Autothrottle:

A Practical Bi-Level Approach to Resource Management for SLO-Targeted Microservices

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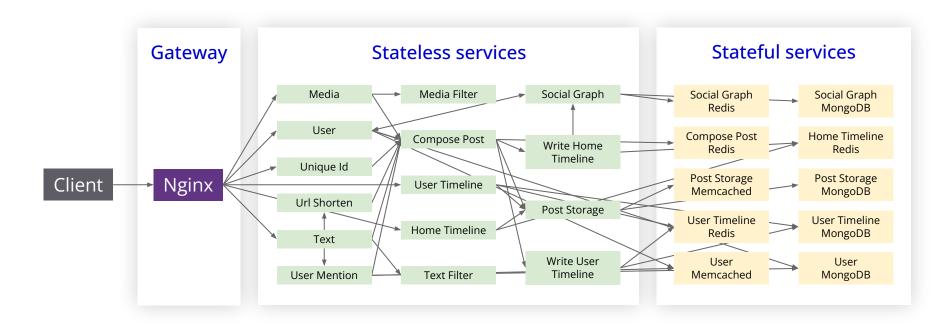
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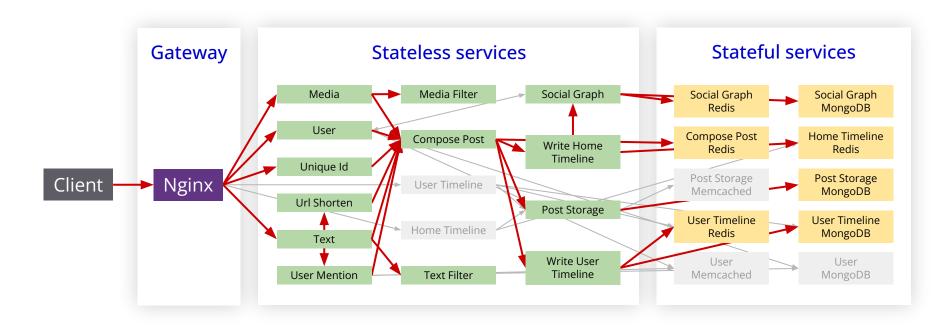
Cloud applications are shifting toward microservices



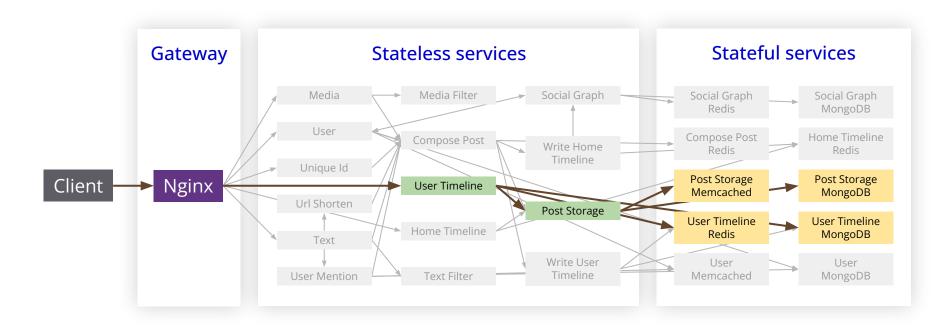
What microservice applications look like



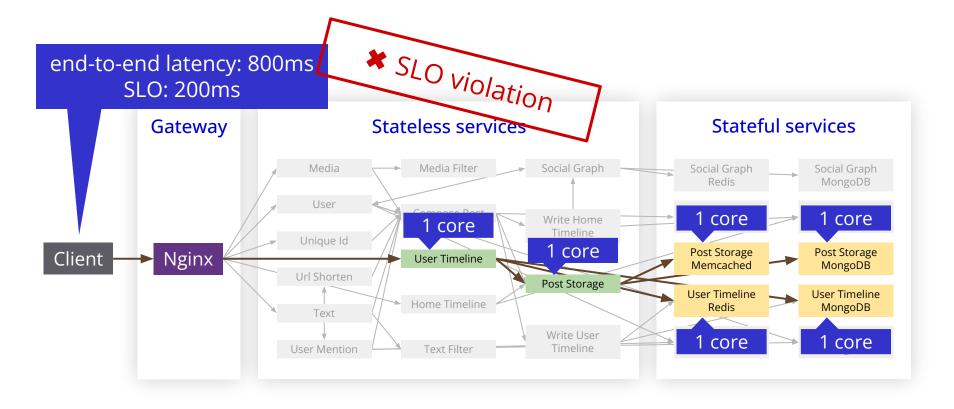
A client request traverses many services



