Alpa: Automating Inter/Intra Operator Parallelism for Distributed DL

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https://arxiv.org/pdf/2201.12023

Presenter: Ben Xia

Refresher: Data/Intra Op Parallelism

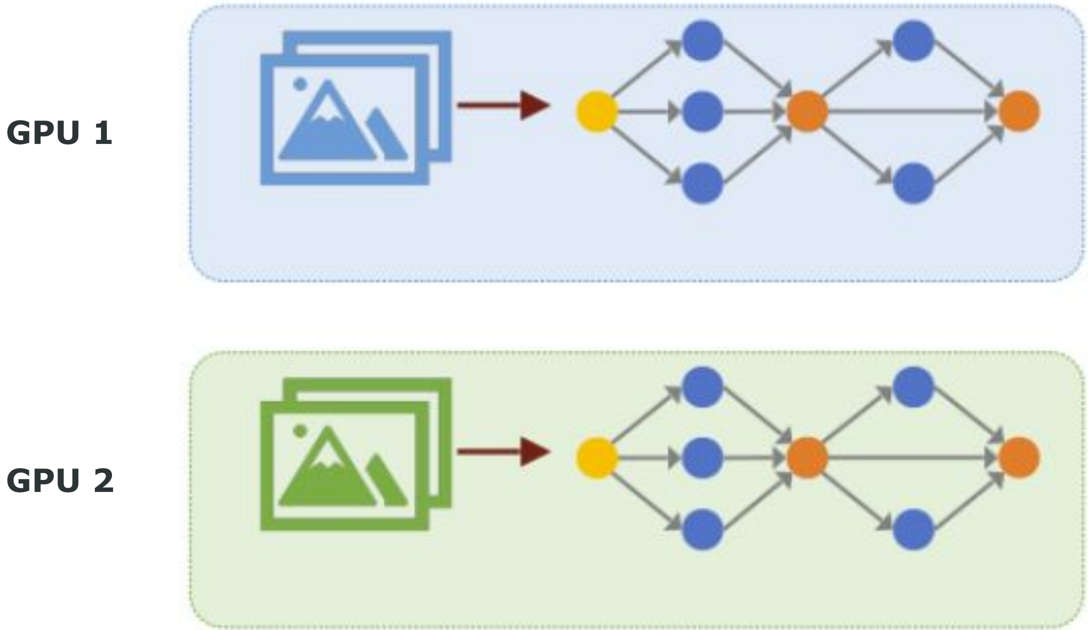


Figure from CMU 15-849 [Jia 2022]

