Accelerating Neural Network Training with Distributed Asynchronous and Selective Optimization (DASO)

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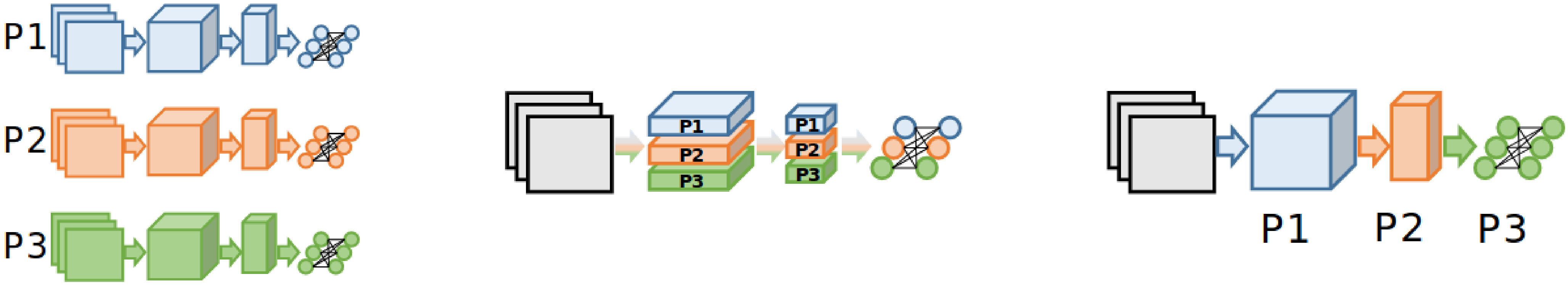
1: KIT: SCC
2: DLR: SC

Parallel Neural Networks

Training Networks Faster

- **Data parallel: networks mirrored on all processes**
- Model parallelism: network layers are divided across processes
- Pipelining: network is divided between processes by layer

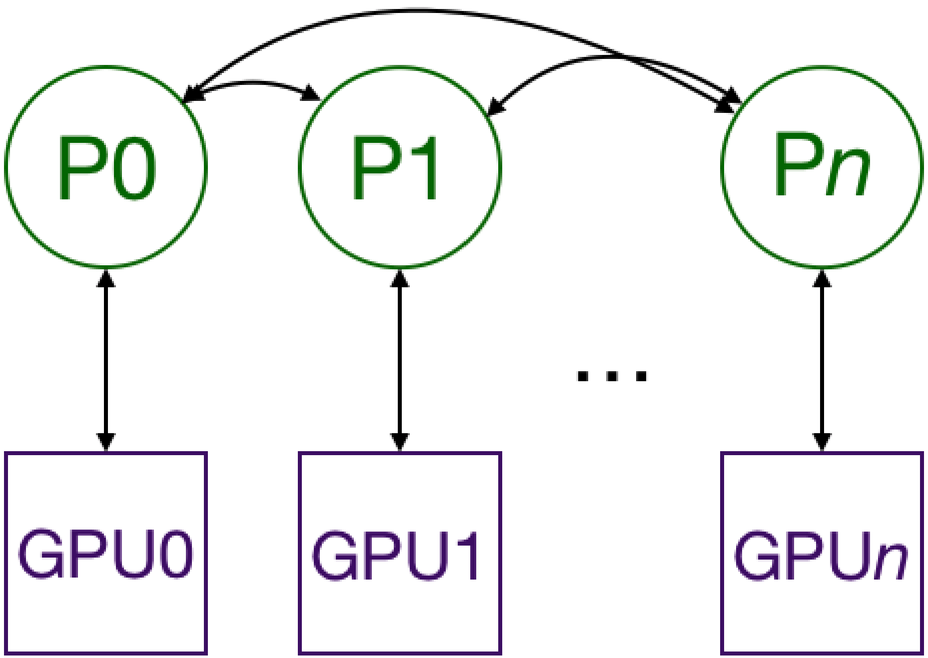


(a) Data Parallelism (b) Model Parallelism (c) Layer Pipelining

Data Parallel Neural Networks

Optimizing -- Focusing on SGD

- In DPNNs model parameters must be synchronized
  - Often done after each batch
  - All processes talk to each other
- Synchronous vs Asynchronous methods
- Regardless of method: this is one of the most prominent training bottlenecks!

