# Large-scale Deployment of Emerging LLMs

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Llama-3.1 405B	16	1	July 2024	
Gemma-2 27B	16	1	August 2024	
Qwen-2.5 72B	8	1	September 2024	
Phi-4 15B	10	1	December 2024	
DeepSeek-3 685B	1 (MLA)	256	December 2024	
Llama-4 402B	8	128	April 2025	
Qwen-3 235B	4	128	May 2025	
GLM-4.5 355B	8	160	July 2025	
Kimi-K2 1T	1 (MLA)	384	July 2025	
gpt-oss 120B	8	128	August 2025	

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- Less heads for KV cache
- Larger expert size

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- Large TP for FFN is expensive: scaled-out communication volume for all-reduce

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#### Trends in Model Architecture

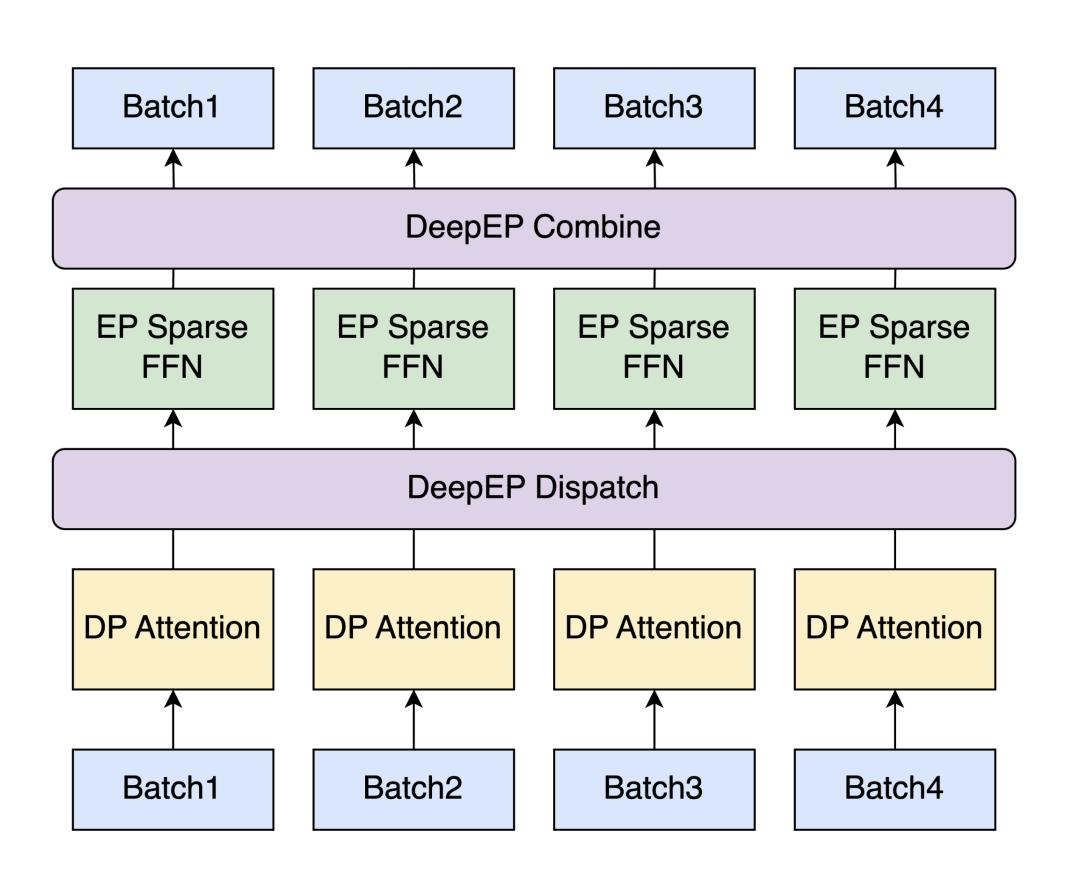
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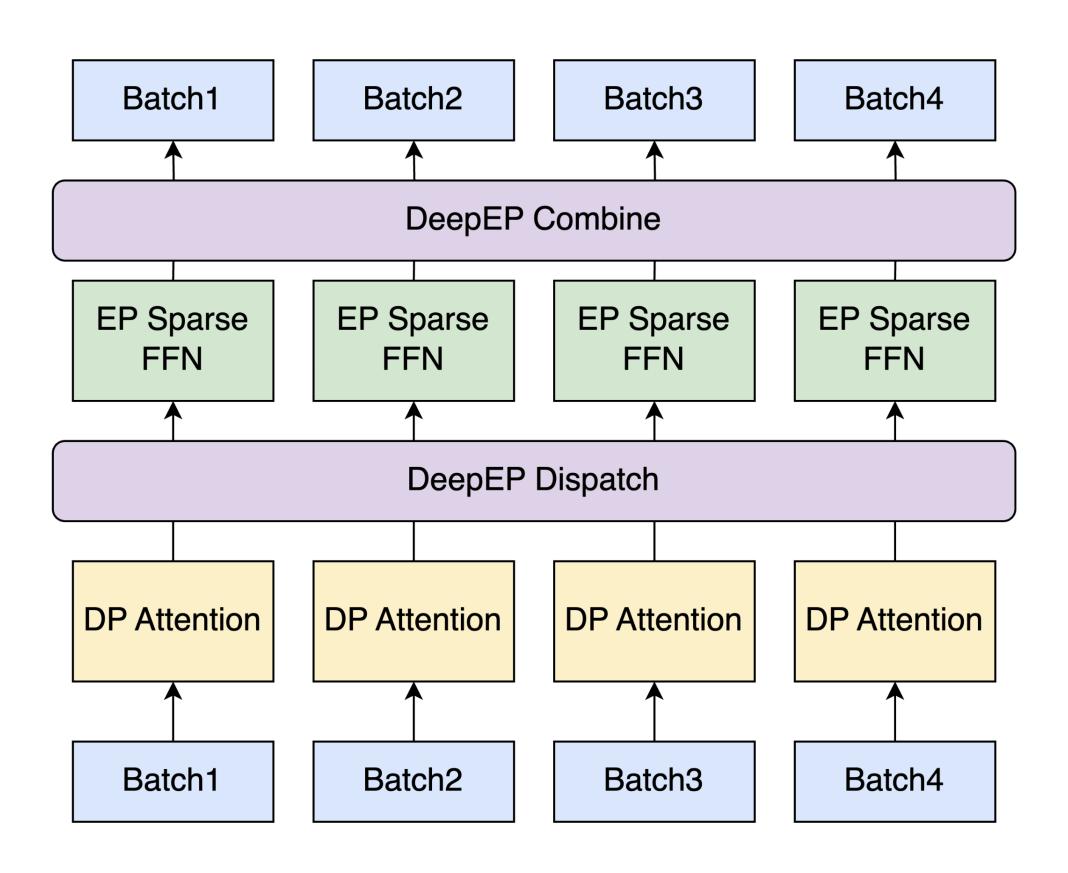
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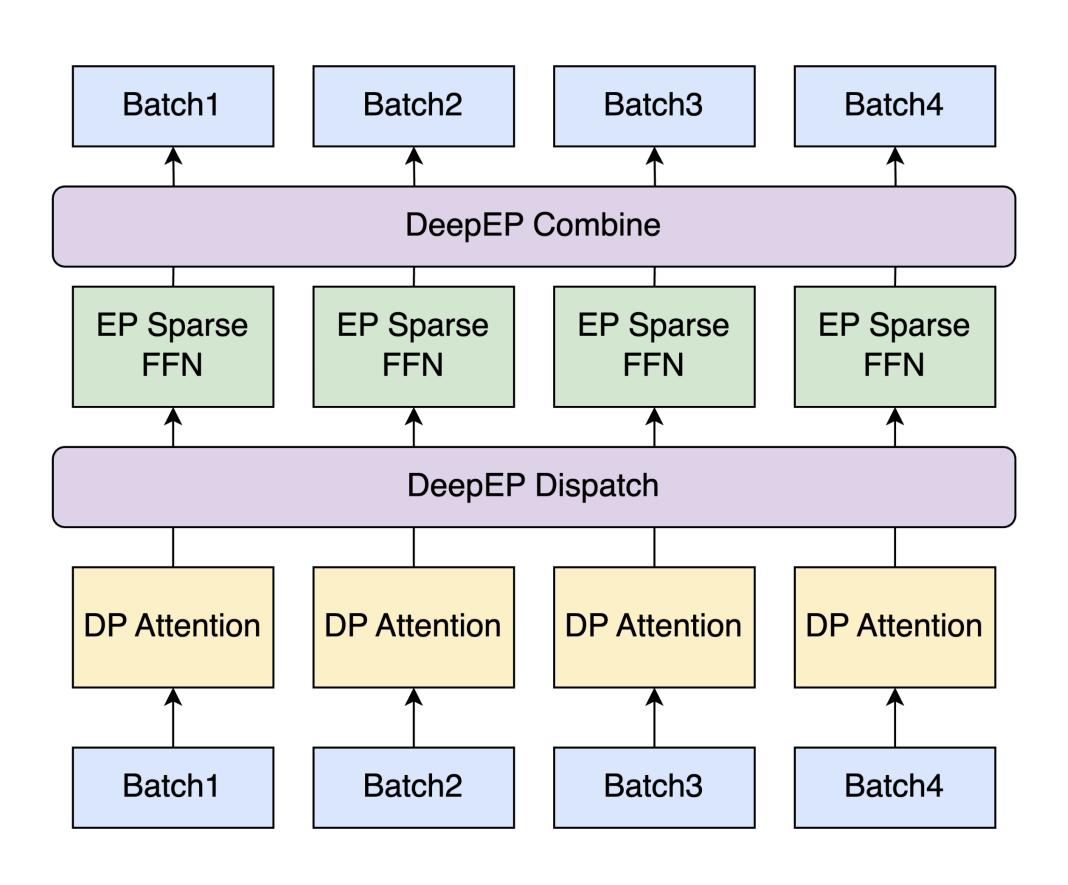
### New System Design

