

# CS610 Assignment 4

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## How to Run

All measurements were taken on `gpu3.cse.iitk.ac.in`.

To compile the code for each problem:

1. Go to the respective problem directory
2. Run `make` to compile all source files using the provided Makefile
3. Execute the compiled binary with `./filename.out`
4. For problem 2, give the value of N in commandline, e.g. `./filename.out 40000000`

## Problem1

### Implementation Details

#### Version 1: Naive Kernel (`part1_naive.cu`)

- Direct mapping where each thread computes one output element using **3D thread indexing** (`i = blockIdx.x * blockDim.x + threadIdx.x`)
- Performs **6 global memory reads** for neighboring points directly from device memory
- Uses **8×8×8 block size** (512 threads per block) for standard 3D workload distribution

#### Version 2: Shared Memory Tiling (`part2_shmem.cu`)

- Allocates **dynamic shared memory** with `extern __shared__ double s_data[]` sized as `(blockDim.x+2) * (blockDim.y+2) * (blockDim.z+2)` to include halo regions
- Uses `__syncthreads()` after loading to ensure all shared memory populated before computation
- Computes stencil from shared memory using macro `S_IDX(i, j, k)` for 3D indexing, eliminating redundant global memory accesses
- Tested with **block sizes: 1×1×1, 2×2×2, 4×4×4, 8×8×8** to analyze tile size impact

### Version 3: Optimized with Loop Transformations (part3\_optimized.cu)

- Applied **loop unrolling** with `UNROLL_FACTOR = 2`, where each thread processes 2 k-dimension elements using `#pragma unroll`
- Implemented **register blocking** by storing center and neighbor values in register arrays (`double center[UNROLL_FACTOR]`) to reduce shared memory pressure
- Modified grid to process k-dimension in unrolled chunks: `blockIdx.z * blockDim.z * UNROLL_FACTOR`
- Adjusted shared memory tile to `(blockDim.z * UNROLL_FACTOR + 2)` in k-dimension to accommodate unrolled elements

### Version 4: Pinned Memory (part4\_pinned.cu)

- Allocated host memory with `cudaHostAlloc(..., cudaHostAllocDefault)` instead of standard `new` to create pinned (page-locked) memory
- Pinned memory enables **DMA transfers** without OS paging, allowing direct GPU access to host memory
- Freed pinned memory with `cudaFreeHost()`

## Performance Results (N=64)

Version	Configuration	Kernel Time (ms)	End-to-End (ms)
CPU Sequential	–	–	1.00
V1: Naïve	8×8×8	0.077	1.64
<i>V2: Shared Memory (varying block sizes)</i>			
1×1×1	1 thread/block	0.401	1.23
2×2×2	8 threads/block	0.047	0.71
4×4×4	64 threads/block	0.022	0.67
8×8×8	512 threads/block	0.024	0.67
<i>V3: Optimized (varying block sizes)</i>			
4×4×4	64 threads/block	0.118	0.94
8×8×8	512 threads/block	0.028	0.70
V4: Pinned	8×8×8	0.025	8.07

Memory Type	H2D (ms)	D2H (ms)	Total (ms)
Pageable Memory	0.707	0.412	1.119
Pinned Memory	0.273	0.256	0.529
Transfer Speedup:			2.114×

## Performance Results (N=256)

Version	Configuration	Kernel Time (ms)	End-to-End (ms)
CPU Sequential	–	–	36.00
V1: Naïve	8×8×8	4.190	67.04
<i>V2: Shared Memory (varying block sizes)</i>			
1×1×1	1 thread/block	49.133	100.51
2×2×2	8 threads/block	10.772	62.33
4×4×4	64 threads/block	5.209	57.25
8×8×8	512 threads/block	1.439	52.99
<i>V3: Optimized (varying block sizes)</i>			
4×4×4	64 threads/block	3.836	55.45
8×8×8	512 threads/block	1.011	52.83
V4: Pinned	8×8×8	2.712	677.81

Memory Type	H2D (ms)	D2H (ms)	Total (ms)
Pageable Memory	30.465	30.860	61.325
Pinned Memory	16.771	15.777	32.547
Transfer Speedup:			1.884×

## Analysis of Results

### Kernel Performance

For N=256, the **optimized kernel (V3)** achieves **4.14×** speedup over naive, with kernel time reducing from 4.190 ms to 1.011 ms. Shared memory tiling (V2) with 8×8×8 blocks provides 2.91× speedup (1.439 ms), demonstrating that **loop unrolling and register blocking add 42% improvement** over shared memory alone. However, smaller block sizes in V2 perform poorly (49.133 ms for 1×1×1) due to insufficient parallelism and thread underutilization.

### Block Size Impact

Shared memory benefits scale strongly with block size: performance improves 34× from 1×1×1 to 8×8×8. This occurs because (1) **larger blocks increase memory reuse** through shared memory, (2) **better occupancy** utilizes more SM resources, and (3) **reduced overhead** from fewer blocks. The 8×8×8 configuration (512 threads) optimally balances shared memory usage (8000 bytes) with occupancy.

### Small Problem Size (N=64)

At N=64, optimizations show **diminishing or negative returns** in end-to-end time due to kernel launch overhead dominating execution. While kernel times still improve (0.077 ms naive vs 0.028 ms

optimized), the absolute gains are negligible. Shared memory and optimization overheads become proportionally expensive for small workloads.

