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Laboratory for Statistical Artificial InteLligence & INtegrative Genomics

Strategies & Principles for Distributed Machine Learning

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Acknowledgement:

Wei Dai, Qirong Ho, Jin Kyu Kim, Abhimanu Kumar, Seunghak Lee, Jinliang Wei, Pengtao Xie, Yaoliang Yu, Hao Zhang, Xun Zheng

James Cipar, Henggang Cui,

and, Phil Gibbons, Greg Ganger, Garth Gibson

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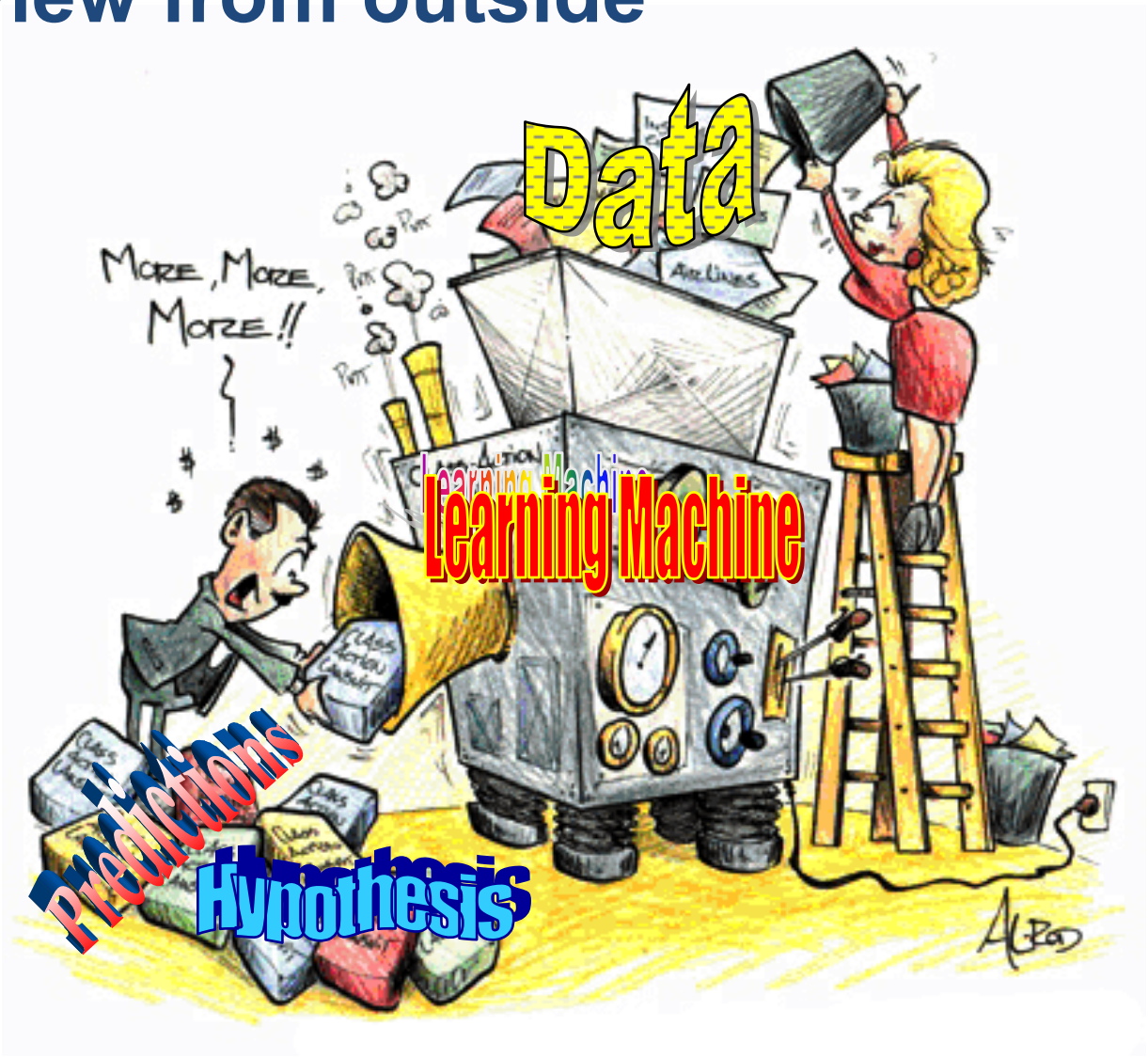
Machine Learning:
-- a view from outside



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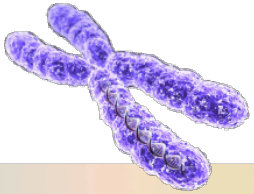
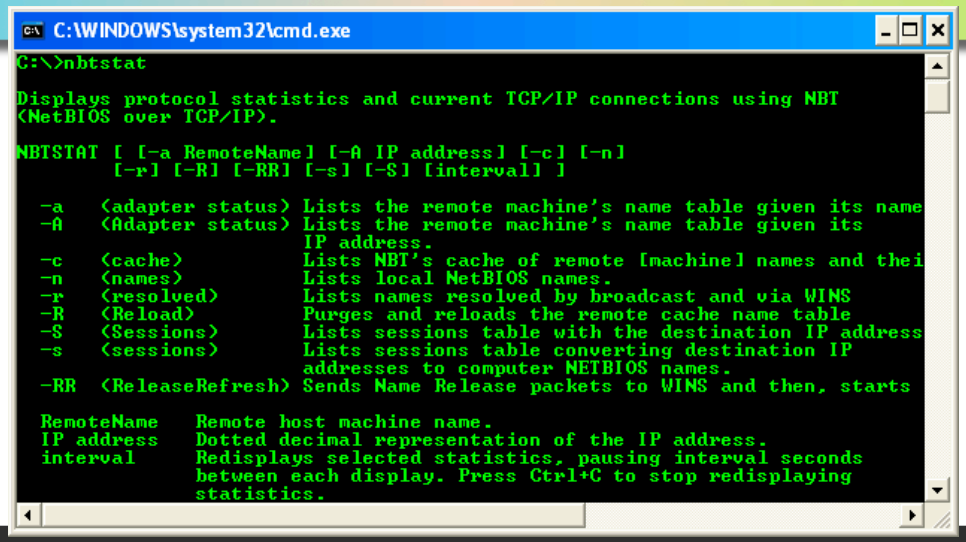
Inside ML …





- Graphical Models
- Nonparametric Bayesian Models
- Regularized Bayesian Methods
- Large-Margin
- Deep Learning
- Sparse Coding
- Spectral/Matrix Methods
- Sparse Structured I/O Regression



Hardware and infrastructure

- Network switches
- Infiniband
- Network attached storage
- Flash storage
- Server machines
- Desktops/Laptops
- NUMA machines
- GPUs
- Cloud compute (e.g. Amazon EC2)
- Virtual Machines

An ML Program

$$\arg\max_{\vec{\theta}} \equiv \mathcal{L}(\{\mathbf{x}_i, \mathbf{y}i\}_{i=1}^{N} \; ; \; \vec{\theta}) + \Omega(\vec{\theta})$$

Model **Data** **Parameter**

Solved by an iterative convergent algorithm

```
for (t = 1 to T) {
  doThings()
```

$$\vec{\theta}^{t+1} = g(\vec{\theta}^{t}, \Delta_f \vec{\theta}(\mathcal{D}))$$

```
  doOtherThings()
}
```

This computation needs to be parallelized!

Massive Data

1B+ USERS
30+ PETABYTES

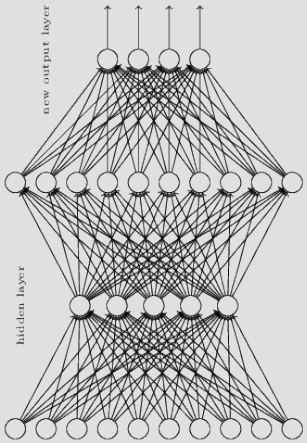
32 million pages

WIKIPEDIA
The Free Encyclopedia

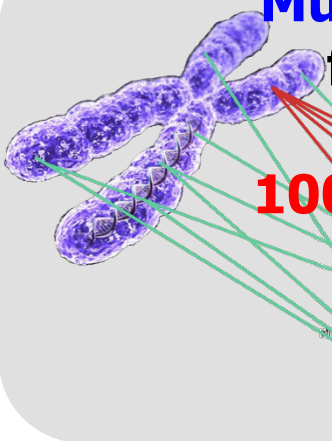
100+ hours video uploaded every minute

645 million users
500 million tweets / day

Growing Model Complexity



Google Brain
Deep Learning
for images:
1~10 Billion
model parameters



Multi-task Regression
for simplest whole-genome analysis:
100 million ~ 1 Billion
model parameters

Topic Models
for news article analysis:
Up to 1 Trillion
model parameters

Collaborative filtering
for Video recommendation:
1~10 Billion
model parameters

NETFLIX

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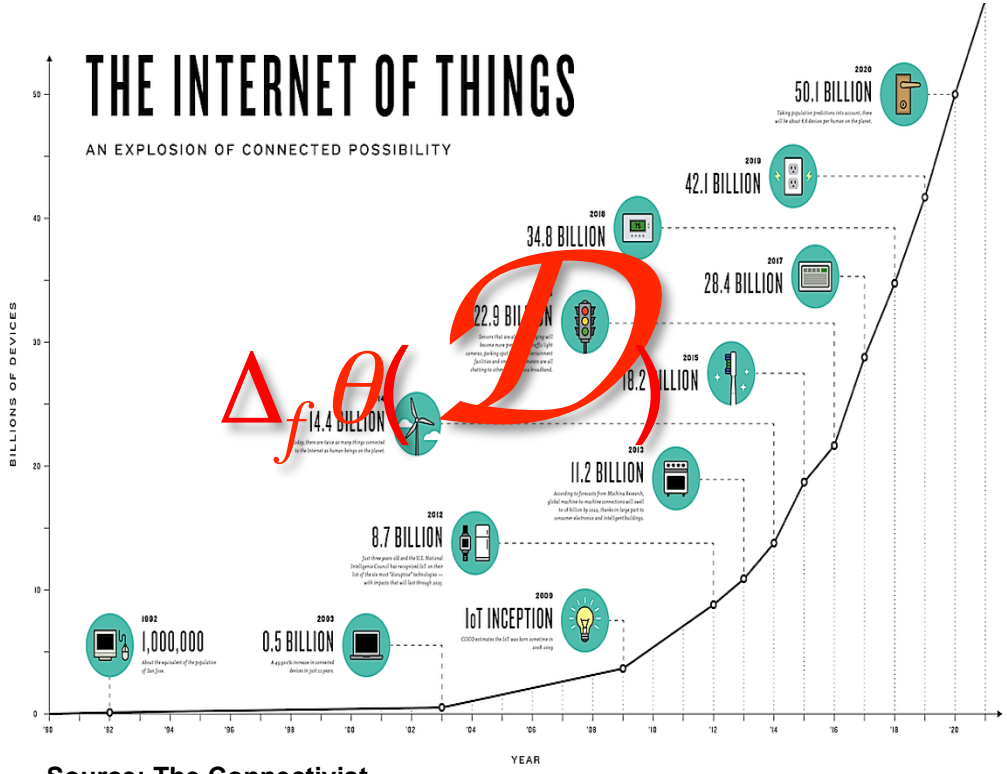
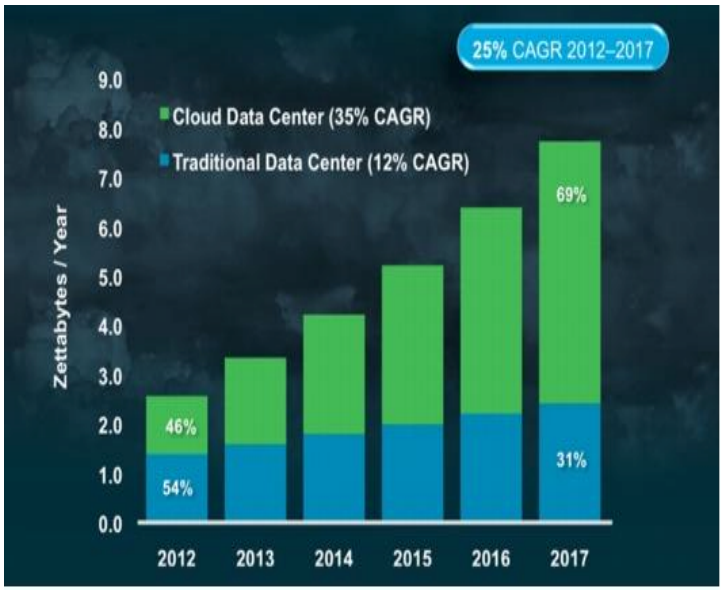
```
for (t = 1 to T) {
  doThings()
  parallelUpdate(x,θ)
  doOtherThings()
}
```

Challenge #1 – Massive Data Scale



Source: The Connectivist



Source: Cisco Global Cloud Index

Familiar problem: data from 50B devices, data centers won't fit into memory of single machine

