ASAP: Asynchronous Approximate Data-Parallel Computation

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Abstract

Emerging workloads, such as graph processing and machine learning are approximate because of the scale of data involved and the stochastic nature of the underlying algorithms. These algorithms are often distributed over multiple machines using bulk-synchronous processing (BSP) or other synchronous processing paradigms such as map-reduce. However, data parallel processing primitives such as repeated barrier and reduce operations introduce high synchronization overheads. Hence, many existing data-processing platforms use asynchrony and staleness to improve data-parallel job performance. Often, these systems simply change the synchronous communication to asynchronous between the worker nodes in the cluster. This improves the throughput of data processing but results in poor accuracy of the final output since different workers may progress at different speeds and process inconsistent intermediate outputs.

In this paper, we present ASAP, a model that provides asynchronous and approximate processing semantics for data-parallel computation. ASAP provides fine-grained worker synchronization using NOTIFY-ACK semantics that allows independent workers to run asynchronously. ASAP also provides stochastic reduce that provides approximate but guaranteed convergence to the same result as an aggregated all-reduce. In our results, we show that ASAP can reduce synchronization costs and provides 2-10X speedups in convergence and up to 10X savings in network costs for distributed machine learning applications and provides strong convergence guarantees.

1 Introduction

Large-scale data-parallel computation across multiple machines often provide two fundamental constructs to scale-out local data processing. First, a merge or a reduce operation to allow the workers to merge updates from all other workers and second, a barrier or an implicit wait operation to ensure that all workers can synchronize and operate at similar speeds. For example, the bulk-synchronous model is a general paradigm to model data-intensive distributed processing [57]. Here, each node after processing a specific amount of data synchronizes with the other nodes using barrier and reduce operations. The BSP model is widely used to implement many big data applications, frameworks and libraries such as in the areas of graph processing and machine learning [1, 26, 31, 32, 40, 51]. Other synchronous paradigms such as the map-reduce [24, 62], the parameter server [23, 38] and dataflow based systems [5, 34, 43] use similar constructs to synchronize outputs across multiple workers.

There is an emerging class of big data applications such as graph-processing and machine learning that are approximate because of the stochastic nature of the underlying algorithms that converge to a final solution in an iterative fashion. These iterative-convergent algorithms operate on large amounts of data and unlike traditional TPC style workloads that are CPU bound [49], these iterative algorithms incur significant network and synchronization costs by communicating large vectors between their workers. These applications can gain an increase in performance by reducing the synchronization costs in two ways. First, the workers can operate over stale intermediate outputs. The stochastic algorithms operate over input data in an iterative fashion to produce and communicate intermediate outputs with other workers. However, it is not imperative that the workers perform a reduce on all the intermediate outputs at every iteration. Second, the synchronization requirements between the workers may be relaxed, allowing partial, stale or overwritten outputs. This is possible because in some cases the iterative nature of data processing and the stochastic nature of the algorithms may provide an opportunity to correct any errors introduced from staleness or incorrect synchronization.

There has been recent research that explores this opportunity by processing stale outputs, or by removing all synchronization [52, 59]. However, naïvely converting the algorithms from synchronous to asynchronous can increase the throughput but may not improve the convergence speeds. Furthermore, these bounds may not generalize across applications or datasets. Finally, an increase
in the data processing throughput may not translate to an improved speedup with the same final output accuracy and in some cases may even converge the underlying algorithm to an incorrect value [42].

Hence, to provide asynchronous and approximate semantics with reasonable correctness guarantees for iterative convergent algorithms, we present Asynchronous and Approximate abstractions for data-parallel computation. To facilitate approximate processing, we describe stochastic reduce, a sparse reduce primitive, that mitigates the communication and synchronization costs by performing the reduce operation with fewer workers. We construct a reduce operator by choosing workers based on sparse expander graphs on underlying communication nodes that mitigates CPU and network costs during reduce for iterative convergent algorithms. Furthermore, stochastic reduce allows developers to reason about convergence times and network communication costs, by evaluating the specific properties of the underlying node communication graphs.

To reduce synchronization costs, we propose a fine-grained communication using an OS style NOTIFY-ACK mechanism that provides performance improvement over barrier style synchronization. NOTIFY-ACK allows independent worker threads (such as those in stochastic reduce) to run asynchronously instead of blocking on a coarse-grained global barrier at every iteration. Additionally, NOTIFY-ACK provides stronger consistency than just using a barrier to implement synchronous data-parallel processing.

ASAP is not a programming model (like map-reduce [24]) or is limited to a set of useful implementation mechanisms. It introduces semantics for approximate and asynchronous execution which are amiss in the current flurry of distributed machine learning systems which often use asynchrony and staleness to improve the input processing throughput.

The contributions of this paper are as follows:

- We present ASAP, an asynchronous approximate computation model for large scale data parallel applications. We introduce stochastic reduce for approximate semantics and fine-grained synchronization based on NOTIFY-ACK to allow independent threads run asynchronously.

- We apply ASAP to distributed machine learning. We empirically and formally show that data parallel learning using ASAP semantics converges to the same result as synchronous all-reduce.

In our results, we show that when ASAP semantics are applied to distributed machine learning problems, the resulting system can achieve strong consistency, provable convergence and provides 2-10X in convergence and up to 10X savings in network costs. The rest of the paper is organized as follows. In the next section, we provide a background on data-parallel distributed machine learning. We then describe the ASAP model which consists of the stochastic reduce and fine-grained synchronization primitives that reduces synchronization costs. Finally, we evaluate ASAP and discuss related work.

