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Petuum: A Framework for Iterative-Convergent Distributed ML

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Abstract

A major bottleneck to applying advanced ML programs at industrial scales is the migration of an academic implementation, often specialized for a small, well-controlled computer platform such as desktop PCs and small lab-clusters, to a big, less predicable platform such as a corporate cluster or the cloud. This poses enormous challenges: how does one train huge models with billions of parameters on massive data, especially when substantial expertise is required to handle many low-level systems issues? We propose a new architecture of systems components that systematically addresses these challenges, thus providing a general-purpose distributed platform for Big Machine Learning. Our architecture specifically exploits the fact that many ML programs are fundamentally loss function minimization problems, and that their iterative-convergent nature presents many unique opportunities to minimize loss, such as via dynamic variable scheduling and error-bounded consistency models for synchronization. Thus, we treat data, parameter and variable blocks as computing units to be dynamically scheduled and updated in an error-bounded manner, with the goal of minimizing the loss function as quickly as possible.

1 Introduction

Machine learning is becoming the primary mechanism by which information is extracted from Big Data, and which artificial intelligence is built upon. However, despite the rapid and voluminous emergence in recent years of new models, algorithms [9, 23, 15, 27, 1, 6] and execution frameworks [10, 18, 17, 16, 3, 5, 26, 19] across a wide spectrum of applications, successful and effective adoption of ML technology based on truly advanced and large-scale probabilistic or optimization programs — i.e., programs that involve billions of variables, with massive amount of relational or sparsity constraints, processing petabyte-scale datasets, and operating perpetually and autonomously on large computer clusters or in the cloud — remain largely unseen. Most existing large-scale applications still seem to rely on classical approaches such as kNN and decision trees, which impose modest challenges on model and algorithm design, while scalable computational support for such methods can be straightforwardly handled by existing representation, programming, and hardware technology. Thus it is tempting to ask, where have all the latest exciting developments in ML research – such as nonparametric Bayesian models, advanced subspace models beyond topic models, multitask and nonlinear high-dimensional inference theory, and consistent graph learning algorithms, to name a few – gone to in the broader application domains? We conjecture that, from the scalable execution point of view, what prevents many state-of-the-art ML models and algorithms from being more widely adopted is the lack of satisfactory answers to the following needs: 1) a turnkey inference engine; 2) ways to scale on data; 3) ways to scale on model size; and 4) abstraction of hardware/system configuration. Our goal is to develop a distributed Big ML framework that aims at providing a generic yet effective interface to a broad spectrum of ML programs.

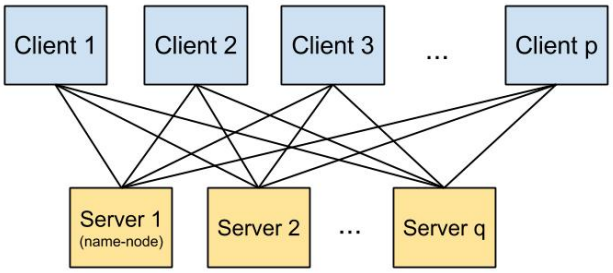

Figure 1: Petuum parameter server topology. Servers and clients interact via a bipartite topology, while a name-node machine handles bookkeeping and assignment of keys to servers.

Our design philosophy is rooted in *iterative-convergent* solutions to loss function minimization. A great number of ML algorithms are formulated in this manner, which involves repeatedly executing update equations that decrease some error function. Examples of such algorithms include variational methods for graphical models [15], proximal optimization for structured sparsity problems [8], back-propagation on deep neural networks [9], MCMC for determining point estimates in latent variable models [13], among many others. Thus, the core goal of our framework is to execute these iterative updates in a manner that most quickly minimizes the loss function in a large-scale distributed environment. We do so by employing statistical insights such as error-bounded consistency schemes to decrease network communication, and rescheduling of updates to decrease correlation effects and optimizing load-balancing, which are executed by systems components such as a parameter server for global parameter synchronization and a dynamic scheduler to organize and distribute worker tasks. In summary, our system views the iterative-convergent nature of ML as the prime opportunity to be exploited in realizing scalable execution of generic Big ML problems.

