IMPROVING RESOURCE EFFICIENCY IN CLOUD COMPUTING

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Abstract

Cloud computing is at a critical juncture. An increasing amount of computation is now hosted in private and public clouds. At the same time, datacenter resource efficiency, i.e., the effective utility we extract from system resources has remained notoriously low, with utilization rarely exceeding 20-30%. Low utilization coupled with the lack of scaling in hardware due to technology limitations poses threatening scalability roadblocks for cloud computing.

At a high level, two main reasons hinder efficient scalability in datacenters. First, the reservation-based interface through which resources are currently allocated is fundamentally flawed. Users must determine how many resources a new application requires to meet its quality of service (QoS) constraints. Unfortunately this is extremely difficult for users that tend to overprovision their reservations, resulting in mostly-allocated, but lightly-utilized systems. Second, underutilization is aggravated by performance unpredictability; the result of heterogeneity in hardware platforms, interference between applications contending in shared resources, and spikes in input load. Unpredictability results in further resource overprovisioning by users.

The focus of this dissertation is to enable efficient, scalable and performance-aware datacenters with tens to hundreds of thousands of machines by improving cluster management. To this end, we present contributions that address both the system-user interface, and the complexity of resource management at scale. These techniques are directly applicable to current systems, with modest design alterations.

We first present a new declarative interface between users and cluster manager that centers around performance, instead of resource reservations. This enables users to focus on the high level performance objectives an application must meet, as opposed
to the intrinsics on how these objectives should be achieved using low level resources.

On the system side, we make two fundamental contributions. First, we design a practical system that leverages data mining to quickly understand the resource requirements of incoming applications in an online manner. We establish that resource management at this scale cannot be solved with the traditional trial-and-error approach of conventional architecture and system design. We show that instead we can introduce data mining principles which leverage the knowledge the system accumulates over time from incoming applications, to significantly benefit both performance and efficiency. We first use this approach in Paragon to tackle the platform heterogeneity and workload interference challenges in datacenter management. The cluster manager relies on collaborative filtering to identify the most suitable hardware platform for a new, unknown application and its sensitivity to interference in various shared resources. We then extend a similar approach to address the larger problem of resource assignment and resource allocation with Quasar. To ensure minimal management overheads, we decompose the problem to four dimensions; platform heterogeneity, application interference, resource scale-up and scale-out. This enables the majority of applications to meet their QoS targets, while operating at 70% utilization, on a cluster with several hundred servers. In contrast, a reservation-based system rarely exceeds 15-20% utilization, with worse per-application performance.

Our second contribution pertains to designing scalable scheduling techniques that use the information from Paragon and Quasar to perform efficient and QoS-aware resource allocations. We develop Tarcil, a scalable scheduler that reconciles the high quality of sophisticated centralized schedulers with the low latency of distributed sampling-based systems. Tarcil relies on a simple analytical framework to sample resources in a way that provides statistical guarantees on a job meeting its QoS constraints. It incurs a few milliseconds of scheduling overhead, making it appropriate for highly-loaded clusters, servicing both short- and long-running applications. Finally, we design HCloud, a resource provisioning system for public cloud providers. HCloud leverages the information on the resource preferences of applications to determine the type (e.g., reserved versus on-demand) and size of required instances. The system guarantees high application performance, while securing significant cost savings.
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“Have Ithaka always in your mind.
Your arrival there is what you are destined for.
But don’t in the least hurry the journey... ”

C.P. Cavafy
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Chapter 1

Introduction

Cloud computing is at a critical junction. Its popularity has increased drastically over the past decade, with a growing number of applications and data hosted both on public and private clouds. At a high level, cloud computing offers three premises, both from the perspective of datacenter operators and end users: flexibility as resources can easily be obtained and released, high performance, and cost efficiency, as the infrastructure is shared across multiple users.

Despite its prevalence, cloud computing today faces significant scalability challenges. Traditionally, to scale a datacenter, operators would improve its cost efficiency or improve its compute capabilities. With respect to cost efficiency, two approaches have prevailed: switching from the specialized machines that used to populate these systems to commodity computing, and reducing the cost of power delivery and cooling. With most datacenters already consisting of commodity servers, and power delivery and cooling introducing less than 10% cost overheads, both approaches are reaching the point of diminishing returns. On the other hand, we can improve scalability by increasing the compute capabilities of a datacenter. This requires either building more datacenters, which requires a capital investment of hundreds of millions of dollars [24, 109], increasing the number of servers in each datacenter, albeit with bounded benefits, given the provisioning constraints of power delivery and cooling, or relying on the process technology to provide higher performance for the same power consumption. Unfortunately, process technology in microprocessors has slowed down
with the end of voltage (or Dennard) scaling, and with Moore’s Law projected to end in the next five to ten years, relying on hardware alone to improve datacenter scalability is not a viable option. This underlines the importance of operating datacenters at high utilization.

Unfortunately, while the large-scale datacenters that host cloud computing services have grown in number and size, the utilization at which they operate has remained prohibitively low [24, 66]. Even at the high end of the spectrum of production datacenters, utilizations rarely exceed 20-30% [24, 66], with most systems operating at even lower utilizations. This is the case even for systems that use virtualization [140] for multi-tenancy, and employ sophisticated systems to manage resources across applications. In the rest of this Section, we highlight the reasons behind low datacenter utilization, and the contributions of this thesis towards improving datacenter resource efficiency.

1.1 Resource Efficiency Challenges

At a high level, datacenter underutilization stems from two interacting factors. The first is the current interface between the users that submit applications to clusters and the system that must schedule these applications. Resources in datacenters today are allocated using a reservation-based API, where the user has to determine how many resources an application needs. Unfortunately this is extremely difficult for users, that tend to request a lot more resources than their applications truly require, resulting in grossly underutilized clusters.

The second reason behind datacenter underutilization justifies these exaggerated resource reservations. Performance unpredictability is the result of resource contention between applications sharing the system, platform heterogeneity as machines get progressively replaced over the provisioned lifetime of a datacenter, and fluctuations in user load. Unpredictability becomes even more of a challenge for user-interactive applications, like search, which have millions of users, experience spikes in their traffic and are provisioned for future growth. The performance metric of interest for such services is tail latency, which is much more difficult to satisfy than
average performance [60]. The risk of unpredictable performance together with the complexity of resource management leads users to significantly overprovisioning their resource reservations.

1.2 Contributions

The focus of this dissertation is to improve datacenter scalability, by increasing resource efficiency. While inefficiencies exist across the hardware and software stack, application performance and datacenter utilization are to a large extent determined by the cluster manager; the system that orchestrates resource allocation and application scheduling in large-scale systems. To this end, our contributions focus on increasing datacenter-wide utilization, by improving cluster management, while guaranteeing that each scheduled application satisfies its performance requirements.

To achieve this goal, we use three main insights. First, we take a top-down approach that bridges the different layers of the system stack from the user interface, to the cluster scheduler and down to hardware issues. Tackling the problem of datacenter efficiency cannot be addressed in a single level of the system stack, for example in hardware or software only. It requires in-depth understanding of the challenges and opportunities that each layer presents as well as their interactions. To this end, this work spans several levels of the stack from high-level distributed system design, to low-level architectural considerations.

Second, we introduce a high-level, declarative interface between users and system that focuses on performance, not resource reservations. We demonstrate that the existing reservation-based interface is poorly formalized and overly complex, leading to low system utilization. Instead, by simplifying the interface, the user is tasked with specifying what performance an application must achieve, not how to achieve it with low-level, raw resources.

Third, we show that the traditional, trial-and-error approach used in computer architecture and systems is prohibitively impractical at datacenter scale. We instead propose a new approach that leverages the knowledge on application behavior the system accumulates through data collection over time. By applying data mining
principles to these datasets in a mindful fashion we significantly improve both the quality and practicality of large-scale scheduling.

Using the insights described before, we have designed and built several systems, which together improve the performance and resource efficiency of cloud computing. Below, we provide a brief overview of each system.

**Paragon: QoS-aware application assignment.** Paragon is an online datacenter manager that, given a resource reservation, accounts for platform heterogeneity and workload interference in scheduling decisions [63, 67, 64, 65]. Paragon leverages two main insights.

First, Paragon takes into account the various shared resources where interference may occur, including the CPU, memory and I/O subsystems. To measure the sensitivity of an application to different sources of interference we designed iBench [61], a suite that consists of a set of benchmarks that put progressively more pressure on a specific resource, and can be used to determine how much interference a workload can tolerate in shared resources and how much pressure it itself creates.

Second, Paragon does not require detailed application profiling to extract its platform and interference preferences. Instead, it leverages the knowledge the system already has from previously-scheduled workloads. To this end, we designed an online recommender system, based on matrix factorization (SVD) and latent-factor models, that determines which platforms, and co-scheduled workloads will allow the job to satisfy its QoS constraints. The system is similar to the recommender systems used in sites like Netflix or e-commerce, where a sparse information signal for a new user is projected against the rich information from previous users to provide the new user with accurate movie or item recommendations.

Paragon is a practical system: the profiling and data mining techniques add minimal scheduling overheads. Using the information from the recommender system allows the scheduler to improve performance, and because applications are packed more tightly it also improves system utilization. In a 5,000 application scenario running on 1,000 servers on Amazon EC2, Paragon achieves performance within 4% of the optimal for that cluster. In comparison, a heterogeneity- and interference-agnostic scheduler degrades performance by 48% on average and violates QoS for
97% of workloads.

**Quasar: Resource-efficient cluster management.** Quasar takes the approach in Paragon one step further to address the more general problem of cluster management in datacenters [66]. Paragon has one limitation. While it can determine where to place an application in a large-scale system, it lacks the ability to determine how many resources that application needs to satisfy its performance constraints. This means that the user is still tasked with requesting an appropriate resource amount for a new job. However, because resource allocation is a complex, multi-dimensional problem, users rarely estimate their resource needs correctly. More often they over-provision their reservations, hurting system utilization. During a study of Twitter’s datacenters, we verified that reservations often exceed usage by an order of magnitude. Quasar addresses this issue through two main contributions.

First, Quasar shifts from the traditional reservation-based interface between user and system to a *high-level declarative interface*, which draws from the concept of Domain-Specific Languages (DSLs) and SQL. Now, instead of the user specifying the low-level, raw resources (e.g., memory, cores, storage) he expects an application to need, he simply specifies the performance target the new application must meet, for example tail latency. This simplifies the responsibility of the user, and gives enough flexibility to the cluster manager to better place jobs on available resources. Subsequently the cluster manager translates this performance goal to resources.

To perform this translation, Quasar leverages *fast data mining techniques* in a similar way to Paragon. The difference is that the system must also provide recommendations on the amount of resources a job needs, specifically the resources per node and the number of nodes across which the workload should be distributed. At first glance this adds significant complexity to the recommender system, posing the question: can we maintain all this information, but solve a much simpler problem? We address this question by decomposing the problem to the four dimensions of resource allocation that affect application performance: platform heterogeneity, workload interference, scale-up (resources per node) and scale-out (number of nodes). This dramatically reduces the scheduling overheads, without sacrificing scheduling quality. Importantly, Quasar enables common datacenter application functionality, including
both distributed batch workloads and user-interactive services that are more sensitive to unpredictability.

Quasar is practical. The information required for the cluster manager’s decisions adds negligible overheads to application execution. These overheads can be further reduced as more sophisticated data mining techniques are designed. In a 200-server EC2 cluster Quasar meets the QoS requirements of 95% out of 1,200 applications, while increasing system utilization by more than 2x. In contrast, a traditional reservation-based cluster manager with a baseline least-loaded scheduler violates QoS for most workloads, despite system utilization rarely exceeding 25%. The approach proposed with Quasar has had some early adoption in real production systems, with both Twitter and AT&T adopting similar approaches in their latest system designs.

**Tarcil: Improving scheduling scalability.** The structure of the scheduler itself and the algorithms it employs are critical components of a cluster manager. Traditionally there has been a disparity in cluster scheduling. On one hand there are sophisticated, centralized schedulers, that examine all (or most) of the cluster state to improve scheduling quality (e.g., Quasar). On the other hand there are distributed, typically sampling-based, schedulers that make fast decisions by only examining a small subset of resources. Unfortunately, neither approach achieves both high scheduling quality and high scheduling speed. To bridge this gap we developed Tarcil [68, 69], a cluster scheduler designed both for short and long jobs. Tarcil is built on two insights: first, it accounts for the resource preferences of incoming workloads, to keep scheduling quality high. Second, it uses adaptive resource sampling to reduce the latency of each scheduling decision. The sample size is set based on how strictly QoS must be met, following a simple analytical framework that provides statistical guarantees on scheduling quality. Tarcil also uses admission control that takes action when load is very high to avoid overloading the system. Admission control determines how long applications should be queued for before being scheduled [59]. Finally, Tarcil is structured as a distributed system with multiple concurrent scheduling agents making task placement decisions.

In EC2 clusters with several hundred machines, Tarcil improves performance by 41% on average for short tasks over state-of-the-art distributed schedulers, and
scheduling latency by 1-2 orders of magnitude compared to sophisticated, centralized systems.

**Cost-efficient cloud provisioning strategies.** So far we assume that the cluster manager has full control over the entire system. In practice, many systems are deployed in public cloud providers where the visibility an external scheduler has is limited. In this case, apart from deciding the amount of needed resources, the user must also decide between on-demand, reserved and spot instances, each of which has different advantages and challenges. In this work, we present a set of provisioning techniques that, based on the characteristics of incoming workloads, determine the most appropriate type and size of instances that should be purchased. They also determine how long resources should be retained for once idle, to prevent re-instantiation overheads during periods of high load.

We have evaluated the system on a large Google Compute Engine cluster with several hundred instances, and showed that a hybrid configuration with both reserved and on-demand instances improves performance by 2.1× over a fully on-demand system, and reduces cost by 46% over a fully-reserved system [62].

**Other contributions:** Finally, a major roadblock in datacenter research in academia is the lack of representative, open-source datacenter applications. To address this issue, we designed analytically-driven models that capture the temporal and spatial characteristics of datacenter application storage and network activity and can generate representative access patterns [70, 71, 72, 73, 74, 75]. These models are validated against real datacenter applications running in Microsoft’s cloud facilities and used for troubleshooting and to identify hardware and software inefficiencies, such as imbalanced data sharding and suboptimal SSD caching without the need for a full system deployment.
1.3 Thesis Organization

The rest of this thesis is organized as follows. Chapter 2 provides relevant background and motivation. Chapter 3 presents Paragon, a QoS-aware datacenter scheduler that accounts for platform heterogeneity and application interference. Chapter 4 discusses Quasar, a new cluster manager that introduces a high-level declarative interface between users and system, and leverages data mining to provide efficient, and high-quality resource allocations. In Chapter 5 we present iBench, a benchmark suite that quantifies the impact of interference in the various shared system resources. In Chapter 6 we describe ARQ, a multi-class admission control protocol that prevents the system from becoming oversubscribed. Chapter 7 discusses Tarcil, a scalable and low-latency sampling-based datacenter scheduler, and Chapter 8 presents resource provisioning strategies in the presence of hybrid resources, i.e., when part of the system resides on a public cloud provider. Finally, Chapter 9 concludes this dissertation. Appendices ?? and ?? discuss an analytical model for the storage activity of datacenter workloads, and a bandwidth-aware storage consolidation system that leverages this model. Appendix ?? presents a similar analytical approach for the network activity of distributed datacenter applications.
Chapter 2

Background & Motivation

2.1 Cloud Computing Background

Datacenters, the large-scale infrastructures that host cloud computing services, have experienced a rapid increase in both their number and size in the past ten years [24]. Cloud computing has become an essential tool and a catalyst for innovation in all aspects of endeavor, including healthcare, education and science [171]. Both private and public datacenters with tens of thousand of machines now host popular services, such as search, social networking, email, video streaming, enterprise management tools, maps, natural language processing, big-data analytics and general purpose storage platforms [10, 220, 35, 172, 90, 53]. We have come to expect that these services provide us with real-time, personalized, and contextual access to terabytes of data.

The popularity of cloud computing services has led to significant work on analyzing these workloads and the infrastructure that supports them. Researchers have characterized the behavior of webserving environments [5, 32, 170], search engines [23, 174], distributed computing frameworks like MapReduce [45, 124, 56], memory-based storage services [17, 57], and large-scale storage systems [7, 123, 105, 72]. Recent studies have used datacenter traces to extract observations on the duration, CPU and memory usage, and variability of cloud workloads [176, 76, 177, 142, 234]. These observations are particularly important in guiding scheduling decisions. Finally, researchers have
developed guidelines on how to study and benchmark these workloads at scale [184].

Datacenter services fall in one of two main categories; batch analytics workloads [56, 228], and latency-critical online services [23, 87, 38, 40]. Analytics optimize for computation throughput as they process vasts amounts of data, for example user preferences for advertisements or movies. Online services, on the other hand, are user-interactive applications, such as search and email, and they must meet strict latency (or response time) constraints. Additionally, due to the organization of these distributed services, latency requirements are formalized with respect to tail latency, for example 99th percentile, instead of average response time [55]. This puts increased pressure on the system to behave in a high-performant and predictable way.

In general, cloud computing offers three main premises, both to end users and datacenter operators; resource flexibility, high performance, and cost efficiency. Users can increase or decrease the resources they use at runtime according to the needs of their applications, and only pay for resources used at each point in time. Additionally, hosting applications in the cloud is less costly for users than setting up and maintaining a local infrastructure, even for large-scale services that require thousands of machines, such as Netflix [159]. At the same time, datacenter operators achieve cost benefits by sharing their infrastructure across multiple tenants.

The primary cost metric in datacenters is the total cost of ownership (TCO). The TCO includes both the capital expenditures to build a datacenter and populate it with servers (CAPEX), and its operational expenses in terms of power consumption,
cooling and maintenance (OPEX). Figure 2.1 shows a breakdown of the TCO of a large-scale datacenter [109]. The capital expenses for purchasing the servers accounts for 61% of the total cost of the system, while the energy to power the machines amounts to another 18%. This places a particular emphasis on how well datacenter resources are being used. The next section details the scalability challenges that stem from poor datacenter utilization.

2.2 Datacenter Scalability Challenges

In the past ten years, operators have scaled the capabilities of cloud services by building larger datacenters that can host tens to hundreds of thousands of multi-core servers [110]. The servers are connected by networks with high-speed links (e.g., 10Gbps Ethernet) and advanced topologies that support high bandwidth between any two servers [8, 100]. At the same time, operators leveraged two approaches to improve cost efficiency. First, they switched from the specialized machines that used to populate datacenters to commodity servers that benefit from economies of scale. Second, they reduced the cost and energy overheads of the power delivery and cooling infrastructure [110]. While a few years ago the power usage effectiveness (PUE) of datacenters was as high as 3.0, the PUE of modern facilities is as low as 1.1, reaching the point of diminishing returns\(^1\).

Unfortunately, we have reached the end of the road for these scaling techniques. Datacenters are already consuming tens of MWatts, stressing the capabilities of power generation facilities and making it difficult to continuously increase the number of servers per facility [110, 204]. At the same time, the end of voltage (or Dennard) scaling, and the projected end of Moore’s Law mean that hardware alone can no longer provide improved performance for the same power budget [113, 80, 125, 52].

To achieve further improvements in datacenter scalability, we must improve their

\(^1\)PUE of 3.0 indicates that for every 1W consumed by the servers, another 2W are consumed by the power delivery and cooling infrastructure. PUE of 1.1 indicates that the overhead of power delivery and cooling is merely 10%.
resource efficiency, i.e., we must extract as much compute as possible from the resources available in these systems today [22]. Figure 2.2 shows the probability distribution function of CPU utilization in a production datacenter at Twitter (left) and Google (right) [66, 24]. Both systems consist of several thousand machines servicing user-interactive and analytics jobs, and enable resource sharing across applications with techniques like containerization and virtualization. Nevertheless, utilization is quite low, typically ranging from 10% to 30% of the system’s nominal compute capabilities, and wasting a significant fraction of capital expenses invested towards purchasing the server infrastructure. Hence the obvious path forward is to increase the utilization of datacenter servers. High server utilization is also beneficial for energy efficiency. Since most servers are not energy proportional, consuming 40% to 60% of their peak power when idling [25, 22, 24, 135, 152], they operate more efficiently at high utilization.

Nevertheless, there are several challenges towards achieving resource efficiency through high server utilization.

First, datacenter operators must plan for diurnal usage patterns, unexpected spikes in user demands, and future growth. This results in significantly overprovisioned resource allocations, leaving servers underutilized for most of the time.

Second, datacenters are inherently heterogeneous, both in an effort to match the requirements of widely diverse applications, and due to the progressive server replacement during the typical 15-year lifetime of a datacenter infrastructure [24, 109, 110,
At any point in time, a datacenter may host 3-5 server generations with a few hardware configurations per generation, in terms of the specific speeds and capacities of the processor, memory, storage and networking subsystems. Hence, it is common to have 10 to 40 configurations throughout the datacenter. Ignoring heterogeneity can lead to significant inefficiencies, as some workloads are sensitive to the hardware configuration.

Third, and most important, increasing server utilization by scheduling multiple services on each server leads to performance loss due to interference. Even when using different processor cores, co-scheduled applications can interfere on shared caches, memory channels, storage and networking devices [98, 149, 157].

Interference is particularly detrimental for latency-critical, user-facing services with strict quality-of-service (QoS) guarantees. For instance, updating a social networking news feed involves queries for the user’s connections and recent status updates; ranking, filtering, and formatting updates; retrieving related media files; and selecting and formatting relevant advertisements and recommendations. Since tens of servers are involved in each user query, low average latency is not sufficient. The requirement is for low tail latency (e.g., low 95th or 99th percentile) so that latency variability does not impact a significant percentage of user requests. Assigning additional workloads to each server to raise utilization typically leads to higher latency and higher variability. Latency-critical requests may be queued for milliseconds if other tasks occupy processing cores. But even if cores are available, the latency-critical requests may underperform due to interference and contention on shared resources. Hence, it is common for latency-critical services to be deployed on dedicated machines, which are underutilized for the majority of time.

2.3 Cluster Management

Datacenters are commonly orchestrated by systems called cluster managers. Cluster managers are primarily responsible for scheduling incoming applications and managing system resources [183, 112, 208]. They also have additional responsibilities that pertain to fault tolerance [138, 94, 112], reliability [202, 238], enforcement of security
constraints [116], and various monitoring capabilities [50, 112]. In the context of this dissertation we focus on the responsibilities of cluster managers with respect to the management of applications and system resources.

Figure 2.3 shows a simplified overview of the functionality of a cluster manager with respect to managing system resources. This functionality can be divided to two main components: first, the system must understand the resource requirements incoming, potentially-unknown applications have. This includes determining both the amount of resources an application needs, and the specific configuration of resources required. Second, the system must make and enforce resource allocation decisions in a way that satisfies the resource requirements of incoming jobs. For both components there is a wide spectrum of designs and implementations. The following sections provide an overview of related work in each area.

2.3.1 Understanding Resource Requirements

Cloud services are widely diverse with respect to their resource requirements. While certain applications, such as websearch, require the latest platforms to deliver low end-to-end request latencies, other services, such as background analytics and logging operations are less sensitive to allocated resources. Current cluster management interfaces are reservation-based, tasking users with specifying the resources a new, potentially-unknown job should receive. However, determining the appropriate resources for a new application is a very complex, multidimensional problem. Consider, for example, a single service whose required resources we want to establish. For the
purpose of the example, we select memcached, a low-latency, in-memory key-value store [87]. We first need to determine how the performance for memcached scales as we increase the number of cores allocated to the application in a single node (scale-up). For simplicity memory is unconstrained. We are interested in the maximum throughput, in queries per second (QPS) that memcached can achieve, such that its 99th percentile latency is below 200usec. Figure 2.4a shows this scaling experiment. Since memcached is memory-bound, increasing the number of cores beyond a certain point does not benefit performance. The experiment is conducted on a 12 core Intel Xeon server (CPU E5-2630 @ 2.30GHz) with 64GB of RAM. Since datacenters consist of several hardware platforms, we need to repeat this experiment on each of them. Figure 2.4b shows the different scaling curves for servers ranging from low-end Clovertown-based servers to high-end Haswell-based machines. Performance varies widely, as the low-end platforms become saturated much faster. In addition to the type of platform, a user must also know how the performance of a job scales as the load becomes distributed across an increasing number of servers (scale-out). Figure 2.4c shows the throughput of memcached in QPS when scaling out from a single Xeon server to 8 servers of the same type. Since there is limited communication between servers, performance is almost linear for memcached. This, however, is not the case in general, especially for applications sharing common state.

So far we have maintained the characteristics of the input load constant, i.e., same key-value distributions. In real datacenter settings load fluctuates widely as user traffic is higher during the day, and drops during the night. This is mostly the case for user-interactive services, such as search, email, and social networks. Batch applications, like analytics, also experience variations in the size and characteristics of their input datasets. Figure 2.4d shows how performance changes, as we vary the read:write request ratio and the size of keys and values. As expected when requests are write-dominated (L3), the throughput is significantly lower.

Finally, a principal objective of the cluster manager is to increase system utilization, by sharing resources across applications. Unfortunately, resource sharing incurs interference due to contention. Understanding the sensitivity of an application to different types and intensities of interference is a critical dimension in cluster
management. Figure 2.4e shows how the performance of memcached changes with increasing amounts of interference in various resources. Moreover, since most of these dimensions are affected by the application itself and the system setup, the exploration must be repeated upon application updates, operating system upgrades, or the introduction of new hardware platforms.

This analysis highlights the fact that understanding the resource requirements of a potentially new application is a challenging problem. This is, however, the task that most cluster management frameworks require users to perform. These interfaces foster underutilization, as conservative users overprovision their reservations to avoid insufficient resources, and performance unpredictability.

There has been significant work on determining the amount of resources needed by an application in both virtualized and non-virtualized systems [39, 43, 49, 78, 82, 96, 97, 102, 188, 193, 203, 217, 237, 239]. Rightscale [178], for example, uses a load threshold to automatically scale out 3-tier applications to react to changes in
the load in Amazon’s cloud service [10]. CloudScale identifies application resource requirements using online demand prediction and prediction error handling, without a priori assumptions on application behavior [190]. Dejavu serves a similar goal by identifying a few workload classes and based on them, reuses previous resource allocations to minimize reallocation overheads [207]. Dominant Resource Fairness (DRF) [93] provides a generalization of max-min fairness across multiple resources that disincentivizes users from lying about their requirements, and preventing resource sharing. Zhu et al. [239] present a resource management scheme for virtualized datacenters that preserves service level agreements (SLAs), and Gmach et al. [95] present a resource allocation scheme for datacenter applications that relies on the ability to predict their behavior a priori. Finally, there is a lot of work on determining allocation requirements in virtualized environments [3, 225, 194, 195], and reclaiming unused resources that can service new load [1, 37, 215, 213].

Resource assignment, i.e., determining the appropriate type of allocated resources, is equally critical to resource sizing. Given the fact that platforms vary considerably in modern datacenters, and that interference in shared resources is detrimental to performance, understanding how application behavior changes with platform heterogeneity and workload interference is essential.

Recent work on datacenter management has highlighted the importance of these two factors. Mars et al.[147, 148] have shown that the performance of Google workloads can vary by up to 40% due to heterogeneity even when considering only two server configurations and up to 2x due to interference even when considering only two colocated applications. In [147], they present a system that uses combinatorial optimization to select the proper server configuration for a given workload. In [148], they present a two-step method to characterize the sensitivity of workloads to memory pressure and the stress each application exercises to the memory subsystem. In the same spirit Yang et al. [226] apply a dynamic interference sensitivity detection scheme to preserve the performance of batch and latency-critical applications under colocation scenarios. Govindan et al. [98] also present a scheme to quantify the effects of cache interference between consolidated workloads, although they require access to physical memory addresses. Zhang et al. [235] use cycles-per-instruction (CPI)
as a proxy for interference between workloads and throttle the offending co-runners such that the applications return to their expected behavior. Quincy [118] formulates resource assignment as a graph optimization problem, accounting for fairness, and placement constraints application may have. Finally, Nathuji et al. [157] present a control-based resource allocation scheme that mitigates the effects of cache, memory and hardware prefetching interference between co-scheduled workloads. While these systems highlight the importance of factoring heterogeneity and interference in scheduling decisions, they incur significant profiling overheads, and are limited to capturing interference in a small number of shared resources.

The problem of resource assignment is well-established in systems using virtualization. VM management systems such as vSphere [214], XenServer [4] or the VM platforms on EC2 [10] and Windows Azure [220] can schedule diverse workloads submitted by a large number of users on the available servers. In general, these platforms account for application resource requirements which they learn over time by monitoring workload execution. VMWare’s Distributed Resources Scheduler (DRS) [212] for example accounts for CPU and memory requirements when scheduling applications. Recently, DeepDive [161] proposed a black-box system for management of virtual machines which accounts for interference, while minimizing migration overheads.

Finally, resource management in heterogeneous CMPs shares some concepts and challenges with datacenter management. Fedorova et al. [85] discuss OS level scheduling for heterogeneous multi-cores as having the following three objectives: optimal performance, core assignment balance and response time fairness. Shelepov et al. [189] present a resource manager that exhibits some of these features and is simple and scalable, while Craeynest et al. [205] use performance statistics to estimate which workload-to-core mapping is likely to provide the best performance. Datacenter management also has similar requirements as applications should observe their QoS, resource allocation should follow application requirements closely and fairness between co-scheduled workloads should be preserved.
2.3.2 Resource Management Decisions

Once the cluster manager has been given, or has determined itself, the resource requirements of a new application, it must perform a scheduling decision. Ideally, datacenter management should have three desirable properties. First, each workload should receive the resources that enable it to achieve *high and predictable performance*. Second, jobs should be tightly packed on available servers to achieve *high cluster utilization*. Third, scheduling overheads should be minimal to allow the scheduler to *scale to large clusters and high job arrival rates*. With these three objectives in mind, cluster schedulers follow a diverse set of designs.

Cluster managers can be examined along two dimensions with respect to their scheduling decisions: *scheduling concurrency (throughput)* and *scheduling speed (latency)*.

With respect to scheduling concurrency, there are two groups of work. In the first, scheduling is serialized, with a centralized scheduler making all decisions [118, 66]. However, application scheduling in clusters with thousands of servers and high workload churn becomes a bottleneck. The second group of work addresses this problem by scheduling multiple jobs in parallel through two-level, distributed or shared-state designs [112, 183]. Two-level schedulers, such as Mesos and YARN, use a centralized coordinator to divide resources between frameworks like Hadoop, Spark and MPI [112, 208]. Each framework uses its own scheduler to assign resources to tasks. Since neither the coordinator nor the framework schedulers have a complete view of the cluster state and all task characteristics, scheduling is suboptimal [183]. Shared-state schedulers like Omega [183] allow multiple scheduling agents to concurrently access the whole cluster state using atomic transactions. As long as these agents rarely attempt to schedule work to the same servers (infrequent conflicts), concurrency comes with a low performance cost. Finally, Sparrow uses multiple concurrent, stateless schedulers to sample and allocate resources [166].

With respect to the speed at which scheduling decisions happen, there are again two groups of work. The first group examines most of (or all) the cluster state to determine the most suitable resources for incoming tasks, in a way that addresses...
the performance impact of hardware heterogeneity and interference in shared resources [63, 98, 226, 157, 147, 235, 191]. For instance, Quincy [118] formulates scheduling as a cost optimization problem that accounts for job preferences with respect to locality, fairness and starvation-freedom. Similarly, Tetris [99] uses a greedy algorithm to pack machines in a way that matches the resource requirements of tasks to the resource availability of a particular machine. These schedulers make high-quality decisions that lead to high application performance and high cluster utilization. However, they inspect the full cluster state on every scheduling event. Their decision overhead can be prohibitively high for large clusters, and in particular for the very short jobs of real-time analytics (100 ms–10 s) [166, 228]. Using multiple greedy schedulers improves scheduling throughput but not latency, and terminating the greedy search early hurts decision quality, especially at high cluster loads.

The second group leverages results from randomized load balancing [154, 168], to design sampling-based cluster schedulers [41, 77, 166]. Sampling the state of just a few servers reduces the latency of each scheduling decision and the probability of conflicts between concurrent agents, and is likely to find available resources in non heavily-loaded clusters. The recently-proposed Sparrow scheduler uses batch sampling and late binding [166]. Batch sampling examines the state of two servers for each of \( m \) required cores by a new job and selects the \( m \) best cores. If the selected cores are busy, tasks are queued locally in the sampled servers and assigned to the machine where resources become available first. While sampling-based schedulers improve scheduling speed, their decisions can be poor because they ignore the resource preferences of jobs. Typically concurrent schedulers follow sampling schemes, while centralized systems are paired with sophisticated algorithms. In Section 7 we present a cluster scheduler that bridges the disparity between the high quality and low speed centralized schedulers and the high speed and low quality of distributed, sampling-based systems.

Public clouds becoming the platform of choice for many cloud services users has also motivated a large body of work on optimizing cloud provisioning for both performance and cost. For example, Deelman et al. [58] discuss cost-efficient provisioning strategies for specific astronomy applications on a cloud provider. Li et al. [137]
compare the resource pricing of several cloud providers to help users provision their applications. There are also studies that analyze resource pricing strategies in public clouds, and contest whether pricing is indeed market-driven, for example for spot instances on Amazon EC2, compared to alternative strategies \cite{28}. Finally, Guevara et al. \cite{103} and Zahed et al. \cite{230} have incorporated the economics of heterogeneous resources in market-driven and game-theoretic strategies for resource allocation in shared environments.

While cloud providers are suitable for several online services, there are others that due to security and privacy concerns or cost limitations are still hosted on private systems. Trying to achieve the best of both worlds, many cloud computing users now deploy \textit{hybrid clouds}, which consist of both privately-owned and publicly-rented machines \cite{14, 34, 114, 126, 233}. Hybrid clouds raise additional provisioning challenges, as a user must now determine not only the type and configuration of resources rented on a public cloud, but in addition how to partition the load (and data) between private and public machines. Breiter et al. \cite{34}, for example, have described a framework that allows service integration in hybrid cloud environments, including actions such as overflowing in on-demand resources during periods of high load. Farahabady et al. \cite{114} also present a resource allocation strategy for hybrid clouds that attempts to predict the execution times of incoming jobs and based on these predictions generate Pareto-optimal resource allocations. Finally, Annapureddy et al. \cite{14} and Zhang et al. \cite{233} discuss the security challenges of hybrid environments, and propose ways to leverage the private portion of the infrastructure for privacy-critical computation. In such settings, where the options for resource offerings are plentiful, understanding the requirements of scheduled applications becomes even more critical. In Section 8 we show that by accounting for the resource preferences of incoming workloads, a hybrid provisioning system can improve over the performance of public resources, and the cost efficiency of private, reserved servers.
2.4 Data Mining in Systems

The conventional design approach in architecture and systems has several drawbacks for large-scale datacenters. For example, while in a traditional desktop or mobile system, exhaustively characterizing the behavior of the handful of applications of interest would be a viable solution, the scale at which datacenters operate do not allow for such best-effort designs. Specifically, because instead of a few cores or servers, we now have tens to hundreds of thousands of machines running diverse applications with a high churn, we need practical solutions, that quickly and accurately determine the resource requirements of new workloads, and can provide guarantees on performance and system efficiency. Unfortunately, the empirical approach adopted so far cannot provide such practical designs, and instead results in overly complex solutions with poor predictability, leading to overprovisioning and underutilization.

