DynamoLLM: Designing LLM Inference Clusters for Performance and Energy Efficiency

HPCA 2025

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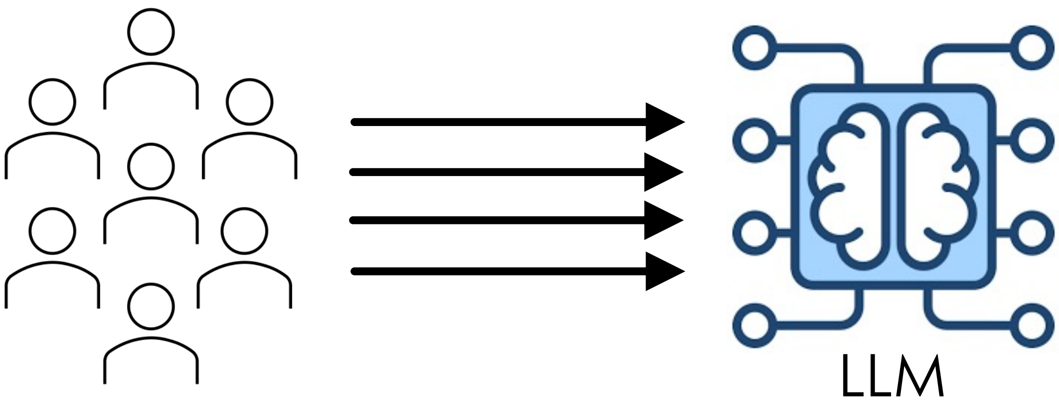
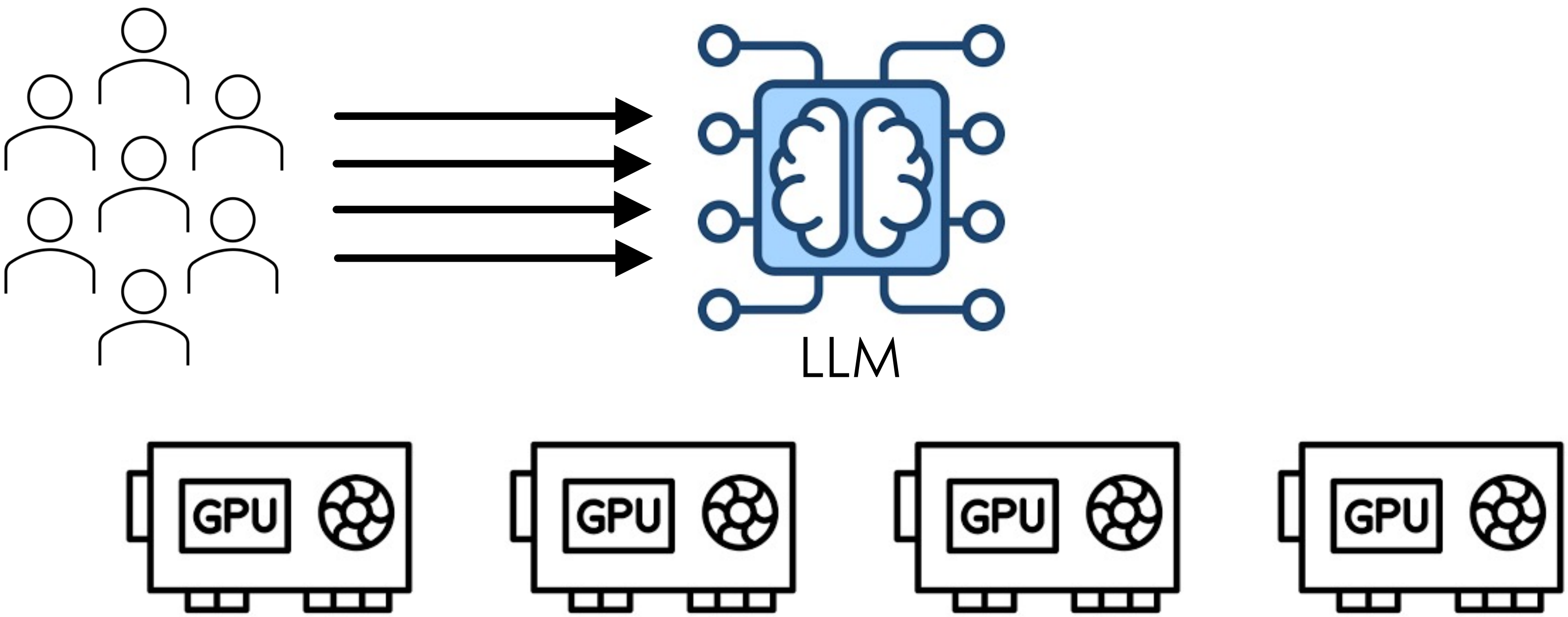
LLM inference is emerging in the Cloud

- Modern generative LLMs are turning ubiquitous
  - Use cases: programming, chat-bots, education, healthcare

LLM inference stresses cloud infrastructure



LLM inference stresses cloud infrastructure



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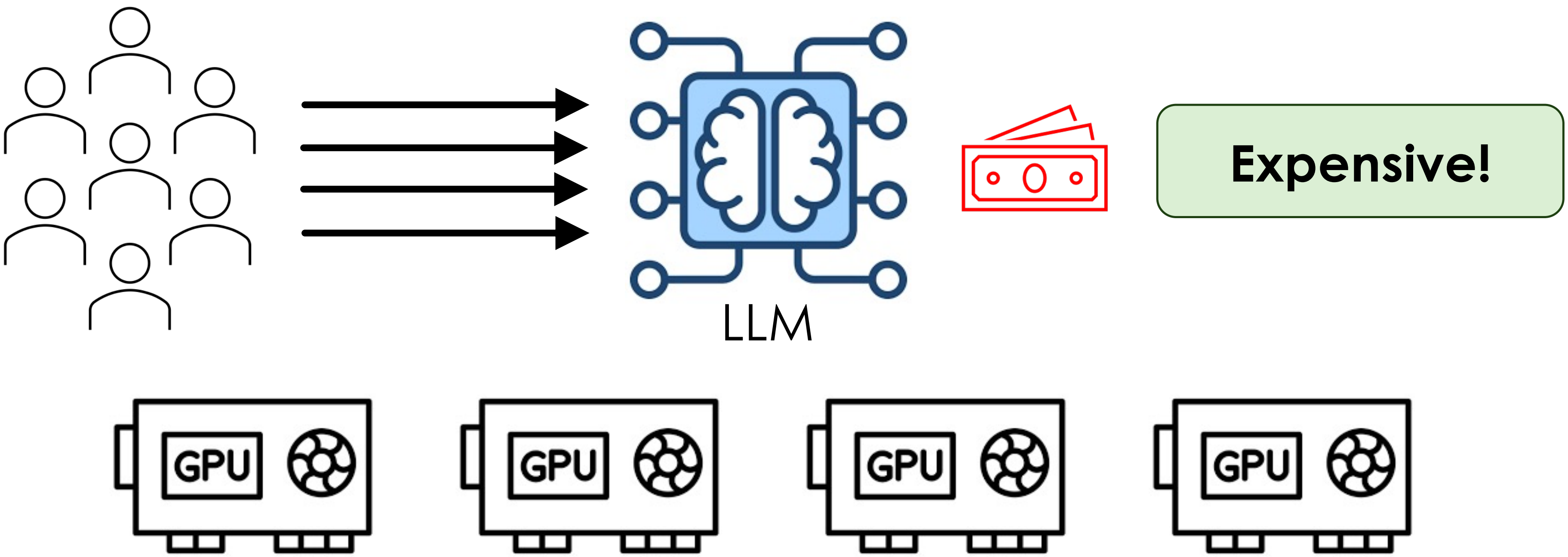

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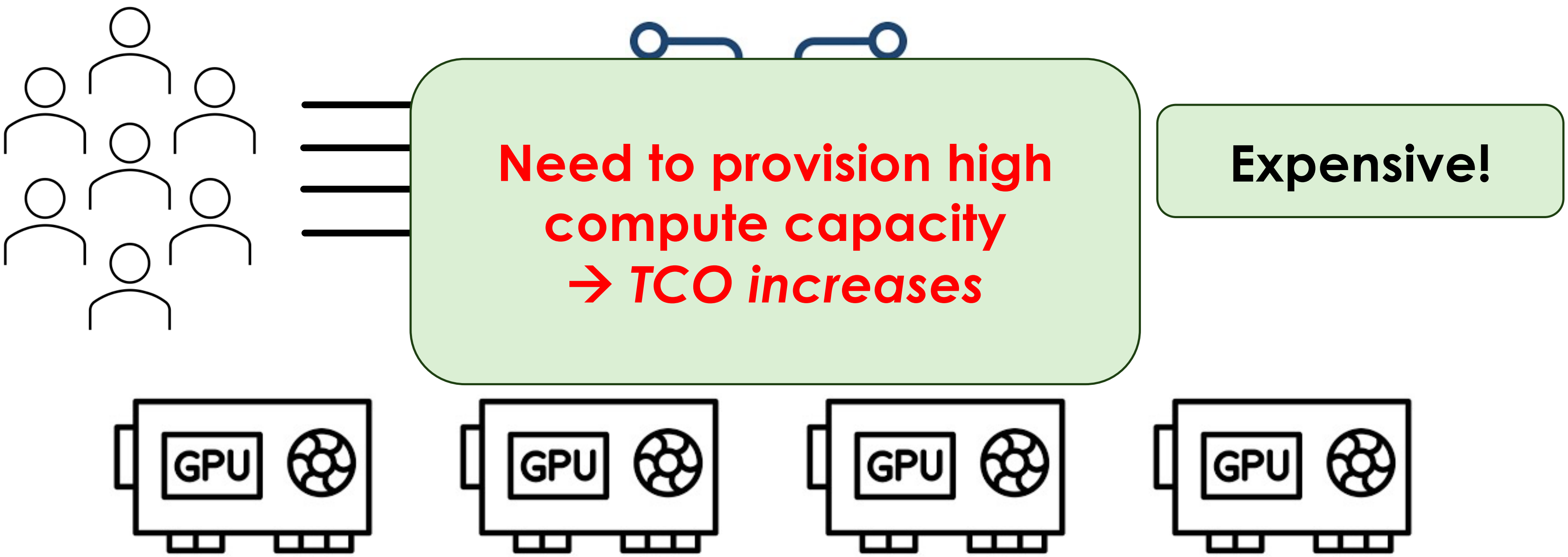

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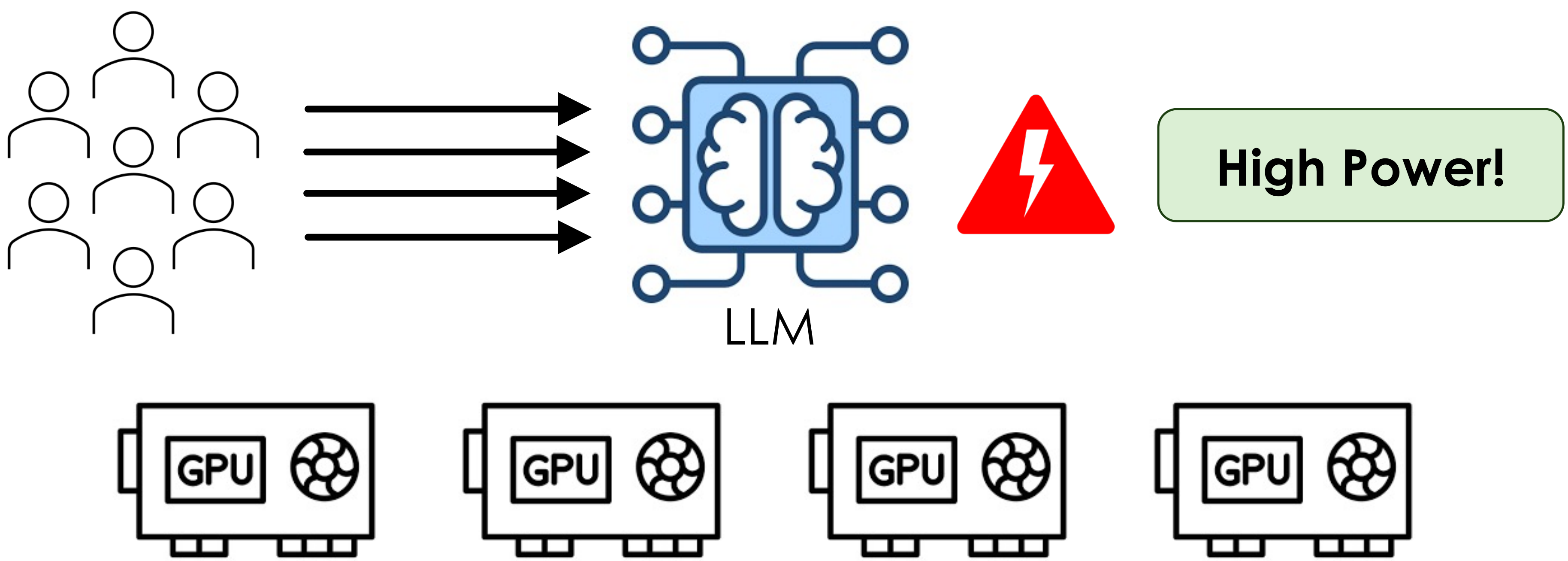
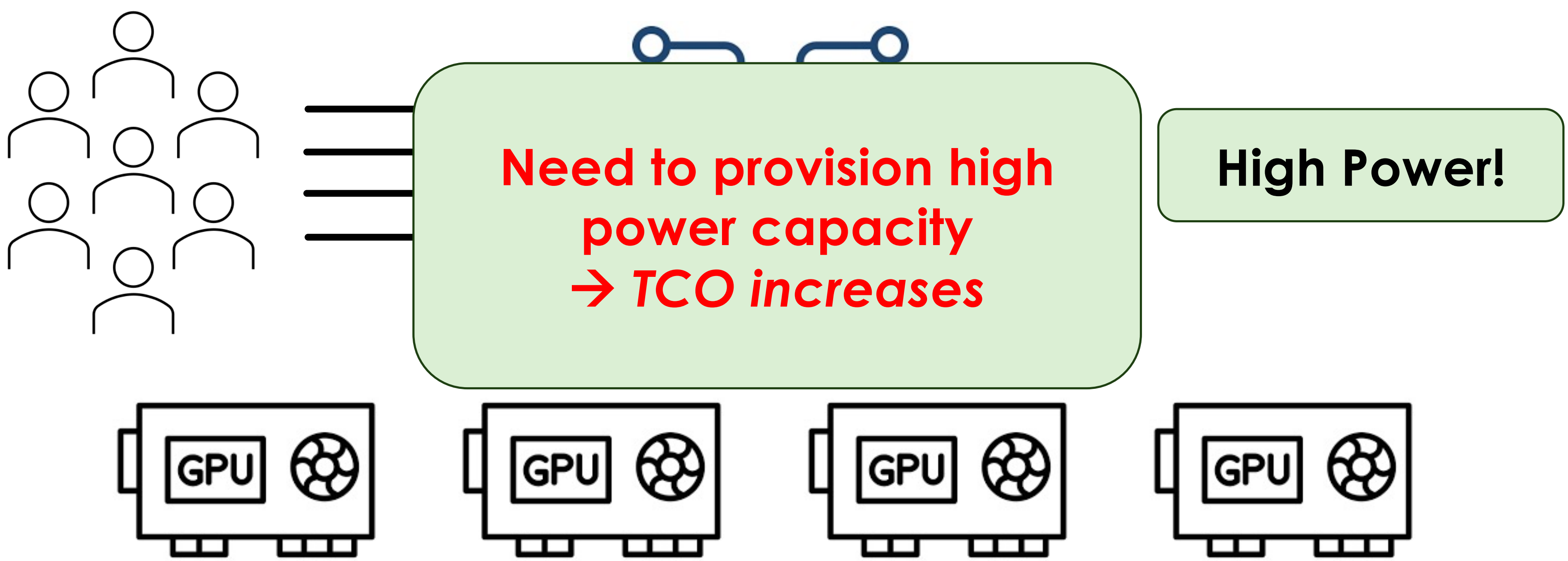
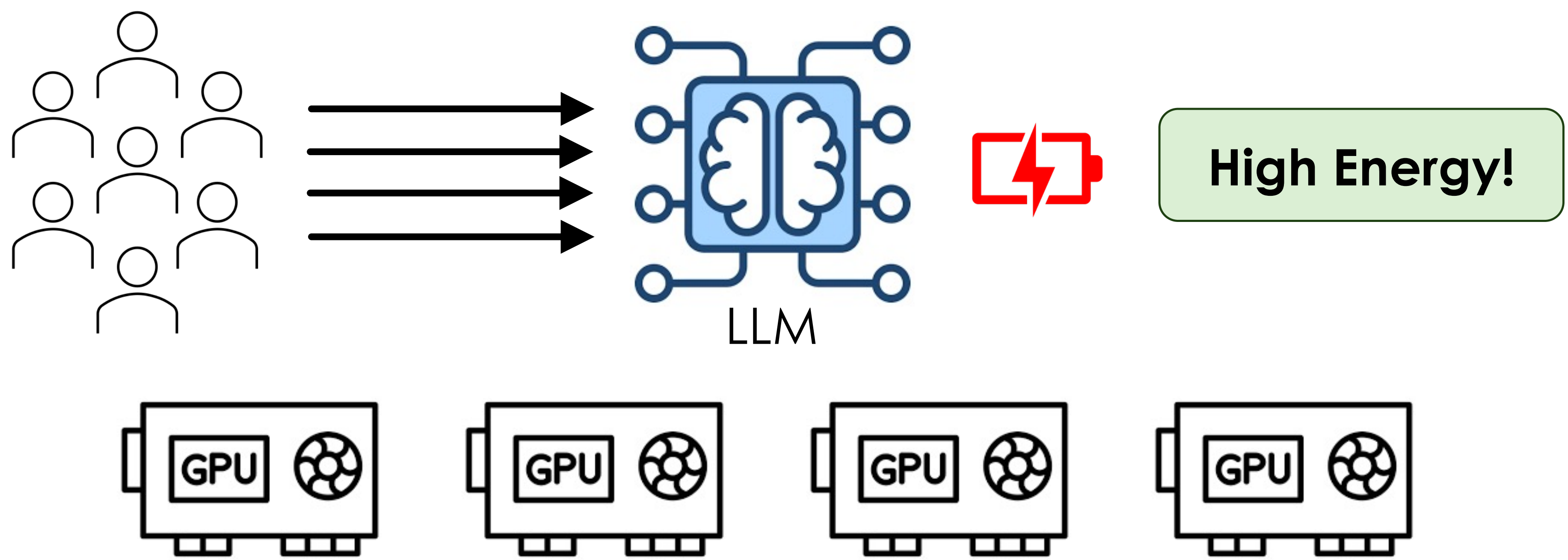


