CS 181AI
Lecture 21

Distributed Training Pt. 1

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Logistics

- Assignment 5 (last assignment!) due on Friday
- Outline of rest of semester (!!)
  - Today (4/5): Distributed Training part 1
  - 4/10: Distributed Training part 2
  - 4/12: Profiling + debugging
  - 4/17: Efforts to lower model resource usage (+ different types of models)
  - 4/19: Working session
  - 4/24: Scale of models/resources in industry + look at full stack of ML pipelines
  - 4/26: Project presentations

Today

- Why and how do we use multiple GPUs for training?
- What are the methods for aggregating gradients across GPUs?

Distributed Training

- Distributed training is the use of multiple GPUs working together on one training job

- Why would we need more than one GPU?

Distributed Training

- Distributed training is the use of multiple GPUs working together on one training job
- It can lower the time needed for training
- It can allow you to train when a model is too large for a single GPU

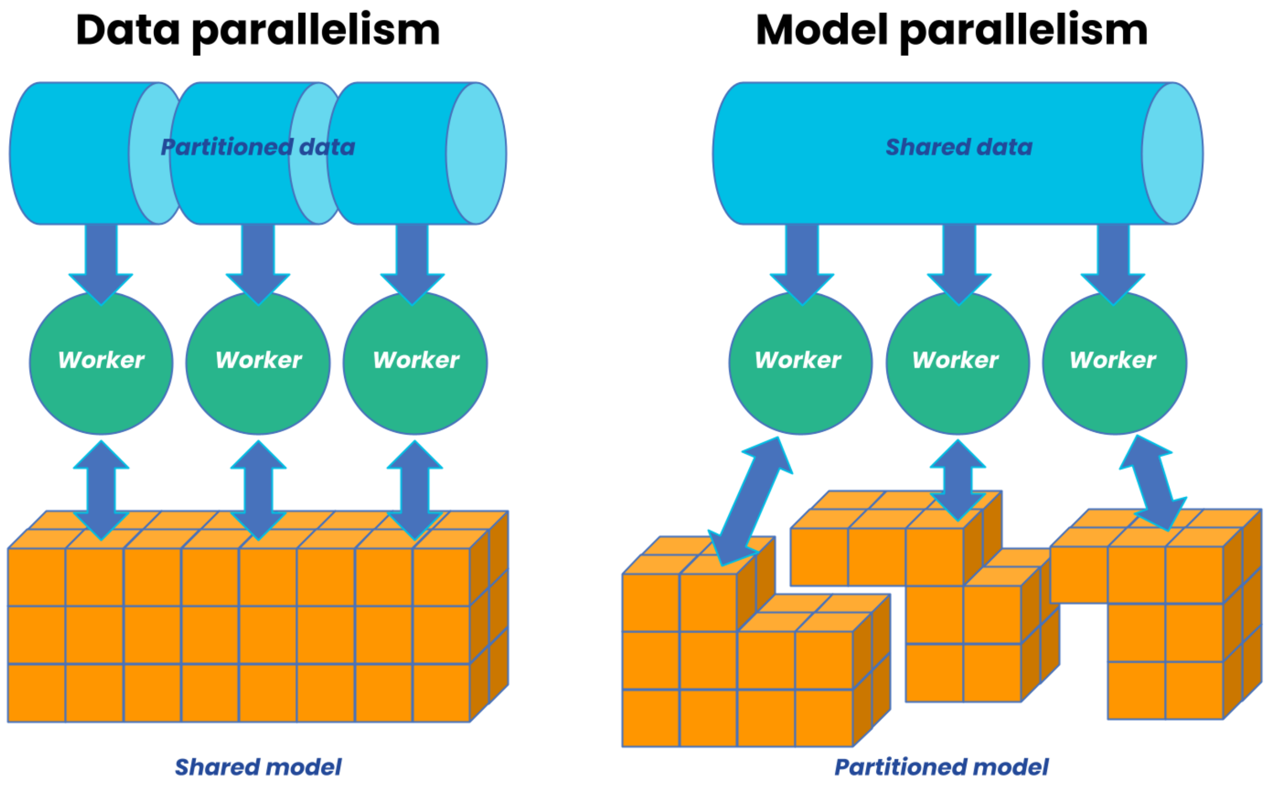
Distributed Training

- Distributed training is the use of multiple GPUs working together on one training job

- It can lower the time needed for training
  - Running a single batch across several GPUs allows for increased batch size and lower training time -> **Data Parallelism**

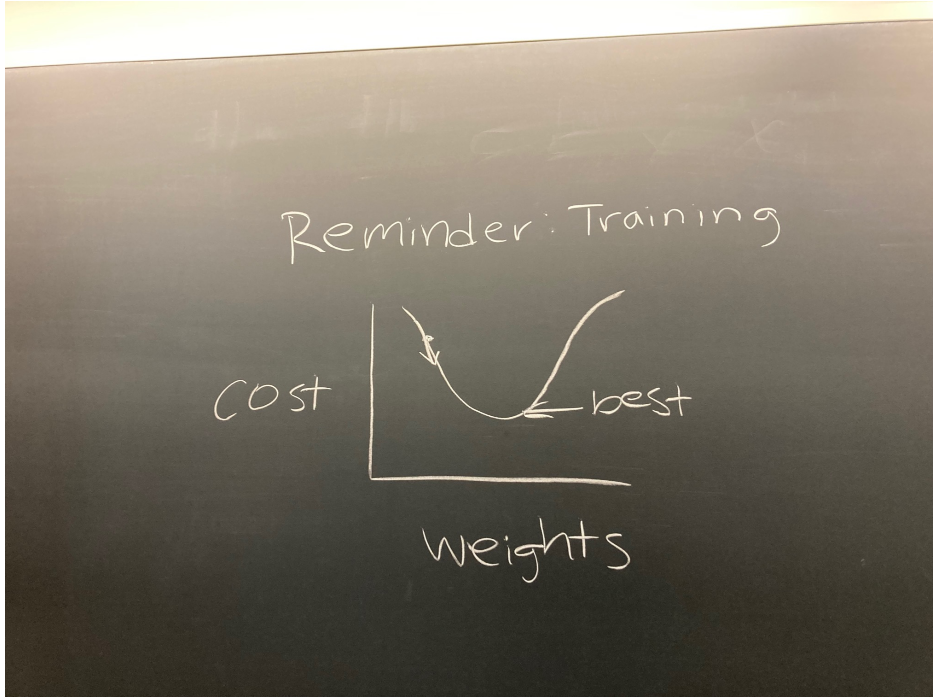
- It can allow you to train when a model is too large for a single GPU
  - Splitting up a model such that different parts are on different GPUs -> **Model Parallelism**

Data vs. Model Parallelism



Reminder: Training Process

- Run inputs through model with weights *w*
- Calculate loss function
- Calculate gradients of loss function
- Update *w*



Reminder: Training Process

- Run inputs through model with weights *w*
- Calculate loss function
- Calculate gradients of loss function
- Update *w*

- Inputs = 1 batch

```
train_gen = torch.utils.data.DataLoader(dataset = train_data,
                                        batch_size = batch_size,
                                        shuffle = True)
```

Training Batch Size

- Higher batch size = faster training
- What is limiting factor for batch size?

Training Batch Size

- Higher batch size = faster training

- GPU memory is limiting factor for batch size

- Using multiple GPUs allows us to effectively use a higher batch size
  - batch_size = batch_size per GPU * num_GPUs

Data Parallelism quiz

- Which of the following is true about data parallelism across 4 GPUs?

