

Toward Efficient Inference for Mixture of Experts

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Duke



DEPARTMENT of
COMPUTER SCIENCE



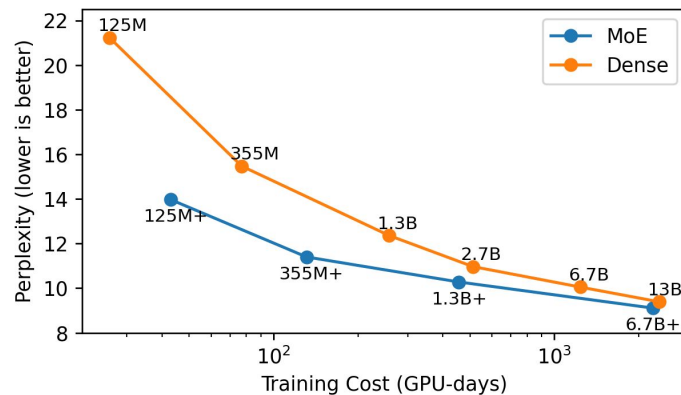
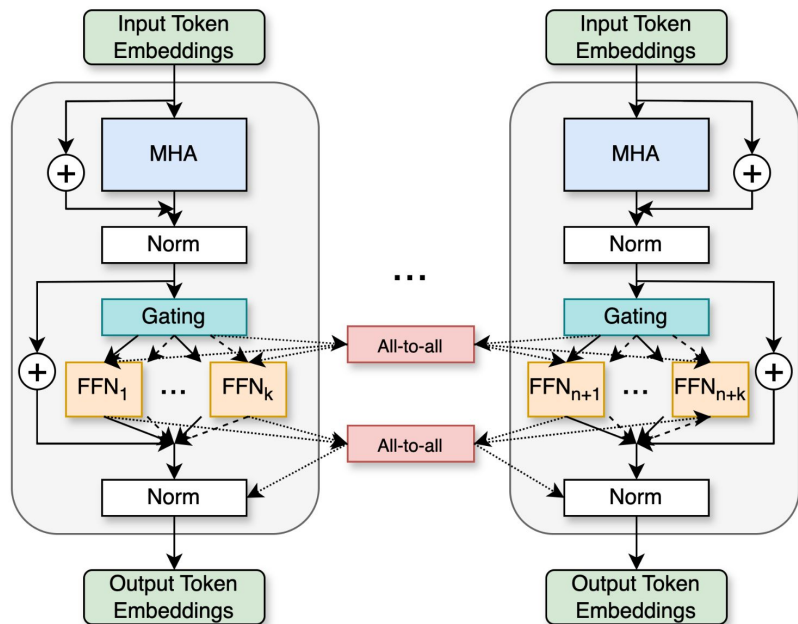
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MoE Performance in Training Scenario

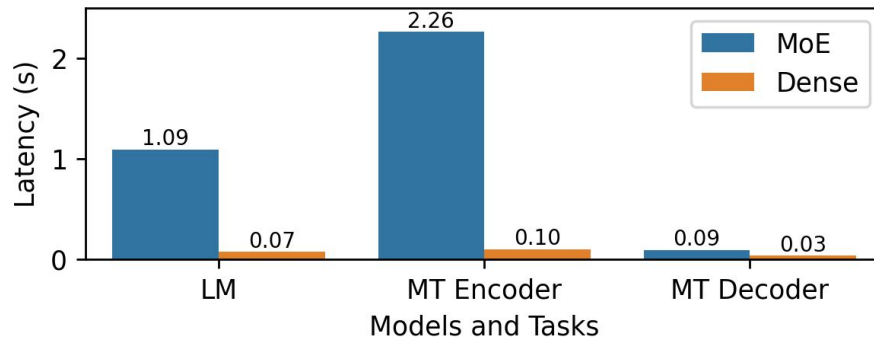
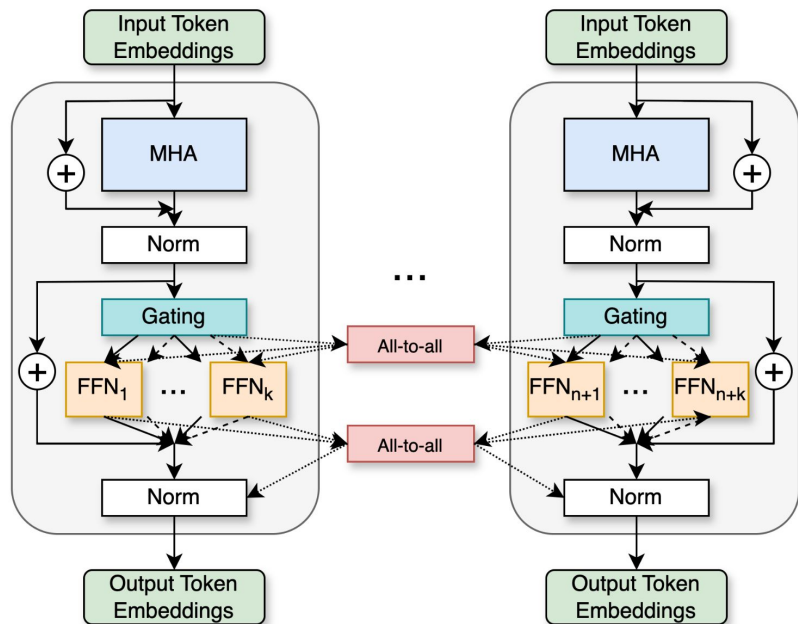
Mixture of Experts (MoE) models with expert parallelism