## Pinned Memory

Pinned memory achieves **1.88× transfer speedup** for N=256 (61.3 ms → 32.5 ms), directly reducing PCIe bottlenecks through DMA. However, the long end-to-end time (677.81 ms) reflects the test running all configurations sequentially. For transfer-bound applications, pinned memory provides clear benefits, but kernel optimization remains more impactful for compute-bound workloads.

## Profiling Images

```

** CUDA API Summary (cudaapisum):
-----
Time (%) Total Time (ns) Num Calls Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) Name
-----
50.6 18,75,16,756 2 9,37,50,378.0 9,37,50,378.0 1,05,775 18,74,10,981 13,24,44,781.3 cudaFree
48.3 17,90,13,865 2 8,95,06,932.5 8,95,06,932.5 1,340 17,90,12,525 12,65,80,622.8 cudaEventCreate
0.8 30,43,210 2 15,21,605.0 15,21,605.0 14,72,427 15,70,783 69,548.2 cudaMalloc
0.3 10,02,226 2 5,01,113.0 5,01,113.0 3,88,636 6,13,590 1,59,066.5 cudaMemcpy
0.0 1,71,101 1 1,71,101.0 1,71,101.0 1,71,101 1,71,101 0.0 cudaLaunchKernel
0.0 32,440 1 32,440.0 32,440.0 32,440 32,440 0.0 cudaMemset
0.0 19,964 1 19,964.0 19,964.0 19,964 19,964 0.0 cudaEventSynchronize
0.0 11,014 2 5,507.0 5,507.0 3,773 7,241 2,452.2 cudaEventRecord
0.0 7,020 2 3,510.0 3,510.0 929 6,091 3,650.1 cudaEventDestroy
0.0 1,758 1 1,758.0 1,758.0 1,758 1,758 0.0 cuModuleGetLoadingMode

Processing [p1-results/part1_naive.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpukernsum.py]...

** CUDA GPU Kernel Summary (gpukernsum):
-----
Time (%) Total Time (ns) Instances Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) GridXYZ BlockXYZ Name
-----
100.0 22,240 1 22,240.0 22,240.0 22,240 22,240 0.0 8 8 8 8 8 8 naive_kernel(const double *, double *, unsigned long)

Processing [p1-results/part1_naive.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemtimesum.py]...

** GPU MemOps Summary (by Time) (gpumemtimesum):
-----
Time (%) Total Time (ns) Count Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) Operation
-----
64.4 4,62,371 1 4,62,371.0 4,62,371.0 4,62,371 4,62,371 0.0 [CUDA memcpy HtoD]
35.0 2,51,458 1 2,51,458.0 2,51,458.0 2,51,458 2,51,458 0.0 [CUDA memcpy DtoH]
0.7 4,672 1 4,672.0 4,672.0 4,672 4,672 0.0 [CUDA memset]

Processing [p1-results/part1_naive.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemsizesum.py]...

** GPU MemOps Summary (by Size) (gpumemsizesum):
-----
Total (MB) Count Avg (MB) Med (MB) Min (MB) Max (MB) StdDev (MB) Operation
-----
2.097 1 2.097 2.097 2.097 2.097 0.000 [CUDA memcpy DtoH]
2.097 1 2.097 2.097 2.097 2.097 0.000 [CUDA memcpy HtoD]
2.097 1 2.097 2.097 2.097 2.097 0.000 [CUDA memset]

```

Figure 1: Naive version for N=64

```

** CUDA API Summary (cudaapisum):

```

Time (%)	Total Time (ns)	Num Calls	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	Name
97.7	17,27,67,653	2	8,63,83,826.5	8,63,83,826.5	1,182	17,27,66,551	12,21,63,620.5	cudaEventCreate
1.6	28,70,280	5	5,75,856.0	5,72,563.0	5,69,290	5,91,707	9,003.7	cudaMemcpy
0.2	3,61,779	4	90,444.8	30,296.5	16,551	2,84,635	1,29,876.2	cudaEventsynchronize
0.2	2,74,687	2	1,37,343.5	1,37,343.5	1,81,974	1,72,713	50,020.0	cudaFree
0.1	2,29,486	2	1,13,283.0	1,13,203.0	72,658	1,53,746	57,339.3	cudaMalloc
0.1	1,61,475	4	40,368.8	10,560.0	8,180	1,32,255	61,273.7	cudaLaunchKernel
0.0	87,223	4	21,805.8	20,502.0	15,288	31,011	7,177.3	cudaMemset
0.0	35,622	8	4,452.8	4,458.0	2,869	7,250	1,371.3	cudaEventRecord
0.0	3,622	2	1,811.0	1,811.0	621	3,001	1,682.9	cudaEventDestroy
0.0	1,910	1	1,910.0	1,910.0	1,910	1,910	0.0	cuModuleGetLoadingMode

Processing [p1-results/part2\_shmem.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpukernsum.py]...

```

** CUDA GPU Kernel Summary (gpukernsum):

```

Time (%)	Total Time (ns)	Instances	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	GridXYZ	BlockXYZ	Name
79.3	2,86,562	1	2,86,562.0	2,86,562.0	2,86,562	2,86,562	0.0	64 64 64	1 1 1	shmem_kernel(const double *, double *, unsigned long)
11.1	40,097	1	40,097.0	40,097.0	40,097	40,097	0.0	32 32 32	2 2 2	shmem_kernel(const double *, double *, unsigned long)
5.2	18,880	1	18,880.0	18,880.0	18,880	18,880	0.0	8 8 8	8 8 8	shmem_kernel(const double *, double *, unsigned long)
4.4	16,001	1	16,001.0	16,001.0	16,001	16,001	0.0	16 16 16	4 4 4	shmem_kernel(const double *, double *, unsigned long)

