Optimizing CPU Performance and Scalability of Google Tensorflow for Manycore CPU

Abstract. We propose an optimization method for Google Tensorflow on a single shared-memory manycore architecture using a new CPU optimizing method and an efficient memory placement method to improve performance scalability. The performance problems of Tensorflow frameworks have only considered on large distributed clusters with GPUs resulting from the cluster-based algorithms that only focused on avoiding high network costs and improving GPU performance. However, some of large scale machine learning data sets can be processed with a single commodity manycore machine instead of using distributed clusters with GPUs since shared-memory manycore machine can reduce network and PCI-E bus transfers. The proposed methods can improve performance and scalability on the unoptimized Tensorflow with a single manycore machine by using efficient vectorization, maximizing the CPU utilization and efficient memory placement. Our method will provide the basis towards practical design of deep learning framework for a single manycore server to collaborate CPUs and GPUs. Our evaluation study based on benchmark programs revealed that our optimizing method will show better performance improvement through on a 64 core Intel Xeon-phi KNL, self-bootable single manycore CPUs, compared to unoptimized Tensorflow.

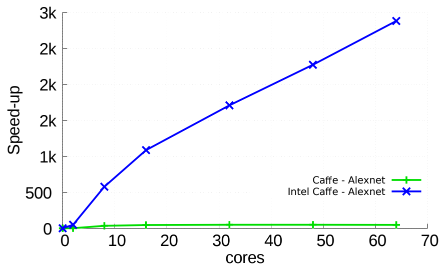
Keywords. Mayncore, Tensorflow, Intel Xeon-phi KNL,

1. Introduction

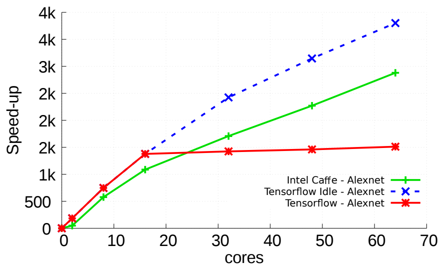
In recent years, deep learning has produced several domains ranging from speech recognition, visual object recognition, to text processing. However, deep learning data sets have substantially grown during the last decade. To solve large data sets, the current design trend is to use large-scale clusters of machines, which is distribute training and inference in deep networks using the state of the art deep learning frameworks.

Google Tensorflow [1] is one of widely used deep learning analytics framework to solve large data sets problem, and it becomes more and more a versatile framework for distributed clusters, local workstations, mobile devices, and custom-designed accelerators. However, Tensorflow does not scale on the single manycore machine resulting from our preliminary experiments (see Section 2) because Tensorflow was the successor to DistBelief [2], a heavyweight system, and it only added support for GPU acceleration [1].

A. Matveev *et al.* proposed a deep learning algorithm and CPU optimizing methods that eliminate the bottleneck of transferring data to the cloud thereby reducing the transferring overheads [3]. Therefore, we also believed that some of workloads on a single manycore machine can perform faster than a distributed clusters of CPUs and GPUs, so CPU scaling problem server must be solved on Tensorflow. Our optimizing method will provide the basis towards practical design to collaborate CPUs and GPUs.



(a) Scale-up server scalability of Caffe



(b) Scale-up server scalability of Tensorflow

2. Preminerly Expermiments

As noted earlier, Tensorflow does not scale on the single manycore machine. In order to achieve the high performance on Tensorflow, we need to understand the problem of Tensorflow on a single manycore machine. Figure **??** (a) explains the improving point of original Caffe on Intel Xeon-phi KNL; original Caffe didn't scale well. On the other hand, Intel optimized Caffe on Intel Xeon-phi KNL processor improved the performance scalability significantly. However, until recently, Figure **??** (b) shows that Tensorflow has not been optimized on Intel Xeon-phi KNL processor due to the it does not support CPU optimization technique such as OpenMP and Intel MKL library. This results show us to problem of performance and scalability on a single manycore machine.

3. Proposed Methods

In order to achieve the high performance and scalability on a single manycore machine, we may use a method to optimize vectorization, multithreading, and better cache traffic. In conclusion, optimizing CPU performance and scalability on Tensorflow can replace the use of a larget distributed system with a single manycore machine through benefits of the low shared-memory communication overheads, and parallelize. This is the main focus of our research and implementation.

References

[1] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, M. Kudlur, J. Levenberg, R. Monga, S. Moore, D. G. Murray, B. Steiner, P. Tucker, V. Vasudevan, P. Warden, M. Wicke, Y. Yu, and X. Zheng. TensorFlow: A System for Large-scale Machine Learning. In *Proceedings of the 12th USENIX Conference on Operating Systems Design and Implementation*, OSDI'16, pages 265–283, 2016.

[2] J. Dean, G. S. Corrado, R. Monga, K. Chen, M. Devin, Q. V. Le, M. Z. Mao, M. Ranzato, A. Senior, P. Tucker, K. Yang, and A. Y. Ng. Large Scale Distributed Deep Networks. In *Proceedings of the 25th International Conference on Neural Information Processing Systems*, NIPS'12, pages 1223–1231, 2012.

[3] A. Matveev, Y. Meirovitch, H. Saribekyan, W. Jakubiuk, T. Kaler, G. Odor, D. Budden, A. Zlateski, and N. Shavit. A Multicore Path to Connectomics-on-Demand. In *Proceedings of the 22Nd ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming*, PPoPP '17, pages 267–281, 2017.