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CSDS 451: Designing High Performant Systems for AI

Lecture 14

10/14/2025

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Outline

- Distributed Training Basics
- Pytorch Lightning

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Outline

- Distributed Training Basics
- Pytorch Lightning

Training

$$E(W): \min_{W} \sum (y_i - F(x_i : W))\text{^}2$$

$$W_{t+1} \leftarrow W_t - \alpha \frac{\delta E(W)}{\delta W}$$

Iteratively

$$\frac{\delta E(W)}{\delta W} = 2 \sum_i \left(y_i - F(x_i : W)\right) \times \frac{\delta F(x_i : W)}{\delta W}$$

For all samples, in each iteration

Error

Training

L layers in CNN

$$W_1, W_2, W_3, \dots, W_L$$

Weights (Filters/Kernels)

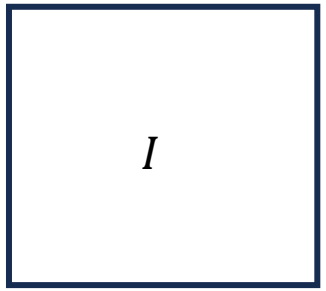
$$O_1, O_2, O_3, \dots, O_L$$

Output of layer

$$2 * Error * \frac{\delta F(x_i : W_{1:L})}{\delta W_1}, \frac{\delta F(x_i : W_{1:L})}{\delta W_2}, \dots, \frac{\delta F(x_i : W_{1:L})}{\delta W_L}$$

Compute these for all the samples

CNN Training: Forward Propagation



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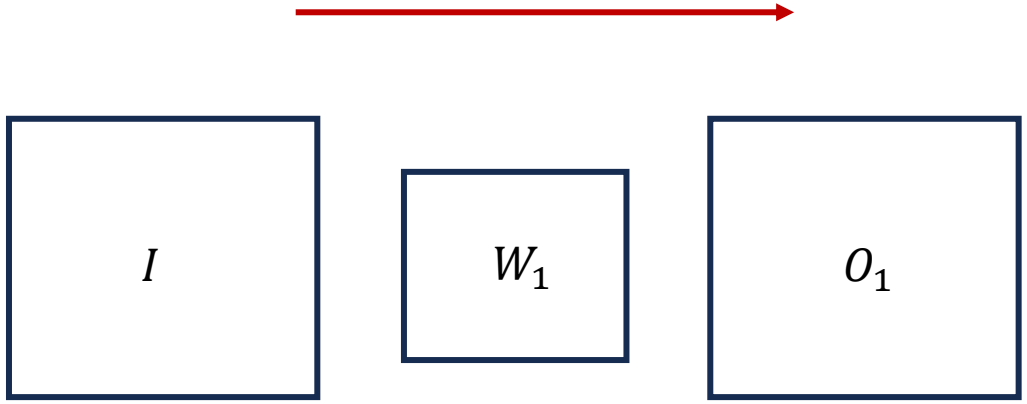
CNN Training: Forward Propagation



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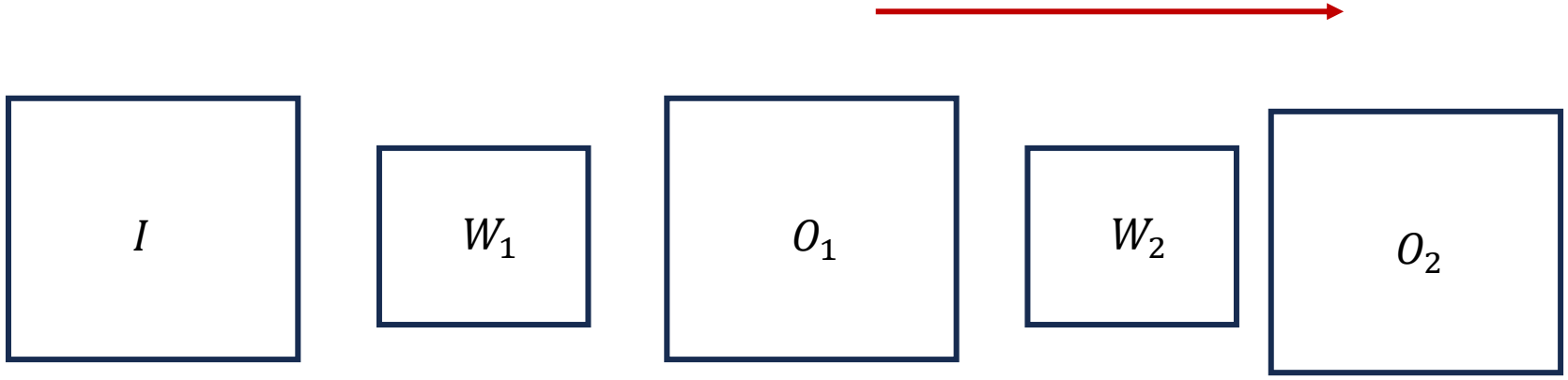
CNN Training: Forward Propagation



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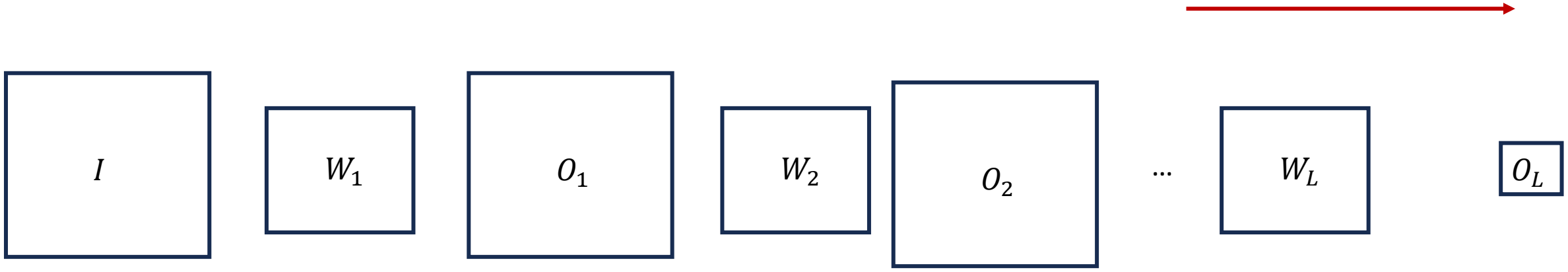

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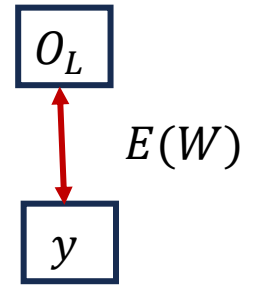
CNN Training: Error Calculation



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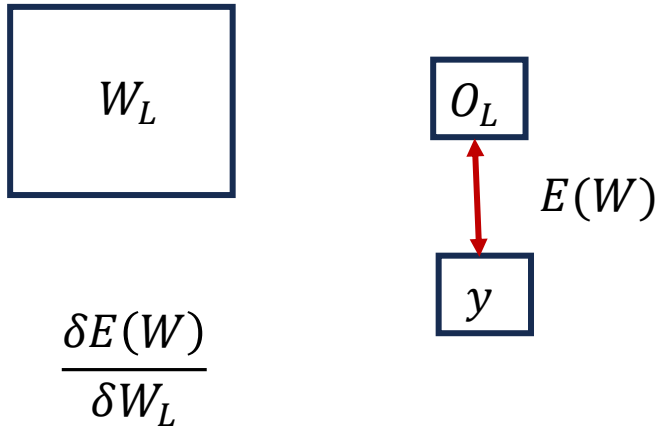
CNN Training: Backward Propagation



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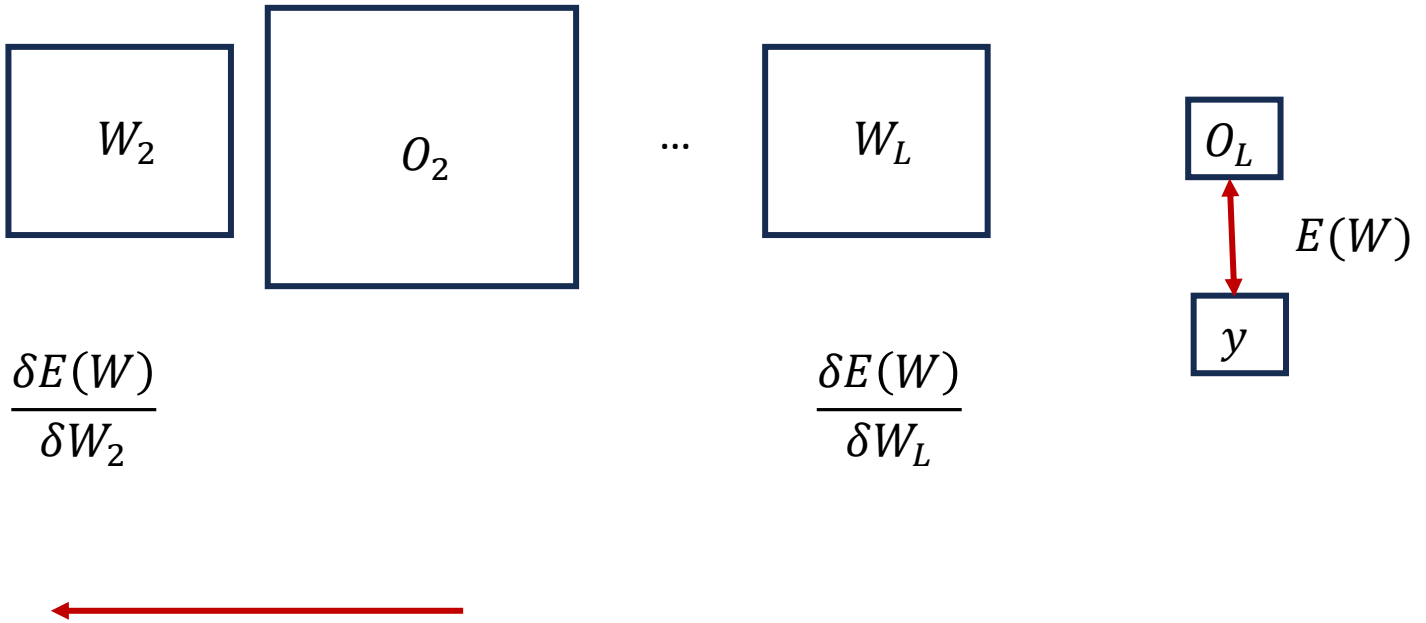
CNN Training: Backward Propagation



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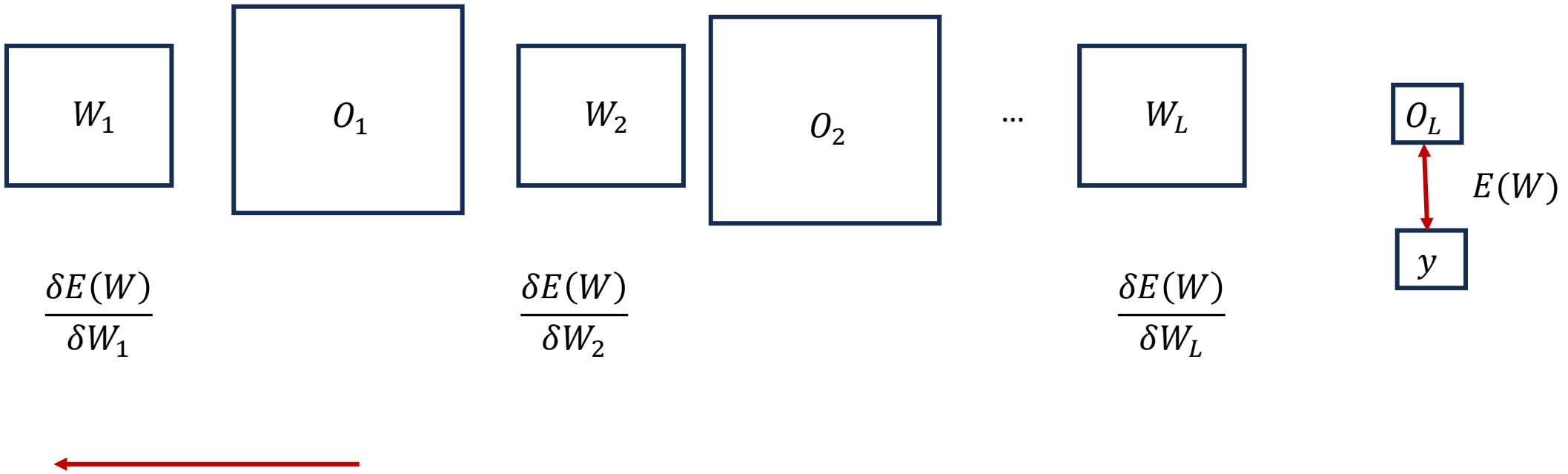
CNN Training: Backward Propagation



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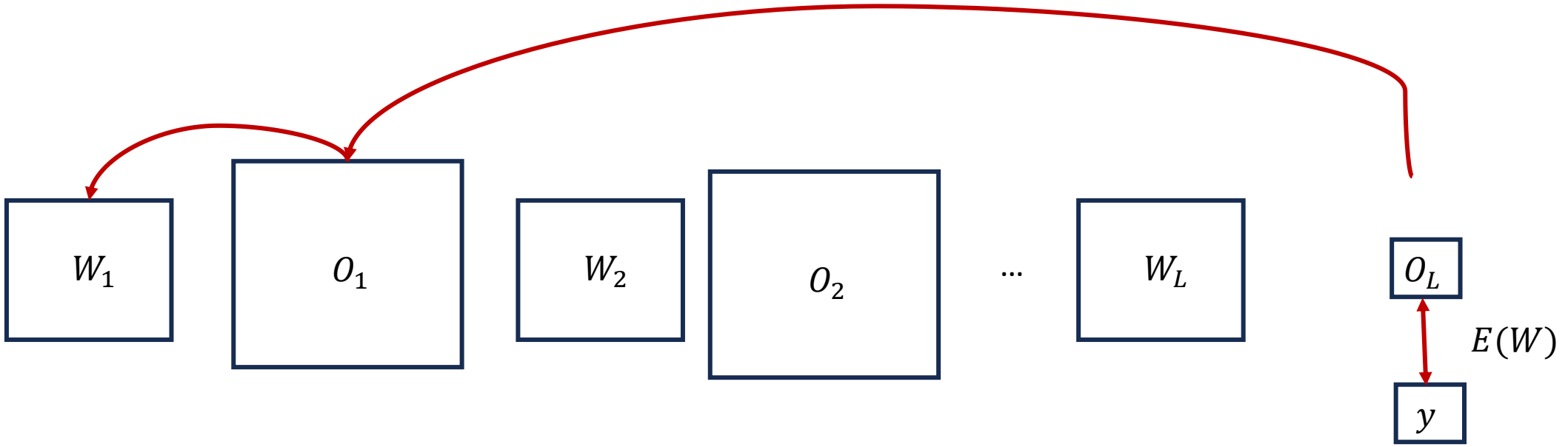
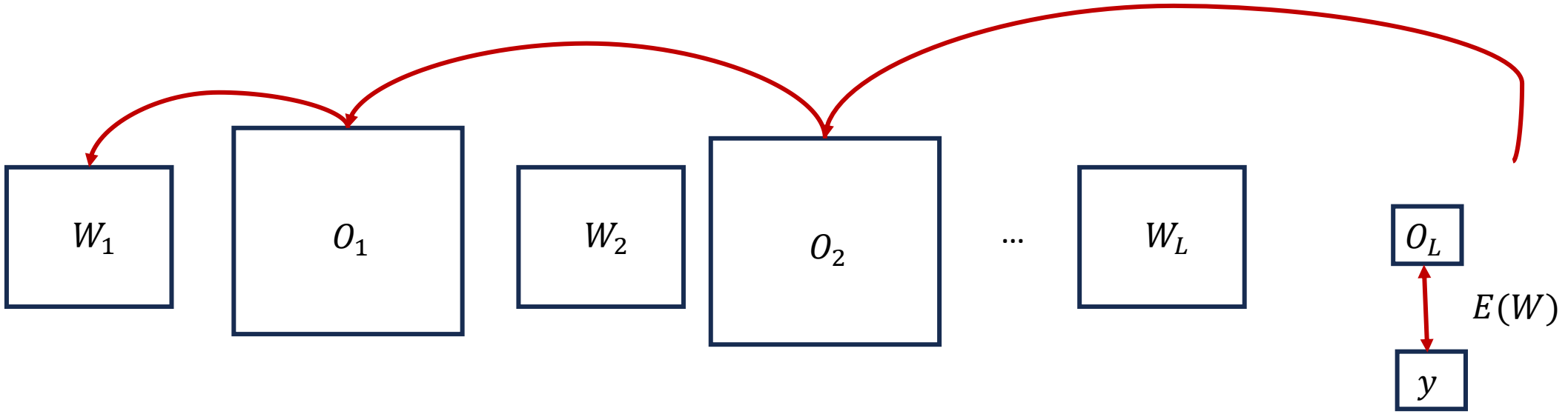
CNN Training: Backward Propagation



$$\frac{\delta E(W)}{\delta W_1} = \frac{\delta O_1}{\delta W_1} \times \frac{\delta E(W)}{\delta O_1}$$

