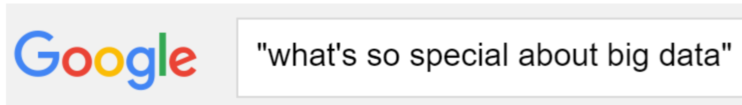
Future of Computing II:
What's So Special About Big Learning?

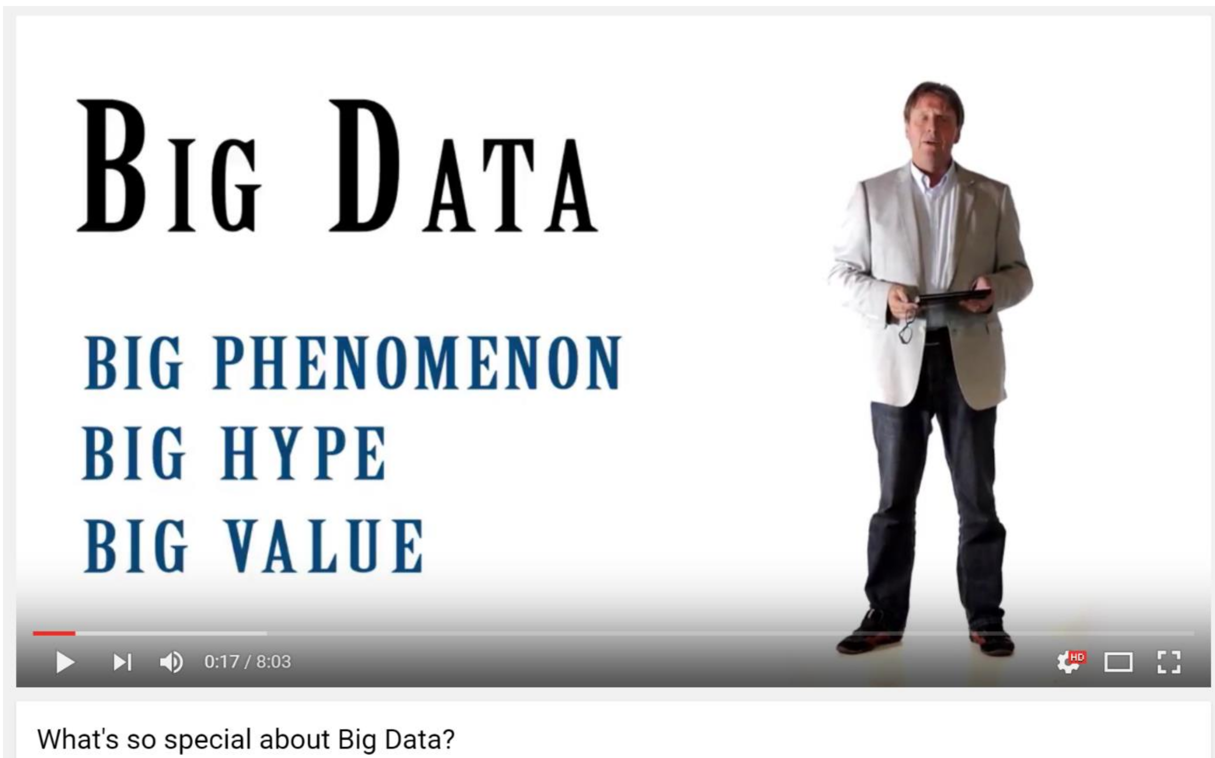
15-213 / 18-213 / 15-513: Introduction to Computer Systems
28th Lecture, December 5, 2017

Today's Instructor:

Phil Gibbons

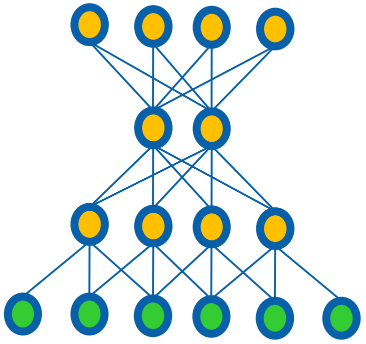
What’s So Special about…Big Data?





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

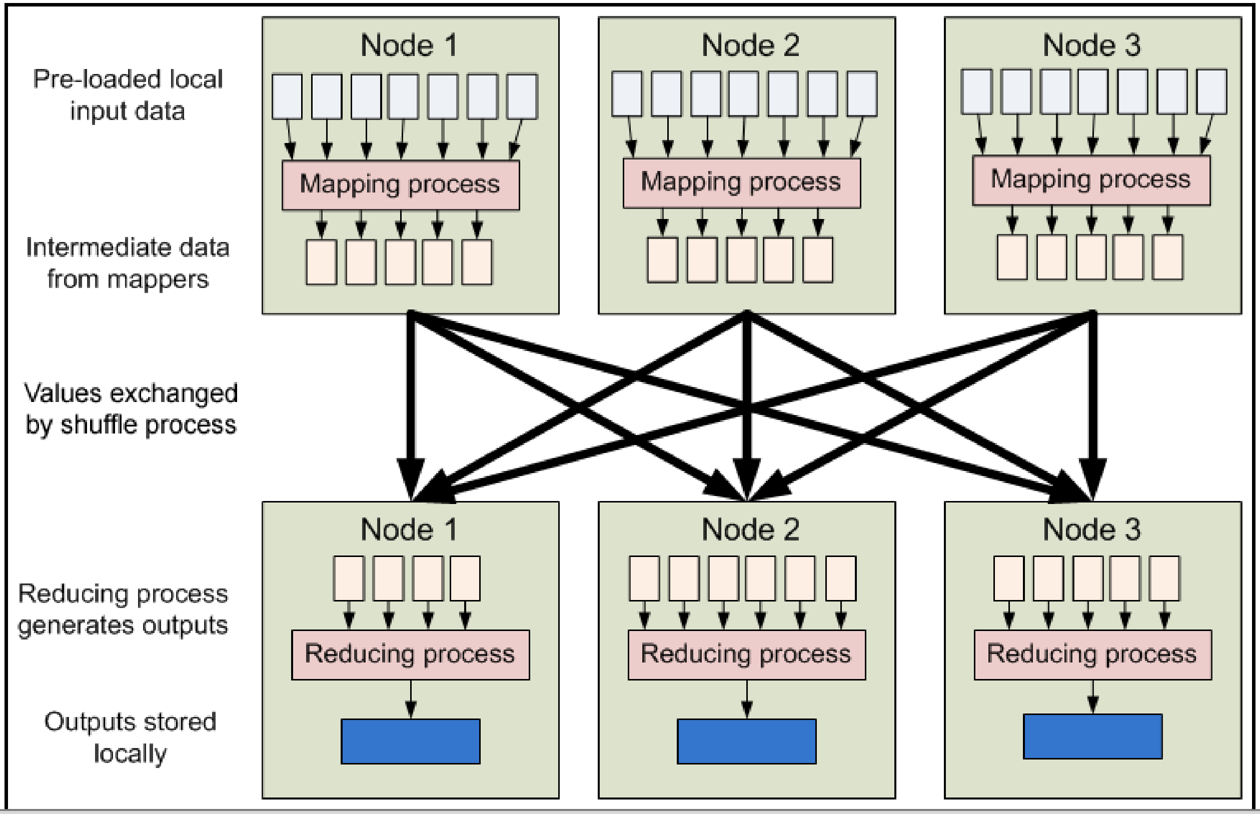
Big Learning Frameworks & Systems

- **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-)

Hadoop

- **Hadoop Distributed File System (HDFS)**
- **Hadoop YARN resource scheduler**
- **Hadoop MapReduce**

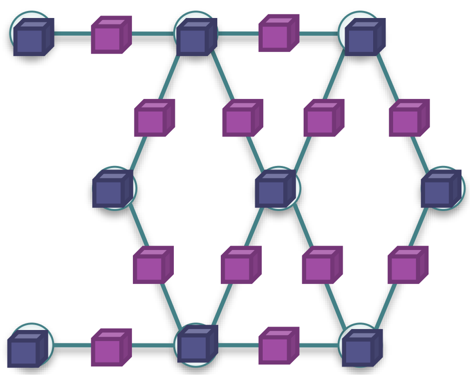


Key Learning: Ease of use trumps performance

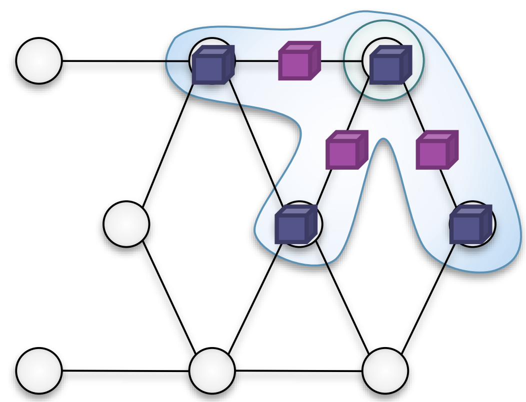
GraphLab

Graph Parallel: "Think like a vertex"

