Distributed Machine Learning Frameworks

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2020-12-07
The Course Web Page

https://fid3024.github.io
Review of the Current Frameworks
TensorFlow supports data parallelism and model partitioning (as of v0.8).
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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.
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]
GPipe is a pipeline parallelism library implemented under Lingvo (a TensorFlow framework focusing on seq-to-seq models).

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

[Huang et al., GPipe: Efficient Training of Giant Neural Networks using Pipeline Parallelism, 2019]
HyPar-Flow is an implementation of data, model, and hybrid parallelization on Eager TensorFlow.

[Awan et al., HyPar-Flow: Exploiting MPI and Keras for Scalable Hybrid-Parallel DNN Training with TensorFlow, 2020]
HyPar-Flow is an implementation of data, model, and hybrid parallelization on Eager TensorFlow.

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.

[Awan et al., HyPar-Flow: Exploiting MPI and Keras for Scalable Hybrid-Parallel DNN Training with TensorFlow, 2020]
Caffe is a DL framework that does not support distributed training out-of-the-box.
PyTorch (1/4)

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- **Intel-Caffe** and **NUMA-Caffe** support **data parallelism** training on **CPU-based clusters**.

- **S-Caffe** is a **CUDA-Aware MPI runtime** and Caffe for **data parallelism** on **GPU clusters**.
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- It only supports **data parallelism**.
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It has a synchronous decentralized design for allreduce communication.
PyTorch is a successor of Caffe2, which is inspired by Chainer.
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PyTorch (3/4)

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PyTorch RPC is developed to support model parallelism.
- **PyTorch Distributed Data Parallel (DPP)** is an extra feature to **PyTorch** (available as of v1.5).
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  - Gradient bucketing (small tensors bucket into one allreduce operation)
  - Overlapping communication with computation
  - Skipping synchronization
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MXNet (1/2)

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- It blends declarative symbolic expression with imperative tensor computation.

- It uses a distributed key-value store for data synchronization over multiple devices.
MXNet-MPI is the extension of MXNet that replaces each worker in a parameter server architecture with a group of workers.

Workers of each group are synced together using an MPI collective operation.
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Workers of each group are synced together using an MPI collective operation.

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

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- 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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FlexFlow can parallelize a DNN in the **Sample, Operation, Attribute, and Parameter (SOAP)** dimensions.

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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- It runs a series of Spark jobs, which are scheduled by Spark.
- Due to using Spark, it is equipped with fault tolerance and a fair load balancing mechanism.
ZeRO and DeepSpeed

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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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Big Data vs. Deep Learning Frameworks

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- Several connectors, e.g., **TFX, CaffeOnSpark, TensorFlowOnSpark, SageMaker**.
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- Big data and deep learning systems have different distributed execution model.
- Big data tasks are embarrassingly parallel and independent of each other.
- Deep learning tasks need to coordinate with and depend on others.
- Several connectors, e.g., TFX, CaffeOnSpark, TensorFlowOnSpark, SageMaker.
- However, the adaptation between different frameworks can impose very large overheads in practice.
Job is described based on directed acyclic graphs (DAG) data flow.
Spark Dataflow Model

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- A *data flow* is composed of any number of *data sources, operators, and data sinks* by connecting their inputs and outputs.
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- A **data flow** is composed of any number of **data sources, operators, and data sinks** by connecting their inputs and outputs.

- **Parallelizable operators**
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]
BigDL