1. The time per batch remains about the same. The number of batches per epoch decreases by a factor of 4. The time per epoch remains about the same. The overall training time decreases by a factor of 4.
2. The time per batch remains about the same. The number of batches per epoch decreases by a factor of 4. The time per epoch decreases by a factor of 4. The overall training time decreases by a factor of 4.
3. The time per batch decreases by a factor of 4. The number of batches per epoch stays the same. The time per epoch decreases by a factor of 4. The overall training time decreases by a factor of 4.

Data Parallelism quiz

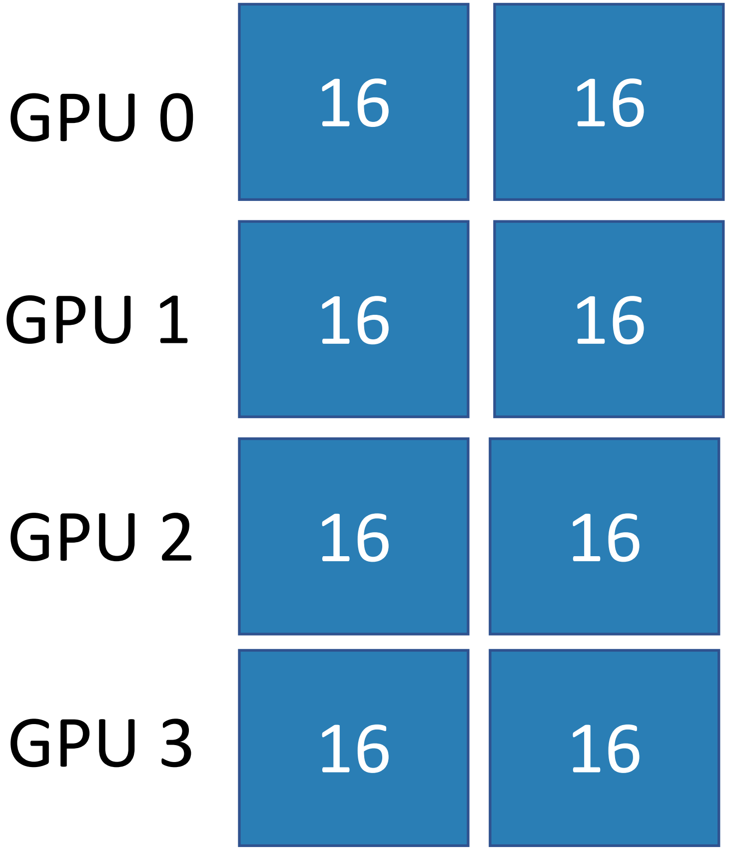
- Suppose batch size = 16, 1 GPU

All Data (128 samples)

Data Parallelism quiz

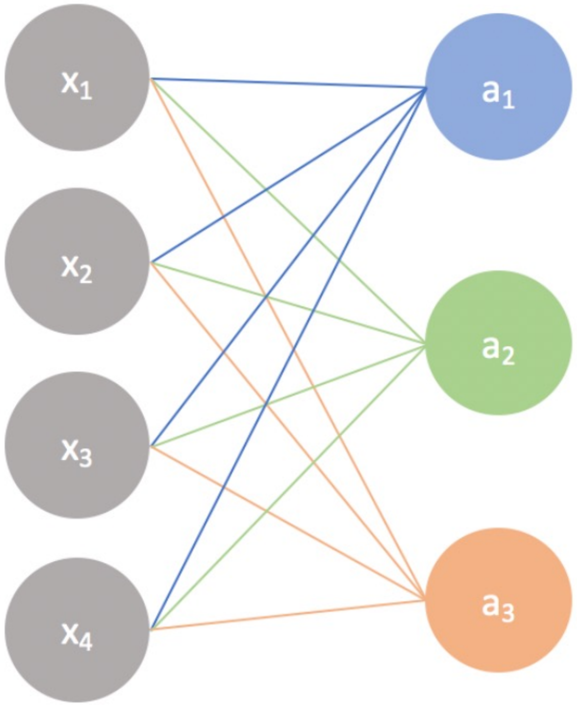
- Suppose batch size = 16, 1 GPU
- 8 batches of 16 = 128 samples

Data Parallelism quiz



- Suppose batch size = 16, 4 GPUs
- 2 batches of 16*4 = 128 samples
- Time per batch is similar*
- Number of batches per epoch decreased
- Time per epoch decreased
- Overall training time decreased

