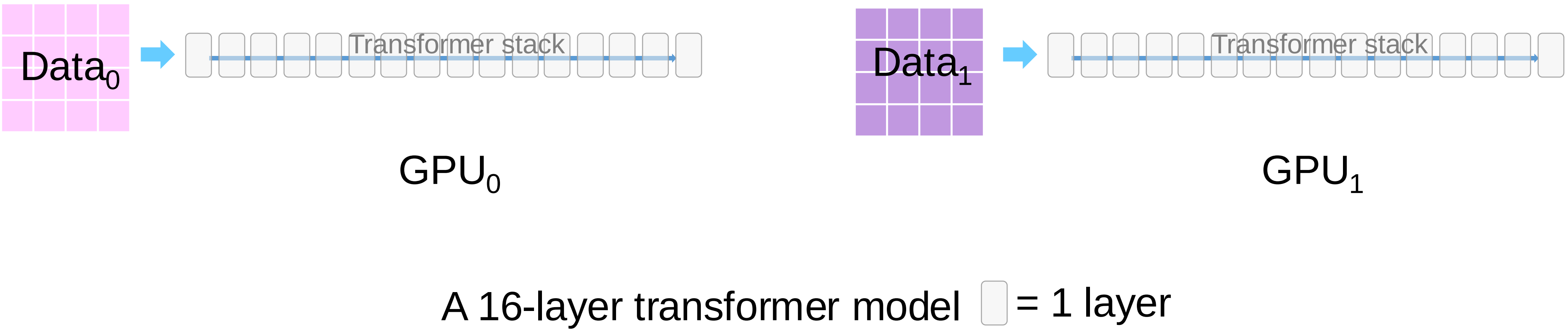
Transformer for Language Models





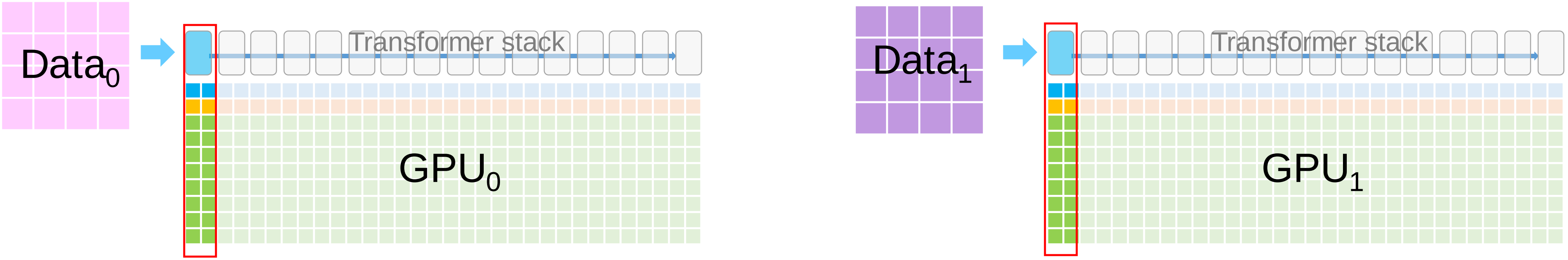
Ashish Vaswani et. al. Attention is all you need.

Understanding Memory Consumption



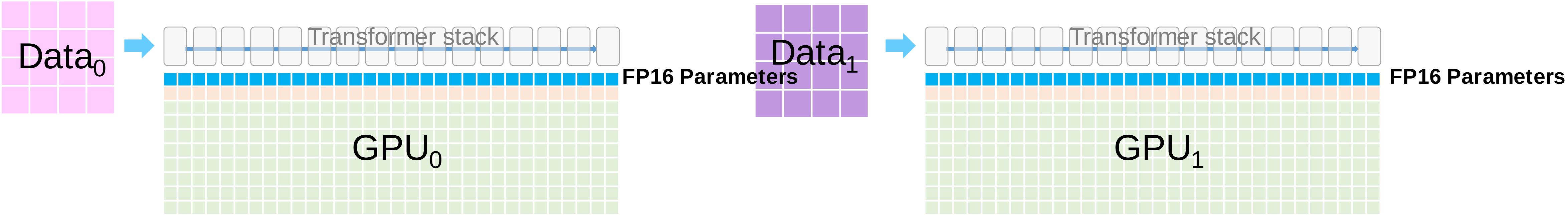
Adapted from Minjia Zhang, DeepSpeed Presentation

Understanding Memory Consumption



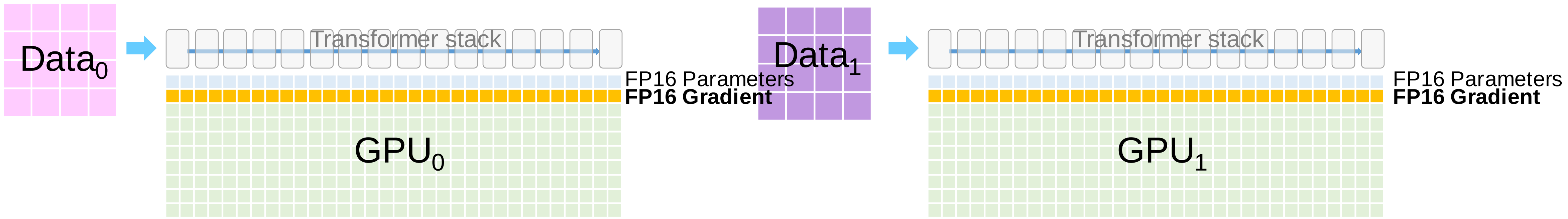
Each cell represents GPU memory used by its corresponding transformer layer

