Power/Performance Analysis and Optimization for Deep Learning on CPU-GPU Platforms

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Abstract

Due to the intrinsic data parallelism characteristic of deep learning, GPU is a much better platform for deep learning applications compared to CPU. This work focuses on understanding what is left to be done for CPU given that GPU has to run deep learning applications on embedded platform. In modern mobile SoC, e.g. Nvidia Tegra X1, GPU and CPU shares same power budget and memory budget, and hence affects each other cohesively. By characterizing different deep learning workloads and CPU workloads under different kind of CPU-GPU frequencies, we investigate what is left to be done for CPU and how those workloads affect the tasks on GPU.

1. Introduction

With the recent success of machine learning workloads, there are growing interests in understanding the speed/power consumption trade-offs of CPU, GPU, FPGA, and ASIC while running those intelligent workloads [5, 6]. However, there is no prior art that analyzes the workloads for CPU given that GPU is running a deep learning workload in the meantime. We find this question interesting and easily neglected since people focus on deep learning on GPU. Our argument is that even though deep learning task is considered the top priority task in the whole system, there is still a lot of CPU resources to utilize. For example, suppose the mobile device that equips with both CPU and GPU has to run deep learning model in the background all the time to analyze the context of users, we expect users to run applications in the meantime. However, it is not clear, given that both CPU and GPU share the same power and memory budget, what kind of tasks are allowed to utilize the CPU without affecting the performance of the deep learning task.

In this work, we try to understand and analyze what type of tasks, under what kind of frequencies can the CPU run under various GPU constraint. We consider the deep neural network that runs on GPU the top priority task of the overall system. Hence, the performance of it acts as the constraints in our analysis. We specifically focus on the embedded platform and we use Nvidia's Tegra X1 throughout our study. In embedded MPSoC where CPU-GPU are integrated on the same chip, it is shown that global power management that controls the frequency of both CPU and GPU is essential due to shared power budget [7]. Hence, if one wants neither under-utilize the quad-core CPU nor performance degradation for the deep neural network, analysis is required to understand the sweet spot.

We study the 3 types of CPU benchmarks, 3 types of deep neural network, and different CPU-GPU frequencies. For CPU, we mainly investigate the workloads in MiBench benchmark suite [1] and use memory-intensive, compute-intensive, and mid-level workload in both compute and memory. For GPU, we target specifically on image classification task and includes three types of deep neural network from small to large. We also consider 3 different frequencies for CPU and 3 different frequencies for GPU.

2. Related Work

In terms of the performance and power analysis for deep learning tasks, prior art focuses on characterizing the difference between various platforms running different deep learning workloads. Nurvitadhi et al. [6] compares the power/performance characteristics of binarized neural networks on CPU, GPU, FPGA, and ASIC, which shows FPGA implementation have much better performance per watts compared to both CPU and GPU. Malik et al. [5] shows that GPU and FPGA can compete in energy delay product and depends on the input size, or the level of data parallelism.

This work obviously diverges from prior works since we focus on what tasks can be done on CPU while GPU is running deep learning workloads. In other words, since it is

shown that GPU is almost always better than CPU in deep learning workloads, we want to understand the role for CPU in the big deep learning era.

3. Methodology

In this project, Nvidia Jetson TX1 embedded platform will be used for power and performance analysis. We run various deep neural network architectures for image classification task on GPU. We use small, medium, and large deep neural networks to make a thorough power and performance analysis with different network characteristics. Caffe framework [3] is used to implement deep neural networks on GPU. Similarly, we use MiBench benchmark suite for CPU. Various MiBench benchmarks is used to cover different workload characteristics such as memory-intensive and compute-intensive workloads. Furthermore, we run these CPU-GPU benchmarks with using three different frequency values for both CPU and GPU. First, we run them individually to obtain power, performance, and temperature results for the baseline. Secondly, we run them jointly to do analysis and optimization for deep learning on embedded CPU-GPU platforms.

Power values are calculated by using current sensors in Nvidia Jetson TX1 platform. Temperature results also are collected by using thermal sensors in TX1. Performance results for CPU are calculated by using performance counters as an instruction per cycle (IPC) metric. Moreover, we obtain CPU utilization results using system calls. Execution time of deep neural network are calculated using Caffe framework. We also include performance results for GPU benchmarks such as latency and memory usage.

