RUBIK: FAST ANALYTICAL POWER MANAGEMENT FOR LATENCY-CRITICAL SYSTEMS

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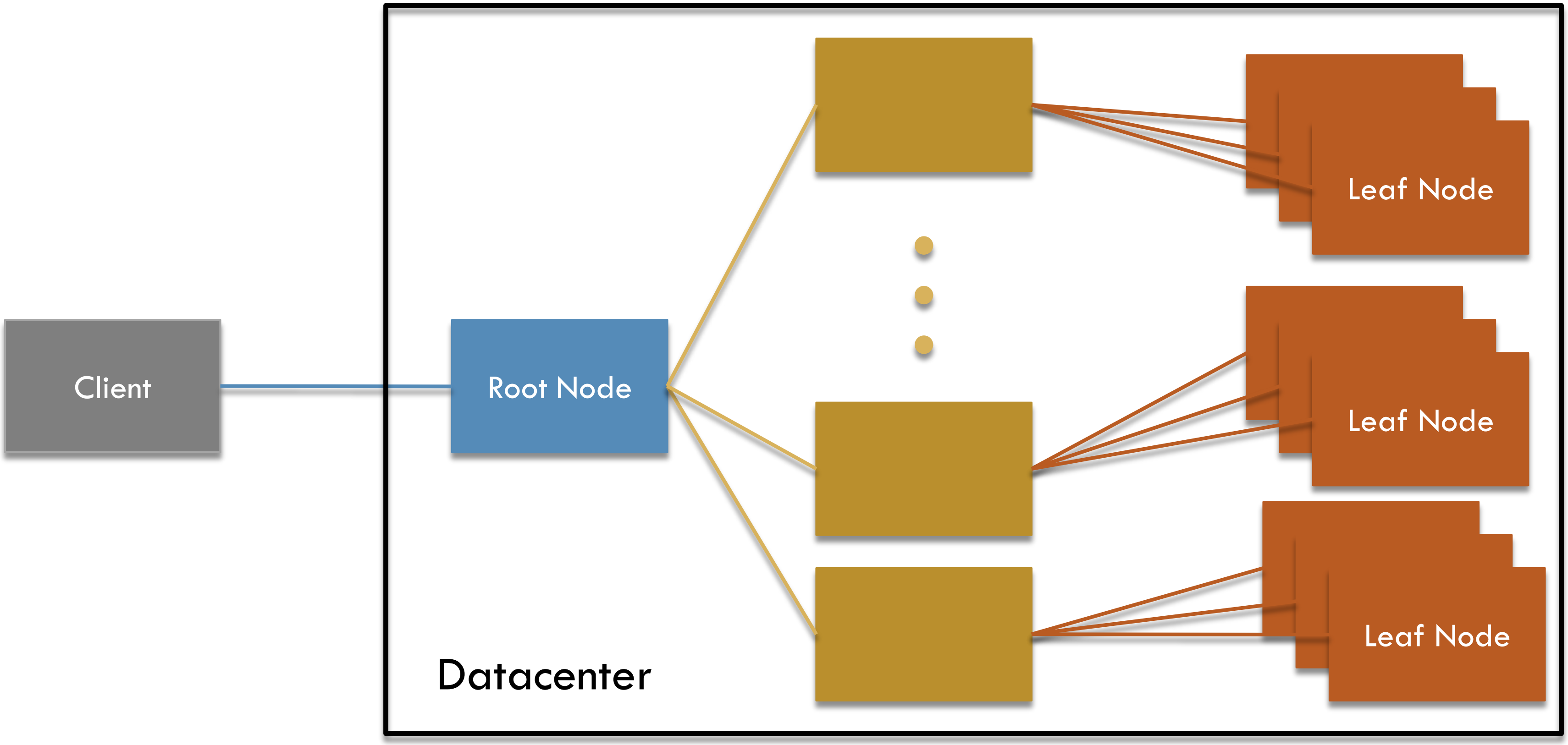
Motivation

- Low server utilization in today’s datacenters results in resource and energy inefficiency
- Stringent latency requirements of user-facing services is a major contributing factor
- Power management for these services is challenging
    - Strict requirements on tail latency
    - Inherent variability in request arrival and service times
- Rubik uses statistical modeling to adapt to short-term variations
    - Respond to abrupt load changes
    - Improve power efficiency
    - Allow colocation of latency-critical and batch applications

Understanding Latency-Critical Applications



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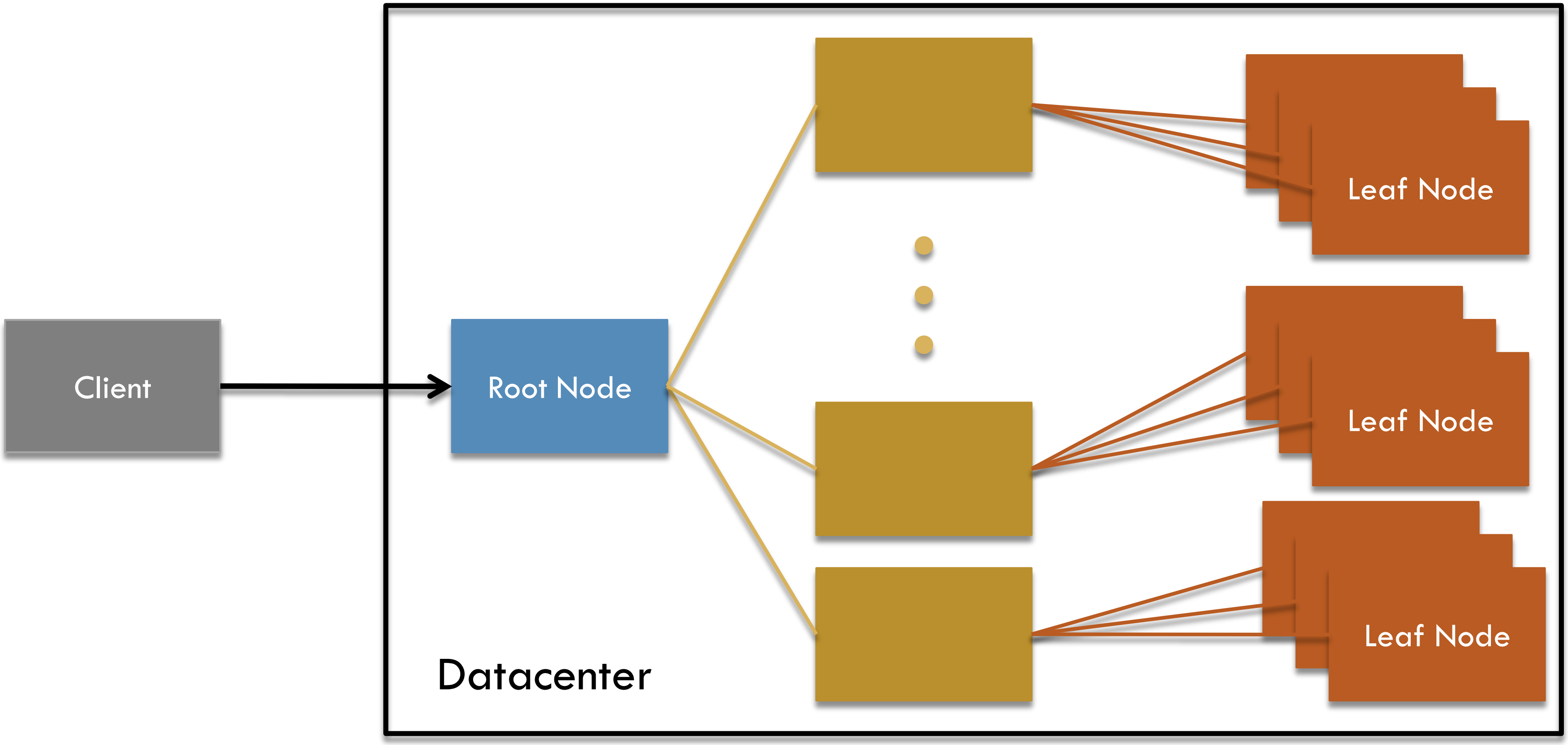

