GPU-Disaggregated Serving for Deep Learning Recommendation Models at Scale

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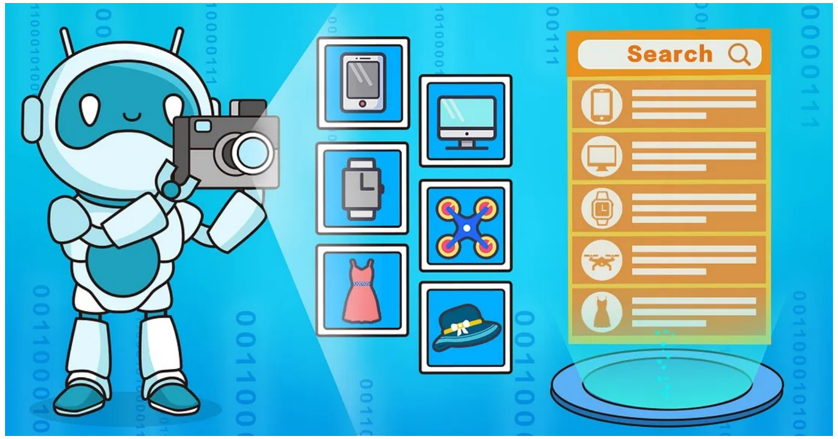
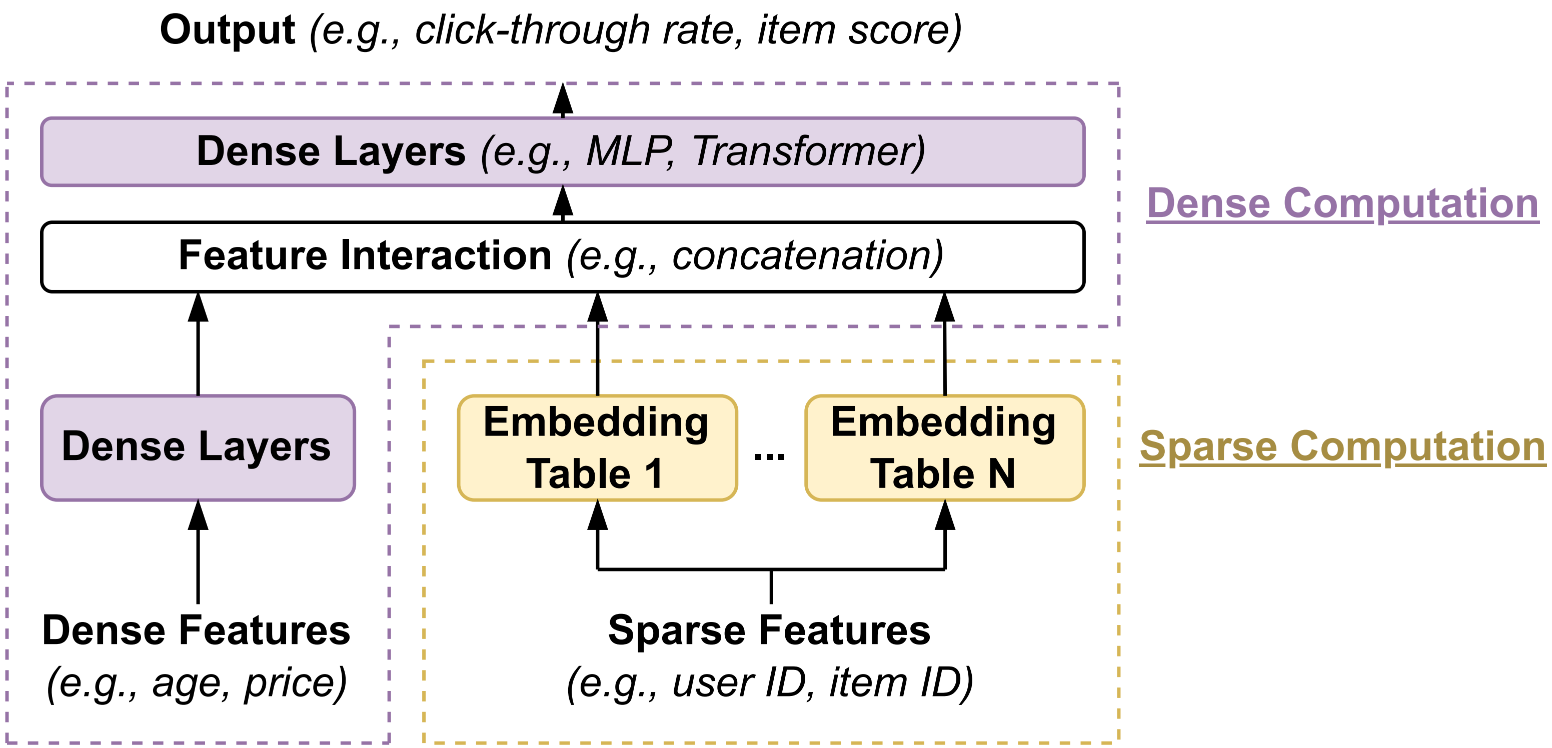
Deep Learning Recommendation Model (DLRM)

- DLRMs are widely used in e-commerce platform to provide accurate, personalized recommendations to improve customer experience
- Applications: web search, recommendation, advertisements, etc.



Images credit to: https://alibabatech.medium.com

An Illustration for DLRM Serving



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<u>Dense network component</u> is better executed on GPUs

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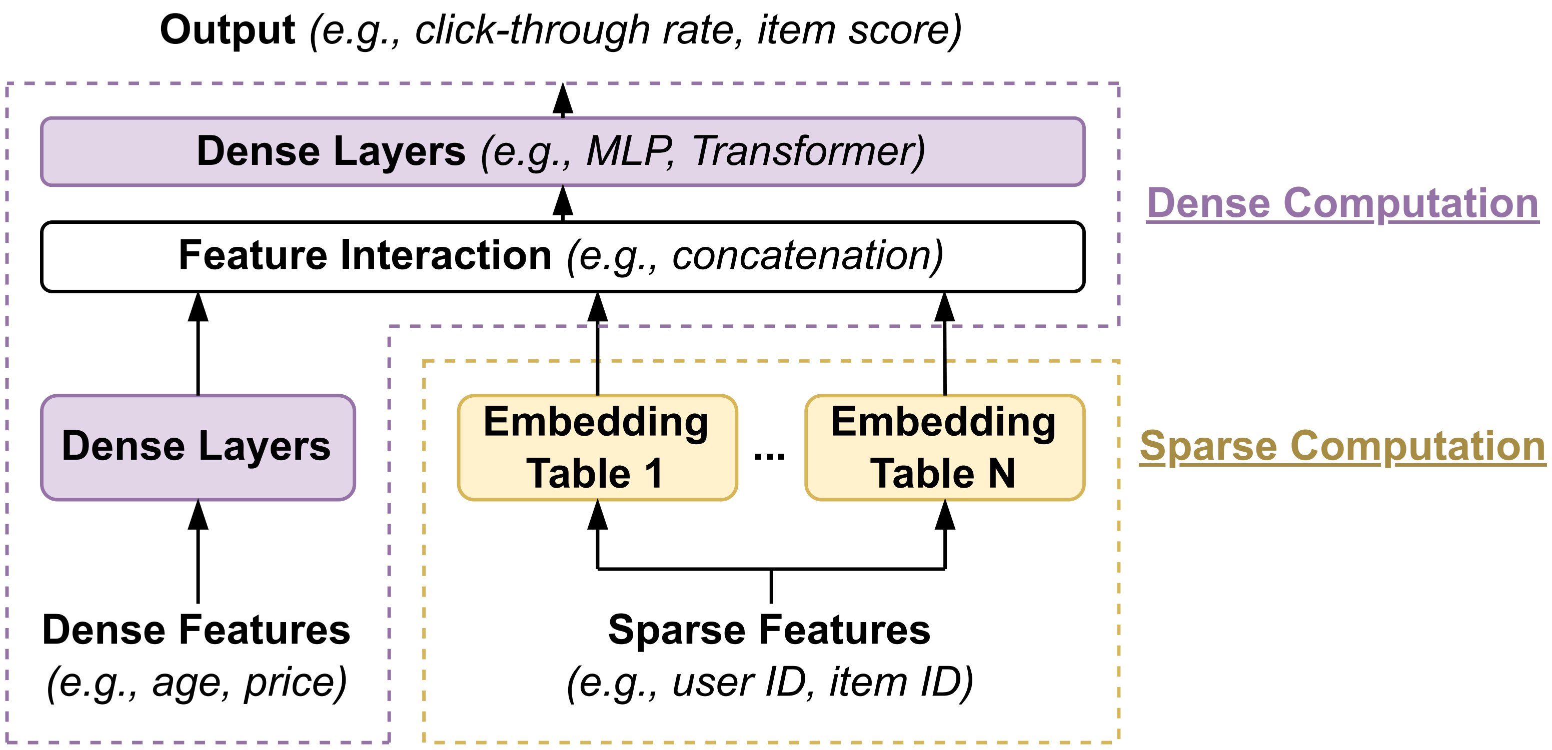

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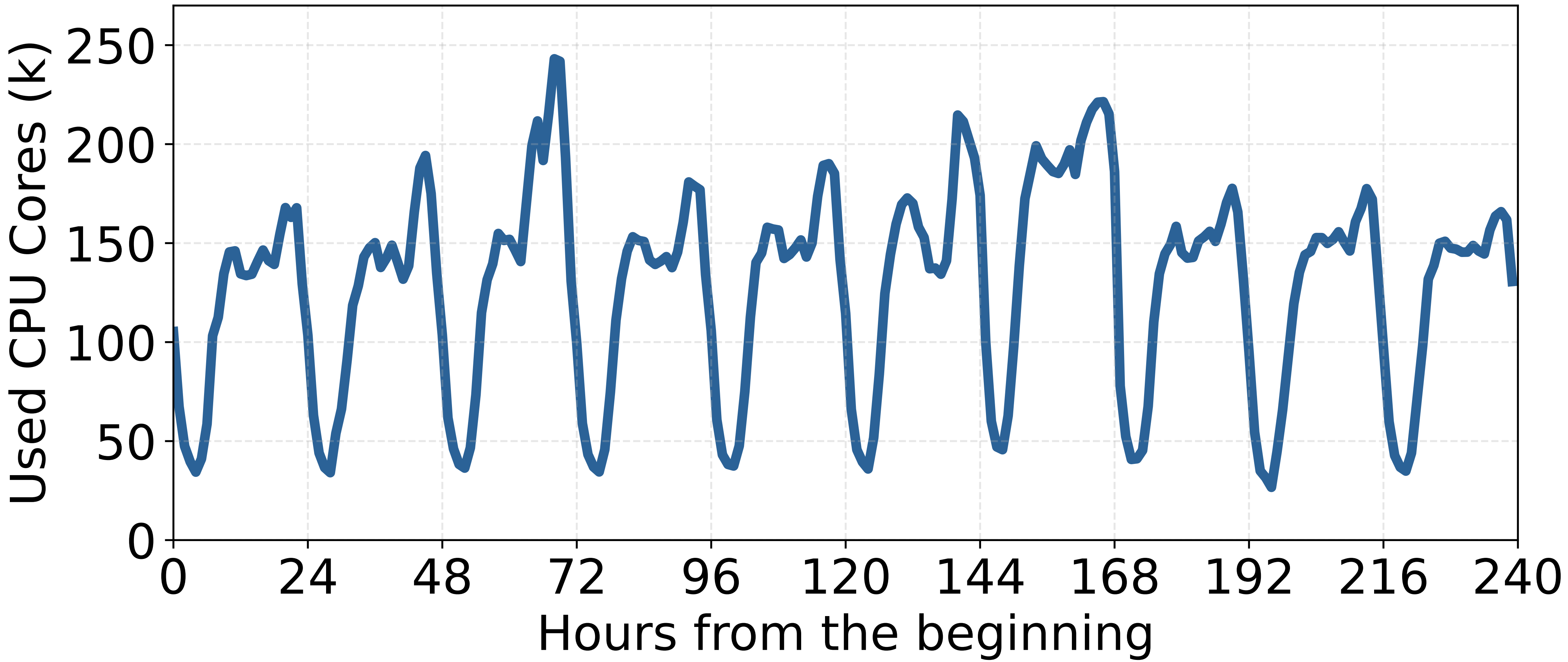
A typical DLRM task may require <48 CPUs, 1 GPU>

