

An Optimization Technique for Hiding Communication Costs in 3D Parallel Training of DL



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Best Paper Award



Background

- DNN models have grown rapidly in accuracy, but this progress has come with a training cost (e.g., 100Bs-Ts params)
- Training large models takes tremendous time and memory capacity → Parallel training, but challenging in decomposition
- Auto-parallelization (e.g., Alpa) finds the optimal balance of DP/TP/PP without expertise for parallel training in HPC systems
- XLA is a domain-specific compiler, XLA: high-level computation graph (e.g., JAX, PyTorch) → Optimized machine code
- An XLA compiler in Alpa produces inefficient all-reduce stages in PP backward computation [Fig.1]

Approach: Comm-Shift Optimization at the level of an XLA compiler used in Alpa

*XLA: Accelerated Linear Algebra

- We analyze computation graph and shift gradient-averaging communication from backward to parameter update [Fig.2] → eliminate synchronization time from one pipeline stage from another → Reduce overall training times

Results

- Comm-Shift improves the training performance across various models up to 27% at maximum (GPT-J-6B) [Table 1]
- Improvement becomes more significant with more communication in larger models

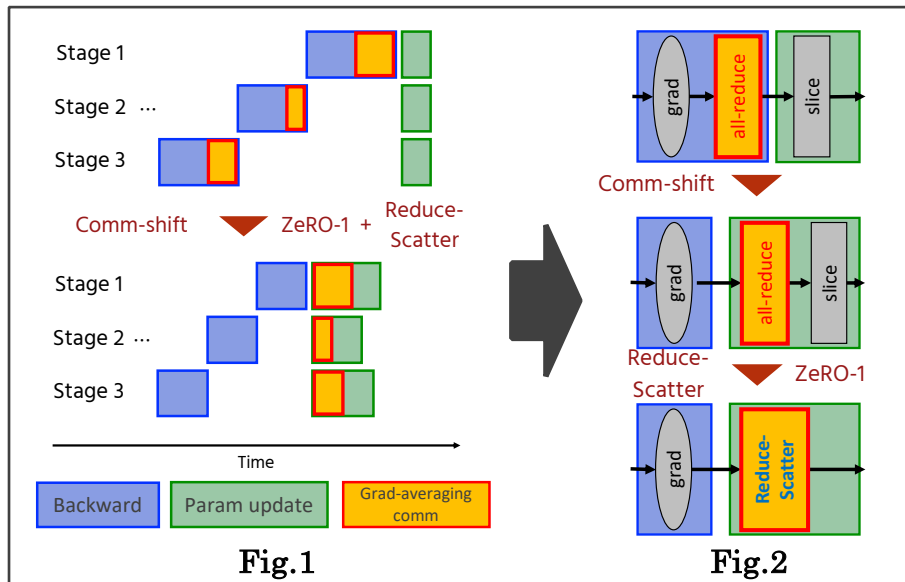


Table 1: Experimental results on TSUBAME4.0
(NVIDIA H100 SXM5 /InfiniBand NDR200 x4 (Fat Tree))

Task	Model	# of GPUs	Strategy	Throughput		Speedup
				w/o comm-shift opt.	w/ comm-shift opt.	
NLP	GPT-2 Small	16	[(8x1), (8x1)]	2019190 token/s	2073480 token/s	+2.69%
	GPT-2 Large	16	[(8x1), (8x1)]	403880 token/s	419156 token/s	+3.78%
	GPT-2 XL	32	[(16x1), (16x1)]	477236 token/s	508616 token/s	+6.58%
	GPT-J-6B	32	[(8x1), (4x2), (4x2), (4x2)]	143158 token/s	181812 token/s	+27.00%
	Mamba-1.4B	16	[(2x1), (2x1), (2x1), (2x1), (2x1), (2x1), (2x1), (2x1)]	29786 token/s	30913 token/s	+3.79%
Image Classification	ViT-base	8	[(2x1), (2x1), (2x1), (2x1)]	1192 image/s	1306 image/s	+9.55%
	SwinV2-L	16	[(4x1), (2x1), (4x1), (4x1), (2x1)]	1827 image/s	1893 image/s	+3.60%
	CoAtNet-7	16	[(8x1), (8x1)]	384 image/s	444 image/s	+15.36%