Topic: Distributed and Federated learning

PipeDream: Generalized Pipeline Parallelism for DNN Training & A Unified Architecture for Accelerating Distributed DNN Training in Heterogeneous GPU/CPU Clusters

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PipeDream: Generalized Pipeline Parallelism for DNN Training

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SOSP 2019 - Symposium on Operating Systems Principles

Overview

- Introduction
  - Data parallelism
  - Model parallelism
  - Pipelining (GPipe)
- PipeDream
  - Principles
  - Challenges
- Implementation and Evaluation

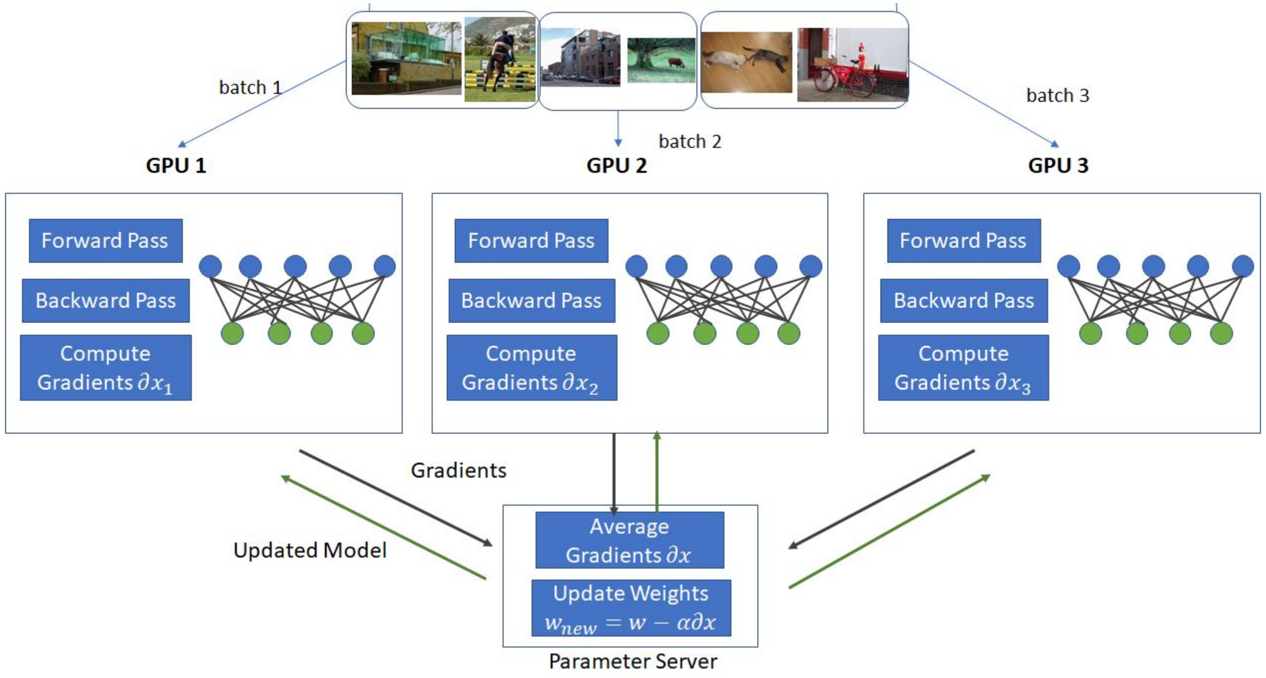
Distributed Training Approaches

- Intra-batch
  - Data parallelism (Data Partition)
  - Model parallelism (Model Partition)
  - Hybrid (e.g., For AlexNet, data partition in the convolutional layers)

- Inter-batch
  - Pipelining (GPipe)

- PipeDream: integrated intra-batch and inter-batch

Data parallelism



- Each worker will have the whole model but part of data

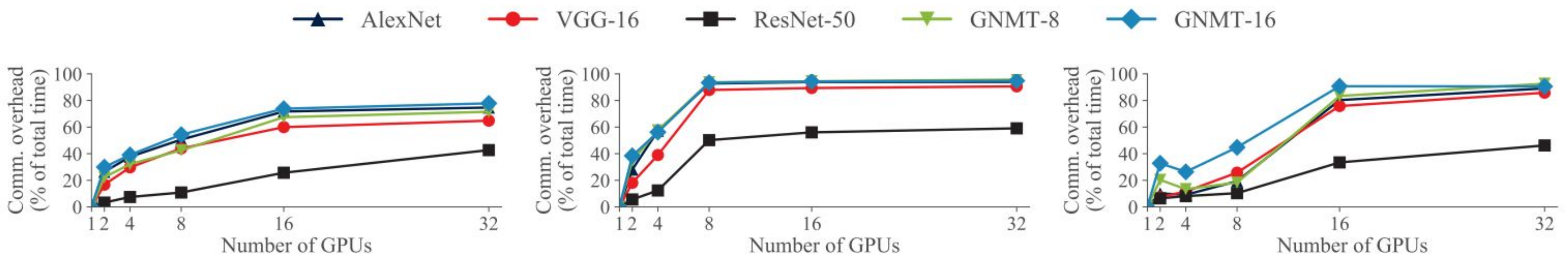
- Client-worker architecture (Parameter server)
- peer-to-peer architecture (ring all reduce algorithm)

The figure is from Telesens blog (https://www.telesens.co/2017/12/25/understanding-data-parallelism-in-machine-learning/).

Data parallelism

- Significant communication overhead

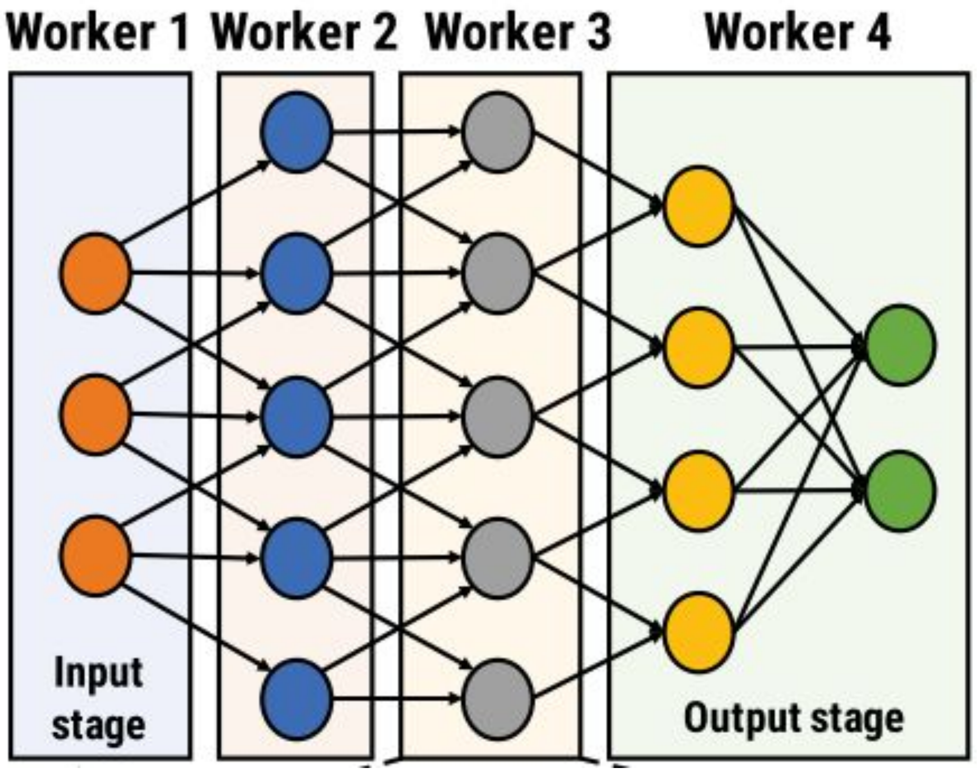
- Scales well for ResNet-50 (convolutional layers)
- Does not scale well for dense connected model

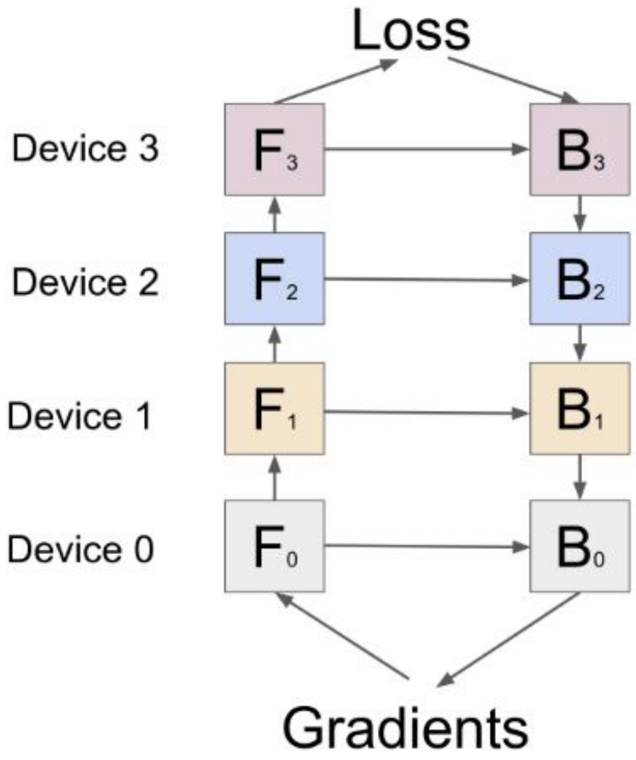


(a) Instances with 8 1080Tis (private cluster). (b) Instances with 4 V100s (Azure). (c) Instances with 8 V100s and NVLink (EC2).

