How to Go Really Big in AI:

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
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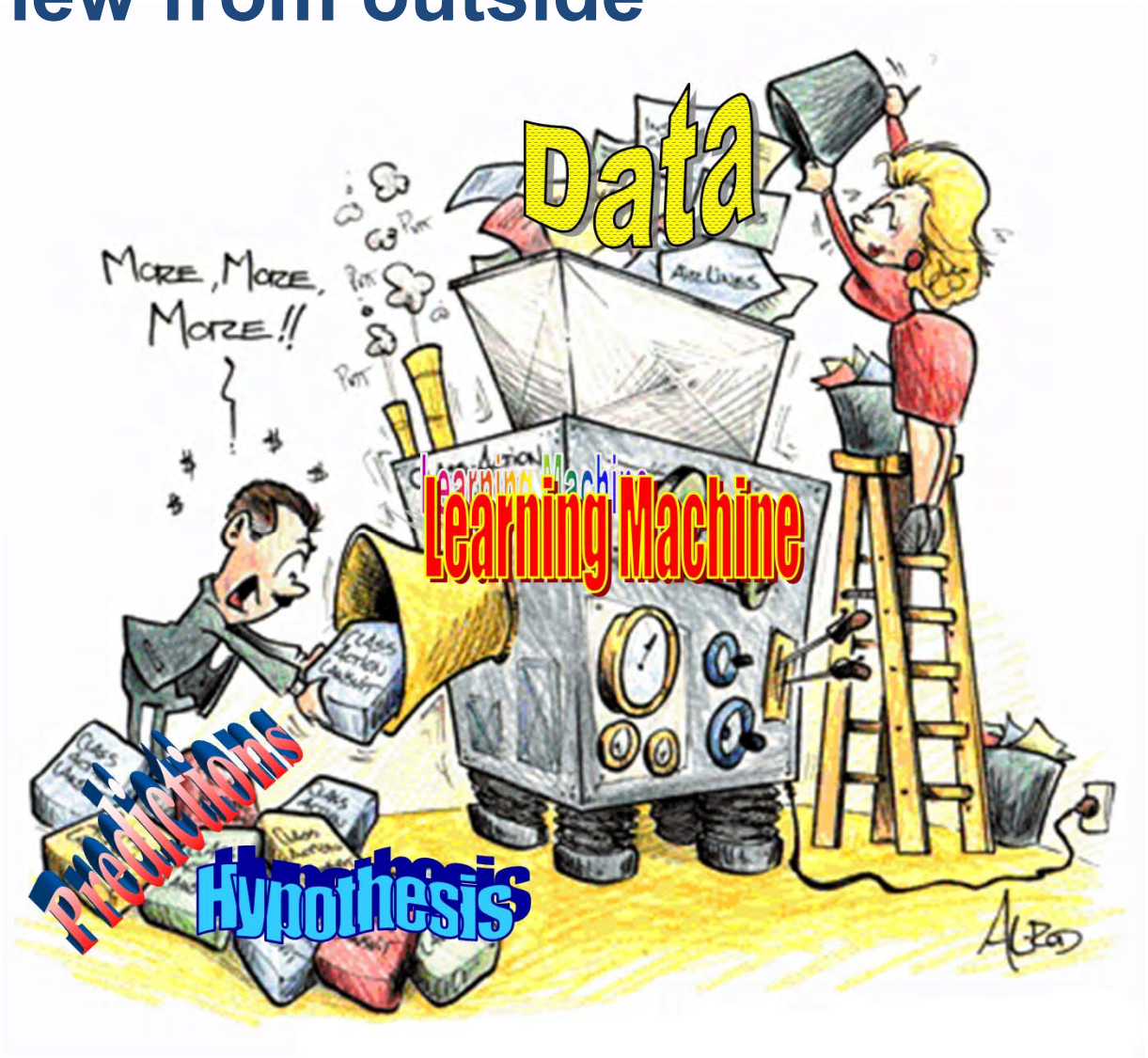
Machine Learning:
-- a view from outside



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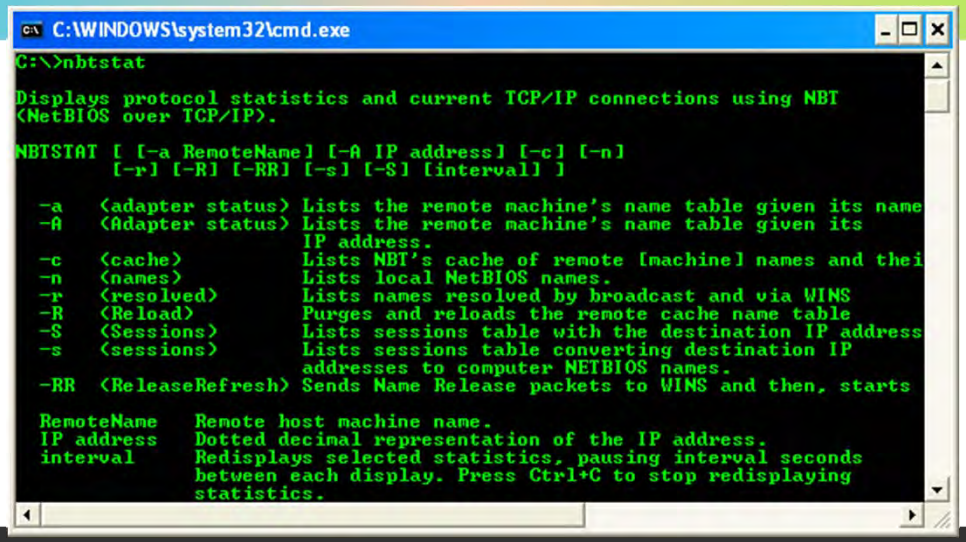
Inside ML …





- 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

Massive Data

facebook

1B+ USERS
30+ PETABYTES

WIKIPEDIA
The Free Encyclopedia

32 million
pages

YouTube

100+ hours video
uploaded every minute

twitter

645 million users
500 million tweets / day

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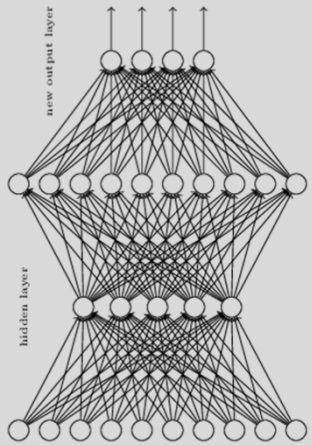
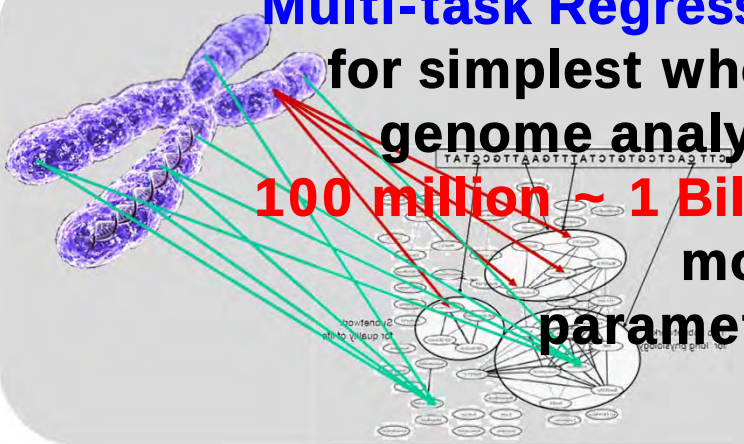
Growing Model Complexity



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



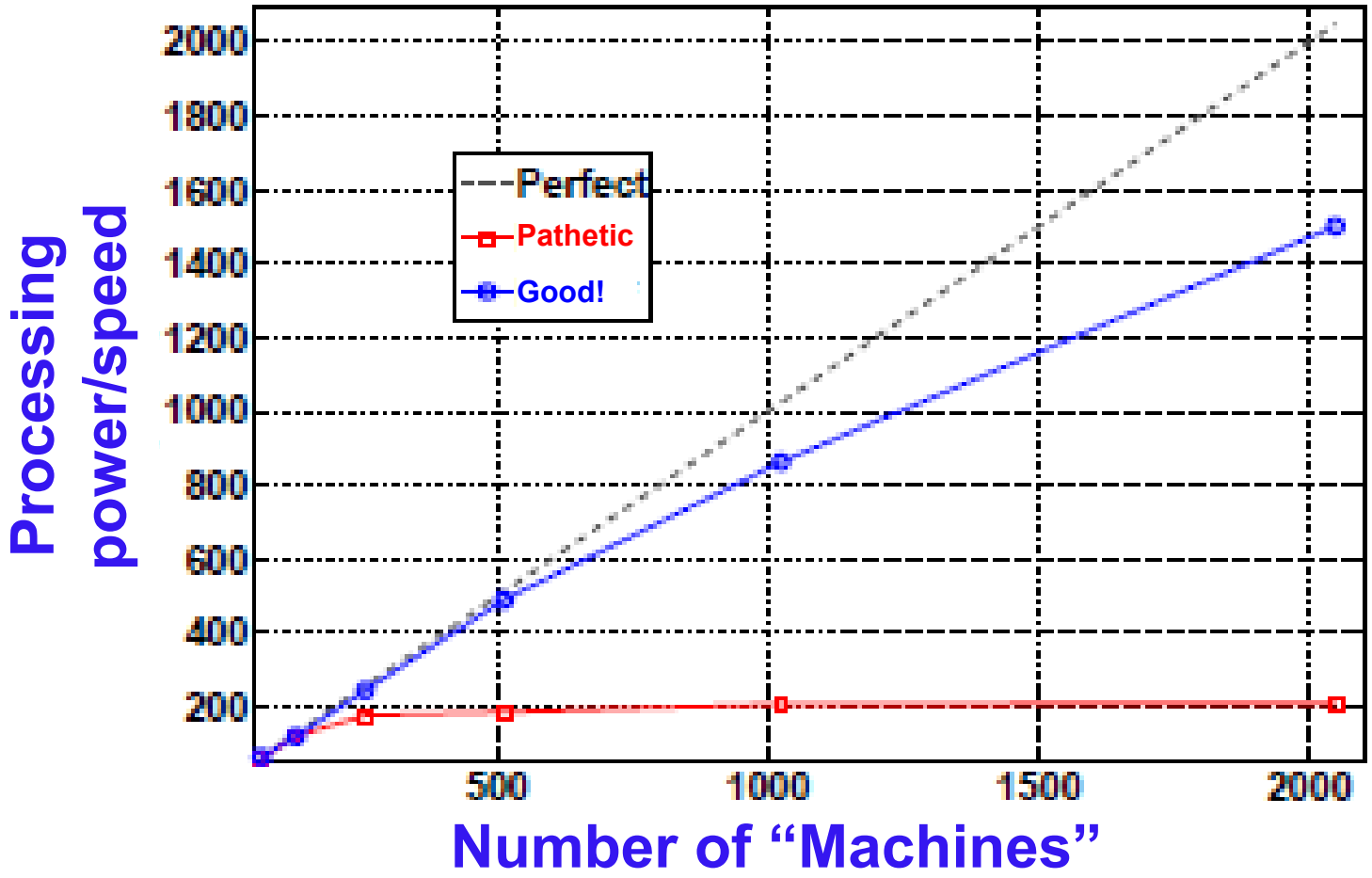
Multi-task Regression
for simplest whole-genome analysis:
100 million ~ 1 Billion
model parameters

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

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

NETFLIX

The Scalability Challenge



Why need new Big ML systems?

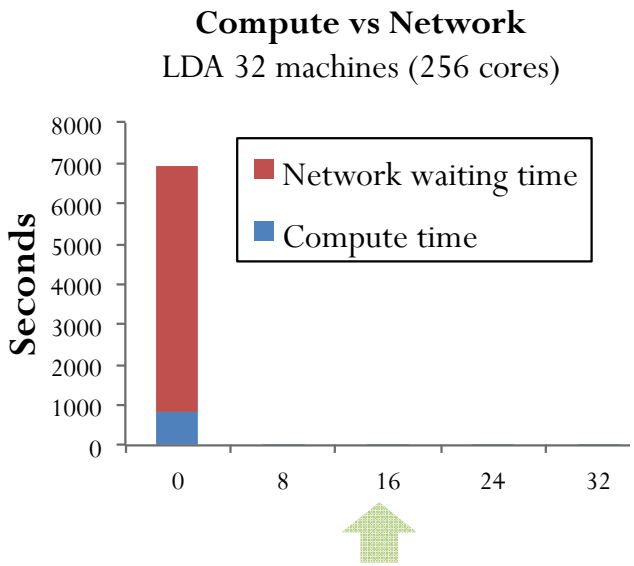
Today's AI & ML imposes high CAPEX and OPEX

- **Example: The Google Brain AI & ML system**
- **High CAPEX**
  - 1000 machines
  - $10m+ capital cost (hardware)
  - $500k+/yr electricity and other costs
- **High OPEX**
  - 3 key scientists ($1m/year)
  - 10+ engineers ($2.5m/year)
- **Total 3yr-cost = $20m+**
- **Small to mid companies and the Academic do not have such luxury**
- **1000 machines only 100x as good as 1 machine!**

Why need some new thinking?

MLer's view

- Focus on
  - Correctness
  - fewer iteration to converge,
- but assuming an ideal system, e.g.,
  - **zero-cost sync,**
  - **uniform local progress**




```
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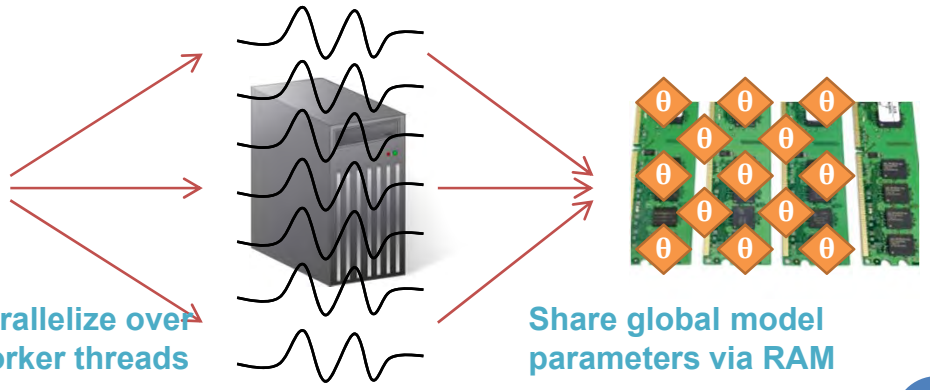

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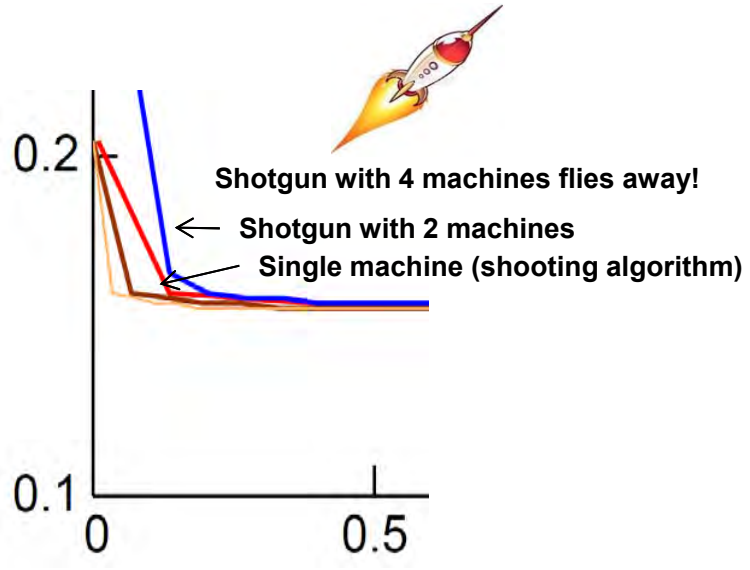
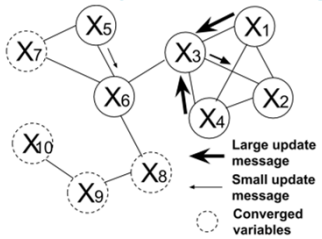
Why need some new thinking?



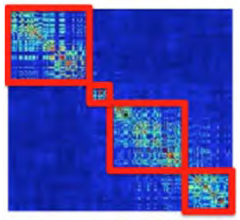
Systems View:

- Focus on
  - high iteration throughput (more iter per sec)
  - strong fault-tolerant atomic operations,
- but assume ML algo is a black box
  - **ML algos "still work" under different execution models**
  - **"easy to rewrite" in chosen abstraction**

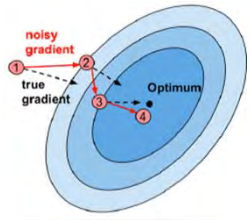
Agonistic of ML properties and objectives in system design



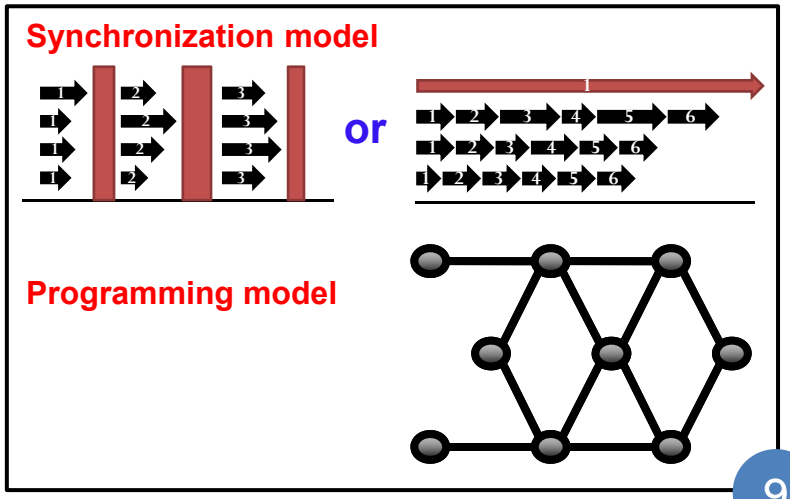
Non-uniform convergence



Dynamic structures



Error tolerance



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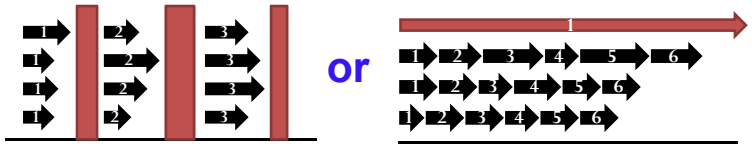

Oversimplify systems issues

- need machines to perform consistently
- need lots of synchronization
- or even try not to communicate at all

Oversimplify ML issues and/or ignore ML opportunities

- ML algos "just work" without proof
- Conversion of ML algos across different program models (graph programs, RDD) is easy

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Existing Solution:





Machine Learning Models/Algorithms

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

Hardware and infrastructure

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How about this … [Xing et al., 2015]





Machine Learning Models/Algorithms

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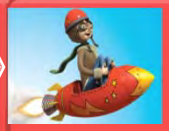
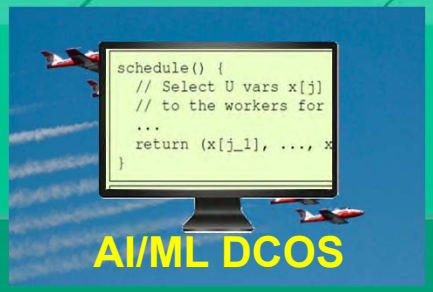


AI/ML [illegible]ourses



AI/ML DCOS

Hardware and infrastructure

- Network switches
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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()
      θ⃗^{t+1} = g(θ⃗^t, Δ_f θ⃗(D))
  doOtherThings()
}
```

This computation needs to be parallelized!

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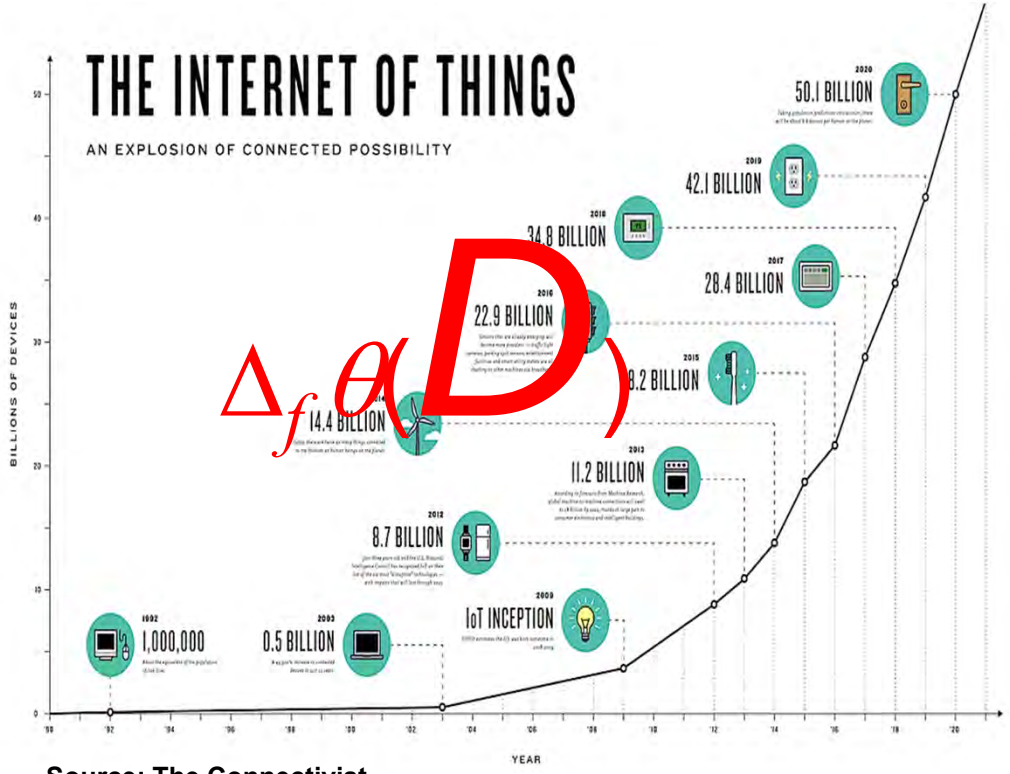
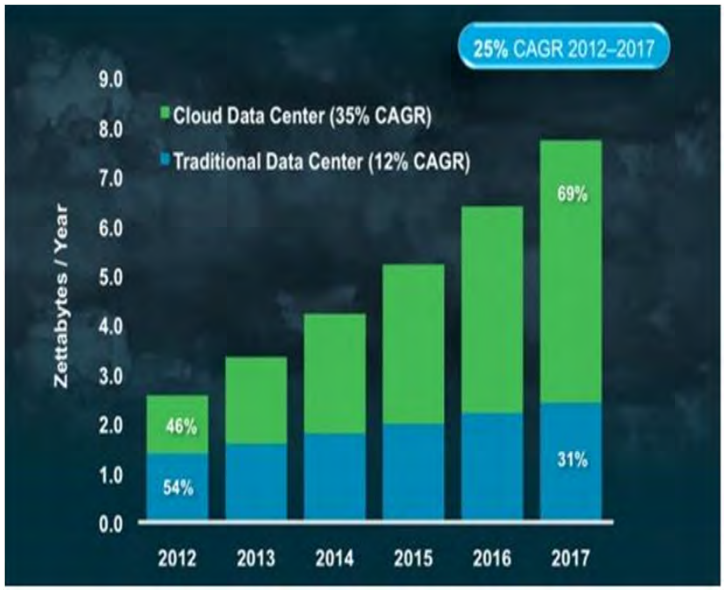
Challenge #1 – Massive Data Scale



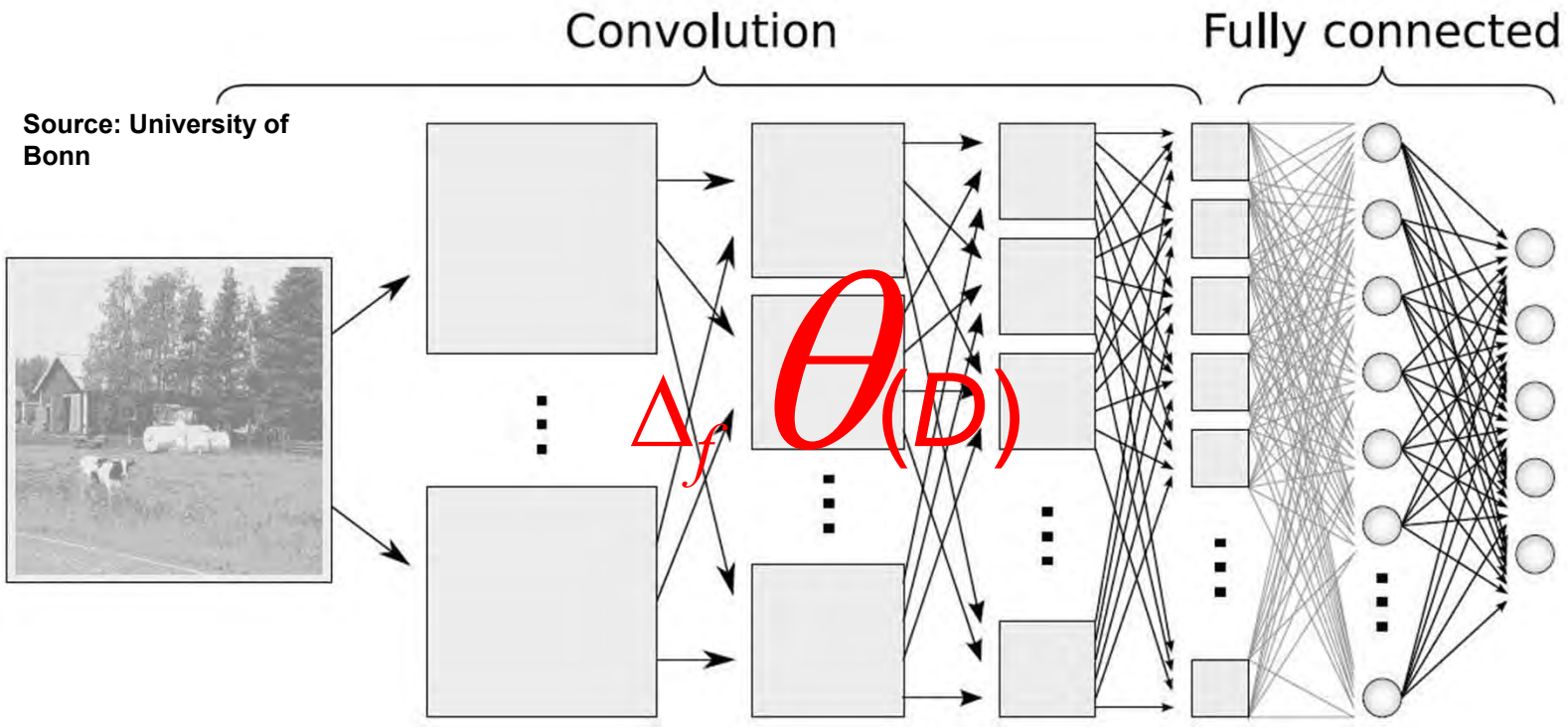
Source: The Connectivist



Source: Cisco Global Cloud Index

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

Challenge #2 – Gigantic Model Size

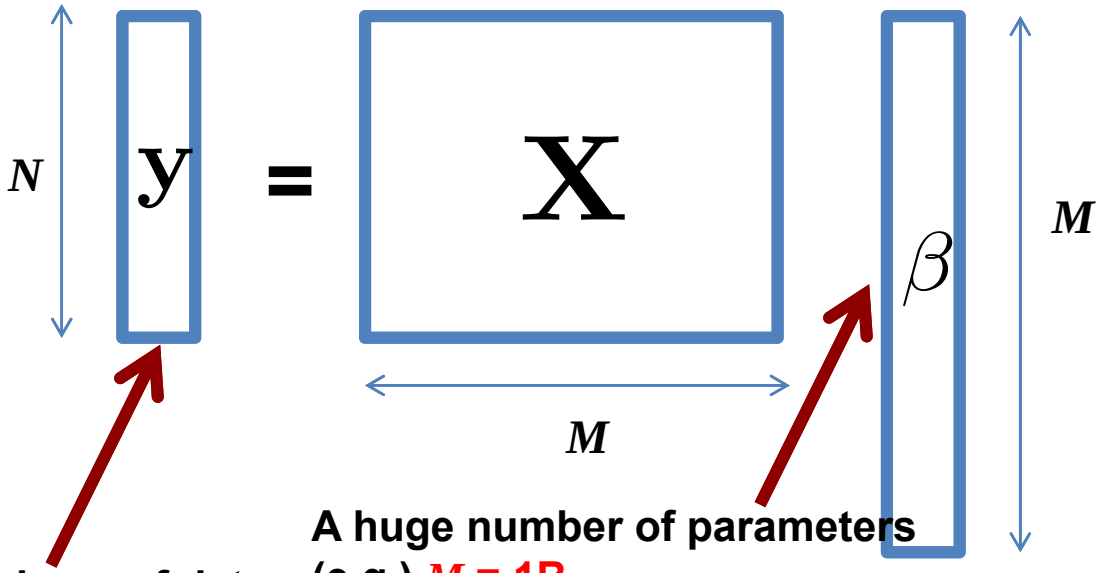


Big Data needs Big Models to extract understanding
But ML models with >1 trillion params also won't fit!

