# *Perflso*: Performance Isolation for Commercial Latency-Sensitive Services

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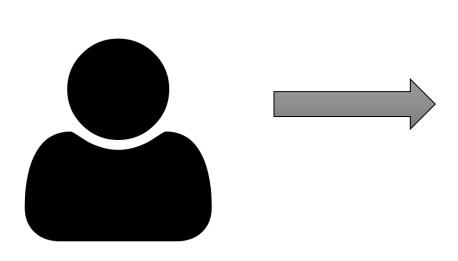
Alex Chen Jack Zhang Microsoft Bing Junhua Wang

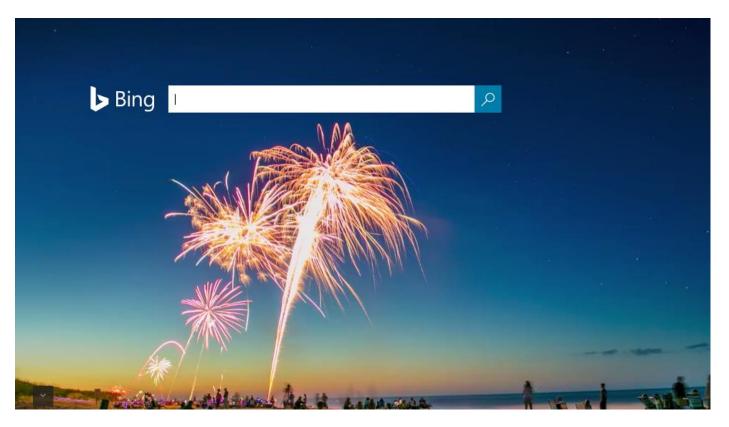
Microsoft



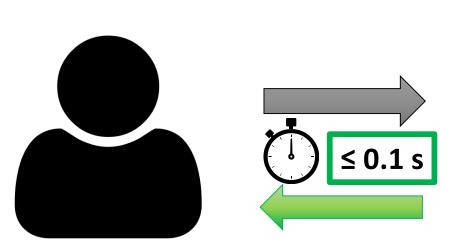
## Interactive services must feel <u>instantaneous</u>

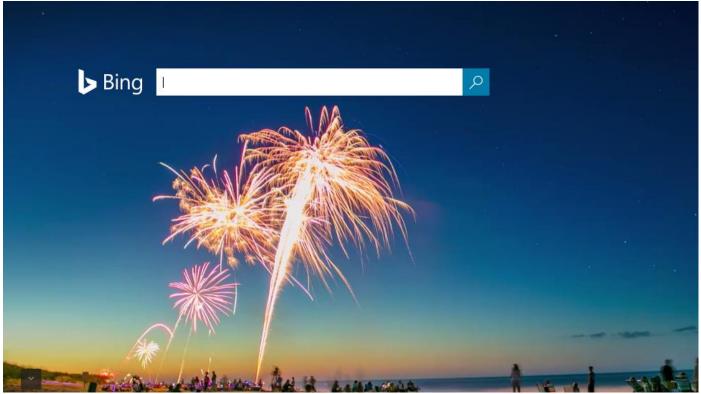
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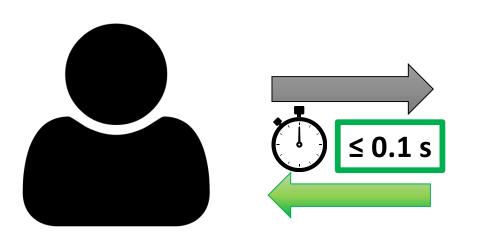




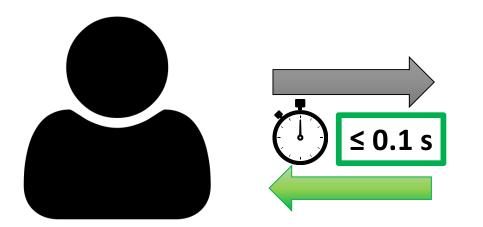
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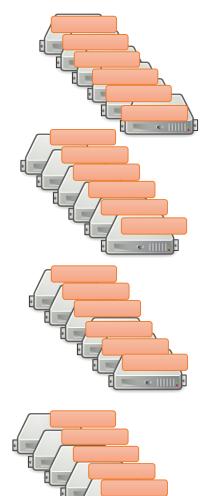


