Learning on Cores, Clusters, and Clouds

Alekh Agarwal (Berkeley)

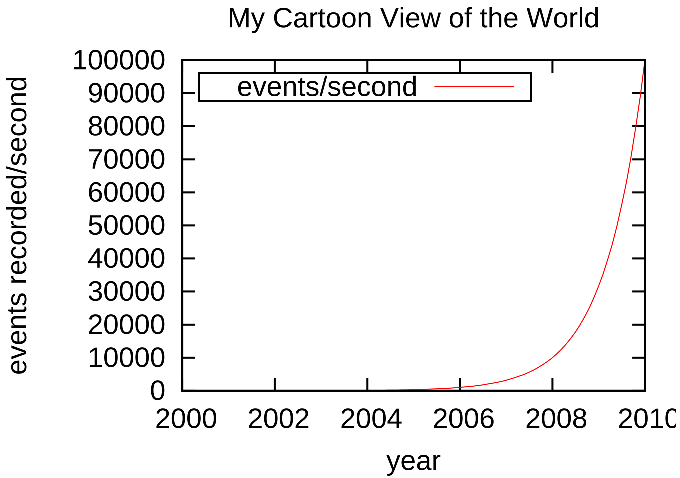
Lawrence Cayton (MPI-Tuebingen)

Ofer Dekel (Microsoft)

John Duchi (Berkeley & Google)

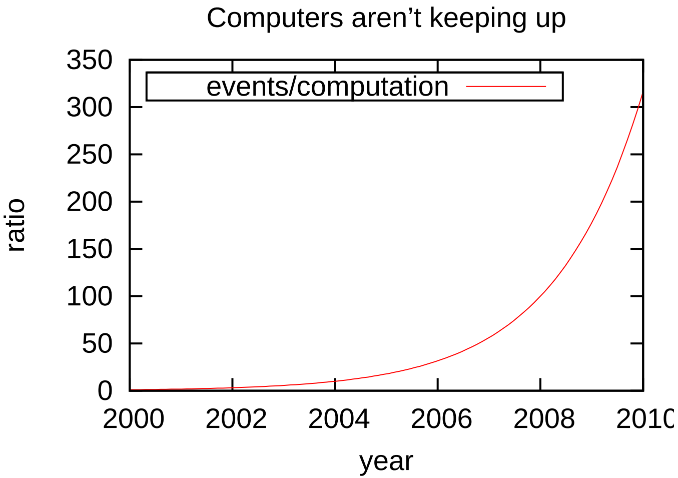
John Langford (Yahoo!)

Why a workshop?



Anecdotally: Startups with 10^9 events/day.

Old techniques don't work



Linear work is unavoidable but even linear time often inadequate.

Core Issues

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Spam became a business model. Individual email servers are typically overwhelmed. Large spam filters at centralized email providers— Google Microsoft Research Yahoo! Labs

How do we Efficiently learn to classify Spam in a Parallel Distributed environment?

The Wider Context

3 Years ago: Samy Bengio, Corinna Cortes, Dennis DeCoste, Francois Fleuret, Ramesh Natarajan, Edwin Pednault, Dan Pelleg, Elad Yom-Tov Efficient Machine Learning - Overcoming Computational Bottlenecks in Machine Learning

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Next Year: Large Scale Learning Book with 20+ chapters edited by Ron Bekkerman, Misha Bilenko, & me.

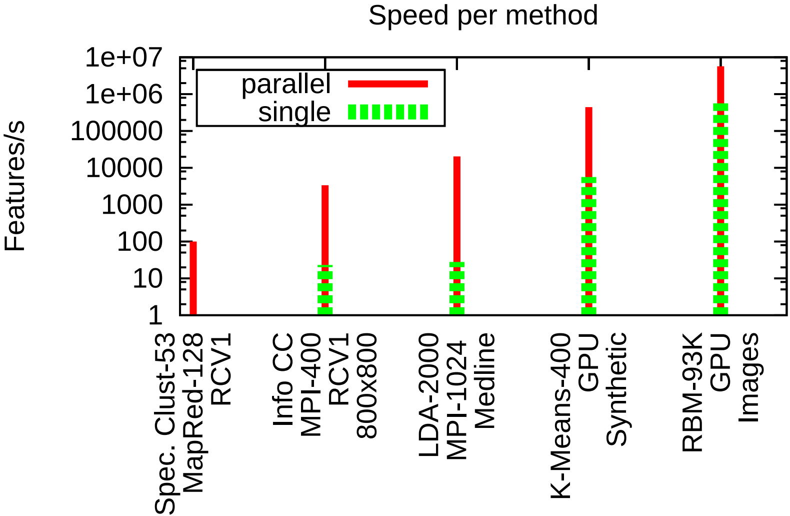
What's in the book?

