The 30000' Summary and 3 Cool Results

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Misha Bilenko(Microsoft)

`http://hunch.net/~large_scale_survey`

This hour's outline

1. A summary of results
2. Cool uses of GPUs
3. Terascale linear

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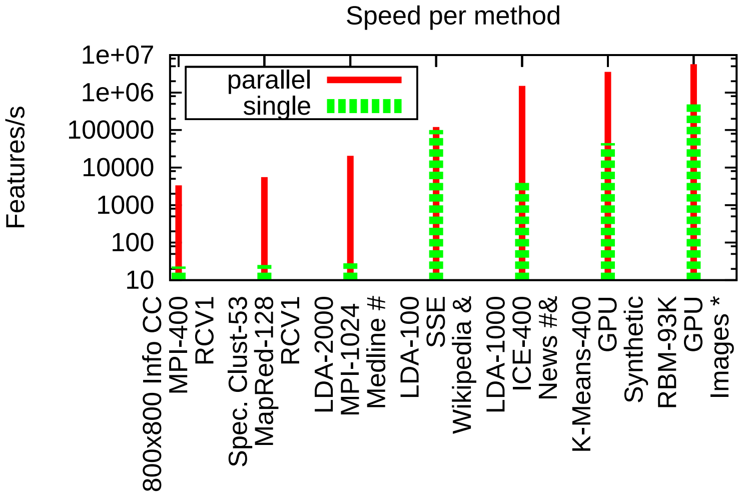
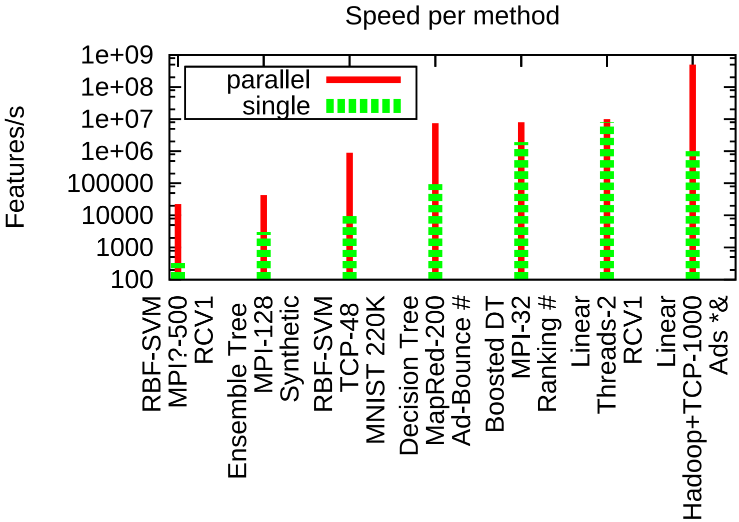
Most interesting results reported. Some cases require creative best-effort summary.

Unsupervised Learning



= Prev. * = Next. & = New

Supervised Training



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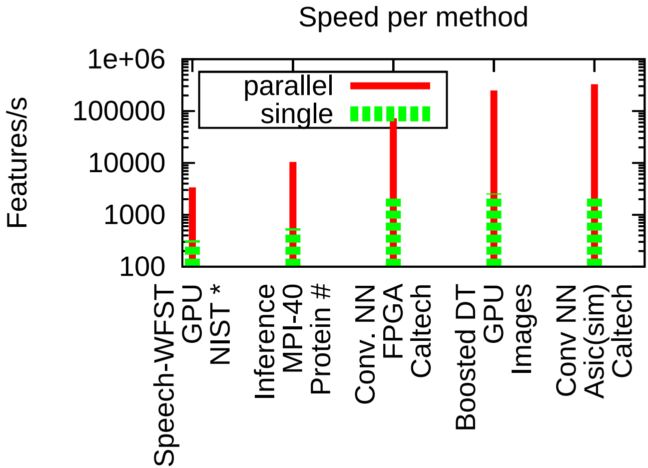
Supervised Testing (but not training)



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My Flow Chart for Learning Optimization

1. Choose an efficient effective algorithm
2. Use compact binary representations.
3. If (Computationally Constrained)
4. then GPU
5. else
    1. If few learning steps
    2. then ~~Map-Reduce~~ AllReduce
    3. else Research Problem.

