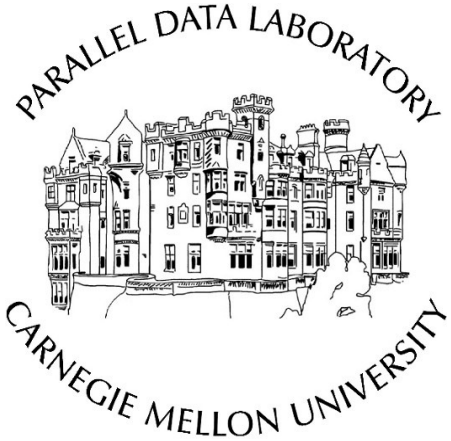

SMPFRAME: A Distributed Framework for Scheduled Model Parallel Machine Learning

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Abstract

Machine learning (ML) problems commonly applied to big data by existing distributed systems share and update all ML model parameters at each machine using a partition of data — a strategy known as data-parallel. An alternative and complimentary strategy, model-parallel, partitions model parameters for non-shared parallel access and update, periodically repartitioning to facilitate communication. Model-parallelism is motivated by two challenges that data-parallelism does not usually address: (1) parameters may be dependent, thus naive concurrent updates can introduce errors that slow convergence or even cause algorithm failure; (2) model parameters converge at different rates, thus a small subset of parameters can bottleneck ML algorithm completion. We propose scheduled model parallellism (SMP), a programming approach where selection of parameters to be updated (the schedule) is explicitly separated from parameter update logic. The schedule can improve ML algorithm convergence speed by planning for parameter dependencies and uneven convergence. To support SMP at scale, we develop an archetype software framework SMPFRAME which optimizes the throughput of SMP programs, and benchmark four common ML applications written as SMP programs: LDA topic modeling, matrix factorization, sparse least-squares (Lasso) regression and sparse logistic regression. By improving ML progress per iteration through SMP programming whilst improving iteration throughput through SMPFRAME we show that SMP programs running on SMPFRAME outperform non-model-parallel ML implementations: for example, SMP LDA and SMP Lasso respectively achieve 10x and 5x faster convergence than recent, well-established baselines.

1 Introduction

Machine Learning (ML) algorithms are used to understand and summarize big data, which may be collected from diverse sources such as the internet, industries like finance and banking, or experiments in the physical sciences, to name a few. The demand for cluster ML implementations is driven by two trends: (1) **big data:** a single machine's computational power is inadequate with big datasets; (2) **large models:** with ML applications striving for larger numbers of model parameters (at least hundreds of millions [18]), computational power requirements must scale, even if datasets are not too big.

In particular, the trend towards richer, larger ML models with more parameters (up to trillions [20]) is driven by the need for more "explanatory power": it has been observed that big datasets contain "longer tails", rare-yet-unique events, than smaller datasets, and detection of such events can be crucial to downstream tasks [33, 31]. Many of these *big models* are extremely slow to converge when trained with a sequential algorithm, leading to *model-parallelism* [8, 19, 33, 21], which as the name suggests, splits ML model parameters across machines, and makes each machine responsible for updating only its assigned parameters (either using the full data, or a data subset). Even when the model is relatively small, model-parallel execution can still mean the difference between hours or days of compute on a single machine, versus minutes on a cluster [5, 30].

Model-parallelism can be contrasted with *data-parallelism*, where each machine gets one partition of the data, and iteratively generates sub-updates that are applied to *all* ML model parameters, until convergence is reached. This is possible because most ML algorithms assume data independence under the model — *independent and identically distributed data* in statistical parlance — and as a result, all machines' sub-updates can be easily combined, provided every machine has access to the same global model parameters.

This convenient property does not apply to model-parallel algorithms, which introduce new subtleties: (1) unlike data samples, the model parameters are not independent, and (2) model parameters may take different numbers of iterations to converge (*uneven convergence*). Hence, the effectiveness of a model-parallel algorithm is greatly affected by its *schedule*: which parameters are updated in parallel, and how they are prioritized [21, 37].

Poorly-chosen schedules decrease the progress made by each ML algorithm iteration, or may even cause the algorithm to fail. Note that progress per iteration is distinct from iteration throughput (number of iterations executed per unit time); effective ML implementations combine high progress per iteration with high iteration throughput, yielding high progress per unit time. Despite these challenges, model-parallel algorithms have shown promising speedups over their data-parallel counterparts [33, 31].

In the ML literature, there is a strong focus on verifying the safety or correctness of parallel algorithms via statistical theory [5, 23, 38], but this is often done under simple assumptions about distributed environments — for example, network communication and synchronization costs are often ignored. On the other hand, the systems literature is focused on developing distributed systems [9, 34, 20, 22], with high-level programming interfaces that allow ML developers to focus on the ML algorithm's core routines. Some of these systems enjoy strong fault tolerance and synchronization guarantees that ensure correct ML execution [9, 34], while others [16, 20] exploit the error-tolerance of data-parallel ML algorithms, and employ relaxed synchronization guarantees in exchange for higher iterations-per-second throughput. In nearly all of these systems, the ML algorithm is treated as a black box, with little opportunity to control the parallel schedule of updates (in the sense that we defined earlier). As a result, these systems offer little support for model-parallel ML algorithms, in which it is often vital to re-schedule updates in response to model parameter dependencies and uneven convergence.

These factors paint an overall picture of model-parallel ML that is at once promising, yet under-supported from the following angles: (1) limited understanding of model-parallel execution order, and how it can improve the speed of model-parallel algorithms; (2) limited systems support to investigate and develop better model-parallel algorithms; (3) limited understanding of the safety and correctness of model-parallel

algorithms under realistic systems conditions. To address these challenges, this paper proposes **scheduled model parallelism (SMP)**, where an ML application scheduler generates model-parallel *schedules* that improve model-parallel algorithm progress per update, by considering dependency structures and prioritizing parameters. Essentially, SMP allows model-parallel algorithms to be separated into a *control component* responsible for dependency checking and priortization, and an *update component* that executes iterative ML updates in the parallel schedule prescribed by the control component.

To realize SMP, we develop **a prototype SMP framework called SMPFRAME** that parallelizes SMP ML applications over a cluster. While SMP maintains high progress per iteration, the SMPFRAME software improves iterations executed per second, by (1) pipelining SMP iterations, (2) overlapping SMP computation with parameter synchronization over the network, and (3) streaming computations over a ring topology. Through SMP on top of SMPFRAME, we achieve high parallel ML performance through increased progress per iteration, as well as increased iterations per second — the result is substantially increased *progress per second*, and therefore faster ML algorithm completion. We benchmark various SMP algorithms implemented on SMPFRAME — Gibbs sampling for topic modeling [4, 15], stochastic gradient descent for matrix factorization [12], and coordinate descent for sparse linear (i.e., Lasso [28, 10]) and logistic [11] regressions — and show that SMP programs on SMPFRAME outperform non-model parallel ML implementations.

2 Model Parallelism

Although machine learning problems exhibit a diverse spectrum of model forms, such as probabilistic topic models, optimization-theoretic regression formulations, etc., their algorithmic solutions implemented by a computer program typically take the form of an iterative convergent procedure, meaning that they are optimization or Markov Chain Monte Carlo (MCMC [29]) algorithms that repeat some set of fixed-point update routines until convergence (i.e. a stopping criterion has been reached):

$$A^{(t)} = A^{(t-1)} + \Delta(D, A^{(t-1)}), \tag{1}$$

where index t refers to the current iteration, A are the model parameters, D is the input data, and $\Delta()$ is the model update function [1]. Such iterative-convergent algorithms have special properties that we shall explore: tolerance to (non-recursive) errors in model state during iteration, dependency structures that must be respected during parallelism, and uneven convergence across model parameters.

In *model-parallel* ML programs, parallel workers recursively update subsets of model parameters until convergence — this is in contrast to data-parallel programs, which parallelize over subsets of data samples. A model-parallel ML program extends Eq. (1) to the following form:

$$A^{(t)} = A^{(t-1)} + \textstyle\sum_{p=1}^{P} \Delta_p(D, A^{(t-1)}, S_p(D, A^{(t-1)})),$$

where $\Delta_p()$ is the model update function executed at parallel worker p. The "schedule" $S_p()$ outputs a subset of parameters in A, which tells the p-th parallel worker which parameters it should work on *sequentially* (i.e. workers may not further parallelize within $S_p()$). Since the data D is unchanging, we drop it from the notation for clarity:

$$A^{(t)} = A^{(t-1)} + \textstyle\sum_{p=1}^{P} \Delta_p(A^{(t-1)}, S_p(A^{(t-1)})). \tag{2}$$

Parallel coordinate descent solvers are a good example of model parallelism, and have been applied with great success to the Lasso sparse regression problem [5]. In addition, MCMC or sampling algorithms can also

[1] The summation between $\Delta()$ and $A^{(t-1)}$ can be generalized to a general aggregation function $F(A^{(t-1)}, \Delta())$; for concreteness we restrict our attention to the summation form, but the techniques proposed in this paper can be applied to F.

be model-parallel: for example, the Gibbs sampling algorithm normally processes one model parameter at a time, but it can be run in parallel over many variables at once, as seen in topic model implementations [13, 33]. Unlike data-parallel algorithms which parallelize over independent data samples, model-parallel algorithms parallelize over model parameters that are, in general, not independent; this can cause poor performance (or sometimes even algorithm failure) if not handled with care [5, 25], and usually necessitate approaches and theories very different from that of data parallelism, which is our main focus in this paper.

