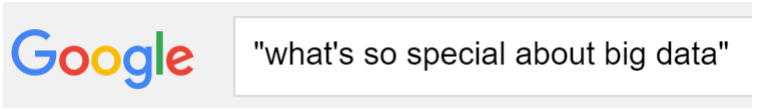
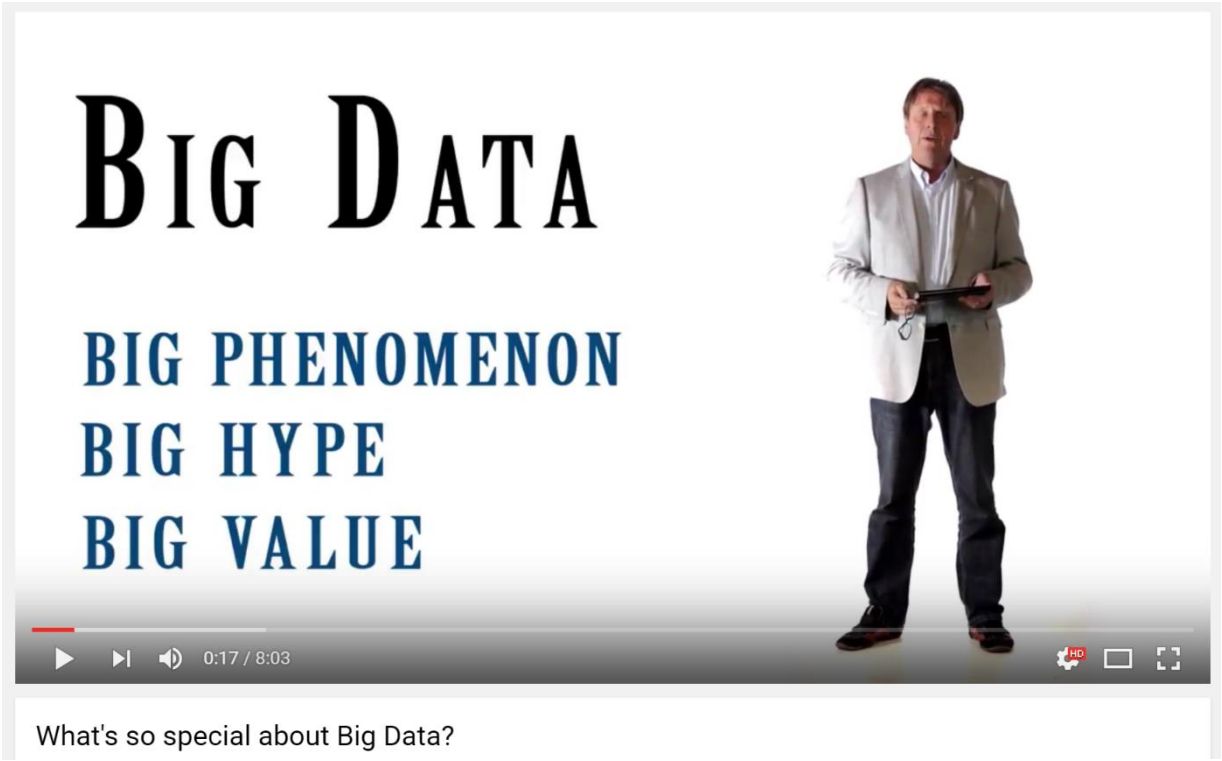
# Future of Computing II: What's So Special About Big Learning?

15-213 / 18-213 / 15-513: Introduction to Computer Systems
28th Lecture, December 4, 2018

**Today's Instructor:**
Phil Gibbons

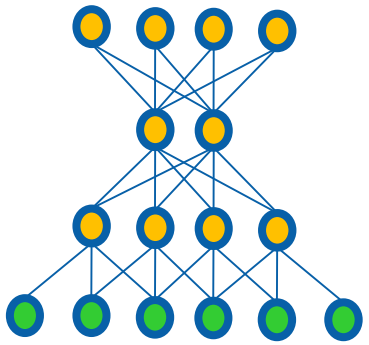
# What's So Special about…Big Data?



# Focus of this Talk: Big Learning

- **Machine Learning over Big Data**
- **Examples:**
  - Collaborative Filtering (via Matrix Factorization)
    - Recommending movies
  - Topic Modeling (via LDA)
    - Clusters documents into K topics
  - Multinomial Logistic Regression
    - Classification for multiple discrete classes
  - Deep Learning neural networks:



  - Also: Iterative graph analytics, e.g. PageRank

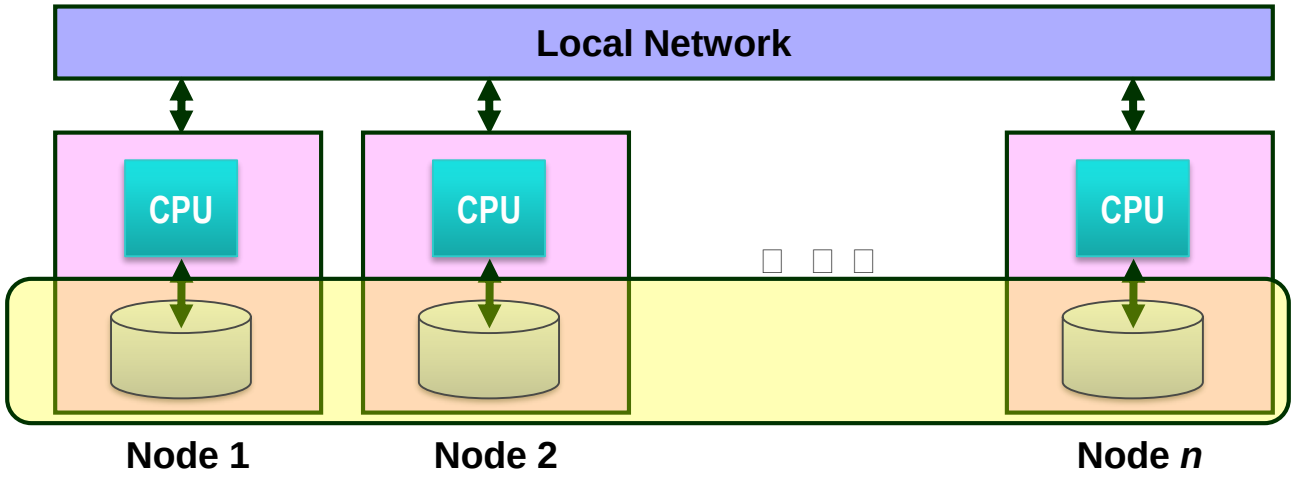
# Big Learning Frameworks & Systems

- **Goal: Easy-to-use programming framework for Big Data Analytics that delivers good performance on large (and small) clusters**

- **A few popular examples (historical context):**
  - Hadoop (2006-)
  - GraphLab / Dato (2009-)
  - Spark / Databricks (2009-)

# Recall: Hadoop Project


- **File system with files distributed across nodes**

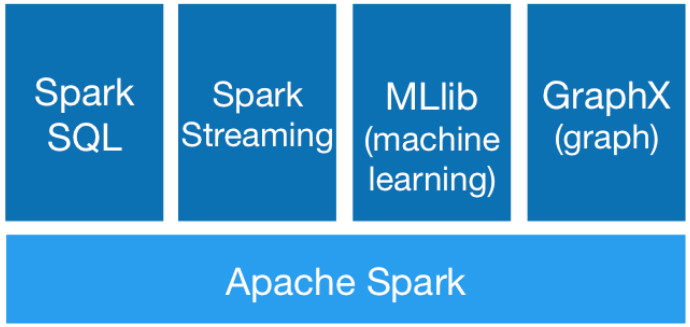



  - Store multiple (typically 3 copies of each file)
    - If one node fails, data still available
  - Logically, any node has access to any file
    - May need to fetch across network

- **Map / Reduce programming environment**
  - Software manages execution of tasks on nodes

# Recall: Recent Programming Systems

- **Spark Project**




  - at U.C., Berkeley
  - Grown to have large open source community


**Machine Learning Startup GraphLab Gets A New Name And An $18.5M Check**

Posted Jan 8, 2015 by Jonathan Shieber (@jshieber)

- **GraphLab**
  - Started as project at CMU by Carlos Guestrin
  - Environment for describing machine-learning algorithms
    - Sparse matrix structure described by graph
    - Computation based on updating of node values

# Big Learning Frameworks & Systems

- **Goal: Easy-to-use programming framework for Big Data Analytics that delivers good performance on large (and small) clusters**

- **A few popular examples (historical context):**
  - Hadoop (2006-)
  - GraphLab / Dato (2009-)
  - Spark / Databricks (2009-)

- **Our Idea: Discover & take advantage of distinctive properties ("what's so special") of Big Learning training algorithms**

# What's So Special about Big Learning? …A Mathematical Perspective

- **Formulated as an optimization problem**
  - Use training data to learn model parameters that minimize/maximize an objective function
- **No closed-form solution, instead algorithms iterate until convergence**
  - E.g., **Stochastic Gradient Descent**

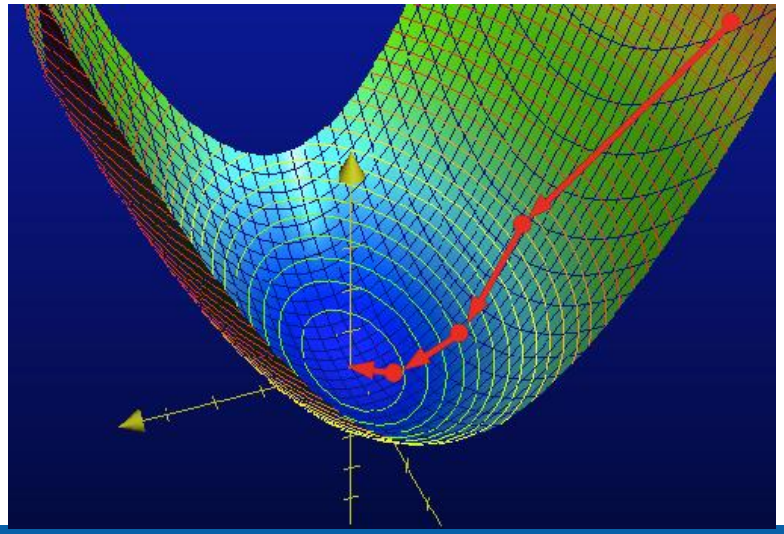


Image from charlesfranzen.com

# What's So Special about Big Learning? …A Distributed Systems Perspective

## The Bad News

- **Lots of Computation / Memory**
  - Many iterations over Big Data
  - Big Models

