Accelerating Distributed MoE Training and Inference with Lina

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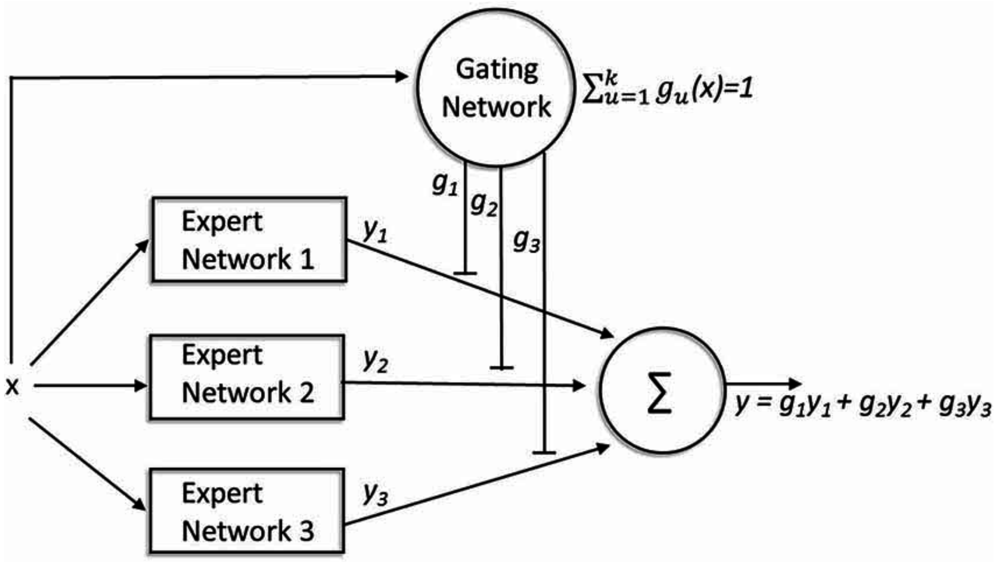
Sparsely-Activated Mixture-of-Experts (MoE)



MoE architecture

An ensemble of experts.

Figure credit to Anatomical and Functional Plasticity in Early Blind Individuals and the Mixture of Experts Architecture

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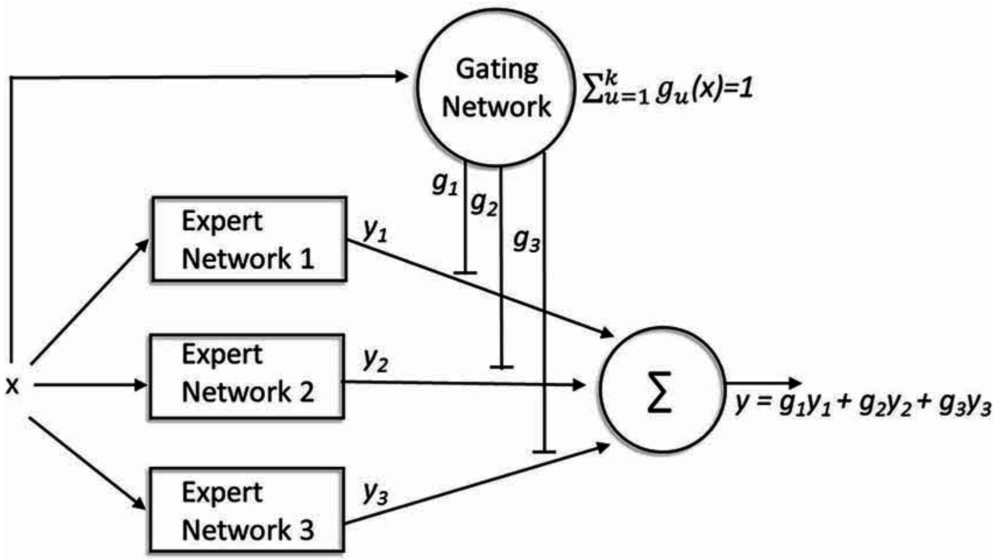

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An ensemble of experts.

- *Sparsely-activated* MoE: each input selects just a few (1 or 2) experts for processing
- Benefit: sub-linear scaling of FLOPS with model size

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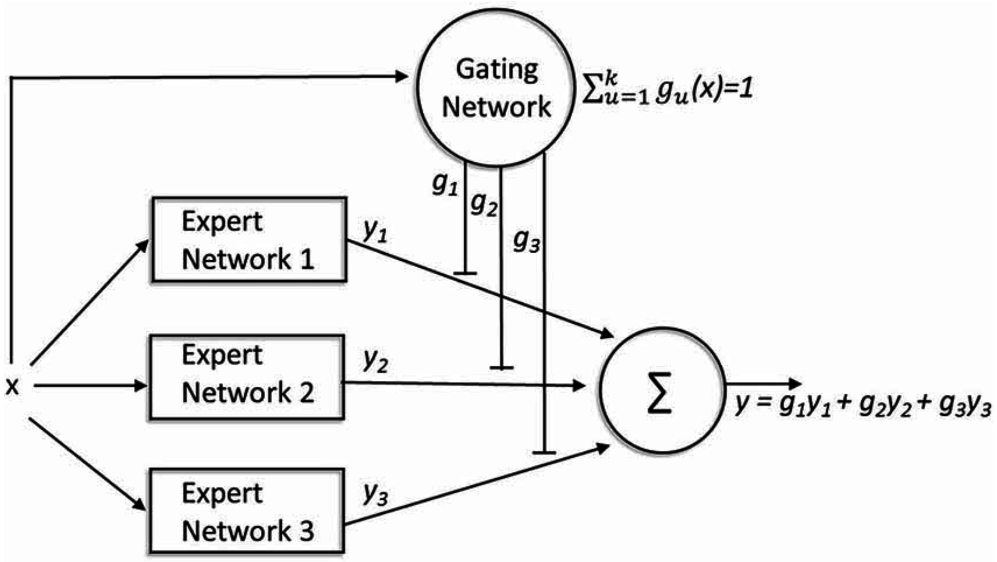

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Massive model parameters with constant computation cost.

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Potential of MoE in Transformer Models

- GLaM by Google
  - GLaM outperforms GPT-3 on 29 tasks

		GPT-3	GLaM	relative
cost	FLOPs / token (G)	350	**180**	−48.6%
	Train energy (MWh)	1287	**456**	−64.6%
accuracy on average	Zero-shot	56.9	**62.7**	+10.2%
	One-shot	61.6	**65.5**	+6.3%
	Few-shot	65.2	**68.1**	+4.4%

- DeepSpeed MoE models
  - Model quality: 6.7B-parameter dense = 1.3B-parameter MoE - 128
  - Training compute reduction of 5x

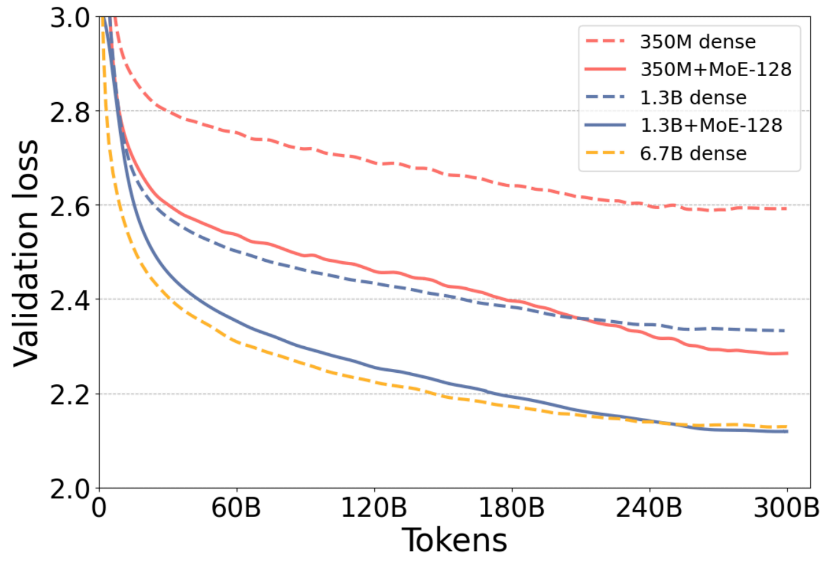


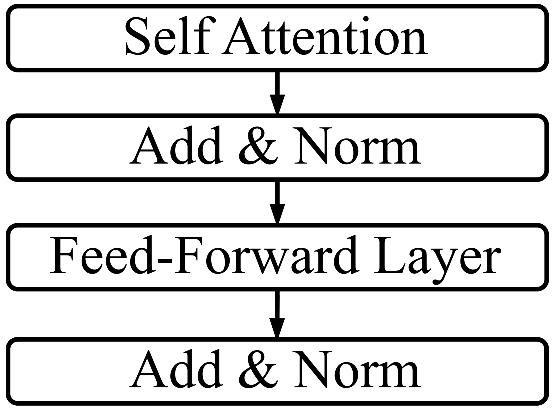
Figure credit to GLaM and DeepSpeed MoE.

MoE in Transformer-based Language Models

- Feed forward layers (FFN) are replaced with MoE layers.
- MoE layer = gate + experts
  - Expert: feed forward neural network

    => *same* architecture, *different* parameters
  - Gate: a *trainable* matrix to select expert for each data sample
    - Top-2 in training, Top-1 in inference

Transformer block



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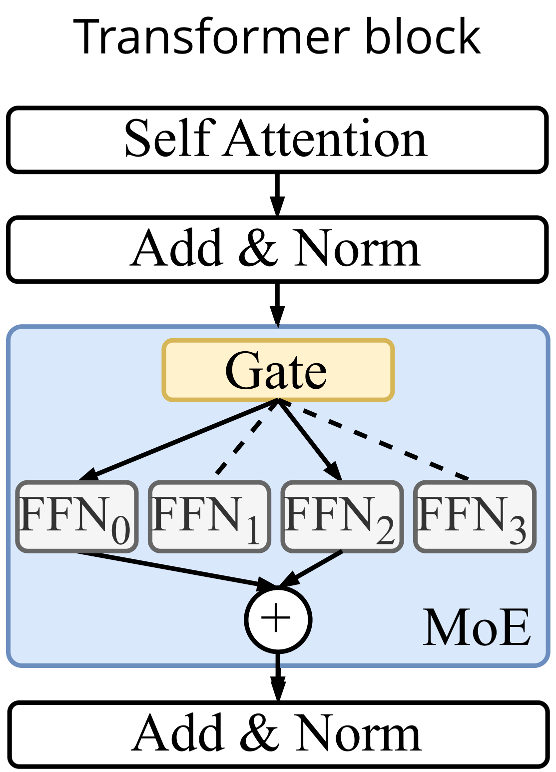

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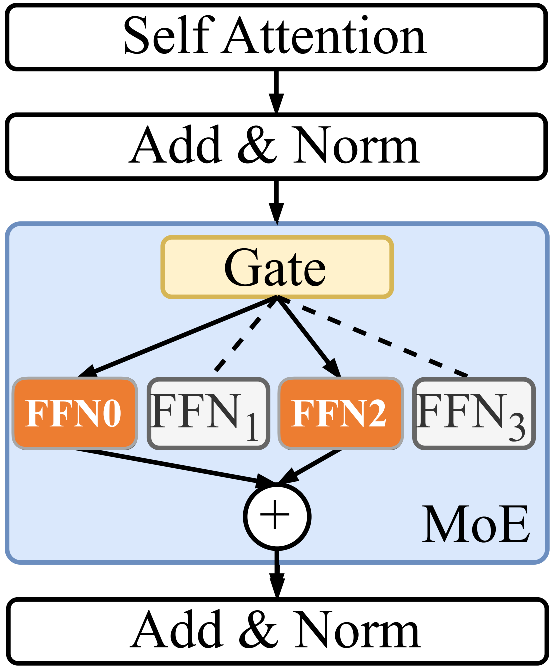