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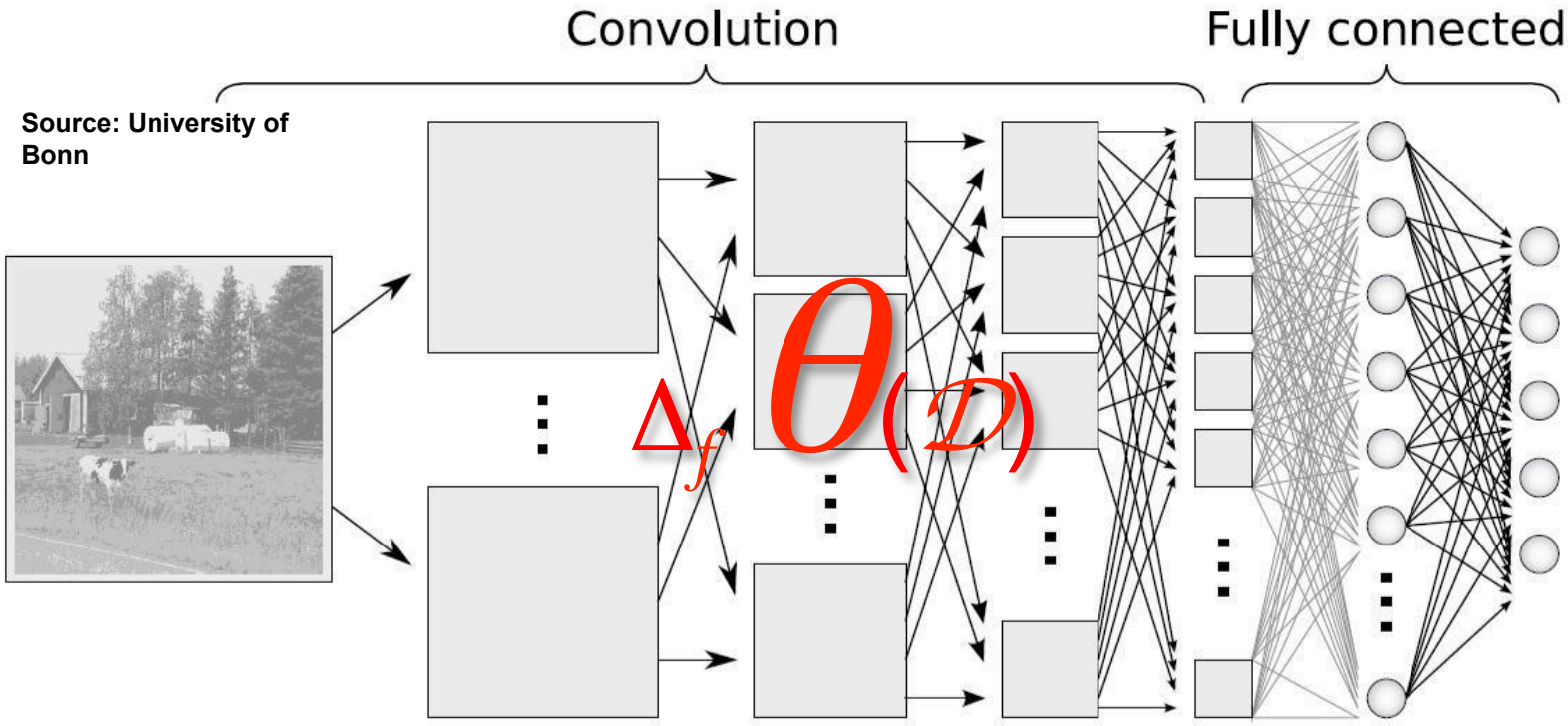
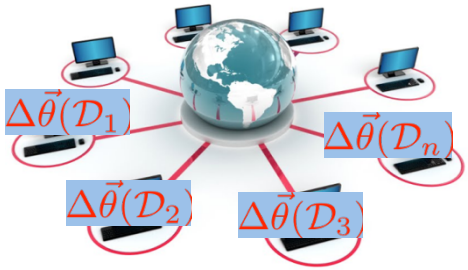
```
for (t = 1 to T) {
  doThings()
  parallelUpdate(x,θ)
  doOtherThings()
}
```

Challenge #2 – Gigantic Model Size



Big Data needs Big Models to extract understanding
But ML models with >1 trillion params also won't fit!

Issues with Hadoop and I-C ML Algorithms



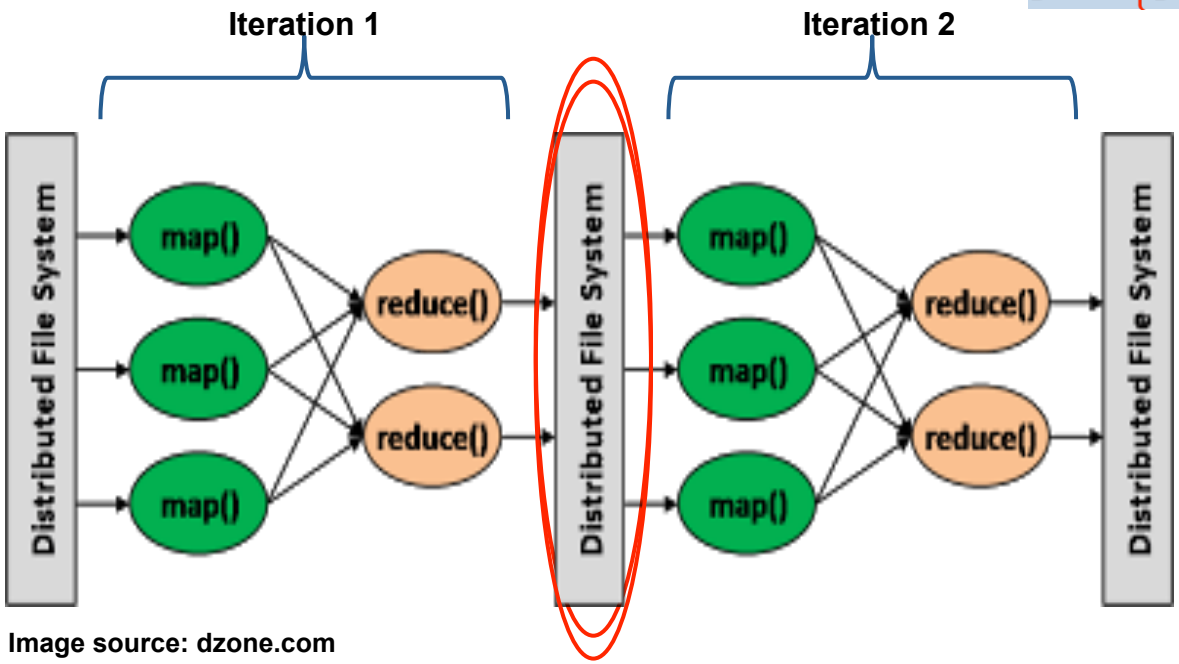


Image source: dzone.com

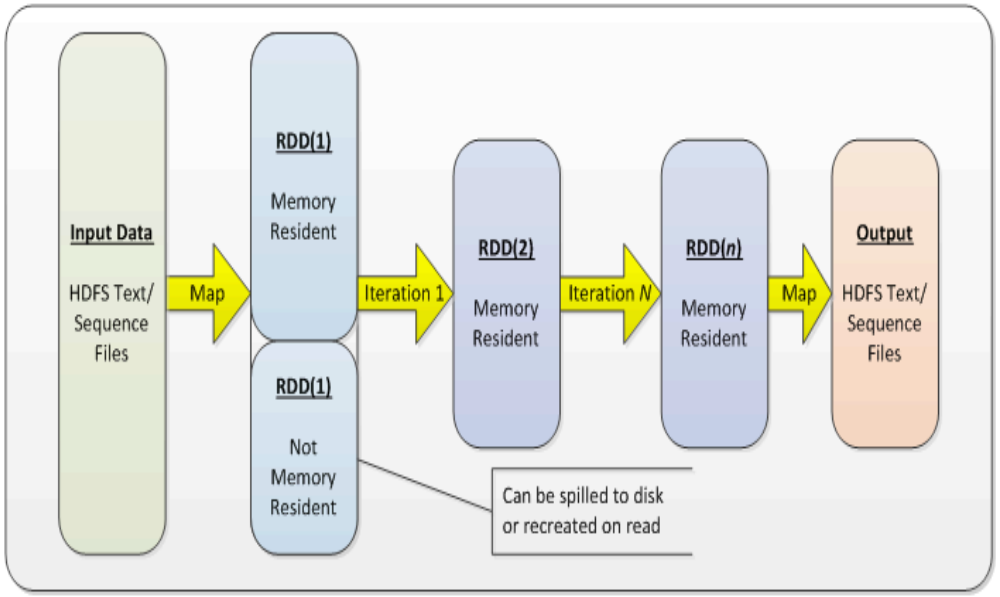
HDFS Bottleneck

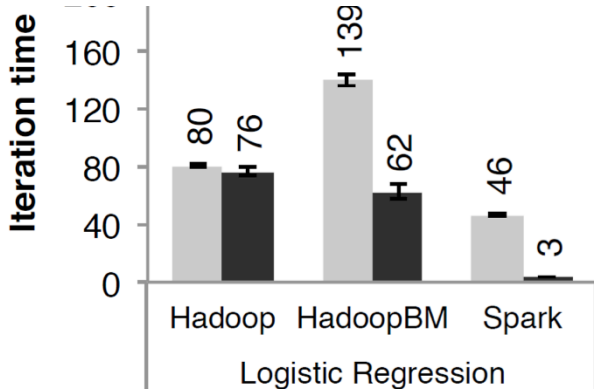
Naïve MapReduce not best for ML

- Hadoop can execute iterative-convergent, data-parallel ML...
  - map() to distribute data samples i, compute update $\Delta(D_i)$
  - reduce() to combine updates $\Delta(D_i)$
  - Iterative ML algo = repeat map()+reduce() again and again
- But reduce() writes to HDFS before starting next iteration's map() - very slow iterations!

Spark: Faster MapR on Data-Parallel

- Spark's solution: **Resilient Distributed Datasets (RDDs)**
  - Input data → load as RDD → apply transforms → output result
  - RDD transforms strict superset of MapR
  - RDDs cached in memory, avoid disk I/O





- **Spark ML library supports data-parallel ML algos, like Hadoop**
  - Spark and Hadoop: comparable first iter timings…
  - But Spark's later iters are much faster

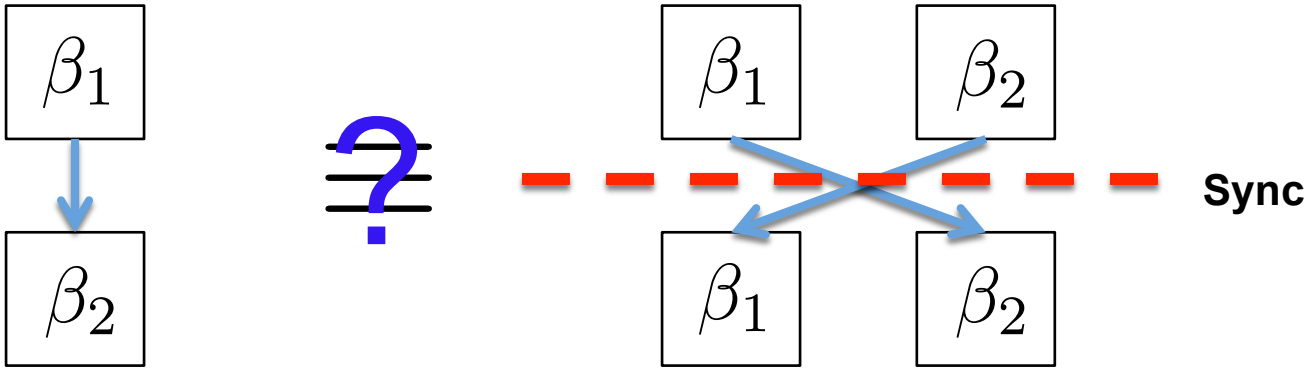
Source: ebaytechblog.com

```
for (t = 1 to T) {
  doThings()
  parallelUpdate(x,θ)
  doOtherThings()
}
```

Parallelization Strategies

Usually, we worry …

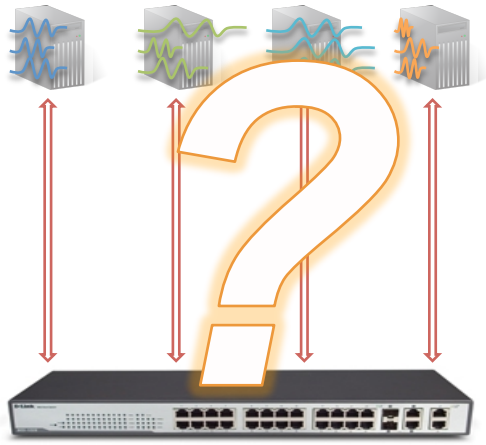
A sequential program ? **A parallel program**

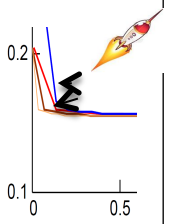


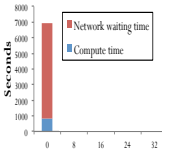
- but assuming an ideal system, e.g.,
  - zero-cost sync,
  - zero-cost fault recovery
  - uniform local progress
  - …

Unequal performance

Low bandwidth, High delay







Intrinsic Properties of ML Programs

[Xing et al., 2015]

- ML is … gent algori … on
  - **Err** erro
  - **Dyn** cha criti
  - **Non** can
- Wher … only guara …
- How do existing Big Data platforms fit the above?

4 Principles of ML System Design

How to execute distributed-parallel ML programs?