A major contribution of this thesis is the introduction of a new approach in solving large-scale systems problems that relies on data mining. While machine learning techniques have been previously applied in system management [108, 121, 219, 31, 151], they were designed for small-scale systems, making their computational overheads when scaling to the hundreds of thousands of servers in modern datacenters impractical. Instead, in this dissertation we focus on simple data mining techniques that leverage the massive amounts of monitoring data, including information on the behavior of scheduled applications, datacenters collect today. We show that by mining this data in a mindful fashion we can not only get rich insights on the resource requirements of previously-unseen applications, but also produce practical solutions for cluster management that can be deployed in real-world environments and benefit both performance and resource efficiency. Specifically, with Paragon we show that data mining can help the scheduler determine which hardware platform is most suitable for a given workload, as well as the sensitivity an application has to different types of interference. With Quasar we generalize this insight to solve the more general cluster management problem, where the system must also determine the amount of resources needed by an application, without burdening the user with specifying
resource reservations. This enables not only high and predictable application performance, but allows datacenters to operate at 2-3x higher utilizations than before.
Chapter 3

Paragon: QoS-Aware Scheduling in Heterogeneous Datacenters

3.1 Introduction

An increasing amount of computing is performed in the cloud, primarily due to cost benefits for both the end-users and the operators of datacenters (DC) that host cloud services [24]. Large-scale providers such as Amazon EC2 [10], Microsoft Windows Azure [220], Rackspace [172] and Google Compute Engine [90] host tens of thousands of applications on a daily basis. Several companies also organize their IT infrastructure as private clouds, using management systems such as VMware vSphere [214] or Citrix XenServer [4].

The operator of a cloud service must schedule the stream of incoming applications on available servers in a manner that achieves both fast execution (user’s goal) and high resource efficiency (operator’s goal), enabling better scaling at low cost. This scheduling problem is particularly difficult as cloud services must accommodate a diverse set of workloads in terms of resource and performance requirements [24]. Moreover, the operator often has no a priori knowledge of workload characteristics.

In this chapter, we focus on two basic challenges that complicate scheduling in large-scale DCs: hardware platform heterogeneity and workload interference.

Heterogeneity occurs because servers are gradually provisioned and replaced over
CHAPTER 3. PARAGON

Figure 3.1: Performance degradation for 5,000 applications on 1,000 EC2 servers with heterogeneity-oblivious, interference-oblivious and baseline least-loaded schedulers compared to ideal scheduling (application runs alone on best platform). Results are ordered from worst to best-performing workload.

The typical 15-year lifetime of a DC [24, 109, 130, 149, 156]. At any point in time, a DC may host 3-5 server generations with a few hardware configurations per generation, in terms of the specific speeds and capacities of the processor, memory, storage and networking subsystems. Hence, it is common to have 10 to 40 configurations throughout the DC. Ignoring heterogeneity can lead to significant inefficiencies, as some workloads are sensitive to hardware configurations. Figure 3.1 shows that a heterogeneity-oblivious scheduler will slow applications down by 22% on average, with some running nearly 2x slower (see Section 3.4 for methodology). This is not only suboptimal from the user’s perspective, but also for the DC operator as workloads occupy servers for significantly longer.

Interference is the result of co-scheduling multiple workloads on a single server to increase utilization and achieve better cost efficiency. By co-locating applications a given number of servers can host a larger set of workloads (better scalability). Alternatively, by packing workloads in a small number of servers when the overall load is low, the rest of the servers can be turned off to save energy. The latter is needed because modern servers are not energy-proportional and consume a large fraction of peak power even at low utilization [22, 24, 136, 152]. Co-scheduled applications may interfere negatively even if they run on different processor cores because they share
caches, memory channels, storage and networking devices [98, 148, 157]. Figure 3.1 shows that an interference-oblivious scheduler will slow workloads down by 34% on average, with some running more than 2x slower. Again, this is undesirable for both users and operators. Finally, a baseline scheduler that is both interference and heterogeneity-oblivious and schedules applications to least-loaded servers is even worse (48% average slowdown), causing some workloads to crash due to resource exhaustion on the server.

Previous work has showcased the potential of heterogeneity and interference-aware scheduling [149, 148]. However, techniques that rely on detailed application characterization cannot scale to large DCs that receive tens of thousands of potentially unknown workloads every day [35]. Most cloud management systems have some notion of contention or interference-awareness [112, 157, 207, 2, 224, 4]. However, they either use empirical rules for interference management or assume long-running workloads (e.g., online services), whose repeated behavior can be progressively modeled. In this work, we target both heterogeneity and interference and assume no a priori analysis of the application. Instead, we leverage information the system already has about the large number of applications it has previously seen.

We present Paragon, an online and scalable datacenter scheduler that is heterogeneity and interference-aware. The key feature of Paragon is its ability to quickly and accurately classify an unknown application with respect to heterogeneity (which server configurations it will perform best on) and interference (how much interference it will cause to co-scheduled applications and how much interference it can tolerate itself in multiple shared resources). Paragon’s classification engine exploits existing data from previously scheduled applications and offline training and requires only a minimal signal about a new workload. Specifically, it is organized as a low-overhead recommendation system similar to the one deployed for the Netflix Challenge [27], but instead of discovering similarities in users’ movie preferences, it finds similarities in applications’ preferences with respect to heterogeneity and interference. It uses singular value decomposition to perform collaborative filtering and identify similarities between incoming and previously scheduled workloads.

Once an incoming application is classified, a greedy scheduler assigns it to the
server that is the best possible match in terms of platform and minimum negative interference between all co-scheduled workloads. Even though the final step is greedy, the high accuracy of classification leads to schedules that satisfy both user requirements (fast execution time) and operator requirements (efficient resource use). Moreover, since classification is based on robust analytical methods and not merely empirical observation, we have strong guarantees on its accuracy and strict bounds on its overheads. Paragon scales to systems with tens of thousands of servers and tens of configurations, running large numbers of previously unknown workloads.

We implemented Paragon and evaluated its efficiency using a wide spectrum of workload scenarios (light, high, and oversubscribed). We use Paragon to schedule applications on a private cluster with 40 servers of 10 different configurations and on 1000 exclusive servers on Amazon EC2 with 14 configurations. We compare Paragon to a heterogeneity-oblivious, an interference-oblivious and a state-of-the-art least-loaded scheduler, which ignores both heterogeneity and interference. For the 1000-server experiments and a scenario with 2500 workloads, Paragon maintains QoS for 91% of workloads (within 5% of their performance running alone on the best server). The heterogeneity-oblivious, interference-oblivious and least-loaded schedulers offer such QoS guarantees for only 14%, 11%, and 3% of applications respectively. The results are more striking in the case of an oversubscribed workload scenario, where efficient resource use is even more critical. Paragon provides QoS guarantees for 52% of workloads and bounds the performance degradation to less than 10% for an additional 33% of workloads. In contrast, the least-loaded scheduler dramatically degrades performance for 99.9% of applications. We also evaluate Paragon on a Windows Azure and a Google Compute Engine cluster and show similar gains. Finally, we validate that Paragon’s classification engine achieves the accuracy and bounds predicted by the analytical methods and evaluate various parameters of the system.

### 3.2 Fast & Accurate Classification

The key requirement for heterogeneity and interference-aware scheduling is to quickly and accurately classify incoming applications. First, we need to know how fast an
application will run on each of the tens of server configurations available. Second, we need to know how much interference it can tolerate from other workloads in each of several shared resources without significant performance loss and how much interference it will generate itself. Our goal is to perform online scheduling for large-scale DCs without any a priori knowledge about incoming applications. Most previous schemes address this issue with detailed but offline application characterization or long-term monitoring and modeling approaches \cite{148, 157, 207}. Instead, Paragon takes a different perspective. Its core idea is that, instead of learning each new workload in detail, the system leverages information it already has about applications it has seen to express the new workload as a combination of known applications. For this purpose we use collaborative filtering techniques that combine a minimal profiling signal about the new application (e.g., a minute’s worth of profiling data on two servers) with the large amount of data available from previously scheduled applications. The result is fast and highly accurate classification of incoming applications with respect to both heterogeneity and interference. Within a minute of its arrival, an incoming workload can be scheduled efficiently on a large-scale cluster.

3.2.1 Collaborative Filtering Background

Collaborative filtering techniques are frequently used in recommendation systems. We will use one of their most publicized applications, the Netflix Challenge \cite{27}, to provide a quick overview of the two analytical methods we rely upon, Singular Value Decomposition (SVD) and PQ-reconstruction (PQ) \cite{173}. In this case, the goal is to provide valid movie recommendations for Netflix users given the ratings they have provided for various other movies.

The input to the analytical framework is a sparse matrix $A$, the utility matrix, with one row per user and one column per movie. The elements of $A$ are the ratings that users have assigned to movies. Each user has rated only a small subset of movies; this is especially true for new users who may only have a handful of ratings or even none. While there are techniques that address the cold start problem, i.e., providing recommendations to a completely fresh user with no ratings, here we focus on users
for which the system has some minimal input. If we can estimate the values of the missing ratings in the sparse matrix $A$, we can make movie recommendations: suggest that users watch the movies for which the recommendation system estimates that they will give high ratings with high confidence.

The first step is to apply singular value decomposition (SVD), a matrix factorization method used for dimensionality reduction and similarity identification. Factoring $A$ produces the decomposition to matrices $U$, $V$ and $\Sigma$.

$$A_{m,n} = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{pmatrix} = U \cdot \Sigma \cdot V^T$$

where

$$U_{m \times r} = \begin{pmatrix} u_{11} & \cdots & u_{1r} \\ u_{21} & \cdots & u_{2r} \\ \vdots & \ddots & \vdots \\ u_{m1} & \cdots & u_{mr} \end{pmatrix}, V_{n \times r} = \begin{pmatrix} v_{11} & v_{12} & \cdots & v_{1r} \\ \vdots & \vdots & \ddots & \vdots \\ v_{n1} & v_{n2} & \cdots & v_{nr} \end{pmatrix}$$

$$\Sigma_{r \times r} = \begin{pmatrix} \sigma_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_r \end{pmatrix}$$

are the matrices of left and right singular vectors and the diagonal matrix of singular values.

Dimension $r$ is the rank of matrix $A$ and it represents the number of similarity concepts identified by SVD. For instance, one similarity concept may be that certain movies belong to the drama category, while another may be that most users that liked the movie “Lord of the Rings 1” also liked “Lord of the Rings 2”. Similarity concepts are represented by singular values ($\sigma_i$) in matrix $\Sigma$ and the confidence in a similarity concept by the magnitude of the corresponding singular value. Singular values in $\Sigma$ are ordered by decreasing magnitude. Matrix $U$ captures the strength of the correlation between a row of $A$ and a similarity concept. In other words, it expresses how users relate to similarity concepts such as the one about liking drama
movies. Matrix $V$ captures the strength of the correlation of a column of $A$ to a similarity concept. In other words, to what extent does a movie fall in the drama category. The complexity of performing SVD on a $m \times n$ matrix is $\min(n^2m, m^2n)$. SVD is robust to missing entries and imposes relaxed sparsity constraints to provide accuracy guarantees. Density less than 1% does not reduce the recommendation accuracy [198].

Before we can make accurate score estimations using SVD, we need the full utility matrix $A$. To recover the missing entries in $A$, we use PQ-reconstruction. Building from the decomposition of the initial, sparse $A$ matrix we have $Q_{m \times r} = U$ and $P_{r \times n}^T = \Sigma \cdot V^T$. The product of $Q$ and $P^T$ gives matrix $R$ which is an approximation of $A$ with the missing entries. To improve $R$, we use Stochastic Gradient Descent (SGD), a scalable and lightweight latent factor model [33, 128, 122, 222] that iteratively recreates $A$:

\[
\forall r_{ui}, \text{ where } r_{ui} \text{ an element of the reconstructed matrix } R
\]

\[
\epsilon_{ui} = r_{ui} - q_i \cdot p_u^T
\]

\[
q_i \leftarrow q_i + \eta (\epsilon_{ui} p_u - \lambda q_i)
\]

\[
p_u \leftarrow p_u + \eta (\epsilon_{ui} q_i - \lambda p_u)
\]

until $|\epsilon|_{L_2} = \sqrt{\sum_{u,i} |\epsilon_{ui}|^2}$ becomes marginal.

In the process above $\eta$ is the learning rate and $\lambda$ is the regularization factor. The complexity of PQ is linear with the number of $r_{ui}$ and in practice takes up to a few ms for matrices with $m, n \sim 1,000$. Once the dense utility matrix $R$ is recovered we can make movie recommendations. This involves applying SVD to $R$ to identify which of the reconstructed entries reflect strong similarities that enable making accurate recommendations with high confidence.

### 3.2.2 Classification for Heterogeneity

**Overview:** We use collaborative filtering to identify how well an incoming application will run on the different hardware platforms available. In this case, the rows in matrix $A$ represent applications, the columns server configurations (SC) and the ratings represent normalized application performance on each server configuration.
As part of an offline step, we select a small number of applications, a few tens, and profile them on all different server configurations. We normalize the performance results and fully populate the corresponding rows of $A$. This only needs to happen once. If a new configuration is added in the DC, we need to profile these applications on it and add a column in $A$. In the online mode, when a new application arrives, we profile it for a period of 1 minute on any two server configurations, insert it as a new row in matrix $A$ and use the process described in Section 3.2.1 to derive the missing ratings for the other server configurations.

In this case, $\Sigma$ represents similarity concepts such as the fact that applications that benefit from SC1 will also benefit from SC3. $U$ captures how an application correlates to the different similarity concepts and $V$ how a server platform correlates to them. Collaborative filtering identifies similarities between new and known applications. Two applications can be similar in one characteristic (they both benefit from high clock frequency) but different in others (only one benefits from a large L3 cache). This is especially common when scaling to large application spaces and several hardware configurations. SVD addresses this issue by uncovering hidden similarities and filtering out the ones less likely to have an impact on the application’s behavior.

The size of the offline training set is important as a certain number of ratings is necessary to satisfy the sparsity constraints of SVD. However, over that number the accuracy quickly levels off and scales well with the number of applications thereafter (smaller fractions for training sets of larger application spaces). For our experiments we use 20 and 50 offline workloads for a 40 and 1,000-server cluster respectively. Additionally, as more incoming applications are added in $A$ the density of the matrix increases and the recommendation accuracy further improves. Note that online training is performed only on two server configurations. This not only reduces the training overhead compared to exhaustive search but since training requires dedicated servers, it also reduces the number of servers necessary for it. In contrast, if we attempted to classify applications through exhaustive profiling, the number of profiling runs would equal the number of server configurations (e.g., 40). For a cloud service with high workload arrival rates, this would be infeasible to support, underlining the importance of keeping training overheads low, something that Paragon does.
Classification is very fast. On a production-class Xeon server, this takes 10-30 msec for thousands of applications and tens of server platforms. We can perform classification for one application at a time or for small groups of incoming applications (batching) if the arrival rate is high without impacting accuracy or speed.

**Performance scores:** We populate $A$ with normalized scores that represent how well an application performs on a server configuration. We use the following performance metrics based on application type:

(a) **Single-threaded workloads:** We use instructions committed per second (IPS) as the initial performance metric. Using execution time would require running applications to completion in the profiling servers, increasing the training overheads. We have verified that using IPS leads to similar classification accuracy as using full execution time. For multi-programmed workloads we use aggregate IPS.

(b) **Multithreaded workloads:** In the presence of spin-locks or other synchronization schemes that introduce active waiting, aggregate IPS can be deceiving [9, 218]. We address this by periodically polling low-overhead performance counters, to detect changes in the register file (read and writes that would denote regular operations other than spinning) and weight-out of the IPS computation such execution segments. We have verified that scheduling with this "useful" IPS leads to similar classification accuracy as using full execution time. When workloads are not known, or multiple workload types are present "useful" IPS is used to drive the scheduling decisions.

The choice of IPS as the base of performance metrics is influenced by our current evaluation which focuses on single-node CPU, memory and I/O intensive programs.
The same methodology holds for higher-level metrics, such as queries per second (QPS), which cover complex multi-tier workloads as well.

**Validation:** We evaluate the accuracy of heterogeneity classification on a 40-server cluster with 10 server configurations. We use a large set of single-threaded, multi-threaded, multi-programmed and I/O-bound workloads. For details on workloads and server configurations, see Section 3.4. The offline training set includes 20 applications selected randomly from all workload types. The recommendation system achieves 24% performance improvement for single-threaded, 20% for multi-threaded, 38% for multi-programmed, and 40% for I/O workloads on average, while some applications have a 2x performance difference. Table 3.1 summarizes key statistics on the classification quality. Our classifier correctly identifies the best server platform for 84% of workloads and a platform within 5% of optimal for 90%. The predicted ranking of platforms is exactly correct for 58% and almost correct (single reordering) for 65% of workloads. In almost all cases 50% of server configurations are ranked correctly by the classification scheme. Finally, it is important to note that the accuracy does not depend on the two platforms selected for training. The training platform matched the top performing configuration only for 20% of workloads.

We also validate the analytical methods. We compare performance predicted by the recommendation system to performance obtained through experimentation. The deviation is less than 3.8% on average.

### 3.2.3 Classification for Interference

**Overview:** There are two types of interference we are interested in: interference that an application can tolerate from pre-existing load on a server and interference the application will cause on that load. We detect interference due to contention on shared resources and assign a score to the sensitivity of an application to a type of interference. To derive sensitivity scores we develop several microbenchmarks, each stressing a specific shared resource with tunable intensity. We run an application concurrently with a microbenchmark and progressively tune up its intensity until the application violates its QoS, which is set at 95% of the performance achieved in
### Table 3.2: Validation metrics for interference classification.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average sensitivity error across all SoIs</td>
<td>5.3%</td>
</tr>
<tr>
<td>Average error for sensitivities &lt; 30%</td>
<td>7.1%</td>
</tr>
<tr>
<td>Average error for sensitivities &lt; 60%</td>
<td>5.6%</td>
</tr>
<tr>
<td>Average error for sensitivities &gt; 60%</td>
<td>3.4%</td>
</tr>
<tr>
<td>Apps with &lt; 5% error</td>
<td></td>
</tr>
<tr>
<td>Apps with &lt; 10% error</td>
<td></td>
</tr>
<tr>
<td>Apps with &lt; 20% error</td>
<td></td>
</tr>
<tr>
<td>SoI with highest error</td>
<td></td>
</tr>
<tr>
<td>for ST: L1 i-cache</td>
<td>15.8%</td>
</tr>
<tr>
<td>for MT: LLC capacity</td>
<td>7.8%</td>
</tr>
<tr>
<td>Frequency L1 i-cache used as offline SoI</td>
<td>14.6%</td>
</tr>
<tr>
<td>Frequency LLC cap used as offline SoI</td>
<td>11.5%</td>
</tr>
<tr>
<td>SoI with lowest error</td>
<td></td>
</tr>
<tr>
<td>for ST: network bandwidth</td>
<td>1.8%</td>
</tr>
<tr>
<td>for MT: storage bandwidth</td>
<td>0.9%</td>
</tr>
</tbody>
</table>

Applications with high tolerance to interference (e.g., sensitivity score over 60%) are easier to co-schedule than applications with low tolerance (low sensitivity score). Similarly, we detect the sensitivity of a microbenchmark to the interference the application causes by increasing its intensity and recording when the performance of the microbenchmark degrades by 5% compared to its performance in isolation. In this case, high sensitivity scores, e.g., over 60% correspond to applications that cause a lot of interference in the specific shared resource.

**Identifying sources of interference (SoI):** Co-scheduled applications may contend on a large number of shared resources. We identified ten such sources of interference (SoI) and designed a tunable microbenchmark for each one. SoIs span resources such as memory (bandwidth and capacity), cache hierarchy (L1/L2/L3 and TLBs) and network and storage bandwidth. The same methodology can be expanded to any shared resource.

**Collaborative filtering for interference:** We classify applications for interference tolerated and caused, using twice the process described in Section 3.2.1. The two utility matrices have applications as rows and SoIs as columns. The elements of the
matrices are the sensitivity scores of an application to the corresponding microbenchmark (sensitivity to tolerated and caused interference respectively). Similarly to classification for heterogeneity, we profile a few applications offline against all SoIs and insert them as dense rows in the utility matrices. In the online mode, each new application is profiled against two randomly chosen microbenchmarks for one minute and its sensitivity scores are added in a new row in each of the matrices. Then, we use SVD and PQ reconstruction to derive the missing entries and the confidence in each similarity concept. This process performs accurate and fast application classification and provides information to the scheduler on which applications should be assigned to the same server (see Section 3.3.2).

**Validation:** We evaluated the accuracy of interference classification using the single-threaded and multi-threaded workloads and the same systems as for the heterogeneity classification. Table 3.2 summarizes some key statistics on the classification quality. Our classifier, achieves an average error of 5.3% between estimated and measured sensitivity both for tolerated and caused interference across all SoIs. For high values of sensitivity, i.e., applications that tolerate and cause a lot of interference, the error is even lower (3.4%), while for most applications (both single-threaded and multi-threaded) the errors are lower than 5%. The SoIs with the highest errors are the L1 instruction cache for single-threaded workloads and the LLC capacity (L2 or L3) for multi-threaded workloads. The high errors are not a weakness of the classification, since both resources are profiled adequately, but rather of the difficulty to consistently characterize contention in certain shared resources [148]. On the other hand, network and storage bandwidth have the lowest errors, primarily due to the fact that we used CPU and memory intensive workloads for this evaluation.

### 3.2.4 Putting It All Together

Overall, Paragon requires two short runs (∼1 minute) on two server configurations to classify incoming applications for heterogeneity. Another two short runs against two microbenchmarks on a high-end server configuration are needed for interference classification. We use a high-end platform to decouple server features from interference
analysis. Running for 1 minute provides some signal on the new workload without introducing significant profiling overheads. In Section 3.3.4 we discuss the issue of workload phases, i.e., transient effects that do not appear in the 1 minute profiling period. Next, we use collaborative filtering to classify the application in terms of heterogeneity and interference, tolerated and caused. This cumulatively requires a few msec even when considering thousands of applications and several tens of platforms or sources of interference. The classification for heterogeneity and interference is performed \textit{in parallel}. For the applications we considered, the overall profiling and classification overheads are 1.2\% and 0.09\% on average.

Using analytical methods for classification has two benefits; first, we have \textit{strong analytical guarantees} on the quality of the information used for scheduling, instead of relying mainly on empirical observations. The analytical framework provides low and tight error bounds on the accuracy of classification, statistical guarantees on the quality of colocation candidates and detailed characterization of system behavior. Moreover, the scheduler design is workload independent, which means that the analytical or statistical properties the scheme provides hold for any workload. Second, these methods are \textit{computationally efficient, scale well} with the number of applications and server configurations, do not introduce significant training and decision overheads and enable exact complexity evaluation.

### 3.3 Paragon

#### 3.3.1 Overview

Once an incoming application is classified with respect to heterogeneity and interference, Paragon schedules it on one of the available servers. The scheduler attempts to assign each workload to the server of the best SC and colocate it with applications so that interference is minimized for workloads running on the same server. The scheduler is online and greedy so we cannot make holistic claims about optimality. Nevertheless, the fact that we start with highly accurate classification helps achieve
very efficient schedules. The interference information allows Paragon to pack applications on a subset of servers without significant performance loss. The heterogeneity information allows Paragon to assign to each SC only applications that will benefit from its characteristics. Both these properties lead to faster execution, hence resources are freed as soon as possible, making it easier to schedule future applications (more unloaded servers) and perform power management (more idling servers that can be placed in low-power modes).

Figure 3.2 presents an overview of Paragon and its components. The scheduler maintains per-application and per-server state. Per-application state includes information for the heterogeneity and interference classification of every submitted workload. For a DC with 10 SCs and 10 SoIs, we store 64B per application. The per-server state records the IDs of applications running on a server and the cumulative sensitivity to interference (roughly 64B per server). The per-server state needs to be updated as applications are scheduled and, later on, complete. Paragon also needs some storage for the intermediate and final utility matrices and temporary storage for ranking possible candidate servers for an incoming application. Overall, state overheads are marginal and scale logarithmically or linearly with the number of applications (N) and servers (M). In our experiments with thousands of applications and servers, a single server could handle all processing and storage requirements of scheduling.

We present two methods for selecting candidate servers; a fast, greedy algorithm that searches for the optimal candidate, and a statistical scheme of constant runtime that provides strong guarantees on the quality of candidates as a function of examined servers.

3.3.2 Greedy Server Selection

In examining candidates, the scheduler considers two factors: first, which assignments minimize negative interference between the new application and existing load and second, which servers have the best SC for this workload. Decisions are made in this

---

1Packing applications with minimal interference should be a property exhibited by any optimal schedule.

2Additional scheduling servers can be used for fault-tolerance.
Selection of Colocation Candidates

State: \(M^{*16B}\)
Per-server state (~64B)
Per-app state (~64B)

Step 2: Server Selection

State: \((2*(SCs+2)^N*4B)\)

Classication for heterogeneity (SVD+PQ)

Classification for interference (SVD+PQ)

Overall, the state requirements are marginal and scale linearly or logarithmically with the number of applications (N), servers (M) and configurations.

order; first identifying servers that do not violate QoS and then selecting the best SC between them. This is based on the observation that interference typically leads to higher performance loss than suboptimal SCs.

The greedy scheduler strives to minimize interference, while also increasing server utilization. The scheduler searches for servers whose load can tolerate the interference caused by the new workload and vice versa, the new workload can tolerate the interference caused by the server load. Specifically it evaluates two metrics, \(D_1 = t_{server} - c_{newapp}\) and \(D_2 = t_{newapp} - c_{server}\), where \(t\) is the sensitivity score for tolerated and \(c\) for caused interference for a specific SoI. The cumulative sensitivity of a server to caused interference is the sum of sensitivities of individual applications running on it, while the sensitivity to tolerated interference is the minimum of these values. The optimal candidate is a server for which \(D_1\) and \(D_2\) are exactly zero for all SoIs. This implies that there is no negative impact from interference between new and existing applications and that the server resources are perfectly utilized. In practice, a good selection is one for which \(D_1\) and \(D_2\) are bounded by a positive and small \(\epsilon\) for all SoIs. Large, positive values for \(D_1\) and \(D_2\) indicate suboptimal resource utilization. Negative \(D_1\) and/or \(D_2\) imply violation of QoS and identify poor candidates that should be avoided.

We examine candidate servers for an application in the following way. The process is explained for interference tolerated by the server and caused by the new workload
(\(D_1\)) and is exactly the same for \(D_2\). Given the classification of an application, we start from the resource that is most difficult to satisfy (highest sensitivity score to caused interference). We query the server state and select the server set for which \(D_1\) is non-negative for this SoI. Next, we examine the second SoI in order of decreasing sensitivity scores, filtering out any servers for which \(D_1\) is negative. The process continues until all SoIs have been examined. Then, we take the intersection of candidate server sets for \(D_1\) and \(D_2\). We now consider heterogeneity. From the set of candidates we select servers that correspond to the best SC for the new workload and from their subset we select the server with \(\min(||D_1 + D_2||_{L_1})\).

As we filter out servers, it is possible that at some point the set of candidate servers becomes empty. This implies that there is no single server for which \(D_1\) and \(D_2\) are non-negative for some SoI. In practice this event is extremely unlikely, but is supported for completeness. We handle this case with backtracking. When no candidates exist the algorithm reverts to the previous SoI and relaxes the QoS constraints until the candidate set becomes non empty, before it continues. If still no candidate is found backtracking is extended to more levels. Given \(M\) servers, the worst-case complexity of the algorithm is \(O(M \cdot \text{SoI}^2)\), since theoretically backtracking might extend all the way to the first SoI. In practice, however, we observe that for a 1000-server system, 89% of applications were scheduled without any backtracking. For 8% of these, backtracking led to negative \(D_1\) or \(D_2\) for a single SoI and for 3% for multiple SoIs. Additionally, we bound the runtime of the greedy search using a timeout mechanism, after which the best server from the ones already examined is selected in the way previously described (best SC and minimum interference deviation). In our experiments timeouts occurred in less than 0.1% of applications and resulted in a server within 10% of optimal.

### 3.3.3 Statistical Framework for Server Selection

The greedy algorithm selects the best server for an application - or a near-optimal server. However, for very large DCs, e.g., 10-100k servers, the overhead from examining the server state in the first step of the search might become high. Additionally,
the results depend on the active workloads and do not allow strict guarantees on the server quality under any scenario. We now present an alternative, statistical framework for server selection in very large DCs based on sampling, which has constant runtime and enables such guarantees.

Instead of examining the entire server state we sample a small number of servers. We use cryptographic hash functions to introduce randomness in the server selection. We hash the scores of tolerated interference of each server using variations of SHA-1 [122] as different hash functions \( (h_j) \) for each SoI to increase entropy. The input to a \( h_j \) is a sensitivity score for an SoI and the output a hashed value of that score. Outputs have the same precision as inputs (14bits). This process is done once, unless the load of a server changes. When a new application arrives, we obtain candidate servers by hashing its sensitivity scores to caused interference for each SoI. For example, the input to \( h_1 \) for SoI 1 is \( a \). The output will be a new number, \( b \) which corresponds to server ID \( u \). Re-hashing \( b \) obtains additional IDs of candidate servers. This produces a random subset of the system’s servers. After a number of re-hashes the algorithm ranks the examined servers and selects the best one. Candidates are ranked by colocation quality, which is a metric of how suitable a given server is for a new workload. For candidate \( i \), colocation quality is defined as:

\[
Q_i = \left\lfloor \text{sign} \left( \sum_{k=1}^{\text{SoIs}} (t(k) - c(k))_i \right) \right\rfloor 1 - ||t - c||_1 = \left\lfloor \text{sign} \left( \sum_{k=1}^{\text{SoIs}} (t(k) - c(k))_i \right) \right\rfloor 1 - \sum_{k=1}^{\text{SoIs}} |t(k) - c(k)|_1
\]

\( t \) is the original, unhashed sensitivity to tolerated interference for a server and \( c \) the original sensitivity to caused interference for the new workload. The \( \text{sign} \) in \( Q_i \) reflects whether a server preserves (positive) or violates QoS (negative). The L1 norm of \( t - c \) reflects how closely the server follows the application’s requirements and is normalized to its maximum value, 10, which happens when for all ten SoIs \( t = 100\% \) and \( c = 0 \). High and positive \( Q_i \) values reflect better candidates, as the deviation between \( t \) and \( c \) is small for all SoIs. Poor candidates have small \( Q_i \) or even negative when they violate QoS in one or more SoIs. Quality is normalized to the range \([0, 1]\). For example, for unnormalized qualities in the range \([-1.2, 0.8]\) and a candidate with \( Q = -1.0 \), the normalized quality will be:

\[
\frac{(-1.0 + |\text{min}|)}{|\text{max}| + |\text{min}|} = \frac{-1.0}{|2| + |0.8|} = 0.2/2 = 0.1
\]
We now make an assumption on the distribution of quality values, which we verify in practice. Because of the way candidate servers are selected and the independence between initial workloads, \( Q_i \)'s approximate a uniform distribution, for problems with tens of thousands of servers and applications. Figure 3.3a shows the CDF of measured quality for 16, 64 and 128 candidates and the corresponding uniform distributions \( F(x) = x^R \), where \( R \) the number of candidates examined) in a system with 1,000 servers. In all cases, the assumption of uniformity holds in practice with small deviations. When we exceed 128 candidates (1/8 of the cluster) the distribution starts deviating from uniform. We have observed that for even larger systems, e.g., a 5,000-server Windows Azure cluster, uniform distributions extend to larger numbers of candidates (up to 512) as well. The probability of a candidate having quality \( a \) is \( Pr(a) = a^R \). For example, for 128 candidates there is a \( 10^{-6} \) probability that no candidate will have quality over 0.9.

We now compare the statistical scheme with the greedy algorithm (Figure 3.3b). While the latter finds a server with quality \( Q \) after a random number of steps, the statistical scheme provides strong guarantees on the number of candidates required for the same quality. For example, for a candidate with \( Q = 0.9 \), the greedy algorithm needs 87 steps, but cannot provide ad hoc guarantees on the quality of the result, while the statistical scheme guarantees that for the same requirements, with 64 candidates, there is a \( 10^{-3} \) chance that no server has \( Q \geq 0.9 \). The guarantees become
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stricter as the distribution gets skewed towards 1 (more candidates). Therefore, although the statistical scheme cannot guarantee optimality, it shows that examining a small number of servers provides strict guarantees on the obtained quality and makes scheduling efficiency workload independent.

In our 1,000-server experiments, the overhead of executing the greedy algorithm is marginal compared to application execution time (less than 0.1% in most cases), while the statistical scheme induces 0.5-2% overheads due to the computation required for hashing. Because at this scale the greedy algorithm is faster, all results in this work are obtained using greedy search. However, for problems of larger scale the statistical scheme can be more efficient.

3.3.4 Discussion

Workload phases: Application classification in Paragon is performed once for each new workload, using the information from its 1 minute profiling. It is possible that some applications will go through various phases that are not captured during profiling. Hence, the schedule will be suboptimal. We detect such workloads by monitoring their performance scores (e.g., IPS) during execution. If the monitored performance deviates significantly and for long periods of time from the performance predicted by the classification engine, the application may have changed behavior. Upon detection we do one of the following. First, we can avoid scheduling a large number of other workloads on the same server as the interference information for this workload is likely incorrect. Second, if there is a migration mechanism available (process or VM migration), we can clone the workload, repeat the classification from its current execution point and evaluate whether re-scheduling to another server is beneficial. Note that migration can involve significant overheads if the application operates on significant amounts of state. Section 3.5 includes an experiment where workload behavior experiences different phases. We assume that there exists an underlying mechanism, such as vSphere [214], that performs the live migration.
**Suboptimal scheduling:** A second concern apart from application phases is suboptimal scheduling, either due to the greedy selection algorithm which assigns applications to servers in a per-workload fashion, or due to pathological behavior in application arrival patterns. Suboptimal scheduling can be detected exactly as the problem of workload phases and can potentially be resolved by re-scheduling several active applications. Although re-scheduling was not needed for the examined applications, Paragon provides a general methodology to detect such deviations and leverage mechanisms like VM migration to re-schedule the sub-optimally scheduled workloads.

**Latency-critical applications and workload dependencies:** Finally, Paragon does not explicitly consider latency-critical applications or dependencies between application components, e.g., a multi-tier service, such as search or webmail, where tiers communicate and share data. One differentiation in this case comes from the metrics the scheduler must consider. It is possible that the interference classification should use microbenchmarks that aim to degrade the per-query latency as opposed to the workload’s throughput. Another differentiation comes from the possible workload scenarios. One scenario can involve a latency-critical application running as the primary process, e.g., memcached, and the remaining server capacity being allocated to best-effort applications, such as analytics or background processes using Paragon. A different scenario is one where a throughput-bound distributed workload, e.g., MapReduce runs with high priority and the remaining server capacity is used by instances of a latency-critical application. Paragon does not currently enforce fine-grain priorities between application components or user requests, or optimize for shared data placement, which might be beneficial for these scenarios.

### 3.4 Methodology

**Server systems:** We evaluated Paragon on a small local cluster and three major cloud computing services. Our local cluster includes servers of ten different configurations shown in Table 6.1. We also show how many servers of each type we use. Note that these configurations range from high-end Xeon systems to low-power Atom-based boards. There is a wide range of core counts, clock frequencies and memory
Table 3.3: Main characteristics of the servers of the local cluster. The total core count is 178 for 40 servers of 10 different server configurations.