2.1 Properties of ML Algorithms

Some intrinsic properties of ML algorithms (i.e., Eq. (1)) can provide new opportunities for effective parallelism when correctly explored: (1) **Model Dependencies**, which refers to the phenomenon that different elements in A are coupled, meaning that an update to one element will strongly influence the next update to another parameter. If such dependencies are violated, which is typical during random parallelization, they will incur errors to the ML algorithm's progress, leading to reduced convergence speed (or even algorithm failure) when we increase the degree of parallelism [5]. Furthermore, not all model dependencies are explicitly specified in an ML program, meaning that they have to be computed from data, such as in Lasso [5]. (2) **Uneven Convergence**, which means different model parameters may converge at different rates, leading to new speedup opportunities via parameter prioritization [21, 37]. Finally, (3) **Error-Tolerant** — a limited amount of stochastic error during computation of $\Delta(D, A^{t-1})$ in each iteration does not lead to algorithm failure (though it might slow down convergence speed).

Sometimes, it is not practical or possible to find a "perfect" parallel execution scheme for an ML algorithm, which means that some dependencies will be violated, leading to incorrect update operations. But, unlike classical computer science algorithms where incorrect operations always lead to failure, iterative-convergent ML programs (also known as "fixed-point iteration" algorithms) can be thought of as having a buffer to absorb inaccurate updates or other errors, and will not fail as long as the buffer is not overrun. Even so, there is a strong incentive to minimize errors: the more dependencies the system finds and avoids, the more progress the ML algorithm will make each iteration — unfortunately, finding those dependencies may incur non-trivial computational costs, leading to reduced iteration throughput. Because an ML program's convergence speed is essentially progress per iteration multiplied by iteration throughput, it is important to balance these two considerations. Below, we explore this idea by explicitly discussing some variations within model parallelism, in order to expose possible ways by which model parallelization can be made efficient.

2.2 Variations of Model-Parallelism

We restrict our attention to model-parallel programs that partition M model parameters across P worker threads in an approximately load-balanced manner; highly unbalanced partitions are inefficient and undesirable. Here, we introduce variations on model-parallelism, which differ on their partitioning quality. Concretely, partitioning involves constructing a size-M^2 dependency graph, with weighted edges e_{ij} that measure the dependency between parameters A_i and A_j. This measure of dependency differs from algorithm to algorithm: e.g., in Lasso regression e_{ij} is the correlation between the i-th and j-th data dimensions. The total violation of a partitioning is the sum of weights of edges that cross between the P partitions, and we wish to minimize this.

Ideal Model-Parallel: Theoretically, there exists an "ideal" load-balanced parallelization over P workers which gives the highest possible progress per iteration; this is indicated by an ideal (but not necessarily computable) schedule $S_p^{ideal}()$ that replaces the generic $S_p()$ in Eq. (2). There are two points to note: (1) even this "ideal" model parallelization can still violate model dependencies and incur errors, compared to sequential execution because of residue cross-worker coupling; (2) computing $S_p^{ideal}()$ is expensive in general because graph-partitioning is NP-hard. Ideal model parallelization achieves the highest progress per iteration amongst load-balanced model-parallel programs, but may incur a large one-time or even every-iteration partitioning cost, which can greatly reduce iteration throughput.

Random Model-Parallel: At the other extreme is random model-parallelization, in which a schedule $S_p^{rand}()$ simply chooses one parameter at random for each worker p [5]. As the number of workers P increases, the expected number of violated dependencies will also increase, leading to poor progress per iteration (or even algorithm failures). However, there is practically no cost to iteration throughput.

Approximate Model-Parallel: As a middle ground between ideal and random model-parallelization, we may *approximate* $S_p^{ideal}()$ via a cheap-to-compute schedule $S_p^{approx}()$. A number of strategies exist: one may partition small subsets of parameters at a time (instead of the M^2-size full dependency graph), or apply approximate partitioning algorithms [26] such as METIS [17] (to avoid NP-hard partitioning costs), or even use strategies that are unique to a particular ML program's structure.

In this paper, our goal is to explore strategies for efficient and effective approximate model parallelization. We focus on ideas for generating model partitions and schedules:

Static Partitioning: A fixed, static schedule $S_p^{fix}()$ hard-codes the partitioning for every iteration beforehand. Progress per iteration varies depending on how well $S_p^{fix}()$ matches the ML program's dependencies, but like random model-parallel, this has little cost to iteration throughput.

Dynamic Partitioning: Dynamic partitioning $S_p^{dyn}()$ tries to select independent parameters for each worker, by performing pair-wise dependency tests between a small number L of parameters (which can be chosen differently at different iterations, based on some priority policy as discussed later); the GraphLab system achieves a similar outcome via graph consistency models [21]. The idea is to only do L^2 computational work per iteration, which is far less than M^2 (where M is the total number of parameters), based on a priority policy that selects the L parameters that matter most to the program's convergence. Dynamic partitioning can achieve high progress per iteration, similar to ideal model-parallelism, but may suffer from poor iteration throughput on distributed clusters: because only a small number of parameters are updated each iteration, the time spent computing $\Delta_p()$ at the P workers cannot amortize away network latencies and the cost of computing $S_p^{dyn}()$.

Pipelining: This is not a different type of model-parallelism per se, but a complementary technique that can be applied to any model-parallel strategy. Pipelining allows the next iteration(s) to start before the current one finishes, ensuring that computation is always fully utilized; however, this introduces *staleness* into the model-parallel execution:

$$A^{(t)} = A^{(t-1)} + \sum_{p=1}^{P} \Delta_p(A^{(t-s)}, S_p(A^{(t-s)})). \tag{3}$$

Note how the model parameters $A^{(t-s)}$ being used for $\Delta_p(), S_p()$ come from iteration $(t-s)$, where s is the pipeline depth. Because ML algorithms are error-tolerant, they can still converge under stale model images (up to a practical limit) [16, 7]. Pipelining therefore sacrifices some progress per iteration to increase iteration throughput, and is a good way to raise the throughput of dynamic partitioning.

Prioritization: Like pipelining, prioritization is complementary to model-parallel strategies. The idea is to modify $S_p()$ to prefer parameters that, when updated, will yield the most convergence progress [21], while avoiding parameters that are already converged [20]; this is effective because ML algorithms exhibit uneven parameter convergence. Since computing a parameter's potential progress can be expensive, we may employ cheap-but-effective approximations or heuristics to estimate the potential progress (as shown later). Prioritization can thus greatly improve progress per iteration, at a small cost to iteration throughput.

2.3 Scheduled Model Parallelism for Programming

Model-parallelism accommodates a wide range of partitioning and prioritization strategies (i.e. the schedule $S_p()$), from simple random selection to complex, dependency-calculating functions that can be more expensive than the updates $\Delta_p()$. In existing ML program implementations, the schedule is often written as part of the

SMP Function	Purpose	Available Inputs	Output
`schedule()`	Select parameters A to update	model A, data D	P parameter jobs $\{\mathbf{S}_p\}$
`update()`	Model-parallel update equation	one parameter job $\mathbf{S}_p$, local data D_p, parameters A	one intermediate result R_p
`aggregate()`	Collect R_p and update model A	P intermediate results $\{R_p\}$, model A	new model state $A_p^{(t+1)}$

Table 1: **SMP Instructions**. To create an SMP program, the user implements these Instructions. The available inputs are optional — e.g. `schedule()` does not necessarily have to read A, D (such as in static partitioning).

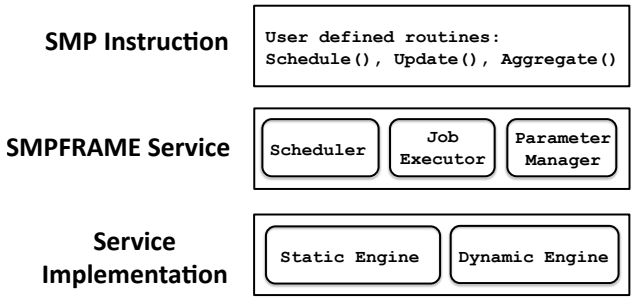


Figure 1: SMPFRAME: To create an SMP program, the user codes the SMP Instructions, similar to MapReduce. The Services are system components that execute SMP Instructions over a cluster. We provide two Implementations of the Services: a Static Engine and a Dynamic Engine, specialized for high performance on static-schedule and dynamic-schedule SMP programs respectively. The user chooses which engine (s)he would like to use.

update logic, ranging from simple for-loops that sweep over all parameters one at a time, to sophisticated systems such as GraphLab [21], which "activates" a parameter whenever one of its neighboring parameters changes. We contrast this with **scheduled model parallelism** (SMP), in which the schedule $S_p()$ computation is explicitly separated from update $\Delta_p()$ computation. The rationale behind SMP is that the schedule can be a distinct object for systematic investigation, separate from the updates, and that a model-parallel ML program can be improved by simply changing $S_p()$ without altering $\Delta_p()$.

In order to realize SMP programming, we have developed a framework called SMPFRAME, that exposes parameter schedules $S_p()$ and parameter updates $\Delta_p()$ as separate functions for the user to implement (analogous to how MapReduce requires the user to implement Map and Reduce). This separation allows generic optimizations to be applied and enjoyed by many model-parallel programs: e.g., our SMPFRAME implementation performs automatic pipelining for dynamic model-parallelism, and uses a ring communication topology for static model-parallelism; we believe further yet-unexplored optimizations are possible.

3 The SMPFRAME System

SMPFRAME is a system to execute SMP programs, in which low-level machine/traffic coordination issues are abstracted away. The goal is to improve ML convergence speed in two ways: (1) users can easily experiment with new model-parallel schedules for ML programs, using the aforementioned techniques to improve ML algorithm *convergence per iteration*; (2) the SMPFRAME provides systems optimizations such as pipelining to automatically increase the *iteration throughput* of SMP programs.

