A Reliable Effective Terascale Linear Learning System

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ABSTRACT

We present a system and a set of techniques for learning linear predictors with convex losses on terascale datasets, with trillions of features, billions of training examples and millions of parameters in an hour using a cluster of 1000 machines. Individually none of the component techniques is new, but the careful synthesis required to obtain an efficient implementation is a novel contribution. The result is, up to our knowledge, the most scalable and efficient linear learning system reported in the literature. We describe and thoroughly evaluate the components of the system, showing the importance of the various design choices.

1. INTRODUCTION

Distributed machine learning is a research area that has seen a growing body of literature in recent years. Much work focuses on problems of the form

$$\min_{w \in \mathbb{R}^d} \sum_{i=1}^{n} f(w^T x_i; y_i) + \lambda R(w),$$

(1)

where $x_i$ is the feature vector of the $i$-th example, $y_i$ is the label, $w$ is the linear predictor, $f$ is a loss function and $R$ a regularizer. Much of this work exploits the natural decomposability over examples in (1), partitioning the examples over different nodes in a distributed environment such as a cluster.

Perhaps the simplest learning strategy when the number of samples $n$ is very large is to subsample a smaller set of examples that can be tractably learned with. However, this strategy only works if the problem is simple enough or the number of parameters is very small. The setting of interest here is when a large number of samples is really needed to learn a good model, and distributed algorithms are a natural choice for such scenarios.

The number of features here refers to the number of non-zero entries in the data matrix.

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Some prior works (McDonald et al., 2010; Zinkevich et al., 2010) consider online learning with averaging and (Duchi et al., 2010a) propose gossip-style message passing algorithms extending the existing literature on distributed convex optimization (Bertsekas and Tsitsiklis, 1989; Langford et al., 2009) analyze a delayed version of distributed online learning. (Dekel et al., 2010) consider mini-batch versions of online algorithms which are extended to delay-based updates in Agarwal and Duchi (2011). A recent article of Boyd et al. (2011) describes an application of the ADMM technique for distributed learning problems. GraphLab (Low et al., 2010) is a parallel computation framework on graphs. More closely related to our work is that of Teo et al. (2007) who use MPI to parallelize a bundle method for optimization.

However, all of the aforementioned approaches seem to leave something to be desired empirically when deployed on large clusters. In particular their throughput—measured as the input size divided by the wall clock running time—is smaller than the the I/O interface of a single machine for almost all parallel learning algorithms (Bekkerman et al., 2011 Part III, page 8). The I/O interface is an upper bound on the speed of the fastest sequential algorithm since all sequential algorithms are limited by the network interface in acquiring data. In contrast, we were able to achieve a throughput of 500M features/s, which is about a factor of 5 faster than the 1Gb/s network interface of any one node.

An additional benefit of our system is its compatibility with MapReduce clusters such as Hadoop (unlike MPI-based systems) and minimal additional programming effort to parallelize existing learning algorithms (unlike MapReduce approaches).

One of the key components in our system is a communication infrastructure that efficiently accumulates and broadcasts values across all nodes of a computation. It is functionally similar to MPI AllReduce (hence we use the name), but it takes advantage of and is compatible with Hadoop so that programs are easily moved to data, automatic restarts on failure provide robustness, and speculative execution speeds completion. Our optimization algorithm is a hybrid online+batch algorithm with non-uniform parameter averaging.

The paper is organized as follows. In Section 2 we discuss the approach used and the communication infrastructure we setup. Most of our effort is devoted to Section 3 where we conduct many experiments comparing with existing algo-

http://www.mcs.anl.gov/research/projects/mpi/
rithms and various design choices within our own algorithm. In Section 2 we discuss and contrast our approach with the many approaches people have proposed for parallel learning.

2. COMPUTATION AND COMMUNICATION FRAMEWORK

Map-Reduce [Dean and Ghemawat 2008] and its open source implementation Hadoop have become the overwhelmingly favorite platforms for distributed data processing in general. However, the abstraction is rather ill-suited for machine learning algorithms as several researchers in the field have observed (Low et al., 2010; Zaharia et al., 2011), because it does not easily allow iterative algorithms, such as typical optimization algorithms used to solve the problem 1.