Refresher: Model Parallelism

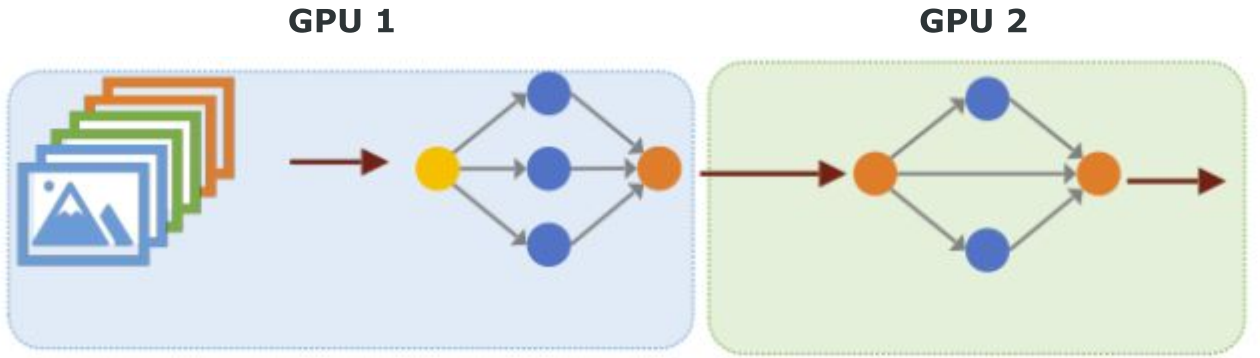
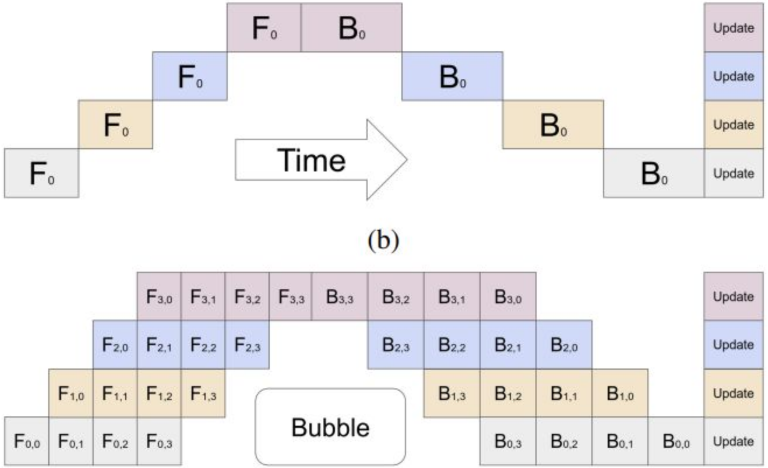
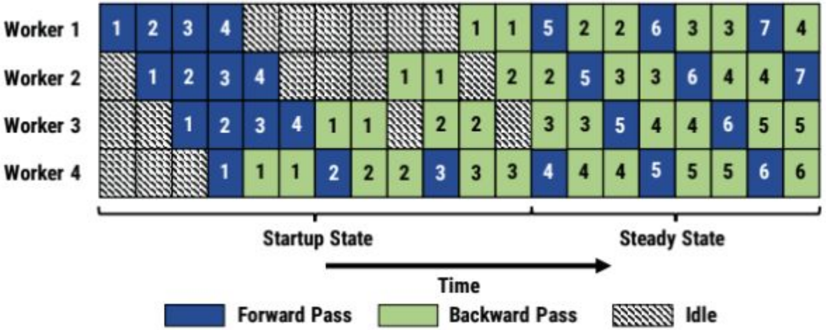


Figure from CMU 15-849 [Jia 2022]

Refresher: Pipeline Parallelism

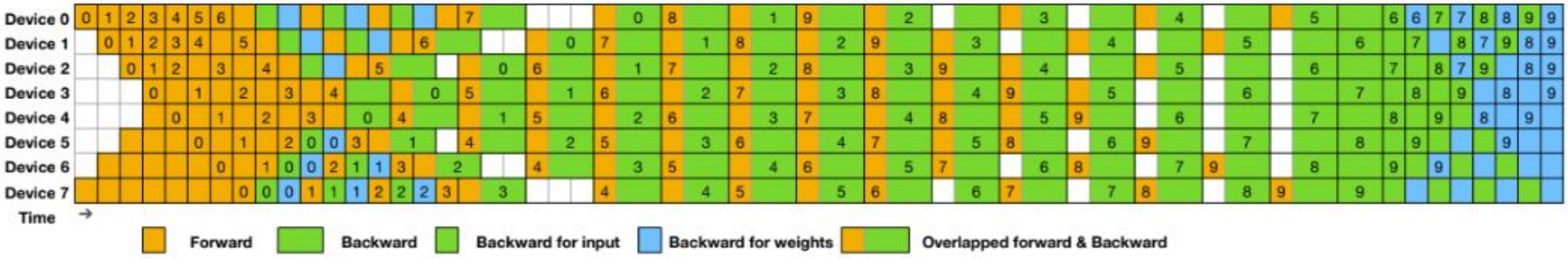


Source: GPipe: Easy Scaling with Micro-Batch Pipeline Parallelism https://arxiv.org/pdf/1811.06965



