Sibyl: a system for large scale machine learning

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Machine Learning Background

Use the past to predict the future

Core technology for internet-based prediction tasks

Examples of problems that can be solved with machine learning:

- Classify email as spam or not
- Estimate relevance of an impression in context:
  - Search, advertising, videos, etc.
  - Rank candidate impressions

The internet adds a scaling challenge:

- 100s of millions of users interacting every day
- Good solutions require a mix of theory and systems

Overview of Results

Built a large scale machine learning system:

- Used recently developed machine learning algorithm
- Algorithms have provable convergence & quality guarantees
- Solves internet scale problems with reasonable resources
- Flexible: various loss functions and regularizations

Used numerous well known systems techniques

- MapReduce for scalability
- Multiple cores and threads per computer for efficiency
- GFS to store lots of data
- Compressed column-oriented data format for performance

Inference and Learning

- Objective: draw reliable inferences from all the evidence in our data
  - Is this email SPAM?
  - Is this webpage porn?
  - Will this user click on that ad?
- Learning: create concise representations of the data to support good inferences

Many, Sparse Features

- Many elementary features: words, etc.
- Most elementary features are infrequent
- Complex features:
  - combination of elementary features
  - discretization of real-valued features
- Most complex features don't occur at all
- We want algorithms that scale well with number of features that are actually present, **not** with the number of possible features

Supervised Learning

- Given feature-based representation
- Feedback through a label:
  - Good or Bad
  - Spam or Not-spam
  - Relevant or Not-relevant
- Supervised learning task:
  - Given training examples, find an accurate model that predicts their labels

Machine learning overview

Training data

Label	Feature 1,	...	Feature n
Label	Feature 1',	...	Feature n'
Label	Feature 1'',	...	Feature n''

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Model

Feature 1 = 0.2, ... Feature n = -0.5

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+

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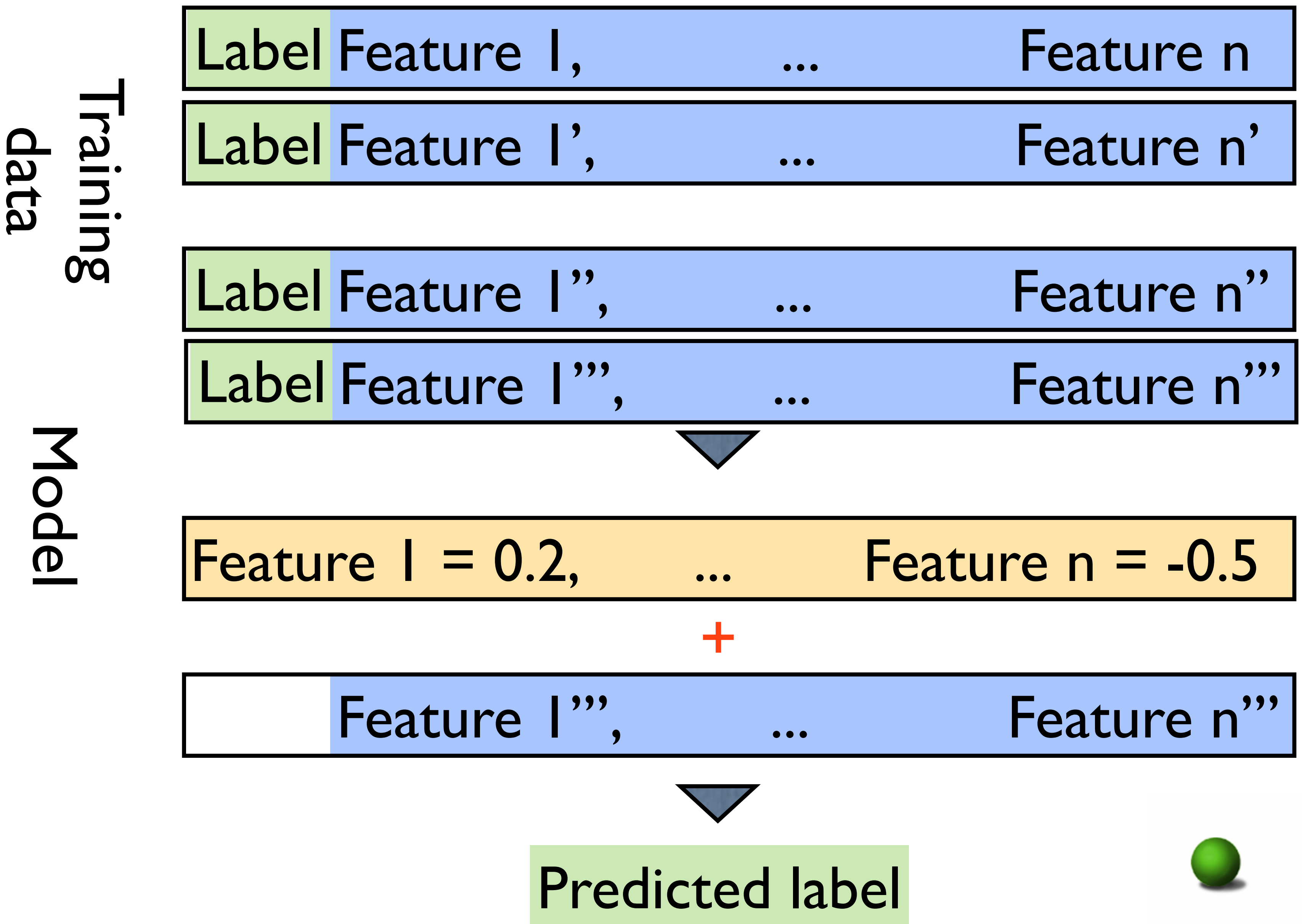
Predicted label

Machine learning overview



Example: Spam Prediction

- Feedback on emails:
  "Move to Spam" , "Move to Inbox"
- Lots of features:
  - `Viagra ∈ Document`
  - `IP Address of sender is bad`
  - `Sender's domain @google.com`
  - `...`
- Feedback returned daily and grows with time
- New features appear every day

From Emails to Vectors

- User receives an email from an unknown sender
- Email is tokenized:

```
...
Viagra  ∈ Document
Sudafed ∈ Document
Find a young wife ∈ Document
...
```

- Compressed instance:

$$\mathbf{x} \in \{0,1\}^n \quad (0,0,1,0,1,0,\ldots,0,0,1,0)$$

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Prediction Models

Captures importance of features

```
Viagra  ∈ Document => score +2.0
Sudafed ∈ Document => score +0.5
Sender's domain @google.com => score -1.0
```

Represented as a vector of weights

w = (0, 0, 2.0, -0.1, 0.5, ..., -1.0, ...)

