What's So Special about Big Learning?

A Distributed Systems Perspective

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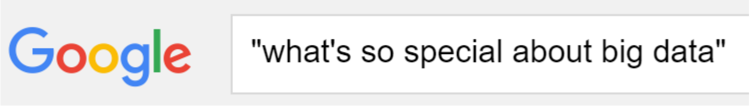
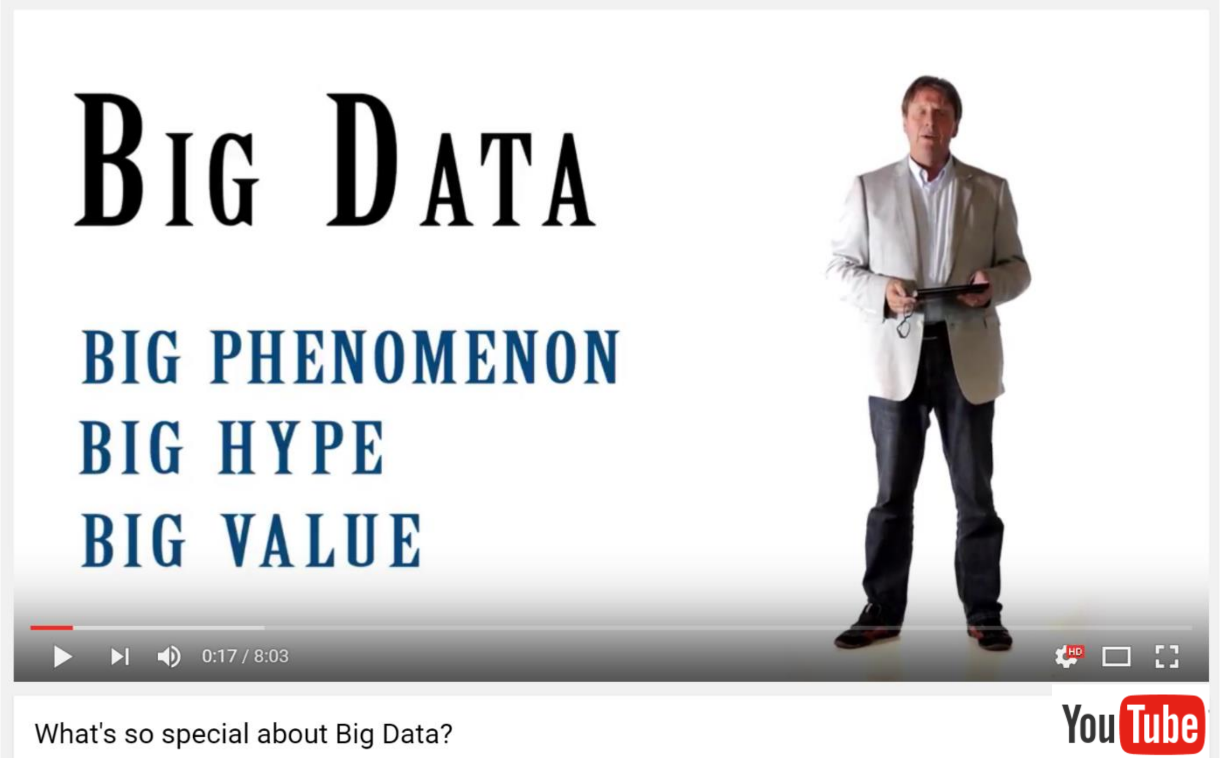
ICDCS'16 Keynote Talk, June 28, 2016

What’s So Special about…Big Data?

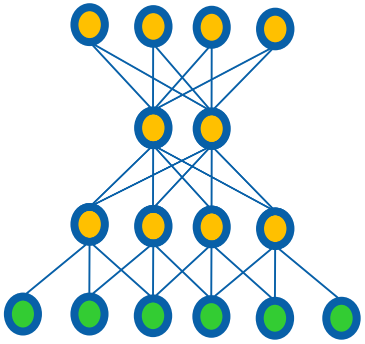
Keynote #2: Prof. Masaru Kitsuregawa
“Power of Big Data — from Commercial Profits to Societal Benefits”





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**

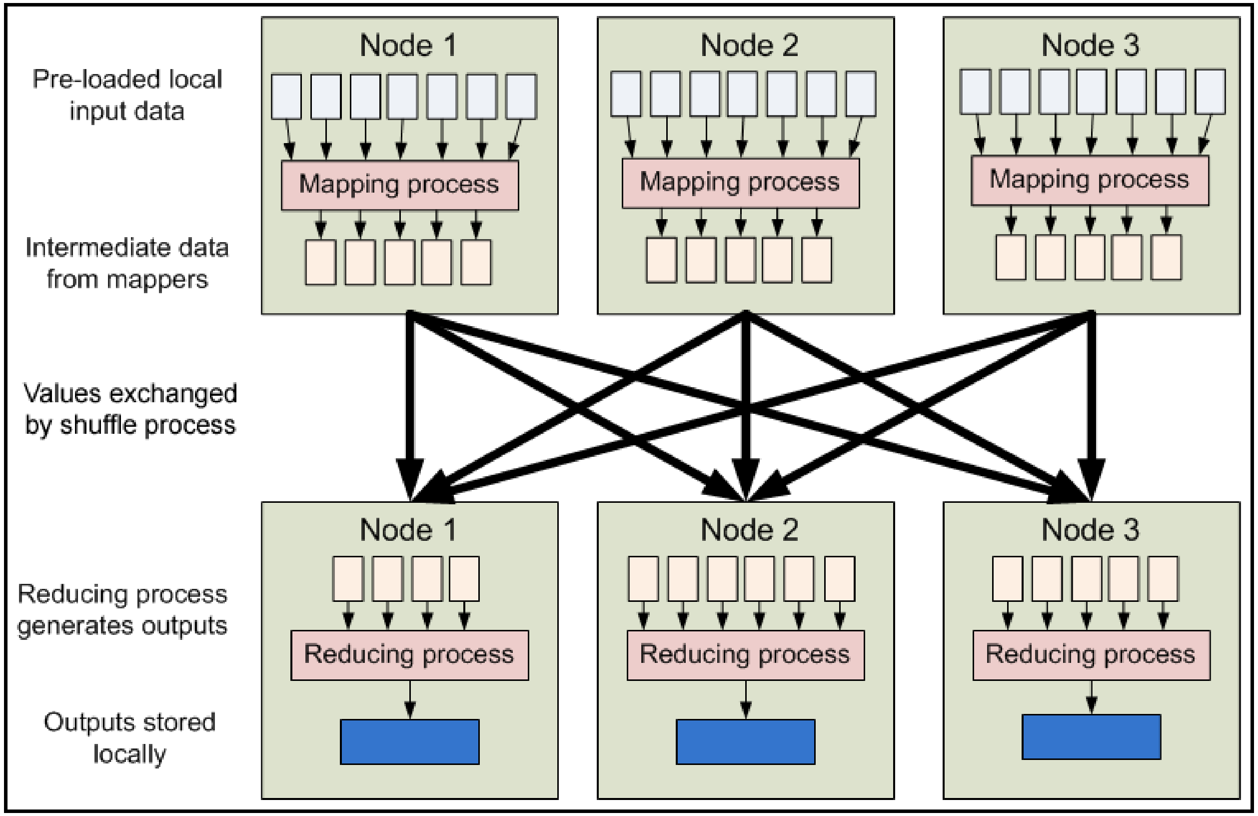
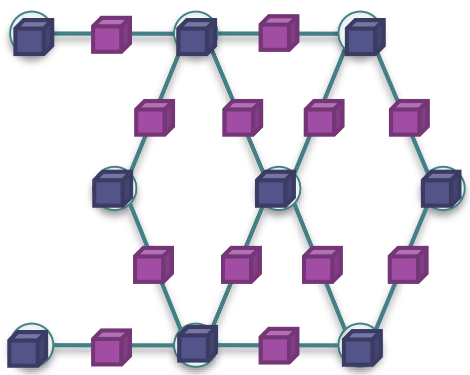


Image from: developer.yahoo.com/hadoop/tutorial/module4.html

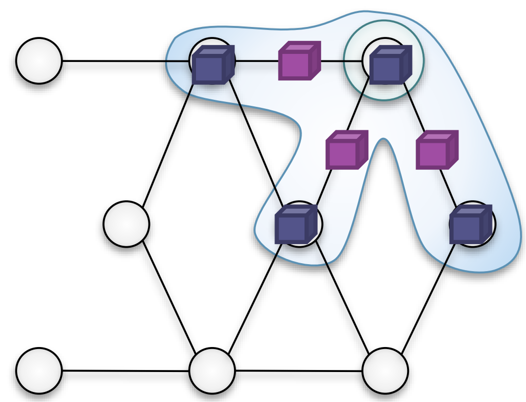
GraphLab

Graph Parallel: "Think like a vertex"