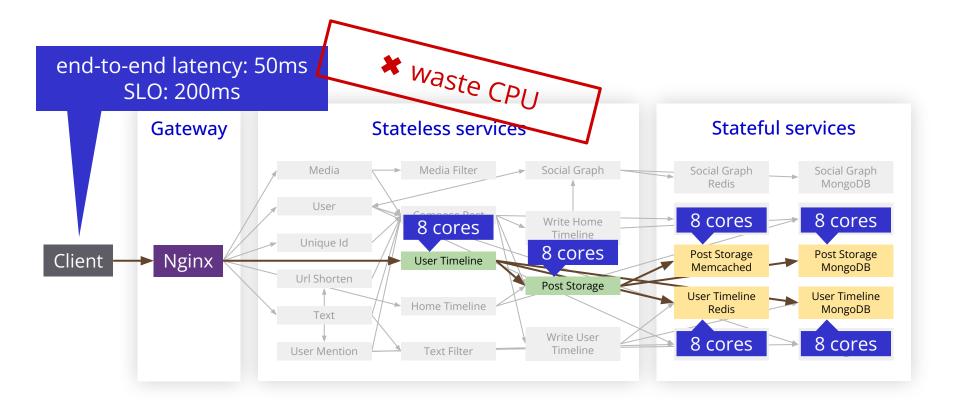
Different requests have different trajectories



Inadequate CPU allocations => high application latency

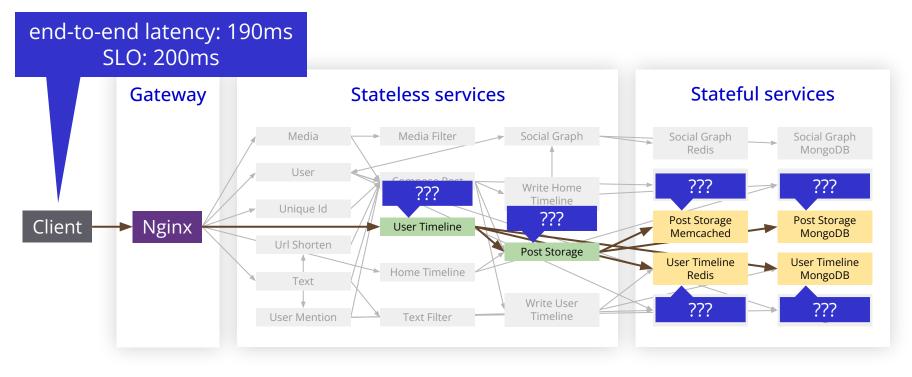


Excessive CPU allocations => waste of resources



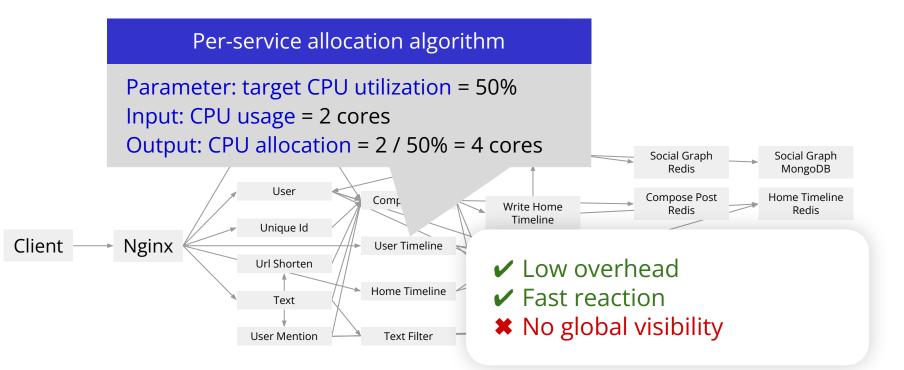
Minimizing CPU allocation while meeting SLO

- Search space grows exponentially with number of services
- Mapping from CPU allocations to latency is unclear



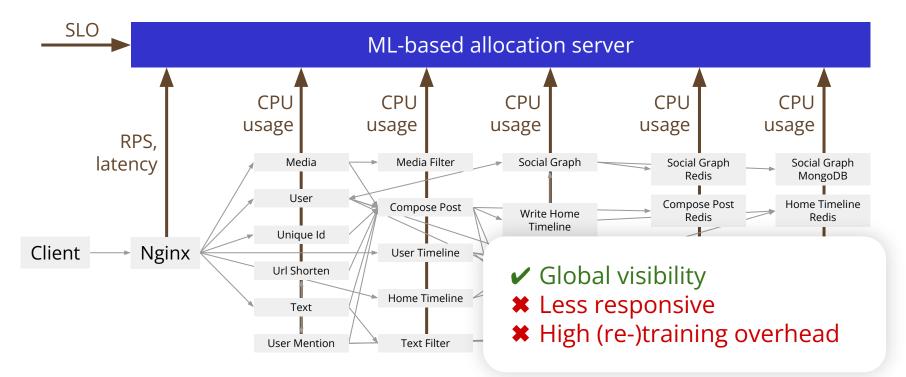
Existing approach: service-level allocation

