## Lecture 8:

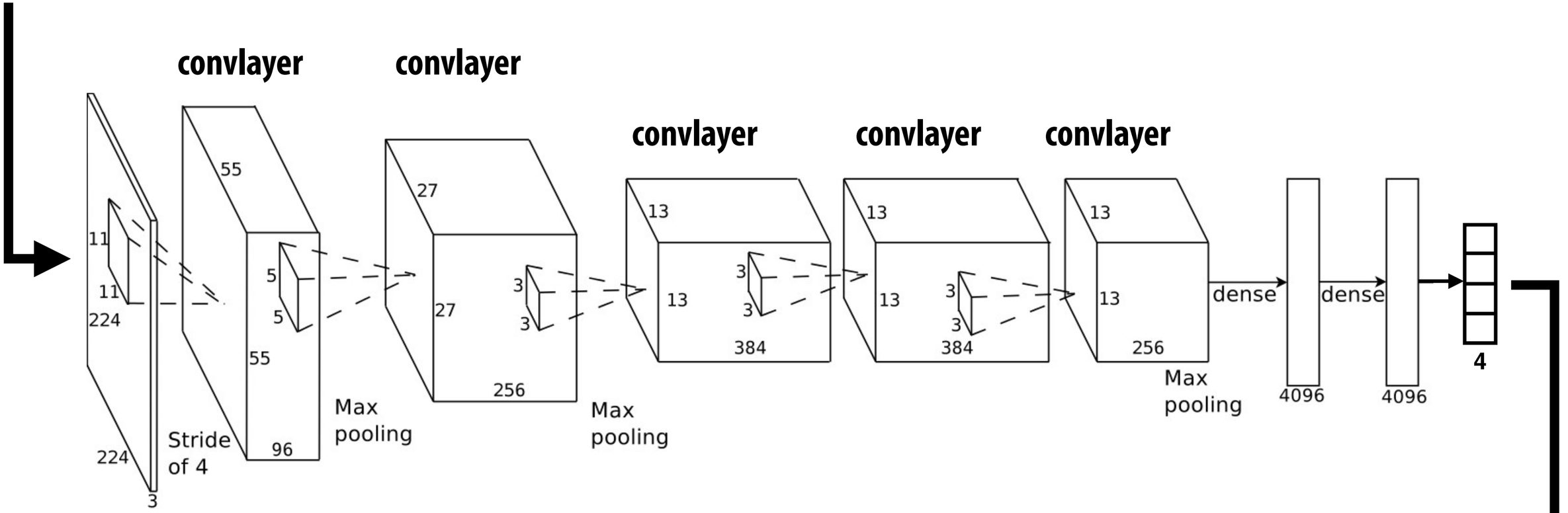
# Parallel DNN Training

**Parallel Computing**
**Stanford CS348K, Spring 2021**

# Professor classification network

**Ground truth**
**(what the answer should be)**

| | |
|---|---|
| Easy: | 0.0 |
| Mean: | 0.0 |
| Boring: | 0.0 |
| Nerdy: | 1.0 |




**Easy:** 0.26
**Mean:** 0.08
**Boring:** 0.14
**Nerdy:** 0.52

**Network output**

# Error (loss)

**Ground truth:**
**(what the answer should be)**

| | |
|---|---|
| **Easy:** | **0.0** |
| **Mean:** | **0.0** |
| **Boring:** | **0.0** |
| **Nerdy:** | **1.0** |

**Network output: ***

| | |
|---|---|
| **Easy:** | **0.26** |
| **Mean:** | **0.08** |
| **Boring:** | **0.14** |
| **Nerdy:** | **0.52** |

**Common example: softmax loss:**

$$L = -log\left(\frac{e^{f_c}}{\sum_j e^{f_j}}\right)$$

**Output of network for correct category (Nerdy)**

**Output of network for all categories**

*** In practice a network using a softmax classifier outputs unnormalized, log probabilities ($f_j$), but I'm showing a probability distribution above for clarity**

# DNN training

**Goal of training: learning good values of network parameters so that the network outputs the correct classification result for any input image**

**Idea: minimize loss for all the training examples (for which the correct answer is known)**

$$L = \sum_i L_i$$ **(total loss for entire training set is sum of losses $L_i$ for each training example $x_i$)**

**Intuition: if the network gets the answer correct for a wide range of training examples, then hopefully it has learned parameter values that yield the correct answer for future images as well.**

# Gradient descent


Stanford CS248, Winter 2021

# Basic gradient descent

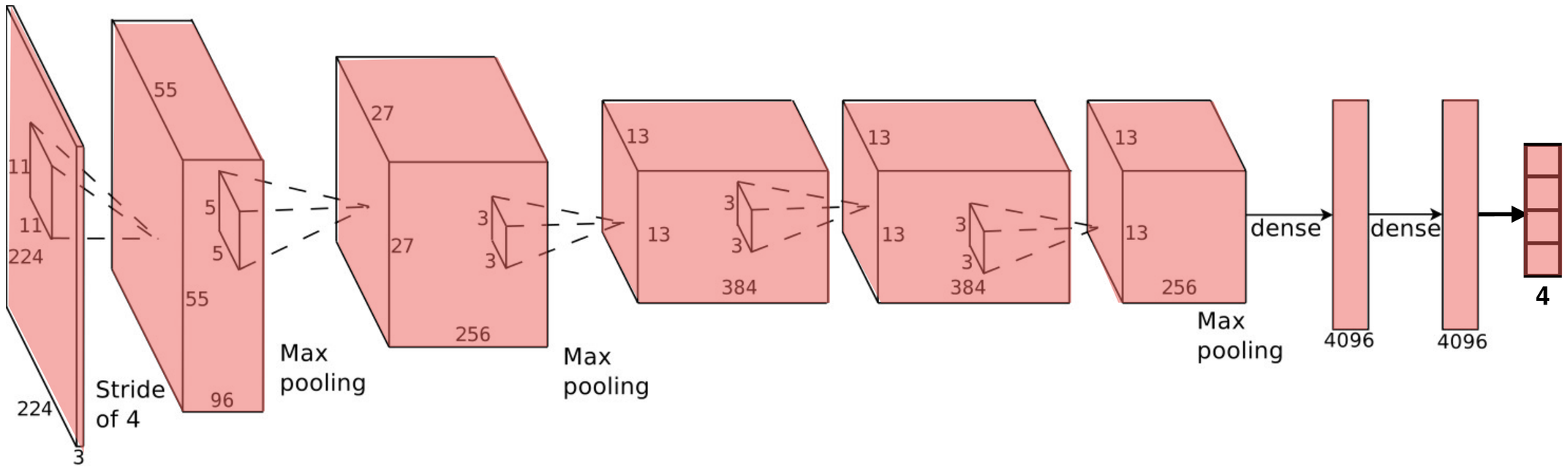
```
while (loss too high):
  for each epoch: // a pass through items in training dataset
     grad = 0
     for each item x_i in training set:
        grad += evaluate_loss_gradient(f, params, loss_func, x_i)
     params += -grad * learning_rate;
```

**Mini-batch stochastic gradient descent (mini-batch SGD):**

**choose a random (small) subset of the training examples to use to compute the gradient in each iteration of the while loop**

```
while (loss too high):
  for each epoch:
     for all mini batches in training set:
       grad = 0;
       for each item x_i in minibatch:
          grad += evaluate_loss_gradient(f, params, loss_func, x_i)
       params += -grad * learning_rate;
```

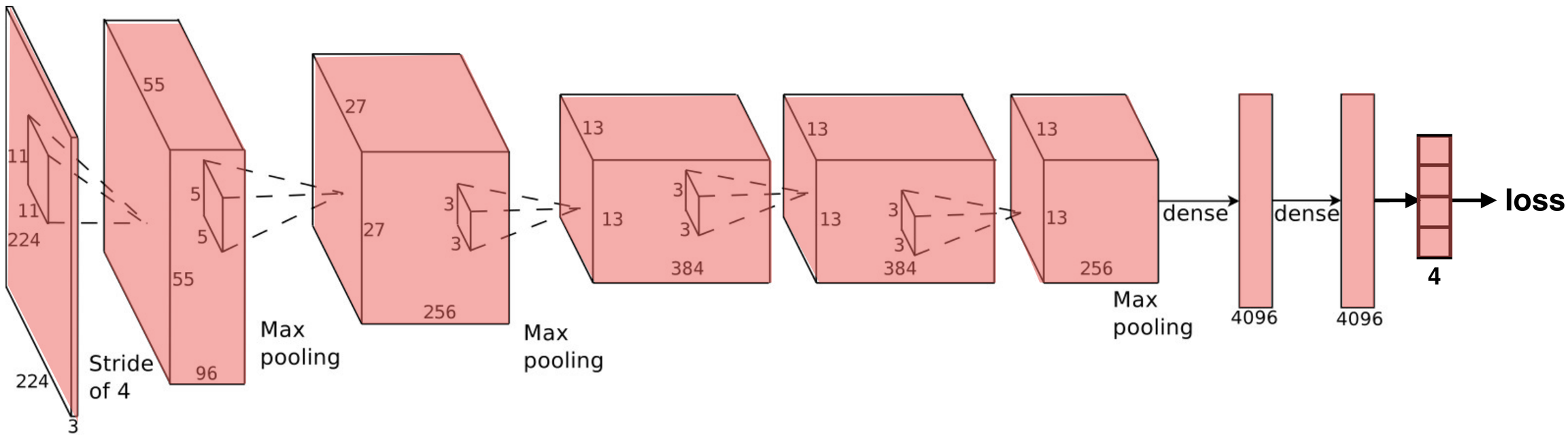
# Data lifetimes during network evaluation



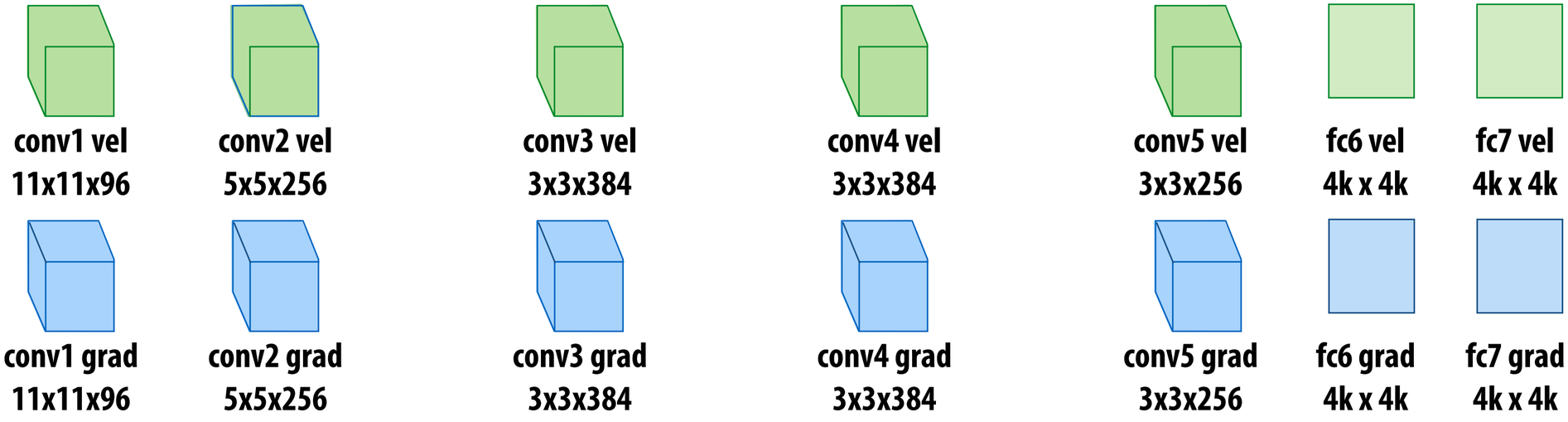

**Weights (read-only) reside in memory**

**After evaluating layer i, can free outputs from layer i-1**

# Data lifetimes during training




**Must retain outputs for all layers because they are needed to compute gradients during back-prop**




- Parallel back-prop will require storage for per-weight gradients
- In practice: store per-weight gradient velocity (if using SGD with "momentum") or step size cache in adaptive step size schemes like Adagrad

```
vel_new = mu * vel_old - step_size * grad
w_new = w_old + vel_new
```

# SGD workload

```
while (loss too high):
```

At first glance, this loop is sequential (each step of "walking downhill" depends on previous step)

```
    for each item x_i in mini-batch:
        grad += evaluate_loss_gradient(f, loss_func, params, x_i)
```

Parallel across training images

sum reduction

large computation with its own parallelism (but working set may not fit on single machine)

```
params += -grad * step_size;
```

trivially data-parallel over parameters

# DNN training workload

- **Large computational expense**
  - Must evaluate the network (forward and backward) for millions of training images
  - Must iterate for many iterations of gradient descent (100's of thousands)
  - Training modern networks on big datasets takes days