For a single image

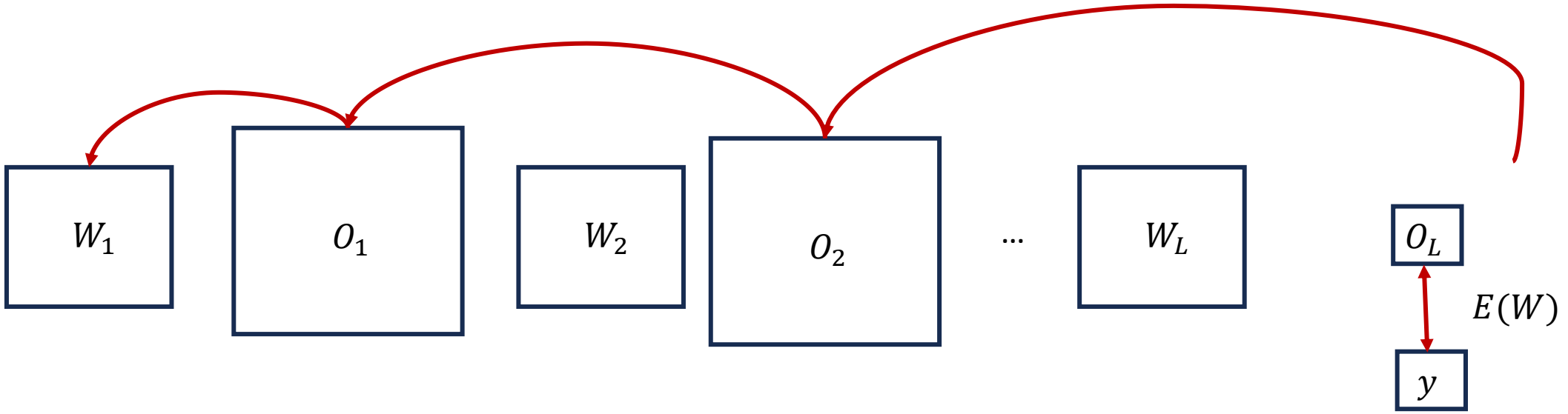
CNN Training: Backward Propagation



$$\frac{\delta E(W)}{\delta W_1} = \frac{\delta O_1}{\delta W_1} \times \frac{\delta O_2}{\delta O_1} \times \frac{\delta E(W)}{\delta O_2}$$

For a single image

CNN Training: Backward Propagation



$$\frac{\delta E(W)}{\delta W_1} = \frac{\delta O_1}{\delta W_1} \times \frac{\delta O_2}{\delta O_1} \times \frac{\delta O_3}{\delta O_2} \times \cdots \times \frac{\delta O_L}{\delta O_{L-1}} \times \frac{\delta E(W)}{\delta O_L}$$

For a single image

Training

$$E(W): \min_{W} \sum (y_i - F(x_i: W))\text{^}2$$

$$W_{t+1} \leftarrow W_t - \alpha \frac{\delta E(W)}{\delta W}$$

Iteratively

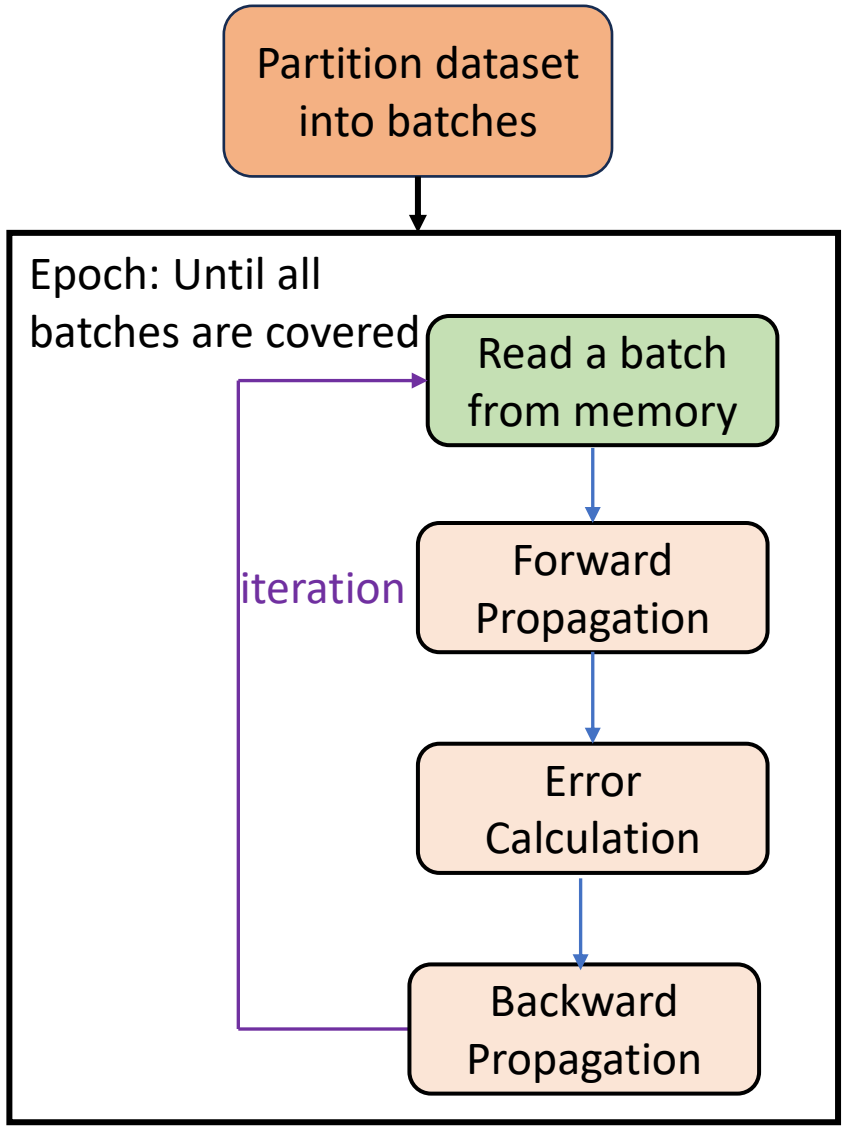
$$\frac{\delta E(W)}{\delta W} = 2\sum \underbrace{\left(y_i - F(x_i: W)\right)}_{\text{Error}} \times \frac{\delta F(x_i: W)}{\delta W}$$

For all samples, in each iteration

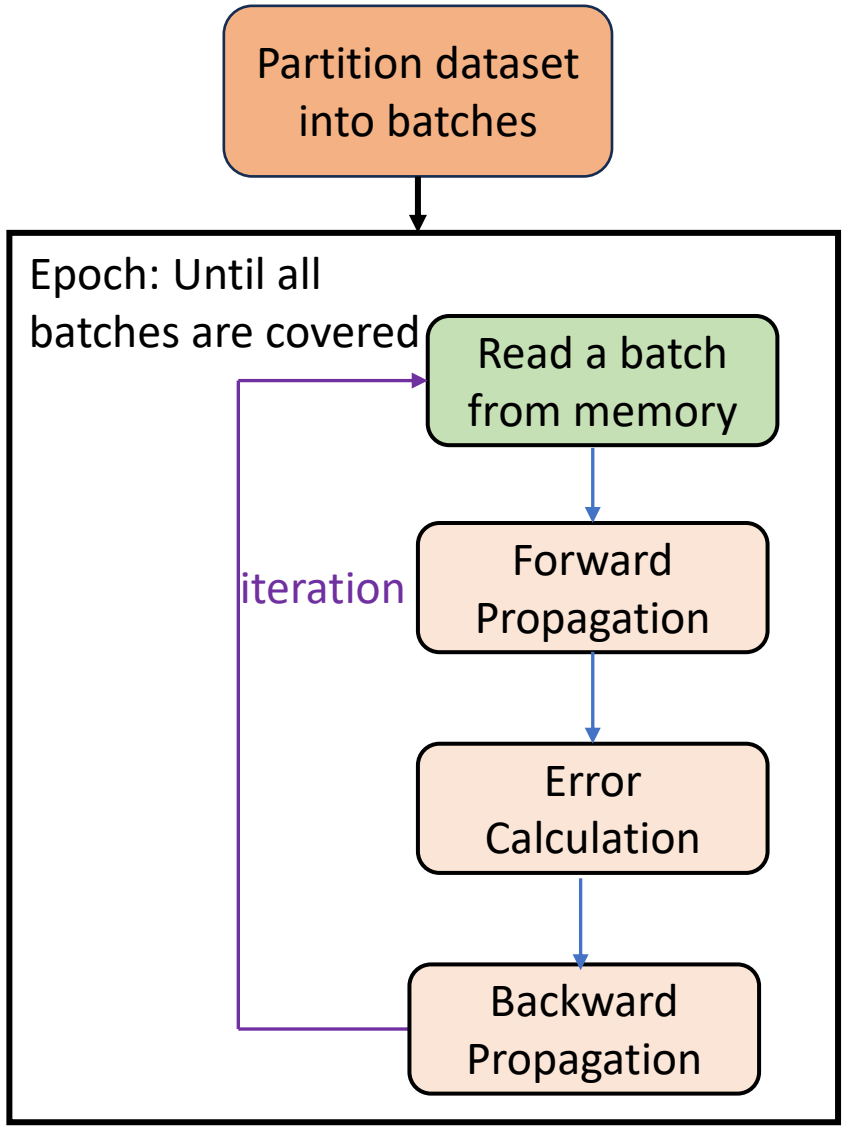
$$\frac{\delta E(W)}{\delta W_l} = \boxed{\frac{\delta O_l}{\delta W_l} \times \frac{\delta O_{l+1}}{\delta O_l} \times \frac{\delta O_{l+2}}{\delta O_{l+1}} \times \cdots \times \frac{\delta O_L}{\delta O_{L-1}}} \times \boxed{\frac{\delta E(W)}{\delta O_L}}$$

For multiple images in a batch: Simply sum up the gradients

Training a Machine Learning Model



Data Parallel Distributed Training



- Mini batches further partitioned in independent subsets.
- Each subset performs the iteration in parallel
- Need synchronization???

Gradient Update

$$W \leftarrow W \ - \alpha \frac{\delta E(W)}{\delta W}$$

- Lets dig deeper into Gradient Update

Gradient Update

- For a mini-batch with M samples and mean squared error
- $E(W) = \sum_{i=1}^{M} E_i(W)$
- $E_i(w) = (\mathrm{O_{Li}} - \mathrm{y_i})^2$
- $\frac{\delta E(W)}{\delta W} = \sum_{i=1}^{M} \frac{\delta E_i(W)}{\delta W}$

Gradient Update

$$\frac{\delta E(W)}{\delta W} = \frac{\delta E_1(W)}{\delta W} + \frac{\delta E_2(W)}{\delta W} + \ \ldots + \frac{\delta E_M(W)}{\delta W}$$

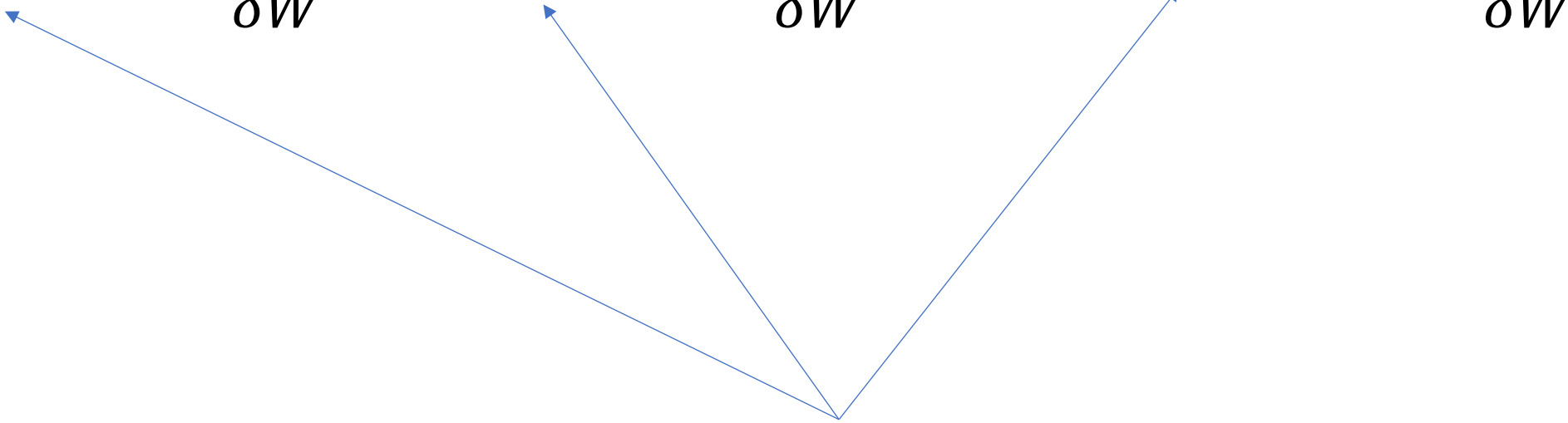
$$= \underbrace{2(\mathrm{O_{L1}} - \mathrm{y_1})\frac{\delta O_{L1}}{\delta W}} + \underbrace{2(\mathrm{O_{L2}} - \mathrm{y_2})\frac{\delta O_{L2}}{\delta W}} + \ \ldots + \underbrace{2(\mathrm{O_{LM}} - \mathrm{y_M})\frac{\delta O_{LM}}{\delta W}}$$

Can be calculated in parallel

Gradient Update

$$\frac{\delta E(W)}{\delta W} = \frac{\delta E_1(W)}{\delta W} + \frac{\delta E_2(W)}{\delta W} + \ \ldots + \frac{\delta E_M(W)}{\delta W}$$

$$= 2(\mathrm{O_{L1}} - \mathrm{y_1})\frac{\delta O_{L1}}{\delta W} + 2(\mathrm{O_{L2}} - \mathrm{y_2})\frac{\delta O_{L2}}{\delta W} + \ \ldots + 2(\mathrm{O_{LM}} - \mathrm{y_M})\frac{\delta O_{LM}}{\delta W}$$

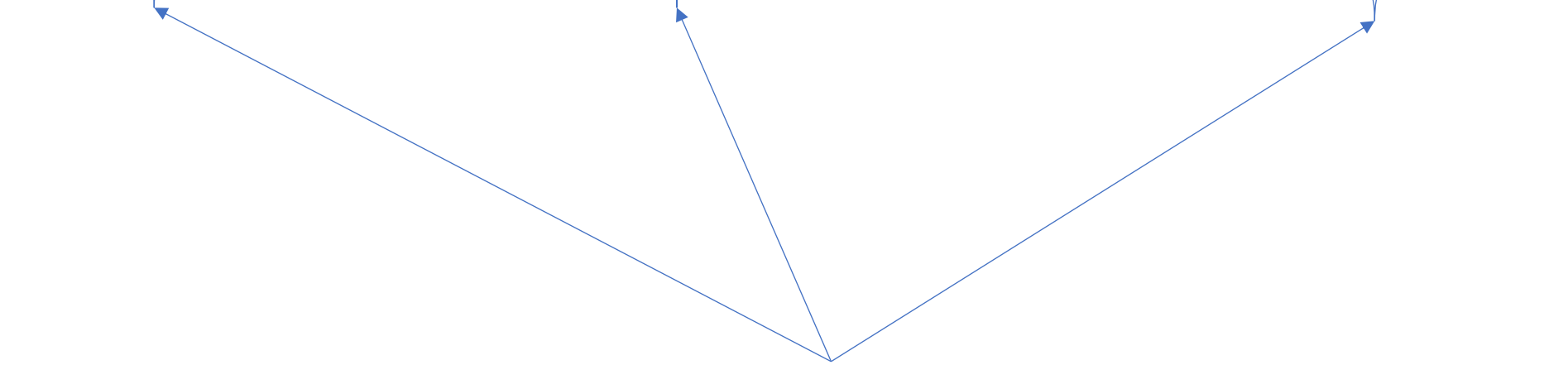


Forward propagation in parallel – Need multiple copies of model

Gradient Update

$$\frac{\delta E(W)}{\delta W} = \frac{\delta E_1(W)}{\delta W} + \frac{\delta E_2(W)}{\delta W} + \ \ldots + \frac{\delta E_M(W)}{\delta W}$$

$$= 2(\mathrm{O_{L1}} - \mathrm{y_1})\frac{\delta O_{L1}}{\delta W} + 2(\mathrm{O_{L2}} - \mathrm{y_2})\frac{\delta O_{L2}}{\delta W} + \ \ldots + 2(\mathrm{O_{LM}} - \mathrm{y_M})\frac{\delta O_{LM}}{\delta W}$$

