ZeRO: Memory Optimizations Toward Training Trillion Parameter Models

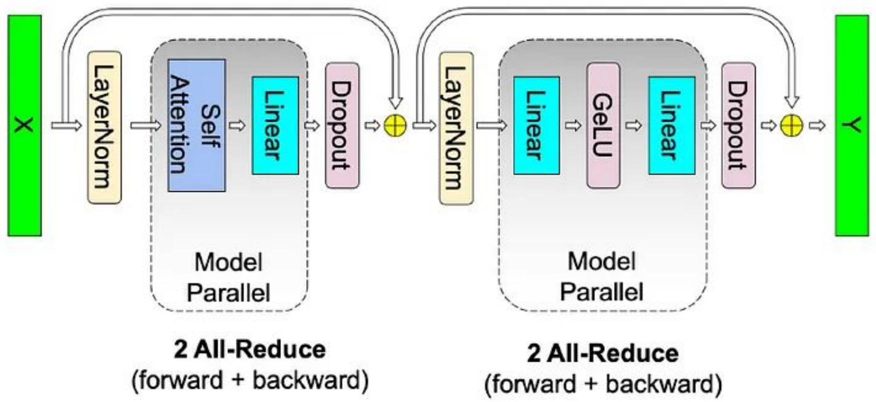
Related Works

Model Parallelism

Model Parallel: memory usage and computation of a model is distributed across multiple workers

Megatron-LM:

- + Split the matrix into multiple parts and do matmul separately.
- + No sync point within Linear and Self-attn.



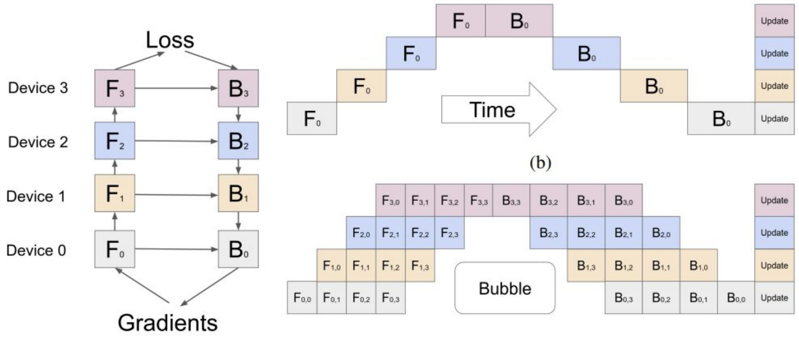
Pipeline Parallelism

The model is distributed across multiple GPUs over layers.

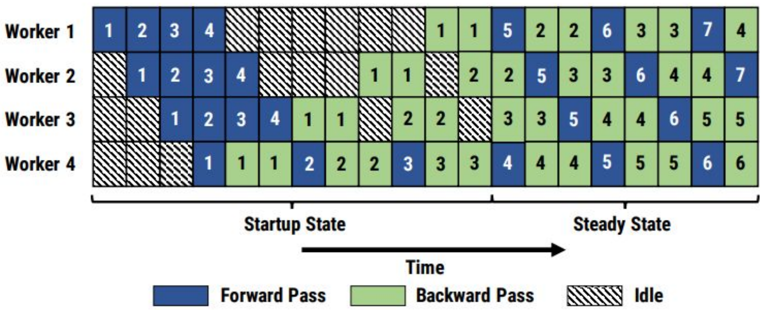
Devices can be idle while waiting for others

Pipeline Parallelism is a specific form of model parallelism

+ **GPipe:** Divides input data mini-batches into smaller micro-batches.
+ **PipeDream:** Start backward as soon as possible. Do async gradient update.
+ Note that PipeDream is not equivalent to traditional DL.



GPipe

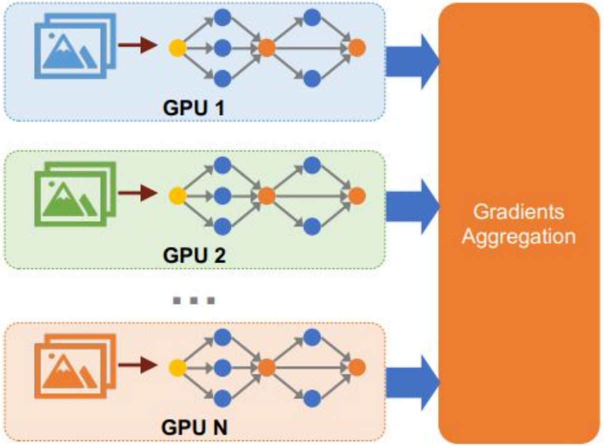


PipeDream

Data Parallelism

Each device has the same model and do forward and backward on a mini-batch separately. Quite easy and intuitive, but …

1. Cannot train LLM that cannot fit into one device.
2. Each device has the whole replica of the model.



Reduce

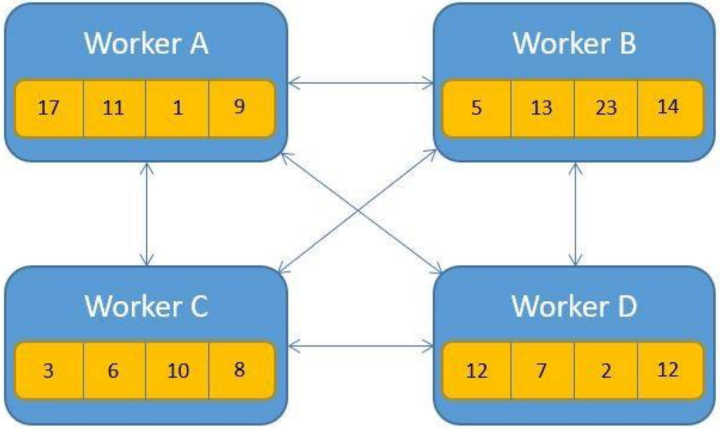
Goal: In data parallelism, it is essential to ensure that each device is updated coherently, therefore we need to aggregate(reduce) gradients across different devices.

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

- **All Reduce**
  - Naïve AllReduce
  - Ring AllReduce

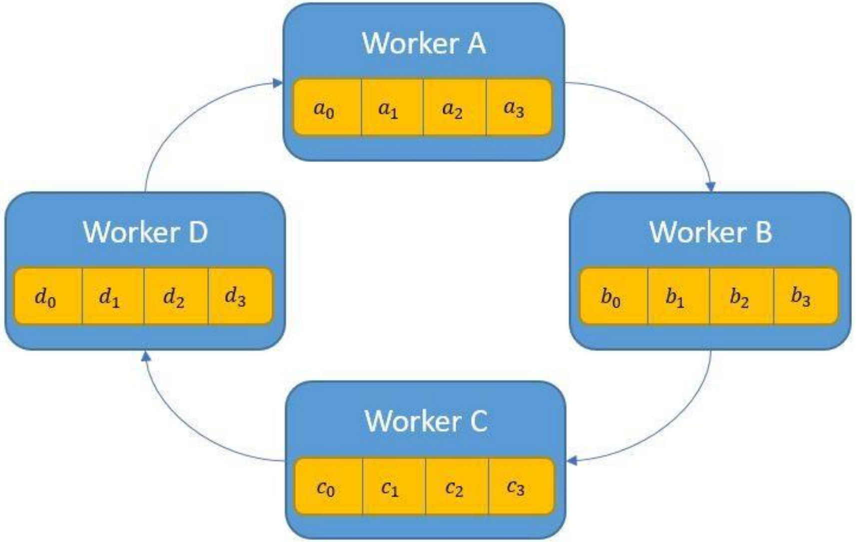
Naïve AllReduce

- 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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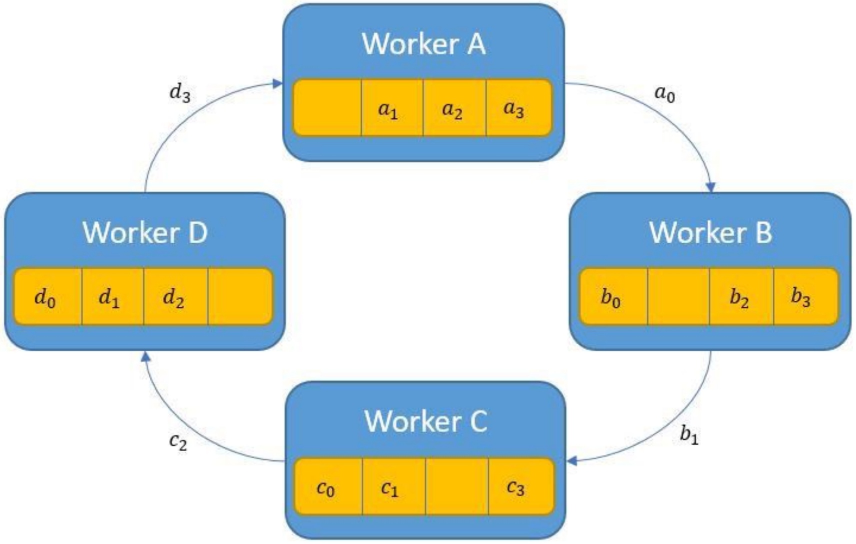

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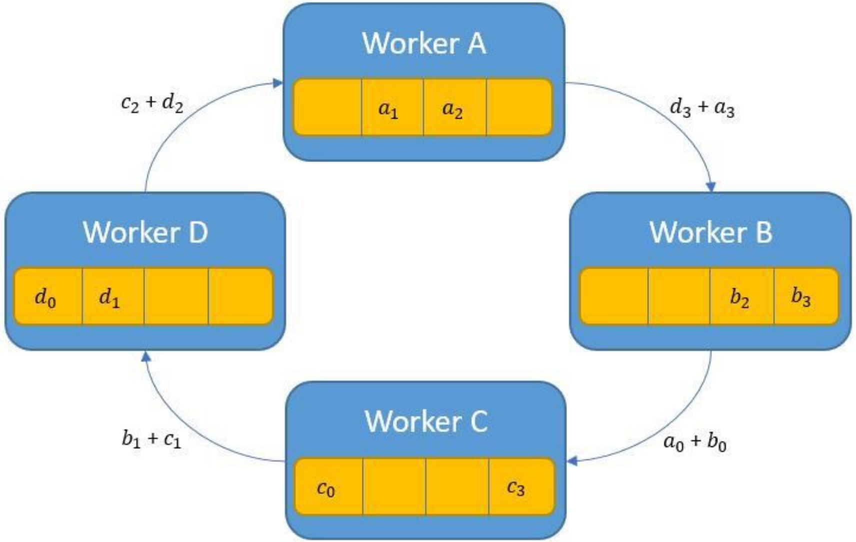

Ring AllReduce

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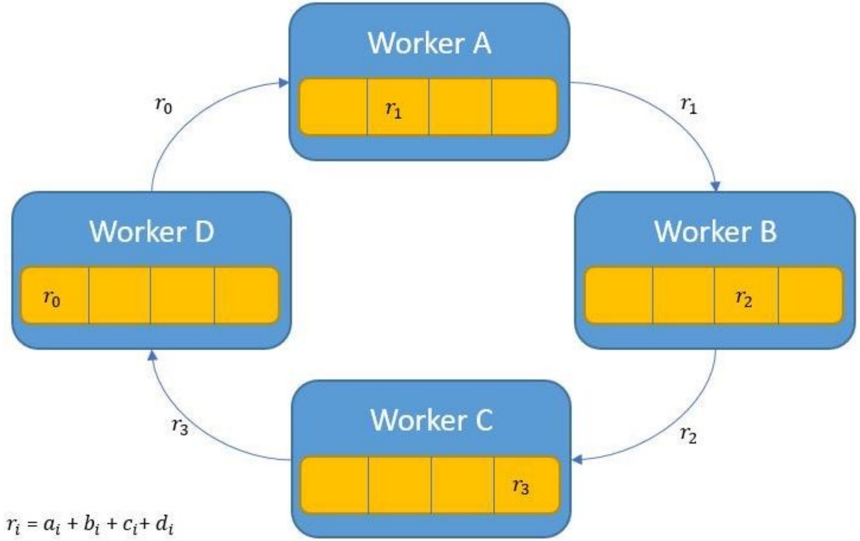
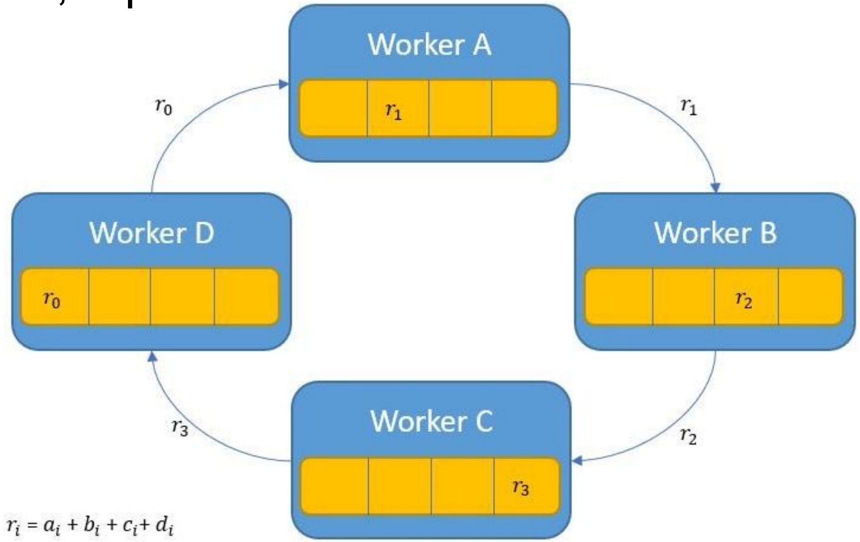
- Step 1 (Aggregation): each worker send one slice (M/N parameters) to the next worker on the ring; repeat N times
- After step 1, each worker has the aggregated version of M/N parameters



