NEURAL INFORMATION PROCESSING SYSTEMS

Block-Diagonal LoRA for Eliminating Communication Overhead in Tensor Parallel LoRA Serving

aws

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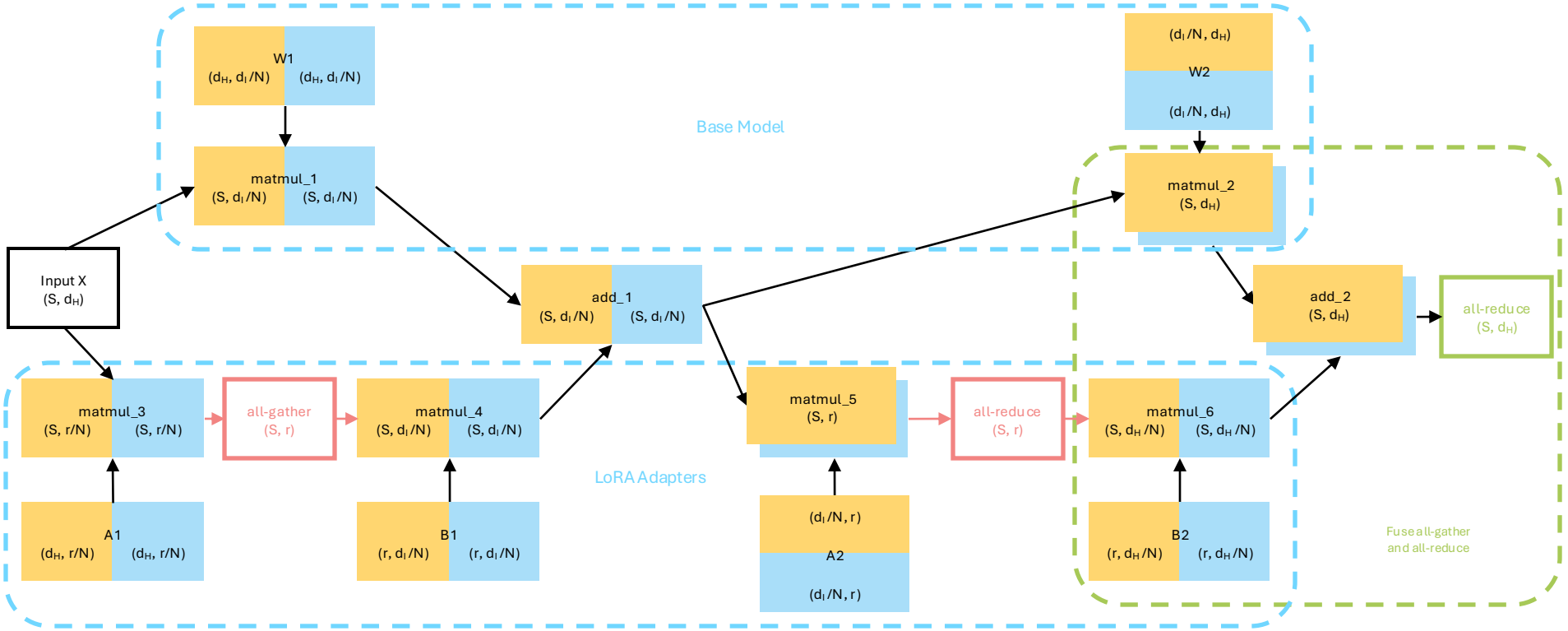
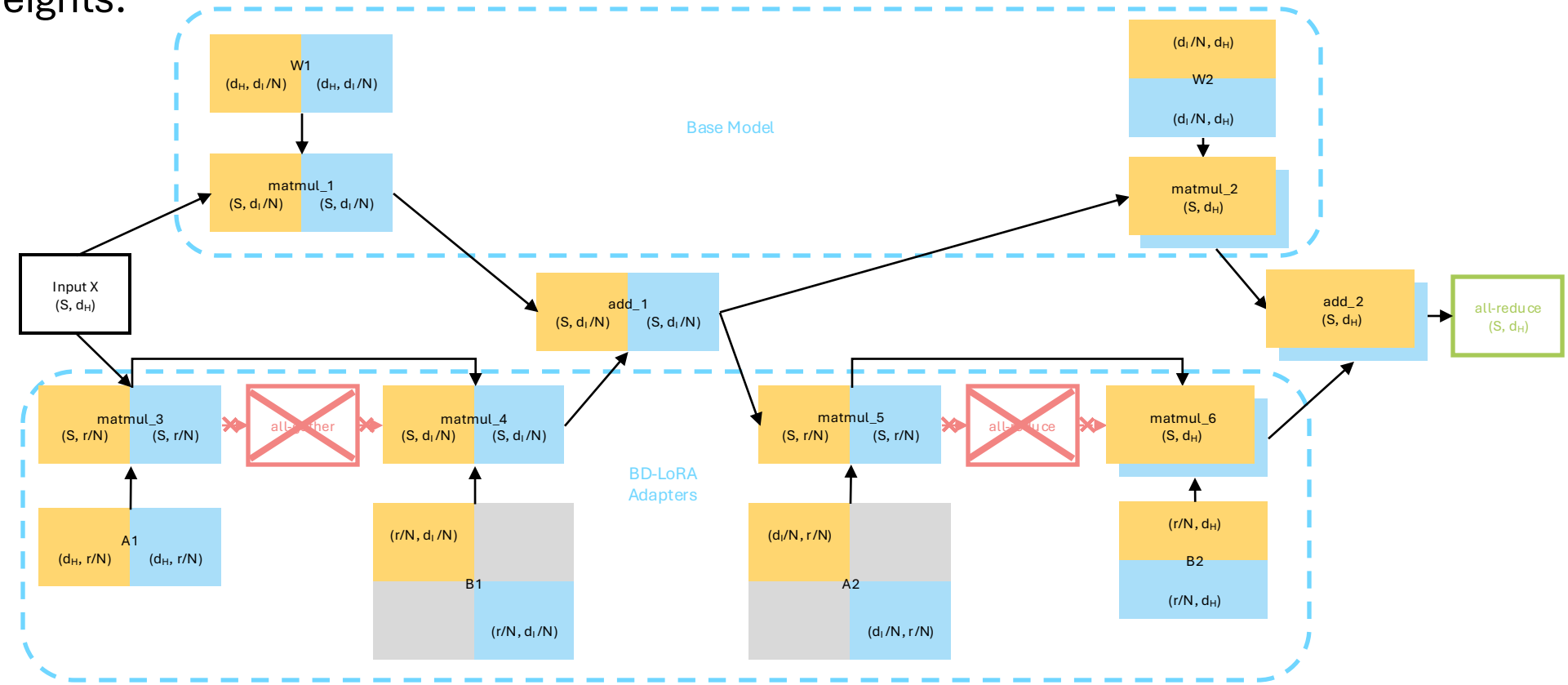
Problem and Motivation