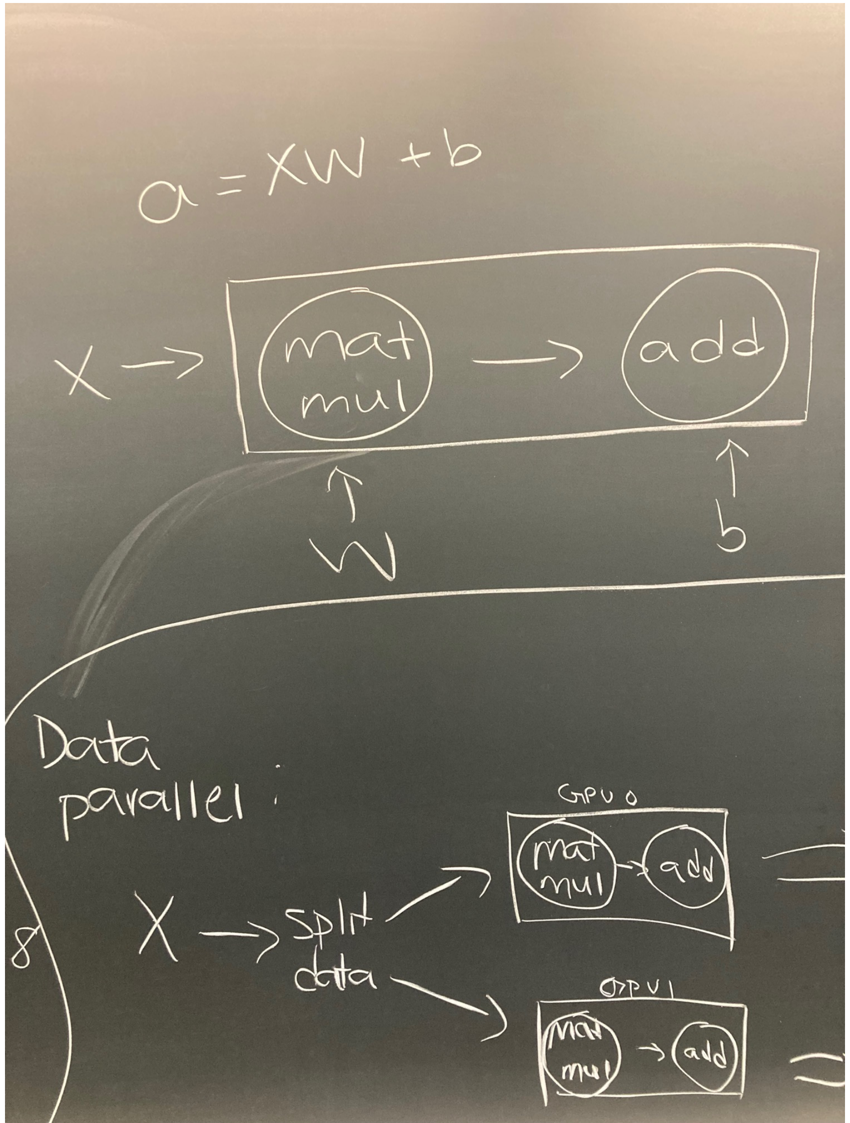
Reminder: Matrix Multiplication + Bias

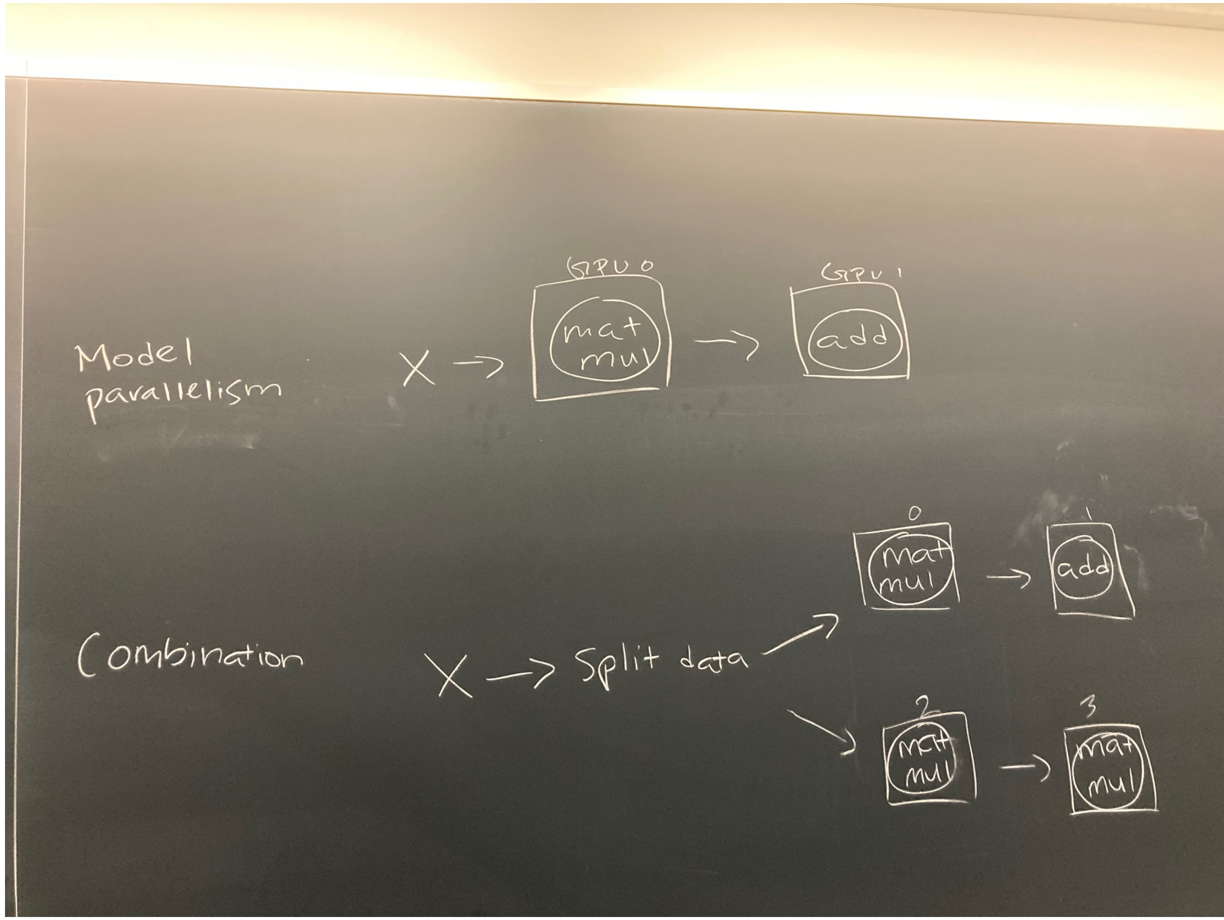


$$\begin{bmatrix} w_1 & w_2 & w_3 & w_4 \\ w_1 & w_2 & w_3 & w_4 \\ w_1 & w_2 & w_3 & w_4 \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} b \\ b \\ b \end{bmatrix} = \begin{bmatrix} w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \\ w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \\ w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + b \end{bmatrix} \xrightarrow[\text{activation}]{} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}$$

