10-414/714 – Deep Learning Systems: Algorithms and Implementation

Training Large Models

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Outline

Techniques for memory saving

Parallel and distributed training

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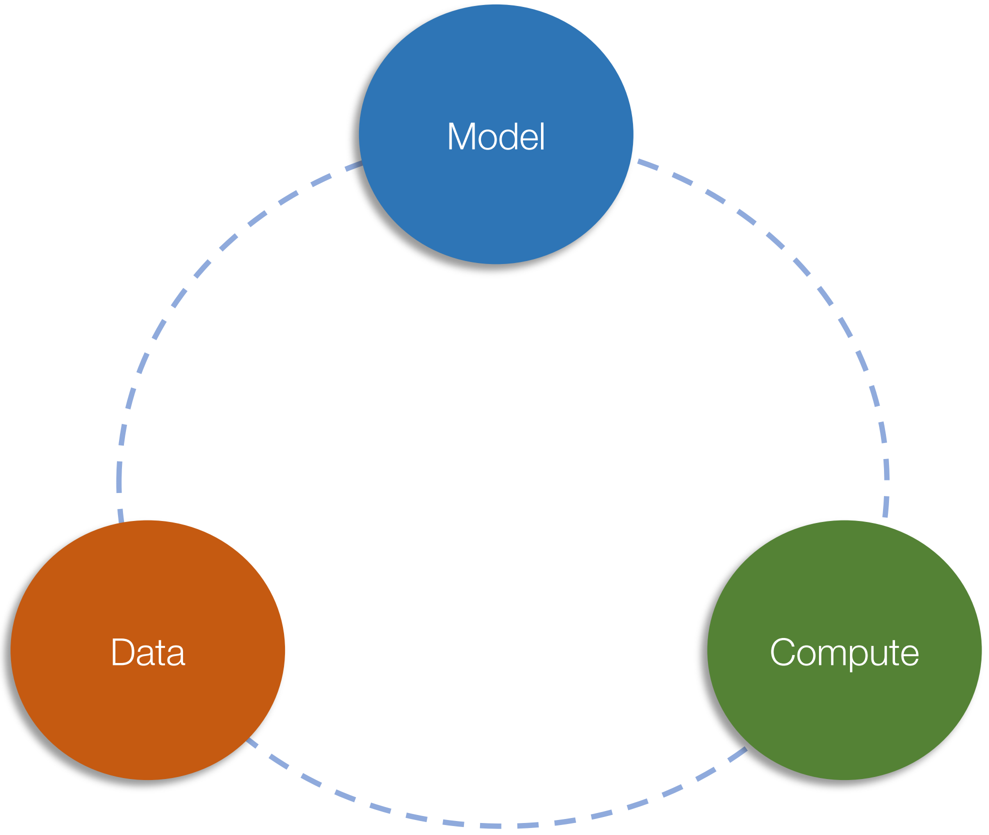
Parallel and distributed Training