- For multi-LoRA serving with a shared base LLM, merging adapters prevents batching and incurs swap overhead.
- S-LoRA TP strategy adds extra all-gather/all-reduce beyond the base model.
- The additional cost is significant in practice and exacerbated at larger ranks.



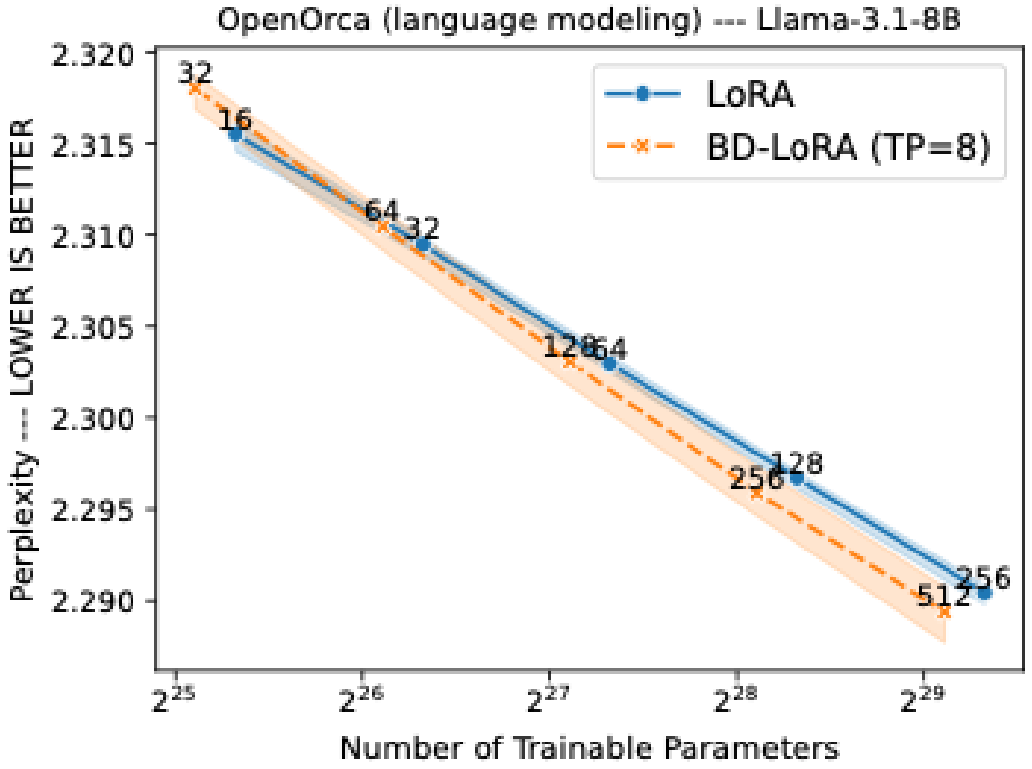
BD-LoRA

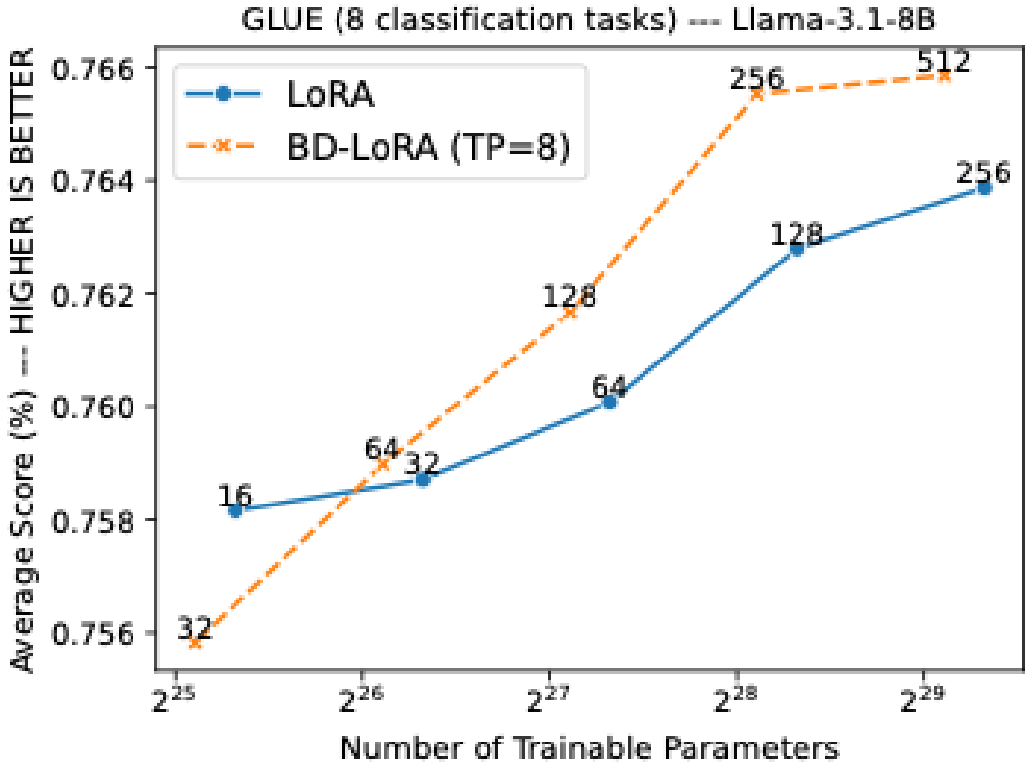
- Constrain specific LoRA factors (B_1 and A_2) to be block-diagonal so they align with base TP sharding -> no extra all-gathers/all-reduces for LoRA.
- BD-LoRA can be interpreted as attaching independent LoRA adapters to each shard of the base weights.