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   1. RBM learning
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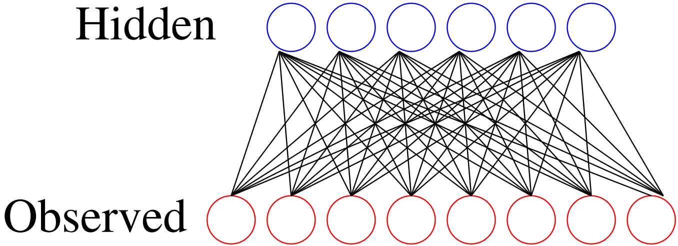
Restricted Boltzmann Machine learning CRN11 Chapter 18

Goal: Learn weights which predict hidden state given features that can predict features given hidden state *



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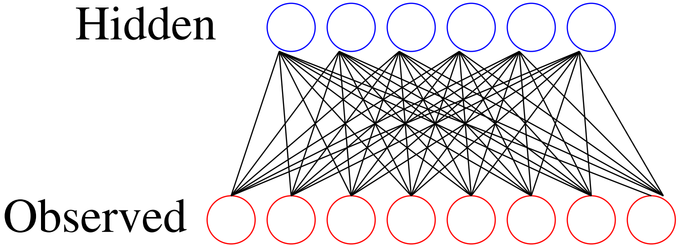

1. Number of parameters = hidden*observed = quadratic pain
2. An observed useful method for creating relevant features for supervised learning.

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RBM parallelization

GPU = hundreds of weak processors doing vector operations on shared memory.

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RBM parallelization

GPU = hundreds of weak processors doing vector operations on shared memory.

1. Activation levels of hidden node i is $\text{sig}(\sum_j w_{ij}x_j)$. A GPU is perfectly designed for a dense matrix/vector dot product.
2. Given activation levels, hidden nodes are independently randomly rounded to $\{0, 1\}$. Good for GPUs
3. Predict features given hidden units just as step 1. Perfect for GPUs
4. Shift weights to make reconstruction more accurate. Perfect for GPUs

Parallelization Techniques

1. Store model in GPU memory and stream data.
2. Use existing GPU-optimized matrix operation code.
3. Use multicore GPU parallelism for the rest.

This is a best-case situation for GPUs. x10 to x55 speedups observed.

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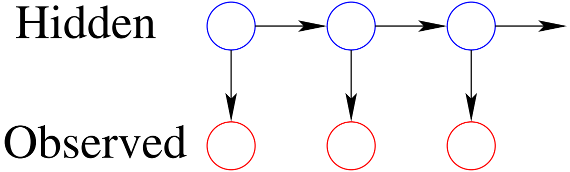
But, maybe we just sped up a slow algorithm?

GPUs for Speech Recognition CGYK11 Chapter 21

Given observed utterances, we want to reconstruct the original (hidden) sequence of words via an HMM structure.



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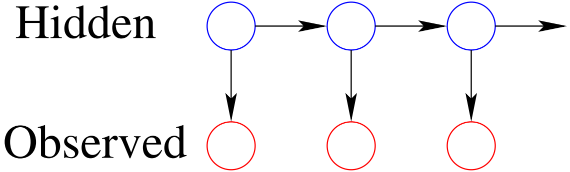

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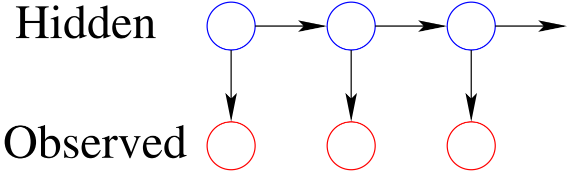

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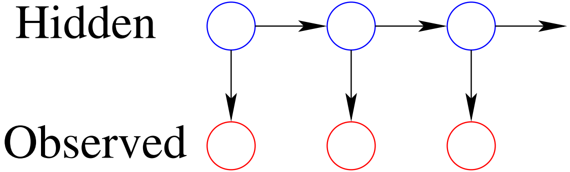

Standard method of decoding: forward-backward algorithm using Bayes law to find the most probable utterance.

Naively, this is trivially parallelized just as before. But it's not.

1. The observation is non-binary. The standard approach matches the observed sound with one of very many different recorded sounds via nearest neighbor search.
2. The state transitions are commonly beam searched rather than using Bayesian integration.
3. The entire structure is compiled into a weighted finite state transducer, which is what's really optimized.

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1. SIMD instructions: Use carefully arranged datastructures so single-instruction-multiple-data works.
2. Multicore over 30 cores of GPU.
3. Use Atomic instructions (Atomic max, Atomic swap) = thread safe primitives.
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Result: x10.5 speedup. Crucially, this makes the algorithm faster than real time.
GPUs help, even for highly optimized algorithms.

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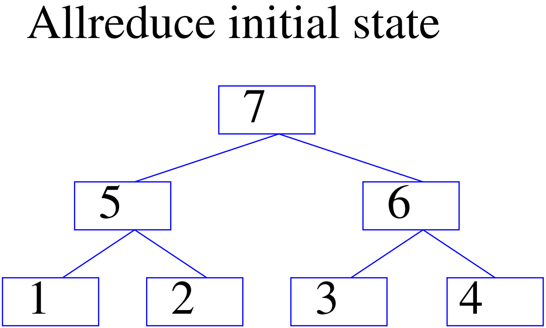
It is necessary but not sufficient to have an efficient communication mechanism.

