Federation of Experts: Efficient Distributed Inference for Large Language Models

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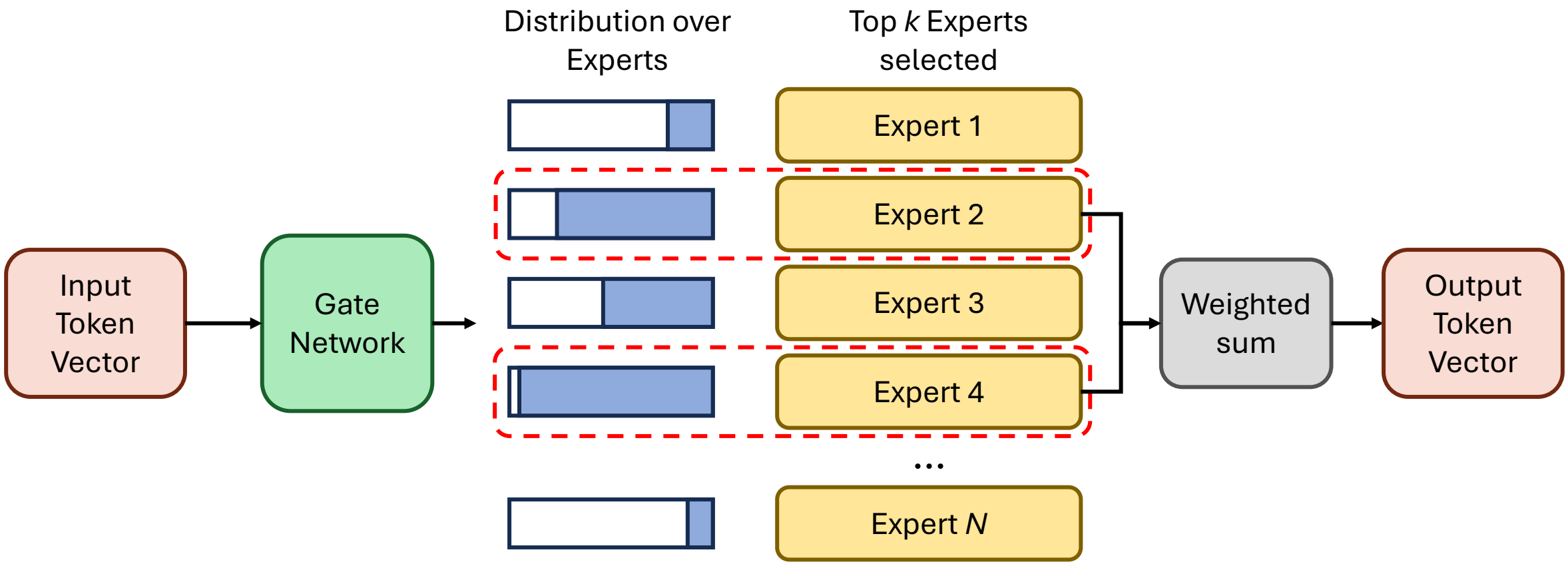
Why Mixture of Experts?

- Large Language Models (LLMs) consistently improve as parameter counts increase.
- However, computation scales proportionally with active parameters, imposing limits on both training and inference.
- Mixture-of-Experts (MoE) architectures mitigate this by activating only a subset of the neural network per token, decoupling total parameters from active parameters.
- These efficiency gains, however, introduce new performance bottlenecks.