4. Objectives and Deliverables

We investigate how various CPU workloads and frequencies affect the performance of the deep learning task and system power under thermal design power (TDP) constraint. We fix GPU to do inference for an image classification task. Meanwhile, we run meaningful tasks on CPU to utilize the remaining resources of the embedded platform. Hence, we can better understand what is acceptable to run CPU without affecting the performance of the deep learning task. Moreover, we analyze how CPU-GPU workloads affect temperature values where CPU and GPU share the same power budget. Last but not least, we investigate the trade-off between the performance of the CPU workload and the performance of the deep learning task by investigating the instruction per cycle (IPC) for CPU as well as the latency for the deep learning task.

5. Results

5.1. GPU Baseline Results

In this section, we elaborate on the benchmarking deep neural networks that we choose, then we run them in 3 kinds of GPU frequencies to obtain the power, performance, and temperature profiles. These profiles act as the baseline for the study of the CPU-GPU execution scenario.

Benchmarks We choose small, medium, and large deep neural networks in terms of the depth of the network. Specifically, we choose 3 neural networks from those that are used to tackle image classification task of the ImageNet dataset. We summarize the benchmark we choose in Table. 1. We measure the memory overhead by using *tegrastat* provided by NVIDIA while inferencing the image.

Notice that there is only 4GB of RAM available on TX1, which is shared between CPU and GPU, with 1GB reserved by the operating system (Ubuntu). Hence, in the case of ResNet-152, it almost consumes all the available memory of the system that might leave barely nothing for the CPU. On the other hand, the shallowest neural network we have is AlexNet, and it still consumes a large amount of memory, i.e. 720 MB.

	Memory (MB)	# Layers	Top-1 Acc.
AlexNet[4]	720	7	57.2%
GoogLeNet[8]	820	22	68.7%
ResNet-152[2]	2224	152	77.0%

Table 1. The descriptions of the deep neural networks we choose, including the memory overhead during inference (single image), number of layers, and the reported top-1 accuracy on ImageNet.

We choose 3 kinds of GPU voltage/frequency pairs, i.e. the smallest (0.82 V, 76.8 Mhz), the medium (0.85 V, 537.6 Mhz), and the largest (1.1 V, 998.4 Mhz), from the 13 available voltage and frequency pairs on NVIDIA Tegra X1 to further investigate the power, latency, and temperature profiles of the aforementioned benchmarks.

Profiling We sweep through 3 different voltage and frequency pairs for each of the benchmark that we study and collect the temperature of both CPU and GPU, the power consumption of the GPU, and the latency of the tasks.

Figure 1 and Figure 2 show both the power and latency profile of the aforementioned DNN benchmarks running under different GPU voltage/frequency pairs. As expected,

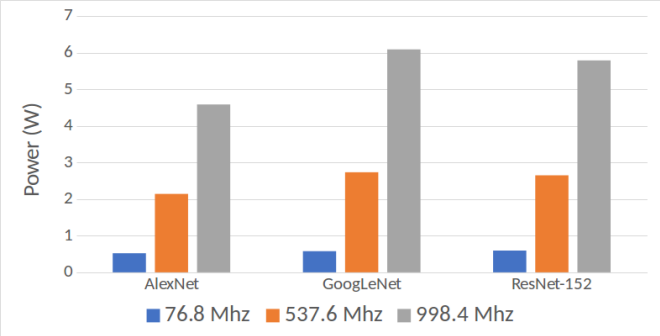


Figure 1. The power profile when running DNN benchmarks under different GPU voltage/frequency pairs.

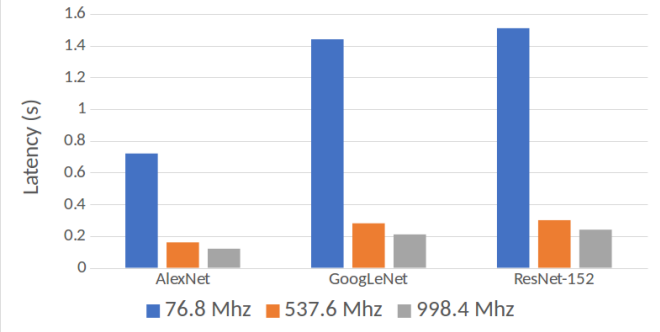


Figure 2. The latency profile when running DNN benchmarks under different GPU voltage/frequency pairs.

