LazyTable: Distributed Machine Learning with the Stale Synchronous Parallel Model

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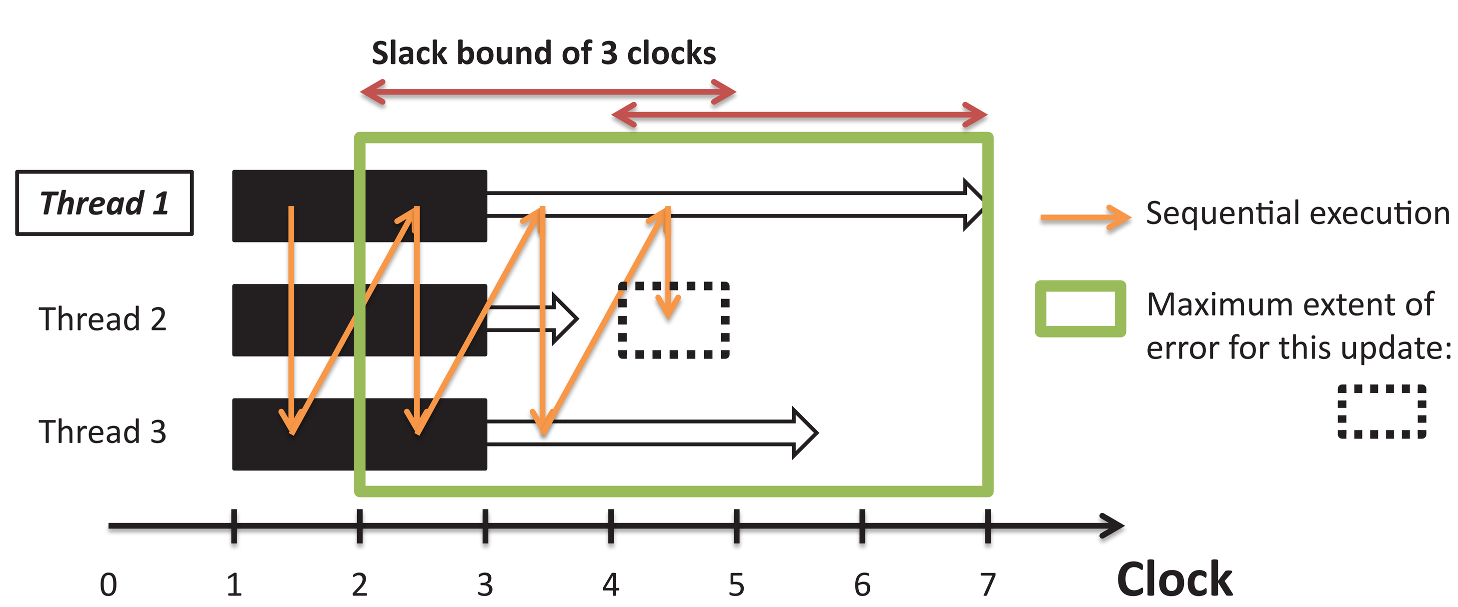
PARALLEL MACHINE LEARNING

