DistServe: Disaggregating Prefill and Decoding for Goodput-optimized Large Language Model Serving

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Various applications are powered by LLMs

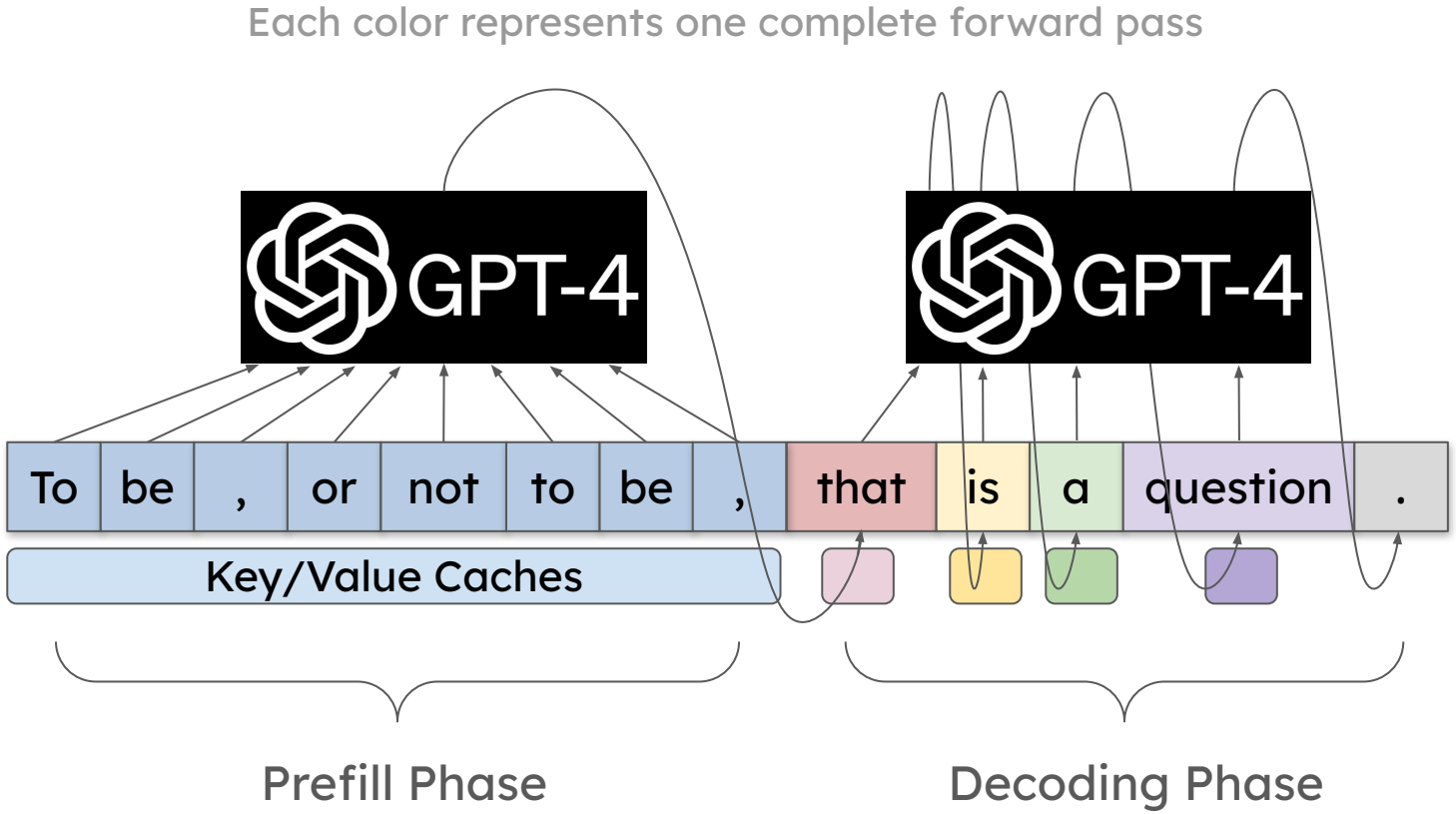
Search

OS

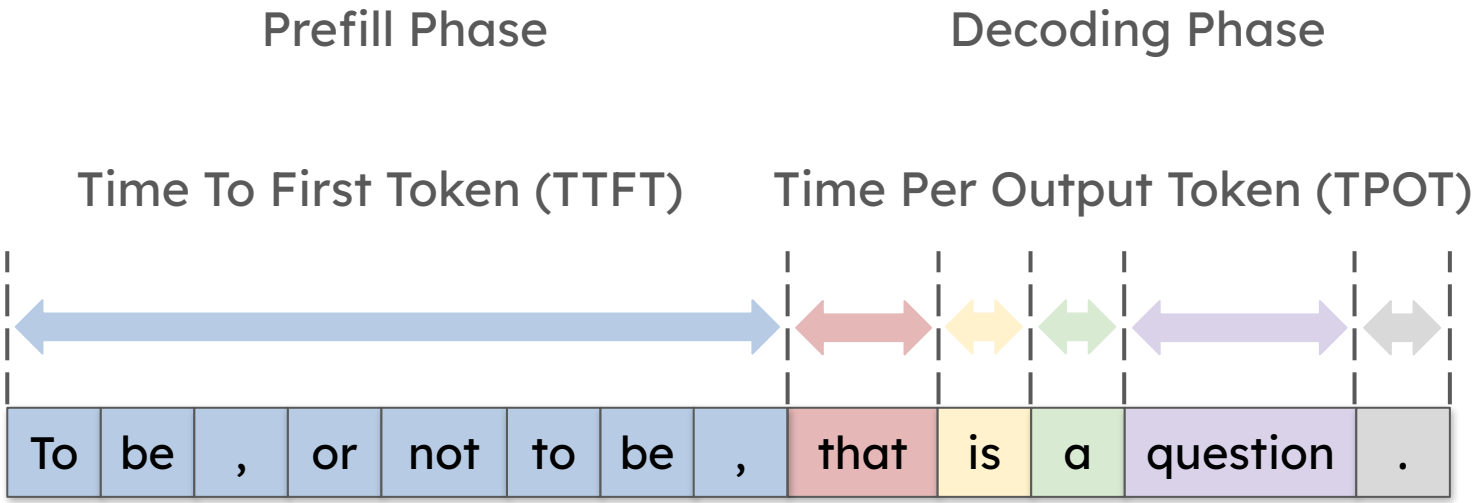
Chat

Program

LLM Inference



LLM Inference Latency



Latency = TTFT + TPOT * #Token