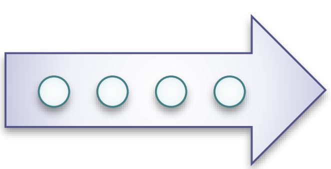
Graph Based
Data Representation



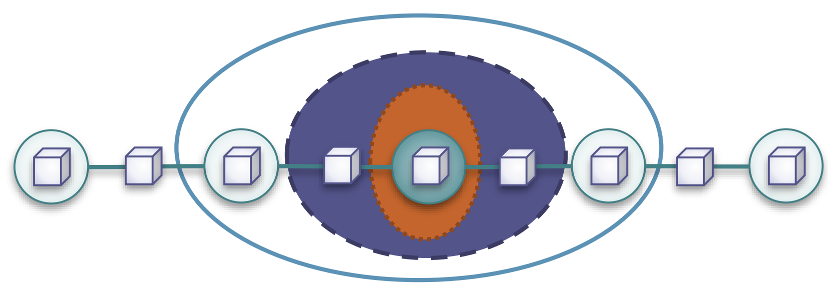
Update Functions
User Computation



Scheduler



Consistency Model



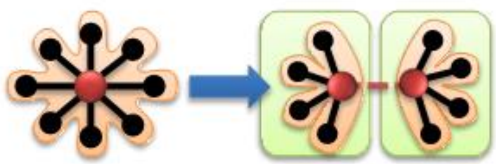
Slide courtesy of Carlos Guestrin

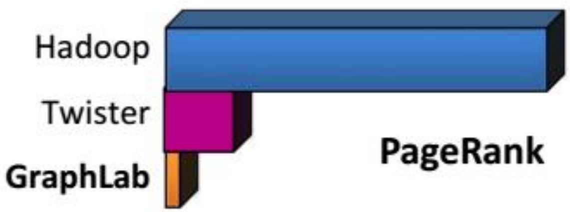
GraphLab & GraphChi

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

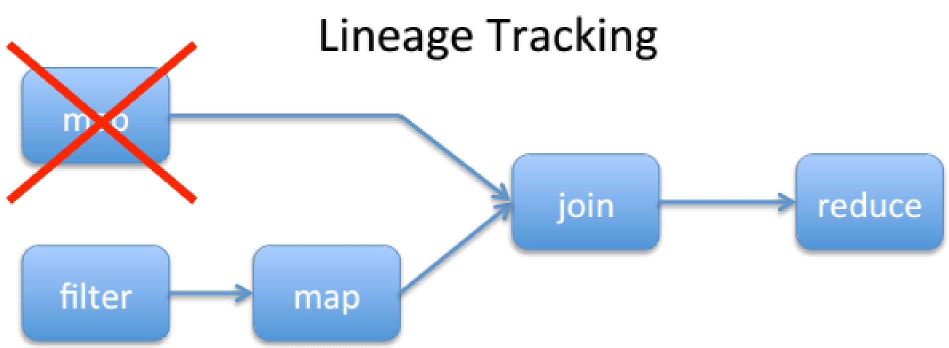
Slide courtesy of Carlos Guestrin

Spark: Key Idea

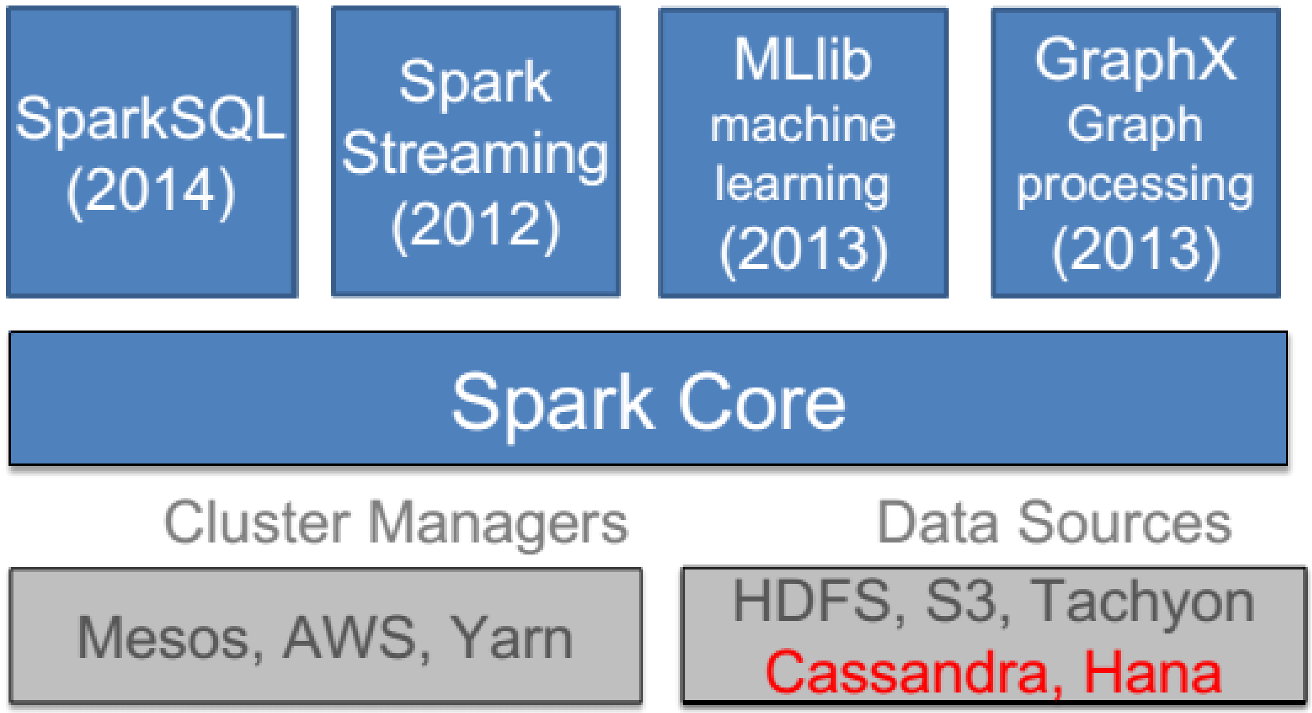
Features:
- In-memory speed w/fault tolerance via lineage tracking
- Bulk Synchronous

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

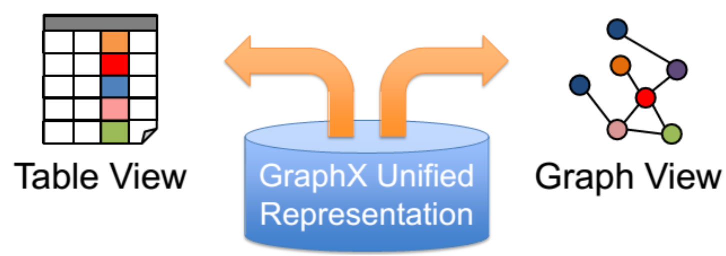


Spark Stack Components



Tachyon: Memory-speed data sharing among jobs in different frameworks (e.g., Spark & Hadoop). Keeps in-memory data safe even when job crashes

GraphX: Tables & Graphs are views of same physical data, exploit semantics of view for efficient operation



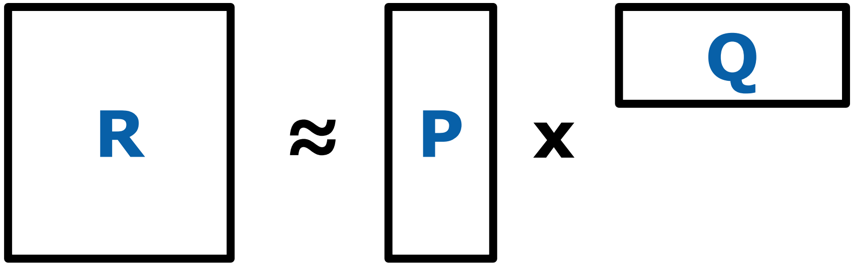
Big Learning Frameworks & Systems

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

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

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

- **Formulated as an optimization problem**
  - mathematical "model"
  - determine "parameters" of the model that minimizes (or maximizes) "objective function"
- **E.g., Matrix Factorization: sparse ratings matrix**



  - Find P & Q that minimizes error term:

$$\sum_{r_{ij} \in R} \left(r_{ij} - \sum_{k=1}^{K} p_{ik}\, q_{kj}\right)^2 + regularization\ term$$

- **Use training data (R) to learn parameters (P, Q)**

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

- **Formulated as an optimization problem**
  - Use training data to learn model parameters
- **No closed-form solution, instead algorithms iterate until convergence**
  - E.g., **Stochastic Gradient Descent** for Matrix Factorization or Multinomial Logistic Regression, LDA via Gibbs Sampling, Deep Learning, Page Rank