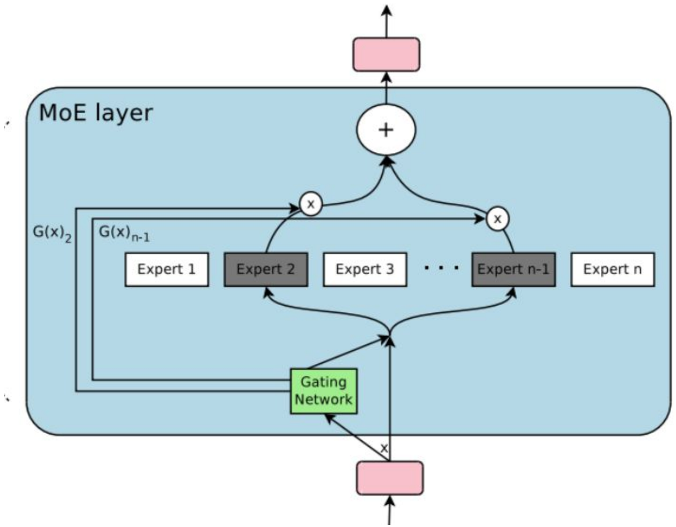
Source: PipeDream: Generalized Pipeline Parallelism for DNN Training https://arxiv.org/pdf/1806.03377

Refresher: Pipeline Parallelism

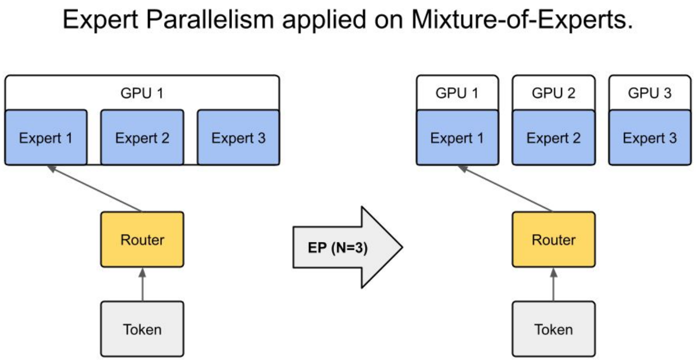


Source: DeepSeek-V3 Technical Report https://arxiv.org/pdf/2412.19437

Refresher: Expert Parallelism

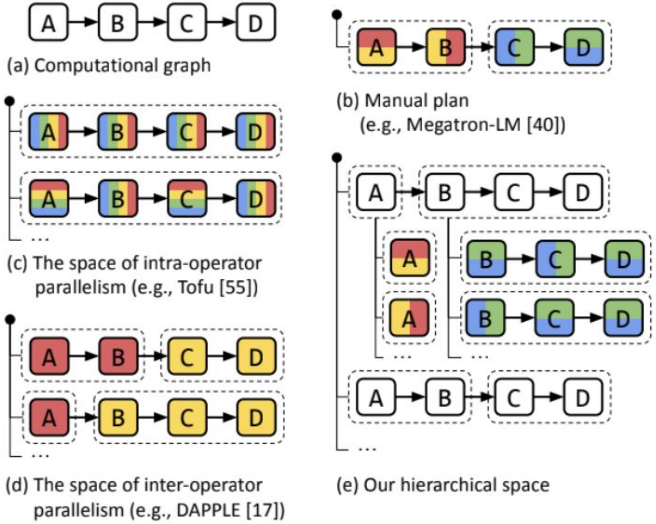


Source: Outrageously Large Neural Networks: The Sparsely Gated Mixture of Experts Layer
https://arxiv.org/pdf/1701.06538



Source: https://docs.nvidia.com/nemo-framework/user-guide/latest/nemotoolkit/features/parallelisms.html