ML program equations tell us “What to Compute”. But…

1. **How to Distribute?**
2. **How to Bridge Computation and Communication?**
3. **How to Communicate?**
4. **What to Communicate?**

Principles of ML system Design [Xing et al., to appear 2016]

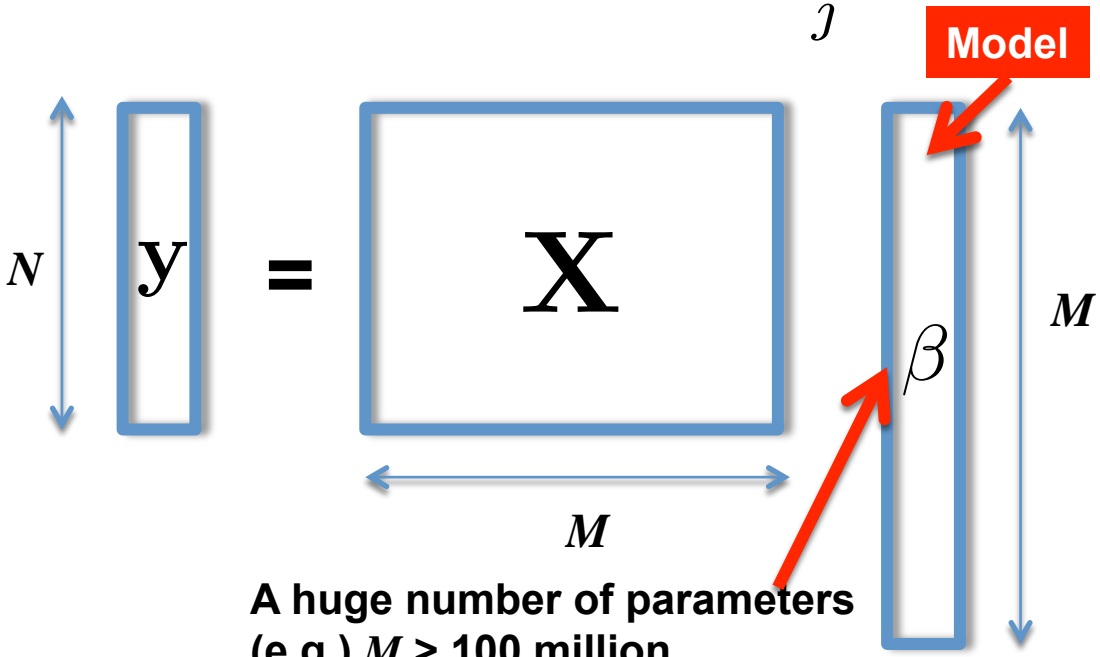
1. How to Distribute:

Scheduling and Balancing workloads

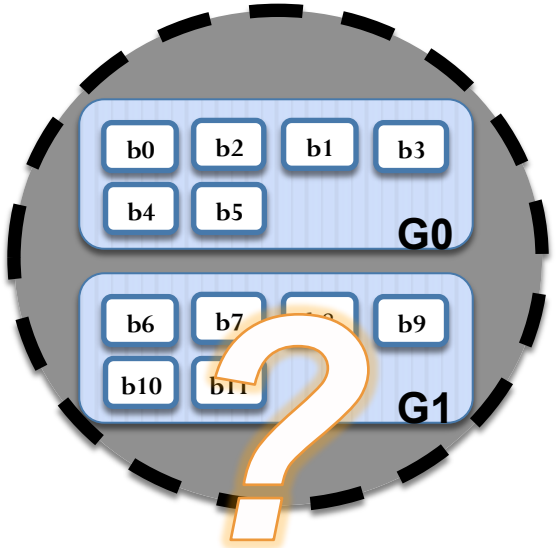
Example: Model Distribution

Lasso via coordinate descent:

$$\min_{\beta} \|\mathbf{y} - \mathbf{X}\beta\|_2^2 + \lambda \sum_j |\beta_j|$$



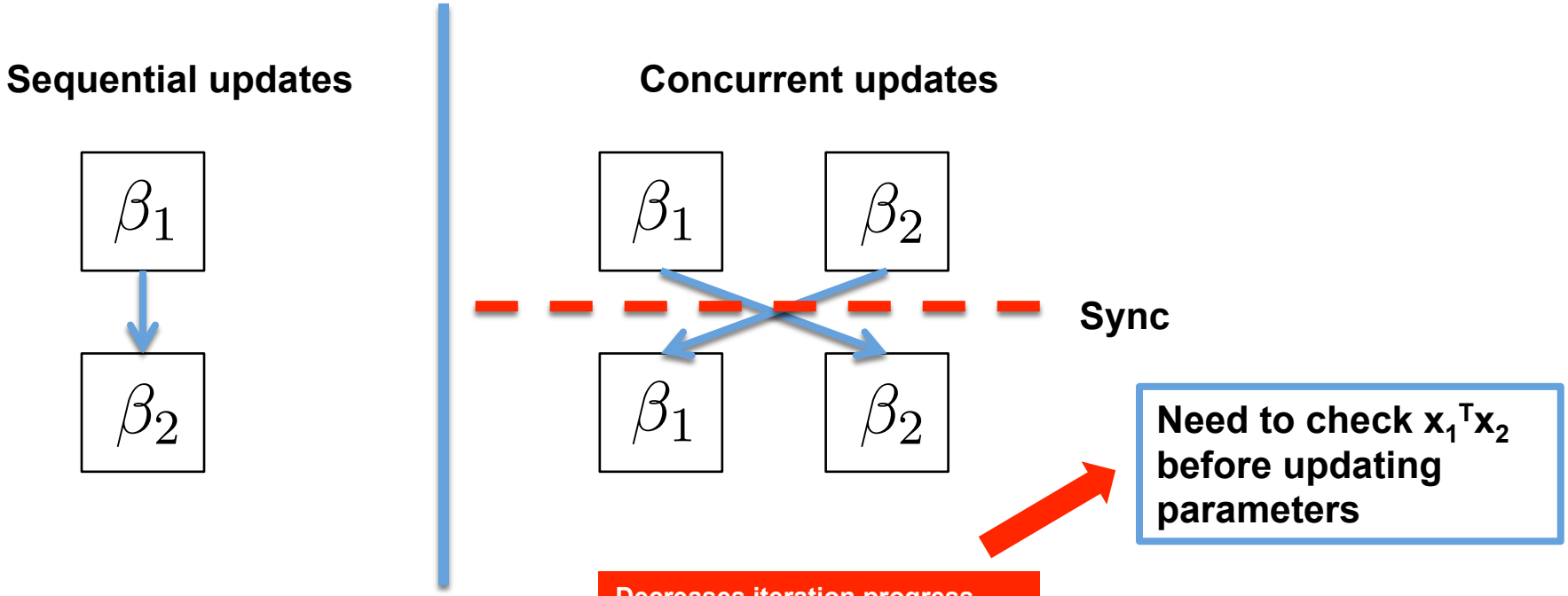
A huge number of parameters (e.g.) M > 100 million



- **How to correctly divide computational workload across workers?**
- **What is the best order to update parameters?**

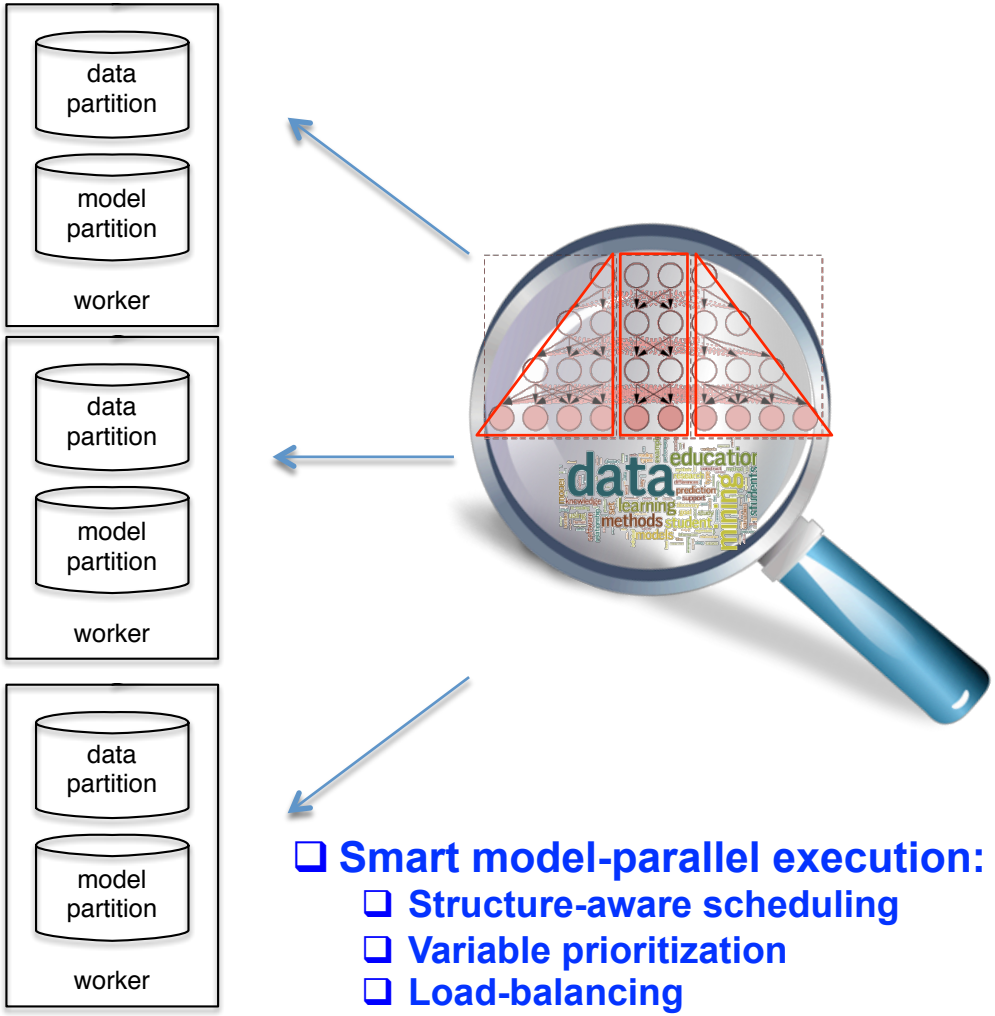
Model Dependencies

- Concurrent updates of β may induce errors



Avoid Dependency Errors via Structure-Aware Parallelization (SAP)

[Lee et al., 2014] [Kim et al, 2016]



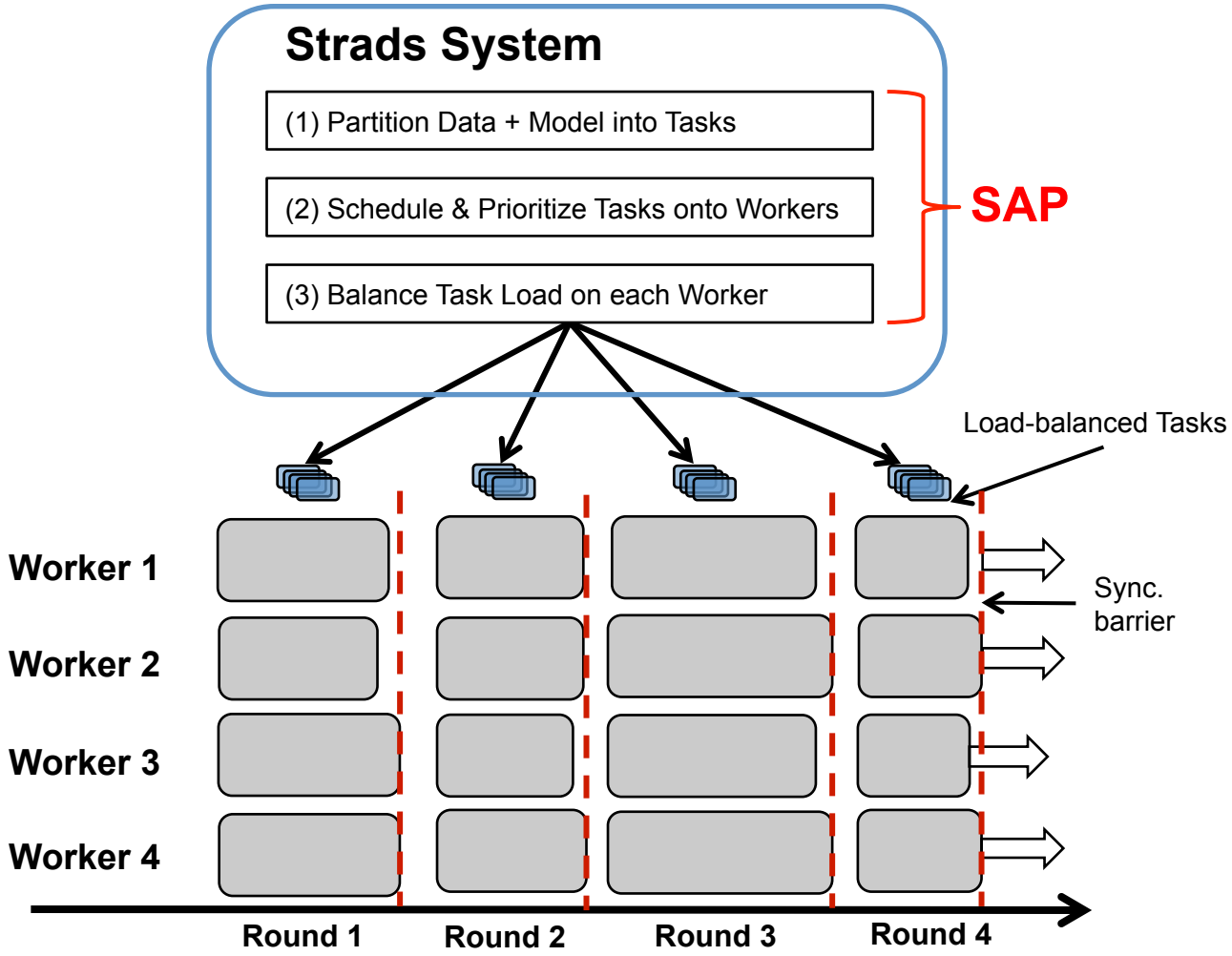

```
schedule() {
  // Select U vars x[j] to be sent
  // to the workers for updating
  ...
  return (x[j_1], ..., x[j_U])
}
```

```
push(worker = p, vars = (x[j_1],...,x[j_U])) {
  // Compute partial update z for U vars x[j]
  // at worker p
  ...
  return z
}
```

```
pull(workers = [p], vars = (x[j_1],...,x[j_U]),
     updates = [z]) {
  // Use partial updates z from workers p to
  // update U vars x[j]. sync() is automatic.
  ...
}
```

- ❑ **Smart model-parallel execution:**
  - ❑ Structure-aware scheduling
  - ❑ Variable prioritization
  - ❑ Load-balancing
- ❑ **Simple programming:**
  - ❑ Schedule()
  - ❑ Push()
  - ❑ Pull()

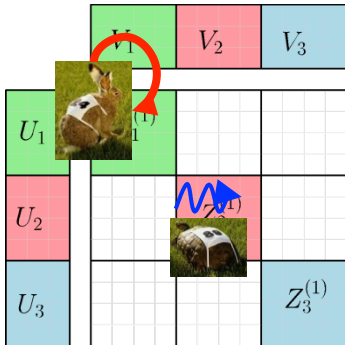
A Structure-aware Dynamic Scheduler (Strads) [Lee et al., 2014] [Kim et al, 2016]



- **Priority Scheduling**

$$\{\beta_j\} \sim \left(\delta\beta_j^{(t-1)}\right)^2 + \eta$$

- **Block scheduling**



[*Kumar, Beutel, Ho and Xing,* ***Fugue: Slow-worker agnostic distributed learning****, AISTATS 2014*]

