iSingLab HKUST

Towards Optimal Rack-scale µs-level CPU Scheduling through In-Network Workload Shaping

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Microsecond-scale workloads in datacenter

Datacenter application

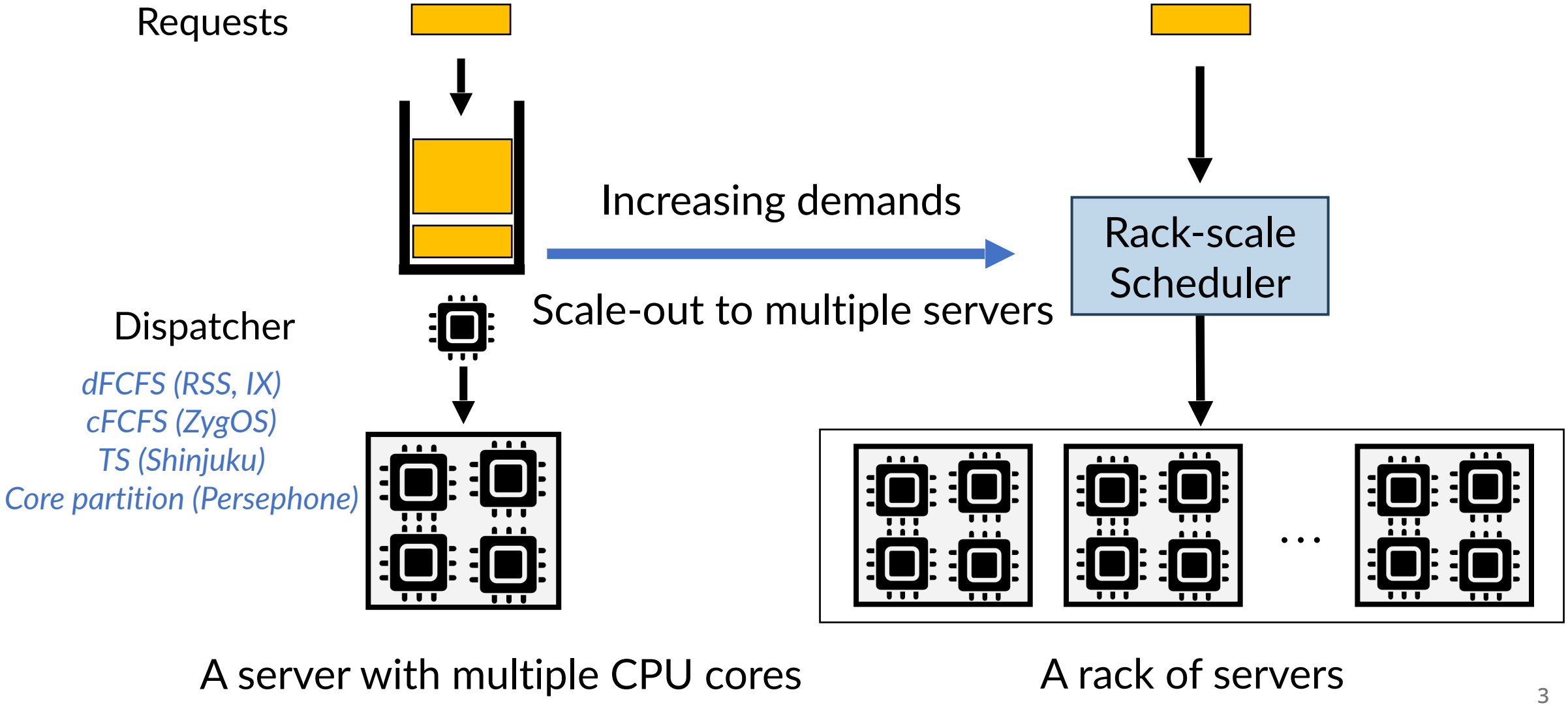
- µs-scale Remote Procedure Calls: 10s ~ 100s of microseconds



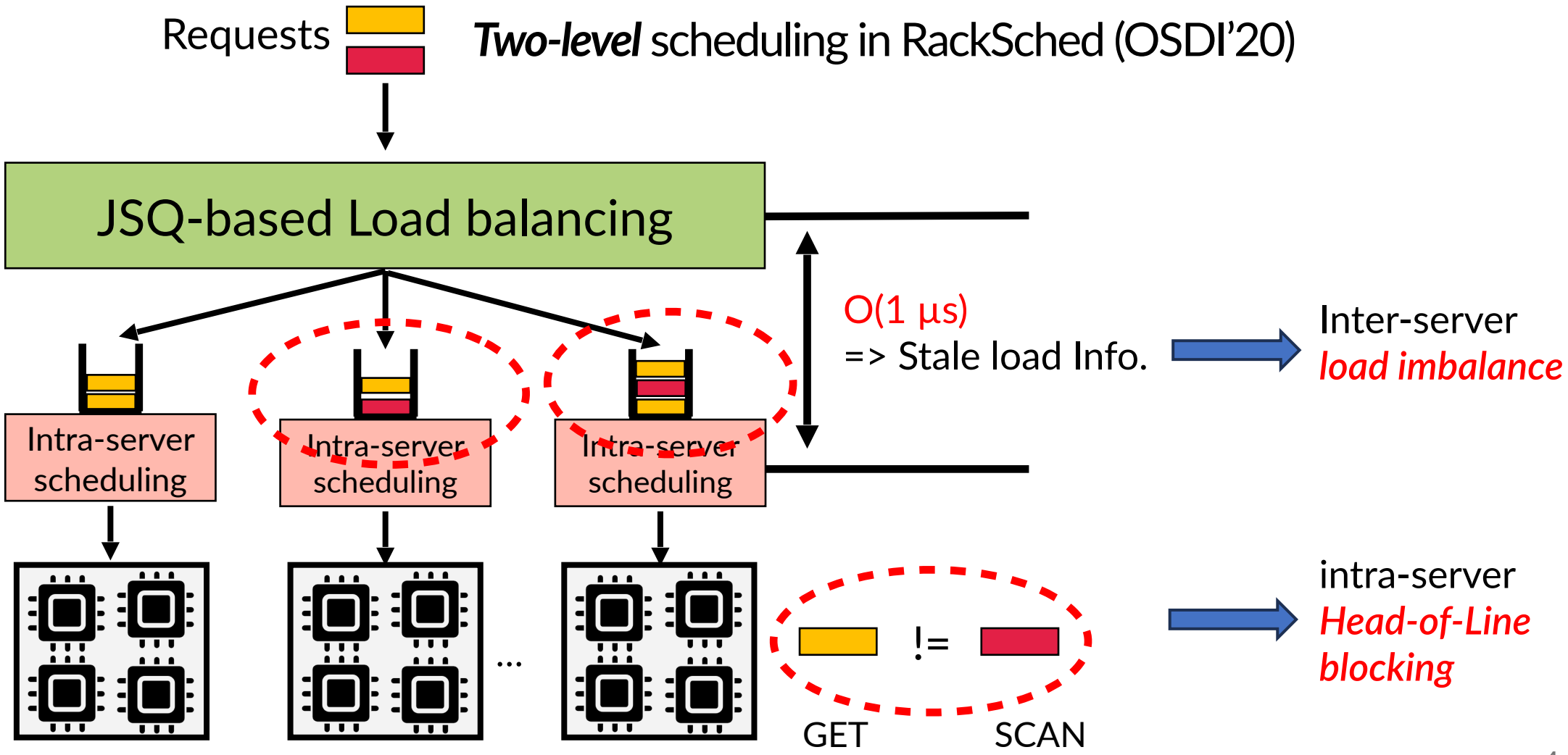
- Tight tail-latency SLOs for online services.

