Abstract

The paper presents a parallel math library, dMath, that demonstrates leading scaling when using intranode, internode, and hybrid-parallelism for deep learning (DL). dMath provides easy-to-use distributed primitives and a variety of domain-specific algorithms including matrix multiplication, convolutions, and others allowing for rapid development of scalable applications like deep neural networks (DNNs). Persistent data stored in GPU memory and advanced memory management techniques avoid costly transfers between host and device. dMath delivers performance, portability, and productivity to its specific domain of support.

1 Introduction

High-speed machine learning is becoming one of the most important areas of high performance computing (HPC) in the commercial, academic, and other spaces. Machine-learning algorithms leverage traditional scientific computing – correlations, convolutions, FFTs, matrix and tensor multiplications, and combinations thereof. Thus, central to the solution of key machine learning algorithms is the need for both scalable architectures and algorithmic libraries that implement these kernels efficiently with strong scaling.

This paper presents dMath, a new scalable distributed math library. dMath provides key linear algebra operations, convolutions and other fundamental algorithms in the implementation of deep neural networks (DNNs). The key features of the library include: a) support for persistent storage of operands in GPU memory; b) a data management service to cache shared objects over the course of data parallel operations; c) data reorganization to support optimization of operations in series; d) a mixed precision mode, e.g. double, float, and half; e) an automatically tuned, extendable data loading and augmentation pipeline; f) an effective master-worker model to allow users to utilize dMath without requiring detailed knowledge of CUDA, MPI, or data distribution. The library uses pooling of unused GPU memory to avoid costly CUDA memory allocations and registrations with the InfiniBand (IB) driver.

Another notable feature of the system is the ability to “keep what you’ve seen.” Because the data management layer has semantic understanding of matrices and vectors, as algorithms progress, portions of the parallel matrix can be retained in a cache (within each MPI process). This allows for reduced communication in subsequent steps, such as in the back-propagation stage of DNN training. For problems where computation is memory bound, caching is avoided.

Lastly, we exploit GPU-enabled MPI to enhance performance and utilize non-blocking MPI operations to overlap communication and computation, where appropriate.
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2.1 Managing Persistent Data in the GPUs

When working with GPU accelerators, copying data across the CPU-GPU boundary is extremely undesirable. Persistent storage of operands within the GPUs is therefore a critical feature of dMath that improves the efficiency of CUDA-accelerated computation. Strong adherence to this model means that comparatively little of the multicore CPUs are utilized apart from servicing MPI middleware APIs and underlying MPI transport.

In dMath, a distributed matrix is split into multiple non-overlapping blocks that are stored on individual workers. Each worker is aware of the layout of every matrix, which allows the workers to operate without the intervention of the master process. Often it is desirable to have a copy of a matrix on each worker. In situations where the data rarely changes and memory is abundant, this sort of caching is beneficial to reduce communication. dMath supports both synchronous and asynchronous matrix replication.

Replication allows us to perform efficient parameter redistribution when training deep neural networks. After each worker computes the weight updates for its chunk of the model, asynchronous replications are initiated for learnable parameters that will be needed by all workers for the forward pass. This effectively overlaps parameter updates with the forward pass computation.

2.2 Data Loading

As training accelerates, larger data, and more complex data augmentation pipelines can become the bottleneck when training in many-GPU distributed systems. To avoid this bottleneck, data augmentation is done in parallel with network training. dMath supports multi-threading, and the movement of the computation for individual stages in the data augmentation pipeline between host and device. At runtime, dMath dynamically tunes the number of worker threads and the location of each data augmentation operation to optimize overall iteration time. Host computation, transfers to the device, and computation on the GPU are overlapped to reduce the processing time for each datum. To minimize data transfers from the host to the device, promotion of data to higher precision types is done lazily by the pipeline as needed for higher precision operations (e.g., mean subtraction).