<table>
<thead>
<tr>
<th>Server Type</th>
<th>GHz</th>
<th>sockets</th>
<th>cores</th>
<th>L1(KB)</th>
<th>LLC(MB)</th>
<th>mem(GB)</th>
<th>#</th>
</tr>
</thead>
<tbody>
<tr>
<td>Xeon L5609</td>
<td>1.87</td>
<td>2</td>
<td>8</td>
<td>32/32</td>
<td>12</td>
<td>24 DDR3</td>
<td>1</td>
</tr>
<tr>
<td>Xeon X5650</td>
<td>2.67</td>
<td>2</td>
<td>12</td>
<td>32/32</td>
<td>12</td>
<td>24 DDR3</td>
<td>2</td>
</tr>
<tr>
<td>Xeon X5670</td>
<td>2.93</td>
<td>2</td>
<td>12</td>
<td>32/32</td>
<td>12</td>
<td>48 DDR3</td>
<td>2</td>
</tr>
<tr>
<td>Xeon L5640</td>
<td>2.27</td>
<td>2</td>
<td>12</td>
<td>32/32</td>
<td>12</td>
<td>48 DDR3</td>
<td>1</td>
</tr>
<tr>
<td>Xeon MP</td>
<td>3.16</td>
<td>4</td>
<td>4</td>
<td>16/16</td>
<td>1</td>
<td>8 DDR2</td>
<td>5</td>
</tr>
<tr>
<td>Xeon E5345</td>
<td>2.33</td>
<td>1</td>
<td>4</td>
<td>32/32</td>
<td>8</td>
<td>32 FB-DIMM</td>
<td>8</td>
</tr>
<tr>
<td>Xeon E5335</td>
<td>2.00</td>
<td>1</td>
<td>4</td>
<td>32/32</td>
<td>8</td>
<td>16 FB-DIMM</td>
<td>8</td>
</tr>
<tr>
<td>Opteron 240</td>
<td>1.80</td>
<td>2</td>
<td>2</td>
<td>64/64</td>
<td>2</td>
<td>4 DDR2</td>
<td>7</td>
</tr>
<tr>
<td>Atom 330</td>
<td>1.60</td>
<td>1</td>
<td>2</td>
<td>32/24</td>
<td>1</td>
<td>4 DDR2</td>
<td>5</td>
</tr>
<tr>
<td>Atom D510</td>
<td>1.66</td>
<td>1</td>
<td>2</td>
<td>32/24</td>
<td>1</td>
<td>8 DDR2</td>
<td>1</td>
</tr>
</tbody>
</table>

For the cloud-based clusters we used exclusive (reserved) server instances, i.e., no other users had access to these servers. We verified that no external scheduling decisions or actions such as auto-scaling or workload migration are performed during the course of the experiments. We used 1,000 servers on Amazon EC2 [10] with 14 different server configurations, ranging from small, low-power, dual-core machines to high-end, quad-socket, multi-core servers with hundreds of GBs of memory. All 1,000 machines are private, i.e., there is no interference in the experiments from external workloads. We also conducted experiments with 500 servers on Windows Azure [220] with 8 different server configurations and 100 servers on Google Compute Engine [90] with 4 server configurations.

Schedulers: We compared Paragon to three alternative schedulers. First, we evaluate a baseline scheduler that preserves an application’s core and memory requirements but ignores both its heterogeneity and interference profiles. In this case, applications are assigned to the least-loaded (LL) machine. Second, we examine a heterogeneity-oblivious (NH) scheme that uses the interference classification in Paragon to assign applications to servers without visibility in their server platforms. Finally, we evaluate an interference-oblivious (NI) scheme that uses the heterogeneity classification in Paragon but has no insight on workload interference. The overheads for the heterogeneity and interference-oblivious schemes are the corresponding classification and
server selection overheads.

Workloads: We used 29 single-threaded (ST), 22 multi-threaded (MT) and 350 multi-programmed (MP) workloads and 25 I/O-bound workloads. We use the full SPEC CPU2006 suite and workloads from PARSEC [30] (blackscholes, bodytrack, facesim, ferret, fluidanimate, raytrace, swaptions, canneal), SPLASH-2 [223] (barnes, fft, lu, ocean, radix, water), BioParallel [119] (genenet, svm), Minebench [155] (semphy, plsa, kmeans) and SPECjbb (2, 4 and 8-warehouse instances). For multiprogrammed workloads, we use 350 mixes of 4 applications, based on the methodology in [181]. The I/O-bound workloads are data mining applications, such as clustering and recommender systems [173], in Hadoop and Matlab running on a single-node. Workload durations range from minutes to hours. For workload scenarios with more than 426 applications we replicated these workloads with equal likelihood (1/4 ST, 1/4 MT, 1/4 MP, 1/4 I/O) and randomized their interleaving.

Workload scenarios: To explore a wide range of behaviors, we used the applications listed above to create multiple workload scenarios. Scenarios vary in the number, type and inter-arrival times of submitted applications. The load is classified based on its relation to available resources; low: the required core count is significantly lower than the available processor resources; high: the required core count approaches the load the system can support but does not surpass it; and oversubscribed: the required core count often exceeds the system’s capabilities, i.e., certain machines are oversubscribed.

For the small-scale experiments on the local cluster we examine four workload scenarios. First, a low load scenario with 178 applications, selected randomly from the pool of workloads, which are submitted with 10 sec inter-arrival times. Second, a medium load scenario with 178 applications, randomly selected as before and submitted with inter-arrival times that follow a Gaussian distribution with \( \mu = 10 \) sec and \( \sigma^2 = 1.0 \). Third, a high load scenario with 178 workloads, each corresponding to a sequence of three applications with varying memory loads. Each application goes through three phases; first medium, then high and again medium memory load. Workloads are submitted with 10 sec intervals. Finally, we examine a scenario, where
178 randomly-chosen applications arrive with 1 sec intervals. Note that the last scenario is an over-subscribed one. After a few seconds, there are not enough resources in the system to execute all applications concurrently, and subsequent submitted applications are queued.

For the large-scale experiments on EC2 we examine three workload scenarios; a low load scenario with 2,500 randomly-chosen applications submitted with 1 sec intervals, a high load scenario with 5,000 applications submitted with 1 sec intervals and an oversubscribed scenario where 7,500 workloads are submitted with 1 sec intervals and an additional 1,000 applications arrive in burst (less than 0.1 sec intervals) after the first 3,750 workloads.

3.5 Evaluation

3.5.1 Comparison of Schedulers: Small Scale

QoS guarantees: Figure 3.4 summarizes the performance results across the 178 workloads on the 40-server cluster for the medium load scenario where application arrivals follow a Gaussian distribution. Applications are ordered in the x-axis from worst to best-performing workload. The y-axis shows the performance (execution time) normalized to the performance of an application when it is running in the best platform in isolation (without interference). Each line corresponds to the performance achieved with a different scheduler. Overall, Paragon (P) outperforms the other schedulers, in terms of preserving QoS (95% of optimal performance), and bounding performance degradation when QoS requirements cannot be met. 78% of workloads maintain their QoS with Paragon, while the heterogeneity-oblivious (NH), interference-oblivious (NI) and least-loaded (LL) schedulers provide similar guarantees only for 23%, 19% and 7% of applications respectively. Even more, for the case of the least-loaded scheduler some applications failed to complete due to memory exhaustion on the server. Similarly, while the performance degradation with Paragon is smooth (94% of workloads have less than 10% degradation), the other three schedulers dramatically degrade performance for most applications, in almost
Figure 3.4: Performance impact from scheduling with Paragon for *medium load*, compared to heterogeneity and/or interference-oblivious schedulers. Application arrival times follow a Gaussian distribution. Applications are ordered from worst to best.

Linear fashion with the number of workloads. For this scenario, the heterogeneity and interference-oblivious schedulers perform almost identically, although ignoring interference degrades performance slightly more. This is due to workloads that arrive at the peak of the Gaussian distribution, when the cluster’s resources are heavily utilized. For the same workloads, Paragon limits performance degradation to less than 10% in most cases. This figure also shows that a small number of workloads experience speedups compared to their execution in isolation. This is a result of cache effects or instruction prefetching between similar co-scheduled workloads. We expect positive interference to be less prevalent for a more diverse application space.

**Scheduling decision quality:** Figure 3.5 explains why Paragon achieves better performance. Each bar represents a percentage of applications based on the performance degradation they experience due to the quality of decisions of each of the four schedulers in terms of platform selection (left) and impact from interference. Blue bars reflect good and red bars poor scheduling decisions. In terms of platform decisions, the least-loaded scheduler (LL) maps applications to servers with no heterogeneity considerations, thus it significantly degrades performance for most applications. The
heterogeneity-oblivious (NH) scheduler assigns more than 40% of workloads to suboptimal server platforms, although fewer than LL, as it often steers workloads to high-end server platforms that tend to tolerate more interference. However, as these servers become saturated, applications that would benefit from them are scheduled suboptimally and NH ends up making poor quality assignments afterwards. On the other hand, the schedulers that account for heterogeneity explicitly (interference-oblivious (NI) and Paragon (P)) have much better decision quality. NI induces no degradation to 47% of workloads and less than 10% for an additional 38%. The reason why NI does not behave better in terms of platform selection is that it has no input on interference, therefore it assigns most workloads to the best server configurations. As these machines become saturated, destructive interference increases and
performance degrades, although, unlike NH, which selects a random server configuration next, NI selects the server configurations that is ranked second for a workload. Finally, Paragon outperforms the other schedulers and assigns 84% of applications to their optimal server configuration.

The right part in Figure 3.5 shows decision quality with respect to interference. LL behaves the worst for similar reasons, while NI is slightly better than LL since it assigns more applications to high-end server configuration, that are more likely to tolerate interference. NH outperforms NI as expected, since NI ignores interference altogether. Paragon assigns 83% of applications to servers that induce no negative interference. Considering both graphs establishes why Paragon significantly outperforms the other schedulers, as it has better decision quality both in terms of heterogeneity and interference.

**Other workload scenarios:** Figure 3.6 compares Paragon to the three schedulers for the other three scenarios; low load, oversubscribed, and workloads with phases. For low load, performance degradation is small for all schedulers, although LL degrades performance by 46% on average. Since the cluster can easily accommodate the load of most workloads, classifying incoming applications has a smaller performance impact. Nevertheless, Paragon outperforms the other three schedulers and achieves 99% of optimal performance on average. It also improves resource efficiency during low load by completing the scenario 15% faster than the least-loaded scheduler. For the oversubscribed scenario, Paragon guarantees QoS for the largest workload fraction, 75% and bounds degradation to less than 10% for 99% of workloads. In this case, accounting for interference is much more critical than accounting for heterogeneity as the system’s resources are fully utilized.

Finally, for the case where workloads experience phases, we want to validate two expectations. First, Paragon should outperform the other schedulers, since it accounts for heterogeneity and interference (66% of workloads preserve their QoS). Second, Paragon should adapt to the changes in workload behavior, by detecting deviations from the expected IPS, re-classifying the offending workloads and re-scheduling them if a more suitable server is available. To verify this, in Figure 3.6d we show the average performance for each scheduler over time. The points where workloads start
changing phases are denoted with vertical lines. First, at phase change, Paragon induces much less degradation than the other schedulers, because applications are assigned to appropriate servers to begin with. Second, Paragon recovers much faster and better from the phase change. Performance rebounces to values close to 1 as the deviating workloads are re-scheduled to appropriate servers, while the other schedulers achieve progressively worse average performance.

**Resource allocation:** Ideally, the scheduler should closely follow application resource requirements (cores, cache capacity, memory bandwidth, etc.) and provide them with the minimum number of servers. This improves performance (applications execute as fast as possible without interference) and reduces overprovisioning (number of servers used, periods for which they are active). The latter particularly benefits the DC operator, as it reduces both capital and operational expenses. A smaller number of servers needs to be purchased to support a certain load (capital savings). During low load, many servers can be turned off to save energy (operational savings).

Figure 3.7a shows how Paragon follows the resource requirements for the medium load scenario shown in Figure 3.4. The green line shows the ideally required core count of active applications based on arrival rate and ideal execution time and the blue line the allocated core count by Paragon. Because the scheduler tracks application behavior in terms of heterogeneity and interference it is able to follow their requirements with minimal deviation (less than 3.5%), excluding periods when the
system is oversubscribed and the required cores exceed the total number of cores in the system. In comparison, NI (Figure 3.7b) and similarly for NH, either overprovisions or oversubscribes servers, resulting in increased execution time; per-application and for the overall scenario. Finally, Figure 3.7c shows the resource allocation for the least-loaded scheduler. There is significant deviation, since the scheduler ignores both heterogeneity and interference. All cores are used but in a suboptimal manner. Hence, execution times are increased for individual workloads and the overall scenario. Total execution time increases by 15%, but more importantly per-application time degrades (Figure 3.4), which is harmful both for users and DC operators.

Server utilization: In Figure 3.8 we plot heat maps of the server utilization over time for Paragon and the interference-oblivious (NI) scheduler. Server utilization is defined as average CPU utilization across the cores of a server. For Paragon, utilization is high in the middle of the scenario when many applications are active (47% higher than without colocation), and returns to zero when the scenario finishes. In this case, resource usage improves compared to the interference-oblivious scheduler without performance degradation due to interference. On the other hand, NI keeps server utilization high in some servers and underutilizes others, while violating per-application QoS and extending the scenario’s execution time. This is undesirable both for the user who gets lower performance and for the DC operator, since the high utilization in certain servers does not translate to faster execution time, adhering scalability to servicing more workloads.
Scheduling overheads: Finally, we evaluate the total scheduling overheads for the various schemes. These include the overheads of offline training, classification and server selection using the greedy algorithm. Figure 3.9 shows the execution time breakdown for selected single-threaded and multi-threaded applications. These applications are representative of workloads submitted throughout the execution of the medium load scenario. All bars are normalized to the execution time of the application in isolation in the best server configuration. Training and classification for heterogeneity and interference are performed in parallel so there is a single bar for each, for every workload. There is no bar for the least-loaded scheduler for mcf, since it was one of the benchmarks that did not terminate successfully. Paragon achieves lower execution times for the majority of applications and close to optimal. The overheads of the recommendation system are low; 1.2% for training and 0.09% for classification. The overheads of the greedy algorithm are less than 0.1% in most cases with the exceptions of soplex and genenet that required extensive backtracking which was handled with a timeout. Overall, Paragon performs accurate classification and efficient scheduling within 1 minute of the application’s arrival, which is marginal for most workloads.

3.5.2 Comparison of Schedulers: Large Scale

Performance impact: Figure 3.10 shows the performance for the three workload scenarios on the 1,000-server EC2 cluster. Similar to the results on the local cluster, the low load scenario, in general, does not create significant performance challenges.
Figure 3.10: Performance comparison between the four schedulers, for three workload scenarios on 1,000 EC2 servers.

Nevertheless, Paragon outperforms the other three schemes, it maintains QoS for 91% of workloads and achieves on average 0.96 of the performance of a workload running in isolation in the best server configuration. When moving to the case of high load, the difference between schedulers becomes more obvious. While the heterogeneity and interference-oblivious schemes degrade performance by an average of 22% and 34% and violate QoS for 96% and 97% of workload respectively, Paragon degrades performance only by 4% and guarantees QoS for 61% of workloads. The least-loaded scheduler degrades performance by 48% on average, while some applications do not terminate (crash). The differences in performance are larger for workloads submitted when the system is heavily loaded and becomes oversubscribed. Although, we simply queue applications in FIFO order until resources become available, Paragon bounds performance degradation (only 0.6% of workloads degrade more than 20%), since it co-schedules workloads that minimize destructive interference. We plan to incorporate a better admission control protocol in the scheduler in future work.

Finally, for the oversubscribed case, NH, NI and LL dramatically degrade performance for most workloads, while the number of applications that do not terminate successfully increases to 10.4%. Paragon, on the other hand, provides strict QoS guarantees for 52% of workloads, while the other schedulers provide similar guarantees only for 5%, 1% and 0.09% of workloads respectively. Additionally, Paragon
Figure 3.11: Breakdown of decision quality in terms of heterogeneity (left) and interference for the three EC2 scenarios.

limits degradation to less than 10% for an additional 33% of applications and maintains performance degradation moderate (no cliffs in performance such as for NH in applications [1-1000]).

**Decision quality:** Figure 3.11 shows a breakdown of the decision quality of the different schedulers for heterogeneity (left) and interference (right) across the three experiments. LL induces more than 20% performance degradation to most applications, both in terms of heterogeneity and interference. NH has low decision quality in terms of platform selection, while NI causes performance degradation by colocating unsuitable applications. The errors increase as we move to scenarios of higher load. Paragon decides optimally for 65% of applications for heterogeneity and 75% for interference on average, significantly higher than the other schedulers. It also constrains decisions that lead to larger than 20% degradation due to interference to less than 8% of workloads. The results are consistent with the findings for the small-scale experiments.

**Resource allocation:** Figure 3.12 shows why this deviation exists. From left to right we show the graphs for low, high, and oversubscribed load. The yellow line represents the required core count based on the applications running at a snapshot of the system, while the other four lines show the allocated core count by each of the schedulers. Since Paragon optimizes for increased utilization within QoS constraints, it follows the application requirements closely. It only deviates when the required
core count exceeds the resources available in the system. NH has mediocre accuracy, while NI and LL either significantly overprovision the number of allocated cores, or oversubscribe certain servers. There are two important points in these graphs: first, as the load increases the difference in execution time exceeds the optimal one, which Paragon approximates with minimal deviation. Second, for higher loads, the errors in core allocation increase dramatically for the other three schedulers, while for Paragon the average deviation remains constant, excluding the part where the system is oversubscribed.

**Windows Azure & Google Compute Engine:** We validate our results on a 500-server Azure and a 100-server Compute Engine (GCE) cluster (Figure 3.13). We run a scenario with 2,500 and 500 workloads respectively. In Azure, Paragon achieves 94.3% of the performance in isolation and maintains QoS for 61% of workloads, while the other three schedulers provide the same guarantees for 1%, 2% and 0.7% of workloads. Additionally, this was the only time where NI outperformed NH, most likely due to the wide variation between server configurations which increases the importance of accounting for heterogeneity. In the GCE cluster, which has only 4 server configurations, workloads exhibit mediocre benefits from heterogeneity-aware scheduling (7% over random), while the majority of gains comes from accounting for interference. Overall, Paragon achieves 96.8% of optimal performance and NH
Figure 3.13: Performance comparison between the schedulers on the Windows Azure and Google Compute Engine (GCE) clusters.

90%. The consistency between experiments, despite the different cluster configurations and underlying hardware, shows the robustness of the analytical methods that drive Paragon.

3.6 Related Work

We discuss work relevant to Paragon in the areas of DC scheduling, VM management and workload rightsizing. We also present related work from scheduling for heterogeneous multi-core chips.

**Datacenter scheduling:** Recent work on DC scheduling has highlighted the importance of platform heterogeneity and workload interference. Mars et al. [149, 148] showed that the performance of Google workloads can vary by up to 40% due to heterogeneity even when considering only two SCs and up to 2x due to interference even when considering only two colocated applications. In [149], they present an offline scheme that used combinatorial optimization to select the proper SC for each workload. In [148], they present an offline, two-step method to characterize the sensitivity of workloads to memory pressure and the stress each application exercises to the memory subsystem. Govindan et al. [98] also present a scheme to quantify the effects of cache interference between consolidated workloads, although they require
access to physical memory addresses. Finally, Nathuji et al. [157] present a control-based resource allocation scheme that mitigates the effects of cache, memory and hardware prefetching interference of co-scheduled workloads. In Paragon, we extend the concepts of heterogeneity and interference-aware DC scheduling in several ways. We provide an online, highly-accurate and low-overhead methodology that classifies applications for both heterogeneity and interference across multiple resources. We also show that our classification engine allows for efficient, online scheduling without using computationally intensive techniques which require exhaustive search between colocation candidates.

**VM management:** VM management systems such as vSphere [214], XenServer [4] or the VM platforms on EC2 [10] and Windows Azure [220] can schedule diverse workloads submitted by a large number of users on the available servers. In general, these platforms account for application resource requirements which they learn over time by monitoring workload execution. Paragon can complement such systems by making efficient scheduling decisions based on heterogeneity and interference and detecting when an application should be considered for migration (re-scheduling).

**Resource management and rightsizing:** There has been significant work on resource allocation in virtualized and non-virtualized large-scale DCs, including Mesos [112], Rightscale [178], resource containers [20], Dejavu [207] and the work by Chase et al. [43]. Mesos performs resource allocation between distributed computing frameworks like Hadoop or Spark [112]. Rightscale automatically scales out 3-tier applications to react to changes in the load in Amazon’s cloud service [18]. Dejavu serves a similar goal by identifying a few workload classes and based on them, reuses previous resource allocations to minimize reallocation overheads [207]. Zhu et al. [239] present a resource management scheme for virtualized DCs that preserves SLAs and Gmach et al. [95] a resource allocation scheme for DC applications that relies on the ability to predict their behavior a priori. In general, Paragon is complementary to resource allocation and rightsizing systems. Once such a system determines the amount of resources needed by an application (e.g., number of servers, memory capacity, etc.), Paragon can classify and schedule it on the proper hardware platform in a way that minimizes interference. Currently, Paragon focuses on online scheduling of previously
unknown workloads. We will consider how to integrate Paragon with a rightsizing system for scheduling long running, 3-tier services in future work.

**Scheduling for heterogeneous multi-core chips:** Finally, scheduling in heterogeneous CMPs shares some concepts and challenges with scheduling in heterogeneous DCs, therefore some of the ideas in Paragon can be applied in heterogeneous CMP scheduling as well. Fedorova et al. [85, 84] discuss OS level scheduling for heterogeneous multi-cores as having the following three objectives: optimal performance, core assignment balance and response time fairness. Shelepov et al. [189] present a scheduler that exhibits some of these features and is simple and scalable, while Craeynest et al. [205] use performance statistics to estimate which workload-to-core mapping is likely to provide the best performance. DC scheduling also has similar requirements as applications should observe their QoS, resource allocation should follow application requirements closely and fairness between co-scheduled workloads should be preserved. Given the increasing number of cores per chip and co-scheduled tasks, techniques such as those used for the classification engine of Paragon can be applicable when deciding how to schedule applications to heterogeneous cores as well.

### 3.7 Conclusions

In this chapter, we have presented Paragon, a scalable scheduler for DCs that is both heterogeneity and interference-aware. Paragon is derived from validated analytical methods, such as collaborative filtering to quickly and accurately classify incoming applications with respect to platform heterogeneity and workload interference. Classification uses minimal information about the new application and relies mostly on information from previously scheduled workloads. The output of classification is used by a greedy scheduler to assign workloads to servers in a manner that maximizes application performance and optimizes resource usage. We have evaluated Paragon with both small and large-scale systems. Even for very demanding scenarios, where heterogeneity and interference-agnostic schedulers degrade performance for up to 99.9% of workloads, Paragon maintains QoS guarantees for 52% of the applications and bounds degradation to less than 10% for an additional 33% out of 8500 applications
on a 1,000-server cluster. Paragon preserves QoS guarantees while improving server utilization, hence it benefits both the DC operator, who achieves perfect resource use and the user, who gets the best performance. In the following chapter we discuss how a similar approach can be applied towards resource provisioning in large-scale datacenters.
Chapter 4

Quasar: QoS-Aware and Resource Efficient Cluster Management

4.1 Introduction

In the previous chapter, we discussed how fast data mining techniques can be used to manage platform heterogeneity and workload interference to improve performance in datacenter workloads. Nevertheless, managing the type of resources assigned to a new application is not sufficient the resolve the underutilization problem in datacenters. In fact, most cloud facilities operate at very low utilization, even when using cluster management frameworks that enable cluster sharing across workloads [22, 177]. In this chapter we discuss the reasons behind underutilization, and propose a new cluster management approach that significantly improves resource efficiency. In Figure 4.1, we present a utilization analysis for a production cluster at Twitter with thousands of servers, managed by Mesos [112] over one month. The cluster mostly hosts user-facing services. The aggregate CPU utilization is consistently below 20%, even though reservations reach up to 80% of total capacity (Figure 4.1.a). Even when looking at individual servers, their majority does not exceed 50% utilization on any week (Figure 4.1.c). Typical memory use is higher (40-50%) but still differs from the reserved capacity. Figure 4.1.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% [177]. 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 colocate workloads the way Google and Twitter do with Borg and Mesos respectively. Various analyses estimate industry-wide utilization between 6% [51] and 12% [206, 89]. A recent study estimated server utilization on Amazon EC2 in the 3% to 17% range [140]. Overall, low utilization is a major challenge for cloud facilities. Underutilized servers contribute to capital expenses and, since they are not energy proportional [134, 152], to operational expenses as well. Even if a company can afford the cost, low utilization is still a scaling limitation. With many cloud DCs consuming 10s of megawatts, it is difficult to add more servers without running into the limits of what the nearby electricity facility can deliver.

We focus on increasing resource utilization in datacenters through better cluster management. The manager is responsible for providing resources to various workloads in a manner that achieves their performance goals, while maximizing the utilization of available resources. The manager must make two major decisions; first allocate the
right amount of resources for each workload (resource allocation) and then select the specific servers that will satisfy a given allocation (resource assignment). While there has been significant progress in cluster management frameworks [81, 112, 183, 211], there are still major challenges that limit their effectiveness in concurrently meeting application performance and resource utilization goals. First, it is particularly difficult to determine the resources needed for each workload. The load of user-facing services varies widely within a day, while the load of analytics tasks depends on their complexity and their dataset size. Most existing cluster managers side-step allocation altogether, requiring users or workloads to express their requirements in the form of a reservation. Nevertheless, the workload developer does not necessarily understand the physical resource requirements of complex codebases or the variations in load and dataset size. As shown in Figure 4.1.d, only a small fraction of the workloads submitted to the Twitter cluster provided a right-sized reservation. Undersized reservations lead to poor application performance, while oversized reservations lead to low resource utilization.

Equally important, resource allocation and resource assignment are fundamentally linked. The first reason is heterogeneity of resources, which is quite high as servers get installed and replaced over the typical 15-year lifetime of a DC [22, 63]. A workload may be able to achieve its current performance goals with ten high-end or twenty low-end servers. Similarly, a workload may be able to use low-end CPUs if the memory allocation is high or vice versa. The second reason is interference between colocated workloads that can lead to severe performance losses [149, 226]. This is particularly problematic for user-facing services that must meet strict, tail-latency requirements (e.g., low 99th percentile latency) under a wide range of traffic scenarios ranging from low load to unexpected spikes [55]. Naïvely colocating these services with low-priority, batch tasks that consume any idling resources can lead to unacceptable latencies, even at low load [149]. This is the reason why cloud operators deploy low-latency services on dedicated servers that operate at low utilization most of the time. In facilities that share resources between workloads, users often exaggerate resource reservations to side-step performance unpredictability due to interference. Finally, most cloud facilities are large and involve thousands of servers and workloads, putting tight
constraints on the complexity and time that can be spent making decisions [183]. As new, unknown workloads are submitted, old workloads get updated, new datasets arise, and new server configurations are installed, it is impractical for the cluster manager to analyze all possible combinations of resource allocations and assignments.

We present Quasar, a cluster manager that maximizes resource utilization while meeting performance and QoS constraints for each workload. Quasar includes three key features. First, it shifts from a reservation-centric to a performance-centric approach for cluster management. Instead of users expressing low-level resource requests to the manager, Quasar allows users to communicate the performance constraints of the application through a high-level, declarative interface. Performance constraints are expressed in terms of throughput and/or latency, depending on the application type. This high-level interface allows Quasar to determine the least amount of the available resources needed to meet performance constraints at any point, given the current state of the cluster in terms of available servers and active workloads. The allocation varies over time to adjust to changes in the workload or system state. The performance-centric approach simplifies both the user and cloud manager’s roles as it removes the need for exaggerated reservations, allows transparent handling of unknown, evolving, or irregular workloads, and provides additional flexibility towards cost-efficient allocation.

Second, Quasar uses fast classification techniques to determine the impact of different resource allocations and assignments on workload performance. This problem is much more complex than the one addressed in Chapter 3, since apart from heterogeneity and interference, the system must also determine the amount of resources an application should receive within a node, the ratio of resources in the allocation, the number and topology of nodes in the case of distributed applications, and the way parameters in frameworks such as Hadoop and Spark should be configured. Exhaustively exploring the space would require billions of profiling runs for clusters with a few hundred nodes. Instead in Quasar, by combining a small amount of profiling information from the workload itself with the large amount of data from previously-scheduled workloads, we can quickly and accurately generate the information needed for efficient resource assignment and allocation without the need for a priori analysis.
of the application and its dataset. Applying classification to cluster management as a whole is also impractical. To solve the problem in a practical way, Quasar performs four parallel classifications on each application to evaluate the four main aspects of resource allocation and assignment: the impact of scale-up (amount of resources per server), the impact of scale-out (number of servers per workload), the impact of server configuration, and the impact of interference (which workloads can be colocated).

Third, Quasar performs resource allocation and assignment jointly. The classification results are used to determine the right amount and specific set of resources assigned to the workload. Hence, Quasar avoids overprovisioning workloads that are currently at low load and can compensate for increased interference or the unavailability of high-end servers by assigning fewer or lower-quality resources to them. Moreover, Quasar monitors performance throughout the workload’s execution. If performance deviates from the expressed constraints, Quasar reclassifies the workload and adjusts the allocation and/or assignment decisions to meet the performance constraints or minimize the resources used.

We have implemented and evaluated a prototype for Quasar managing a local 40-server cluster and a 200-node cluster of dedicated EC2 servers. We use a wide range of workloads including analytics frameworks (Hadoop, Storm, Spark), latency-critical and stateful services (memcached, Cassandra), and batch workloads. We compare Quasar to reservation-based resource allocation coupled with resource assignment based on load or similar classification techniques. Quasar improves server utilization at steady state by 47% on average at high load in the 200-server cluster, while also improving performance of individual workloads compared to the alternative schemes. We show that Quasar correctly determines the amount of resources needed by analytics and latency-critical workloads better than built-in schedulers of frameworks like Hadoop, or auto-scaling systems. It also selects assignments that take heterogeneity and interference into account so that throughput and latency constraints are closely met.
4.2 Motivation

4.2.1 Cluster Management Overview

A cluster management framework provides various services including security, fault tolerance, and monitoring. This work focuses on the two tasks most relevant to resource efficiency: resource allocation and resource assignment of incoming workloads. Previous work has mostly treated the two separately.

**Resource allocation:** Allocation refers to determining the amount of resources used by a workload: number of servers, number of cores and amount of memory and bandwidth resources per server. Managers like Mesos [112], Torque [202], and Omega [183] expect workloads to make resource reservations. Mesos processes these requests and, based on availability and fairness issues [93], makes resource offers to individual frameworks (e.g., Hadoop) that the framework can accept or reject. Dejavu identifies a few workload classes and reuses previous resource allocations for each class to minimize reallocation overheads [207]. CloudScale [190], PRESS [96], AGILE [160] and the work by Gmach et al. [95] perform online prediction of resource needs, often without a priori workload knowledge. Finally, auto-scaling systems such as Rightscale [178] automatically scale the number of physical or virtual instances used by webserving workloads to react to observed changes in server load.

**Resource assignment:** Assignment refers to selecting the specific resources that satisfy an allocation. The two biggest challenges of assignment are server heterogeneity and interference between colocated workloads [149, 156, 226], when servers are shared to improve utilization. The most closely related work to Quasar is Paragon [63]. Given a resource allocation for an unknown, incoming workload, Paragon uses classification techniques to quickly estimate the impact of heterogeneity and interference on performance. Paragon uses this information to assign each workload to server type(s) that provide the best performance and colocate workloads that do not interfere with each other. Nathuji et al. [157] developed a feedback-based scheme that tunes resource assignment to mitigate interference effects. Yang et al. developed an online scheme that detects memory pressure and finds colocations that avoid interference
Figure 4.2: The impact of heterogeneity, interference, scale-out, scale-up, and dataset on the performance of Hadoop (top row) and memcached (bottom row). Server configurations, interference patterns, and datasets are summarized in Table 4.1. For Hadoop, the variability in the violin plots is due to scaling-up the resource allocations within a server (cores and/or memory).

on latency-sensitive workloads [226]. Similarly, DeepDive detects and manages interference between co-scheduled applications in a VM system [161]. Finally, CPI2 [235] throttles low-priority workloads that induce interference to important services. In terms of managing heterogeneity, Nathuji et al. [156] and Mars et al. [147] quantified its impact on conventional benchmarks and Google services and designed schemes to predict the most appropriate server type for each workload.

4.2.2 The Case for Coordinated Cluster Management

Despite the progress in cluster management technology, resource utilization is quite low in most private and public clouds (see Figure 4.1 and [51, 89, 140, 177, 206]). There are two major shortcomings current cluster managers have. First, it is particularly difficult for a user or workload to understand its resource needs and express them as a reservation. Second, resource allocation and assignment are fundamentally linked. An efficient allocation depends on the amount and type of resources available and the behavior of other workloads running on the cluster.

Figure 4.2 illustrates these issues by analyzing the impact of various allocations,
assignments, and workload aspects on two representative applications, one batch and one latency-critical: a large Hadoop job running a recommendation algorithm on the Netflix dataset [27] and a memcached service under a read-intensive load. For Hadoop, we report speedup over a single node of server configuration A using all available cores and memory. Server configurations, interference settings and datasets are summarized in Table 4.1. The variability in each violin plot is due to the different amounts of resources (cores and memory) allocated within each server. For memcached, we report the latency-throughput graphs. Real-world memcached deployments limit throughput to achieve 99th-percentile latencies between 0.2ms and 1ms.

The first row of Figure 4.2 illustrates the behavior of Hadoop. The heterogeneity graph shows that the choice of server configuration introduces performance variability of up to 7x, while the amount of resources allocated within each server introduces variability of up to 10x. The interference graph shows that for server A, depending on the amount of resources used, Hadoop may be insensitive to certain types of interference or slowdown by up to 10x. Similarly, the scale-out graph shows that depending on the amount of resources per server, scaling may be sublinear or superlinear. Finally, the dataset graph shows that the dataset complexity and size can have 3x impact on Hadoop’s performance. Note that in addition to high variability, the violin plots show that the probability distributions change significantly across different allocations. The results are similar for memcached, as shown in the second row of Figure 4.2. The position of the knee of the throughput-latency curve depends heavily on the type of server used (3x variability), the interference patterns (7x variability), the amount of resources used per server (8x variability), and workload characteristics.

<table>
<thead>
<tr>
<th>platforms</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>J</th>
</tr>
</thead>
<tbody>
<tr>
<td>cores</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>12</td>
<td>12</td>
<td>16</td>
<td>24</td>
</tr>
<tr>
<td>memory(GB)</td>
<td>4</td>
<td>8</td>
<td>12</td>
<td>16</td>
<td>20</td>
<td>24</td>
<td>16</td>
<td>24</td>
<td>48</td>
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</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>interference</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
</tr>
</thead>
<tbody>
<tr>
<td>pattern</td>
<td>-</td>
<td>memory</td>
<td>L1I</td>
<td>$</td>
<td>LL</td>
<td>$</td>
<td>disk I/O</td>
<td>network</td>
<td>L2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>input</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>hadoop</td>
<td>netflix: 2.1GB</td>
<td>mahout: 10GB</td>
<td>wikipedia: 55GB</td>
</tr>
<tr>
<td>memcached</td>
<td>100B reads</td>
<td>2KB reads</td>
<td>100B reads-100B writes</td>
</tr>
</tbody>
</table>

Table 4.1: Server platforms (A-J), interference patterns (A-I) and input datasets (A-C) used for the analysis in Figure 4.2.
such as data size and read/write mixes (3x variability).

It is clear from Figure 4.2 that it is quite difficult for a user or workload to translate a performance goal to a resource reservation. To right-size an allocation, we need to understand how scale-out, scale-up, heterogeneity in the currently available servers, and interference from the currently running jobs affect a workload with a specific dataset. Hence, separating resource allocation and assignment through reservations is bound to be suboptimal, either in terms of resource efficiency or in terms of workload performance (see Figure 4.1). Similarly, performing first allocation and then assignment in two separate steps is also suboptimal. Cluster management must handle both tasks in an integrated manner.

4.3 Quasar

4.3.1 Overview

Quasar differs from previous work in three ways. First, it shifts away from resource reservations and adopts a performance-centric approach. Quasar exports a high-level interface that allows users or the schedulers integrated in some frameworks (e.g., Hadoop or Spark) to express the performance constraint the workload should meet. The interface differentiates across workload types. For latency-critical workloads, constraints are expressed as a queries per second (QPS) target and a latency QoS constraint. For distributed frameworks like Hadoop, the constraint is execution time. For single node, single-threaded or multi-threaded workloads the constraint is a low-level metric of instructions-per-second (IPS). Once performance constraints are specified, it is up to Quasar to find a resource allocation and assignment that satisfies them.