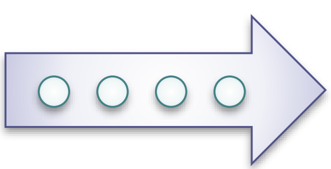
Graph Based
Data Representation



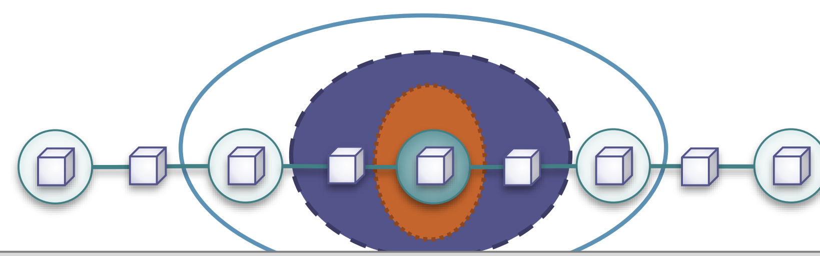
Update Functions
User Computation



Scheduler



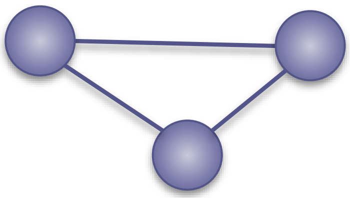
Consistency Model



Slide courtesy of Carlos Guestrin

Key Learning: Graph Parallel is quite useful

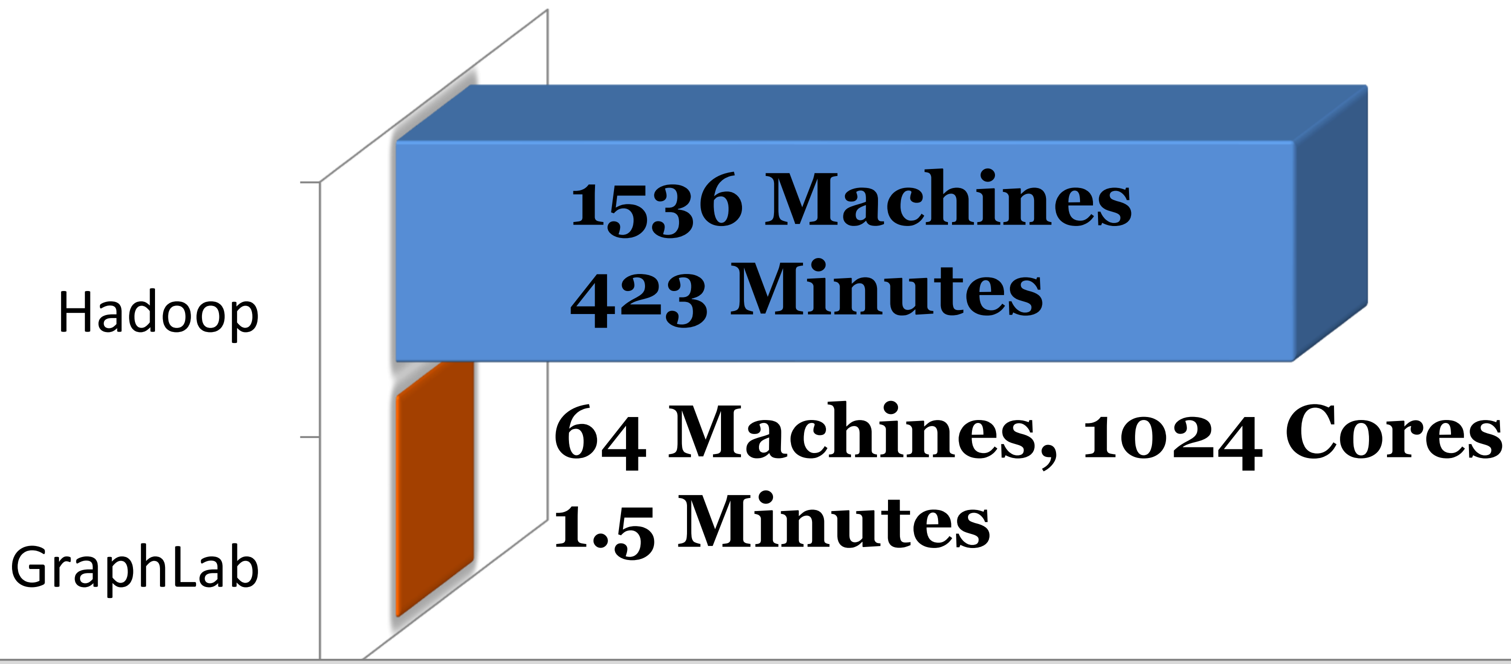
Triangle Counting* in Twitter Graph



***How often are two of a user's friends also friends?**

40M Users
1.2B Edges

Total: 34.8 Billion Triangles



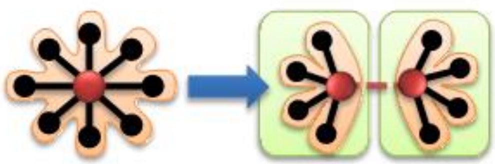
Key Learning:
Graph Parallel is MUCH faster than Hadoop!

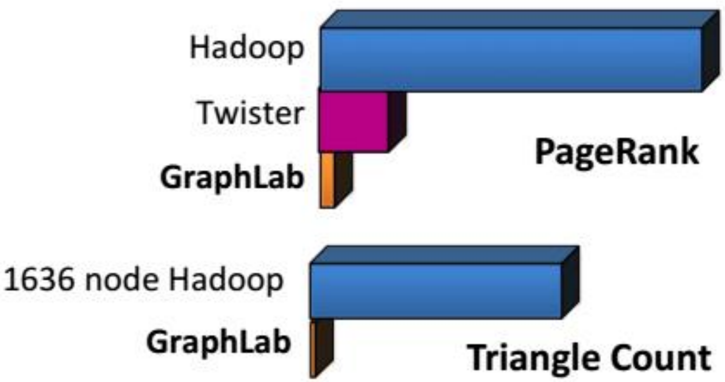
GraphLab & GraphChi

GraphLab 2

Distributed Graph Processing System

How Fast Can we Go?





Disk/SSD Graph Processing System

How Large Can we Go?

20B edges on one Laptop

How to handle high degree nodes: GAS approach

Can do fast BL on a machine w/SSD-resident data

Spark: Key Idea

Features:

- In-memory speed w/fault tolerance via lineage tracking
- Bulk Synchronous

Resilient Distributed Datasets: A Fault-Tolerant Abstraction for InMemory Cluster Computing, [Zaharia et al, NSDI'12, best paper]

A restricted form of shared memory, based on coarse-grained deterministic transformations rather than fine-grained updates to shared state: expressive, efficient and fault tolerant

Lineage Tracking

In-memory compute can be fast & fault-tolerant

Spark's Open Source Impact

Spark Timeline

- Research breakthrough in 2009
- First open source release in 2011
- Into Apache Incubator in 2013
- In all major Hadoop releases by 2014

- Pipeline of research breakthroughs (publications in best conferences) fuel continued leadership & uptake
- Start-up (Databricks), Open Source Developers, and Industry partners (IBM, Intel) make code commercial-grade

Fast path for Academics impact via Open Source: Pipeline of research breakthroughs into widespread commercial use in 2 years!

Big Learning Frameworks & Systems

- **<u>Goal</u>: 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-)

- **<u>Our Idea</u>: 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**

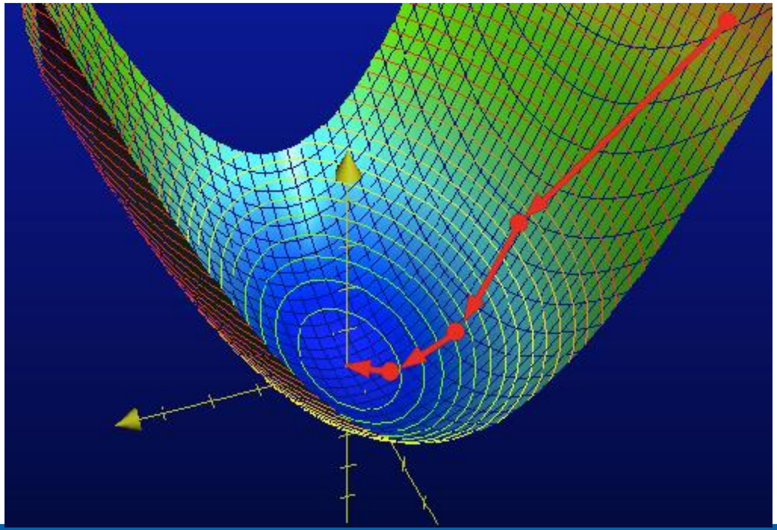


Image from charlesfranzen.com

Recall: Training DNNs

Characteristics

- Iterative numerical algorithm
- Regular data organization

Project Adam Training

- 2B connections
- 15M images
- 62 machines
- 10 days

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

The Bad News

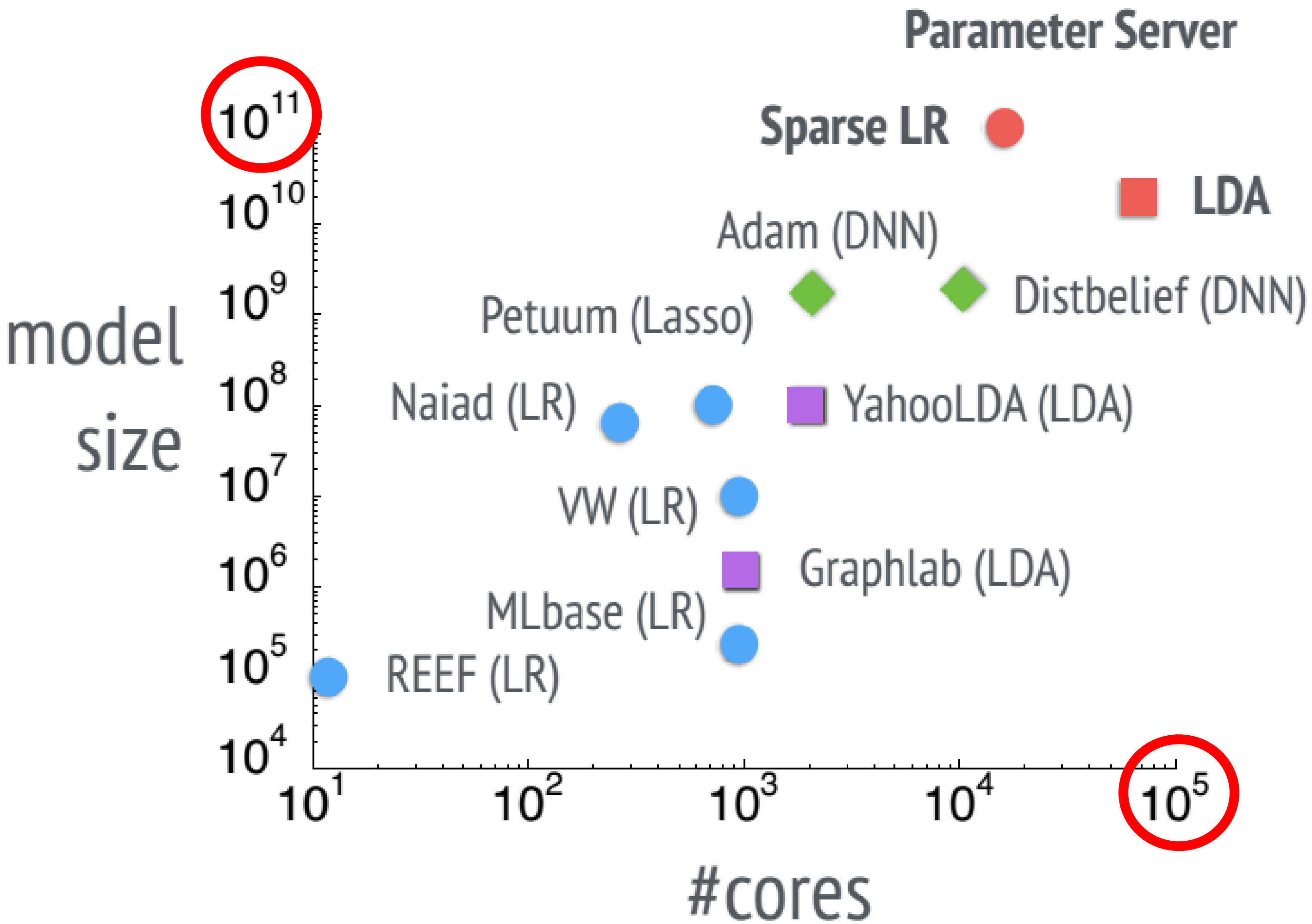
- **Lots of Computation / Memory**
  - Many iterations over Big Data
  - Big Models
  - ➡ Need to distribute computation widely
- **Lots of Communication / Synchronization**
  - Not readily "partitionable"

