More Effective Distributed ML via a Stale Synchronous Parallel Parameter Server

Q. Ho, J. Cipar, H. Cui, J.K. Kim, S. Lee,
**P.B. Gibbons, G.A. Gibson, G.R. Ganger, E.P. Xing*

Carnegie Mellon University
***Intel Labs**

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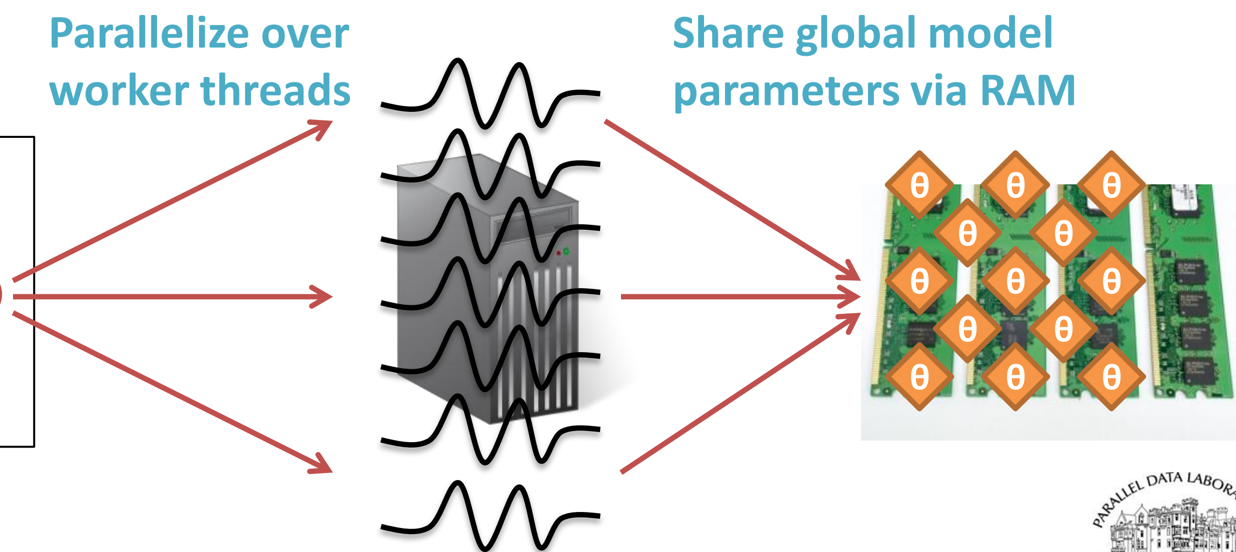
Distributed ML: one machine to many

- **Setting:** have iterative, parallel ML algorithm
  - E.g. optimization, MCMC algorithms
  - For topic models, regression, matrix factorization, SVMs, DNNs, etc.

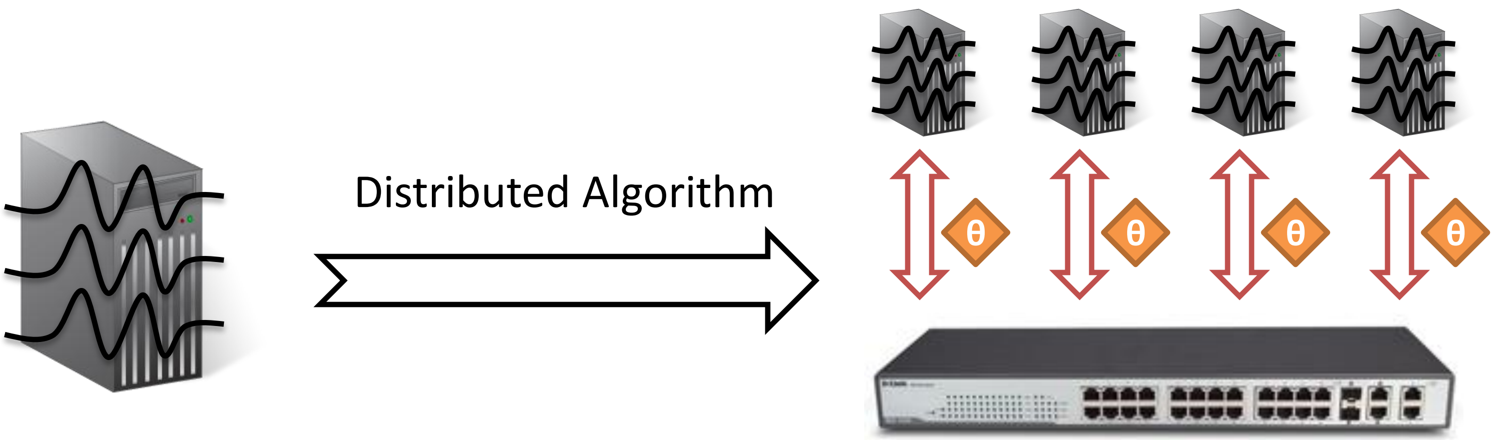
- Critical updates executed on one machine, in parallel
  - Worker threads share global model parameters θ via RAM

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



Distributed ML: one machine to many

- **Want:** scale up by distributing ML algorithm
  - Must now share parameters over a network
- Seems like a simple task…
  - Many distributed tools available, so just pick one and go?

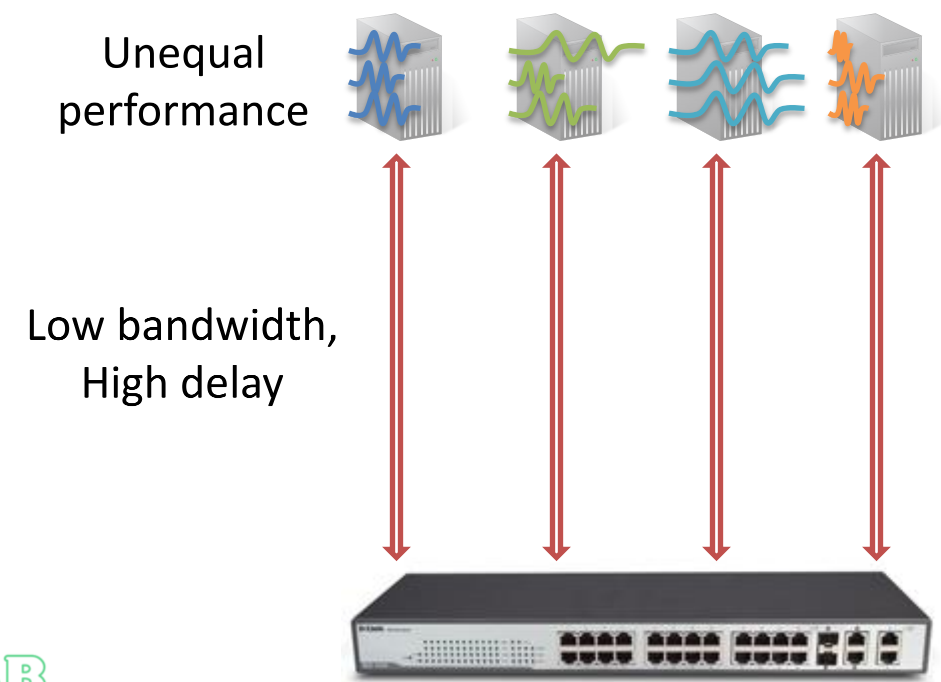


Single machine, multiple threads

Multiple machines, communicating over network switches

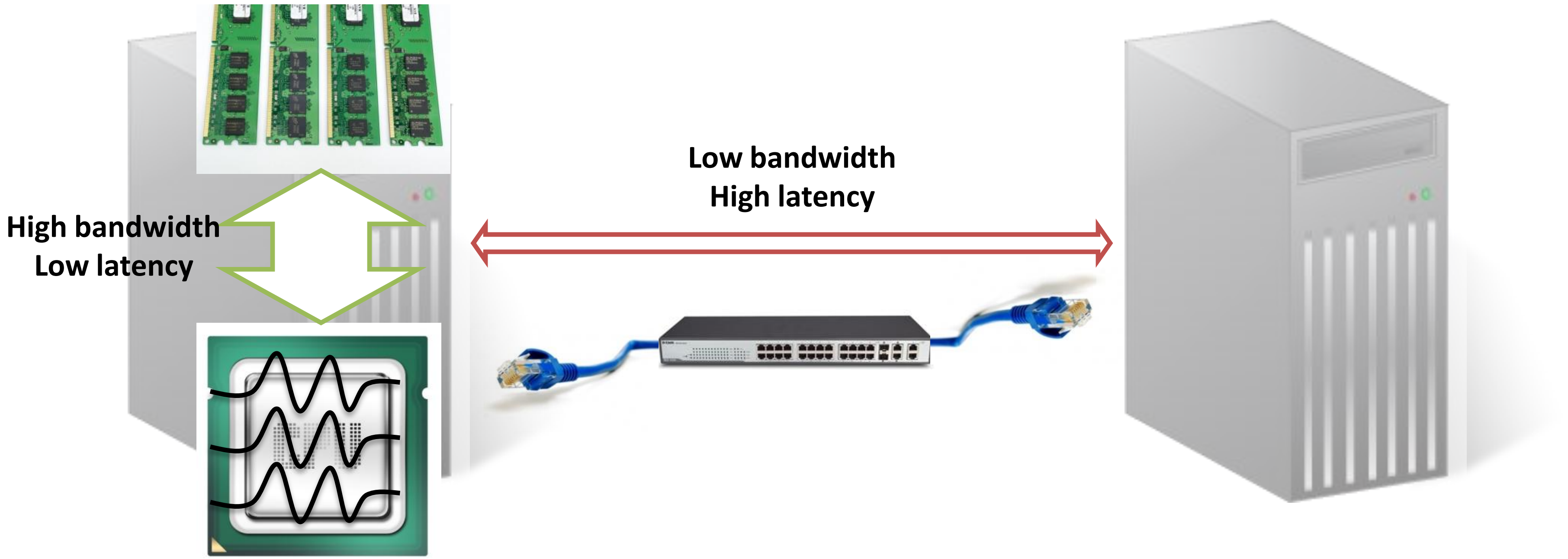
Distributed ML Challenges

- Not quite that easy…
- **Two distributed challenges:**
  - Networks are slow
  - “Identical” machines rarely perform equally



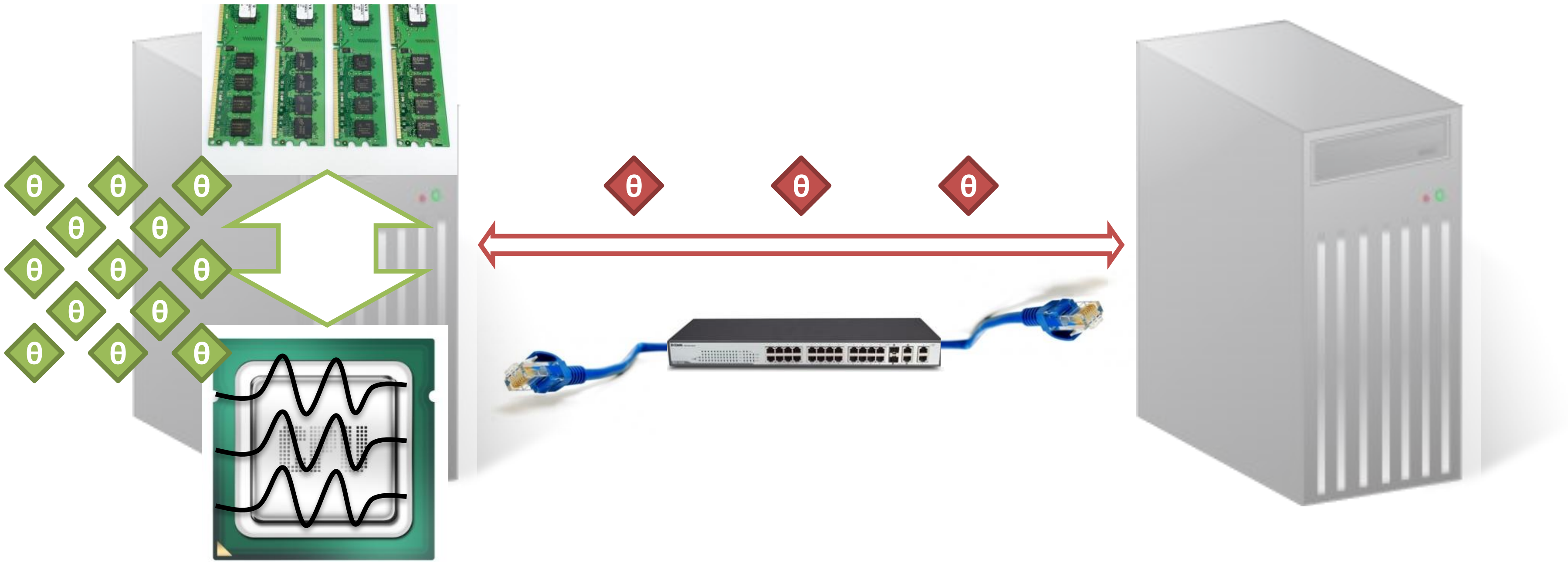
Networks are (relatively) slow

- **Low network bandwidth:**
  - 0.1-1GB/s (inter-machine) vs ≥20GB/s (CPU-RAM)
  - Fewer parameters transmitted per second
- **High network latency (messaging time):**
  - 10,000-100,000 ns (inter-machine) vs 100 ns (CPU-RAM)
  - Wait much longer to receive parameters



Networks are (relatively) slow

- **Parallel ML requires frequent synchronization**
  - Exchange 10-1000K scalars per second, per thread
  - Parameters not shared quickly enough → communication bottleneck
- Significant bottleneck over a network!