Second, Quasar uses fast classification techniques to quickly and accurately estimate the impact different resource allocation and resource assignment decisions have on workload performance. Upon admission, an incoming workload and dataset is profiled on a few servers for a short period of time (a few seconds up to a few minutes
This limited profiling information is combined with information from the few workloads characterized offline and the many workloads that have been previously scheduled in the system using classification techniques. The result of classification is accurate estimates of application performance as we vary the type or number of servers, the amount of resources within a server, and the interference from other workloads. In other words, we estimate graphs similar to those shown in Figure 4.2. This classification-based approach eliminates the need for exhaustive online characterization and allows efficient scheduling of unknown or evolving workloads, or new datasets. Even with classification, exhaustively estimating performance for all allocation-assignment combinations would be infeasible. Instead, Quasar decomposes the problem to the four main components of allocation and assignment: resources per node and number of nodes for allocation, and server type and degree of interference for assignment. This dramatically reduces the complexity of the classification problem.

Third, Quasar uses the result of classification to jointly perform resource allocation and assignment, eliminating the inherent inefficiencies of performing allocation without knowing the assignment challenges. A greedy algorithm combines the result of the four independent classifications to select the number and specific set of resources that will meet (or get as close as possible to) the performance constraints. Quasar also monitors workload performance. If the constraint is not met at some point or resources are idling, either the workload changed (load or phase change), classification was incorrect, or the greedy scheme led to suboptimal results. In any case, Quasar adjusts the allocation and assignment if possible, or reclassifies and reschedules the workload from scratch.

Quasar uses similar classification techniques as those introduced in Paragon [63]. Paragon handles only resource assignment. Hence, its classification step can only characterize workloads with respect to heterogeneity (server type) and interference. In contrast, Quasar handles both resource allocation and assignment. Hence, its classification step also characterizes scale-out and scale-up issues for each workload.
Moreover, the space of allocations and assignments that Quasar must explore is significantly larger than the space of assignments explored by Paragon. Finally, Quasar introduces an interface for performance constraints in order to decouple user goals from resource allocation and assignment. In Section 4.6, we compare Quasar to Paragon coupled with current resource allocation approaches to showcase the advantages of Quasar.

4.3.2 Fast and Accurate Classification

Collaborative filtering techniques are often used in recommendation systems with extremely sparse inputs [173]. One of their most publicized uses was the Netflix Challenge [27], where techniques such as Singular Value Decomposition (SVD) and PQ-reconstruction [33, 128, 173, 222] were used to provide movie recommendations to users that had only rated a few movies themselves, by exploiting the large number of ratings from other users. The input to SVD in this case is a very sparse matrix $A$ with users as rows, movies as columns and ratings as elements. SVD decomposes $A$ to the product of the matrix of singular values $\Sigma$ that represents similarity concepts in $A$, the matrix of left singular vectors $U$ that represents correlation between rows of $A$ and similarity concepts, and the matrix of right singular vectors $V$ that represents the correlation between columns of $A$ and similarity concepts ($A = U \cdot \Sigma \cdot V^T$). A similarity concept can be that users that liked “Lord of the Rings 1” also liked “Lord of the Rings 2”. PQ-reconstruction with Stochastic Gradient Descent (SGD), a simple latent-factor model [33, 222], uses $\Sigma$, $U$, and $V$ to reconstruct the missing entries in $A$. Starting with the SVD output, $P^T$ is initialized to $\Sigma V^T$ and $Q$ to $U$ which provides an initial reconstruction of $A$. Subsequently, SGD iterates over all elements of the reconstructed matrix $R=Q \cdot P^T$ until convergence.

For each element $r_{ui}$ of $R$:

$$\epsilon_{ui} = r_{ui} - \mu - b_u - q_i \cdot p_u^T$$

$$q_i \leftarrow q_i + \eta(\epsilon_{ui}p_u - \lambda q_i)$$

$$p_u \leftarrow p_u + \eta(\epsilon_{ui}q_i - \lambda p_u)$$
until $|\epsilon|_{L_2} = \sqrt{\sum_{u,i} |\epsilon_{ui}|^2}$ becomes marginal. $\eta$ is the learning rate and $\lambda$ the regularization factor of SGD and their values are determined empirically. In the above model, we also include the average rating $\mu$ and a user bias $b_u$ that account for the divergence of specific users from the norm. Once the matrix is reconstructed, SVD is applied once again to generate movie recommendations by quantifying the correlation between new and existing users. The complexity of SVD is $O(\min(N^2M, M^2N))$, where $M, N$ the dimensions of $A$, and the complexity of PQ-reconstruction with SGD is $O(N \cdot M)$.

In Paragon [63], collaborative filtering was used to quickly classify workloads with respect to interference and heterogeneity. A few applications are profiled exhaustively offline to derive their performance on different servers and with varying amounts of interference. An incoming application is profiled for one minute on two of the many server configurations, with and without interference in two shared resources. SVD and PQ-reconstruction are used to accurately estimate the performance of the workload on the remaining server configurations and with interference on the remaining types of resources. Paragon showed that collaborative filtering can quickly and accurately classify unknown applications with respect to tens of server configurations and tens of sources of interference.

The classification engine in Quasar extends the one in Paragon in two ways. First, it uses collaborative filtering to estimate the impact of resource scale-out (more servers) and scale-up (more resources per server) on application performance. These additional classifications are necessary for resource allocation. Second, it tailors classifications to different workload types. This is necessary because different types for workloads have different constraints and allocation knobs. For instance, in a web-server we can apply both scale-out and scale-up and we must monitor queries per second (QPS) and latency. For Hadoop, we can also configure workload parameters such as the number of mappers per node, heapsize, and compression. For a single-node workload, scaling up might be the only option while the metric of interest can be instructions per second. The performance constraints interface of Quasar allows users to specify the type of submitted applications.

Overall, Quasar classifies for scale-up, scale-out, heterogeneity, and interference.
The four classifications are done independently and in parallel to reduce complexity and overheads. The greedy scheduler combines information from all four. Because of the decomposition of the problem the matrix dimensions decrease, and classification becomes fast enough that it can be applied on every workload submission, even if the same workload is submitted multiple times with different datasets. Hence there is no need to classify for dataset sensitivity.

**Scale-up classification:** This classification explores how performance varies with the amount of resources used within a server. We currently focus on compute cores, memory and storage capacity. We will address network bandwidth in future work. We perform scale-up classification on the highest-end platform, which offers the largest number of scale-up options. When a workload is submitted, we profile it briefly with two randomly-selected scale-up allocations. The parameters and duration of profiling depend on workload type. Latency-critical services, like memcached are profiled for 5-10 seconds under live traffic, with two different core/thread counts and memory allocations (see the validation section for a sensitivity analysis on the number of profiling runs). For workloads like Hadoop, we profile a small subset (2-6) of map tasks with two different allocations and configurations of the most important framework parameters (e.g., mappers per node, JVM heapsize, block size, memory per task, replication factor, and compression). Profiling lasts until the map tasks reach at least 20% of completion, which is typically sufficient to estimate the job’s completion time using its progress rate [229] and assuming uniform task duration [112]. Section 4.4.3 addresses the issue of non-uniform task duration distribution and stragglers. Finally, for stateful services like Cassandra [38], Quasar waits until the service’s setup is complete before profiling the input load with the different allocations. This takes at most 3-5 minutes, which is tolerable for long-running services. Section 4.4.2 discusses how Quasar guarantees side-effect free application copies for profiling runs.

Profiling collects performance measurements in the format of each application’s performance goal (e.g., expected completion time or QPS) and inserts them into a matrix $A$ with workloads as rows and scale-up configurations as columns. A configuration includes compute, memory, and storage allocations or the values of the framework parameters for a workload like Hadoop. To constrain the number of columns, we
quantize the vectors to integer multiples of cores and blocks of memory and storage. This may result into somewhat suboptimal decisions, but the deviations are small in practice. Classification using SVD and PQ-reconstruction then derive the workload’s performance across all scale-up allocations.

**Scale-out classification:** This type of classification is only applicable to workloads that can use multiple servers, such as distributed frameworks (e.g., Hadoop or Spark), stateless (e.g., webserving) or stateful (e.g., memcached or Cassandra) distributed services, and distributed computations (e.g., MPI jobs). Scale-out classification requires one more run in addition to single-node runs done for scale-up classification. To get consistent results, profiling is done with the same parameters as one of the scale-up runs (e.g., JVM heapsize) and the same application load. This produces two entries for matrix $A$, where rows are again workloads and columns are scale-out allocations (numbers of servers). Collaborative filtering then recovers the missing entries of performance across all node counts. Scale-out classification requires additional servers for profiling. To avoid increasing the classification overheads when the system is online, applications are only profiled on one to four nodes for scale-out classification. To accurately estimate the performance of incoming workloads for larger node counts, in offline mode, we have exhaustively profiled a small number of different workload types (20-30) against node counts 1 to 100. These runs provide the classification engine with dense information on workload behavior for larger node counts. This step does not need to repeat unless there are major changes in the cluster’s hardware or application structure.

**Heterogeneity classification:** This classification requires one more profiling run on a different and randomly-chosen server type using the same workload parameters and for the same duration as a scale-up run. Collaborative filtering estimates workload performance across all other server types.

**Interference classification:** This classification quantifies the sensitivity of the workload to interference caused and tolerated in various shared resources, including the CPU, cache hierarchy, memory capacity and bandwidth, and storage and network bandwidth. This classification does not require an extra profiling run. Instead, it leverages the first copy of the scale-up classification to inject, one at a time, two
microbenchmarks that create contention in a specific shared resource [61]. Once the microbenchmark is injected, Quasar tunes up its intensity until the workload performance drops below an acceptable level of QoS (typically 5%). This point is recorded as the workload’s sensitivity to this type of interference in a new row in the corresponding matrix $A$. The columns of the matrix are the different sources of interference. Classification is then applied to derive the sensitivities to the remaining sources of interference. Once the profiling runs are complete the different types of classification reconstruct the missing entries and provide recommendations on efficient allocations and assignments for each workload. Classification typically takes a few msec even for thousands of applications and servers.

Multiple parallel versus single exhaustive classification: Classification is decomposed to the four components previously described for both accuracy and efficiency reasons. The alternative design would consist of a single classification that examines all combinations of resource allocations and resource assignments at the same time. Each row in this case is an incoming workload, and each column is an allocation-assignment vector. Exhaustive classification addresses pathological cases that the four simpler classifications estimate poorly. For example, if TCP incast occurs for a specific allocation, only on a specific server platform that is not used for profiling, its performance impact will not be identified by classification. Although these cases are rare, they can result in unexpected performance results. On the other hand, the exponential increase in the column count in the exhaustive scheme increases the time required to perform classification [222, 128, 173] (note that this occurs at every application arrival). Moreover, because the number of columns now exceeds the number of rows, classification accuracy decreases, as SVD finds fewer similarities with high confidence [169, 216, 92].

To address this issue without resorting to exhaustive classification, we introduce a simple feedback loop that updates the matrix entries when the performance measured at runtime deviates from the one estimated through classification. This loop addresses such misclassifications, and additionally assists with scaling to server counts that exceed the capabilities of profiling, i.e., more than 100 nodes.

Validation: Table 4.2 summarizes a validation of the accuracy of the classification
CHAPTER 4. QUASAR

Table 4.2: Validation of Quasar’s classification engine. We present average, \(90^{th}\) percentile and maximum errors between estimated values and actual values obtained with detailed characterization.

<table>
<thead>
<tr>
<th>Classification</th>
<th>scale-up</th>
<th>scale-out</th>
<th>heterogeneity</th>
<th>interference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>avg (90^{th})</td>
<td>max</td>
<td>avg (90^{th})</td>
<td>max</td>
</tr>
<tr>
<td>Hadoop (10 Jobs)</td>
<td>5.2%</td>
<td>9.8%</td>
<td>11%</td>
<td>5.0%</td>
</tr>
<tr>
<td>Memcached (10)</td>
<td>6.3%</td>
<td>9.2%</td>
<td>11%</td>
<td>6.6%</td>
</tr>
<tr>
<td>Webserver (10)</td>
<td>8.0%</td>
<td>10.1%</td>
<td>13%</td>
<td>7.5%</td>
</tr>
<tr>
<td>Single-node (413)</td>
<td>4.0%</td>
<td>8.1%</td>
<td>9%</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 4.3: We also compare the classification errors of the four parallel classification to a single, exhaustive classification that accounts for all combinations of resource allocation and resource assignment jointly.

<table>
<thead>
<tr>
<th>Classification error</th>
<th>exhaustive classification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>avg (90^{th}) %ile</td>
</tr>
<tr>
<td>Hadoop (10 Jobs)</td>
<td>14.1%</td>
</tr>
<tr>
<td>Memcached (10)</td>
<td>14.1%</td>
</tr>
<tr>
<td>Webserver (10)</td>
<td>16.5%</td>
</tr>
<tr>
<td>Single-node (413)</td>
<td>11.6%</td>
</tr>
</tbody>
</table>

e engine in Quasar. We use a 40-server cluster and applications from Hadoop (10 data-mining jobs), latency-critical services (10 memcached jobs, and 10 Apache webserver loads), and 413 single-node benchmarks from SPEC, PARSEC, SPLASH-2, BioParallel, Minebench and SpecJbb. The memcached and webserving jobs differ in their query distribution, input dataset and/or incoming load. Hadoop jobs additionally differ in terms of the application logic. Details on the applications and systems can be found in Section 4.5. We show average, \(90^{th}\) percentile and maximum errors for each application and classification type. The errors show the deviation between estimated and measured performance or sensitivity to interference. On average, classification errors are less than 8% across all application types, while maximum errors are less than 17%, guaranteeing that the information that drives cluster management decisions is accurate. Table 4.2 also shows the corresponding errors for the exhaustive classification. In this case, average errors are slightly higher, especially for applications arriving early in the system [169], however, the deviation between average and maximum errors is now lower, as the exhaustive classification can accurately predict performance for the pathological cases that the four parallel classifications miss.
We also validate the selected number of profiling runs, i.e., how classification accuracy changes with the density of the input matrices. Figure 4.3(a-d) shows how the 90\textsuperscript{th} percentile of errors from classification changes as the density of the corresponding input matrix increases. For clarity, we omit the plots for Webserver, which has similar patterns to memcached. For all four classification types, a single profiling run per classification results in high errors. Two or more entries per input row result in decreased errors, although the benefits reach the point of diminishing returns after 4-5 entries. This behavior is consistent across application types, although the exact values of errors may differ. Unless otherwise specified, we use 2 entries per row in subsequent experiments. Figure 4.4 shows the overheads (profiling and classification) for the three application classes (Hadoop, memcached, single node) as input matrix density increases. Overheads are calculated with respect to the useful execution time for each workload. We assume that the hardware resources used towards profiling and classification are kept constant. Obviously as the number of profiling runs
increases the overheads increase significantly, without equally important accuracy improvements. The figure also shows the overheads from classification only (excluding profiling) for the four parallel classifications (4 parallel) and the exhaustive scheme (exhaustive). As expected, the increase in column count corresponds in an increase in decision time, often by two orders of magnitude.

4.3.3 Greedy Allocation and Assignment

The classification output is given to a greedy scheduler that jointly determines the amount, type, and exact set of allocated resources. The scheduler’s objective is to allocate the least amount of resources needed to satisfy a workload’s performance target. This greatly reduces the space the scheduler traverses, allowing it to examine higher quality resources first, as smaller quantities of them will meet the performance constraint. This approach also scales well to many servers.

The scheduler uses the classification output, to first rank the available servers by decreasing resource quality, i.e., high performing platforms with minimal interference first. Next, it sizes the allocation based on available resources until the performance constraint is met. For example, if a webserver must meet a throughput of 100K QPS with 10msec 99th percentile latency and the highest-ranked servers can achieve at most 20K QPS, the workload would need five servers to meet the constraints. If the number of highest-ranked servers available is not sufficient, the scheduler will also allocate lower-ranked servers and increase their number. The feedback between allocation and assignment ensures that the amount and quality of resources are accounted for jointly. When sizing the allocation, the algorithm first increases the per-node resources (scale-up) to better pack work in few servers, and then distributes the load across machines (scale-out). Nevertheless, alternative heuristics can be used based on the workload’s locality properties or to address fault tolerance concerns.

The greedy algorithm has $O(M \cdot \log M + S)$ complexity, where the first component accounts for the sorting overhead and the second for the examination of the top $S$ servers, and in practice takes a few msec to determine an allocation/assignment even for systems with thousands of servers. Despite its greedy nature, we show in
Section 4.6 that the decision quality is quite high, leading to both high workload performance and high resource utilization. This is primarily due to the accuracy of the information available after classification. A potential source of inefficiency is that the scheduler allocates resources on a per-application basis in the order workloads arrive. Suboptimal assignments can be detected by sampling a few workloads (e.g., based on job priorities if they are available) and adjusting their assignment later on as resources become available when other workloads terminate. Finally, the scheduler employs admission control to prevent oversubscription when insufficient resources are available.

### 4.3.4 Putting it All Together

Figure 4.5 shows the different steps of cluster management in Quasar. Upon arrival of a workload, Quasar collects profiling data for scale-out and scale-up allocations, heterogeneity, and interference. This requires up to four profiling runs that happen in parallel. All profiling copies are sandboxed (as explained in Section 4.4.2), the two platforms used are A and B (two nodes of A are used for the scale-out classification) and each profiling type produces two points in the corresponding speedup graph of the workload. The profiling runs happen with the actual dataset of the workload. The total profiling overhead depends on the workload type and is less than 5 min in all cases we examined. For non-stateful services, e.g., small batch workloads that are a large fraction of DC workloads [183], the complete profiling takes 10-15 seconds. Note that for stateful services, e.g., Cassandra, where setup is necessary, it only affects one of the profiling runs. Once the service is warmed-up, subsequent profiling only requires a few seconds to complete. Once the profiling results are available, classification provides the full workload characterization (speedup graph). Next, the greedy scheduler assigns specific servers to the workload. Overall, Quasar’s overheads are quite low even for short-running applications (batch, analytics) or long running online services.

Quasar maintains per-workload and per-server state. Per-workload state includes
Figure 4.5: The steps for cluster management with Quasar. Starting from the top, short runs using sandboxed workload copies produce the initial profiling signal that classification techniques expand to information about relationship between performance and scale-up, scale-out, heterogeneity, and interference. Finally, the greedy scheduler uses the classification output to find the number and type of resources that maximize utilization and application performance.
the classification output. For a cluster with 10 server types and 10 sources of interference, we need roughly 256 bytes per workload. The per-server state includes information on scheduled applications and their cumulative resource interference, roughly 128B in total. The per-server state is updated on each workload assignment. Quasar also needs some storage for the intermediate classification results and for server ranking during assignment. Overall, state overheads are marginal and scale linearly with the number of workloads and servers. In our experiments, a single server was sufficient to handle the total state and computation of cluster management. Additional servers can be used for fault-tolerance.

4.4 Implementation

We implemented a prototype for Quasar in about 6KLOC of C, C++, and Python. It runs on Linux and OS X and currently supports applications written in C/C++, Java, and Python. The API includes functions to express the performance constraints and type of submitted workloads, and functions to check job status, revoke it, or update the constraints. We have used Quasar to manage analytics frameworks such as Hadoop, Storm, and Spark, latency-critical services such as NoSQL workloads, and conventional single-node workloads. There was no need to change any applications or frameworks. The framework-specific code in Quasar is 100-600 LOC per framework. In the future, we plan to merge the Quasar classification and scheduling algorithms in a cluster management framework like OpenStack or Mesos.

4.4.1 Dynamic Adaptation

Some workloads change behavior during their runtime, either due to phase changes or due to variation in user traffic. Quasar detects such changes and adjusts resource allocation and/or assignment to preserve the performance constraints.

Phase detection: Quasar continuously monitors the performance of all active workloads in the cluster. If a workload runs below its performance constraint, it either went through a phase change or was incorrectly classified or assigned. In
any case, Quasar reclassifies the application at its current state and adjusts its resources as needed (see discussion below). We also proactively test for phase changes and misclassifications/misscheduling by periodically sampling a few active workloads and injecting interfering microbenchmarks to them. This enables partial interference classification in place. If there is a significant change compared to the original classification results, Quasar signals a phase change. Proactive detection is particularly useful for long-running workloads that may affect colocated workloads when entering a phase change. We have validated the phase detection schemes with workloads from SPECCPU2006, PARSEC, Hadoop and memcached. With the reactive-only scheme, Quasar detects 94% of phase changes. By sampling 20% of active workloads every 10 minutes, we detect 78% of changes proactively with 8% probability of false positives.

Allocation adjustment: Once the phase has been detected or load increases significantly for a user-facing workload, Quasar changes the allocation to provide more resources or reclaim unused resources. Quasar adjusts allocations in a conservative manner. It first scales up or down the resources given to the workload in each of the servers it currently occupies. If needed, best-effort (low priority) workloads are evicted from these servers. If possible, a scale-up adjustment is the simplest option as it typically requires no state migration. If scale-up is not possible or cannot address the performance needs, scale-out and/or migration to other servers is used. For stateless services (e.g., adding/removing workers to Hadoop or scaling a webserver), scale-out is straightforward. For stateful workloads, migration and scale-out can be expensive. If the application is organized in microshards [55], Quasar will migrate a fraction of the load from each server to add capacity at minimum overhead. At the moment, Quasar does not employ load prediction for user-facing services [96, 160]. In future work, we will use such predictors as an additional signal to trigger adjustments for user-facing workloads.

4.4.2 Side Effect Free Profiling

To acquire the profiling data needed for classification, we must launch multiple copies of the incoming application. This may cause inconsistencies with intermediate results,
duplicate entries in databases, or data corruption on file systems. To eliminate such issues, Quasar uses sandboxing for the training copies during profiling. We use Linux containers [20] with chroot to sandbox profiling runs and create a copy-on-write filesystem snapshot so that files (including framework libraries) can be read and written as usual [231]. Containers enable full control over how training runs interact with the rest of the system, including limiting resource usage through cgroups. Using virtual machines (VMs) for the same purpose is also possible [161, 210, 211, 224], but we chose containers as they incur lower overheads for launching.

### 4.4.3 Stragglers

In frameworks like Hadoop or Spark, individual tasks may take much longer to complete for reasons that range from poor work partitioning to network interference and machine instability [12]. These straggling tasks are typically identified and relaunched by the framework to ensure timely job completion [6, 11, 12, 56, 88, 139, 229]. We improve straggler detection in Hadoop in the following manner. Quasar calls the TaskTracker API in Hadoop and checks for underperforming tasks (at least 50% slower than the median). Straggling tasks are typically stalling in specific resources, which would alter the original interference profile. To detect this, Quasar injects two contentious microbenchmarks in the corresponding servers and reclassifies the underperforming tasks with respect to interference caused and tolerated. If the results of the in-place classification differ from the original by more than 20%, we signal the task as a straggler and notify the Hadoop JobTracker to relaunch it on a newly assigned server. This allows Quasar to detect stragglers 19% earlier than Hadoop, and 8% earlier than LATE [229] for the Hadoop applications described in the first scenario in Section 4.5.

### 4.4.4 Discussion

**Cost target:** Apart from a performance target, a user could also specify a cost constraint, priorities, and utility functions for a workload [188]. These can either serve as a limit for resource allocation or to prioritize allocations during very high
load.

**Resource partitioning:** Quasar does not explicitly partition hardware resources. Instead, it reduces interference by colocating workloads that do not contend on the shared resources. Resource partitioning is orthogonal. If mechanisms like cache partitioning or rate limiting at the NIC are used, interference can be reduced and more workload colocations will be possible using Quasar. In that case, Quasar will have to determine the settings for partitioning mechanisms, in the same way it determines the number of cores to use for each workload. We will consider these issues in future work.

**Fault tolerance:** We use master-slave mirroring to provide fault-tolerance for the server that runs the Quasar scheduler. All system state (list of active applications, allocations, QoS guarantees) is continuously replicated and can be used by hot-standby masters. Quasar can also leverage frameworks like ZooKeeper \[15\] for more scalable schemes with multiple active schedulers. Quasar does not explicitly add to the fault tolerance of frameworks like MapReduce. In the event of a failure, the cluster manager relies on the individual frameworks to recover missing worker data. Our current resource assignment does not account for fault zones. However, this is a straightforward extension for the greedy algorithm.

### 4.5 Methodology

**Clusters:** We evaluated Quasar on a 40-server local cluster and a 200-server cluster on EC2. The ten platforms of the local cluster range from dual core Atom boards to dual socket 24 core Xeon servers with 48GB of RAM. The EC2 cluster has 14 server types ranging from small to x-large instances. All servers are dedicated and managed only by Quasar, i.e., there is no interference from external workloads.

The following paragraphs summarize the workload scenarios used to evaluate Quasar. Scenarios include batch and latency-critical workloads and progressively evaluate different aspects of allocation and assignment. Unless otherwise specified experiments are run 7 times for consistency and we report the average and standard deviation.
**Single Batch Job:** Analytics frameworks like Hadoop [107], Storm [197], and Spark [228] are large consumers of resources on private and public clouds. Such frameworks have individual schedulers that set the various framework parameters (e.g., mappers per node and block size) and determine resource allocation (number of servers used). The allocations made by each scheduler are suboptimal for two reasons. First, the scheduler does not have full understanding of the complexity of the submitted job and dataset. Second, the scheduler is not aware of the details of available servers (e.g., heterogeneity), resulting in undersized or overprovisioned allocations. In this first scenario, a single Hadoop job is running at a time on the small cluster. This simple scenario allows us to compare the resource allocation selected by Hadoop to the allocation/assignment of Quasar on a single job basis. We use ten Hadoop jobs from the Mahout library [145] that represent data mining and machine learning analyses. The input datasets vary between 1 and 900GB. Note that there is no workload co-location in this scenario.

**Multiple Batch Jobs:** The second scenario represents a realistic setup for batch processing clusters. The cluster is shared between jobs from multiple analytics frameworks (Hadoop, Storm, and Spark). We use 16 Hadoop applications running on top of the Mahout library, four workloads for real-time text and image processing in Storm, and four workloads for logical regression, text processing and machine learning in Spark. These jobs arrive in the cluster with 5 sec inter-arrival times. Apart from the analytics jobs, a number of single-server jobs are submitted to the cluster. We use workloads from SPECCPU2006, PARSEC [30], SPLASH-2 [223], BioParallel [119], Minebench [155] and 350 multiprogrammed 4-app mixes from SPEC [181]. These single-server workloads arrive with 1 second inter-arrival times and are treated as best-effort (low priority) load that fills any cluster capacity unused by analytics jobs. There are not guarantees on performance of best-effort tasks, which may be migrated or killed at any point to provide resources for analytics tasks.

We compare Quasar to allocations done by the frameworks themselves (Hadoop, Spark, Storm schedulers) and assignments by a least-loaded scheduler that accounts for core and memory use but not heterogeneity or interference.

**Low-Latency Service:** Latency-critical services are also major tenants in cloud
facilities. We constructed a webserving scenario using the HotCRP conference management system \cite{115}, which includes the Apache webserver, application logic in PHP, and data stored in MySQL. The front- and back-end run on the same machine, and the installation is replicated across several machines. The database is kept purposefully small (5GB) so that it is cached in memory and emphasis is placed on compute, cache, memory and networking issues, and not on disk performance. HotCRP traffic includes requests to fill in paper abstracts, update author information, and upload or read papers. Apart from throughput constraints, HotCRP requires a 100msec per-request latency.

We use three traffic scenarios: flat, fluctuating, and large spike. Apart from satisfying HotCRP constraints, we want to use any remaining cluster capacity for single-node, best-effort tasks (see description in previous scenario). We compare Quasar to a system that uses an auto-scaling approach to scale HotCRP between 1 and 8 servers based on the observed load of the servers used \cite{18}. Auto-scale allocates an additional, least-loaded server for HotCRP when current load exceeds 70\% \cite{19} and redirects a fair share of the traffic to the new server instance. Load balancing happens on the workload generator side. Best-effort jobs are assigned by a least-loaded (LL) scheduler. Quasar deals with load changes in HotCRP by either scaling-up existing allocations or scaling-out (more servers) based on how the two affect performance.

Stateful Latency-Critical Services: This scenario extends the one above in two ways. First, there are multiple low-latency services. Second, these services involve significant volumes of state. Specifically, we examine the deployment of memory-based memcached \cite{87} and disk-based Cassandra \cite{38}, two latency-critical NoSQL services. Memcached (1TB state) is presented with load that fluctuates following a diurnal pattern with maximum aggregate throughput target of 2.4M QPS and a 200usec latency constraint. The disk-bound Cassandra (4TB state) has a lower load of 60K QPS of maximum aggregate throughput and a 30 msec latency constraint. Any cluster capacity unused by the two services is utilized for best-effort workloads which are submitted with 10sec inter-arrival times. To show the fluctuation of utilization with load, and since scaling now involves state migration, this scenario runs over 24 hours and is repeated 3 times for consistency. Similarly to the previous scenario, we compare
Quasar with the auto-scaling approach and measure performance (throughput and latency) for the two services and overall resource utilization. Scale-out in this case involves migrating one (64MB) or more microshards to a new instance, which typically takes a few msec.

**Large-Scale Cloud Provider:** Finally, we bring everything together in a general case where 1200 workloads of all types (analytics batch, latency-critical, and single-server jobs) are submitted in random order to a 200-node cluster of dedicated EC2 servers with 1 sec inter-arrival time. All applications have the same priority and no workload is considered best-effort (i.e., all paying customers have equal importance). The scenario is designed to use almost all system cores at steady-state, without causing oversubscription, under ideal resource allocation. We do, however, employ admission control to prevent machine oversubscription, when allocation is imperfect [59]. Wait time due to admission control counts towards scheduling overheads. Quasar handles allocation and assignment for all workloads. For comparison, we use an auto-scale approach for resource allocation of latency-critical workloads. For frameworks like Hadoop and Storm, the framework estimates its resource needs and we treat that as a reservation. For resource assignment, we use two schedulers: a least-loaded scheduler that simply accounts for core and memory availability and Paragon that, given a resource allocation, can do heterogeneity- and interference-aware assignment. The latter allows us to demonstrate the benefits of jointly solving allocation and assignment over separate (although optimized) treatment of the two.

### 4.6 Evaluation

#### 4.6.1 Single Batch Job

**Performance:** Figure 4.6 shows the reduction in execution time of ten Hadoop jobs when resources are allocated by Quasar instead of Hadoop itself. We account for all overheads, including classification and scheduling. Quasar improves performance for all jobs by an average of 29% and up to 58%. This is significant given that these
Hadoop jobs take two to twenty hours to complete. The yellow dots show the execution time improvement needed to meet the performance target the job specified at submission. Targets are set to the best performance achieved after a parameter sweep on the different server platforms. Quasar achieves performance within 5.8% of the constraint on average, leveraging the information of how resource allocation and assignment impact performance. When resources are allocated by Hadoop, performance deviates from the target by 23% on average.

**Efficiency:** Table 4.7 shows the different parameter settings selected by Quasar and by Hadoop for the H8 Hadoop job, a recommendation system that uses Mahout with a 20GB dataset [145]. Apart from the block size and replication factor, the two frameworks set job parameters differently. Quasar detects that interference between mappers is low and increases the mappers per node to 12. Similarly, it detects that...
heap size is not critical for this job and reduces its size, freeing resources for other workloads. Moreover, Quasar allocates tasks to the two most suitable server types (E and F), while Hadoop chooses from all available server types.

4.6.2 Multiple Batch Frameworks

Performance: Figure 4.9 shows the reduction in execution times for Hadoop, Storm, and Spark jobs when Quasar manages resource allocation and assignment. On average, performance improves by 27% and comes within 5.3% of the provided constraint, a significant improvement over the baseline. Apart from sizing and configuring jobs better, Quasar can aggressively colocate them. For example, it can detect when two memory-intensive Storm and Spark jobs interfere and when they can efficiently share a system. Quasar allows the remaining cluster capacity to be used for best-effort jobs without disturbing the primary jobs because it is interference-aware. Best-effort jobs come within 7.8% on average of the peak performance each job could achieve if it was running alone on the highest performing server type.

Utilization: Figure 4.10 shows the per-server CPU utilization (average across
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Figure 4.11: Throughput for HotCRP under (a) flat input load, and (b) fluctuating load. Figure 4.12(c) shows the core allocation in Quasar for the fluctuating load.

Figure 4.12: Throughput for HotCRP under (a) load with spikes. Figure 4.12(b) shows the fraction of queries meeting the latency constraint for the load with spikes.

all cores) over time in the form of a heatmap. Utilization is sampled every 5 sec. In addition to improving individual job performance, Quasar increases utilization, achieving 62% on average versus 34% with the individual framework schedulers (right heatmap). Because performance is now higher the whole experiment completes faster. Workloads after $t = 14400$ are mostly best-effort jobs that take longer than the main analytics workloads to complete.

4.6.3 Low-Latency Service

Performance: Figure 4.11a shows the aggregate throughput for HotCRP achieved with Quasar and the auto-scaling system when the input traffic is flat. While the absolute differences are small, it is important to note that the auto-scaling manager causes frequent QPS drops due to interference from best-effort workloads using idling resources. With Quasar, HotCRP runs undisturbed and the best-effort jobs achieve runtimes within 5% of minimum, while with auto-scale, they achieve runtimes within 24% of minimum. When traffic varies (Figure 4.11b), Quasar tracks target QPS
closely, while autoscale provides 18% lower QPS on average, both due to interference and suboptimal scale-up configuration. Quasar’s smooth behavior is due to the use of both scale-out and scale-up to best meet the new QPS target, leaving the highest number of cores possible for best-effort jobs (Figure 4.11c). For the load with the sharp spike, Quasar tracks QPS within 4% on average (Figure 4.12a) and meets the latency QoS for nearly all requests (Figure 4.12b). When the spike arrives, Quasar first scales up each existing allocation, and then only uses two extra servers of suitable type to handle remaining traffic. The auto-scaling system observes the load increase when the spike arrives and allocates four more servers. Due to the higher latency of scale-out and the fact that auto-scaling is not aware of heterogeneity or interference, it fails to meet the latency guarantees for over 20% of requests around the spike arrival.

4.6.4 Stateful Latency-Critical Services

Performance: Figure 4.13 shows the throughput of memcached and Cassandra over time and the distribution of query latencies. Quasar tracks throughput targets closely for both services, while the auto-scaling manager degrades throughput by 24% and
Figure 4.14: Average resource usage across all servers for four 6-hour snapshots. The cluster is running memcached (green), Cassandra (blue), and best-effort tasks (yellow) and is managed by Quasar.

12% on average for memcached and Cassandra respectively. The differences in latency are larger between the two managers. Quasar meets latency QoS for memcached for 98.8% of requests, while auto-scaling only for 80% of requests. For Cassandra, Quasar meets the latency QoS for 98.6% of requests, while the auto-scaling for 93% of requests. Memcached is memory-based and has an aggressive latency QoS, making it more sensitive to suboptimal resource allocation and assignment on a shared cluster.

**Utilization:** Figure 4.14 shows the utilization of CPU, memory capacity, and disk bandwidth across the cluster servers when managed by Quasar over 24h. Each column is a snapshot of average utilization over 6 hours. Since memcached and Cassandra have low CPU requirements, excluding the period 18:00-24:00 when Cassandra performs garbage collection, most of the CPU capacity is allocated to best-effort jobs. The number of best-effort jobs varies over time because the exact load of memcached and Cassandra changes. Most memory is used to satisfy the requirements of memcached, with small amounts needed for Cassandra and best-effort jobs. Cassandra is the nearly exclusive user of disk I/O. Some servers do not exceed 40-50% utilization for most of the experiment’s duration. These are low-end machines, for which higher utilization dramatically increases the probability of violating QoS constraints for latency-critical services. In general, the cluster utilization is significantly higher
4.6.5 Large-Scale Cloud Provider

**Performance:** Figures 4.15 and 4.16 present the overall evaluation of Quasar managing a 200-node cluster running all previously-discussed types of workloads. We compare to resource allocation based on reservations (e.g., expressed by the Hadoop scheduler or an auto-scaling system) and resource assignment on least-loaded machines (LL) or based on the interference and heterogeneity-aware Paragon. Figure 4.15a shows the performance of the 1,200 workloads ordered from worst- to best-performing, normalized to their performance target. Quasar achieves 98% of the target on average, while the reservation-based system with Paragon achieves 83%. This shows the need to perform allocation and assignment together; the intelligent resource assignment by Paragon is not sufficient. Using reservations and LL assignment performs quite poorly, only achieving 62% of the target on average.