• Example: Kubernetes' default heuristics

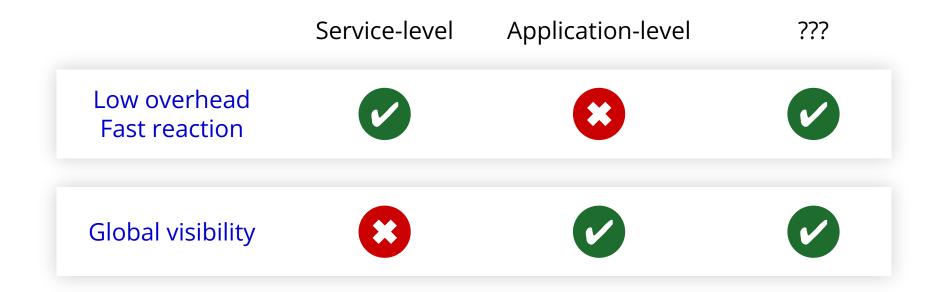


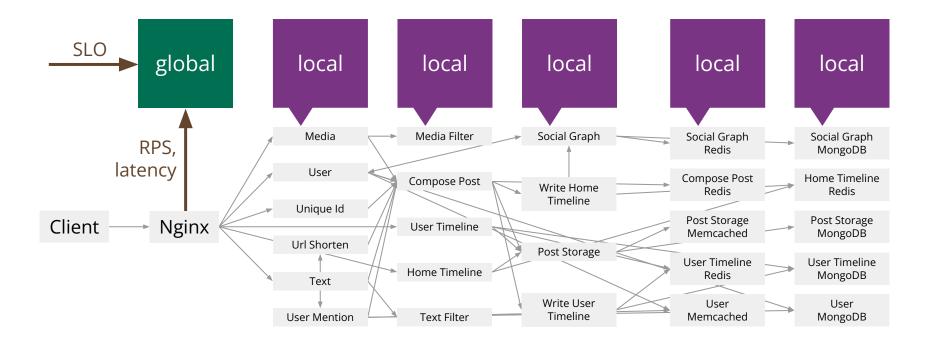
Existing approach: application-level allocation

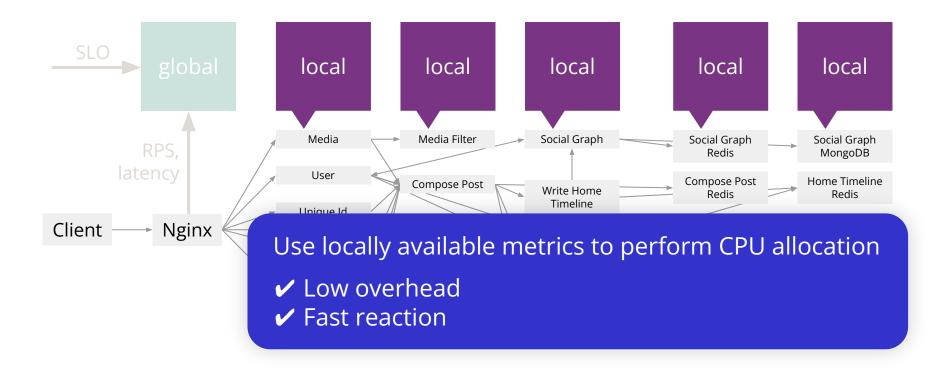
• Example: Sinan (ASPLOS '21)

