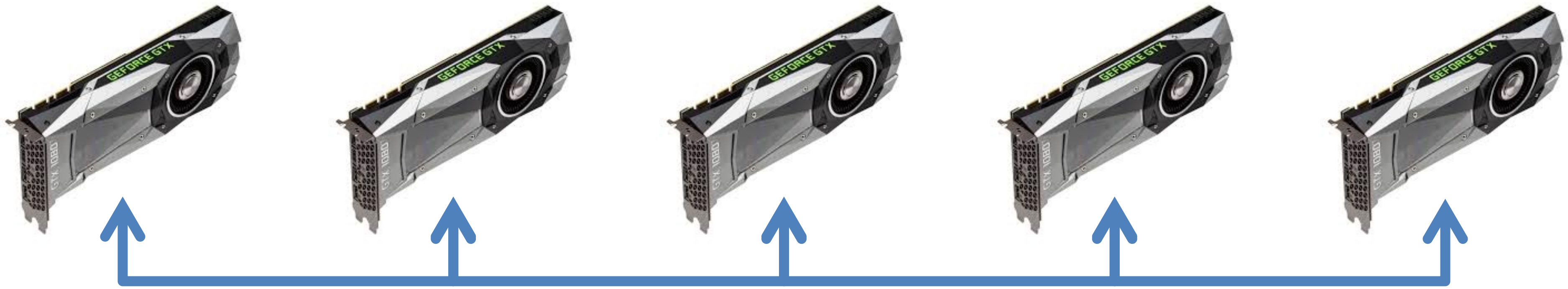
# Distributed Machine Learning and the Parameter Server

CS4787 Lecture 24 — Fall 2023

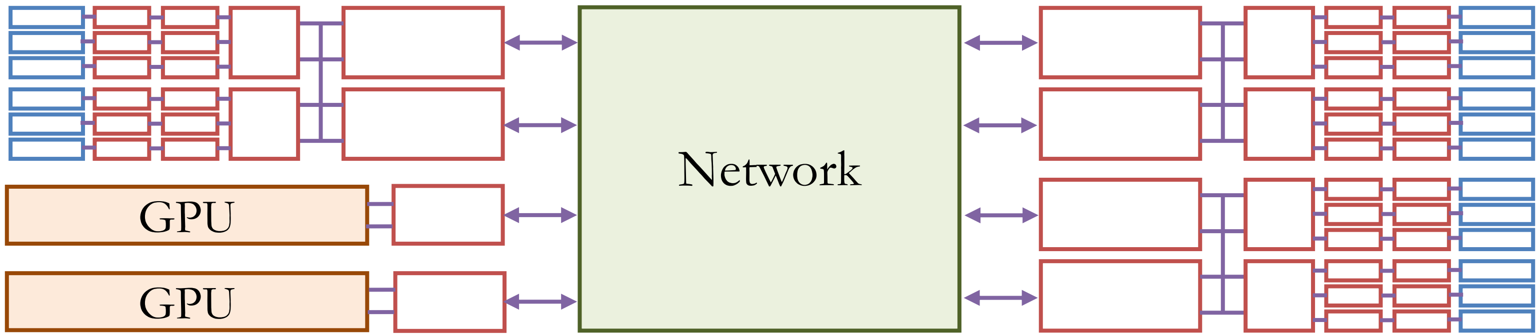
So far, we've been talking about ways to scale our machine learning pipeline that focus on a single machine. But if we *really* want to scale up to *huge* datasets and models, eventually one machine won't be enough.

This lecture will cover methods for **using multiple machines to do learning**.



# Distributed computing basics

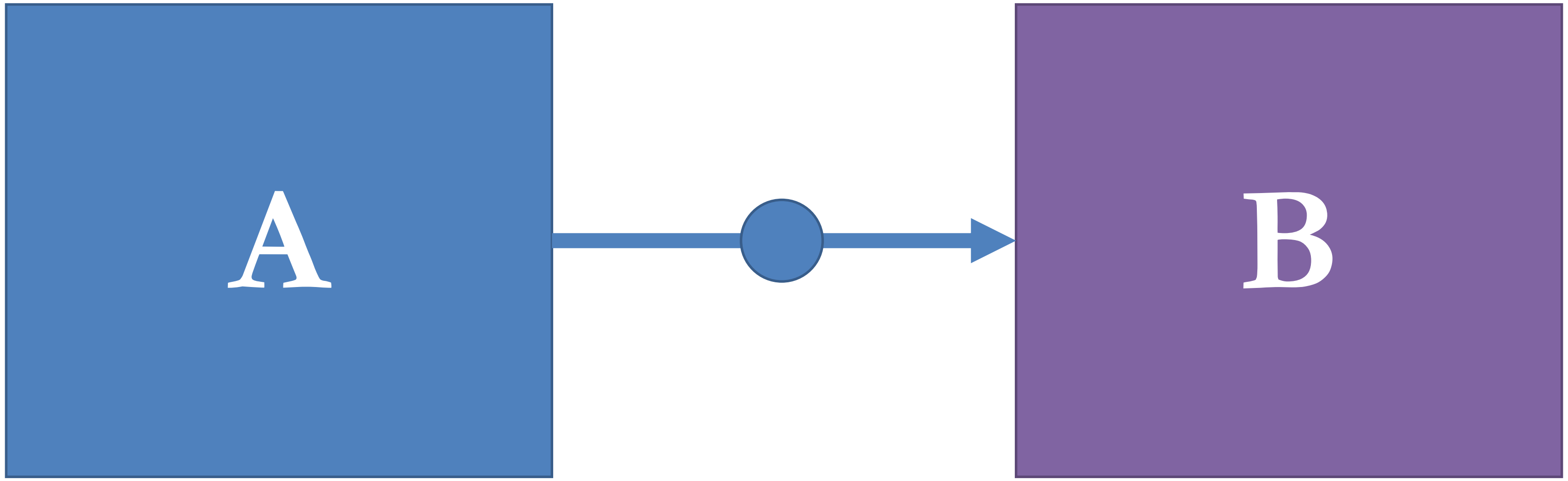
- Distributed parallel computing **involves two or more machines collaborating on a single task by communicating over a network**.
  - Unlike parallel programming on a single machine, distributed computing requires explicit (i.e. written in software) communication among the workers.