X*W + b = a

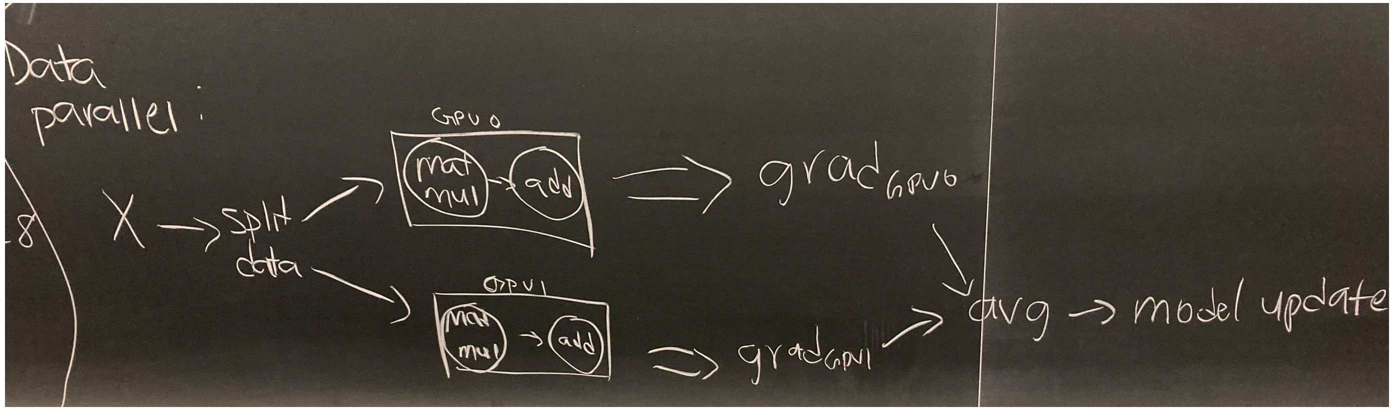
Data Parallelism





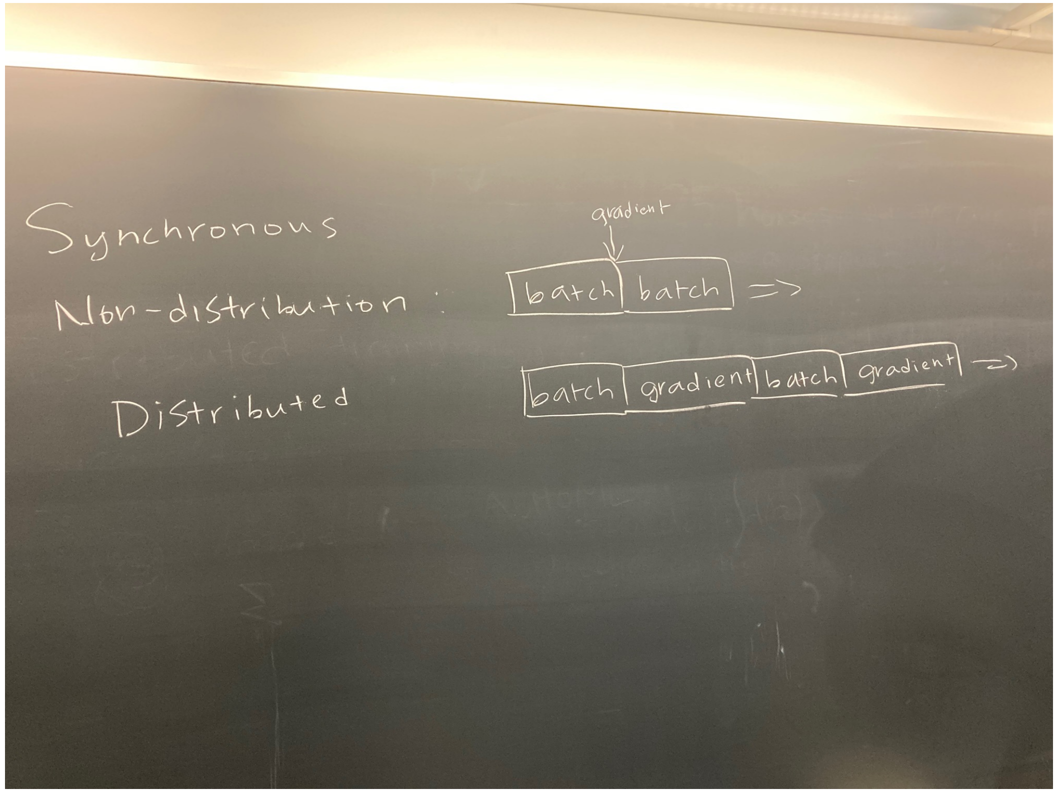
Gradient Update

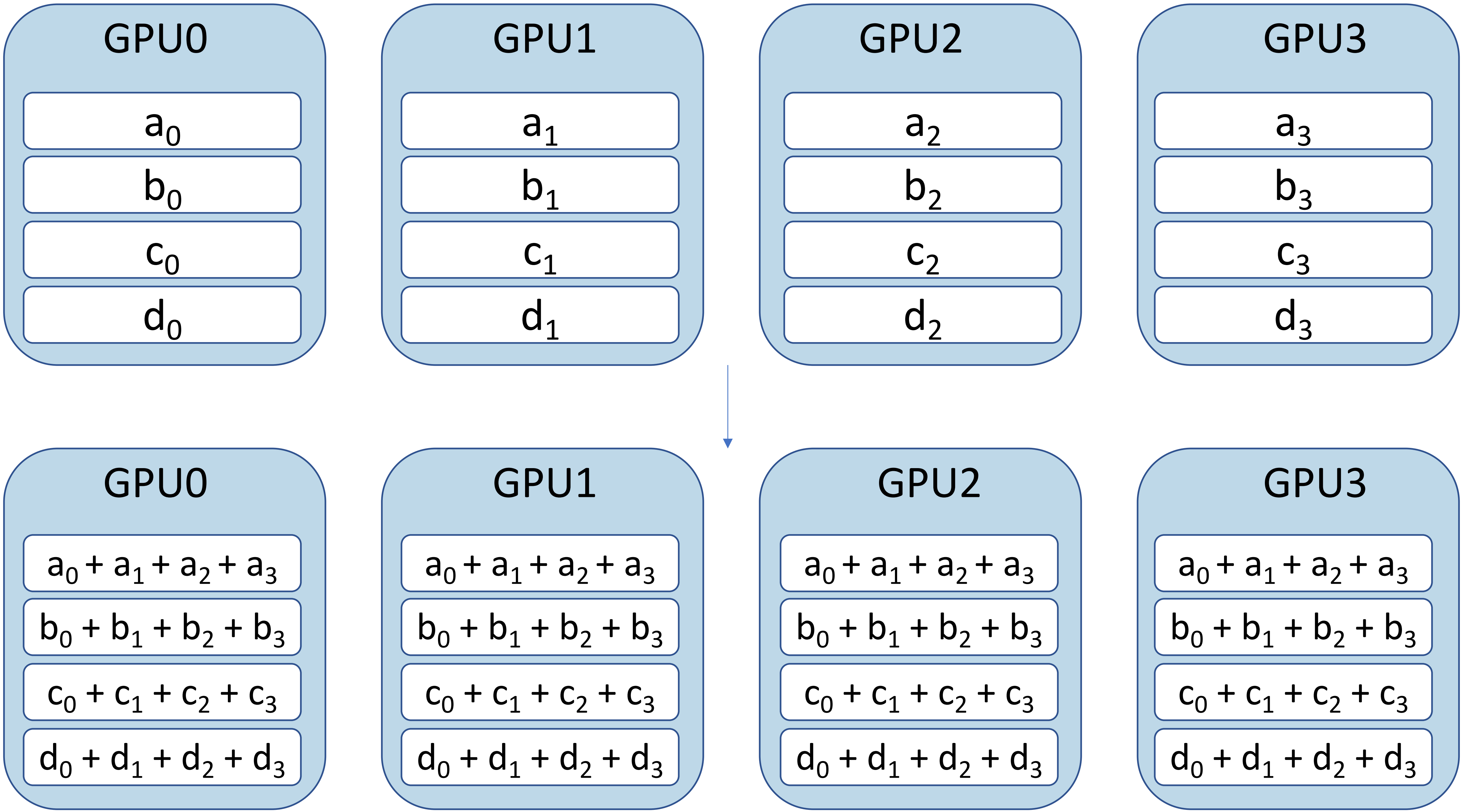
- Reminder: at the end of every batch, gradients for the whole model are updated
- How does this work if each GPU sees part of the batch?
  - Each GPU computes its own loss and gradients. Gradients are averaged and result is used to update the model



Synchronous

- Gradients are computed and model is updated after each batch
- Calculation must happen very efficiently





GPU0
a_0
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GPU1
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GPU2
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GPU3
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GPU0
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GPU3
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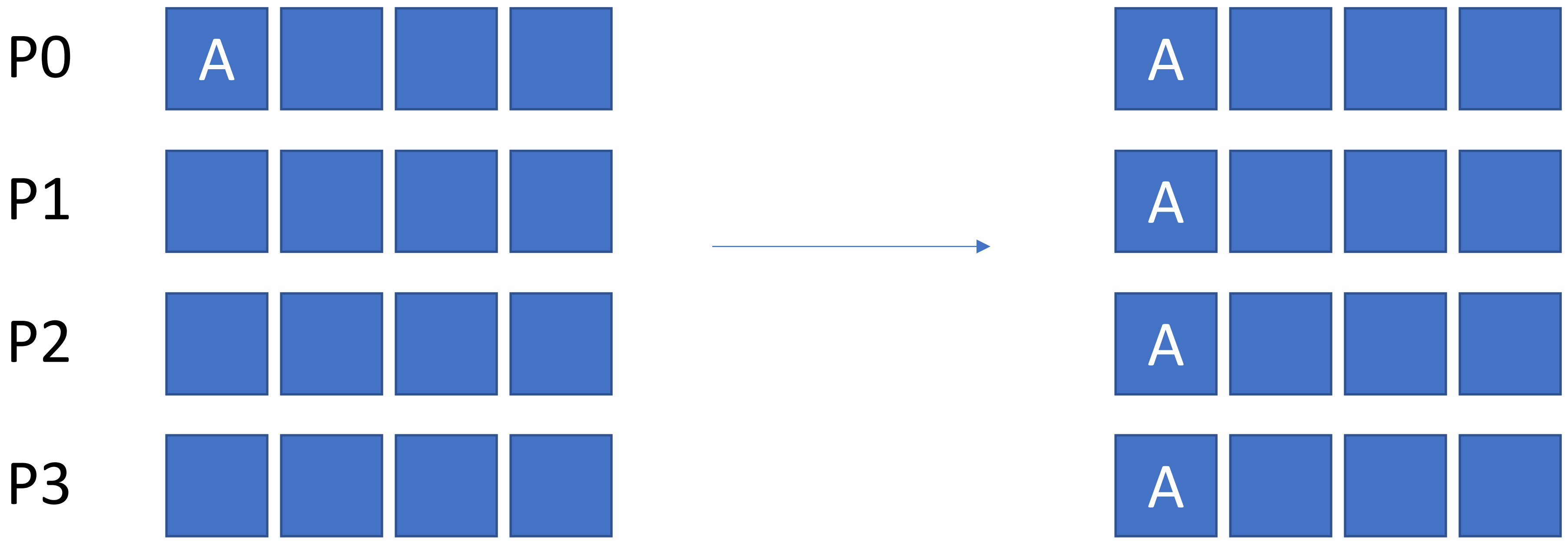
$d_0 + d_1 + d_2 + d_3$

