Mechanisms for Parallel Online Learning

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(on joint work with Daniel Hsu & Alex Smola & Martin Zinkevich)

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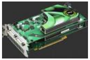
2. Switch architectures. Canonical example = GPU  Useful for computationally intense learning, but...

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   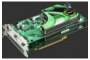Useful for computationally intense learning, but... doesn't address problems with large amounts of data.

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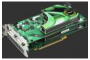
2. Switch architectures. Canonical example = GPU  Useful for computationally intense learning, but... doesn't address problems with large amounts of data.
3. Start with a fast learning algorithm and design a new parallel algorithm that competes with it. Canonical fast algorithm = linear prediction via online gradient descent.

Core Problems for Parallel algorithms = Bandwidth & Latency

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Many tricks to reduce the problem:

1. Sparse feature representation
2. Implicit feature representation
3. Compressed format

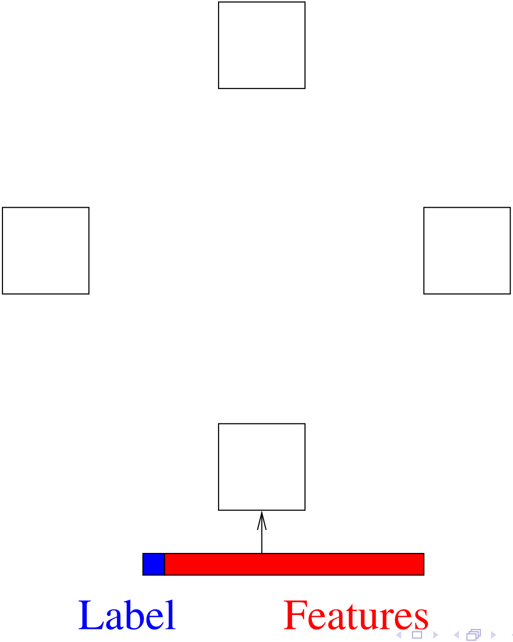
(Vowpal Wabbit has all of these.)
But in the end the problem must be addressed.

Bad news: Delay is pretty bad.

Theorem: (Mesterharm 2005) Delayed updates reduce convergence by delay factor in worst case for expert algorithms.
Theorem: (LSZ 2009) Same for linear predictors.
(Caveat: there are some special cases where you can do better.)

What is an architecture for minimum latency delayed updates?

How can we avoid delay?



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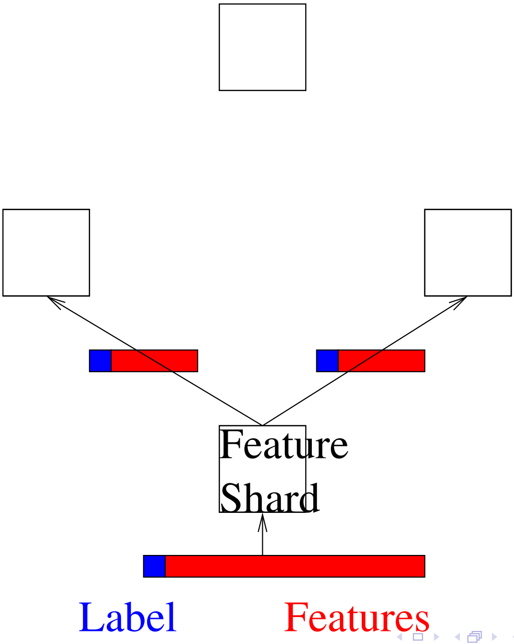

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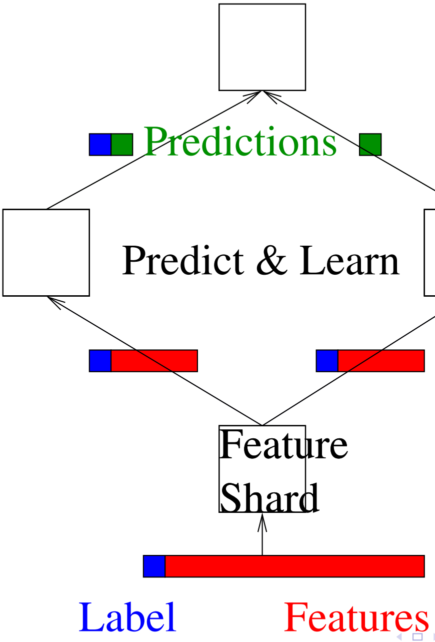

