FUNDAMENTALS OF SCALING OUT DL TRAINING

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HotChips 2020, DL Scale Out Tutorial

Larger is Better in DL

- **Larger models lead to higher task accuracies**
  - Language models: in the past 2 years grew from 340M to 175B parameters
  - Recommender models: largest ones are reaching O(1B) parameters
  - Vision models: deeper and wider Resnets and ResNeXTs
- **Larger datasets lead to higher accuracies**
  - Recommender data (user behavior): terabytes to petabytes
  - Image data: 1B Instagram dataset, JFT (300M images)
- **Challenges:**
  - Larger models -> training state no loner fits on a single processor
  - Larger {models, datasets} -> long time to train
- **Solution: scale out computing**

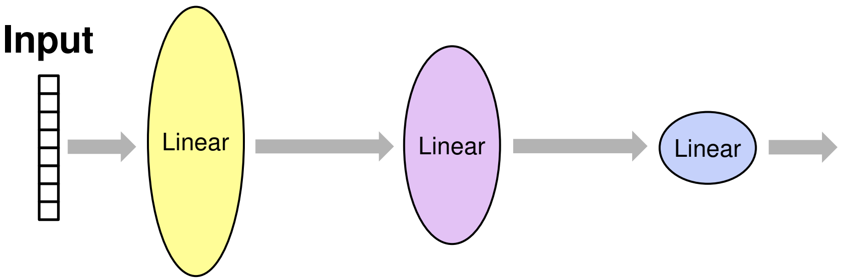
Outline

- **Brief Review of DNN Training**
- **Data Parallelism**
- **Model Parallelism**
  - Pipeline
  - Intra-layer
- **Communication Pattern Review**
- **Summary**

Neural Network Training

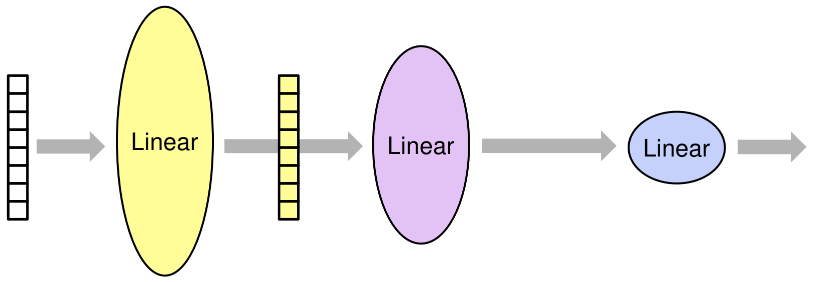
- **Start with randomly initialized weights**
- **Iterate through your data a minibatch of training data samples at a time:**
  - Forward pass
  - Backward pass
  - Weight update

Simplified Example



- **Network of 3 linear layers**
- **Each layer:**
  - Input: vector
  - Output: vector
  - Learned parameters (weights): projection matrix
  - Operation:
    - Multiply the input vector with the matrix
    - Apply a point-wise nonlinearity, say, ReLU

Forward Pass



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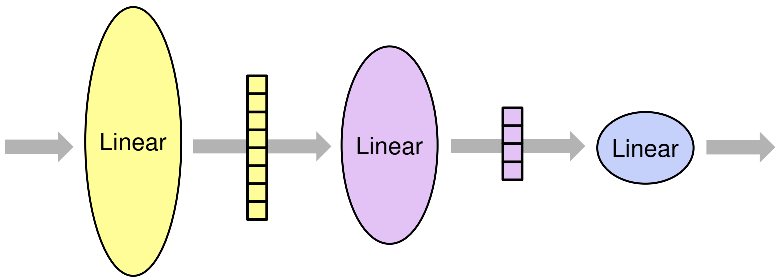

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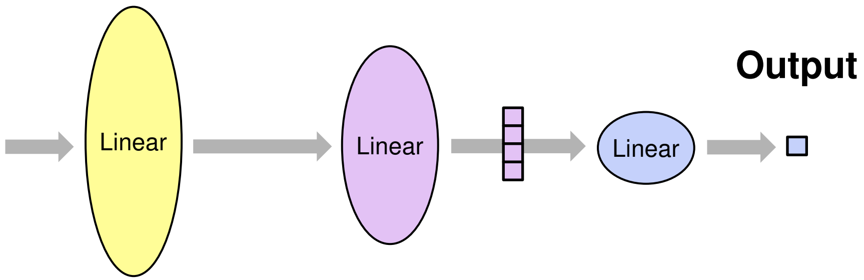

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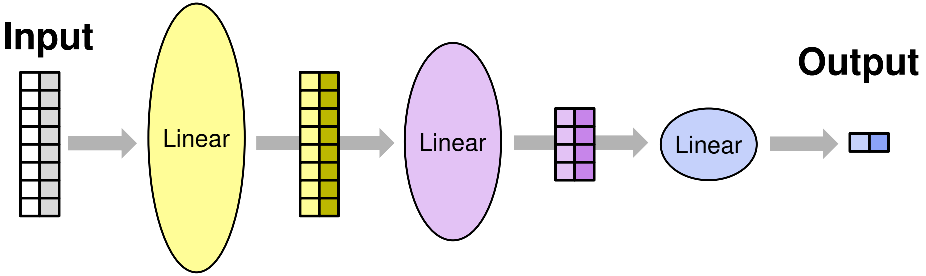
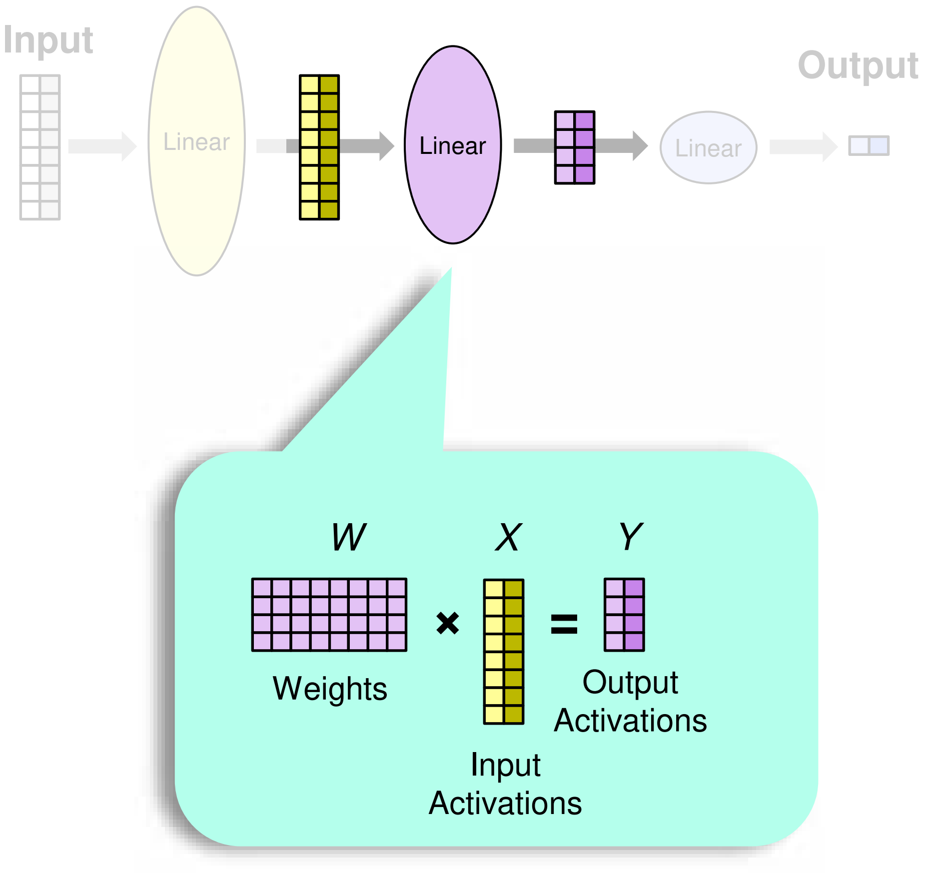
Forward Pass: minibatch of 2 inputs



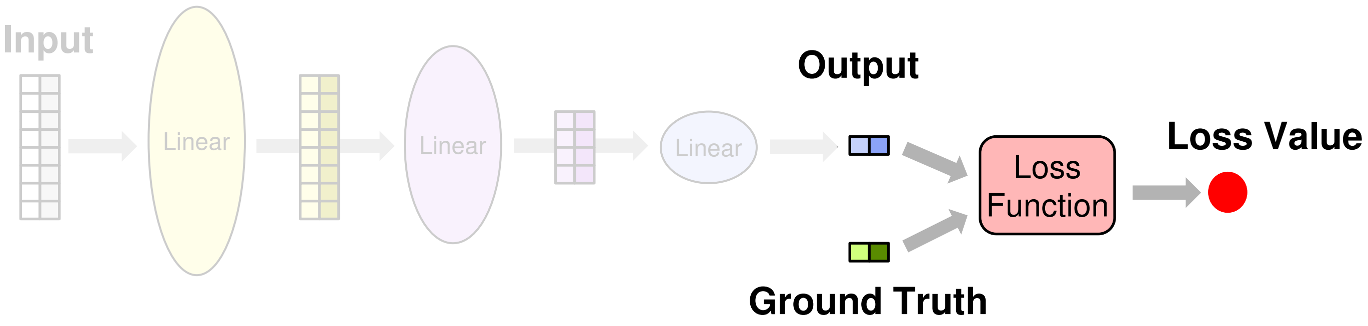
- **Matrix-vector multiplies turn into matrix-matrix multiplies**

Simplified Example: Forward Pass, batch of 2



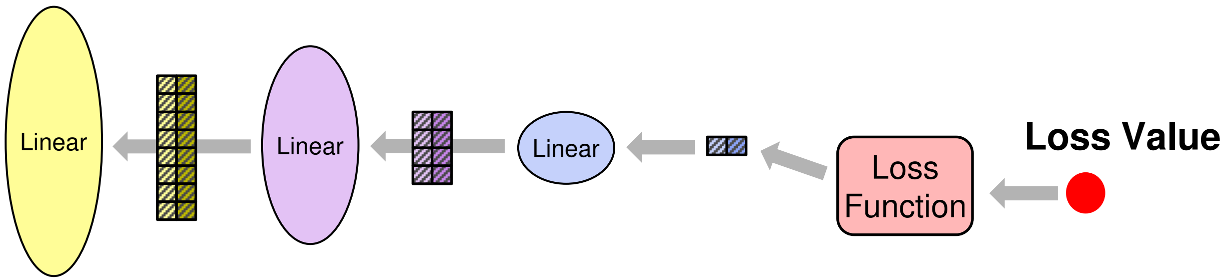
- **Matrix-vector multiplies turn into matrix-matrix multiplies**