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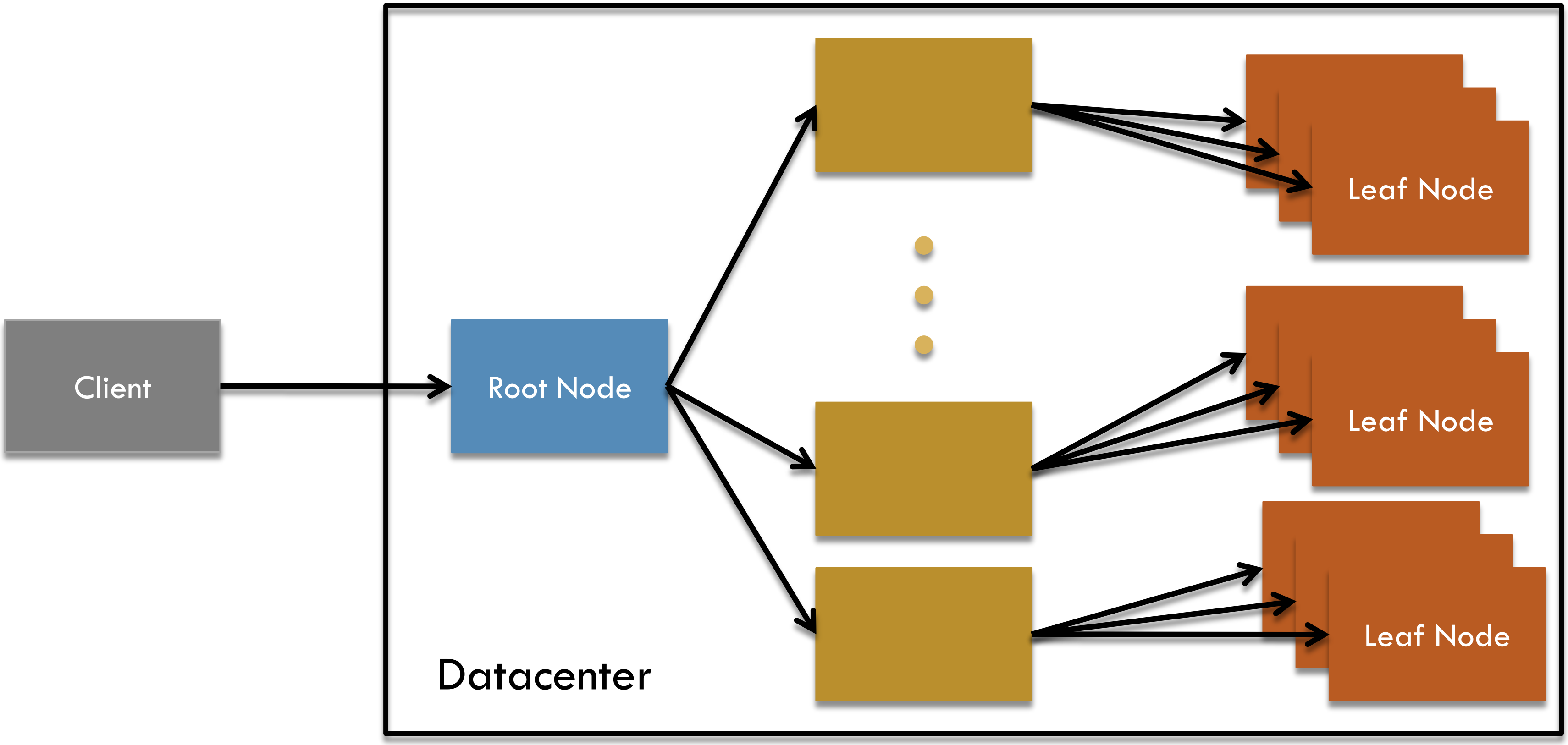
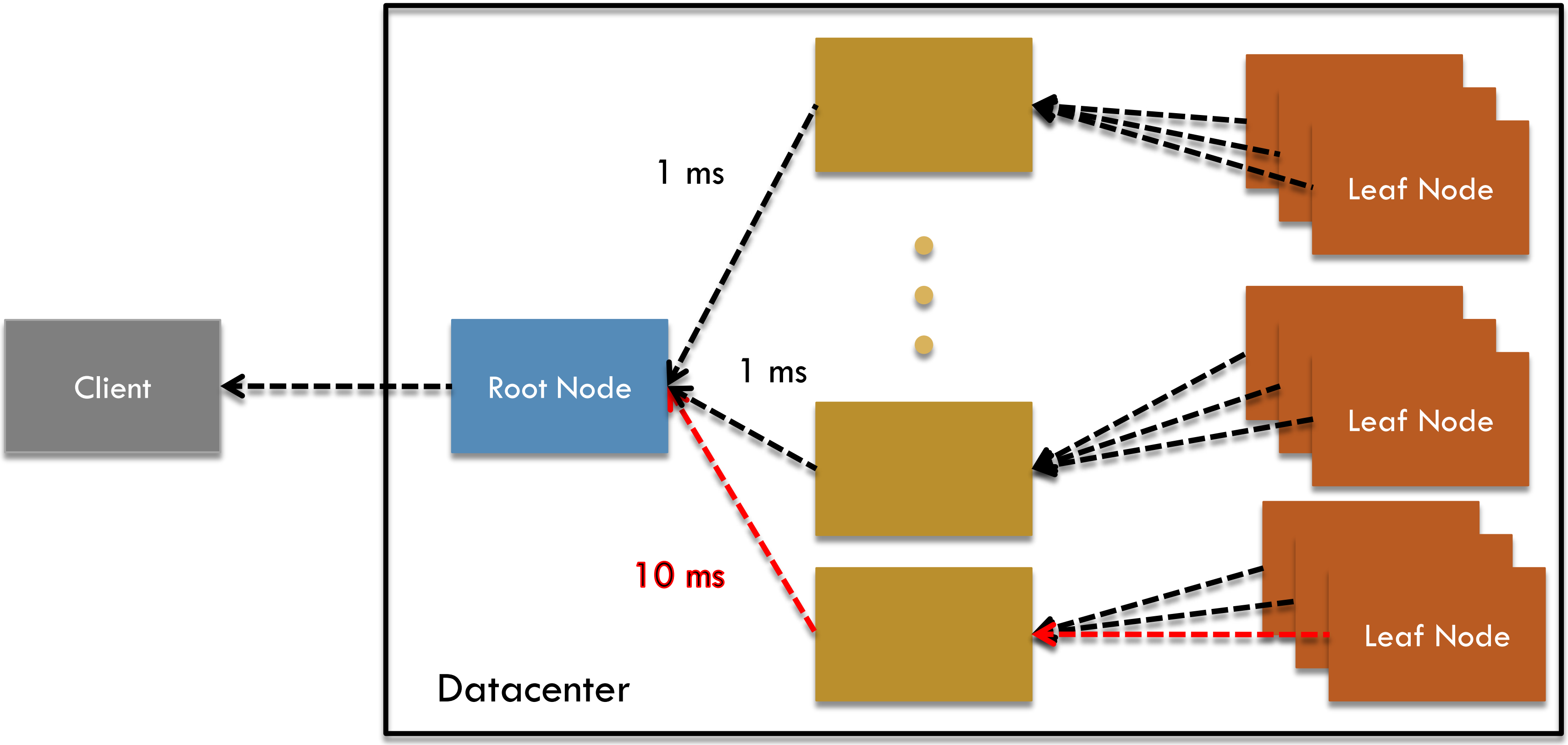