2.1 Hadoop-compatible AllReduce

AllReduce is a more suitable abstraction for machine learning algorithms. AllReduce is an operation where every node starts with a number and ends up with the sum of the numbers at all the nodes. A typical implementation is done by imposing a tree structure on the communicating nodes—numbers can be summed up the tree (this is the reduce phase) and then broadcast down to all nodes—hence the name AllReduce. See Figure 1 for a graphical illustration. When doing summing or averaging of a long vector, such as the weight vector w in the optimization 1, the reduce and broadcast operations can be pipelined over the vector entries hence the latency of going up and down the tree becomes negligible on a typical Hadoop cluster.

For problems of the form 1, AllReduce provides straightforward parallelization—we just accumulate local gradients for a gradient based algorithm like gradient descent or L-BFGS. In general, any statistical query algorithm (Kearns 1993) can be parallelized with AllReduce with only a handful of additional lines of code. This approach also easily implements averaging parameters of online learning algorithms.

An implementation of AllReduce is available in the MPI package. However, it is not easy to run MPI on top of existing Hadoop clusters (Ye et al. 2009). Moreover, MPI implements little fault tolerance, with the bulk of robustness left to the programmer.

To address the reliability issues better, we developed an implementation of AllReduce that is compatible with Hadoop. Implementation of AllReduce using a single tree is clearly less desirable than MapReduce in terms of reliability, because if any individual node fails, the entire computation fails. To deal with this, we use a simple trick below which makes AllReduce reliable enough to use in practice for computations up to 10K node hours.

2.2 Proposed Algorithm

Our main algorithm is a hybrid online+ batch approach. We start with each node making one online pass over its local data according to adaptive gradient updates (Duchi et al., 2010b; McMahan and Streeter, 2010) modified for loss non-linearity (Karampatziakis and Langford, 2011). AllReduce is used to average these weights non-uniformly using the local gradients. Concretely, node k maintains a local weight vector w^k and a diagonal matrix G^k based on the gradients in the adaptive gradient updates (see Algorithm 1). We compute the following weighted average over all m nodes

\[
    w = \left( \sum_{k=1}^{m} G^k \right)^{-1} \left( \sum_{k=1}^{m} G^k w^k \right).
\]

This has the effect of weighing each dimension according to how “confident” each node is in its weight (i.e., more weight is assigned to a given parameter of a given node, if that node has seen more examples with the corresponding feature). We note that this averaging can indeed be implemented using AllReduce by two calls to the routine since G^k are only diagonal. This solution w is used to initialize L-BFGS (Nocedal, 1980) with the standard Jacobi preconditioner. At each iteration, the local gradients are summed up using AllReduce, while all the other operations can be done locally at each node. The algorithm benefits from the fast reduction of error initially that an online algorithm provides, and rapid convergence in a good neighborhood guaranteed by Quasi-Newton algorithms.

Another strategy we evaluate is that of repeated online learning with averaging using the adaptive updates. In this setting, each node performs an online pass over its data and then we average the weights according to Equation 2. We average the scaling matrices similarly

\[
    G = \left( \sum_{k=1}^{m} G^k \right)^{-1} \left( \sum_{k=1}^{m} G^k \right)^2.
\]

and use this averaged state to start a new online pass over the data. We will see in the next section that this strategy can be very effective at getting a moderately small test error very fast, but might not be able to get a very small test error.

Note that our implementation is open source in Vowpal Wabbit (Langford et al. 2007) and is summarized in algorithm 2. It makes use of the stochastic gradient descent (Algorithm 1) for the initial pass.

2.3 Speculative Execution

It is common for large clusters of machines to be busy with many jobs which use the cluster in an uneven way, commonly resulting in one of a thousand nodes being very slow. To avoid this, Hadoop can speculatively execute a job on identical data, using the first job to finish and killing the other one. In our framework, it can be tricky to handle duplicates once a spanning tree topology is created for AllReduce. For this reason, we delay the initialization of the spanning tree until each node completes a pass over the data, building the spanning tree on only the speculative execution survivors.