**Cluster management overheads:** Figure 4.15b shows the cluster management overheads across the 1200 workloads. For most applications the overheads of Quasar from profiling, classification, greedy selection and adaptation are low, 4.1% of execution time on average. For short-lived batch workloads, overheads are up to 9%. The overheads are negligible for any long-running service, and even for jobs lasting a few seconds, they only induce single-digit increases in execution time. In contrast with reservation+LL, Quasar does not introduce any wait time overheads due to
Figure 4.16: Cluster utilization for 1200 workloads on 200 EC2 servers with (a) Quasar and (b) the reservation+LL system. Figure 4.16(c) shows the allocated versus used resources for Quasar and allocated for reservation+LL.

Utilization: Figures 4.16a-b show the per-server CPU utilization throughout the scenario’s execution for Quasar and the reservation+LL system. Average utilization is 62% with Quasar, while meeting performance constraints for both batch and latency-critical workloads. The reservation+LL manager achieves average utilization of 15%, 47% lower than Quasar. Figure 4.16c shows the allocated and used resources for Quasar compared to the resources reserved by the reservation+LL manager over time. Overprovisioning with Quasar is low, with the difference between allocated and used being roughly 10%. This is significantly lower than the resources reserved by the reservation-based manager, which exceed the capacity of the cluster during most of the scenario. Because Quasar has detailed information on how different allocations/assignments affect performance, it can rightszie the allocations more aggressively, while meeting the performance constraints without QoS violations.

4.7 Conclusions

We have presented Quasar, a cluster management system that performs coordinated resource allocation and assignment. Quasar moves away from the reservation-based standard for cluster management. Instead of users requesting raw resources, they specify a performance target the application should meet and let the manager size resource allocations appropriately. Quasar leverages robust classification techniques...
to quickly analyze the impact of resource allocation (scale-up and scale-out), resource type (heterogeneity), and interference on performance. A greedy algorithm uses this information to allocate the least amount of resources necessary to meet performance constraints. Quasar currently supports distributed analytics frameworks, web-serving applications, NoSQL datastores, and single-node batch workloads. We evaluated Quasar over a variety of workload scenarios and compared it to reservation/auto-scaling-based resource allocation systems and schedulers that use similar classification techniques for resource assignment (but not resource allocation). We showed that Quasar improves aggregate cluster utilization and individual application performance.
Chapter 5

iBench: Quantifying Interference in Datacenter Workloads

5.1 Introduction

In the previous two chapters we discussed the challenges that interference in shared resources poses to both performance and efficiency. We also presented a fast technique to estimate the sensitivity of a new application to different types of interference. In this chapter we expand on this analysis, and present a new benchmark suite that enables this characterization.

Resource requirements vary widely across application types. Figure 5.1 for example, shows the memory capacity and memory bandwidth requirements of a wide set of application types, including single-threaded (ST) and multi-threaded (MT) benchmark suites such as SPECCPU2006, PARSEC [30], SPLASH-2 [223], BioParallel [119] and MineBench [155], multiprogrammed (MP) mixes of these workloads, distributed batch (Hadoop) and latency-critical (memcached) applications, as well as traditional relational database workloads (MySQL). Capacity and bandwidth demands are normalized to the provisioned system values. The size of each bubble corresponds to the size of each job (number of tasks or clients). It becomes obvious that even when looking only at memory requirements, demands vary widely. Therefore, understanding the sensitivity workloads have to contention is critical towards reducing and managing
Figure 5.1: Pressure in memory capacity and memory bandwidth from a wide set of applications, as measured by iBench. The bubble size is proportional to the number of tasks (for Hadoop) or clients (for memcached) of the corresponding application.

interference in a way that enables QoS-aware operation at high utilization.

Previous work has shown the importance of accounting for interference in data-center scheduling [63, 148] and has developed hardware and software mechanisms to minimize interference effects. Mars et al. [148] show that ignoring the interference characteristics of large cloud applications in the memory subsystem can cause significant performance degradations that violate the workloads’ QoS constraints. Typically, determining the interference profile of a workload involves either retroactively observing which co-scheduled applications contend in shared resources and annotating the offending workloads [235] or profiling the workload against a carefully-crafted benchmark that puts pressure on a specific shared resource [63, 148]. The disadvantage of the first approach is that interference is determined after performance degradation has occurred, and, currently, requires manual annotation of contending workloads. The second approach is less invasive, enables interference detection before this reflects into performance degradation, but requires effort in designing targeted benchmarks that put pressure on specific resources. Currently, there is no open-source benchmark suite that enables fast characterization of the interference an application tolerates and causes in various subsystems.

In this chapter we present iBench, a novel benchmark suite that helps quantify
the sensitivity of datacenter (and conventional) applications to interference. iBench consists of a set of carefully-crafted benchmarks that generate contention of tunable intensity in various shared resources which include the core, the cache and memory hierarchy, and the storage and networking subsystems. iBench workloads are called SoIs (sources of interference). Injecting an SoI in a machine hosting an application identifies the interference that application can tolerate in the corresponding shared resource before it violates its QoS, and the interference it itself creates in the same resource. We validate iBench against a set of datacenter applications that range from distributed frameworks such as Hadoop [107], latency-critical online services like memcached [87] and conventional single-threaded, multithreaded and multiprogrammed single-node applications, and verify the accuracy and consistency of the interference measurements.

We have used iBench in various system studies, and specifically in this work we show that it improves decision quality in four use cases that extend to cloud and chip multiprocessor (CMP) systems and span hardware and software challenges. First, we use the benchmark suite to quantify the interference sensitivity of a large set of applications resembling a cloud provider mix and use this information to make resource-efficient scheduling decisions. Second, we use iBench to guide the hardware configuration of datacenter servers, such that the system is appropriately provisioned to tolerate the pressure workloads put in different resources. Third, we move the interference characterization one step in advance and use it to guide application software development, before the workload’s full deployment. iBench here is used to determine the resources where an application induces contention, and to assist the software developer to design more resource-efficient code. Given the speed of interference characterization, using iBench significantly accelerates the iterative testing process of application software. Finally, we show that iBench is applicable to studies outside datacenters and use the interference characterization to guide scheduling decisions in a large-scale heterogeneous CMP. Note that in this case characterization needs to also account for the different core designs, while being lightweight and transparent to the workload. In all cases, using iBench significantly improves the system’s ability to preserve QoS guarantees in a resource-efficient manner. Specifically, scheduling in
a datacenter using iBench preserves performance for the majority of workloads, while significantly increasing utilization, by 42%. Also, by revising code regions, based on indications from iBench, we managed to reduce the application footprint of a large, data mining application by 49%, while speeding up the workload by 35%.

5.2 Related Work

DC benchmark suites: A major roadblock when studying DC applications is the unavailability of representative workloads and input loads. Given this challenge, there is extensive work on characterization and modeling of DC applications [17, 72, 71, 74, 73, 75, 70, 120, 185] that leads to generated workloads with characteristics that closely resemble those of the original application. The generated workloads can then be used in system studies without the limitation of needing access to real DC workloads. While this is a viable approach in some cases, modeling has limitations; there are workload aspects that are not captured in the model to preserve simplicity. However omitting these aspects can cause the generated workload to deviate from its expected behavior. Additionally, modeling is more applicable to large, long-running applications that can be characterized in detail to provide some input to the model, but is less beneficial in systems like Amazon’s EC2 or Windows Azure where submitted workloads are typically unknown and no a priori assumptions can be made about their behavior.

A different track to side-step DC workload unavailability is the design of open-source versions of popular applications, which resemble their behavior and structure. Examples of such workloads are Lucene [144] and Nutch [162] for Websearch, Roundcube [179] for Webmail, or Hadoop [107] for MapReduce [56]. In the same spirit, CloudSuite [86] is an open-source benchmark suite that aggregates a set of such applications, including data analytics, media streaming and web serving. While open-source applications cannot be exact replicas of production-class workloads, they provide a reasonable approximation of their behavior.

Interference-related workloads: Recent work has shown that reducing interference is critical to preserving application performance in DCs [63, 98, 148, 200]. Govindan et al. [98] designed a synthetic cache loader to profile an application’s
cache behavior and the pressure it would put on co-scheduled workloads. Similarly, to demonstrate the impact of interference in the memory subsystem, Mars et al. [148] designed two microkernels that create tunable contention in memory capacity and memory bandwidth. These kernels are then used to quantify the sensitivity of a workload to memory interference. Additionally, Tang et al. [200] designed Smash-Bench, a benchmark suite for cache and memory contention. Benchmarks include operations on binary search trees (BSTs), arrays and 3D arrays.

With iBench we extend the resources in which interference is quantified to the core, the memory hierarchy, and the storage and networking subsystems. This enables iBench to provide critical insights on the sensitivity of applications to resource contention that can guide both software (e.g., scheduling) and hardware (e.g., server provisioning) system studies.

5.3 iBench Workloads

5.3.1 Overview

The goal of iBench is to identify the shared resources an application creates contention to, and similarly the type and amount of contention the application is sensitive to. For this purpose, all iBench workloads have tunable intensity that progressively puts more pressure on a specific shared resource until the behavior of the application changes (i.e., performance degrades). A similar technique has been shown to provide accurate estimations on sensitivity to contention in the memory subsystem [148, 200]. In total, iBench consists of 15 carefully-crafted workloads, which we call sources of interference (SoIs), each for a different shared resource. The following section describes each one of them in detail. To provide some proportionality between the intensity of the benchmark and its impact on the corresponding resource, SoIs are designed such that their impact increases almost linearly with the intensity of the benchmark. Finally, we try to ensure that the impact of the different iBench workloads is not overlapping, e.g., that the memory bandwidth SoI does not cause significant contention in memory capacity and vice versa. Section 5.4 validates that this is indeed the case across SoIs.
5.3.2 Designing the SoIs

Memory capacity (SoI1): This kernel progressively accesses larger memory footprints until it takes over the entire memory capacity. The access pattern of addresses in this case is random, but can also be set to perform strided memory accesses. The following snippet shows the basic operation of SoI1:

```c
int t = 0;
while (t < duration) {
    int ts = time(NULL);
    while (coverage < x) {
        // SSA: to increase ILP
        access[0] += data[r] << 1;
        access[1] += data[r] << 1;
        ...
        access[30] += data[r] << 1;
        access[31] += data[r] << 1;
        wait(t * acc / acc);
    }
    x++;
    t += time(NULL) - ts;
}
```

The kernel identifies automatically the size of memory available in the system and scales its footprint “almost” proportionately with time. From the snippet above, \( t \) is the total time the SoI will run for. The benchmark uses single static assignment (SSA) to increase the ILP in memory accesses, and launches as many requests as necessary to guarantee the appropriate capacity coverage at each point during its execution, e.g., at 8% intensity, capacity coverage should be 8%. The memory addresses \( r \) are selected randomly with a low-overhead random generator function. For low intensities the kernel may switch to an idle state between memory requests. \( t_x \) is the time the kernel spends at a specific intensity level, and is a function of the benchmark duration.
$t$ and the intensity level $x$. $acc_x$ is the number of accesses required to reach a specific coverage level and is also a function of the intensity $x$. The time the kernel can remain idle is proportional to $t_x$ and inversely proportional to $acc_x$. As the kernel moves to higher intensities, the fraction of time the kernel remain idle reduces as more accesses are required to achieve a certain memory coverage. By default all kernels run for 10msec, however duration is a configurable parameter.

**Memory bandwidth (SoI2):** The benchmark in this case performs streaming (serial) memory accesses of increasing intensity to a small fraction of the address space. The intensity increases until the SoI consumes 100% of the sustained memory bandwidth of the specific machine. The intensity of accesses increases linearly with the memory bandwidth used. The reason why accesses happen to a relatively small fraction of memory (e.g., 10%) is to decouple the effects of contention in memory bandwidth from contention in memory capacity. The following snippet captures the main operation of the streaming kernel:

```c
int t = 0;
while (t < duration) {
    ts = time(NULL);
    for (int cnt = 0; cnt < acc_x; cnt++) {
        access[cnt] = data[cnt]*data[cnt+4];
        wait(t_x/acc_x);
    }
    x++;
    calculate acc_x;
    t += time(NULL) - ts;
}
```

The definition of $t_x$ and $acc_x$ is the same as before. In the subsequent SoIs we skip the code snippets in the interest of space, and describe their main operation.

**Storage capacity (SoI3):** Storage corresponds to the non-volatile secondary devices, e.g., disk drives or flash that store data. We assume these are disk drives for simplicity. The microbenchmark accesses random data segments across the disk’s
sectors. The amount of accessed data increases linearly with the SoI’s intensity, i.e., at 20% intensity close to 20% of disk capacity is accessed by the SoI.

**Storage bandwidth (SoI4):** This benchmark creates traffic of increasing intensity to the hard drives of the system. Disk accesses in this case are serial and the consumed disk bandwidth increases almost linearly with the intensity of the SoI, e.g., at 100% intensity, the SoI uses close to 100% of the sustained disk bandwidth of the system.

**Network bandwidth (SoI5):** This SoI is of interest to workloads with network connectivity, e.g., online services or distributed frameworks like MapReduce. It operates by issuing network requests of increasing intensity (size and frequency of requests) to a remote host. We currently do not deploy rate limiting mechanisms, therefore the SoI can take over 100% of the available network bandwidth, essentially starving any co-scheduled application.

**Last level cache (LLC) capacity (SoI6):** The benchmark mines the `/proc/cpuinfo` of the system and adjusts its footprint, access pattern and the pace that its intensity increases based on the size and associativity of the specific LLC. The kernel issues random accesses that cover an increasing size of the LLC capacity. Because caches are structured in sets, it is easy to mathematically prove and practically guarantee that the footprint of the benchmark increases linearly with the intensity of the SoI and that its accesses are uniformly distributed. We skip the proof in the interest of space. Finally, to guarantee that accesses are not intercepted in the lower levels of the hierarchy (L1, L2) we concurrently run small tests that sweep the smaller caches (without introducing additional misses) to ensure that all accesses from the SoI go to the LLC.

**LLC bandwidth (SoI7):** This benchmark is similar to the SoI for memory bandwidth in that it performs streaming data accesses to the LLC. In this case the size and peak bandwidth the SoI targets are tuned to the parameters of the specific last level cache. Because accesses are streaming over a fraction of the cache, the lower levels of the hierarchy do not play as important a role as with random accesses. We have found that running the sweep tests for L1 and L2 does not make a significant difference when measuring sensitivity to contention in LLC bandwidth.
Figure 5.2: The iBench workloads. For each benchmark we show the system impact for increasing SoI intensity. We do not include the graphs for the L2 capacity and bandwidth SoIs. These are similar to the ones for LLC capacity and bandwidth.
**L2 capacity (SoI6’):** This is a similar benchmark to SoI6 (LLC Capacity), and is applicable in systems with 3+ levels of cache hierarchy. The footprint in this case grows up to the L2 cache size and the L2 associativity is used to tune how intensity changes over the kernel’s duration.

**L2 bandwidth (SoI7’):** Similar to SoI7 (LLC bandwidth), but tuned to the size and associativity of the L2. Accesses in this case are streaming.

**L1 i-cache (SoI8):** A simple kernel that sweeps through increasing fractions of the i-cache, until it populates its full capacity. Accesses in this case are again random.

**L1 d-cache (SoI9):** A copy of the previous SoI, tuned to the specific structure and size of the d-cache (typically the same as the i-cache).

**Translation lookahead buffer (TLB) (SoI10):** This benchmark fetches pages from memory at increasing rates until it occupies all the TLB entries. This forces long page walks for any co-scheduled application, inducing high performance degradations. Again, because of the structure of TLBs it is easy to compute the pace at which SoI intensity should increase to guarantee a linear relation with the occupied entries.

**Integer processing units (SoI11):** While the core can be approached as a single shared resource, we decide to separate the different types of operations to integer, floating point (and an optional vector SoI when SSE extensions are available). All three SoIs are assembly-level benchmarks that issue an increasing number of the corresponding type of instructions. For SoI11 these are instructions between integers.

**FP processing units (SoI12):** Similarly here, floating point instructions are issued at an increasing rate. SoIs 11 and 12 (and 15 when applicable) can run both on the same hardware thread and on different threads sharing the same core.

**Prefetchers (SoI13):** This benchmark tries to inject unpredictability in the instructions the prefetcher brings from memory, and decrease its effectiveness. This may seem similar to the operation of the L1 i-cache benchmark, however the prefetcher SoI employs a different access pattern than SoI8. Instead of simply sweeping through the L1 and evicting the co-runner’s instructions, the SoI here is a small program that only takes up a fraction of the L1 i-cache, but interleaves its instructions with the examined application’s instructions. This way the prefetcher gets tricked into
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bringing the SoI’s next “expected” instructions from memory instead of the primary application’s. Intensity here translates to the time the SoI is non-idle. This SoI also interacts in part with the system’s branch predictor.

**Interconnection network (SoI14):** This benchmark is designed using message passing primitives between cores. As the SoI intensity goes up the number and fanout of messages sent by the kernel increases. For high intensities the injected traffic becomes adversarial, leading the remaining system cores to starvation.

**Vector processing units (SoI15):** This SoI is only applicable in systems with SIMD ISA extensions, e.g., SSE3/4. It takes advantage of these extensions to launch 256-wide SIMD instructions with increasing frequency. Instructions are issued on a small data set to avoid interfering with the cache/memory hierarchy. None of the systems we tested uses extensive memoization techniques therefore operating on the same data does not reduce the load to the vector units.

## 5.4 Validation

We want to validate three aspects of iBench; first that the benchmarks indeed induce contention in their corresponding resources, and that their impact increases almost linearly with their intensity. Second, we want to evaluate the impact of iBench on conventional and DC applications and verify that the SoIs can be used to detect sensitivity to interference. Finally, we want to verify that the different SoIs do not overlap with each other in a way that voids the insights drawn about an application’s behavior, e.g., that the memory bandwidth SoI does not introduce significant contention in memory capacity.

### 5.4.1 Individual SoIs Validation

Figure 5.2 shows the impact of the 15 SoIs across their intensity spectrum (0-100%). For capacity-related benchmarks we show their cache, memory or disk footprint. For the bandwidth-related SoIs we show the fraction of bandwidth they consume normalized to the provisioned sustained cache, memory or disk bandwidth. For the
core-related SoIs we show the utilization they induce in the corresponding functional units (int, fp or vector). Finally, for the TLB benchmark we show TLB misses and for the prefetcher benchmark, prefetch misses. All measurements are collected using performance counters on a dual-socket, 8-core Nehalem server with private L1s and L2s and a shared 8MB L3 cache and 32GB of RAM. The server has a 1GB NIC and 4 500GB hard drives. Each SoI runs for 10msec on its own and covers its full range of 0 to 100% of intensity. Each SoI automatically detects the system parameters that it needs in order to adjust its operation, e.g., cache or TLB size, core count or NIC type. From Figure 5.2 we see that for all benchmarks the impact to the corresponding resource increases almost linearly with their intensity. The only SoIs that slightly deviate from linear are the core-related benchmarks Int and FP. This happens because correlating the number of issued instructions to the eventual system utilization is harder than correlating the number of cache accesses to the capacity used. We plan to further refine these workloads to better approach linear load increase as part of future work.

5.4.2 SoI Impact on Applications

iBench is aimed to detect and quantify the sensitivity of DC and conventional workloads to various sources of interference. Here we validate that this operation is accurate. We inject iBench workloads in a conventional application (mcf from the SPECCPU2006 suite) and in a DC latency-critical application (memcached [87]) and measure their sensitivity to interference in the corresponding resources. Each application runs on a single server, and memcached is set up with 1000 clients launching 40,000 QPS in total, with a target per-request latency of 200usec. mcf is profiled for 10msec against the LLC capacity SoI, and memcached against the network bandwidth SoI. Both SoIs inflate to full intensity (100%). Figure 5.3a, b shows the results for mcf and Figure 5.3c, d for memcached. Figure 5.3a shows the performance impact of contention in LLC capacity for mcf and the corresponding miss rate curve as the intensity of the SoI increases. Comparing the two shows that the SoI indeed induces significant performance degradation to the application due to cache contention. The
Figure 5.3: Validation of the impact contention generated using iBench has on mcf and memcached. Figure 5.3a shows the performance of mcf when co-scheduled with the LLC capacity SoI, while Figure 5.3b shows its new miss rate curve as SoI intensity increases. Figure 5.3c shows the performance of memcached when running with the network bandwidth SoI and Figure 5.3d shows its bandwidth share compared to when running alone.

point when performance gets a significant hit coincides with the moment when the miss rate increases rapidly, therefore the SoI is correctly stressing its target resource. Similarly, for memcached we show the performance impact from increased contention in the network and the bandwidth fraction memcached manages to extract compared to the target fraction it needs to preserve its performance requirements. Again there is a direct correlation between performance degradation and its cause. As SoI intensity increases, the goodput of memcached (fraction of requests that meet their target latency) rapidly decreases. Figure 5.3d shows the reason behind this degradation. For high SoI intensities, the bandwidth share of memcached becomes increasingly smaller, introducing queueing delays to incoming requests. At the same time, examining its cache miss rate or memory behavior does not show significant variations compared to when memcached is running alone. This verifies that the SoI is confined to its specific resource and does not violently disrupt the utilization of other subsystems. We further validate this observation in the following subsection. We have also verified
that these results are consistent across the different SoIs for various workload types.

5.4.3 Correlation between SoIs

Finally, we verify that different sources of interference (SoIs) do not overlap and interfere with each other. For this purpose we co-schedule two SoIs at a time in the same core of the 8-core system previously used. Figure 5.4 shows the increase in intensity and corresponding performance normalized to isolation for a co-schedule of the memory capacity and memory bandwidth SoIs. As shown in the figure, for high system loads, there is a small impact in the ability of each SoI to reach its full intensity. Similarly there is a slight degradation in performance compared to running in isolation. However, for both SoIs degradations are mild, which means that the different benchmarks do not induce significant contention outside their target resource. This is important to both obtain accurate interference measurements, and make valid assumptions on their causes. We have performed this experiment with different SoI combinations with similar results.
5.5 Use Cases

5.5.1 Datacenter Scheduling

Currently, DC operators often disallow application co-scheduling in shared servers to preserve QoS guarantees. However, this leads to serious resource underutilization. On the other hand, co-scheduling applications can induce interference due to contention in shared resources. We use iBench to quantify the tolerance a workload has to various sources of interference, and similarly the interference it causes in shared resources. Given this information, a scheduler determines the applications that can be safely co-scheduled without performance degradation from interference. For this use case, the scheduler simply tries to minimize:

$$||i_t - i_c||_{L_1}$$

(5.1)

where $i_t$ and $i_c$ the tolerated and caused interference for two examined applications. The tolerated interference is calculated as described in Section 5.4. The caused interference is similarly calculated, by quantifying the impact the examined workload has on the performance of an SoI. The $L_1$ norm is calculated across the different SoIs. More sophisticated scheduling techniques can be deployed to take better advantage of the information provided by iBench [63]. Obviously applications can change behavior during their execution. This is especially true for DC workloads [24, 152]. The scheduler adapts to these changes to preserve QoS throughout an application’s execution. If at any point in time it detects that an application is running under its QoS, the scheduler injects iBench workloads to the system to construct a new interference profile. Any further scheduling decisions use the new interference profile. Required migrations due to behavior changes are handled by a low-overhead live migration system present in the cluster. In the event where migration is not possible, the scheduler disallows additional applications to be placed on the same machine as the affected workload.

We design three scenarios; first a cloud workload mix that resembles a system like EC2, where 200 applications are submitted in a 40-machine cluster with 1 sec
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inter-arrival times. All nodes are dual socket, 4-12 core machines with private L1 and L2 caches and shared L3 caches, and 16-48GB of RAM. All applications are selected randomly from a pool consisting of the full SPECCPU2006 suite, 22 workloads from PARSEC [30], SPLASH-2 [223], BioParallel [119] and Minebench [155], 140 multiprogrammed workloads of 4 SPEC applications each, based on the methodology in [181], and 10 I/O-bound data mining workloads [173]. The second scenario involves a Hadoop workload running distributed on 40 nodes with low-priority best-effort (BE) applications occupying the remaining server capacity, and the third scenario involves a 40-node installation of memcached, running as the primary process and best-effort applications using the remaining resources. Figure 5.5a compares application performance for the first scenario when quantifying interference using iBench, against a baseline scheduler that only considers the CPU and memory requirements of an application and assigns workloads to least-loaded (LL) servers (w/o iBench). The latter is common practice in many cloud providers today [212]. Performance is normalized to running in isolation and applications are ordered from worst- to best-performing.
Figure 5.6: Utilization achieved by a scheduler that uses iBench compared to a system that ignores interference in scheduling decisions. For the first scenario fewer machines are needed (and for less time) (Figure 5.6a, b), while for the second (Figure 5.6c) and third scenarios (Figure 5.6d) more best-effort applications are co-scheduled with the primary workload.

Using iBench to quantify the pressure applications put on various system resources improves performance, by 15.7% on average and up to 25%. Similarly, performance improves in the second and third scenario both for the primary workloads (Hadoop and memcached respectively) and the best-effort applications. Managing interference is beneficial to utilization as well, since more applications can be scheduled on the same machine. Figure 5.6 shows the utilization for each of the three scenarios when accounting for interference using iBench and when using the baseline least-loaded (LL) scheduler. The benefits are twofold; first utilization increases, improving resource-efficiency for the DC operator (Figure 5.6a). Second, the duration of the scenario reduces because applications are running near their target performance. Figure 5.6b offers a closer look at utilization across the different servers in the cluster throughout the scenario’s execution. The increase in utilization is also consistent for the other two scenarios (35.6% and 27.1% respectively on average). There is still some performance degradation in these scenarios, which iBench cannot prevent. This is due to
Figure 5.7: Using iBench to provision a server that hosts a specific workload improves performance and reduces resource contention. Figure 5.7a compares the old and new interference profiles of the workload. Figure 5.7b shows the CPI distribution for memcached in the original system configuration and after reconfiguring the system based on the interference profile from iBench, and Figure 5.7c shows that utilization decreases, as resources are appropriately balanced to reduce contention.

fast-changing workloads, complex applications that introduce inaccuracies in interference measurements, or workloads that have pathologies when co-scheduled with specific applications. Additional mechanisms can be used to address these issues.

5.5.2 Server Provisioning

Provisioning servers is especially difficult for cloud providers that have to accommodate any - possibly unknown - submitted workload. Even in the case of well-studied, long-running applications the datacenter architect must deal with evolving application code and varying user patterns. Here we use the output of iBench to guide the way system resources are balanced in a DC server running memcached [87]. The workload runs with 1000 clients launching a total of 40,000QPS with a latency constraint of 200usec. Figure 5.7a shows the interference profile of the application running on a default server configuration (4 cores, 8MB L3, 16GB RAM, 1GB NIC) across the
different SoIs. It is evident that the application puts significant pressure on the cache hierarchy and the network and memory subsystems (SoI2: memory bandwidth, SoI5: network bandwidth, SoI7: LLC bandwidth and SoI11-12: core). Based on this information we adjust the parameters of the system. To alleviate the contention in the memory hierarchy we switch to a triple-memory channel server with 24GB of total memory capacity. Similarly, we move from a server with a 1GB to a 10GB NIC to accommodate the application’s network demands. We maintain the core count and the rest of the system parameters the same. Figure 5.7a also shows the new interference profile, where both the contention in the cache/memory hierarchy and the network subsystem are now significantly reduced. Figure 5.7b shows the distribution of CPI in the default server configuration and in the server provisioned based on the output of iBench, while Figure 5.7c compares the CPU utilization in the two systems. In both cases accounting for contention when provisioning the system improves application performance (the CPI curve is shifted to the left in the new system) and reduces CPU throttling due to memory stalls. Similarly, we can use the information on resource contention to guide the microarchitecture design (cache hierarchy, pipeline organization, etc.) of hardware aimed to service a particular application.

5.5.3 Application Development/Testing

An important reason behind resource inefficiency is poor application design. Workloads are often written without sufficient considerations of sensible resource usage, resulting in unnecessarily bloated code, huge memory footprints, and high CPU utilization. This problem is even more prominent in DC workloads, which are often complex, multi-tier applications with several interdependent components. Despite the long testing periods devoted to these workloads, robustness and performance are typically the main optimization objectives, with resource-efficiency being less important. Here we show that using iBench to identify code regions that cause high contention not only improves efficiency by eliminating unnecessary resource consumption, but is also beneficial to performance by reducing resource contention.
Figure 5.8: Performance (IPC), CPU utilization and memory bandwidth utilization for the testing application across three optimization iterations using iBench. While performance for the original application is low, with the CPU being saturated, identifying contentious regions in the code progressively improves throughput and decreases resource utilization, improving resource efficiency.
For this purpose we start with an unoptimized data mining application that performs collaborative filtering on a large dataset of sparse data. The data are movie ratings from 180k users. Running the original version of the code, which relies on Singular Value Decomposition and PQ-reconstruction [173, 33] results in very high contention in LLC capacity, bandwidth, L1 d-cache and L2 cache capacity and bandwidth, memory bandwidth and FP computation. Running the program to completion takes approximately 1.6h. The performance of the original code is shown in Figure 5.8 (first row, leftmost figure). The second and third figures in the first row show the CPU and memory bandwidth utilization of the program (normalized to sustained memory bandwidth for the server). After detecting the points of contention using iBench, we optimize parts of the code to make better use of system resources. In the first code iteration we switch to SIMD operations using SSE4 [158]. As shown in the second row in Figure 5.8 both performance and resource efficiency benefit. The boost in performance comes from leveraging spatial locality in matrix accesses, while the decrease in required resources comes from performing fewer operations on larger chunks of data and reducing the misses to the cache hierarchy. We now repeat the interference characterization for the new program. iBench again helps identify remaining inefficiencies in the code that induce resource contention. We progressively address these with optimizations such as reordering of operations to the matrix elements or memoizing intermediate results. After each iteration we reevaluate the application’s performance and resource utilization. As shown in the last row of Figure 5.8 the final code runs in 35% less time than the original unoptimized version while requiring fewer system resources. While the code optimizations shown here are relatively straightforward, we believe that given the speed of obtaining the interference profile, using signals from iBench can significantly facilitate the development and testing process of large applications.

5.5.4 Scheduling in Heterogeneous CMPs

Finally, we show that iBench is applicable outside DC system studies. CMPs today consist of tens of - often - heterogeneous cores [205, 189, 221, 240]. Scheduling for these
systems is challenging because in addition to the interference between applications that share resources, the scheduler should account for system heterogeneity. Similarly to the first use case, we design a simple scheduler that takes the interference profile obtained by iBench and identifies how each application from a multiprogrammed mix should be mapped to heterogeneous cores. When the mix is submitted to the system, each workload is briefly profiled against the iBench workloads to obtain its interference profile. Each SoI requires at most 10msec and runs can be done in parallel by replicating and sandboxing the application binary. Profiling can additionally leverage classification techniques to reduce the training overhead, by only profiling against a subset of SoIs and deriving the missing entries based on similarities with previous applications [27, 63]. We first create 40 4-SPECCPU2006 application mixes and schedule them on a simulated 4-core CMP [181] with 2 Xeon-like and 2 Atom-like cores from different generations each. The simulator captures contention in the cache and memory hierarchy, therefore the same process as before is used to quantify the impact of interference on application performance. The examined workloads do not exhibit storage or network activity hence we do not use the SoIs creating contention in those resources (SoI3-5). SPEC workloads are classified with regards to their cache demands as insensitive (n), friendly (f), fitting (t) and streaming (s), and mixes are created based on the methodology in [181]. Cores differ in their frequency, private cache hierarchy and microarchitectural details (e.g., pipeline, prefetchers, branch predictors, issue width). All cores share an 8MB last level cache (LLC) and 16GB of memory. The scheduler uses iBench to identify the type of core and co-scheduled applications that constrain interference and selects the mapping that minimizes the average interference across workloads. Although this is not necessarily a global optimum it is good enough that performance does not degrade and utilization increases. The scheduler can also take advantage of workload signatures [205] to further refine the application-to-core mapping search space. We also create 60 16-application mixes and schedule them in a similar system with 16 cores. The variability in frequencies and cache hierarchies here is more widespread. Figure 5.9 shows the performance obtained when using iBench to guide the scheduling decisions. The upper figures show the performance of the 4-app mixes ordered from worst to best-performing compared
Figure 5.9: Scheduling in heterogeneous CMPs. The upper figures show performance across the 4-application mixes and a per-application breakdown for selected mixes. The lower figures show the performance for the 16-application mixes and a breakdown of execution time to various subsystems for select mixes, before (B) and after (A) the use of iBench for scheduling.

to isolated runs, and the breakdown to per-application performance for selected mixes. Performance degradations are marginal for most workloads. The lower figures show the performance across the 16-app mixes and the breakdown of clock cycles to the various subsystems for selected mixes. While without the use of iBench several mixes spend significant fractions waiting in memory instead of executing instructions, by minimizing interference larger fractions of time are devoted to useful execution. We plan to perform a more detailed study of scheduling tradeoffs in heterogeneous CMPs as part of future work.

5.6 Conclusions

We presented iBench, a benchmark suite that measures the tolerated and caused interference of a workload in various shared resources. iBench is geared towards DC applications, but can also be applied to conventional workloads. It consists of 15
benchmarks (SoIs) that induce pressure over a wide range of shared resources that span the core, cache hierarchy, memory, storage and networking subsystems. iBench quantifies the type and degree of interference that an application generates in this set of shared resources. Similarly, it measures the type and intensity of interference an application can tolerate before violating its QoS across the same resources. We have validated the accuracy and consistency of iBench against a number of DC applications, ranging for conventional single-node applications, to distributed Hadoop workloads, and latency-critical online services. We have also evaluated a number of use cases for iBench. First, we use the interference information obtained with iBench to schedule workloads in an EC2-like environment in a way that minimizes interference between co-scheduled applications and improves system utilization. Second, we have shown how iBench can assist towards making informed decisions on the hardware specifications of a chip aimed for DC workloads, or on the provisioning of a DC server. Third, we have shown how iBench can be used by software developers to design more resource-efficient applications during testing. Finally, we have shown that iBench is applicable outside the context of DCs, and have used it for scheduling in large-scale heterogeneous CMPs. In all cases, using iBench significantly improves the decision quality, performance, and resource efficiency of the system.
Chapter 6

ARQ: QoS-Aware Admission Control

6.1 Introduction

An increasing amount of computing is performed in the cloud, primarily due to cost benefits for both the end-users and the operators of datacenters (DC) that host cloud services [24]. The operator of a cloud service must schedule the stream of incoming applications on available servers in a resource-efficient manner, i.e., achieving fast execution (user’s goal) at high resource utilization (operator’s goal). This scheduling problem is particularly difficult for several reasons, including diverse application characteristics [24, 130], insufficient workload knowledge, co-scheduled application interference and platform heterogeneity. An additional challenge occurs during periods of adversarial traffic, i.e., intervals with very high load, when the system can become oversubscribed, resulting in poor performance. Most DCs employ some admission control to minimize such effects.

DC users are interested in two performance metrics; how fast the application starts running (waiting time) and how fast it completes thereafter (execution time). While recent work has shown how to improve execution time in the presence of unknown workloads, varying interference sensitivities and heterogeneous servers [63], it does not solve the “head of line blocking” problem [183]. Additionally, some applications have
strict scheduling deadlines, while others can tolerate delays in order to be assigned to preferred servers. In all cases, resource requirements should be taken into account at admission point [36].

We propose ARQ (Admission control with Resource Quality-awareness), a QoS-aware admission control protocol that builds on Paragon and accounts for the resource quality an application needs to preserve its QoS. Resource quality reflects the additional load a server can support without violating application QoS, given its configuration and the applications it currently hosts. For example, a server hosting a low-latency key-value store and a relational database has high resource quality for a Spark job, if it can accommodate it without any performance violations for the new or previous applications. ARQ divides workloads into multiple classes and directs them to different queues. This way demanding workloads do not block easy-to-satisfy applications, as they wait for an appropriate server to become available. On the other hand, since DC applications have strict QoS guarantees, they can only be queued for limited amounts of time, while waiting for an appropriate server. ARQ detects when an application is about to violate its performance requirements and re-directs it to a different queue before the QoS violation occurs. We explore the trade-off between waiting time and quality of resources and solve the corresponding optimization problem to find the optimal switching point.