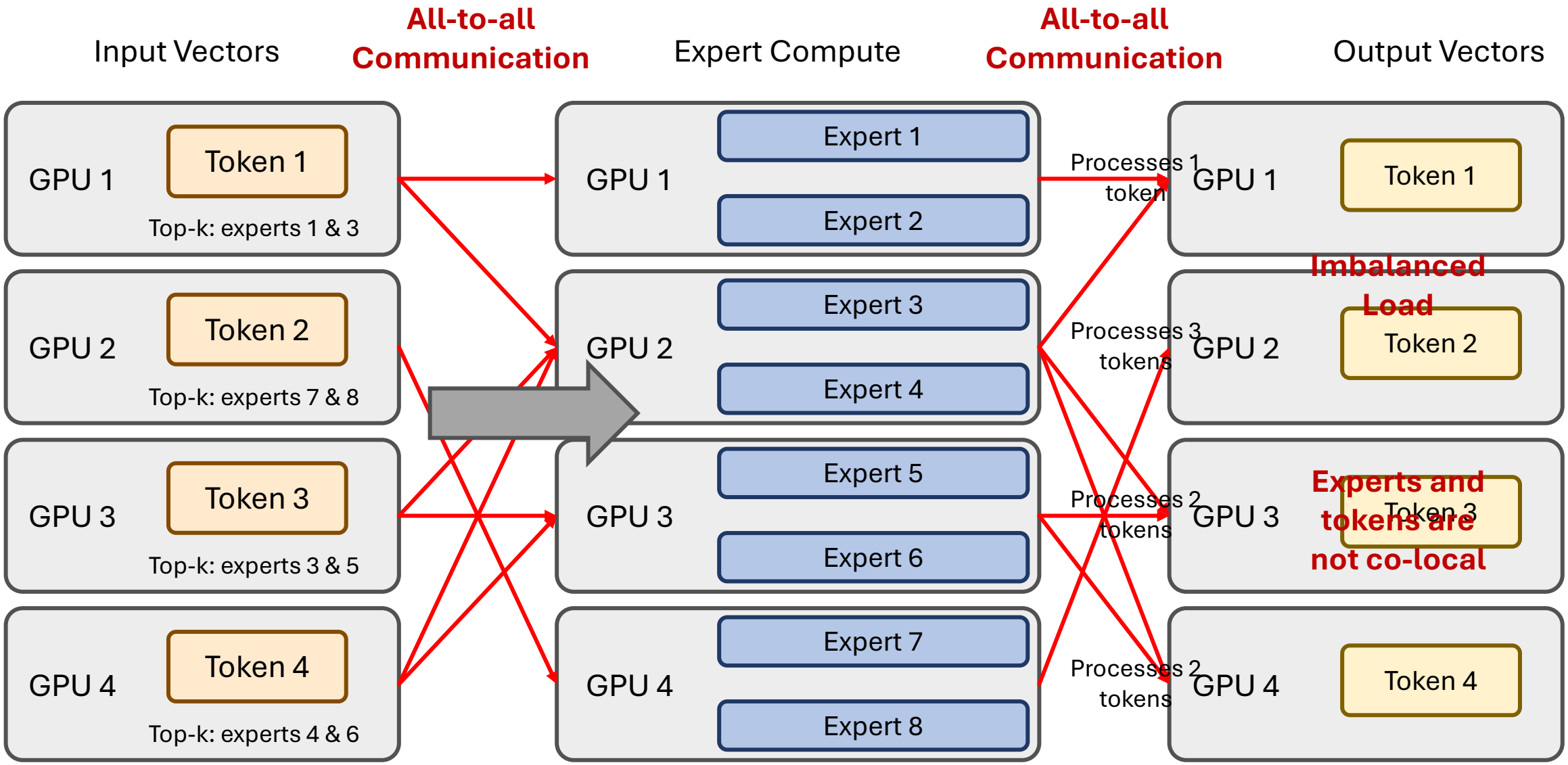
Mixture of Experts Network



Performance Challenges in Mixture of Experts

- Mixture of Expert models introduces major performance bottlenecks:
  - Load balancing of expert compute across GPUs
  - Co-location of expert parameters and tokens
  - All-to-all communication across GPUs
- Existing work focuses on faster execution but does not tackle the problem directly
  - Faster kernels for expert parallelism
  - Speculative expert-GPU placement

Distributed Mixture of Experts



Data-Compute Dependency

- There are 3 compute dependencies that enforce the all-to-all requirement in an expert parallel setup:
  1. The selection of *k* experts for each token, that can differ from layer to layer
  2. The weighted sum of the outputs from the *k* experts selected for each token
  3. The attention computation of the current token with all previous tokens which have different selected experts than the current token
- When expert parameters (memory) and tokens (compute) are no co-located, expensive bandwidth-bound communication is needed

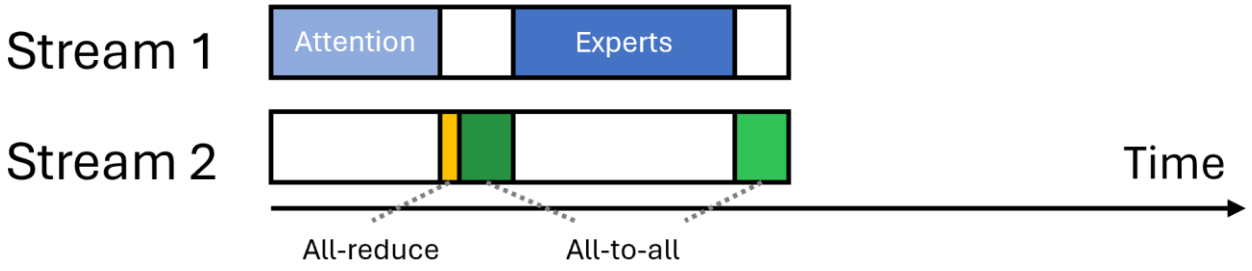
Federation of Experts

- We present the novel Federation of Experts architecture, which restructures the transformer layer to co-locating memory and compute thus reducing communication and improving load balancing.
- Compared to FoE, a standard MoE model has:
  - End-to-end latency: 1.0-5.2x
  - Time to first token: 2.6-3.6x
  - Time between tokens: 1.1-2.0x
- FoE maintains the same model quality as MoE at equivalent number of parameters.

Tackling the Performance Bottlenecks

- Federation of Experts (FoE) solves this by restructuring the MoE architecture to co-locate memory and compute
- FoE additionally uses all-reduce which saves significant bandwidth over traditional all-to-all
- Total forward-pass latency is significantly reduced

