Team Profile
Name: cudafree
Member1: Chenwei Zhang NetID: chenwei6
Member2: Tinghui Liao NetID: tinghui4
Member3: Kun Qiao NetID: kunqiao2
Affiliation: UIUC

Milestone 1

1. A list of all kernels that collectively consume more than 90% of the program time.

Time (%)	Name
37.23%	CUDA memcpy HtoD
22.28%	volta_scudnn_128x32_relu_interior_nn_v1
21.16%	void cudnn::detail::implicit_convolve_sgemm<…>(…)
7.40%	void cudnn::detail::activation_fw_4d_kernel<…>(…)
6.83%	volta_sgemm_128x128_tn
4.39%	void cudnn::detail::pooling_fw_4d_kernel<…>(…)

2. A list of all CUDA API calls that collectively consume more than 90% of the program time.

Time (%)	Name
40.92%	cudaStreamCreateWithFlags
33.41%	cudaMemGetInfo
22.44%	cudaFree
1.06%	cudaMemcpy2DAsync
0.81%	cudaStreamSynchronize

3. Explanation of the difference between kernels and API calls.

Kernels are low-level computer programs interfacing with the hardware (i.e. GPU) on top of which applications are running. Kernels could also manage input/output requests from software.

But API calls are sets of protocols, subroutine definitions, and tools for building application software. API calls will provide interfaces that developers should use when writing code using libraries and a kind of programming language.

4. Show output of rai running MXNet on the CPU

Loading fashion-mnist data... done
Loading model... done
New Inference
EvalMetric: {'accuracy': 0.8177}

5. List program run time(CPU)

19.88user 3.70system 0:13.53elapsed 174%CPU (0avgtext+0avgdata 5956128maxresident)k
0inputs+2856outputs (0major+1585668minor)pagefaults 0swaps

6. Show output of rai running MXNet on the GPU

Loading fashion-mnist data... done
Loading model... done
New Inference
EvalMetric: {'accuracy': 0.8177}

7. List program run time(GPU)

4.34user 2.44system 0:04.75elapsed 142%CPU (0avgtext+0avgdata 2849272maxresident)k
0inputs+4568outputs (0major+706602minor)pagefaults 0swaps

Milestone 2

1. Create a CPU implementation

```
void forward(mshadow::Tensor<cpu, 4, DType> &y, const mshadow::Tensor<cpu, 4, DType> &x,
const mshadow::Tensor<cpu, 4, DType> &k)
{
  const int B = x.shape_[0];
  const int M = y.shape_[1];
  const int C = x.shape_[1];
  const int H = x.shape_[2];
  const int W = x.shape_[3];
  const int K = k.shape_[3];

  int H_out = H - K + 1;
  int W_out = W - K + 1;

  for (int b = 0; b < B; ++b)
    for(int m = 0;  m < M;  m++)
      for(int h = 0; h < H_out; h++)
        for(int w = 0; w < W_out; w++) {
          y[b][m][h][w] = 0;
          for(int c = 0;  c < C; c++)       // sum over all input feature maps
            for(int p = 0; p < K; p++)       // KxK  filter
              for(int q = 0; q < K; q++)
                y[b][m][h][w] += x[b][c][h + p][w + q] * k[m][c][p][q];
        }
}
```

2. List whole program execution time

133.67user 4.39system 2:07.99elapsed 107%CPU (0avgtext+0avgdata 5951716maxresident)
k
0inputs+1464outputs (0major+2266968minor)pagefaults 0swaps

3. List Op Times

Op Time: 21.634391
Op Time: 102.079140

4. Check correctness on the full data size of 10000

✱ Running python m2.1.py 10000
Loading fashion-mnist data... done
Loading model... done
New Inference
Op Time: 21.515465
Op Time: 102.543038
Correctness: 0.8171 Model: ece408

Milestone3

1. Implement a GPU convolution

a. dataset sizes = 100

```
✱ Running python m3.1.py 100
Loading fashion-mnist data... done
Loading model... done
New Inference
Op Time: 0.000610
Op Time: 0.001632
Correctness: 0.85 Model: ece408
```

b. dataset sizes = 1000

```
✱ Running python m3.1.py 1000
Loading fashion-mnist data... done
Loading model... done
New Inference
Op Time: 0.006196
Op Time: 0.016092
Correctness: 0.827 Model: ece408
```