Daily and Seasonal Variations of DLRM Services



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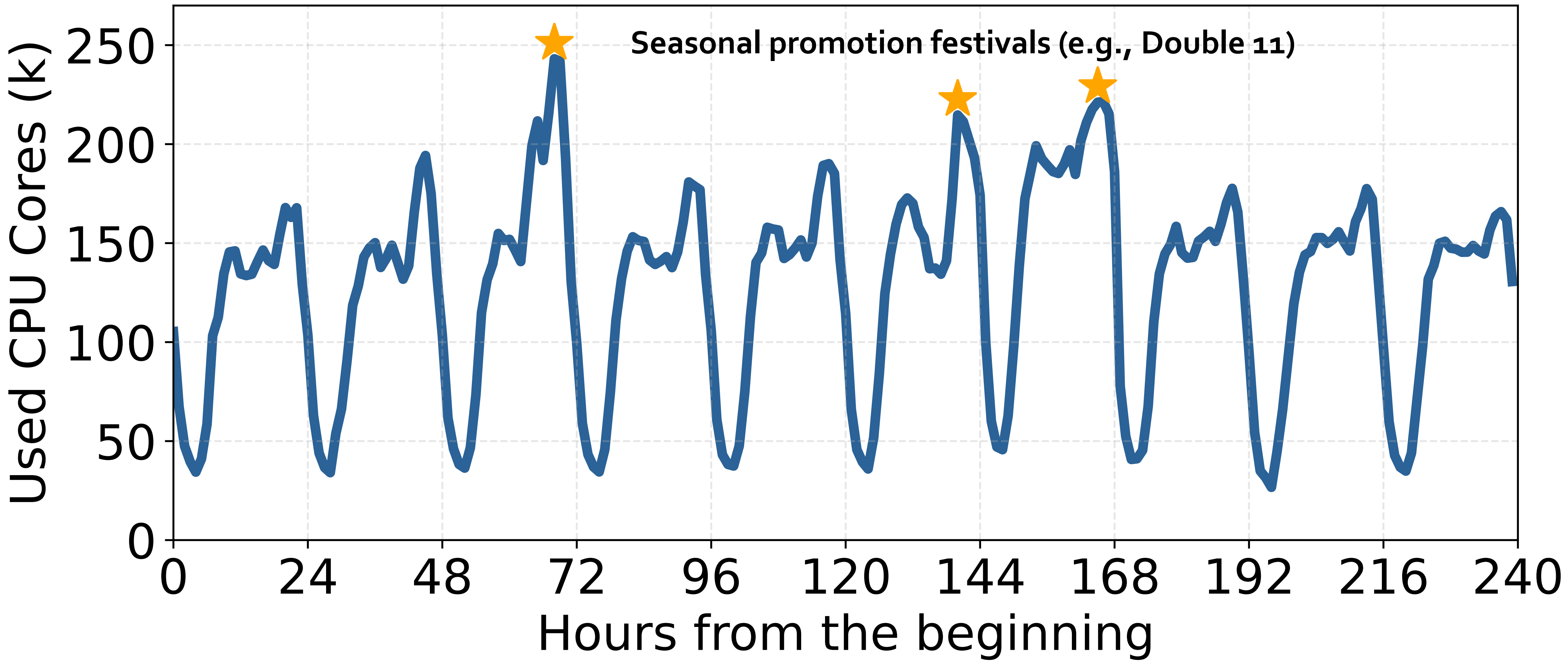

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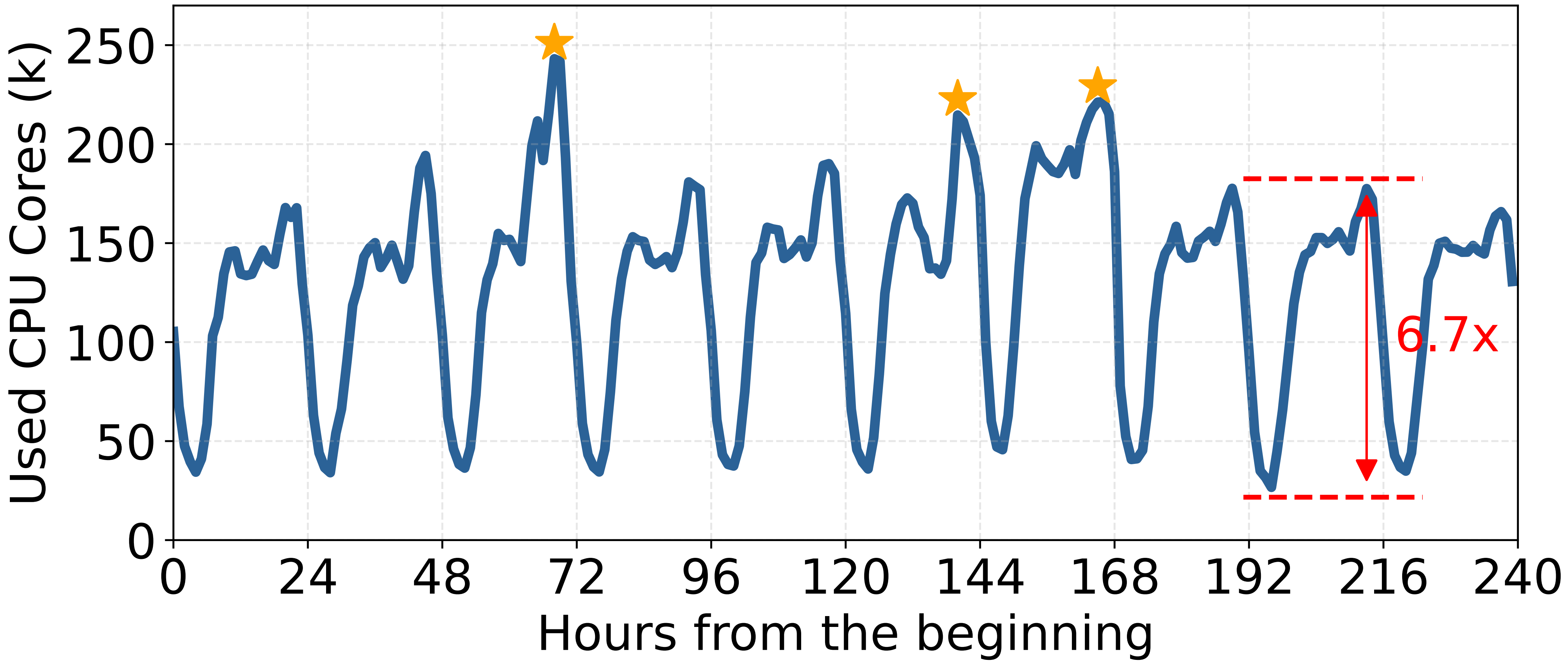

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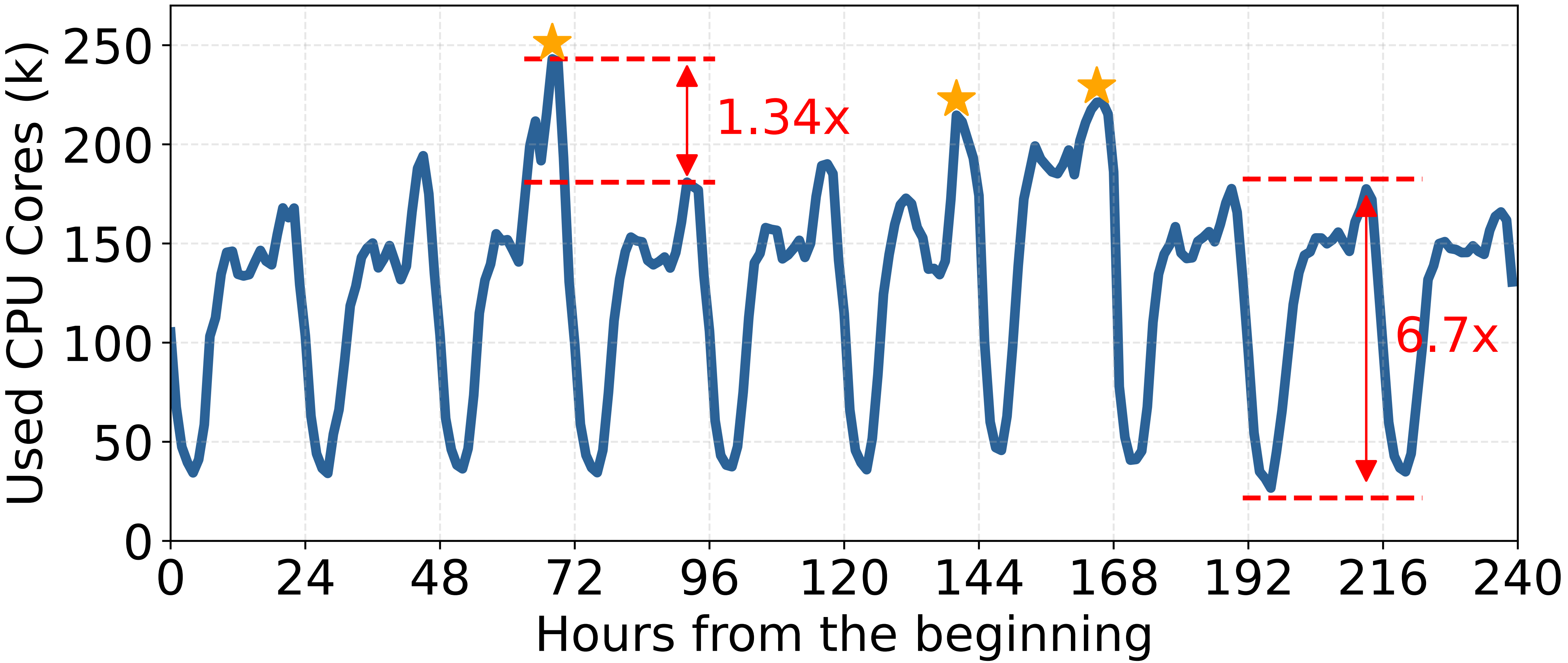
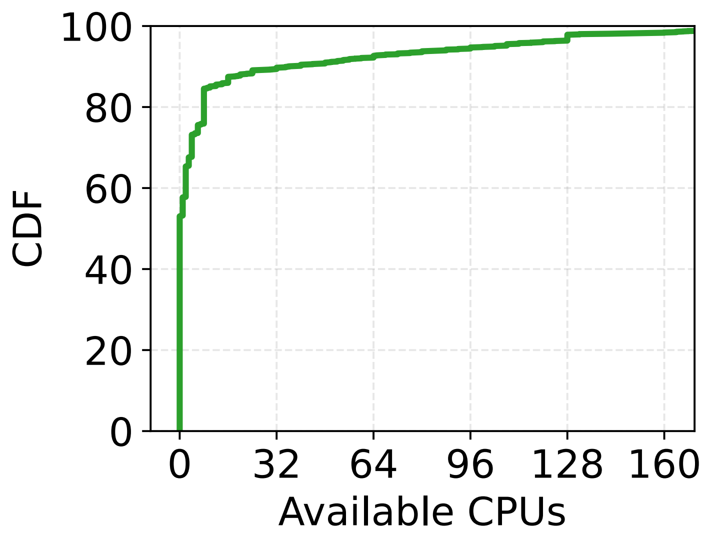
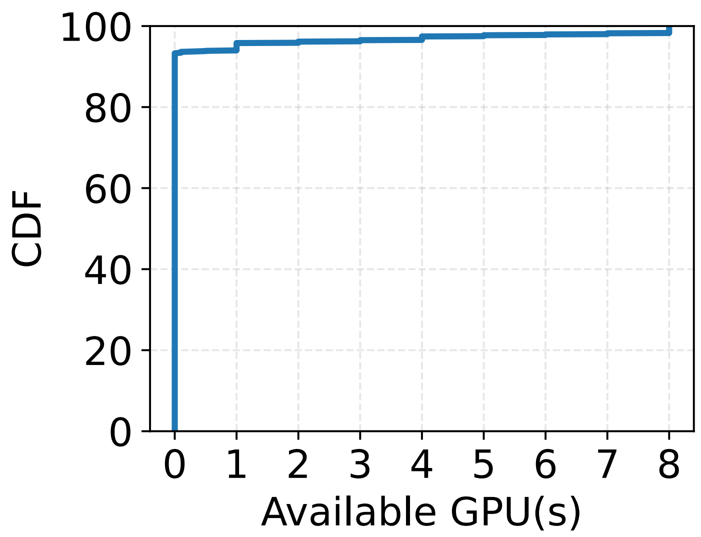


C1: Resource Fragmentation for Daily DLRM Serving

- Shared clusters have high allocation rates (e.g., > 90%)

- Hard to scale DLRM instances due to severe fragmentation





- 4k nodes
- 640k CPU cores
- 11k GPUs

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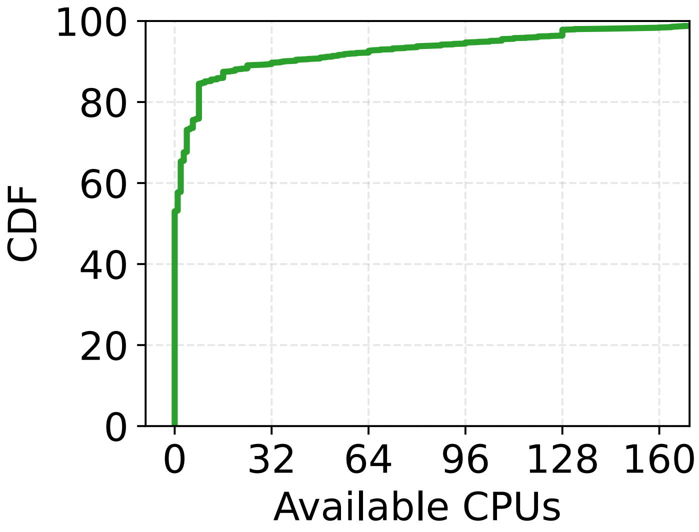