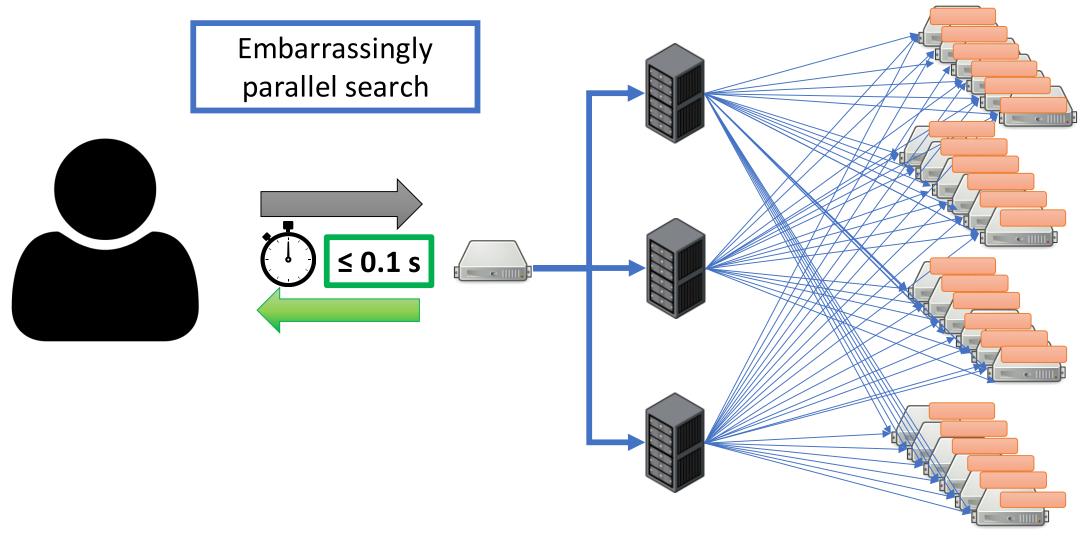


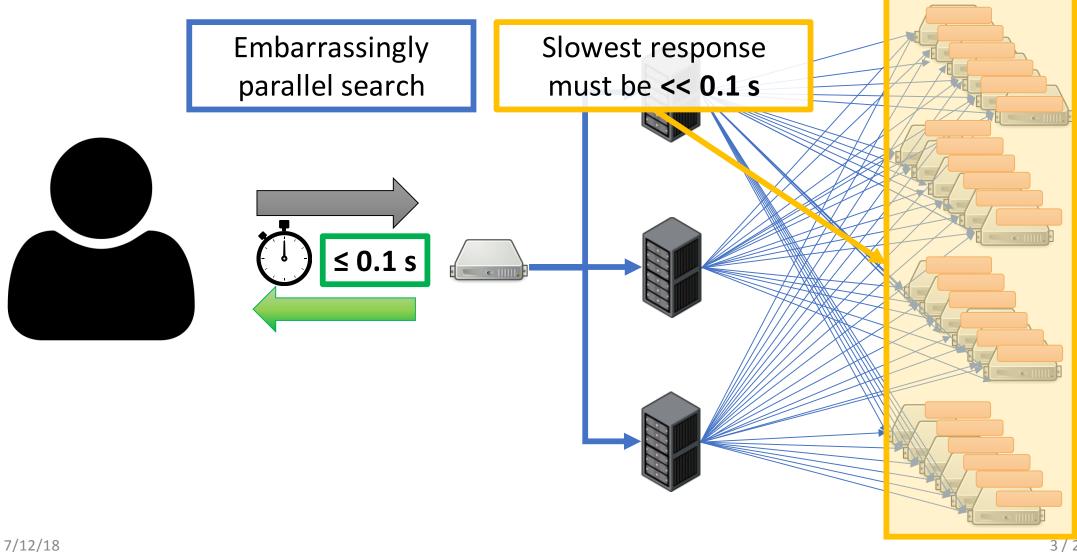


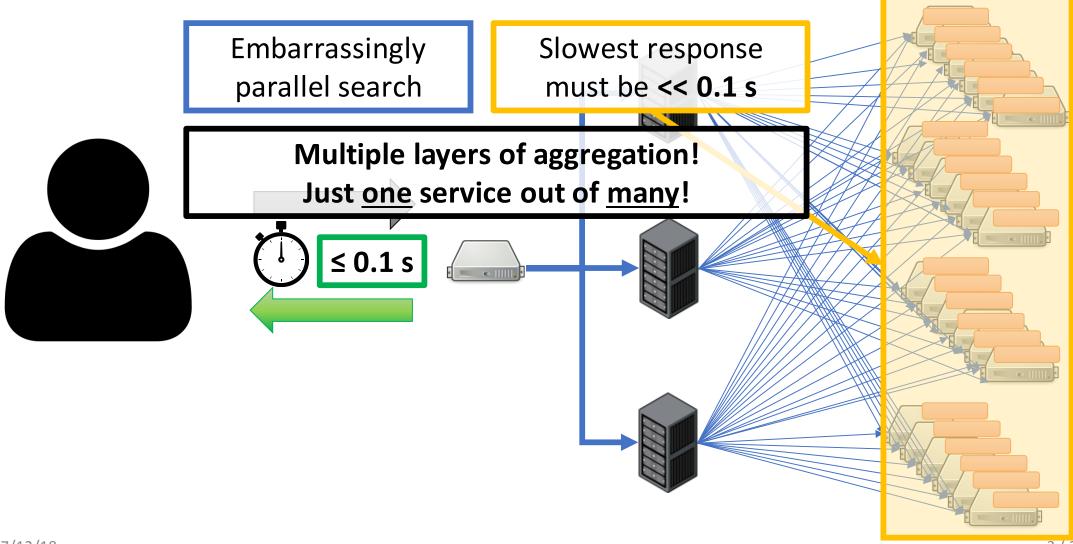
Web Index



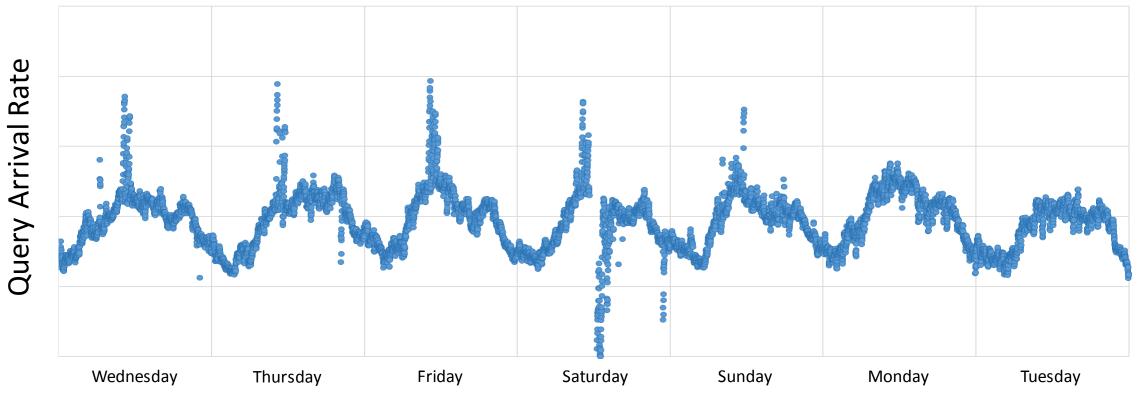


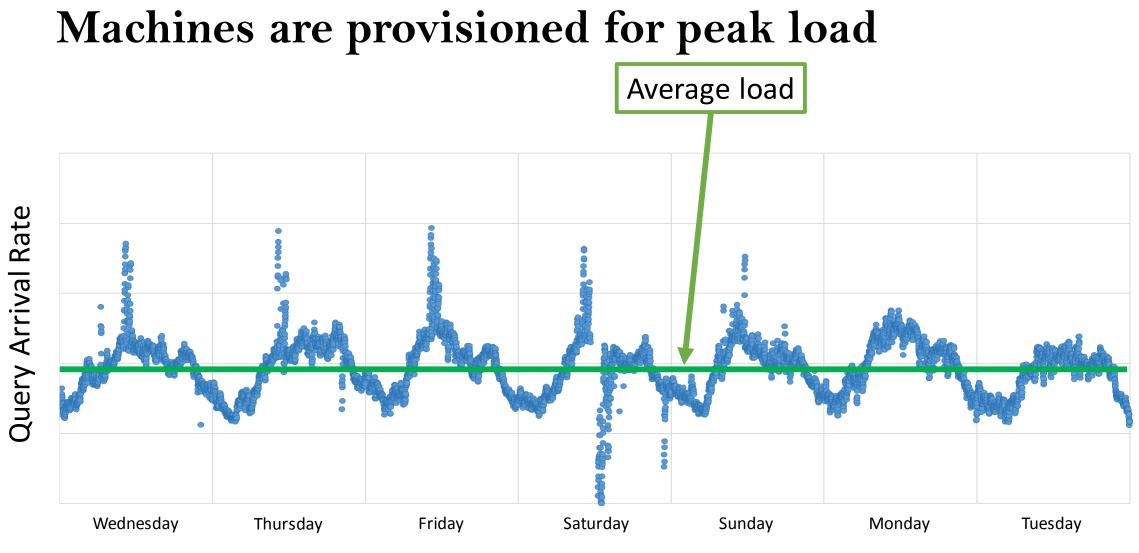


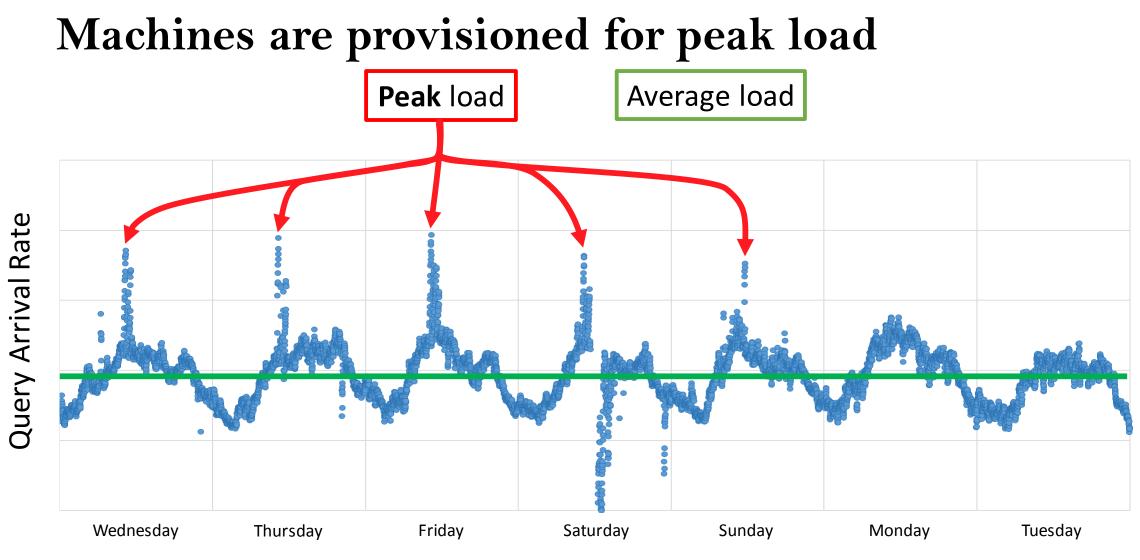




## Machines are provisioned for peak load

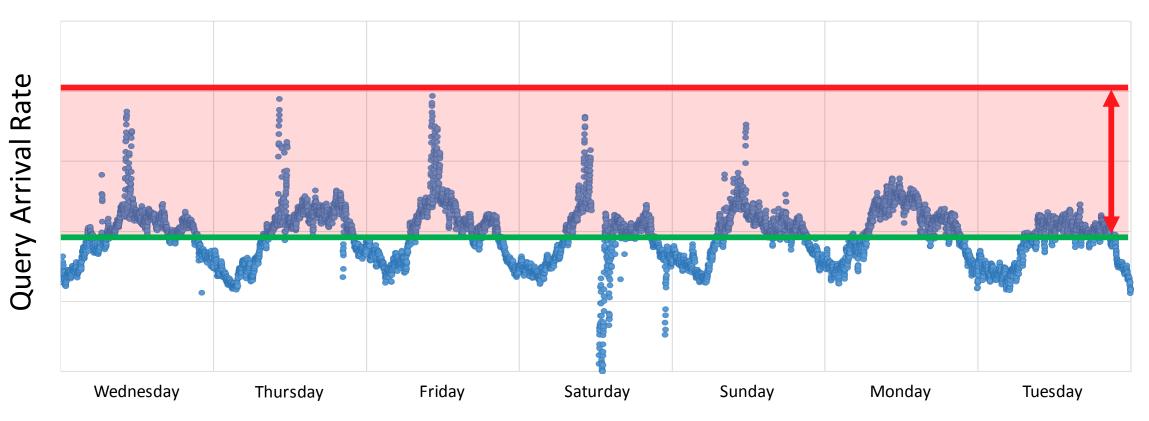






## Machines are provisioned for peak load

Peak load

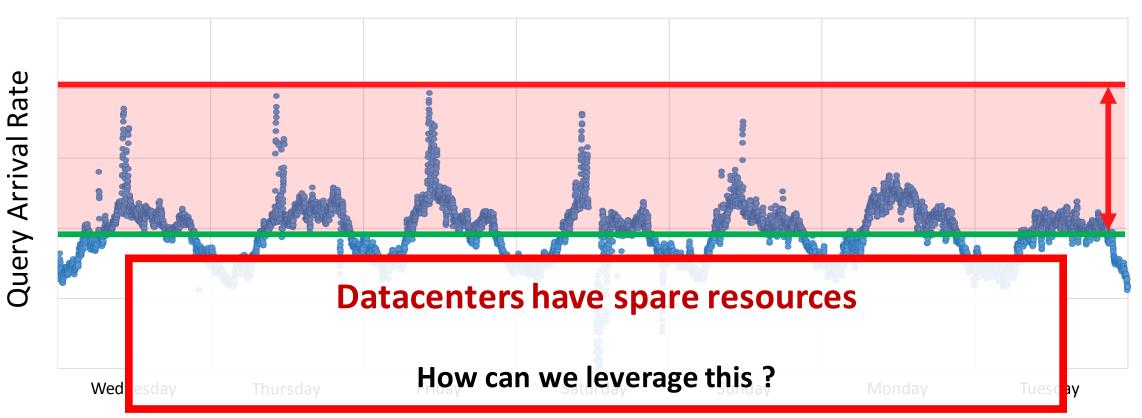


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Average load

## Machines are provisioned for peak load

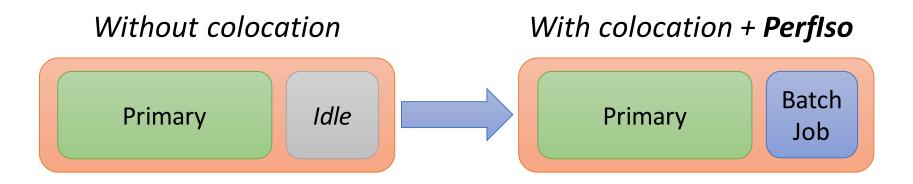
Peak load



Average load

## Solution: colocate batch jobs with online services

- Get spare resources to do useful work
- **Primary** tenant <u>guaranteed</u> performance
  - e.g., Bing IndexServe
- Secondary tenant <u>best-effort</u> performance
  - e.g., Apache Spark



