15-442/15-642: Machine Learning Systems

Memory Optimizations

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Outline

Activation Checkpointing and Rematerialization

Mixed Precision

Fully Sharded Data Parallelism

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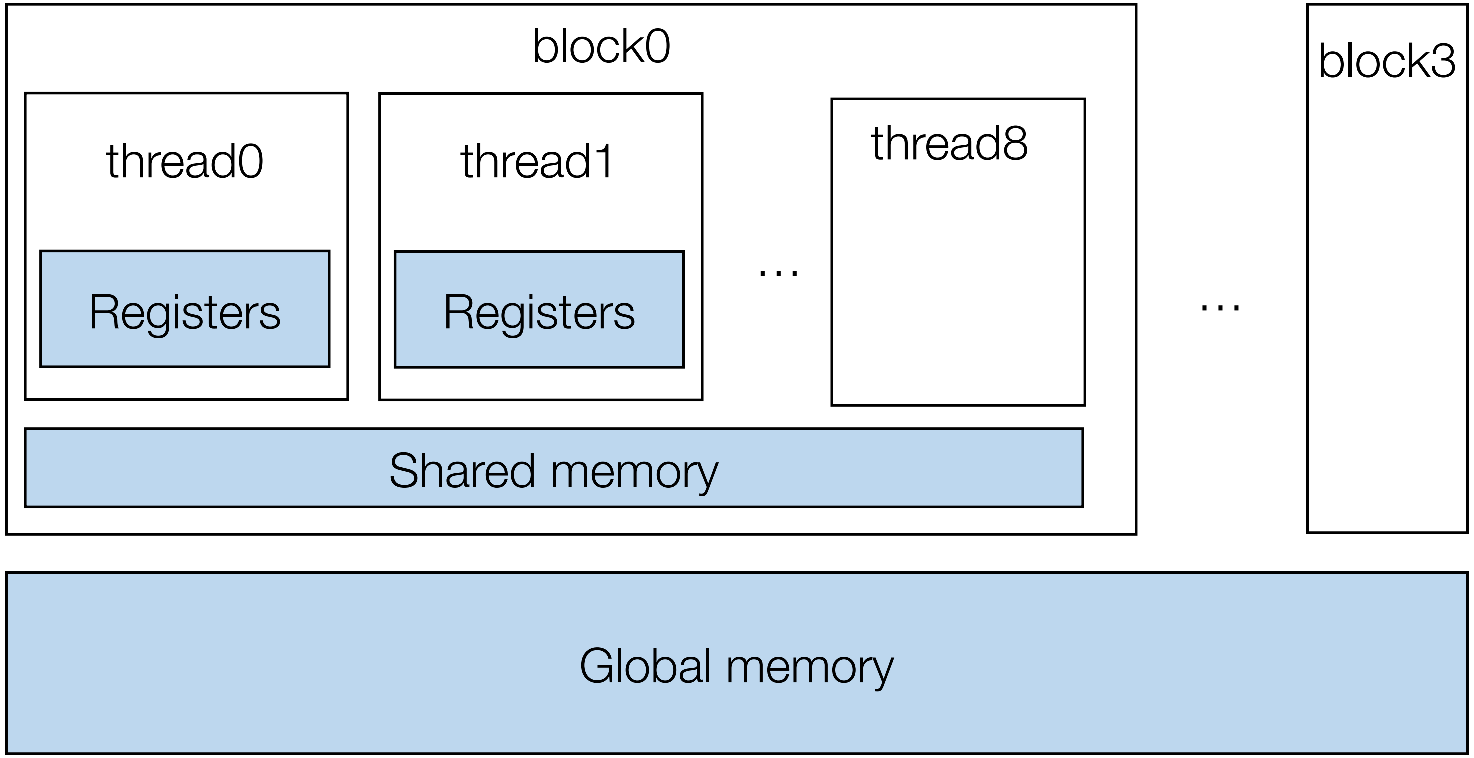
Recap: GPU memory hierarchy



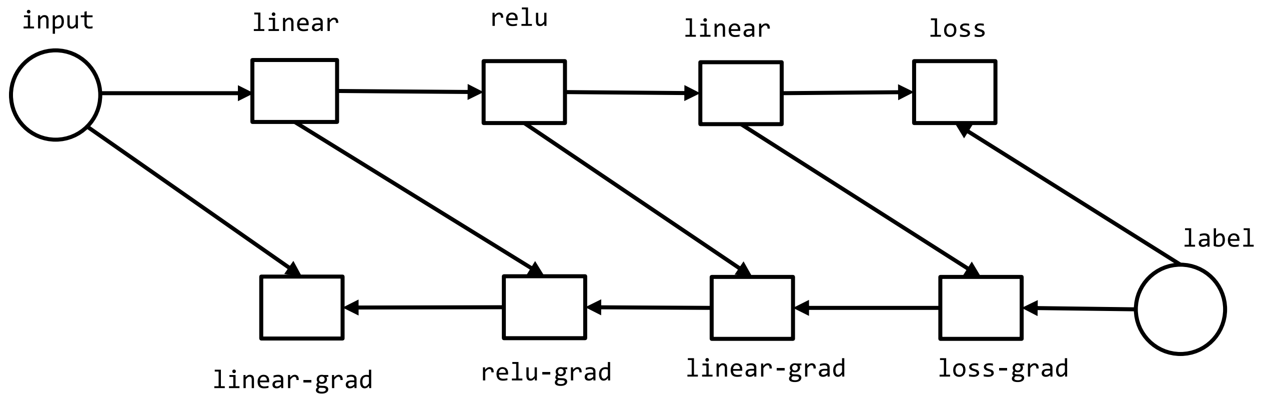
Shared memory: 64 KB per core

GPU memory(Global memory):

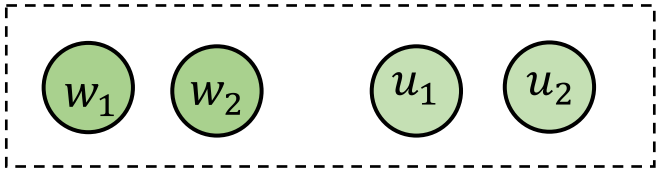
RTX3080	10GB
RTX3090	24GB
A100	40/80 GB

Sources of memory consumption

A simplified view of a typical computational graph for training, weights are omitted and implied in the grad steps.