Scoring the email

w.x = 2.0 + 0.5 - 1.0

Logistic regression (used for probability predictions)

$$\text{Probability} = \frac{1}{1 + e^{-w.x}}$$

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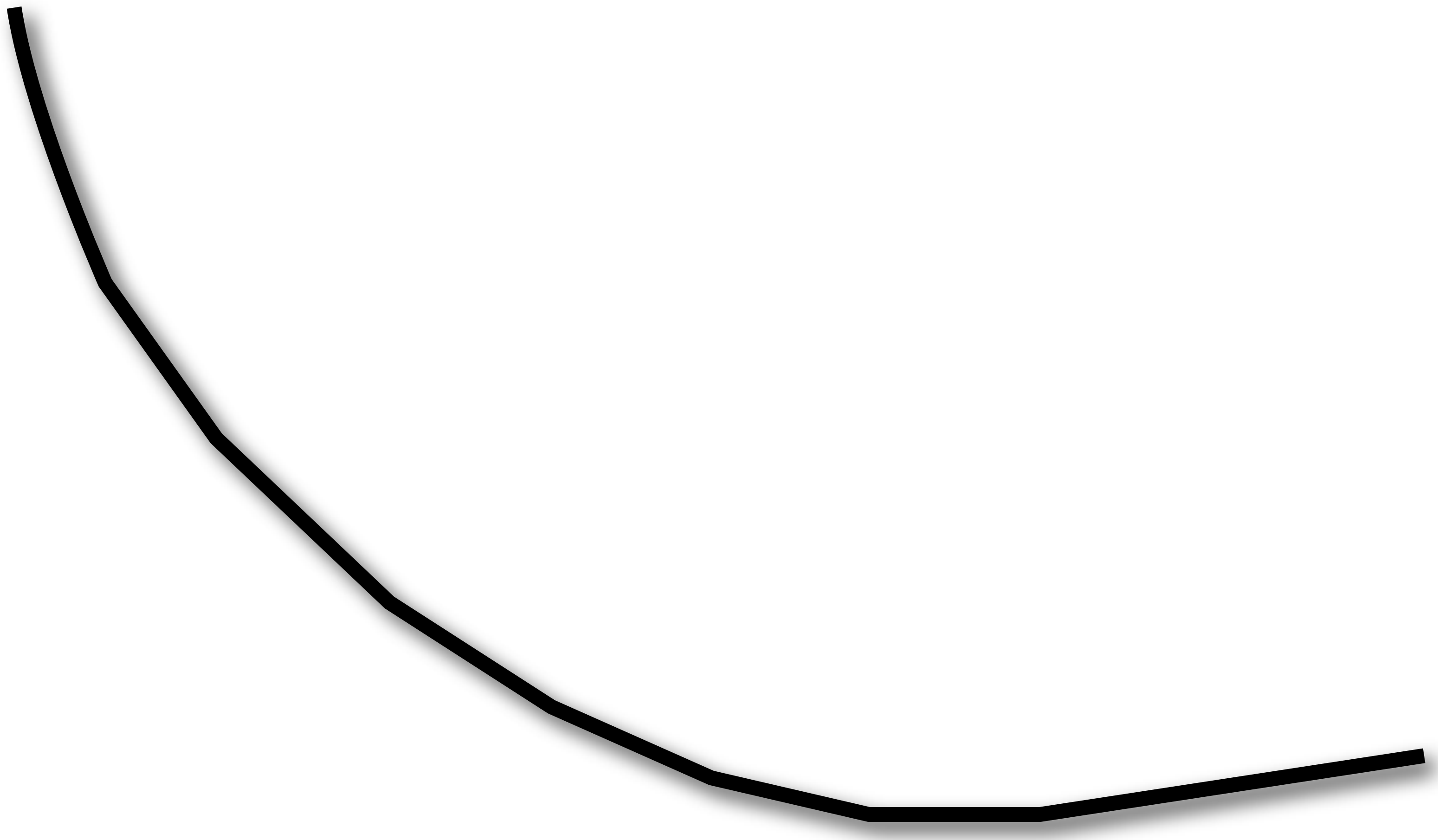
Parallel Boosting (Collins, Schapire, Singer 2001)

- 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

Boosting: Illustration



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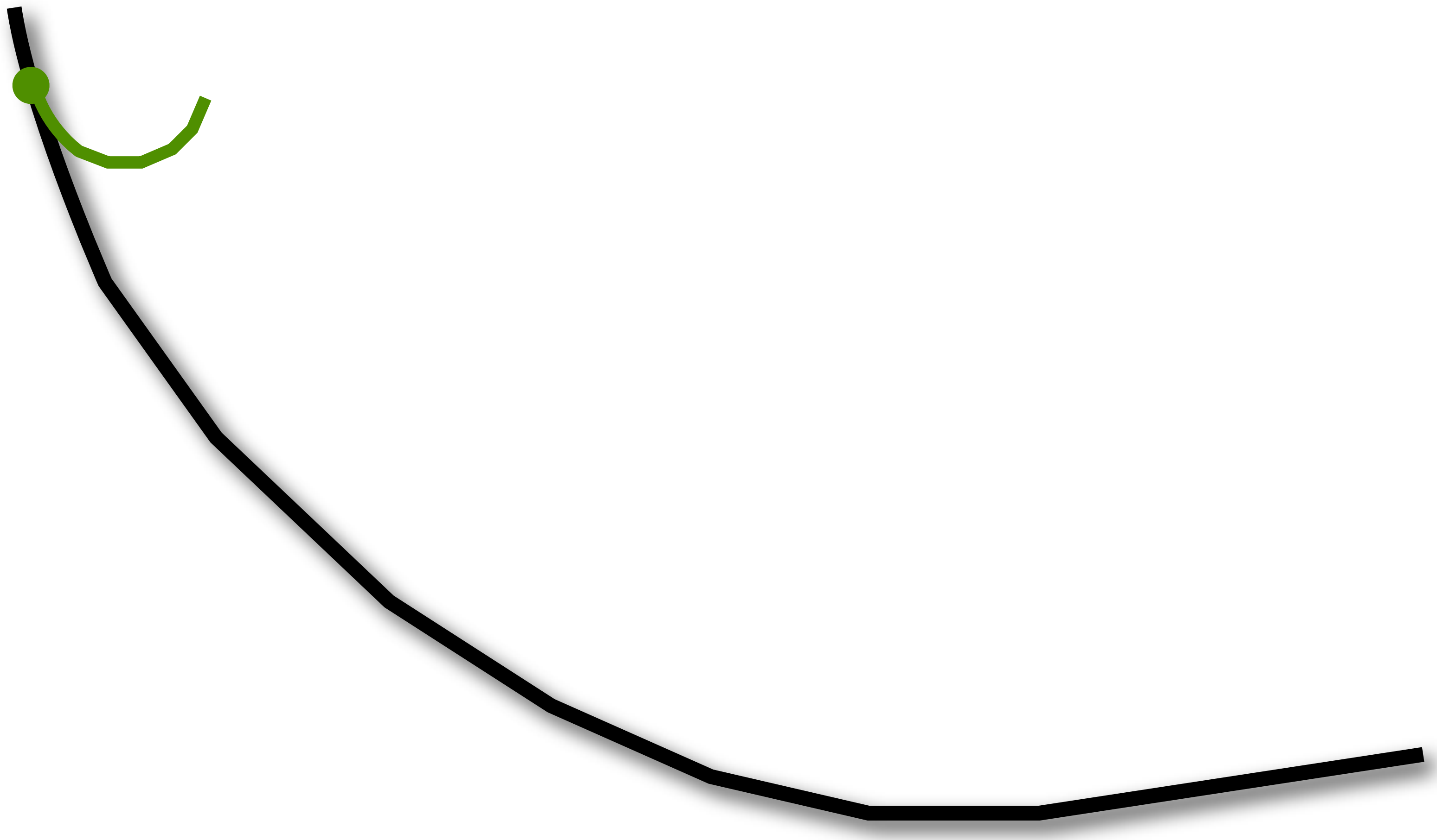

