FlowMoE: A Scalable Pipeline Scheduling Framework for Distributed Mixture-of-Experts Training

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Motivation

- MoE scales LLM without increasing computational costs.
- Existing works pipeline only expert + all-to-all, ignoring MHA, gating, and all-reduce.
- Ignored tasks = 30-40% of iteration time \rightarrow huge inefficiency.

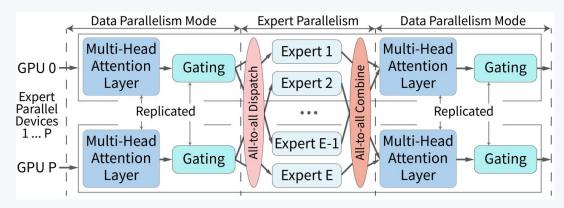


Fig. 1: Training MoE model with expert parallelism

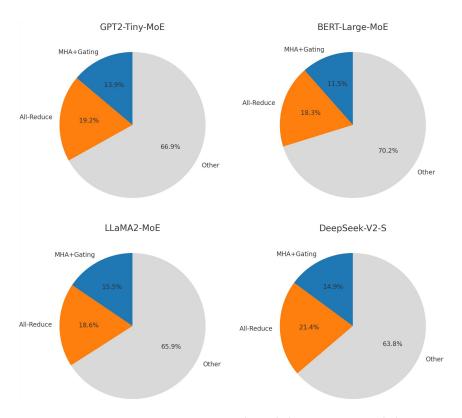
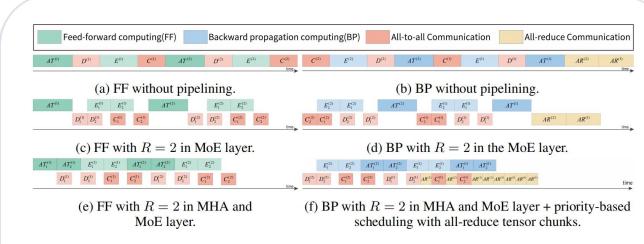


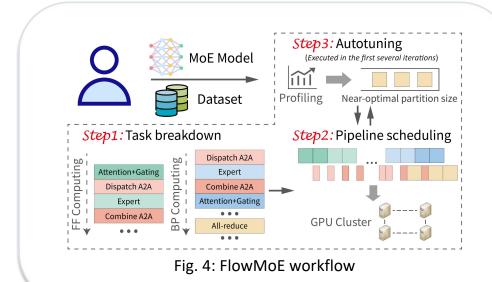
Fig. 2: One iteration time breakdown per model



FlowMoE — Key Ideas







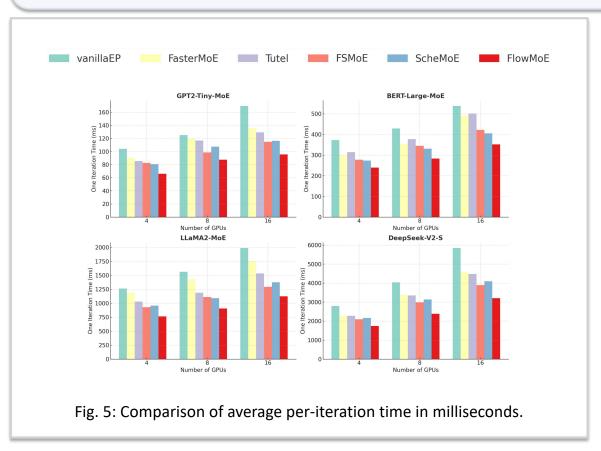
- Unified pipeline scheduling strategy: Schedules MHA, gating, expert, and A2A together.
- Priority scheduling mechanism for heterogeneous communication tasks: Cut all-reduce chunks and execute them in all-to-all task gaps.
- Lightweight adaptive optimizer and system integration: Tiny Bayesian optimizer for automatic tuning. Deploying FlowMoE to the PyTorch engine.

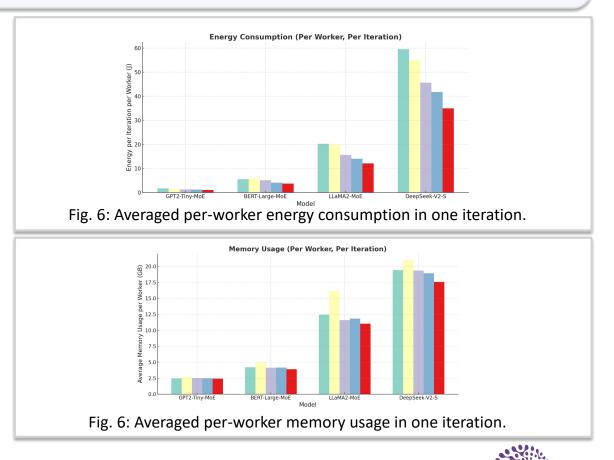


Experimental Results

Experimental Settings

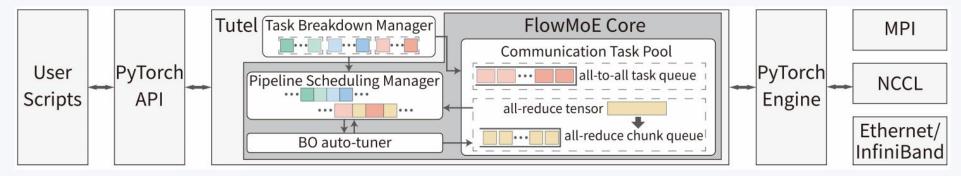
- 675 customized MoE layers, 4 real-world MoE models
- Clusters: RTX3090 (16 GPUs), RTX2080Ti (8 GPUs).





System Implementation & Conclusion

System Implementation



- Framework: Implemented on PyTorch , leveraging Tutel for optimized communication.
- Compatibility: Supports multiple optimization frameworks and communication stacks.

Conclusions

- The unified scheduling across all major MoE-related tasks.
- Enabling the optimal coexistence of heterogeneous communication tasks.
- Substantially advancing distributed pipeline training.
- Open-source: github.com/ZJU-CNLAB/FlowMoE

