EcoRNN: Efficient Computing of LSTM RNN on GPUs
Extended Abstract

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Figure 1: Left: A single-layer LSTM RNN that scans through an input sequence. Right: A zoom-in view of an LSTM cell. Both diagrams have been greatly simplified.

1 INTRODUCTION

Long-Short-Term-Memory Recurrent Neural Network (LSTM RNN [7], Figure 1) is a state-of-the-art model for analyzing sequential data. Current implementations of LSTM RNN in machine learning (ML) frameworks usually either lack performance or flexibility (i.e. the ability to modify existing computation of LSTM RNN). For example, default implementations (which we will further refer to as Default) in Tensorflow [1] and MXNet [3] invoke many tiny GPU kernels, leading to excessive overhead in launching GPU threads (a.k.a. cudaLaunch, Figure 2a). Although cuDNN [5], NVIDIA’s deep learning library, can accelerate performance by around 2×, it is closed-source and inflexible, hampering further research and performance improvements in frameworks, such as PyTorch [17], that use cuDNN as their backend [6]. In this work, we introduce a new RNN implementation called EcoRNN that is significantly faster than the open-source implementation in MXNet and is competitive with the closed-source cuDNN. We show that applying data layout optimization, with other techniques that are shown in Appleyard et al.’s work, can give us a maximum performance boost of 3× over MXNet default and 1.5× over cuDNN implementations. We integrate EcoRNN into MXNet Python library and open-source it to benefit ML practitioners. We also find that ML compilers [19, 4, 18] can be helpful in making the frontend programming interface more flexible by automatically configuring the data layout to be optimal, which is not possible in cases other than LSTM RNN since it has the property of "optimizing once and for all".

2 KEY OBSERVATIONS

We make the following observations during our optimization of LSTM RNN computation on the GPUs.

Observation 1. The runtime bottleneck of LSTM RNN is fully-connected (FC) layers. We obtain the runtime breakdown of cuDNN GPU kernels using nvprof [15], and the result is shown in Figure 2b (due to the fact that Default slices the computation of "f" block in Figure 1 into small pieces, its result is difficult to interpret). Figure 2b shows that more than 85% of the time spent on compute has been allocated to matrix multiply kernels (sgemm is the name for single-precision matrix multiply kernels in cuBLAS library [12]). The annotations beside the stacked bar in Figure 2b group GPU kernels together according to their counterpart in Figure 1, which explains why FC layers in LSTM RNN should be the top candidate for optimization.

Observation 2. Data layout optimization can speed up FC layers. Data layout optimization is a technique that originates from compiler research [9]. The idea behind data layout optimization is that changing data layout (usually from row-major to column-major or vice versa) can result in better locality in the data access pattern, which will further lead to higher cache hit rate, faster memory accesses, and, eventually, better runtime performance. We discover that two computations, \( Y = XW^T \) and \( Y^T = WX^T \) (Figure 3a), that are mathematically the same can have different cache hit rates. Figure 3b shows an example of such comparison where \( X : [64 \times 512] \) and \( W : [2048 \times 512] \) (this mimics the FC layers of an LSTM RNN that has batch size and hidden dimension equal to 64 and 512 respectively). We observe that \( Y^T = WX^T \) is almost twice as fast as \( Y = XW^T \) under this parameter setting, and the reason is that the former has better cache hit rate (50% vs. 10% of latter). Therefore, it can feed data faster into compute units, and thus spend more time in compute rather than waiting for data to arrive from main memory.

3 PRELIMINARY RESULTS

All the experiments are done on a single machine with Intel®Core™i5-3570 [8] CPU and Titan Xp [16] GPU. We have been using CUDA 8.0 [14] toolkit and cuDNN 6.0 [13] for our experiments. To provide fair comparison against Default and cuDNN, we integrate our implementation of EcoRNN into MXNet ver. 0.12.1. We test all three
which is a NP-complete problem in generic settings, can be reduced in ways significantly better than (left) and hardware utilization (right) comparison between Y = XW^T and Y^T = WX^T.

The trade-off between performance and flexibility is ubiquitous in (PTB) [10] and Wikitext-2 [11] dataset. Figure 4 shows the results of training throughput comparison. We observe that EcoRNN is always significantly better than Default and in most cases better than cuDNN. Even in a few cases where cuDNN slightly outperforms EcoRNN, the performance difference is below 20%.

4 OPTIMIZING ONCE AND FOR ALL

The trade-off between performance and flexibility is ubiquitous in high-performance-computing. With the advent of machine learning compilers [19, 4, 18], it is made possible to perform dynamic code optimization under a easily programmable frontend interface, therefore achieving both high performance and flexibility simultaneously. We notice that the optimization of LSTM RNN exhibits the property of “once and for all” – optimizations that are performed for one single cell can be generalized immediately to all other cells of different layers and time steps. Therefore, data layout optimization, which is a NP-complete problem in generic settings, can be reduced to a binary problem in the case of LSTM RNN. We aim to investigate the use of ML compilers in RNN training, which can help us dynamically select between the transposed and legacy layout depending on the hyperparameter settings at runtime. Figure 5 demonstrates how it works – at the frontend, machine learning programmers specify the hyperparameters that they are hoping to use, our microbenchmark then quickly does runtime comparison between different implementation backends (i.e. Default, cuDNN, and EcoRNN) in milliseconds, the best of which will be used in actual training that lasts for hours.

REFERENCES