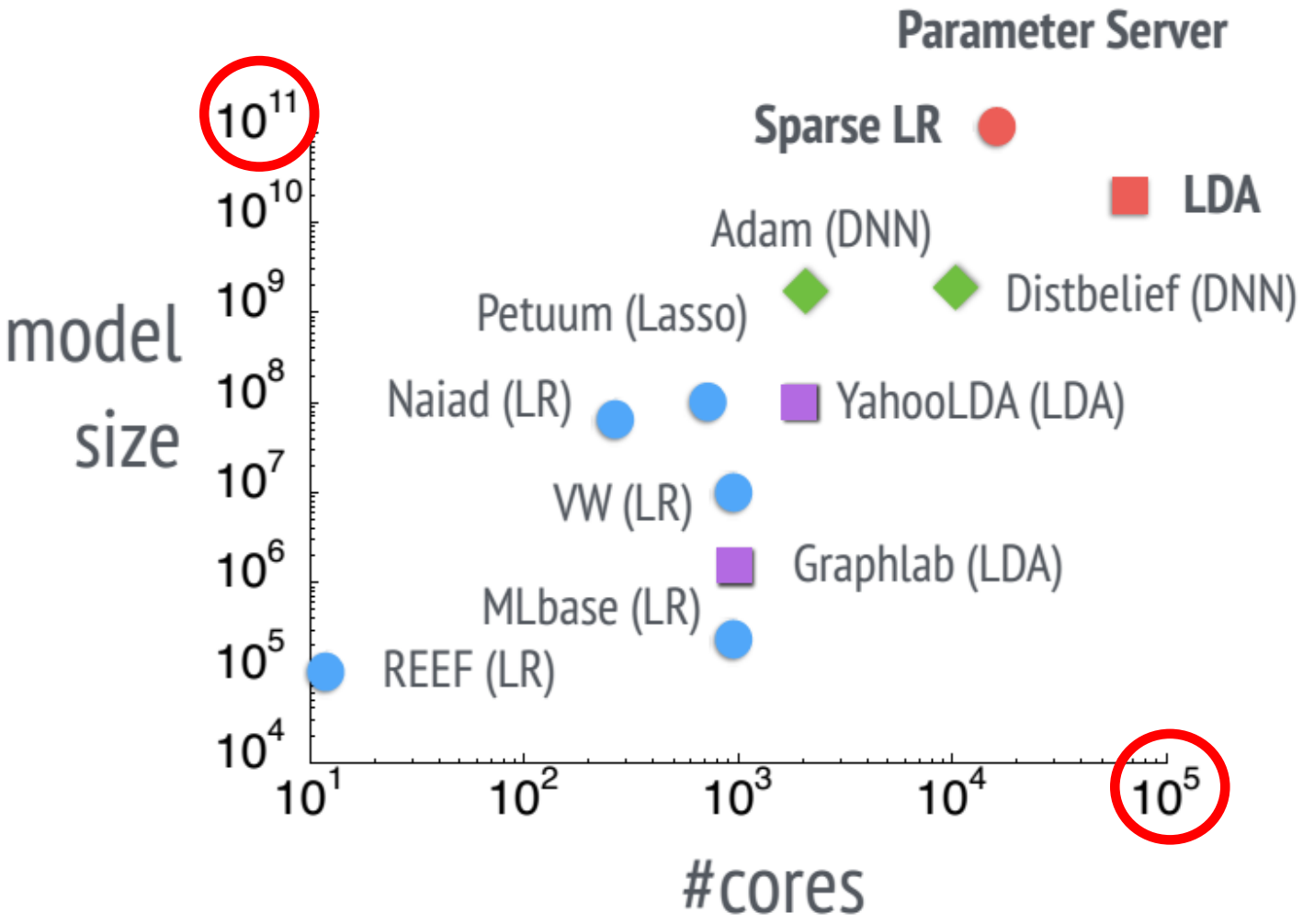
  ➡ Need to distribute computation widely
- **Lots of Communication / Synchronization**
  - Not readily "partitionable"

➡ **Model Training is SLOW**

- hours to days to weeks, even on many machines

**…why good distributed systems research is needed!**

# Big Models, Widely Distributed




[Li et al, OSDI'14]

# Why Big Models: Improved Accuracy

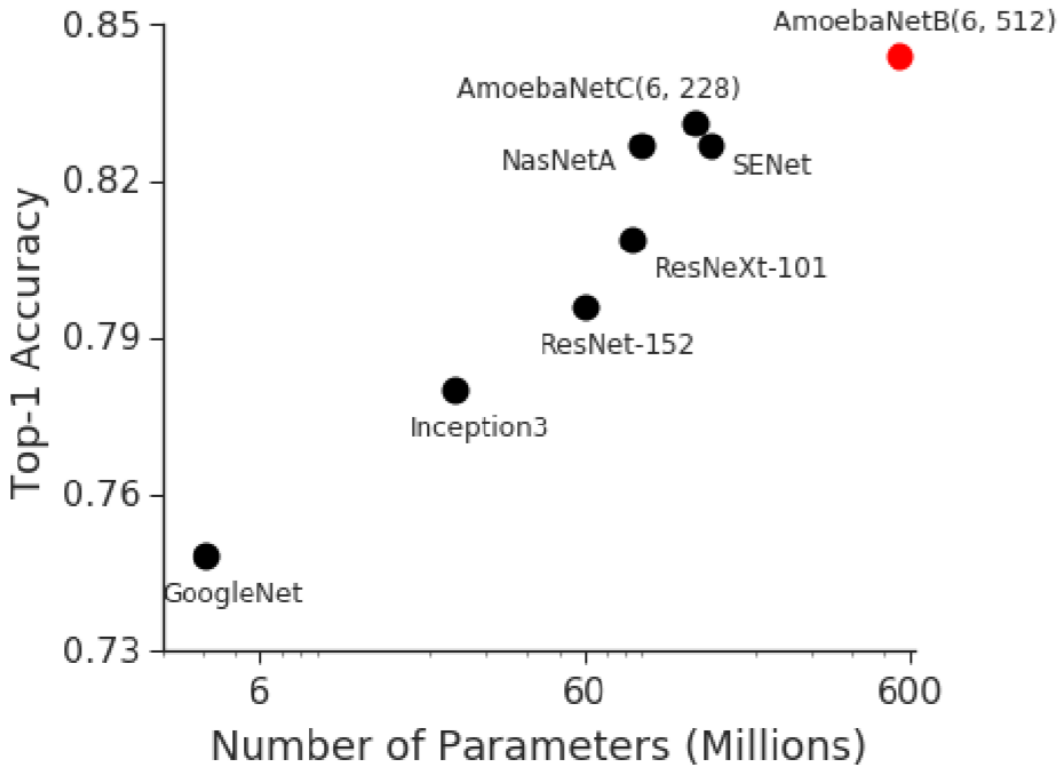
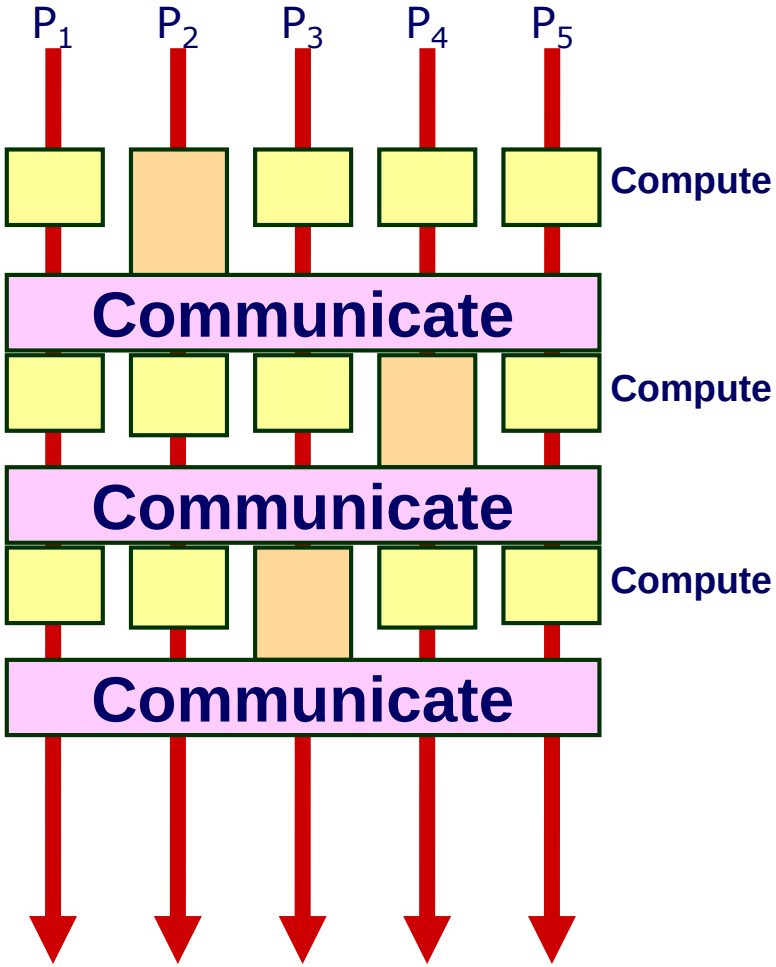



Figure 1: Strong correlation between top-1 accuracy on ImageNet 2012 validation dataset and model size for representative state-of-the-art image classification models in recent years [48, 49, 23, 52, 24, 55, 44]. Red dot shows 84.3% top-1 accuracy for a giant AmoebaNet model trained by GPipe.