Lower **training** cost by up to 5x compared to dense Transformer

MoE Performance in Inference Scenario

Mixture of Experts (MoE) models with expert parallelism

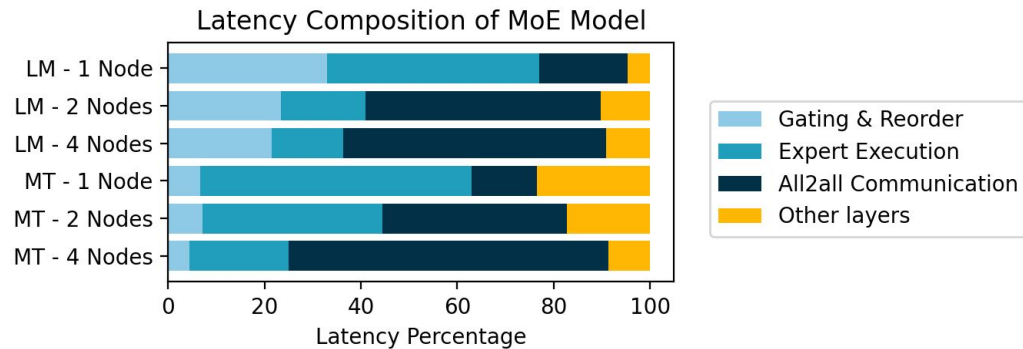
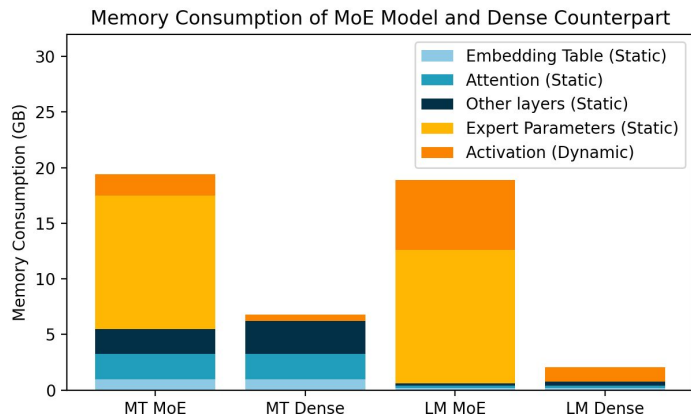


Lower **training** cost by up to 5x compared to dense Transformer.