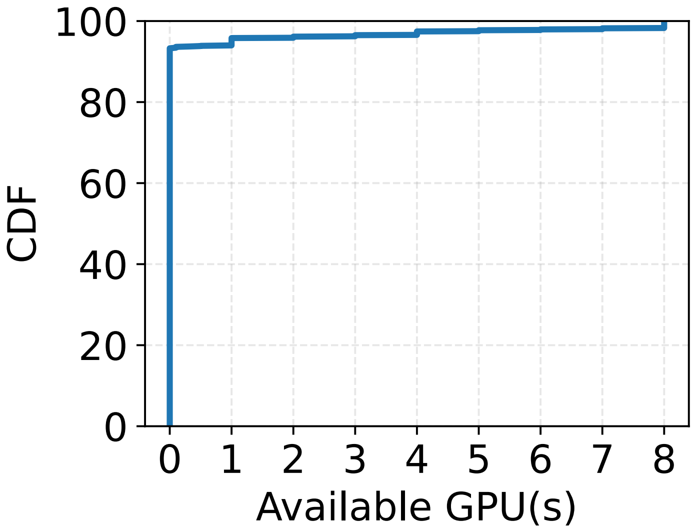

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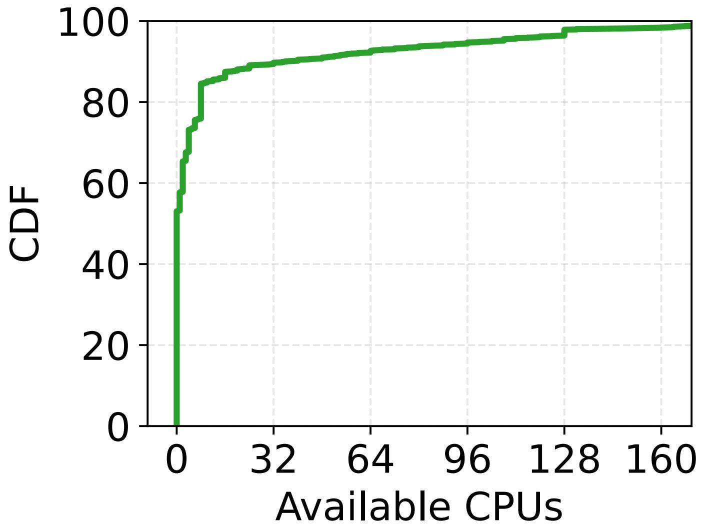
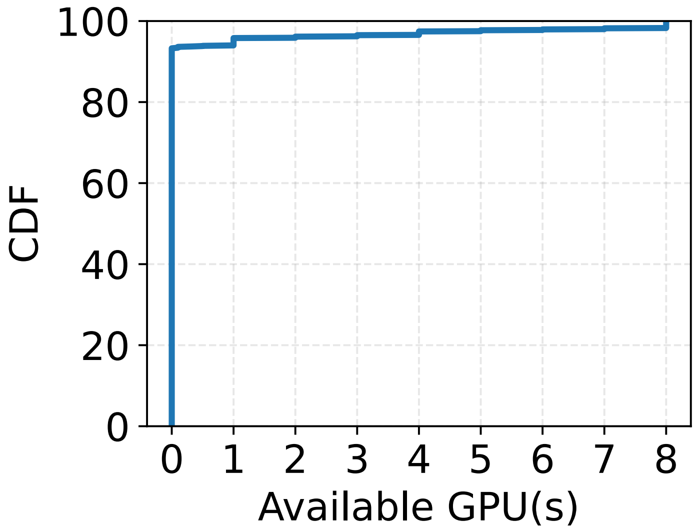
  - DLRM instances typically have high CPU-to-GPU ratio
  - Over 30k fragmented CPUs and more than 200 fragmented GPUs





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- Over-provisioning for the peak load
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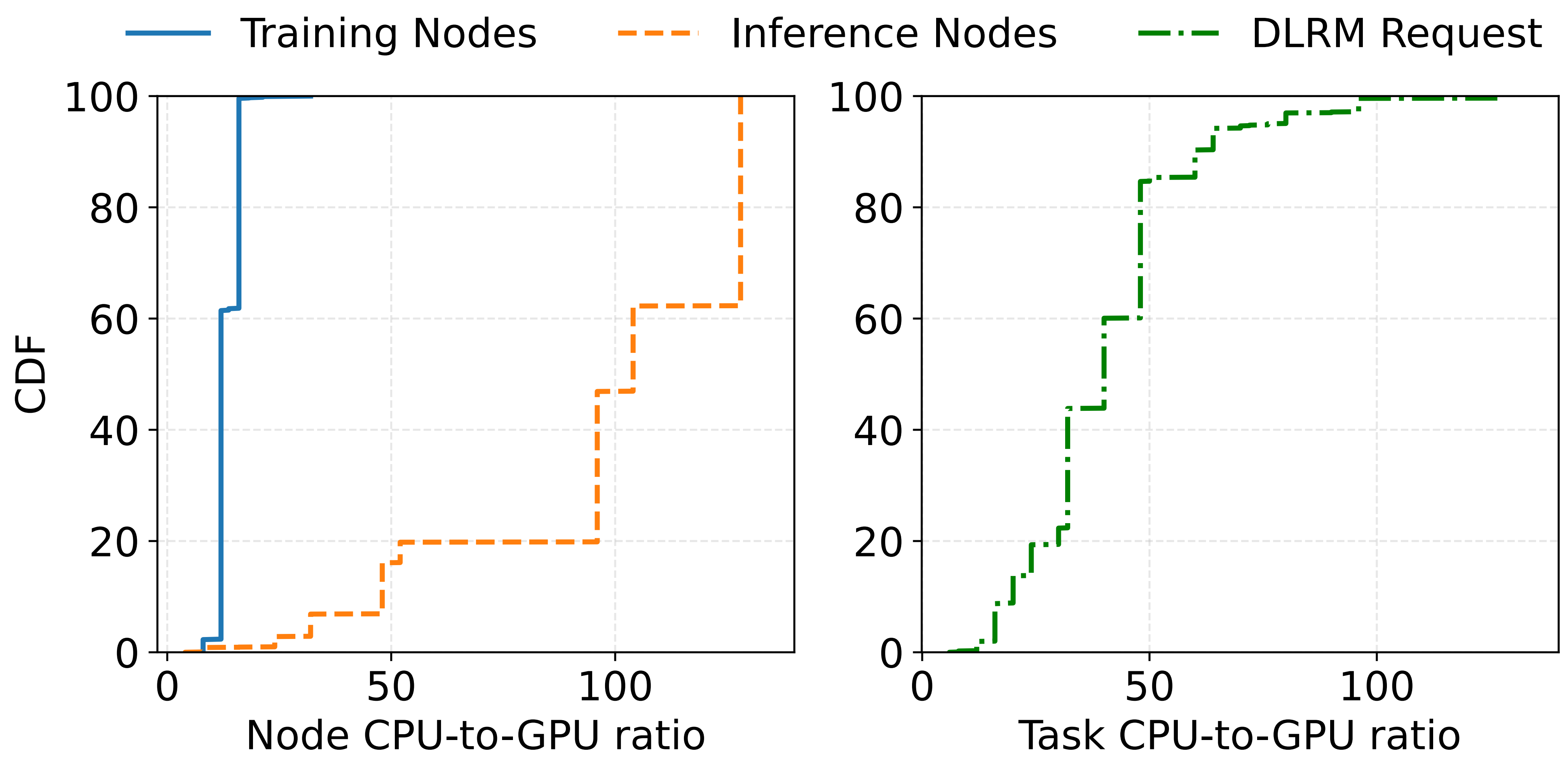
  - Can we temporarily loan GPU servers from **training clusters** to handle excessive recommendation queries?
  - The mismatch between server configuration and resource demand renders capacity loaning ineffective!

Resource Heterogeneity in GPU Clusters



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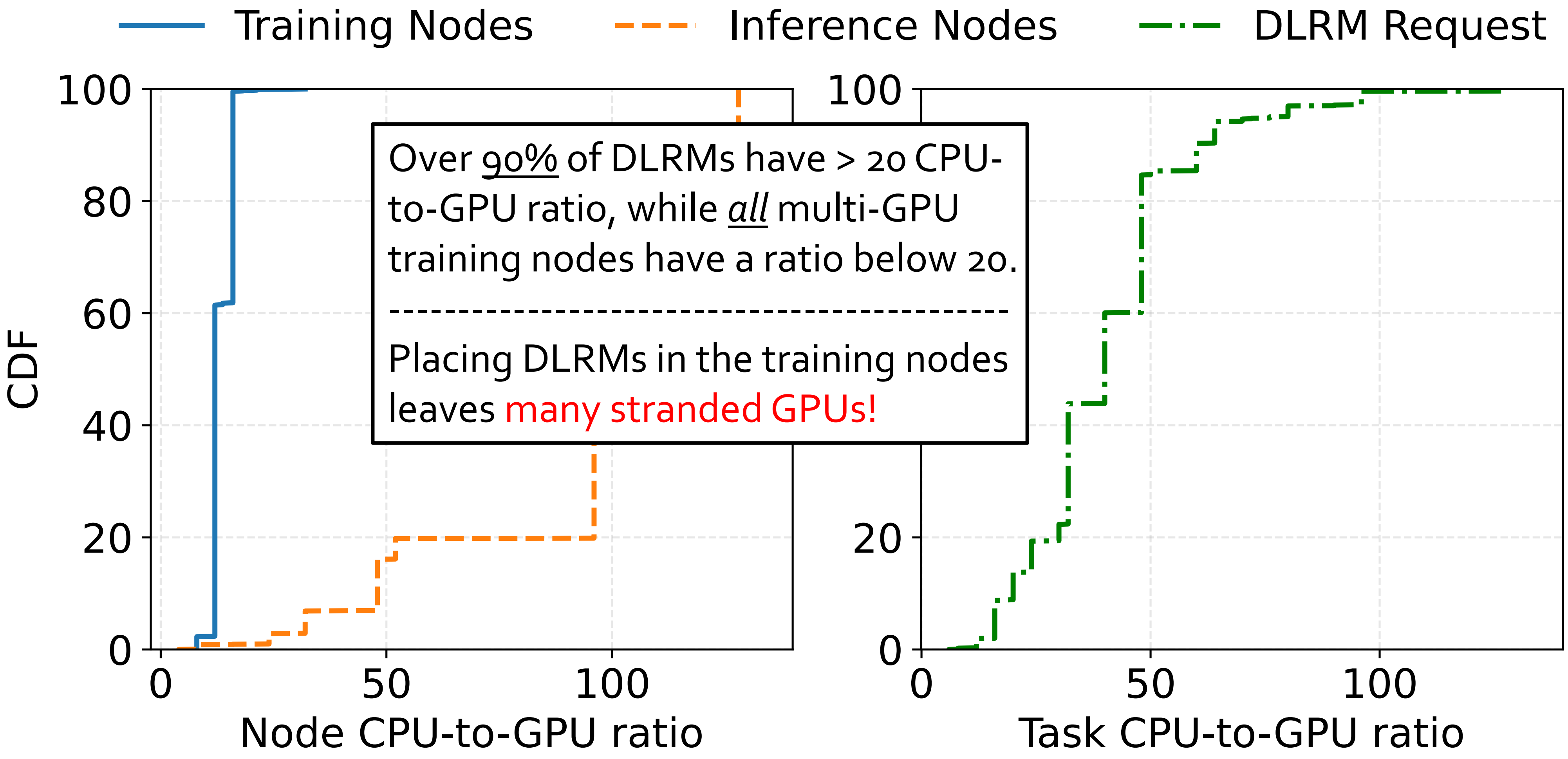

Over <u>90%</u> of DLRMs have > 20 CPU-to-GPU ratio, while <u>*all*</u> multi-GPU training nodes have a ratio below 20.

Placing DLRMs in the training nodes leaves many stranded GPUs!

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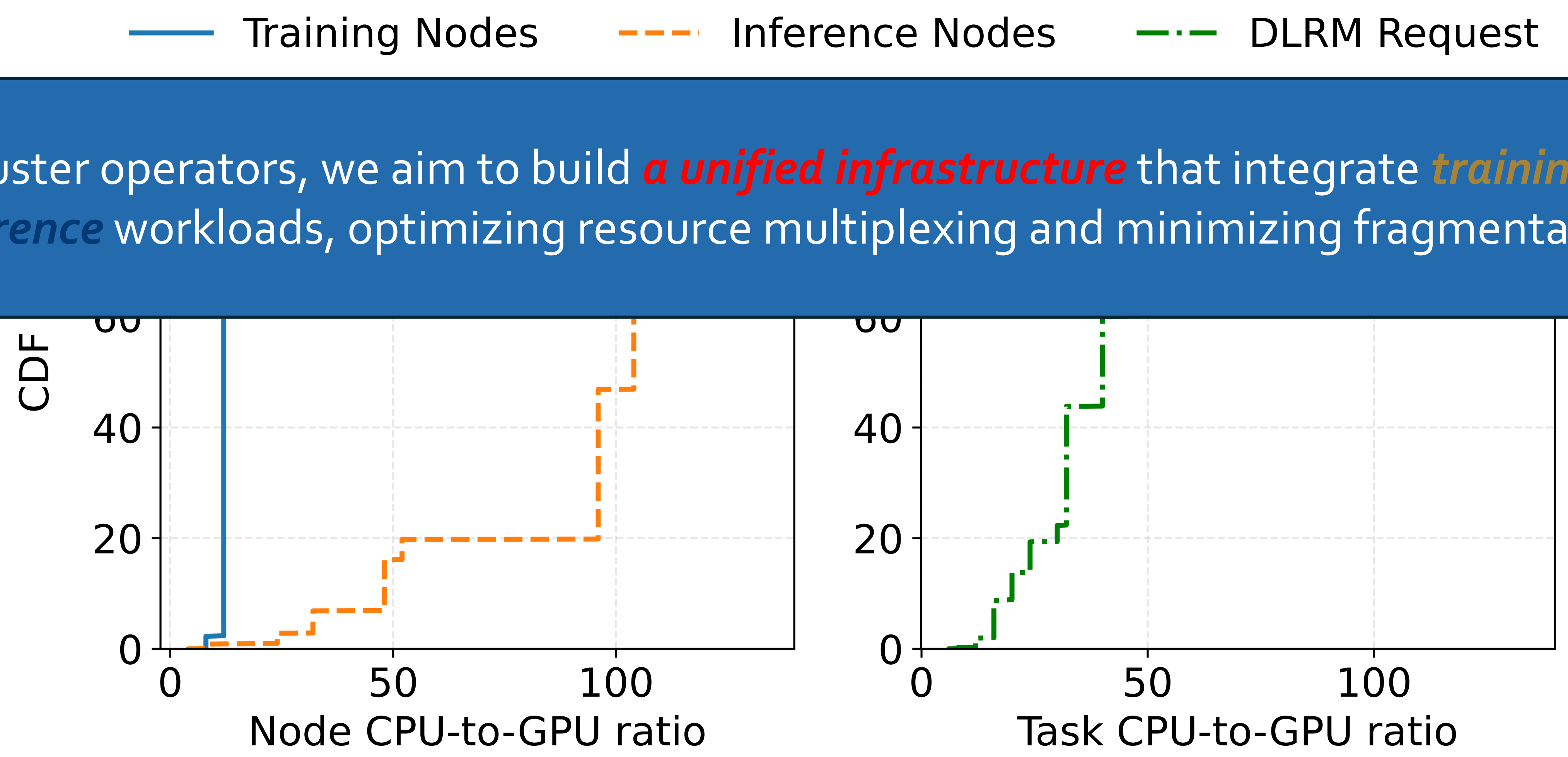

As cluster operators, we aim to build ***a unified infrastructure*** that integrate ***training*** and ***inference*** workloads, optimizing resource multiplexing and minimizing fragmentation.

