Distributed Machine Learning Frameworks

Amir H. Payberah
payberah@kth.se
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The Course Web Page

`https://fid3024.github.io`

Review of the Current Frameworks

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- As of v2.2, the Multi Worker Mirrored Strategy (allreduce) is integrated into TensorFlow for data parallelism.
    - Its update rule is synchronous and it has communication and computation overlapped.
- TensorFlow also has extensions to support different parallelization approaches.

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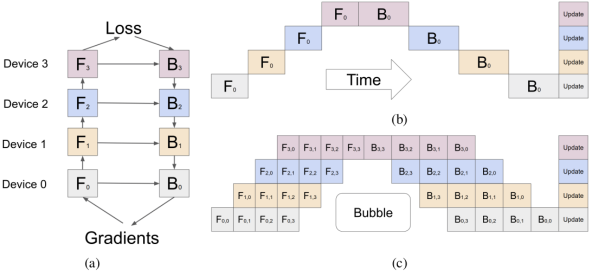
- A mesh is an n-dimensional array of processors, connected by a network.
- Each tensor is distributed across all processors in a mesh.

TensorFlow (3/4)

- GPipe is a pipeline parallelism library implemented under Lingvo (a TensorFlow framework focusing on seq-to-seq models).



[Huang et al., GPipe: Efficient Training of Giant Neural Networks using Pipeline Parallelism, 2019]

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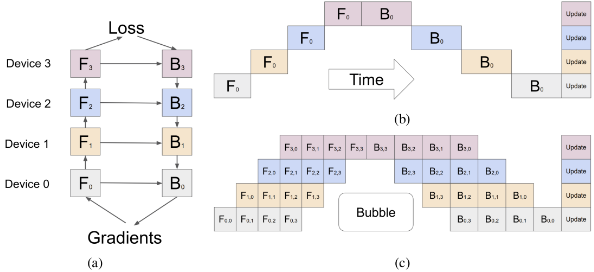
- Partitions operation in the forward and backward pass and allows data transfer between neighboring partitions.



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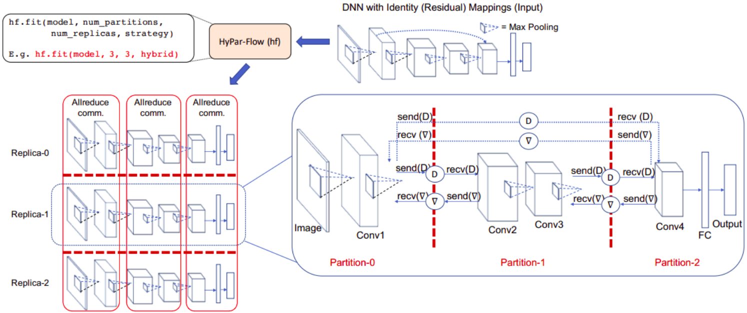

[Awan et al., HyPar-Flow: Exploiting MPI and Keras for Scalable Hybrid-Parallel DNN Training with TensorFlow, 2020]

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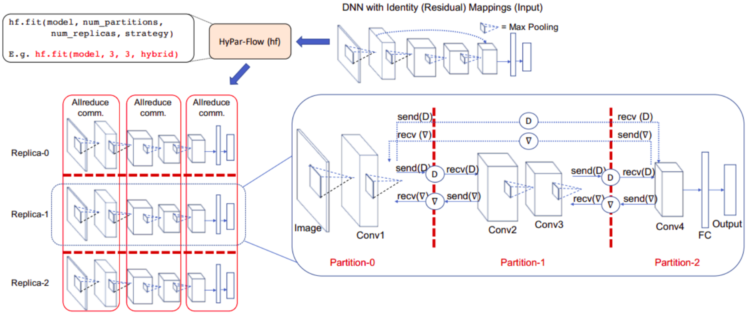
- It only requires the strategy, the number of model partitions, and the number of model replicas from the user to utilize them with every possible intra-iteration parallelization.