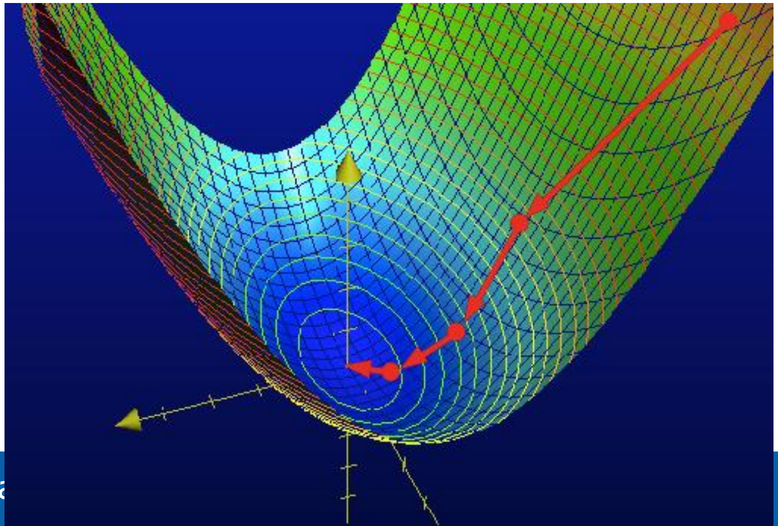


Image from charlesfranzen.com

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

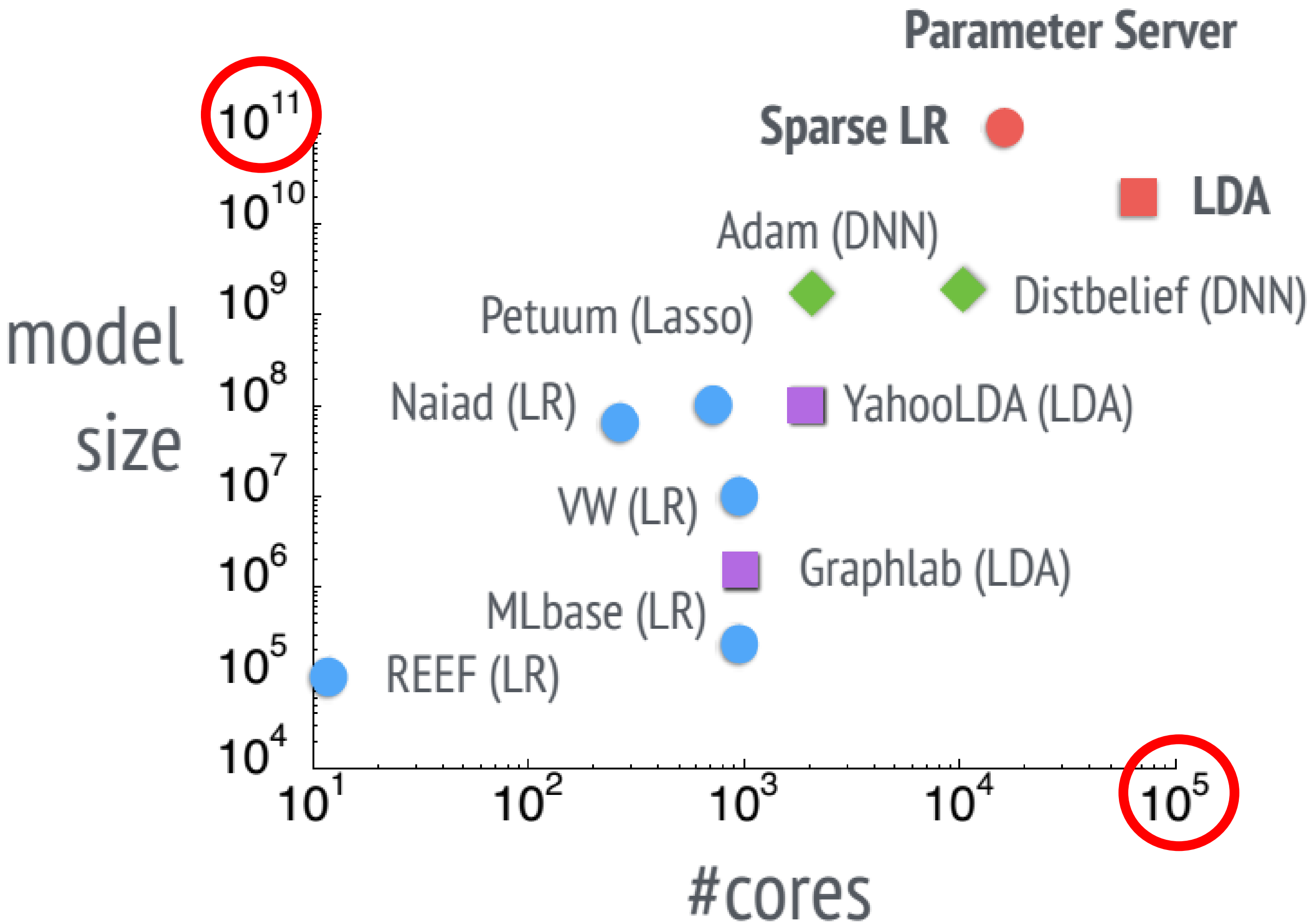
The Bad News

- **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

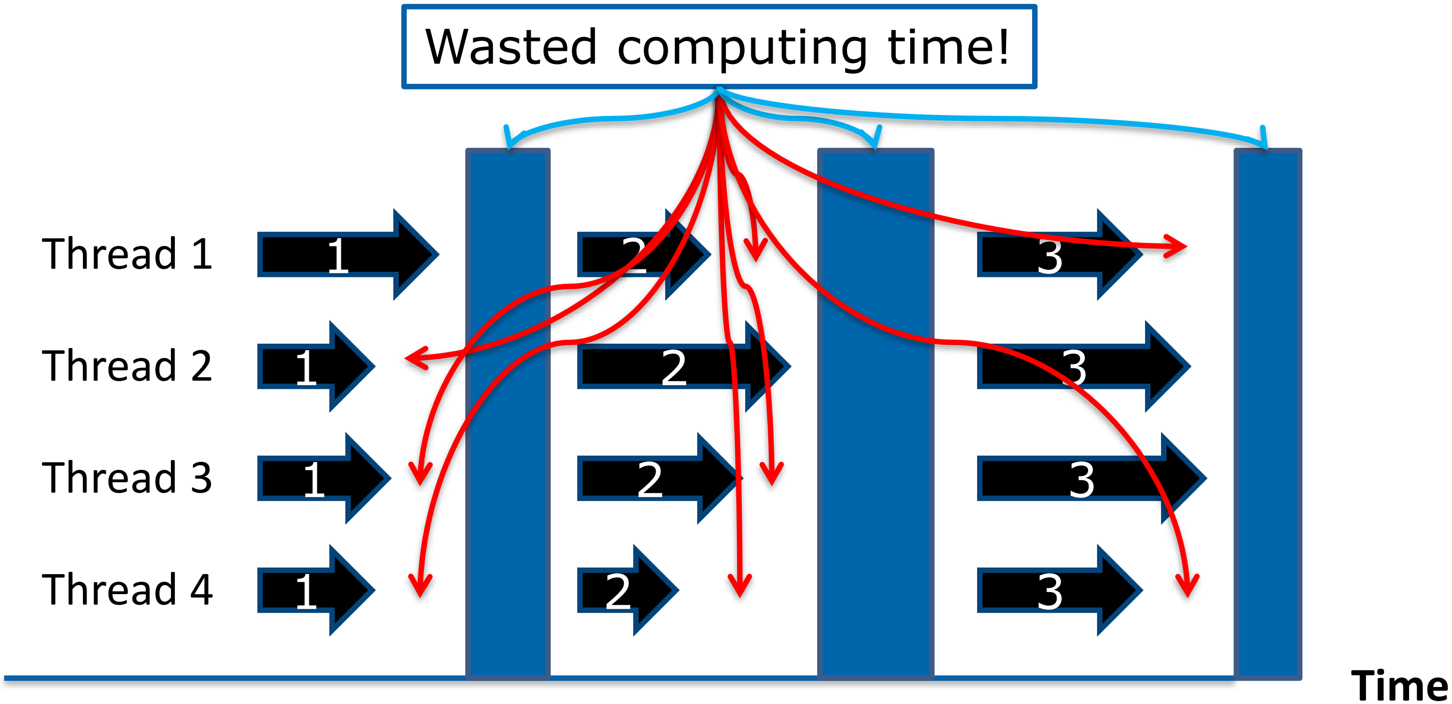
…why good distributed systems research is needed!

Big Models, Widely Distributed



[Li et al, OSDI'14]

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

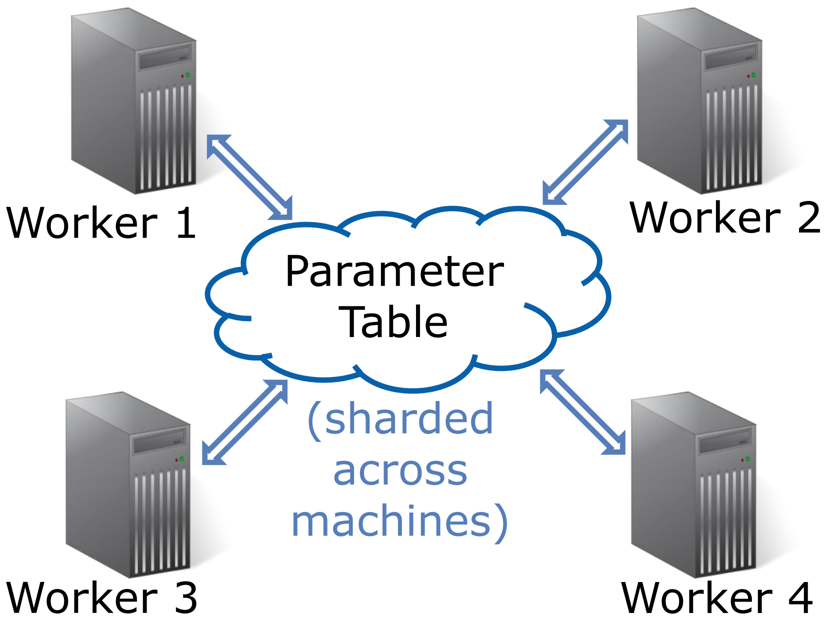
The Good News

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

…can exploit to run orders of magnitude faster!

Parameter Servers for Distributed ML

- **Provides all workers with convenient access to global model parameters**
- **Easy conversion of single-machine parallel ML algorithms**
  - "Distributed shared memory" programming style
  - Replace local memory access with PS access



Single Machine Parallel

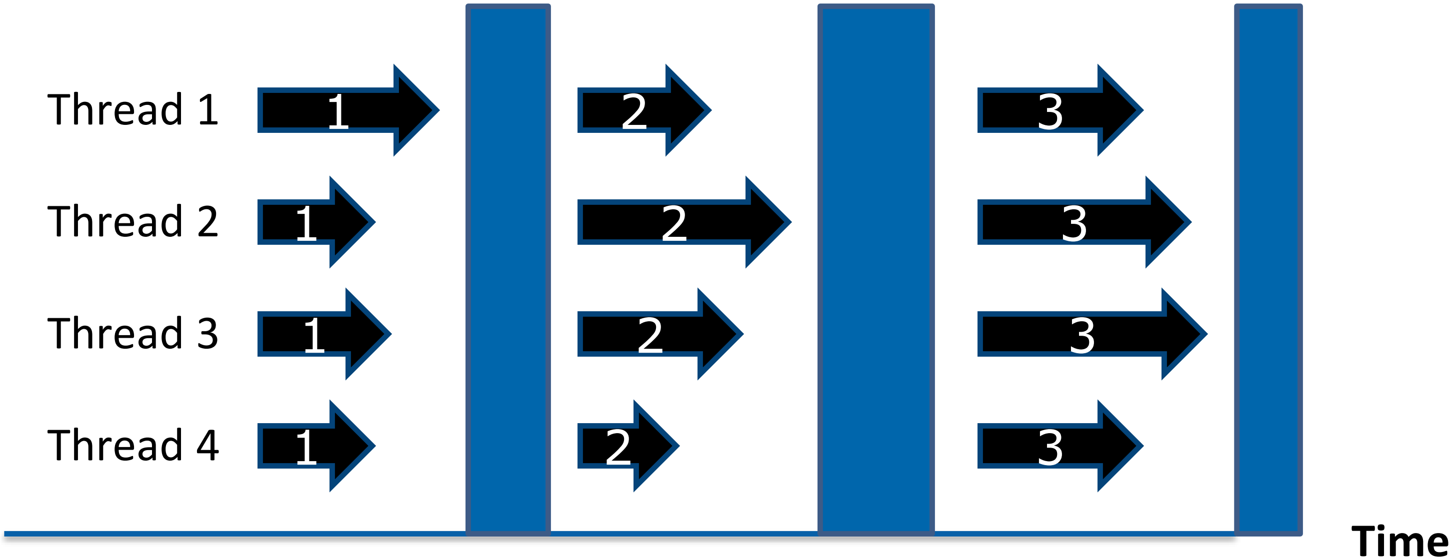
```
UpdateVar(i) {
  old = y[i]
  delta = f(old)
  y[i] += delta }
```