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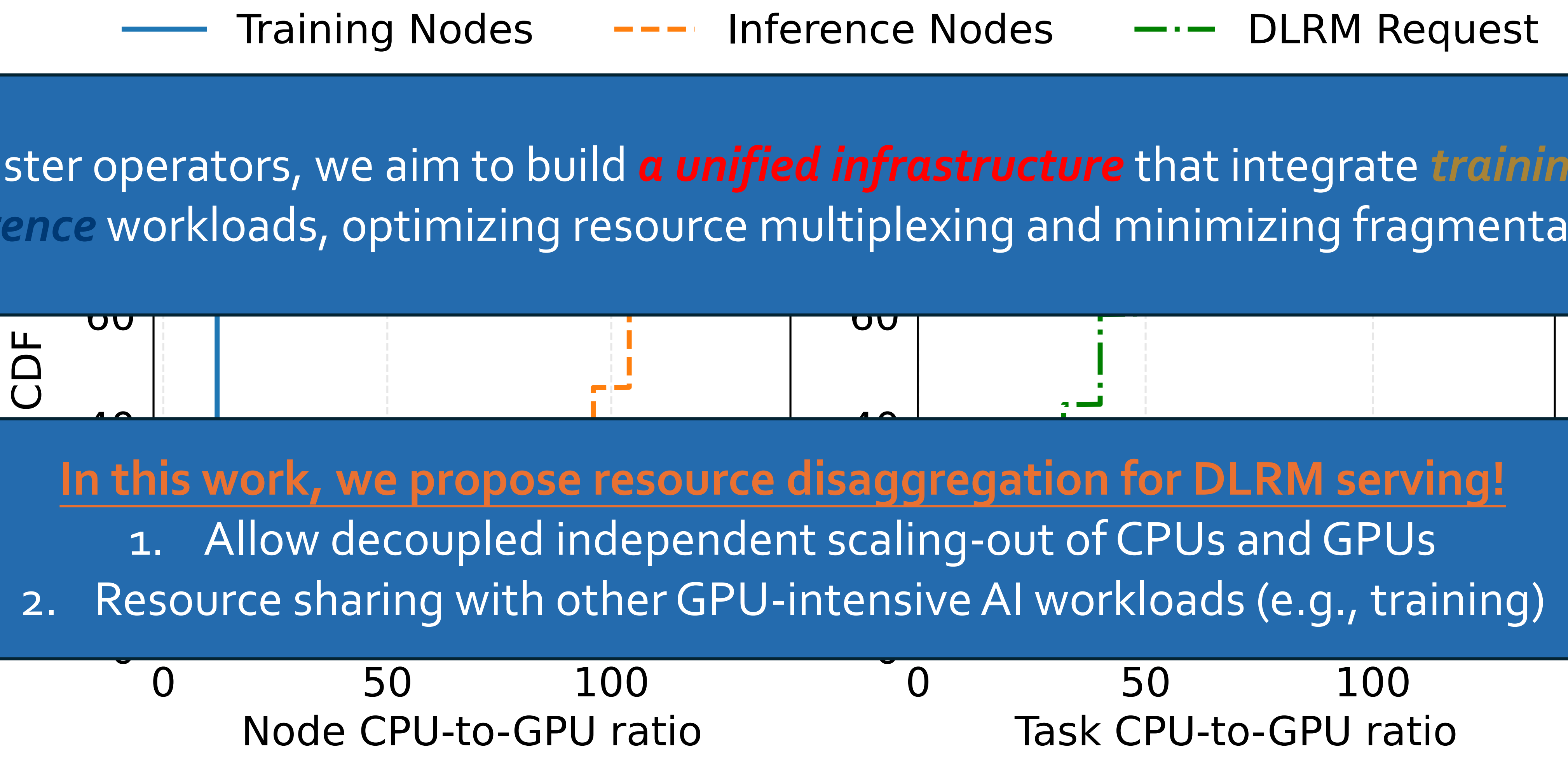

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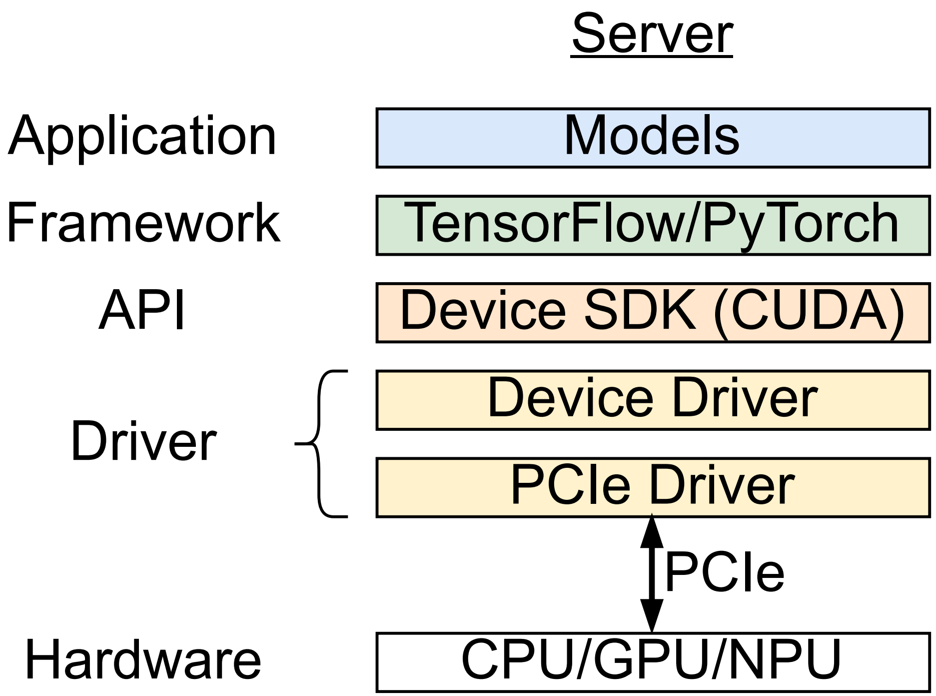
In this work, we propose resource disaggregation for DLRM serving!

1. Allow decoupled independent scaling-out of CPUs and GPUs
2. Resource sharing with other GPU-intensive AI workloads (e.g., training)

Approaches to GPU Disaggregation

- GPU disaggregation at different levels
  - Graph-level disaggregation
    - Partition the compute graph into a CPU sub-graph and a GPU sub-graph
    - Schedule sub-graphs on selected CPU and GPU nodes for disaggregated execution
  - API-level disaggregation
    - Intercept program calls to CUDA APIs (rCUDA [HPCS'10])
    - Redirect them to a remote GPU node for execution
  - Hardware-level disaggregation
    - Enabled with specialized hardware
    - Examples: customized multi-hop PCIe switches (DxPU [TACO'23]) and CXL 3.0



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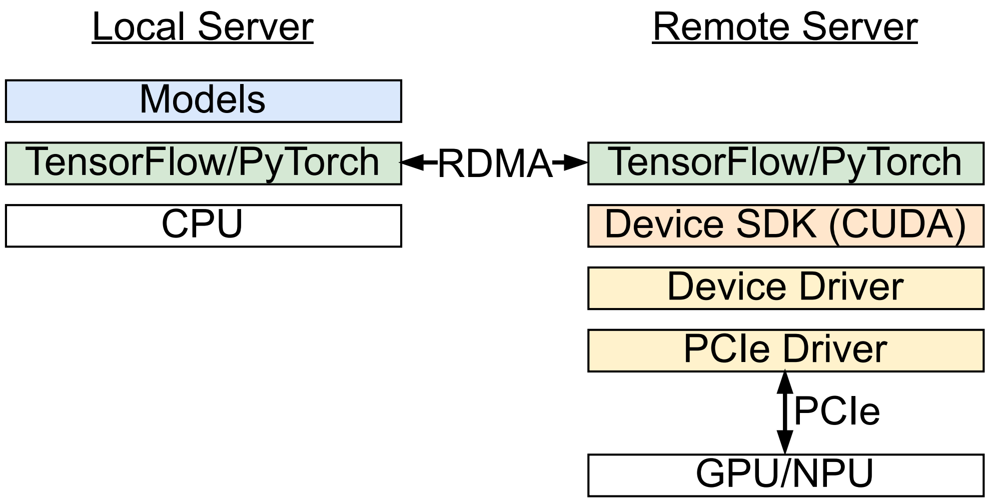


- Design considerations
  - DLRM exhibits distinct resource consumption
  - Easy to support heterogeneous AI accelerators
  - Adapt to the existing infrastructure (i.e., no specialized hardware, high-bandwidth RDMA)

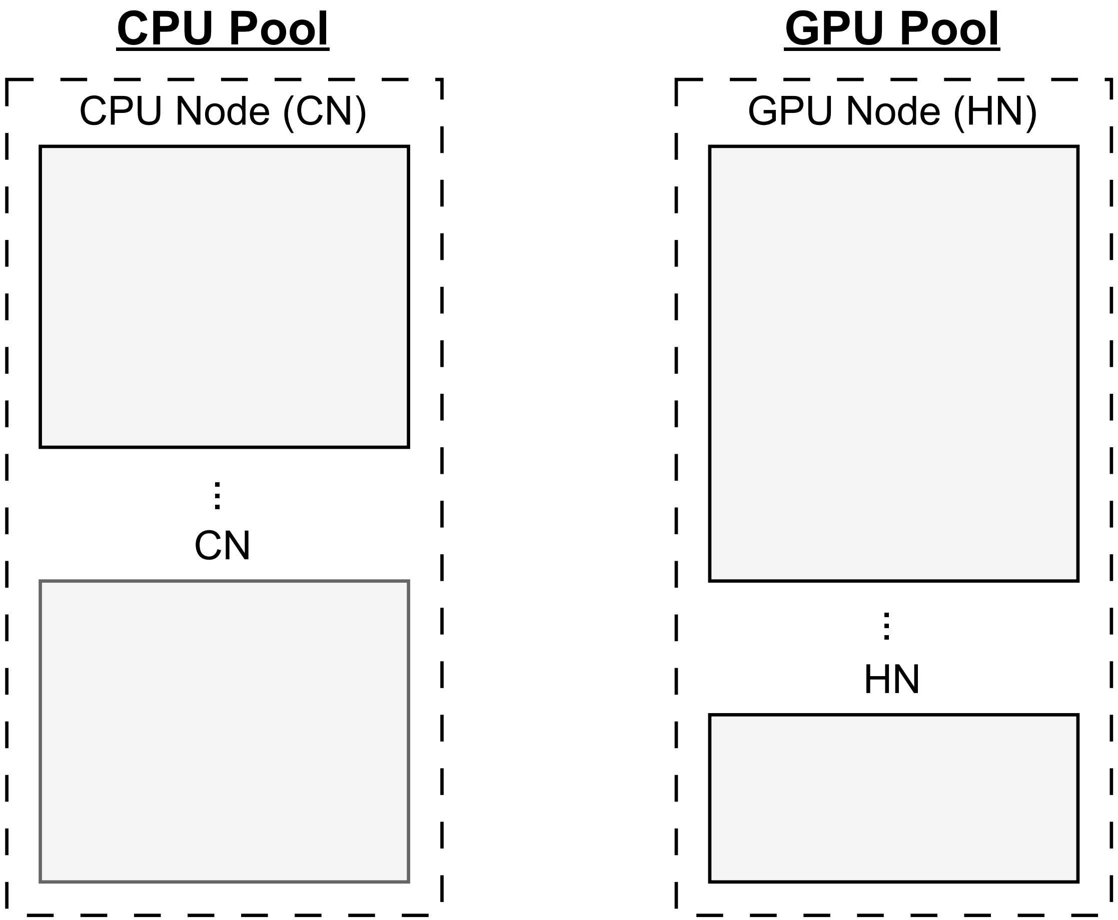
Prism Overview

- Prism is a large-scale DLRM system that enables GPU-disaggregated serving by means of graph partitioning