Forward Pass: Compute Loss



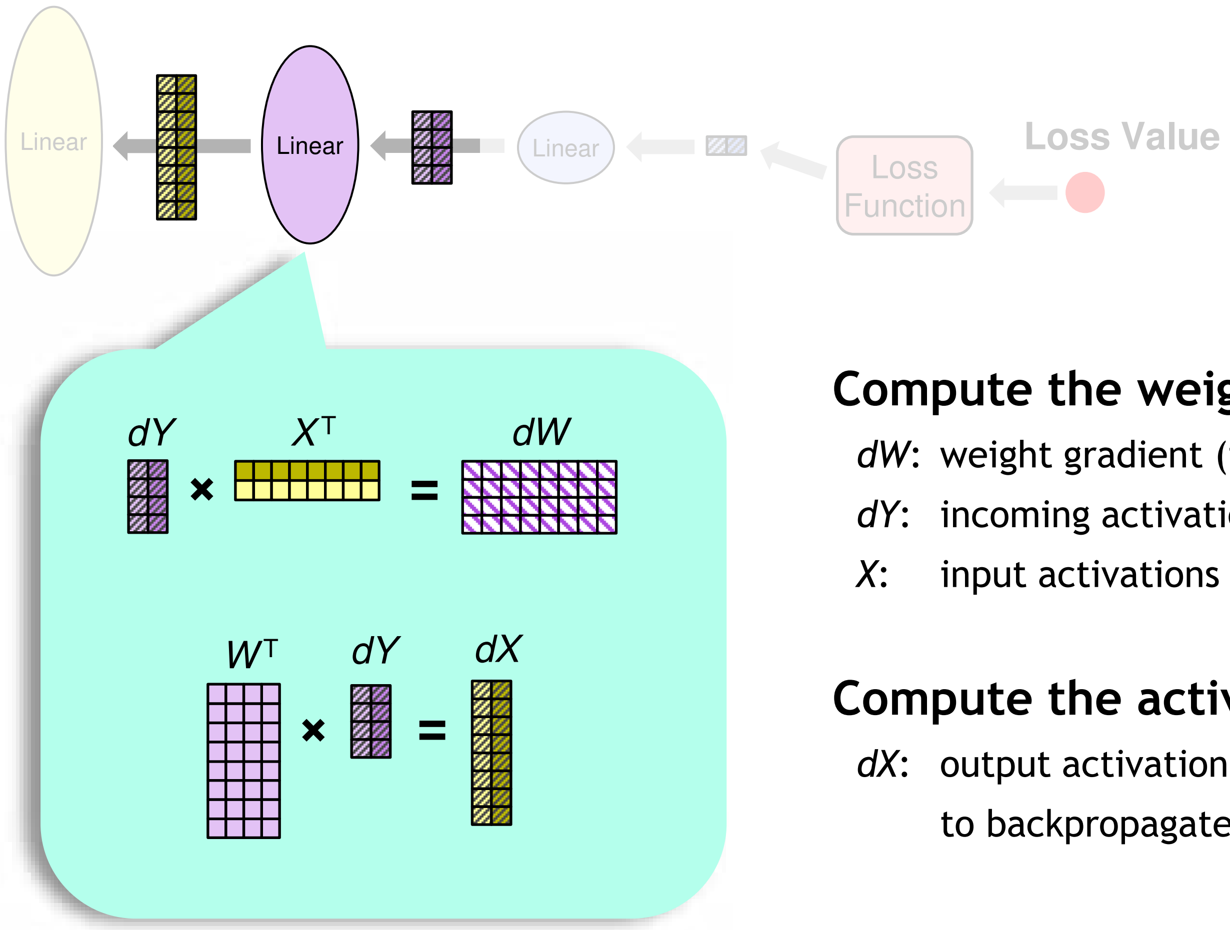
- **Loss function:**
  - Produces a loss value that indicates how “wrong” the network was
    - Compares the output to the ground truth for each sample
    - Exact function math varies by task, doesn’t matter for our discussion
- **Goal of training: minimize the loss value**
  - Update network weights so the output closely matches ground truth

Backward Pass



- **Goal is to compute the updates to the layer weights**
- **Achieved by "back propagating" the loss through the layers**
  - Each layer computes weight gradient, used to update the weights
  - Each layer computes activation gradient, to be backpropagated to preceding layer

Backward Pass



Compute the weight gradient

dW: weight gradient (to update weights)

dY: incoming activation gradient

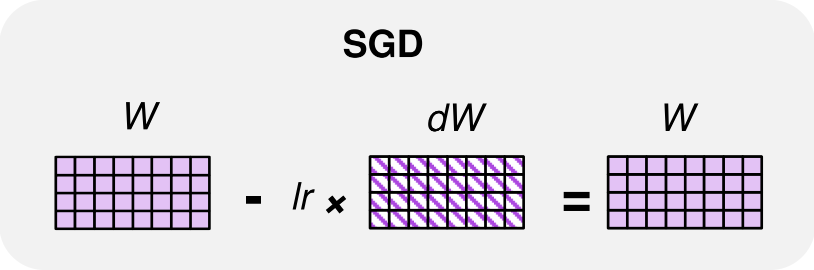
X: input activations (from fwd pass)

Compute the activation gradient

dX: output activation gradient to backpropagate to the preceding layer

Weight Update

- **Also known as ‘optimizer step’**
  - Optimizer choices: SGD, Adam, Adagrad, …
- **Input:**
  - Current network weights
  - Weight gradients (computed during bwd pass)
- **Output:** updated weights
- **Operation:**
  - Increment each weight with the corresponding gradient value
  - In practice, operation is more complex:
    - Update internal state with weight gradient, then update weights using internal state
    - Exact math doesn’t matter for our discussion
- **Internal state:**
  - 1 or 2 “momenta”
  - Each momentum is as big as the weights
    - Usually fp32 in reduced precision (FP16/BF16) training
    - Optimizer may need 2-6x more memory than just the model



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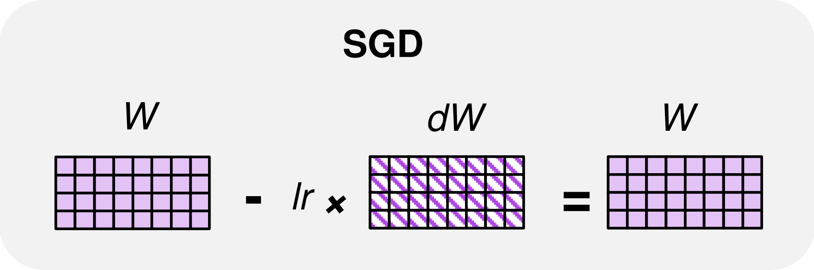
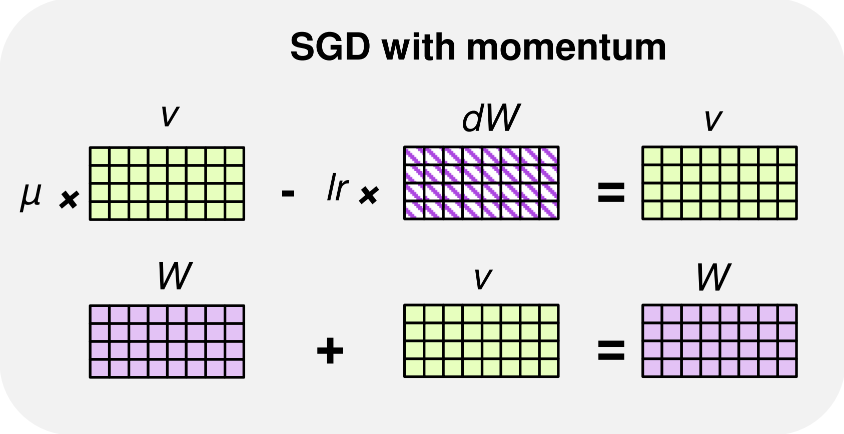




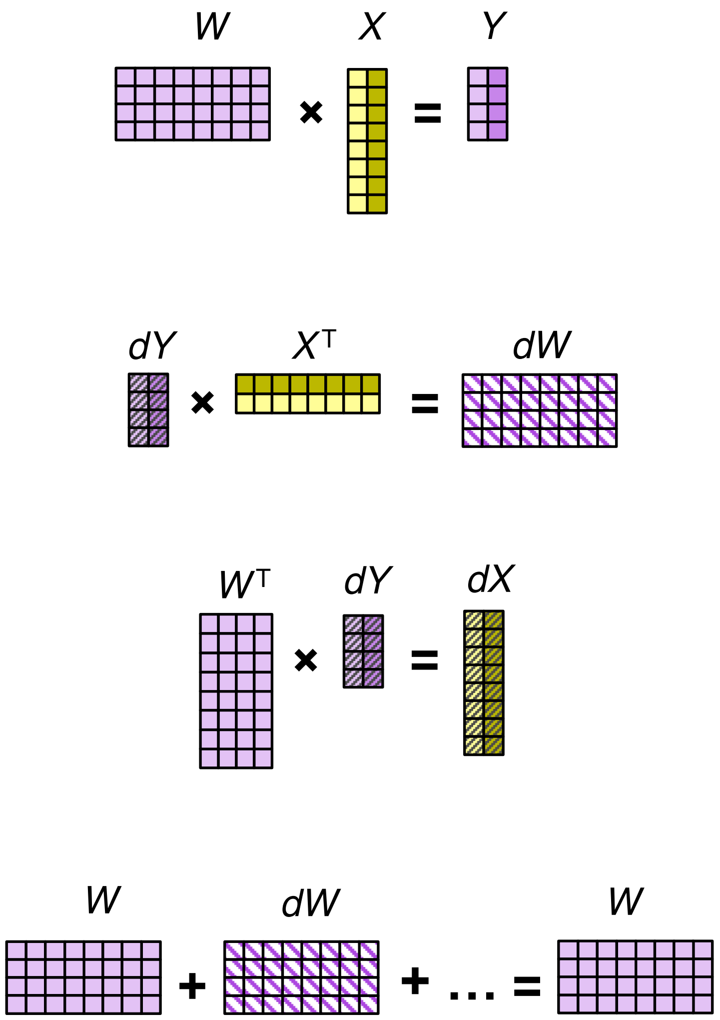
Summary of Compute Stages per Layer

Forward Pass

Backward Pass:
weight gradients

Backward Pass:
activation gradients

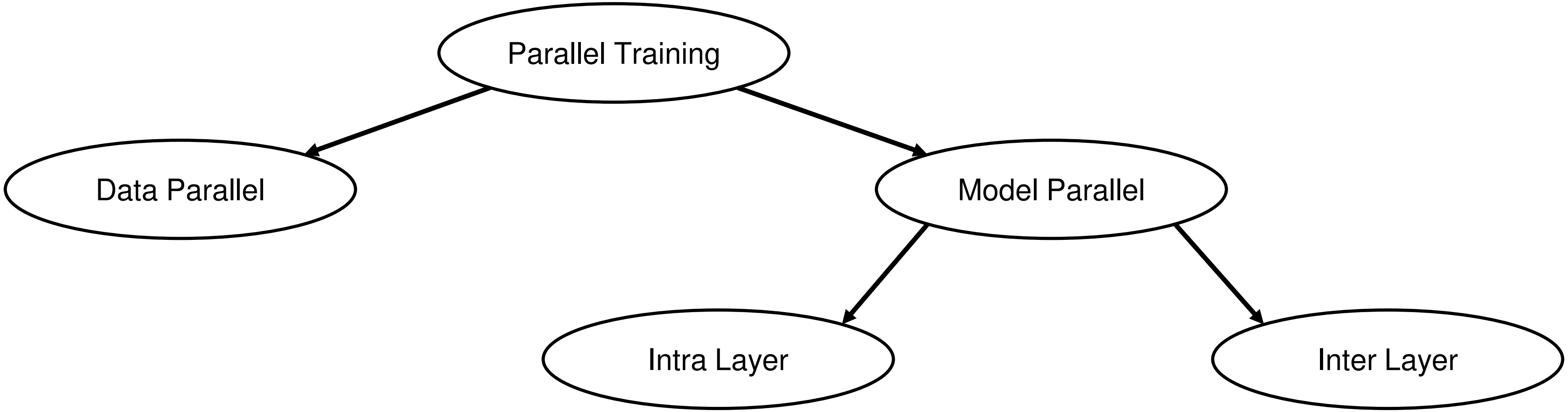
Weight update:



- **Backward compute is ~2x of forward**
- **Backward pass requires activations computed during the fwd pass**
  - *X* in the example (produced by a preceding layer)
  - This can be a major fraction of memory required to train, leading to scale-out for the larger models

Example:
R50 training in fp16 at batch size 256:
- requires ~15 GB of memory
- ~12 GB of that is for activations

