ECE 408 Project Report

Team Name: fast_af
Names: Omar Taha, Jason Gong, Shreyas Byndoor
NetIDs: otaha2, xg8, byndoor2
Rai IDs: 5c78c4b084318364bab96f01,
Affiliation: Chicago City Scholars

Milestone 1

Kernels that collectively consumed more than 90% of the program time:

- [CUDA memcpy HtoD]
- cudnn::detail::implicit_convolve_sgemm
- volta_cgemm_64x32_tn
- op_generic_tensor_kernel
- fft2d_c2r_32x32
- volta_sgemm_128x128_tn
- cudnn::detail::pooling_fw_4d_kernel
- fft2d_r2c_32x32

CUDA API calls that collectively consume more than 90% of the program time:

- cudaStreamCreateWithFlags
- cudaMemGetInfo
- cudaFree

Kernels vs. API Calls:
CUDA Kernels are simply defined as regular C functions. However, unlike typical C functions, CUDA Kernels are executed N times in parallel by N different CUDA threads. Meanwhile, CUDA APIs provide C functions that execute on the host to allocate and deallocate device memory, transfer data between host memory and device memory, manage systems with multiple devices, etc. They are not executed by each CUDA thread as a Kernel is.

Output of rai running MXNet on the CPU:

```
Loading fashion-mnist data... done
Loading model... done
New Inference
EvalMetric: {'accuracy': 0.8236}
9.30user 3.46system 0:05.34elapsed 239%CPU (0avgtext+0avgdata
2471560maxresident)k
0inputs+2824outputs (0major+666761minor)pagefaults 0swaps
```

Program run time:

```
0:05.34 elapsed
```

Output of rai running MXNet on the GPU:

```
Loading fashion-mnist data... done
Loading model... done
New Inference
EvalMetric: {'accuracy': 0.8236}
4.41user 3.28system 0:04.34elapsed 177%CPU (0avgtext+0avgdata
2837968maxresident)k
0inputs+4552outputs (0major+661333minor)pagefaults 0swaps
```

Program run time:

```
0:04.34 elapsed
```

Milestone 2

program execution time:

0:15.52 elapsed

Op Times:

1) Op Time: 2.826305

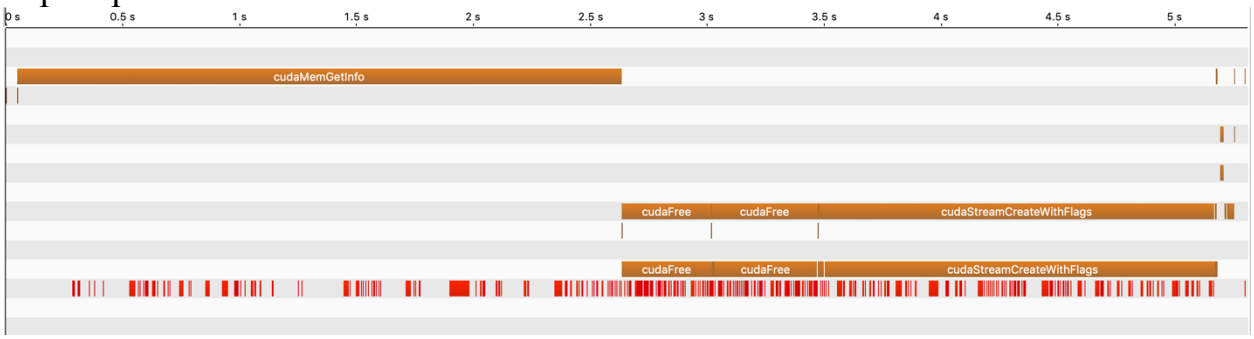
2) Op Time: 11.143122

Milestone 3

Correctness & Timing:

	DataSet 100	DataSet 1000	DataSet 10000
Op Time #1	0.000079	0.000558	0.005636
Op Time #2	0.000216	0.001974	0.021531
Correctness	0.84	0.852	0.8397

