A Method for Parallel Online Learning

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

MMDS 2010

My Personal Supercomputer

A RCV1 derived binary classification task:

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

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2. PSVM (2007): 23K features/second using 500 nodes (on RCV1)
3. PLANET (depth 10 tree) (VLDB2009): 3M features/second using 200 nodes

How does Vowpal Wabbit work?

Start with $\forall i: \quad w_i = 0$, 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).
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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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Outline

1. Multicore parallelization
2. Multinode parallelization

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But, again, this is just for a special case. Need multinode parallelization to address data scaling.

Algorithms for Speed

1. Multicore parallelization
2. Multinode parallelization

Multinode = inevitable delay

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

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Theorem: (LSZ NIPS 2009) Same for linear predictors.
(Caveat: there are some special cases where you can do better.)
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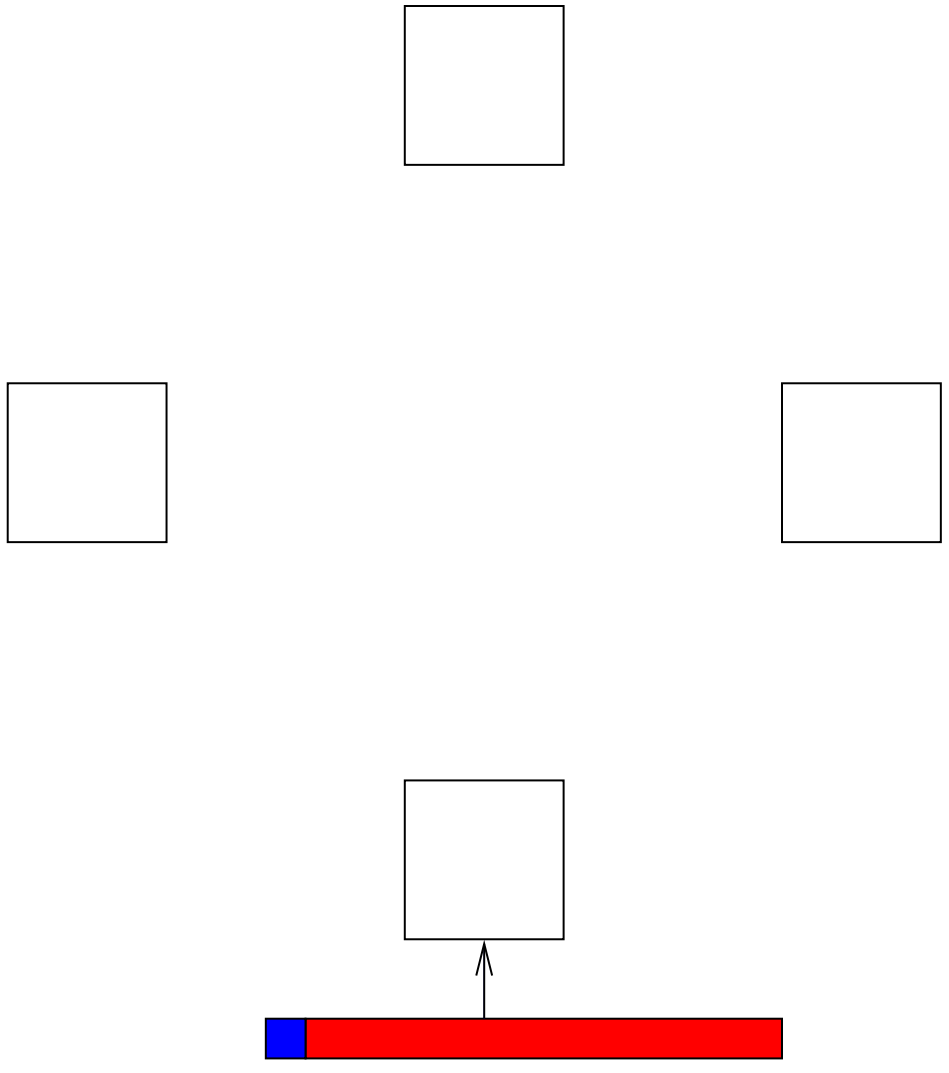
What do we do?