➡ **Model Training is SLOW**

- hours to days to weeks, even on many machines

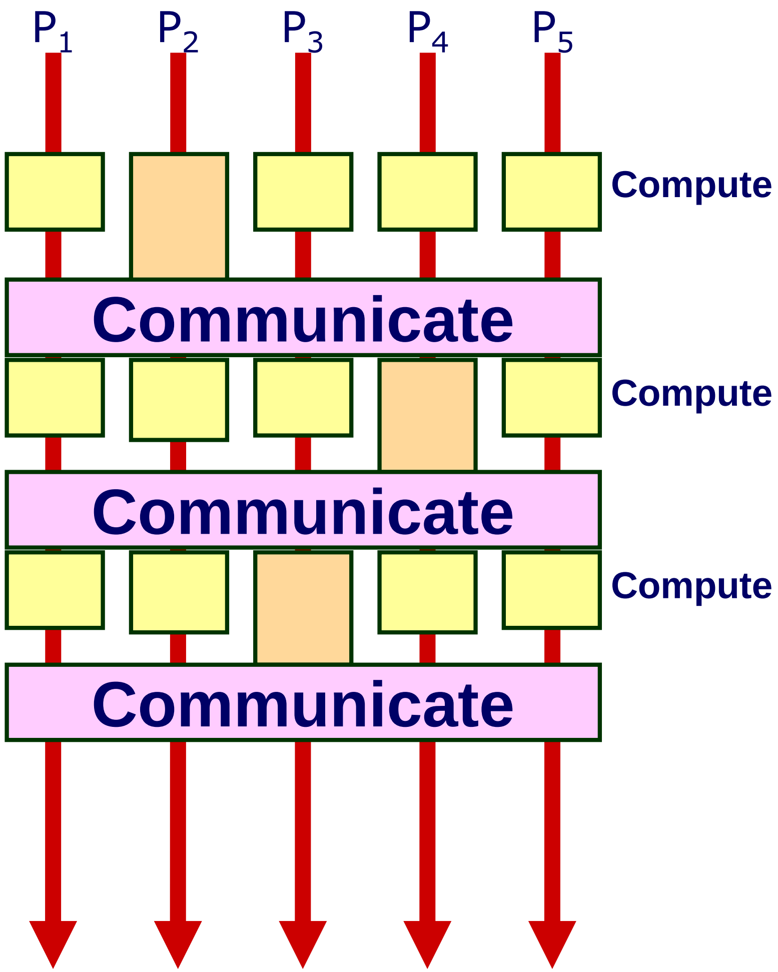
…why good distributed systems research is needed!

Big Models, Widely Distributed



[Li et al, OSDI'14]

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
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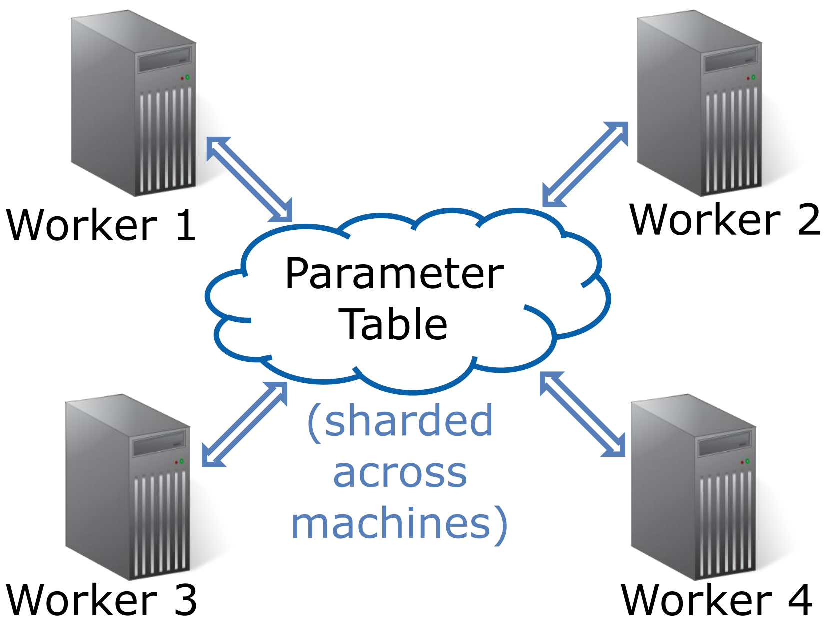
…can exploit to run orders of magnitude faster!

Parameter Servers for Distributed ML

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



Single Machine Parallel

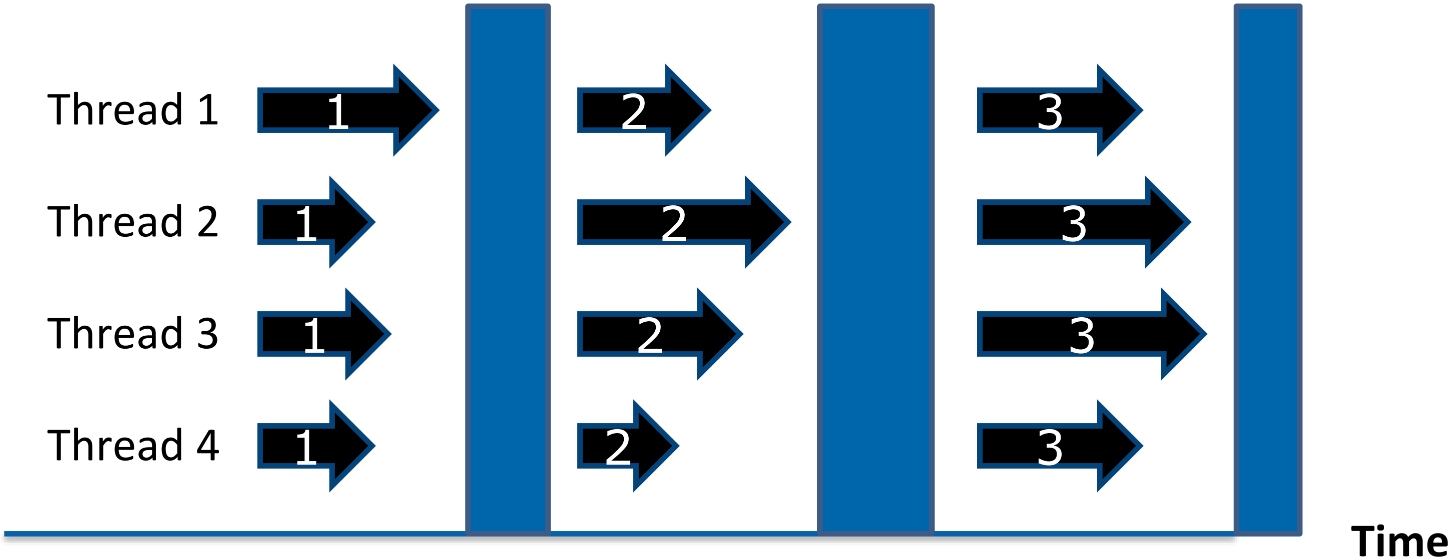
```
UpdateVar(i) {
  old = y[i]
  delta = f(old)
  y[i] += delta }
```

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

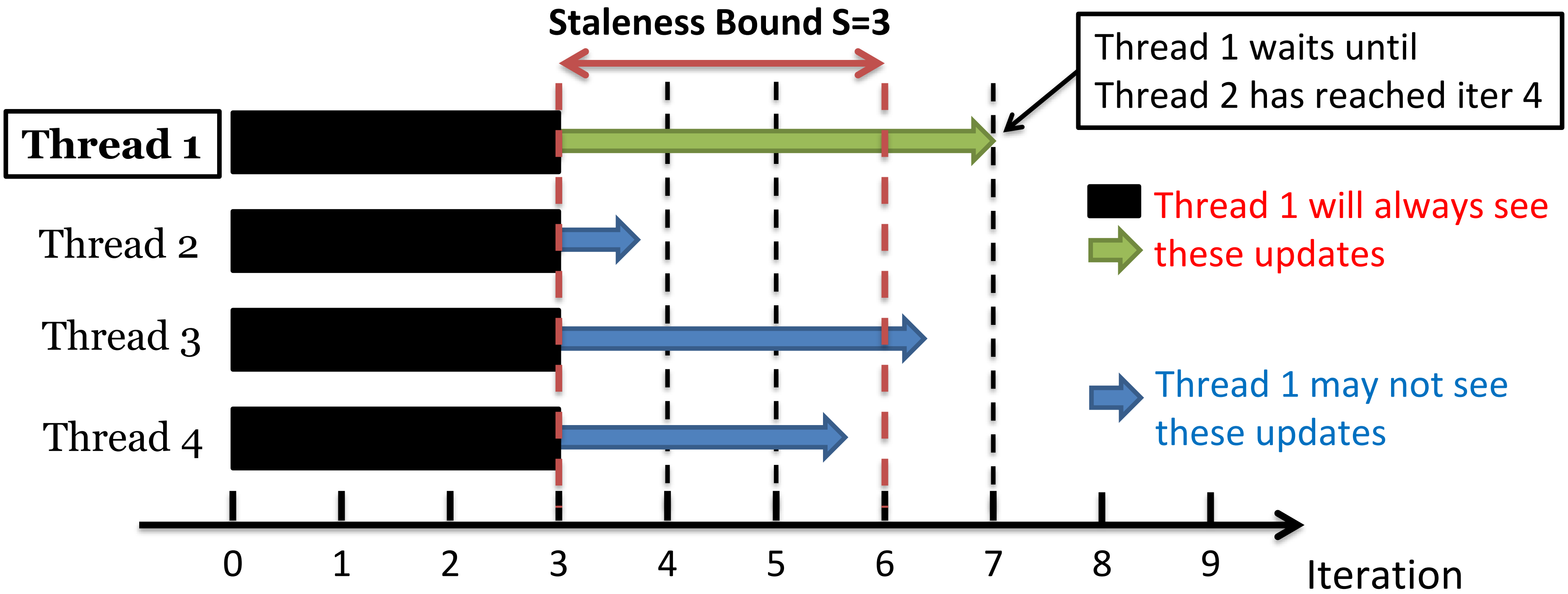


- **Exchange ALL updates at END of each iteration**
- **Synchronize ALL threads each iteration**