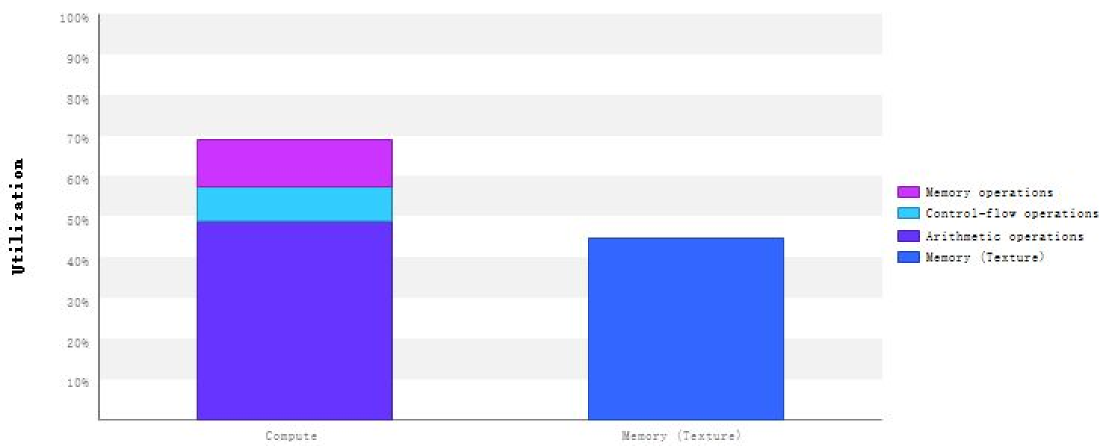
c. dataset sizes = 10000

```
* Running python m3.1.py 10000
Loading fashion-mnist data... done
Loading model... done
New Inference
Op Time: 0.064463
Op Time: 0.149743
Correctness: 0.8171 Model: ece408
```

2. Demonstrate nvprof profiling execution

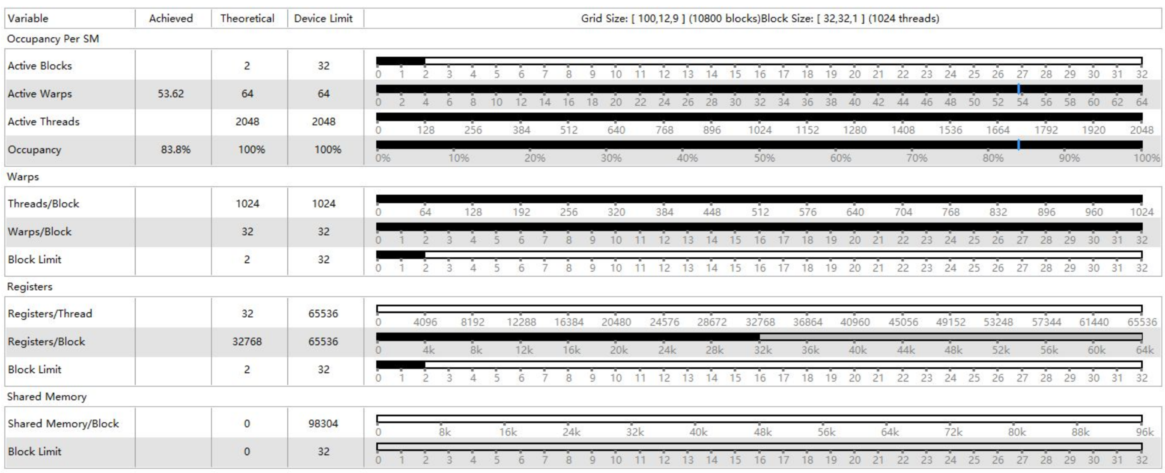
In milestone 3, we just use a kernel and simply mapping CPU computation into GPU computation, so its performance is not not good. We will try to do some optimizations in milestone 4. Here are the performance report for our kernel:

a. kernel perfomance limiter



This kernel exhibits low compute throughput and memory bandwidth utilization, which are below 60%. Its performance is most likely limited by the latency of arithmetic or memory operations.