Figure 1: AllReduce

http://hadoop.apache.org/
Algorithm 1 Stochastic gradient descent algorithm on a single node using adaptive gradient update \cite{Duchi+10b,McMahan+10}.

\begin{algorithm}[ht]
\caption{Stochastic gradient descent algorithm on a single node using adaptive gradient update (Duchi et al., 2010b; McMahan and Streeter 2010).}
\begin{algorithmic}
\Require Invariance update function $s$
\State $w = 0$, $G = I$
\ForAll{$(x, y)$ in training set}
\State $g$ $\leftarrow$ $\nabla_w \ell(w^T x; y)$
\State $w$ $\leftarrow$ $w - s(w, x, y)G^{-1/2}g$
\State $G_{jj}$ $\leftarrow$ $G_{jj} + g^2_j$ for all $j = 1, \ldots, d$
\EndFor
\end{algorithmic}
\end{algorithm}

Algorithm 2 Sketch of the proposed learning architecture.

\begin{algorithm}[ht]
\caption{Sketch of the proposed learning architecture}
\begin{algorithmic}
\Require Data split across nodes
\ForAll{nodes $k$ do}
\State $w^k$ = result of stochastic gradient descent on the data of node $k$ using Algorithm 1
\EndFor
\State Compute the weighted average $\bar{w}$ as in (2) using AllReduce.
\State Start a preconditioned L-BFGS optimization from $\bar{w}$.
\ForAll{nodes $k$ do}
\For{$t = 1, \ldots, T$ do}
\State Compute $g_k^t$ the (local batch) gradient of examples on node $k$
\State Compute $g = \sum_{k=1}^n g_k$ using AllReduce.
\State Add the regularization part in the gradient.
\State Take an L-BFGS step.
\EndFor
\EndFor
\end{algorithmic}
\end{algorithm}

The net effect of this speculative execution trick is perhaps another order of magnitude of scalability and reliability in practice. Indeed, we found the system reliable enough for up to 1000 nodes running failure-free for hundreds of trials. This significant gain from Hadoop’s built-in fault tolerance highlights the benefits of a Hadoop-compatible implementation of AllReduce. We will show the substantial gains from speculative execution in mitigating the “slow node” problem in the experiments.

3. EXPERIMENTS

3.1 Datasets

Display advertising.

In online advertising, given a user visiting a publisher page, the problem is to select the best advertisement for that user. A key element in this matching problem is the click-through rate (CTR) estimation: what is the probability that a given ad will be clicked given some context (user, page visited)? Indeed, in a cost-per-click (CPC) campaign, the advertiser only pays when the ad gets clicked, so even modest improvements in predictive accuracy directly effect revenue.

There are several features representing the user, page, ad, as well as conjunctions of these features. Some of the features include identifiers of the ad, advertiser, publisher and visited page. These features are hashed \cite{Weinberger+09} and each training sample ends up being represented as sparse binary vector of dimension $2^{24}$ with around 100 non-zero elements. Let us illustrate the construction of a conjunction feature with an example. Imagine that an ad from etrade was placed on finance.yahoo.com. Let $h$ be a 24 bit hash of the string “publisher=finance.yahoo.com and advertiser=etrade”. Then the (publisher, advertiser) conjunction is encoded by setting to 1 the $h$-th dimension of the feature vector for that example.

Since the data is unbalanced (low CTR) and because of the large number samples, we subsampled the negative examples resulting in a class ratio of about 2 negatives for 1 positive, and used a large test set drawn from days later than the training set. There are 2.3B samples in the training set.

Splice Site Recognition.

The problem consists of recognizing a human acceptor splice site \cite{Sonnenburg+10}. We considered this learning task because this is, as far as known, the largest public data set for which subsampling is not an effective learning strategy. \cite{Sonnenburg+07} introduced the weighted degree kernel to learn over DNA sequences. They also proposed an SVM training algorithm for that kernel; the learning over 10M sequences took 24 days. In \cite{Sonnenburg+10}, an improved training algorithm is proposed in which the weight vector—in the feature space induced by the kernel—is learned, but the feature vectors are never explicitly computed. This resulted in a faster training: 3 days with 50M sequences.