2 System Components

We have develop a prototypic framework for Big ML called *Petuum*, which comprises several interrelated components, each focused on exploiting various specific properties of iterative-convergent behavior in ML. The components can be used individually, or combined to handle tasks that require their collective capabilities. In this workshop, we focus on two components:

- **Parameter Server for global parameters:** Our parameter server (Petuum-PS) is a distributed key-value store that enables an easy-to-use, distributed-shared-memory model for writing distributed ML programs over BIG DATA. Petuum-PS supports novel consistency models such as bounded staleness, which achieve provably good results on iterative-convergent ML algorithms [14]. Petuum-PS additionally offers several "tuning knobs" available to experts but otherwise hidden from regular users such as thread and process-level caching and read-my-write consistency. We also support out-of-core data streaming for datasets that are too large to fit in machine memory.
- **Variable Scheduler for local variables:** Our scheduler (STRADS) analyzes the variable structure of ML problems, in order to find parallelization opportunities over BIG MODEL while avoiding error due to strong dependencies. STRADS then dispatches parallel variable updates across a distributed cluster, while prioritizing them for maximum objective function progress. Throughout this, STRADS maintains load balance by dispatching new variable updates as soon as worker machines finish existing ones.

2.1 Parameter Server

Big Machine Learning is challenging because the global model parameters can be massive in size (billions to trillions), while the use of terabyte-scale Big Data places high algorithmic complexity demands on inference.

Such memory and computational needs necessitate the use of many machines, thus we develop a general-purpose parameter server (PS) for iterative-convergent ML programming called Petuum-PS. Petuum-PS is a distributed key-value store that provides client machines shared-memory access to global parameters sharded on the server machines. Unlike conventional key-value stores that offer consistency models such as the eventual consistency and the strong consistency, Petuum-PS features a continuum of bounded-staleness consistency guarantees across all clients, which has been shown to achieve provably good results on iterative-convergent ML programs while largely reducing communication overhead [14].

Petuum-PS offers a table-based user interface: users create global tables in which each entry of the table can be accessed globally by a row-column ID pair, providing a general-purpose, easy-to-program interface [20]. Because the parameter server abstracts away the communication and synchronization, the distributed global table appears to be local to the user program executed on the client machines (distributed shared memory). This allows Petuum-PS to retro-fit eixisting single-machine parallel implementations with minimal modification. In the following sections we highlight several tunable system features: bounded consistency, thread and process-level caching, and the use of out-of-core (disk-based) storage.

2.1.1 Bounded Consistency

For Big Data+Model tasks, many variable blocks must access just as many parameter and data blocks, all spread over 100s -1000s of machines. To reduce network costs and eliminate global barriers/locking, we exploit the error-resistant iterative-convergence nature of ML programs — in other words, their robustness against minor inconsistency in their model state. Petuum-PS provides theoretically-guaranteed consistency schemes that reduce inter-machine synchronization and network communication, such as:

- **Stale Synchronous Parallel (SSP) Consistency:** SSP is based on the concept of *iteration-bounded staleness*: using parameters from a few iterations ago still preserves convergence guarantees [14]. Our PS exploit this by serving locally-cached versions of parameter blocks that are $\leq s$ iterations old, thus eliminating network traffic. Extensions to the SSP model include *heterogenous staleness*, in which different parameter blocks are read with different staleness, and *adaptive staleness*, in which the staleness values are automatically tuned for different phases of the ML algorithm.
- **Value-Bounded Consistency:** In value-bounded consistency, clients and servers are synchronized only when their parameter versions deviate by more than some threshold δ. For global parameter blocks that change infrequently, this strategy requires even less network synchronization than iteration-bounded staleness. Our proposed system will dynamically adjust δ to minimize user intervention.