# Lots of Communication / Synchronization e.g. in BSP Execution (Hadoop, Spark)

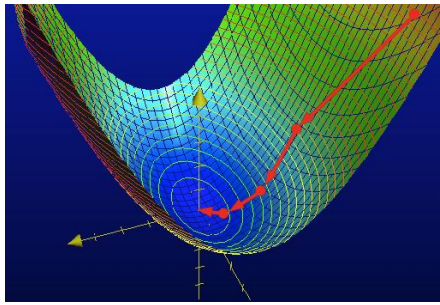



- **Exchange ALL updates at END of each iteration**
  - Frequent, bursty communication
- **Synchronize ALL threads each iteration**
  - Straggler problem: stuck waiting for slowest

# What's So Special about Big Learning? …A Distributed Systems Perspective

## The Good News

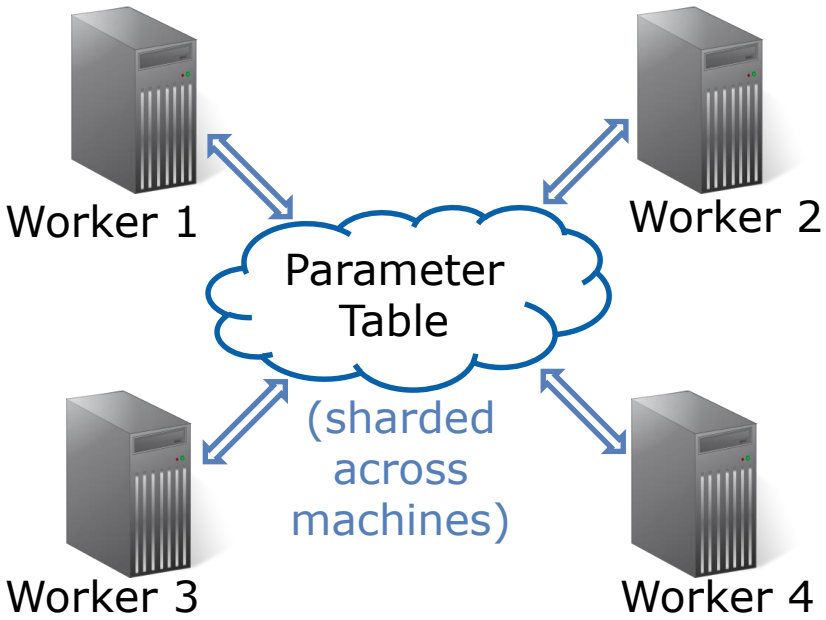
1. Commutative/Associative parameter updates
2. Tolerance for lazy consistency of parameters
3. Repeated parameter data access pattern
4. Intra-iteration progress measure
5. Parameter update importance hints
6. Layer-by-layer pattern of deep learning
7. Most parameter updates are insignificant



**…can exploit to run orders of magnitude faster!**

# Parameter Servers for Distributed ML

- **Provides all workers with convenient access to global model parameters**
  - "Distributed shared memory" programming style




**Single Machine Parallel**

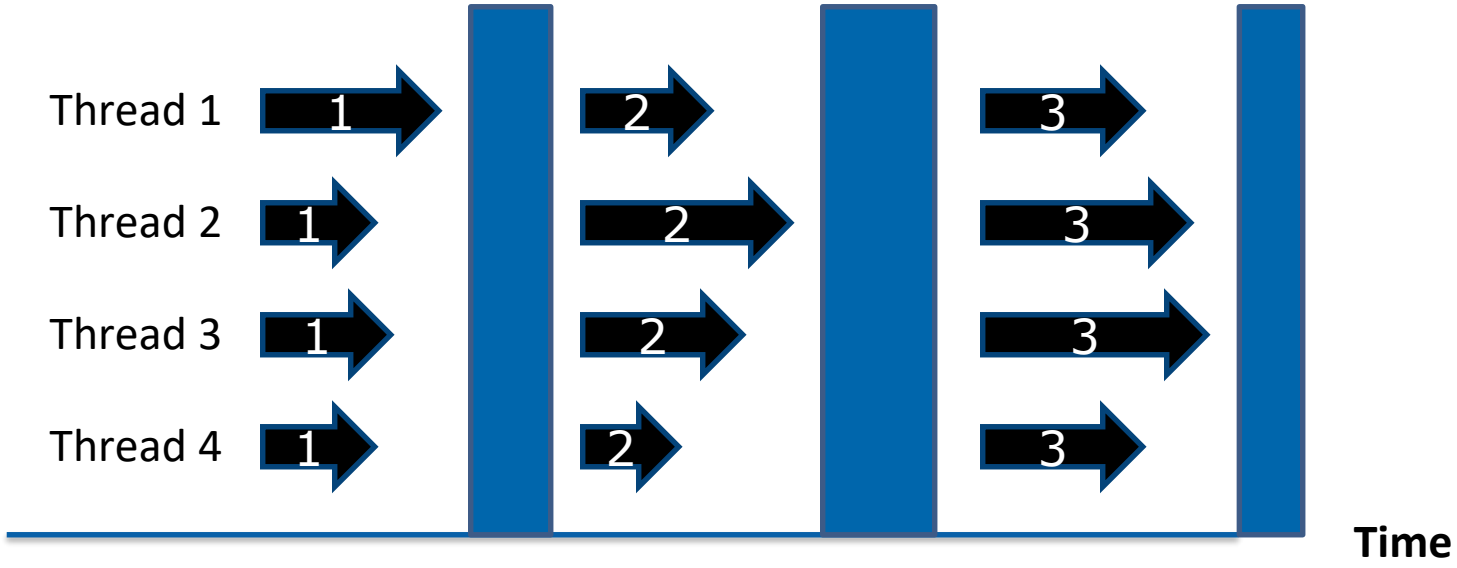
```
UpdateVar(i) {
  old = y[i]
  delta = f(old)
  y[i] += delta }
```

**Distributed with PS**

```
UpdateVar(i) {
  old = PS.read(y,i)
  delta = f(old)
  PS.inc(y,i,delta) }
```

[Power & Li, OSDI'10], [Ahmed et al, WSDM'12], [NIPS'13], [Li et al, OSDI'14], Petuum, MXNet, TensorFlow, etc

# Problem: Cost of Bulk Synchrony

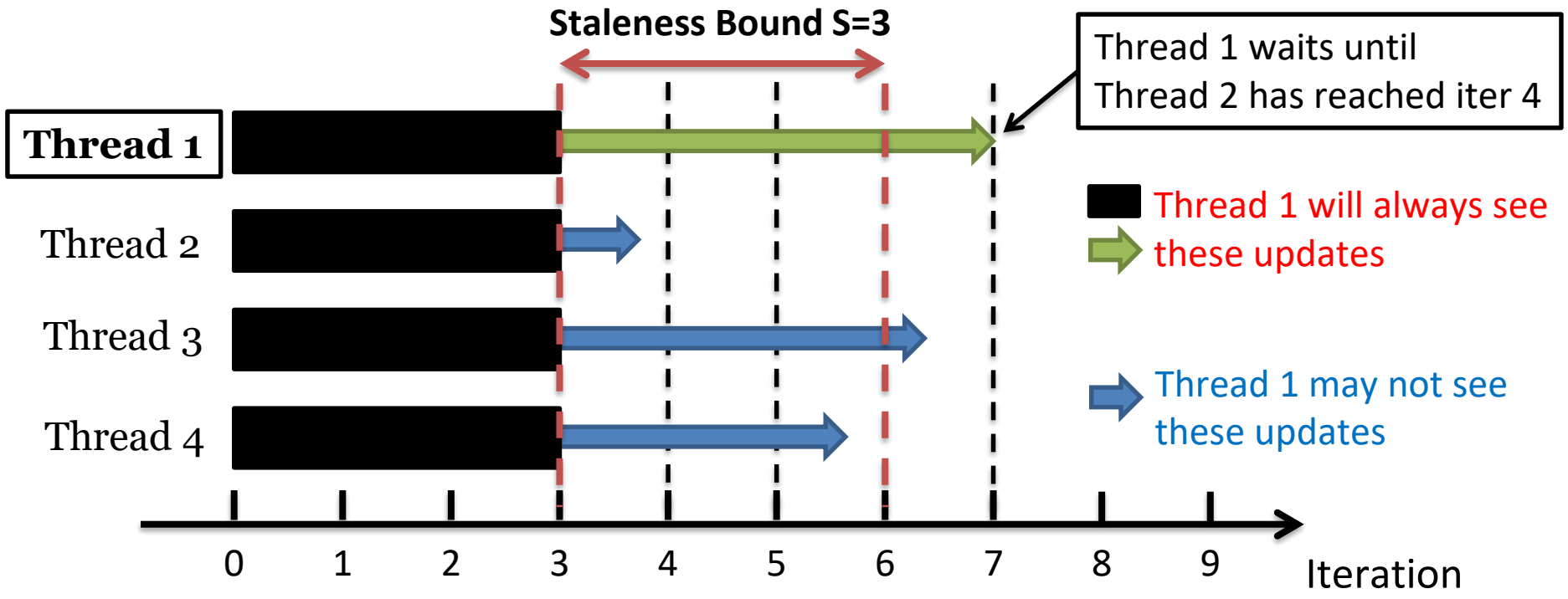



- **Exchange ALL updates at END of each iteration**
- **Synchronize ALL threads each iteration**

**Bulk Synchrony** => Frequent, bursty communication & stuck waiting for stragglers

But: **Fully asynchronous** => No algorithm convergence guarantees

# Stale Synchronous Parallel (SSP)




**Fastest/slowest threads not allowed to drift >S iterations apart**

**Allow threads to *usually* run at own pace**

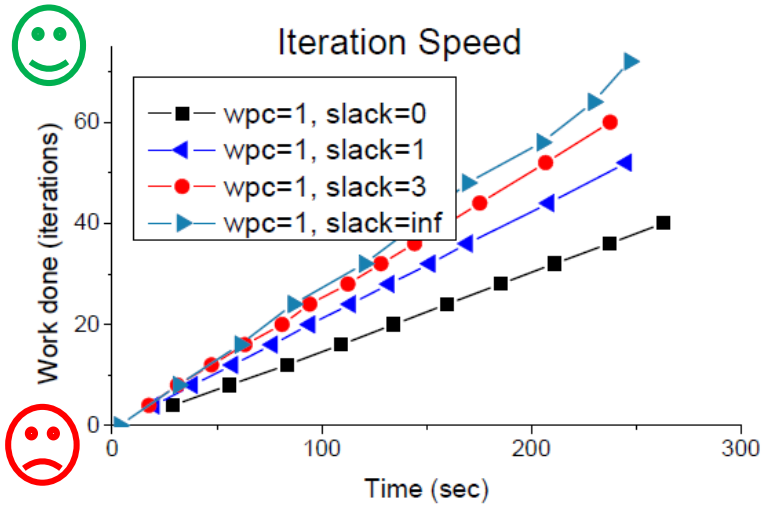
Protocol: check cache first; if too old, get latest version from network

