PennState

Fifer: Tackling Resource Underutilization in the Serverless Era

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Mahmut Kandemir, Chita Das

ACM/IFIP Middleware'21
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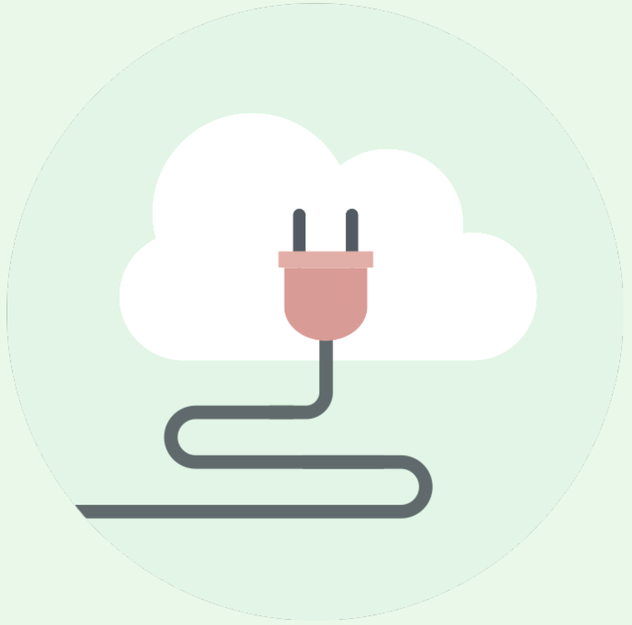
PennState
College of Engineering

PennState
High Performance
Computing Lab

Executive Summary

Tenants

Providers



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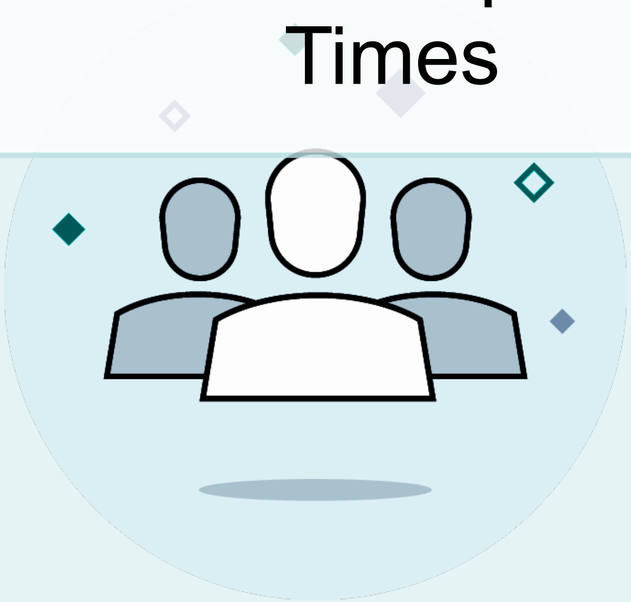
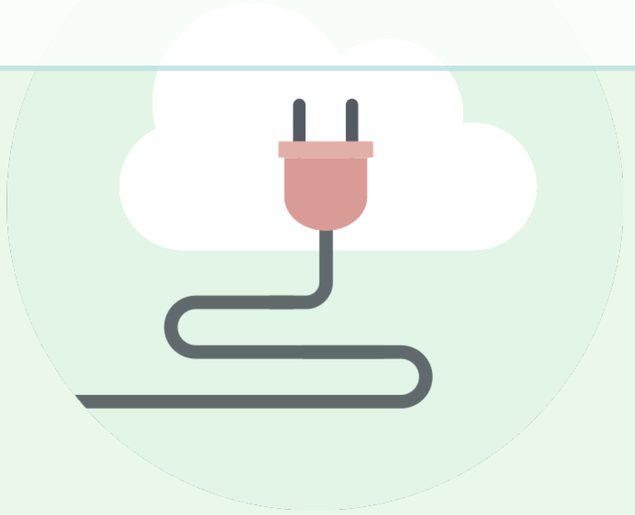
Faster Response Times



Providers

Serverless Functions



EXECUTIVE SUMMARY

TENANTS		PROVIDERS
Faster Response Times	→	Serverless Functions
SLO violations Cold-starts	↔	Over Provisioning & Underutilization

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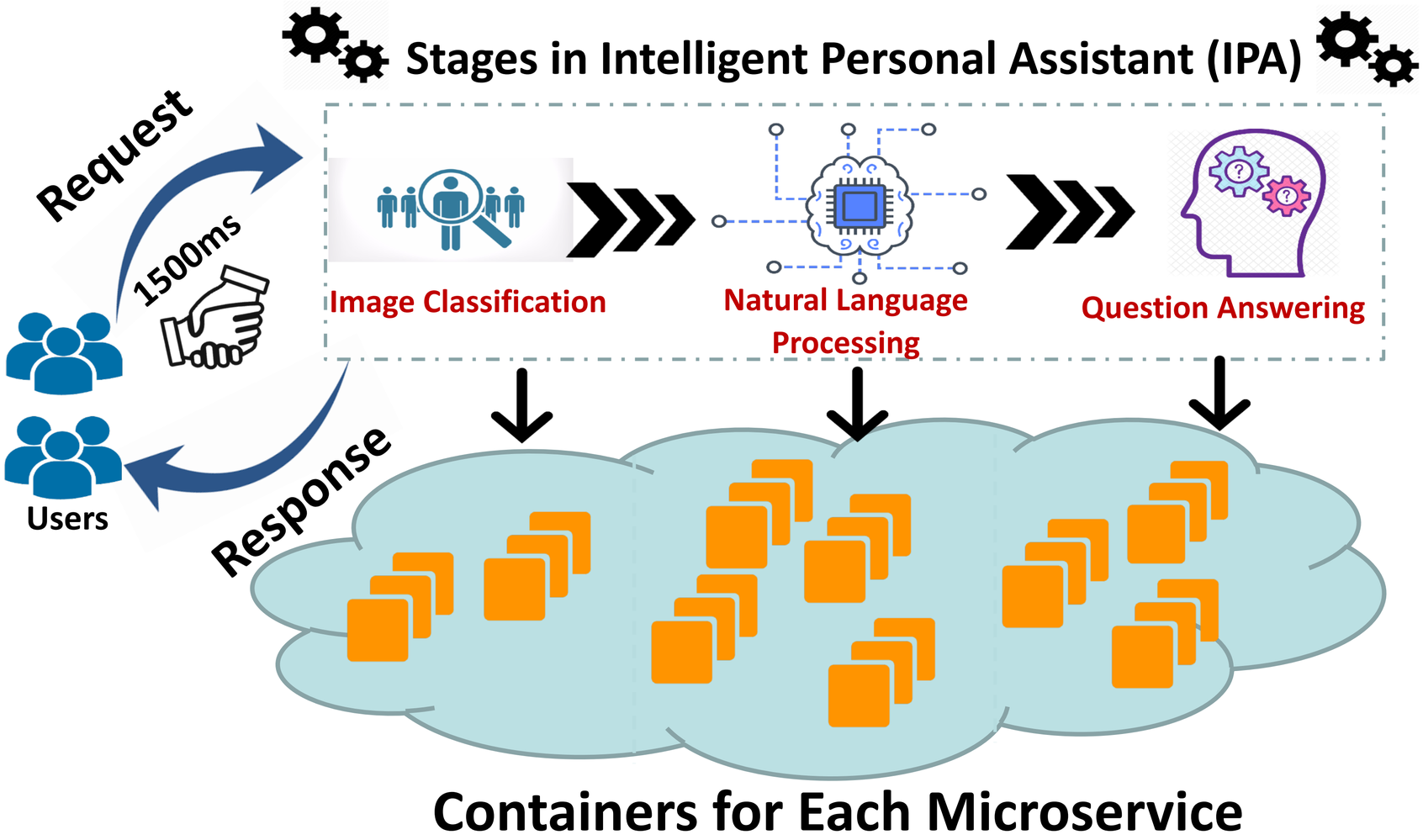
Faster Response Times	→	Serverless Functions
SLO violations Cold-starts	↔	Over Provisioning & Underutilization
Guarantee SLOs	↔	Leverage Application Info Fully Utilize

Serverless Function Chains



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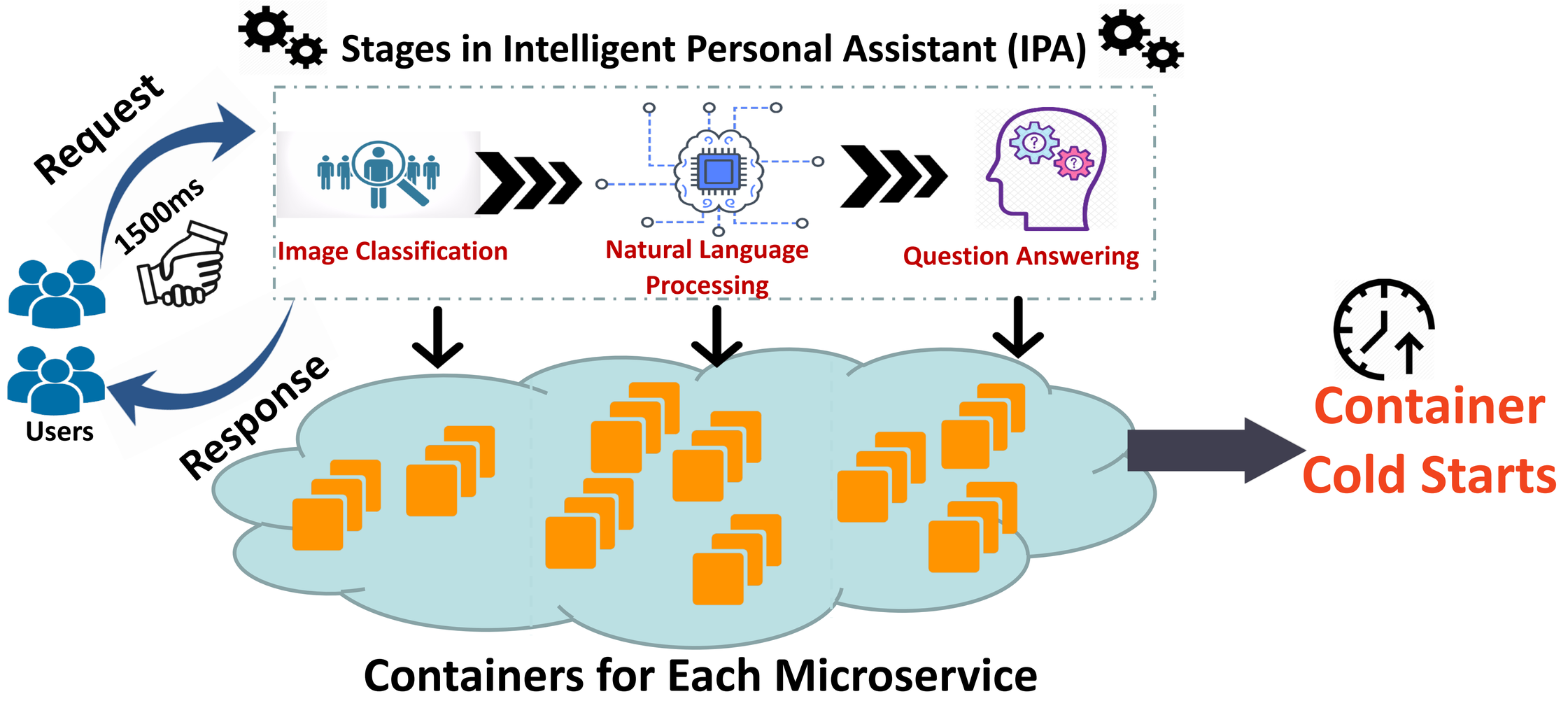

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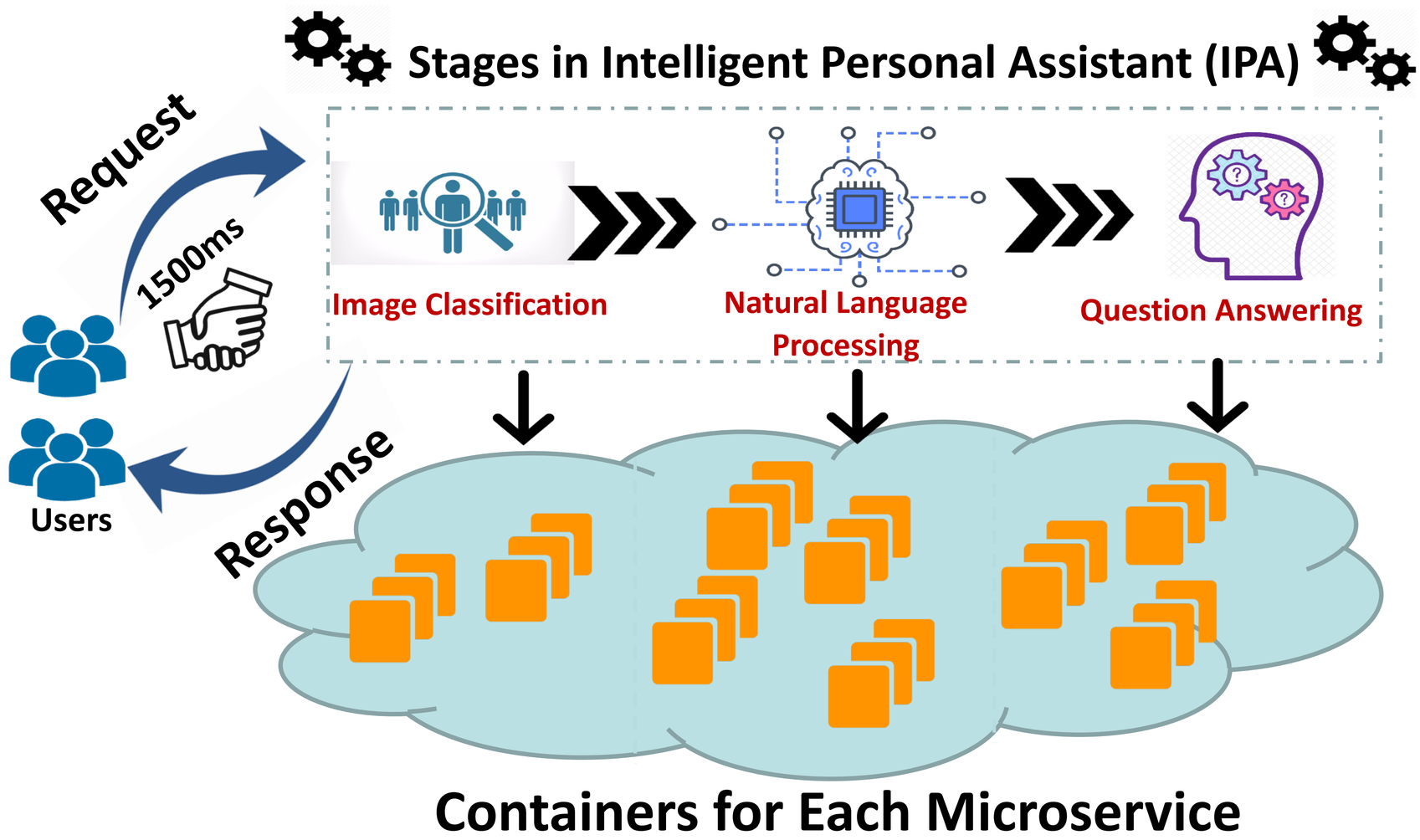
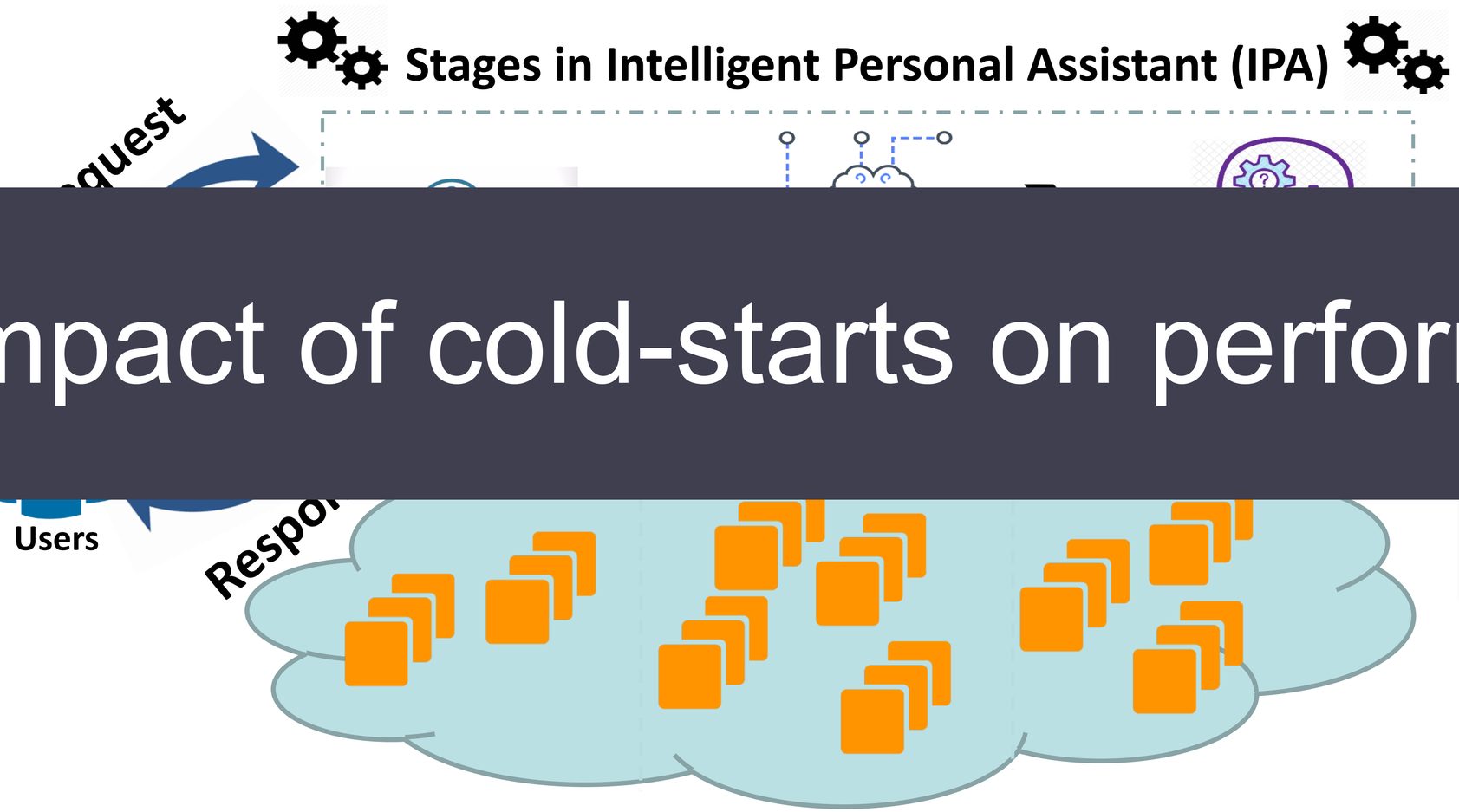


