More Effective Distributed ML with a stale synchronous parallel parameter server

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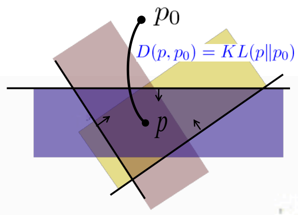
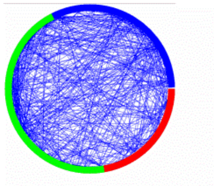
Machine Learning is Ubiquitous

Learning of graphical models

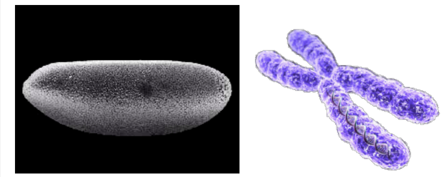


App 1: Social networks and social media

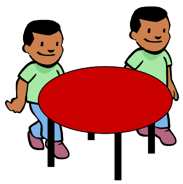
Estimating time-evolving network topology

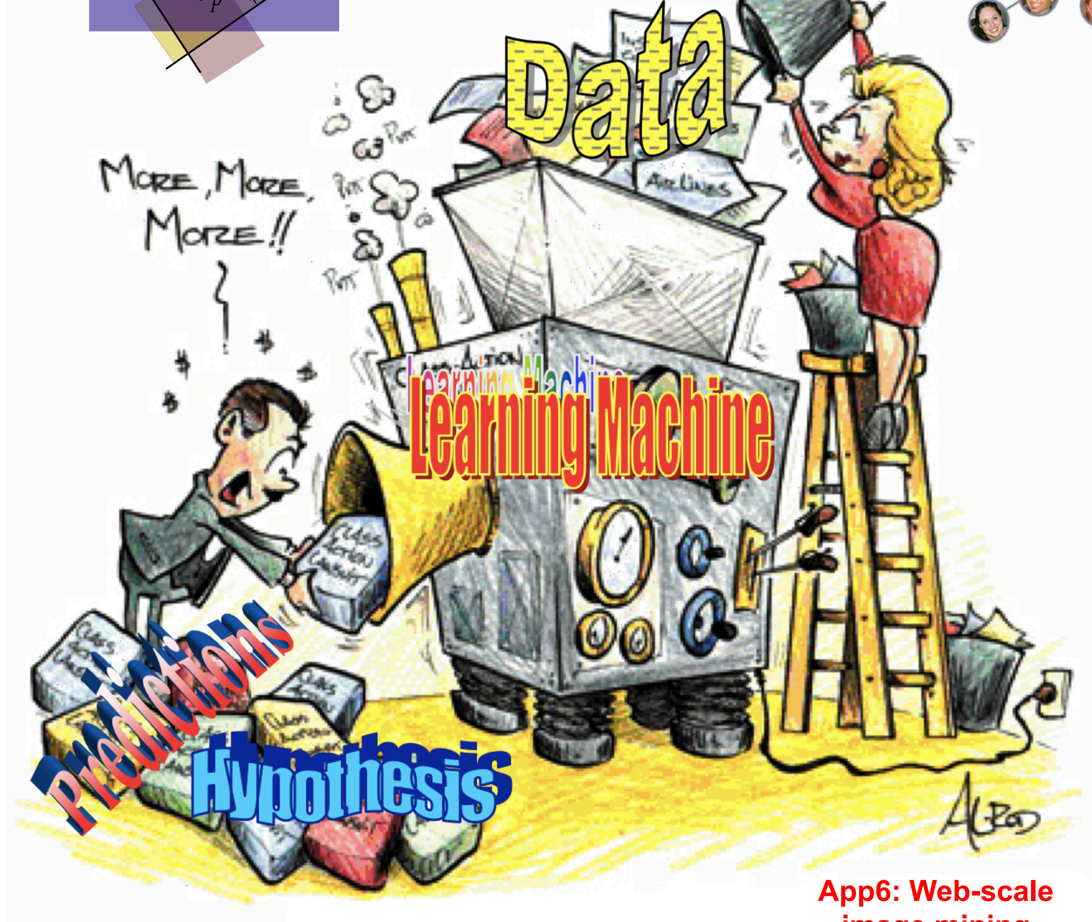


App I: Computational biology, and genomics



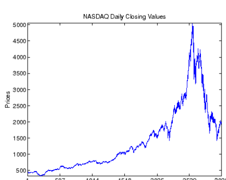
Nonparametric Bayesian inference





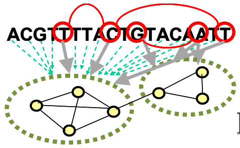
App3: Web-scale text mining and NLP

Nonstationary time series analysis

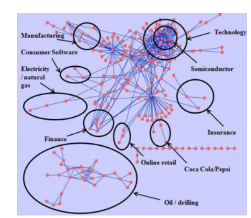


App4: Anomaly detection and video surveillance

Multi-task Learning & structured I/O models



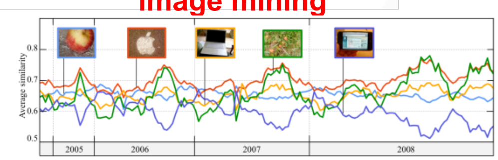
App5: Computational finance



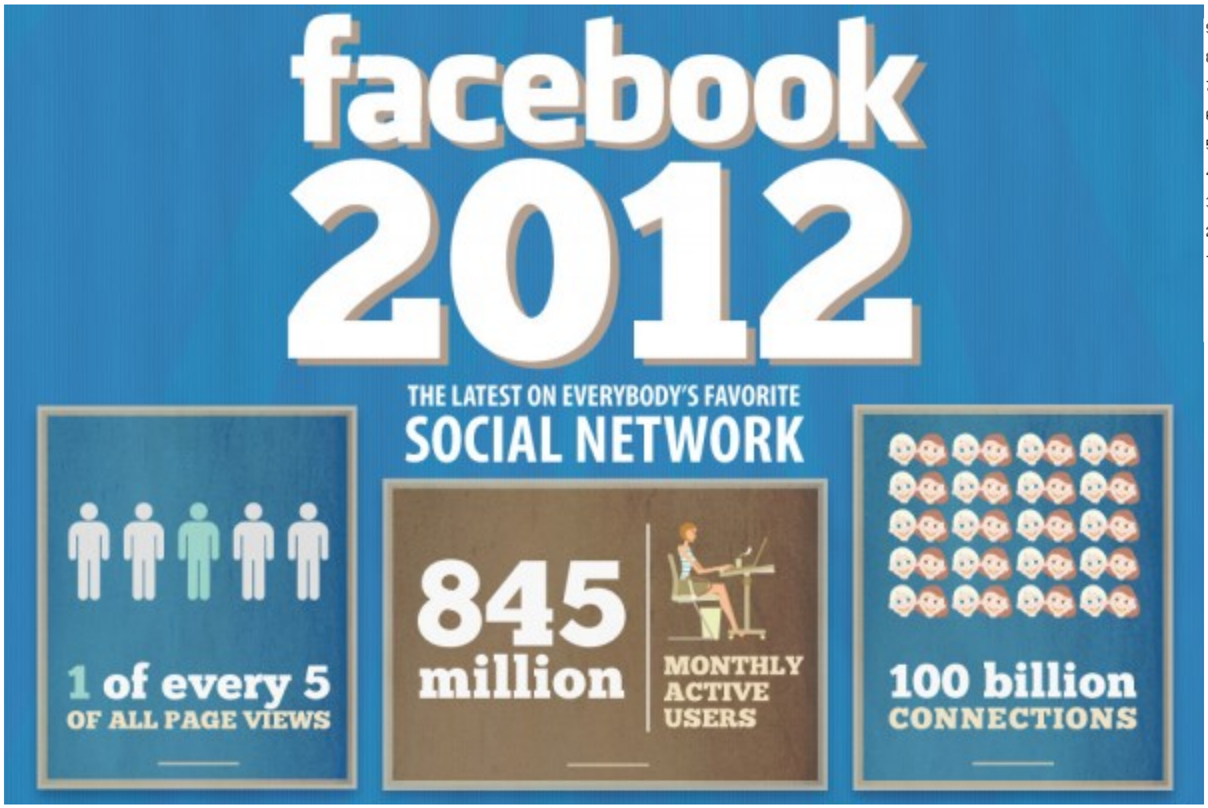
Theory of nonparametric high-dimensional inference

