Linear Learning with AllReduce

NYU Large Scale Learning Class

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March 24, 2014

Applying for a fellowship in 1997

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John: I'd like to solve AI.
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The worst part: he had a point.

Terascale Linear Learning ACDL11

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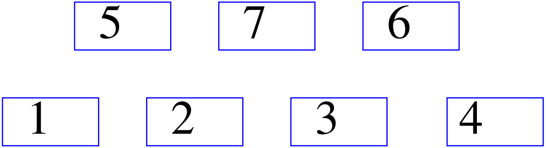
70 minutes = 500M features/second: faster than the IO bandwidth of a single machine$\Rightarrow$ faster than all possible single machine linear learning algorithms.

MPI-style AllReduce

Allreduce initial state



MPI-style AllReduce

Allreduce final state

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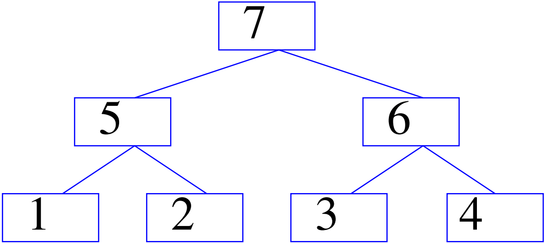
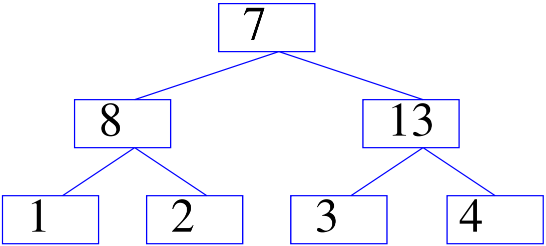
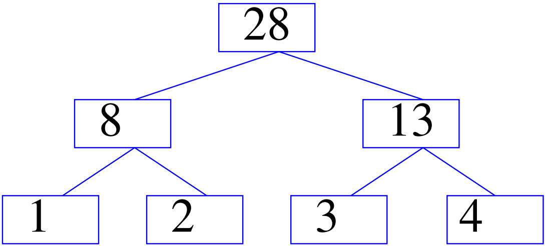
Create Binary Tree



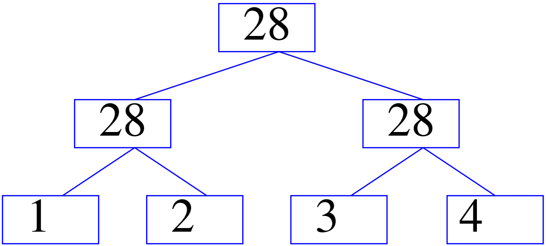
Reducing, step 1



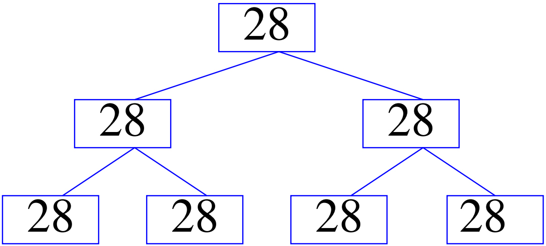
Reducing, step 2



Broadcast, step 1

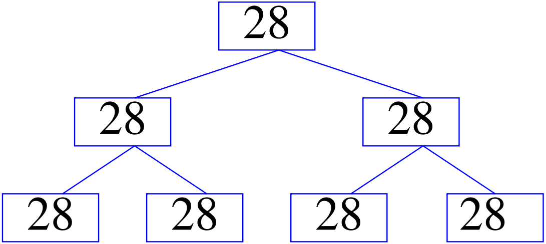


Allreduce final state



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

$n =$ AllReduce(1)
While (pass number $<$ max)

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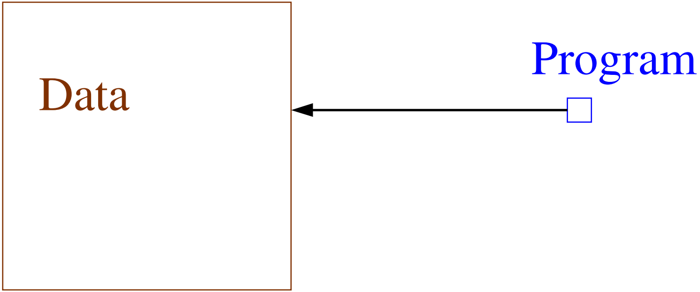
Other algorithms implemented:

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

What is Hadoop AllReduce?



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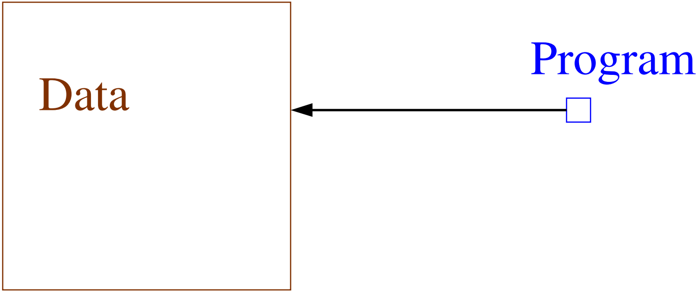
1. 