Container Cold Starts

- Container creation
- Model fetch time

Serverless Function Chains



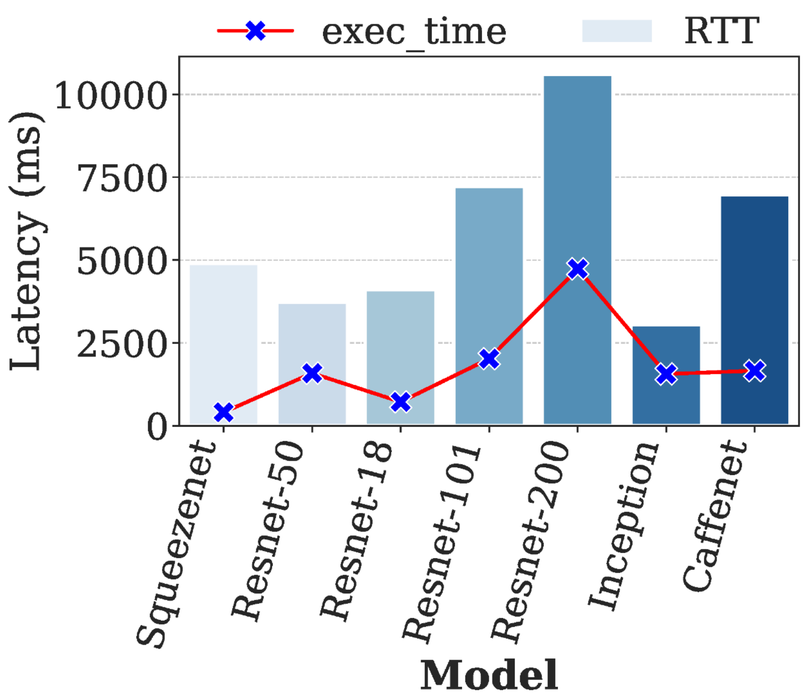
Container

- Model fetch time

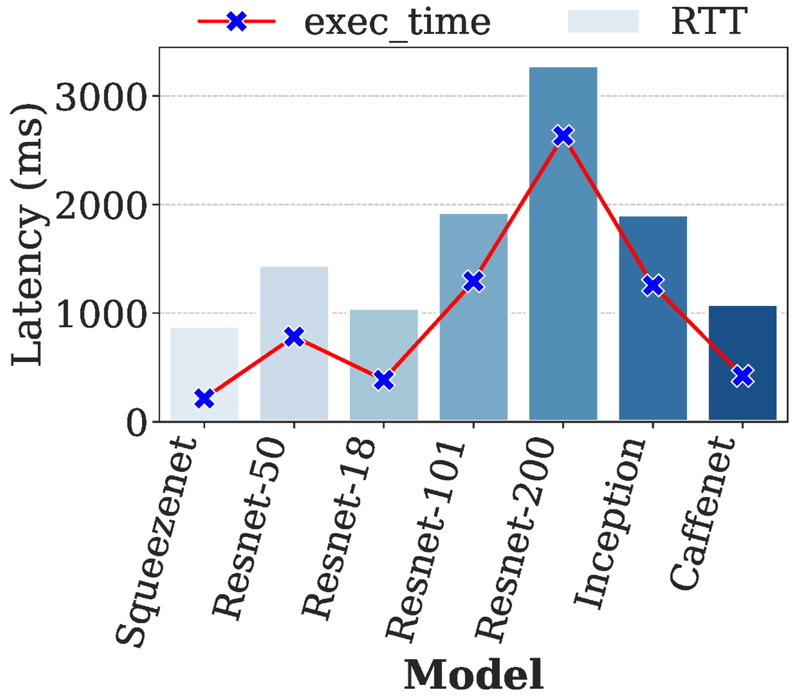
Impact of cold-starts on performance?

Why Cold Starts are bad?

Cold Start (First invocation)



Warm Start (Concurrent Invocations)



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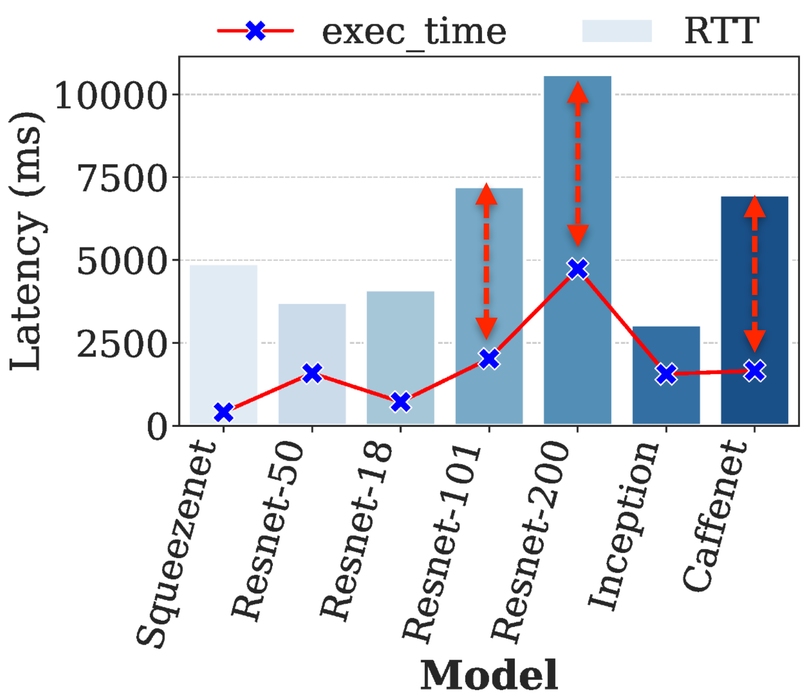

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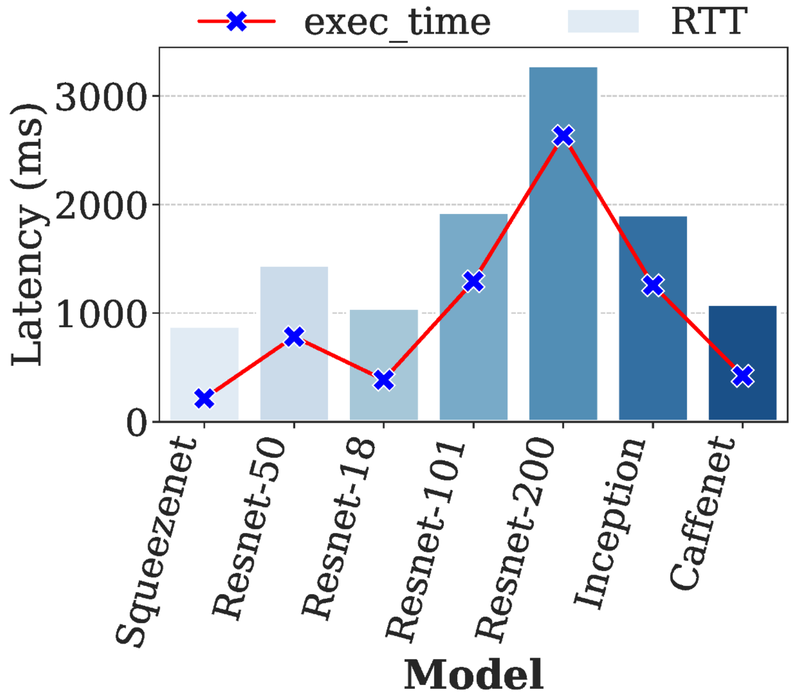

Cold starts contribute ~2000 to 7500 ms on top of execution time

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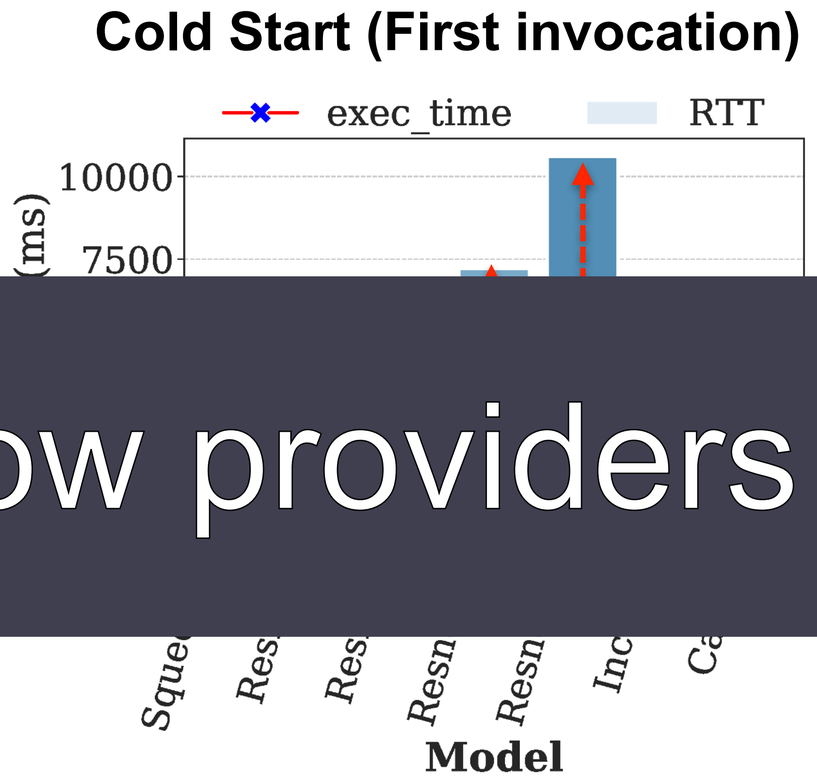

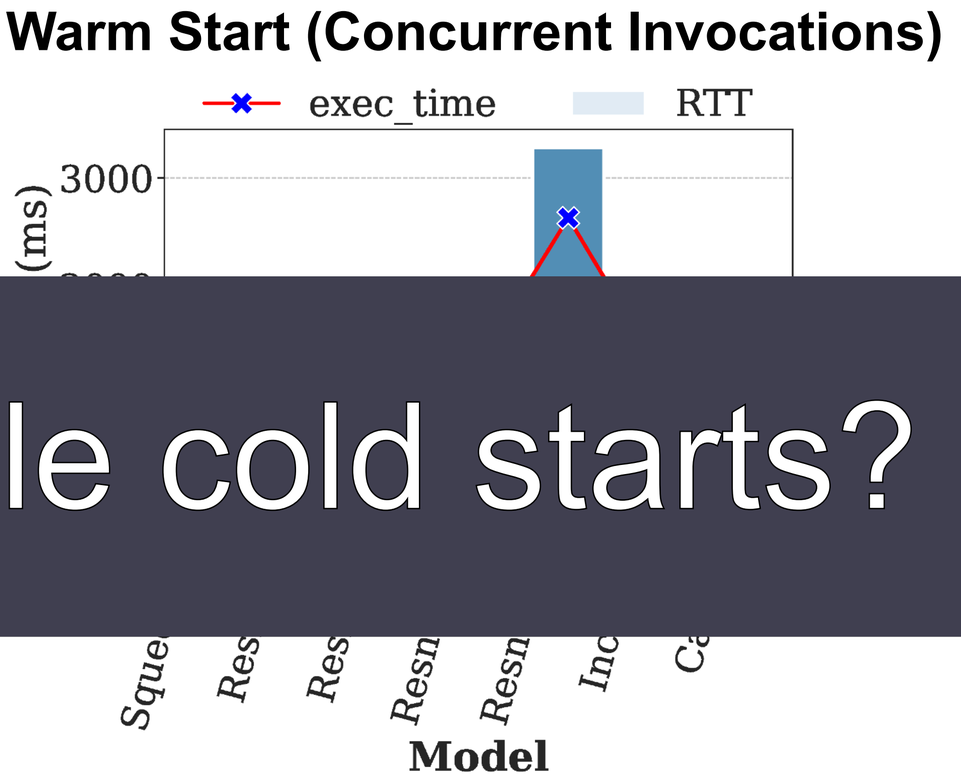

How providers handle cold starts?

Cold starts contribute ~2000 to 7500 ms on top of execution time

Current Serverless Platforms

Wang et al, Peeking behind the curtains of Serverless Platforms in ATC'18

Current Serverless Platforms

- Spawn new containers if existing containers are busy.
  - ➡ Leads to SLO violations due to cold-starts.
  - ➡ Many idle containers. Wasted power and energy.

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How can we do better?