- There are a **few basic patterns of communication** that are used by distributed programs.

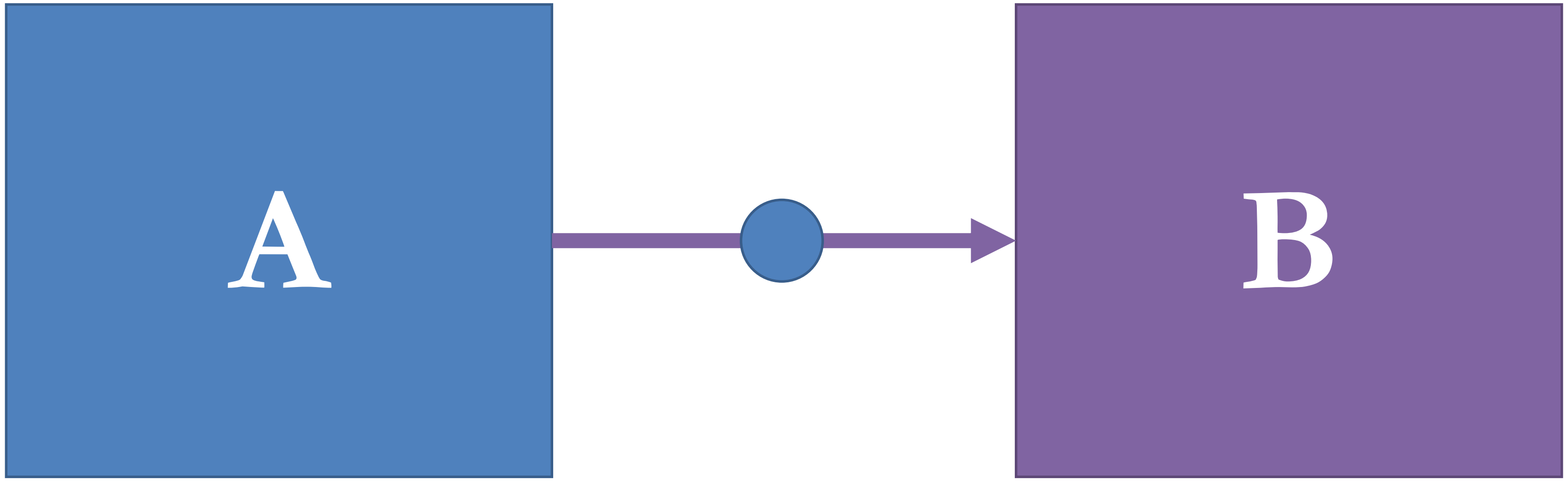
# Basic patterns of communication
## Push

- Machine A sends some data to machine B.



# Basic patterns of communication
## Pull

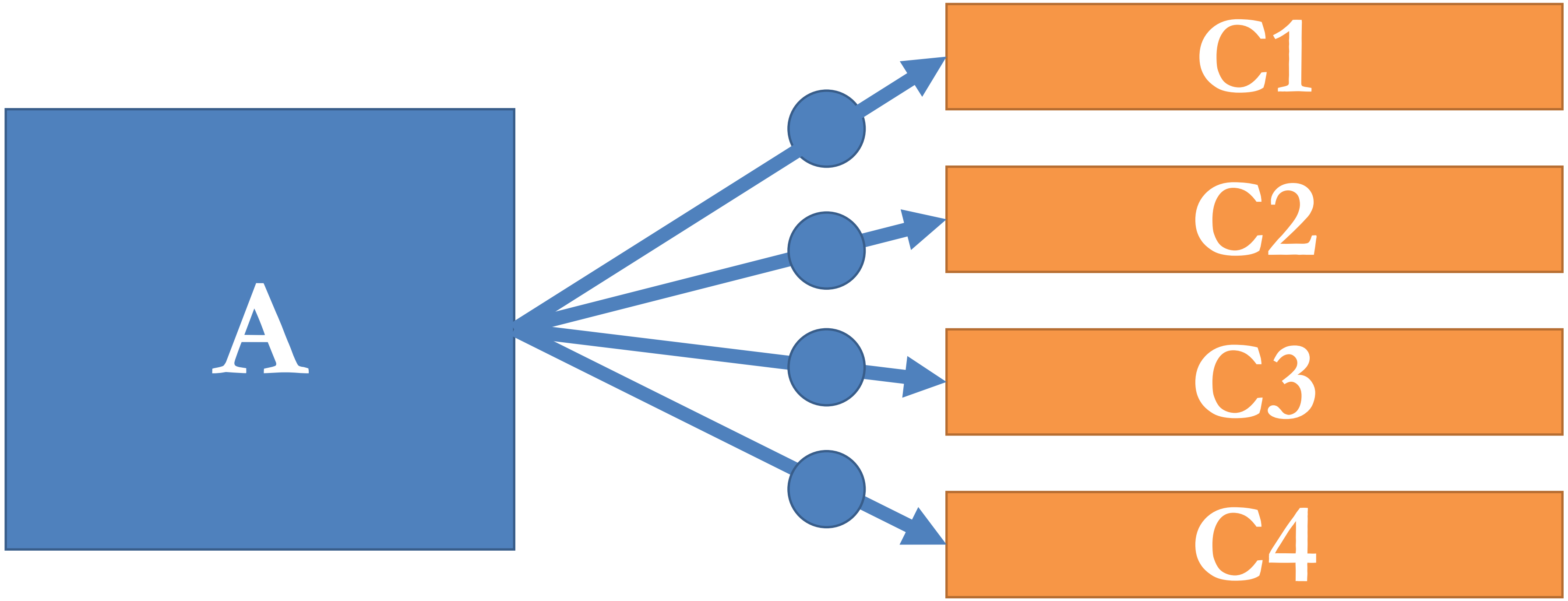
- Machine B requests some data from machine B.