2 Background

Large-scale problems such as training image classification models, page-rank computation and matrix factorization operate on large amounts of data. As a result, many algorithms that are used to discover relationships amongst data have been re-written in the form of distributed optimization problems that iterate over the input data and approximate the solution over small batches of data. For example, to scale better, matrix factorization methods have moved from direct and exact factorization methods such as singular value decomposition to iterative and approximate factorization using gradient descent style algorithms [27].

Hence, many algorithms that are used to discover relationships amongst data have been re-written in the form of distributed optimization problems that iterate over the input data and approximate the solution. In this paper, we describe how to provide asynchronous and approximate semantics to these distributed optimization based applications. We specifically focus on the design and performance benefits for distributed machine learning applications using ASAP.

2.1 Distributed Machine Learning

Machine learning algorithms process data to build a training model that can generalize over new data. The training output model, or the parameter vector (represented by \( w \)) is computed to perform future predictions over new data. To train over large data, ML methods often use the Stochastic Gradient Descent (SGD) algorithm that can train over a single (or a batch) of examples over time. The SGD algorithm processes data examples to compute the gradient of a loss function. The parameter vector is then updated based on this gradient value after processing each training data example. After a number of iterations, the parameter vector or the model converges towards acceptable error values over test data. Hence, SGD can be used to train ML models iteratively over the training data as shown in Figure 1.

To scale out the computation over multiple machines, the SGD algorithm can be distributed over a cluster by us-
Parameters \( w_1, w_2, \ldots, w_n \)

**Figure 1:** The machine learning training process. The computation can be distributed over a cluster of machines with data parallelism, by splitting the input \((x_1, x_2, \ldots, x_n)\) or model parallelism, by splitting the model \((w_1, w_2, \ldots, w_n)\). The goal of parallelization is not only to process the input quickly but also to maintain low error rates \((e_1, e_2, \ldots, e_n)\).

The goal: Minimize \( \sum_{i=1}^{n} \text{Cost}(e_i) \)

Input \( x_1, x_2, \ldots, x_n \) → Expected O/P \( y_1, y_2, \ldots, y_n \) → Output \( e_1, e_2, \ldots, e_n \)

3 **Stochastic reduce for approximate processing**

In this section, we describe how data-parallel applications can use stochastic reduce to mitigate network and processing times for iterative machine learning algorithms. We then introduce a metric to compare convergence speeds of stochastic reduce with all-reduce.

With distributed machine learning, parallel machines or cores (workers) train on model replicas in parallel and exchange model parameters after processing a set of examples. Hence, after processing a batch of examples, the parallel model replicas perform a reduce over the incoming parameters, update their local models and continue to train. In the map-reduce model, all workers syn-
chronize with one another and this operation is referred to as the all-reduce step. In the parameter server model, this synchronization and reduce occurs with a single or distributed master [23, 39]. To mitigate the reduce overheads, efficient all-reduce has been explored in the map-reduce context where nodes perform partial aggregation in a tree-style to reduce network costs [16, 10, 60]. However, these methods decrease the network and processing costs at the cost of increasing the latency of the reduce operation proportional to the height of the tree.

The network of worker nodes, i.e. the node communication graph of the cluster determines how rapidly the intermediate model parameters are propagated to all other machines and also determines the associated network and processing costs. For example, all-reduce and the parameter server represent different types of communication graphs that describe how the workers communicate the intermediate results as shown in Figure 2. Intuitively, when the workers communicate with all machines at every reduce step, this network is densely connected and convergence is rapid since all the machines get the latest intermediate updates. However, if the network of nodes is sparsely connected, the convergence may be slow due to stale, indirect updates being exchanged between machines. However, with sparse connectivity, there are savings in network and CPU costs (fewer updates to process at each node), that can result in an overall speedup in job completion times. Furthermore, if there is a heterogeneity in communication bandwidths between the workers (or between the workers and the master, if a master is used), many workers may end up waiting. As an example, if one is training using GPUs over a cluster, GPUs within one machine can synchronize at far lower costs over the PCI bus than over the network. Hence, frequent reduce across interconnects with varying latency may introduce a large number of stragglers which can increase the cost of synchronization for all workers.

Hence, instead of synchronizing and performing a reduce with every other node, parallel nodes training ML tasks can synchronize with fewer nodes by performing a sparse or stochastic reduce using a sparse node communication graph. Since machine learning algorithms that use SGD are stochastic, as long as all machines are connected and they receive parameter updates directly or indirectly from others, the underlying optimization algorithm will converge to the same result as an all-reduce. When the nodes have strong connectivity properties, i.e. the nodes are connected such that the parameter updates from one node disperse to all other nodes in fewest time steps at low network costs, the convergence is network efficient. We propose using stochastic reduce based on sparse graphs with strong connectivity properties.

3.1 Rapid convergence at fixed communication costs

The goal of stochastic reduce is to improve performance by reducing network and processing costs by using sparse reduce graphs. Recent work has shown that every dense graph can be reduced to an equivalent approximate sparse graph with fewer edges [7]. This is a significant result since it implies that stochastic reduce can be applied to save network costs for almost any network topology. Expander graphs, which are sparse graphs with strong connectivity properties have been explored in the context of data centers and distributed communities to communicate data with low overheads [55, 56]. An expander graph has fixed out-degrees as the number of vertices increase while maintaining approximately the same connectivity between the vertices. Hence, using expander graphs for stochastic reduce provides approximately the same convergence as all-reduce while keeping network costs low, as the number of nodes increase.