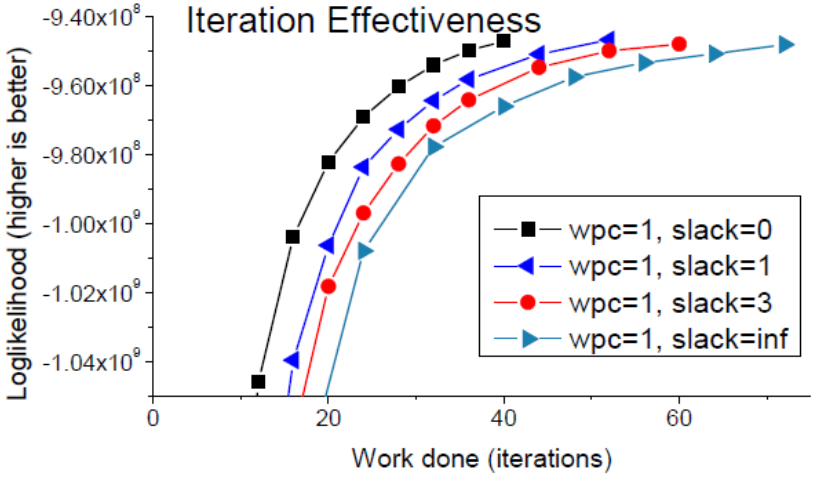
Choice of S: Staleness "sweet spot"

**Exploits: 1. commutative/associative updates &**
**2. tolerance for lazy consistency (bounded staleness)**

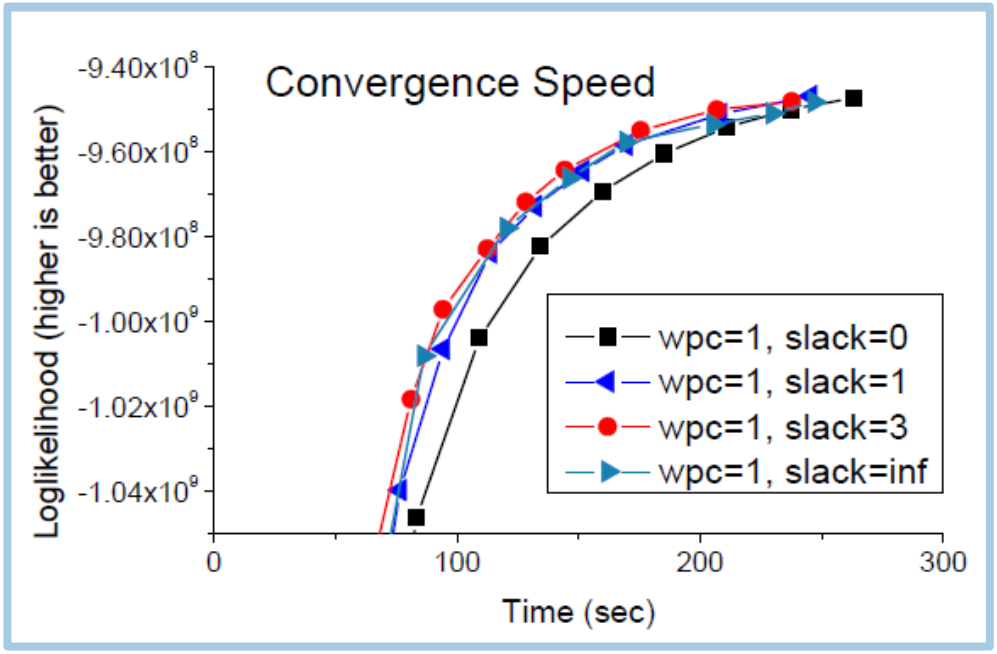
[NIPS'13]
[ATC'14]

# Staleness Sweet Spot




**Topic Modeling**
Nytimes dataset
400k documents
100 topics
LDA w/Gibbs sampling
8 machines x 64 cores
40Gbps Infiniband




[ATC'14]

# What's So Special about Big Learning? …A Distributed Systems Perspective

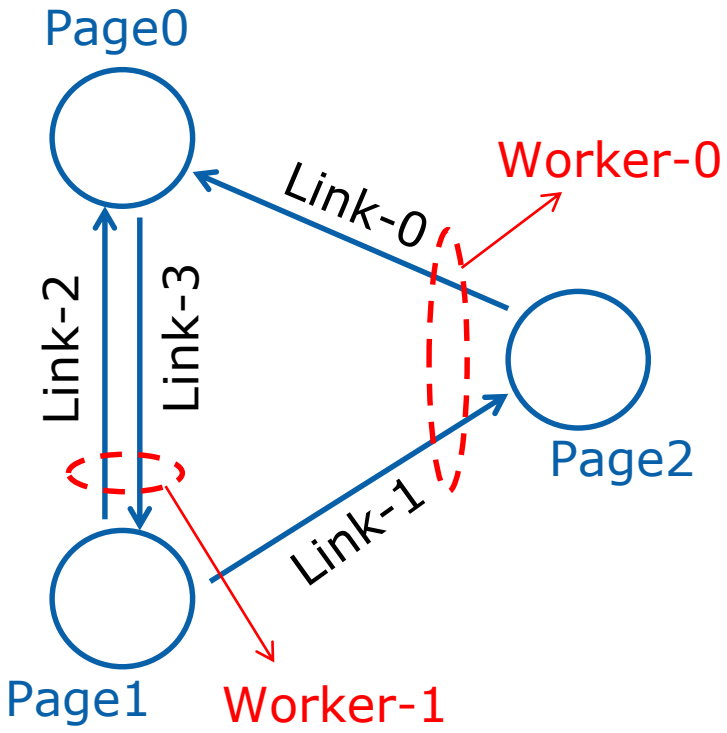
**The Good News**

1. **Commutative/Associative parameter updates**
2. **Tolerance for lazy consistency of parameters**
3. **Repeated parameter data access pattern** ⬅
4. **Intra-iteration progress measure**
5. **Parameter update importance hints**
6. **Layer-by-layer pattern of deep learning**
7. **Most parameter updates are insignificant**

**…can exploit to run orders of magnitude faster!**

# Repeated Data Access in PageRank

**Input data:** a set of links, stored locally in workers
**Parameter data:** ranks of pages, stored in PS




```
Init ranks to random value
loop
   foreach link from i to j {
      read Rank(i)
      update Rank(j)
   }
while not converged
```

# Repeated Data Access in PageRank

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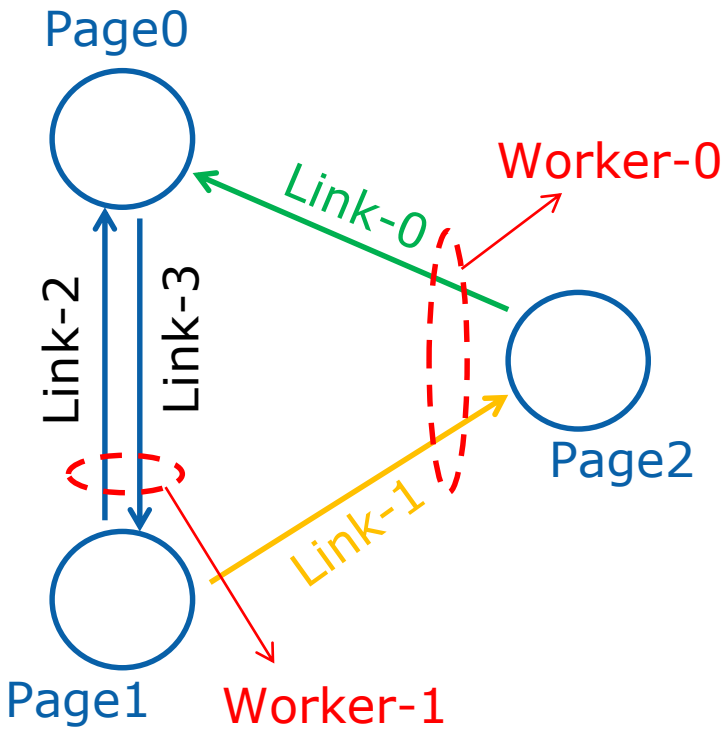
**Parameter data:** ranks of pages, stored in PS




Worker-0

**loop**
```
    # Link-0
    read page[2].rank
    update page[0].rank
    # Link-1
    read page[1].rank
    update page[2].rank
    clock()
```
**while** not converged

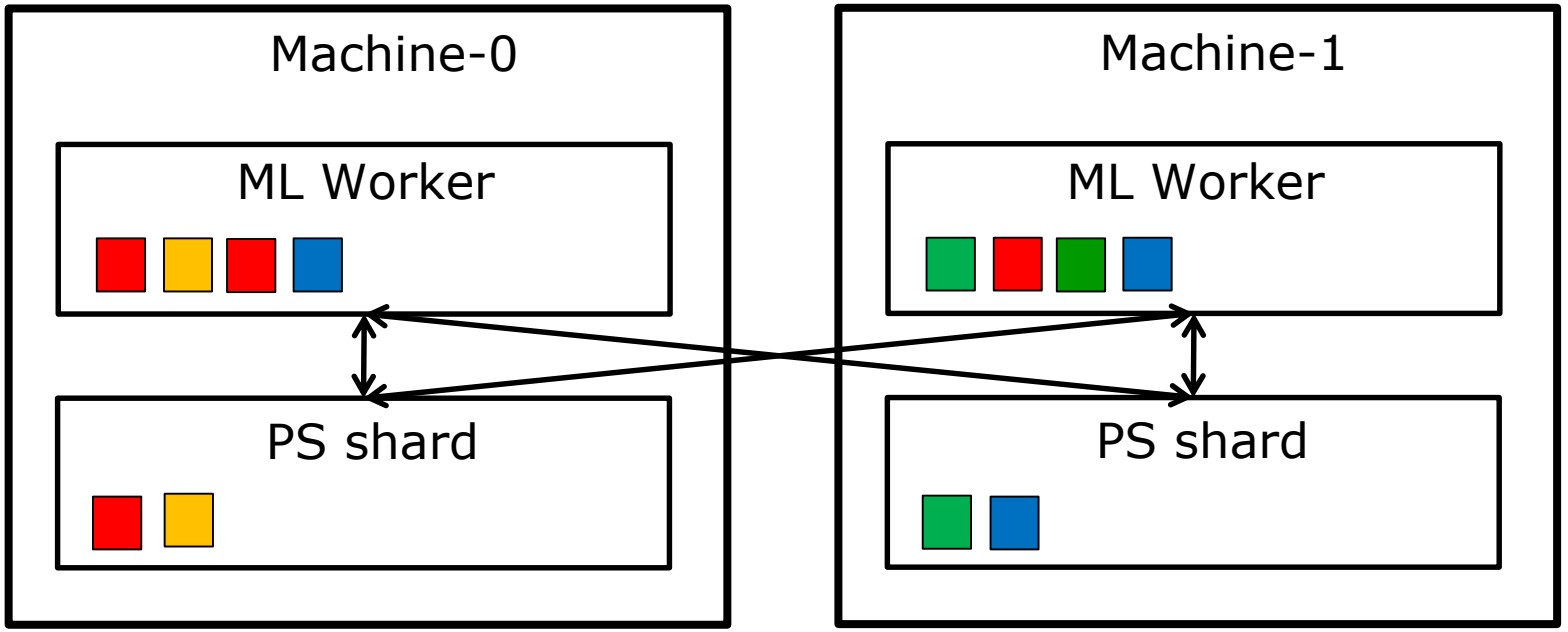
**Repeated access sequence depends only on input data (not on parameter values)**