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

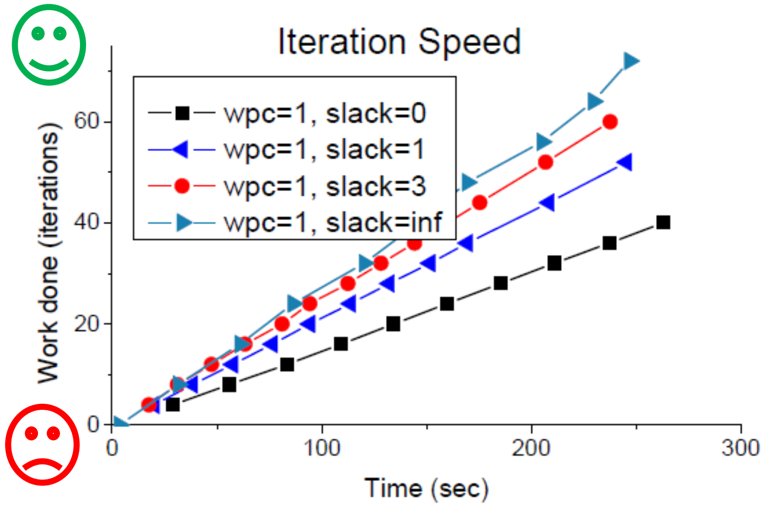
Protocol: check cache first; if too old, get latest version from network

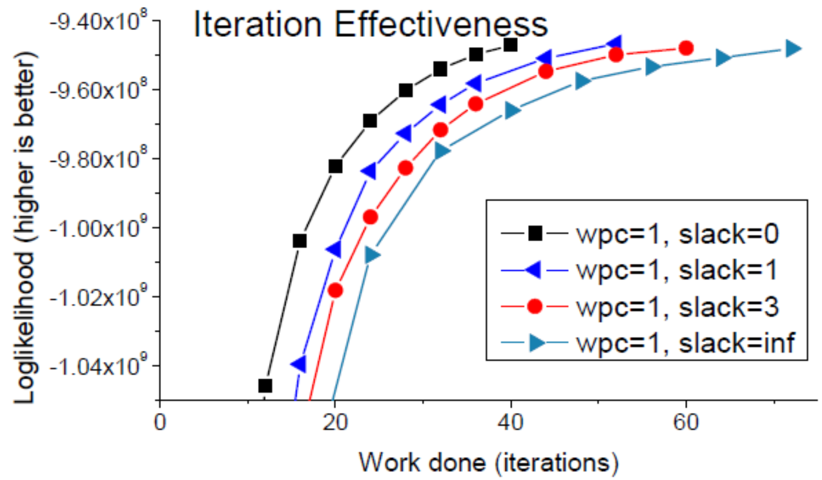
Choice of S: Staleness "sweet spot"

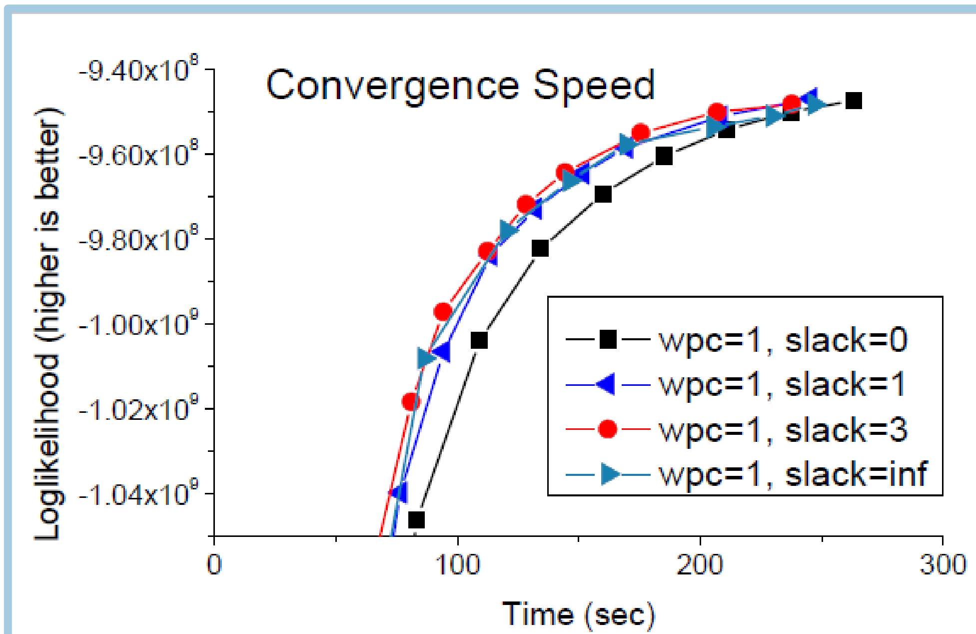
Exploits: 1. commutative/associative updates &
2. tolerance for lazy consistency (bounded staleness)

[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]

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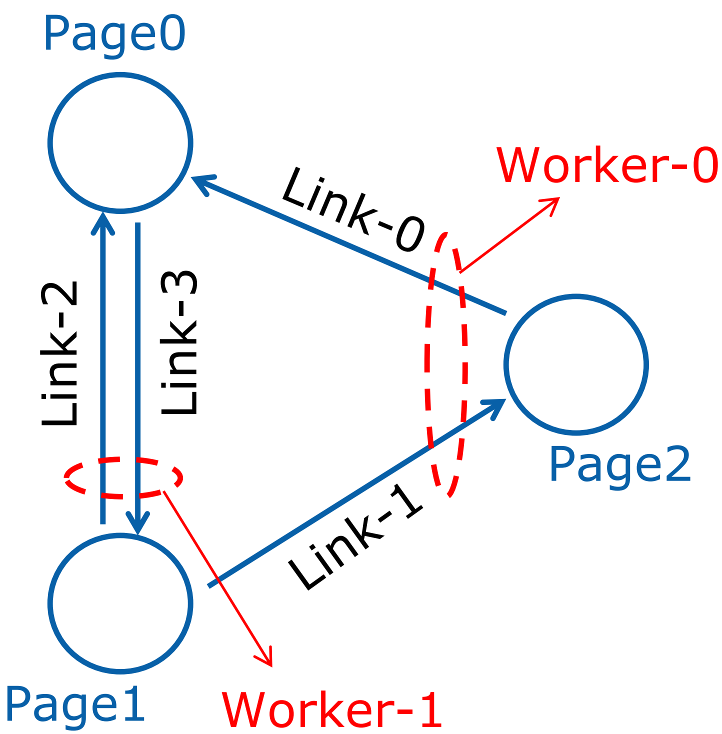
Repeated Data Access in PageRank

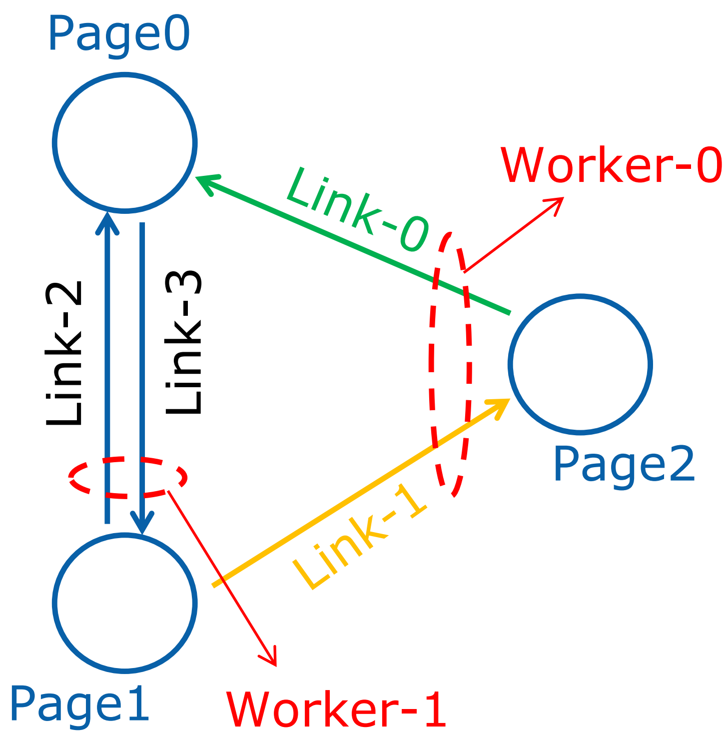
Input data: a set of links, stored locally in workers
Parameter data: ranks of pages, stored in PS



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

Input data: a set of links, stored locally in workers
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