Different apps have various latency requirements

	TTFT	TPOT
Chat	Low (< 1s)	Match read speed (~ 100ms)
Search	Very Low (~ 200ms)	Match read speed (~ 100ms)
Program	Very Low (~ 200ms)	Very Low (~ 50ms)

Our Goal

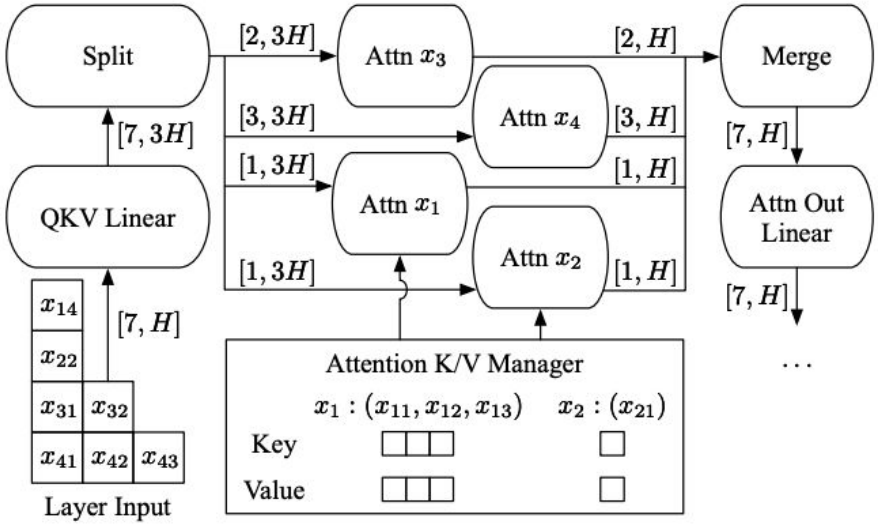
Use the fewest #GPUs to serve as many requests as possible while subject to various latency requirements of apps.