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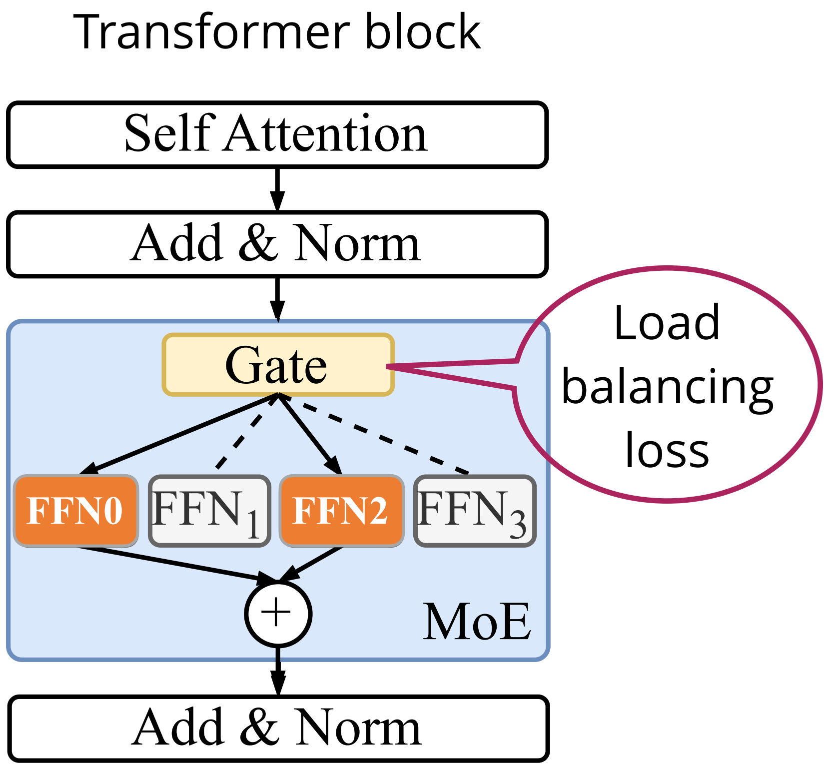
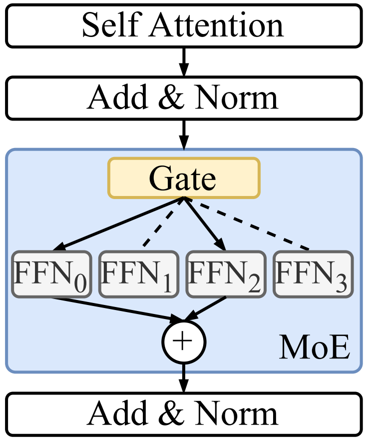
    - Top-2 in training, Top-1 in inference
  - Load balancing loss during training: <u>*even*</u> distribution among experts.



Distributed MoE

- Hybrid parallelism:
  - Expert parallelism: each device hosts one unique expert
  - Data parallelism: replicate non-expert parameter on each device



Single-device

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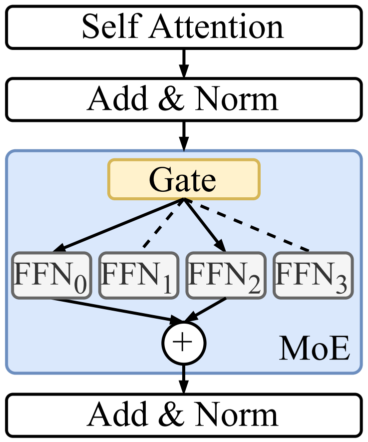

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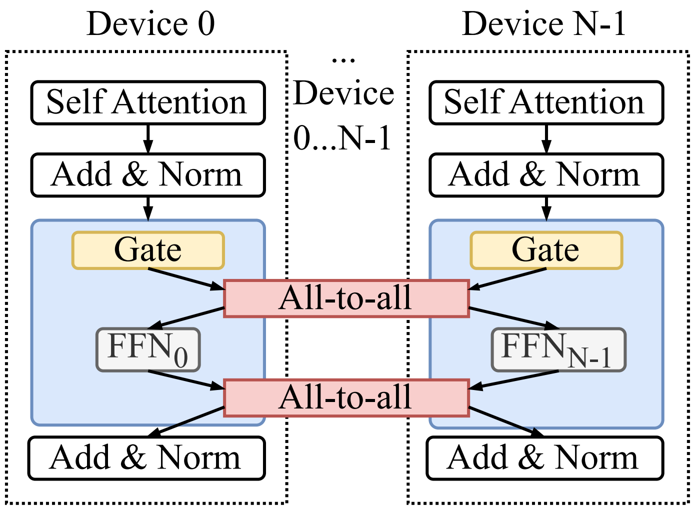

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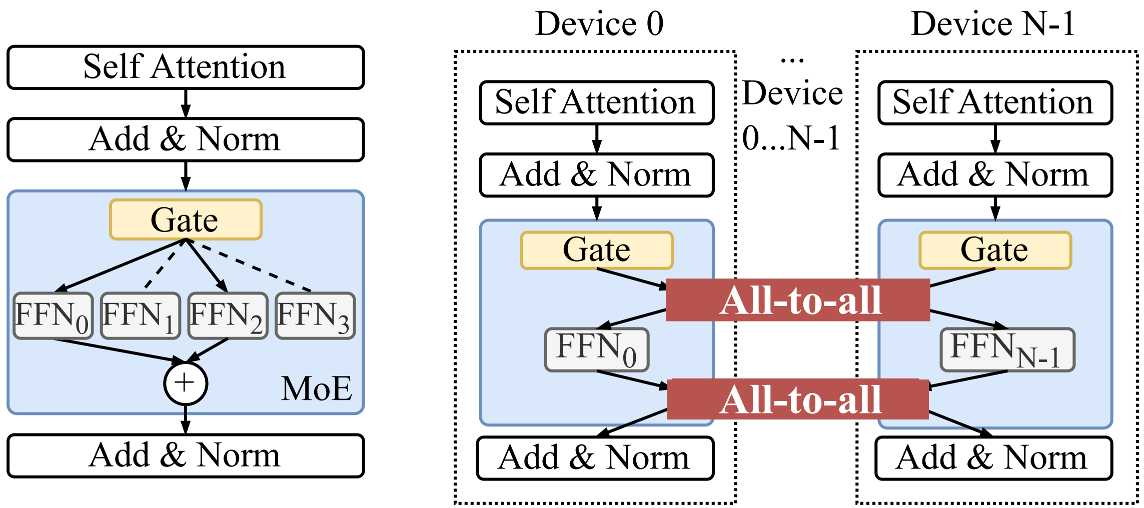

Single-device　　　Distributed

- All-to-all communication
  - 1st: send data samples to experts.
  - 2nd: restore data samples back

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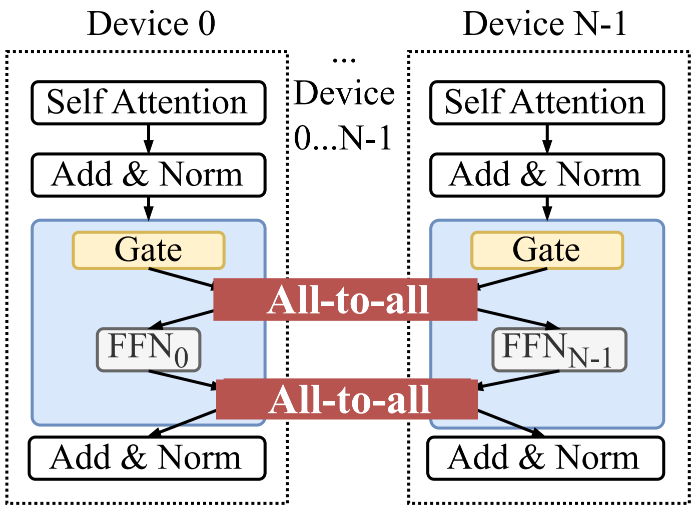

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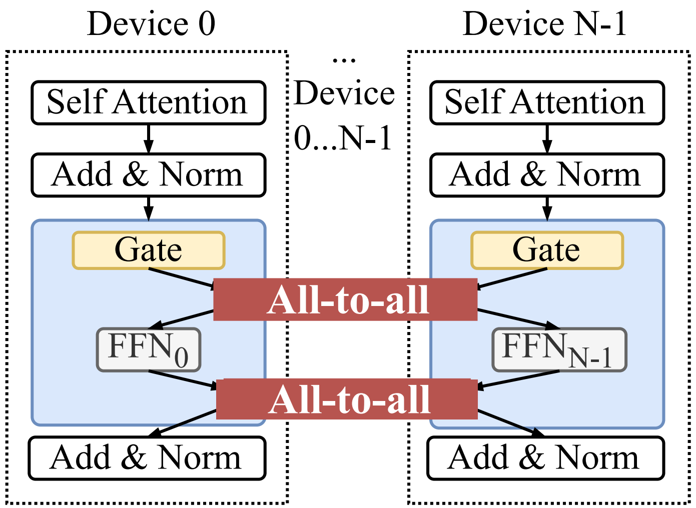
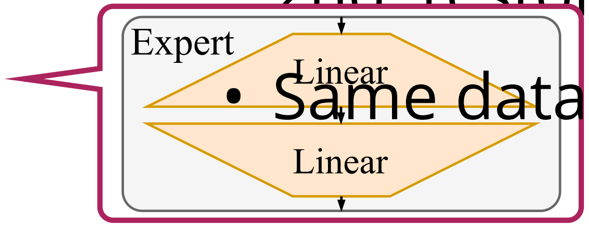


Distributed

- All-to-all communication
  - 1st: send data samples to experts.
  - 2nd: restore data samples back
  - Same data transfer size



Distributed MoE is not efficient

Model	Training (ms)		Inference (ms)	
#Layers & Params	All-to-all	Ratio	All-to-all	Ratio
12L + 117M	259	36.7%	73	27.4%
24L + 233M	589	35.4%	103	26.2%
36L + 349M	979	38.2%	153	28.3%
12L + 419M	333	39.5%	102	32.5%
24L + 838M	715	37.6%	177	31.7%
36L + 1.2B	1145	36.8%	243	27.4%

All-to-all takes an average of 34.1% of the step time.

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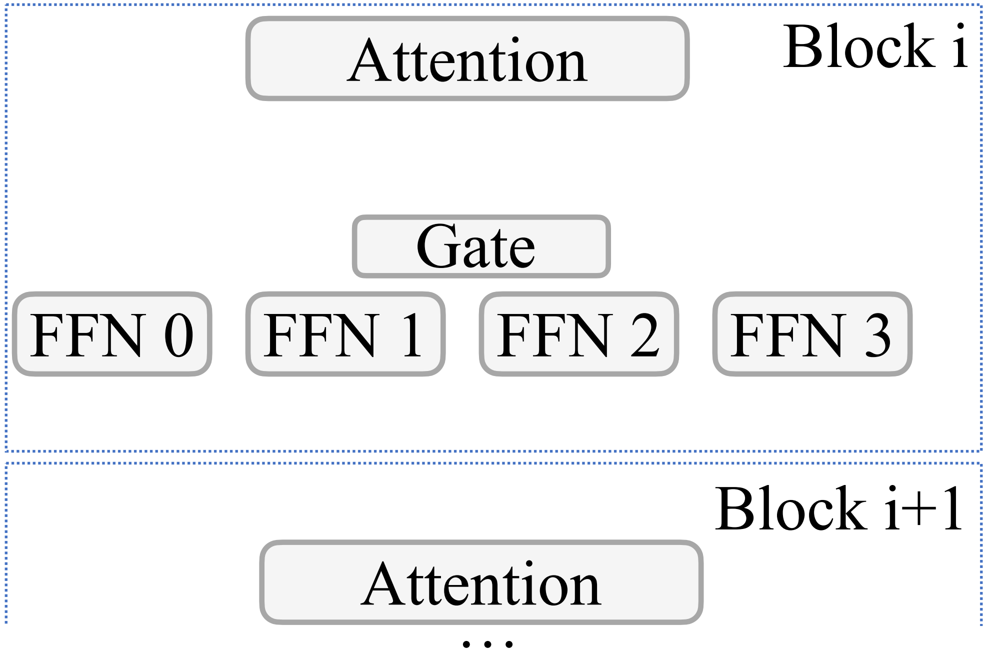

In MoE Transformer:

- Attention -> a complete sequence
- FFN expert -> one single token

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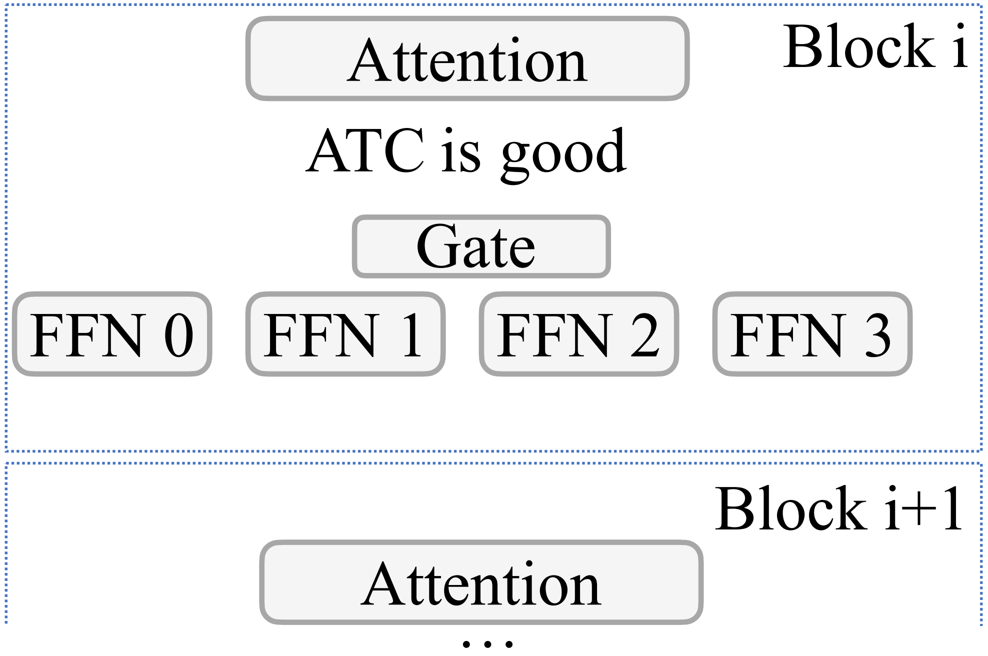