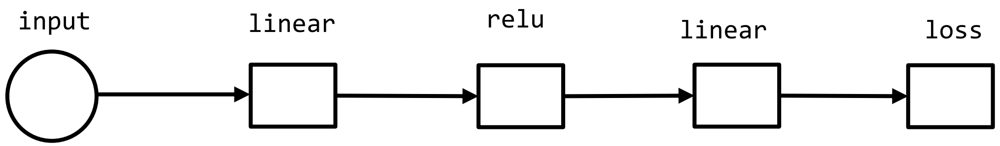
Optimizer states



Sources of memory consumption

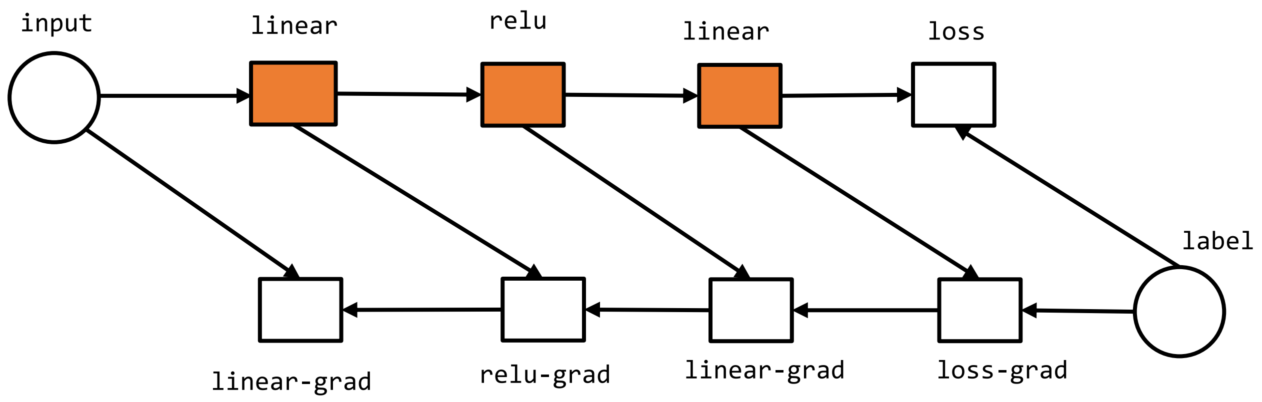
- Model weights
- Optimizer states
- Intermediate activation values

Techniques for Memory Saving, Inference Only



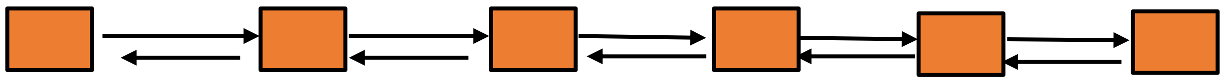
We only need O(1) memory for computing the final output of a N layer deep network by cycling through two buffers

Activation Memory Cost for Training



Because the need to keep intermediate value around (checkpoint) for the gradient steps. Training a N-layer neural network would require $O(N)$ memory.

We will use the following simplified view to combine gradient and forward computation

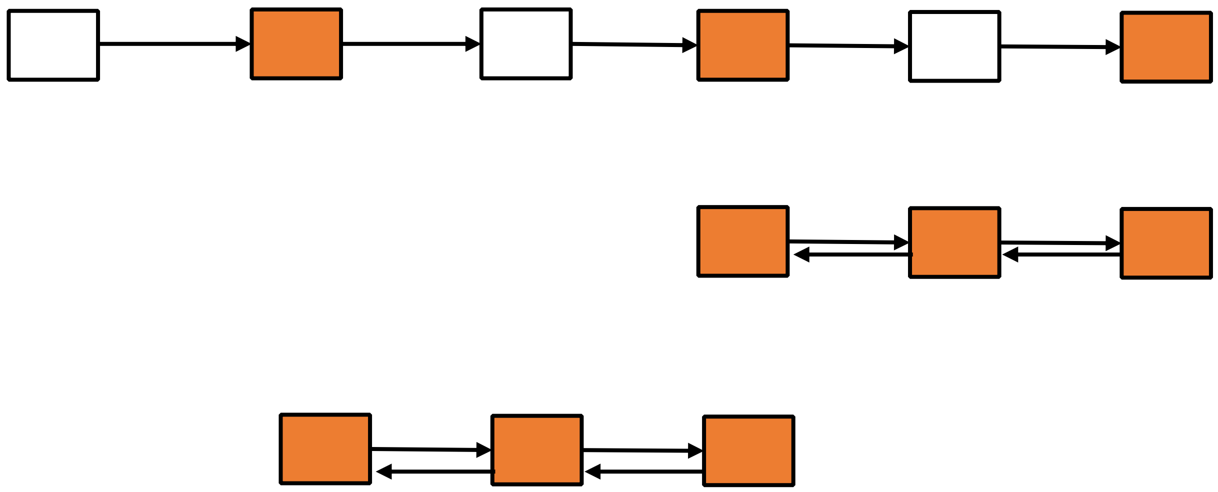


Checkpointing Techniques in AD

Step 0:

Step 1:

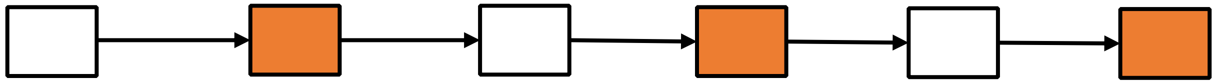
Step 2:



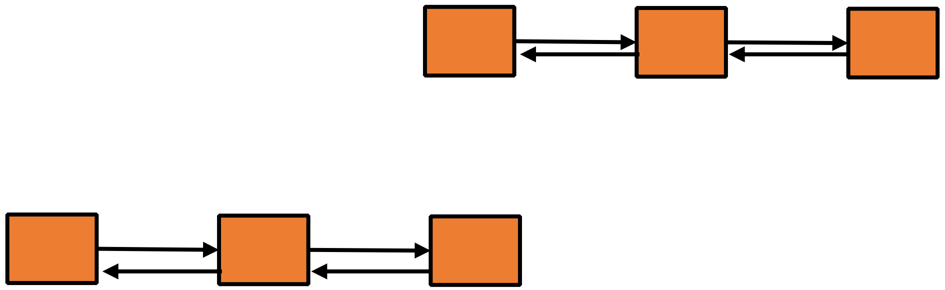
- Only checkpoint colored nodes (step 0)
- Recompute the missing intermediate nodes in small segments (step 1, 2)

Sublinear Memory Cost

Forward computation



Gradient per segment
with re-computation



For a N layer neural network,
if we checkpoint every K layers

$$Memory\ cost = \underbrace{O\left(\frac{N}{K}\right)}_{\text{Checkpoint cost}} + \underbrace{O(K)}_{\text{Re-computation cost}}$$