Understanding Memory Consumption



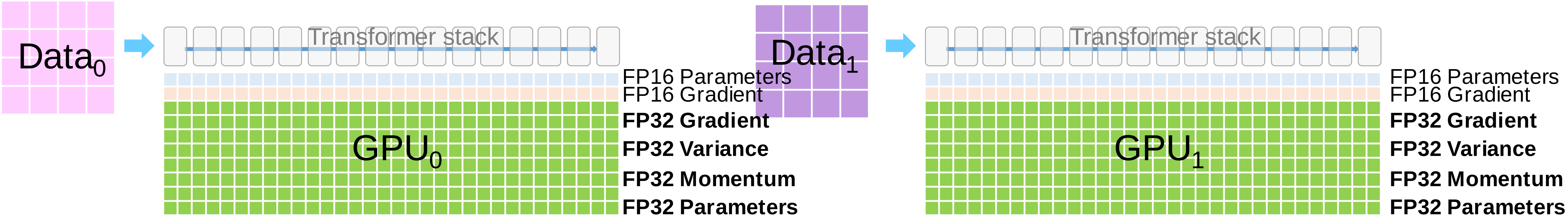
- FP16 parameter

Understanding Memory Consumption



- FP16 parameter
- FP16 Gradients

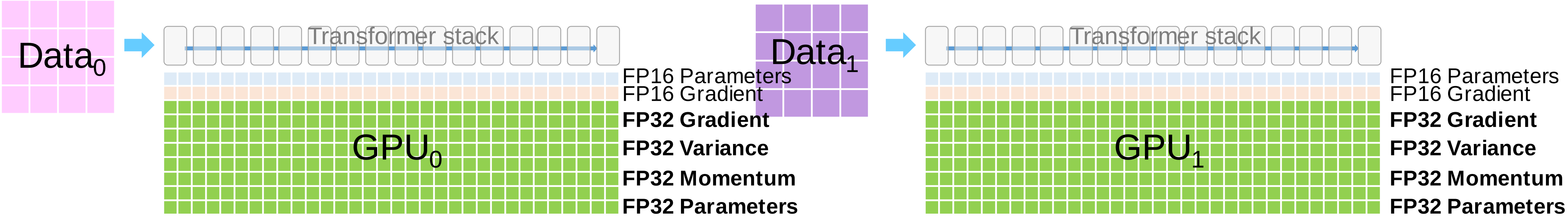
Understanding Memory Consumption



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

Adapted from Minjia Zhang, DeepSpeed Presentation

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

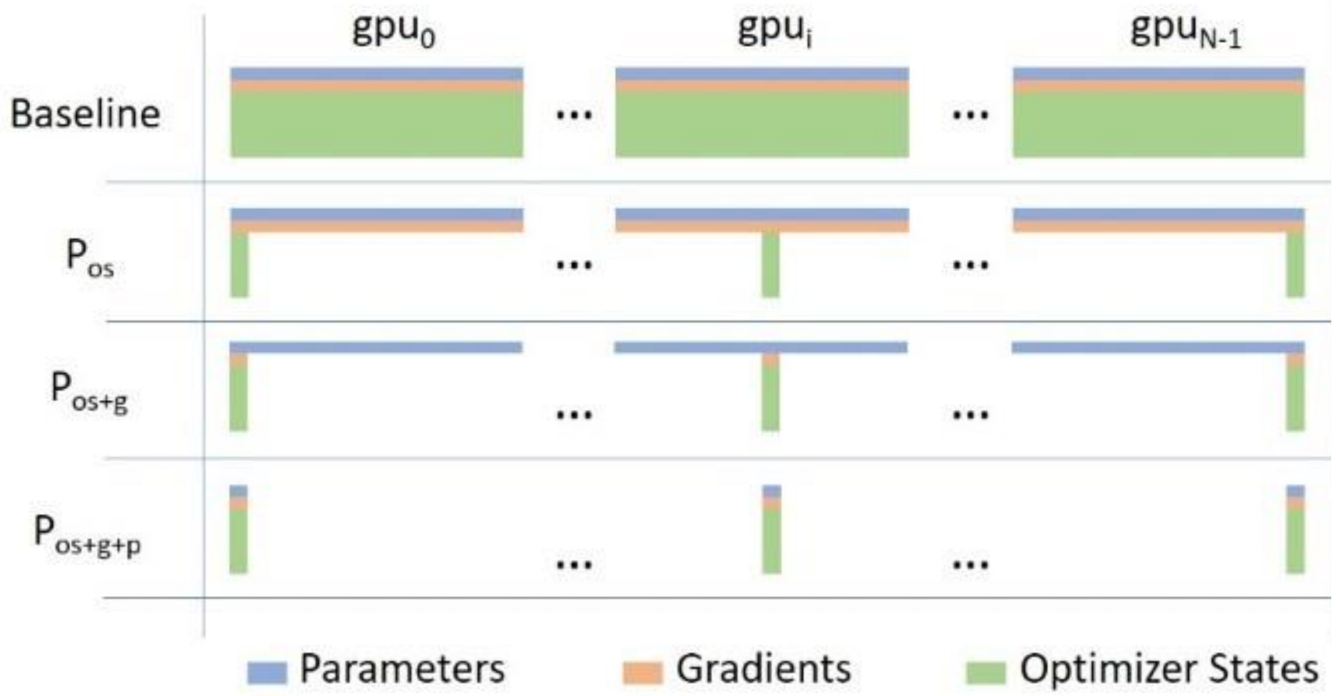
Example 1B parameter model -> 20GB/GPU

Memory consumption doesn’t include:
- Input batch + activations

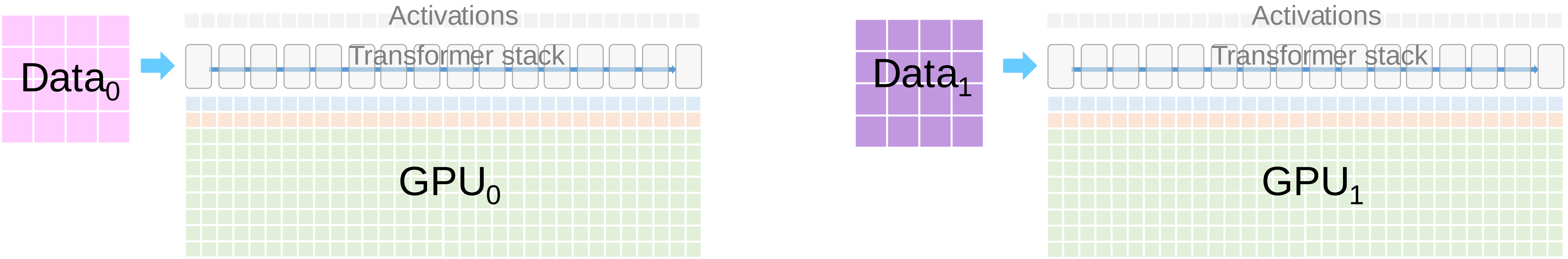
Adapted from Minjia Zhang, DeepSpeed Presentation

ZeRO-DP: ZeRO powered Data Parallelism

- ZeRO removes the redundancy across data parallel process
- Stage 1: partitioning optimizer states
- Stage 2: partitioning gradients
- Stage 3: partitioning parameters



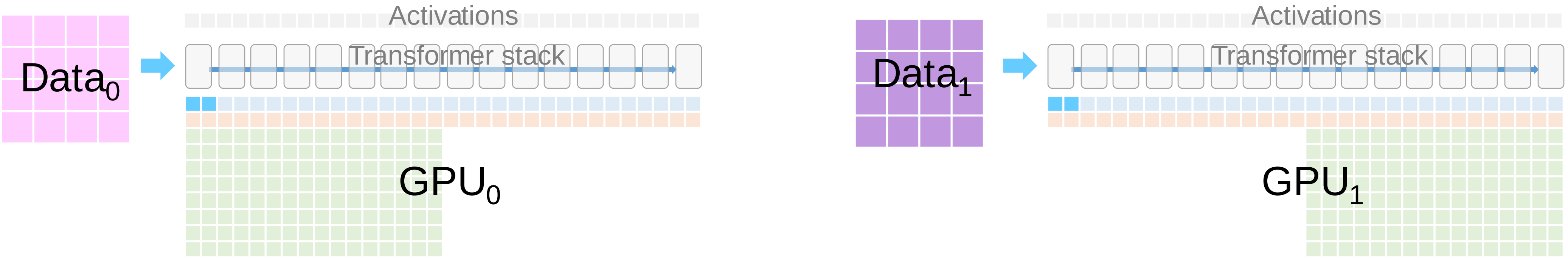
ZeRO Stage 1: Partitioning Optimizer States



- ZeRO Stage 1

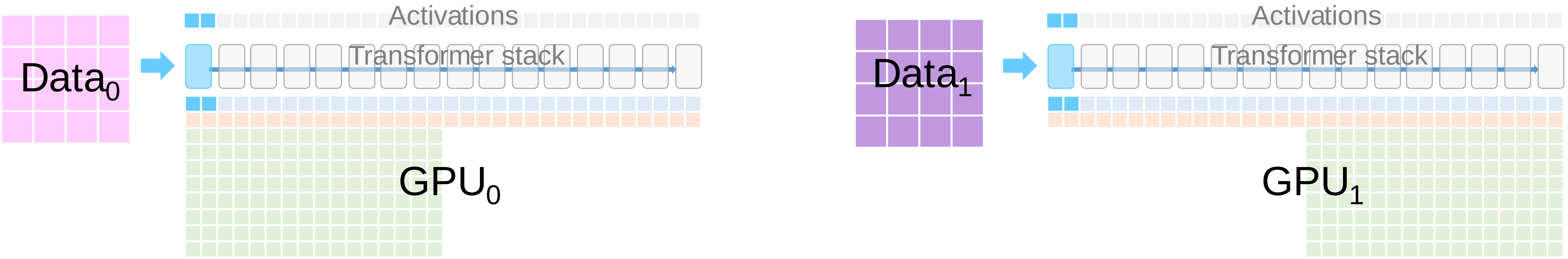
Adapted from Minjia Zhang, DeepSpeed Presentation

ZeRO Stage 1: Partitioning Optimizer States



- ZeRO Stage 1
- Partitions optimizer states across GPUs

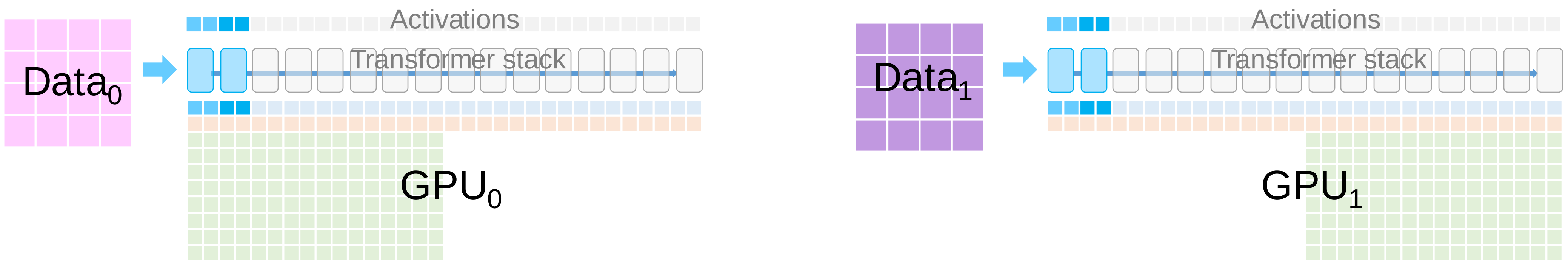
ZeRO Stage 1: Partitioning Optimizer States



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

Adapted from Minjia Zhang, DeepSpeed Presentation

ZeRO Stage 1: Partitioning Optimizer States



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Adapted from Minjia Zhang, DeepSpeed Presentation

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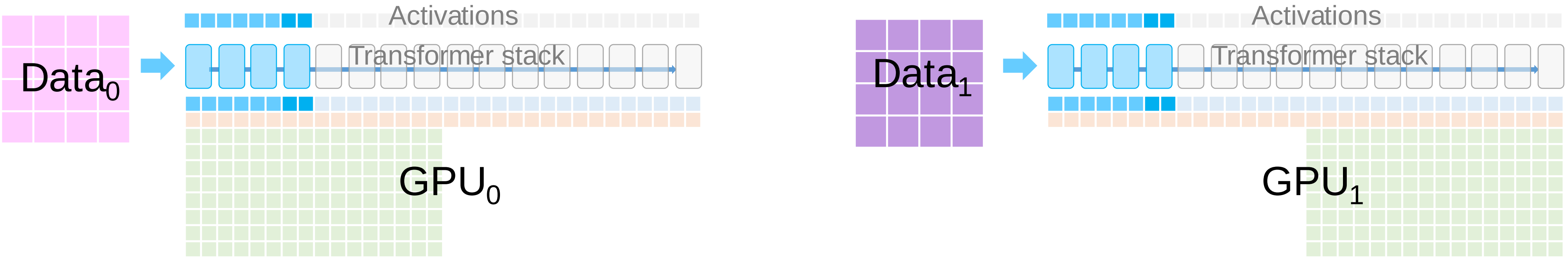

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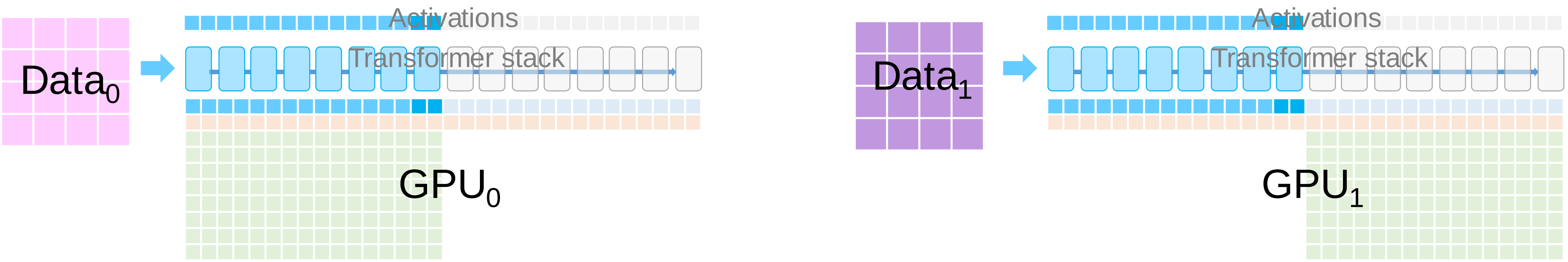

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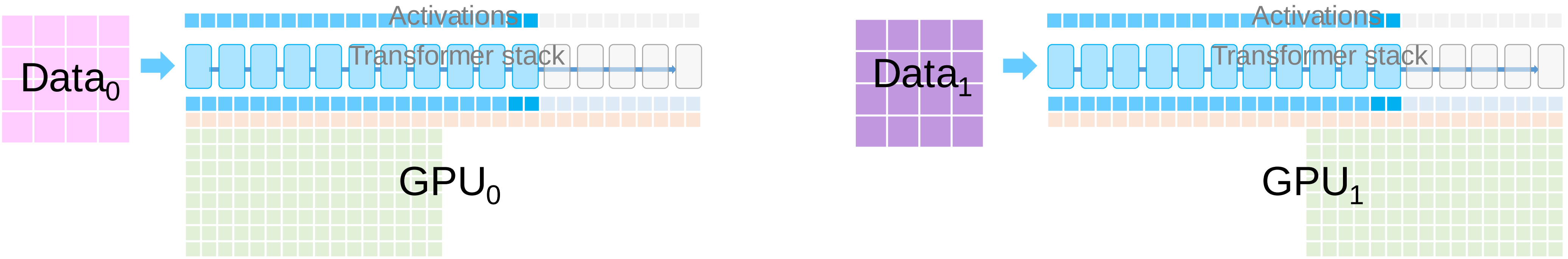