- *Service Level Objective (SLO)*
- *SLO Attainment*
- *Per-GPU Goodput*

Formally, our goal is to maximize the Per-GPU Goodput

Existing systems maximize the overall throughput

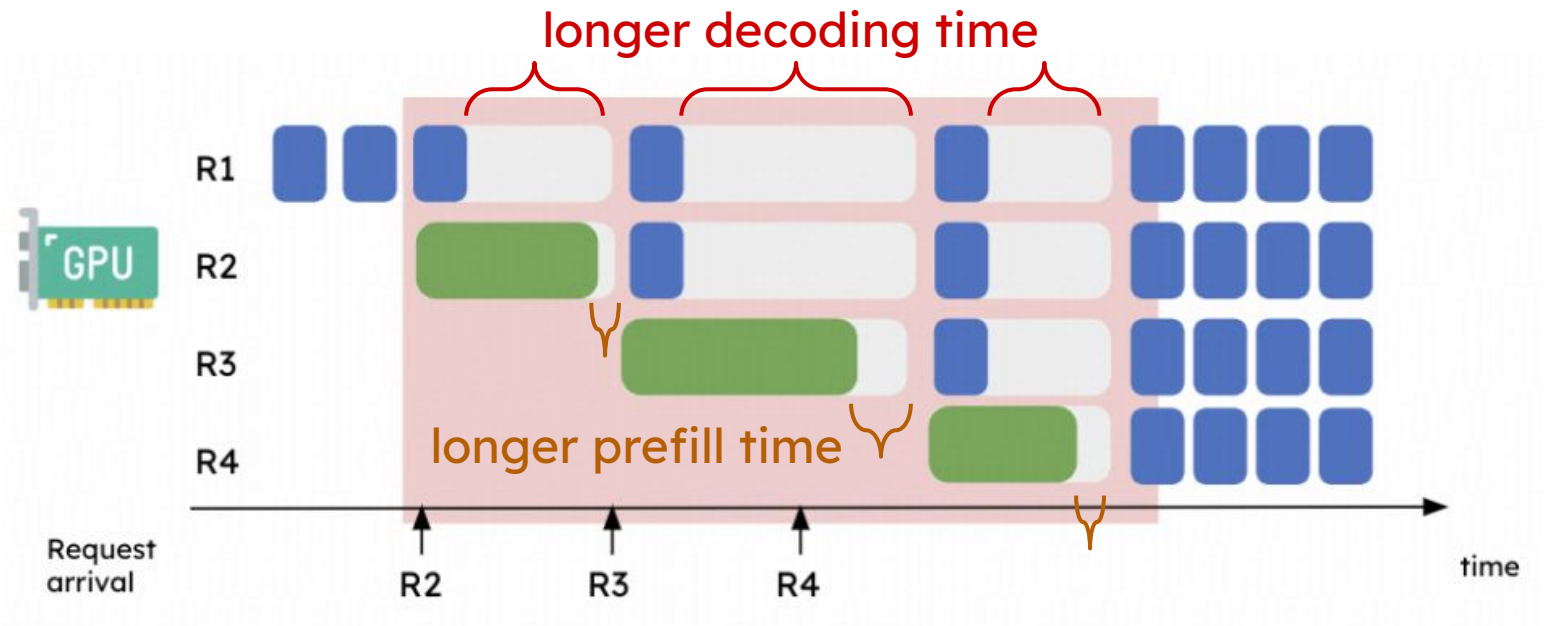
Existing approach: Batch requests in prefill and decoding phase together



Source: Gyeong-In Yu, et al. “Orca: A Distributed Serving System for Transformer-Based Generative Models”

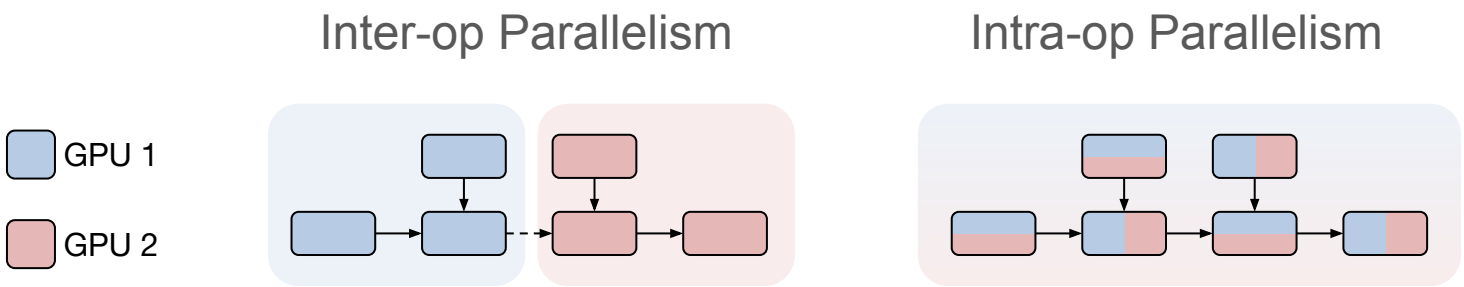
Problem 1: Prefill-Decoding Interference