Provides performance isolation of Primary

• Maintains P99 of response-times (10s of ms) under colocation

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Increases system efficiency

• 45% of the CPU is used to do useful batch work

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• Maintains P99 of response-times (10s of ms) under colocation

Increases system efficiency

• 45% of the CPU is used to do useful batch work

Deployed on over 90,000 servers

• Many different interactive services and hardware setups

## Many papers published on performance isolation

### Quasar [ASPLOS '14]

### Quasar: Resource-Efficient and QoS-Aware Cluster Management

Christina Delimitrou and Christos Kozvrakis Stanford University {cdel, kozvraki}@stanford.edu

### Abstract

Cloud computing promises flexibility and high performance for users and high cost-efficiency for operators. Nevertheless, most cloud facilities operate at very low utilization, hurting both cost effectiveness and future scalability.

We present Quasar, a cluster management system that increases resource utilization while providing consistently high application performance. Quasar employs three techniques. First, it does not rely on resource reservations, which lead to underutilization as users do not necessarily understand workload dynamics and physical resource requirements of complex codebases. Instead, users express performance constraints for each workload, letting Quasar determine the right amount of resources to meet these constraints at any point. Second, Quasar uses classification techniques to quickly and accurately determine the impact of the amount of resources (scale-out and scale-up), type of resources, and interference on performance for each workload and dataset. Third, it uses the classification results to jointly perform resource allocation and assignment, quickly exploring the large space of options for an efficient way to pack workloads on available resources. Quasar monitors workload performance and adjusts resource allocation and assignment when needed. We evaluate Quasar over a wide range of workload scenarios, including combinations of distributed analytics frameworks and low-latency, stateful ser vices, both on a local cluster and a cluster of dedicated EC2 servers. At steady state, Quasar improves resource utilization by 47% in the 200-server EC2 cluster, while meeting performance constraints for workloads of all types.

Categories and Subject Descriptors C.5.1 [Computer Sys tem Implementation]: Super (very large) computers; D.4.1 [Process Management]: Scheduling

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Keywords Cloud computing, datacenters, resource efficiency, quality of service, cluster management, resource allocation and assignment.

### Introduction

An increasing amount of computing is now hosted on public clouds, such as Amazon's EC2 [2], Windows Azure [65] and Google Compute Engine [25], or on private clouds managed by frameworks such as VMware vCloud [61]. Open-Stack [48], and Mesos [32]. Cloud platforms provide two major advantages for end-users and cloud operators: flexibility and cost efficiency [9, 10, 31]. Users can quickly launch jobs that range from short, single-process applications to large, multi-tier services, only paying for the resources used at each point. Cloud operators can achieve economies of scale by building large-scale datacenters (DCs) and by sharing their resources between multiple users and workloads. Nevertheless, most cloud facilities operate at very low utilization which greatly adheres cost effectiveness [9, 51]. This is the case even for cloud facilities that use cluster nanagement frameworks that enable cluster sharing across workloads. In Figure 1, we present a utilization analysis for a production cluster at Twitter with thousands of servers. nanaged by Mesos [32] over one month. The cluster mostly hosts user-facing services. The aggregate CPU utilization stently below 20%, even though reservations reach up to 80% of total capacity (Fig. 1.a). Even when looking at individual servers, their majority does not exceed 50% utilization on any week (Fig. 1.c). Typical memory use is higher (40-50%) but still differs from the reserved capacity. Figure 1.d shows that very few workloads reserve the right amount of resources (compute resources shown here. similar for memory); most workloads (70%) overestimate reservations by up to 10x, while many (20%) underestimate reservations by up to 5x Similarly Reiss et al, showed that a 12.000-server Google cluster managed with the more mature Borg system consistently achieves aggregate CPU utilization of 25-35% and aggregate memory utilization of 40% [51]. In contrast, reserved resources exceed 75% and 60% of available capacity for CPU and memory respectively. Twitter and Google are in the high end of the utilization spectrum. Utilization estimates are even lower for cloud facilities that do not co-locate workloads the way Google and

### Heracles [ISCA '15]

### Heracles: Improving Resource Efficiency at Scale

David Lo<sup>†</sup>, Liqun Cheng<sup>‡</sup>, Rama Govindaraju<sup>‡</sup>, Parthasarathy Ranganathan<sup>‡</sup> and Christos Kozyrakis<sup>†</sup> Google, Inc.<sup>‡</sup> Stanford University

### Abstract

User-facing, latency-sensitive services, such as websearch, ilize their computing resources during daily periods of low traffic. Reusing those resources for other tasks is rarely done in production services since the contention for shared resource can cause latency spikes that violate the service-level objective of latency-sensitive tasks. The resulting under-utilization hurts both the affordability and energy-efficiency of large-scale data-centers. With technology scaling slowing down, it becomes important to address this opportunit We present Heracles, a feedback-based controller that en-

ables the safe colocation of best-effort tasks alongside a latency critical service. Heracles dynamically manages multiple hardware and software isolation mechanisms such as CPU memory and network isolation, to ensure that the latency-sensitive jo meets latency targets while maximizing the resources given to best-effort tasks. We evaluate Heracles using production latency-critical and batch workloads from Google and demonstrate averare server utilizations of 90% without latency violations across all the load and colocation s arios that we evaluated.

### 1 Introduction

Public and private cloud frameworks allow us to host an increasing number of workloads in large-scale datacenters with tens of thousands of servers. The business models for cloud services emphasize reduced infrastructure costs. Of the total cost of ownership (TCO) for modern energy-efficient datacenters, servers are the largest fraction (50-70%) [7]. Maximizing ar utilization is therefore important for continued scaling Until recently, scaling from Moore's law provided higher compute per dollar with every server generation, allowing datacenters to scale without raising the cost. However, with several imminent challenges in technology scaling [21, 25], alter-nate approaches are needed. Some efforts seek to reduce the server cost through balanced designs or cost-effective compo nents [31, 48, 42]. An orthogonal approach is to improve the return on investment and utility of datacenters by raising server utilization. Low utilization negatively impacts both operational and capital components of cost efficiency. Energy proportionality can reduce operational expenses at low utilization [6, 47].

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear make or distributed for positi or commercial advantage and that copies hear this notice and the full ciation on the first page. Copyrights for components of this stork and the full ciation on the first page. Copyrights for components of this stork and the first page of the positivities to first page of the first page of the first page of the positivities of the first page of the positivities of the first page of the first

lization in most datacenters is low, ranging between 10% and 50% [14, 74, 66, 7, 19, 13]. A primary reason for the low utilization is the popularity of latency-critical (LC) services such as social media, search engines, software-as-a-service, online maps vebmail, machine translation, online shopping and advertising These user-facing services are typically scaled across thousand of servers and access distributed state stored in memory or Flash across these servers. While their load varies significantly due to diurnal patterns and unpredictable spikes in user accesses, it is olidate load on a subset of highly utilized server because the application state does not fit in a small number of servers and moving state is expensive. The cost of such under-utilization can be significant. For instance, Google websearch servers often have an average idleness of 30% over a 24 hour period [47]. For a hypothetical cluster of 10,000 servers, this idleness translates to a wasted capacity of 3,000 servers. A promising way to improve efficiency is to launch best-

But, to amortize the much larger capital expenses, an increased

Several studies have established that the average server uti-

emphasis on the effective use of server resources is warranted.