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- S-Caffe is a CUDA-Aware MPI runtime and Caffe for data parallelism on GPU clusters.

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  - Overlapping communication with computation
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- It uses a distributed key-value store for data synchronization over multiple devices.

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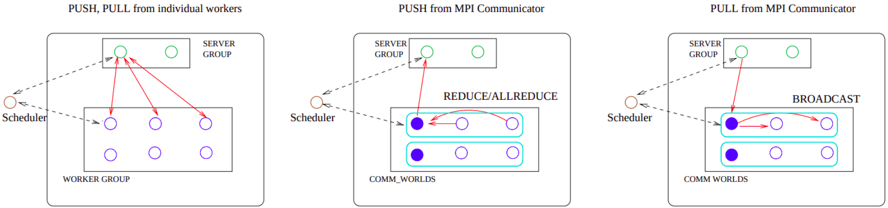

[Mamidala et al., MXNet-MPI: Embedding MPI parallelism in Parameter Server Task Model for Scaling Deep Learning, 2018]

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- It works on top of another DL framework (e.g., TensorFlow, PyTorch, and MXNET).
- It has one of the most optimized asynchronous collectives.
- However, the communication overhead significantly grows with the number of nodes.

FlexFlow

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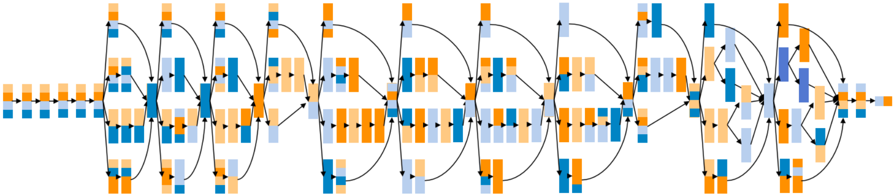
- It uses guided randomized search of the SOAP space to find a fast parallelization strategy for a specific parallel machine.



[Jia et al., Beyond Data and Model Parallelism for Deep Neural Networks, 2019]

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- Due to using Spark, it is equipped with fault tolerance and a fair load balancing mechanism.

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- DeepSpeed brings ZeRO techniques through lightweight APIs compatible with PyTorch.

BigDL: A Distributed Deep Learning Framework for Big Data

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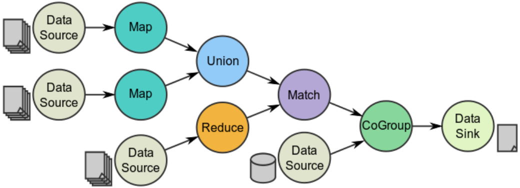
- Several connectors, e.g., TFX, CaffeOnSpark, TensorFlowOnSpark, SageMaker.
- However, the adaptation between different frameworks can impose very large overheads in practice.

Spark Dataflow Model

- Job is described based on directed acyclic graphs (DAG) data flow.



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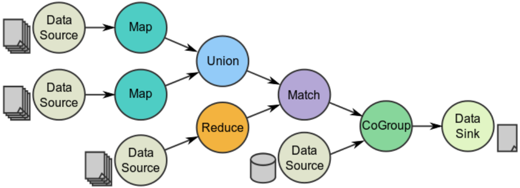

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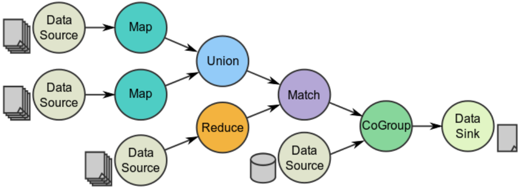