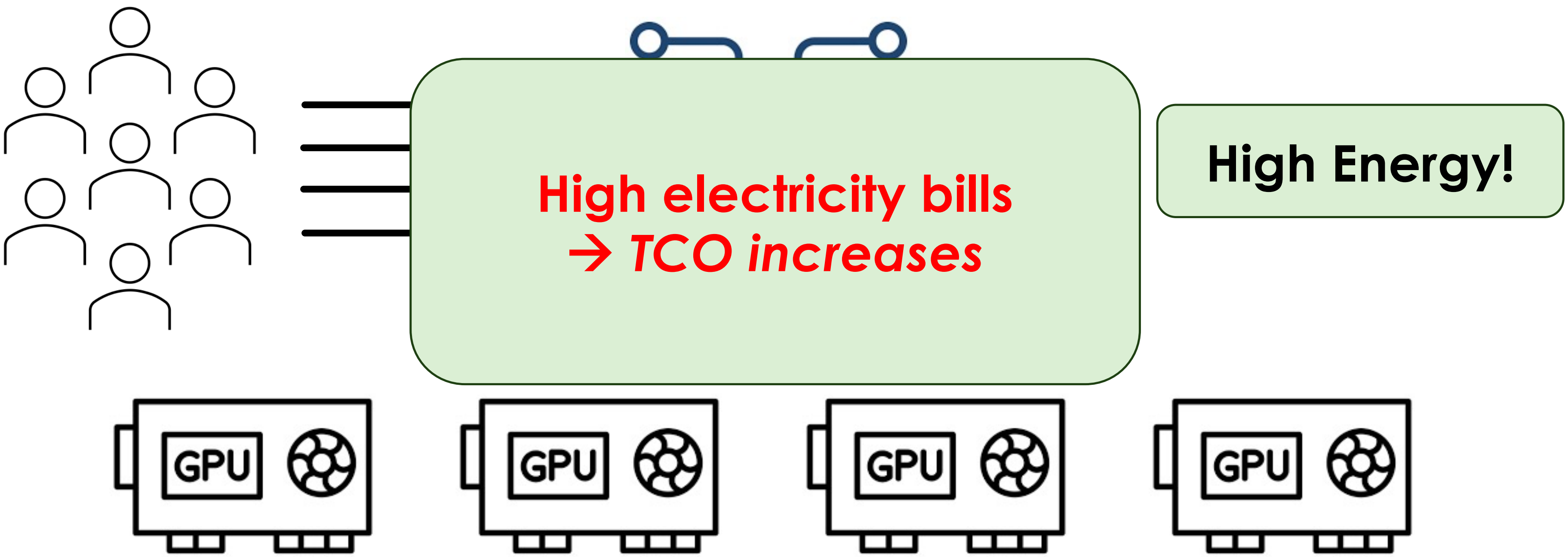
LLM inference stresses cloud infrastructure



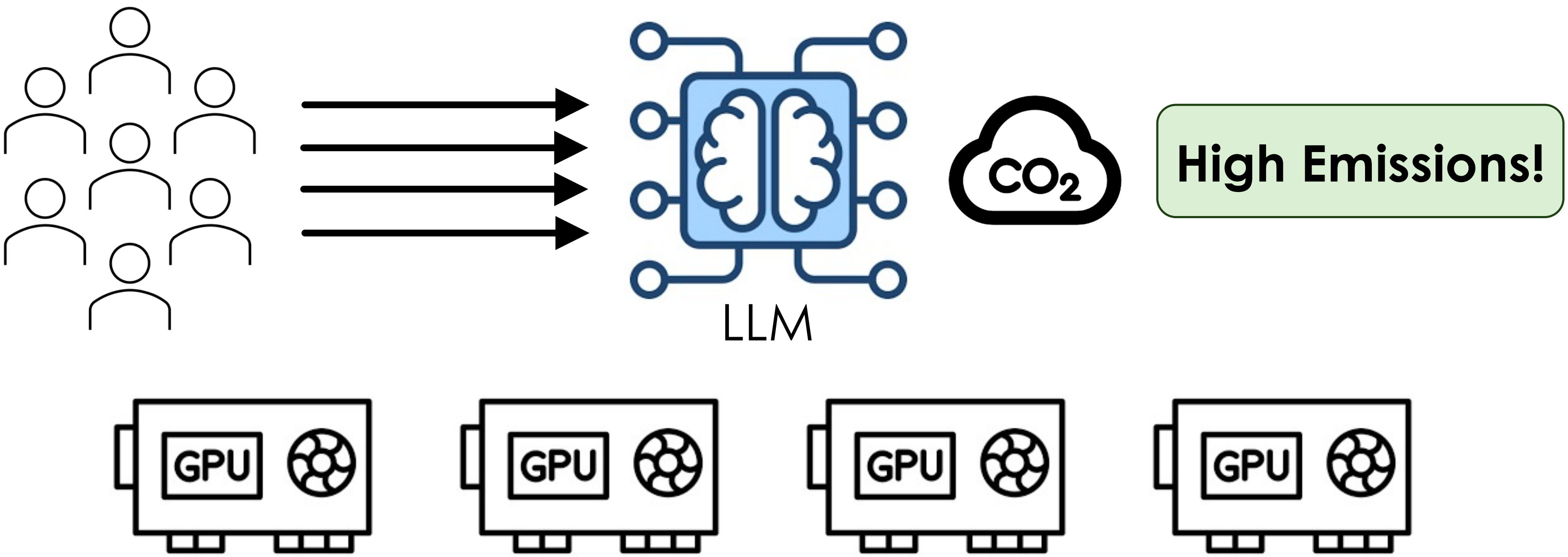
LLM inference stresses cloud infrastructure



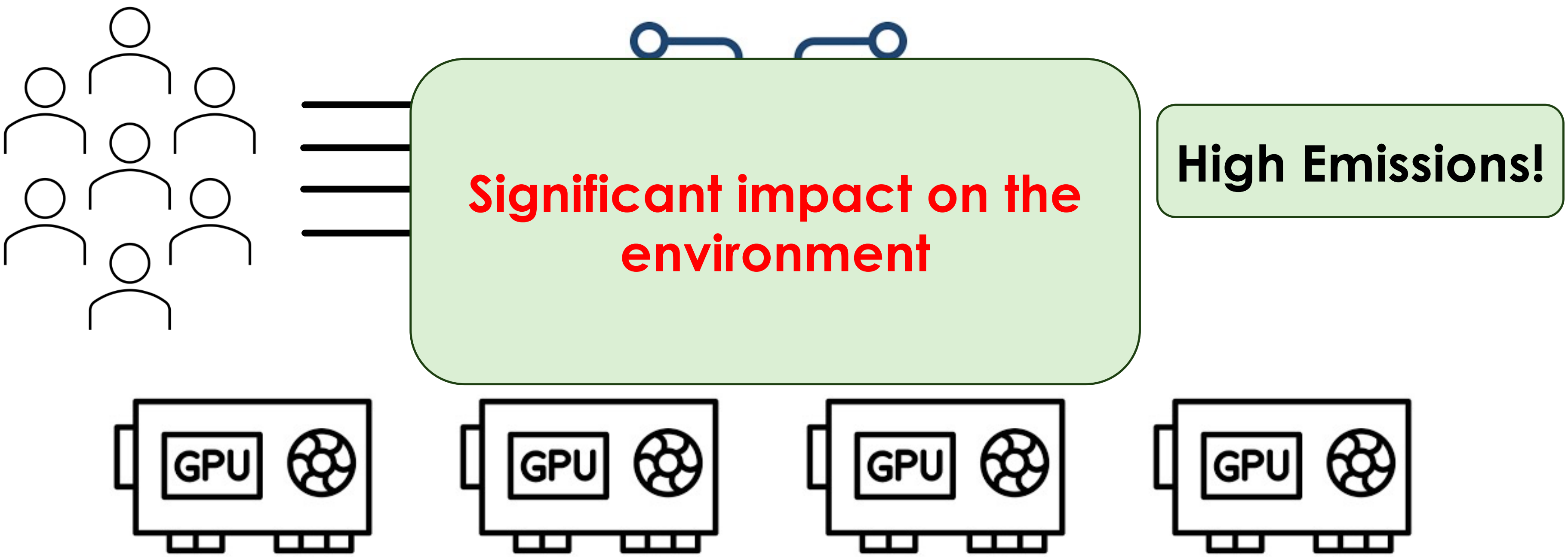
LLM inference stresses cloud infrastructure



LLM inference stresses cloud infrastructure

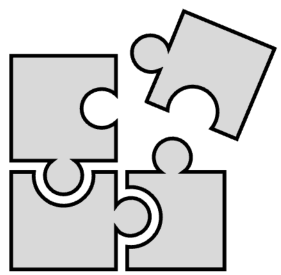


LLM inference stresses cloud infrastructure



How to tame the LLMs?

- Lots of work on performance, accuracy, scalability
- LLMs cause the datacenter cost, energy, and carbon emissions to skyrocket



Energy efficiency of LLMs is a missing piece of a puzzle!

Contributions

- Characterize energy properties of LLMs
- **DynamoLLM:** the first energy-management framework for LLM inference clusters
- Evaluate DynamoLLM at a large scale
  - 53% less energy and 38% less carbon emissions

How to tune LLMs?

Knob	Energy	Power	Perf	Quality

How to tune LLMs?

Knob	Energy	Power	Perf	Quality
Model Size ↓	↑	↑	↑	↓↓

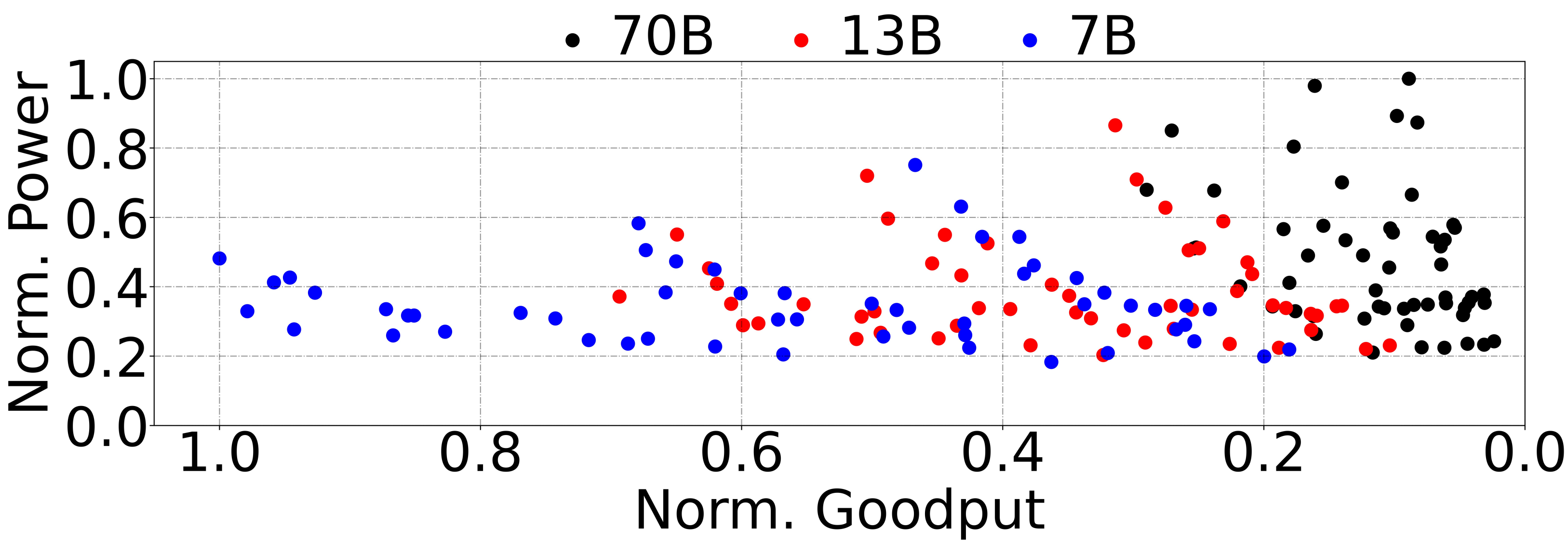
How to tune LLMs?

Knob	Energy	Power	Perf	Quality
Model Size ↓	↑	↑	↑	↓↓
Quantize ↓	↑	↑	↑	↓

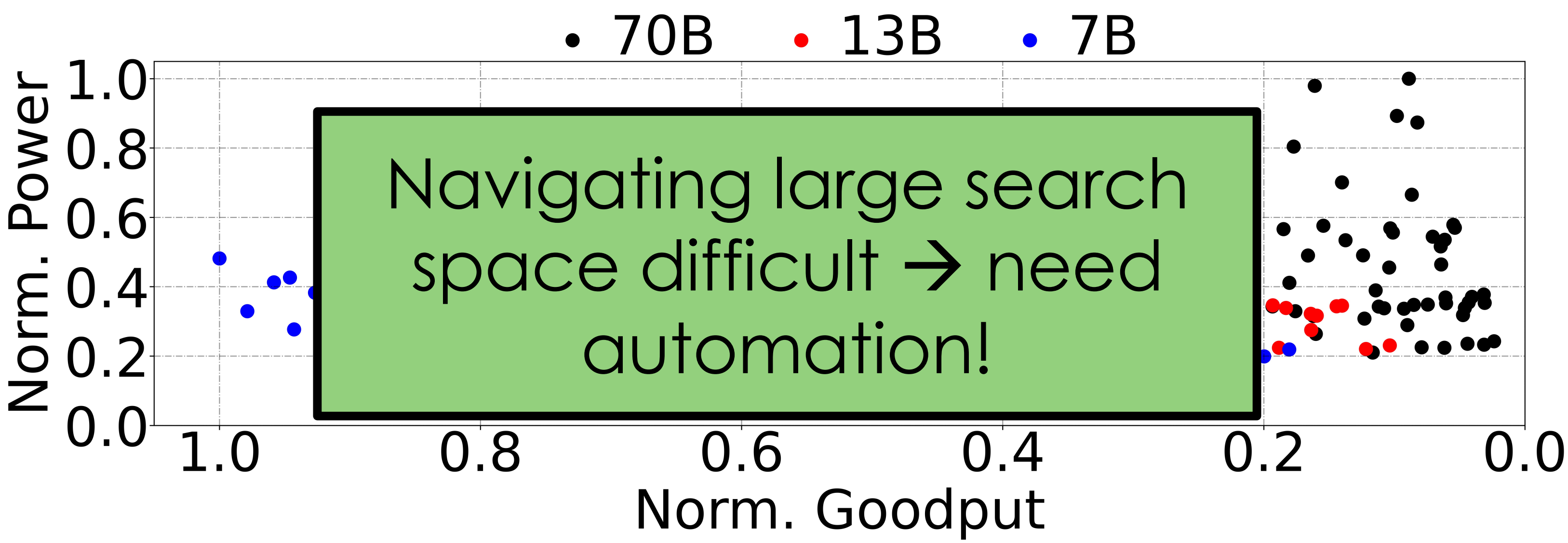
How to tune LLMs?

