Towards Performance Robustness for Microservices

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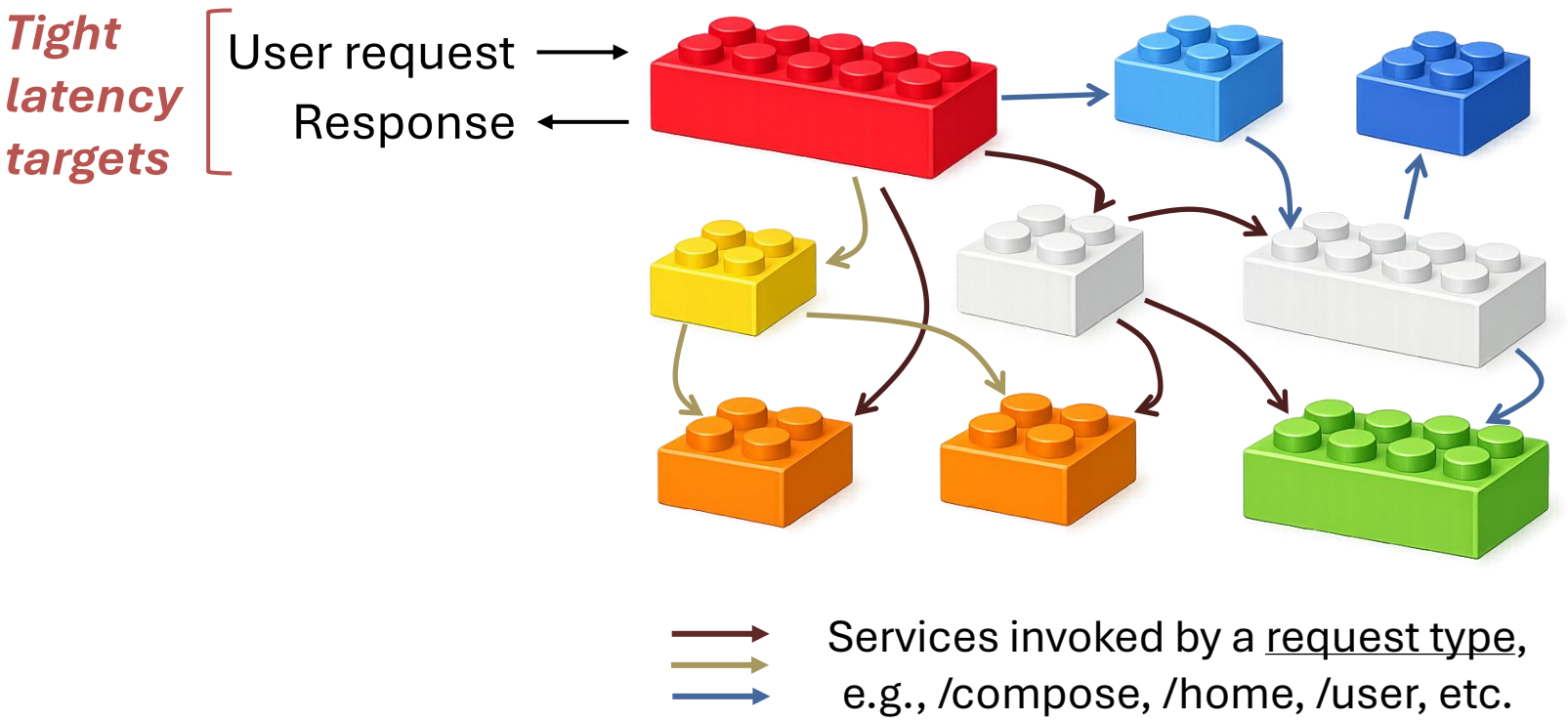
A Primer on Microservice Applications



Simplifies development but ensuring good performance becomes challenging.

Latent Factors Affect Microservice Performance

Sudden bursts in arrival rates
20% increase⟶1.7X p99 latency
3X arrival rates within 5 minutes*

Co-located background jobs
5.3X spike in p99 latency due to CPU contention

Concurrent request types
Shared microservices can become bottlenecks

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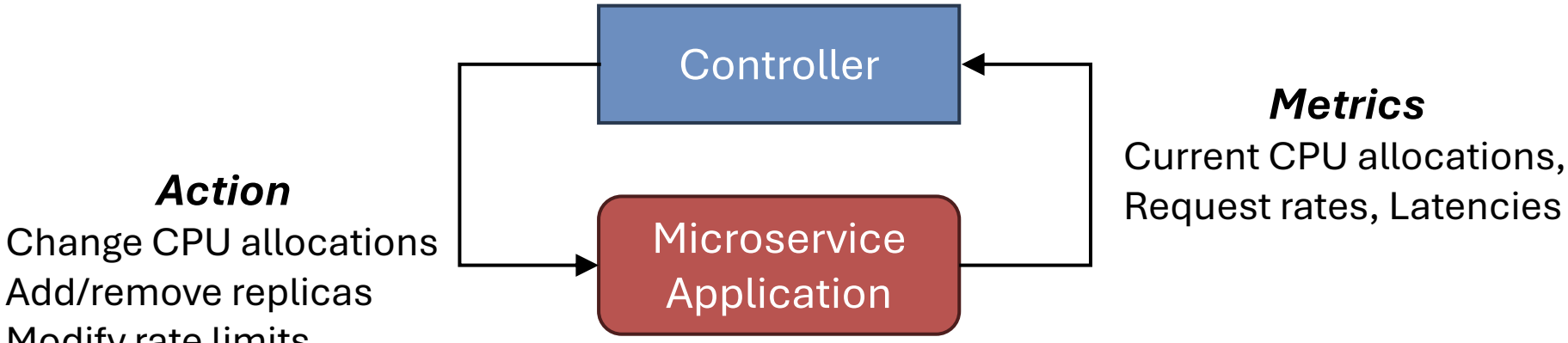

Controllers to manage microservices

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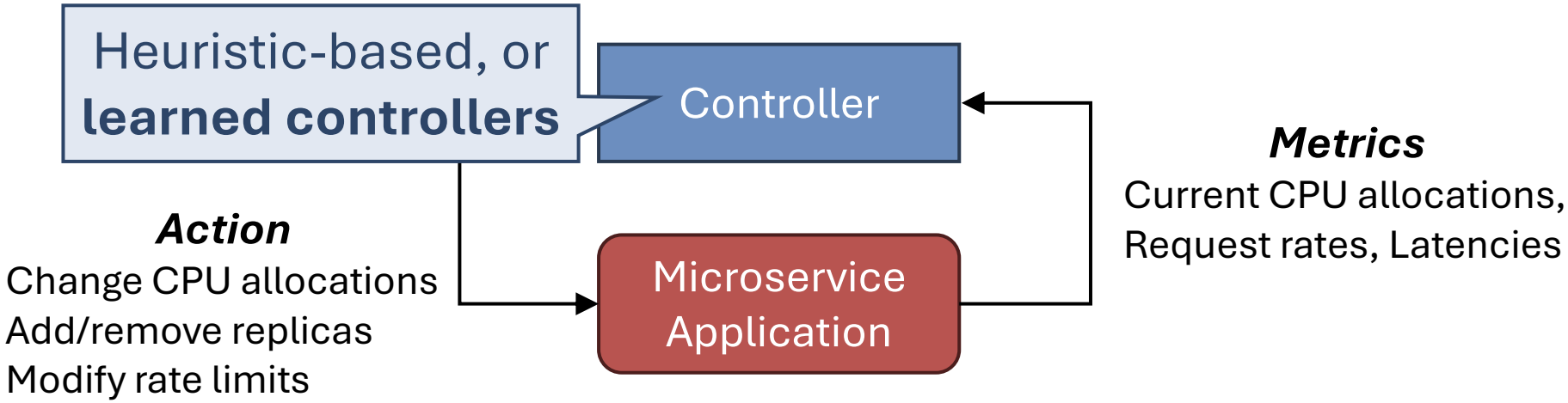

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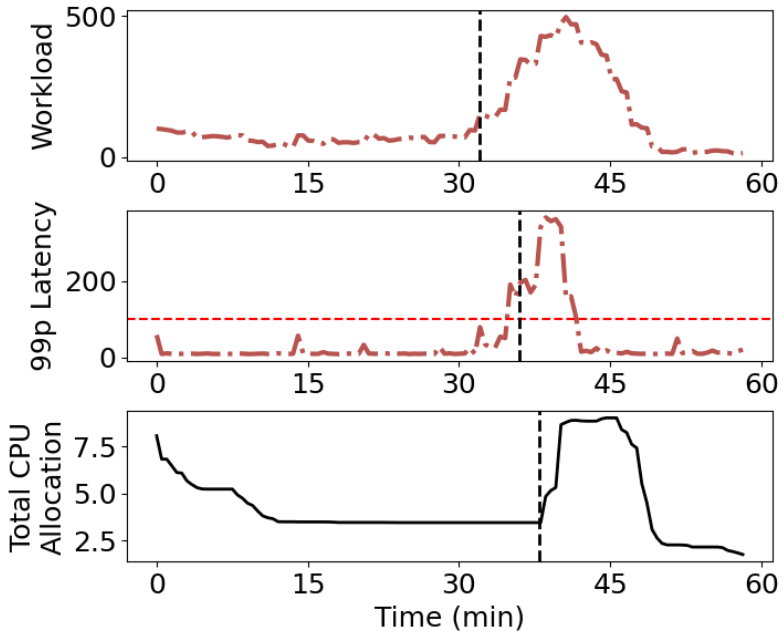
Learned Controllers Fail to Address Latent Factors

Autothrottle* uses current request rates and latencies to allocate CPU resources…
…but does not ramp up CPU allocations quickly enough.



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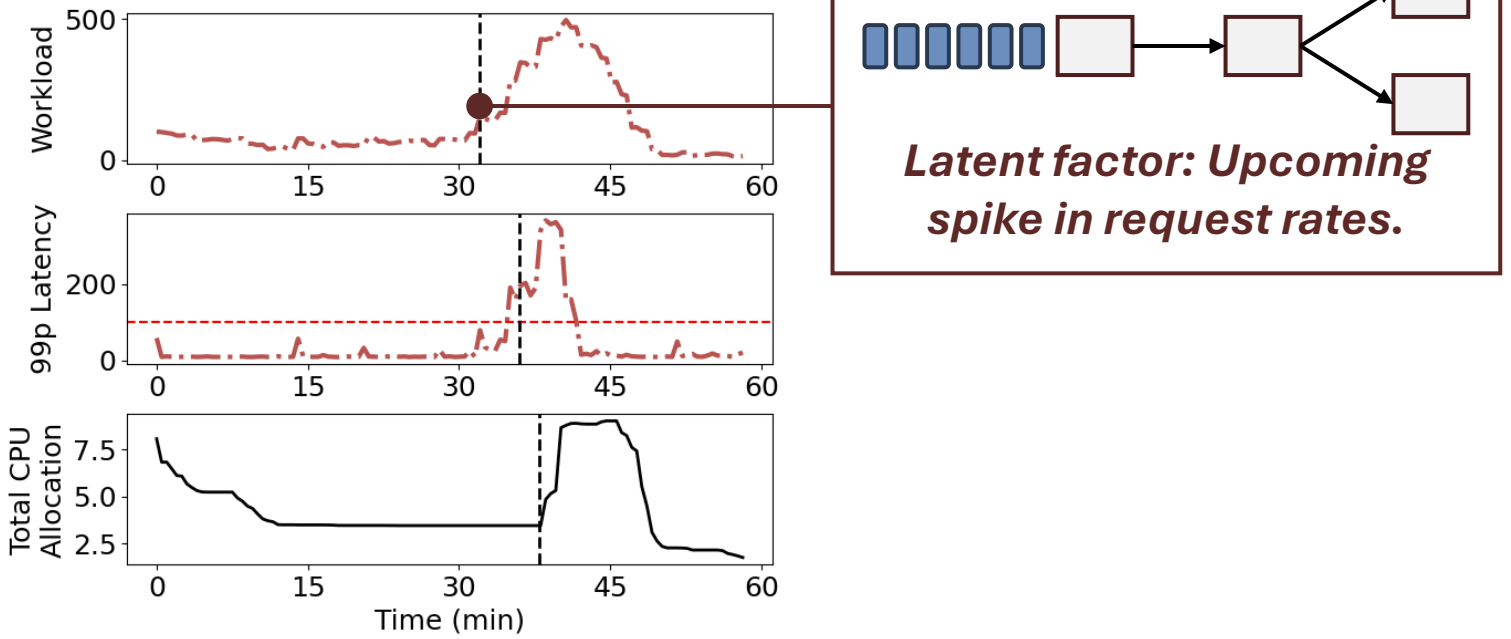