Conceptually, SMPFRAME is divided into three parts (Figure 1): (1) SMP Instructions (`schedule()`, `update()`, `aggregate()`), which the *user implements* to create an SMP program; (2) Services, which execute SMP Instructions over a cluster (**Scheduler**, **Job Executors**, **Parameter Manager**); (3) Implementations of the Services, specialized for high performance on different types of SMP programs (Static Engine and Dynamic Engine).

Algorithm 1 Generic SMP ML program template

A: model parameters
D_p: local data stored at worker p
P: number of workers **Function** `schedule`(A, D):
  Generate P parameter subsets $[\mathbf{S}_1, \ldots, \mathbf{S}_P]$
  Return $[\mathbf{S}_1, \ldots, \mathbf{S}_P]$ **Function** `update`$(p, \mathbf{S}_p, D_p, A)$: // In parallel over $p = 1..P$
  For each parameter a in $\mathbf{S}_p$:
    $R_p[a]$ = updateParam(a, D_p)
  Return R_p **Function** `aggregate`$([R_1, \ldots, R_P], A)$:
  Combine intermediate results $[R_1, \ldots, R_P]$
  Apply intermediate results to A

3.1 User-implemented SMP Instructions

Table 1 shows the three SMP Instructions, which are abstract functions that a user implements in order to create an SMP program. All SMP programs are iterative, where each iteration begins with `schedule()`, followed by parallel instances of `update()`, and ending with `aggregate()`; Figure 1 shows the general form of an SMP program.

3.2 SMPFRAME Services

SMPFRAME executes SMP Instructions across a cluster via three Services: the **Scheduler**, **Job Executors**, and the **Parameter Manager**. The **Scheduler** is responsible for computing `schedule()` and passing the output jobs $\{\mathbf{S}_p\}$ on; most SMP programs only require one machine to run the **Scheduler**, others may benefit from parallelization and pipelining over multiple machines (see the following sections). The **Scheduler** can keep local program state between iterations (e.g. counter variables or cached computations).

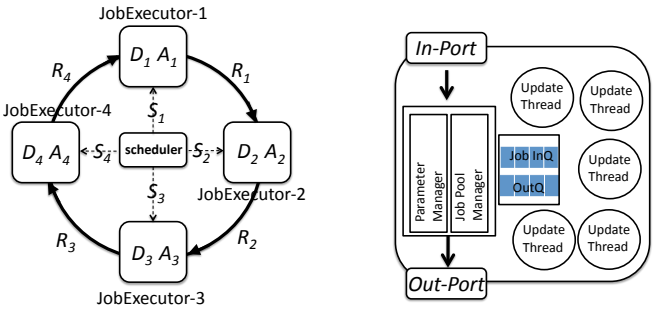
The P jobs $\{\mathbf{S}_p\}$ are distributed to P **Job Executors**, which start worker processes to run `update()`. On non-distributed file systems, the **Job Executors** must place worker processes exactly on machines with the data. Global access to model variables A is provided by the **Parameter Manager**, so the **Job Executors** do not need to consider model placement. Like the **Scheduler**, the **Job Executors** may keep local program state between iterations.

Once the worker processes finish `update()` and generate their intermediate results R_p, the aggregator process on **scheduler** (1) performs `aggregate()` on $\{R_p\}$, and (2) commit model updates and thus reach the next state $A_p^{(t+1)}$. Control is then passed back to the **Scheduler** for the next iteration $(t+1)$. Finally, the **Parameter Manager** supports the **Scheduler** and **Job Executors** by providing global access to model parameters A. The Static Engine and Dynamic Engine implement the **Parameter Manager** differently, and we will discuss the details later.

3.3 Service Implementations (Engines)

Many ML algorithms use a "static" schedule, where the order of parameter updates is known or fixed in advance (e.g. Matrix Factorization and Topic Modeling). One may also write "dynamic" schedules that change in response to the model parameters, and which can outperform static-schedule equivalents — our SMP-Lasso program is one example. These two classes of schedules pose different systems requirements; static `schedule()` functions tend to be computationally light, while dynamic `schedule()` functions are computationally intensive.

Static-schedule algorithms usually generate jobs $\mathbf{S}_p$ with many parameters; it is not uncommon to cover the whole parameter space A in a single SMP iteration, and communication of parameters A across the network can easily become a bottleneck. On the other hand, dynamic-schedule algorithms prefer to create small parameter update jobs $\mathbf{S}_p$, which not only reduces the computational bottleneck at the scheduler, but



(a) Ring topology (b) Job Executor

Figure 2: **Static Engine:** (a) Parameters A_p and intermediate results R_p are exchanged over a ring topology. (b) **Job Executor** architecture: the **Parameter Manager** and a job pool manager receive and dispatch jobs to executor threads; results R_p are immediately forwarded without waiting for other jobs to complete.

also allows the ML algorithm to quickly react to and exploit uneven parameter convergence. However, this makes the SMP iterations very short, and therefore latency (from both scheduler computation and network communication) becomes a major issue.

Because static- and dynamic-schedule SMP algorithms have different needs, we provide two distinct but complete Implementations ("engines") of the three Services: a Static Engine specialized for high performance on static-schedule algorithms, and a Dynamic Engine specialized for dynamic-schedule algorithms. For a given ML program, the choice of Engine is primarily driven by domain knowledge — e.g. it is known that coordinate descent-based regressions benefit greatly from dynamic schedules [26, 19]. Once the user has chosen an Engine, SMPFRAME provides default `schedule()` implementations appropriate for that Engine (described in the next Section) that can used as-is. These defaults cover a range of ML programs, from regressions through topic models and matrix factorization.

3.3.1 Static Engine

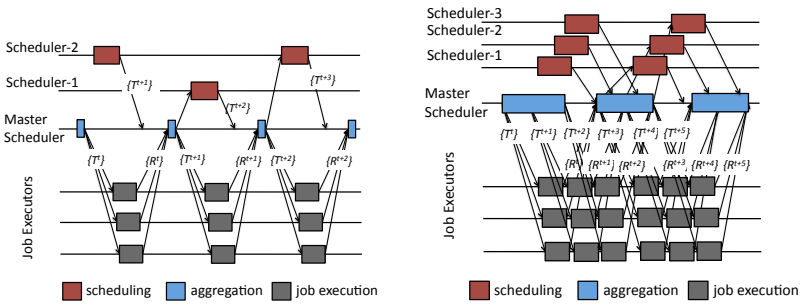
In static-schedule algorithms, every iteration reads/writes to many parameters, causing bursty network communication. To avoid network hot spots and balance communication, the Static Engine's **Parameter Manager** connects **Job Executors** into a logical ring (Figure 2), used to transfer parameters A_p and intermediate results R_p.

The **Job Executors** forward received parameters A_p and results R_p to their next ring neighbor, making local copies of needed A_p, R_p as they pass by. Once A_p, R_p return to their originator on the ring, they are removed from circulation. The Static Engine uses a straightforward, single-threaded implementation for its **Scheduler** (because static `schedule()`s are not computationally demanding).

3.3.2 Dynamic Engine

Dynamic-schedule algorithms have short iterations, hence computation time by **Job Executors** is often insufficient to amortize away network communication time (Figure 3a). To address this, the Dynamic Engine uses pipelining (Figure 3b) to overlap communication and computation; the **Scheduler** will start additional iterations before waiting for the previous one to finish. The pipeline depth (number of in-flight iterations) can be set by the user.

Although pipelining improves iteration throughput and overall convergence speed, it may lower progress per iteration due to (1) using the old model state $A^{(t)}$ instead of new updates $A^{(t+s)}$, and (2) dependencies between pipelined iterations due to overlapping of update jobs $\mathbf{S}_p$. This does not lead to ML program failure because ML algorithms can tolerate some error and still converge — albeit more slowly. Pipelining is



(a) Non-pipelined (b) Pipelined

Figure 3: **Dynamic Engine** pipelining: (a) Non-pipelined execution: network latency dominates; (b) Pipelining overlaps networking and computation.

basically execution with stale parameters, $A^{(t)} = F(A^{(t-s)}, \{\Delta_p(A^{(t-s)}, S_p(A^{(t-s)}))\}_{p=1}^{P})$ where s is the pipeline depth.

3.4 Other Considerations

Fault tolerance: SMPFRAME execution can be made fault-tolerant, by checkpointing the model parameters A every x iterations. Because ML programs are error-tolerant, background checkpointing (which may span several iterations), is typically sufficient.

Avoiding lock contention: To avoid lock contention, the SMPFRAME **Scheduler** and **Job Executors** avoid sharing data structures between threads in the same process. For example, when jobs $\mathbf{S}_p$ are being assigned by a **Job Executor** process to individual worker threads, we use a separate, dedicated queue for each worker thread.

Dynamic Engine parameter reordering: Within each Dynamic Engine iteration, SMPFRAME re-orders the highest priority parameters to the front of the iteration, which improves the performance of pipelining. The intuition is as follows: because high-priority parameters have a larger effect on subsequent iterations, we should make their updated values available as soon as possible, rather than waiting until the end of the pipeline depth s.

4 SMP Implementations of ML Programs

We describe how two ML algorithms can be written as Scheduled Model Parallel (SMP) programs. The user implements `schedule()`, `update()`, `aggregate()`; alternatively, SMPFRAME provides pre-implemented `schedule()` functions for some classes of SMP programs. Algorithm 1 shows a typical SMP program.