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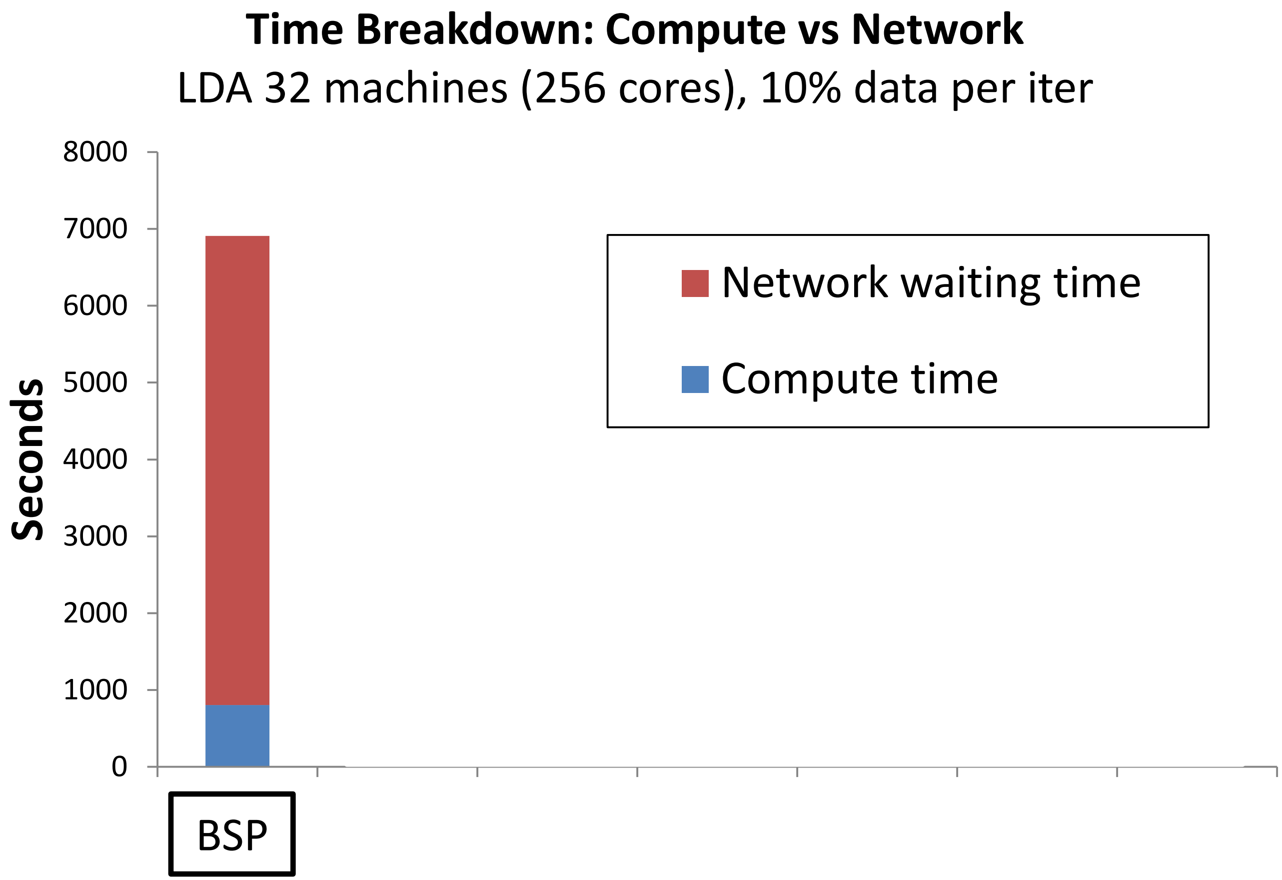
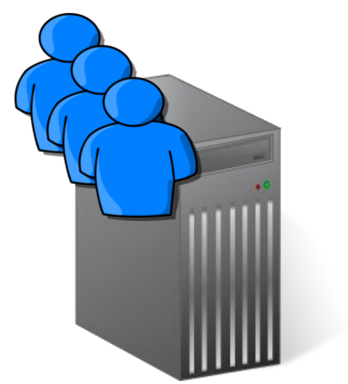


For a "clean" setting with <u>full control over machines</u> and <u>full network capacity</u>

Real clusters with many users have even worse network:compute ratios!

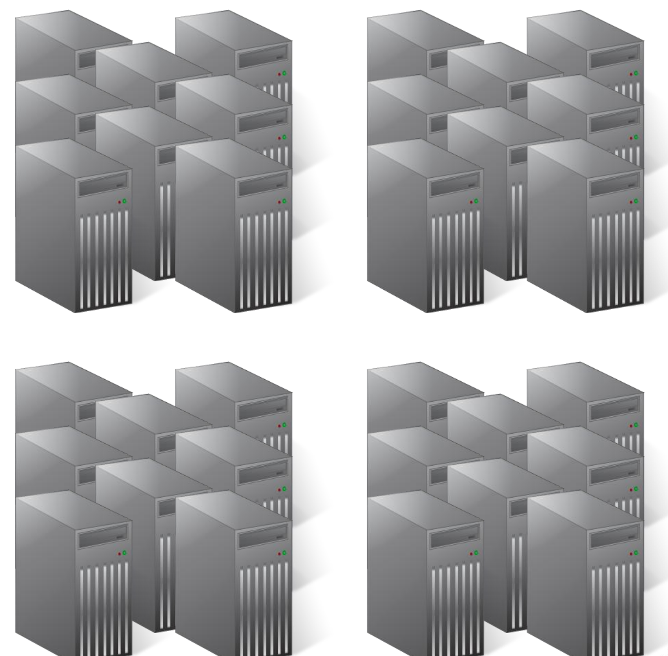
Machines don’t perform equally

- Even when configured identically
- **Variety of reasons:**
  - Vibrating hard drive
  - Background programs; part of a distributed filesystem
  - Other users
  - Machine is a VM/cloud service
- Occasional, random slowdowns in different machines



Consequence: Scaling up ML is hard!

- **Going from 1 to N machines:**
  - Naïve implementations rarely yield N-fold speedup
    - Slower convergence due to machine slowdowns, network bottlenecks
  - If not careful, even worse than a single machine!
    - Algorithm diverges due to errors from slowdowns!



Existing general-purpose scalable ML

Theory-oriented

- Focus on algorithm correctness/convergence

- Examples:
  - **Cyclic fixed-delay schemes** (Langford et al., Agarwal & Duchi)
  - **Single-machine asynchronous** (Niu et al.)
  - **Naively-parallel SGD** (Zinkevich et al.)
  - **Partitioned SGD** (Gemulla et al.)

- May oversimplify systems issues
  - e.g. need machines to perform consistently
  - e.g. need lots of synchronization
  - e.g. or even try not to communicate at all

Systems-oriented

- Focus on high iteration throughput

- Examples:
  - **MapReduce**: Hadoop and Mahout
  - **Spark**
  - **Graph-based**: GraphLab, Pregel

- May oversimplify ML issues
  - e.g. assume algorithms "just work" in distributed setting, without proof
  - e.g. must convert programs to new programming model; nontrivial effort

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Can we take both sides into account?

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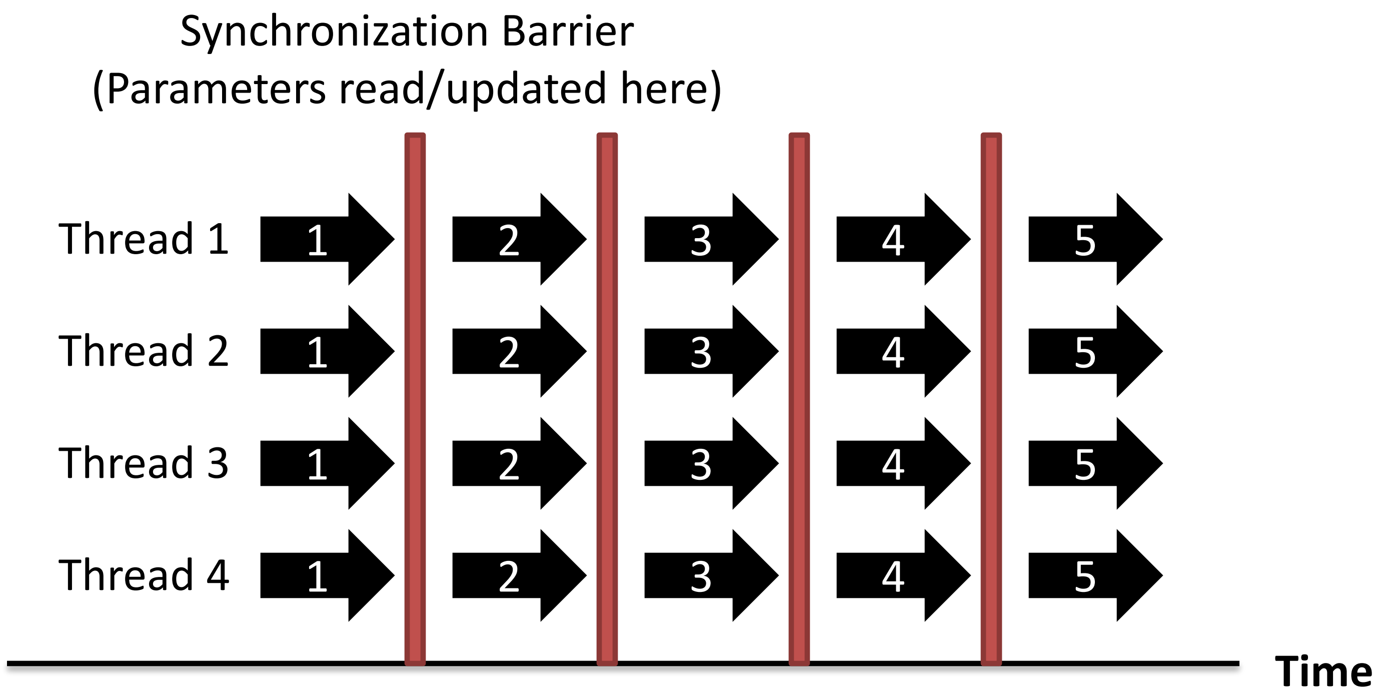
Middle of the road approach

- **Want:** ML algorithms converge quickly under imperfect systems conditions
  - e.g. slow network performance
  - e.g. random machine slowdowns
  - Parameters are not communicated consistently
- **Existing work:** mostly use one of two communication models
  - Bulk Synchronous Parallel (BSP)
  - Asynchronous (Async)
- **First, understand pros and cons of BSP and Async**