# Exploiting Repeated Data Access

## Collect access sequence in "virtual iteration"

**Enables many optimizations:**

1. **Parameter data placement across machines**



# Exploiting Repeated Data Access

## Collect access sequence in "virtual iteration"

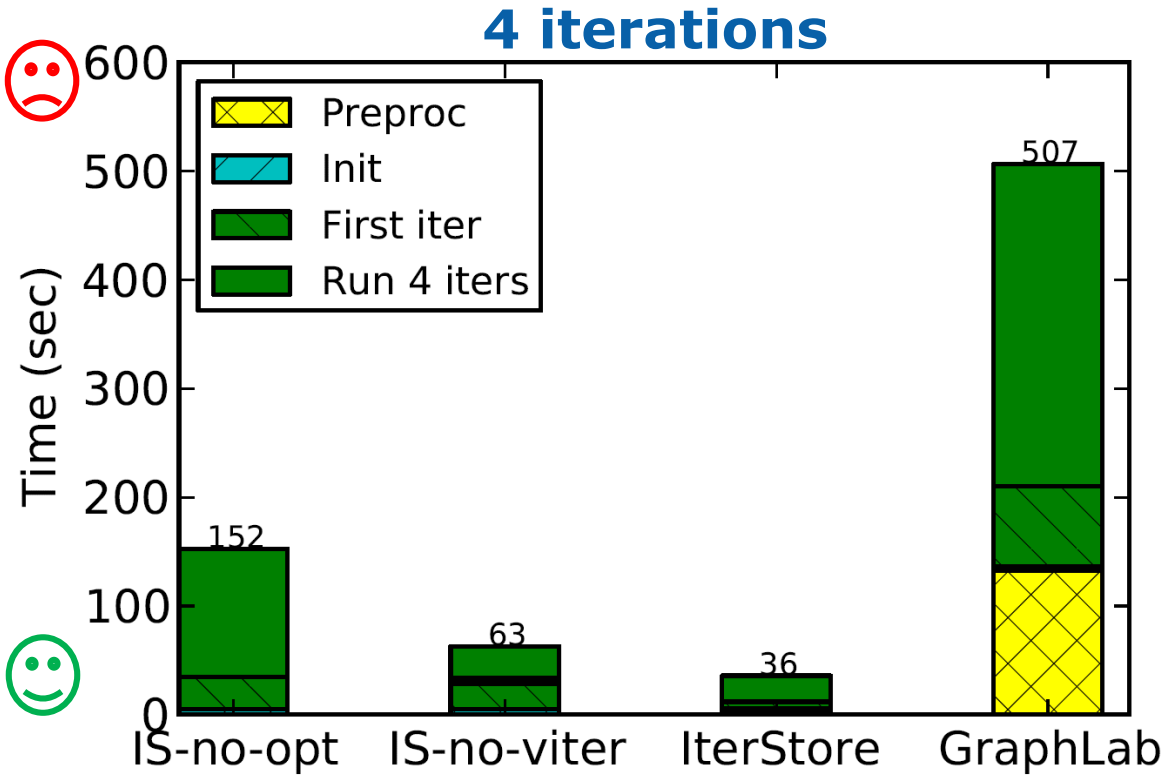
**Enables many optimizations:**

1. **Parameter data placement across machines**
2. **Prefetching**
3. **Static cache policies**
4. **More efficient marshalling-free data structures**
5. **NUMA-aware memory placement**

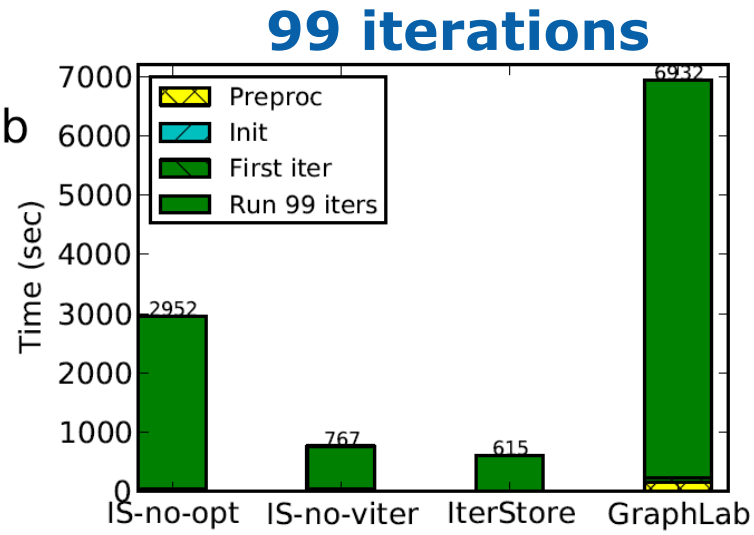
- **Benefits are resilient to moderate deviation in an iteration's actual access pattern**

# IterStore: Exploiting Iterativeness

[SoCC'14]




Collaborative Filtering
(Matrix Factorization)
NetFlix data set
8 machines x 64 cores
40 Gbps Infiniband




**4-5x faster than baseline**
**11x faster than GraphLab**

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# Addressing the Straggler Problem

- **Many sources of transient straggler effects**
  - Resource contention
  - System processes (e.g., garbage collection)
  - Slow mini-batch at a worker

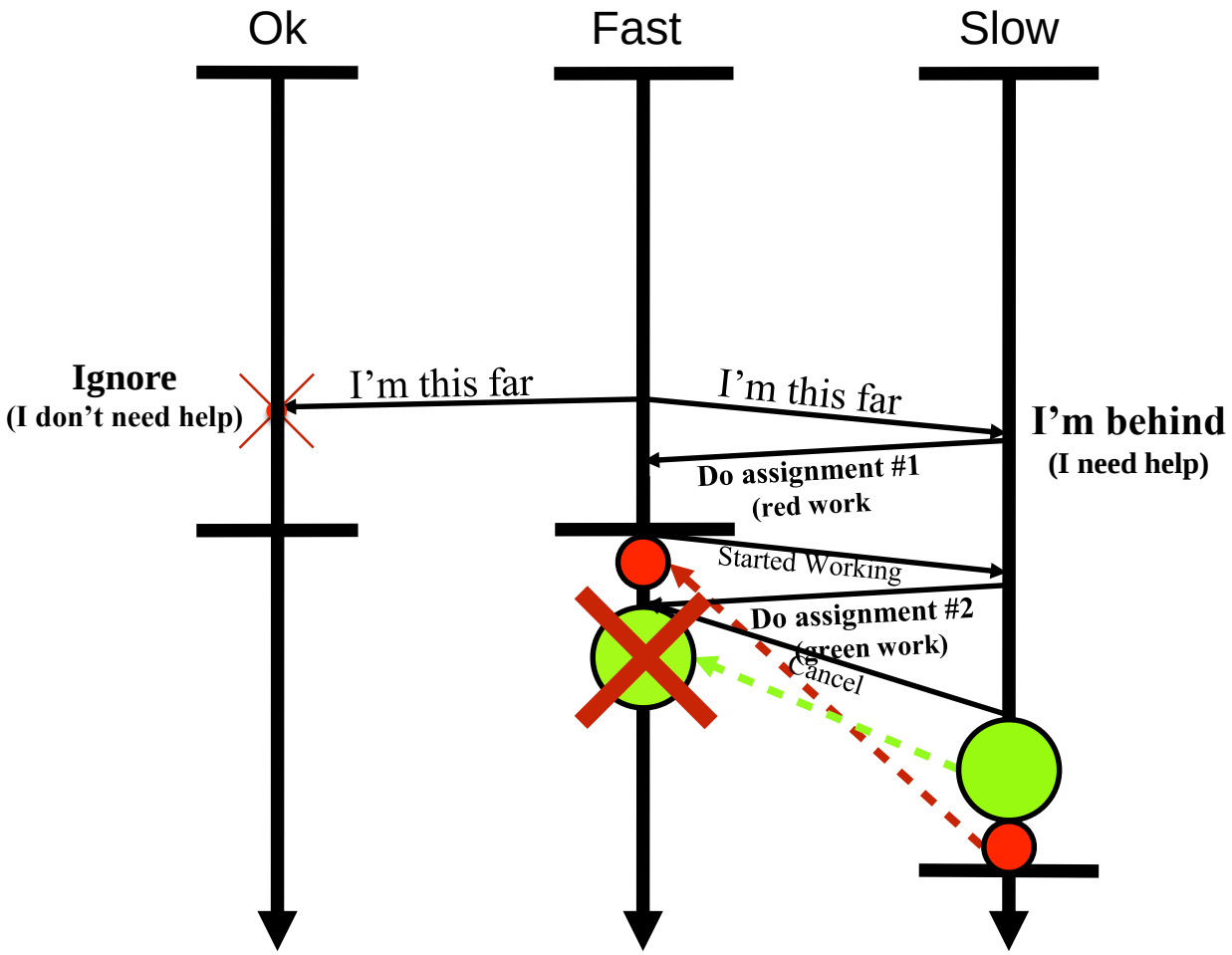
  **Causes significant slowdowns for Big Learning**

- **FlexRR: SSP + Low-overhead work migration (RR) to mitigate transient straggler effects**
  - Simple: Tailored to Big Learning's special properties