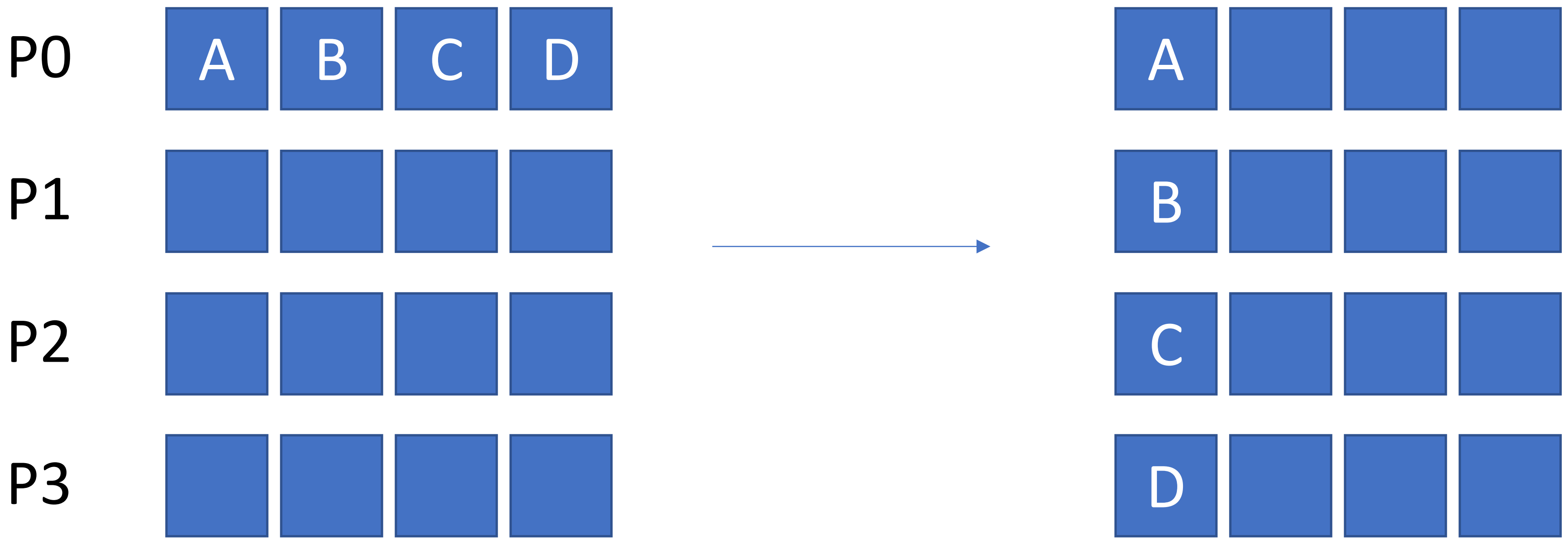
Message Passing Interfaces (MPI)

- We are going to explore how to do that, but first, we'll look at the common message passing operations in parallel computing