Batching prefill and decoding phase together hurt both TTFT and TPOT

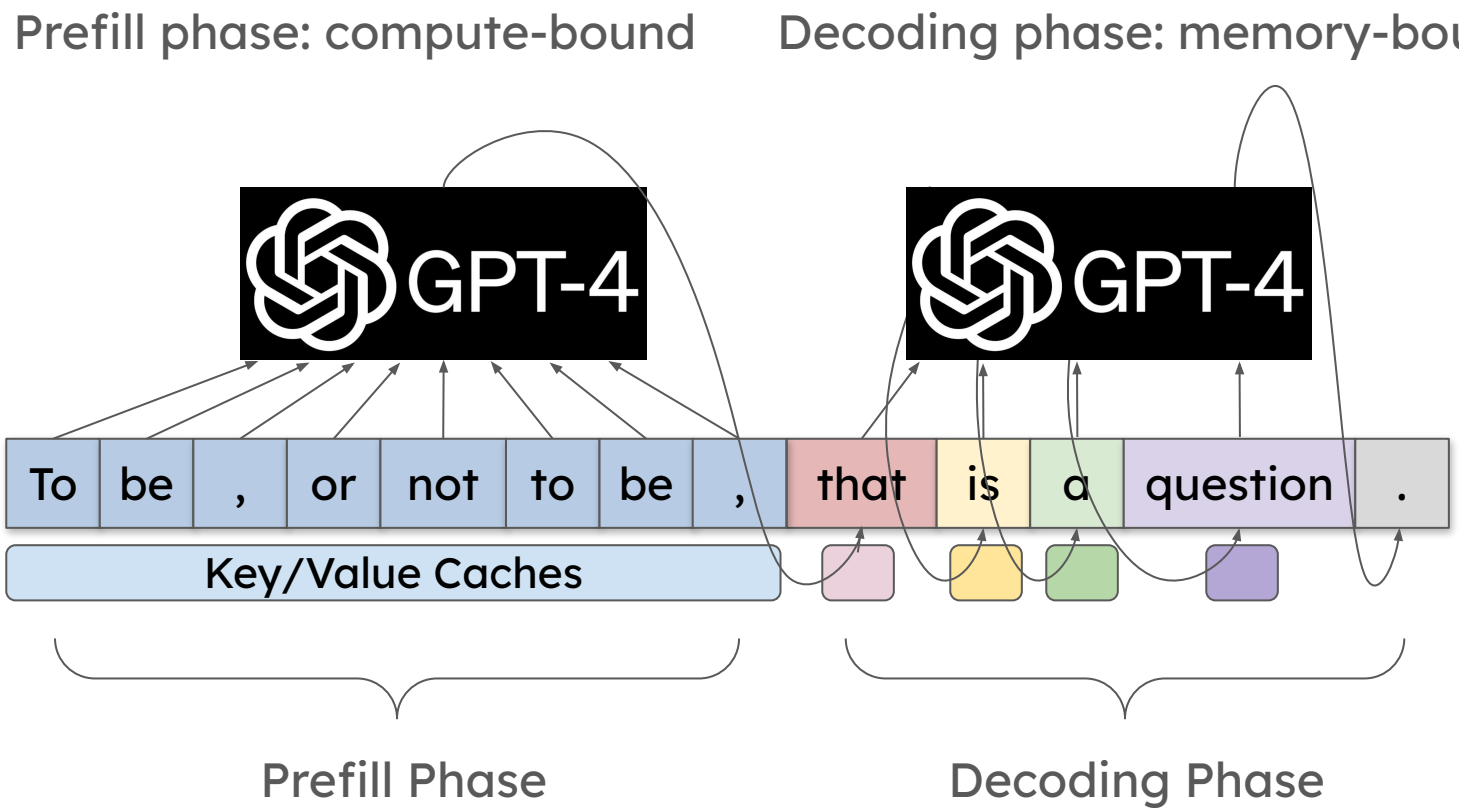


Problem 2: Resource and Parallelism Coupling

Batching the two phases make them share the same parallel strategy

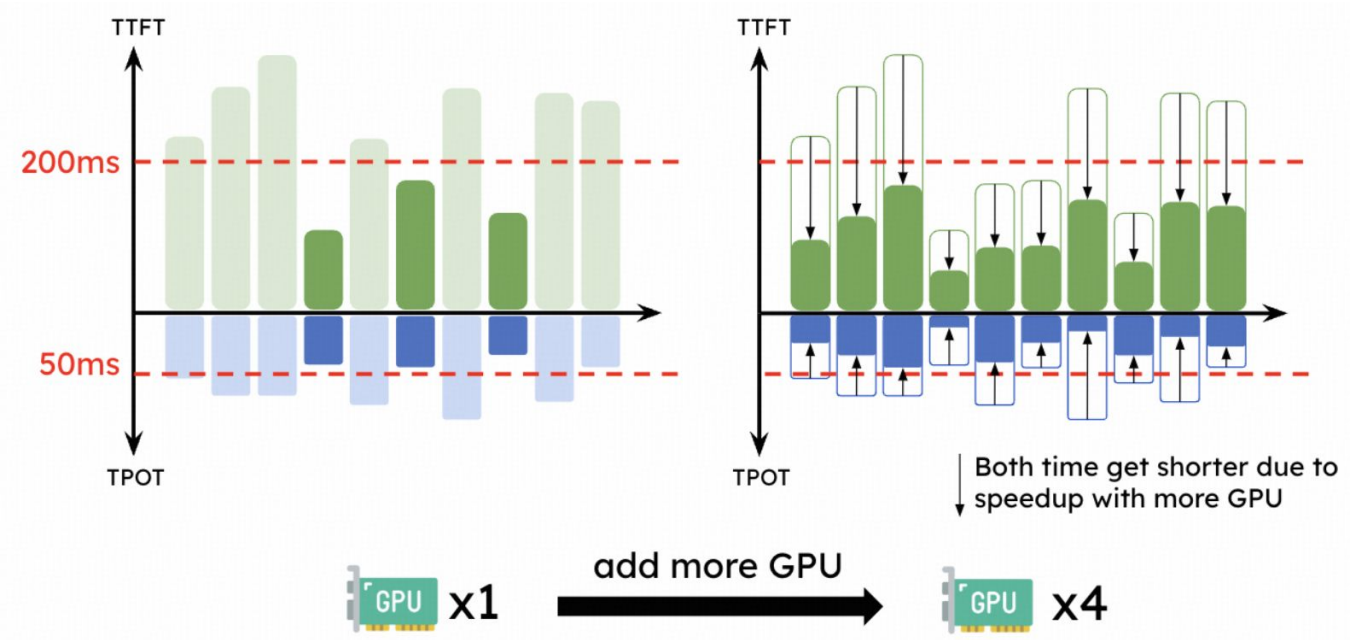


Problem 2: Resource and Parallelism Coupling