Downstream performance

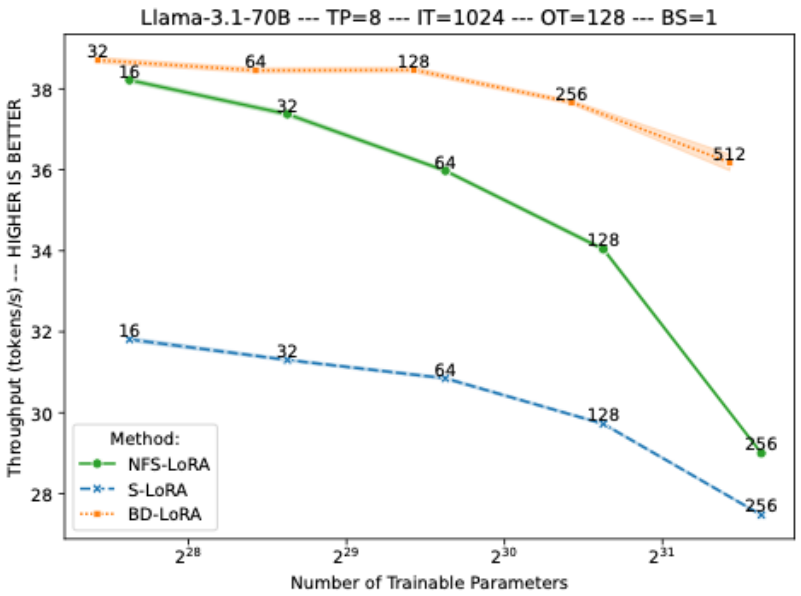
- For a similar number of trainable parameters, BD-LoRA shows comparable performance to LoRA.