Elements of machine learning systems

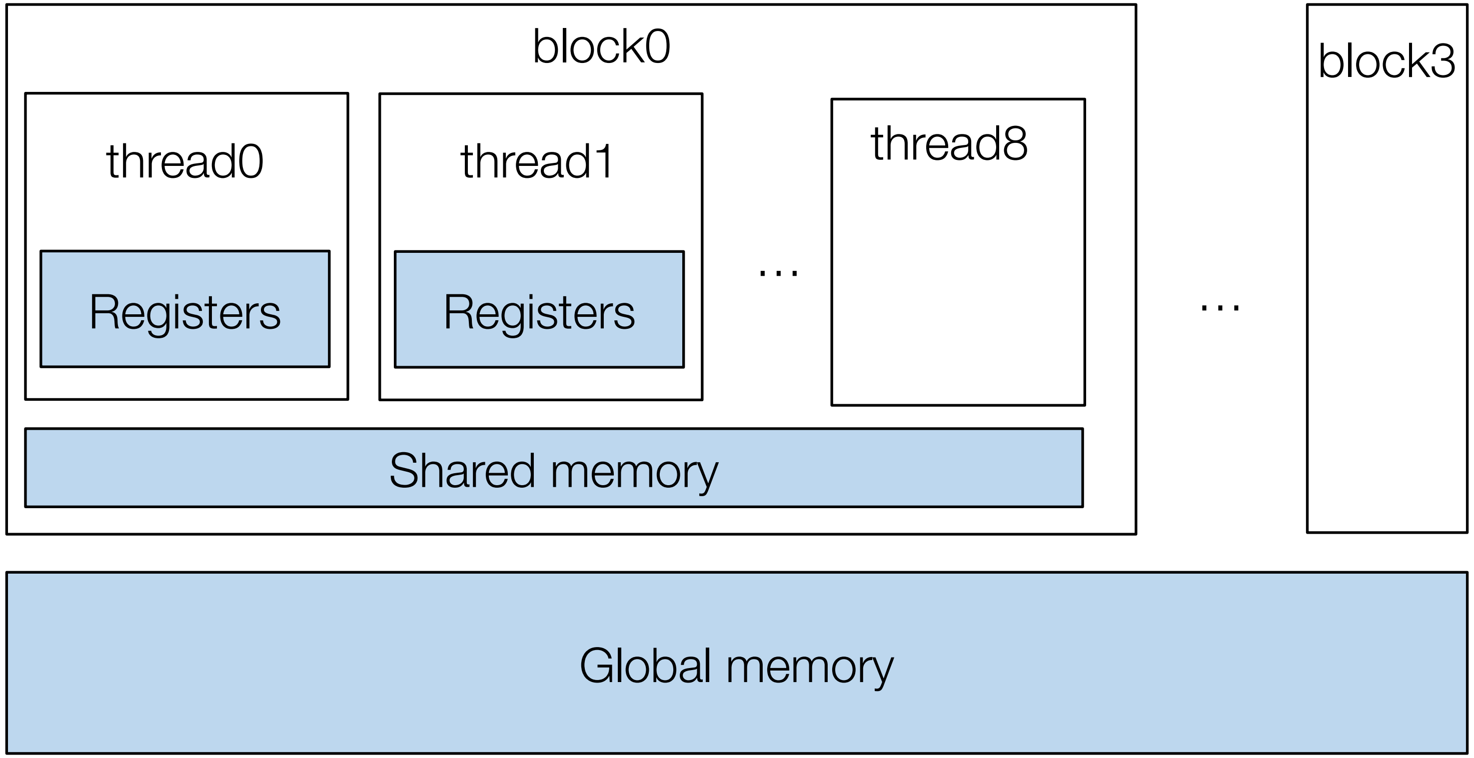


Bigger dataset requires larger model capacity. Which in turn puts demands on computing devices. The success of machine learning is a combination of all the three elements. Many recent advances requires us to push all three to their limits.

Today we will study two topics:

- How to reduce the memory consumption, so we can fit bigger models into a single device.
- How to scale up the training process

Recap: GPU memory hierarchy



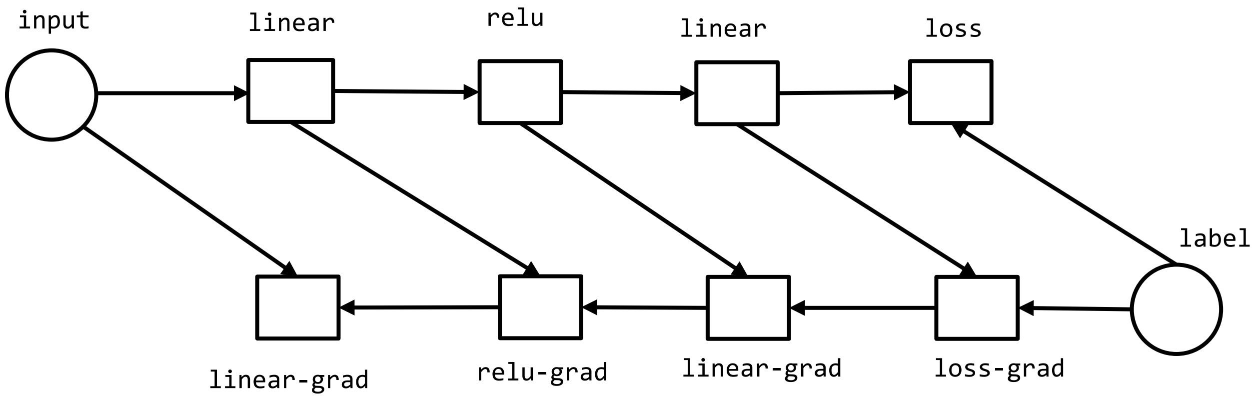
Shared memory: 64 KB per core

GPU memory(Global memory):

RTX3080 10GB
RTX3090 24GB
A100 40/80 GB

Sources of memory consumption

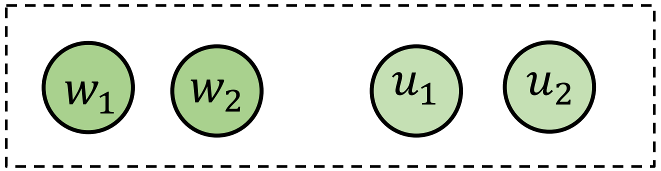
A simplified view of a typical computational graph for training, weights are omitted and implied in the grad steps.