- This differs from push only in terms of who initiates the communication

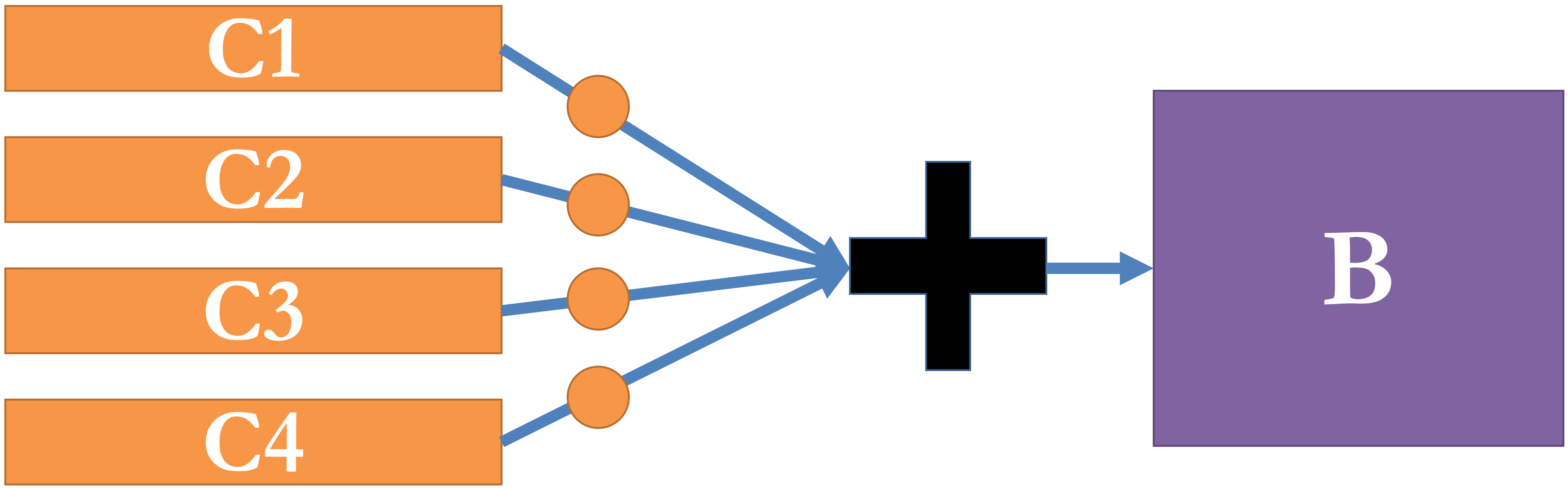
# Basic patterns of communication
## Broadcast

- Machine A sends data to many machines.



# Basic patterns of communication
## Reduce

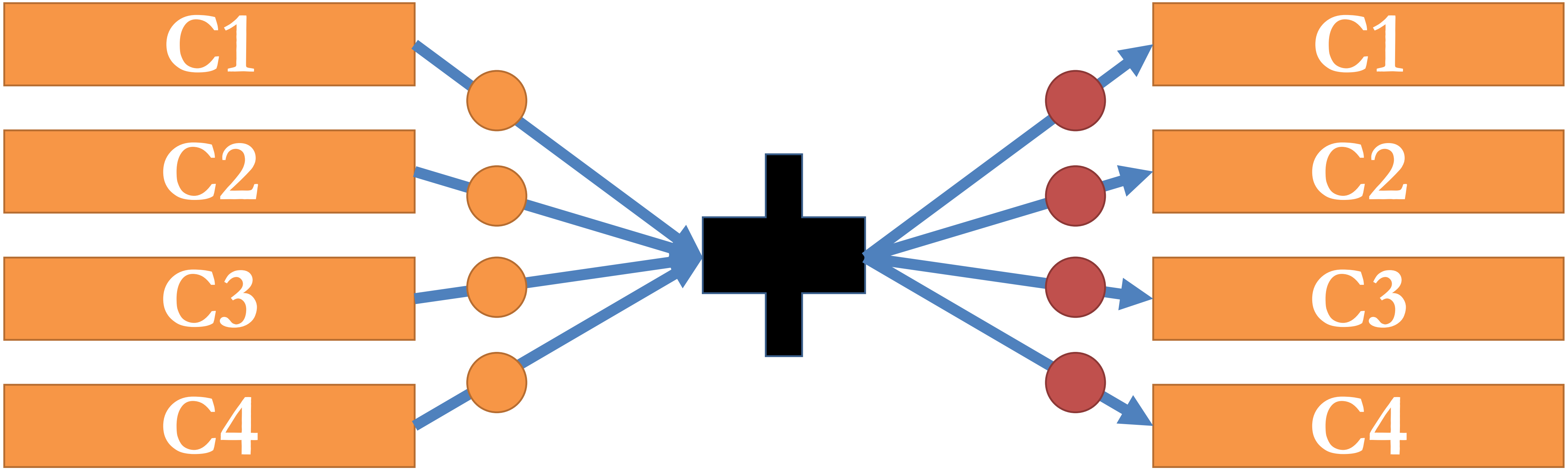
- Compute some reduction (usually a sum) of data on multiple machines C1, C2, …, Cn and materialize the result on one machine B.