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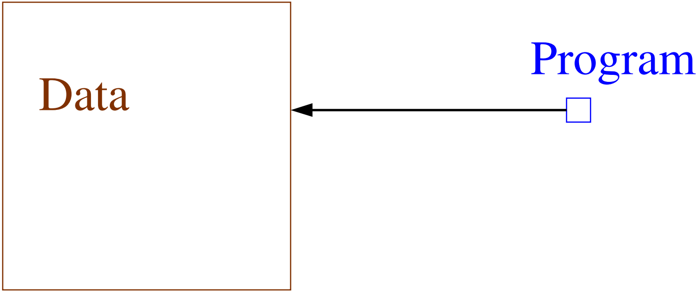

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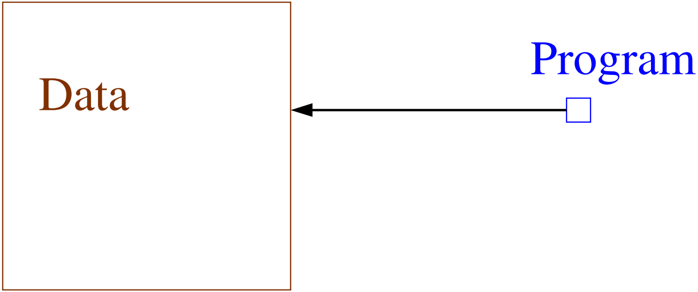

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The net effect: Reliable execution out to perhaps $10K$ node-hours.

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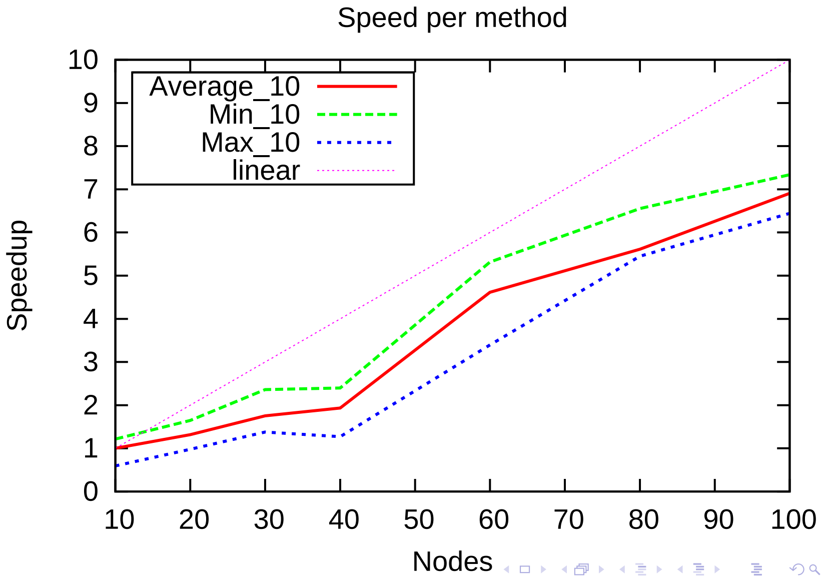
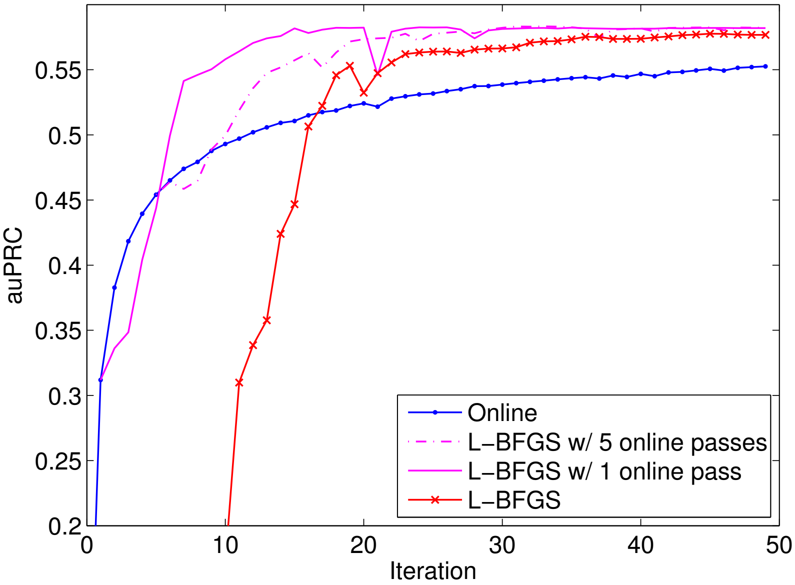
In Vowpal Wabbit. Allreduce is a separate easily linked library.

Robustness & Speedup



Splice Site Recognition



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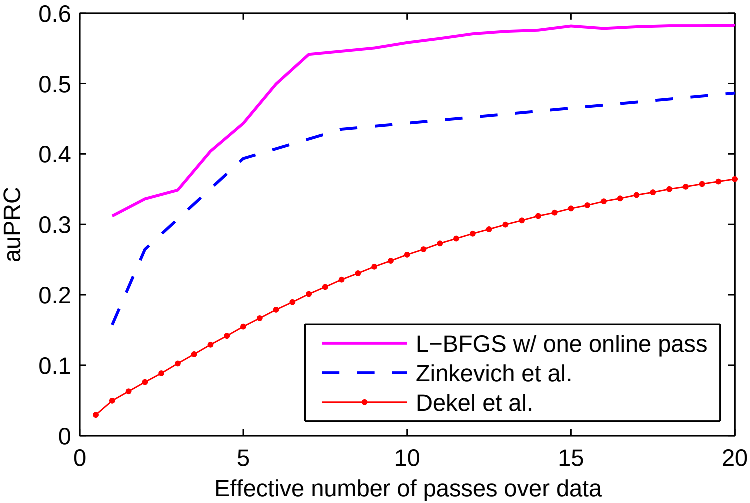

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