How can we avoid delay?



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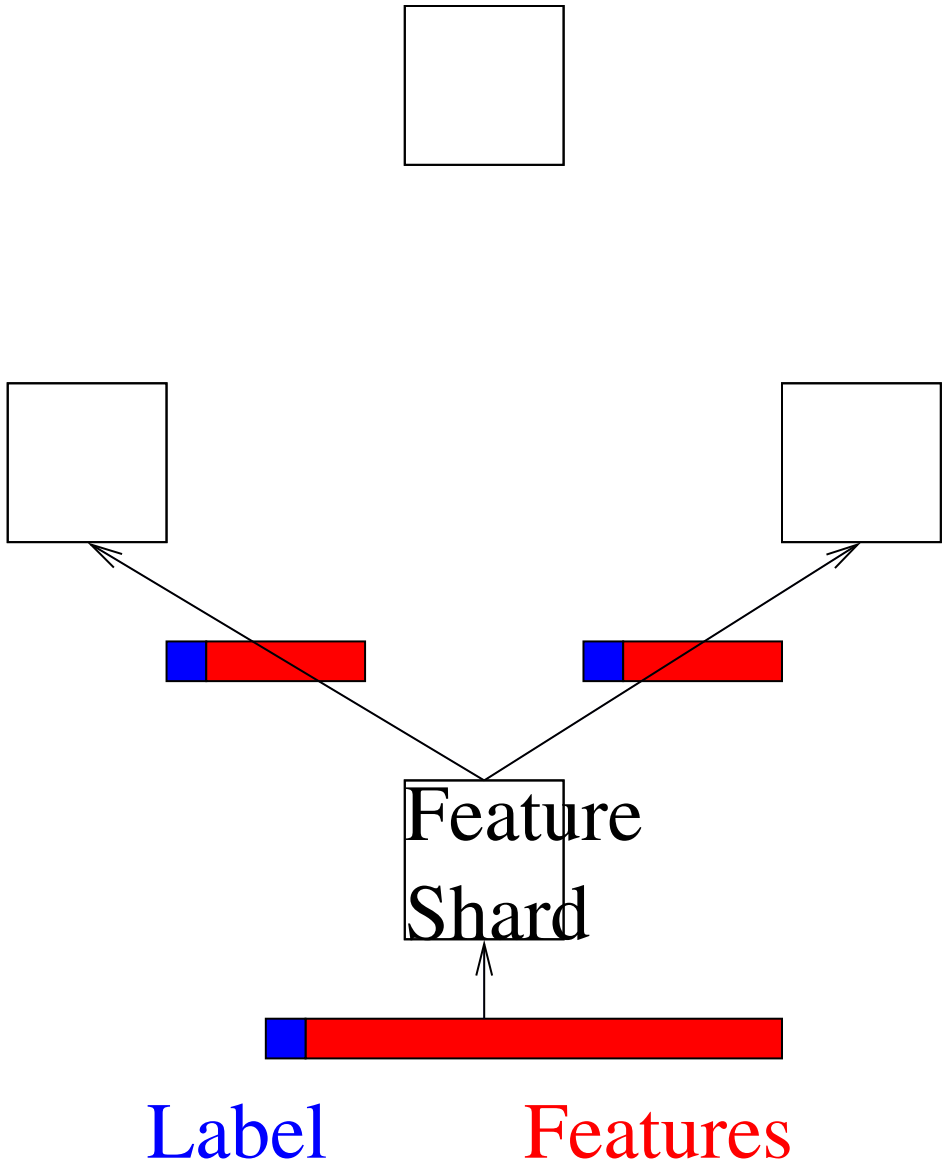