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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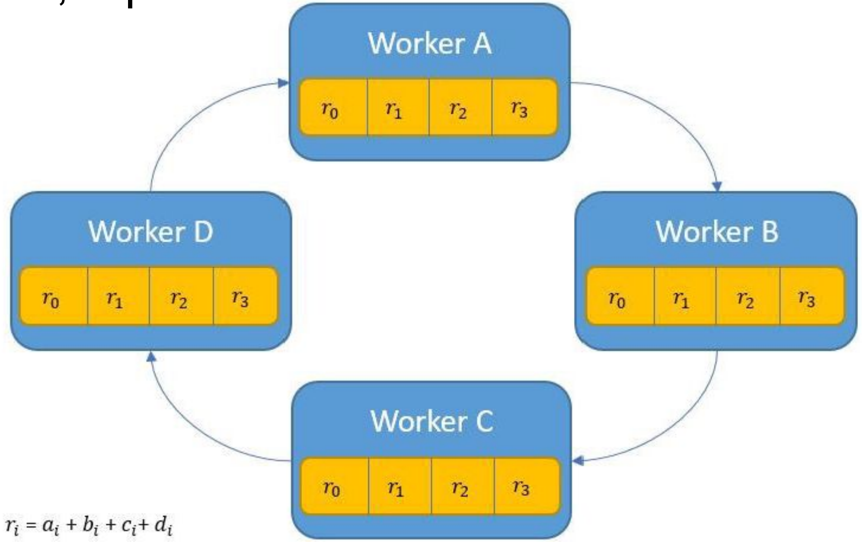

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- Overall communication: 2 * M * N parameters
    - Aggregation: M * N parameters
    - Broadcast: M * N parameters

Summary

	Pros	Cons
Model Parallelism	Good memory efficiency	Poor compute /communication efficiency (5% of peak perf in training 40B model with Megatron)
Data parallelism	Good compute/communication efficiency	Poor memory efficiency (Every device has one copy of model)

Question: How can we reduce memory footprint of DP?

Understanding Memory Consumption

The GPUs need to store

- Model weights
- Forward activation
- Backward gradient
- Optimizer state

Memory Usage

Common methods in optimization: Adam + Mixed-precision Training

- Optimizer States: Momentum + Variance
- Model: Parameters and Gradients

while θ_t not converged **do**

$t \leftarrow t + 1$

$g_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$ (Get gradients w.r.t. stochastic objective at timestep t)

$m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$ (Update biased first moment estimate)

$v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$ (Update biased second raw moment estimate)

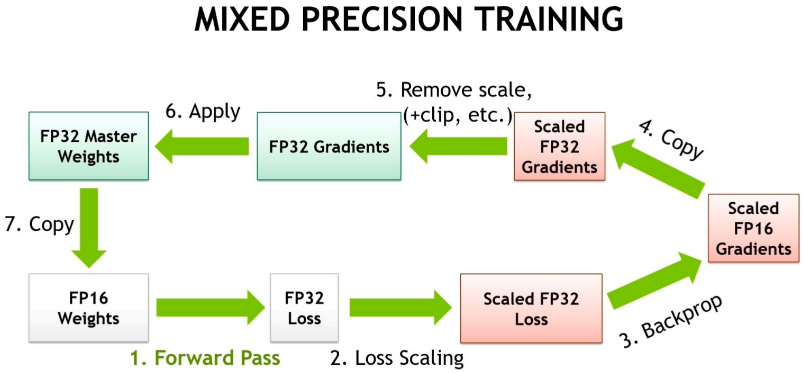
$\widehat{m}_t \leftarrow m_t / (1 - \beta_1^t)$ (Compute bias-corrected first moment estimate)

$\widehat{v}_t \leftarrow v_t / (1 - \beta_2^t)$ (Compute bias-corrected second raw moment estimate)

$\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t / (\sqrt{\widehat{v}_t} + \epsilon)$ (Update parameters)

end while

Adam Optimizer



Mixed-precision Training

Memory Usage

Example: Adam as optim, and Mixed-precision Training. N parameters

+ FP32 master parameters: 4N Bytes
+ FP32 optimizer states: 4N * 2 Bytes (Momentum and Variance)
+ FP16 model parameters: 2N Bytes
+ FP16 optimizer states: 2N Bytes (Momentum only)

16N Bytes in total !

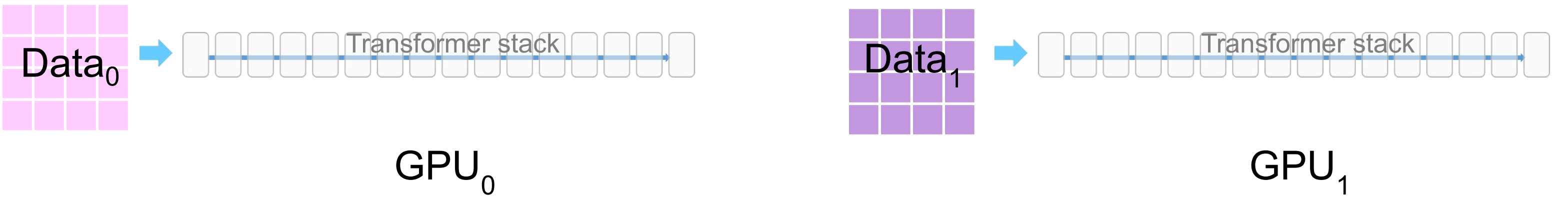
For 1.5B GPT-2, 24GB vMem

For 175B GPT-3, 2800GB vMem

Other Memory Usages

- Activations:
  - As a concrete example, the 1.5B parameter GPT-2 model trained with sequence length of 1K and batch size of 32 requires about 60 GB of memory
- Temporary Buffers:
  - Storing intermediate results. Operations such as gradient all-reduce, or gradient norm computation tend to fuse all the gradients into a single flattened buffer before applying the operation in an effort to improve throughput.
- Memory Fragmentation:
  - In extreme cases can be 30%.

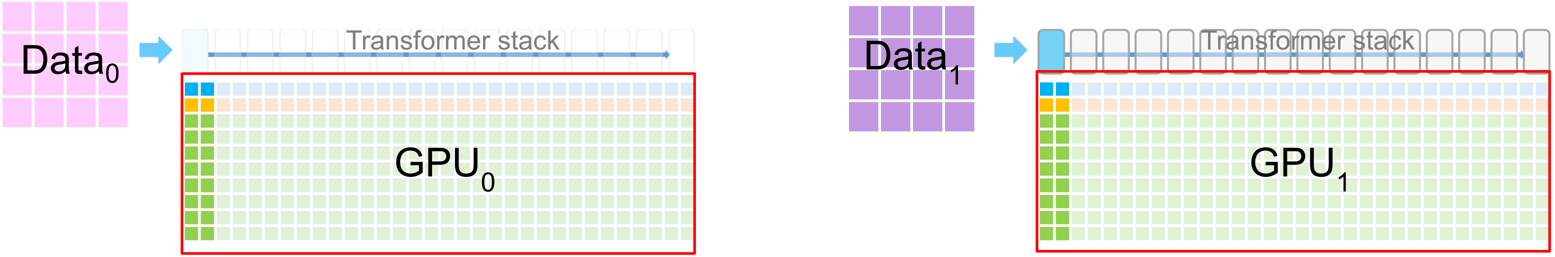
Memory Consumption



Suppose there are

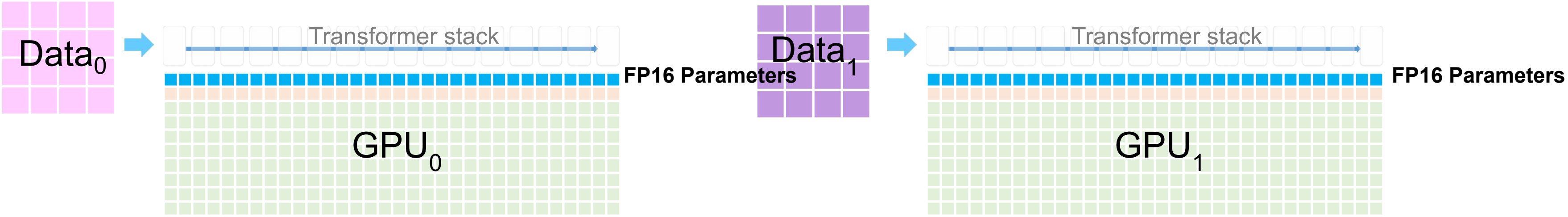
- Two data splits: $Data_0$ and $Data_1$
- Two GPUs: GPU_0 and GPU_1
- 16 layer Transformer Model

Memory Consumption



Each cell represents GPU memory used by the corresponding transformer layer

Memory Consumption



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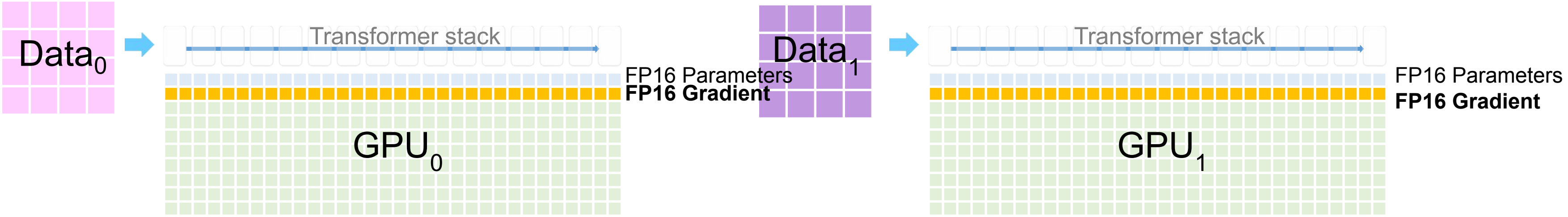
- **FP16 parameters**
- FP16 Gradients
- FP32 Optimizer States (Gradients, Variance, Momentum, Parameters)

Memory Consumption



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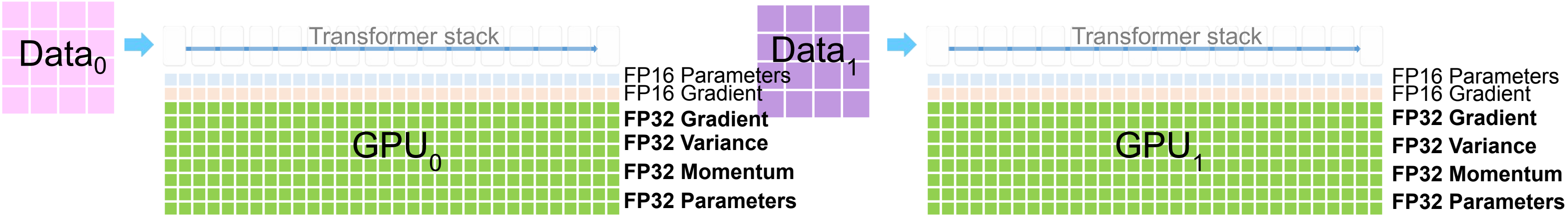

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Common Approaches to Reduce Memory