Mixture of Experts Timing

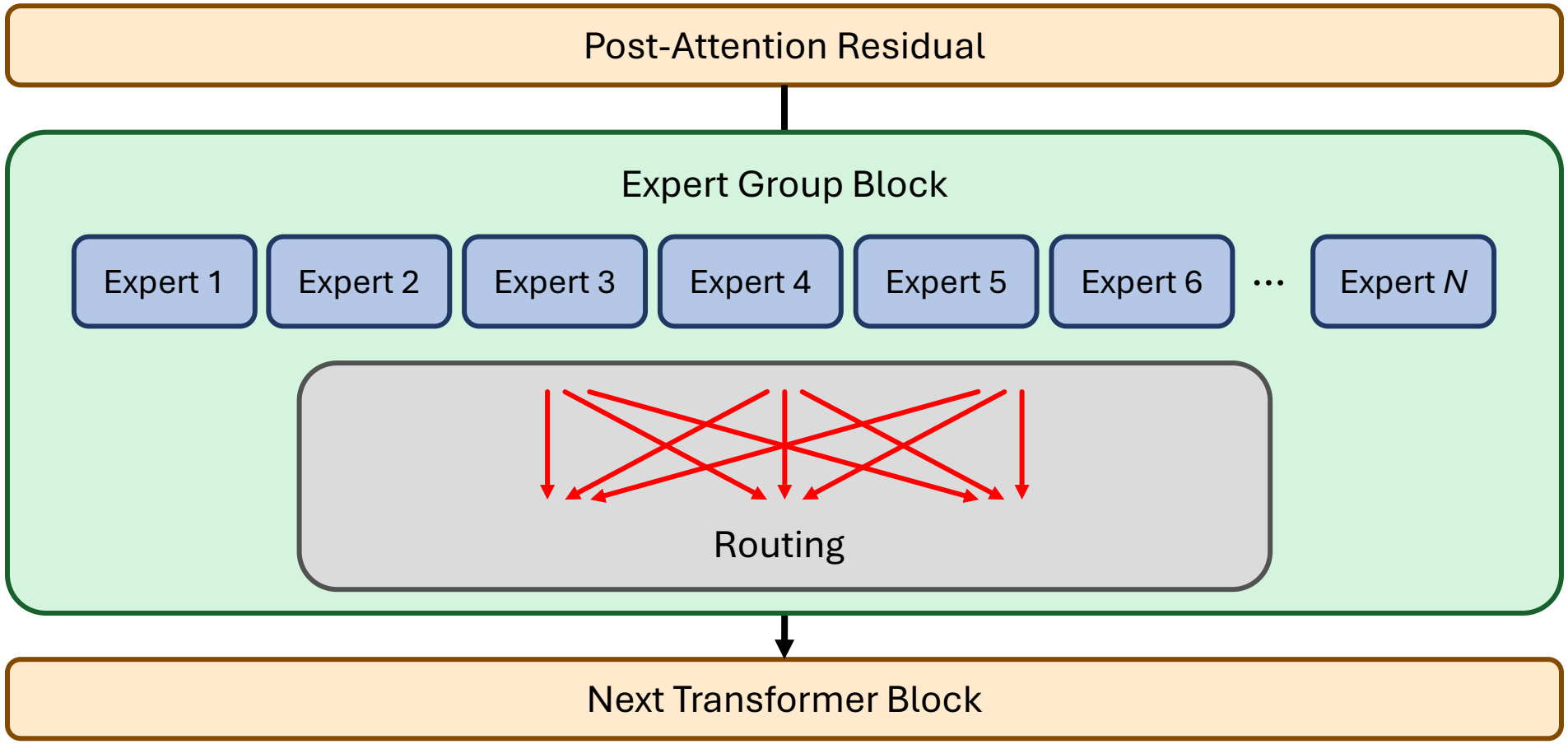


Federation of Experts Timing

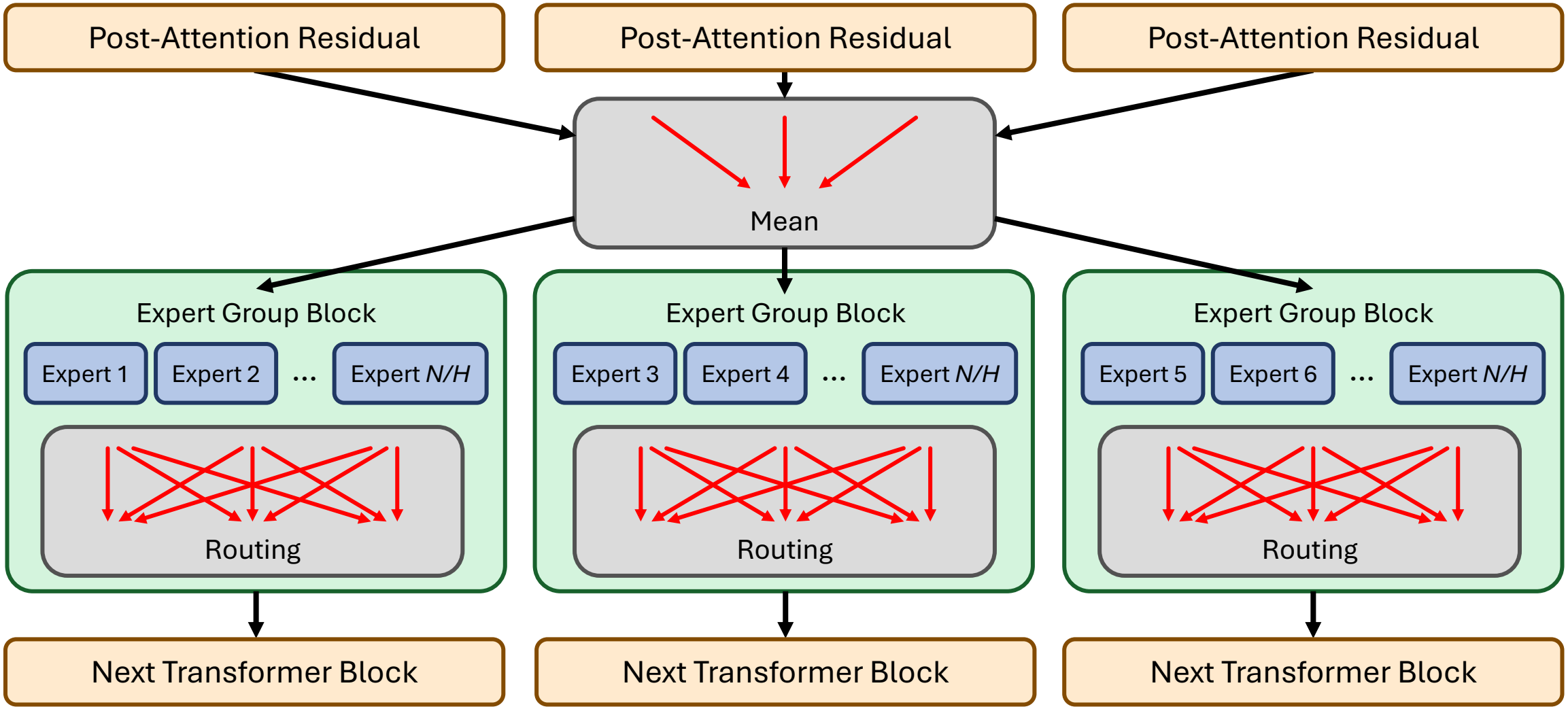
Federation of Experts

- Restructures the attention and FFN layers into $H = n_{kv}$ independent MoE groups
- Each group consists of:
  - Independent attention layer $1/H$ of the KV heads
  - Expert group with $1/H$ of the total experts
- A token's experts include k/H experts from each group
  - Tokens are routed between experts in a group, but never between groups
- Results are synchronized between groups using a sum
- Single-node: all-to-all is eliminated, only all-reduce remains
- Multi-node: all-to-all intra-node, all-reduce inter-node

