Layer-Parallel Training with GPU Concurrency of Deep Residual Networks via Nonlinear Multigrid

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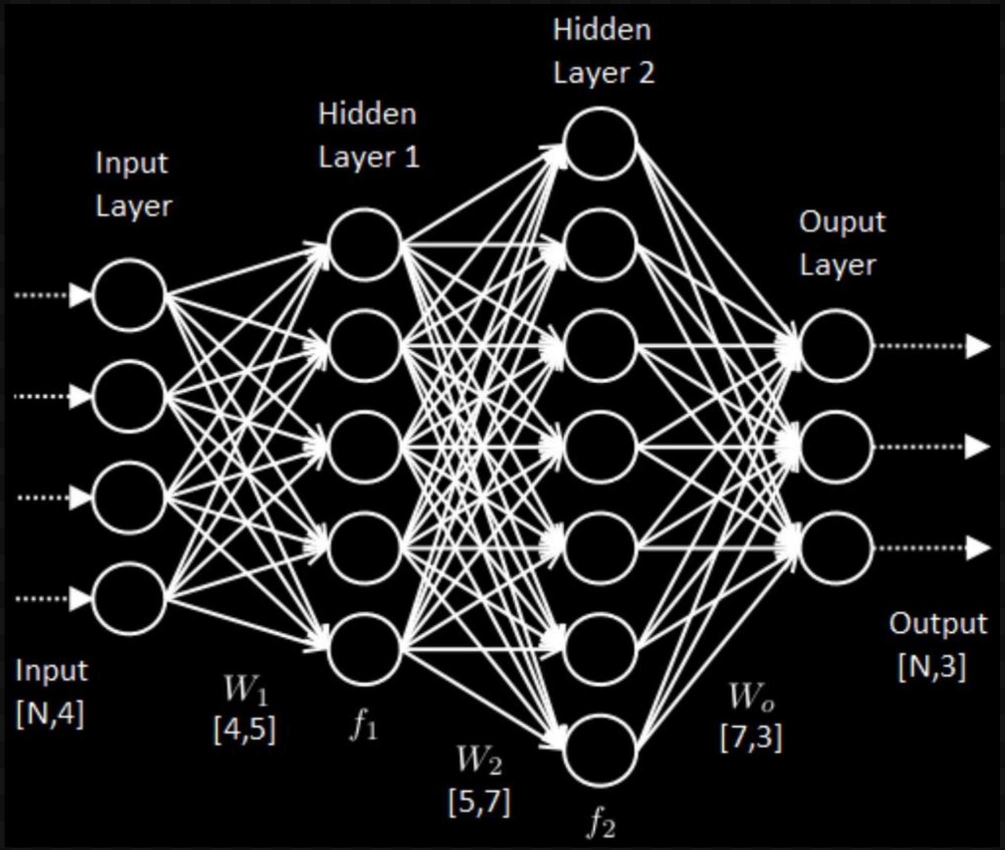
Motivation

- Information travels sequentially through network
  - Forward propagation sets the neural states
  - Back propagation updates the weights and bias
  - Amdahl's Law
    - Theoretical speedup limited by serial execution
- Goal: minimize loss by updating the weight coefficients and bias vectors iteratively
  - Updates to unknowns are *approximate*
    - Optimization opportunities for accelerating training