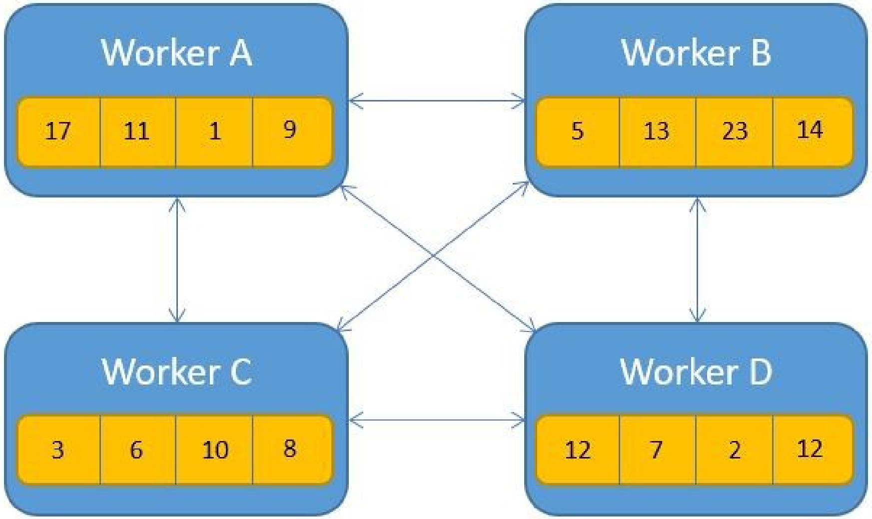


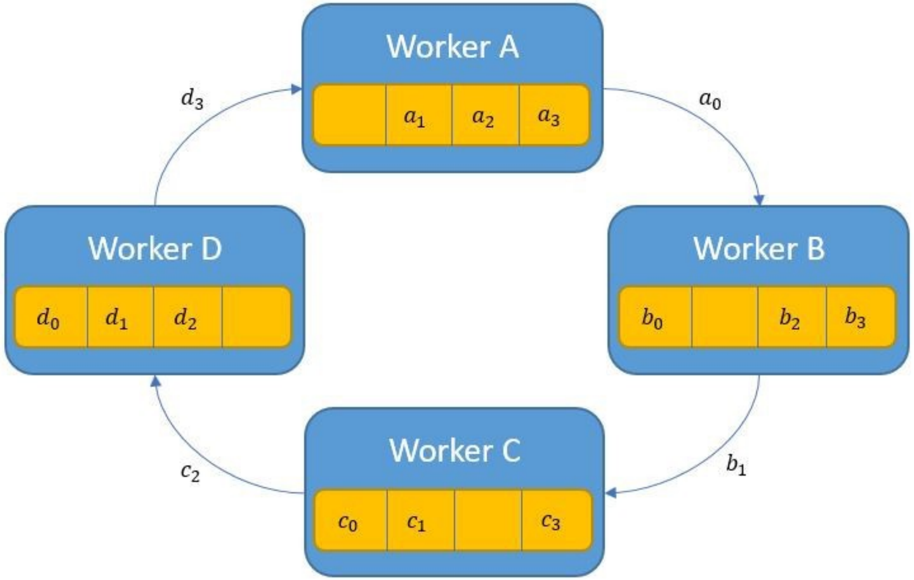
Optimizing DPNN Synchronization

Methods for Reducing Communication Time

- Tensor Fusion
- Compression

- Modified Allreduce logic
- Sending data during the backward step

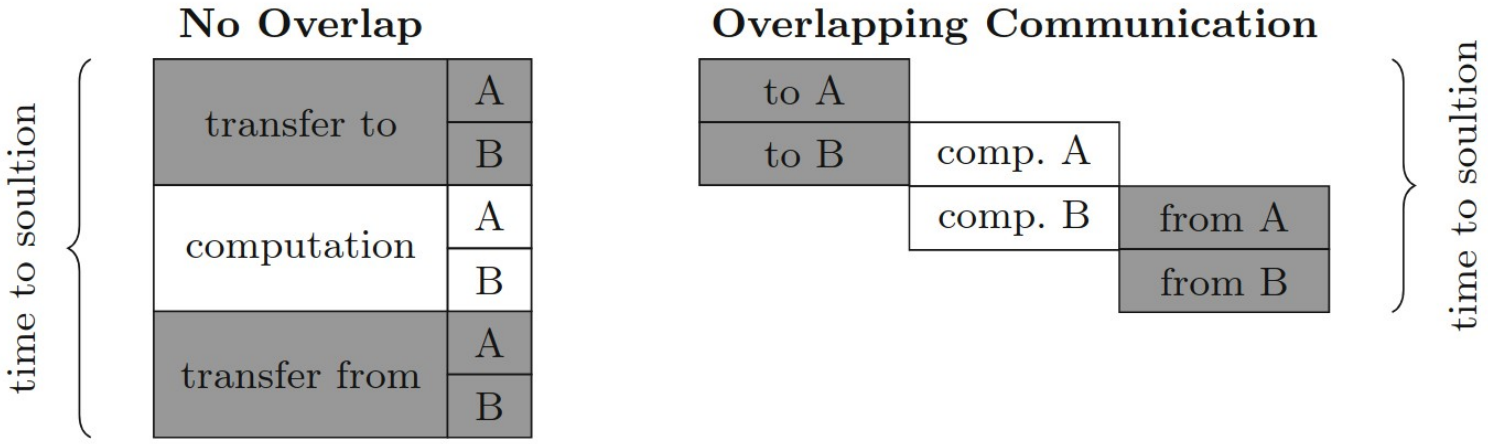




Old-School Distributed Computing

Hiding Communication Behind Computation

- Long studied, highly desired, arduous to do well
- When done well -> much faster execution without loss of accuracy



HeAT – The Helmholtz Analytics Toolkit

A Distributed and Accelerated Tensor Framework

- Distributed tensor framework
  - NumPy-like, Python interface
- Accelerated and distributed processing
  - **GPU Computing**
  - **Multiple cluster nodes via MPI**
- Seamlessly use GPUs and CPUs on both common clusters, personal workstations, and HPC systems
- Algorithms specifically tailored to distributed data
- High-level algorithms
  - Sklearn-like machine-learning
  - **PyTorch-style Neural Networks**