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

Recall: Bulk Synchrony & Its Costs



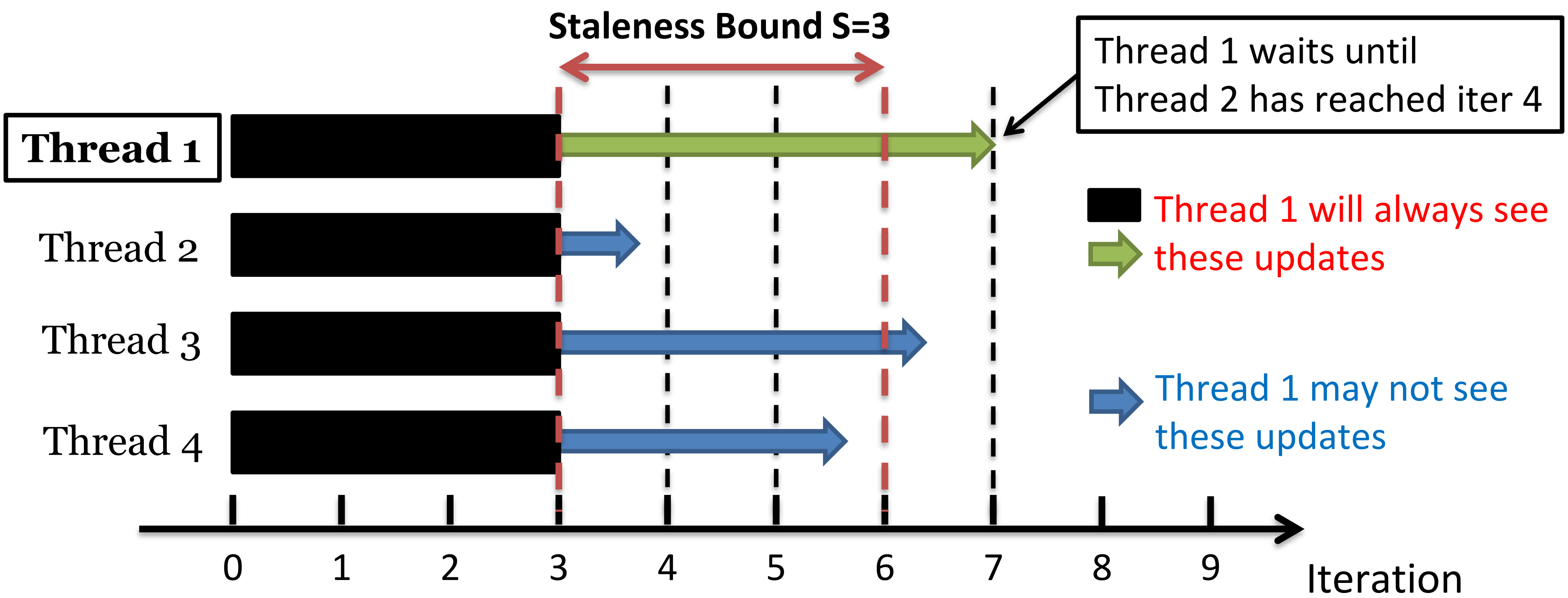
- **Exchange ALL updates at END of each iteration**
- **Synchronize ALL threads each iteration**

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

Slow threads check only every S iterations – fewer network accesses, so catch up!

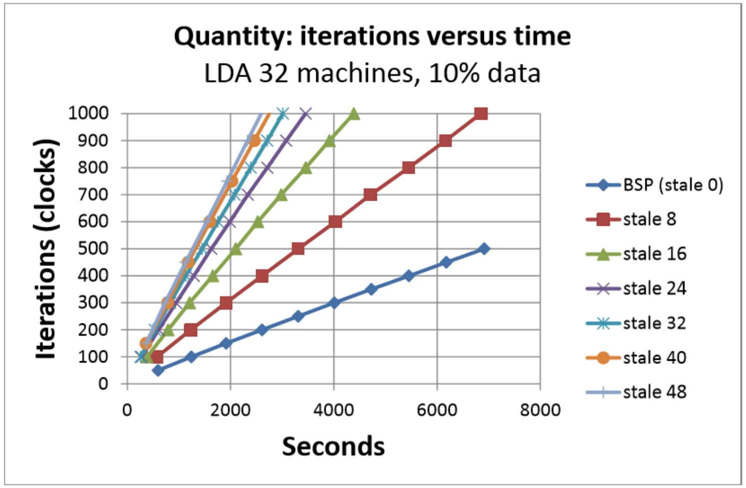
Exploits: 1. commutative/associative updates &

2. tolerance for lazy consistency (bounded staleness) [NIPS'13]

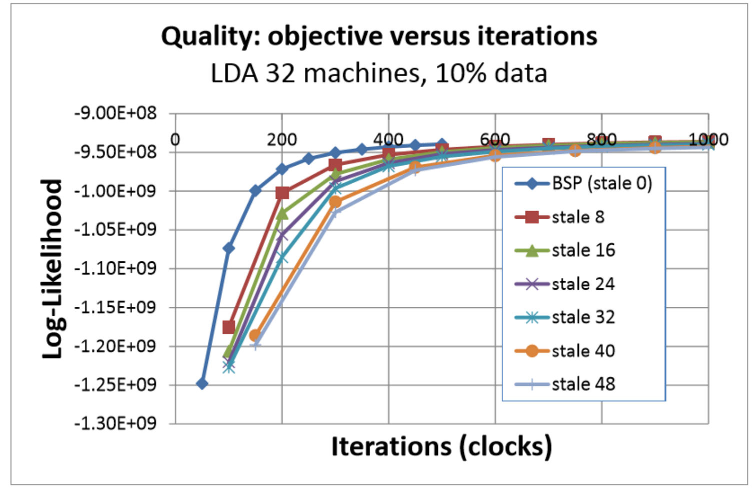
Staleness Sweet Spot

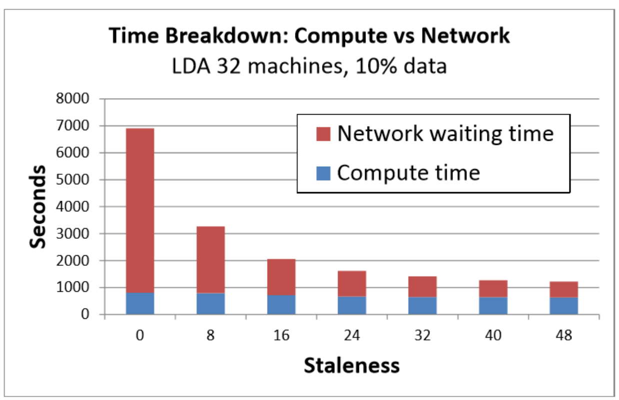
Topic Modeling: Iteration Quantity and Quality