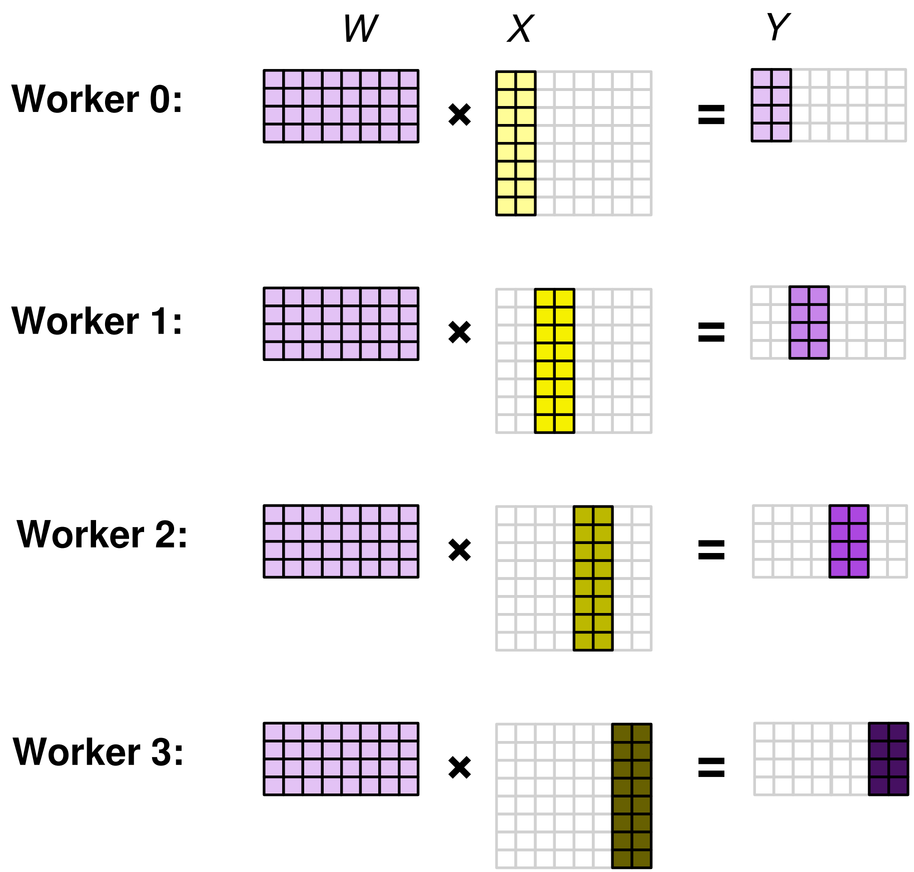
Parallelism Taxonomy



Data Parallel

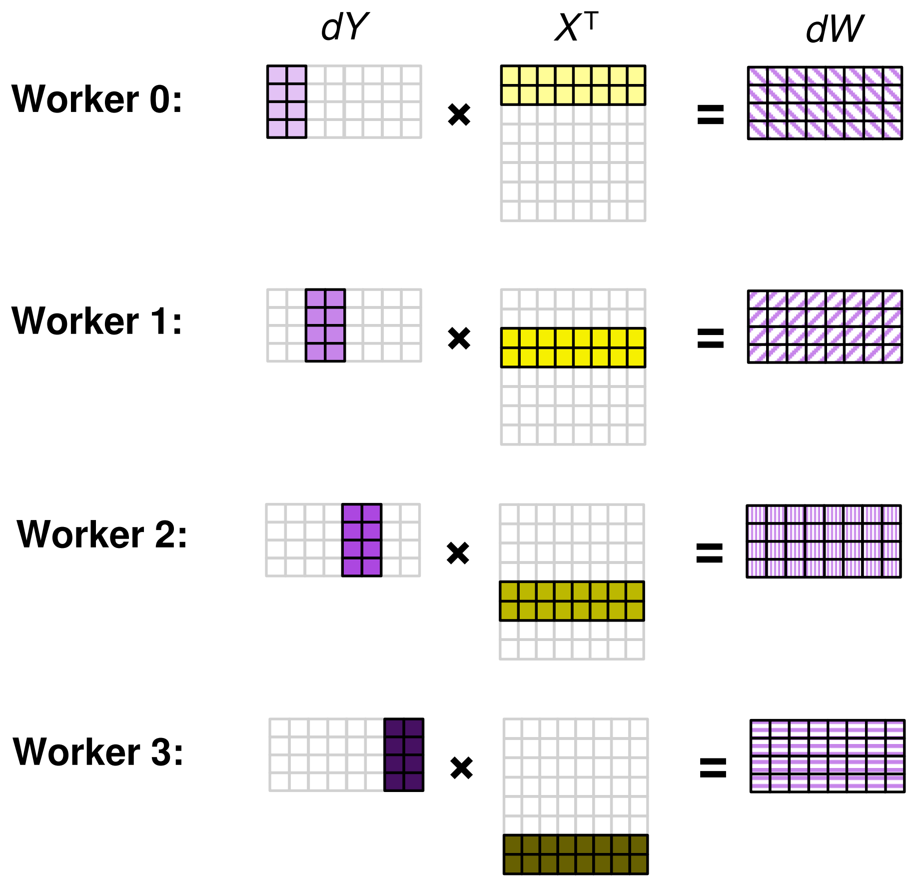
- **Each worker:**
  - Has a copy of the entire neural network model
  - Responsible for compute of a portion of data (training minibatch)
- **Forward pass:**
  - Computes output activations for its portion of minibatch
  - No communication is needed
- **Backward pass:**
  - Computes activation gradients for its portion of minibatch
  - Computes <u>contribution</u> to the weight gradient based on its portion of minibatch
    - All workers' contributions must be summed before weight update
- **Weight update:**
  - Each worker updates its copy of the model with combined gradients
  - Variants: distributed optimizer

Data Parallel: Forward Pass



- **No communication needed**
  - Own portion of output becomes own portio nof input for next layer
- **Backward activation-gradient compute is essentially the same**

Data Parallel: Backward Pass



- **Each worker computes a different weight gradient (*dW*)**
  - Based only on its own unique portion of data
- **Weight gradients will have to be communicated so that after update each worker has the same exact weights**

Data Parallel: Communication

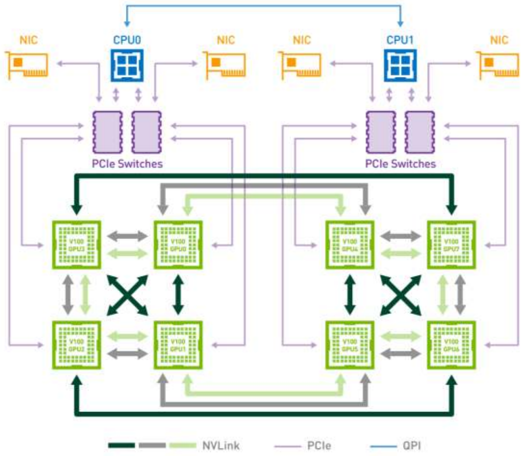
- **Allreduce:**
  - Sum all the workers' gradients
  - Distribute the sum to all the workers
- **After Allreduce each worker has the same "global" gradient**
  - Can execute a weight update on its own model -> all workers will have the same model
- **Any exposed communication is overhead, thus:**
  - Use efficient communication (hw and sw), overlap communication, etc.

Allreduce Implementation Choices

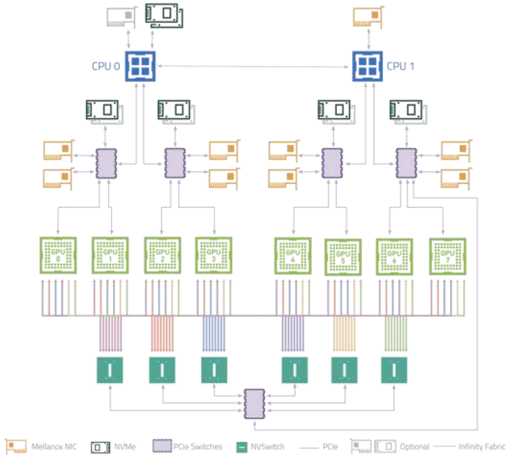
- **Each of *N* workers is responsible for:**
  - Summing 1/*N* gradients collected from (*N* – 1) peers
  - Distributing the sums to the (*N* – 1) peers
- **"Ring" reduction**
  - For any topology that contains a 1D torus (ring)
  - Each worker communicates with 2 neighbors
  - 2(*N* – 1) steps, worker sends/receives 1/*N* of all bytes
    - Each step requires a synchronization -> 2(*N* – 1) syncs total
- **"One-shot" reduction:**
  - For fully-connected topologies (switches)
  - Each worker communicates with (*N* – 1) neighbors
  - 2 steps, each with (*N* – 1) substeps
    - One step per synchronization -> 2 syncs total
  - Allows the use of arithmetic in switches (Mellanox SHARP)
    - Reduces memory accesses and math by the worker

Communication Implementation

- **Communication libraries take care of complex details**
  - Accelerator can have multiple ports
  - Links can be duplex
  - Pipelining is used to hide latencies and syncs
- **NCCL: NVIDIA Collective Communication Library**
- **Examples:**
  - NVIDIA DGX-1
    - Each of 8 GPUs has 6 NVLINK ports
    - Each NVLINK port is duplex
    - GPUs are connected via hybrid mesh
    - NCCL uses multiples of 12 rings are used for allreduce
  - NVIDIA DGX-A100
    - Each of 8 GPUs has 12 NVLINK ports
    - Each NVLINK port is duplex (25 GB/s per direction)
    - GPUs are fully-connected through switches
    - NCCL uses multiples of 24 rings or one-shots are used for allreduce



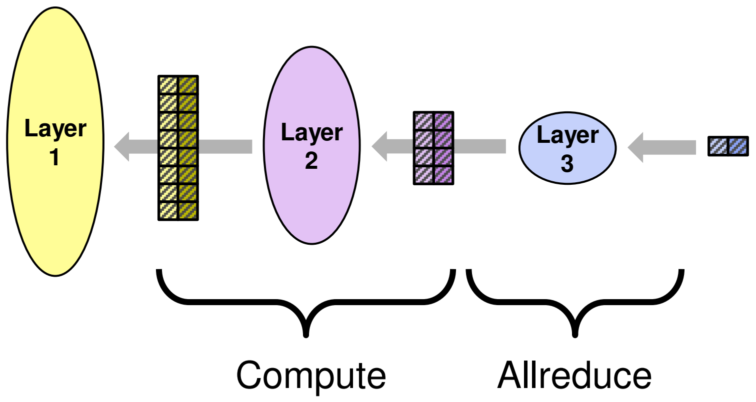
DGX-1



DGX-A100

Communication Overlap

- **Data Parallel training can overlap compute and communication**
  - Allreduce gradients for layer *K*, while computing gradients for layer (*K* – 1)
  - Cannot be hidden completely – last portion of the pipeline is exposed
  - Tradeoff between communication granularity and link bw utilization
    - Made by training framework SW and libraries like Horovod
- **Reduction in switches (Mellanox SHARP) helps free up compute resources**
  - Allreduce will compete for resources (memory and math bw) with computation



Distributed Optimizer

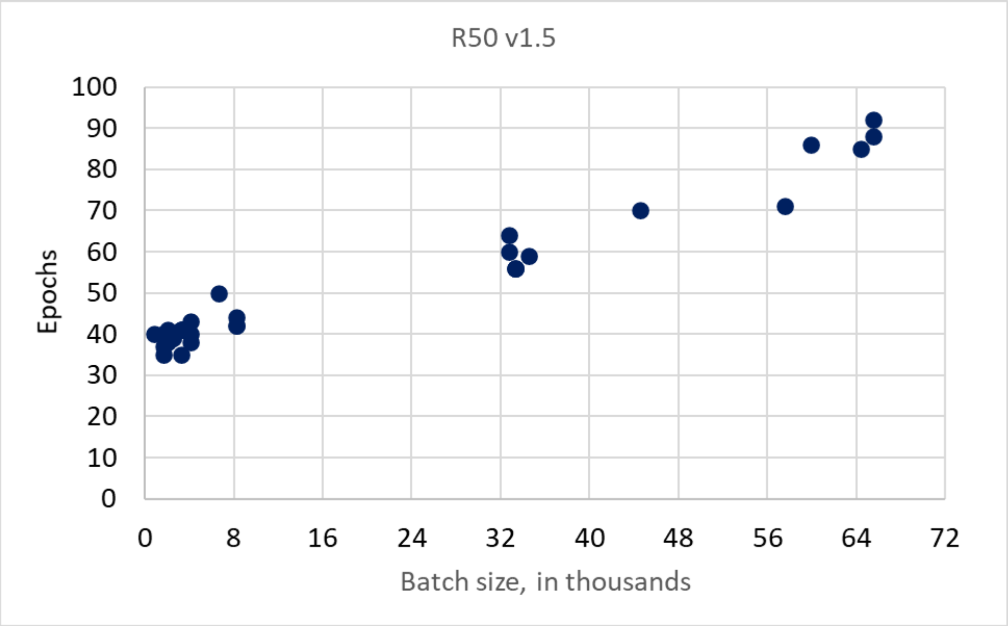
- **At larger scales optimizer (weight update) can start dominating time**
  - Each of N workers does $1/N$ of compute for fwd/bwd passes
  - Each of N workers does <u>all</u> the work to update model weights (stays constant with N)
- **Solution: distributed optimizer**
  - Appeared in: MLPerf v0.6 and later, ZERO paper
  - Include weight update as part of allreduce (each worker is responsible for $1/N^{th}$ of the weights)
    1) Collect and sum up the gradients from peers
    2) Update own portion of the weights ($1/N^{th}$ of the work compared to before)
    3) Broadcast own portion of the updated weights to peers