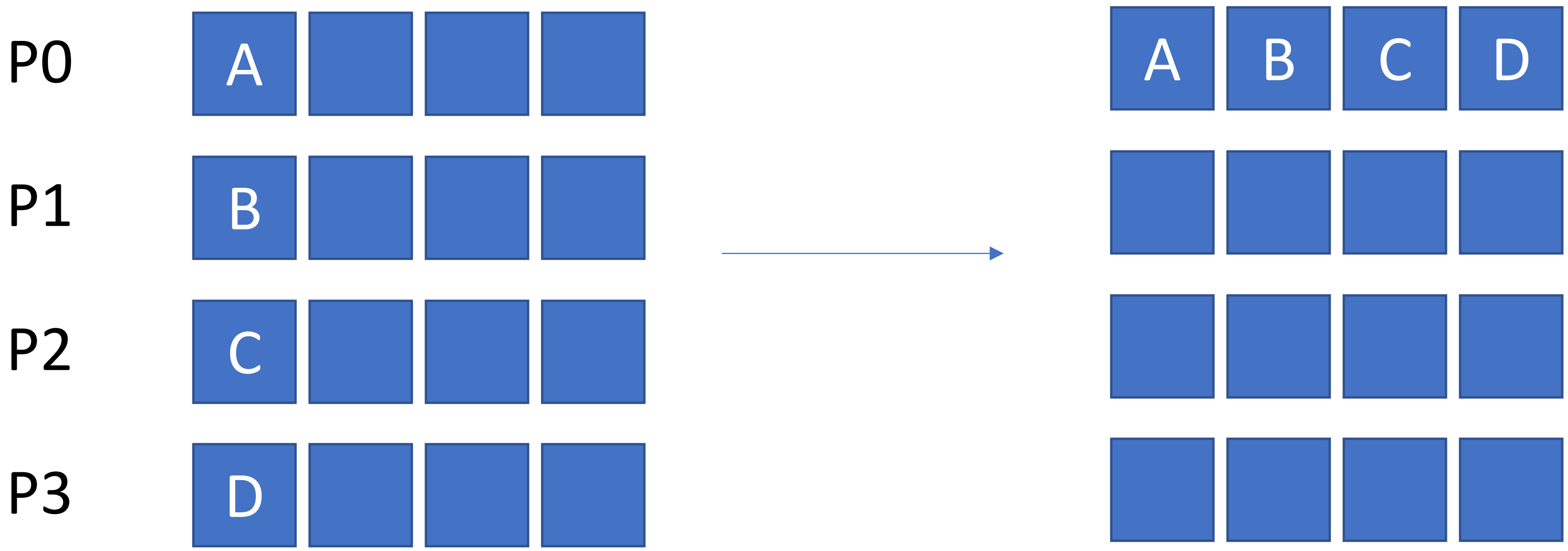
Broadcast



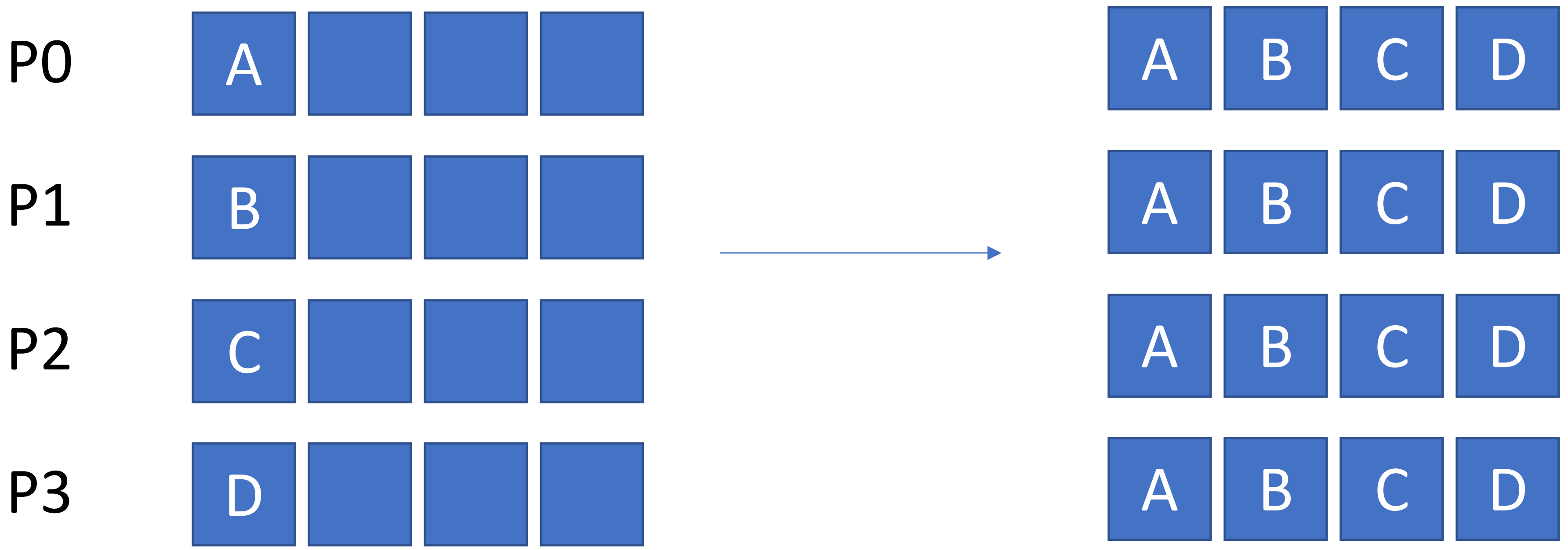
Scatter



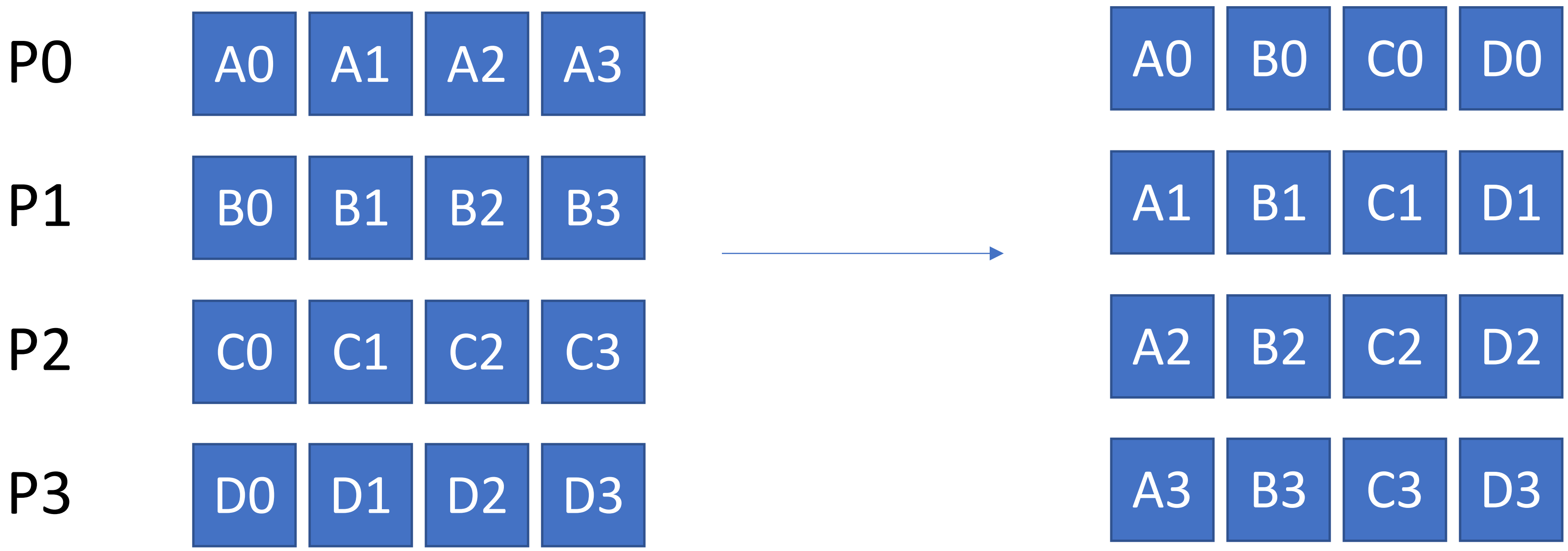
Gather



All-Gather



All-to-All


P0