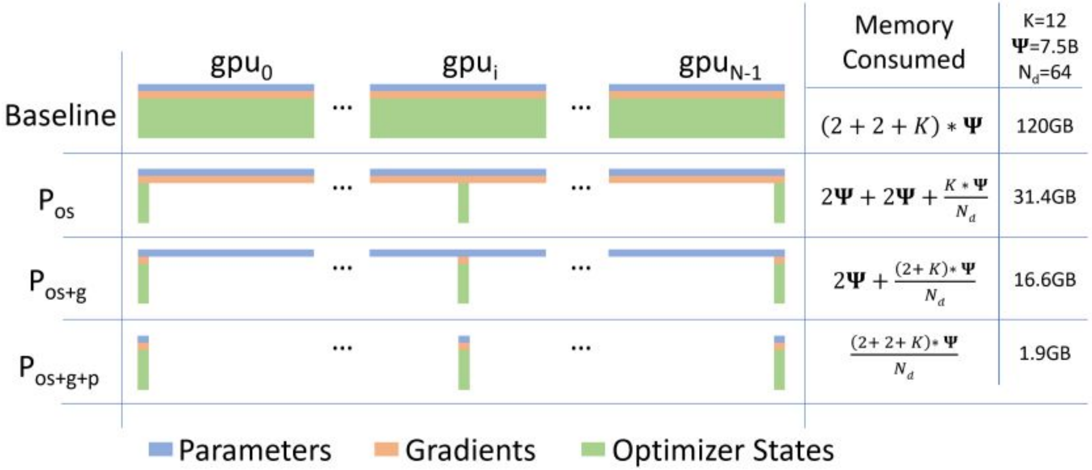
- Reducing Activation Memory
  - Activation Checkpoint, Compression
  - All Work in parallel with ZeRO
- CPU Offload
  - Requires CPU-GPU-CPU transfer, which can take 50% time
- Memory Efficient Optimizer
  - Maintaining coarser-grained statistics of model parameters and gradients.
  - Works in parallel with ZeRO

ZeRO - Zero Redundancy Optimizer

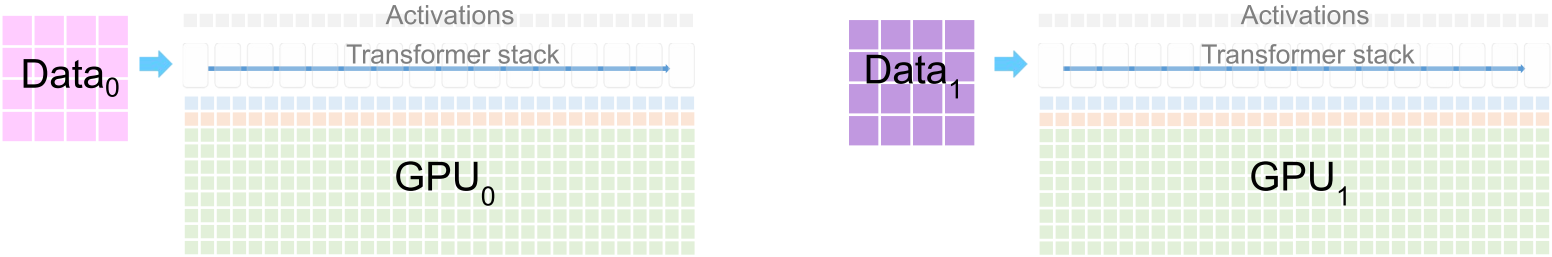
Work done by Microsoft, implemented in Deepspeed.

Features:

+ Eliminating data redundancy in **data parallel training**
+ Can be widely used in large language model training.



ZeRO Stage 1: Partitioning Optimizer States

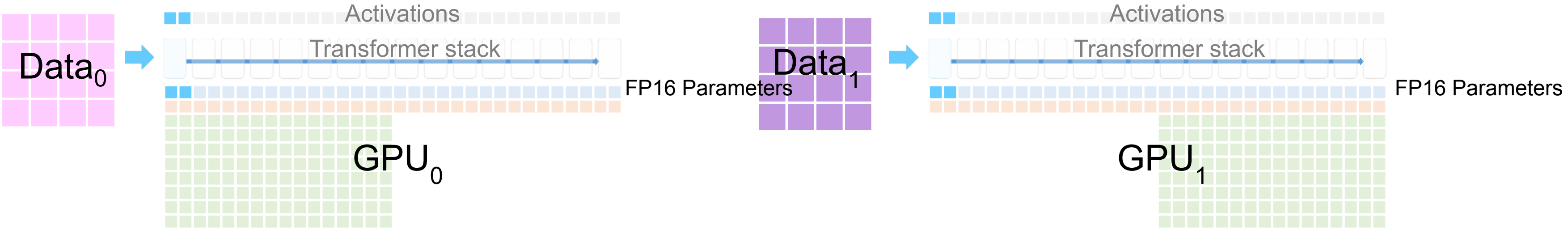


Question: How can we partition optimizer states?

ZeRO Stage 1: Partitioning Optimizer States

- **forward pass to produce activations and loss (by fp16 parameters)**

ZeRO Stage 1: Partitioning Optimizer States



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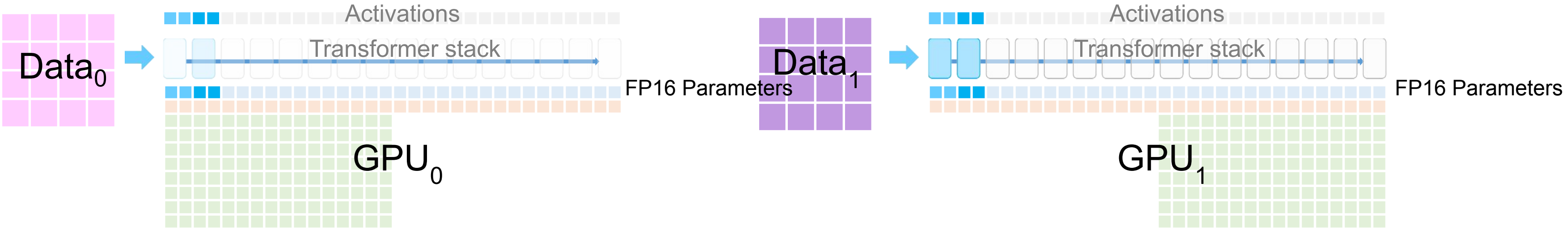

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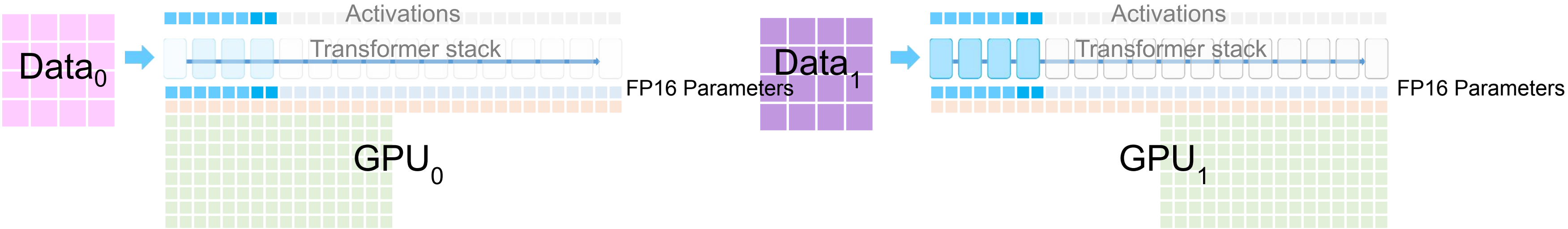

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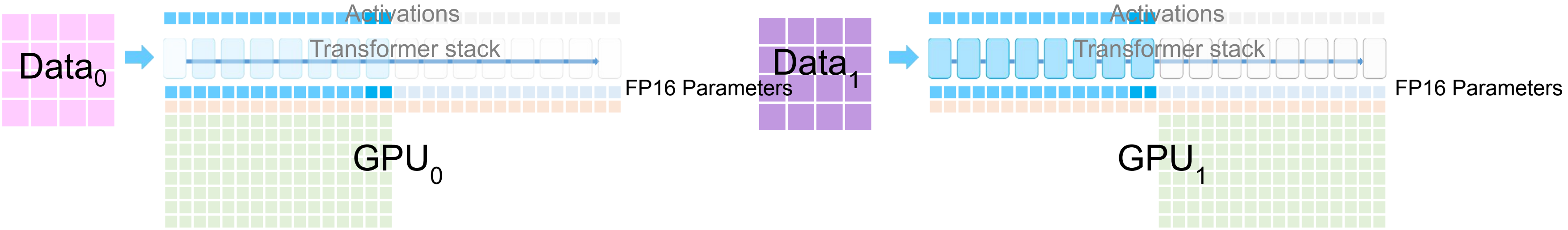

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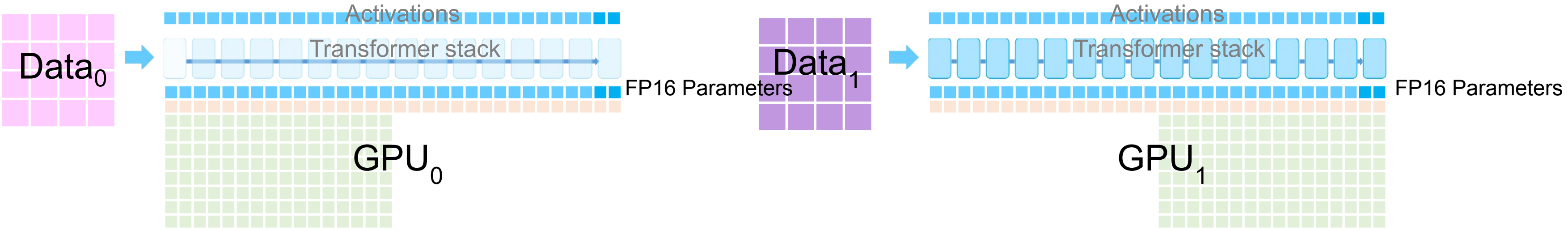

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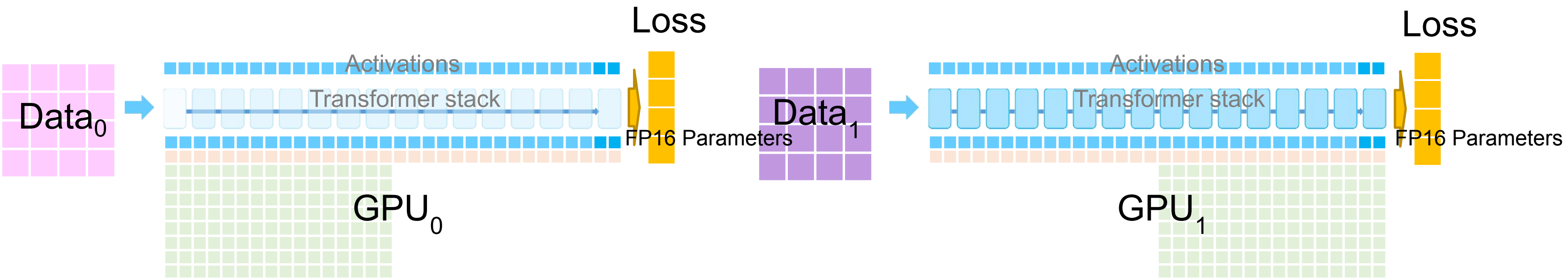

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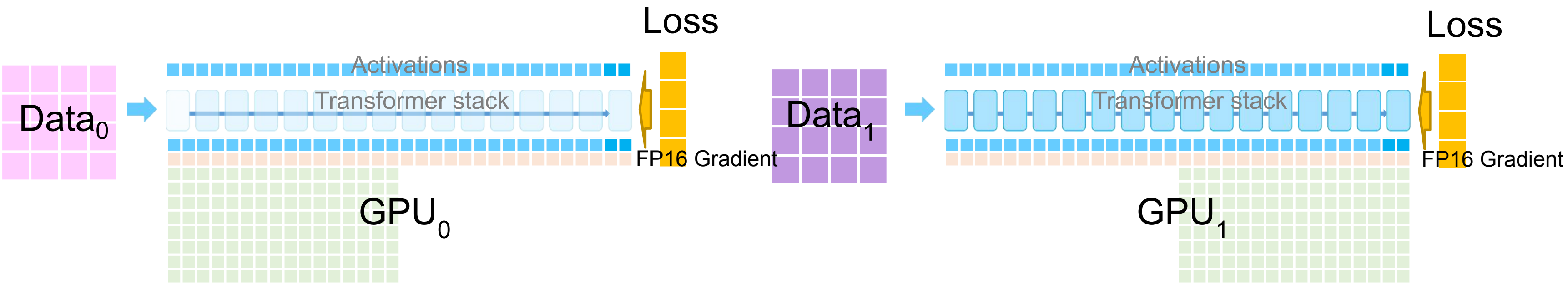
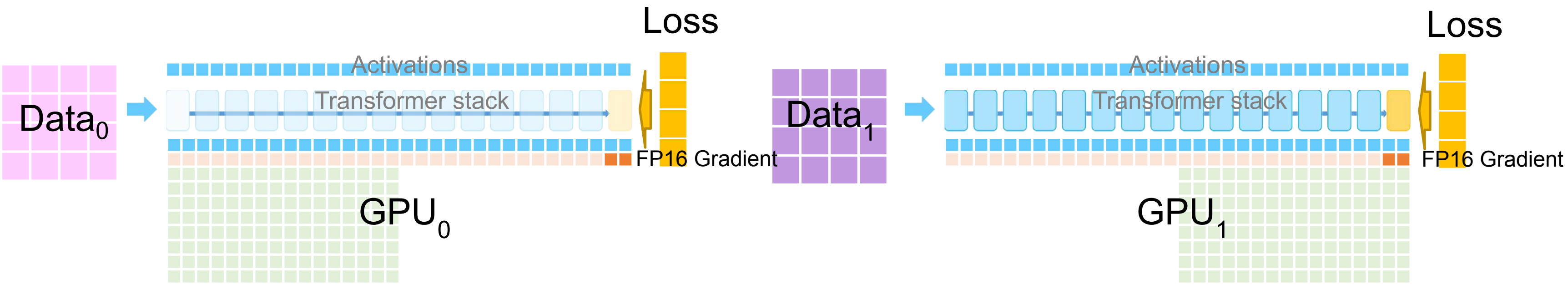