Source: https://miro.medium.com/max/2500/1*ZB6H4HuF58VcMOWbdpcRxQ.png

Deep Residual Networks

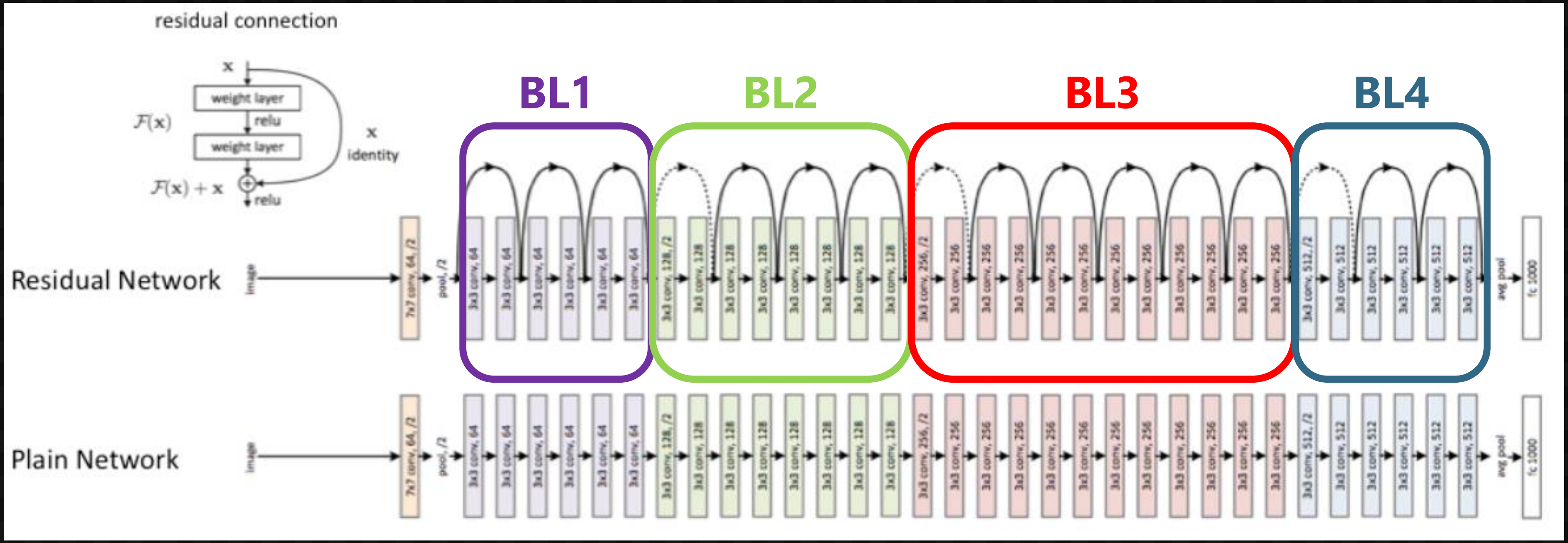
$$\boldsymbol{u}^{n+1} = \boldsymbol{u}^{n} + hF\left(\boldsymbol{u}^{n}; \boldsymbol{\theta}^{n}\right), \quad \text{for } n = 0, \ldots, N-1$$