4.1 Parallel Coordinate Descent for Lasso

Lasso, or ℓ_1-regularized least-squares regression, is used to identify a small set of important features from high-dimensional data. It is an optimization problem

$$\min_\beta \quad \frac{1}{2}\sum_{i=1}^{n}\left(\mathbf{y}^i - \mathbf{x}^i\beta\right)^2 + \lambda\|\beta\|_1 \tag{4}$$

where $\|\beta\|_1 = \sum_{a=1}^{d}|\beta_a|$ is a sparsity-inducing ℓ_1-regularizer, and λ is a tuning parameter that controls the sparsity level of $\mathbf{w}$. $\mathbf{X}$ is an N-by-M design matrix ($\mathbf{x}^i$ represents the i-th row, $\mathbf{x}_a$ represents the a-th column), $\mathbf{y}$ is an N-by-1 observation vector, and β is the M-by-1 coefficient vector (the model parameters). The Coordinate Descent (CD) algorithm is used to solve Eq. (4), and thus learn β from the inputs $\mathbf{X}, \mathbf{y}$; the

Algorithm 2 SMP Dynamic, Prioritized Lasso

$\mathbf{X}, \mathbf{y}$: input data
$\{\mathbf{X}\}^p, \{\mathbf{y}\}^p$: rows/samples of $\mathbf{X}, \mathbf{y}$ stored at worker p
β: model parameters (regression coefficients)
λ: ℓ_1 regularization penalty
τ: $\mathcal{G}$ edges whose weight is below τ are ignored

Function `schedule`$(\beta, \mathbf{X})$:
  Pick $L > P$ params in β with probability $\propto (\Delta\beta_a)^2$
  Build dependency graph $\mathcal{G}$ over L chosen params:
    edge weight of (β_a, β_b) = correlation$(\mathbf{x}^a, \mathbf{x}^b)$
  $[\beta_{\mathcal{G}_1}, \ldots, \beta_{\mathcal{G}_K}]$ = findIndepNodeSet$(\mathcal{G}, \tau)$
  For $p = 1..P$:
    $\mathbf{S}_p = [\beta_{\mathcal{G}_1}, \ldots, \beta_{\mathcal{G}_K}]$
  Return $[\mathbf{S}_1, \ldots, \mathbf{S}_P]$

Function `update`$(p, \mathbf{S}_p, \{\mathbf{X}\}^p, \{\mathbf{y}\}^p, \beta)$:
  For each param β_a in $\mathbf{S}_p$, each row i in $\{\mathbf{X}\}^p$:
    $R_p[a]$ += $x_a^i y^i - \sum_{b \neq a} x_a^i x_b^i \beta_b$
  Return R_p

Function `aggregate`$([R_1, \ldots, R_P], \mathbf{S}_1, \beta)$:
  For each parameter β_a in $\mathbf{S}_1$:
    temp = $\sum_{p=1}^{P} R_p[a]$
    $\beta_a = \mathcal{S}$(temp, λ)

CD update rule for β_a is

$$\beta_a^{(t)} \leftarrow \mathcal{S}(\mathbf{x}_a^\top \mathbf{y} - \textstyle\sum_{b \neq a} \mathbf{x}_a^\top \mathbf{x}_b \beta_b^{(t-1)}, \lambda), \tag{5}$$

where $\mathcal{S}(\cdot, \lambda)$ is a soft-thresholding operator [10].

Algorithm 2 shows an SMP Lasso that uses dynamic, prioritized scheduling. It expects that each machine locally stores a subset of data samples (which is common practice in cluster ML), however the Lasso update Eq. (5) uses a feature/column-wise access pattern. Therefore every worker $p = 1..P$ operates on the same scheduled set of L parameters, but using their respective data partitions $\{\mathbf{X}\}^p, \{\mathbf{y}\}^p$. Note that `update()` and `aggregate()` are a straightforward implementation of Eq. (5).

We direct attention to `schedule()`: it picks (i.e. prioritizes) L parameters in β with probability proportional to their squared difference from the latest update (their "delta"); parameters with larger delta are more likely to be non-converged. Next, it builds a dependency graph over these L parameters, with edge weights equal to the correlation[2] between data columns $\mathbf{x}^a, \mathbf{x}^b$. Finally, it removes all edges in $\mathcal{G}$ below a threshold $\tau > 0$, and extracts nodes $\beta_{\mathcal{G}_k}$ that do not have common edges. All chosen $\beta_{\mathcal{G}_k}$ are thus pairwise independent and safe to update in parallel.

Why is such a sophisticated `schedule()` necessary? Suppose we used random parameter selection [5]: Figure 4 shows its progress, on the Alzheimer's Disease (AD) data [36]. The total compute to reach a fixed objective value goes up with more concurrent updates — i.e. progress per unit computation is decreasing, and the algorithm has poor scalability. Another reason is uneven parameter convergence: Figure 5 shows how many iterations different parameters took to converge on the AD dataset; $> 85\%$ of parameters converged in < 5 iterations, suggesting that the prioritization in Algorithm 2 should be very effective.

Default `schedule()` functions: The squared delta-based parameter prioritization and dynamic dependency checking in SMP Lasso's `schedule()` (Algorithm 2) generalize to other regression problems — for example, we also implement sparse logistic regression using the same `schedule()`. SMPFRAME allows ML programmers to re-use Algorithm 2's `schedule()` via a library function `scheduleDynRegr()`.

[2] On large data, it suffices to estimate the correlation with a data subsample.

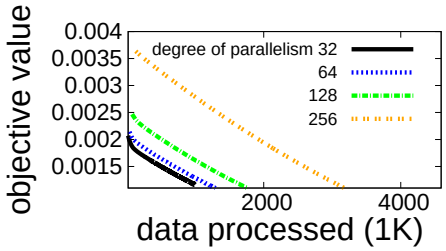


Figure 4: **Random Model-Parallel Lasso:** Objective value (lower the better) versus processed data samples, with 32 to 256 workers performing concurrent updates. Under naive (random) model-parallel, higher degree of parallelism results in worse progress.

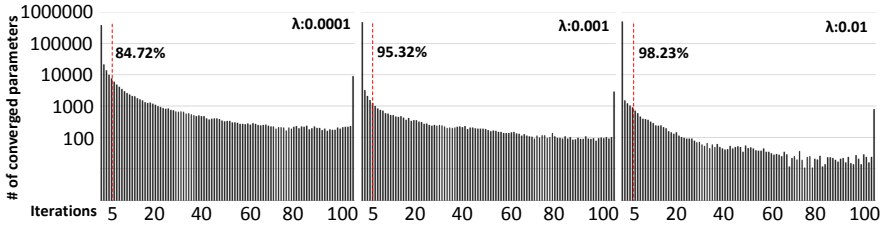


Figure 5: **Uneven Parameter Convergence:** Number of converged parameters at each iteration, with different regularization parameters λ. Red bar shows the percentage of converged parameters at iteration 5.

4.2 Parallel Gibbs Sampling for Topic Modeling

Topic modeling, a.k.a. Latent Dirichlet Allocation (LDA), is an ML model for document soft-clustering; it assigns each of N text documents to a probability distribution over K topics, and each topic is a distribution over highly-correlated words. Topic modeling is usually solved via a parallel Gibbs sampling algorithm, involving three data structures: an N-by-K document-topic table U, an M-by-K word-topic table V (where M is the vocabulary size), and the topic assignments z_{ij} to each word "token" j in each document i. Each topic assignment z_{ij} is associated with the j-th word in the i-th document, w_{ij} (an integer in 1 through M); the z_{ij}, w_{ij} are usually pre-partitioned over worker machines [1].

The Gibbs sampling algorithm iteratively sweeps over all z_{ij}, assigning each one a new topic via this probability distribution over topic outcomes $k = 1..K$:

$$P(z_{ij} = k \mid U, V) \propto \frac{\alpha + U_{ik}}{K\alpha + \sum_{\ell=1}^{K} U_{i\ell}} + \frac{\beta + V_{w_{ij},k}}{M\beta + \sum_{m=1}^{M} V_{mk}}, \tag{6}$$

where α, β are smoothing parameters. Once a new topic for z_{ij} has been sampled, the tables U, V are updated by (1) decreasing $V_{i,oldtopic}$ and $U_{w_{ij},oldtopic}$ by one, and (2) increasing $U_{i,newtopic}$ and $V_{w_{ij},newtopic}$ by one.

Eq. (6) is usually replaced by a more efficient (but equivalent) variant called SparseLDA [32], which we also use. We will not show its details within `update()` and `aggregate()`; instead, we focus on how `schedule()` controls which z_{ij} are being updated by which worker. Algorithm 3 shows our SMP LDA implementation, which uses a static "word-rotation" schedule, and partitions the documents over workers. The word-rotation schedule partitions the rows of V (word-topic table), so that workers never touch the same rows in V (each worker just skips over words w_{ij} associated with not-assigned rows). The partitioning is "rotated" P times, so that every word w_{ij} in each worker is touched exactly once after P invocations of `schedule()`.

As with Lasso, one might ask why this `schedule()` is useful. A common strategy is to have workers sweep over all their z_{ij} every iteration [1], however, as we show later in Sec 6, this causes concurrent writes to the same rows in V, breaking model dependencies.