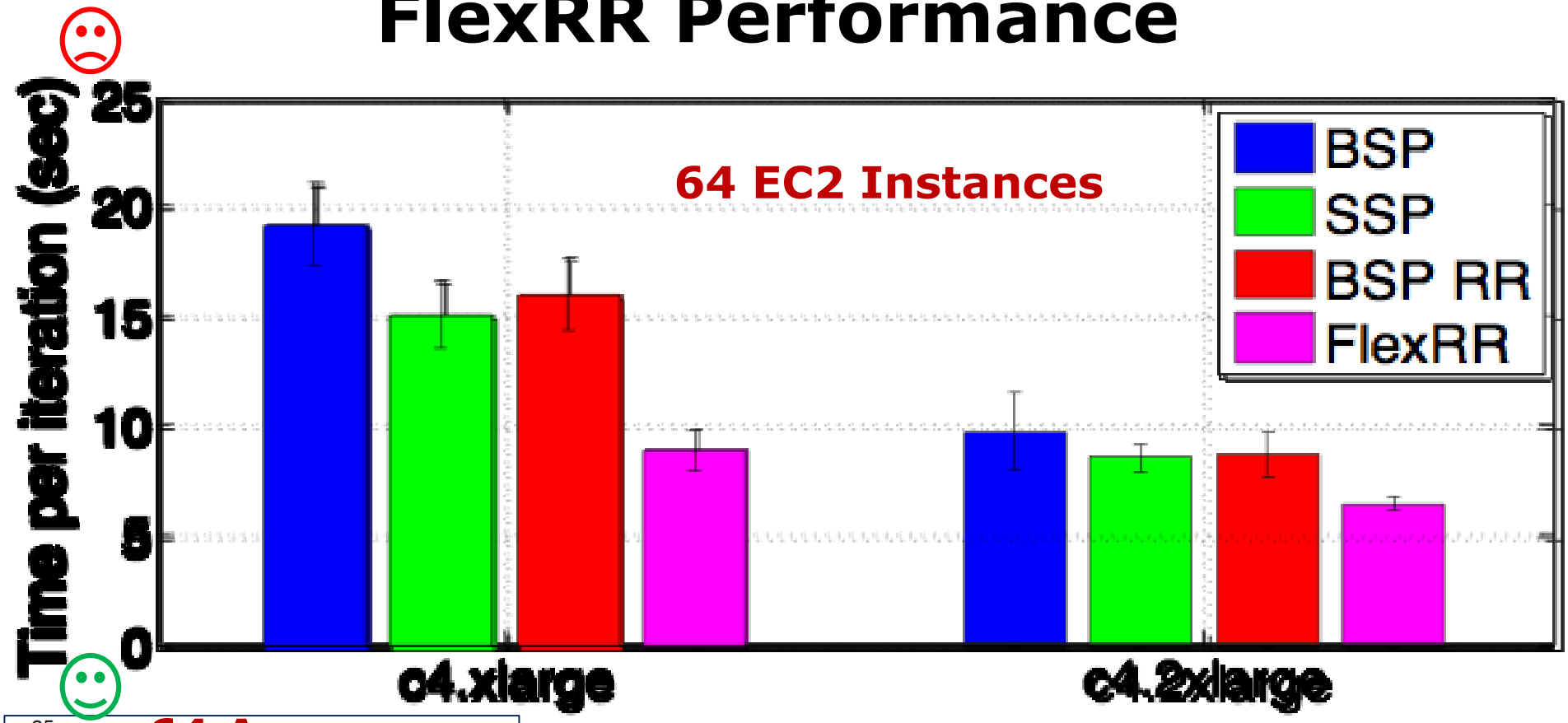
    E.g., cloning (used in MapReduce) would break the algorithm (violates idempotency)!
  - Staleness provides slack to do the migration

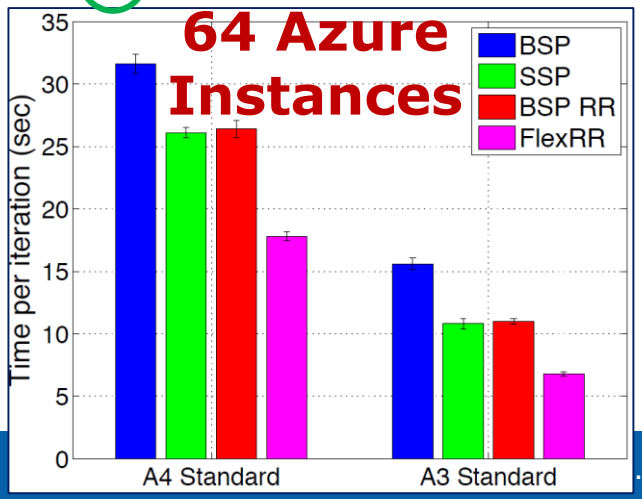
# Rapid-Reassignment (RR) Protocol

- Multicast to preset possible helpees (has copy of tail of helpee's input data)
- Intra-iteration progress measure: percentage of input data processed
- Can process input data in any order
- Assignment is percentage range
- State is only in PS
- Work must be done exactly once



# FlexRR Performance




Matrix Factorization
Netflix dataset

[SoCC'16]

**Both SSP & RR required.**
**Nearly ideal straggler mitigation**

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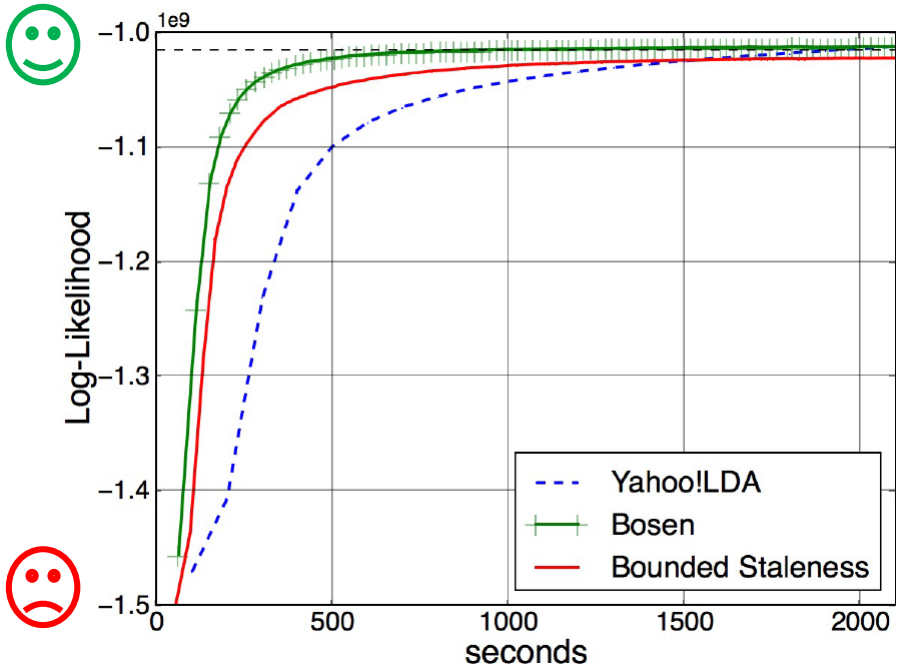
# Bosen: Managed Communication

- **Combine SSP's lazy transmission of parameter updates with:**
  - early transmission of larger parameter changes

  (Idea: larger change likely to be an important update)
  - up to bandwidth limit & staleness limit




LDA Topic Modeling
Nytimes dataset
16x8 cores

[SoCC'15]

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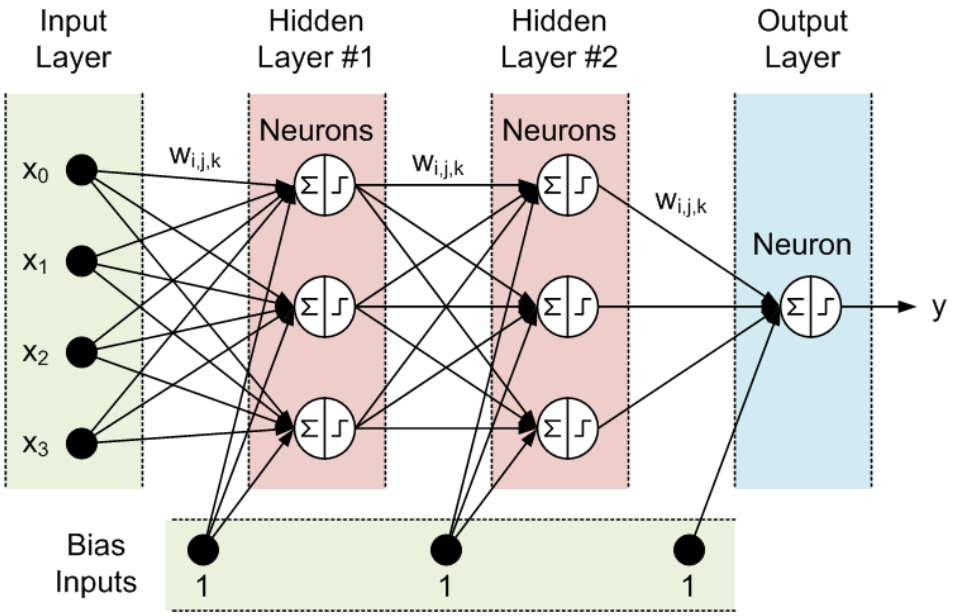
# Recall: Data Analysis with Deep Neural Networks