Parallelization Approaches

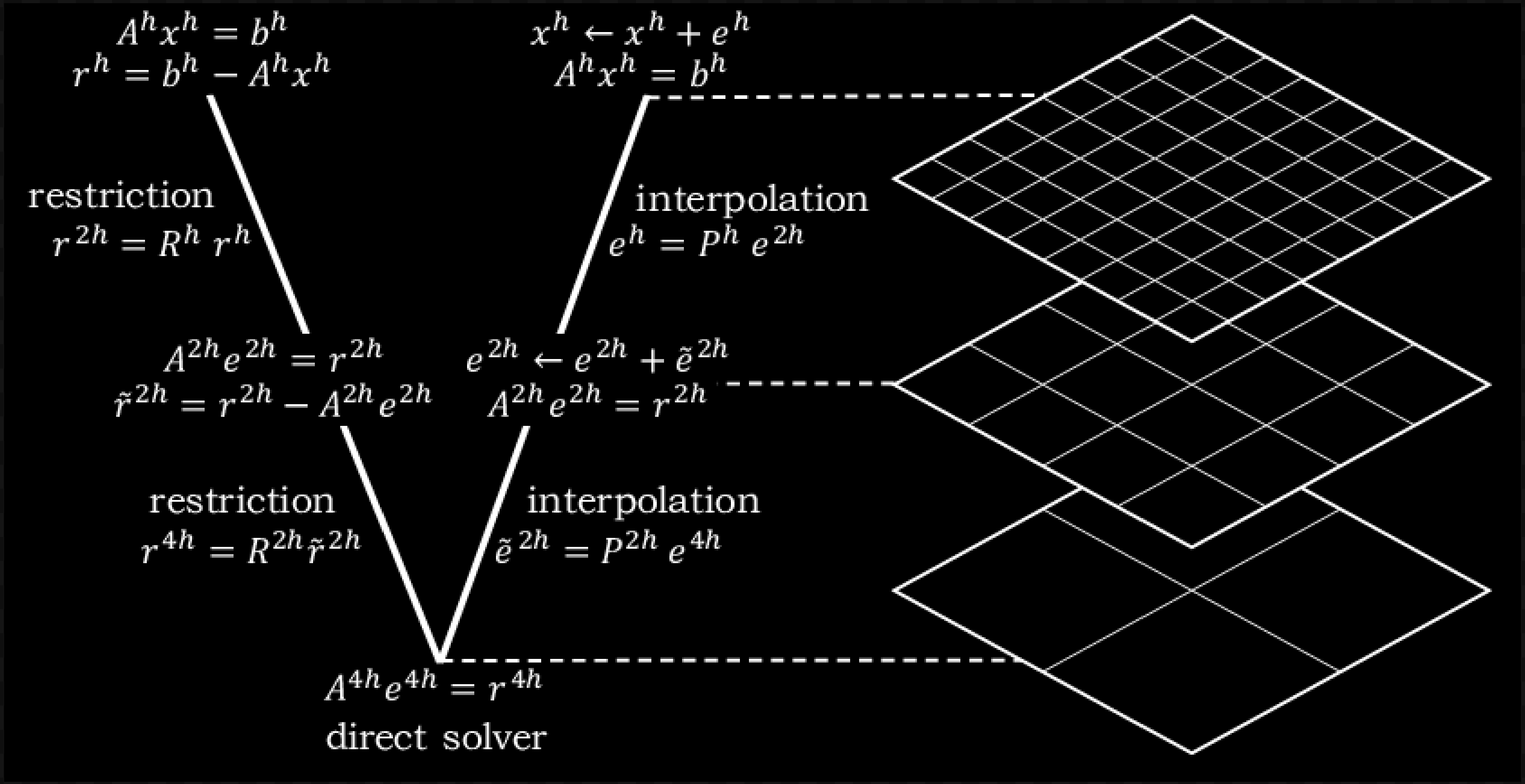
- Data-Parallel (easy – e.g. Horovod)
- Model-Parallel (hard – not *model-partitioned* serial propagation of data)

True Model Parallelism via Iterative Approach: Solve Each Block in Parallel

- Combine with Data-Parallel Techniques for multiplicative parallelization
  - e.g. DP = 4-way parallelism, MP = 2-way parallelism, Total = 8-way parallelism