Algorithm 3 SMP Static-schedule Topic Modeling

U, V: doc-topic table, word-topic table (model params)
N, M: number of docs, vocabulary size
$\{z\}_p, \{w\}_p$: topic indicators and token words stored at worker p
c: persistent counter in `schedule()` **Function** `schedule()`:
  For $p = 1..P$: // "word-rotation" schedule
    $x = (p - 1 + c) \bmod P$
    $\mathbf{S}_p = (xM/P, (x+1)M/P)$ // p's word range
  $c = c + 1$
  Return $[\mathbf{S}_1, \ldots, \mathbf{S}_P]$ **Function** `update`$(p, \mathbf{S}_p, \{U\}_p, V, \{w\}_p, \{z\}_p)$:
  [lower,upper] = $\mathbf{S}_p$ // Only touch w_{ij} in range
  For each token z_{ij} in $\{z\}_p$:
    If $w_{ij} \in$ range(lower,upper):
      old = z_{ij}
      new = SparseLDAsample(U_i, V, w_{ij}, z_{ij})
      Record old, new values of z_{ij} in R_p
  Return R_p **Function** `aggregate`$([R_1, \ldots, R_P], U, V)$:
  Update U, V with changes in $[R_1, \ldots, R_P]$

Default `schedule()` functions: Like SMP Lasso, SMP LDA's `schedule()` (Algorithm 3) can be generically applied to ML program where each data sample touches just a few parameters (Matrix Factorization is one example). The idea is to assign disjoint parameter subsets across workers, who only operate on data samples that "touch" their currently assigned parameter subset. For this purpose, SMPFRAME provides a generic `scheduleStaticRota()` that partitions the parameters into P contiguous (but disjoint) blocks, and rotates these blocks amongst workers at the beginning of each iteration.

4.3 Other ML Programs

In our evaluation, we consider two more SMP ML Programs — sparse Logistic Regression (SLR) and Matrix Factorization (MF). SMP SLR uses the same dynamic, prioritized `scheduleDynRegr()` as SMP Lasso, while the `update()` and `aggregate()` functions are slightly different to accommodate the new LR objective function. SMP MF uses `scheduleStaticRota()` that, like SMP LDA, rotates disjoint (and therefore dependency-free) parameter assignments amongst the P distributed workers.

5 SMP Theoretical Guarantees

SMP programs are iterative-convergent algorithms that follow the general model-parallel Eq. (2). Here, we briefly state guarantees about their execution. SMP programs with static schedules are covered by existing ML analysis [5, 26].

Theorem 1 Dynamic scheduling converges: *Recall the Lasso Algorithm 2. Let* $\epsilon := \frac{(P-1)(\rho-1)}{M} < 1$, *where P is the number of parallel workers, M is the number of features (columns of the design matrix $\mathbf{X}$), and ρ is the "spectral radius" of $\mathbf{X}$. After t iterations, we have*

$$\mathbb{E}[F(\beta^{(t)}) - F(\beta^\star)] \leq \frac{CM}{P(1-\epsilon)} \frac{1}{t} = \mathcal{O}\left(\frac{1}{t}\right), \tag{7}$$

where $F(\beta)$ is the Lasso objective function Eq. (4), $\beta^\star$ is an optimal solution to $F(\beta)$, and C is a constant specific to the dataset $(\mathbf{X}, \mathbf{y})$ that subsumes the spectral radius ρ, as well as the correlation threshold τ in Algorithm 2. The proof can be generalized to other coordinate descent programs.

ML app	Data set	Workload	Feature	Raw size
MF	Netflix	100M ratings	480K users, 17K movies (rank=40)	2.2 GB
MF	x256 Netflix	25B ratings	7.6M users, 272K movies (rank=40)	563 GB
LDA	NYTimes	99.5M tokens	300K documents, 100K words 1K topics	0.5 GB
LDA	PubMed	737M tokens	8.2M documents, 141K words, 1K topics	4.5GB
LDA	ClueWeb	10B tokens	50M webpages, 2M words, 1K topics	80 GB
Lasso	AlzheimerDisease (AD)	235M nonzeros	463 samples, 0.5M features	6.4 GB
Lasso	LassoSynthetic	2B nonzeros	50K samples, 100M features	60 GB
Logistic	LogisticSynthetic	1B nonzeros	50K samples, 10M features	29 GB

Table 2: Data sets used in our evaluation.

Dynamic scheduling ensures the gap between the objective at the t-th iteration and the optimal objective is bounded by $\mathcal{O}\left(\frac{1}{t}\right)$, which decreases as $t \to \infty$, ensuring convergence. A more important corollary is that non-scheduled execution does not enjoy this guarantee — the objective may only improve slowly, or even diverge.

Theorem 2 Dynamic scheduling is close to ideal: *Consider $S^{ideal}()$, an ideal model-parallel schedule that proposes P random features with zero correlation. Let $\beta^{(t)}_{ideal}$ be its parameter trajectory, and let $\beta^{(t)}_{dyn}$ be the parameter trajectory of Algorithm 2. Then,*

$$E[|\beta^{(t)}_{ideal} - \beta^{(t)}_{dyn}|] \leq C\frac{2M}{(t+1)^2}\mathbf{X}^\top\mathbf{X}, \tag{8}$$

where C is a dataset-specific constant that subsumes the correlation threshold τ in Algorithm 2.

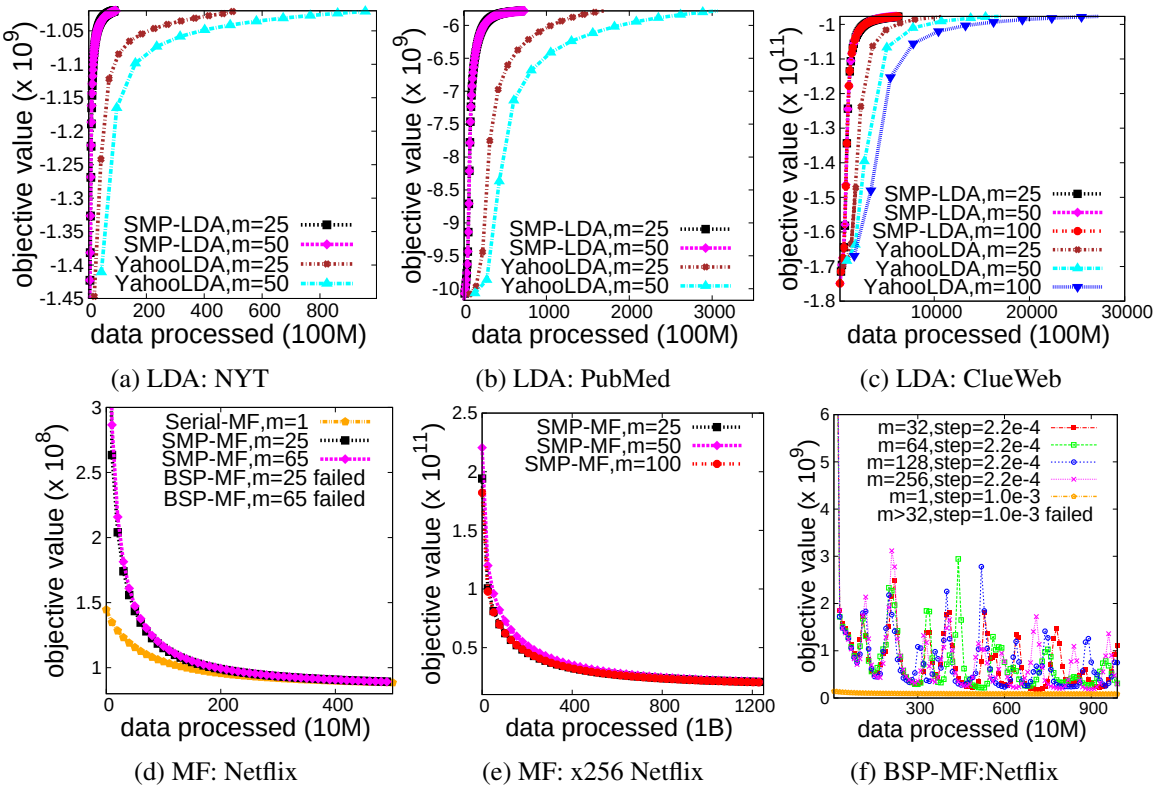
Under dynamic scheduling, coordinate descent regression enjoys algorithm progress per iteration nearly as good as ideal model-parallelism. Intuitively, this is almost by definition — ideal model-parallelism seeks to minimize the number of parameter dependencies crossing between workers $p = 1..P$; dynamic scheduling (Algorithm 2) does the same thing, but instead of considering all M parameters, it only looks at $L \ll M$ parameters. We end by remarking that SMP-Lasso's prioritization can also be proven to be ideal.

6 Evaluation

We compare SMP ML programs implemented on SMPFRAME against existing parallel execution schemes — either a well-known publicly-available implementation, or if unavailable, we write our own implementation — as well as sequential execution. Our intent is to show (1) SMP implementations executed by SMPFRAME have significantly improved progress per iteration over other parallel execution schemes, coming fairly close to "ideal" sequential execution in some cases. At the same time, (2) the SMPFRAME system can sustain high iteration throughput (i.e. model parameters and data points processed per second) that is competitive with existing systems. Together, the high progress per iteration and high iteration throughput lead to faster ML program completion times (i.e. fewer seconds to converge).

Cluster setup: Unless otherwise stated, we used 100 nodes each with 4 quad-core processors (16 physical cores) and 32GB memory; this configuration is similar to Amazon EC2 c4.4xlarge instances (16 physical cores, 30GB memory). The nodes are connected by 1Gbps ethernet as well as a 20Gbps Infiniband IP over IB interface. Most experiments were conducted on the 1Gbps ethernet; we explicitly point out those that were conducted over IB.

Datasets: We use several real and synthetic datasets — see Table 2 for details. All real datasets except AD are public.