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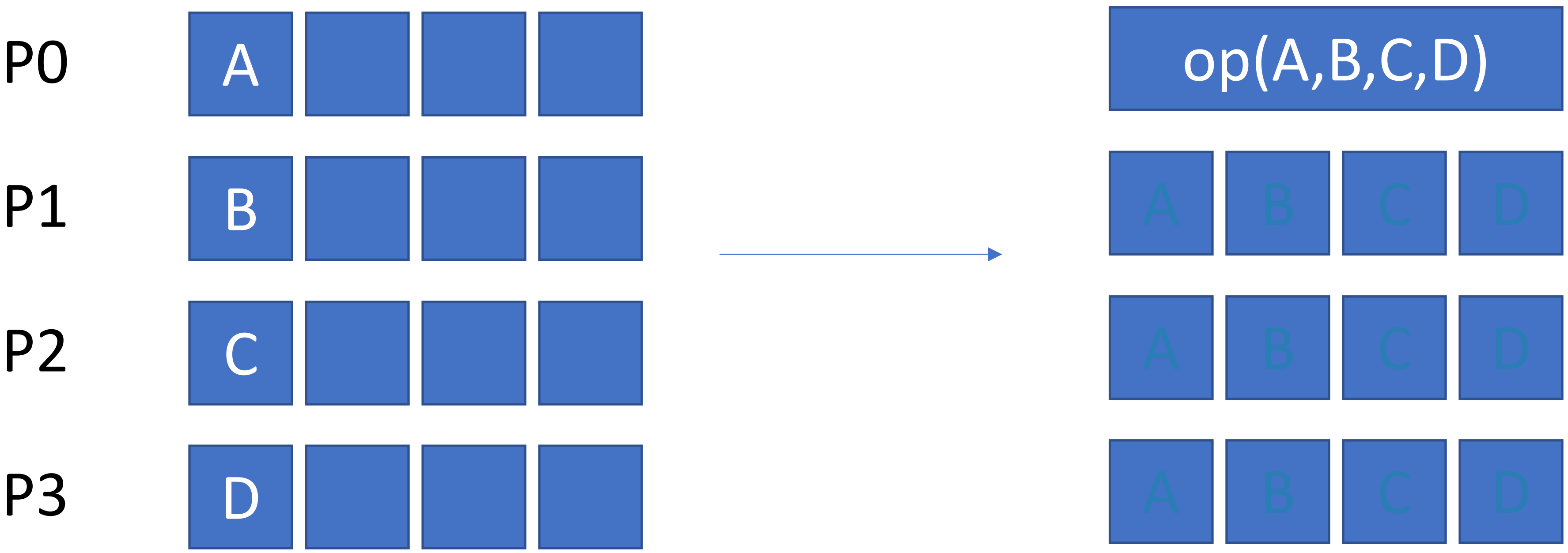
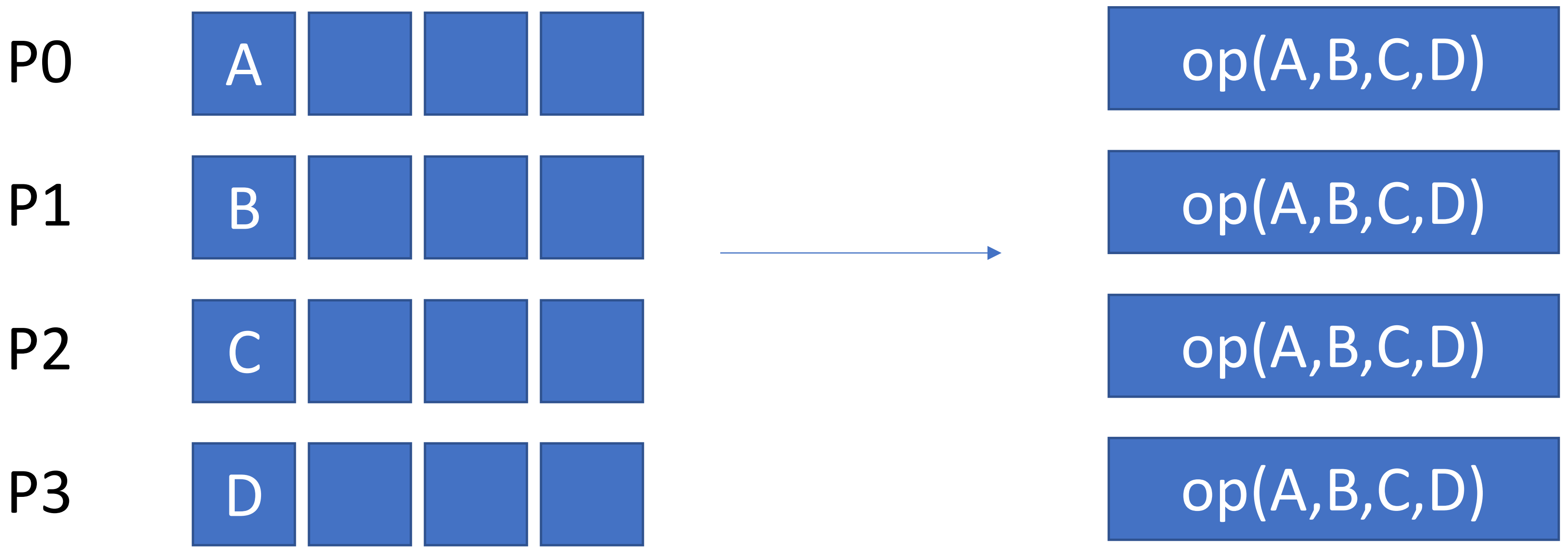
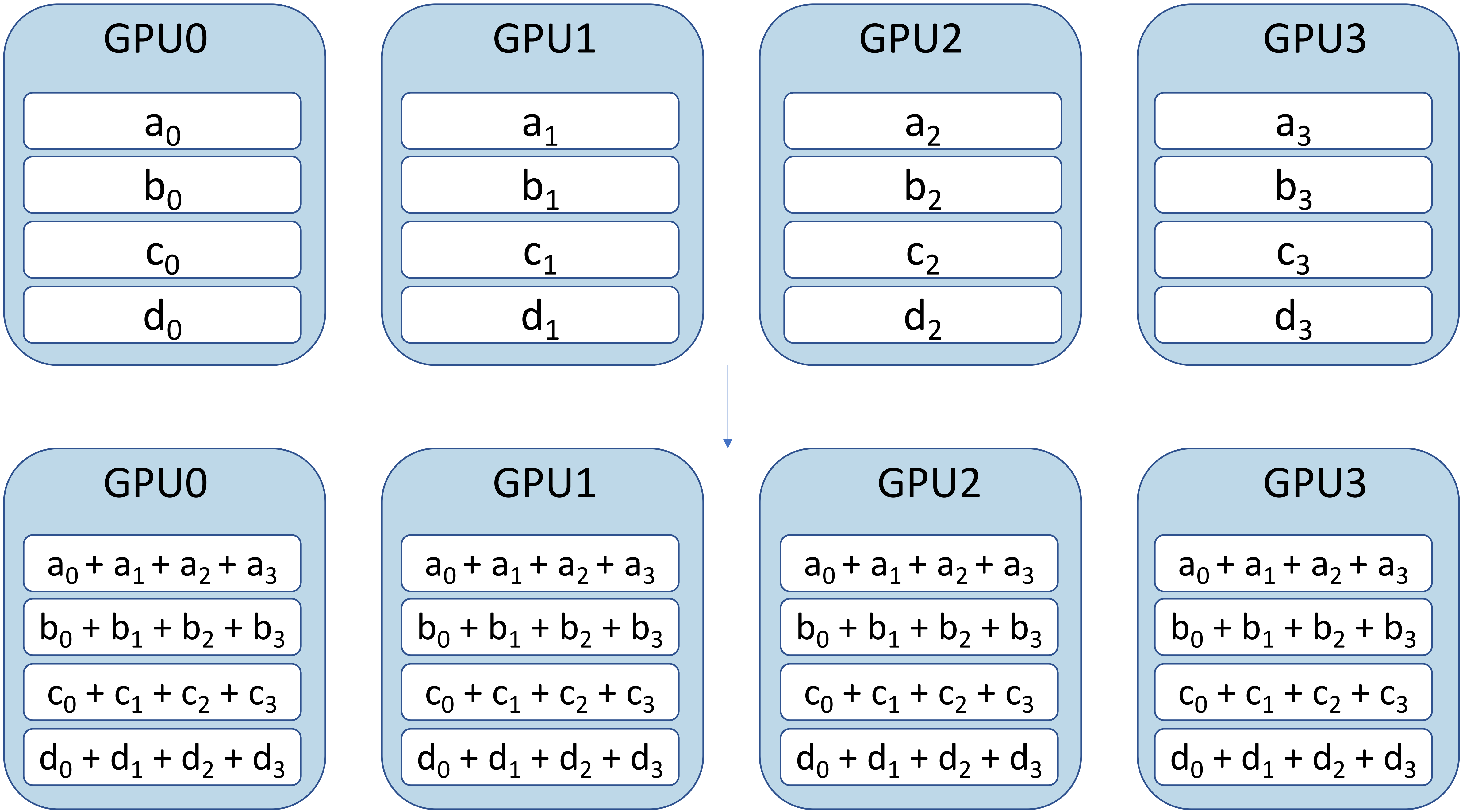
D0 D1 D2 D3
A0 B0 C0 D0
A1 B1 C1 D1
A2 B2 C2 D2
A3 B3 C3 D3