Model Parallelism

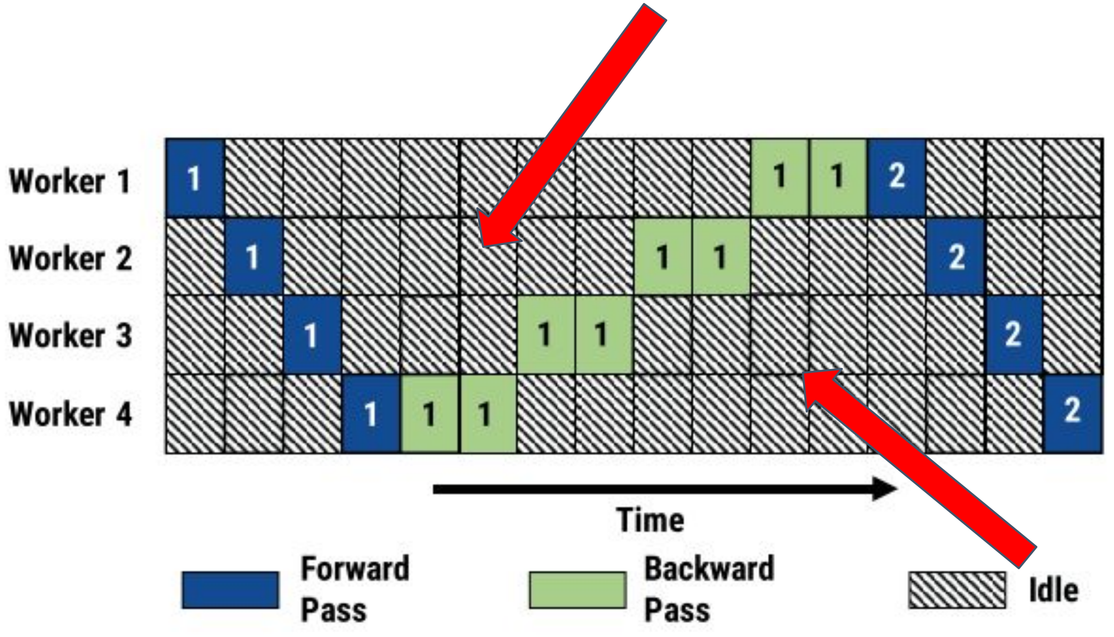
- Each worker will get the same data but have part of the model





The Right figure is from Huang et al. GPipe: Easy Scaling with Micro-Batch Pipeline Parallelism. NeurIPS 2019.

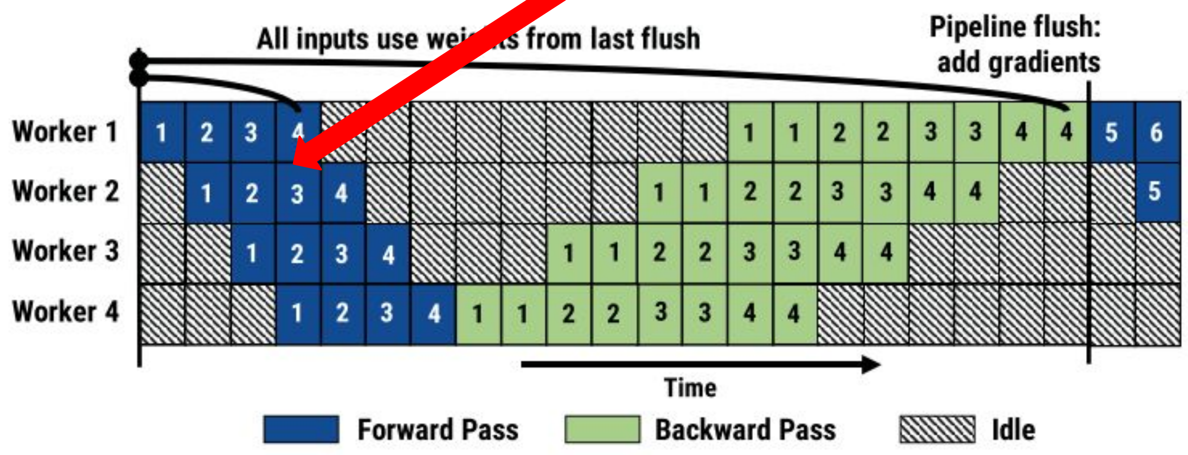
Model Parallelism

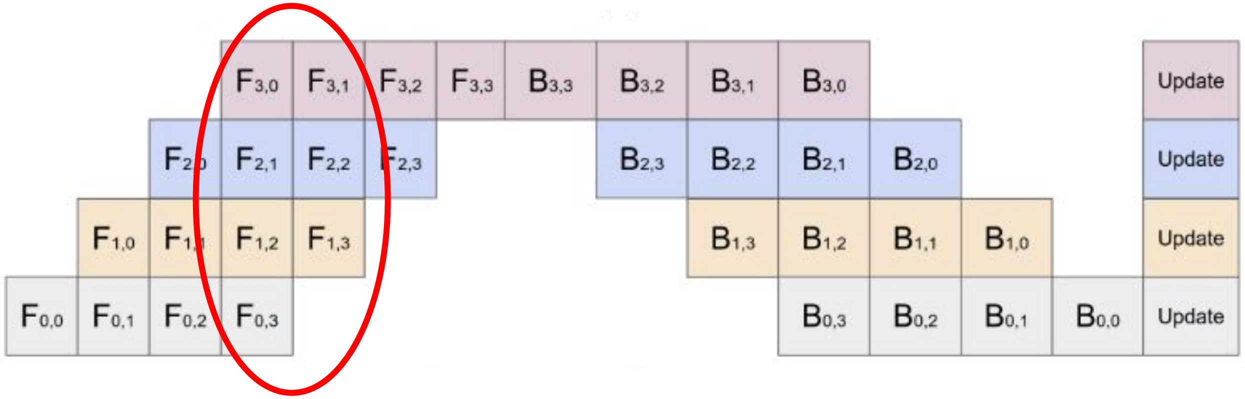


- The amount of data communicated is the size of intermediate outputs and and corresponding gradients
- Will not accelerate training
  - under-utilization of computing resources
- manually partition the mode

GPipe

Microbatch not minibatch



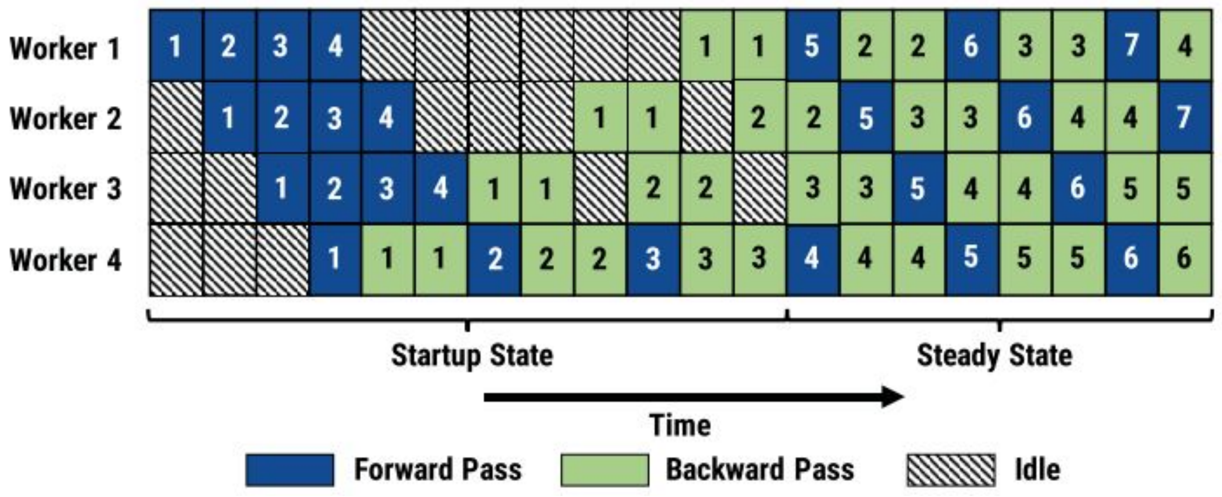


- Divide minibatch into microbatch. Pipeline microbatch across workers
- Works can be used concurrently (improves the model parallelism)

- Frequent pipeline flush reduces the hardware efficiency
- Still has relatively large idle in the system
- Manually partition model

The bottom figure is from Huang et al. GPipe: Easy Scaling with Micro-Batch Pipeline Parallelism. NeurIPS 2019.