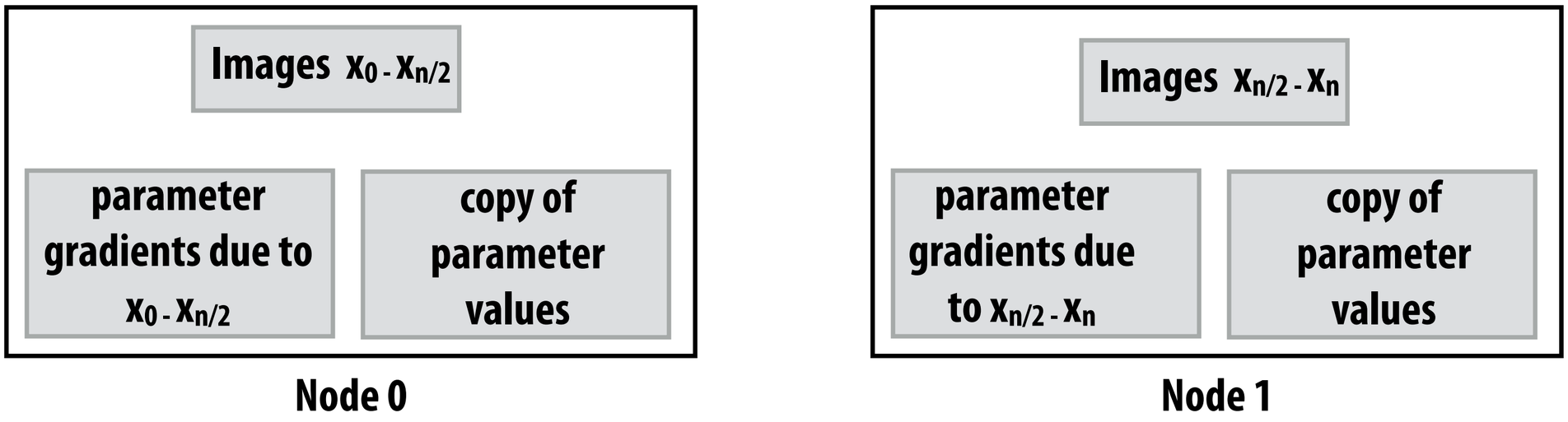
- **Large memory footprint**
  - Must maintain network layer outputs from forward pass
  - Additional memory to store gradients/gradient velocity for each parameter
  - Scaling to large networks requires partitioning DNN across nodes to keep DNN + intermediates in memory

- **Dependencies /synchronization (not embarrassingly parallel)**
  - Each parameter update step depends on previous
  - Many units contribute to same parameter gradients (fine-scale reduction)
  - Different images in mini batch contribute to same parameter gradients

# Synchronous data-parallel training (across images)

```
for each item x_i in mini-batch of size n:
   grad += evaluate_loss_gradient(f, loss_func, params, x_i)
params += -grad * learning_rate;
```

**Consider parallelization of the outer for loop across machines in a cluster**




```
partition dataset across nodes
for each item x_i in mini-batch assigned to local node:
   // just like single node training
   grad += evaluate_loss_gradient(f, loss_func, params, x_i)
barrier();
sum reduce gradients, communicate results to all nodes
barrier();
update copy of parameter values
```

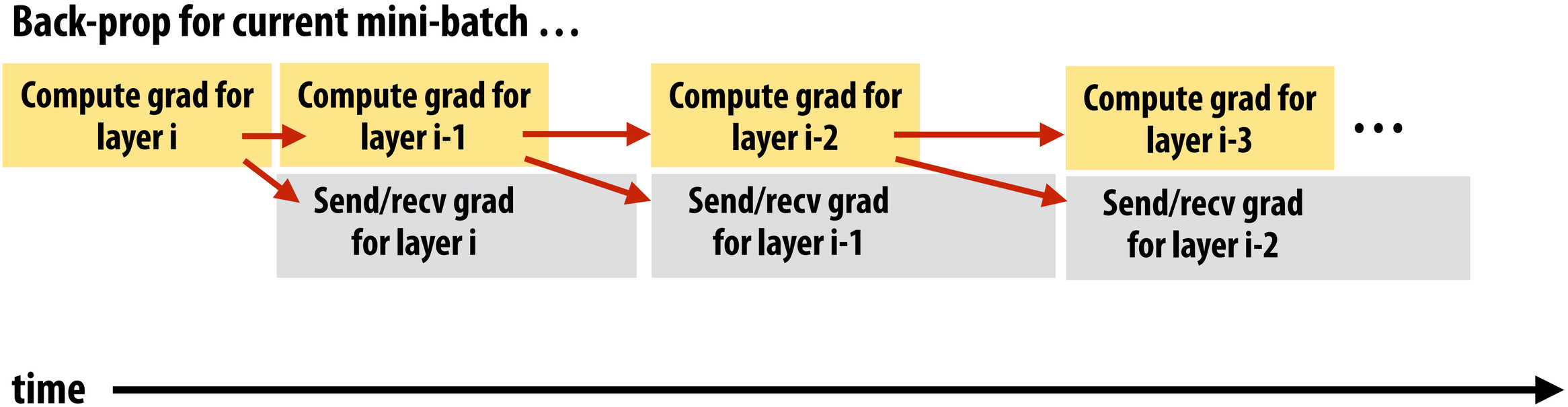
# Synchronous training

- All nodes cooperate to compute gradients for a mini-batch *
- Gradients are summed (across the entire machine)
  - All-to-all communication
- Update model parameters
  - Typically done without wide parallelism (e.g. each machine computes its own update)
- All nodes proceed to work on next mini-batch given new model parameters

* If curious about batch norm in a parallel training setting. In practice each of *k* nodes works on a set of *n* images, with batch norm statistics computed independently for each set of n (so the overall mini-batch size is *kn*).

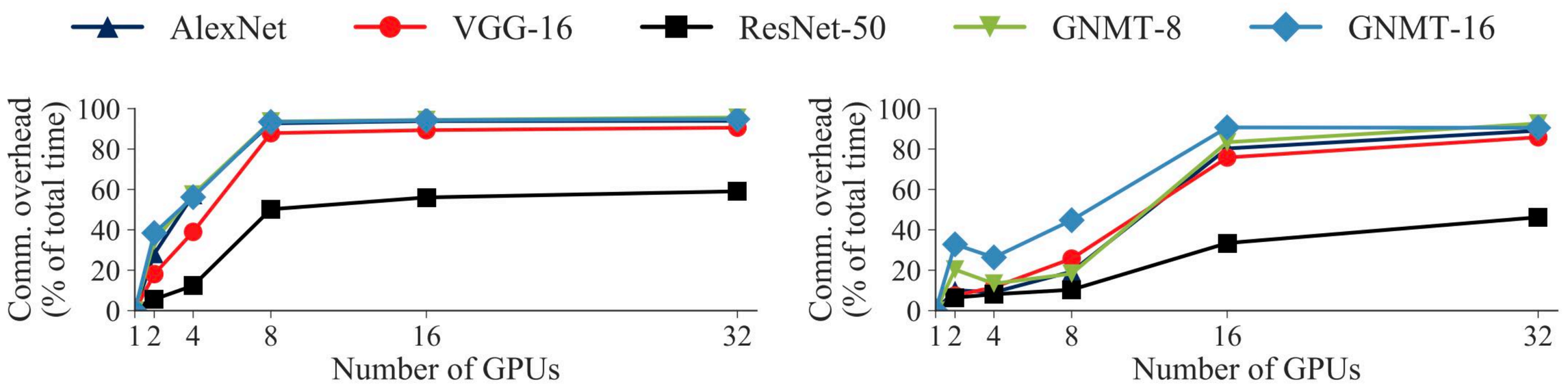
# Overlapping communication and computation during back-propagation

## ("Wait-free back propagation")



# Challenge of scaling data parallel training out to many nodes

- Slow communication between nodes
  - Synchronous SGD involves all-to-all communication after each mini-batch
  - GPUs in the same system have high communication cost (e.g., compared to communication between cores on the same GPU)
  - Commodity clusters do not feature high-performance interconnects between nodes typical of supercomputers (e.g., infiniband)

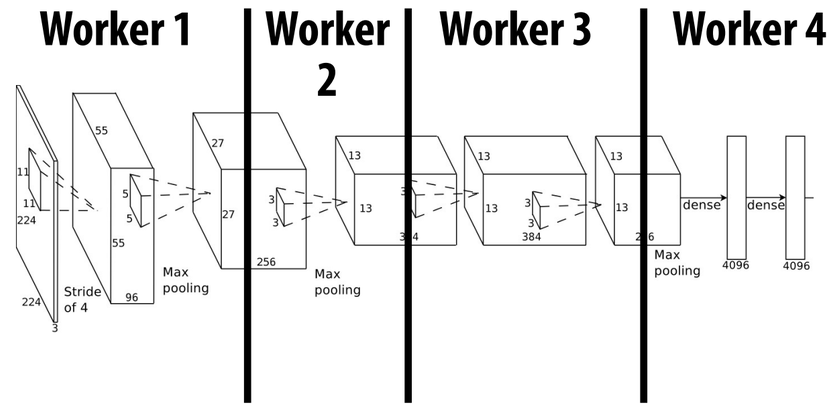


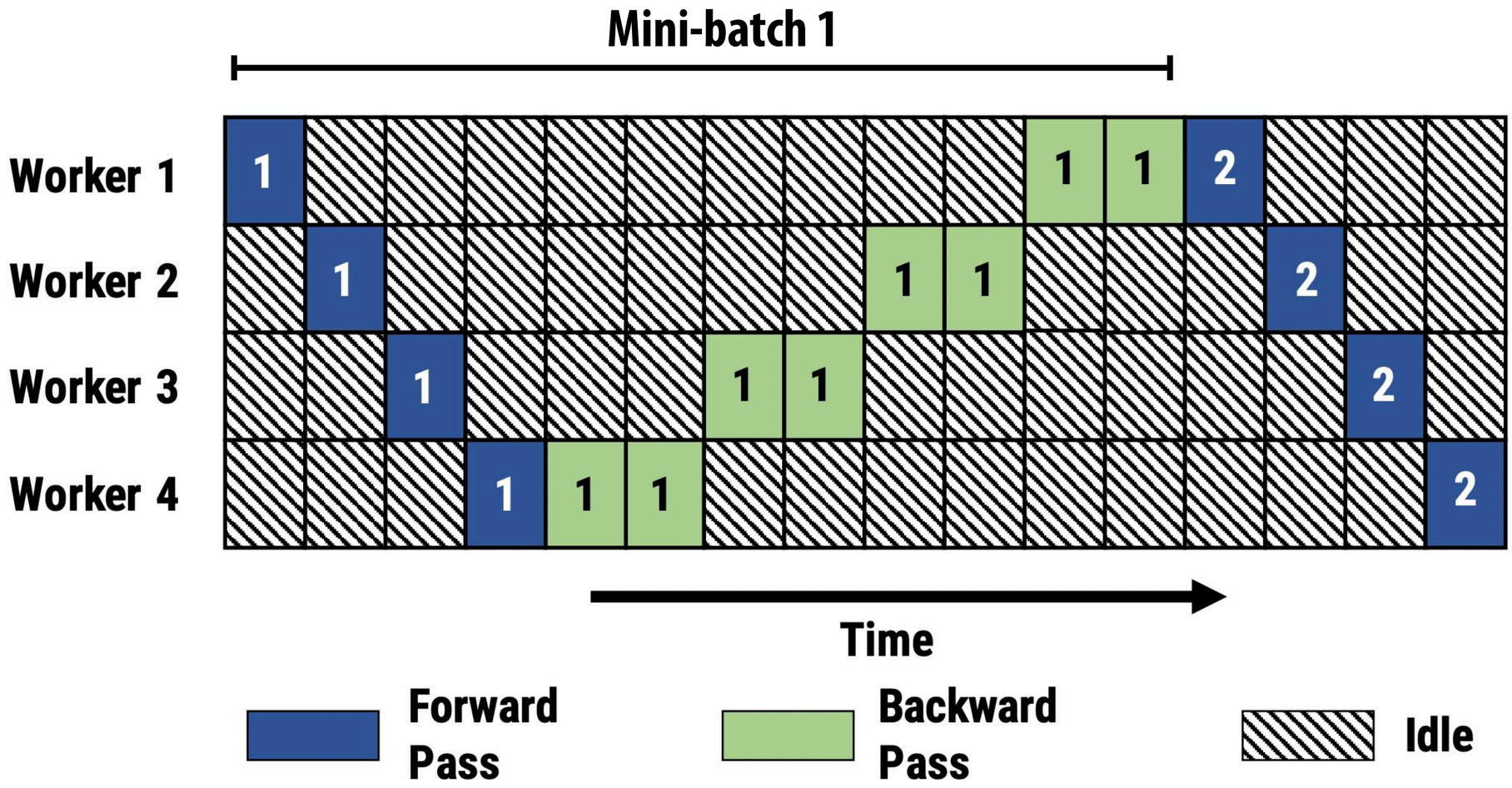

**(b) Instances with 4 V100s (Azure).** **(c) Instances with 8 V100s and NVLink (EC2).**

**[Figure credit: Narayanan et al. SOSP 19]**

# Model parallelism

- For large models that do not fit on a single node
- Partition model weights across workers
- Naive solution: dependencies result in low utilization
- Notice: communication between nodes is point-to-point (not broadcast)



