APMA 2822b Homework 4

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Code is attached in the email. I have included a CMakeLists.txt file which can be used to compile the code on the CCV. The `cuda/9.1.85.1` module must be loaded. CUDA 10 also works, but results in errors when using nvprof. I also added the SLURM scripts I used.

Algorithm and Implementation

I implemented sparse matrix vector multiplication using the CRS and ELLPACK data formats. The ELLPACK data format constructs a dense matrix with the same number of rows as the sparse matrix and as many columns as the maximum number of non-zero elements in the sparse matrix. As such, the data format performs well when the number of non-zeros in most rows is close to the maximum number of non-zeros. This provided sparse matrix is well suited to the ELLPACK data format because the maximum number of non-zeros in a column (87) is very close to the average number of non-zeros (54.8). The ELLPACK data format takes the non-zero elements in each row and packs them into this dense matrix. The column indexes of the entires are recorded in another dense matrix with the same shape. To perform multiplication, each entry in the dense matrix may be looped through and multiplied by the corresponding element in the vector. The matrix of indexes is used to determine which vector element to use. I also stored the number of elements in each row and only looped through that many elements as a further optimization. On the CPU ELLPACK implementation, the loop was unrolled over rows to improve vectorization. The cuSPARSE library was used for comparison. Specifically, I tested using `cusparseDcsrmv` which operates on data in the CRS format. Both approaches were evaluated on the CPU, and on the GPU using both unified and device only memory. I also tested storing the vector in texture memory, which improves mostly random, but spatially local data access. Hypothetically, this is advantageous because each a group of threads will be operating on the same part of the vector at once.

2 Results

All testing was done on the CCV with a GPU (TITAN V) and a CPU core. Time required to copy data and convert between formats wasn't counted. I ran each test 10 times and timed each run individually so that the start up memory transfer cost for each approach could be evaluated. Results are reported in terms of the time required for one iteration of

Method	Average time	1	2	3
CPU	1.600510e-04	7.989560e-04	1.593470e-04	1.586510e-04
GPU	4.646400e-05	5.334400e-05	4.668800e-05	4.742400e-05
GPU texture memory	4.848800e-05	1.091520e-04	5.129600e-05	4.912000e-05
CPU managed before GPU	1.610724e-04	2.447670e-04	2.344980e-04	1.753500e-04
GPU managed	4.674400e-05	4.469568e-03	4.918400e-05	4.796800e-05
CPU managed after GPU	1.610724e-04	2.447670e-04	2.344980e-04	1.753500e-04
cuSPARSE	3.886400e-05	1.065280e-04	4.323200e-05	3.977600e-05

Table 1: The recorded timings for each method utilizing the CRS data format. The average is the average over the 10 runs excluding the first two runs. Only the first 3 runs are shown to highlight transfer times associated with managed memory.

the provided matrix. The exact time and GLOPS of the computation will depend on the characteristics of the sparse matrix.

On the GPU, the cuSPARSE implementation was the fastest. The ELLPACK and standard implementations were very similar and almost as fast as the cuSPARSE implementation. On the CPU, the CRS implementation was the fastest. The optimal value for ELLPACK row loop unrolling was found to be 4. Storing the number of elements in each row and only looping through the required elements improved CPU and GPU performance. Using a texture resulted in no improvement for CRS or ELLPACK. The timing results can be seen in tables 1 and 2.

Unified and device memory had similar performance after the first iteration. The first iteration using managed memory which switched from the CPU to GPU was substantially slower because the managed memory needed to be transfered from device to host.

Interestingly, the average kernel timings reported by nvprof were substantially different from the timing found by the code. I used the CUDA event API to time CUDA kernels in the code. I tested on both my laptop and the CCV and the disparity wasn't at all present on my laptop. The average kernels durations as reported by nvprof are given in table 3 below. I think that most likely the kernel timings reported by nvprof are incorrect and the issue may be related to the nvprof error which using CUDA 10. The issue may also be occurring in CUDA 9, but isn't properly reported.

