Allreduce for Parallel Learning

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May 8, 2017

Applying for a fellowship in 1997

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John: I'd like to solve AI.

I: How?

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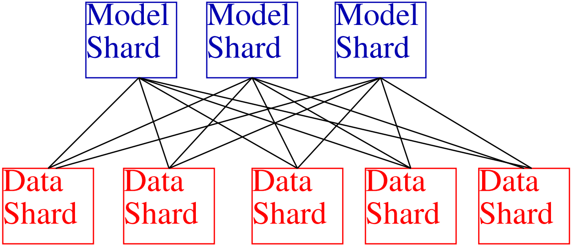
The worst part: he had a point.

Why is it hard?

Everyone's first instinct: Try using parameter servers.



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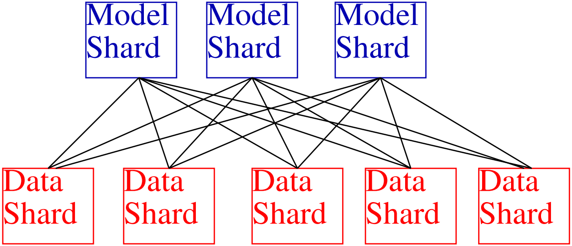

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Big problems in practice:

1. Overwhelmingly inefficient. Best case: marginally faster with x100 electricity.
2. Nondeterministic. Minor bugs incredibly difficult to track.

Terascale Linear Learning ACDL11

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How long does it take?

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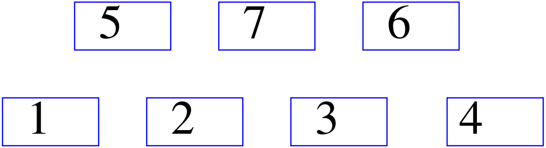
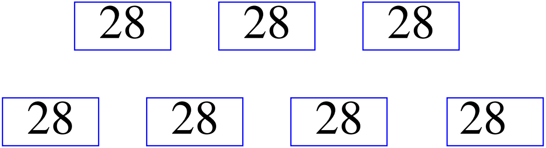
70 minutes = 500M features/second: faster than the IO bandwidth of a single machine⇒ faster than all possible single machine linear learning algorithms.

MPI-style AllReduce

Allreduce initial state

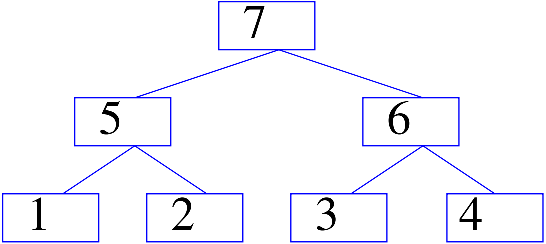


Allreduce final state

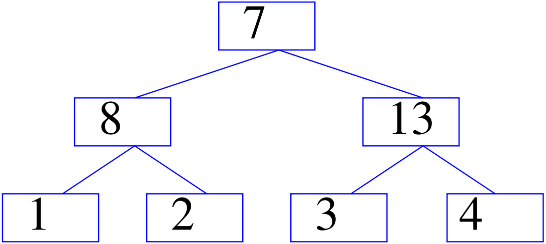


MPI-style AllReduce

Create Binary Tree

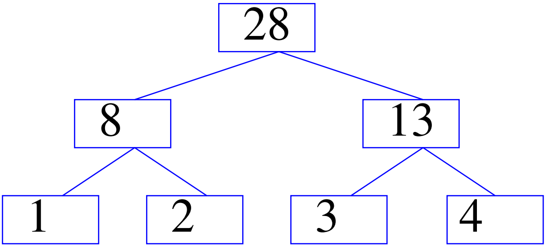


Reducing, step 1

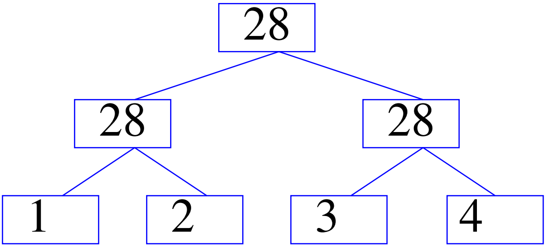


MPI-style AllReduce

Reducing, step 2



Broadcast, step 1



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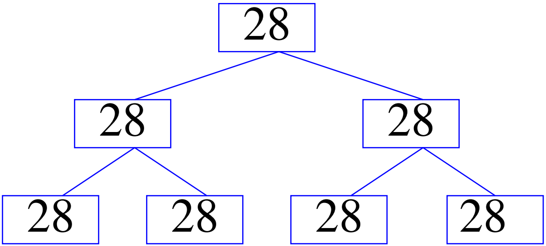
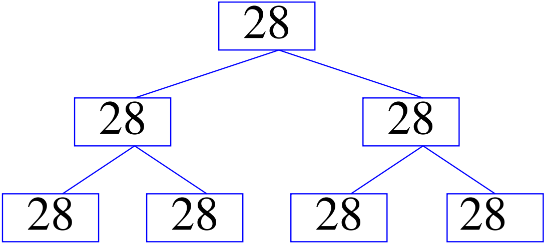