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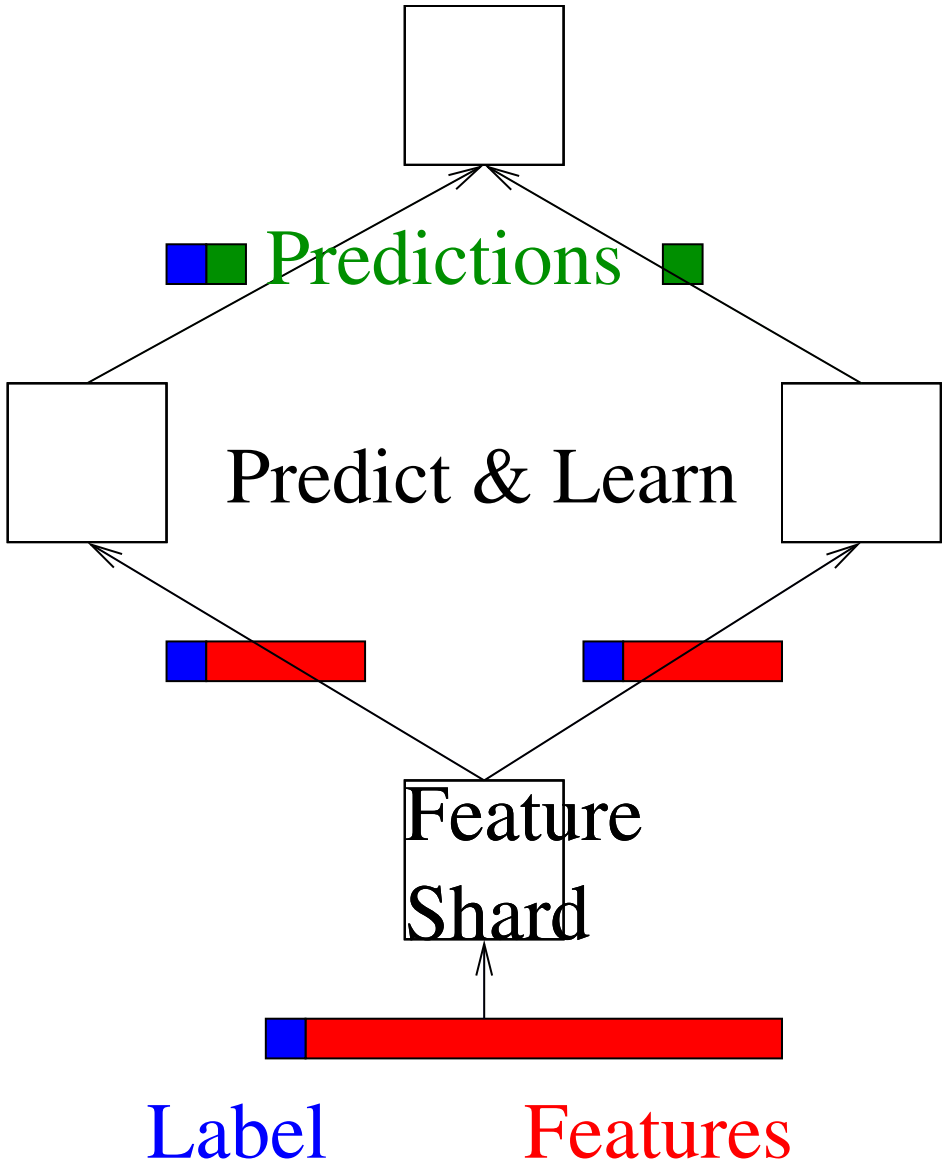