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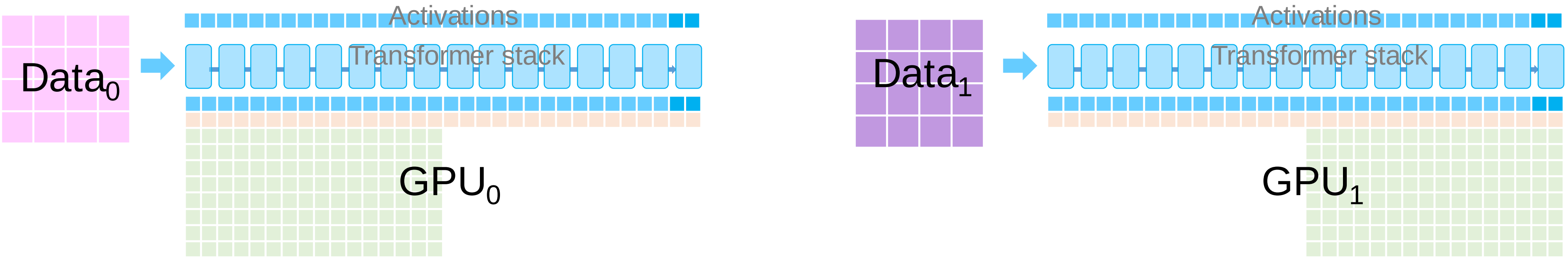
ZeRO Stage 1: Partitioning Optimizer States



- ZeRO Stage 1
- Partitions optimizer states across GPUs
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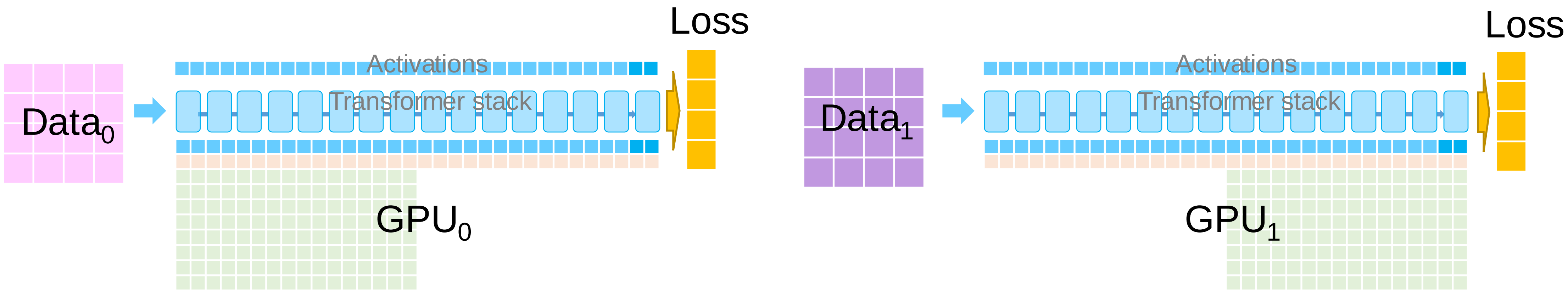
Adapted from Minjia Zhang, DeepSpeed Presentation

ZeRO Stage 1: Partitioning Optimizer States



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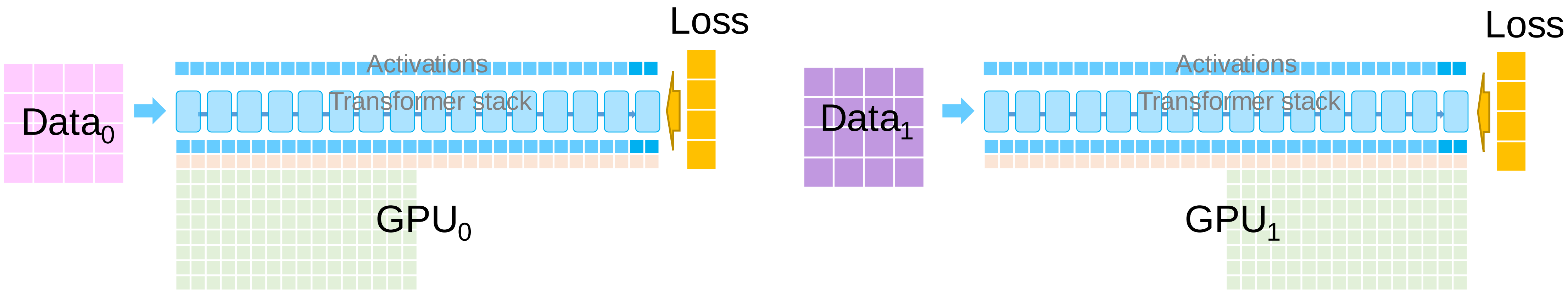
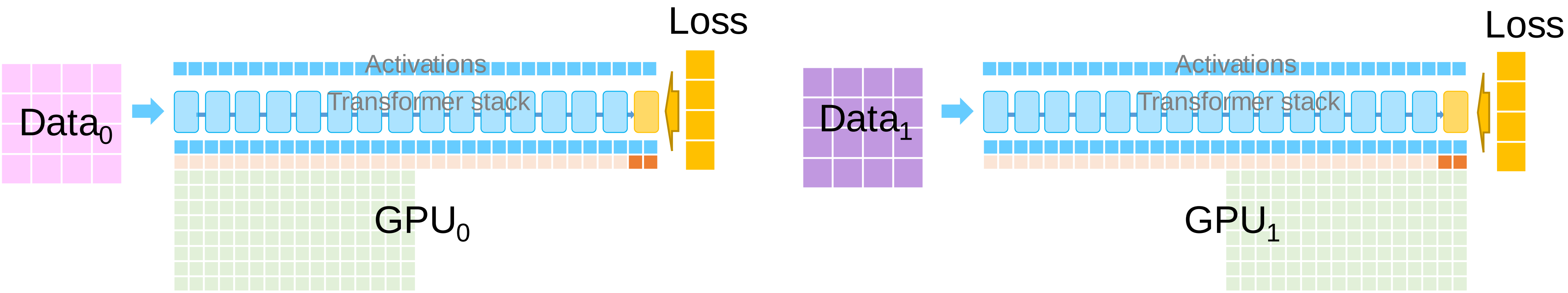
ZeRO Stage 1: Partitioning Optimizer States



- ZeRO Stage 1
- Partitions optimizer states across GPUs
- Run Forward across the transformer blocks
- Backward propagation to generate FP16 gradients

Adapted from Minjia Zhang, DeepSpeed Presentation

ZeRO Stage 1: Partitioning Optimizer States



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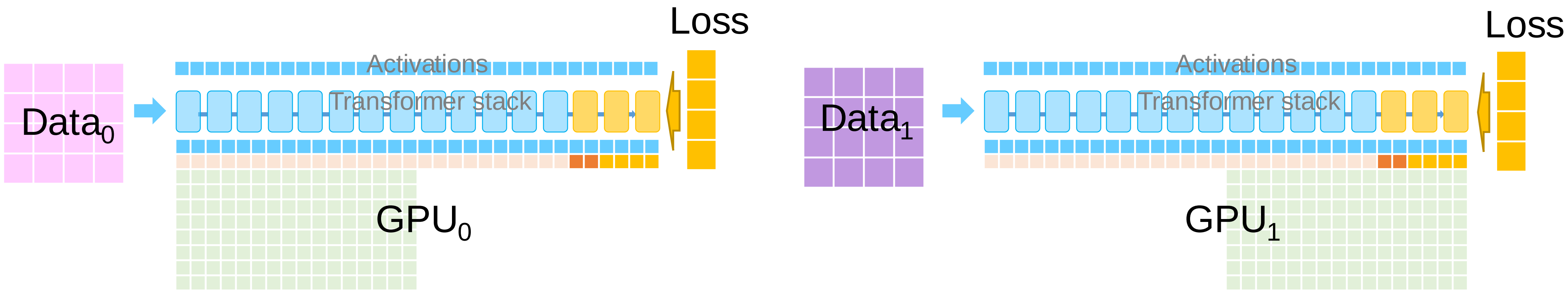
- Run Forward across the transformer blocks
- Backward propagation to generate FP16 gradients

Adapted from Minjia Zhang, DeepSpeed Presentation

ZeRO Stage 1: Partitioning Optimizer States



- ZeRO Stage 1
- Partitions optimizer states across GPUs
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Adapted from Minjia Zhang, DeepSpeed Presentation

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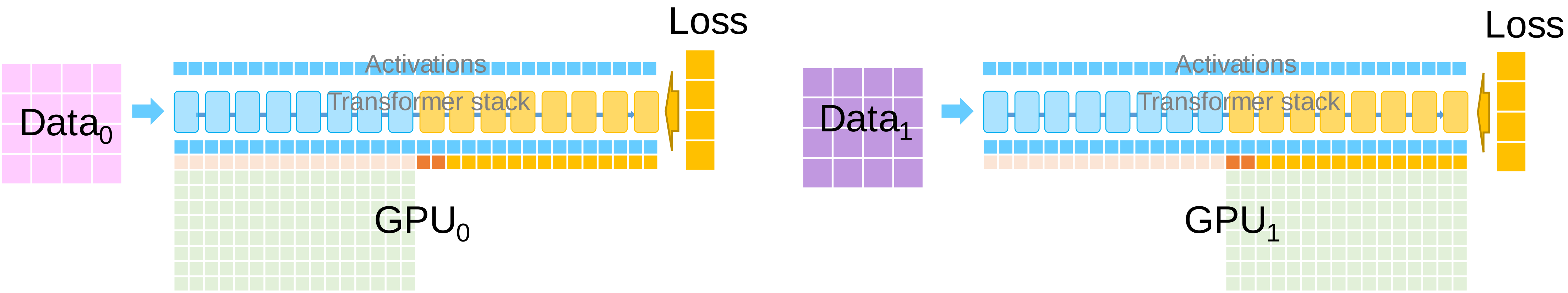