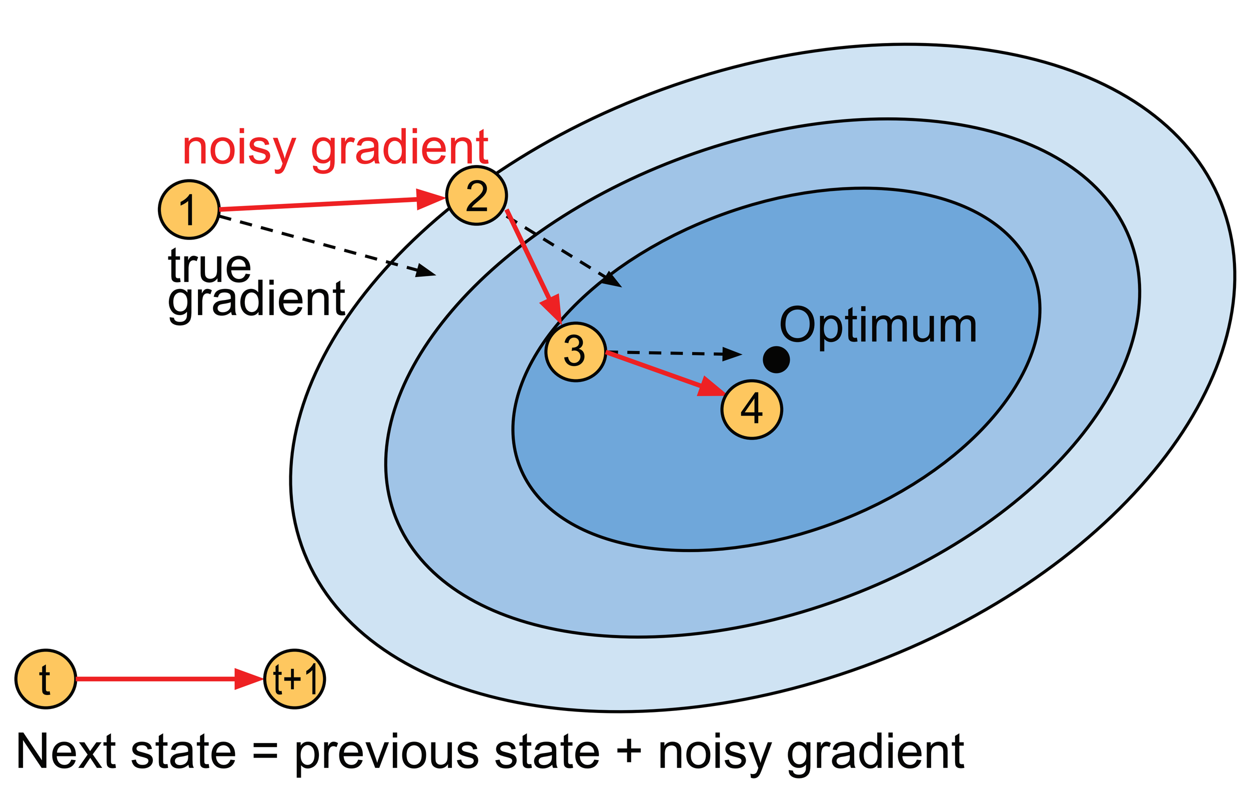
- Learn model parameters from a big dataset
  - Work is partitioned among multiple threads
  - Each thread processes a partition of input data
  - Threads iteratively update the shared parameter state based on their input data
- Parameter server
  - Maintains shared values for worker threads
  - Tradeoff between fresh views and synchronization
- Most ML algorithms tolerate bounded staleness
  - Common model: Bulk Synchronous Parallel
    - Barrier and data update at end of each clock
    - Worker guaranteed to see updates up to previous clock
  - New model: Stale Synchronous Parallel
    - Better straggler tolerance

WHY DOES SSP CONVERGE?

- Theorem 1: SSP approximates sequential execution
  - Error at each update is strictly bounded



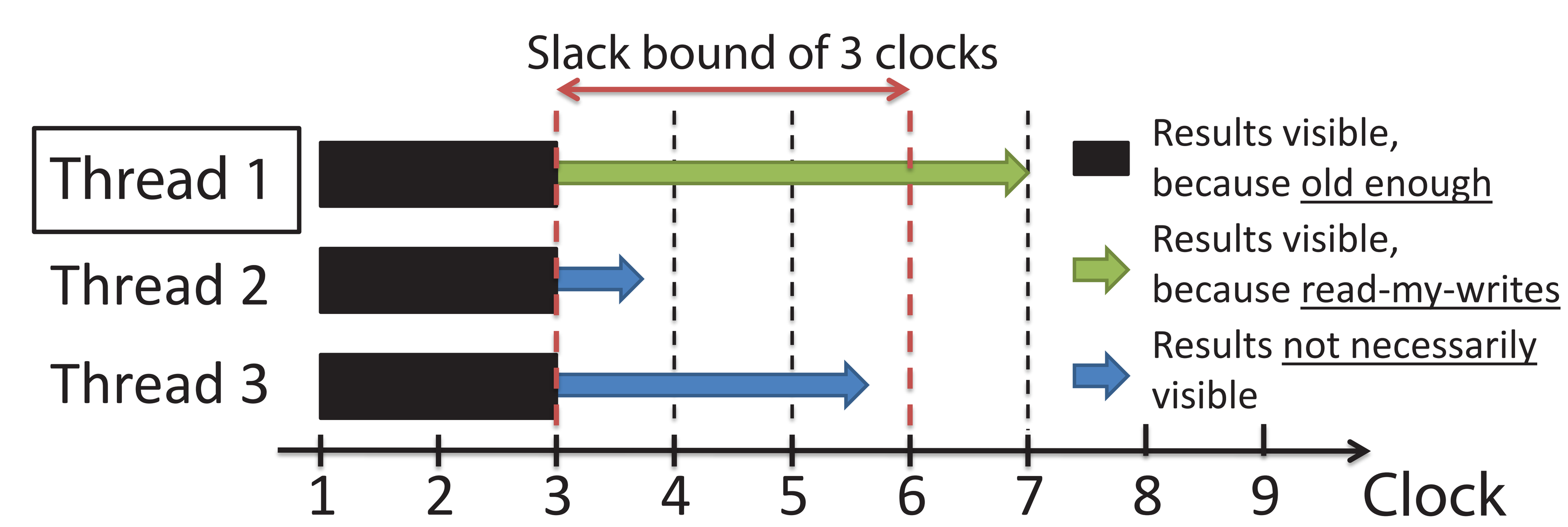
- Theorem 2: For iterative-convergent ML problems, SSP guarantees algorithm convergence