Typical ML Programs (about the "*f*")

- **Optimization programs:**

$$\Delta \leftarrow \sum_{i=1}^{N} \left[\frac{d}{d\theta_1}, \ldots, \frac{d}{d\theta_M} \right] f(\mathbf{x}_i, \mathbf{y}_i; \vec{\theta})$$



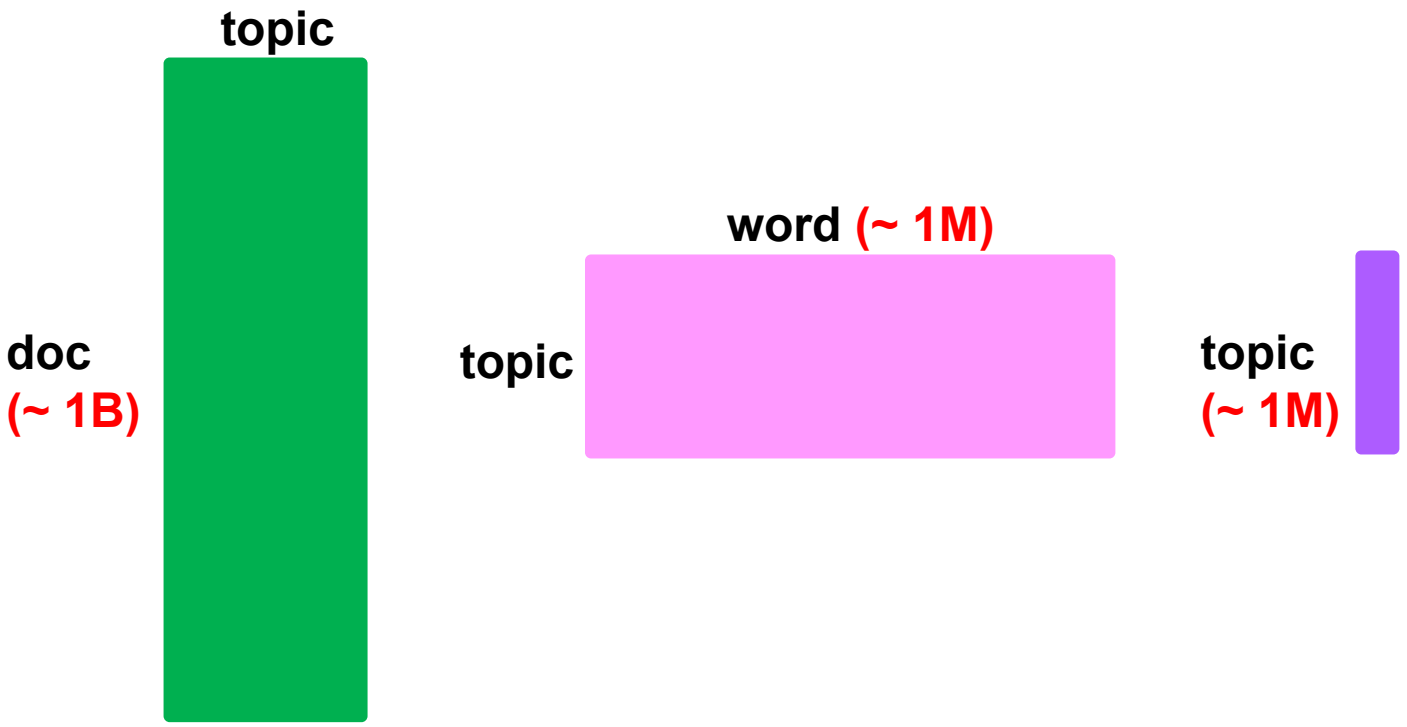
A huge volume of data
(e.g.) *N* = 1B

A huge number of parameters
(e.g.) *M* = 1B

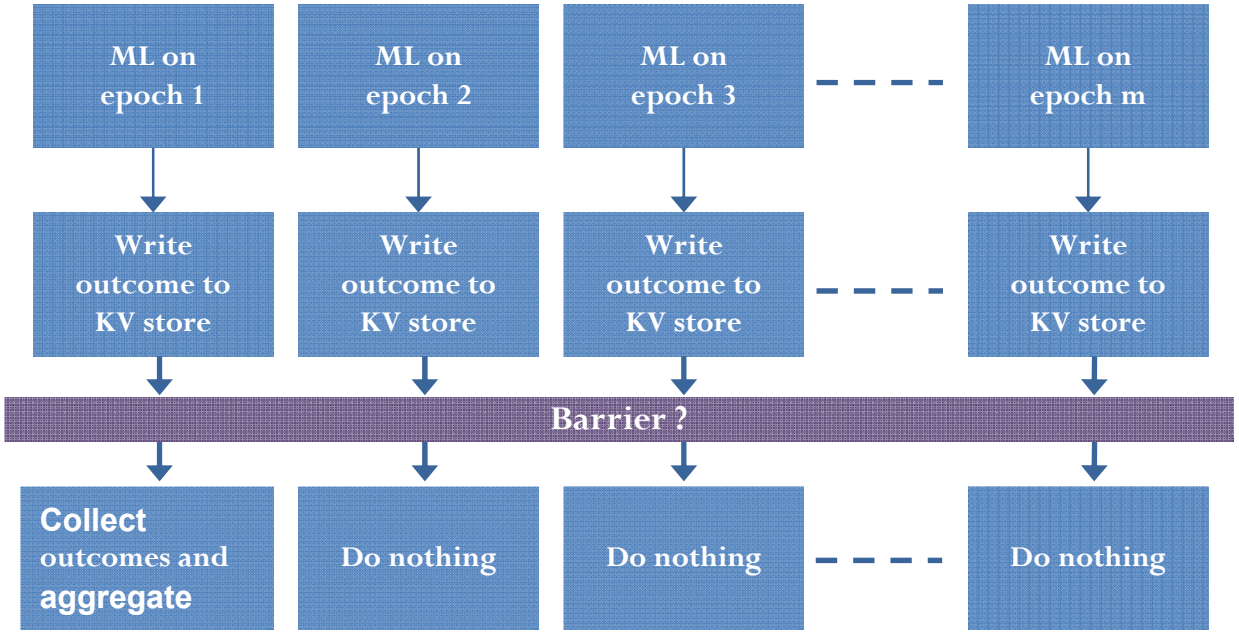
Typical ML Programs (about the "*f*")

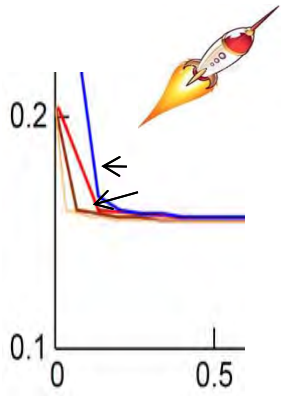
- **Probabilistic programs**

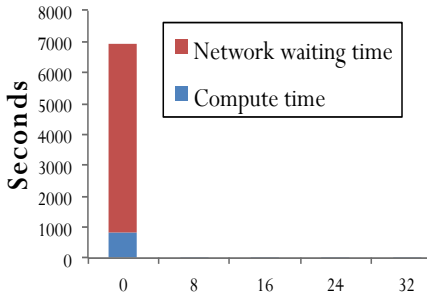
$$z_{di} \sim p(z_{di} = k|\text{rest}) \propto (n_{kd}^{-di} + \alpha_k) \cdot \frac{n_{kw}^{-di} + \beta_w}{(n_k^{-di} + \bar{\beta}V)}$$



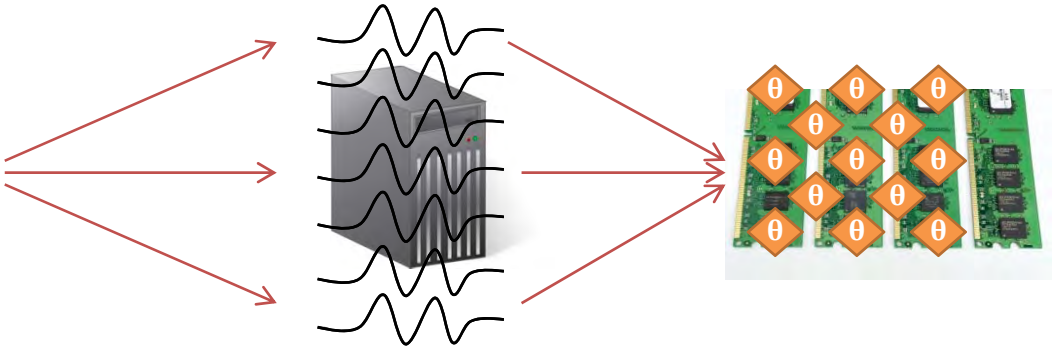
Parallelization Strategy








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



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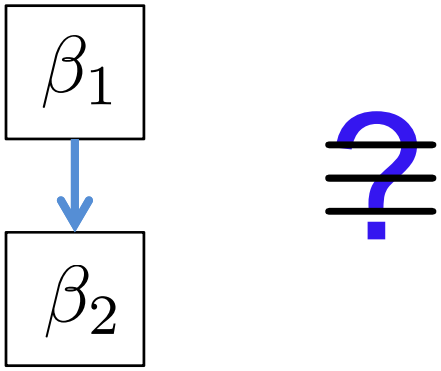

Usually, we worry …

A sequential program



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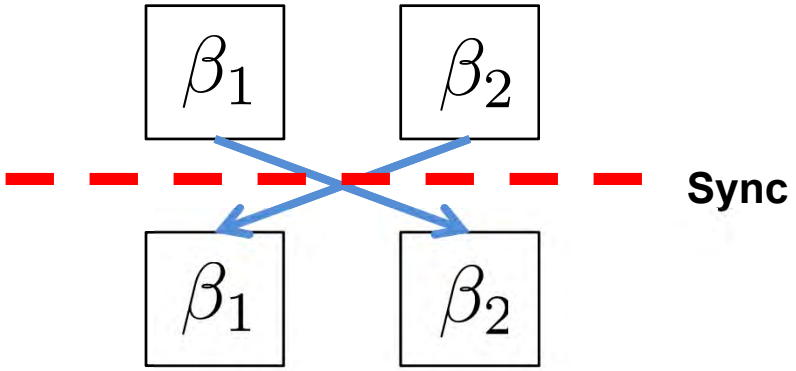
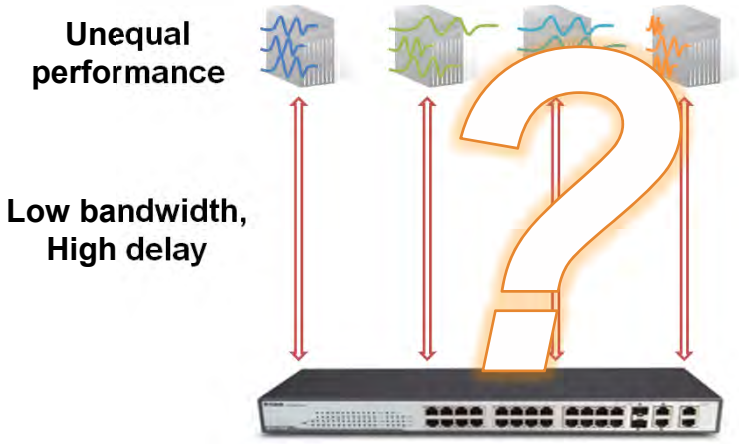
A parallel program



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



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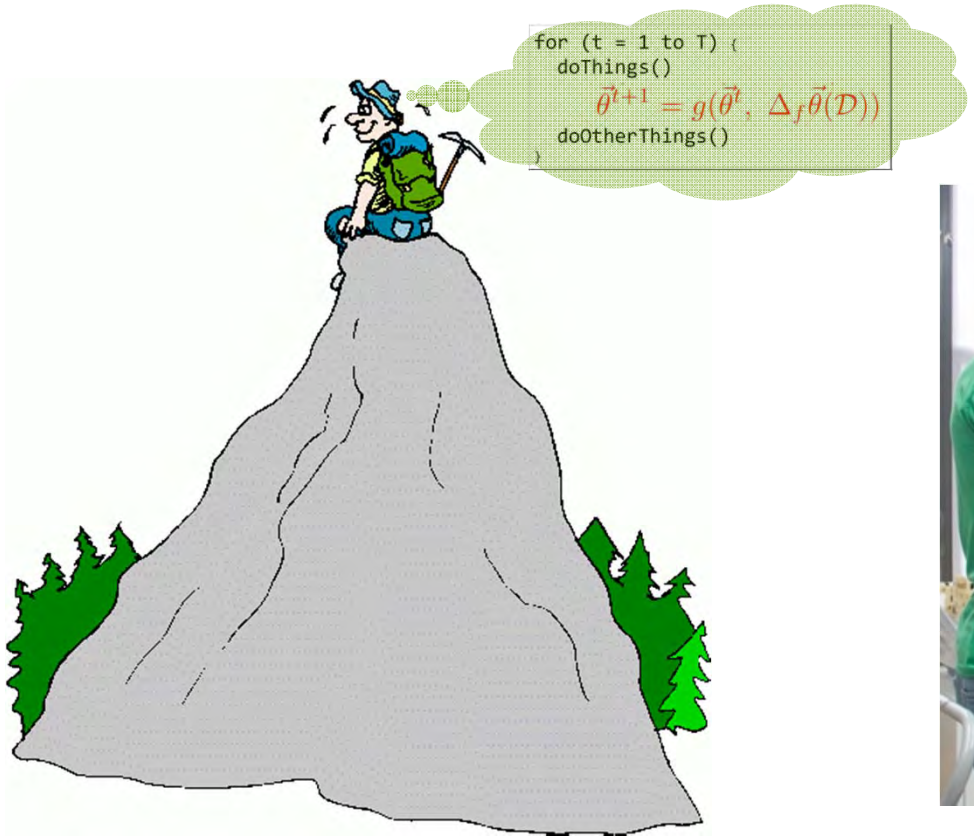
ML Computation vs. Classical Computing Programs

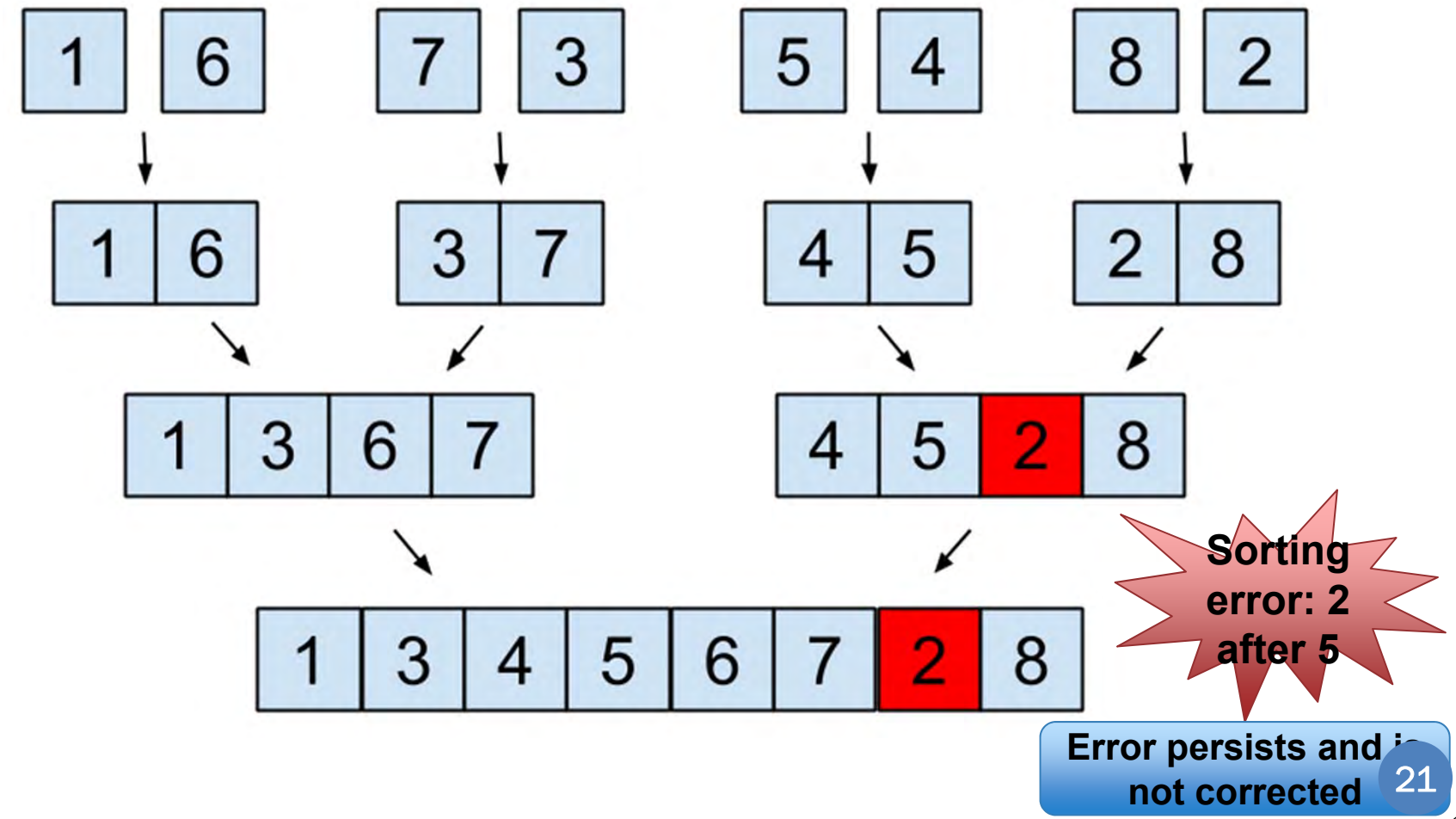


ML Program: optimization-centric and iterative convergent

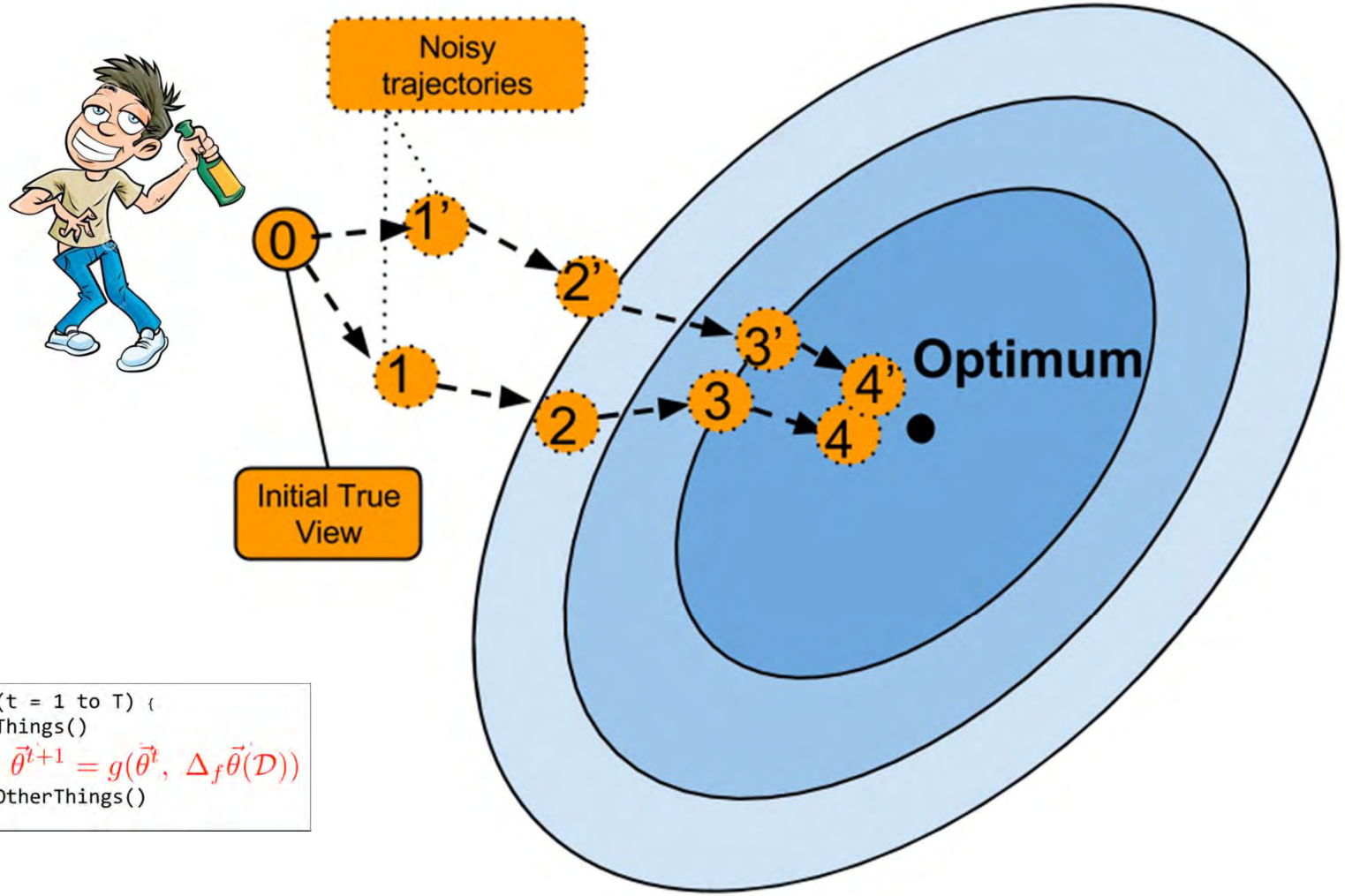
Traditional Program: operation-centric and deterministic

Traditional Data Processing needs operational correctness

Example: Merge sort



ML Algorithms can Self-heal




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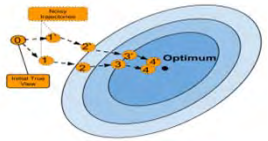
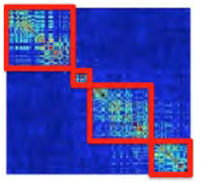

Intrinsic Properties of ML Programs

[Xing et al., 2015]

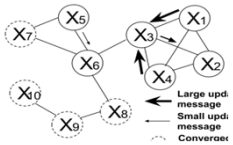
- ML is **optimization-centric**, and admits an **iterative convergent** algorithmic solution rather than a one-step closed form solution
  - **Error tolerance**: often robust against limited errors in intermediate calculations



  - **Dynamic structural dependency**: changing correlations between model parameters critical to efficient parallelization



  - **Non-uniform convergence**: parameters can converge in very different number of steps



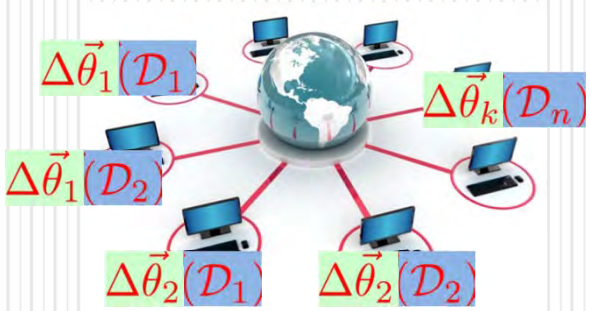
- Whereas traditional programs are **transaction-centric**, thus only guaranteed by **atomic correctness** at every step

Intrinsic Properties of ML Programs

[Xing et al., 2015]

- ML is … gent
  algori … on
  - **Err** …
    erro
  - **Dyn** …
    cha …
    criti
  - **Nor** …
    can …
- Wher … only
  guara …
- How do existing Big Data platforms fit the above?