Understanding Latency-Critical Applications



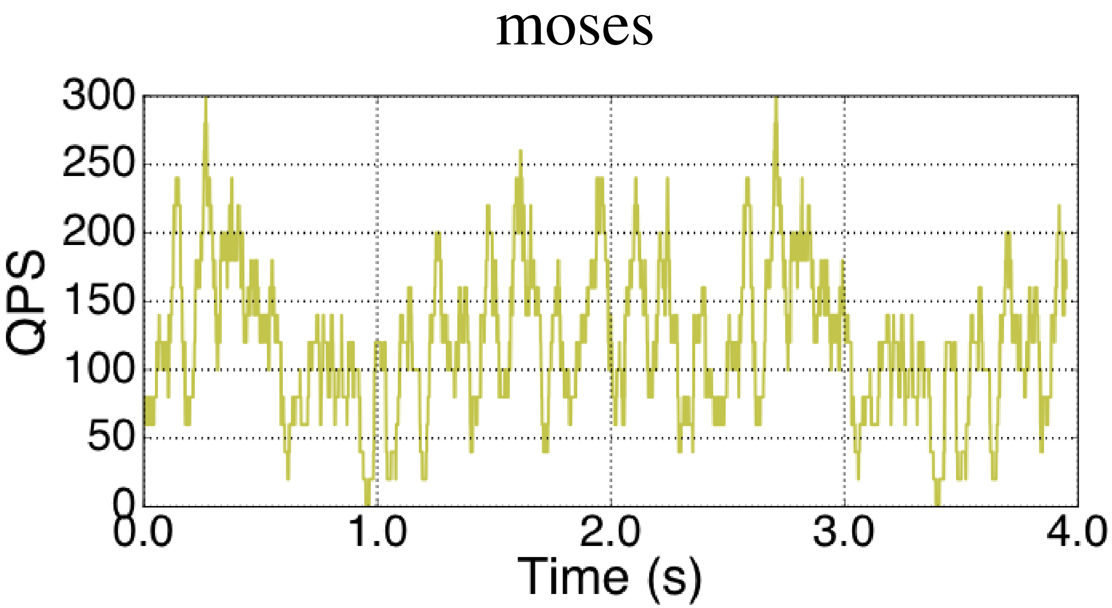
- The few slowest responses determine user-perceived latency
  - Tail latency (e.g., 95th / 99th percentile), not mean latency, determines performance

Prior Schemes Fall Short

- Traditional DVFS schemes (cpufreq, TurboBoost…)
  - React to coarse grained metrics like processor utilization, oblivious to short-term performance requirements
- Power management for embedded systems (PACE, GRACE…)
  - Do not consider queuing
- Schemes designed specifically for latency-critical systems (PEGASUS [Lo ISCA’14], Adrenaline [Hsu HPCA’15])
  - Rely on application-specific heuristics
  - Too conservative

Insight 1: Short-Term Load Variations

- Latency-critical applications have significant short-term load variations

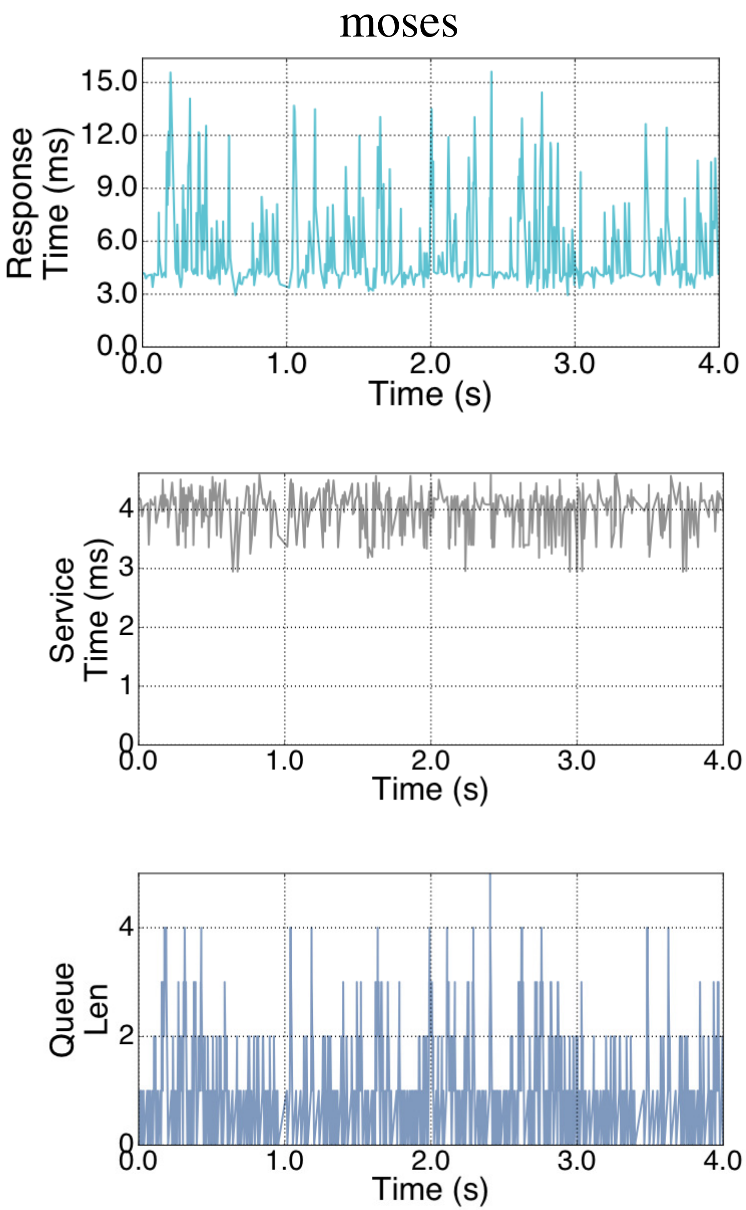


- PEGASUS [Lo ISCA'14] uses feedback control to adapt frequency setting to diurnal load variations
  - Deduce server load from observed request latency
  - Cannot adapt to short-term variations

Insight 2: Queuing Matters!

- Tail latency is often determined by queuing, not the length of individual requests

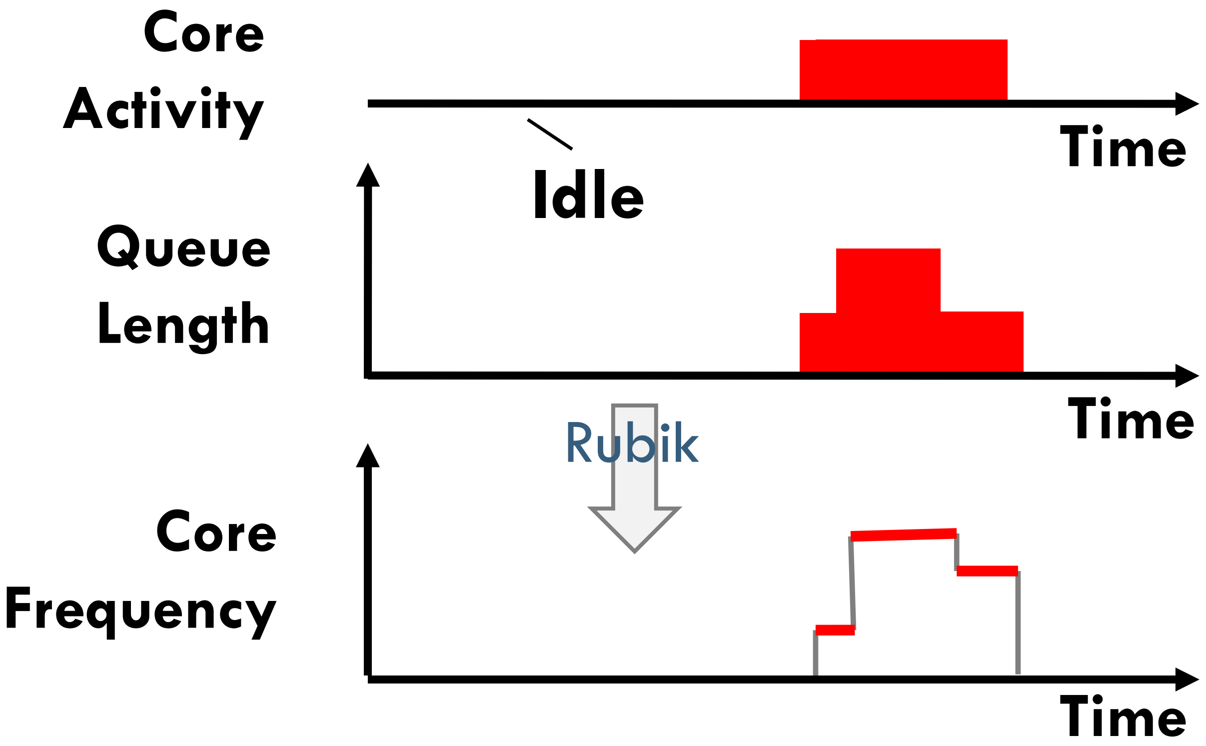
- Adrenaline [Hsu HPCA'15] uses application-level hints to distinguish long requests from short ones
  - Long requests *boosted* (sped up)
  - Frequency settings must be conservative to handle queuing