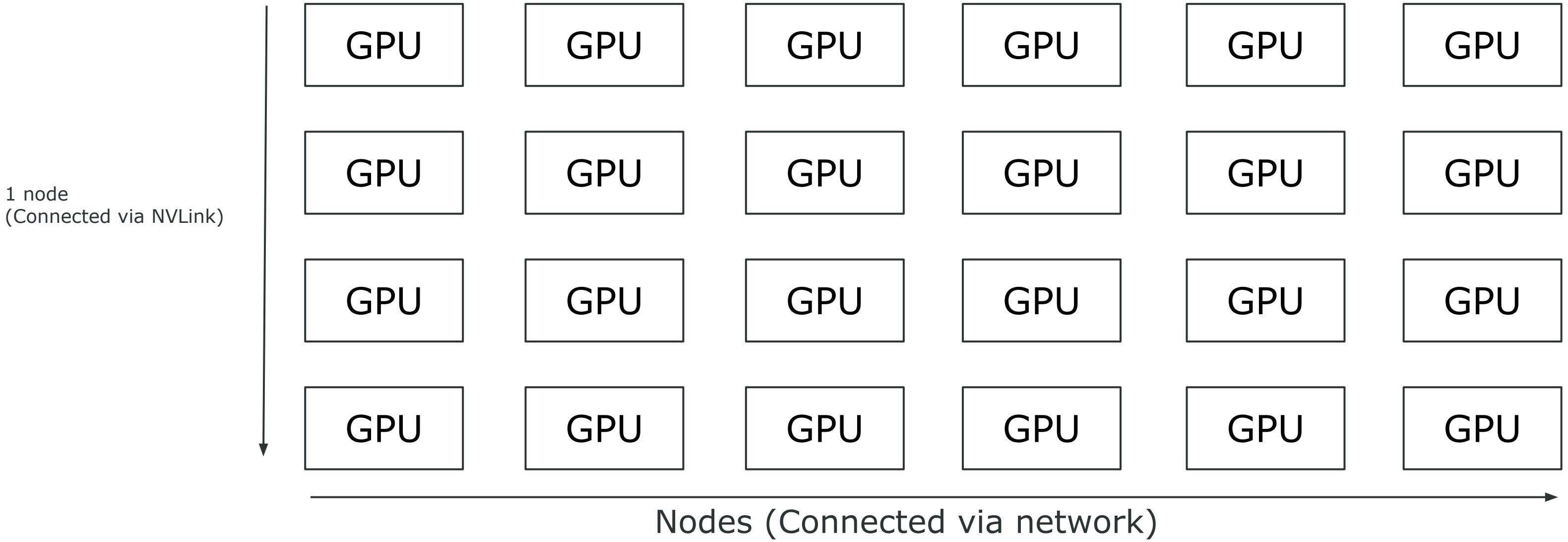
Alpa: Compiler for Parallel Execution Plans



Source: Alpa: Automating Inter- and Intra-Operator Parallelism for Distributed Deep Learning https://arxiv.org/pdf/2201.12023

Alpa: Device Mesh Formulation

- Compute clusters are viewed as a simplified 2D grid.
- Communication along each dimension of the grid w/ different bandwidths and speed.