Distributed Asynchronous and Selective Optimization - DASO

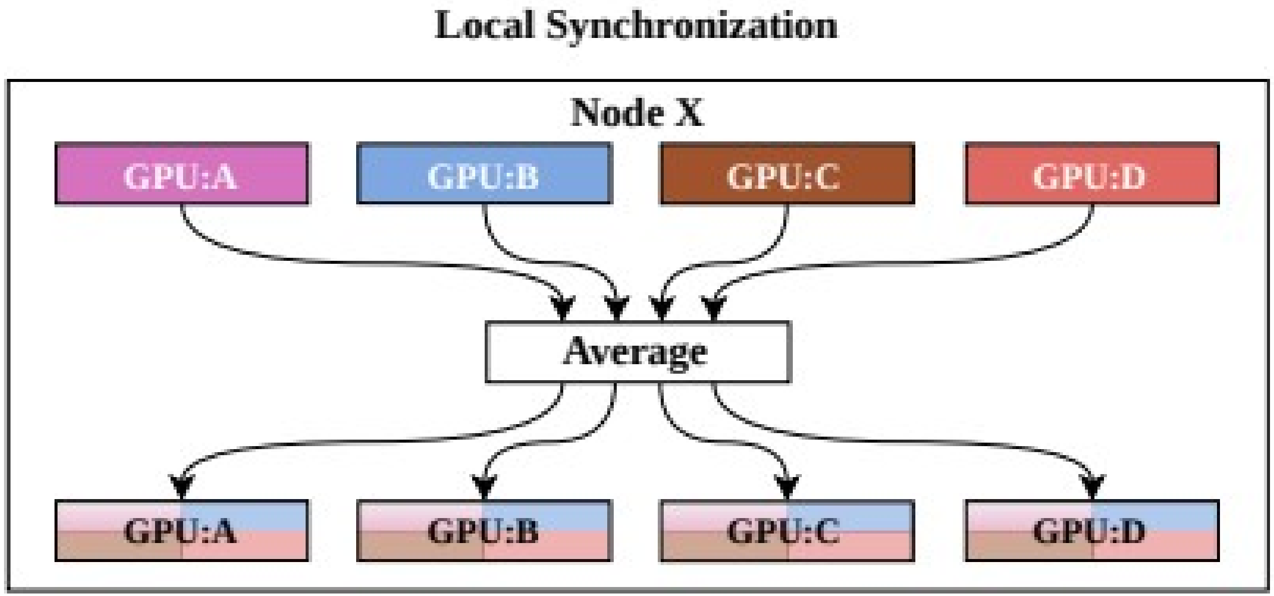
Motivation

- Better utilize cluster architecture
- Reduce communication overhead
- Increase speed with selective global updates
- Divide the global synchronization into three steps:
  1) Local Synchronization
  2) Global Synchronization
  3) Local Update

Distributed Asynchronous and Selective Optimization - DASO

Local Synchronization

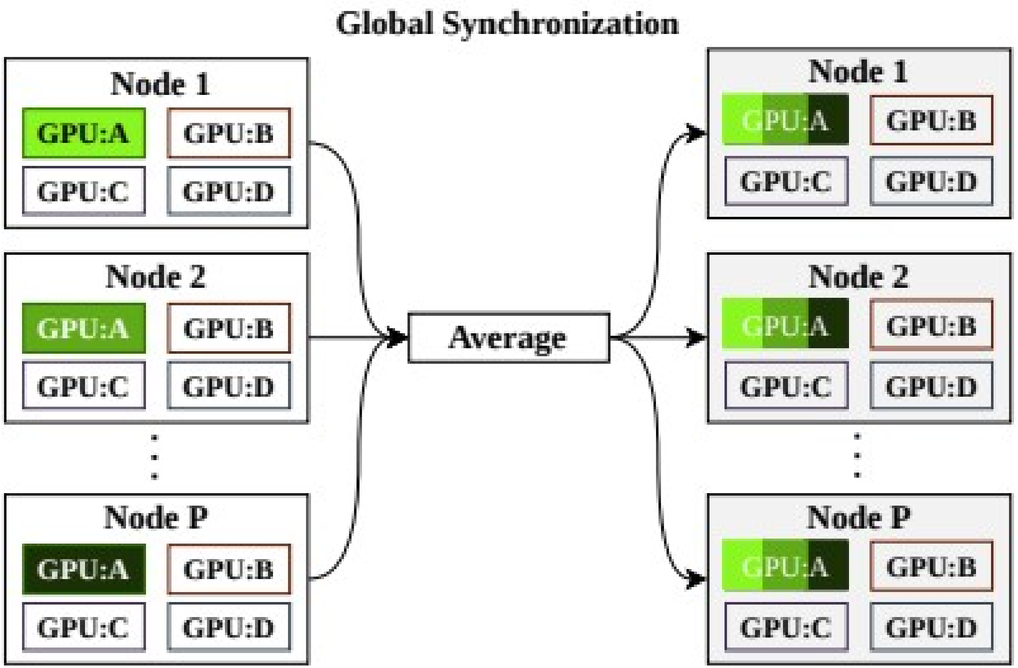
- Traditional synchronization of gradients
- torch.nn.DistributedDataParallel