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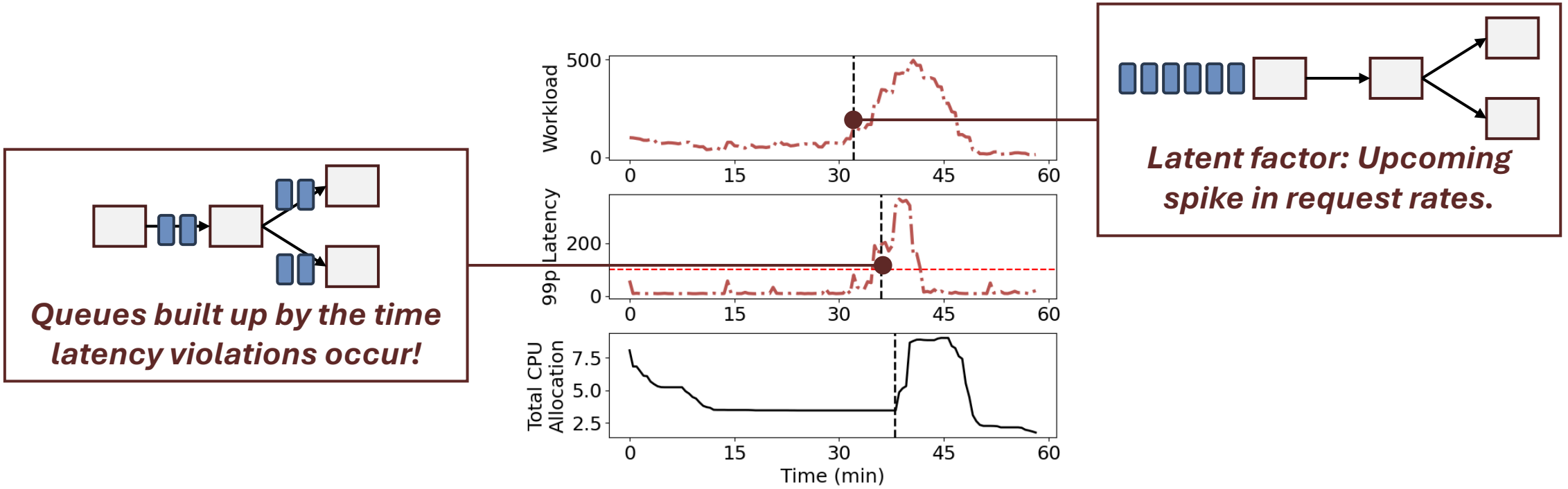

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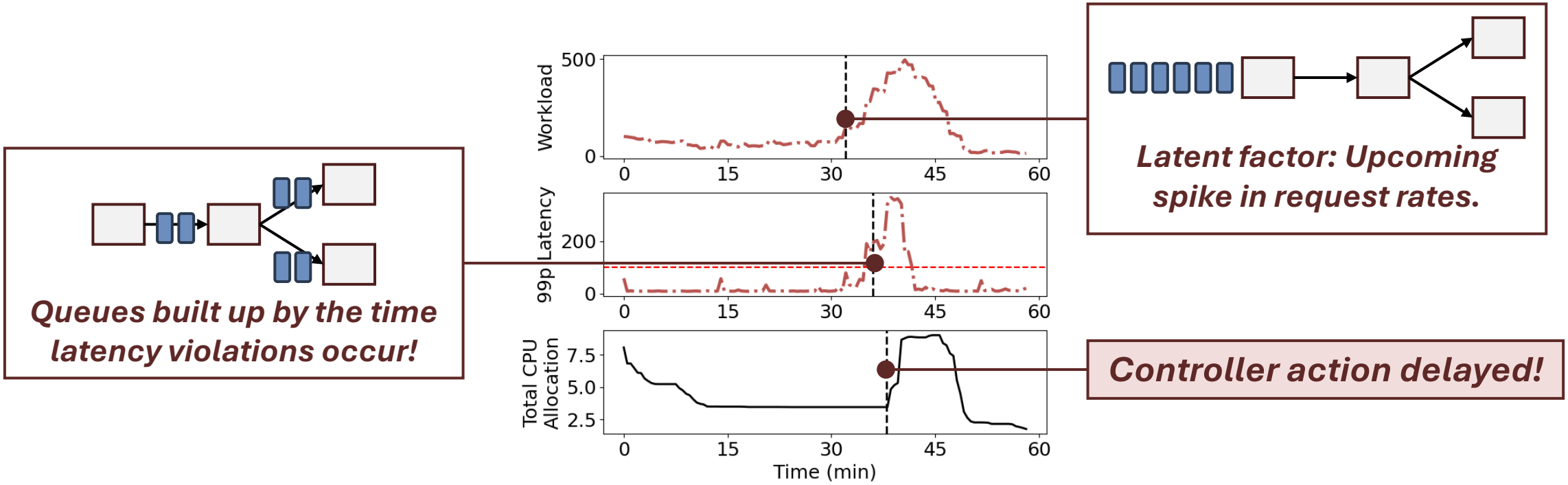

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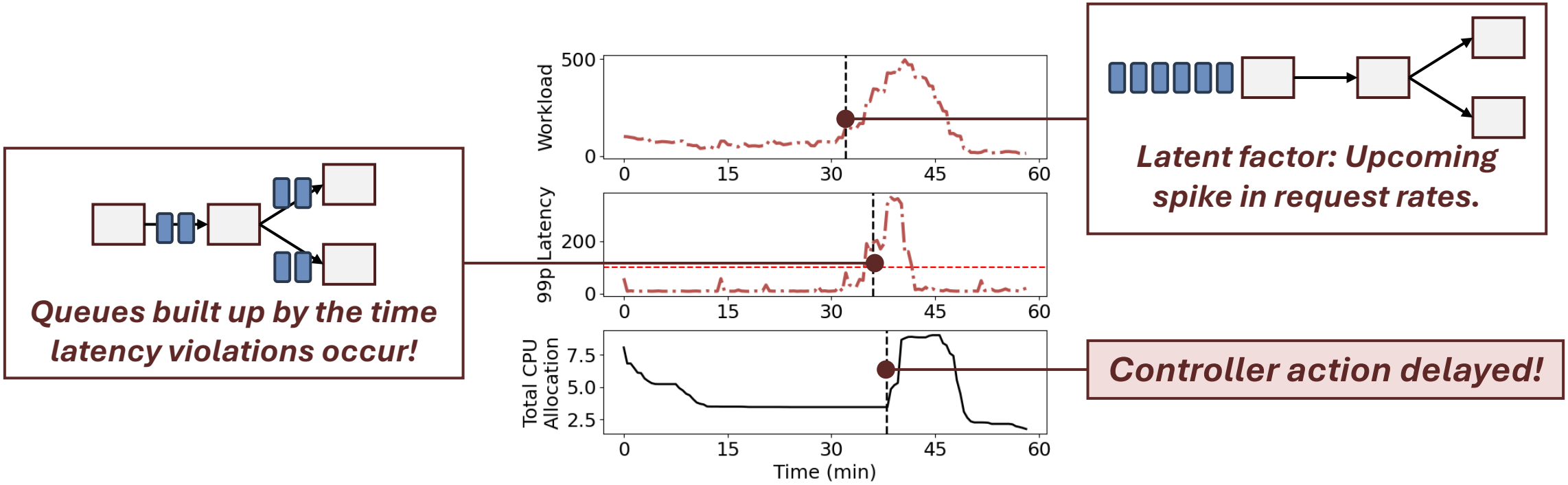

Controllers are unaware of how latent factors evolve and impact performance!

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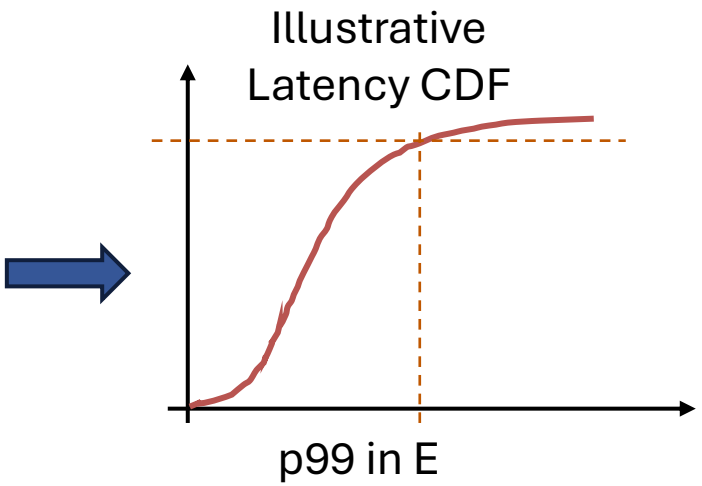
How to achieve ***performance robustness*** –
consistently meet latency targets despite latent factors?

