Mechanisms for Parallel Online Learning

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(on joint work with Daniel Hsu & Alex Smola & Martin Zinkevich)
How should we write fast learning algorithms?

1. Speed up slow learning algorithms.
2. Switch architectures. Canonical example = GPU. Useful for computationally intense learning, but...
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.
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Core Problems for Parallel algorithms = Bandwidth & Latency

1 Gb/s ethernet = 450GB/hour \Rightarrow 1 \text{Terafeature} \text{ is reasonable.}
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1 Gb/s ethernet = 450GB/hour ⇒ 1 Terafeature is reasonable.
Latency = 1ms ≃ 10^6 cycles.
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?
How can we avoid delay?

Predictions

Predict & Learn

Feature Shard

Label Features
How can we avoid delay?

Predict & Learn

Predictions

Predict & Learn

Feature

Shard
Observations about Feed Forward

1. No longer the same algorithm—it’s designed for parallel environments.
2. Bandwidth = few bytes per example, per node ⇒ Tera-example feasible with single master, arbitrarily more with hierarchical structure.
3. No delay.
4. Feature Shard is stateless ⇒ parallelizable & cachable.
Bad News: Feed Forward can’t compete with general linear predictors.

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<th>$x_2$</th>
<th>$x_3$</th>
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</table>

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. ~100G when gzip compressed.
2. ~10M examples.
3. ~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 vs shard count

r. squared loss vs r. time

shard count

0 0.2 0.4 0.6 0.8 1 1.2

0 0.2 0.4 0.6 0.8 1

1 2 4 8
Initial Experiments, Training & Combining

relative squared loss or time

shard count

r. squared loss
r. time

shard count
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