Pick $K = \sqrt{N}$

Outline

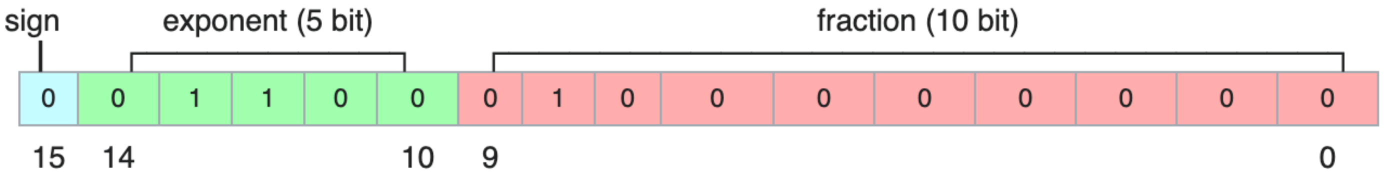
Rematerialization

Mixed Precision

Fully Sharded Data Parallelism

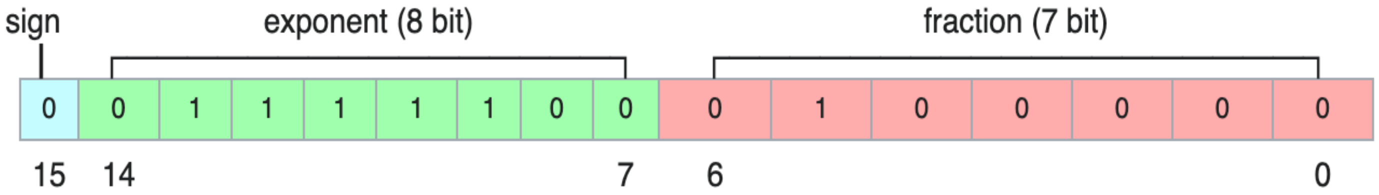
16bit Floating Points

float16



More fraction bits

bfloat16

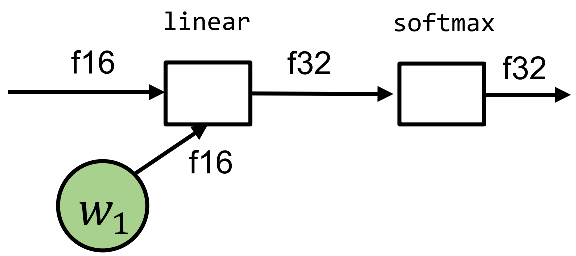


Less easy to overflow

source: wikipedia

Mixed Precision

- Some layers are more sensitive to dynamic range
- Common issues: aggregation of a lot of entries
- Mixed precision: different input/output/accumulation types



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Recap: AllReduce Abstraction

Interface

```
result = allreduce(float buffer[size])
```

Running Example

Worker 0

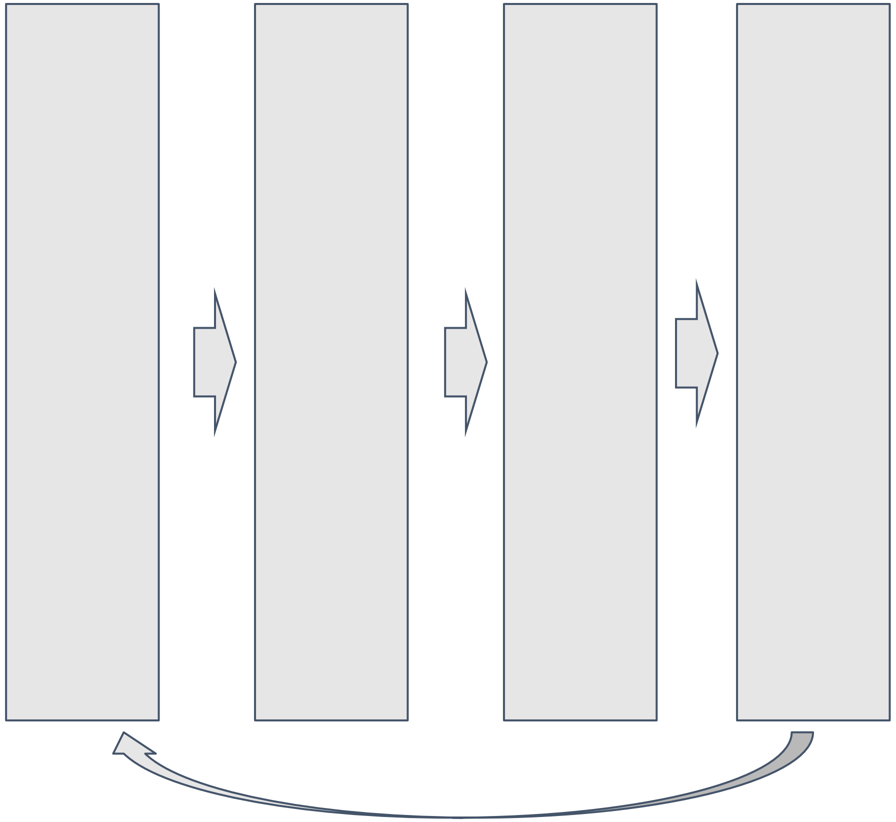
```
comm = communicator.create()
a = [1, 2, 3]
b = comm.allreduce(a, op=sum)
-----------------------------
assert b == [2, 2, 4]
```