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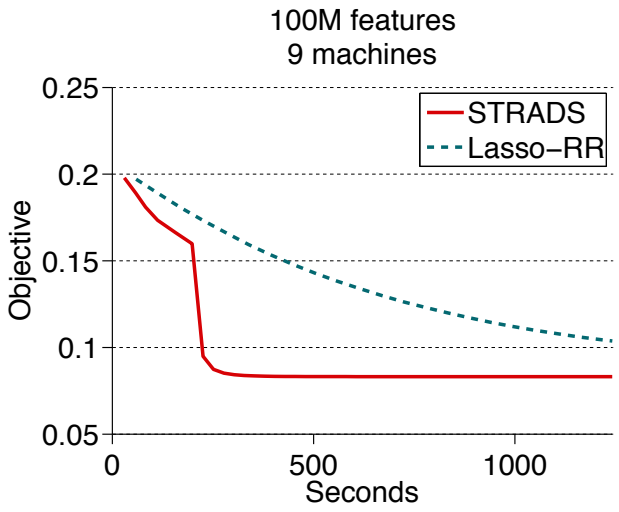
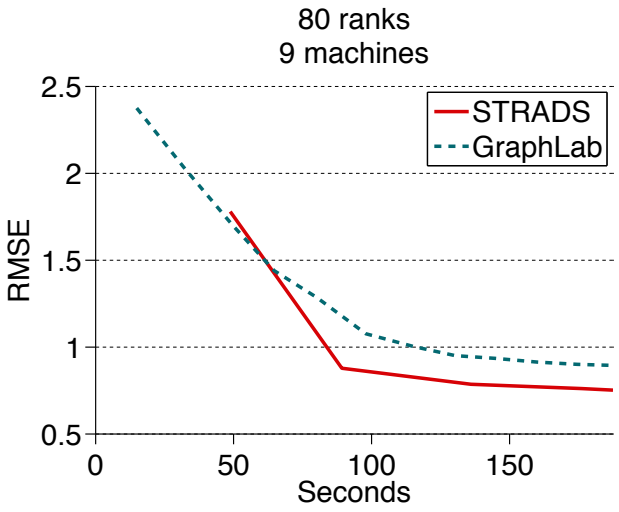
SAP Scheduling: Faster, Better Convergence across algorithms

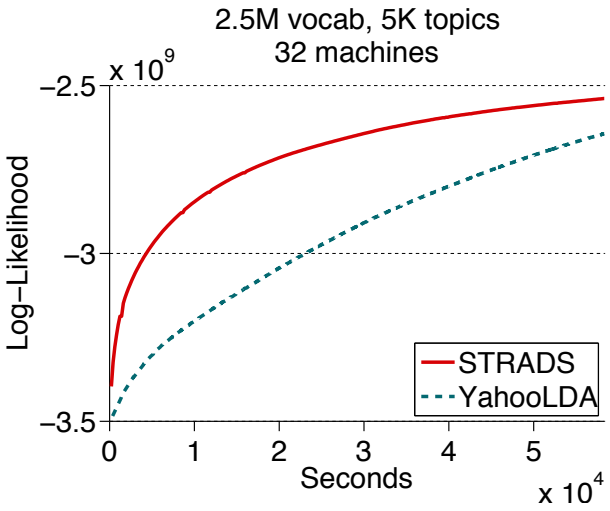
- SAP on Strads achieves better speed and objective



Lasso

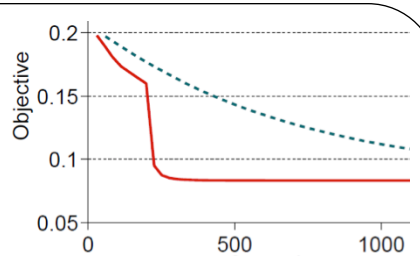


MF



LDA

SAP gives Near-Ideal Convergence Speed [Xing et al., 2015]



- **Goal:** solve sparse regression problem
  - Via coordinate descent over "SAP blocks" $X^{(1)}, X^{(2)}, ..., X^{(B)}$
    - $X^{(b)}$ are data columns (features) in block (b)
  - P parallel workers, M-dimensional data
  - ρ = Spectral Radius[BlockDiag[$(X^{(1)})^{\mathrm{T}}X^{(1)}, ..., (X^{(t)})^{\mathrm{T}}X^{(t)}$]]; this block-diagonal matrix quantifies max level of correlation within all SAP blocks $X^{(1)}, X^{(2)}, ..., X^{(t)}$

- **SAP converges according to**

Gap between current parameter estimate and optimum

SAP explicitly minimizes ρ, ensuring as close to $1/P$ convergence as possible

$$\mathbb{E}\left[f(X^{(t)}) - f(X^*)\right] \leq \frac{\mathcal{O}(M)}{P - \frac{\mathcal{O}(P^2\rho)}{M}} \frac{1}{t} = \mathcal{O}\left(\frac{1}{Pt}\right)$$

where t is # of iterations

- **Take-away:** SAP minimizes ρ by searching for feature subsets $X^{(1)}, X^{(2)}, ..., X^{(B)}$ w/o cross-correlation => as close to P-fold speedup as possible

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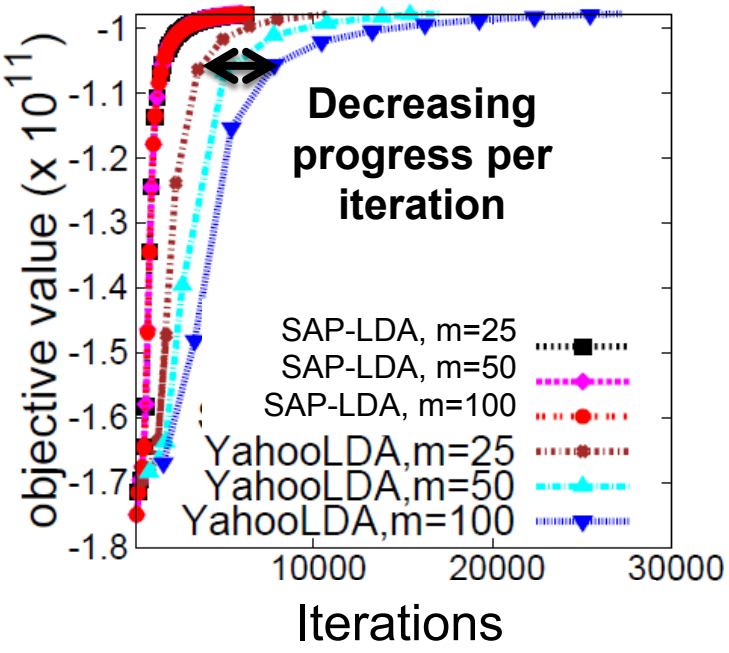
Correctly Measuring Parallel Performance [blinded, to appear]

YahooLDA progress per iteration



80GB data, 2M words, 1K topics, 100 machines

	YahooLDA data throughput
25 machines	39.7 M/s (1x)
50 machines	78 M/s (1.96x)
100 machines	151 M/s (3.8x)

- YahooLDA attains near-ideal throughput (1→3.8x)…
- … but progress per iteration gets worse with more machines

- **YahooLDA only <2x speedup from 25 →100 machines**
  - 6.7x slower compared to SAP-LDA

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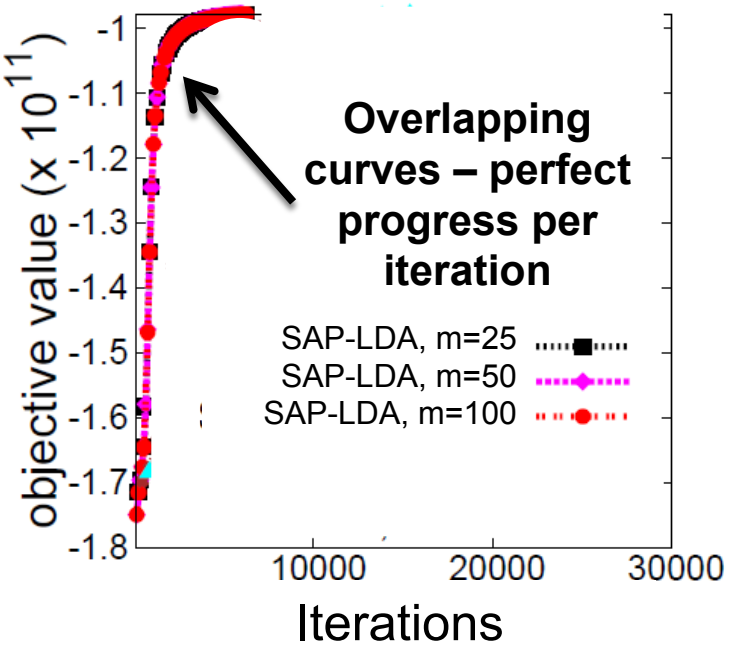
Correctly Measuring Parallel Performance [blinded, to appear]

SAP-LDA progress per iteration



80GB data, 2M words, 1K topics, 100 machines

	SAP-LDA data throughput
25 machines	58.3 M/s (1x)
50 machines	114 M/s (1.96x)
100 machines	204 M/s (3.5x)

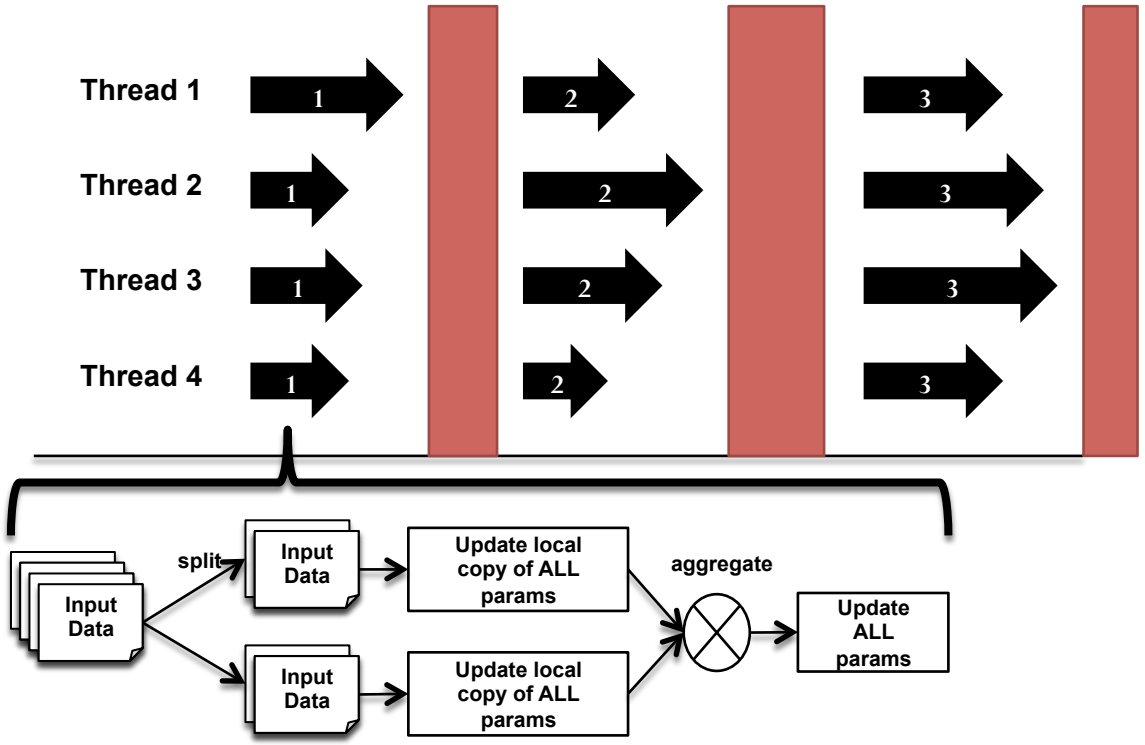
- **Ideal rate:** progress per iter preserved from 25 → 100 machines
  - Thanks to dependency checking
- **Near-ideal throughput:** data rate 1x → 3.5x from 25→100 machines
  - Thanks to load balancing
- **Convergence Speed = rate x throughput**
  - **Therefore near-ideal 3.5x speedup from 25→100 machines**

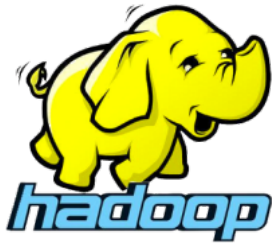
Principles of ML system Design [Xing et al., to appear 2016]

2. How to Bridge Computation and Communication:

Bridging Models and Bounded Asynchrony

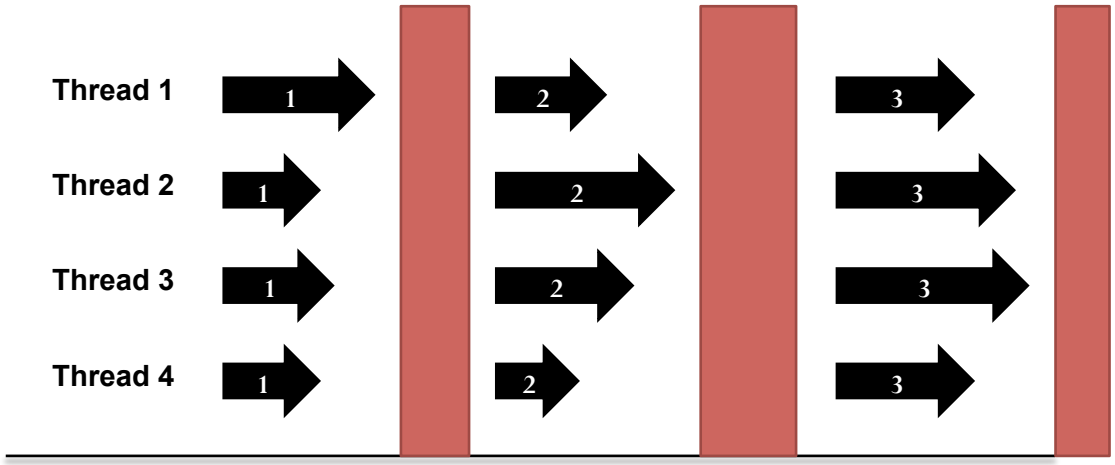
The *Bulk Synchronous Parallel* Bridging Model [Valiant & McColl]

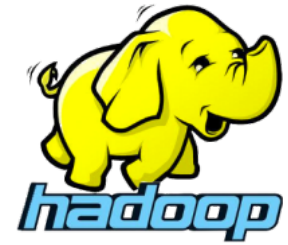




- Perform barrier in order to communicate parameters
- Mimics sequential computation – "serializable" property
- Enjoys same theoretical guarantees as sequential execution

