Project Report

Architecture and Platforms for AI (M2)

BY HANYING ZHANG

August, 2021

1 Brief Problem Description

In this project we implement a simplified Neural Network. For each layer, the difference from a standard FC layer is that, when computing the value of each neuron in the output layer, instead of using all neurons in the input layer, we use only R neurons, as shown in the figure below. The activation function we use here is *Sigmoid*.

We then combine K such layers to form a Neural Network. The W and b parameters of each layer may be different while R is always the same for all layers.

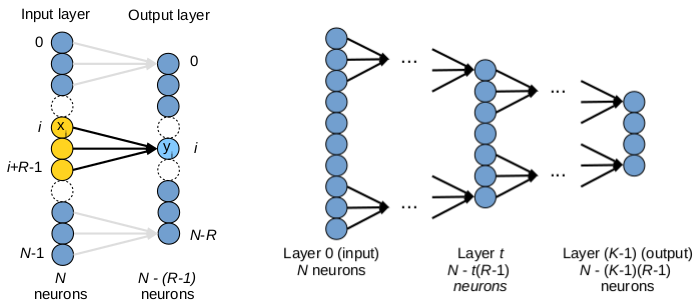


Figure 1. The simplified NN

2 Machine Specific

The whole project was written and tested on my local machine. The CPU is a i7-6700HQ which has 4 physical cores. It uses *Intel*'s *Hyper-threading* technology which needs to be turned down because the performance of the virtual cores is only 15-30% of the physical ones on average.[1]

The GPU is a Nvidia GTX 1060 with 6 GB global memory. The specifications is shown in the image below:

1. https://en.wikipedia.org/wiki/Hyper-threading

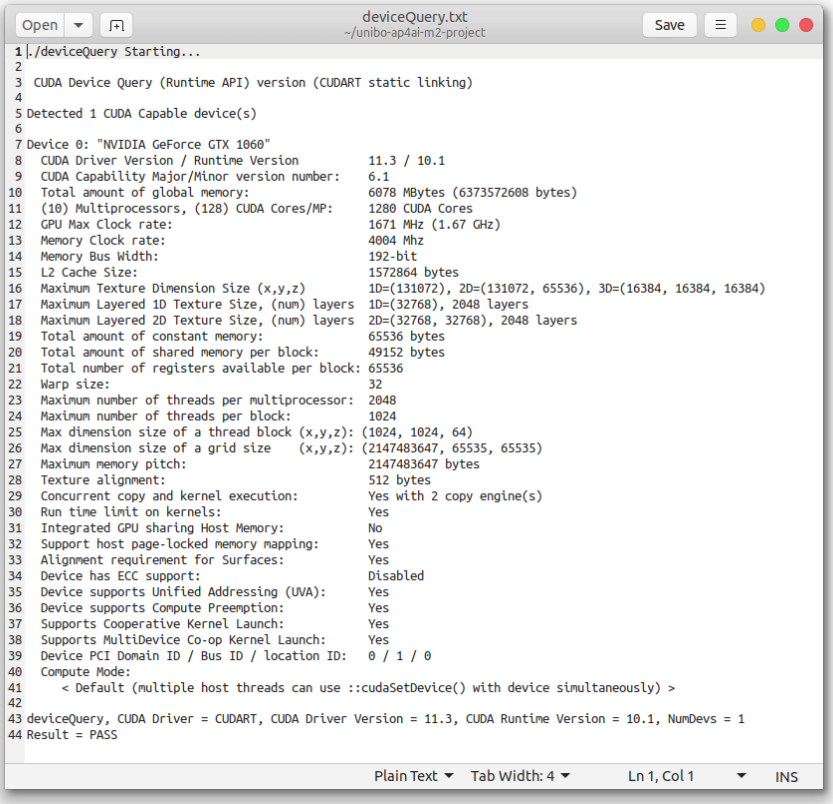


Figure 2. GTX 1060 specifications

The operating system is Ubuntu 20.04.1 LTS. The GCC version is 9.3.0. The CUDA version is 11.3 and NVCC version is 10.1.243.

3 Base(Serial) Implementation

The main purpose of the serial implemention is to check the correctness of the OpenMP and CUDA implementations. It also provides the skeleton for the parallel implementations.

The serial implementation is very straitforward. It's basiclly a 3-layer nested loop. In the main function, all K layers are looped over. For each layer, there's a function performing the culculation in which there's a loop over all the neurons in the output layer. For each neuron, a loop over the R corresponding neurons in the previous layer is implemented.

The header file *hpc.h* provided during the lectures is used in this assignment to provide facility functions such as time recording.

3.1 Parameter Parsing

The C library function named *getopt*[2] which is included in *unistd.h* is used for parameter parsing. It is a part of the POSIX specification, and is universal to Unix-like systems. In the serial and CUDA implementations, the parameters N and K are parsed by -n and -k options respectivelly. In the OpenMP implementation, the number of threads is also parsed by a -t option.