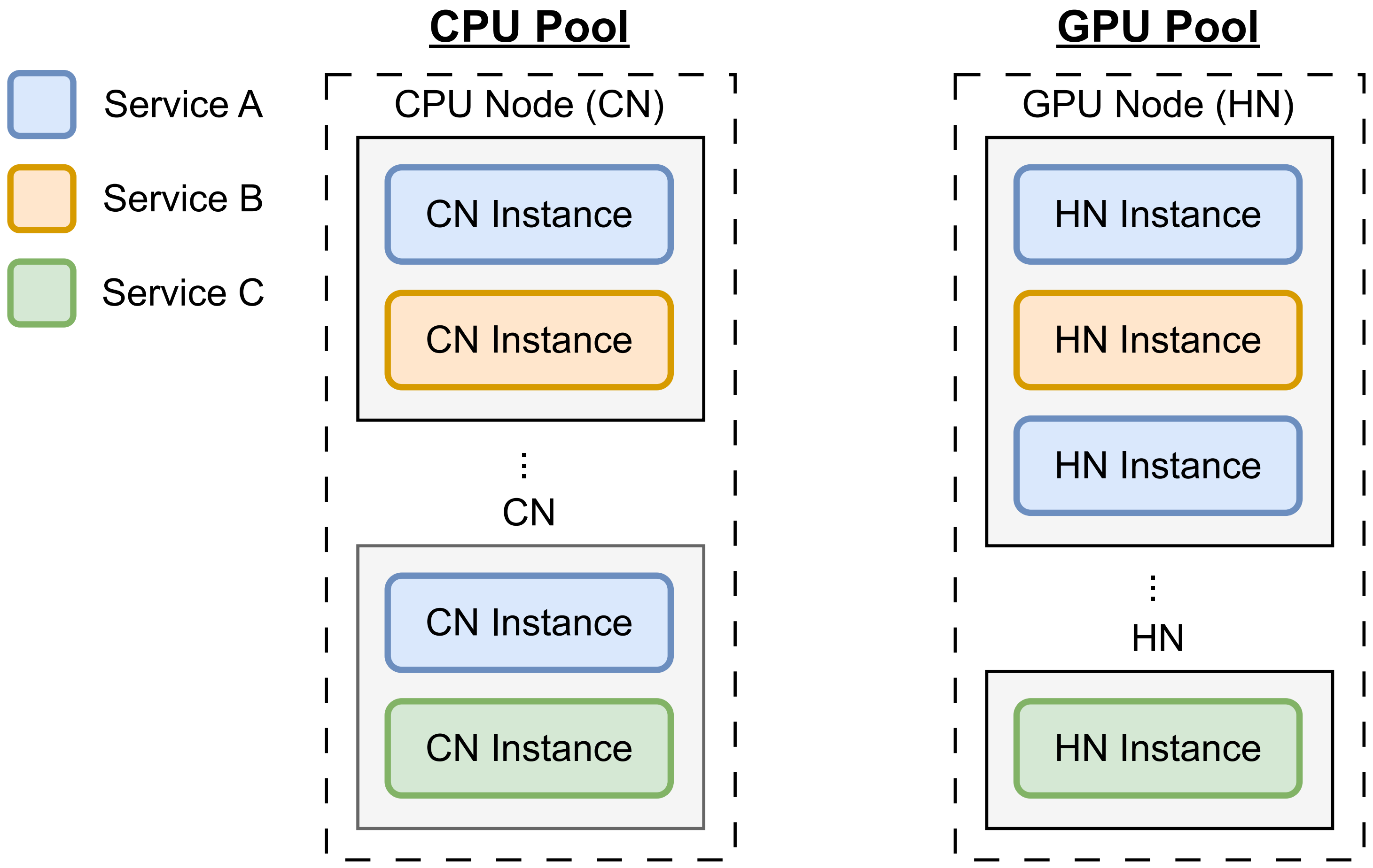
- Prism operates on a cluster where a fleet of heterogeneous GPU nodes (HNs) interconnects with a number of CPU nodes (CNs) via a high-speed RDMA network; automatically partitions recommendation models for distributed inference on CNs and HNs

- Prism has been deployed in production clusters for over two years and now runs over 10k GPUs

Rectified Execution Flow with **Prism**



Rectified Execution Flow with Prism



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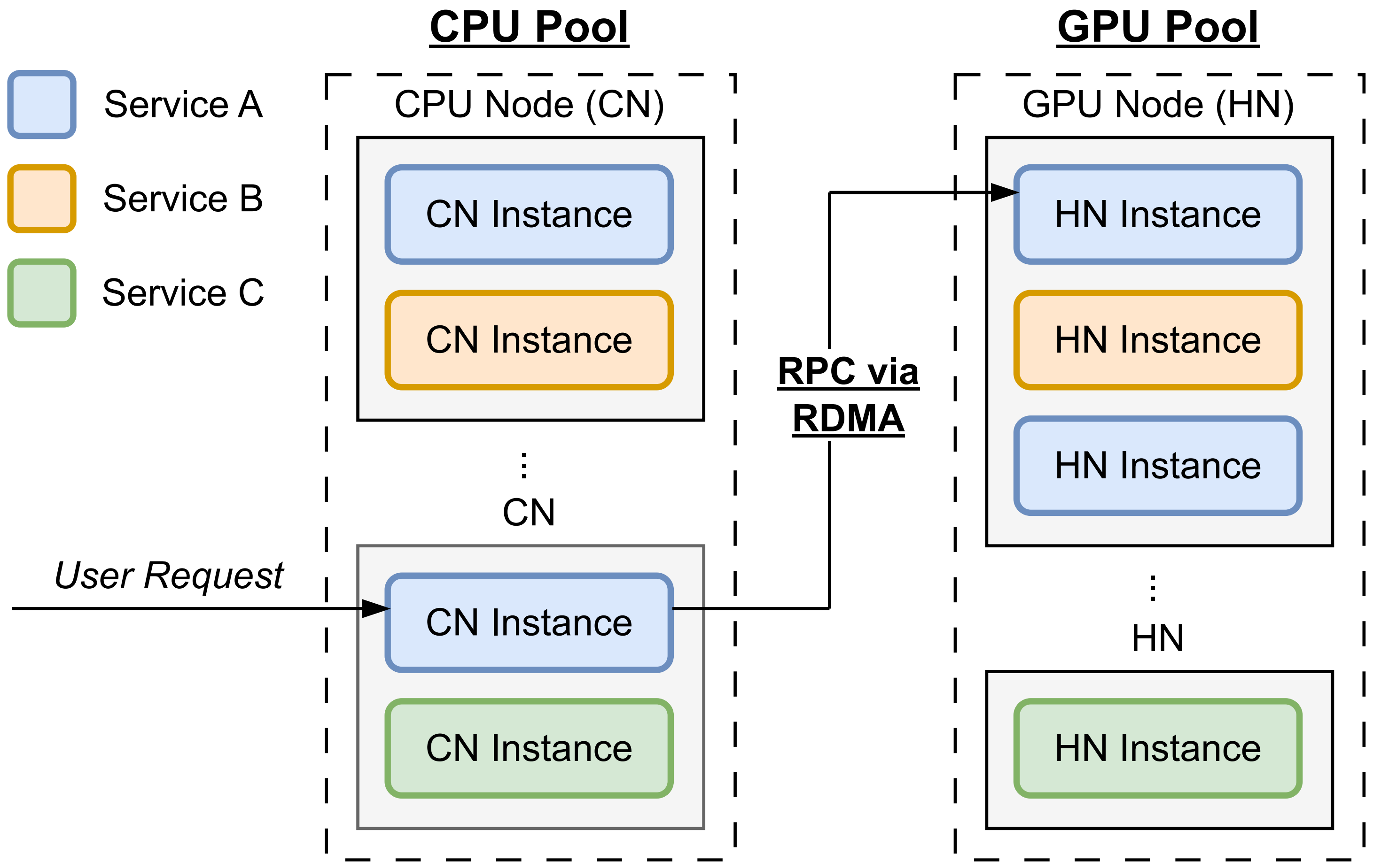

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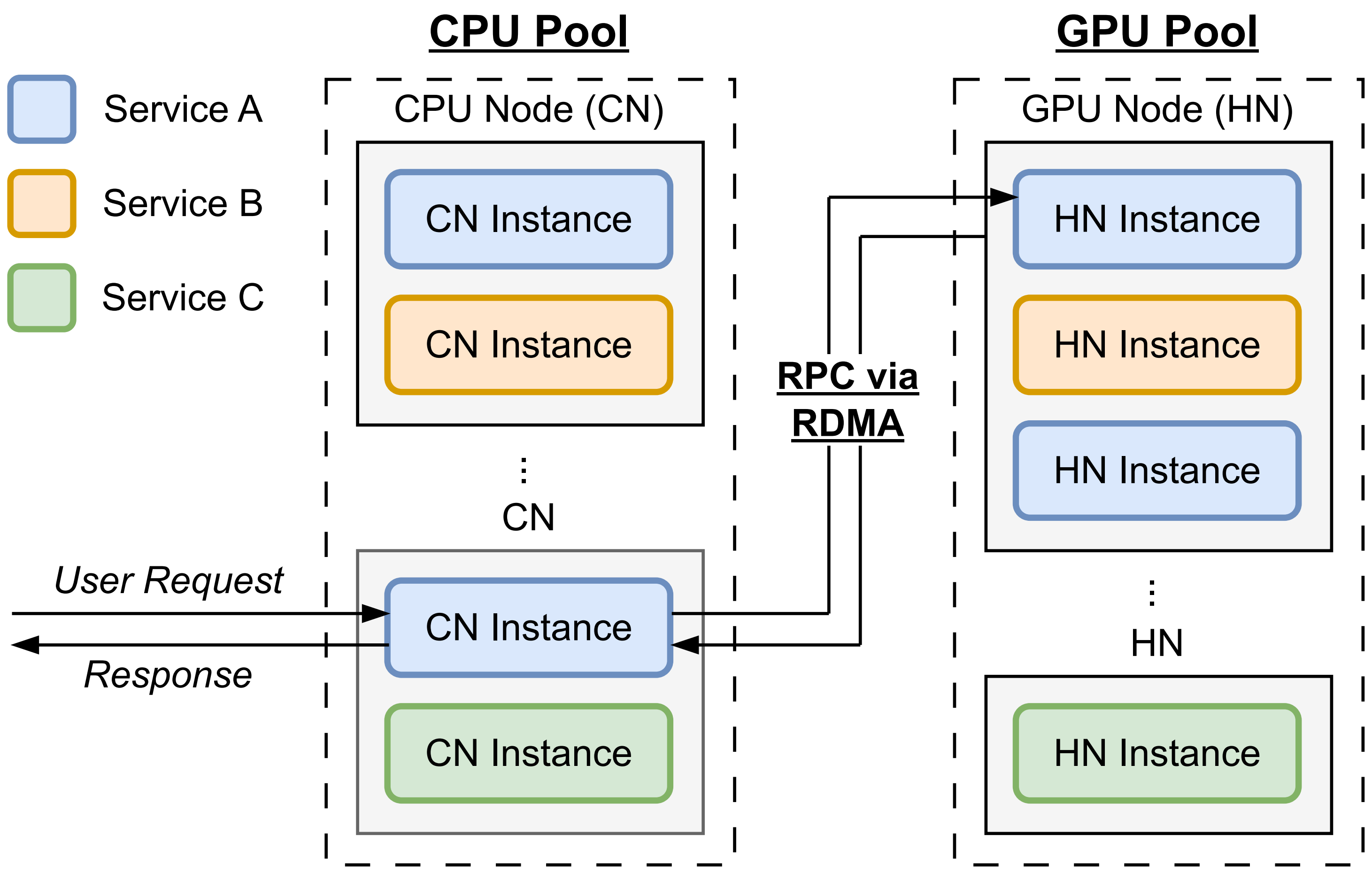

Requirements of Disaggregated DLRM Serving

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- Transparency to model development and optimization
  - Automated graph partitioning to support disaggregated inference for various recommendation models
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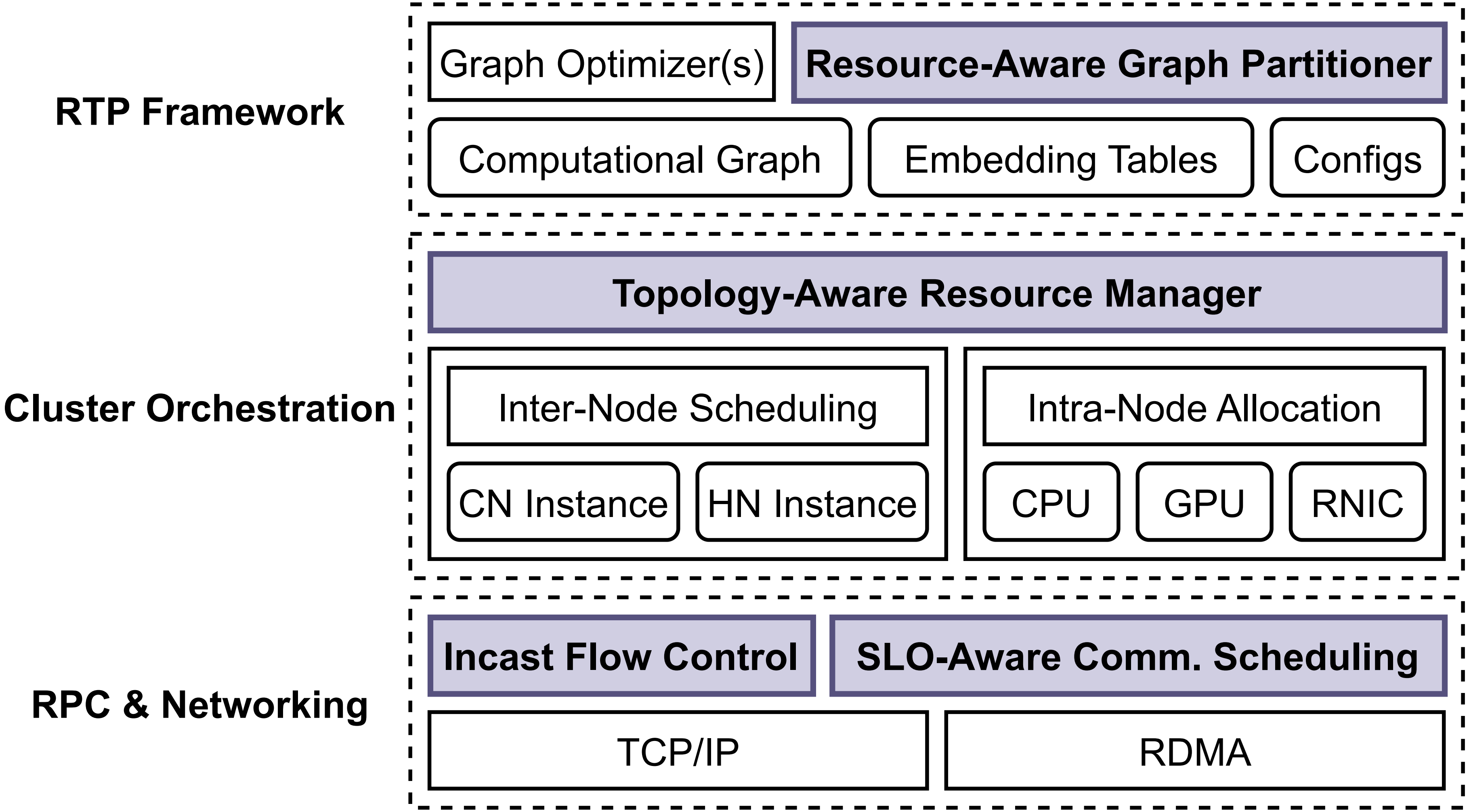
- Compliance to SLOs (e.g., 20ms latency)
  - Require a joint optimization approach across various system components to minimize the impact on service performance
- Good scalability
  - Ensure service performance remains unaffected, even under conditions of high traffic loads in production environments