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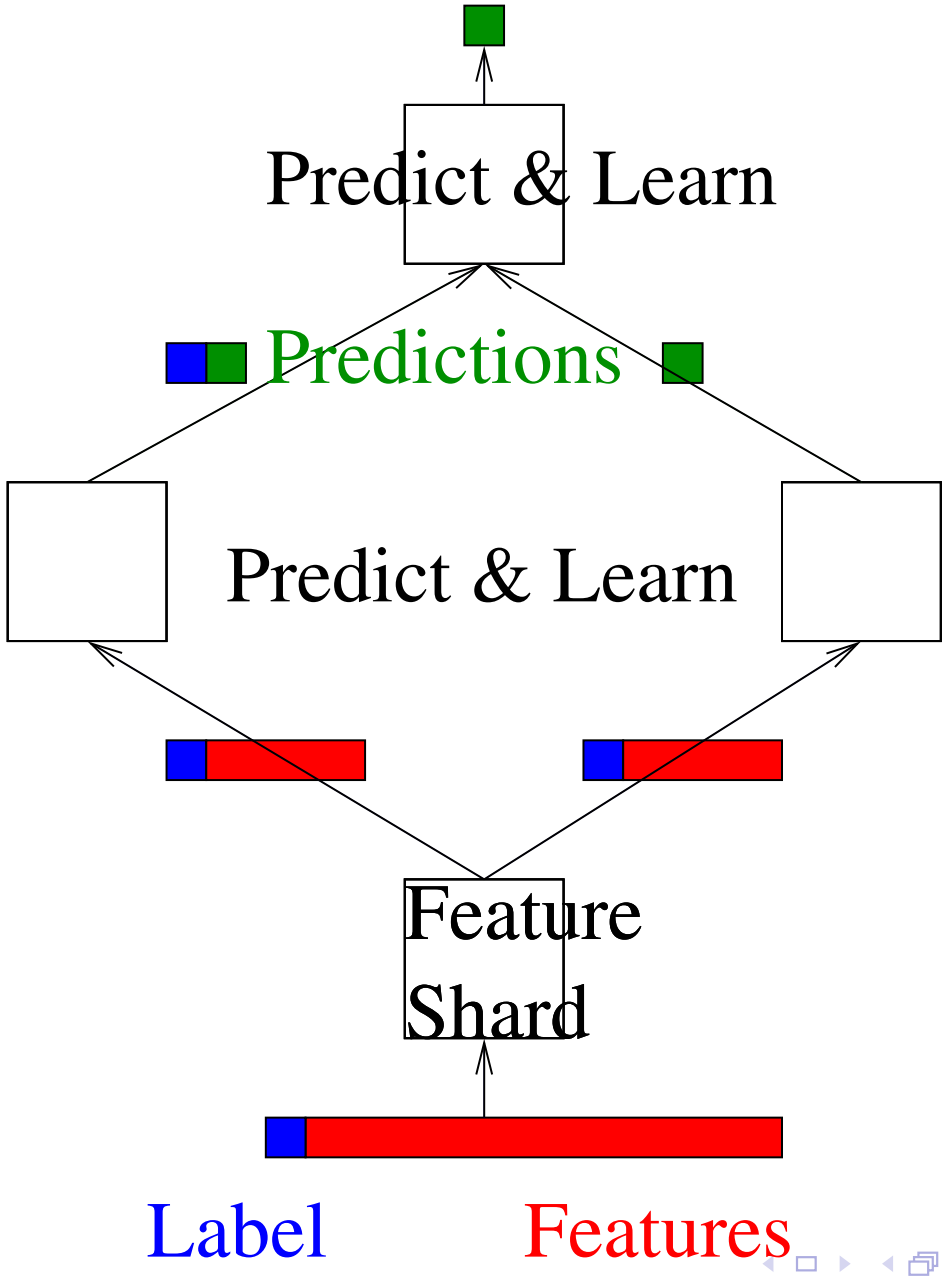


Observations about Feed Forward

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.