- Hence, ML algorithms converge under SSP
  - albeit via a noisy trajectory

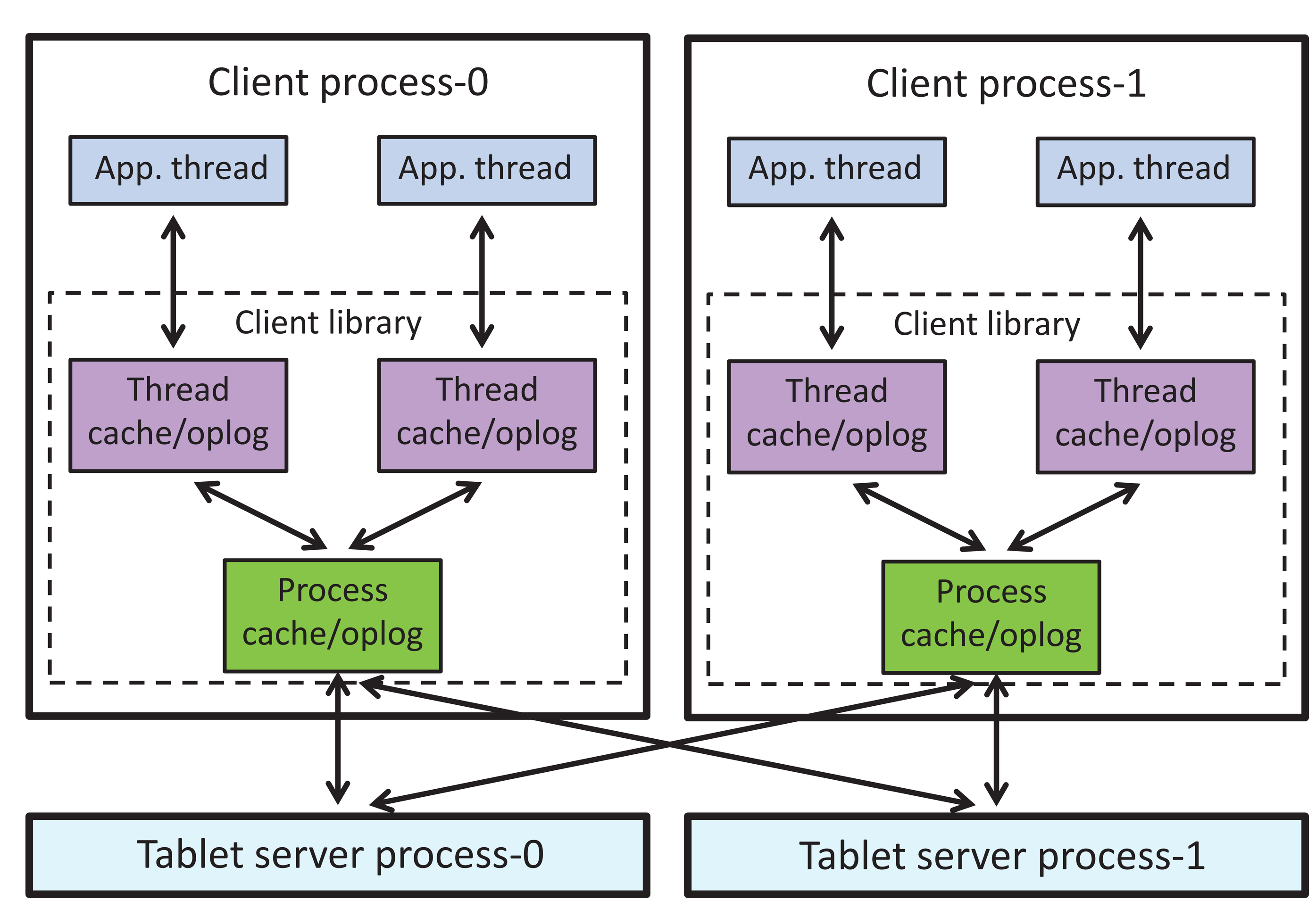
STATE SYNCHRONOUS PARALLEL MODEL

- Tunable data staleness ("slack")
- Any thread can be up to slack clocks ahead of slowest thread



LAZYTABLE SYSTEM OVERVIEW

- Parameter server based on SSP
  - A client library with a cluster of tablet servers
- Multiple layers of caches and operation logs
  - Closer caches tend to be more stale, but faster
- Slack bound specified in each read operation
  - Data allowed to be "slack" clocks stale
  - Cache data returned, if fresh enough



RESULTS & DIRECTIONS

- Many results found on companion poster
- Key takeaways: converge faster with SSP
  - More staleness → more iters/sec, less effective/iter
    - Sweet spot balances the two
  - Works well for range of ML approaches
    - Topic Modeling (LDA with Gibbs sampling)
    - Sparse Matrix Factorization (stochastic gradient descent)
    - Shotgun (coordinate gradient descent)
- Continuing to explore iterative nature
  - Better data assignment to tablet servers
  - Memory/thread scheduling on multi-core machines
  - Try for near-ideal straggler tolerance

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