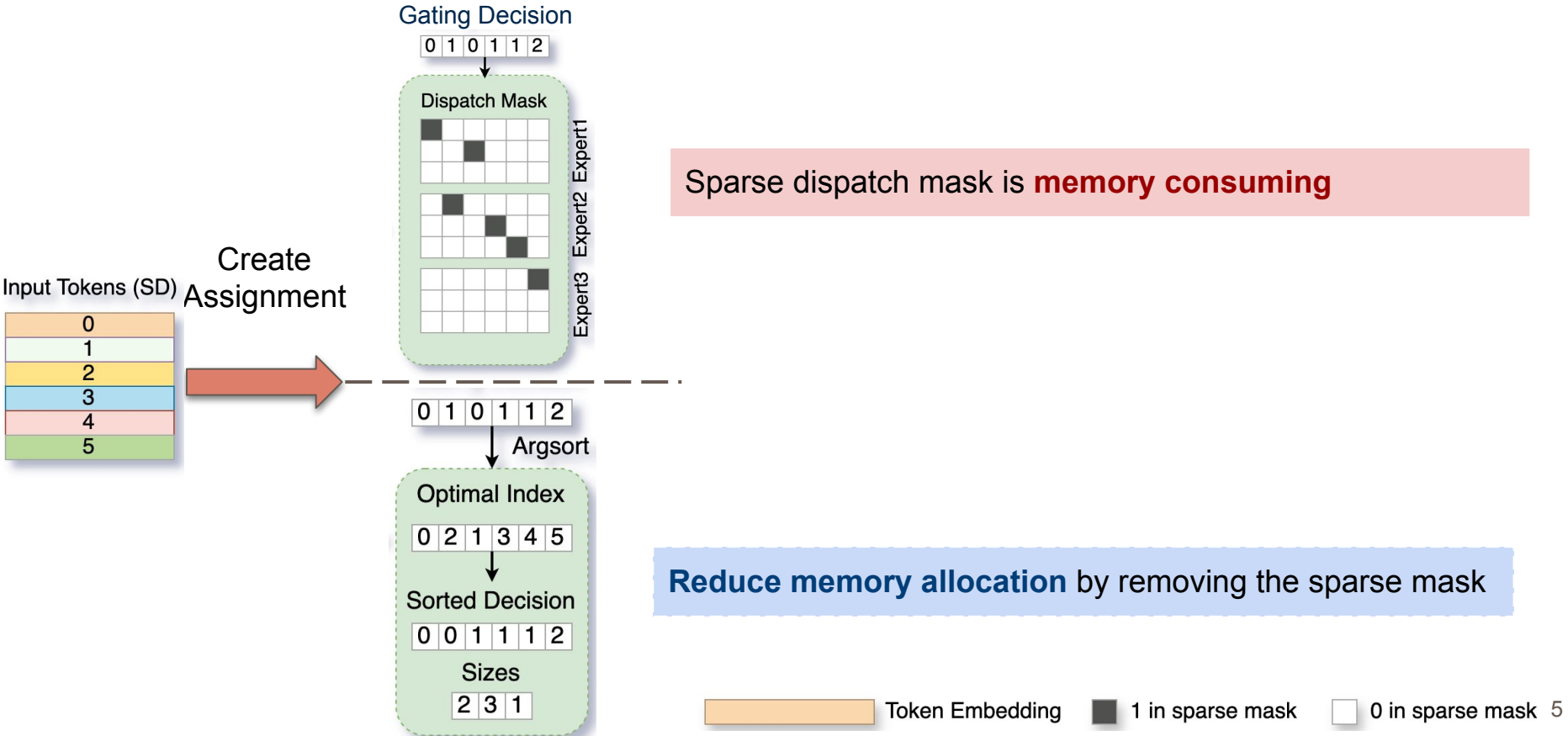
Higher **inference** cost, 15x slower for language models and >3x slower for machine translation.