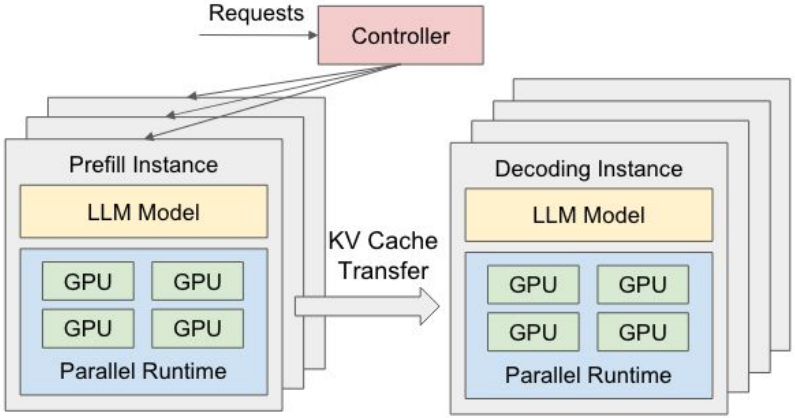
Problem 2: Resource and Parallelism Coupling

Coupling leads to overprovision resources to meet the more demanding SLO

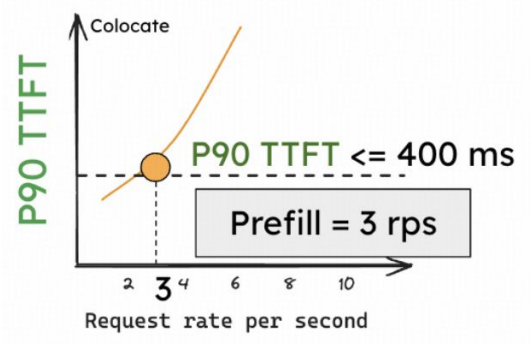


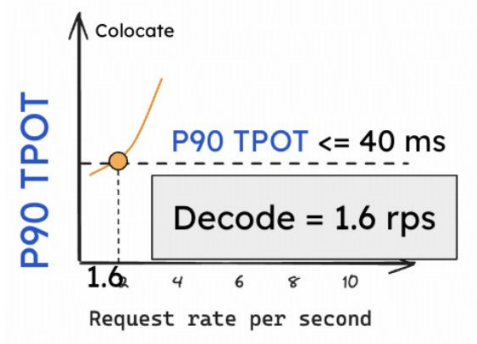
Opportunity: Disaggregating Prefill and Decoding