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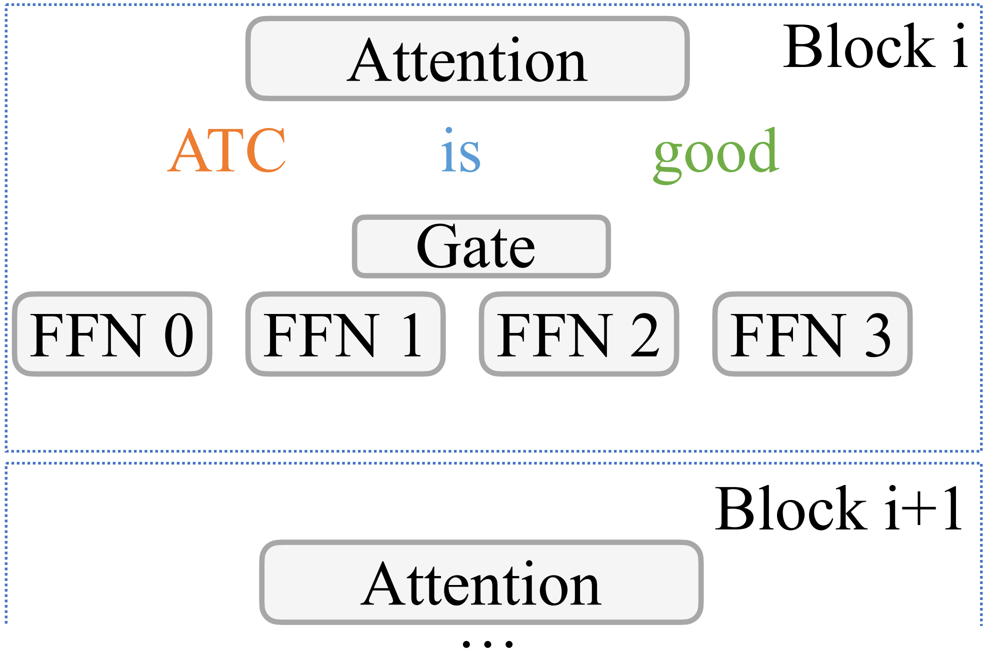

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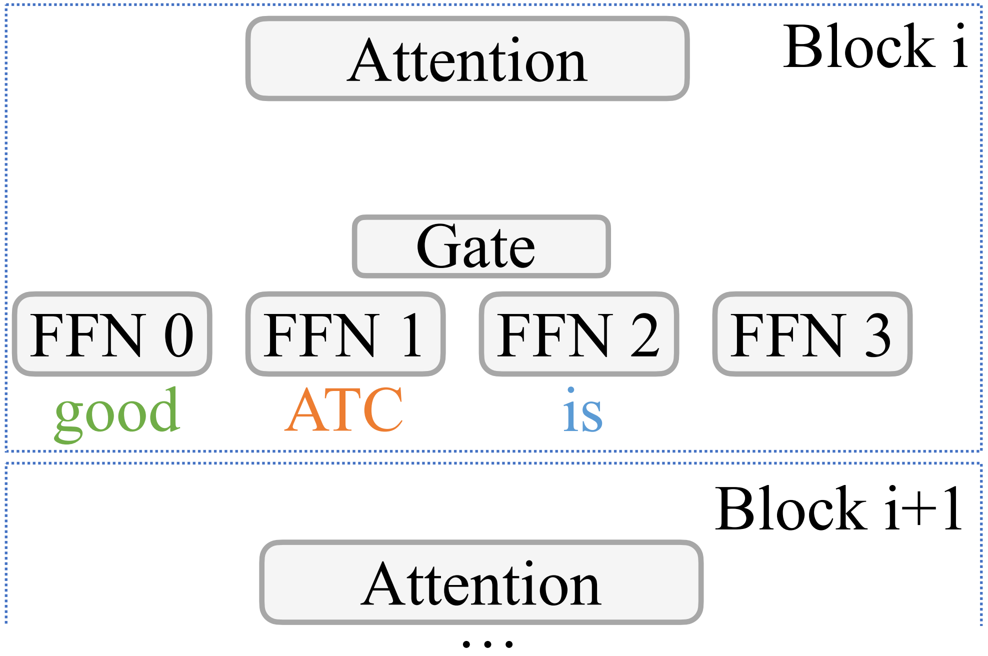

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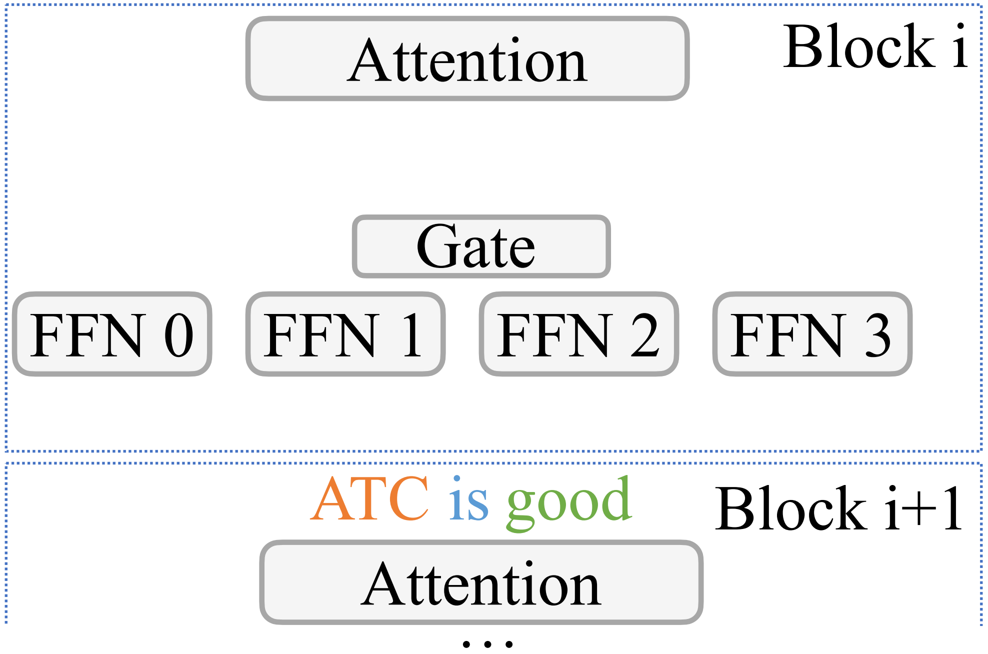

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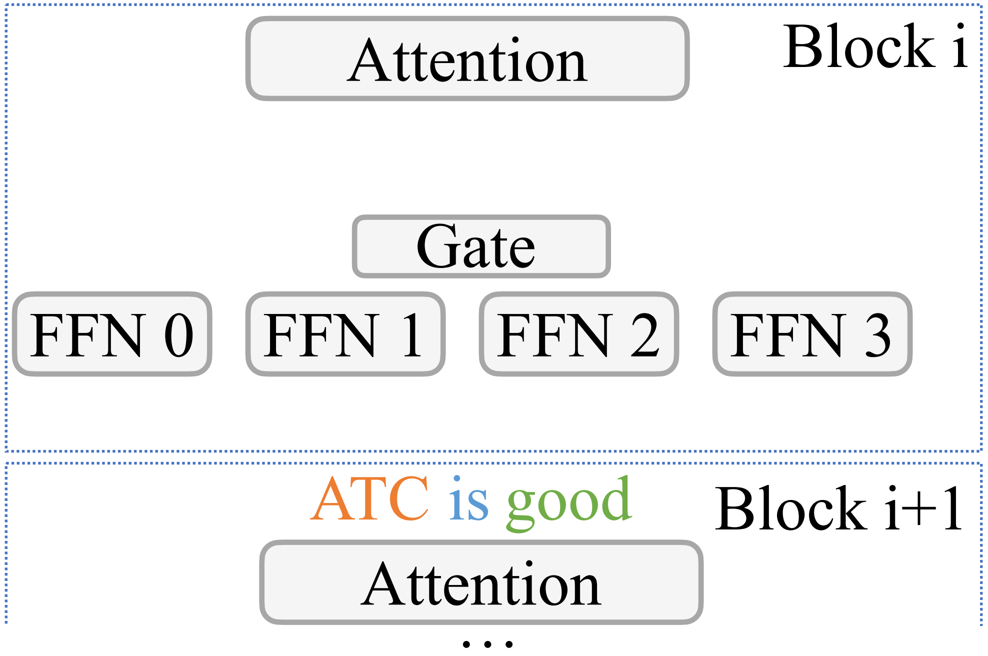

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To restore to a sequence, we must wait for the processing of all tokens.

All-to-all is the bottleneck

- Synchronous and blocking operation & large amounts of data transfer.

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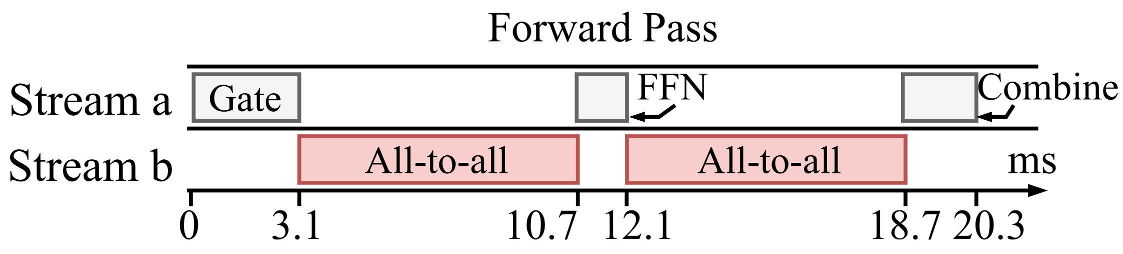

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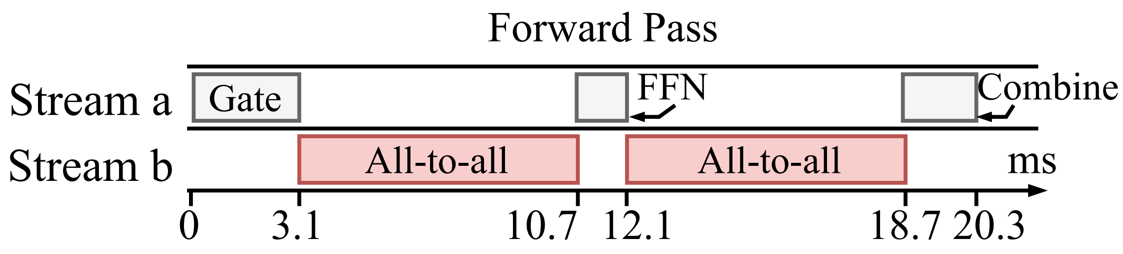

