Neural Network Acceleration on GPUs

By

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Agenda

- Version 1: Sequential CPU
- Version 2: Naïve CUDA
- Version 3: Optimized CUDA
- Version 4: Tensor-Core Acceleration
- Comparative Results
- Conclusion

Version 1: Sequential CPU

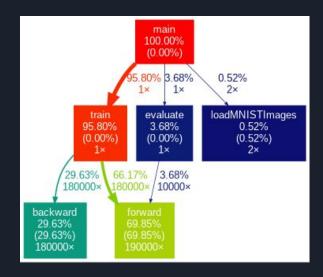
1. Results:

Total training time: 22.233 s Test Accuracy: 96.78%. End-to-end execution: 23.589

s.

2. Observations:

Loop-carried Dependencies (forward/backward). Serves as the baseline for the speedup.



Version 2: Naïve CUDA

Key changes:

cudaMalloc/cudaMemcpy.

Two kernels:

forward/backward pass.

Results:

Total training time: 206.037 s

Test Accuracy: 96.58%

Execution time: 207.567 s

Observations:

GPU overhead > compute

Low Occupancy

Memory-bound operations are

the bottleneck now

Version 3: Optimized CUDA

Key changes:

Launch & Occupancy: tuned dim3 grid/block (256–512 threads)

Communication: batched H2D/D2H, streams overlap

Memory: shared-memory, coalesced access

Results:

Total training time: 0.856s

Test Loss: 0.3440

Execution time: 1.097s

Observations:

~210 speedup in its training compared with V2.

Memory-bound operations are now well-optimized, with compute-bound kernels being the bottleneck now.

Version 4: Tensor-Core Acceleration

Key changes:

Precision: FP16 inputs/weights,

FP32 accumulations

API: NVIDIA WMMA (16×16 warp

tiles)

Alignment: data padded to 16×16

blocks

Results:

Total training time: 0.262 s

Test accuracy: 88.76% Execution time: 0.435 s

Observations:

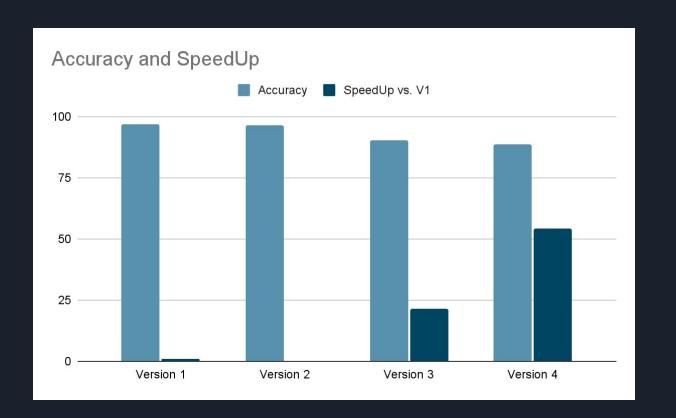
 \sim 3.3× faster than V3; \sim 54× faster than V1.

Occupancy still high; tensor cores peak compute.

Comparative Results

Version	Train Time (s)	Exec Time (s)	Test Acc.	Speedup vs. V1
V1	22.233	23.589	96.78	1×
V2	206.037	207.567	96.58	0.11×
V3	0.856	1.097	90.27	21.5×
V4	0.262	0.435	88.76	54.2×





Conclusion

Moving from CPU \rightarrow naïve CUDA (V1 \rightarrow V2) without algorithmic changes delivers poor speedup due to overheads.

Advanced optimizations (shared memory, streams, WMMA) add significant code complexity and tuning effort - though yielding diminishing results.

The performance improvement trajectory showed a distinct drop from 23.6 s on CPU (V1) down to 0.44s using tensor cores (V4) at a speedup of \sim 54 \times . The accuracy drops slightly when one is too aggressive on optimizations - speedup.