- **loss backward to calculate fp16 gradients**

ZeRO Stage 1: Partitioning Optimizer States



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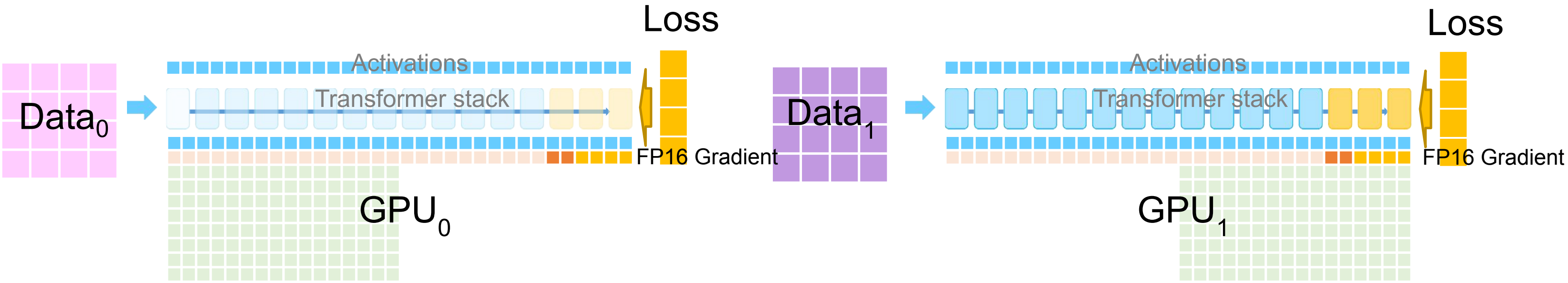

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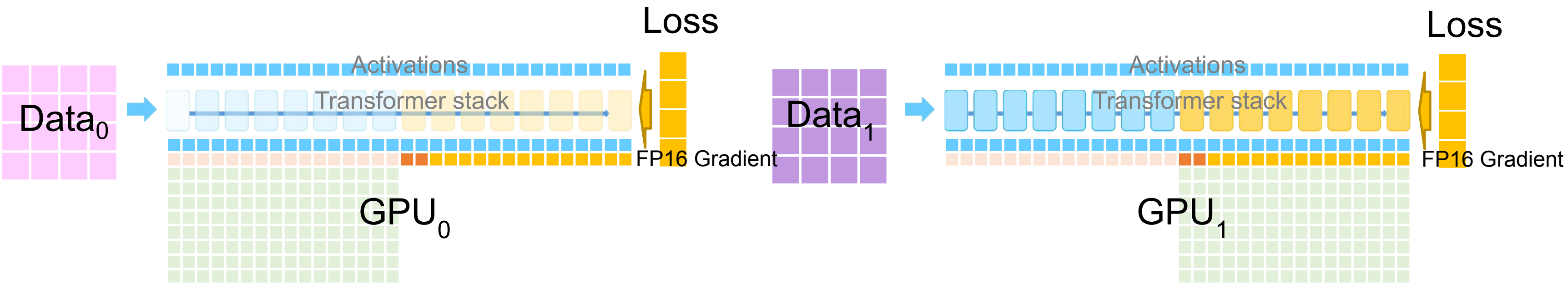

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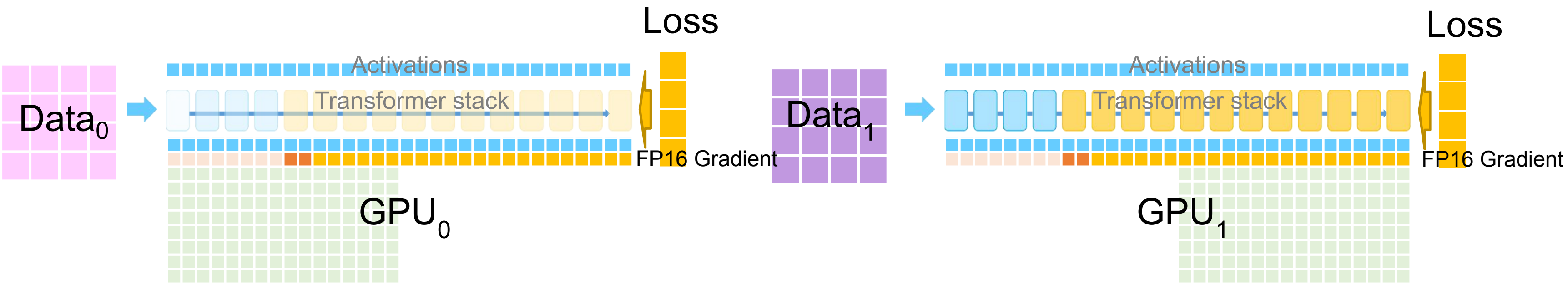

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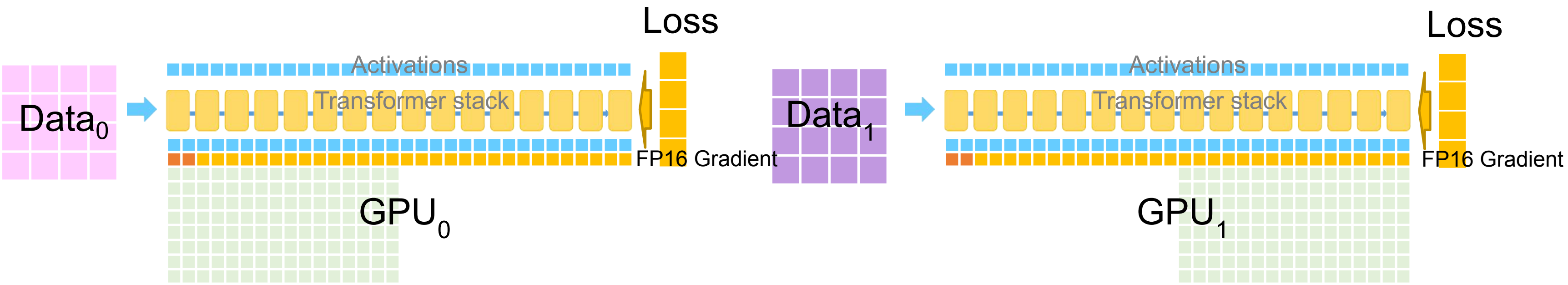

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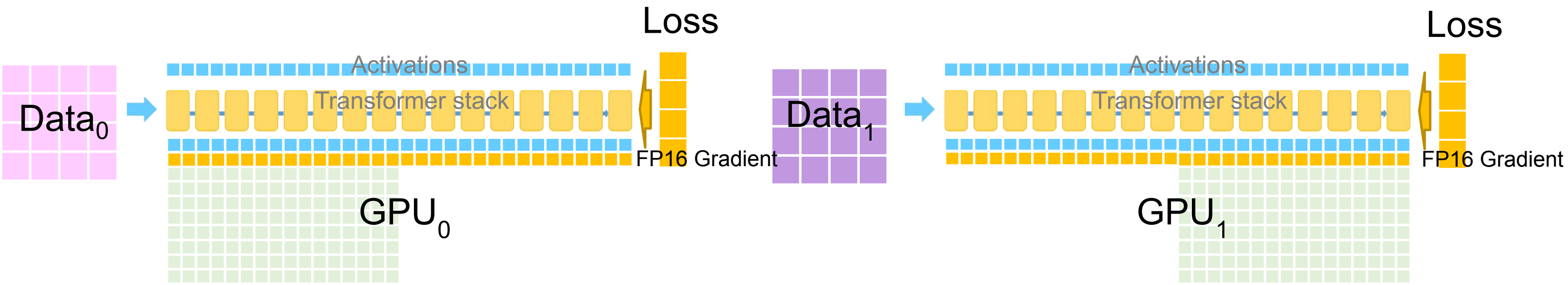

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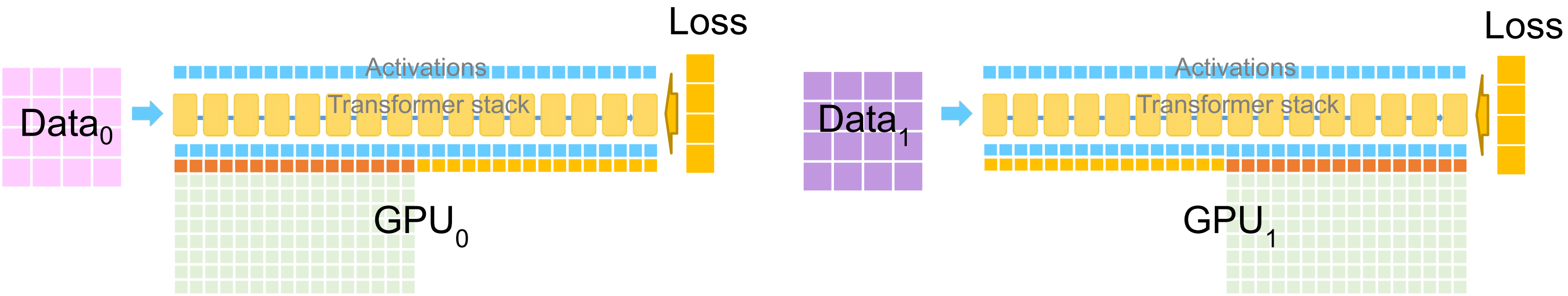
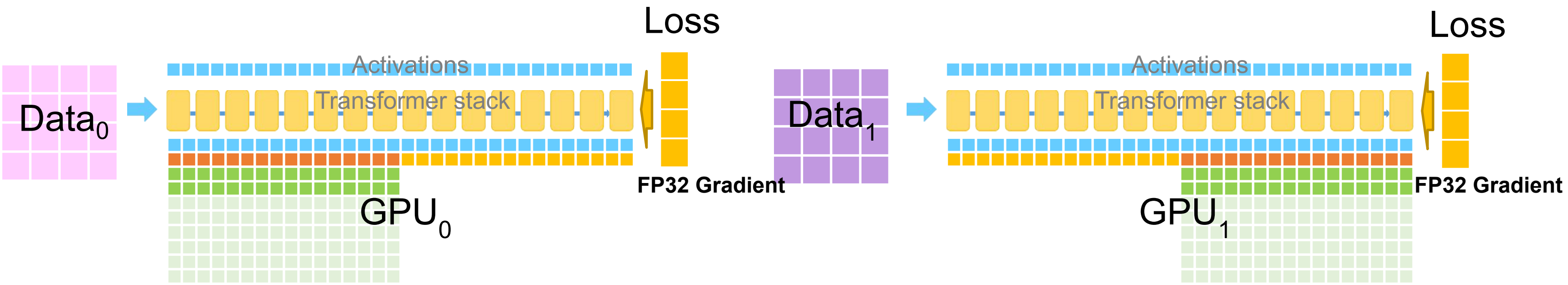


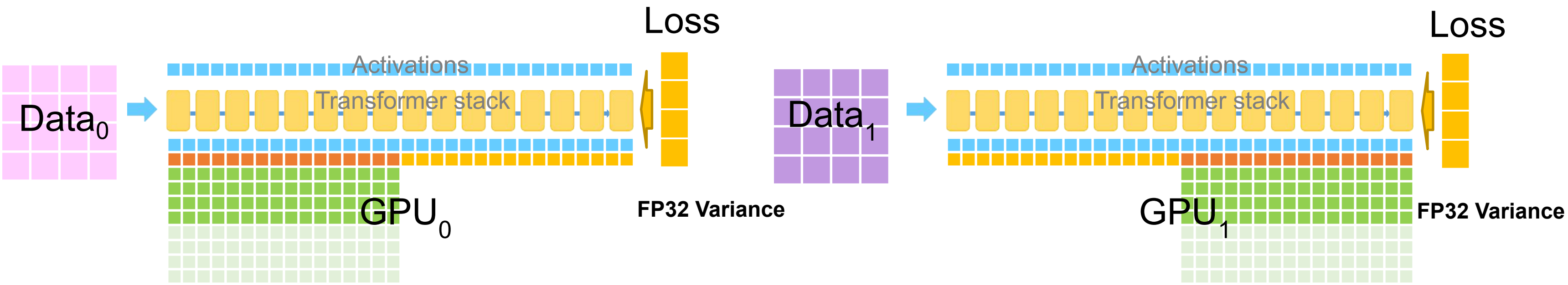
- **gradient gathering from another GPU and average gradient calculation**