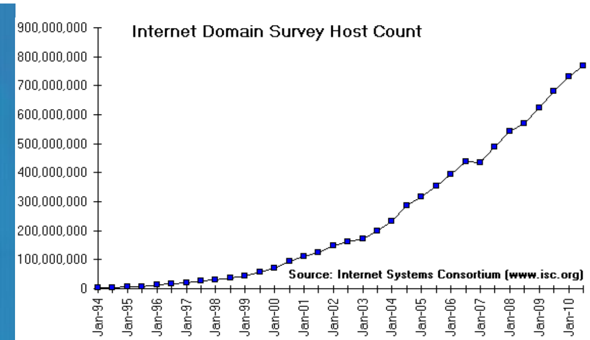
$$\mathbb{P}\left[\hat{G}(\lambda_1, h_n, t^*) \neq G^{t^*}\right] = \mathcal{O}\left(\exp\left(-C\frac{nh_n}{s_n^3} + C'\log p\right)\right) \to 0$$

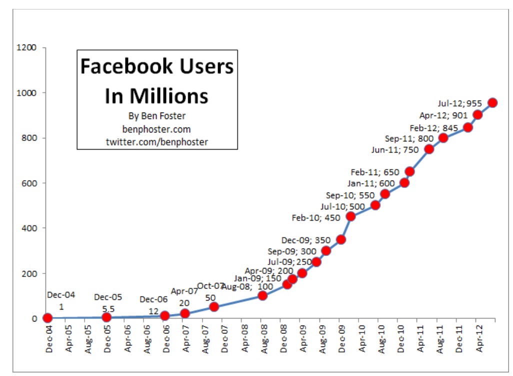
App6: Web-scale image mining



Challenge #1 – Massive Data Scale

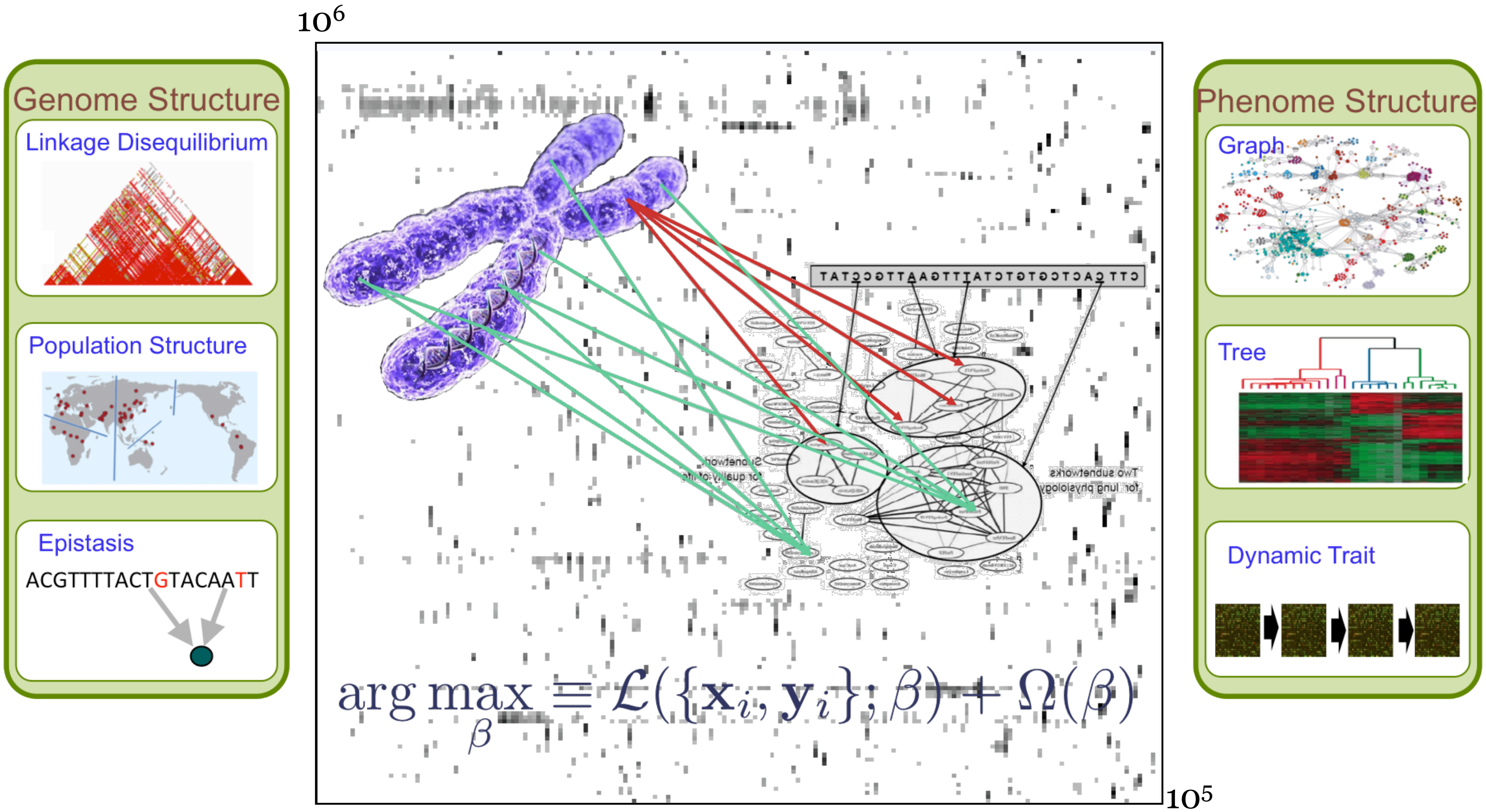






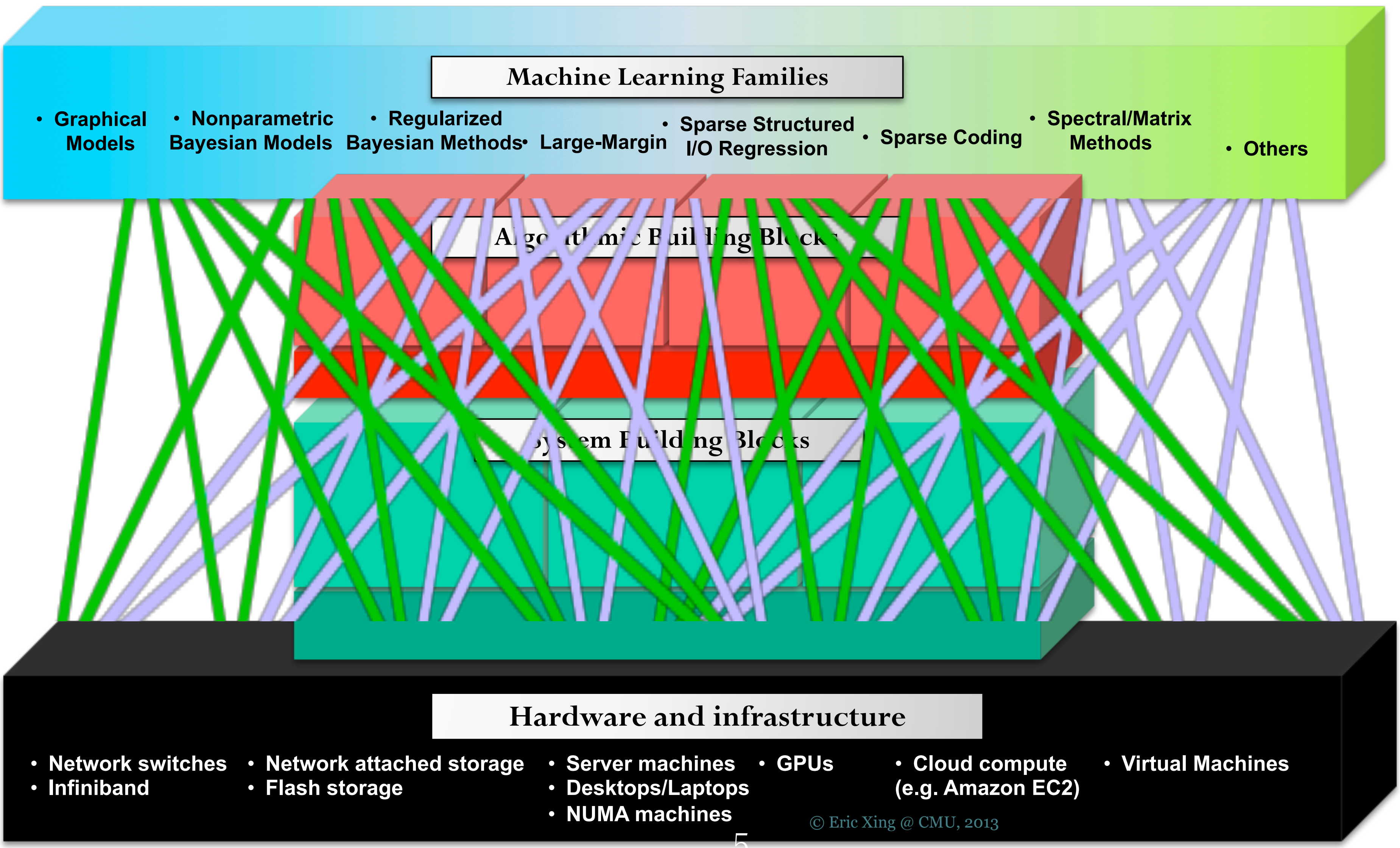
~1B nodes, do not fitting into the main memory of a single machine, a familiar problem!