effort batch (BE) tasks on the same servers and exploit any reources underutilized by LC workloads [52, 51, 18]. Batch analytics frameworks can generate numerous BE tasks and derive significant value even if these tasks are occasionally deferred or restarted [19, 10, 13, 16]. The main challenge of this approach is interference between colocated workloads on shared resources such as caches, memory, I/O channels, and network links. LC tasks operate with strict service level objectives (SLOs) on tail igher utilization through colocation work aims to enable aggressive colocation of LC workloads and BE jobs by automatically coordinating multiple hardware and

latency, and even small amounts of interference can cause significant SLO violations [51, 54, 39]. Hence, some of the pa work on workload colocation focused only on throughput work loads [58, 15]. More recent systems predict or detect when a LC task suffers significant interference from the colocated tasks, and avoid or terminate the colocation [75, 60, 19, 50, 51, 81]. These systems protect LC workloads, but reduce the opportunities for Recently introduced hardware features for cache isolation and fine-grained power control allow us to improve colocation. This

software isolation mechanisms in modern servers. We focus on wo hardware mechanisms, shared cache partitioning and fine rained power/frequency settings, and two software mechanisms core/thread scheduling and network traffic control. Our goal

to eliminate SLO violations at all levels of load for the LC job while maximizing the throughput for BE tasks. There are several challenges towards this goal. First, we must carefully share each individual resource; conservative allocation will minimize the throughput for BE tasks, while optimistic al-location will lead to SLO violations for the LC tasks. Second, the performance of both types of tasks depends on multiple resources, which leads to a large allocation space that must be

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### Elfen [USENIX ATC '16]

### Elfen Scheduling: Fine-Grain Principled Borrowing from Latency-Critical Workloads using Simultaneous Multithreading

Xi Yang<sup>†</sup> Stephen M. Blackburn<sup>†</sup> Kathryn S. McKinley <sup>†</sup>Australian National University <sup>‡</sup>Microsoft Research

Abstract Web services from search to games to stock trading imnose strict Service Level Objectives (SLOs) on tail latency. Meeting these objectives is challenging because the computational demand of each request is highly variable and load is bursty. Consequently, many servers run at low utilization (10 to 45%); turn off simultaneous multithread ing (SMT): and execute only a single service --- wasting hardware, energy, and money. Although co-running batch jobs with latency critical requests to utilize multiple SMT hardware contexts (lanes) is appealing, unmitigated sharing of core resources induces non-linear effects on tail latency and SLO violations.

We introduce principled borrowing to control SMT hardware execution in which batch threads borrow core resources. A batch thread executes in a reserved batch SMT lane when no latency-critical thread is executing in the partner request lane. We instrument batch thread to quickly detect execution in the request lane, step out of the way, and promptly return the borrowed resources. We introduce the nanonap system call to stop the batch thread's execution without yielding its lane to the OS scheduler, ensuring that requests have exclusive use of the core's resources. We evaluate our approach for colocating batch workloads with latency-critical requests using the Apache Lucene search engine. A conservative policy that executes batch threads only when request lane is idle improves utilization between 90% and 25% on one core depending on load, without compromising request SLOs. Our approach is straightforward, robust, and unobtrusive, opening the way to substantially improved resource utilization in datacenters running latency-critical workloads

### 1 Introduction

USENIX Association

Latency-critical web services, such as search, trading, games, and social media, must consistently deliver low stency responses to attract and satisfy users. This requirement translates into Service Level Objectives (SLOs) governing latency. For example, an SLO may include an average latency constraint and a tail constraint, such as that 99% of requests must complete within 100 ms [6, 7, 13, 34]. Many such services, such as Google Search and Twitter [6, 8, 18], systematically underutilize the available hardware to meet SLOs. Furthermore,

Since these services are widely deployed in large numbers of datacenters, their poor utilization incurs enormout commensurate capital and operating costs. Even small improvements substantially improve profitability. Meeting SLOs in these highly engineered systems is challenging because: (1) requests often have variable computational demands and (2) load is unpredictable and bursty. Since computation demands of requests ma differ by factors of ten or more and load bursts induce queuing delay, overloading a server results in highly nonlinear increases in tail-latency. The conservative solution providers often take is to significantly over-provision. Interference arises in chip multiprocessors (CMPs) and in simultaneous multithreading (SMT) cores when contending for shared resources. A spate of recent research explores how to predict and model interference between different workloads executing on distinct CMF cores [8, 23, 25, 28], but these approaches target and exploit large scale diurnal patterns of utilization, e.g., colocating batch workloads at night when load is low. Lo et al. explicitly rule out SMT because of the highly unpredictable and non-linear impact on tail latency (which we confirm) and the inadequacy of high-latency OS scheduling [23]. Zhang et al. do not attempt to reduce SMTnduced overheads, but rather they accommodate them us ing a model of interference for co-running workloads [35] Their approach requires ahead-of-time profiling of all colocated workloads and over-provisioning. Prior work lacks dynamic mechanisms to monitor and control batch workloads on SMT with low latency. This research exploits SMT resources to increase

rvers often execute only one service to ensure that

latency-critical requests are free from interference. The

result is that server utilizations are as low as 10 to 45%.

utilization without compromising SLOs. We introduce principled borrowing, which dynamically identifies idle cycles and borrows these resources. We implement borrowing in the ELFEN1 scheduler, which co-runs batch threads and latency-critical requests, and meets request SLOs. Our work is complementary to managing shared cache and memory resources. We first show that latency critical workloads impose many idle periods and they are short. This result confirms that scheduling at OS granu-<sup>1</sup>In the Grimm fairy tale, Die Wichtelmänner, elve n's tools while he sleeps, making him beautiful shoe elves borrow a cob

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## Many papers published on performance isolation

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- 2. "Standalone": Primary acts like it runs alone (negligible interference)

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- 2. "Standalone": Primary acts like it runs alone (negligible interference)
- 3. "Integrability": Minimize software-stack changes (easy deployment)

Why is Performance Isolation hard?

## **Interactive services – highly sensitive to interference!**

### Leaf-servers keep 99<sup>th</sup> percentile low

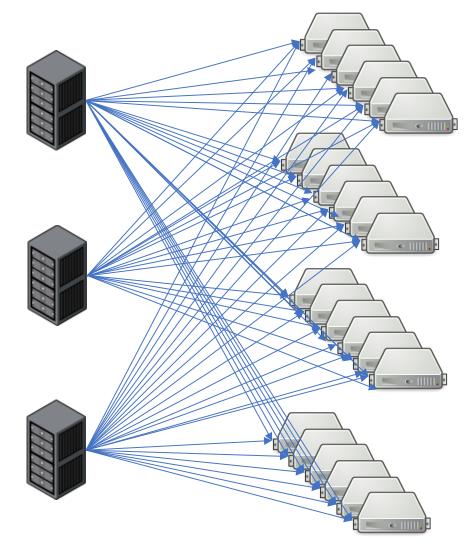
- Over 10 years of optimization work!
  - e.g., compression, adaptive parallelism, etc.

### How often does the 99<sup>th</sup> percentile occur?

• For 10,000 queries / s  $\rightarrow$  100 times / s

### What happens in a 100-node fanout?

• Every query runs at the 99<sup>th</sup> percentile!



## The Primary demands many resources quickly

• **Bing IndexServe**: multi-threaded web-index server

 $\succ$  Up to 15 threads wake up in 5 $\mu$ s<sup>1</sup>

<sup>1</sup>Constant query rate 4,000 Q/s, 500k queries experiment

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- Burstiness due to query-processing optimizations!
  - some queries will spawn many workers
- Workload arrives in bursts exacerbates problem

<sup>1</sup>Constant query rate 4,000 Q/s, 500k queries experiment

• Primary's resource demands must be <u>fulfilled instantly</u>.

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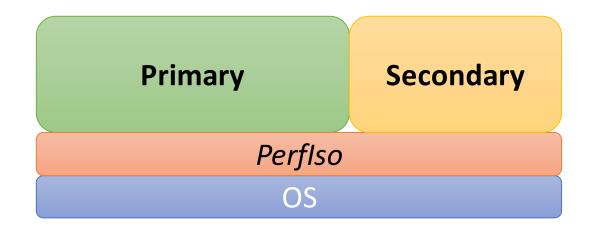
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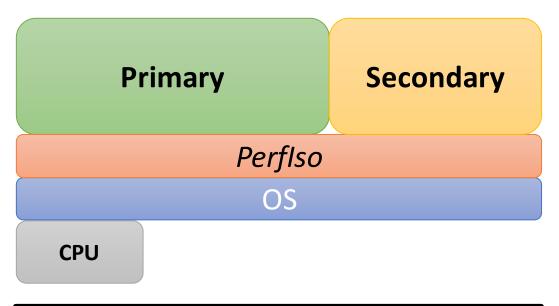
### If a query is delayed, it is already too late!