Alpa: Hierarchical Search

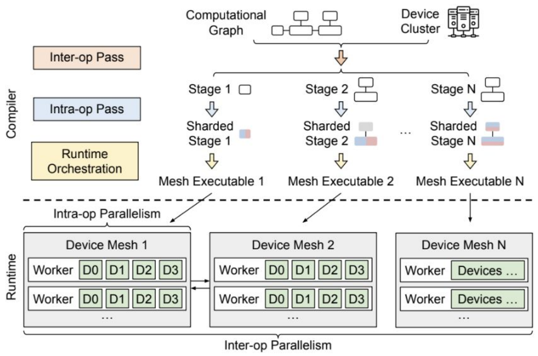
Inter-Op Pass

Dynamic Programming

Intra-Op Pass

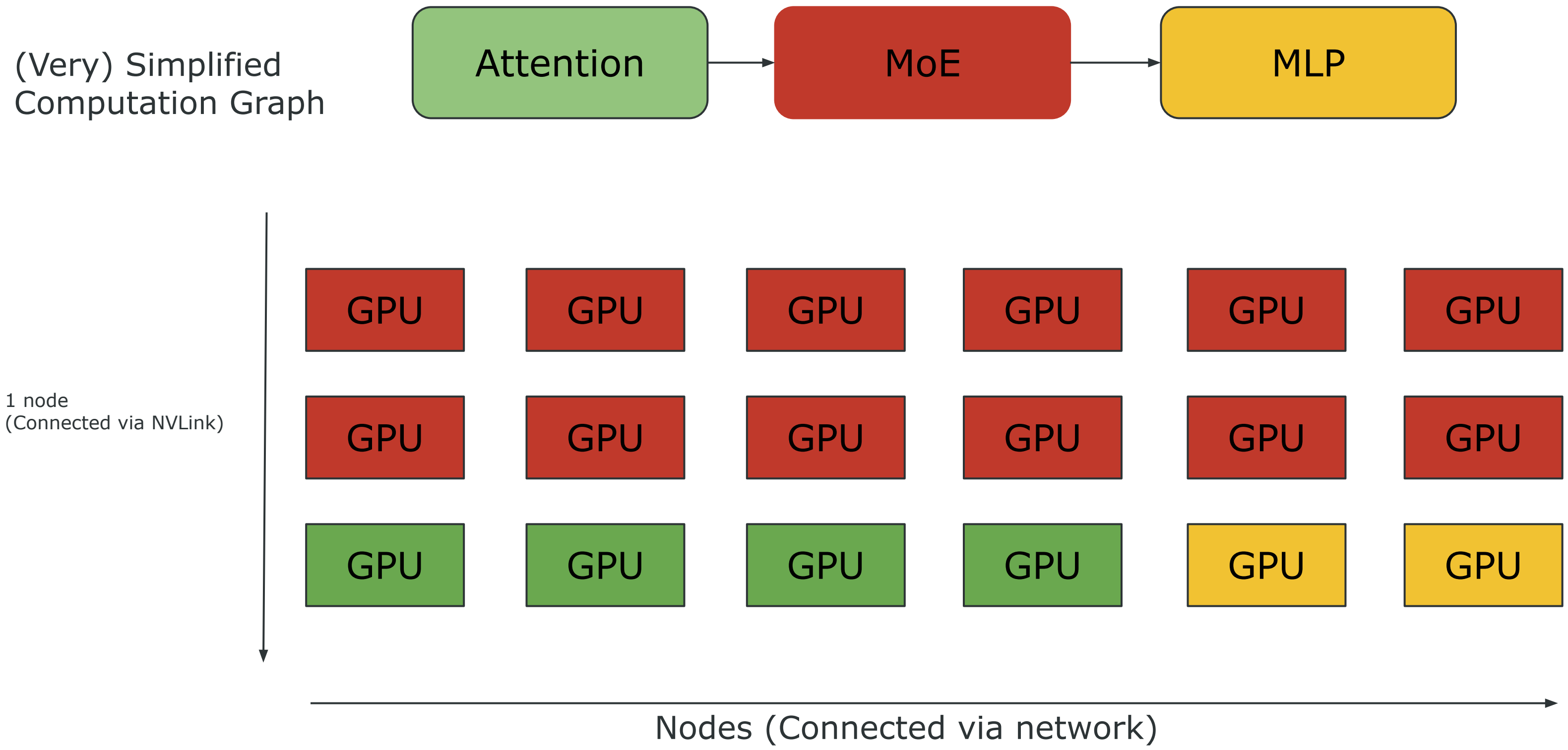
Integer Linear Programming

Runtime Orchestration



Source: Alpa: Automating Inter- and Intra-Operator Parallelism for Distributed Deep Learning https://arxiv.org/pdf/2201.12023

Alpa: Inter Op Pass



Alpa: Inter Op Pass

$$T^* = \min_{\substack{s_1,\ldots,s_S;\\(n_1,m_1),\ldots,(n_S,m_S)}} \left\{ \sum_{i=1}^{S} t_i + (B-1) \cdot \max_{1 \le j \le S} \{t_j\} \right\}.$$

$$F(s,k,d;t_{max}) = \min_{\substack{k \le i \le K\\ n_s \cdot m_s \le d}} \left\{ \begin{array}{l} t_{intra}((o_k,\ldots,o_i), Mesh(n_s,m_s), s) \\ + F(s-1, i+1, d - n_s \cdot m_s; t_{max}) \\ \mid t_{intra}((o_k,\ldots,o_i), Mesh(n_s,m_s), s) \le t_{max} \end{array} \right\}$$

$$T^*(t_{max}) = \min_s \{F(s,0,N \cdot M; t_{max})\} + (B-1) \cdot t_{max}.$$

$$G(k,r) = \min_{1 \le i \le k} \left\{ \begin{array}{l} \max\{G(i-1,r-1), C(i,k)\} \\ \mid FLOP(o_i,\ldots,o_k) \le \dfrac{(1+\delta) FLOP_{total}}{L} \end{array} \right\}$$

Find the optimal submesh assignments via dynamic programming to minimize total runtime.