Challenge #2 – Gigantic Model Size

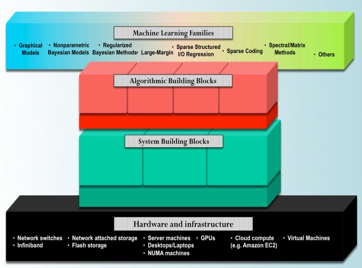


> 10^{11} parameters, do not fitting into the main memory of a single machine either!

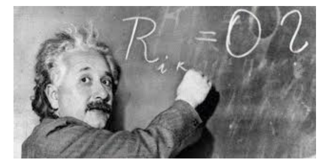
A Thin Waist ?


Machine Learning Families
• Graphical Models
• Nonparametric Bayesian Models
• Regularized Bayesian Methods
• Large-Margin
• Sparse Structured I/O Regression
• Sparse Coding
• Spectral/Matrix Methods
• Others
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

Toward A General-Purpose



Theory: Degree of parallelism, convergence analysis, sub-sample complexity …



Representation: Compact and informative features

Model: Generic building blocks: loss functions, structures, constraints, priors …

Algorithm: Parallelizable and stochastic MCMC, VI, Opt, Spectrum …

Programming model & Interface: High: Matlab/R; Medium: C/JAVA; Low: MPI

System: Distributed architecture: DFS, parameter server, task scheduler…

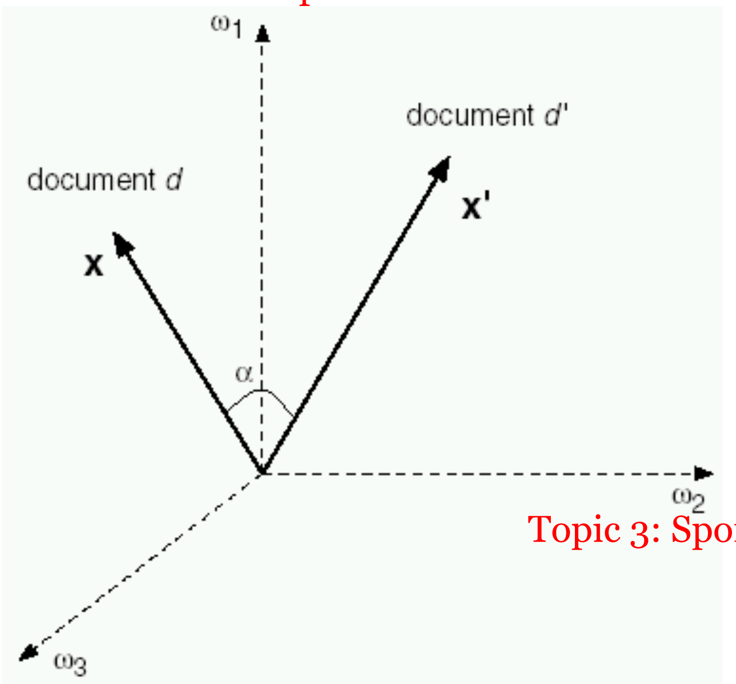
Hardware: GPU, flash storage, cloud …

An Example Task: Topical Inference

- Say, we want to have a mapping …, so that

⇒

Topic 1: Politics



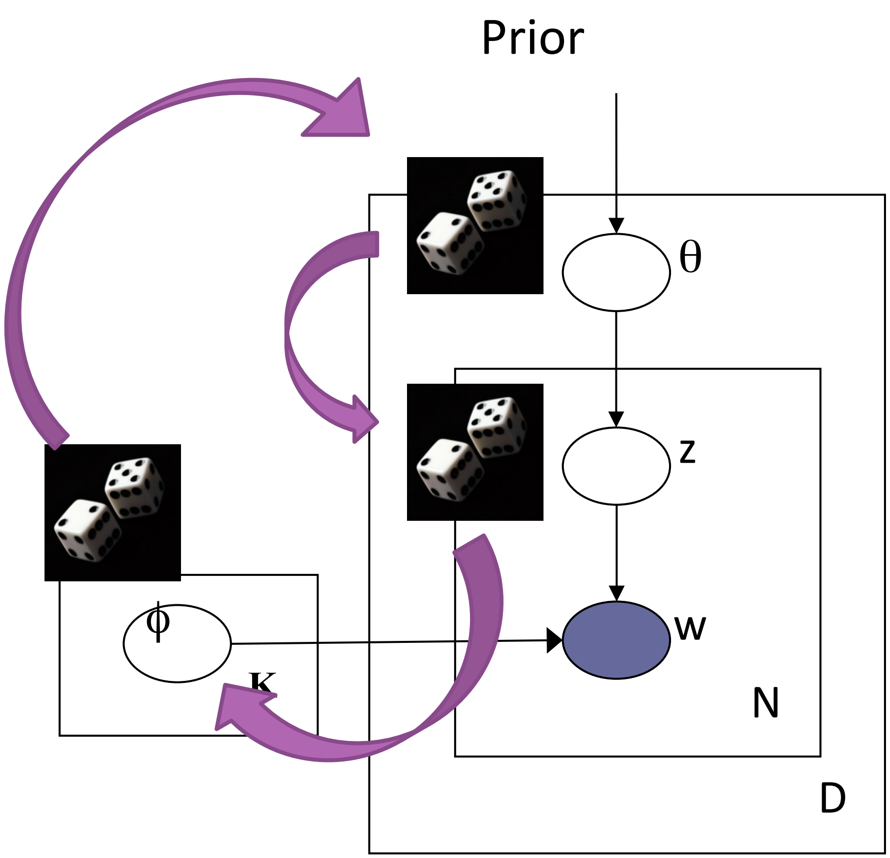
Topic 3: Sports

Topic 2: Economics

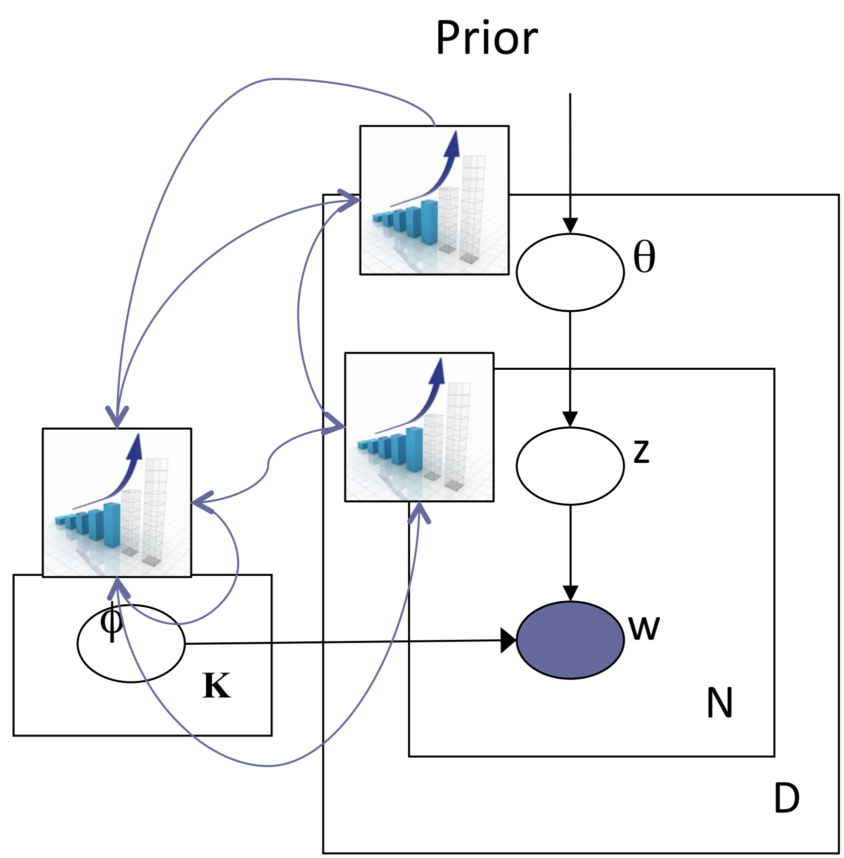
  - Compare similarity
  - Classify contents
  - Cluster/group/categorize docs
  - Distill semantics and perspectives
  - ..

Topic Modeling Algorithms: MCMC and SVI

Markov Chain Monte Carlo:
Randomly sample each variable in sequence



Stochastic Variational Inference:
Gradient ascent on randomly-chosen variables



The Need for Distributed Computation

- Ex: Topic Modeling MCMC samplers process 100K-1M words per second for 100 topics, on an 8-core machine
