EURO

Multi-GPU and Multi-Node with PyTorch DDP

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Agenda

- Parallelism
- Distributed Training
- Native Data Parallel Training
- PyTorch DDP
- Hands-On: PyTorch DDP

Parallelism

Parallelism can be found in:

- Low level operations in the network
- Parallelized networks
- Distributed training

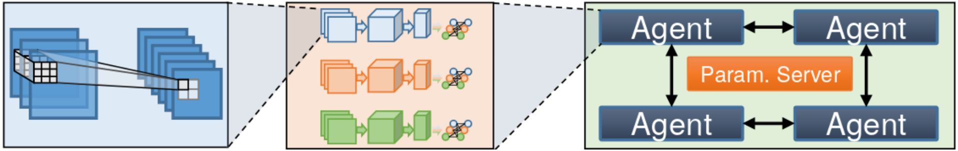
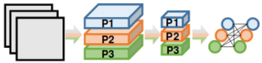
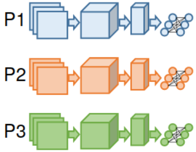


Image: Ben-Nun, et al.

Difference Data vs. Model Parallelism



- Network layers assigned to different workers
- Every worker trains with the same data
- Activations are exchanged (requires large I/O bandwidth)
- **Enables bigger models**



- All workers see the same network
- Every worker trians with different data
- Gradints (weights) are exchanged (averaging to common model)
- Side effect: "sharp" minima
- **Enables faster training**

Images: Ben-Nun, et al.

Distributed Training

What if one node (GPU) is not enough?

- Model Consistency
- Parameter Distribution and Communication:
  Centralization and Compression (e.g. FP16)
- Training Distribution:
  Model Consolidation and Optimization Algorithms

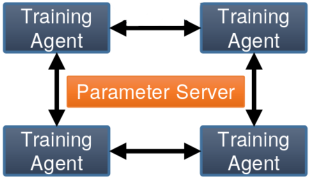
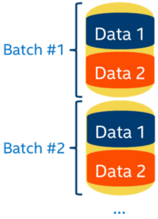
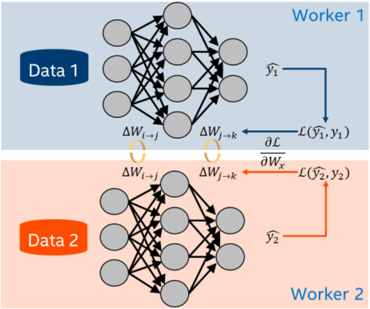


Image: Ben-Nun, et al.

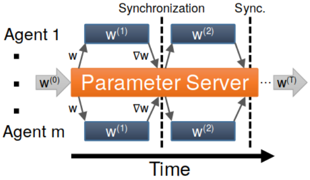
Distributed Training: Data Parallelism in Detail



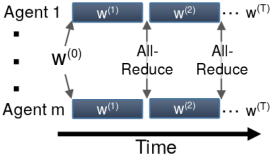


- Batch size limits parallelism
- Scaling batch size requires scaling of learning rate (linearly)

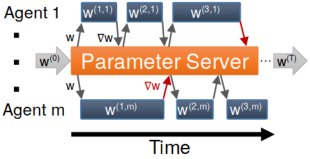
Distributed Training: Model Consistency



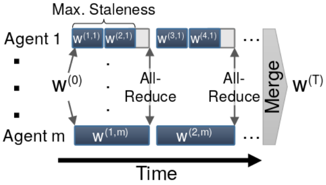
(a) Synchronous, Parameter Server



(b) Synchronous, Decentralized



(c) Asynchronous, Parameter Server



(d) Stale-Synchronous, Decentralized

Image: Ben-Nun, et al.

Distributed Training: Libraries

Different backends:

- Message Passing Interface (MPI)
- NVIDIA Collective Communications Library (NCCL)
- Intel oneAPI Collective Communications Library (oneCCL) ▸ Intel oneCCL
  ~~Intel Machine Learning Scaling Library~~ ▸ Intel MLSL

Strategies vary among frameworks:

- ▸ Horovod for Tensorflow/Keras, PyTorch and MXNet (NCCL + MPI, or Gloo)
- Tensorflow has different "strategies" (e.g. `MultiWorkerMirroredStrategy`)
- PyTorch supports MPI, NCCL and Gloo

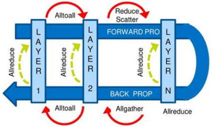


Image: Intel (MLSL)

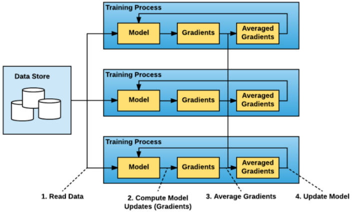


Image: Uber

NVIDIA Collective Communications Library

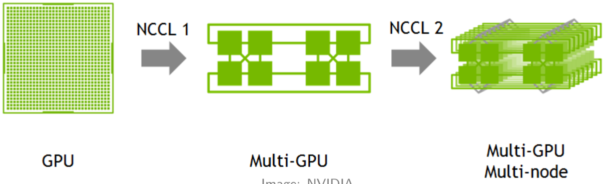


Image: NVIDIA

NVIDIA Collective Communications Library (NCCL):