- Prefill-Decoding interference is immediately eliminated
- Naturally divide the SLO satisfaction problem into two optimizations:
  - Prefill instance optimizes for TTFT.
  - Decoding instance optimizes for TPOT.
  - Choose the most suitable parallelism and resource allocation for each phase.

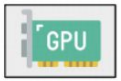


Opportunity: Disaggregting Prefill and Decoding





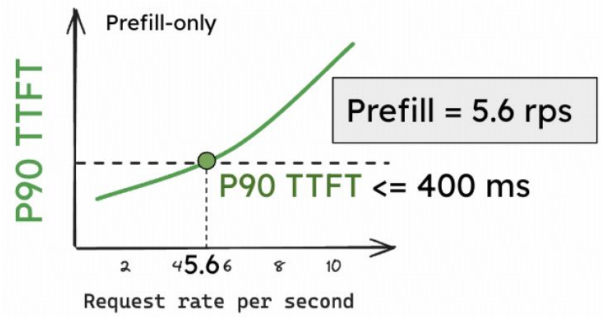
Colocation

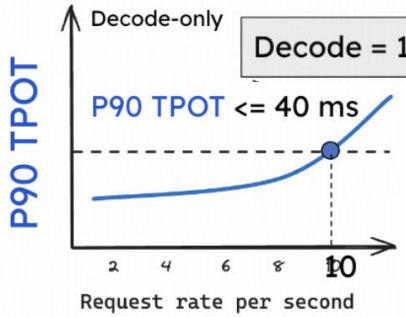


Max System rps

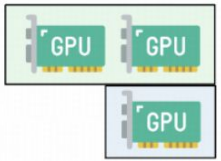
= Min(Prefill, Decode)

= 1.6 rps / GPU





Disaggregation (2P1D)



Max System rps

= Min (5.6 x **2**, 10) rps / 3 GPU

= 3.3 rps / GPU

Challenges of Disaggregation

- Communication overhead for KV-Cache transmission
- The optimization target — ***per-GPU goodput***, is difficult to optimize:
  - the workload pattern
  - SLO requirements
  - parallelism strategies
  - resource allocation
  - network bandwidth

DistServe Overview

Definition of Placement:

(1) parallelism strategy for prefill/decoding instance
(2) the number of each instance to deploy
(3) how to place them onto the physical cluster

Featured algorithms:

- Placement for High Node-Affinity Cluster
- Placement for Low Node-Affinity Cluster
- Online Scheduling Optimization

Placement for High Node-Affinity Cluster

Assumption:

- Nodes are connected with high bandwidth network, e.g., InfiniBand.

Observation:

- We can optimize prefill and decoding instances separately.

Algorithm Sketch:

- Use simulation to measure the goodput for a specific parallelism config.
- Obtain the optimal parallelism config for each phase.
- Use replication to match the overall traffic.

Placement for Low Node-Affinity Cluster

Assumption:

- GPUs inside one node are connected with NVLINK.

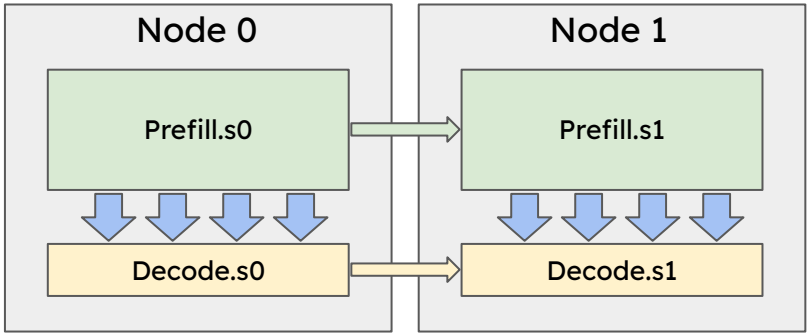
Observation:

- KV-Cache transmission only happens between ***the same layer.***

Algorithm Sketch:

- Similar to the previous one but add the constraint to require the same stage of prefill/decoding instances to be on the same node.