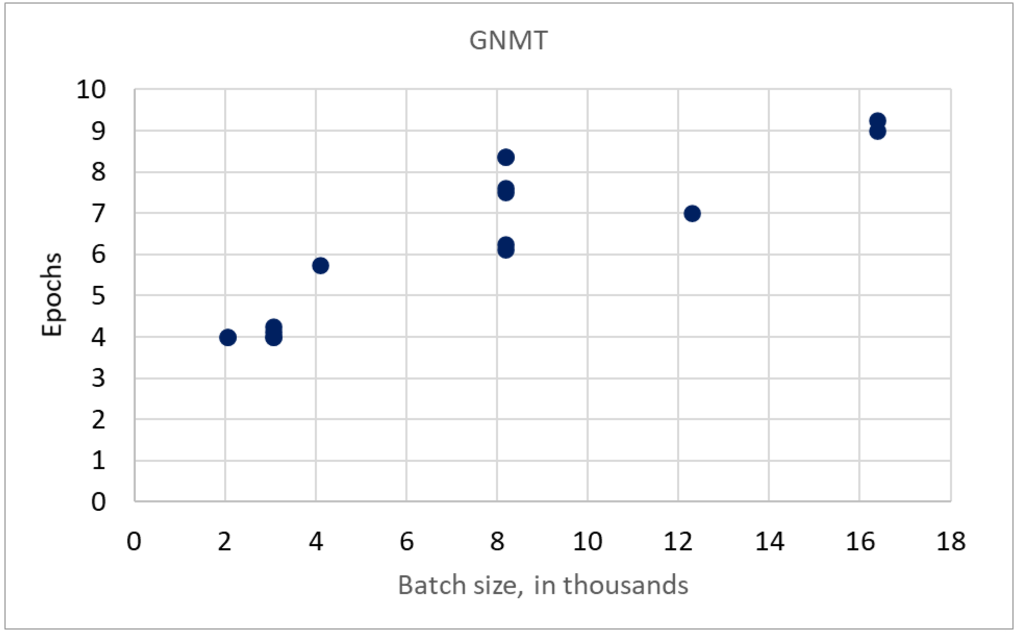
Data Parallel: Challenges

- **Strong scaling (increase the number of workers, keep minibatch size constant)**
  - Certain layers require minimum minibatch sizes to properly operate
    - Example: batch normalization (BN) generally requires 16+ samples
  - Extra communication is needed between workers when worker minibatch is small
    - Reductions within small subsets of workers
- **Weak scaling (increase the number of workers, increase minibatch size)**
  - Training networks with large minibatches requires hyper-parameter adjustment
    - Learning rate schedule, BN decay, …
    - Example: R50 (SGD up to bs=16K, LARS above 16K, …)
  - Often increase the amount of work required to reach the same model accuracy

Workoad Increase with Batch Size

- **Epochs to reach the same model accuracy (from various submissions to MLPerf v0.7)**
  - Epoch = 1 processing pass through entire dataset

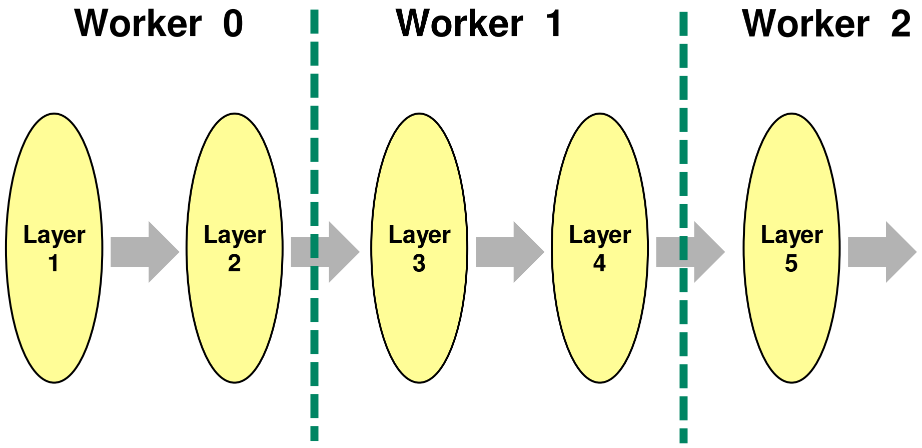




Model Parallel

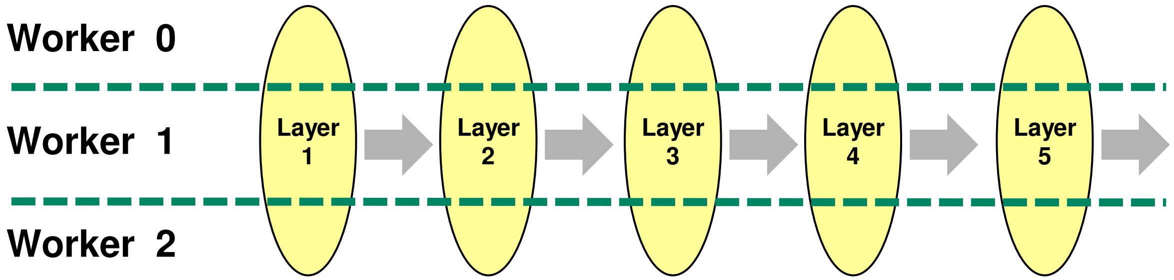
Inter-layer Parallel (aka Pipeline Parallel):

A worker is responsible for its portion of the layers

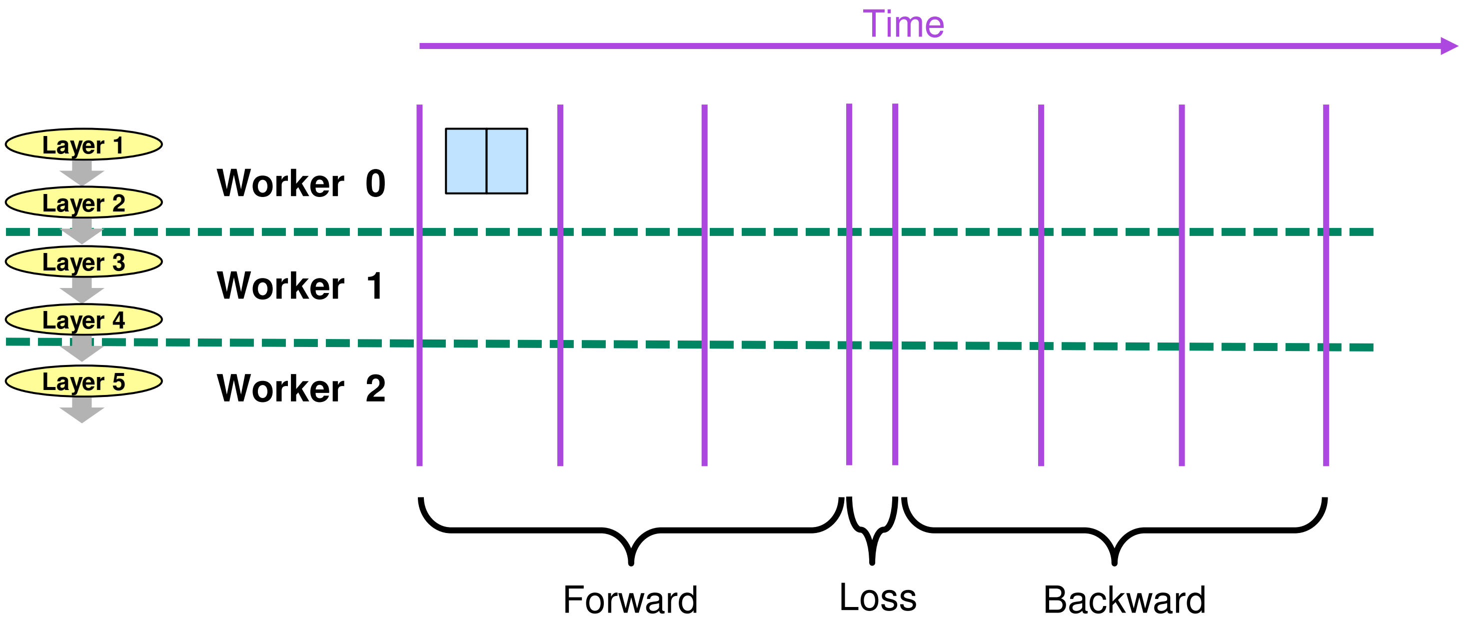


Intra-layer Parallel:

A worker is responsible for its portion of each layer



Pipeline Parallel



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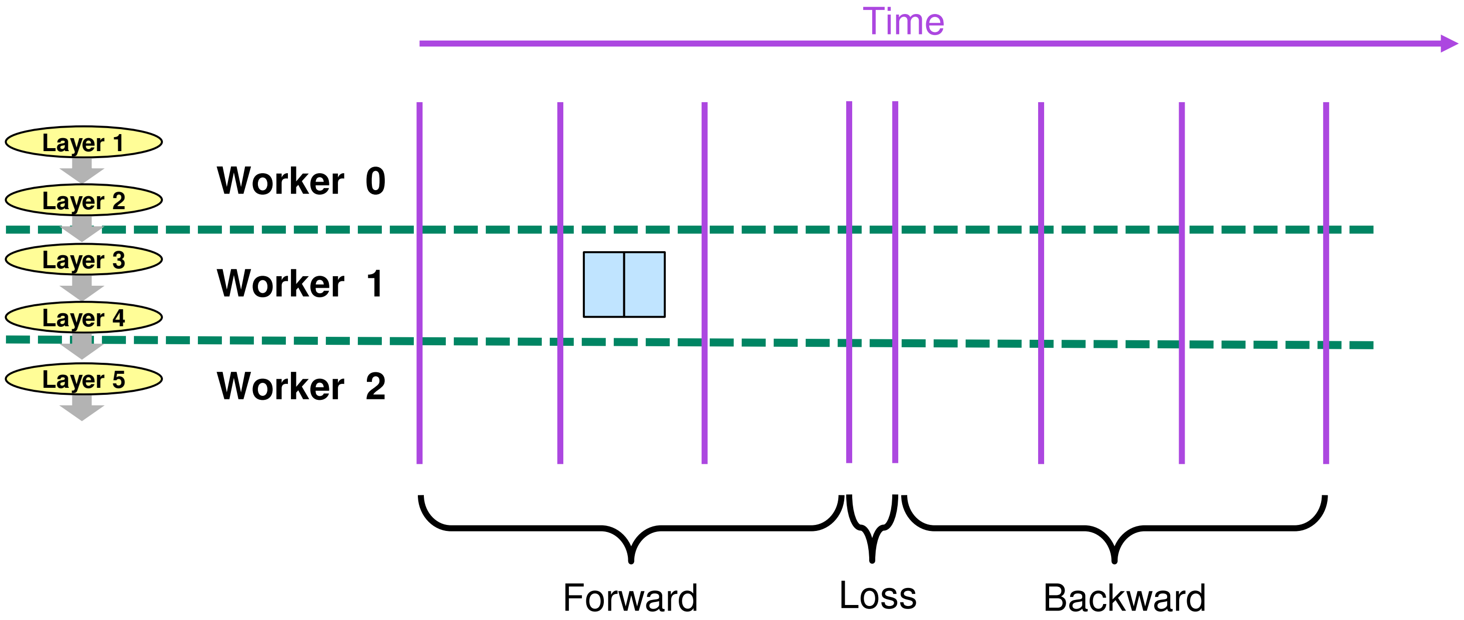

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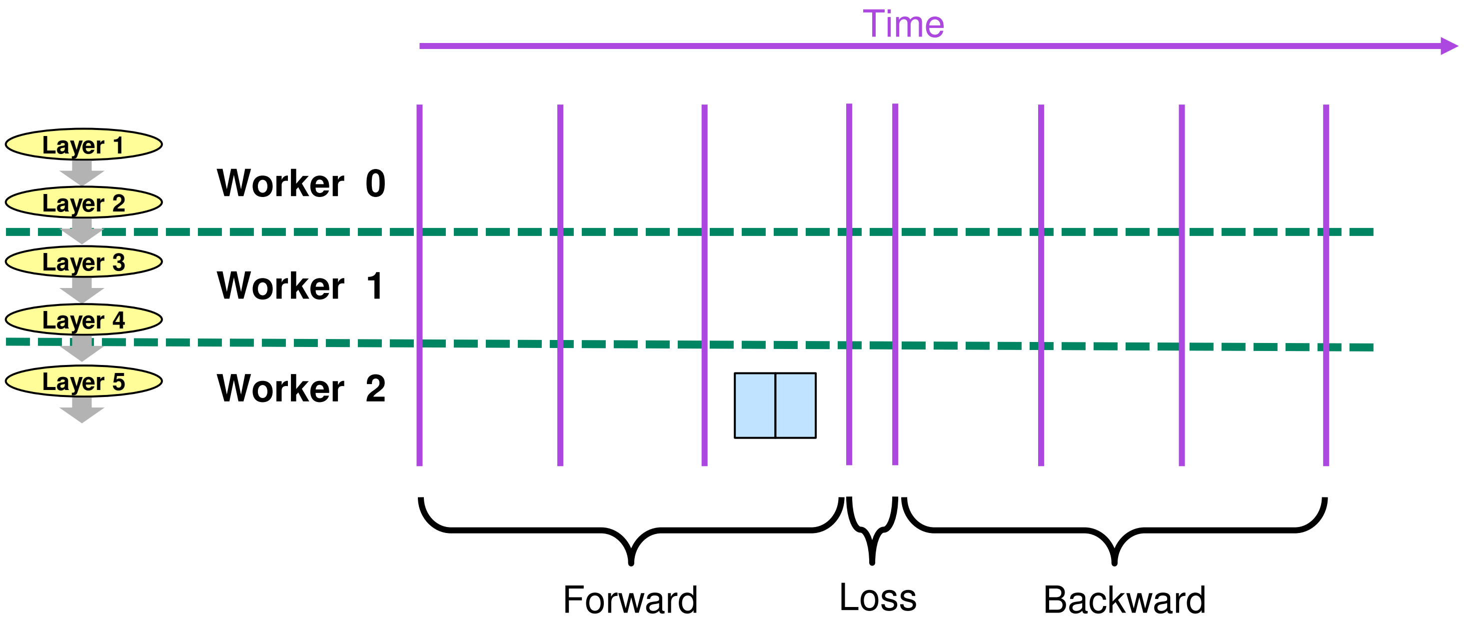

