Scaling Distributed Machine Learning with In-Network Aggregation

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Machine Learning

Innovation fueled by leaps in (costly) infrastructure:

Clusters with hundreds of machines, each with many HW accelerators (GPUs)

Training models is still **time-consuming**: hours, days or even weeks!
Can the network be the ML accelerator?
Outline

• The distributed training process
• In-network aggregation design
• Evaluation
• Future work and conclusion
Data-parallel distributed training

Worker 1

Local copy of model

Worker 2

Local copy of model
Phase 1: Workers learn independently

Worker 1

Worker 2

A1
U1

A2
U2
Phase 2: Workers exchange what they’ve learned
Aggregation is communication-intensive

~100 ms
Worker 1

Worker 2 ~100 ms

~100’s of MB

100s of MBs in each iteration
→ ~800-1000ms
Aggregation is communication-intensive

Problem:
Intensive, all-to-all communication!

If only I could help...

Faster GPUs push training speed bottleneck to the network!
Programmable data plane switches to the rescue!

- 6.5 Tbps
- 100 Gbps line rate processing
SwitchML: the network is the ML accelerator

Worker 1

Worker 2

Worker 3

Worker 4

Switch

Aggregate model updates in-network
Co-design ML and networking for efficiency

Challenges
- Limited storage
- Limited computation
- No floating point
- Packet loss

Design
- Pool-based streaming aggregation
- Combined switch-host architecture
- Quantized integer operations
- Failure-recovery protocol

6.5 Tbps programmable data plane
Streaming aggregation with a pool

Worker 1

Worker 2

Pool

Switch

~100’s of MB

~10’s – 100’s of KB
Combined switch-host architecture

Worker Responsibilities
- Chunking up vectors
- Quantization and scaling
- Detecting and recovering from packet drops

Switch Responsibilities
- Integer vector addition (32 elements per packet)
- Counting and comparison to detect complete slots
Quantization

• Convert floating point to 32-bit fixed-point values
\[ \tilde{U}_j^i = \text{round}(sf \times U_j^i) \]
• Updates are scaled by multiplying for a scaling factor \( sf \)
\[ \tilde{A}_j^i = A_j^i / sf \]
• Approach 1: (restricted) 16-bit floating point ↔ 32-bit fixed point conversion
  → Directly in the switch
• Approach 2: 32-bit floating point ↔ 32-bit fixed point conversion
  → At workers with AVX instructions
  With single scaling factor obtained by profiling

This quantization allows training to similar accuracy in a similar number of iterations as an unquantized network for a large range of scaling factors
Packet loss tolerance

• Packet loss can happen in two directions
• Workers detect losses using timers
• Lost packets are retransmitted
  • A model update must not be applied twice
  • A model update must not be applied to a “full” slot

• Workers’ per-slot contributions tracked with a bitmap
  • Ignores duplicates
• Shadow copy of the previous result for a slot
  • Retransmits a dropped result packet
Implementation

• Switch program written in P4 for Barefoot Tofino

• End-host C++ library providing a familiar all-reduce API
  • Kernel bypass

• We have integrated SwitchML with:
  • TensorFlow using Horovod,
  • PyTorch/Caffe2 using Gloo
Evaluation

Testbed:
• 16 servers (8 w/ P100 GPUs)
  10 Gbps (Intel 82599ES)
  100 Gbps (Mellanox Connect-X 5)
• 64 x 100 Gbps switch (Barefoot Tofino)

• Models:
  • 9 standard CNN benchmarks
  • Training on ImageNet
    (except synthetic data with AlexNet)
  • Compared with TensorFlow using the Nvidia Collective Comm. Library (NCCL)
How much faster is SwitchML?

SwitchML provides a speedup from 20% to 300% compared to Tensorflow/NCCL (with direct GPU memory access)
How does SwitchML scale with the number of workers?

SwitchML performance does not depend on the number of workers
How does SwitchML perform with packet losses?

SwitchML has a lower inflation than TCP

Reasonable packet loss rates have no impact on performance
Future work

• Multi-rack
  • Can we use multiple switches to implement hierarchical SwithML?

• Multiple jobs, multiple tenants
  • Can we support the multiple jobs in the same rack by partitioning slots?

• Better numeric representations
  • Can we quantize without having to choose a scaling factor?

• More data per packet
  • Full MTU packets would provide ~31% better performance.
Summary

• SwitchML uses **in-network aggregation** to synchronize model updates
  • Reduce network traffic volume and latency

• SwitchML speeds up training up to 300% with real-world DNN benchmarks

• Aggregation time does not depend on the number of workers

• Preprint on arXiv: [https://aka.ms/switchml](https://aka.ms/switchml)
How does SwitchML scale with the number of workers?

SwitchML performance does not depend on the number of workers.

![Graph showing SwitchML performance comparison with other frameworks at 10 Gbps and 100 Gbps data rates across different numbers of workers. The graph illustrates that SwitchML maintains consistent performance regardless of the number of workers, whereas other frameworks like Gloo, NCCL, Dedicated PS, and Colocated PS show varying performance.]
Packet loss tolerance

- Workers contribution per-slot tracked with a bitmap
  - Ignores duplicates
- Shadow copy of the previous result for a slot
  - Retransmits a dropped result packet
How does SwitchML perform with packet losses?

SwitchML has a lower inflation than TCP.

Reasonable packet loss rates have no impact on performance.
Does quantization affect aggregation speed?

Tensor Aggregation Time unaffected by quantization thanks to AVX instructions

![Graph showing TAT (Tensor Aggregation Time) for different data types and libraries.](image-url)
How much does packet size affect performance?

SwitchML reaches line rate with small packets
Would have ~30% better performance if the switch could support MTU-sized packets
Quantization

- Convert floating point to 32-bit fixed-point values
- Updates are scaled by multiplying for a scaling factor $sf$

$$\tilde{U}_j^i = \text{round}(sf \times U_j^i) \quad \tilde{A}_j^i = A_j^i / sf$$

- 32-bit floating point ↔ 32-bit fixed point conversion → At workers with AVX instructions
- 16-bit floating point ↔ 32-bit fixed point conversion → Directly in the switch
  - Scaling is still done by the worker using AVX instructions

This quantization allows training to similar accuracy in a similar number of iterations as an unquantized network for a large range of scaling factors
Problem: Very intensive communication in all-to-all fashion! Network increasingly the bottleneck to training speed