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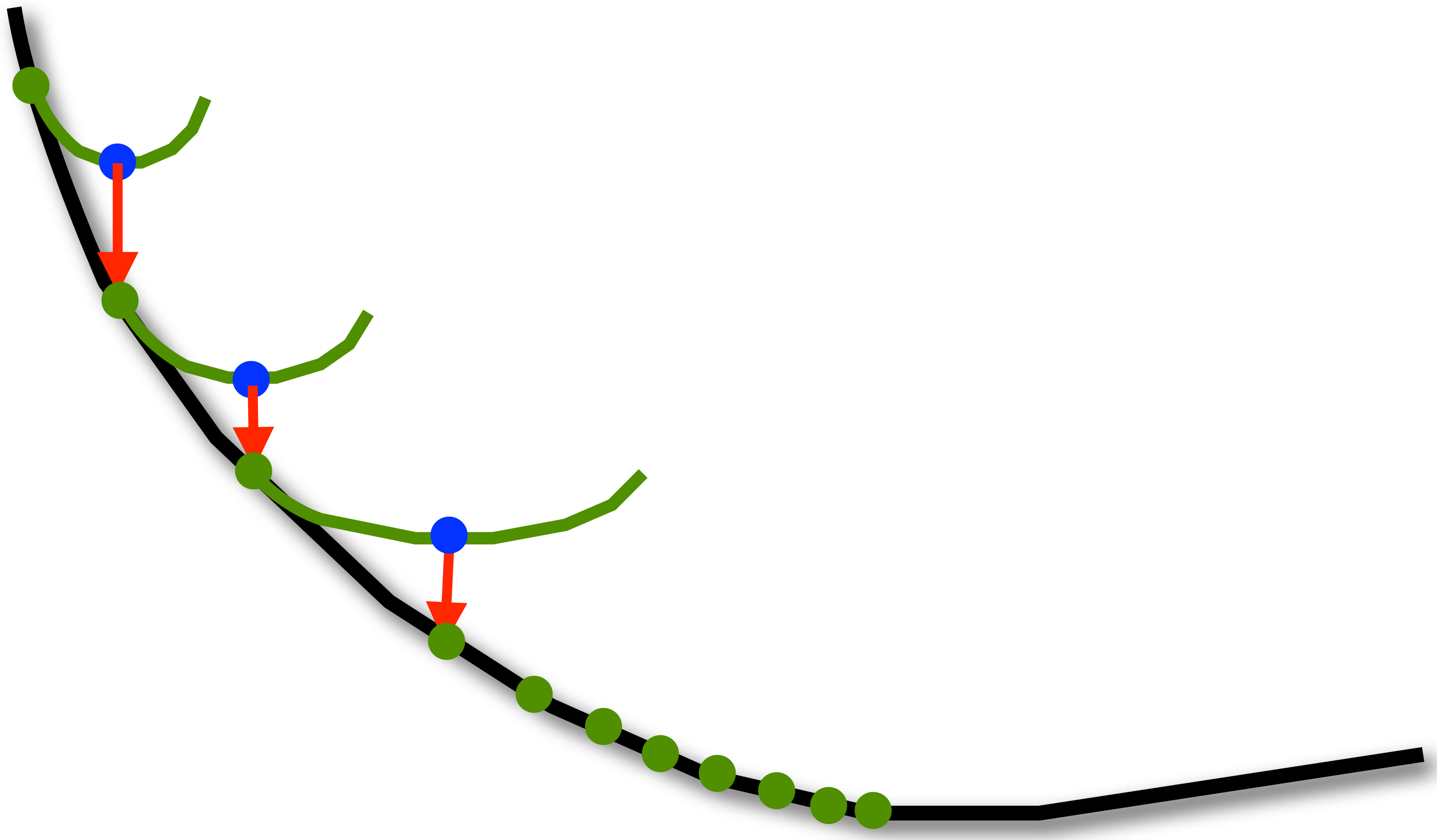
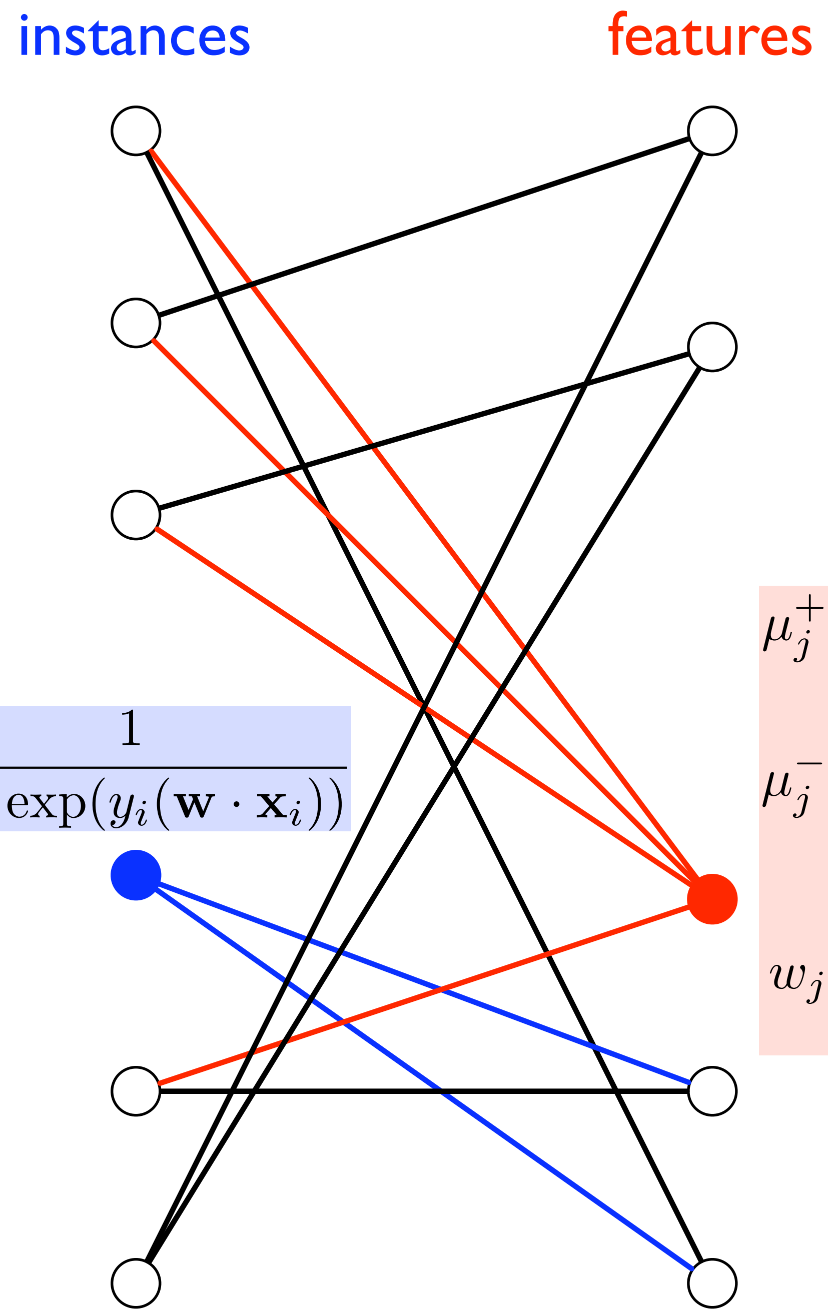