# Basic patterns of communication

## All-Reduce

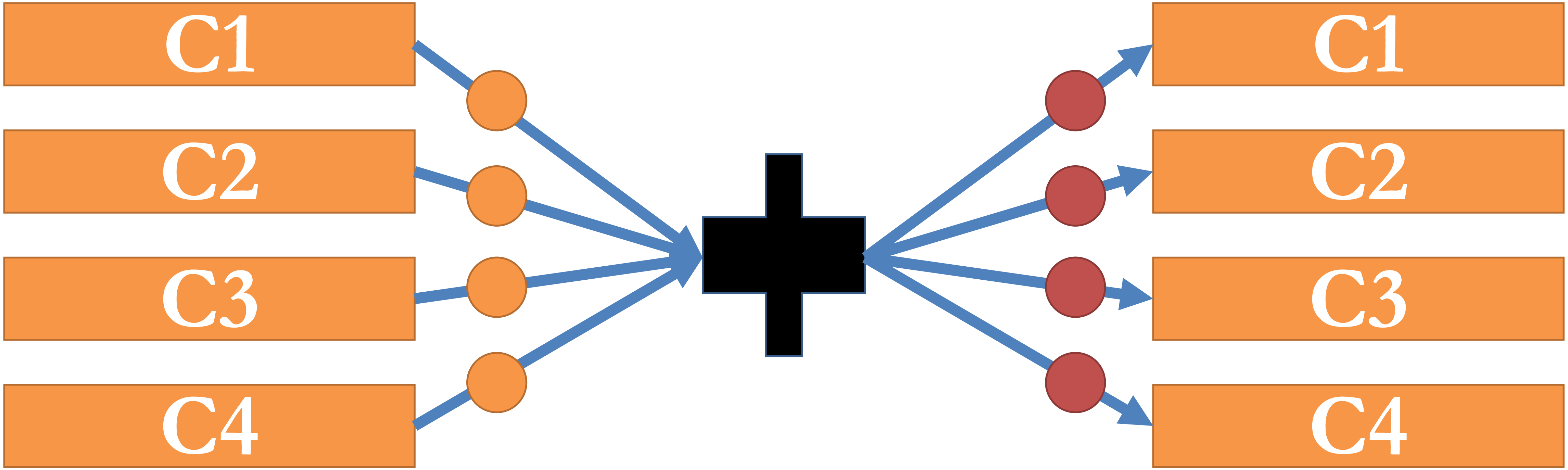
- Compute some reduction (usually a sum) of data on multiple machines and materialize the result on all those machines.



# Basic patterns of communication

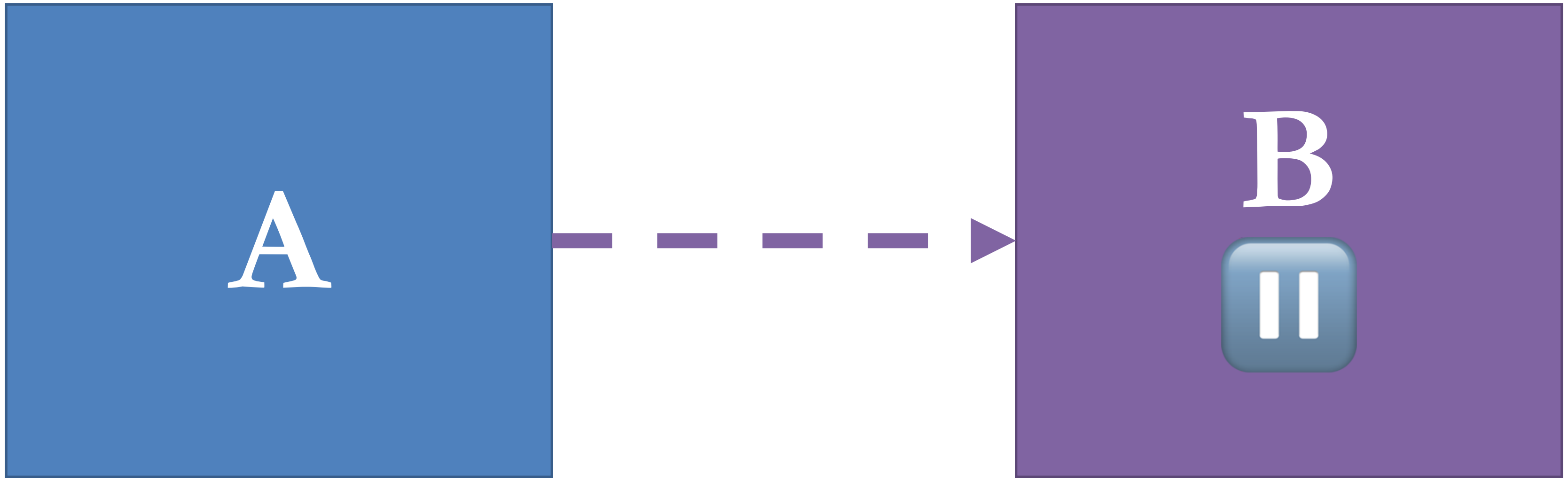
## Scatter-Reduce

- Compute some reduction of data on **M** machines and materialize **1/M** of the result on each machine (sharding the result).