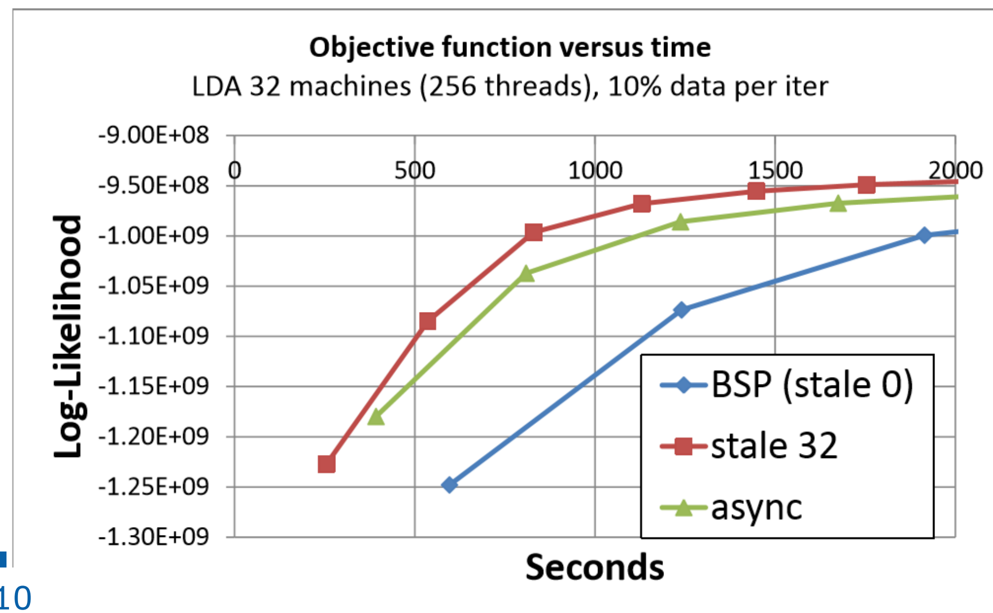
32 VMs, 10% minibatches



32 VMs, 10% minibatches





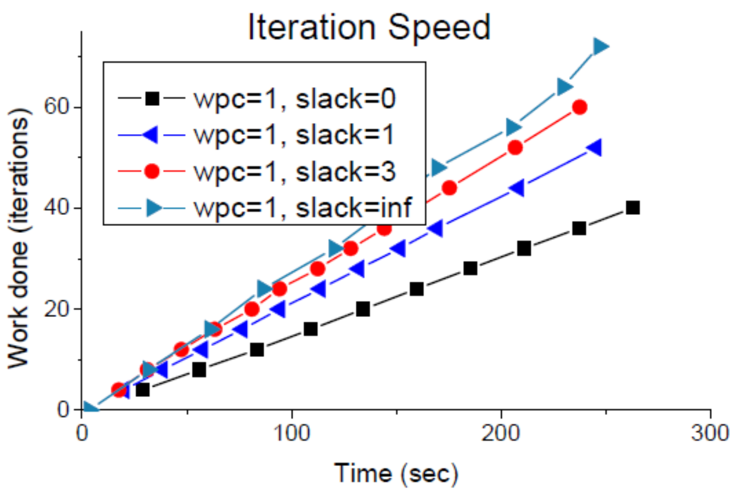


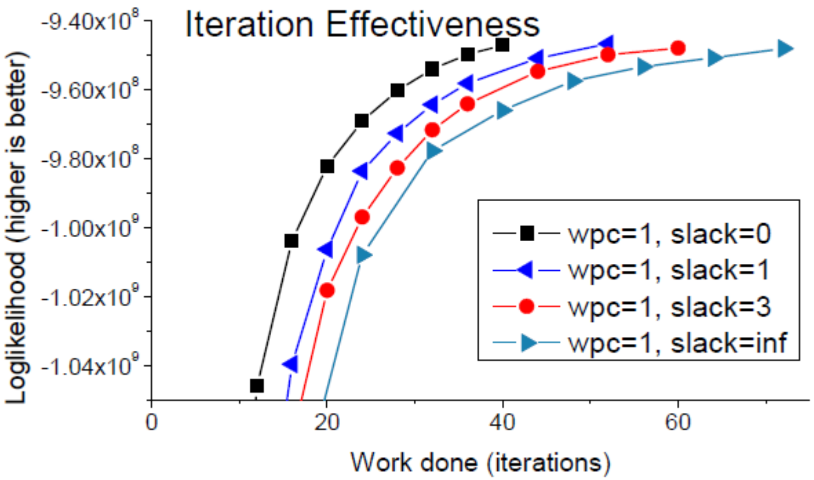
32 x 8 cores w/10Gbps Ethernet

Nytimes dataset

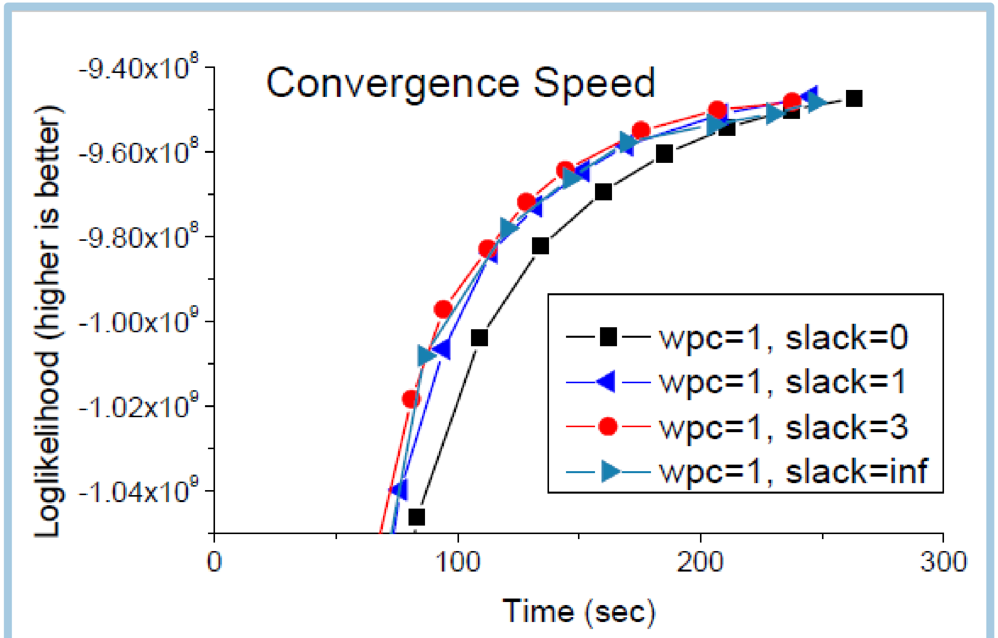
* 10% implies should divide all staleness bounds by 10

Staleness Sweet Spot





Topic Modeling
Nytimes dataset
400k documents
100 topics
LDA w/Gibbs sampling
8x4x16 cores
40Gbps Infiniband



[ATC'14]

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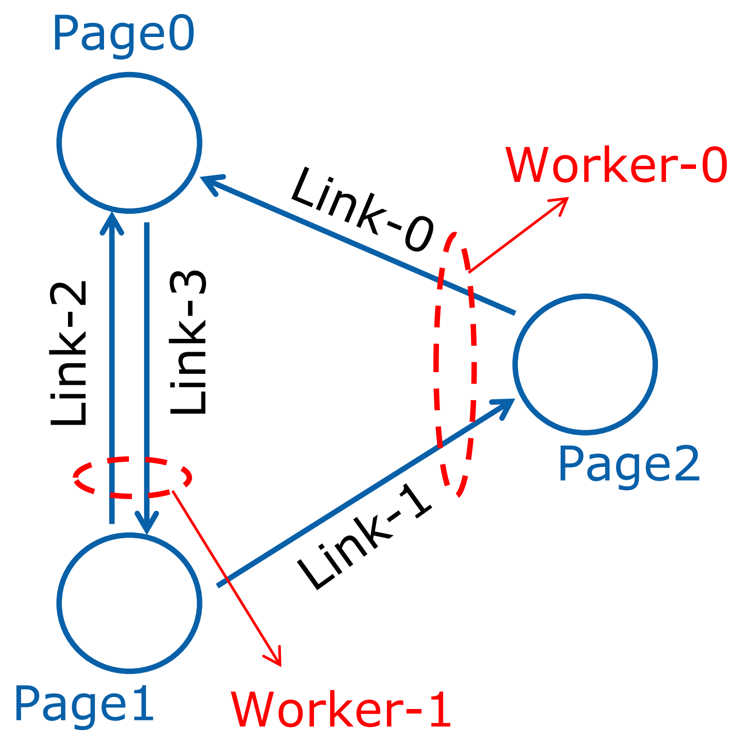
The Good News

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

...can exploit to run orders of magnitude faster!

Repeated Data Access in PageRank

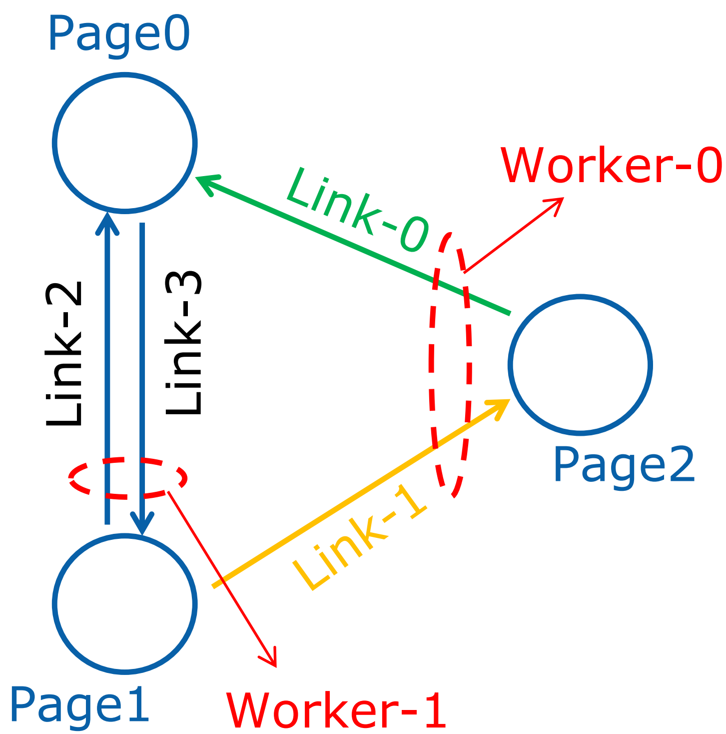
Input data: a set of links, stored locally in workers
Parameter data: ranks of pages, stored in PS




```
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

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
```

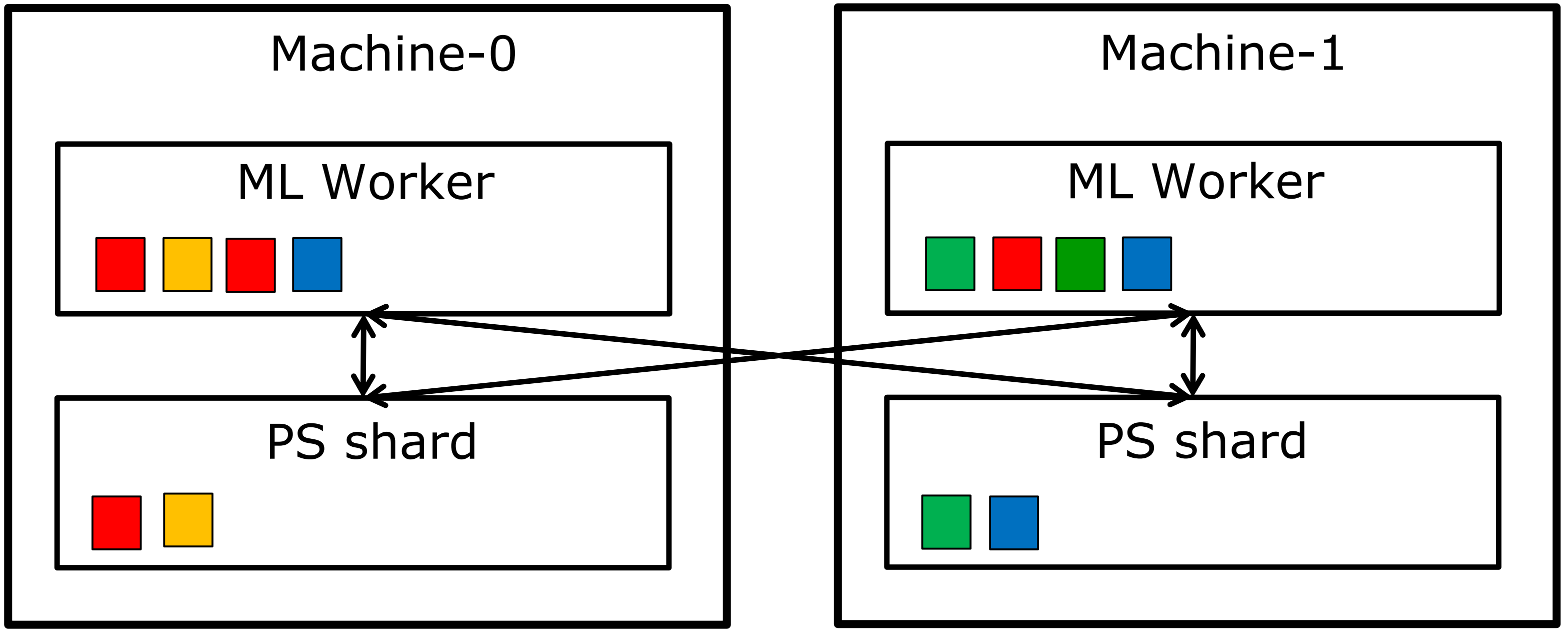
Repeated access sequence depends only on input data (not on parameter values)

Optimizations on Informed Access

Collect access sequence in "virtual iteration"

Useful for many optimizations:

1. **Parameter data placement across machines**



Optimizations on Informed Access

Collect access sequence in "virtual iteration"

Useful for many optimizations:

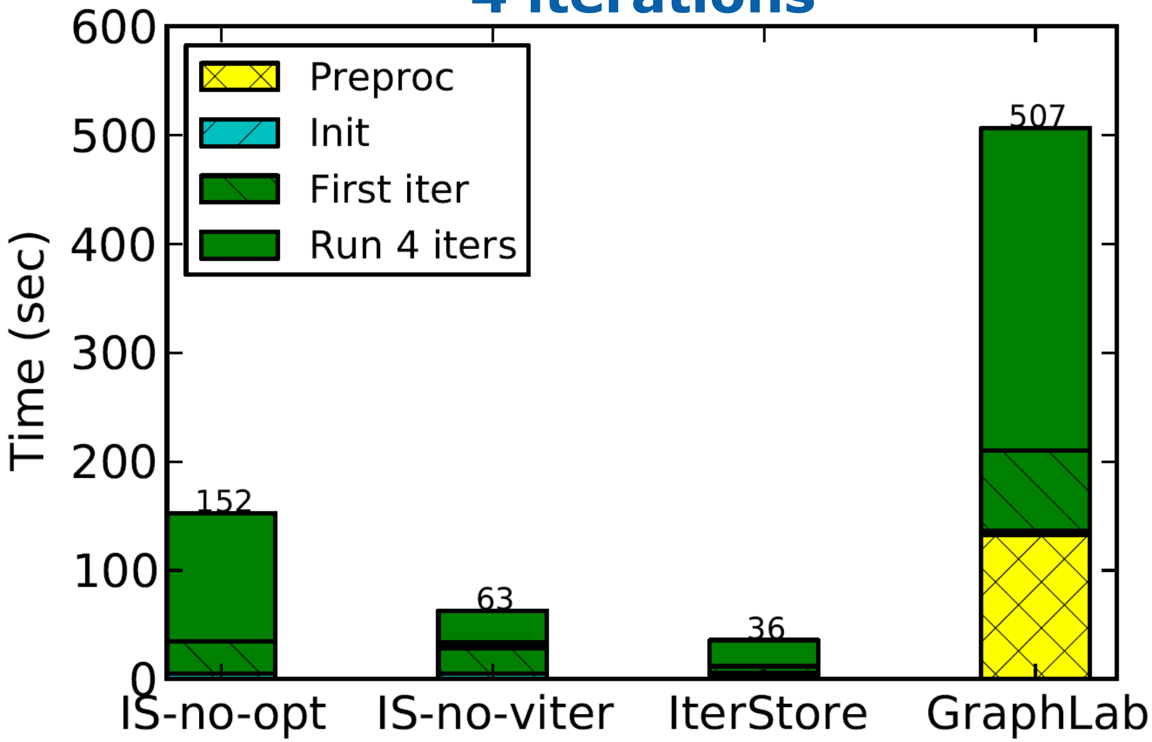
1. **Parameter data placement across machines**
2. **Prefetching**
3. **Static cache policies**
4. **More efficient marshalling-free data structures**
5. **NUMA-aware memory placement**

- **Benefits resilient to imperfect Informed Access**

IterStore: Exploiting Iterativeness

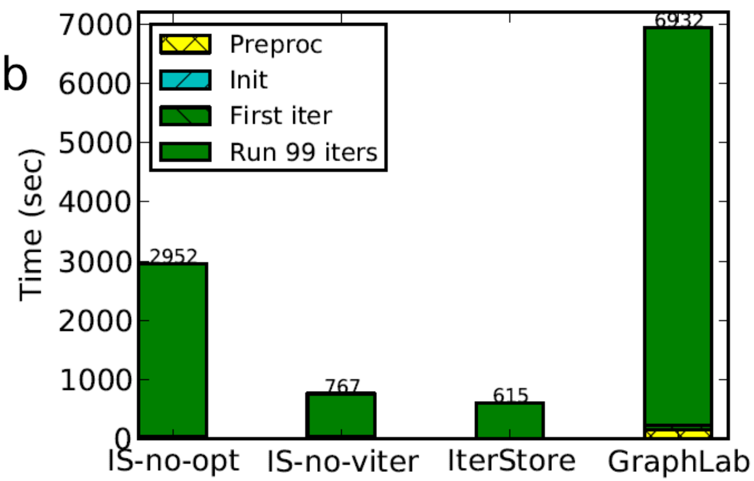
[SoCC'14]

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

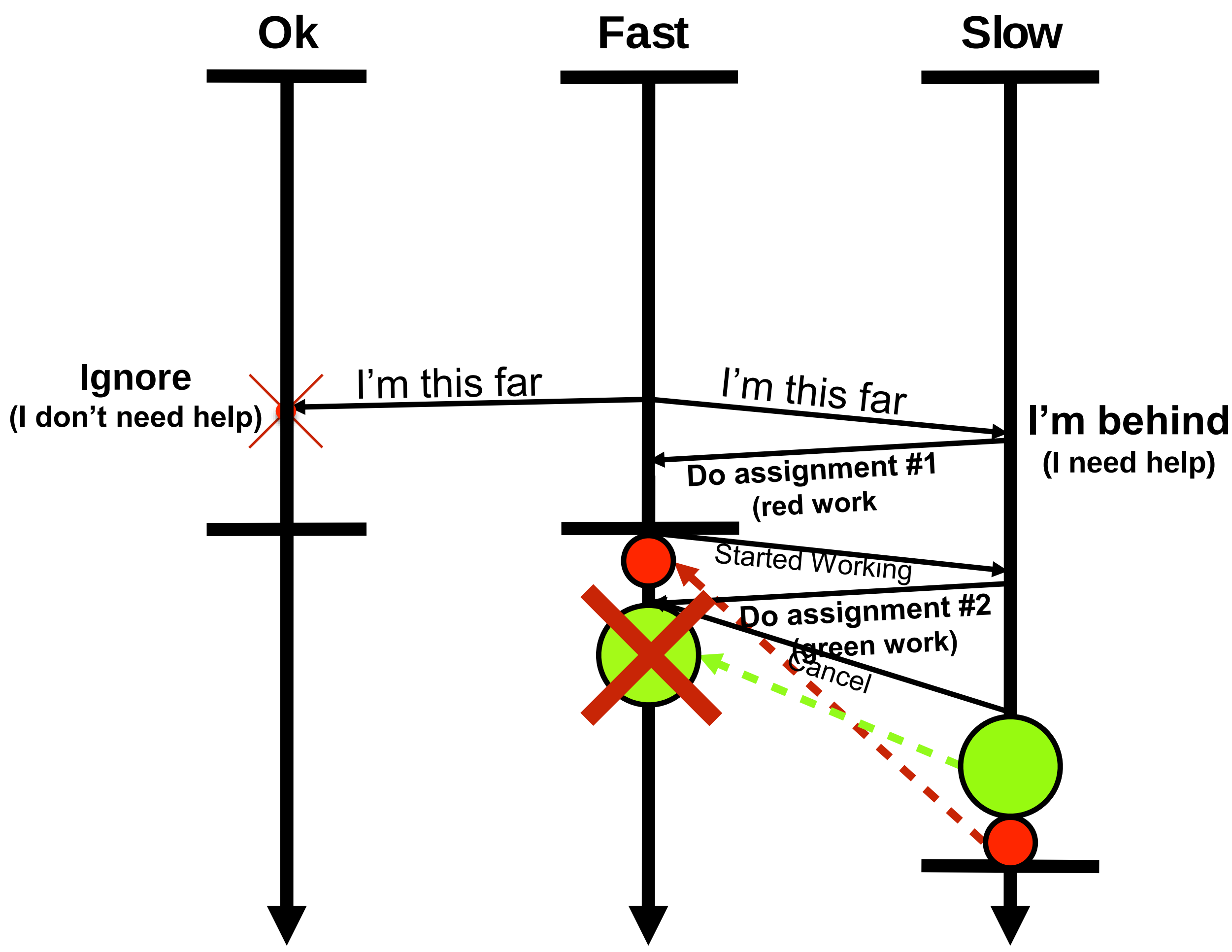
  Causes significant slowdowns for Big Learning

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

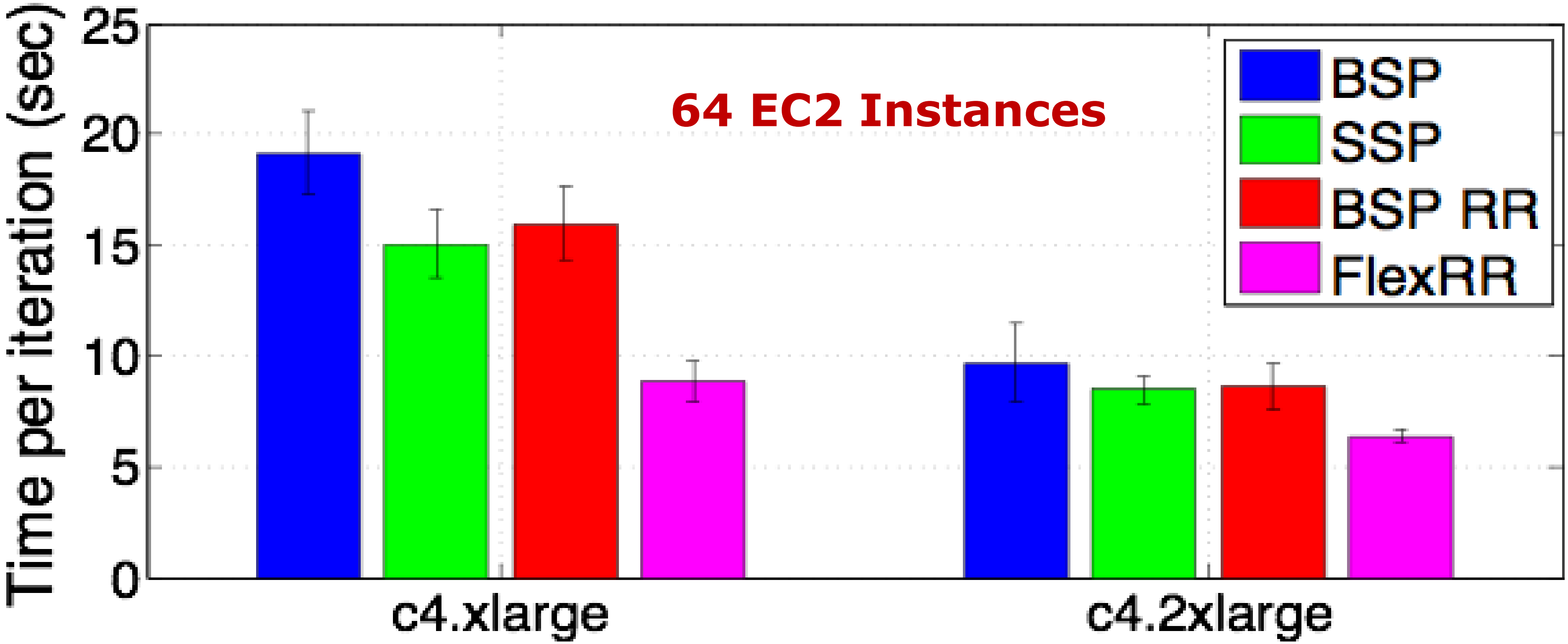
    E.g., cloning (used in MapReduce) would break the algorithm (violates idempotency)!
  - Staleness provides slack to do the migration

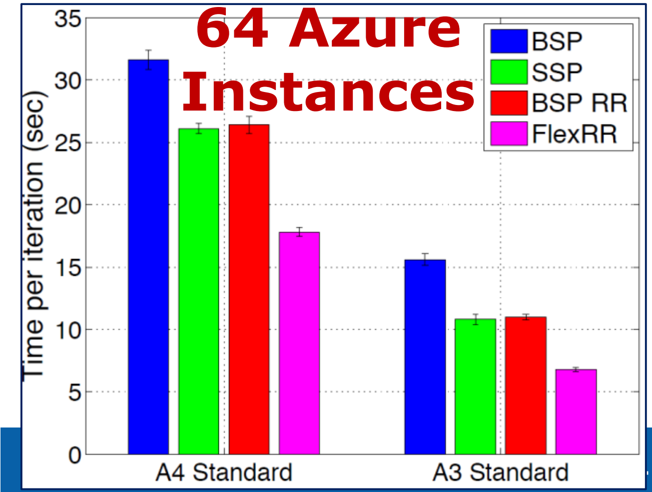
Rapid-Reassignment Protocol

- 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

[under submission]