PipeDream



- In the startup phase: Inject multiple minibatchs to keep pipeline full (Similar to GPipe)
- In the steady state: each worker alters between forward and backwarpasses.
- Each worker once complete the forward pass for a minibatch, each stage will asynchronously sends the output to the next stage while starting to process another minibatch

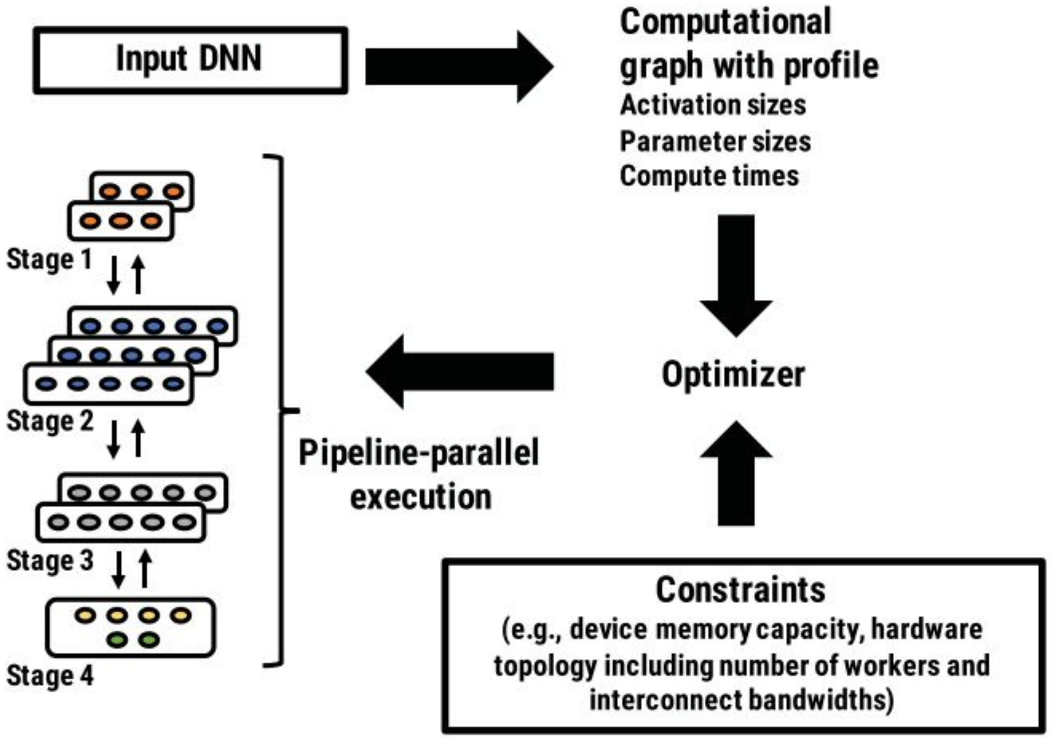
PipeDream

- No pipeline stalls in the steady state

- Pipelining communicates less. Each worker in PipeDream only need to communicate a subset of gradients and output activations, to only a single other worker. While in data parallelism, each worker need to send and receive the all parameters on the model.

- Pipelining overlaps computation and communication: Asynchronous communication of forward activations and backwards gradients across stages lead to the overlap of communication and computation

PipeDream Challenge 1: Work Partitioning



- PipeDream uses partitioning algorithm to automatically split the model
- Profiler:
  - Using a short (few minutes) profiling run 1000 minibatches on a single GPU
  - Record total computation time, the size of output activation (and input gradients) in bytes, and the size of weight parameters in bytes for each layer
  - Communication time is related to number of workers and parameter size in each layer

PipeDream Challenge 1: Work Partitioning

- Partitioning algorithm: (1) partition layers into stages, (2) the number of workers in each stage, and (3) optimal number of in-flight minibatches to full the pipeline
- The high level intuition is that the PipeDream's optimizer solves the dynamic programing problem and finds the optimal partitioning within a server and then split a model across servers
- $T^k(i \to j, m)$ is the total time taken by as single stage (layer i to j) replicated over m workers; $A^k(i \to j, m)$ is the slowest stage (layer i to j) in the optimal pipeline

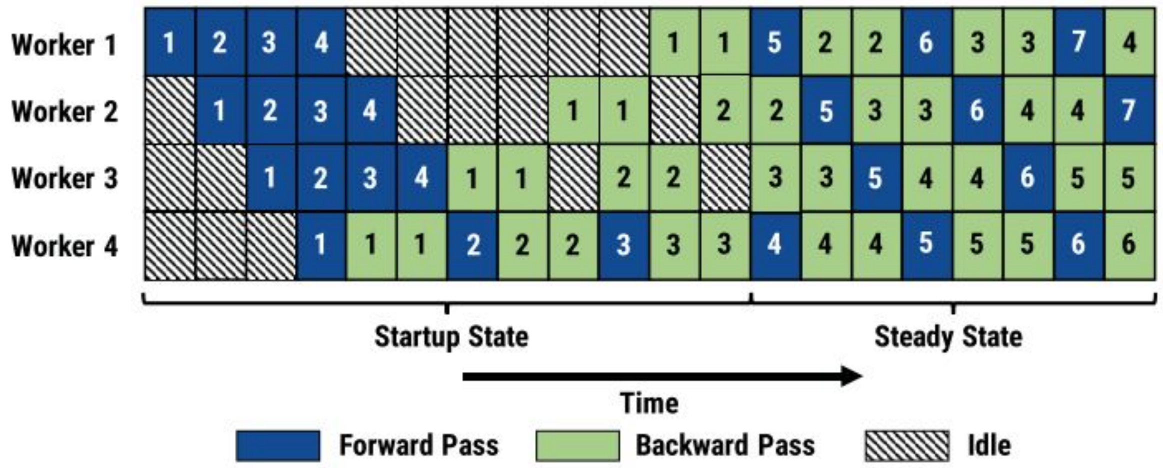
$$T^k(i \to j, m) = \frac{1}{m} \max \begin{cases} A^{k-1}(i \to j, m_{k-1}) \\ \dfrac{2(m-1)\sum_{l=i}^{j} |w_l|}{B_k} \end{cases}$$

$$A^k(i \to j, m) = \min_{i \le s < j} \min_{1 \le m' < m} \max \begin{cases} A^k(i \to s, m - m') \\ 2a_s / B_k \\ T^k(s+1 \to j, m') \end{cases}$$

PipeDream Challenge 2: Work Scheduling

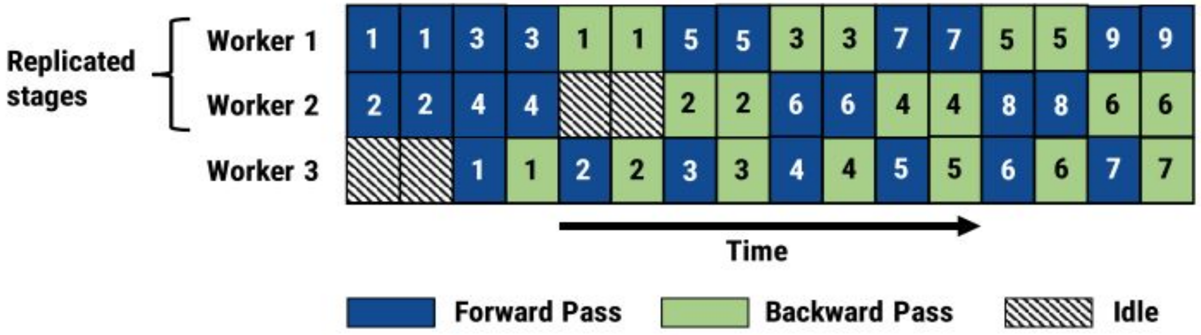
- To determine whether the worker should compute the forward or backward.