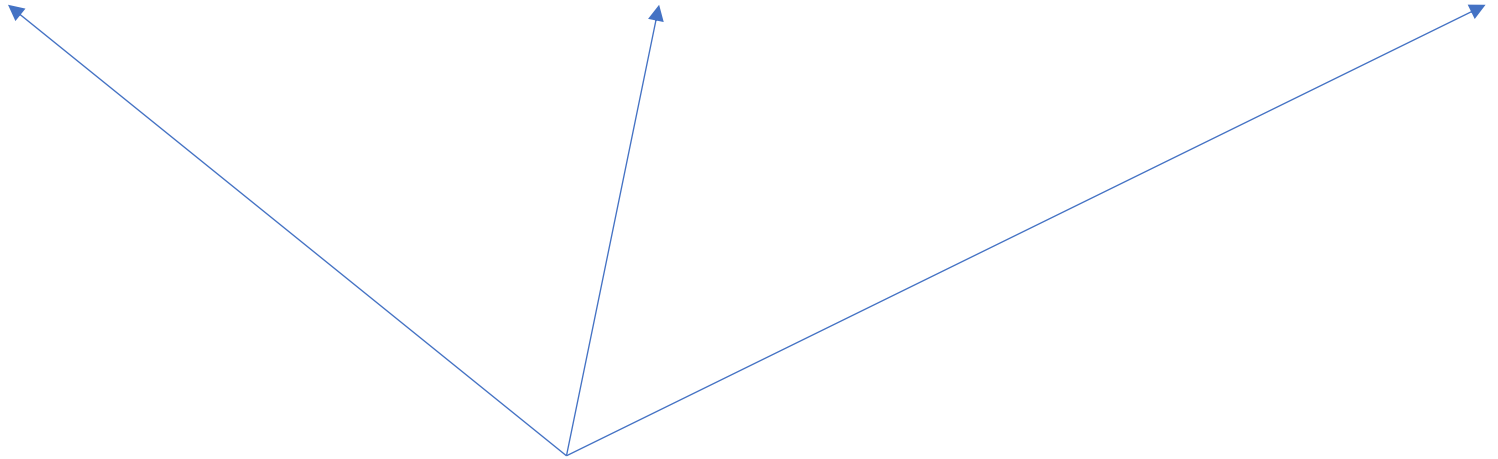


Error Calculation in parallel

Gradient Update

$$\frac{\delta E(W)}{\delta W} = \frac{\delta E_1(W)}{\delta W} + \frac{\delta E_2(W)}{\delta W} + \ \ldots + \frac{\delta E_M(W)}{\delta W}$$

$$= 2(\mathrm{O_{L1}} - \mathrm{y_1})\frac{\delta O_{L1}}{\delta W} + 2(\mathrm{O_{L2}} - \mathrm{y_2})\frac{\delta O_{L2}}{\delta W} + \ \ldots + 2(\mathrm{O_{LM}} - \mathrm{y_M})\frac{\delta O_{LM}}{\delta W}$$



Backward Propagation in parallel

Gradient Update

- If using p processes (or GPUs) for a mini-batch of size M
- Each process (or GPU) keeps a copy of the model W
- Each process performs the computations of M/p samples independently using its own model
- Note: No synchronization was needed till now

Gradient Update

- Weight Update Step:

$$W \leftarrow W - \alpha \frac{\delta E(W)}{\delta W}$$

- No synchronization needed till now.

Gradient Update

- Weight Update Step:

$$W \leftarrow W - \alpha \frac{\delta E(W)}{\delta W}$$

- Do we need synchronization now???

Gradient Update

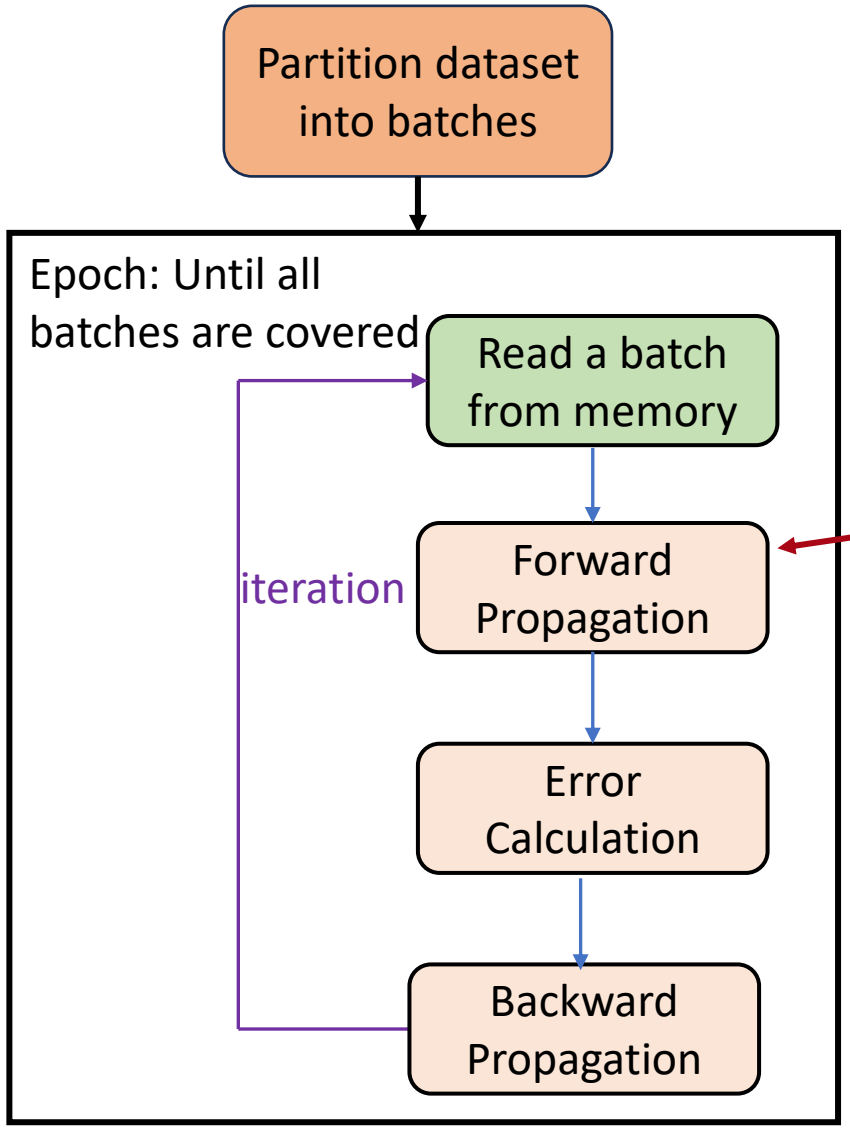
- Weight Update Step:

$$W \leftarrow W \ - \alpha \frac{\delta E(W)}{\delta W}$$

- Do we need synchronization now??? Yes.

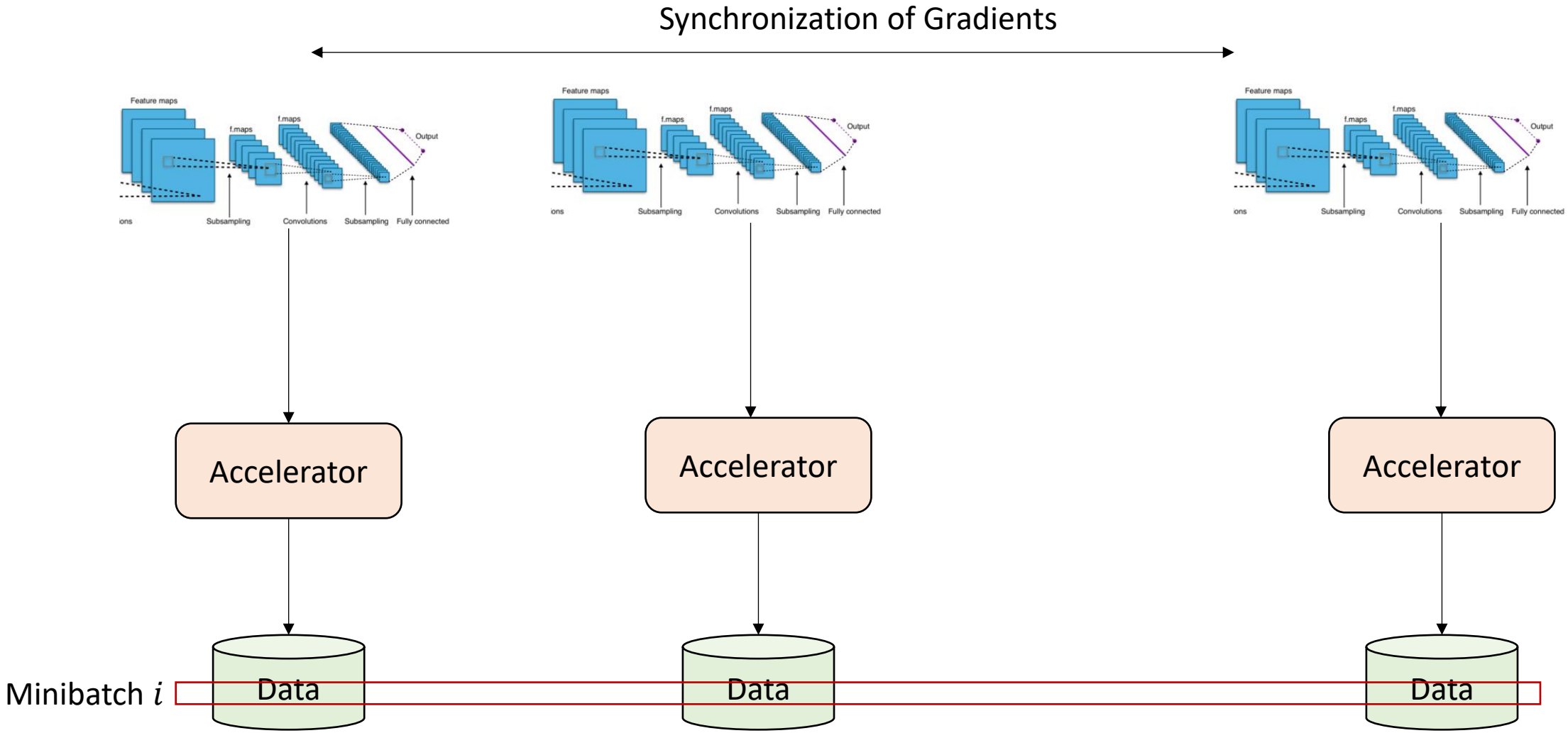
- Need to make sure that all GPUs have the same weights before they start processing the next mini-batch

Data Parallel Distributed Training



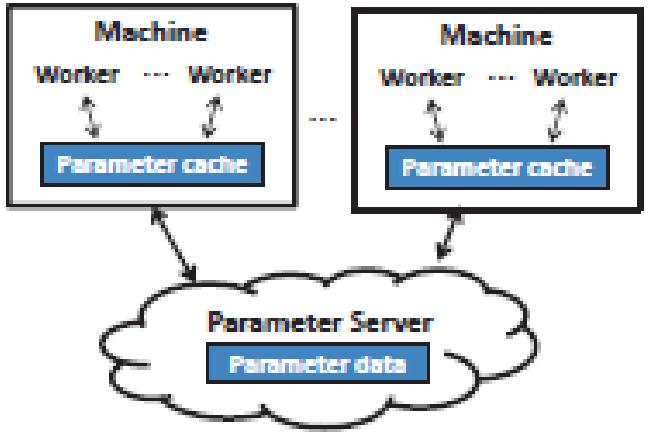
After each iteration, all parallel processors should use the same model weights to do the forward propagation on their portion of mini-batch

Data Parallel Training of Neural Networks



Data Parallel Training of Neural Networks

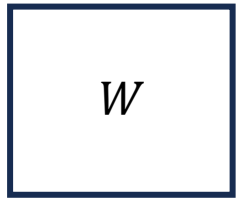
- How do we synchronize?
- Model #1: Parameter Server Model
- A dedicated server performs the weight updates and distributes the models to all the workers
- Resource: Li, Mu, et al. "Scaling distributed machine learning with the parameter server." *11th USENIX Symposium on operating systems design and implementation (OSDI 14)*. 2014.



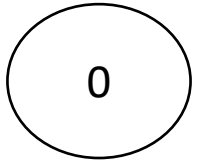
Cui, H., Zhang, H., Ganger, G. R., Gibbons, P. B., & Xing, E. P. (2016, April). Geeps: Scalable deep learning on distributed gpus with a gpu-specialized parameter server. In *Proceedings of the eleventh european conference on computer systems* (pp. 1-16).

