THEANO-BASED LARGE-SCALE VISUAL RECOGNITION WITH MULTIPLE GPUs

Weiguang Ding & Ruoyan Wang
School of Engineering, University of Guelph
{wding, ruoyanry}@uoguelph.ca

Fei Mao
Sharcnet, Compute Canada
feimao@sharcnet.ca

Graham Taylor
School of Engineering, University of Guelph
gwtaylor@uoguelph.ca

ABSTRACT

In this report, we describe a Theano-based AlexNet [Krizhevsky et al., 2012] implementation and its naive data parallelism on multiple GPUs. Our performance on 2 GPUs is comparable with the state-of-art Caffe library [Jia et al., 2014] run on 1 GPU. To the best of our knowledge, this is the first open-source Python-based AlexNet implementation to-date.

1 INTRODUCTION

Deep neural networks have greatly impacted many application areas. In particular, AlexNet [Krizhevsky et al., 2012], a type of convolutional neural network (LeCun et al., 1998) (ConvNet), has significantly improved the performance of image classification by winning the 2012 ImageNet Large Scale Visual Recognition Challenge [Russakovsky et al., 2014] (ILSVRC 2012). With the increasing popularity of deep learning, many open-source frameworks have emerged with the capability to train deep ConvNets on datasets with over 1M examples. These include Caffe [Jia et al., 2014], Torch7 [Collobert et al., 2011] and cuda-convnet [Krizhevsky et al., 2012]. However, the convenience of using them is limited to building “standard” architectures. To experiment with brand new architectures, researchers have to derive and implement the corresponding gradient functions in order to do backpropagation or other types of gradient descent optimizations.

Theano [Bergstra et al., 2010; Bastien et al., 2012], on the other hand, provides the automatic differentiation feature, which saves researchers from tedious derivations and can help in avoiding errors in such calculations. The other advantage of Theano is that it has a huge existing user and developer base which leverages the comprehensive scientific Python stack (102 contributors at the time of writing). However, there is no previously reported work of using Theano to do large scale experiments, such as the above mentioned ILSVRC 2012.

Here, we report a Theano-based AlexNet trained on ImageNet data. We also introduce a naive data parallelism implementation on multiple GPUs, to further accelerate training.

2 METHODS

“AlexNet” is a now a standard architecture known in the deep learning community and often used for benchmarking. It contains 5 convolutional layers, 3 of which are followed by max pooling layers.
2 fully connected layers, and 1 softmax layer \cite{Krizhevsky2012}. In our AlexNet implementation, we used 2 types of convolution and max pooling operators. The 1st is from the Pylearn2 \cite{Goodfellow2013} wrapper of cuda-convnet, the original implementation of AlexNet. The 2nd is the recently developed Theano wrapper of cuDNN \cite{Chetlur2014}. We also use functions in the PyCUDA library \cite{Klockner2012} to transfer Theano shared variables between different python processes for two tasks: 1. loading image mini-batches into GPUs during training; and 2. exchanging weights between models trained on multiple-GPUs.

2.1 Parallel Data Loading

Figure 1 illustrates the process of parallelized training and data loading. Two processes run at the same time, one is for training, and the other one is for loading image mini-batches. While the training process is working on the current minibatch, the loading process is copying the next minibatch from disk to host memory, preprocessing it and copying it from host memory to GPU memory. After training on the current minibatch finishes, the data batch will be moved "instantly" from the loading process to the training process, as they access the same GPU.

2.2 Data Parallelism

In this implementation, 2 AlexNets are trained on 2 GPUs. They are initialized identically. At each step, they are updated on different minibatches respectively, and then their parameters (weights, biases) as well as momentum are exchanged and averaged.