Knob	Energy	Power	Perf	Quality
Model Size ↓	↑	↑	↑	↓ ↓
Quantize ↓	↑	↑	↑	↓
Parallelism ↓	↓ ↑	↑	↓	
Frequency ↓	↓ ↑	↑	↓	
Batch size ↓	↓ ↑	↑	↓	

Large configuration search-space



Large configuration search-space

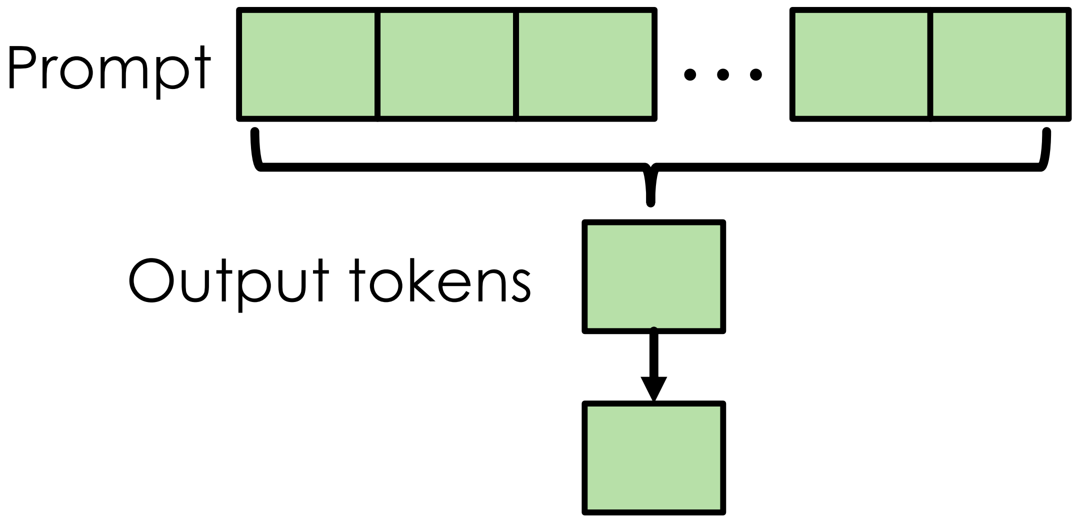


Navigating large search space difficult → need automation!

Goal: Make LLMs energy-efficient

- Challenges
  1. Request heterogeneity
  2. Workload dynamics
  3. Reconfiguration overheads

Challenge #1: Request Heterogeneity



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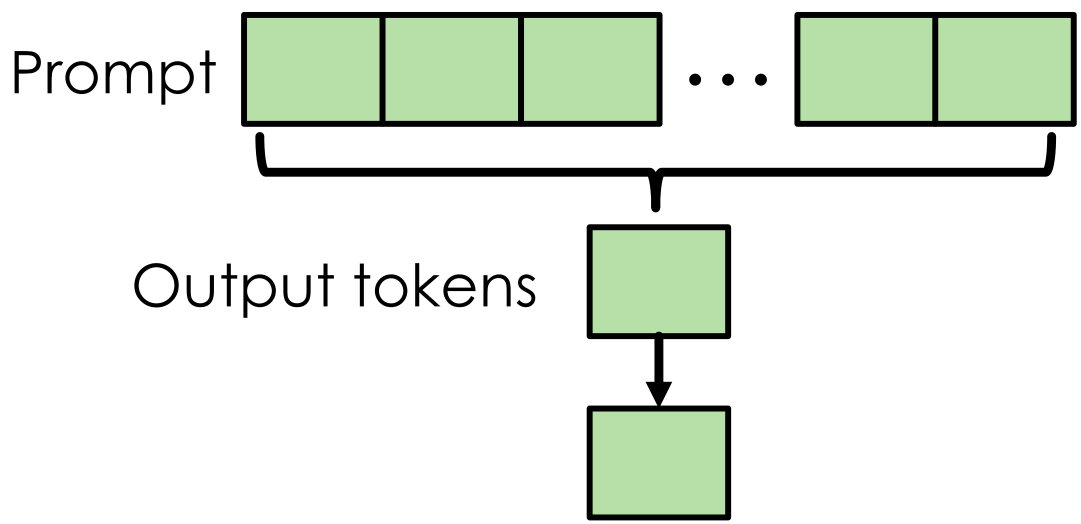
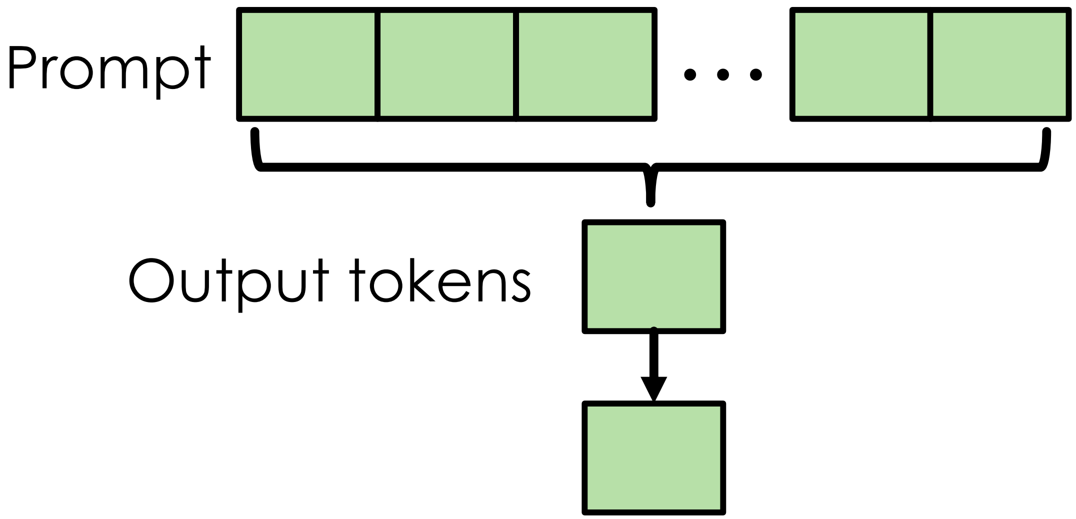


Long input, short output

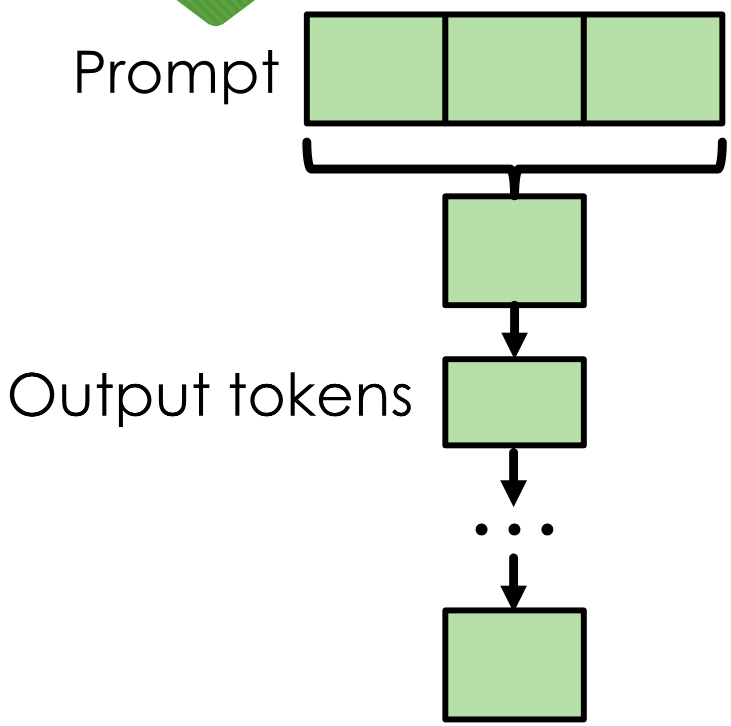
Challenge #1: Request Heterogeneity



Long input, short output

Compute-bound

Challenge #1: Request Heterogeneity



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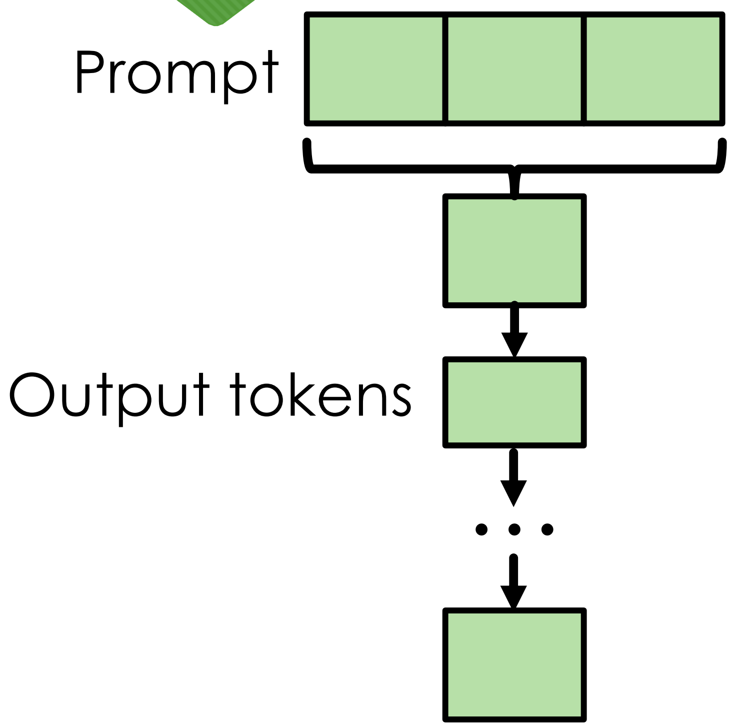

Short input, long output

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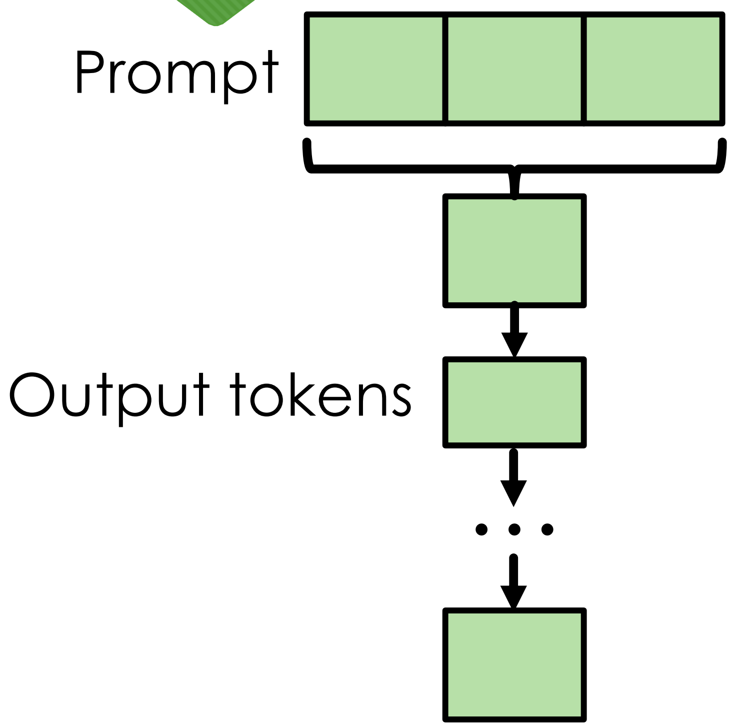

Short input, long output

Memory-bound

Challenge #1: Request Heterogeneity

Shard	TP2				TP4				TP8			
Freq [GHz]	0.8	1.2	1.6	2	0.8	1.2	1.6	2.0	0.8	1.2	1.6	2.0
SS												
SL												
LS												
LL												

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Shard	TP2				TP4				TP8			
Freq [GHz]	0.8	1.2	1.6	2	0.8	1.2	1.6	2.0	0.8	1.2	1.6	2.0
SS												
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SS: Short input, short output

LL: Long input, long output

Challenge #1: Request Heterogeneity

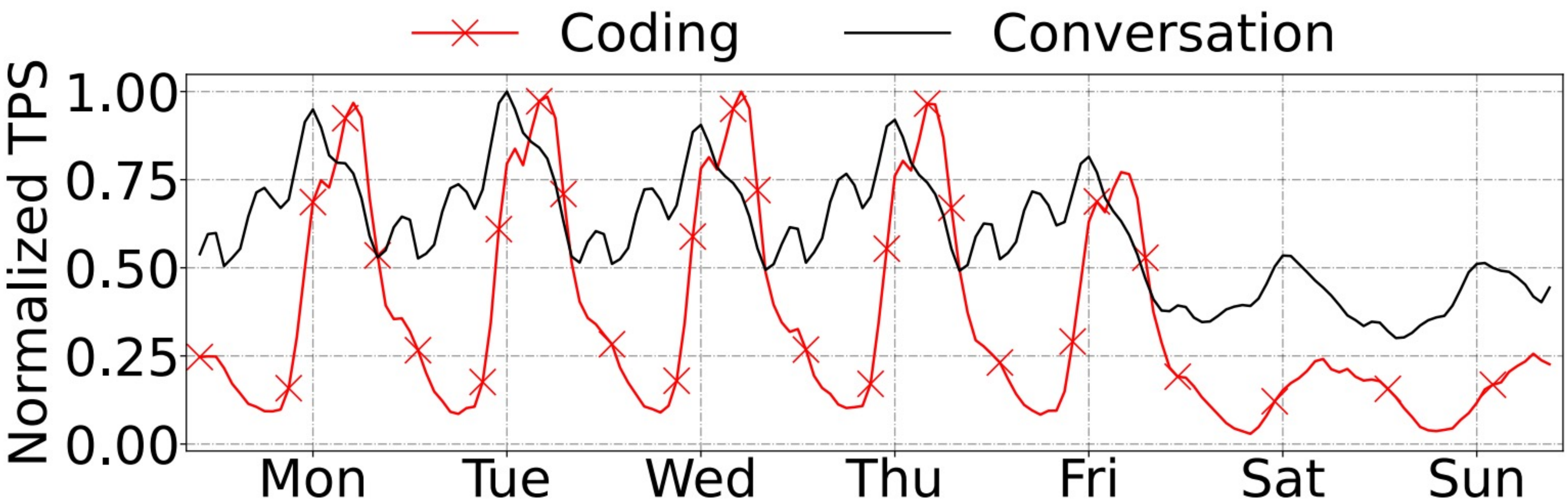
Shard	TP2				TP4				TP8			
Freq [GHz]	0.8	1.2	1.6	2	0.8	1.2	1.6	2.0	0.8	1.2	1.6	2.0
SS		✓										
SL						✓						
LS						✓						
LL											✓	

Challenge #1: Request Heterogeneity

Shard	TP2				TP4				TP8			
Freq [GHz]	0.8	1.2	1.6	2	0.8	1.2	1.6	2.0	0.8	1.2	1.6	2.0
SS		✓										
SL												
LS						✓						
LL											✓	

Challenge #1: Different request types require different configurations

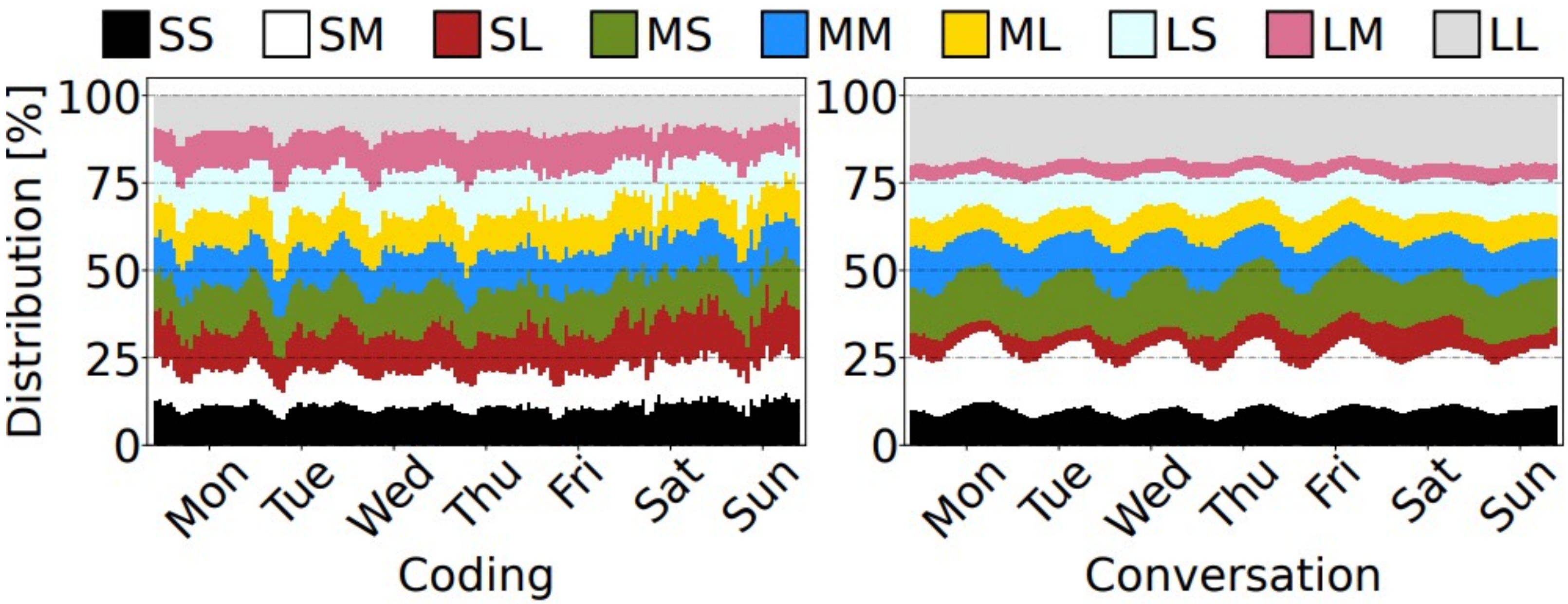
Challenge #2: Workload Dynamics



Challenge #2: Workload Dynamics

Sharding	TP4			
Frequency	0.8 GHz	1.2 GHz	1.6 GHz	2.0 GHz
Low Load		✓		
Med Load	✗		✓	
High Load	✗	✗		✓