MoE Inference Latency and Memory Characterizations

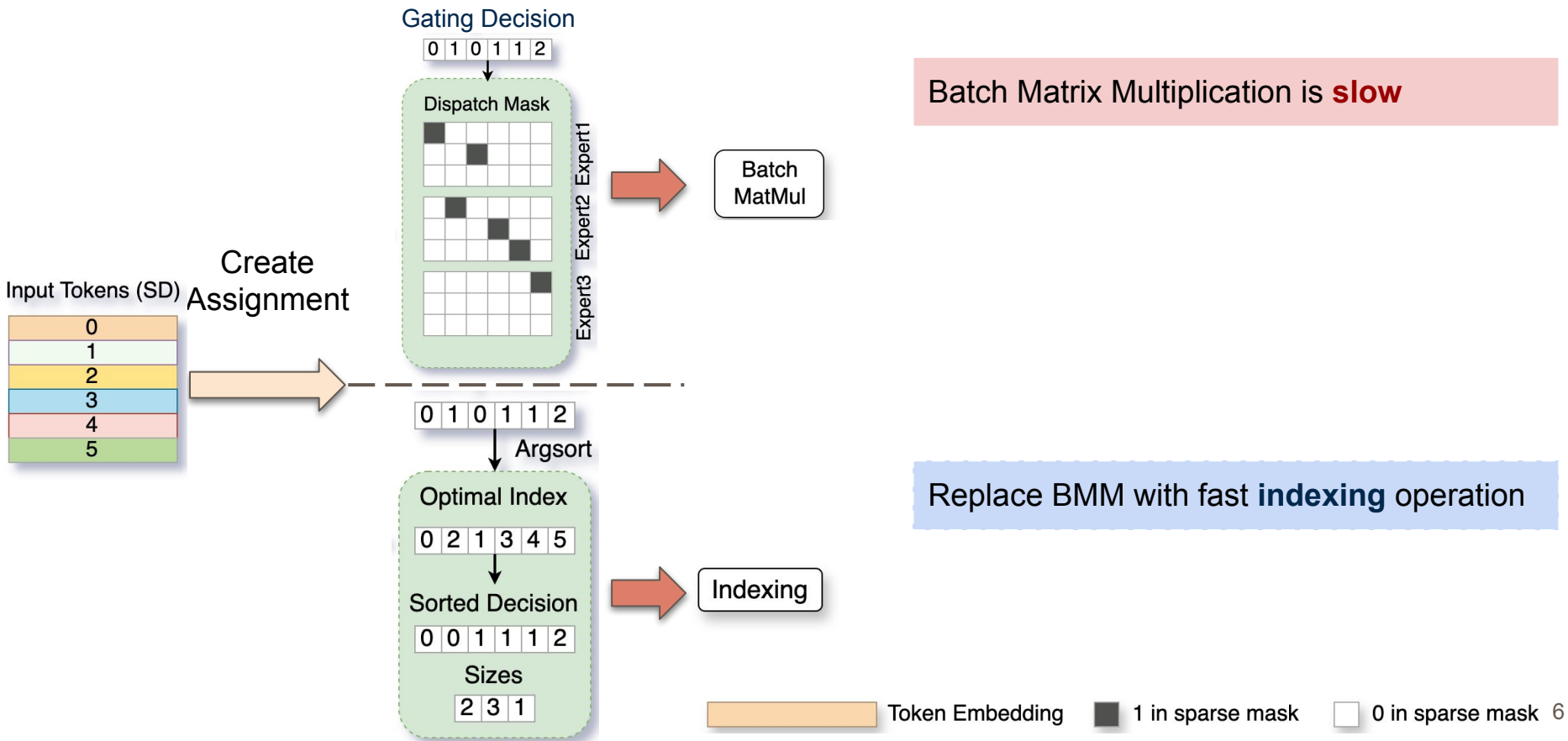
- **slower** than equivalent* dense counterparts
- consumes **more memory** than equivalent* dense counterparts