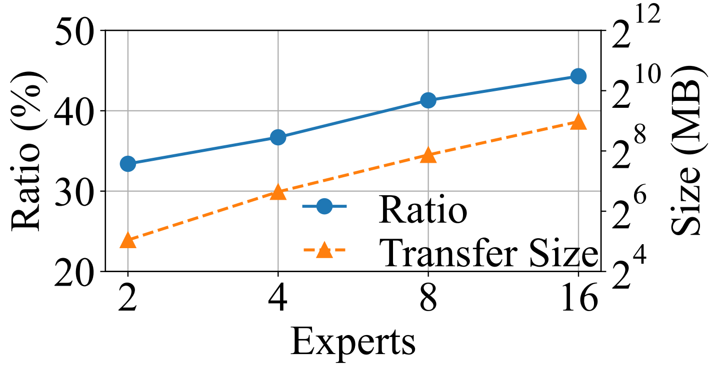

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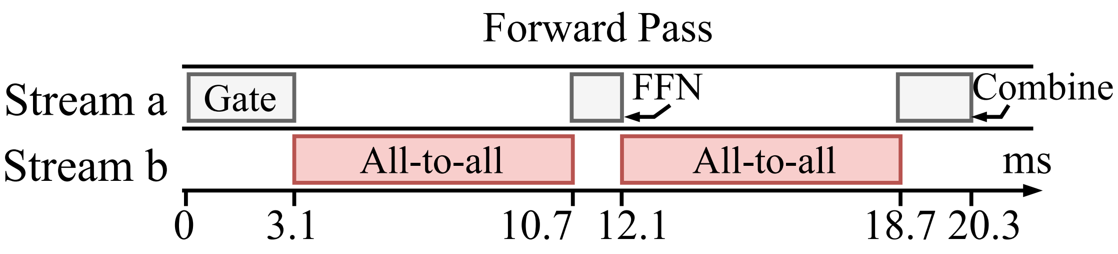

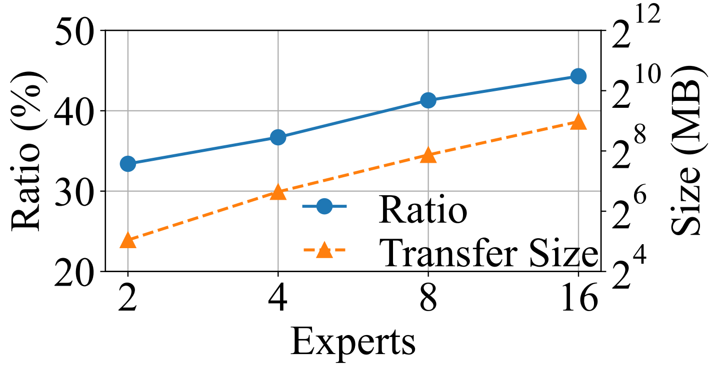

Is it the only cause of all-to-all being the bottleneck?

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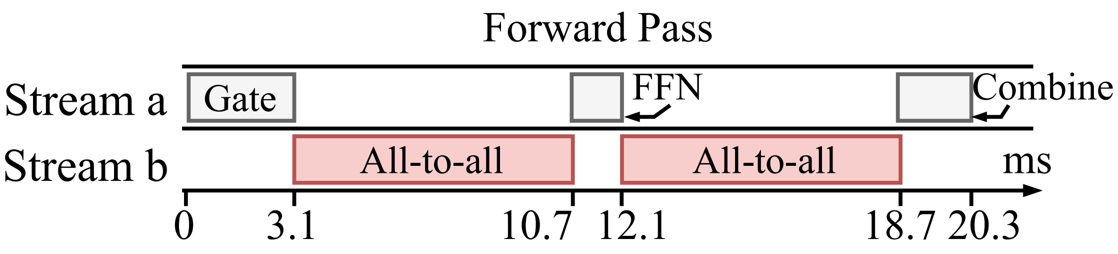

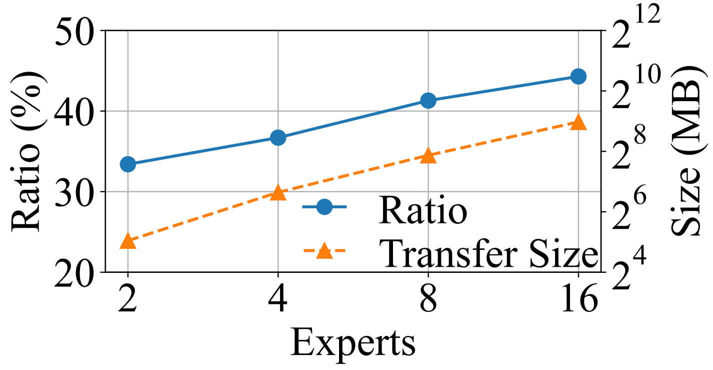

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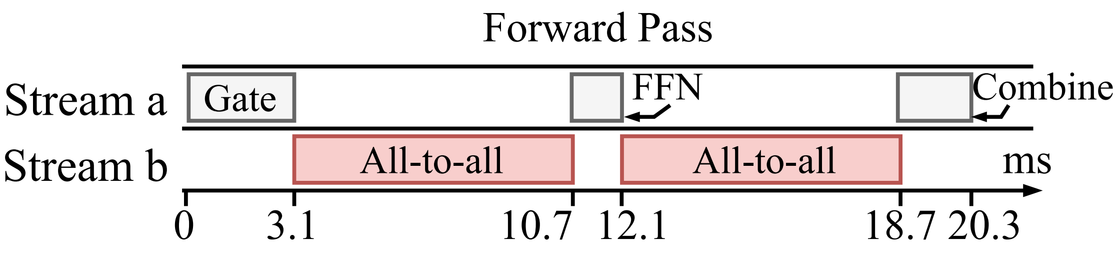

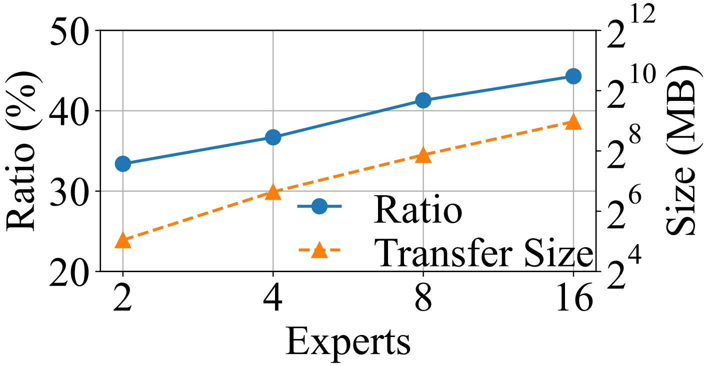

Is it the only cause of all-to-all being the bottleneck?

- MoE training and inference have their *unique* problems.
  - Training has backward pass
  - Inference is purely workload-driven

MoE Training in Data & Expert Parallel

In backward pass,

- Allreduce: asynchronously aggregate *non-expert* gradients in data parallel.
- All-to-all: exchange token gradients to compute *expert* gradients.

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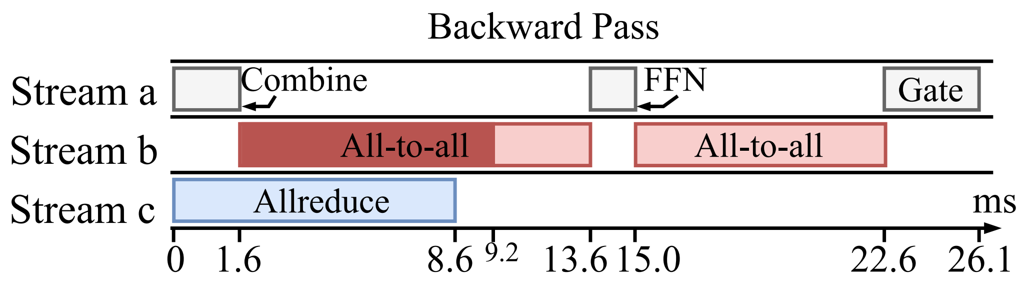

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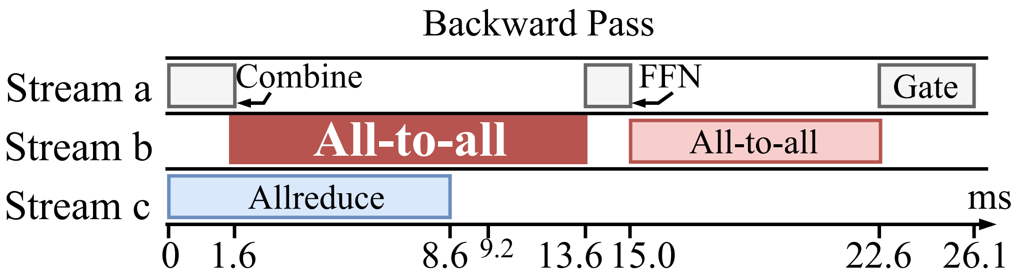

All-to-all is prolonged when it overlaps with allreduce and directly impacts step time.

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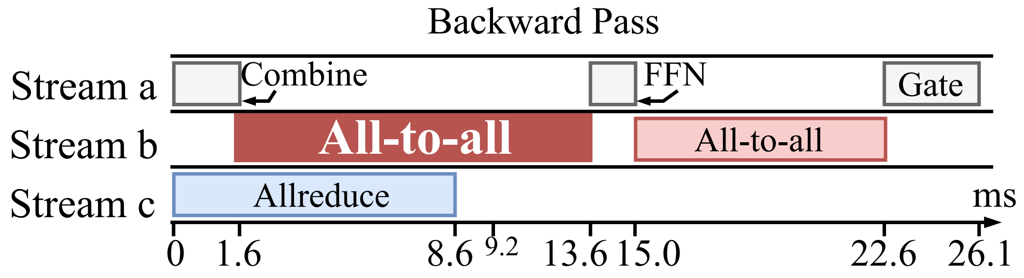

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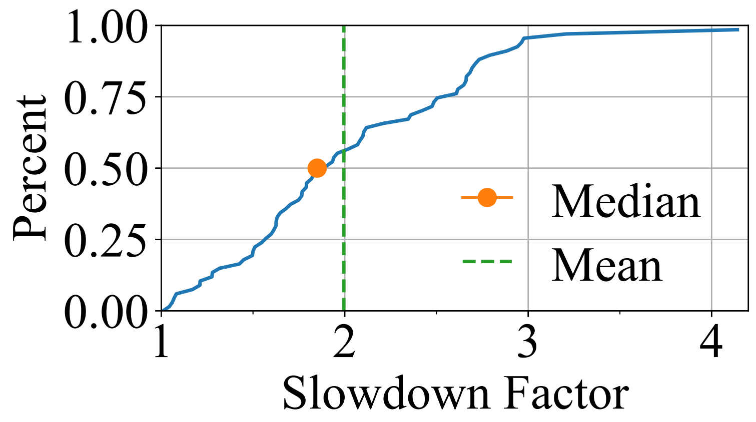
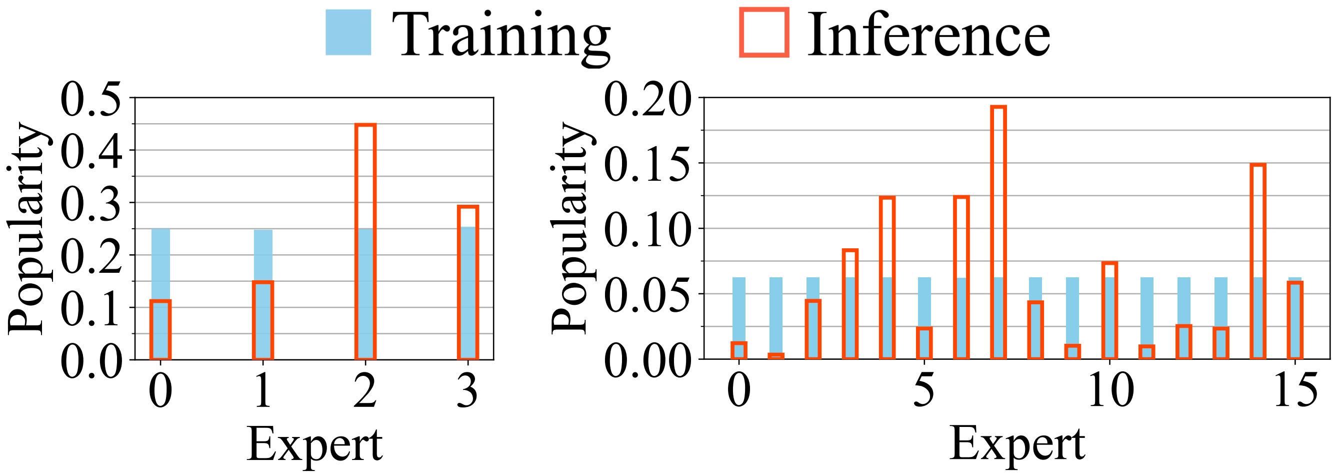
Slowdown of all-to-all varies:

Median: 2x; Maximum: ~4x



Expert Popularity in MoE Inference

- Inference: no load balancing constraints => expert selection is workload-driven, therefore, much more *biased*.