To measure the convergence of algorithms that use stochastic reduce, i.e. to compare the sparsity of the adjacency graph of communication, we calculate the spectral gap of the adjacency matrix of the network of workers. The spectral gap is the difference between the two largest singular values of the adjacency matrix normalized by the in-degree of every node. The spectral gap of a communication graph determines how rapidly a distributed, iterative sparse reduce converges when performing distributed optimization over a network of nodes represented by this graph. For strong convergence properties, this value should be as high as possible. Hence, well-connected graphs have a high spectral gap value and converge faster but will have high communication costs. Conversely, if the graph is disconnected, the spectral gap value is zero, and with data partitioned across machines, the final model may not converge to a correct value. We discuss

![Figure 2](image-url)
the formal conditions of convergence based on spectral gap for any optimization problem using stochastic reduce in Appendix A.

Past work using partial-reduce for optimization problems has explored specific fixed communication graphs such as butterfly or logarithmic sequences [9, 37]. These communication sequences provide fixed network costs but may not generalize to networks with complex topologies or networks with dissimilar bandwidth edges such as distributed GPU environments. Additionally, ASAP introduces the ability to reason convergence using the spectral gap of a network graph and developers can reason why some node graphs have stronger convergence properties than others. Finally, existing approaches use a global barrier after each communication step and require all machines to wait for all other nodes after each reduce, incurring extra synchronization overheads. We describe how fine-grained communication of ASAP improves reduce this synchronization overhead in Section 4. We now describe how a developer can generate sparse graphs with good convergence properties given fixed network costs or fixed out-degrees for vertices in the communication graph.

Figure 2 shows six nodes connected using four distributed machine learning training architectures, the all-reduce, the parameter server (non-distributed), an expander graph with a fixed out-degree of two, and a chain like architecture and their respective spectral-gap values for 6 and 25 nodes. As expected, architectures with more edges, have a high-spectral gap and provide good convergence. Figure 2 (a) shows the all-reduce, where all machines communicate with one-another and increasing the number of nodes, significantly increases the network costs. Figure 2 (b) shows the parameter server has a reasonably high spectral gap but using a single master with a high fanout requires considerable network bandwidth and Paxos-style reliability for the master. Figure 2 (c) shows a root expander graph has a fixed out-degree of two, and in a network of \( N \) total nodes, each node \( i \) sends the intermediate output to its neighbor \( (i + 1) \) (to ensure connectivity) and to \( i + \sqrt{N} \) th node. Such root expander graphs ensure that the updates are spread across the network as \( N \) scales since the root increases with \( N \). Finally, figure 2(d), shows a chain like graph, where the nodes are connected in a chain-like fashion, the intermediate parameter updates from node \( i \) may spread to \( i + 1 \) in a single time step, but will require \( N \) time steps to reach to the last node in the cluster and has low spectral gap values. In the rest of the paper, we use the root sparse expander graph, as shown in Figure 2(c), with a fixed out-degree of two, to evaluate stochastic reduce. A full discussion of various expander graph architectures and their corresponding convergence is interesting but outside the scope of this paper.

We find that by using sparse expander reduce graphs, with just two out-degrees often provides good convergence and speedup over all-reduce i.e. high enough spectral gap values with reasonably low communication costs. Using sparse directed reduce graphs with stochastic reduce results in faster model training times because: First, the amount of network time is reduced. Second, the synchronization time is reduced since each machine communicates with fewer parallel models. Finally, the CPU times at each model replica is reduced since it needs to process fewer incoming intermediate parameter updates.

For stochastic reduce to be effective, the following properties are desirable. First, the generated node communication graph should have a high-spectral gap. This ensures that the model updates from each machine are diffused across the network rapidly. Second, the node-communication graphs should have low communication costs. For example, the out-degrees of each node in the graph should have small out-degrees. Finally, the graph should be easy to generate such as using a sequence to accommodate variable number of machines or a possible re-configuration in case of a failure. These properties can be used to guide existing data-parallel optimizers [33] or schedulers [14], to reduce data shuffling costs by constructing sparse reduce graphs while accommodating real world constraints such as avoiding cross-rack or cross-interconnect reduce. We now discuss how to reduce the synchronization costs with fine-grained communication.

4 Fine-grained synchronization

Barrier based synchronization is an important and widely used operation for synchronizing parallel machine learning programs across multiple machines. After executing a barrier operation, a parallel worker waits until all the processes in the system have reached a barrier. Parallel computing libraries like MPI, as well as data parallel frameworks such as BSP systems and some parameter servers expose this primitive to the developers [12, 31, 40, 38]. Furthermore, machine learning systems based on map-reduce use the stage barrier between the map and reduce tasks to synchronize intermediate outputs across machines [15, 28].

Figure 3 shows a parallel training system on \( n \) processes. Each process trains on a subset of data, and computes new model parameter values and sends it to all other machines and the waits on the barrier primitive. When all processes arrive at the barrier i.e. all other machines issue a send with their intermediate model parameters,
the workers perform a \texttt{reduce} operation over the incoming model parameters and continue processing more input data.