Achieving microsecond-scale tail latency is critical for better user experiences!

How to schedule µs-scale workloads at rack-scale?

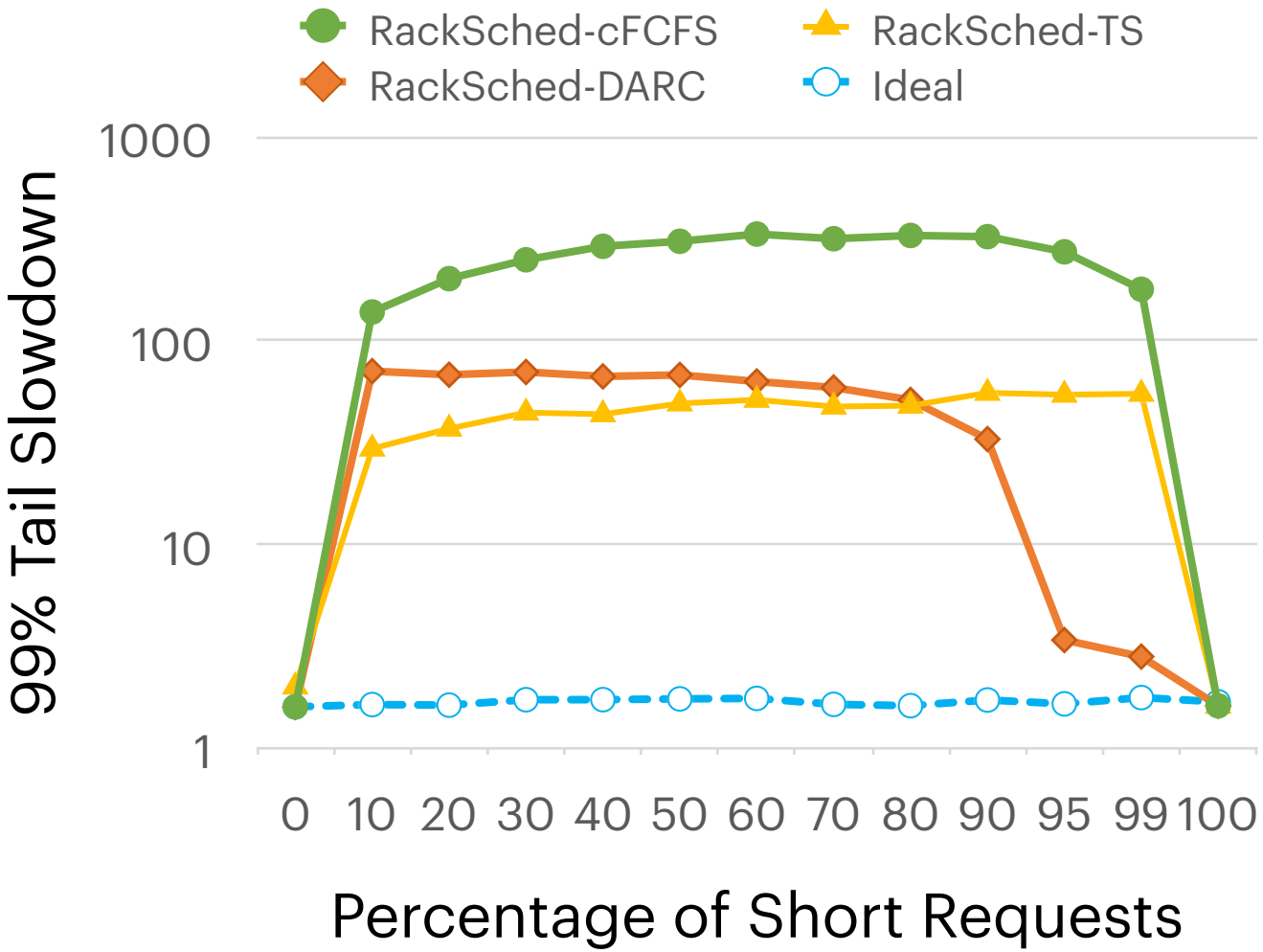


Limitations of current rack-scale scheduling



Limitations of current rack-scale scheduling

- Existing work suffers from bad tail latency due to the ***application-agnosticism***.
  - JSQ-based LB leads to inaccurate inter-server load imbalance.
  - Complex intra-server scheduling algorithms cannot mitigates ***HoL*** blocking optimally.



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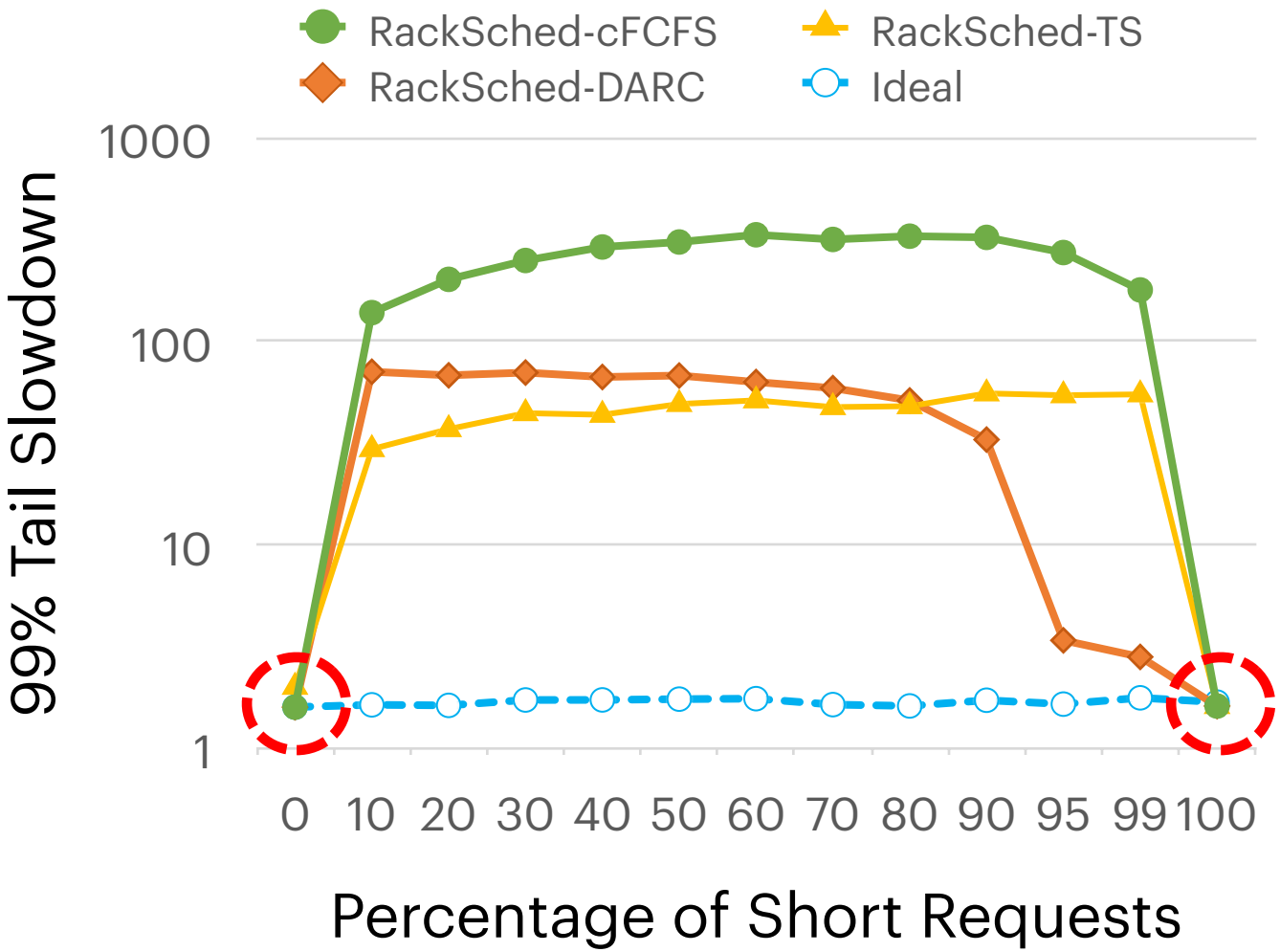