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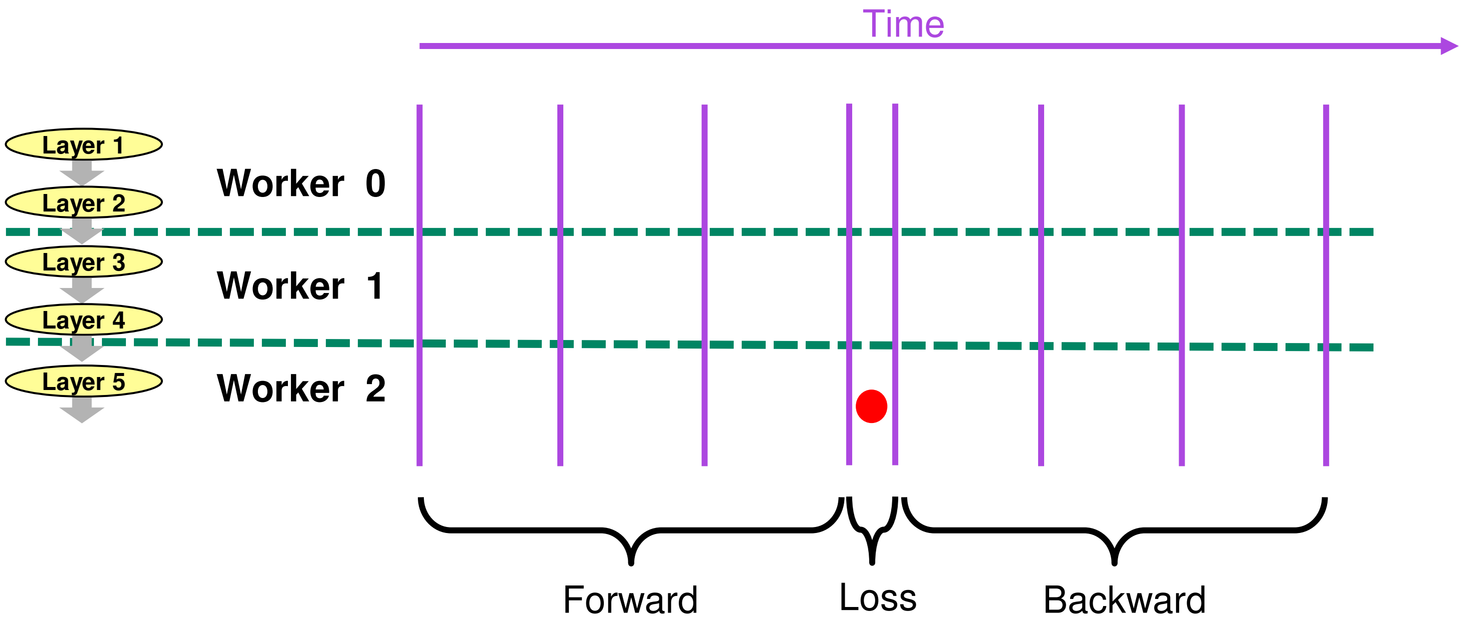

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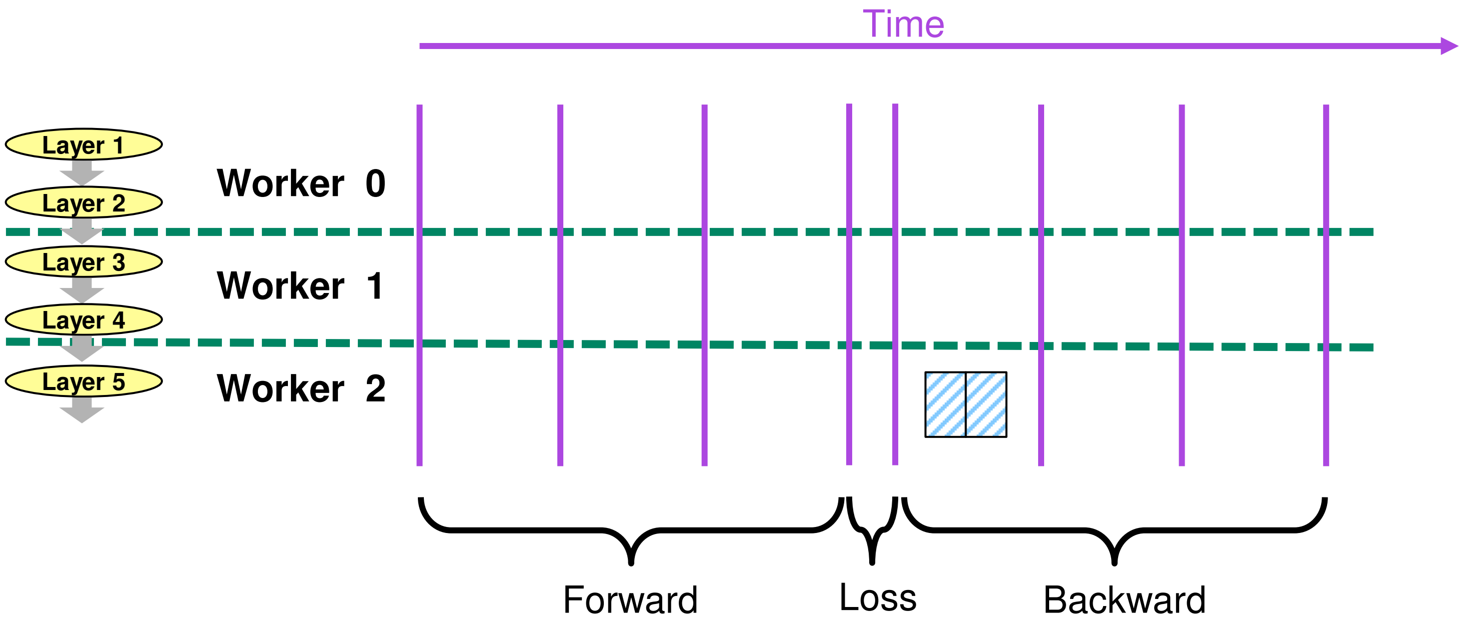

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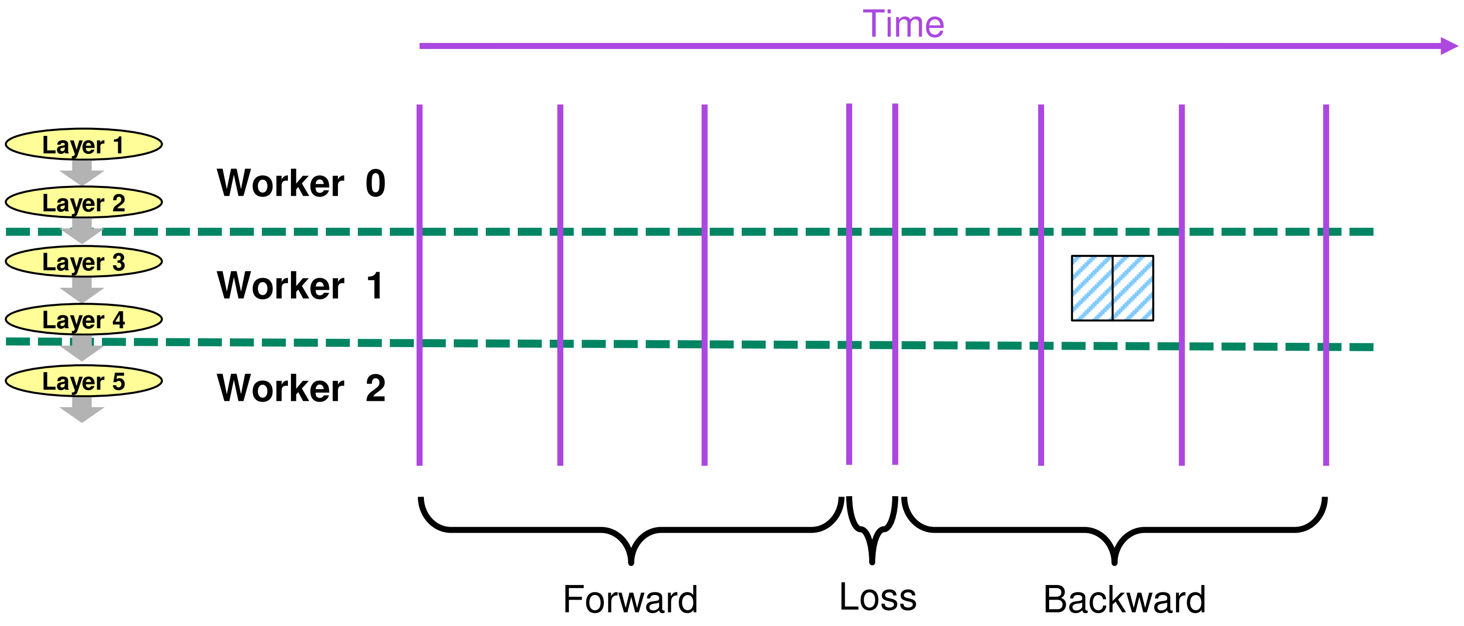