Worker 1

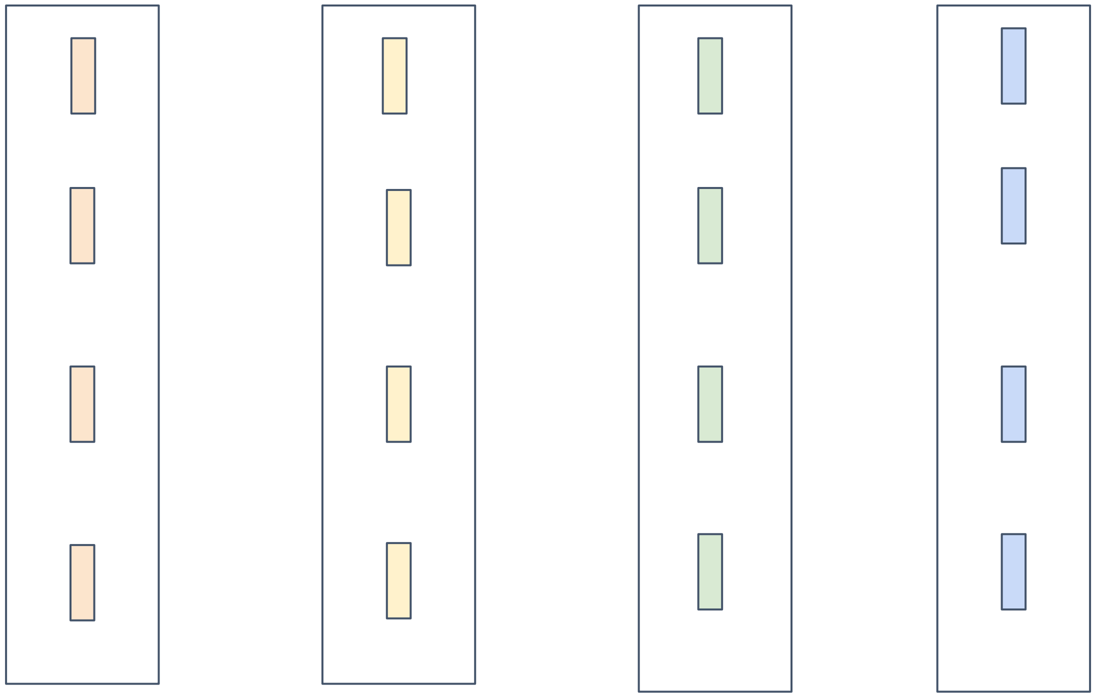
```
comm = communicator.create()
a = [1, 0, 1]
b = comm.allreduce(a, op=sum)
-----------------------------
assert b == [2, 2, 4]
```

Ring based Reduction

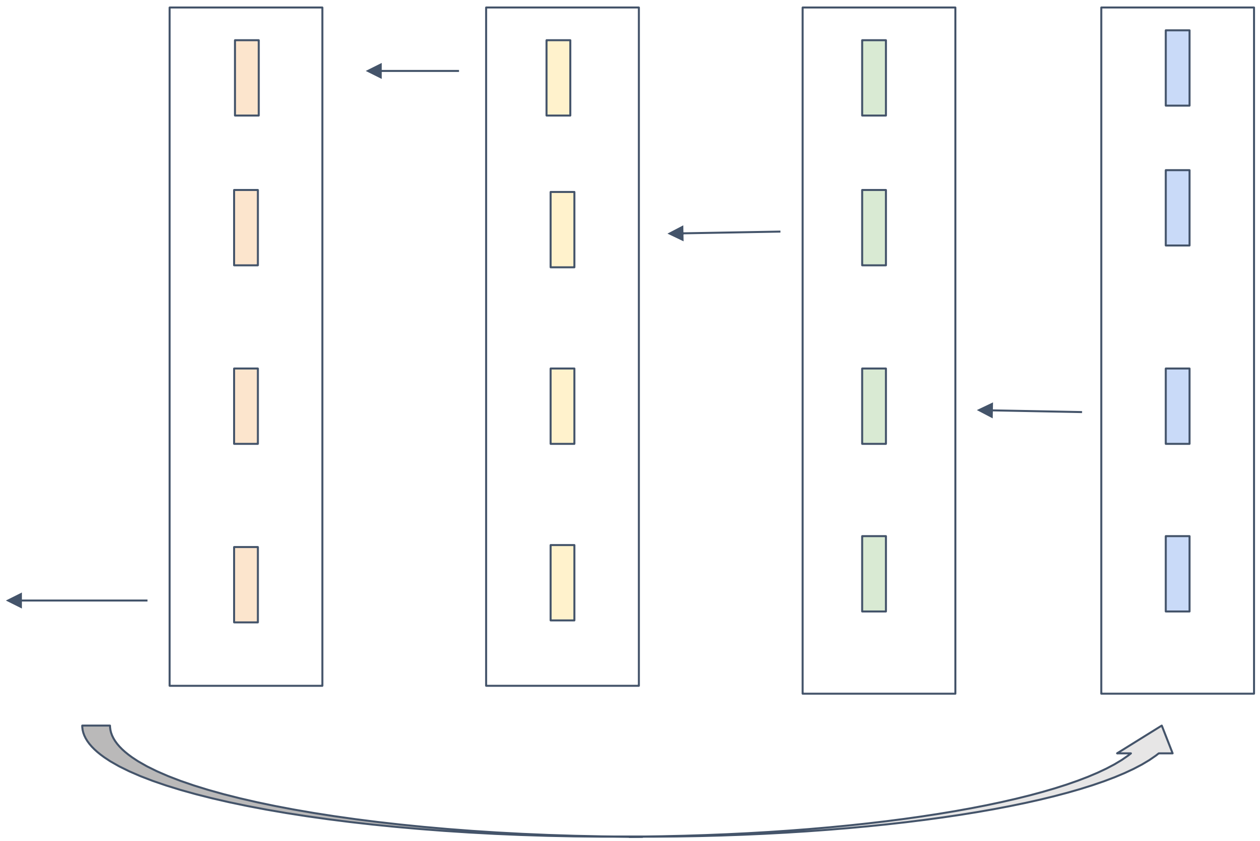
- Form a logical ring between nodes
- Streaming aggregation