Bulk Synchronous Parallel

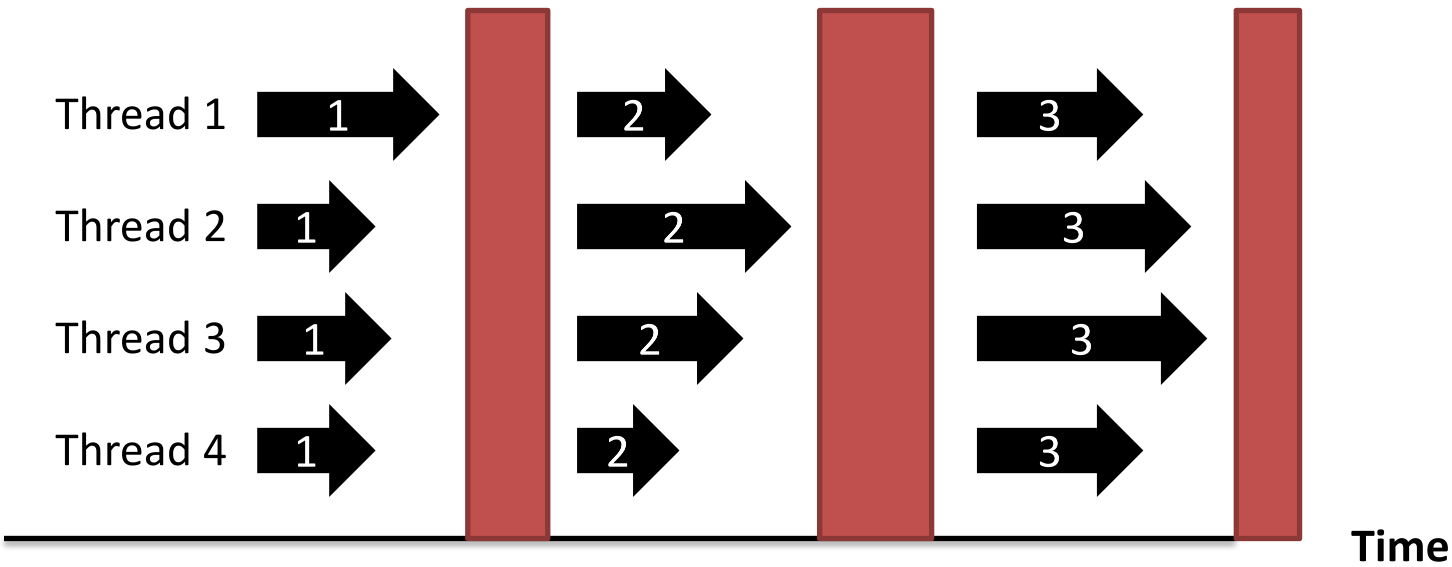


Threads synchronize (wait for each other) every iteration

Threads all on same iteration #

Parameters read/updated at synchronization barriers

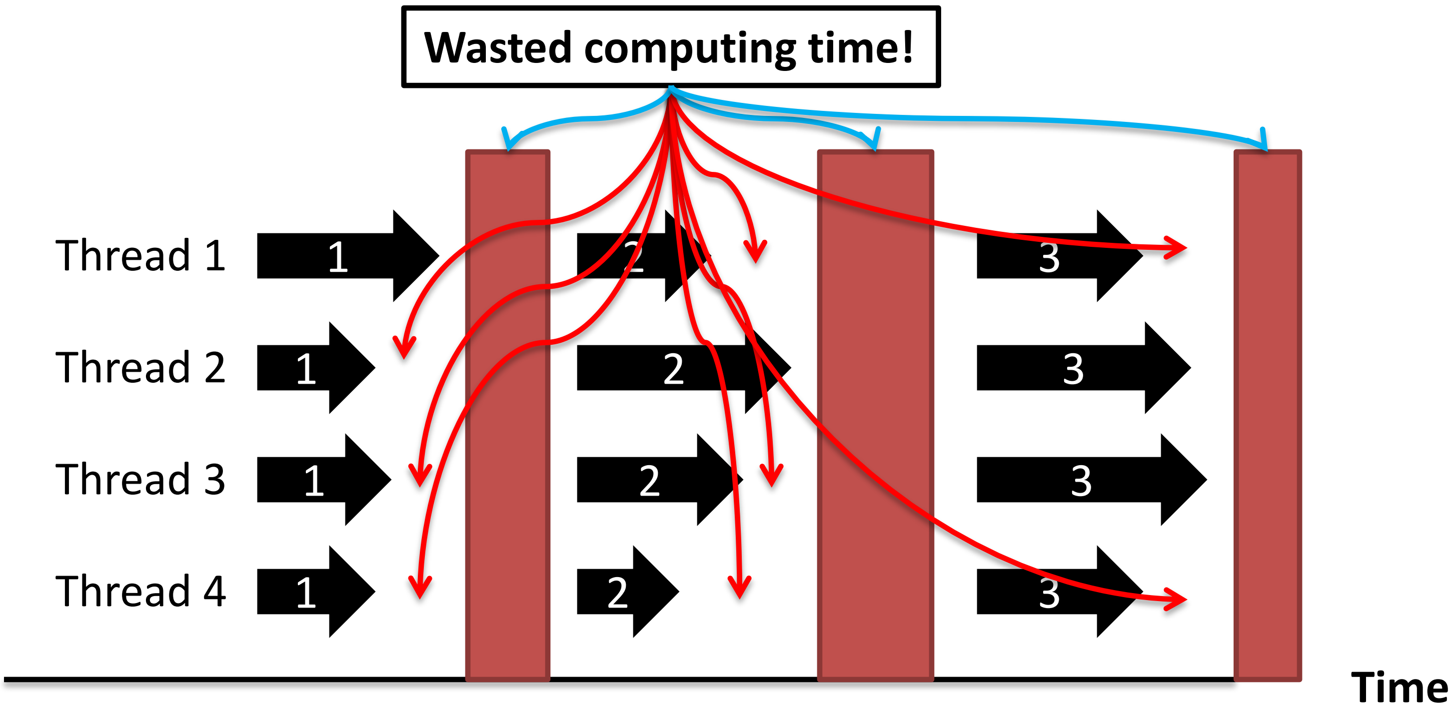
The cost of synchronicity



(a) Machines perform unequally
(b) Algorithmic workload imbalanced
So threads must wait for each other

End-of-iteration sync gets longer with larger clusters (due to slow network)

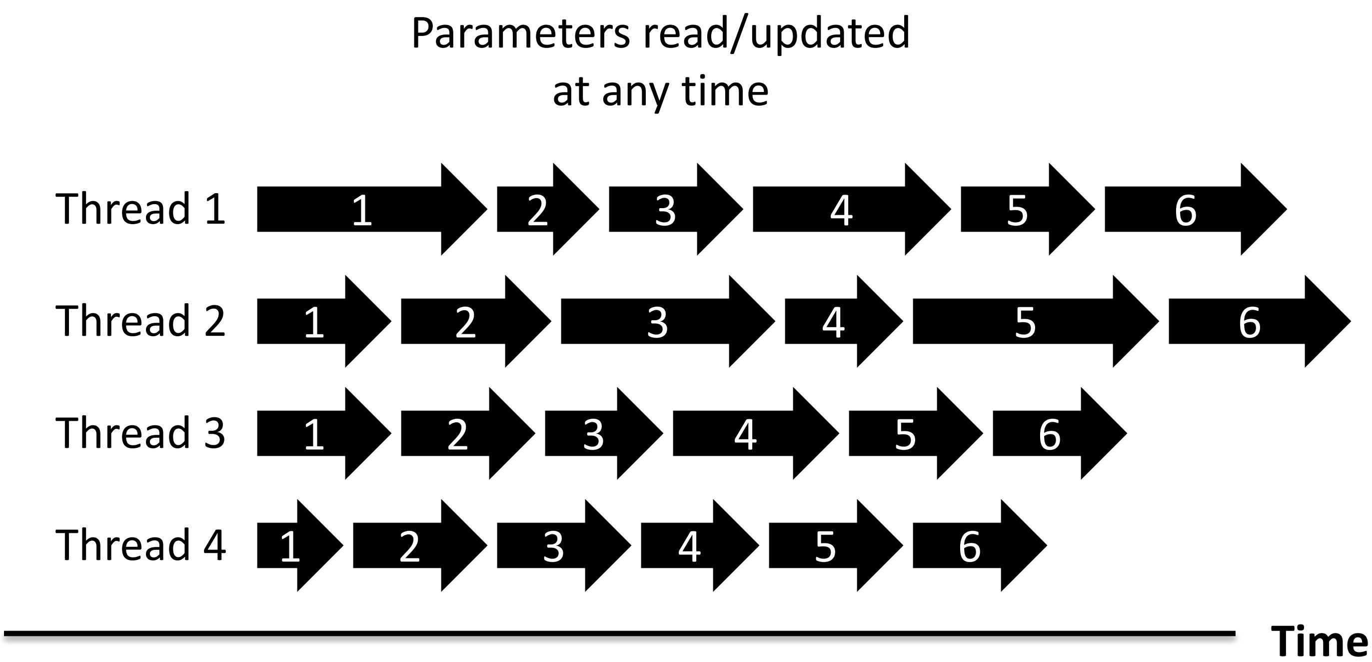
The cost of synchronicity



Threads must wait for each other
End-of-iteration sync gets longer with larger clusters

Precious computing time wasted

Asynchronous



Threads proceed to next iteration without waiting

Threads not on same iteration #

Parameters read/updated any time

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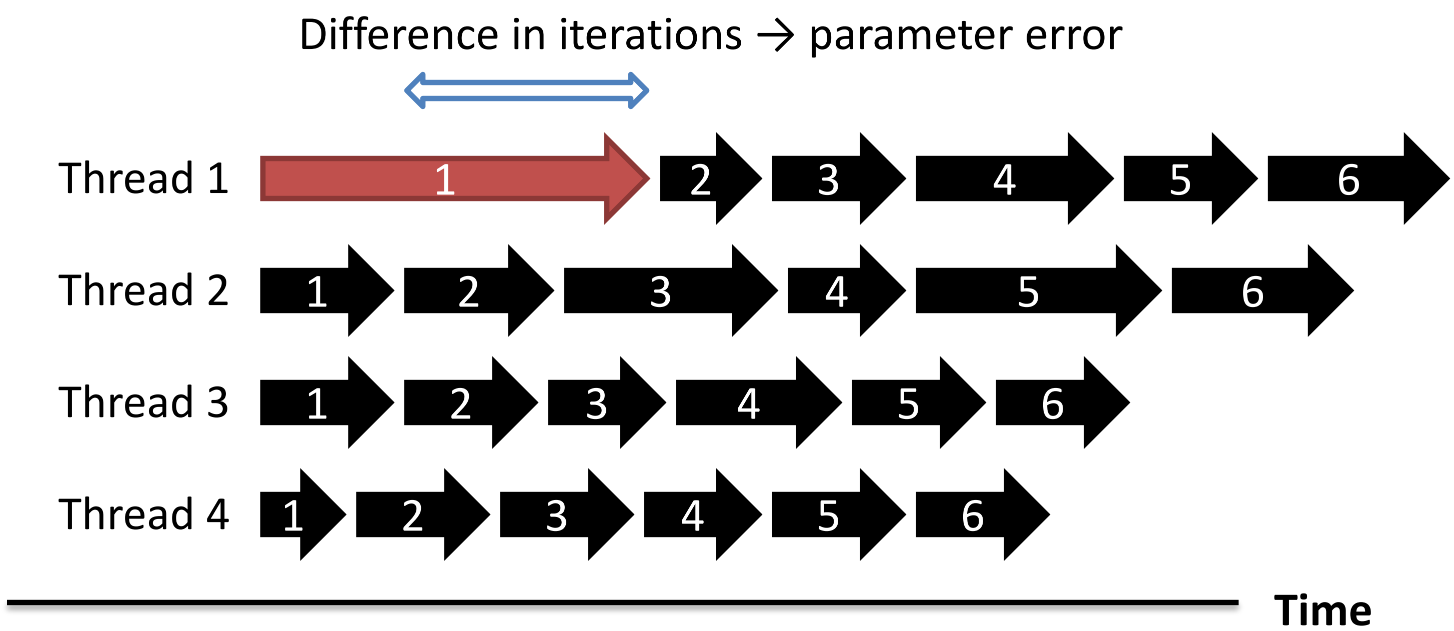
Slowdowns and Async



Machine suddenly slows down (hard drive, background process, etc.)

Causing iteration difference between threads

Leading to error in parameters

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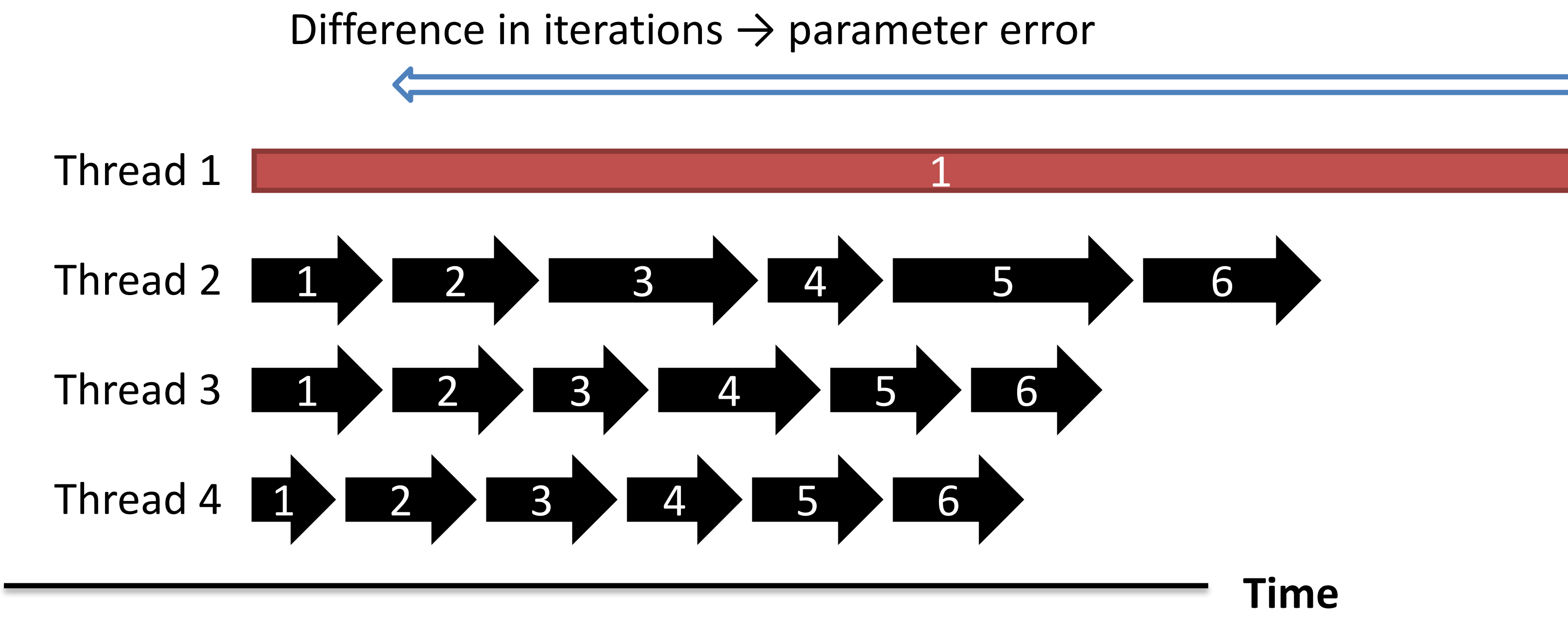
Async worst-case situation



Large clusters have arbitrarily large slowdowns!

Machines become inaccessible for extended periods

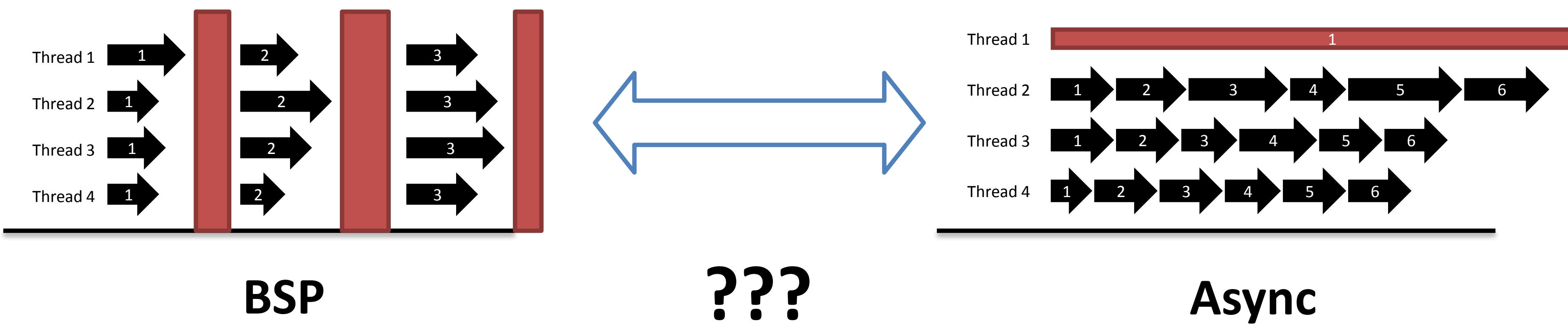
Error becomes unbounded!

What we really want

- **"Partial" synchronicity**
  - Spread network comms evenly (don't sync unless needed)
  - Threads usually shouldn't wait – but mustn't drift too far apart!