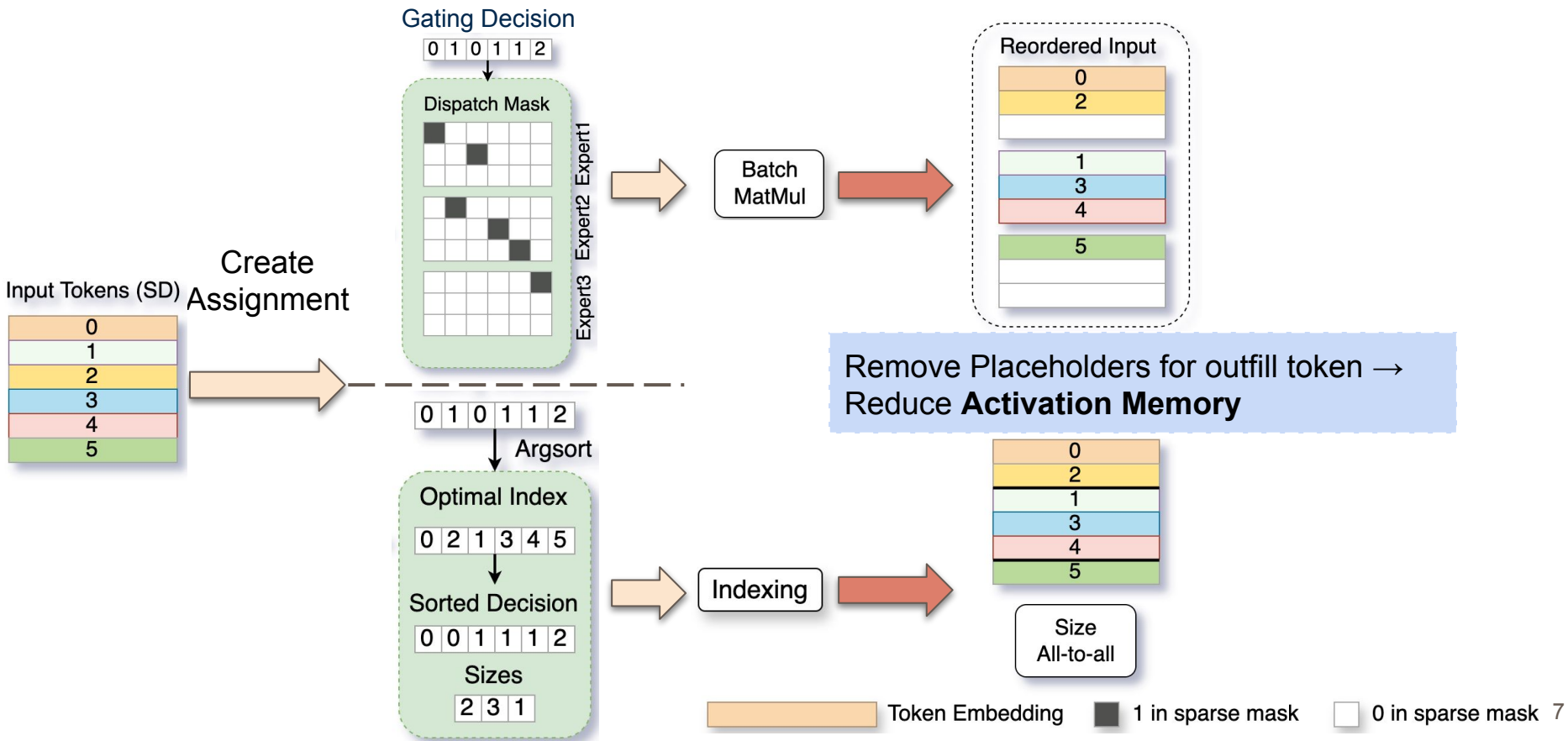
Dynamic Gating: Less Memory



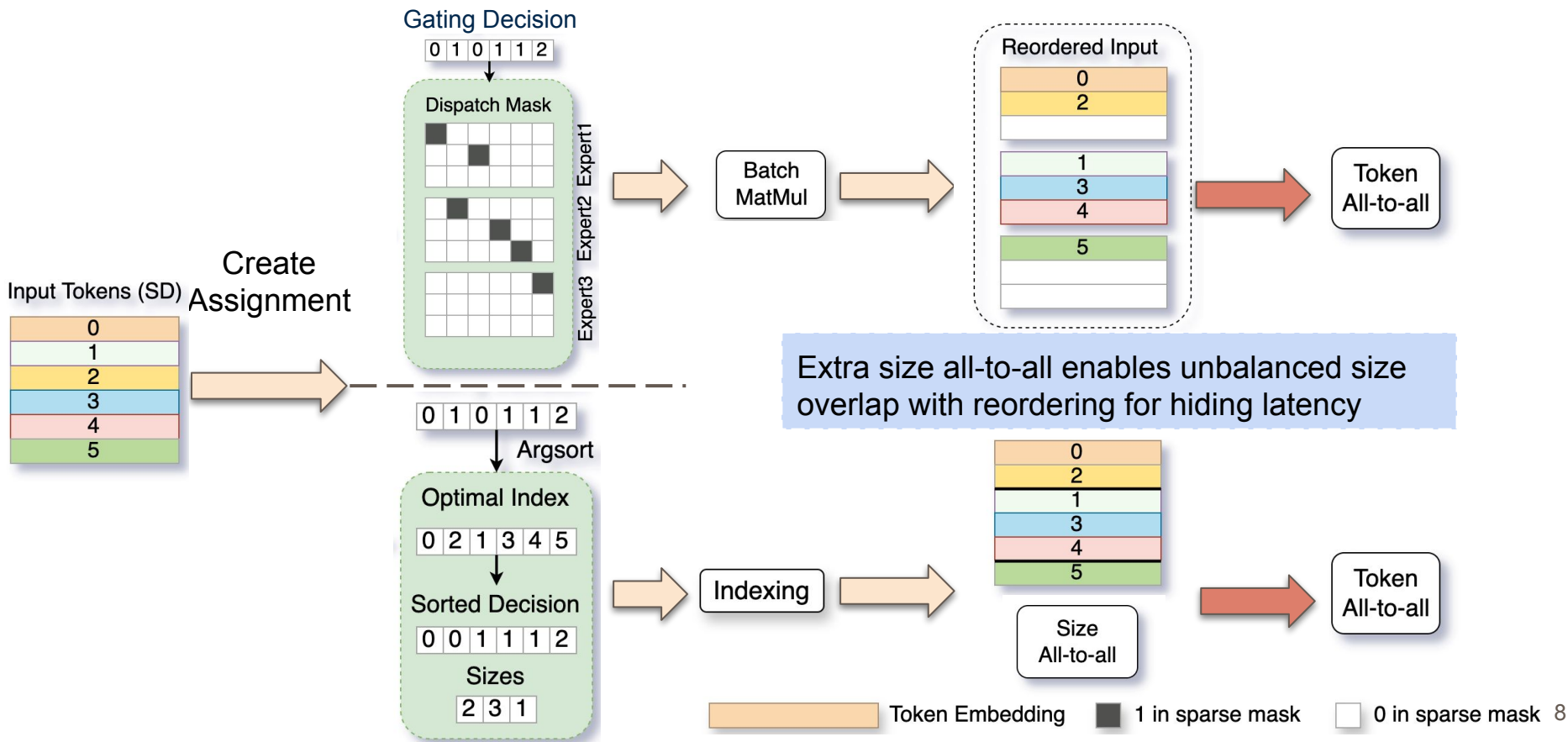
Dynamic Gating: Less Latency



Dynamic Gating: No More Placeholders

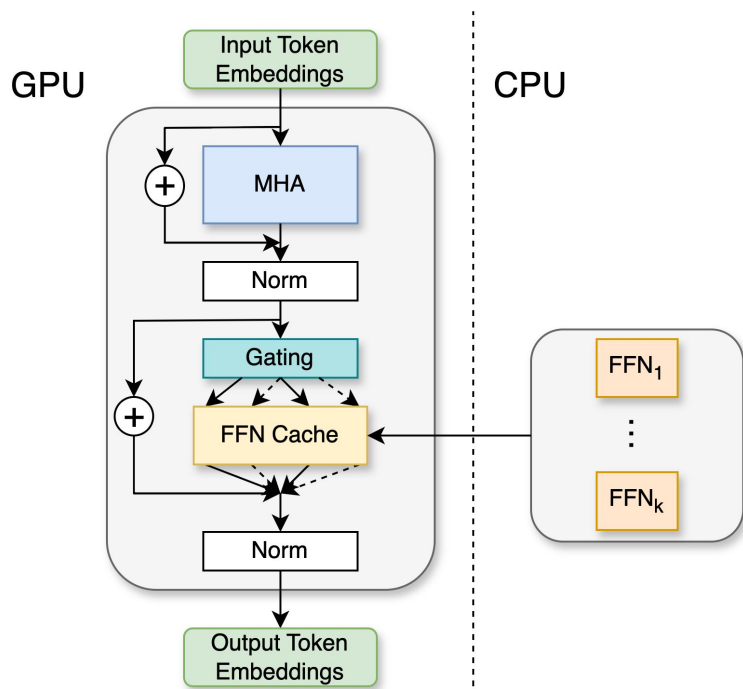


Dynamic Gating: Dynamic All-to-all



Expert Buffering: Reduce Static Memory Usage