- In the startup phase: need to decide how many minibatch to inject to keep the pipeline full in the steady stage. [#workers / #replicas in the input stage]
- In the steady phase: one-forward-one-backward (1F1B) schedule. To ensure each stage to produce the output at roughly the same rate



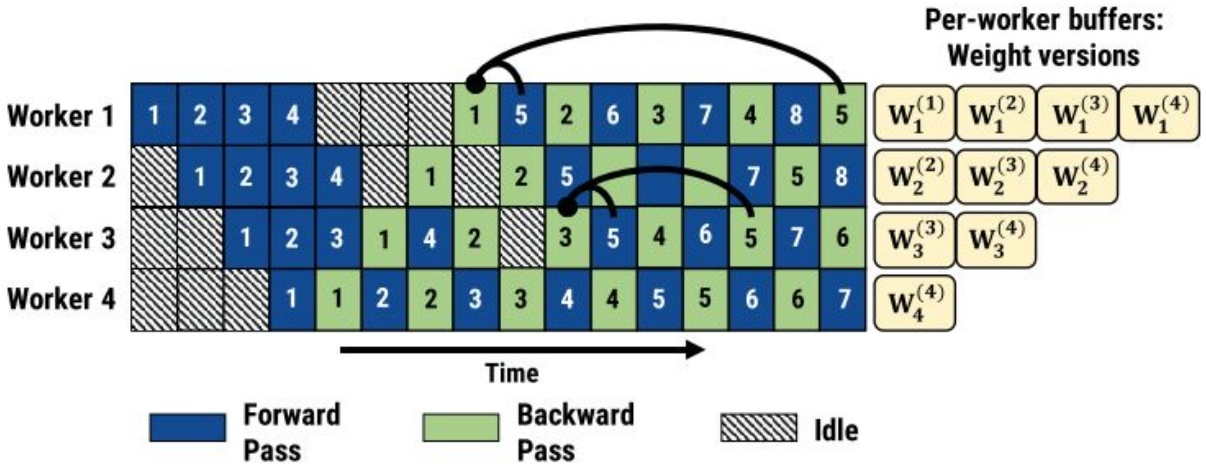
PipeDream Challenge 2: Work Scheduling

- When there is data parallelism in the stage, use the one-forward-one-backward round-robin (1F1B-RR).
- The figure below shows a 2-1 configuration. Worker 1 and worker 2 process different minibatch, while worker 3 process all minibatches.
- Worker 1 and 2 process replicated minibatches, worker 3 unreplicate.



PipeDream Challenge 3: Effective Learning

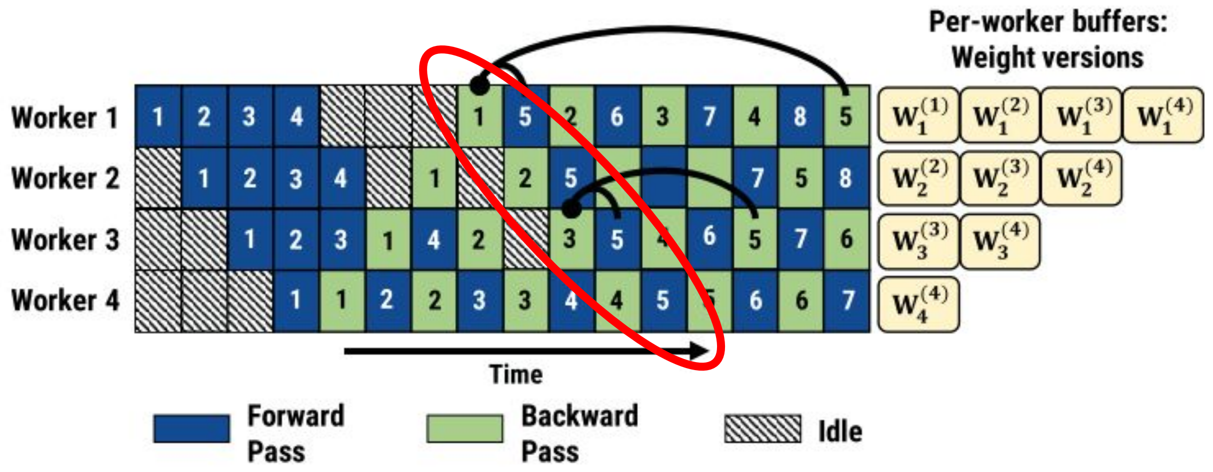
- Weight version mismatch challenge. The model parameters used for forward and backward should be the same for one minibatch
- Weight stashing: PipeDream will keep multiple weight versions one for each active minibatch.
- $$w^{(t+1)} = w^{(t)} - \nu \cdot \nabla f(w_1^{(t-n+1)}, w_2^{(t-n+2)}, \ldots, w_n^{(t)})$$



PipeDream Challenge 3: Effective Learning

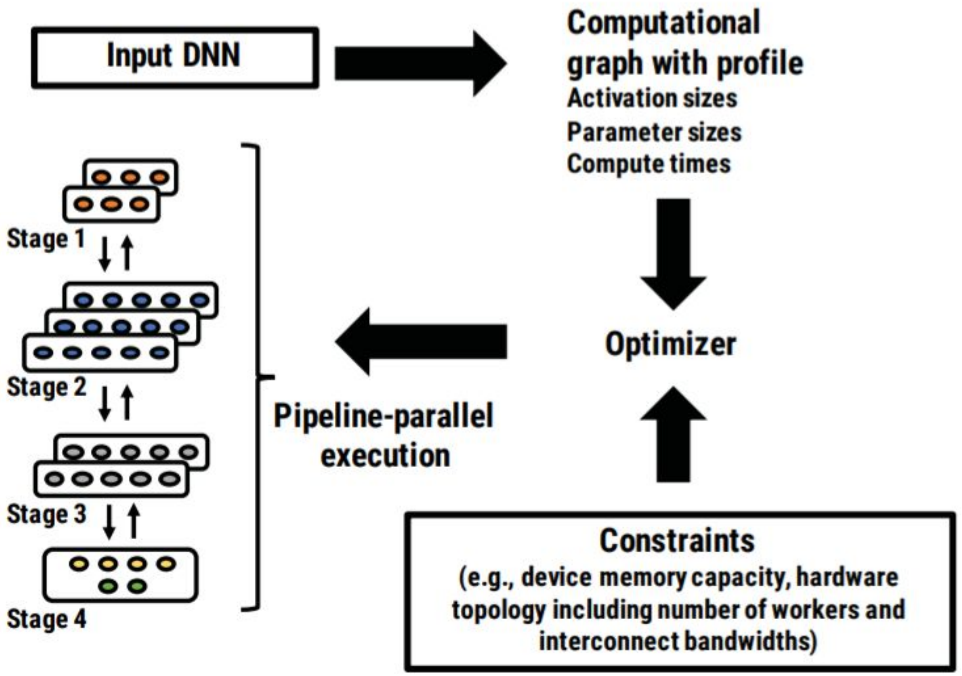
- Weight stashing does not guarantee the consistency of parameter versions for one minibatch across stages (Vertical Sync is an optional technique for this)

- Weight stashing does not significantly increase the per-worker memory

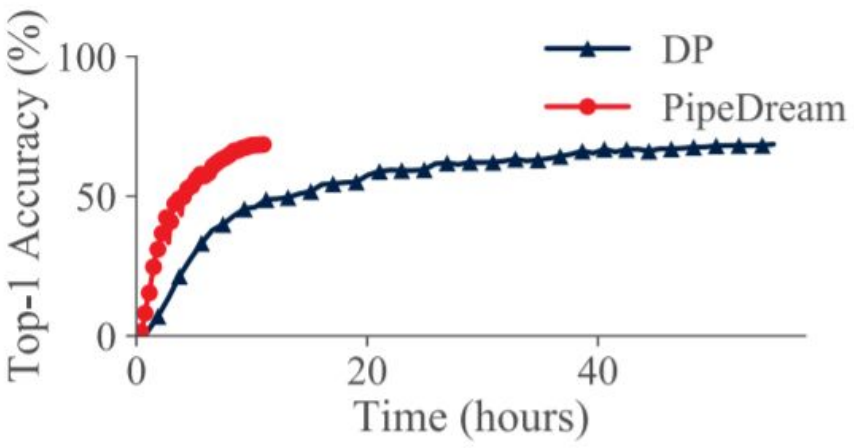


PipeDream Implementation

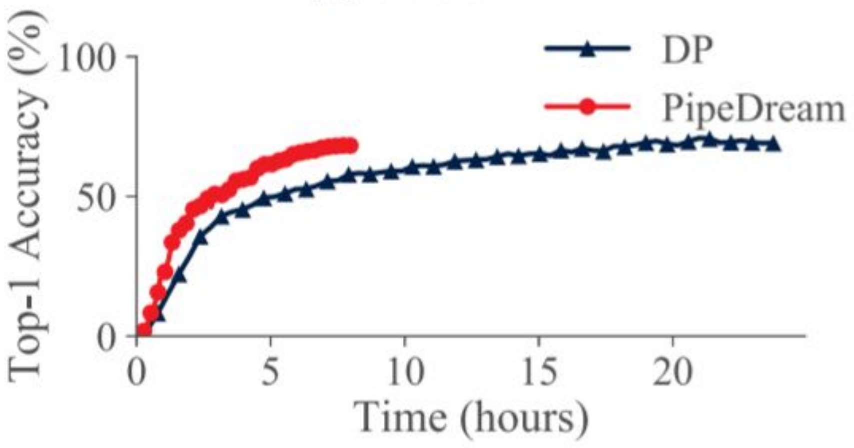
- A standalone Python library
- Uses PyTorch but can be integrated with other frameworks
- Some highlights:
    - Parameter State
    - Intermediate State
    - Stage Replication
    - Checkpointing