Both SSP & RR required.
Nearly ideal straggler mitigation

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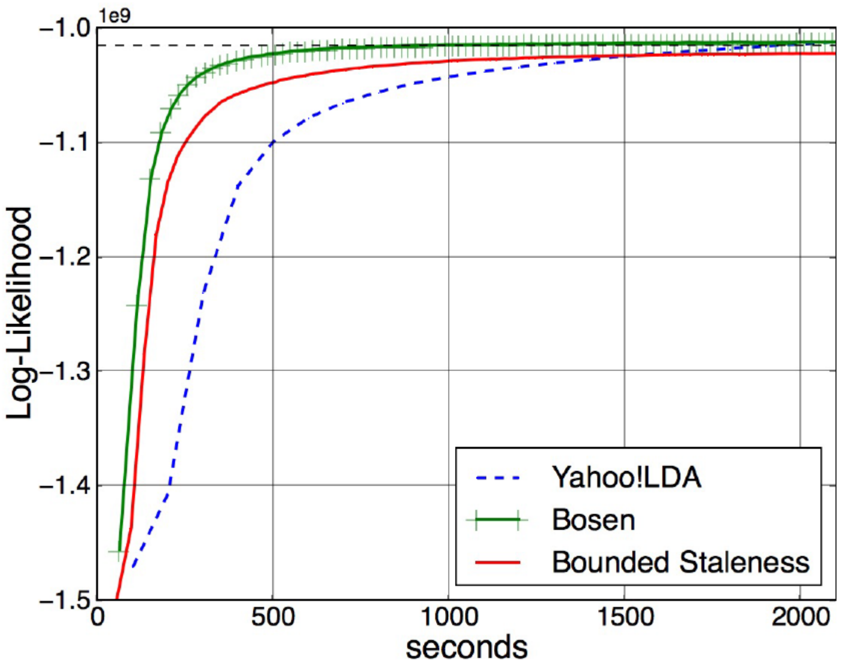
Bosen: Managed Communication

- **Combine SSP's lazy transmission of parameter updates with:**
  - early transmission of larger parameter changes
  - up to bandwidth limit & staleness limit

(Idea: larger change likely to be an important update)



LDA Topic Modeling
Nytimes dataset
16x8 cores

[SoCC'15]

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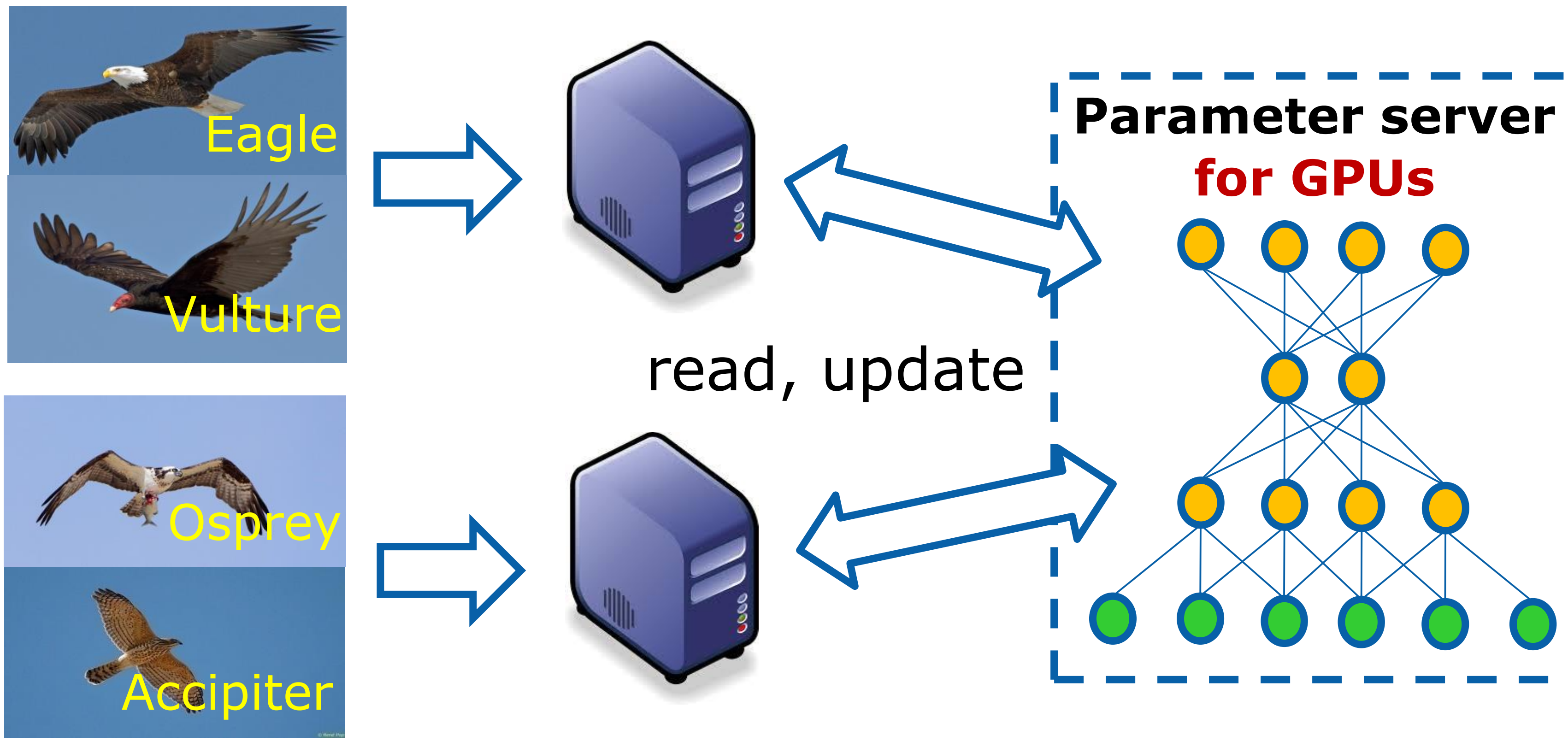
Distributed Deep Learning