Key Idea: Anticipate Performance Under Perturbations

E
Current
Environment



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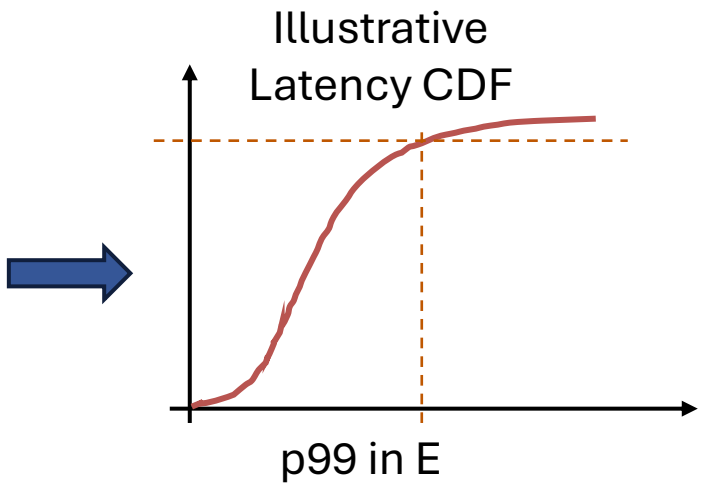

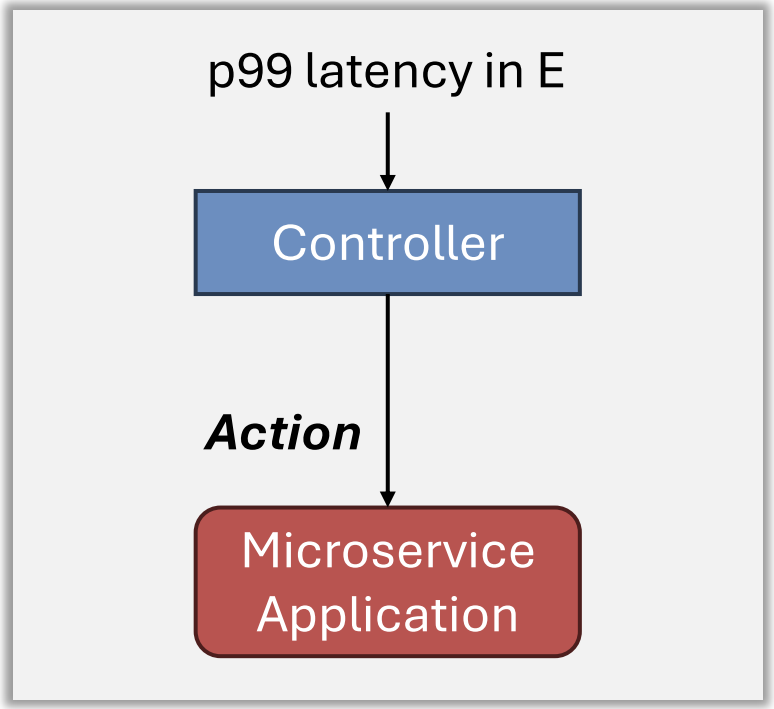

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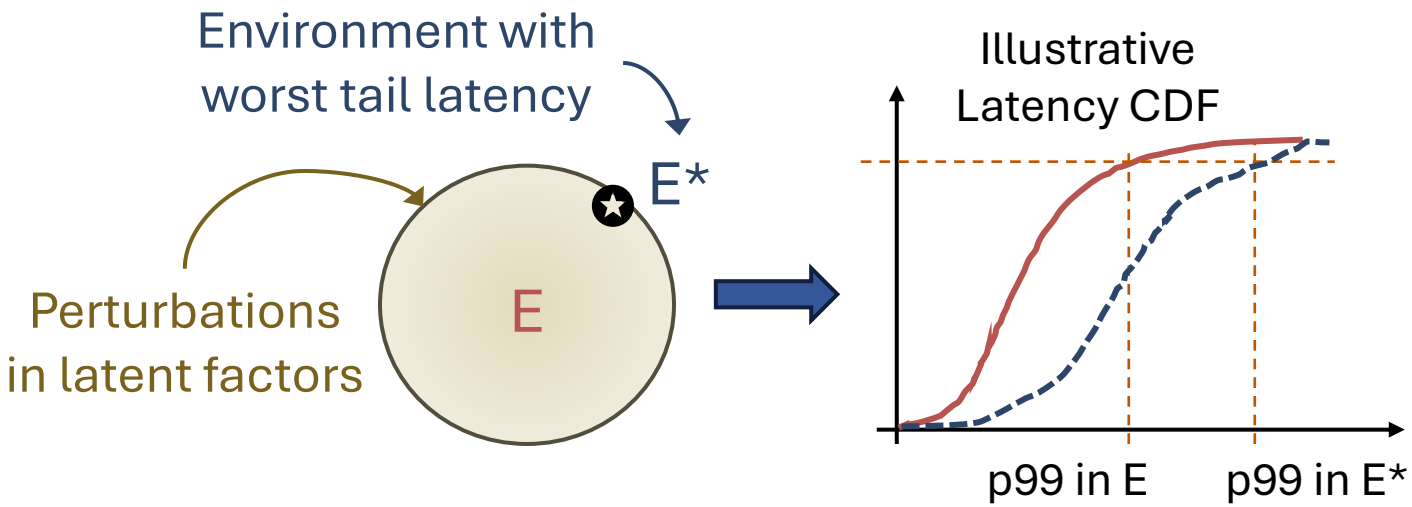

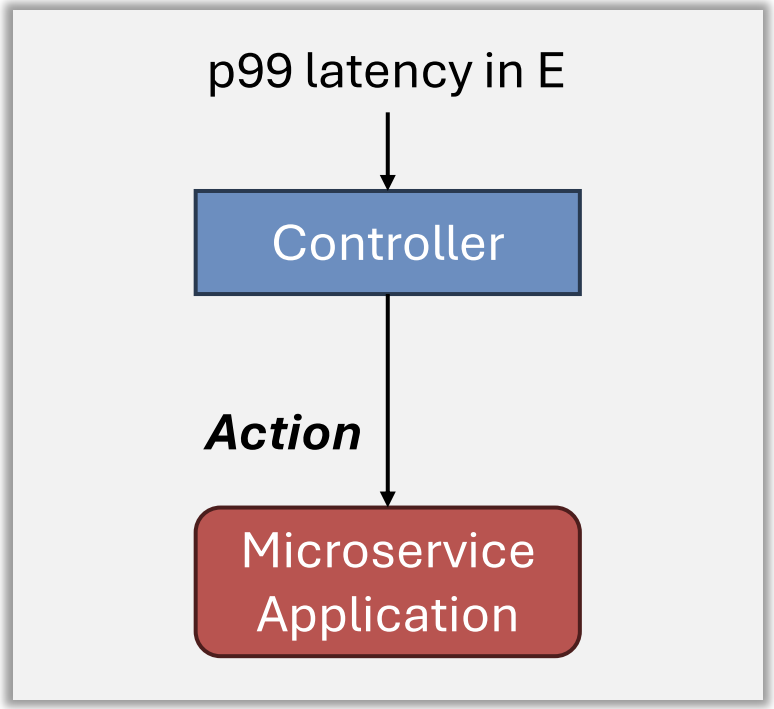

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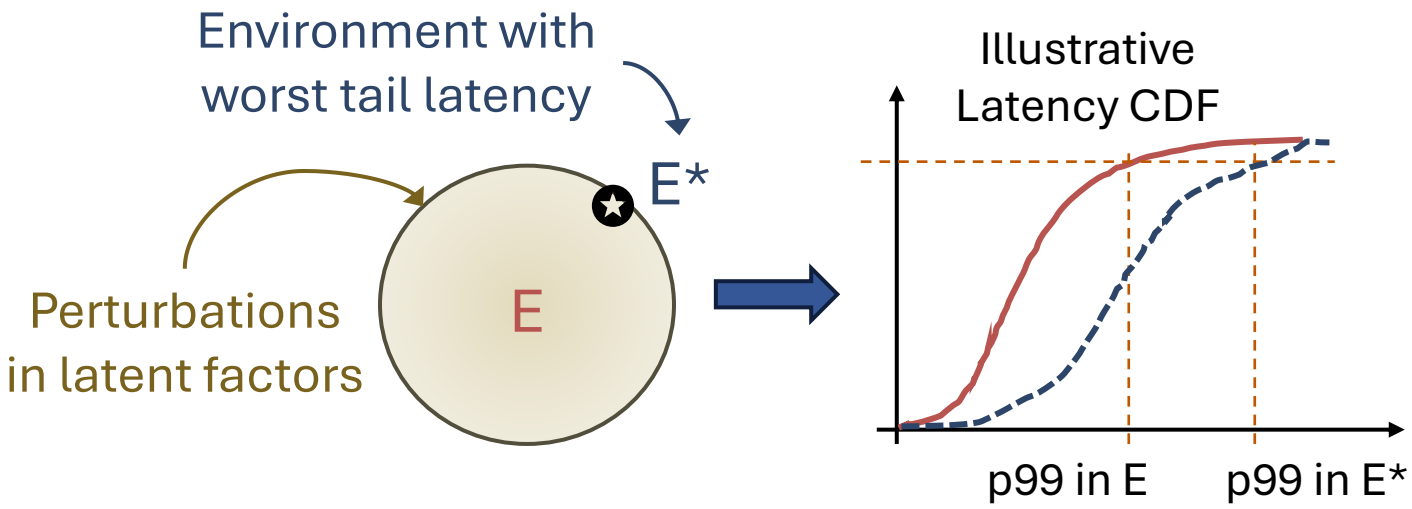

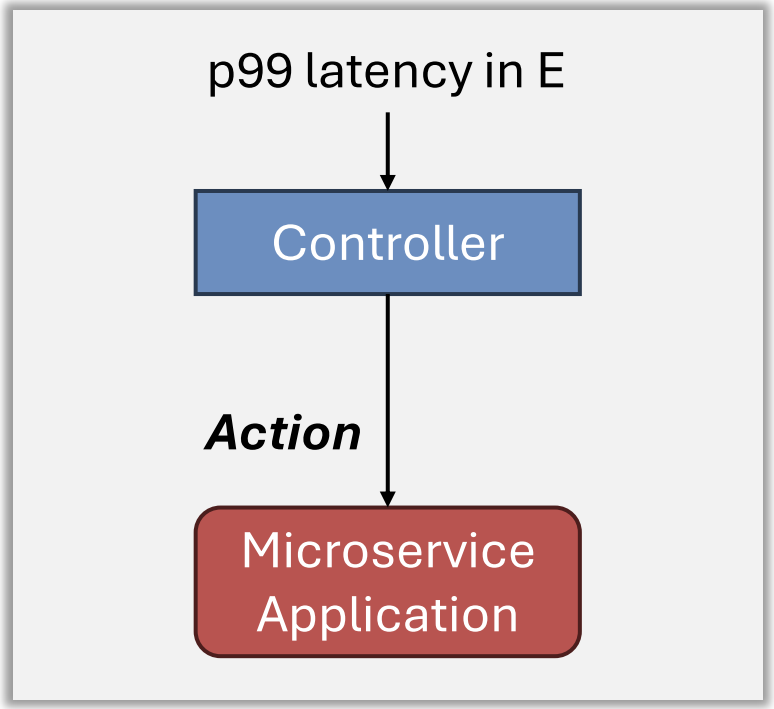

Performance Robustness Certificate (PERC)

Worst tail latency under environment perturbations.

$\text{PERC} = \max\{l_{99}(E') \mid E' \in \Delta_E\}$

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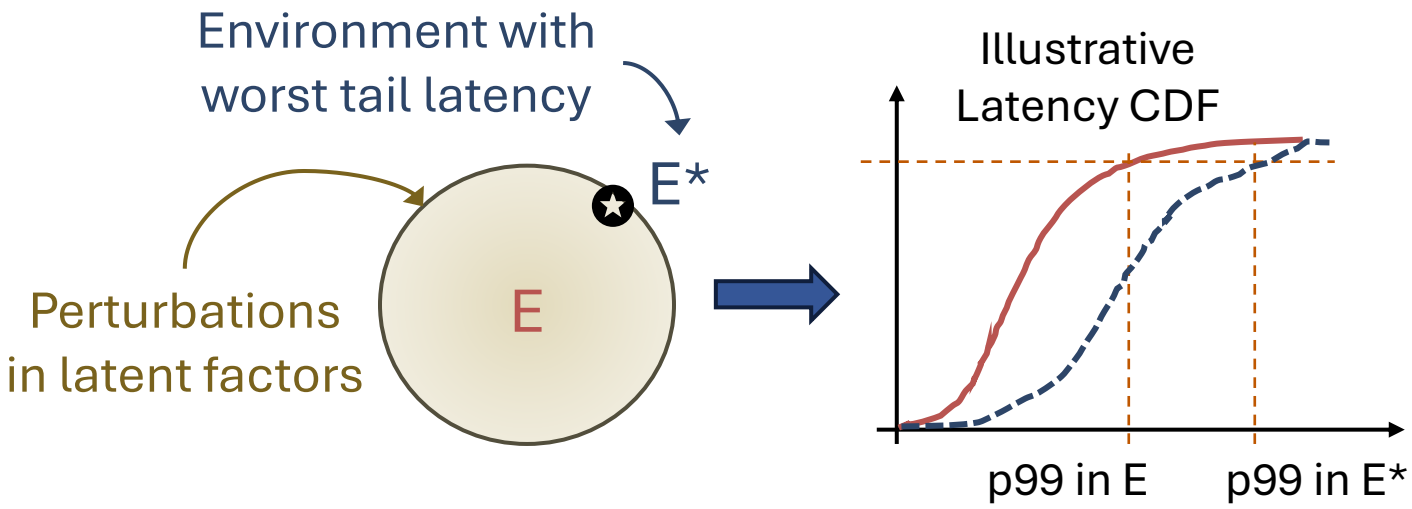