However, using the \texttt{barrier} as a synchronization point in the code suffers from several problems: First, the BSP protocol described above, suffers from mixed-version issues i.e. in the absence of additional synchronization or serialization at the receive side, a receiver may perform a \texttt{reduce} with partial or torn model updates (or skip them if a consistency check is enforced). This is because just using a \texttt{barrier} gives no information if the recipient has finished receiving and consuming the model update. Second, most \texttt{barrier} implementations synchronize with all other processes in the computation. In contrast, with stochastic reduce, finer grained synchronization primitives are required that will block on only the required subset of workers to avoid unnecessary synchronization costs. A global \texttt{barrier} operation is slow and removing this operation can reduce synchronization costs, but makes the workers process the input data at different speeds that may slow down the overall time to achieve the final accuracy. Finally, using a \texttt{barrier} can cause network resource spikes if all the processes send their parameters at the same time.

Adding extra barriers before/after push and reduce, does not produce a strongly consistent BSP that can incorporate model updates from all replicas since the actual send operation may be asynchronous and there is no guarantee the receivers receive these messages when the perform a \texttt{reduce}. Unless a blocking receive is added after every send, the consistency is not guaranteed. However, this introduces a significant synchronization overhead.

Hence, to provide efficient coordination among parallel model replicas, we require the following three properties from any synchronization protocol. First, the synchronization should be \textit{fine-grained}. Coarse-grained synchronization such as \texttt{barrier} impose high overheads as discussed above. Second, the synchronization mechanism should provide \textit{consistent} intermediate outputs. Strong consistency methods avoid torn-reads and mixed version parameter vectors, and improve performance [11, 61]. Finally, the synchronization should be \textit{efficient}. Excessive receive-side synchronization for every \texttt{reduce} and \texttt{send} operation can significantly increase blocking times.

In data-parallel systems with \texttt{barrier} based synchronization, there is often no additional explicit synchronization between the sender and receiver when an update arrives. Furthermore, any additional synchronization may reduce the performance especially when using low latency communication hardware such as RDMA that allow one-sided writes without interrupting the receive-side CPU [35]. In the absence of synchronization, the rate at which the intermediate outputs arrive varies. As a result, a fast sender can overwrite the receive buffers or the receiver may perform a \texttt{reduce} with a fewer of senders instead of consuming every worker’s intermediate output hurting convergence.

Naiad, a dataflow based data-parallel system, provides a \texttt{notify} mechanism to inform the receivers about the incoming model updates [43]. This ensures that when a
node performs a local reduce, it consumes the intermediate outputs from all machines. Hence, a per-receiver notification allows for finer-grained synchronization. However, simply using a notify is not enough since a fast sender can overwrite the receive queue of the receiver and a barrier or any other style of additional synchronization is required to ensure that the parallel workers process incoming model parameters at the same speeds.

To eliminate the barrier overheads for stochastic reduce and to provide strong consistency, we propose using a NOTIFY-ACK based synchronization mechanism that gives stricter guarantees than using a coarse grained barrier. This can also improve convergence times in some cases since it facilitates using consistent data from dependent workers during the reduce step.

In ASAP, with NOTIFY-ACK, the parallel workers compute and send their model parameters with notifications to other workers. They then proceed to wait to receive notifications from all its senders as defined by their node communication graphs as shown in figure 4. The wait operation counts the NOTIFY events and invokes the reduce when a worker has received notifications from all its senders as described by the node communication graph. Once all notifications have been received, it can perform a consistent reduce.

After performing a reduce, the worker sends an ACK, indicating that the intermediate output in previous iteration has been consumed. Only when a worker receives an ACK for a previous send, indicating that the receiver has consumed the previously sent data, the worker may proceed to send the data for the next iteration. Unlike a barrier based synchronization, where there is no guarantee that a receiver has consumed the intermediate outputs from all senders, waiting on ACKs from receivers ensures that a sender never floods the receive side queue and avoids any mixed version issues from overlapping intermediate outputs. Furthermore, fine-grained synchronization allows efficient implementation of stochastic reduce since each sender is only blocked by dependent workers and other workers may run asynchronously.

NOTIFY-ACK provides clean synchronization semantics in few steps. Furthermore, it requires no additional receive-side synchronization making it ideal for direct-memory access style protocols such as RDMA or GPU Direct [2]. However, NOTIFY-ACK requires ordering guarantees of the underlying implementation to guarantee that a NOTIFY arrives after the actual data. Furthermore, in a NOTIFY-ACK based implementation, the framework should ensure that the workers send their intermediate updates and then wait on their reduce inputs to avoid any deadlock from a cyclic node communication graphs.

5 Implementation

We develop our second generation distributed learning framework using the ASAP model to incorporate stochastic reduce and fine-grained synchronization. We implement distributed data-parallel model averaging over stochastic gradient descent (SGD). We implement our reference framework with stochastic reduce and NOTIFY-ACK support in C++ and provide Lua bindings to run existing Torch and RAPID deep learning networks [18, 44].

For distributed communication, we use MPI and create the model parameters in distributed shared memory. In our implementation, parallel model replicas create a model vector in the shared memory and train on a portion of the dataset using the SGD algorithm. To reduce synchronization overheads, each machine maintains a per-sender receive queue to receive the model updates from other machines [51]. The queues and the shared memory communication between the parallel model replicas are created based on a node communication graph provided as an input when launching a job. Periodically, after processing few data examples and updating the local model $w$, the parallel replicas communicate the model parameters. The model replicas then average the incoming parameters with their own local model vector($w$).

We use the infiniBand transport and each worker directly writes the intermediate model to its senders without interrupting the receive side CPU, using one-sided RDMA operations. After the reduce operation, each machine sends out the model updates to other machines’ queues as defined by the communication graph. Our system can perform reduce over any user-provided node communication graph allowing us to evaluate stochastic reduce for different node communication graphs.