We evaluate ARQ both in small and large-scale experiments. First, we compare the system without and with ARQ in a local cluster with 40 machines and show the benefits in performance and efficiency. We also evaluate ARQ on a 1000-server cluster on Amazon EC2. For an oversubscribed scenario with 8500 applications, Paragon with ARQ guarantees that 99% of workloads have less than 10% performance degradation, while improving utilization by 46%.

6.2 Background

As we described in Chapter 3, Paragon is a QoS-aware scheduler that accounts for server platform heterogeneity and interference between co-scheduled applications.
While accounting for these factors allows Paragon to improve application performance, and cluster utilization, the scheduler has no logic to decide when applications should be admitted and scheduled. Paragon accounts for workload characteristics to decide where to assign a workload, but it does not solve the “head of line blocking” problem that can cause high waiting times. By default, applications are scheduled in a simple FIFO order. This has two shortcomings; first, easy-to-satisfy workloads can get trapped behind demanding applications, e.g., workloads that require exclusive instances of high-end, multi-socket servers to preserve their QoS. Second, in the event of an oversubscribed scenario, i.e., when the required resources are more than the total resources available in the system, Paragon implements an application-agnostic admission control protocol. It queues applications in a single queue until the first server becomes available, and then resumes FIFO-ordered scheduling. This ignores the fact that applications need resources of a certain quality to meet their QoS, and can result in performance degradation.

6.3 Admission Control

6.3.1 Overview

Large cloud providers such as Amazon EC2 and Windows Azure, typically deploy some admission control protocol. This prevents machine oversubscription, i.e., the same core servicing more than one application, resulting in high interference and QoS violations.

We design ARQ, a \textit{QoS-aware admission control protocol} that queues and schedules applications based on the quality of resources they need. This solves two problems; first, applications that demand few, easy-to-satisfy resources are not blocked behind demanding workloads. Second, if no suitable servers are available for a given application, the workload waits for a server of appropriate quality to be freed. Alternatively, the application would be directed to the first free server to avoid queueing delays, with the risk of performance losses.

\textbf{Resource quality:} The resource demands of a workload reflect the load a server
should support for the application to meet its QoS. This is a function of the interference the server can tolerate from the new application, and the interference the new workload can tolerate from applications already running on the machine. We use the classification engine of Paragon to derive the interference each server tolerates ($t_k$) and the interference each application causes ($c_k$) on a set of shared resources. Shared resources include the cache and memory hierarchy, CPU modules and storage and network devices. Details on how $c_k$'s and $t_k$'s are obtained can be found in Chapter 3.

The interference profile of a server is updated upon initiation or completion of an application’s execution. This information guides scheduling decisions by assigning applications to suitable servers. Given the interference profile of application $i$, we define resource quality as:

$$Q_i = \sum_k c_k$$  \hspace{1cm} (6.1)

Similarly, resource quality for a server is defined as the sum of $t_k$ over the different shared resources. $Q_i$'s are normalized in 0 to 100%. Conceptually, high $Q_i$ reflects applications sensitive to interference, that need high quality resources. Low $Q_i$ on the other hand, corresponds to workloads that are insensitive to interference, and can satisfy their QoS even when assigned to servers of poor resource quality, e.g.,
highly-loaded machines, or machines with few cores.

**Multi-class admission control:** We design ARQ as an admission control protocol with multiple classes of “customers” [16, 29, 111, 131, 153], where customers in this case correspond to applications. The class an application belongs to is determined by its $Q_i$ value. Applications with $Q_i$ values that fall in the same range are assigned to the same class. We assume ten classes of applications for now, and justify this selection in the evaluation section (see sensitivity study in Section 6.5). Figure 6.1 shows an overview of ARQ. Each queue corresponds to applications of a specific class. From top to bottom we move from more to less demanding applications. Upon arrival, the cluster manager determines the class an application belongs to and queues it appropriately. Each class has a corresponding server pool of appropriate resource quality. Separating applications based on their resource quality requirements helps ARQ resolve bottlenecks where applications that are sensitive to interference block workloads that are not. On the other hand, applications cannot be queued indefinitely waiting for the perfect server. We address this issue by diverting workloads to queues with better or worse resource qualities.

### 6.3.2 Waiting Time versus Resource Quality

Diverging an application to a different queue creates a trade-off between the time an application is waiting in a queue, and the quality of resources it is allocated. We approach this trade-off as an optimization problem.

**Queue bypassing:** When there is no available server in the pool of a class, queued workloads should be diverted to another queue. There are two possible options for where a workload can be redirected. First, it can be *diverted to a higher queue*. If the queue directly above the queue the workload was originally placed in is empty, the workload is assigned to one of its servers. This hurts utilization, since resources of higher quality than necessary are allocated, but preserves the workload’s QoS requirements. In the opposite case the workload is *diverted to a lower queue*. In that case, performance may be degraded, since the application receives resources of lower quality than required. However, the scheme guarantees that in all cases the
Figure 6.2: CDF of server busy times and CDF of the probability that there will be at least one free server within a specific time window from an application’s arrival.

application will be assigned to a server within the time window dictated by its QoS constraints.

**Free-server probability distributions:** ARQ needs to know the likelihood that a server of a specific class will become available within the time an application can be queued for, to decide when the workload should be diverted to the next queue. We statistically analyze the server busy time periods for each server pool to obtain these probability distributions. Busy periods are defined as the per-server time intervals from the moment a server is assigned a workload, until that workload completes.

We first use distribution fitting to represent the per-pool server busy time in a closed form using known distributions. Figure 6.2a shows the CDF of server busy time for the first server pool (highest quality servers) in a 1,000 server experiment. More details on the methodology can be found in Section 6.4. We show the experimental data (dots) and the closed form representation, derived from distribution fitting. In this case, the data is fitted to a curve resembling a normal distribution. The CDF reflects the fraction of servers that are freed within some time after they have been allocated to an application. For example, 60% of servers in this server pool are freed within 2700 sec from the time an application is scheduled to them.

Using this closed form CDF we easily derive the free-server CDF, which reflects the probability that within a time interval from an application’s arrival, at least one server of the corresponding pool will be available. Figure 6.2b shows the free-server probability CDF for the first server pool. The highlighted point shows that there is a
60% probability that within 56 sec from an application’s arrival to that queue, there
will be at least one free server in the pool. Free-server CDFs are updated during
workload execution to capture changes in application behavior.

**Switching between queues:** ARQ determines the switching point between queues
with the objective to maximize the probability that a server becomes available within
a certain window from an application’s arrival. For simplicity of explanation we
assume that an application’s QoS is defined at 0.95x of the application’s optimal
performance. This means that the workload can tolerate at most a 5% performance
degradation. Scheduling deadlines or queries-per-second (QPS) can also serve as
queueing constraints. Given the free-server CDFs for each server pool, ARQ solves
the following optimization problem for application $a$, switching between queues $i$ and
$j$:

$$\max \{ (S_a - wt_i(t)) \cdot Q_i \cdot Pr_i[t], (S_a - wt_j(t)) \cdot Q_j \cdot Pr_j[t] \}$$

$$s.t. (wt_i(t) + wt_j(t) + P_a) < 0.05 \cdot CT_a$$

where $Pr_i[t]$ is the probability that there is a free server in queue $i$, $Q_i$ is the
resource quality of queue $i$, $CT_a$ is the optimal execution time for application $a$, $P_a$
is the classification overhead of Paragon, and $S_a = 1.05 \cdot CT_a - P_a$ is the available
“slack” that can be used for queueing, before the application violates its QoS con-
straints. ARQ finds the switching time that maximizes the probability that a server
of either queue $i$ or $j$ will become available such that the application preserves its
QoS guarantees. It also promotes waiting longer for a server of the same class rather
than eagerly switching to the next queue ($Q_i > Q_j$).

In our analysis we assume batch, single-node applications. In the case of interac-
tive or transactional workloads additional care must be taken to accommodate load
changes, e.g., through VM migration. The scheduler detects such changes and ad-
justs workload placement to preserve QoS. Detection is based on SoI injection and
application reclassification.
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<td>2.27</td>
<td>2</td>
<td>12</td>
<td>32/32</td>
<td>12</td>
<td>48 DDR3</td>
<td>1</td>
</tr>
<tr>
<td>Xeon MP</td>
<td>3.16</td>
<td>4</td>
<td>4</td>
<td>16/16</td>
<td>8</td>
<td>8 DDR2</td>
<td>5</td>
</tr>
<tr>
<td>Xeon E5345</td>
<td>2.33</td>
<td>1</td>
<td>4</td>
<td>32/32</td>
<td>8</td>
<td>32 FB-DIMM</td>
<td>8</td>
</tr>
<tr>
<td>Xeon E5335</td>
<td>2.00</td>
<td>1</td>
<td>4</td>
<td>32/32</td>
<td>8</td>
<td>16 FB-DIMM</td>
<td>8</td>
</tr>
<tr>
<td>Opteron 240</td>
<td>1.80</td>
<td>2</td>
<td>2</td>
<td>64/64</td>
<td>2</td>
<td>4 DDR2</td>
<td>7</td>
</tr>
<tr>
<td>Atom 330</td>
<td>1.60</td>
<td>1</td>
<td>2</td>
<td>32/24</td>
<td>1</td>
<td>4 DDR2</td>
<td>5</td>
</tr>
<tr>
<td>Atom D510</td>
<td>1.66</td>
<td>1</td>
<td>2</td>
<td>32/24</td>
<td>1</td>
<td>8 DDR2</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 6.1: Main characteristics of the servers of the local cluster. The total core count is 178 for 40 servers of 10 different SCs.

### 6.4 Methodology

**Server systems:** We evaluated Paragon on a 40-machine local cluster (Table 6.1) and a 1000-machine cluster with 14 server types on EC2. We used exclusive (reserved) server instances, i.e., there is no interference from external workloads. We also verified that no external scheduling decisions or actions such as auto-scaling or migration are performed during the course of the experiments.

**Schedulers:** We compared Paragon with ARQ to four schedulers. First, Paragon without admission control, second, a heterogeneity-oblivious scheme that only accounts for interference but not heterogeneity. Third, an interference-oblivious scheme and finally, a scheduler that is both heterogeneity and interference-agnostic, and assigns applications to least-loaded machines.

**Workloads:** We used 29 single-threaded, 22 multithreaded, 350 multi-programmed and 12 I/O-bound workloads. We use the full SPEC CPU2006 suite and workloads from PARSEC [30], SPLASH-2 [223], BioParallel [119], Minebench [155] and SPECjbb. For multiprogrammed workloads, we use 350 mixes of 4 applications each [181]. The I/O-bound workloads are data mining applications in Hadoop and Matlab. For scenarios with more than 413 applications we replicated these workloads with equal likelihood and randomized their interleaving.

**Workload scenarios:** For the small-scale experiments we examine three workload
Figure 6.3: Performance comparison of Paragon and ARQ, across two workload scenarios, against Paragon without admission control, a heterogeneity-oblivious, an interference-oblivious and a least-loaded scheduler.

Figure 6.4: Overheads from classification, queueing and scheduling compared to useful execution time. Overall, the overheads in Paragon with ARQ are less than 5% for most applications.

scenarios. First, we examine a low-load scenario with 178 applications, selected randomly from the workload pool, and submitted with 10 sec inter-arrival times. Second, a high-load scenario where 178 applications arrive following a Gaussian distribution ($\mu=10$, $\sigma^2=1$) that experience significant phases during their execution. Finally, we examine a scenario, where 178 applications arrive with 1 sec intervals. This is an oversubscribed scenario, since after a few seconds there are not enough resources to execute all applications concurrently. For the large-scale experiments on EC2 we examine an oversubscribed scenario where 7,500 workloads arrive with 1 sec intervals and an additional 1,000 applications arrive in burst after the first 3,750 workloads.
CHAPTER 6. ARQ

6.5 Evaluation

6.5.1 Small-scale Experiments

Performance: Figure 6.3 shows the performance comparison between the different schedulers for the second and third scenarios in the small-scale cluster. The differences for the low-load scenario where resources are plentiful are small. We focus on the differences between Paragon without and with the use of ARQ. Applications are ordered from worst to best performing. For the scenario with workload phases the applications that preserve their QoS increase from 66% to 91%, and the average performance improves to 99.3%. For the oversubscribed system, while without ARQ only 64% of applications maintain their QoS, with ARQ 88% of workloads preserve their performance requirements. This shows that accounting for resource quality at admission point drains the backlog of queued workloads much faster.

Overheads: ARQ limits waiting time to preserve QoS. Figure 6.4 shows the breakdown of execution time for selected applications in the oversubscribed scenario. Time is divided in useful execution time, overheads from training and classification, overheads from the greedy server selection [63] and overheads from queueing. mcf and blackscholes do not have a bar for the least-loaded (LL) scheduler because they did not complete successfully due to memory exhaustion in the server. In all cases overheads are very low and execution time for most workloads is very close to one (optimal). The overheads from queueing are less than 5% at all times. The cases where queueing
CHAPTER 6. ARQ

is high correspond to workloads that had to be diverged to queues of lower resource quality, in which case useful execution time is also suboptimal.

**Resource allocation:** Figure 6.5a shows the required versus allocated core count for Paragon with and without ARQ for the oversubscribed scenario. Once the system enters the oversubscribed phase ([9000-17000] sec), Paragon without ARQ allocates all available cores and then queues applications, while Paragon with ARQ will only dispatch applications if an appropriate server is freed. This drains the backlog faster since, even though applications are queued for longer, they run in higher quality platforms.

**Server utilization:** We also measure server utilization before and after the use of ARQ. We focus on the oversubscribed scenario where ARQ has the highest impact. Paragon without ARQ improves utilization by 47% compared to a LL scheduler. Adding ARQ slightly reduces this improvement since applications are queued instead of being dispatched immediately. Despite this, utilization still improves by 45.5%. This means that the performance benefits of ARQ do not incur an efficiency penalty.

**Sensitivity to design parameters:** Figure 6.5b shows the performance - utilization tradeoff for different numbers of queues. Both metrics are normalized to the values for 10 queues. More queues result in fewer cases of workloads being blocked behind demanding applications, therefore they improve performance, but reduce the number of servers in the corresponding pools, hurting utilization. In contrast, few queues revert to the default scheduler where many applications are scheduled in FIFO order, increasing utilization and hurting performance. 10 queues achieve both high performance and efficiency.

**Additional policies:** Finally, we evaluate ARQ when computation time and priorities are taken into account in the admission control. Table 6.2 shows the harmonic mean (hmean) and standard deviation of the difference between the expected and achieved computation time when ARQ implements Shortest Job First (SJF). Workloads are grouped based on their ideal computation time from most short-running to most long-running. SJF prioritizes short over long running applications for all workload classes, with the additional constraint that long applications should still maintain their QoS, therefore cannot be indefinitely bypassed. Results are shown for
Table 6.2: Deviation between expected and achieved *computation time* for workloads in the oversubscribed scenario when ARQ implements SJF. Applications are ranked by increasing expected computation time.

<table>
<thead>
<tr>
<th>Workloads</th>
<th>hmean</th>
<th>standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shortest 5%</td>
<td>0.20%</td>
<td>0.15%</td>
</tr>
<tr>
<td>Shortest 10%</td>
<td>0.30%</td>
<td>0.08%</td>
</tr>
<tr>
<td>Shortest 25%</td>
<td>1.20%</td>
<td>0.30%</td>
</tr>
<tr>
<td>Shortest 50%</td>
<td>1.45%</td>
<td>0.34%</td>
</tr>
<tr>
<td>Shortest 75%</td>
<td>1.78%</td>
<td>0.26%</td>
</tr>
<tr>
<td>Shortest 90%</td>
<td>2.31%</td>
<td>0.55%</td>
</tr>
<tr>
<td>Shortest 95%</td>
<td>2.32%</td>
<td>0.57%</td>
</tr>
<tr>
<td>All</td>
<td>2.28%</td>
<td>0.53%</td>
</tr>
</tbody>
</table>

Table 6.3: Deviation between expected and achieved *completion time* for workloads in the oversubscribed scenario when ARQ implements priorities. Applications are grouped in high priority and low priority ones.

<table>
<thead>
<tr>
<th>Workloads</th>
<th>hmean</th>
<th>standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>High-priority (20%)</td>
<td>0.80%</td>
<td>0.06%</td>
</tr>
<tr>
<td>Low-priority (80%)</td>
<td>2.74%</td>
<td>0.32%</td>
</tr>
</tbody>
</table>

the oversubscribed scenario. As shown in the table, short running jobs experience minimal performance degradation, while the long running applications have higher degradations, but still within their QoS requirements (5% execution time increase).

Additionally, we evaluate ARQ in the presence of workload priorities. We increase the priorities of 20% of workloads in the oversubscribed scenario and compare the expected and achieved completion time for them (see Table 6.3). As seen in the table, the high-priority workloads complete within 2% of their ideal completion time. Low-priority applications also complete within their QoS constraints, in most cases, but experience higher performance degradations than high priority workloads.

**Large-scale experiments:** Figure 6.6 compares the performance of the different schedulers for the large-scale scenario. While Paragon without ARQ only preserves QoS for 61% of workloads, introducing admission control increases that fraction to 83%. Additionally, it bounds degradation to less than 10% for 99% of workloads. This shows that the protocol scales well with the number of servers and applications,
Figure 6.6: Performance for the different schedulers in the oversubscribed scenario on 1,000 EC2 machines.

while maintaining overheads similar to the ones for the small-scale experiments.

6.6 Related Work

We discuss work related to ARQ in terms of admission control in computer systems and analysis of multi-class queueing networks.

Admission control systems: A lot of work has highlighted the importance of admission control in computer systems, including datacenters (DCs). Cherkasova et al. [47, 48] propose a predictive and a session-based admission control scheme respectively for overloaded web servers. The schemes monitor the utilization and QoS achieved at runtime and preemptively adjust the admission policy to more or less aggressive, such that QoS is preserved. In the same spirit, Bartolini et al. [26] propose a self-configurable overload control policy that adjusts the rate of admitted sessions to preserve SLAs and improve utilization. Liu et al. [141] propose an adaptive scheme based on queueing theory to control the performance of multi-tier web applications. Carlstrom et al. [36] also design a session-based admission control protocol for web servers that leverages generalized processor sharing (GPS) [167] to maximize a reward function that corresponds to the rate of completed jobs. Similarly, Salehi et al. [180] propose a preemption-aware admission control system for virtualized systems, where
the system services both internal and external requests, with the internal requests having preemptive priority over external requests. The scheme maximizes the rate of admitted requests, subject to preserving per-application SLAs. Cheng et al. [46] also divide the application space to high and low-priority workloads and partition the server’s capacity to service workloads with different priorities. The authors propose a threshold-based admission control algorithm where thresholds depend on the application’s priority, and rewards are higher for critical versus non-critical applications. Finally, Guitart et al. [104] consider the problem of admission control in the context of a secure web application and propose an adaptive overload control strategy based on SSL connection differentiation.

Techniques such as predictive admission control [47, 141], protection against DoS attacks, or schemes that additionally account for application security at admission control [104], are orthogonal to the design of ARQ, and can be incorporated in the scheme if the corresponding functionality is desired.

**Multi-class queueing networks:** Multiclass queueing networks have applications in a wide spectrum of systems ranging from banks, to product lines and network systems. Miller [153] analyzes a multi-class queueing network that optimizes the rewards obtained by accepting or rejecting customers in a system with multiple customer classes. Bertsimas et al. [29] study the distribution of steady-state queue lengths for a multi-class markovian queueing network and propose a methodology based on Lyapunov functions for the performance analysis of MCs with infinite states, including multi-class queueing networks. Kulkarni et al. [131] examine an admission control protocol for multi-class traffic with service priorities in high-speed networks. They assign different size buffers to each class and derive policies to guarantee per-class QoS. Stolyar [196] discusses the stability of multi-class queueing networks, whose stochastic process is a continuous time MC. He shows that the sequence of underlying stochastic processes converges to a fluid process with sample paths defined as fixed points of a special operator and defines the conditions under which the network is stable. In the same context, Chen [44] studies the fluid approximation and stability of a multi-class queueing network.
Gurvich [106] provides an overview of the design and control of multi-class queueing networks (M/M/N queues with multiple types of customers and many servers). He analyzes the V-Model of skills-based routing, and examines how different customer classes are scheduled to servers and how many servers are required to minimize staffing and waiting costs. Sethuraman et al. [186] propose that globally optimal scheduling for a multi-class system with parallel queues reduces to finding the optimal routing matrix under the assumption that the optimal sequencing strategy for each server is a simple static priority policy. Atar et al. [16] also consider asymptotic optimality in a multi-class queueing system with many exponential servers, under the presence of heavy traffic.

In the context of computer systems, Gemikonakli et al. [91] model the performance of a virtualized server using a multi-class M/M/1 queueing model, where applications of different rates arrive in each queue. They analyze the stability, backlog and throughput of the system using an MC model. In a system that resembles a multi-class queue, Yolken et al. [227] propose a game-based capacity allocation system, where each client receives service rate proportional to the bid on resources he submitted to the system operator. Each client has a flow of jobs and although applications are serviced in a FCFS manner, service rates vary across jobs.

### 6.7 Conclusions

We have presented ARQ, a QoS-aware admission control protocol for heterogeneous datacenters. ARQ divides applications to classes based on their resource quality requirements and queues them separately in a multi-class network. ARQ is derived from validated queueing models, and it improves system throughput by reducing application waiting time, and diverging workloads to different queues when necessary. In an oversubscribed scenario with 8,500 applications on 1,000 servers, 99% of workloads experience less than 10% degradation compared to 79% of workloads without ARQ.
Chapter 7

Tarcil: Reconciling Scheduling Speed and Quality in Large Shared Clusters

7.1 Introduction

In the previous chapters we have presented practical systems that accurately determine the resource requirements of new, previously-unknown cloud applications. Once these requirements are identified, the cluster scheduler must decide where in a cluster to place a new workload. The large size of these clusters (up to tens of thousands of servers) and the high arrival rate of jobs (up to millions of tasks per second) make cluster scheduling quite challenging. The scheduler must determine which specific hardware resources, e.g., servers and cores, should be used by each job. Ideally, scheduling decisions lead to three desirable properties. First, each workload receives resources that enable it to achieve predictably high performance. Second, jobs are packed tightly on available servers, achieving high cluster utilization. Third, decisions introduce minimal scheduling overheads, allowing the scheduler to handle large clusters and high job arrival rates.

Recent research on cluster scheduling can be examined along two dimensions; scheduling concurrency (throughput) and scheduling speed (latency).
With respect to scheduling concurrency, there are two groups of work. In the first scheduling is serialized, with a centralized scheduler making all decisions [118, 66]. In the second group, decisions are parallelized through two-level, distributed or shared-state designs. Two-level schedulers, such as Mesos and YARN, use a centralized coordinator to divide resources between frameworks like Hadoop and MPI [112, 208]. Each framework uses its own scheduler to assign resources to incoming tasks. Since neither the coordinator nor the framework schedulers have a complete view of the cluster state and all task characteristics, scheduling is suboptimal [183]. Shared-state schedulers like Omega [183] allow multiple schedulers to concurrently access the whole cluster state using atomic transactions. Finally, Sparrow uses multiple concurrent, stateless schedulers to sample and allocate resources [166].

With respect to the speed at which scheduling decisions happen, there are again two groups of work. The first group examines most of (or all) the cluster state to determine the most suitable resources for incoming tasks, in a way that addresses the performance impact of hardware heterogeneity and interference in shared resources [63, 98, 147, 157, 226, 235]. For instance, Quasar [66] uses classification to determine the resource preferences of incoming jobs. Then, it uses a greedy scheduler to search the cluster state for resources that meet the application’s demands on servers with minimal contention. Similarly, Quincy [118] formulates scheduling as a cost optimization problem that accounts for preferences with respect to locality, fairness and starvation-freedom. Such schedulers make high quality decisions that lead to high application performance and high cluster utilization. Unfortunately, they need to greedily inspect the cluster state on every scheduling event. Their decision overhead can be prohibitively high for large clusters, and in particular for the very short jobs of real-time analytics (100ms - 10s) [166, 228]. Using multiple greedy schedulers improves scheduling throughput but not latency, and terminating the greedy search early typically lowers the decision quality, especially at high cluster loads.

The second group improves the speed of each scheduling decision by only examining a small number of machines. Sparrow reduces scheduling latency through resource sampling [166]. The scheduler examines the state of two randomly-selected servers for each required core and selects the one that becomes available first. While Sparrow
Figure 7.1: Distribution of job performance on a 200-server cluster with concurrent, sampling-based [166] and centralized greedy [63] schedulers and Tarcil for three scenarios: 1) short, homogeneous Spark [228] tasks (100ms average duration), 2) Spark tasks of medium duration (1s–10s), and 3) long Hadoop analytics tasks (10s–10min). The ideal performance (100%) assumes no scheduling overheads and no performance degradation due to interference. The cluster utilization is 80%. 
improves scheduling speed, its decisions can be poor because it ignores the heterogeneity and interference preferences of jobs. Typically concurrent schedulers follow sampling schemes, while centralized systems are paired with sophisticated scheduling algorithms.

Figure 7.1 illustrates the tradeoff between scheduling speed and quality. Figure 7.1a shows the probability distribution function (PDF) of application performance for three scenarios of variable job duration using Sparrow [166] on a 200-server EC2 cluster. For very short jobs (100ms), fast scheduling allows most workloads to achieve 80% to 95% of the ideal performance on this cluster. In contrast, jobs with medium (1s–10s) or long duration (10s–1min) suffer significant degradation and achieve 50% to 30% of ideal performance. As duration increases, jobs become more heterogeneous in their resource requirements (e.g., preference for high-end cores), and interference between jobs sharing a server matters. In contrast, the scheduling decision speed is not as critical.

Figure 7.1b shows the PDF of job performance using the Quasar scheduler that accounts for heterogeneity and interference [66]. The centralized scheduler leads to near-optimal performance for long jobs. In contrast, medium and short jobs are penalized by the latency of scheduling decisions, which can exceed the execution time of the shortest jobs. Even if we use multiple schedulers to increase the scheduling throughput [183], the per-job overhead remains prohibitively high.

We propose Tarcil, a scheduler that achieves the best of both worlds: high quality and high speed decisions, making it appropriate for large, highly-loaded clusters that host both short and long jobs. Similar to Quasar [63, 66], Tarcil starts with rich information on the resource preferences and interference sensitivity of incoming jobs. Similar to Sparrow [166], it uses sampling to avoid examining the whole cluster state on every decision. However, there are two key differences in Tarcil’s architecture. First, Tarcil uses sampling not merely to find available resources but to identify resources that best match a job’s resource preferences. The sampling scheme is derived using analytical methods that provide statistical guarantees on the quality of scheduling decisions. Tarcil additionally adjusts the sample size dynamically based on the quality of available resources. Second, Tarcil uses admission control to avoid
scheduling a job that is unlikely to find appropriate resources. To handle the tradeoff between long queueing delays and suboptimal allocations, Tarcil uses a small amount of coarse-grain information on the quality of available resources.

We use two clusters of 100 and 400 servers on Amazon EC2 to show that Tarcil leads to low scheduling overheads and predictably high performance for a wide range of workload scenarios. For a heavily-loaded, heterogeneous cluster running short Spark jobs, Tarcil improves average performance by 41% over Sparrow [166], with some jobs running 2-3x faster. For a cluster running a wide range of applications from short Spark tasks to long Hadoop jobs and low-latency services, Tarcil achieves near-optimal performance for 92% of jobs, in contrast with only 22% of jobs with a distributed, sampling-based scheduler and 48% with a centralized greedy scheduler [66]. Finally, Figure 7.1c, shows that Tarcil enables close to ideal performance for the vast majority of jobs of the three scenarios.

7.2 Background

Our work draws from related efforts to improve scheduling speed and quality in large, shared datacenters:

Concurrent scheduling:

Scheduling becomes a bottleneck for clusters with thousands of servers and high workload churn. An obvious solution is to schedule multiple jobs in parallel [112, 183]. We assume a structure similar to Google’s Omega [183], where multiple scheduling agents can access the whole cluster state. As long as these agents rarely attempt to assign work to the same servers (infrequent conflicts), they proceed concurrently without additional delays. Section 7.5 discusses conflict resolution.

Sampling-based scheduling:

Based on results from randomized load balancing [154], we can design sampling-based cluster schedulers [166]. Sampling the state of just a few servers reduces the latency
of scheduling decisions and the probability of conflicts between concurrent scheduling
agents, and is likely to find available resources in lightly- or medium-loaded clusters.
The recently-proposed Sparrow scheduler uses batch sampling and late binding [166].
Batch sampling examines the state of two servers for each of $m$ required cores by an
incoming job and selects the $m$ best cores. If the selected cores are busy, tasks are
queued locally in the sampled servers and assigned to the machine where resources
become available first. In our evaluation we compare Tarcil with Sparrow.

**Heterogeneity & interference-aware scheduling:**

Hardware heterogeneity occurs in large clusters because servers are populated and re-
placed over time [63, 226]. Moreover, the performance of tasks sharing a server may
degrade significantly due to interference on shared resources such as caches, memory
and I/O channels [63, 98, 147, 161]. A scheduler can improve task performance signifi-
cantly by taking into consideration its resource preferences. For instance, a particular
task may perform much better on 2.3GHz Ivy-Bridge cores compared to 2.6GHz Ne-
halem cores, while another task may be particularly sensitive to interference from
cache-intensive workloads executing on the same server.

The key challenge in heterogeneity and interference-aware scheduling is knowing
the preferences of incoming jobs. We start with a system like Quasar that automatic-
ically estimates resource preferences and interference sensitivity [63, 66]. Quasar
profiles each incoming job for a few seconds on two server types, while two mi-
crobenchmarks place pressure on two shared resources. The sparse profiling sig-
nal on resource preferences is transformed into a dense signal using collaborative
filtering [33, 128, 173, 222]. Collaborative filtering projects the signal against all in-
formation available from previously-run jobs, identifying similarities in resource and
interference preferences. These include examples such as the preferred core frequency
and cache size for a job or the memory and network contention it generates. Quasar
performs profiling and collaborative filtering online. We perform this analysis offline,
given that workloads like real-time analytics are repeated multiple times, potentially
over different data (e.g., daily or hourly).
7.3 The Tarcil Scheduler

7.3.1 Overview

Tarcil is a shared-state scheduler that allows multiple, concurrent agents to operate on the cluster state [183]. In this section, we describe the operation of a single agent.

The scheduler processes incoming workloads as follows. Upon submission, Tarcil first looks up the job’s resource and interference sensitivity preferences [63, 66]. This information provides estimates of the relative performance on the different server platforms, as well as estimates of the interference the workload can tolerate and generate in shared resources (caches, memory, I/O channels). Next, Tarcil performs admission control. Given statistics on the cluster state, it determines whether the scheduler is likely to quickly find resources of satisfactory quality for a job, or whether it should queue it for a while. Admission control is useful when the cluster is highly loaded. A queued application waits until it has a high probability of finding appropriate resources or until a queueing-time threshold is reached. Tarcil maintains coarse-grained statistics on available resources for admission control decisions. These statistics are updated as jobs begin and end execution.

For admitted jobs, Tarcil performs sampling-based scheduling with the sample size adjusted to satisfy statistical guarantees on the quality of allocated resources. The scheduler also uses batch sampling if a job requests multiple cores. Tarcil examines the quality of sampled resources to select those best matching the job’s preferences. It additionally monitors the performance of running jobs. If a job runs significantly below its expected performance, the scheduler adjusts the scheduling decisions. This is useful for long-running workloads; for short jobs, the initial scheduling decision determines performance with little space for adjustments.

7.3.2 Analytical Framework

We use the following framework to design and analyze sampling-based scheduling in Tarcil.

Resource unit (RU): Tarcil manages resources at RU granularity using Linux
containers [54]. Each RU consists of one core and an equally partitioned fraction of the server’s memory and storage capacity and the provisioned network bandwidth. For example, a server with 16 cores, 64GB DRAM, 480GB of Flash and a 10GE NIC has 16 RUs, each with 1 core, 4 GB DRAM, 30GB of Flash and 625ME of network bandwidth. Because all our experiments are on public cloud providers where the network topology is unknown, in our evaluation we do not partition network bandwidth.

**RU quality:** The utility an application can extract from an RU depends on the hardware type (e.g., 2GHz vs 3GHz core) and the interference on shared resources from other jobs on the same server. Classification [63, 66] obtains the interference preferences of an incoming job using a small set of microbenchmarks to inject pressure of increasing intensity (from 0 to 99%) on one of ten shared resources of interest [61]. Interference preferences capture, first, the amount of pressure $t_i$ a job can tolerate in each shared resource $i$ ($i \in [1, N]$), and second, the amount of pressure $c_i$ it itself will generate in the same resource. High values of $t_i$ or $c_i$ imply that a job will tolerate or cause a lot of interference on resource $i$. $t_i$ and $c_i$ take values in $[0, 99]$. In most cases, jobs that cause a lot of interference in a resource are also sensitive to interference on the same resource. Hence, to simplify the rest of the analysis we assume that $t_i = 99 - c_i$ and express resource quality as a function of caused interference in an RU.

Let $W$ be an incoming job and $V_W$ the vector of interference it will cause in the $N$ shared resources, $V_W = [c_1, c_2, ..., c_N]$. To capture the fact that different jobs are sensitive to interference on different resources [147], we reorder the elements of $V_W$ by decreasing value of $c_i$ and get $V'_W = [c_j, c_k, ..., c_n]$, with $c_j > c_k > ... > c_n$. Finally, we obtain a single value for the resource requirements of $W$ using an order-preserving encoding scheme that transforms $V'_W$ to a concatenation of its elements:

$$V_{W_{enc}} = c_j \cdot 10^{(2 \cdot (N-1))} + c_k \cdot 10^{(2 \cdot (N-2))} + ... + c_n$$

(7.1)

For example if $V'_W = [84, 31]$ then $V_{W_{enc}} = 8431$. The expression above is provably the most dense encoding that preserves the full entropy of the values of vector $V'_W$ and their ordering, for general $V'_W$. Finally, for simplicity we normalize $V_{W_{enc}}$ in $[0, 1]$
and derive the target resource quality for job $W$: \[
T_W = \frac{V_{W_{enc}}}{10^{2N} - 1}, \quad T_W \in [0, 1]
\] (7.2)

A high value for the quality target $T_W$ implies that job $W$ is resource-intensive. Its performance will depend a lot on the quality of the scheduling decision.

We now need to find RUs that closely match this target quality. To determine if an available resource unit $H$ is appropriate for job $W$, we calculate the interference caused on this RU by all other jobs occupying RUs on the same server. Assuming $M$ resource units in the server, the total interference $H$ experiences on resource $i$ is:

\[
C_i = \frac{\sum_{m \neq H} c_i}{M - 1}
\] (7.3)

Starting with vector $V_H = [C_1, C_2, ..., C_N]$ for $H$ and using the same reordering and order-preserving encoding as for $T_W$, we calculate the quality of resource $H$ as:

\[
U_H = 1 - \frac{V_{H_{enc}}}{10^{2N} - 1}, \quad U_H \in [0, 1]
\] (7.4)

The higher the interference from colocated tasks, the lower $U_H$ will be. Resources with low $U_H$ are more appropriate for jobs that can tolerate a lot of interference and vice versa.