Parallel Unsupervised Learning Methods

1. Information-Theoretic Co-Clustering with MPI
2. Spectral Clustering MapReduced
3. K-Means with GPU
4. Latent Dirichlet Analysis with MPI

It's *very* hard to compare different results.

... But let's try



Speed per method
Features/s
1e+07
1e+06
100000
10000
1000
100
10
1
parallel
single
Spec. Clust-53 MapRed-128 RCV1
Info CC MPI-400 RCV1 800x800
LDA-2000 MPI-1024 Medline
K-Means-400 GPU Synthetic
RBM-93K GPU Images

Ground Rules

Ginormous caveat: Prediction performance varies wildly depending on the problem–method pair.

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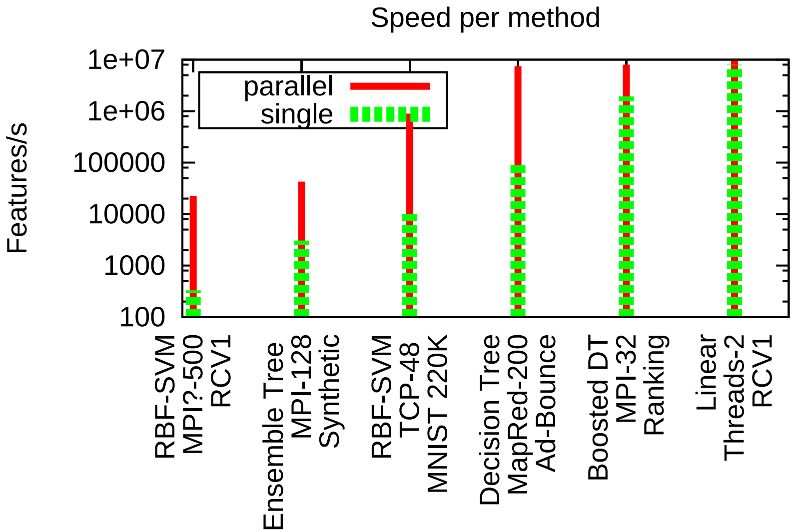
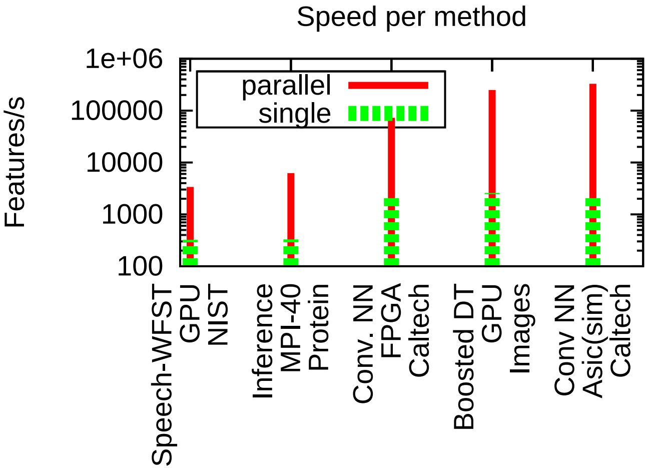
Most interesting results reported. Some cases require creative best-effort summary.

Supervised Training



Supervised Testing (but not training)



The rest

Many others defy summarization. Highlights:

1. Feature selection & frequent item systems.
2. Chapters on new parallel computing frameworks of plausible interest to ML people.

The Morning

7:00	Poster setup
7:30	Langford—Intro
8:00	Tsitsiklis—Averaging algorithms and distributed optimization
9:00	Coffee & Posters
9:20	Xiao—Optimal Distributed Online Prediction Using Mini-Batches
9:45	Petrov—MapReduce/Bigtable for Distributed Optimization
10:10	Minitalks
10:30	Posters & Break

The Afternoon

- 2:00 Unofficial Vowpal Wabbit Tutorial
- 3:30 Guestrin—Machine Learning in the Cloud with GraphLab
- 4:30 Singh—Distributed MAP Inference for Undirected Graphical Models
- 4:55 Posters & Break
- 5:15 Ye—Gradient Boosted Decision Trees on Hadoop
- 5:40 More Minitalks
- 6:00 Summary/Panel/Discussant
- 6:30 Posters & talking

Have Fun!