the power consumption is higher when the GPU voltage and frequency are higher. Also, the deeper the neural network the higher the latency. Interestingly, the power consumption of GoogLeNet is higher than ResNet-152 at each voltage and frequency pair, which implies that the utilization of the GPU when running GoogLeNet is higher than ResNet-152. On the other hand, the three benchmarks share similar temperature profiles, i.e. around 40C on average, which is far from the throttling temperature of the GPU on TX1, i.e. 89.5C.

To further compare and analyze the characteristics of these benchmarks, we normalize the latency, power consumption, and accuracy to AlexNet as shown in Figure 3. From AlexNet to GoogLeNet, the major increase of the cost is latency and power consumption with slightly increase in memory overhead. Though at the first glance that accuracy improves from 57.2% to 68.7% is not much compared to the increment in cost, it is hard to judge the impact of accuracy on the quality of services. On the other hand, from GoogLeNet to ResNet-152, the major cost increase is memory, i.e. more than 2x. In terms of memory overhead and accuracy, it seems that it does not worth it to go from GoogLeNet to ResNet-152 unless there is a hard target for the accuracy since it requires much more memory with small accuracy improvement.

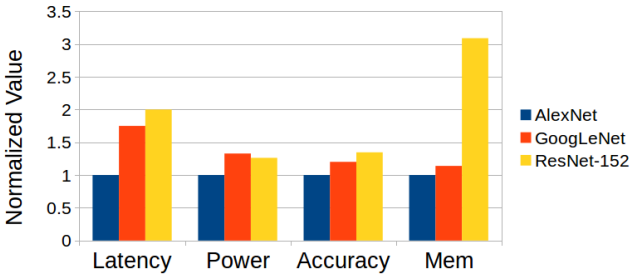


Figure 3. Compare the benchmarks in terms of latency, power consumption, memory overhead, and accuracy. The values are normalized to AlexNet. We fix the voltage/frequency pair to the highest one.

5.2. CPU Baseline Results

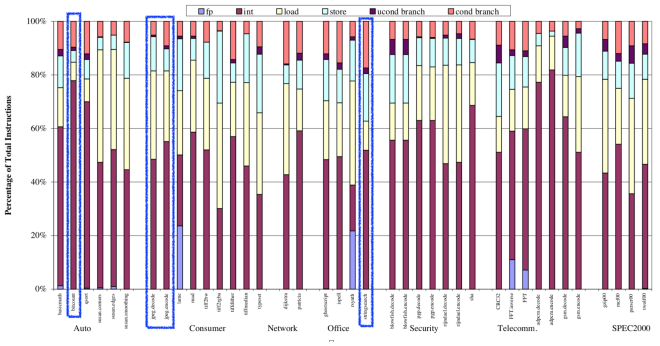
We choose 3 different benchmarks for CPU in MiBench benchmark suite. We run them in 3 CPU frequencies and obtain power, performance, and temperature results. These results provide baseline profiles for our final analysis in which we run CPU and GPU benchmarks together to better understand the trade-offs between various power and performance metrics.

Benchmarks We choose memory-intensive (jpeg), compute-intensive (bitcount), and a balanced (stringsearch) benchmarks from MiBench. In the previous report, we proposed to use SPLASH2 [9] benchmark suite. However, we changed it to MiBench and more daily usage benchmarks such as stringsearch which is an office benchmark. Our motivation to choose these benchmarks is doing meaningful work while running DNN on GPU. Hence, one may use CPU to run office programs while running a DNN inference on GPU.

We run these benchmarks at 3 different frequency values which are the lowest (102 Mhz), the middle (921.6 Mhz), and the highest (1.73 Ghz) available frequency values for CPU.

Profiling We run aforementioned 3 benchmarks with 3 different frequency values for CPU while not running anything on GPU to obtain a baseline for CPU. We calculate power, performance, and temperature results for CPU.

Figure 4. Characteristics of chosen CPU benchmarks.