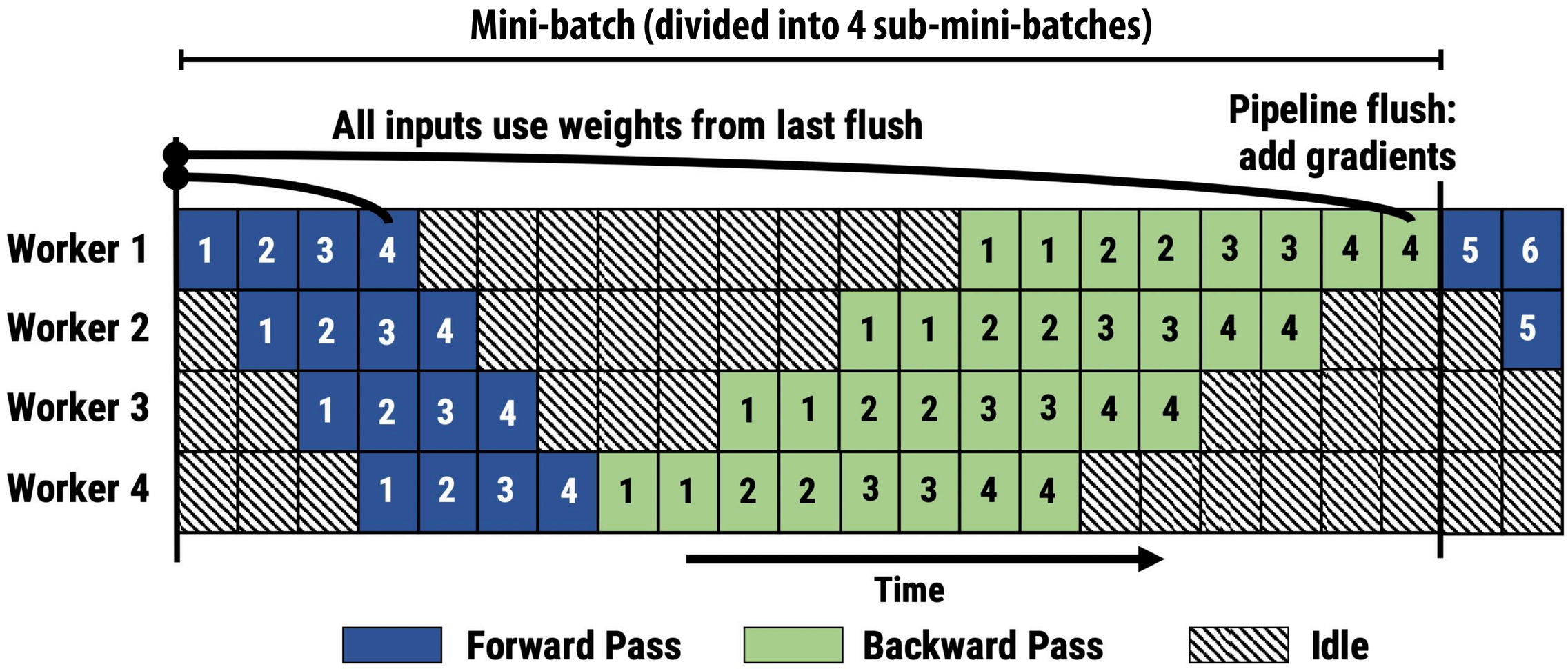




* In diagram backward pass shown to take 2x longer than forward pass

[Figure credit: Narayanan et al. SOSP 19]

# Model parallelism (pipelined)

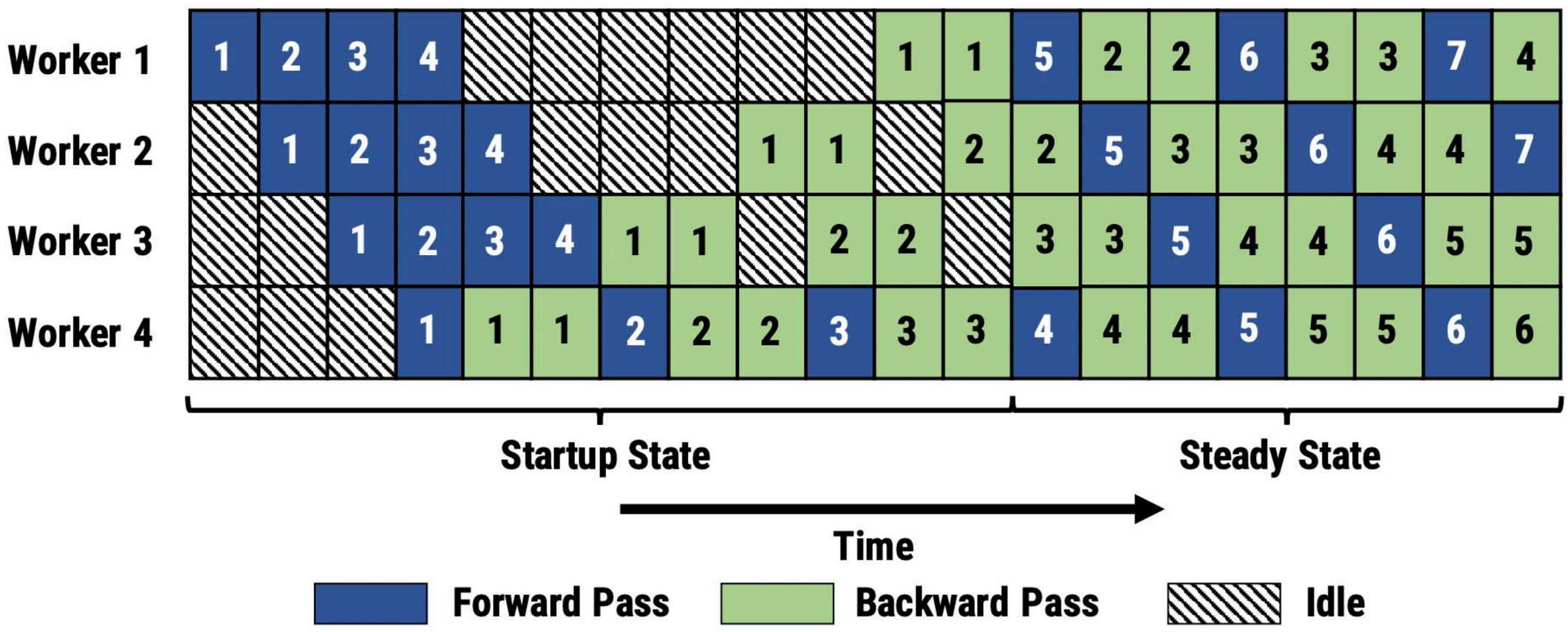
- Divide mini-batch into sub-mini-batches (shown here as 1-4)
- Pipeline forward/backward pass for one sub-mini-batch with communication of activations/gradients for another




[Figure credit: Narayanan et al. SOSP 19]

# Model parallelism (aggressively pipelined)

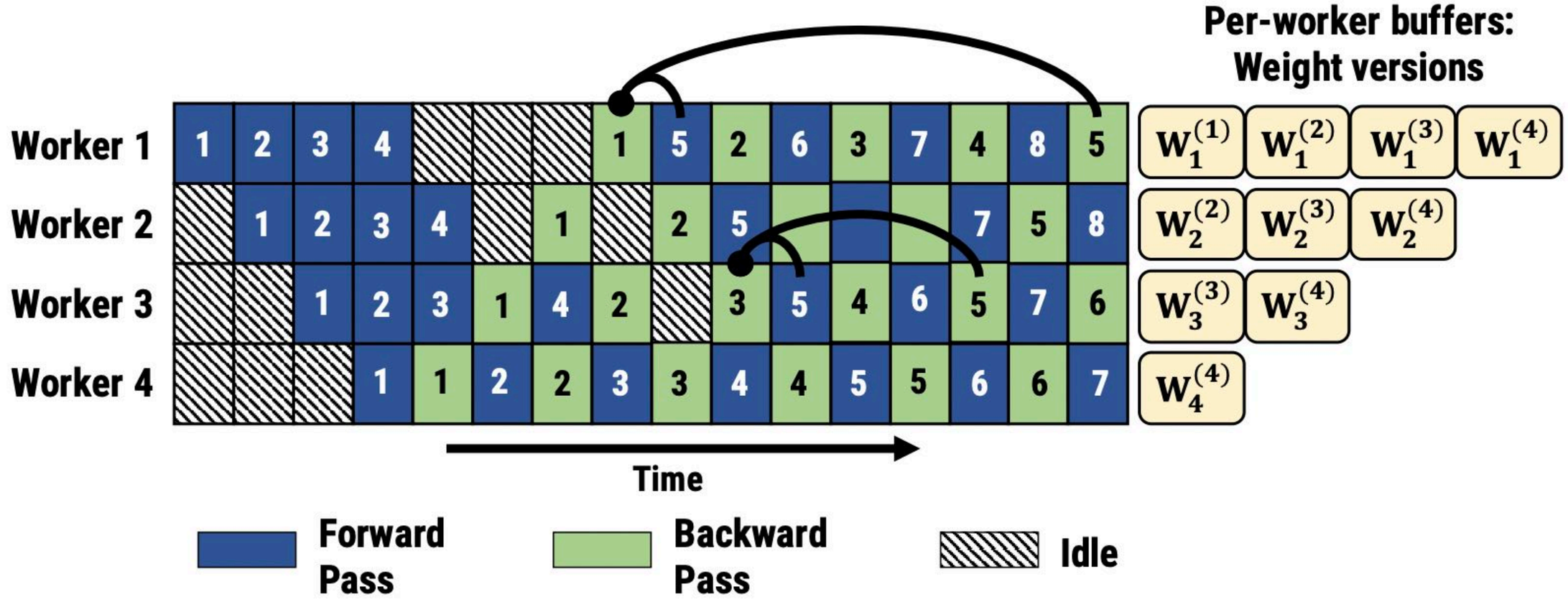
- Immediately begin backward pass for "1" before forward pass for other mini-batches are complete.
- Problem: first stage of forward pass of "5" uses weights that reflect gradient update from "1", but during backward pass through same stage, weights reflect gradient updates from "1,2,3,4".




[Figure credit: Narayanan et al. SOSP 19]

# Model parallelism (aggressively pipelined)

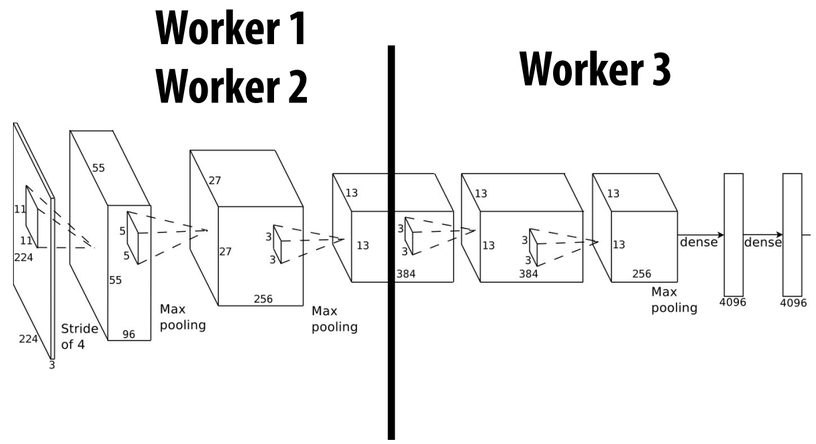
- Solution: "weight stashing": each worker maintains multiple versions of model weights, always uses same weights for forward and backward pass.

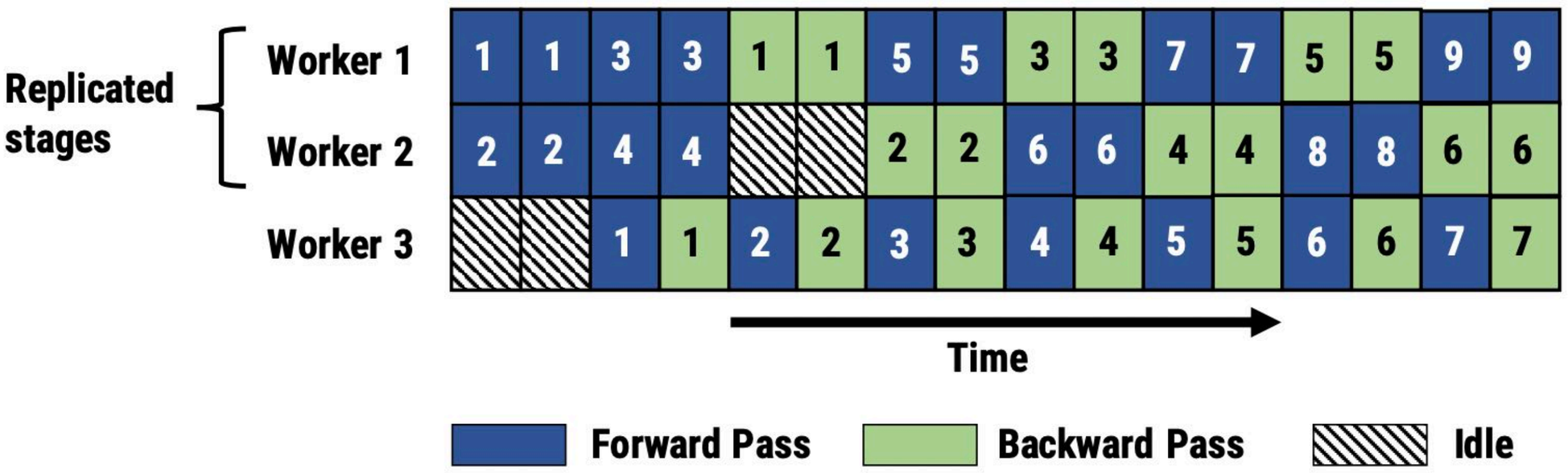



[Figure credit: Narayanan et al. SOSP 19]

# Mixing data and pipeline parallelism

- Workers 1 and 2 maintain duplicate copies of stage part of model
- Mini-batch is partitioned across these two workers (data parallel)




[Figure credit: Narayanan et al. SOSP 19]