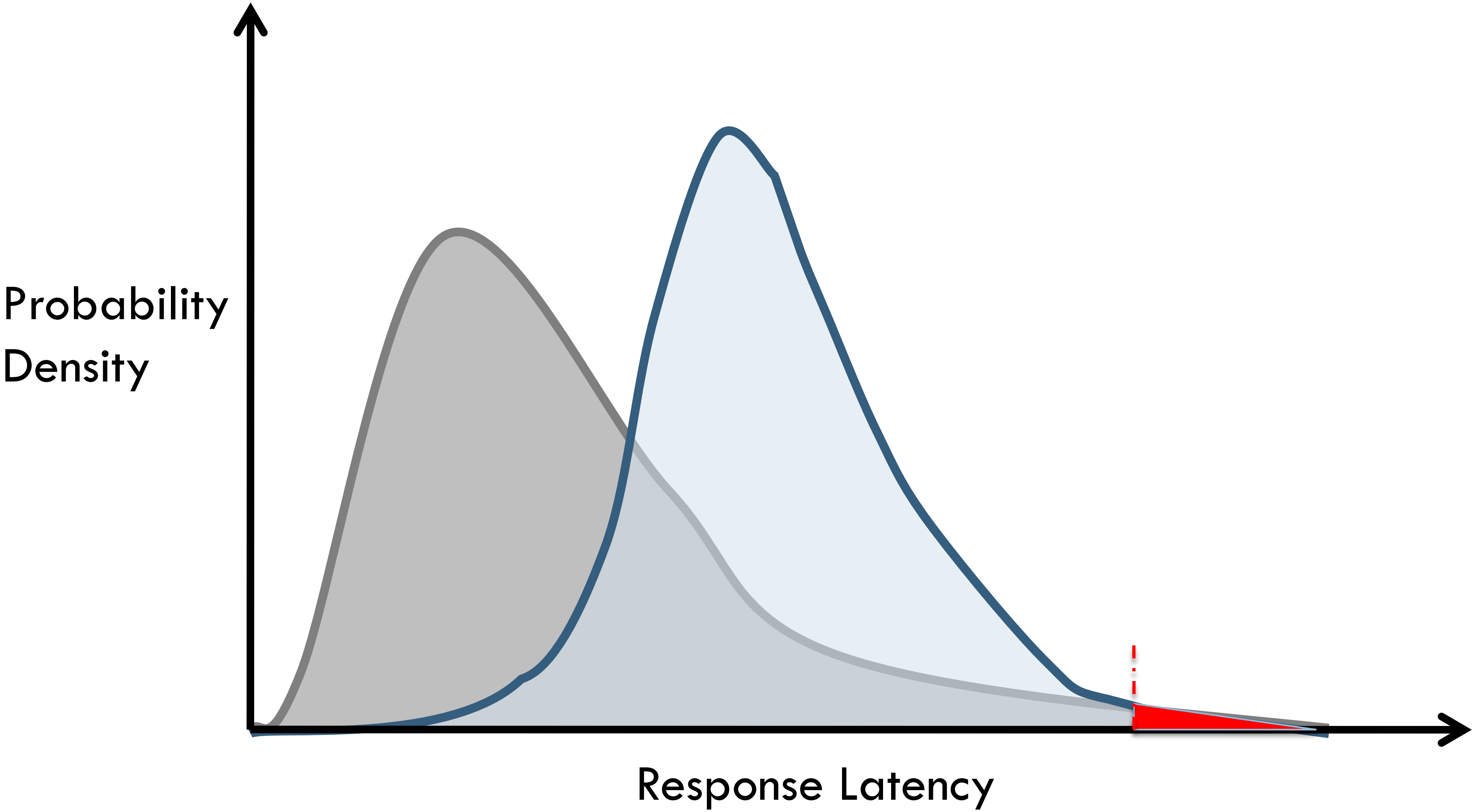
moses

Rubik Overview

- Use queue length as a measure of instantaneous system load
- Update frequency whenever queue length changes
  - Adapt to short-term load variations



Goal: Reshaping Latency Distribution

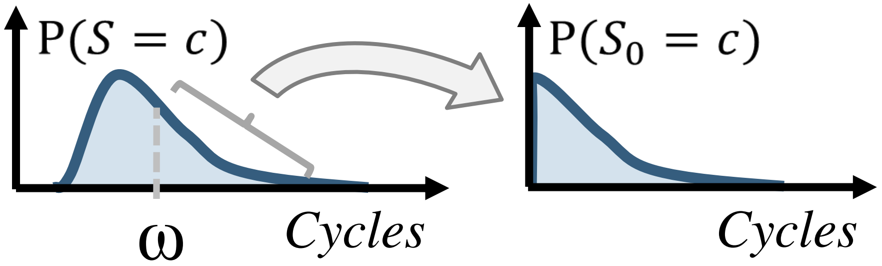


Key Factors in Setting Frequencies

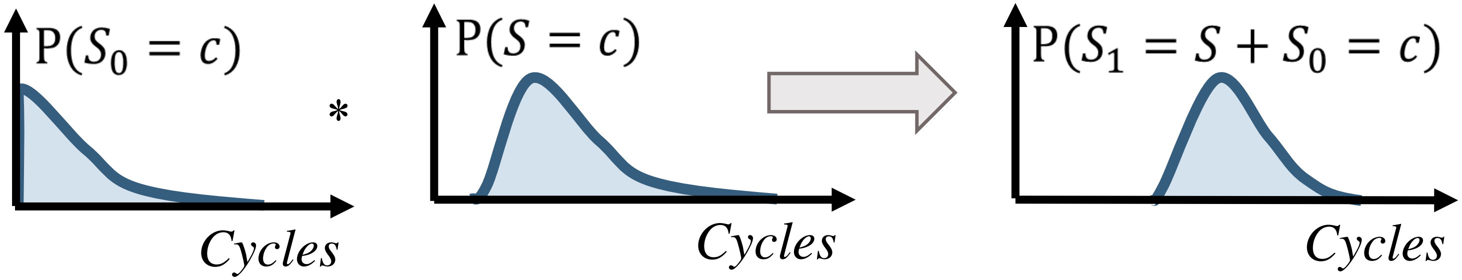
- Distribution of cycle requirements of individual requests
  - Larger variance → more conservative frequency setting
- How long has a request spent in the queue?
  - Longer wait times → higher frequency
- How many requests are queued waiting for service
  - Longer queues → higher frequency

There’s Math!

$$P[S_0 = c] = P[S = c + \omega \mid S > \omega] = \frac{P[S = c + \omega]}{P[S > \omega]}$$



$$P_{S_i} = P_{S_{i-1}} * P_S = P_{S_0} * \overbrace{P_S * P_S * \ldots * P_S}^{i\ times}$$