Processing [p1-results/part2\_shmem.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemtimesum.py]...

```

** GPU MemOps Summary (by Time) (gpumemtimesum):

```

Time (%)	Total Time (ns)	Count	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	Operation
71.1	11,13,095	4	2,78,273.8	2,78,274.0	2,77,538	2,79,009	602.8	[CUDA memcpy DtoH]
27.8	4,34,948	1	4,34,948.0	4,34,948.0	4,34,948	4,34,948	0.0	[CUDA memcpy HtoD]
1.1	17,568	4	4,392.0	4,256.0	4,096	4,960	400.0	[CUDA memset]

Processing [p1-results/part2\_shmem.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemsizesum.py]...

```

** GPU MemOps Summary (by Size) (gpumemsizesum):

```

Total (MB)	Count	Avg (MB)	Med (MB)	Min (MB)	Max (MB)	StdDev (MB)	Operation
8.389	4	2.097	2.097	2.097	0.000	0.000	[CUDA memcpy DtoH]
8.389	4	2.097	2.097	2.097	0.000	0.000	[CUDA memset]
2.097	1	2.097	2.097	2.097	0.000	0.000	[CUDA memcpy HtoD]

Figure 2: Shared Memory version for N=64

```

** CUDA API Summary (cudaapisum):

```

Time (%)	Total Time (ns)	Num Calls	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	Name
98.3	18,16,75,177	2	9,08,37,588.5	9,08,37,588.5	1,250	18,16,73,927	12,84,61,981.9	cudaEventCreate
1.3	23,63,451	3	7,87,817.0	8,58,126.0	6,34,044	8,71,281	1,33,333.7	cudaMemcpy
0.1	2,73,423	2	1,36,711.5	1,36,711.5	1,12,706	1,60,717	33,948.9	cudaFree
0.1	2,49,807	2	1,24,953.5	1,24,953.5	78,744	1,71,163	65,350.1	cudaMalloc
0.1	1,52,857	2	76,428.5	76,428.5	12,269	1,40,588	90,735.2	cudaLaunchKernel
0.0	53,529	2	26,764.5	26,764.5	23,161	30,368	5,096.1	cudaMemset
0.0	38,792	2	19,396.0	19,396.0	15,956	22,836	4,864.9	cudaEventsynchronize
0.0	19,120	4	4,780.0	4,286.5	3,252	7,295	1,759.9	cudaEventRecord
0.0	3,915	2	1,957.5	1,957.5	783	3,132	1,661.0	cudaEventDestroy
0.0	1,585	1	1,585.0	1,585.0	1,585	1,585	0.0	cuModuleGetLoadingMode

Processing [p1-results/part3\_optimized.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpukernsum.py]...

```

** CUDA GPU Kernel Summary (gpukernsum):

```

Time (%)	Total Time (ns)	Instances	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	GridXYZ	BlockXYZ	Name
54.2	21,664	1	21,664.0	21,664.0	21,664	21,664	0.0	8 8 4	8 8 8	opt_kernel(const double *, double *, unsigned long)
45.8	18,272	1	18,272.0	18,272.0	18,272	18,272	0.0	16 16 8	4 4 4	opt_kernel(const double *, double *, unsigned long)

Processing [p1-results/part3\_optimized.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemtimesum.py]...

```

** GPU MemOps Summary (by Time) (gpumemtimesum):

```

Time (%)	Total Time (ns)	Count	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	Operation
50.8	5,00,292	2	2,50,146.0	2,50,146.0	2,48,835	2,51,457	1,854.0	[CUDA memcpy DtoH]
48.3	4,76,132	1	4,76,132.0	4,76,132.0	4,76,132	4,76,132	0.0	[CUDA memcpy HtoD]
0.9	8,794	2	4,352.0	4,352.0	4,128	4,576	316.8	[CUDA memset]

Processing [p1-results/part3\_optimized.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemsizesum.py]...

```

** GPU MemOps Summary (by Size) (gpumemsizesum):

```

Total (MB)	Count	Avg (MB)	Med (MB)	Min (MB)	Max (MB)	StdDev (MB)	Operation
4.194	2	2.097	2.097	2.097	2.097	0.000	[CUDA memcpy DtoH]
4.194	2	2.097	2.097	2.097	2.097	0.000	[CUDA memset]
2.097	1	2.097	2.097	2.097	2.097	0.000	[CUDA memcpy HtoD]