We follow the same experimental protocol as in \cite{Sonnenburg+10}: we use the same training and test sets of respectively 50M and 4.6M samples. We also consider the same kernel of degree $d = 20$ and hash size $\gamma = 12$. The feature space induced by this kernel has dimensionality 11,725,480. The number of non-zero features per sequence is about 3,300. Unlike \cite{Sonnenburg+10}, we explicitly compute the feature space representation of the samples, yielding about 3TB of data. This explicit representation is a disadvantage we imposed on our method, purely as a matter of implementation time.

3.2 Results

Effect of subsampling.

The easiest way to deal with a very large training set is to subsample it as discussed in the introduction. Sometimes similar test errors can be achieved with smaller training sets and there is no need of large scale learning in these cases. For splice site recognition, Table 2 of \cite{Sonnenburg+10} shows that smaller training sets do hurt the area under the precision/recall curve on the test set.

For display advertising, we subsampled the data at 1% and 10%. The results in Table 1 show that there is a noticeable drop in accuracy after subsampling. Note that even if the drop does not appear large at a first sight, it can cause a substantial loss of revenue. Thus, for both datasets, the entire training data is needed to achieve optimal performances.

The three metrics reported in Table 1 are area under the ROC curve (auROC), area under the precision/recall curve (auPRC) and negative log-likelihood (NLL). Since auPRC is the most sensitive metric, we report test results using that metric in the rest of the paper. This is also the metric used in \cite{Sonnenburg+10}.

Running time.
Table 1: Test performance on the display advertising problem as a function of the subsampling rate.

|       | 1%     | 10%    | 100%   |
|-------|--------|--------|--------|
| auROC | 0.8178 | 0.8301 | 0.8344 |
| auPRC | 0.4505 | 0.4753 | 0.4856 |
| NLL   | 0.2654 | 0.2582 | 0.2554 |

Table 2: Distribution of computing time (in seconds) over 1000 nodes. First three columns are quantiles. Times are average per iteration (excluding the first one) for the splice site recognition problem. The first row is without speculative execution while the second row is with speculative execution.

|               | 5%  | 50% | 95% | Max | Comm. time |
|---------------|-----|-----|-----|-----|------------|
| Without       | 29  | 34  | 60  | 758 | 26         |
| With          | 29  | 33  | 49  | 63  | 10         |

We ran 5 iterations of L-BFGS on the splice site data with 1000 nodes. On each node, we recorded for every iteration the time spent in AllReduce and the computing time—defined as the time not spent in AllReduce. The time spent in AllReduce can further be divided into stall time—waiting for the other nodes to finish their computation—and communication time. The communication time can be estimated by taking the minimum value of the AllReduce times across nodes.

The distribution of the computing times is of particular interest because the speed of our algorithm depends on the slowest node. Statistics are shown in Table 2. It appears that most computing times are concentrated around the median, but there are a few outliers. Without speculative execution, one single node was about 10 times slower than the other nodes; this has the catastrophic consequence of slowing down the entire process by a factor 10. The use of speculative execution successfully mitigated this issue.

Finally, we study the running time as a function of the number of nodes. For the display advertising problem, we varied the number of nodes from 10 to 100 and computed the speed-up factor relative to the run with 10 nodes. In each case, we measured the amount of time needed to get to a fixed test error. Since there can be significant variations from one run to the other—mostly because of the cluster utilization—each run was repeated 10 times. Results are reported in Figure 2. We note that speculative execution was not turned on in this experiment, and we expect better speedups with speculative execution.

Table 3: Computing time on the splice site recognition data with various number of nodes for obtaining a fixed test error. The first 3 rows are average per iteration (excluding the first one).

| Nodes   | 100  | 200  | 500  | 1000 |
|---------|------|------|------|------|
| Comm time / pass | 5    | 12   | 9    | 16   |
| Median comp time / pass | 167  | 105  | 43   | 34   |
| Max comp time / pass    | 462  | 271  | 172  | 95   |
| Wall clock time         | 3677 | 2120 | 938  | 813  |

Figure 2: Speed-up for obtaining a fixed test error, on the display advertising problem, relative to the run with 10 nodes, as a function of the number of nodes. The dashed corresponds to the ideal speed-up, the solid line is the average speed-up over 10 repetitions and the bars indicate maximum and minimal values.

Figure 3: Effect of initializing the L-BFGS optimization by an average solution from online runs on individual nodes.
of the display advertising data (16B examples). Using 1000 nodes and 10 passes over the data, the training took only 70 minutes.