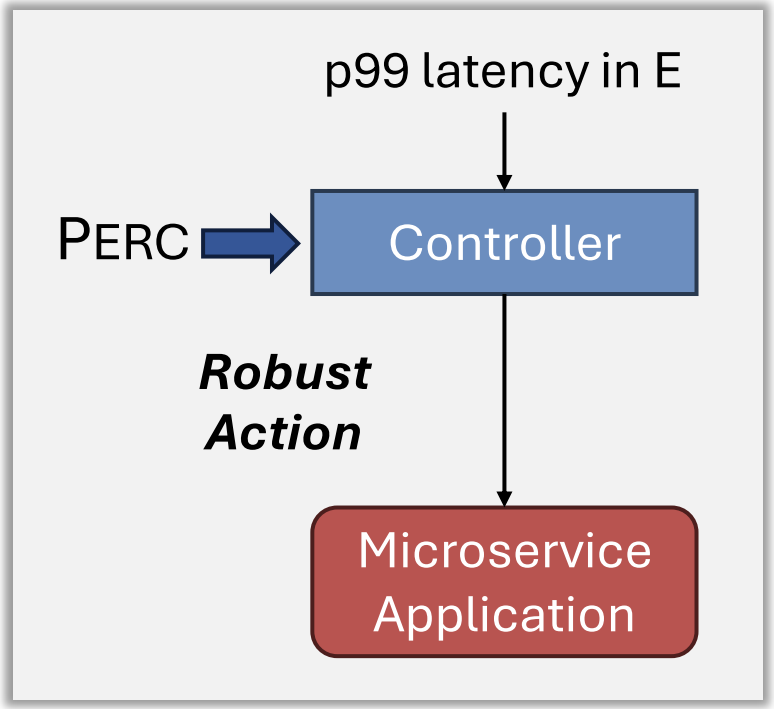

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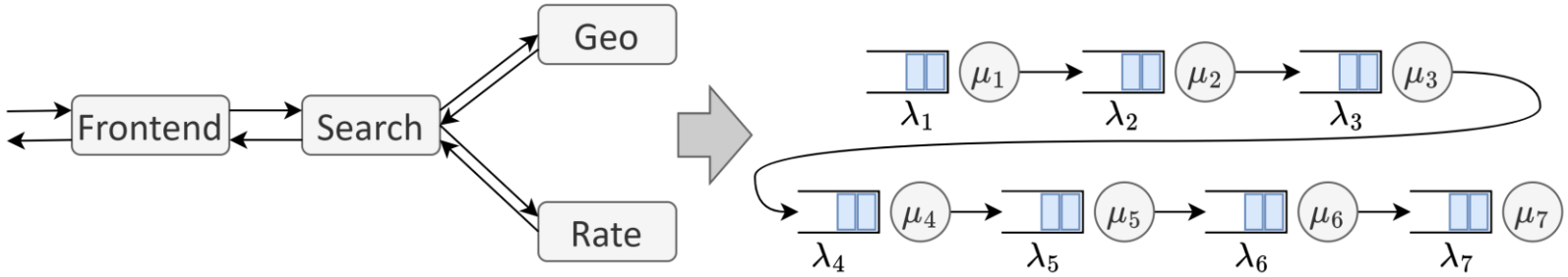
Performance Reasoning Rooted in Queueing Theory



Path of each request of a given type ⟶ network of $\mathrm{M/M/1\text{-}PS}$ queues

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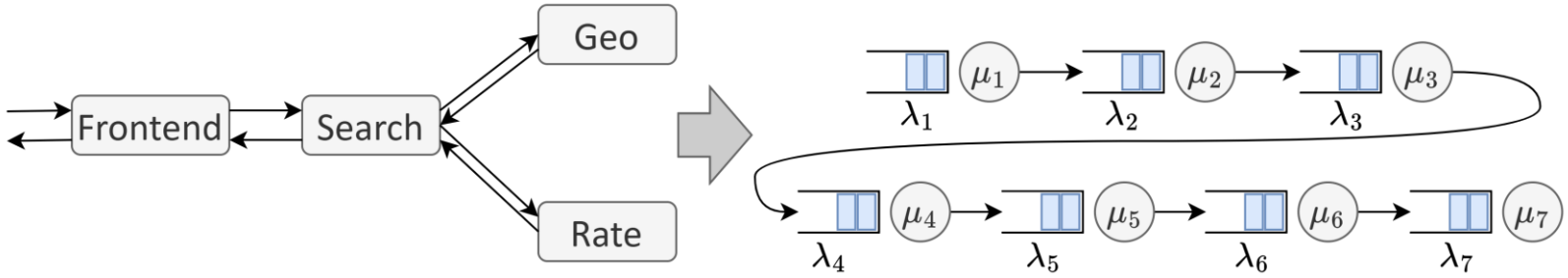

Why queueing theory?

Matches microservice processing

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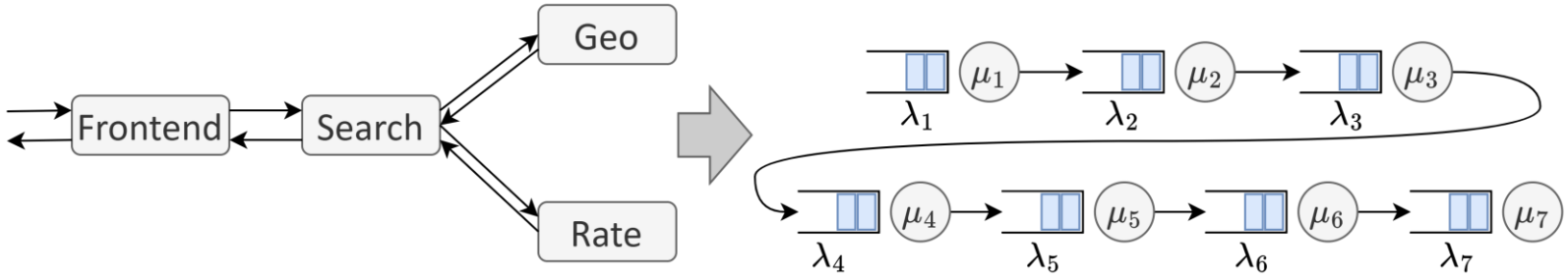

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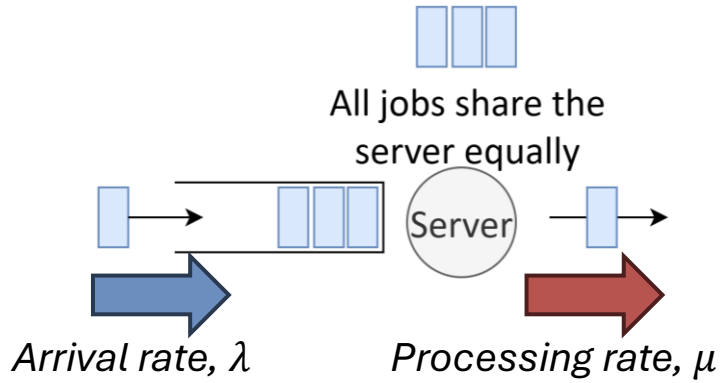

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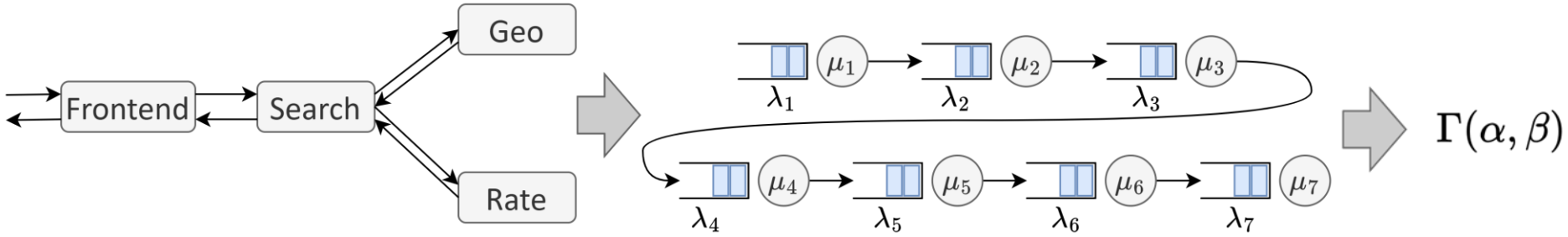

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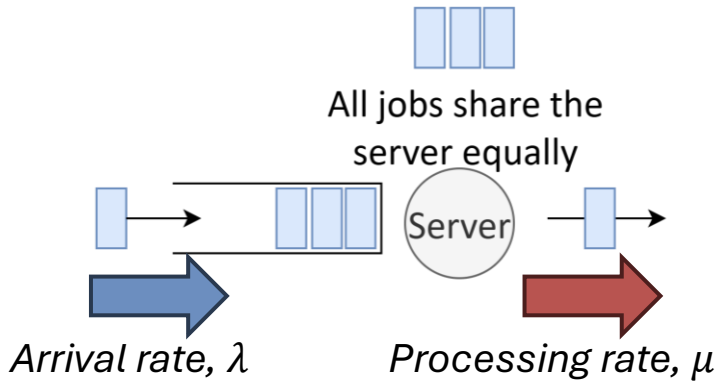

For the network of queues

End-to-end latency distribution:
$\boldsymbol{Pr(W = t) \sim \Gamma(\alpha, \beta)}$

Empirically: 4-19% average error in tail latency estimates!!