Comparing $U_H$ for an RU against $T_W$ allows us to judge the quality of resource $H$ for incoming job $W$:
Figure 7.3: Resource quality CDFs under the uniformity assumption in linear and log scale for sample size R=8, 16, 32 and 64.

\[ Q = \begin{cases} 
1 - (U_H - T_W), & \text{if } U_H \geq T_W \\
T_W - U_H, & \text{if } U_H < T_W
\end{cases} \] (7.5)

If \( Q \) equals 1, we have an ideal assignment with the server tolerating as much interference as the new job generates. If \( Q \) is within \([0, T_W]\), selecting RU \( H \) will degrade the job’s performance. If \( Q \) is within \([T_W, 1)\), the assignment will preserve the workload’s performance but is suboptimal. It would be better to assign a more demanding job on this resource unit.

**Resource quality distribution:** Figure 7.2 shows the distribution of \( Q \) for a 100-server cluster with \( \sim 800 \) RUs (see Section 7.6 for cluster details) and one hundred, 10-min Hadoop jobs as resident load (50% cluster utilization). For a non-demanding new job with \( T_W = 0.3 \) (left), there are many appropriate RUs at any point in time. In contrast, for a demanding job with \( T_W = 0.8 \), only a small number of resources will lead to good performance. Obviously, the scheduler must adjust the sample size for incoming jobs based on \( T_W \).

### 7.3.3 Sampling-based Scheduling with Guarantees

We can now derive the sample size that provides statistical guarantees on the quality of scheduling decisions.

**Assumptions and analysis:** To make the analysis independent of cluster load, we make \( Q \) an absolute ordering of RUs in the cluster. Starting with equation (5),
Figure 7.4: Comparison of resource quality CDFs under the uniformity assumption, and as measured in a 100-server cluster.

we sort RUs based on $Q$ for incoming job $W$, breaking any ties in quality with a fair coin, and distribute them uniformly in $[0, 1]$, i.e., for $N_{RU}$ total RUs, $Q(i) = i/(N_{RU} - 1)$, $i \in [0, N_{RU} - 1]$. Because $Q$ is now a probability distribution function of resource quality, we can derive the sample size in the following manner.

Assume that the scheduler samples $R$ RU candidates for each RU needed by an incoming workload. If we treat the qualities of these $R$ candidates as random variables $Q_i (Q_1, Q_2, ..., Q_R \sim U[0, 1])$ that are uniformly distributed by construction and statistically independent from each other (i.i.d), we can derive the distribution of quality $Q$ after sampling. The cumulative distribution function (CDF) of the resource quality of each candidate is: $F_{Q_i}(x) = \text{Prob}(Q_i \leq x) = x$, $x \in [0, 1]$. Since the candidate with the highest quality is selected from the sampled set, its resource quality is the random variable $A = \max\{Q_1, Q_2, ..., Q_R\}$, and its CDF is:

$$F_A(x) = \text{Prob}(A \leq x) = \text{Prob}(Q_1 \leq x \land ... \land Q_R \leq x) = \text{Prob}(Q_i \leq x)^R = x^R, \ x \in [0, 1]$$ (6)

This implies that the distribution of quality after sampling only depends on the sample size $R$. Figure 7.3 shows CDFs of resource quality distributions under the uniformity assumption, for sample sizes $R = \{8, 16, 32, 64\}$. The higher the value of $R$, the more skewed to the right the distribution is, hence the probability of finding only candidates of low quality quickly diminishes to 0. For example, for $R = 64$ there

\[1\]This assumes $Q_i$ to be continuous variables, although in practice they are discrete. This makes the analysis independent of the cluster size $N_{RU}$. The result holds for the discretized version of the equation.
is a $10^{-6}$ probability that none of the sampled RUs will have resource quality of at least $Q = 80\%$ ($\text{Prob}(Q < 0.8 | \forall RU) = 10^{-6}$).

Figure 7.4 validates the uniformity assumption on a 100-server EC2 cluster running short Spark tasks (100msec ideal duration) and longer Hadoop jobs (1-10min). The cluster load is 70-75% (see methodology in Section 7.6). In all cases, the deviation between the analytically derived and measured distributions of $Q$ is minimal, which shows that the analysis above holds in practice. In general, the larger the cluster, the more closely the quality distribution approximates uniformity.

Large jobs: For jobs that need multiple RUs, Tarcil uses batch sampling [166, 168]. For $m$ requested units, the scheduler samples $R \cdot m$ RUs and selects the $m$ best among them as shown in Figure 7.5a. Some applications experience locality between sub-tasks or benefit from allocation of all resources in a small set of machines (e.g., within a single rack). In such cases, for each sampled RU, Tarcil examines its neighboring resources and makes a decision based on their aggregate quality as shown in Figure 7.5b. Alternatively, if a job prefers distributing its resources across machines the scheduler will allocate RUs in different machines, racks and/or cluster switches, assuming knowledge of the cluster’s topology. Placement preferences for reasons such as security [187] can also be specified in the form of attributes at submission time by the user.

Sampling at high load: Equation (6) estimates the probability of finding near-optimal resources accurately when resources are not scarce. When the cluster operates at high load, we must increase the sample size to guarantee the same probability of finding a candidate of equally high quality, as when the system is unloaded. Assume a system with $N_{RU} = 100$ RUs. Its discrete CDF is $F_A(x) = P[A \leq x] = x, \ x = 0, 0.01, 0.02, ..., 1$. For sample size $R$, this becomes: $F_A(x) = x^R$, and a quality target of $Pr[Q < 0.8] = 10^{-3}$ is achieved with $R = 32$. Now assume that 60% of the RUs are already busy. If, for example, only 8 of the top 20 candidates for this task are available at this point, we need to set $R$ s.t. $Pr[Q < 0.92] = 10^{-3}$, which requires a sample size of $R = 82$. Hence, the sample size for a highly loaded cluster can be quite high, degrading scheduling latency. In the next section, we introduce an admission control scheme that bounds sample size and scheduling latency, while still allocating
Figure 7.5: Batch sampling in Tarcil with sample size $R = 4$ for (a) a job with two independent tasks $A$ and $B$, and (b) a job with two subtasks $A_1$ and $A_2$ that exhibit locality. $x$-marked RUs are already allocated, striped RUs are sampled, and solid black RUs are allocated to the incoming job after sampling.

high quality resources.

7.4 Admission Control

7.4.1 Pre-scheduling Queueing

When available resources are plentiful, jobs are immediately scheduled using the sampling scheme described in Section 7.3. However, when load is high, the number of resources of sufficient quality may be very small and the sample size needed to find them can become quite large. Tarcil employs a simple admission control scheme that queues jobs until resources of proper quality become available and estimates how long an application should wait at admission control.

A simple indication to trigger job queueing is the count of available RUs in the cluster. This, however, does not yield sufficient insight into the quality of available RUs. If most RUs have poor quality for an incoming job, it may be better for it to
wait. Unfortunately, a naïve quality check involves accessing the state of the whole cluster, which would introduce prohibitive overheads. Instead, we maintain a small amount of coarse-grain information which allows for a fast check. We leverage the information on contention scores that is already maintained for each RU to construct a contention score vector $[C_1 C_2 ... C_N]$ from the resource contention $C_i$ it experiences in each of its resources, due to interference from neighboring RUs. We use locality sensitive hashing (LSH) based on random selection to hash these vectors into a small set of buckets [13, 42, 173]. LSH computes the cosine distance between vectors and assigns RUs with similar contention scores in the respective resources to the same bucket. We also separate RUs by platform type to account for heterogeneity. We only keep a single count of available RUs for each bucket. The hash for an RU (and the counter of the corresponding bucket) needs to be recalculated upon instantiation or completion of a job in an RU. Updating the per-bucket counters is a fast operation, out of the critical path for scheduling. Note that excluding updates in RU status, LSH is only performed once.

Admission control works as follows. We check the bucket(s) that correspond to the resources with quality that matches the incoming job’s preferences. If these buckets have counters close to the number of RUs the job needs, the application is queued. Queued applications wait until the probability that resources are freed increases or until an upper bound for waiting time is reached. To estimate waiting time, Tarcil records the rate at which RUs of each bucket became available in recent history. Specifically, it uses a simple feedback loop to estimate when the probability that an appropriate RU exists approximates 1 for a target bucket. The distribution is updated every time an RU from that bucket is freed. Tarcil also sets an upper bound for waiting time at $\mu + 2 \cdot \sigma$, where $\mu$ and $\sigma$ are the mean and standard deviation of the corresponding “time-until-free” PDF. If the estimated waiting time is less than the upper bound, the job waits for resources to be freed; otherwise it is scheduled to avoid excessive queueing. Although admission control adds some complexity, in practice it only delays workloads at very high cluster utilizations (over 80%-85%).

Validation of waiting time estimation: Figure 7.6 shows the probability that
Figure 7.6: Actual and estimated (dot) probability for a target RU to exist as a function of waiting time for three buckets.

A desired RU will become available within time $t$ for different buckets for a heterogeneous 100-server EC2 cluster running short Spark tasks and longer Hadoop jobs. The cluster utilization is approximately 85%. We show the probabilities for r3.2xlarge (8 vCPUs) instances with CPU contention ($A$), r3.2xlarge instances with network contention ($B$), and c3.large (2 vCPUs) instances with memory contention ($C$). The distributions are obtained from recent history and vary across buckets. The dot in each line shows the estimated waiting time by Tarcil, which closely approximates the measured time for an appropriate RU to be freed (less than 8% deviation on average). In all experiments, we use 20 buckets, and history of the past 2 hours, which was sufficient to make accurate estimations of available resources. The number of buckets and/or history length may vary for different systems.

7.4.2 Post-scheduling Queueing

A job that exceeds the upper bound on queueing may still require a high sample size. To avoid excessive scheduling overheads, we cap the sample size at 32 and instead use late binding on the sampled servers until resources become available [166]. If the best two of the 32 sampled RUs are currently busy, the job is locally queued in both until the first RU is freed and is subsequently removed from the queue of the second RU. Note that local queueing is unlikely in practice.
CHAPTER 7. TARCIL

7.5 Tarcil Implementation

7.5.1 Tarcil Components

Figure 7.7 shows the components of the scheduler. Tarcil is a distributed, shared-state scheduler and, unlike Quincy or Mesos, it does not have a central coordinator [112, 118]. Scheduling agents work in parallel, are load-balanced by the cluster front-end, and each agent has a local copy of the shared server state, which contains the list and status of all RUs in the cluster.

Since all schedulers have full access to the cluster state, conflicts are possible. Conflicts between agents are resolved using lock-free optimistic concurrency as discussed in [183]. The system maintains one resilient master copy of state. Each scheduling agent has a local copy of this state which is updated frequently. When an agent makes a scheduling decision it attempts to update the master copy of the state using an atomic write operation. While an agent performs this action no other agent can update these resources in the master copy. Once the commit is successful the resources are yielded to the corresponding agent. Any other agent with conflicting decisions needs to resample resources. The local copy of state of each agent is periodically synced (every 5-10sec) with the master. The timing of the updates includes a small random seed such that not all agents update their state at exactly the same time, making the master the bottleneck. When the sample size is small, decisions of scheduling agents rarely overlap and each scheduling action is fast (~ 10 − 20ms, for a 100-server cluster and \( R = 8 \), over an order of magnitude faster than centralized approaches). When the number of sampled RUs increases beyond \( R = 32 \) for very large jobs, conflicts can become more frequent, which we resolve using incremental transactions on the non-conflicting resources [183]. In the event where one scheduling agent crashes, an idle cluster server resumes its role, once it has obtained a copy of the master state.

Each worker server has a local monitor module that handles scheduling requests, federates resource usage in the server, and updates the quality of RUs. When a new task is assigned to a server by a scheduling agent, the monitor updates the status of the RU in the master copy and notifies the scheduling agent and admission
Figure 7.7: The different components of the scheduler and their interactions. Each of the scheduling agents has a local copy of the cluster state, while an additional server has the master copy of the state, for scheduling actions. Each worker server has a local monitor that tracks resource usage, and handles scheduling requests.
control. Finally, a per-RU load monitor evaluates performance in real time. When the monitor detects that a job’s performance deviates from its expected target, it notifies the proper agent for a possible allocation adjustment. The load monitor also notifies agents of CPU or memory saturation, which triggers resource autoscaling (see Section 7.5.2).

We currently use Linux containers to partition servers into RUs. Containers enable CPU, memory and I/O isolation. Each container is configured to a single core and a fair share of the memory and storage subsystem, and the network bandwidth. Containers can be merged to accommodate multicore workloads, using cgroups. Virtual machines (VMs) can also be used to enable workload migration, but would incur higher overheads.

Figure 7.8 traces a scheduling event. Once a job is submitted, admission control evaluates whether it should be queued or not. Once the assigned scheduling agent sets the sample size according to the job’s constraints, it samples the shared cluster state for the required number of RUs. Sampling happens locally in each agent. The agent computes the resource quality of sampled resources and selects the ones that should be allocated to the job. The actual selection takes into account the resource quality and platform preferences, as well as any locality preferences of a task. The agent then attempts to update the master copy of the state. Upon a successful commit the agent notifies the local monitor of the selected server(s) over RPC and launches the task in the target RU(s). The local monitor notifies admission control, and the master copy to update their state. Once the task completes, the local monitor issues RPCs that update the master state and notify the agent and admission control; the scheduling agent then informs the cluster front-end.

7.5.2 Adjusting Allocations

For short-running tasks, the quality of the initial assignment is particularly important. For long-running tasks, we must also consider the different phases the program can go through. Similarly, we must consider cases where Tarcil makes a suboptimal allocation due to inaccurate classification, deviations from fully random selection in
the sampling process, or a compromise in resource quality at admission control. Tarcil uses the per-server load monitor, i.e., a local daemon running in each RU, to measure the performance of active workloads in real time. This can correspond to instructions per second (IPS), packets per second or a high-level application metric, depending on the application type. Tarcil compares this metric to any performance targets the job provides or are available from previous runs of the same application. If there the job is not satisfying its QoS constraints, the scheduler takes action. Since we are using containers, the primary action we take is to avoid scheduling other jobs on the same server. For scale-out workloads, the system also employs a simple autoscale service which allocates more RUs (locally or not) to improve the job’s performance.

7.5.3 Fairness

Users can submit jobs with priorities. Jobs with higher priority will bypass others at admission control and preempt lower-priority jobs during resource selection. Tarcil also allows the user to select between incremental scheduling, where tasks from a job get progressively scheduled as resources become available and all-or-nothing gang scheduling, where either all or no task from a job is scheduled. We leave the experimental evaluation of priorities and other policies to future work.
Figure 7.9: Sensitivity of sampling overheads and response times to sample size.

7.6 Evaluation

7.6.1 Tarcil Analysis

We first evaluate Tarcil’s scalability and its sensitivity to parameters such as the sample size and task duration.

Sample size: Figure 7.9 shows the sensitivity of sampling overheads and response times to the sample size for homogeneous Spark jobs with 100msec duration and cluster loads varying from 10% to 90% on the 110-server EC2 cluster. All machines are r3.2xlarge memory-optimized instances (61GB of RAM). 10 servers are used by the scheduling agents, and the remaining 100 machines serve incoming load. The boundaries of the boxplots depict the 25th and 75th percentiles, the whiskers the 5th and 95th percentiles and the horizontal line in each boxplot shows the mean. As sample size increases, the overheads increase. Until $R = 32$ overheads are marginal even at high loads, but they increase substantially for $R \geq 64$, primarily due to the overhead of resolving conflicts between the 10 scheduling agents used. Hence, we cap sample size to $R = 32$ even under high load. Response times are more sensitive to
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Figure 7.10: Sensitivity to the number of concurrent scheduling agents. Figure 7.10a shows the scheduling latency, and Figure 7.10b the fraction of jobs that meet QoS.

Sample size. At low load, high quality resources are plentiful and increasing $R$ makes little difference to performance. As load increases, sampling with $R = 2$ or $R = 4$ is unlikely to find good resources. Sample size of $R = 8$ is optimal for both low and high cluster loads, in this scenario.

**Number of scheduling agents:** We now examine how the number of agents that perform concurrent scheduling actions affects the quality and latency of scheduling. Figure 7.10a shows how scheduling latency changes as we increase the number of scheduling agents. The cluster load varies again from 10% to 90%, and the load is the same homogeneous Spark tasks with 100msec optimal duration, as before. We set the sample size to $R = 8$, which was the optimal, based on the previous experiment. When the number of schedulers is very small (below 3), latency suffers at high loads due to limited scheduling parallelism. As the number of agents increases latency drops, until 12 agents. Beyond that point, latency slowly increases due to increasing conflicts among agents. For larger cluster sizes, the same number of agents would not induce as many conflicts. Figure 7.10b shows how the fraction of tasks that meet QoS changes as the number of scheduling agents increases. As previously seen, if the number of agents is very small, many jobs experience increased response times. As more agents are added, the vast majority of jobs meet their QoS until high cluster loads. When cluster load exceeds 80%, QoS violations are caused primarily due to queueing at admission control, instead of limited scheduling concurrency. In general, 3 scheduling agents are sufficient to get the minimum scheduling latency; in following
comparisons with Sparrow we use 10 agents to ensure a fair comparison, since Sparrow uses a 10:1 worker to agent ratio.

**Cluster load:** Figure 7.11a shows the average and 95th percentile response times when we scale the cluster load in the 110-server EC2 cluster. The incoming jobs are homogeneous Spark tasks with 100msec target duration. We increase the task arrival rate to increase cluster load. The target performance of 100msec includes no scheduling overheads or degradation due to suboptimal scheduling. The reported response times include the task execution time and all overheads. The mean of response times with Tarcil remains almost constant until loads over 85%. At very high loads, admission control and the large sample size increase the scheduling overheads, affecting performance. The 95th percentile is more volatile at high loads, but only exceeds 250msec at cluster loads of 80% or higher. Tasks with very high response times are typically those delayed by admission control until the wait-time threshold is reached. Sampling itself adds marginal overheads until 90% load. At very high loads scheduling overheads are dominated by queueing time and increased sample sizes.

**Task duration:** Figure 7.11b shows the average and 95th percentile response times as a function of task duration, which ranges from 10msec to 600sec. The cluster load is 80% in all cases. For long tasks the mean and 95th percentile closely approximate the target performance. When task duration is below or close to 100msec, the scheduling overhead dominates. Despite this, the mean and 95th percentile remain very close, which shows that performance unpredictability is limited. For long jobs, configuring and allocating large amounts of resources dominates the scheduling overheads, while
for large numbers of short tasks, queueing delay dominates.

### 7.6.2 Comparison with Other Schedulers

**Methodology:** We compare Tarcil to Sparrow [166] and Quasar [66]. Sparrow uses multiple scheduling agents and sampling ratio of $R = 2$ servers for every core required, as recommended in [166]. Quasar has a centralized greedy scheduler that searches the cluster state with a scheduling timeout of 2 seconds. Sparrow does not take into account heterogeneity or interference preferences for incoming jobs, while Tarcil and Quasar do. We evaluate these schedulers on the same 110-server EC2 cluster with
r3.2xlarge memory-optimized instances (61GB of RAM). 10 servers are dedicated to
the scheduling agents for Tarcil and Sparrow and a single server for Quasar. While
we could replicate Quasar’s scheduler for fault tolerance, it would not help with the
latency of each scheduling decision. Additionally, Quasar schedules applications at
job, not task, granularity (when applicable), which reduces its scheduling load. Unless
otherwise specified, Tarcil uses sample sizes of $R = 8$ during low load.

**TPC-H workload**

We compare the three schedulers on the TPC-H decision support benchmark.
TPC-H is a standard proxy for ad-hoc, low-latency queries that comprise a large
fraction of load in shared clusters. We use a similar setup as the one used to evaluate
Sparrow [166]. TPC-H queries are compiled into Spark tasks using Shark [79], a dis-
tributed SQL data analytics platform. The Spark plugin for Tarcil is 380 lines of code
in Scala. Each task triggers a scheduling request for the distributed schedulers (Tarcil
and Sparrow), while Quasar schedules jointly all tasks from the same computation
stage. We constrain tasks in the first stage of each query to the machines holding
their input data (3-way replication). All other tasks are unconstrained. We run each
experiment for 30 minutes, with multiple users submitting randomly-ordered TPC-
H queries to the cluster. The results discard the initial 10 minutes (warm-up) and
capture a total of 40k TPC-H queries and approximately 134k jobs. Utilization at
steady state is 75-82%.

**Unloaded cluster:** We first examine the case where TPC-H is the only workload
present in the cluster. Figure 7.12a shows the response times for seven representative
query types [232]. Response times include all scheduling overheads from sampling or
the greedy selection, and queueing. Boundaries show 25th and 75th percentiles and
whiskers the 5th and 95th percentiles. The ideal scheduler corresponds to a system
that identifies the resources of optimal quality (including heterogeneity and interfer-
ence preferences) with zero delay. Figure 7.12a shows that the centralized scheduler
experiences the highest variability in performance. Although some queries complete
Figure 7.13: Performance of scheduled Spark tasks and resident memcached load (aggregate and over time).

very fast because they receive high quality resources, most experience high scheduling delays. To verify this, we also show the scheduling time CDF on the right of Figure 7.12a. While Tarcil and Sparrow have tight bounds on scheduling overheads, the centralized scheduler adds up to 2 seconds of delay (timeout threshold). Comparing the query performance using Sparrow and Tarcil, we see that the difference is small, 8% on average. Tarcil approximates the ideal scheduler more closely, as it accounts for each task’s resource preferences. Additionally, Tarcil constrains performance unpredictability. The 95th percentile is reduced by 80%-2.4x compared to Sparrow.

Cluster with resident load: The difference in scheduling quality becomes more clear when we introduce cross-application interference. Figure 7.12b shows a setup where 40% of the cluster is busy servicing background applications, including other Spark jobs for machine learning processing, long Hadoop workloads, and latency-critical services like memcached. These jobs are not being scheduled by the examined schedulers. While the centralized scheduler still adds considerable overhead to each job (Figure 7.12b, right), its performance is now comparable to Sparrow. Since Sparrow does not account for sensitivity to interference, the response time of queries that experience resource contention is high. Apart from average response time, the 95th percentile also increases significantly (poor predictability). In contrast, Tarcil accounts for resource preferences and only places tasks on machines with acceptable interference levels. It maintains an average performance only 6% higher compared to the unloaded cluster across query types. More importantly, it preserves the low performance jitter by bounding the 95th percentile of response times.
**Heterogeneous cluster with resident load:** Next, in addition to interference, we also introduce hardware heterogeneity. The cluster size remains constant but 75% of the worker machines are replaced with less or more powerful servers, ranging from general purpose medium and large instances to quadruple compute- and memory-optimized instances. Figure 7.12c shows the new performance for the TPC-H queries. As expected, response times increase, since some of the high-end machines are replaced by less powerful servers. More importantly, performance unpredictability increases when the resource preferences of incoming jobs are not accounted for. In some cases ($q_9$, $q_{10}$), the centralized scheduler now outperforms Sparrow despite its much higher scheduling overheads. Tarcil preserves response times close to those in the unloaded cluster and very close to those achieved with the ideal scheduler.

**Impact on Resident Memcached Load**

Finally, we examine the impact of scheduling decisions on resident cluster load. In the same heterogeneous cluster (110 nodes on EC2, 100 workers and 10 schedulers), we place long-running memcached instances as resident load. These instances serve read and write queries following the Facebook etc workload characteristics [17]. etc is the large memcached deployment in Facebook, has a 3:1 read:write ratio, and a value distribution between 1B and 1KB. Memcached occupies about 40% of the total system capacity and has a QoS target of 200usec for the 99th percentile of response latency.

The incoming jobs are homogeneous, short Spark tasks (100msec ideal duration, 20 tasks per job) that perform logistic regression. A total of 300k jobs are submitted over 900 seconds. Figure 7.13a shows the response times of the Spark tasks for the three schedulers. The centralized scheduler adds significant overheads, while Sparrow and Tarcil lead to small overheads and behave similarly for 80% of the tasks. For the remaining tasks, Sparrow increases response times significantly, as it is unaware of the interference induced by memcached. Tarcil maintains low response times for most tasks.
It is also important to consider the impact on the memcached load. Figure 7.13b shows the latency CDF of the memcached requests. The black diamond depicts the QoS constraint of 200usec for the 99th request percentile. With Tarcil and the centralized scheduler, memcached does not suffer as both schedulers attempt to minimize interference. Sparrow, however, leads to large latency increases for memcached. Even though the performance of the short tasks is satisfactory, not accounting for resource preferences has an impact on the longer jobs in the cluster. Finally, Figure 7.13c shows how the 99th percentile of memcached requests changes throughout the execution of the experiment. Initially memcached meets its QoS for all three schedulers. As the cluster becomes more loaded the tail latency increases significantly for Sparrow.

Note that a naïve coupling of Sparrow – for short jobs – with Quasar – for long jobs – is inadequate for three reasons. First, Tarcil achieves higher performance for short tasks because it accounts for their resource preferences. Second, even if the long-running resident load was scheduled using Quasar, scheduling short tasks with Sparrow would degrade its performance. Third, while the difference in execution time achieved by Quasar and Tarcil for long jobs is small, scheduling overheads are significantly reduced, without sacrificing the scheduling decision quality.

7.6.3 Large-Scale Evaluation

Methodology: We also evaluated Tarcil on a 400-server EC2 cluster with 10 server types ranging from 4 to 32 cores. The total core count in the cluster is 4,178. All servers are dedicated and managed only by the examined schedulers and there is no external interference from other workloads.

We use applications including short Spark tasks, longer Hadoop jobs, streaming Storm jobs [197], latency-critical services (memcached [135] and Cassandra [38]), and single-server benchmarks (SPEC CPU2006, PARSEC [30], etc.). In total, 7,200 workloads are submitted with 1 second inter-arrival times. These applications stress different resources, including CPU, memory and I/O (network, storage). We measure job performance (from submission to completion), cluster utilization, scheduling overheads and quality of allocation decisions.
Figure 7.14: (a) Performance across 7,200 jobs on a 400-server EC2 cluster for the Sampling-based and Centralized schedulers and Tarcil, normalized to optimal performance, (b) cluster utilization achieved by Tarcil throughout the duration of the experiment, (c) quality of resource allocation across all RUs, and (d) scheduling overheads in Tarcil and the Centralized scheduler.

We compare Tarcil, Quasar and Sparrow. Because this scenario includes long-running jobs, such as memcached, that are not supported by the open-source implementation of Sparrow, we use Sparrow when applicable (e.g., Spark) and a Sampling-based scheduler that follows Sparrow’s principles (sample size 2, batch sampling and late binding) for the remaining jobs.

Performance: Figure 7.14a shows the performance (time between submission and completion) of the 7,200 workloads ordered from worst to best-performing, and normalized to their optimal performance in this cluster. Optimal corresponds to the performance on the best available resources and zero scheduling delay. The Sampling-based scheduler degrades performance for more than 75% of jobs. While Centralized behaves better, achieving an average of 82% of optimal, it still violates QoS for a large fraction of applications, particularly short-running workloads (0-3900 for this scheduler). Tarcil outperforms both schedulers, leading to 97% average performance and bounding maximum performance degradation to 8%.

Cluster utilization: Figure 7.14b shows the system utilization across the 400 servers of the cluster when incoming jobs are scheduled with Tarcil. CPU utilization is averaged across the cores of each server, and sampled every 2 sec. Utilization is
70% on average at steady-state (middle of the scenario), when there are enough jobs to keep servers load-balanced. The maximum in the x-axis is set to the time it takes for the Sampling-based scheduler to complete the scenario (∼35,000 sec). The additional time corresponds to jobs that run on suboptimal resources and take longer to complete.

**Core allocation:** Figure 7.14c shows a snapshot of the RU quality across the cluster as observed by the job that is occupying each RU when using Tarcil. The snapshot is taken at 8,000s when all applications have arrived and the cluster operates at maximum utilization. White tiles correspond to unallocated resources. Dark blue tiles denote jobs with resources very close to their target quality. Lighter blue RUs correspond to jobs that received good but suboptimal resources. The graph shows that the majority of jobs are given appropriate resources. Note that high $Q$ does not imply low server utilization. Utilization at the time of the snapshot is approximately 75%.

**Scheduling overheads:** Figure 7.14d shows the scheduling overheads for the Centralized scheduler and Tarcil. The results are consistent with the TPC-H experiment in Section 7.6.2. The overheads of the Centralized scheduler increase significantly with scale, adding approximately 1 sec to most workloads. Tarcil keeps overheads low, adding less than 150msec to more than 80% of workloads. This is essential for scalability. At high load, Tarcil increases the sample size to preserve the statistical guarantees and/or resorts to local queueing. The overheads for the Sampling-based scheduler are similar to Tarcil and are omitted from the graph for clarity.

**Predictability:** Figure 7.15 shows the fraction of allocated RUs that are over
Figure 7.16: Resource quality distributions for the Sampling-based scheduler and Tarcil with $R = 8$ and 16 RUs across different permutations of the EC2 scenario.

a certain resource quality at each point of the duration of the scenario. Results are shown for the Sampling-based scheduler (left) and Tarcil (right). Darker colors towards the bottom of the graph denote that a larger fraction of allocated RUs have poor quality. At time 16,000sec, when the cluster is highly-loaded, the Sampling-based scheduler leads to 70% of allocated cores having quality less than 0.4. For Tarcil, only 18% of cores have less than 0.9 quality. Also note that, as the scenario progresses, the Sampling-based scheduler starts allocating resources of worse quality, while Tarcil maintains almost the same quality throughout the experiment.

Figure 7.16 explains this dissimilarity. It shows the CDF of resource quality for this scenario, and 5 random permutations of it (different job submission order). We show the CDF for the Sampling-based scheduler and Tarcil with 8 and 16 candidates. We omit the centralized scheduler which allocates resources of high quality most of the time. The sampling-based scheduler deviates significantly from the uniform distribution, since it does not account for the quality of allocated resources. In contrast, Tarcil closely follows the uniform distribution, improving the predictability of scheduling decisions.

### 7.7 Conclusions

We have presented Tarcil, a cluster scheduler that improves both scheduling speed and quality, making it appropriate for large, highly-loaded clusters running both short and long jobs. Tarcil uses an analytically-derived sampling framework that provides guarantees on the quality of allocated resources, and adjusts the sample size
to match application preferences. It also employs admission control to avoid excessive sampling and poor scheduling decisions at high load. We have compared Tarcil to existing parallel and centralized schedulers for a variety of workload scenarios on 100- to 400-server clusters on Amazon EC2. We have shown that it provides low scheduling overheads, high application performance, and high cluster utilization. Moreover, it reduces performance jitter, improving predictability in large, shared clusters.
Chapter 8

HCloud: Optimizing Resource Provisioning in Public Clouds

8.1 Introduction

An increasing amount of computing is now hosted in public clouds, such as Amazon’s EC2 [10], Windows Azure [220] and Google Compute Engine [90], or in private clouds managed by frameworks such as VMware vCloud [209], OpenStack [163], and Mesos [112]. Cloud platforms provide two major advantages for end-users and cloud operators: flexibility and cost efficiency [22, 24, 109]. Users can quickly launch jobs without the overhead of setting up a new infrastructure every time. Cloud operators can achieve economies of scale by building large-scale datacenters (DCs) and by sharing their resources between multiple users and workloads.

Users can provision resources for their applications in two basic manners; using reserved and on-demand resources. Reserved resources consist of servers reserved for long periods of time (typically 1-3 years [10]) and offer consistent service, but come at a significant upfront cost for the purchase of the long-term resource contract. In the other extreme are on-demand resources, which can be full servers or smaller instances and are progressively obtained as they become necessary. In this case, the user pays only for resources used at each point in time, but the per hour cost is 2-3x higher compared to reserved resources. Moreover, acquiring on-demand resources induces
<table>
<thead>
<tr>
<th>Configuration</th>
<th>Cost</th>
<th>Performance unpredictability</th>
<th>Spin-up</th>
<th>Flexibility</th>
<th>Typical usage</th>
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<tbody>
<tr>
<td>Reserved</td>
<td>High upfront, low per hour</td>
<td>no</td>
<td>no</td>
<td>no</td>
<td>long-term</td>
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<tr>
<td>On-demand</td>
<td>No upfront, high per hour</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>short-term</td>
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<tr>
<td>Hybrid</td>
<td>Medium upfront, medium per hour</td>
<td>low</td>
<td>some</td>
<td>yes</td>
<td>long-term</td>
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Table 8.1: Comparison of system configurations with respect to: cost, performance unpredictability, overhead and flexibility.

instantiation overheads and depending on the type of instance, the variability in the quality of service obtained can be significant.

Since provisioning must determine the necessary resources, it is important to understand the extent of this unpredictability. Performance varies both across instances of the same type (spatial variability), and within a single instance over time (temporal variability) [21, 164, 117, 83, 127, 137, 146, 165, 175, 216, 182]. Figure 8.1 shows the variability in performance for a Hadoop job running a recommender system using Mahout [145] on various instance types on Amazon EC2 [10] and on Google Compute Engine (GCE) [90]. Analytics such as Hadoop and Spark [228] are throughput-bound applications, therefore performance here corresponds to the completion time of the job. The instances are ordered from smallest to largest, with respect to the number of virtual CPUs and memory allocations they provide. We show 1 vCPU micro, 1-8 vCPU standard (stX) and 16 vCPU memory-optimized instances (mX) [10, 90]. Each graph is the violin plot of completion time of the Hadoop job over 40 instances of the corresponding type. The dot shows the mean performance for each instance type. It becomes clear that especially for instances with less than 8 vCPUs unpredictability is significant, while for the micro instances in EC2 several jobs fail to complete due to the internal EC2 scheduler terminating the VM. For the larger instances (m16), performance is more predictable, primarily due to the fact that these instances typically occupy a large fraction of the server, hence they have a much lower probability of suffering from interference from co-scheduled workloads, excluding potential network interference. Between the two cloud providers, EC2 achieves higher average performance than GCE, but exhibits worse tail performance (higher unpredictability).
Figure 8.1: Performance unpredictability on Amazon EC2 and Google Compute Engine for a Hadoop job.

Figure 8.2: Performance unpredictability on Amazon EC2 and Google Compute Engine for memcached.

Figure 8.2 shows a similar experiment for a latency-critical service (memcached) on the same instance types. Note that the number of memcached clients is scaled by the number of vCPUs of each instance type, to ensure that all instances operate at a similar system load. Unpredictability is even more pronounced now, as memcached needs to satisfy tail latency guarantees [55], as opposed to average performance. The results from above hold, with the smaller instances (less than 8 vCPUs) experiencing significant variability in their tail latency. Performance jitter decreases again for the 8-16 vCPU VMs, especially in the case of the memory-optimized instances (m16). Additionally GCE now achieves better average and tail performance compared to EC2.

The goal of this work is to optimize performance over cost for cloud systems,
similarly to the way work on system design and resource management optimized performance per Watt for small- and large-scale systems [133, 236, 199, 132, 201]. We first explore the implications of the two main provisioning approaches (reserved and on-demand resources), with respect to performance variability and cost efficiency. We perform this analysis on Google Compute Engine (GCE) [90] using three representative workload scenarios with mixes of batch and latency-critical applications, and increasing levels of load variability. We assume no a priori knowledge of the applications in each scenario, except for the minimum and maximum aggregate load for each scenario, which is needed for a comparison with an idealized statically-reserved provisioning strategy.

Our study reveals that while reserved resources are superior with respect to performance (2.2x on average over on-demand), they require a long-term commitment, and are therefore beneficial for use cases over extended periods of time. Fully on-demand resources, on the other hand, are more cost-efficient for short-term use cases (2.5x on average), but are prone to performance unpredictability, especially when using smaller instances. They also incur instantiation overheads to spin-up new VMs. Our study also shows that to achieve reasonable performance predictability with either strategy, it is crucial to understand the resource preferences and sensitivity to interference of individual applications [66, 147, 177]. Recent work has shown that a combination of lightweight profiling and classification-based analysis can provide accurate estimations of job preferences with respect to the different instance types, the sensitivity to interference in shared resources and the amount of resources needed to satisfy each job’s performance constraint (Chapter 4).