**Online and batch learning.**

We now investigate the number of iterations needed to reach a certain test performance for different learning strategies: batch, online and hybrid.

First, Figure 3 compares two learning strategies—batch with and without an initial online pass—on the training set. It plots the optimality gap, defined as the difference between the current objective function and the optimal one (i.e. minimum value of the objective), as a function of the number of iterations. From this figure, one can see that the initial online pass results in a saving of about 10-15 iterations.

Figure 4 shows the test auPRC, on both datasets, as a function of the number of iterations for 4 different strategies: online learning, only L-BFGS learning, and hybrid methods consisting of 1 or 5 passes of online learning followed by L-BFGS optimization. L-BFGS with one online pass appears to be the most effective strategy.

For the splice recognition problem, an initial online pass and 14 L-BFGS iterations yield an auPRC of 0.581, which is just a bit higher than Sonnenburg and Franc (2010). This was achieved in 1960 seconds using 500 machines, resulting in a 68 speed-up factor (132581 seconds on a single machine reported in Table 2 of Sonnenburg and Franc (2010)).

**Averaging.**

Table 4 compares picking one online run at random, using uniform weight averaging, or using non-uniform weight averaging according to Equation 2 from adaptive updates. Note that the random pick for splice was apparently lucky, and that weighted averaging works consistently well.

### 3.3 Comparison with previous approaches

**AllReduce vs. MapReduce.**

The standard way of using MapReduce for iterative machine learning algorithms is the following (Chu et al., 2007): every iteration is a M/R job where the mappers compute some local statistics (such as a gradient) and the reducers sum them up. This is ineffective because each iteration has large overheads (job scheduling, data transfer, data parsing, etc.). We have an internal implementation of such a M/R algorithm. We updated this code to use AllReduce instead and compared both versions of the code in Table 3. This table confirms that Hadoop MapReduce has substantial overheads since the training time is not much affected by the dataset size. The speedup factor of AllReduce over Hadoop MapReduce can become extremely large for smaller datasets, and remains noticeable even for the largest datasets.

It is also noteworthy that all algorithms described in Chu et al. (2007) can be parallelized with AllReduce, plus further algorithms such as parameter averaging approaches.

**Overcomplete average.**

We implemented oversampled stochastic gradient with final averaging (Zinkevich et al., 2010), and compared its performance to our algorithm. We used stochastic gradient descent with the learning rate in the $t$-th iteration as

$$\eta_t = \frac{1}{L + \gamma \sqrt{t}}.$$  

We tune $\gamma$ and $L$ on a small subset of the dataset.

In Figure 5, we see that the oversampled SGD is competitive with our approach on the display advertising data set, but its convergence is much slower on splice site recognition data.

**Parallel online mini-batch.**

Dekel et al. (2010) propose to perform online convex optimization using stochastic gradients accumulated in small mini-batches across all nodes. We implemented SGD version of their algorithm using AllReduce. They suggest global minibatch sizes of no more than $b \propto \sqrt{t}$. On $m$ nodes, each node accumulates gradients from $b/m$ examples, then an AllReduce operation is carried out, yielding the mini-batch gradient, and each node performs a stochastic gradient update with the learning rate of the form

$$\eta_t = \frac{1}{L + \gamma \sqrt{t/m}}.$$  

We tuned $L$ and $\gamma$ on a smaller dataset. In Figure 6, we report the results on splice data set, using 500 nodes, and mini-batch size $b = 100k$. Twenty passes over the data thus corresponded to 10k updates. Due to the overwhelming communication overhead associated with the updates, the overall running time was 40 hours. In contrast, L-BFGS took less than an hour to finish 20 passes, and obtained a much superior performance. The difference in the running time between 1h and 40h is solely due to communication. Thus, in this instance, we can conservatively conclude that the communication overhead of 10k mini-batch updates is 39 hours.

We should point out that it is definitely possible that the mini-batched SGD would reach similar accuracy with much smaller mini-batch sizes (for 10k updates theory suggests we should use mini-batches of size at most 10k), however, the 39 hour communication overhead would remain. Using larger mini-batches, we do expect that the time to reach 20
Figure 4: Test auPRC for 4 different learning strategies. Left: splice site recognition; right: display advertising.

passes over data would be smaller (roughly proportional to the number of mini-batch updates), but according to theory (as well as our preliminary experiments on smaller subsets of splice data), we would have inferior accuracy. Because of the prohibitive running time, we were not able to tune and evaluate this algorithm on display advertising data set.

