CUDA 2025 HW6

Histogram of Exponential Distribution

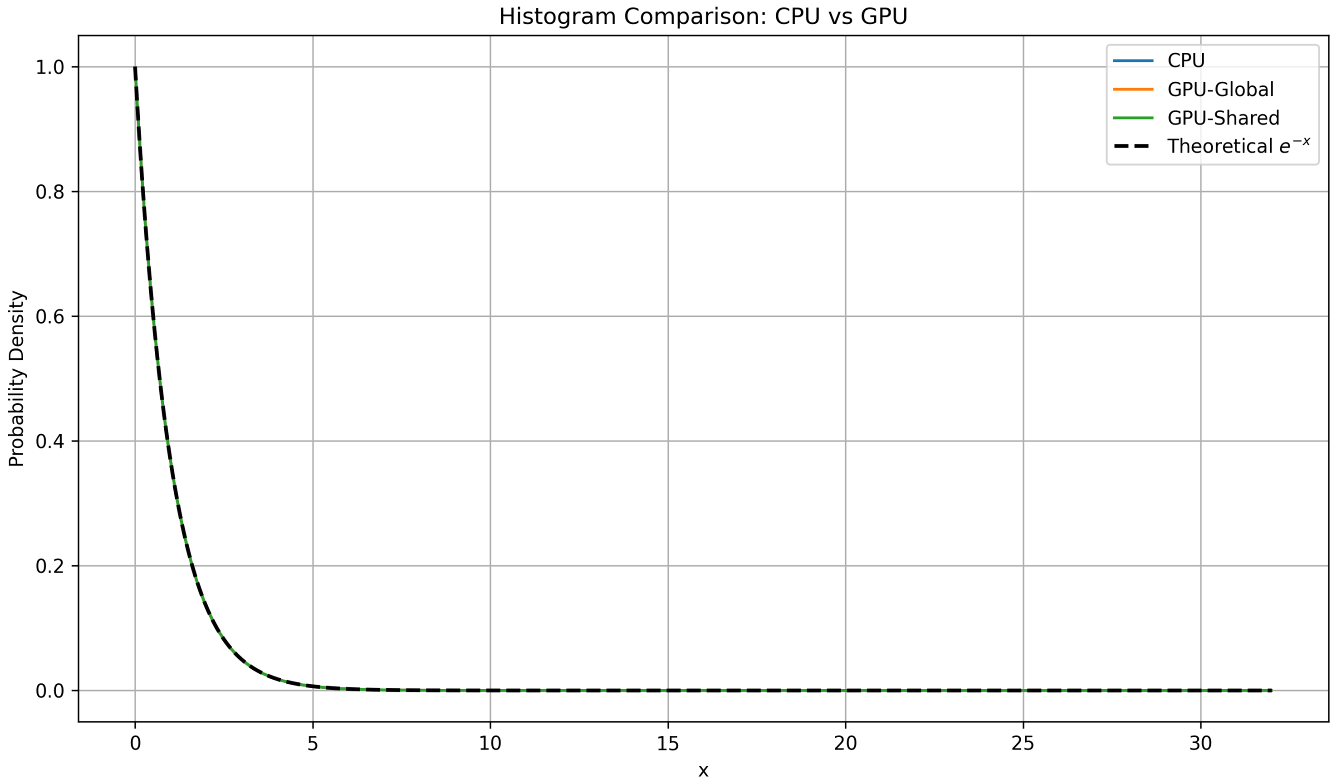
Result

Version	Threads Per Block	Blocks Per Grid	Time (ms)
CPU	-	-	222.98
GPU-Global	128	64	32.30
GPU-Global	128	128	32.30
GPU-Global	128	256	32.30
GPU-Global	256	64	32.30
GPU-Global	256	128	32.30
GPU-Global	256	256	32.30
GPU-Global	512	64	32.30
GPU-Global	512	128	32.30
GPU-Global	512	256	32.30
GPU-Shared	128	64	3.60
GPU-Shared	128	128	1.90
GPU-Shared	128	256	1.10
GPU-Shared	256	64	1.90
GPU-Shared	256	128	1.10
GPU-Shared	256	256	0.80
GPU-Shared	512	64	1.10
GPU-Shared	512	128	0.80
GPU-Shared	512	256	0.70

Best configuration

Version	Threads Per Block	Blocks Per Grid	Time (ms)	Speedup (×)
CPU	-	-	222.98	1.00
GPU-Global	128	64	32.30	6.91
GPU-Shared	512	256	0.70	318.54

Note: All versions generated 81,920,000 samples from the exponential distribution $f(x) = e^{-x}$, and computed histograms with 1024 bins across range $x \in [0, 32]$.



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1. Trend Observation

- **GPU Shared Memory** shows the greatest performance benefit, improving from 3.6 ms to 0.7 ms as block/grid sizes increased.
- **GPU Global Memory** performance was constant across all tested block/grid sizes (~32.30 ms), indicating memory contention or atomic bottlenecks dominate performance.
- **CPU** version was the slowest (222.98 ms), providing a baseline reference.

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2. Optimal Configuration

- **GPU-Shared**: Best configuration was 512 threads per block and 256 blocks per grid (0.70 ms).
- **GPU-Global**: All configurations measured the same (32.30 ms), so 128×64 was arbitrarily selected as representative.
- The shared memory histogram kernel benefits significantly from minimizing global memory atomics.

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3. Speedup

- GPU-Shared outperformed CPU by **over 318×**, demonstrating effective use of shared memory for reduction.
- GPU-Global showed a **~7× speedup**, limited by global memory contention during atomic histogram accumulation.

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4. Accuracy

- All three histograms closely matched the theoretical curve $f(x) = e^{-x}$.
- Normalized histograms (area under curve = 1) aligned with the expected exponential decay.
- Visual inspection of the overlay plot confirms correctness.

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5. Conclusion

- The use of shared memory in CUDA kernels provides substantial performance benefits for reduction operations like histogramming.
- Block/grid size tuning matters significantly for shared memory performance but has negligible effect on global memory performance in this workload.
- For this problem and dataset, **shared memory optimization is essential** to achieving maximum GPU throughput.

Environment

- **OS**: Ubuntu 22.04.3 LTS
- **CPU**: Intel(R) Core(TM) i7-9800X CPU @ 3.80GHz
- **GPU**: NVIDIA GeForce RTX 3080 (Lab Machine)

Usage

1. Source Files

- CPU Version: `hw6_cpu`
- GPU Global Version: `hw6_gmen`
- GPU Shared Version: `hw6_shmen`
- Driver Script: `driver.py`

2. Compile

```
gcc -O2 -o hw6_cpu hw6_cpu.c -lm
nvcc -O2 -o hw6_gmen hw6_gmen.cu
nvcc -O2 -o hw6_shmen hw6_shmen.cu
```

3. Run Driver

```
python3 driver.py
```