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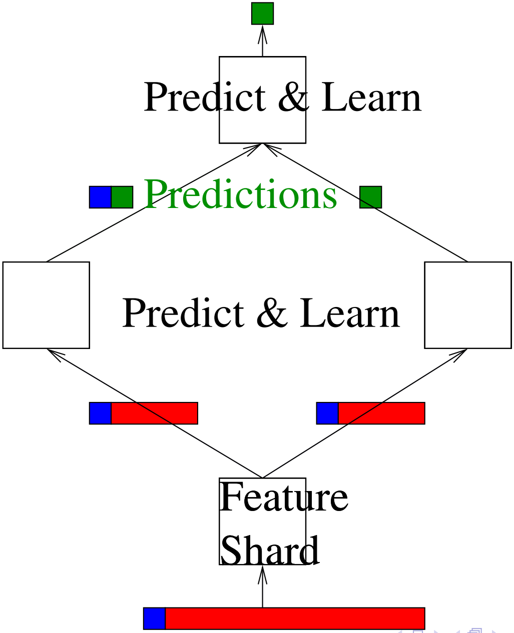


Observations about Feed Forward

1. No longer the same algorithm—it's designed for parallel environments.
2. Bandwidth $=$ few bytes per example, per node $\Rightarrow$ Tera-example feasible with single master, arbitrarily more with hierarchical structure.
3. No delay.
4. Feature Shard is stateless $\Rightarrow$ parallelizable & cachable.

Bad News: Feed Forward can't compete with general linear predictors.

Probability	y	x_1	x_2	x_3
0.25	1	1	1	0
0.125	1	1	0	1
0.125	1	0	1	1
0.25	0	0	0	1
0.125	0	1	0	0
0.125	0	0	1	0

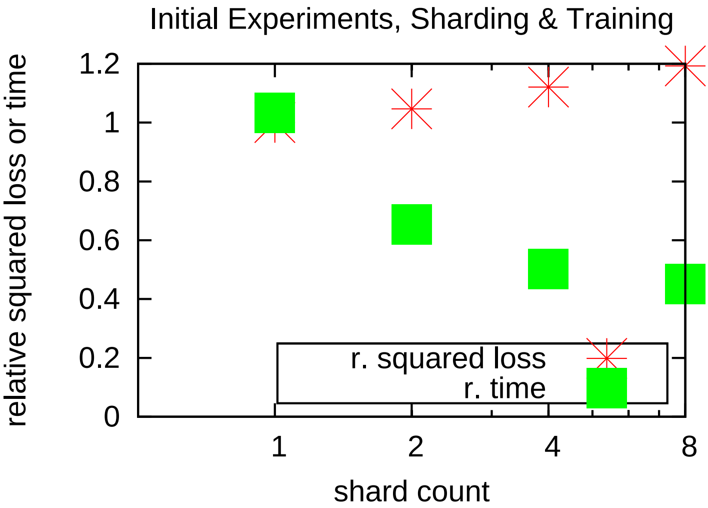
Features 1&2 are imperfect predictors. Feature 3 is uncorrelated with truth. Optimal predictor = majority vote on all 3 features.

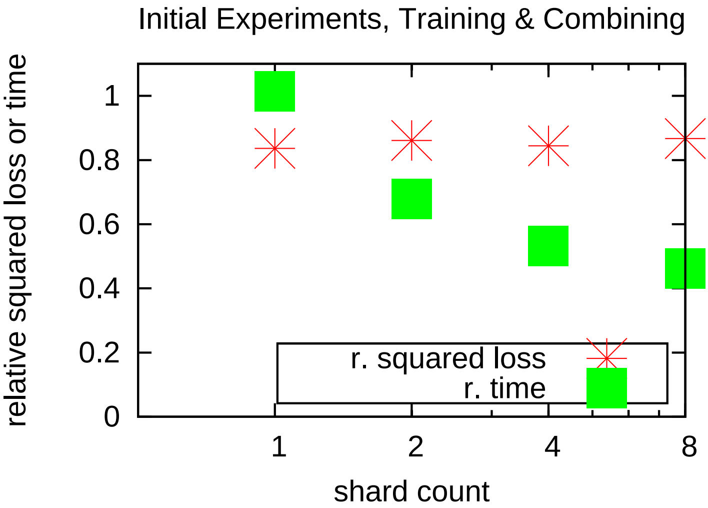
Good news: If Naive Bayes holds $P(x_1|y)P(x_2|y) = P(x_1, x_2|y)$, you win.
Better news: $x_1 =$ first shard, $x_2 =$ second shard
Even better: There are more complex problem classes for which this also works.

Initial experiments on a medium size text Ad dataset @ Yahoo!

1. $\sim$100G when gzip compressed.
2. $\sim$10M examples.
3. $\sim$125G nonzero features
4. Computational constraint weakly active due to implicit features.

Relative progressive validation squared loss & relative wall-clock time reported.


Initial Experiments, Sharding & Training
relative squared loss or time
1.2
1
0.8
0.6
0.4
0.2
0
1
2
4
8
shard count
r. squared loss
r. time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Final thoughts

We compete with & beat multicore parallelized online gradient descent.

This general approach, unlike averaging approaches, is fully applicable to nonlinear systems.

Backprop & Delayed GD coming soon.

Code at: http://github.com/JohnLangford/vowpal_wabbit

Patches welcome.

Tutorial@2pm (No skiing for me!)

Some further discussion @ http://hunch.net