4-expert MoE

16-expert MoE

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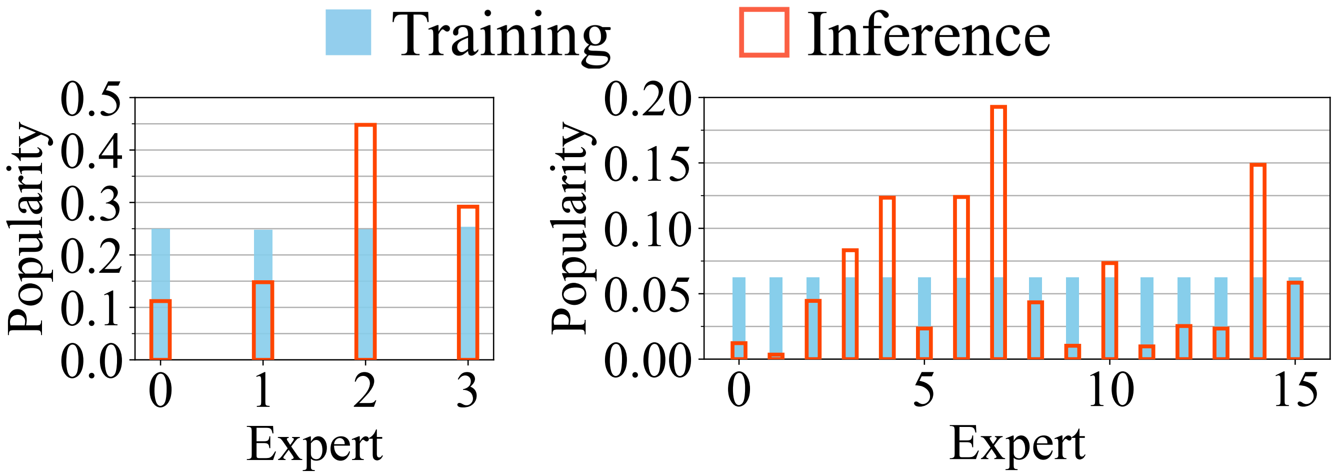

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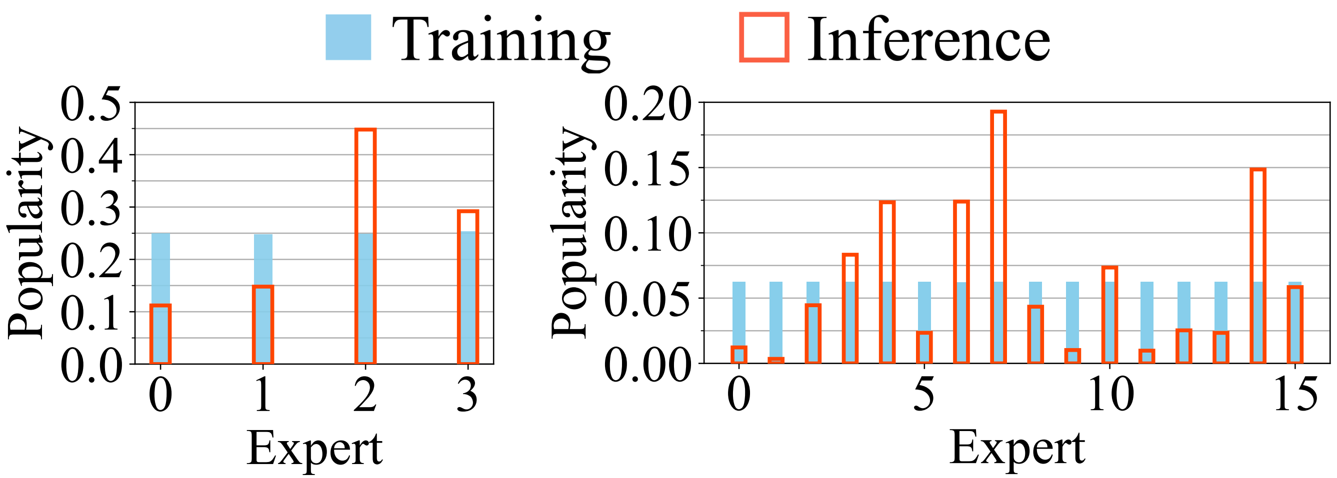


4-expert MoE

16-expert MoE

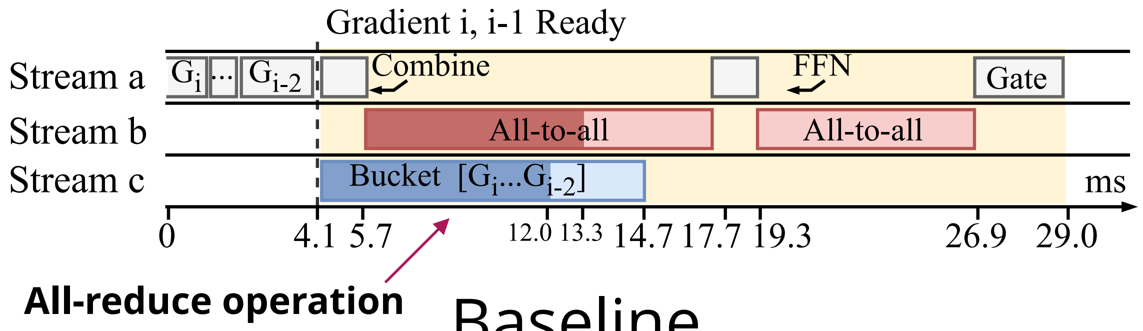
Maximum idle time of the least popular expert
=> 29.4% of the inference time.

Devices with unpopular experts have to wait for those with popular experts.

Training: Challenges

Intuition: always prioritise all-to-all and avoid bandwidth sharing.

- Minimise the blocking period incurred by all-to-all



Baseline

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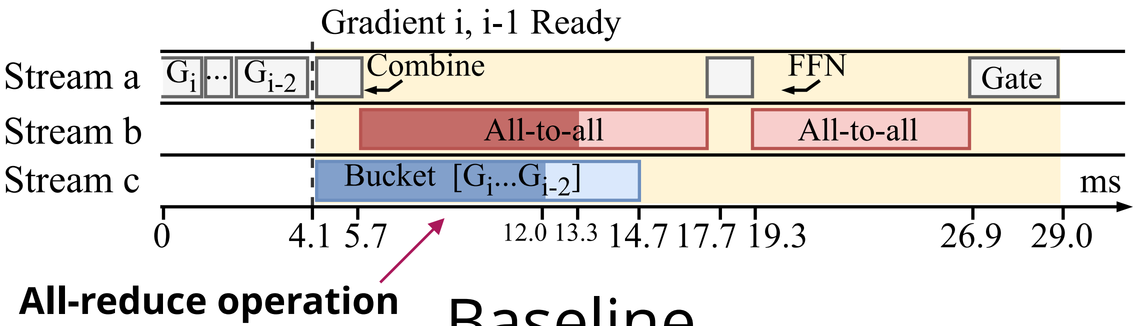

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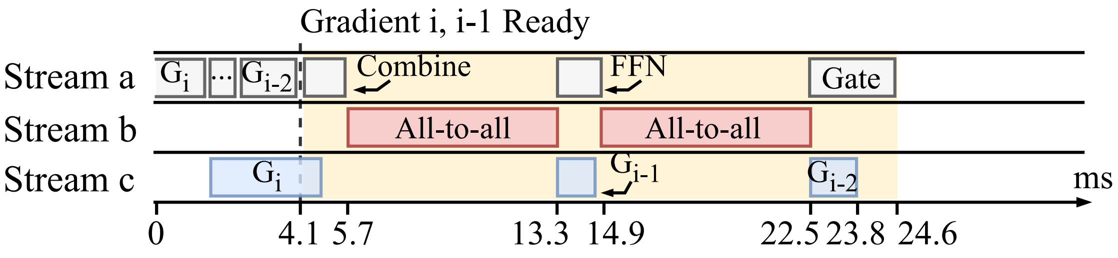

Optimal

Training: Challenges

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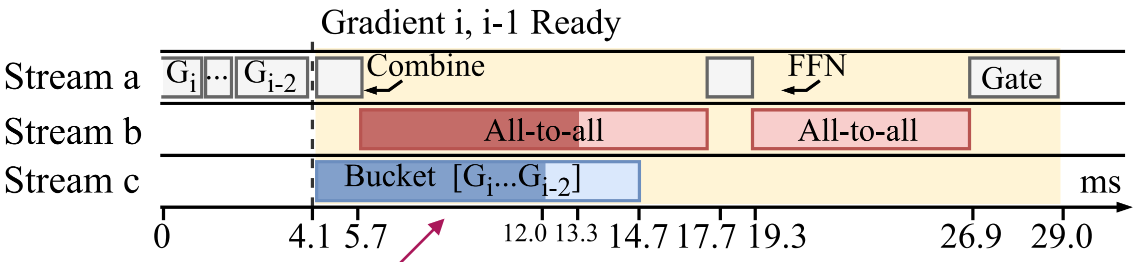
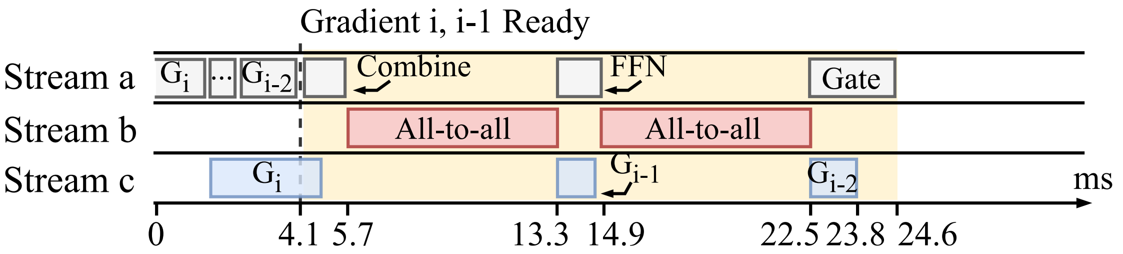
Backward pass



All-reduce operation

Baseline



Optimal

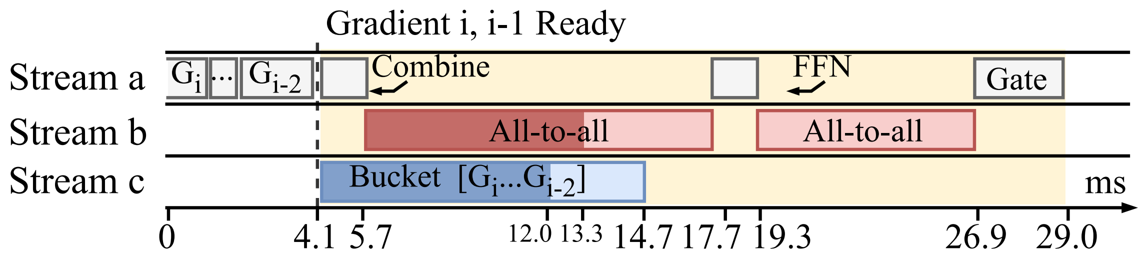
Challenges:

1. NCCL Communication primitives cannot be preempted.

2. No control knob to adjust resource sharing (GPU SM, network bandwidth…).

Training: Micro-op Scheduling

- Tensor Partitioning
  - Partition allreduce into micro-ops
  - Prioritise all-to-all whenever possible



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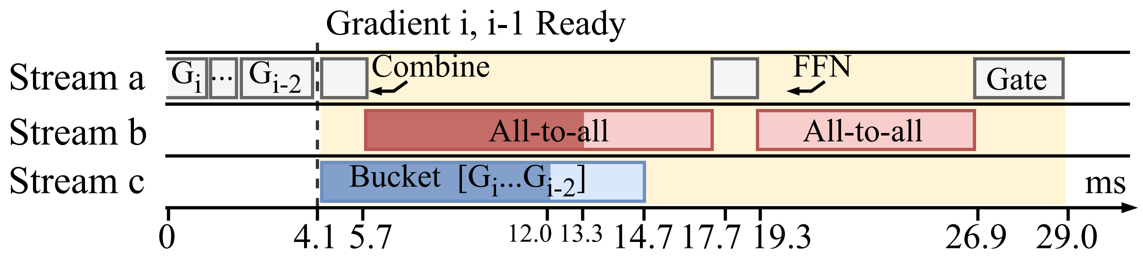

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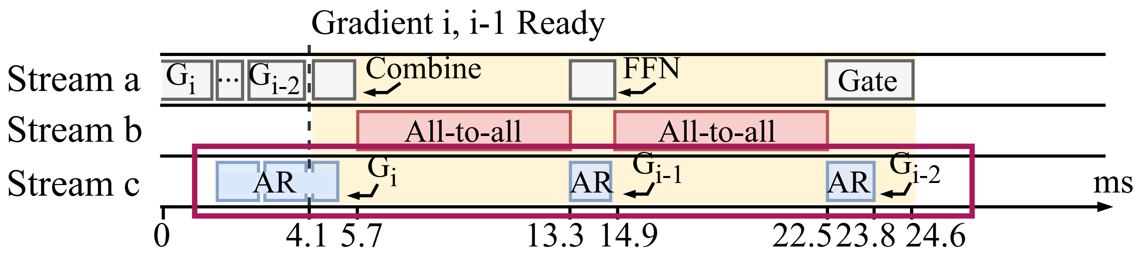

