Scalable Distributed Training with Parameter Hub: a whirlwind tour

TVM Stack

Groundwork for bringing TVM to the distributed world for training and inference, on commercial cloud, or in your own cluster.

Parameter Hub

Optimized, topology-aware and dynamic mechanism for inter-machine communication

Liang Luo, *Jacob Nelson,* Luis Ceze, *Amar Phanishayee* and Arvind Krishnamurthy

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Optimized, topology-aware and dynamic mechanism for inter-machine communication

* In the cloud-based training context

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Deep Learning constitutes an important workload in cloud today.

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Server demand for DL inference across data centers nearly quadrupled in less than 2 years. Source: Facebook

EC2 reclaims your GPU instances as they run out of capacity

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Distributed Training INDEPENDENT FORWARD/BACKWARD PASSES + COORDINATED PARAMETER EXCHANGE

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Distributed Training Today IN THE CONTEXT OF THE CLOUD

Distributed Training Today FORWARD AND BACKWARD PASSES IN WORKER

Distributed Training Today AGGREGATION AND OPTIMIZATION IN PS

Distributed training is communication bound

- Problem gets worse over time: shifting bottleneck.
- Seconds - With modern GPUs most of the time is spent[®] on communication.
- Making GPUs faster will do little to increase throughput
- Wasting compute resources.

Distributed training is communication bound

Bottlenecks in DDNN training MAPPING OF TRAINING WORKLOAD TO THE CLOUD IS INEFFICIENT.

Bottlenecks in DDNN training FRAMEWORK BOTTLENECKS

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Bottlenecks in DDNN training BANDWIDTH BOTTLENECK

1000 Gbps

Minimum bandwidth required 1300 Gbps for each of the popular NNs for communication to not bottleneck computation?

8 workers, GTX 1080 Ti, central parameter servers. **MxNet**

25 Gbps

10 Gbps

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Bottlenecks in Cloud-based DDNN training MAPPING OF TRAINING WORKLOAD TO THE CLOUD IS INEFFICIENT.

Bottlenecks in Cloud-based DDNN training DEPLOYMENT-RELATED OVERHEAD

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- Transient congestion, or oversubscription by design
- Cross-rack communication cost is higher than Intra-rack communication.

Parameter Hub Optimizations

CODESIGNING SOFTWARE, HARDWARE WITH CLUSTER CONFIGURATION FOR EFFICIENT CLOUD-BASED DDNN TRAINING

PS 2

Eliminating framework bottlenecks:

PHub Optimizations: streamlining DDNN training pipeline

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Requires synchronization. Great locality. No synchronization

Each core reads the input Q from different workers and writes to different locations to the output queue

For each input Q, launch a series of threads for aggregation. This is used in MxNet. (Wide Aggregation)

Sequentially aggregates the same portion of gradients within each queue. (Tall Aggregation)

Organize processors into hierarchy. Perform NUMA aware tree reduction.

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Great locality. No synchronization Too much coherence and synchronization

NUMA 0 NUMA 1

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- Chunk a gradient into a series of virtual gradients deterministically.
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- Chunk a gradient into a series of virtual gradients deterministically.
- A virtual gradient is mapped to a particular core on the server.
- Virtual gradients are transferred independently.
- A chunk is only processed by a single core : maintaining maximum locality.

Gey 0 from 8 workers

When Aggregation is done, PHub:

- PHub optimizes a chunk with the same core that aggregates that chunk.

Gey 0 from 8 workers

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Eliminating deployment bottlenecks:

PHub hierarchical reduction: reducing cross rack traffic

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Two-Phase Hierarchical Aggregation RACK SCALE PARAMETER SERVICE

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Two-Phase Hierarchical Aggregation ADAPTING TO THE DATACENTER NETWORK TOPOLOGY

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VMs Azure/EC2

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Performance in commercial cloud with PHub

38 Windows Azure and Amazon EC2. 32 instances. Up to 10 Gbps. Standard_NC6: Nvidia K80. Batch Size = 512. P3.2xLarge: Nvidia V100. Batch Size = 512. Facebook Caffe2/ Pytorch. ResNet 50.

Framework Integration

Support for Mxnet/Pytorch/Caffe2.

var pHub = std::make_shared<PHub>(cfg.redisIp, nMap, **keySize**, **appAddrs**, cntr, sizeof(float), cfg.rank, plp); pHub->ToggleUseSchedule(pSchedule); **pHub->Reduce();**

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Balanced computation and communication resource.

- 10 ConnectX-3 Card
- 560+Gbps Network BW
- 800Gbps PCIe
- Fully supported by Software Parameter Hub

35GB/s aggregation throughput. Supports 100+ ResNet-50 training nodes with a single machine.

ResNet-50. See paper for detailed estimates.

Better training throughput/\$.
Hardware Parameter Hub

ResNet-50. See paper for detailed estimates.

Better training throughput/\$.