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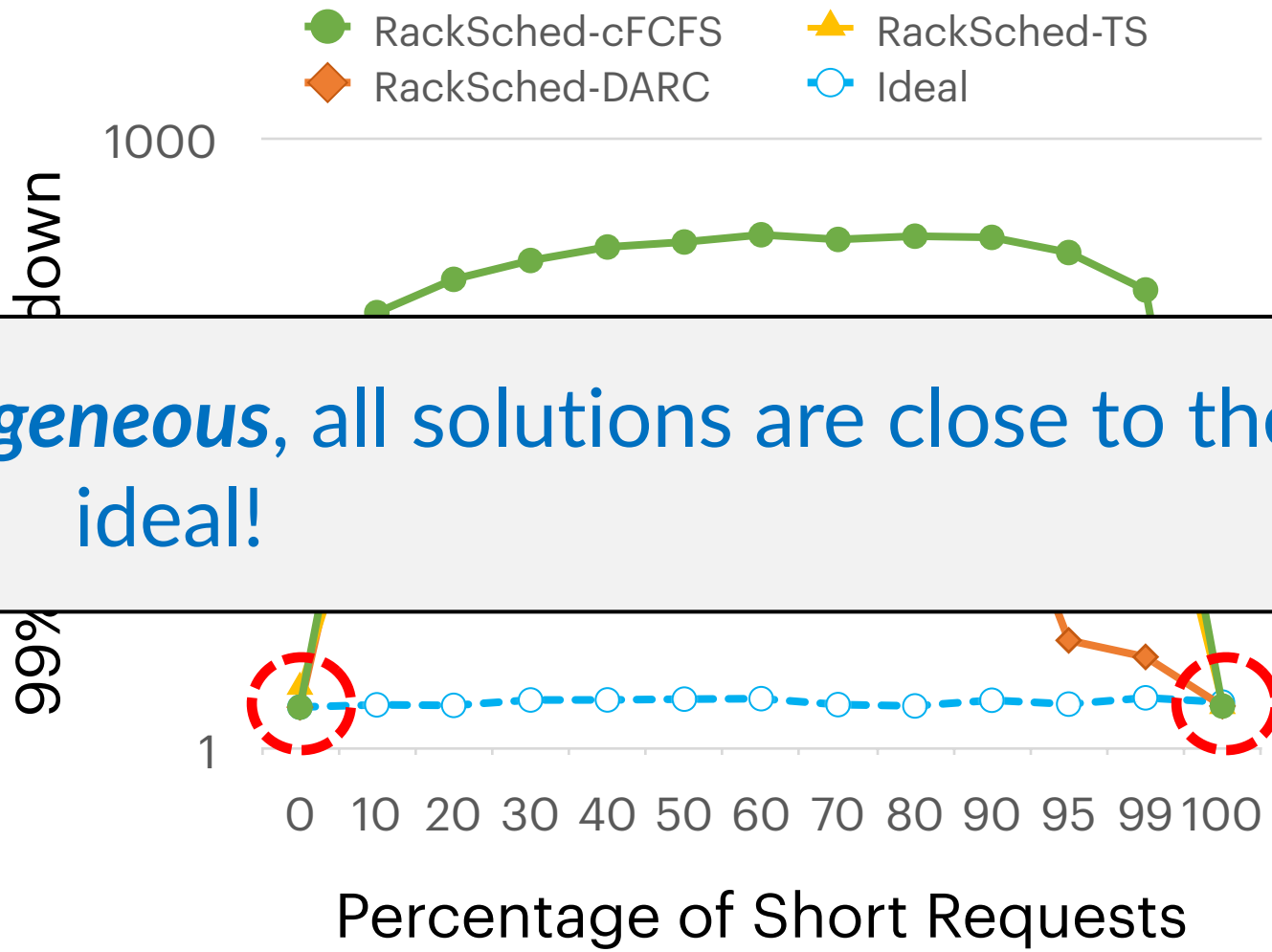
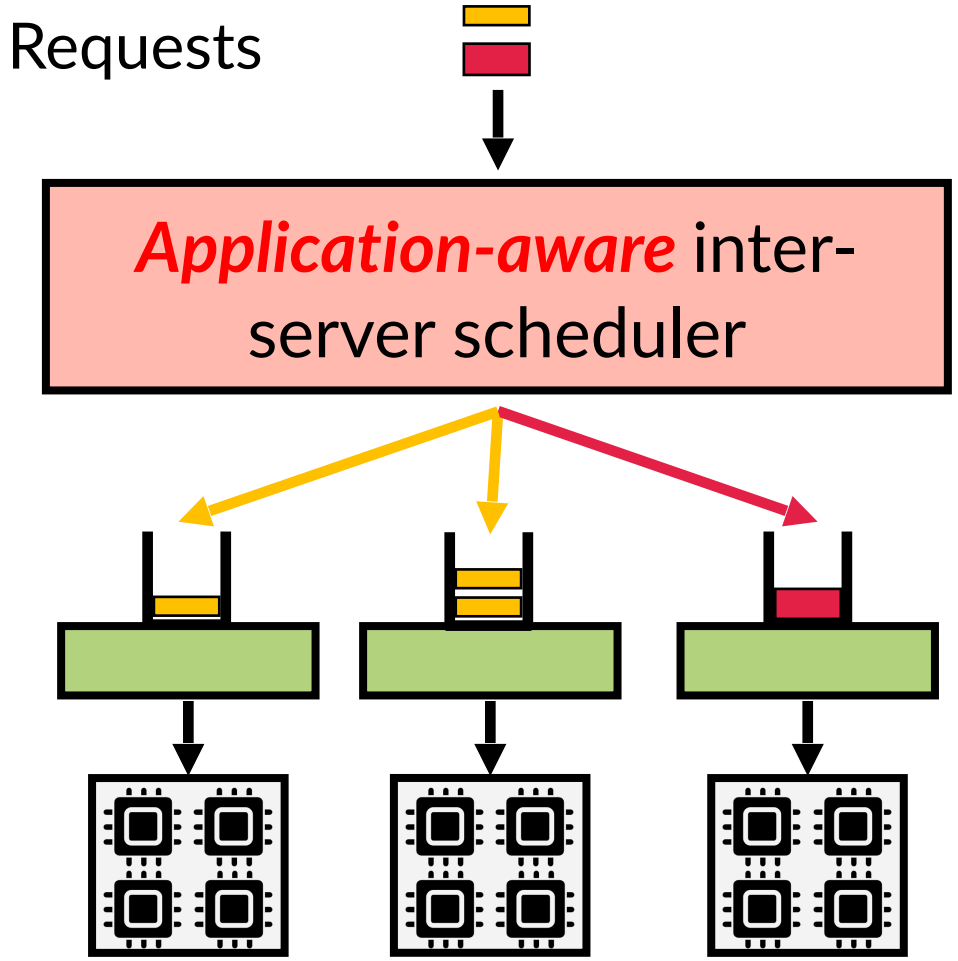
- Existing work suffers from bad tail latency due to the ***application-agnosticism***.
  - cannot mitigates ***HoL*** blocking optimally.