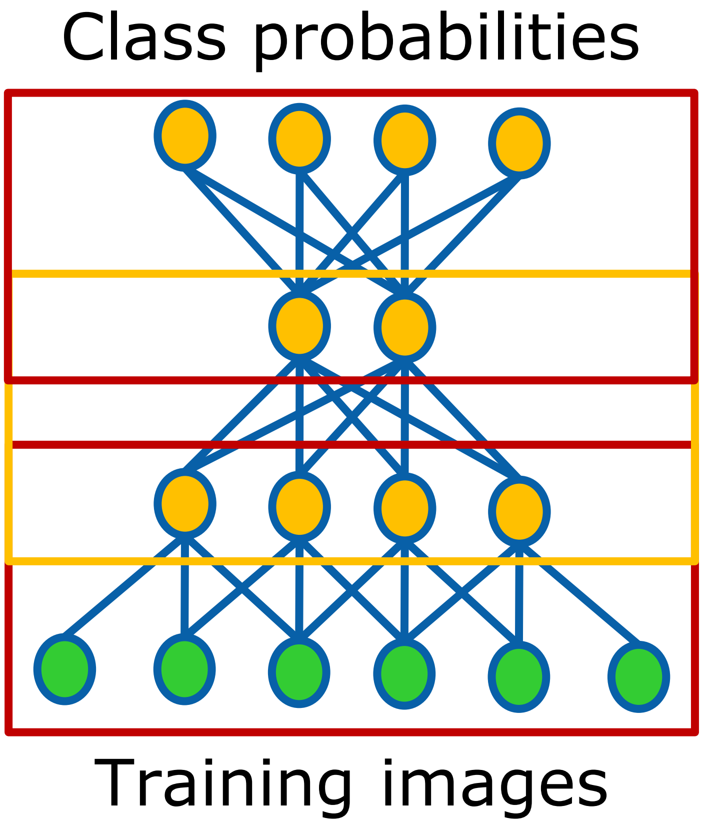


Partitioned
training data

Distributed
ML workers

Shared
model parameters

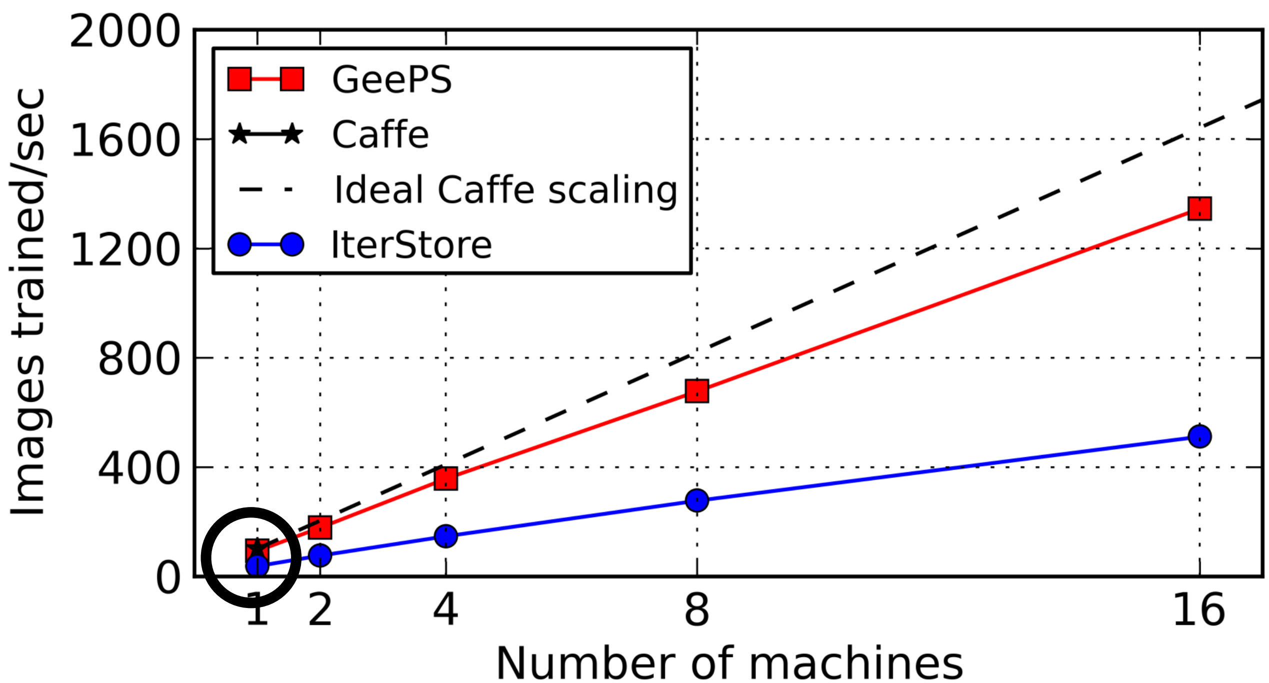
Layer-by-Layer Pattern of DNN



- 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



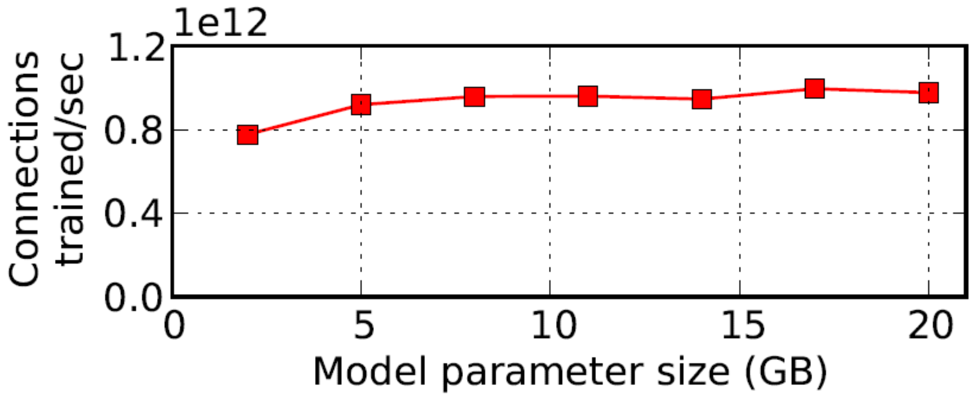
ImageNet22K
Adam model

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

GeePS: Parameter Server for GPUs

- **Careful memory management**
  - 13x faster than Caffe (1 GPU) on 16 machines, 2.6x faster than IterStore (CPU PS)
- **Efficiently handle problems > GPU memory**
  - Support 4x longer videos for video classification
  - Handle models as large as 20 GB with 5 GB GPUs

    (prior data-parallel ML is limited to <5 GB models)



5GB GPU memory
20GB model
= 70GB data

[EuroSys'16]

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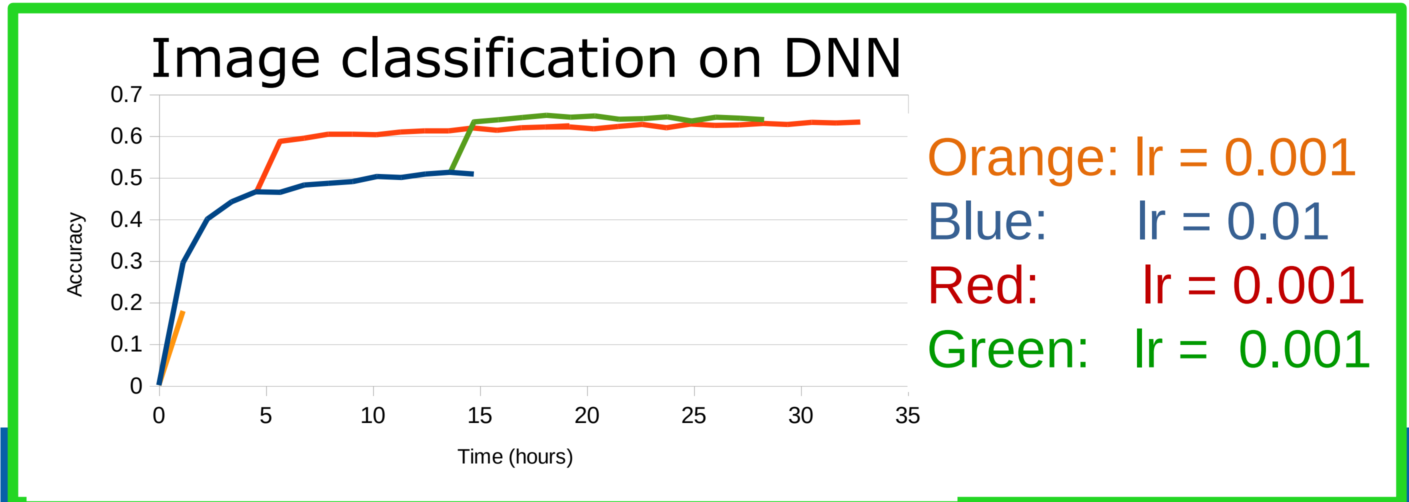
What's So Special about Big Learning? …A Distributed Systems' Perspective

More Bad News

- Sensitivity to tunables
- Costly: can we use spot instances?
- Streaming/incremental data
- Geo-distributed data (with skew)

Sensitivity to Tunables

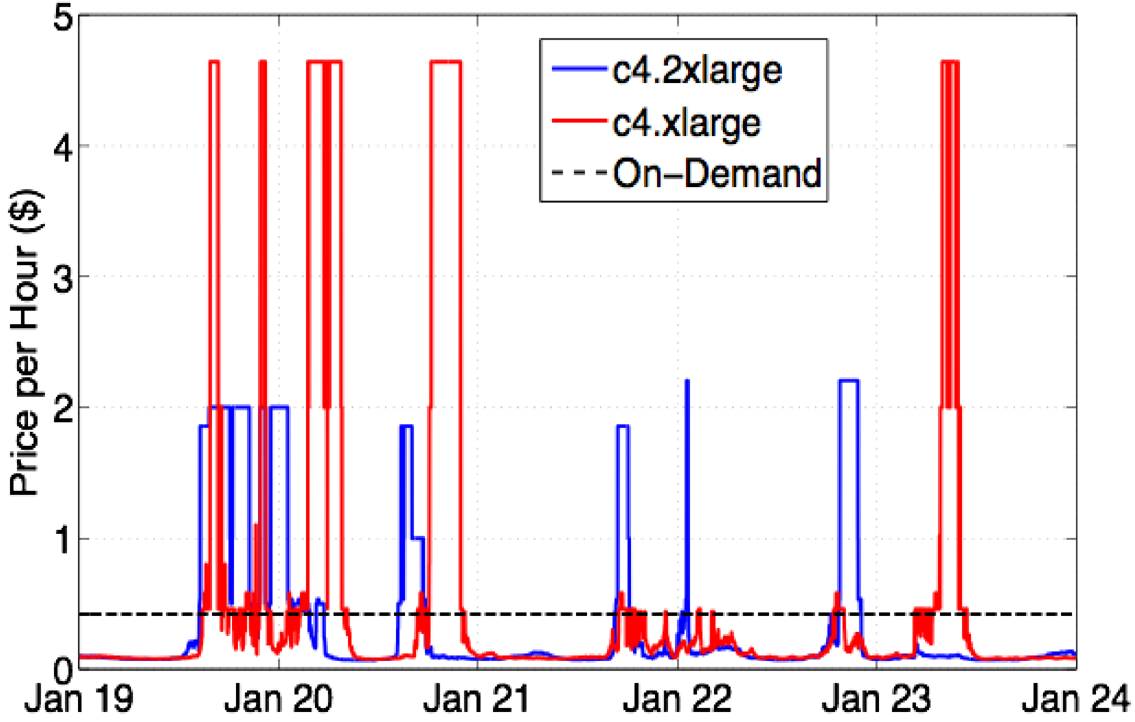
- **Many tunables in ML algorithms:**
  - Coefficients in optimization function, e.g., weights on regularization terms
  - Configuration tunables in optimization algorithm, e.g., learning rate, mini-batch size, staleness
- **Quality of solution & rate of convergence are highly sensitive to these tunables**
  - Today, mostly human trial-and-error



Open Problem: How to automate?

Costly => Use Spot Instances?

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



Open Problem: Effective, elastic Big Learning

Streaming / Incremental Data

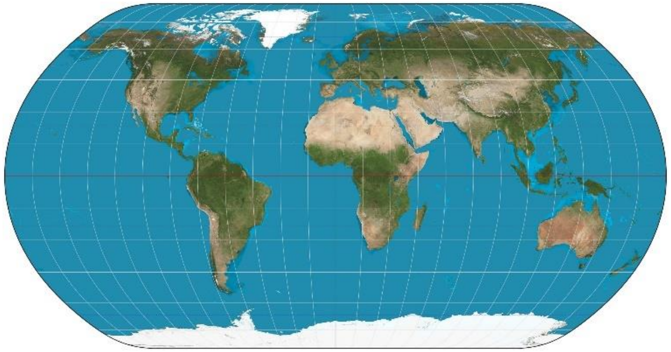
- **Training data is continually arriving**
- **Newest data is often the most valuable**

- **Scenario:**
  - 20 iterations have been run on existing data
  - Now, new batch of data arrives
  - What should be done?

Open Problem: How to best incorporate incrementally arriving data?

Geo-Distributed Data (with Skew)

- **Data sources are everywhere (geo-distributed)**
  - Too expensive (or not permitted) to ship all data to single data center
- **Big Learning over geo-distributed data**
  - **Low Bandwidth & High Latency** of Inter-data-center communication relative to Intra-data-center
  - Geo-distributed data may be **highly skewed**
  - **Regional answers** also of interest



Open Problem:
Effective Big Learning systems for Geo-distributed data

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- **CMU/ex-CMU Students:** James Cipar, **Henggang Cui**, Wei Dai, Jesse Haber-Kucharsky, **Aaron Harlap**, **Qirong Ho**, Kevin Hsieh, Jin Kyu Kim, Dimitris Konomis, Abhimanu Kumar, Seunghak Lee, Aurick Qiao, Alexey Tumanov, **Jinliang Wei**, Lianghong Xu, Hao Zhang

(Bold=first author)

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  - **National Science Foundation**

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

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

The Bad News: Model Training is SLOW

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

  => Need to distribute computation widely

- **Lots of Communication / Synchronization**
  - Not readily "partitionable"

More Bad News: Sensitivity to tunables

Costly=>spot instances?

Streaming/incremental data

Geo-distributed data (with skew)

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

The Good News

- Commutative/Associative parameter updates
- Tolerance for lazy consistency of parameters
- Repeated parameter data access pattern
- Intra-iteration progress measure
- Parameter update importance hints
- Layer-by-layer pattern of deep learning
- Others to be discovered ⬅

…can exploit to run orders of magnitude faster!

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