ZeRO Stage 1: Partitioning Optimizer States



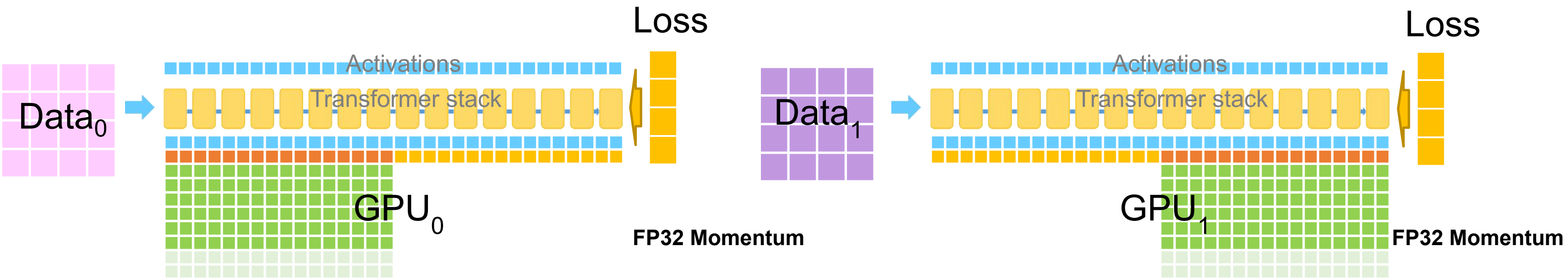
- **fp32 gradient update**

ZeRO Stage 1: Partitioning Optimizer States



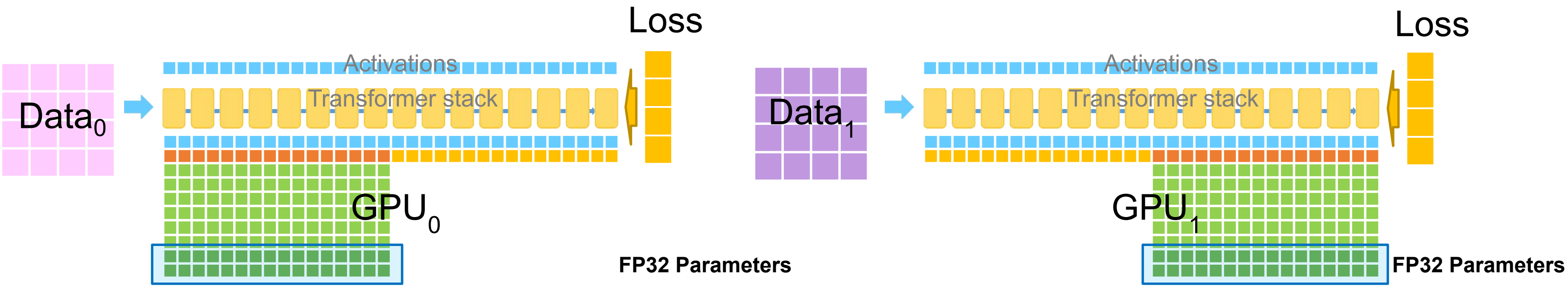
- **fp32 variance update**

ZeRO Stage 1: Partitioning Optimizer States



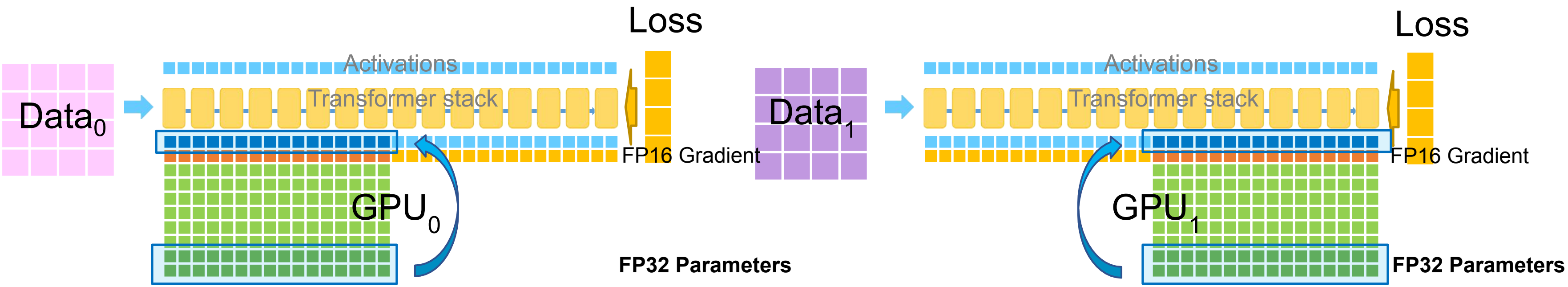
- **fp32 momentum update**

ZeRO Stage 1: Partitioning Optimizer States



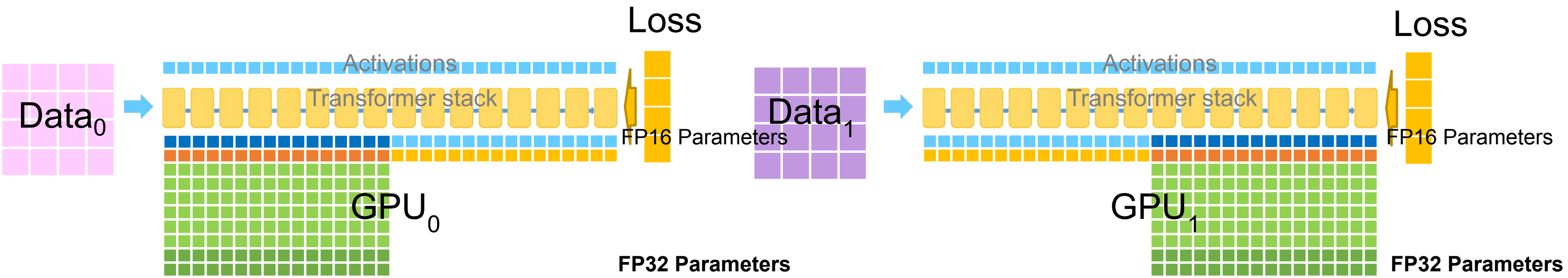
- **fp32 parameters update**

ZeRO Stage 1: Partitioning Optimizer States



- **fp32 parameters update using fp16 gradient**

ZeRO Stage 1: Partitioning Optimizer States



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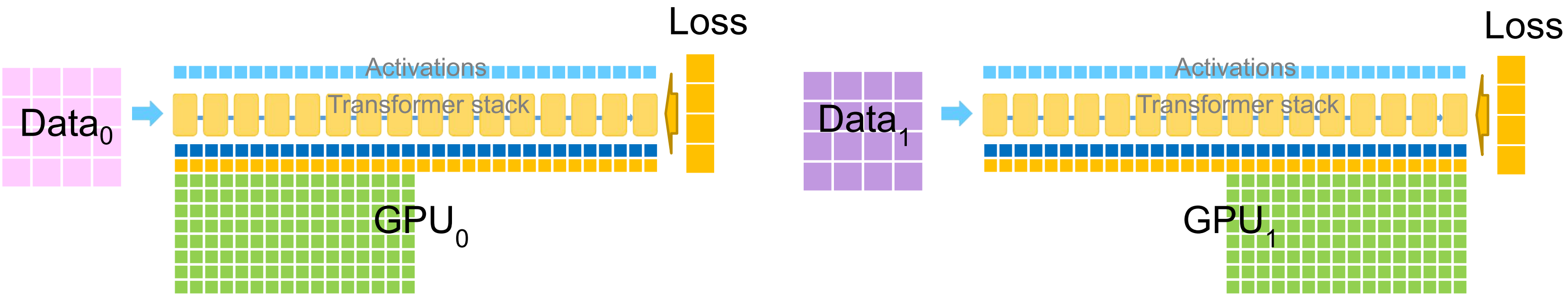


- **all gather the gp16 weights to complete the iteration**

ZeRO Stage 2: Partition Gradients

Key idea:

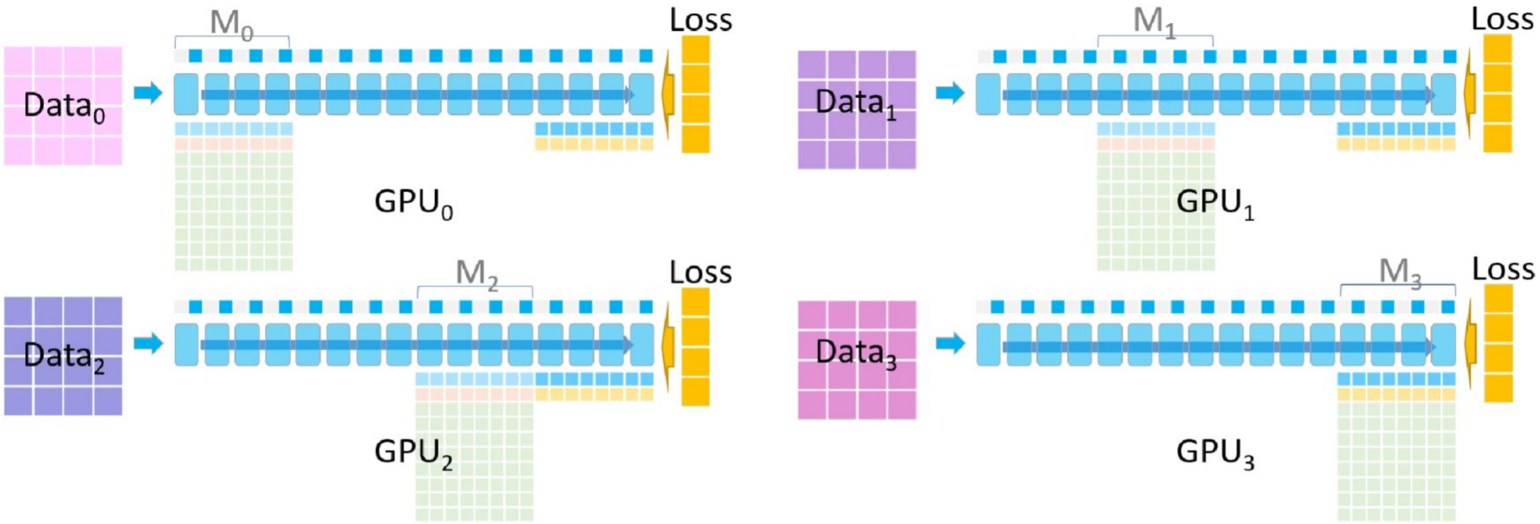
- Each GPU is only responsible for one partition of the parameters, so it should also only be responsible for one partition of gradients that are corresponding to their designated parameters.

- But different GPUs are responsible for different data, meaning we still need to run all GPUs for all gradients.

- Therefore, during backward pass, a GPU can immediately delete the gradients that it’s not responsible for, after it passes those gradients(computed with its data) to the GPU responsible for those gradients.