Two Parallel Strategies for ML

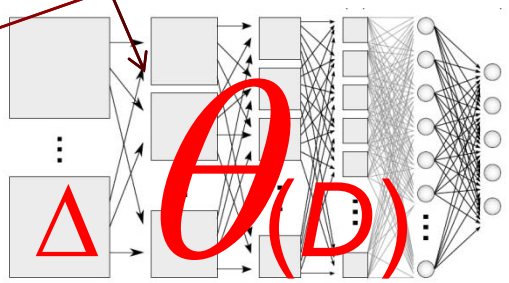


$$\mathcal{D} \equiv \{\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_n\}$$

$$\vec{\theta} \equiv [\vec{\theta}_1^{\,\mathrm{T}}, \vec{\theta}_2^{\,\mathrm{T}}, \ldots, \vec{\theta}_k^{\,\mathrm{T}}\}^{\mathrm{T}}$$

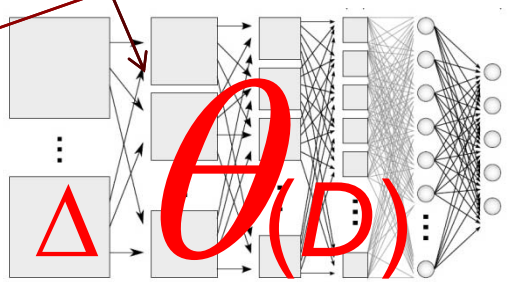
A Dichotomy of Data and Model in ML Programs

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



A Dichotomy of Data and Model in ML Programs

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

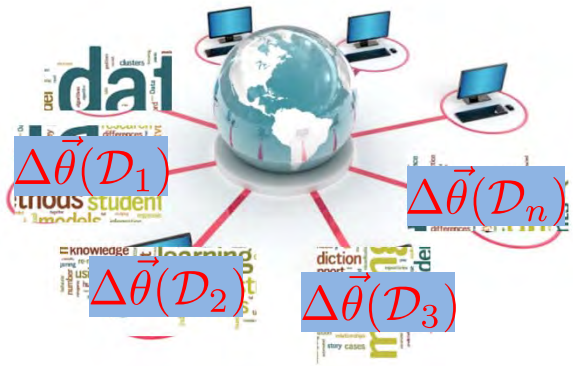


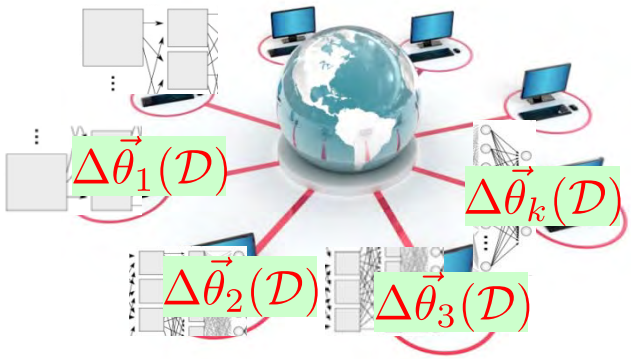
$\mathcal{D} \equiv \{\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_n\}$

$\vec{\theta} \equiv [\vec{\theta}_1^{\mathrm{T}}, \vec{\theta}_2^{\mathrm{T}}, \ldots, \vec{\theta}_k^{\mathrm{T}}]^{\mathrm{T}}$

Data Parallel

Model Parallel

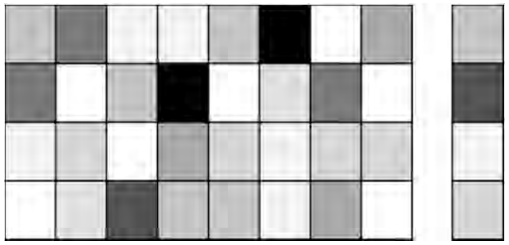




$\mathcal{D}_i \perp \mathcal{D}_j \mid \theta,\ \forall i \neq j$

$\vec{\theta}_i \not\perp \vec{\theta}_j \mid \mathcal{D},\ \exists (i,j)$

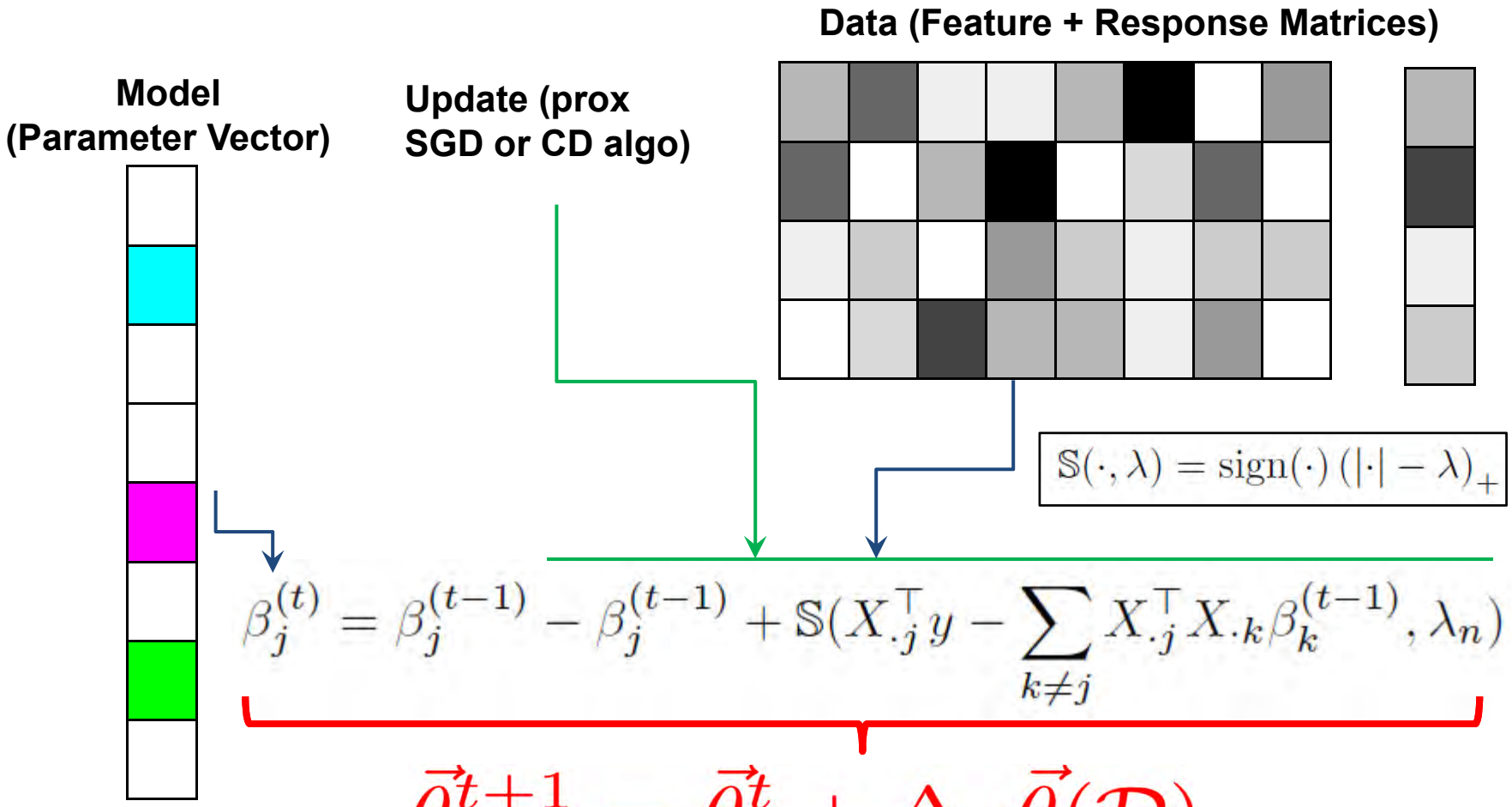
Optimization Example:



Lasso Regression

- Data, Model
  - D = {feature matrix X, response vector y}
  - θ = {parameter vector β)
- Objective $L(\theta, D)$
  - Least-squares difference between y and $X\beta$: $\sum_{i=1}^{N} \|y_i - X_i\beta\|_2^2$
- Regularization $\Omega(\theta)$
  - L_1 penalty on β to encourage sparsity: $\lambda \sum_{j=1}^{D} |\beta_j|$
  - λ is a tuning parameter
- Algorithms
  - Coordinate Descent
  - Stochastic Proximal Gradient Descent

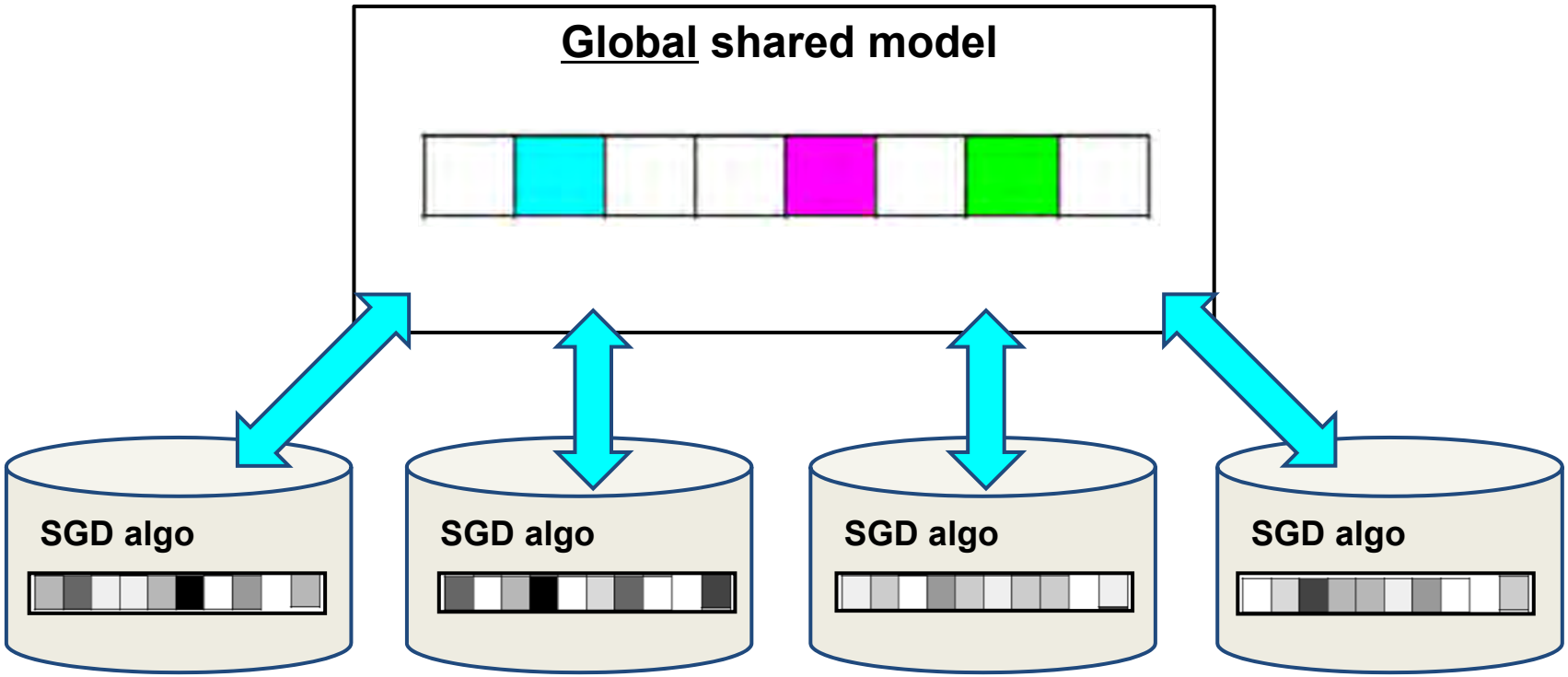
Optimization Example:



Data-Parallel Lasso

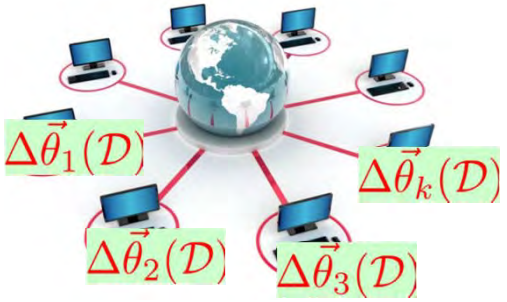
$$\mathcal{D} \equiv \{\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_n\}$$

Proximal SGD:



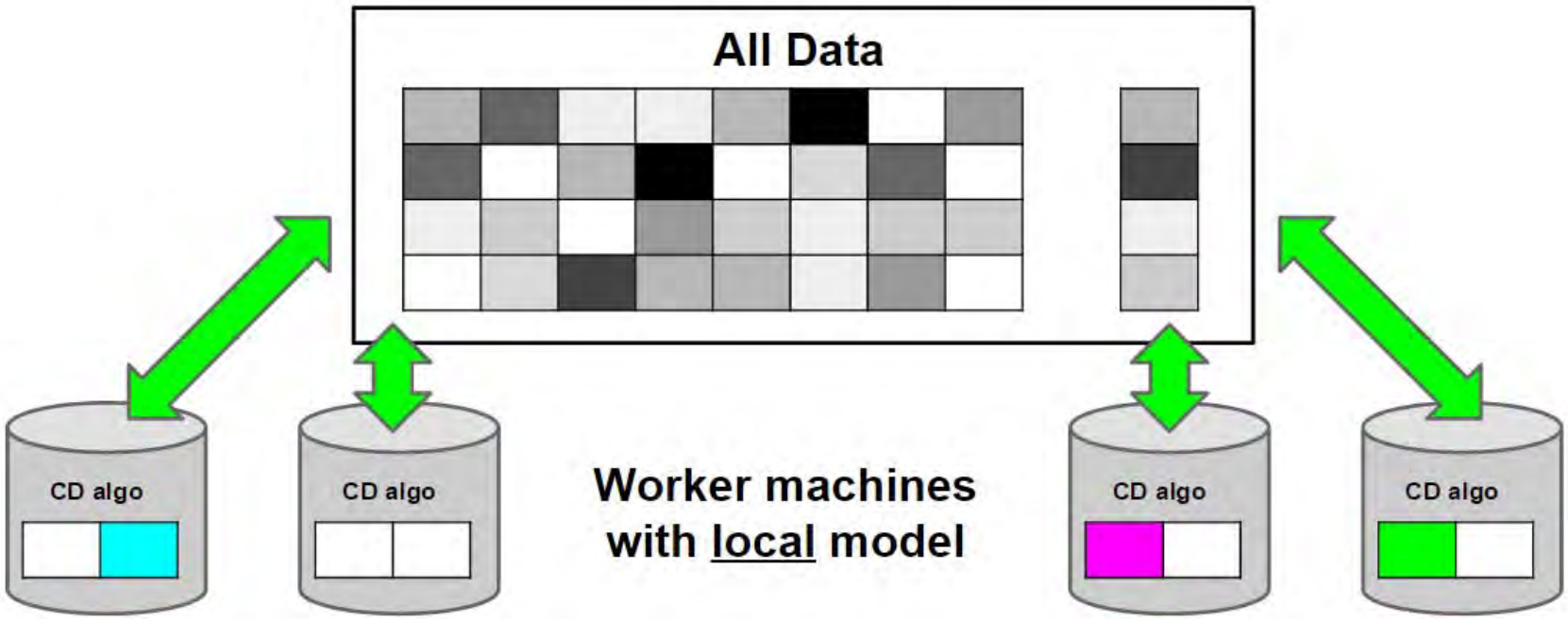
Partition rows of Feature+Response Matrices across workers

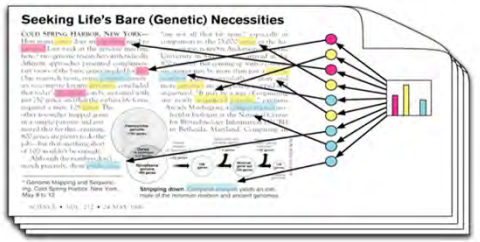
Model-Parallel Lasso



$$\vec{\theta} \equiv [\vec{\theta}_1^{\,\mathsf{T}}, \vec{\theta}_2^{\,\mathsf{T}}, \ldots, \vec{\theta}_k^{\,\mathsf{T}}\}^{\mathsf{T}}$$

Coordinate Descent:





Probabilistic Example:

Topic Models

- Objective $L(\theta, D)$
  - Log-likelihood of D = {document words x_{ij}} given unknown θ = {document word topic indicators z_{ij}, doc-topic distributions δ_i, topic-word distributions B_k}:

$$\sum_{i=1}^{N}\sum_{j=1}^{N_i} \ln \mathbb{P}_{Categorical}(x_{ij} \mid z_{ij}, B) + \sum_{i=1}^{N}\sum_{j=1}^{N_i} \ln \mathbb{P}_{Categorical}(z_{ij} \mid \delta_i)$$

- Prior $\rho(\theta)$
  - Dirichlet prior on θ = {doc-topic, word-topic distributions}

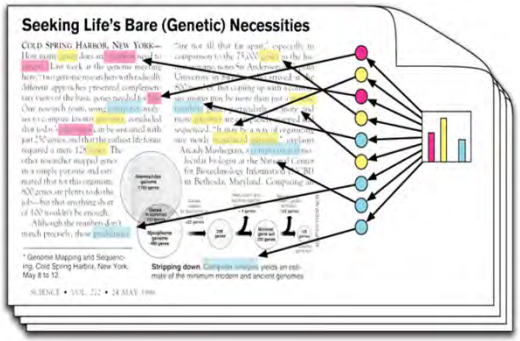
$$\sum_{i=1}^{N} \ln \mathbb{P}_{Dirichlet}(\delta_i \mid \alpha) + \sum_{i=k}^{K} \ln \mathbb{P}_{Dirichlet}(B_k \mid \beta)$$

  - α, β are "hyperparameters" that control the Dirichet prior's strength
- Algorithm
  - Collapsed Gibbs Sampling

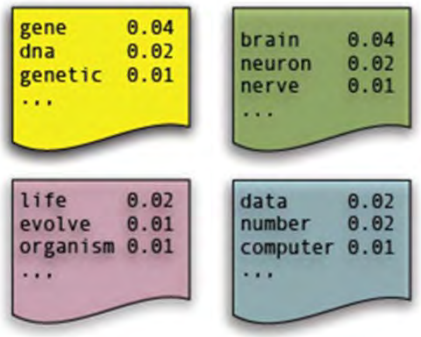
Probabilistic Example:

Collapsed Gibbs sampling

Data (Docs) = x_{ij}



Model (Topics) = B_k



For each doc i**, each token** j**:**

Set $k_{old} = z_{ij}$

Gibbs sample new value of z_{ij}, according to $\mathbb{P}(z_{ij} \mid x_{ij}, \delta_i, B)$

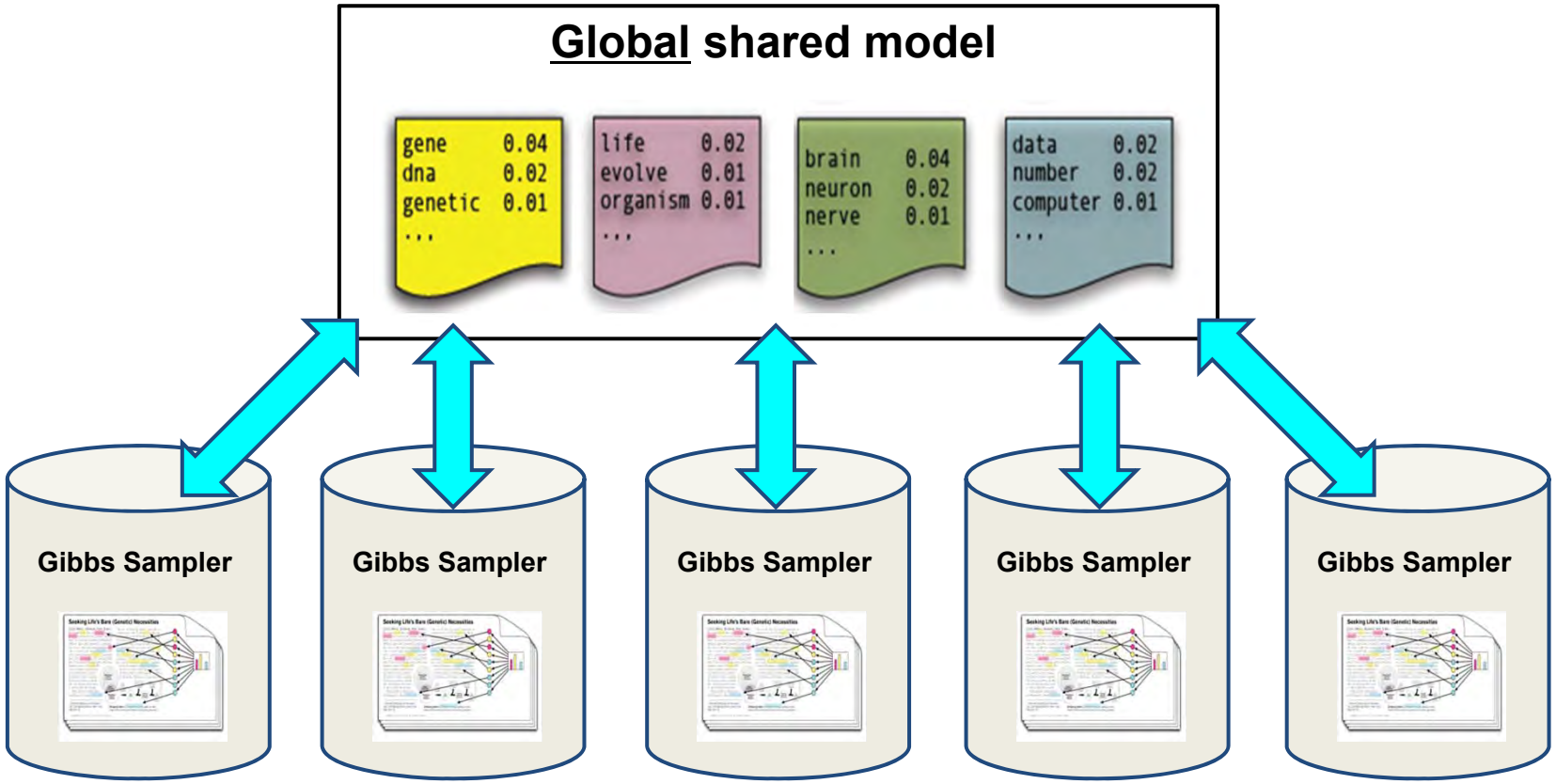
Set $k_{new} = z_{ij}$

Perform updates to B, δ**:**

$$\left.\begin{aligned} B_{k_{old},w_{ij}} &= B_{k_{old},w_{ij}} - 1 \\ B_{k_{new},w_{ij}} &= B_{k_{new},w_{ij}} + 1 \\ \delta_{i,k_{old}} &= \delta_{i,k_{old}} - 1 \\ \delta_{i,k_{new}} &= \delta_{i,k_{new}} + 1 \end{aligned}\right\} \vec{\theta}^{t+1} = \vec{\theta}^{t} + \Delta_f \vec{\theta}(\mathcal{D})$$

Data Parallel Gibbs

$$\mathcal{D} \equiv \{\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_n\}$$

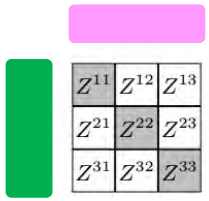


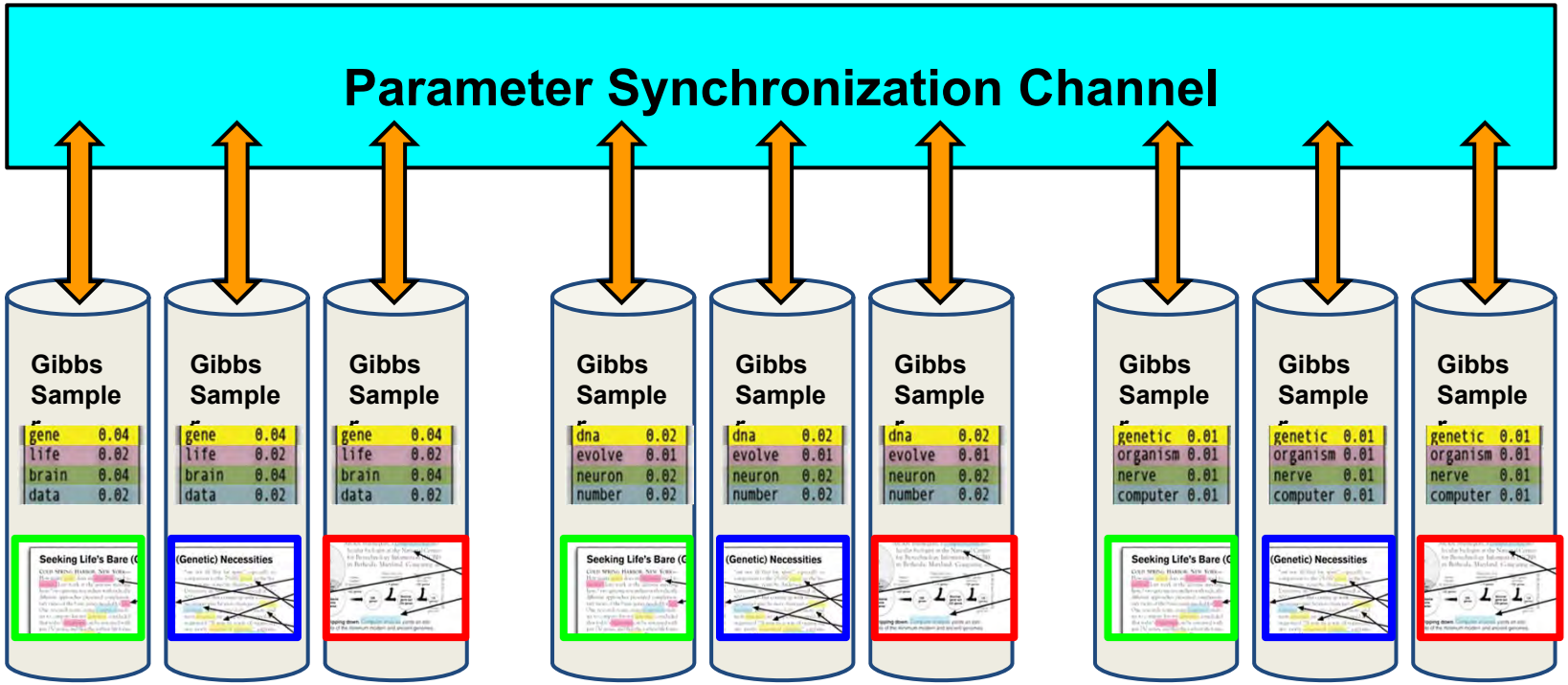
D+M Parallel Gibbs

$$\mathcal{D} \equiv \{\mathcal{D}_1, \mathcal{D}_2, \ldots, \mathcal{D}_n\}$$

$$\vec{\theta} \equiv [\vec{\theta}_1^{\mathrm{T}}, \vec{\theta}_2^{\mathrm{T}}, \ldots, \vec{\theta}_k^{\mathrm{T}}\}^{\mathrm{T}}$$

Pair up vocabulary words with documents, divide across workers





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What's Next?