System Components in Prism



① Resource-Aware Graph Partitioner

- Retrofit for the existing workflow
  - Existing optimizers are typically applied *in a sequential manner* → Rewrite the original computation graph and generate an optimized computation graph tailored for deployment
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  - *Graph partitioning* and *disaggregation optimization* serve as the final stages
- Employ a heuristic approach to split the GPU subgraph
  - Offline profiling and operator categorization → CPU-intensive ops (e.g., embedding table lookup) and GPU-efficient ops (e.g., MatMul, Attention)
  - Perform a DFS coloring process to encompass the maximum number of operators feasible for GPU computation
- In 80% of DLRM services, RDMA transfer size per request < 10 MiB

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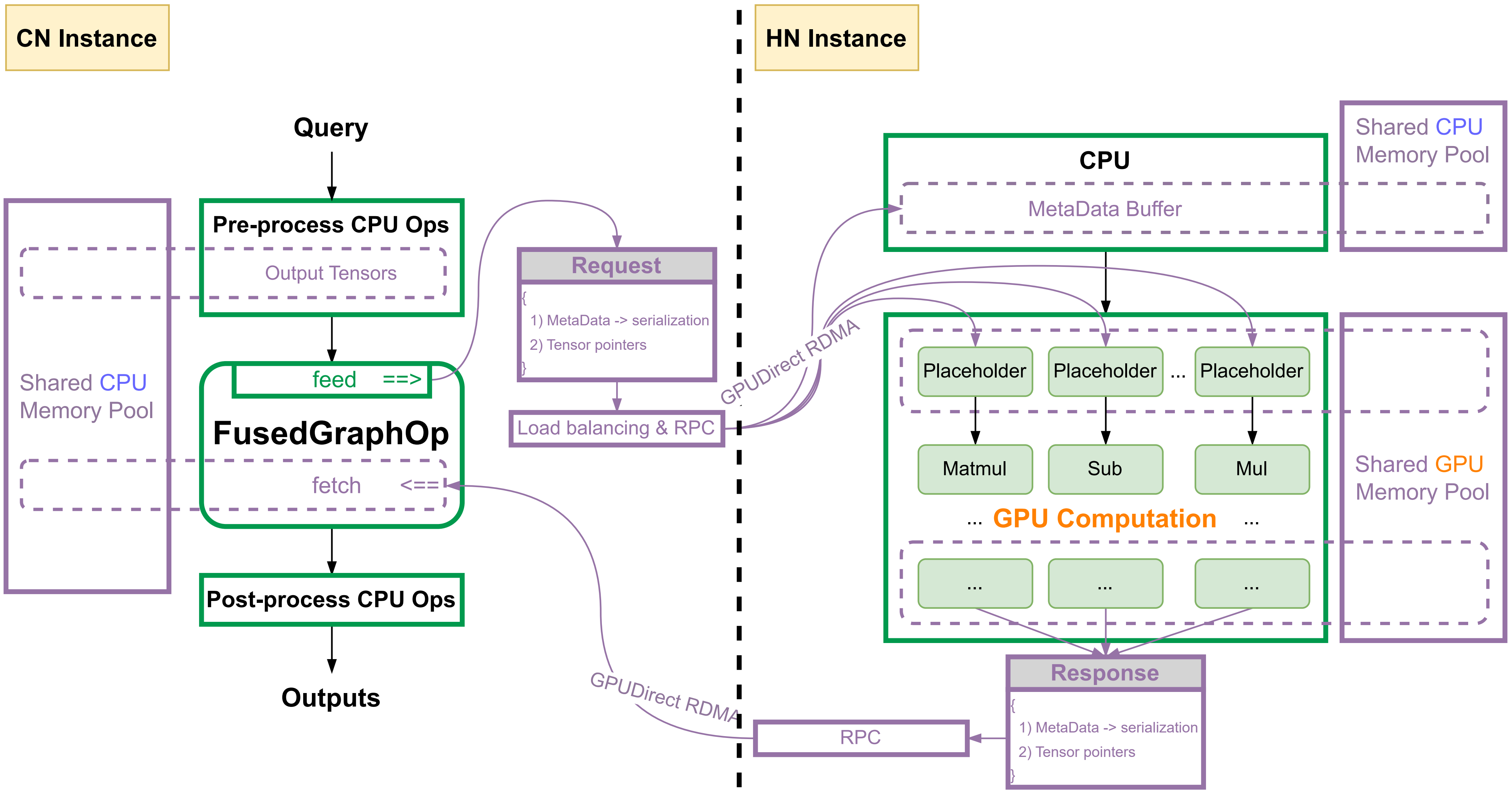


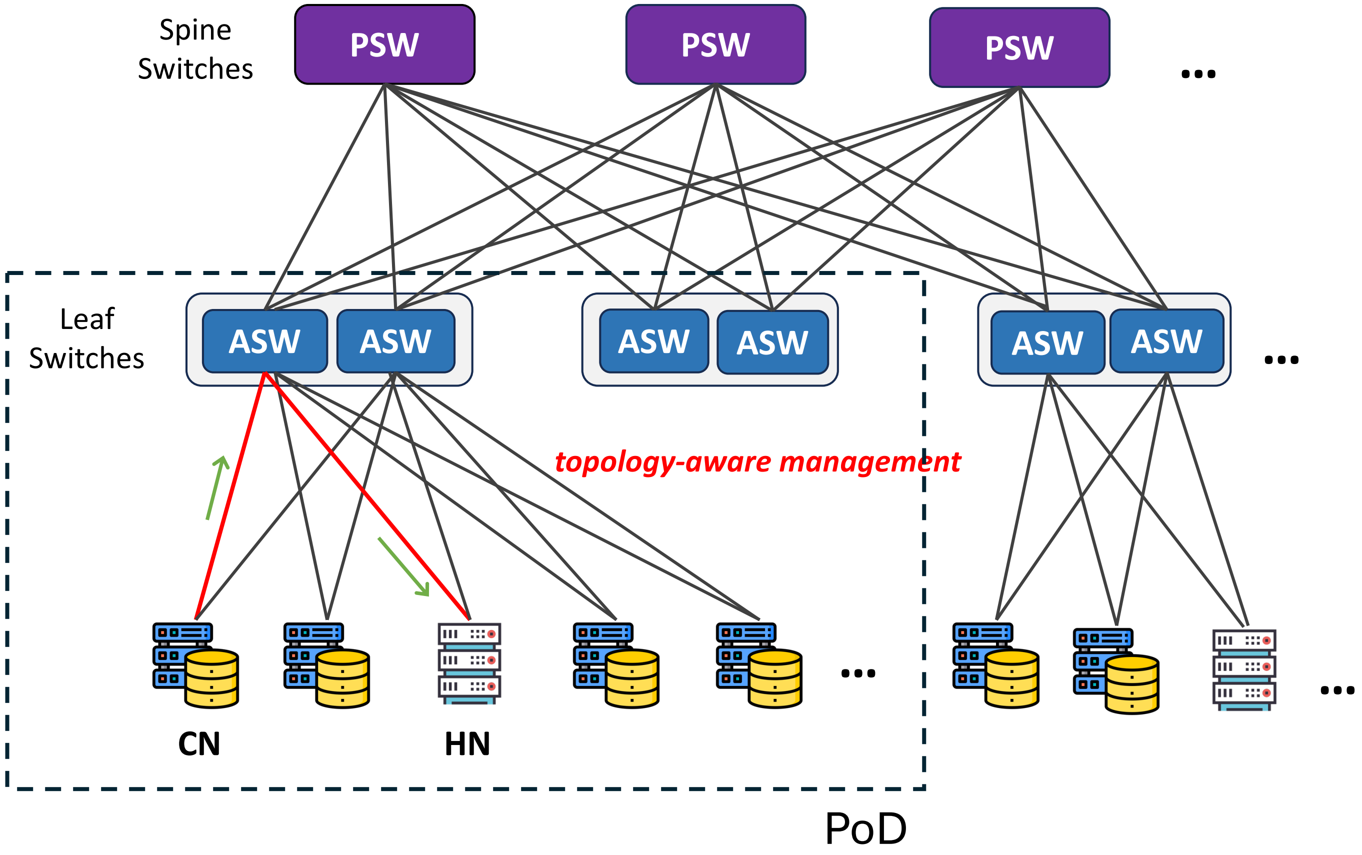
② Topology-Aware Resource Manager

- Place a group of CN and HN instances into a shared cluster
- Different role of instances can be scaled independently
- Principle: <u>topology-aware</u> node scheduling and resource allocation

② Resource Manager: Inter-node scheduling

- Two policies
  - Confine all instances within the same PoD
  - Schedule new instance(s) to the ASW with the most existing instances

- Deployment constraints at different levels
  - Node
  - NIC switch

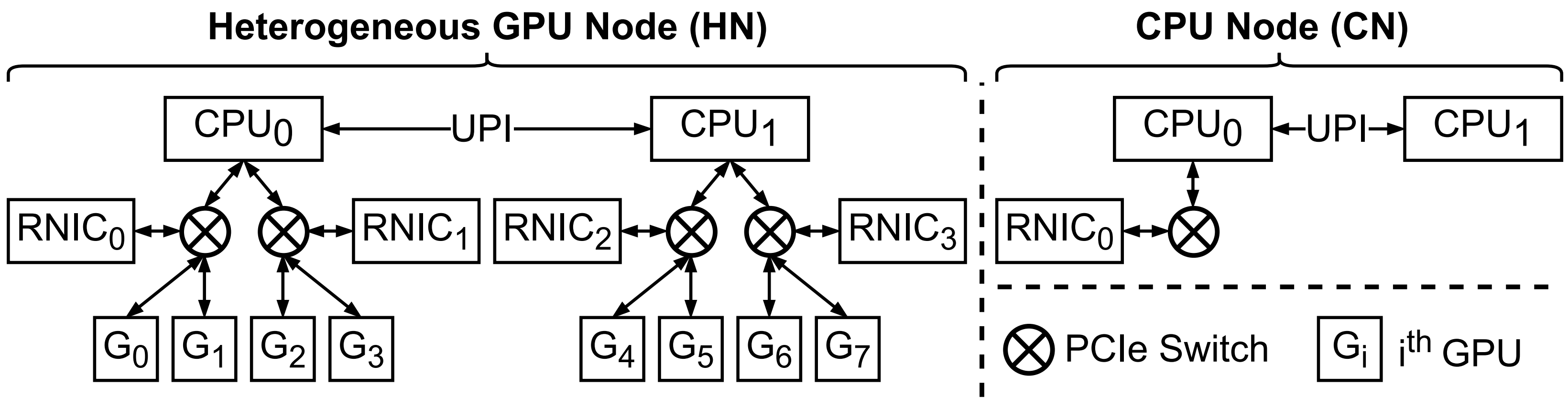


For more details of data center network, please refer to:
"Alibaba HPN: A Data Center Network for Large Language Model Training", SIGCOMM'24

② Resource Manager: Intra-node allocation

- HN instance
  - Arbitrary bindings of GPUs and RNICs can induce 21–36% performance loss
  - Assign RNIC and GPU on the same PCIe switch; enable GPUDirect RDMA

- CN instance
  - Prioritize CPU allocation under the same PCIe switch connected to the RNIC



③ SLO-Aware Communication Scheduler

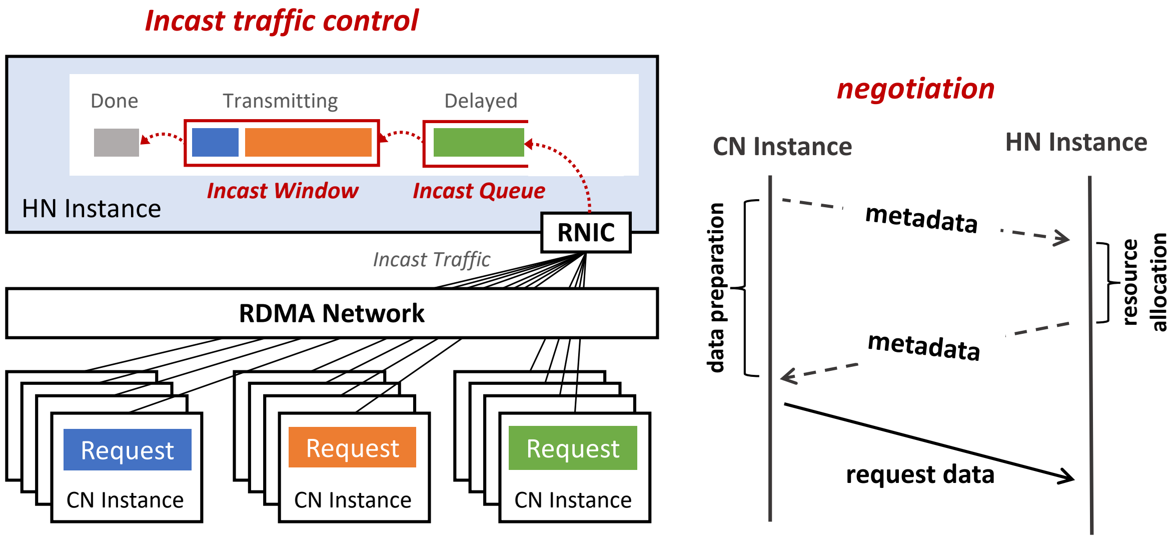
- Extend the native RoCEv2 stack and implement a middleware to leverage RDMA capabilities in a *virtualized* environment