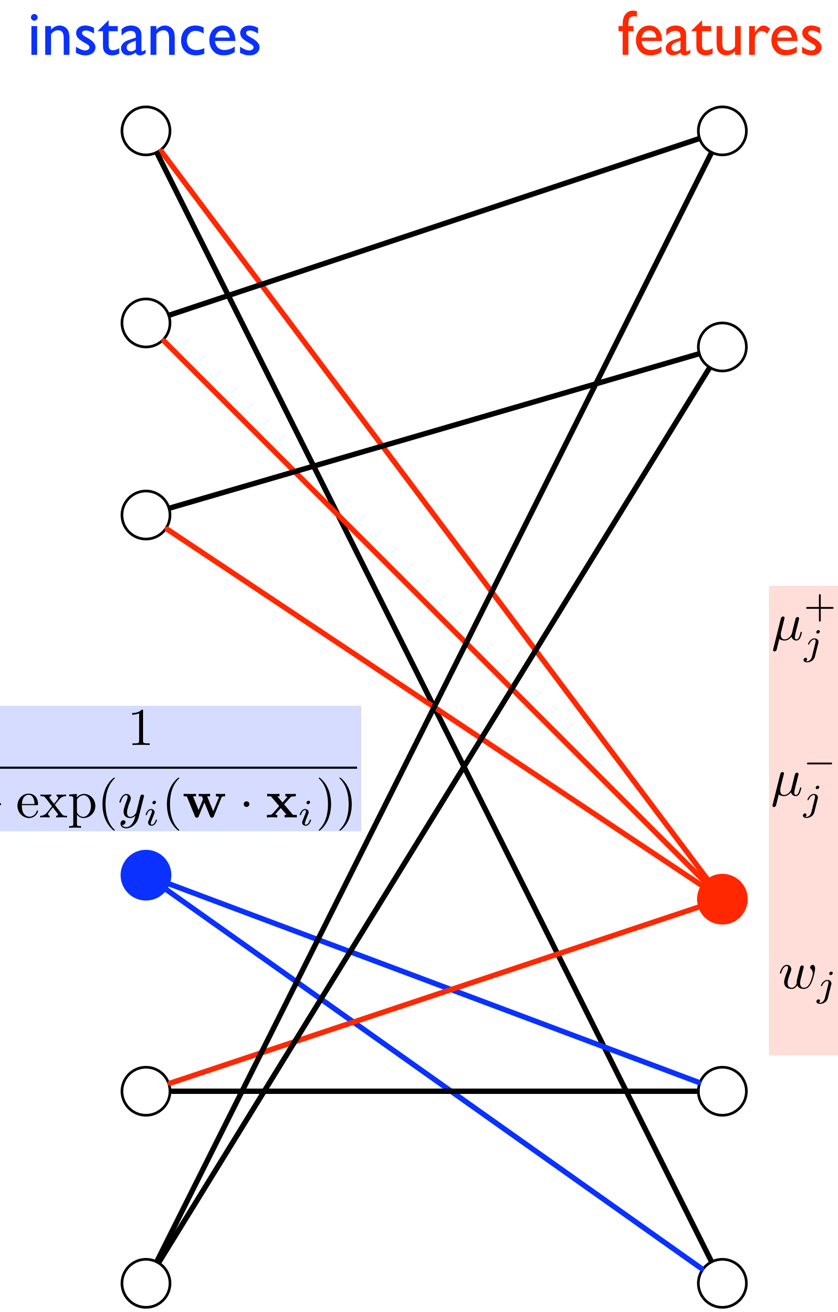
Parallel Boosting Algorithm



$$q(i) = \frac{1}{1 + \exp(y_i(\mathbf{w} \cdot \mathbf{x}_i))}$$

$$\begin{aligned}
\mu_j^+ &= \sum_{i: y_i = 1 \wedge x_{ij} = 1} q(i) \\
\mu_j^- &= \sum_{i: y_i = -1 \wedge x_{ij} = 1} q(i) \\
w_j &\mathrel{+}= \eta \log\left(\frac{\mu_j^+}{\mu_j^-}\right)
\end{aligned}$$

Parallel Boosting Algorithm



$$q(i) = \frac{1}{1 + \exp(y_i(\mathbf{w} \cdot \mathbf{x}_i))}$$

mistake probability

$$\mu_j^+ = \sum_{i: y_i = 1 \wedge x_{ij} = 1} q(i)$$

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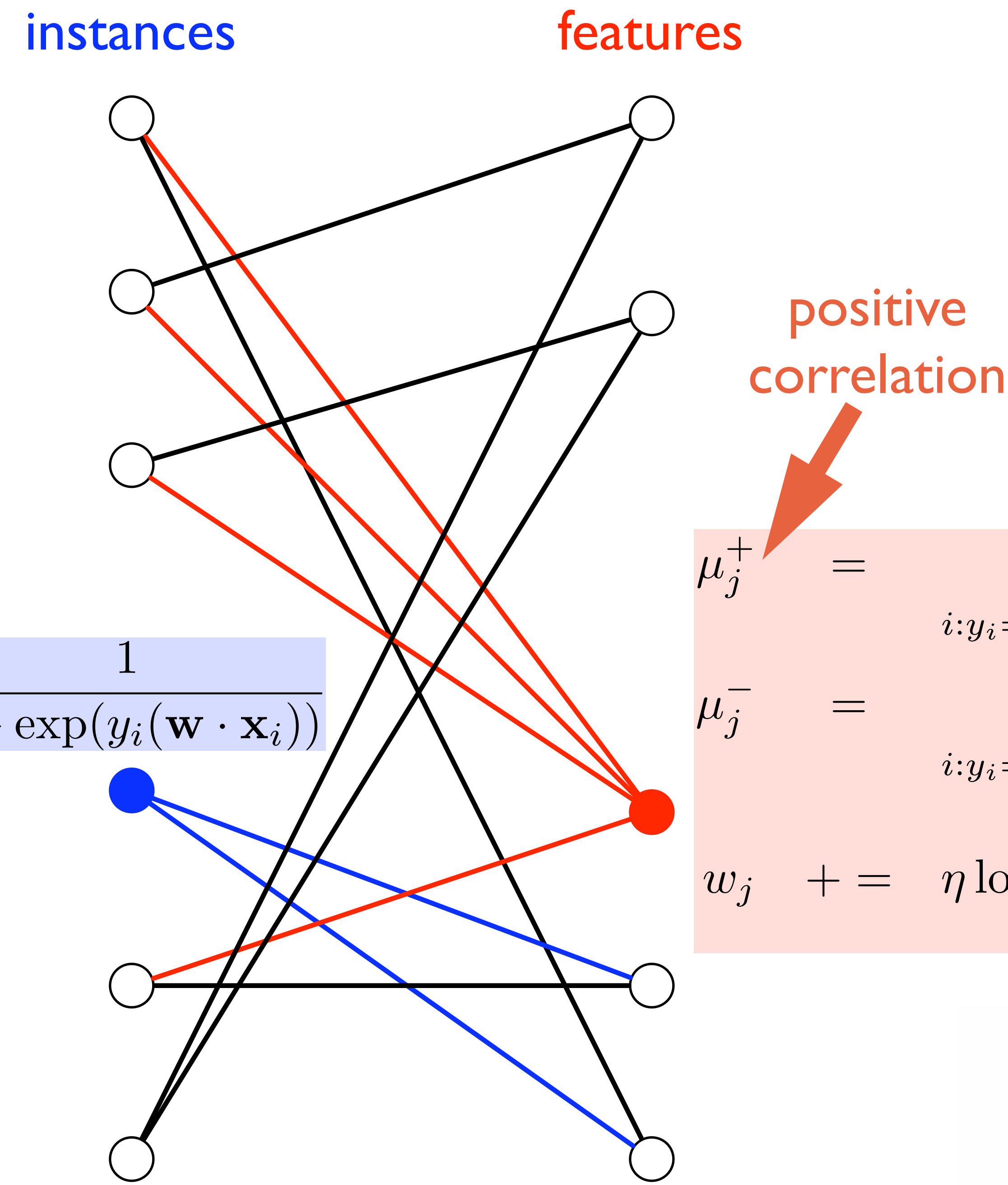
Parallel Boosting Algorithm