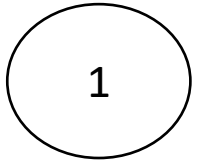
Parameter Server Model

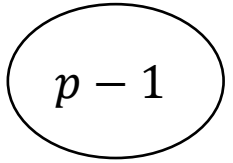
Parameter Server



Data Parallel GPUs



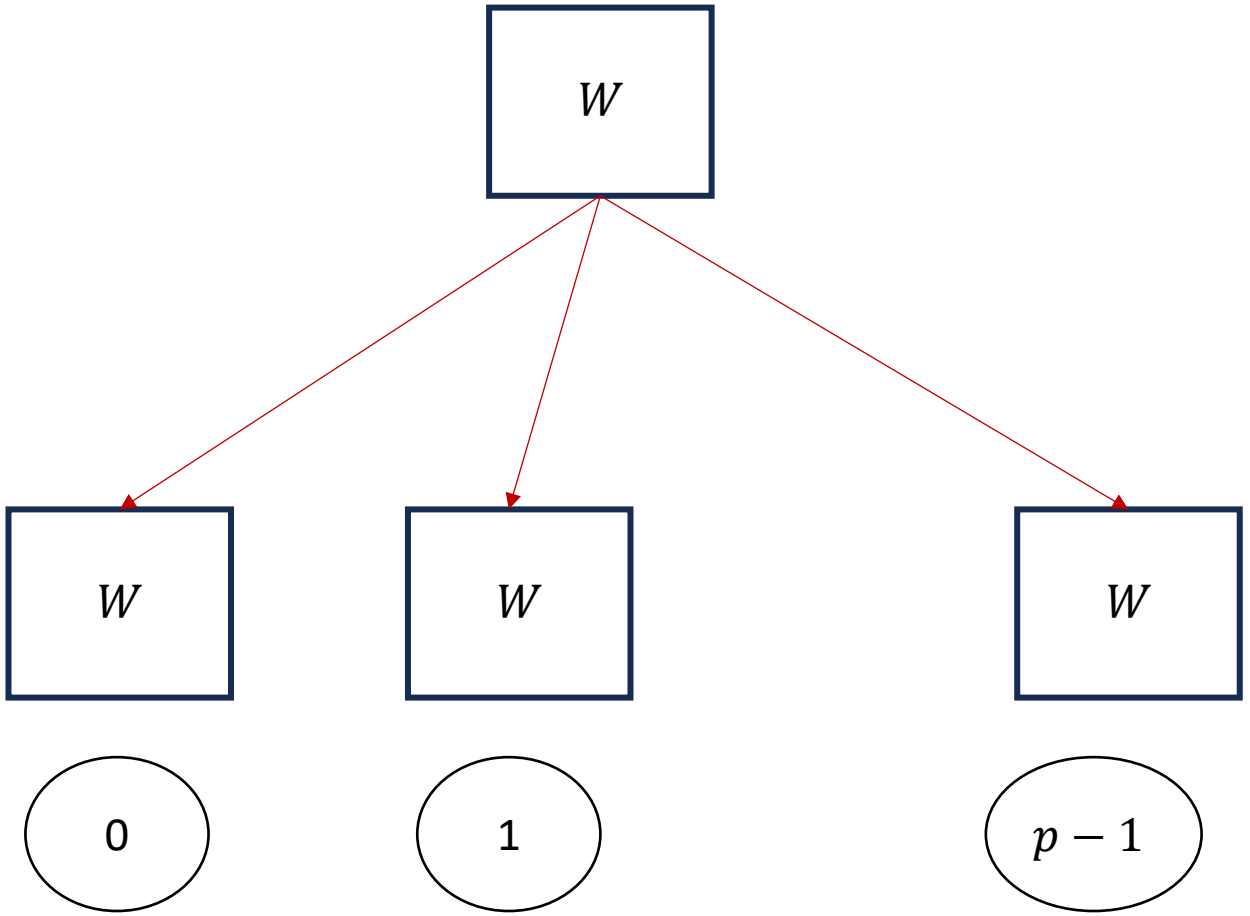




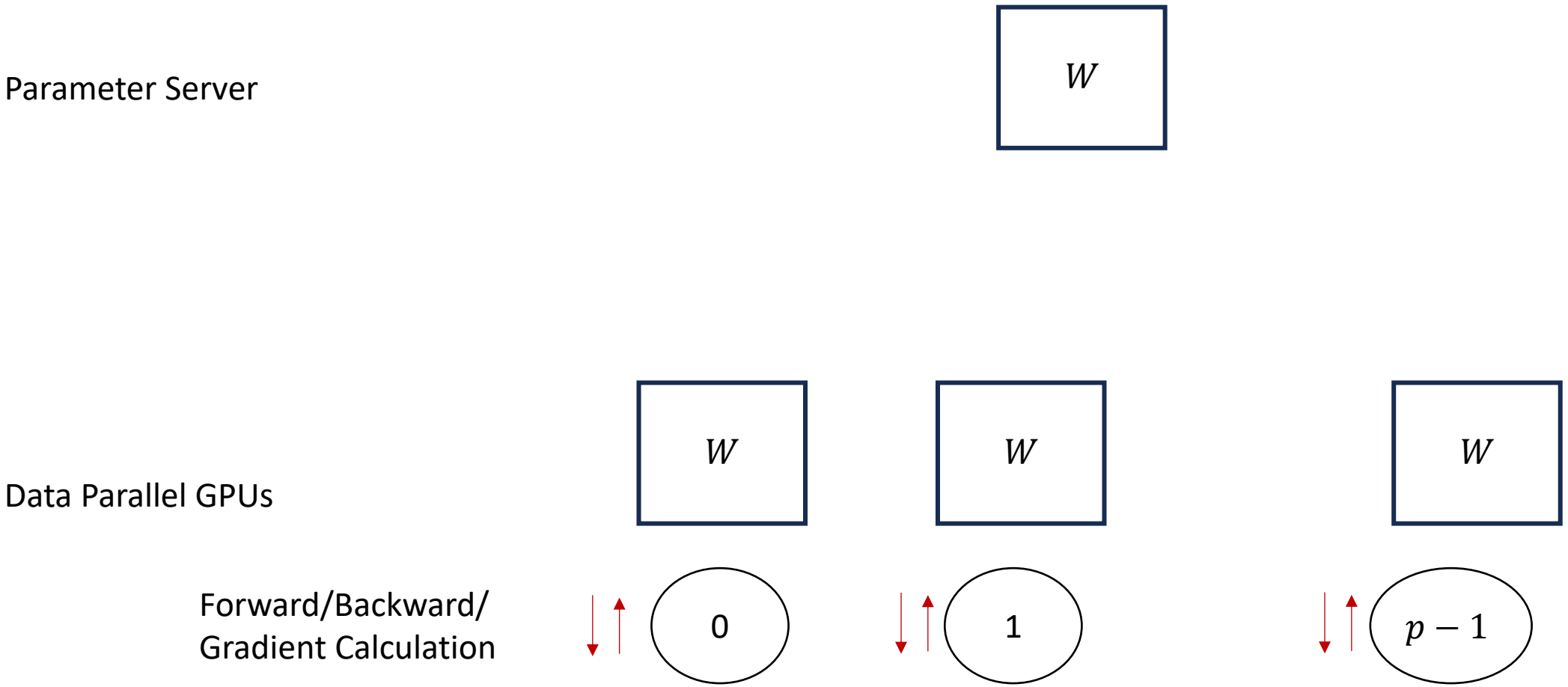
Parameter Server Model

Parameter Server

Data Parallel GPUs



Parameter Server Model



Parameter Server Model

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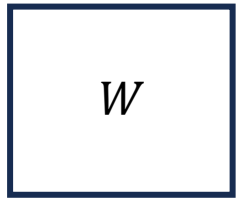
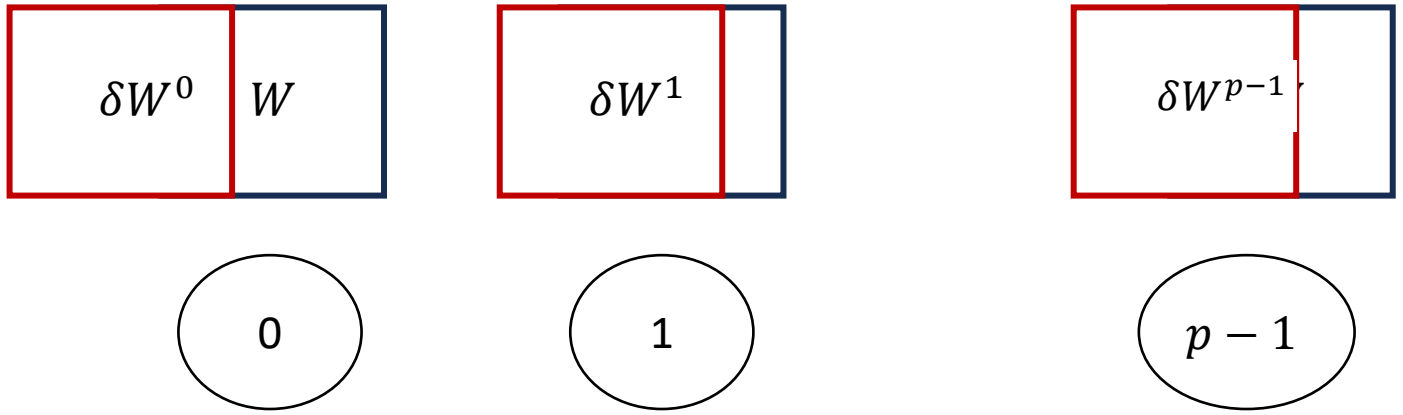


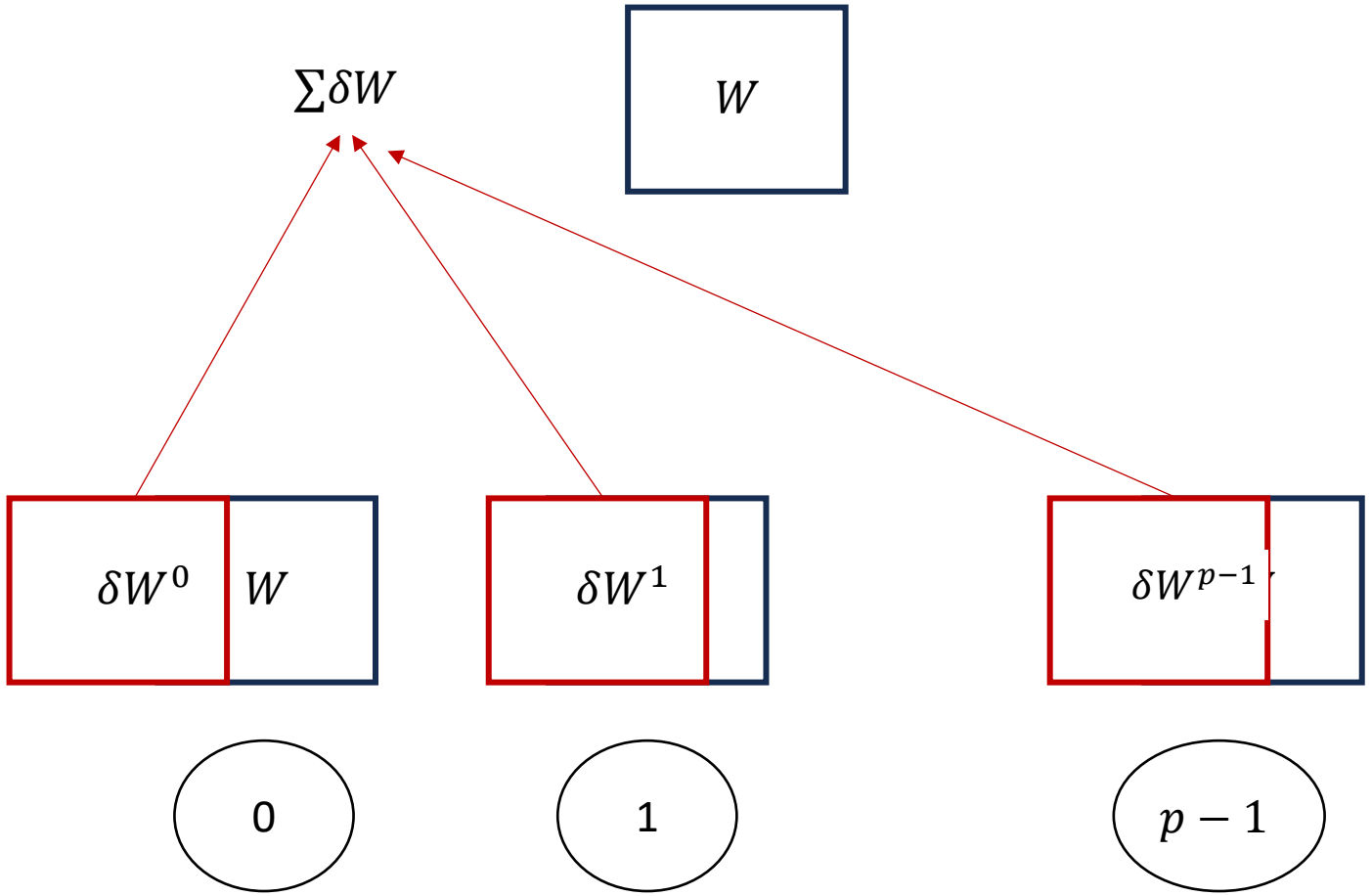
Data Parallel GPUs



Parameter Server Model

Parameter Server

Data Parallel GPUs

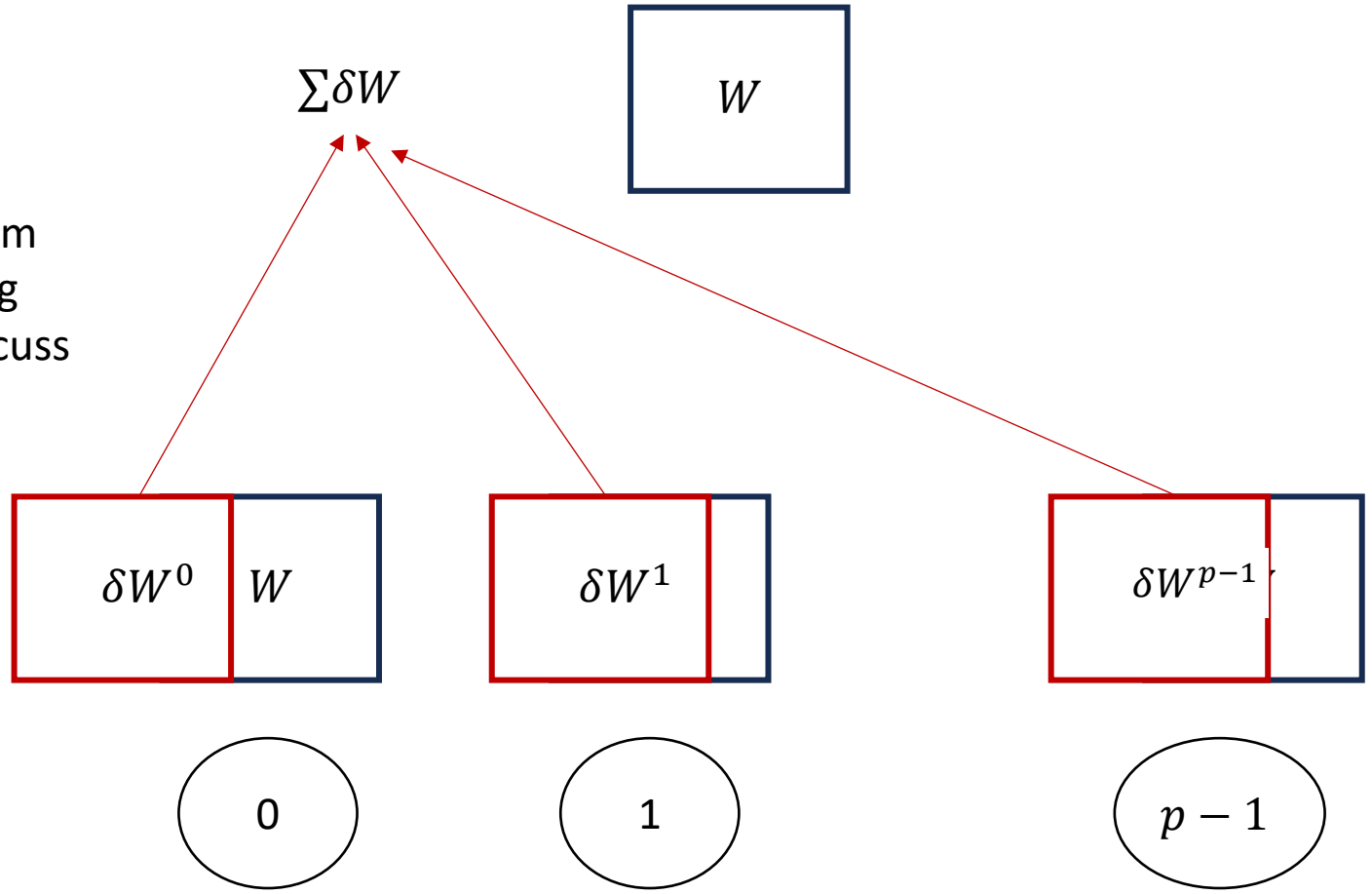


Parameter Server Model

Parameter Server

This operation of collecting data from different processors and aggregating them is called **Reduce** – We will discuss more when we discuss cluster of accelerators

Data Parallel GPUs



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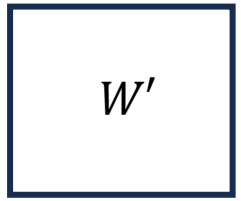
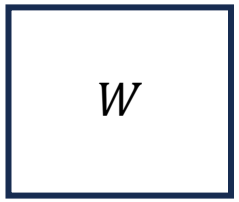
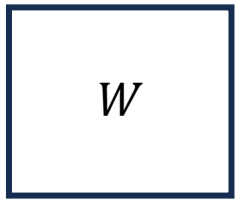
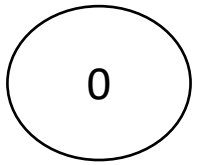
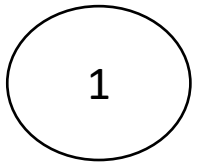