## Task:

- Compute classification of set of input signals



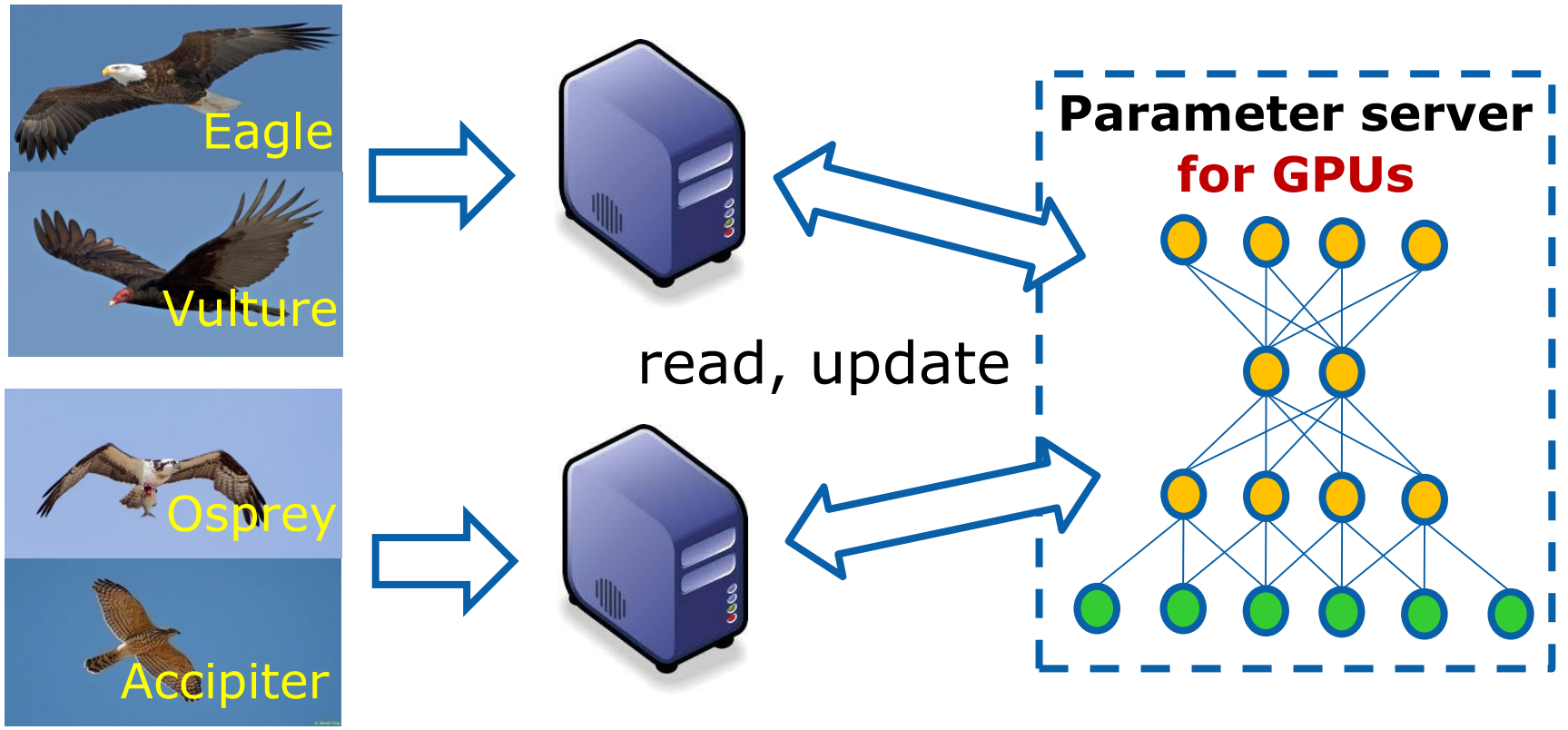

## Training

- Use many training samples of form input / desired output
- Compute weights that minimize classification error

## Operation

- Propagate signals from input to output

# Distributed Deep Learning

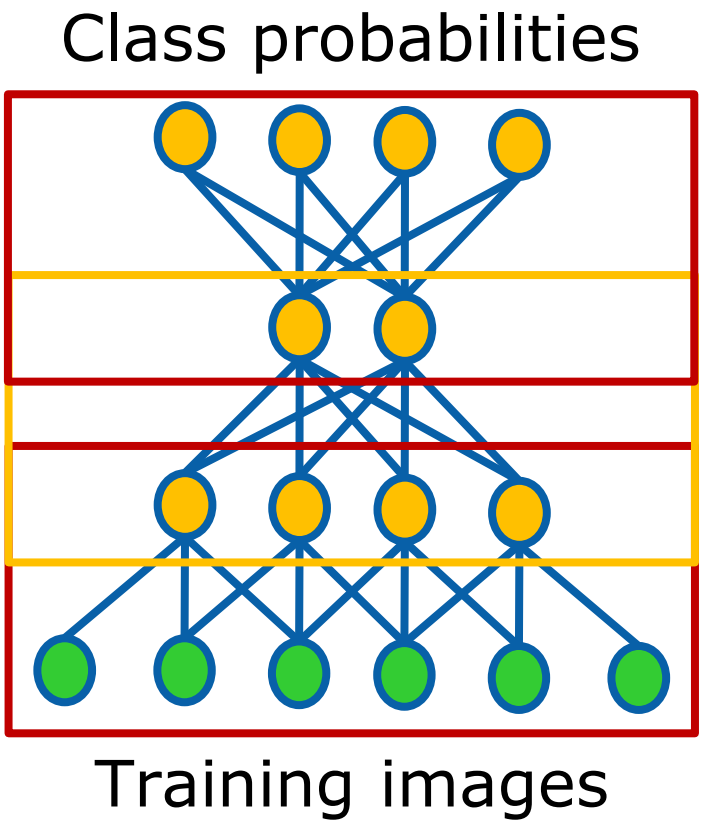



**Partitioned** training data

**Distributed** ML workers

**Shared** model parameters

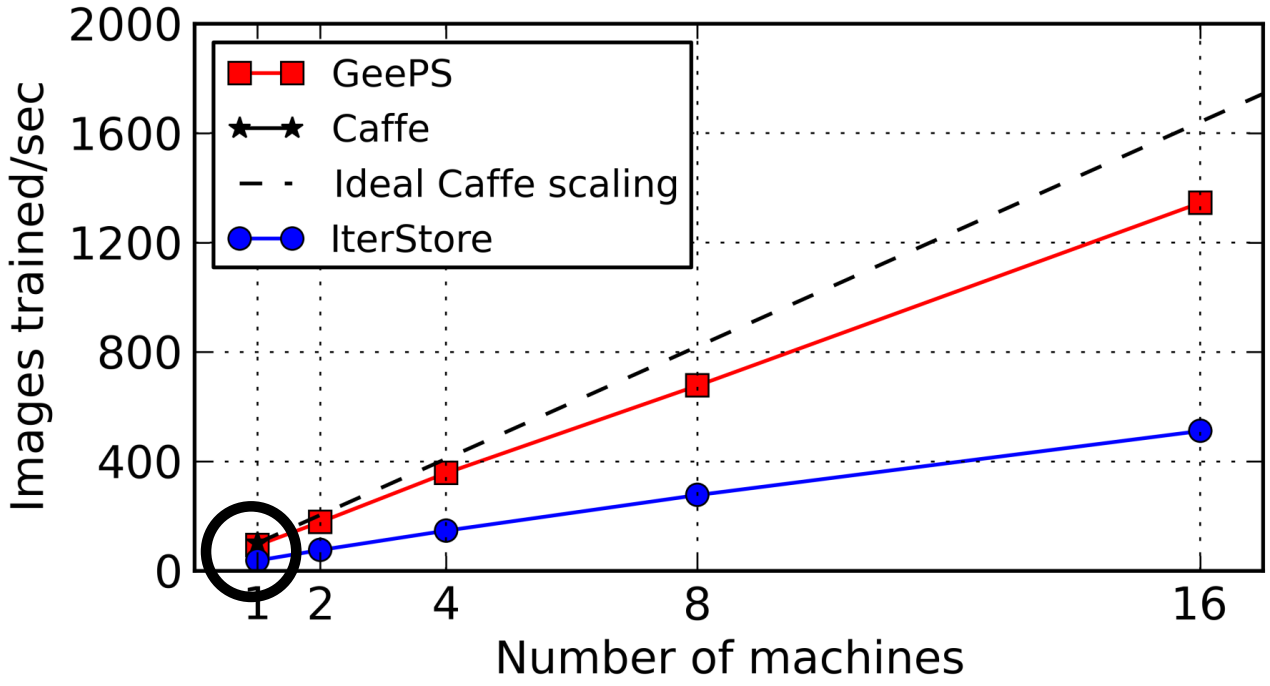
# Layer-by-Layer Pattern of DNN




- For each iteration (mini-batch)
  - A forward pass
  - Then a backward pass
- Pairs of layers used at a time

# GeePS: Parameter Server for GPUs

- **Careful management of GPU & CPU memory**
  - Use GPU memory as cache to hold pairs of layers
  - Stage remaining data in larger CPU memory




ImageNet22K
Adam model

[EuroSys'16]

GeePS is 13x faster than Caffe (1 GPU) on 16 machines,
2.6x faster than IterStore (CPU parameter server)

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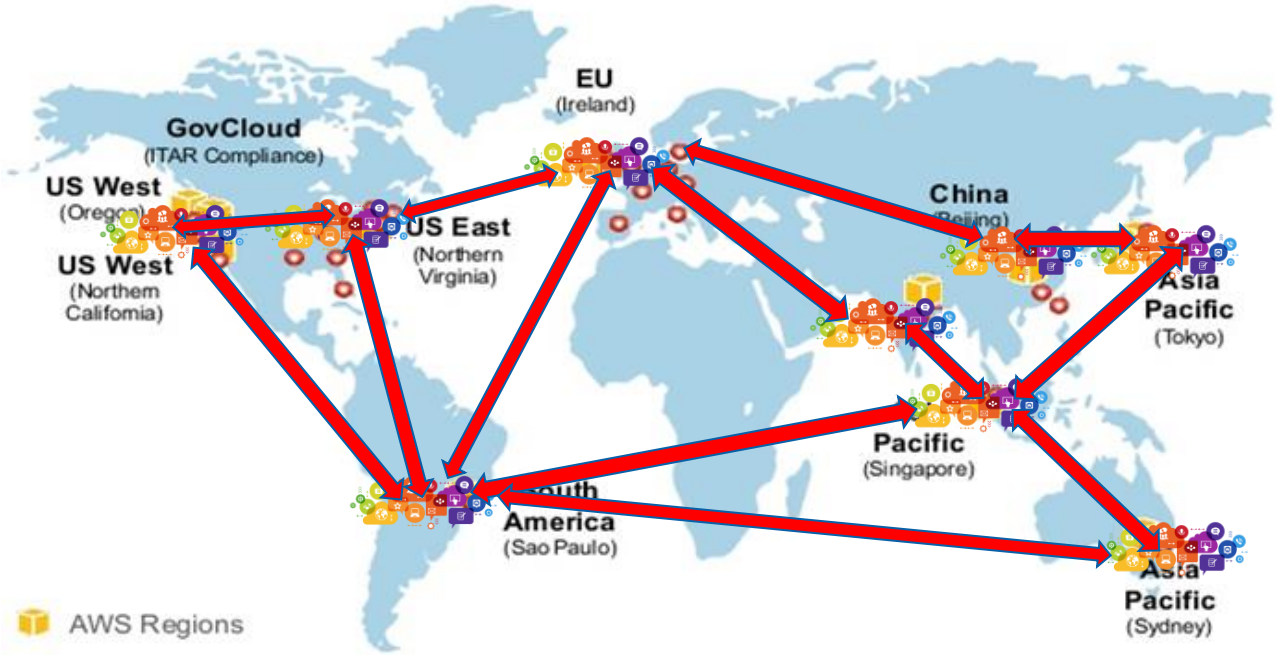
# Geo-Distributed Machine Learning