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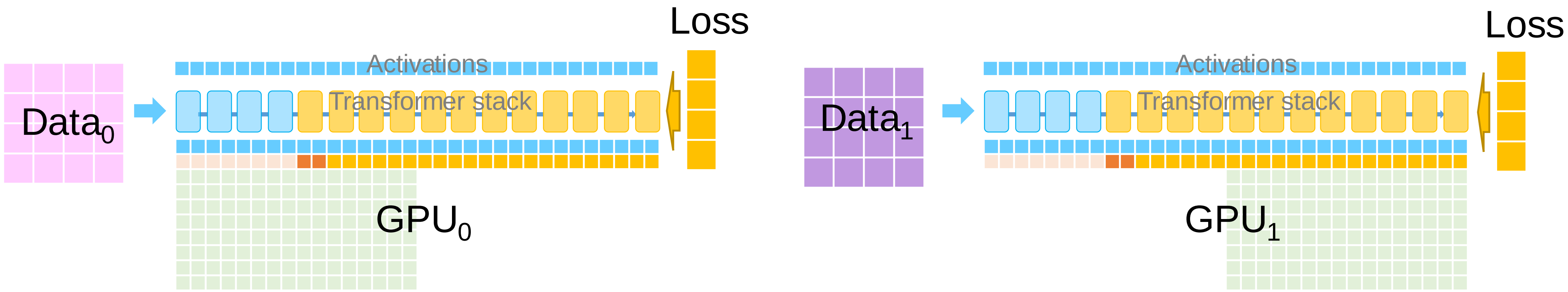

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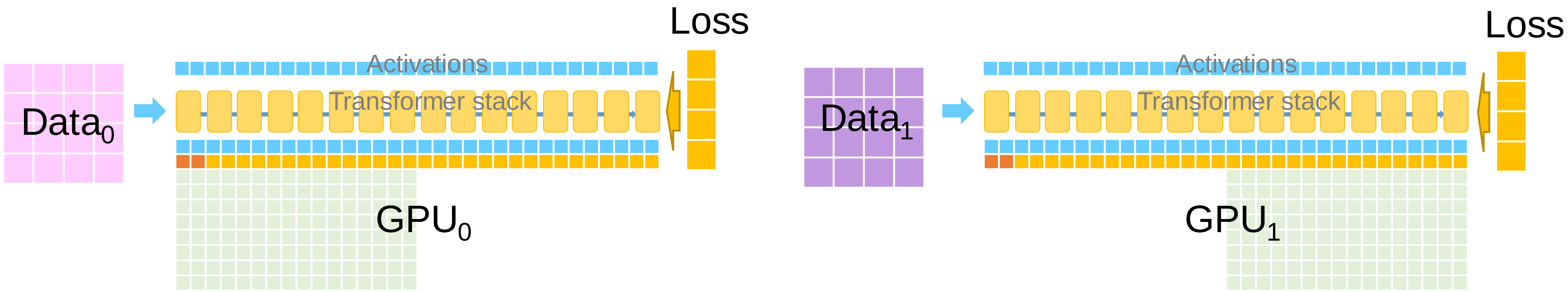

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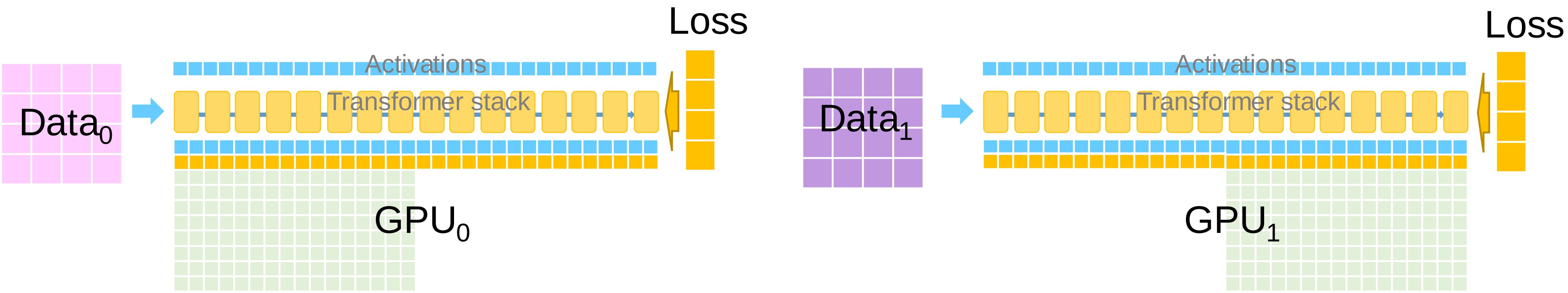

- ZeRO Stage 1
- Partitions optimizer states across GPUs
- Run Forward across the transformer blocks
- Backward propagation to generate FP16 gradients and AllReduce to average

Adapted from Minjia Zhang, DeepSpeed Presentation

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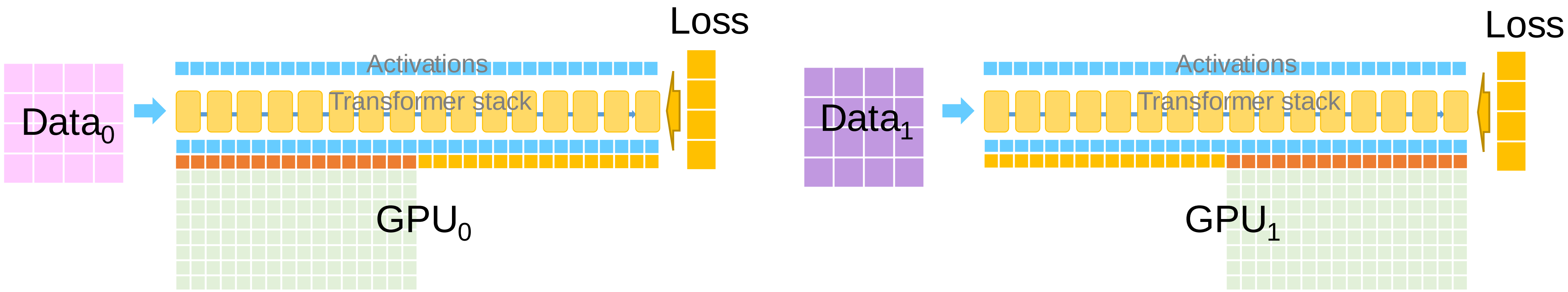

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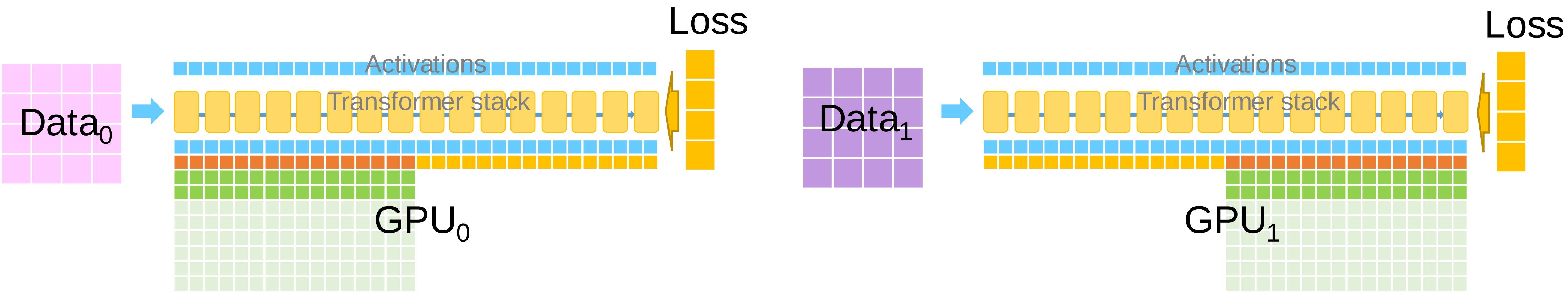
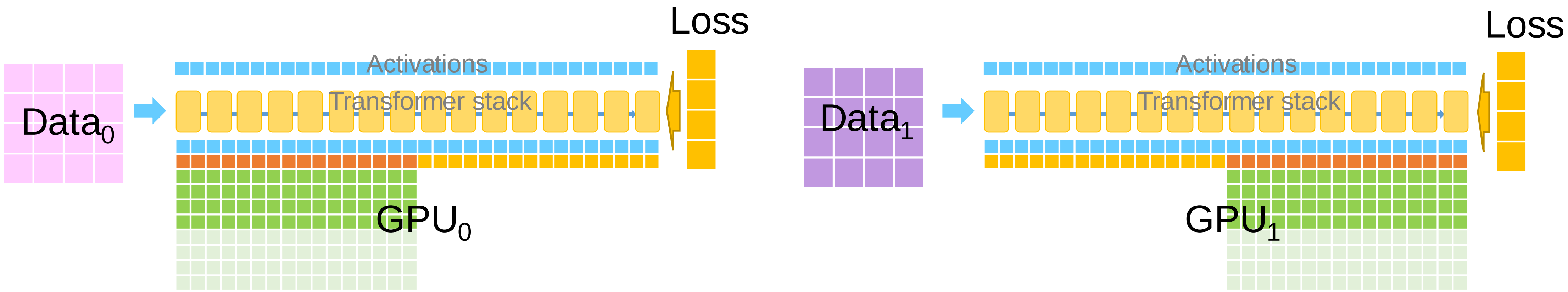


- ZeRO Stage 1
- Partitions optimizer states across GPUs
- Run Forward across the transformer blocks
- Backward propagation to generate FP16 gradients and AllReduce to average
- Update the FP32 weights with ADAM optimizer

Adapted from Minjia Zhang, DeepSpeed Presentation

ZeRO Stage 1: Partitioning Optimizer States



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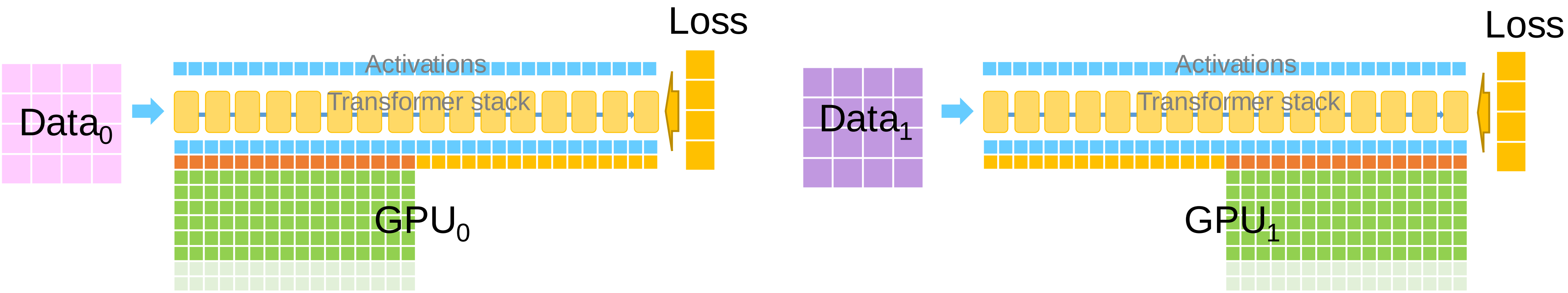