Challenge #2: Workload Dynamics



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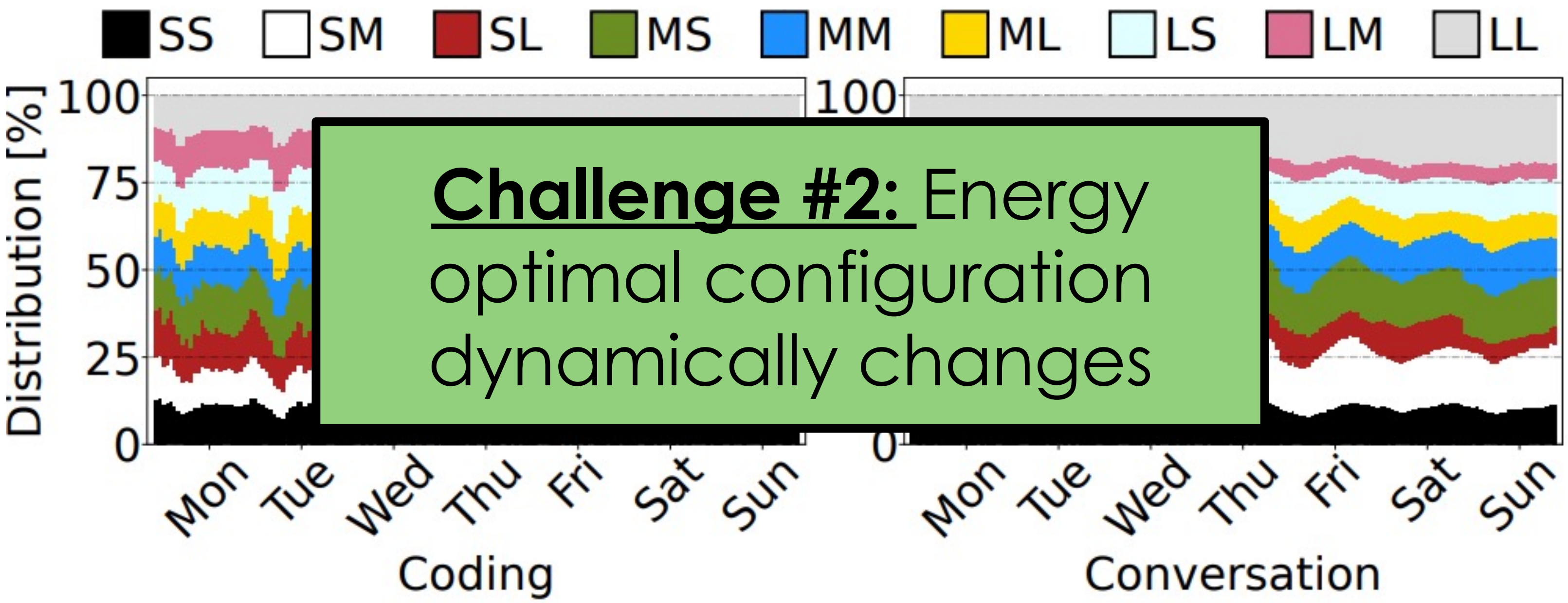


Challenge #2: Energy optimal configuration dynamically changes

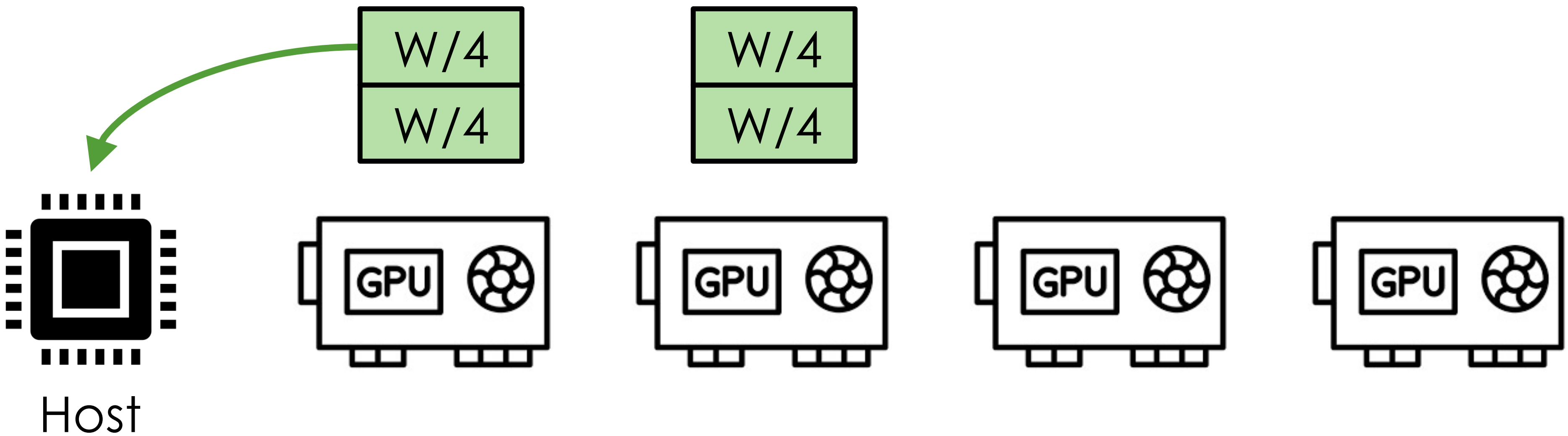
Challenge #3: Re-configuration expensive

- Reconfiguration
  1. Scale in/out
  2. Shard in/out
  3. Scale up/down

Challenge #3: Re-configuration expensive
i) Scale in/out costs

Overhead source	Time
Create an H100 VM	1-2 min
Init distributed environment	2 min
Download model weight	3 min
Setup inference engine	20 seconds
Install weights and KV cache on GPU	15 seconds
Total	***6-8 min***

Challenge #3: Re-configuration expensive
ii) Shard in/out costs



Challenge #3: Re-configuration expensive
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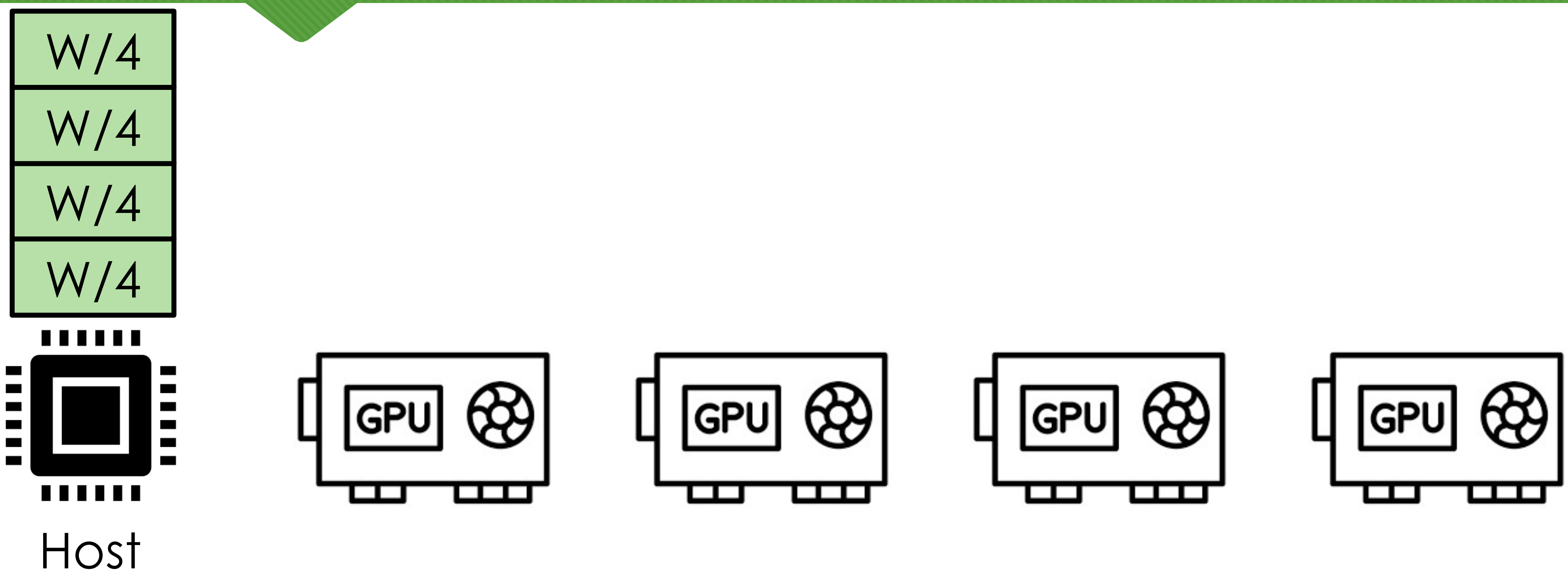

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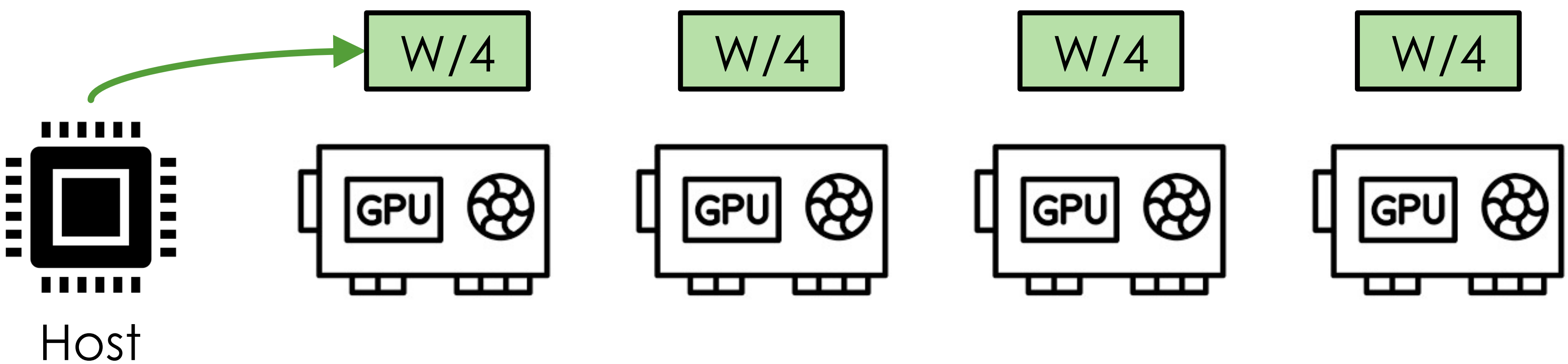
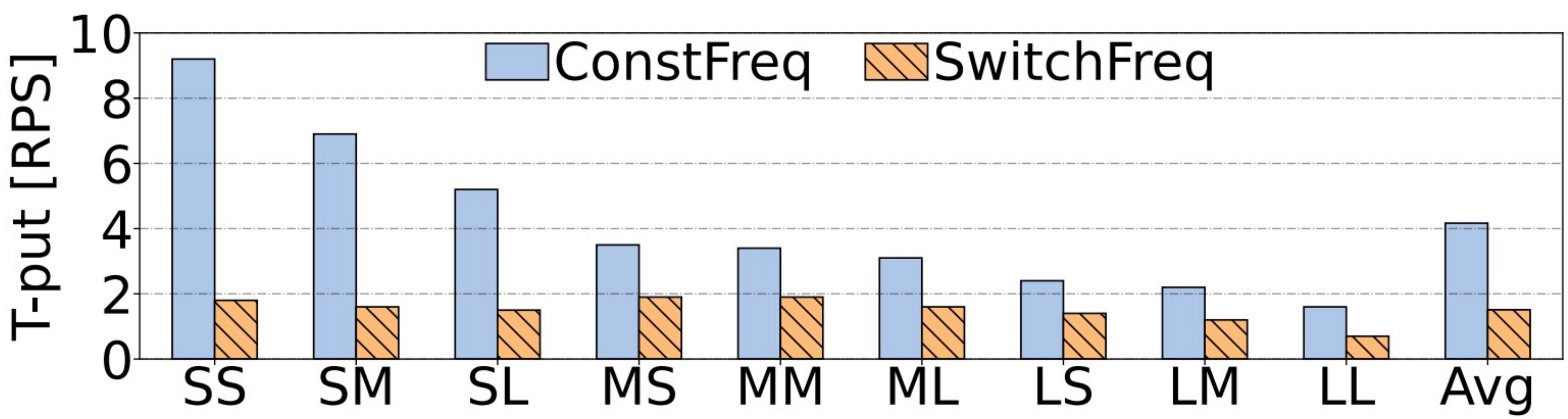


Challenge #3: Re-configuration expensive
iii) Scale up/down costs



Challenge #3: Re-configuration expensive
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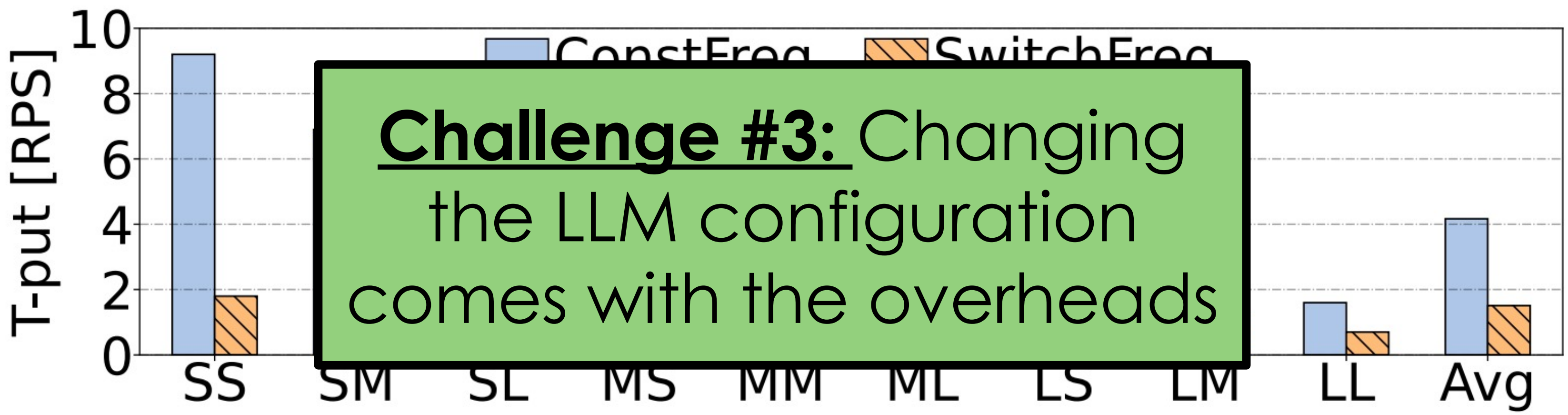
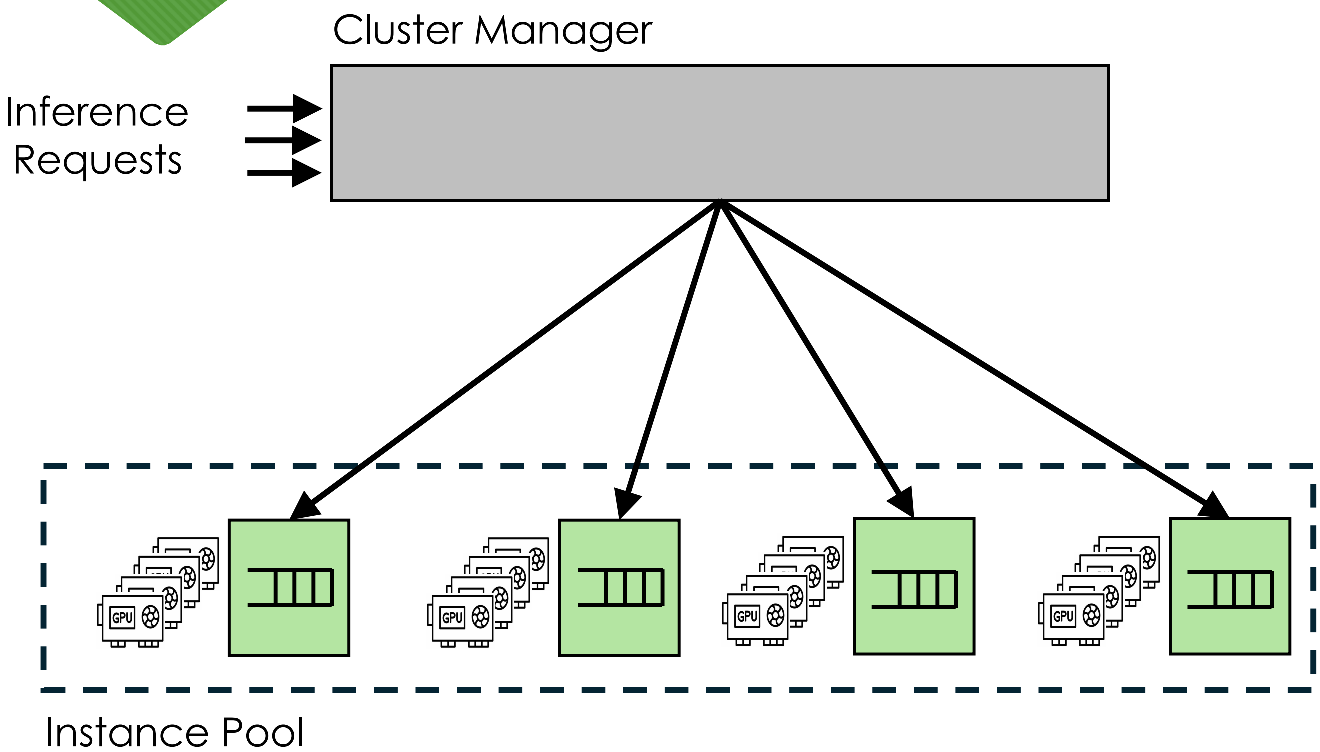