First-timer's "Ideal View" of ML

```
global model = (a,b,c,...)
global data = load(file)

Update(var a):
  a = doSomething(data,model)

Main:
  do Update() on all var in
    model until converged
```

Reality of High-performance implementations

Many considerations

- What data batch size?
- How to partition model?
- When to sync up model?
- How to tune step size?
- What order to Update()?

1000s of lines of extra code

Need a System Interface for Parallel ML
– Does ML really Stop at the Ideal View?

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]

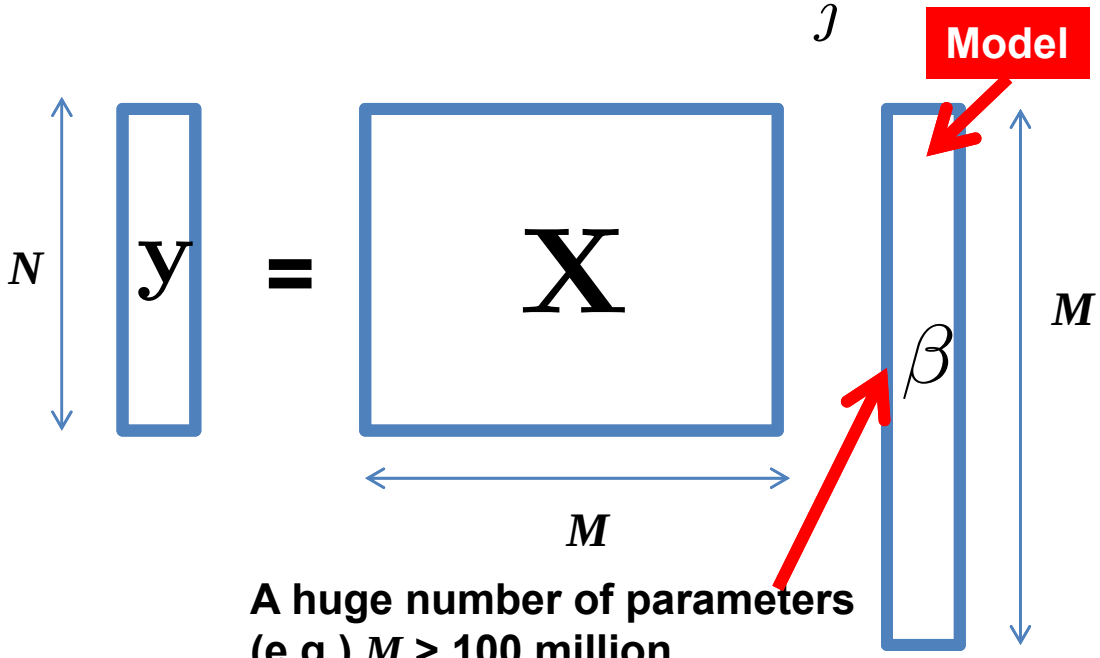
1. How to Distribute:

Scheduling and Balancing workloads

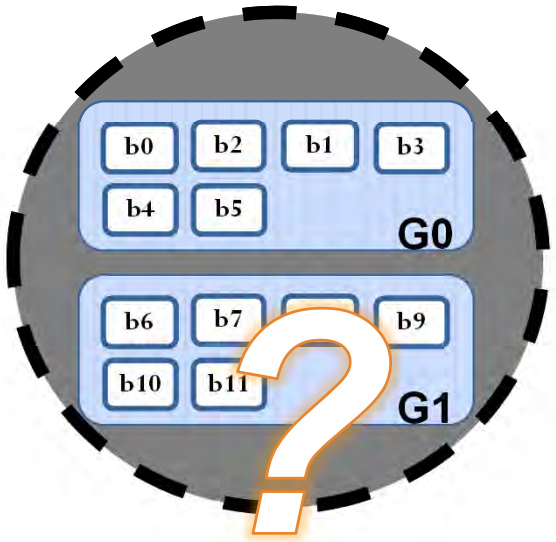
Example: Model Distribution

Lasso via coordinate descent:

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



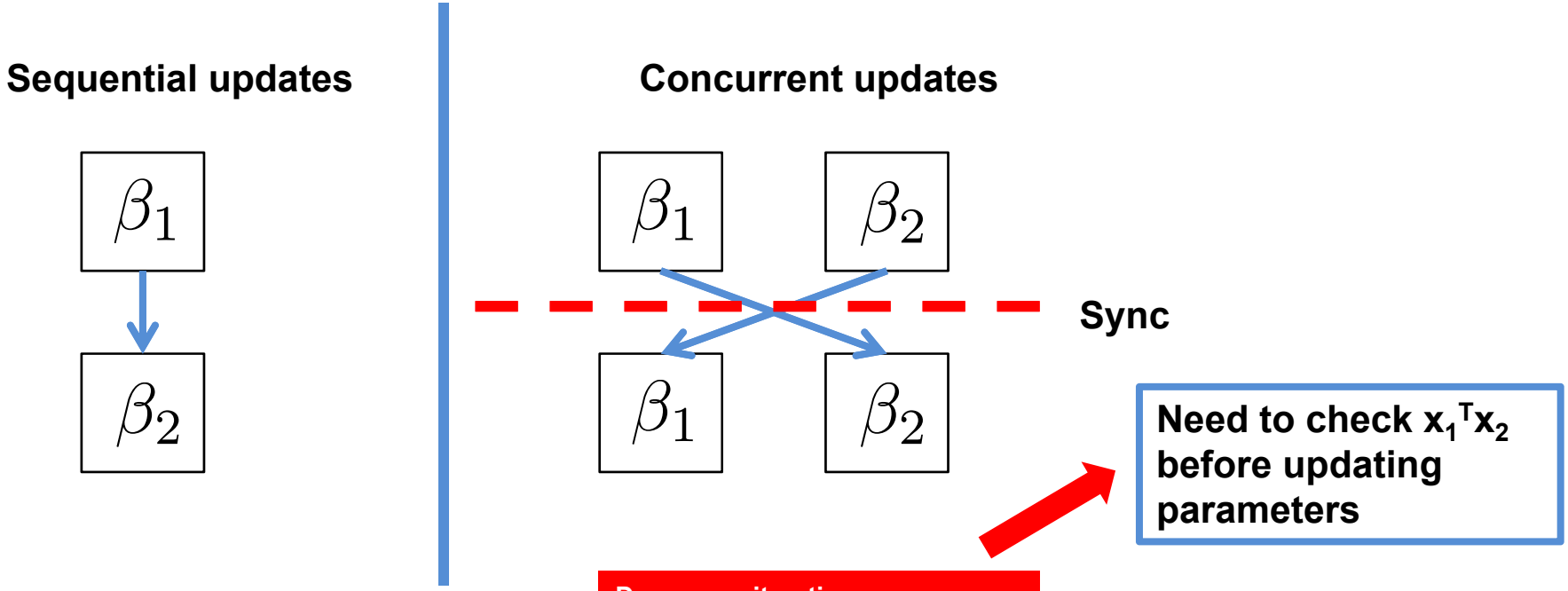
A huge number of parameters (e.g.) M > 100 million



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

Beware Model Dependencies

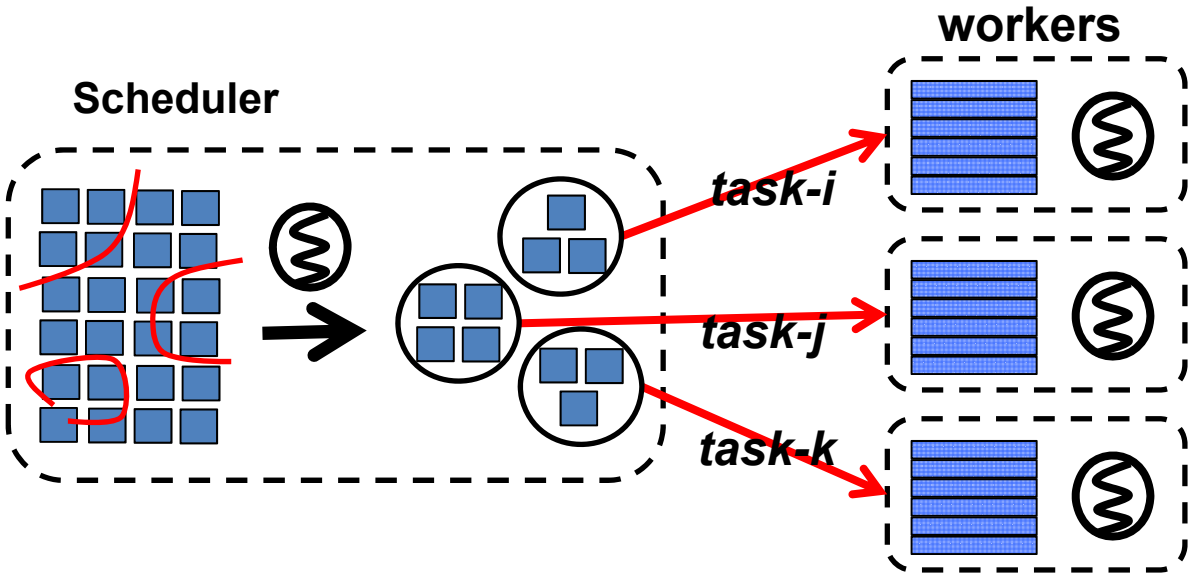
- Concurrent updates of β may induce errors



Decreases iteration progress

$$\beta_1^{(t)} \leftarrow S(\mathbf{x}_1^T \mathbf{y} - \mathbf{x}_1^T \mathbf{x}_2 \beta_2^{(t-1)}, \lambda)$$

Avoid Dependency Errors via Data+Model Scheduling [Lee et al., 2014]



task: subset of data (X,y) & model (β)

schedule: find parallel task plan that minimizes parameter dependencies $\mathbf{x}_1^T \mathbf{x}_2 \beta_2^{(t-1)}$

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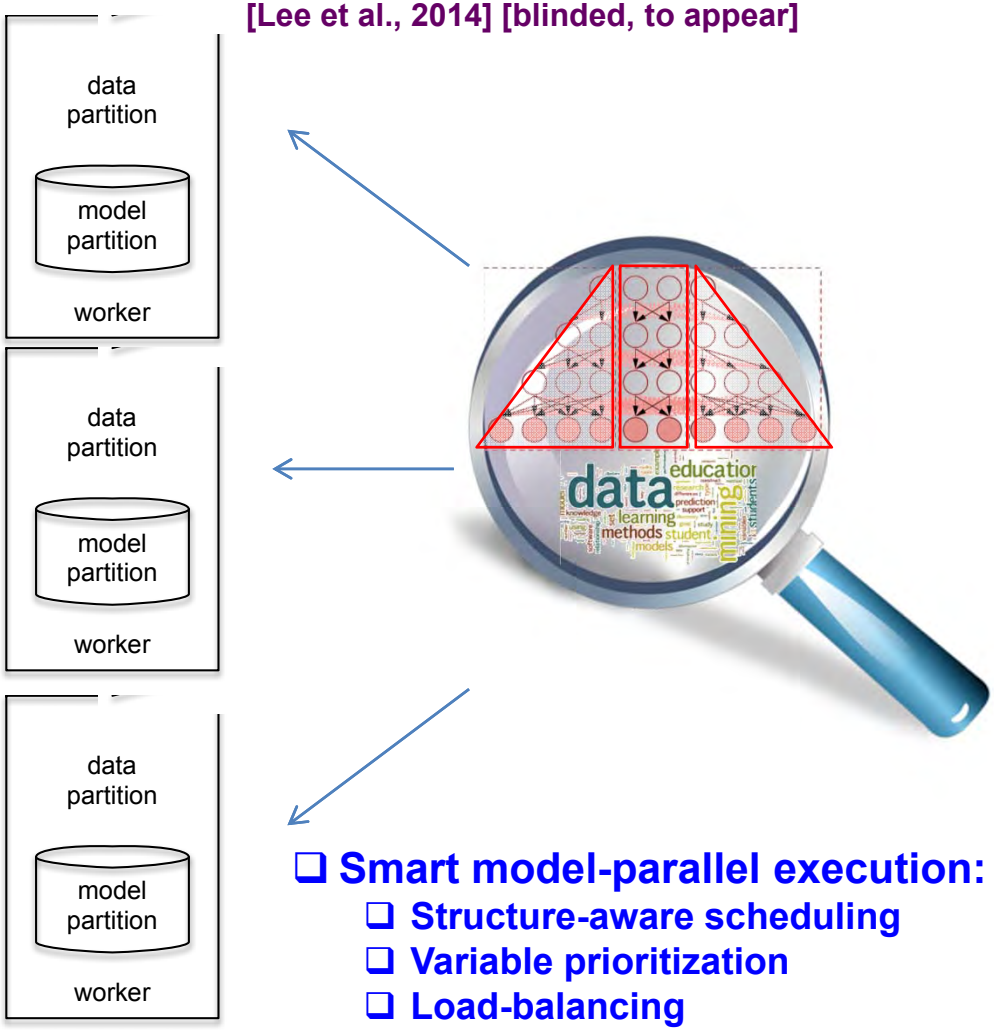
Structure-Aware Parallelization (SAP)

[Lee et al., 2014] [blinded, to appear]