2.1.2 Process-Level and Thread-Level Caching

Each PS client stores commonly used rows in local memory (process-level "caches") to reduce synchronization and network costs. To reduce the lock-contention between threads on process-level cache, every worker thread on a client machine has its own thread "cache", which is memory exclusive to the thread. A frequently accessed row in table could potentially be cached at both the process-level and thread-level cache. In order to keep memory usage at a reasonable level, intelligent caching and eviction strategies are necessary. Our system offers multiple strategies such as Least-Recently Used (LRU), Two-List LRU, and Priority LRU, in order to handle different scenarios.

Petuum-PS allows user to specify the number of rows to cache at each cache level, which controls the memory footprint on the client machine. These parameters provide interesting performance trade-offs: increasing the thread-level cache size provides faster data access but data in thread cache, duplicated for each thread, could crowd out the process-level cache storage. Petuum-PS provides reasonable default values but we expect expert users have much to gain by experimenting with these parameters.

2.1.3 Out-of-Core Storage Support

In many cases, running ML algorithms on Big Data requires a cost-prohibitive amount of memory (e.g., $10^9 \sim 10^{10}$ documents in topic model). By discovering sequential access patterns in the algorithm (e.g.

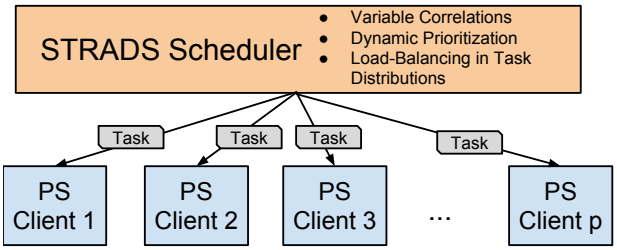

Figure 2: STRADS architecture. The worker machines can be Petuum-PS clients (as shown in the diagram) or nodes without PS support.

sequential read of documents), we can utilize the out-of-core (disk-based) storage by efficiently streaming data from hard disks or SSDs. Petuum-PS uses queue-based read-buffer and write-buffer to perform asynchronous disk I/O and hide latency. One can thus iterate over a large dataset with a small sliding window that fits in memory. While such out-of-core execution may result in speed penalty, it nonetheless enables ML algorithms on otherwise-intractable datasets.

2.2 STRADS Scheduler

Big Models contain millions (e.g., whole-genome regression), if not billions (e.g., Google brain DeepNet) of parameters, which require clusters with 100s - 10,000s of processors running inference algorithms in parallel. Examples of big models include ultra-high dimensional regression, DNN, and complex latent space models, which allow for rich data analysis far beyond simple classification or clustering. The complexity of these models raises two major issues: 1) a strategy is needed to divide and exploit model structure, in a way that ensures iterative-convergent consistency and statistical guarantees; 2) different model variables may have non-uniform importance to overall convergence, which must be taken into account. We develop a structure-aware dynamic scheduler (STRADS) to address these issues in distributed inference/learning on large models.

2.2.1 Dynamic Scheduling and Adaptive Load Balancing

For distributed model variables updates to be efficient, a scheduler is needed to partition the variables in a manner that minimizes parallelization error. Our STRADS scheduler accounts for the relationships between variables and the relative importance of each variable to the objective function; thus, STRADS can dynamically prioritize the most important variables for distributed updates, while minimizing parallelization error due to interference between variables via a *interference checking* procedure. In this manner, we use information about the ML problem to guarantee convergence at the fastest possible rate. As an example, the Lasso parallel coordinate descent algorithm is known to converge slowly when highly correlated variables are updated simultaneously [6]. STRADS avoids scheduling correlated variables together, as schematically shown in Figure (3, right) . thus minimizing any loss in convergence rate.

The updates on model variables may also change in computational complexity as the ML algorithm progresses, leading to uneven network and CPU workloads. STRADS actively monitors the contribution of each variable update to the objective function, and weighs it against the actual time taken for the update. It then uses this information to re-prioritize variables as the algorithm progresses, thus shifting computation to parts of the model that can benefit more. A simple example is to update variables with larger contributions more frequently via “delta sampling” as shown in Figure (3 Left), where Delta is defined as the decrement of objective function from the last update. This principle can be applied to problems with more complex structures. For example, in a structured-input-output regression algorithm, each worker will estimate new coefficients for every input and output group, via an expensive proximal operator. However, for groups with all-zeros, a cheap thresholding operator can be used instead, and furthermore, the emergence of such groups can be predicted a few iterations in advance. STRADS uses such knowledge of computational requirements to schedule jobs in a load-balanced manner.