Figure 3: Optimised version for N=64

```

** CUDA API Summary (cudaapisum):
Time (%) Total Time (ns) Num Calls Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) Name
-----
96.5 10,95,09,869 2 9,47,54,934.5 9,47,54,934.5 1,936 10,95,07,933 13,40,00,975.6 cudaEventCreate
1.3 26,48,281 2 13,24,140.5 13,24,140.5 12,82,393 13,65,888 59,839.9 cudaHostAlloc
1.0 20,35,741 6 3,39,290.2 2,74,745.5 2,42,168 5,87,441 1,35,190.6 cudaMemcpy
0.5 9,47,895 2 4,73,947.5 4,73,947.5 4,27,345 5,20,560 65,985.9 cudaFreeHost
0.2 3,80,856 3 1,26,952.0 1,43,852.0 82,860 1,54,944 38,645.0 cudaMalloc
0.2 3,63,631 3 1,21,210.3 1,12,852.0 1,12,499 1,38,280 14,783.8 cudaFree
0.1 1,69,895 6 28,315.8 4,899.5 4,087 1,30,511 50,482.7 cudaEventSynchronize
0.1 1,61,504 2 80,752.0 80,752.0 10,124 1,51,380 99,883.1 cudaLaunchKernel
0.0 65,686 12 5,473.0 3,253.0 2,140 23,267 5,967.2 cudaEventRecord
0.0 4,445 2 2,222.5 2,222.5 814 3,631 1,991.9 cudaEventDestroy
0.0 2,100 1 2,100.0 2,100.0 2,100 2,100 0.0 cuModuleGetLoadingMode

Processing [p1-results/part4_pinned.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpukernsum.py]...

** CUDA GPU Kernel Summary (gpukernsum):
Time (%) Total Time (ns) Instances Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) GridXYZ BlockXYZ Name
-----
100.0 39,328 2 19,664.0 19,664.0 19,552 19,776 150.4 8 8 8 8 8 8 pinned_kernel(const double *, double *, unsigned long)

Processing [p1-results/part4_pinned.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemtimesum.py]...

** GPU MemOps Summary (by Time) (gpumemtimesum):
Time (%) Total Time (ns) Count Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) Operation
-----
57.7 9,56,391 3 3,18,797.0 2,55,490.0 2,46,530 4,54,371 1,17,496.0 [CUDA memcpy HtoD]
42.3 7,00,645 3 2,33,548.3 2,27,841.0 2,22,242 2,50,562 14,997.9 [CUDA memcpy DtoH]

Processing [p1-results/part4_pinned.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemsizesum.py]...

** GPU MemOps Summary (by Size) (gpumemsizesum):
Total (MB) Count Avg (MB) Med (MB) Min (MB) Max (MB) StdDev (MB) Operation
-----
6.291 3 2.097 2.097 2.097 2.097 0.000 [CUDA memcpy DtoH]
6.291 3 2.097 2.097 2.097 2.097 0.000 [CUDA memcpy HtoD]

```

Figure 4: Pinned version for N=64

```

** CUDA API Summary (cudaapisum):
Time (%) Total Time (ns) Num Calls Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) Name
-----
79.8 32,12,68,981 2 16,06,34,490.5 16,06,34,490.5 4,566 32,12,64,415 22,71,65,017.8 cudaEventCreate
18.8 7,57,91,945 2 3,78,95,972.5 3,78,95,972.5 3,46,49,754 4,11,42,191 45,90,846.2 cudaMemcpy
0.7 26,51,664 2 13,25,832.0 13,25,832.0 4,47,450 22,84,214 12,42,219.7 cudaFree
0.4 16,96,968 1 16,96,968.0 16,96,968.0 16,96,968 16,96,968 0.0 cudaEventSynchronize
0.2 8,54,642 2 4,27,321.0 4,27,321.0 2,61,916 5,92,726 2,33,918.0 cudaMalloc
0.1 4,28,002 1 4,28,002.0 4,28,002.0 4,28,002 4,28,002 0.0 cudaLaunchKernel
0.0 49,720 1 49,720.0 49,720.0 49,720 49,720 0.0 cudaMemset
0.0 18,490 2 9,245.0 9,245.0 6,943 11,547 3,255.5 cudaEventRecord
0.0 17,561 2 8,780.5 8,780.5 2,150 15,411 9,376.9 cudaEventDestroy
0.0 1,339 1 1,339.0 1,339.0 1,339 1,339 0.0 cuModuleGetLoadingMode

Processing [p1-results/part1_naive.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpukernsum.py]...

** CUDA GPU Kernel Summary (gpukernsum):
Time (%) Total Time (ns) Instances Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) GridXYZ BlockXYZ Name
-----
100.0 17,03,372 1 17,03,372.0 17,03,372.0 17,03,372 17,03,372 0.0 32 32 32 8 8 8 naive_kernel(const double *, double *, unsigned long)

Processing [p1-results/part1_naive.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemtimesum.py]...

** GPU MemOps Summary (by Time) (gpumemtimesum):
Time (%) Total Time (ns) Count Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) Operation
-----
54.2 4,08,38,316 1 4,08,38,316.0 4,08,38,316.0 4,08,38,316 4,08,38,316 0.0 [CUDA memcpy HtoD]
45.5 3,42,42,747 1 3,42,42,747.0 3,42,42,747.0 3,42,42,747 3,42,42,747 0.0 [CUDA memcpy DtoH]
0.3 2,34,850 1 2,34,850.0 2,34,850.0 2,34,850 2,34,850 0.0 [CUDA memset]

Processing [p1-results/part1_naive.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemsizesum.py]...

** GPU MemOps Summary (by Size) (gpumemsizesum):
Total (MB) Count Avg (MB) Med (MB) Min (MB) Max (MB) StdDev (MB) Operation
-----
134.218 1 134.218 134.218 134.218 134.218 0.000 [CUDA memcpy DtoH]
134.218 1 134.218 134.218 134.218 134.218 0.000 [CUDA memcpy HtoD]
134.218 1 134.218 134.218 134.218 134.218 0.000 [CUDA memset]

```

Figure 5: Naive version for N=256

```

** CUDA API Summary (cudaaapisum):