- DP for attention layers
- EP for FFN layers

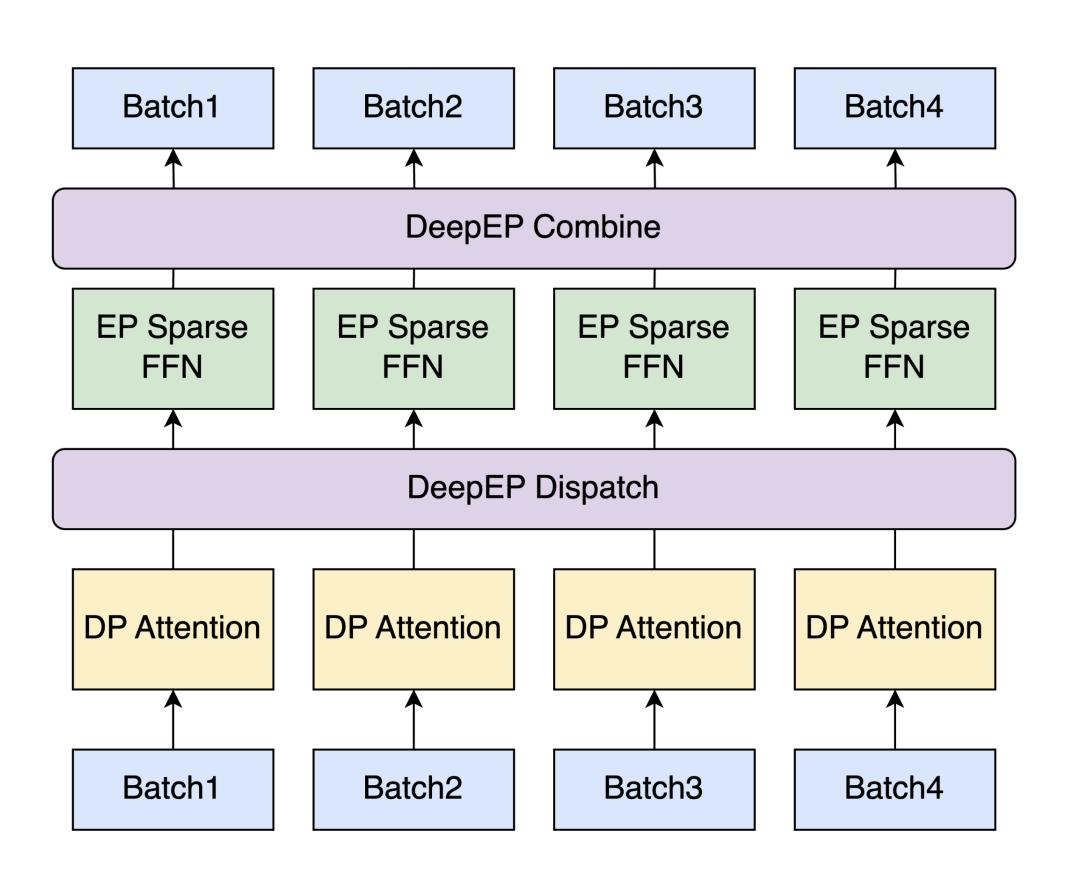




• Scalable KV Cache: DP attention avoids duplication for KV cache.

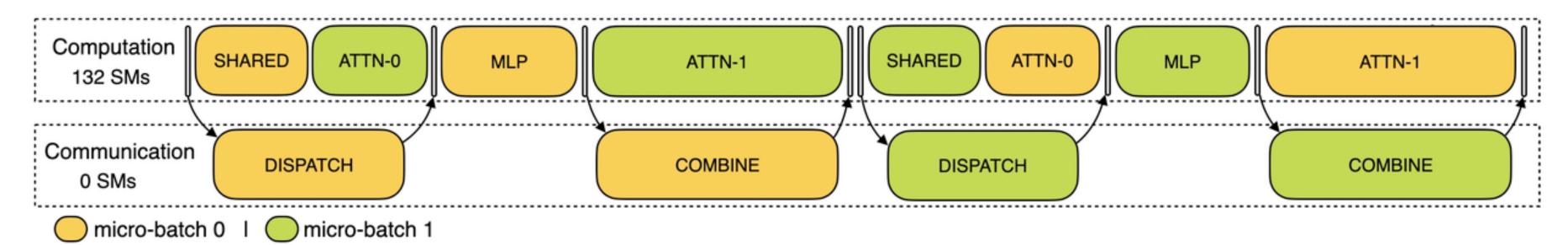


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- Optimized Communication: Follows a