# Basic patterns of communication
## Wait

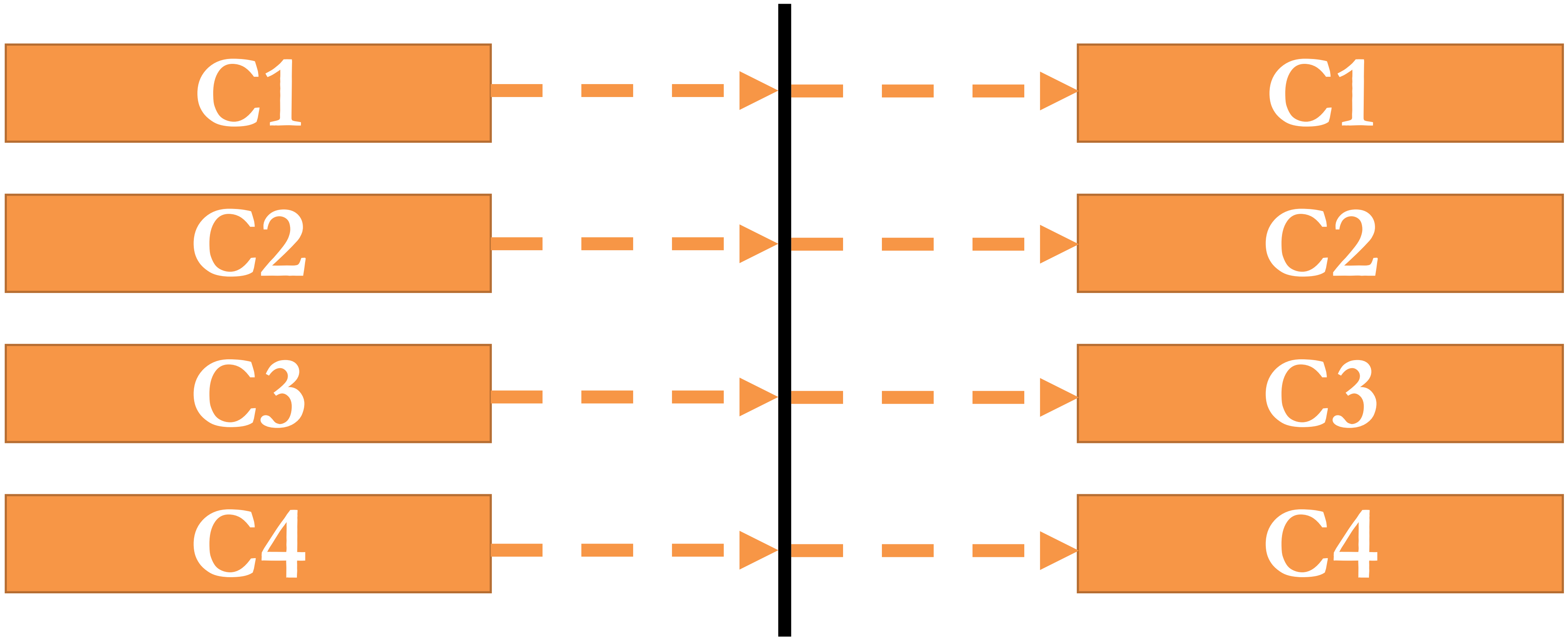
- One machine pauses its computation and waits on a signal from another machine



# Basic patterns of communication

## Barrier

- Many machines wait until all those machines reach a point in their execution, then continue from there



# Patterns of Communication Summary

- **Push/Pull.** Machine A sends data to machine B, or B requests data from A.
- **Broadcast.** Machine A sends some data to many machines C1, C2, …, Cn.
- **Reduce.** Compute some reduction (usually a sum) of data on multiple machines C1, C2, …, Cn and materialize the result on one machine B.
- **All-reduce.** Compute some reduction (usually a sum) of data on multiple machines C1, C2, …, Cn and materialize the result on all those machines.
- **Scatter-reduce.** Compute some reduction (usually a sum) of data on multiple machines C1, C2, …, Cn and materialize the result in a sharded fashion.
- **Wait.** One machine pauses its computation and waits for data to be received from another machine.
- **Barrier**. Many machines wait until all other machines reach a point in their code before proceeding.

# Overlapping computation and communication

- Communicating over the network can have high latency
  - we want to hide this latency
- An important principle of distributed computing is **overlapping computation and communication**
- For the best performance, we want our workers to **still be doing useful work while communication is going on**
  - rather than having to stop and wait for the communication to finish
  - sometimes called a **stall**

# Running SGD with All-reduce

- All-reduce gives us a simple way of running learning algorithms such as SGD in a distributed fashion with **data parallelism**.
- Simply put, the idea is to just **parallelize the minibatch.** We start with an identical copy of the parameter on each worker.
- Recall that SGD update step looks like:

$$w_{t+1} = w_t - \alpha_t \cdot \frac{1}{B} \sum_{b=1}^{B} \nabla f_{i_{b,t}}(w_t),$$

# Running SGD with All-reduce (continued)

- If there are $M$ worker machines such that $B = M \cdot B'$, then

$$w_{t+1} = w_t - \alpha_t \cdot \frac{1}{M} \sum_{m=1}^{M} \frac{1}{B'} \sum_{b=1}^{B'} \nabla f_{i_{m,b,t}}(w_t).$$

- Now, we assign the computation of the sum when m = 1 to worker 1, the computation of the sum when m = 2 to worker 2, et cetera.

- After all the gradients are computed, we can perform the outer sum with an **all-reduce operation**.