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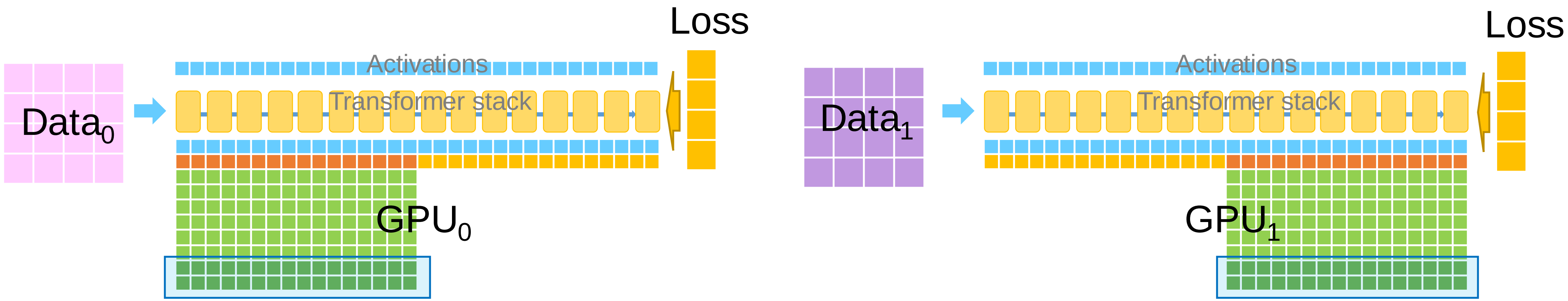

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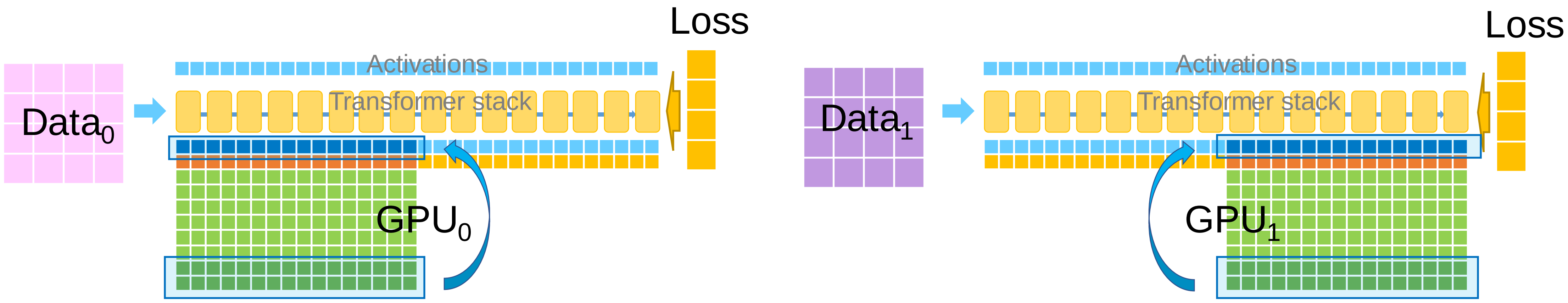

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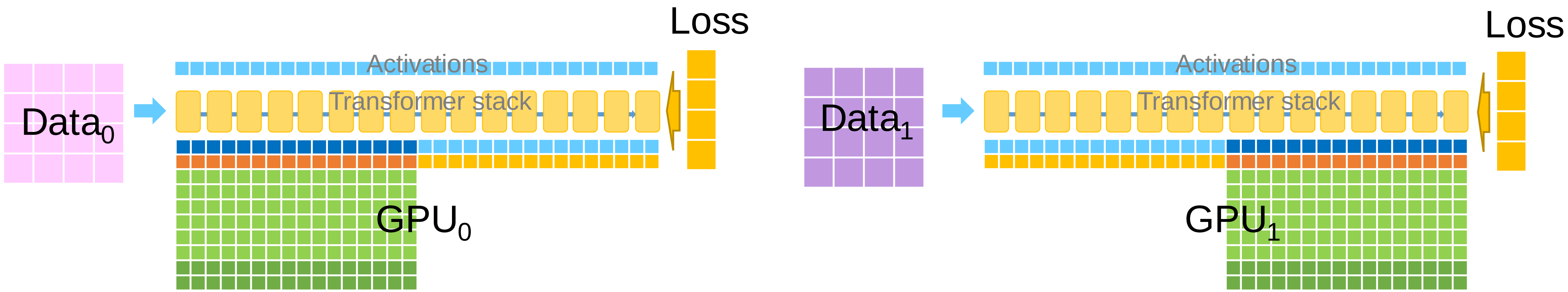
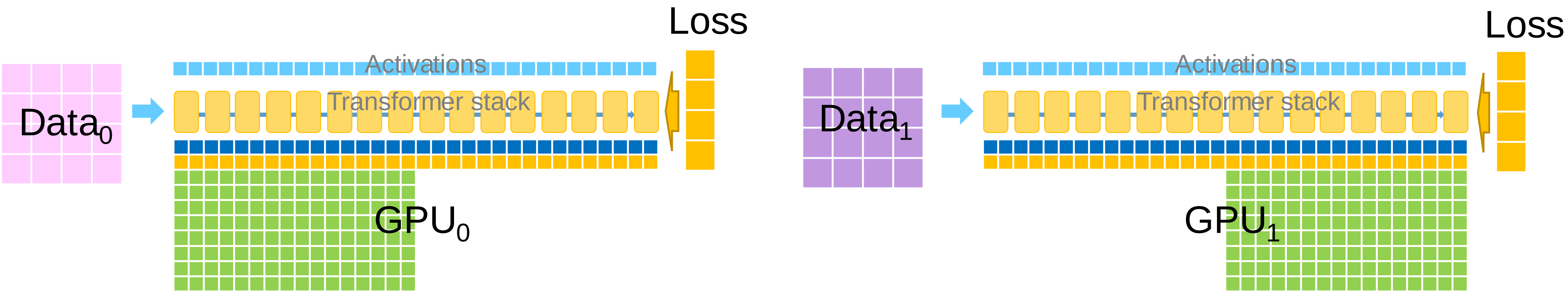


- Run Forward across the transformer blocks
- Backward propagation to generate FP16 gradients and AllReduce to average
- Update the FP32 weights with ADAM optimizer
- Update the FP16 weights
- All Gather the FP16 weights to complete the iteration

Adapted from Minjia Zhang, DeepSpeed Presentation

ZeRO Stage 1: Partitioning Optimizer States



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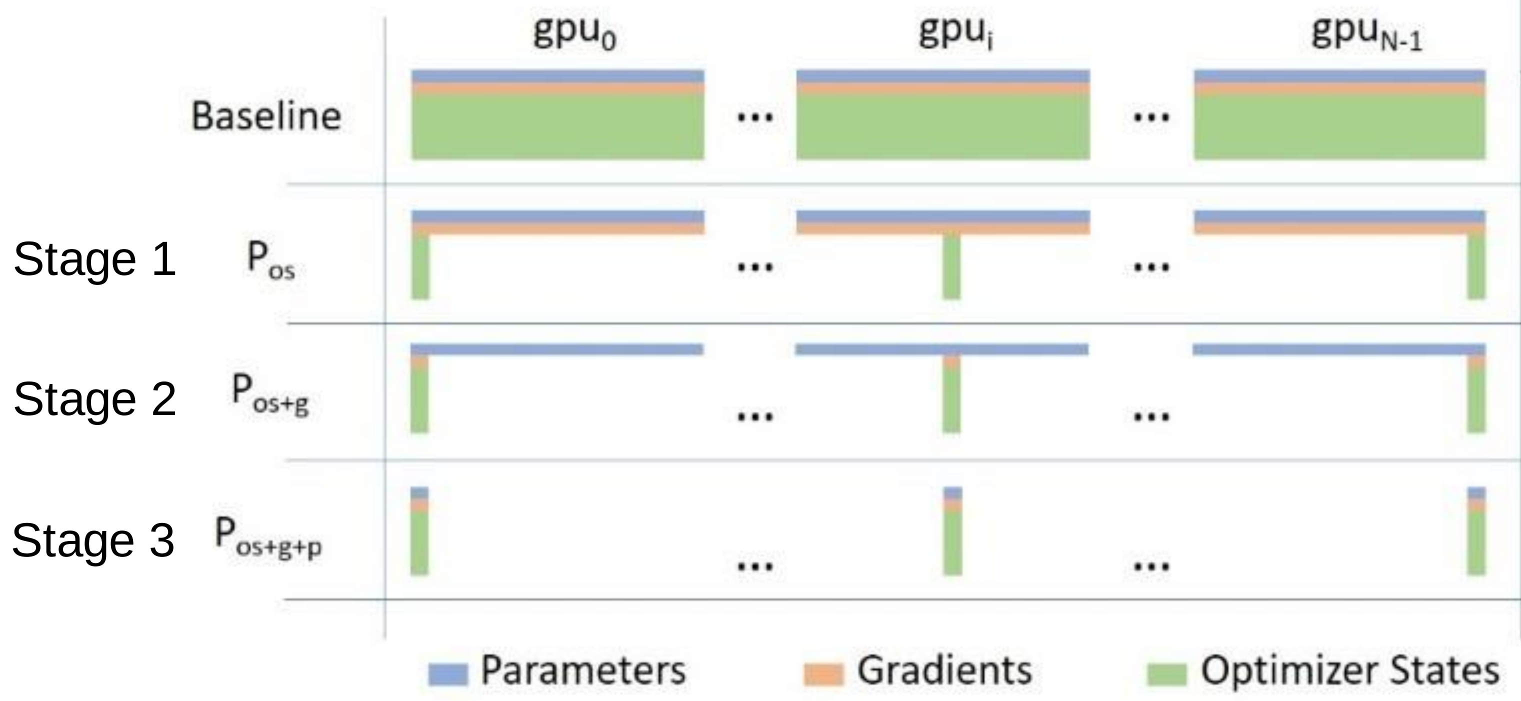
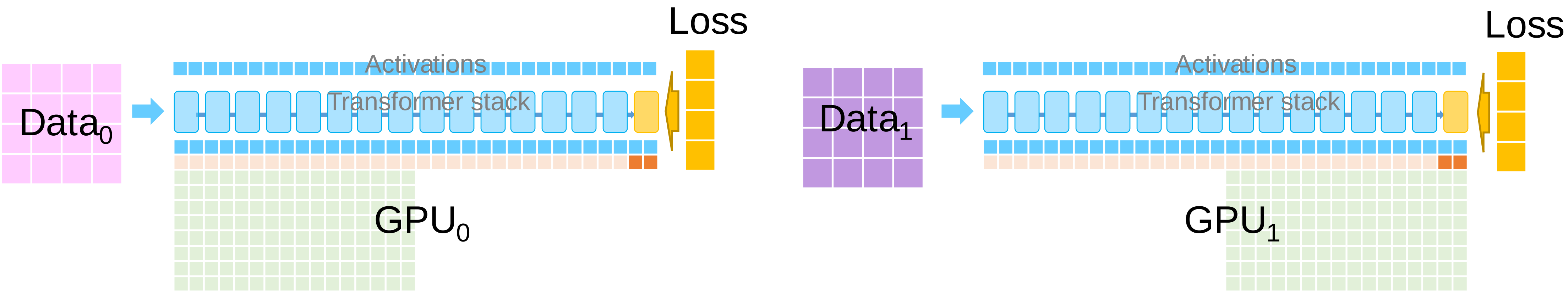
ZeRO: Zero Redundancy Optimizer