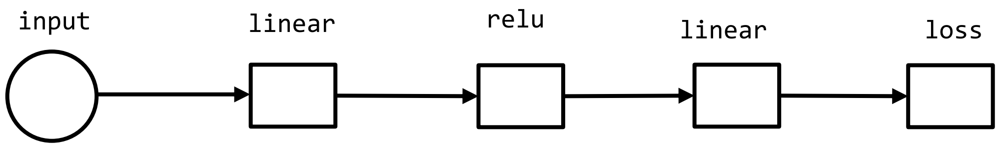
Sources of memory consumption

- Model weights
- Optimizer states
- Intermediate activation values

Optimizer states

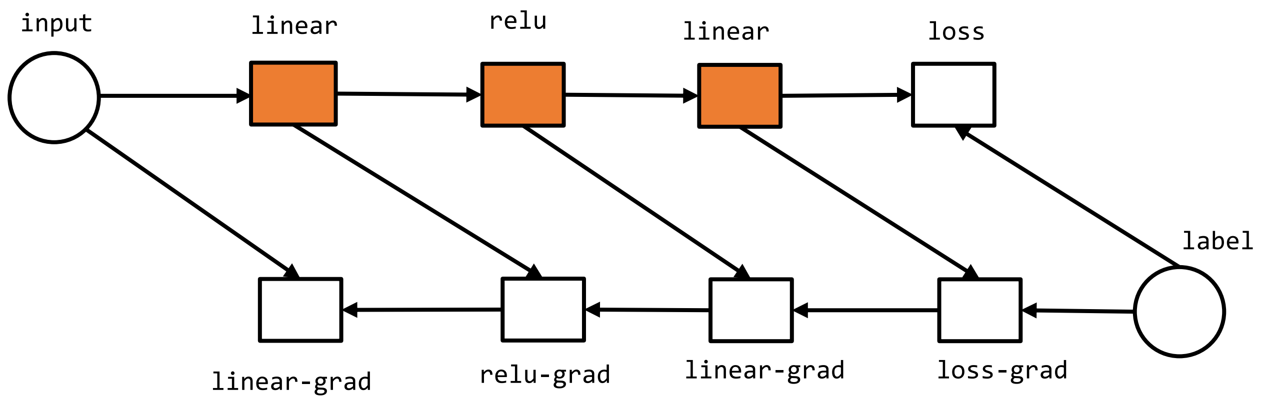


Techniques for memory saving inference only



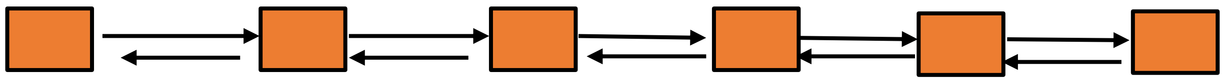
We only need O(1) memory for computing the final output of a N layer deep network by cycling through two buffers

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

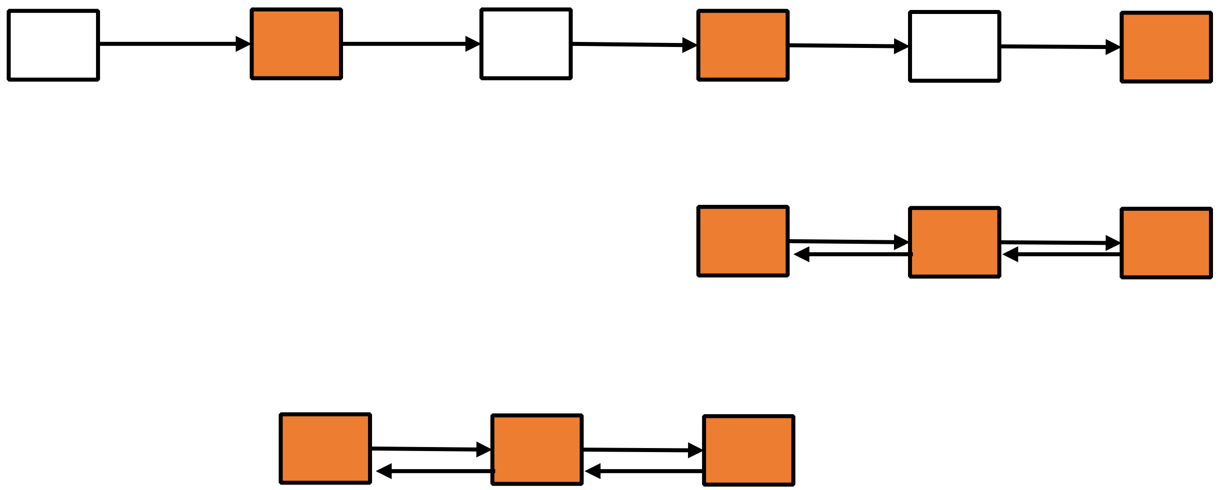


Checkpointing techniques in AD

Step 0:

Step 1:

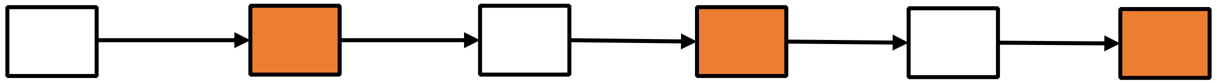
Step 2:



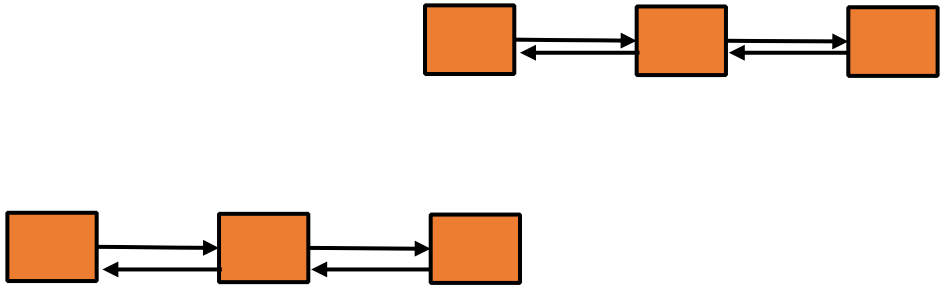
- Only checkpoint colored nodes (step 0)
- Recompute the missing intermediate nodes in small segments (step 1, 2)

Sublinear memory cost

Forward computation



Gradient per segment
with re-computation



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

$$Memory\ cost = O\left(\frac{N}{K}\right) + O(K)$$

Pick $K = \sqrt{N}$

Checkpoint cost

Re-computation cost

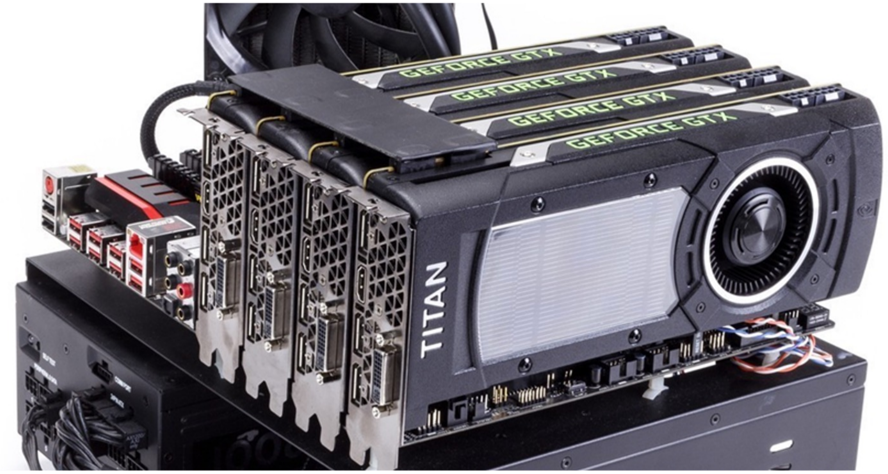
Outline

Programming abstractions

Parallel and distributed training

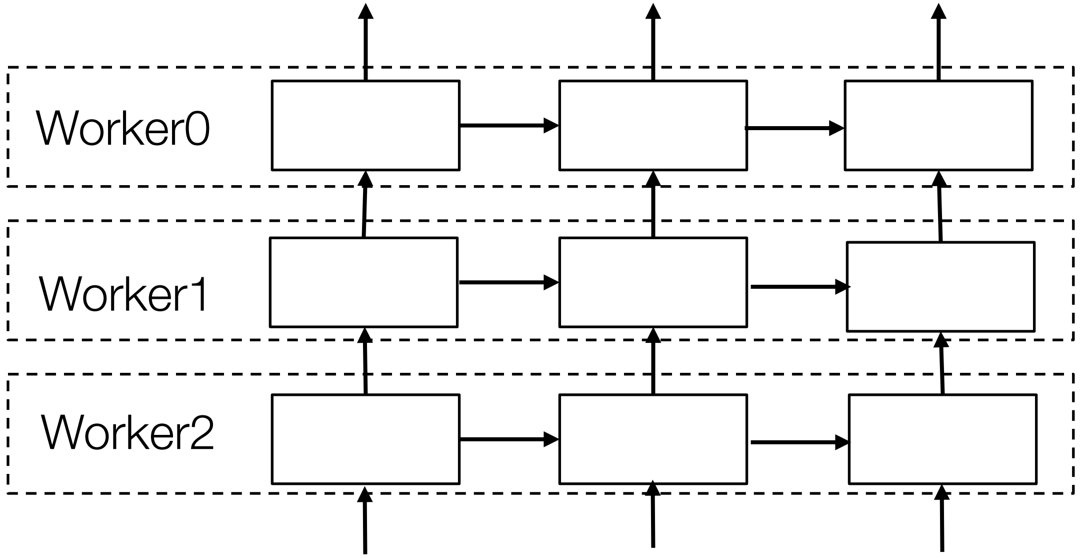
Parallel training problem

Leverage multiple (GPU) devices that are possibly distributed over several worker nodes to train a model.