(a) LDA: NYT (b) LDA: PubMed (c) LDA: ClueWeb

(d) MF: Netflix (e) MF: x256 Netflix (f) BSP-MF:Netflix

Figure 6: **Static SMP:** OvD. (a-c) SMP-LDA vs YahooLDA on three data sets; (d-e) SMP-MF vs BSP-MF on two data sets; (f) parallel BSP-MF is unstable if we use an ideal sequential step size. m denotes number of machines.

Performance metrics: We compare ML implementations using three metrics: (1) *objective function value* versus *total data samples operated upon*[3], abbreviated **OvD**; (2) *total data samples operated upon* versus *time (seconds)*, abbreviated **DvT**; (3) *objective function value* versus *time (seconds)*, referred to as **convergence time**. The goal is to achieve the best objective value in the least time — i.e. fast convergence.

OvD is a uniform way to measure ML progress per iteration across different ML implementations, as long as they use identical parameter update equations — we ensure this is always the case, unless otherwise stated. Similarly, DvT measures ML iteration throughput across comparable implementations. Note that high OvD and DvT imply good (i.e. small) ML convergence time, and that measuring OvD or DvT alone (as is sometimes done in the literature) is *insufficient* to show that an algorithm converges quickly.

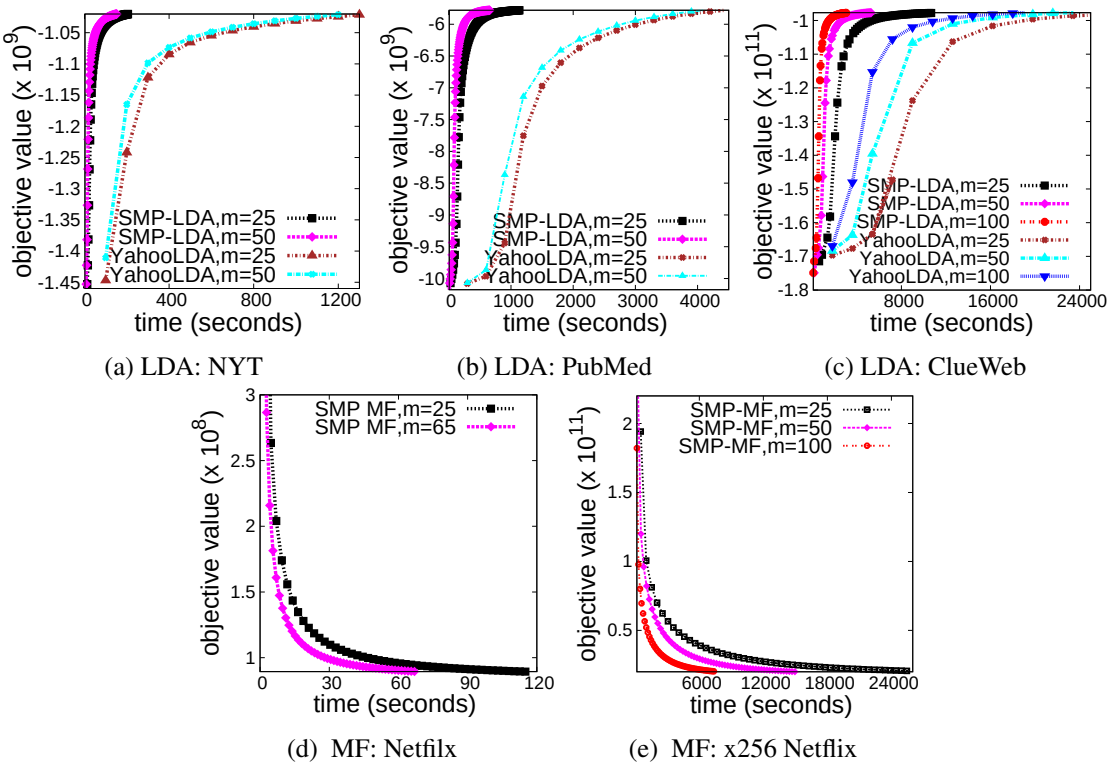
6.1 Static SMP Evaluation

Our evaluation considers static-schedule SMP algorithms separately from dynamic-schedule SMP algorithms, because of their different service implementations (Section 3.3). We first evaluate static-schedule SMP algorithms running on the SMPFRAME Static Engine.

ML programs and baselines: We evaluate the performance of LDA (a.k.a. topic model) and MF (a.k.a collaborative filtering). SMPFRAME uses Algorithm 3 (**SMP-LDA**) for LDA, and a scheduled version of the Stochastic Gradient Descent (SGD) algorithm[4] for MF (**SMP-MF**). For baselines, we used **YahooLDA**,

[3]ML algorithms operate upon the same data point many times. The total data samples operated upon exceeds N, the number of data samples.

[4]Due to space limits, we could not provide a full Algorithm figure. Our SMP-MF divides up the input data such that different workers never update the same parameters in the same iteration.



(a) LDA: NYT (b) LDA: PubMed (c) LDA: ClueWeb

(d) MF: Netflix (e) MF: x256 Netflix

Figure 7: **Static SMP:** convergence times. (a-c) SMP-LDA vs YahooLDA; (d-e) SMP-MF with varying number of machines m.

and **BSP-MF** – our own implementation of the classic BSP SGD for MF ; both are data-parallel algorithms, meaning that they do not use SMP schemes. These baselines were chosen to analyze how SMP affects OvD, DvT and convergence time; later will we show convergence time benchmarks against the GraphLab system which does use model parallelism.

To ensure a fair comparison, YahooLDA was modified to (1) dump model state at regular intervals for later objective (log-likelihood) computation[5]; (2) keep all local program state in memory, rather than streaming it off disk, because it fits for our datasets. All LDA experiments were performed on the 20Gbps Infiniband network, so that bandwidth would not be a bottleneck for the parameter server used by YahooLDA. Note that in LDA OvD and DvT measurements, we consider each word token as one data sample.

6.1.1 Improvement in convergence times

Static SMP has high OvD: For LDA, YahooLDA's OvD decreases substantially from 25 to 100 machines, whereas SMP-LDA maintains the same OvD (Figures 6a, 6b, 6c). For MF, Figure 6f shows that BSP-MF is sensitive to step size[6]; if BSP-MF employs the ideal step size determined for serial execution, it does not properly converge on $\geq$ 32 machines. In contrast, SMP-MF can safely use the ideal serial step size (Figures 6d,6e), and approaches the same OvD as serial execution within 20 iterations.

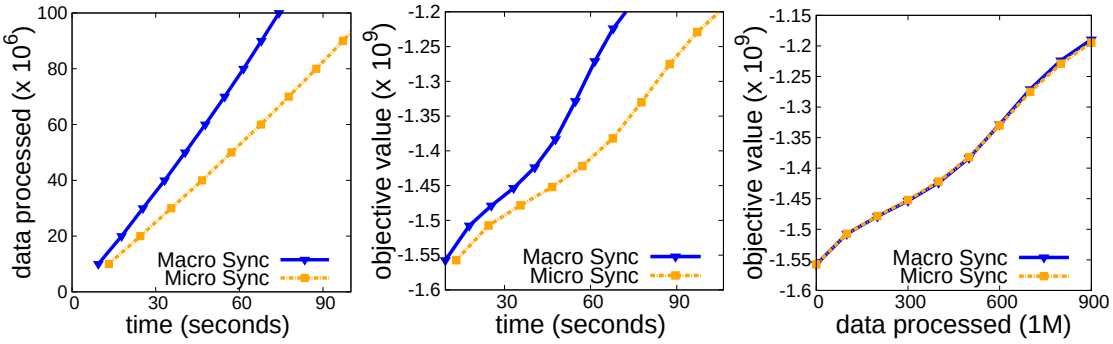
SMPFRAME Static Engine has high DvT: For LDA, table 3 shows that SMP-LDA enjoys higher DvT than YahooLDA; we speculate that YahooLDA's lower DvT is primarily due to lock contention on shared data structures between application and parameter server threads (which the SMPFRAME Static Engine tries

[5]With overhead less than 1% of total running time.

[6]A required tuning parameter for SGD MF implementations; higher step sizes lead to faster convergence, but step sizes that are too large can cause algorithm divergence/failure.

Data set(size)	#machines	YahooLDA	SMP-LDA
NYT(0.5GB)	25	38	43
NYT(0.5GB)	50	79	62
PubMed(4.5GB)	25	38	60
PubMed(4.5GB)	50	74	110
ClueWeb(80GB)	25	39.7	58.3
ClueWeb(80GB)	50	78	114
ClueWeb(80GB)	100	151	204

Table 3: **Static SMP:** DvT for topic modeling (million tokens operated upon per second).



(a) DvT (b) Time (c) OvD

Figure 8: **Static Engine:** synchronization cost optimization. (a) macro synchronization improves DvT by 1.3 times; (b) it improves convergence speed by 1.3 times; (c) This synchronization strategy does not hurt OvD.

to avoid).

Static SMP on SMPFRAME has low convergence times: Thanks to high OvD and DvT, SMP-LDA's convergence times are not only lower than YahooLDA, but also scale better with increasing machine count (Figures 7a, 7b, 7c). SMP-MF also exhibits good scalability (Figure 7d, 7e).