Prioritise all-to-all

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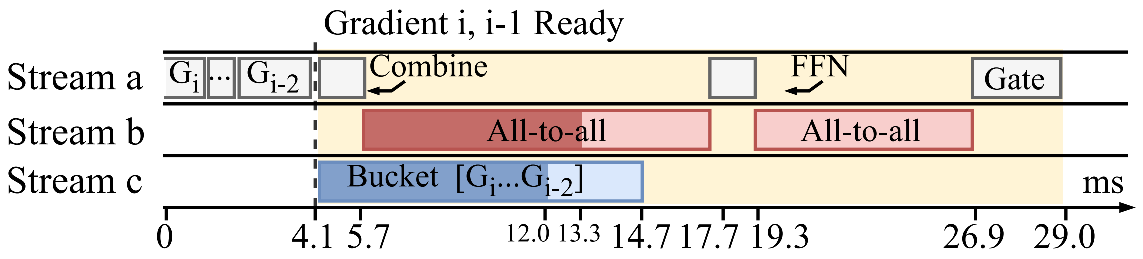
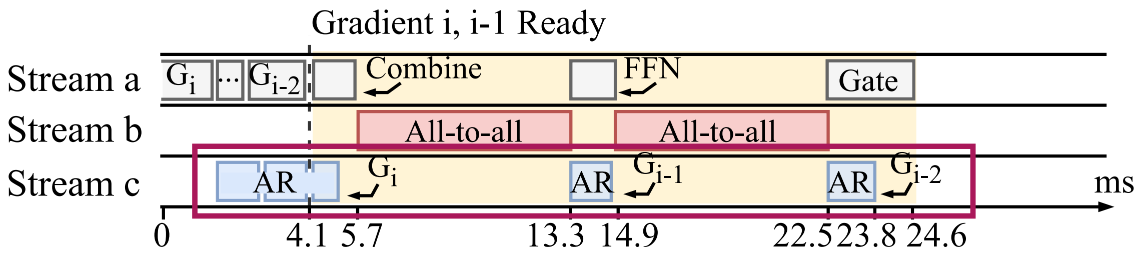


Baseline



Prioritise all-to-all

- Partition all-to-all into micro-ops
- Pipelining computation and all-to-all

Training: Micro-op Scheduling

- Tensor Partitioning
  - Partition allreduce into micro-ops
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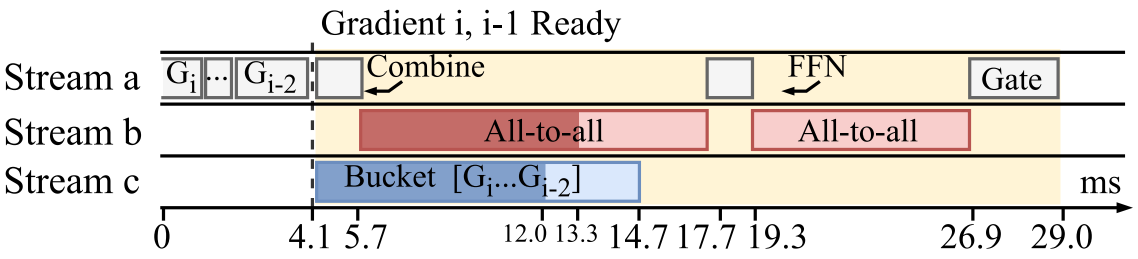

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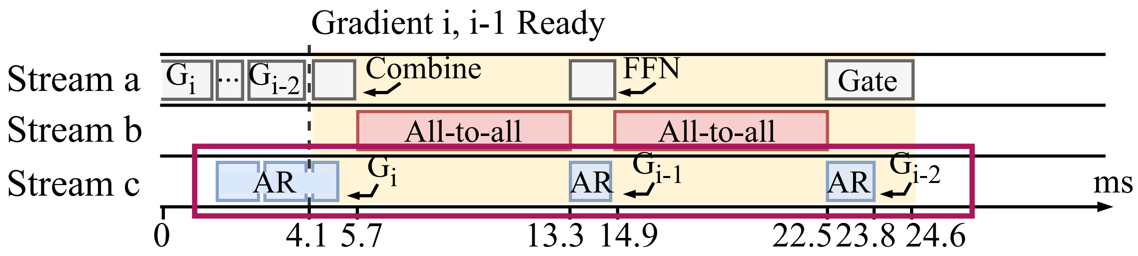

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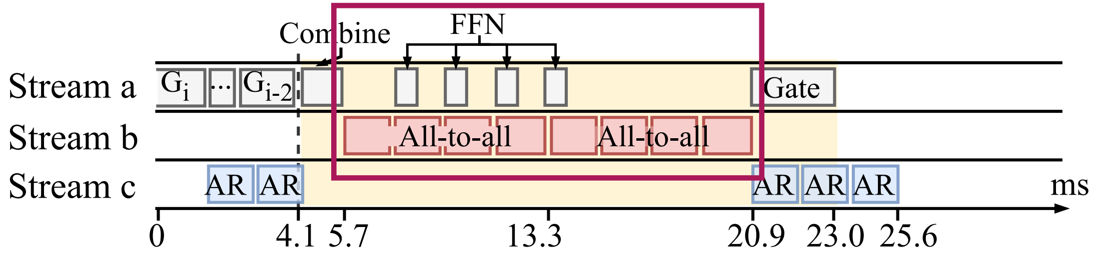
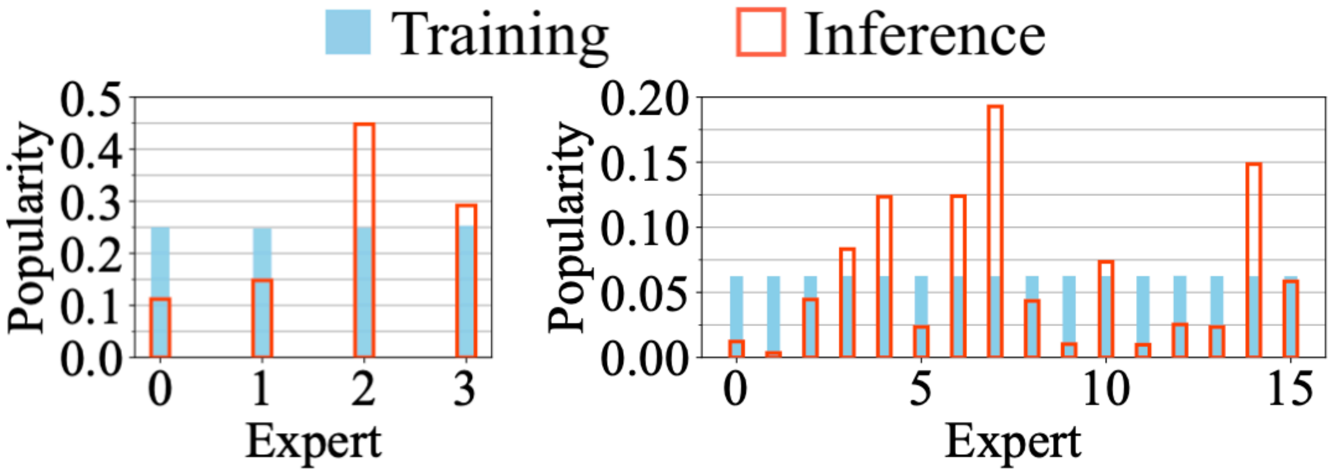


Inference: Challenges

- MoE inference: no load balancing constraints => expert selection is workload-driven, therefore, much more *biased*.



4-expert MoE

16-expert MoE

Maximum idle time of the least popular expert
=> 29.4% of the inference time.

Devices with unpopular experts have to wait for those with popular experts.

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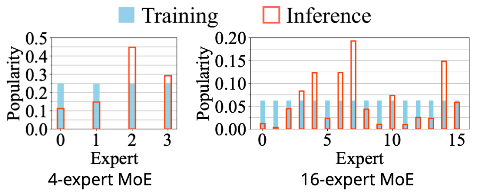

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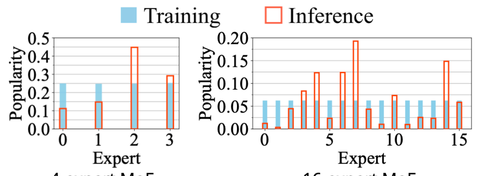

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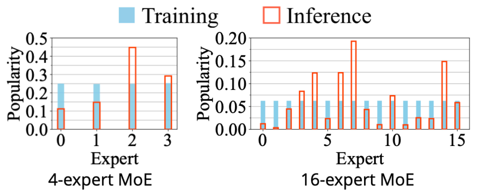

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	4	5	7	8	10
	8	9	2	3	13
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BERT-Large & WMT En-De (Translation)	6	7	6	10	1
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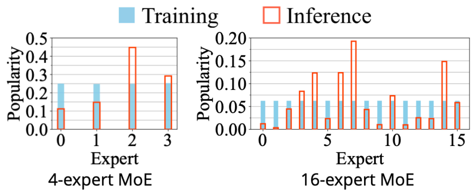

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Resource scheduling after gating network.

Inefficient practice for latency-sensitive tasks!

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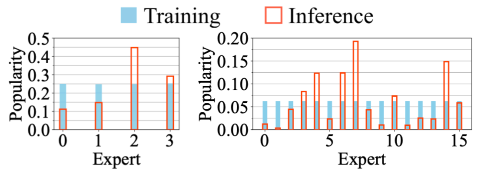

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Resource scheduling after gating network.

<u>Inefficient practice for latency-sensitive tasks!</u>

How to achieve low-overhead resource scheduling to balance device load?

Inference: Pattern in Expert Selection

- Findings: similar tokens tend to be processed by the same or similar experts in each layer.
- Tokens selecting the same expert in layer i tend to select the same expert again in layer i + 1.

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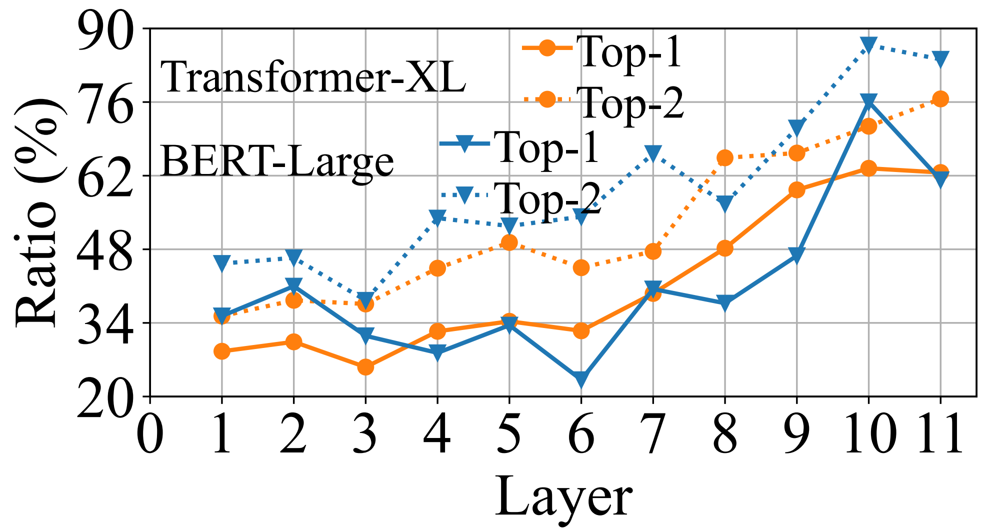

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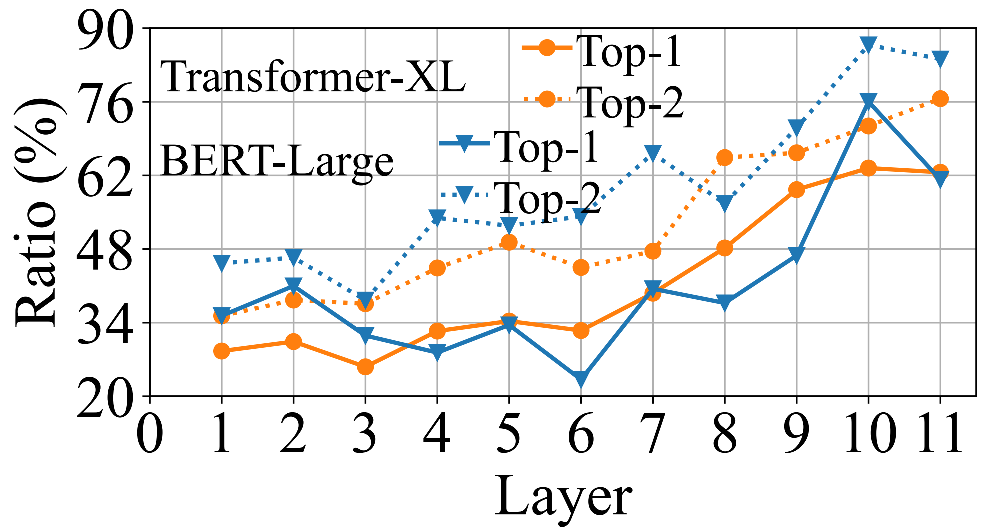