The *Bulk Synchronous Parallel* Bridging Model [Valiant & McColl]





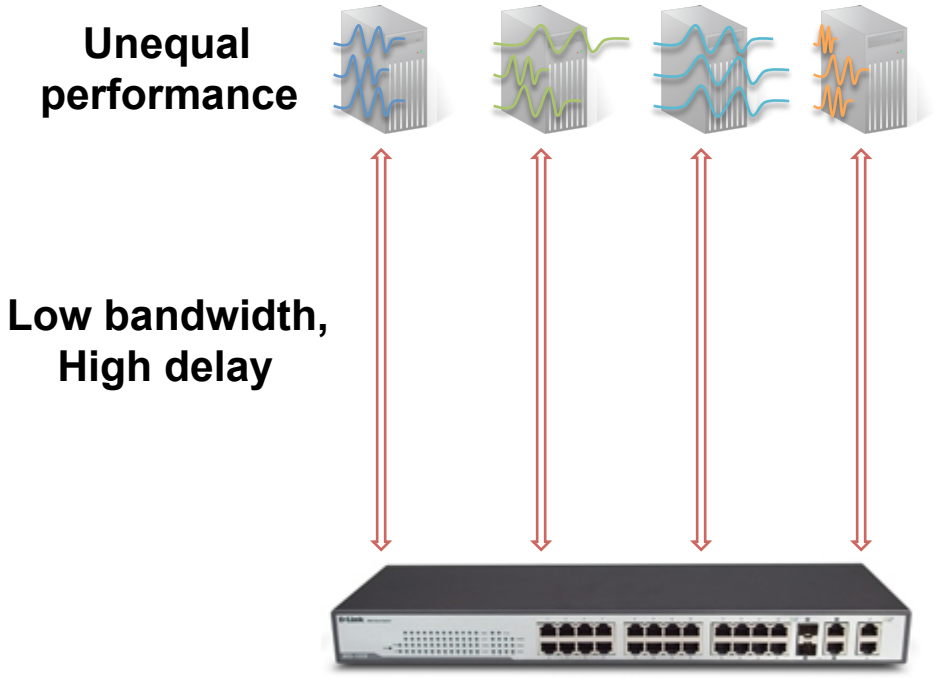
The success of the von Neumann model of sequential computation is attributable to the fact it is an efficient bridge between software and hardware… an analogous bridge is required for parallel computation if that is to become as widely used – **Leslie G. Valiant**

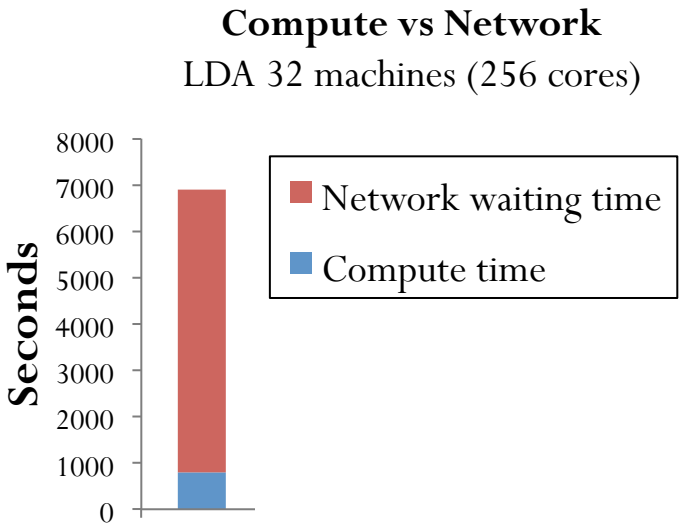
- Numerous implementations since 90s (list by **Bill McColl**):
  - Oxford BSP Toolset (‘98), Paderborn University BSP Library (‘01), Bulk Synchronous Parallel ML (‘03), BSPonMPI (’06), ScientificPython (’07), Apache Hama (’08), Apache Pregel (‘09), MulticoreBSP (’11), BSPedupack (‘11), Apache Giraph (’11), GoldenOrb (‘11), Stanford GPS Project (‘11) …

But There Is No Ideal Distributed System!

- **Two distributed challenges:**
  - Networks are slow
  - "Identical" machines rarely perform equally

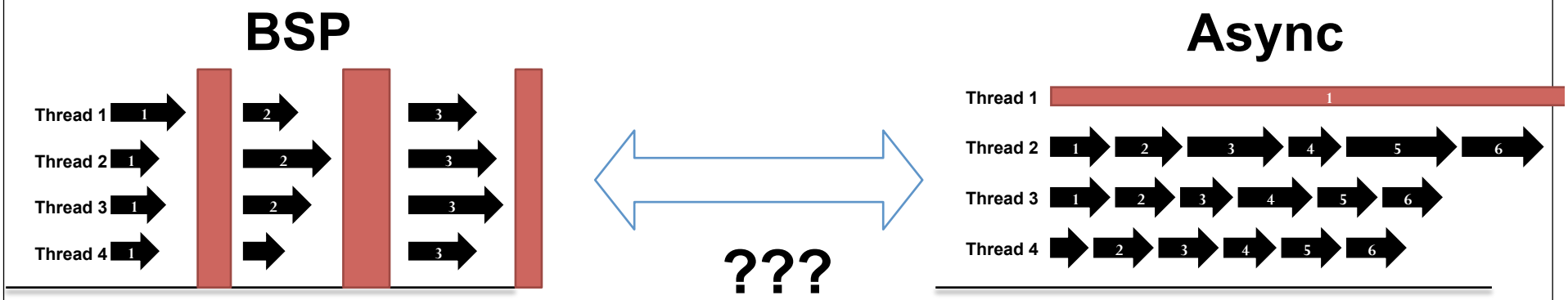
Result: BSP barriers can be slow





Is there a better way to interleave computation and communication?

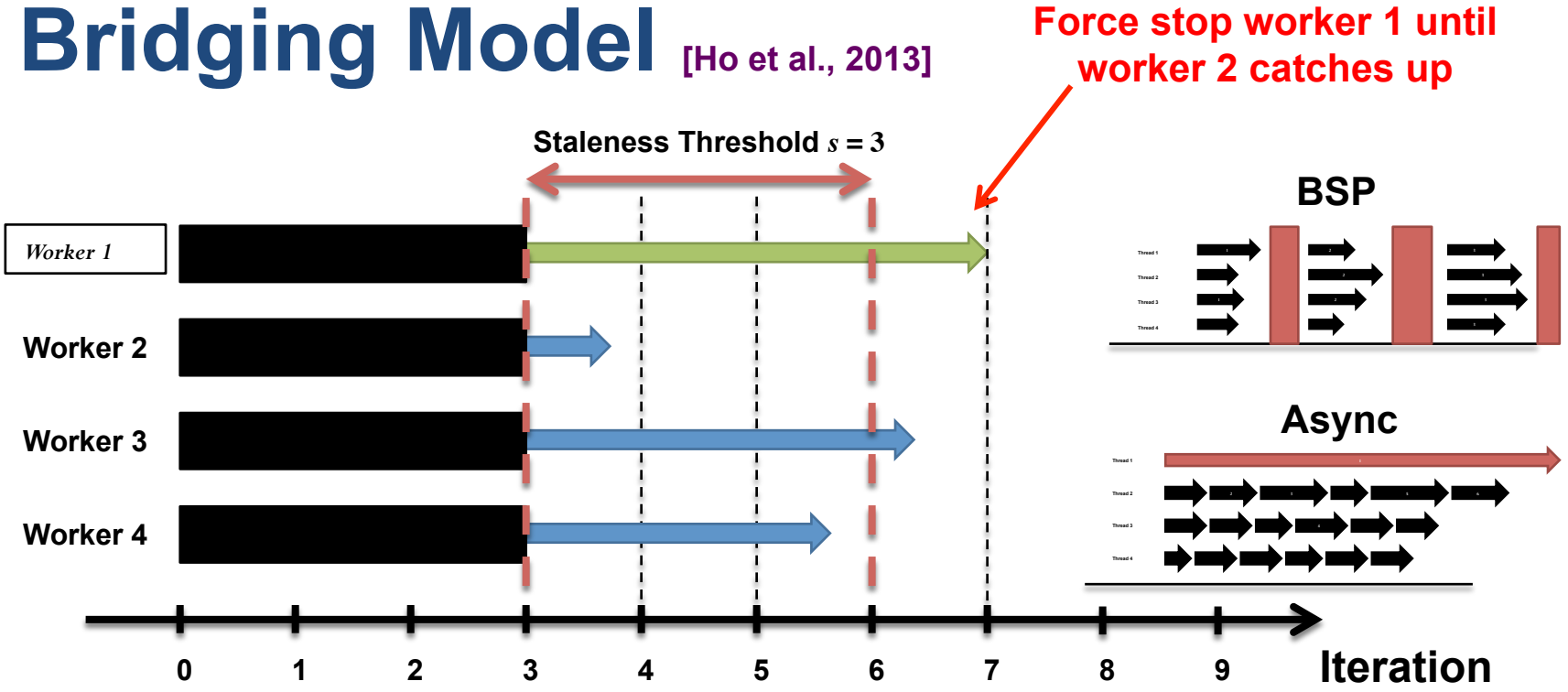
- **Safe/slow (BSP) vs. Fast/risky (Async)?**
- **Challenge 1: Need "Partial" synchronicity**
  - Spread network comms evenly (don't sync unless needed)
  - Threads usually shouldn't wait – but mustn't drift too far apart!
- **Challenge 2: Need straggler tolerance**
  - Slow threads must somehow catch up



hadoop Spark

Is persistent memory really necessary for ML?

A Stale Synchronous Parallel Bridging Model [Ho et al., 2013]



Stale Synchronous Parallel (SSP)

- Fastest/slowest workers not allowed to drift $>s$ iterations apart

Consequence

- Fast like async, yet correct like BSP
- Why? Workers' local view of model parameters "not too stale" ($\leq s$ iterations old)

Data-Parallel Proximal Gradient under SSP

- Model (e.g. SVM, Lasso …):

$$\min_{\mathbf{a}\in\mathbb{R}^d} \mathcal{L}(\mathbf{a}, D), \quad \text{where } \mathcal{L}(\mathbf{a}, D) = f(\mathbf{a}, D) + g(\mathbf{a})$$

data D, model a

- Algorithm:
  - Update

$$\mathbf{a}(t) := \text{prox}_g\left(\mathbf{a}^p(t) - \eta(t)\sum_{(p',t')\in Recv^p(t)} \Delta(\mathbf{a}^{p'}(t'), D_{p'})\right)$$

sub-update

proximal step wrt g

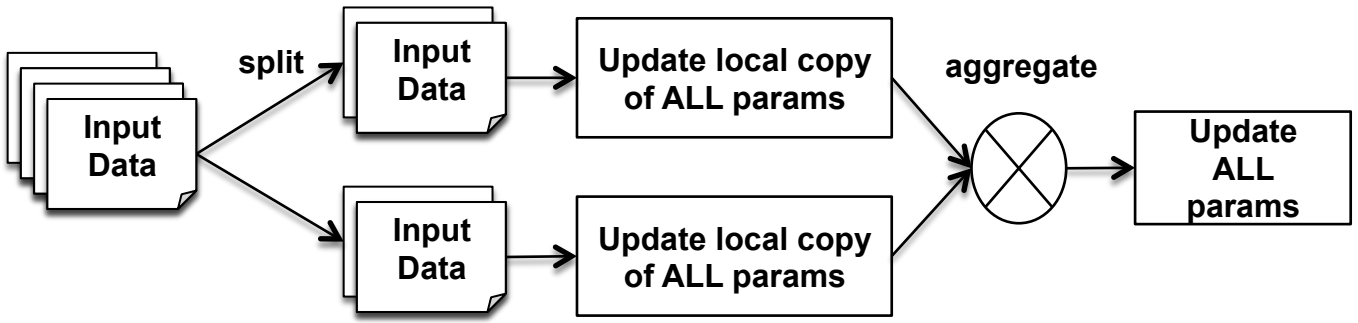
stale sub-updates Δ() received by worker p at iteration t

  - sub-update

$$\Delta(\mathbf{a}^p(t), D_p) := \nabla f(\mathbf{a}^p(t), D_p)$$

gradient step wrt f

- Data parallel:
  - Data D too large to fit in a single worker, divide among P workers



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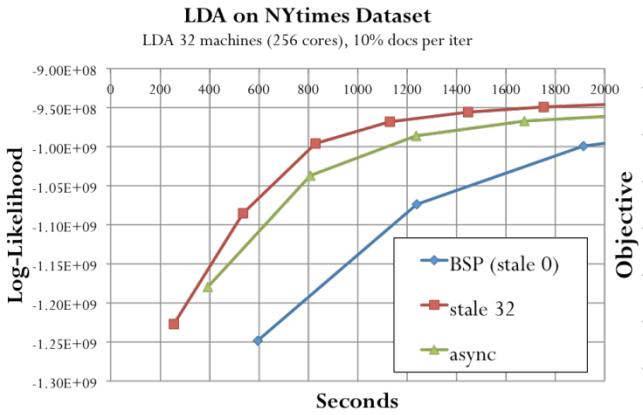
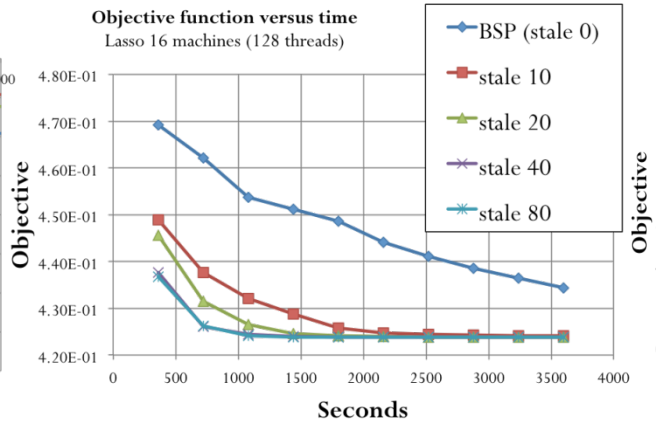
SSP Data-Parallel
Async Speed, BSP Guarantee

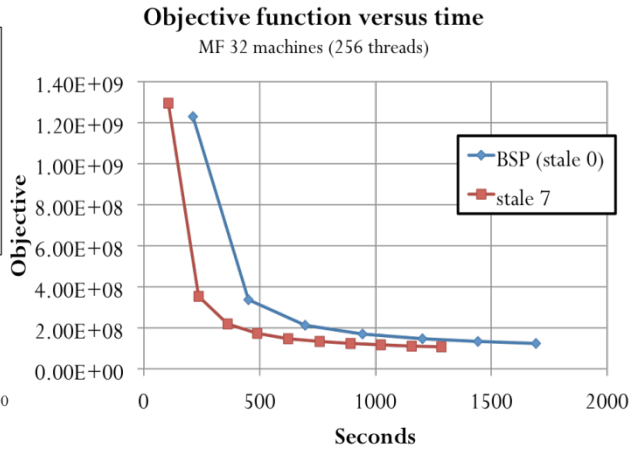
LDA



Lasso



Matrix Fact.