Furthermore, we also implement the synchronous, asynchronous and NOTIFY-ACK based synchronization. We implement synchronous (BSP) training by using the MPI provided barrier primitives. We use low-level distributed wait and notify primitives to implement NOTIFY-ACK. We maintain ACK counts at each node and send all outputs before waiting for ACKs across iterations to avoid deadlocks.

We use separate infiniBand queues for transmitting short messages (ACKs and other control messages) and large model updates (usually a fixed size for a specific dataset). For Ethernet based implementation, separate TCP flows can be used to reduce the latency of control messages [46]. We provide fault tolerance by checkpointing the trained model periodically to the disk. Additionally, for synchronous methods, we implement a dataset specific dynamic timeout which is a function of
6 Evaluation

In this section, we evaluate the ASAP model using the following criterion.

- What is the benefit of stochastic reduce? Do networks with a higher spectral gap exhibit better convergence?

- What is the benefit of using fine-grained synchronization over a barrier? Is it consistent?

We evaluate the ASAP model for applications that are commonly used today including text classification, spam classification, image classification and Genome detection. Our baseline for evaluation is our BSP/synchronous and asynchronous based all-reduce implementations which is provided by many other distributed big data or machine learning systems [5, 1, 22, 26, 31, 32, 40, 51]. We use an efficient infiniBand implementation stack that improves performance for all methods. However, stochastic reduce and NOTIFY-ACK can be implemented and evaluated over any existing distributed learning platform such as GraphLab or TensorFlow.

We run all our experiments on eight Intel Xeon 8-core, 2.2 GHz Ivy-Bridge processors and 64 GB DDR3 DRAM. All connected via a Mellanox Connect-V3 56 Gbps infiniBand cards to an infiniBand backplane. Our 56 Gbps infiniBand network architecture provides a peak throughput of slightly over 40 Gbps after accounting for the bit-encoding overhead for reliable transmission. All machines load the input data from a shared NFS partition. We run multiple processes, across these machines and run multiple processes on each machine, especially for models with less than 1M parameters, where a single model replica is unable to saturate the network and CPU. All reported times do not account for the initial one-time cost for the loading the data-sets in memory. All times are reported in seconds.

We evaluate the two machine learning methods:

1. SVM: We test ASAP on distributed SVM based on Bottou’s SVM-SGD [8]. Each machine computes the model parameters and communicates them to other machines as described in the machine communication graph. We train SVM over the RCV1 dataset (document classification), the web-spam dataset (webspam detection) and the splice-site dataset (Genome classification) [3].

2. Convolutional Neural Networks (CNNs): We train CNNs for image classification over the CIFAR-10 dataset [4]. The dataset consists of 50K train and 10K test images and the goal is to classify an input image to one amongst 10 classes. We use the VGG network to train 32x32 CIFAR-10 images with 11 layers that has 7.5M parameters [54]. We run data parallel replicas on multiple machines. We use OMP_PARALLEL_THREADS to parallelize the convolutional operations within a single machine.

6.1 Approximate processing benefits

Speedup with stochastic reduce We measure the speedups of all applications under test as the time to reach a specific accuracy. We first evaluate a small dataset (RCV1, 700MB, document classification) for the SVM application. The goal here is to demonstrate that for problems that fit in one machine, our data-parallel system outperforms a single thread for each workload [41]. Figure 5 shows the convergence speedup for 4 machines for the RCV1 dataset. We compare the performance for all-reduce against a root graph with a fixed out degree of two, where each node sends the model updates to two nodes – its neighbor and rootNth node. We find that for the RCV1 dataset, the root expander graph converges marginally faster than the all-reduce primitive, owing to lower network costs of sending the intermediate model and lower CPU costs of processing fewer incoming models at each of the machines.
Figure 6: This figure shows the convergence of a root expander graph with all-reduce graph for the splice-site dataset. Each machine in root graph transmits 219GB data/process while all-reduce transmits 2.08TB/worker of data to reach the desired accuracy. Speedups are measured over all-reduce.

Figure 6 shows the convergence for the SVM application using the splice-site dataset on 8 machines with 8 processes. The splice site training dataset is about 250GB, and does not fit in-memory in any one of our machines. This is one of the largest public dataset that cannot be subsampled and requires training over the entire dataset to converge correctly [6]. Figure 6 compares the two communication graphs – an all-reduce graph and a root expander graph with an out-degree of 2. We see that the expander graph can converge faster, and requires about 10X lower network bandwidth. Hence, stochastic reduce can improve convergence time and reduce network bandwidth requirement as compared to a naïve all-reduce.

Figure 7 shows the convergence for the SVM application on 25 processes using the webspam dataset consisting of 250K examples. The data is split across all processes and each machine only trains over 31.25K training set examples. We compare three node communication graphs – a root expander graph (with a spectral gap of 0.2 for 25 nodes) and a (one) chain-like architecture where each machine maintains a model and communicates its updates in the form a chain to one other machine, with the all-reduce implementation. The chain node graph architecture has lower network costs, but very low spectral values (around 0.008). Hence, it converges slower than the expander graph. Both the sparse graphs provide a speedup over all-reduce since the webspam dataset has a large dense parameter vector of about 11M float values. However, the chain graph requires more epochs to train over the dataset and sends 50433 MB/node to converge while the root node requires 44351 MB/node even though the chain graph transmits less data per epoch. Hence, one should avoid sparse reduce graphs with very low spectral gap values and use expander graphs provide good convergence with reasonable network costs.