When workloads are ***homogeneous***, all solutions are close to the ideal!



The case for application-aware scheduling



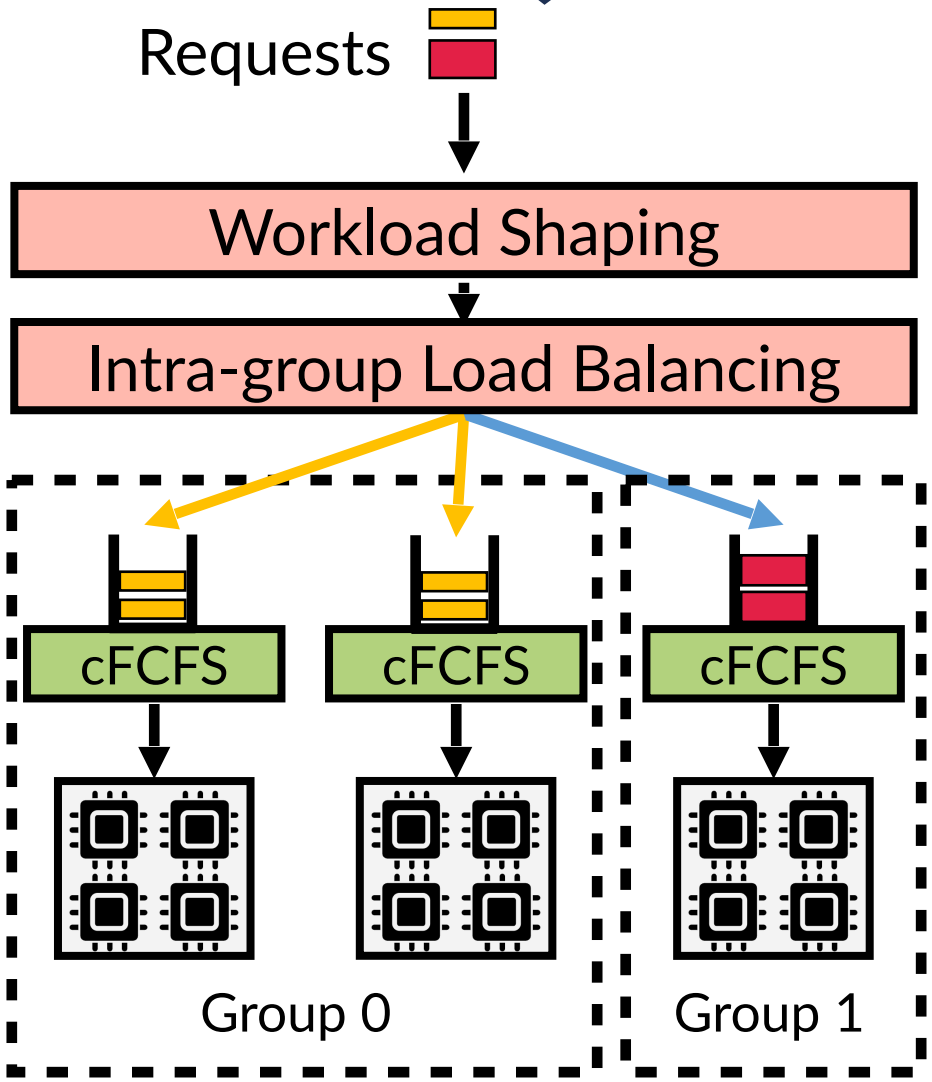
Opportunities:

- Request execution time can be inferred from request headers
  - Monitor and estimate the request load in the *application-aware manner*
- Datacenters are equipped with programmable switches
  - Categorize and schedule requests within the network

Pallas architecture

See the optimality analysis in the paper!

- ***In-network workload shaping***
  - Separate requests into different groups with homogeneity
- ***Accurate*** Intra-group load balancing
  - Req num → cumulative load
- ***Near-optimal*** intra-server scheduling
  - Most servers only face homogeneous workloads, entirely eliminates the HoL blocking.