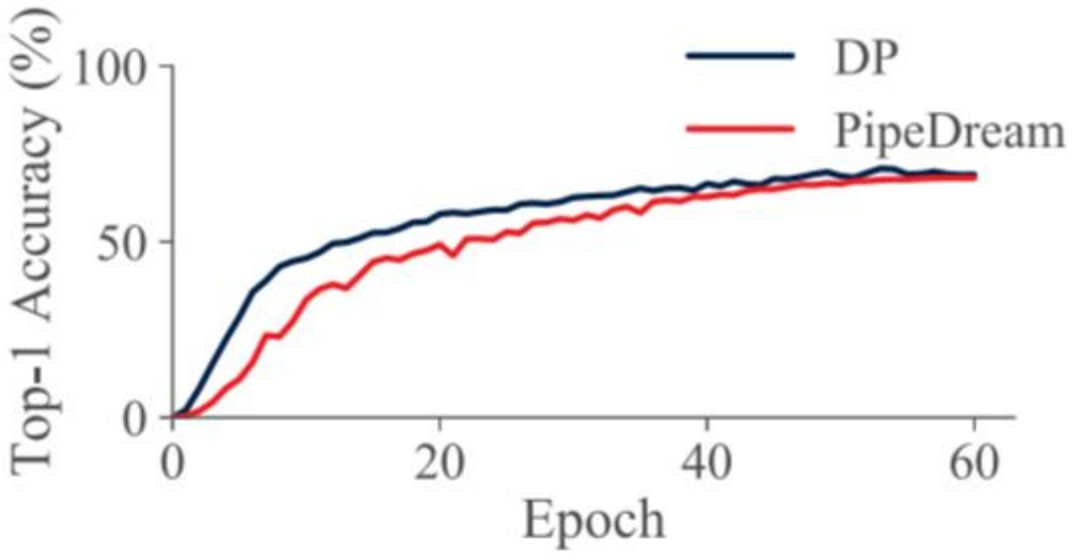
PipeDream Evaluation: Image Classification



(a) Cluster-A.



(b) Cluster-B.



PipeDream Evaluation: Other Tasks

Task	Model	Dataset	Accuracy Threshold	# Servers × # GPUs per server (Cluster)	PipeDream Config	Speedup over DP	
						Epoch time	TTA
Translation	GNMT-16 [55]	WMT16 EN-De	21.8 BLEU	1x4 (A)	Straight	1.46×	2.2×
				4x4 (A)	Straight	2.34×	2.92×
				2x8 (B)	Straight	3.14×	3.14×
	GNMT-8 [55]	WMT16 EN-De	21.8 BLEU	1x4 (A)	Straight	1.5×	1.5×
				3x4 (A)	Straight	2.95×	2.95×
				2x8 (B)	16	1×	1×
Language Model	AWD LM [40]	Penn Treebank [41]	98 perplexity	1x4 (A)	Straight	4.25×	4.25×
Video Captioning	S2VT [54]	MSVD [11]	0.294 METEOR	4x1 (C)	2-1-1	3.01×	3.01×

PipeDream Evaluation: Comparison To GPipe

- Pipeline depth equal to PipeDream optimal:
    - 55% throughput slowdown on Cluster-A
    - 71% slowdown on Cluster-B
- Pipeline depth to max:
    - 35% slowdown on Cluster-A
    - 42% slowdown on Cluster-B
- Due to more frequent pipeline flushes

Questions and Break

A Unified Architecture for Accelerating Distributed DNN Training in Heterogeneous GPU/CPU Clusters

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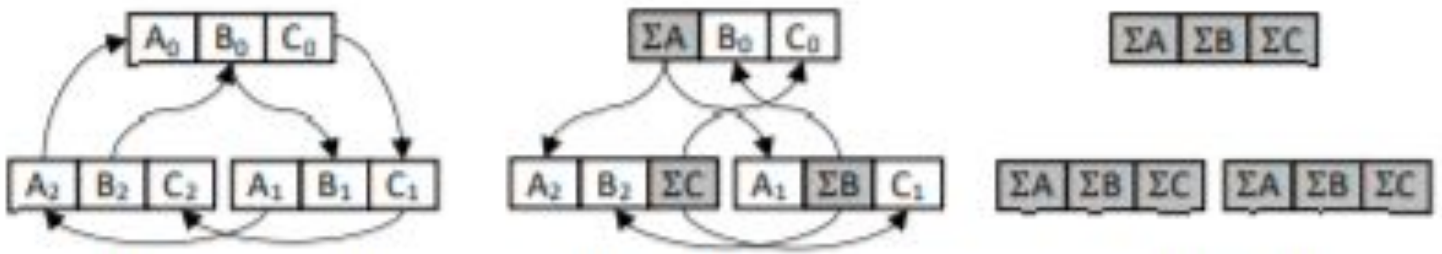
OSDI'20 - the 14th USENIX Symposium on Operating Systems Design and Implementation

Overview

- Recap
  - All-reduce
  - Parameter Server
- BytePS
  - Inter-machine communication
  - Intra-machine communication
- Implementation and Evaluation

Recap

All-reduce

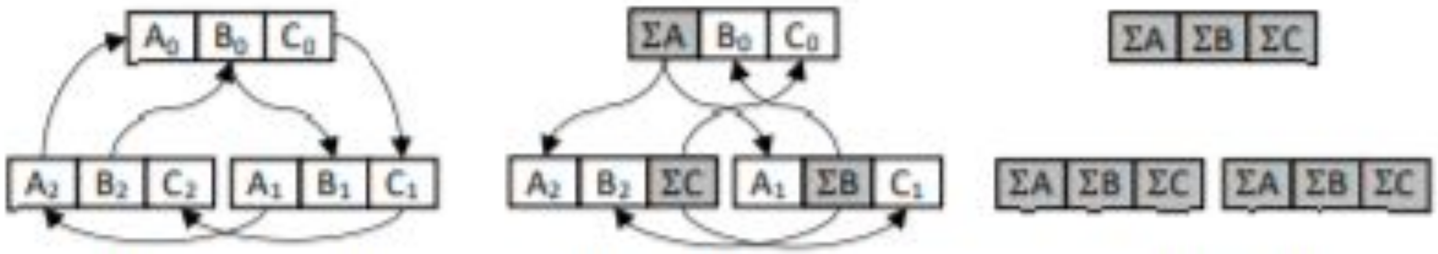


(a) Reduce-scatter (b) All-gather (c) Result

Figure 1: The communication workflow of all-reduce.

- utilize a ring-based structure to enable parallel communication
- each node serves as a starter of a ring and an end of another ring

Analysis



(a) Reduce-scatter (b) All-gather (c) Result

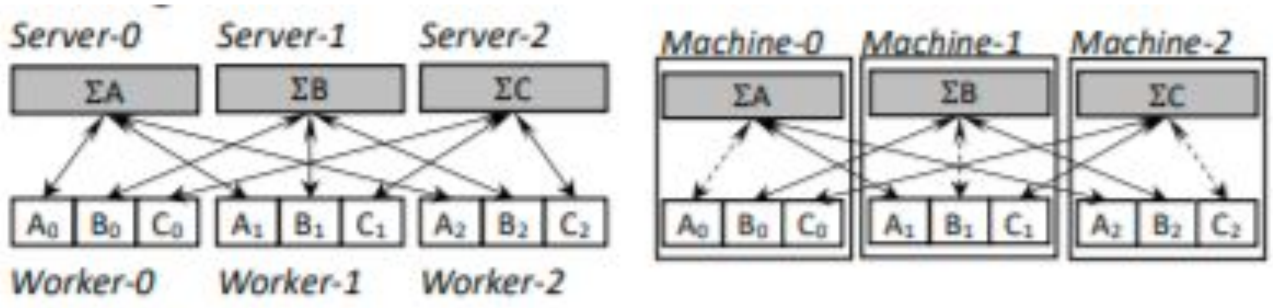
Figure 1: The communication workflow of all-reduce.

- Reduce-scatter: Each node sends(and receives) $\frac{(n-1)M}{n}$ bytes to(and from) other nodes
- All-gather: Each node sends(and receives) $\frac{(n-1)M}{n}$ bytes to(and from) other nodes
- Total traffic: $\frac{2(n-1)M}{n}$ bytes. Total communication time: $\frac{2(n-1)M}{nB}$

Notation: M: model size n: number of nodes B: network bandwidth

Continue recapping...