Multigrid

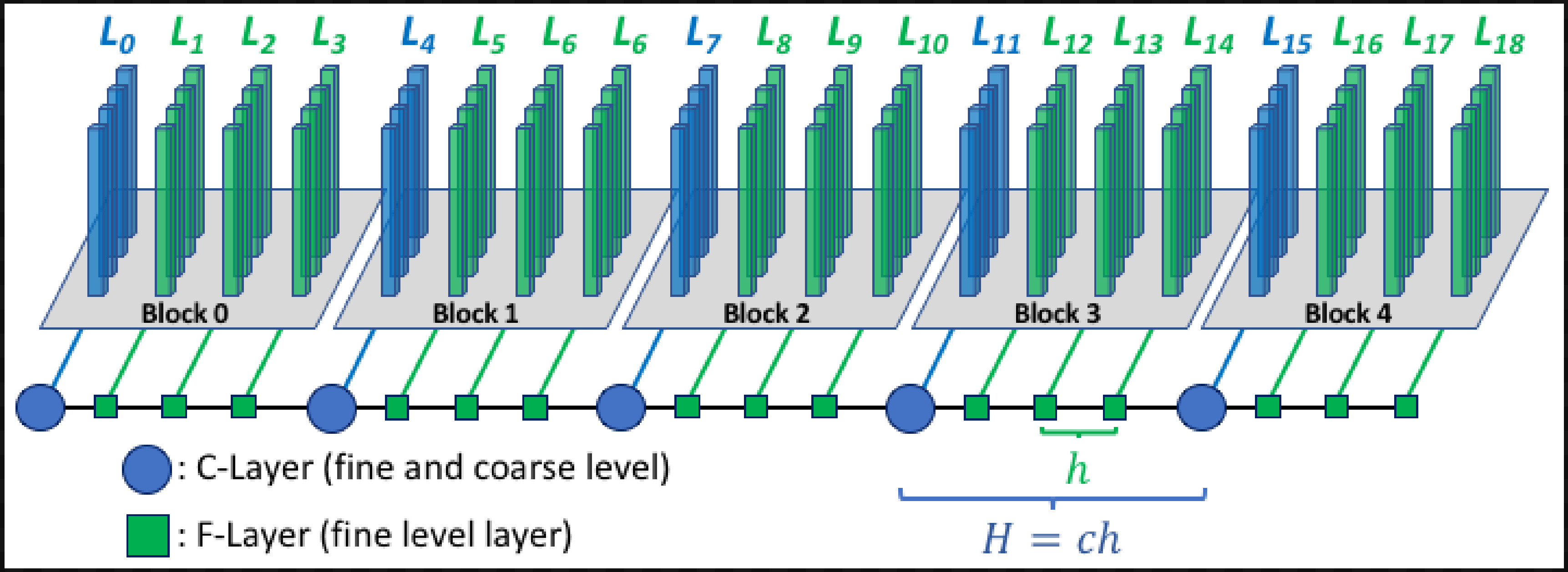


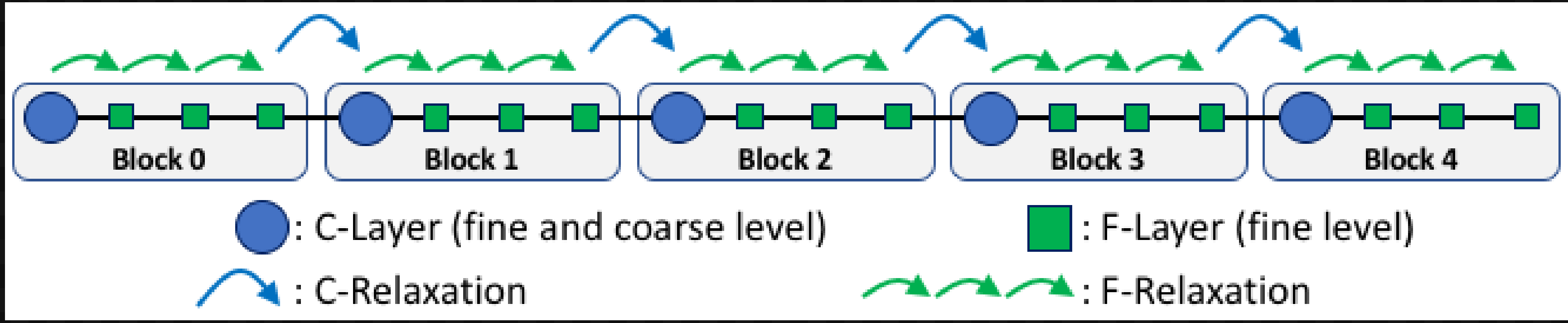
[Reference] S. Gunther, et. al, "Layer-Parallel Training of Deep Residual Neural Networks", SIAM.