   Dispatch → Expert → Combine pattern;
   powered by DeepEP and Two-Batch Overlap to minimize latency and overhead.

## Two-batch Overlap (TBO)



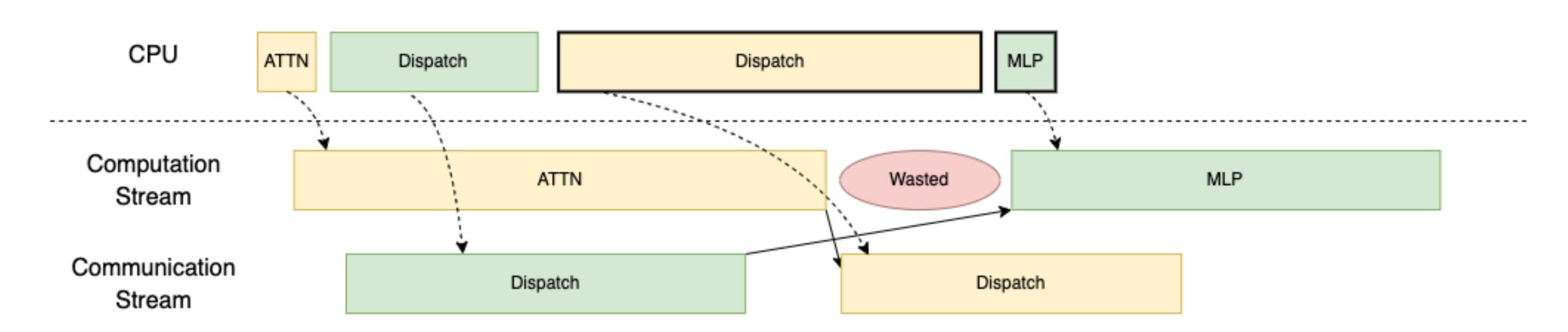
ATTN-0: MLA down/up projection and other ops after combine all-to-all and before core attention