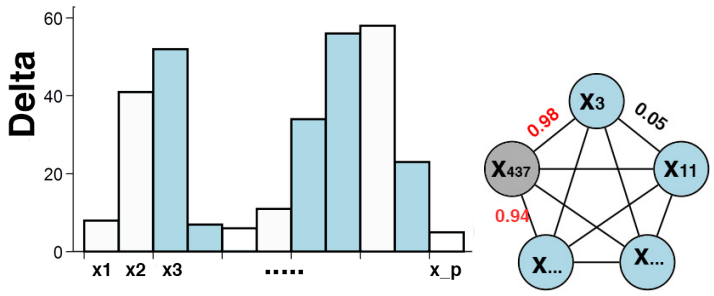

Figure 3: Cartoon of STRADS scheduler applied to Lasso. **Left**: STRADS samples the model parameters to update based on the contribution to objective criterion from the last update (Delta). In the context of Lasso it is the decrement of objective function. **Right**: After sampling, STRADS ensures the variables to be updated in parallel have low correlation to guarantee convergence.

3 Experiments and Results

We have published results for parameter server performance under the SSP consistency model for a variety of algorithms (LDA, MF, Lasso) [14]. Here we demonstrate SSP consistency with Petuum-PS at much larger scales on LDA and Mixed Membership Triangular Model (MMTM), which is a network analysis model. We show that Petuum can solve LDA more efficiently than GraphLab on a corpus of 8M documents and 7.5B tokens, and Petuum-assisted MMTM achieves state-of-the-art speed and size on a 39M-node network. We apply STRADS scheduler to solve Lasso at unprecedented scales with up to 100 million feature dimensions.

3.1 Topic Model (LDA)

Latent Dirichlet Allocation (LDA) is a popular unsupervised model that discovers latent thematic structure in document collections [4]. Much research has gone into scaling up the Gibbs sampler for LDA [2, 17, 22]. Conventional distributed Gibbs sampler for LDA adopts the document-centric partitioning scheme where the documents, with associated document-topic statistics, are partitioned onto worker machines and each machine samples the latent topics of tokens in the assigned documents [2, 22]. We develop a novel word-centric sampling scheme and partition the corpus by word, and thus each worker samples all occurrences of the assigned words (vocabularies) across all documents. Word-centric sampling scheme potentially exhibits statistical advantages, but it also poses challenges to the system, as the document-topic statistics needs to be globally accessed and updated, which grows linearly in the number of documents. Here we compare our implementation of this more challenging sampling scheme with the LDA sampler implemented on Distributed GraphLab using a fast sampling scheme by Yao *et al* [24]. To the best of our knowledge, this sapmler is the fastest LDA implementation available in GraphLab.

We use two large corpus summarized in Table 3.1. Our experiments use identical system configuration to compare our implementation on Petuum-PS and GraphLab[1]. Figure 4 shows throughput (measured in millions tokens per second) and memory usage (in GB permachine) using NYTimes data set with number of topics ranging from 100 to 10K. Petuum has higher throuhgput than GraphLab for 100 and 2K topics. GraphLab exceeds 32GB memory limit for 5K and 10K topics due to the large model size linear in number of topics; Petuum continues at a reduced throughputs and stay within the memory budget, demonstrating Petuum's memory efficiency and flexibility to system constraints.

Figure 5 shows the throughputs when running LDA on Pubmed data set for 100 and 10K topics with the same system setup. Petuum's throughput compares favorably with GraphLab's for 100 topics. In case of

[1]The cluster has 8 machines, each with 16 cores Intel Xeon 2.3 GHz, connected by 10Gbps Ethernet. Each machine is equipped with 128GB physical memory but were restricted to 32GB to simulate more common cluster environment.