To summarize, we find that stochastic reduce can provide significant speedup in convergence (by 2-10X) and reduces the network and CPU costs. However, if the node communication graph is sparse and has low spectral gap values (usually less than 0.01), the convergence can be slow. Hence, stochastic reduce provides a quantifiable measure using the spectral gap values to sparsify the node communication graphs. For models where the network capacity and CPU costs can match the model costs, using a network that can support the largest spectral gap is recommended.

6.2 Fine-grained synchronization benefits

We evaluate the benefits of fine-grained synchronization in this section. We compare the performance of NOTIFY-ACK, synchronous and asynchronous implementation. We implement the BSP algorithm using a barrier in the training loop, and all parallel models perform each iteration concurrently. However, simply using a barrier may not ensure consistency at the receive queue. For example, the parallel models may invoke a barrier after sending the models and then perform a reduce. This does not guarantee that each machine receives all the intermediate outputs during reduce. Hence, we perform a consistency check on the received intermediate outputs and adjust the number of intermediate models to compute the model average correctly. Each parameter update carries a unique version number in the header.
and footer we verify the version values in the header and footer are identical before and after reading the data from the input buffers.

For asynchronous processing, we perform no synchronization between the workers once they finish loading data and start training. We check the incoming intermediate model updates for consistency as described above. For the NOTIFY-ACK implementation, we send intermediate models with notifications and wait for the ACK before performing a reduce. Some network interconnects (or libraries over these interconnects) may not guarantee that the notifications arrive with the data, and we additionally check the incoming model updates and adjust the number of reducers to compute the model average correctly. We first perform a micro-benchmark to measure how many consistent reduce operations do synchronous (SYNC), asynchronous (ASYNC) and NOTIFY-ACK style of synchronization provide.

Figure 8 shows, for a graph of 8 nodes with each machine having an in-degree 7, the distribution of correct buffers reduced. NOTIFY-ACK, reduces with all 7 inputs and is valid 100% of the time. BSP has substantial torn reads, and 77% of the time performs a reduce with 5 or more workers. ASYNC can only perform 39% of the reduce operations correctly with 5 or more workers. Hence, we find that NOTIFY-ACK provides the most consistent data during reduce and fewest torn buffers followed by BSP using a barrier, followed by asynchronous. We now evaluate the benefits of NOTIFY-ACK with all-reduce communication.

Figure 9 shows the convergence for the CIFAR-10 dataset for eight machines in an all-reduce communication. We calculate the time to reach 99% training accuracy on the VGG network which corresponds to an approximately 84% test accuracy. We train our network with a mini-batch size of 1, with no data augmentation and a network wide learning rate schedule that decays every epoch. We find that with CNNs, NOTIFY-ACK provides superior convergence over BSP and ASYNC. Even with a dense communication graph of all-reduce, we find that NOTIFY-ACK reduces barrier times and provides stronger consistency than BSP providing competitive throughput and fast convergence. Furthermore, we find that ASYNC initializes slowly and converges slower than synchronous and NOTIFY-ACK methods.

We also measure the throughput (examples/second processed) for the three different synchronization methods – synchronous (BSP), asynchronous and the NOTIFY-ACK method. With NOTIFY-ACK, we avoid coarse-grained synchronization and achieve a throughput of 229.3 frames per second (or images per second) for eight machines. This is the average processing time and includes the time for forward and backward propagation, adjusting the weights and communicating and averaging the intermediate updates. With BSP, we achieve 217.8 fps. Finally, we find that even though ASYNC offers the highest throughput of on an average 246 fps, Figure 9 shows that the actual convergence is poor. Hence, to understand the benefits of approaches like relaxed consistency, one should consider speedup towards a (good) final accuracy apart from throughput. However, there are some cases where ASYNC may provide good performance when the communication between the workers is not crucial for convergence. This may happen when the dataset is highly redundant. Second, if the model is sufficiently sparse which makes the reduce operation commutative and reduces conflicting updates.

Figure 10 shows the convergence for the SVM application using the webspam dataset on 25 processes. We use the root-expander graph as described earlier, where each node receives the model updates with two other nodes. We find that using fine-grained NOTIFY-ACK improves the convergence performance and is about 3X faster than BSP for the webspam dataset. Furthermore, the asynchronous algorithm does not converge to the correct value even though it operates at a much higher throughput. NOTIFY-ACK provides good performance for three reasons. First, NOTIFY-ACK provides stronger consistency than BSP implemented using a barrier. In the absence of additional heavy handed synchronization with each sender, the model replicas may reduce with fewer incoming model updates. NOTIFY-ACK provides stronger guarantees since each worker waits for the NOTIFYs before performing the reduce and sends out additional data with after receiving the ACK messages. Second, for
Figure 9: This figure shows the convergence of NOTIFY-ACK, BSP, ASYNC with eight machines using all-reduce for training CNNs over the CIFAR-10 dataset with a VGG network. Speedups are measured over a single machine implementation.

approximate processing i.e. when the communication graph is sparse, a barrier blocks all parallel workers while when using fine-grained communication with NOTIFY-ACK independent workers run asynchronously with respect to one another.

To summarize, we find that NOTIFY-ACK eliminates torn buffers and provides stronger consistency over BSP and asynchronous communication for dense as well as sparse node graphs. We describe our results for the BSP/all-reduce model. However, these results can also be extended to bi-directional communication architectures such as the parameter server or the butterfly architecture.

7 Related Work

We discuss related work about batch processing systems, data-parallel approximate and asynchronous processing and distributed machine learning frameworks.