Source: https://www.researchgate.net/figure/Illustration-of-the-multigrid-V-cycle_fig2_328599327

Network Partitioning

- Iterative Solution Procedure
  - Propagate guess in block and 1st neighbor layer, restrict, solve coarse solution, update





Implementation & Algorithm Verification

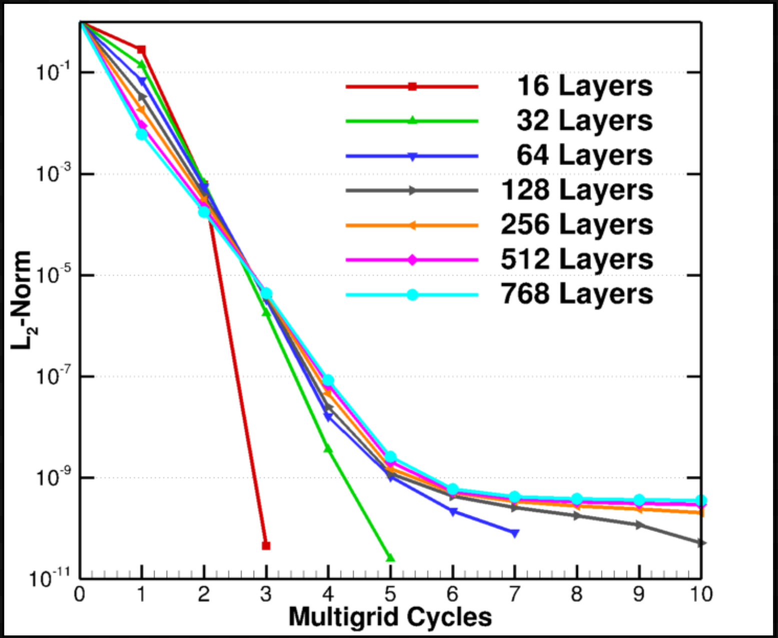
Implementation

- Forward Propagation Only (Back Propagation possible)
- C++: Wrap CuDNN kernels
  - Enabled CUDA Streams for asynchronous execution
- MPI:
  - Point-to-Point Communications (i.e. layer to layer comm.)
  - No Collective Communication needed (e.g. no use of NCCL)
- TX-GAIA Supercomputer: 32 GB NVIDIA V100s

Algorithm 1: ResNet Multigrid FAS Scheme

1. FCF-Relaxation to $\boldsymbol{L}_h\left(\boldsymbol{U}_h, \boldsymbol{\theta}_h\right) = f_h$
2. Restrict residual $\boldsymbol{R}_h$ and approximate solution $\overline{\boldsymbol{U}}_h$:
   $\boldsymbol{R}_H^n \leftarrow \boldsymbol{R}_h^{nc}$, $\overline{\boldsymbol{U}}_H^n \leftarrow \overline{\boldsymbol{U}}_h^{nc}$ for $n = 0, \ldots, N_H - 1$
3. Solve $\boldsymbol{L}_H\left(\boldsymbol{V}_H, \boldsymbol{\theta}_H\right) = \boldsymbol{L}_H\left(\overline{\boldsymbol{U}}_H, \boldsymbol{\theta}_H\right) + \boldsymbol{R}_H$
4. Solve coarse-level error: $\delta \boldsymbol{U}_H = \boldsymbol{V}_H - \overline{\boldsymbol{U}}_H$
5. Update fine-level approximate solution:
   $\overline{u}_h^{nc} \leftarrow \overline{u}_h^{nc} + \delta \boldsymbol{u}_H^n$ for $n = 0, \ldots, N_H - 1$
6. Check convergence:

if $||\boldsymbol{R}_h|| \leq tol$ **then**
  Return;
end
Proceed to step 1;