- Progressive memory savings and communication volume
- Turning NLR 17.2B is powered by Stage 1 and Megatron



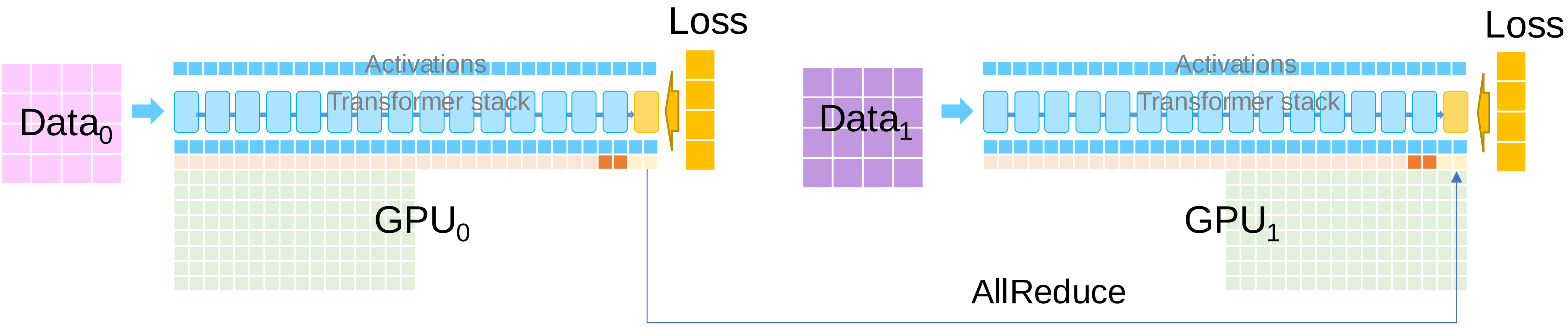
	Memory Consumption		Comm Volume
	Formulation	Specific Example $K=12$ $\Psi=7.5B$ $N_d=64$	
Baseline	$(2+2+K)*\Psi$	120GB	1x
Stage 1 (P_{os})	$2\Psi+2\Psi+\frac{K*\Psi}{N_d}$	31.4GB	1x
Stage 2 (P_{os+g})	$2\Psi+\frac{(2+K)*\Psi}{N_d}$	16.6GB	1x
Stage 3 (P_{os+g+p})	$\frac{(2+2+K)*\Psi}{N_d}$	1.9GB	1.5x

ZeRO Stage 2: Partitioning Gradients



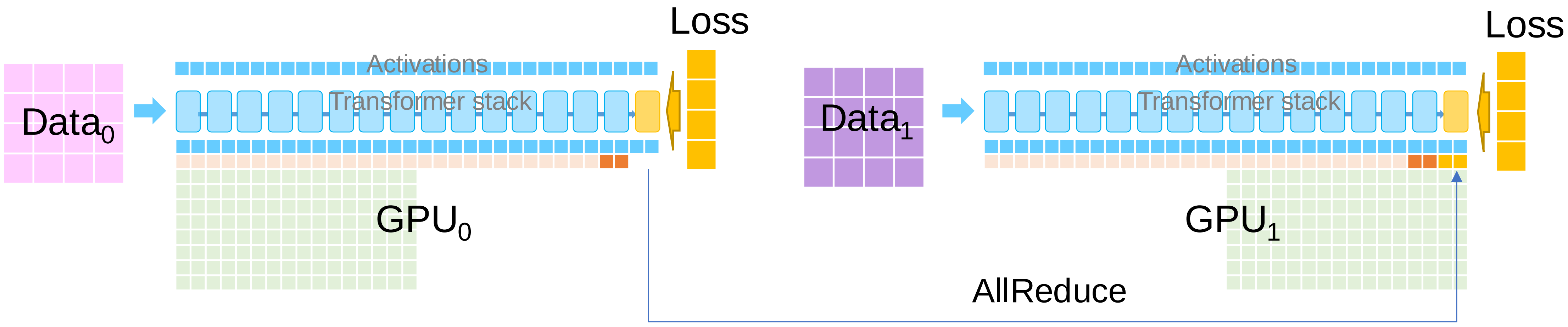
- Partitioning gradients across GPUs
- The forward process remains the same as stage 1

ZeRO Stage 2: Partitioning Gradients



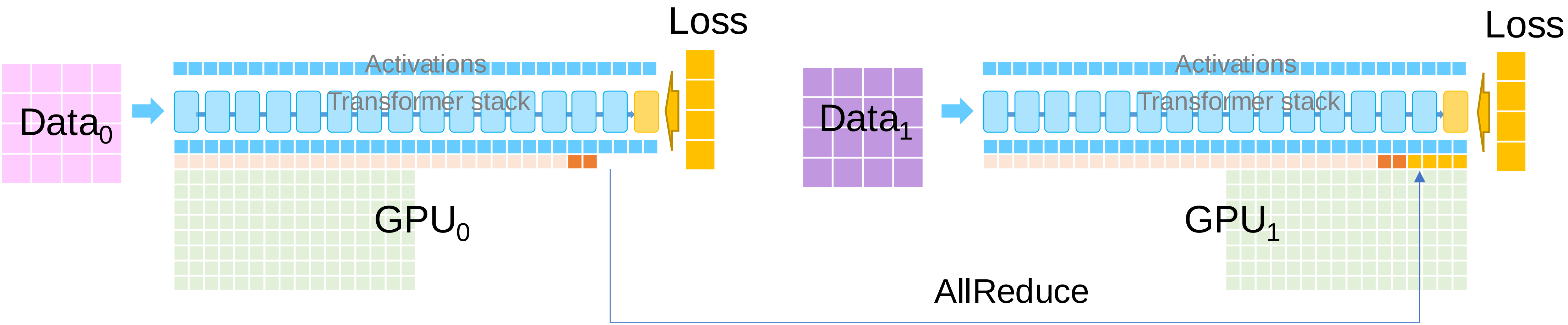
- Partitioning gradients across GPUs
- Perform AllReduce right after back propagation of each layer

ZeRO Stage 2: Partitioning Gradients



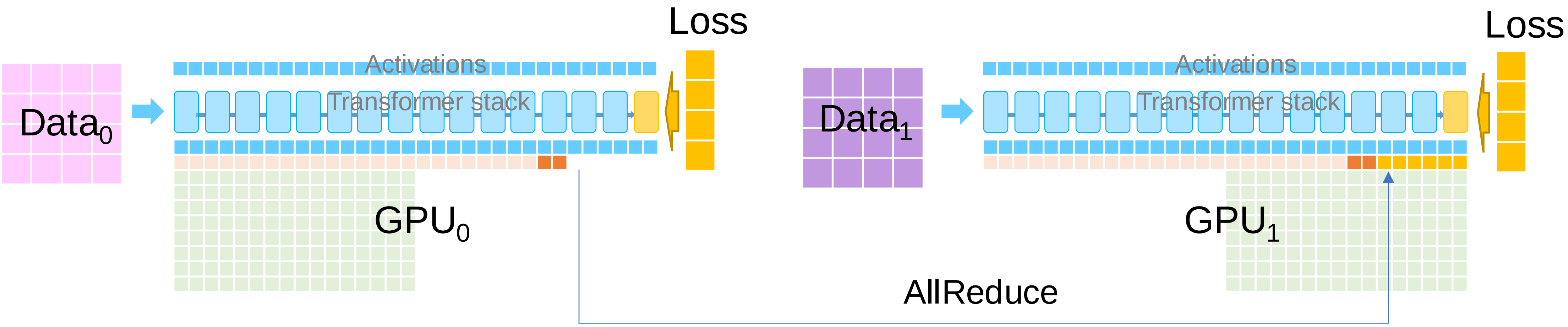
- Partitioning gradients across GPUs
- Only one GPU keeps the gradients after AllReduce

ZeRO Stage 2: Partitioning Gradients



- Partitioning gradients across GPUs
- Reduce gradients on GPUs responsible for updating parameters

ZeRO Stage 2: Partitioning Gradients



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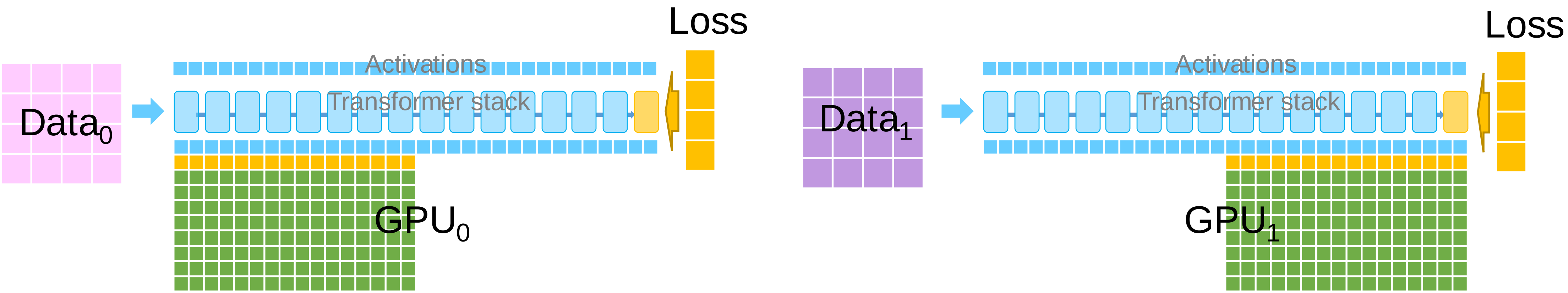