- **Straggler tolerance**
  - Slow threads must somehow catch up

- **Is there a middle ground between BSP and Async?**



That middle ground

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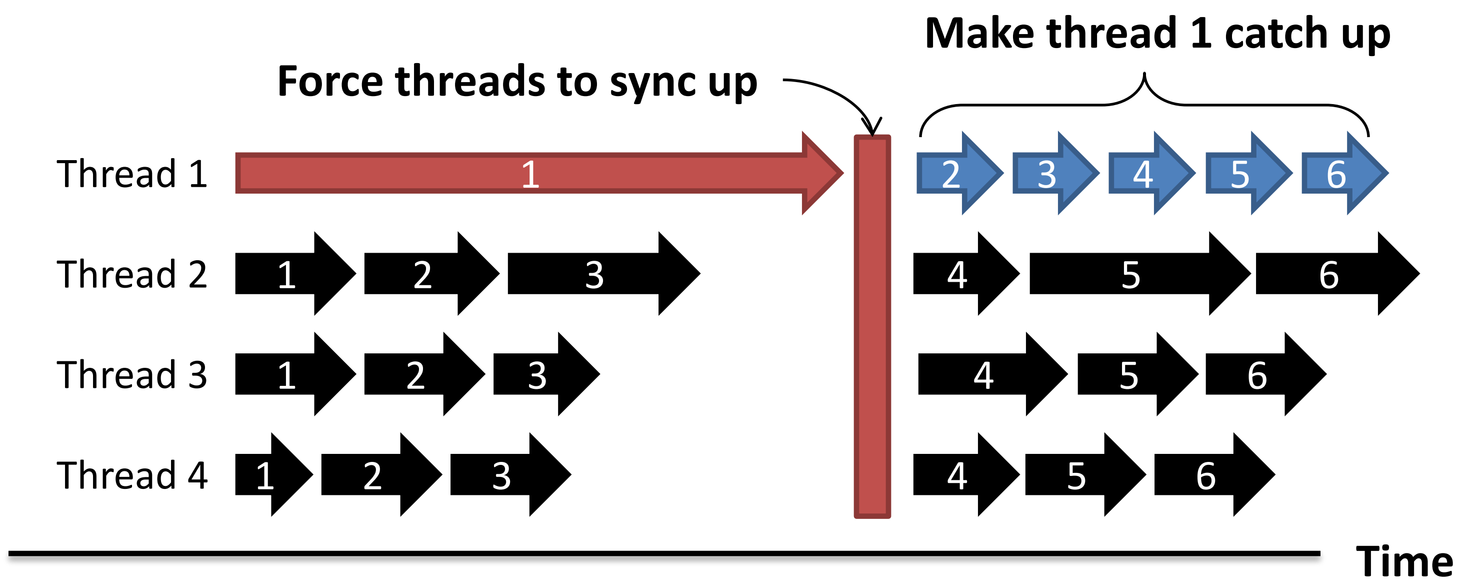
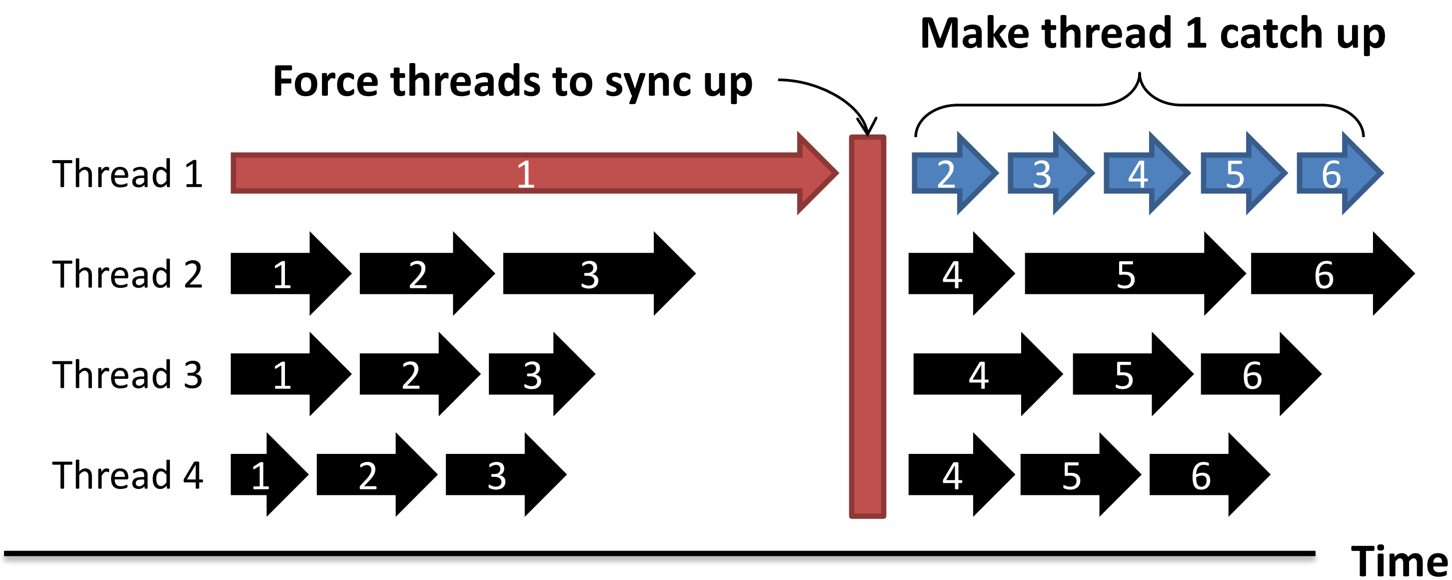


That middle ground

How do we realize this?



Stale Synchronous Parallel

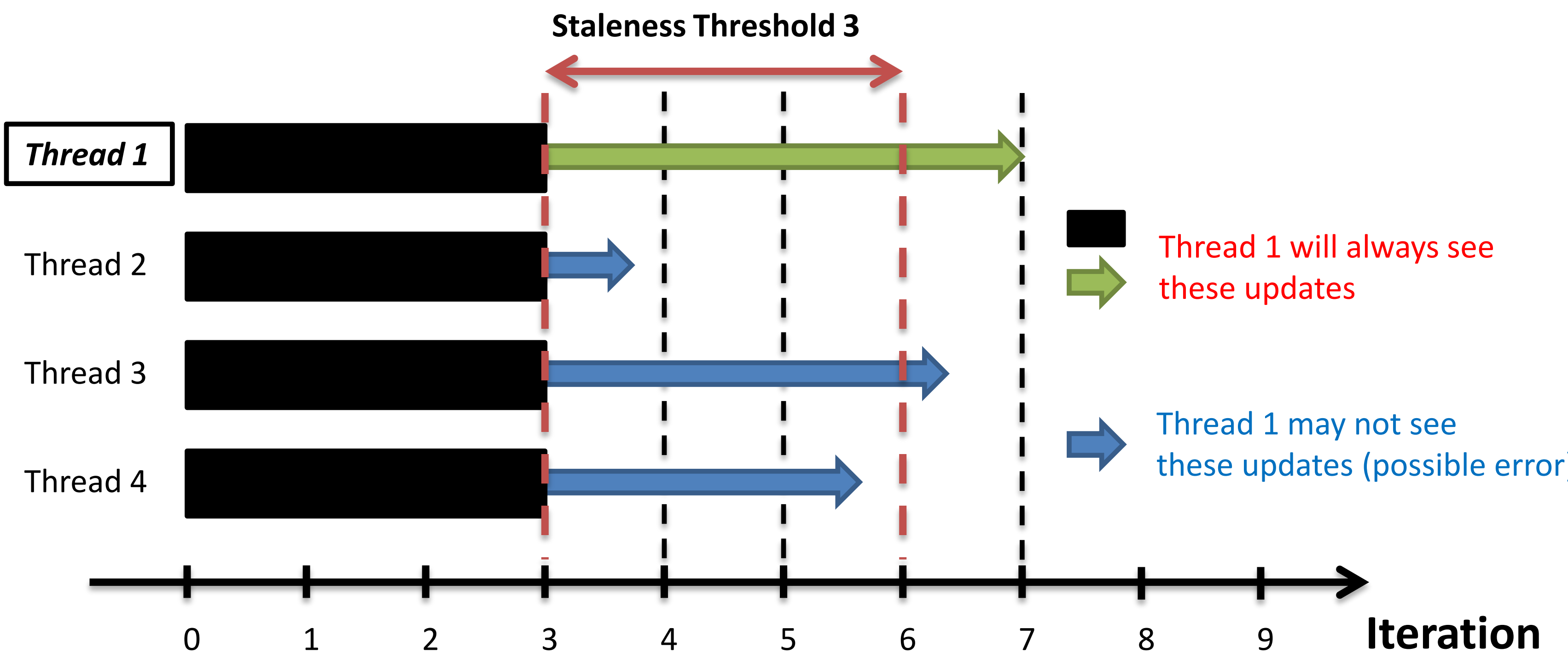
Note: x-axis is now iteration count, not time!

Allow threads to *usually* run at own pace

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

Threads cache local (stale) versions of the parameters, to reduce network syncing

Stale Synchronous Parallel



A thread at iter T <u>sees all parameter updates</u> before iter T-S

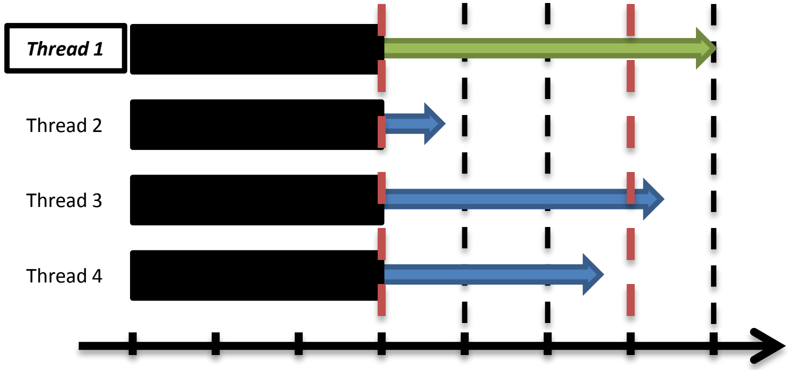
Protocol: check cache first; if too old, get latest version from network

Consequence: fast threads must check network every iteration

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

SSP provides best-of-both-worlds

- **SSP combines best properties of BSP and Async**
- BSP-like convergence guarantees
  - Threads cannot drift more than S iterations apart
  - Every thread sees all updates before iteration T-S
- Asynchronous-like speed
  - Threads usually don’t wait (unless there is drift)
  - Slower threads read from network less often, thus catching up
- **SSP is a spectrum of choices**
  - Can be fully synchronous (S = 0) or very asynchronous (S → ∞)
  - Or just take the middle ground, and benefit from both!



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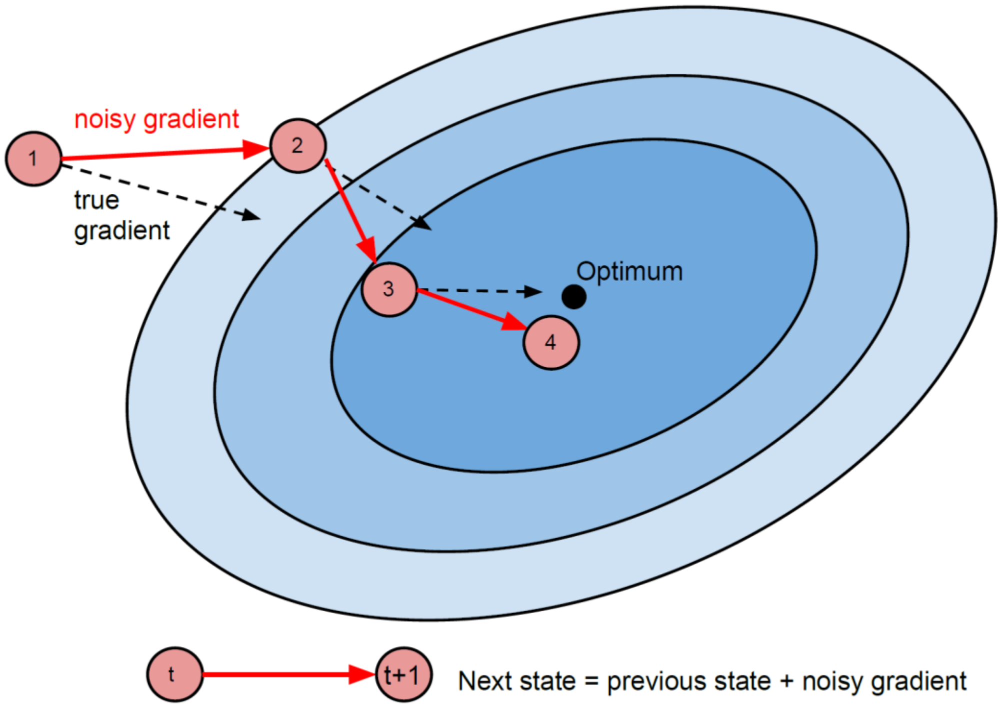
Why does SSP converge?