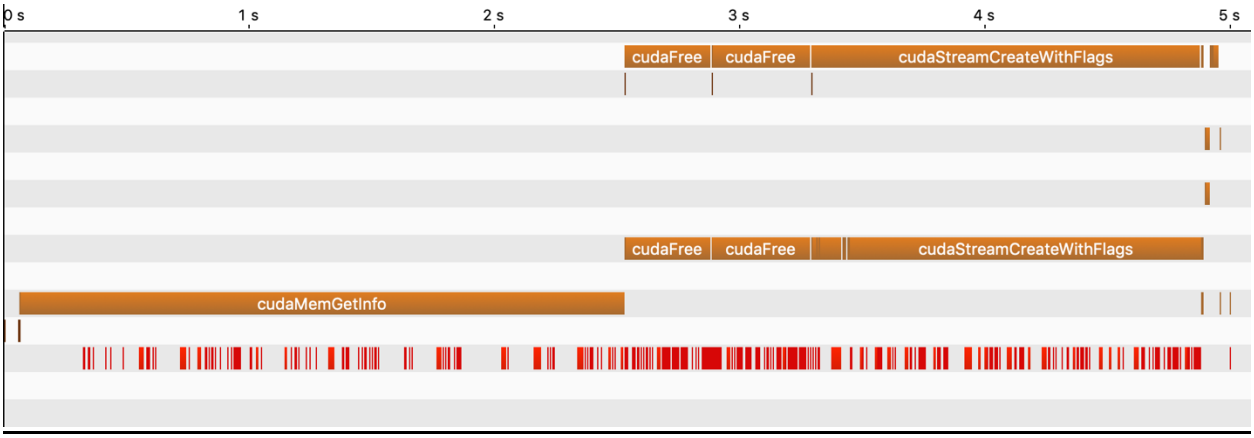
nvprof profile:

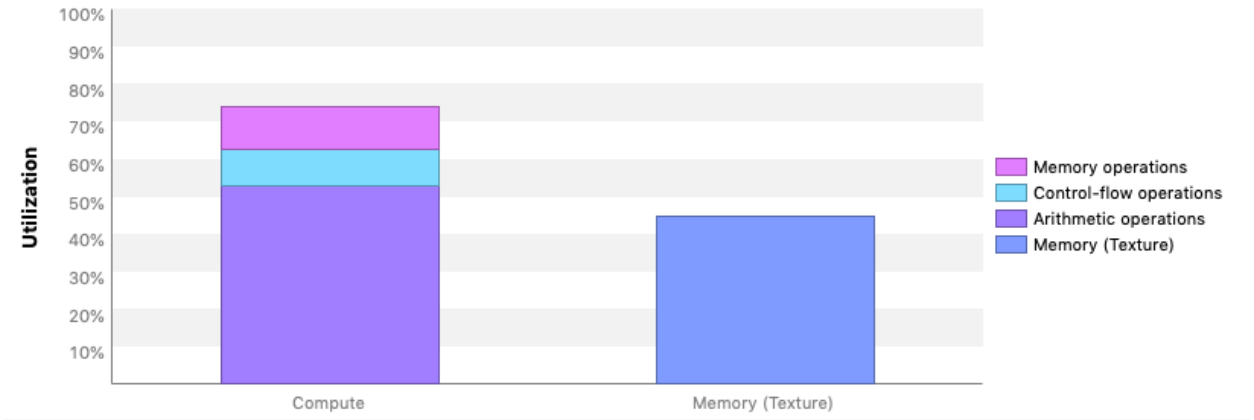


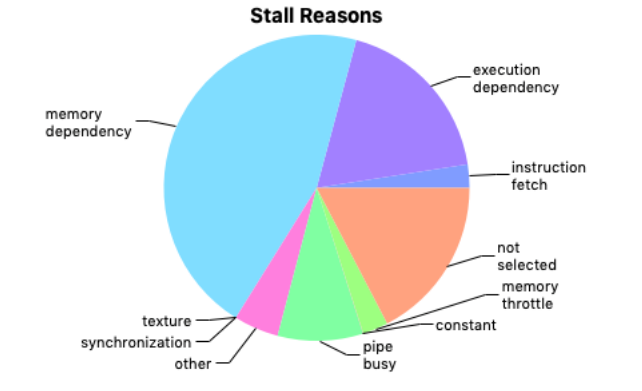
Milestone 4

All Kernel Optimization Code can be found in their respective src code file “new-forwardOp#<Optimization Number>.cuh”

Base Profiling:



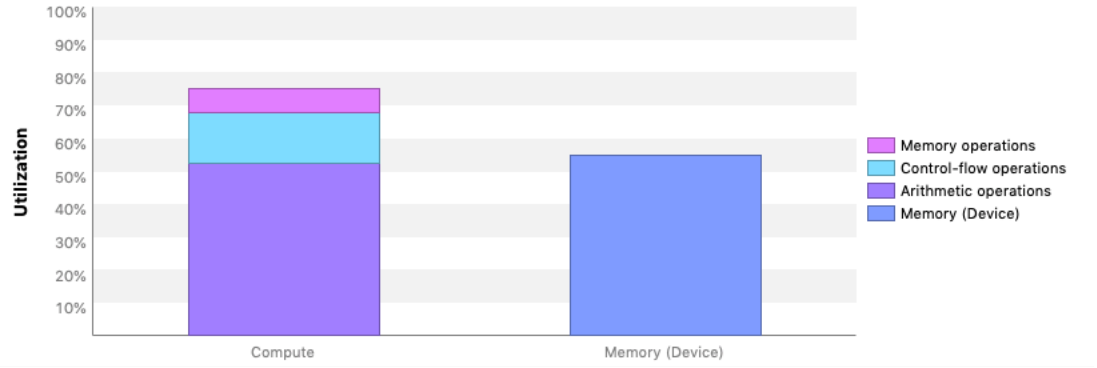




Optimization #1: Weight Matrix in Constant Memory

The Weight Matrix is a set matrix that is constantly being reused by the kernel to perform the convolution operation. By copying the weight matrix into constant memory before kernel execution, we are drastically decreasing the number of global memory reads. The kernel then reads from constant memory for the entire weight matrix.

This has resulted in a decrease in the Avg. Runtime Duration from ~5.26 ms to ~4.697 ms. This is because we are no longer doing many costly global memory reads for the weight matrix data. More importantly, from the graph below, we see that the Memory Operations utilization decreased compared to the Base Kernel Memory Operation (see above). This is good in that we are decreasing the amount of time and resources that are spent on memory operations (read/writes).

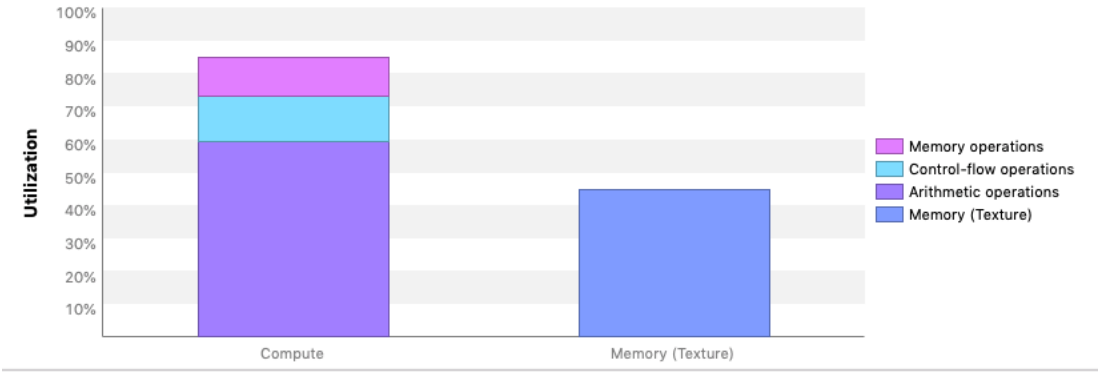


Optimization #2: Input Data in Shared Memory

Input Data is constantly being used by the kernel, and different threads are reusing input data. If we are not careful about the use of input data, we will have a large number of global memory reads that will cause a memory bottleneck causing the kernel to slow down due to memory latency. To address this, we will read input data once and store it into the devices shared memory. Then we are saving many global memory reads for every reuse of a input element.

We viewed that the Base Kernel had 53.22 Active Warps resulting in an 83.2% Occupancy Per SM. After the shared memory optimization, that number jumped to 61.78 Active Warps resulting in a 96.5% Occupancy Per SM. In addition to this, according to the chart below, we noticed that the Compute Utilization jumped up to ~85% from ~75%. This is due to both a jump in the Control-flow Operations as well as Arithmetic Operations. This tells us we must decrease the control divergence caused by this optimization. The L2 Cache usage was also increased to 454.5 GB/s from 276.5 GB/s; This means we are utilizing shared memory much more in the kernel

*This analysis was done on the forward:1 Kernel but was also compared to the forward:1 Kernel of the Base Naïve implementation



Optimization #3: Double Buffering

To ensure that all shared data is up to date and has not change, we must have 2 syncthreads() API calls. The first is to ensure data is loaded, and the second is to ensure the data has been consumed before rewriting the data in the next iteration. In an effort to get around this, we utilized Double Buffering. The idea was to have 2 sections of shared memory in which we switch the pointers each iteration. This way, we eliminate the need for the second syncthreads() API call.

We found that this optimization greatly reduced the stall due to synchronization. The two charts below show the effect before and after Double Buffering. The left shows before, and the right shows after. As we can see, the synchronization stall was approximately halved. However, although the synchronization stall was decreased, the operational run time of the kernel did not seem to be affected.