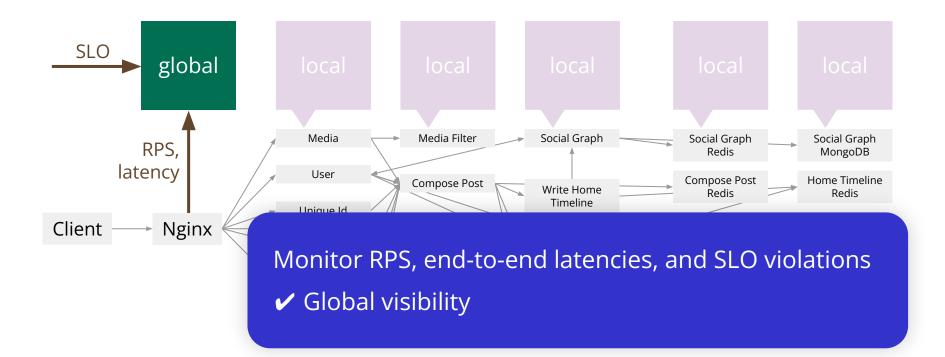


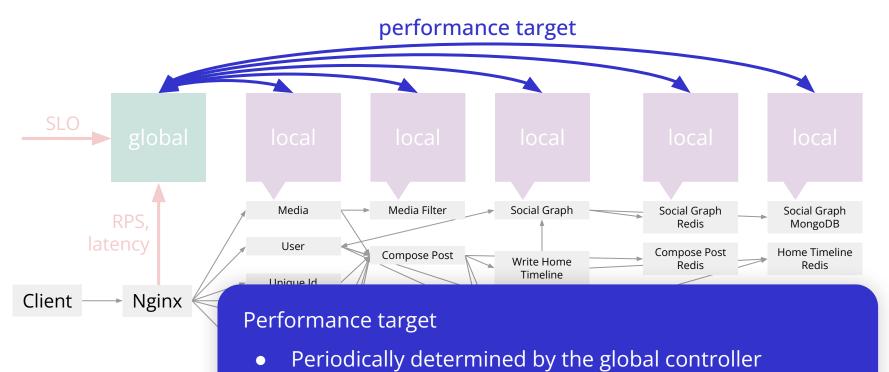
How to obtain the best of both worlds?