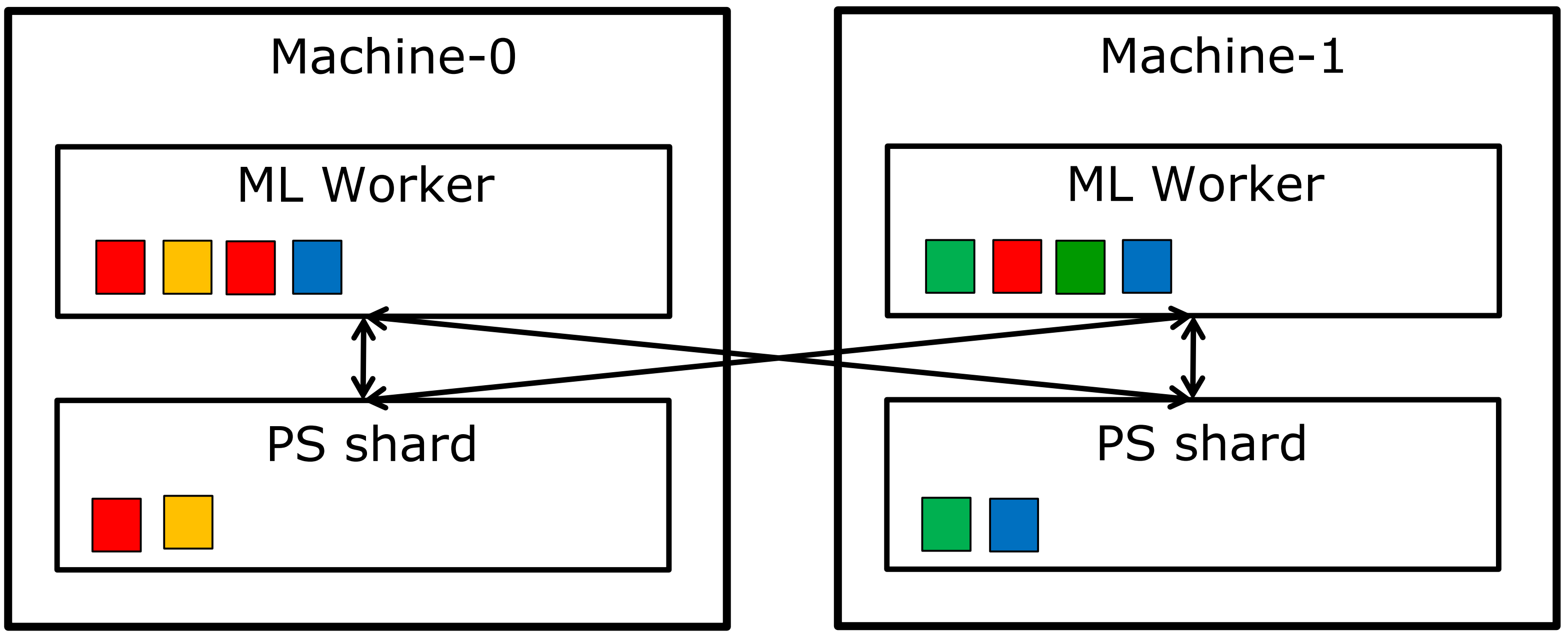
Repeated access sequence depends only on input data (not on parameter values)

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:

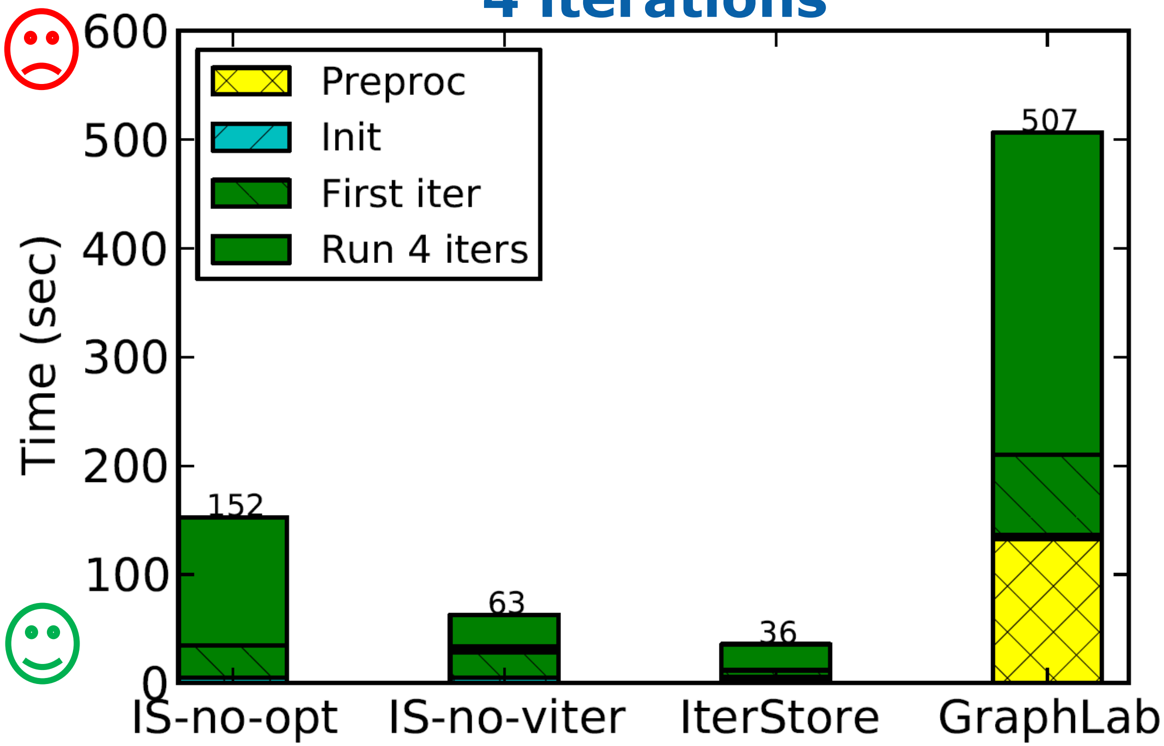
1. Parameter data placement across machines
2. Prefetching
3. Static cache policies
4. More efficient marshalling-free data structures
5. NUMA-aware memory placement

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

IterStore: Exploiting Iterativeness

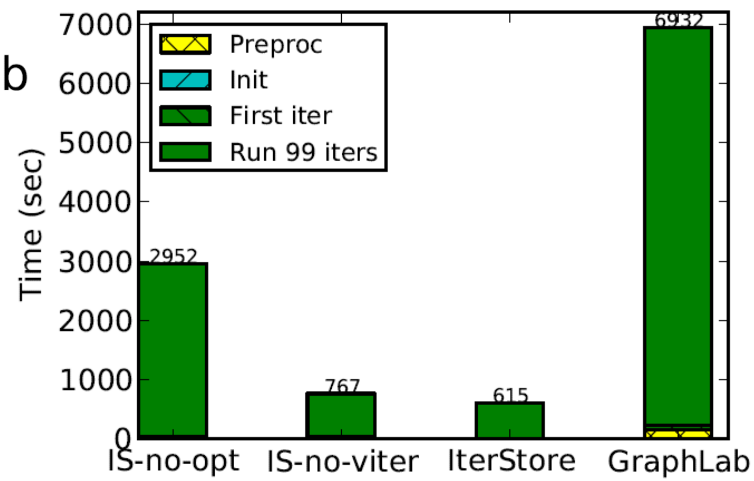
[SoCC'14]

4 iterations



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

99 iterations



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

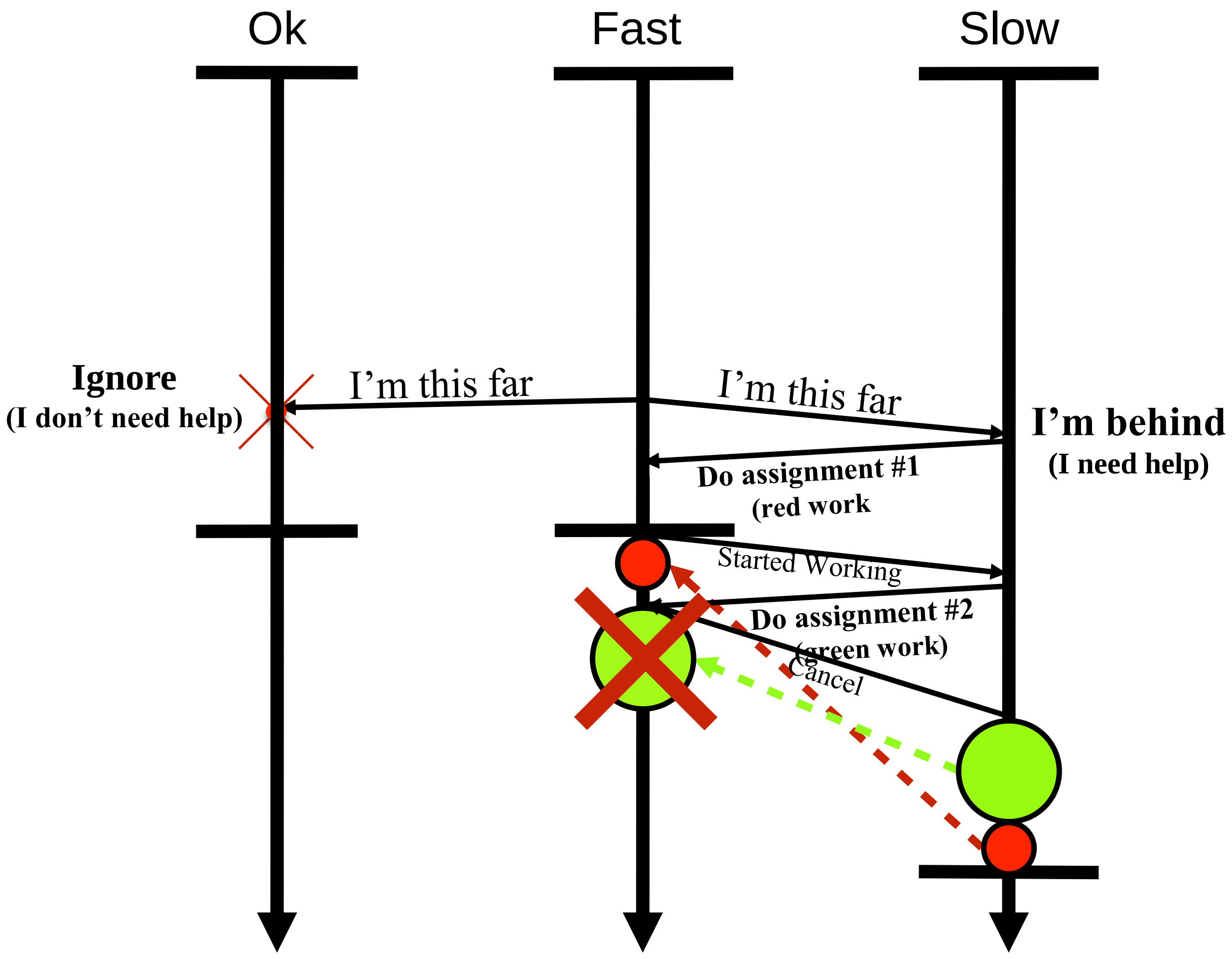
  Causes significant slowdowns for Big Learning