Distributed Asynchronous and Selective Optimization - DASO

Global Synchronization

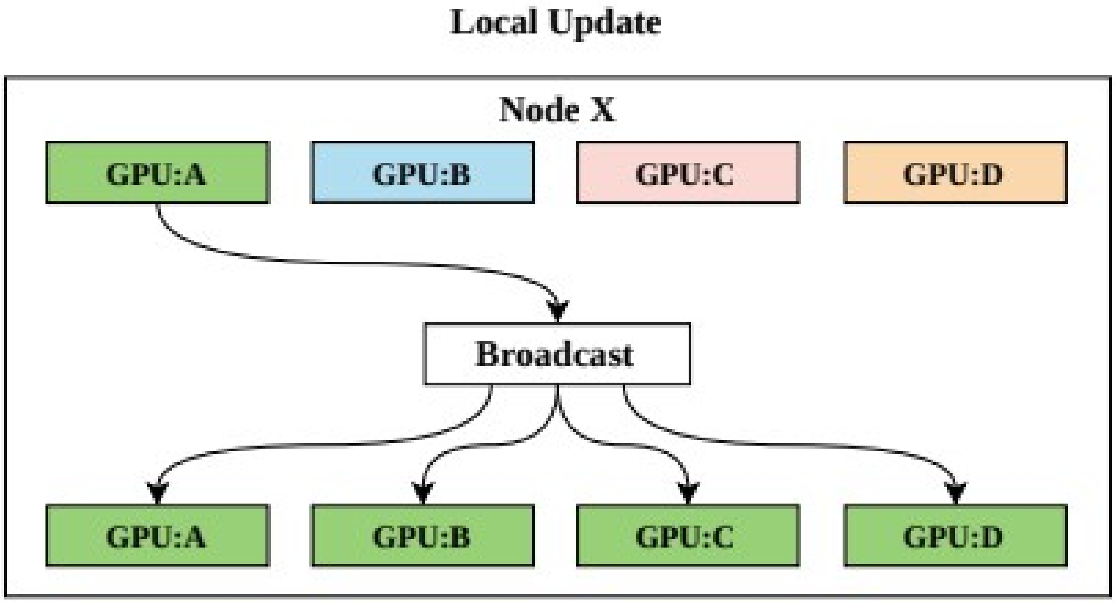
- One GPU/node communicates parameters with the other **nodes**
- MPI Groups
- Average operation only occurs within this group



Distributed Asynchronous and Selective Optimization - DASO

Local Update

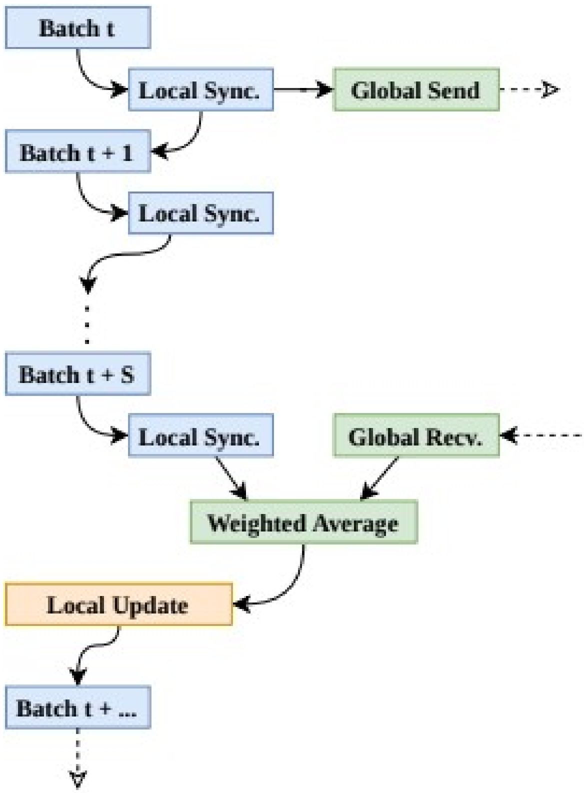
- After averaging, the MPI Group member sends it to overwrite the network parameters on the other GPUs



Distributed Asynchronous and Selective Optimization - DASO

Synchronization Order in Practice

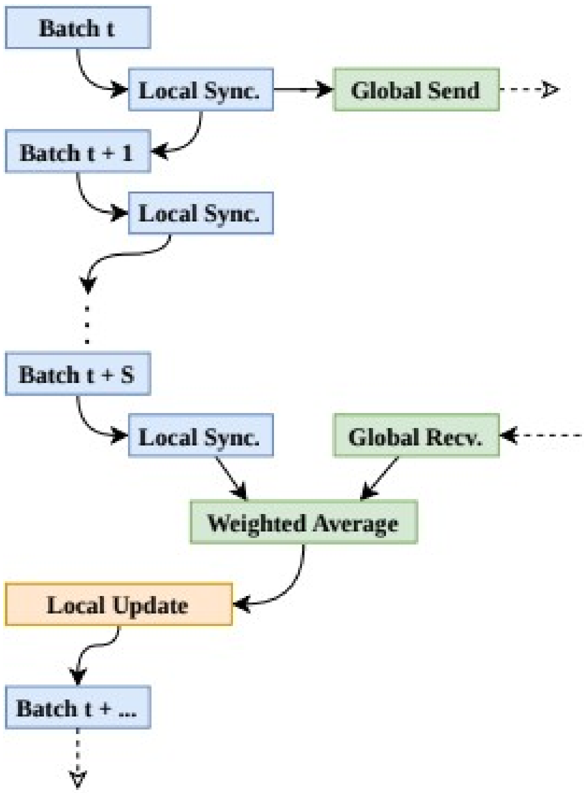
- Warm-up : traditional DPNN training
- Cycling
  - delay between sending and receiving global parameters
  - weighted average for folding in global parameters to updated model states
- Cool-down: traditional DPNN training