# Challenges of scaling out (many nodes)

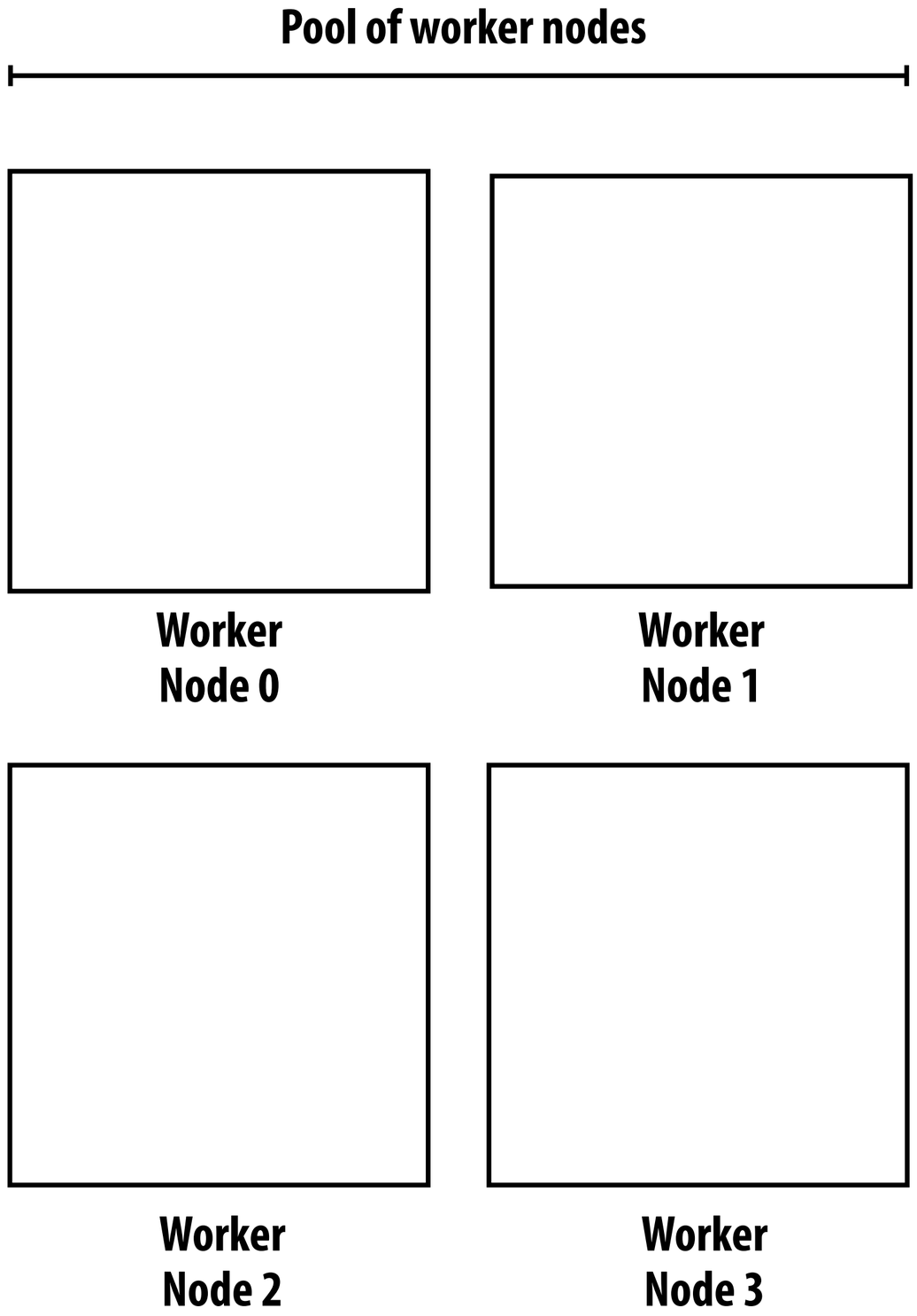
- Slow communication between nodes

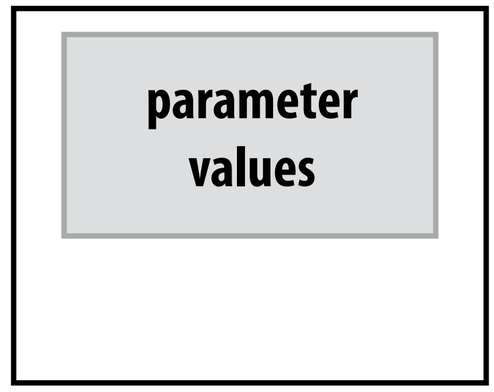
- Nodes with different performance (even if machines are the same)
  - Workload imbalance at barriers (sync points between nodes)

## Alternative solution: exploit properties of SGD by using asynchronous execution

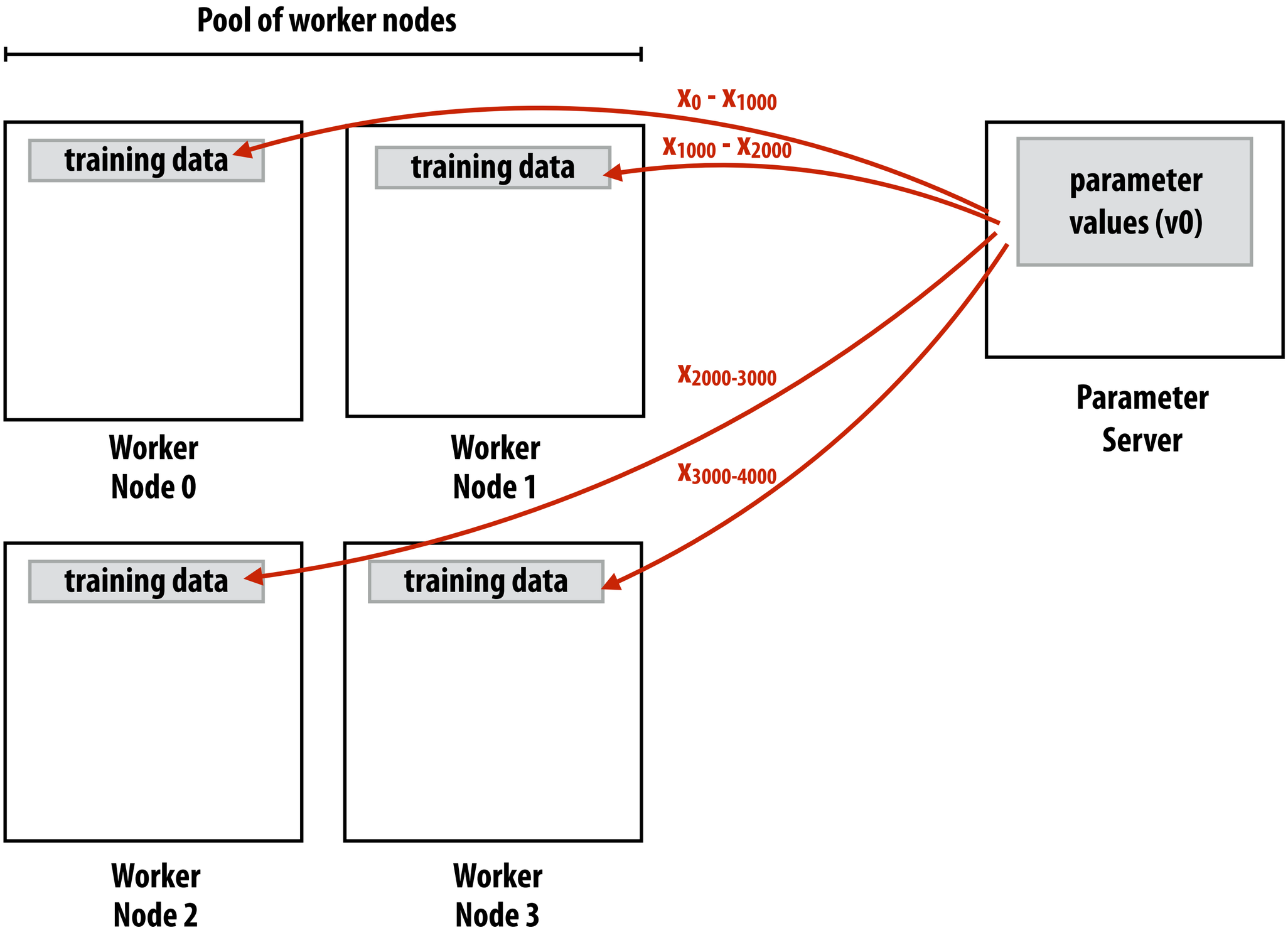
# Parameter server design

Google's DistBelief [Dean NIPS12]
Parameter Server [Li OSDI14]
Microsoft's Project Adam [Chilimbi OSDI14]

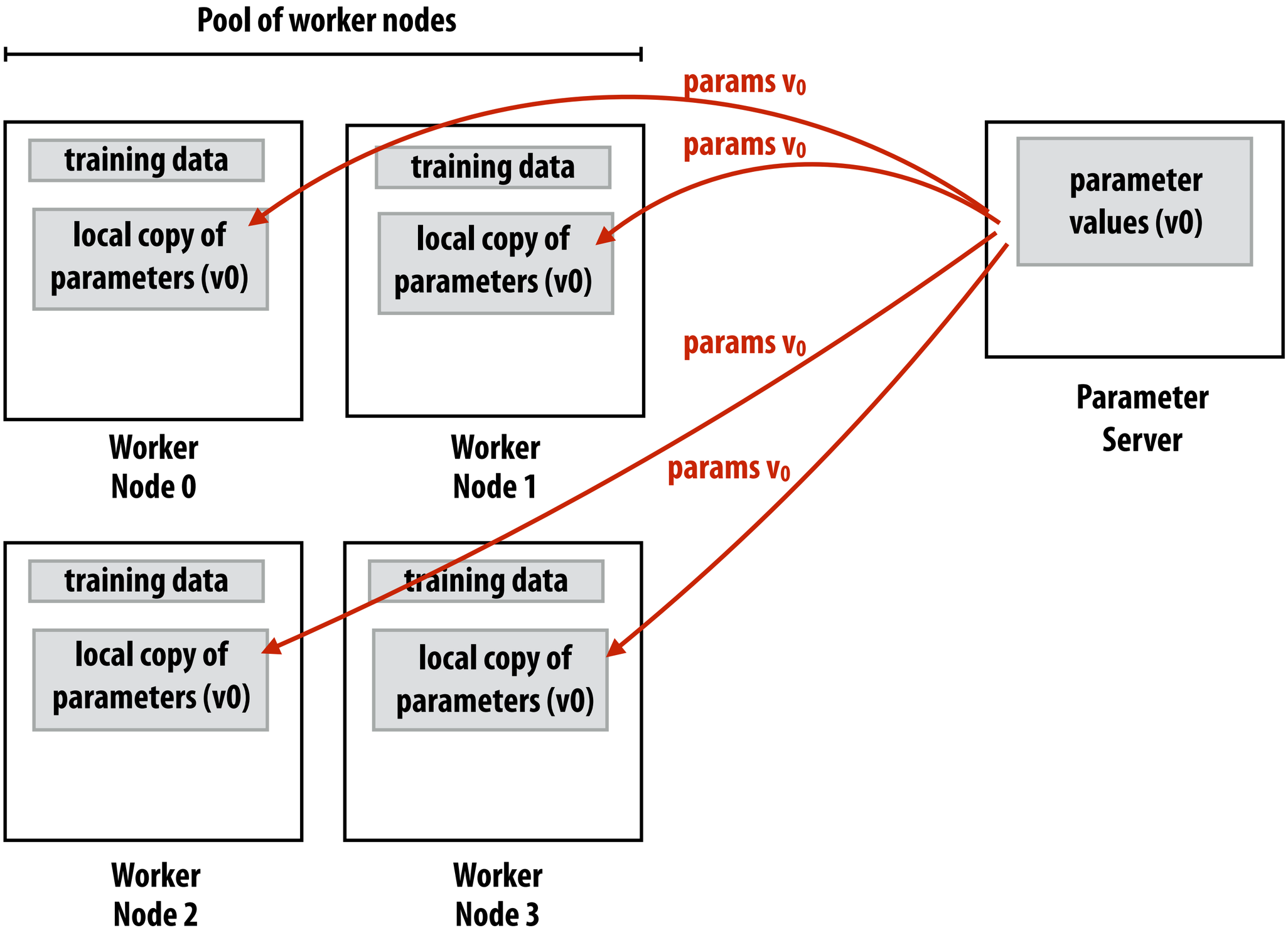


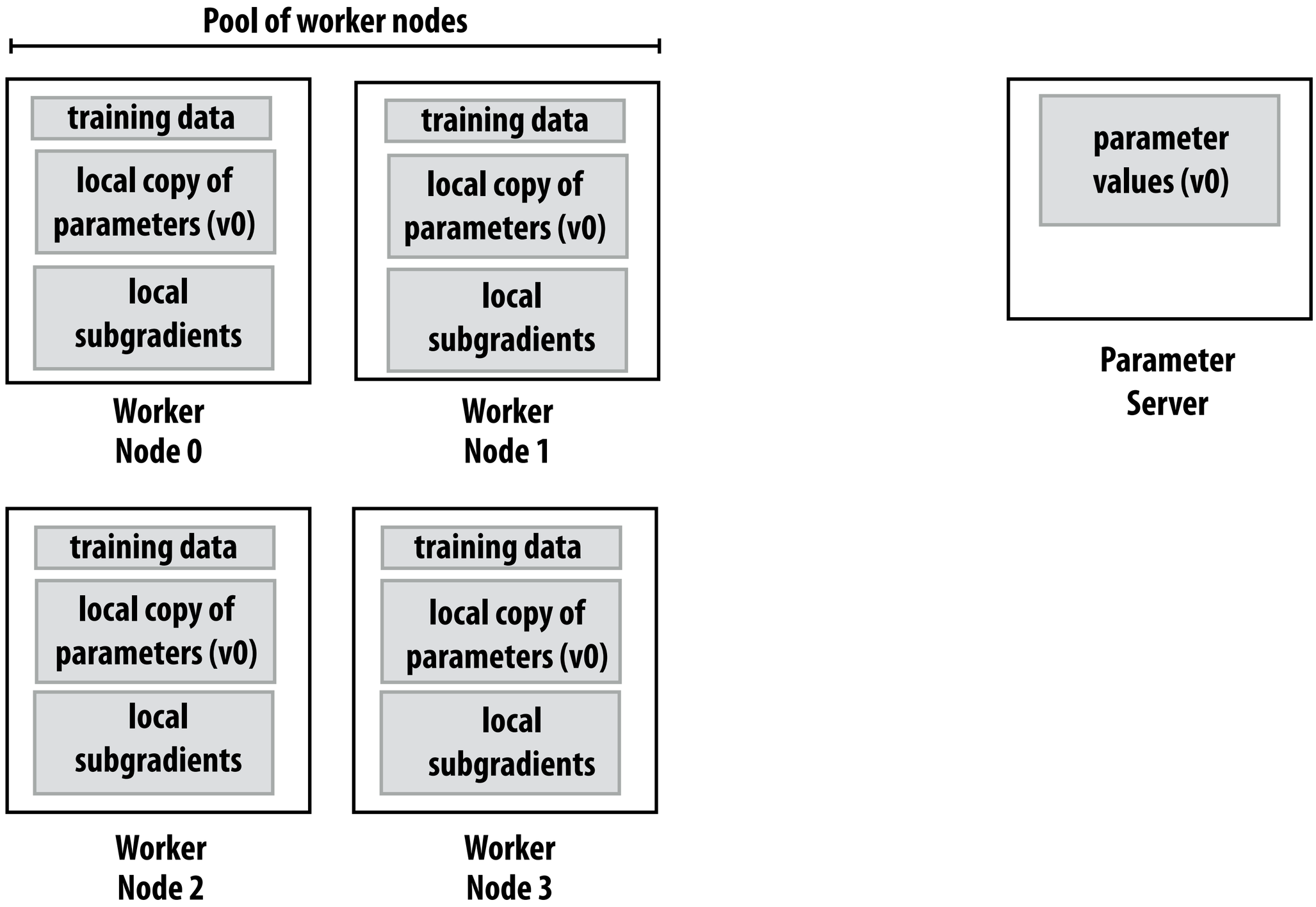
# Training data partitioned among workers