- Similarity to MPI collectives
- Pre NCCL 2.4: ring communication
- NCCL 2.4: double binary tree communication with improved latency
- Supported by major Deep Learning frameworks, e.g. Tensorflow, PyTorch
- Supported by distributed training framework Horovod

Native Data Parallel Training

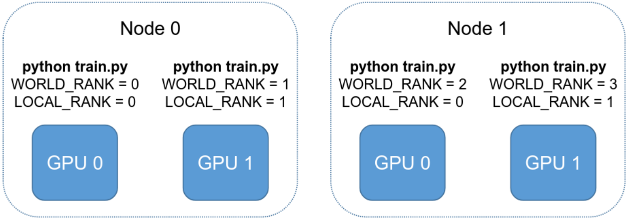
One of the first ways was Uber's Horovod:

- Aimed at and demonstrated for large scale
- Uses MPI based collective communication (synchronous & decentralized)
- Only small code modifications needed
- Supports Tensorflow (1.x & 2.x) + Keras, PyTorch, and MXNet

Native support of (sync.) data parallel training is available meanwhile:

- Tensorflow:
  `tf.distribute.Strategy` with different strategies (MirroredStrategy, TPUStrategy, MultiWorkerMirroredStrategy, CentralStorageStrategy, ParameterServerStrategy)
  ▸ Documentation
- PyTorch:
  `torch.distributed` with three backends (GLOO, MPI, NCCL) ▸ Documentation
  Use ▸ `torch.nn.parallel.DistributedDataParallel` (DDP) with **NCCL** backend for multi-node/-GPU.

PyTorch DDP



1. Initialize:

```
import os
import torch
import torch.distributed as dist

LOCAL_RANK = int(os.environ['OMPI_COMM_WORLD_LOCAL_RANK'])
WORLD_SIZE = int(os.environ['OMPI_COMM_WORLD_SIZE'])
WORLD_RANK = int(os.environ['OMPI_COMM_WORLD_RANK'])

os.environ["MASTER_ADDR"] = "acn1" # Master node (rank 0 process)
os.environ["MASTER_PORT"] = "6006" # Some free port on master node

dist.init_process_group(backend="nccl", rank=WORLD_RANK, world_size=WORLD_SIZE)
```

PyTorch DDP - cont'd

2. Assign to GPU(s)

```
device = torch.device("cuda:" + str(LOCAL_RANK))
model = my_model.to(device)
```

3. Make model aware of DDP

```
ddp_model = torch.nn.parallel.DistributedDataParallel(model, device_ids=[LOCAL_RANK], output_device=LOCAL_RANK)
```

4. Data partitioning

```
train_sampler = torch.utils.data.distributed.DistributedSampler(train_set, num_replicas=WORLD_SIZE, rank=WORLD_RANK)
train_loader = torch.utils.data.DataLoader(train_set, batch_size=batch_size, sampler=train_sampler)
```

5. I/O on master only

```
if WORLD_RANK == 0: # for shared file system
    mnist_trainset = datasets.MNIST(root='./data', train=True, download=True, transform=None)
...
if WORLD_RANK == 0:
    print("Epoch␣=␣{:2d}:␣Validation␣Loss␣=␣{:5.3f},␣Validation␣Accuracy␣=␣{:5.3f}".format(epoch+1, v_loss, val_accuracy))
...
if WORLD_RANK == 0:
    torch.save(model.state_dict(), 'model.pt')
```

PyTorch DDP - cont'd

Run in an MPI environment:

- OpenMPI:

```
$ mpirun -np 4 --map-by ppr:2:node --host node1,node2 python train.py
```

- Intel MPI:

```
$ mpirun -n 4 -np 2 -hosts node1,node2 python train.py
```

Note:
This runs four processes, two on each node, each executing the **same** `train.py` script!

Difference PyTorch and Tensorflow/Horovod

- Tensorflow/Horovod:
  - Data parallelization is done in optimizer
  - Decomposition of data is done with `tf.data.Dataset.shard`
- PyTorch:
  - Data parallelization is done in model:

```
import os
import torch.distributed as dist
from torch.nn.parallel import DistributedDataParallel as DDP
...
num_gpus = int(os.environ['OMPI_COMM_WORLD_SIZE'])
rank = int(os.environ['OMPI_COMM_WORLD_RANK'])

dist.init_process_group("nccl", rank=rank, world_size=num_gpus)

model = Model().to(rank) # Move to GPU
ddp_model = DDP(model, device_ids=[rank])
```

  - Data decomposition with `torch.utils.data.distributed.DistributedSampler`, e.g.:

```
from torch.utils.data import DataLoader
from torch.utils.data.distributed import DistributedSampler
...
sampler = DistributedSampler(dataset, num_replicas=num_gpus, rank=rank)
loader = DataLoader(dataset, sampler=sampler)
```

Hands-On Time

Thank you!

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