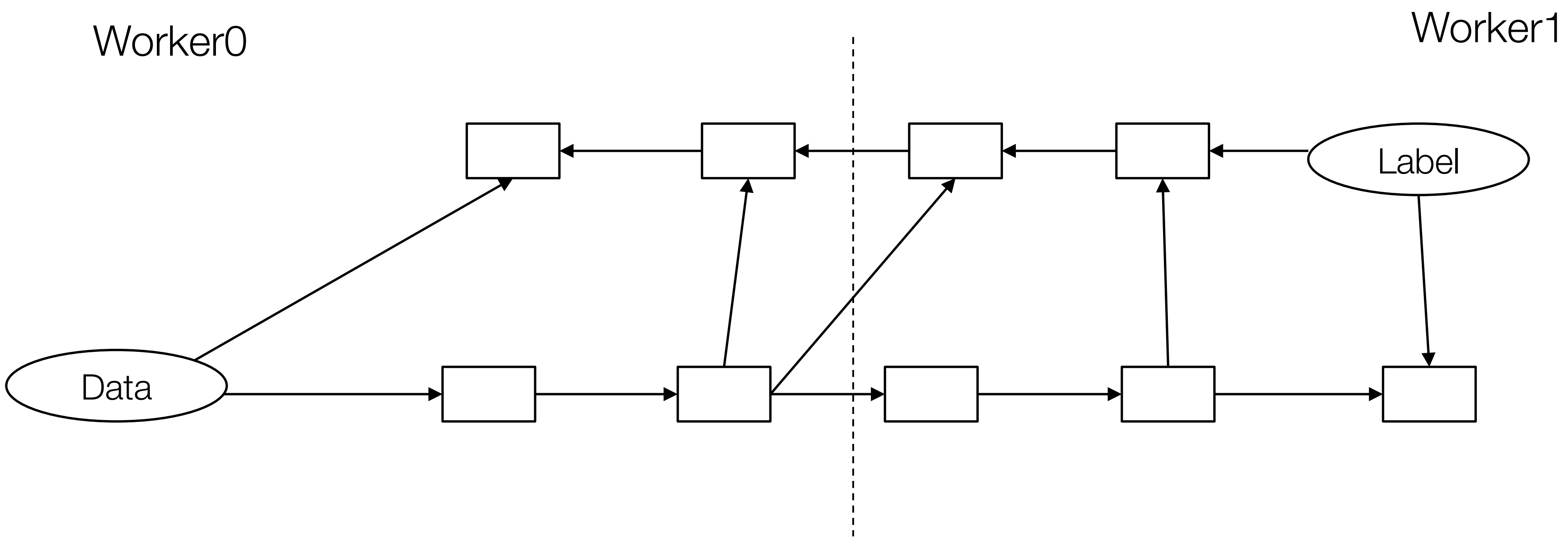


Model parallel training

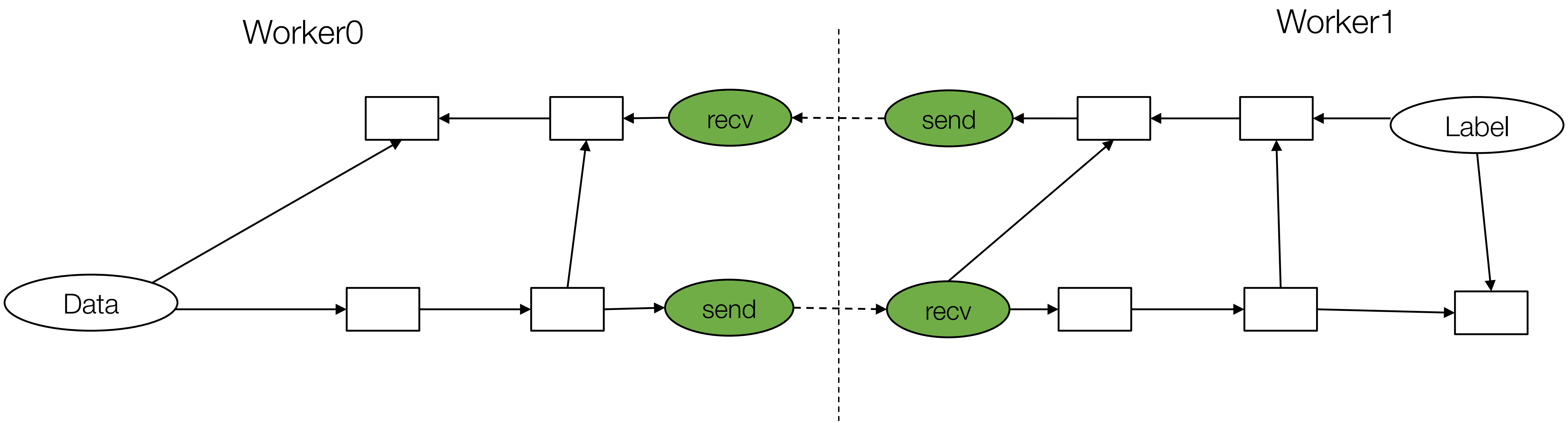
Maps parts of the computation graph to workers