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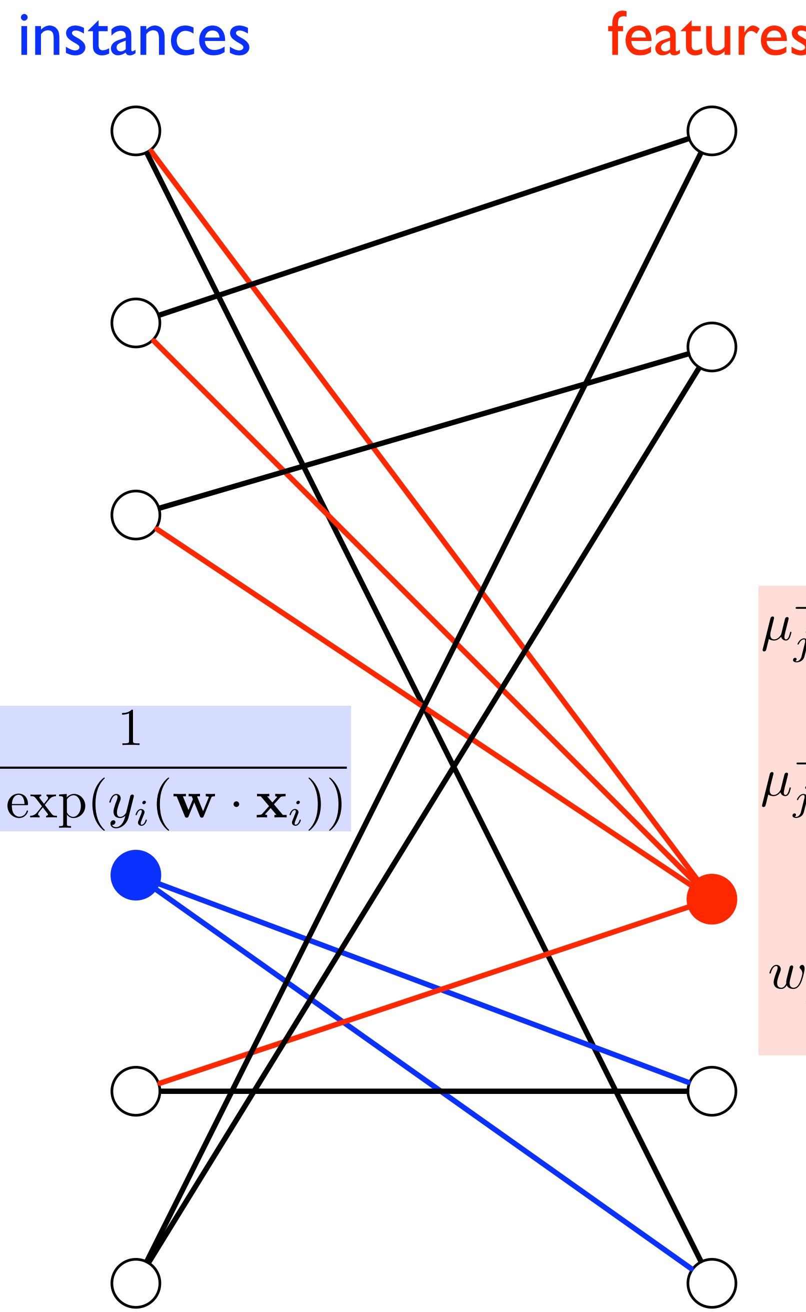

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mistake probability

positive correlation

negative correlation

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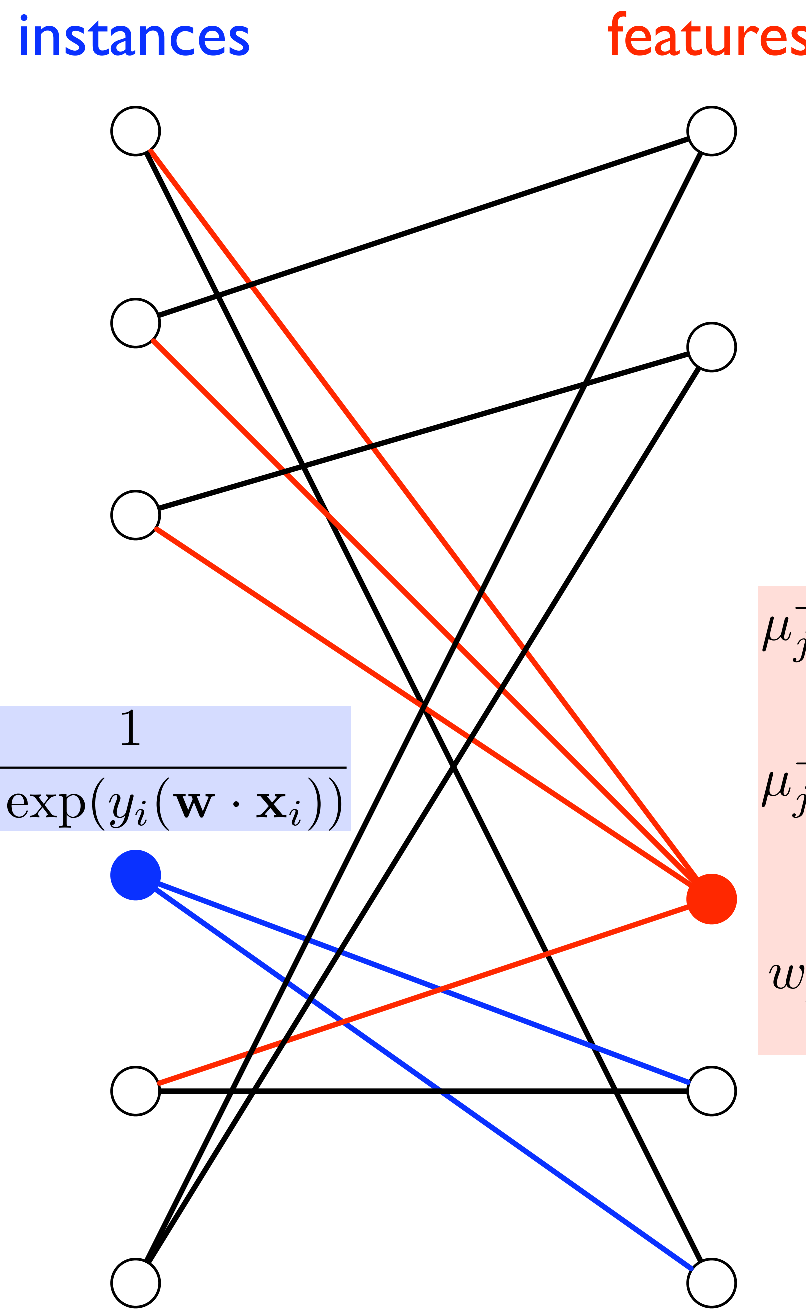
Parallel Boosting Algorithm