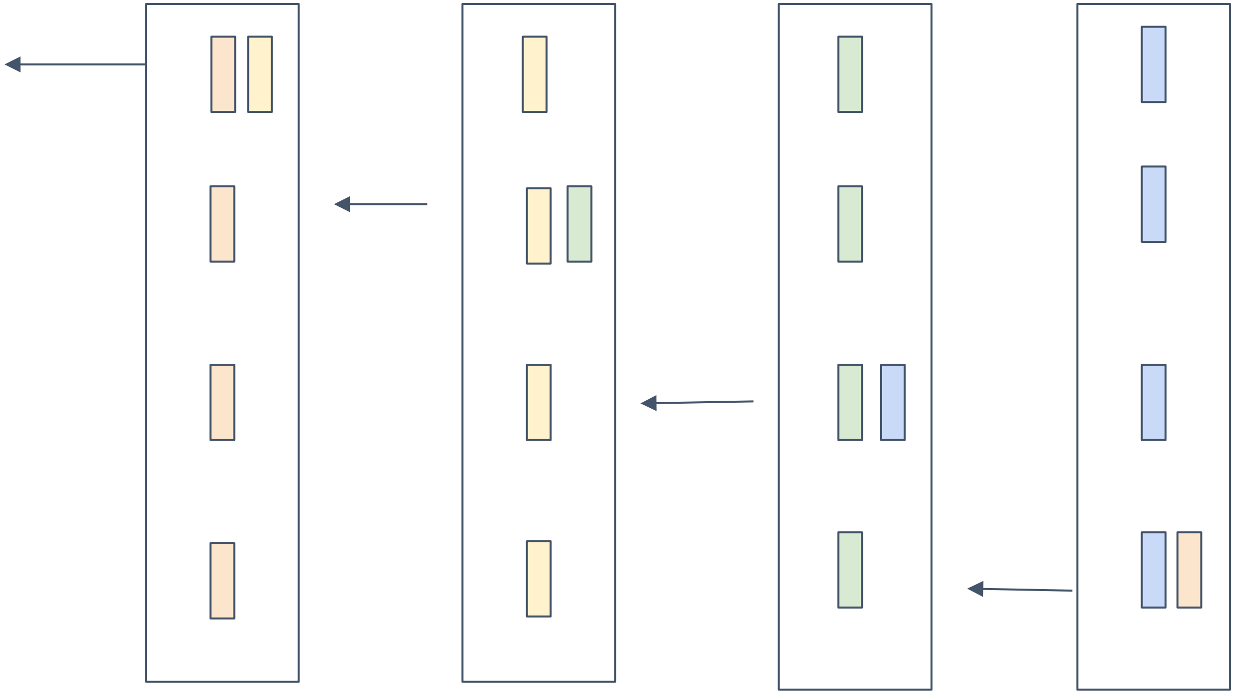
Ring based Reduction



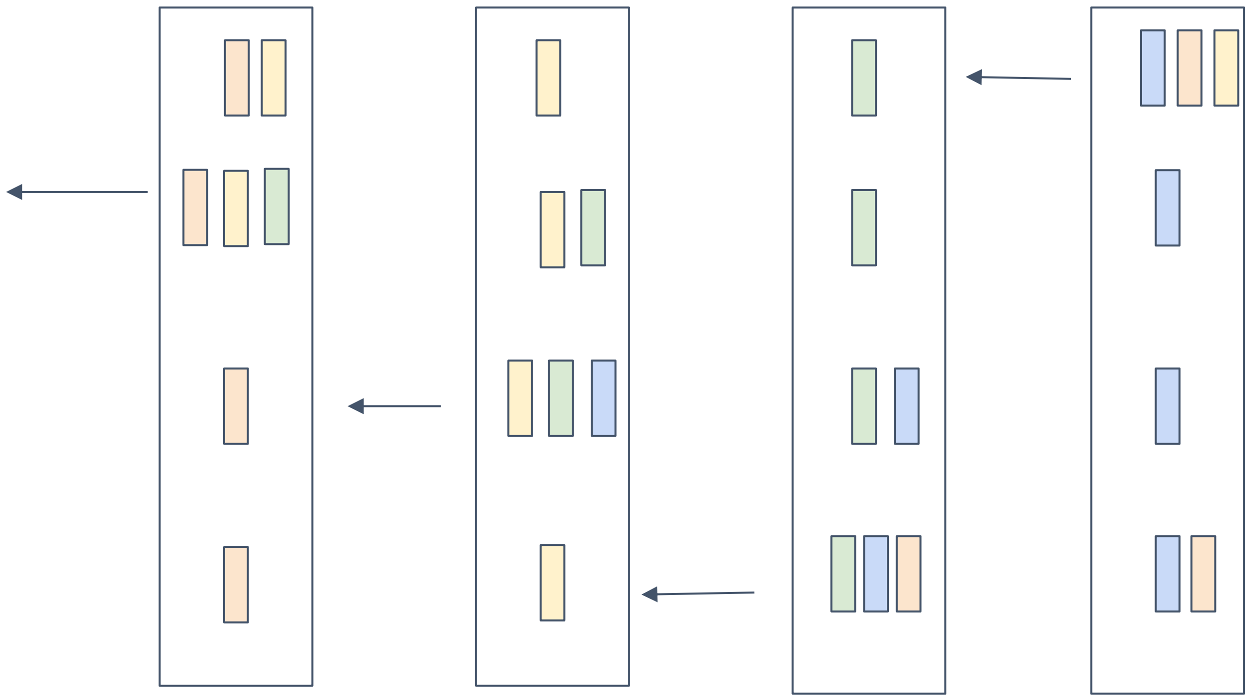
Ring based Reduction



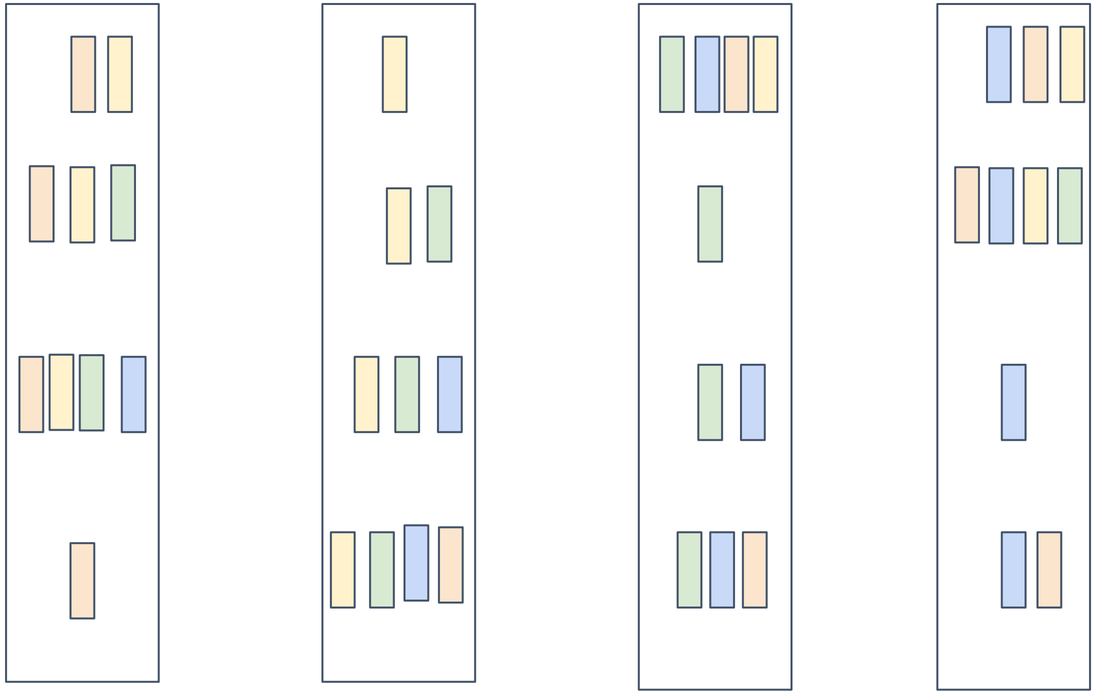
Ring based Reduction



Ring based Reduction



Ring based Reduction



Each node have correctly reduced result of one segment!