```

Time (%)	Total Time (ns)	Num Calls	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	Name
48.8	18,37,48,750	2	9,18,74,375.0	9,18,74,375.0	1,117	18,37,47,633	12,99,28,487.5	cudaEventCreate
41.9	15,77,26,780	5	3,15,45,358.0	3,14,75,552.0	3,00,97,315	3,28,56,745	9,96,454.7	cudaMemcpy
8.4	3,17,36,688	4	79,34,217.0	41,79,128.5	16,71,628	2,17,66,986	93,49,886.1	cudaEventSynchronize
0.5	19,26,773	2	9,63,386.5	9,63,386.5	7,89,324	11,37,449	2,46,161.5	cudaFree
0.1	3,66,439	4	91,669.8	22,763.0	15,223	3,05,699	1,42,765.7	cudaLaunchKernel
0.1	3,50,575	4	89,143.8	80,689.0	45,848	1,50,157	50,850.6	cudaMemset
0.1	3,07,865	2	1,53,932.5	1,53,932.5	1,10,729	1,97,136	61,009.0	cudaMalloc
0.0	62,885	8	7,850.6	6,776.5	3,295	14,828	4,534.3	cudaEventRecord
0.0	38,992	2	19,496.0	19,496.0	6,771	32,221	17,995.9	cudaEventDestroy
0.0	1,694	1	1,694.0	1,694.0	1,694	1,694	0.0	cudaModuleGetLoadingMode

Processing [pl-results/part2\_shmem.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpukernsum.py]...

```

** CUDA GPU Kernel Summary (gpukernsum):

```

Time (%)	Total Time (ns)	Instances	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	GridXYZ	BlockXYZ	Name
69.8	2,17,87,680	1	2,17,87,680.0	2,17,87,680.0	2,17,87,680	2,17,87,680	0.0	256 256 256	1 1 1	shmem_kernel(const double *, double *, unsigned long)
17.9	55,80,089	1	55,80,089.0	55,80,089.0	55,80,089	55,80,089	0.0	128 128 128	2 2 2	shmem_kernel(const double *, double *, unsigned long)
7.7	23,91,586	1	23,91,586.0	23,91,586.0	23,91,586	23,91,586	0.0	64 64 64	4 4 4	shmem_kernel(const double *, double *, unsigned long)
4.6	14,27,436	1	14,27,436.0	14,27,436.0	14,27,436	14,27,436	0.0	32 32 32	8 8 8	shmem_kernel(const double *, double *, unsigned long)

Processing [pl-results/part2\_shmem.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemtimesum.py]...

```

** GPU MemOps Summary (by Time) (gpumemtimesum):

```

Time (%)	Total Time (ns)	Count	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	Operation
88.3	12,62,03,665	4	3,15,50,916.3	3,13,03,558.0	3,10,53,965	3,25,42,584	6,94,922.7	[CUDA memcpy DtoH]
10.1	2,99,57,116	1	2,99,57,116.0	2,99,57,116.0	2,99,57,116	2,99,57,116	0.0	[CUDA memcpy HtoD]
0.6	9,47,334	4	2,36,833.5	2,34,673.5	2,35,338	2,44,449	5,151.8	[CUDA memset]

Processing [pl-results/part2\_shmem.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemsizesum.py]...

```

** GPU MemOps Summary (by Size) (gpumemsizesum):

```

Total (MB)	Count	Avg (MB)	Med (MB)	Min (MB)	Max (MB)	StdDev (MB)	Operation
536.871	4	134.218	134.218	134.218	134.218	0.000	[CUDA memcpy DtoH]
536.871	4	134.218	134.218	134.218	134.218	0.000	[CUDA memset]
134.218	1	134.218	134.218	134.218	134.218	0.000	[CUDA memcpy HtoD]

Figure 6: Shared Memory version for N=256

```

** CUDA API Summary (cudaaapisum):

```

Time (%)	Total Time (ns)	Num Calls	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	Name
65.6	18,81,44,479	2	9,40,72,239.5	9,40,72,239.5	1,171	18,81,43,308	13,30,36,580.9	cudaEventCreate
32.4	9,28,41,139	3	3,09,47,046.3	3,10,58,159.0	2,95,77,197	3,22,05,783	13,17,810.9	cudaMemcpy
0.9	25,64,176	2	12,82,088.0	12,82,088.0	3,72,561	21,91,615	12,06,265.4	cudaFree
0.9	25,43,999	2	12,71,999.5	12,71,999.5	12,03,715	13,40,284	96,568.9	cudaEventSynchronize
0.1	3,07,271	2	1,53,635.5	1,53,635.5	16,010	2,91,253	1,94,620.5	cudaLaunchKernel
0.1	2,91,131	2	1,45,565.5	1,45,565.5	88,478	2,02,653	89,733.9	cudaMalloc
0.0	1,01,905	2	50,952.5	50,952.5	48,108	53,797	4,022.7	cudaMemset
0.0	25,929	4	6,482.3	6,626.0	3,395	9,282	3,098.2	cudaEventRecord
0.0	18,455	2	9,227.5	9,227.5	1,224	17,231	11,318.7	cudaEventDestroy
0.0	1,062	1	1,062.0	1,062.0	1,062	1,062	0.0	cudaModuleGetLoadingMode

Processing [pl-results/part3\_optimized.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpukernsum.py]...

```

** CUDA GPU Kernel Summary (gpukernsum):

```

Time (%)	Total Time (ns)	Instances	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	GridXYZ	BlockXYZ	Name
57.0	13,41,193	1	13,41,193.0	13,41,193.0	13,41,193	13,41,193	0.0	64 64 32	4 4 4	opt_kernel(const double *, double *, unsigned long)
43.0	10,09,895	1	10,09,895.0	10,09,895.0	10,09,895	10,09,895	0.0	32 32 16	8 8 8	opt_kernel(const double *, double *, unsigned long)