Reduce



All-Reduce

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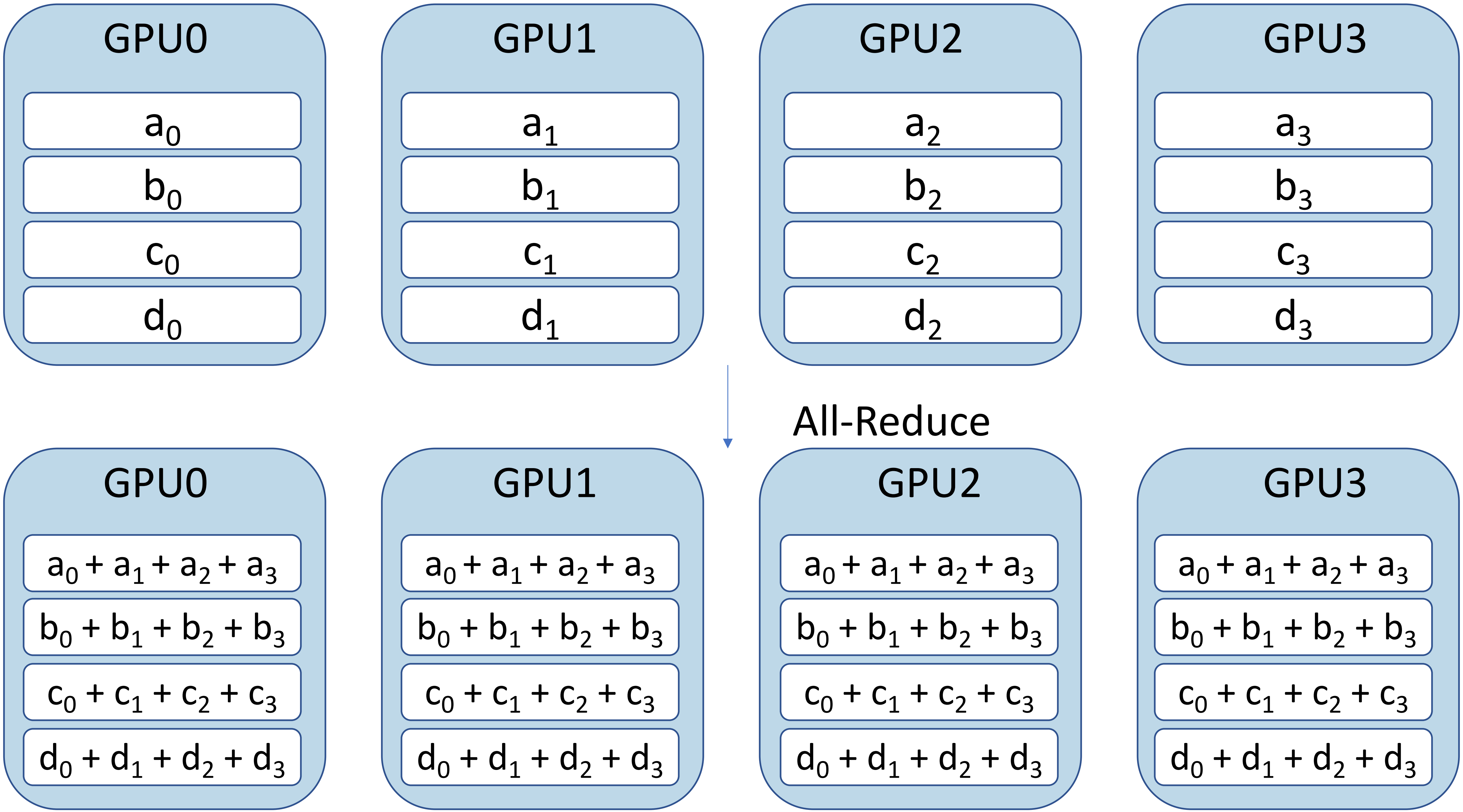
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All-Reduce
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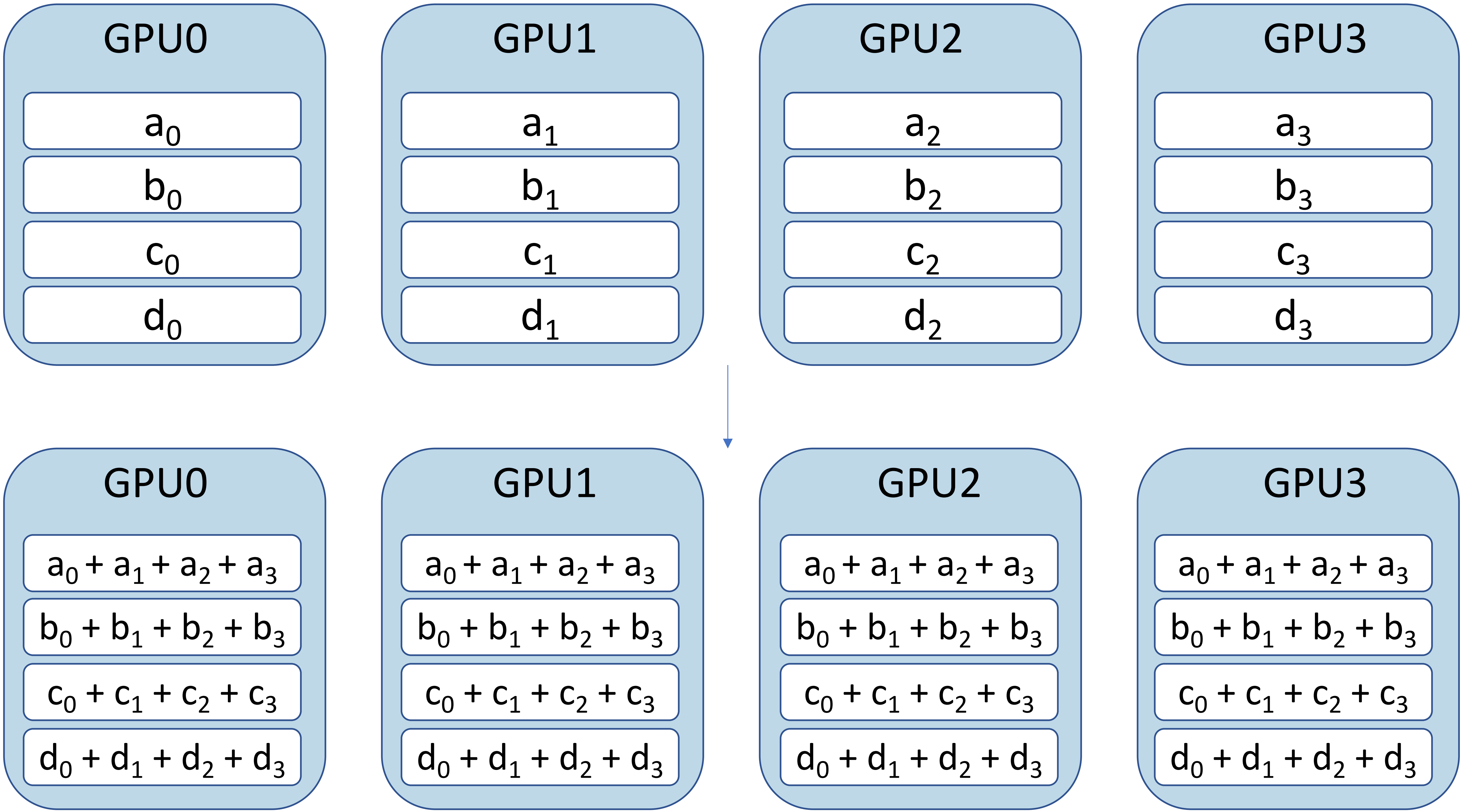
All-Reduce

- “Operation that reduces a set of arrays on distributed workers to a single array that is then redistributed back to each worker”

All-Reduce

- Metrics
  - Bandwidth (number of messages)



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Next Time

- Ring-All-Reduce
- Analysis/comparison of Ring All-Reduce vs other strategies
- Asynchronous Gradient Update (strong vs. weak consistency)

Acknowledgments

- Nikita Namjoshi, Google Cloud Developer Advocate