  - If one document is 1000 words, that's 100-1000 docs per second
- What if we want 1B docs and 10K topics?
- Memory:
  - 1B * 10K = 10 trillion parameters = 40TB of RAM
- Computation:
  - 1B docs, 10K topics -> 100M seconds on one machine -> 1000+ days!
- Need many machines for memory, computational requirements!

Distributed Sampling Cycle

Sample Z For epoch 1

Sample Z For epoch 2

Sample Z For epoch 3

Sample Z For epoch m

Sample Ω_t

Requires a reduction step

Parameter Servers for ML

- Provide simple table-based API for quick porting of single-machine parallel ML programs
  - **read_row(table,row,s)**
    - Retrieve table-row with staleness s
  - **inc(table,row,el,val)**
    - Increment table(row,el) by val
  - **clock()**
    - Inform all servers that current/thread processor has completed one clock

- ML programmers simply replace array/matrix data structures with parameter server calls

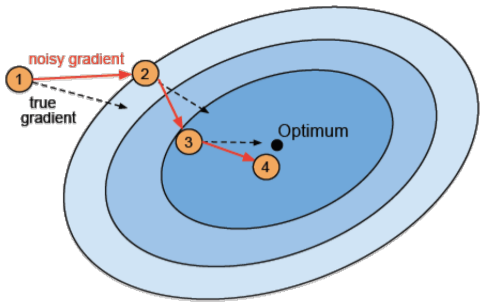
- Question: what synchronizing scheme to use?

Synchronization Models for PS

- Bulk Synchronous Parallel execution
  - No update errors, but synchronization barriers introduce stragglers and waste computational time
- Asynchronous execution
  - No stragglers, but update errors can end up unbounded in distributed settings (e.g. one machine is systematically slower than the rest)

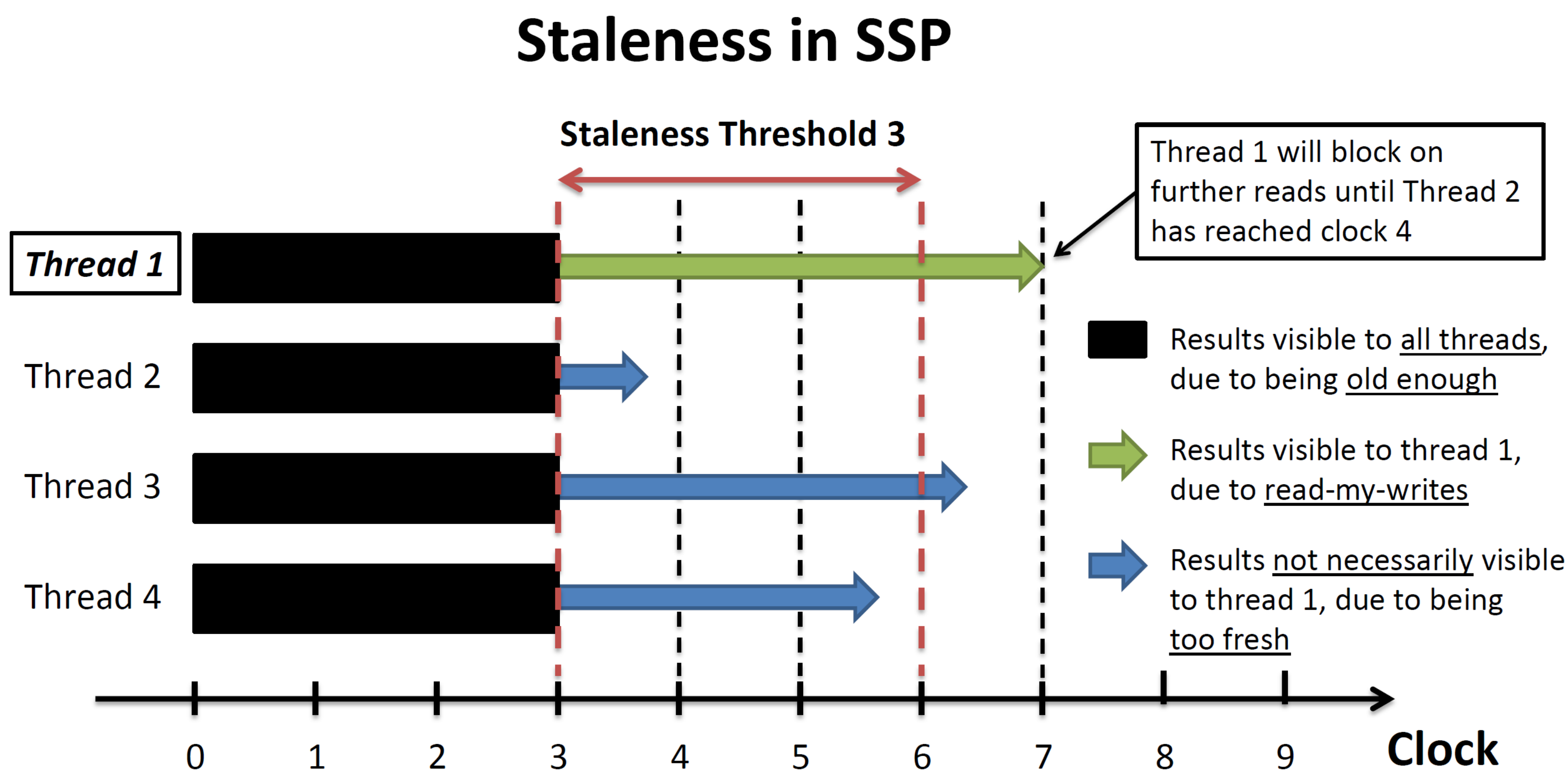
Iterative-Convergence in ML

- ML programs are **iterative-convergent**
  - Repeatedly execute update equations to minimize a loss function
  - Examples:
    - Variational inference for topic models
    - Stochastic gradient descent for matrix factorization
    - MCMC to find posterior distribution modes
    - Block coordinate descent for Lasso regression