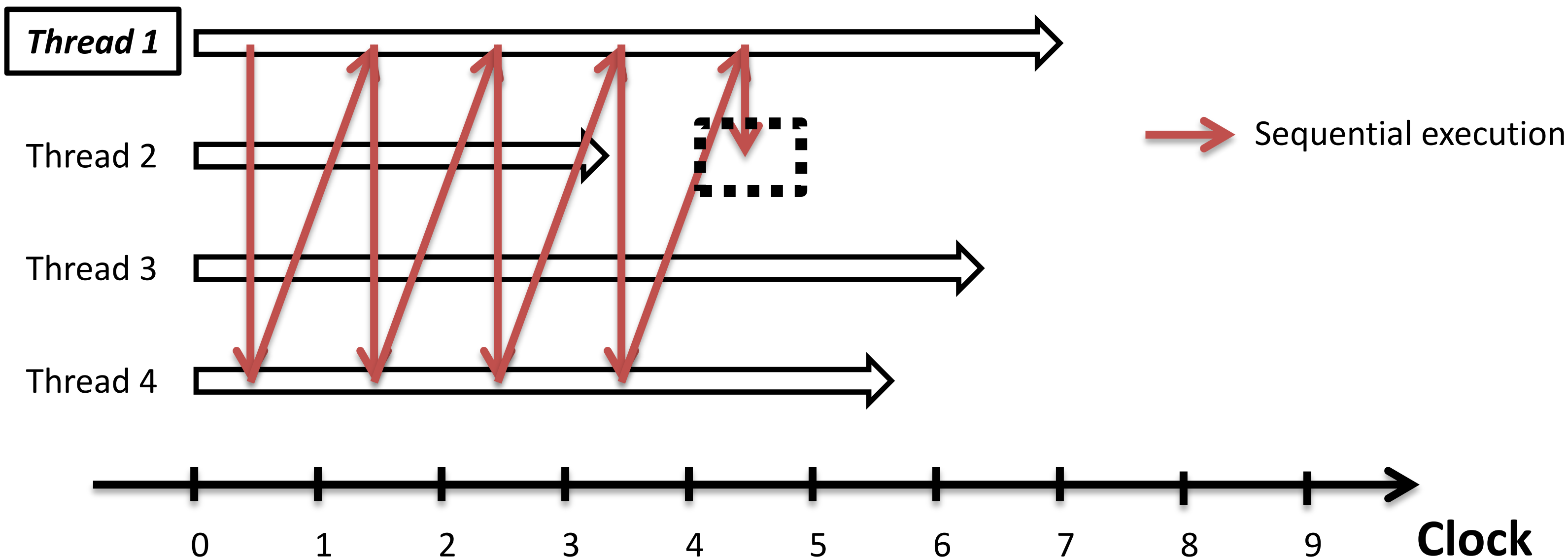
Instead of $\boldsymbol{x}_{\textit{true}}$, SSP sees $\boldsymbol{x}_{\textit{stale}} = \boldsymbol{x}_{\textit{true}}$ + ***error***

The *error* caused by staleness is <u>bounded</u>

Over many iterations, average error goes to zero

Why does SSP converge?

SSP approximates sequential execution



Compare actual update order to ideal sequential execution

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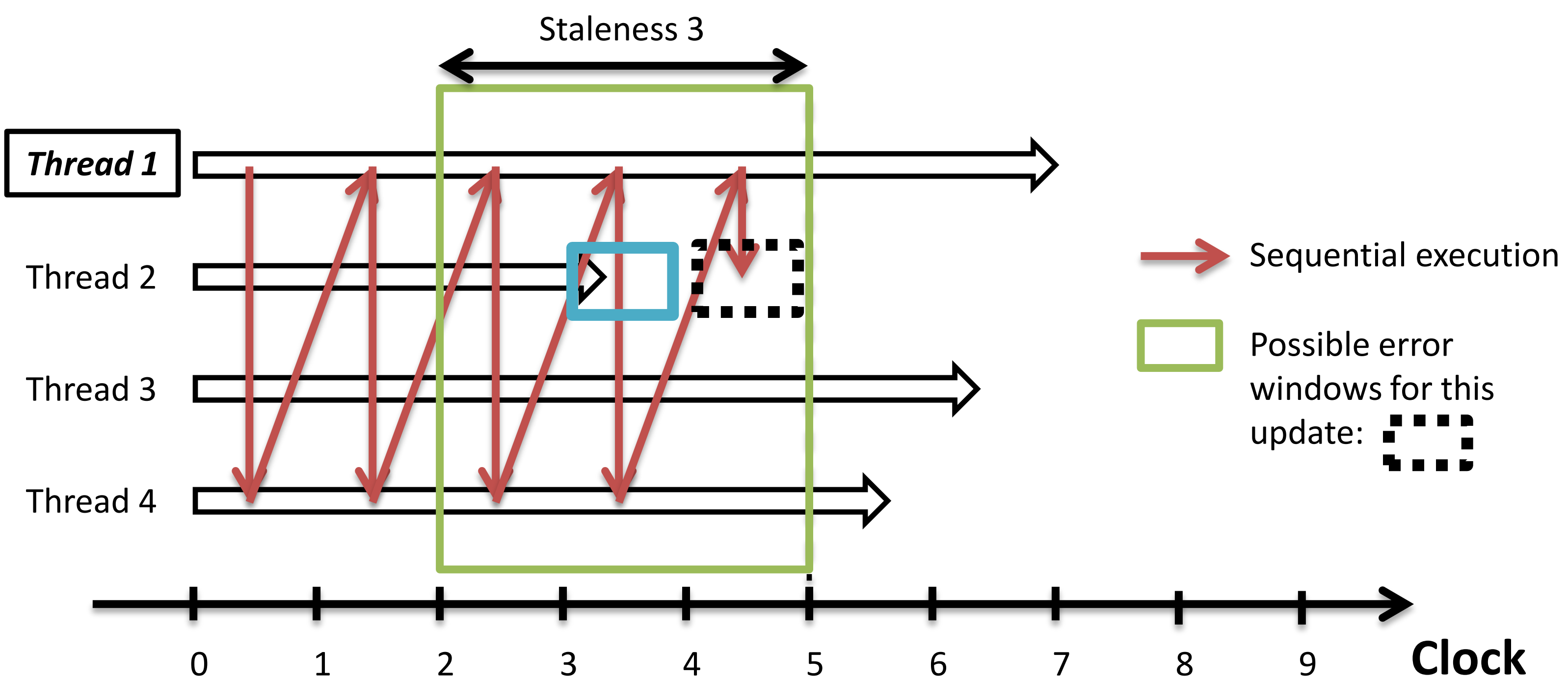
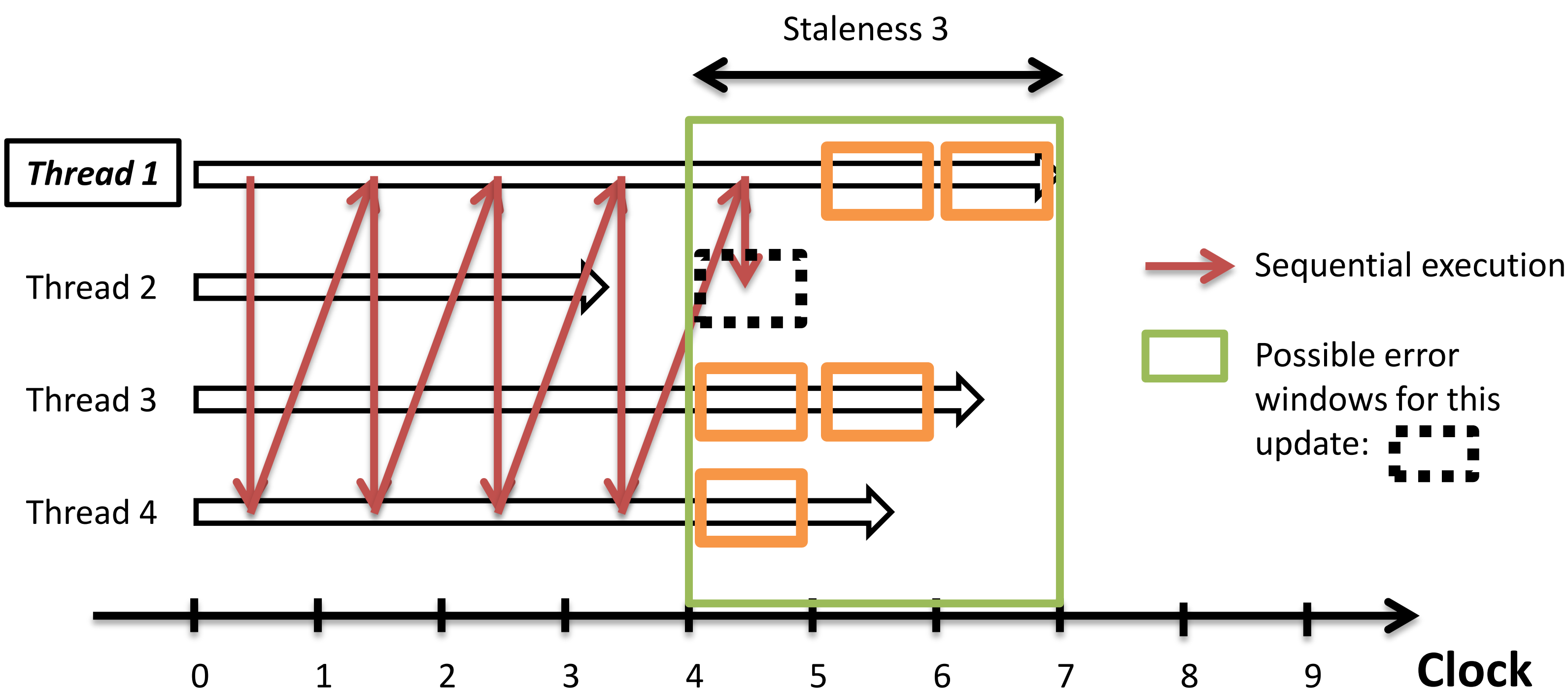


SSP may lose up to S iterations of updates to the left…

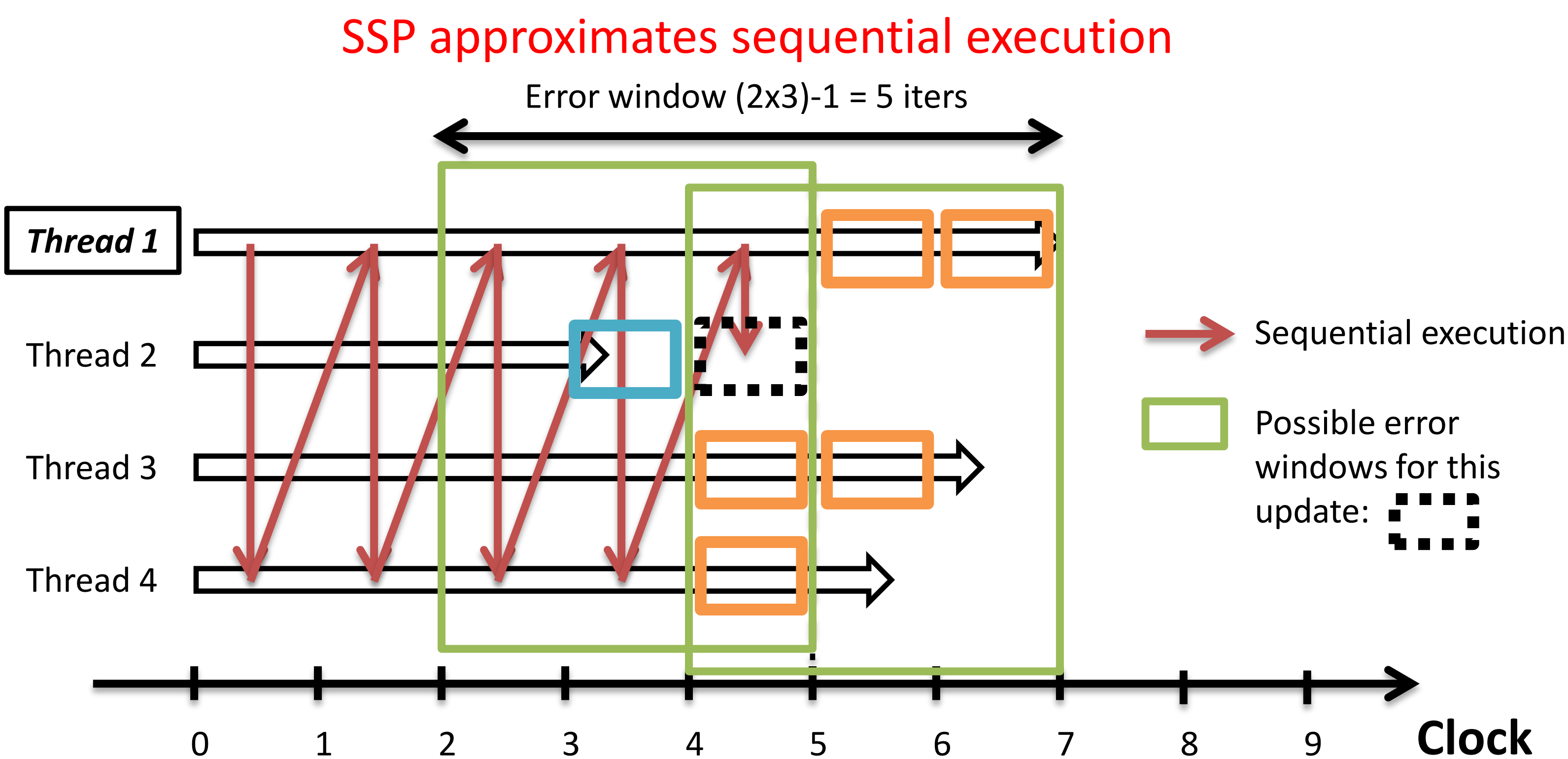
Why does SSP converge?

SSP approximates sequential execution



… as well as gain up to S iterations of updates to the right

Why does SSP converge?