2.3 Reproducibility

The ability to reproduce results is incredibly important, and when certain subroutines are stochastic in nature, one can get different results that may be difficult to duplicate. In dMath, we use seed values that are distributed via the master node to workers to ensure reproducible results. However, there are a few subroutines where concurrency and non-deterministic ordering of operations can lead to small differences in results. For example, in the distributed version of our AddRowColSumMatrix subroutine we sacrifice deterministic outcomes for speed and scalability.

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3.1 dMath Kernels

dMath combines a set of innovative ideas that simplify writing parallel algorithms while supporting key kernels. In this section, we consider some of the key features of dMath operations.
3.1 Algorithms

_dMath_ provides many numerical kernels/operations that are distributed over MPI, including hundreds of algorithms and methods common to a DNN computational pipeline. These building blocks allow a variety of DNN pipelines to be created (implicitly with distributed backends).

3.2 Data Distribution Independence

Algorithms in _dMath_ are correct independent of the how the distributed objects are mapped to the workers. _dMath_ performs any needed communication to ensure compatibility, rather than limiting the distributions to block-cyclic (and/or linear) 1D or 2D decompositions. Previous libraries (e.g., [3, 4]) achieve data distribution independence and varying degrees of compatibility with rectangular matrices and cartesian decompositions, but notably require that the objects be laid out compatibly at the beginning of the GEMM function, rather than offering remapping services. As with other libraries, the shape of the data and concurrency can affect the performance of _dMath_ kernels.

3.3 Data Reorganization and Caching

Where appropriate, _dMath_ allows an algorithm to reshape (including a change of concurrency and layout), over the same group of processes or a superset/subset, and/or change precision during reshape. All metadata for a distributed operation can also be cached. We utilize this feature when dealing with fixed pipelines and it provides greater scalability by allowing the workers to remember the entire forward and backward computations. This prevents thousands of costly broadcasts of metadata to the workers by replacing each one with a single cached identifier.

4 DNN Training Results

In this section, we present performance results training AlexNet [5], GoogLeNet v1 [6], and Inception v3 [7] using Expresso, a Samsung internal fork of Caffe, powered by _dMath_, that employs hybrid parallelism [8]. We compare Expresso to leading open-source frameworks.

4.1 Scaling Experiments

In the left-hand side of Table 1, we provide scaling performance results for Expresso v0.5. We compare our performance to Nvidia’s NVcaffe v0.14 [9], which provides leading open-source intranode scaling via data parallelism. The AlexNet experiments use a batch size of 1024 on 2-64 GPUs, and a 512 batch size on 1 GPU due to memory constraints. All tests in Table 1 were conducted on Nvidia Tesla K80 GPUs. Experiments with GoogLeNet were conducted using a 1024 batch size on 8-64 GPUs, and 128 batch size for 1-4 GPUs.

On startup, _dMath_ automatically selects the optimal convolution algorithm based on timing samples and system constraints. The single asterisk on Expresso results designates a sub-optimal algorithm choice because of memory constraints; hence the super-linear scaling from two to four GPUs. The double asterisk signifies GPU memory thrashing, which is a significant detriment to the performance of NVcaffe for some batch sizes.

While it is significantly easier to weakly scale training, it eventually leads to large batch sizes that could potentially harm the convergence of the network parameters. The results from these experiments demonstrate weak scaling from 1-2 GPUs and 4-8 GPUs for AlexNet and GoogLeNet respectively, but maintain the batch size beyond these points.