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```python
#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)
```
BigDL provides **synchronous data-parallel** training to **train** an NN model.
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- **RDD of Samples**, which are automatically **partitioned** across the Spark cluster.
BigDL provides synchronous data-parallel training to train an NN model.

- RDD of Samples, which are automatically partitioned across the Spark cluster.
- RDD of models, each of which is a replica of the original NN model.

[Dai et al., BigDL: A Distributed Deep Learning Framework for Big Data, 2019]
In each iteration, a single model forward-backward Spark job.
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Applies the functional zip operator to the co-located partitions of the two RDDs.

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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.
Data-Parallel Training in BigDL (3/3)

Algorithm 1 Data-parallel training in BigDL

1: for $i = 1$ to $M$ do
2:   // “model forward-backward” job
3:   for each task in the Spark job do
4:     read the latest weights;
5:   get a random batch of data from local Sample partition;
6:   compute local gradients (forward-backward on local model replica);
7:   end for
8:   // “parameter synchronization” job
9:   aggregate (sum) all the gradients;
10:  update the weights per specified optimization method;
11: end for

[Dai et al., BigDL: A Distributed Deep Learning Framework for Big Data, 2019]
Parameter synchronization based using parameter server or AllReduce requires fine-grained data access.
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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.
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

[Dai et al., BigDL: A Distributed Deep Learning Framework for Big Data, 2019]
PyTorch Distributed: Experiences on Accelerating Data Parallel Training
PyTorch organizes values into **Tensors**, generic *n*-dimensional arrays.

- A **Module** defines a transform from input values to output values.
  - In this class, applications provide their model at construction time.
  - Its behavior during the forward pass is specified by its `forward` member function.

- A **Module** can contain **Tensors** as parameters.
  - 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.
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- An application **composes** its own **Module** by stitching together **Modules** (e.g., linear, convolution) and **Functions** (e.g., relu, pool) in a **forward** function.
```python
import torch
torch.nn as nn
import torch.nn.parallel as par
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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PyTorch provides distributed data parallel as an nn.Module class.
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They synchronize gradients to keep parameters consistent across training iterations.
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- **DataParallel** for **data parallel** training on the **same machine**.
- **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)

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- **AllReduce** is the primitive communication API used by **DDP**.

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

AllReduce is the primitive communication API used by DDP.

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

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Gradient Reduction - Naive Solution (1/3)

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  1. Start from the **same model state**.
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- **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**.
To implement the step 2, the PyTorch accepts custom backward hooks.
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When fired, each hook scans through all local model parameters, and retrieves the gradient tensor from each parameter.
To implement the **step 2**, the PyTorch accepts **custom backward hooks**.

**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**.
Two performance concerns:

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.
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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 bucket 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.
Gradient Reduction - Gradient Bucketing (2/2)

- Not to launch `AllReduce` immediately after each gradient tensor becomes available.

- 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.
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- The hook fires after its corresponding accumulator updating the gradients.
Overlap Computation with Communication (1/2)

- **AllReduce** on gradients can **start before** the **local backward pass finishes**.

- With **bucketing**, **DDP** needs to **wait for all contents** in the **same bucket** before launching communications.

- **DDP** registers one **autograd hook** for each gradient **accumulator**.

- The **hook fires** after its corresponding **accumulator** updating the gradients.

- If hooks of **all gradients** in the **same buckets** have fired, then **AllReduce** on that **bucket** will be triggered.
The **reducing order** must be the same across all processes, otherwise, **AllReduce** contents might mismatch.

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All processes must use the same bucketing order.

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

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

- Reduce gradient synchronization frequencies to speed up distributed data parallel training.
  - It can split one input batch into multiple micro-batches.
  - Run local forward and backward passes on every micro-batch.
  - Only launch gradient synchronization at the boundaries of large batches.
Reduce gradient synchronization frequencies to speed up distributed data parallel training.

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Gradient Accumulation

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ZeRO: Memory Optimizations Toward Training Trillion Parameter Models
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Zero Redundancy Optimizer (ZeRO) eliminates memory redundancies in data-parallel and model-parallel training.

It retains low communication volume and high computational granularity.

Therefore, it allows to scale the model size proportional to the number of devices.
Where Did All the Memory Go?

- **Model** states
  - Optimizer states
  - Gradients
  - Parameters

- **Residual** memory consumption
  - Activations
  - Temporary buffers
  - Memory fragmentation
ZeRO has two sets of optimizations:

- ZeRO-DP (ZeRO Data Parallelism): aims at reducing the memory footprint of the model states.
- ZeRO-R (ZeRO Residual): targets towards reducing the residual memory consumption.
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ZeRO-DP
Optimizing Model State Memory

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- Data-Parallel (DP) has good compute/communication efficiency, but poor memory efficiency.