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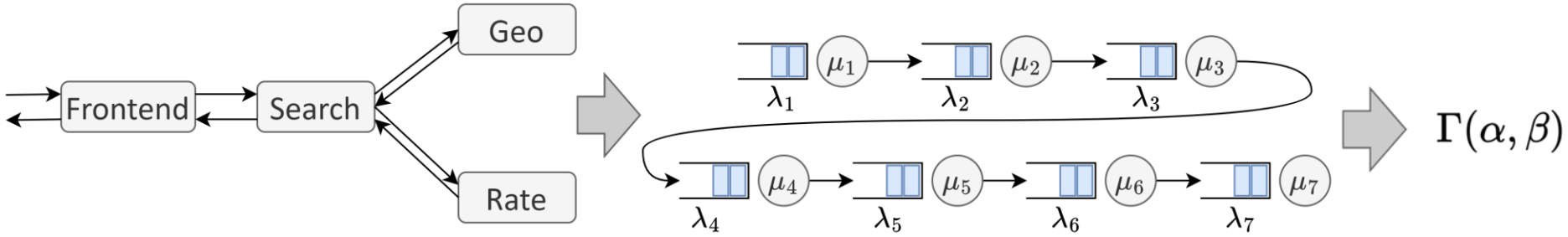

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Perturbations captured as changes to model parameters

Any change in latent factors → Changes processing or arrival rates → Changes resulting (α, β)

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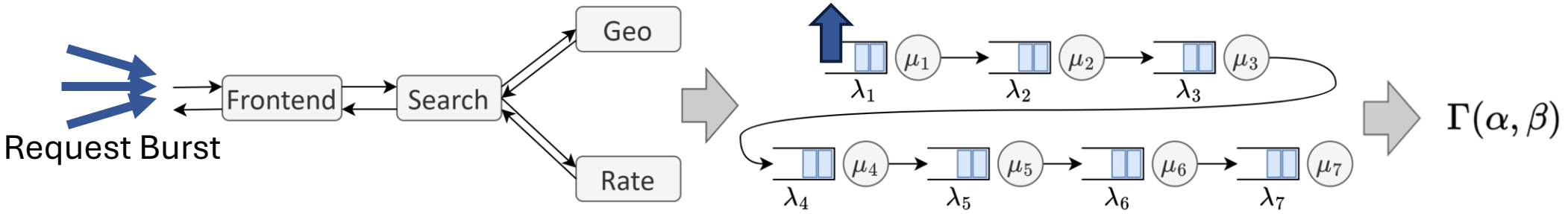

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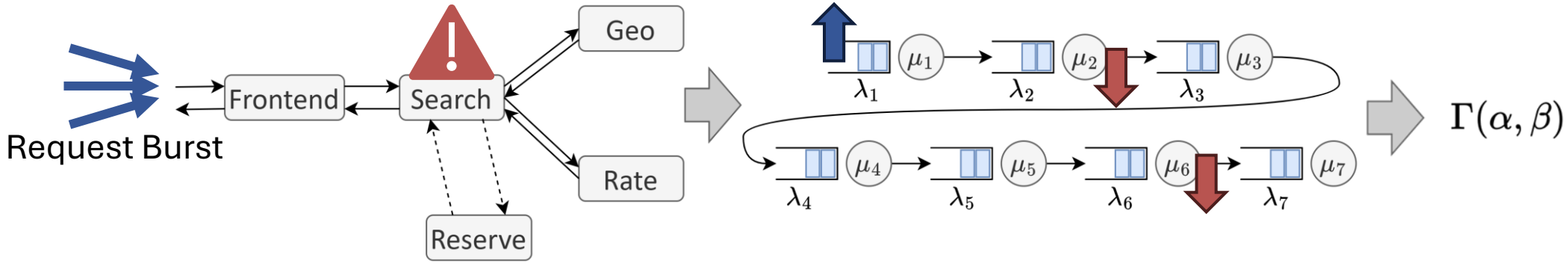

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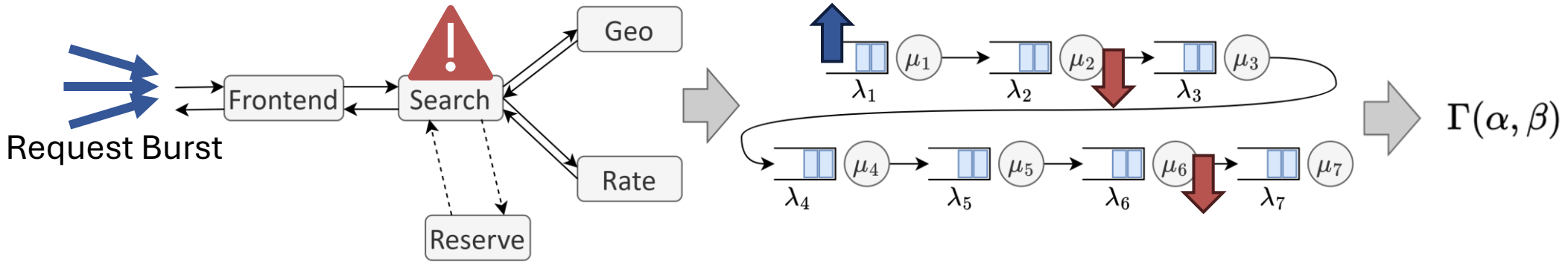

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In our model, environment can take two types of actions:
1. Change processing rate at a queue.
2. Change arrival rate at a queue.

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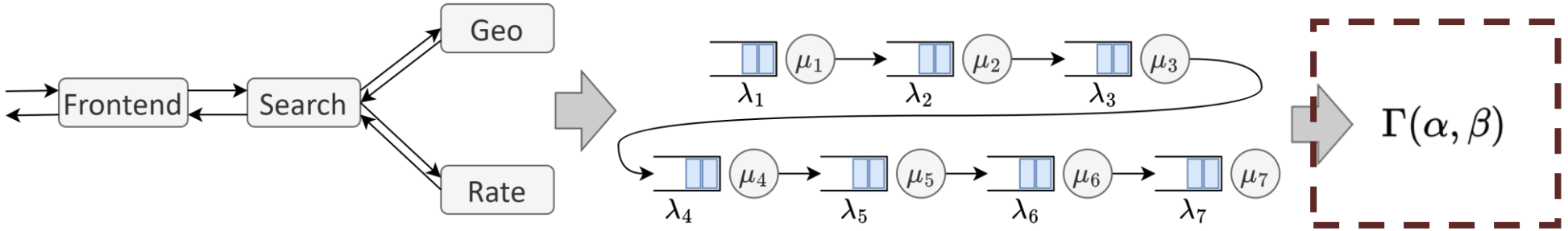

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Perturbations captured as changes to model parameters

Easy to calibrate using live data

Fit (α, β) using end-to-end latency measurements.
No additional instrumentation needed!

Encapsulates performance in a two-parameter model.
Can be fit using limited data!

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Simulating the Impact of Latent Factors

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Perturbation ball: **at most δ change** in arrival/processing rates of any queue.

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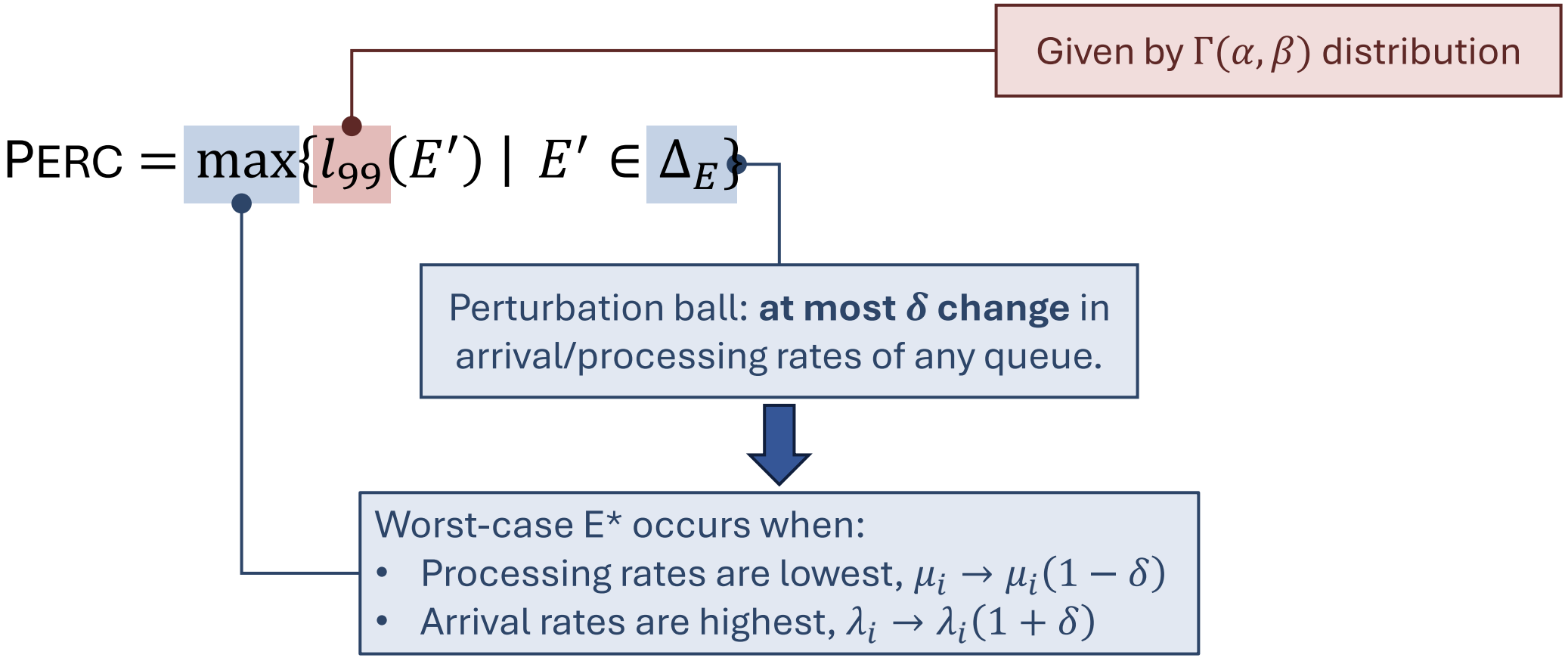

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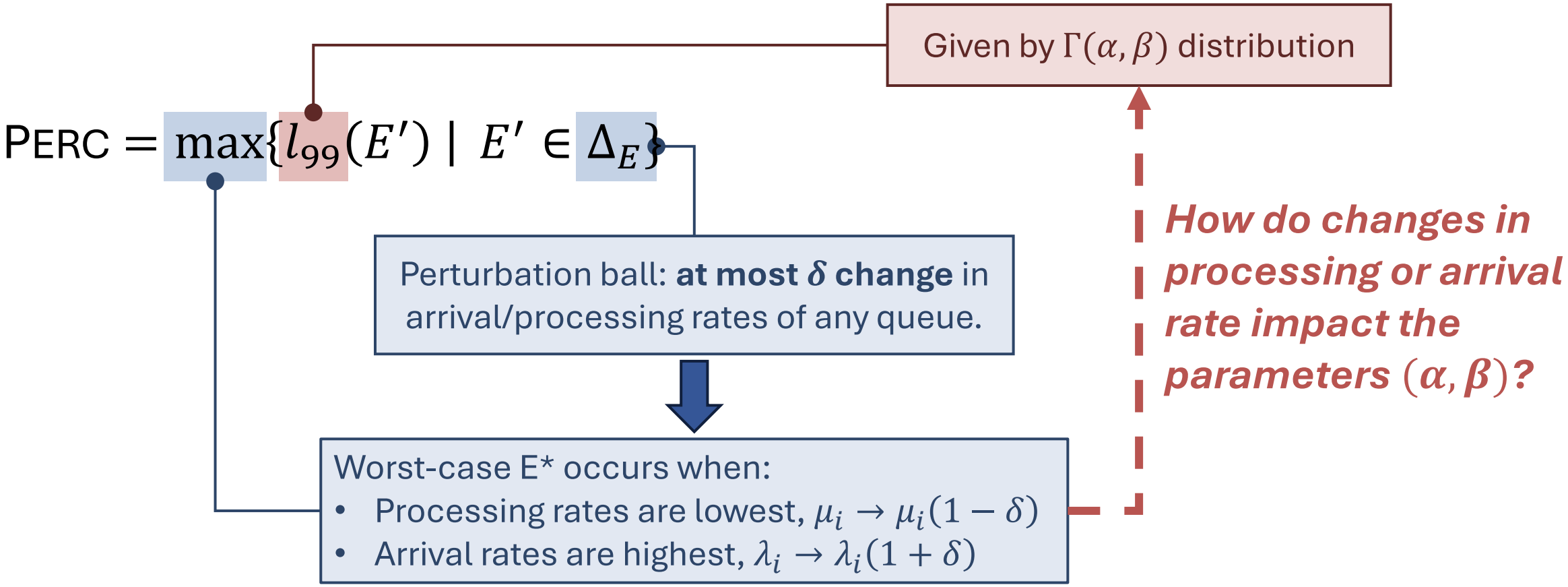