Parameter Server(PS)

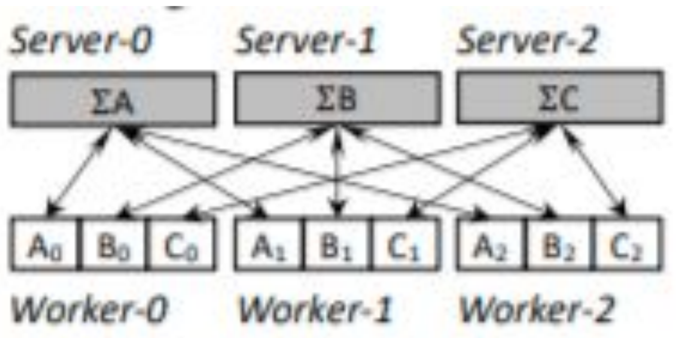


(a) Non-colocated mode (b) Colocated mode

Figure 2: The communication pattern of PS. A solid arrow line indicates the network traffic. A dashed arrow line represents the loop-back (local) traffic.

- consists of two types of nodes: servers and workers
- workers running on GPU machines push gradients to servers
- servers aggregate gradients and update the parameters
- workers pull the latest parameters from servers for next iteration

Analysis

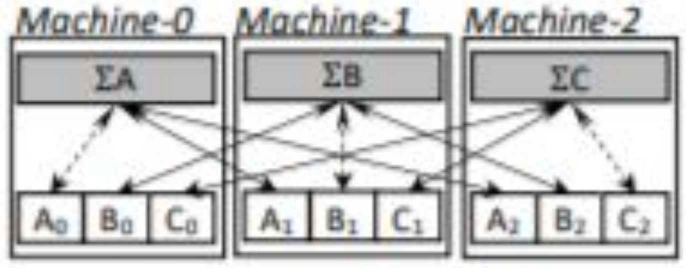


(a) Non-colocated mode

(a) Non-colocated mode
- server processes deployed on dedicated CPU machines
- model partitioned into k parts on k different CPU machines
- Each GPU worker sends and receives M bytes
- Each CPU server receives and sends $\frac{nM}{k}$ bytes
- Communication time per iteration: $\max\left(\frac{M}{B}, \frac{nM}{kB}\right)$

Notation: M: model size n: number of nodes B: network bandwidth k: number of dedicated CPU machines

Analysis



(b) Colocated mode

(b) Colocated mode

- server processes deployed on GPU machines
- model partitioned into k parts on k different CPU machines
- Each node sends and receives M bytes
- Total traffic: $\frac{2(n-1)M}{n}$ bytes. Total communication time: $\frac{2(n-1)M}{nB}$

PS in colocated mode has the same communication time per iteration as all-reduce!

However, both all-reduce and PS architecture have limitations...

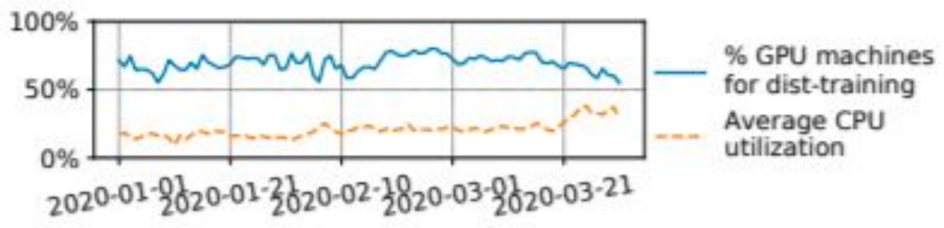


Figure 3: Daily statistics of our internal DNN training clusters from 2020-01-01 to 2020-03-31.

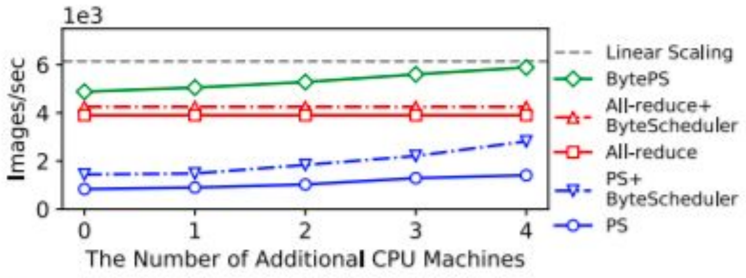


Figure 4: VGG-16 training performance of different architectures. We use 4 GPU machines with 32 GPUs in total. *Linear Scaling* represents the maximal performance (in theory) of using 32 GPUs.

- Spare CPUs and bandwidth are not fully utilized on production GPU clusters
- Existing all-reduce and PS architectures not insufficient in performance
- This is why we need BytePS architecture, which mitigates the low utilization of these spare CPUs and bandwidth.

BytePS Architecture

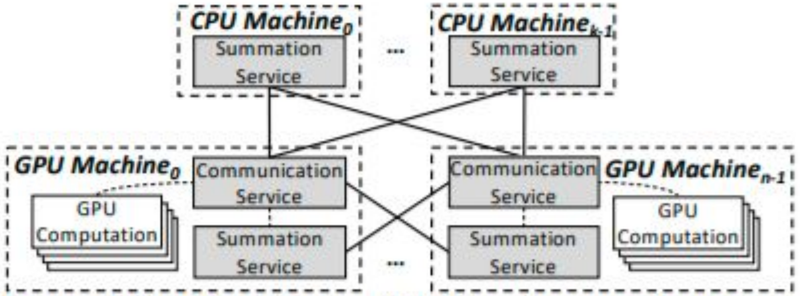


Figure 5: BytePS architecture. Solid lines: the connection between CPU machines and GPU machines. Dashed lines: the data flow inside GPU machines.

- Two main modules: Communication Service(CS) and Summation Service(SS)
- SS runs on the CPUs of both CPU and GPU machines
- CS performs GPU computation on every GPU machine

How to achieve optimal inter-machine communication for the BytePS architecture?

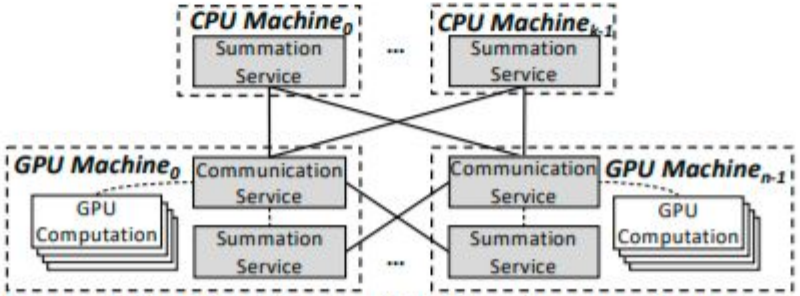


Figure 5: BytePS architecture. Solid lines: the connection between CPU machines and GPU machines. Dashed lines: the data flow inside GPU machines.

- An optimal communication requires wise SS workload assignment among CPU machines and GPU machines
- In the next slide, we use the following notation:

$M_{SS_{CPU}}$: workload of SS on CPU machines

$M_{SS_{GPU}}$: workload of SS on GPU machines

Analysis

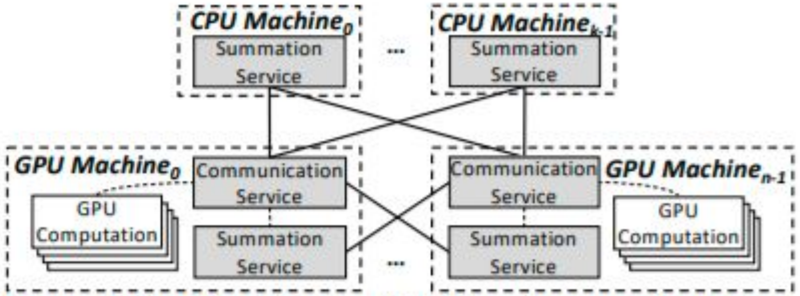


Figure 5: BytePS architecture. Solid lines: the connection between CPU machines and GPU machines. Dashed lines: the data flow inside GPU machines.