2. https://en.wikipedia.org/wiki/Getopt

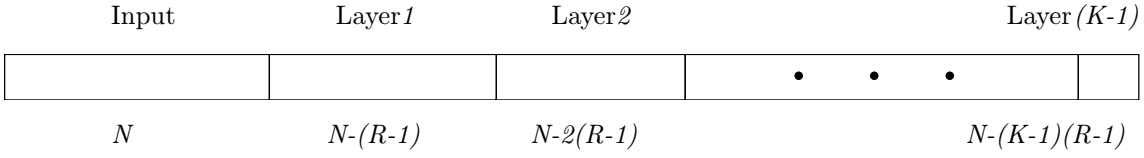
3.2 The Memory Management Method

In the first versions, one array in the stack is used to store the latest layer got calculated. Then the *N-t(R-1)* elements from the beginning of this array are re-used when calculating the *t-th* layer. The benefit of this method is the small memory costage. But it is very different from the real life implementation of Neural Networks. For instance, if we want to extend our project to be able to do the back propagation in future, then we will have to face the problem of lacking of information.

So the memory management method is changed by storing all the parameters and results in the heap. In this method we consumed more memory but we also kept the necessary information.

Specifically, one array named y is used to store all layers of neurons, input layer included. Two other arrays named b and W are used to store all the bias and weights respectively. When doing the calculation of the *t-th* layer, the starting indices of the corresponding data for this layer are calculated.

The diagram below shows how the neurons(y) are stored in the array. The other two parameters, i.e. b and W, are stored in the same way. The starting indices could be got by accumulating the length of all previous layers.



4 OpenMP Implementation

The OpenMP implementation is very similar to the serial one. In the layer-calculation function, two *omp for* under one *omp parallel* are used. The first one is used to do the MAC calculation in which an *array reduction* and a *collapse(2)* are used. The second one is used to do the *Sigmoid* calculation. For both of them a *static schedule* is used because they are pre-determined and predictable work.

5 CUDA Implementation

When doing the CUDA implementation, the first idea came into mind is using one block to calculate one neuron in the output layer. The problem with this method is that most threads in each block are wasted if R is a small value, as the warp size is 32.

So using one block to calculate more than one neuron is a better idea. The BLKDIM is defined to *(n_nodes/R*R)*R* in which *(n_nodes/R*R)* is the number of neurons being able to be divided by R. The value of *n_nodes* used in the code is 64.

One array named *local_y[BLKDIM]* is used in the shared memory to store the values of multiplications of x and W. Then R these local values are accumulated and feed to the *Sigmoid* function. The *Sigmoid* function is a device function in which *expf()* is used instead of *exp()*.

6 Correctness Checking

The way we do correctness checking is to make sure that the OpenMP version and CUDA version could get the same result as the serial version.

In order to do this, we must make sure that the initial values of the parameters are all the same in these 3 implementations. A random seed is used to make sure the random values are the same. We also have to make sure that all parameters are initialized in the exactly same order.

One function named *random_init_small()* is used to provide random float values between -1 and 1.

7 Performance Analysis

In order to get the result as accurate as possible, when booting into the operating system, text mode is activated instead of the default graphic mode, to avoid the interruptions of other unnecessary applications. For each time costage, the code is run for 5 times and their mean value is used.

What we need here is **Wall Clock Time** instead of **CPU Time**, thus the *clock()* function defined in *time.h* is not suitable. What used in this assignment is the *hpc_ gettime()* function in *hpc.h* file provided in the course.

7.1 OpenMP Performance

7.1.1 Strong Scaling

For strong scaling performace of OpenMP implementation, we need to keep the same overall workload while increasing the cores. The parameters used here are $N=2M$ and $K=100$. The result is shown in figure 3. It could be seen that the first two cores keep nearly the linear performance but the performace of the last two cores decrease a lot.