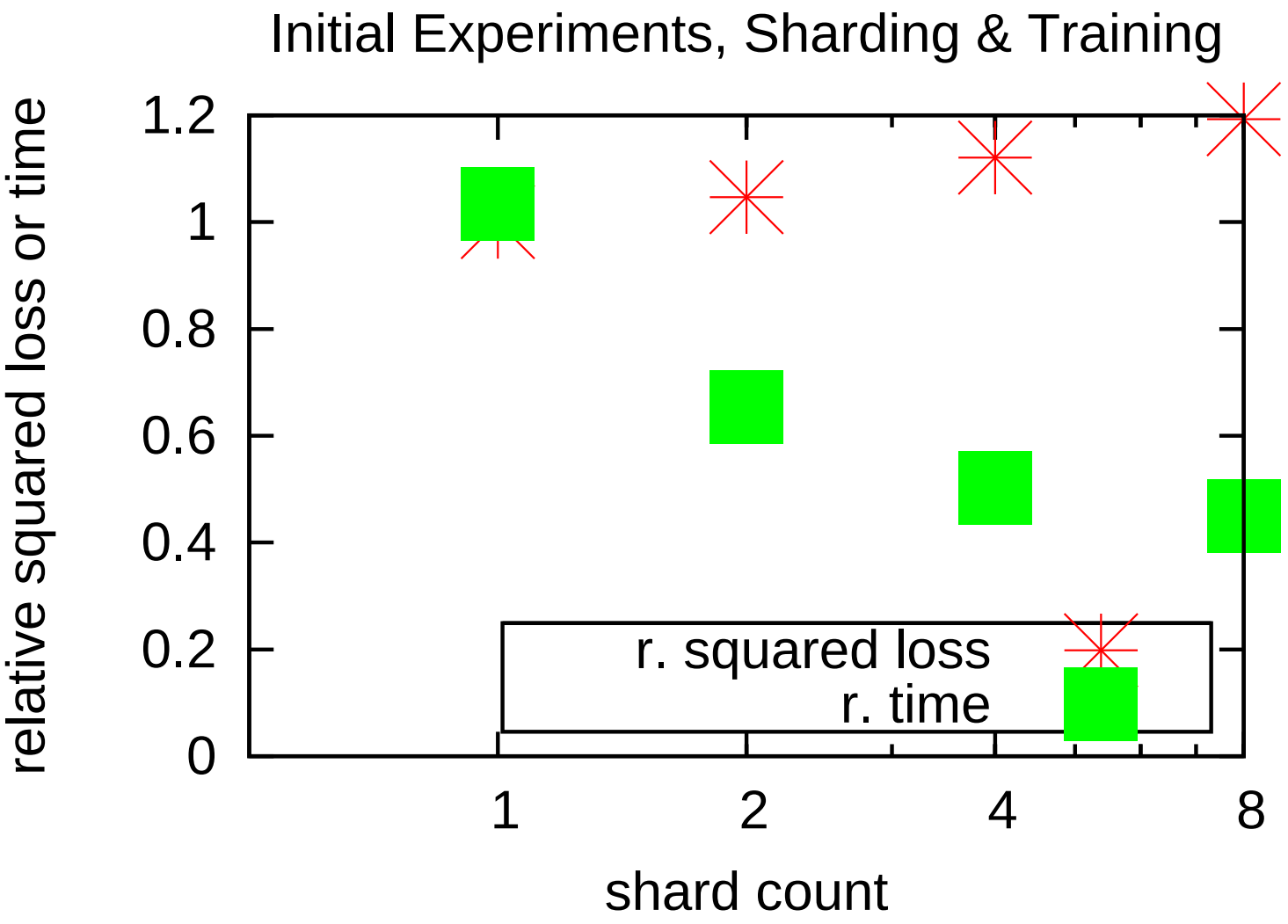
Good news

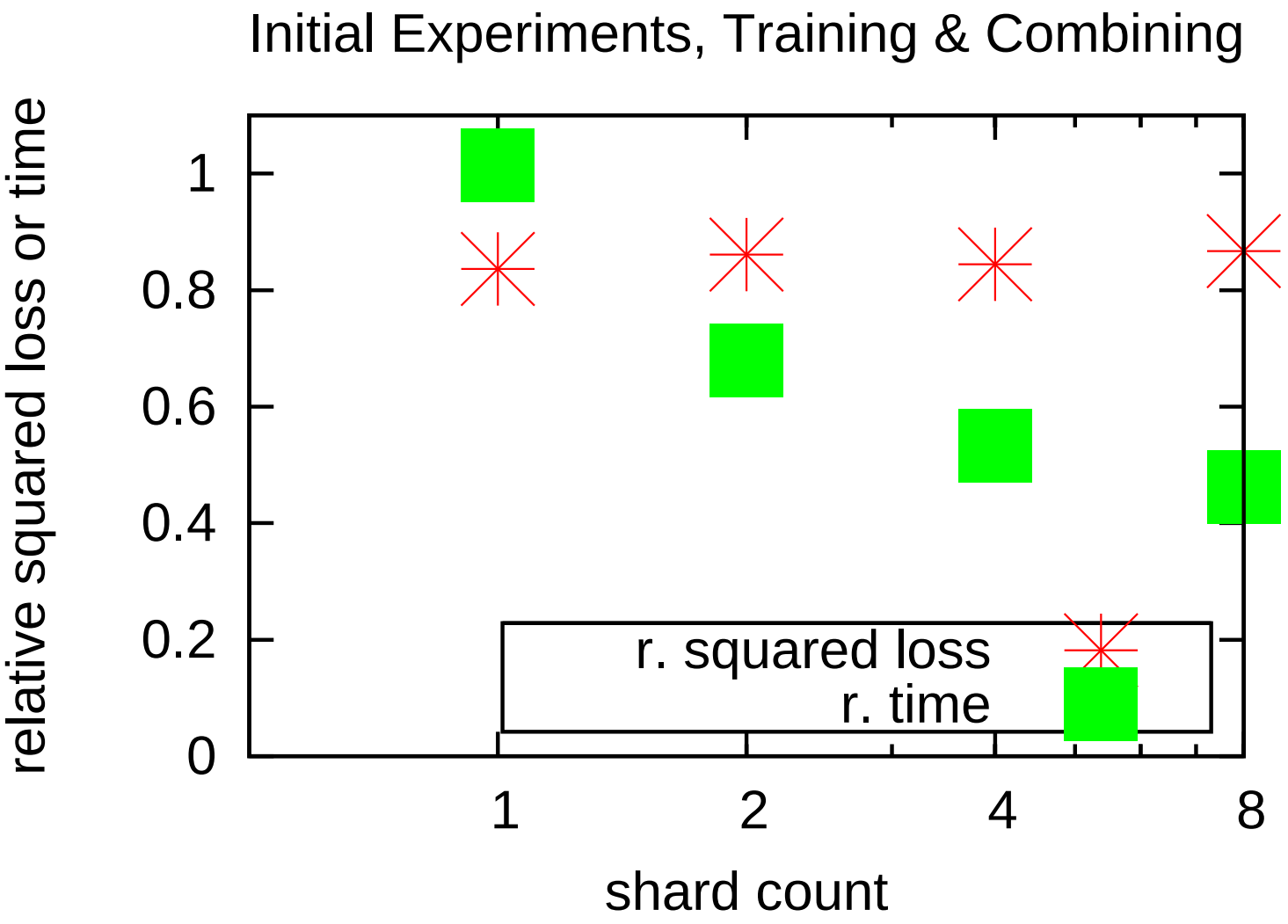
If Naive Bayes holds $P(x_1|y)P(x_2|y) = P(x_1, x_2|y)$, you win.
Better news: x_1 = first shard, x_2 = second shard
Even better: There are more complex problem classes for which this also works.

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

1. $\sim$100GB when gzip compressed.
2. $\sim$10M examples.
3. $\sim$125G 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
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

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