Thus, at most 2S-1 iterations of erroneous updates

Hence numeric error in parameters is also bounded

Partial, but bounded, loss of serializability

Convergence Theorem

- **Want:** minimize convex $f(\mathbf{x}) = \frac{1}{T}\sum_{t=1}^{T} f_t(\mathbf{x})$ (Example: Stochastic Gradient)
  - L-Lipschitz, problem diameter bounded by F^2
  - Staleness s, using P threads across all machines
  - Use step size $\eta_t = \frac{\sigma}{\sqrt{t}}$ with $\sigma = \frac{F}{L\sqrt{2(s+1)P}}$

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  - Staleness $\boldsymbol{s}$, using $\boldsymbol{P}$ threads across all machines
  - Use step size $\eta_t = \frac{\sigma}{\sqrt{t}}$ with $\sigma = \frac{F}{L\sqrt{2(s+1)P}}$

- **SSP converges according to** $$R[\mathbf{X}] := \underbrace{\left[\frac{1}{T}\sum_{t=1}^{T} f_t(\tilde{\mathbf{x}}_t)\right] - f(\mathbf{x}^*)}_{\text{Difference between SSP estimate and true optimum}} \leq 4FL\sqrt{\frac{2(s+1)P}{T}}$$
  - Where $\boldsymbol{T}$ is the number of iterations

- Note: RHS bound contains $(\boldsymbol{L}, \boldsymbol{F})$ and $(\boldsymbol{s}, \boldsymbol{P})$
  - The interaction between theory and systems parameters

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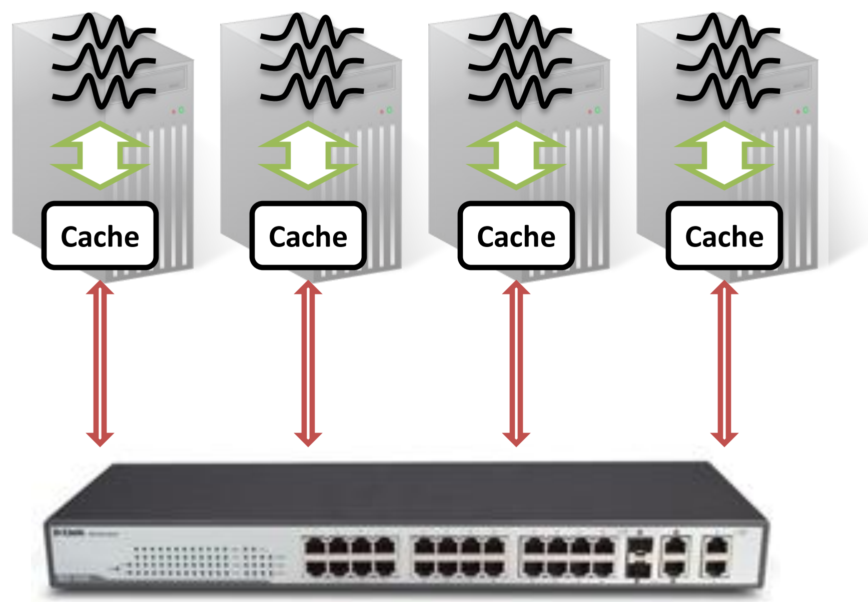
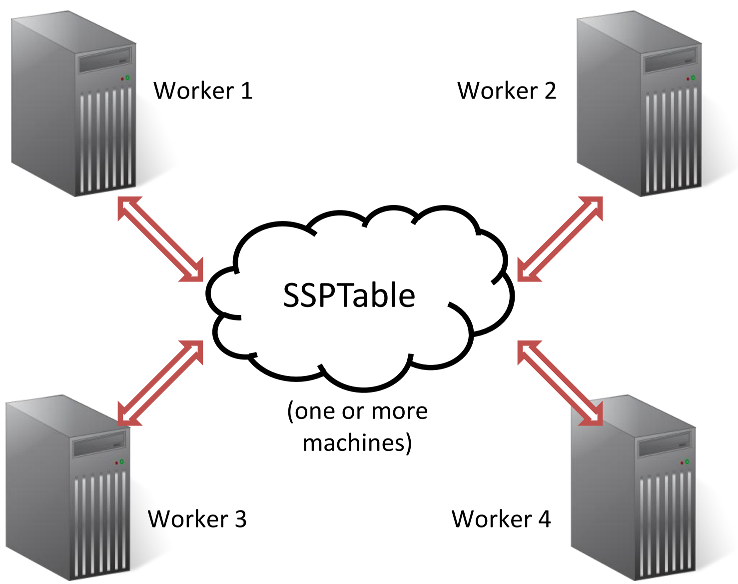
SSP solves Distributed ML challenges

- **SSP is a synchronization model for fast and correct distributed ML**
  - For "abelian" parameter updates of the form $\theta_{new} = \theta_{old} + \Delta$
- **SSP reduces network traffic**
  - Threads use stale local cache whenever possible
  - Addresses slow network and occasional machine slowdowns



SSP + Parameter Server = Easy Distributed ML

- **We implement SSP as a "parameter server" (PS)†, called SSPTable**
  - Provides all machines with convenient access to global model parameter
  - Can be run on multiple machines – reduces load per machine
- **SSPTable allows easy conversion of single-machine parallel ML algorithms**
  - "Distributed shared memory" programming style
  - No need for complicated message passing
  - Replace local memory access with PS access



Single Machine Parallel

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

Distributed with SSPTable

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

† **Ahmed et al. (WSDM 2012), Power and Li (OSDI 2010)**

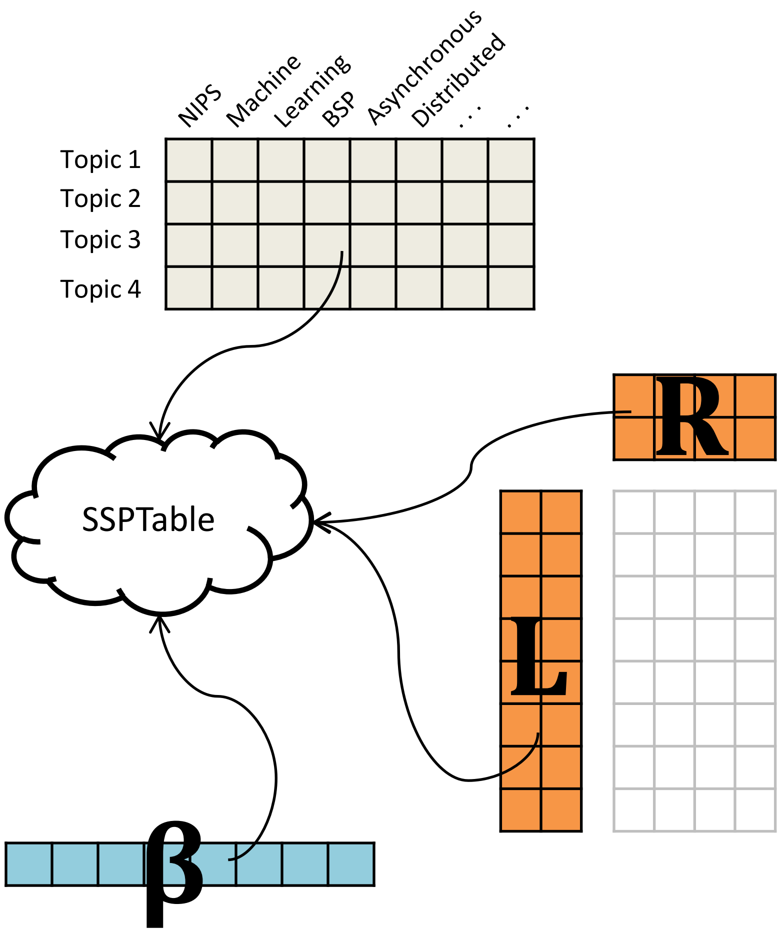
SSPTable Programming

- Easy, table-based programming – just 3 commands!
  - No message passing, barriers, locks, etc.

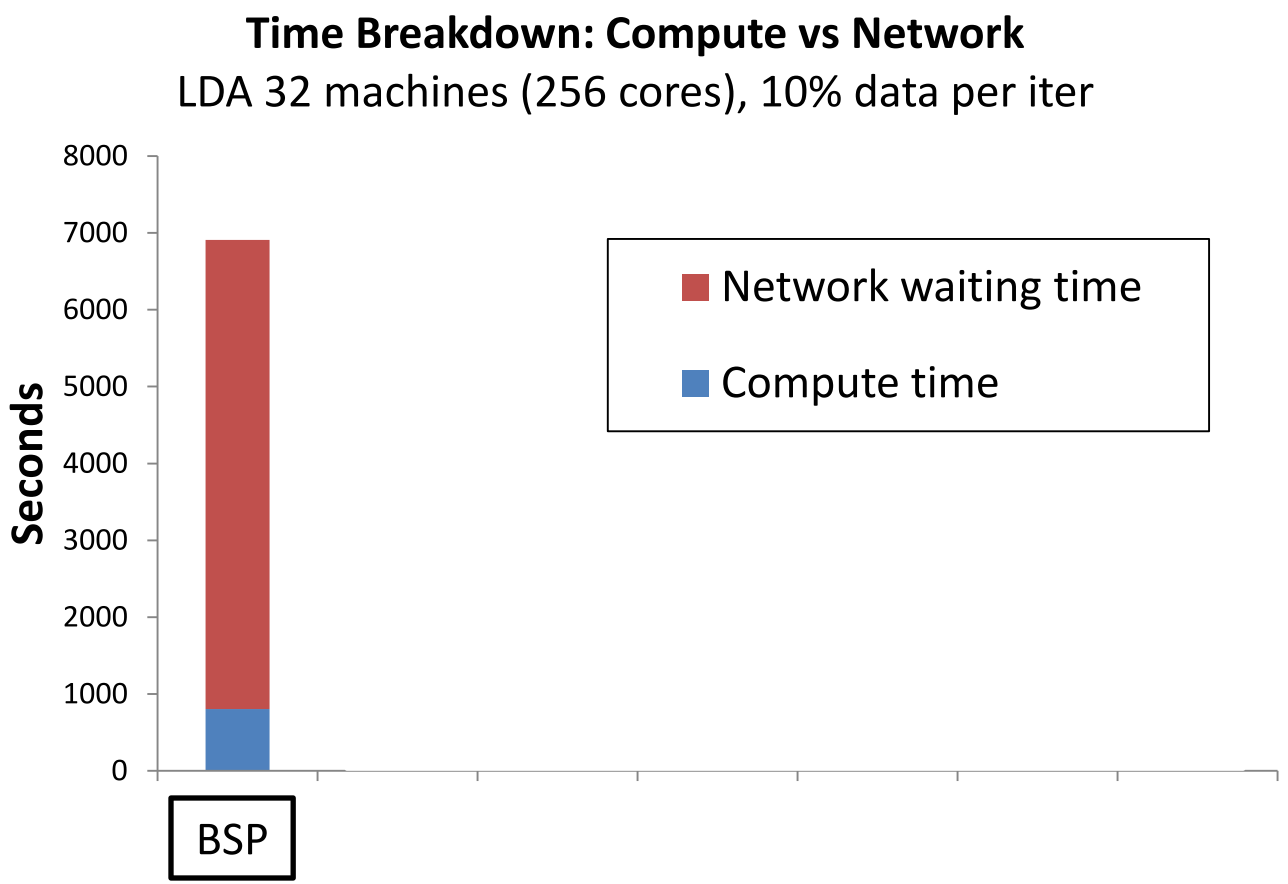
- `read_row(table,row,s)`
  - Retrieve a table row with staleness s
- `inc(table,row,col,value)`
  - Increment table's (row,col) by value
- `clock()`
  - Inform PS that this thread is advancing to the next iteration

SSPTable Programming

- Just put global parameters in SSPTable! Examples:
- **Topic Modeling (MCMC)**
  - Topic-word table
- **Matrix Factorization (SGD)**
  - Factor matrices L, R
- **Lasso Regression (CD)**
  - Coefficients β
- SSPTable supports generic classes of algorithms
  - With these models as examples