This is called *reduce_scatter*

Reduce Scatter Abstraction

Interface

```
result = reduce_scatter(float buffer[size])
```

Running Example

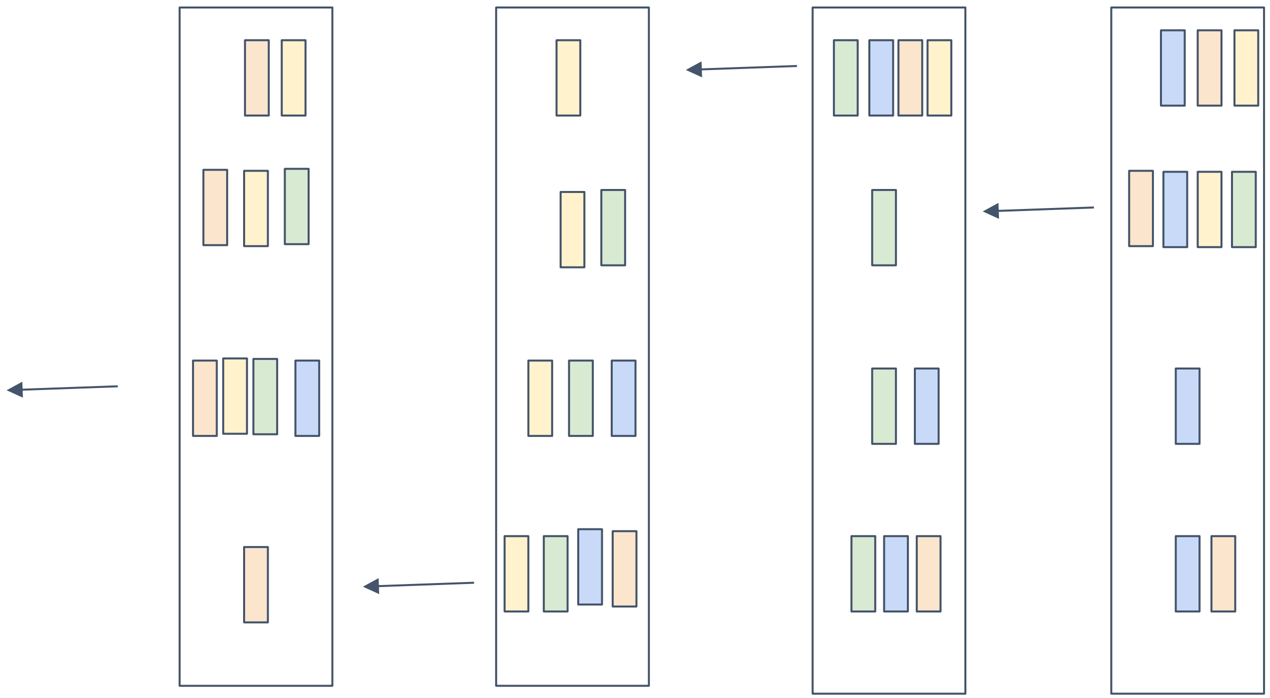
Worker 0

```
comm = communicator.create()
a = [1, 2, 3, 4]
b = comm.allreduce(a, op=sum)
---
assert b == [2, 2]
```

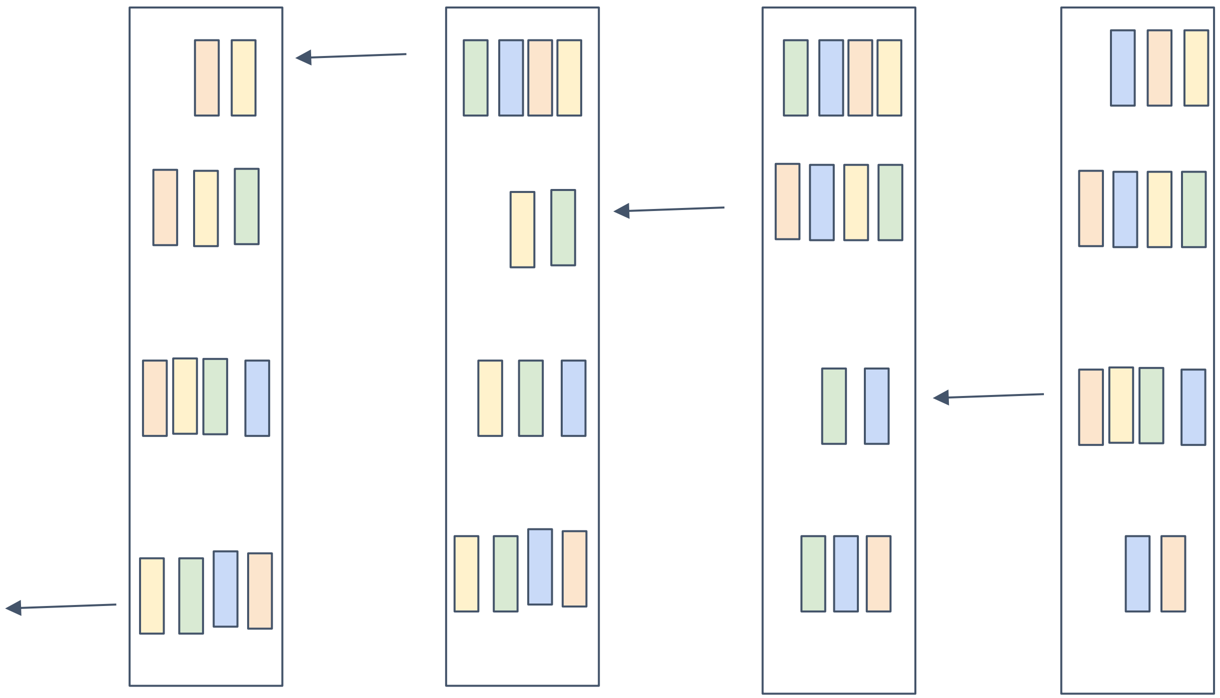
Worker 1

```
comm = communicator.create()
a = [1, 0, 1, 1]
b = comm.allreduce(a, op=sum)
---
assert b == [4, 5]
```