<u>Challenge #3:</u> Changing the LLM configuration comes with the overheads

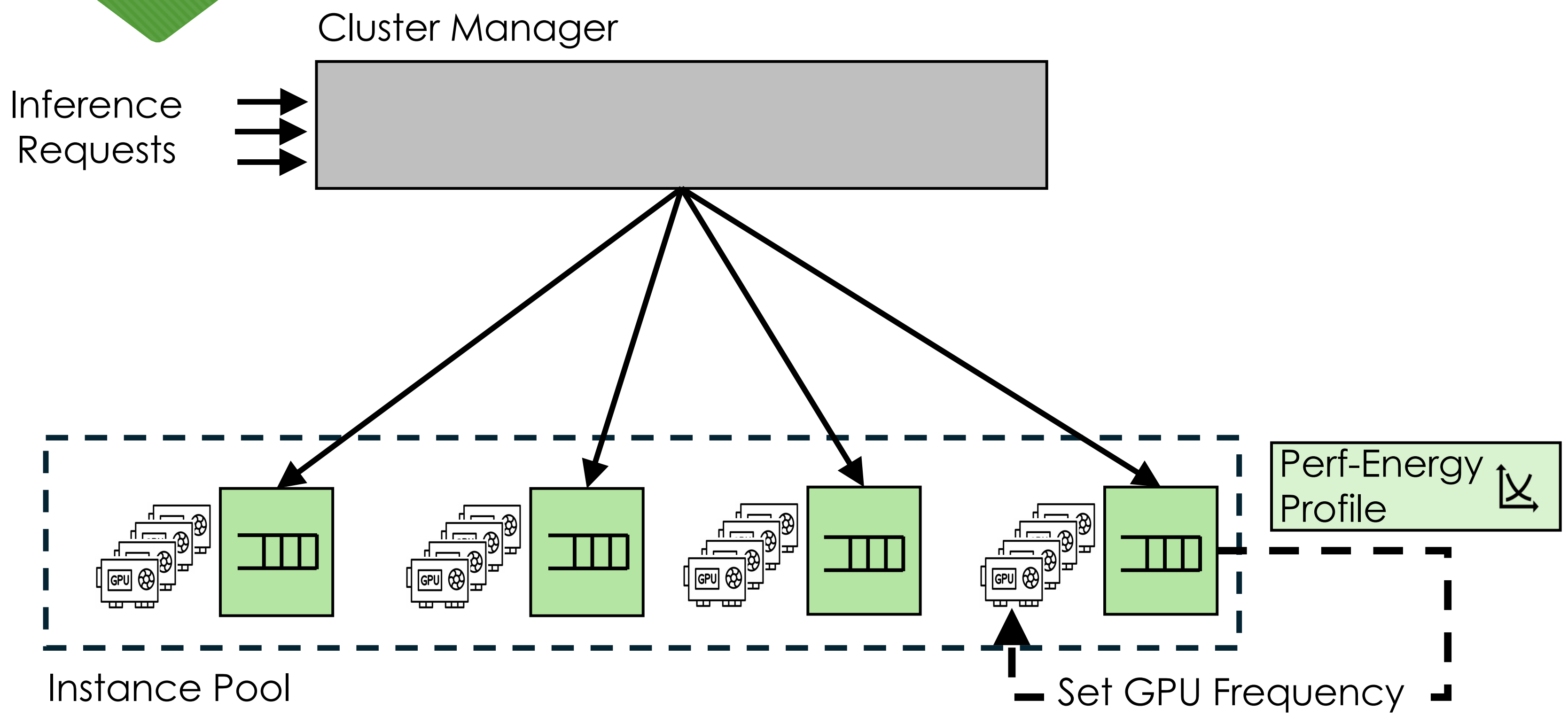
DynamoLLM: Energy-Management Framework for LLM Inference Clusters

- DynamoLLM
  i. Profile-driven energy configuration setting
  ii. Instance pools for diverse workloads
  iii. Hierarchical control for dynamic load

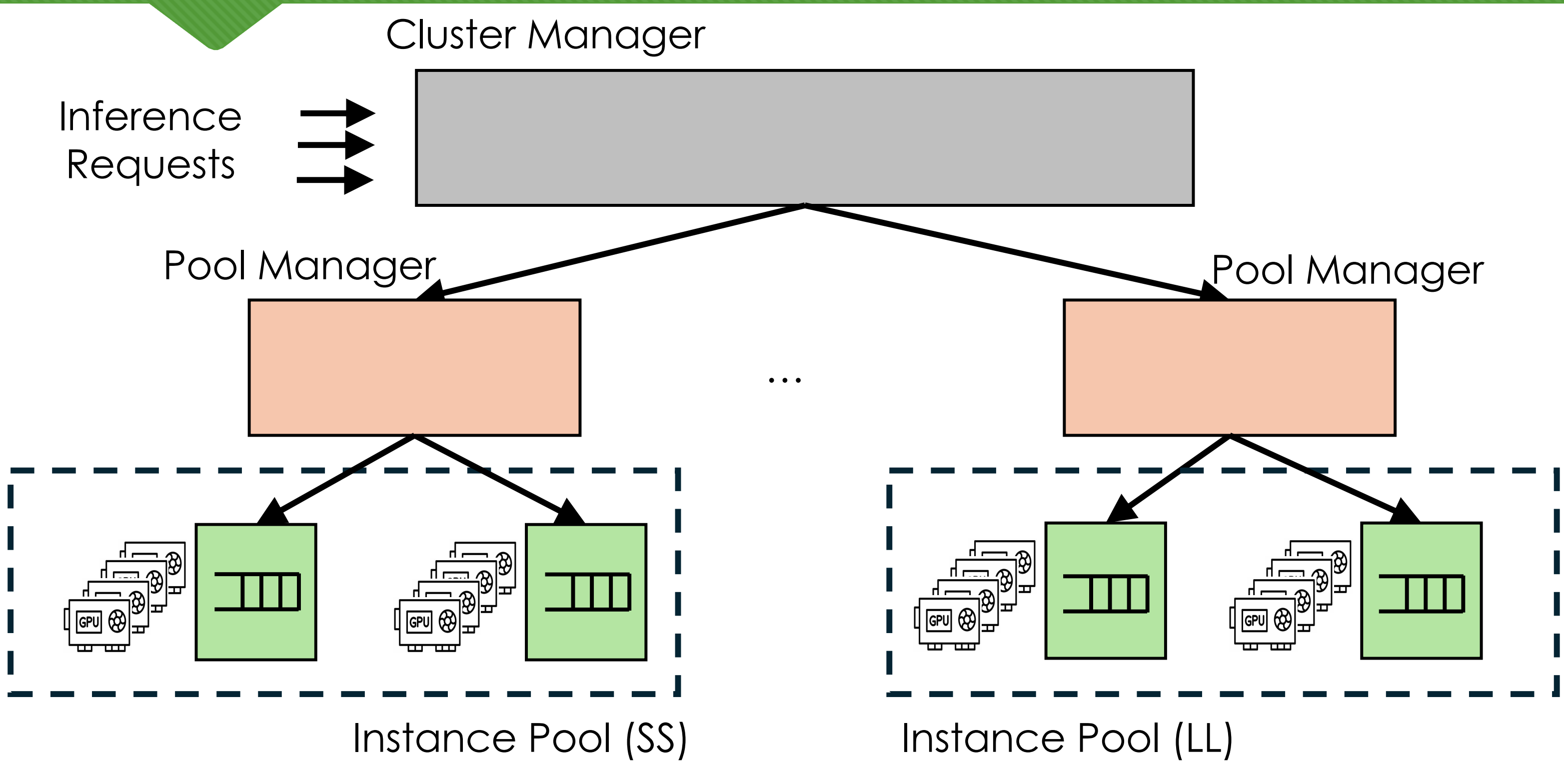
DynamoLLM: Energy-Management Framework for LLM Inference Clusters



DynamoLLM:
1. Profile-Driven Energy Configuration Setting



DynamoLLM:
2. Instance Pools for Diverse Workload



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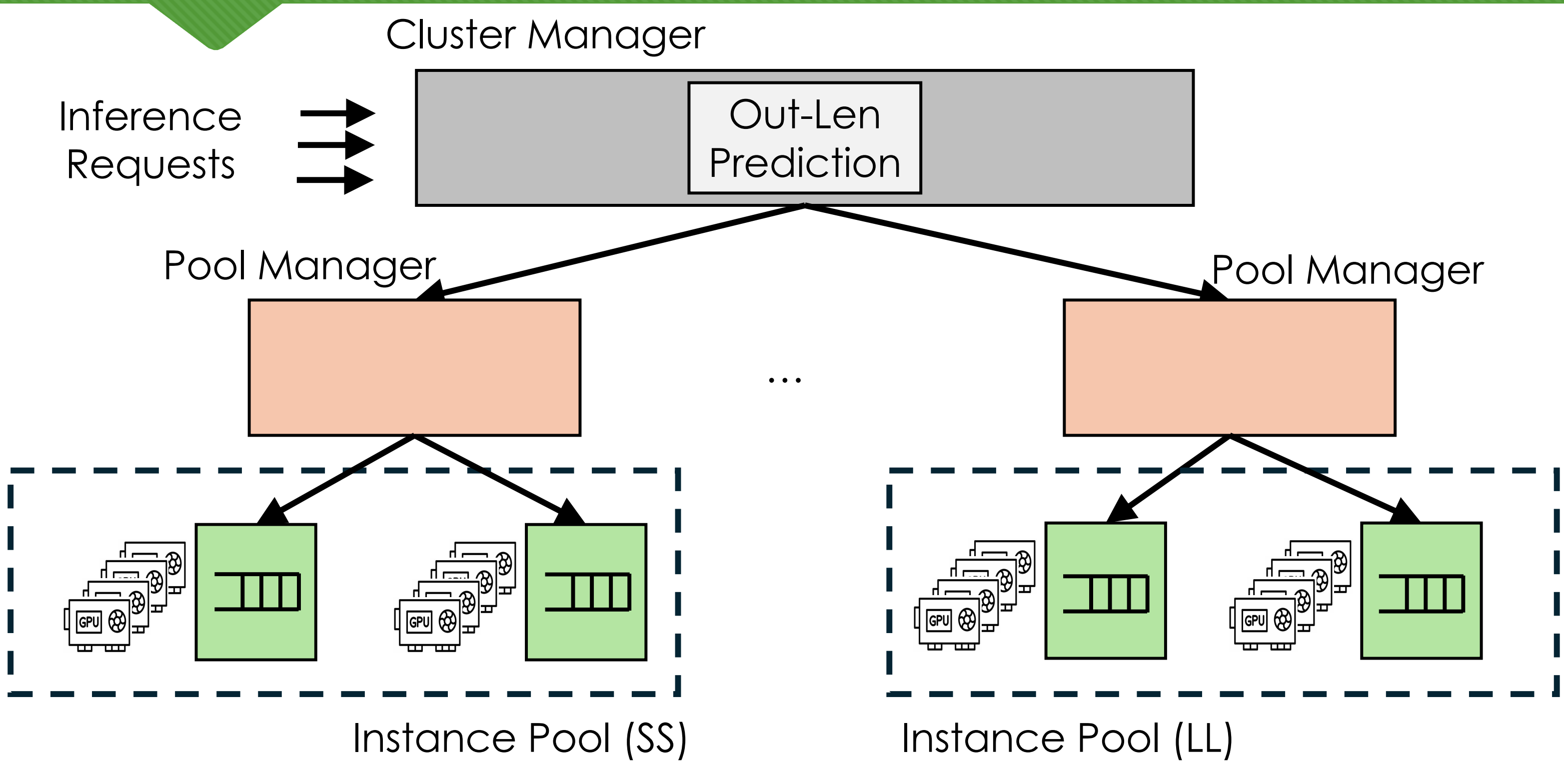