Profiling the code using nvprof allowed for detailed inspection of the time required for each CUDA API call. The timings for each CUDA API call are given in table 4 below. `cudaFree` was found to use a large percentage of the overall time of the program (437.68 ms). It isn't clear to me why this would be the case. `cudaMalloc`, `cudaMallocManaged`, and `cudaMallocPitch` also took substantial program execution time. `cudaMemcpy` consumed most of the remaining time spent on CUDA API calls.

Method	Average time	1	2	3
CPU	2.352189e-04	7.101640e-04	3.498100e-04	2.545160e-04
GPU	4.766800e-05	5.331200e-05	4.723200e-05	4.729600e-05
GPU texture memory	4.765600e-05	4.881280e-04	4.928000e-05	4.761600e-05
CPU managed before GPU	2.949605e-04	1.024591e-03	8.099850e-04	3.533850e-04
GPU managed	4.756000e-05	8.975392e-03	5.948800e-05	4.678400e-05
CPU managed after GPU	2.949605e-04	1.024591e-03	8.099850e-04	3.533850e-04

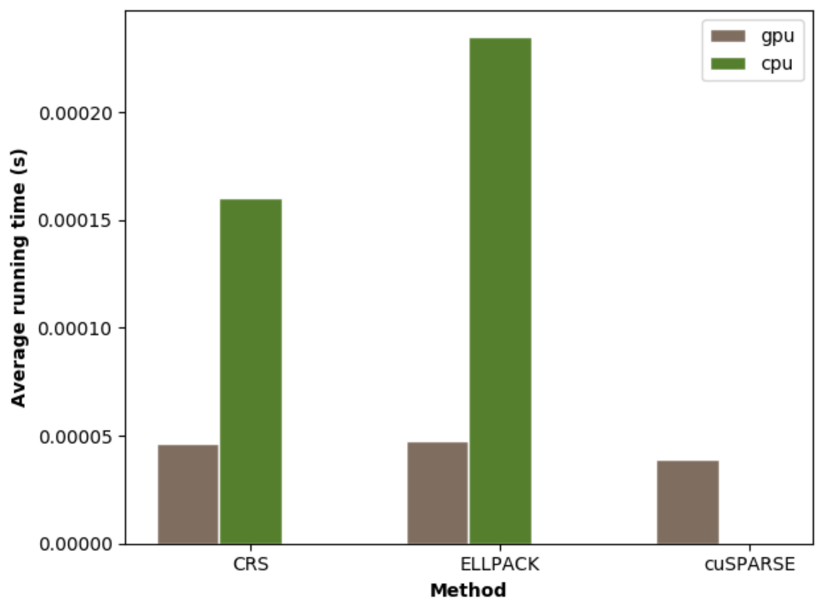
Table 2: The recorded timings for each method utilizing the ELLPACK data format. The average is the average over the 10 runs excluding the first two runs. Only the first 3 runs are shown to highlight transfer times associated with managed memory.

Method	Average kernel time
ELLPACK	865.07us
CRS	260.40us
ELLPACK texture memory	82.038us
CRS texture memory	43.023us
cuSPARSE	38.012us

Table 3: The average running time of each kernel as reported by nvprof. I think these timings are likely wrong.

API call	Time
cudaFree	437.68ms
cudaMalloc	296.62ms
cudaMemcpy	30.429ms
cudaMallocManaged	20.848ms
cudaEventSynchroni	16.806ms
cudaDeviceSynchron	8.6555ms
cuDeviceGetAttribu	1.2526ms
cudaLaunchKernel	607.89us
cuDeviceTotalMem	551.48us
cudaEventRecord	321.05us

Table 4: The total time for all API calls which took longer than 200 us.


gpu
cpu
Average running time (s)
0.00000
0.00005
0.00010
0.00015
0.00020
CRS
ELLPACK
cuSPARSE
Method