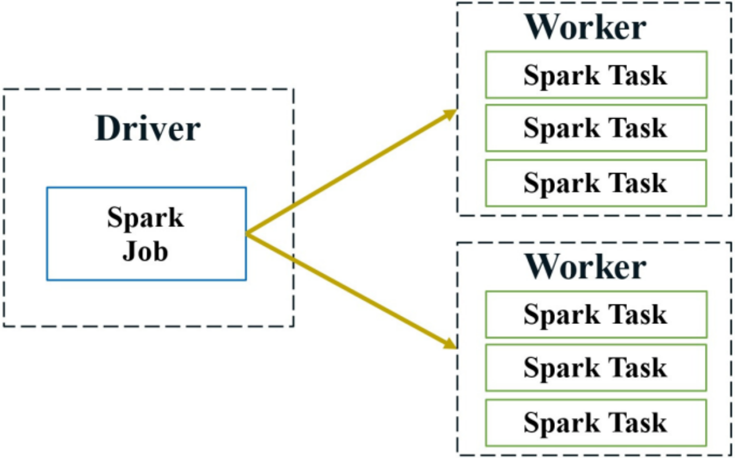
Resilient Distributed Datasets (RDD) (1/2)

- A distributed memory abstraction.
- Immutable collections of objects spread across a cluster.
    - Like a `LinkedList <MyObjects>`

Resilient Distributed Datasets (RDD) (2/2)

- An RDD is divided into a number of partitions, which are atomic pieces of information.
- Partitions of an RDD can be stored on different nodes of a cluster.

Spark Execution Model



[Dai et al., BigDL: A Distributed Deep Learning Framework for Big Data, 2019]

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```
#distributed data processing
spark = SparkContext(appName="text_classifier", ...)
input_rdd = spark.textFile("hdfs://...")
train_rdd = input_rdd.map(lambda x: read_text_and_label(x))
                     .map(lambda data: decode_to_ndarrays(data))
                     .map(lambda arrays: to_sample(arrays))

#distributed training
model = Sequential().add(Recurrent().add(LSTM(...)))
                    .add(Linear(...)).add(LogSoftMax())
optimizer = Optimizer(model=model, training_rdd=train_rdd,
                      criterion=ClassNLLCriterion(),
                      optim_method=Adagrad(), ...)
trained_model = optimizer.optimize()

#distributed inference
test_rdd = ...
prediction_rdd = trained_model.predict(test_rdd)
```

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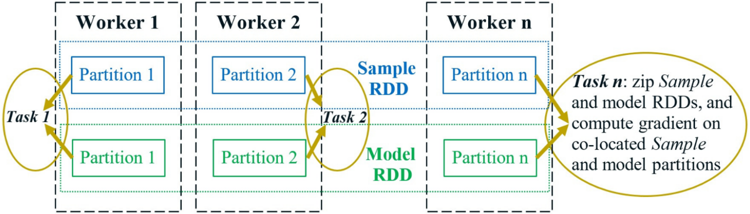

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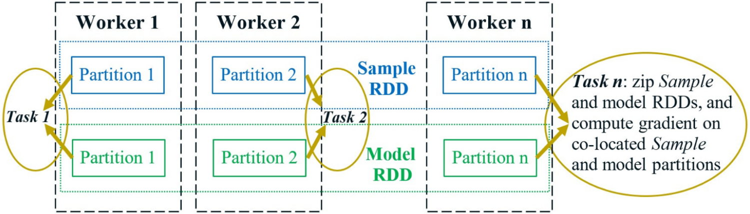
- RDD of models, each of which is a replica of the original NN model.



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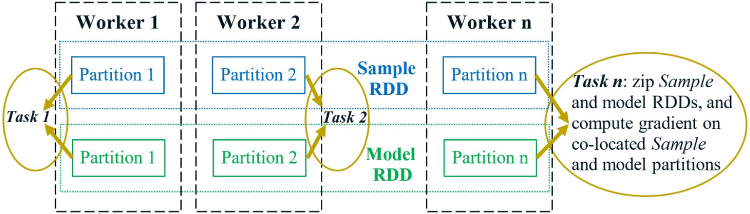
- In each iteration, a single model forward-backward Spark job.



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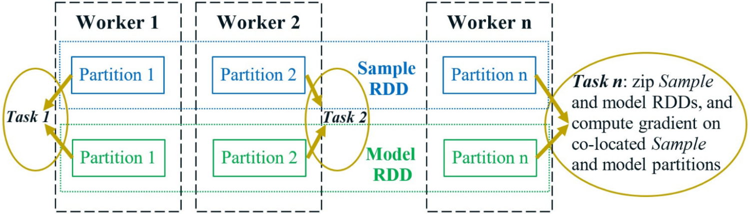

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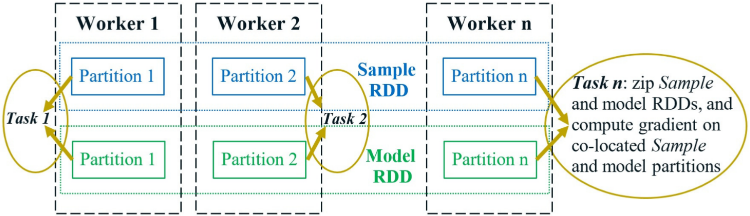
Data-Parallel Training in BigDL (2/3)

- In each iteration, a single model forward-backward Spark job.
- Applies the functional zip operator to the co-located partitions of the two RDDs.
- Then, computes the local gradients in parallel for each model replica.



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Data-Parallel Training in BigDL (3/3)

Algorithm 1 Data-parallel training in BigDL