- Model-Parallel (MP) can have poor compute/communication efficiency, but good memory efficiency.

- 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.
Optimization Phases of ZeRO-DP

- **Optimizer state** partitioning $P_{os}$
- **Gradient** partitioning $P_g$
- **Parameter** partitioning $P_p$
Optimizer State Partitioning $P_{os}$

- $N_d$: number of data parallel processes

Group the optimizer states into $N_d$ equal partitions ($\frac{1}{N_d}$) on each data parallel process. Each data parallel process only updates its corresponding optimizer states. Performs an all-gather across the data parallel processes at the end of each training step to get the fully updated parameters across all data parallel processes.
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Each **data parallel process** only needs the **reduced gradients** for the **corresponding parameters**.
Gradient Partitioning $P_g$

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

After the reduction, the gradients are no longer needed and their memory can be released.
Parameter Partitioning $P_p$

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- When the parameters outside of its partition are required for forward and backward propagation, they are received from the appropriate data parallel process through broadcast.

- 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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Optimizing Residual State Memory

- **ZeRO-DP** boosts memory efficiency for model states.

- The *rest of the memory* consumed by activations, temporary buffers, and unusable memory fragments.

- **ZeRO-R** optimizes the *residual memory* consumed by the following three factors:
  1. Optimizes activation memory (stored from forward pass in order to perform backward pass) by activation partitioning. It also offloads activations to CPU when appropriate.
Optimizing Residual State Memory

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- ZeRO-R optimizes the residual memory consumed by the following three factors:
  1. Optimizes activation memory (stored from forward pass in order to perform backward pass) by activation partitioning. It also offloads activations to CPU when appropriate.
  2. Defines appropriate size for temporary buffers to strike for a balance of memory and computation efficiency.
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ZeRO-R optimizes the residual memory consumed by the following three factors:

1. Optimizes activation memory (stored from forward pass in order to perform backward pass) by activation partitioning. It also offloads activations to CPU when appropriate.

2. Defines appropriate size for temporary buffers to strike for a balance of memory and computation efficiency.

3. Proactively manages memory based on the different lifetime of tensors, preventing memory fragmentation.
Optimization Phases of ZeRO-R

- Partitioned activation checkpointing $P_a$
- Constant size buffers $C_B$
- Memory defragmentation $M_D$
ZeRO partitions the activations.
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At this point, ZeRO uses an all-gather operation to re-materialize a replicated copy of the activations.

It works in conjunction with activation checkpointing, storing partitioned activation checkpoints only instead of replicated copies.
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Constant Size Buffers $C_B$

- ZeRO selects the sizes of the temporal-data buffers to balance memory and compute efficiency.
- During training, the computational efficiency of some operations can be highly dependent on the input size, with larger inputs achieving higher efficiency.
- To get better efficiency, it fuses all the parameters into a single buffer before applying these operations.
- The memory overhead of the fused buffers is proportional to the model size, and can become inhibiting.
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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.
Memory Defragmentation $M_D$ (1/2)

- Memory fragmentation in model training occurs as a result of activation checkpointing and gradient computation.
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  - Most activations are discarded as they can be recomputed again during the back propagation.
Memory Defragmentation $M_D$ (1/2)

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- During the forward propagation with activation checkpointing, only selected activations are stored for back propagation.
  - Most activations are discarded as they can be recomputed again during the back propagation.
  - Short lived memory (discarded activations) and long lived memory (checkpointed activation).
During the backward propagation, the parameter gradients are long lived, while activation gradients and any other buffers required to compute the parameter gradients are short lived.
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This interleaving of short term and long term memory causes memory **fragmentation**.

ZeRO does memory defragmentation on-the-fly by **pre-allocating contiguous memory chunks** for **activation checkpoints and gradients** produced.
Summary
Summary

- BigDL
- PyTorch Distributed
- ZeRO
Reference

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Questions?