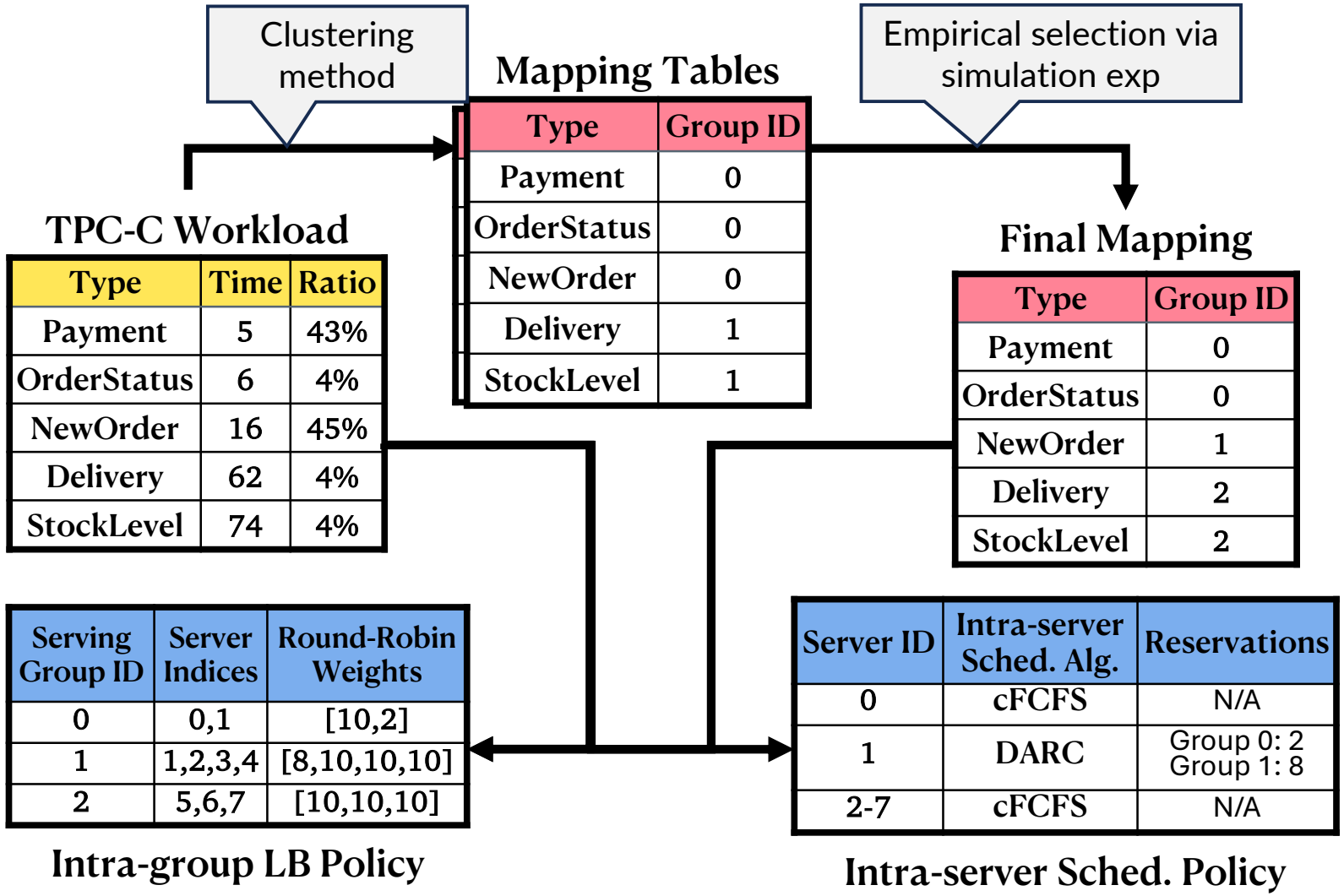


Key challenges in designing Pallas

- How to efficiently shape the workload?
  - More groups leads to more homogeneity but scarifies resource efficiency.
- How to gracefully handle *long-term workload changes*?
  - Request distribution may change over time, simply replacing the scheduling policy is insufficient.
- How to mitigate *short-term workload bursts*?
  - Coarse-grained control granularity is hard to address us-level transient bursts.

Scheduling policy generation

1) Find grouping policies
2) Select candidate
3) Provision resource & generate LB policy & generate Intra-server scheduling policy



Type	Time	Ratio
Payment	5	43%
OrderStatus	6	4%
NewOrder	16	45%
Delivery	62	4%
StockLevel	74	4%

Type	Group ID
Payment	0
OrderStatus	0
NewOrder	0
Delivery	1
StockLevel	1

Type	Group ID
Payment	0
OrderStatus	0
NewOrder	1
Delivery	2
StockLevel	2

Serving Group ID	Server Indices	Round-Robin Weights
0	0,1	[10,2]
1	1,2,3,4	[8,10,10,10]
2	5,6,7	[10,10,10]

Server ID	Intra-server Sched. Alg.	Reservations
0	cFCFS	N/A
1	DARC	Group 0: 2 Group 1: 8
2-7	cFCFS	N/A

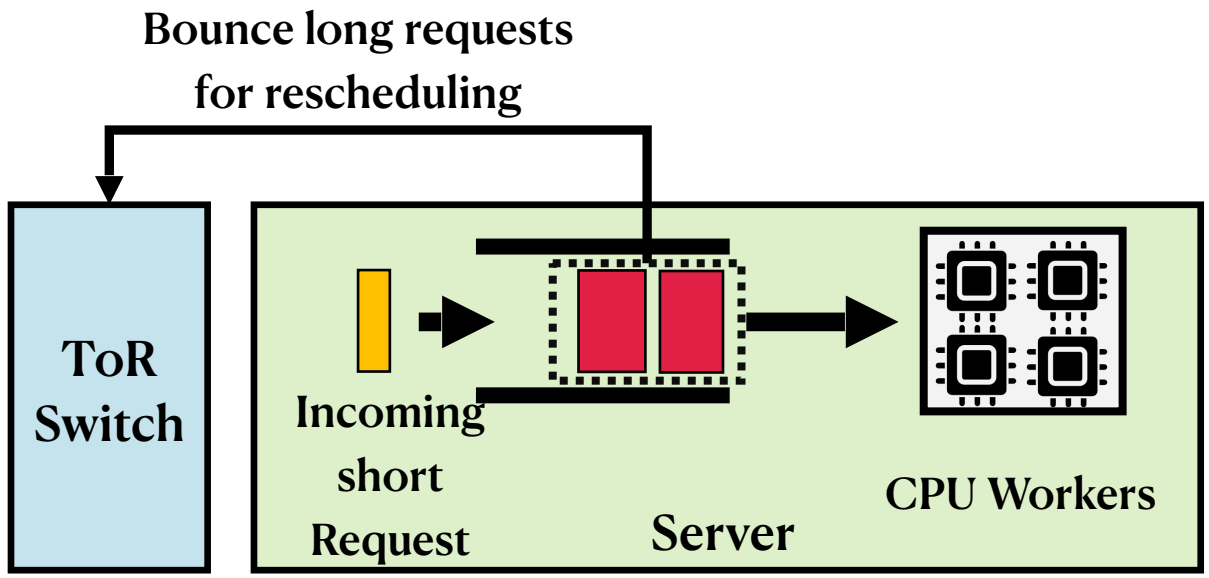
Long-term workload adaptation

➢Workload change detection

- Record request num and exec. time inside switch dataplane registers
- Trigger actions when real time demand deviates from last monitored one by δ

➢Reaction – policy re-generation

- Re-trigger the workload estimation and update the scheduling policy
- *Graceful request bouncing*