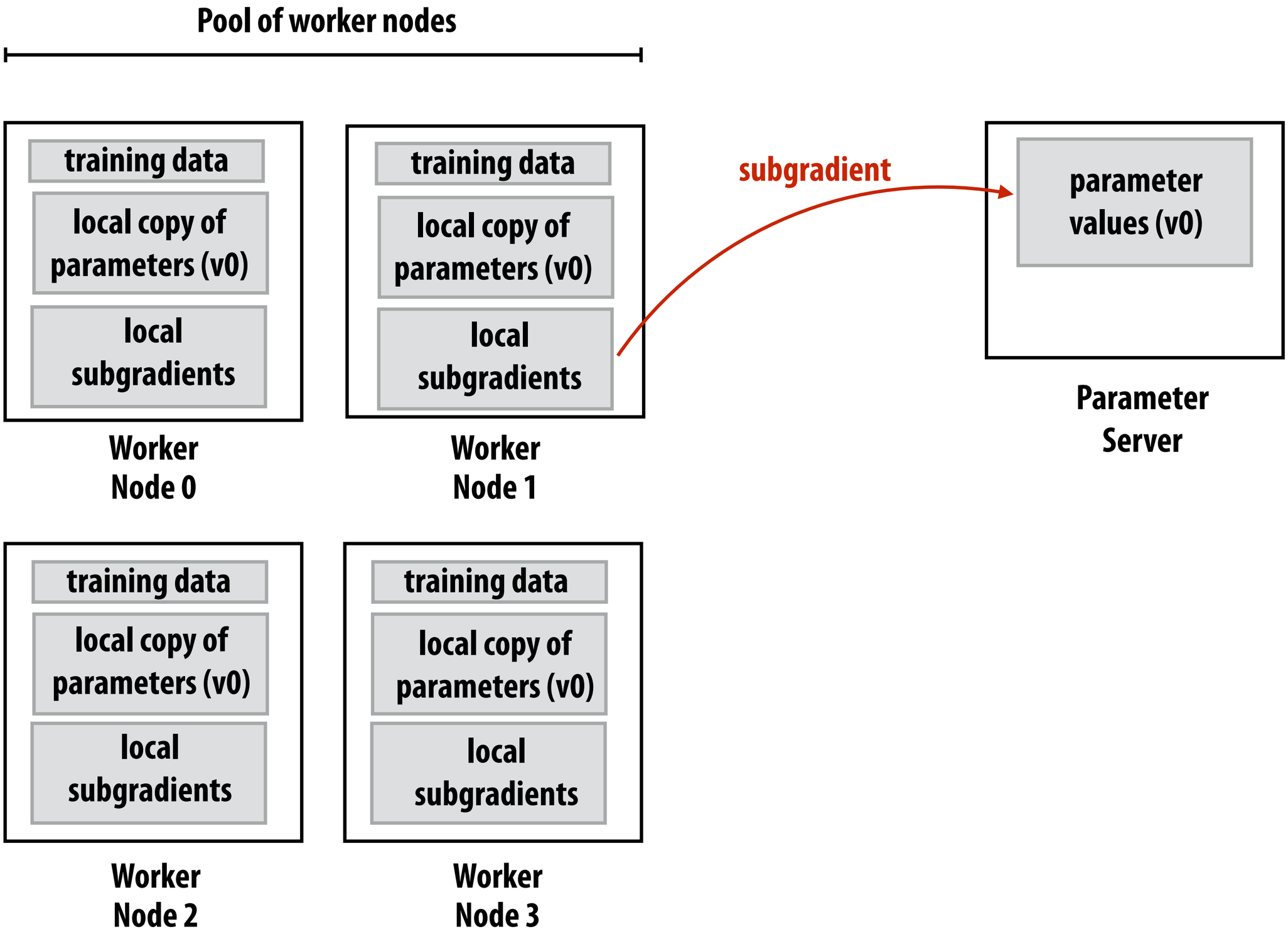
# Copy of parameters sent to workers



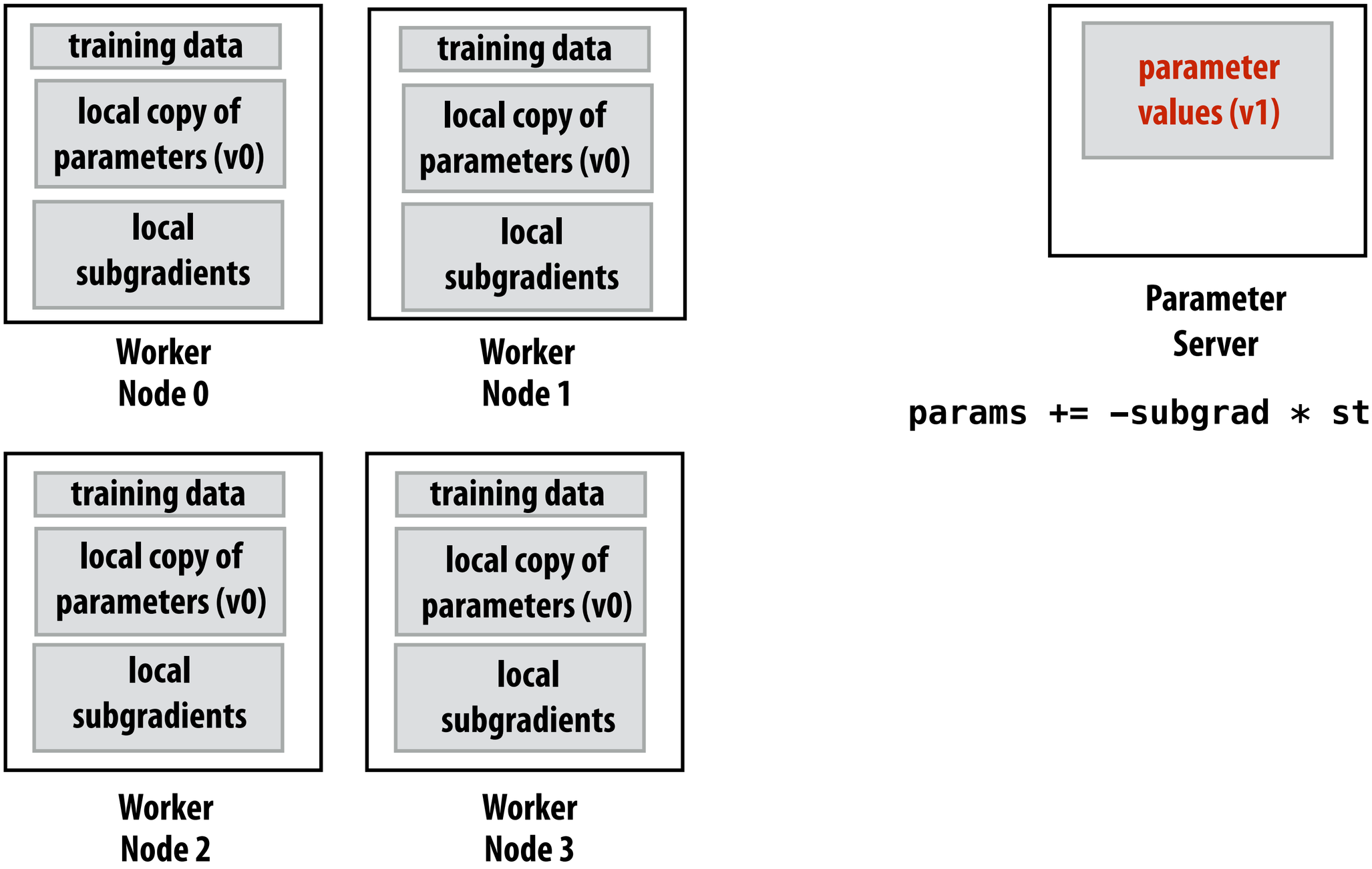
# Data parallelism: workers independently compute local "sub-gradients" on different pieces of data