- a CS module sends and receives $M - M_{SS_{GPU}}$ bytes
- a SS module on a GPU machine receives and sends $M_{SS_{GPU}}$ bytes from other n-1 GPU machines
- a GPU machine requires communication time $t_g = \frac{M + (n-2)M_{SS_{GPU}}}{B}$
- a CPU machine requires communication time $t_c = M_{SS_{CPU}}/B$
- the sum of all SS workloads should be M

Analysis

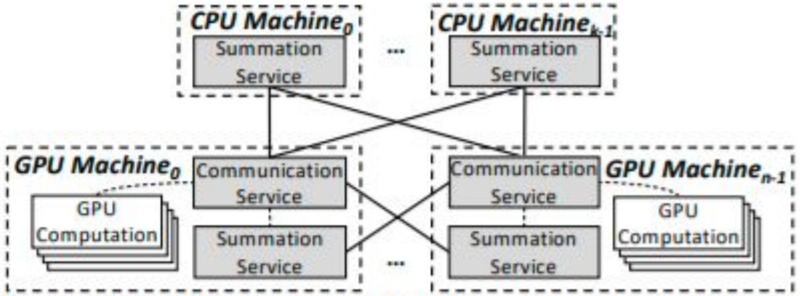


Figure 5: BytePS architecture. Solid lines: the connection between CPU machines and GPU machines. Dashed lines: the data flow inside GPU machines.

- GPU machine communication time t_g and CPU machine communication time t_c need to be equal to prevent one of them from being the bottleneck
- optimal workload assignment is given as

$$M_{SS_{CPU}} = \frac{2(n-1)}{n^2+kn-2k}M \qquad M_{SS_{GPU}} = \frac{n-k}{n^2+kn-2k}M$$

Intra-machine communication

PCIe-only topology

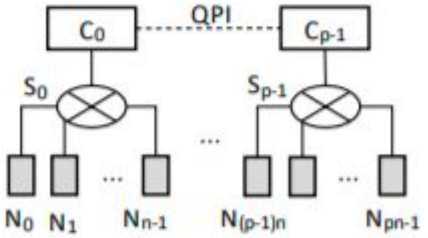


Figure 7: Notations of the PCIe-only topology.

- CPUs connected by QPI
- GPUs split into groups and connected to PCIe switches
- GPU-to-GPU memory copy across PCIe switches is more of a bottleneck

CPU-assisted aggregation(PCIe-only topology)

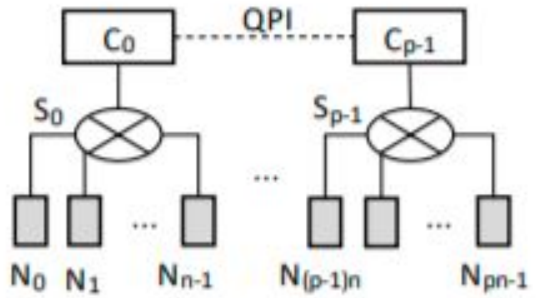
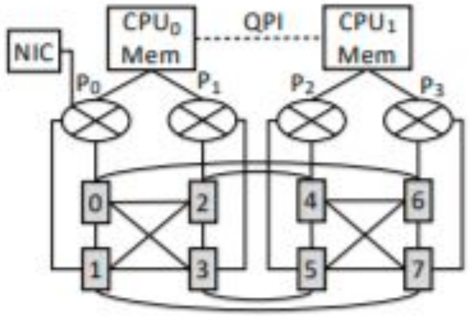


Figure 7: Notations of the PCIe-only topology.

Reduce-Scatter ⇨ GPU-CPU copy ⇨ CPU-reduce ⇨ Networking ⇨ CPU-GPU copy ⇨ All-Gather

- CPU-assisted aggregation is proved to be near-optimal in both theory and practice

NVLink-based topology



(a) NVLink-based topology

- GPUs split to different PCIe switches
- All GPUs interconnected by NVLinks
- CPU-assisted aggregation no longer needed
- Asymmetric architecture causes competition of PCIe bandwidth

BytePS's solution of Summation Service(SS)

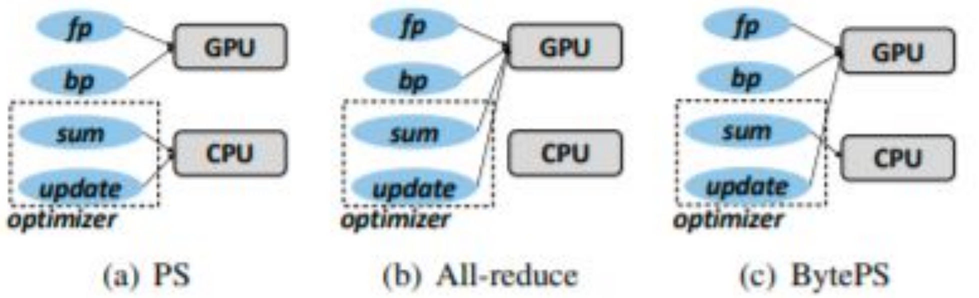


Figure 10: Component placement comparison between all-reduce, PS and BytePS.

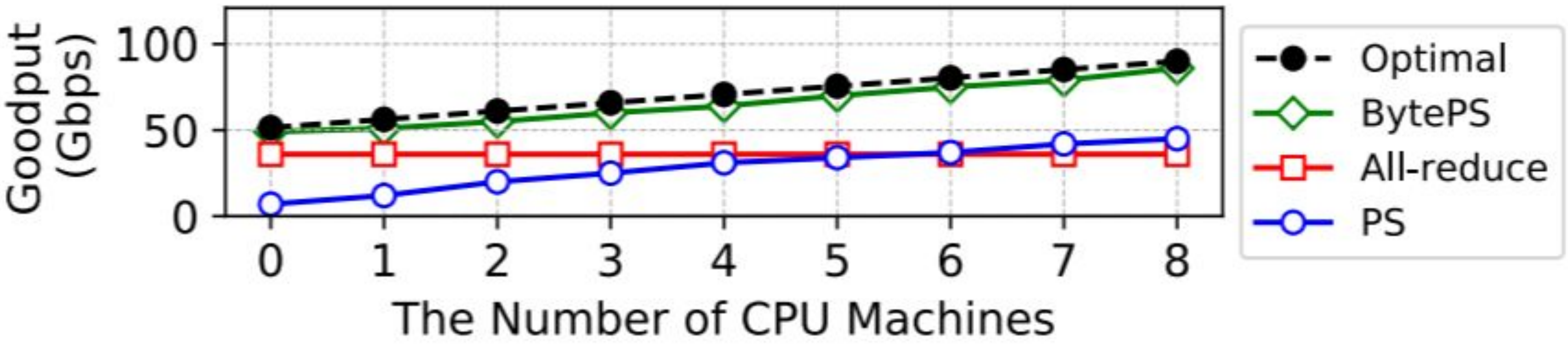
- CPU becomes a bottleneck as it cannot match increasing network bandwidth
- BytePS moves parameter update step to GPU machines

BytePS: Implementation

- Multi-stage Pipeline
  - Tensor partition and pipelining
- RDMA Performance Optimization
  - Reduces RDMA WRITE operation to one round-trip by storing remote buffer address
  - Eliminates internal loopback on GPU machines
  - Uses page-aligned memory
- Provides native Python interfaces

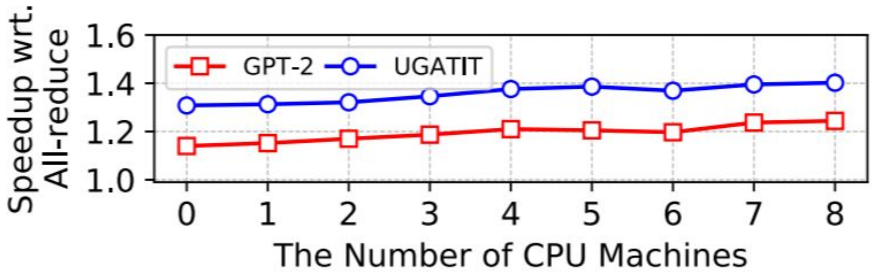
BytePS: Evaluation

- Performance is close to optimal, better than all-reduce/PS

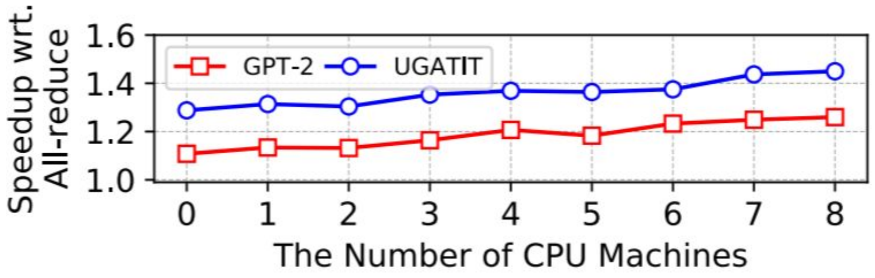


BytePS: Evaluation

- Running more CPU machines achieves up to 20% speed increase with <<10% cost, since GPU is much more expensive