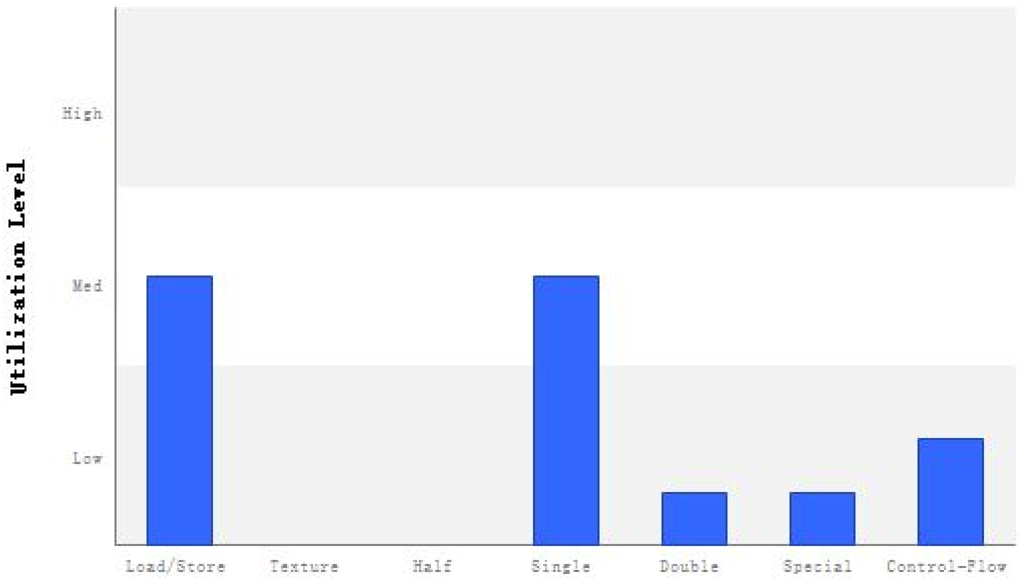
b. resource utilization



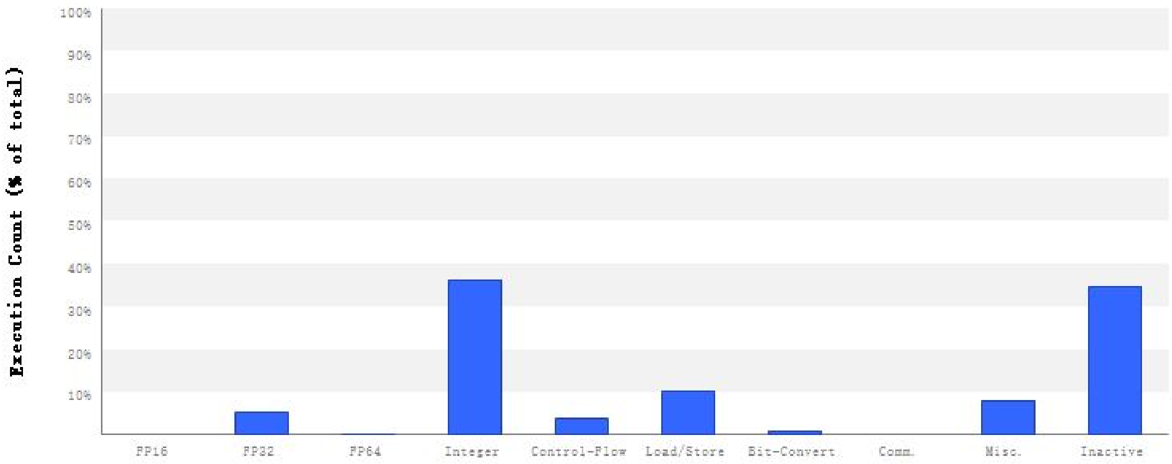
Variable	Achieved	Theoretical	Device Limit	Grid Size: [100,12,9] (10800 blocks)Block Size: [32,32,1] (1024 threads)
Occupancy Per SM				
Active Blocks		2	32	
Active Warps	53.62	64	64	
Active Threads		2048	2048	
Occupancy	83.8%	100%	100%	
Warps				
Threads/Block		1024	1024	
Warps/Block		32	32	
Block Limit		2	32	
Registers				
Registers/Thread		32	65536	
Registers/Block		32768	65536	
Block Limit		2	32	
Shared Memory				
Shared Memory/Block		0	98304	
Block Limit		0	32	

It shows that the kernel's block size, register usage, and shared memory usage allow it to fully utilize all warps on the GPU.