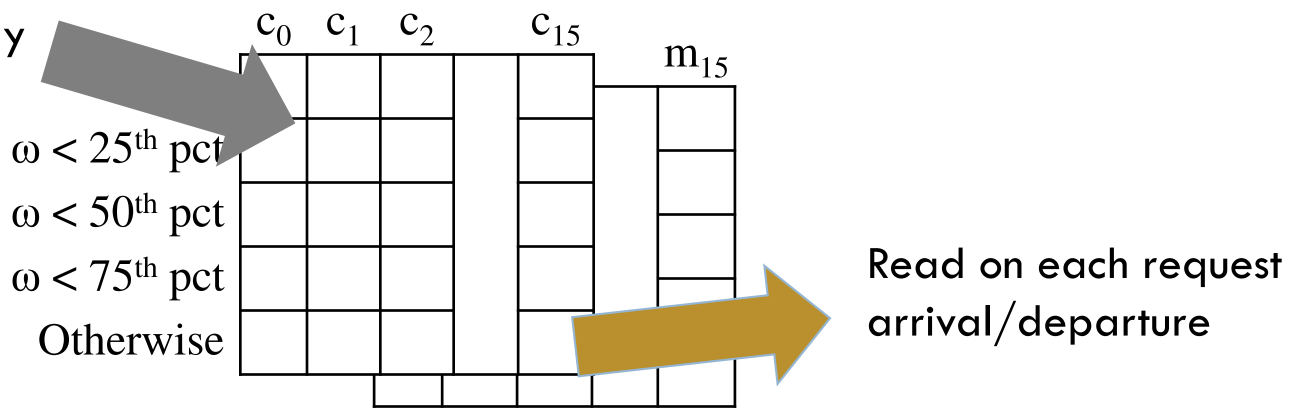


$$\boxed{f \geq \max_{i=0\ldots N} \frac{c_i}{L - (t_i + m_i)}}$$

Efficient Implementation

- Pre-computed tables store most of the required quantities

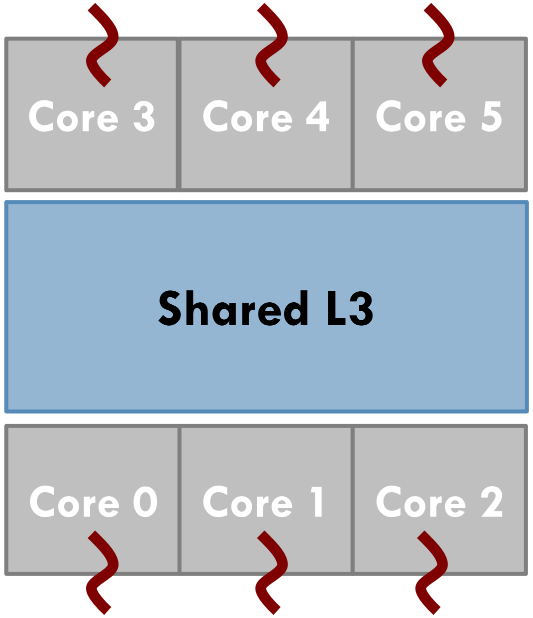
Target Tail Tables



- Table contents are independent of system load!
- Implemented as a software runtime
  - Hardware support: fast, per-core DVFS, performance counters for CPI stacks

Evaluation

- Microarchitectural simulations using zsim
  - Power model tuned to a real system



- ○ Westmere-like OOO cores
- ○ Fast per-core DVFS
- ○ CPI stack counters
- ○ Pin threads to cores

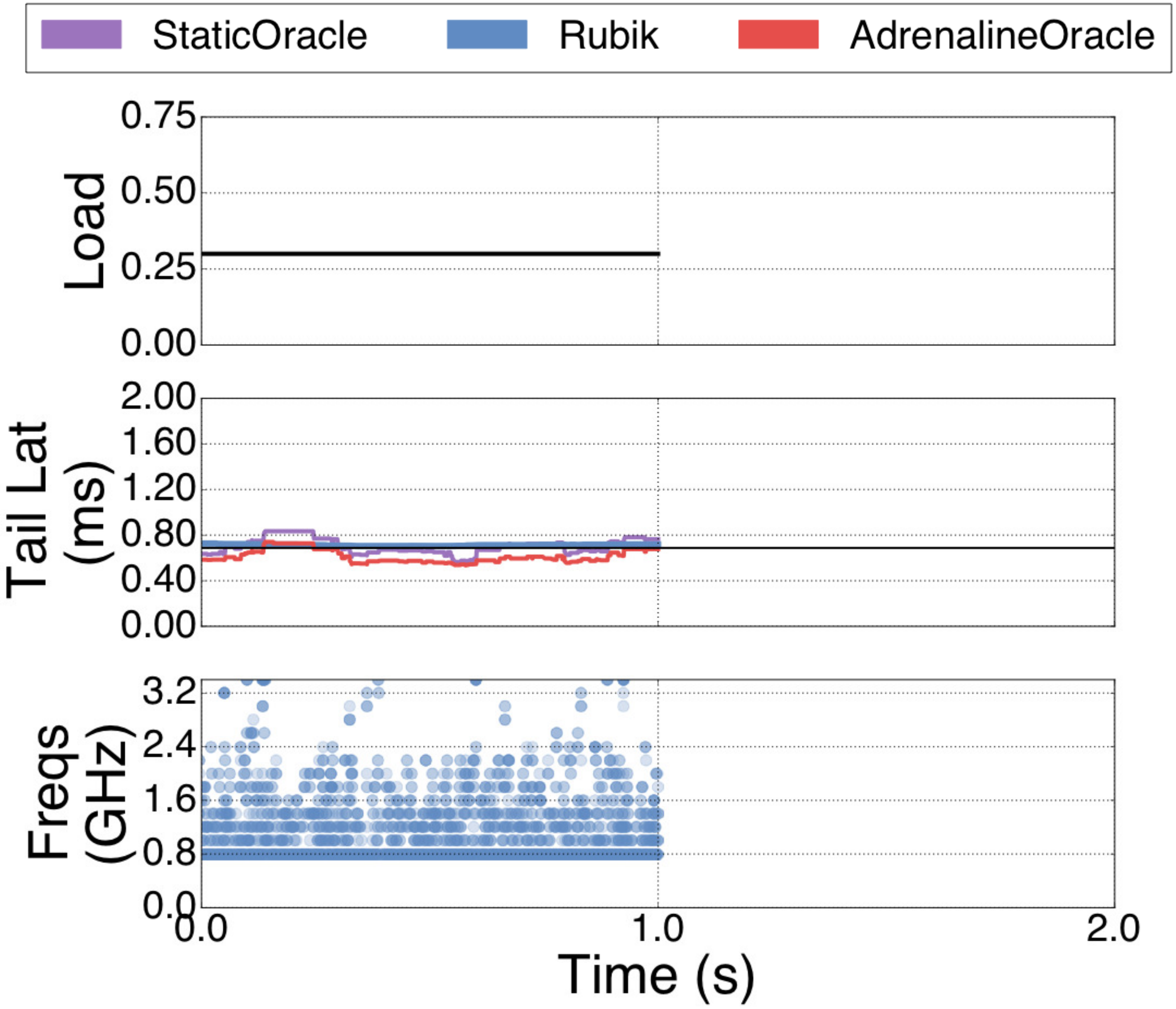
- Compare Rubik against two oracular schemes:
  - StaticOracle: Pick the lowest static frequency that meets latency targets for a given request trace
  - AdrenalineOracle: Assume oracular knowledge of long and short requests, use offline training to pick frequencies for each