```
for i = 1 to M do
    //"model forward-backward" job
    for each task in the Spark job do
        read the latest weights;
        get a random batch of data from local Sample partition;
        compute local gradients (forward-backward on local model
         replica);
    end for
    //"parameter synchronization" job
    aggregate (sum) all the gradients;
    update the weights per specified optimization method;
end for
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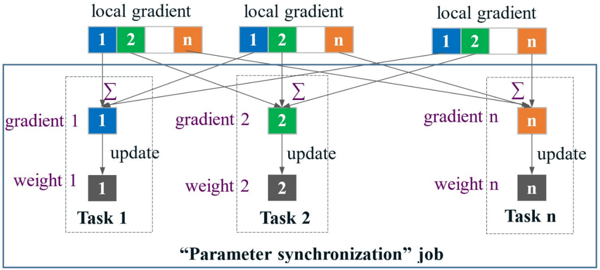
- Fine-grained operations are not supported by Spark.
- BigDL directly implements an efficient AllReduce-like operation using existing primitives in Spark.

Parameter Synchronization in BigDL (2/2)



Algorithm 2 "Parameter synchronization" job

1: **for** each task n in the "parameter synchronization" job **do**
2: **shuffle** the n^{th} partition of all gradients to this task;
3: aggregate (sum) these gradients;
4: updates the n^{th} partition of the weights;
5: **broadcast** the n^{th} partition of the updated weights;
6: **end for**

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PyTorch Distributed: Experiences on Accelerating Data Parallel Training

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  - A `LinearModule` contains a `weight` and a `bias` parameter.
  - Whose `forward` function generates the output by multiplying the input with the `weight` and adding the `bias`.
- An application composes its own `Module` by stitching together `Modules` (e.g., linear, convolution) and `Functions` (e.g., relu, pool) in a `forward` function.

PyTorch (2/2)

```python
import torch
import torch.nn as nn
import torch.nn.parallel as par
import torch.optim as optim

# initialize torch.distributed properly
# with init_process_group

# setup model and optimizer
net = nn.Linear(10, 10)
opt = optim.SGD(net.parameters(), lr=0.01)

# run forward pass
inp = torch.randn(20, 10)
exp = torch.randn(20, 10)
out = net(inp)

# run backward pass
nn.MSELoss()(out, exp).backward()

# update parameters
opt.step()
```

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- They synchronize gradients to keep parameters consistent across training iterations.

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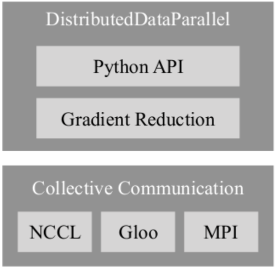
- `DistributedDataParallel` (DDP) for data parallel training across GPUs and machines.
- `RPC` for general distributed model parallel training.