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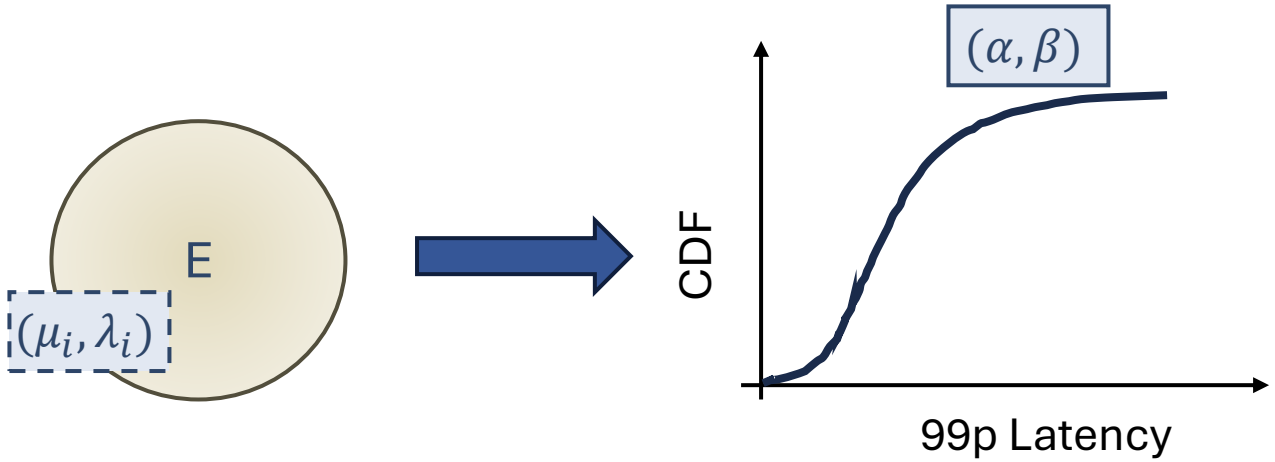

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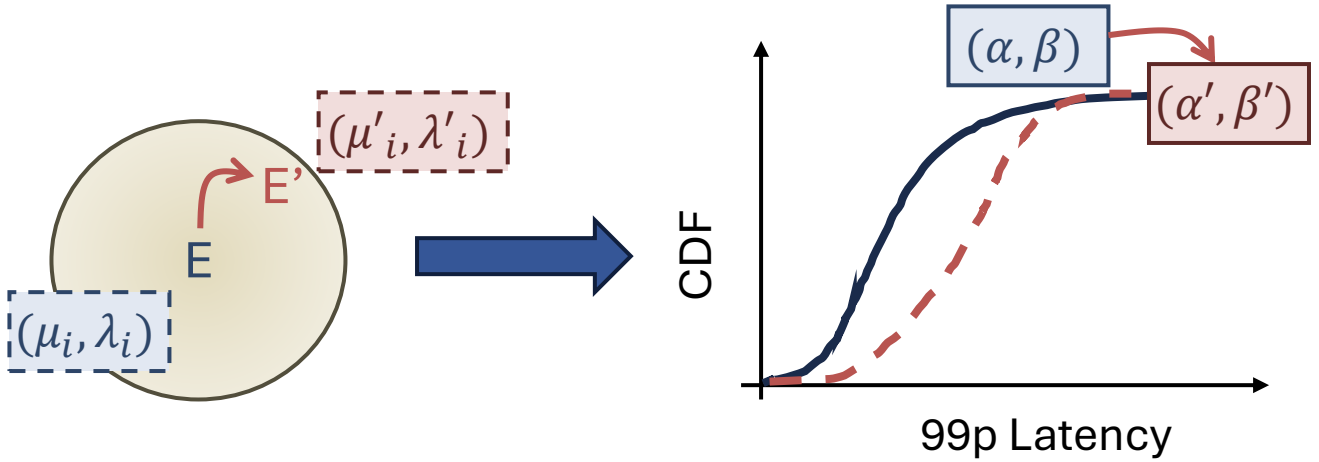

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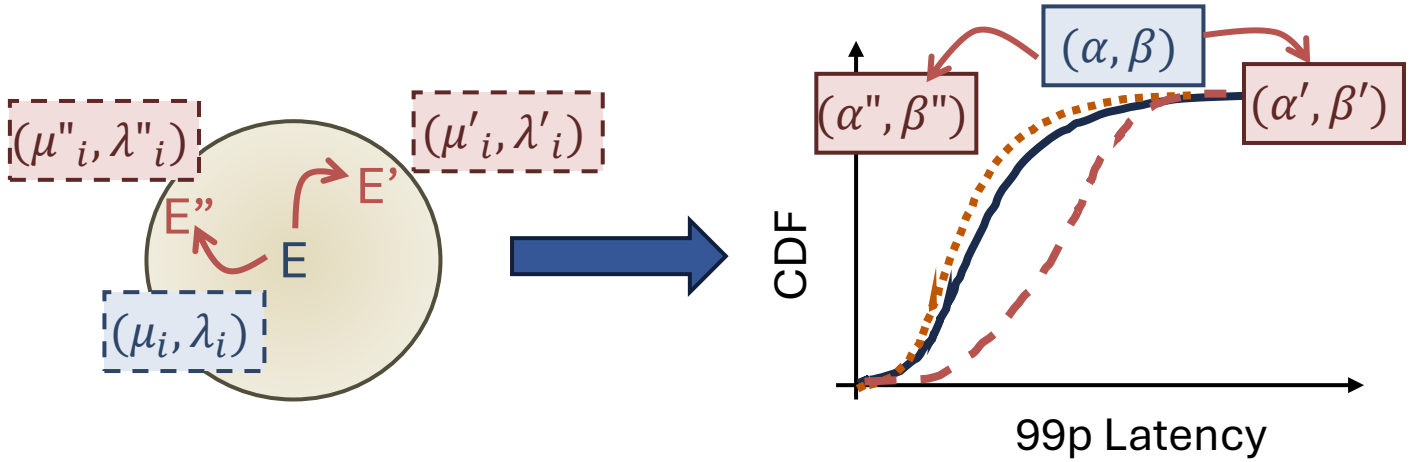

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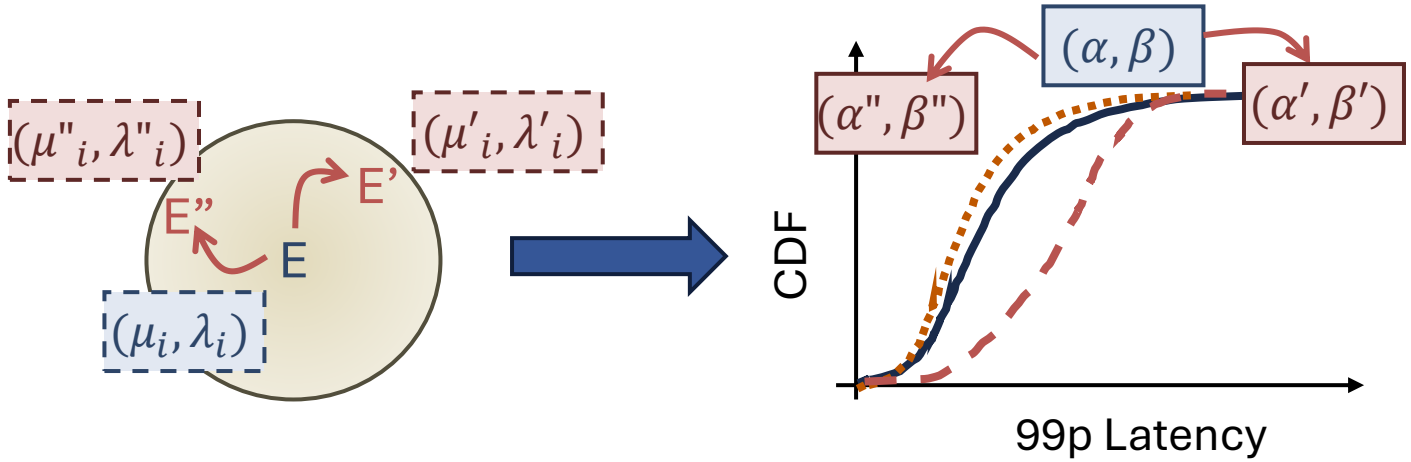
$(\alpha, \beta) \rightarrow (\alpha + \eta\partial\alpha, \beta + \eta\partial\beta)$.



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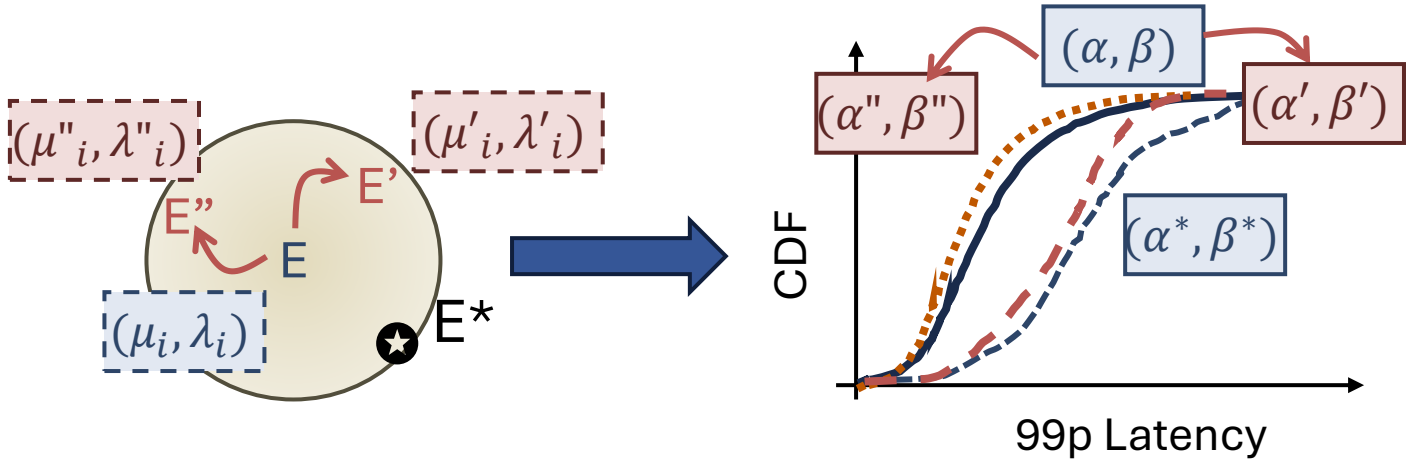

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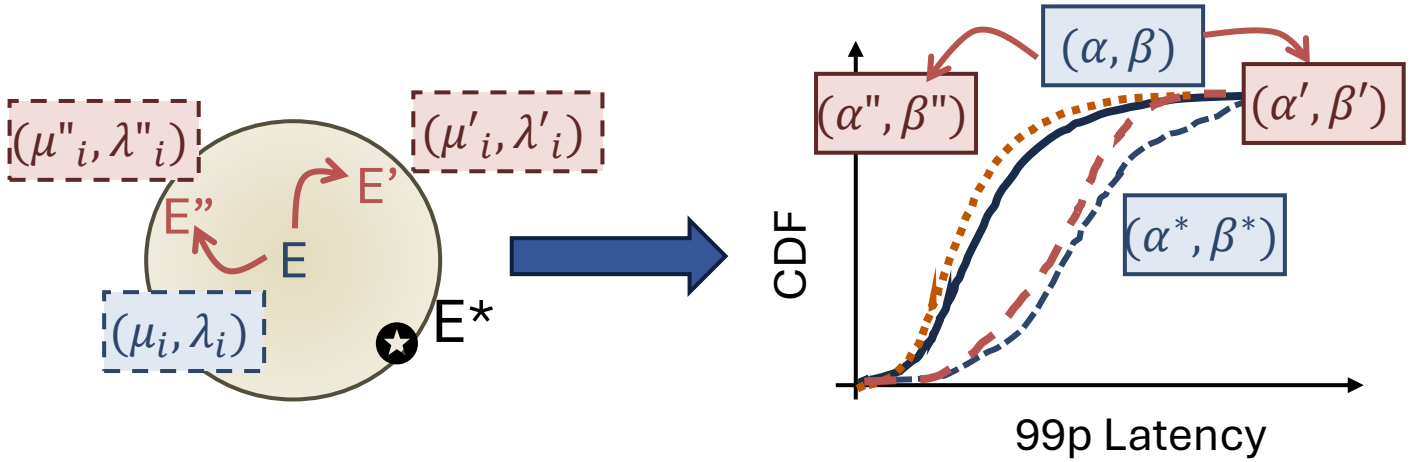

Need **multiple samples** across **all dimensions!**

Use **compressive sensing*** to estimate gradients in fewer samples.