ATTN-1: Core attention, attention output projection and MoE routing gate

SHARED: Shared experts

• Two Batch Overlap (TBO): Executing communication and computation simultaneously.

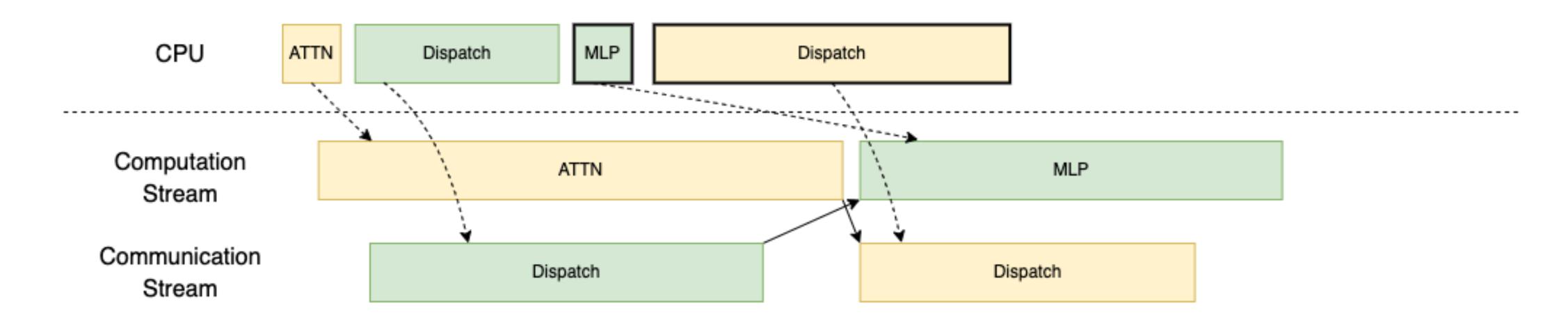
## Improper Launch Order of TBO



(a) Two-batch overlap with an improper launch order

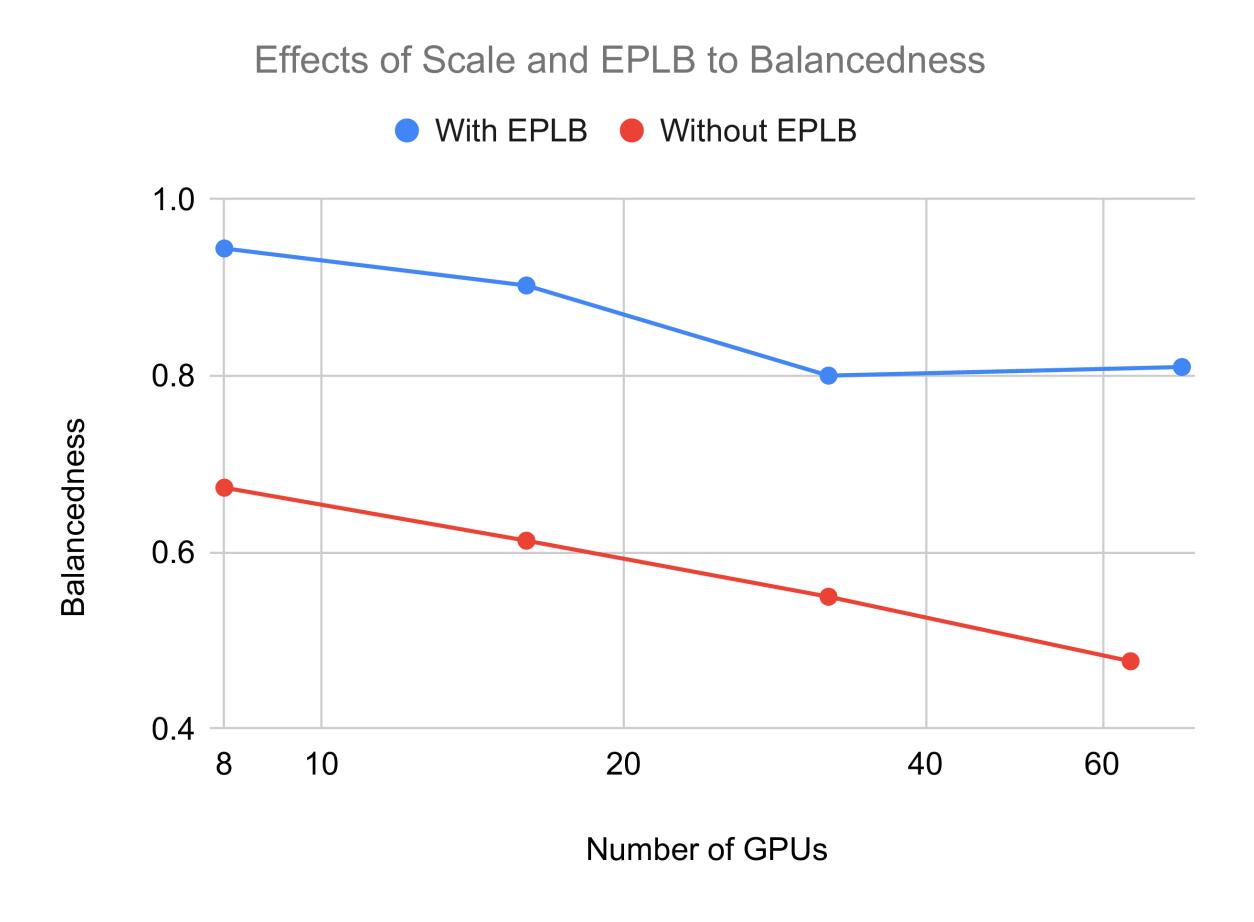
- Two Batch Overlap (TBO): Executing communication and computation simultaneously.
- Dispatch brings **synchronization**, which blocks the CPU until the GPU receives metadata (required for allocating correctly sized tensors).
- **Improper launch order**, e.g. dispatch before MLP, will block the launching and leave the computation stream idle.