Example:



Online Scheduling Optimization

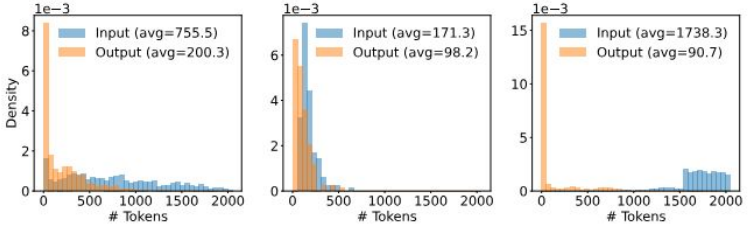
- Scheduling to reduce pipeline bubbles
- Combat workload burstiness
- Periodic Replaning

Evaluations

- Setup:
  - 4 x DGX-A100, each with 8 x NVIDIA A100-80GB
  - intra-node network bandwidth: 600GB/s
  - cross-node network bandwidth 25Gbps
- Workloads:

Application	Model Size	TTFT	TPOT	Dataset
Chatbot OPT-13B	26GB	0.25s	0.1s	ShareGPT [8]
Chatbot OPT-66B	132GB	2.5s	0.15s	ShareGPT [8]
Chatbot OPT-175B	350GB	4.0s	0.2s	ShareGPT [8]
Code Completion OPT-66B	132GB	0.125s	0.2s	HumanEval [14]
Summarization OPT-66B	132GB	15s	0.15s	LongBench [13]

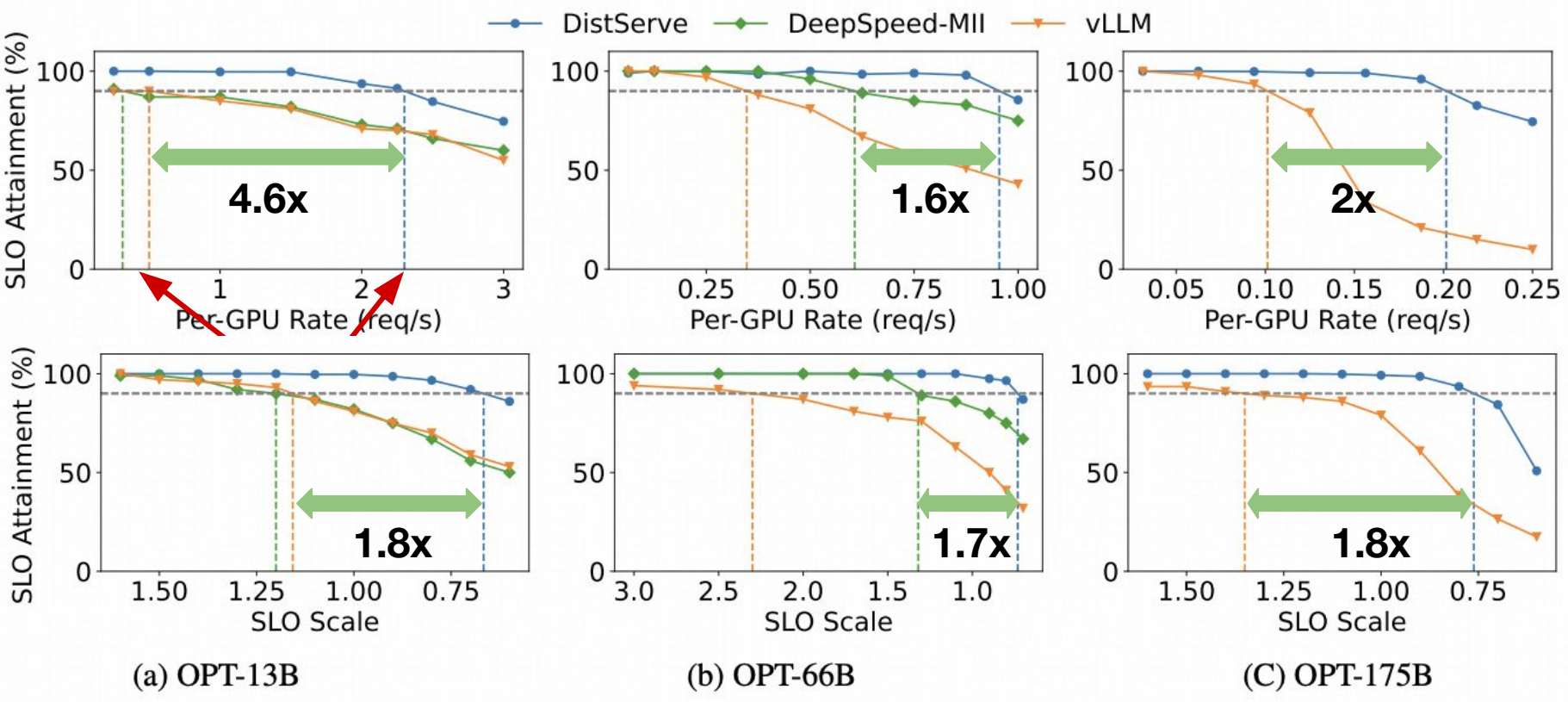
Table 1: Workloads in evaluation and latency requirements.



