Sibyl: A system for large scale supervised machine learning

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Goal

- Users respond differently to different information in different contexts
- Learn model of what information gets the best user response in different contexts
- ... use model do decide what to present

Uses of machine learning

- Improve relevance
- Improve site monetization
- Reduce spam
- Improve advertiser return on investment
- ... etc ...

Problem scale

- 100M views per day (or more)
- Businesses worth $100M (or more)

Problem scope

- There are many such problems at Google
  - Search, YouTube, Gmail, Android, G+, etc
  - Relevance, monetization, spam, etc

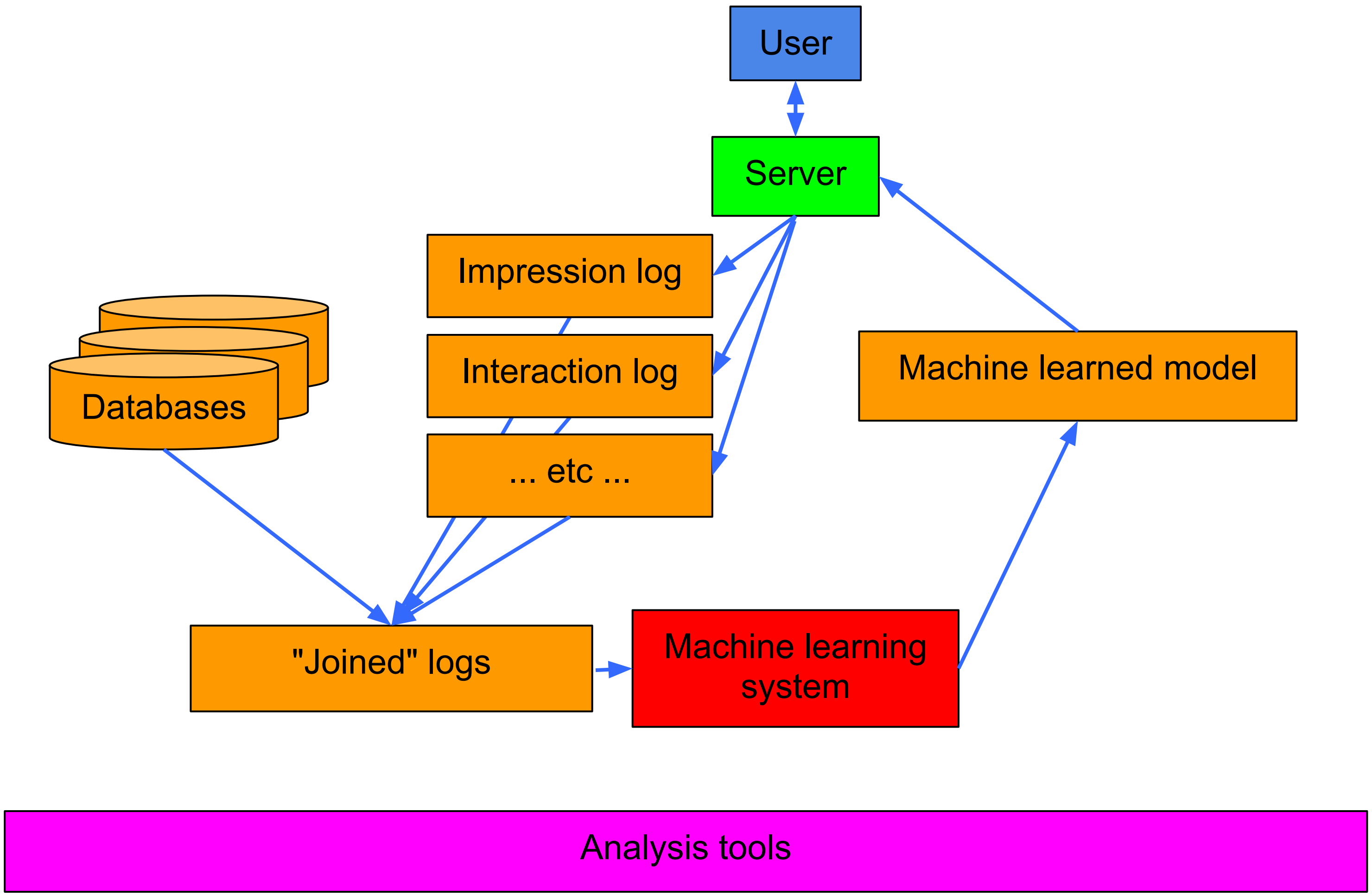
- ML typically generates 10+% improvements