## Proper Launch Order of TBO



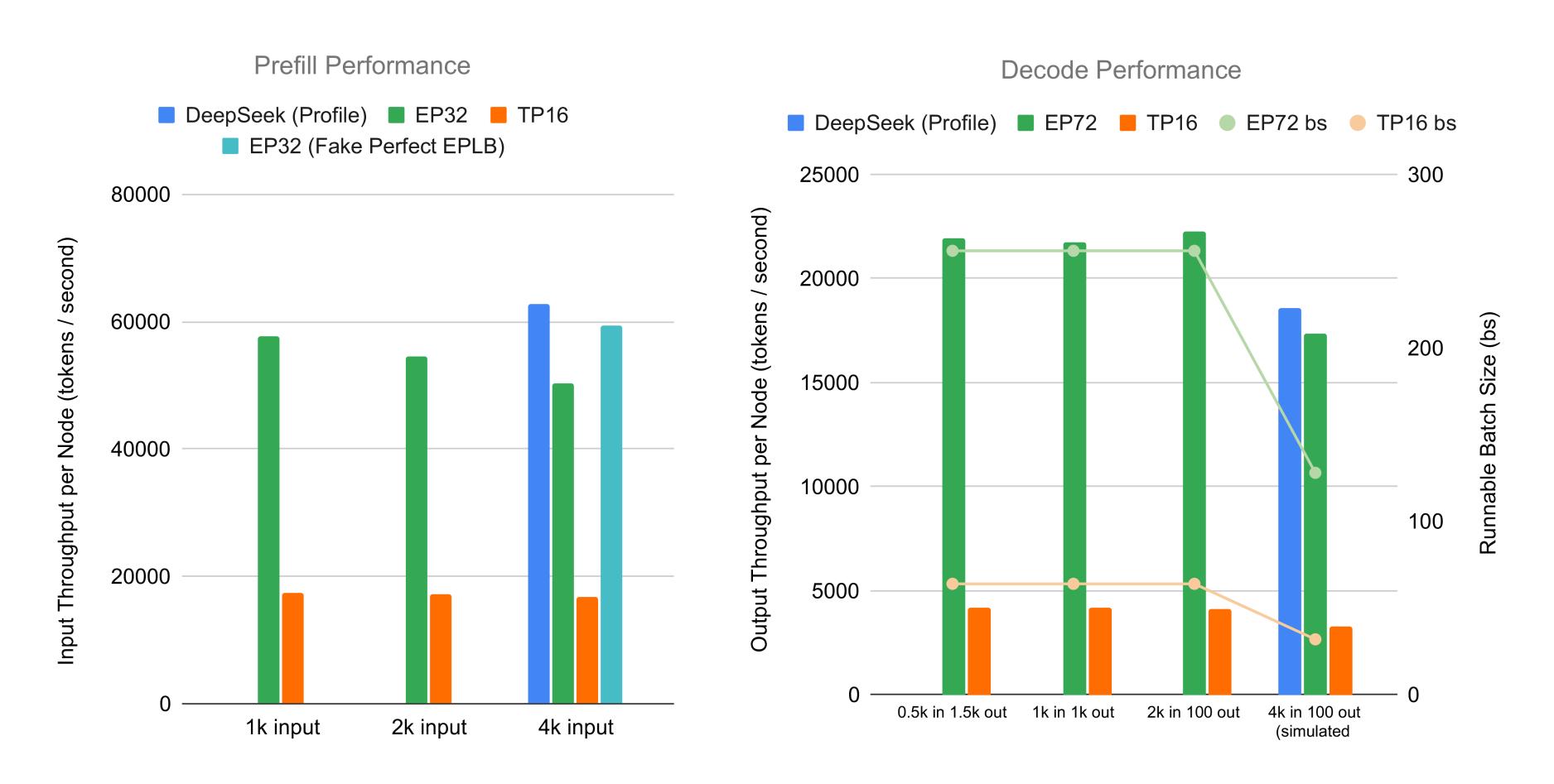
- (b) Two-batch overlap with a proper launch order
- Proper launch order: submitting computation tasks to the GPU before launching CPU-blocking communication.
- Computation → Communication: enabling GPU to remain active during communication.

## EPLB for Balancing Workload



- Balancedness: the ratio between mean computation time and maximum computation time for a MoE layer among GPUs.
- Balancedness decreases when the system scales with the number of nodes.
- Enabling EPLB significantly improves the balancedness.

## Throughput Performance



Throughputs of prefill (P) and decode (D) phases are evaluated independently, assuming unlimited resources for the non-tested phase to isolate and maximize the load on the tested nodes—mirroring the setup used by DeepSeek.

### Deployment of DeepSeek R1 and Kimi K2

Model	Experts	GPUs	Prefill Throughput (tokens/sec)	Decode Throughput (tokens/sec)	Cost per 1M Output Tokens
DeepSeek R1	256	96 × H100	52.3k / node	22.3k / node	\$0.20
Kimi K2	384	128 × H200	56k / node	24.0k / node	\$0.21

- With large-scale DP attention and EP FFN, trillion-scale models achieve 20+k output throughput per node.
- Cost: ~\$0.20 per 1M tokens

# Q&A