The original map-reduce uses a stage barrier i.e. all mapper tasks synchronize intermediate outputs over a distributed file-system [24]. This provides synchronization and fault tolerance for the intermediate job states but can affect the job performance due to frequent disk I/O. Spark [62] implements the map-reduce model in-memory using copy-on-write data-structures (RDDs). The fault-tolerance is provided by checkpoint and replay of these RDDs which restrict applications from running asynchronously. ASIP [30] adds asynchrony support in Spark by decoupling fault tolerance and coarse-grained synchronization and incorporates fully asynchronous execution in Spark. However, ASIP finds that asynchronous execution may lead to incorrect convergence, and presents the case for running asynchronous machine learning jobs using second order methods that provides stronger guarantees but can be extremely CPU intensive [50]. Finally, there are many existing general purpose dataflow based systems that use barriers or block on all inputs to arrive [19, 34, 43, 48]. ASAP uses fine-grained synchronization with partial reduce to mitigate communication and synchronization overheads. Fault tolerance can be incorporated in the ASAP model by using application checkpoints as described in our example implementation.

Past work on partial aggregation has proposed efficient tree-style all-reduce primitive to mitigate communication costs. This is extensively used in batch systems to reduce network costs by combining results at various levels such as machine, rack etc. [10, 60]. However, the reduce operation suffers from additional latency proportional to the height of the tree. Furthermore, when partial aggregation is used with iterative-convergent algorithms, the workers wait for a significant aggregated latency time which can be undesirable. Other work on partial-aggregation produces variable accuracy intermediate outputs over different computational budgets [36, 53]. ASAP exploits the iterative nature of machine learning algorithms for sparse aggregation of intermediate outputs that are propagated indirectly to all other workers over successive iterations reducing synchronization costs. ASAP provides the same final accuracy as an aggregated all-reduce over successive iterations. The workers communicate over a network topology designed to disperse the intermediate outputs over fewer iterations. Other methods to reduce net-
work costs include using lossy compression [5] or KKT filters [38]. The latter method determines the utility of intermediate updates are before sending them over the network. These methods can be applied with stochastic reduce even though they may incur additional CPU costs unlike stochastic reduce.

Past work has explored removing barriers in Hadoop to start reduce operations as soon as some of the mappers finish execution [29, 58]. HogWild [52] provides a single shared parameter vector and allows parallel threads to update model parameters without locks thrashing one another’s updates. However, HogWild may not converge to a correct final value if the parameter vector is dense and the updates from different machines overwrite one another frequently. Project Adam [13], DogWild [47] and other systems that use HogWild in a distributed setting results in excessive wasted communication especially when used to communicate dense parameter updates. A large number of previous systems propose removing the barriers which may provide faster throughput but may lead to slower or incorrect convergence towards the final optimization goal. To overcome this problem, bounded-staleness [20] provides asynchrony within bounds for the parameter server i.e. the forward running threads wait for the stragglers to catch up. However, determining these bounds empirically is difficult, and in some cases they may not more relaxed than synchronous. ASAP instead proposes using fine-grained synchrony that reduces synchronization overhead and provides stronger guarantees than what can be provided through barriers.

There has been a flurry of distributed machine learning platforms developed recently. Parameter Server [23, 38] provide a master-slave style communication framework. Here, workers compute the parameter updates and send it to a central server (or a group of servers). The parameter server computes and updates the global model and sends it to the workers and they continue to train new data over this updated model. Hence, in the parameter server the workers need to wait after every batch to receive an updated model. Here, the overall communication is low even though the master has a high-fanout of nodes it communicates with. Furthermore, since the master maintains a global model and resets the stragglers with its own updated model, the parameter server architecture always converges to the correct value. On the contrary, all-reduce based systems, usually implemented over map-reduce or BSP based systems, use a network of workers that synchronize using a barrier. All-reduce may operate fully asynchronously since unlike parameter server there is no consensus operation to exchange the gradients. However, they suffer from high communication costs as the number of workers increase. ASAP reduces communication overheads in the all-reduce model and by proposing partial-reduce based on information dispersal properties of underlying nodes.

TensorFlow runs a dataflow graph across a cluster. Unlike some other parameter servers that use barrier for synchronous training, TensorFlow uses a queue abstraction and uses the asynchronous parameter server to train large models [5]. Recently, instead of using asynchronous synchronization methods, Tensorflow has introduced synchronization with backup workers that skips synchronizing with the tail of the workers [11]. Using ASAP’s NOTIFY-ACK style synchronization can provide stronger consistency without any additional workers. Additionally, for large models, the large fanout of the master can be a bottleneck and the model parameters are aggregated at bandwidth hierarchies [11]. Using ASAP’s stochastic reduce to improve the convergence behavior of such network architectures can reduce the wait times. The parameter server architecture has also been proposed over GPUs [21, 63] and the communication and synchronization costs can be reduced in these systems by using the ASAP model.

8 Conclusion

Existing big-data processing frameworks use approximation and asynchrony to accelerate job processing throughput (i.e. examples/second processed). However, these optimizations may not benefit the overall accuracy of the job output and may even result in a slowdown as compared to the bulk-synchronous model. In this paper, we introduce an asynchronous and approximate processing model that reduces synchronization costs and provides strong quantifiable guarantees allowing application developers to reason about the guarantees they provide. In our results, we demonstrate that a framework written using the ASAP model provides 2-10X speedups in convergence and up to 10X savings in network costs. Other optimization problems such as graph-processing face similar trade-offs, and can benefit from using the ASAP model.