Distributed Asynchronous and Selective Optimization - DASO

Cycling Phase

- After parameters are sent, GPUs local to one node continue to train
- After `S` batches, the global parameters are received
- Weighted average to merge local paramters
  - local parameters are doubly weighted
- The number of batches, `S`, between sending and receiving parameters cycles by factors of two
  - i.e. 4, 2, 1, 4, 2, 1, ...



Distributed Asynchronous and Selective Optimization - DASO

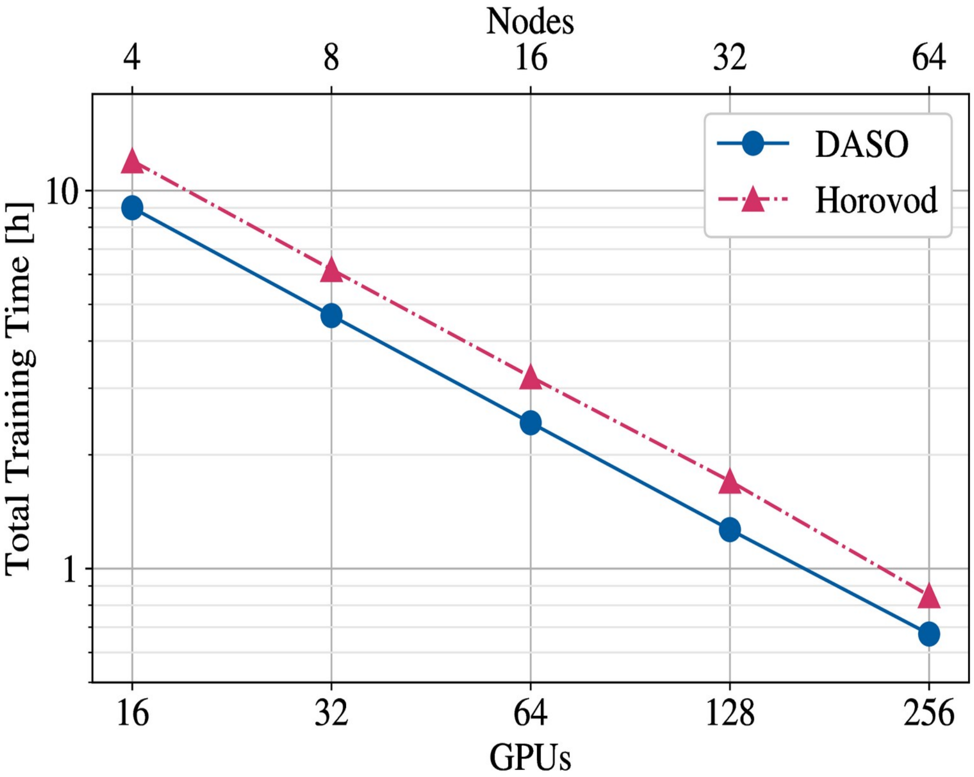
Benefits

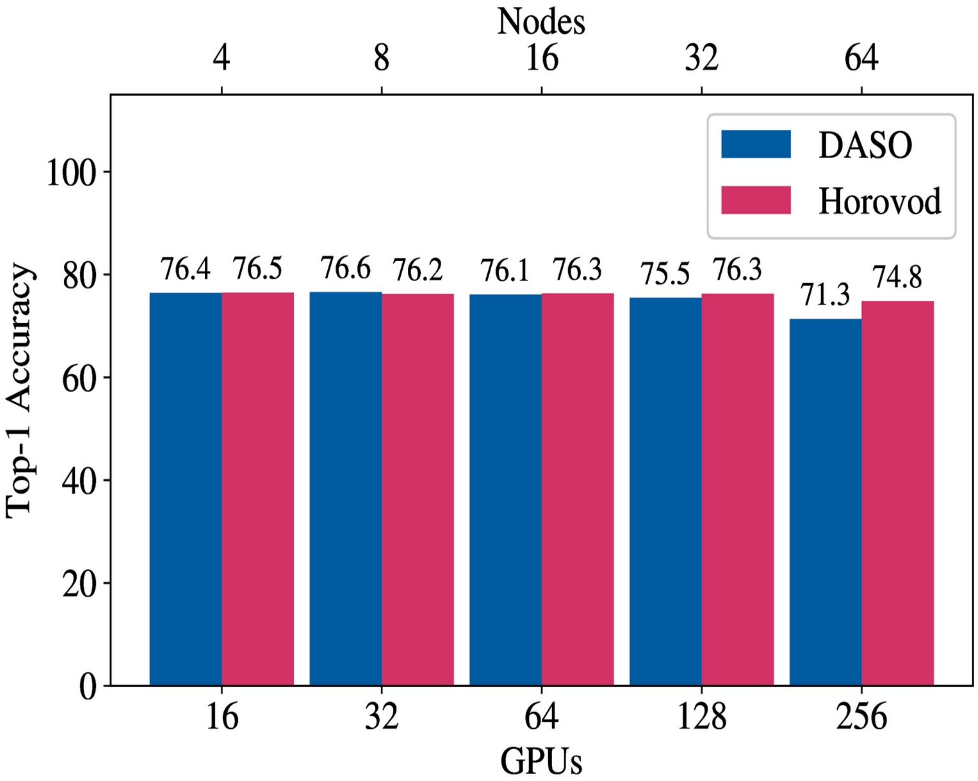
- Fully utilize computing clusters
- Maintain accuracy at large node counts
- Easy to use / implement