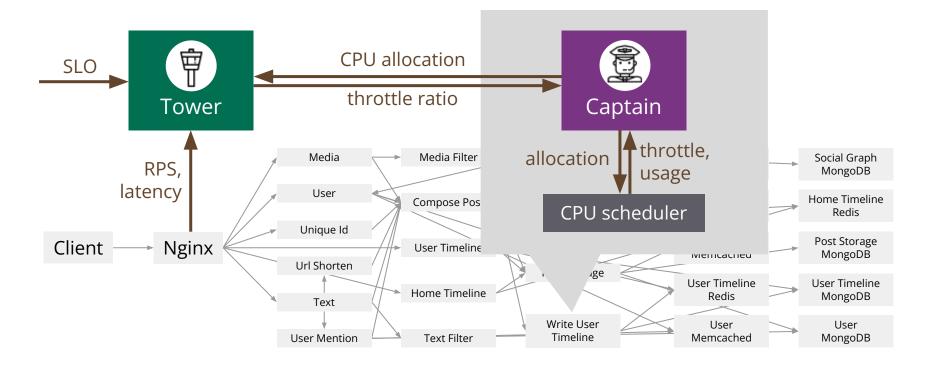




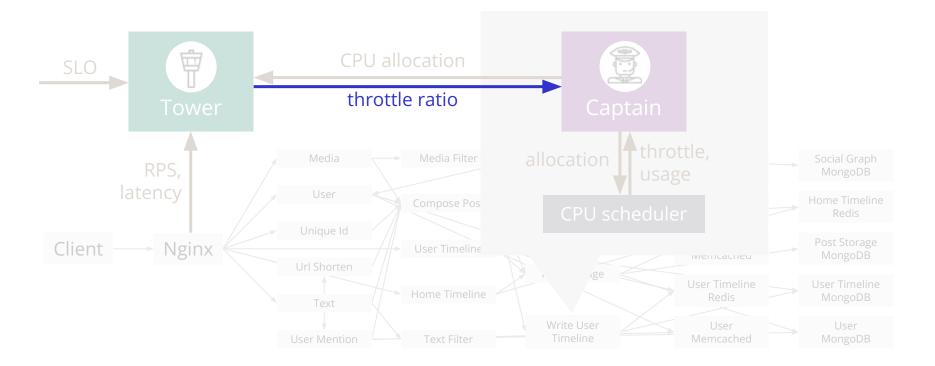


Enabling local controllers to remain autonomous

Implementing bi-level approach with Autothrottle

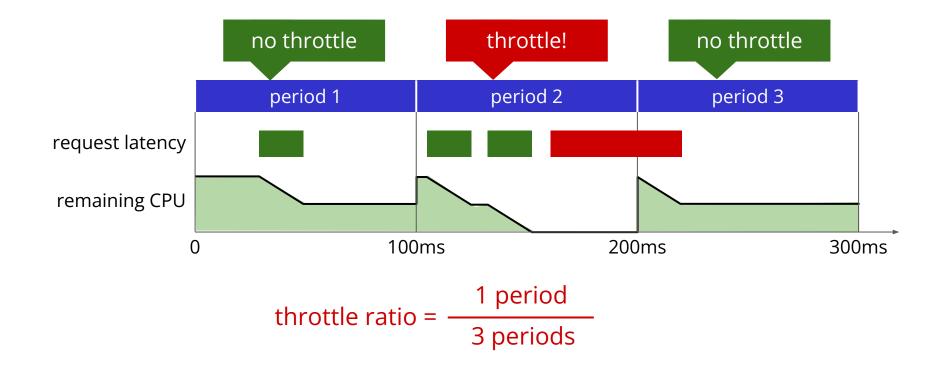


Interface: throttle ratio

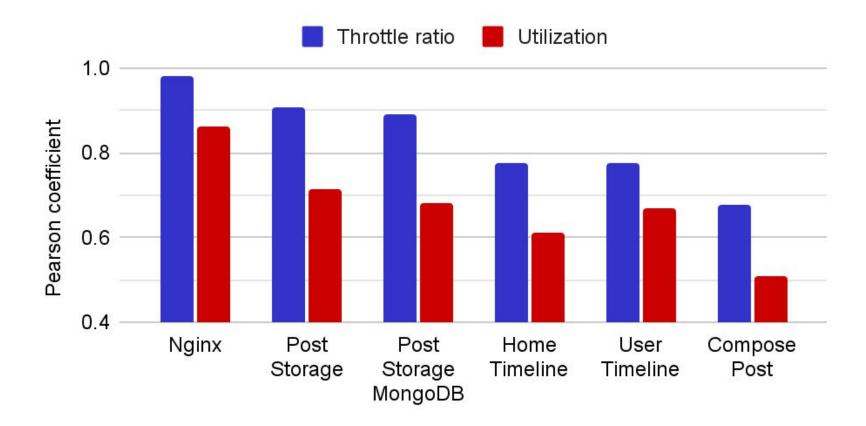


Interface: throttle ratio

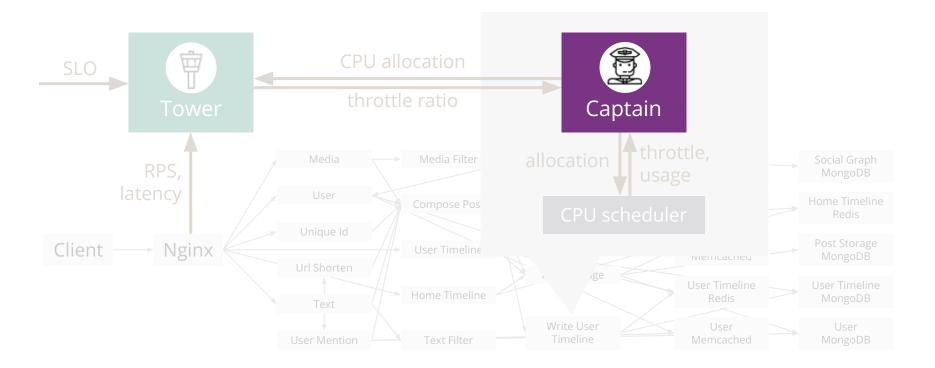
• Example: Linux CFS (Completely Fair Scheduler)



Throttle ratio has a higher correlation with latency



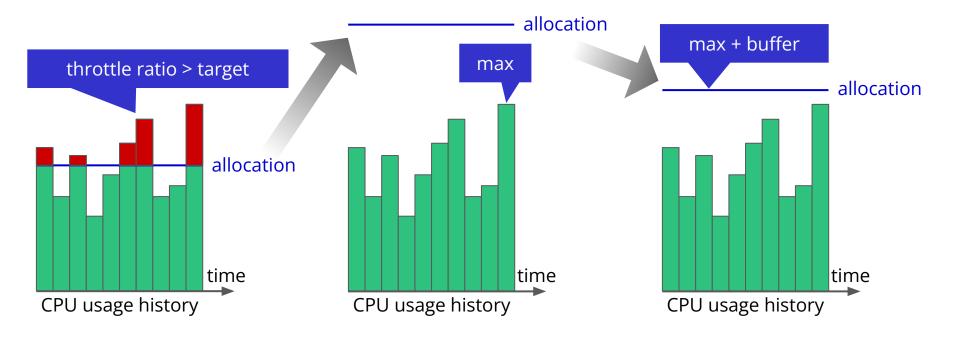
Service-level: fast and lightweight Captains



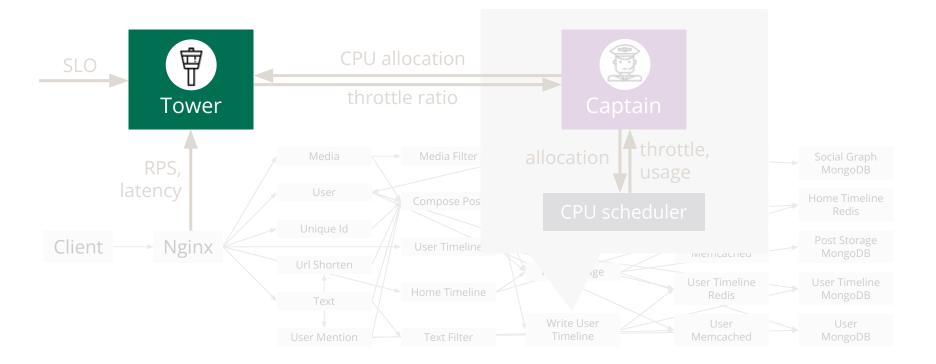
Service-level: fast and lightweight Captains