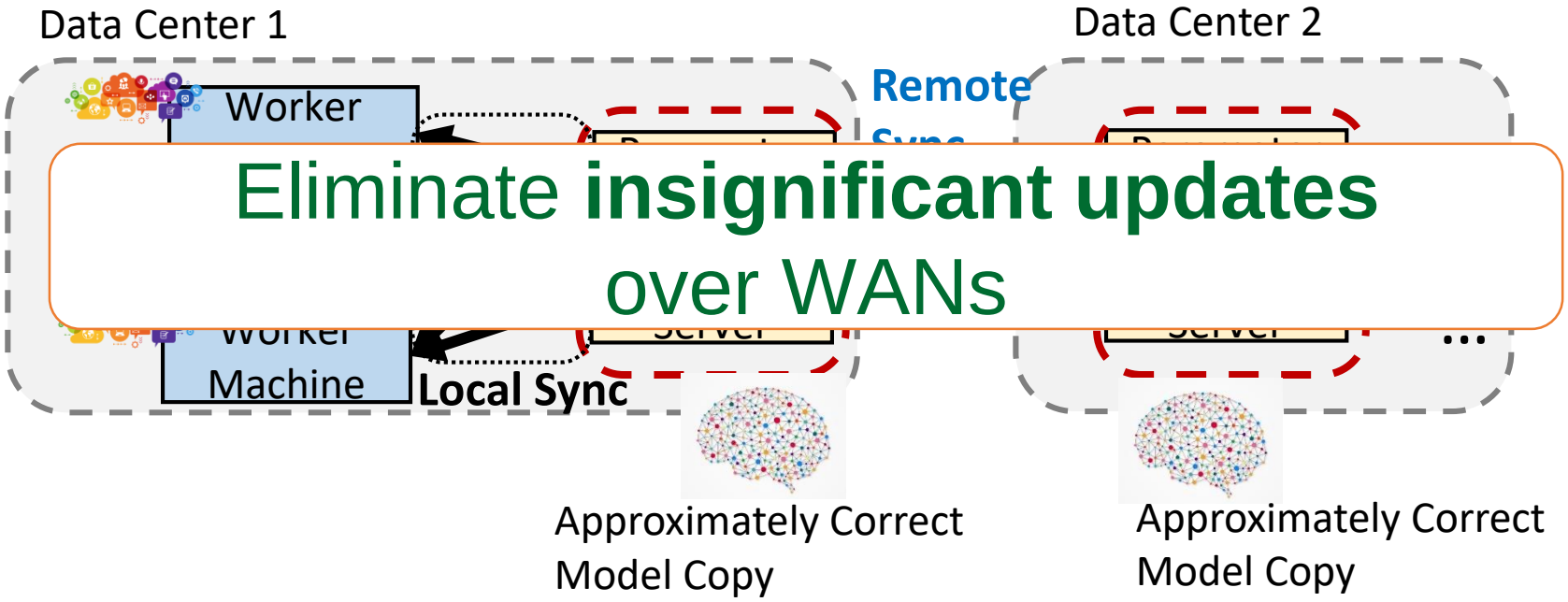
- **Data sources are everywhere (geo-distributed)**
  - Too expensive (or not permitted) to ship all data to single data center




- **ML training done across the WAN**

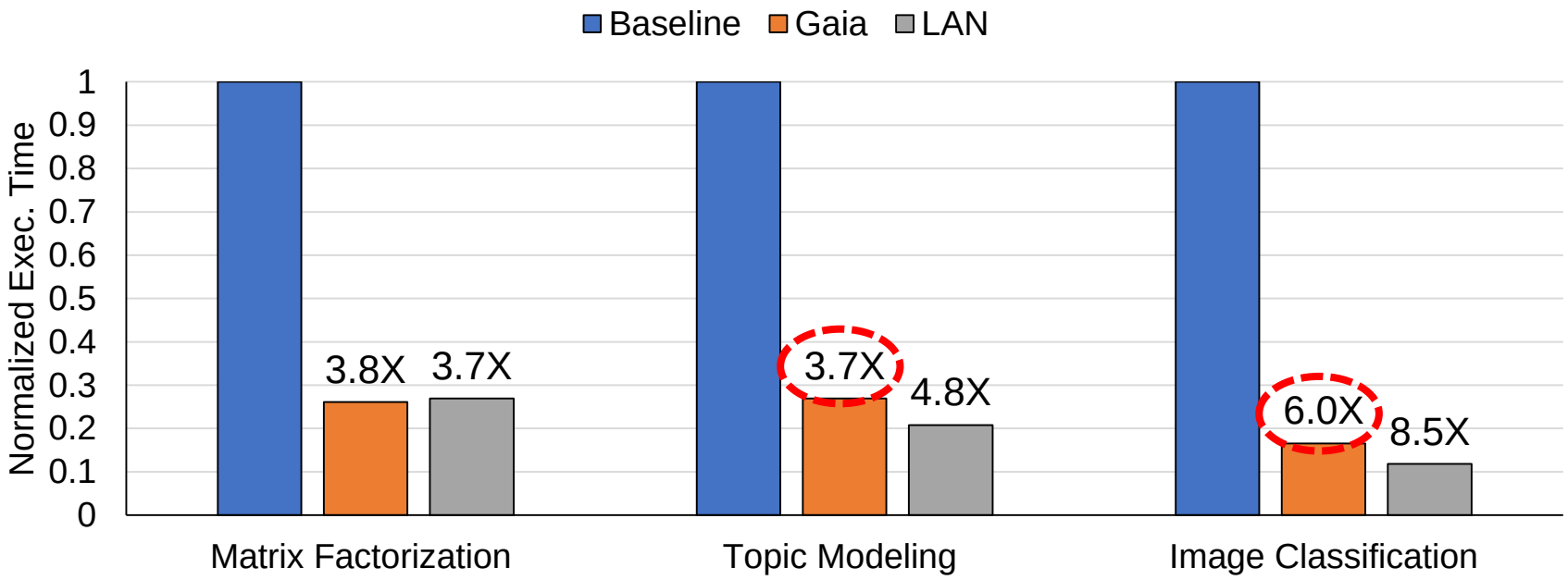
# Gaia System Overview

- **Key idea**: Decouple the synchronization model *within* the data center from the synchronization model *between* data centers




[NSDI'17]

# Performance – 11 EC2 Data Centers




**Gaia achieves 3.7-6.0X speedup over Baseline**

**Gaia is within 1.40X of LAN speeds**

**Also: Gaia is 2.6-8.5X cheaper than Baseline**

Baseline: IterStore for CPUs, GeePS for GPUs

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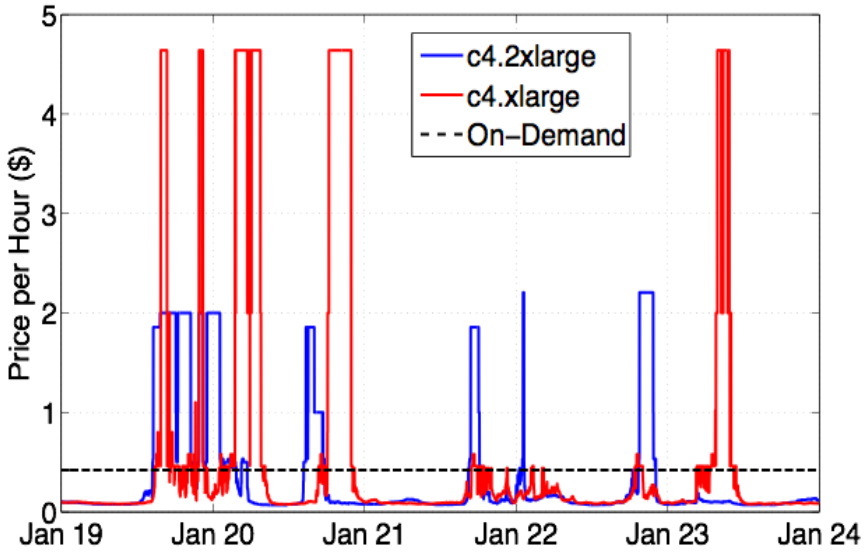
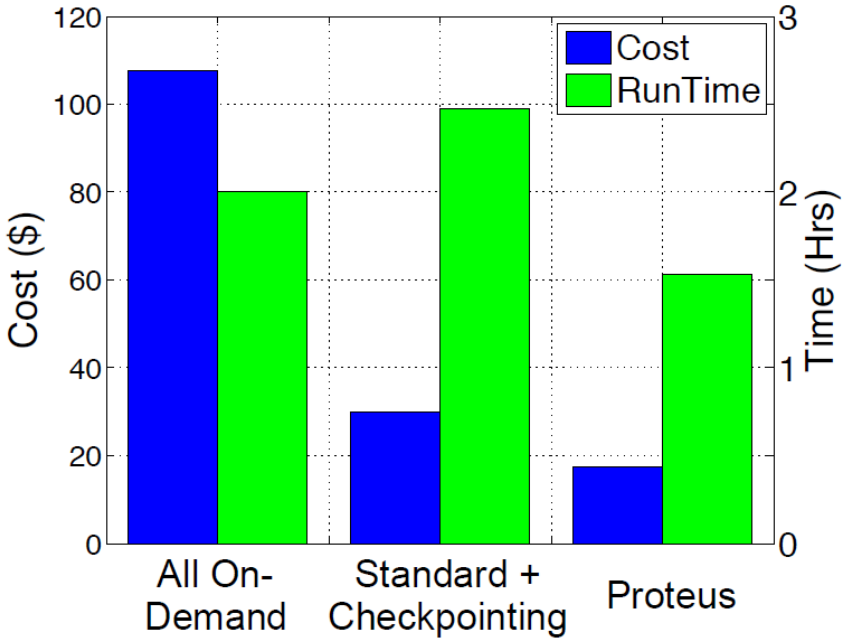
# Proteus: Playing the Spot Market

- **Spot Instances are often 85%-90% cheaper, but can be taken away at short notice**




Different machine types have uncorrelated spikes




[EuroSys'17]

**Proteus uses agile tiers of reliability + aggressive bidding for cheap (free) compute**

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# Thanks to Collaborators & Sponsors

- **CMU Faculty:** **Greg Ganger**, **Garth Gibson**, **Eric Xing**

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(Many of these slides adapted from slides by the students)

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# Thanks for a Great Semester!


# Good Luck on the Final!