```python
import heat as ht
import torch
...
# create PyTorch distributed group
world_size = ht.MPI_WORLD.size
rank = ht.MPI_WORLD.rank
local_rank = rank % num_local_gpus
torch.distributed.init_process_group(
    backend="nccl",
    rank=local_rank,
    world_size=world_size
)
...
# the DASO optimizer is created
daso_optimizer = ht.optim.DASO(
    local_optimizer=optimizer,
    total_epochs=num_epochs
)
...
# the hierarchical network is created
ht_model = ht.nn.DataParallelMultiGPU(
    net,
    daso_optimizer
)
```

DASO vs Horovod – ImageNet Training with ResNet-50

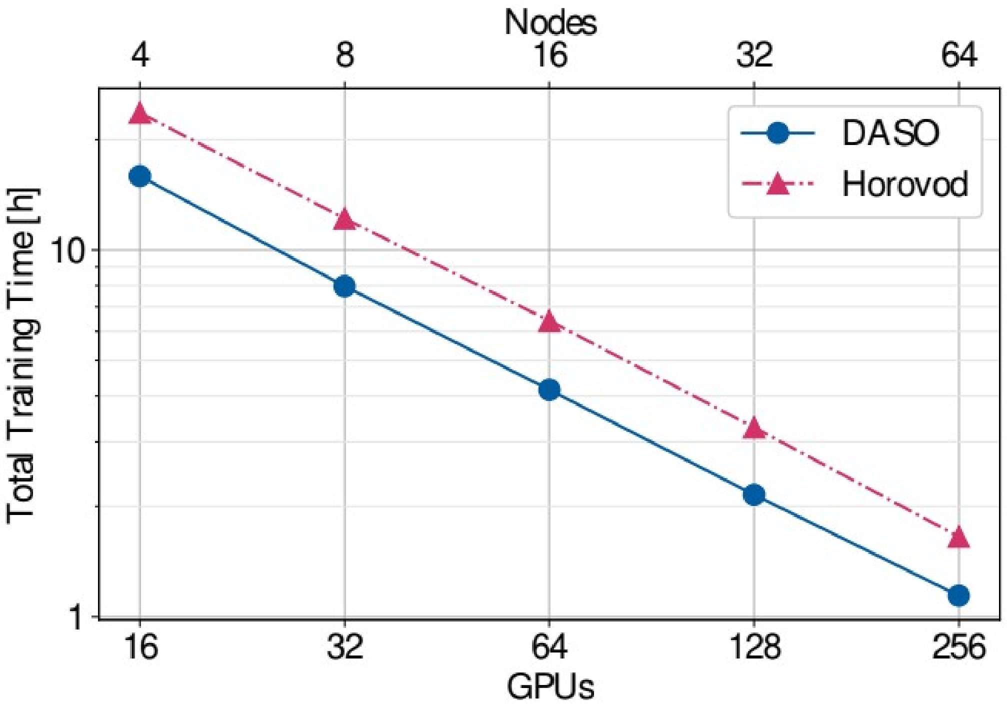
DASO - Distributed Asynchronous and Selective Optimization