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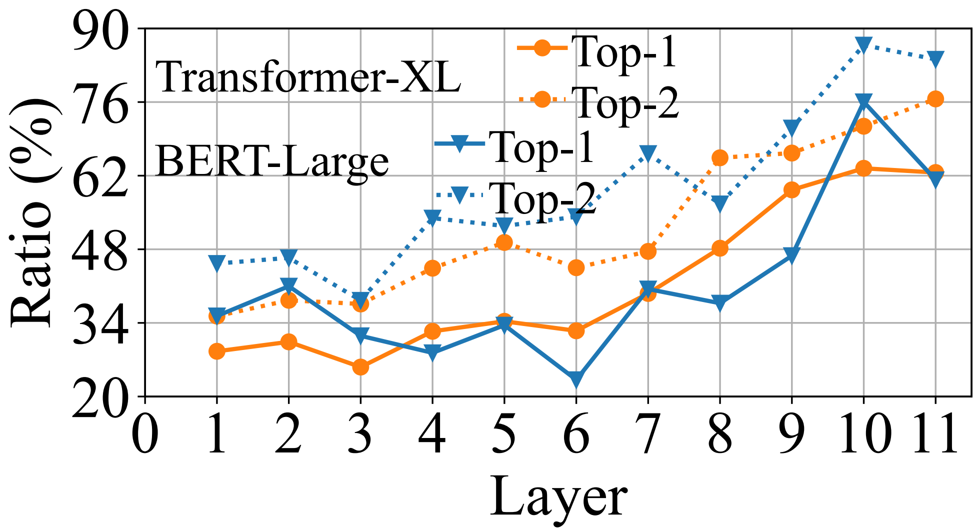

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Exploit this pattern to estimate the overall expert popularity

Inference: Expert Popularity Estimation

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- Idea: Collect the expert selection distribution during training *after the load balancing loss is minimised.*

layer i-2	E0	E1	E2	E3
layer i-1	E0	E1	E2	E3
layer i	E0	E1	E2	E3
layer i+1	E0	E1	E2	E3

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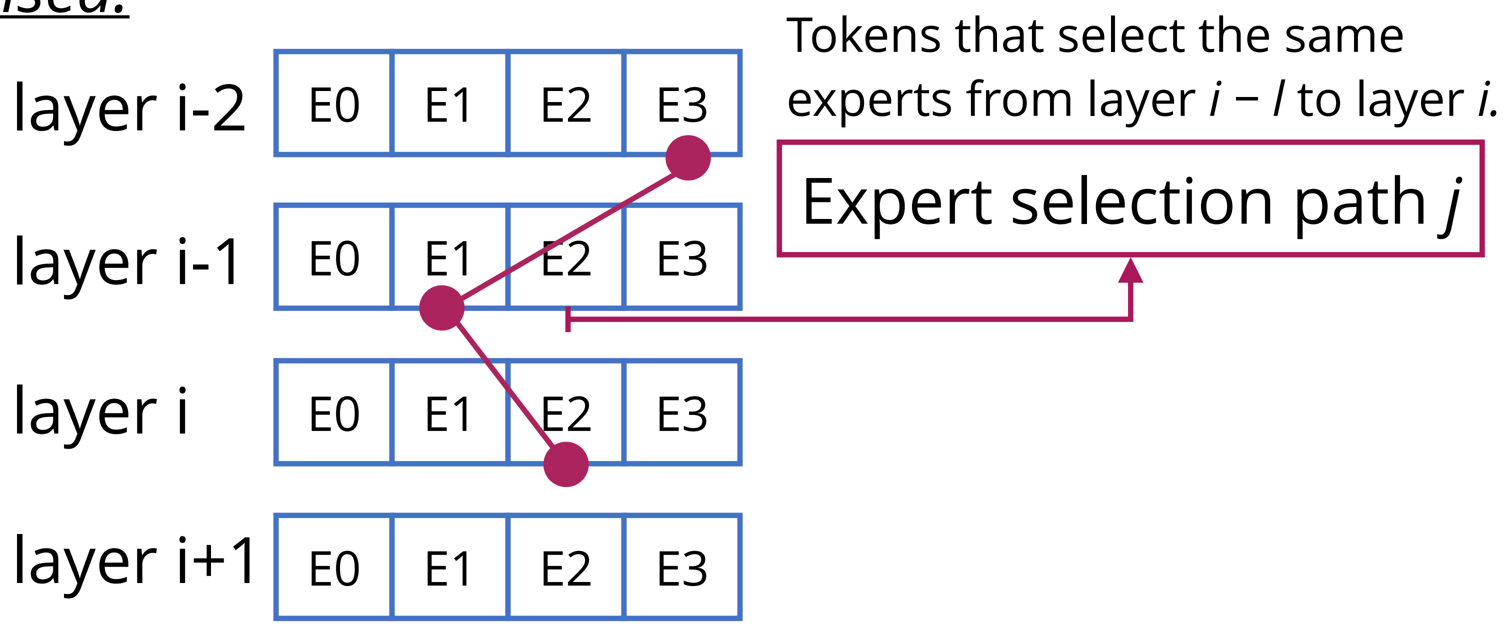

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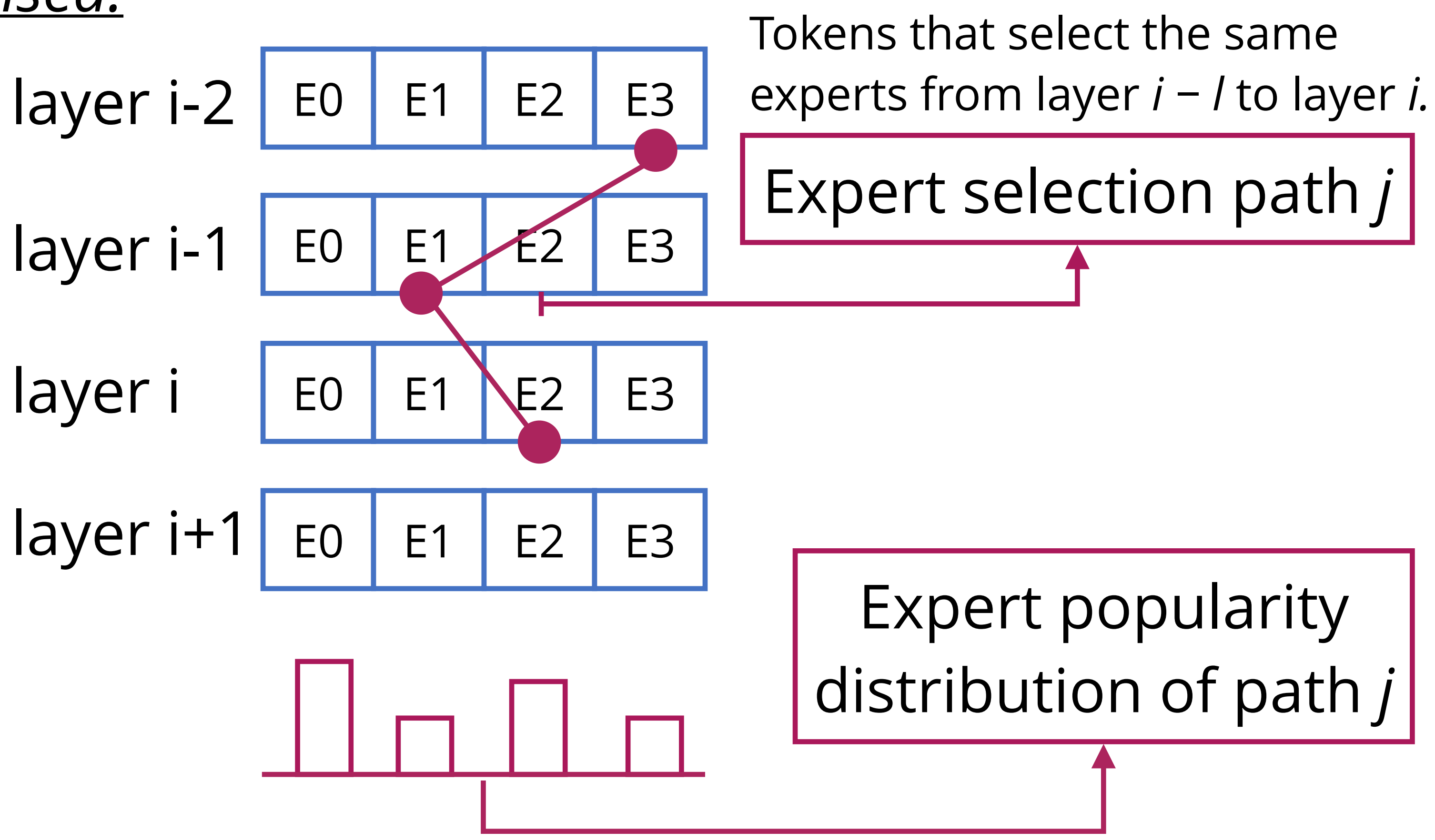

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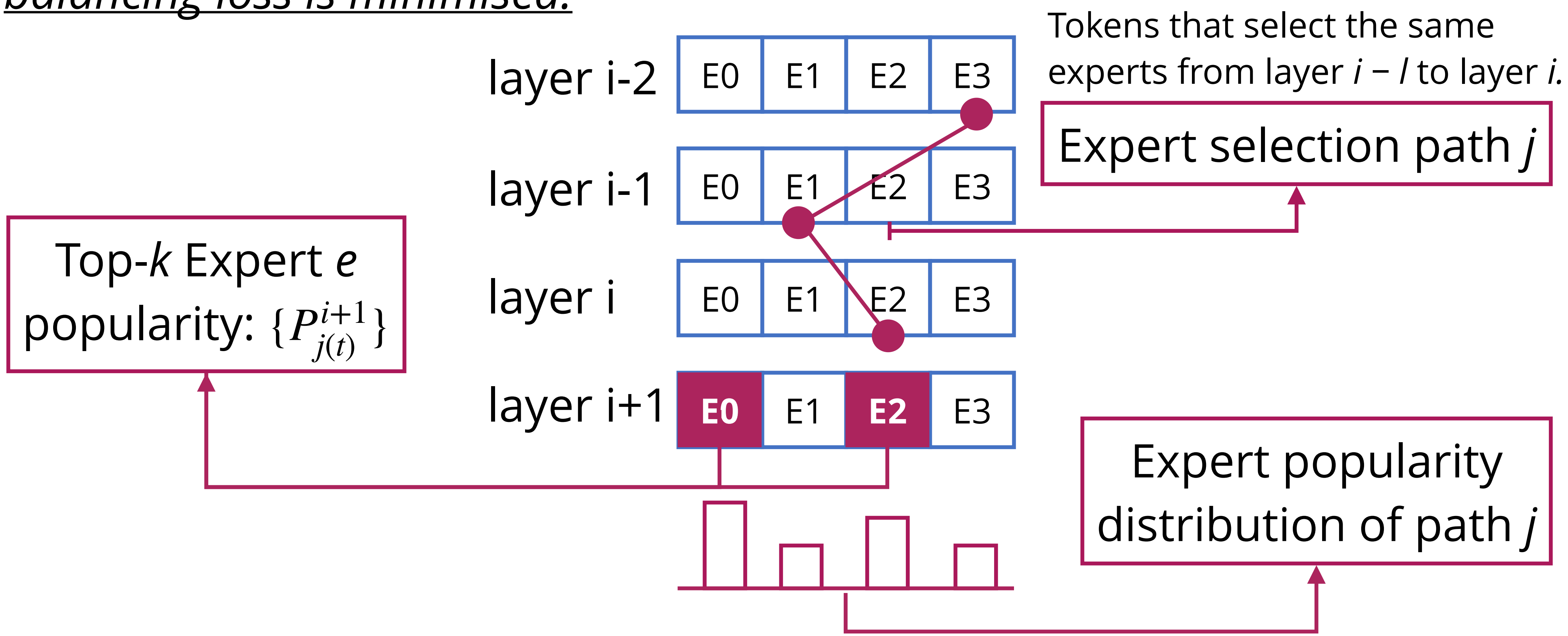