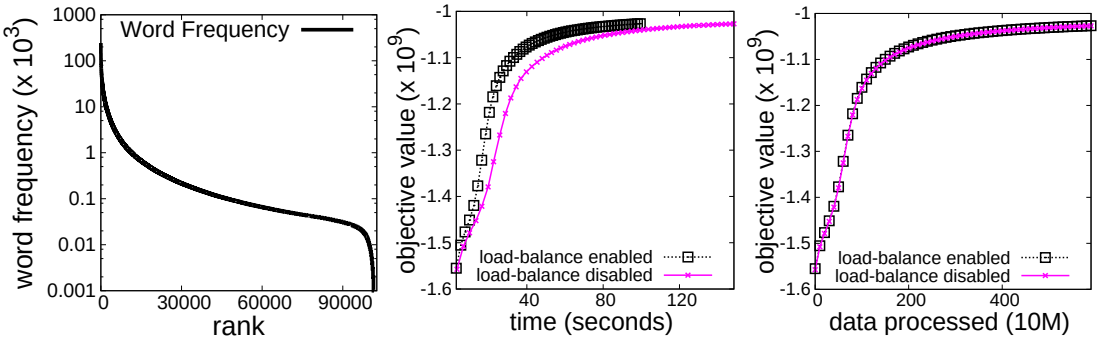
6.1.2 Benefits of Static Engine optimizations

The SMPFRAME Static Engine achieves high DvT (i.e iteration throughput) via two system optimizations: (1) reducing synchronization costs via the ring topology; (2) using a job pool to perform load balancing across **Job Executors**.

Reducing synchronization costs: Static SMP programs (including SMP-LDA and SMP-MF) do not require all parameters to be synchronized across all machines, and this motivates the use of a ring topology. For example, consider SMP-LDA Algorithm 3: the word-rotation `schedule()` directly suggests that **Job Executors** can pass parameters to their ring neighbor, rather than broadcasting to all machines; this applies to SMP-MF as well.

SMPFRAME's Static Engine implements this parameter-passing strategy via a ring topology, and only performs a global synchronization barrier after all parameters have completed one rotation (i.e. P iterations) — we refer to this as "Macro Synchronization". This has two effects: (1) network traffic becomes less bursty, and (2) communication is effectively overlapped with computation; as a result, DvT is improved by 30% compared to a naive implementation that invokes a synchronization barrier every iteration ("Micro Synchronization", Figure 8a). This strategy does not negatively affect OvD (Figure 8c), and hence time to convergence improves by about 30% (Figure 8b).

Job pool load balancing: Uneven workloads are common in Static SMP programs: Figure 9a shows that the word distribution in LDA is highly skewed, meaning that some SMP-LDA `update()` jobs will be much



(a) NYTimes (b) Time (c) OvD

Figure 9: **Static Engine:** Job pool load balancing. (a) Biased word frequency distribution in NYTimes data set; (b) by dispatching the 300 heaviest words first, convergence speed improves by 30 percent to reach objective value -1.02e+9; (c) this dispatching strategy does not hurt OvD.

longer than others. Hence, SMPFRAME dispatches the heaviest jobs first to the **Job Executor** threads. This improves convergence times by 30% on SMP-LDA (Figure 9b), without affecting OvD.

6.1.3 Comparison against other systems:

We compare SMP-MF with GraphLab's SGD MF implementation, on a different set of 8 machines — each with 64 cores, 128GB memory. On Netflix , GL-SGDMF converged to objective value 1.8e+8 in 300 seconds, and SMP-MF converged to 9.0e+7 in 302 seconds (i.e. better objective value in the same time). In terms of DvT, SMP-MF touches 11.3m data samples per second, while GL-MF touches 4.5m data samples per second.

6.2 Dynamic SMP Scheduling

Our evaluation of dynamic-schedule SMP algoritms on the SMPFRAME Dynamic Engine shows significantly improved OvD compared to random model-parallel scheduling. We also show that (1) in the single machine setting, Dynamic SMP comes at a cost to DvT, but overall convergence speed is still superior to random model-parallel; and (2) in the distributed setting, this DvT penalty mostly disappears.

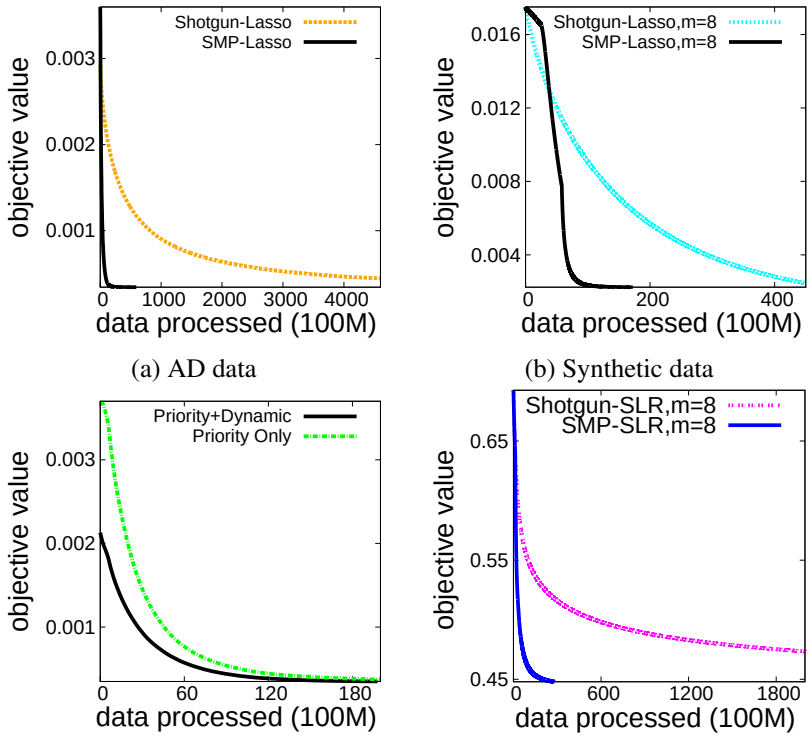
ML programs and baselines: We evaluate ℓ_1-regularized linear regression (Lasso) and ℓ_1-regularized Logistic regression (sparse LR, or SLR) – SMPFRAME uses Algorithm 2 (SMP-Lasso) for the former, and we solve the latter using a minor modification to SMP-Lasso[7] (called SMP-SLR). To the best of our knowledge, there are no open-source distributed Lasso/SLR baselines that use coordinate descent, so we implement the Shotgun Lasso/SLR algorithm [5] (Shotgun-Lasso, Shotgun-SLR), which uses random model-parallel scheduling[8]

6.2.1 Improvement in convergence times

Dynamic SMP has high OvD: Dynamic SMP achieves high OvD, in both single-machine (Figure 10a) and distributed, 8-machine (Figure 10b) configurations; here we have compared SMP-Lasso against random model-parallel Lasso (Shotgun-Lasso) [5]. In either case, Dynamic SMP decreases the data samples required for convergence by an order of magnitude. Similar observations hold for distributed SMP-SLR versus Shotgun-SLR (Figure 10d).

[7]Lasso and SLR are solved via the coordinate descent algorithm, hence SMP-Lasso and SMP-SLR only differ slightly in their update equations. We use coordinate descent rather gradient descent because it has no step size tuning and more stable convergence [25, 24].

[8]Using coordinate descent baselines is essential to properly evaluate the DvT and OvD impact of SMP-Lasso/SLR; other algorithms like stochastic gradient descent are only comparable in terms of convergence time.



(a) AD data

(b) Synthetic data

(c) AD data

(d) Synthetic data

Figure 10: **Dynamic SMP:** OvD. (a) SMP-Lasso vs Shotgun-Lasso [5] on one machine (64 cores); (b) SMP-Lasso vs Shotgun-Lasso on 8 machines; (c) SMP-Lasso with & w/o dynamic partitioning on 4 machines; (d) SMP-SLR vs Shotgun-SLR on 8 machines. m denotes number of machines.

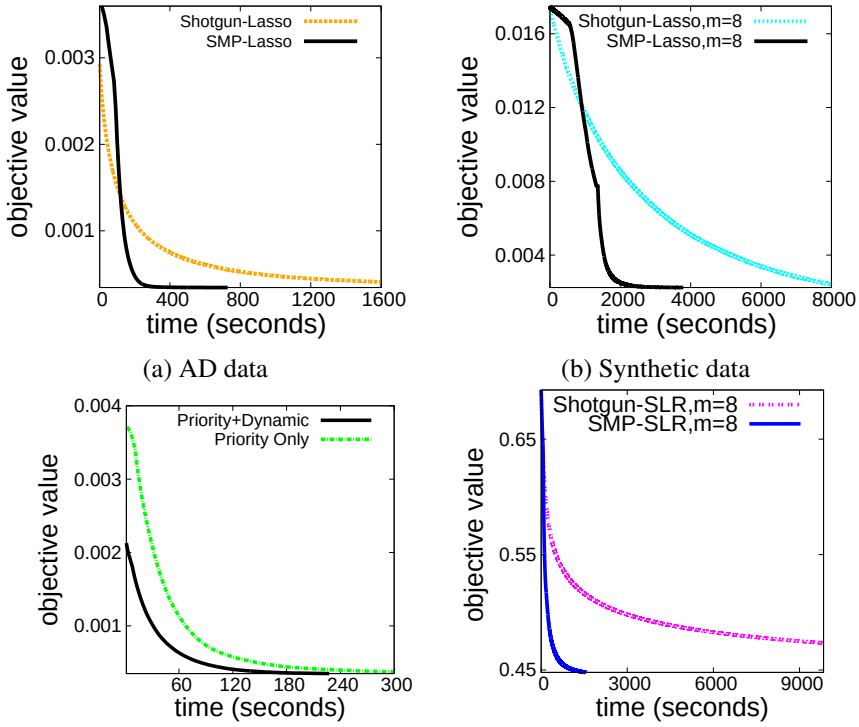
SMPFRAME Dynamic Engine DvT analysis: Table 4 shows how SMPFRAME Dynamic Engine's DvT scales with increasing machines. We observe that DvT is limited by dataset density — if there are more nonzeros per feature column, we observe better DvT scalability with more machines. The reason is that the Lasso and SLR problems' model-parallel dependency structure (Section 4.1) limits the maximum degree of parallelization (number of parameters that can be correctly updated each iteration), thus Dynamic Engine scalability does not come from updating more parameters in parallel (which may be mathematically impossible), but from processing more data per feature column.