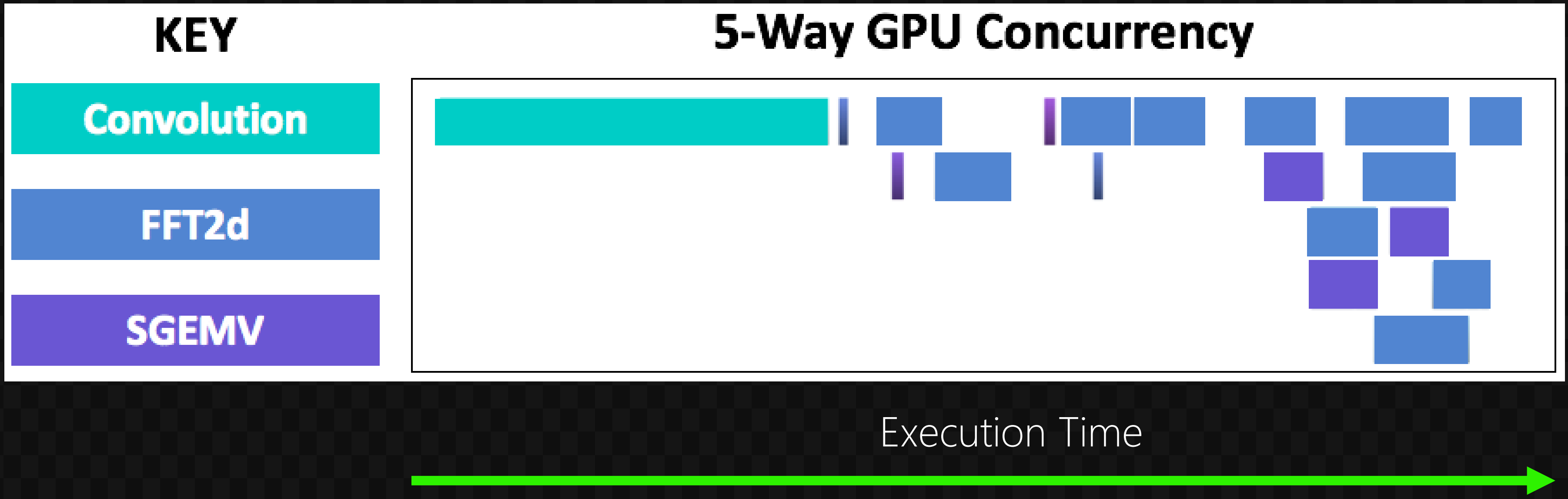


Results: GPU Concurrency

<u>Implementation</u>

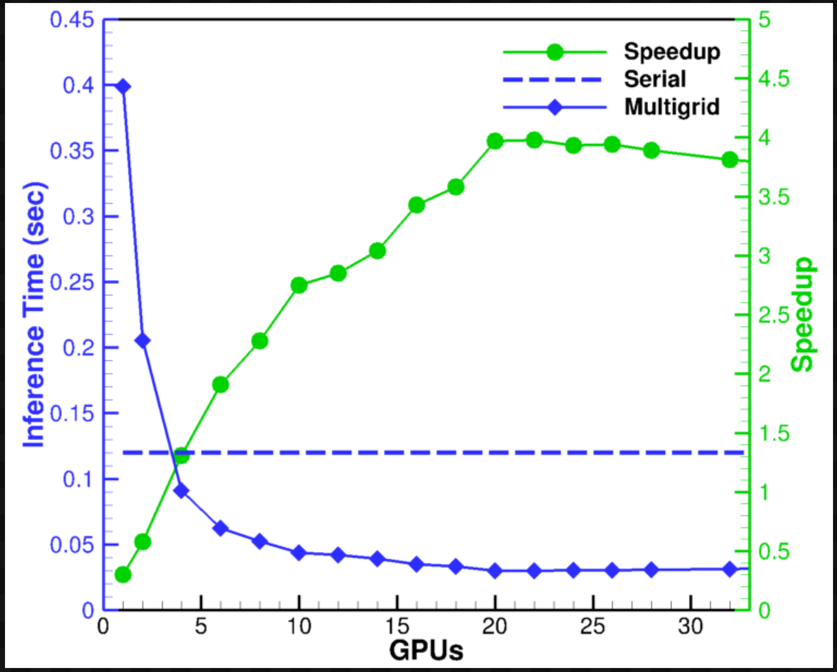
- Wrapped CuDNN kernels
  - Enabled CUDA Streams for asynchronous execution