AllReduce = Reduce+Broadcast

Allreduce final state



AllReduce = Reduce+Broadcast

Properties:

1. Easily pipelined so no latency concerns.
2. Bandwidth $\leq 6n$.
3. No need to rewrite code!

An Example Algorithm: Weight averaging

$n = \text{AllReduce}(1)$

While (pass number $<$ max)

1. While (examples left)
   1. Do online update.
2. AllReduce(weights)
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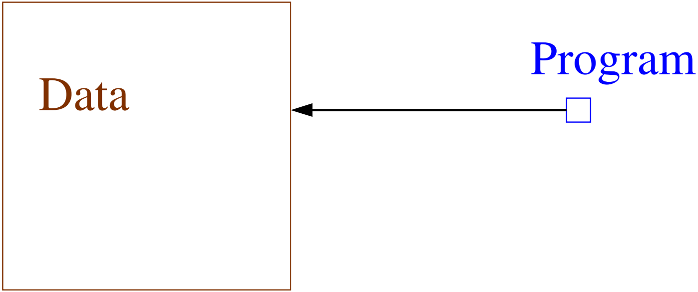
Other algorithms implemented:

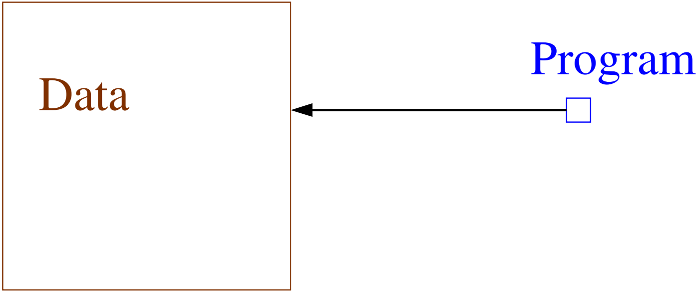
1. Nonuniform averaging for online learning
2. Conjugate Gradient
3. LBFGS

Hadoop AllReduce



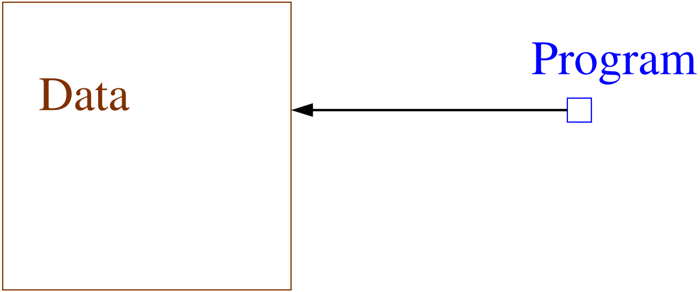
1. "Map" job moves program to data.

Hadoop AllReduce

1. 

"Map" job moves program to data.
2. Delayed initialization: Most failures are disk failures. First read (and cache) all data, before initializing allreduce. Failures autorestart on different node with identical data.

Hadoop AllReduce

1. 

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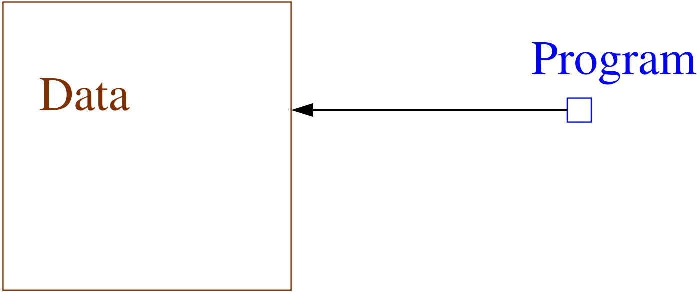
1. 