- Incast: A substantial number of CN instances concurrently transmit data to a limited number of HN instances

Incast Size	**Latency**	**% of Failed Requests**
10	10 ms	$\approx 33\%$
20	40 ms	$\approx 50\%$
100	10 s	$\approx 100\%$

③ SLO-Aware Communication Scheduler

- Adaptive incast window
  - Adapt to the congestion level of network links and PCIe links
  - The number of CNPs serves as an estimator of the congestion level



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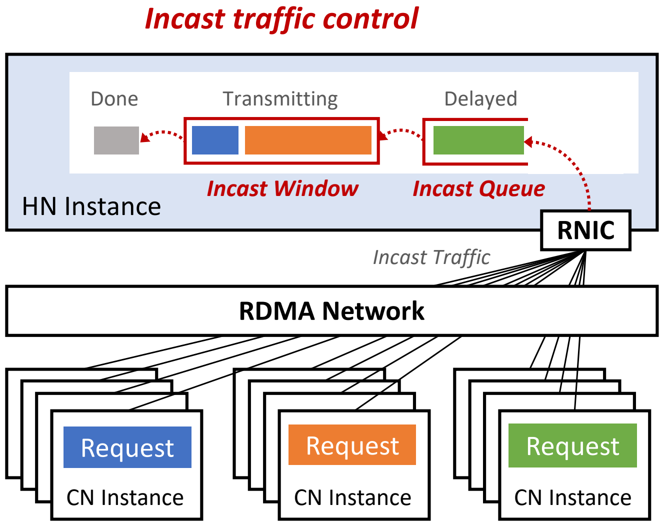
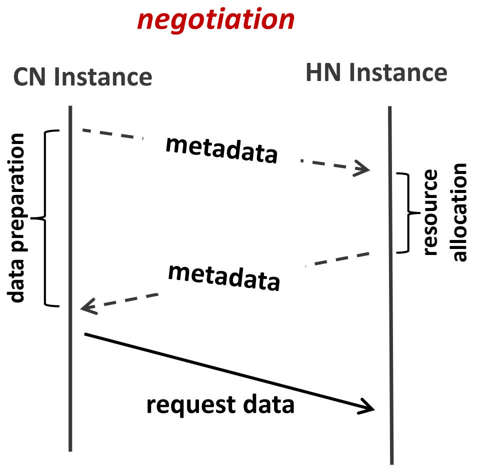
  - The number of CNPs serves as an estimator of the congestion level
- Deadline-aware request scheduling
  - The <u>deadline</u> of a comm request: the latest time to initiate parameter transmission to meet the SLO
  - <u>Reorder</u> the requests in the incast queue to maximize the number of requests meeting their SLOs



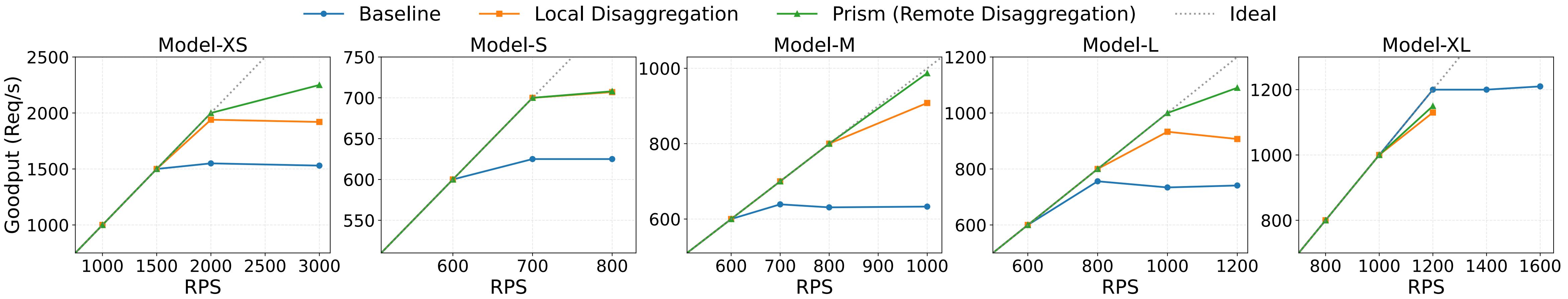


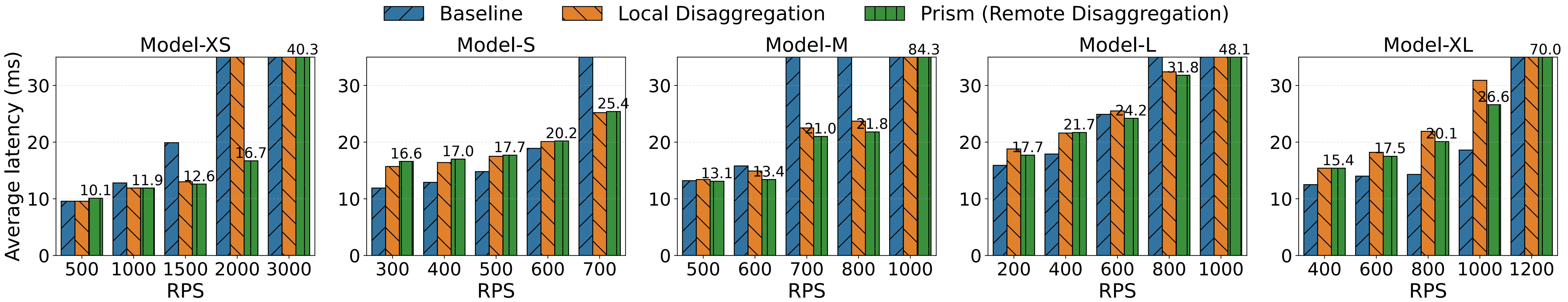
Evaluation

- Production workloads
- Machine specifications
  - CPU node (CN)
    - **128** vCPU cores
    - **1** 200 Gbps RNIC
  - GPU node (HN)
    - **128** vCPU cores
    - **8** A100 GPUs with 80 GiB GPU memory each
    - **4** 200 Gbps RNICs
  - All nodes use Intel(R) Xeon(R) Platinum 8369B CPUs, with **1024 GiB** memory

Model	**Emb Size** (Approximate)	**RDMA TX** (Per Req)	**Dense Features**
Model-XS	100 GiB	552.96 KiB	338.67 MiB
Model-S	450 GiB	6.84 MiB	57.20 MiB
Model-M	500 GiB	3.87 MiB	21.46 MiB
Model-L	600 GiB	3.69 MiB	20.79 MiB
Model-XL	700 GiB	9.03 MiB	8.73 GiB

Performance under varying traffic loads





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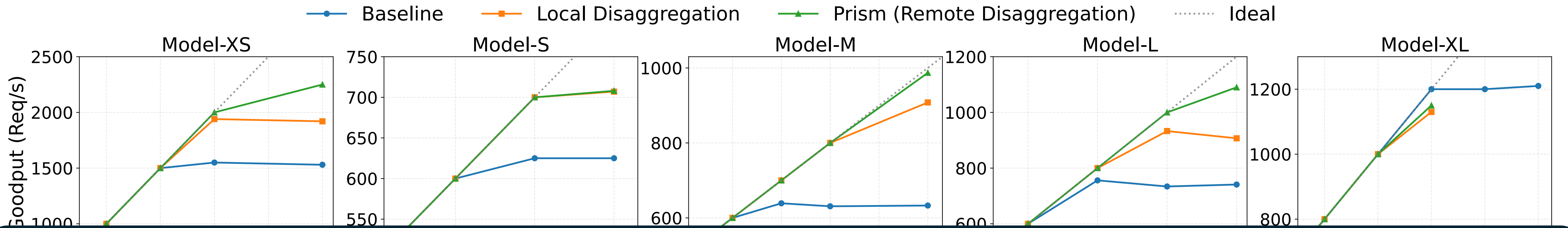
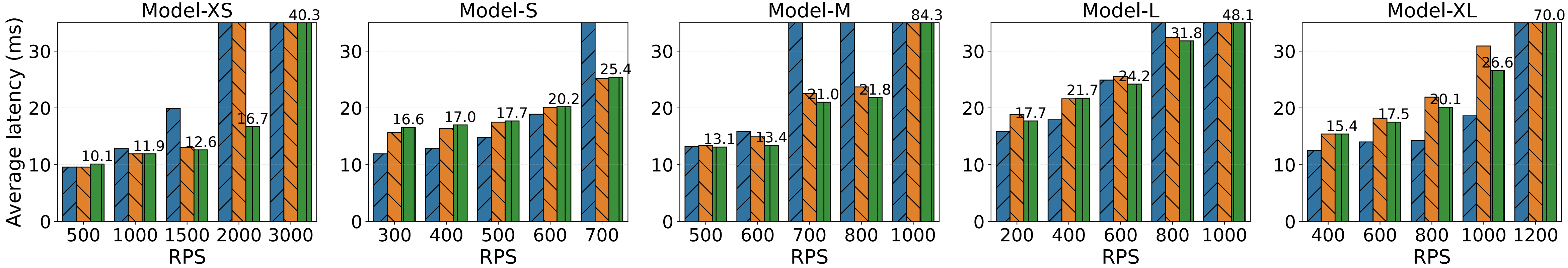


Prism can maintain service performance under <u>high traffic</u> scenarios!



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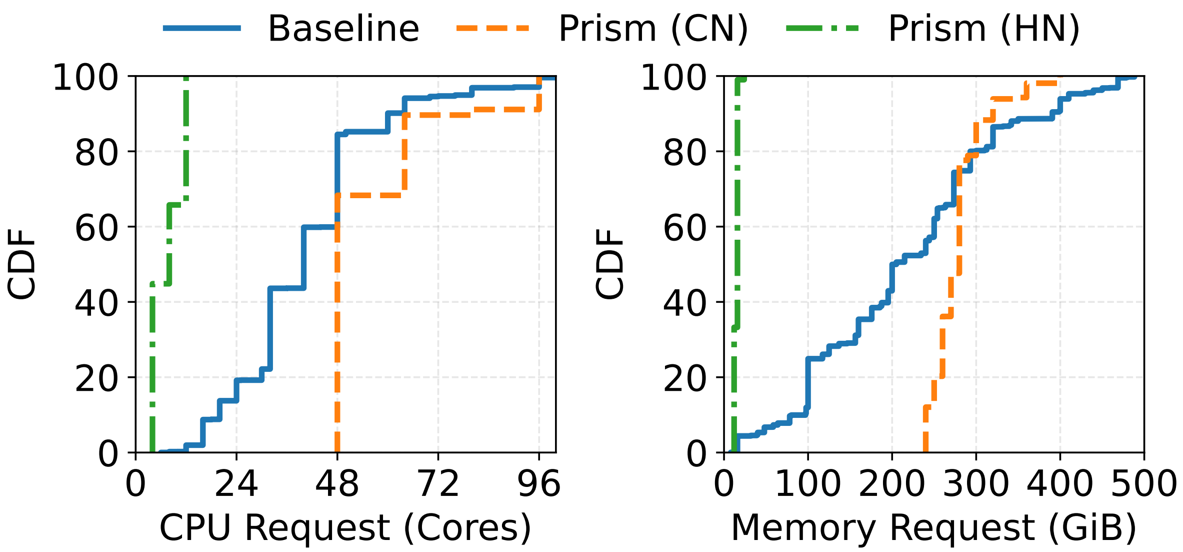

- HN instances that require GPU allocation, their CPU requests are < 12 cores, and memory requests < 24 GiB
- CN instances have CPU requests > 48 cores and memory requests > 240 GiB

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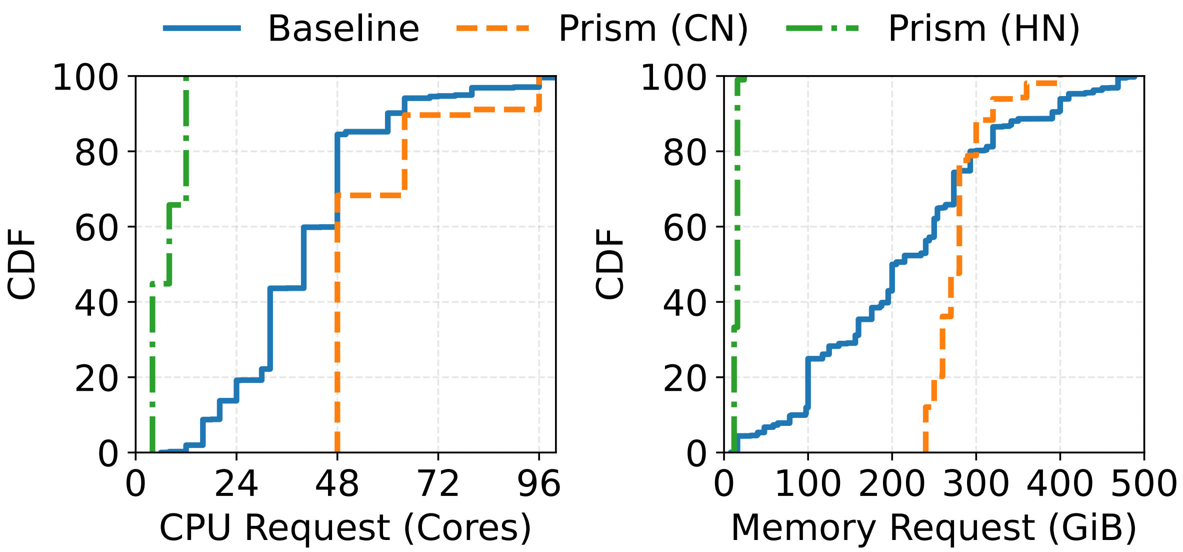

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Prism can separates resource requirements of DLRM inference services.