Data Parallelism in PyTorch (3/4)

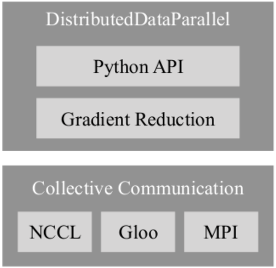
- DDP module enables data parallel training across multiple processes and machines.



[Li et al., PyTorch Distributed: Experiences on Accelerating Data Parallel Training, 2020]

Data Parallelism in PyTorch (3/4)

- DDP module enables data parallel training across multiple processes and machines.
- AllReduce is the primitive communication API used by DDP.



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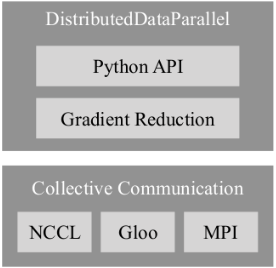
- It is supported by multiple communication libraries, including NCCL, Gloo, and MPI.



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Data Parallelism in PyTorch (4/4)

```python
import torch
import torch.nn as nn
import torch.nn.parallel as par
import torch.optim as optim

# initialize torch.distributed properly
# with init_process_group

# setup model and optimizer
net = nn.Linear(10, 10)
opt = optim.SGD(net.parameters(), lr=0.01)

# run forward pass
inp = torch.randn(20, 10)
exp = torch.randn(20, 10)
out = net(inp)

# run backward pass
nn.MSELoss()(out, exp).backward()

# update parameters
opt.step()
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- DDP guarantees correctness by letting all training processes:
  1. Start from the same model state.
  2. Consume the same gradients in every iteration.
- Step 1 can be achieved by broadcasting model states from one process to all others.
- Step 2 can be achieved by inserting a gradient synchronization phase after the local backward pass and before updating local parameters.

Gradient Reduction - Naive Solution (2/3)

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- `DDP` can register autograd hooks to trigger computation after every backward pass.
- When fired, each hook scans through all local model parameters, and retrieves the gradient tensor from each parameter.
- Then, it uses the `AllReduce` collective communication call to calculate the average gradients on each parameter across all processes, and writes the result back to the gradient tensor.

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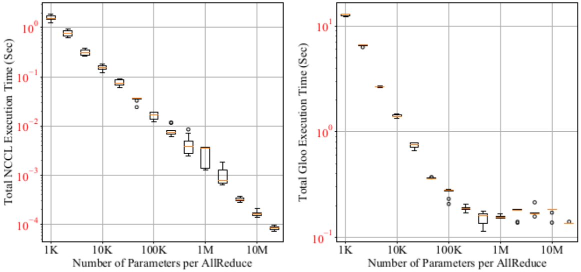
- 1. Collective communication performs poorly on small tensors, which will be especially prominent on large models with massive numbers of small parameters.
- 2. Separating gradient computation and synchronization forfeits the opportunity to overlap computation with communication due to the hard boundary in between.

Gradient Reduction - Gradient Bucketing (1/2)

- Collective communications are more efficient on large tensors.



(a) NCCL (b) GLOO

[Li et al., PyTorch Distributed: Experiences on Accelerating Data Parallel Training, 2020]

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- Instead, waits for a short period and buckets multiple gradients into one `AllReduce` operation.
- But not to communicate all gradients in one single `AllReduce`, otherwise, no communication can start before the computation is over.
- With relatively small bucket sizes, DDP can launch `AllReduce` operations concurrently with the backward pass to overlap communication with computation.

Overlap Computation with Communication (1/2)

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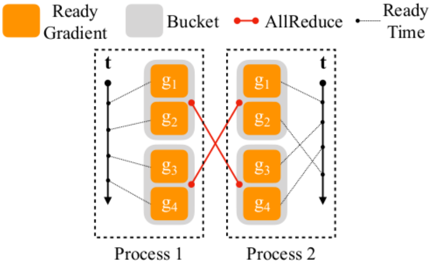
- If hooks of all gradients in the same buckets have fired, then `AllReduce` on that bucket will be triggered.

Overlap Computation with Communication (2/2)

- The reducing order must be the same across all processes, otherwise, `AllReduce` contents might mismatch.



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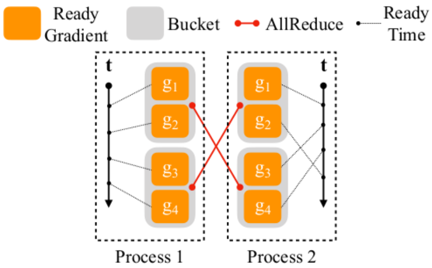

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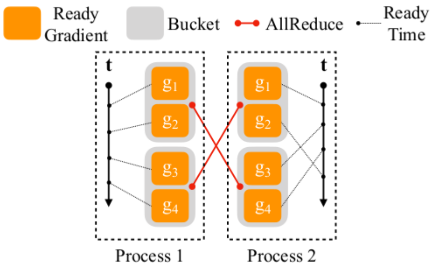
- No process can launch `AllReduce` on bucket $i + 1$ before embarking bucket i.