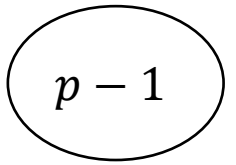
Data Parallel GPUs







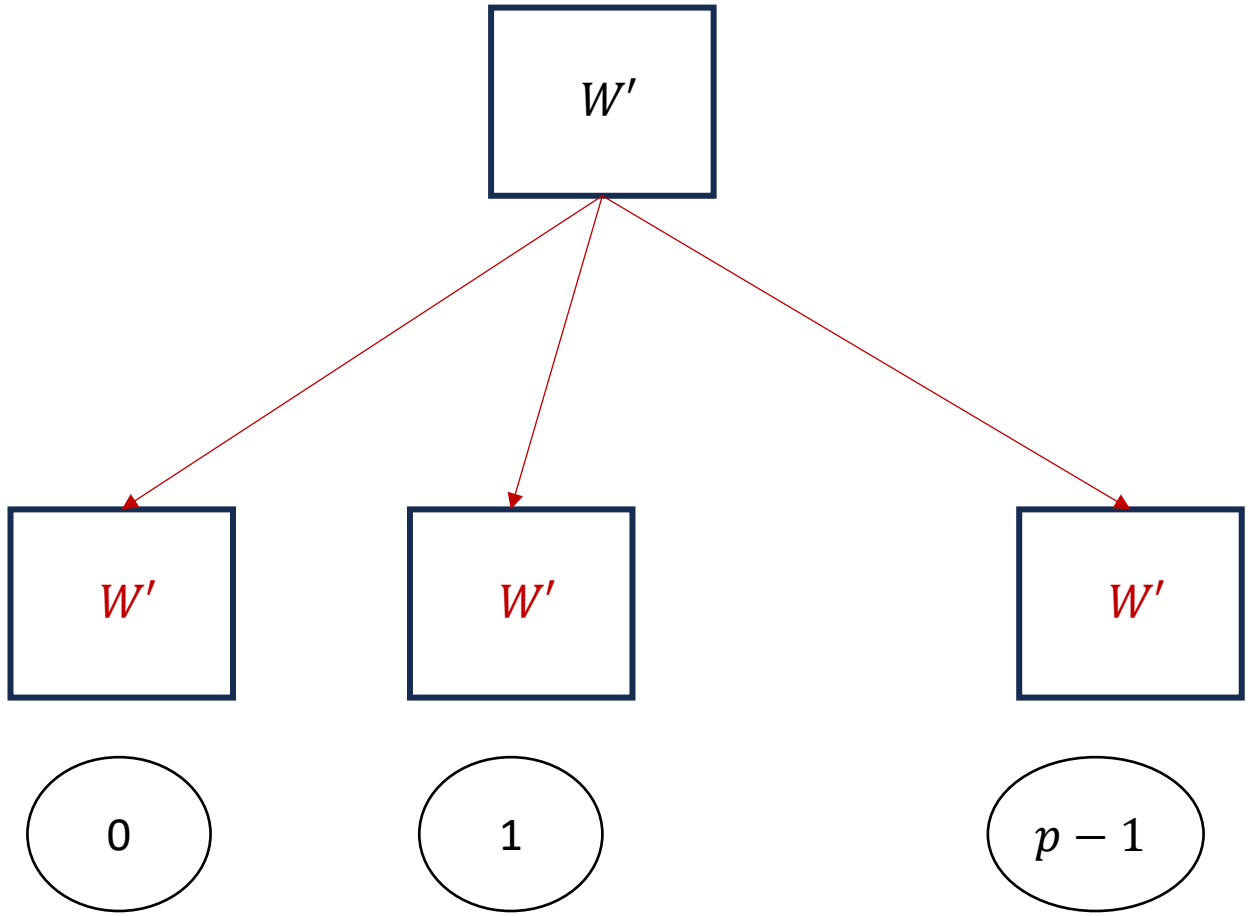




Parameter Server Model

Parameter Server

Data Parallel GPUs

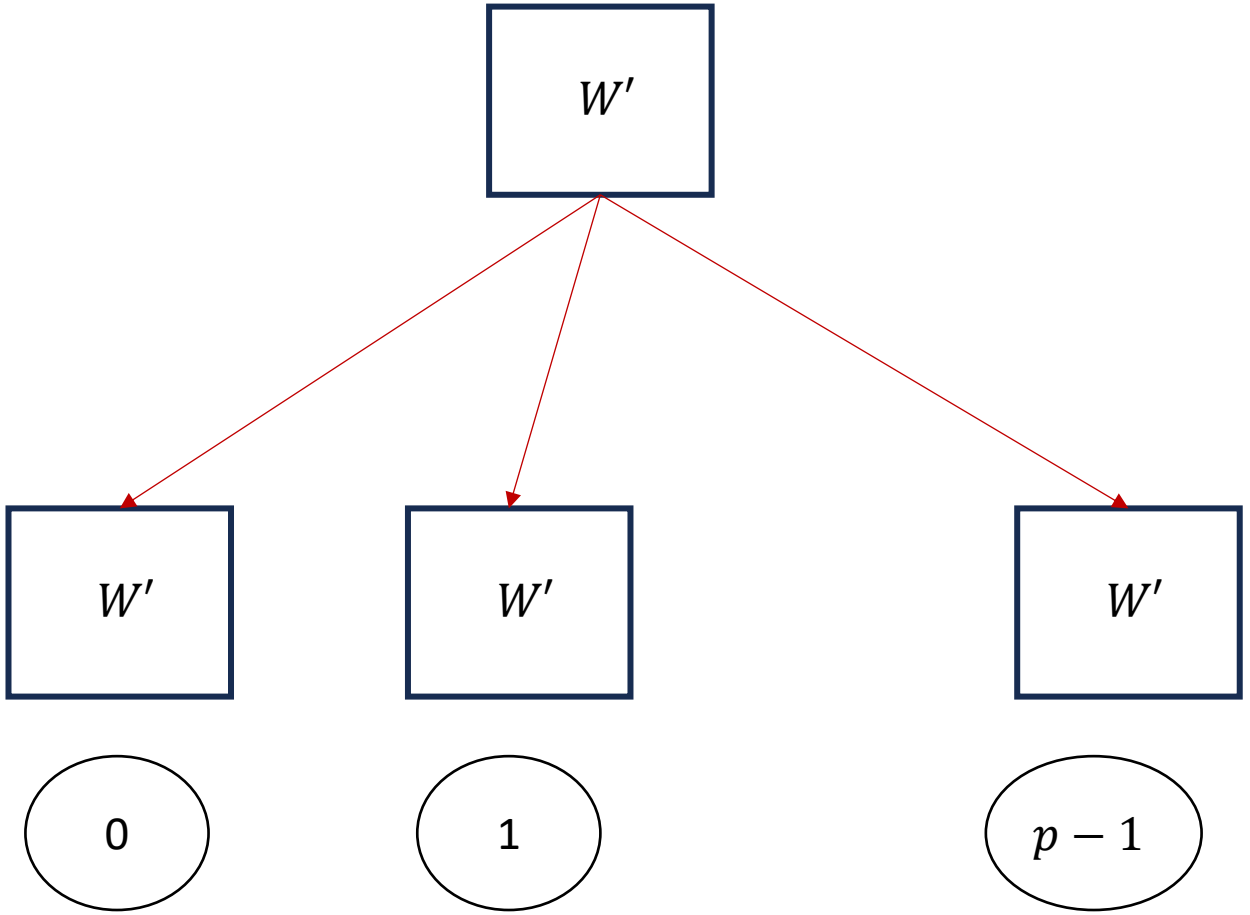


Parameter Server Model

Parameter Server

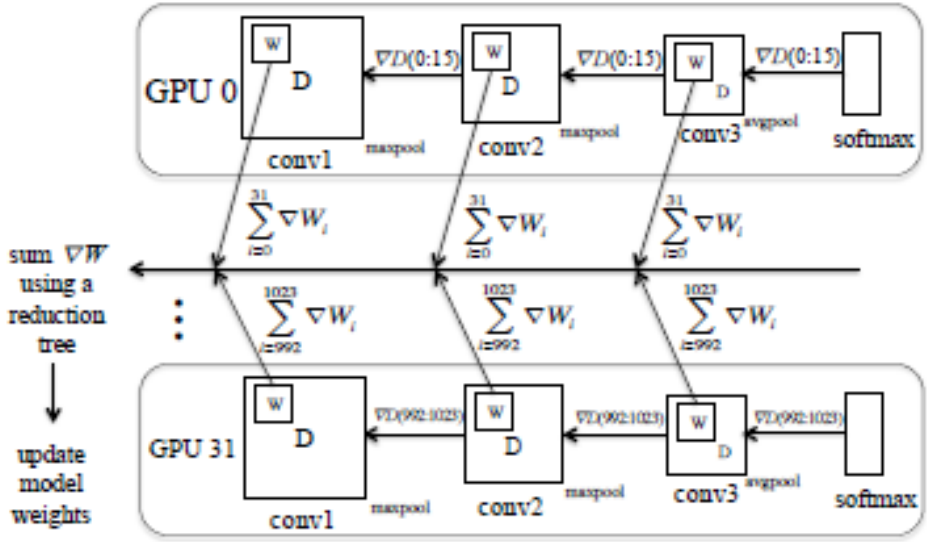
This operation of sending the same data from a single source to different processors is called **Broadcast** – We will discuss more when we discuss cluster of accelerators

Data Parallel GPUs



Data Parallel Training of Neural Networks

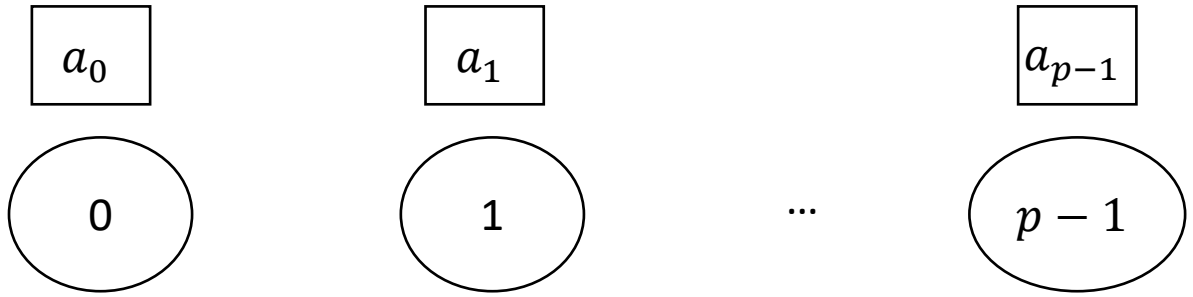
- How do we synchronize?
- Model #2: All-reduce based Synchronization
- No dedicated parameter server. Each worker calculates the gradients and broadcasts it to all other workers
- Each worker aggregates the gradients collected by all other workers and performs the update step



Iandola, F. N., Moskewicz, M. W., Ashraf, K., & Keutzer, K. (2016). Firecaffe: near-linear acceleration of deep neural network training on compute clusters. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2592-2600).

All Reduce Operation

- Each processor collects data from all the other processors and performs a reduce operation



All Reduce Operation

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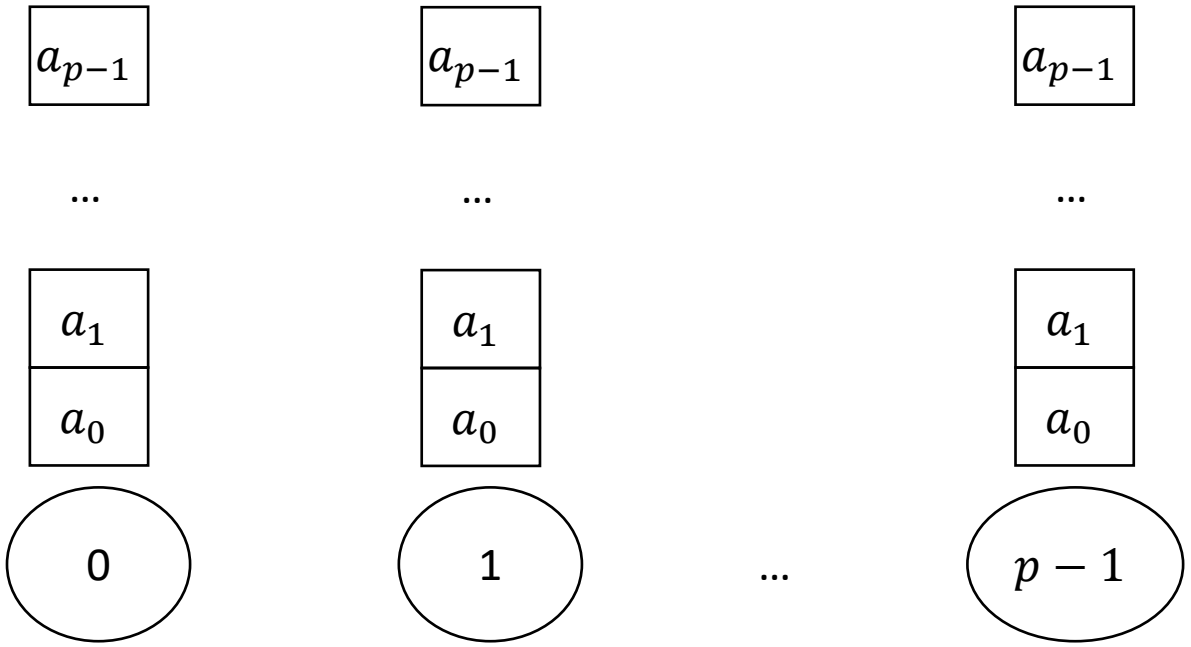
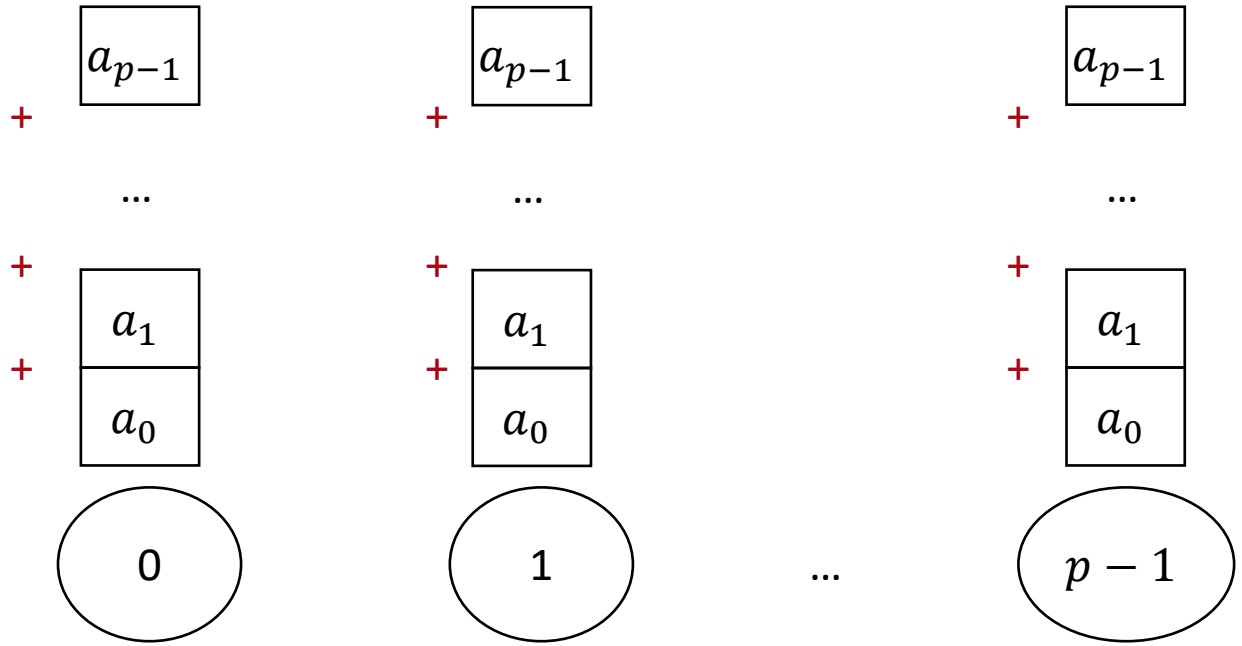


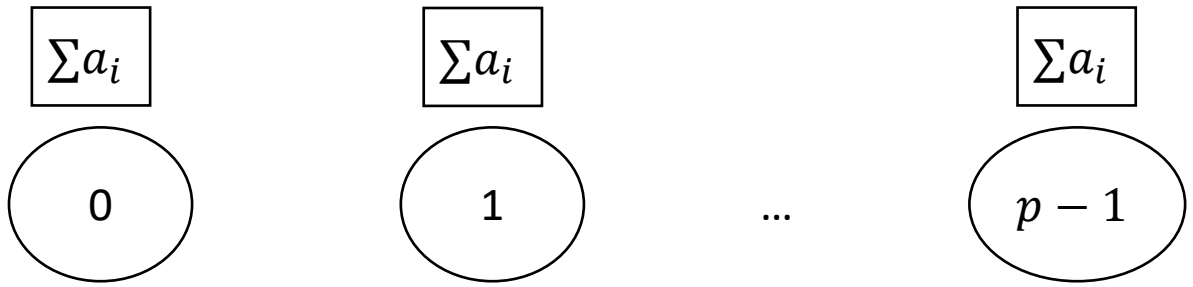
All Reduce Operation

- Each processor collects data from all the other processors and performs a reduce operation



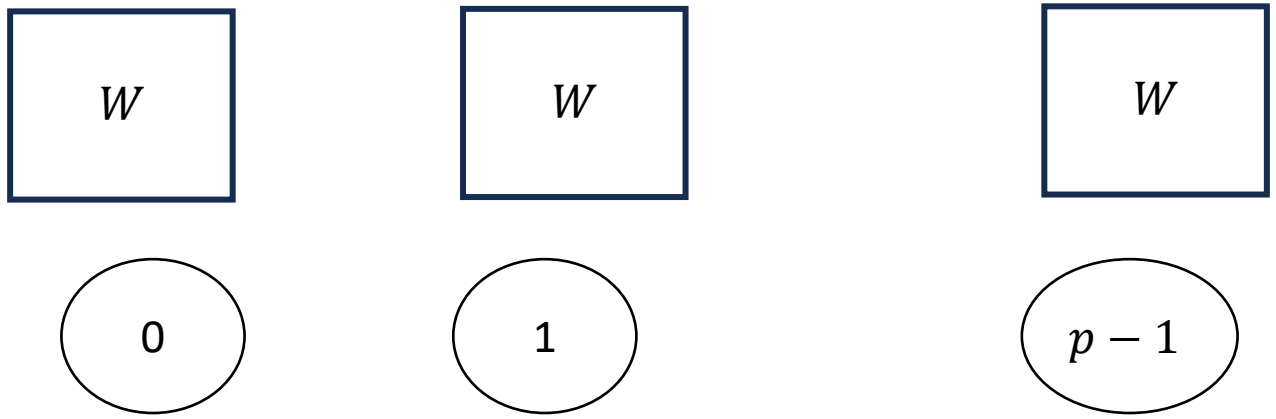
All Reduce Operation

- Each processor collects data from all the other processors and performs a reduce operation
- We will discuss how to efficiently implement this on a cluster of accelerators later in the class