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A Stochastic reduce convergence analysis

In this section, we provide the supplementary material to analyse the convergence for any optimization algorithm that is implemented using stochastic reduce. Mathematically, the optimization problem is defined on a connected undirected network and solved by $n$ nodes collectively,

$$\min_{x \in \mathcal{X} \subseteq \mathbb{R}^d} \tilde{f}(x) := \sum_{i=1}^{n} f_i(x). \quad (A.1)$$

The feasible set $\mathcal{X}$ is a closed and convex set in $\mathbb{R}^d$ and is known by all nodes, whereas $f_i : \mathcal{X} \in \mathbb{R}$ is a convex function privately known by the node $i$. We also assume that $f_i$ is $L$-Lipschitz continuous over $\mathcal{X}$ with respect to the Euclidean norm $\|\cdot\|$. The network $\mathcal{G} = (\mathcal{N}, \mathcal{E})$, with the node set $\mathcal{N} = \{n\} := \{1, 2, \cdots, n\}$ and the edge set $\mathcal{E} \subseteq \mathcal{N} \times \mathcal{N}$, specifies the topological structure on how the information is spread amongst the nodes through local node interactions over time. Each node $i$ can only send and retrieve information as defined by the node communication graph $\mathcal{N}(i) := \{j \mid (j, i) \in \mathcal{E}\}$ and itself.

In this algorithm, each node $i$ keeps a local estimate $x_i$ and a model variable $w_i$ to maintain an accumulated subgradient. At iteration $t$, to update $w_i$, each node needs to collect the model update values of its neighbors which is the gradient value denoted by $\nabla f_i(w_i)$, and forms a convex combination with an equal weight of the received information. The learning rate is denoted by $\eta_i$. Hence, the updates received by each machine can be expressed as:

$$w_i^{t+1/2} \leftarrow w_i^t - \eta_i \nabla f_i(w_i^t)$$
$$w_i^{t+1} \leftarrow \frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} w_i^{t+1/2} \quad (A.2)$$

**Network requirement.** In order to make the above algorithm work, we need a network over which each node has the same influence. To understand and quantify this requirement, we denote the adjacency matrix as $A$, i.e. $A_{ij} = 1$ if $(j, i) \in \mathcal{A}$ and 0 otherwise, and denote $P$ as the matrix after scaling each $i$-th row of $A$ by the in-degree of node $i$, i.e. $P = \text{diag}(d_{in})^{-1} A$, where $d_{in} \in \mathbb{R}^k$ and $d_{in}(i)$ equals the in-degree of node $i$. For ease of illustration, we assume that $d = 1$ and $w_{0i} = 0$. Denote $g_t = (g_{t1}, g_{t2}, \ldots, g_{tk})$, and $w_t = (w_{t1}, w_{t2}, \ldots, w_{tk})^T$.

Then the updates can be tersely expressed as:

$$w_1 = -\eta_0 P g_0$$
$$w_2 = -\eta_0 P^2 g_0 - \eta_1 P g_1$$
$$\vdots$$
$$w_i = -\eta_0 P^i g_0 - \eta_1 P^{i-1} g_1 - \cdots - \eta_{i-1} P g_{i-1}$$
$$w_i = -\sum_{k=0}^{i-1} \eta_k P^{i-k} g_k \quad (A.3)$$

It can be easily verified that $P^\infty := \lim_{t \to \infty} P^t = \pi^\top$, where $\pi$ is a probability distribution (known as stationary distribution). Thus, $\pi_i$ here represents the influence that node $i$ played in the network. Therefore, to take a fair treatment of each node, $\pi_i = \frac{1}{k}$ is desired, which is equivalent to saying the row sums and column sums of $P$ are all equal to one, i.e. $P$ is a doubly stochastic matrix.

In the context of our network setting, we need a network whose nodes all have the same in-degree. Indeed, when $f_i$ is convex, the convergence results have been established under this assumption [45].

**Spectral Gap:** Besides being regular, the network $\mathcal{N}(i)$ should also be constructed in a way such that the information can be effectively spread out over the entire network, which is closely related with the concept of spectral gap. We denote $\sigma_1(P) \geq \sigma_2(P) \geq \cdots \geq \sigma_k(P) \geq 0$, where $\sigma_i(P)$ is the $i$th largest singular value of $P$. Clearly, $\sigma_1(P) = 1$. From the expression (A.3), we can see that the speed of convergence depends on how fast $P^t$ converges to $\frac{1}{n} 11^\top$, and based on the Perron-Frobenius theory, we have,

$$\|P^t x - \frac{1}{n} 1\| \leq \sigma_2(P)^t,$$

for any $x$ in the $k$-dimensional probability simplex. Therefore, the network with large spectral gap, $1 - \sigma_2(P)$, is greatly desired. For additional discussions on the importance of this spectral gap, please refer to [25].

We calculate the spectral gap as $1 - \sigma_2(P)$, where $\sigma_2(P)$ is the second largest singular value of $P$. The $P$ matrix is defined as $A/d$, where $A$ is the adjacency matrix (including self-loop) and $d$ is the in-degree (including self-loop). The spectral gap here is defined as $\sigma_1(P) - \sigma_2(P)$. But $\sigma_1(P)$ the largest singular value should be $1$. So the gap equals $1 - \sigma_2(P)$, where $\sigma_2(P)$ is the second largest singular value of $P$.

Hence, stochastic reduce network communication graphs with large spectral gap values will converge.
rapidly. Hence, one should construct sparse network communication topologies for reduce such that the communication costs are low while ensuring large possible spectral gap values of the network.

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