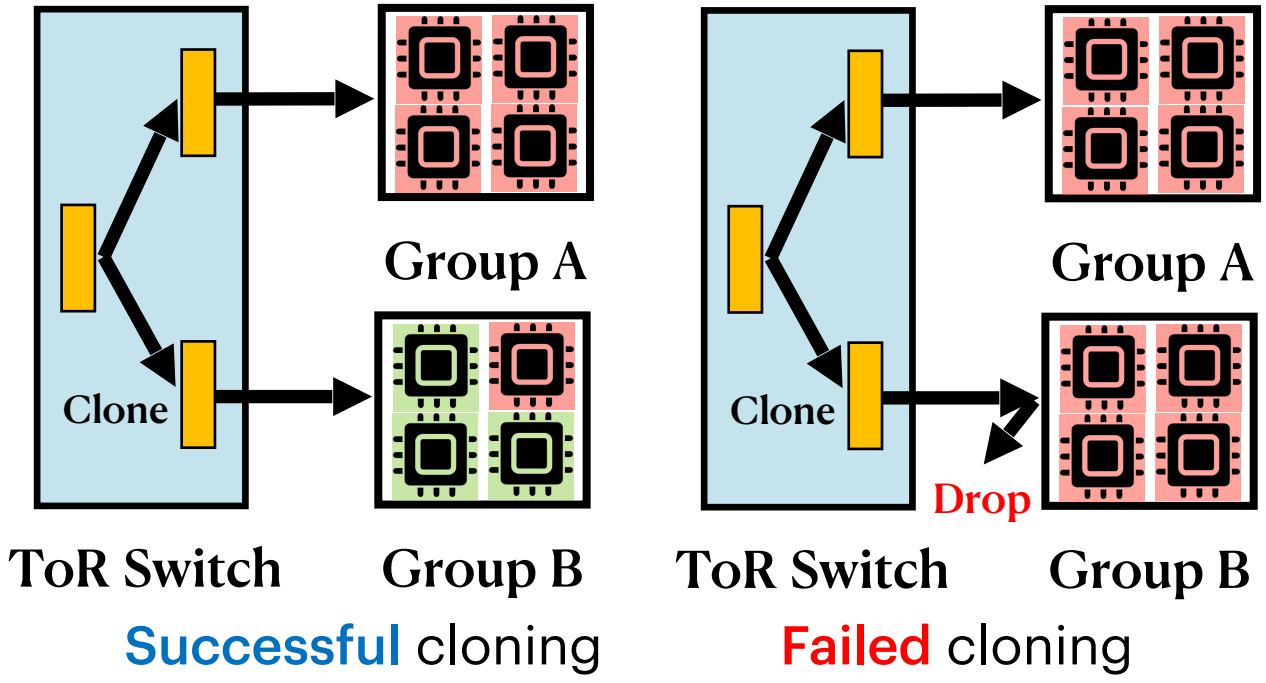
Short-term burst handling

➢Burst detection

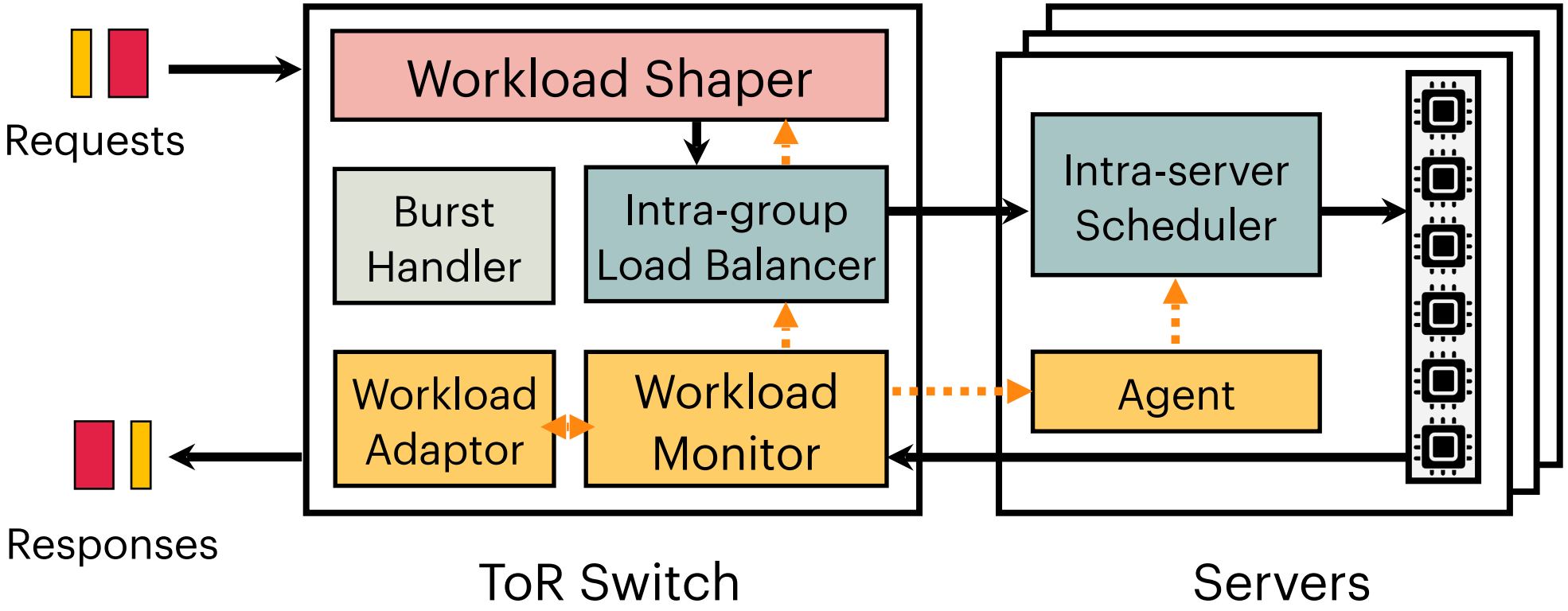
- Real-time observed request num. $\mathbb{C}_{g,t}$ exceeds $\mathbb{C}_{thresh}$ during interval τ
- $\mathbb{C}_{thresh}$ represents upper limit of requests from group g

➢Reaction – Conditional request cloning

- Clone the *bursty portion of requests* to under-utilized groups



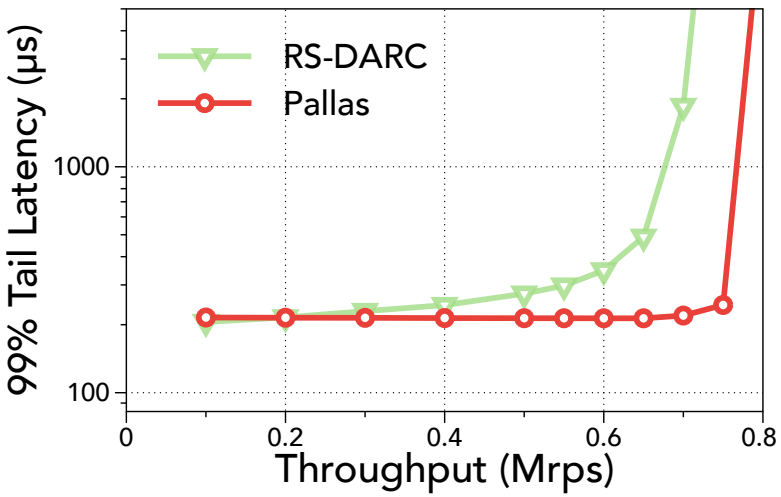
Pallas system overview and workflow



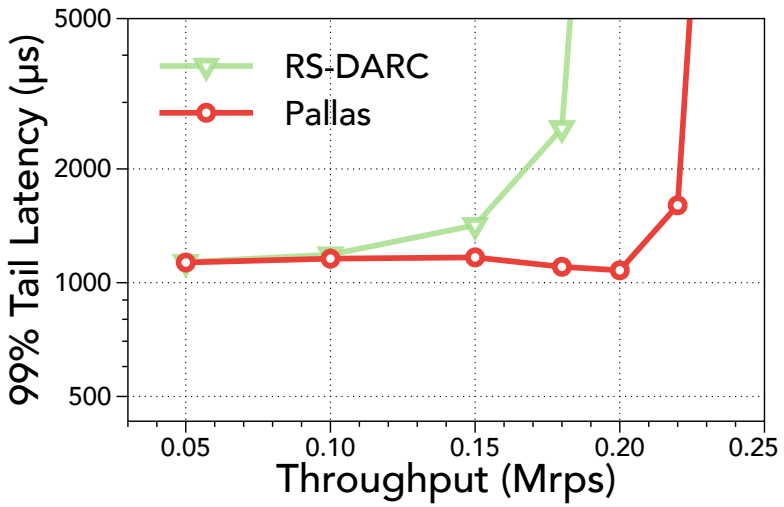
Implementation and evaluation setup

- Implementation
  - Switch Dataplane: workload shaping and WRR intra-group scheduling; request numbering; burst detection
  - Switch control plane: policy enforcement, workload monitoring and change handling
  - Server: simple ***cFCFS*** or ***DARC***
- Testbed
  - Intel Tofino switch
  - 10 servers with Nvidia ConnectX-4 100G NIC and 12 cores
- Workloads
  - Synthetic: exponential, bimodal, trimodal, multi-modal distributions (spin-loop the CPU)
  - Real-world applications: RocksDB with GET and SCAN requests