All Reduce Model

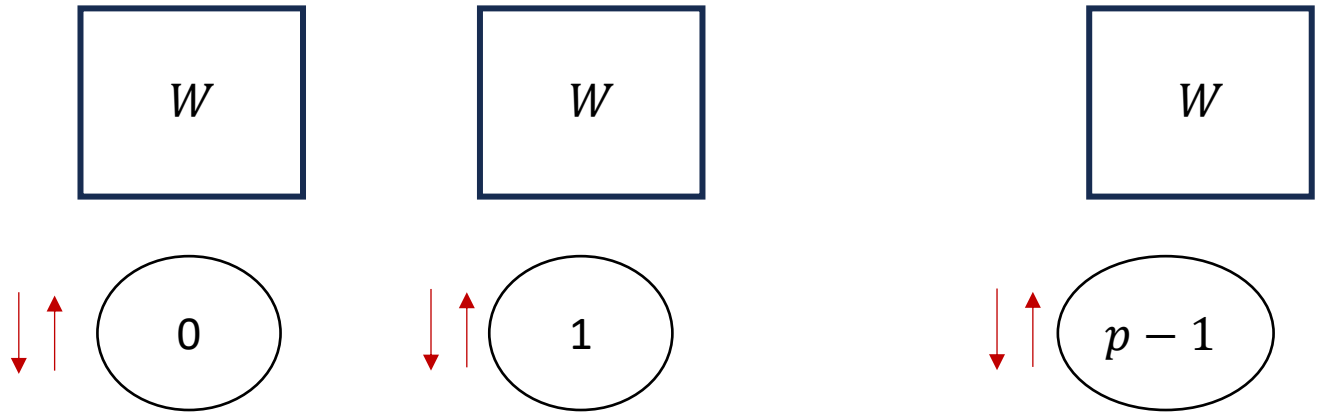
Data Parallel GPUs



All Reduce Model

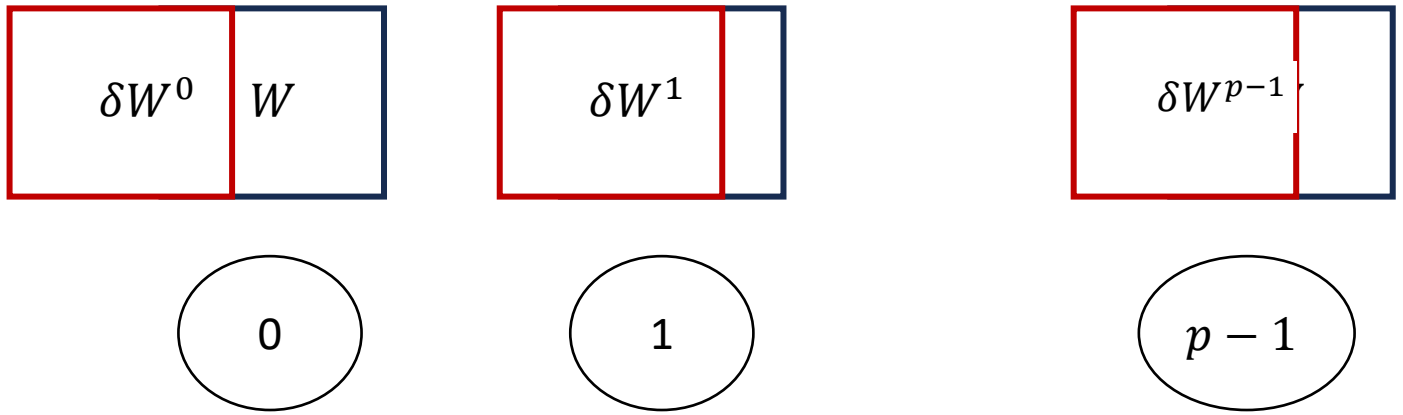
Data Parallel GPUs

Forward/Backward/
Gradient Calculation



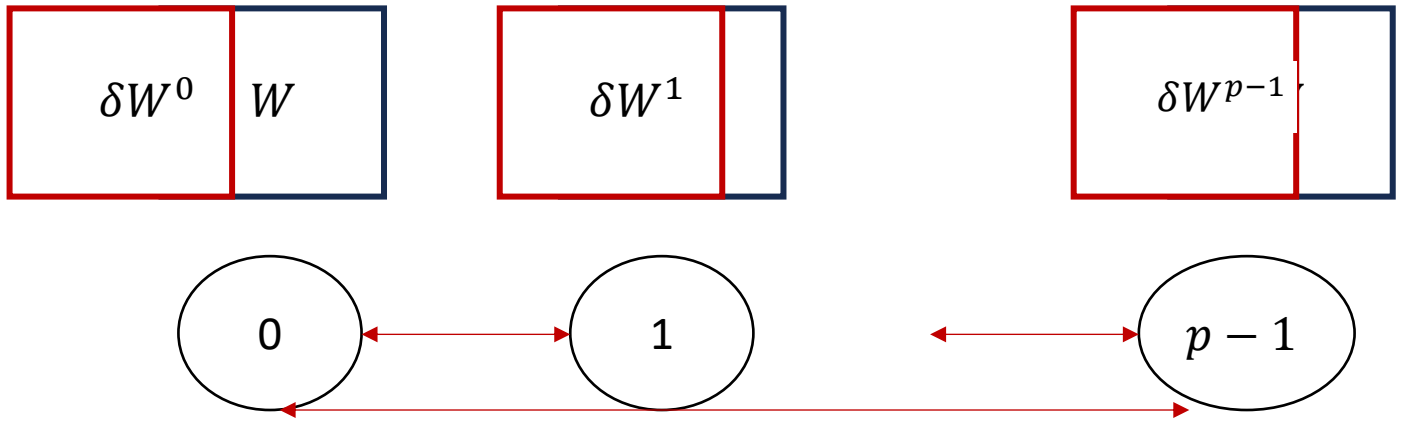
All Reduce Model

Data Parallel GPUs



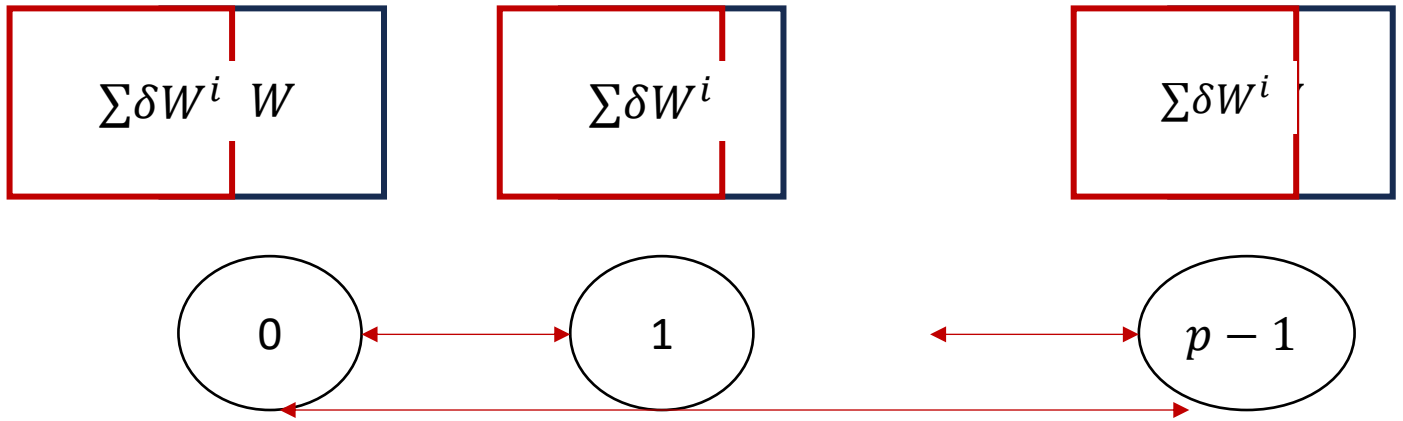
All Reduce Model

Data Parallel GPUs



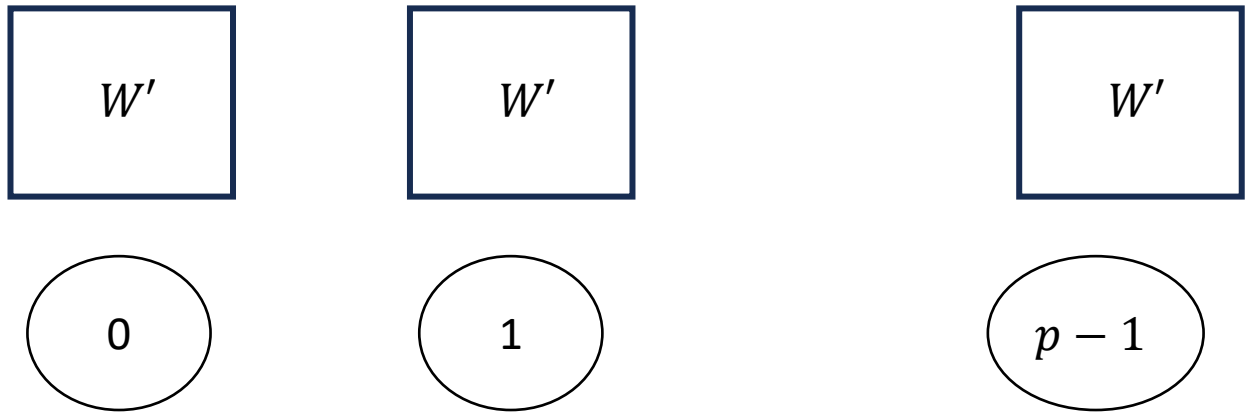
All Reduce Model

Data Parallel GPUs



All Reduce Model

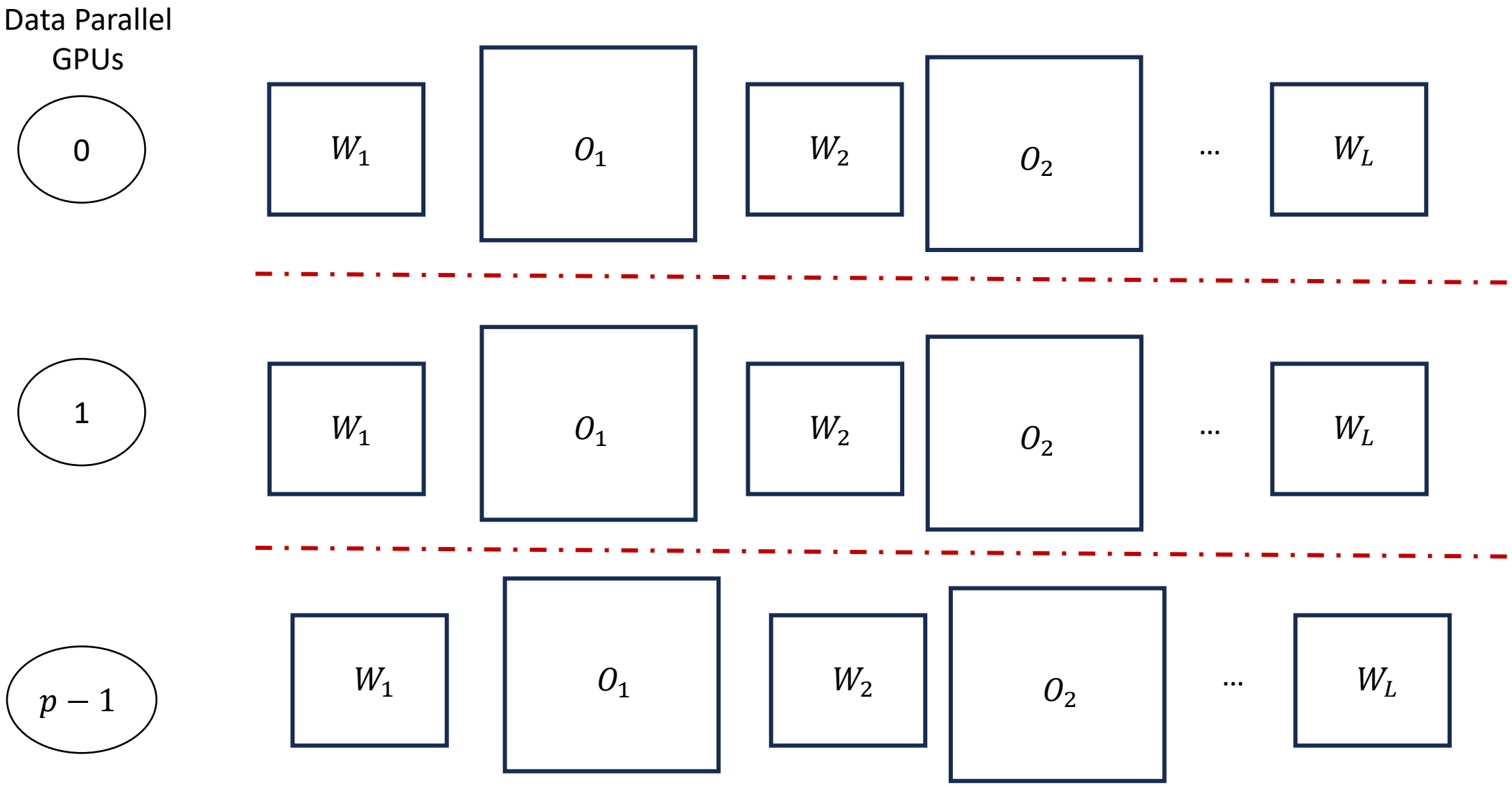
Data Parallel GPUs



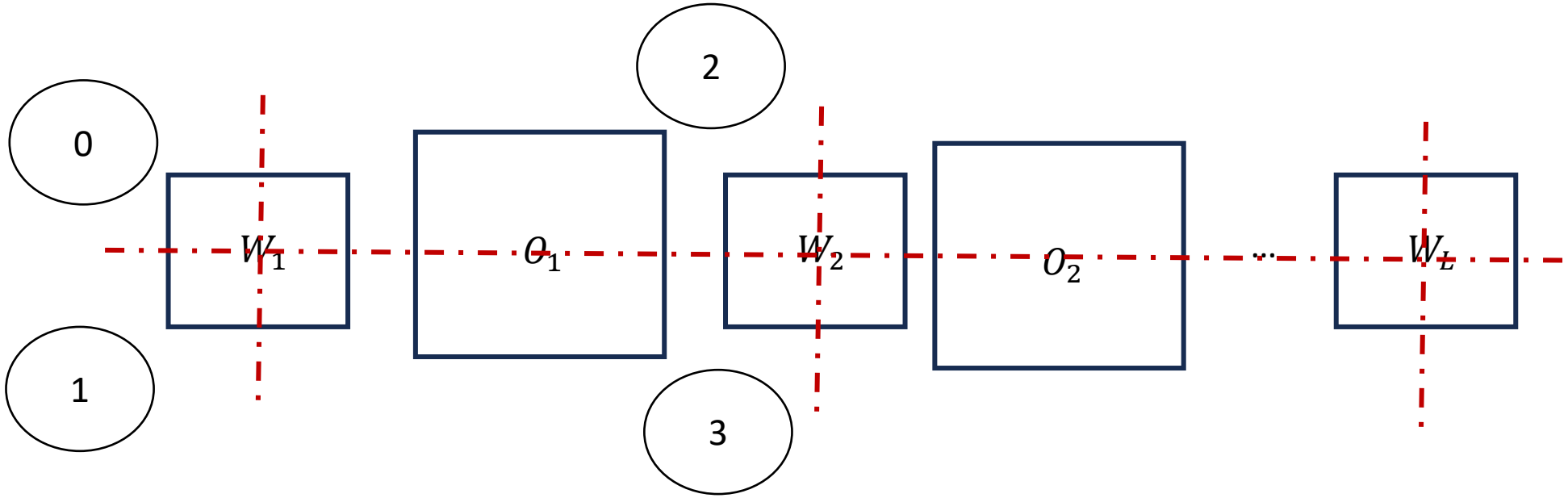
Model Parallel Distributed Training

- Data Parallelism
  - Weights are replicated on each GPU
- What if the model is too big for a single GPU?
- Model Parallelism: Split the model across GPUs

Model Parallel Distributed Training



Model Parallel Distributed Training



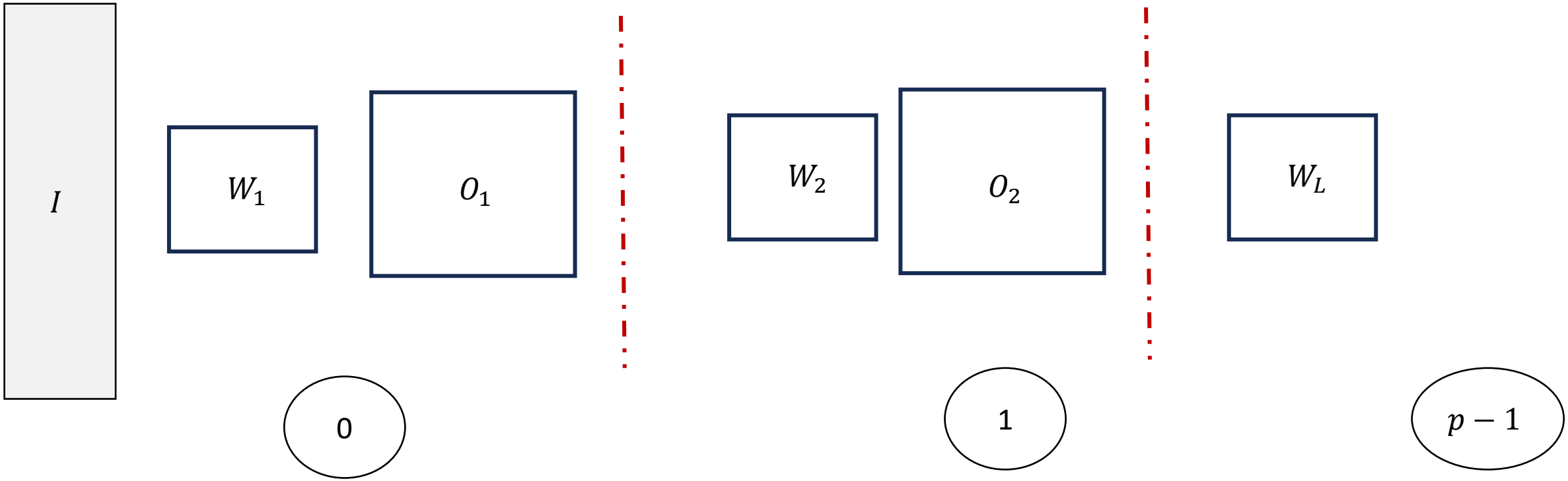
Partition the model across GPUs

Model Parallel Distributed Training

- Different ways to partition the model
- Layerwise Partitioning – Pipeline Parallelism
- Intra-Layer Partitioning – Tensor Parallelism