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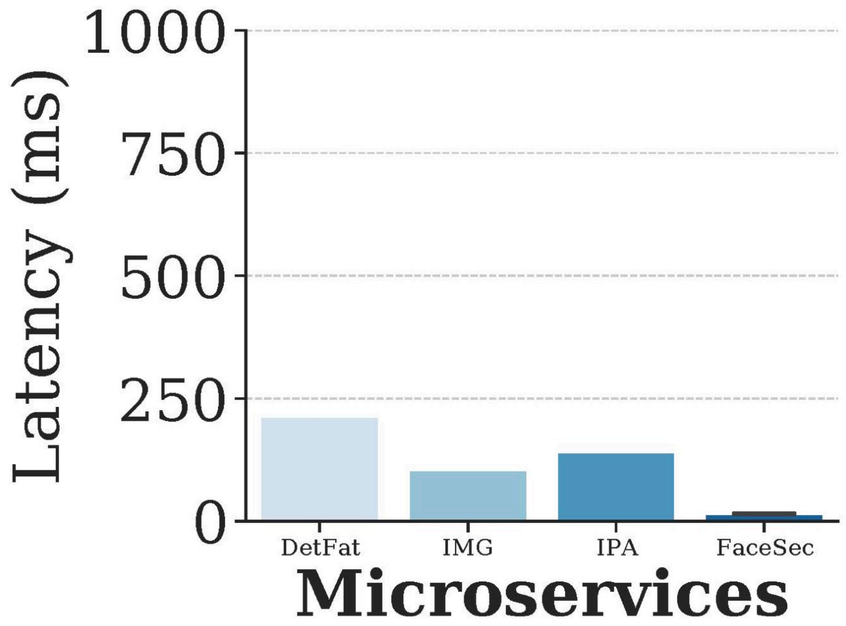
Application Characterization



Djinn and Tonic- DNN Inference Benchmark Suite-ISCA'15

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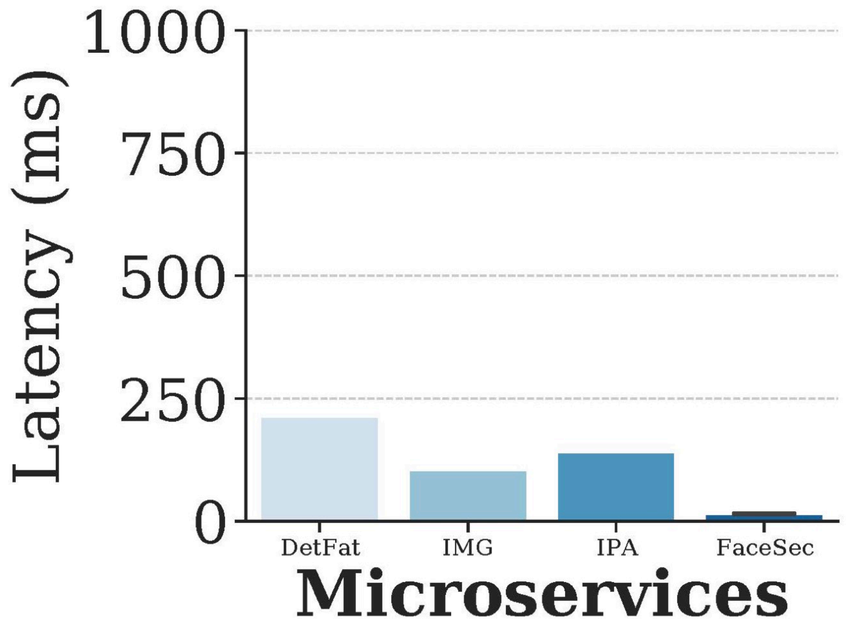

SLO's usually within 1.5s

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Swayam: Distributed Autoscaling to Meet SLAs of Machine Learning Inference Services, Middleware'17

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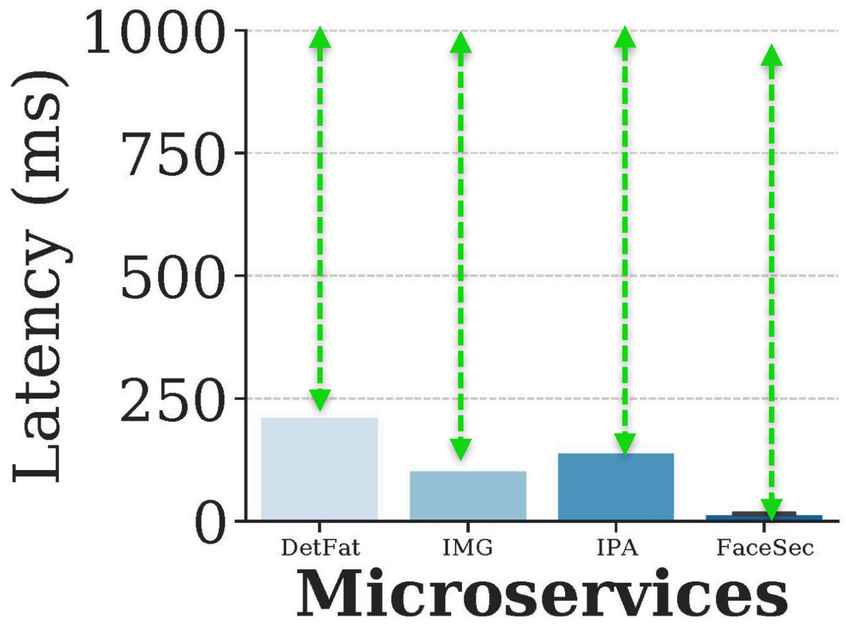

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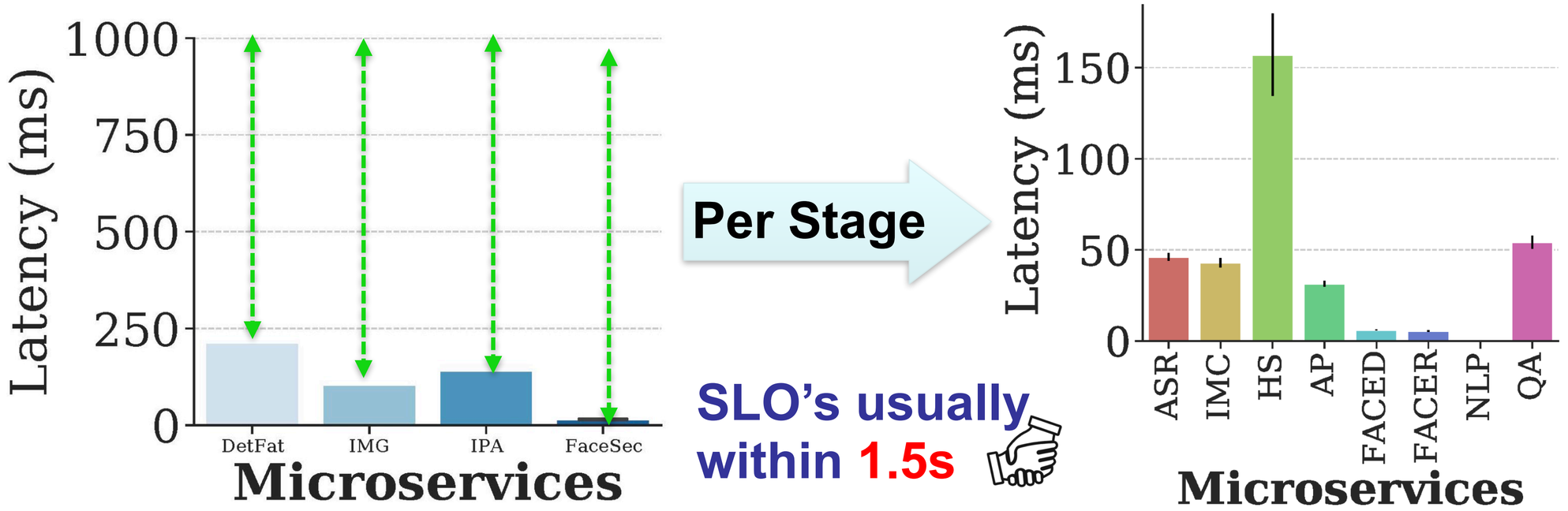

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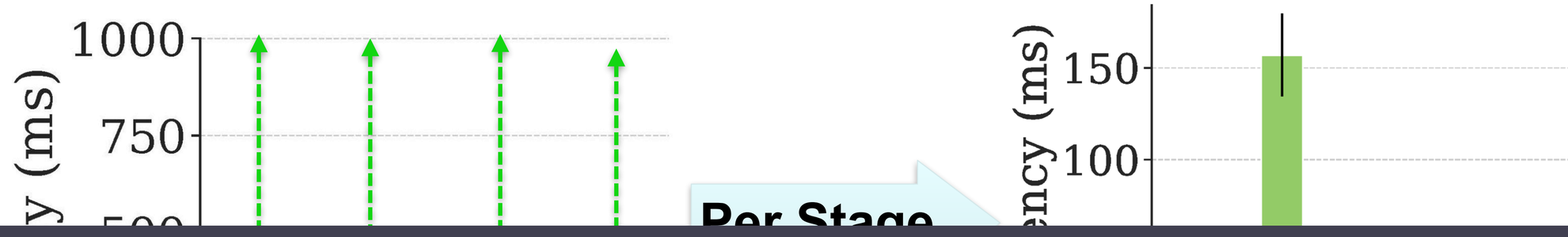

How to exploit the slack and execution time predictability?

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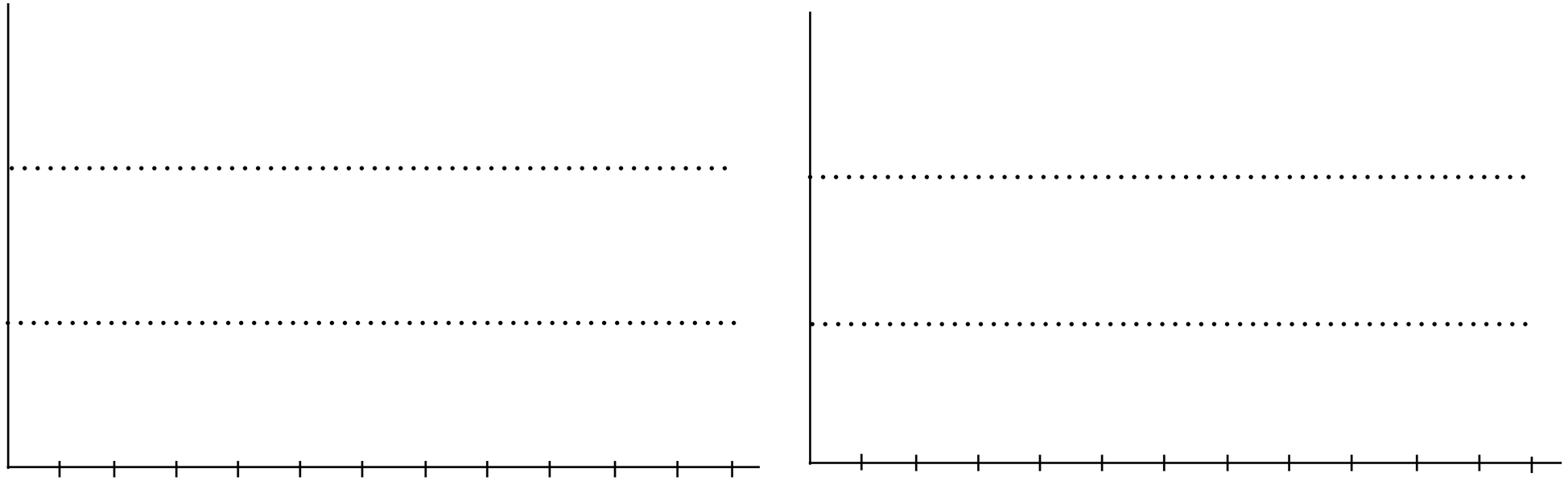
Slack aware queuing



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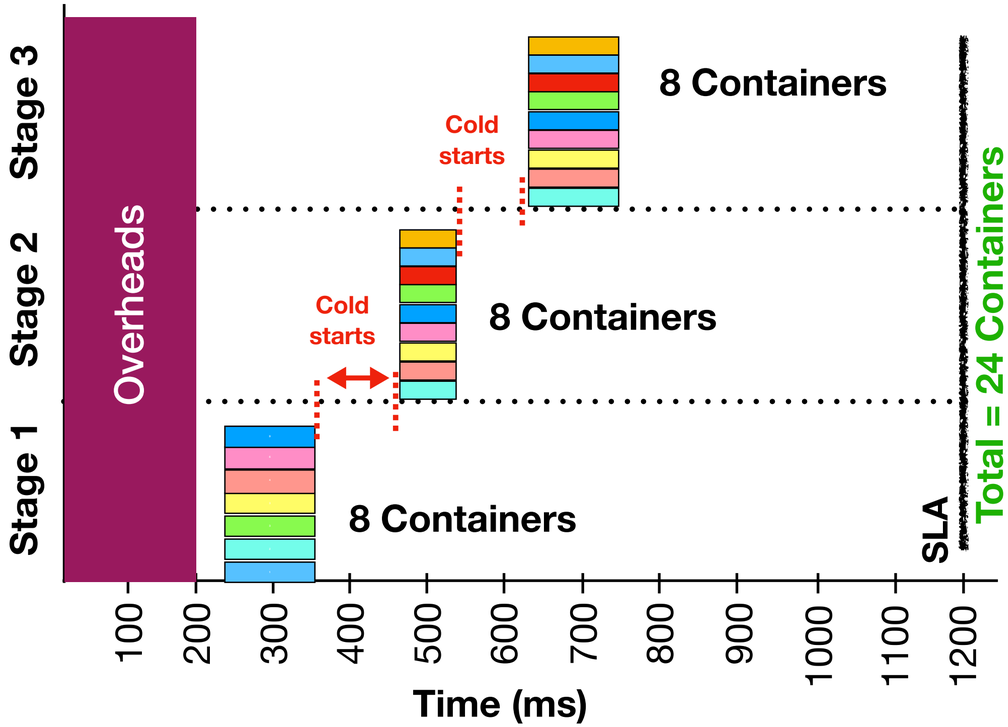
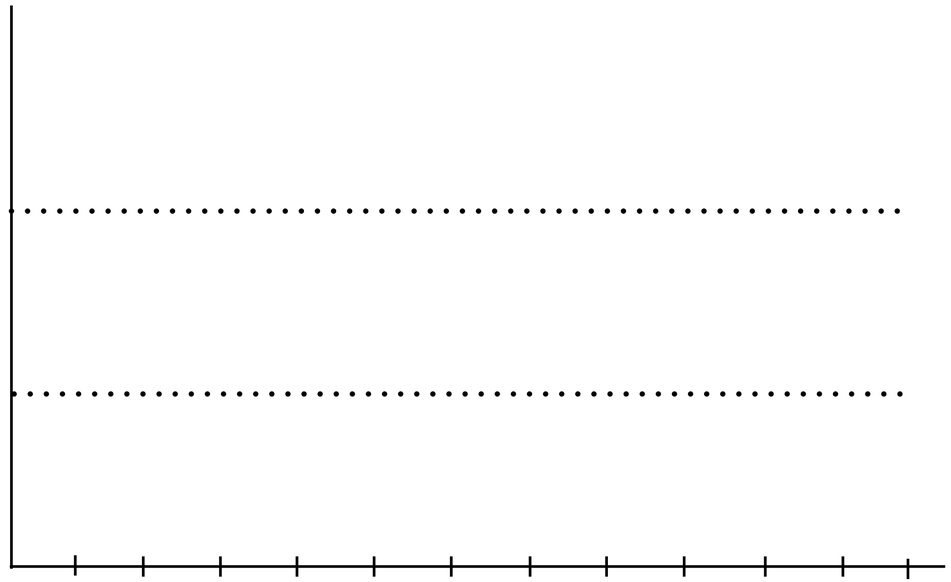