- Closed-loop control based on throttle ratio target
- Collect data every 100ms, adjust allocation every 1s



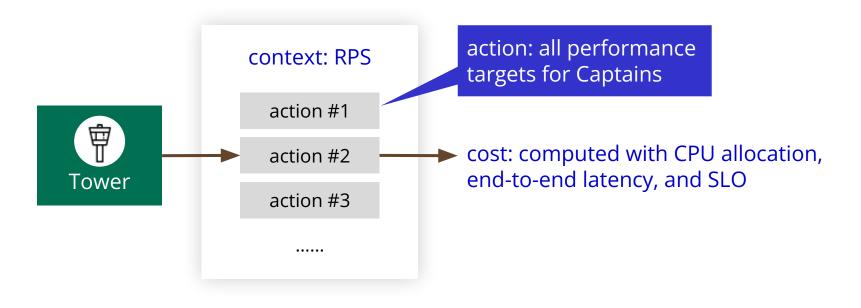


Application-level: online learning Tower



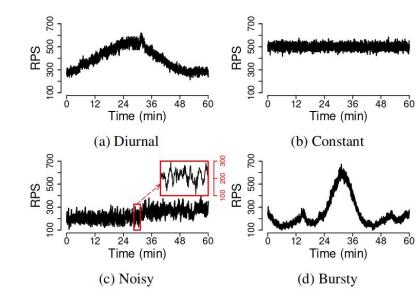
Application-level: online learning Tower

- Determine the best throttle targets for Captains to achieve
- Lightweight online learning: contextual bandit algorithm
 - One step per minute, each step runs in ~100ms

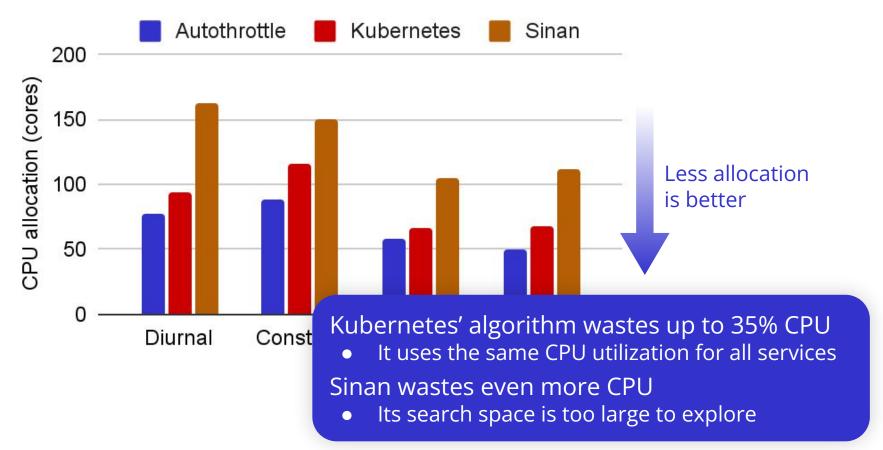


Evaluation methodology

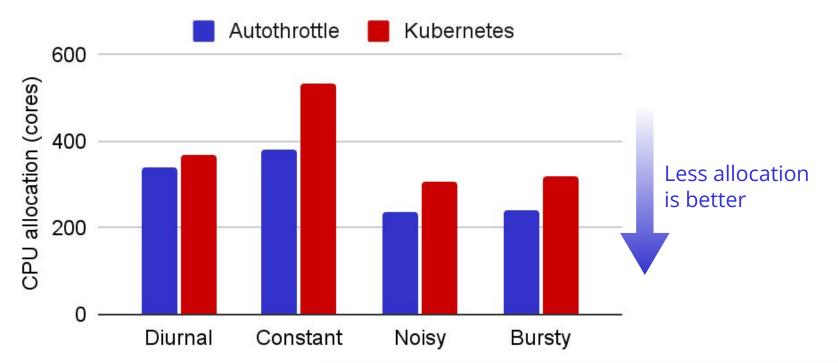
- Testbed: 5 Azure VMs, 160 CPU cores in total
- 4 workload traces
 - with patterns commonly observed in production environments
 - e.g. Puffer's streaming requests, Google's cluster usage, and Twitter tweets
- 3 benchmark applications
 - Train-Ticket
 - Hotel-Reservation from DeathStarBench
 - Social-Network used in Sinan