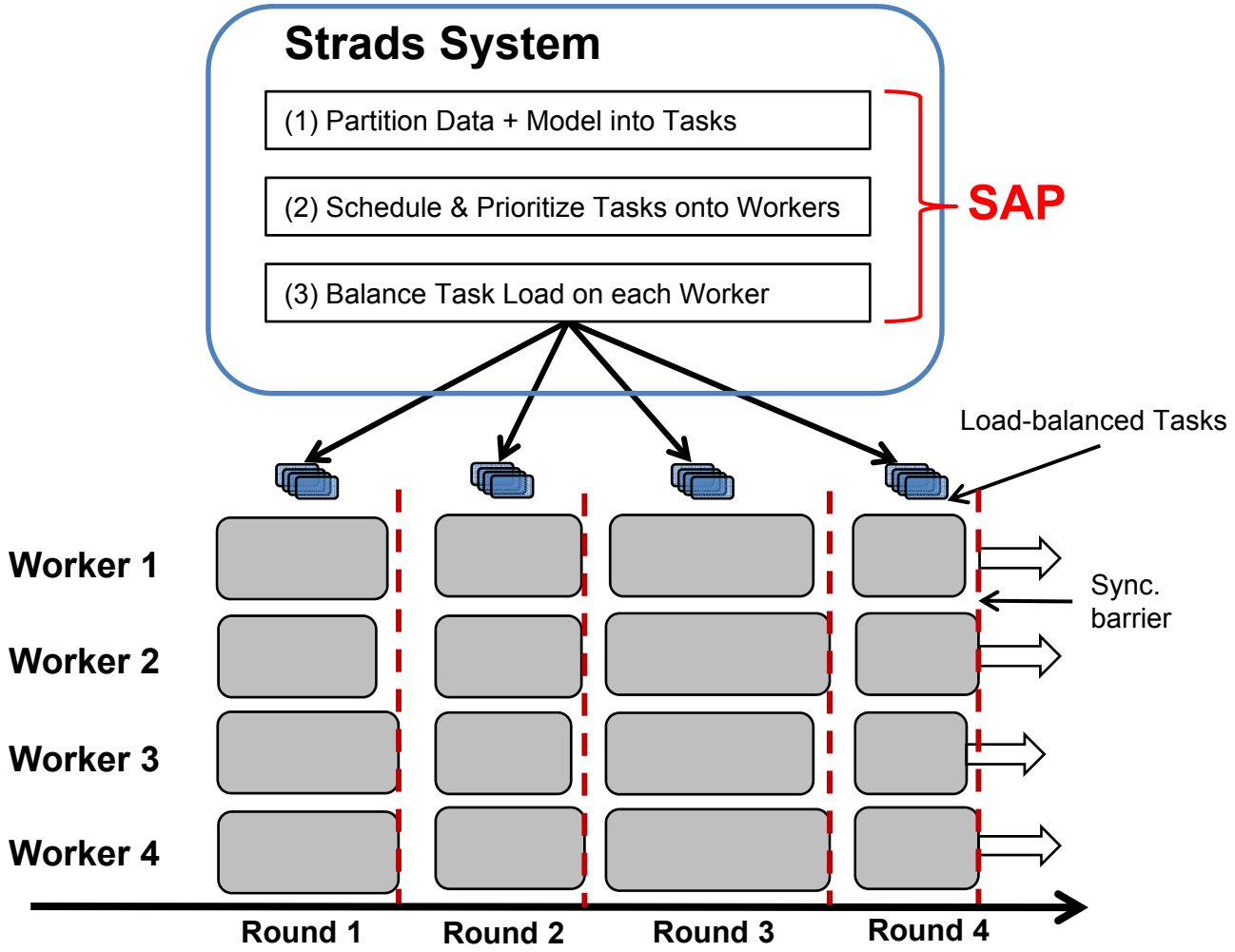

```
schedule() {
  // Select U vars x[j] to be sent
  // to the workers for updating
  ...
  return (x[j_1], ..., x[j_U])
}
```

```
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()**

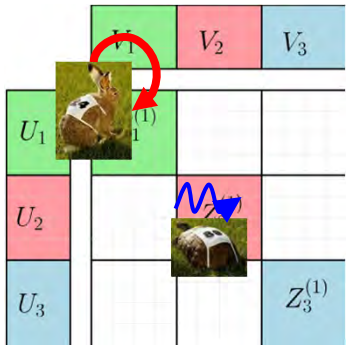
Structure-aware Dynamic Scheduler (Strads) [Lee et al., 2014]



- **Priority Scheduling**

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

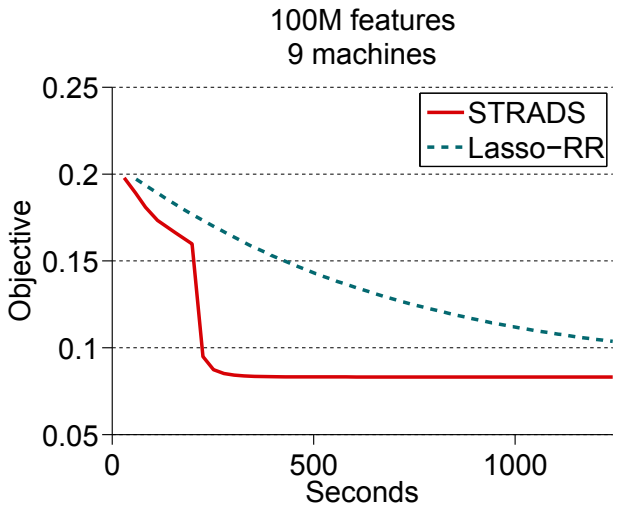
- **Block scheduling**



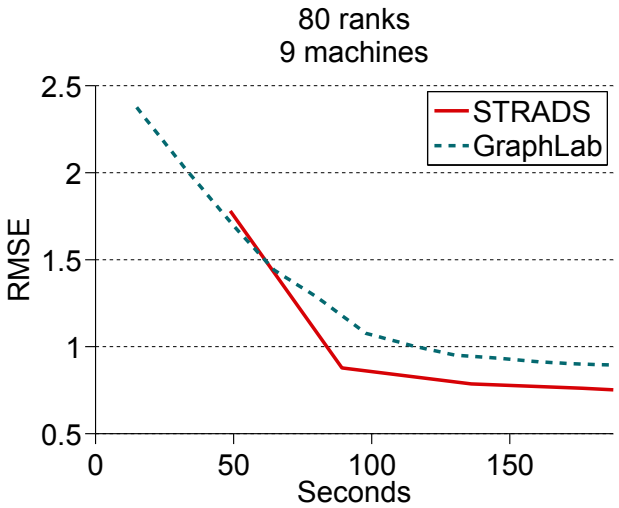
[*Kumar, Beutel, Ho and Xing,* ***Fugue: Slow-worker agnostic distributed learning****, AISTATS 2014*]

SAP Scheduling: Faster, Better Convergence across algorithms

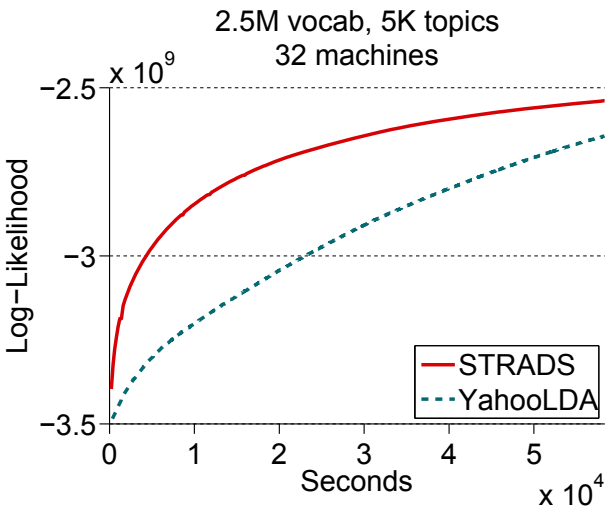
- SAP on Strads achieves better speed and objective



Lasso



MF



LDA

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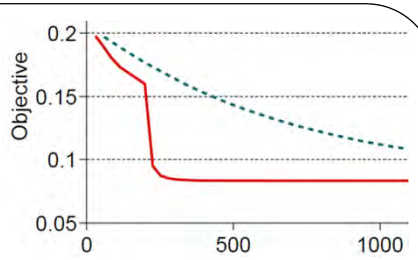
SAP gives Near-Ideal Convergence Speed [Xing et al., 2015]



- **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[$(X^{(1)})^T X^{(1)}$, ..., $(X^{(t)})^T X^{(t)}$]]; 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

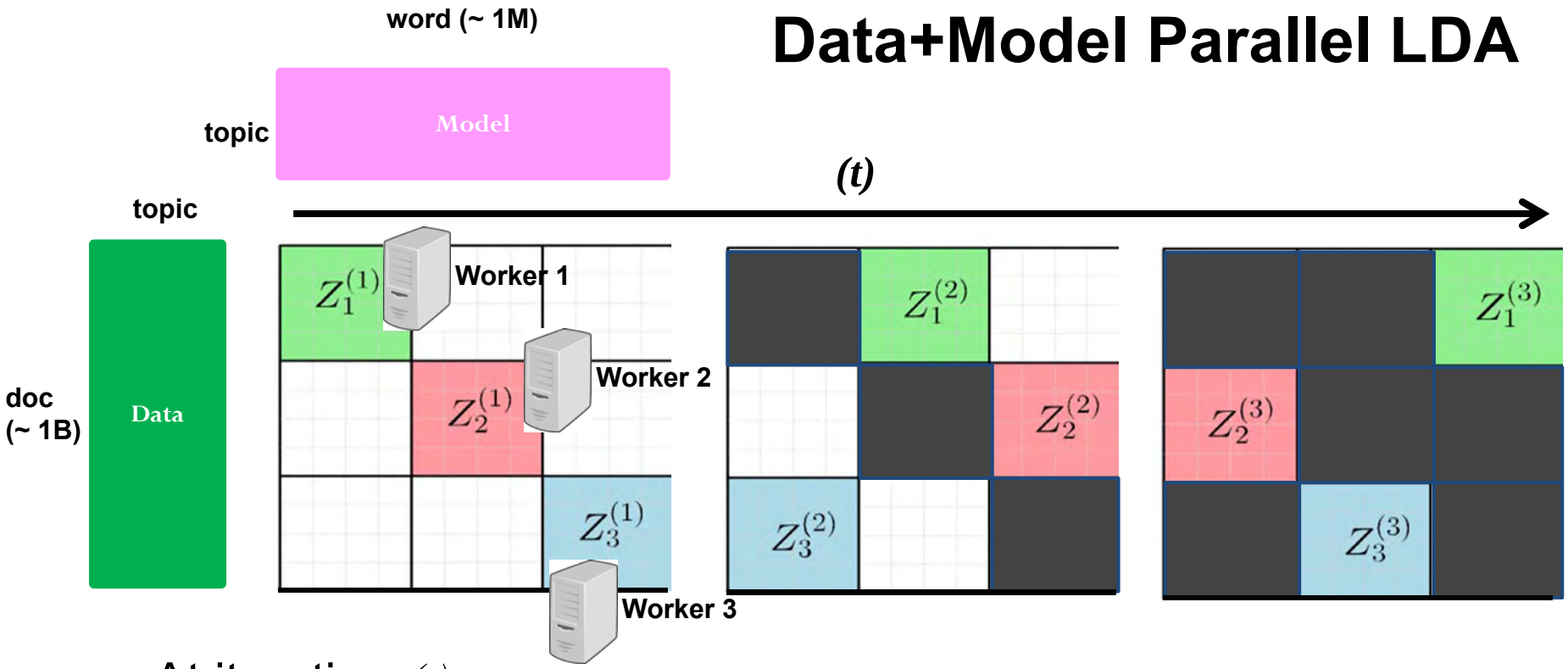
$$\mathbb{E}\left[f(X^{(t)}) - f(X^*)\right] \leq \frac{\mathcal{O}(M)}{P - \frac{\mathcal{O}(P^2\rho)}{M}} \frac{1}{t} = \mathcal{O}\left(\frac{1}{Pt}\right)$$

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

How to SAP-LDA

[Zheng et al., to appear 2015]



- At iteration (t):
  - Worker 1 samples docs+words in $Z_1^{(t)}$
  - Worker 2 ← $Z_2^{(t)}$, Worker 3 ← $Z_3^{(t)}$ and so on…
  - Use different-sized $Z_p^{(t)}$ to load balance power-law tokens

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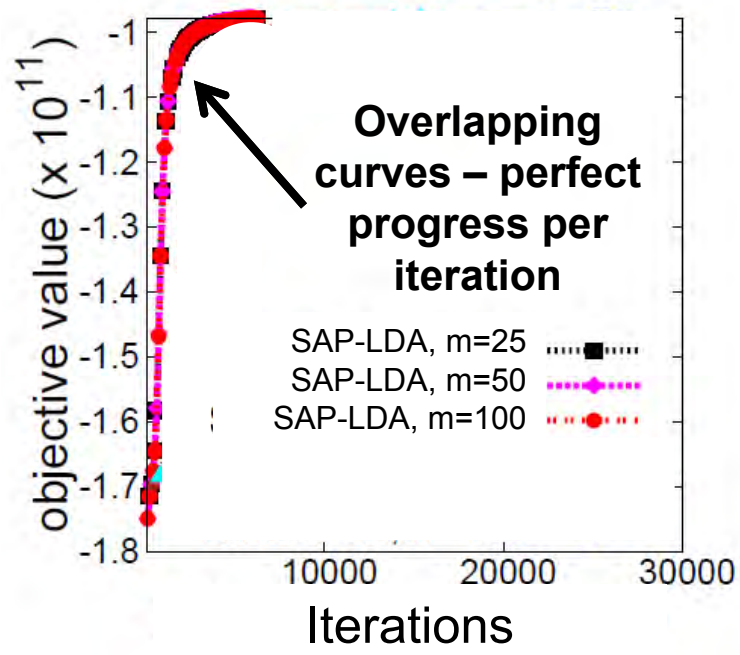
SAP-LDA performance [blinded, to appear]

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**

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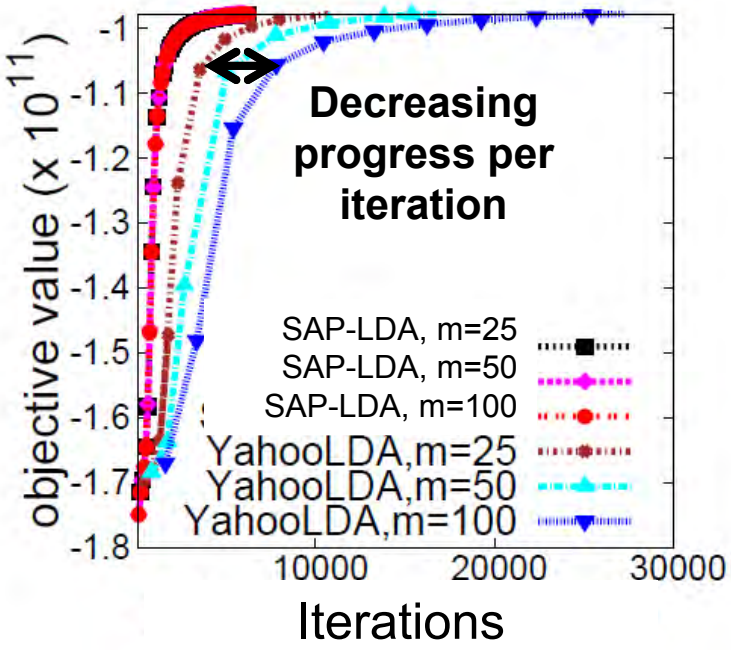
SAP-LDA performance [blinded, to appear]

YahooLDA progress per iteration



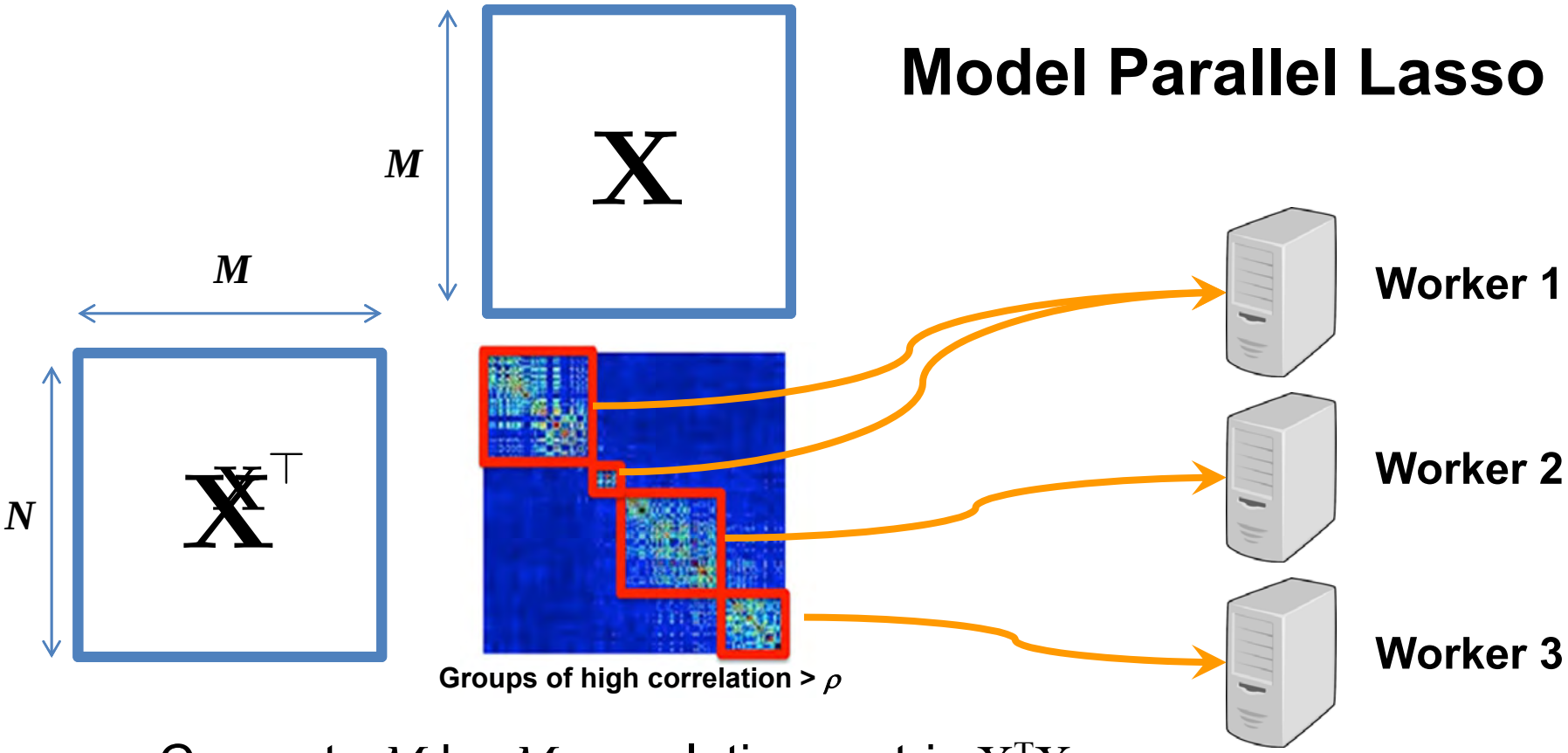
80GB data, 2M words, 1K topics, 100 machines

	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

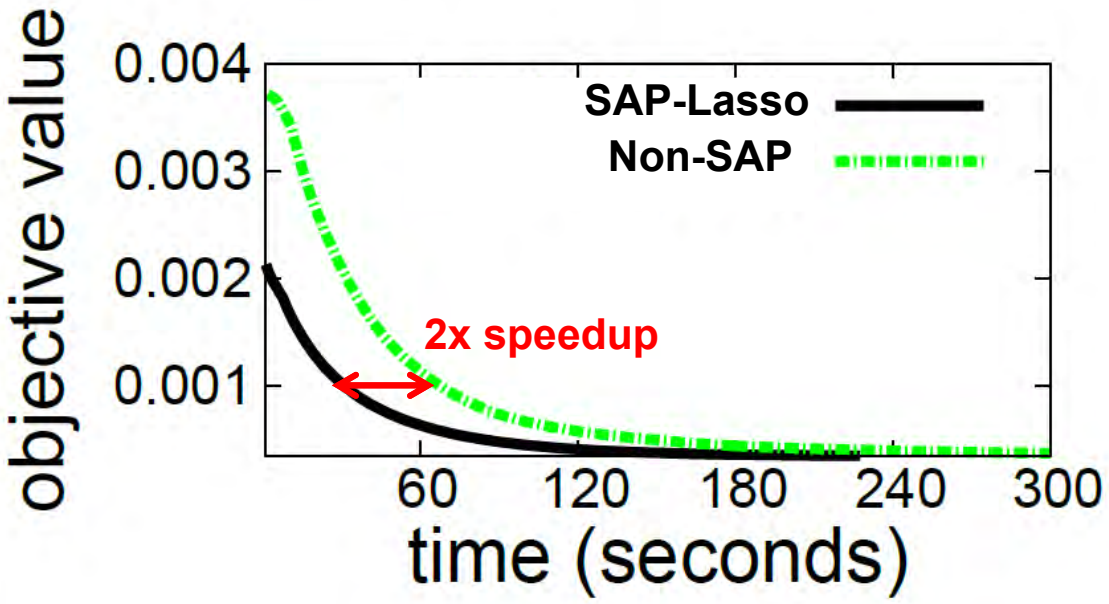
How to SAP-Lasso



- Compute M-by-M correlation matrix $X^T X$
  - Group indices (i,j) with high correlation $(X^T)_{i\cdot} X_{j\cdot} > \rho$
  - Load-balance different-sized groups to parallel workers

SAP-Lasso Performance

6.4GB data, 500M features, 4 machines



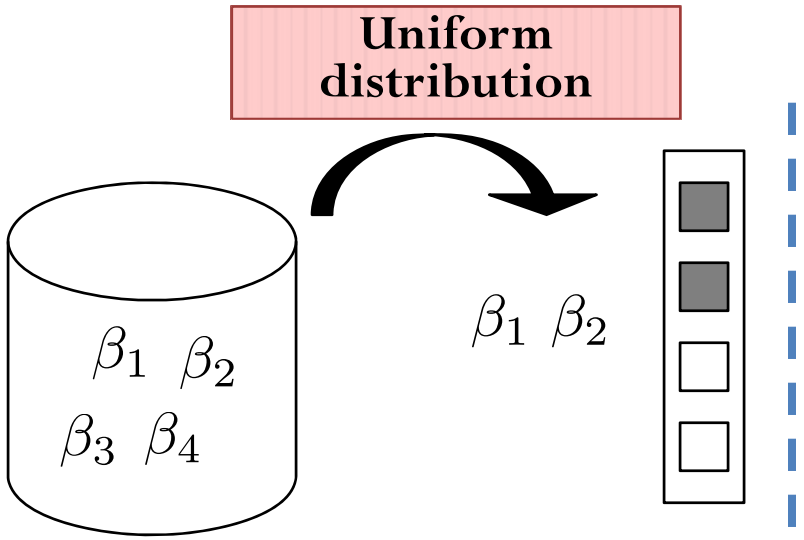
- Even for small # machines (4)…
- … **2x difference** between SAP and non-SAP Lasso

Improving SAP through Prioritization

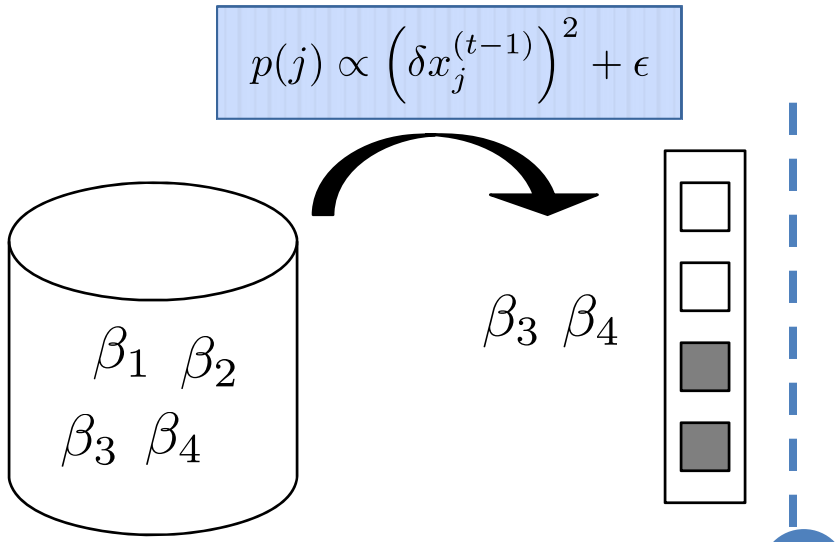
[Lee et al., 2014]

- Choose next param to update via convergence speed
  - Lasso: sample params proportional to recent change
  - Approximately maximizes convergence progress per iteration

Shotgun [Bradley et al. 2011]

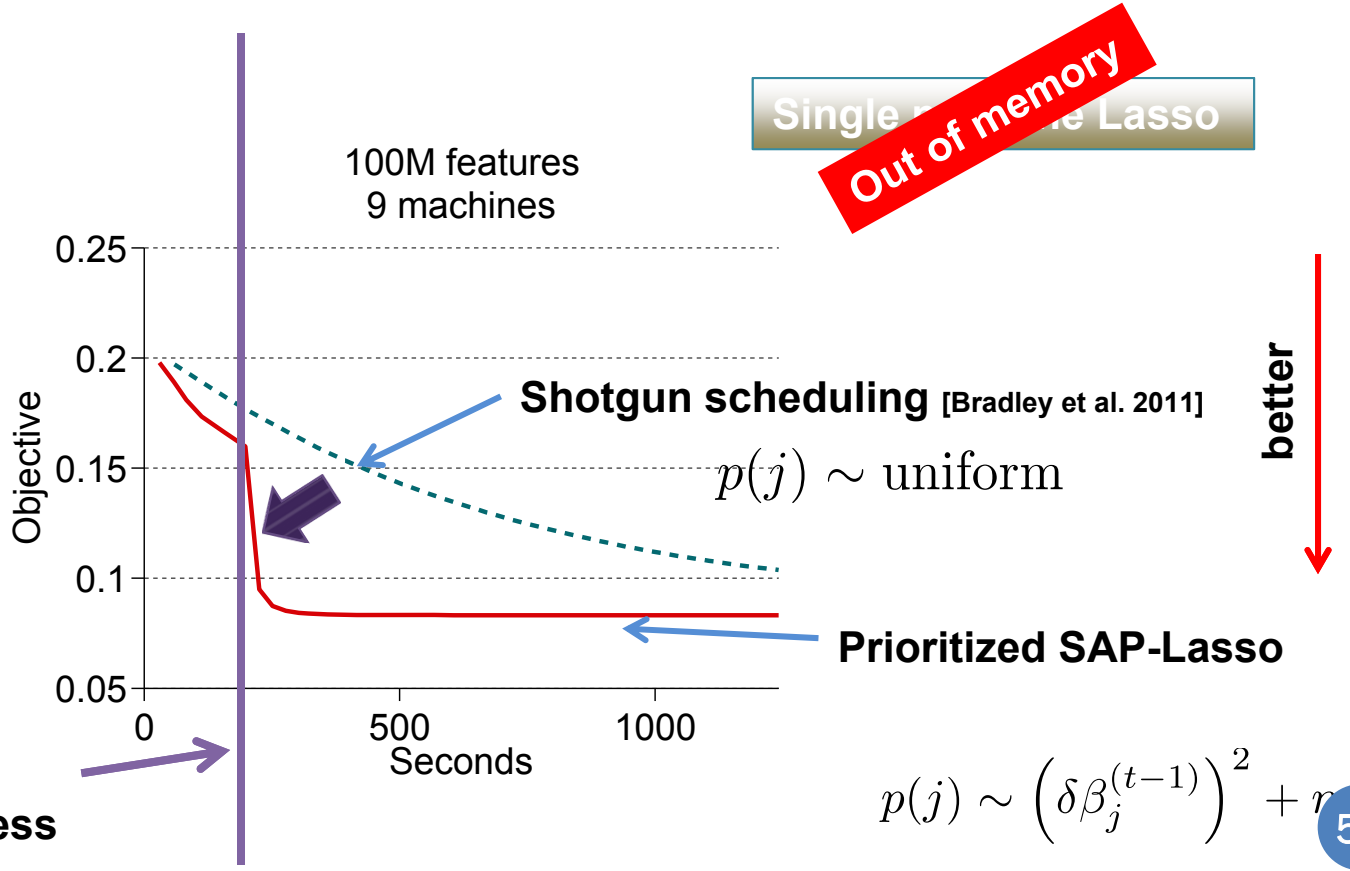


Priority-based scheduling



Prioritized SAP-Lasso vs non-SAP Lasso

- **Prioritized SAP-Lasso convergences much faster than non-SAP Lasso (Shotgun algorithm)**

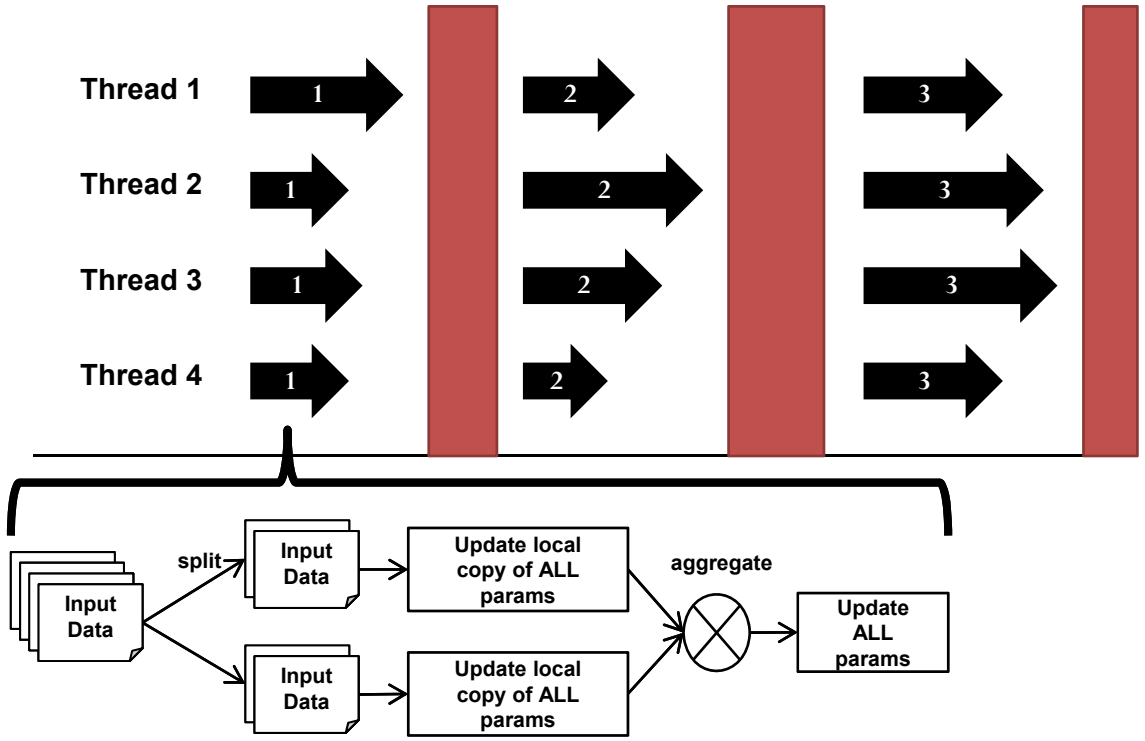


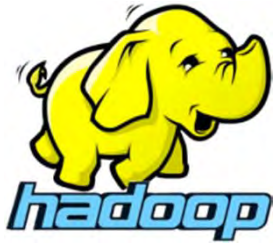
Principles of ML system Design [Xing et al., to appear 2016]

2. How to Bridge Computation and Communication:

Bridging Models and Bounded Asynchrony

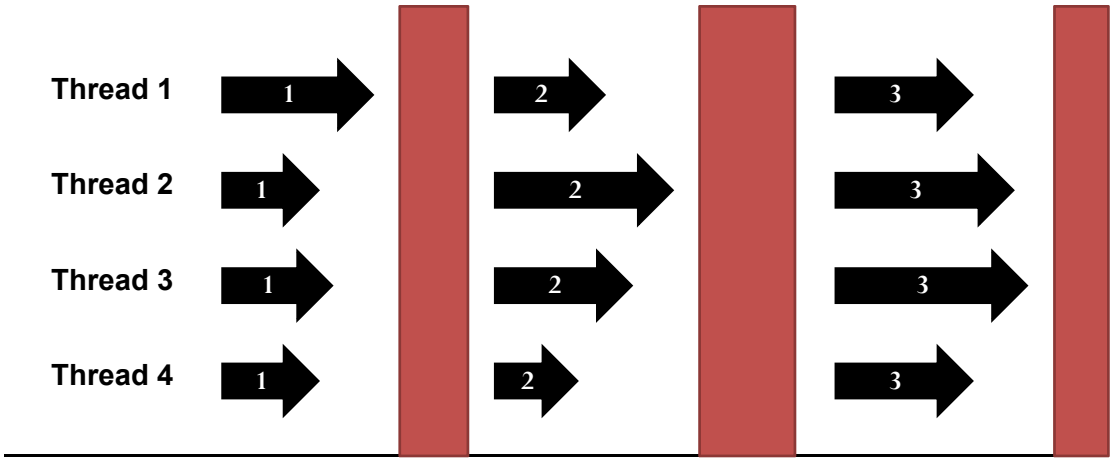
The *Bulk Synchronous Parallel* Bridging Model [Valiant & McColl]

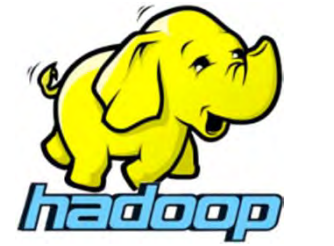




- Perform barrier in order to communicate parameters
- Mimics sequential computation – "serializable" property
- Enjoys same theoretical guarantees as sequential execution

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





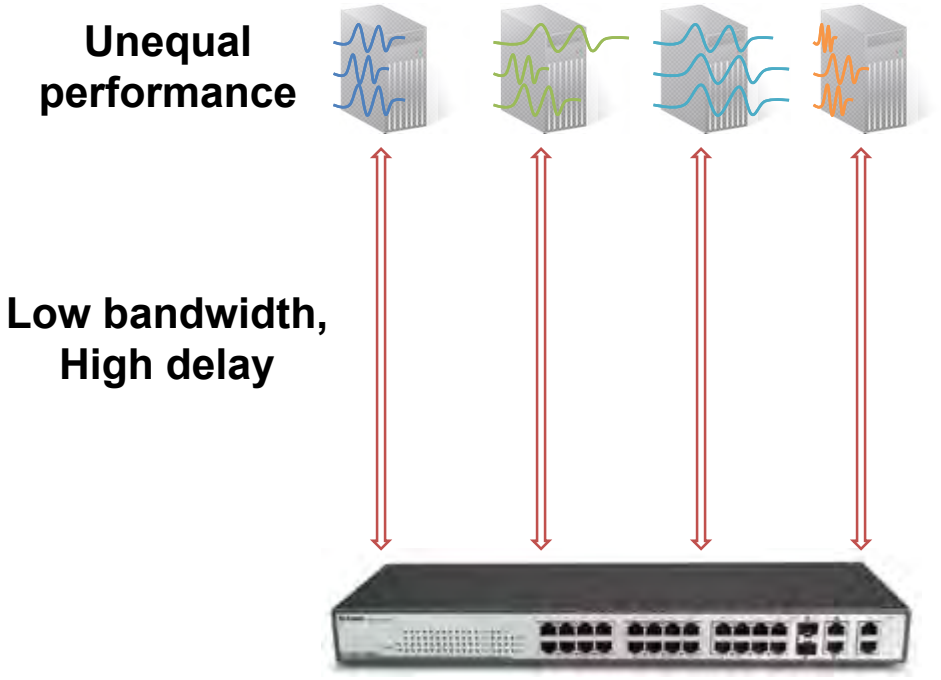
The success of the von Neumann model of sequential computation is attributable to the fact it is an efficient bridge between software and hardware… an analogous bridge is required for parallel computation if that is to become as widely used – **Leslie G. Valiant**

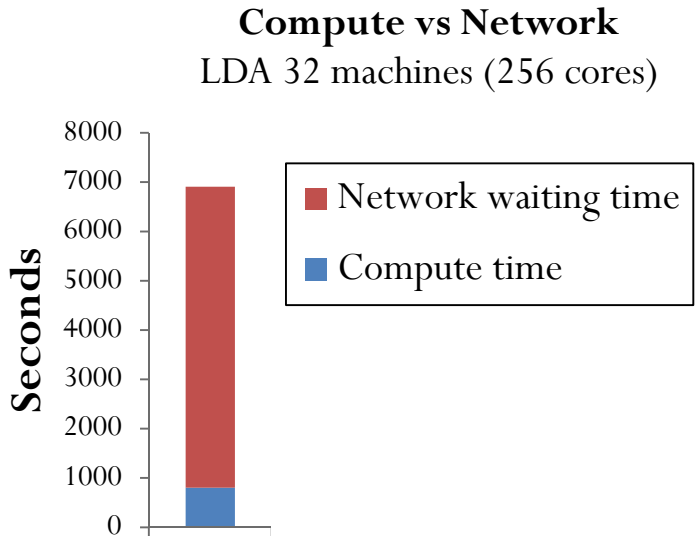