Breaking up the computation for model parallelism



Breaking up the computation for model parallelism



Partition the graph, put send/recv pairs in the boundary

Data parallel training

Loss function $\theta := \theta - \frac{\alpha}{B}\sum_{i=1}^{B} \nabla_\theta \ell\left(h_\theta\left(x^{(i)}\right), y^{(i)}\right)$

Let each worker access $\frac{\mathrm{B}}{K}$ fraction of the minibatch, and run gradient computation then sum up all gradients together.

Every worker runs the same replica of the model

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)
```

Worker 1

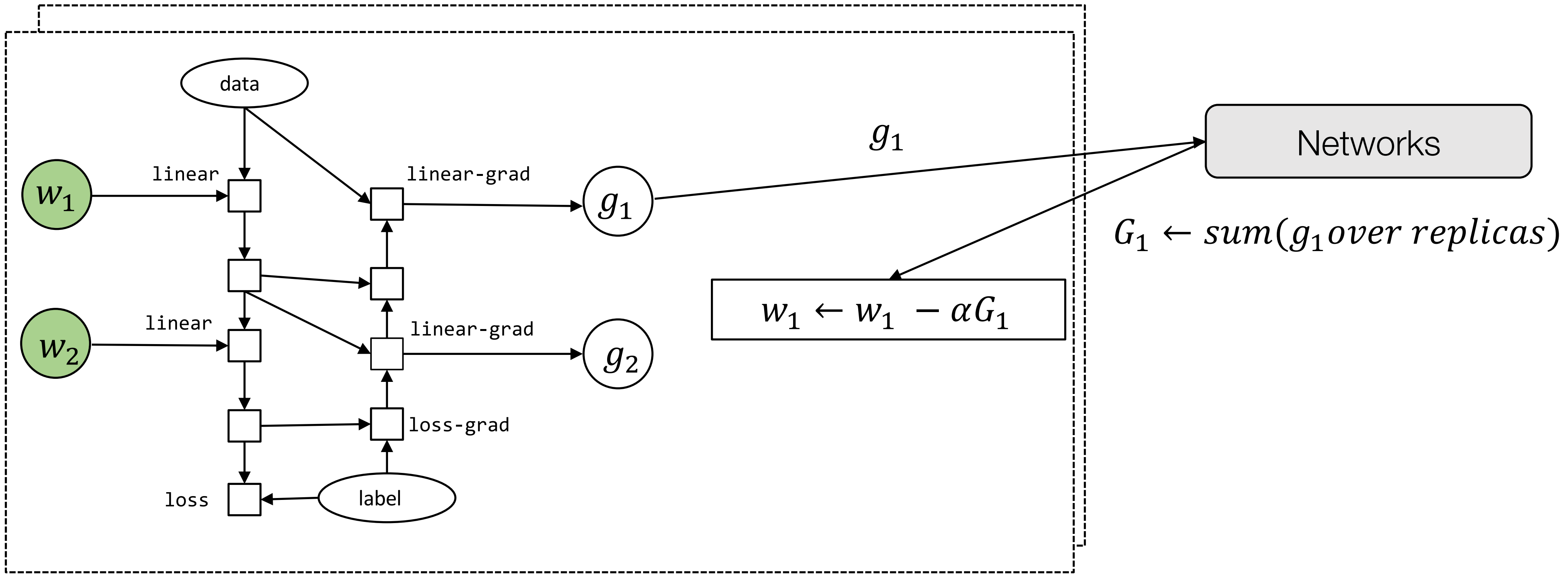
```
comm = communicator.create()
a = [1, 0, 1]
b = comm.allreduce(a, op=sum)
```

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

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

Data parallel training via allreduce

Many replicas of the same graph run in parallel

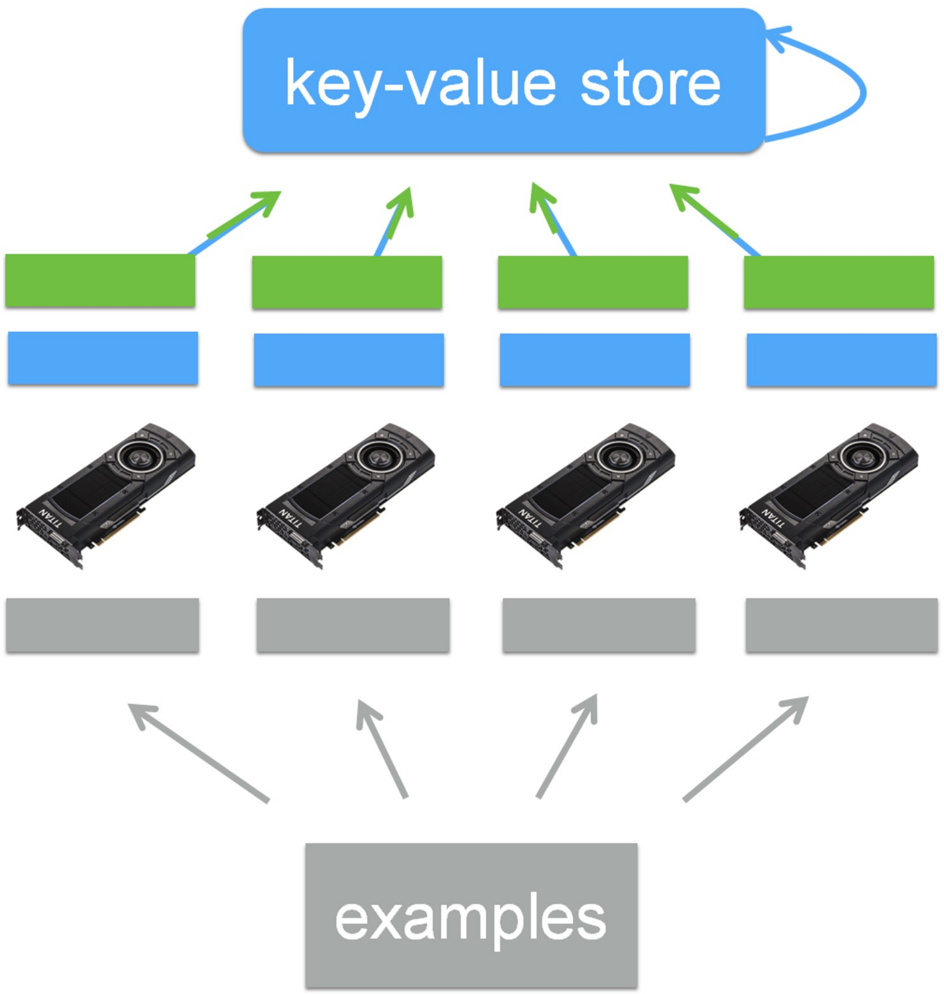


Parameter server abstraction

Interface

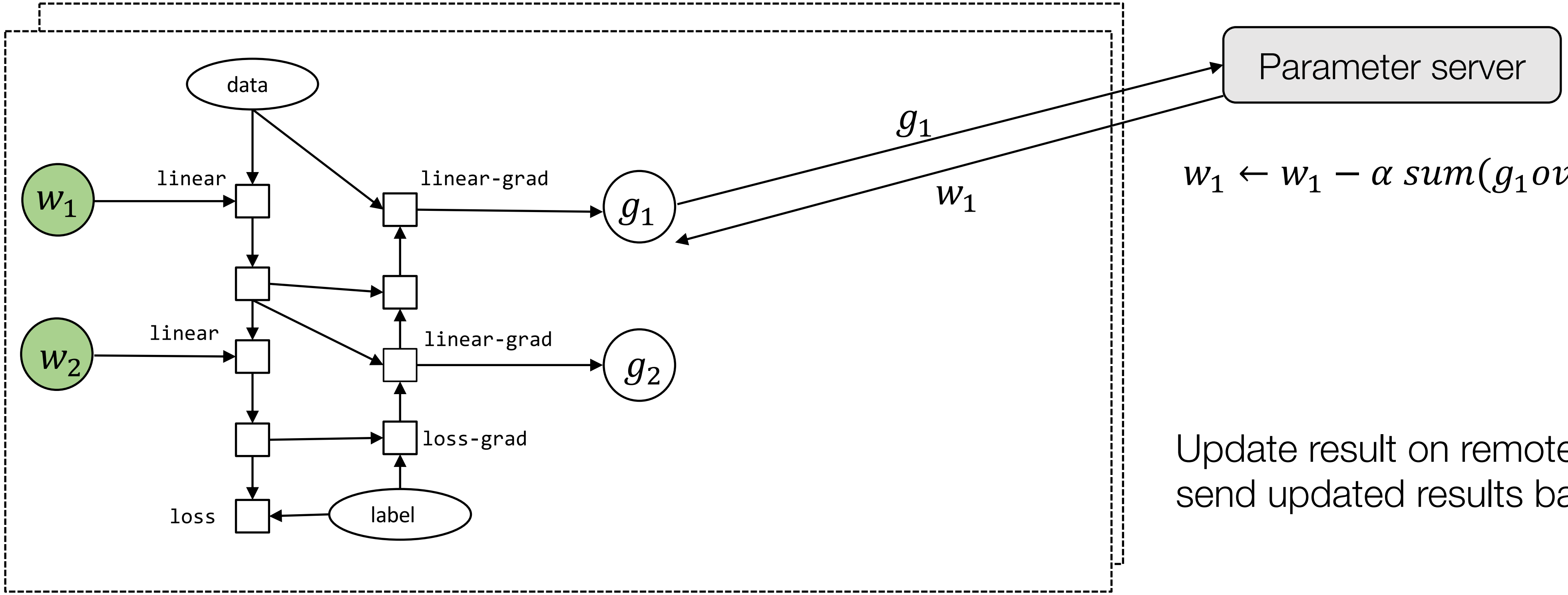
```
ps.push(index, gradient)