=> This is becoming an industry "best practice"

- 1% improvement is a big deal, e.g.:
  - Improves relevance for millions of users
  - Millions of dollars of revenue

=> accuracy is important

Machine learning architecture



Sibyl spec

Google

- 100s of TB of joined logs (uncompressed)
- 100s of billions of training examples
- 100 billion unique features, 10s or 100s per example

=> Must train accurate models
(should be able to train 100s of models Google-wide)

=> Need highly parallel algos that converge quickly
(Algos should leverage Google's scalable infrastructure)

Results overview

Built principled large scale supervised ML system

- Using theoretically sound algorithms
- To solve internet scale problems
- Using reasonable resources
- For multiple loss functions and regularizations

Used techniques that are well known to the systems community

- MapReduce for scalability
- Multiple cores and threads per computer for efficiency
- Google File System (GFS) to store lots of data
- An integerized column-oriented data format for compression & performance

Parallel Boosting Algorithm

(Collins, Schapire, Singer 2001)

- Iterative algorithm, each iteration improves model
- Number of iterations to get within ϵ of the optimum:

$$\log(m)/\epsilon^2$$

- Updates correlated with gradients, but not a gradient algorithm
- Self-tuned step size, large when instances are sparse

Parallel Boosting Algorithm

(Collins, Schapire, Singer 2001)

$\textsc{Input:}$ Training set $S = \{(\boldsymbol{x}_i, y_i) \mid \boldsymbol{x}_i \in \{0,1\}^n, y_i \in \{-1,+1\}\}_{i=1}^m$

$\textsc{Parameters:}$ Regularization λ ; Number of rounds T

$\textsc{For}$ $t = 1$ to T

// *Compute importance weights*

$\textsc{For}$ $i = 1$ to m

$\textsc{Set}$ $q^t(i) = \frac{1}{1+e^{y_i(\boldsymbol{w}^t \cdot \boldsymbol{x}_i)}}$

$\textsc{For}$ $j = 1$ to n

// *Compute features statistics*

$$\mu_j^+ = \sum_{i:y_i=+1 \wedge x_{i,j}=1} q^t(i) \qquad \mu_j^- = \sum_{i:y_i=-1 \wedge x_{i,j}=1} q^t(i)$$