**Parallel online learning.**

Finally we compared our approach using the online parallel learning algorithm of [Hsu et al. (2011)] using the same online advertising dataset in their paper. We note that this is a substantially smaller dataset with about 10M examples, and 125G non-zero features in the data matrix. We did not run this comparison on our larger datasets since the methods in [Hsu et al. (2011)] do not scale well to a large number of nodes, as evident from Figure 5 of their paper: with 8 nodes, the speed-up is only a factor of 2. For both algorithms, we set the number of passes over the data to reach a certain test error. This number turned out to be 18 for the parallel online learning and 20 for our algorithms. The running time using 8 nodes was 35 minutes for the parallel online learning and 16 minutes for ours.

4. **PROBLEMS WITH OTHER APPROACHES AND COMMUNICATION COST**

Here we discuss the limitations of existing approaches and systems. In many cases, it is helpful to compare the communication cost. Computational cost is also important in general, but it turns out to be non-distinguishing for the algorithms we consider here while communication cost analysis aligns well with our empirical observations. Because modern switches are quite good at isolating communicating nodes, the most relevant communication cost is the maximum (over nodes) of the communication cost of a single node.

Several variables are important:

1. $m$ the number of nodes.
2. $n$ the number of examples.
3. $s$ the number of nonzero features per example.
4. $d$ the dimension of the parameters.
5. $T$ the number of passes over the examples.

In the large-scale applications that are subject of this paper, we typically have $s \ll d \ll n$, where both $d$ and $n$ are substantially large (see Section 3.1).

The way that data is dispersed across a cluster is relevant in much of this discussion since an algorithm not using the starting format must pay the communication cost of redistributing that. We assume the data is distributed across the nodes uniformly according to an example partition, as is common.

The per-node communication cost of the hybrid algorithm is $\Theta(dT_{\text{hybrid}})$ where $T_{\text{hybrid}}$ is typically about 15 to maximize test accuracy in our experiments. Note that the minimum possible communication cost is $\Theta(d)$ if we save the model on a single machine. There is no communication involved in getting data to workers based on the data format assumed above. An important point here is that every node has a communication cost functionally smaller than the size of the dataset, because there is no dependence on $ns$.

Similar to our approach, [Teo et al. (2007)] propose a parallel batch optimization algorithm (specifically, a bundle method) using the MPI implementation of AllReduce. This is a solid approach which arrives at an accurate solution with $O(dT_{\text{bundle}})$ communication per node. Our approach improves over this in several respects. First, as Figure 4 demonstrates, we obtain a substantial boost thanks to our warmstarting strategy, hence in practice we expect $T_{\text{bundle}} > T_{\text{hybrid}}$. The second distinction is in the AllReduce implementation. Our implementation is well aligned with Hadoop and takes advantage of speculative execution to mitigate the slow node problem. On the other hand, MPI assumes full control over the cluster, which needs to be carefully aligned with Hadoop’s Map-Reduce scheduling decisions, and by itself, MPI does not provide robustness to slow nodes.

Batch learning can also be implemented using Map-Reduce on a Hadoop cluster [Chu et al., 2007], for example in the
The key problem here is the communication cost. The per-node communication cost is \( O(nT_{\text{online}}) \) where \( T_{\text{online}} \) is the level of replication and \( m \) is the number of nodes. Here, the first term comes from the data transfer required for creating the overcomplete partition and the second term from the parameter averaging. When \( T_{\text{rep}}/m \) is often a constant near 1 (0.25 was observed by Zinkevich et al. (2010) and the theory predicts only a constant factor improvement), this implies the communication cost is \( \Theta(ns) \), the size of the dataset.