# Running SGD with All-reduce (continued)

- After this all-reduce, the whole sum (which is essentially the minibatch gradient) will be present on all the machines
  - so each machine can now update its copy of the parameters
- Since sum is same on all machines, the parameters will update in lockstep
- **Statistically equivalent to sequential SGD!**

**Algorithm 1** Distributed SGD with All-Reduce

**input:** loss function examples $f_1, f_2, \ldots$, number of machines $M$, per-machine minibatch size $B'$
**input:** learning rate schedule $\alpha_t$, initial parameters $w_0$, number of iterations $T$
**for** $m = 1$ **to** $M$ **run in parallel on machine** $m$
  **load** $w_0$ from algorithm inputs
  **for** $t = 1$ **to** $T$ **do**
    **select** a minibatch $i_{m,1,t}, i_{m,2,t}, \ldots, i_{m,B',t}$ of size $B'$
    **compute** $g_{m,t} \leftarrow \frac{1}{B'} \sum_{b=1}^{B'} \nabla f_{i_{m,b,t}}(w_{t-1})$
    **all-reduce** across all workers to compute $G_t = \sum_{m=1}^{M} g_{m,t}$
    **update model** $w_t \leftarrow w_{t-1} - \frac{\alpha_t}{M} \cdot G_t$
  **end for**
**end parallel for**
**return** $w_T$ (from any machine)

**Same approach can be used for momentum, Adam, etc.**

# What are the benefits of distributing SGD with all-reduce? What are the drawbacks?

# **Benefits** of distributed SGD with All-reduce

- The algorithm is easy to reason about, since it's statistically equivalent to minibatch SGD.
  - And we can use the same hyperparameters for the most part.
- The algorithm is easy to implement
  - since all the worker machines have the same role and it runs on top of standard distributed computing primitives.

# **Drawbacks** of distributed SGD with all-reduce

- While the communication for the all-reduce is happening, the workers are (for the most part) idle.
- We're **not overlapping computation and communication**.
  - At least by default
  - We *can* overlap communication with preprocessing/data augmentation
- The **effective minibatch size is growing with the number of machines**, and for cases where we *don't* want to run with a large minibatch size for statistical reasons, this can prevent us from scaling to large numbers of machines using this method.

# Where do we get the training examples from?

- There are two general options for distributed learning.

- **Training data servers**
  - Have one or more non-worker servers dedicated to storing the training examples (e.g. a distributed in-memory filesystem)
  - The worker machines load training examples from those servers.
  - These servers can handle preprocessing and data augmentation (but usually don't)

- **Partitioned dataset**
  - Partition the training examples among the workers themselves and store them locally in memory on the workers.

# The Parameter Server Model

# The Basic Idea

- Recall from the early lectures in this course that a lot of our theory talked about the convergence of optimization algorithms.
  - This convergence was measured by some function over the parameters at time t (e.g. the objective function or the norm of its gradient) that is decreasing with t, which shows that the algorithm is making progress.

- For this to even make sense, though, we need to be able to talk about the value of the parameters at time t as the algorithm runs.
  - E.g. in SGD, we had

$$w_{t+1} = w_t - \alpha_t \nabla f_{i_t}(w_t)$$

# Parameter Server Basics Continued

- For a program running on … time t is just the value of s… DRAM) at that time.

- But in a distributed setting… must be done explicitly.
  - Each machine will usually l… time, some of which may have been u… …ently than others, especially if we want to do something more complicated … reduce.

- This raises the question: **when reasoning about a distributed algorithm, what we should consider to be the value of the parameters a given time**?

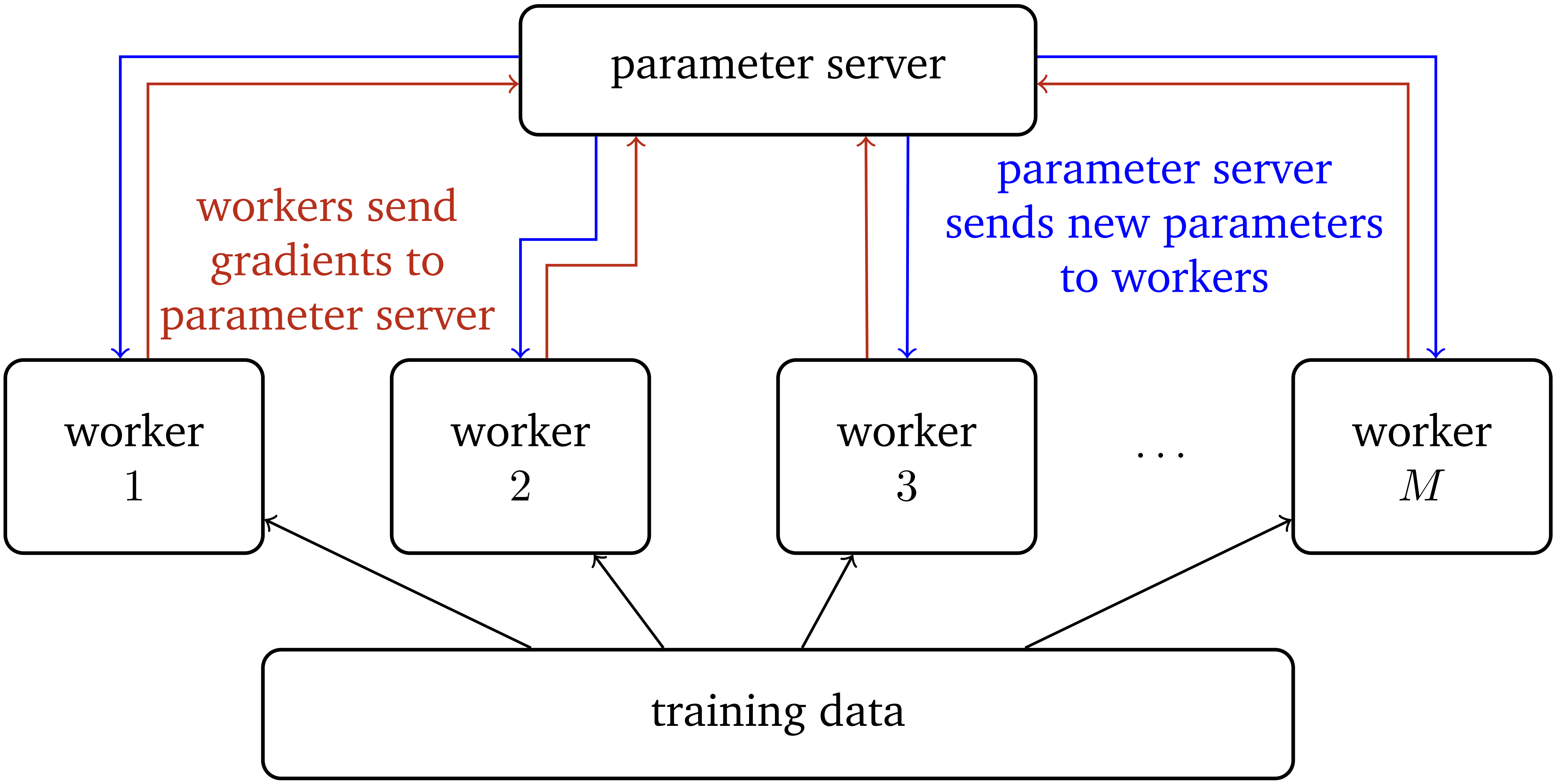
For SGD with all-reduce, we can answer this question easily, since the value of the parameters is the same on all workers (it's guaranteed to be the same by the all-reduce operation). We just appoint this identical shared value to be the value of the parameters at any given time.