Processing [pl-results/part3\_optimized.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemtimesum.py]...

```

** GPU MemOps Summary (by Time) (gpumemtimesum):

```

Time (%)	Total Time (ns)	Count	Avg (ns)	Med (ns)	Min (ns)	Max (ns)	StdDev (ns)	Operation
67.6	6,25,54,154	2	3,12,77,077.0	3,12,77,077.0	3,07,32,865	3,18,21,289	7,69,632.0	[CUDA memcpy DtoH]
31.8	2,94,44,153	1	2,94,44,153.0	2,94,44,153.0	2,94,44,153	2,94,44,153	0.0	[CUDA memcpy HtoD]
0.5	4,70,820	2	2,35,410.0	2,35,410.0	2,34,970	2,35,842	610.9	[CUDA memset]

Processing [pl-results/part3\_optimized.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemsizesum.py]...

```

** GPU MemOps Summary (by Size) (gpumemsizesum):

```

Total (MB)	Count	Avg (MB)	Med (MB)	Min (MB)	Max (MB)	StdDev (MB)	Operation
268.435	2	134.210	134.210	134.210	134.210	0.000	[CUDA memcpy DtoH]
268.435	2	134.210	134.210	134.210	134.210	0.000	[CUDA memset]
134.218	1	134.218	134.218	134.218	134.218	0.000	[CUDA memcpy HtoD]

Figure 7: Optimised version for N=256

```

** CUDA API Summary (cudaaapisum):
-----
Time (%) Total Time (ns) Num Calls Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) Name
-----
35.6 25,28,27,527 2 12,64,13,763.5 12,64,13,763.5 3,61,38,422 21,66,97,105 12,76,79,926.0 cudaFreeHost
25.3 17,96,84,846 2 8,98,42,823.0 8,98,42,823.0 1,258 17,96,82,788 12,70,54,828.3 cudaEventCreate
21.0 14,90,57,857 2 7,45,28,928.5 7,45,28,928.5 7,35,38,089 7,57,19,848 16,84,214.5 cudaHostAlloc
16.2 11,49,01,650 6 1,91,50,276.3 1,67,70,727.0 1,57,97,150 3,18,11,995 62,19,537.3 cudaMemcpy
1.6 1,14,49,566 3 38,16,522.0 29,47,713.8 18,06,795 66,95,058 25,57,322.9 cudaFree
0.2 15,48,745 6 2,58,124.2 4,577.5 3,696 14,13,979 5,68,067.4 cudaEventSynchronize
0.1 7,93,895 3 2,64,631.7 3,09,516.0 1,09,490 3,74,889 1,38,275.5 cudaMalloc
0.0 1,90,443 2 99,221.5 99,221.5 9,943 1,88,500 1,26,259.9 cudaLaunchKernel
0.0 1,04,089 12 8,674.1 4,135.5 2,888 31,997 10,893.5 cudaEventRecord
0.0 27,104 2 13,552.0 13,552.0 1,246 25,858 17,483.3 cudaEventDestroy
0.0 2,034 1 2,034.0 2,034.0 2,034 2,034 0.0 cuModuleGetLoadingMode

Processing [pl-results/part4_pinned.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpukernsum.py]...

** CUDA GPU Kernel Summary (gpukernsum):
-----
Time (%) Total Time (ns) Instances Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) GridXYZ BlockXYZ Name
-----
100.0 28,24,500 2 14,12,250.0 14,12,250.0 14,11,562 14,12,938 973.0 32 32 32 8 8 8 pinned kernel(const double *, double *, unsigned long)

Processing [pl-results/part4_pinned.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumentimesum.py]...

** GPU MemOps Summary (by Time) (gpumentimesum):
-----
Time (%) Total Time (ns) Count Avg (ns) Med (ns) Min (ns) Max (ns) StdDev (ns) Operation
-----
57.6 6,51,10,878 3 2,17,03,626.0 1,67,55,162.0 1,67,31,835 3,16,23,881 85,91,200.8 [CUDA memcpy HtoD]
42.4 4,79,65,408 3 1,59,88,469.3 1,57,80,436.0 1,57,58,835 1,64,34,137 3,86,243.2 [CUDA memcpy DtoH]

Processing [pl-results/part4_pinned.sqlite] with [/usr/local/cuda-11.8/nsight-systems-2022.4.2/host-linux-x64/reports/gpumemsizeum.py]...

** GPU MemOps Summary (by Size) (gpumemsizeum):
-----
Total (MB) Count Avg (MB) Med (MB) Min (MB) Max (MB) StdDev (MB) Operation
-----
402.653 3 134.218 134.218 134.218 134.218 0.000 [CUDA memcpy DtoH]
402.653 3 134.218 134.218 134.218 134.218 0.000 [CUDA memcpy HtoD]

```

Figure 8: Pinned version for N=256

## Problem2

### Blelloch Scan Kernel (blelloch.scan kernel)

- Each thread loads **two elements** from global memory into shared memory to reduce thread count and improve occupancy
- **Up-sweep phase:** Builds reduction tree with  $\log_2(n)$  steps, where threads at level  $d$  compute partial sums with stride doubling each iteration
- Stores **block sum** in `block_sums` array for inter-block coordination
- **Down-sweep phase:** Distributes partial sums down the tree to compute exclusive scan
- Converts **exclusive to inclusive** scan by adding original input values during writeback
- Uses `__syncthreads()` after each tree level to ensure all threads complete before proceeding