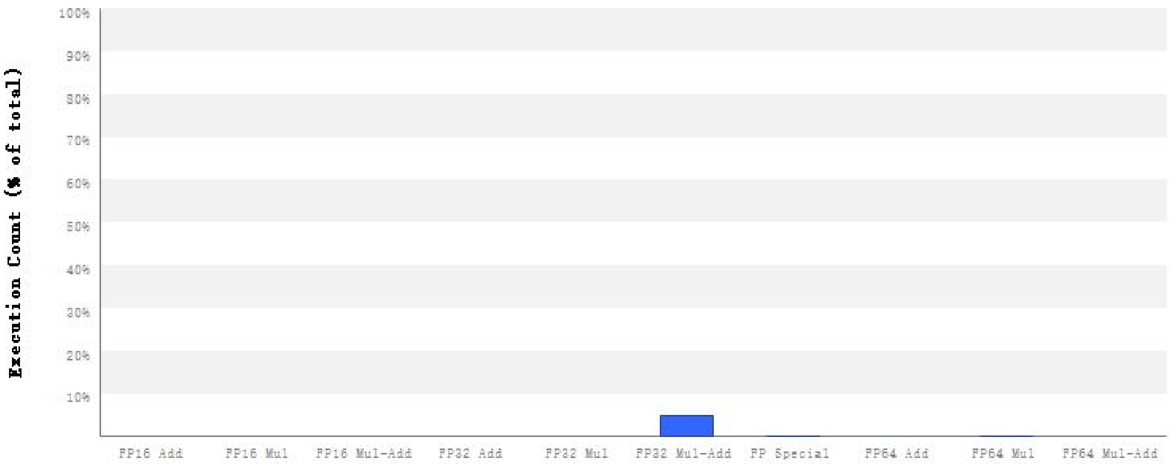
c. **kernel compute**



fuction unit utiliaztion



instruction excecution counts



floating-point operatons count

It is reported that the warp execution efficiency for these kernel is 71.9% if predicated instructions are not taken into account and the kernel's not predicated off warp execution efficiency of 65.1% is less than 100% due to divergent branches and predicated instructions.

d. kernel memory

	Transactions	Bandwidth	Utilization
Shared Memory			
Shared Loads	0	0 B/s	
Shared Stores	0	0 B/s	
Shared Total	0	0 B/s	Idle Low Medium High Max
L2 Cache			
Reads	1065490	62.807 GB/s	
Writes	831616	49.021 GB/s	
Total	1897106	111.828 GB/s	Idle Low Medium High Max
Unified Cache			
Local Loads	0	0 B/s	
Local Stores	0	0 B/s	
Global Loads	53219950	3,137.136 GB/s	
Global Stores	831600	49.02 GB/s	
Texture Reads	24491449	5,774.753 GB/s	
Unified Total	78542999	8,960.909 GB/s	Idle Low Medium High Max
Device Memory			
Reads	69272	4.083 GB/s	
Writes	859137	50.643 GB/s	
Total	928409	54.727 GB/s	Idle Low Medium High Max
System Memory [PCIe configuration: Gen3 x16, 8 Gbit/s]			
Reads	0	0 B/s	Idle Low Medium High Max
Writes	5	294.733 kB/s	Idle Low Medium High Max

As the table shows, our kernel do not use any shared memory. The utilization of L2 cache and device memory is low relative to the maximum throughput supported by the corresponding memory.

e. divergent excecution

Divergence = 22.9% [79200 divergent executions out of 345600 total executions]

The report indicates that divergent executions in our kernel account for 22.9% of total excecutions. Therefore, divergent branches lower warp execution efficiency, which leads to inefficient use of the GPU's compute resources. That's what we need to improve in milestone 4.