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

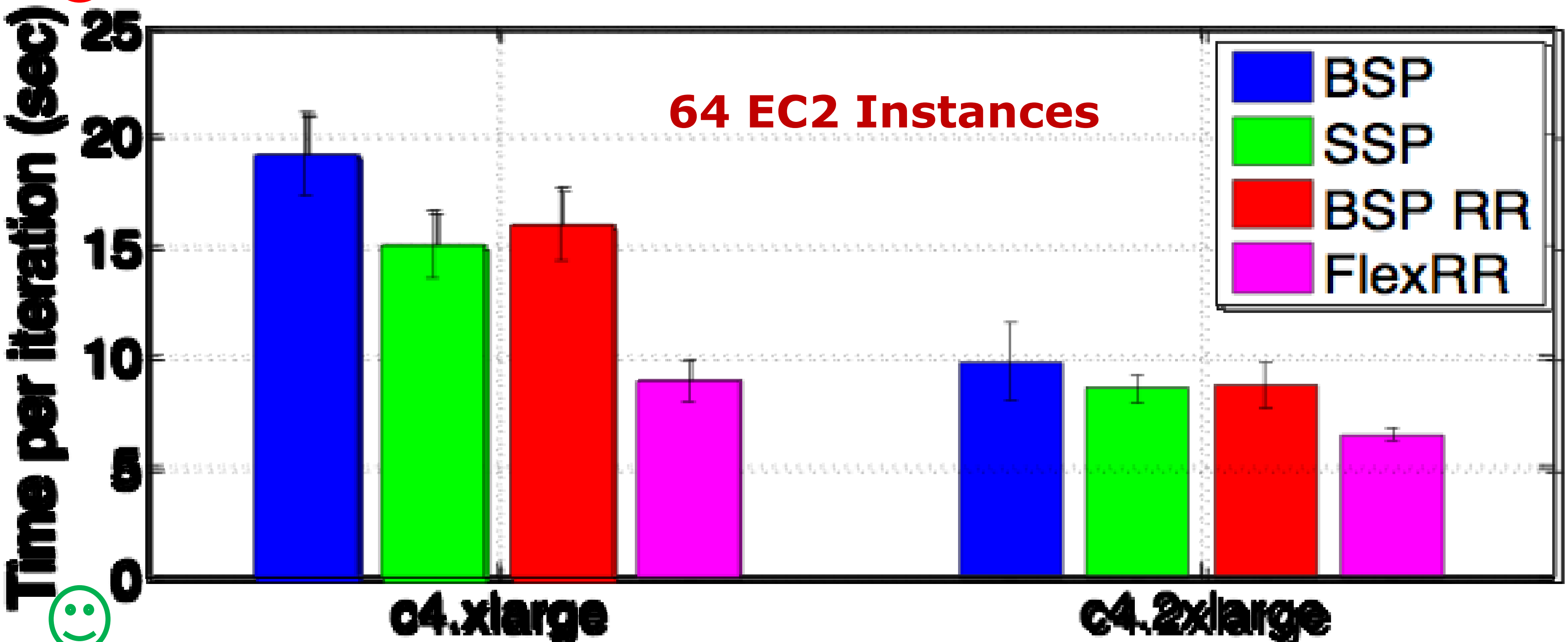
    E.g., cloning (used in MapReduce) would break the algorithm (violates idempotency)!
  - Staleness provides slack to do the migration

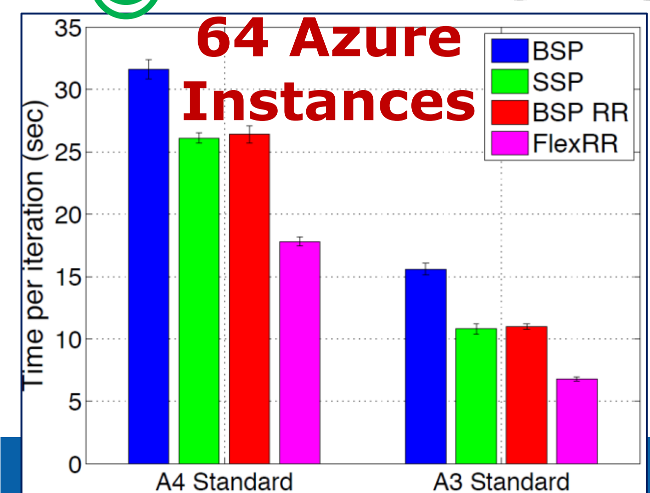
Rapid-Reassignment (RR) Protocol

- 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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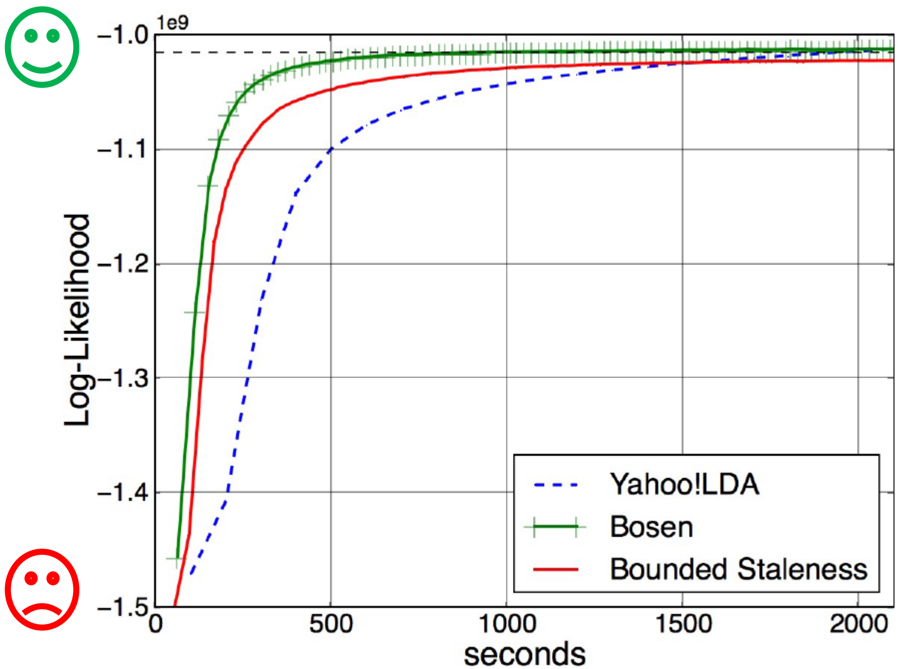
Bosen: Managed Communication

- **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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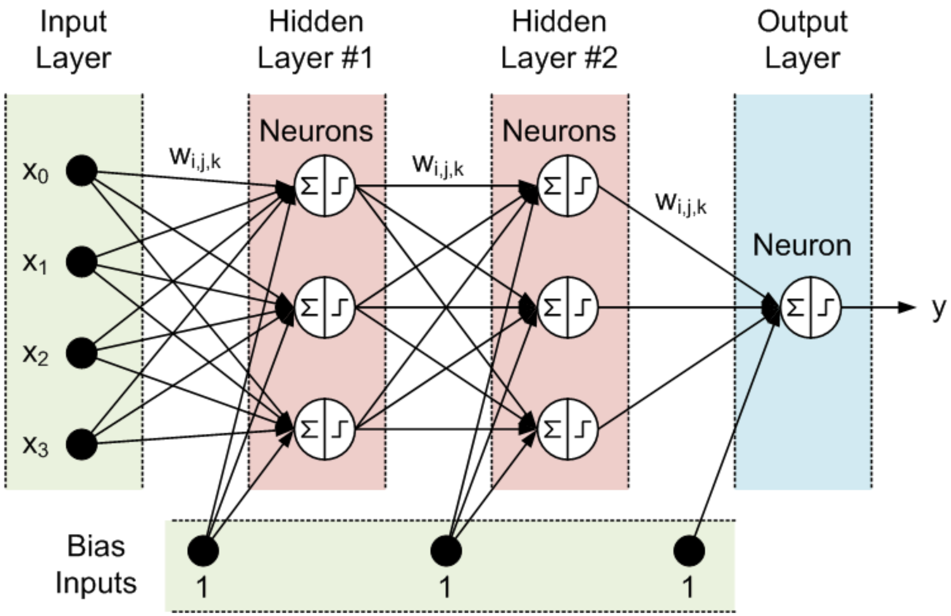
Recall: Data Analysis with Deep Neural Networks

Task:

- Compute classification of set of input signals



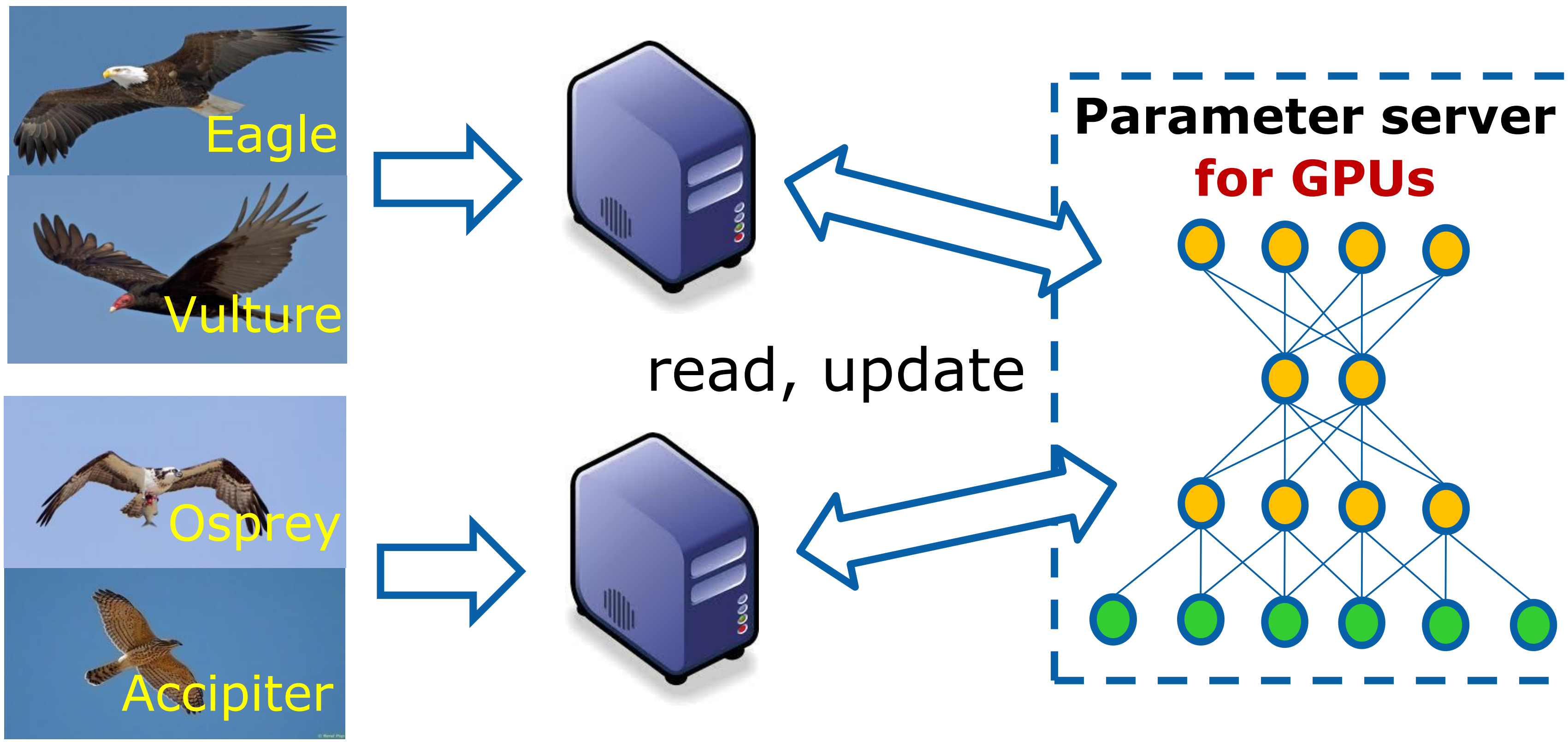
Training

- 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

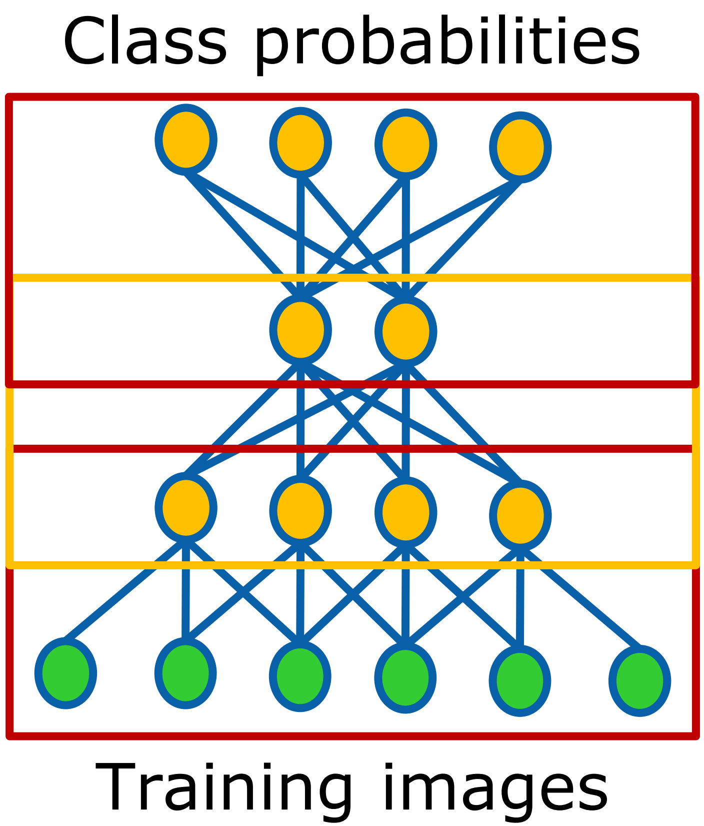


Partitioned
training data

Distributed
ML workers

Shared
model parameters

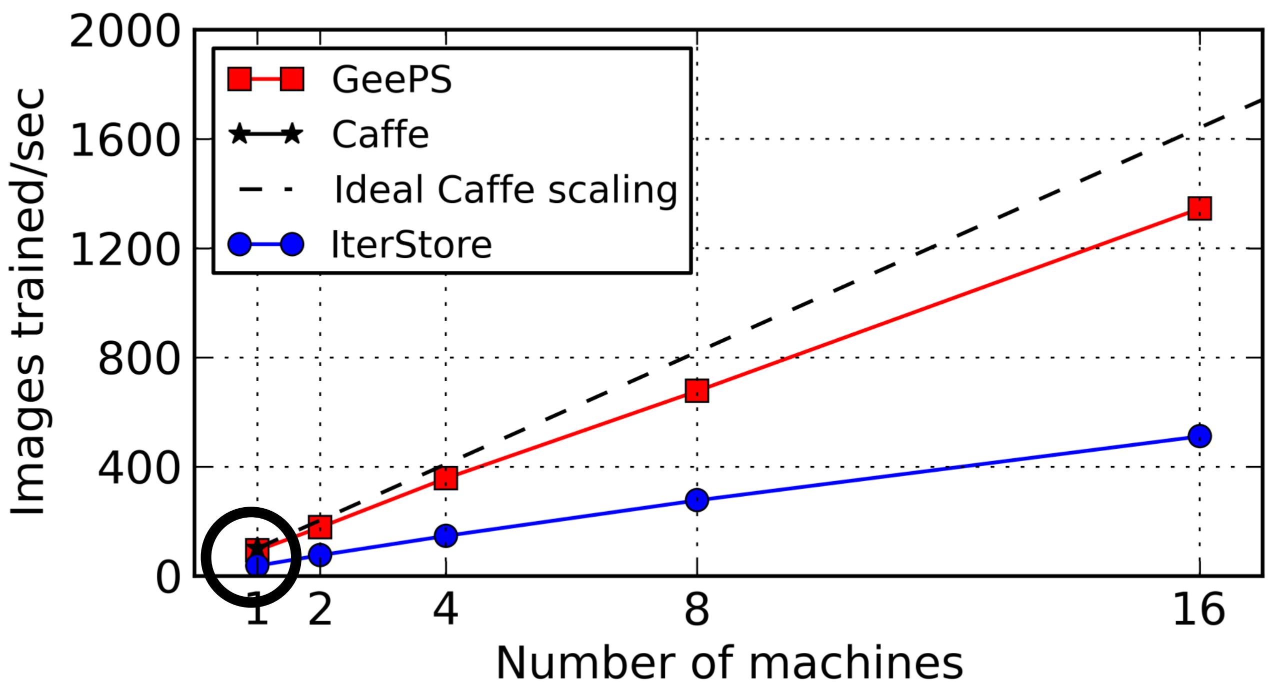
Layer-by-Layer Pattern of DNN



- 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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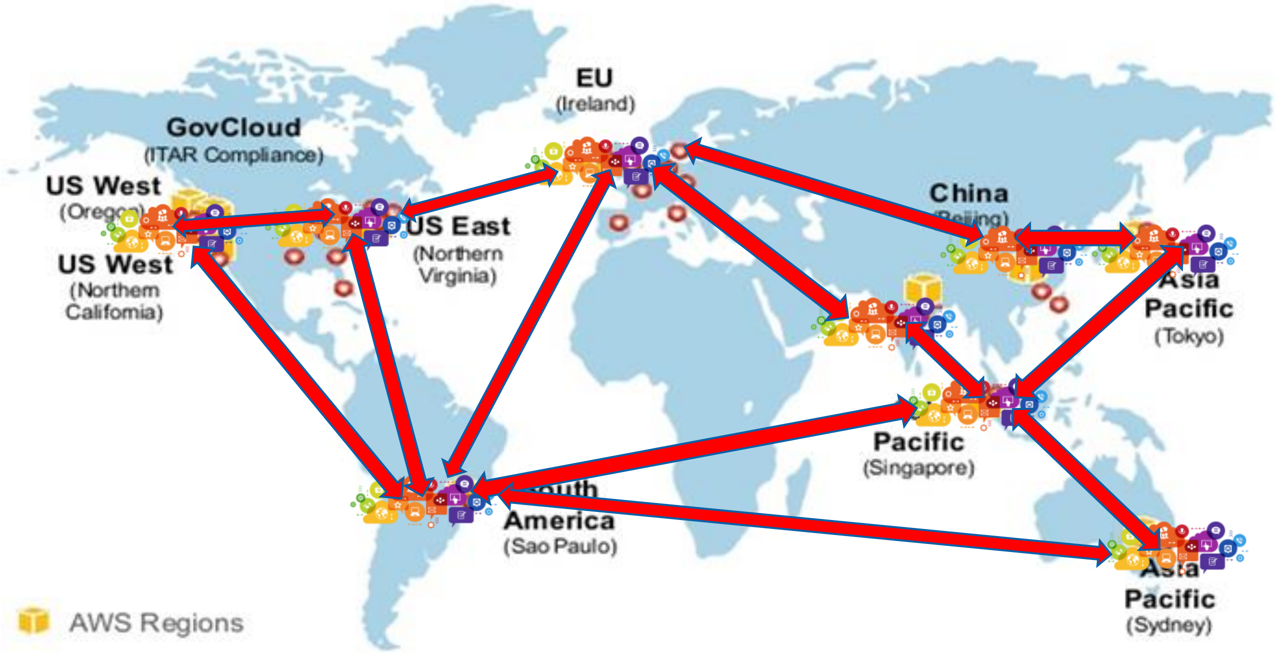
Geo-Distributed Machine Learning