	NYTimes	PubMed
# of docs	300K	8.2M
# of words	101K	141K
# of tokens	99M	7.5B

Table 1: Summary statistics of two corpra used in LDA.

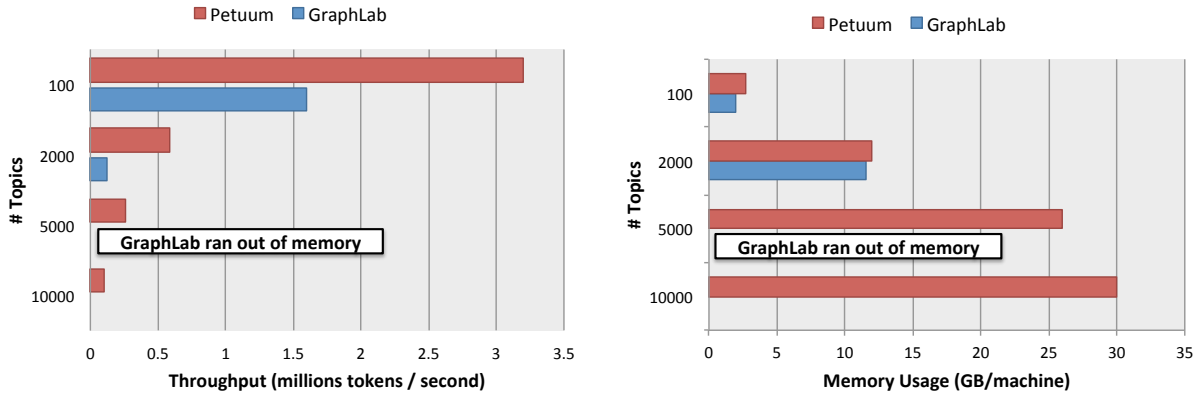

Figure 4: Throughput and Memory of LDA with NYTimes dataset for number of topics ranging from 100 to 10K.

10K topics, GraphLab exceeds the memory limit. These results are evidences that Petuum can solve LDA more efficiently on larger data set and model size than GraphLab.

3.2 Lasso

Lasso [21] is ℓ_1-regularized regression which takes the following form:

$$\min_{\boldsymbol{\beta}} L(\mathbf{X}, \mathbf{y}, \boldsymbol{\beta}) + \lambda \sum_j |\beta_j| \tag{1}$$

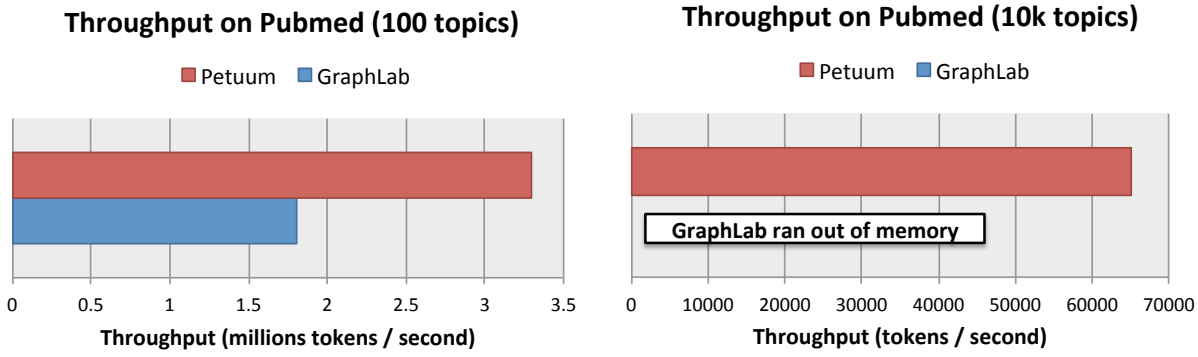

Figure 5: Throughput of LDA using Pubmed data set for 100 and 10K topics on Petuum and GraphLab.