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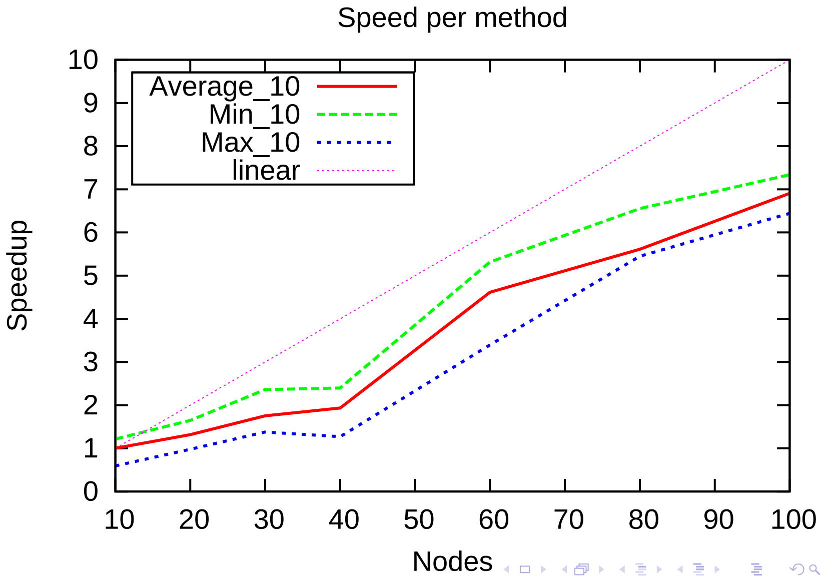
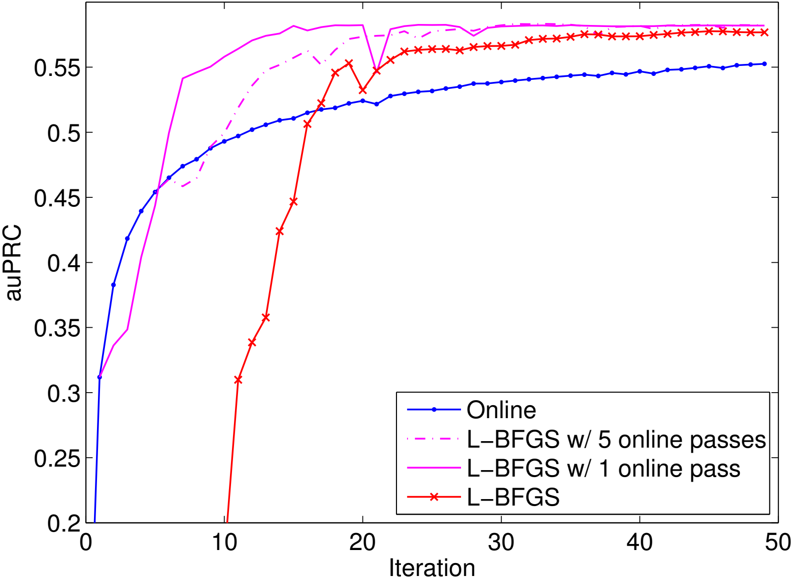
The net effect: Reliable execution out to perhaps $10K$ node-hours.

Robustness & Speedup



Splice Site Recognition



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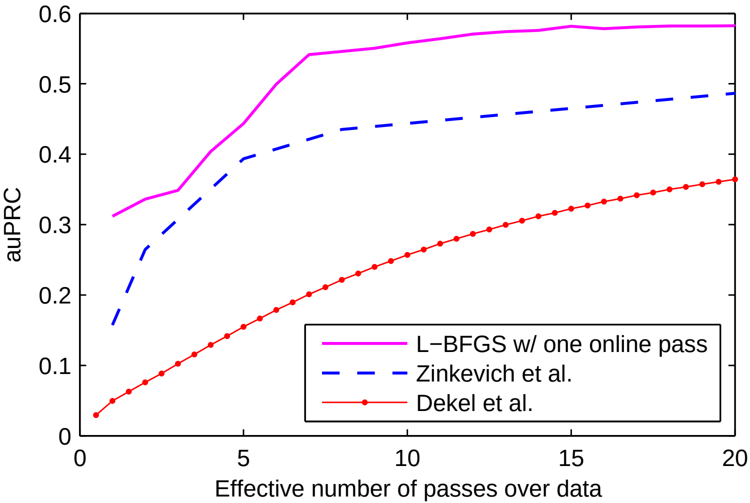

What about parallel deep learning?

Needs to work with a GPU.

GPU Allreduce optimization 1: Minibatch gradient descent

GPUs have much more computation than communication.

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Give every GPU n examples and compute average gradient on them. Synchronize Gradient

GPU Allreduce optimization 1: Half-Batch

Do communication asynchronous to computation.

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1 minibatch communicates while the other computes on older parameters.

GPU Allreduce optimization 1: 1-bit SGD

Discretize the gradient to 1 bit before communicating off GPU.

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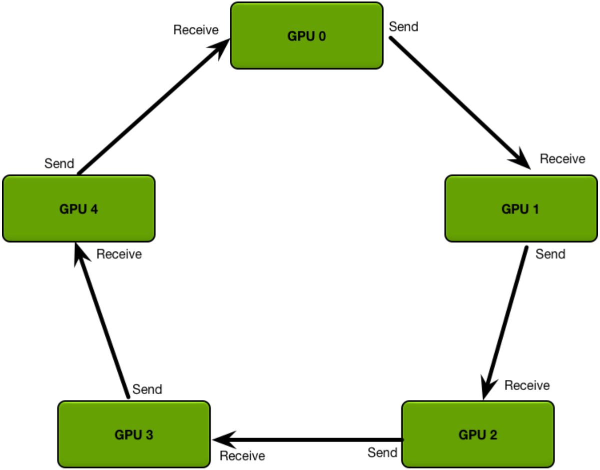
Keep and accumulate discretization errors on GPU.

GPU Allreduce Optimization 2: Ring Allreduce



Every node masters a subset and messages travel in a ring.

1. Downside: latency increase?
2. Upside: perfectly efficient synchronization

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