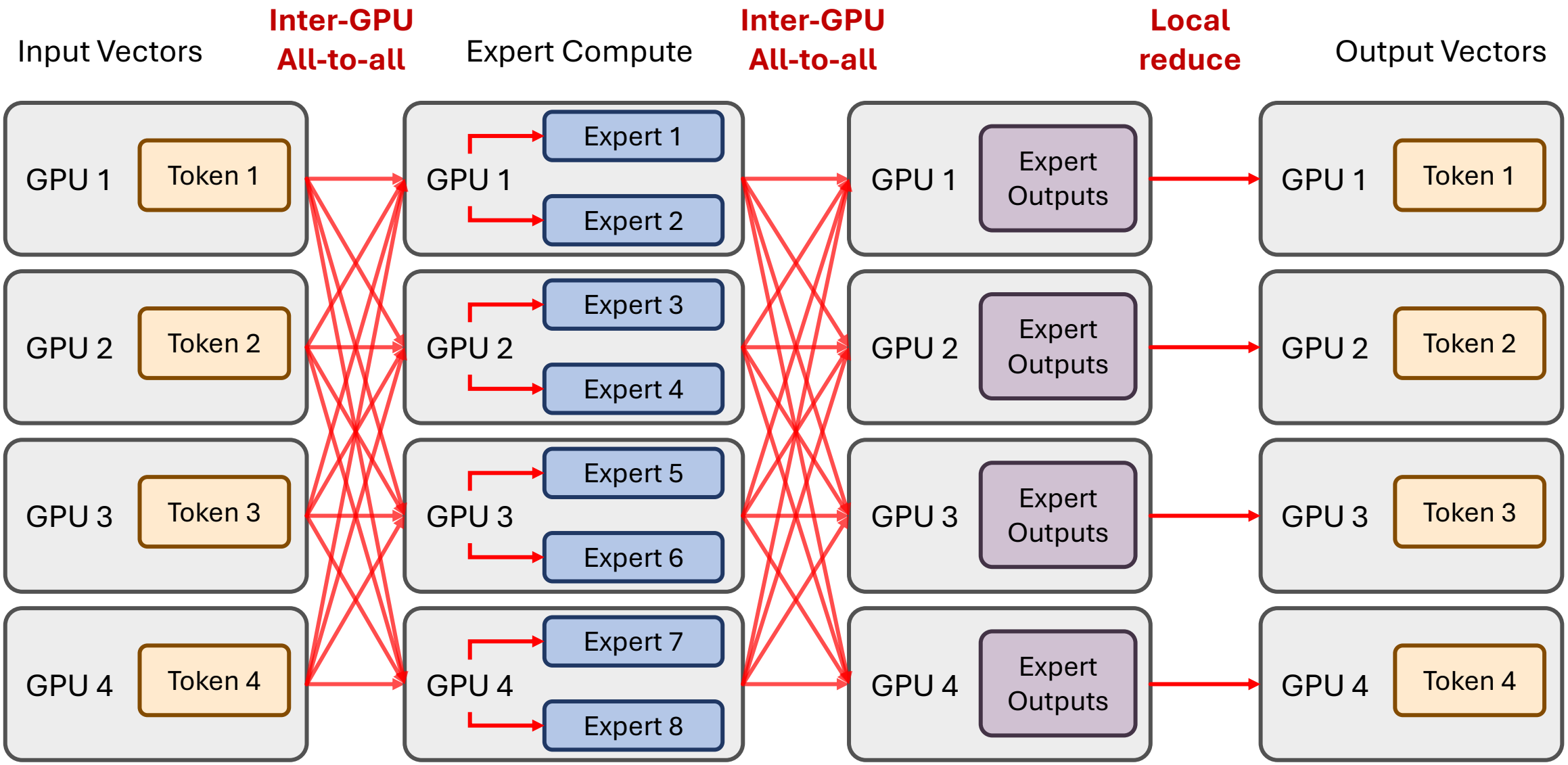
Mixture of Experts Architecture



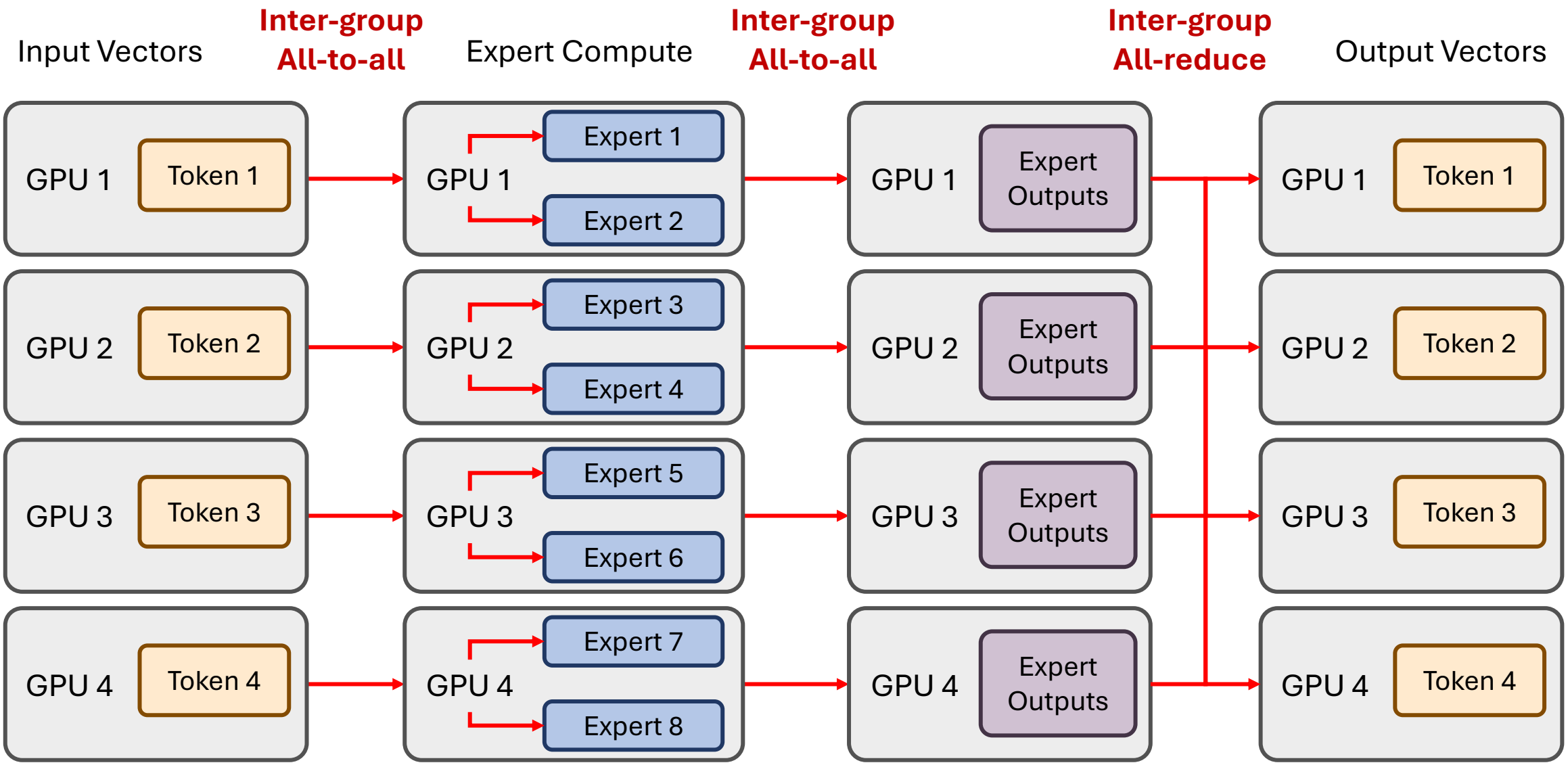
Federation of Experts Architecture



Mixture of Experts Communication



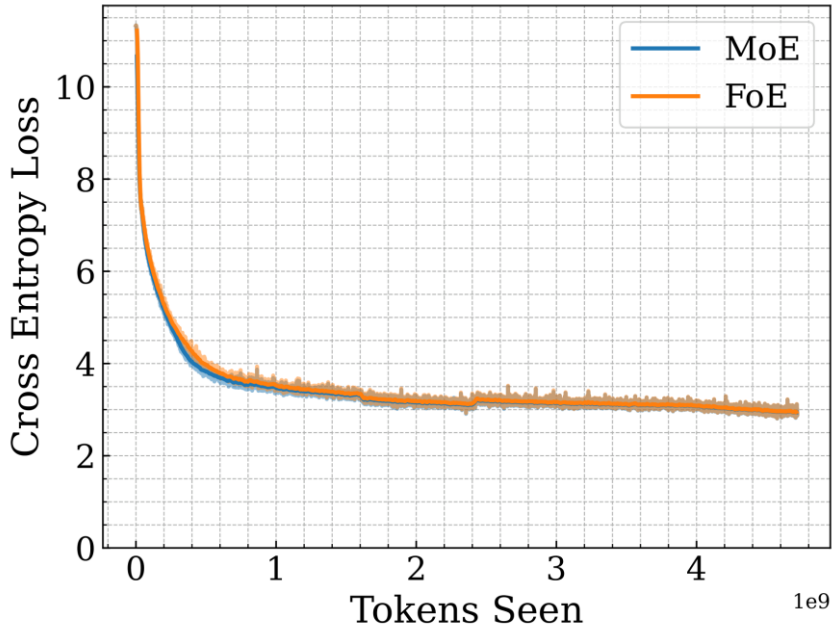
Federation of Experts Communication

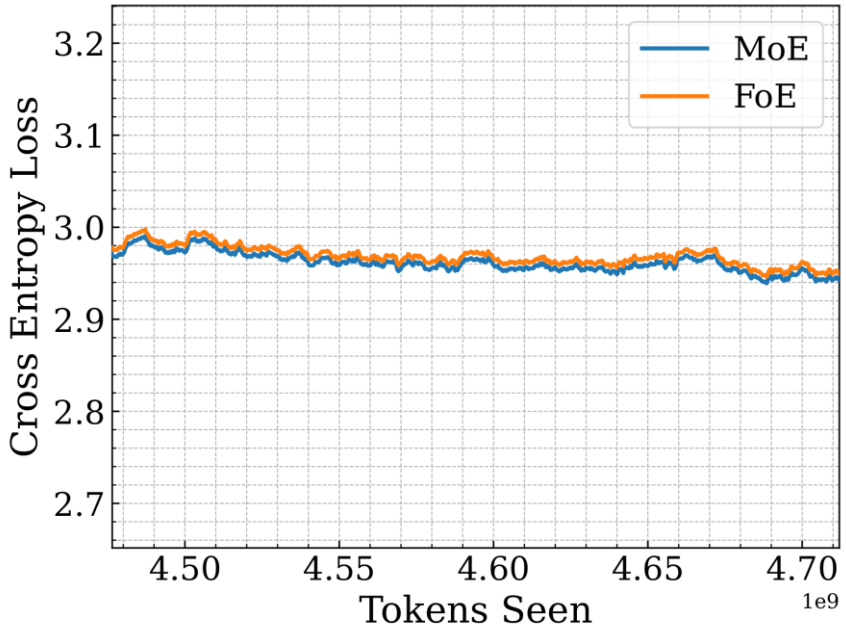


Experimental Setup

- *Hardware*: 8x H100 nodes, 80GB VRAM per GPU, SXM + Infiniband.