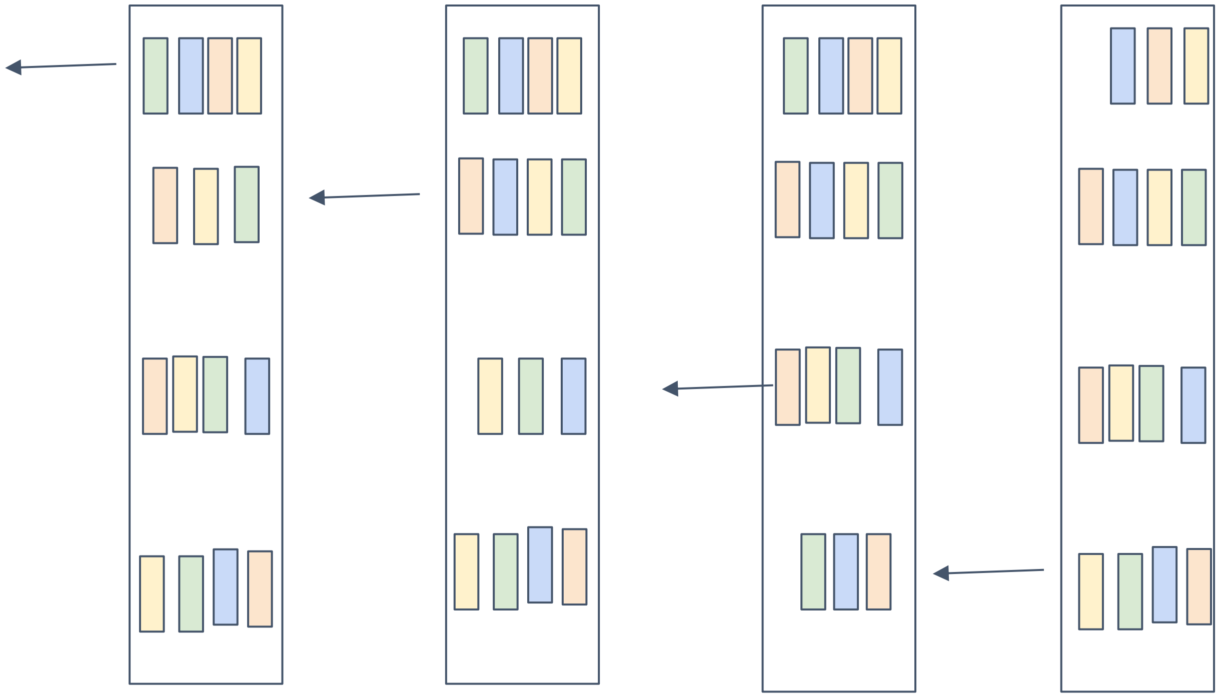
Ring based Reduction: Allgather phase



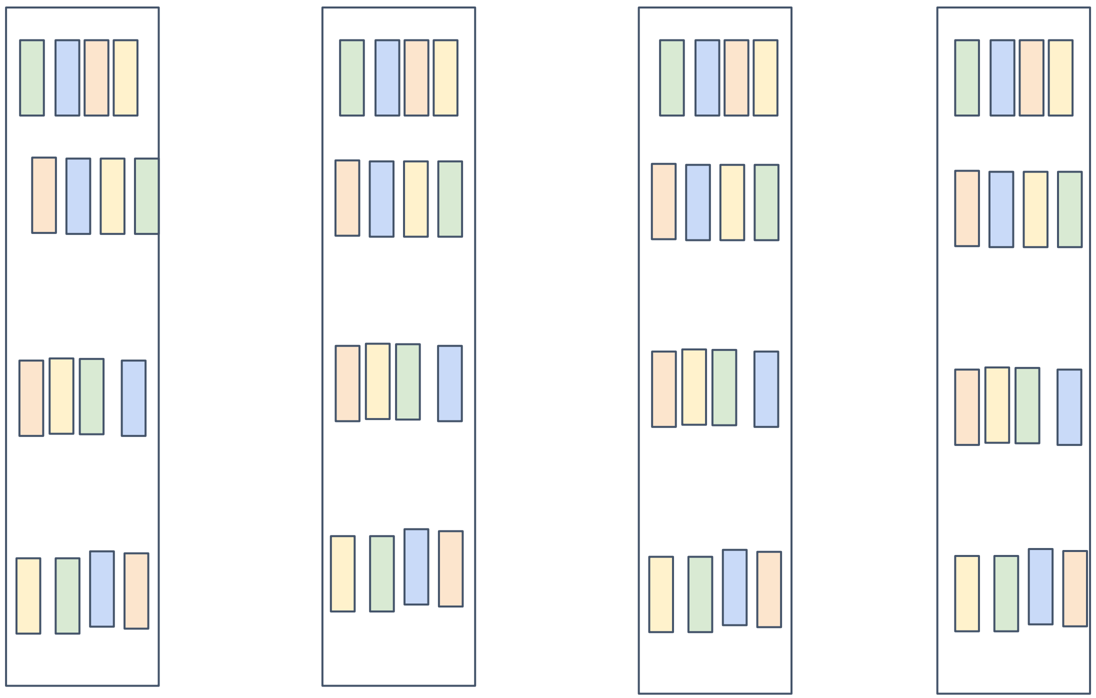
Ring based Reduction: Allgather phase



Ring based Reduction: Allgather phase



Ring based Reduction: Allgather phase



Question: What is Time Complexity of Ring based Reduction

Allgather abstraction

Interface

```
result = allgather(float buffer[size])
```

Running Example

Worker 0

```