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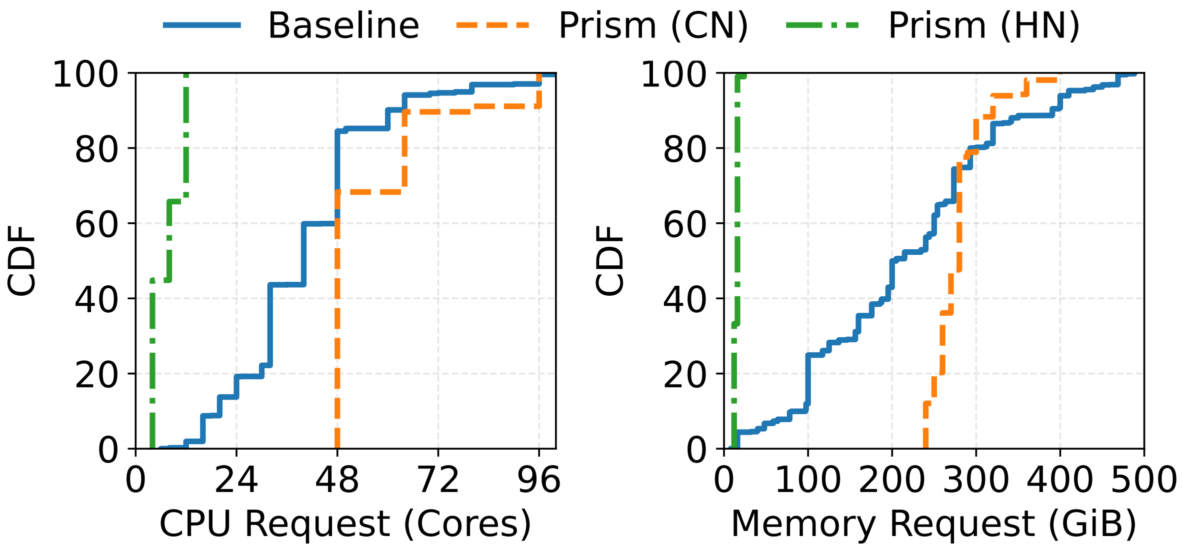

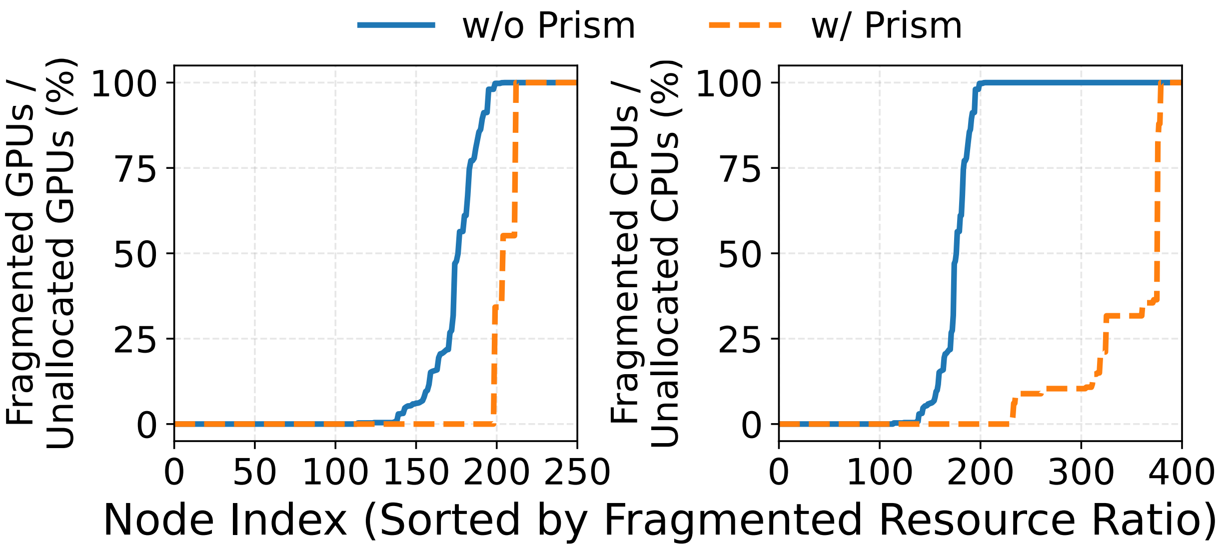

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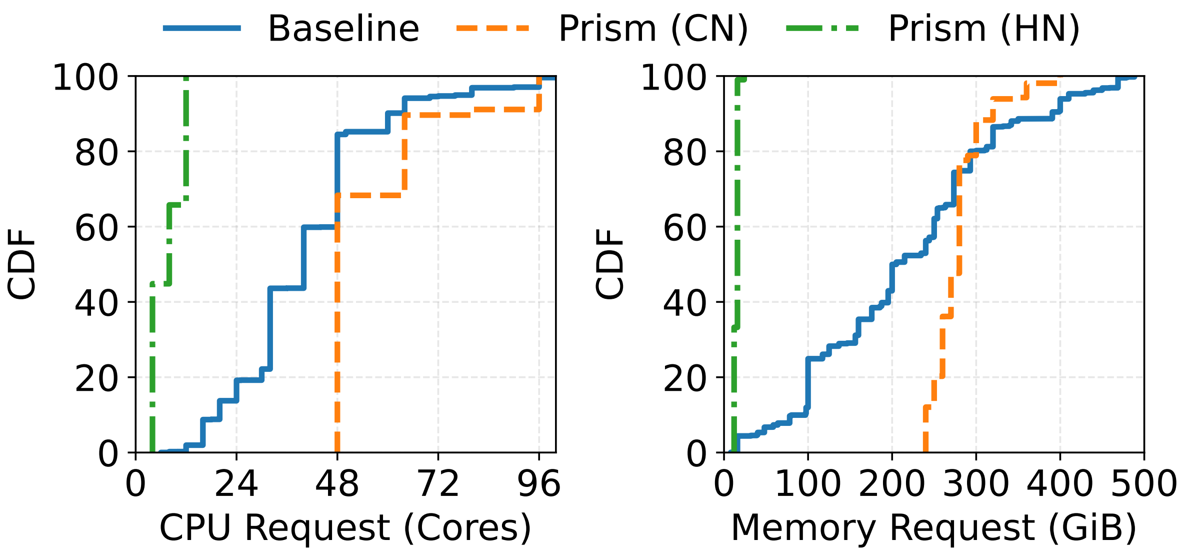

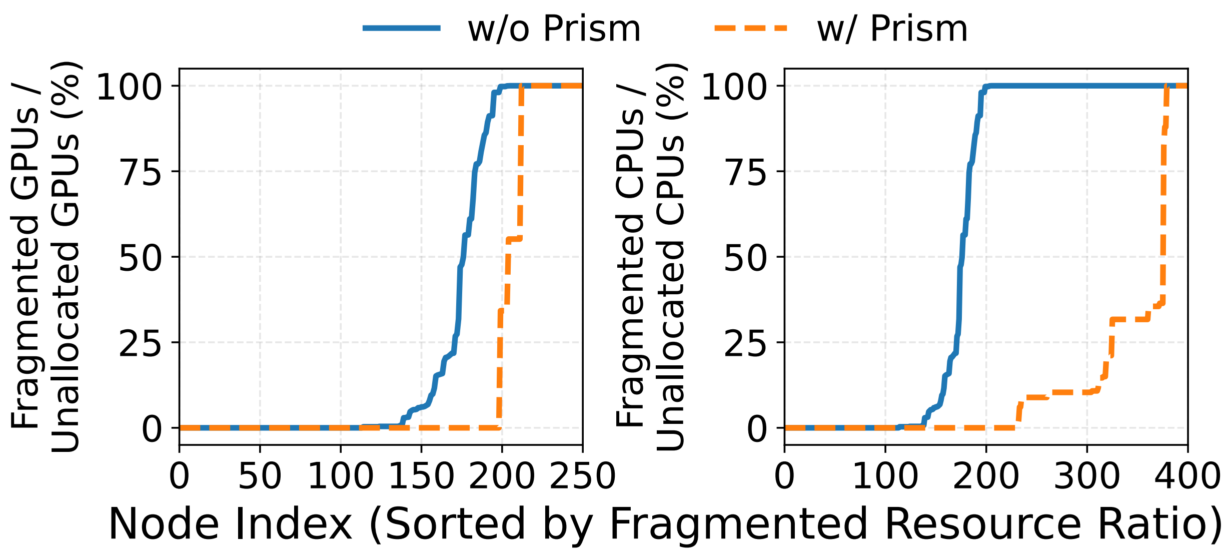

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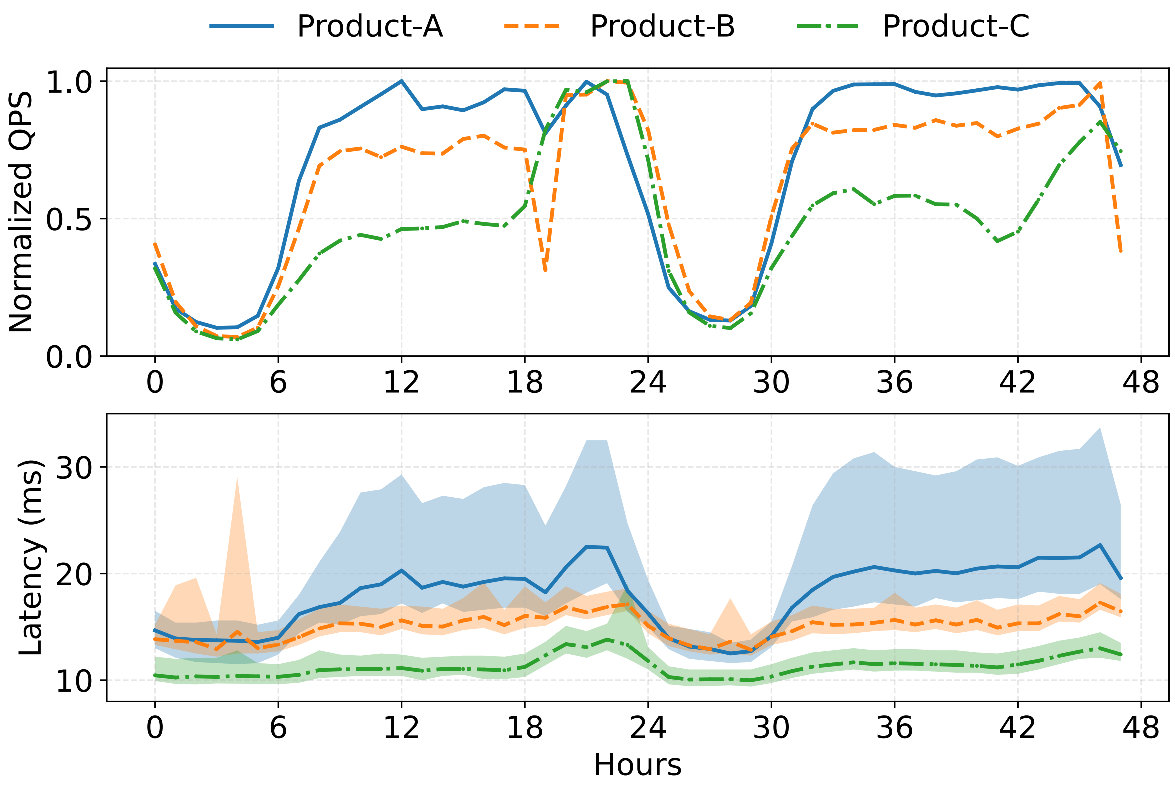
Prism can effectively reduce the cluster's fragmented resources.

Efficient Resource Loans for Peak Demand

- During e-commerce promotional events, Prism can borrow a portion of training nodes to scale out DLRM inference services

Service	Role	# of Instances	CPU	GPU
Product-A	CN	25	48	-
	HN	45	4	MIG 2g.20gb
Product-B	CN	15	48	-
	HN	40	4	MIG 2g.20gb
Product-C	CN	15	48	-
	HN	55	2	MIG 2g.20gb



Discussion and Future Explorations

- Disaggregated serving for different workloads
  - LLM PD disaggregation: decouple the GPU computation and I/O bandwidth
  - DLRM disaggregation: decouple the use of CPU and GPU computation
  - Transform the workload from the perspective of resource provisioning
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  - Transform the workload from the perspective of resource provisioning
  - Decouple *diverse* resource requirements to accommodate the infrastructure
- Fault tolerance
  - Performance isolation between networking resources
  - Dense instance deployment on a single node → High blast radius!

Takeaways

- Prism enables DLRMs to harvest resources from CPU nodes and heterogeneous GPU nodes by means of **disaggregated serving**

- Prism effectively **mitigates resource fragmentation** in daily high-allocation GPU clusters; and enables efficient **capacity loaning** from training clusters during seasonal promotion events

- Prism has been deployed in production clusters for <u>over two years</u> and now runs <u>over 10k GPUs</u>

A production DLRM serving trace is released at: https://github.com/alibaba/clusterdata/tree/master/cluster-trace-gpu-v2025