- Massive Data Parallelism
- Effective across different algorithms

SSP Data Parallel Convergence Theorem

[Ho et al., 2013, Dai et al., 2015]

Let observed staleness be γt

Let staleness mean, variance be $\mu_\gamma = \mathbb{E}[\gamma_t]$, $\sigma_\gamma = var(\gamma_t)$

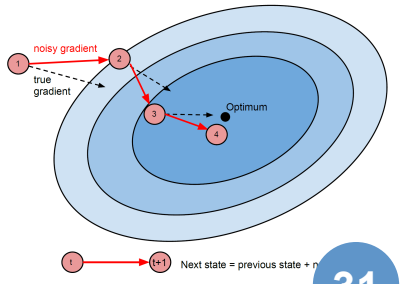
Theorem: Given L-Lipschitz objective f_t and step size h_t,

$$P\left[\frac{R[X]}{T} - \frac{\mathcal{O}(F^2 + \mu_\gamma L^2)}{\sqrt{T}} \geq \tau\right] \leq \exp\left\{\frac{-T\tau^2}{\mathcal{O}(\bar{\eta}_T \sigma_\gamma + L^2 s P \tau)}\right\}$$

where

$$R[X] := \sum_{t=1}^{T} f_t(\tilde{x}_t) - f(x^*) \qquad \bar{\eta}_T = \frac{\eta^2 L^4 (\ln T + 1)}{T} = o(T)$$

Explanation: the distance between true optima and current estimate decreases exponentially with more SSP iterations. *Lower staleness mean, variance μ_γ , σ_γ improve the convergence rate.*



Model-Parallel Proximal Gradient under SSP

- Model (e.g. SVM, Lasso …):

$$\min_{\mathbf{a}\in\mathbb{R}^d} \mathcal{L}(\mathbf{a}, D), \quad \text{where } \mathcal{L}(\mathbf{a}, D) = f(\mathbf{a}, D) + g(\mathbf{a})$$

data D, model a

- Model parallel
  - Model dimension d too large to fit in a single worker
  - Divide model among *P* workers $\mathbf{a} = (a_1, a_2, \ldots, a_P)$
- Algorithm:

$$\underbrace{\forall p,}_{\text{on worker } p}\ a_p(t+1) = a_p(t) + \underbrace{\gamma_p(t)}_{t} \cdot F_p(\mathbf{a}^p(t))$$

workers can skip updates

$$= a_p(0) + \sum_{k=0} \gamma_p(k) \cdot F_p(\mathbf{a}^p(t))$$

staleness

$$\text{(local)} \quad \mathbf{a}^p(t) = \left(a_1(\tau_1^p(t)), \ \ldots\ , a_P(\tau_P^p(t))\right)$$

$$\text{(global)} \quad \mathbf{a}(t) = \left(a_1(t), \ \ldots\ , a_P(t)\right).$$

gradient step wrt *f*

$$\mathbf{a}^p(t+1) := F_p(\mathbf{a}^p(t)) = \underbrace{\text{prox}_{g_p}^{\eta}}_{\text{proximal step wrt } g}(a_p(t) - \eta\nabla_p f(\mathbf{a}^p(t))) - a_p(t)$$

- worker p keeps local copy of the full model (can be avoided for linear models)

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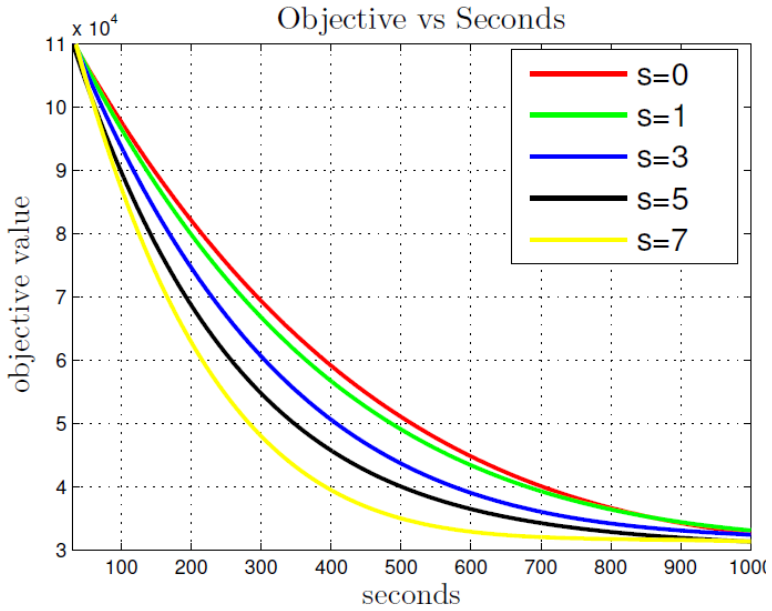
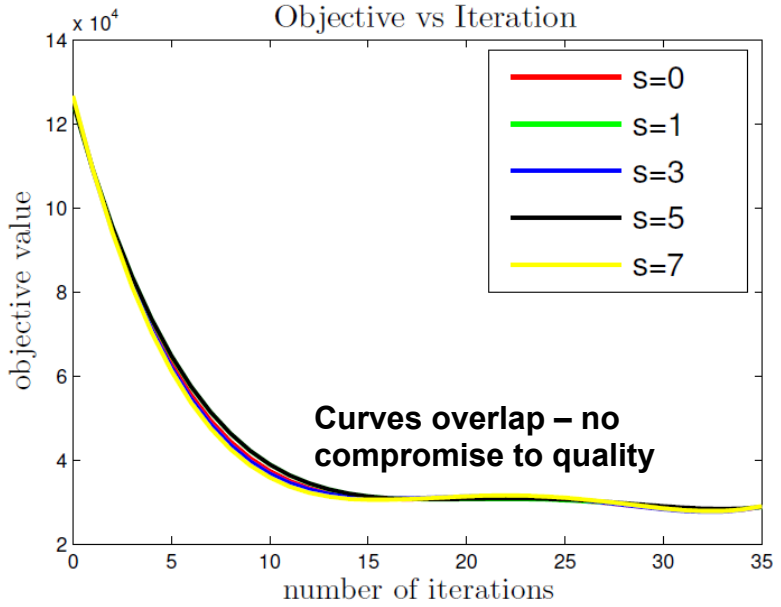
SSP Model-Parallel Async Speed, BSP Guarantee

Lasso: 1M samples, 100M features, 100 machines





- Massive Model Parallelism
- Effective across different algorithms

SSP Model Parallel Convergence Theorem

[Zhou et al., 2016]

Theorem: Given that the SSP delay is bounded, with appropriate step size and under mild technical conditions, then

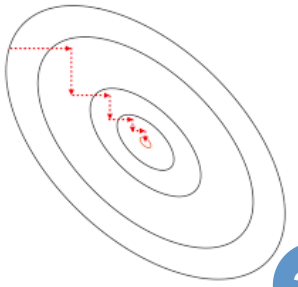
Finite length

$$\sum_{t=0}^{\infty} \|\mathbf{a}(t+1) - \mathbf{a}(t)\| < \infty \qquad \sum_{t=0}^{\infty} \|\mathbf{a}^p(t+1) - \mathbf{a}^p(t)\| < \infty$$

In particular, the global and local sequences converge to the same critical point, with rate $O(t^{-1})$:

$$\mathcal{L}\left(\frac{1}{t}\sum_{k=1}^{t}\mathbf{a}(k)\right) - \inf \mathcal{L} \leq O\left(t^{-1}\right)$$

Explanation: Finite length guarantees that the algorithm stops (the updates must eventually go to zero). Furthermore, the algorithm converges at rate $O(t^{-1})$ to the optimal value; same as BSP model parallel.



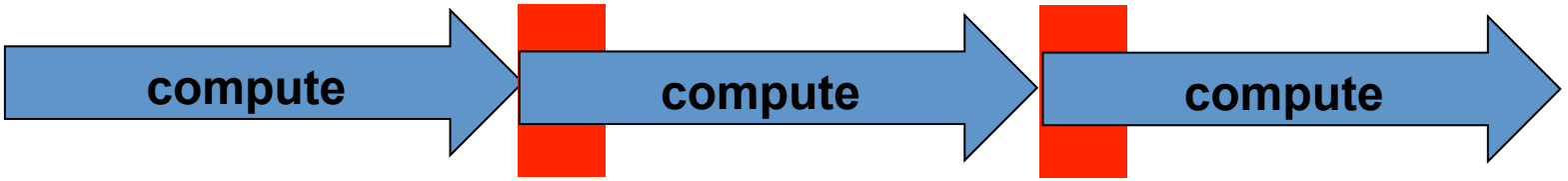
Principles of ML system Design [Xing et al., to appear 2016]

3. How to Communicate:

Managed Communication and Topologies

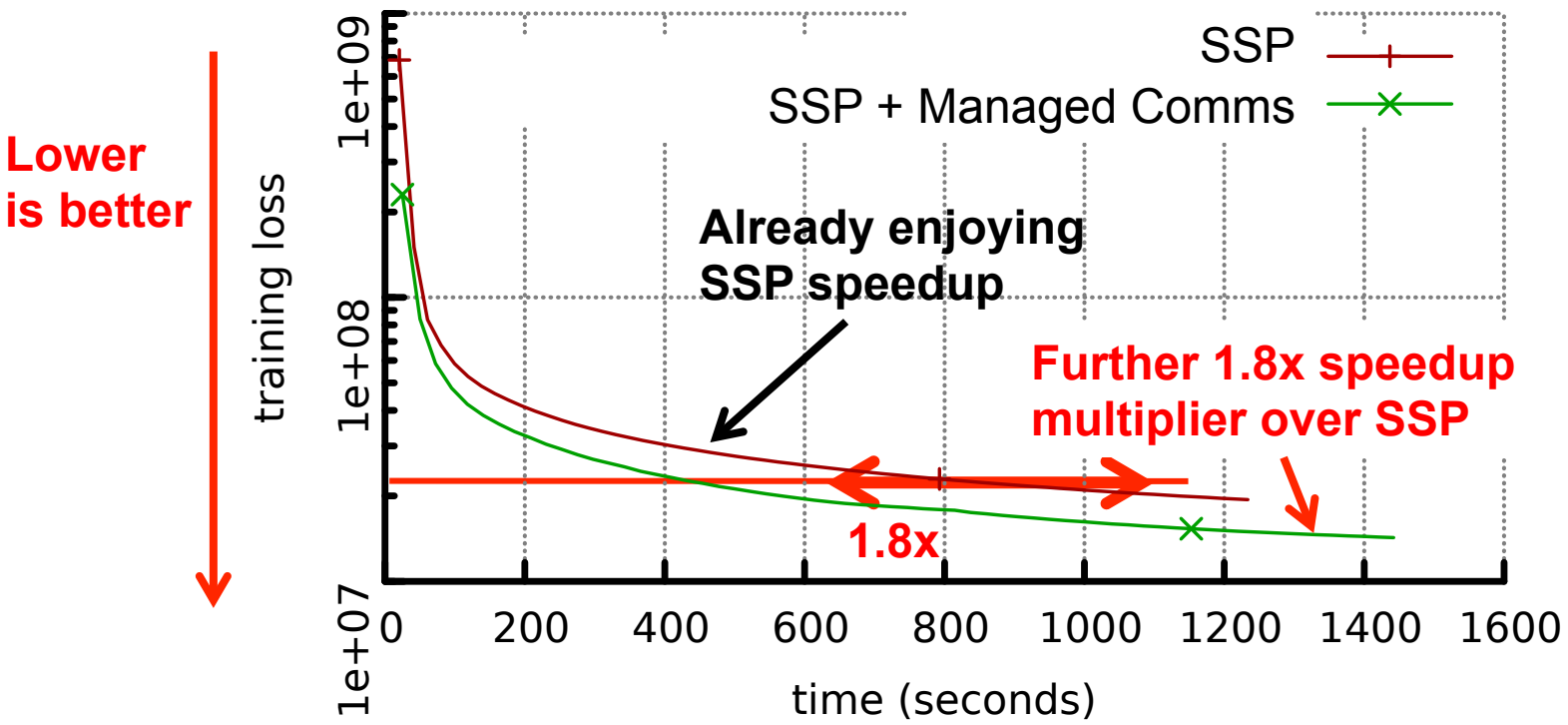
Managed Communication [Wei et al., 2015]

- SSP only
  - Communicates only at iteration boundary
  - Ensures bounded staleness consistency