- The result is each GPU can hold less memory for gradients(linear to # of GPUs)

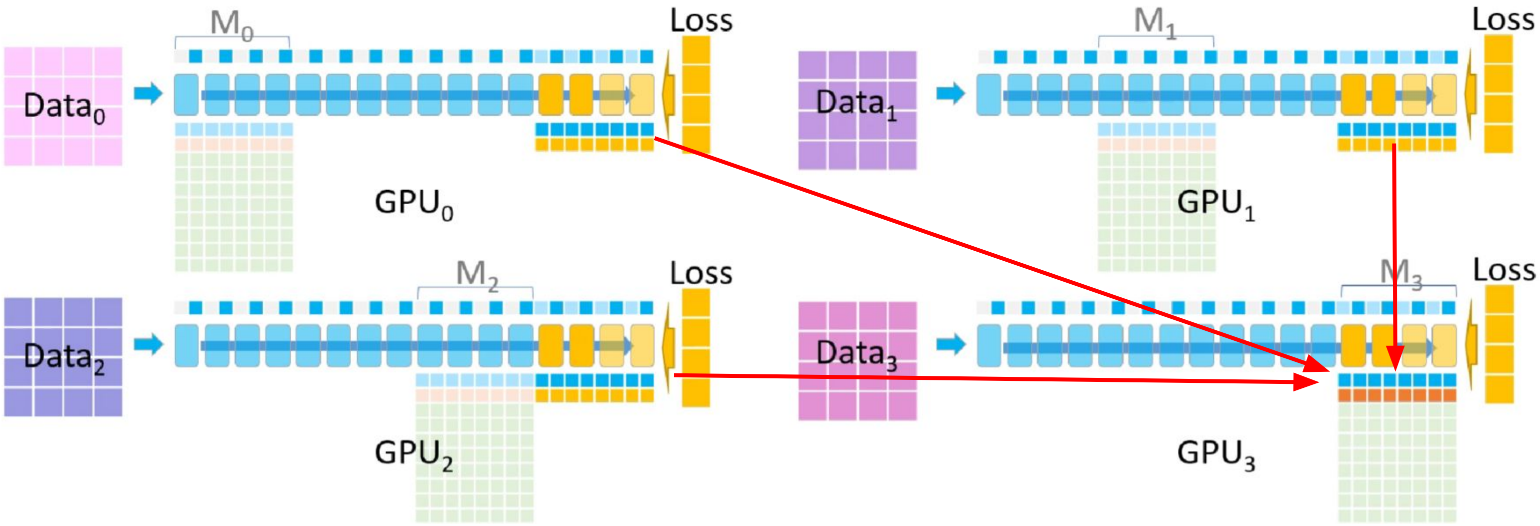
ZeRO Stage 2: Partition Gradients



The backward pass starts

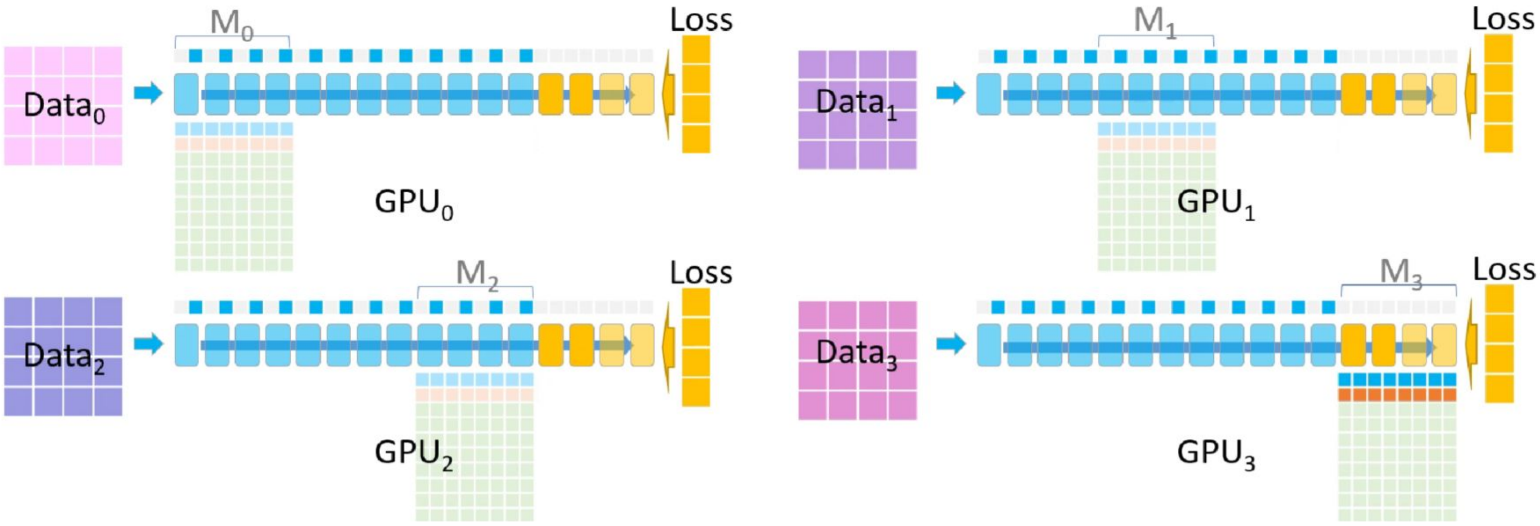
GPU 0,1,2 hold temporary buffers for the gradients that GPU 3 is responsible for (M3)

ZeRO Stage 2: Partition Gradients



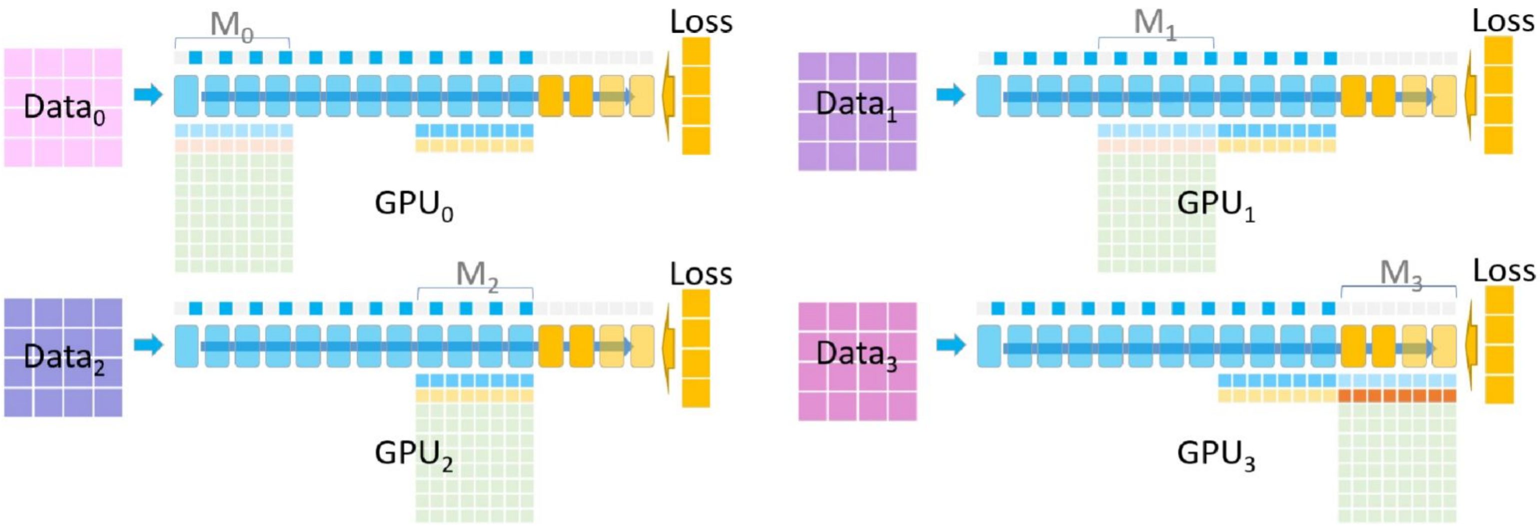
GPU 0,1,2 pass the M3 gradients to GPU 3

ZeRO Stage 2: Partition Gradients



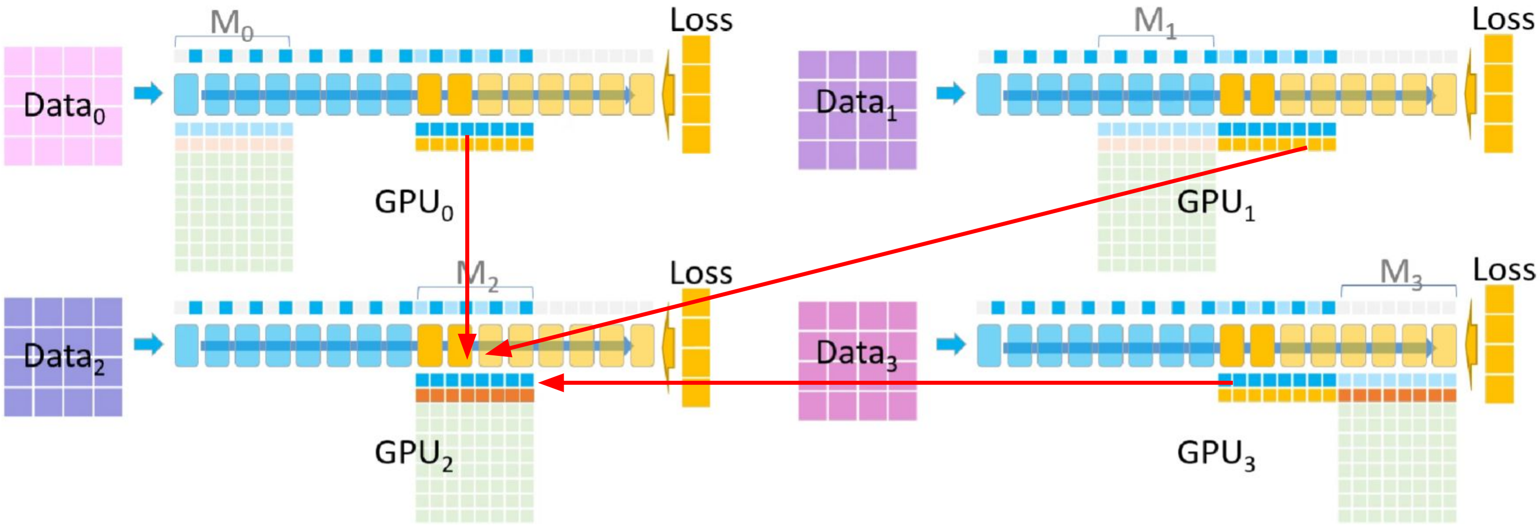
Then they delete M3 gradients, GPU 3 will keep M3 gradients.

ZeRO Stage 2: Partition Gradients



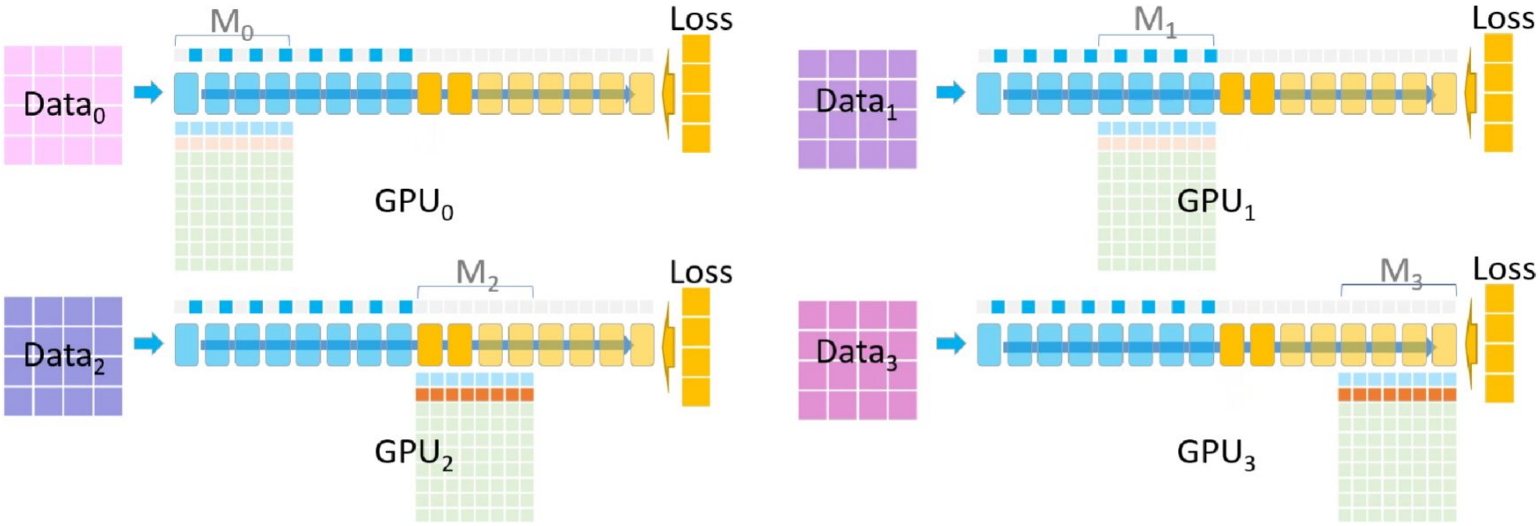
GPU 0,2,3 hold temporary buffers for the gradients that GPU 2 is responsible for (M2)