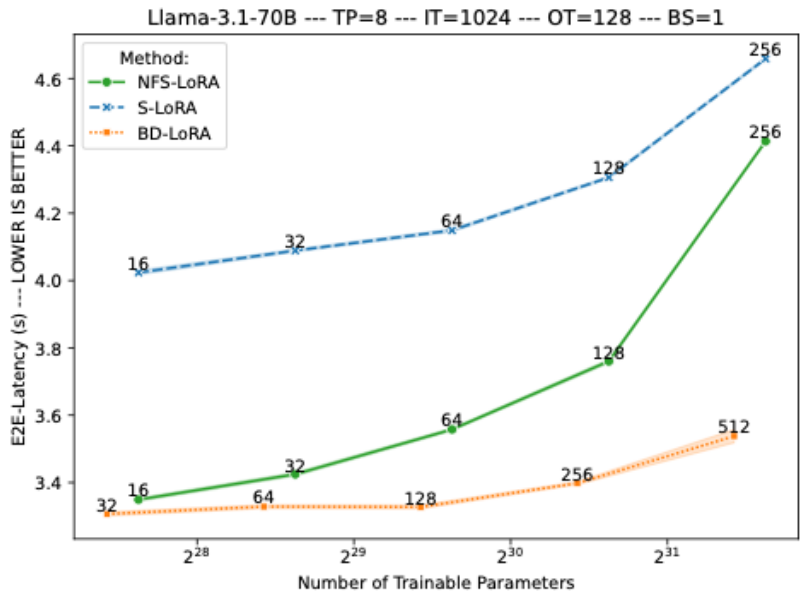


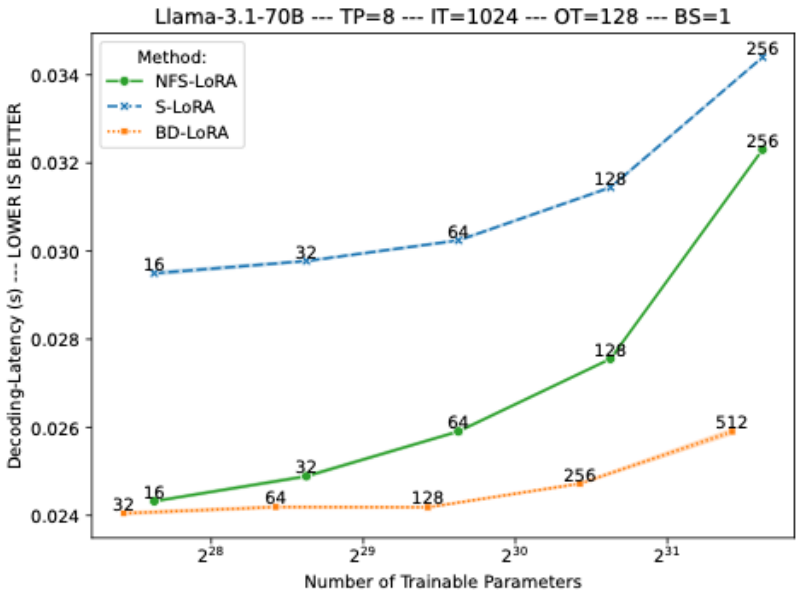


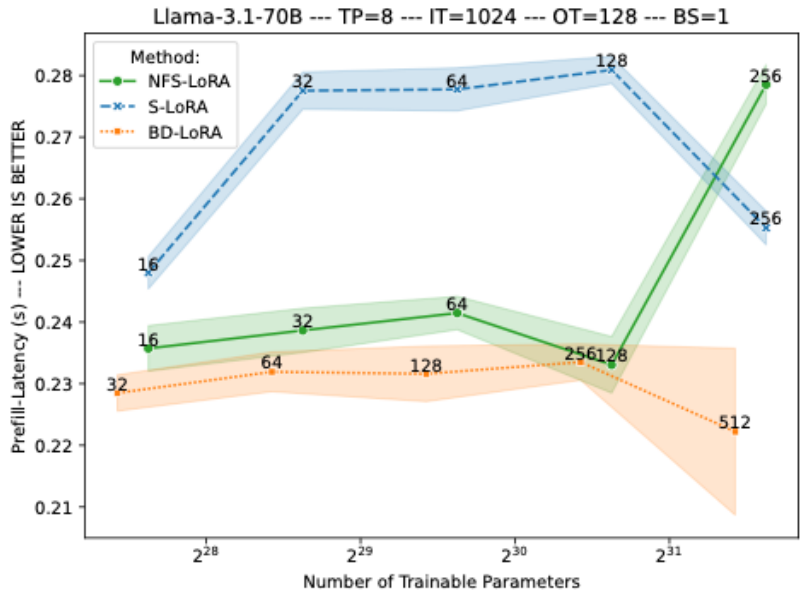
Throughput and Latency

- BD-LoRA yields 1.79x (1.23x) end-to-end speed-up with 0.87x (1.74x) number of adapter parameters on 70B model and 1.63x (1.3x) with 0.86x (1.73x) parameters on 8B model.