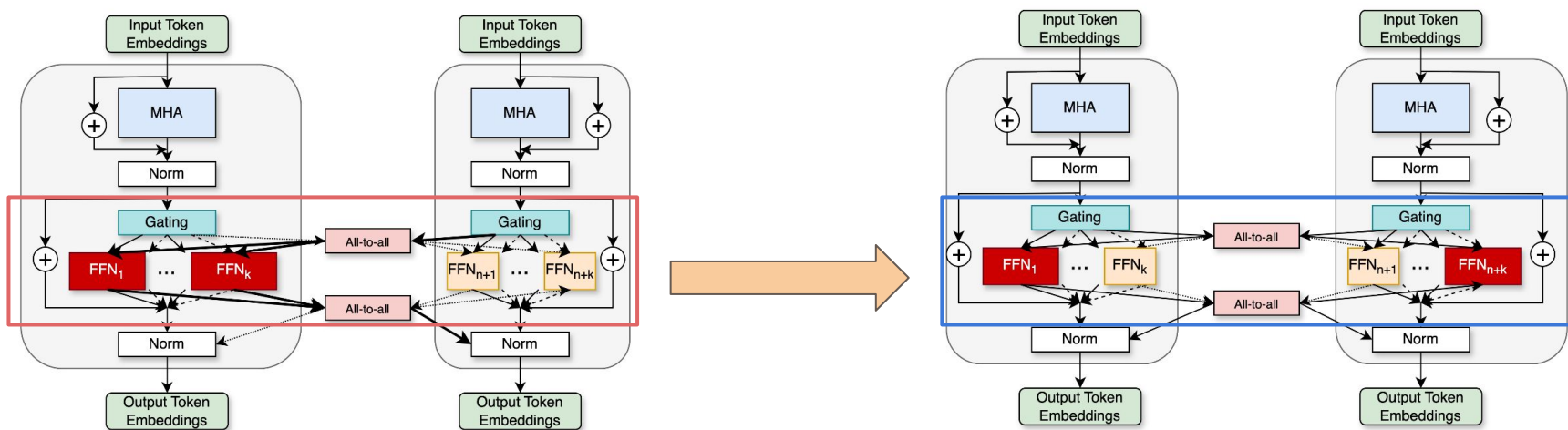
Only a subset of experts is activated in each batch



- Store bulk of the expert parameters in main memory
→ **Reduce Parameter Memory**
- Maintain *LIFO* cache on GPU that stores activated experts
→ **Mitigate GPU-CPU Latency**

Load Balancing: Improve Service Robustness

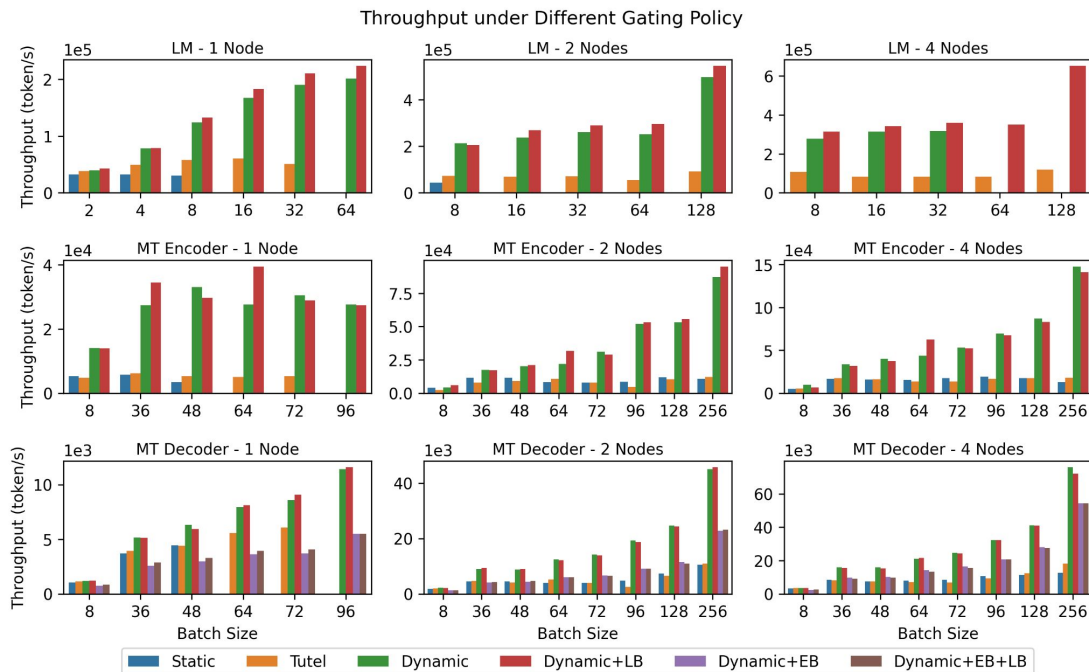
Imbalanced load on each GPU create **memory spikes** and **bottlenecks**



- Estimate expert load from historical activation
- Assign expert based on balancing load

Results

Improved throughput and maximum batch size



Check our paper and code for more information!

Paper



Paper (arXiv version)



Code