## Perflso

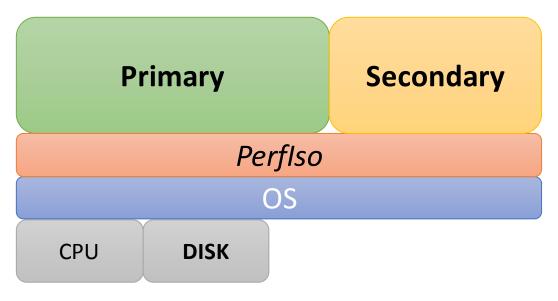
# *PerfIso*: Implemented as a <u>user-mode</u> service

Only keeps track of Secondary's PID

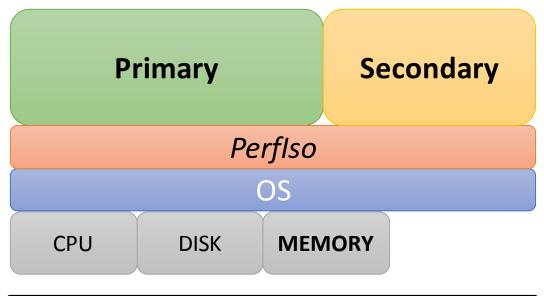




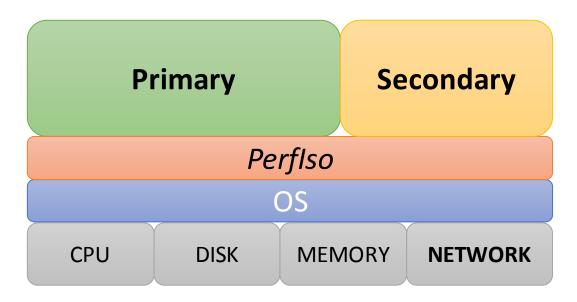






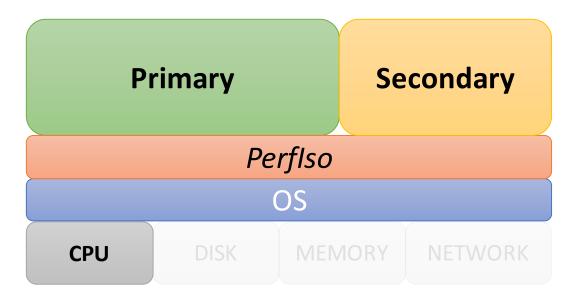








### **PerfIso:** CPU is the most important resource

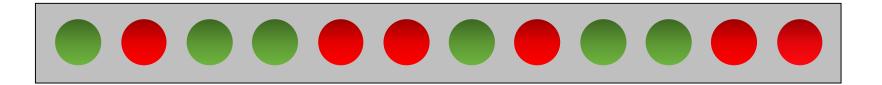




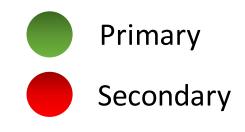
# CPU sharing without *PerfIso*

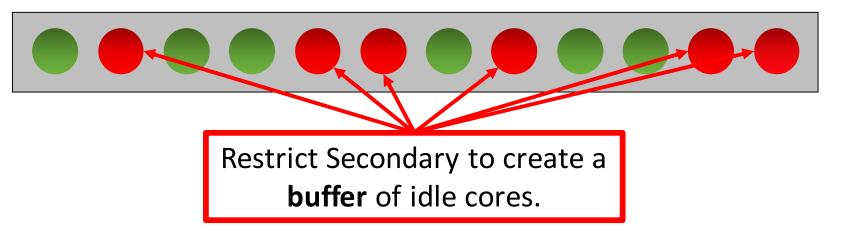
- Primary and Secondary compete for cores.
- Secondary is aggressive: no idle cores exist.



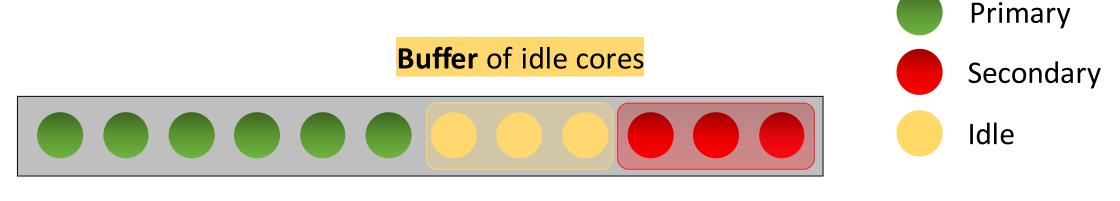


- Perflso only knows the Secondary.
- <u>Restrict</u> Secondary by changing core affinities.



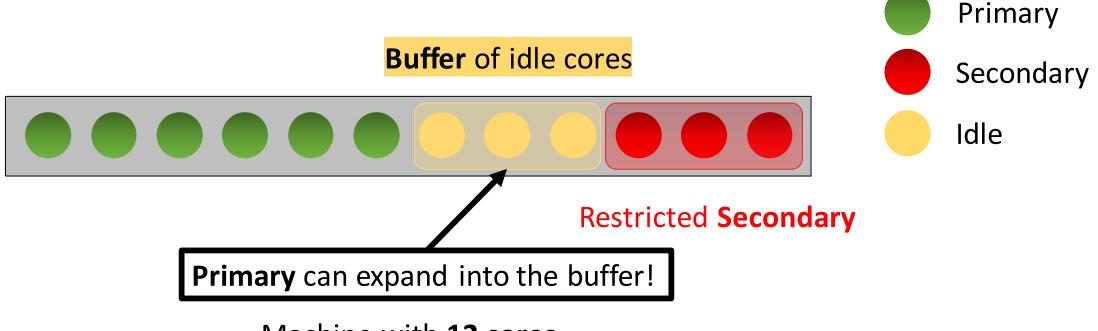


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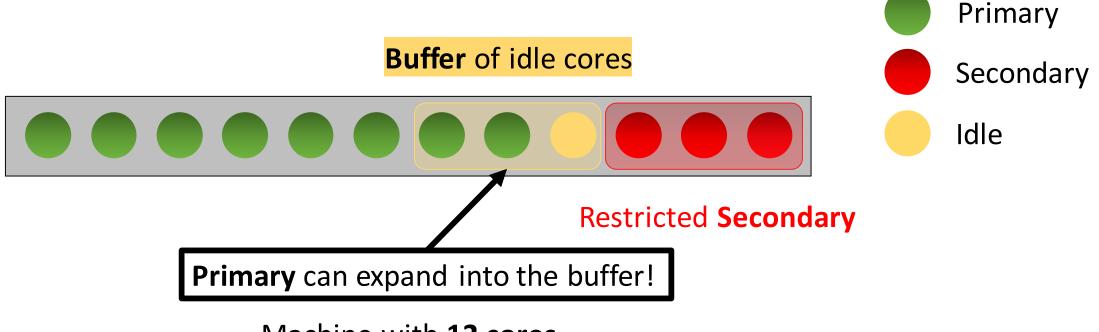


Restricted Secondary

• Primary is <u>unrestricted</u>. Secondary is <u>restricted</u>.

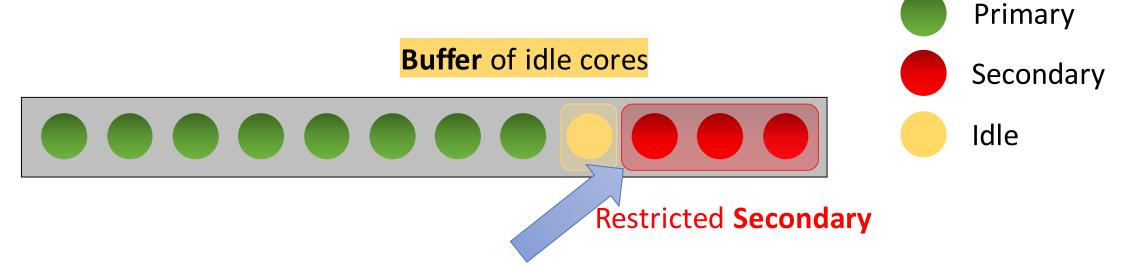


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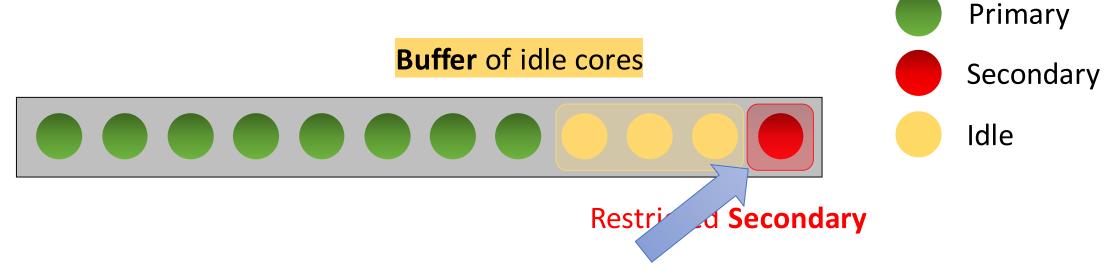
# **CPU Blind Isolation: React to bursts from Primary**

- <u>Continuously</u> read idle core status.
- Adjust Secondary "slice" to maintain buffer.



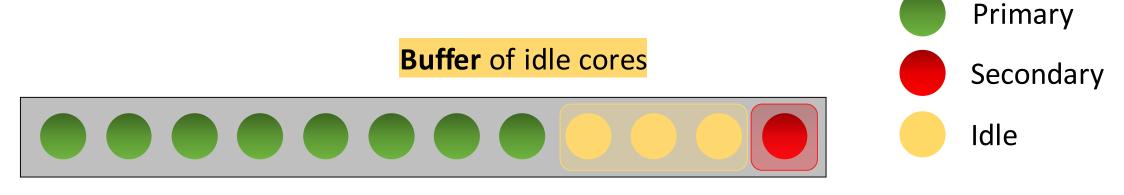
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- <u>Continuously</u> read idle core status.
- Adjust Secondary "slice" to maintain buffer.