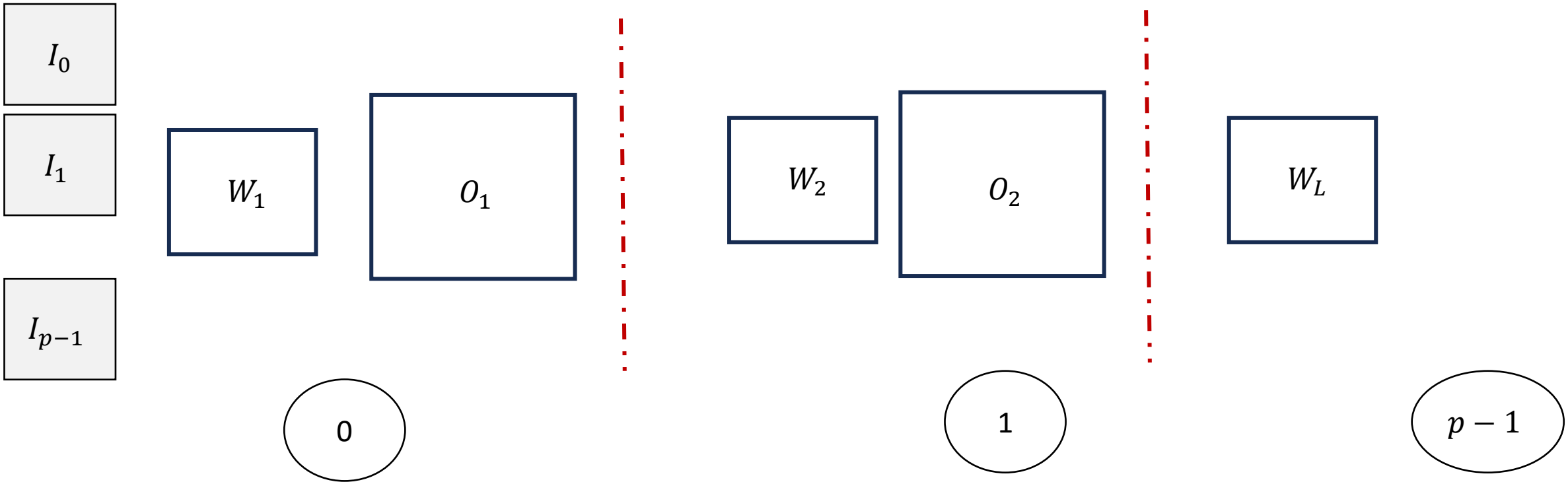
Pipeline Parallelism

Batch of inputs:
e.g., 64 images

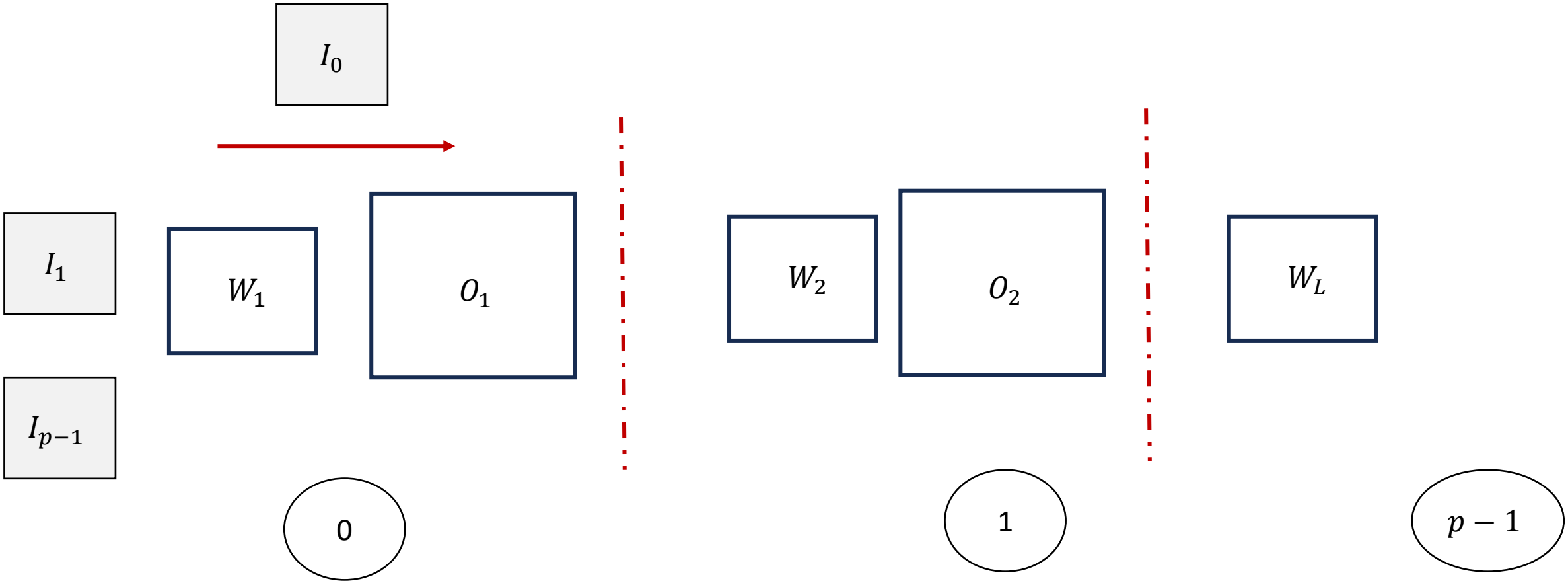


Pipeline Parallelism

Split input batch into p smaller mini-batches

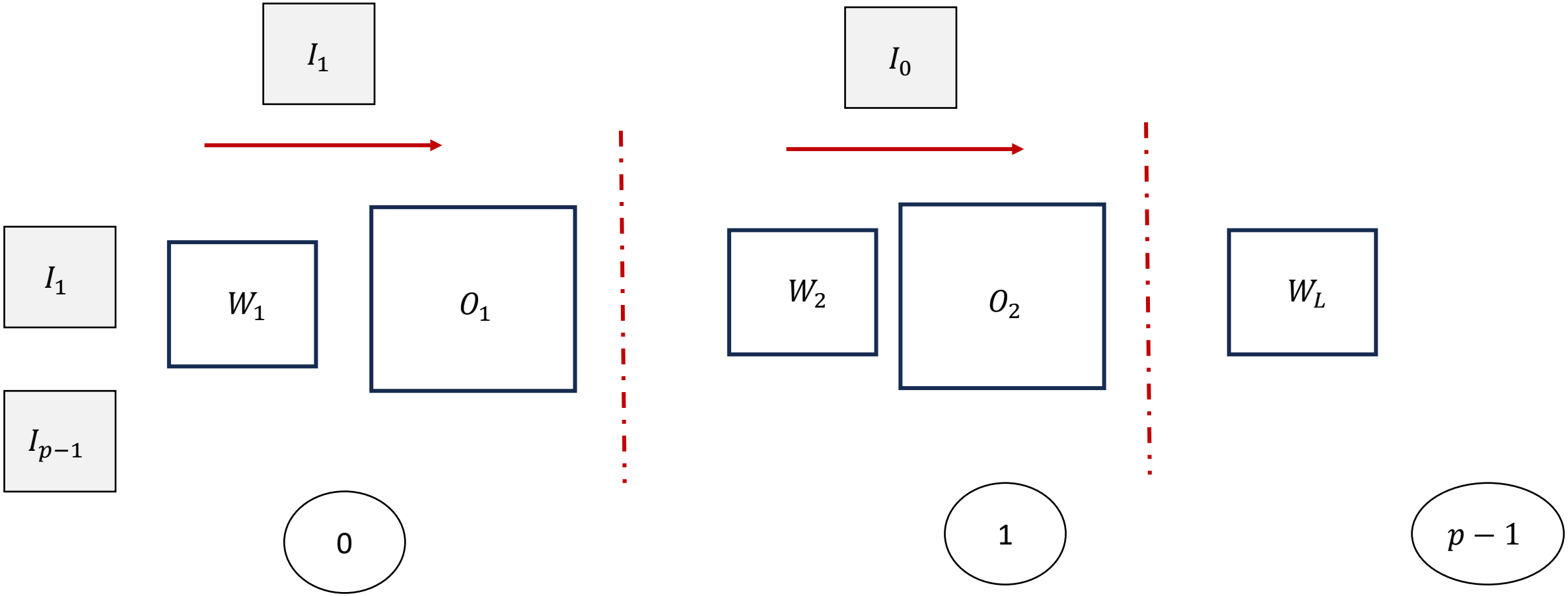


Pipeline Parallelism



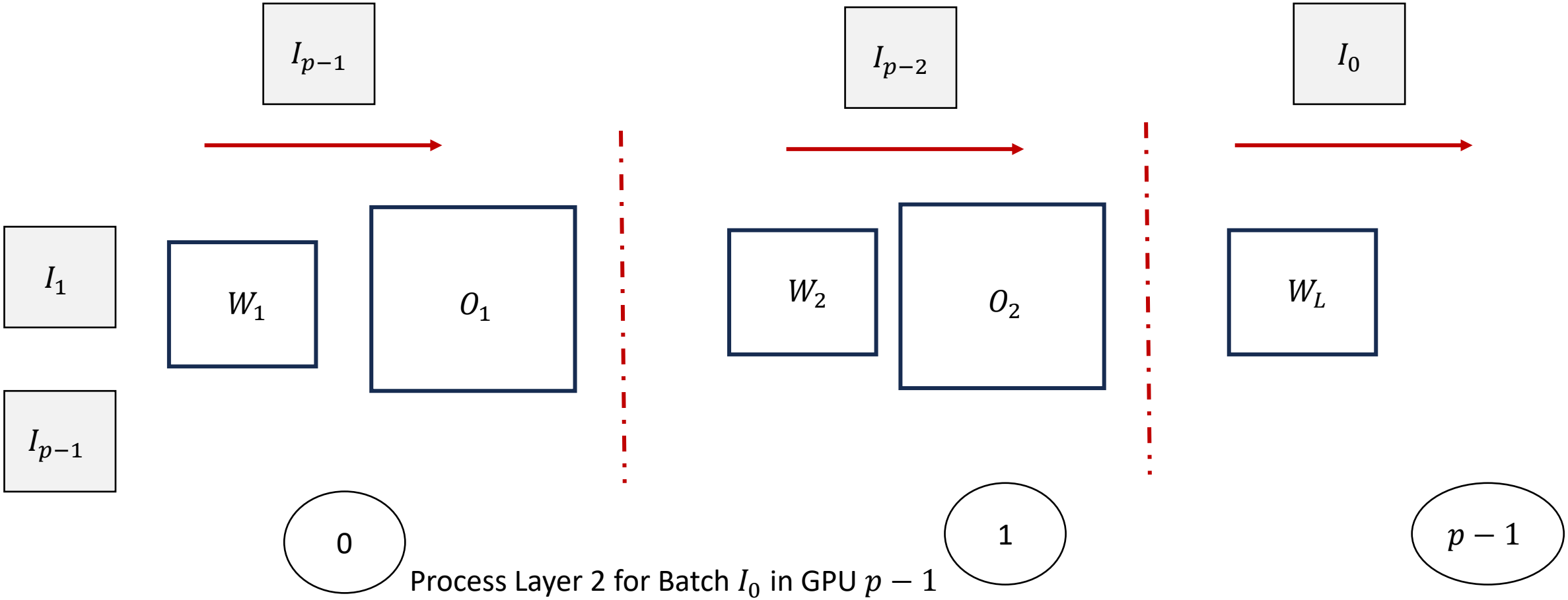
Process Layer 1 for Batch I_0 in GPU 0

Pipeline Parallelism



Process Layer 2 for Batch I_0 in GPU 1
Process Layer 1 for Batch I_1 in GPU 0

Pipeline Parallelism



Process Layer 2 for Batch I_0 in GPU $p-1$

…

Process Layer 2 for Batch I_{p-2} in GPU 1

Process Layer 1 for Batch I_{p-1} in GPU 0

Pipeline Parallelism

- When and what communications are needed?

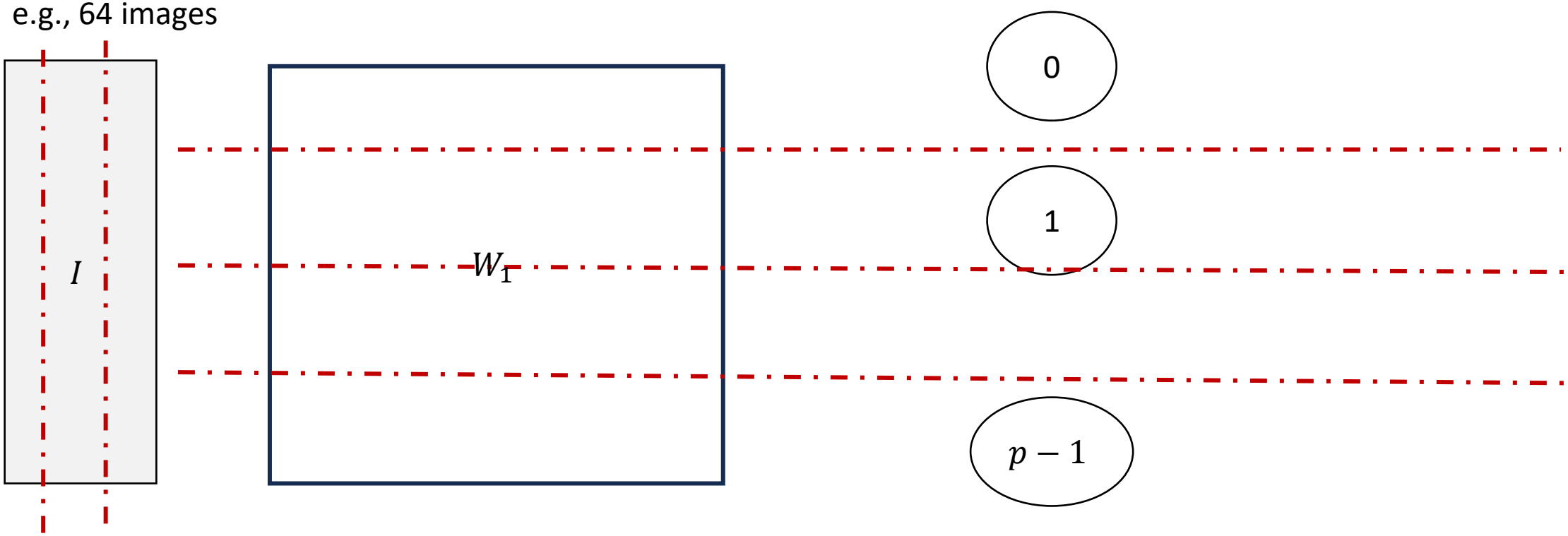
Pipeline Parallelism

- When and what communications are needed?

- Need to communicate the activations after each layer
  - In backward propagation, need to communicate gradients.