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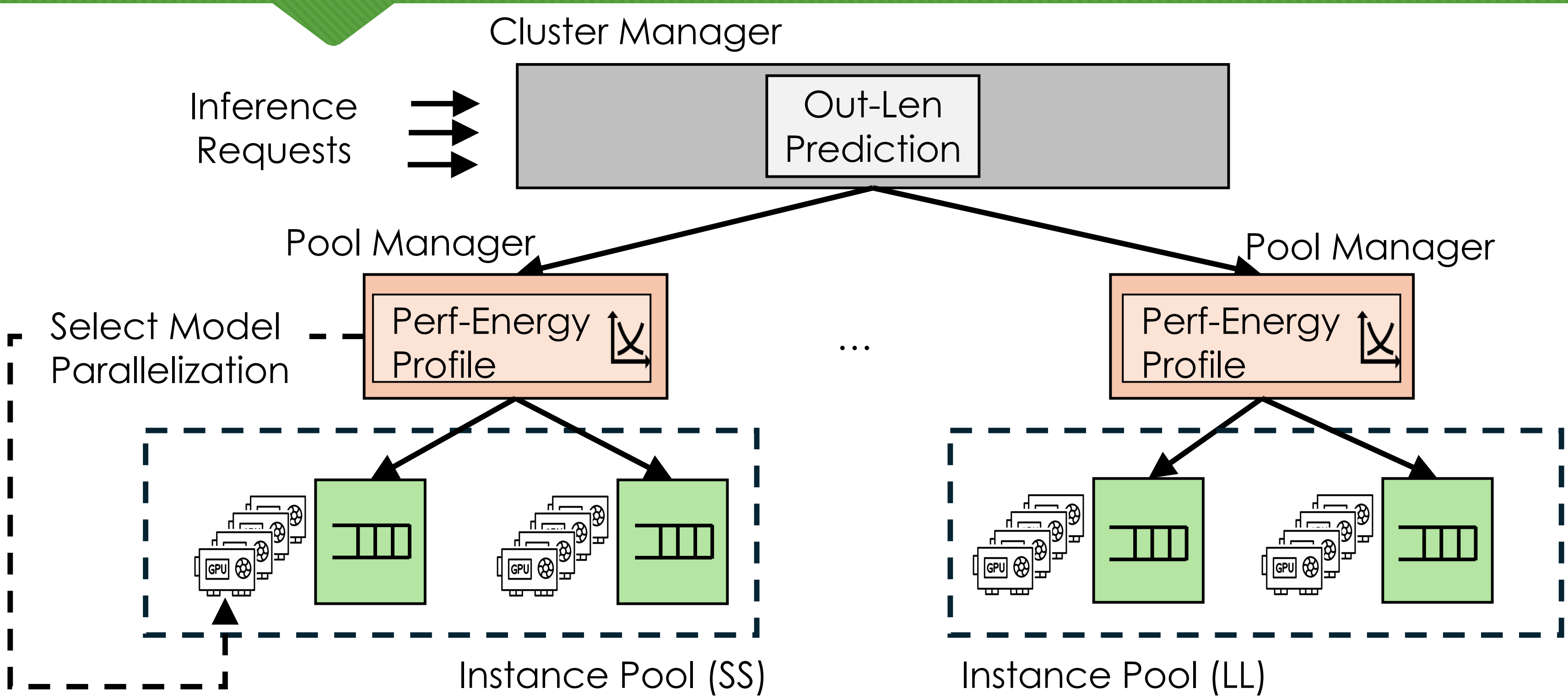
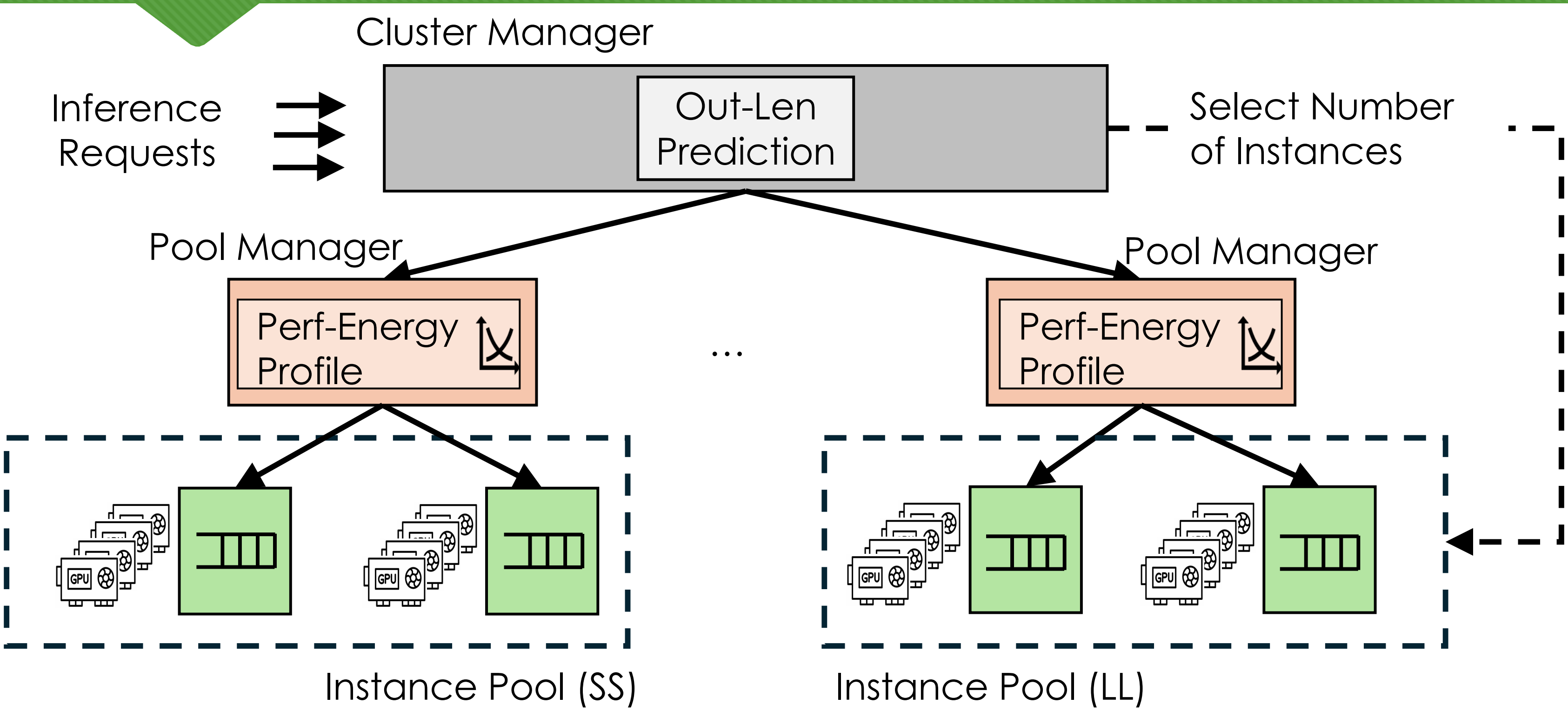


DynamoLLM:
3. Hierarchical Control for Dynamic Load



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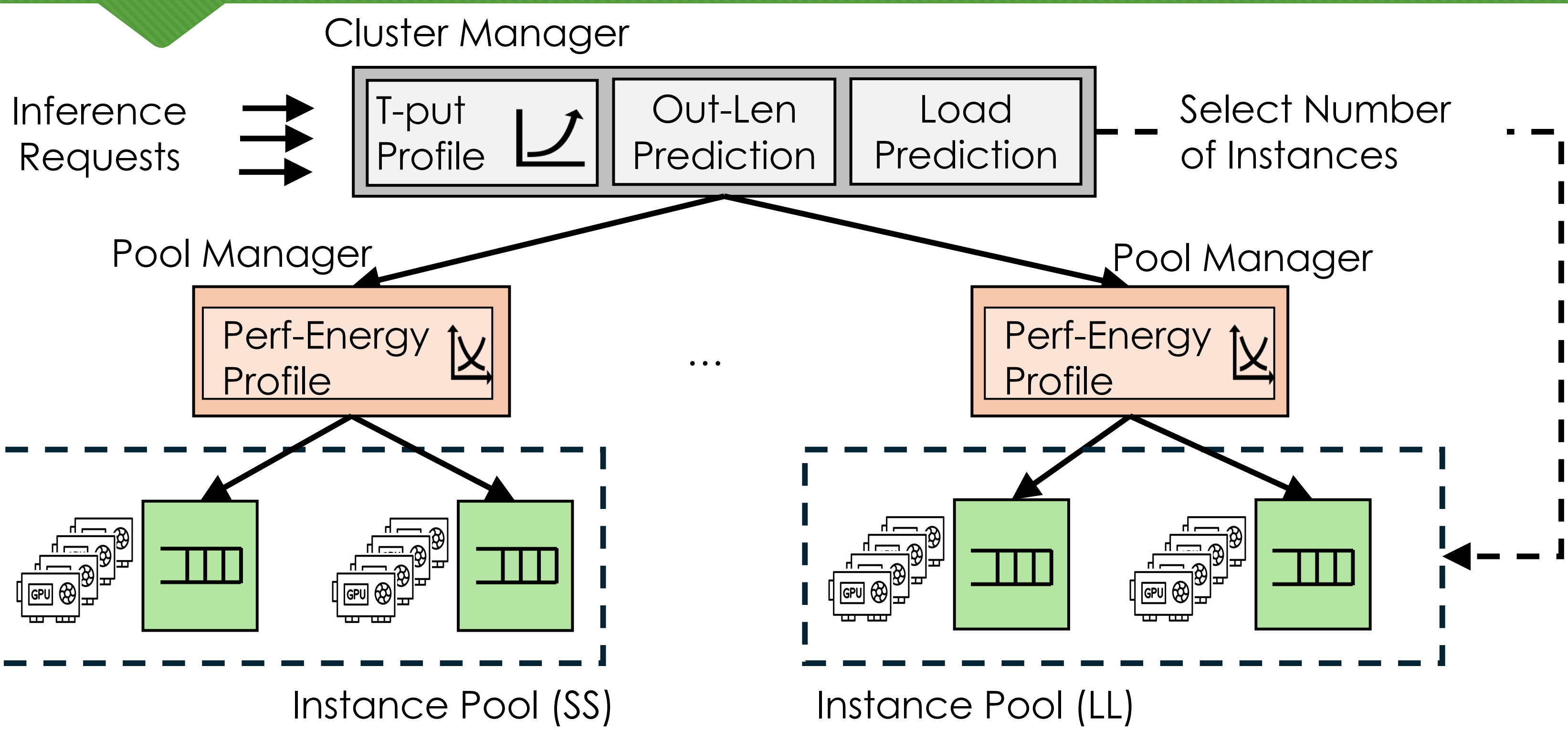


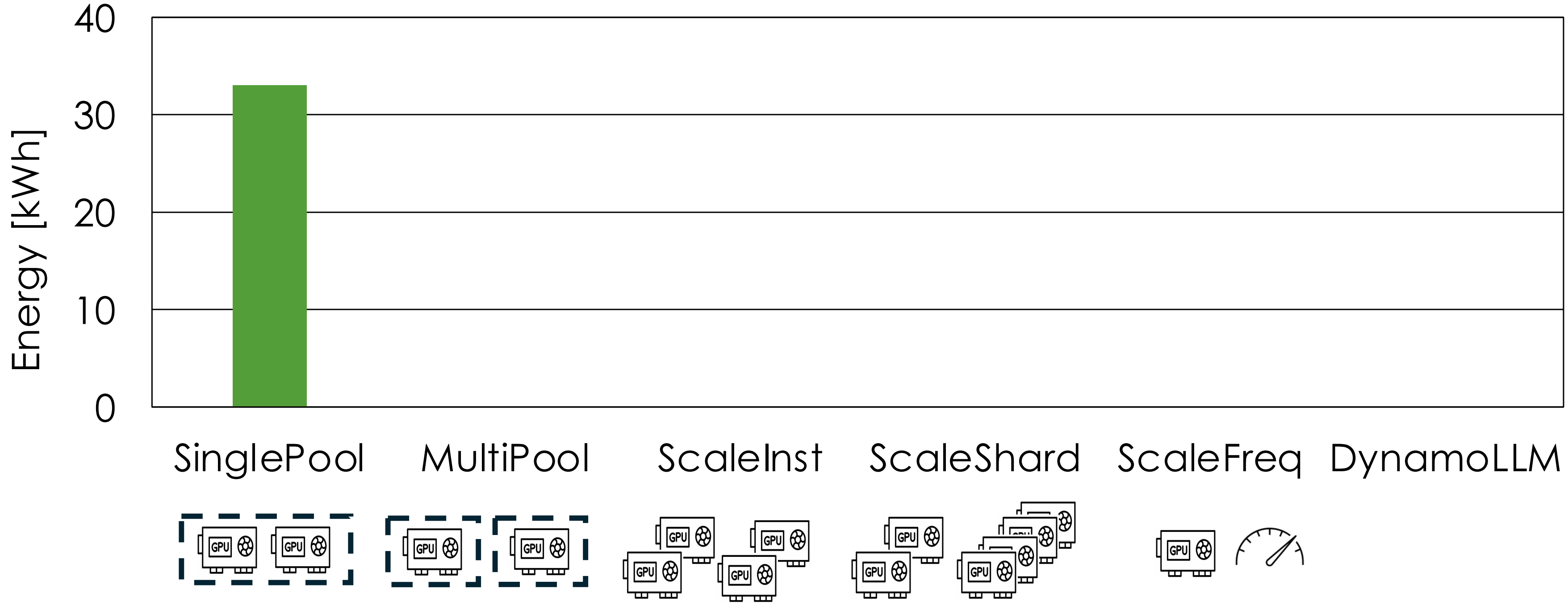
More in the paper

- MILP formulation for optimal energy-efficiency
- Techniques to reduce re-configuration overheads
  - Proactive VM creation
  - Graph-matching algorithm for re-sharding

DynamoLLM Evaluation

- A peak hour (open-source) production traces from Azure
  - 12 x 8 H100 VMs for Baseline
- 1-week production traces from Azure
  - Simulate 40 x 8 H100 VMs for Baseline
- Llama2-70B model

DynamoLLM significantly reduces energy!



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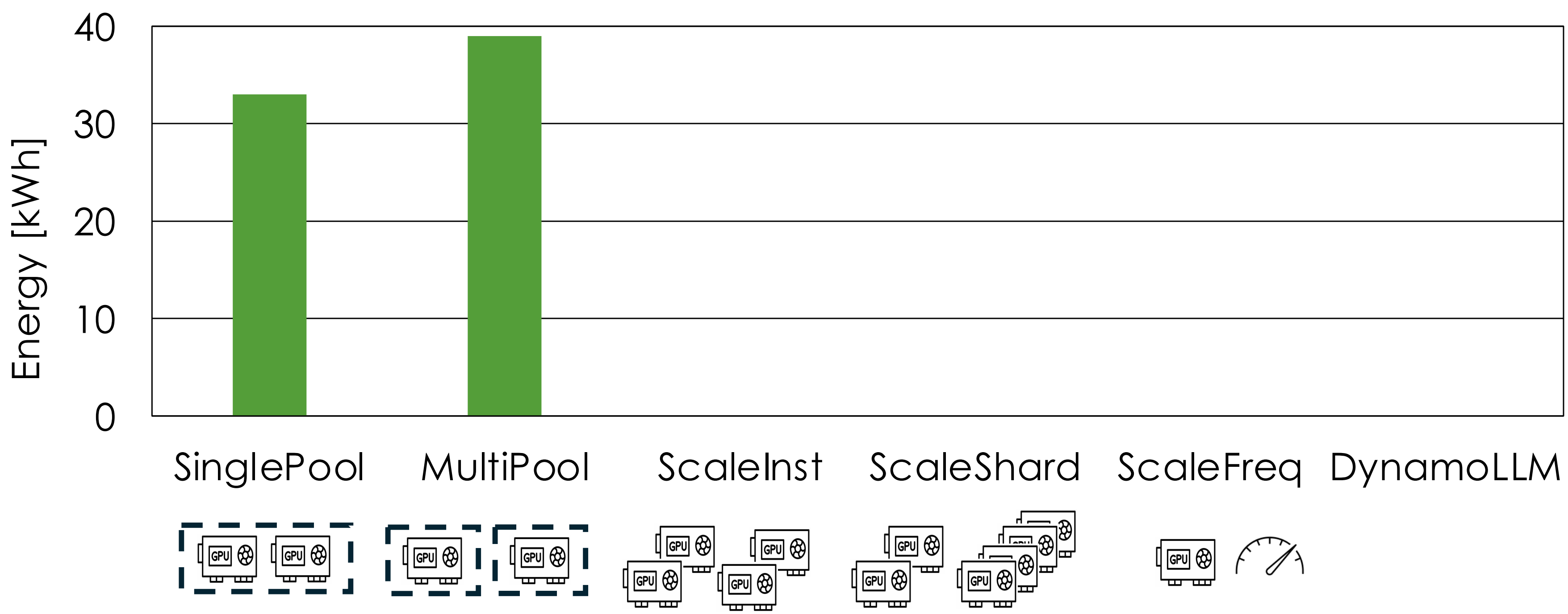

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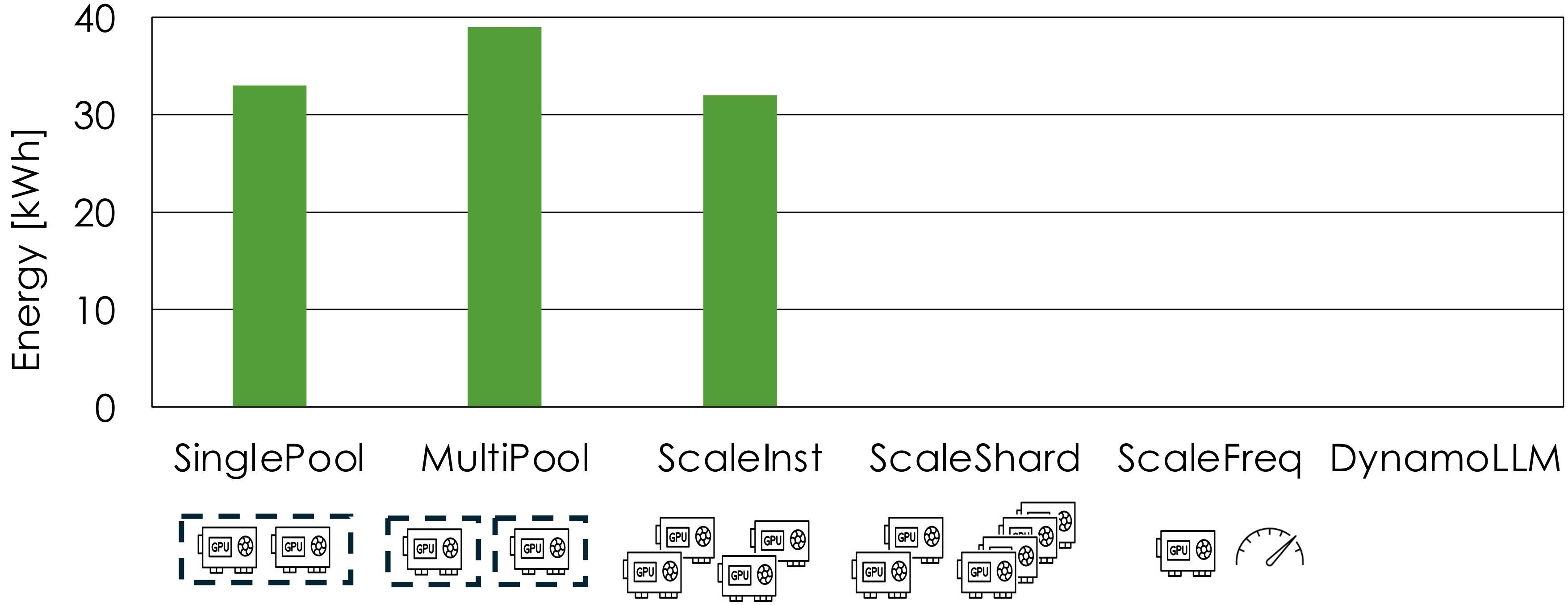