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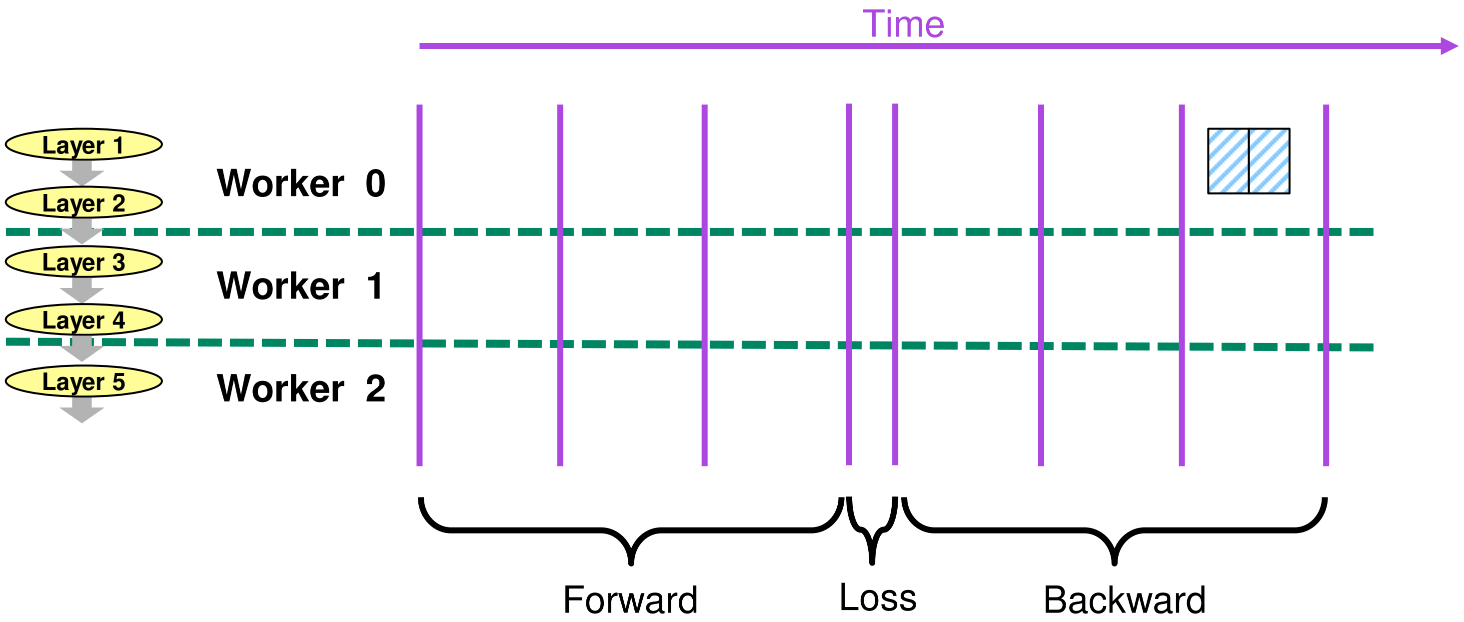
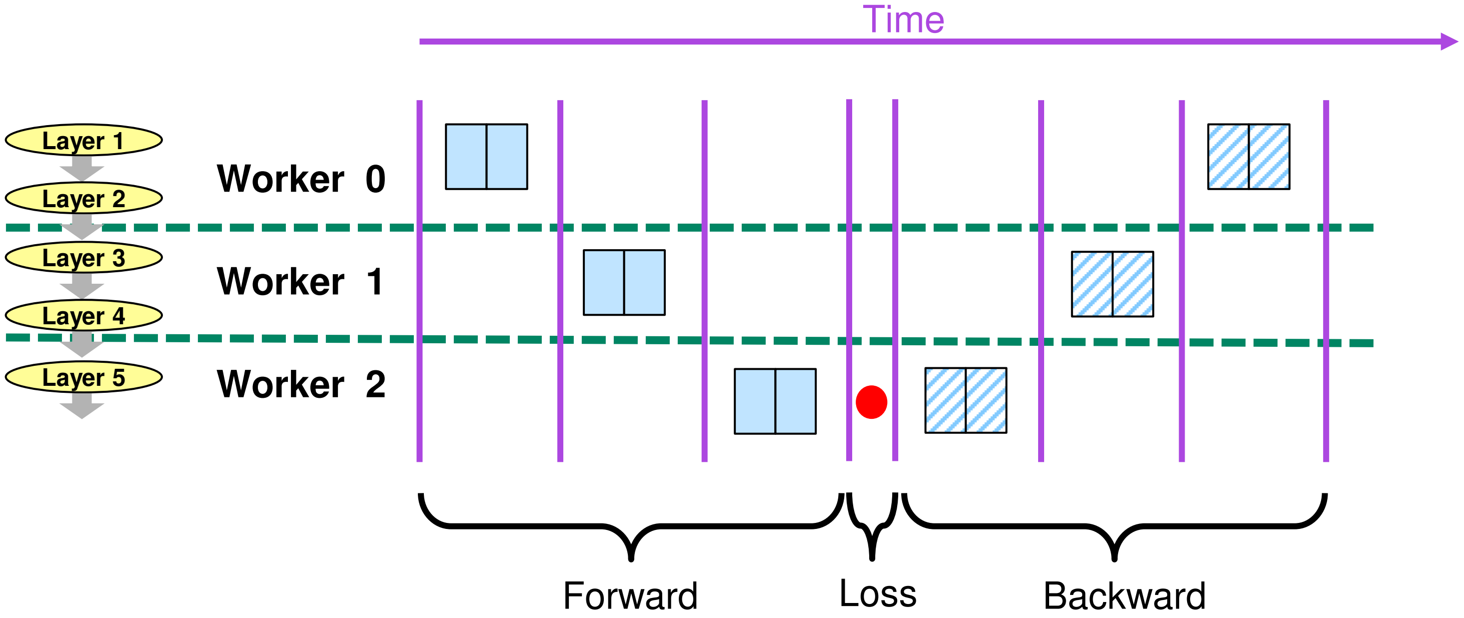
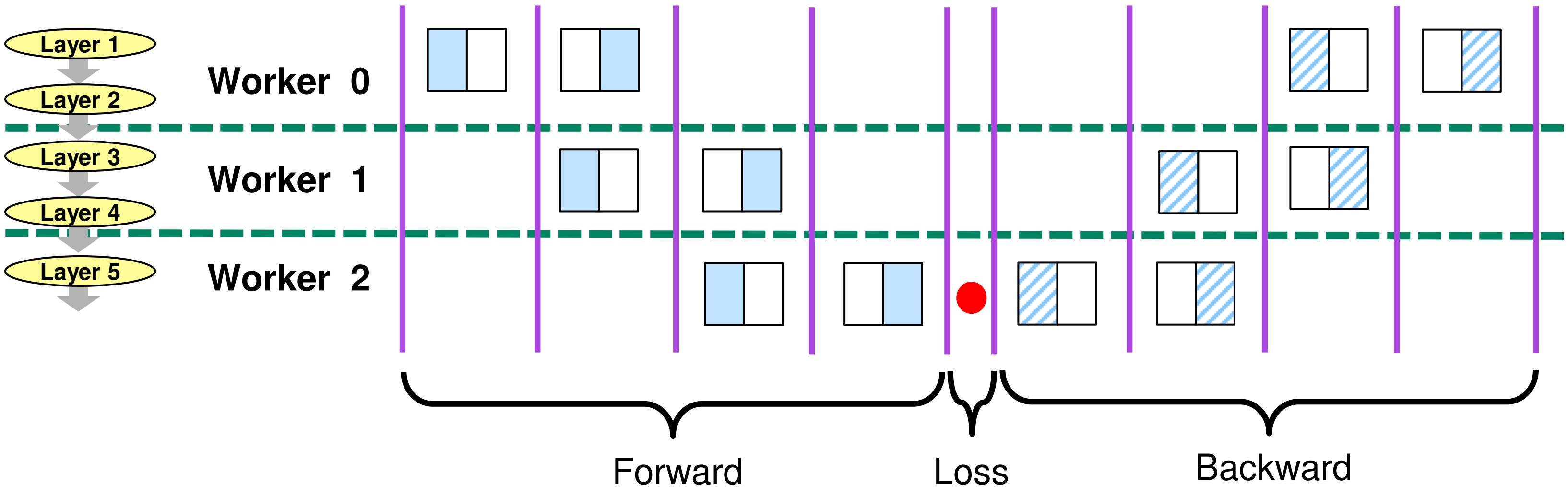


Pipeline Parallel



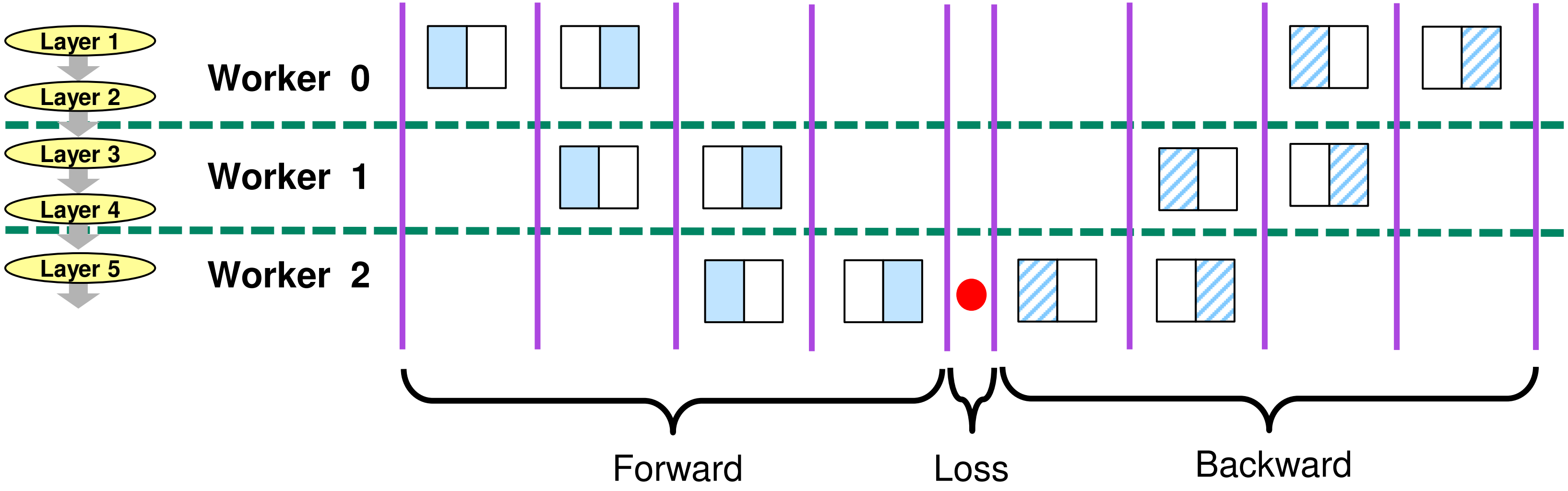
- **Idle bubbles:**
  - 67%: 12/18 step-slots
- **For *N* workers:**
  - $(N - 1)/N$ idle slots

Pipeline Parallel: Subminibatches



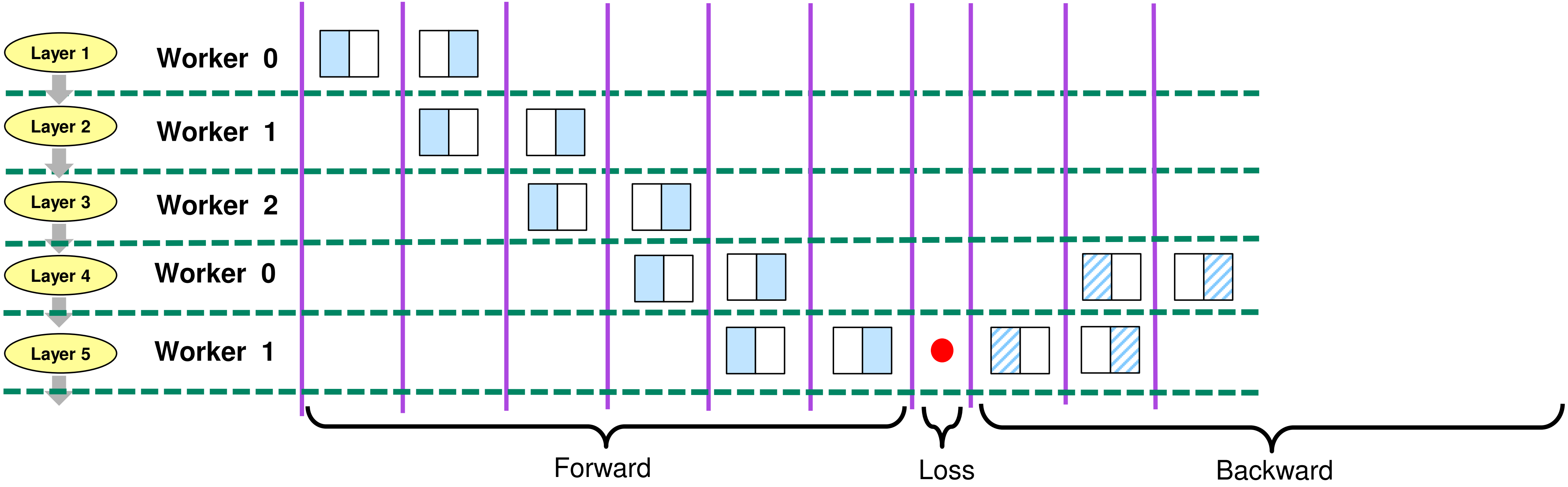
- **2 subminibatches**
  - 2x more steps
  - Each step is ½ compute
- **Idle bubbles: 50%**
  - 12/24 steps-slots

Pipeline Parallel: Subminibatches



- ***N* workers, *K* subminibatches:**
  - $2(N + K - 1)$ steps for fwd/bwd
  - Total step-slots: $2N(N + K - 1)$
  - Idle step-slots: $2N(N - 1)$
  - Fraction of idle slots: $(N - 1)/(N + K - 1)$
- **As *N* grows:**
  - $K = N \rightarrow$ 50% idle slots
  - $K = 4N \rightarrow$ 20% idle slots

Pipeline Parallel: Interleaved Layers



- **Benefit: increases the percentage of time each worker is busy**
  - Worker-0 is busy for 4 out of 6 fwd pass steps (compared to 2/4 in the previous slide)
- **Downsides:**
  - Increases communication linearly (with the number of interleaved layers per worker)
  - Problematic if skip connections cross workers

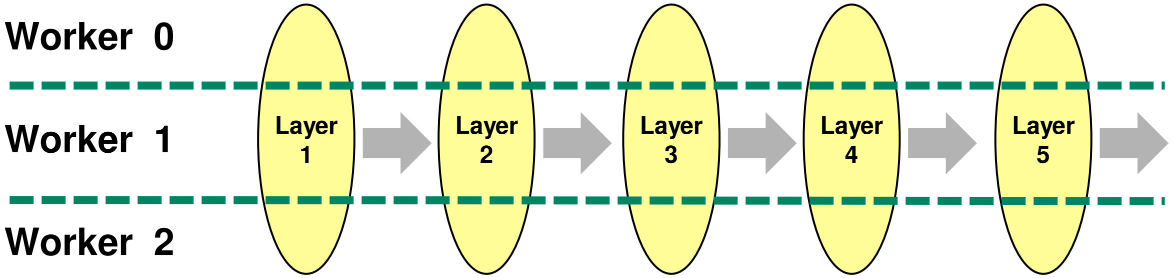
Pipeline Parallel: Communication

- **A worker communicates with its 2 neighbors**
  - 1D mesh topology
  - 1D torus when interleaving layers
- **Communication in each step of the fwd and bwd pass**
  - Activations in fwd, activation gradients in bwd
- **Communication very hard to overlap with computation**