ps.pull(index)
```

Performs weight update on the server(key value store)



Data parallel training via parameter server

Many replicas of the same graph run in parallel



$w_1 \leftarrow w_1 - \alpha\ sum(g_1 over\ replicas)$

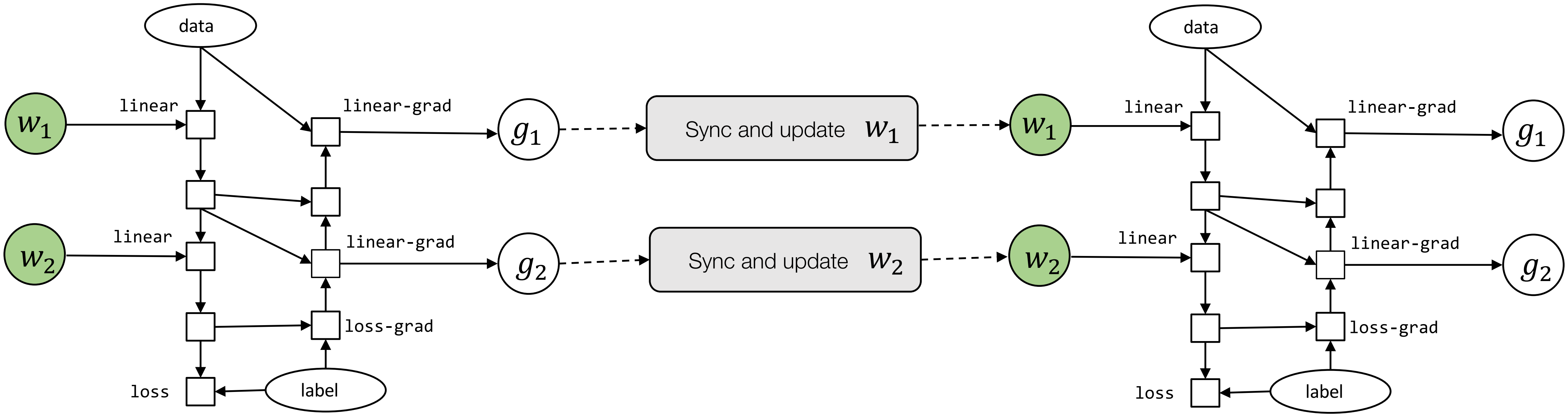
Update result on remote server and send updated results back

Communication computation overlap

Epoch T

Synchronization

Epoch T + 1



Many opportunities to continue computation while sending data over the network

Parallelization summary

Model parallel training partition by parts in the computational graph.

Data parallel training partition by data.

In all cases, leverage the opportunities to overlap compute with communication.

Advanced parallelization methods

There are more ways to parallelize a computational graph.

Some optional reference readings:

ZeRO: Memory Optimizations Toward Training Trillion Parameter Models.

Beyond Data and Model Parallelism for Deep Neural Networks.

GSPMD: General and Scalable Parallelization for ML Computation Graphs

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Techniques for memory saving

Parallel and distributed training