Inference: Two-phase Scheduling

- Phase 1:
  - Compute resource allocation for expert *e* based on popularity estimation:

$$n_e = N \times \sum_{t=1}^{N_t} P_{j(t)}^{i+1}(e)/N_t$$

No. of tokens in a batch

No. of GPUs

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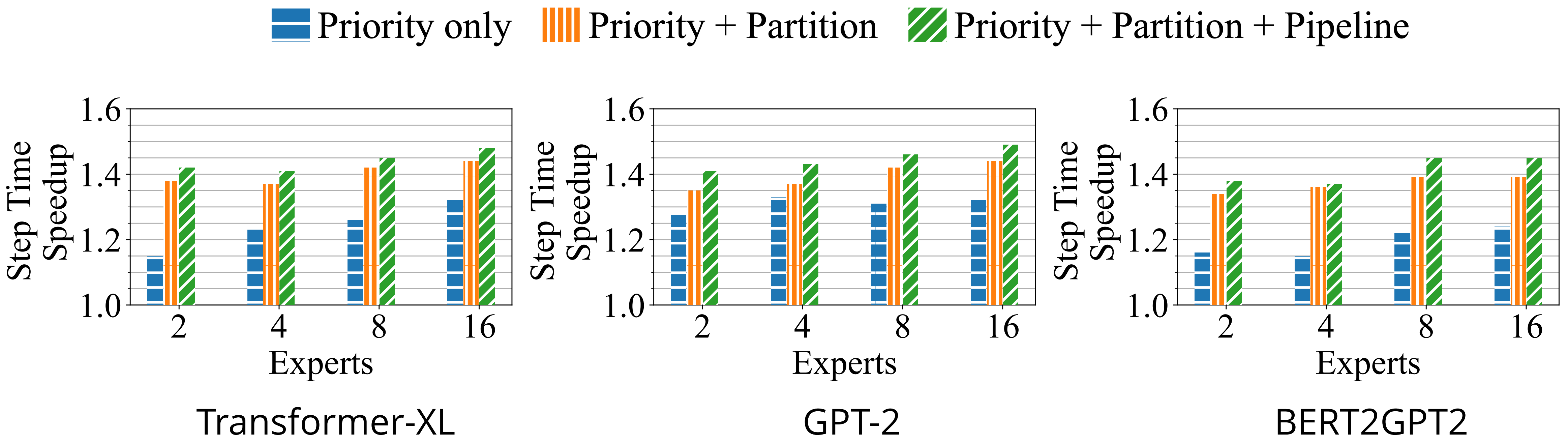
- Phase 2:
  - Fine-tune the allocation with the actual expert selection.
    - Re-compute the allocation when the actual selection deviates significantly from the estimation.

Evaluation

- Testbed: Our testbed has four worker nodes. Each node has 4 Ampere A100 GPUs with 40GB memory and is equipped with 100Gbps InfiniBand.
- Every FFN layer in Transformer is replaced with the MoE layer.
- Training models:
  - Transformer-XL: a 24-layer encoder model.
  - BERT2GPT2: a 12-layer encoder-decoder model.
  - GPT-2: a 12-layer decoder model.
- Inference models:
  - Transformer-XL: text generation with Enwik8 test set.
  - BERT: a 12-layer decoder model for translation using WMT En-De test set.

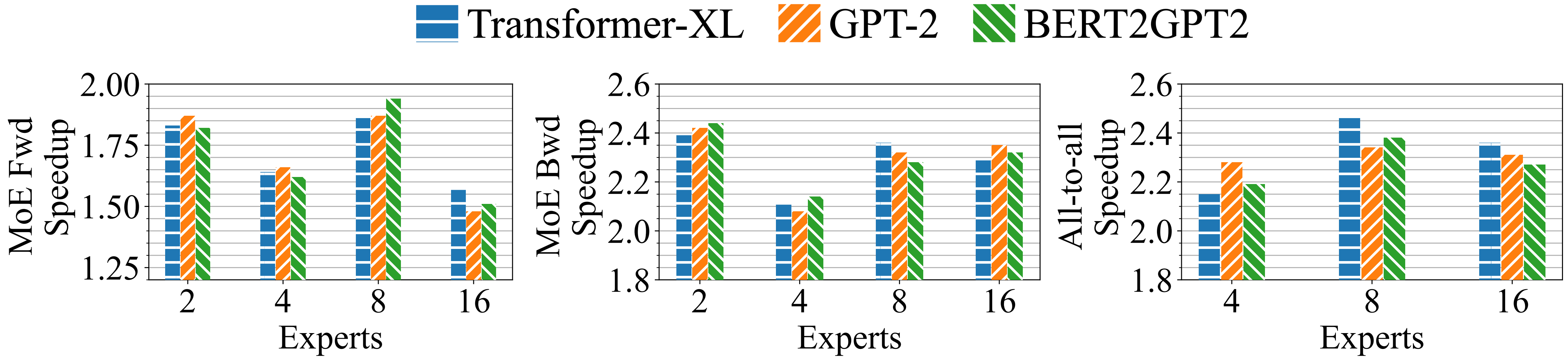
Training Step Time

Training step time speedup over Baseline (DeepSpeed) with different design choices.



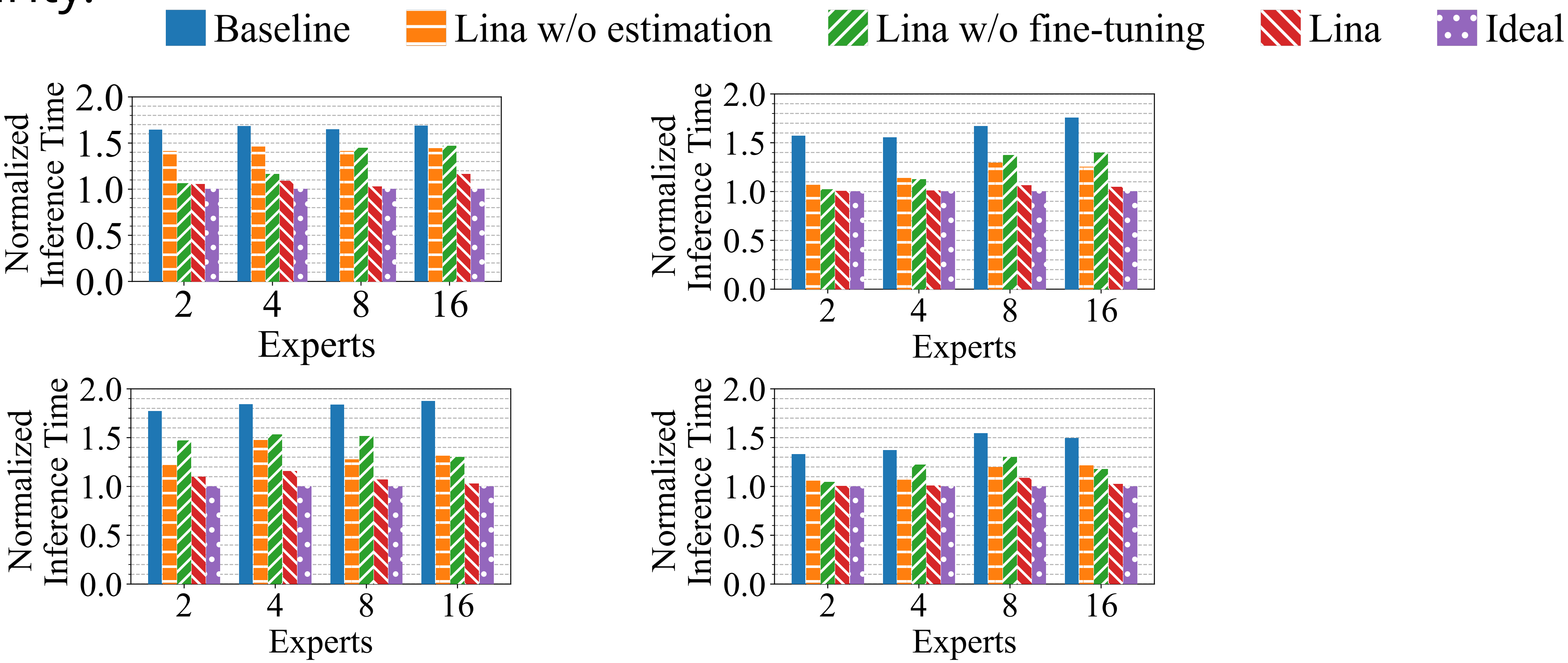
MoE Layer in Training

MoE layer forward, backward, all-to-all running time speedup over Baseline.



Inference Latency

Ideal: schedule resources assuming we have the prior knowledge of exact expert popularity.



Median Latency

95%ile Latency

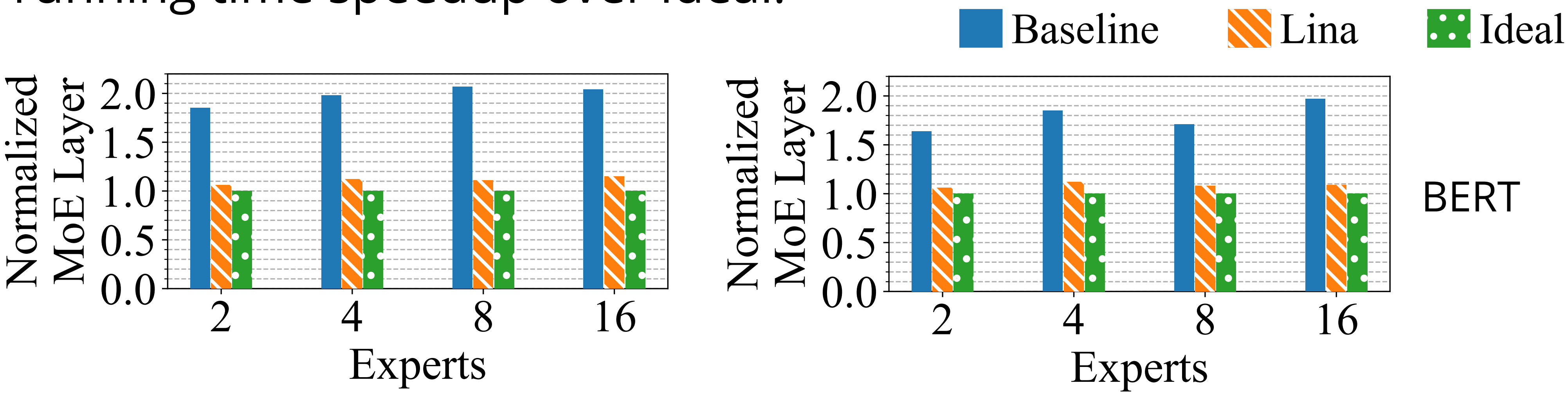
Transformer-XL

BERT

MoE Layer in Inference

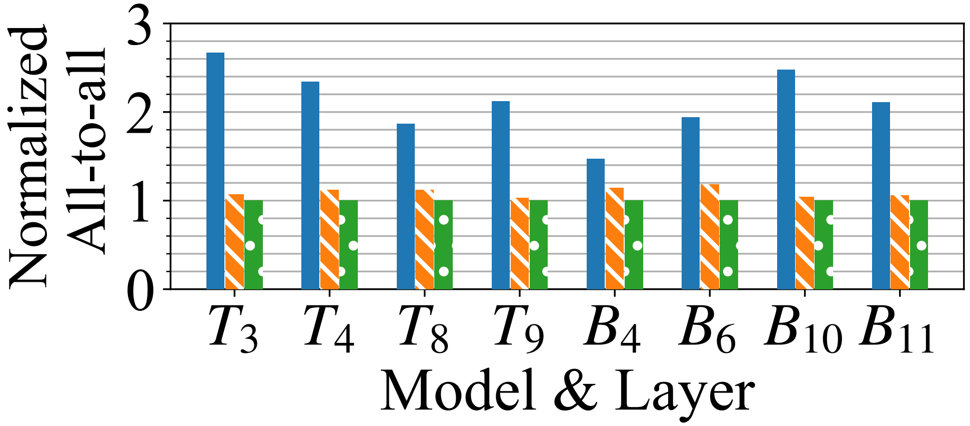
MoE layer running time speedup over Ideal.

Transformer-XL



BERT

All-to-all running time speedup over Ideal in selected layers.



Lina’s Contributions

- An in-depth empirical analysis of distributed MoE
  - Main causes for all-to-all to be the performance bottleneck in training and inference.
- [Training] A scheduler prioritises all-to-all over allreduce to improve its bandwidth and reduce its blocking period.
- [Inference] An estimation method of expert popularity to conduct two-phase resource scheduling.

Thanks!