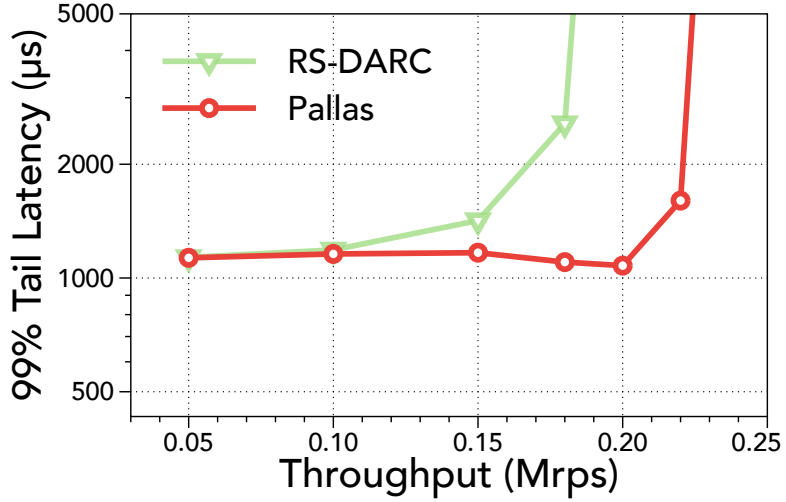
Throughput vs. tail latency in synthetic workloads



Bimodal
(50%-10us, 50%-100us)



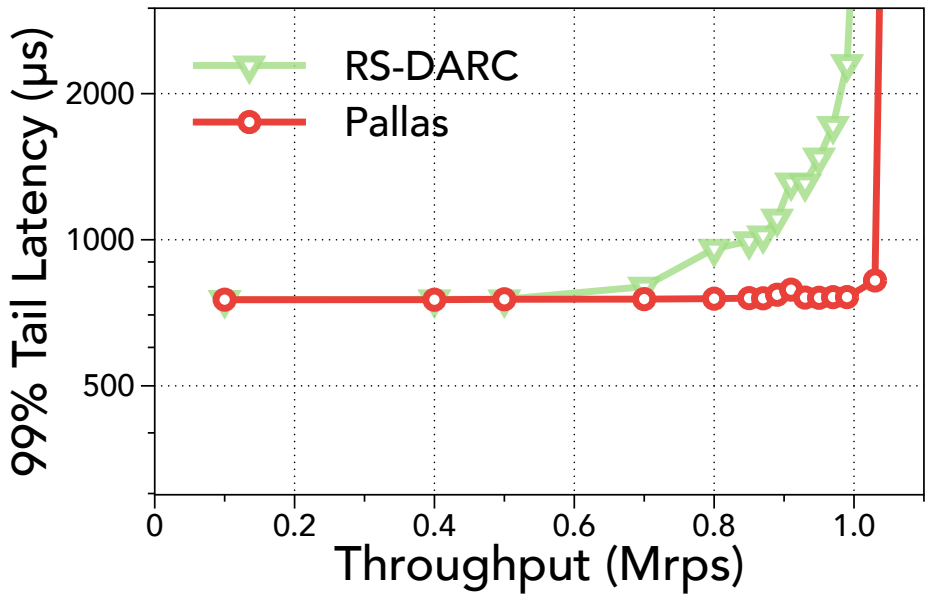
Trimodal
(33%-5us, 33%-50us, 33%-500us)



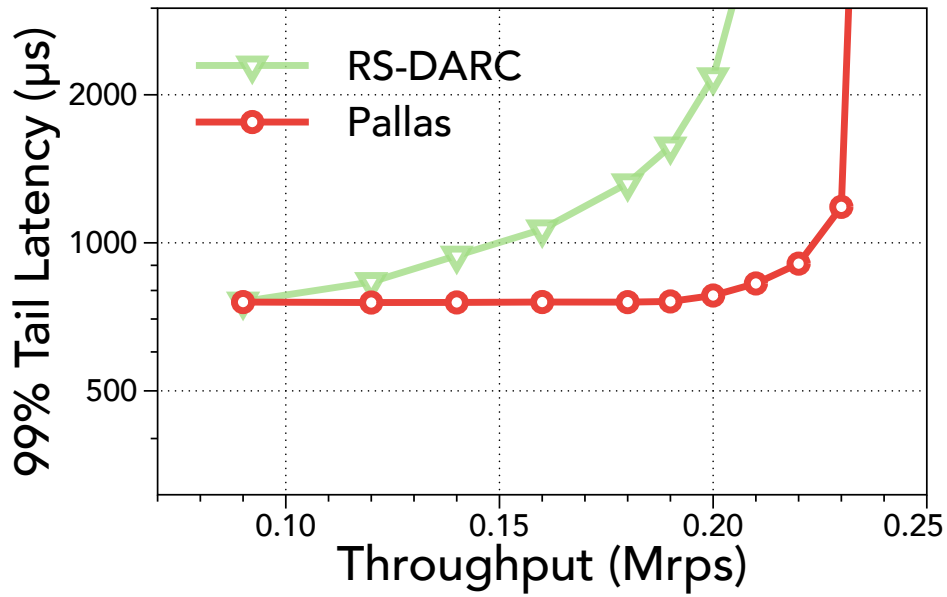
Multi-model from TPC-C

Pallas reduces the tail latency significantly and improves the SLO-target sustainable throughput by up to 2.1x.

Application: RocksDB



Bimodal
(90%-GET, 10%-SCAN)

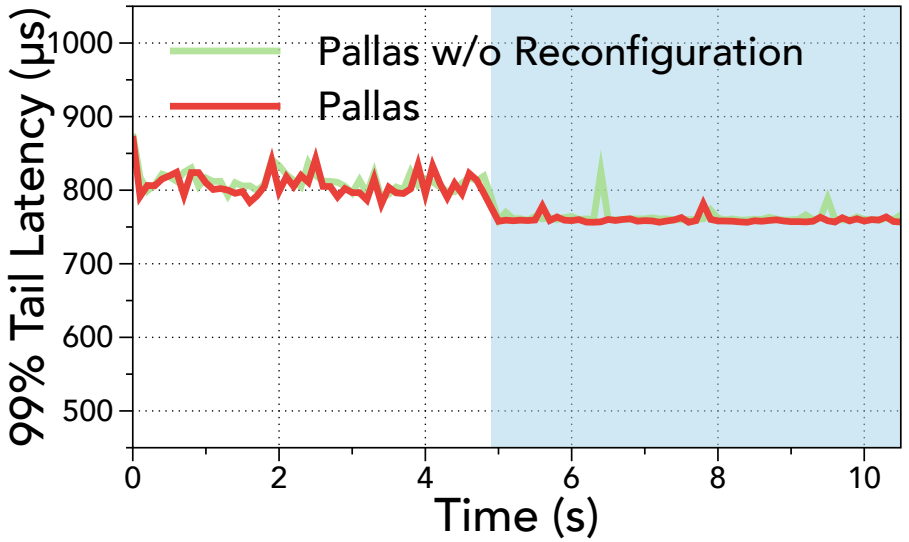


Port Bimodal
(50%-GET, 50%-SCAN)