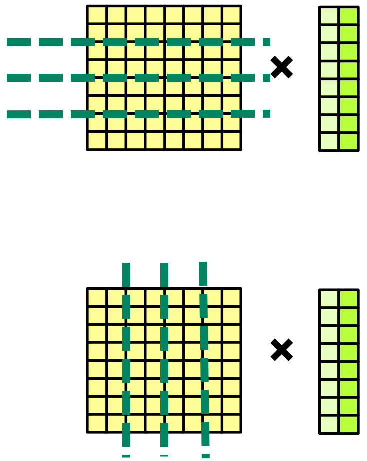
Pipeline Parallel: Challenges

- **Lots of hard hard to hide communication**
- **Idle slots reduce scaling efficiency**
  - Many subminibatches help with this, but run into the same problems as strong-scaling of data-parallel
- **Load balancing workload across workers is difficult**
  - Different layers of a network can take different amounts of time
  - Leads to even busy slots for other workers idling for portions of time

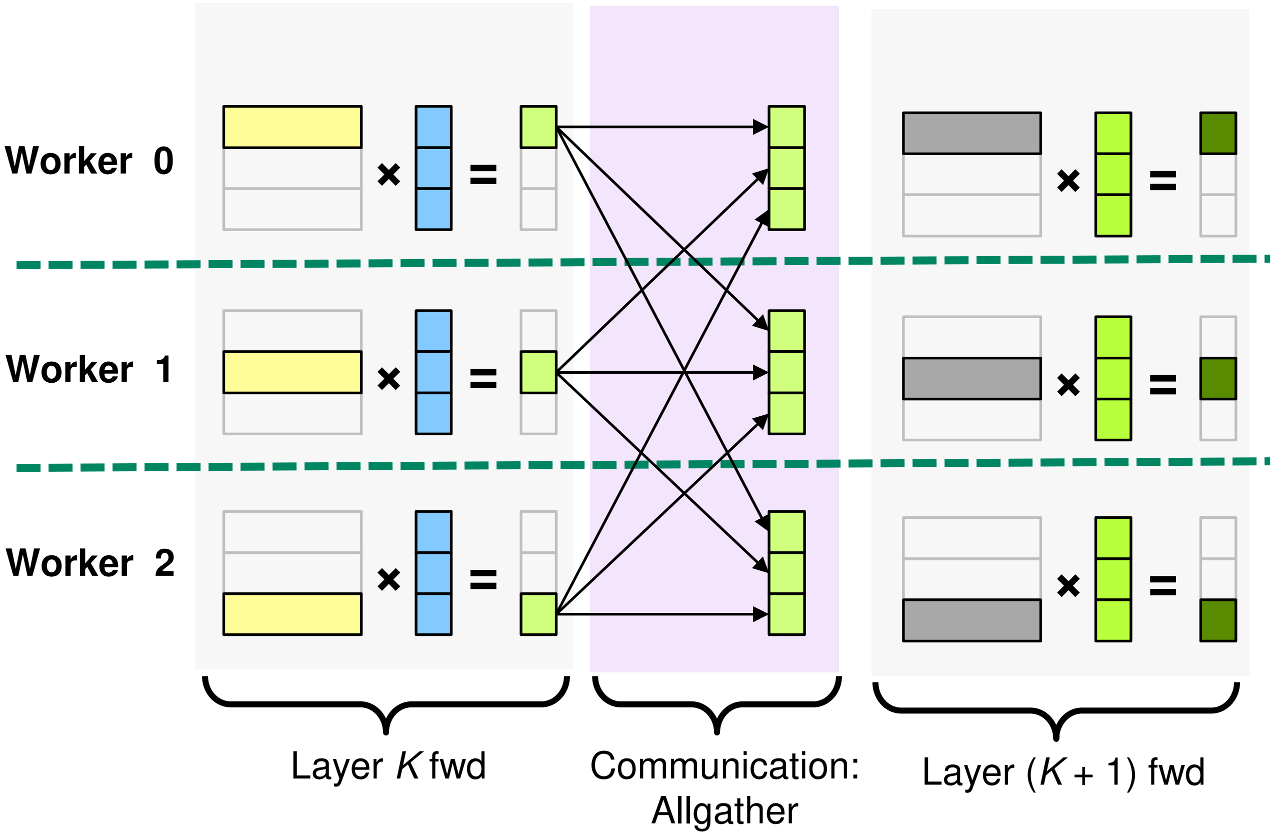
Model Parallel: Intra-Layer Parallel



- **Partition a given layer's weights among the workers**
- **Addresses some of the Pipeline Parallel challenges**
  - Idle slots, load imbalance
- **Two variants:**
  - Row-wise partitioning
  - Column-wise partitioning

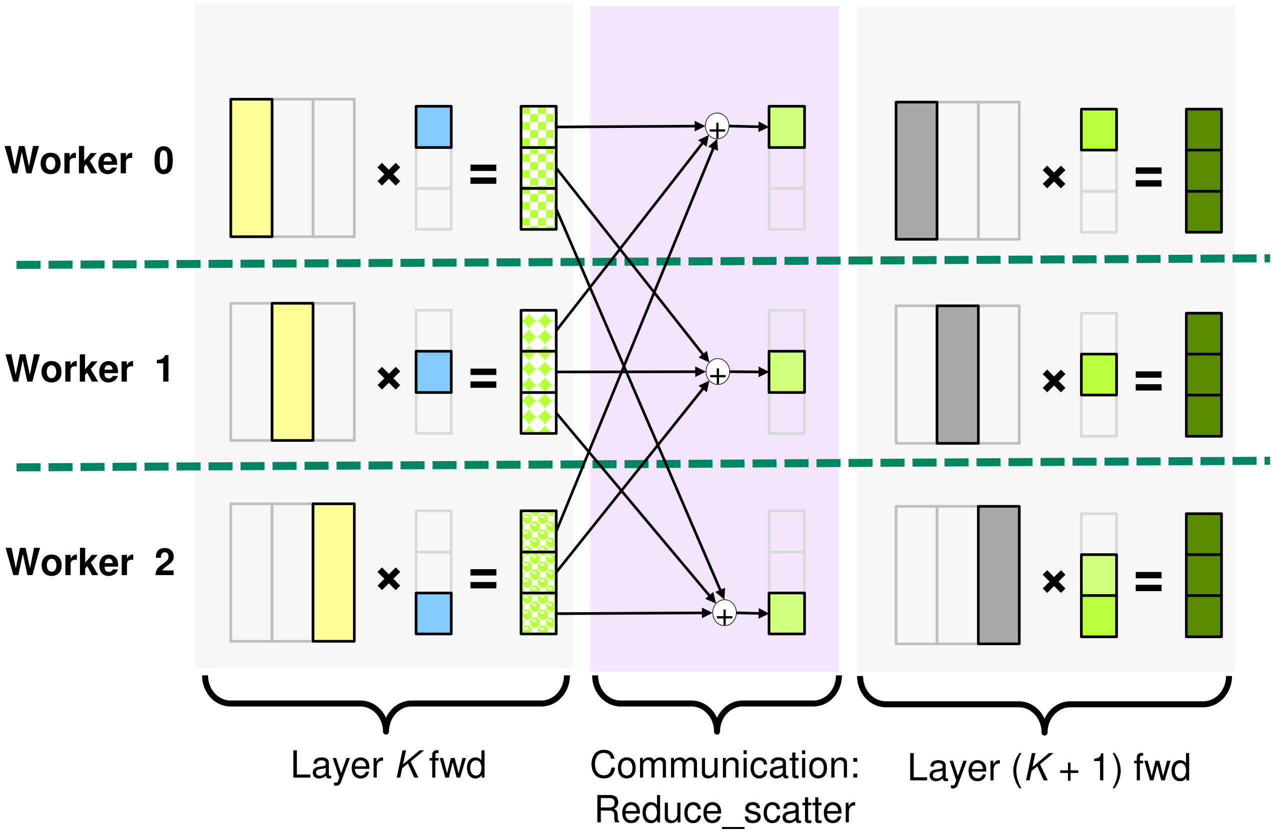


Row-wise Partitioning



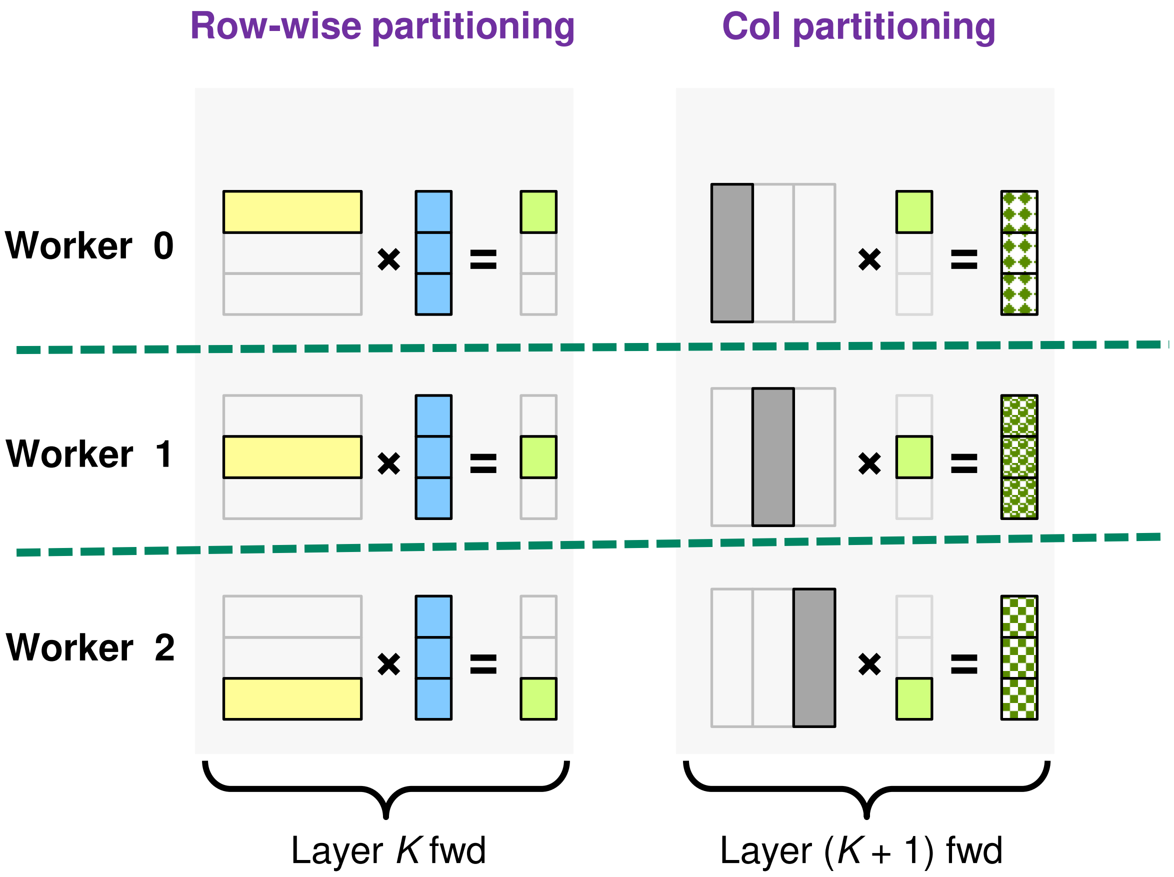
- **Each worker:**
  - Has a portion of weight rows
  - All of input activations
  - Computes a portion of output activations
- **Fwd communication:**
  - Allgather: next layer needs all activations

Column-wise Partitioning



- **Each worker:**
  - Has a portion of weight columns
  - Has a portion of input activations
  - Computes partial activations
- **Fwd communication:**
  - Reduce_scatter: next layer needs full activations

Reducing Synchronization By Alternating Partitioning



- Note: no communication is needed
- Worker *i* produces output, which is its input for the next layer