- Iterative-convergent algorithms are empirically and theoretically resilient to errors in updates
  - Errors will decrease update effectiveness, but will not forfeit convergence and correctness provided they are limited

Stale Synchronous Parallelism (SSP)



Allow threads to run at their own pace, without synchronization

Ensure fastest/slowest threads do not grow more than S iterations apart

Serve data from thread-local and process-local caches rather than over the network

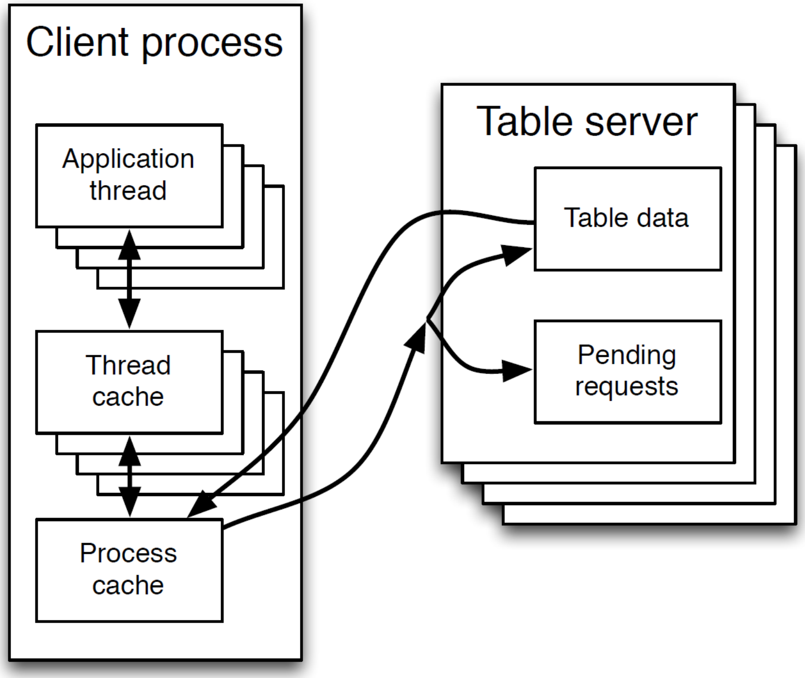
SSP for Iterative-Convergent ML

- Bulk Synchronous Parallel execution
  - No update errors, but synchronization barriers introduce stragglers and waste computational time
- Asynchronous execution
  - No stragglers, but update errors can end up unbounded in distributed settings (e.g. one machine is systematically slower than the rest)
- **Stale Synchronous Parallel (SSP)**
  - Use bounded staleness to strictly limit maximum error, while reducing synchronization costs
  - Aims for a sweet spot between BSP and Async

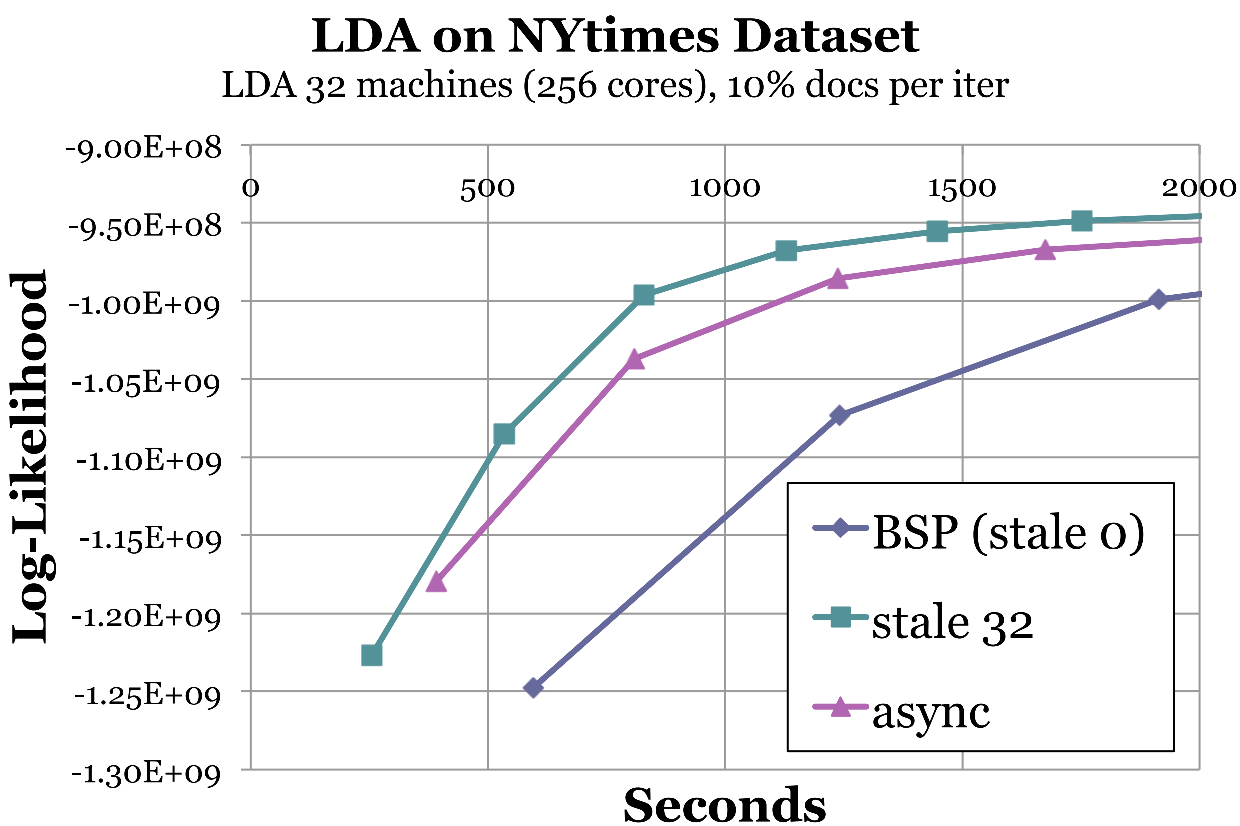
Cache hierarchy for staleness

- LazyTables Parameter Server

- Stale reads served by local thread/ process caches on the client machine
- Only read from server if local caches are too stale
- Writes are immediately committed after each clock()
  - Okay since ML programs perform far more reads than writes