Ok this one is for operator clustering but that's still inter-op

Intra Op Pass

- Once we have a submesh assignment for a group of operators, we need to determine how to optimize its runtime.
  - Different subsets of a layer can either be sharded or replicated across multiple workers.

Spec	Device 0	Device 1	Device 2	Device 3
RR	$A[0:N, 0:M]$	$A[0:N, 0:M]$	$A[0:N, 0:M]$	$A[0:N, 0:M]$
S^0S^1	$A[0:\frac{N}{2}, 0:\frac{M}{2}]$	$A[0:\frac{N}{2}, \frac{M}{2}:M]$	$A[\frac{N}{2}:N, 0:\frac{M}{2}]$	$A[\frac{N}{2}:N, \frac{M}{2}:M]$
S^1S^0	$A[0:\frac{N}{2}, 0:\frac{M}{2}]$	$A[\frac{N}{2}:N, 0:\frac{M}{2}]$	$A[0:\frac{N}{2}, \frac{M}{2}:M]$	$A[\frac{N}{2}:N, \frac{M}{2}:M]$
S^0R	$A[0:\frac{N}{2}, 0:M]$	$A[0:\frac{N}{2}, 0:M]$	$A[\frac{N}{2}:N, 0:M]$	$A[\frac{N}{2}:N, 0:M]$
S^1R	$A[0:\frac{N}{2}, 0:M]$	$A[\frac{N}{2}:N, 0:M]$	$A[0:\frac{N}{2}, 0:M]$	$A[\frac{N}{2}:N, 0:M]$
RS^0	$A[0:N, 0:\frac{M}{2}]$	$A[0:N, 0:\frac{M}{2}]$	$A[0:N, \frac{M}{2}:M]$	$A[0:N, \frac{M}{2}:M]$
RS^1	$A[0:N, 0:\frac{M}{2}]$	$A[0:N, \frac{M}{2}:M]$	$A[0:N, 0:\frac{M}{2}]$	$A[0:N, \frac{M}{2}:M]$
$S^{01}R$	$A[0:\frac{N}{4}, 0:M]$	$A[\frac{N}{4}:\frac{N}{2}, 0:M]$	$A[\frac{N}{2}:\frac{3N}{4}, 0:M]$	$A[\frac{3N}{4}:N, 0:M]$
RS^{01}	$A[0:N, 0:\frac{M}{4}]$	$A[0:N, \frac{M}{4}:\frac{M}{2}]$	$A[0:N, \frac{M}{2}:\frac{3M}{4}]$	$A[0:N, \frac{3M}{4}:M]$

Intra Op Pass

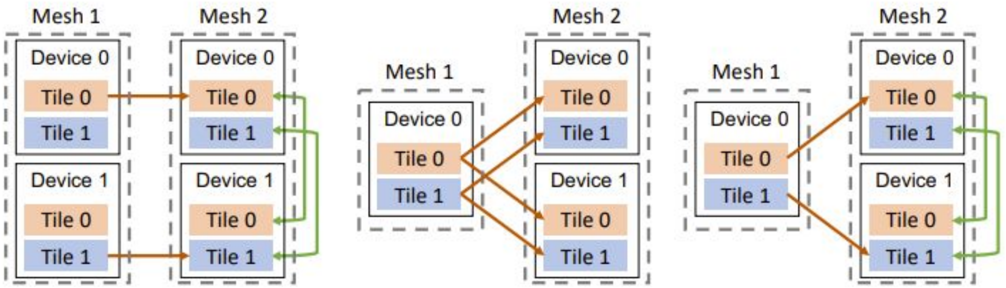
- Once we have a submesh assignment for a group of operators, we need to determine how to optimize its runtime.
    - Intra-Op Parallelism/Data Parallelism
    - Model Parallelism (Placing different operators on different devices)
    - etc.