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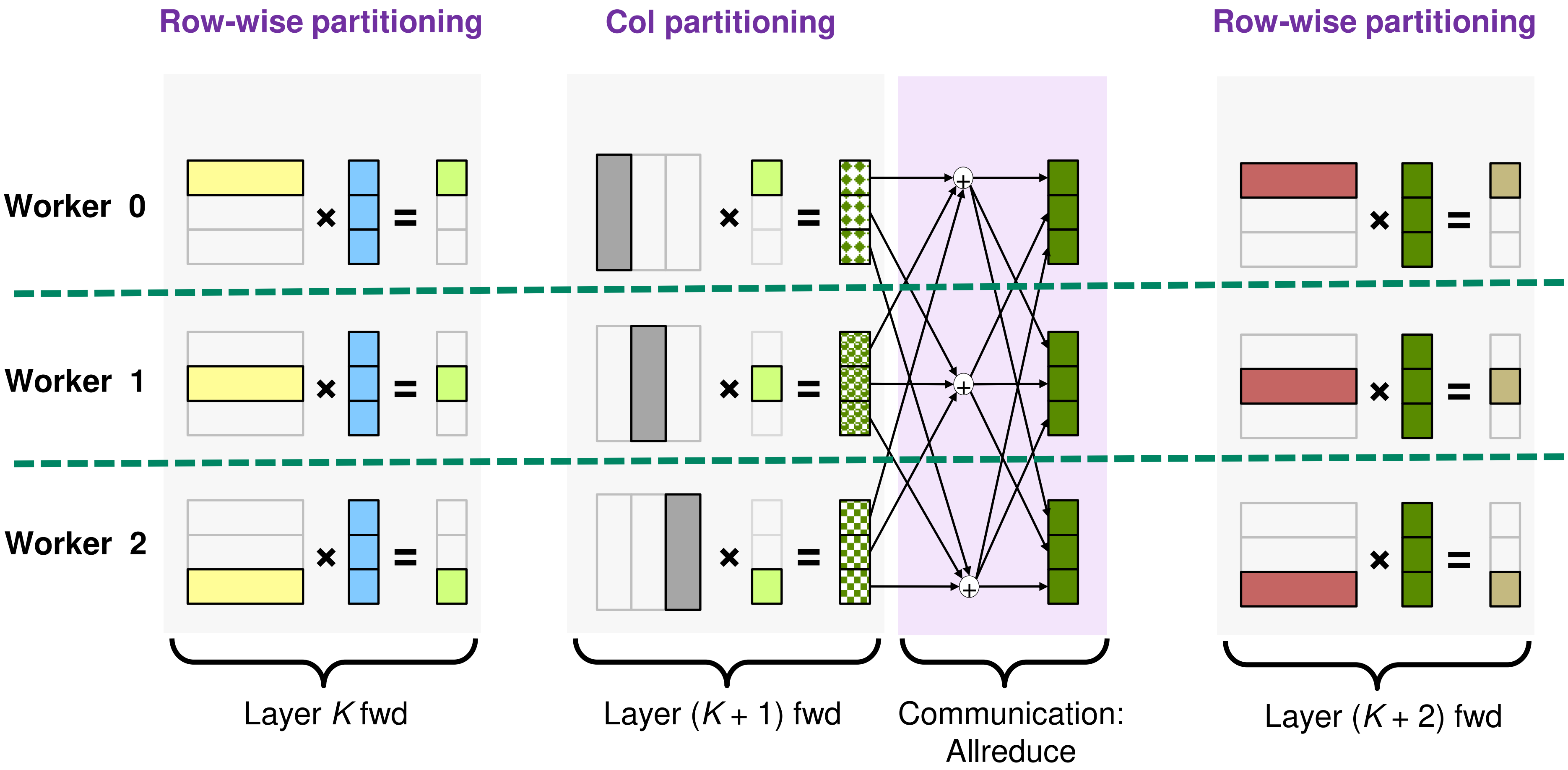

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Intra-Layer Parallel: Communication

- **Row-wise in fwd becomes Col-wise in bwd**
- **Col-wise in fwd becomes Row-wise in bwd**
- **Row-wise:**
  - Fwd: allgather
  - Bwd: reduce_scatter
- **Col-wise:**
  - Fwd: reduce_scatter
  - Bwd: allgather
- **When row- and col- are alternated:**
  - Allreduce every two layers, in fwd and bwd
  - Halves the synchronizations compared to not alternating

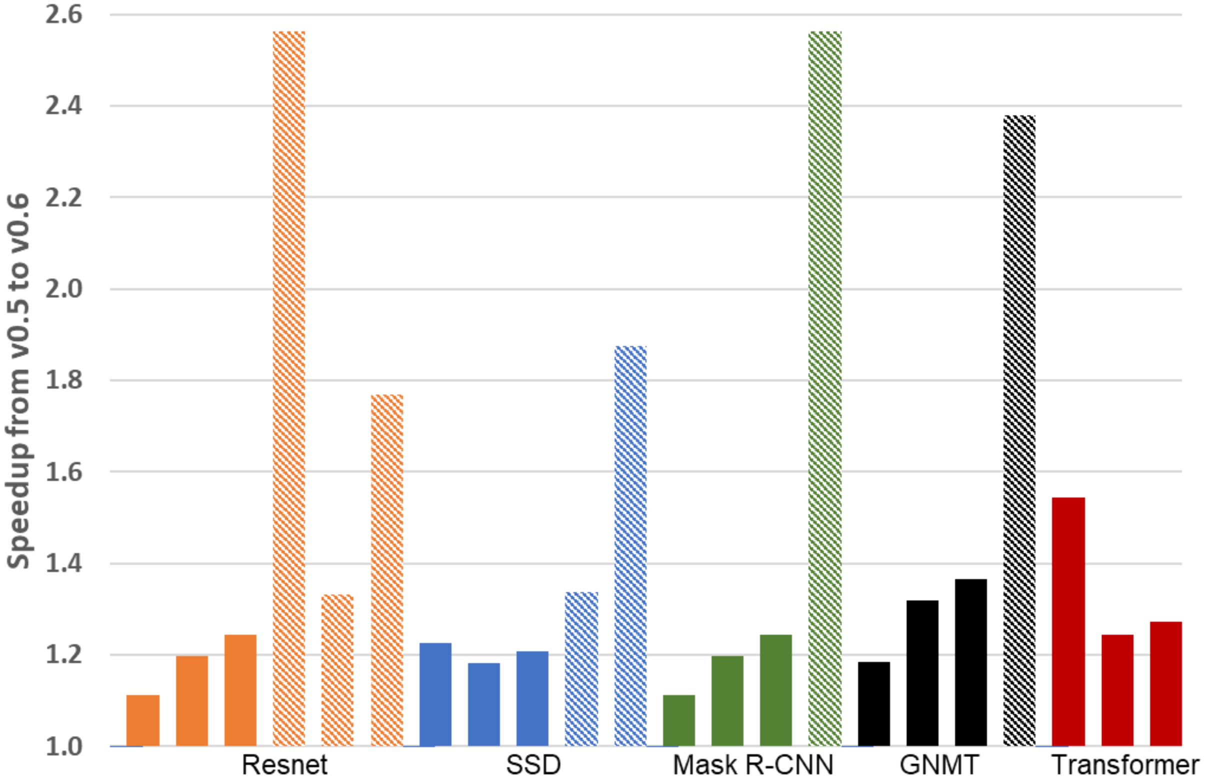
Communication Pattern Summary

- **Data Parallel:**
  - *Allreduce* of weights
  - Can be overlapped with computation
- **Pipeline Parallel:**
  - *Point-wise* communication of activations and activation gradients
  - Hard to overlap with computation
  - Hard to load-balance
- **Intra-layer Parallel:**
  - *Allgather, Reduce_scatter* of activations and activation gradients
  - *Allreduce* if row-wise and col-wise partitioning is alternated
  - Hard to overlap with computation
- **Hybrid Parallel: some layers data parallel, some layer model-parallel**
  - Common for recommendation networks (model parallel embeddings, data-parallel MLP)
  - *Alltoall* of activations and activation gradients: each pair of workers exchange unique values
    - Most performant on switched or fully connected topologies
  - Hard to overlap with computation

Summary

- **Networks and dataset are getting larger to set new state of art results**
- **Scale-out enables these networks to be trained**
- **Success requires many optimized components:**
  - Hardware:
    - Fast accelerators for DL
    - High-bandwidth, low-latency interconnects
      - Topologies matter (must match communication patterns)
      - Network switches with math capabilities free up DL accelerators to do compute
  - Software:
    - Math libraries (CUDNN, CUBLAS, MKL, …)
    - Collective communication libraries (NCCL, Horovod, …)
    - Training frameworks (MxNet, PyTorch, TensoFlow, HugeCTR, …)
  - Proper choice of parallelism (manual, MeshTensorFlow, Gshard, WSE)

Throughput Improvements, MLPerf v0.5 → v0.6
Largest Improvements were due to Scale-Out SW

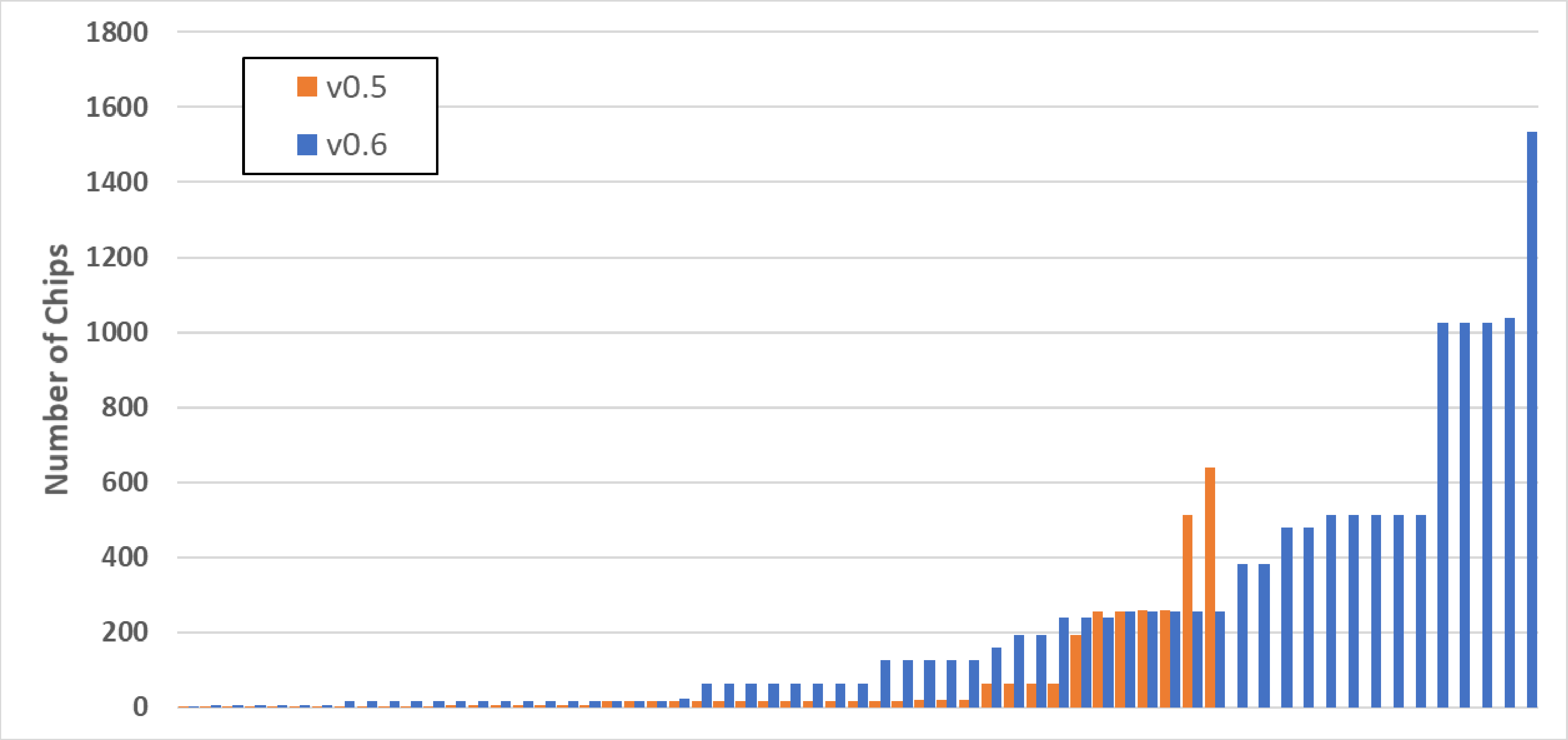


Identical machines submitted to v0.5 and v0.6

- Same chips, chip count, interconnect
- Adjusted for epoch differences
  - Due to some rule and hyper-parameter changes

Patterned bars: multi-node

MLPerf Submission Scale in Chips



MLPerf Submission Scale in Chips, Log Scale