comm = communicator.create()
a = [1, 2]
b = comm.allgather(a)
```

Worker 1

```
comm = communicator.create()
a = [3, 4]
b = comm.allgather(a)
```

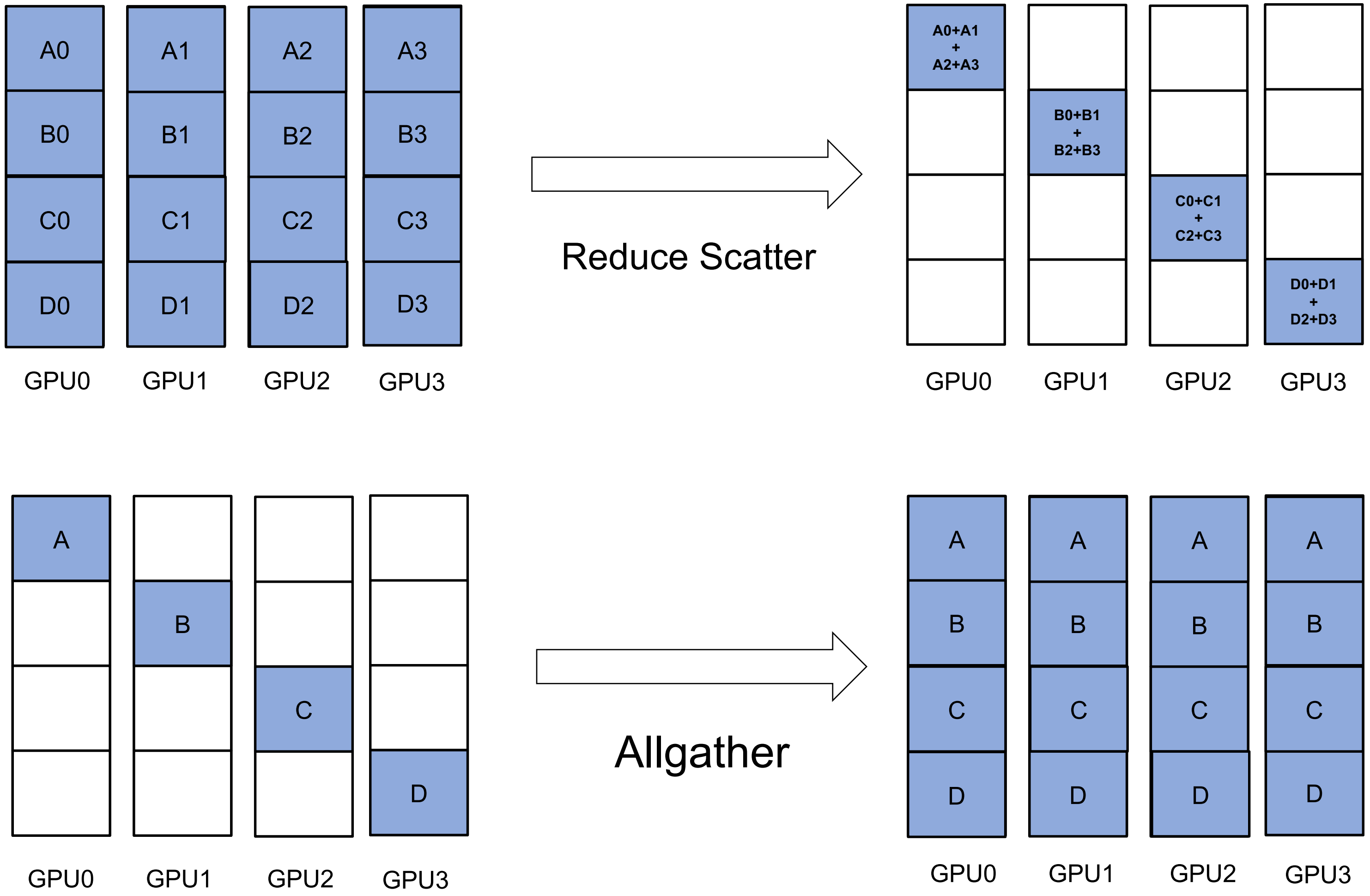
Worker 0:

```
assert b == [1, 2, 3, 4]
```

Worker 1:

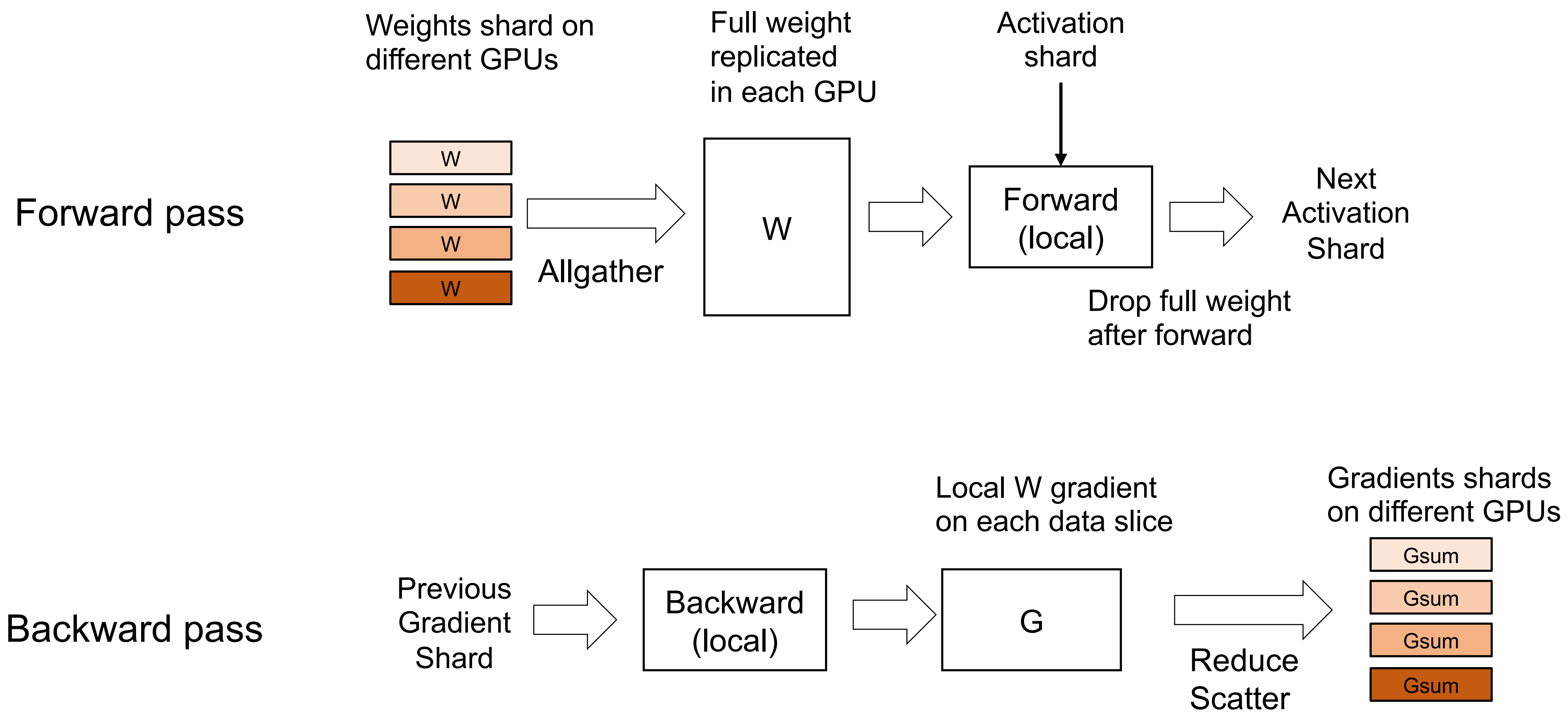
```
assert b == [1, 2, 3, 4]
```

Overall Relations



Combine both we get Allreduce

FSDP: Fully Sharded Data Parallel



Core idea is equivalent to ZeRO3