\footnote{Preprocessing includes subtracting the mean image, randomly cropping and flipping images \cite{Krizhevsky2012}.}
Table 1: Training time per 20 iterations (sec)

| Parallel loading | cuda-convnet 2-GPU | cuda-convnet 1-GPU | cuDNN-R1 2-GPU | cuDNN-R1 1-GPU | cuDNN-R2 2-GPU | cuDNN-R2 1-GPU | Caffe 2-GPU | Caffe with cuDNN 1-GPU |
|------------------|-------------------|-------------------|--------------|--------------|--------------|--------------|------------|-----------------------|
| Yes              | 23.39             | 39.72             | 20.38        | 34.71        | 19.72        | 32.76        | 26.26      | 20.25                 |
| No               | 28.92             | 49.11             | 27.31        | 45.45        | 26.23        | 43.52        |            |                       |

Figure 2 illustrates the steps involved in training on one minibatch. For each weight matrix in the model, there are 2 shared variables allocated: one for updating, and one for storing weights copied from the other GPU. The shared variables for updating on 2 GPUs start the same. In the 1st step, they are updated separately on different data batches. In the 2nd step, weights are exchanged between GPUs. In the 3rd step, these weights (no longer the same) are averaged on both GPUs. At this point, 2 AlexNets sharing the same parameters are ready for training on the next mini-batch.

3 RESULTS

Our experimental system contains 2 Intel Xeon E5-2620 CPUs (6-core each and 2.10GHz), and 3 Nvidia Titan Black GPUs. 2 of the GPUs are under the same PCI-E switch and are used for the 2-GPU implementation. We did not use the third GPU. For the cuDNN library, we performed experiments on both the version of R1 and R2.

For the experiments on a single GPU, we used batch size 256. Equivalently, we used batch size 128 for experiments on 2 GPUs. We recorded the time to train 20 batches (5,120 images) under different settings and compared them with Caffe in Table 1.

We can see that both parallel loading and data parallelism on 2 GPUs bring significant speed ups. The 2-GPU & parallel loading implementation (cuDNN-R2) is on par with the “Caffe with cuDNN” implementation.

After 60 epochs of training, the top-1 class validation error rate is 42.8%, and the top-5 error rate is 20.5%, without the intensity and illumination data augmentation. This is within 1% of the results reported in the similar Caffe implementation.

4 DISCUSSION

4.1 NATIVE THEANO MULTI-GPU SUPPORT

Native Theano multi-GPU support is under development. Our present implementation is a temporary work-around before its release, and might also provide helpful communication components on top of it.

4.2 RELATED WORK

Many multi-GPU frameworks has been proposed and implemented (Yadan et al., 2013; Zou et al., 2014; Paine et al., 2013; Krizhevsky, 2014), usually adopting a mixed data and model parallelism. This report only implements the data parallelism framework, but it could potentially, with a non-trivial amount of effort, be extended to incorporate model parallelism.

---

3 The same operation is performed for biases and momentum.

4 Performance of Caffe is according to [http://caffe.berkeleyvision.org/performance_hardware.html](http://caffe.berkeleyvision.org/performance_hardware.html), where timing information for CaffeNet is provided. As CaffeNet has similar structures, we consider this as a rough reference.

[https://github.com/BVLC/caffe/tree/master/models/bvlc_reference_caffenet](https://github.com/BVLC/caffe/tree/master/models/bvlc_reference_caffenet)

[https://groups.google.com/d/msg/theano-users/vtR_L0Q1tpE/Kp5hK1nFLtsJ](https://groups.google.com/d/msg/theano-users/vtR_L0Q1tpE/Kp5hK1nFLtsJ)
4.3 CHALLENGES IN PYTHON-BASED PARALLELIZATION

The Global Interpreter Lock (GIL) makes parallelization difficult in CPython, by disabling concurrent threads within one process. Therefore, to parallelize, it is necessary to launch multiple processes and communicate between these processes. Straightforward inter-process communication, using the "multiprocessing" module, is very slow for 2 reasons: 1) it serializes Numpy arrays before passing between processes; 2) communication is done through host memory. These problems lead us to GPUDirect peer-to-peer memory copy, which also has many pitfalls under the multi-process setting. For instance, there is no host-side synchronization performed with device-to-device memory copy even when the sync API is called. This problem is dealt with by CUDA context syncing and additional message communications between processes, however, this and similar issues are not straightforward.

4.4 LIMITATIONS

To use the fast peer-to-peer GPU memory copy, GPUs have to be under the same PCI-E switch. Otherwise, communication has to go through the host memory which results in longer latency. Situations involved with more GPUs are discussed in [Krizhevsky, 2014].