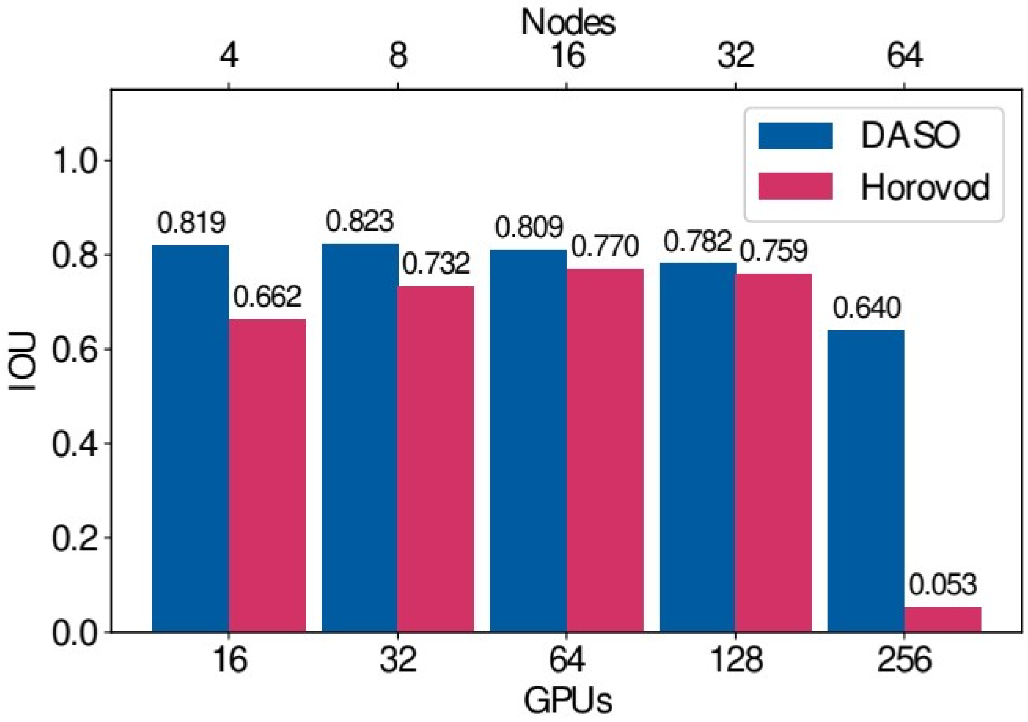




DASO vs Horovod – State-Of-The-Art Model on CityScapes

DASO - Distributed Asynchronous and Selective Optimization





DASO

PyTorch-Style + HPC

- Currently, can you:
  - Train a PyTorch NN with a HeAT dataset? ✓
  - Use PyTorch functions within training? ✓
  - Use the PyTorch Dataloader? ✓
  - Train with a dataset which does not fit into the available memory? ✓
  - Train a network faster than Horovod? ✓

Bottom Line:
DASO trains a network up to 34% faster than Horovod without losing accuracy.

Come and Feel the HeAT!

- Open source software with the liberal MIT license

- Install it with the PIP package:

```
pip install heat
```

  Or join us on GitHub:

```
git clone https://github.com/helmholtz-analytics/heat
```

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Available Features and Ongoing Projects

Simple, 2 process example

- **Available Currently:**
- Mean, Std, Var, Average
- Reshape, flatten, ravel, flip
- Complex numbers
- Matrix multiplication
- Histograms
- K-means + friends
- Spectral clustering
- LASSO
- Data Parallel Neural Networks
- And many more!

- **Ongoing Projects**
- ASSET
- mpi4torch
- SVD
- DPNN improvements and extenstions