Evaluation

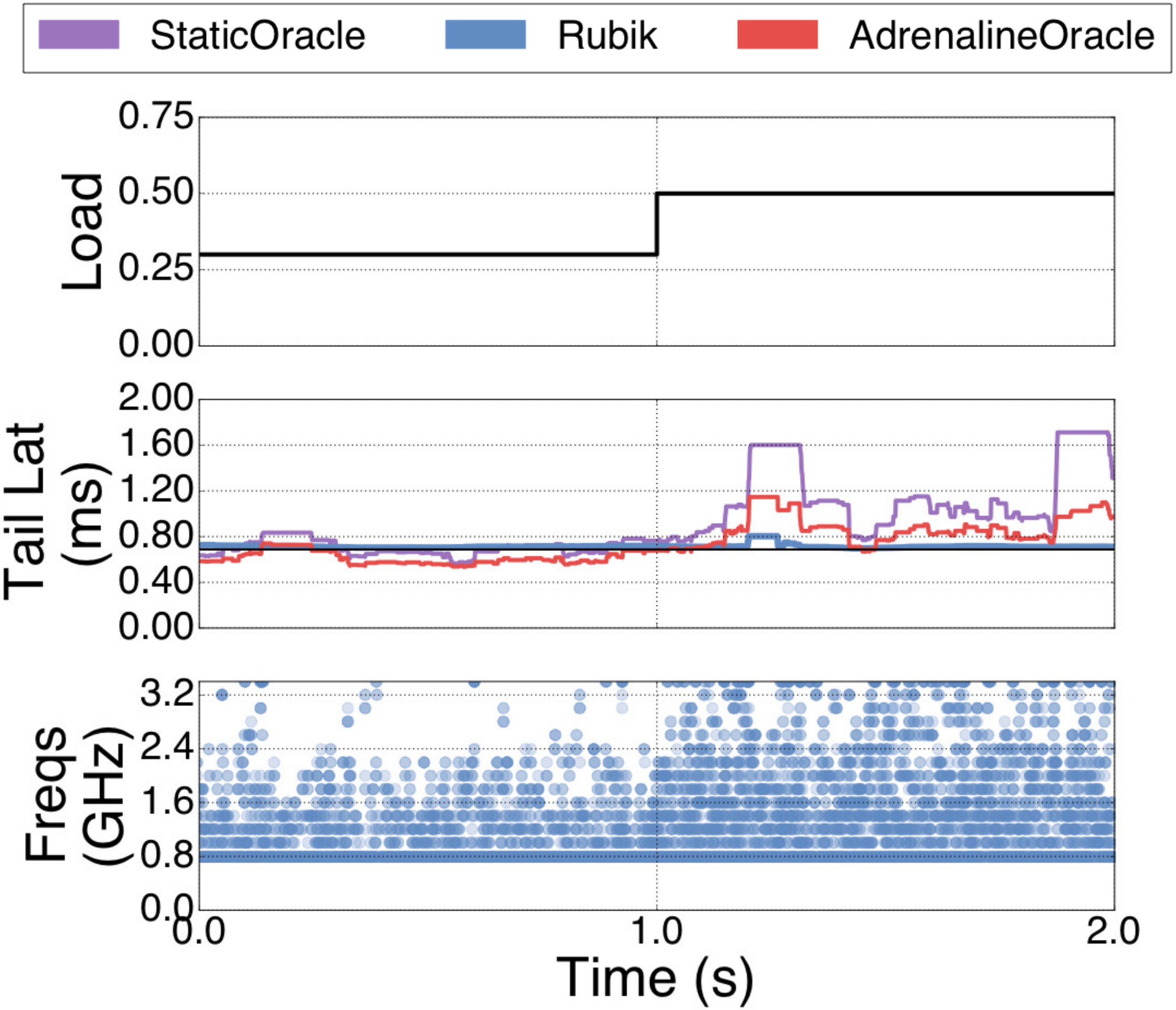
- Five diverse latency-critical applications
  - xapian (search engine)
  - masstree (in-memory key-value store)
  - moses (statistical machine translation)
  - shore-mt (OLTP)
  - specjbb (java middleware)

- For each application, latency target set at the tail latency achieved at nominal frequency (2.4 GHz) at 50% utilization

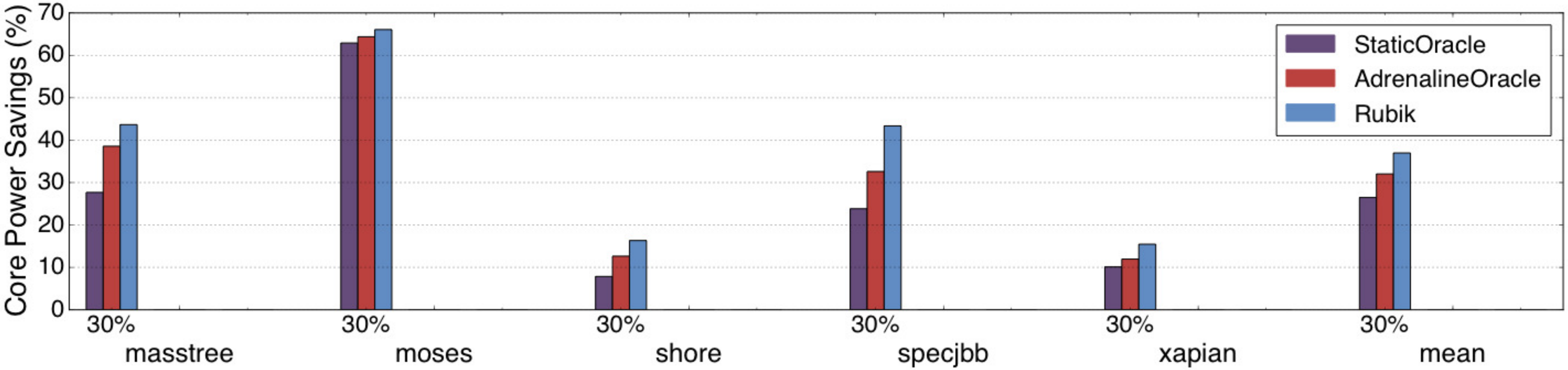
Tail Latency



Tail Latency



Core Power Savings



- All three schemes save significant power at low utilization
  - Rubik performs best, reducing core power by up to 66%

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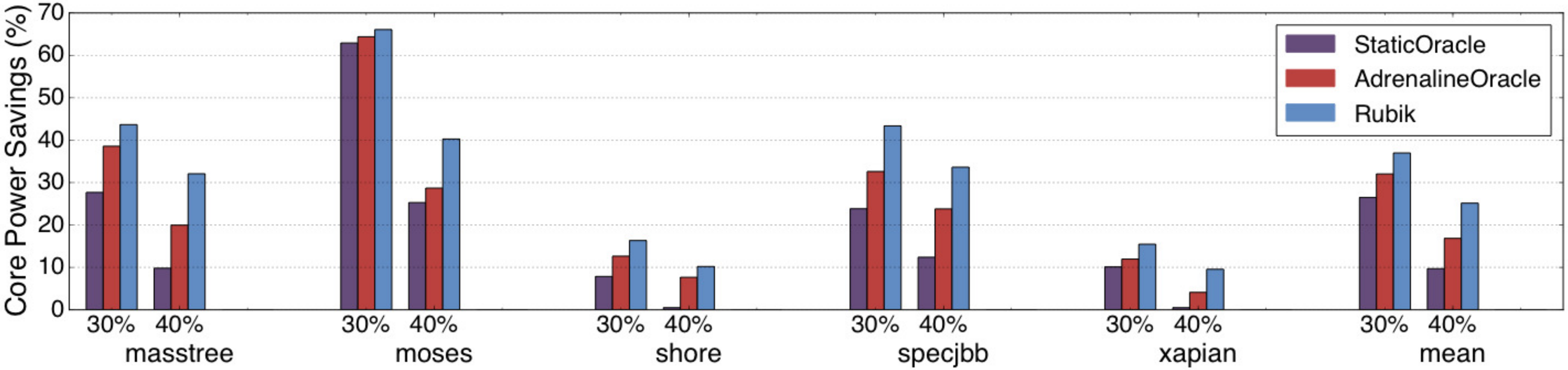