Due to our current hardware limitation, we have only proposed and experimented with a 2-GPU implementation. This report and the code will be updated once experiments on more GPUs are performed.

ACKNOWLEDGMENTS

We acknowledge Lev Givon for giving helpful suggestions on how to use the PyCUDA library. We also acknowledge NVIDIA for an Academic Hardware Grant.

REFERENCES

Bastien, Frédéric, Lamblin, Pascal, Pascanu, Razvan, Bergstra, James, Goodfellow, Ian, Bergeron, Arnaud, Bouchard, Nicolas, Warde-Farley, David, and Bengio, Yoshua. Theano: new features and speed improvements. arXiv preprint arXiv:1211.5590, 2012.

Bergstra, James, Breuleux, Olivier, Bastien, Frédéric, Lamblin, Pascal, Pascanu, Razvan, Desjardins, Guillaume, Turian, Joseph, Warde-Farley, David, and Bengio, Yoshua. Theano: a cpu and gpu math expression compiler. In Proceedings of the Python for scientific computing conference (SciPy), volume 4, pp. 3, 2010.

Chetlur, Sharan, Woolley, Cliff, Vandermersch, Philippe, Cohen, Jonathan, Tran, John, Catanzaro, Bryan, and Shelhamer, Evan. cudnn: Efficient primitives for deep learning. arXiv preprint arXiv:1410.0759, 2014.

Collobert, Ronan, Kavukcuoglu, Koray, and Farabet, Clément. Torch7: A matlab-like environment for machine learning. In BigLearn, NIPS Workshop, number EPFL-CONF-192376, 2011.

Goodfellow, Ian J, Warde-Farley, David, Lamblin, Pascal, Dumoulin, Vincent, Mirza, Mehdi, Pas- canu, Razvan, Bergstra, James, Bastien, Frédéric, and Bengio, Yoshua. Pylearn2: a machine learning research library. arXiv preprint arXiv:1308.4214, 2013.

Jia, Yangqing, Shelhamer, Evan, Donahue, Jeff, Karayev, Sergey, Long, Jonathan, Girshick, Ross, Guadarrama, Sergio, and Darrell, Trevor. Caffe: Convolutional architecture for fast feature embedding. In Proceedings of the ACM International Conference on Multimedia, pp. 675–678. ACM, 2014.

Klöckner, Andreas, Pinto, Nicolas, Lee, Yunsup, Catanzaro, Bryan, Ivanov, Paul, and Fasih, Ahmed. Pycuda and pyopencl: A scripting-based approach to gpu run-time code generation. Parallel Computing, 38(3):157–174, 2012.
Krizhevsky, Alex. One weird trick for parallelizing convolutional neural networks. *arXiv preprint arXiv:1404.5997*, 2014.

Krizhevsky, Alex, Sutskever, Ilya, and Hinton, Geoffrey E. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pp. 1097–1105, 2012.

LeCun, Yann, Bottou, Léon, Bengio, Yoshua, and Haffner, Patrick. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

Paine, Thomas, Jin, Hailin, Yang, Jianchao, Lin, Zhe, and Huang, Thomas. Gpu asynchronous stochastic gradient descent to speed up neural network training. *arXiv preprint arXiv:1312.6186*, 2013.

Russakovsky, Olga, Deng, Jia, Su, Hao, Krause, Jonathan, Satheesh, Sanjeev, Ma, Sean, Huang, Zhiheng, Karpathy, Andrej, Khosla, Aditya, Bernstein, Michael, et al. Imagenet large scale visual recognition challenge. *arXiv preprint arXiv:1409.0575*, 2014.

Yadan, Omry, Adams, Keith, Taigman, Yaniv, and Ranzato, MarcAurelio. Multi-gpu training of convnets. *arXiv preprint arXiv:1312.5853*, 2013.

Zou, Yongqiang, Jin, Xing, Li, Yi, Guo, Zhimao, Wang, Eryu, and Xiao, Bin. Mariana: Tencent deep learning platform and its applications. *Proceedings of the VLDB Endowment*, 7(13), 2014.