Other authors have looked into online mini-batch optimization (Dekel et al., 2010; Agarwal and Duchi, 2011). The key problem here is the communication cost. The per-node communication cost is \( \Theta(T_{\text{rep}}bn/b) \) where \( b \) is the minibatch size (number of examples per minibatch summed across all nodes) and \( T_{\text{rep}} \) is the number of passes over the data. \( n/b \) is the number of minibatch updates per pass and \( d \) is the number of parameters. According to theory \( b \leq \sqrt{n} \),

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Table 6: Communication cost of various learning algorithms. Here \( n \) is the number of examples, \( s \) is the number of nonzero features per example, \( d \) is the number of dimensions, \( T \) is the number of times the algorithm examines each example, and \( b \) is the minibatch size (in minibatch algorithms).

| Algorithm                                      | Per-node communication cost                                                                 |
|------------------------------------------------|---------------------------------------------------------------------------------------------|
| Bundle method (Teo et al., 2007)               | \( O(dT_{\text{bundle}}) \)                                                                 |
| Online with averaging (McDonald et al., 2010)  | \( O(dT_{\text{online}}) \)                                                                  |
| Hall et al. (2010)                             | \( O(ns/m + nT_{\text{online}}) \)                                                            |
| Hsu et al. (2011)                              | \( O(ns + d) \)                                                                               |
| Overcomplete online with averaging (Zinkevich et al., 2010) | \( O(dT_{\text{rep}}n/b) = O(dT_{\text{rep}}\sqrt{n}) \)                                   |
| Dekel et al. (2010)                            | \( O(nsT_{\text{rep}}) \)                                                                    |
| Agarwal and Duchi (2011)                       | \( O(nsT_{\text{rep}}/m + d) \)                                                                |
| Hybrid online+batch                            | \( O(dT_{\text{hybrid}}) \)                                                                   |

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Mahout project\(^7\). Elsewhere it has been noted that MapReduce is not well suited to iterative machine learning algorithms (Low et al., 2010; Zaharia et al., 2011). Evidence of this is provided by the Mahout project itself, as their implementation of logistic regression is not parallelized. Indeed, we observe substantial speedups from a straightforward substitution of AllReduce for MapReduce on Hadoop. It is also notably easier to program with AllReduce, as code does not require refactoring.

Figure 5: Test auPRC for different learning strategies as a function of the effective number of passes over data. In L-BFGS, it corresponds to iterations of the optimization. In overcomplete SGD with averaging (Zinkevich et al.), it corresponds to the replication coefficient. Left: splice site recognition; right: display advertising.

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\(^7\)http://mahout.apache.org/
implying communication costs of $\Theta(T_{\text{min}}d/\sqrt{n})$. While for small minibatch sizes $T_{\text{min}}$ can be quite small (plausibly even smaller than 1), when $d$ is sufficiently large, this communication cost is prohibitively large. In particular, if $T_{\text{min}}$ is at least a constant, the final communication cost is greater than distributing the entire dataset. This is the reason for the slow performance of mini-batched optimization that we observed in our experiments. Reworking these algorithms with sparse parameter updates, the communication cost per observed in our experiments.

The per-node communication costs differ substantially here. The first term is due to shuffling from an example-based format, and the second term is for the run of the actual algorithm. This has a similar tractability to the algorithm we consider here, particularly if the data is organized in a feature partition eliminating the first term. However, the programming is substantially more delicate and no experiments of the scales we consider have been conducted.

Another category of algorithms is those which use online learning with a feature based partition of examples (Hsu et al., 2011). Several families of algorithms have been tested in this setting including delayed updates, minibatch, second order minibatch, independent learning, and backprop. The per-node communication costs differ substantially here. Typical communication costs are $\Theta(ns/m + nT_{\text{online}})$ where $s$ is the number of examples in a batch, $m$ is the number of features, and $n$ is the number of users. The first term is for the run of the algorithm. This has a similar tractability to the algorithm we consider here, particularly if the data is organized in a feature partition eliminating the first term. However, the programming is substantially more delicate and no experiments of the scales we consider have been conducted.

5. CONCLUSION

We have shown that a new architecture for parallel learning based on a Hadoop-compatible implementation of AllReduce can yield a combination of excellent prediction and training time performance in an easy programming style. The hybrid algorithm we employ allows us to benefit from the rapid initial optimization of online algorithms and the high precision of batch algorithms where the last percent of performance really matters.

The combination of these techniques enables the training of linear predictors on datasets of size unmatched in the literature.

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