# Worker sends sub-gradient to parameter server

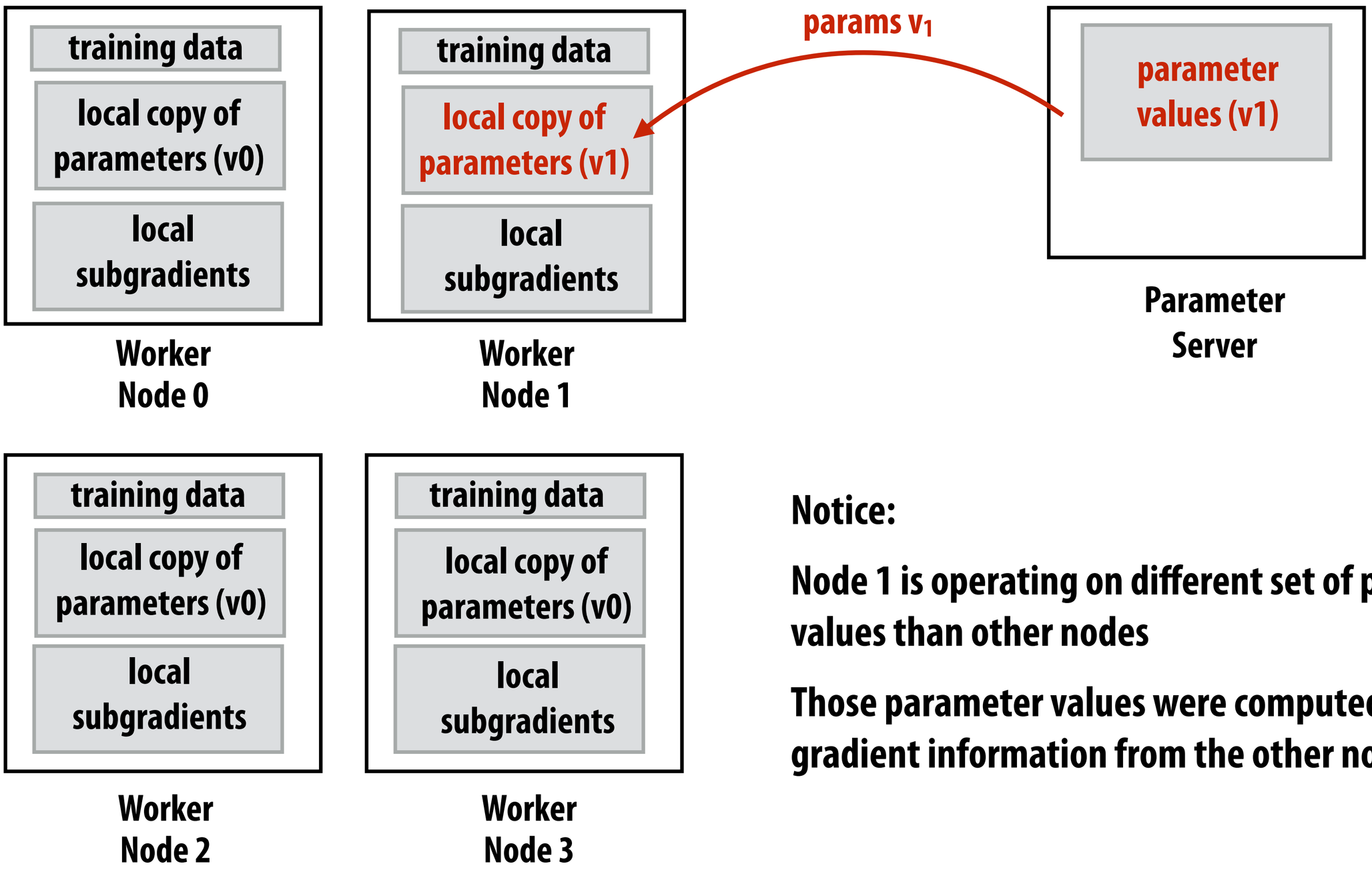


# Server updates global parameter values based on sub-gradient



# Updated parameters sent to worker

## Then worker proceeds with another gradient computation step

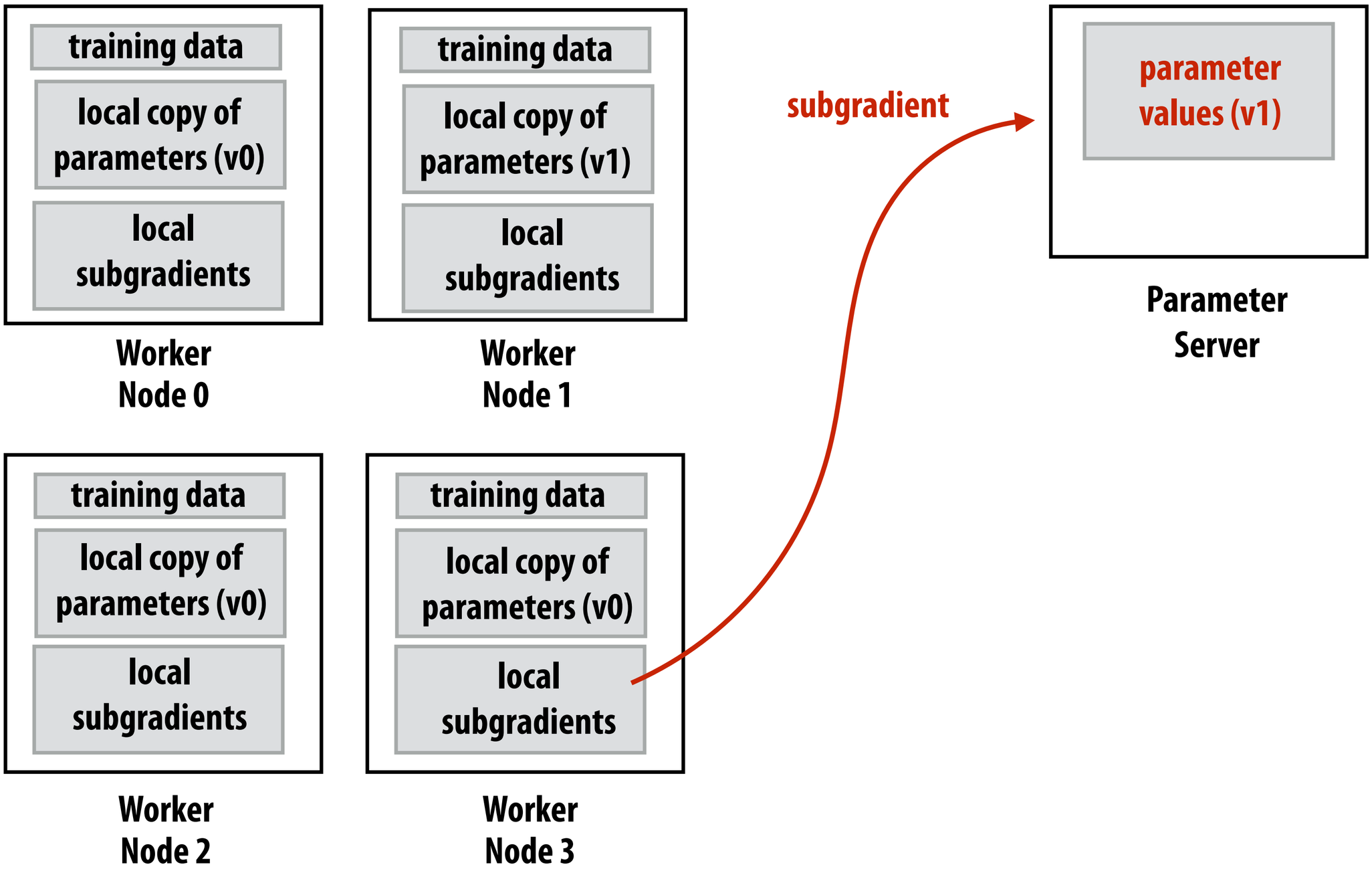



**Notice:**

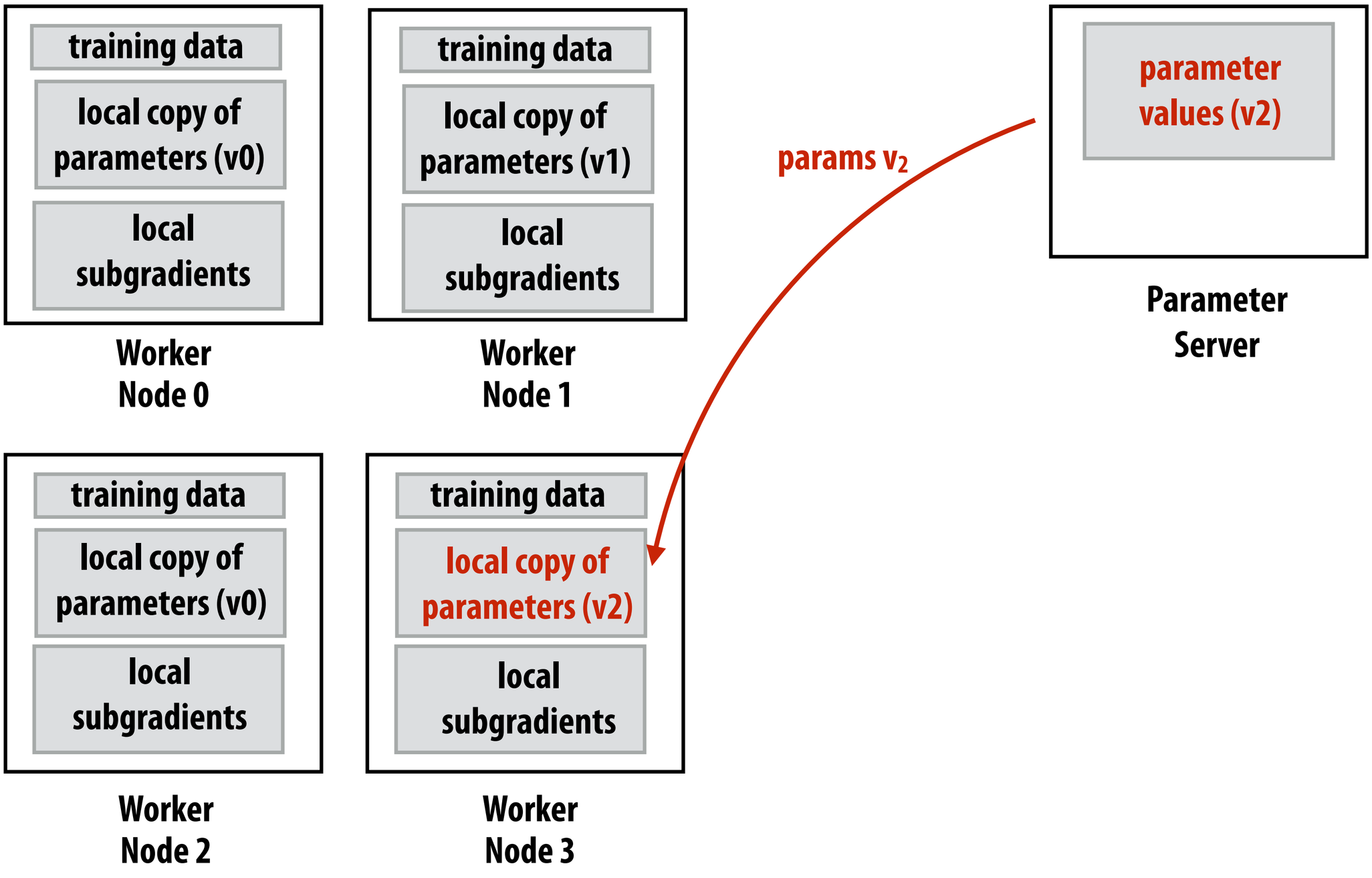
**Node 1 is operating on different set of parameter values than other nodes**

**Those parameter values were computed without gradient information from the other nodes**

# Updated parameters sent to worker (again)



# Worker continues with updated parameters



# Summary: asynchronous parameter update

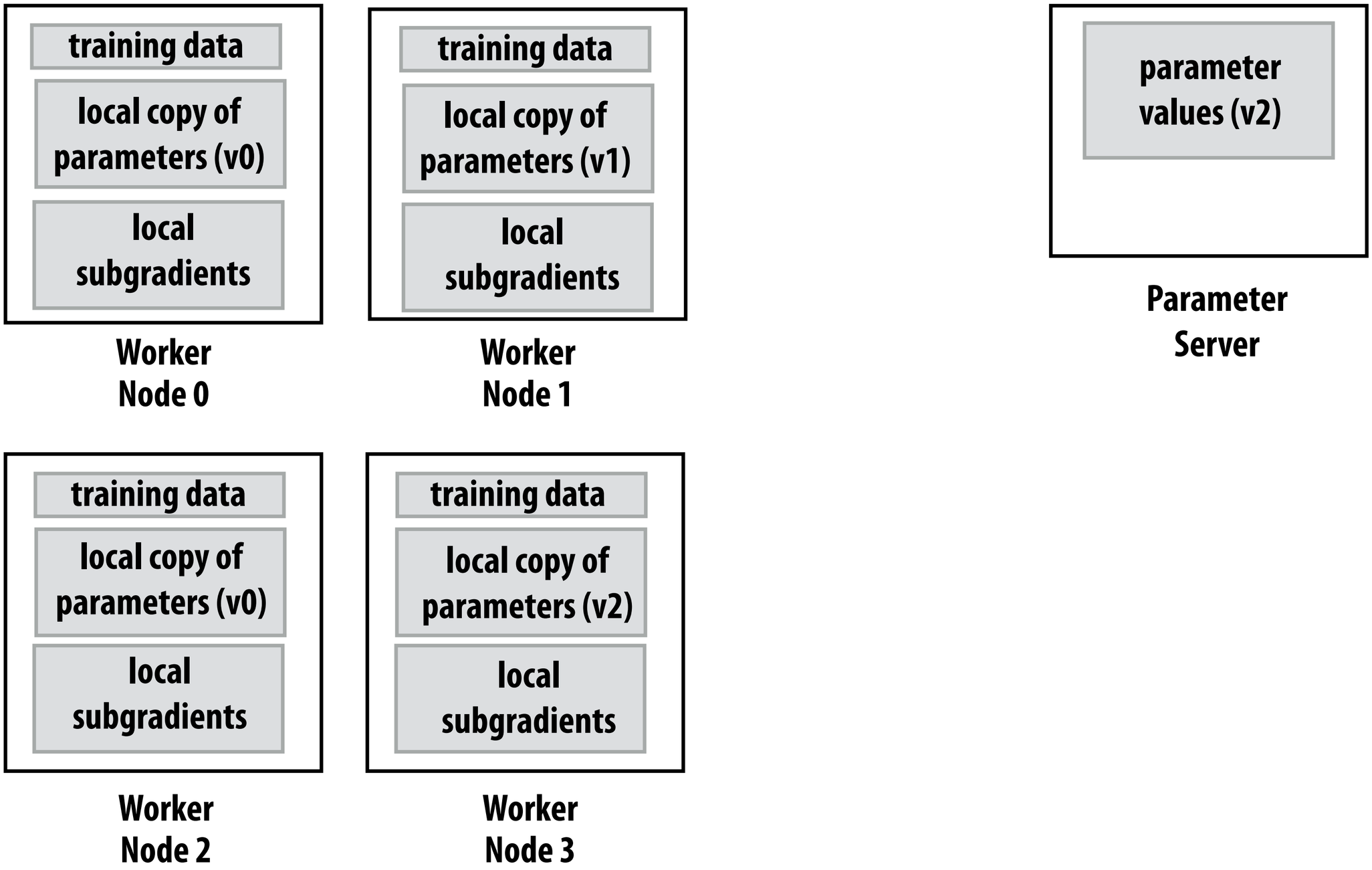
- **Idea: avoid global synchronization on all parameter updates between each SGD iteration**
  - Algorithm design reflects realities of cluster computing:
    - Slow interconnects
    - Unpredictable machine performance

- **Solution: asynchronous (and partial) subgradient updates**

- **Will impact convergence of SGD**
  - Node N working on iteration *i* may not have parameter values that result the results of the *i-1* prior SGD iterations

# Bottleneck?

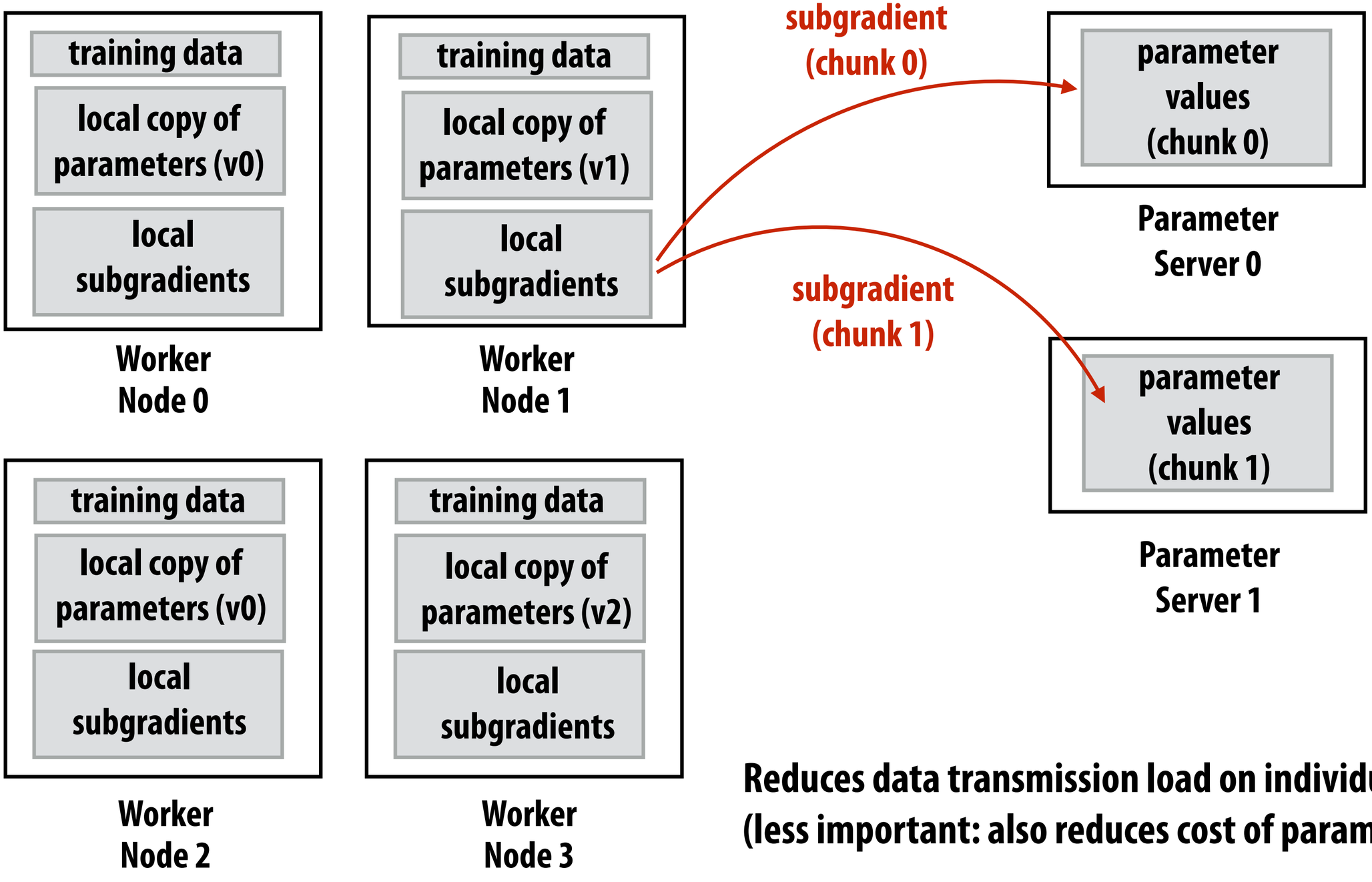
## What if there is heavy contention for parameter server?