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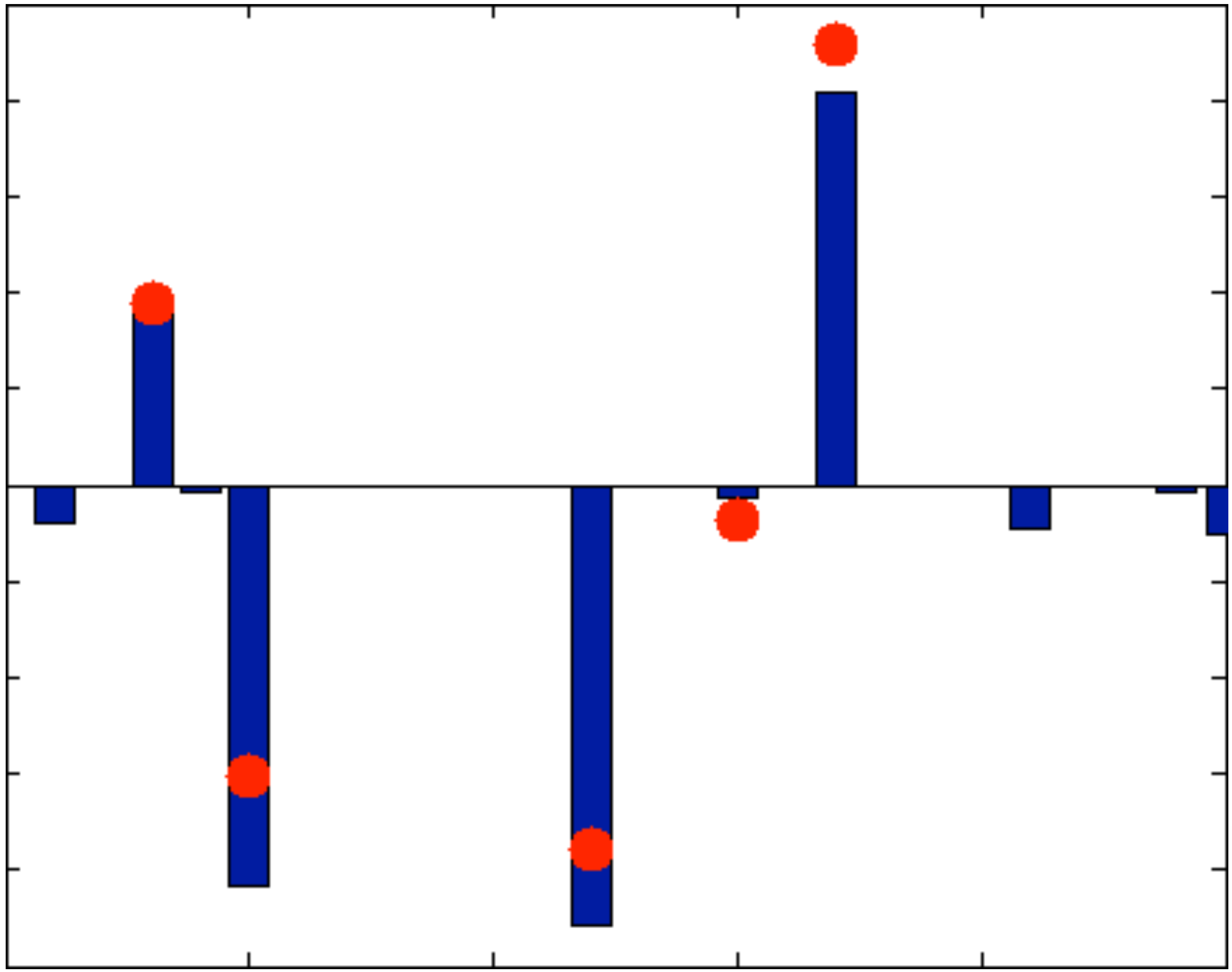
step size

Properties of parallel boosting

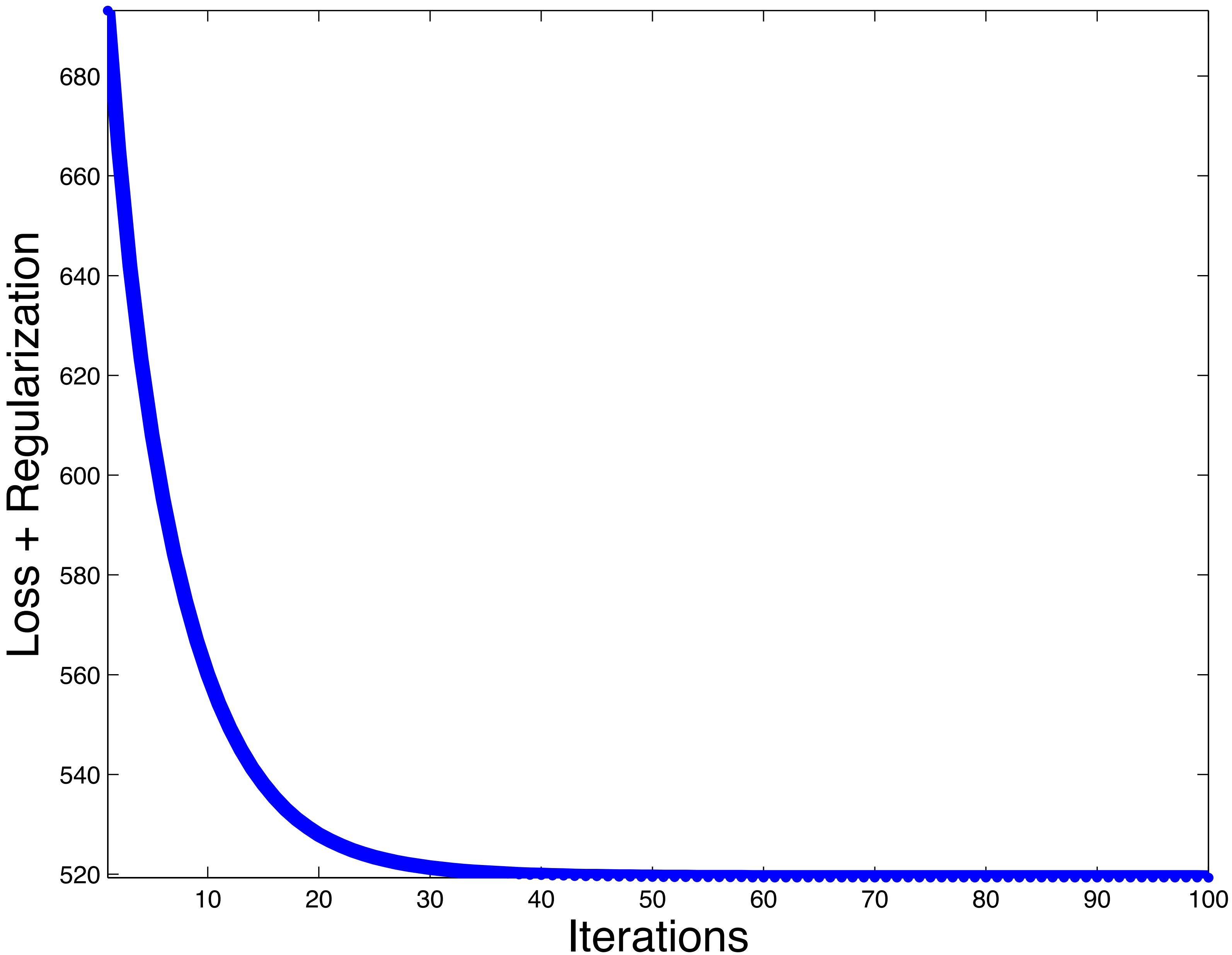
- Embarrassingly parallel:
  1. Computes feature correlations for each example in parallel
  2. Feature are updated in parallel
  - We need to "shuffle" the outputs of Step 1 for Step 2
- Step size inversely proportional to number of active features per example
  - **Not** total number of features
  - Good for sparse training data
- Needs some form of regularization