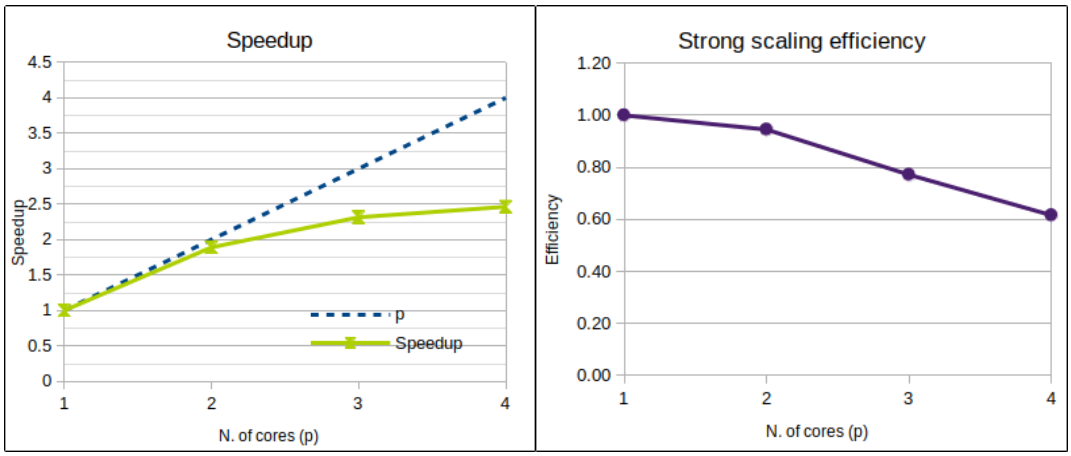


Figure 3. OpenMP Strong Scaling Performance

7.1.2 Weak Scaling

The weak scaling asks us to keep theoretically the same workload for each core. The parameters used are $N=24k$ for each core and K equals to 10, 20, 50 and 100 respectively. The reason we use different values of K is to see whether K could also effect the performance. The final reault is shown in the figure below.

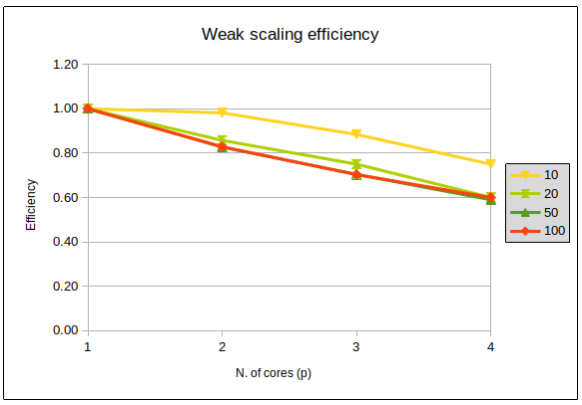


Figure 4. OpenMP Weak Scaling Performance

The theoretical performace could only be achieved when K=*10* and 2 cores are used. We could also see that the performance is better when K is smaller. The performance is almost the same when K=*50* and K=*100*.

7.2 CUDA Performance

When evaluating the performance of the CUDA program, we use two different metrics, i.e. the throughput and the speedup to the CPU performance. The parameter used here are K=*300* and N ranges from *1k* to *1M*. The memcpy time between host and device is excluded in this experiment.

7.2.1 Throughput

The throughput is calculated in this way: number of all processed nuerons/seconds as a function of the input size N. It can be seen from the following image that the performance gets better as the input size grows. There's a leap in the performance when N equals to *500k*.

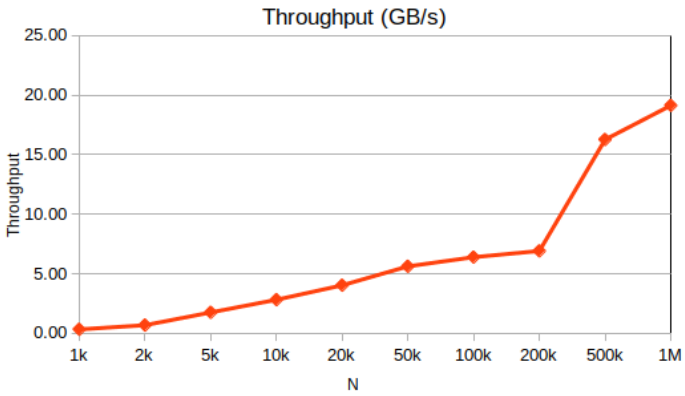


Figure 5. CUDA Throughput

7.2.2 Speedup vs. CPU

To measure the CPU running time, the OpenMP code is used again to make sure that we make the full advantege of all the CPU cores.

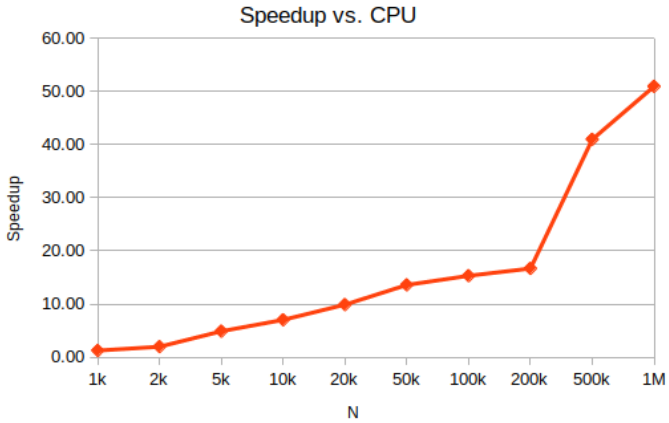


Figure 6. Speedup vs. CPU

The performance follows the same trend as the throughput, as shown in figure 6. There's also a leap when N equals to *500k*, and when N equals to *1M*, we could get a 50 times speedup vs. CPU performance.