Enjoys async speed, but BSP guarantee



SSP is both fast and has convergence guarantees

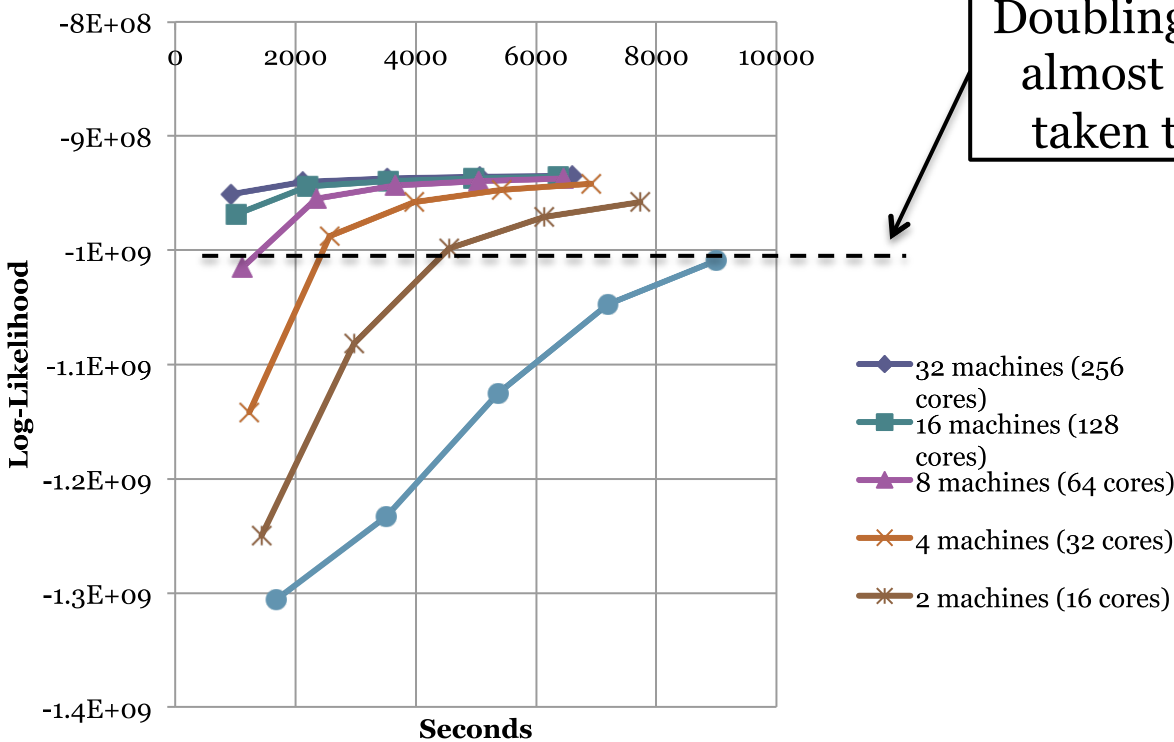
BSP has convergence guarantees but is slow

Full Asynchronous is fast but has weak convergence guarantees

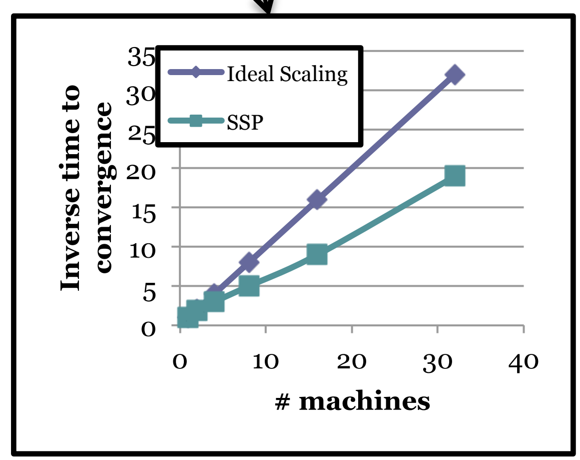
Scaling with # machines

LDA on NYtimes dataset

(staleness = 10, 1k docs per core per iteration)

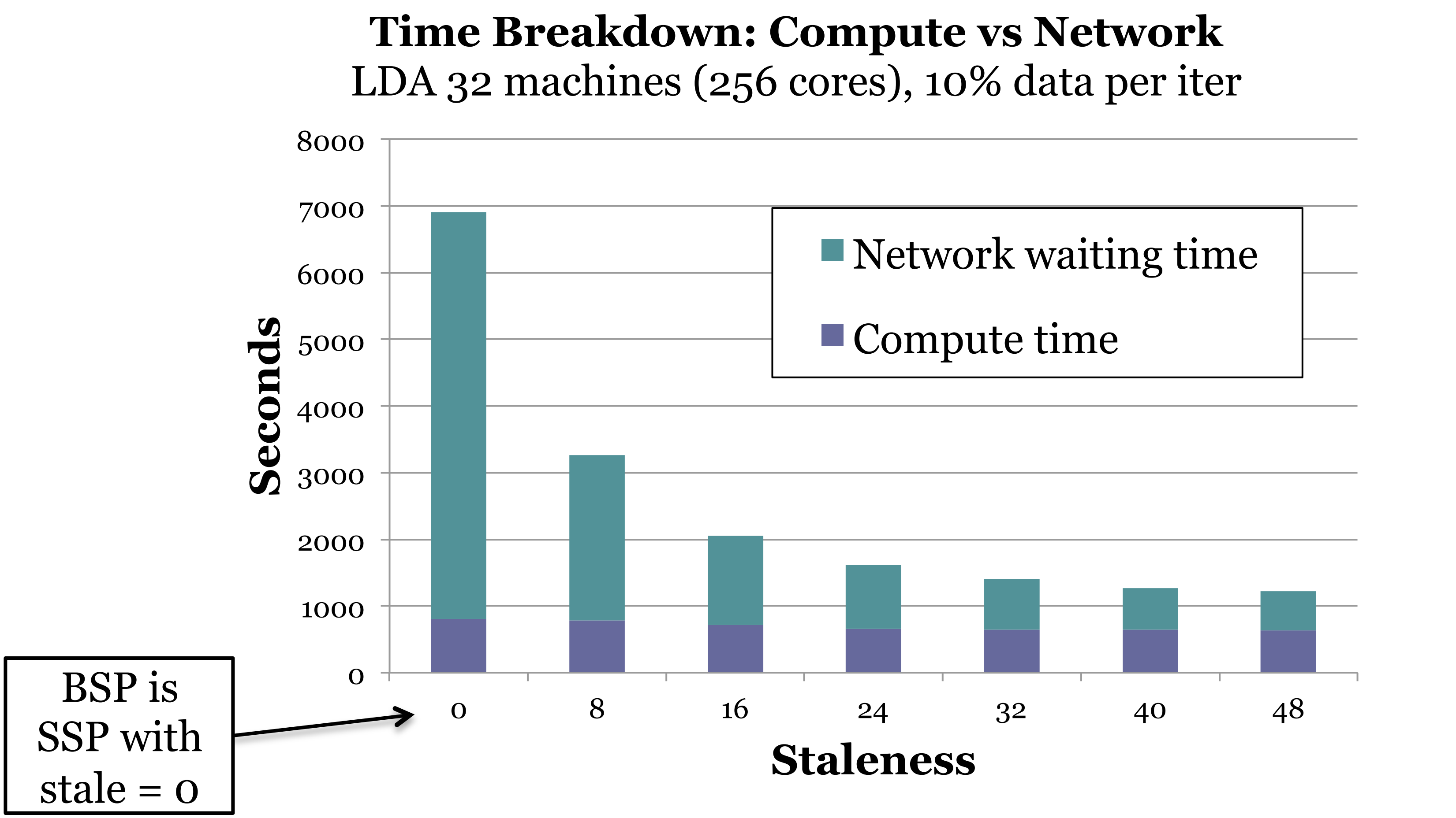


Doubling # machines almost halves time taken to converge



SSP computational model enables linear scaling with # machines (up to at least 32)