(a) Baseline RM



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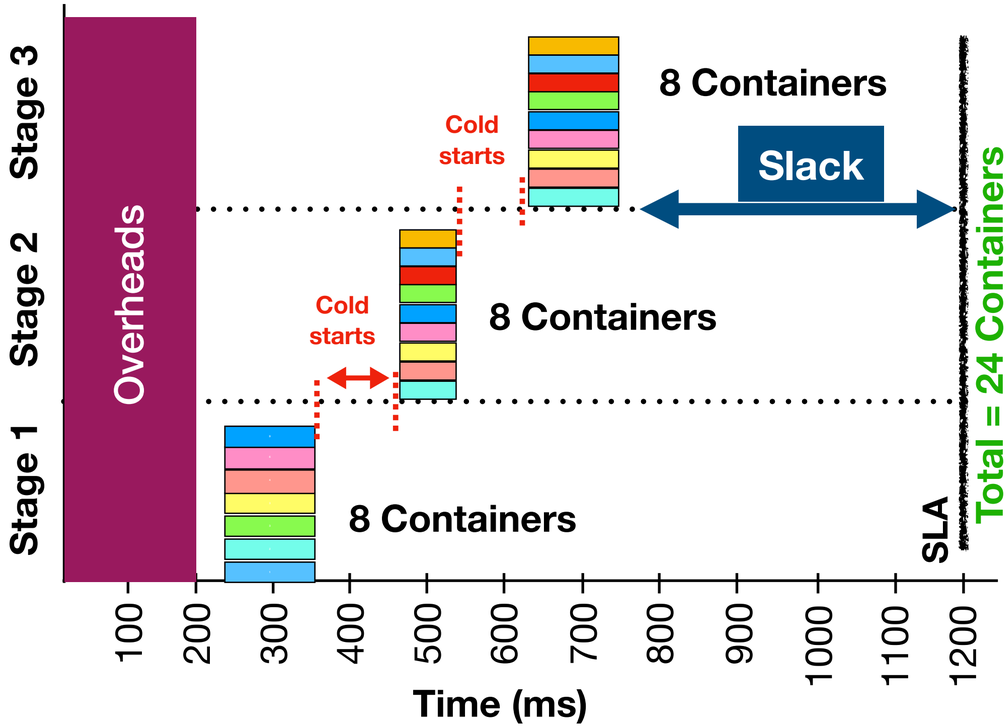

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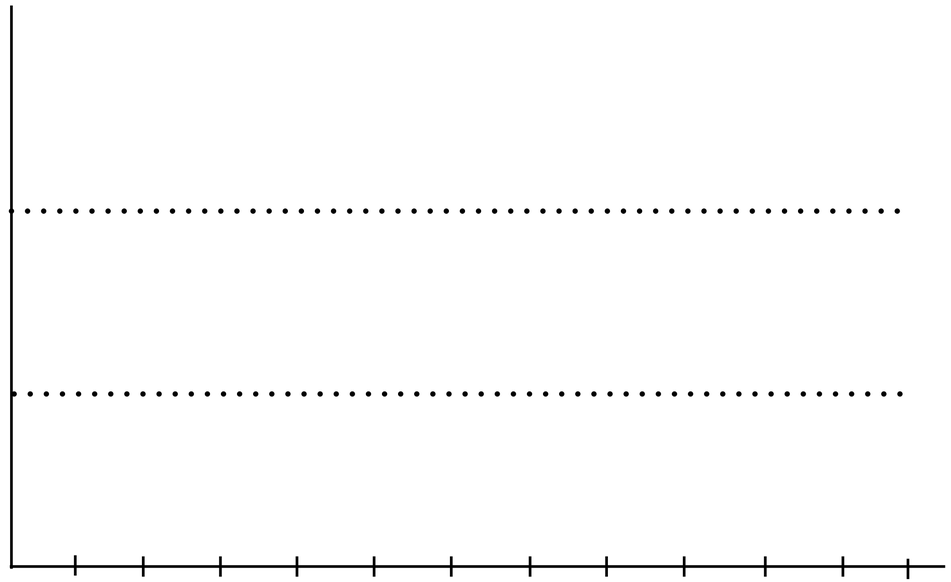

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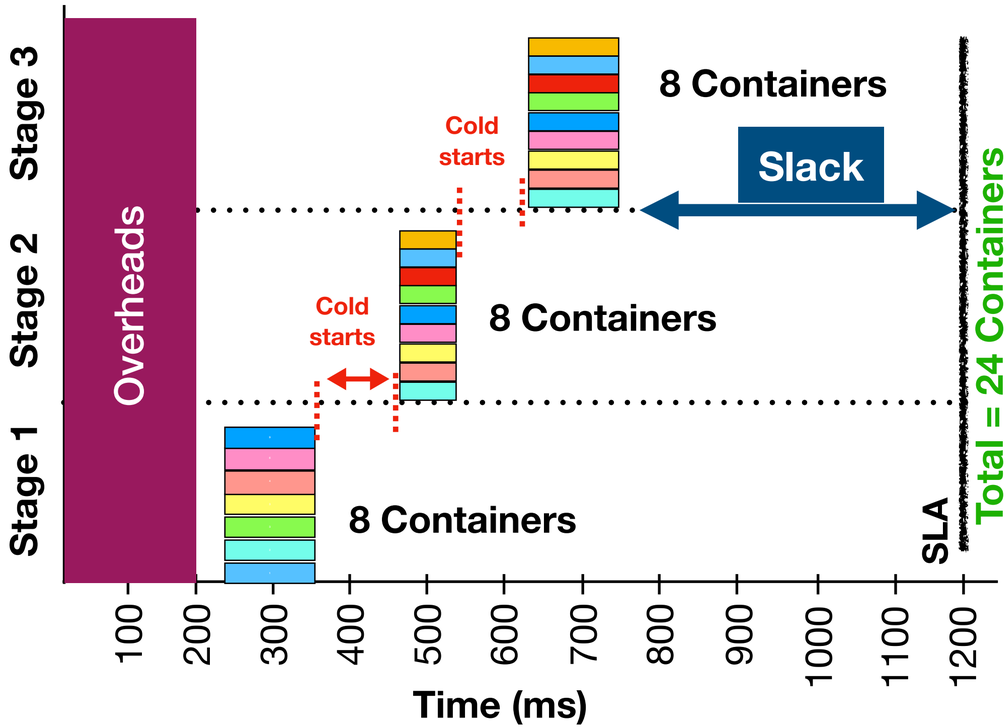

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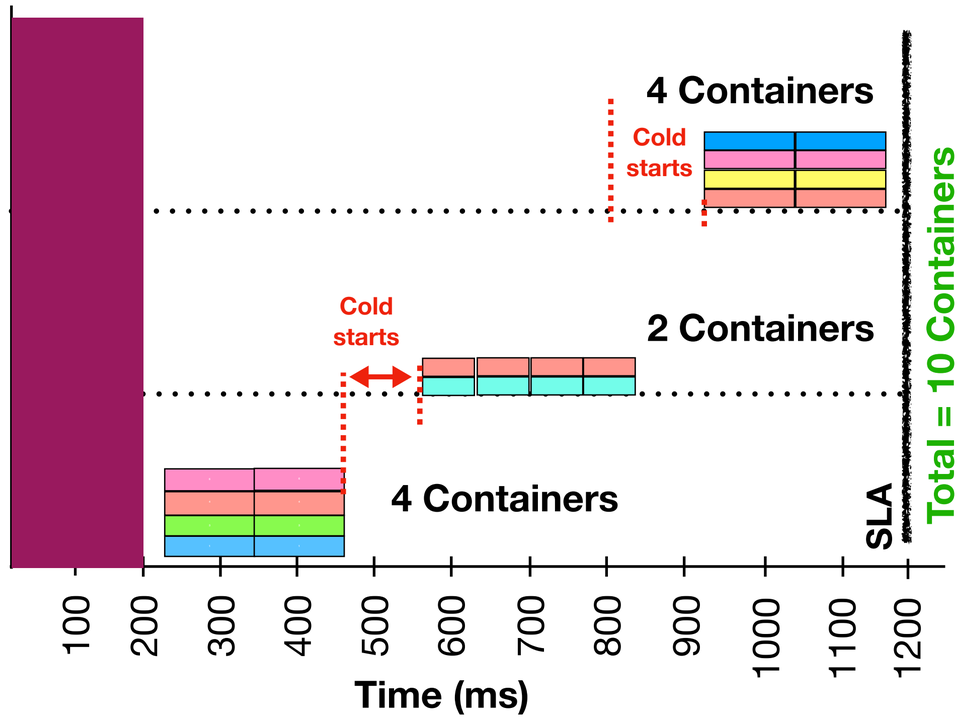

(b) Request-Batching RM

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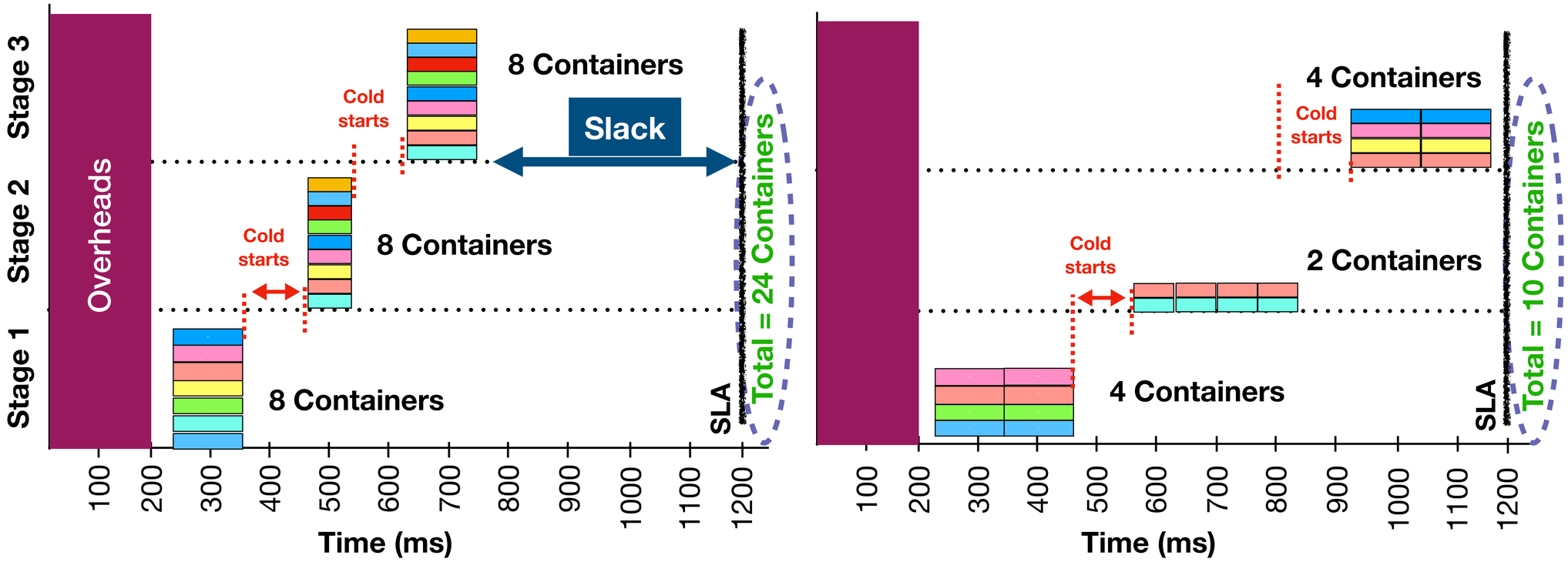

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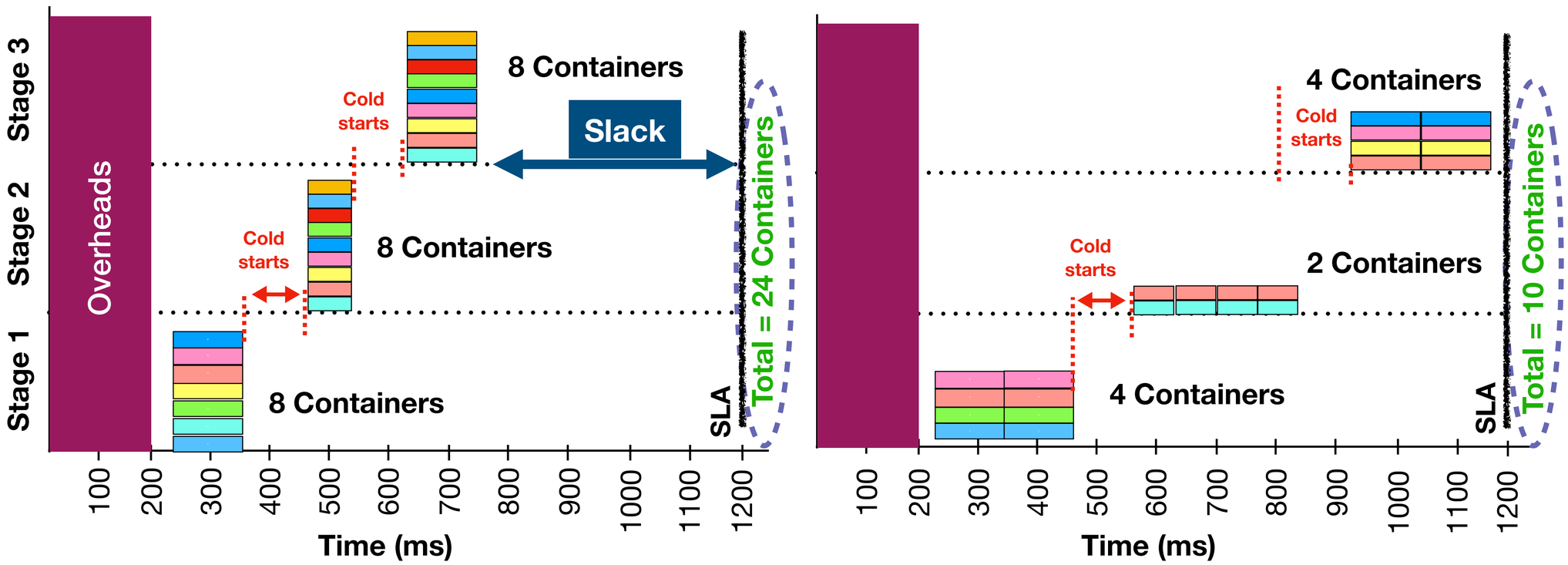

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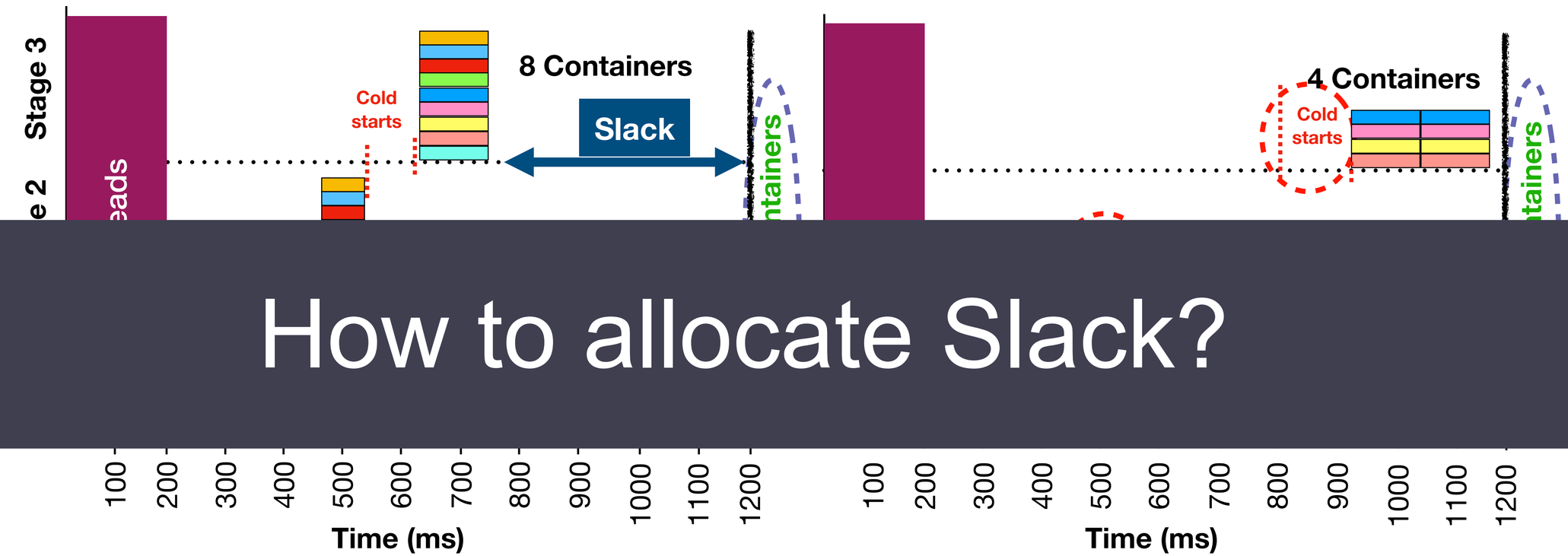
Exploiting Slack to Queue requests can save up to **14 containers**.