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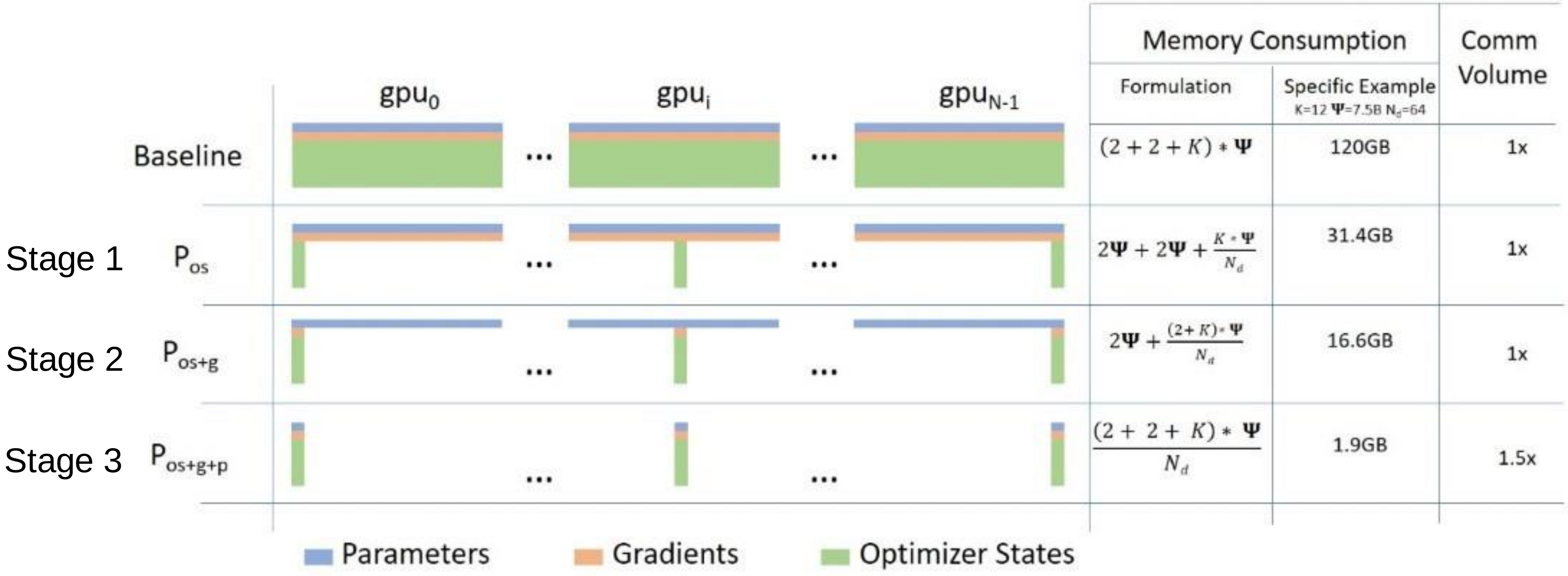
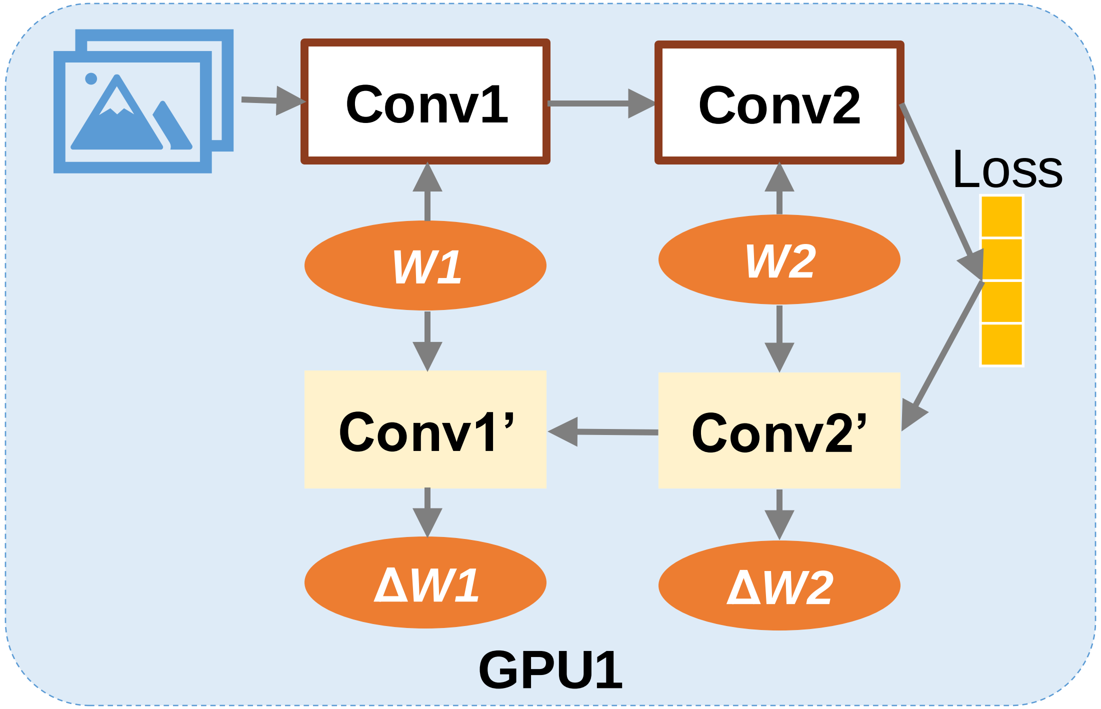
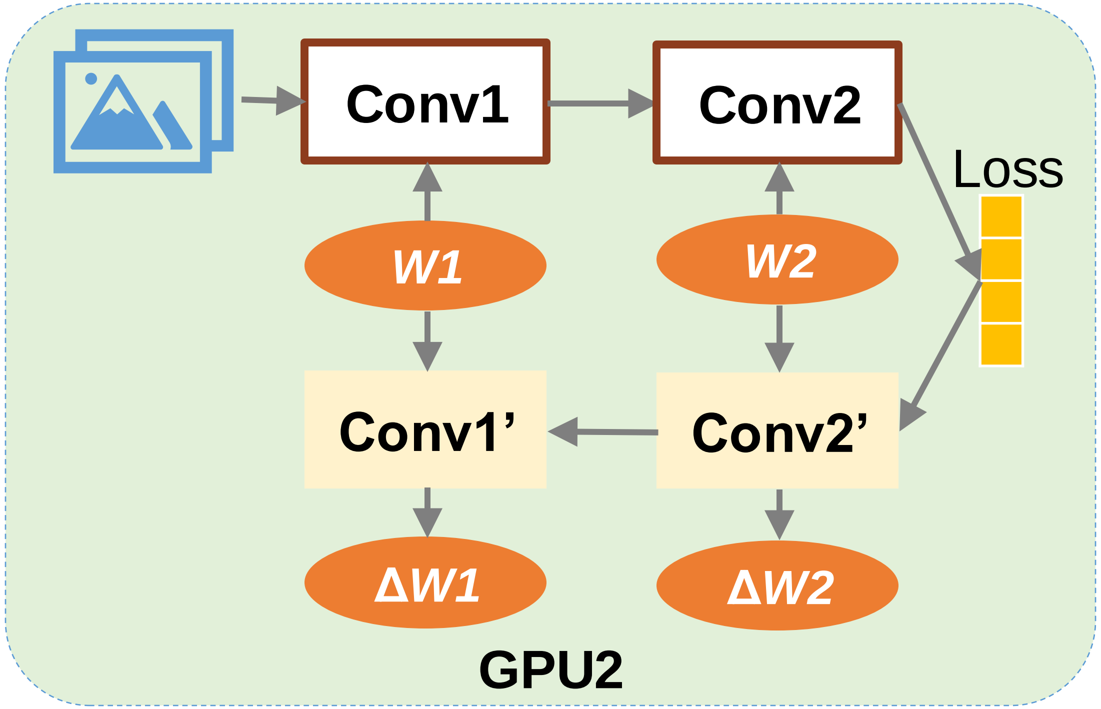


ZeRO Stage 3: Partitioning Parameters

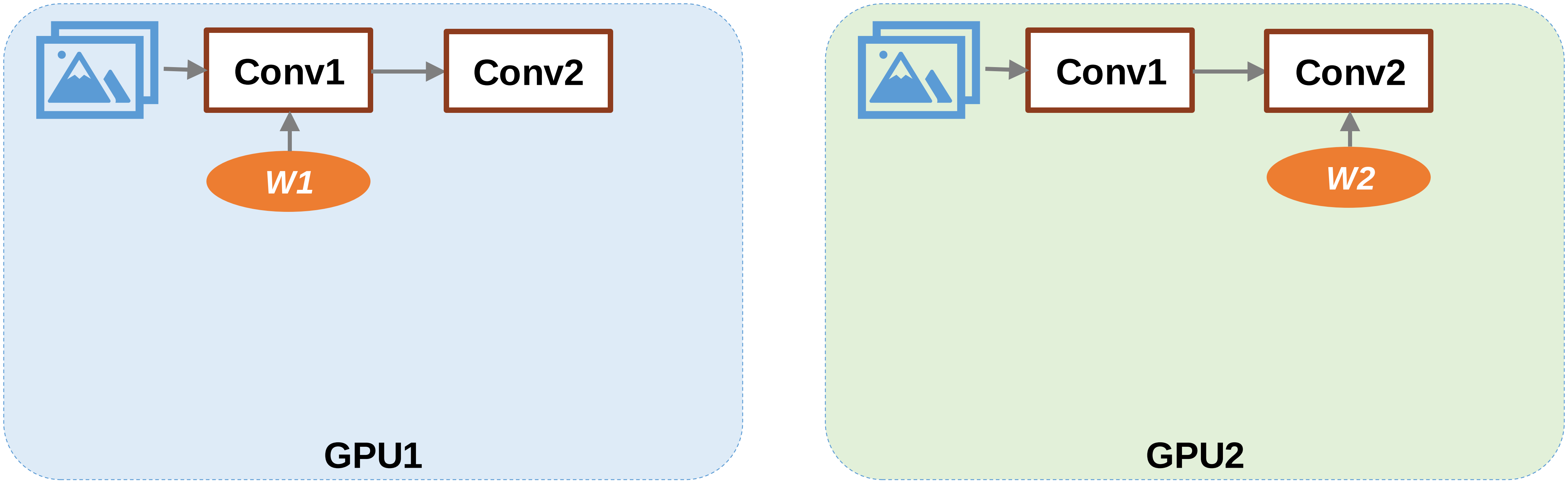
- In data parallel training, all GPUs keep **all** parameters during training