- Numerous implementations since 90s (list by **Bill McColl**):
  - Oxford BSP Toolset (‘98), Paderborn University BSP Library (‘01), Bulk Synchronous Parallel ML (‘03), BSPonMPI (’06), ScientificPython (’07), Apache Hama (’08), Apache Pregel (‘09), MulticoreBSP (’11), BSPedupack (‘11), Apache Giraph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

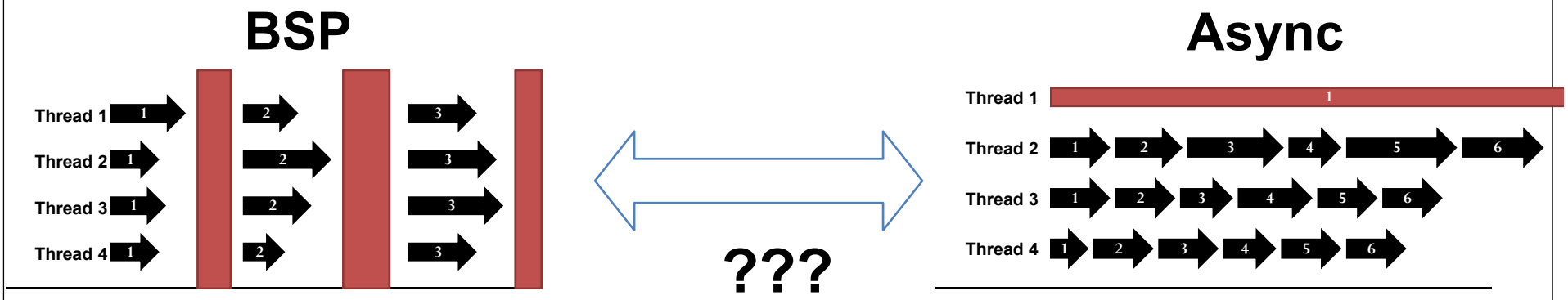
Result: BSP barriers can be slow





Is there a better way to interleave computation and communication?

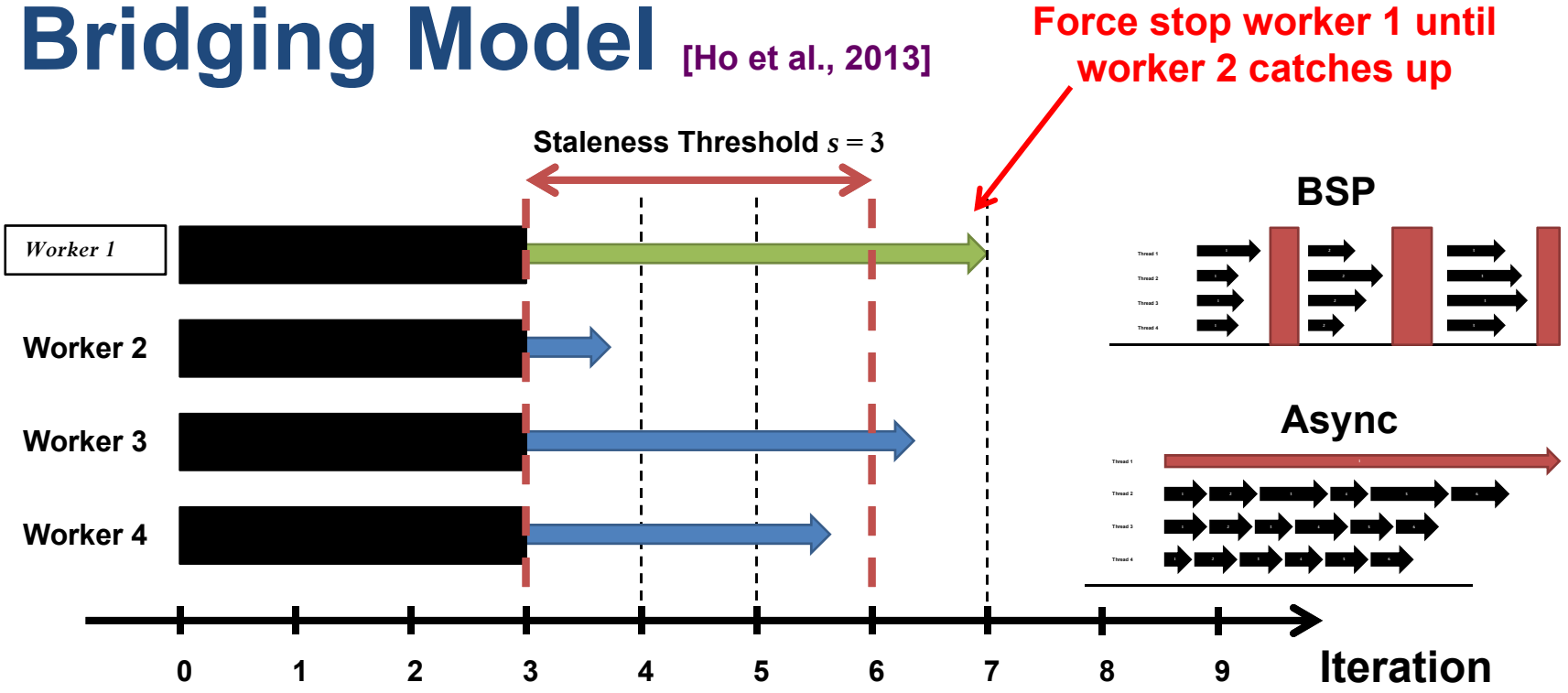
- **Safe/slow (BSP) vs. Fast/risky (Async)?**
- **Challenge 1: Need "Partial" synchronicity**
  - Spread network comms evenly (don't sync unless needed)
  - Threads usually shouldn't wait – but mustn't drift too far apart!
- **Challenge 2: Need straggler tolerance**
  - Slow threads must somehow catch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

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

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

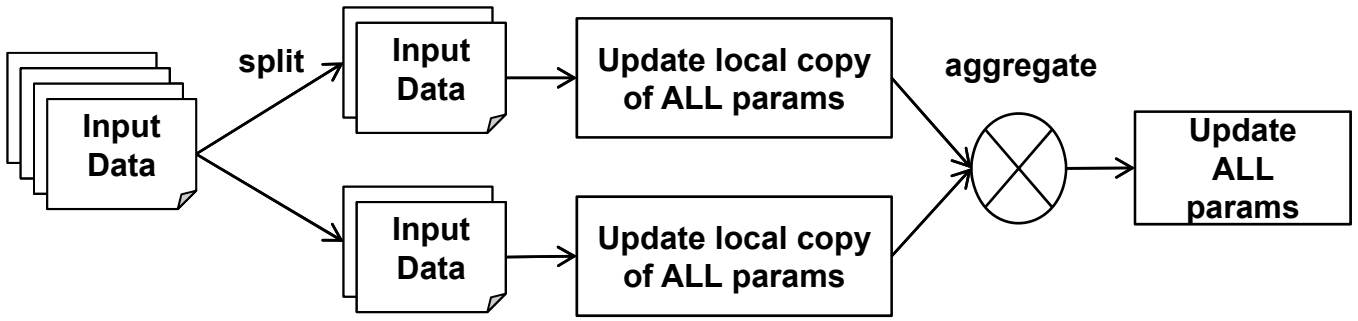
stale sub-updates Δ() received by worker p at iteration t

  - sub-update

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

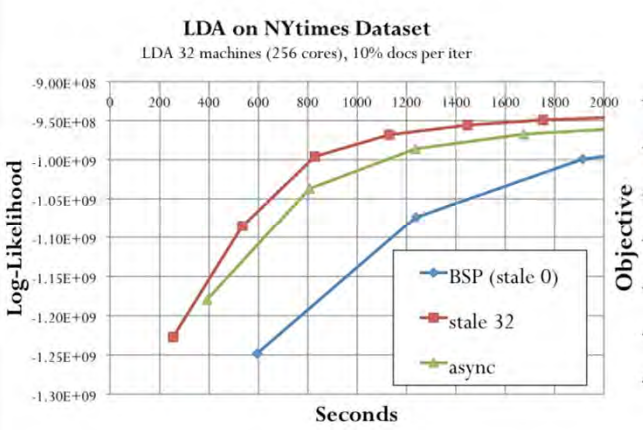
gradient step wrt f

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

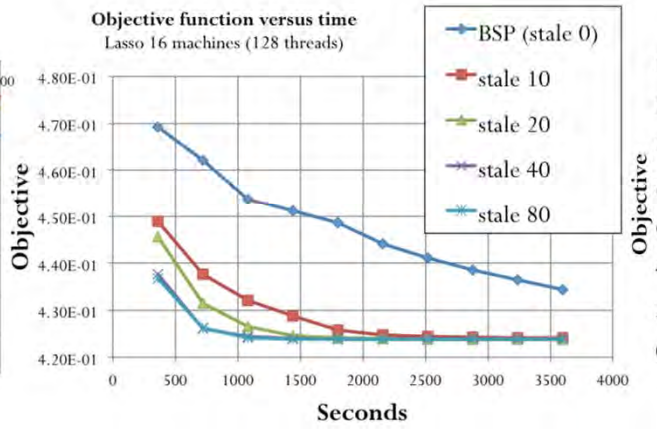


SSP Data-Parallel
Async Speed, BSP Guarantee

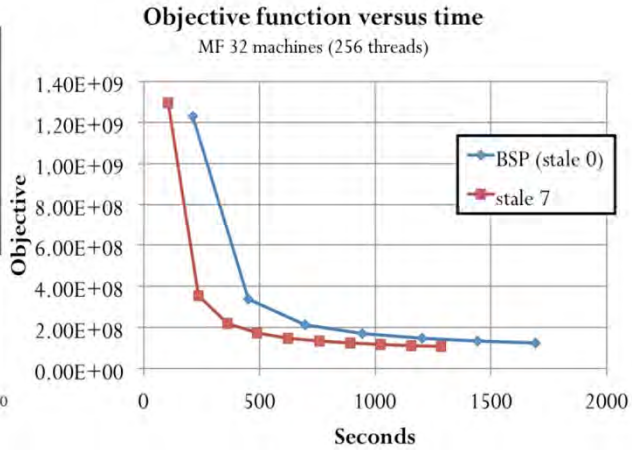
LDA



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 γ_t

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

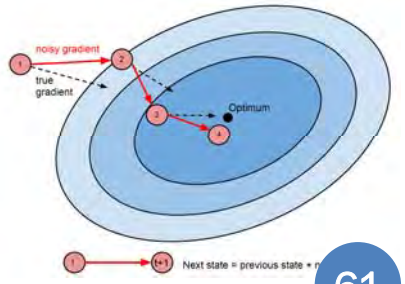
Theorem: Given L-Lipschitz objective f_t and step size h_t,

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

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.*



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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:

$$\forall p, \; a_p(t+1) = a_p(t) + \gamma_p(t) \cdot F_p(\mathbf{a}^p(t))$$

on worker *p*; workers can skip updates

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

staleness

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

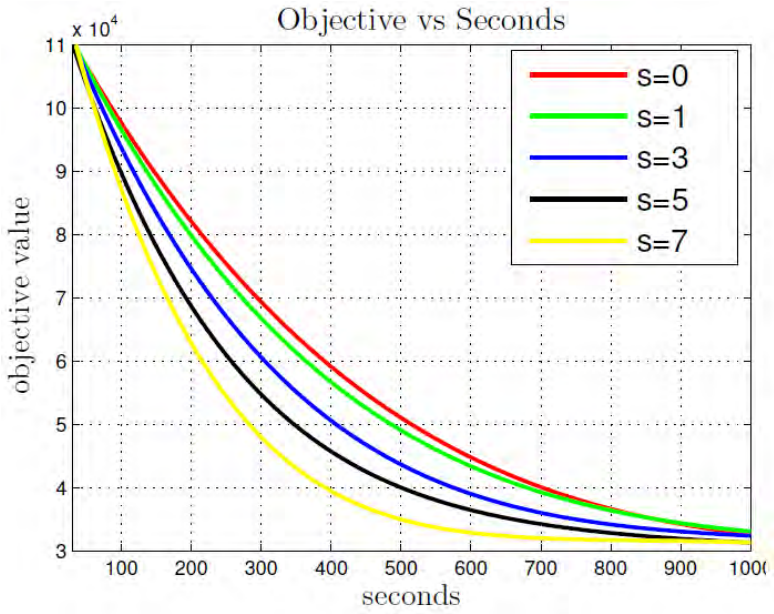
$$\text{(global)} \quad \mathbf{a}(t) = \big(a_1(t), \; \ldots \; , a_P(t)\big).$$

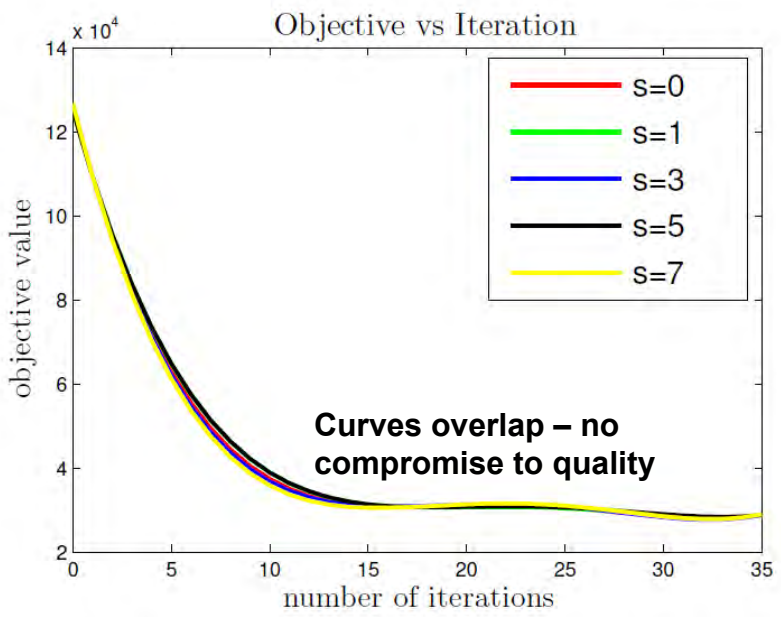
$$\mathbf{a}^p(t+1) := F_p(\mathbf{a}^p(t)) = \underbrace{\text{prox}_{g_p}^{\eta}}_{\text{proximal step wrt } g}(a_p(t) - \overbrace{\eta \nabla_p f(\mathbf{a}^p(t))}^{\text{gradient step wrt } f}) - a_p(t)$$

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

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., to appear 2016]

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

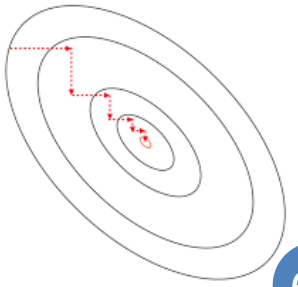
Finite length

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

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

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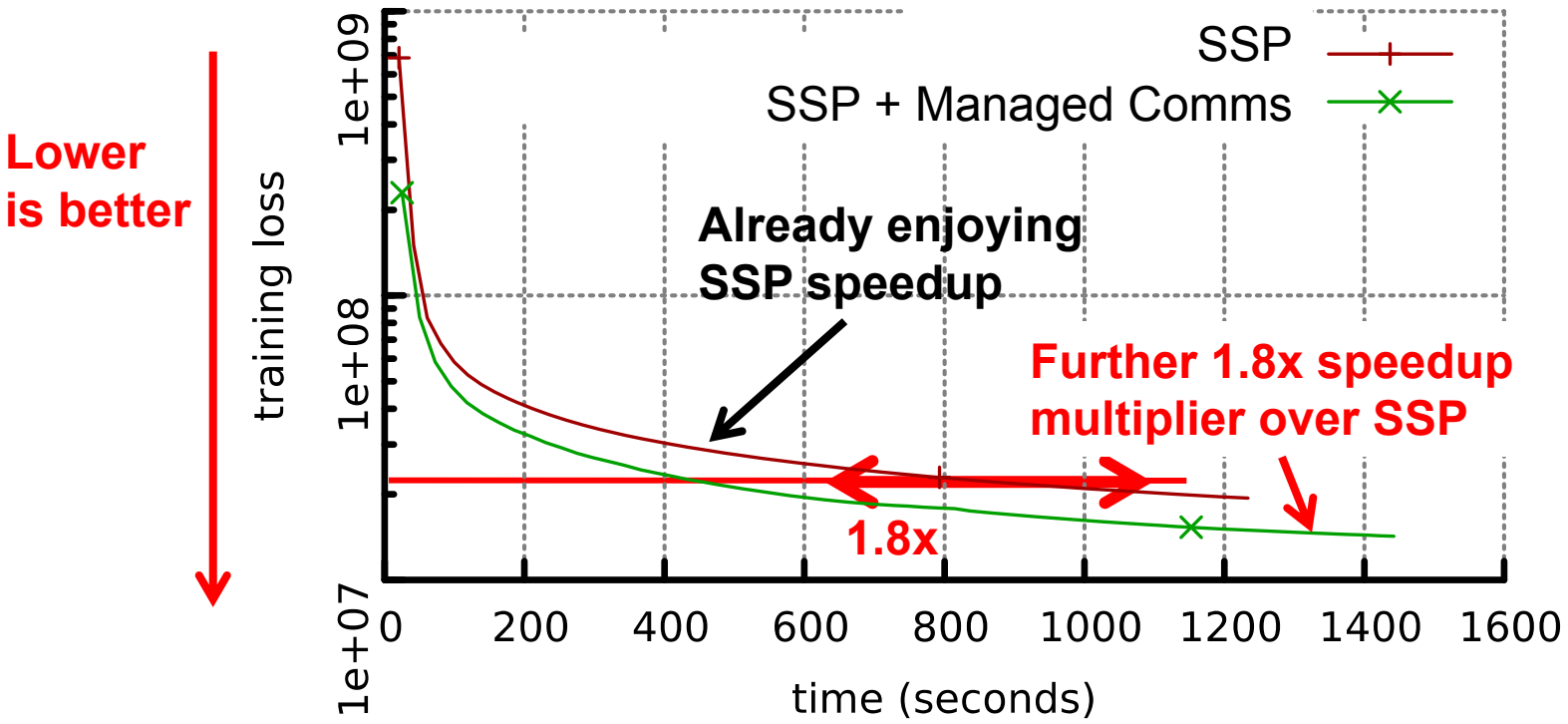
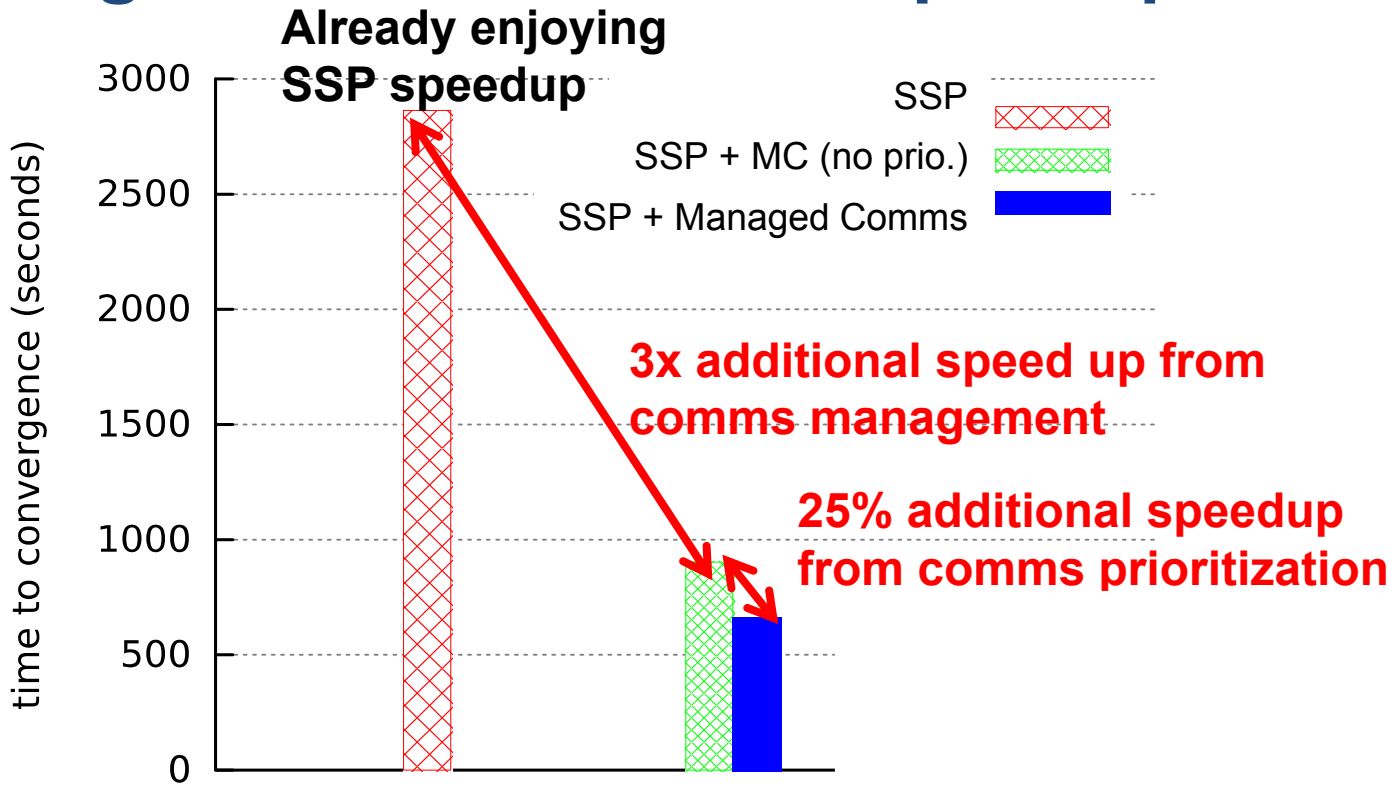
MatrixFact: Managed Communication Speedup



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

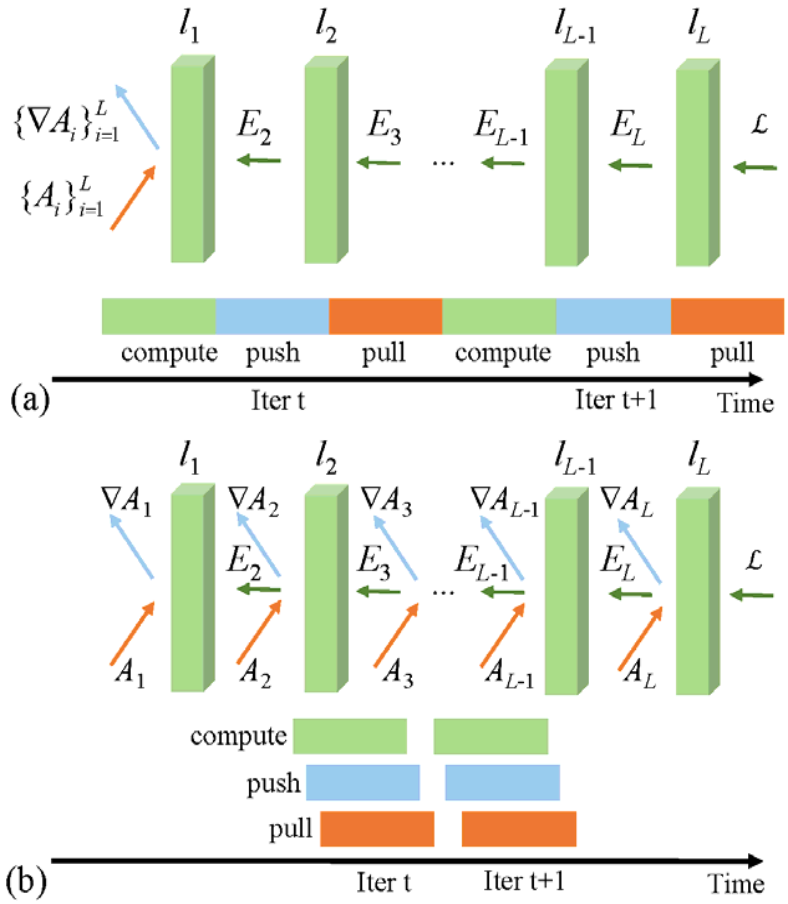
LDA: Managed Communication Speedup



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

Managed Communication: Wait-free back-propagation [Zhang et al., 2015]

- Distributed wait-free back-propagation for Deep Learning
  - Exploit the chain rule in BP
  - Overlap comms/compute every layer
    - Send out gradients once it's ready
    - Sync updated params once it's ready
    - Wait-free!



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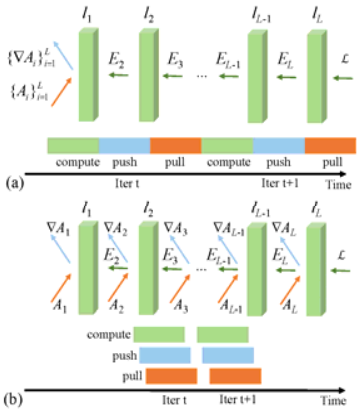
Managed Communication: Wait-free back-propagation



- Effective for today's CNN structures

Params/FLOP distribution of modern CNNs

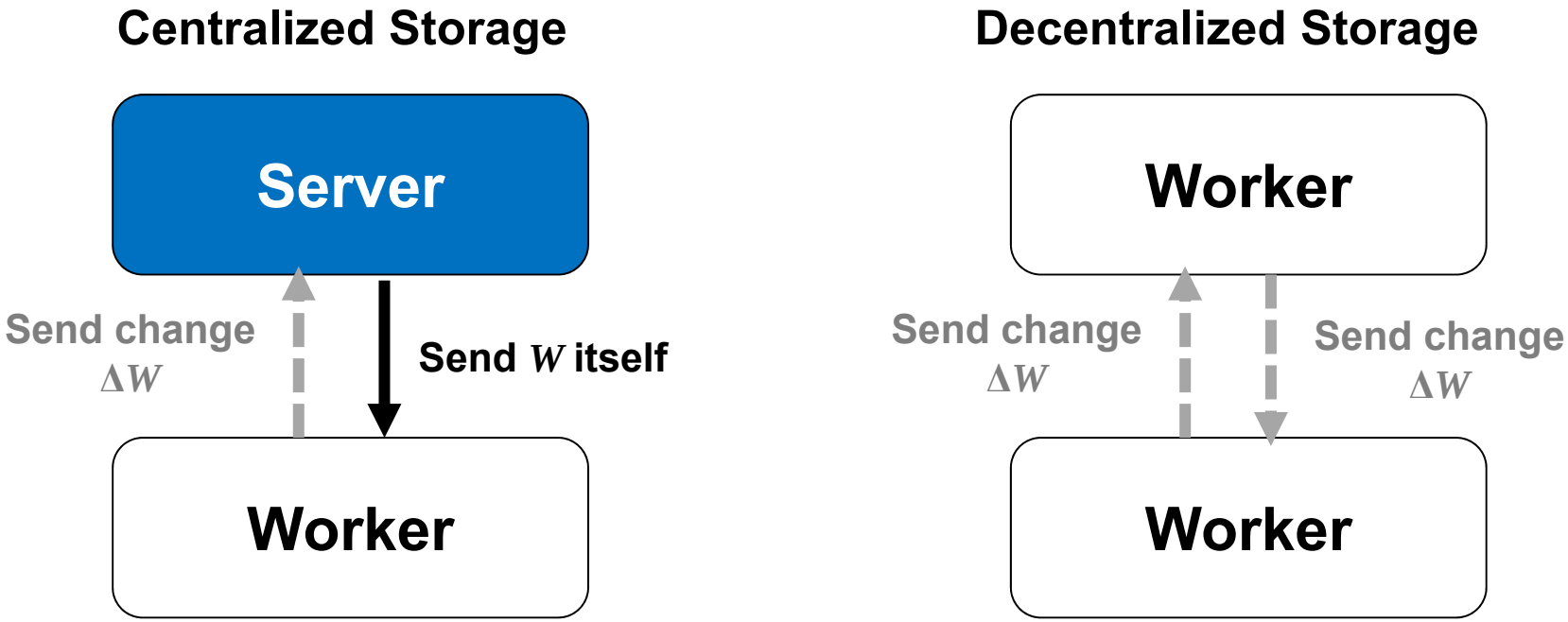
Parameters	CONV Layers (#/%)	FC Layers (#/%)
AlexNet	2.3M / 3.75	59M / 96.25
VGG-16	7.15M / 5.58	121.1M / 94.42
FLOPs	CONV Layers (#/%)	FC Layers (#/%)
AlexNet	1,352M / 92.0	117M / 8.0
VGG-16	10,937M / 91.3	121.1M / 8.7