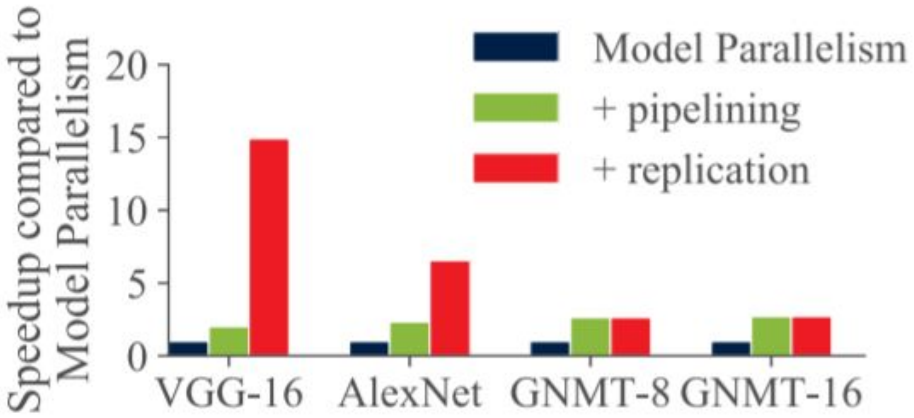
(a) PCIe-only GPU machines



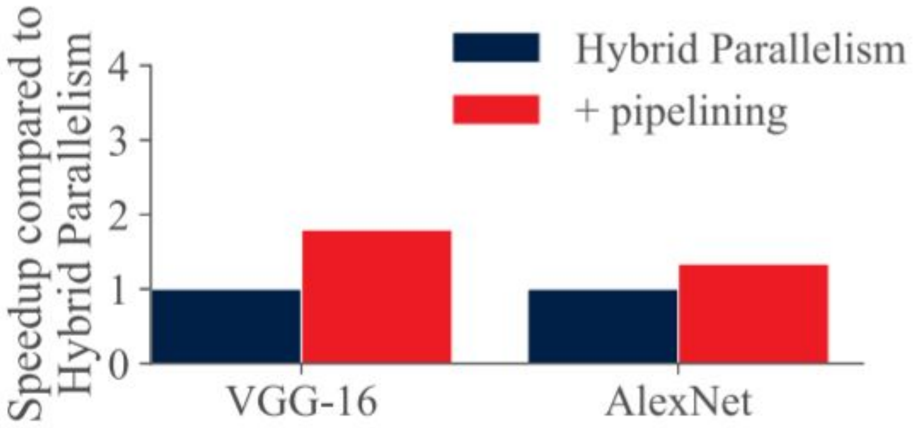
(b) NVLink-based GPU machines

Thank you!

PipeDream Evaluation: Other Intra-batch Schemes



(a) Model Parallelism.



(b) Hybrid Parallelism.

(red is Pipedream)

PipeDream Evaluation: Setup

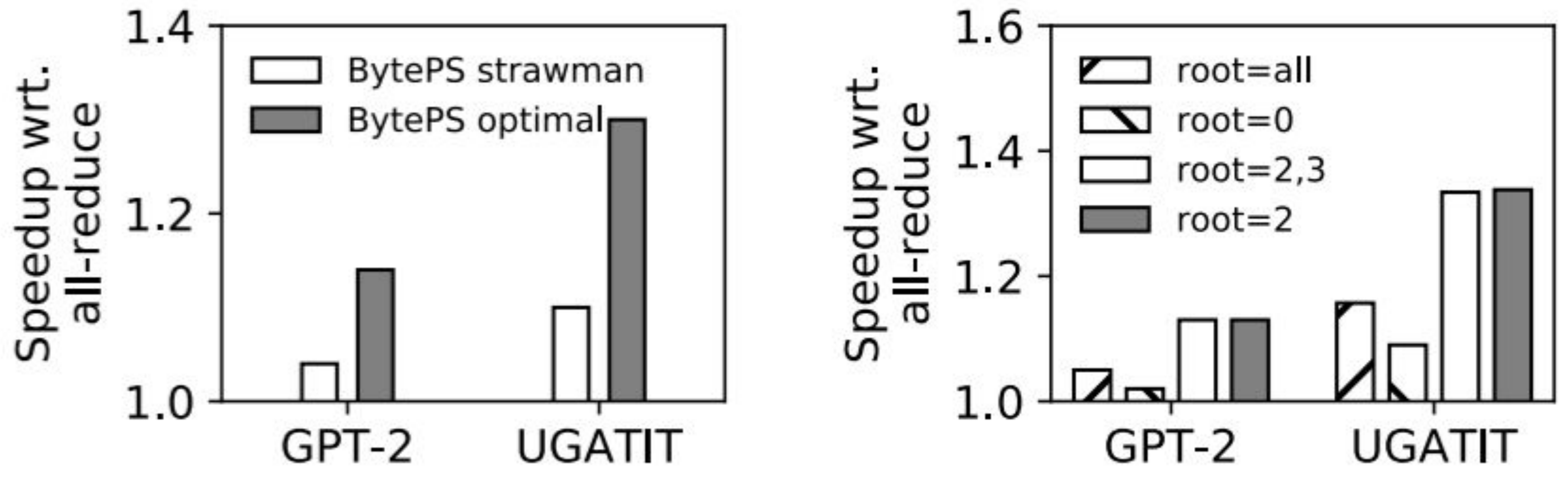
- Tasks:
  - Image Classification
  - Translation
  - Language Modeling
  - Video Captioning
- Clusters:

Cluster name	Server SKU	GPUs per server	Interconnects Intra-, Inter-server
Cluster-A	Azure NC24 v3	4x V100	PCIe, 10 Gbps
Cluster-B	AWS p3.16xlarge	8x V100	NVLink, 25 Gbps
Cluster-C	Private Cluster	1 Titan X	N/A, 40 Gbps

- Models:
  - VGG-16
  - ResNet-50
  - AlexNet
  - GNMT
  - AWD
  - S2VT
- Measure time trained to top-1 accuracy

BytePS: Evaluation

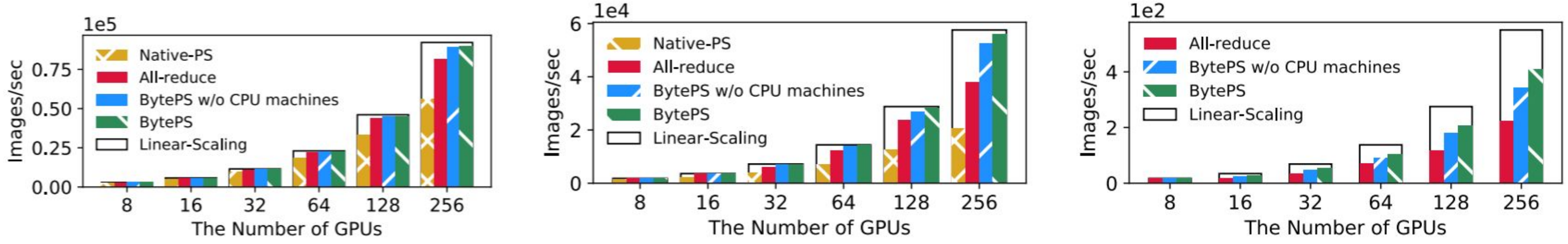
- Adaptation to intra-machine topology without optimization from CPU machines



(a) PCIe-only GPU machines (b) NVLink-based GPU machines

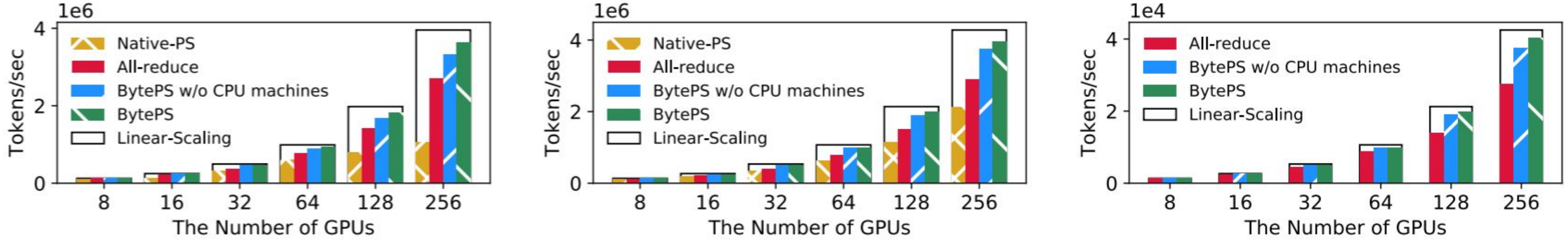
BytePS: Evaluation

- High scalability, speedup becomes larger as number of GPU machines increase



(a) TensorFlow, ResNet-50, batch=256 images (b) MXNet, VGG-16, batch=96 images (c) PyTorch, UGATIT, batch=2 images

Figure 15: Computer Vision models. The batch sizes are per GPU.



(a) TensorFlow, Transformer, batch=3072 tokens (b) MXNet, BERT-Large, batch=8192 tokens (c) PyTorch, GPT-2, batch=80 tokens

Figure 16: NLP models. The batch sizes are per GPU.