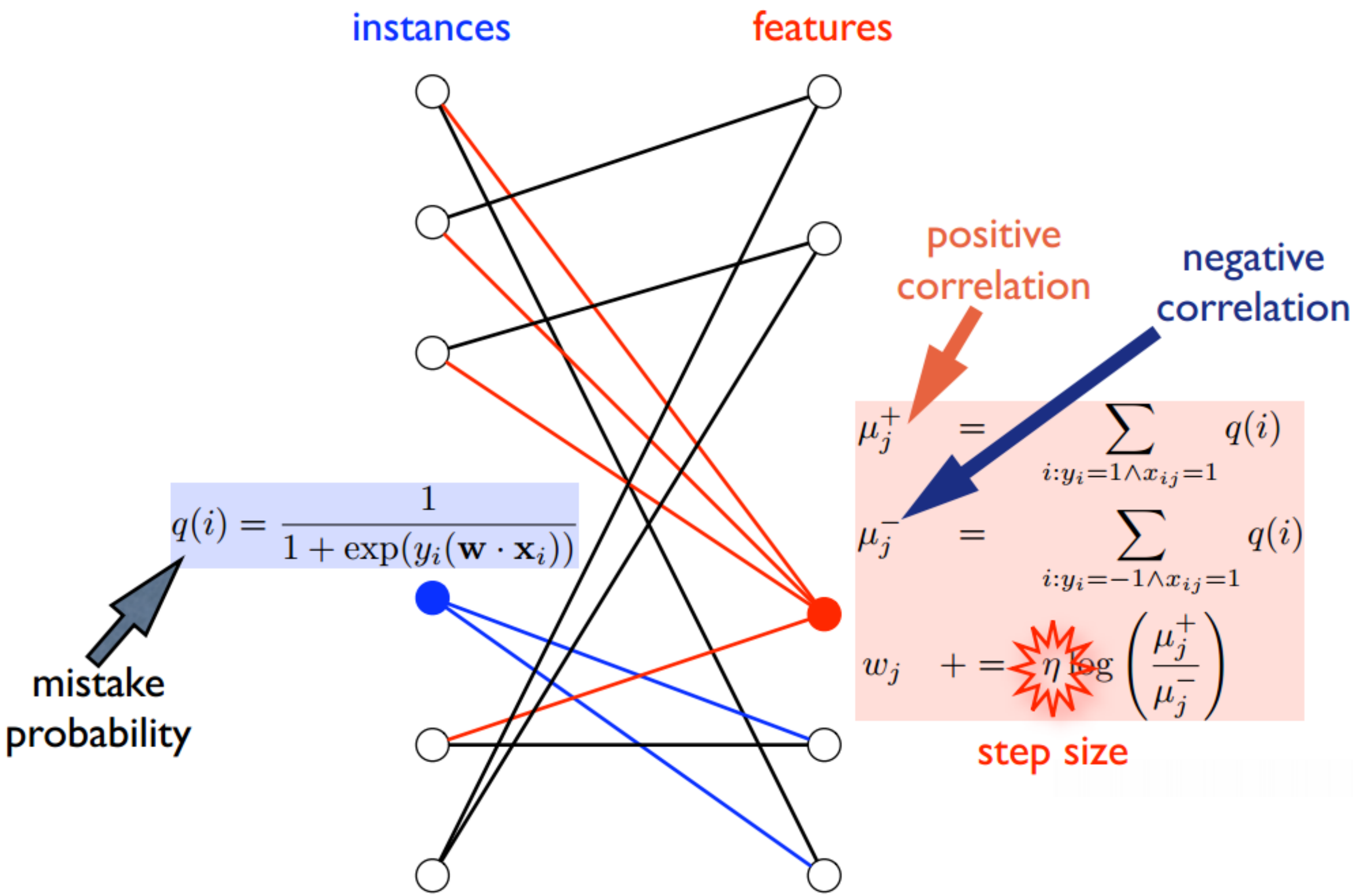
// *Compute change in weights*

$$\delta_j^t = \rho \log \frac{\mu_j^+}{\mu_j^-}$$

$$\boldsymbol{w}^{t+1} = \boldsymbol{w}^t + \boldsymbol{\delta}^t$$

Parallel Boosting Algorithm

(Collins, Schapire, Singer 2001)



Properties of parallel boosting

Embarrassingly parallel:

1. Computes feature correlations for each example in parallel
2. Feature are updated in parallel

We need to “shuffle” the outputs of Step 1 for Step 2

Step size inversely proportional to number of active features per example

- Not total number of features
- Good for sparse training data

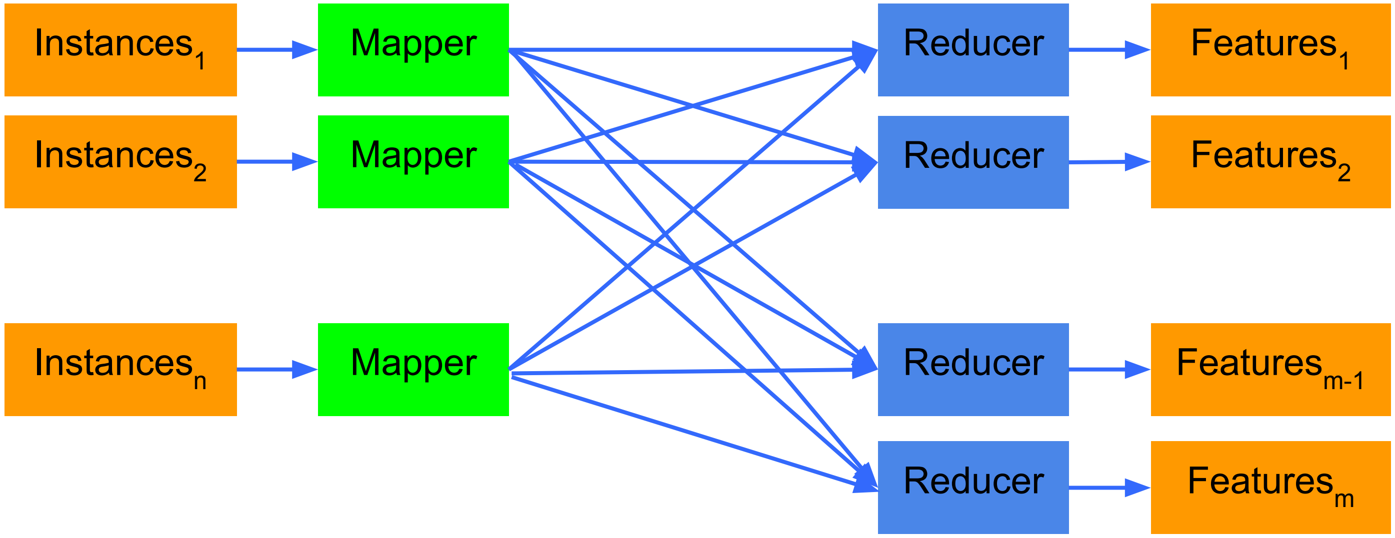
Extensions

- Add regularization
- Support other loss functions

A brief introduction to MapReduce

Programming model for processing large data sets

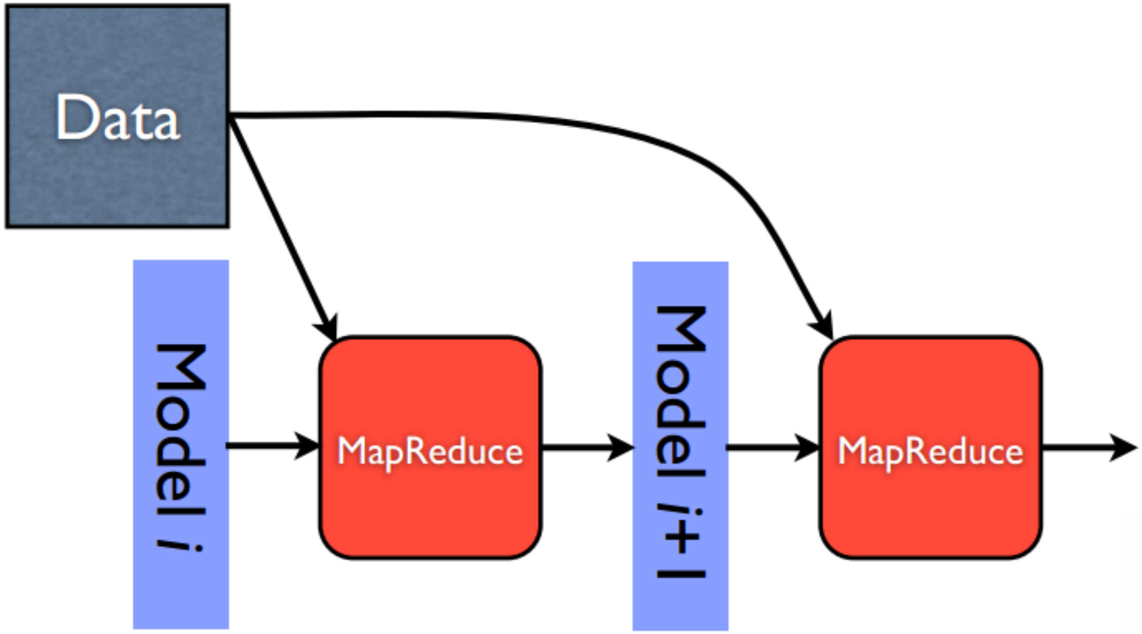
- Proven model and implementation



Implementing parallel boosting

+ Embarrassingly parallel
+ Stateless, so robust to transient data errors
+ Each model is consistent, sequence of models for debugging