Slack aware queuing



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How to allocate Slack?

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Slack Allocation

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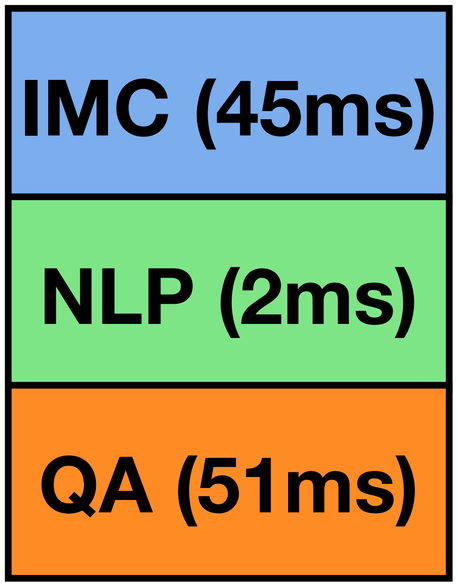
Slack = **700ms**



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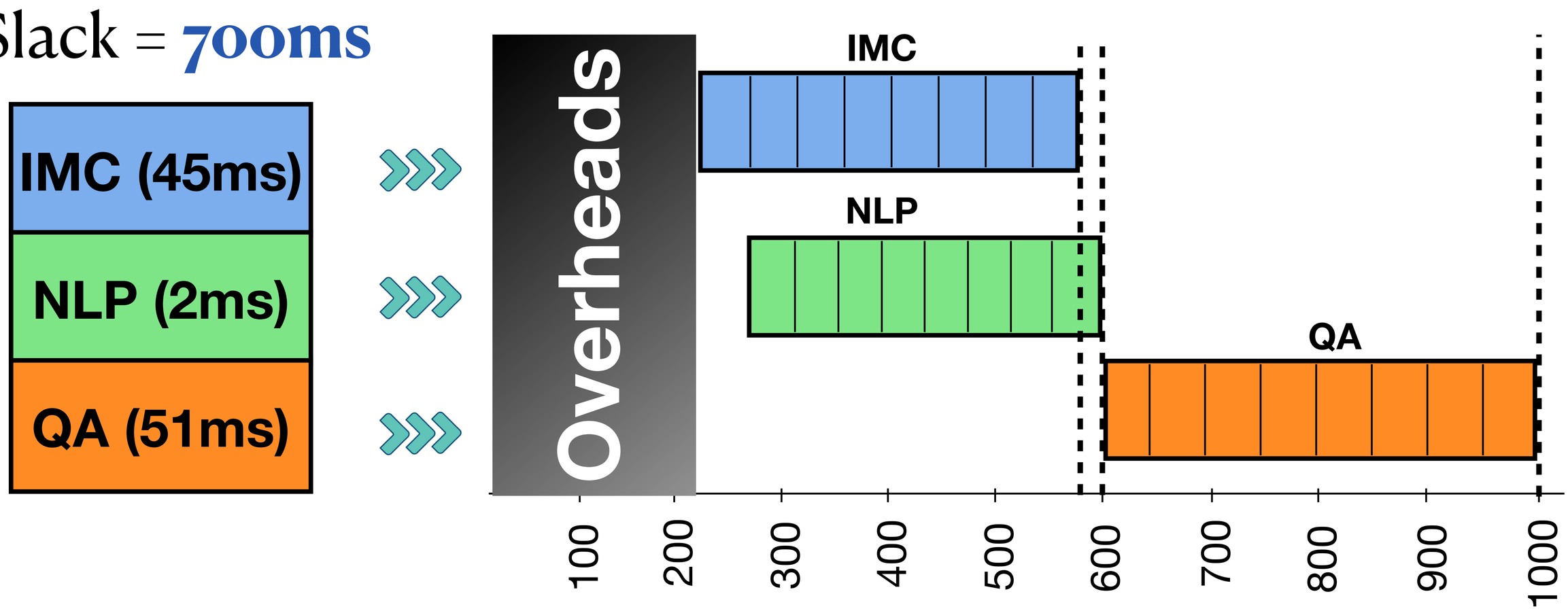

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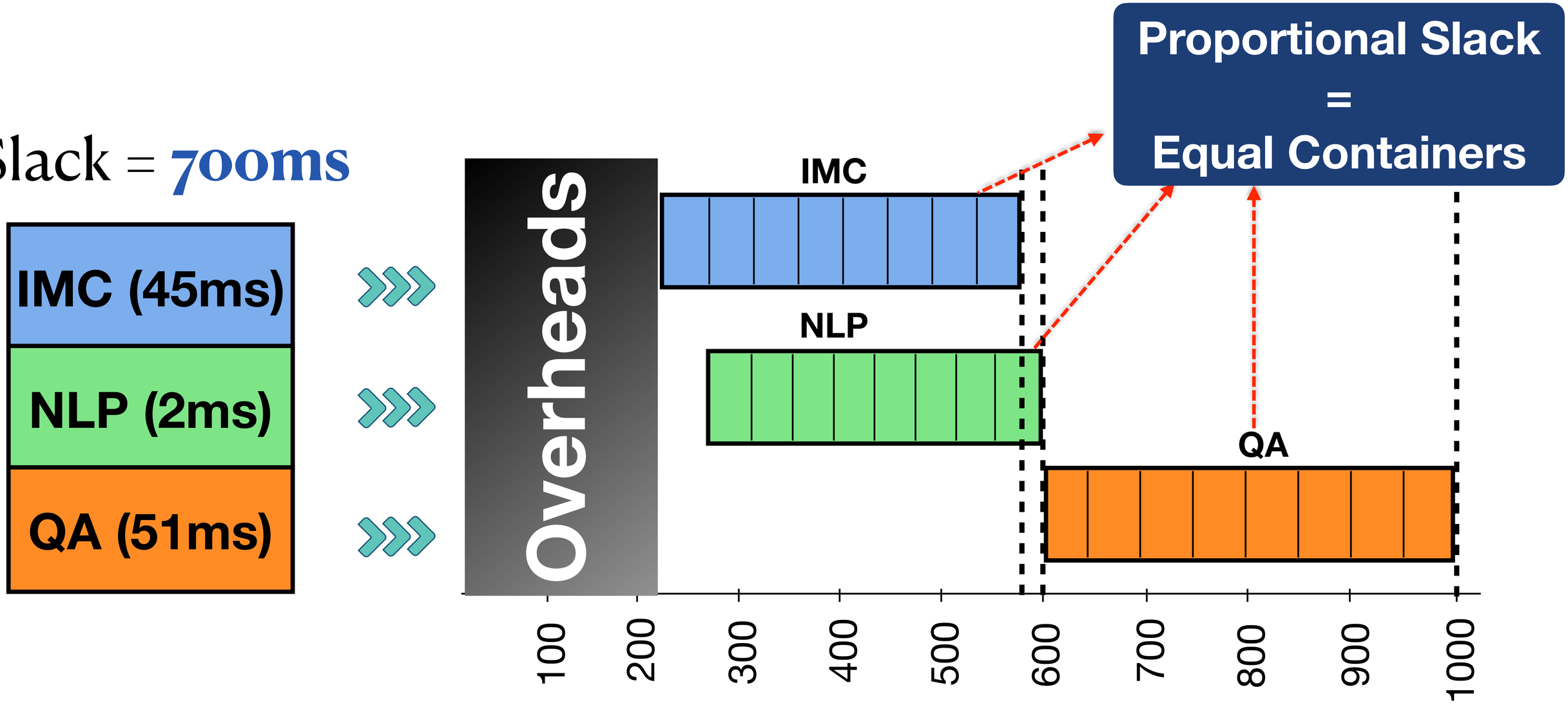

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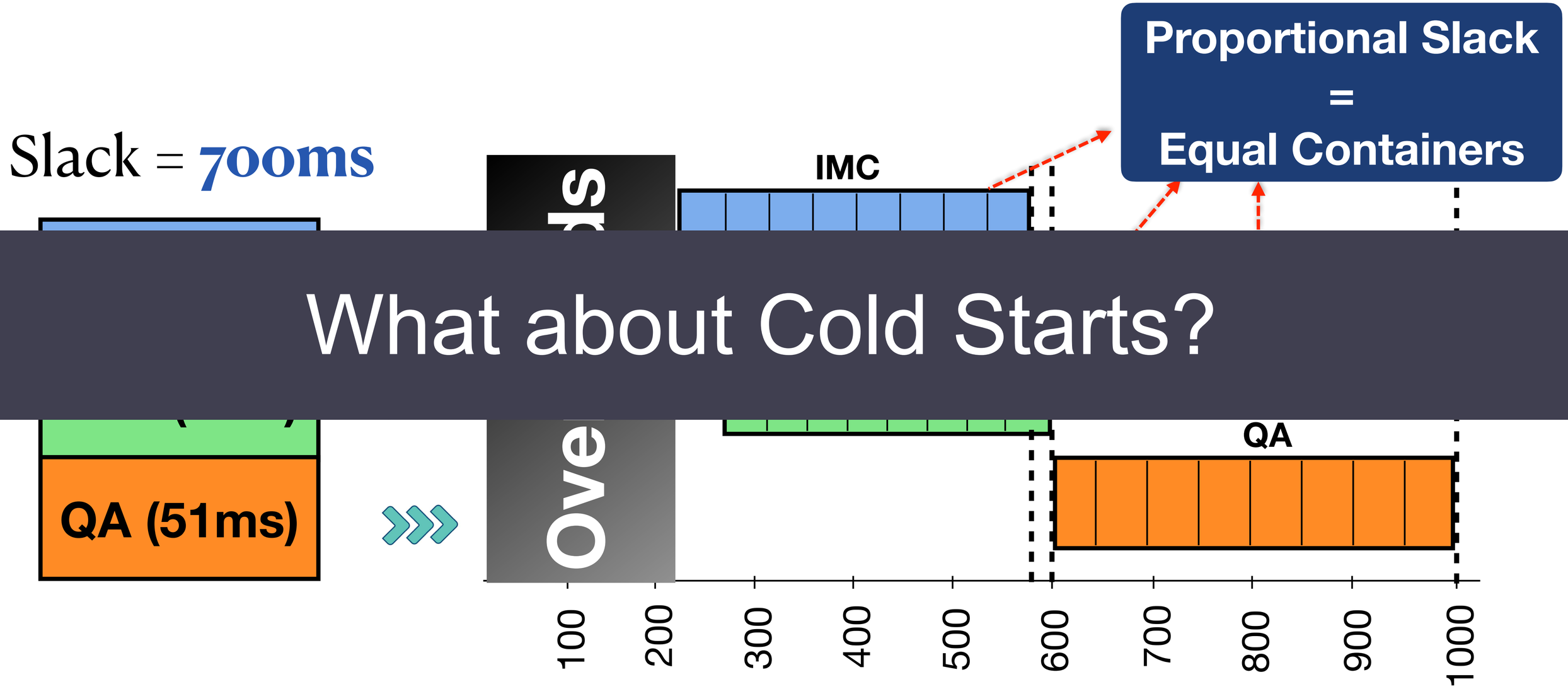
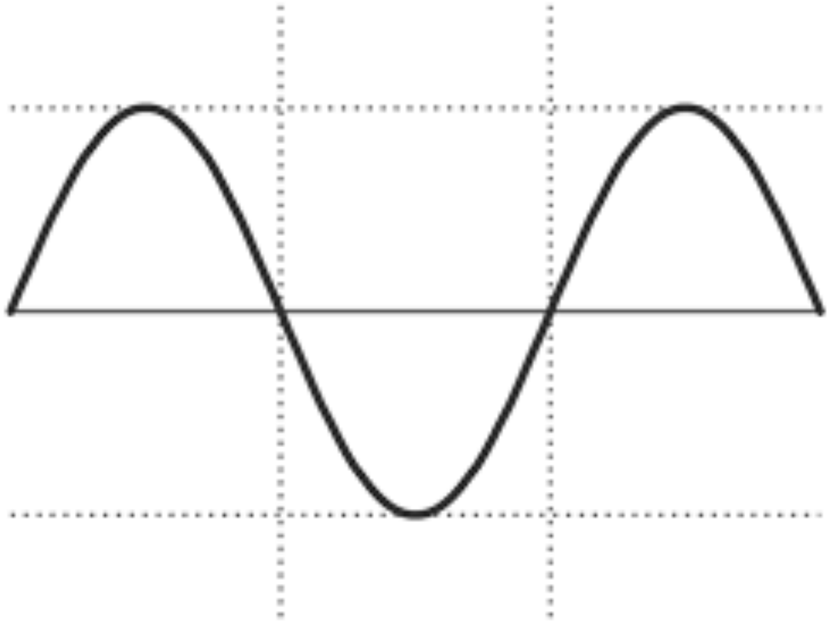
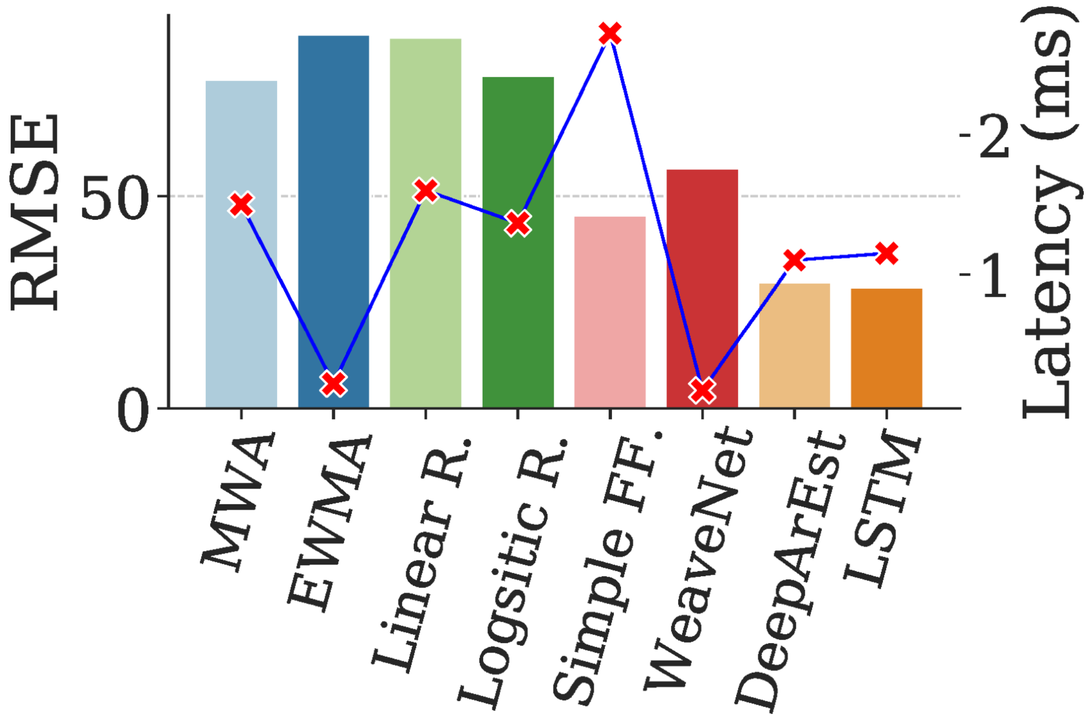


What about Cold Starts?