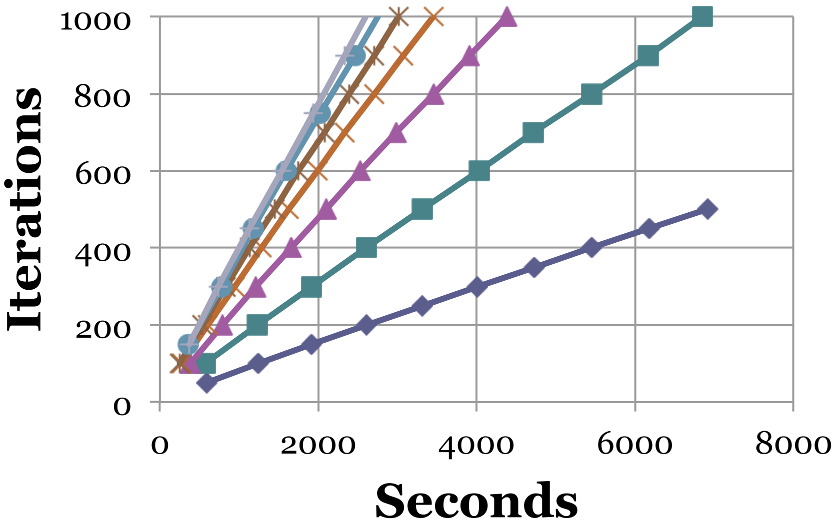
Network bottlenecks in ML Mitigated



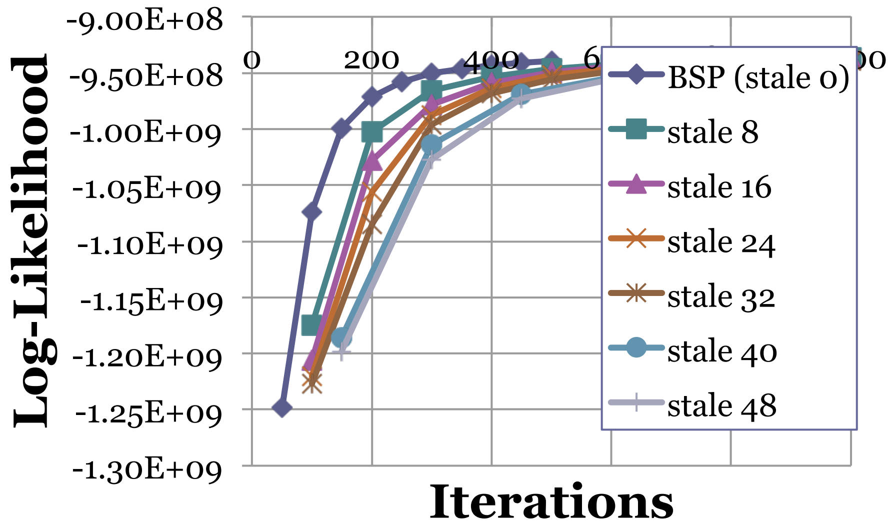
Network communication is a large bottleneck with 10s of machines
SSP balances network and compute time

Quality vs Quantity tradeoff

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



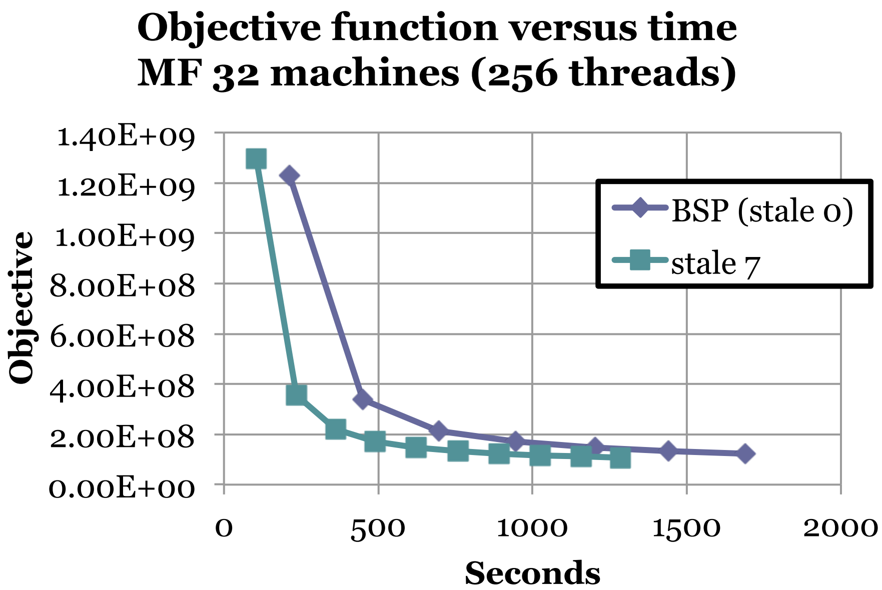
Quality: objective versus iterations
LDA 32 machines, 10% data



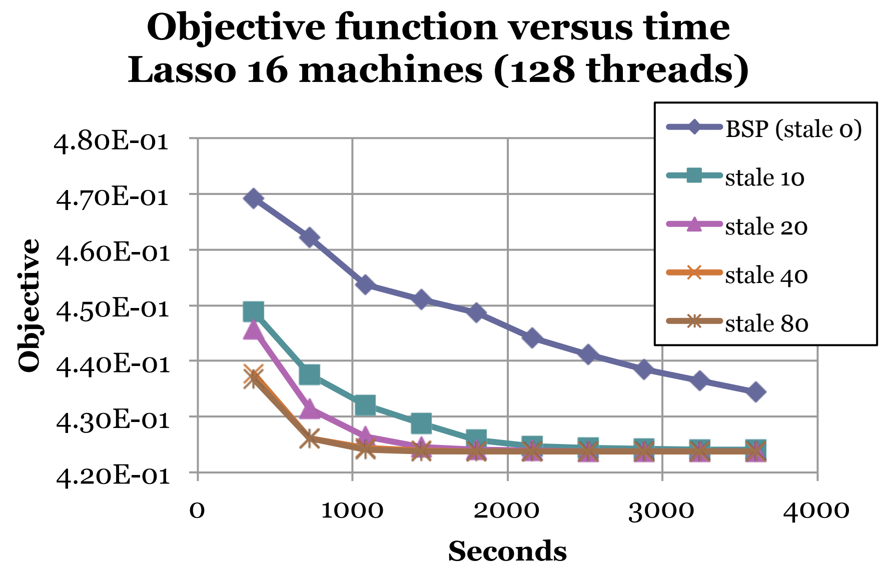
Progress per time is (iters/sec) * (progress/iter)
High staleness yields more iters/ses, but lowers progress/iter
Find the sweet spot staleness >0 that yields maximum progress per time