ZeRO Stage 2: Partition Gradients



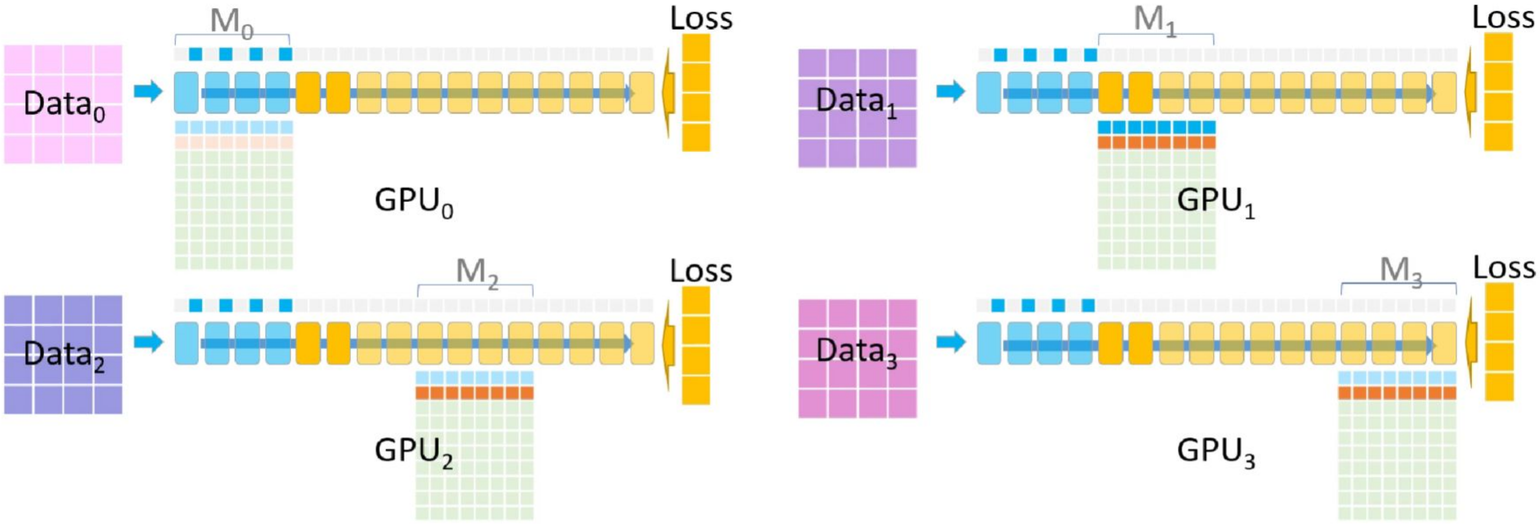
GPU 0,2,3 pass the M2 gradients to GPU 2

ZeRO Stage 2: Partition Gradients



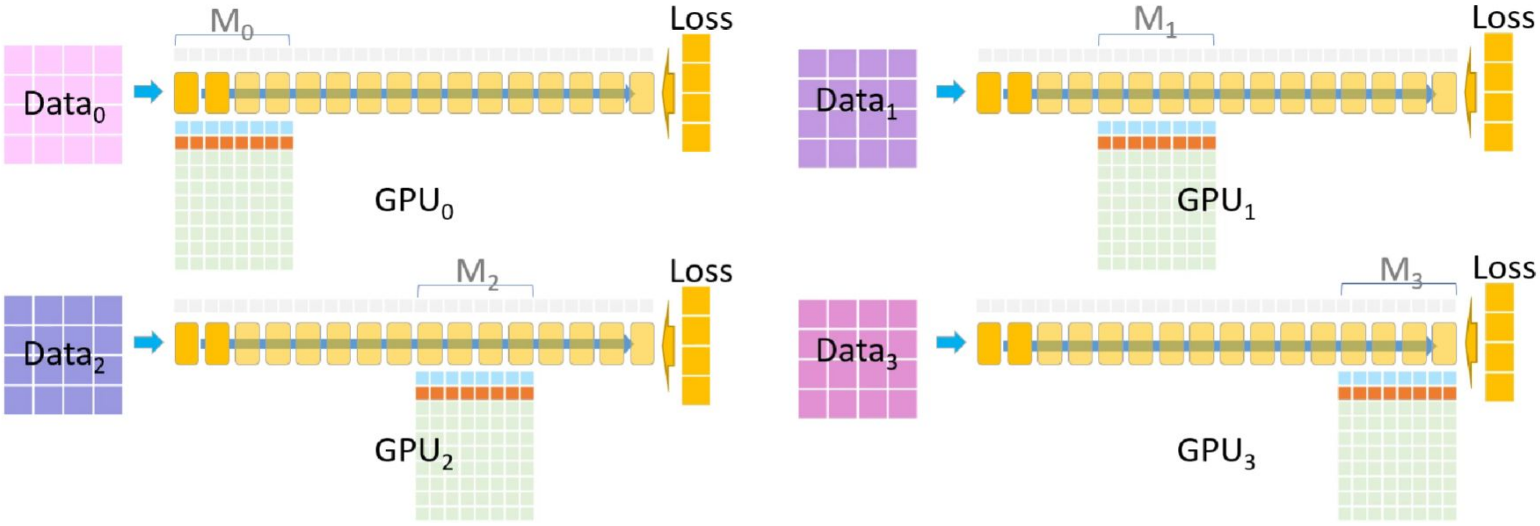
Then they delete M2 gradients, GPU 2 will keep M2 gradients.

ZeRO Stage 2: Partition Gradients



Same thing for GPU1/M1

ZeRO Stage 2: Partition Gradients



Same thing for GPU0/M0

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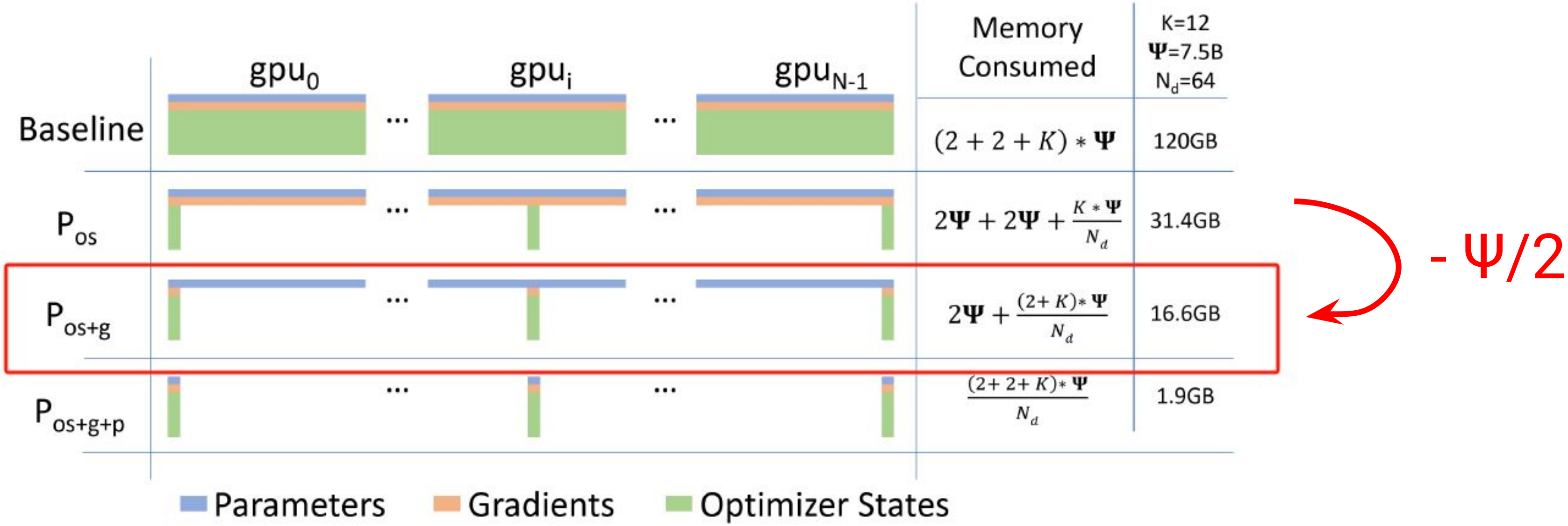


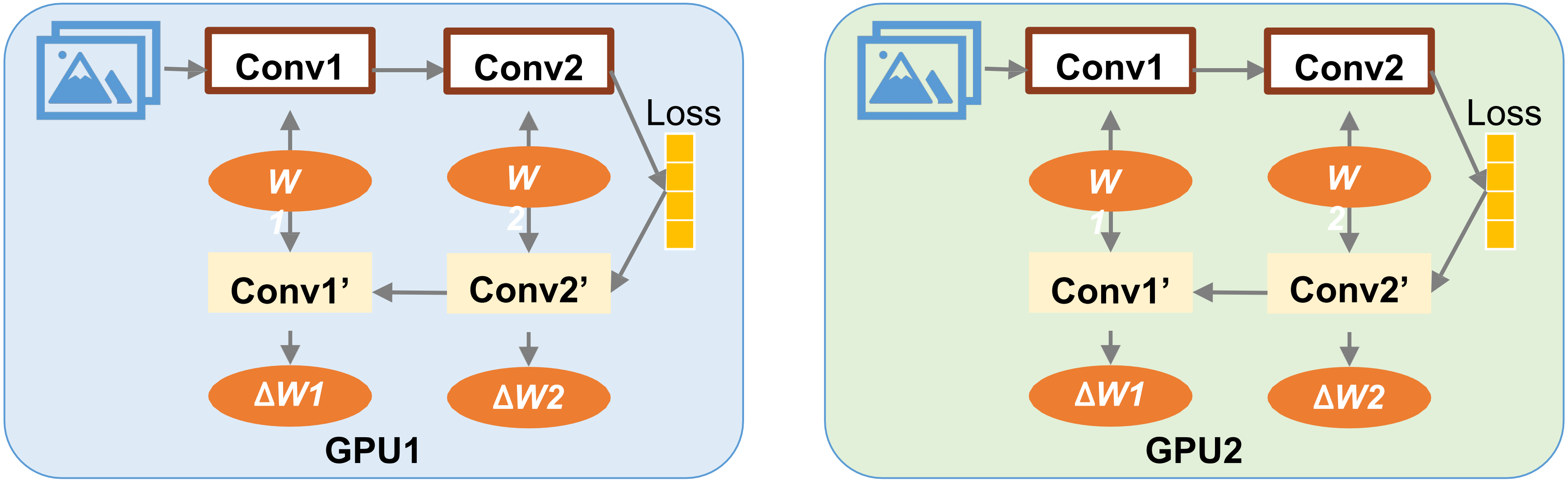
ZeRO Stage 2: Partition Gradients

DP	7.5B Model (GB)			128B Model (GB)			1T Model (GB)		
	P_{os}	P_{os+g}	P_{os+g+p}	P_{os}	P_{os+g}	P_{os+g+p}	P_{os}	P_{os+g}	P_{os+g+p}
1	120	120	120	2048	2048	2048	16000	16000	16000
4	52.5	41.3	**30**	896	704	512	7000	5500	4000
16	35.6	**21.6**	7.5	608	368	128	4750	2875	1000
64	**31.4**	16.6	1.88	536	284	**32**	4187	2218	250
256	30.4	15.4	0.47	518	263	8	4046	2054	62.5
1024	30.1	15.1	0.12	513	257	2	4011	2013	**15.6**

Looks pretty good!