# The Parameter Server Model

- The parameter server model answers this question differently by appointing a single machine, the **parameter server**, the explicit responsibility of maintaining the current value of the parameters.
  - The most up-to-date gold-standard parameters are the ones stored in memory on the parameter server.

- The parameter server updates its parameters by using gradients that are computed by the other machines, known as **workers**, and pushed to the parameter server.

- Periodically, the parameter server **broadcasts its updated parameters** to all the other worker machines, so that they can use the updated parameters to compute gradients.



parameter server
workers send gradients to parameter server
parameter server sends new parameters to workers
worker 1
worker 2
worker 3
. . .
worker $M$
training data

# Learning with the parameter server

- Many ways to learn with a parameter server

- **Synchronous distributed training**
  - Similar to all-reduce, but with gradients summed on a central parameter server

- **Asynchronous distributed training**
  - Compute and send gradients and add them to the model as soon as possible
  - Broadcast updates whenever they are available

# Multiple parameter servers

- If the parameters are too numerous for a single parameter server to handle, we can use **multiple parameter server machines**.
- We partition the parameters among the multiple parameter servers
  - Each server is only responsible for maintaining the parameters in its partition.
  - When a worker wants to send a gradient, it will partition that gradient vector and send each chunk to the corresponding parameter server; later, it will receive the corresponding chunk of the updated model from that parameter server machine.
- This lets us **scale up to very large models!**

# Other Ways To Distribute

The methods we discussed so far distributed across the minibatch (for all-reduce SGD) and across iterations of SGD (for asynchronous parameter-server SGD).

But there are other ways to distribute that are used in practice too.

# Distribution for hyperparameter optimization

- This is something we've already talked about.

- Many commonly used hyperparameter optimization algorithms, such as **grid search and random search**, are very simple to distribute.
  - They can easily be run on many parallel workers to get results faster.

# Model Parallelism

- Main idea: **partition the layers** of a neural network among different worker machines.
- This makes each worker responsible for a subset of the parameters.
- Forward and backward signals running through the neural network during backpropagation now also run across the computer network between the different parallel machines.
  - Particularly useful if the parameters won't fit in memory on a single machine.
  - This is very important when we move to specialized machine learning accelerator hardware, where we're running on chips that typically have limited memory and communication bandwidth.

# A Diagram of Model Parallelism

- From "*PipeDream: Fast and Efficient Pipeline Parallel DNN Training.*"

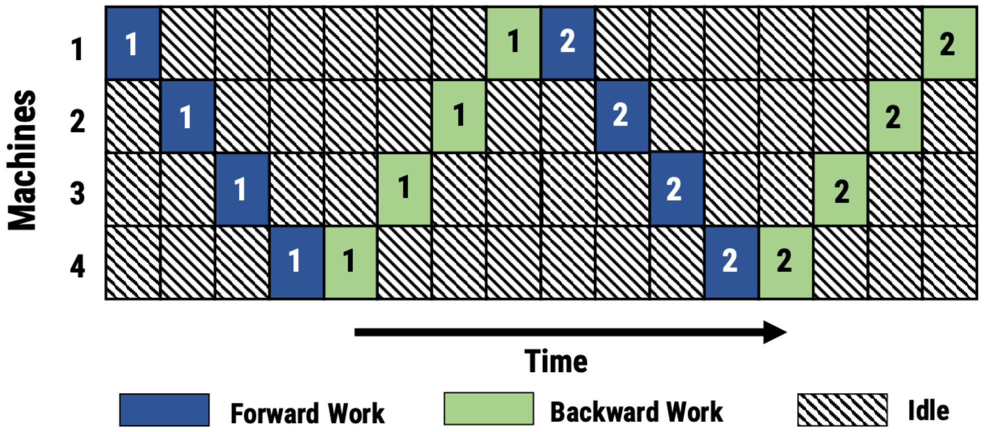
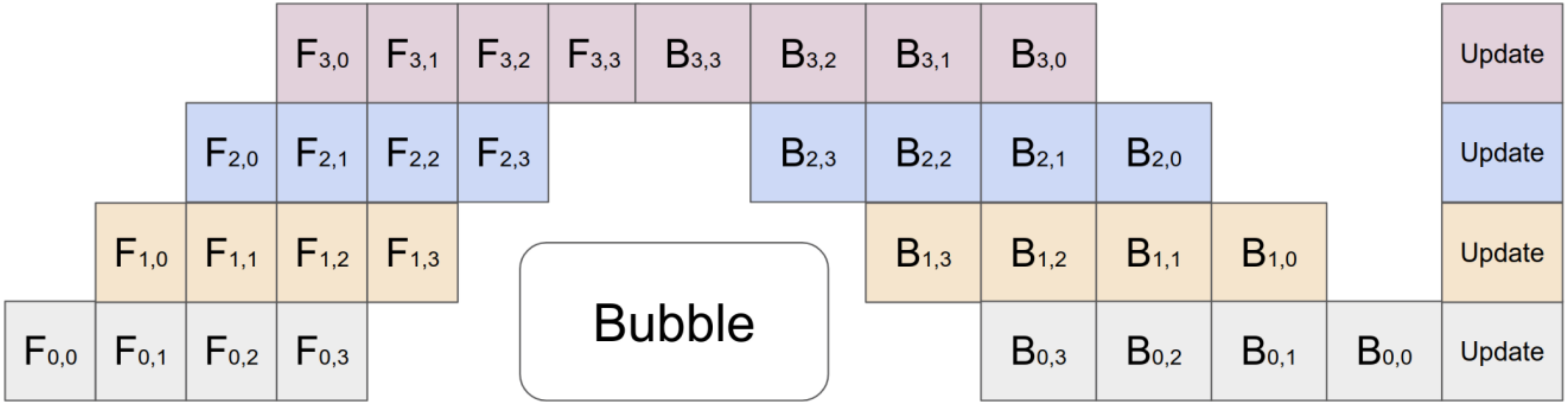