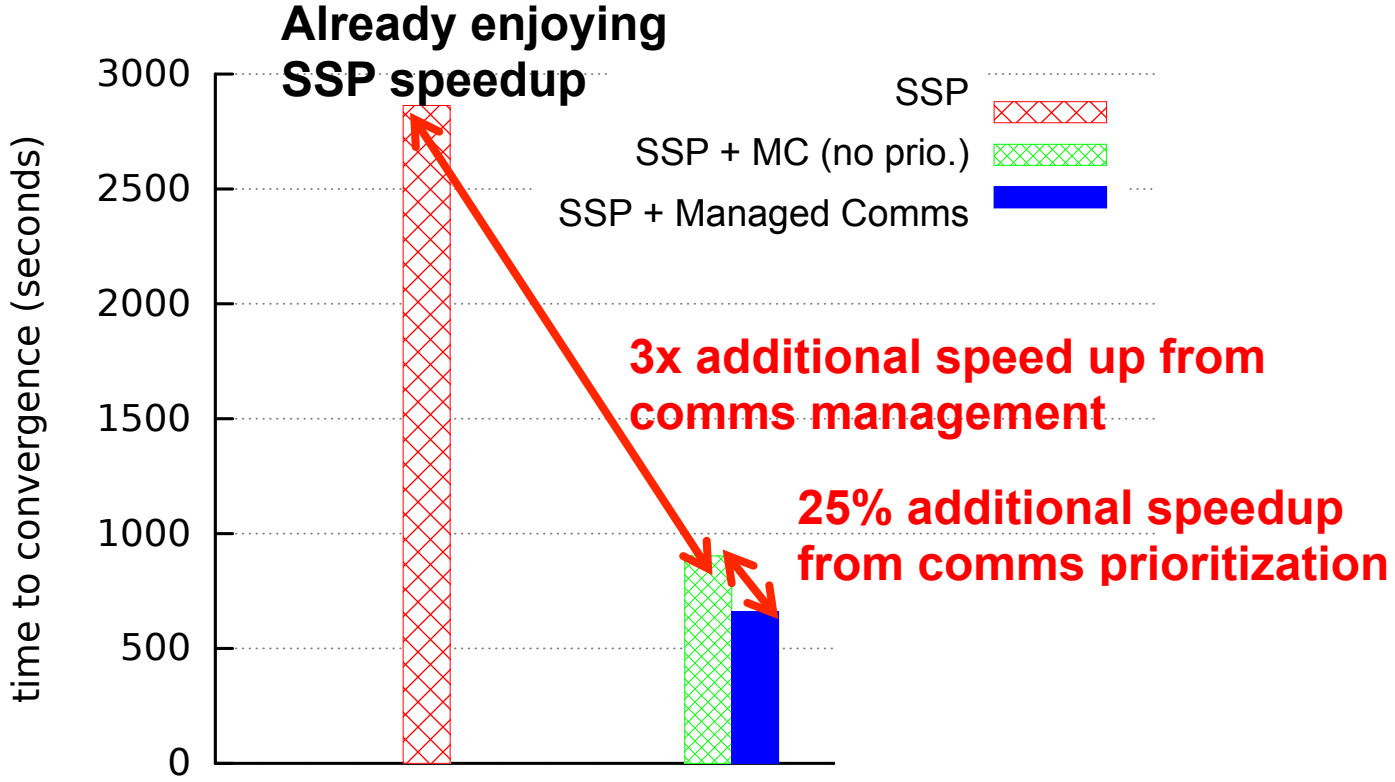
- SSP + Managed Communication
  - Continuous communication/synchronization
  - Update prioritization
  - Same consistency guarantees as SSP

MatrixFact: Managed Communication Speedup



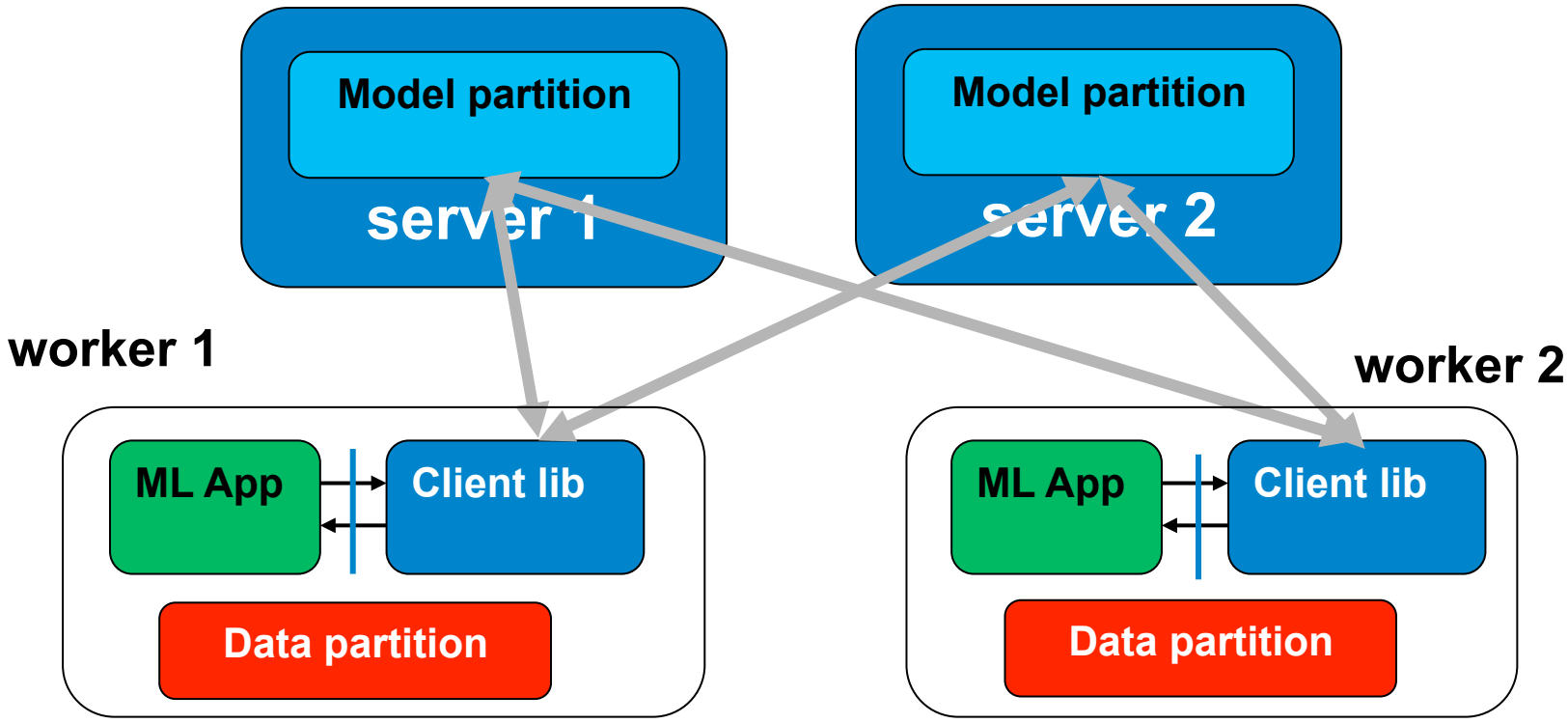
- Matrix Factorization, Netflix data, rank = 400
- 8 machines * 16 cores, 1GbE ethernet

LDA: Managed Communication Speedup



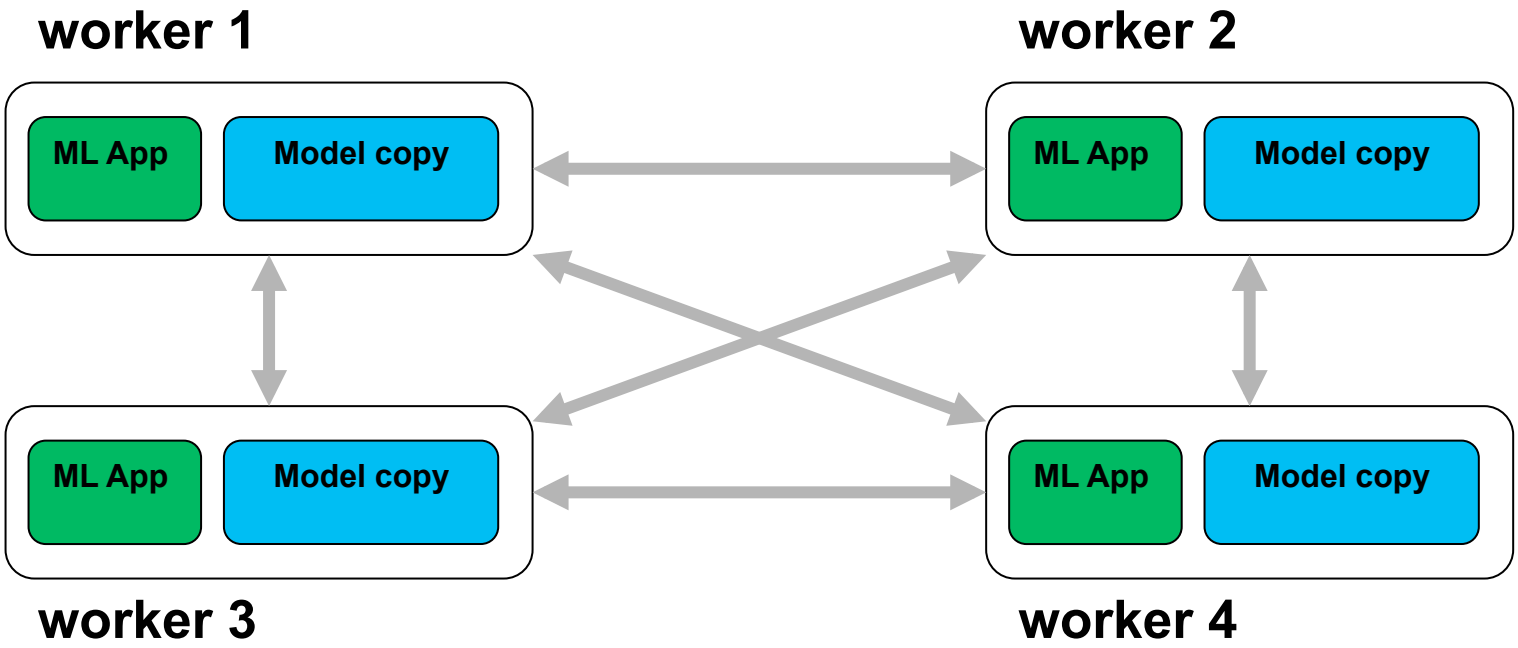
- Latent Dirichlet Allocation, NYTimes, # topics = 1000,
- 16 machines * 16 cores, 1GbE ethernet

Topology: Master-Slave



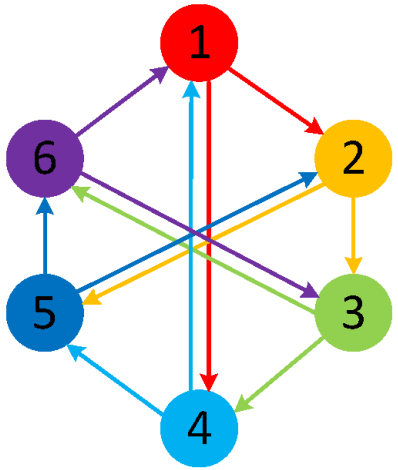
- Used with **centralized storage** paradigm
- Topology = **bipartite graph**: Servers (masters) to Workers (slaves)
- **Disadvantage:** need to code/manage clients and servers separately
- **Advantage:** bipartite topology far smaller than full N^2 P2P connections

Topology: Peer-to-Peer (P2P)



- Used with **decentralized storage** paradigm
- Workers update local parameter view by broadcasting/receiving
- **Disadvantage:** expensive unless updates ΔW are lightweight; expensive for large # of workers
- **Advantage:** only need worker code (no central server code); if ΔW is low rank, comms reduction possible

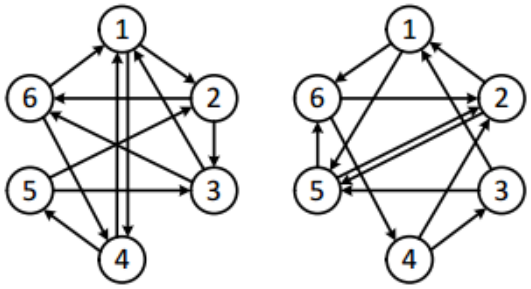
Halton Sequence Topology [Li et al., 2015]



- Used with **decentralized storage** paradigm
- Like P2P topology, but route messages through many workers
  - e.g. to send message from 1 to 6, use 1->2->3->6
- **Disadvantage:** incur higher SSP staleness due to routing, e.g. 1->2->3->6 = staleness 3
- **Advantage:** support bigger messages; support more machines than P2P topology

Random Partial Broadcasting and Diverse Mini-Batch Selection

- Random Partial Broadcasting
  - Each machine randomly selects Q<<P machines to send messages (instead of full broadcast)
  - Message cost reduced: from $O(P^2)$ to $O(PQ)$, scales linearly with machine count P!



- Diverse Mini-batch Selection
  - Choose training data samples that maximize diversity score

$$s = \frac{1}{K(K-1)} \sum_{k=1}^{K} \sum_{j \neq i}^{K} (-\mathbf{x}_k^\top \mathbf{x}_j)$$

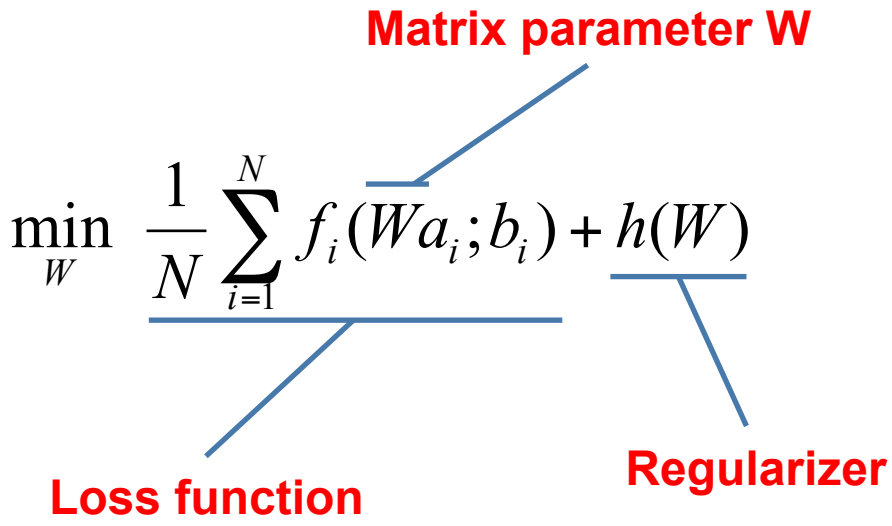
  - Pick few diverse samples instead of many random samples
  - Using few but diverse samples further reduces comms costs without hurting output quality!

Principles of ML system Design [Xing et al., to appear 2016]

4. What to Communicate:

Exploiting Structure in ML Updates

Matrix-Parameterized Models (MPMs)



Distance Metric Learning, Sparse Coding, Distance Metric Learning, Group Lasso, Neural Network, etc.