*Carleton, Vijaykumar, Saxena, et al. 2025. CONGO: Compressive Online Gradient Optimization. ICLR'25

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- Add a *robustness reward* function: “are PERCs within SLOs?”
- *Construct shields* to validate new controller actions

Shields to Train and Deploy Robust Controllers

Stochastic nature of learning algorithms ⟶ May not result in robust actions always!

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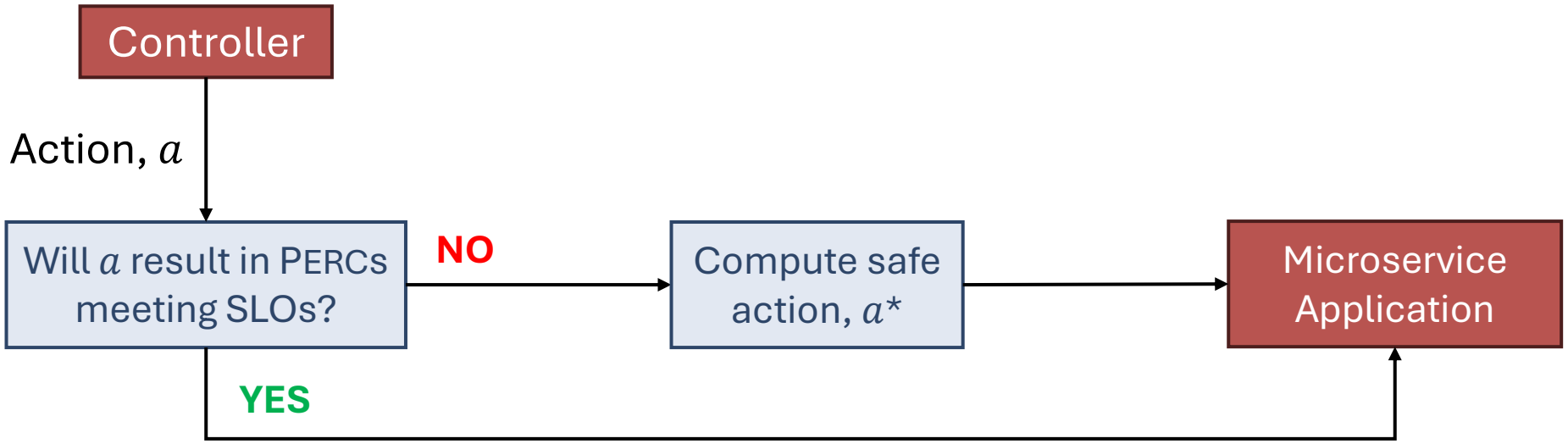

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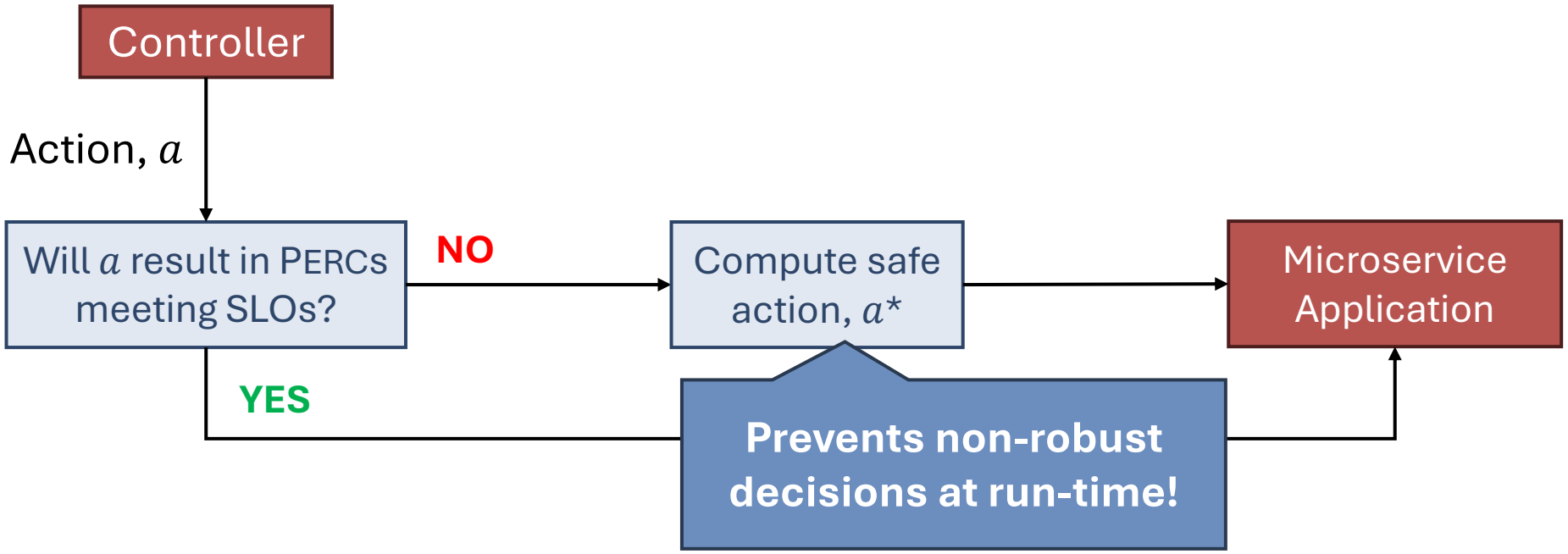

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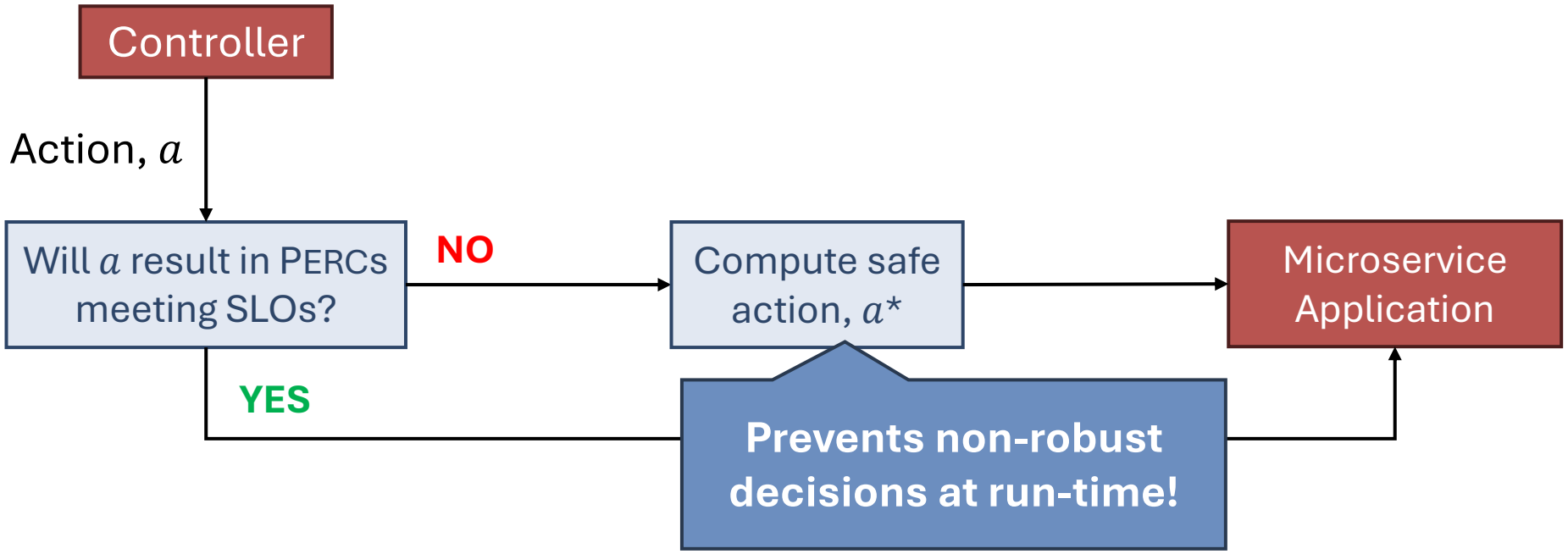
⚠ Cascading impact of controller actions ⟶ Hard to pin-point non-robust actions!



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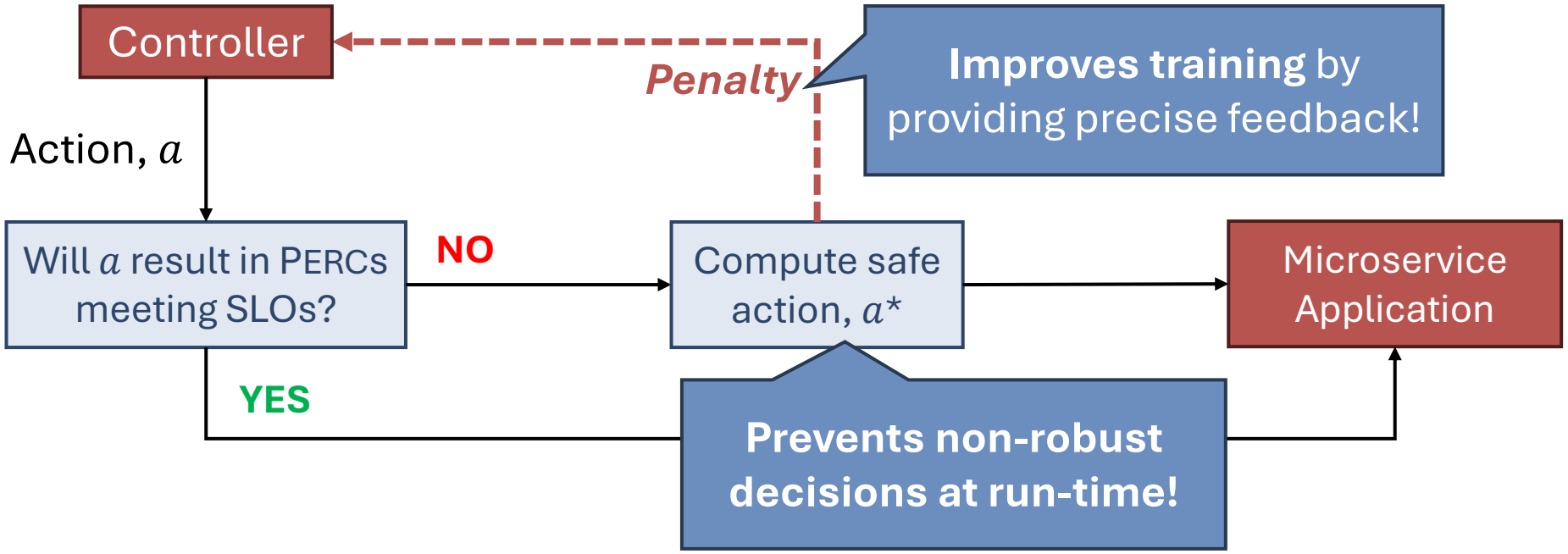
⚠ Stochastic nature of learning algorithms ⟶ May not result in robust actions always!