- *Training*: We train MoE and FoE on our own training engine built from the ground up based on TorchTitan.
- *Inference*: We implement both MoE and FoE on our own inference engine FlexServe built from the ground up based on vLLM & SGLang. This properly isolates architectural gains from framework-level engineering disparities.
- *Models*: We train 1B & 7B parameter models for both FoE & MoE and report end-to-end inference results for the 7B model.

Training Results for 1B Models

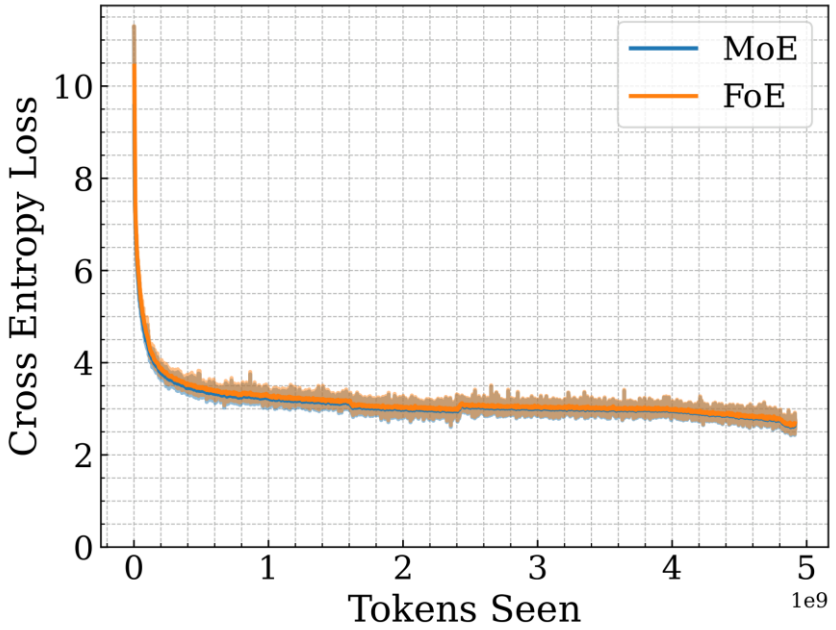


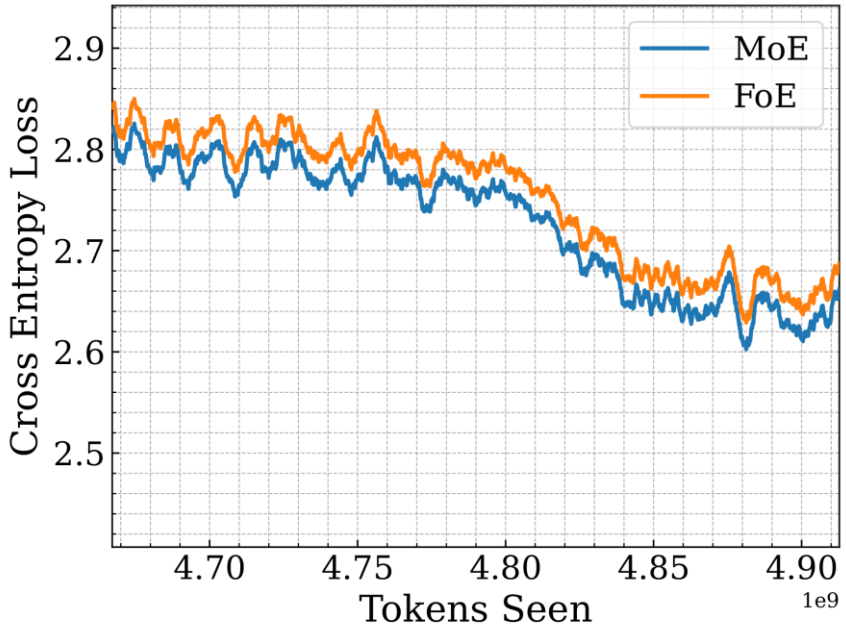


Variant	ARC-Easy	BoolQ	COPA	HellaSwag	PIQA	SciQ
MoE (1B)	53.5%	57.7%	62.0%	30.9%	63.9%	77.7%
FoE (1B)	52.7%	61.4%	61.0%	30.1%	63.8%	74.6%

At 1B total parameters, trained to ~5B tokens, FoE achieves generation comparable quality to MoE.