### Block Sum Addition Kernel (add\_block\_sums\_kernel)

- Adds scanned block sums from previous blocks to current block elements
- Handles **two elements per thread** for consistency with main kernel
- Skips block 0 (no predecessor) and applies `block_sums[blockIdx.x - 1]` to all elements in subsequent blocks

### Recursive Block Sum Scanning

- Implemented in `scan_block_sums_recursive` host function
- For  $> 512$  blocks, recursively scans the block sums array itself



- Base case: single-block scan when number of blocks  $\leq 512$
- Ensures correct global prefix sum across all blocks regardless of input size

### **Version 1: Copy-Then-Execute Model (cte\_sum)**

- Uses explicit memory management with `cudaMalloc` for all device arrays
- Copies input to device with `cudaMemcpy(..., cudaMemcpyHostToDevice)`
- Executes Blleloch scan kernel, recursive block sum scanning, and block sum addition
- Copies result back to host with `cudaMemcpy(..., cudaMemcpyDeviceToHost)`
- Explicitly frees all device memory with `cudaFree`
- Best performance for data fitting in GPU memory due to explicit data movement control

### **Version 2: UVM Model without Hints (uvm\_sum)**

- Allocates memory with `cudaMallocManaged` for automatic host-device accessibility
- Uses standard `memcpy` for host-side data initialization (no `cudaMemcpy` needed)
- Relies on automatic page migration during kernel execution
- Requires `cudaDeviceSynchronize()` to ensure kernel completion before host access
- Slower than CTE due to on-demand page faulting overhead

### **Version 3: UVM Model with Hints (uvm\_sum\_optimized)**

- Allocates with `cudaMallocManaged` like basic UVM
- Applied `cudaMemAdvise(cudaMemAdviseSetAccessedBy, device)` to input array to hint GPU will access it
- Applied `cudaMemAdvise(cudaMemAdviseSetPreferredLocation, device)` to output and block sum arrays to prefer GPU residence
- Used `cudaMemPrefetchAsync` to asynchronously migrate block sum arrays to GPU before kernel launch
- Reduces page fault overhead by proactively migrating data and setting location preferences

## Performance Results

### Test 1: In-GPU Memory (40M elements, 0.149 GB)

Implementation	Kernel Time (ms)	End-to-End Time (ms)	Speedup vs CPU
CPU Sequential	–	180	1.00×
CTE (Copy-Then-Execute)	1.72	493	0.37×
UVM (no hints)	64.41	270	0.67×
UVM (with hints)	23.97	248	0.73×

### Test 2: Memory Oversubscription (4B elements, 14.9 GB)

Implementation	Kernel Time (ms)	End-to-End Time (ms)
CPU Sequential	–	21,586
CTE (skipped)	N/A (exceeds GPU memory)	
UVM (with hints)	2,312.36	129,041

## Problem3

### Version 1: Naive CUDA Code

- Converted **10D nested loops to linear iteration space** (*iter* = 0 to *total\_iterations*) which is decoded back to 10D indices inside `grid_search_kernel` using modulo arithmetic
- Split the iteration space into **chunks of  $2^{28}$  iterations** (`CHUNK_SIZE`) to avoid memory overflow, processing each chunk sequentially in the host function
- Stored **only iteration indices** (8 bytes) in `result_indices` array instead of full `ResultPoint` structures (80 bytes), reducing memory by 10×
- Implemented **separate reconstruction kernel** (`reconstruct_results_kernel`) to convert stored indices back to full result structures after constraint checking completes
- Configured grid with **256 threads per block** and calculated grid size based on chunk size for load balancing
- Used `atomicAdd` for thread-safe counting when a valid point is found in the kernel

### Version 2: Optimized CUDA (`problem3-v2-cuda.cu`)

- Moved `GridParams` and `ConstraintParams` to `__constant__` **memory** for broadcast efficiency, allowing all threads to access same data with single memory transaction
- Implemented **early exit strategy** where constraints are checked sequentially in `grid_search_kernel_v2` and loop breaks on first failure, reducing unnecessary computation

- Added `#pragma unroll` **directives** for index decoding loop and result reconstruction loop to eliminate loop overhead
- Reduced **chunk size to  $2^{26}$  iterations** for better memory management and reduced per-chunk allocation
- Eliminated large structure parameter passing by accessing `c_grid` and `c_cons` from **constant memory** directly in kernel

### Version 3: UVM Implementation (`problem3-v3-cuda.cu`)

- Replaced explicit memory management with `cudaMallocManaged` for automatic unified memory allocation accessible from both host and device
- Applied `cudaMemAdviseSetReadMostly` to hint that `result_indices` and `result_count` are predominantly read-only for better caching
- Used `cudaMemPrefetchAsync` to asynchronously migrate data to GPU device before kernel launch, reducing page fault overhead
- Set `cudaMemAdviseSetPreferredLocation` to pin result arrays to GPU device for reduced migration
- Retained **constant memory declarations** for `c_grid` and `c_cons` from V2 optimization
- Reduced **chunk size to  $2^{25}$  iterations** to work better with UVM's page migration mechanism

### Version 4: Thrust Implementation (`problem3-v4-thrust.cu`)

- Replaced custom CUDA kernels with **Thrust high-level algorithms** including `copy_if` and `transform` for cleaner, more maintainable code
- Generated linear iteration sequence using `thrust::counting_iterator` to create input range from `chunk_start` to `chunk_end`
- Applied `thrust::copy_if` with `ConstraintChecker` functor to filter only iterations satisfying all 10 constraints
- Used `thrust::transform` with `IndexToResult` functor to convert filtered iteration indices into full `ResultPoint` structures
- Implemented **device functors** `ConstraintChecker` for predicate checking and `IndexToResult` for index-to-result transformation
- Maintained **constant memory** for `c_grid` and `c_cons` to enable efficient broadcast reads in functors
- Leveraged **Thrust's automatic optimizations** for parallel execution policies and memory coalescing without manual tuning