$$\min_{s} \sum_{v \in V} s_v^\intercal (c_v + d_v) + \sum_{(v,u) \in E} s_v^\intercal R_{vu} s_u,$$

Computation/Communication Cost   Resharding Cost

Solvable via Integer Linear Programming

Parallelism Orchestration

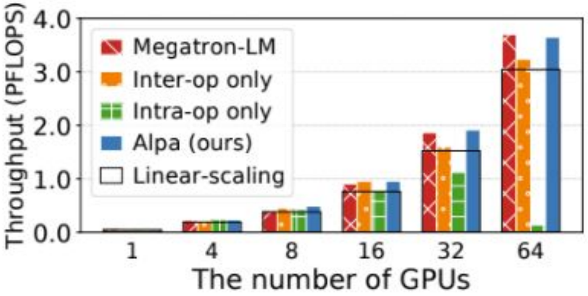


(a) Megatron-LM (b) Naïve send/recv (c) Local all-gather

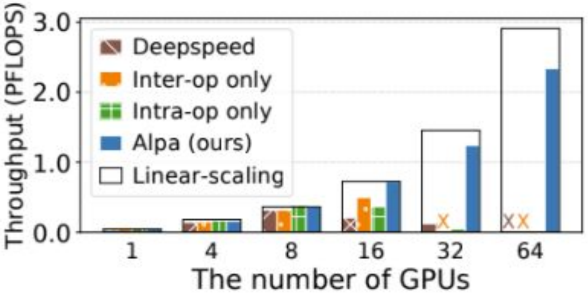
1. Find correspondences between source and destination mesh
   a. Add point-to-point send/recv's
2. Remove redundant send's (based on destination mesh sharding configuration)
   a. Allow destination to all-gather -> Faster communication than point-to-point send's

Performance

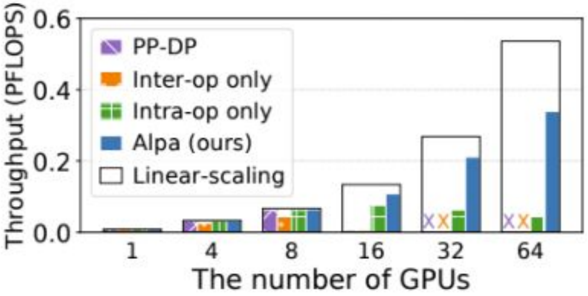
AWS p3.16xLarge



(a) GPT



(b) MoE



(c) Wide-ResNet

Roughly equal performance to Megatron, but generalizes to non-GPT architectures

Pure inter/intra op parallelism fails to scale for larger models
3.5x faster than DeepSpeed on 2 nodes, 9.7x faster on 4 nodes

Compilation Speed

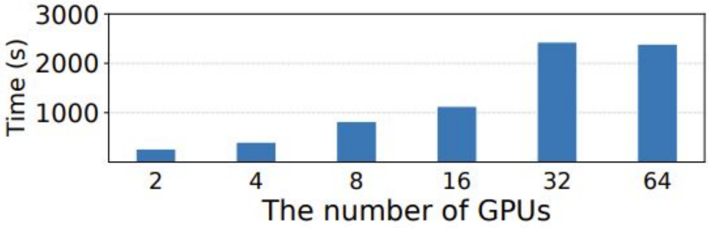


Table 5: Compilation time breakdown of GPT-39B.

Steps	Ours	w/o optimization
Compilation	1582.66 s	> 16hr
Profiling	804.48 s	> 24hr
Stage Construction DP	1.65 s	N/A
Other	4.47 s	N/A
Total	2393.26 s	> 40hr

$$O(K^5 NM(N + \log(M))^2)$$

Dynamic program asymptotic runtime