Tensor Parallelism

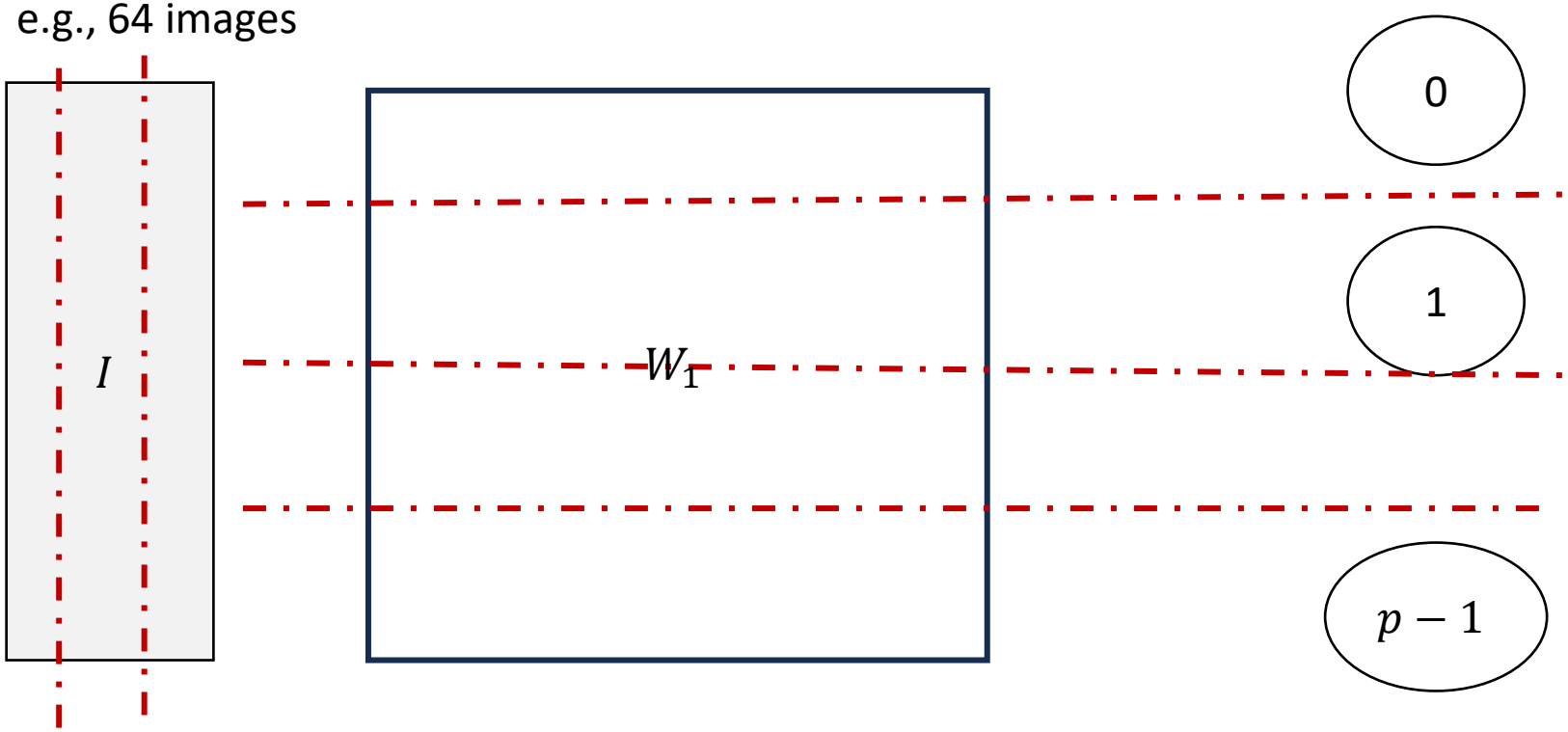
Batch of inputs:
e.g., 64 images



Partition across the embedding dimension of the inputs

Tensor Parallelism

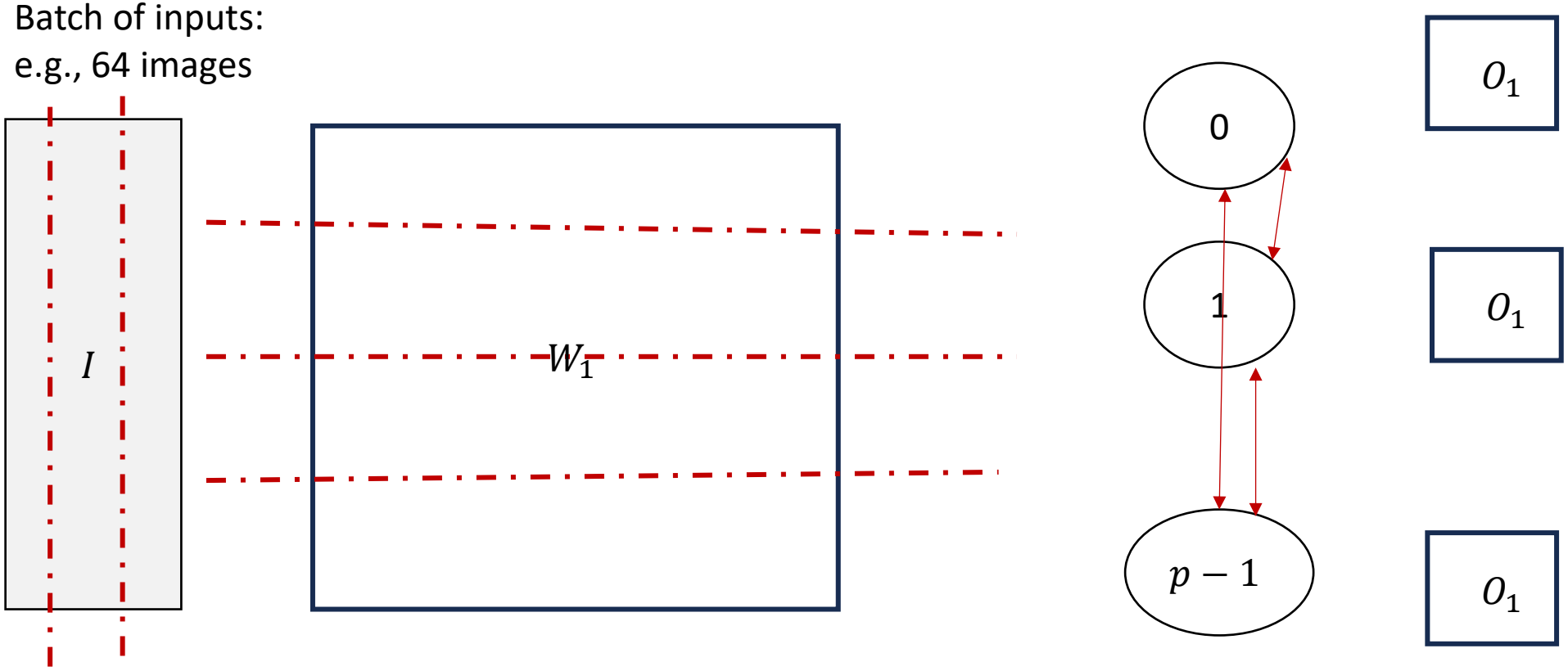
Batch of inputs:
e.g., 64 images



In each layer, each GPU applies a portion of the weights to its portion of the input

Tensor Parallelism

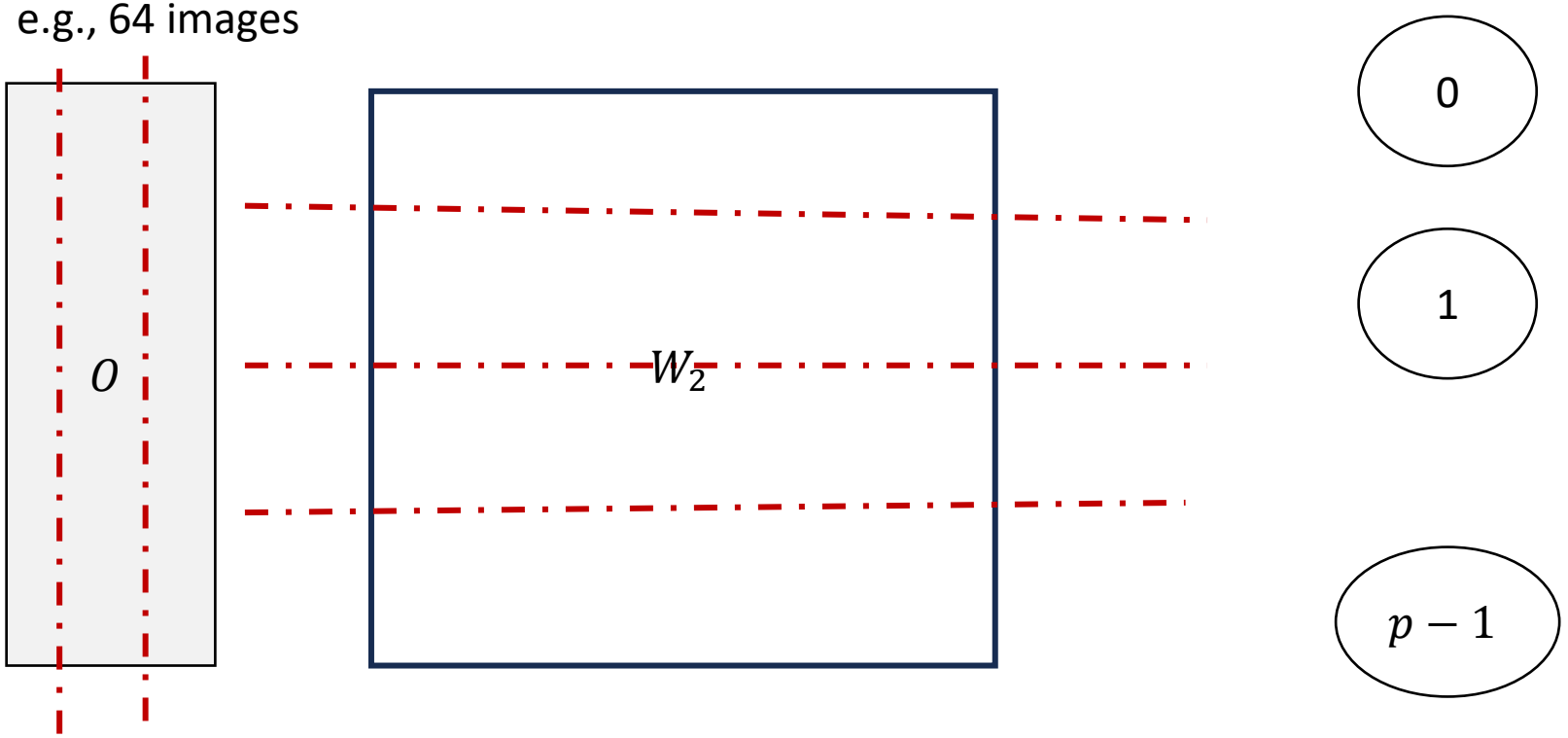
Batch of inputs:
e.g., 64 images



GPU communicate to collective produce output of the layer – Each GPU will get a copy of the output

Tensor Parallelism

Batch of inputs:
e.g., 64 images



Output is again partitioned across the embedding dimension to serve as input to the next layer

3D Parallelism

- In practice, all three parallelisms are combined
- Data + Pipeline + Tensor = 3D parallelism
- DeepSpeed: https://github.com/microsoft/DeepSpeed/tree/master?tab=readme-ov-file

3D Parallelism

- We will discuss the communication and computation optimizations for distributed training in detail when we are looking into cluster of accelerators

Outline

- Distributed Training Basics
- Pytorch Lightning

PyTorch Lightning

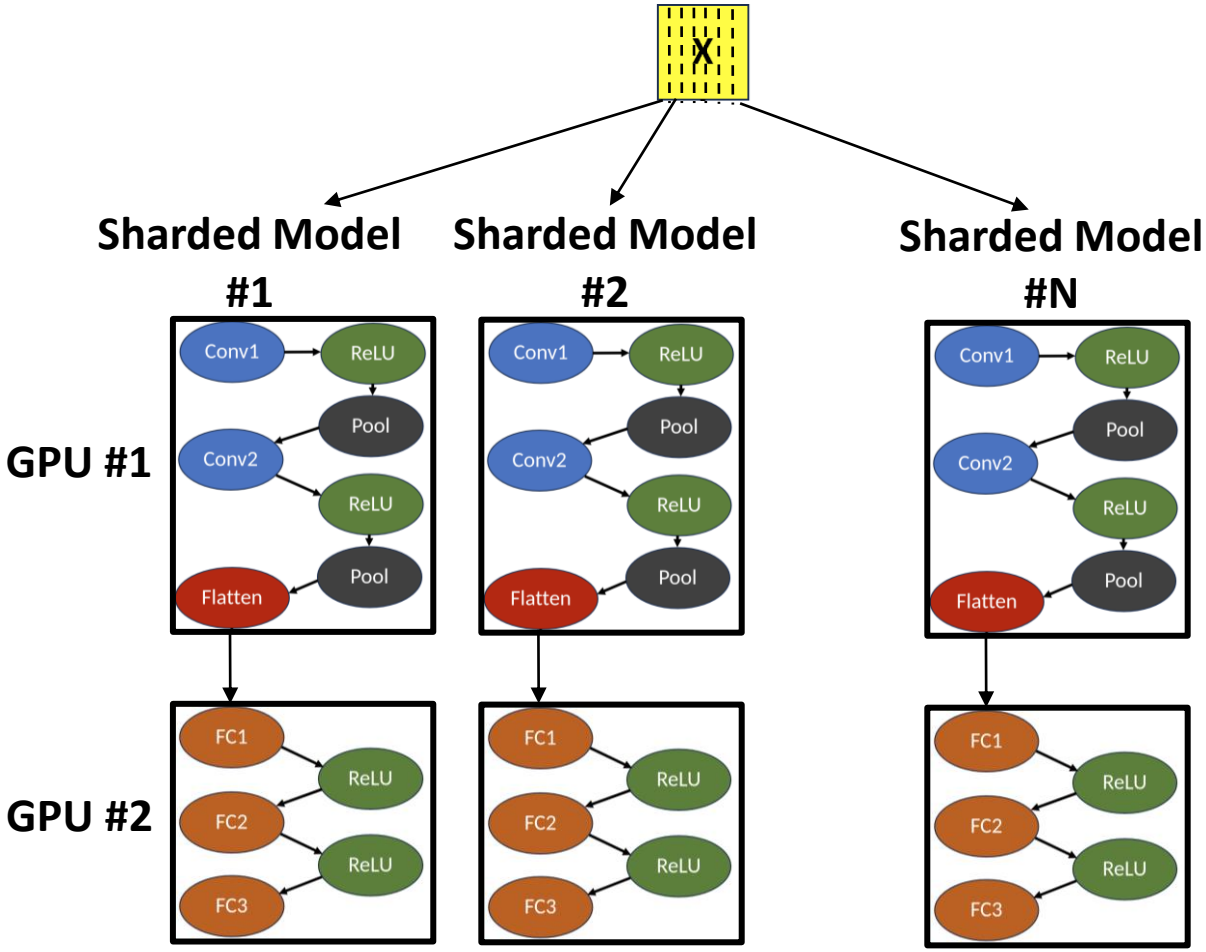
Facilitating Deep Learning

- An open source Python library created in 2019.
  - Offers high-level wrappers for PyTorch.
  - Aims to **decouple research from engineering**.

Pytorch Lightning – Distributed Training

- Supports Distributed Data Parallel and variants https://lightning.ai/docs/pytorch/stable/accelerators/gpu_intermediate.html

- Supports Data+Model Parallel – Fully Sharded Data Parallel
  - Model weights are partitioned
  - https://lightning.ai/docs/pytorch/stable/advanced/model_parallel/fsdp.html



Pytorch Lightning – Distributed Training

- Most of the programming remains similar to PyTorch

- Some additions/modifications include:
  - Define a sub-class of LightningModule to define interactions between the various layers of your models – PyTorch Lightning uses this information to perform FSDP
  - Define training_step within this module – enables PyTorch Lightning to optimizing training step
  - Configure optimizers within this module - enables PyTorch Lightning to apply optimizer specific optimizations

Pytorch Lightning – Distributed Training

```python
# define any number of nn.Modules (or use your current ones)
encoder = nn.Sequential(nn.Linear(28 * 28, 64), nn.ReLU(), nn.Linear(64, 3))
decoder = nn.Sequential(nn.Linear(3, 64), nn.ReLU(), nn.Linear(64, 28 * 28))


# define the LightningModule
class LitAutoEncoder(pl.LightningModule):
    def __init__(self, encoder, decoder):
        super().__init__()
        self.encoder = encoder
        self.decoder = decoder

    def training_step(self, batch, batch_idx):
        # training_step defines the train loop.
        # it is independent of forward
        x, y = batch
        x = x.view(x.size(0), -1)
        z = self.encoder(x)
        x_hat = self.decoder(z)
        loss = nn.functional.mse_loss(x_hat, x)
        # Logging to TensorBoard (if installed) by default
        self.log("train_loss", loss)
        return loss

    def configure_optimizers(self):
        optimizer = optim.Adam(self.parameters(), lr=1e-3)
        return optimizer


# init the autoencoder
autoencoder = LitAutoEncoder(encoder, decoder)
```

Instead of Training Loop, we have the following

```python
# model
autoencoder = LitAutoEncoder(Encoder(), Decoder())

# train model
trainer = L.Trainer()
trainer.fit(model=autoencoder, train_dataloaders=train_loader)
```

Pytorch Lightning – Acceleration and Parallelization

- You don't need to explicitly specify the device

```
# before lightning
def forward(self, x):
    x = x.cuda(0)
    layer_1.cuda(0)
    x_hat = layer_1(x)

# after lightning
def forward(self, x):
    x_hat = layer_1(x)
```

- You can achieve parallel training by simply setting the number of gpus and policy
- ddp – distributed data parallel
- Fsdp – Fully Sharded Data Parallel
  - Requires additional information on which layers to shard

```
# train on 8 GPUs (same machine (ie: node))
trainer = Trainer(gpus=8, accelerator='ddp')

# train on 32 GPUs (4 nodes)
trainer = Trainer(gpus=8, accelerator='ddp', num_nodes=4)
```

Pytorch Lightning – For you to Review

- Pytorch Lightning Training Basics - https://lightning.ai/docs/pytorch/stable/model/train_model_basic.html
- Training on GPU - https://lightning.ai/docs/pytorch/stable/accelerators/gpu_basic.html
- Distributed Training - https://lightning.ai/docs/pytorch/stable/levels/advanced_level_21.html

Next Class

- 10/16 Lecture 15
  - Acceleration of Transformer Models: Basics

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Thank You

- Questions?

- Email: sanmukh.kuppannagari@case.edu