Effective across different ML Programs

Matrix Factorization on Netflix

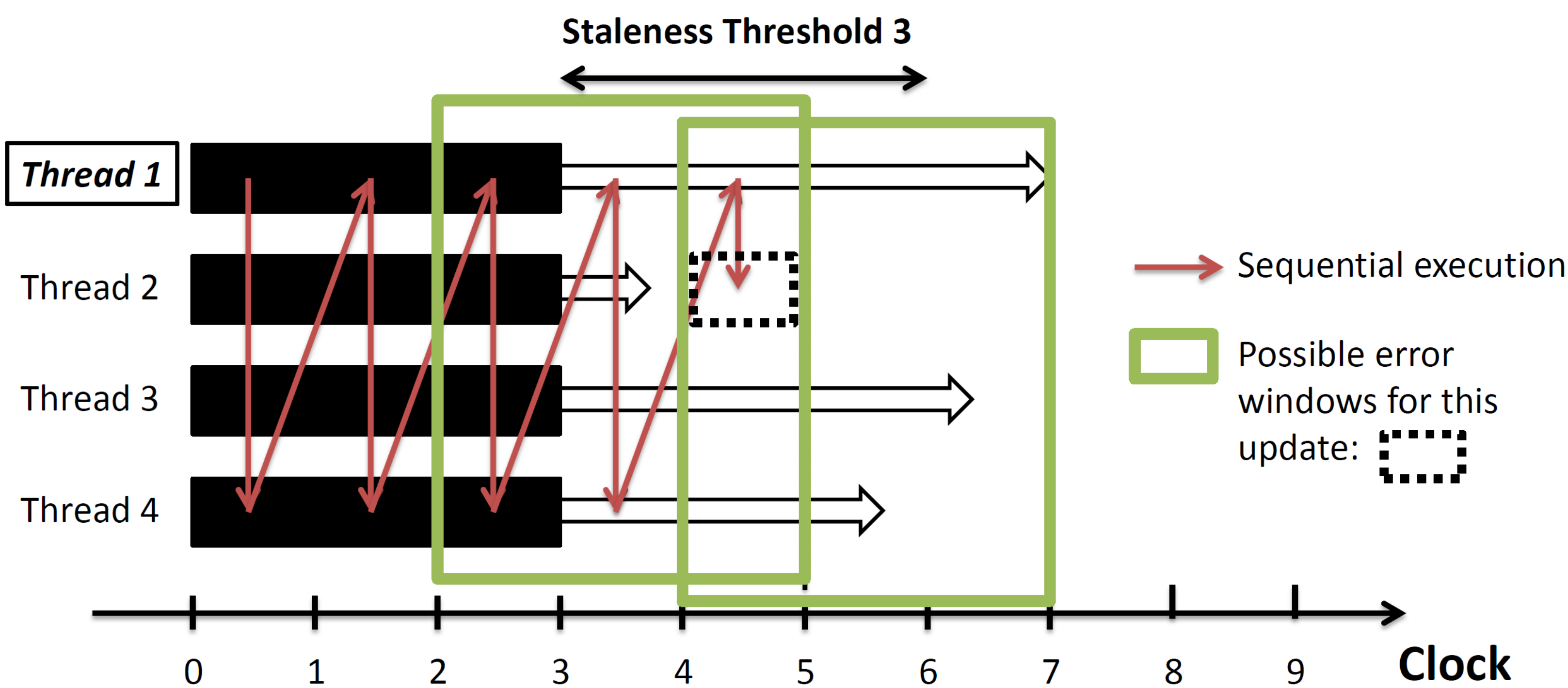


Lasso on synthetic data



Why SSP converges despite error

SSP approximates sequential execution



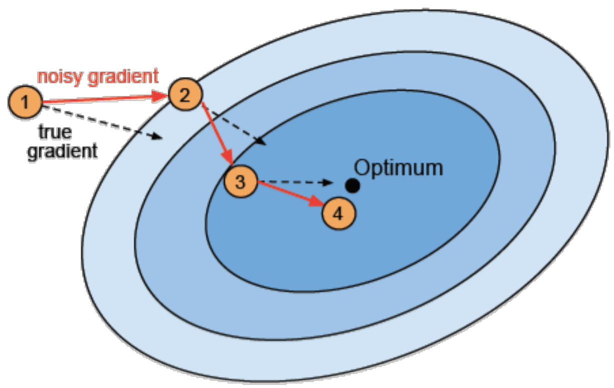
When a thread reads a parameter, the number of "missing updates" is bounded (compared to sequential execution)

Hence numeric error in parameter is also bounded

Why SSP converges despite error

Theorem 1 (SGD under SSP): Suppose we want to find the minimizer $\mathbf{x}^*$ of a convex function $f(\mathbf{x}) = \frac{1}{T}\sum_{t=1}^{T} f_t(\mathbf{x})$, via gradient descent on one component ∇f_t at a time. We assume the components f_t are also convex. Let $\mathbf{u}_t := -\eta_t \nabla f_t(\tilde{\mathbf{x}}_t)$, where $\eta_t = \frac{\sigma}{\sqrt{t}}$ with $\sigma = \frac{F}{L\sqrt{2(s+1)P}}$ for certain constants F, L. Then, under suitable conditions (f_t are L-Lipschitz and the distance between two points $D(x\|x') \leq F^2$),

$$R[\mathbf{X}] := \left[\frac{1}{T}\sum_{t=1}^{T} f_t(\tilde{\mathbf{x}}_t)\right] - f(\mathbf{x}^*) \leq 4FL\sqrt{\frac{2(s+1)P}{T}}$$

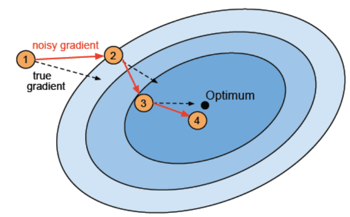


SSP converges for Stochastic Gradient Descent, and does so at a rate no slower than $O(T^{-0.5})$, where T is the number of iterations. This rate is only an upper bound - depending on how the parameter server is implemented, there is room to make the actual convergence rate approach the optimal rate for a single core.

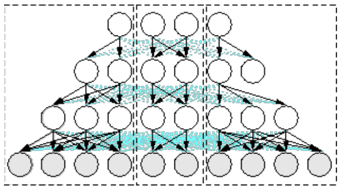
On A General System Interface for Big ML

- **What is an ML program:** An objective or **loss function** that measures solution quality
  - e.g. least-squared loss in regression
  - e.g. negative log-likelihood in probabilistic models
  - e.g. risk in adversarial or bandit problems

- Key Signatures of an ML program
  - ML algorithms are **iterative-convergent**
    - Iterative-convergent algorithms are **resilient to errors in updates**

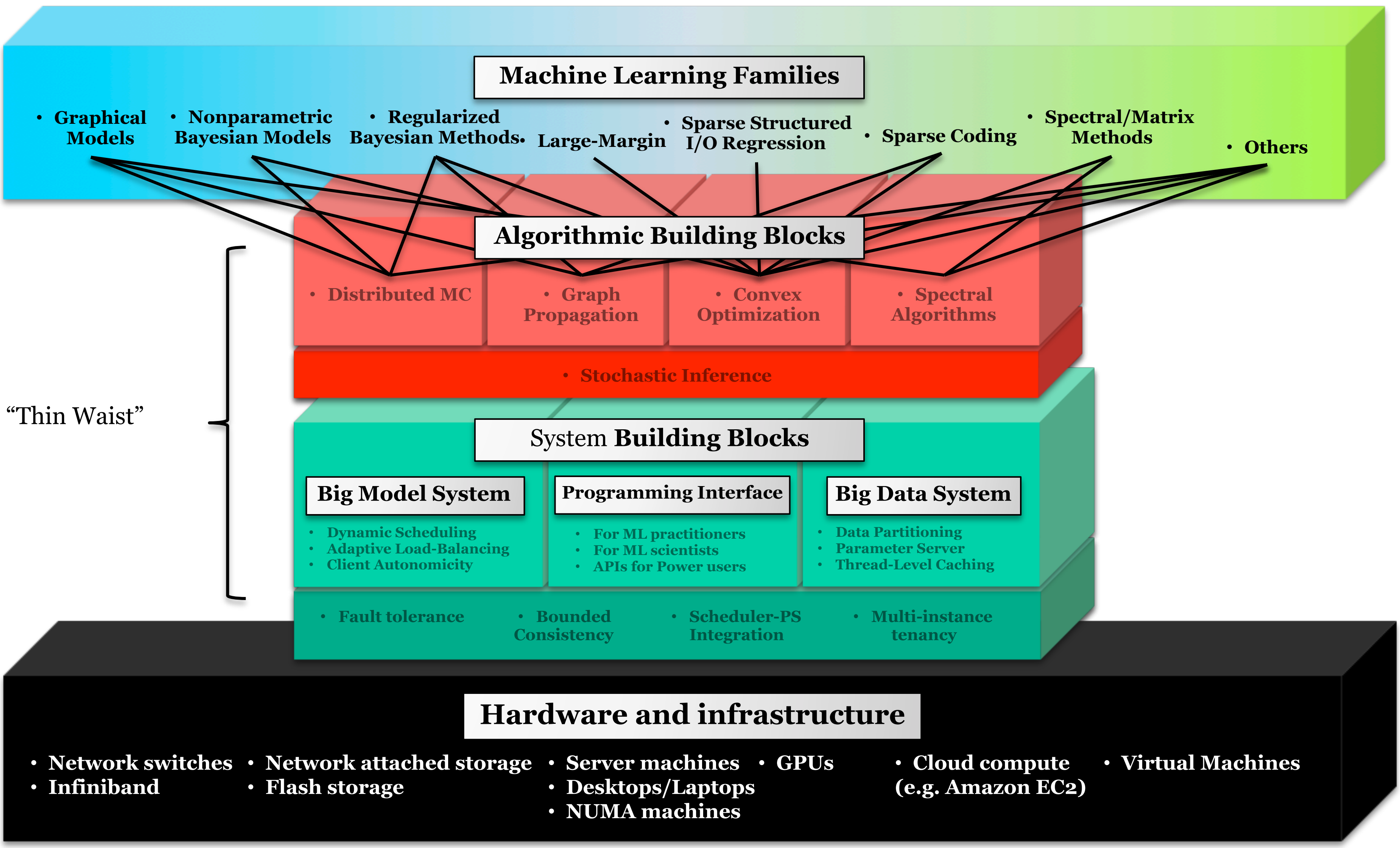


  - ML programs are **blocky**
    - Opportunities for efficient **parallelization under bounded error**



- A general Big ML Framework shall leverage these properties

The Big-ML Framework We Envision



Thank You!