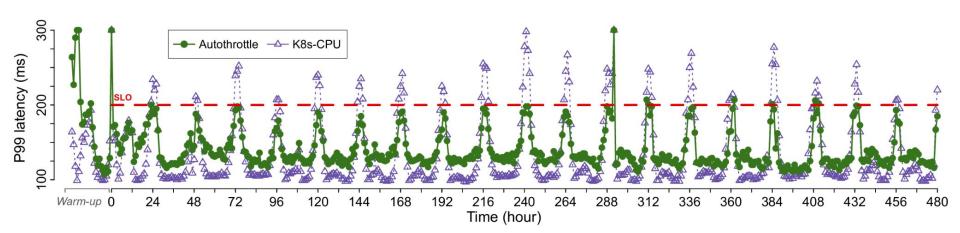
Evaluation results



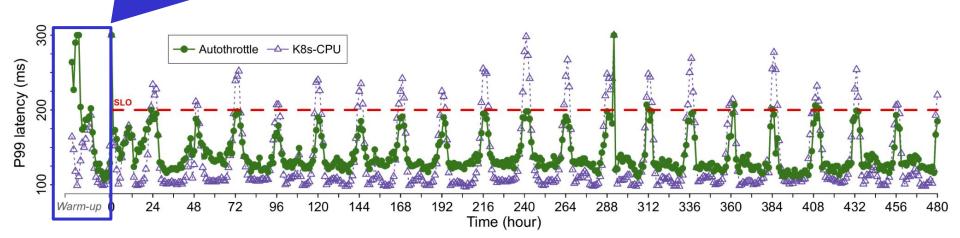
Large-scale evaluation on a 512-core cluster

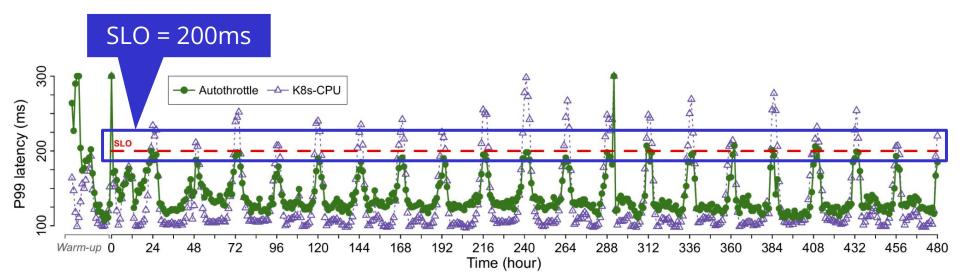


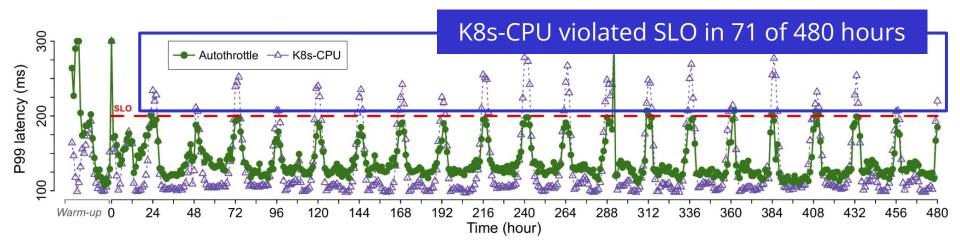
Kubernetes' algorithm wastes up to 39% CPU