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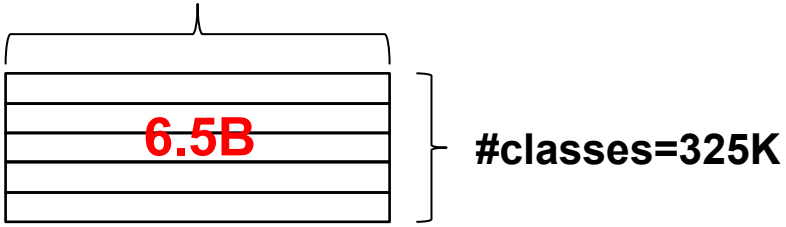
Big MPMs

Billions of params = 10-100 GBs, costly network synchronization

What do we actually need to communicate?

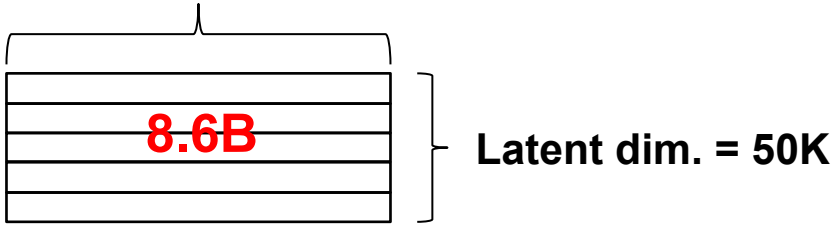
Multiclass Logistic Regression on Wikipedia

Feature dim. = 20K



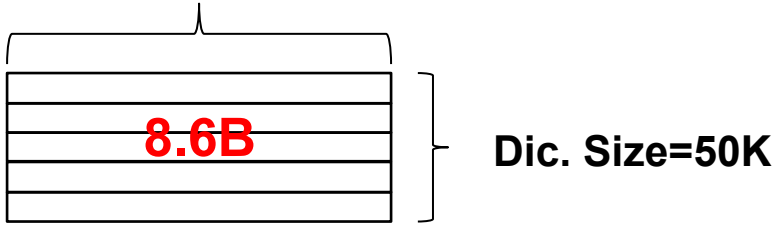
Distance Metric Learning on ImageNet

Feature dim. = 172K



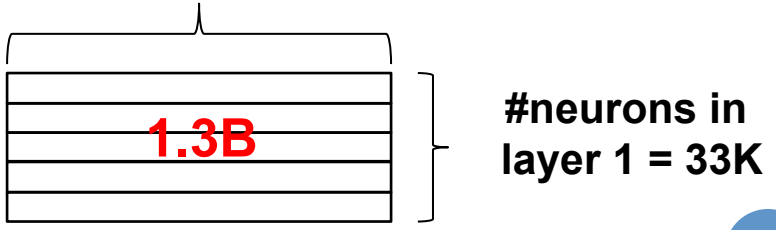
Sparse Coding on ImageNet

Feature dim. = 172K



Neural Network of Google Brain

#neurons in layer 0 = 40K



Full Updates

- Let matrix parameters be W. **Need to send parallel worker updates** ΔW to other machines…
  - Primal stochastic gradient descent (SGD)

$$\min_W \frac{1}{N}\sum_{i=1}^{N} f_i(Wa_i; b_i) + h(W)$$

$$\Delta W = \frac{\partial f(Wa_i, b_i)}{\partial W}$$

  - Stochastic dual coordinate ascent (SDCA)

$$\min_Z \frac{1}{N}\sum_{i=1}^{N} f_i^*(-z_i) + h^*\left(\frac{1}{N} ZA^{\mathrm{T}}\right)$$

$$\Delta W = (\Delta z_i) a_i$$

Sufficient Factor (SF) Updates

[Xie et al., 2015]

- **Full parameter matrix update** ΔW can be computed as **outer product of two vectors** uv^T (called sufficient factors)
  - Primal stochastic gradient descent (SGD)

$$\min_W \frac{1}{N}\sum_{i=1}^{N} f_i(Wa_i; b_i) + h(W)$$

$$\Delta W = uv^{\mathrm{T}} \quad u = \frac{\partial f(Wa_i, b_i)}{\partial (Wa_i)} \quad v = a_i$$

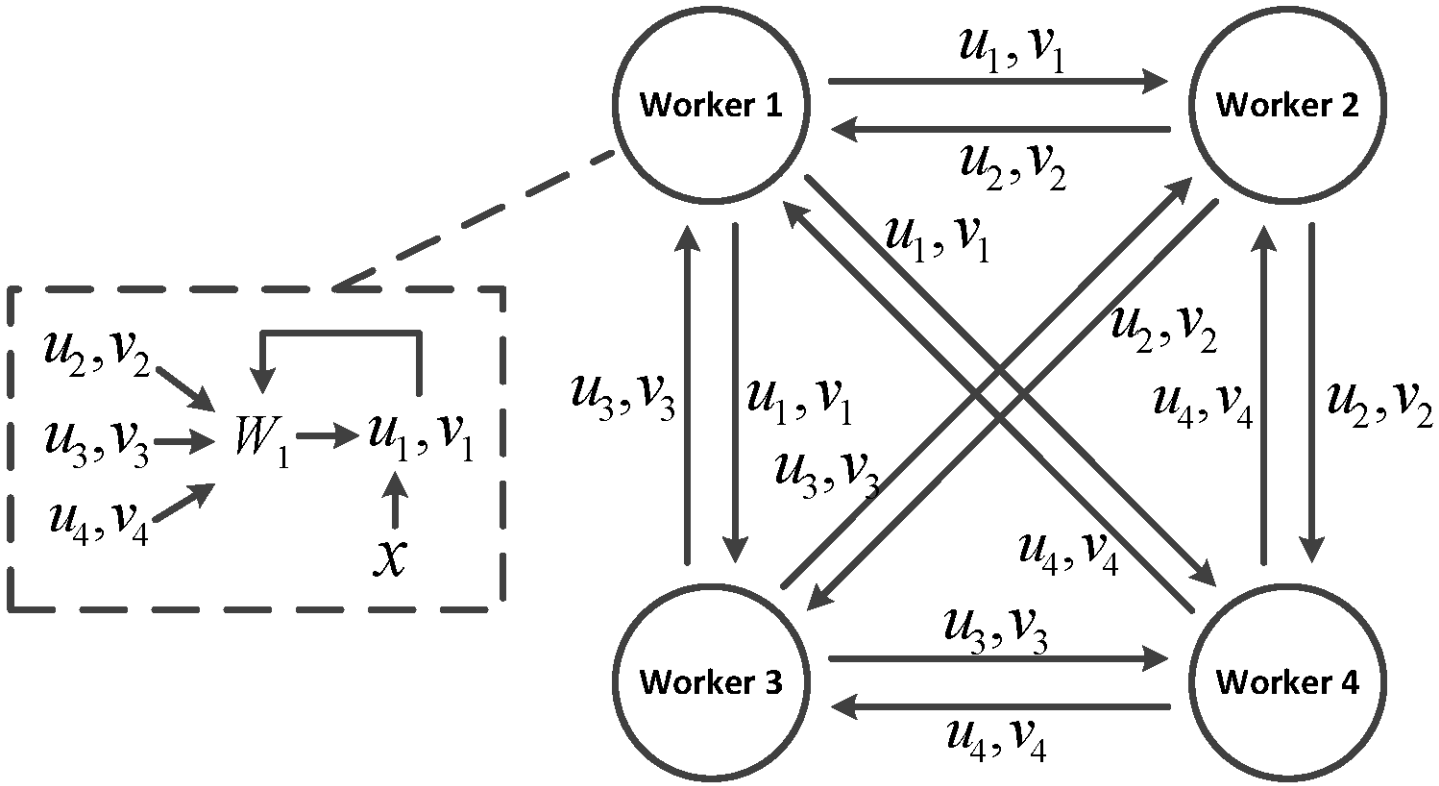
  - Stochastic dual coordinate ascent (SDCA)

$$\min_Z \frac{1}{N}\sum_{i=1}^{N} f_i^*(-z_i) + h^*\left(\frac{1}{N} ZA^{\mathrm{T}}\right)$$

$$\Delta W = uv^{\mathrm{T}} \quad u = \Delta z_i \quad v = a_i$$

- Send the lightweight SF updates (u,v), instead of the expensive full-matrix ΔW updates!

P2P Topology + SF Updates = Sufficient Factor Broadcasting



SFB Convergence Theorem

[Xie et al., 2015]

Theorem 1. *Let* $\{\mathbf{W}_p^c\}$, $p = 1, \ldots, P$, *and* $\{\mathbf{W}^c\}$ *be the local sequences and the auxiliary sequence generated by SFB for problem* (**P**) *(with* $h \equiv 0$*), respectively. Under Assumption 1 and set the learning rate* $\eta_c^{-1} = \frac{L_F}{2} + 2sL + \sqrt{c}$*, then we have*

- $\liminf_{c\to\infty} \mathbb{E}\|\nabla F(\mathbf{W}^c)\| = 0$, *hence there exists a subsequence of* $\nabla F(\mathbf{W}^c)$ *that almost surely vanishes;*
- $\lim_{c\to\infty} \max_p \|\mathbf{W}^c - \mathbf{W}_p^c\| = 0$, i.e. *the maximal disagreement between all local sequences and the auxiliary sequence converges to 0 (almost surely);*
- *There exists a common subsequence of* $\{\mathbf{W}_p^c\}$ *and* $\{\mathbf{W}^c\}$ *that converges almost surely to a stationary point of* F*, with the rate* $\min_{c\le C} \mathbb{E}\| \sum_{p=1}^P \nabla F_p(\mathbf{W}_p^c)\|_2^2 \le O\left(\frac{(L+L_F)\sigma^2 P s \log C}{\sqrt{C}}\right)$.

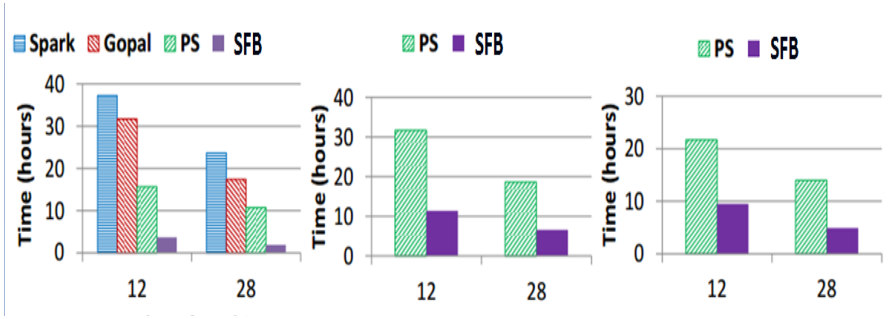
Explanation: Parameter copies W_p on different workers p converge to the same optima, *i.e. all workers reach the same (correct) answer.*

✓Does not need central parameter server or key-value store

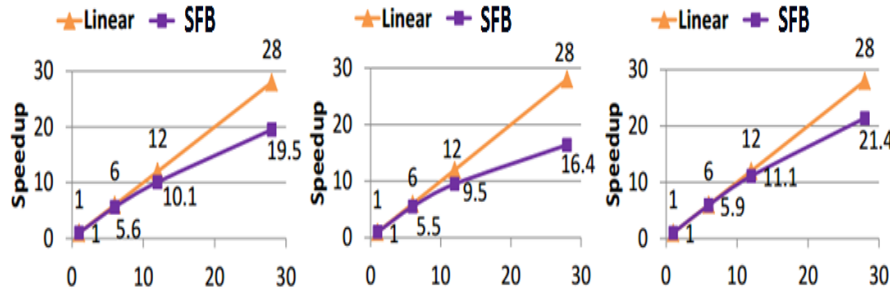
✓Works with SSP bridging model (staleness = s)

Why is SFB faster?

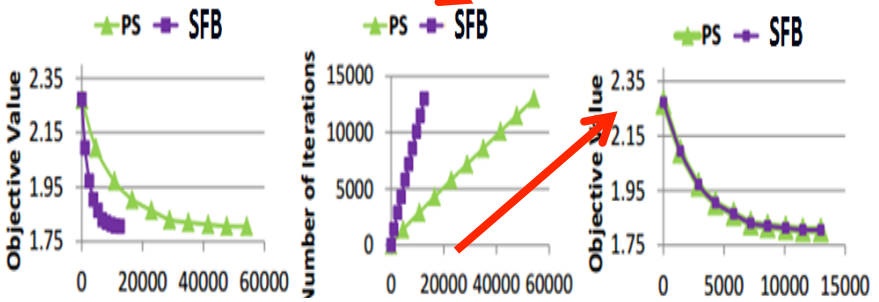
- Faster than PS and Spark



- Near-linear scalability

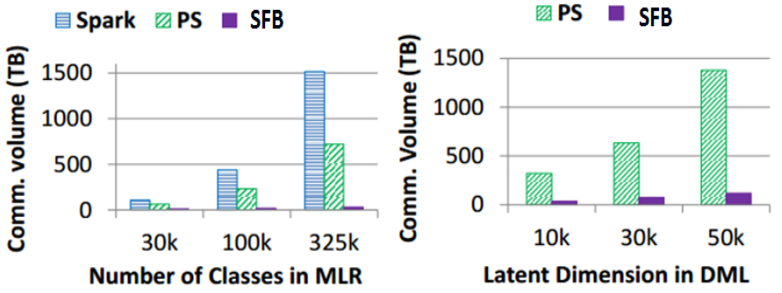


Because SFB has faster iterations (less communication)



… while keeping the same iteration quality as PS

SFB communication up to 100x smaller than PS and Spark



Summary

1. **How to Distribute?**
   - Structure-Aware Parallelization
   - Work Prioritization
2. **How to Bridge Computation and Communication?**
   - BSP Bridging Model
   - SSP Bridging Model for Data and Model Parallel
3. **How to Communicate?**
   - Managed comms – interleave comms/compute, prioritized comms
   - Parameter Storage: Centralized vs Decentralized
   - Communication Topologies: Master-Slave, P2P, Halton Sequence
4. **What to Communicate?**
   - Full Matrix updates
   - Sufficient Factor updates
   - Hybrid FM+SF updates (as in a DL model)