Reactive Scaling + Load Prediction



Prediction Model



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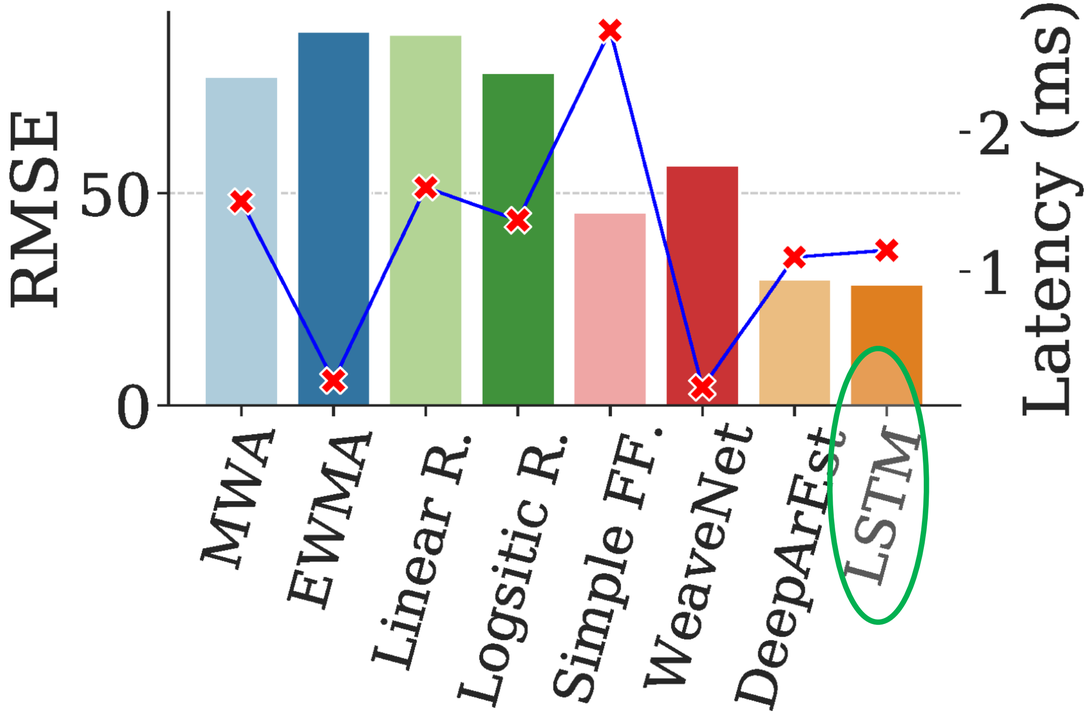

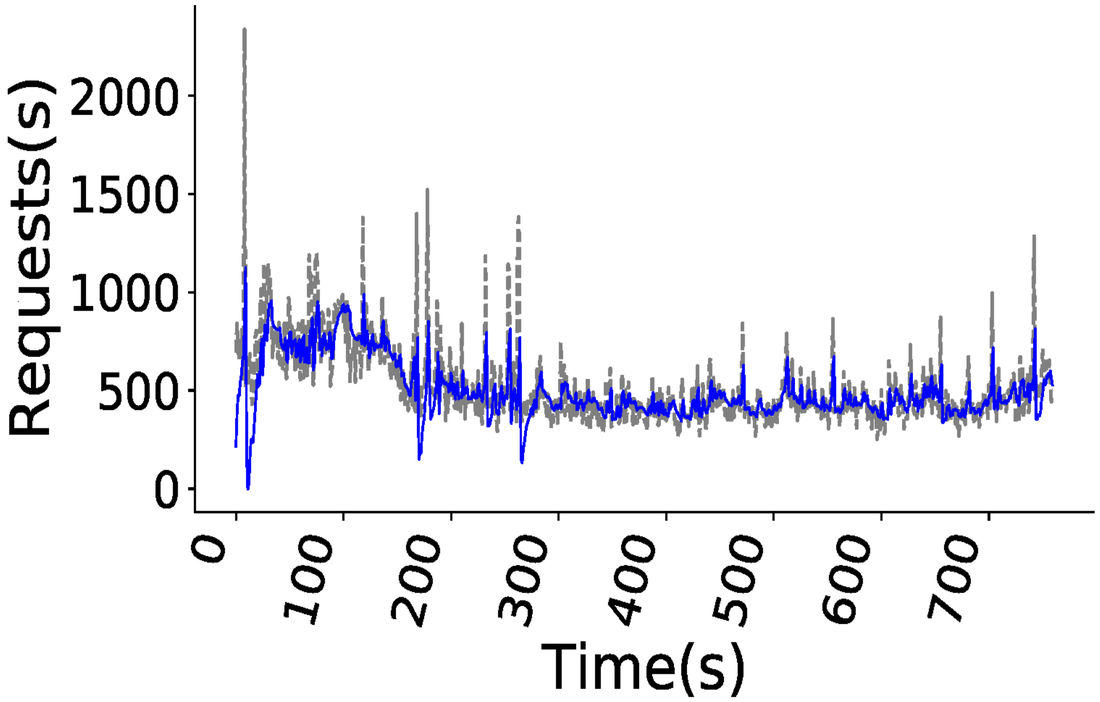

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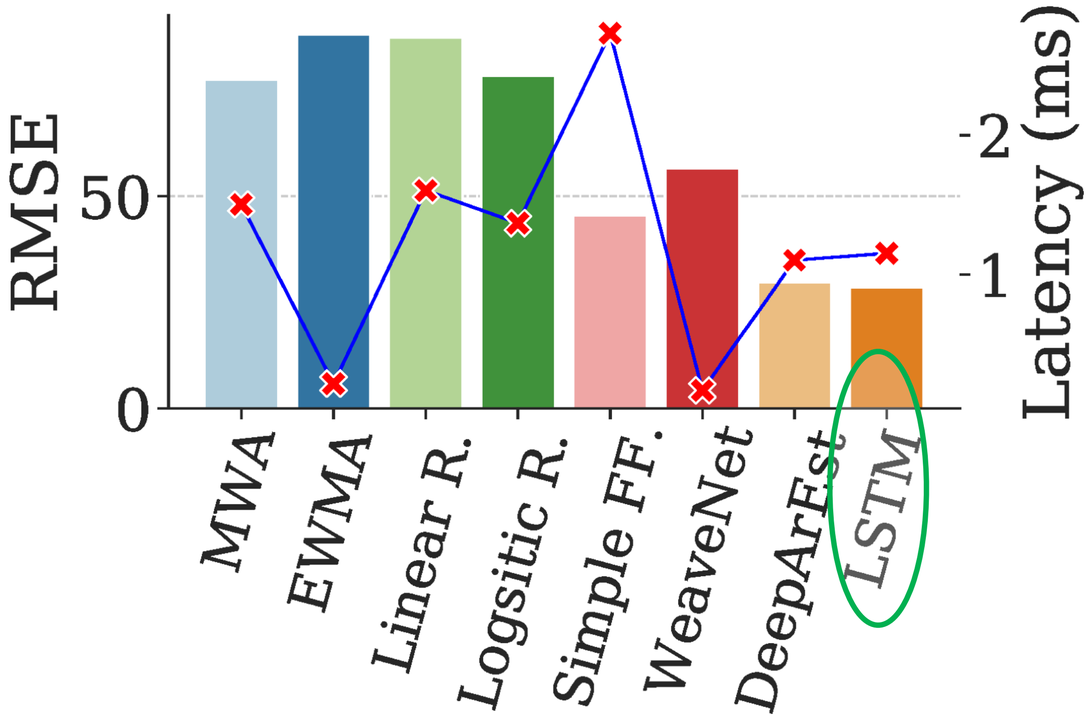

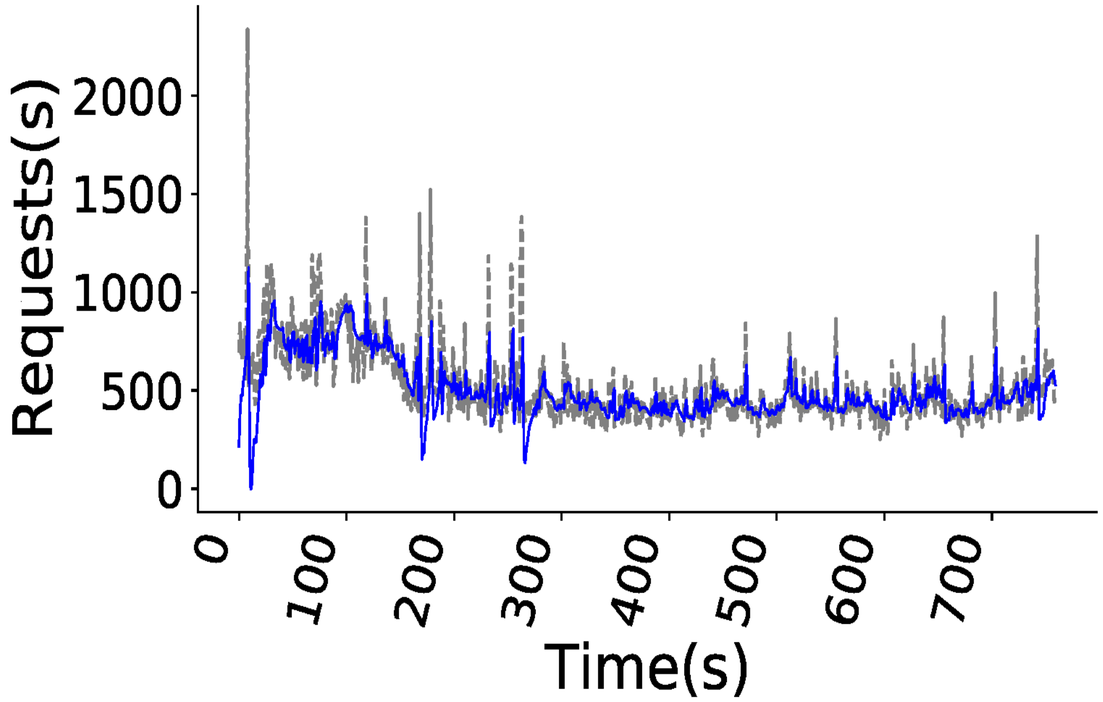

LSTM is the best with least RMSE

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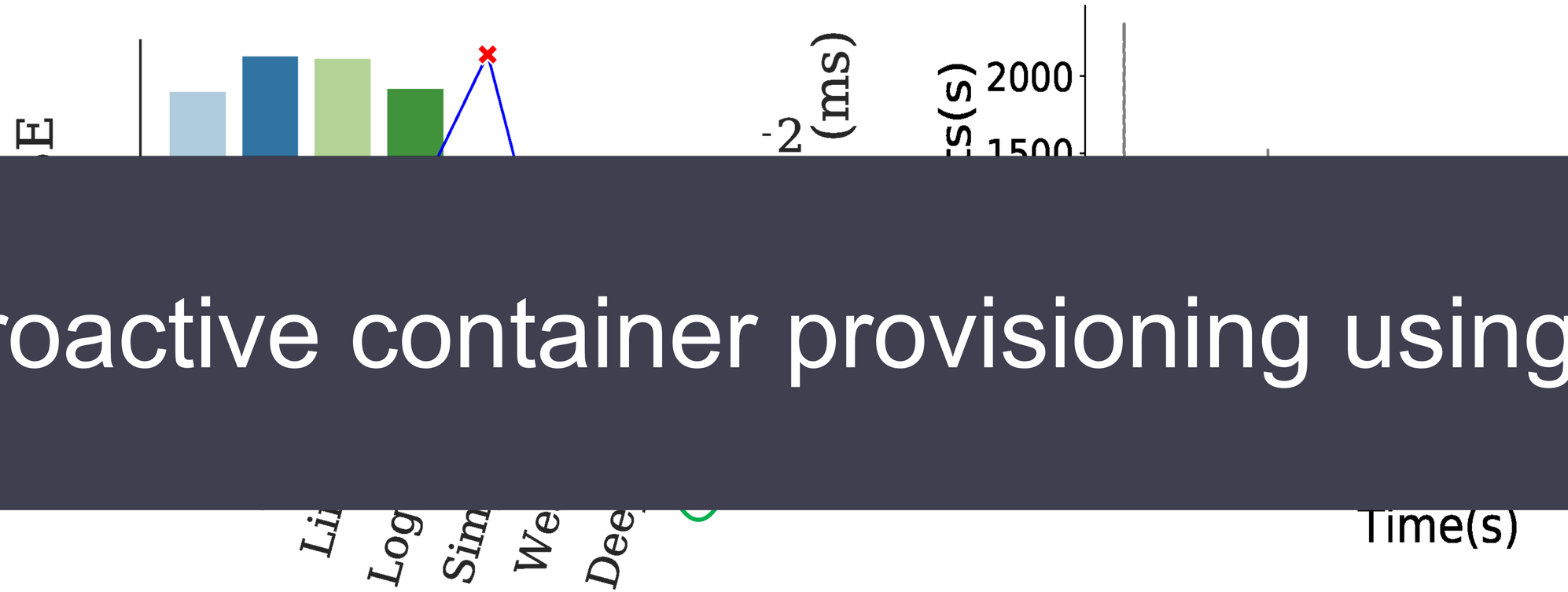

Proactive container provisioning using LSTM

LSTM is the best with least RMSE

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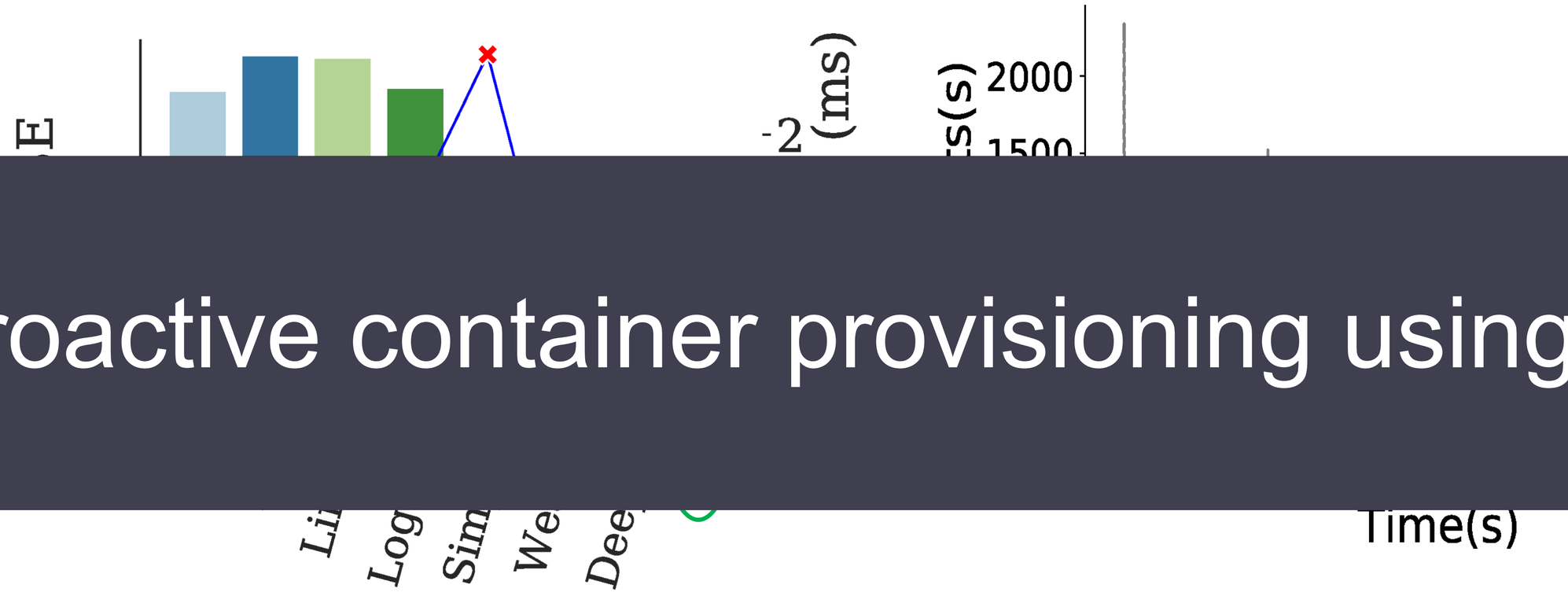