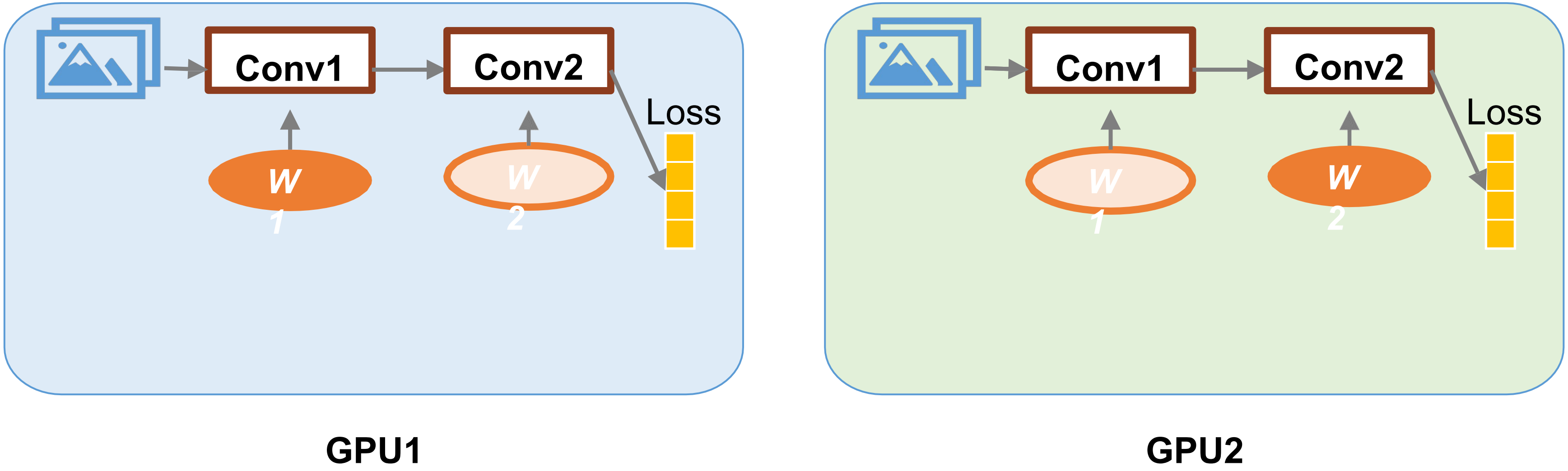
ZeRO Stage 3: Partitioning Parameters

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



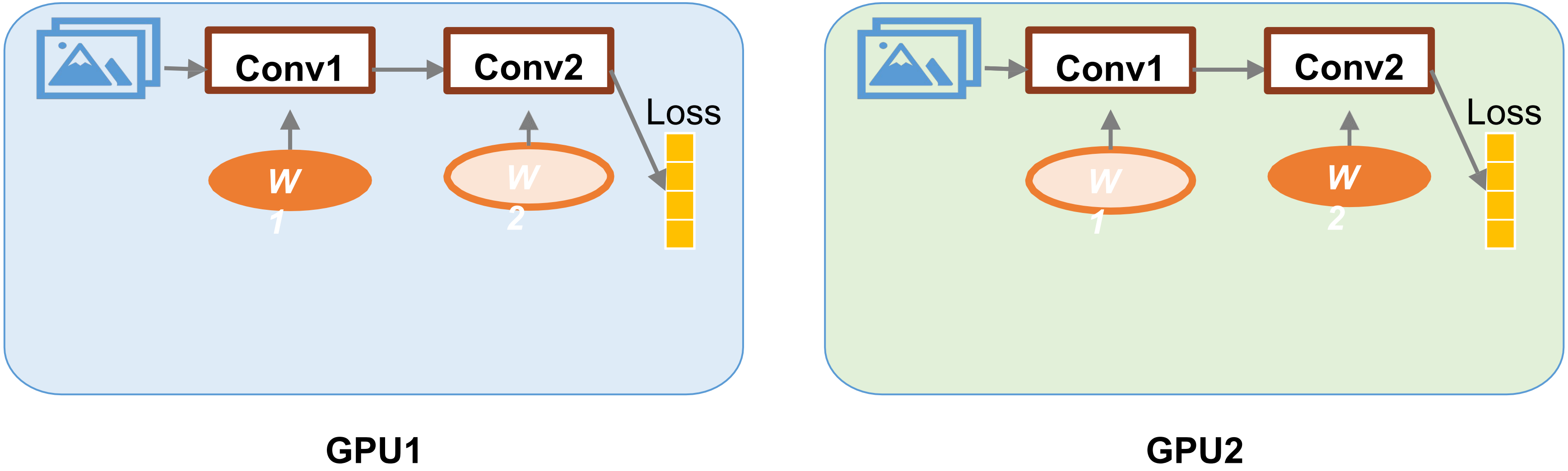
ZeRO Stage 3: Partitioning Parameters

- In ZeRO, model parameters are partitioned across GPUs



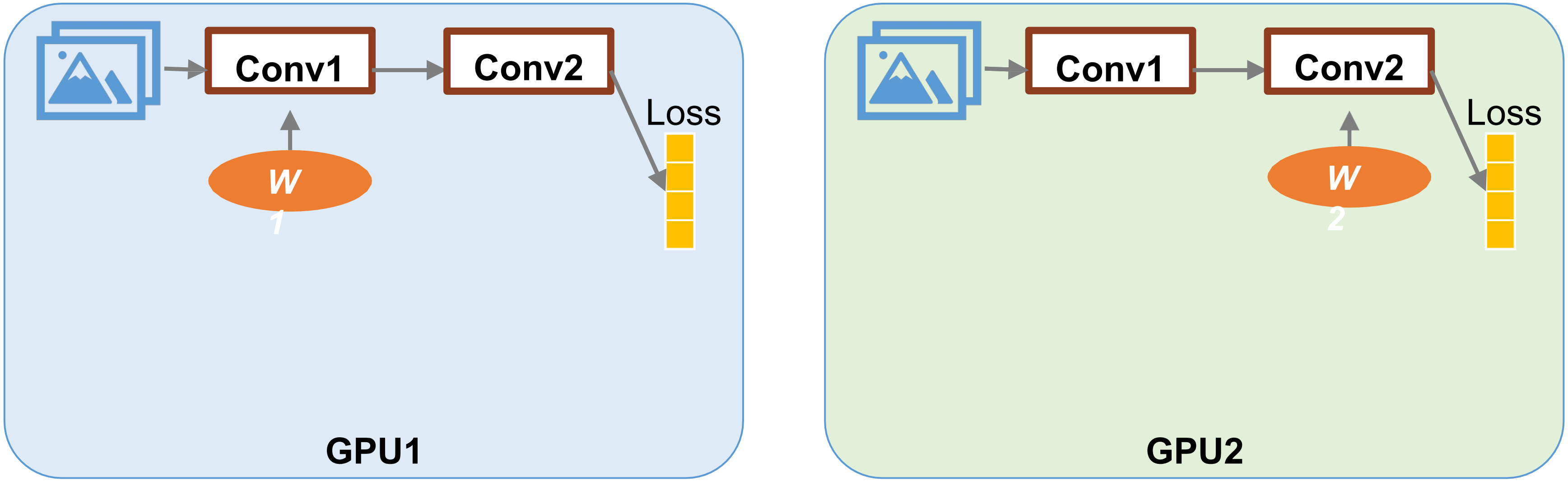
ZeRO Stage 3: Partitioning Parameters

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



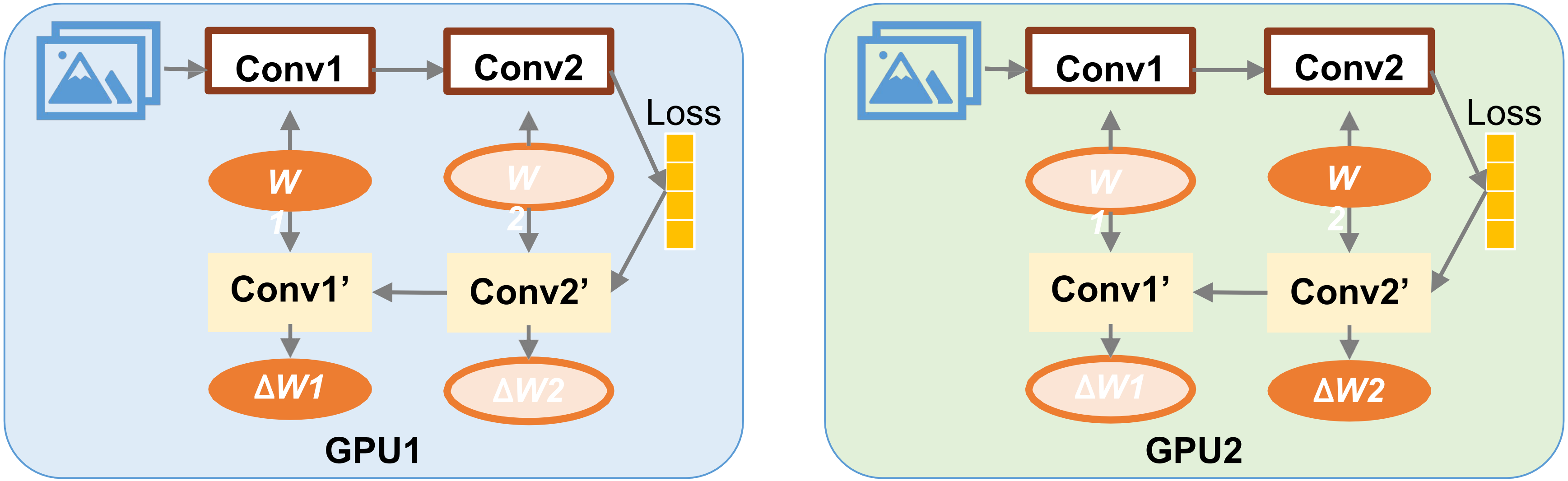
ZeRO Stage 3: Partitioning Parameters

- 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-DP Summary

- Zero-DP stage 1 and 2 (optimizer state and gradient) doesn’t additional communication, while enabling up to 8x memory reduction
- Zero-DP stage 3 (parameter) incurs a maximum of 1.5x communication

ZeRO - R

1. Partitioned Activation Checkpointing
   - Split every activation to different devices. Gather them when needed.
2. Constant Size Buffers
   - Buffer is used in doing all-reduce to improve bandwidth.
   - Modern implementations fuses all the parameters into a single buffer.
   - ZeRO uses constant size buffers to be more efficient for a large model.
3. Memory Defragmentation
   - Long-lived memory (Model parameters, Optimizer state): Store together
   - Short-lived memory (Discarded activations)

Results

Theoretical: On a 32GB V100 clusters (Up to 1024 V100),

1. Enable the training of a model with 1 Trillion (1000B) parameters using 1024 V100.
2. There is no limit to the number of GPUs. (So probably more)

DP	7.5B Model (GB)			128B Model (GB)			1T Model (GB)		
	P_{os}	P_{os+g}	P_{os+g+p}	P_{os}	P_{os+g}	P_{os+g+p}	P_{os}	P_{os+g}	P_{os+g+p}
1	120	120	120	2048	2048	2048	16000	16000	16000
4	52.5	41.3	**30**	896	704	512	7000	5500	4000
16	35.6	**21.6**	7.5	608	368	128	4750	2875	1000
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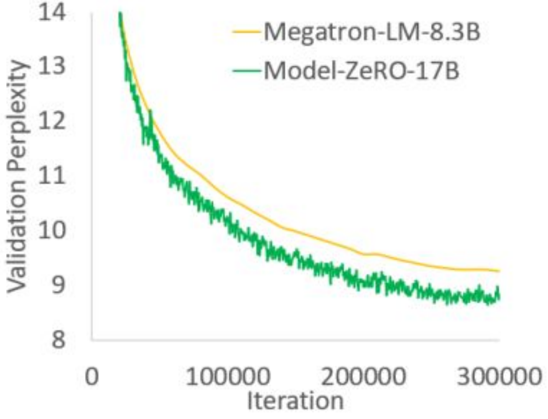
1024	30.1	15.1	0.12	513	257	2	4011	2013	**15.6**

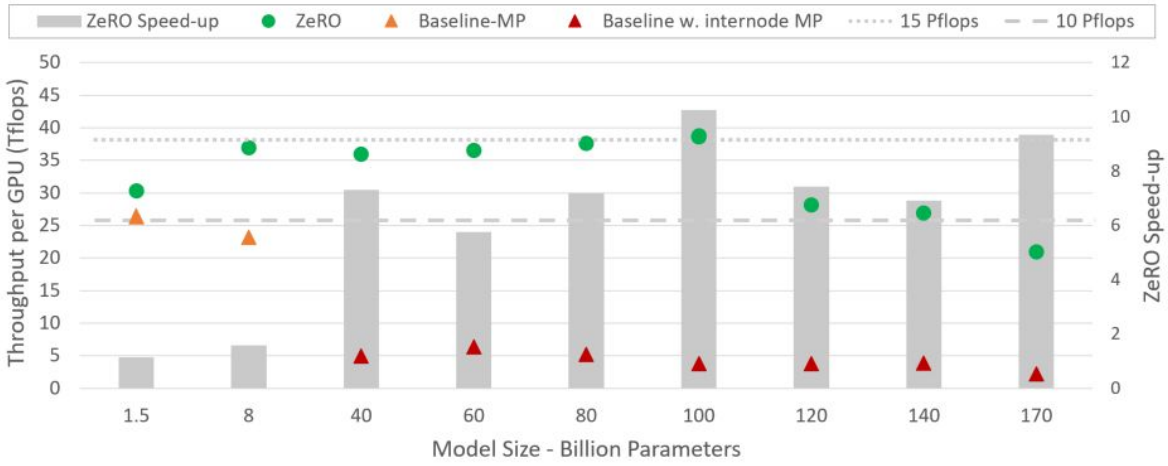
Per-device memory consumption of different optimizations

Results

Practical:

1. Train a 17B model (Turing-NLG. The largest as of 2020.1) and has SOTA perplexity in Webtext-103.
2. Train a 100B model on 400 GPUs, achieving high throughput over baseline (~10x, 30% of the theoretical peak).





Summarization

1. ZeRO is a distributed learning framework with data parallelization.
2. ZeRO partitions model states across devices.
3. ZeRO trains a new SOTA model with 17B models in 2019.