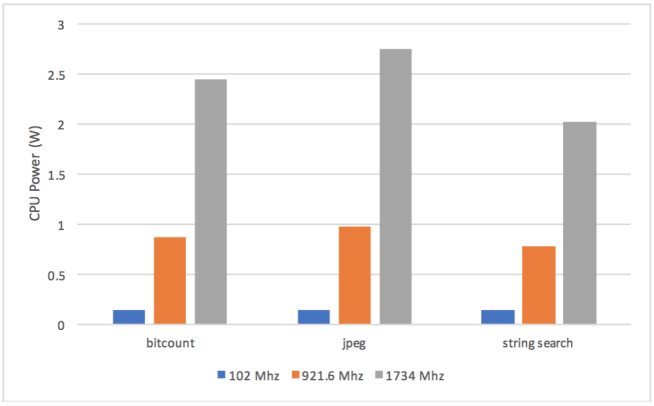


Figure 5. The power profile when running CPU benchmarks under different CPU voltage/frequency pairs.

We calculate power consumption using sensors in TX1 board as it is shown in Figure 5. One of the observations is that power consumption increases as we increase CPU frequency. Another important observation is that power consumption is the highest for jpeg encode/decode benchmark which is an image compression and decompression workload. Furthermore, the lowest power consumption comes from stringsearch benchmark which is an office workload. Moreover, we calculate temperature (Celcius) by using thermal sensors in TX1 board. Figure 6. shows temperature profile of CPU and GPU while running CPU benchmarks with various frequency values. Temperature results also follow the same trend with power results. In addition, GPU temperature also follows the same trend with CPU temperature since GPU does not run anything and CPU temperature affects GPU temperature. We also obtain performance results by using instruction per cycle (IPC) metric and CPU utilization for each frequency and benchmark pairs. Figure 7. shows IPC and CPU utilization results for each benchmark and frequency values. Results show that IPC value does not change when we change frequency values. Furthermore, CPU utilization is also at almost 100% for bitcount and jpeg benchmarks. However, CPU utilization is only 83% at 102 Mhz and it becomes 44% at 1.73 Ghz. It shows us that stringsearch benchmark does not need as much CPU resources as other benchmarks. Another significant conclusion is that IPC value of bitcount is higher than jpeg benchmark. However, power consumption of jpeg is higher than bitcount benchmark. It reveals that jpeg uses more power consuming instructions.

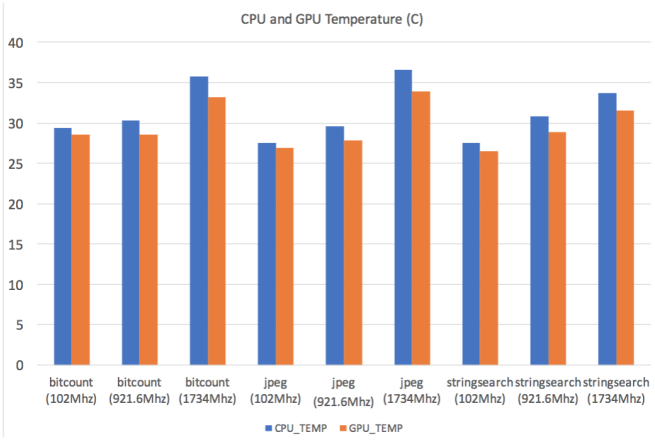


Figure 6. The temperature profile of CPU and GPU while running CPU benchmarks under different CPU voltage/frequency pairs.

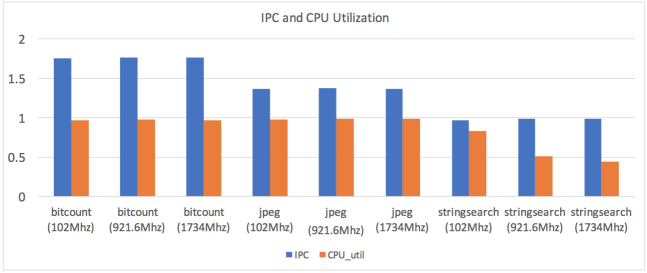


Figure 7. The performance profile of CPU while running CPU benchmarks under different CPU voltage/frequency pairs.

5.3. CPU-GPU Results

In this section, we analyze various power and performance metrics by running CPU and GPU benchmarks together.