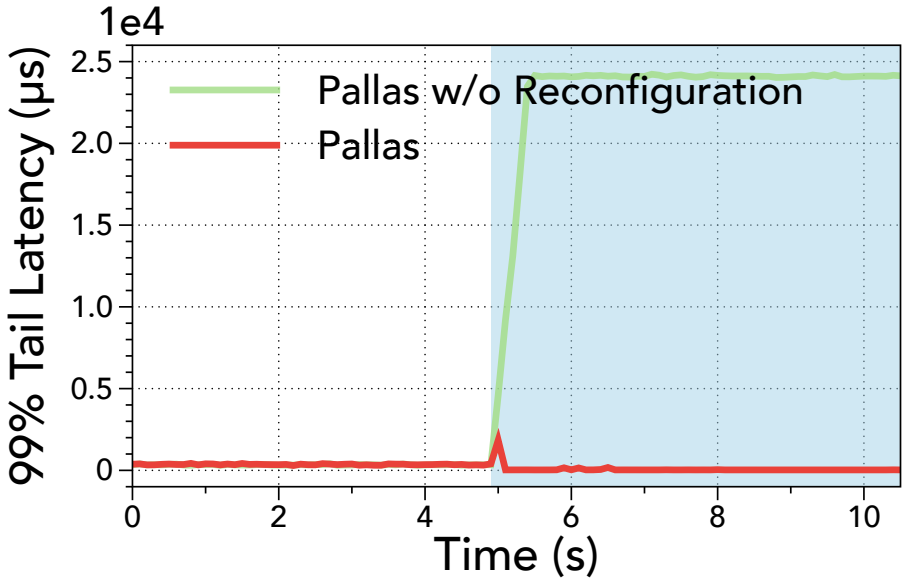
Pallas optimizes the tail latency by 5.5x.

Graceful workload change adaptation

Workload Change from Port Bimodal (50% SCAN) to Bimodal (10% SCAN)



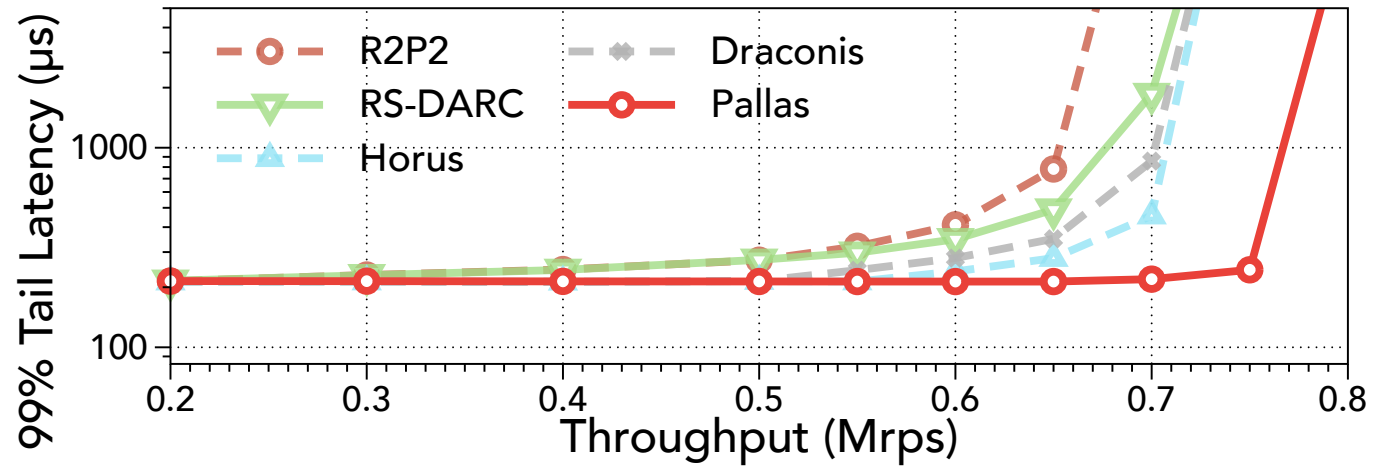
GET Requests



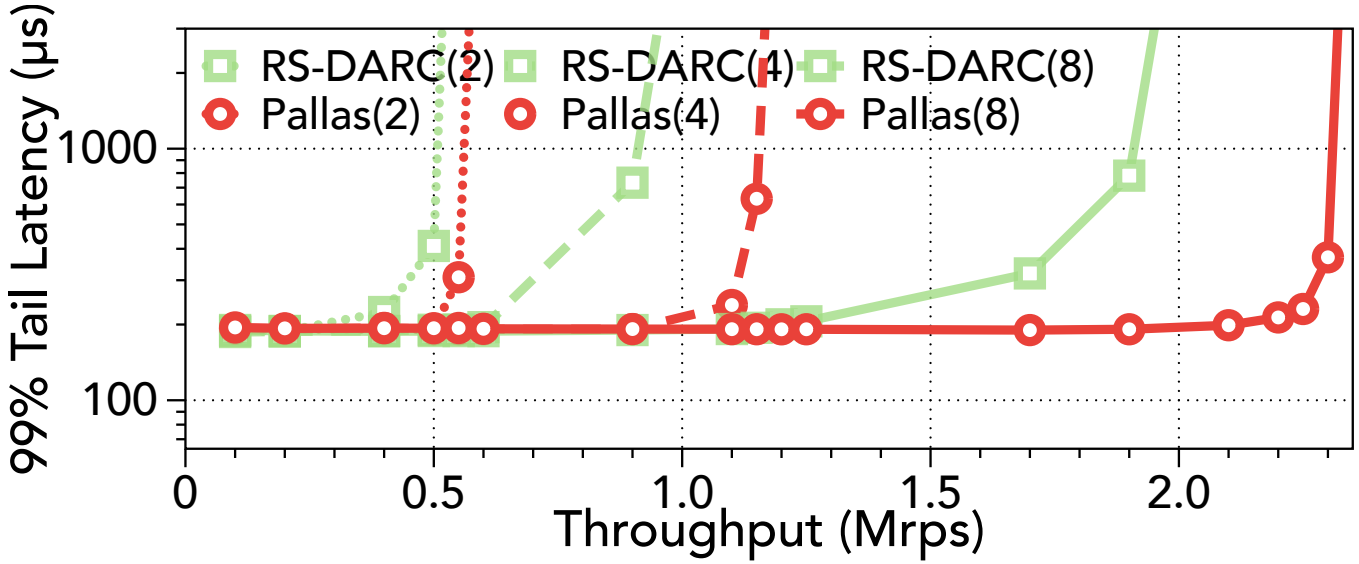
SCAN Requests

Pallas gracefully reacts to workload changes.

Comparison with other methods & Scalability



Pallas is better than other scheduling proposals.



Pallas exhibits almost linear scalability.

See more results in the paper!

Pallas recap

- Pallas is an *application-aware* rack-scale CPU scheduler for microsecond-level workloads.
- The core of Pallas is to proactively transform mixed workloads into uniform ones via in-network workload shaping and then perform ***simple yet near-optimal*** load balancing and intra-server scheduling.
- Pallas is available at https://github.com/HKUST-SING/pallas .

Thank You!

Q&A

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