SSPTable uses networks efficiently



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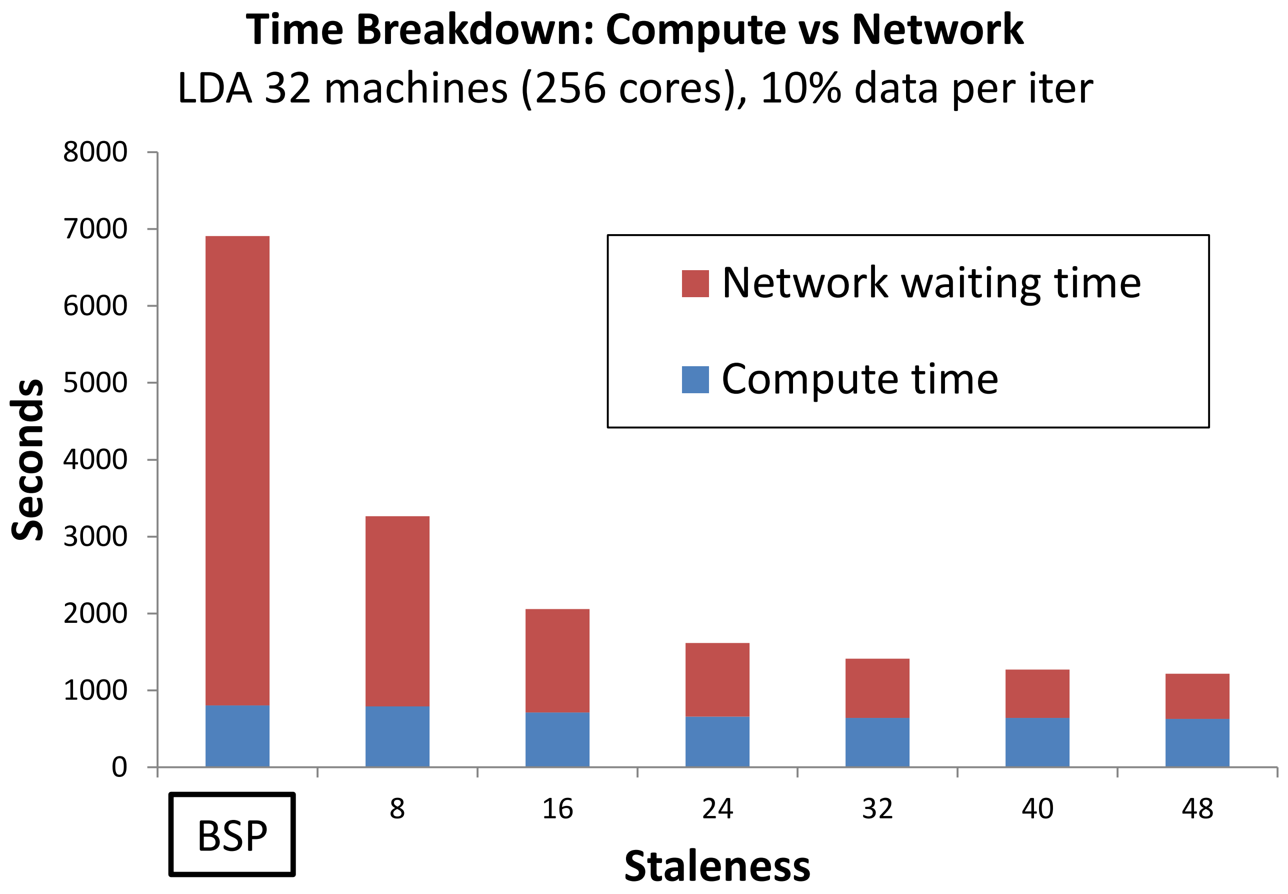
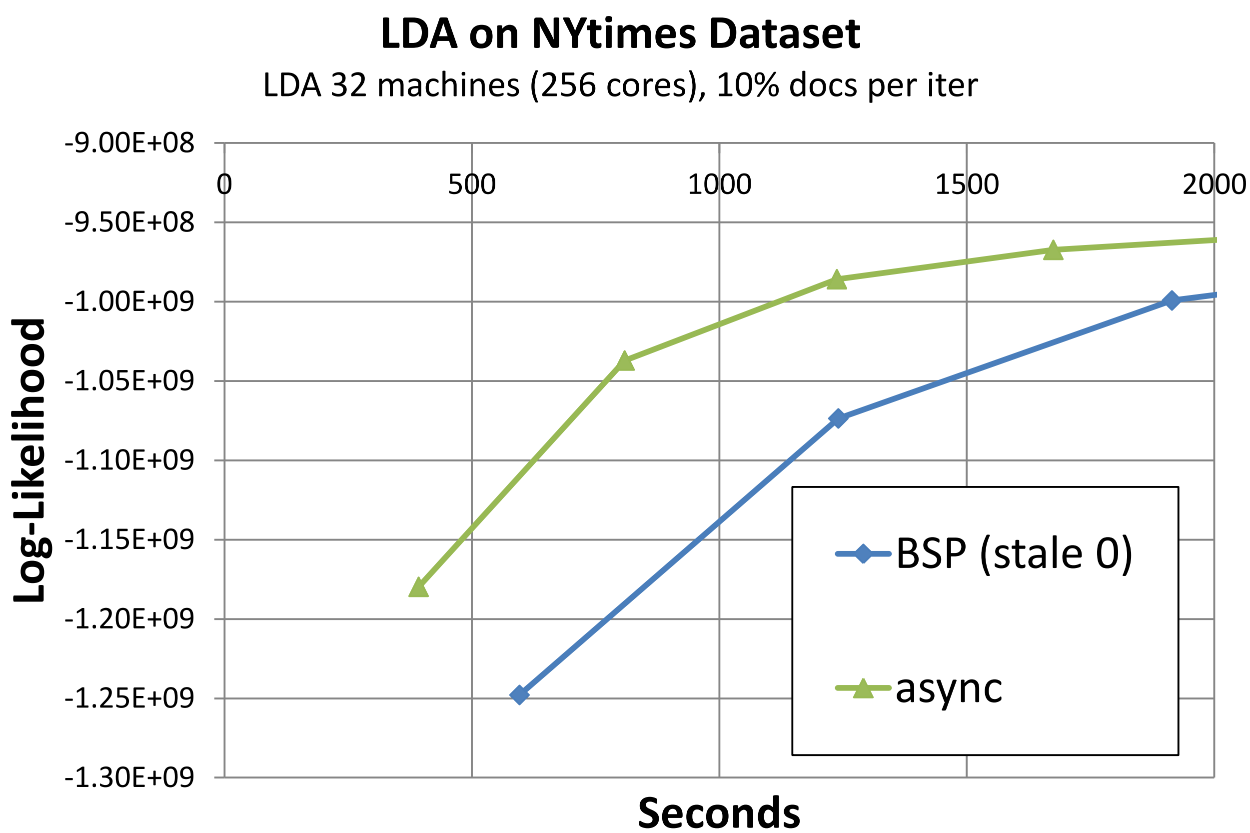


Network communication is a huge bottleneck with many machines

SSP balances network and compute time

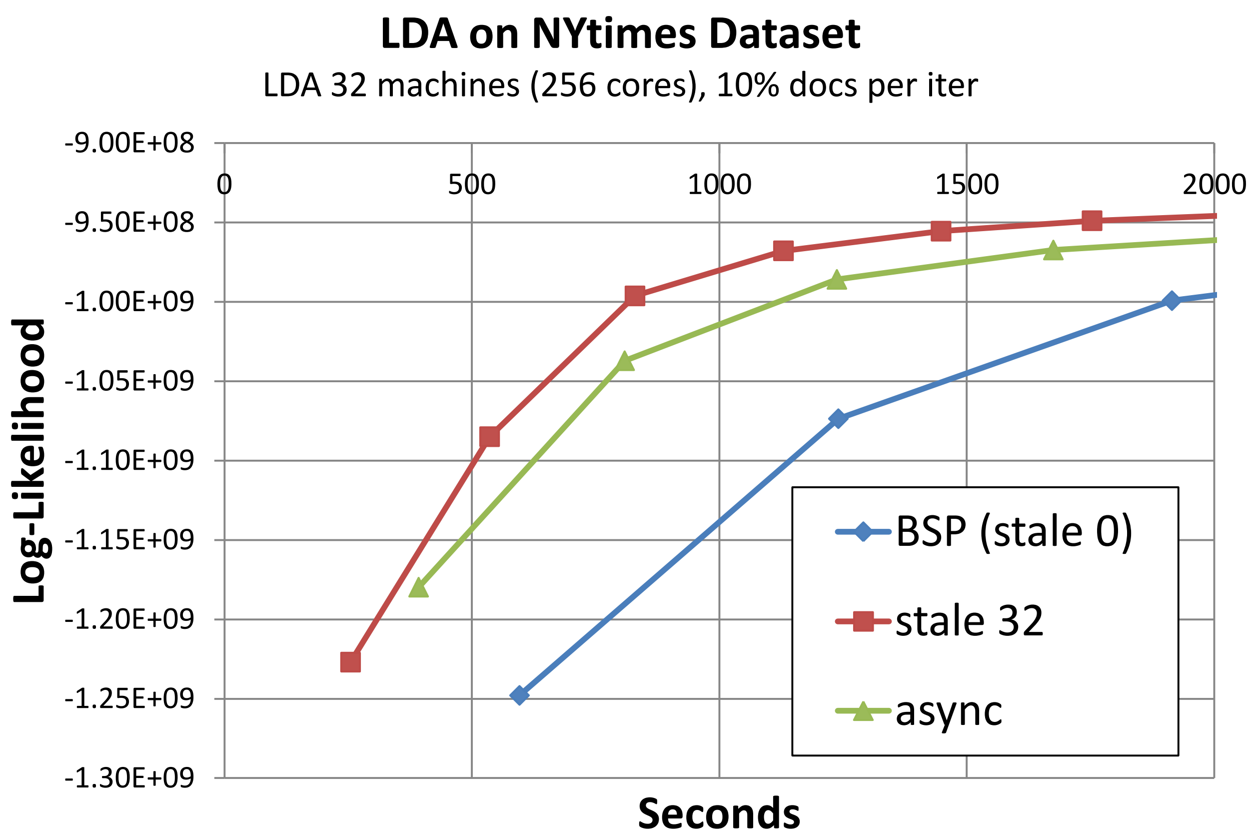
SSPTable vs BSP and Async



NYtimes data
N = 100M tokens
K = 100 topics
V = 100K terms

BSP has strong convergence guarantees but is slow
Asynchronous is fast but has weak convergence guarantees

SSPTable vs BSP and Async



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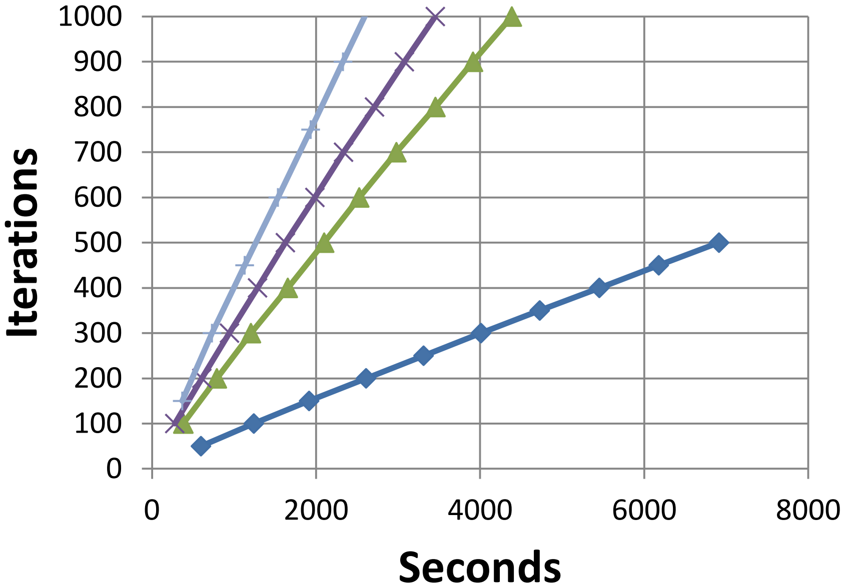
SSPTable is fast and has strong convergence guarantees

The Quality vs Quantity tradeoff

Quantity: iterations versus time
LDA 32 machines, 10% data



Quality: objective versus iterations
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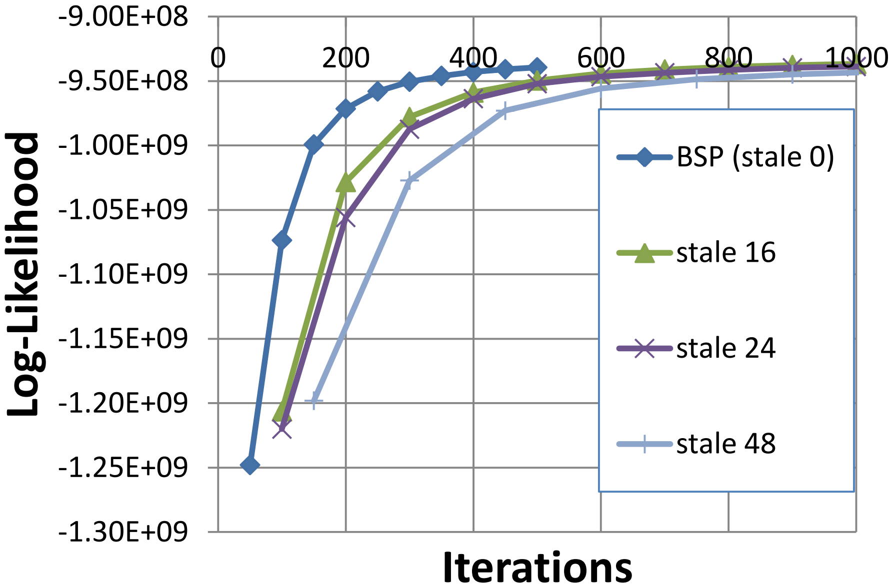
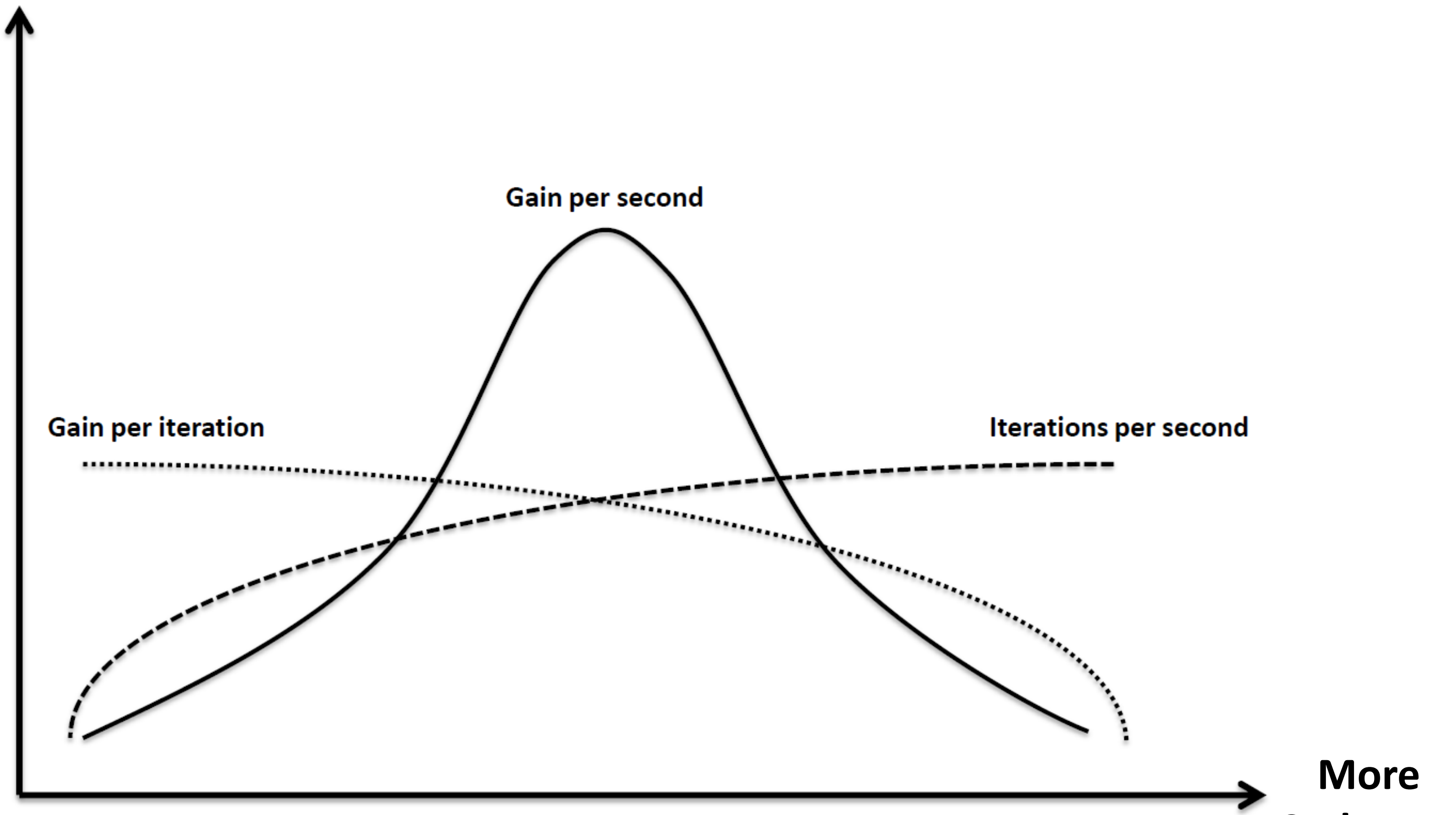