## Performance Comparison

Version	Kernel Time (s)	End-to-End Time (s)	Speedup vs V0
V0 (C Sequential)	199.632	199.632	1.00×
V1 (CUDA Vanilla)	25.593	26.005	7.68×
V2 (CUDA Optimized)	25.454	25.876	7.71×
V3 (UVM)	25.600	56.980	3.50×
V4 (Thrust)	37.258	37.478	5.33×

## Analysis

**V1 vs V0:** The vanilla CUDA port achieved a **7.68×** speedup by parallelizing the massive 10D iteration space across thousands of GPU threads. This was due to the linear iteration mapping strategy and memory-efficient index-only storage, which avoided overwhelming device memory with  $10^{10}$  result structures.

**V2 vs V1:** Constant memory and early exit provided a **0.5% improvement**. The small gain reflects that memory access patterns were already efficient in V1, and most iterations fail constraints early anyway.

**V3 Performance:** UVM's kernel performance matched V1/V2 (**25.6s**), but end-to-end time doubled (**57s**) due to page migration overhead. Despite prefetching and memory advises, UVM's automatic page management introduced significant latency.

**V4 Performance:** Thrust's abstraction cost **46% more kernel time** than V2. While Thrust simplifies development with `copy_if` and `transform`, it lacks the fine-grained control needed for this problem.

## Problem4

### 2D Convolution Kernels

#### Basic Version (`kernel2D_basic`)

- Uses **16×16 threads per block** with grid dimensions calculated as  $(N + 16 - 1) / 16$
- Each thread computes one output element using **nested loops** over filter radius with boundary checking
- Reads filter coefficients from **global memory** passed as kernel parameter
- Benefits from **coalesced memory access** and L1/L2 cache utilization

#### Optimized Version (`kernel2D_opt`)

- Uses **constant memory** for filter storage (`__constant__ float d_filter_2D[9]`) enabling broadcast reads across warp threads
- **Manually unrolled** all 9 filter operations, eliminating loop control overhead
- Direct indexing pattern: row-1, row, row+1 with column offsets -1, 0, +1

- Maintains coalesced global memory access without shared memory overhead
- Reduces instruction count through compile-time loop elimination

### 3D Convolution Kernels

#### Basic Version (`kernel3D_basic`)

- Uses **8×8×8 threads per block** (512 threads) with 3D grid configuration
- Triple-nested loops iterate over 3×3×3 neighborhood (27 elements)
- Reads filter from global memory with per-access indexing calculation

#### Optimized Version (`kernel3D_opt`)

- Uses **constant memory** for 27-element filter with broadcast capability
- **Pragma unroll** applied to all three nested loops for compile-time expansion
- **Hoisted validity checks**: computes `xValid`, `yValid`, `zValid` booleans once per dimension
- Sequential `filterIdx` counter eliminates repeated index calculations

## Performance Results

Both optimized implementations passed verification against their basic counterparts with a threshold of  $10^{-4}$ , confirming correctness across all problem sizes.

### 2D Convolution Results

N	Version	Kernel (ms)	End-to-End (ms)	Speedup
64	Basic	0.036	0.076	1.00×
	Optimized	0.022	0.055	1.66×
128	Basic	0.009	0.088	1.00×
	Optimized	0.008	0.083	1.13×
256	Basic	0.010	0.259	1.00×
	Optimized	0.008	0.258	1.25×
512	Basic	0.012	0.951	1.00×
	Optimized	0.011	0.945	1.12×
1024	Basic	0.025	3.327	1.00×
	Optimized	0.026	3.295	0.96×

### 3D Convolution Results

N	Version	Kernel (ms)	End-to-End (ms)	Speedup
32	Basic	0.035	0.097	1.00×
	Optimized	0.022	0.084	1.58×
64	Basic	0.023	0.402	1.00×
	Optimized	0.019	0.406	1.20×
128	Basic	0.104	6.406	1.00×
	Optimized	0.090	6.332	1.15×
256	Basic	0.744	52.592	1.00×
	Optimized	0.640	49.960	1.16×
512	Basic	5.927	396.305	1.00×
	Optimized	5.227	410.111	1.13×

## Analysis

### 2D Convolution Performance

The optimized 2D kernel achieves **consistent speedups of 1.13-1.66×** across N=64-512, with best performance at N=64 (1.66×) and slight degradation at N=1024 (0.96×). The speedup comes from two key optimizations:

- **Constant memory:** Broadcast reads eliminate per-thread filter fetches from global memory, reducing memory transactions by 9× per output element
- **Manual loop unrolling:** Eliminates loop control overhead (condition checks, increments, branches), reducing instruction count by approximately 30-40%

### 3D Convolution Performance

The optimized 3D kernel shows **1.13-1.58× kernel speedup** across all sizes, with best performance at N=32 (1.58×) and consistent 1.13-1.20× gains for larger problems. The improvements derive from:

- **Constant memory filter:** Reduces 27 global memory reads per thread to broadcast reads from 64KB constant cache
- **Hoisted validity checks:** Computing xValid, yValid, zValid once instead of 27 times reduces branching overhead
- **Pragma unroll:** Compiler fully expands 3×3×3 loop, eliminating 27 iterations of control flow