**Figure 3:** Model parallel training with 4 machines. Numbers indicate minibatch ID. For simplicity, here we assume that forward and backward work in every stage takes one time unit, and communicating activations across machines has no overhead.

# Pipeline Parallelism

- A variant of model parallelism that tries to improve throughput by overlapping minibatch computation.
  - From *"GPipe: Easy Scaling with Micro-Batch Pipeline Parallelism"*

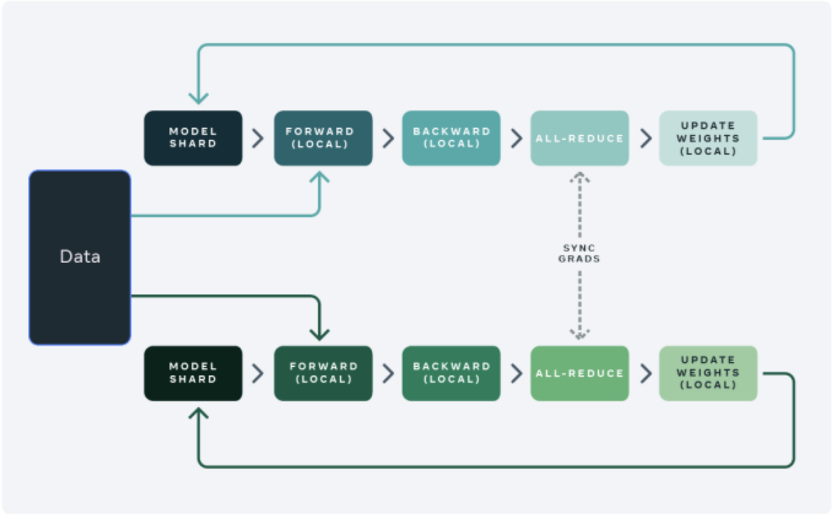


# Fully Sharded Data Parallel

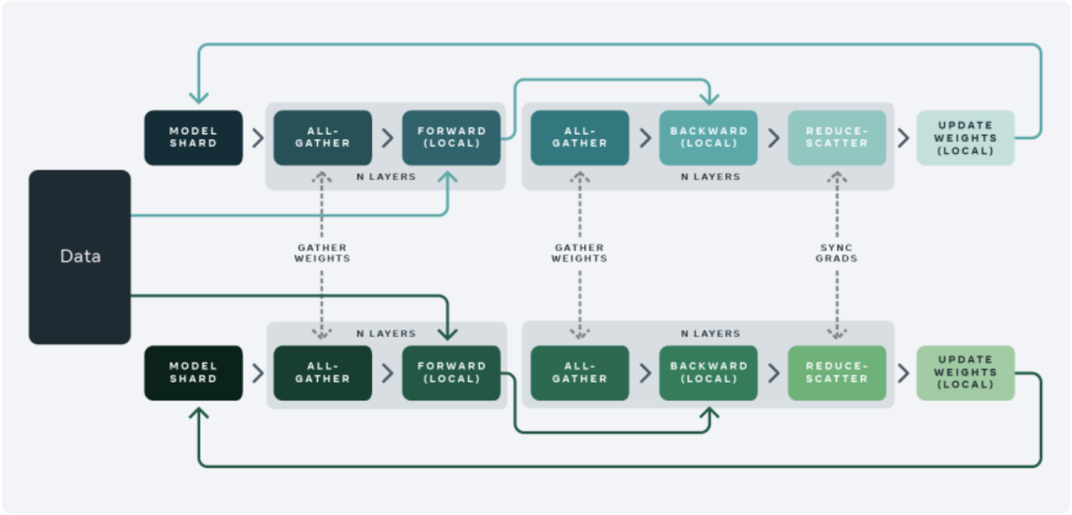
- A hybrid of data parallelism and sharded parameter server strategies.

- Splits the weights for each layer among all machines, then uses a broadcast to get them whenever they're needed.

Standard data parallel training




Fully sharded data parallel training



# Conclusion and Summary

- Distributed computing is a powerful tool for scaling machine learning

- We talked about a few methods for distributed training:
  - Minibatch SGD with All-reduce
  - The parameter server approach
  - Model parallelism

- And distribution can be beneficial for many other tasks too!