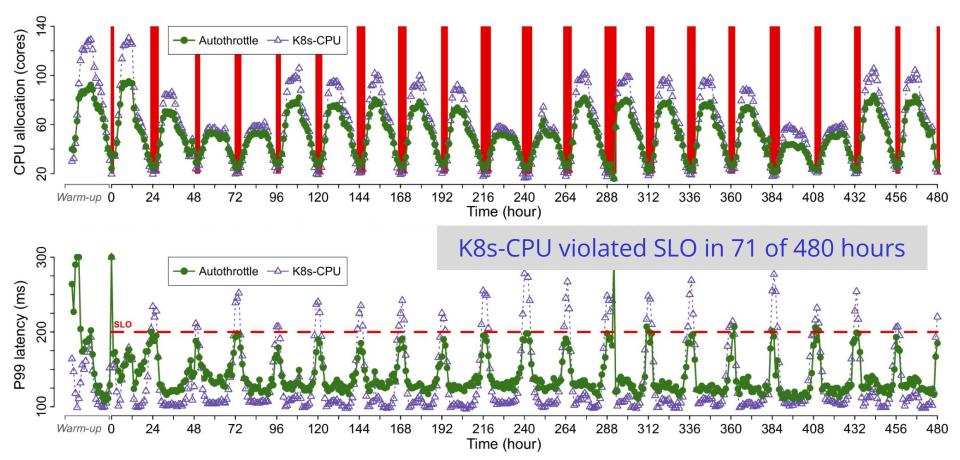


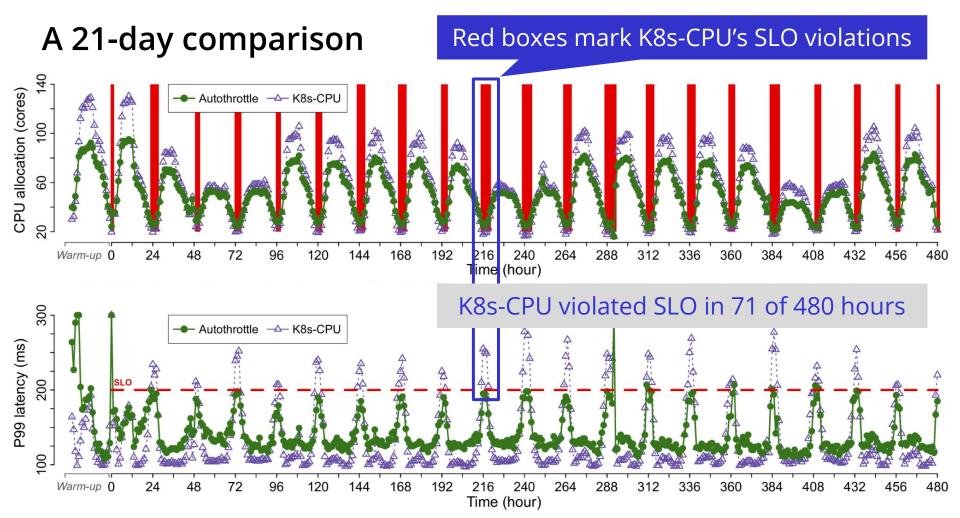
Autothrottle: automatic exploration K8s-CPU: manual parameter tuning

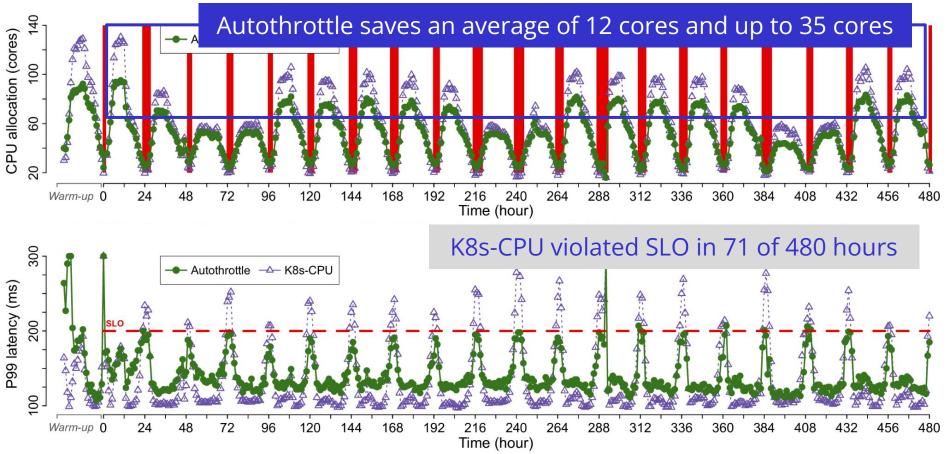




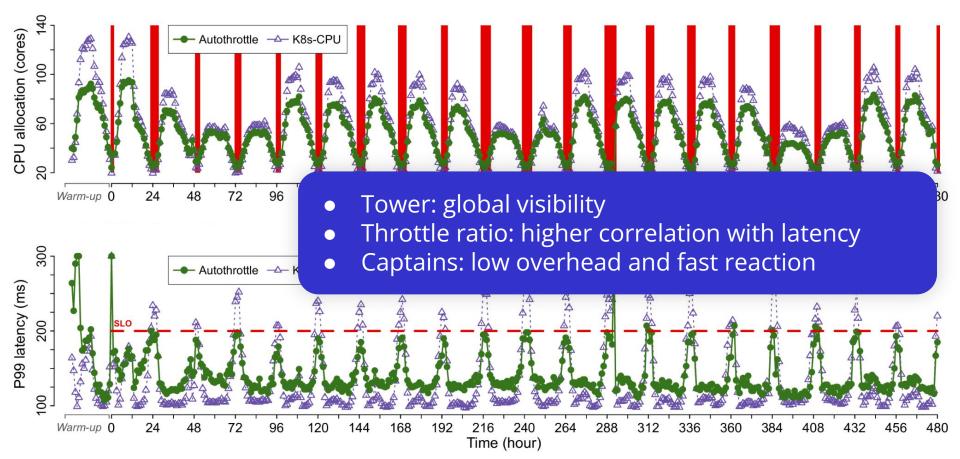








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A 21-day comparison
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Conclusion

- Autothrottle: a bi-level learning-assisted resource management framework for SLO-targeted microservices.
- Results show a CPU saving up to 26% while satisfying SLO
- Open-sourced at <u>https://github.com/microsoft/autothrottle</u>

