Results for CUDA Implementation

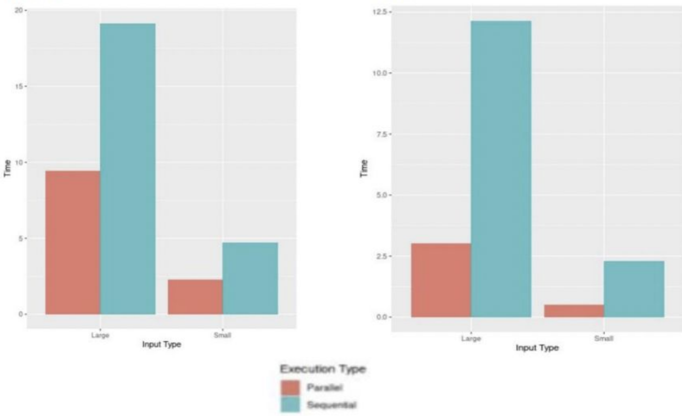
These are the parameters for the two types of problems on which the implementation was tested

Problem Type / Parameters	VSIZE	HSIZE	TIMESTEPS
Small Input Size	8000	50	5000
Large Input Size	8000	125	10000

- TIMESTEPS: number of units of time (typically seconds) that the data spans
- HSIZE: number of features computed in the hidden state of the network (i.e. the dimensionality of the hidden vector `h` for each time step)
- VSIZE: number of values in the output vector (over which an argmax will yield the prediction)
- For all tests, the number of threads launched per block was 5 (empirically found to be a good balance between (under)-utilization and speedup)

Speedup Plots: Before-and-After switch to per-kernel shared memory access (for `h` storage)

Before **After**

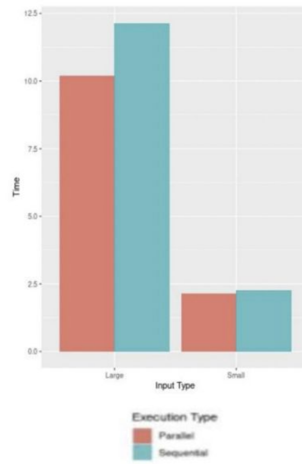


Results for OpenMP Implementation

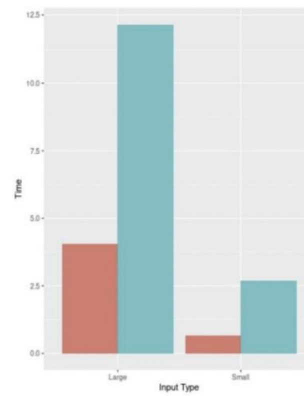
- We observed middling speedups with a logical replication of the code we had for CUDA kernels.
    - So, we devised the forward-filling strategy

Speedups with and without Forward-Filling

without



with

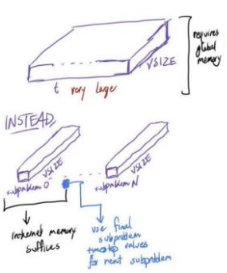


Note: this plot depicts the best result from trials with multiple ff values; the results for ff = 15 when `num_of_threads = 12` were the data for the plot

Because GPUs are much faster than CPUs, we chose the following (smaller) problem parameters to increase comparability with our CUDA impl.

Problem Type / Parameters	VSIZE	HSIZE	TIMESTEPS
Small Input Size	8000	50	500
Large Input Size	8000	125	1000

Discussion of Discoveries, Shortcomings, and Matters for Further Inquiry



CUDA:

- Using shared memory (per-kernel) was very conducive to speedup
- But we still have some aggregation of results that involves global memory
    - May be some optimizations in that approach we overlooked
        - For sufficiently small problem parameters, don't bother with global memory at all?
        - Compute fragmented sub-solutions (of contiguous sections of data) in separate executions and combine later, for bigger input sizes?

OpenMP

- Forward-filling turned out to be great for speedup
- However….
    - Its underlying logic is somewhat unsophisticated
        - interpolating data by copying an average, pretty much
    - Did not impinge correctness too much when the ff exceeded num_of_threads by 1-2 (Occam's Razor!), but correctness declined precipitously thereafter
    - Maybe doing some inference on the values to supply in the forward fill can mitigate this!
        - We are doing machine learning for value prediction after all :)
        - But, might require additional compute power at training time, to also develop neuron-like mechanisms for ff's values

Learning
...(1) network's parameters — We parallelized this
AND
...(2) parameters to interpolate network's outputs (?)
could this help us get more speedup?

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