Training Results for 7B Models



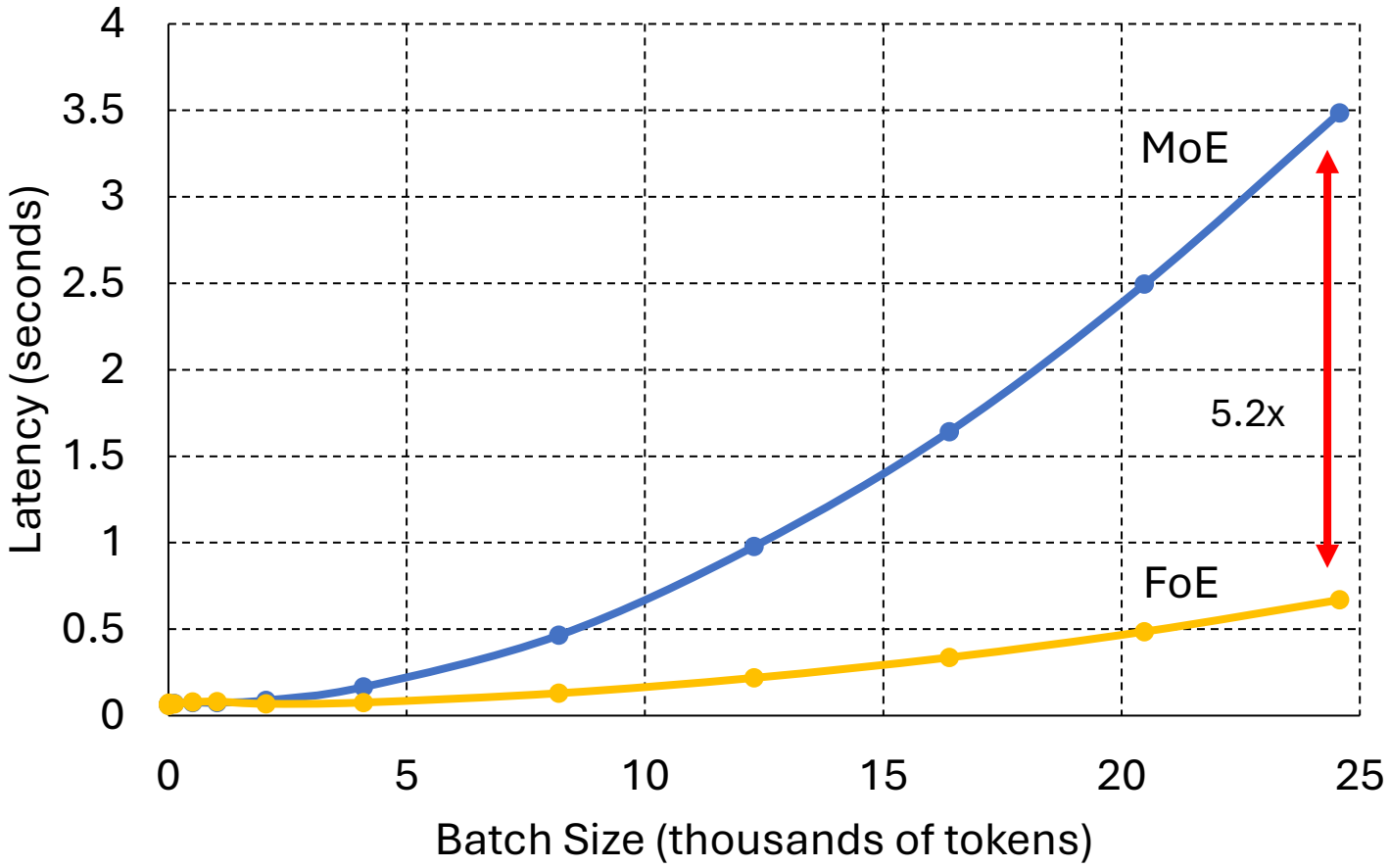


Variant	ARC-Easy	BoolQ	COPA	HellaSwag	PIQA	SciQ
MoE (7B)	59.6%	60.4%	65.0%	33.7%	66.9%	80.0%
FoE (7B)	58.2%	60.9%	66.0%	33.1%	66.6%	80.0%

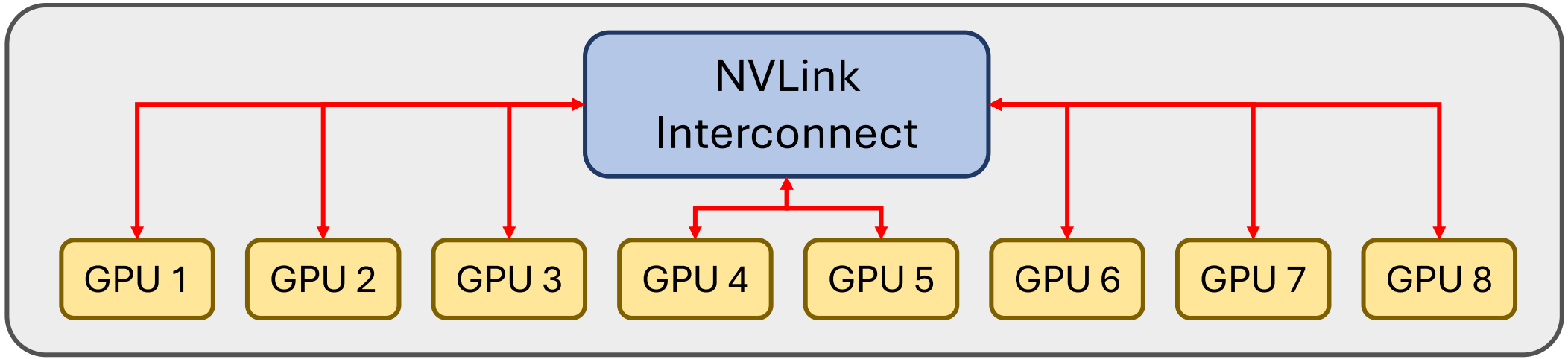
At 7B total parameters, trained to ~5B tokens, FoE achieves generation comparable quality to MoE