⚠ Cascading impact of controller actions ⟶ Hard to pin-point non-robust actions!



Evaluation Highlights

- Implemented over two controllers:
  - Autothrottle*: bandit-based CPU autoscaler
  - TopFull^: RL-based admission controller
- Do PERCs provide tight bounds for latencies under perturbations?
- Are PERCs useful for run-time control?
- Overheads of computing PERCs?
- Impact of hyper-parameters?

*Wang et al. 2024. Autothrottle: A Practical Bi-Level Approach to Resource Management for SLO-Targeted Microservices. NSDI'24
^Park et al. 2024. TopFull: An Adaptive Top-Down Overload Control for SLO-Oriented Microservices. SIGCOMM'24

PERCs Provide Good Upper Bounds

Execution of open-source benchmarks for over 250 hours.

Subject to changing arrival rates, allocations and CPU contention.

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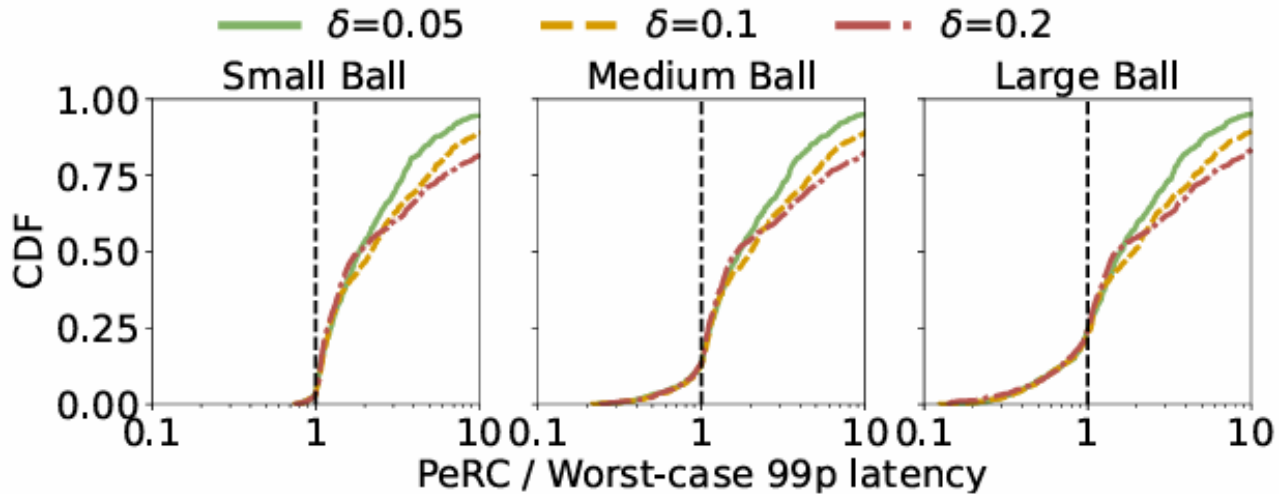

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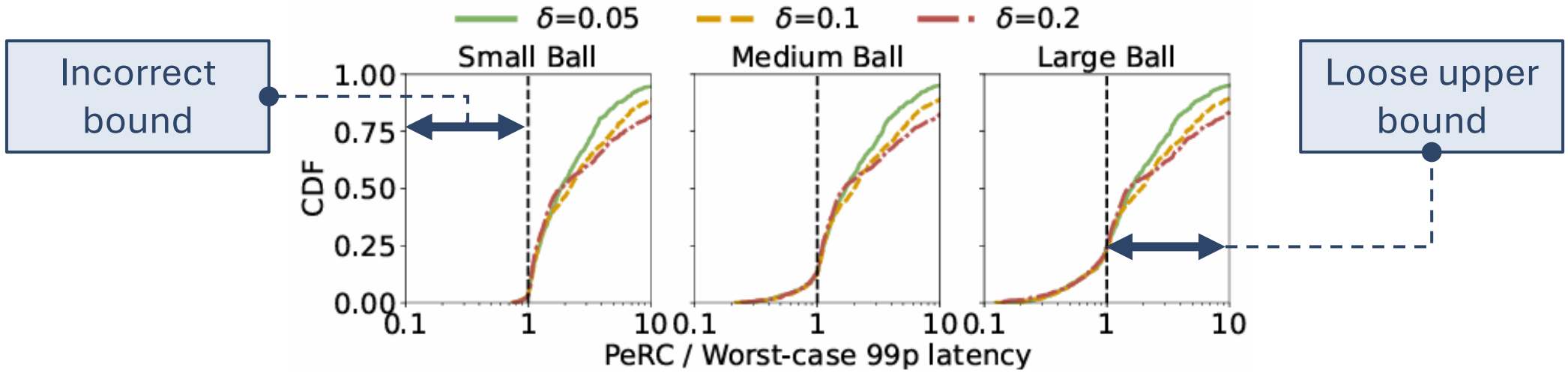
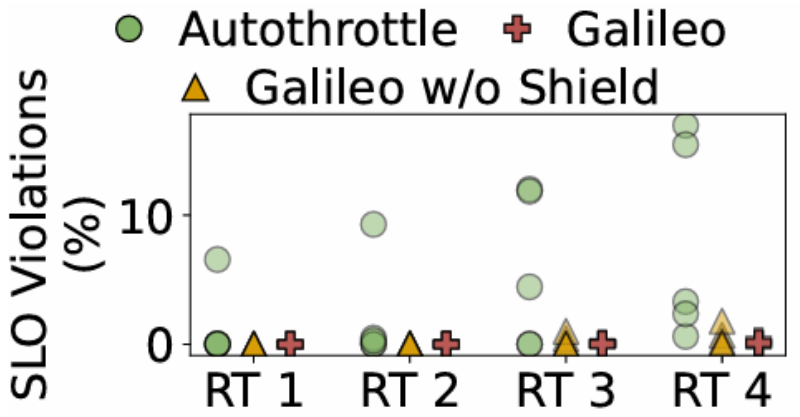


Galileo Controllers Are More Robust



Galileo autoscaler achieves **0.05% SLO violations on average** for Hotel Reservation.

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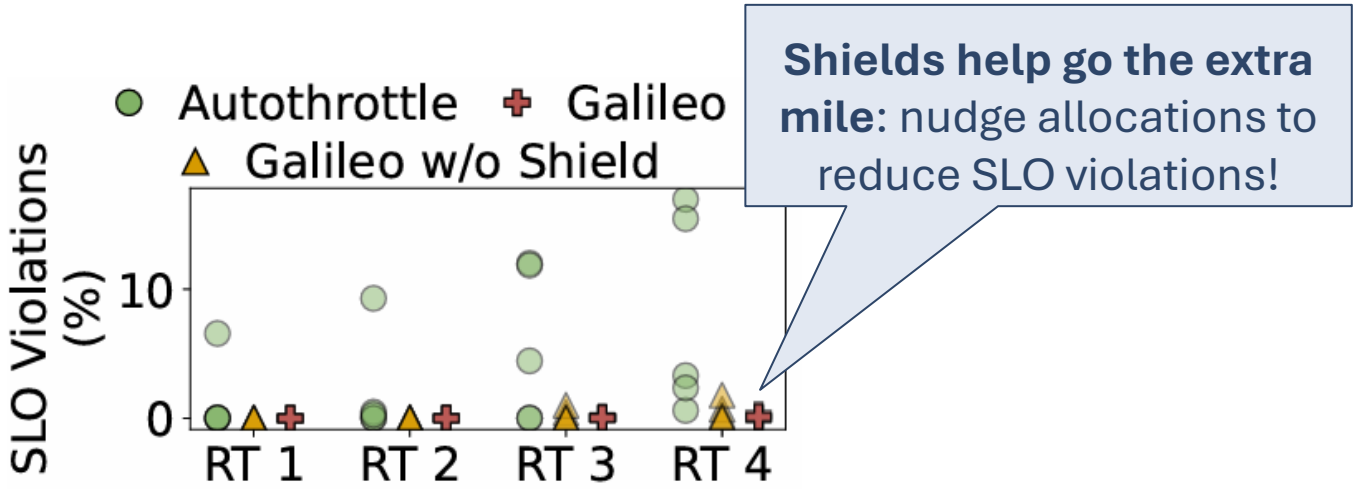

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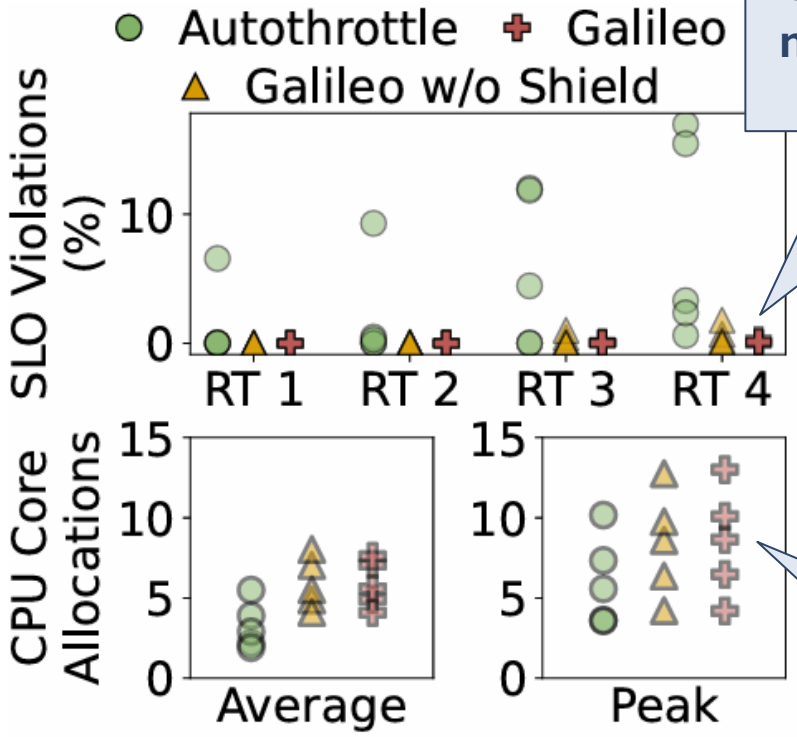

Shields help go the extra mile: nudge allocations to reduce SLO violations!

The cost of robustness: allocate more CPU cores

Galileo autoscaler achieves **0.05% SLO violations on average** for Hotel Reservation.

Summary and Conclusion

- **PERCs:** Bounds on tail latency in a range of perturbations.
- **Galileo:** Compute PERCs using a queueing-based model, combined with gradient-estimation techniques.
- Galileo controllers show significant improvements in SLO violation rates.

Performance robustness is **important**, but **generally hard** and **understudied**.

Galileo is a first attempt at making performance reasoning practical.

PERCs are a general abstraction applicable beyond microservices!

SCAN ME

Open-source project link

LDOS

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