- 10-50 iterations to converge

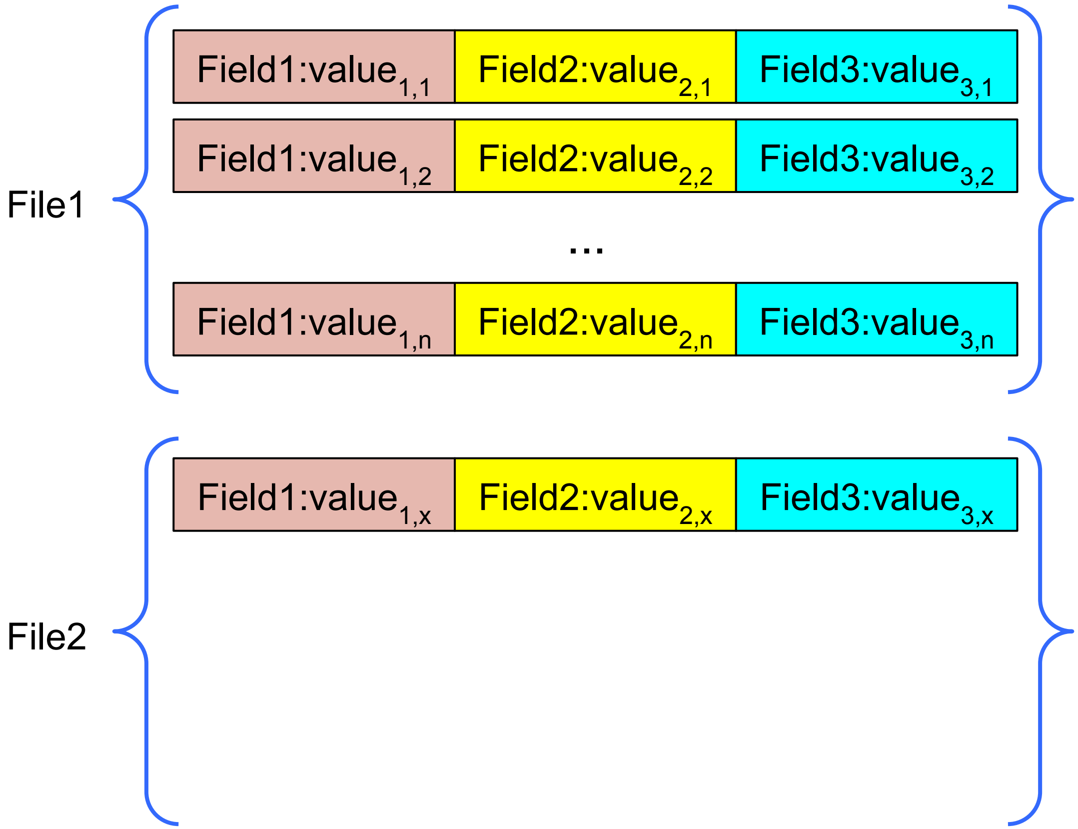


Some observations

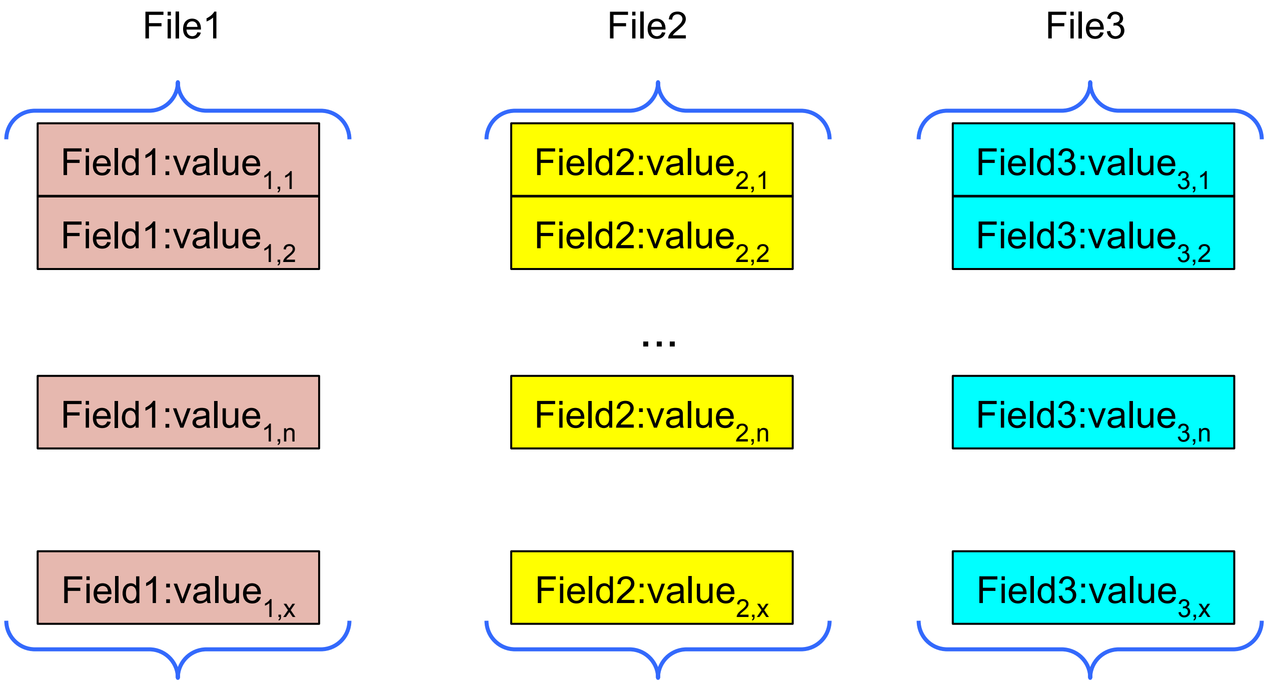
We typically train multiple models

- To explore different types of features
  - Don't read unnecessary features
- To explore different levels of regularization
  - Amortize fixed costs across similar models
- Computers have lots of RAM
  - Store the model and training stats in RAM at each worker
- Computers have lots of cores
  - Design for multi-core
- Training data is highly compressible

Instead of a row-oriented data store ...



Design principle: use column-oriented data store



Design principle: use column-oriented data store

Column for each field

Each learner only reads relevant columns

Benefits

- Learners read much less data
- Efficient to transform fields
- Data compresses better

Design principle: use model sets

- Train multiple similar models together
- Benefit: amortize fixed costs across models
  - Cost of reading training data
  - Cost of transforming data
- Downsides
  - Need more RAM
  - Shuffle more data

Design principle: "Integerize" features

- Each column has its own dense integer space
- Encode features in decreasing order of frequency
- Variable-length encoding of integers
- Benefits:
  - Training data compression
  - Store in-memory model and statistics as arrays rather than hash tables
    - Compact, faster

Design principle: store model and stats in RAM

- Each worker keeps in RAM
  - A copy of the previous model
  - Learning statistics for its training data
- Boosting requires O(10 bytes) per feature
- Possible to handle billions of features