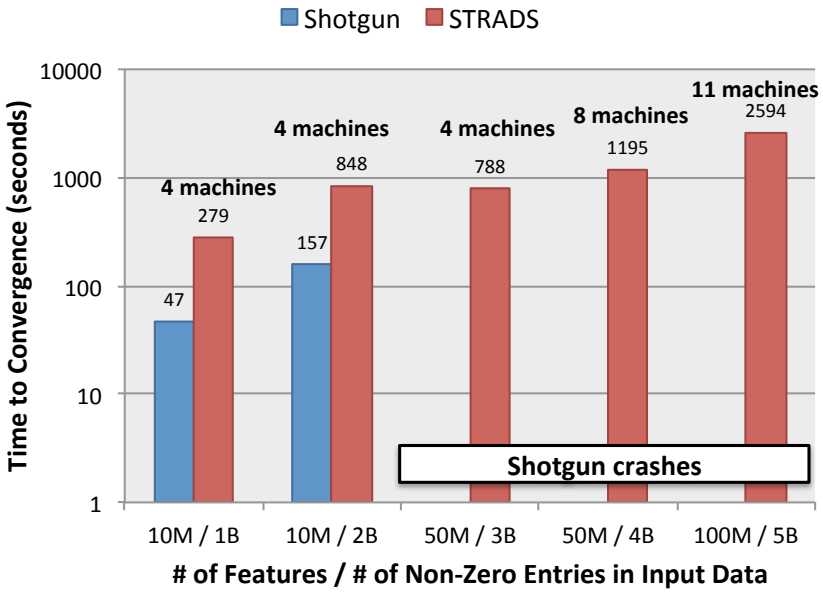

Figure 6: Lasso convergence time (time until the change of objective function value is $< 10^{-4}$) for parallel coordinate descent with STRADS and Shotgun with various input sizes (the number of non-zero entries in the design matrix $\boldsymbol{X}$), feature sizes, and the number of machines.

where λ denotes the regularization parameter that can be tuned, and $L(\cdot)$ is a non-negative convex loss function such as squared-loss or logistic-loss. For simplicity but without loss of generality, we let $L(\mathbf{X}, \mathbf{y}, \boldsymbol{\beta}) = \frac{1}{2} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2$. However, it is straightforward to use other loss functions such as logistic-loss using the same approach shown in [6].

We present experimental results on simulation data. We show comparisons among STRADS and Shotgun [7] in terms of convergence rate. We run all the experiments in Susitna cluster, where each machine has 64 cores and 128GB main memory connected to 1GbE network. We started from $\boldsymbol{\beta} = \mathbf{0}$.

We simulated datasets as follows: To generate $\boldsymbol{X}$, we first sampled $x_1^i \sim \mathcal{U}(-2, 2)$ for all $i = 1, \ldots, N$. Then we sampled $x_j^i \sim M(x_{j-1}^i + \mathcal{U}(-2, 2)) + (1 - M)\mathcal{U}(-2, 2)$, for all $j = 2, \ldots, J, i = 1, \ldots, N$, where $P(M = 1) = P(M = 0) = 0.5$, to simulate some correlations among adjacent covariates. We simulated true $\boldsymbol{\beta}$ by randomly selecting 100 true non-zero coefficients with the value of 10, and then generated $\boldsymbol{y} = \boldsymbol{\beta} + \epsilon$, where $\epsilon \sim \mathcal{N}(0, 1)$.

Figure 6 shows Lasso convergence time for parallel coordinate descent with STRADS and Shotgun with different input sizes (the number of non-zero entries in $\boldsymbol{X}$, feature sizes, and number of machines. In the figure 'STRADS' represents our distributed Lasso solver with STRADS scheduling, and 'Shotgun' is multi-thread parallel coordinate descent [6]. In Figure 6, we can see that our distributed system with STRADS can process large data sets (e.g. 5 billion non-zero entries in $\boldsymbol{X}$ and 100 million features) while Shotgun failed to run when the number of features $\geq 50M$. In MMT sparse matrix format, the largest matrix $\boldsymbol{X}$ we tested was 150GB. Because of data structures needed to implement parallel coordinate descent, 90GB size of $\boldsymbol{X}$ (the case when there are 3B non-zero entries in $\boldsymbol{X}$ and 50M features) could not be stored in a single machine with 128GB main memory, leading to Shotgun's failure. Furthermore, we observed that the converged objective function value of our system was always better than that of Shotgun. Overall, our experiments confirm that our distributed Lasso solver with STRADS can efficiently process very large data sets (e.g. 150G size of $\boldsymbol{X}$) within a reasonable time (e.g. 2594 seconds).