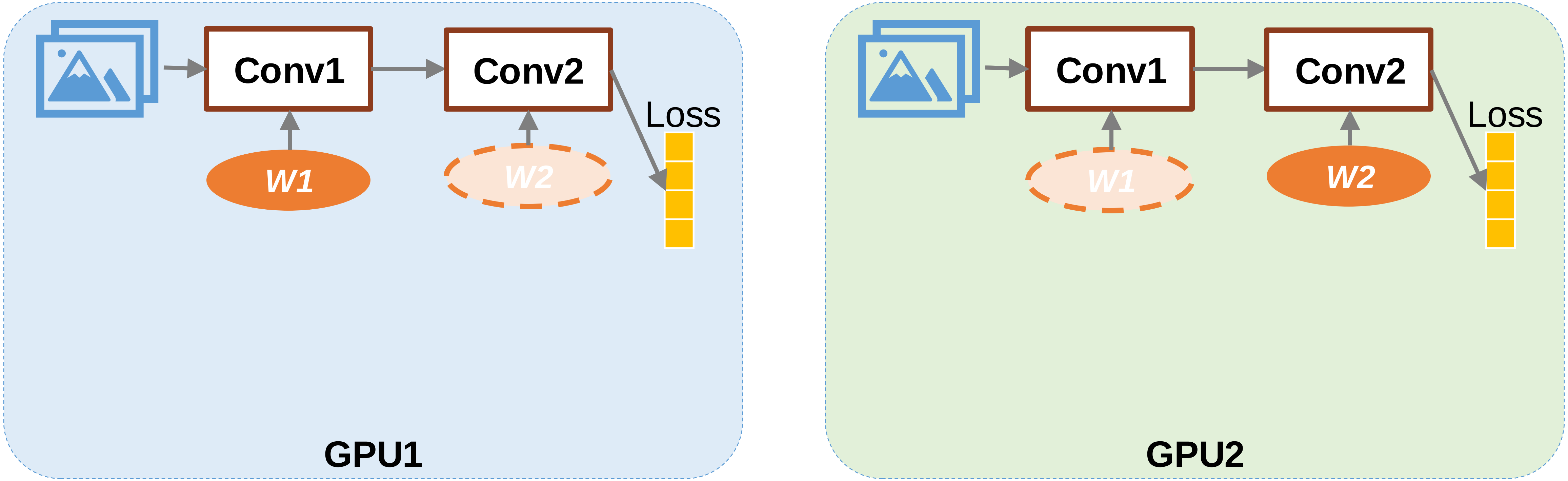
ZeRO Stage 3: Partitioning Parameters

- In ZeRO, model parameters are partitioned across GPUs



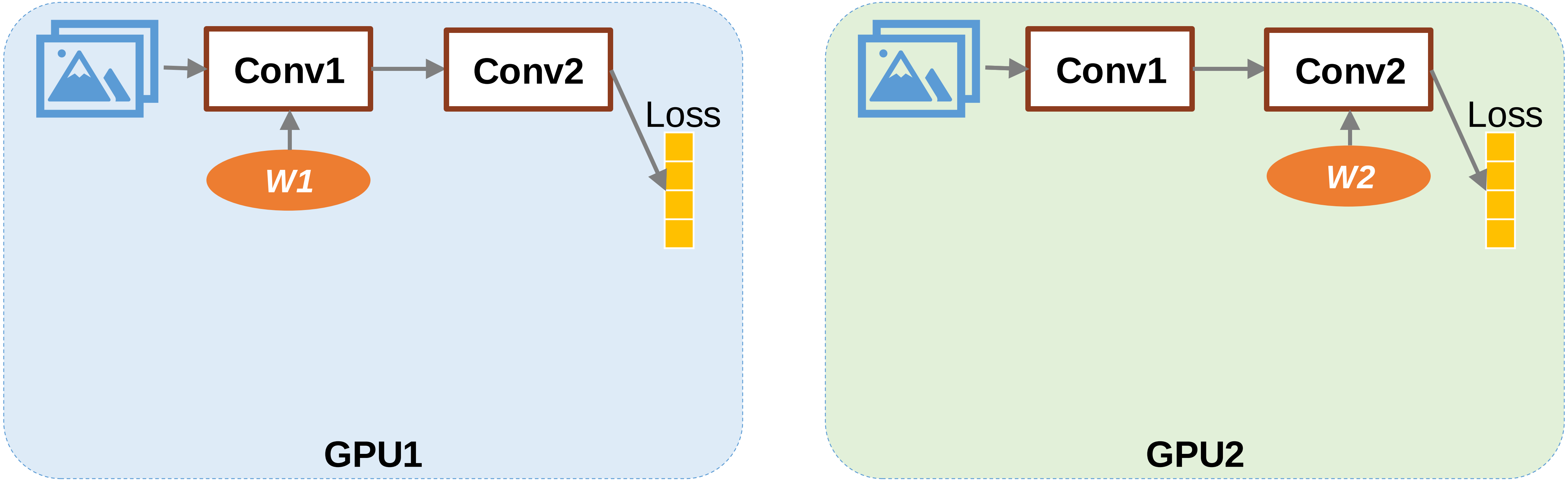
ZeRO Stage 3: Partitioning Parameters

- In ZeRO, model parameters are partitioned across GPUs
- GPUs broadcast their parameters during forward



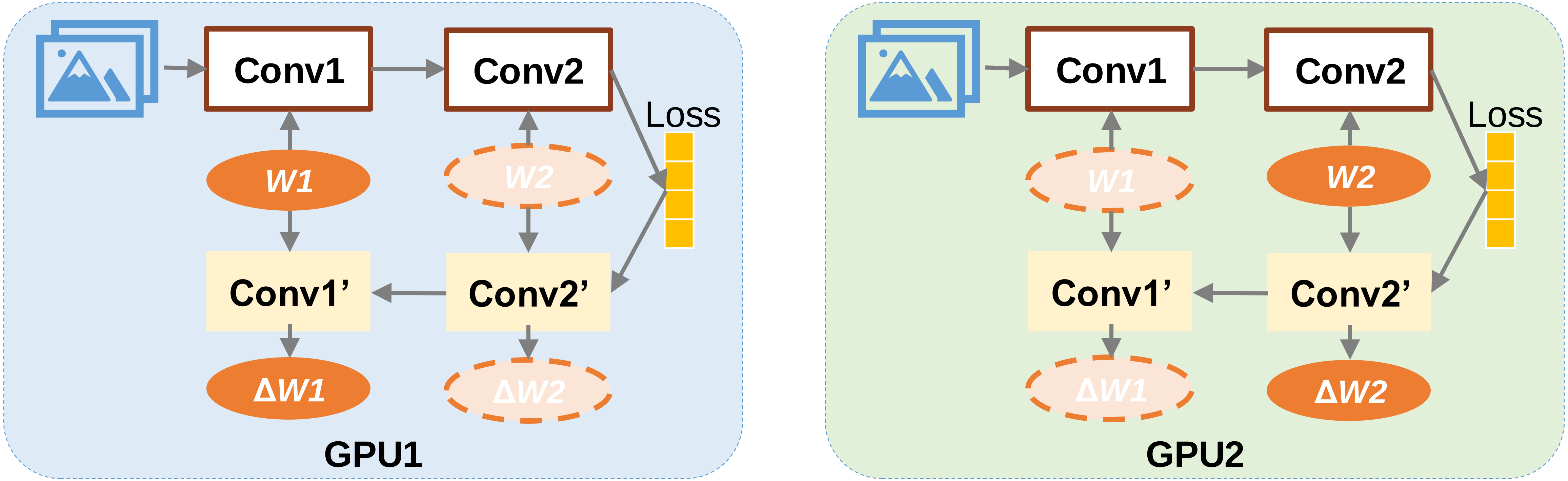
ZeRO Stage 3: Partitioning Parameters

- In ZeRO, model parameters are partitioned across GPUs
- Parameters are discarded right after use



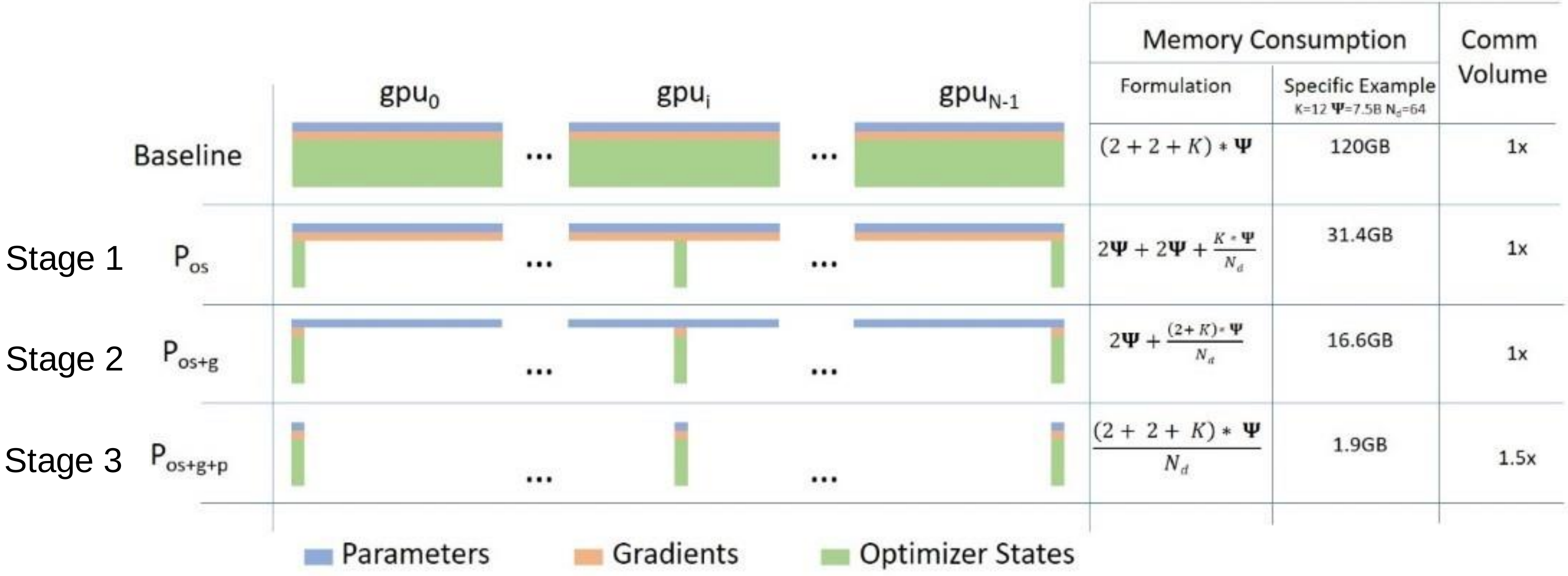
ZeRO Stage 3: Partitioning Parameters

- In ZeRO, model parameters are partitioned across GPUs
- GPUs broadcast their parameters again during backward



ZeRO: Zero Redundancy Optimizer

- ZeRO has three different stages
- Progressive memory savings and communication volume



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Summary

- Data-parallel training
  - Parameter server
  - Ring AllReduce
  - Tree AllReduce
  - Butterfly AllReduce
- ZeRO: zero redundancy optimizer