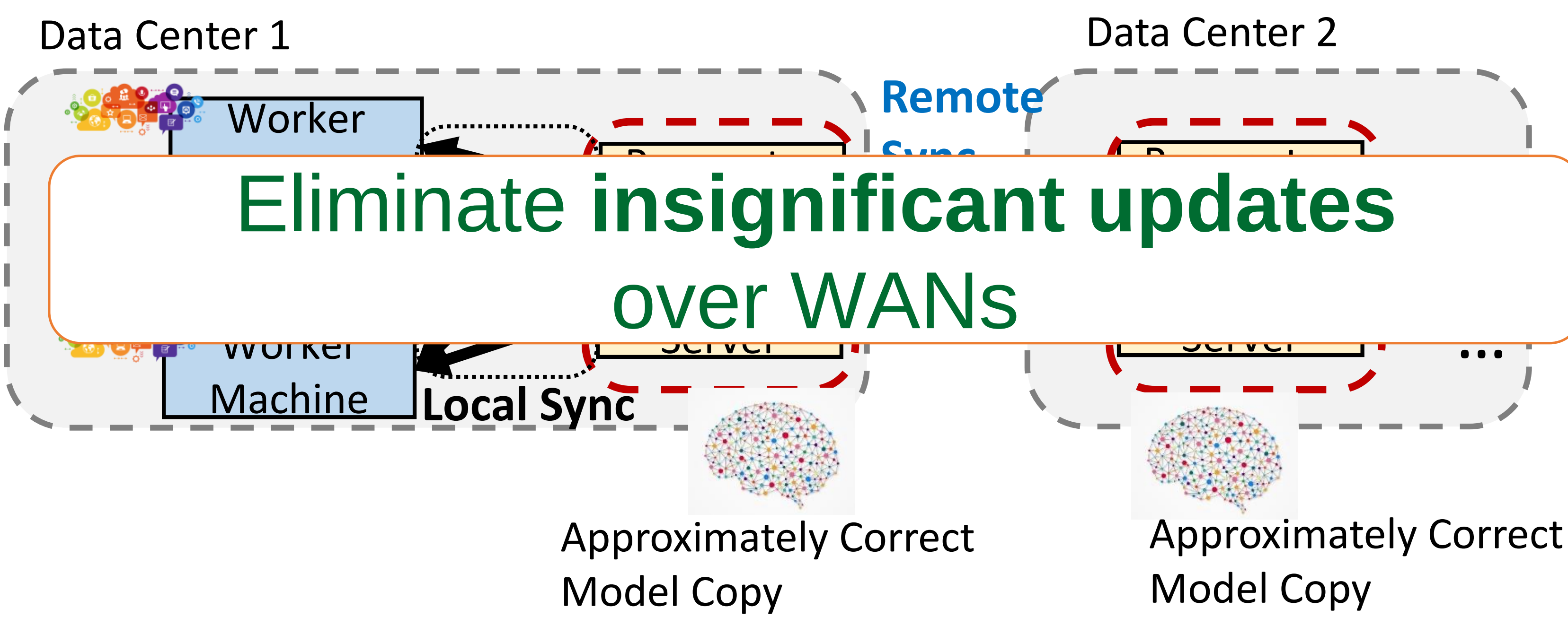
- **Data sources are everywhere (geo-distributed)**
  - Too expensive (or not permitted) to ship all data to single data center



- **ML training done across the WAN**

Gaia System Overview

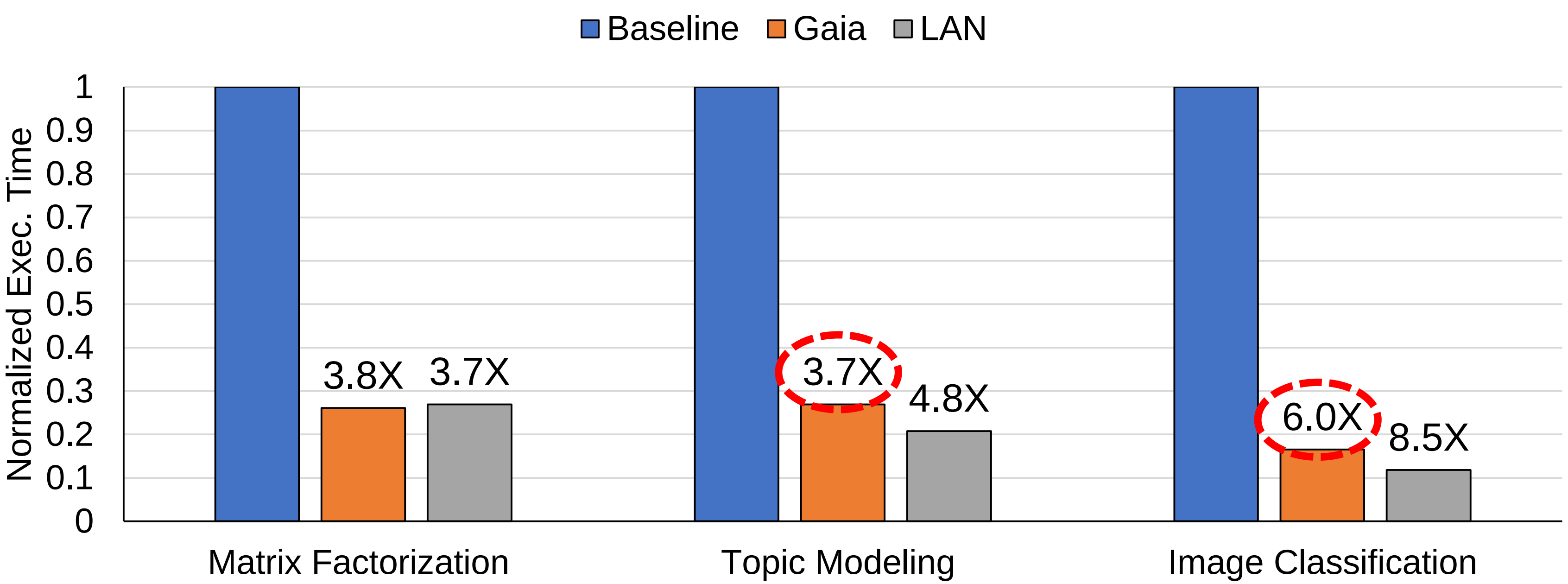
- **Key idea**: Decouple the synchronization model *within* the data center from the synchronization model *between* data centers



Eliminate **insignificant updates** over WANs

[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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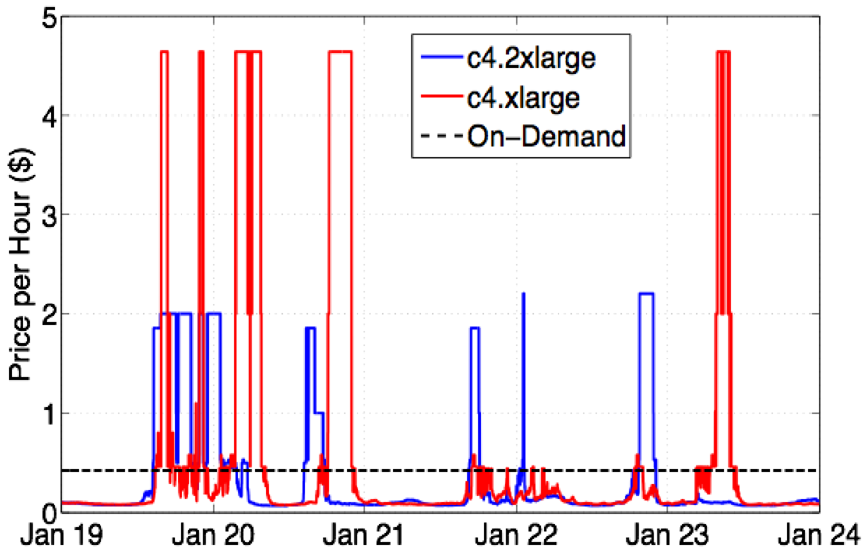
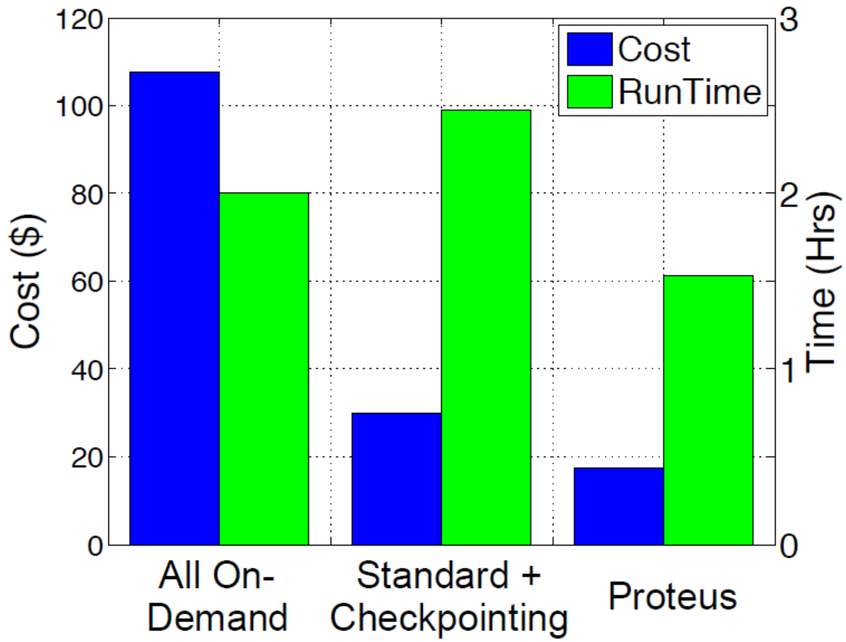
Proteus: Playing the Spot Market

- **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

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(Bold=first author)

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  - **Intel** (via ISTC for Cloud Computing & ISTC for Visual Cloud Systems)
  - **National Science Foundation**

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

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Thanks for a Great Semester!

Good Luck on the Final!