Learning w/ L_1 Regularization

Learning w/ L_1 Regularization

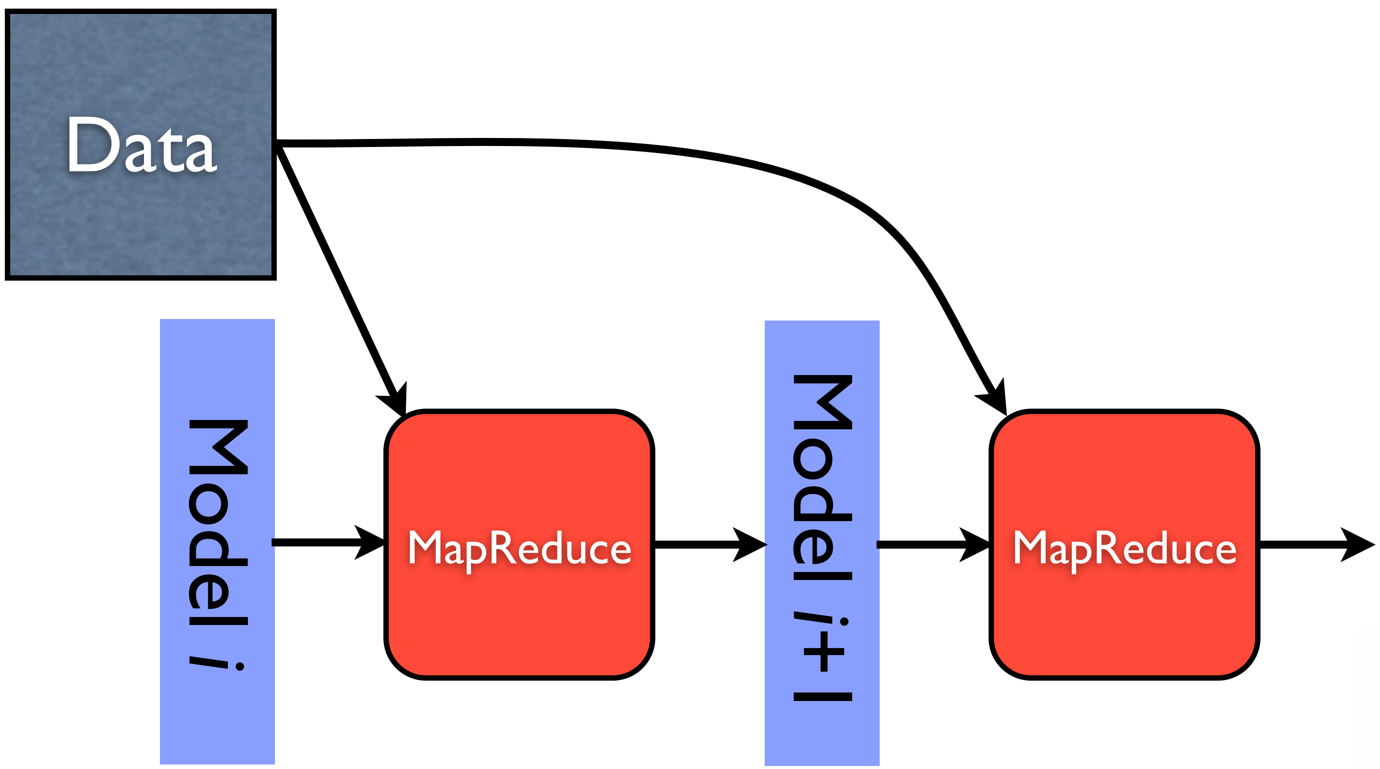


Learning w/ L_1 Regularization



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

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, less data to shuffle

Design principle: store model and stats in RAM

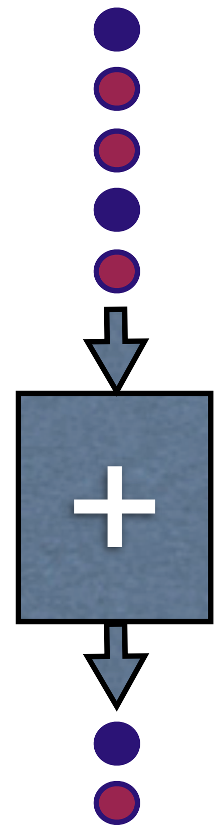
- Each worker keeps in RAM
  - A copy of the previous model
  - Learning statistics for its training data
- Boosting requires O(10 bytes) per feature
- Possible to handle billions of features