Design principle: optimize for multi-core

- Share model across cores
- MapReduce optimizations
  - Multi-shard combiners
    - Share training statistics across cores

Training data

Product	Examples	Compressed Raw data	Training data	Compression	Features per example	bytes per feature
A	59.9B	9.98TB	2.00TB	4.99x	54.9	0.67
B	7.6B	2.67TB	0.71TB	3.78x	94.9	1.07
C	197.5B	66.66TB	15.54TB	4.29x	77.7	1.11
D	129.1B	61.93TB	17.24TB	3.59x	100.57	1.46

Processing throughput

Product	Examples	Features per example	Processing cores	Iteration time (secs)	Number of models	#features per sec per core
A	59.9B	26.59	195	2471	1	3.3M
B	7.6B	27.18	290	599	2	2.4M
C	197.5B	35.09	700	4523	1	2.2M
D	129.1B	54.61	970	3150	1	2.3M

Concurrency

Number of cores	Time per iteration (secs)	Cost per iteration (core x secs)
4 cores x 10 machines	15000	60000
8 cores x 10 machines	7500	60000
12 cores x 10 machines	4500	54000
16 cores x 10 machines	3900	62400

Impact of L1

Product	Number of features	Number of non-zero features	Fraction of non-zero features
A	868M	20.1M	2.31%
B	333M	7.9M	2.37%
C	1762M	251.8M	14.29%
D	2172M	371.6M	17.11%

Other Sibyl features

- Multiple loss functions
- Sophisticated regularization scheme
- Template exploration
- Dynamic stepping for faster convergence
- Online setting

Lesson learnt (future direction): Focus on ease of use

- Cleanly integrated machine learning pipeline
  - Log joining, training, serving, analysis
- Tools for analyzing TB of data
- Incorporate best practices
  - e.g., catch training/serving skew
- Incorporate other machine learning methods
  - e.g, unsupervised learning