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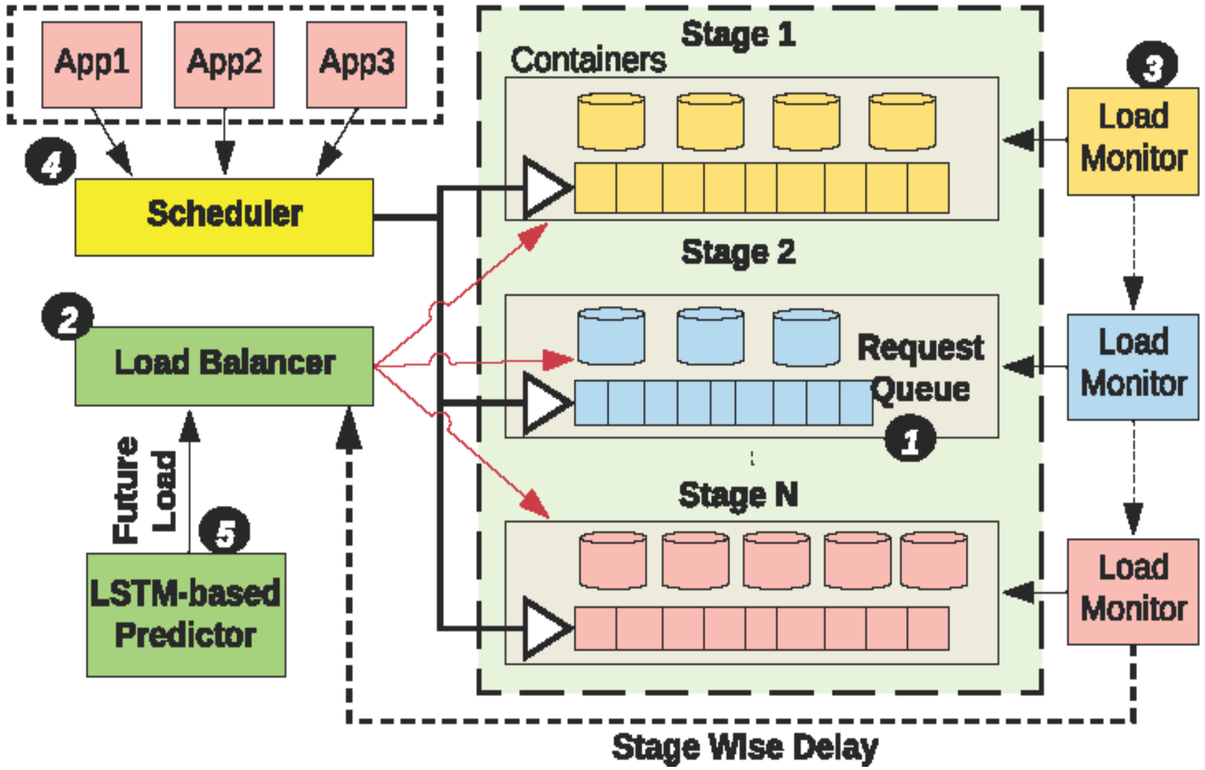
LSTM is the best with least RMSE

Fifer: Stage-aware Proactive container provisioning and management of function chains



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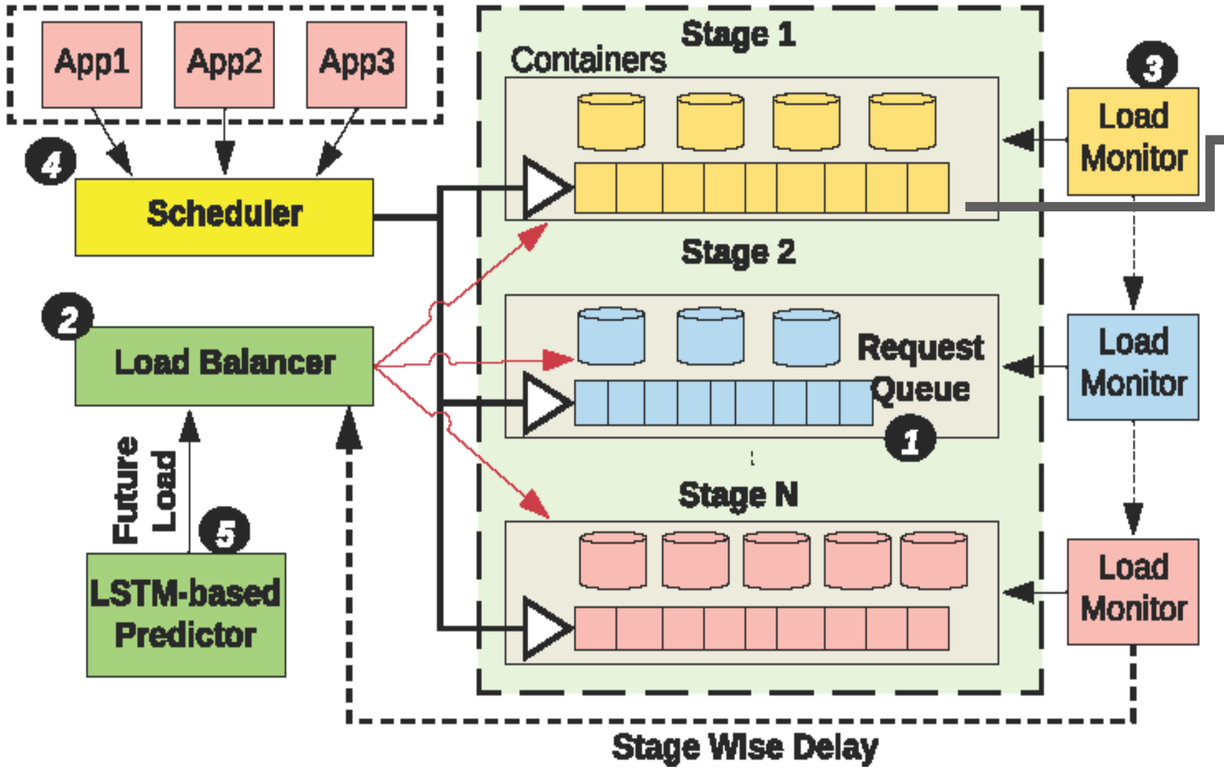

Stage-aware proportionate queuing

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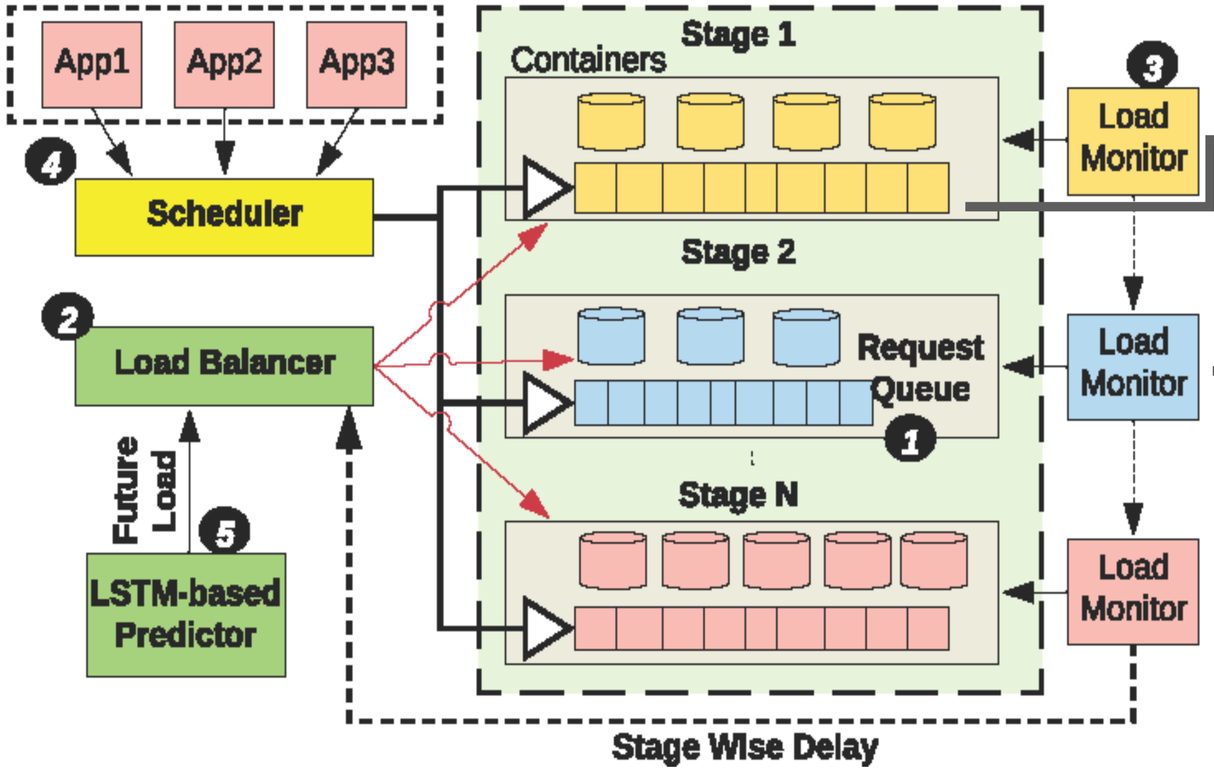

Stage-aware proportionate queuing

Queuing delay-based Reactive container scaling

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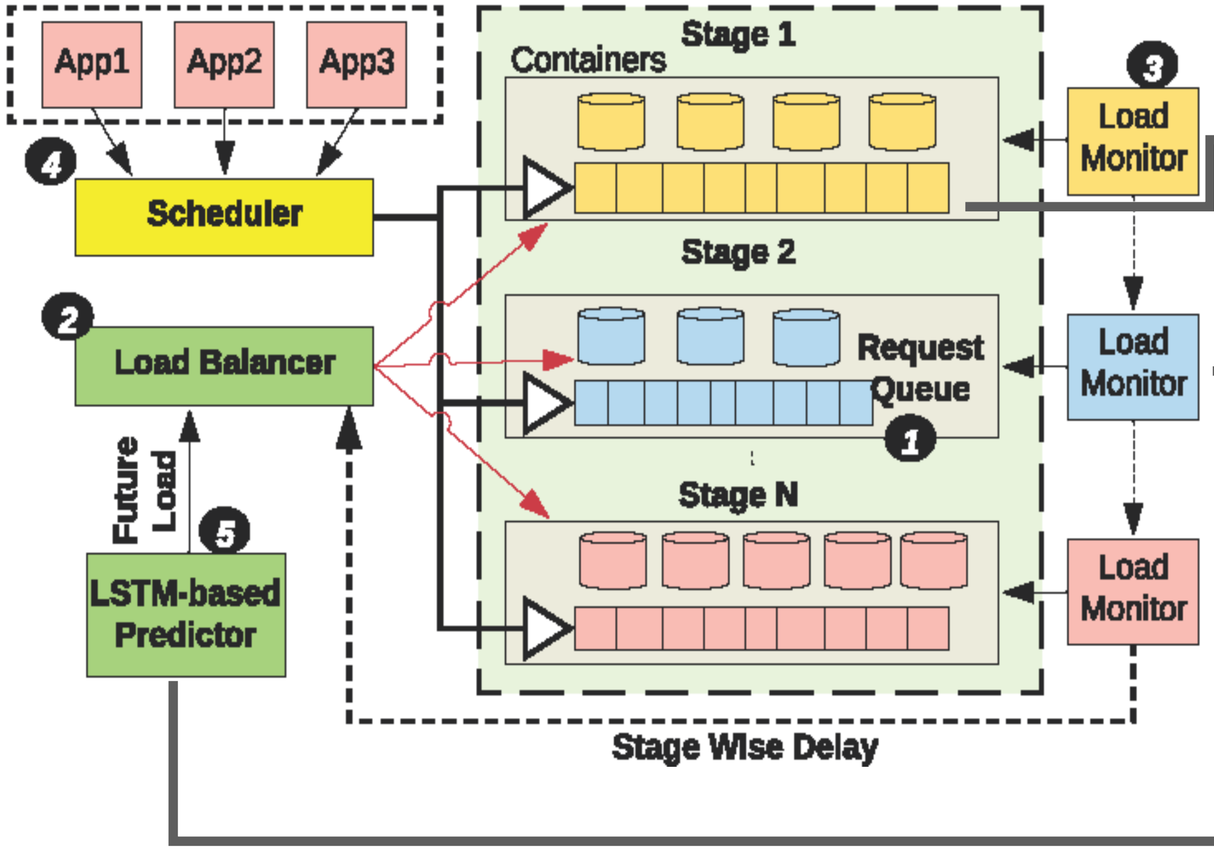
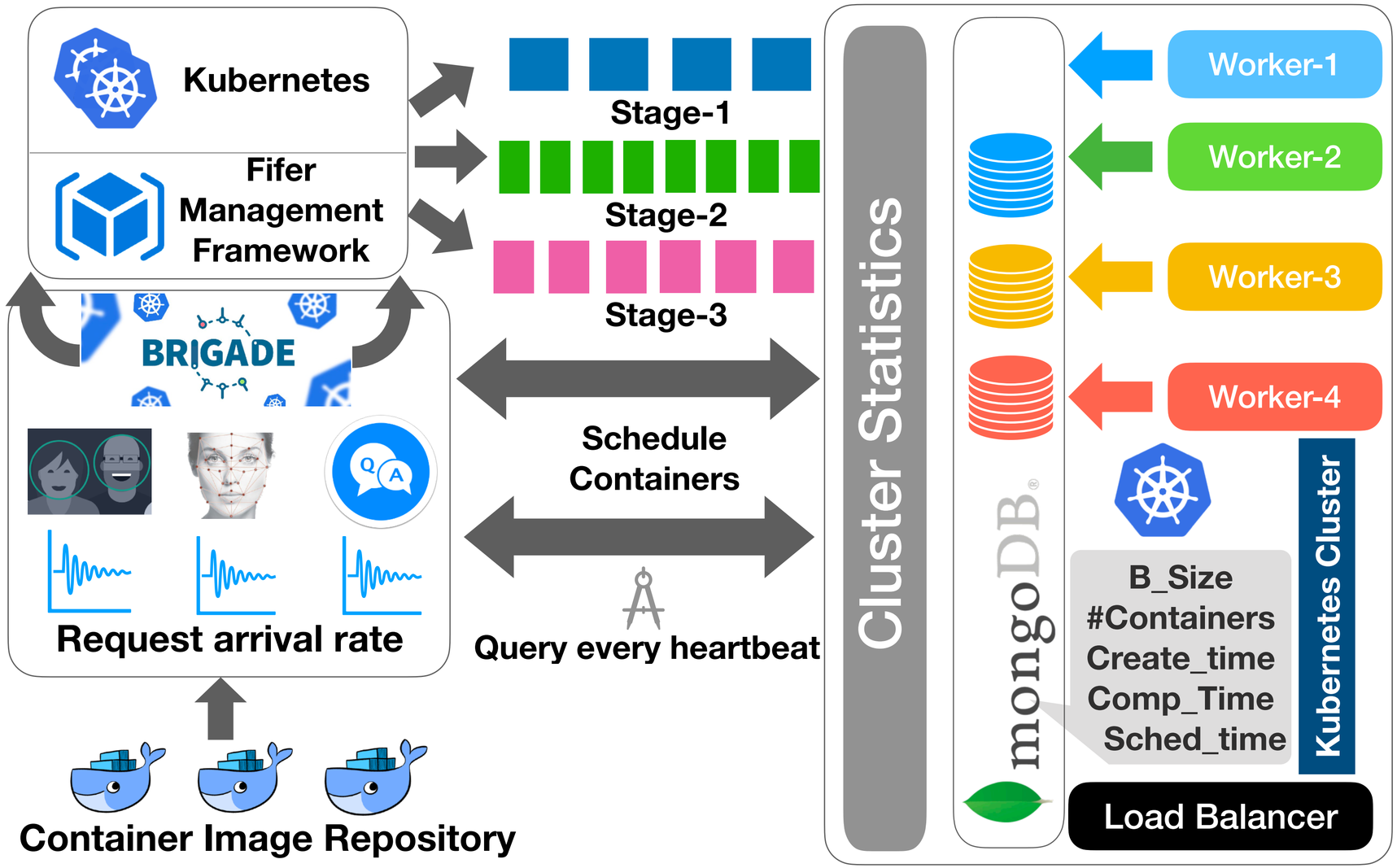