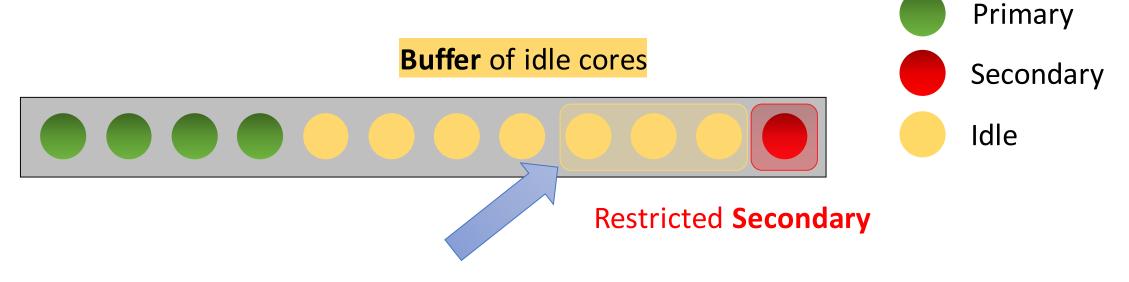
# **CPU Blind Isolation: React to bursts from Primary**

- <u>Continuously</u> read idle core status.
- Adjust Secondary "slice" to maintain buffer.

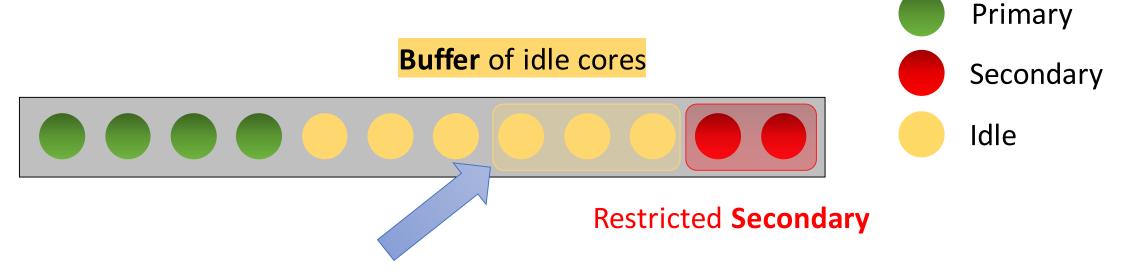


Restricted Secondary

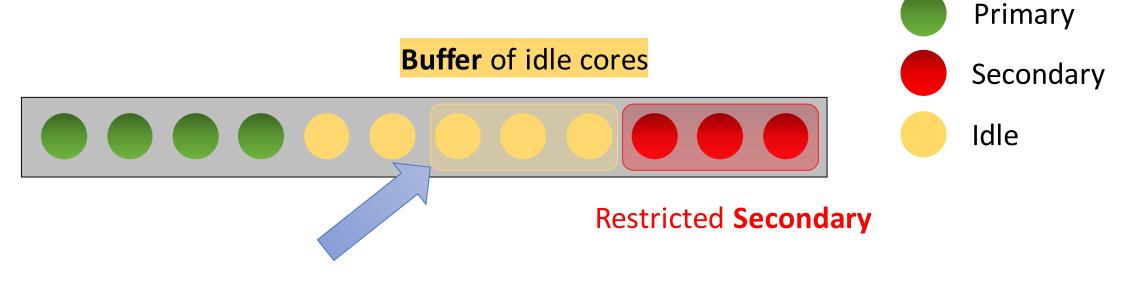
- Allow **Secondary** to use spare idle cores.
- Release spare cores incrementally.



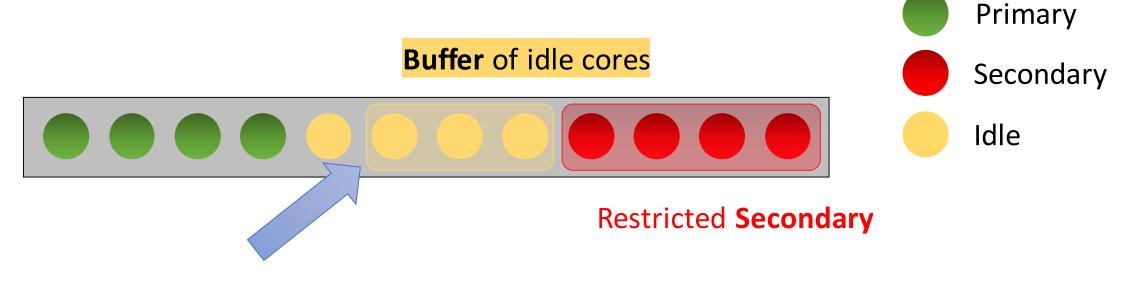
- Allow **Secondary** to use spare idle cores.
- Release spare cores incrementally.



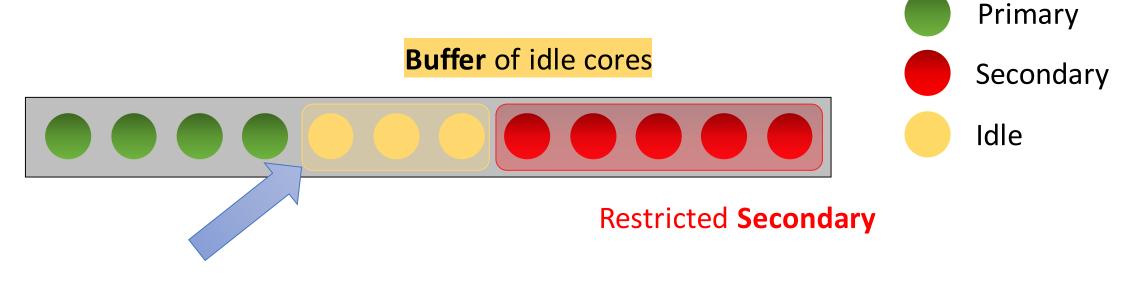
- Allow **Secondary** to use spare idle cores.
- Release spare cores incrementally.



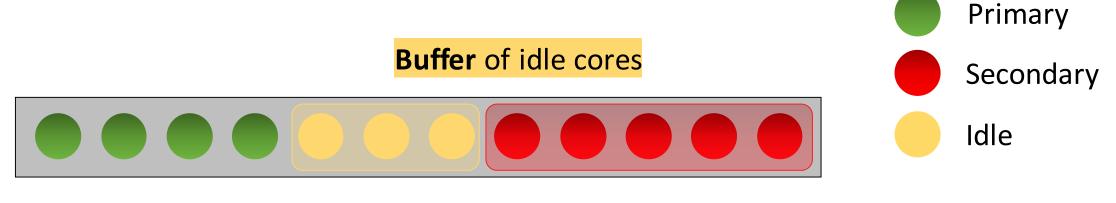
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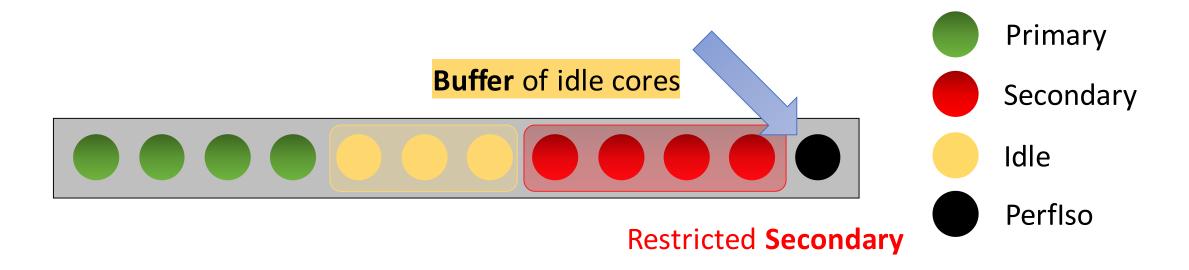
- Allow **Secondary** to use spare idle cores.
- Release spare cores incrementally.



Restricted Secondary

# CPU Blind Isolation: We dedicate 1 core to PerfIso

• **Perflso** does continuous polling  $\rightarrow$  we affinitize it to 1 core.



# Evaluation

# **Experiment testbed**

### Hardware

- Intel Xeon E5 24 cores (48 w/ HT)
- 128GB RAM

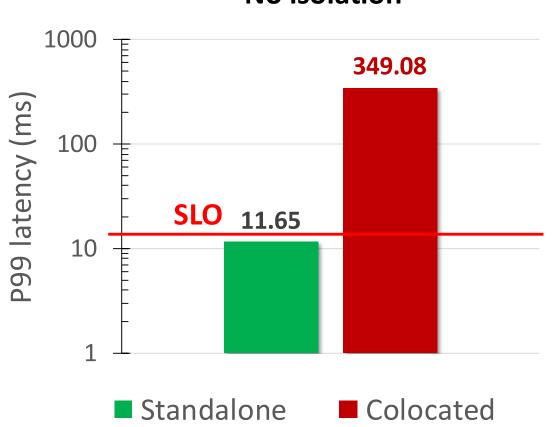
### Primary: Bing IndexServe

- 569 GB index-slice
- Open-loop client
- 500,000 queries @ 2,000 Q / s

### Secondary: CPU micro-benchmark

# Single server: PerfIso protects tail-latency

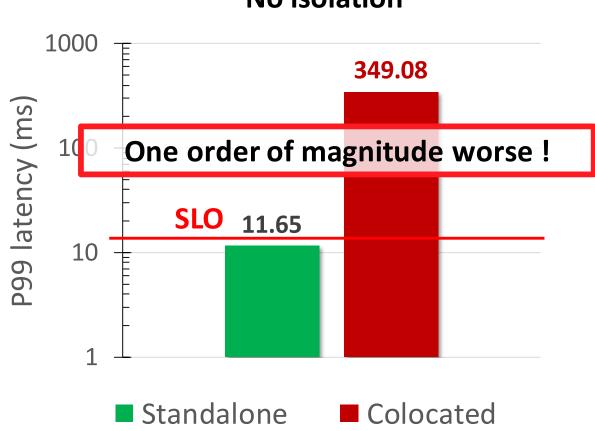
**Secondary**: CPU-intensive micro-benchmark