Fully-Connected layers have **Big Parameters**

Convolutional layers require **Big Computation**

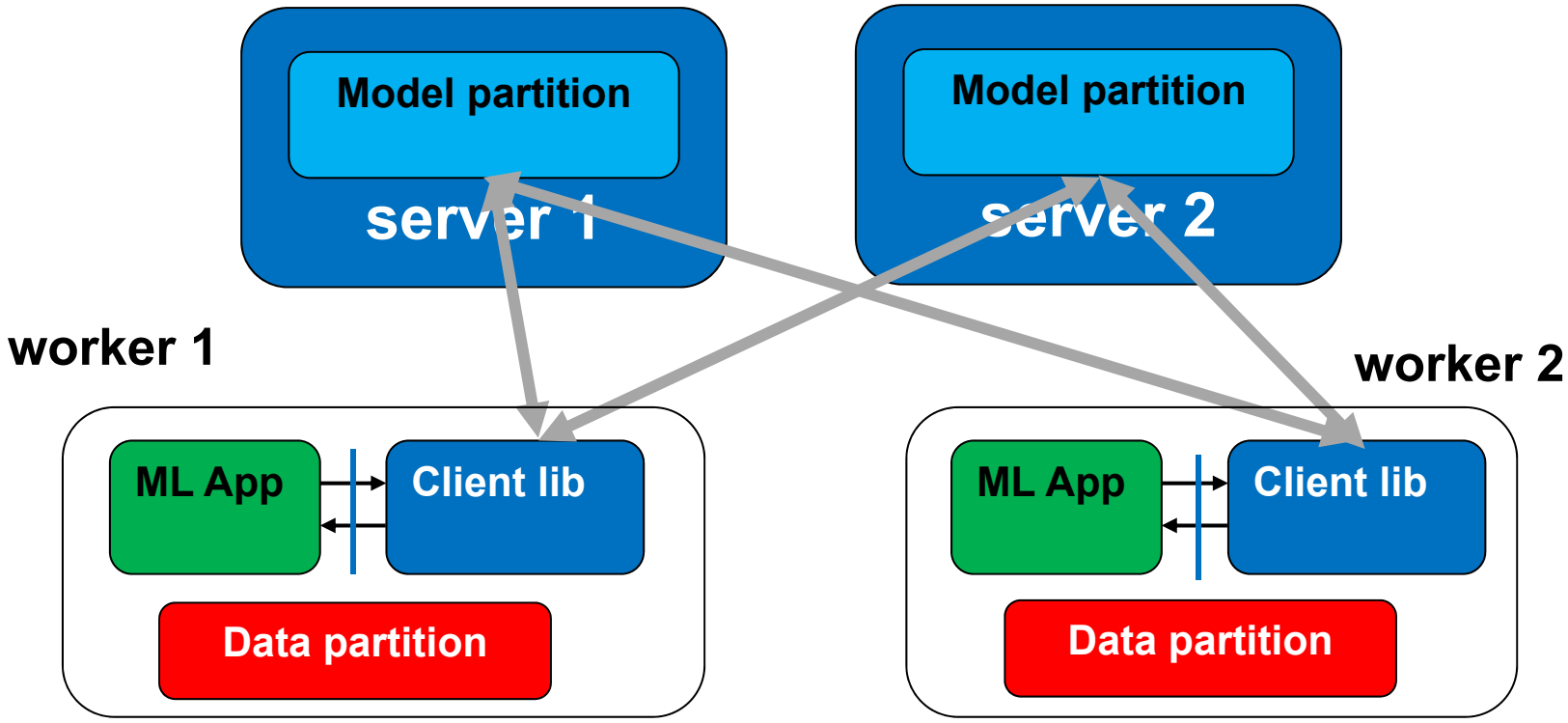
- 90% computation happens at bottom (Conv) layers
- 90% communication happens at top (FC) layers
- Which means… 90% are overlapped with 90%!

Parameter Storage Paradigms



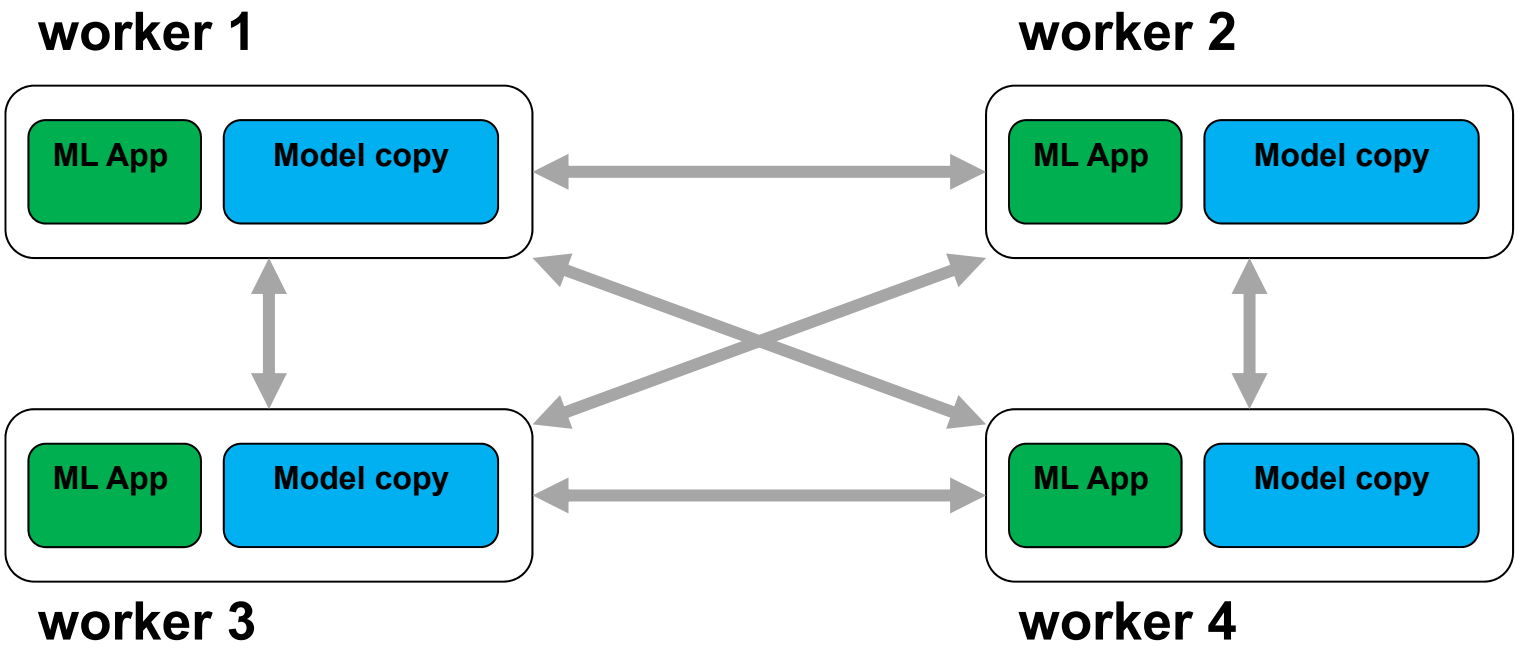
- **Centralized:** send parameter W itself from server to worker
  - Advantage: allows compact comms topology, e.g. bipartite
- **Decentralized:** always send changes ΔW between workers
  - Advantage: can exploit special structure of ΔW to reduce comms

Topology: Master-Slave



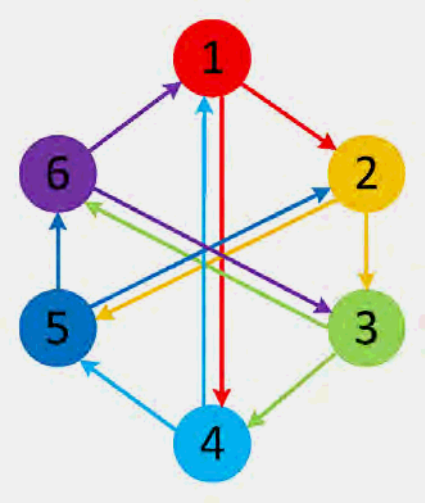
- Used with **centralized storage** paradigm
- Topology = **bipartite graph**: Servers (masters) to Workers (slaves)
- **Disadvantage:** need to code/manage clients and servers separately
- **Advantage:** bipartite topology far smaller than full N^2 P2P connections

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]



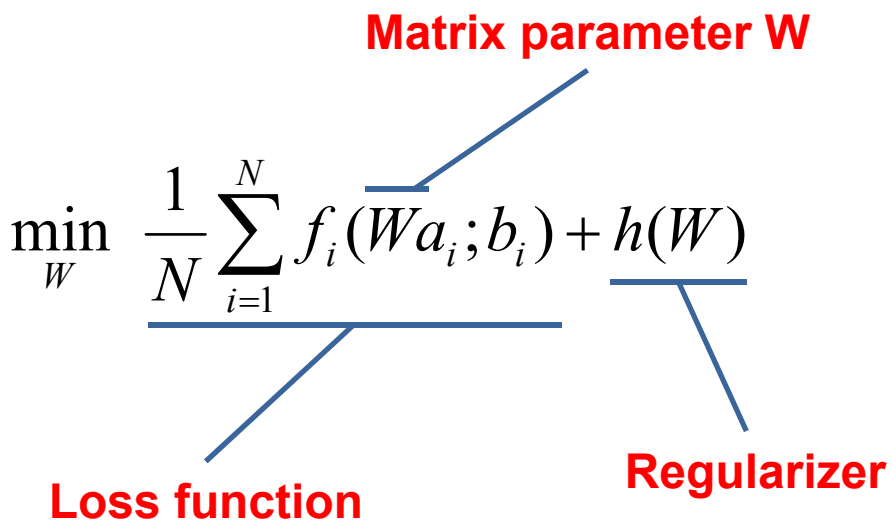
- Used with **decentralized storage** paradigm
- Like P2P topology, but route messages through many workers
  - e.g. to send message from 1 to 6, use 1->2->3->6
- **Disadvantage:** incur higher SSP staleness due to routing, e.g. 1->2->3->6 = staleness 3
- **Advantage:** support bigger messages; support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

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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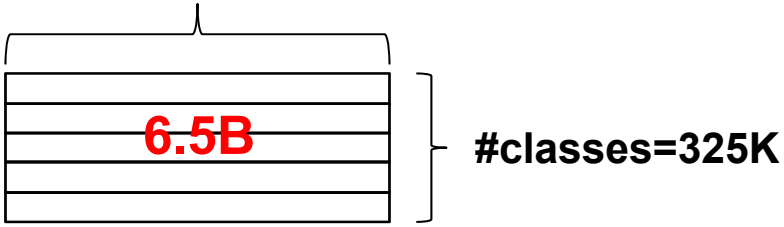
Big MPMs

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

What do we actually need to communicate?

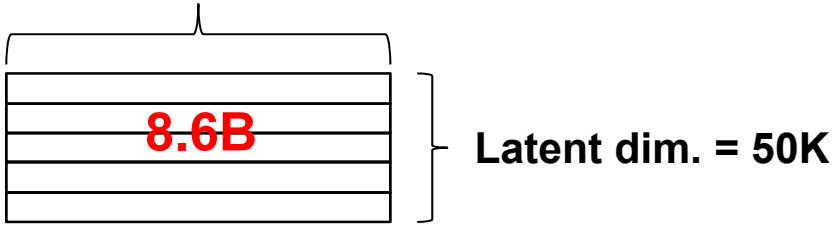
Multiclass Logistic Regression on Wikipedia

Feature dim. = 20K



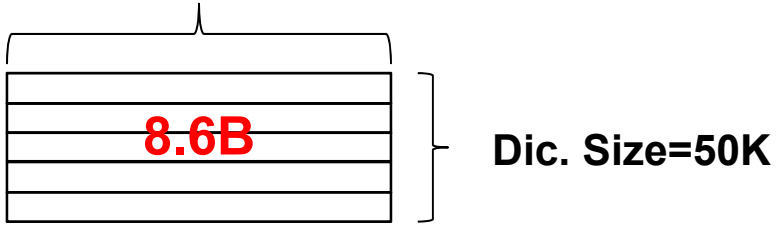
Distance Metric Learning on ImageNet

Feature dim. = 172K



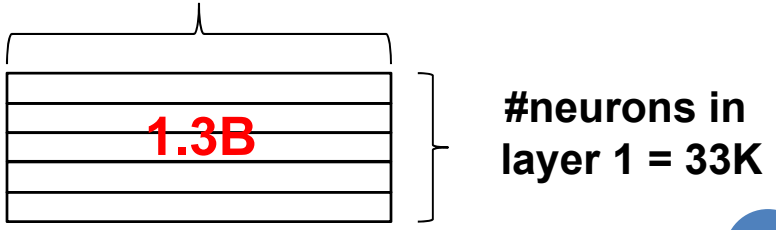
Sparse Coding on ImageNet

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)

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

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

Sufficient Factor (SF) Updates

[Xie et al., 2015]

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

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

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

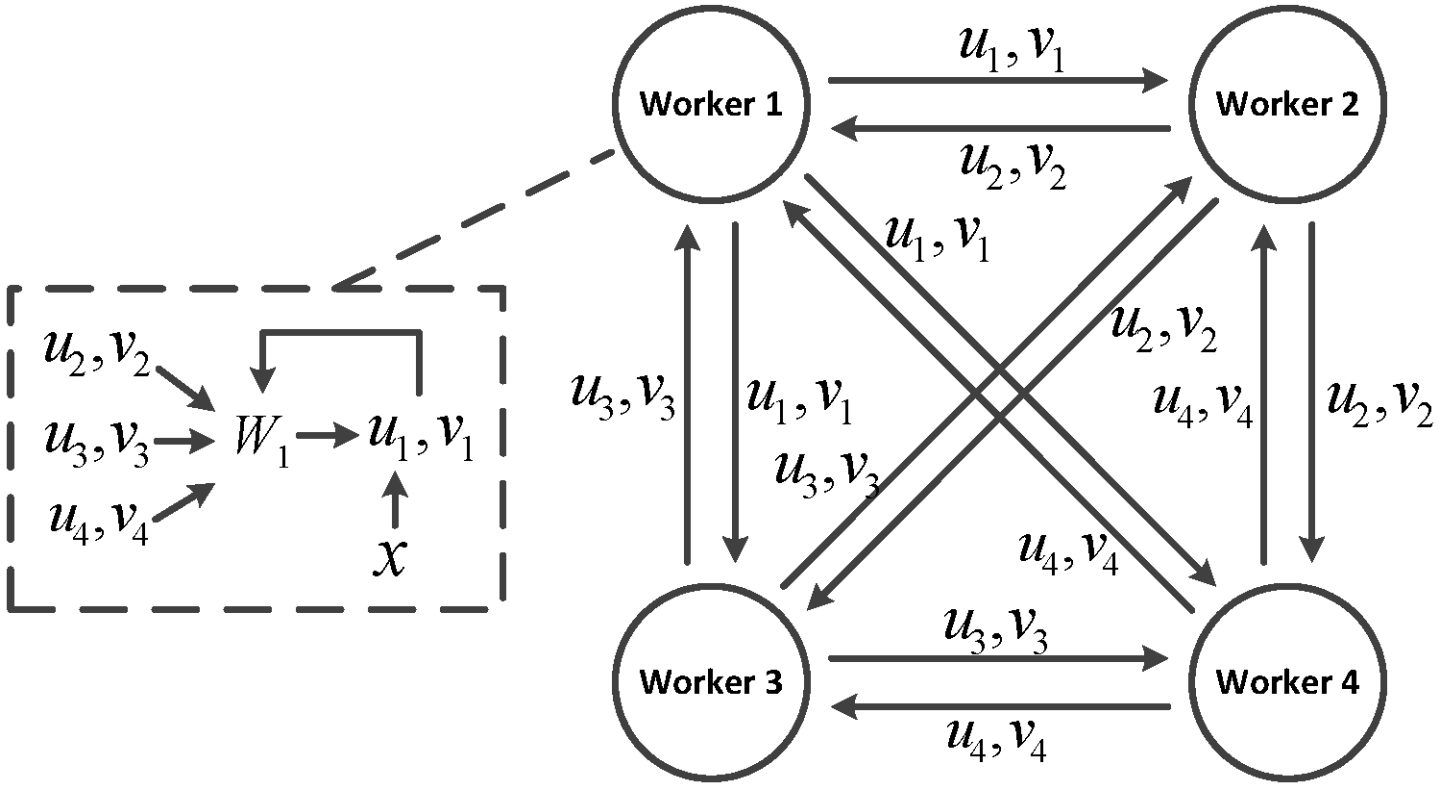
  - Stochastic dual coordinate ascent (SDCA)

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

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

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

P2P Topology + SF Updates = Sufficient Factor Broadcasting



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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*

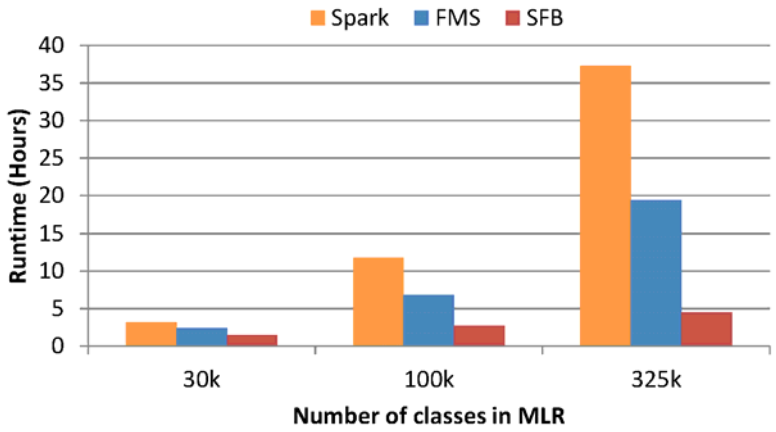
- $\liminf_{c\to\infty} \mathbb{E}\|\nabla F(\mathbf{W}^c)\| = 0$, *hence there exists a subsequence of* $\nabla F(\mathbf{W}^c)$ *that almost surely vanishes;*
- $\lim_{c\to\infty} \max_p \|\mathbf{W}^c - \mathbf{W}_p^c\| = 0$, i.e. *the maximal disagreement between all local sequences and the auxiliary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

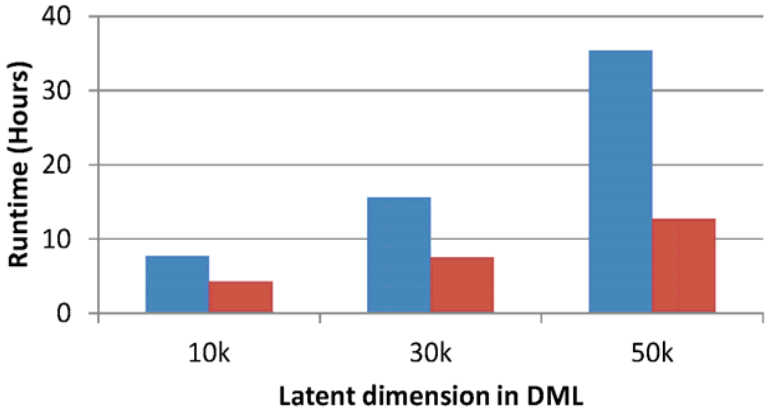
Explanation: Parameter copies W_p on different workers p converge to the same optima, *i.e. all workers reach the same (correct) answer.*

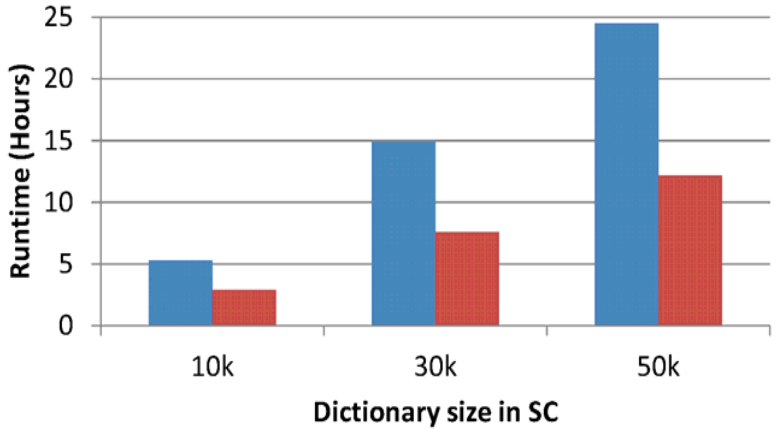
✓Does not need central parameter server or key-value store

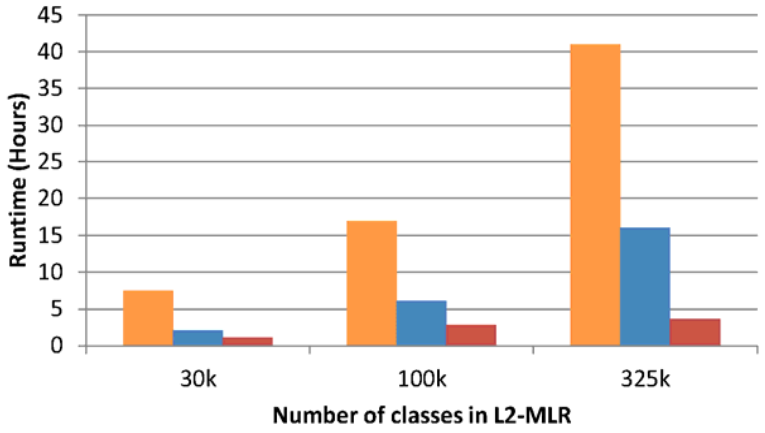
✓Works with SSP bridging model (staleness = s)

SF: Convergence Speedup



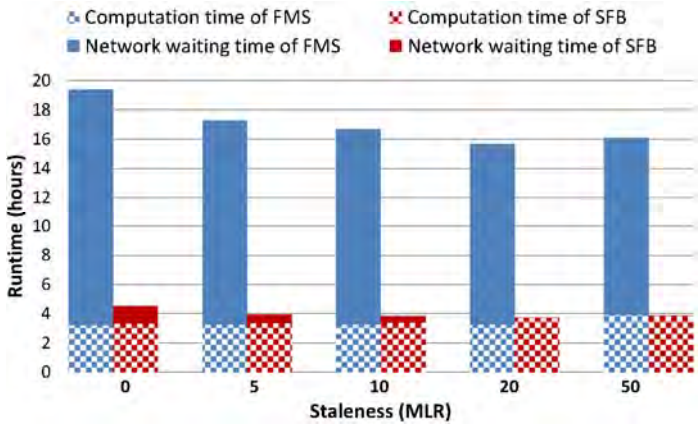


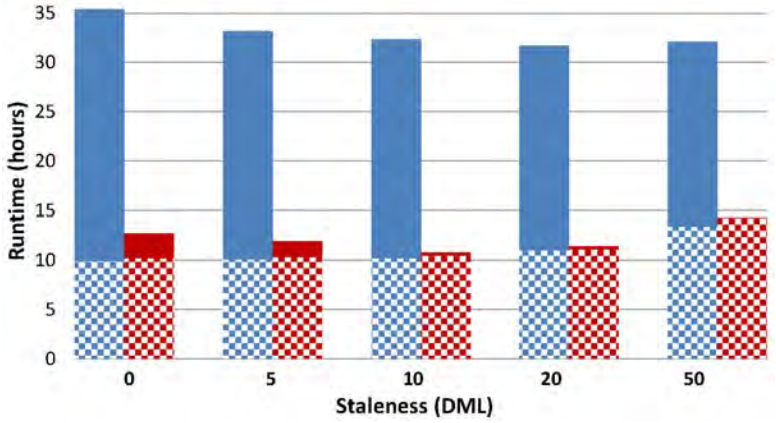


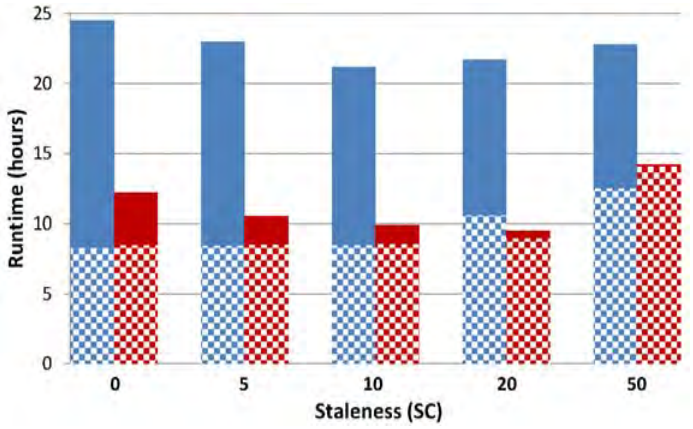


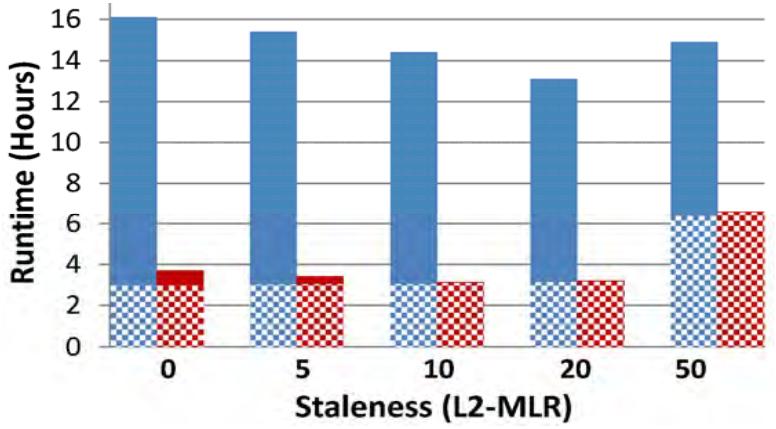
- Convergence time versus model size, under BSP
- FMS = full matrix updates; SFB = sufficient factor updates

SF: Comm.-Time Reduction







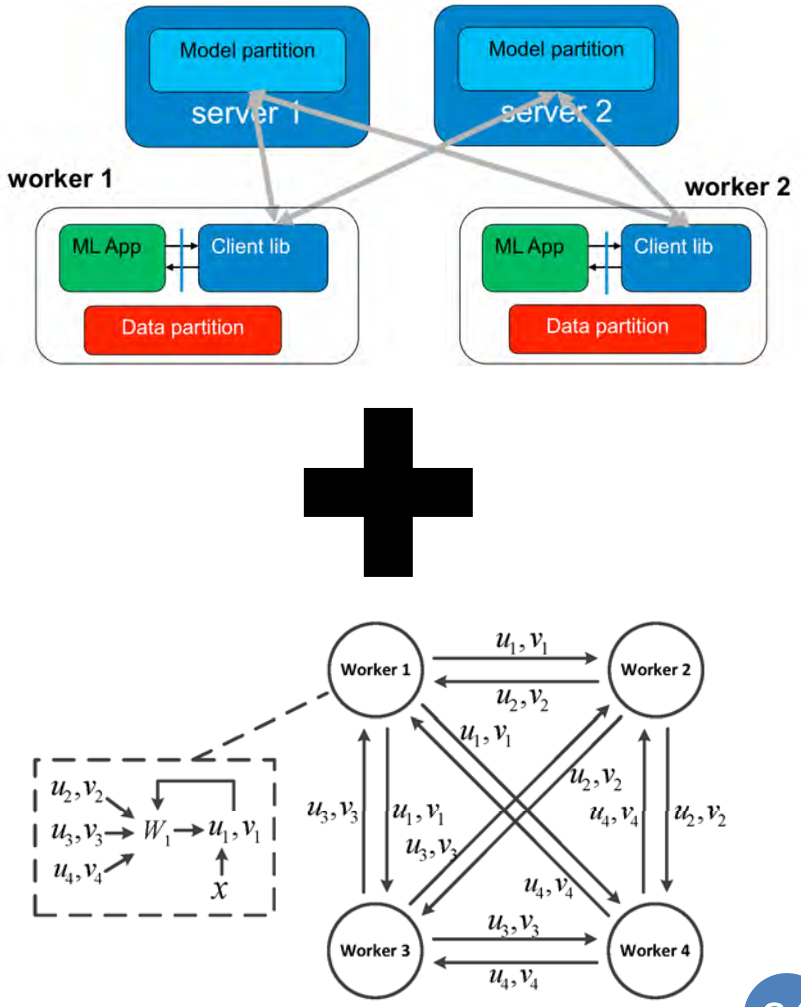


- Computation vs network waiting time
- FMS = full matrix updates; SFB = sufficient factor updates

Hybrid Full Updates + SFB

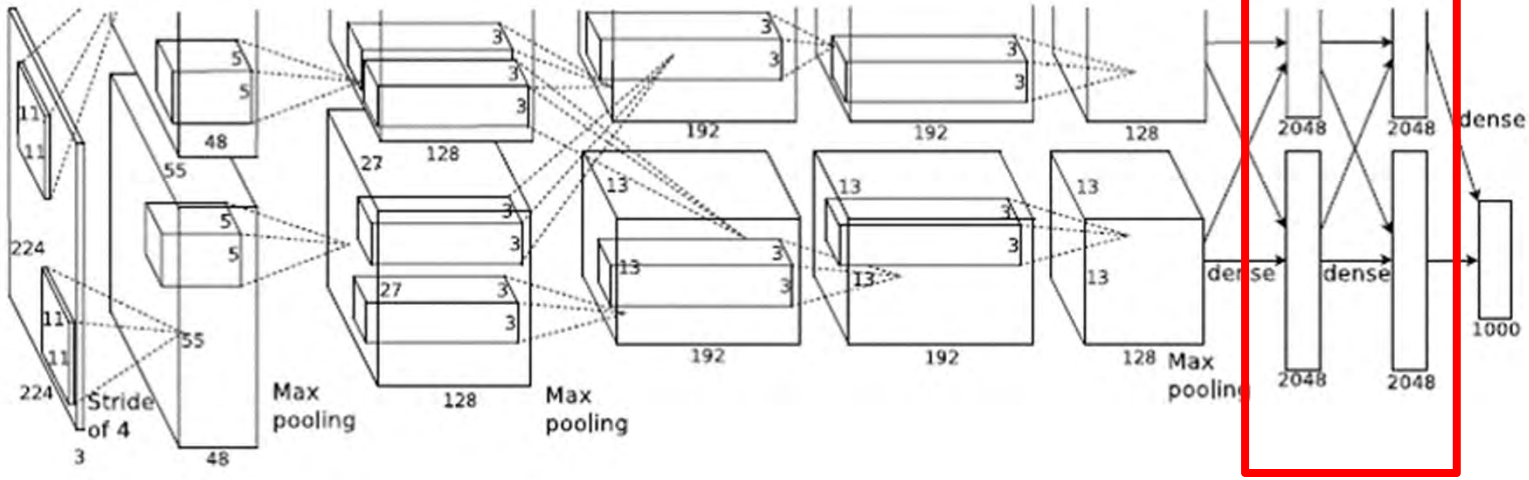