Dynamic SMP on SMPFRAME has low convergence times: Overall, both SMP-Lasso and SMP-SLR enjoy better convergence times than their Shotgun counterparts. The worst-case scenario is a single machine using a dataset (AD) with few nonzeros per feature column (Figure 11a) — when compared with Figure 10a, we see that SMP DvT is much lower than Shotgun (Shotgun-Lasso converges faster initially), but ultimately SMP-Lasso still converges 5 times faster. In the distributed setting (Figure 11b Lasso, Figure 11d SLR), the DvT penalty relative to Shotgun is much smaller, and the curves resemble the OvD analysis (SMP exhibits more than an order of magnitude speedup).

6.2.2 Benefits of Dynamic Engine optimizations

The SMPFRAME Dynamic Engine improves DvT (data throughput) via iteration pipelining, while improving OvD via dynamic partitioning and prioritization in `schedule()`.

Impact of dynamic partitioning and prioritization: Figures 10c (OvD) and 11c (OvT) show that the convergence speedup from Dynamic SMP comes mostly from prioritization — we see that dependency checking approximately doubles SMP-Lasso's OvD over prioritization alone, implying that the rest of the



(a) AD data (b) Synthetic data

(c) AD data (d) Synthetic data

Figure 11: **Dynamic SMP:** convergence time. Subfigures (a-d) correspond to Figure 10.

Application \ nonzeros per column	1K	10K	20K
SMP-Lasso 16 × 4 cores	125	212	202
SMP-Lasso 16 × 8 cores	162	306	344
SMP-LR 16 × 4 cores	75	98	103
SMP-LR 16 × 8 cores	106	183	193

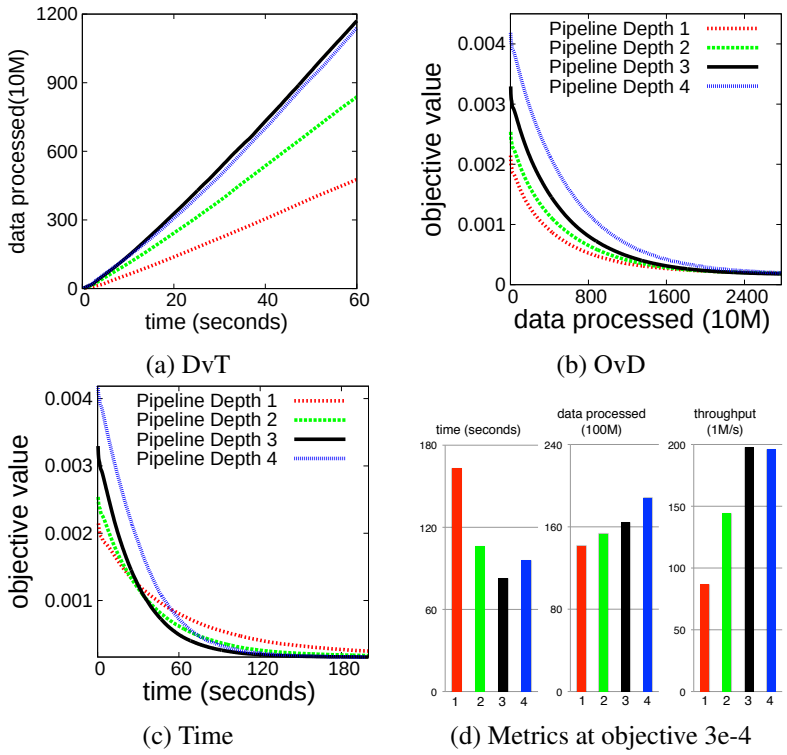
Table 4: **Dynamic SMP:** DvT of SMP-Lasso and SMP-LR, measured as data samples (millions) operated on per second, for synthetic data sets with different column sparsity.

order-of-magnitude speedup over Shotgun-Lasso comes from prioritization. Additional evidence is provided by Figure 5; under prioritization most parameters converge within just 5 iterations.

Pipelining improves DvT at a small cost to OvD: The SMPFRAME Dynamic Engine can pipeline iterations to improve DvT (iteration throughput), at some cost to OvD. Figure 12c shows that SMP-Lasso (on 8 machines) converges most quickly at a pipeline depth of 3, and Figure 12d provides a more detailed breakdown, including the time take to reach the same objective value (0.0003). We make two observations: (1) DvT improvement saturates at pipeline depth 3; (2) OvD, expressed as the number of data samples to convergence, gets proportionally worse as pipeline depth increases. Hence, the sweet spot for convergence time is pipeline depth 3, which halves convergence time compared to no pipelining (depth 1).

6.2.3 Comparisons against other systems

We compare SMP-Lasso/SLR with Spark MLlib (Spark-Lasso, Spark-SLR), which uses the SGD algorithm. As with the earlier GraphLab comparison, we use 8 nodes with 64 cores and 128GB memory each. On the



(a) DvT (b) OvD

(c) Time (d) Metrics at objective 3e-4

Figure 12: **Dynamic Engine:** iteration pipelining. (a) DvT improves 2.5× at pipeline depth 3, however (b) OvD decreases with increasing pipeline depth. Overall, (c) convergence time improves 2× at pipeline depth 3. (d) Another view of (a)-(c): we report DvT, OvD and time to converge to objective value 0.0003.

AD dataset (which has complex gene-gene correlations), Spark-Lasso reached objective value 0.0168 after 1 hour, whereas SMP-Lasso achieved a lower objective (0.0003) in 3 minutes. On the LogisticSynthetic dataset (which was constructed to have few correlations), Spark-SLR converged to objective 0.452 in 899 seconds, while SMP-SLR achieved a similar result. This confirms that SMP is more effective in the presence of more complex model dependencies.

Finally, we want to highlight that the SMPFRAME system can significantly reduce the code required for an SMP program: our SMP-Lasso implementation (Algorithm 2) has 390 lines in `schedule()`, 181 lines in `update()` and `aggregate()`, and another 209 lines for miscellaneous uses like setting up the program environment; SMP-SLR uses a similar amount of code.

7 Related work

Early systems for scaling up ML focus on data parallelism [6] to leverage multi-core and multi-machine architecture, following the ideas in MapReduce [9]. Along these lines, Mahout[3] on Hadoop [2] and more recently MLI [27] on Spark [35] have been developed.

The second generation of distributed ML systems — e.g. parameter servers (PS, [1, 8, 16, 20]) — address the problem of distributing large shared models across multiple workers. Early systems were designed for a particular class of ML problems, e.g., [1] for LDA and [8] for deep neural nets. More recent work [16, 20] have generalized the parameter server concept to support a wide range of ML algorithms. There are counterparts to parameter server ideas in SMPFRAME: for instance, stale synchronous parallel (SSP, [16, 7]) and SMPFRAME both control parameter staleness; the former through bookkeeping on the deviation between workers, and the latter through pipeline depth. Another example is filtering [20], which

resembles parameter scheduling in SMPFRAME, but is primarily for alleviating synchronization costs, e.g., their KKT filter suppresses transmission of "unnecessary" gradients, while SMPFRAME goes a step further and uses algorithm information to make update choices (not just synchronization choices).

None of the above systems directly address the issue of conflict updates, which leads to slow convergence or even algorithmic failure. Within the parallel ML literature, dependency checking is either performed case-by-case [12, 33]; or simply ignored [5, 23]. The first systematic approach was proposed by GraphLab [21, 13], where ML computational dependencies are encoded by the user in a graph, so that the system may select disjoint subgraphs to process in parallel — thus, graph-scheduled model parallel ML algorithms can be written in GraphLab. Intriguing recent work, GraphX [14], combines these sophisticated GraphLab optimizations with database-style data processing and runs on a BSP-style MapReduce framework, sometimes without significant loss of performance.

Task prioritization (to exploit uneven convergence of iterative algorithms) was studied by PrIter [37] and GraphLab [21]. The former, built on Hadoop [2], prioritizes *data points* that contribute most to convergence, while GraphLab ties prioritization to the program's graph representation. SMPFRAME prioritizes the most promising *model parameter* values.

8 Conclusion

We developed SMPFRAME to improve the convergence speed of model-parallel ML at scale, achieving both high progress per iteration (via dependency checking and prioritization through SMP programming), and high iteration throughput (via SMPFRAME system optimizations such as pipelining and the ring topology). Consequently, SMP programs running on SMPFRAME achieve a marked performance improvement over recent, well-established baselines: to give two examples, SMP-LDA converges 10x faster than YahooLDA, while SMP-Lasso converges 5x faster than randomly-scheduled Shotgun-Lasso.

There are some issues that we would like to address in future: chief amongst them is automatic `schedule()` creation; ideally users should only have to implement `update()` and `aggregate()`, while leaving scheduling to the system. Another issue is generalizability and programmability — what other ML programs might benefit from SMP, and can we write them easily? Finally, using a different solver algorithm (e.g. Alternating Least Squares or Cyclic Coordinate Descent instead of SGD) can sometimes speed up an ML application; SMPFRAME supports such alternatives, though their study is beyond the scope of this work.

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