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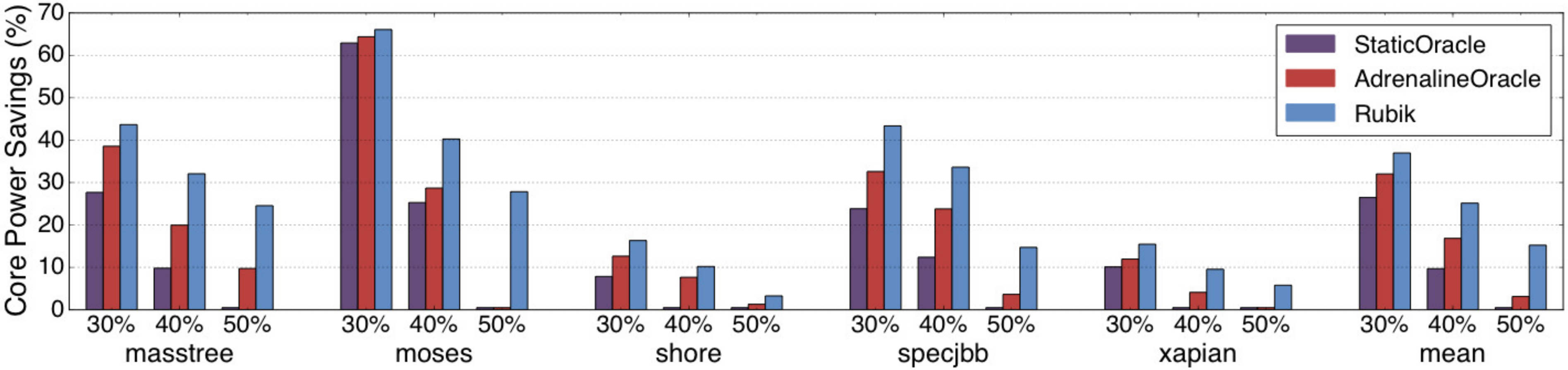
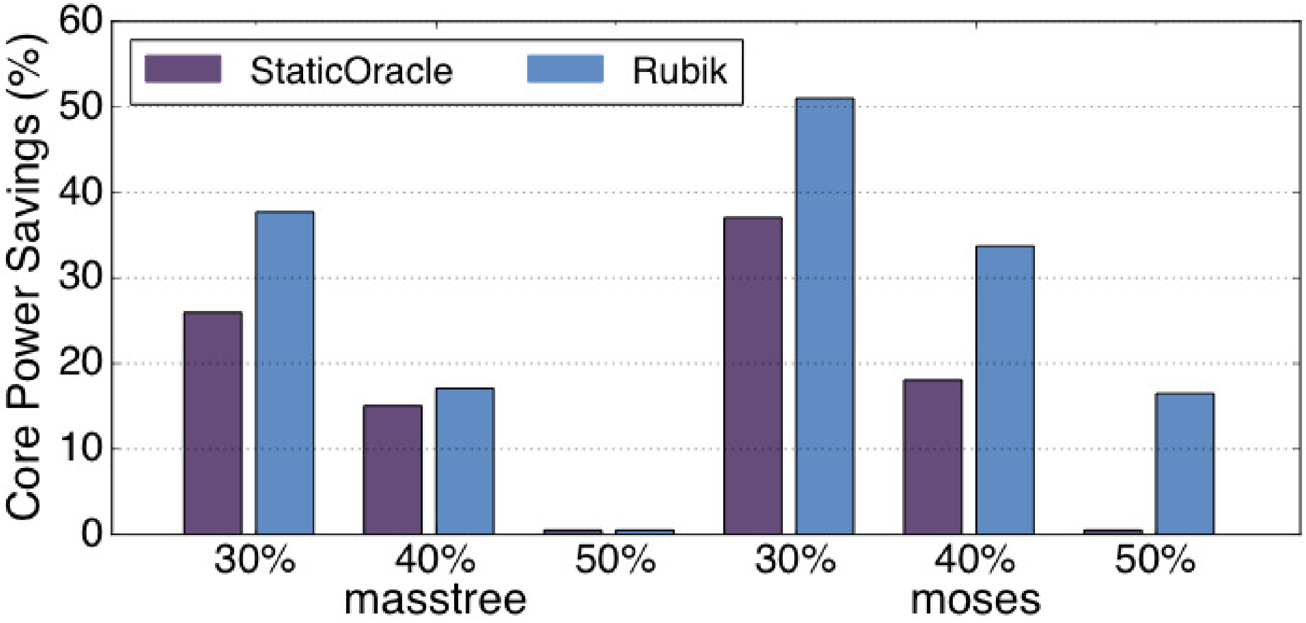


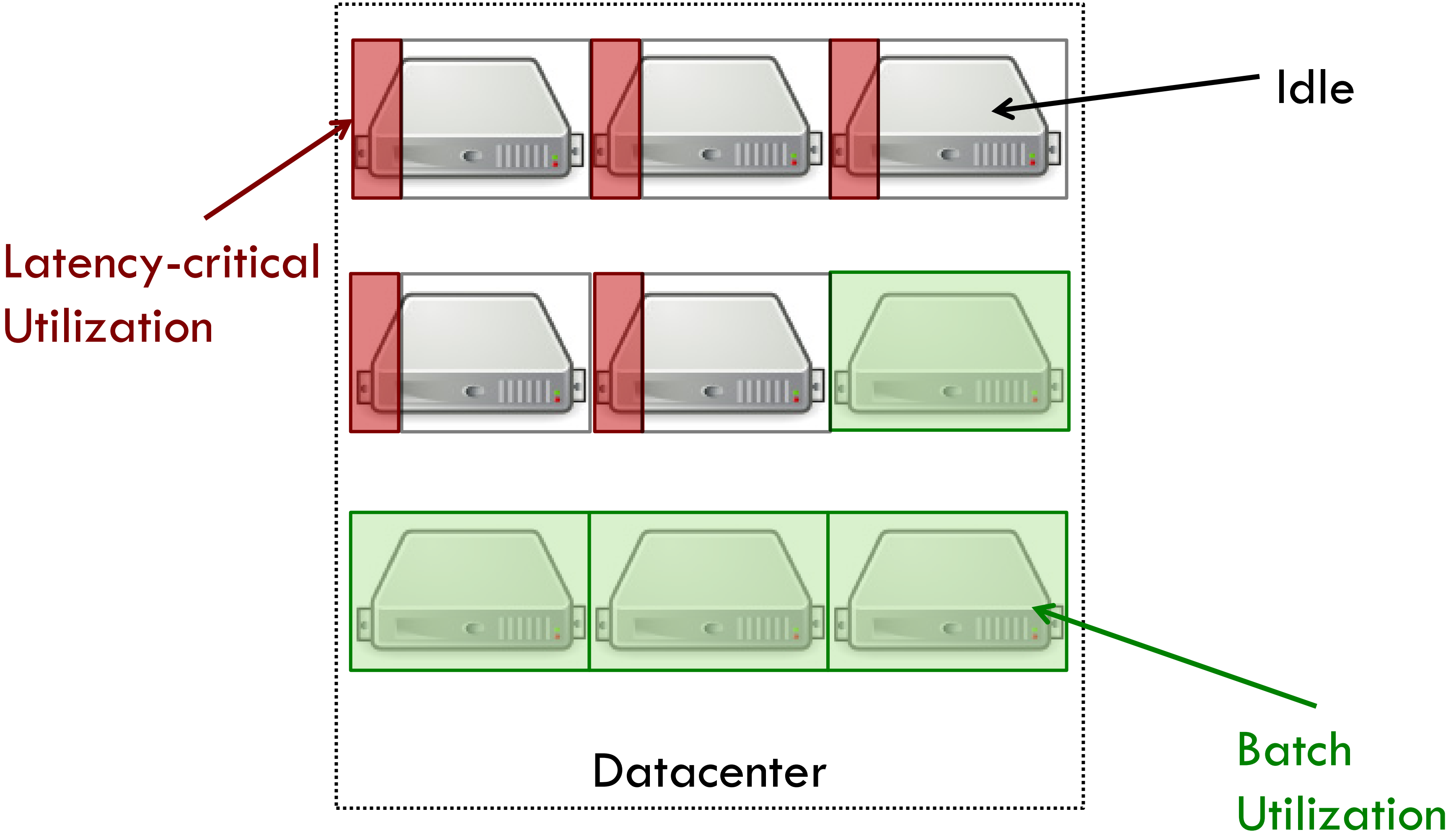
- All three schemes save significant power at low utilization
  - Rubik performs best, reducing core power by up to 66%
- Rubik's relative savings *increase* as short-term adaptation becomes more important
- Rubik saves significant power even at high utilization
  - 17% on average, and up to 34%