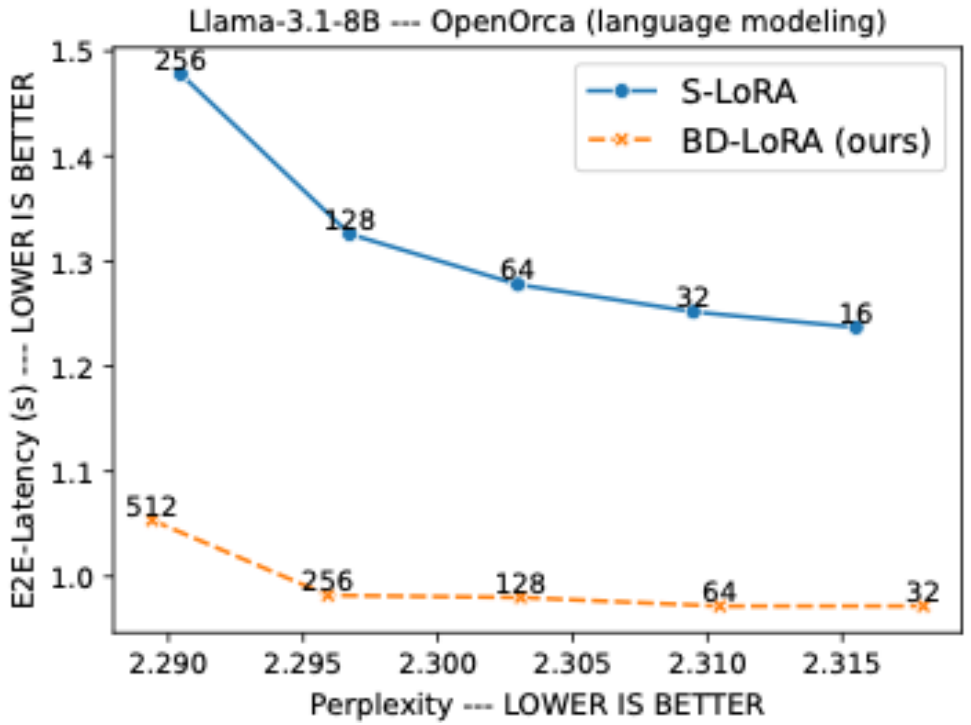


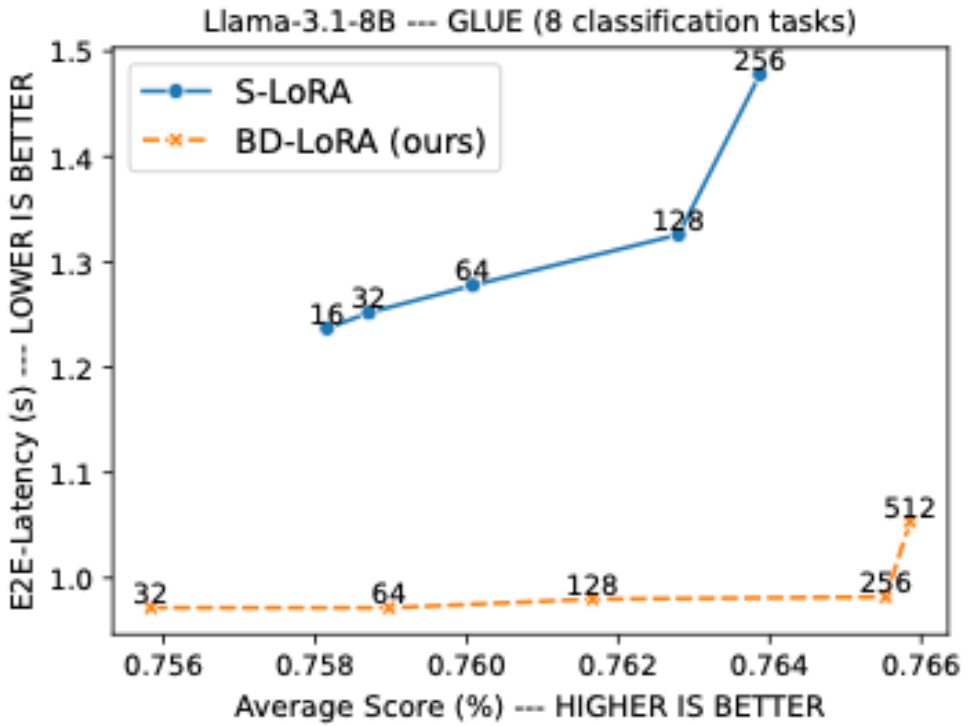




Downstream Performance vs. Run-time Trade-off

- At the same downstream performance, BD-LoRA achieves 1.27x – 1.51x end-to-end speedup.





Takeaway

- BD-LoRA eliminates the additional communication overhead in S-LoRA.
- With the same number of trainable parameters, BD-LoRA and LoRA achieve similar downstream performance.
- With the same number of trainable parameters, BD-LoRA is faster than S-LoRA.
- With the same downstream performance, BD-LoRA is faster than S-LoRA.

Thank You!