A Method for Parallel Online Learning

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

MMDS 2010
A RCV1 derived binary classification task:

1. **424MB** Gzip compressed
2. **781K** examples
3. **60M** (nonunique) features

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Other systems:

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3. **PLANET** (depth 10 tree) (VLDB2009): 3M features/second using 200 nodes
How does Vowpal Wabbit work?

Start with $\forall i : \: w_i = 0$, Repeatedly:

1. Get example $x \in R^*$.
2. Make prediction $\hat{y} = \frac{\sum_i w_i x_i}{\sqrt{|\{i : x_i \neq 0\}|}}$ clipped to interval $[0, 1]$.
3. Learn truth $y \in [0, 1]$ with importance $I$ or goto (1).
4. Update $w_i \leftarrow w_i + \frac{\eta^2 (y - \hat{y}) I x_i}{\sqrt{|\{i : x_i \neq 0\}|}}$ and go to (1).

This is routine, but with old and new optimization tricks like hashing. This is open source @ http://hunch.net/~vw Also reimplemented in Torch, Streams, and Mahout projects.
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Why I’m dissatisfied, and What I’ve learned so far.

1 Ghz processor should imply 1B features/second. And it’s easy to imagine datasets with 1P features. How can we deal with such large datasets?

Core Problem for Learning on much data = Bandwidth limits

1 Gb/s ethernet = 450GB/hour

Outline

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1. Multicore parallelization
2. Multinode parallelization
How do we parallelize across multiple cores?

Answer 1: It's no use because it doesn't address the bandwidth problem. But there's a trick. Sometimes you care about the interaction of two sets of features—queries with results for example. Tweak the algorithm so as to specify (query features, result features), then use a fast hash to compute the outer product in the core.

Possibilities:

1. Example Sharding: Each core handles an example subset.
2. Feature Sharding: Each core handles a feature subset.

Empirically: Feature Sharding > Example Sharding. Both work on two cores, but Example Sharding doesn't scale. Feature sharding provides about x3 speedup on 4 cores. But, again, this is just for a special case. Need multinode parallelization to address data scaling.
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Algorithms for Speed

1. Multicore parallelization
2. Multinode parallelization
Multinode = inevitable delay

Ethernet latency = 0.1 milliseconds = \(10^5\) cycles = many examples.

1. Example Sharding ⇒ weights out of sync by delay factor.
2. Feature Sharding ⇒ global predictions delayed by delay factor.

How bad is delay?
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How bad is delay?
Theorem: (Mesterharm 2005) Delayed updates reduce convergence by delay factor in worst case for expert algorithms.
Theorem: (LSZ NIPS 2009) Same for linear predictors.
(Caveat: there are some special cases where you can do better.)
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What do we do?
How can we avoid delay?
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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 ⇒ 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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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: $x_1 = \text{first shard}, \ x_2 = \text{second shard}$
Even better: There are more complex problem classes for which this also works.
Initial experiments on a medium size text Ad dataset @ Yahoo!

1. \( \sim 100\text{GB} \) when gzip compressed.
2. \( \sim 10\text{M} \) examples.
3. \( \sim 125\text{G} \) nonzero features
4. Uses outerproduct features

Relative progressive validation (BKL COLT 1999) squared loss & relative wall-clock time reported.
Initial Experiments, Sharding & Training

relative squared loss or time vs shard count

- r. squared loss
- r. time

Graph showing the relationship between relative squared loss or time and shard count.
Final thoughts

About x6 speedup achieved over sequential system so far. This general approach, unlike averaging approaches, is fully applicable to nonlinear systems.

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

Patches welcome. Much more work needs to be done.

Some further discussion @ http://hunch.net