Real Machine Power Savings

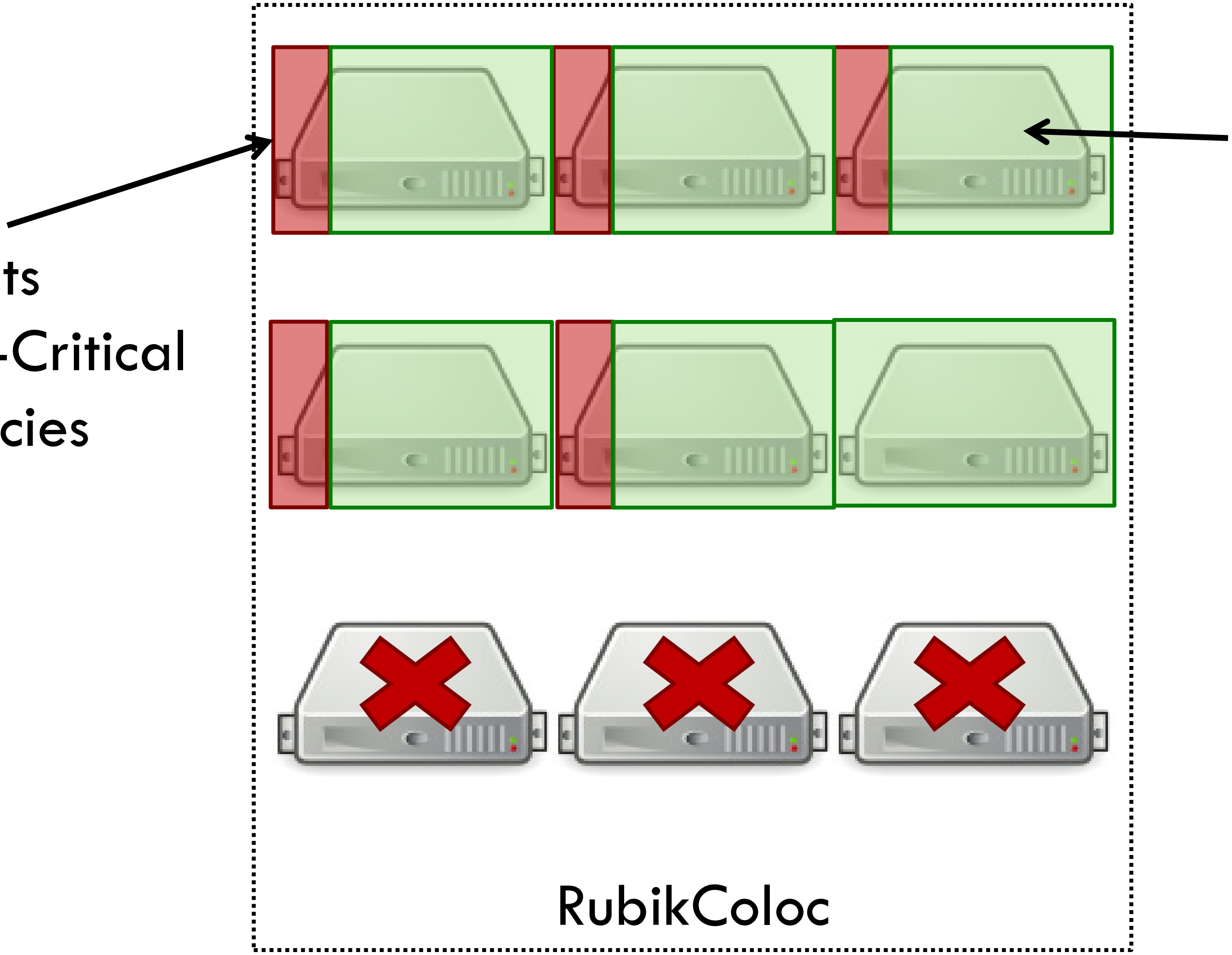
- V/F transition latencies of >100 μs even with integrated voltage controllers
  - Likely due to inefficiencies in firmware
- Rubik successfully adapts to higher V/F transition latencies



Static Power Limits Efficiency



RubikColoc: Colocation Using Rubik

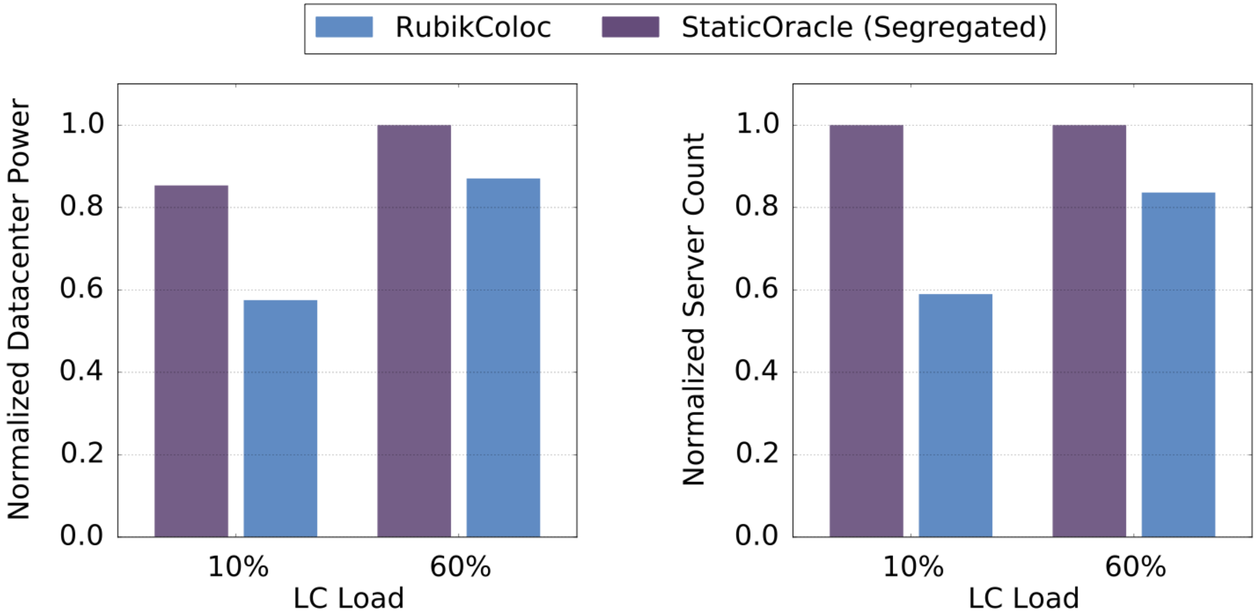


Rubik sets
Latency-Critical
Frequencies

Statically
Partitioned LLC

RubikColoc

RubikColoc Savings



- RubikColoc saves significant power and resources over a segregated datacenter baseline
  - 17% reduction in datacenter power consumption; 19% fewer machines at high load
  - 31% reduction in datacenter power consumption, 41% fewer machines at high load

Conclusions

- Rubik uses fine-grained power management to reduce active core power consumption by up to 66%

- Rubik uses statistical modeling to account for various sources of uncertainty, and avoids application-specific heuristics

- RubikColoc uses Rubik to colocate latency-critical and batch applications, reducing datacenter power consumption by up to 31% while using up to 41% fewer machines

Thanks For Your Attention!

Questions?

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