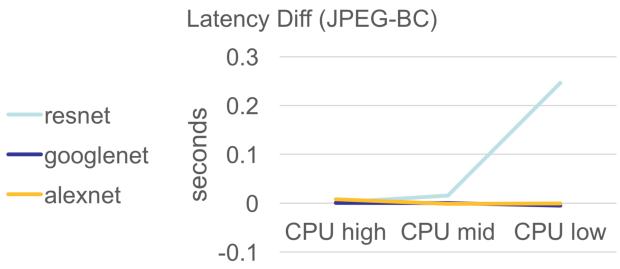


Figure 8. The latency difference between jpeg and bitcount benchmarks for various DNNs by using various CPU frequency values

Figure 8 shows the latency difference between a memory-intensive CPU benchmark (jpeg encode/decode) and a compute-intensive CPU benchmark (bitcount) for various DNNs by using high, mid, and low CPU frequency values. Results show that when we run memory-intensive DNNs such as ResNet, memory-intensive CPU benchmarks such as jpeg encode/decode adversely affects the DNN latency. We observe 13% performance difference with ResNet compared to other DNNs. Hence, these results show that memory consumption of both DNN and CPU benchmarks plays an important role in overall power and performance.

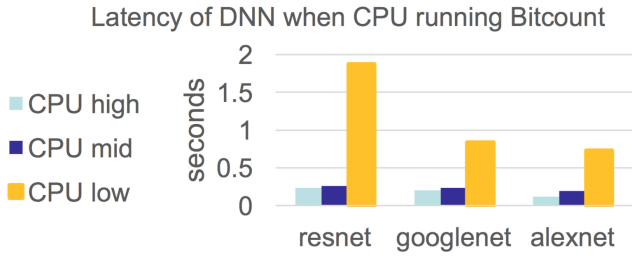


Figure 9. The latency of various DNNs when CPU running bitcount benchmark with various CPU frequency values

Figure 9 shows the latency of various DNNs when CPU running a compute-intensive (bitcount) benchmark by using high, mid, and low cpu frequency values. Results show that although most of the deep learning tasks can be run on GPU, frequency of CPU still plays an important role due to data preparation stage. We observe up to 8.2x performance difference with low CPU frequency and high CPU frequency configurations. This affect increases as we use larger DNNs such as ResNet.

Figure 10 shows the GPU power consumption difference between GoogLeNet and ResNet by using various CPU and GPU frequency configurations. It shows that GoogLeNet consumes more power than ResNet-152, which is deeper and larger, consistently. It exaggerates as the gap between CPU and GPU frequency values grows larger.

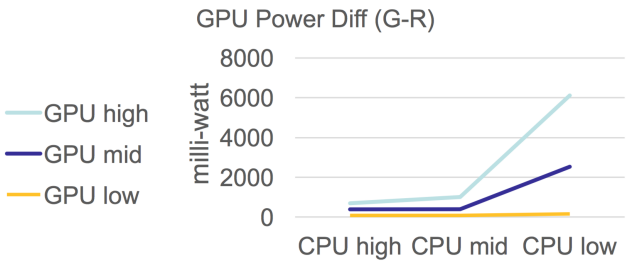


Figure 10. The GPU power consumption difference between GoogLeNet and ResNet by using various CPU and GPU frequency configurations

6. Conclusion

In this project, we analyze power and performance results of various deep neural networks running jointly with various CPU benchmarks on a CPU-GPU platform which is NVIDIA Jetson TX1. Power and performance analysis identify what is left to be done on CPU while GPU is running inference on deep neural network.

Our comprehensive analysis (81 results with different configurations) shows us the best CPU benchmarks to run with various DNN configurations. Our results show that although people focus on GPU for running DNNs, role of CPU is not negligible in deep learning applications. CPU frequency still plays a significant role due to data preparation stage. Another important conclusion is that memory consumption of both CPU and GPU workloads affects overall power and performance. Therefore, memory consumption of both CPU and GPU benchmarks should be taken into consideration while running CPU-GPU benchmarks together.

Group members worked closely on each task to come up with a thorough analysis of power and performance results for deep learning on a CPU-GPU platform. Team members worked jointly on this report and analysis.

Project materials are available in the project website. *https://github.com/afinci/18-743-Power-and-Performance-optimizations-for-DNNs-on-CPU-GPU*

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