No isolation

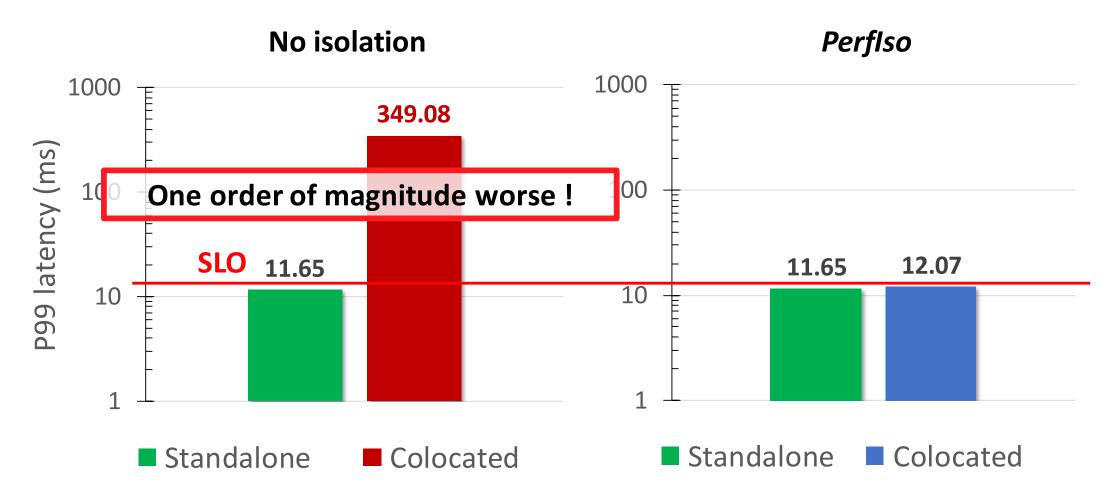
# Single server: *PerfIso* protects tail-latency

**Secondary**: CPU-intensive micro-benchmark

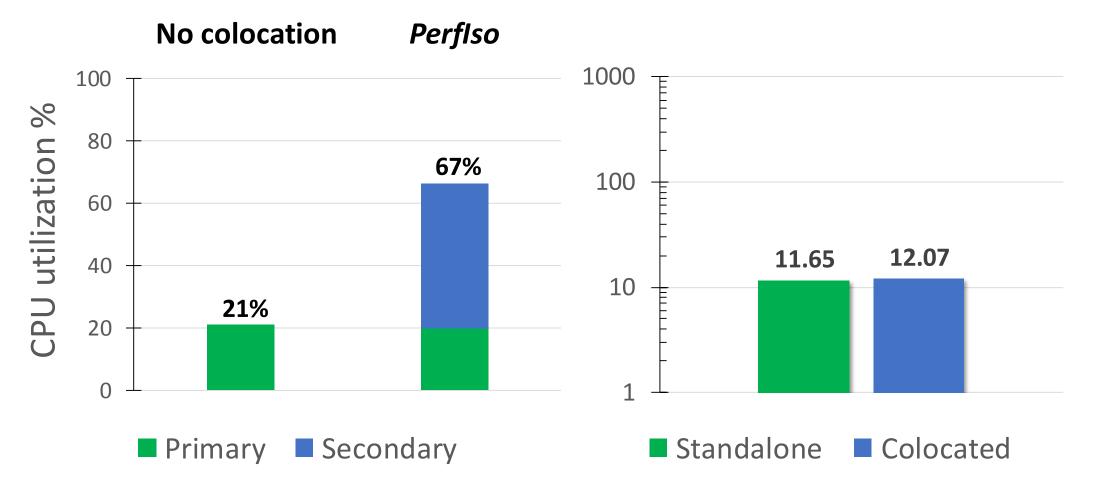


No isolation

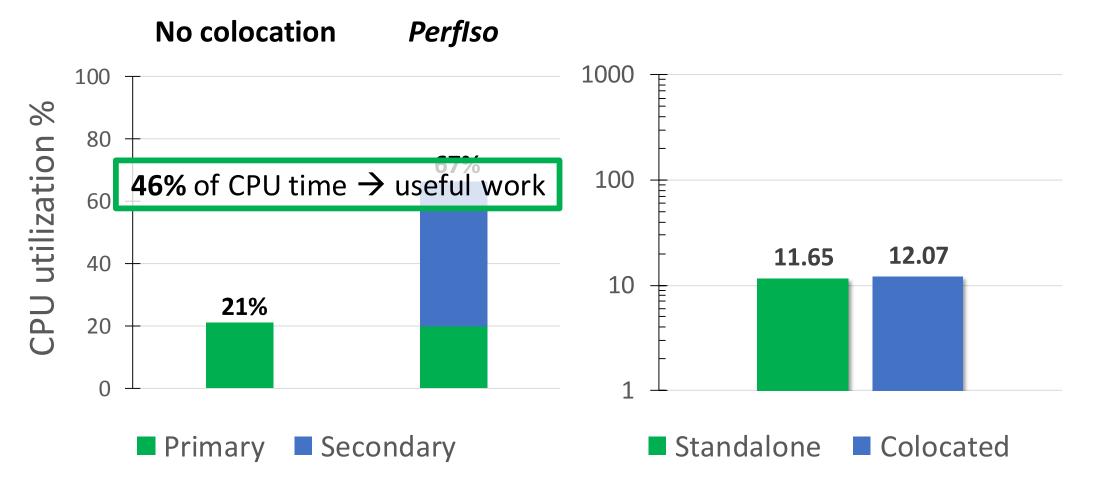
# Single server: *PerfIso* protects tail-latency