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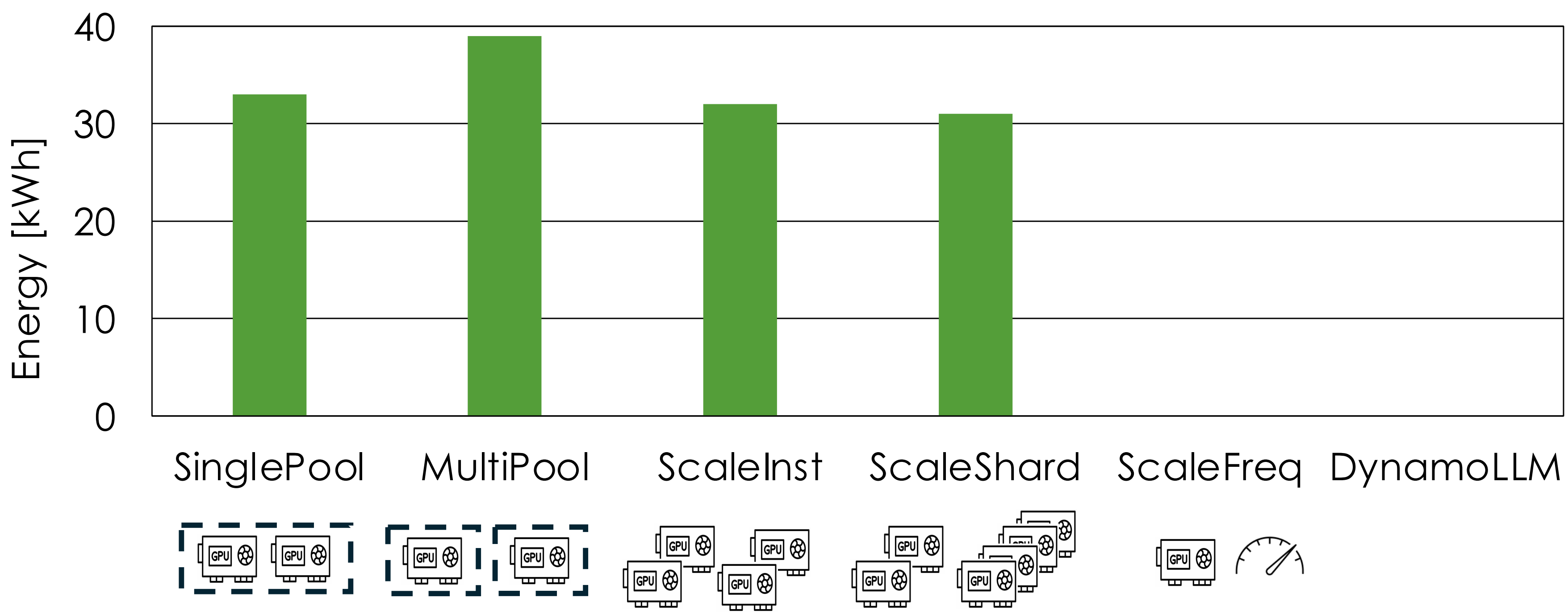

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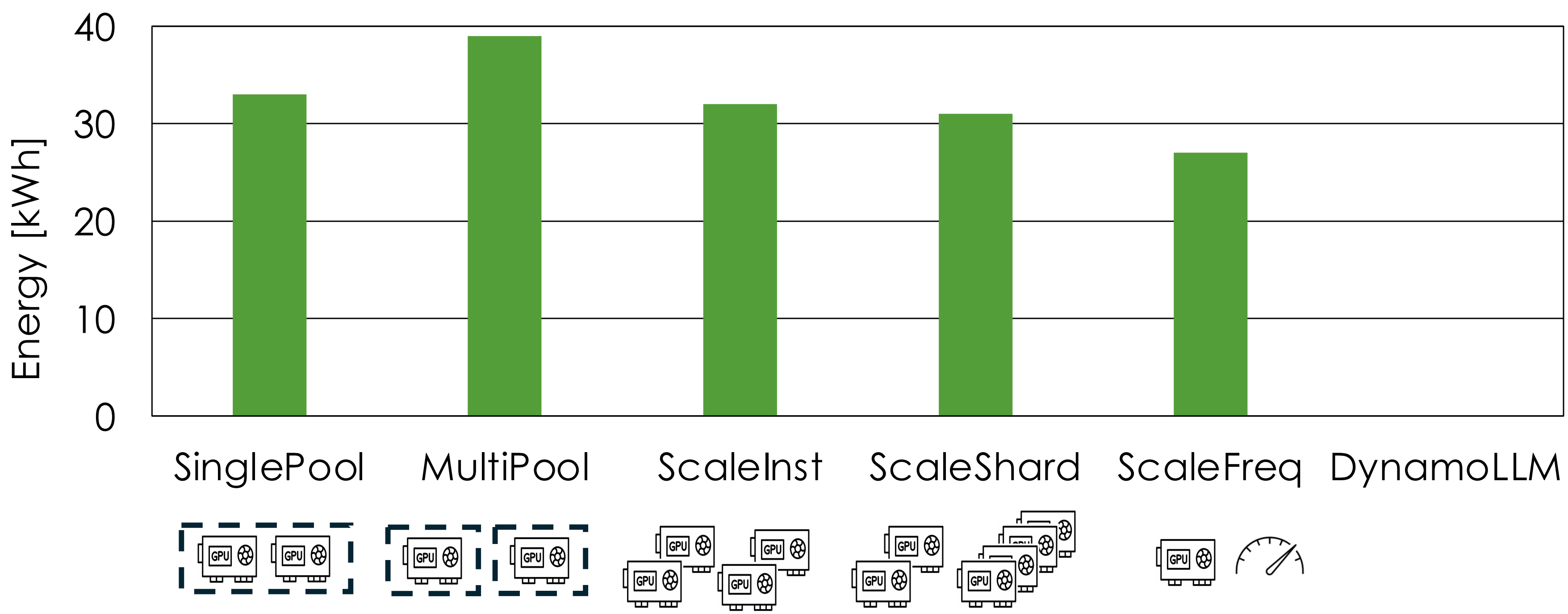

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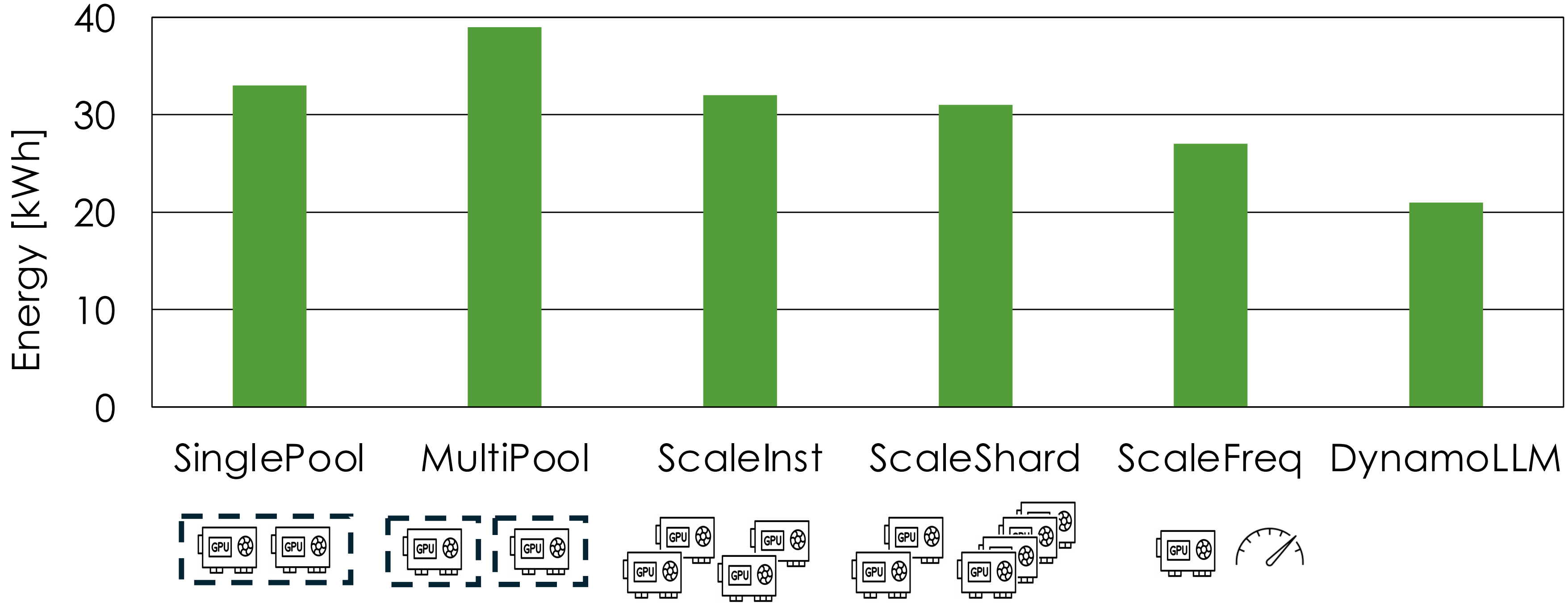

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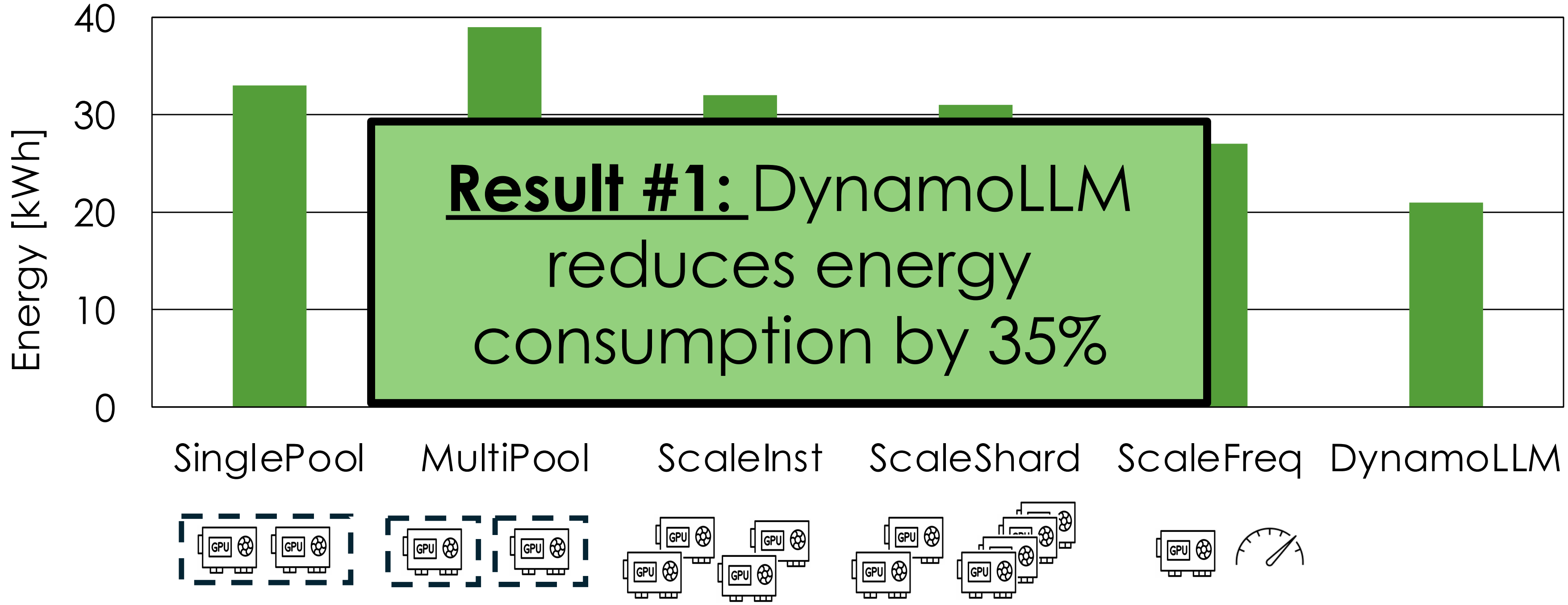
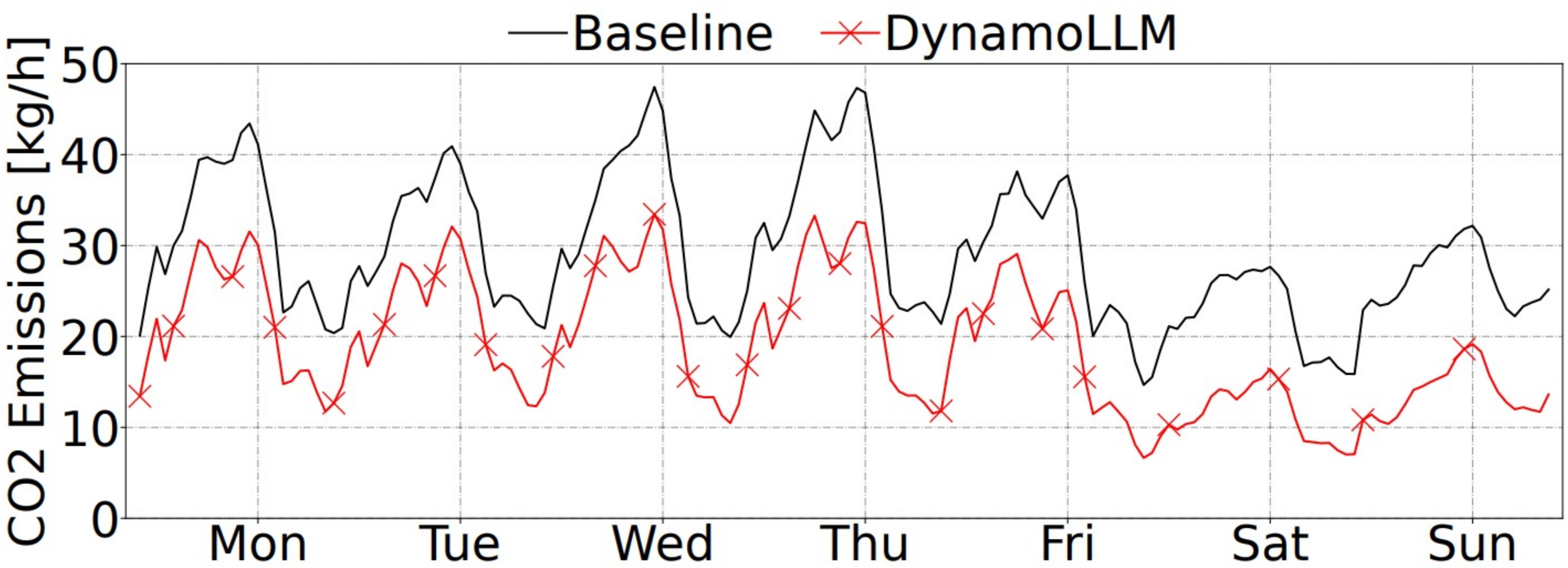


DynamoLLM significantly reduces carbon!



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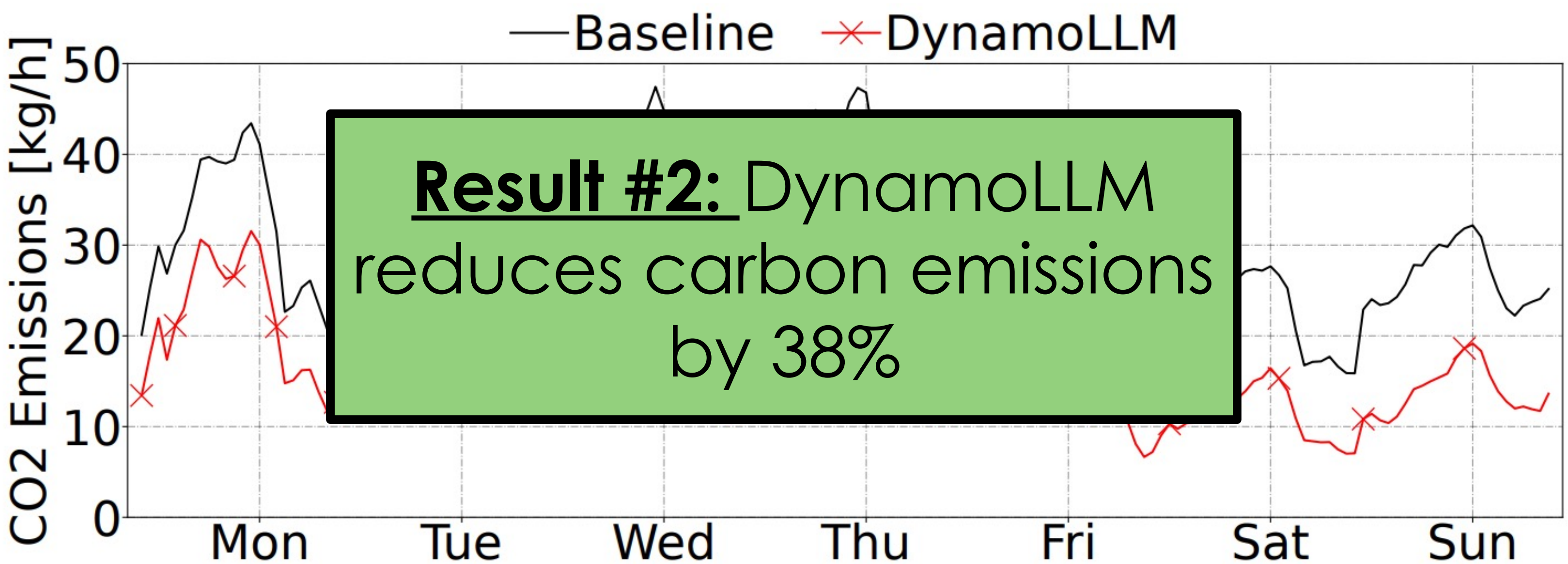

<u>Result #2:</u> DynamoLLM reduces carbon emissions by 38%

Conclusion

- LLM inference emerging workload in the cloud
  - Its execution energy inefficient
- Need to address these challenges for cost-effective and environmentally-conscious datacenters
- ***DynamoLLM*** as the first step towards our goal!