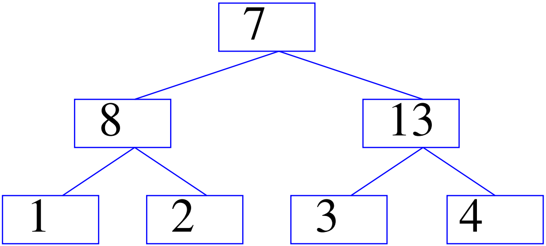
MPI-style AllReduce



AllReduce = Reduce+Broadcast

MPI-style AllReduce

Reducing, step 1



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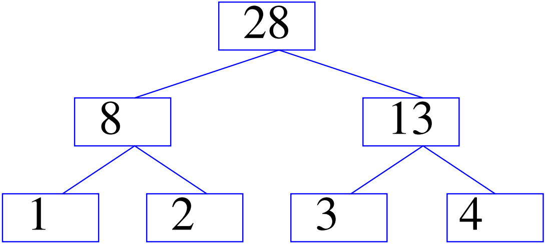
Reducing, step 2



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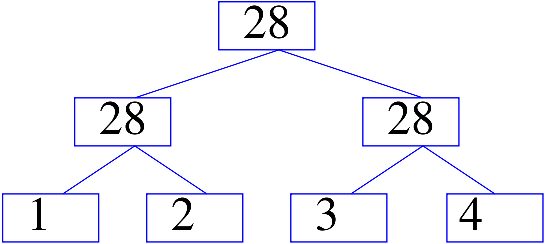
Broadcast, step 1



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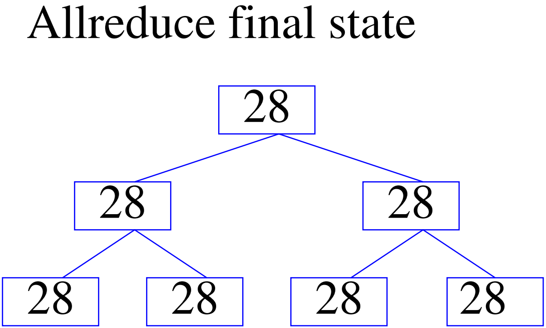

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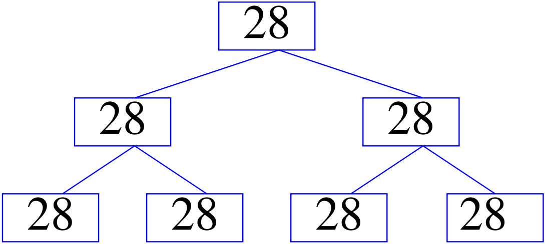
Allreduce final state



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

Approach Used: Preliminaries

Optimize so few data passes required.
Basic problem with gradient descent = confused units.
$f_w(x) = \sum_i w_i x_i$
$\Rightarrow \frac{\partial (f_w(x)-y)^2}{\partial w_i} = 2(f_w(x) - y)x_i$ which has units of i.
But w_i naturally has units of $1/i$ since doubling x_i implies halving w_i to get the same prediction.
Crude fixes:

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Crude fixes:

1. Newton: Multiply inverse Hessian: $\frac{\partial^2}{\partial w_i \partial w_j}^{-1}$ by gradient to get update direction...but computational complexity kills you.
2. Normalize update so total step size is controlled...but this just works globally rather than per dimension.

Approach Used

1. Optimize hard so few data passes required.
    1. L-BFGS = batch algorithm that builds up approximate inverse hessian according to: $\frac{\Delta_w \Delta_w^T}{\Delta_w^T \Delta_g}$ where Δ_w is a change in weights w and Δ_g is a change in the loss gradient g.

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    2. Dimensionally correct, adaptive, online, gradient descent for small-multiple passes.
        1. Online = update weights after seeing each example.
        2. Adaptive = learning rate of feature i according to $\frac{1}{\sqrt{\sum g_i^2}}$ where g_i = previous gradients.
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Open source in Vowpal Wabbit 6.0. Search for it.

Empirical Results

2.1T sparse features
17B Examples
16M parameters
1K nodes
70 minutes

The end

Right now there is extreme diversity:

1. Many different notions of large scale.
2. Many different approaches.

What works generally?
What are the natural “kinds” of large scale learning problems?
And what are good solutions for each kind?
The great diversity implies this is really the beginning.

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