Stage-aware proportionate queuing

Queuing delay-based Reactive container scaling

Proactive container scaling

IMPLEMENTATION

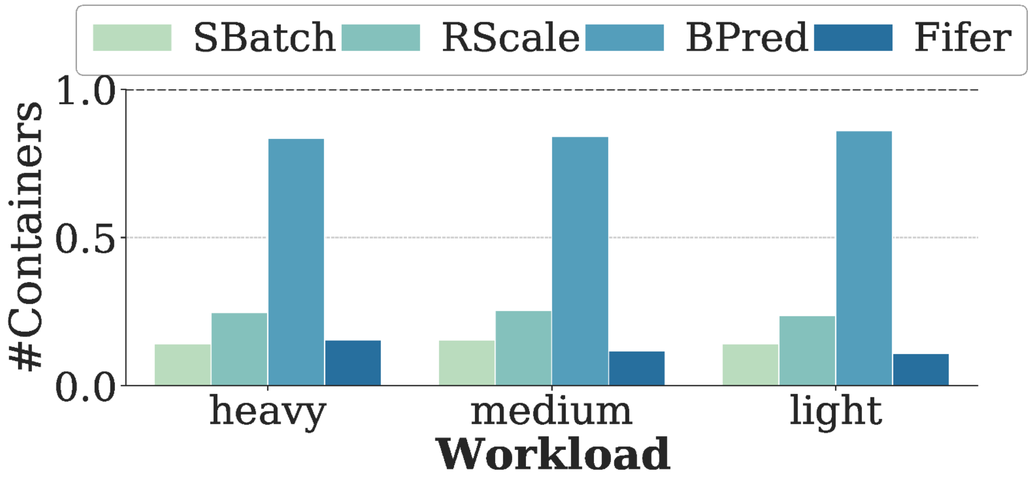


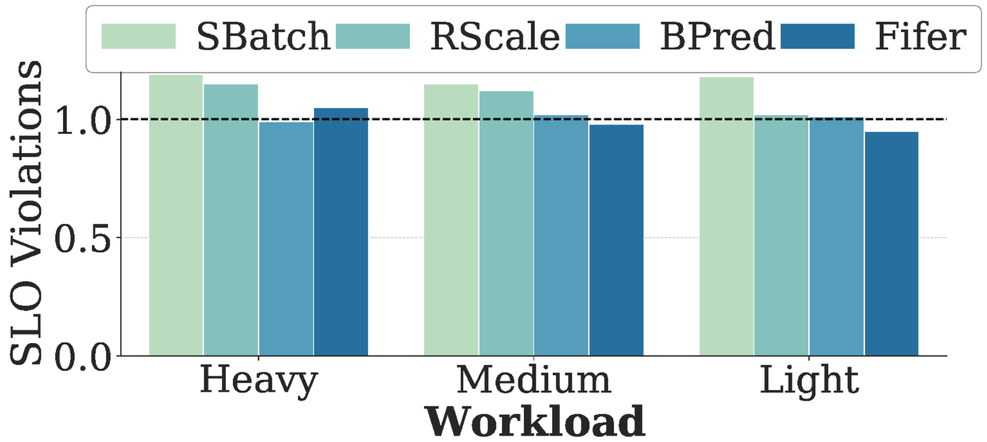
Hardware	Config
CPU	Xeon gold
Sockets	2
Core	16
Threads	2
Clock	2.8Ghz
DRAM	192GB

SLO violations and Containers

SLO violations and Containers

Better





SLO violations and Containers

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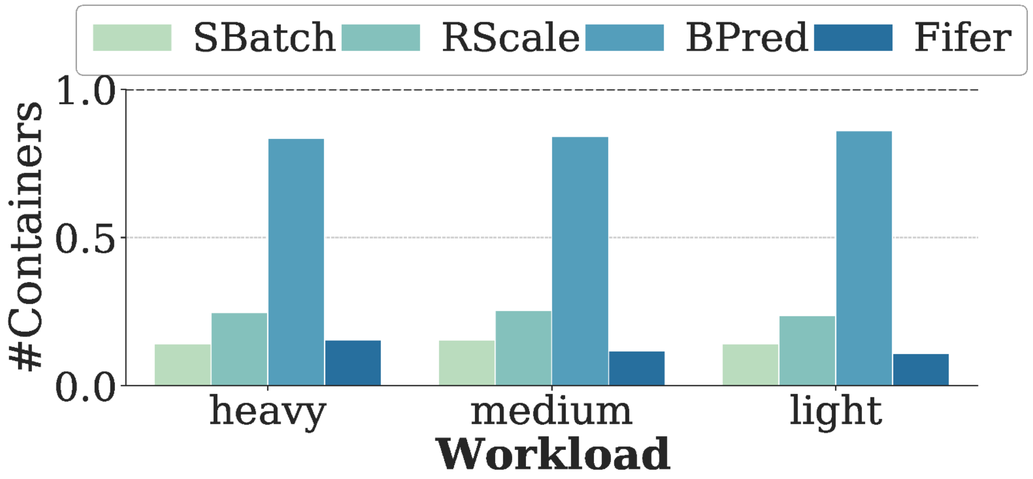
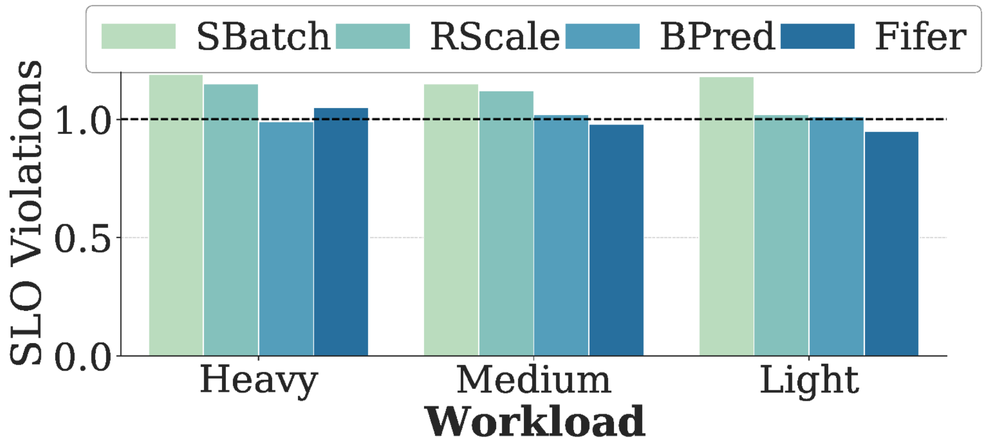
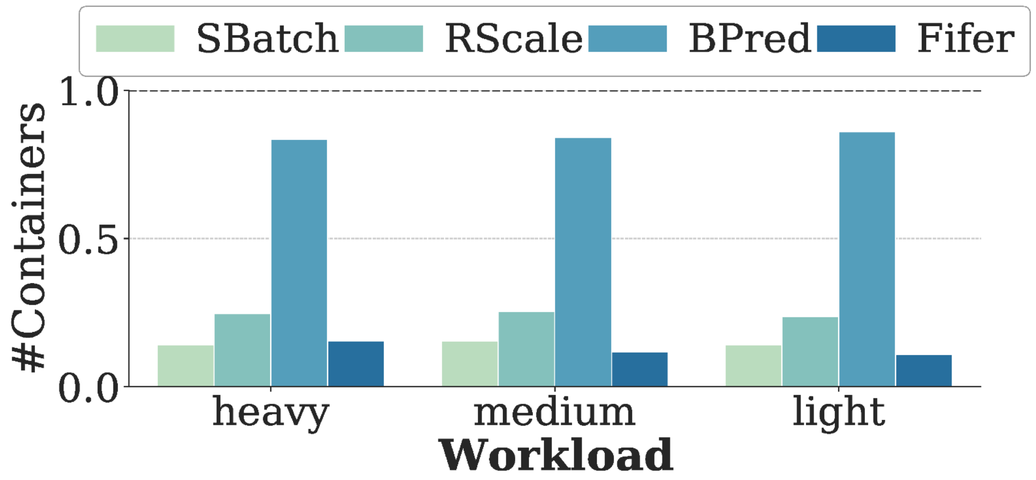




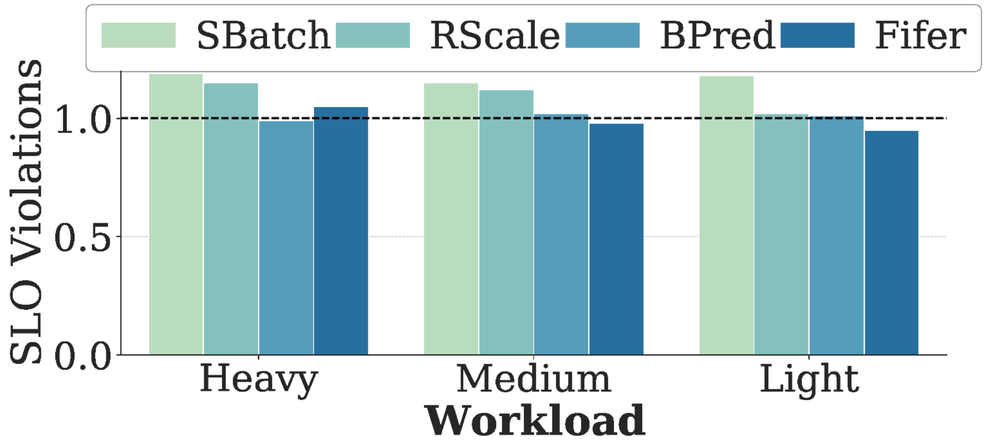
- #Containers normalized to baseline
- Fifer is spawns **20%** less containers

SLO violations and Containers

Better



- #Containers normalized to baseline
- Fifer is spawns **20%** less containers

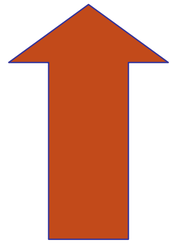


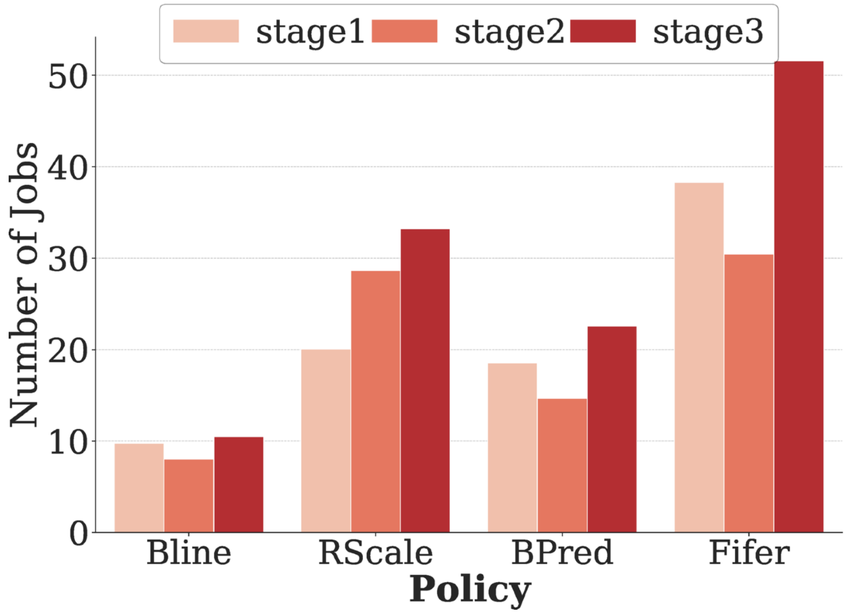
- SLO violations normalized to baseline
- Fifer is similar to baseline with fewer containers

Utilization and Energy

Utilization and Energy

Better

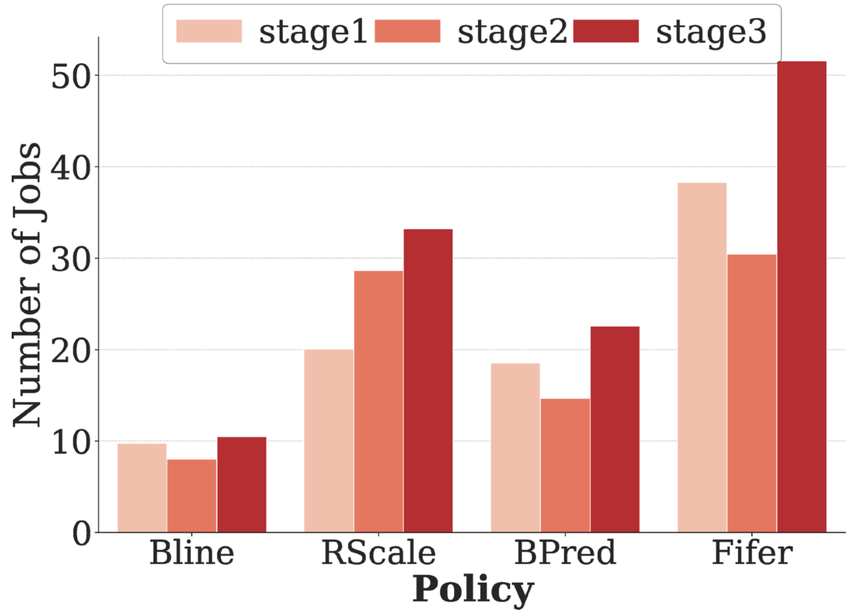




- Average #Requests executed per container (RPC).
- Fifer improves container utilization by **34%**

Utilization and Energy

Better



- Average #Requests executed per container (RPC).
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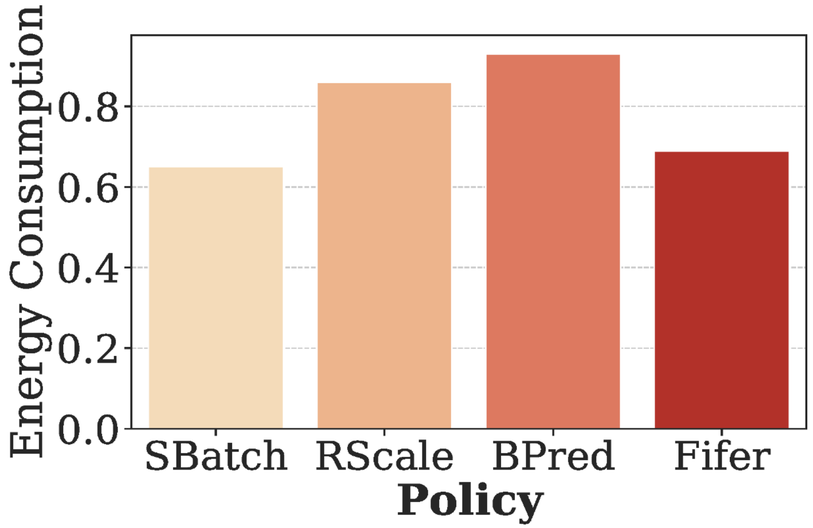
Better



- Energy consumption normalized to Bline.
- Fifer is **31%** more energy efficient

- Details of the workload used.
- Evaluated schemes and policies.
- Details about LSTM training.