Forward Pass Latency

- We run synthetic forward passes at fixed batch sizes
- FoE shows dramatically improved forward-pass latency as batch size increases



Single Node Setup



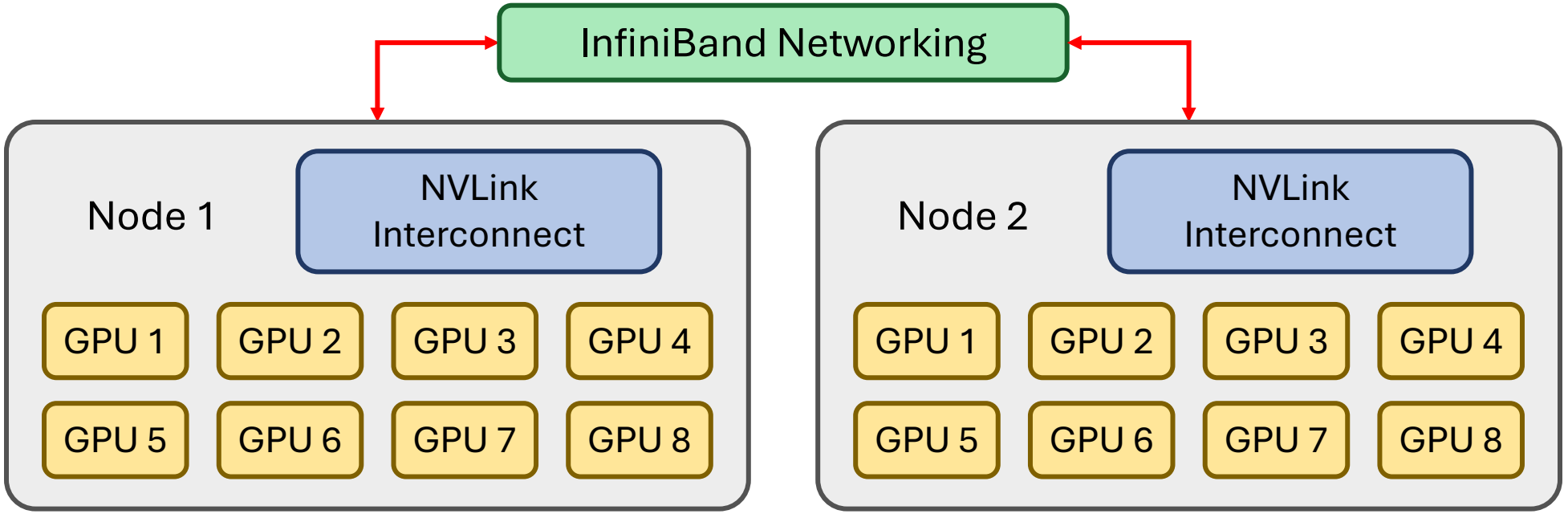
- LongBench NarrativeQA, HotpotQA, TriviaQA and PassageCount tasks (average prompt length is ~9k)
- Requests arrivals according to Poisson distribution with average inter-arrival times (scales) of 0.5, 0.75, & 1.5 seconds

Speedups on Single Node

Scale	Metric	Mean	p50	p99
0.5s	Time to First Token	*2.66x*	*2.99x*	*1.82x*
	Time Between Tokens	*1.38x*	*1.31x*	*1.53x*
	End to End Time	*1.39x*	*1.32x*	*1.54x*
0.75s	Time to First Token	*3.11x*	*3.21x*	*2.77x*
	Time Between Tokens	*1.83x*	*1.90x*	*2.06x*
	End to End Time	*1.85x*	*1.91x*	*2.07x*
1.5s	Time to First Token	*2.87x*	*2.85x*	*3.15x*
	Time Between Tokens	*1.11x*	*1.08x*	*1.53x*
	End to End Time	*1.13x*	*1.09x*	*1.56x*

Reported as ratios of MoE time vs. FoE time

Multi Node Setup



- 2 nodes with identical GPU configurations
- LongBench tasks (average prompt length is ~9k)
- Requests arrivals according to Poisson distribution with average inter-arrival times (scales) of 0.5 & 0.75 seconds

Speedups on Multi Node

Scale	Metric	Mean	p50	p99
0.5s	Time to First Token	*3.44x*	*3.57x*	*2.74x*
	Time Between Tokens	*1.36x*	*1.33x*	*1.57x*
	End to End Time	*1.37x*	*1.34x*	*1.57x*
0.75s	Time to First Token	*3.62x*	*3.59x*	*3.70x*
	Time Between Tokens	*1.95x*	*2.01x*	*2.26x*
	End to End Time	*1.96x*	*2.02x*	*2.27x*

Reported as ratios of MoE time vs. FoE time

Limitations

- Benefits only apply to distributed deployments.
  - On a single GPU, there is no all-to-all communication to reduce, thus the cross-group sums and separate attention layers become additional overhead without offsetting savings.
- Training speed is not improved.
  - Each expert group has its own residual stream, resulting in a significant backward pass overhead.

Conclusions

- FoE achieves a breakthrough in MoE inference performance by restructuring the core architecture.
  - FoE divides experts, attention, and routing into groups thus enabling memory and compute to be co-located.
  - This results in reduced communication and improved load-balancing.
- Communication does not always equal model quality.
  - Existing architectures should undergo ablation experiments to understand whether any expensive data movement is truly needed for good generation.
- Next Steps:
  - Validate model quality scaling to larger parameter counts.
  - Can an existing trained MoE model checkpoint be adapted to an FoE model?

Questions