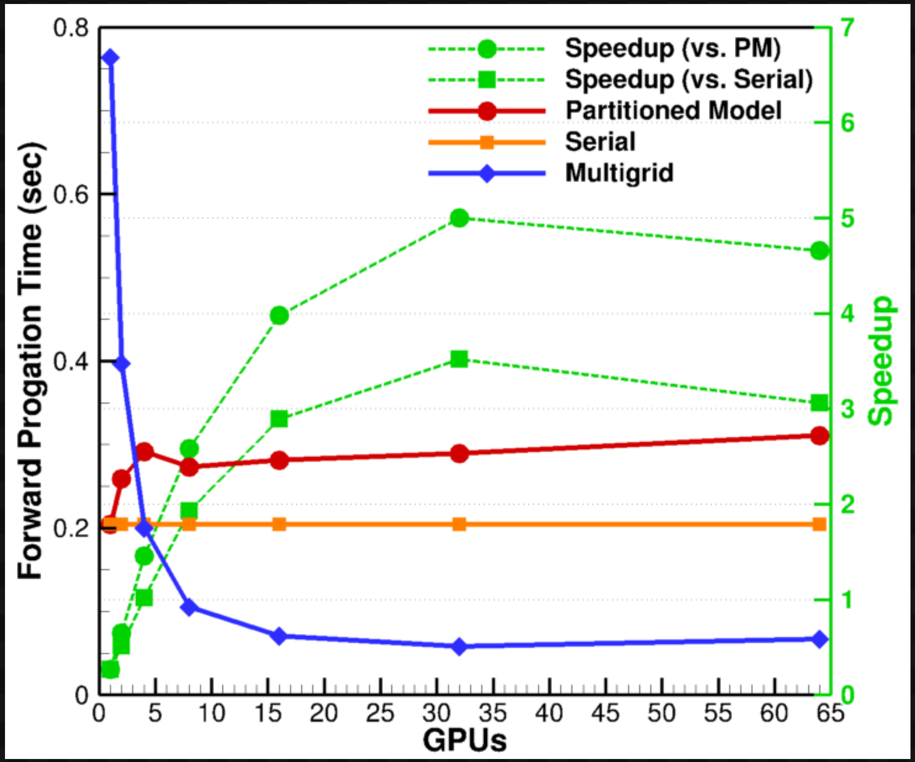
- Placed multiple layer-blocks on same GPU – each with own CUDA Stream
  - Used OpenMP to parallel launch blocks from different CPU-threads

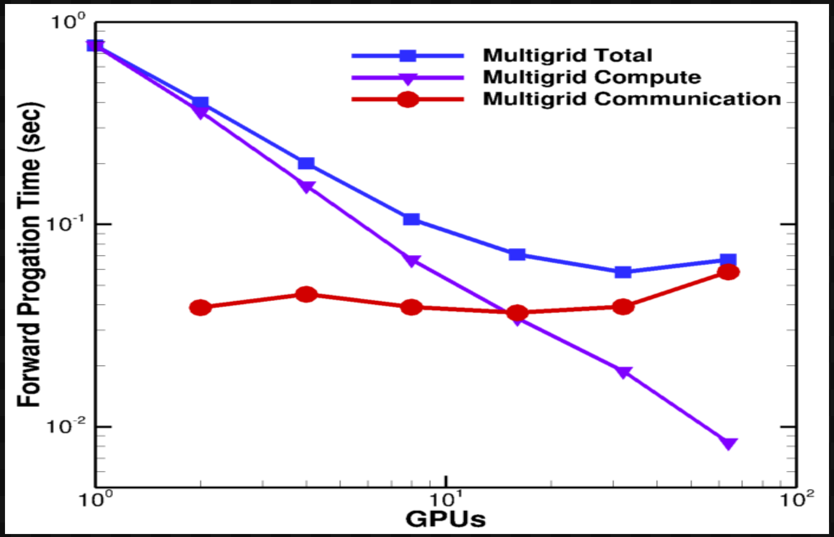


Results

- MNIST Data Set
- 4,096 Layers
  - 7 x 7 convolution layers
  - 50 output channels
  - Padding size: 1
- 3,248,524 parameters