# Shard the parameter server

## Partition parameters across servers

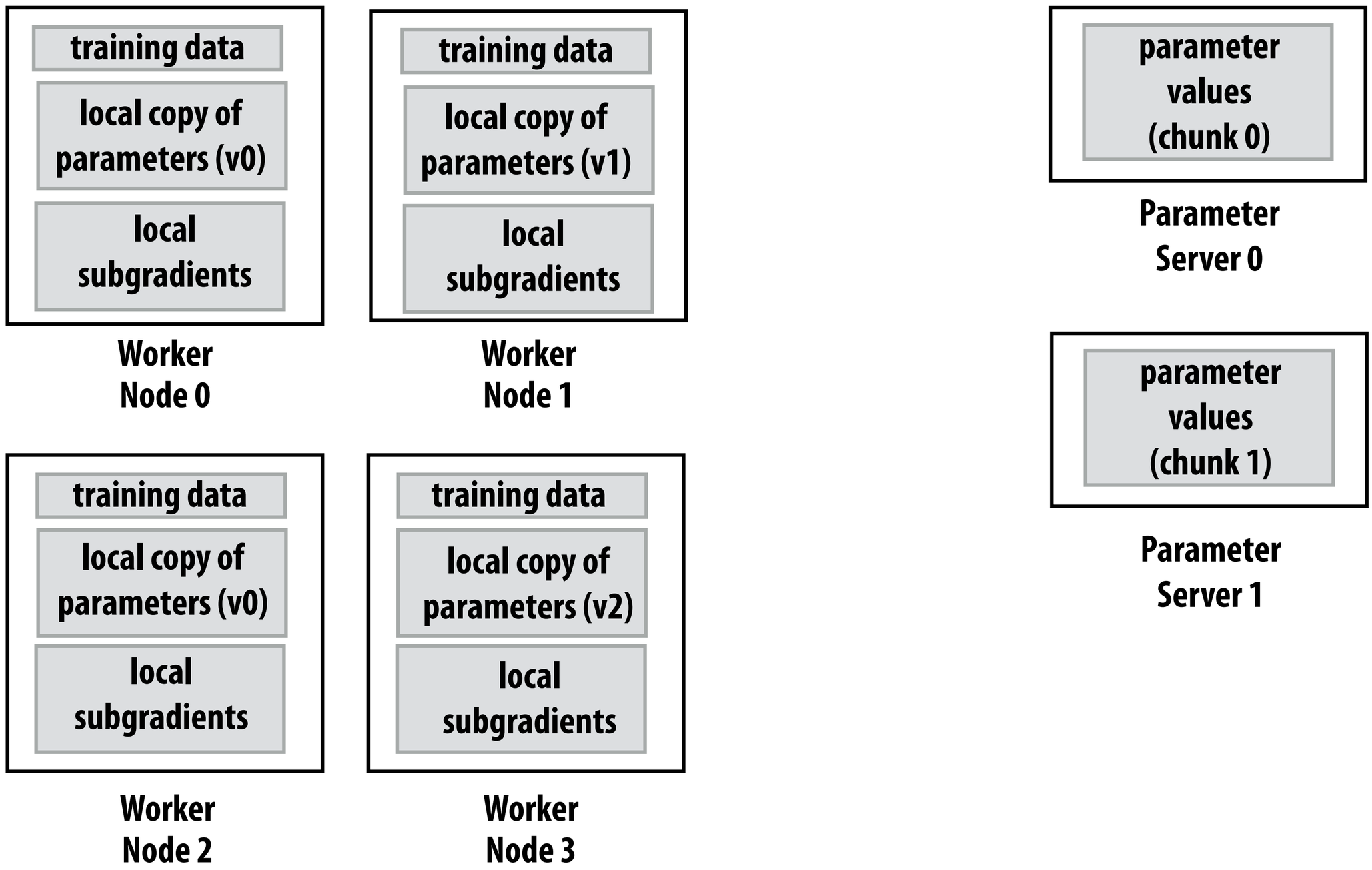
## Worker sends chunk of sub-gradients to owning parameter server



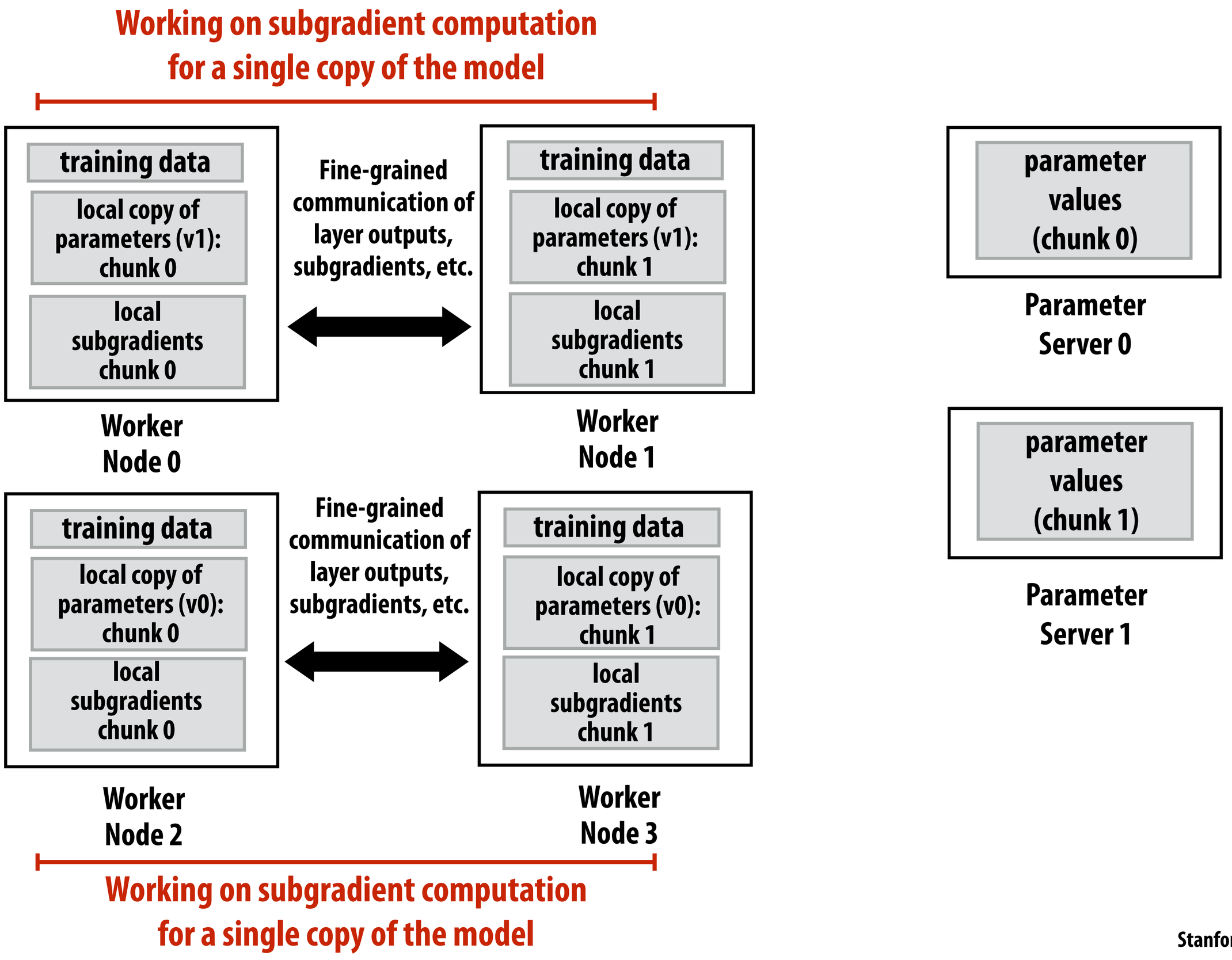

**Reduces data transmission load on individual servers**
**(less important: also reduces cost of parameter update)**

# What if model parameters do not fit on one worker?

## Recall high footprint of training large networks (particularly with large mini-batch sizes)



# Data-parallel and model-parallel execution



# Asynchronous vs. synchronous debate

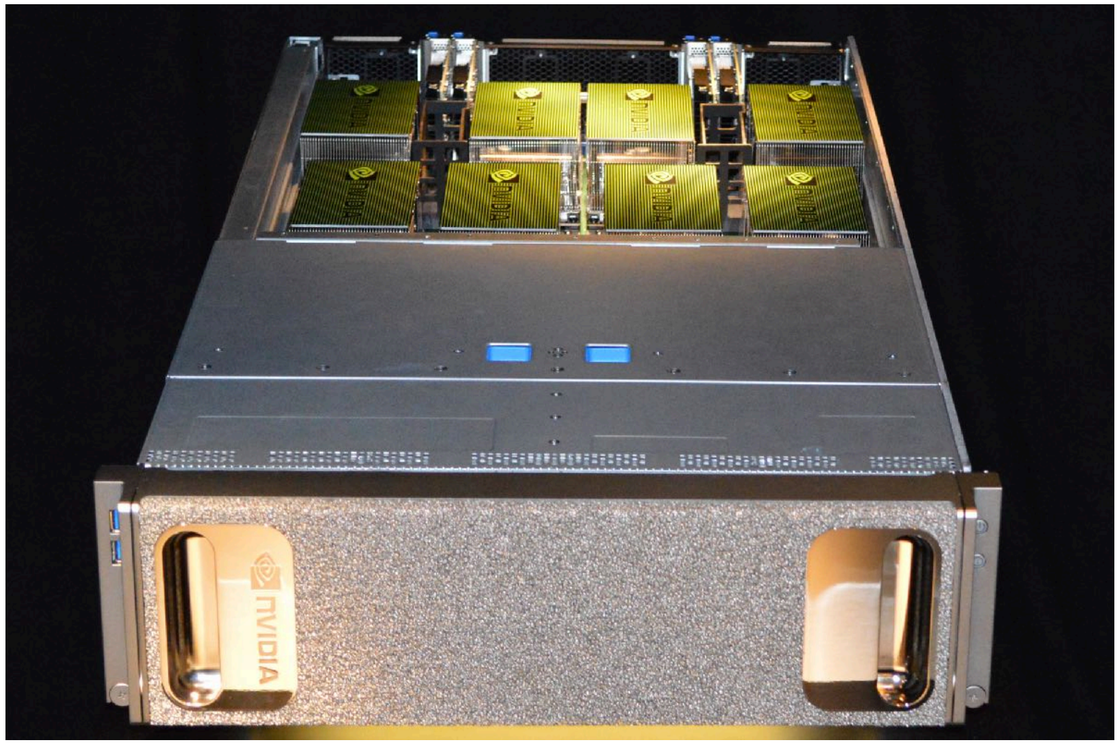
- Asynchronous training: significant distributed system complexity incurred to combat bandwidth/latency constraints of modern cluster computing

- High interest in ways to improve the scalability of synchronous training
  - Better hardware
  - Better algorithms for existing hardware

# Better hardware: using supercomputers for training

- Fast interconnects critical for model-parallel training
  - Fine-grained communication of outputs and gradients
- Fast interconnects diminish need for async training algorithms
  - Avoid randomness in training due to schedule of computation (there remains randomness due to stochastic part of SGD algorithm)

OakRidge Titan Supercomputer (low-latency interconnect used in a number of recent training papers)




NVIDIA DGX-1: 8 GPUs connected via high speed NV-Link interconnect ($150,000 in 2018)

# News from 2019…

—

## NVIDIA buys high-performance chip-maker Mellanox for $6.9 billion

It beat Intel in a bid that will boost its server, self-driving and networking segments.