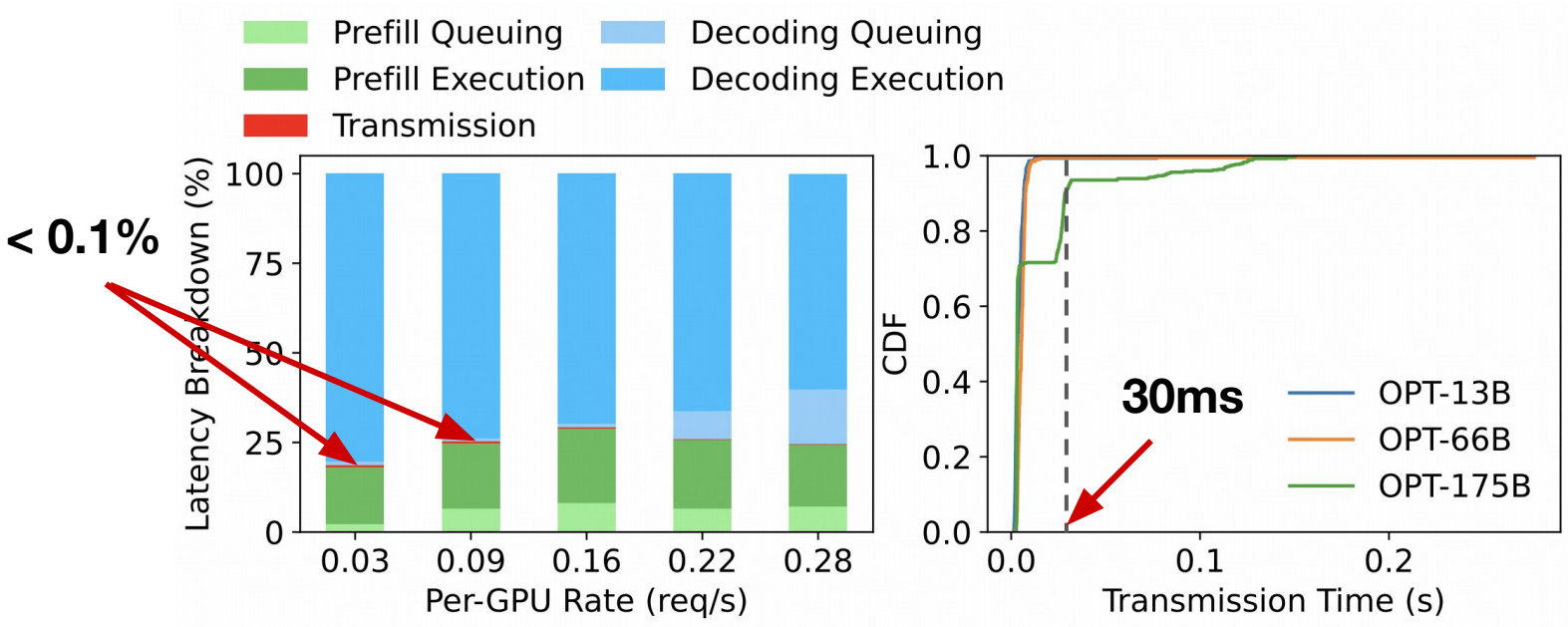
(a) ShareGPT (b) HumanEval (c) LongBench

- Metric: SLO Attainment
- Baseline: vLLM, DeepSpeed-MII

End-to-end Experiment – Chatbot



Latency Breakdown



Summary

- DistServe disaggregates prefill from decoding to serve LLM inference:
  - Bandwidth-aware placement algorithm to minimize communication overhead
  - Co-optimize the parallelism strategies for prefill/decoding instances
  - Online scheduling to handle real-world workload
- Experiments show that DistServe can serve 7.4x more requests or 12.6x tighter SLO, compared to SOTA systems, while staying within latency requirements for > 90% of requests.


https://github.com/LLMServe/DistServe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