Expresso provides class-leading performance for strong scaling, as shown in the right-hand side of Table 1. It is one of _dMath_’s fundamental goals to provide the ability to experiment with extremely large models that are stored in device memory, without being constrained to a subsets of GPUs because of poor strong scaling. The right-hand side of Table 1 shows performance results for Expresso, Microsoft’s CNTK, and NVcaffe, scaling a 256 sample batch from 1-64 GPUs. Testing of CNTK was performed with both the regular and one-bit quantized versions of SGD. Across all experiments, Expresso provides superior scaling while also achieving higher accuracy and a lower memory footprint due to its hybrid data/model parallelism scheme. After extensive debugging, we
Table 1: Framework Comparison

| Number of GPUs | AlexNet 1024 Batch (FPS) | GoogLeNet v1 1024 Batch (FPS) | AlexNet 256 Batch (FPS) |
|----------------|--------------------------|-------------------------------|-------------------------|
|                | Expresso v0.5 nv-caffe v0.14 | Expresso v0.5 nv-caffe v0.14 | Expresso CNTK r2016-02-08 CNTK (1-bit) nv-caffe v0.14 |
| 1              | 479 413                   | 115 102                      | 533 580 588 350         |
| 2              | 9408 **682                 | 215 203                      | 915 487 485 711         |
| 4              | 1996 1165                 | 370 341                      | 1440 428 416 898        |
| 8              | 3103 2204 *873 **510       | 1702 -                        | - 790                   |
| 16             | 4198 2615 1498 1515        | 2008 -                        | - 875                   |
| 32             | 5187 -                     | 2104 -                        | -                        |
| 64             | 5786 -                     | 2071 -                        | -                        |
| Mem. GB (16 GPUs) | 2.29 2.34                 | 5.27 7.65                    | -                        |
| Accuracy(Top-1%) | 55.38 55.14               | 65.39 64.96                  | 58.59 - - 57.01         |

were not able to successfully run the multi-GPU version of CNTK for anything but a few iterations and cannot provide accuracy metrics.

4.2 Accuracy & Half-Precision

Accuracy is an extremely important metric and it is an important attribute of dMath. dMath solves the harder problem, that of hybrid parallelism, and accuracy is never impacted regardless of the number of GPUs. Reduced precision data types enable even better scaling in a distributed environment by reducing data transfer size. dMath supports half-precision for storage and computation. When using GPUs that do not support half-precision computation, dMath works in a mixed-mode in which values are stored in half and upcast to float before computation. With half-precision integration in Expresso, we can train and test larger network on the same devices. Preliminary results indicate that Expresso performs at par in mixed half-mode for inference accuracy on trained GoogLeNet and AlexNet networks. Moving further, we are currently investigating the performance of training and testing on devices with true half-precision support.

4.3 Updated Experimental Results

Using Expresso v0.7 on 32 Tesla K80s (i.e., 64 GPUs) with a 32 batch size per GPU, we are able to train Google’s Inception v3 model at 1443 FPS. Training the IV3 model with a simplistic data augmentation pipeline (random cropping and mirroring) produced 92.8% top-5 and 75.1% top-1 single-crop test accuracy after 200 epochs, with a total runtime of 49.3hrs. Consider Google’s internal TensorFlow takes 65hrs on 100 Tesla K40 GPUs [10], and it is quickly apparent that more HPC centric approaches provide superior performance. Our own experiments with open-source TensorFlow r0.8 were unable to get over 200 FPS on 8, 16, 32, or 64 Tesla K80s, or over 150 FPS on 4 or 8 Tesla M40s. Our TensorFlow experiments used a single parameter server and a 32 batch size per GPU. Scaling out training with Expresso to 96 Tesla M40s with an 80 batch size per GPU, we are able to further reduce the training time to 14hrs with a frame rate of 5150 FPS.

5 Conclusion & Future Work

In this paper we presented dMath, a scalable parallel math library that provides a complete set of primitives for DNN pipelines. We showed experimental results through Expresso, demonstrating superior scaling to leading open-source frameworks. We have demonstrated the effectiveness of dMath, but we also have a version of the popular open-source speech recognition library Kaldi [11], powered by dMath, that shows the generality of the library. In the future we will be introducing new abstractions for alternative accelerators and communication devices, providing greater degrees of asynchronous behavior to increase scalability, and will be exploring ways to further reduce the memory footprint.
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