Design principle: optimize for multi-core

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

Design principle: use combiners to limit communication

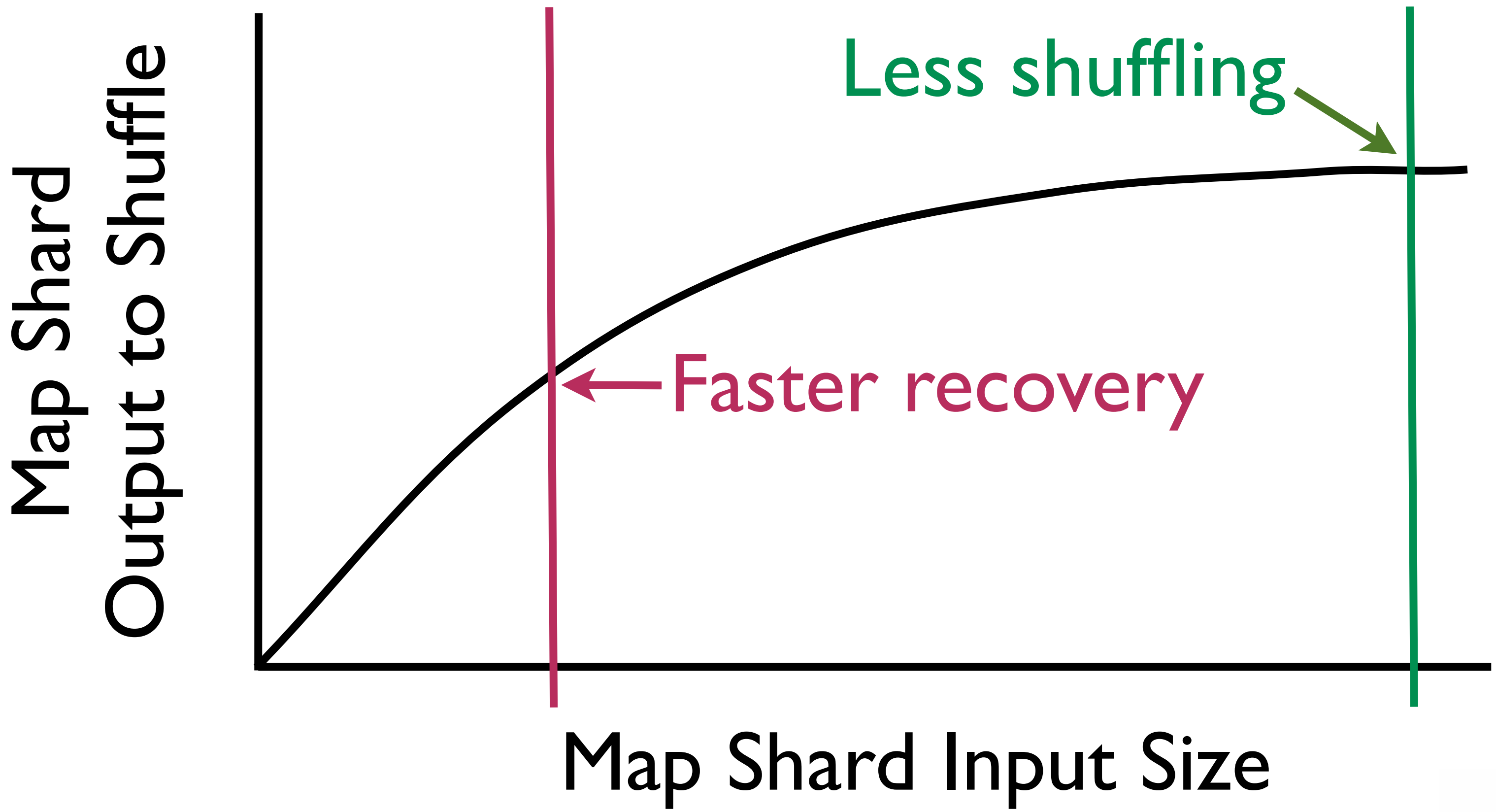
Standard
Mapper



Mapper
with
Combiner

Design principle: use combiners to limit communication

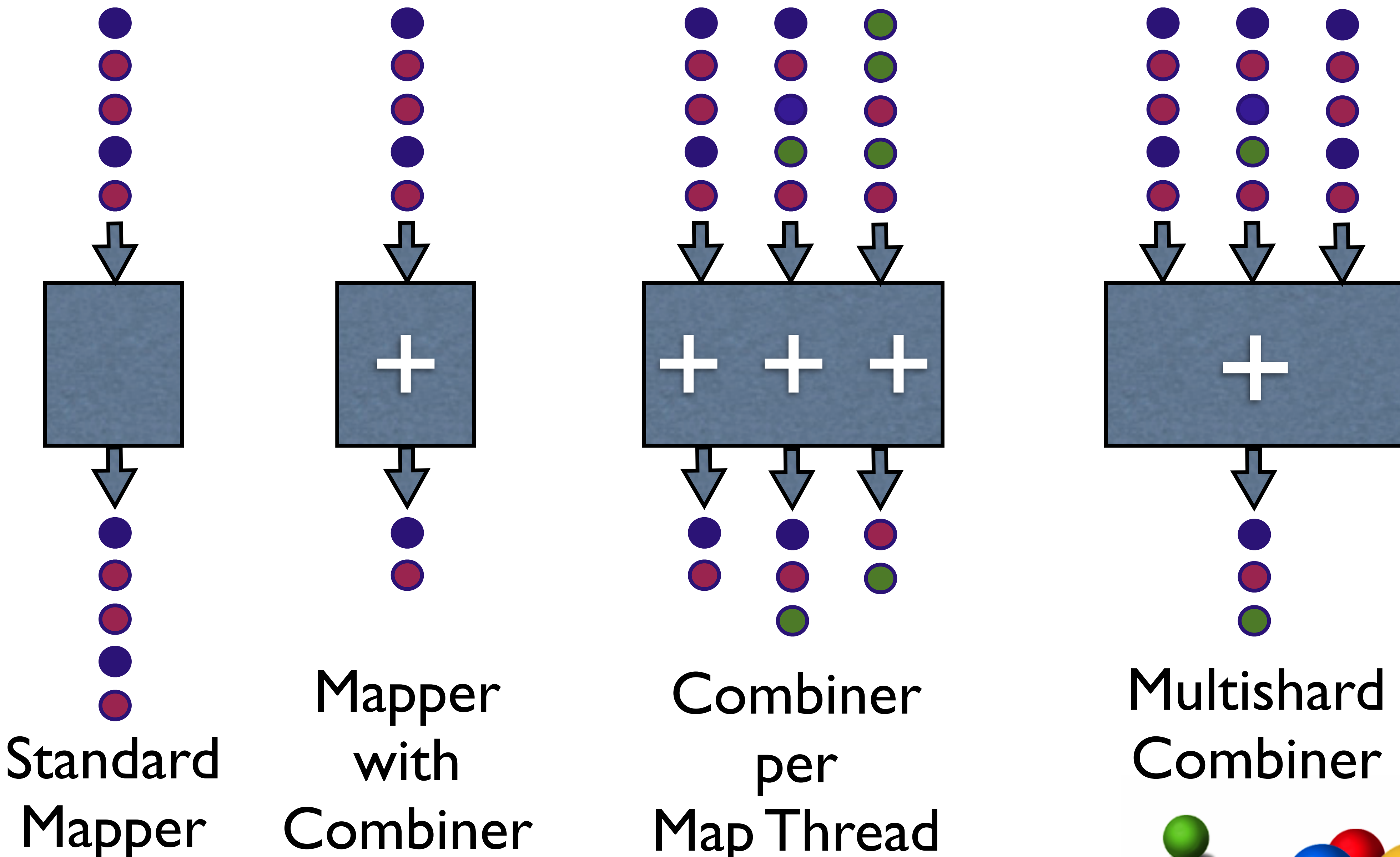
- Fewer large shards mean less shuffling, but possible stragglers when shards fail



Design principle: use combiners to limit communication

- Solution: Multishard Combining
  - Multiple threads per worker
  - Many small map shards per thread
  - One accumulator shared across threads
  - One supershard per worker... less shuffling
  - Spread shards from failed workers across the remaining workers ... fewer stragglers

Design principle: use combiners to limit communication



Compression results

- Data Set 1
  - 3.2x compression (source is unsorted and has medium compression)
  - 2.6x compression (source is sorted and has medium compression)
  - 1.7x compression (source is sorted and has max compression)
  - string -> int map overhead < 0.5%
- Data Set 2
  - 1.8x compression (default compression options)
  - string -> int map overhead < 0.5%

Performance results

Number of models in model set

Cores	1	2	3	4	5
80	1.8M	4.0M	4.4M	5.4M	4.5M
160	1.3M	2.4M	3.0M	4.4M	3.5M
240	1.4M	2.2M	3.0M	3.9M	3.5M
320	1.2M	2.0M	2.4M	2.9M	3.3M
400	1.1M	1.7M	2.4M	2.1M	2.7M

Measurements in features/second per core

Infrastructure challenges

Sibyl is an HPC workload running on infrastructure designed for the web

- Rapidly opens lots of files
    - GFS master overload
- Concurrently reads 100s of files per machine
    - Cluster cross-sectional bandwidth overload
    - Denial of service for co-resident processes
- Random accesses into large vectors
    - Prefetch performance
    - Page-table performance
- MapReduce challenges
    - Multi-shard combiners, column-oriented format
- Column oriented data format creates lots of small files
    - Outside the GFS sweet spot