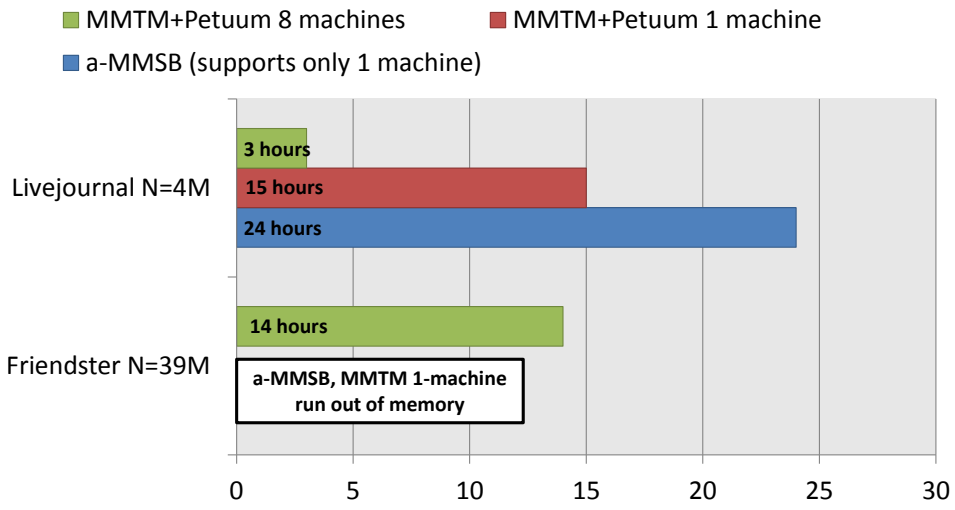

Figure 7: Network modeling experiments: time to convergence for MMTM (implemented on Petuum) vs the a-MMSB baseline.

3.3 Mixed Membership Triangular Model

The Mixed Membership Triangular Model [25] is a latent position network model for large graphs; it outputs a K-dimensional simplical feature vector for every node in the graph (akin to how LDA outputs a K-dimensional simplical topic vector for every document). An example application is overlapping community detection, as explored in [11].

The MMTM algorithm of [25] and the a-MMSB algorithm of [11] are single-machine implementations. We reimplemented MMTM on Petuum, and recorded the time to algorithm convergence for 1 and 8 machines[2], as well as the time to convergence for a-MMSB's publically available implementation. The algorithms were tested on two social networks[3]: the Livejournal social network with 4M nodes and 36M edges (using $K = 100$ roles), and a subsample of the Friendster social network with 39M nodes and 180M edges (using $K = 50$ roles). Because MMTM is much less communication-intensive than the other applications, and because we are only using 8 machines connected to one 10GBe network switch, we decided to use $s = 0$ SSP staleness for the Petuum Parameter Server[4].

The convergence times are shown in Figure 7: for MMTM on Livejournal, going from 1 to 8 machines cuts runtime to only 20% — equivalently, doubling the machine count cuts runtime to 58.5% (compared to the ideal of 50%). On the Friendster network, both single-machine MMTM and a-MMSB exceeded the 128GB memory limit, underscoring the need to distribute the parameter space across multiple machines. We point out that our Petuum MMTM Friendster result, with 39M nodes and 180M edges, is the largest reported experiment for Mixed-Membership network models such as MMTM and a-MMSB[5].

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[2] Each machine was equipped with 2 Xeon E5-2450 2.16GHz processors (16 cores per machine), and 128GB of RAM

[3] Available at `http://snap.stanford.edu/data/`.

[4] Note that with 10s or 100s of machines over multiple switches, we expect that $s > 0$ SSP staleness will be necessary.

[5] To our knowledge, the largest reported result was a-MMSB on 4M nodes [12].

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