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  - Only launch gradient synchronization at the boundaries of large batches.

ZeRO: Memory Optimizations Toward Training Trillion Parameter Models

ZeRO (1/2)

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- Zero Redundancy Optimizer (ZeRO) eliminates memory redundancies in data-parallel and model-parallel training.
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- Therefore, it allows to scale the model size proportional to the number of devices.

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Where Did All the Memory Go?

- Model states
  - Optimizer states
  - Gradients
  - Parameters
- Residual memory consumption
  - Activations
  - Temporary buffers
  - Memory fragmentation

ZeRO-PD

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- Both approaches maintain all the model states required over the entire training process statically, even though not all model states are required all the time during the training.

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- It removes the memory state redundancies across data-parallel processes by partitioning the model states instead of replicating them.
- It retains the compute/communication efficiency by retaining the computational granularity and communication volume of DP using a dynamic communication schedule during training.

Optimization Phases of ZeRO-DP

- Optimizer state partitioning P_{os}
- Gradient partitioning P_g
- Parameter partitioning P_p

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- This is a Reduce-Scatter operation, where gradients corresponding to different parameters are reduced to different process.

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- This approach increases the total communication volume of a baseline DP system to 1.5x, while enabling memory reduction proportional to N_d.

ZeRO-R

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  3. Proactively manages memory based on the different lifetime of tensors, preventing memory fragmentation.

Optimization Phases of ZeRO-R

- Partitioned activation checkpointing $\mathtt{P_a}$
- Constant size buffers $\mathtt{C_B}$
- Memory defragmentation $\mathtt{M_D}$

Partitioned Activation Checkpointing P_a

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- Once the forward propagation for a layer of a model is computed, the activations are partitioned across all the model parallel process, until it is needed again during the backprogation.
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- It works in conjunction with activation checkpointing, storing partitioned activation checkpoints only instead of replicated copies.

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- The memory overhead of the fused buffers is proportional to the model size, and can become inhibiting.
- To address this issue, ZeRO-R uses a constant-size fused buffer when the model becomes too large.

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  - This creates an interleaving of short lived memory (discarded activations) and long lived memory (checkpointed activation), leading to memory fragmentation.

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- ZeRO does memory defragmentation on-the-fly by pre-allocating contiguous memory chunks for activation checkpoints and gradients, and copying them over to the pre-allocated memory as they are produced.

Summary

Summary

- BigDL
- PyTorch Distributed
- ZeRO

Reference

- Hasheminezhad et al., Towards a Scalable and Distributed Infrastructure for Deep Learning Applications, 2020
- Dai et al., BigDL: A Distributed Deep Learning Framework for Big Data, 2019
- Li et al., PyTorch Distributed: Experiences on Accelerating Data Parallel Training, 2020
- Rajbhandari et al., ZeRO: Memory Optimizations Toward Training Trillion Parameter Models, 2020

Questions?