Steve Dent, @stevetdent
03.11.19 in Personal Computing

8 Comments

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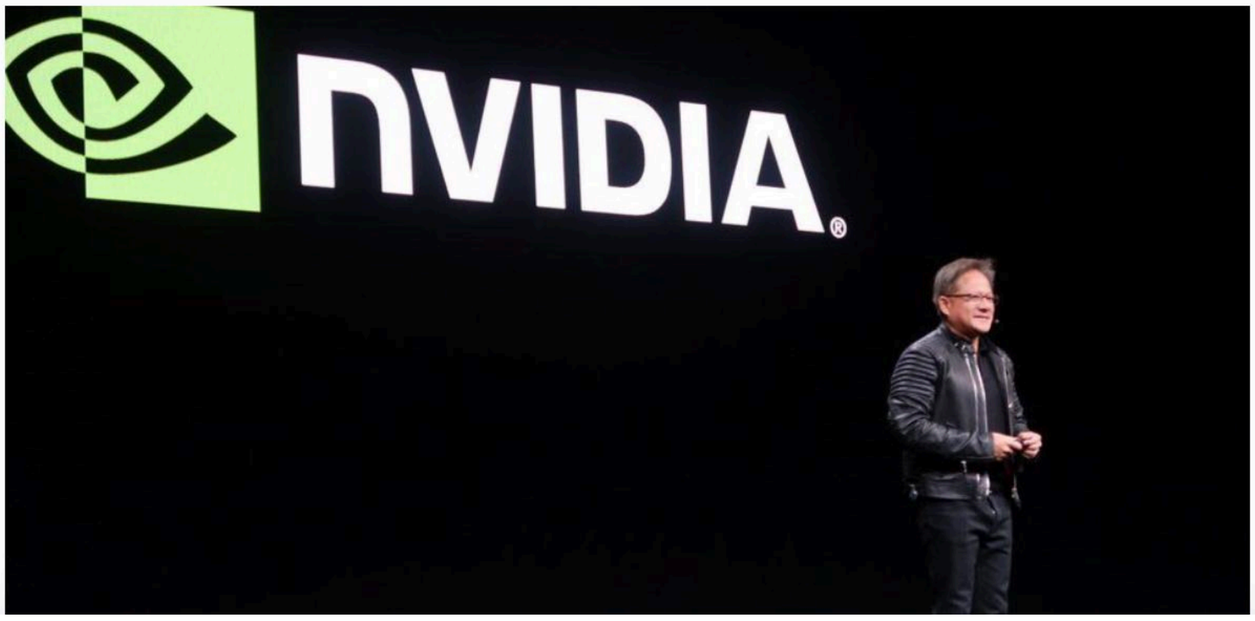
## NVIDIA Buys Mellanox To Bring HPC Scaling To Data Centers

**Kevin Krewell** Contributor
**Tirias Research** Contributor Group
Enterprise & Cloud

The 2019 semiconductor merger and acquisition season has officially been kicked off with a blockbuster $6.9B deal for networking chipset and technology provider Mellanox. Graphic chip maker NVIDIA made the offer after a number of companies, rumored to include Intel, Microsoft, and Xilinx, had bid on buying the company. NVIDIA CEO Jenson Huang said in an analyst call that Mellanox management had invited him to bid on the company and he was happy to do so. By acquiring long-time data center partner Mellanox, Jensen is doubling down on the high-performance data center market.



# Modified algorithmic techniques (again): improving scalability of synchronous training…

- Larger mini-batches increase computation-to-communication ratio: communicate gradients summed over B training inputs

```
for each item x in mini-batch on this node:
   grad += evaluate_loss_gradient(f, loss_func, params, x)
barrier();
sum-reduce gradients across all nodes, communicate results to all nodes
barrier();
update copy of local parameter values
```

- But large mini-batches (if used naively) reduce accuracy of the model trained

# Accelerating data-parallel training

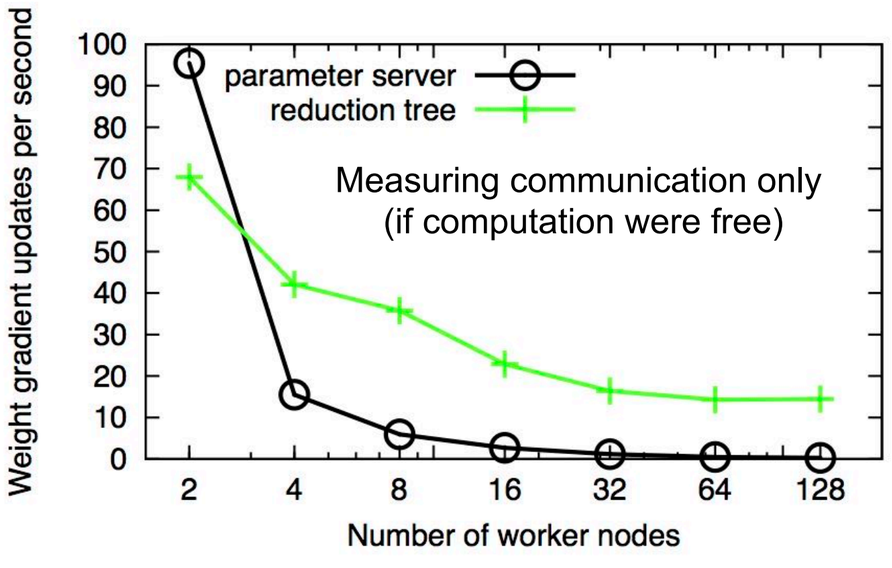
FireCaffe [Iandola 16]

- Use a high-performance Cray Gemini interconnect (Titan supercomputer)
- Use combining tree for accumulating gradients (rather than a single parameter server)
- Use larger batch size (to reduce frequency of communication) and offset by increasing learning rate

| | Hardware | Net | Epochs | Batch size | Initial Learning Rate | Train time | Speedup | Top-1 Accuracy | Top-5 Accuracy |
|---|---|---|---|---|---|---|---|---|---|
| Caffe | 1 NVIDIA K20 | GoogLeNet [41] | 64 | 32 | 0.01 | 21 days | 1x | 68.3% | 88.7% |
| FireCaffe (ours) | 32 NVIDIA K20s (Titan supercomputer) | GoogLeNet | 72 | 1024 | 0.08 | 23.4 hours | 20x | 68.3% | 88.7% |
| FireCaffe (ours) | 128 NVIDIA K20s (Titan supercomputer) | GoogLeNet | 72 | 1024 | 0.08 | 10.5 hours | **47x** | 68.3% | 88.7% |

**Dataset: ImageNet 1K**

**Result: reasonable scalability without asynchronous parameter update for modern DNNs with fewer weights such as GoogLeNet (due to no fully connected layers)**



[Goyal 2017]

# Increasing learning rate with mini-batch size: linear scaling rule

size of mini batch = n
SGD learning rate = $\eta$

**Recall: mini-batch SGD parameter update**

$$w_{t+1} = w_t - \eta \frac{1}{n} \sum_{x \in \mathcal{B}} \nabla l(x, w_t)$$

**Consider processing of k mini-batches (k steps of gradient descent)**

$$w_{t+k} = w_t - \eta \frac{1}{n} \sum_{j<k} \sum_{x \in \mathcal{B}_j} \nabla l(x, w_{t+j})$$

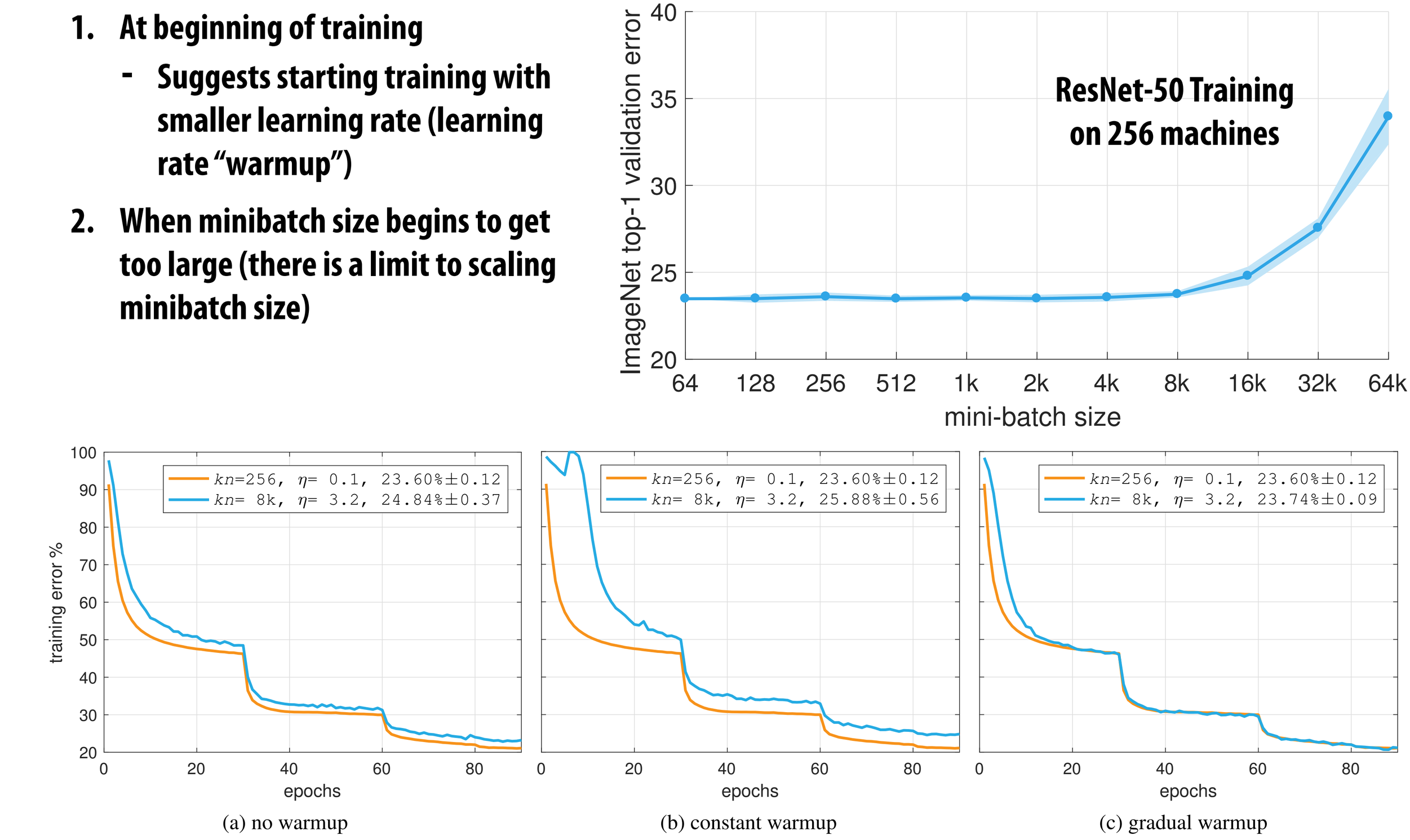
**Consider processing one mini-batch that is of size kn (one step of gradient descent)**

$$\hat{w}_{t+1} = w_t - \hat{\eta} \frac{1}{kn} \sum_{j<k} \sum_{x \in \mathcal{B}_j} \nabla l(x, w_t)$$

**Suggests that if $\nabla l(x, w_t) \approx \nabla l(x, w_{t+j})$ for *j* < *k* then minibatch SGD with size *n* and learning rate $\eta$ can be approximated by large mini batch SGD with size *kn* if the learning rate is also scaled to $k\eta$**

# When does $\nabla l(x, w_t) \approx \nabla l(x, w_{t+j})$ not hold?

1. At beginning of training
   - Suggests starting training with smaller learning rate (learning rate "warmup")
2. When minibatch size begins to get too large (there is a limit to scaling minibatch size)




[Figure credit: Goyal et al. 2017]

**Mini-batch size = 256 (orange) vs. 8192 (blue)**

# Gradient compression

- Since overhead of communication (in particular in a data-parallel training configuration) is sending gradients, perhaps some gradients are more important than others
  - Idea: only send sparse gradient updates to reduce communication costs

[Lin et al. ICLR 2018]

# Gradient compression

- Each node computes gradients for mini-batch, but only sends gradients with magnitude *above a threshold*

- Nodes, locally accumulate gradients below threshold over multiple SGD steps (then send when they exceed threshold)

$G_0^k = 0$

***N* nodes, each computing gradients for a mini-batch of *b* images (across the parallel machine the SGD batch size is *Nb*)**

**for all iterations *t* of SGD:**

$$G_t^k = G_{t-1}^k + \eta \frac{1}{Nb} \sum_{k=1}^{N} \sum_{x \in B_k} \nabla f(x; w_t)$$

**Compress and send ONLY the elements of $G_t^k$ greater than threshold.**
**(then locally zero out the gradients that were sent.)**

**After each iteration, SGD on all nodes only uses the sent weights…**

# Gradient compression is like using a larger mini-batch size for selected weights

## (lower gradients → larger batch size for these weights)

**For weights with low gradients…**

$$\nabla f(x, w_t) \approx \nabla f(x, w_{t+\tau})$$

**So *T* steps of regular SGD (mini-batch *b* processed by all *N* nodes) for weight (i):**

$$w_{t+T}^{(i)} = w_t^{(i)} - \eta \frac{1}{Nb} \sum_{k=1}^{N} \left( \sum_{\tau=0}^{T-1} \sum_{x \in B_{k,\tau}} \nabla^{(i)} f(x, w_{t+\tau}) \right)$$

**Is well approximated despite not updating weight (i) for *T* steps: (effectively a *T* times larger mini-batch size for weight (i)**

$$w_{t+T}^{(i)} = w_t^{(i)} - \eta T \frac{1}{NbT} \sum_{k=1}^{N} \left( \sum_{\tau=0}^{T-1} \sum_{x \in B_{k,\tau}} \nabla^{(i)} f(x, w_t) \right)$$

# Many cool ideas popping up

- Gradient compression
  - Reduce the frequency of gradient update (sparse updates)
  - Apply compression techniques to the gradient data that is sent

- Account for communication latency in SGD momentum calculations
  - Asynchronous execution or sparse gradient updates means SGD continues forward (with potentially stale gradients)
  - SGD with momentum has a similar effect (keep descending in the same direction, don't directly follow gradient)
  - Idea: reduce momentum proportionally to latency of gradient update

# Summary: training large networks in parallel

- Modern DNN designs, large mini-batch sizes, careful learning rate schedules enable scalability without asynchronous execution on commodity clusters

- Data-parallel training with asynchronous update to efficiently use clusters of commodity machines with low speed interconnect
  - Modification of SGD algorithm to meet constraints of modern parallel systems
  - Effects on convergence are problem dependent and not particularly well understood

- High-performance training of deep networks is an interesting example of constant iteration of algorithm design and parallelization strategy
  (a key theme of this course!)