# Single server: CPU utilization 3x higher!

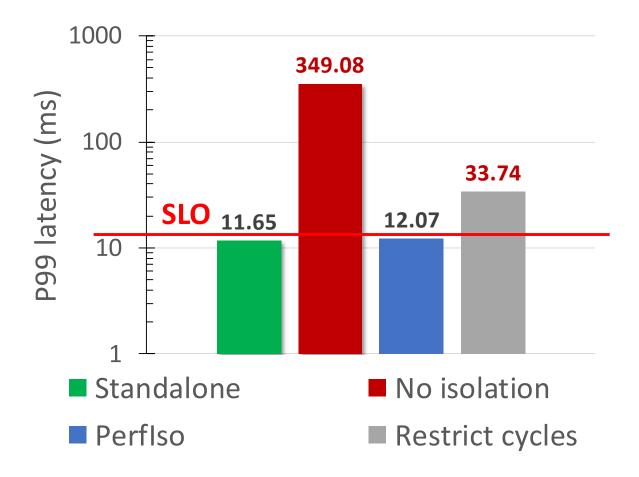


# Single server: CPU utilization 3x higher!



# Restricting <u>CPU cycles</u> does not work

**Secondary**: CPU-intensive micro-benchmark

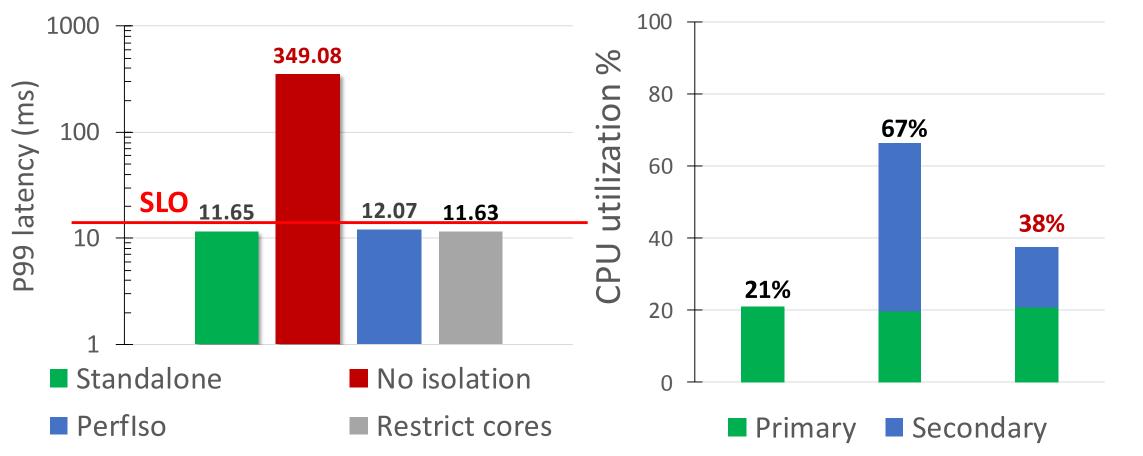


**Secondary**  $\rightarrow$  5% of CPU cycles

#### P99 latency – **3x higher than SLO!**

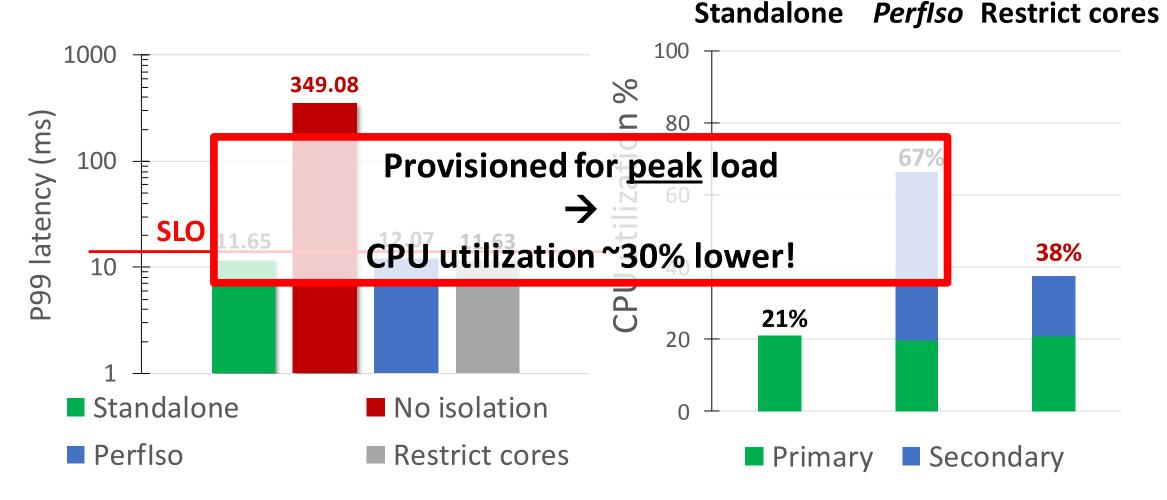
# **Restricting** <u>CPU cores</u> does not work

**Secondary**: CPU-intensive micro-benchmark



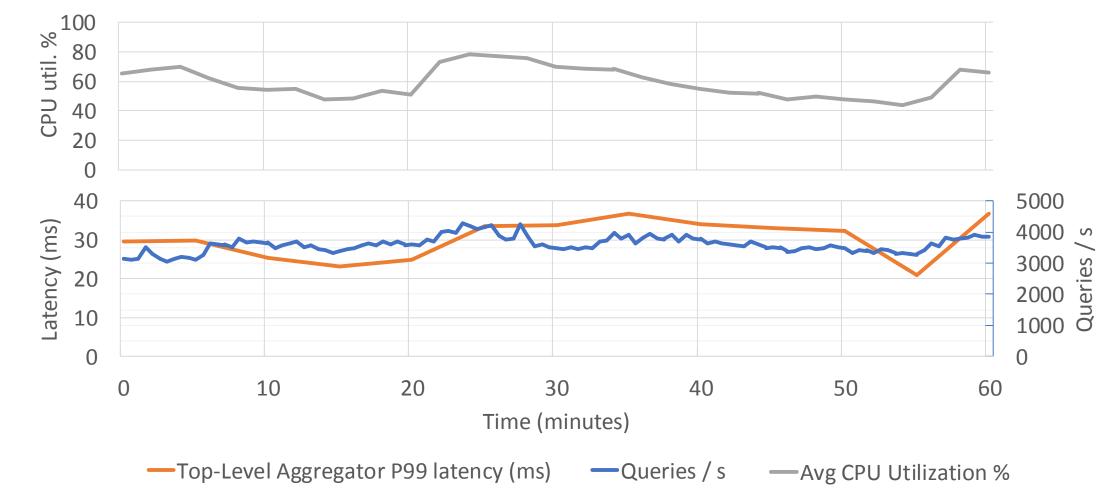
Standalone *Perflso* Restrict cores

# **Restricting** <u>CPU cores</u> does not work



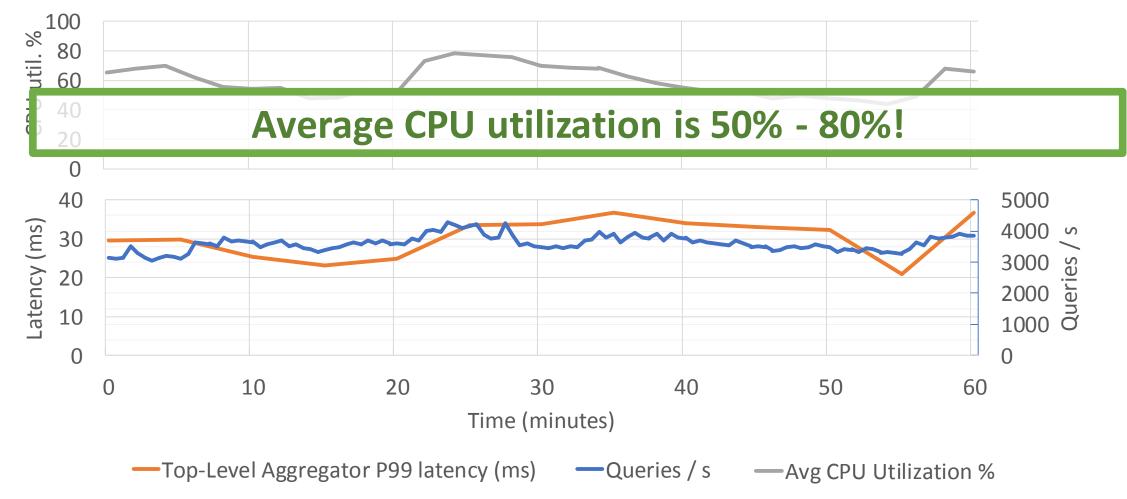
# 1-hour run of 650 machine cluster

Secondary: Machine-Learning computation



# 1-hour run of 650 machine cluster

Secondary: Machine-Learning computation



# Interesting details in the paper

- Effectiveness of static CPU isolation methods
  - Restricting CPU cycles
  - Restricting CPU cores
- Comparison of state-of-the-art techniques
- Managing disk, memory, and network

#### PerfIso: Performance Isolation for Commercial Latency-Sensitive Services

| Cälin lorgulescu*  |                    | Youngjin Kwon*                                     | Sameh Elnikety     |
|--------------------|--------------------|--|--------------------|
| EPFL               |                    | /. Texas at Austin                                 | Microsoft Research |
| Manoj Syamala      | Vivek Narasayya    | Vivek Narasayya Herodotos Herodotou*               |                    |
| Microsoft Research | Microsoft Research | Microsoft Research Cyprus University of Technology |                    |
| Paulo Tomita       | Alex Chen          | Jack Zhang   | Junhua Wang        |
| Microsoft Bing     | Microsoft Bing     | Microsoft Bing                                     | Microsoft Bing     |

#### Abstract

Large commercial latency-sensitive services, such as web search, run on dedicated clusters provisioned for peak load to ensure responsiveness and tolerate data center outages. As a result, the average load is far lower than the peak load used for provisioning, leading to resource under-utilization. The idle resources can be used to run batch jobs, completing useful work and roducing overall data center provisioning costs. However, this is challenging in practice due to the complexity and stringent tail-latency requirements of latency-sensitive services. Left unmanaged, the competition for machine resources can lead to severe response-time degradation and unmet service-level objectives (SLOS).

This work describes Perflox, a performance isolation framework which has been used for nearly three years in Microsoft Bing, a major search engine, to colocate batch jobs with production latency-sensitive services on over 90,000 servers. We discuss the design and implementation of Perflox, and conduct an experimental evaluation in a production environment. We show that colocating CPU-intensive jobs with latency-sensitive services increases average CPU utilization from 21% to 66% for off-peak load without impacting tail latency.

#### 1 Introduction

New server acquisition contributes to over half of the total cost of ownership (TCO) of modern data centers [8]. However, server atilization is low in data centers hosting large latency-sensitive services for two main reasons: First, latency-sensitive services are typically provisioned for the peak load, which occurs only for a fraction of the total running time [13]. Second, business-continuity plans dictate tolerating multiple major data center outages, such as tolerating the failure of two data centers

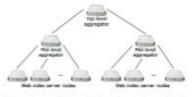


Figure 1: Architecture of index serving system of Web search engine with two aggregation levels (MLA and TLA). The user query is processed on index servers, which send responses to MLAs, which send aggregated responses to TLA.

out of three data centers within a continent while remaining capable of processing peak load. The high degree of over-provisioning is imperative: a livesite incident causing brief downtime results in lost revenue and frustrated users, while an extended downtime comes with negative headline news and irreparable business damage. Even slightly higher response times decrease user satisfaction and impact revenues [29, 10, 17].

Over-provisioning means that resource utilization is low, offering the opportunity to colocate batch jobs alongside latency-sensitive services [52][18]. Colocation must be managed carefully lest it degrades performance due to competition on machine resources. Our main goal is to ensure that the end-to-end service-level objectives (SLOs) are met while increasing the work done by batch jobs. The main technical challenges arise from maintaining short tail latency (e.g., the 99<sup>th</sup> latency percentile also called P99 latency) for the latency-sensitive services coupled with the complexity of commercial software and large deployments.

Oftentimes the service-level-objectives are not known explicitly for each individual component. For example, large commercial search engines contain tens of plat-

<sup>\*</sup> Work done while authors were at Microsoft Research.

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• <u>CPU Blind Isolation → colocation without impacting service performance</u>