Progress per time is (iters/sec) * (progress/iter)

High staleness yields more iters/sec, but lowers progress/iter

Find the sweet spot staleness >0 for maximum progress per second

The Quality vs Quantity tradeoff



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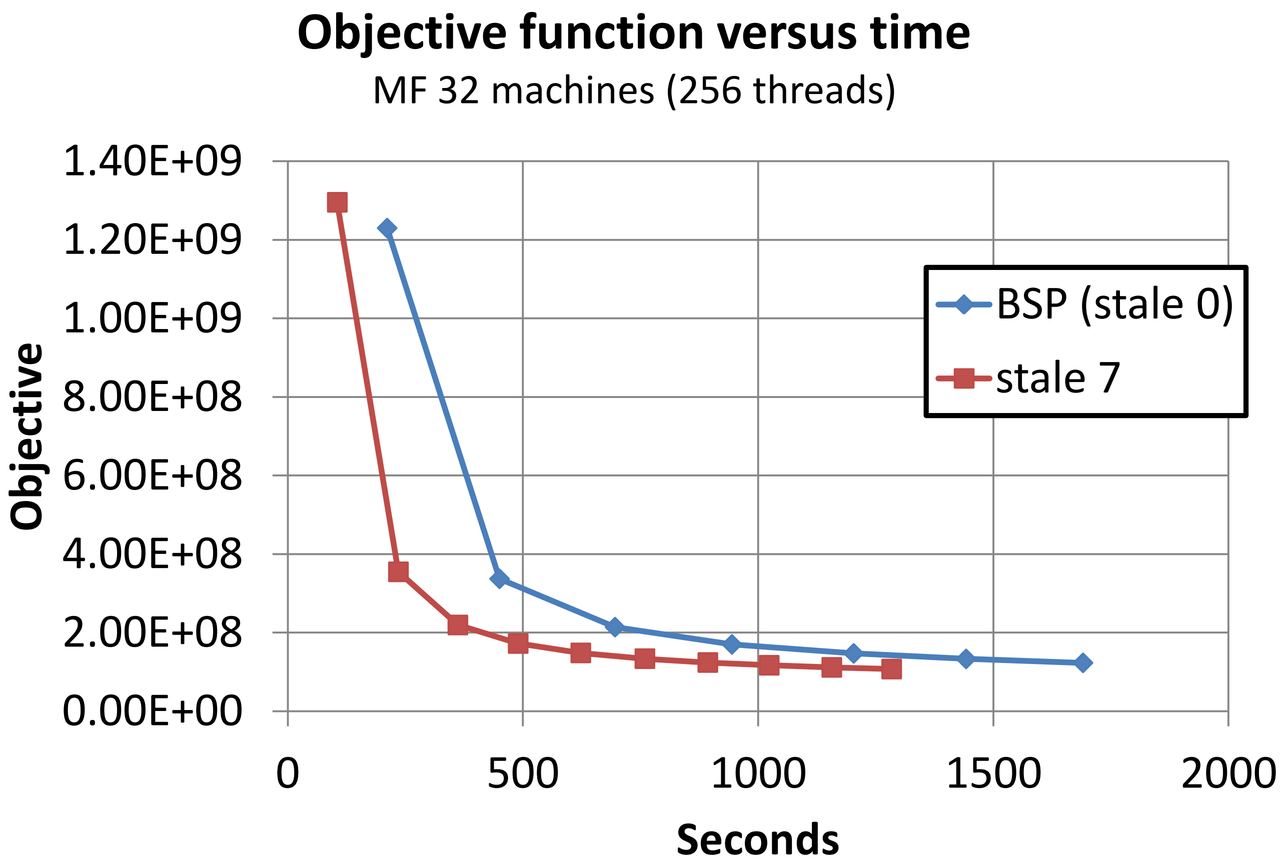
Find the sweet spot staleness >0 for maximum progress per second

Matrix Factorization (Netflix)

Netflix data
100M nonzeros
480K rows
18K columns
rank 100



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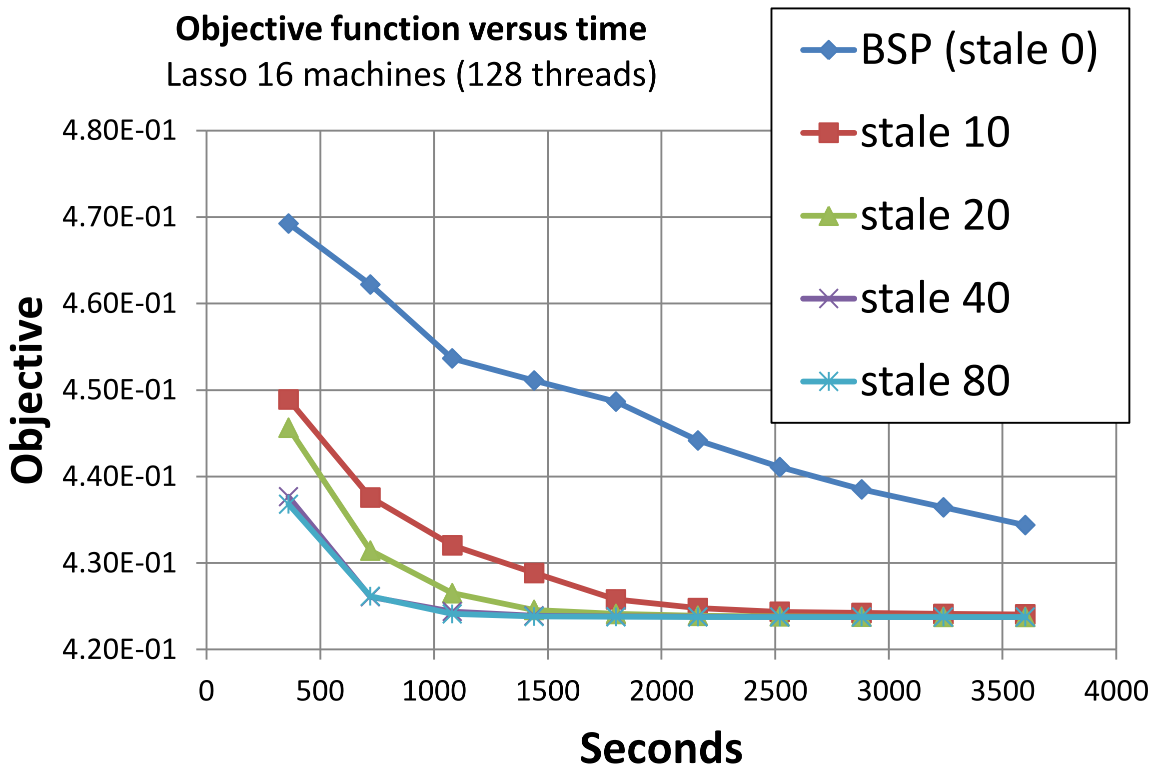
LASSO (Synthetic)

<u>Synthetic data</u>
N = 500 samples
P = 400K features



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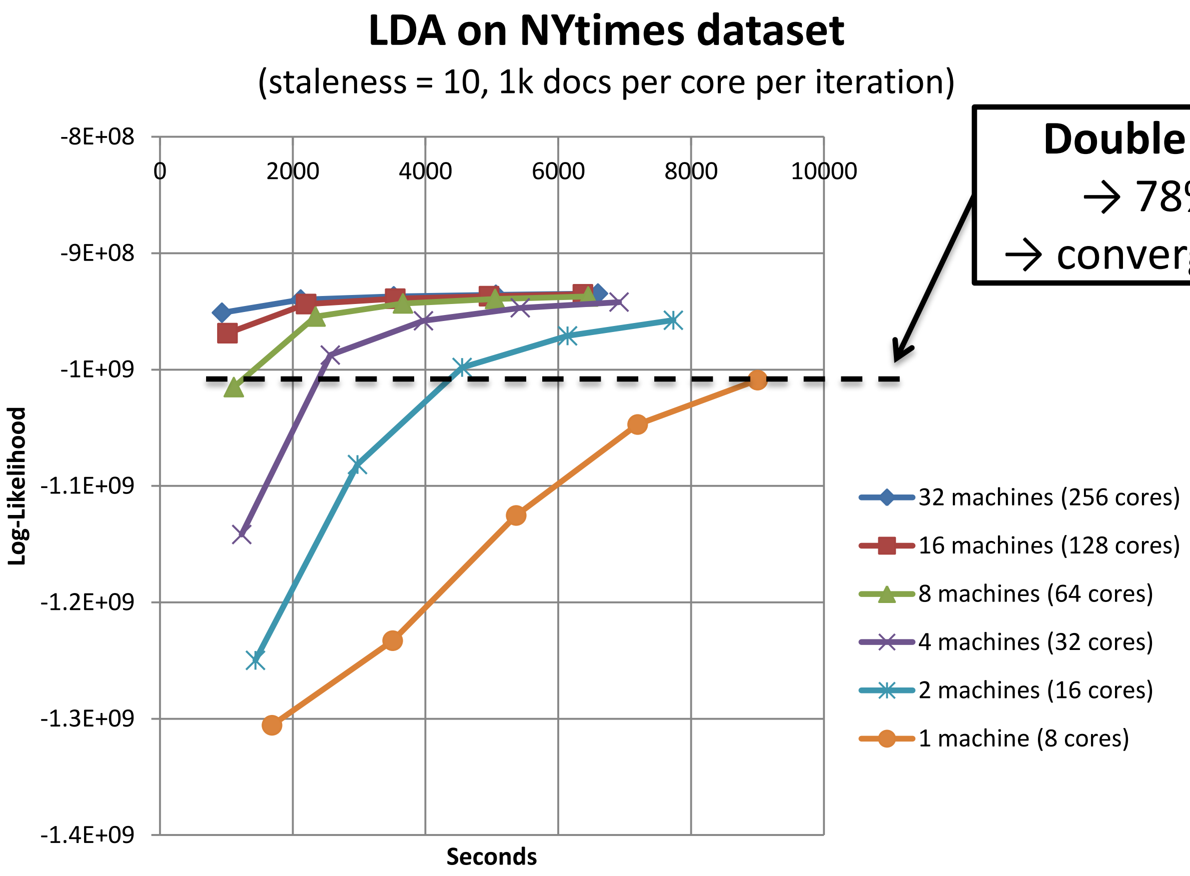
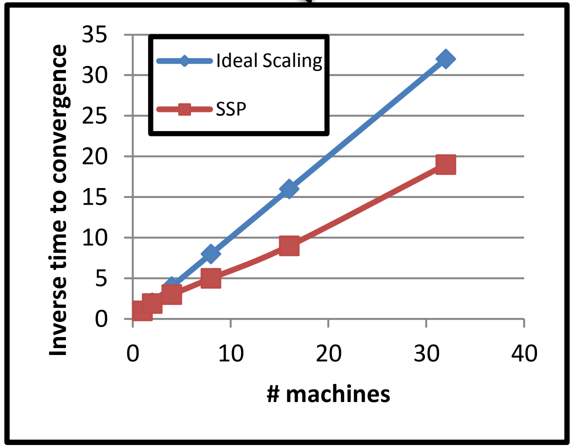
SSPTable scaling with # machines



Double # machines:
→ 78% speedup
→ converge in 56% time



SSP computational model scales with increasing # machines
(given a fixed dataset)

Recent Results

- Using 8 machines * 16 cores = 128 threads
  - 128GB RAM per machine
- Latent Dirichlet Allocation
  - NYTimes dataset (100M tokens, 100K words, **10K topics**)
    - **SSP 100K tokens/s**
    - GraphLab 80K tokens/s
  - PubMed dataset (**7.5B tokens**, 141K words, 100 topics)
    - **SSP 3.3M tokens/s**
    - GraphLab 1.8M tokens/s
- Network latent space role modeling
  - Friendster network sample (**39M nodes**, 180M edges)
  - 50 roles: **SSP takes 14h to converge** (vs 5 days on one machine)

Future work

- **Theory**
  - SSP for MCMC
  - Automatic staleness tuning
  - Average-case analysis for better bounds
- **Systems**
  - Load balancing
  - Fault tolerance
  - Prefetching
  - Other consistency schemes
- **Applications**
  - Hard-to-parallelize ML models
  - DNNs, Regularized Bayes, Network Analysis models

Coauthors


James Cipar


Henggang Cui


Jin Kyu Kim


Seunghak Lee


Phillip B. Gibbons


Garth A. Gibson


Gregory R. Ganger


Eric P. Xing

Workshop Demo

- **SSP is part of a bigger system: Petuum**
  - SSP parameter server
  - STRADS dynamic variable scheduler
  - More features in the works

- We have a demo!
  - **Topic modeling** (8.2M docs, 7.5B tokens, 141K words, 10K topics)
  - **Lasso regression** (100K samples, 100M dimensions, 5 billion nonzeros)
  - **Network latent space modeling** (39M nodes, 180M edges, 50 roles)

- **At BigLearning 2013 workshop (Monday)**
  - http://biglearn.org/

Summary

- **Distributed ML is nontrivial**
  - Slow network
  - Unequal machine performance

- **SSP addresses those problems**
  - Efficiently use network resources; reduces waiting time
  - Allows slow machines to catch up
  - Fast like Async, converges like BSP

- **SSPTable parameter server provides easy table interface**
  - Quickly convert single-machine parallel ML algorithms to distributed

- Slides: `www.cs.cmu.edu/~qho/ssp_nips2013.pdf`

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CARNEGIE MELLON UNIVERSITY