- Hybrid communications: Parameter Server + Sufficient Factor Broadcasting
  - Parameter Server: Master-Slave topology
  - Sufficient factor broadcasting: P2P topology

- For problems with a mix of large and small matrices,
  - Send small matrices via PS
  - Send large matrices via SFB



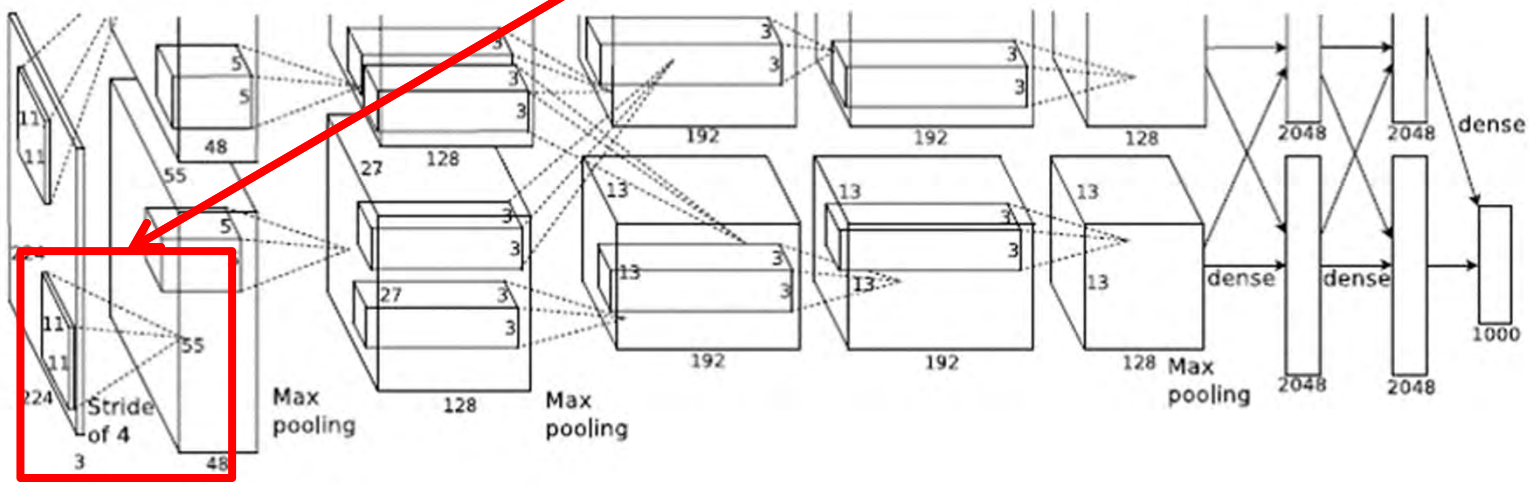
Hybrid example: CNN [Zhang et al., 2015]

- AlexNet CNN model
  - Final layers = 4096 * 4096 matrix (17M parameters)
  - Use SF to communicate
    - 1. Decouple into two 4096 vectors: u, v
    - 2. Transmit two vectors
    - 3. Reconstruct the gradient matrix



Hybrid example: CNN [Zhang et al., 2015]

- AlexNet CNN model
  - Convolutional layers = e.g. 11 * 11 matrix (121 parameters)
  - Use Full-matrix updates to communicate
    - 1. Send/receive using Master-Slave PS topology

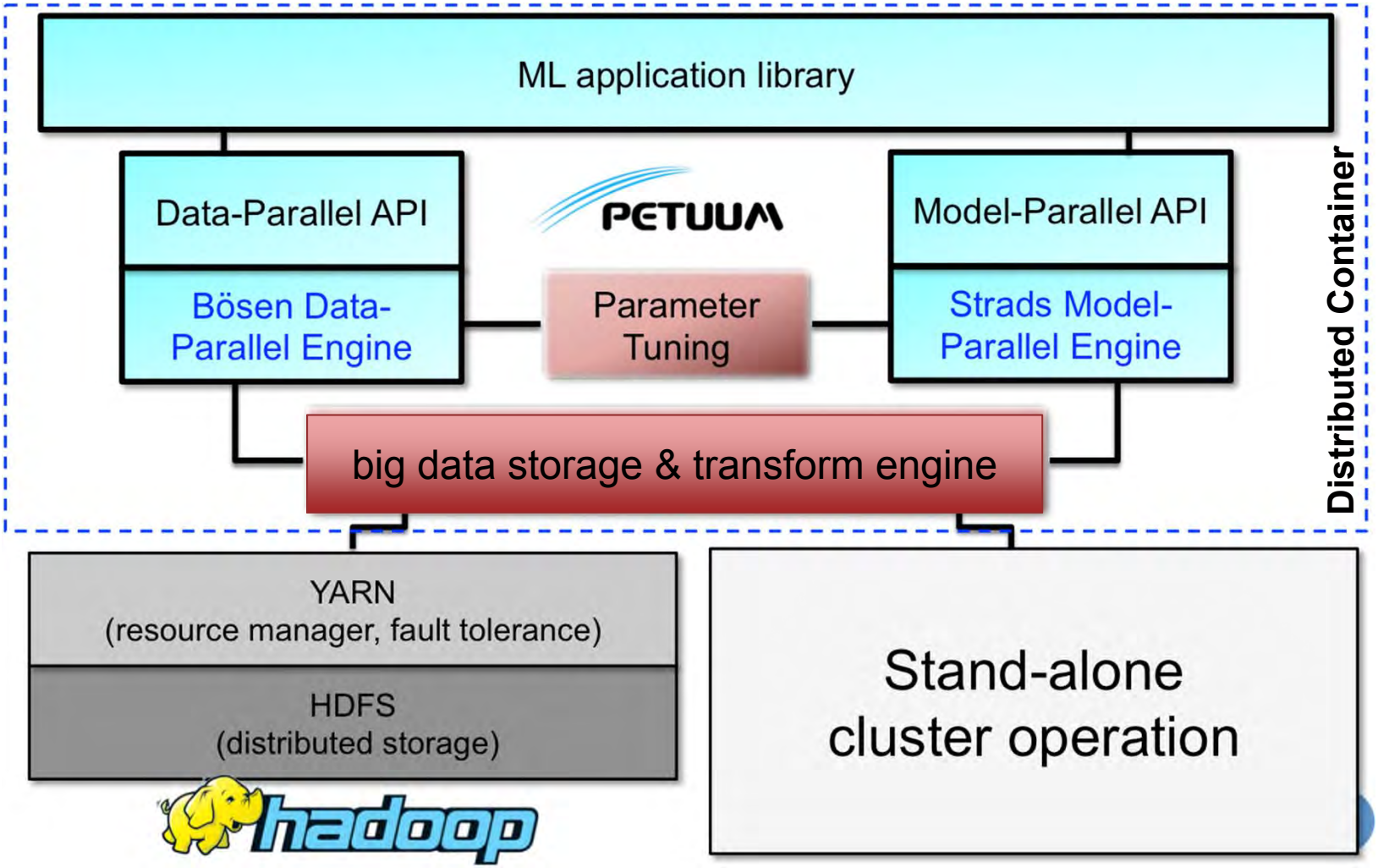


Summary

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 (FM) updates
   - Sufficient Factor (SF) updates
   - Hybrid FM+SF updates

In Closing: A Distributed Framework for Machine Learning

The Petuum Architecture (50,000 feet view)



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Major Releases

(petuum.org)

- **Dec 2013: Petuum 0.1**
  - ***Initial release***
  - Apps: LDA, matrix factorization
  - System: Bosen (parameter server)
- **March 2014: Petuum 0.2**
  - Apps: LDA, matrix factorization, Lasso
  - System: Strads (model-parallel scheduler)
- **July, 2014: Petuum 0.9**
  - Apps: LDA, matrix factorization, Lasso, Logistic Regression
  - System: large performance improvements
  - Patch releases 0.91 (July 2014), 0.92 (Sept 2014), 0.93 (Dec 2014)
- **Jan 2015: Petuum 1.0**
  - ***Many new Apps: MedLDA, NMF, CNN, DML, DNN, DNN speech, Kmeans, MLR, Random forest, Sparse coding***
  - System: more performance improvements
- **July 2015: Petuum 1.1**
  - New Apps: Distributed+GPU CNN, SVM
  - ***Big Data Ecosystem Support: Java parameter server (JBosen), HDFS, YARN***

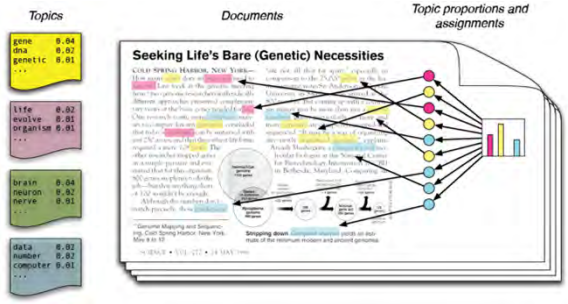
Petuum Speed Advantage

Topic Detection Speed

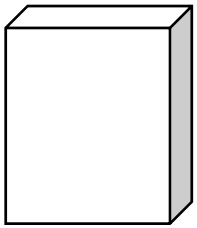
On 128 machines

Spark

1x speed



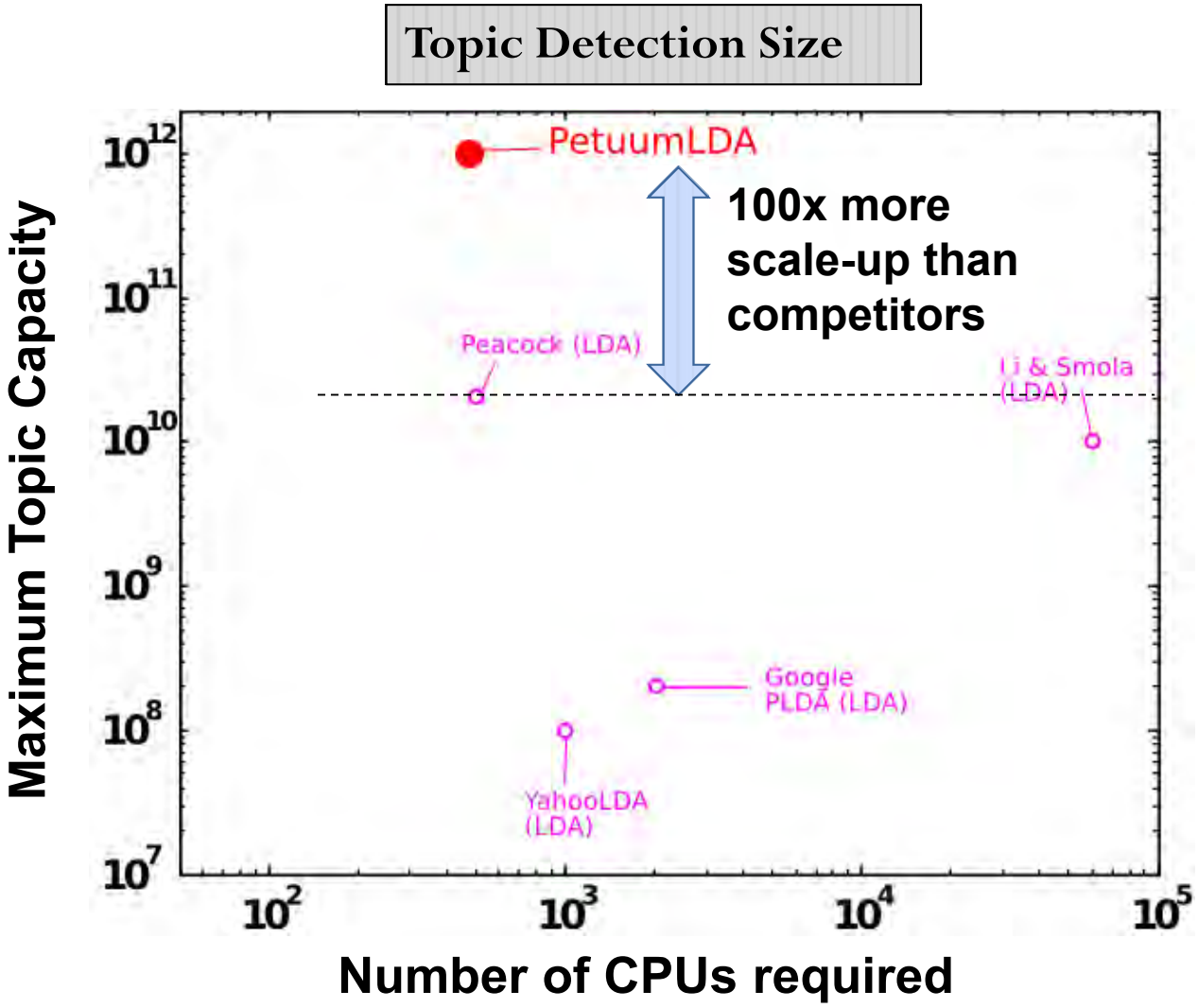
Yahoo



12x speed

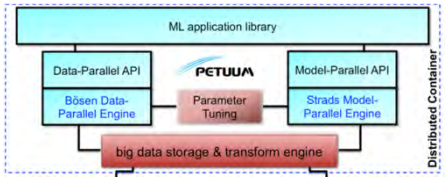
Petuum

Petuum Size Advantage



Petuum Open Source ML apps

- **ML Library (Petuum v1.1):**
  - Topic Modeling
    - LDA
    - MedLDA (supervised topic models)
  - Deep Learning
    - Fully-connected DNN
    - **Convolutional Neural Network (Poseidon)**
  - Matrix Factorization
    - Least-squares Collaborative Filtering (with regularization)
    - Non-negative Matrix Factorization
    - Sparse Coding
  - Regression
    - Lasso Regression
  - Metric Learning
    - Distance Metric Learning
  - Clustering
    - K-means
  - Classification
    - Random Forest
    - Logistic Regression and SVM
    - Multi-class Logistic Regression



Poseidon

torch

theano

dmlc mxnet

TensorFlow

=

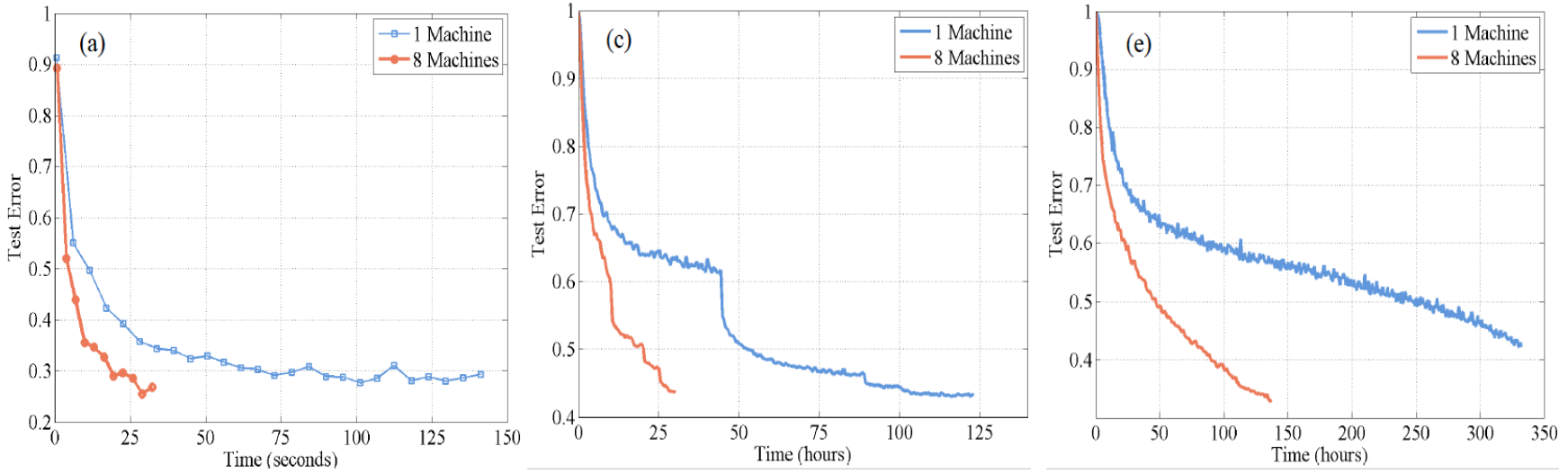
Decaf / Caffe
a Berkeley Vision Project

+

PETUUM

- HDFS+YARN support
- Distributed GPU support (for CNN)
- C++/Java bounded-async key-value store (Bösen)
- C++ scheduler system (Strads)

CNN: Wait-free backprop speedup



Model	Speedup	top-1 accuracy
CIFAR-10 quick	5× with higher accuracy	75%
AlexNet	4.5×	56.5%
GoogLeNet	4×	67.1%

Up to 5x speedup with 8 GPU-equipped machines

Platform vs Tower

- **Platform Approach**
  - Use ideas to build platform that supports many apps
  - Upgrades to platform improve all apps
- **Tower Approach**
  - Build ideas directly into application
  - Best performance; harder to re-use for other apps

PETUUM

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Acknowledgements

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Abhimanu Kumar


Qirong Ho


Aurick Qiao

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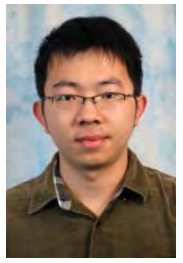
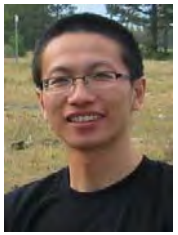
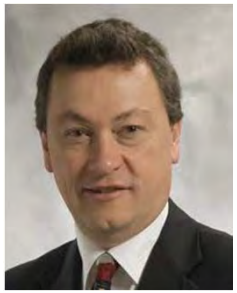

Hao Zhang


Yaoliang Yu

Google IBM


Garth Gibson

Greg Ganger


Phillip Gibbons


James Cipar