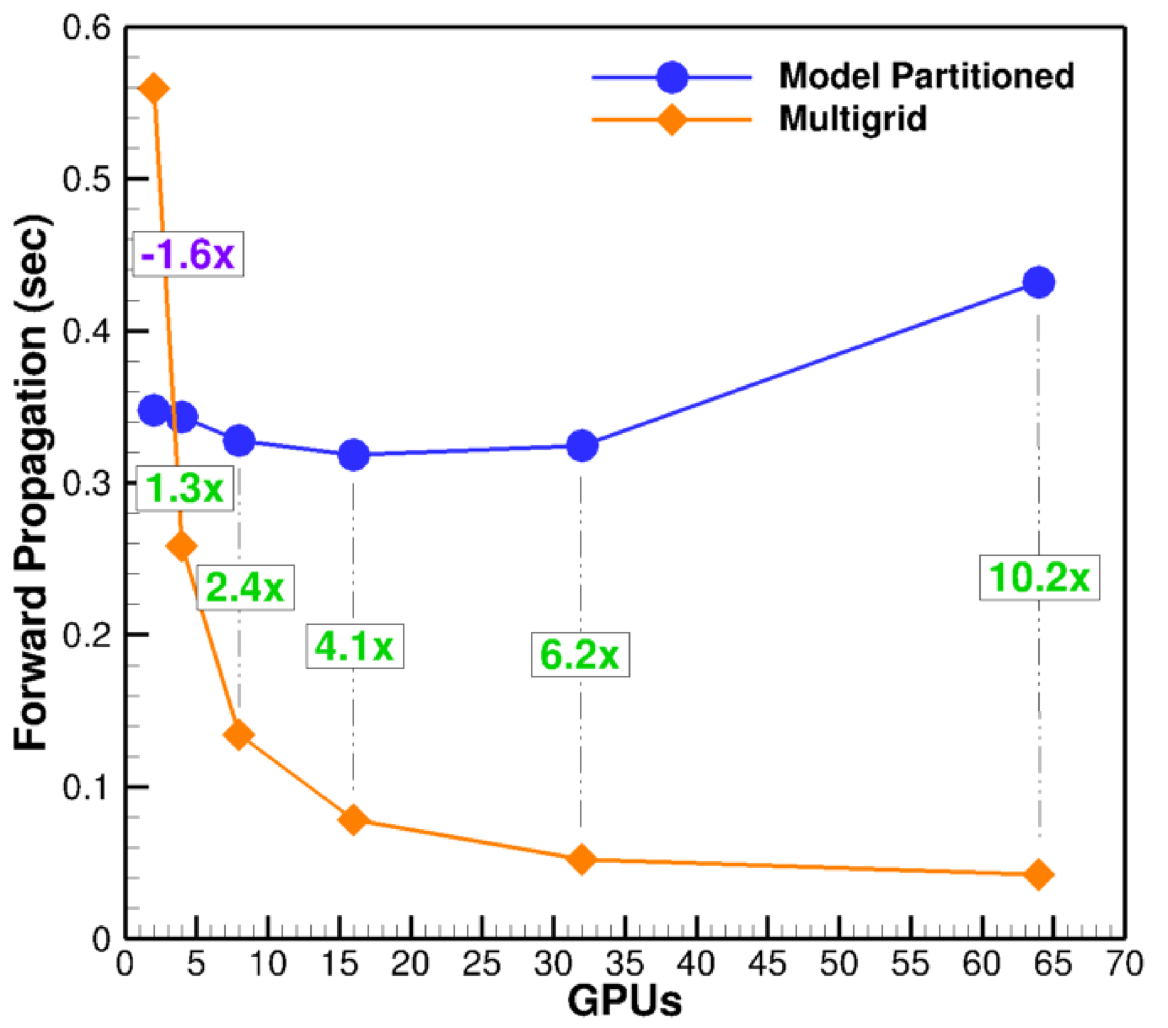


Results

- MNIST Data Set
- 4,115 Layers
  - 7 x 7 convolution layers
  - 20 output channels
  - 16 fully connected layers
  - Padding size: 1
- 2,071,328,150 parameters

4 GPUs: Computation to communication ratio is 92.8%

64 GPUs: Computation to communication ratio is 34.5%



Acknowledgements

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Compute Time

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Thank You

Questions?