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Open-source production traces

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Backup Slides

DynamoLLM – Energy Evaluation

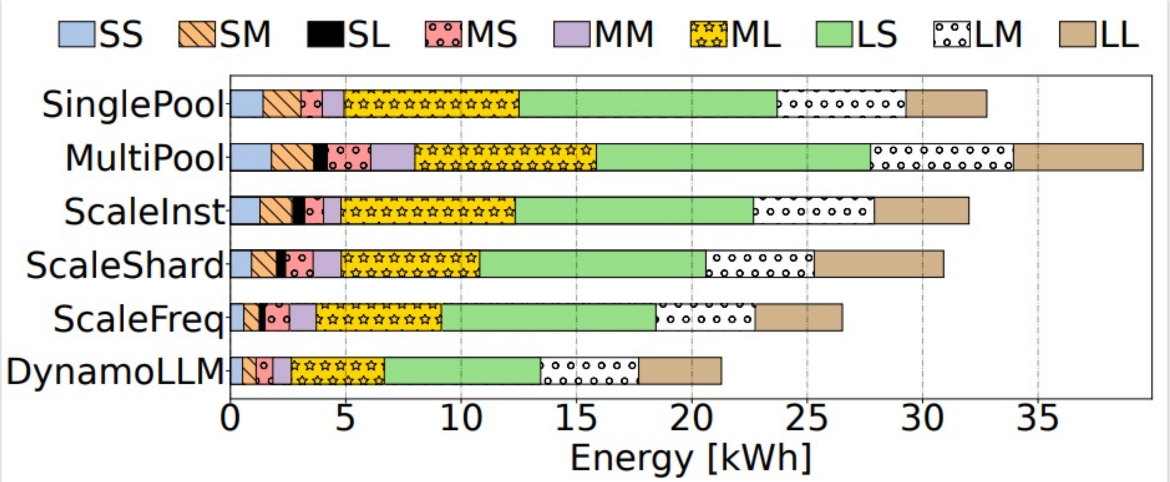

Fig. 6: Energy consumption with the six evaluated systems.

DynamoLLM – Latency Evaluation

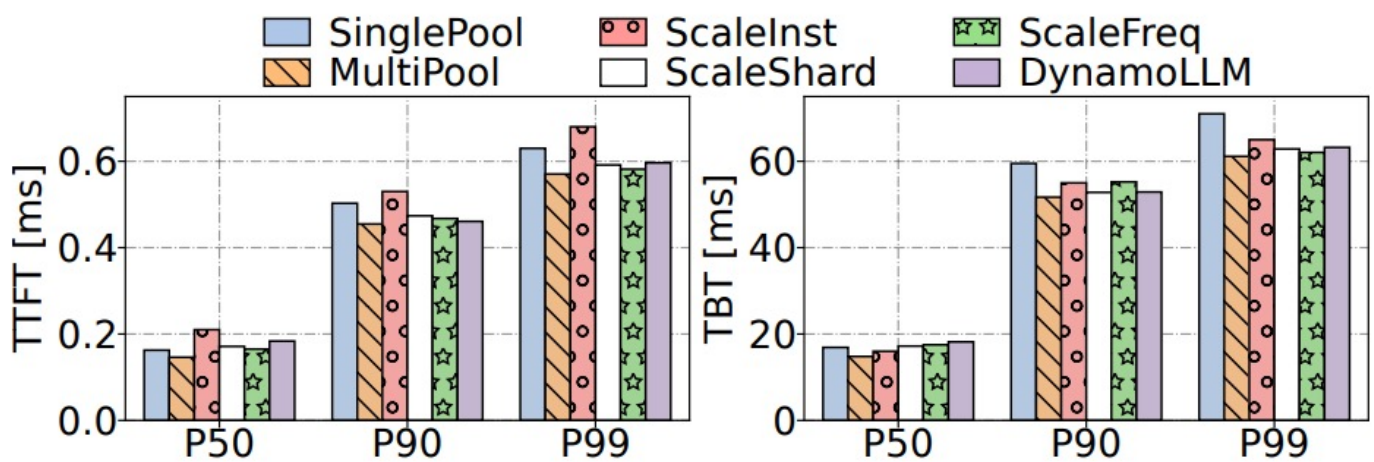

Fig. 7: Summary of the latencies for each of the systems.

Dynamo LLM – Power Evaluation

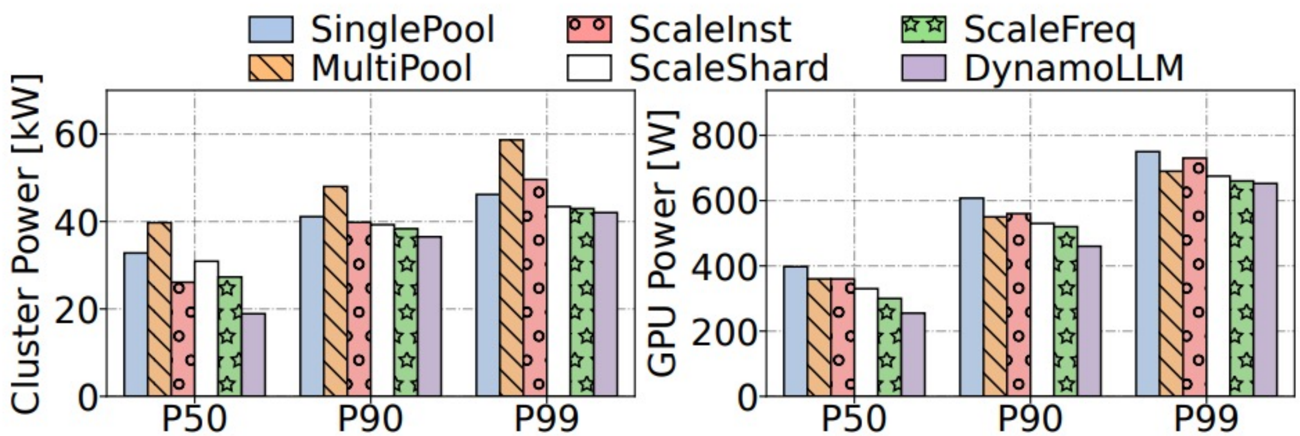

Fig. 8: Summary of the power for each of the systems.

DynamoLLM – Frequency Evaluation

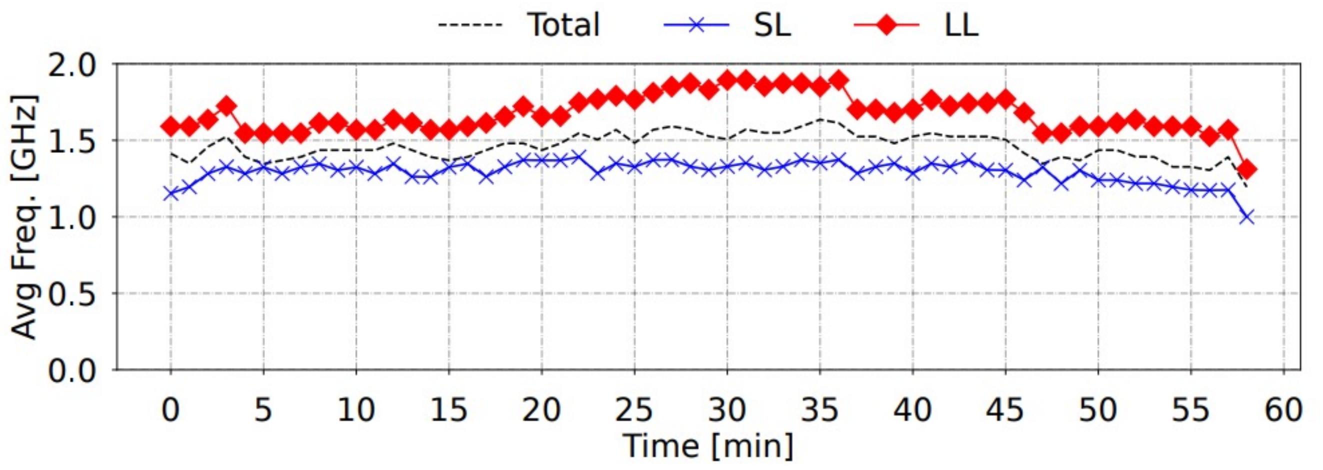

Fig. 9: GPU Frequency over one hour for DynamoLLM.

DynamoLLM – Sharding Evaluation

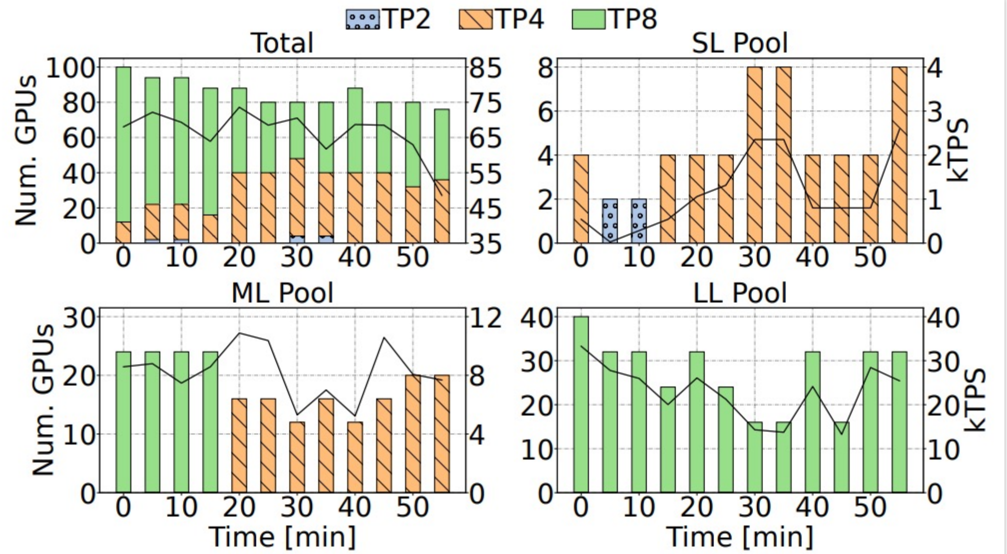

Fig. 10: Number of GPUs assigned to different pools for each sharding configuration (TP2, TP4 or TP8) over time.

DynamoLLM – Sensitivity to Pool Count

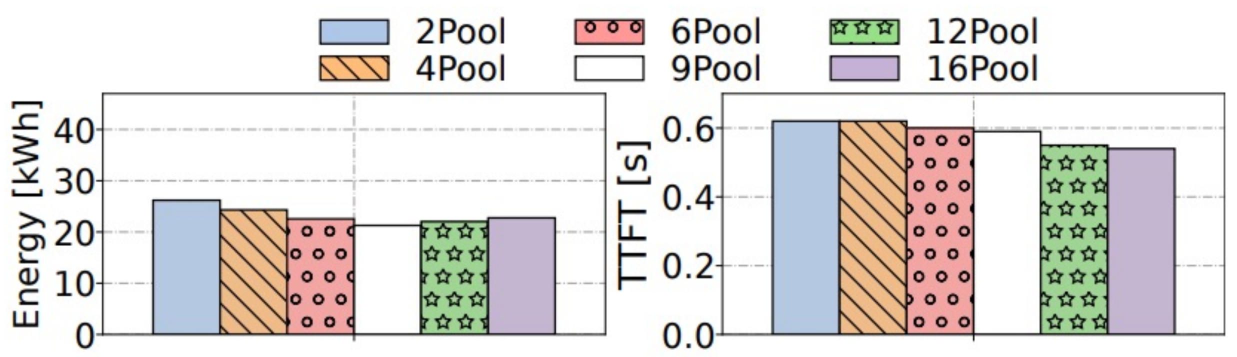

Fig. 13: Energy and performance with different number of pools (or request types).

DynamoLLM – Sensitivity to Accuracy

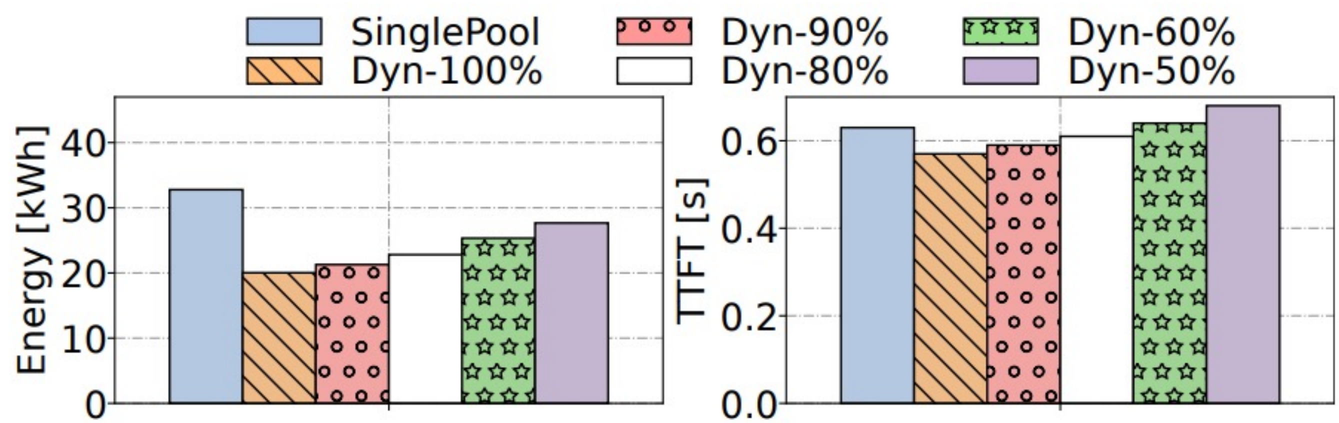

Fig. 11: Energy and performance with different accuracy.

DynamoLLM – Sensitivity to Load

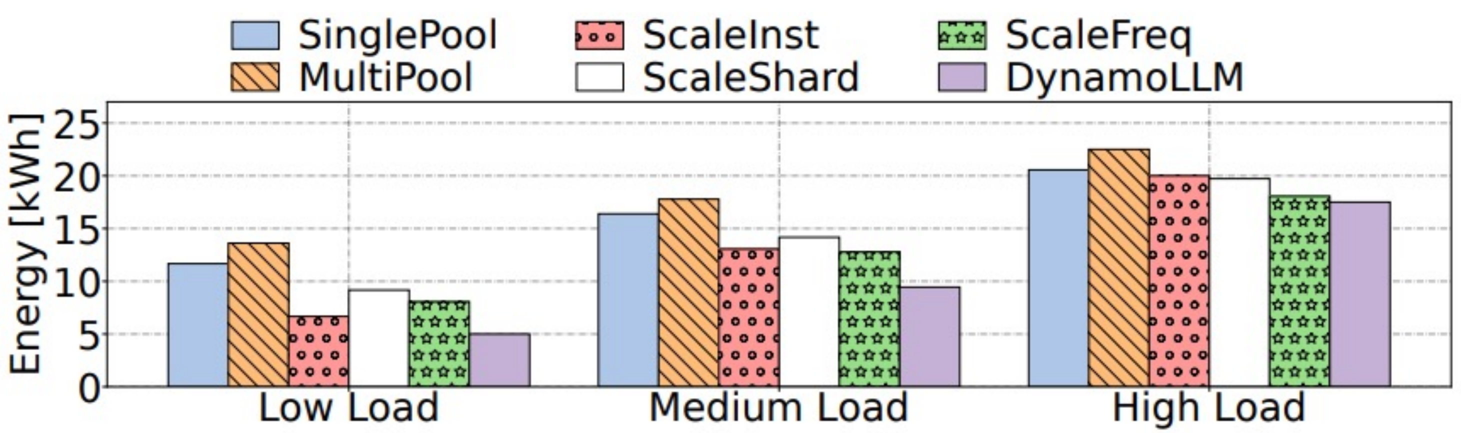

Fig. 12: Energy comparison with different levels of load.