Next, we consider hybrid provisioning strategies that use both reserved (long-term) and on-demand (short-term) resources. A hybrid provisioning strategy has the potential to offer the best of both worlds by allowing users to leverage reserved resources for the steady-state long-term load, and on-demand resources for short-term resource needs. The main challenge with hybrid provisioning strategies is determining how to schedule jobs between the two types of resources. We show that leveraging the knowledge on resource preferences and accounting for the characteristics of on-demand resources, and the system load enables correct mapping of jobs to reserved
and on-demand resources. Table 8.1 shows the differences between the three main provisioning strategies with respect to cost, performance unpredictability, instantiation overheads and provisioning flexibility.

We demonstrate that hybrid provisioning strategies achieve both high resource efficiency and QoS-awareness. They maximize the usage of the already-provisioned reserved resources, while ensuring that applications that can tolerate some performance unpredictability will not delay the scheduling of interference-sensitive workloads. We also compare the performance, cost and provisioning needs of hybrid systems against the fully reserved and fully on-demand strategies examined before over a wide spectrum of workload scenarios. Hybrid provisioning strategies achieve within 8% of the performance of fully reserved systems (and 2.1x better than on-demand systems), while improving their cost efficiency by 46%. Reserved resources are utilized at 80% on average during steady-state. Finally, we perform a detailed sensitivity analysis of performance and cost with job parameters, such as duration, and system parameters such as resource pricing, spin-up overhead, and external load.

8.2 Cloud Workloads and Systems

8.2.1 Workload Scenarios

We examine the three workload scenarios shown in Figure 8.3 and summarized in Table 8.2. Each scenario consists of a mix of batch applications (Hadoop workloads running over Mahout [145] and Spark jobs) and latency-critical workloads (memcached). The batch jobs are machine learning and data mining applications, including recommender systems, support vector machines, matrix factorization, and linear regression. memcached is driven with loads that differ with respect to the read:write request ratio, the size of requests, the inter-arrival time distribution, the client fanout and the size of the dataset.

The first scenario has minimal load variability (Static). In steady-state the aggregate resource requirements are 854 cores on average. Approximately 55% of cores are required for batch jobs and the remaining 45% for the latency-critical services. The
difference between maximum and minimum load is 10% and most jobs last several minutes to a few tens of minutes.

Second, we examine a scenario with mild, long-term load variability (Low Variability). The steady-state minimum load requires on average 605 cores, while in the middle of the scenario the load increases to 900 cores. The surge is mostly caused by an increase in the load of the latency-critical applications. On average 55% of cores are needed for batch jobs and the remaining 45% for the latency-critical services.

Finally, we examine a scenario with large, short-term load changes (High Variability). The minimum load is 210 cores, while the maximum load reaches up to 1226 cores for short time periods. Approximately 60% of cores are needed for batch jobs and 40% for the latency-critical services. Because of the increased load variability, each job is shorter (8.1 min duration on average).

The ideal duration for each scenario, with no scheduling delays or degradation due to interference between workloads, is approximately 2 hours.

8.2.2 Cloud Instances

We use servers on Google Compute Engine (GCE) for all experiments. For provisioning strategies that require smaller instances we start with the largest instances (16 vCPUs) and partition them using Linux containers [20, 54]. The reason for constructing smaller instances as server slices as opposed to directly requesting various instance types is to introduce controlled external interference which corresponds to typical load patterns seen in cloud environments, rather than the random interference patterns present at the specific time we ran each experiment. This ensures repeatable experiments and consistent comparisons between provisioning strategies.

We model external interference by imposing external load that fluctuates ± 10% around a 25% average utilization [24, 66]. The external load is generated using both batch and latency-critical workloads. Section 8.5.1 includes a sensitivity study to the intensity of external load.

We only partition servers at the granularity of existing GCE instances, e.g., 1, 2, 4, 8 and 16 vCPUs. Whenever we refer to the cost of an on-demand instance, we quote
the cost of the instance that would be used in the real environment, e.g., a 2 vCPU instance. Similarly, we account for the spin-up overhead of the instance of the desired size, wherever applicable. Finally, all scheduling actions such as autoscale and migration performed by GCE are disabled.

8.2.3 Cloud Pricing

Google Compute Engine currently only offers on-demand instances. To encourage high instance usage, it provides sustained usage monthly discounts [90]. Although sustained usage discounts reduce the prices of on-demand instances, they do not approximate the price of long-term reserved resources. The most popular alternative pricing model is the one used by AWS, which includes both long-term resource reservations and short-term on-demand instances. Because this pricing model offers more provisioning flexibility and captures the largest fraction of the cloud market today, we use it to evaluate the different provisioning strategies and adapt it to the resource prices of GCE. Specifically, we approximate the cost of reserved resources on GCE based on the reserved to on-demand price ratio for EC2, adjusted to the instance prices of GCE. In Section 8.5.3 we discuss how our results translate to different pricing models, such as the default GCE model and the pricing model used by Windows Azure.
8.3 Provisioning Strategies

The two main types of resource offerings in cloud systems are reserved and on-demand resources. Reserved instances require a high upfront capital investment, but have 2-3x lower per-hour cost than on-demand resources, offer better service availability (1-year minimum), and provide consistent performance. On-demand resources are charged in a pay-as-you-go manner, but incur spin-up overheads and experience performance unpredictability due to interference from external load. We ignore spot instances for the purpose of this work, since they do not provide any availability guarantees.

The provisioning strategy must acquire the right type and number of resources for a workload scenario. Ideally, a provisioning strategy achieves three goals: (1) high workload performance, (2) high resource utilization (minimal overprovisioning), and (3) minimal provisioning and scheduling overheads. We initially study the three obvious provisioning strategies described in Table 8.3: a statically-provisioned strategy using only reserved resources (SR); an on-demand strategy (OdF) that only uses full servers (16 vCPU instances); and an on-demand strategy (OdM) that uses instances of any size and type.

8.3.1 Statically Reserved Resources (SR)

This strategy statically provisions reserved resources for a 1 year period, the shortest contract for reserved resources on cloud systems such as EC2. Reserved resources require significant capital investment upfront, although the per-hour charge is 2-3x lower than for the corresponding on-demand instances. Moreover, reserved resources
are readily available as jobs arrive, eliminating the overhead of spinning up new VMs on-demand. Because SR only reserves large instances (16 vCPU), there is limited interference from external load, except potentially for some network interference.

Because of its static nature, SR must provision resources for the peak requirements of each workload scenario, plus a small amount of overprovisioning. Overprovisioning is needed because all scenarios contain latency-critical jobs, that experience tail latency spikes when using nearly saturated resources [22, 24, 55, 129]. We explain the insight behind the amount of overprovisioning in Section 8.3.3. Peak requirements can be easily estimated for mostly static workload scenarios. For scenarios with load variability, static provisioning results in acquiring a large number of resources which remain underutilized for significant periods of time.

8.3.2 Dynamic On-Demand Resources (OdF, OdM)

We now examine two provisioning strategies that acquire resources as they become necessary to accommodate the incoming jobs of each workload scenario. In this case there is no need for a large expenditure upfront, but the price of each instance per hour is 2-3x higher compared to the corresponding reserved resources. Moreover, each new instance now incurs the overhead needed to spin up the new VMs. This is typically 12-19 seconds for GCE, although the 95th percentile of the spin-up overhead is up to 2 minutes. Smaller instances tend to incur higher spin-up overheads.

Because of spin-up overheads, these two strategies must also decide how long they should retain the resources for after a job completes. If, for example, a workload scenario has no or little load variability, instances should be retained to amortize the spin-up overhead. On the other hand, retaining instances when load variability is high can result in underutilized resources. We determine retention time by drawing from related work on processor power management. The challenge in that case is to determine when to switch to low power modes that enable power savings but incur overheads to revert to an active mode [192, 143, 150]. Given that the job inter-arrival time in our scenarios is 1 second, we set the retention time to 10x the spin-up overhead.
of an instance.  

Table 8.3: Resource provisioning strategies.

We examine two variants of on-demand provisioning strategies. On-demand Full (OdF) only uses large instances (16 vCPUs), which are much less prone to external interference (see Section 8.1). On-demand Mixed (OdM) acquires on-demand resources of any instance type, including smaller instances with 1-8 vCPUs. While OdM offers more flexibility, it introduces the issue that performance unpredictability due to external interference now becomes substantial. There are ways to improve performance predictability in fully on-demand provisioning strategies, e.g., by sampling multiple instances for each required instance and only keeping the better-behaved instances [83]. Although this approach addresses the performance variability across instances, it is still prone to temporal variation within a single instance. Additionally, it is only beneficial for long-running jobs that can afford the overhead of sampling multiple instances. Short jobs, such as real-time analytics (100msec-10sec) cannot tolerate long scheduling delays and must rely on the initial resource assignment.

8.3.3 The Importance of Resource Preferences

So far, we have assumed that the provisioning strategy has limited knowledge about the resource preferences of individual jobs within a workload scenario. Traditionally, the end-users have to specify how many resources each job should use; unfortunately this is known to be error-prone and to frequently lead to significant resource over-provisioning [24, 177, 140, 66, 37]. Moreover, this offers no insight on the sensitivity

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1The benefit of longer retention time varies across instance sizes due to differences in spin-up overheads.
of each job to interference from other jobs, external or not, running on the same physical server. This is suboptimal for both the statically-reserved and on-demand strategies, which will acquire more/less resources than what is truly needed by an application. The lack of interference understanding is equally problematic. SR will likely collocate jobs that interfere negatively with each other on the same instance. OdF and OdM will likely acquire instance types that are prone to higher interference than what certain jobs can tolerate.

The recently-proposed Quasar system provides a methodology to quickly determine the resource preferences of new jobs [66]. When a job is submitted to the system, it is first profiled on two instance types, while injecting interference in two shared resources, e.g., last level cache and network bandwidth. This profiling signal is used by a set of classification techniques which find similarities between the new and previously-scheduled jobs with respect to instance type preferences and sensitivity to interference. A job’s sensitivity to interference in resource \( i \) is denoted by \( c_i \), where \( i \in [1, N] \), and \( N = 10 \) the number of examined resources [66]. Large values of \( c_i \) mean that the job puts a lot of pressure in resource \( i \). To capture the fact that certain jobs are more sensitive to specific resources we rearrange vector \( C = [c_1, c_2, ..., c_N] \) by order of decreasing magnitude of \( c_i \), \( C' = [c_j, c_k, ..., c_n] \). Finally, to obtain a single value for \( C' \), we use an order preserving encoding scheme as follows:

\[
Q = c_j \cdot 10^{(2(N-1))} + c_k \cdot 10^{(2(N-2))} + ... + c_n, \text{ and normalize } Q \text{ in } [0, 1].
\]

\( Q \) denotes the resource quality a job needs to satisfy its QoS constraints. High \( Q \) denotes a resource-demanding job, while low \( Q \) a job that can tolerate some interference in shared resources.

We use Quasar’s estimations of resource preferences and interference sensitivity to improve resource provisioning. For SR, we use these estimations to find the most suitable resources available in the reserved instances with respect to resource size and interference using a simple greedy search [66]. Accounting for the information on resource preferences reduces overprovisioning to 10-15%. For OdF, the estimations are used to select the minimum amount of resources for a job, and to match the resource capabilities of instances to the interference requirements of a job. For OdM, this additionally involves requesting an appropriate instance size and type (standard,
compute- or memory-optimized). Note that because smaller instances are prone to external interference, provisioning decisions may have lower accuracy in this case.

Finally, we must detect suboptimal application performance and revisit the allocation decisions at runtime [178, 18, 19, 43, 66]. Once an application is scheduled its performance is monitored and compared against its expected QoS. If performance drops below QoS we take action [66]. At a high level, we first try to restore performance through local actions, e.g., increasing the resource allocation, and then through rescheduling. Rescheduling is very unlikely in practice.

### 8.3.4 Provisioning Strategies Comparison

**Performance:** We first compare the performance impact of the three provisioning strategies, with and without Quasar’s information on individual job preferences.
Figure 8.4 shows the performance achieved by each of the three provisioning strategies for the three workload scenarios. We separate batch (Hadoop, Spark) from latency-critical applications (memcached), since their critical performance metric is different: completion time for the batch jobs and request latency distribution for memcached. The boundaries in each boxplot depict the 25th and 75th percentiles of performance, the whiskers the 5th and 95th percentile and the horizontal line shows the mean. When the information from Quasar is not used, the resources for each job are sized based on user-defined resource reservations. For batch jobs (Hadoop and Spark) this translates to using the default framework parameters (e.g., 64KB block size, 1GB heapsize for Hadoop), while for memcached resources are provisioned for peak load [177]. OdM requests the smallest instance size that satisfies the resource demands of a job. SR allocates resources for workloads on the reserved instances with the most available resources (least-loaded).

It is clear from Figure 8.4 that all three provisioning strategies benefit significantly from understanding the jobs’ resource preferences and interference sensitivity. Specifically for SR, there is a 2.4x difference in performance on average across scenarios. The differences are even more pronounced in the case of latency-critical applications, where the performance metric of interest is tail, instead of average performance. Omitting the information on interference sensitivity in this case significantly hurts request latency. In all following results, we assume that provisioning takes job preferences into account, unless otherwise stated.

We now compare the performance achieved by the three provisioning strategies. The static strategy SR achieves the best performance for all three scenarios, both for batch and latency-critical workloads. OdF behaves near-optimally for the static
scenario, but worsens for the scenarios where variability is present. The main reason is the spin-up overhead required to obtain new resources as they become necessary. Strategy OdM achieves the worst performance of all three provisioning strategies for every scenario (2.2x worse than SR on average), in part because of the spin-up overhead, but primarily because of the performance unpredictability it experiences from external load in the smaller instances. Memcached suffers a 24x and 42x increase in tail latency in the low- and high-variability scenarios, as it is more sensitive to resource interference.

**Cost:** Figure 8.5 shows the relative cost of each strategy for the three scenarios. All costs are normalized to the cost of the static scenario with SR. Although strategy SR appears to have the lowest cost for a 2 hour run (2-3x lower per hour charge than on-demand), it requires at least a 1-year commitment with all charges happening in advance. Therefore, unless a user plans to leverage the cluster for long periods of time, on-demand resources are dramatically more cost-efficient. Moreover, SR is not particularly cost effective in the presence of high workload variability, since it results in significant overprovisioning. Between the two on-demand strategies, OdM incurs lower cost, since it uses smaller instances, while OdF only uses the largest instances available. Note however that the cost savings of OdM translate to a significant performance degradation due to resource unpredictability (Figure 8.4).

### 8.4 Hybrid Provisioning Strategies

The previous section showed that neither fully reserved nor fully on-demand strategies are ideal. Hybrid provisioning strategies that combine reserved and on-demand resources have the potential to achieve the best of both worlds. This section presents two hybrid provisioning strategies that intelligently assign jobs between reserved and on-demand resources and compares their performance and cost against the strategies of Section 8.3. Again, we make use of the information on resource preferences and interference sensitivity of individual jobs, as estimated by Quasar.
8.4.1 Provisioning Strategies

We design two hybrid strategies that use both reserved and on-demand resources. The first strategy (HF) only uses large instances for the on-demand resources, to reduce performance unpredictability. The second strategy (HM), uses a mix of on-demand instance types to reduce cost, including smaller instances that experience interference from external load. The retention time policy of on-demand resources is the same as for the purely on-demand strategies OdF and OdM. The reserved resources in both cases are large instances, as with the statically-provisioned strategy (SR). We configure the number of reserved instances to accommodate the minimum steady-state load, e.g., 600 cores for the low variability scenario to avoid overprovisioning of reserved resources. For scenarios with low steady-state load but high load variability the majority of resources will be on-demand.

Since HF uses large instances with limited performance unpredictability for both reserved and on-demand resources, it mostly uses on-demand instances to serve overflow load. In contrast, with HM on-demand instances may be smaller and can experience resource interference from external load. Therefore, for hybrid strategies it is critical to determine which jobs should be mapped to reserved versus on-demand resources, based on their interference sensitivity and the availability of reserved resources.

8.4.2 Application Mapping Policies

We first consider a baseline policy that maps applications between the reserved and on-demand resources randomly using a fair coin. Figure 8.6 shows the performance of applications mapped to the reserved (left) and on-demand resources (right) for the two hybrid provisioning strategies in the case of the high variability scenario. Performance is normalized to the performance each job achieves if it runs with unlimited resources alone in the system (in isolation). Figure 8.7 also shows the utilization of the reserved instances and the total cost to run the 2 hour scenario normalized to the cost of the static scenario with SR. Because of the large number of scheduled applications, approximately half of them will be scheduled on reserved and half on on-demand
resources [101]. The random policy hurts performance for jobs mapped to either type of resources. In the reserved resources, performance degrades as more workloads than the instances can accommodate are assigned to them, and are therefore queued. In the on-demand resources, performance degrades for two reasons. First, because of the inherent unpredictability of resources, especially in the case of HM, and, more prominently, because jobs that are sensitive to interference and should have been mapped to reserved resources slow down due to external load.

Ideally, the mapping policy should take into account the sensitivity of jobs to performance unpredictability. The following three policies shown in Figure 8.6 set a limit to the jobs that should be mapped to reserved resources based on the quality of resources they need. \( P_2 \) assigns jobs that need quality \( Q > 80\% \) to the reserved instances to protect them from the variability of on-demand resources. \( P_3 \) and \( P_4 \) set stricter limits, with \( P_4 \) only assigning very tolerant to unpredictability jobs to the on-demand resources. As we move from \( P_2 \) to \( P_4 \) the performance of jobs in the on-demand instances improves, as the number of applications mapped to them decreases. In contrast, the performance of jobs scheduled to reserved resources worsens due to increased demand and queueing for resources. In general, performance is worse for HM in the on-demand resources, due to the increased performance variability of smaller instances.

It is clear that there needs to be an upper load limit for the reserved resources. The next three policies \( P_5 \) - \( P_7 \) set progressively higher, static limits. For low utilization
limits, e.g., 50-70% the performance of jobs on reserved resources is near-optimal. In contrast, jobs assigned to on-demand resources suffer substantial performance degradations, since application mapping is only determined based on load and not based on resource preferences. For a utilization limit of 90%, the performance of jobs in the reserved resources degrades due to excessive load. Low utilization in the reserved resources also significantly increases the cost, as additional on-demand resources have to be obtained. Therefore a policy using a static utilization limit that does not distinguish between the resource preferences of jobs is also suboptimal.

Based on these findings we design a dynamic policy to separate jobs between reserved and on-demand resources. The policy adheres to three principles. First, it utilizes reserved resources before resorting to on-demand resources. Second, applications that can be accommodated by on-demand resources should not delay the scheduling of jobs sensitive to resource quality. Third, the system must adjust the utilization limits of reserved instances to respond to performance degradations due to excessive queueing.

Figure 8.8 explains the dynamic policy. We set two utilization limits for the reserved resources. First, a soft limit is set (experimentally set at 60-65% utilization), below which all incoming jobs are allocated reserved resources. Once utilization exceeds this limit, the policy differentiates between applications that are sensitive to performance unpredictability and applications that are not. The differentiation is done based on the resource quality $Q$ a job needs to satisfy its QoS constraints and
the knowledge on the quality of previously-obtained on-demand instances. Once we determine the instance size a job needs (number of cores, memory and storage), we compare the $90^{th}$ percentile of quality of that instance type (monitored over time) against the target quality ($Q_T$) the job needs. If $Q_{90} > Q_T$ the job is scheduled on the on-demand instance, otherwise it is scheduled on the reserved instances. Examining the $90^{th}$ percentile is sufficient to ensure accurate decisions for the majority of jobs.

Second, we set a hard limit for utilization, when jobs need to get queued until reserved resources become available. At this point, any jobs for which on-demand resources are satisfactory are scheduled in the on-demand instances and all remaining jobs are locally queued [166]. An exception occurs for jobs whose queueing time is expected to exceed the time it would take to spin up a large on-demand instance (16 vCPUs); these jobs are instead assigned to on-demand instances. Queueing time is estimated using a simple feedback loop based on the rate at which instances of a


Figure 8.9: Determining the soft utilization limit (left) and the expected waiting time (right) in HF and HM.

given type are being released over time. For example, if out of 100 jobs waiting for an instance with 4 vCPUs and 15GB of RAM, 99 were scheduled in less than 1.4 seconds, the system will estimate that there is a 0.99 probability that the queueing time for a job waiting for a 4 vCPU instance will be 1.4 seconds. Figure 8.9b shows a validation of the estimation of waiting time for three instance types. The lines show the cumulative distribution function (CDF) of the probability that an instance of a given type becomes available. The dots show the estimated queueing time for jobs waiting to be scheduled on instances with 4 (A), 8 (B) and 16 vCPUs (C) in the high variability scenario. In all cases the deviation between estimated and measured queueing time is minimal.

Third, we adjust the soft utilization limit based on the rate at which applications get queued. If the number of queued jobs increases sharply, the reserved instances should become more selective in the workloads they accept, i.e., the soft limit should decrease. Similarly, if no jobs get queued for significant periods of time, the soft limit should increase to accept more incoming jobs. We use a simple feedback loop with linear transfer functions to adjust the soft utilization limit of the reserved instances as a workload scenario progresses. Figure 8.9a shows how the soft limit changes with execution time and queue length.

8.4.3 Provisioning Strategies Comparison

Performance: Figure 8.10 compares the performance achieved by the static strategy SR and the two hybrid strategies (HF and HM), with and without the profiling
Figure 8.10: Performance of the three scenarios with the statically-reserved and hybrid provisioning strategies. The boundaries of the boxplots depict the 25th and 75th percentiles, the whis kers the 5th and 95th percentiles and the horizontal line in each boxplot shows the mean.

information for new jobs. Again we separate batch from latency-critical jobs. As expected, having the profiling information improves performance significantly for the hybrid strategies, for the additional reason that it is needed to decide which jobs should be scheduled on the reserved resources (2.4x improvement on average for HF and 2.77x for HM). When using the profiling information, strategies HF and HM come within 8% of the performance of the statically reserved system (SR), and in most cases outperform strategies OdF and OdM, especially for the scenarios with significant load variability. The main reason why HF and HM achieve good performance is that they differentiate between applications that can tolerate the unpredictability of on-demand instances, and jobs that need the predictable performance of a fully controlled environment. Additionally hybrid strategies hide some of the spin-up overhead of on-demand resources by accommodating part of the load in the reserved instances.
Cost: Figure 8.11 shows the relative cost of strategies SR, HF and HM for the three scenarios. While the static provisioning strategy (SR) is more cost-efficient in the static scenario where provisioning is straightforward, the hybrid strategies incur significantly lower costs for both scenarios with load variability. Therefore, unless load is almost completely static, statically-provisioned resources is not cost-efficient both due to long-term reservations, and significant overprovisioning. Additionally, because of the lower per-hour cost of reserved resources in HF and HM, the hybrid strategies have lower per-hour cost than fully on-demand resources as well. For HF and HM, most of the cost per hour comes from on-demand resources, since reserved instances are provisioned for the minimum steady-state load. Finally, between the two hybrid strategies, HM achieves higher cost-efficiency since it uses smaller instances.

8.5 Discussion

8.5.1 Sensitivity to Job/System Parameters

We first evaluate the sensitivity of the previous findings to various system and workload parameters. Unless otherwise specified, we use the same strategies as before to provision reserved and/or on-demand resources.

Resource cost: The current average cost ratio of on-demand to reserved resource per hour is 2.74. Figure 8.12 shows how the relative cost of the three scenarios varies for each of the five strategies when this ratio changes. The current ratio is shown with a vertical line at 2.74. All costs are normalized to the cost for the static scenario.
using SR. We change the ratio by scaling the price of reserved resources. We vary the ratio in [0.01, 4]; beyond that point the cost of SR per hour becomes practically negligible. Initially (0.01), strategies using only on-demand resources (OdF, OdM) are significantly more cost-efficient, especially for the scenarios with load variability. For the static scenario, even when on-demand resources are much cheaper than reserved, SR, HF and HM incur similar charges as the fully on-demand systems. For each scenario, there is a price ratio for which SR becomes the most cost-efficient strategy. As variability increases, this value becomes larger (e.g., for the high variability scenario the ratio needs to become 3 for SR to be more cost-efficient per hour than HM). Note that SR still requires at least a 1-year commitment, in contrast to the on-demand strategies. Finally, the hybrid strategies achieve the lowest per-hour cost for significant ranges of the price ratio, especially for scenarios with load variability.

**Scenario duration:** Figure 8.13 shows how cost changes for each strategy, as the scenario duration increases. Because we compare aggregate costs (instead of per-hour), this figure shows the absolute cost in dollars for each strategy. For the static scenario, from a cost perspective, strategy HM is optimal only if duration is [20 – 25] weeks. For durations less than 20 weeks, strategy OdM is the most cost-efficient, while for durations more than 25 weeks the statically-reserved system (SR) is optimal. This changes for scenarios with load variability. Especially in the case of high variability, for durations larger than 18 weeks, strategy HM is the most cost-efficient, with the significantly overprovisioned reserved system (SR) never being the most efficient. Note that the charge for SR doubles beyond the 1 year (52 weeks) mark.
Spin-up overhead: Figure 8.14a shows how the 95th percentile of performance changes as the overhead to spin-up new resources changes for the high variability scenario. The statically-reserved strategy (SR) is obviously not affected by this change. Because in this scenario resources are frequently recycled, increasing the spin-up overhead significantly affects performance. This is more pronounced for the strategies using exclusively on-demand resources (OdF, OdM). The additional degradation for OdM comes from the performance unpredictability of smaller on-demand instances.

External load: Figure 8.14b shows the sensitivity of performance to external load (load in machines due to jobs beyond those provisioned with our strategies). SR provisions a fully-controlled environment, therefore there is no external load to affect performance. OdF and HF are also tolerant to external load, as they only use the largest instances, which are much less prone to external interference. For HM performance degrades minimally until 50% load, beyond which point the estimations on resource quality become inaccurate. OdM suffers most of the performance degradation as all of its resources are susceptible to external interference.

Retention time: Figure 8.15 shows the 95th percentile of performance and the cost of each strategy, as the time for which idle instances are maintained changes for the high variability scenario. As expected, releasing well-behaved instances immediately hurts performance, as it increases the overheads from spinning-up new resources. This is especially the case for this scenario, where load changes frequently. With respect to cost, higher retention time increases the cost of strategies using only on-demand resources (OdF, OdM), while SR remains unchanged; the difference for hybrid strategies is small. An unexpected finding is that excessive resource retention slightly
hurts performance for OdM and HM. The primary reason is the temporal variability in the quality of on-demand resources, which degraded by the time new applications were assigned to these instances.

8.5.2 Provisioning Overheads

In the presented strategies, the provisioning overheads include job profiling and classification (Quasar), provisioning decisions, spin-up of new on-demand instances (where applicable), and rescheduling actions. The profiling that generates the input signal for the classification engine takes 5-10 sec, but only needs to happen the first time a job is submitted. Classification itself takes 50msec on average. Decision overheads include the greedy scheduler in the statically-reserved strategy (SR) and the overhead of deciding whether to schedule a new job on reserved versus on-demand resources in the hybrid strategies. In all cases decision overheads do not exceed 20msec, three orders of magnitude lower than the spin-up overheads of on-demand instances (10-20sec on average). Finally, job rescheduling due to suboptimal performance is very infrequent for all strategies except OdM, where it induces 6.1% overheads to the execution time of jobs on average.

8.5.3 Different Pricing Models

So far we have assumed a pricing model for reserved and on-demand instances similar to the one used by Amazon’s AWS. This is a popular approach followed by many smaller cloud providers. Nevertheless, there are alternative approaches. GCE does
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not offer long-term reservations. Instead it provides sustained usage monthly discounts to encourage high-utilization of on-demand resources. The higher the usage of a set of instances of a type for a fraction of the month, the lower the per-hour instance price for the remainder of the month. This approach does not differentiate whether one uses a single instance of type A for 3 weeks or 3 instances of type A for 1 week each. Microsoft Azure only offers on-demand resources of different types.

Even without reserved resources, the problem of selecting the appropriate instance size and configuration, and determining how long to keep an instance before releasing it remains. Figure 8.16 shows how cost changes for the three workload scenarios, under the Azure (on-demand only) and GCE (on-demand + usage discounts) pricing models, compared to the AWS pricing model (reserved + on-demand). We assume that the resources will be used at least for a one month period, so that GCE discounts can take effect. Cost is normalized to the cost of the static workload scenario under the SR provisioning strategy using the reserved & on-demand pricing model. Even with these alternative pricing models using the hybrid strategies and accounting for the resource preferences of incoming applications to optimize provisioning significantly benefits cost. For example, for the high variability scenario HM achieves 32% lower cost than OdF with the Windows Azure pricing model; similarly for the GCE model with discounts, HM achieves 30% lower cost than OdF.

GCE decouples the level of usage from the specific instance used. For example, monthly usage is considered the same between a single instance used for 50% of the month, and N instances of the same type used for (50/N)% of the month each. This introduces new opportunities to optimize resource provisioning by maximizing the
Figure 8.16: Sensitivity to the cloud pricing model for the three workload scenarios.

time a certain instance type is used during a month. We defer such considerations to future work.

8.5.4 Resource Efficiency

Apart from lowering cost, we also want to ensure that a provisioning strategy is not wasteful in terms of resources. Figure 8.17 shows the resource allocation by each strategy throughout the duration of the high variability scenario. The reserved system (SR) is provisioned statically for the peak requirements plus a 15% overprovisioning as described in Section 8.3.1. Because all instances are private (limited external interference) and all resources are readily available, the scenario achieves near-ideal execution time (∼2hr). However, because there is high load variability, utilization is rarely high, resulting in poor resource efficiency. Strategy OdF obtains resources as they become necessary and because it induces spin-up overheads frequently due to the constant load change, it results in longer execution time (132 min). It also introduces some overprovisioning, as it only requests the largest instances to constrain performance unpredictability. OdM does not overprovision allocations noticeably since it uses smaller instances, however, it significantly hurts performance, resulting in the scenario completing in 48% more time. Performance degradation is partially the result
of variability in the quality of an instance, and of the high instance churn (releasing instances immediately after use), due to their poor behavior. 43% of obtained instances were released immediately after use. The hybrid strategies (HF and HM) provision reserved resources for the minimum, steady-state load and use on-demand resources beyond that. Spin-up overheads induce some delay in the completion of the scenario, although this only amounts to 2.6% over SR. With HM, this delay is primarily due to instances that misbehaved and were immediately released after the completion of their jobs, requiring resources to be obtained anew (about 11% of instances). This issue is less pronounced when all on-demand resources are large instances (HF).

Figure 8.18 shows the CPU utilization of each instance throughout the execution of the high variability scenario for the five provisioning strategies. CPU utilization is sampled every 2 seconds and averaged across the cores of an instance. For the hybrid strategies we separate the reserved from the on-demand resources. For the on-demand resources, instances are ranked in the order in which they are obtained.

In the case of the fully reserved provisioning strategy (SR), a small fraction of the
instances operate at high utilization as we try to co-schedule as many applications as possible, however, the majority of instances are greatly underutilized. This is consistent with the findings of Figure 8.17a; because resources are provisioned for peak load most of the machines operate at low utilization when load is lower than the maximum. The majority of resources are used only during the two load surges at 32 and 60 minutes. Strategies OdF and OdM obtain resources as they become necessary (shown by the fact that not all instances exist at time 0). Although the total number of instances used during the execution of the scenario with OdF is similar to SR, most instances are released when no longer needed, hence the number of active instances during off-peak load is significantly lower. In the case of the OdM strategy instances are additionally released when they behaved poorly for a given application. Note that because of the high instance churn, the total number of instances used throughout the execution of the scenario is higher for OdM than for OdF. The scenario also takes longer to complete for OdM (178 as opposed to 120 minutes).

Finally the hybrid strategies maintain the utilization of reserved resources high throughout the execution of the workload scenario, and obtain on-demand resources as needed. HF needed in total 72 on-demand instances, although only 34 of those are used on average. More than 60 on-demand instances are only used during load surges. HM needs a higher number of on-demand resources, because it also uses smaller instances, and because poorly-performing instances are released and replaced by new ones. Note that the fraction of released instances due to poor performance is lower for HM than for OdM, since only jobs that can tolerate some performance
unpredictability are mapped to smaller on-demand instances. Both hybrid strategies complete the scenario in the same time as SR.

Figure 8.19 breaks down the allocation of the low variability scenario by application type, for strategy HM. Initially the reserved resources are used for most applications, until load reaches the soft utilization limit. Beyond that, the interference-sensitive memcached occupies most of the reserved resources, while the batch workloads are mostly scheduled on the on-demand side. When the increase in the memcached load exceeds the capabilities of the reserved resources, part of the latency-critical service is scheduled on on-demand resources to avoid long queueing delays, although it is often allocated larger on-demand instances to meet its resource quality requirements.

8.5.5 Additional Provisioning Considerations

Spot instances: Spot instances consist of unallocated resources that cloud providers make available to users through a bidding interface. Spot instances do not have availability guarantees, and may be terminated at any point in time if the bidding price is lower than the market price for an instance type. Incorporating spot instances in provisioning strategies for non-critical tasks or jobs with very relaxed performance requirements can further improve the system’s cost-efficiency.

Reducing unpredictability: Resource partitioning (e.g., cache or network bandwidth partitioning) has the potential to improve isolation between instances sharing one or more resources, thus reducing performance unpredictability in fully on-demand provisioning strategies. We plan to investigate how resource partitioning complements provisioning decisions in future work.

Data management: In our current infrastructure both reserved and on-demand resources are in the same cluster. When reserved resources are deployed as a private facility, the provisioning strategy must also consider how to minimize and manage data transfers and replication across the private and on-demand resources.
8.5.6 Sensitivity to Workload Characteristics

We now evaluate how the performance and cost results change as the characteristics of the applications change with respect to how sensitive they are to interference. Figure 8.20 shows the 95th percentile of performance for the five strategies as the percentage of jobs that are sensitive to interference increases. We modify the high variability scenario used before, such that the number of jobs that cannot tolerate performance unpredictability increases. In the left-most part of the graph, most jobs are batch Hadoop applications, which can tolerate some resource contention; as we move to the right part of the graph the majority of jobs are latency-critical memcached applications and real-time Spark jobs.

The statically-provisioned strategy (SR) behaves well even when most applications need resources of high quality, as it is provisioned for peak load, and there is no external load. The two hybrid strategies also behave well, until the fraction of sensitive applications increases beyond 80%, at which point queueing in the reserved resources becomes significant. The purely on-demand strategies are the ones that suffer the most from increasing the fraction of sensitive applications. OdF and especially OdM significantly degrade the performance of scheduled applications, both due to increased spin-up overheads, and because more applications are now affected by external contention.

With respect to cost, increasing the fraction of applications that are sensitive to interference impacts all strategies except for SR. Since HF and HM can use the reserved resources for the sensitive jobs, their cost increases only beyond the 30% mark, at which point more on-demand resources have to be purchased to avoid increased
queueing in the reserved resources. The two on-demand strategies experience a significant cost surge, as increasing the fraction of sensitive applications results in a lower degree of co-scheduling and the need for new resources.

8.5.7 Cost Impact of Information from Quasar

Finally, we examine how removing the information on the resource preferences of new jobs affects the cost of the five provisioning strategies. In this case, latency-critical applications, such as memcached are provisioned for their peak load, and batch jobs (Hadoop and Spark) use the default framework parameters, for example for the number of tasks per core, heapsize, etc. Figure 8.21 shows the cost with and without the information from Quasar for the three workload scenarios. Since overprovisioning is now much more prominent both the statically-reserved and the on-demand strategies incur significantly higher costs. The differences become more pronounced for scenarios with load variability, where overprovisioning is higher. For most cases the relative ordering between strategies remains the same; for example in the high variability scenario even without the information from Quasar the hybrid strategies have lower cost than SR and significantly lower than the on-demand strategies.
8.6 Related Work

Cluster management: The increase in the size and number of large-scale DCs has motivated several designs for cluster management. Systems like Mesos [112], Torque and Omega [183] all address the problem of allocating resources and scheduling applications in large, shared clusters. Mesos is a two-level scheduler. It has a central coordinator that makes resource offers to application frameworks, and each framework has an individual scheduler that handles its assigned resources. Omega on the other hand, follows a shared-state approach, where multiple concurrent schedulers can view the whole cluster state, with conflicts being resolved through a transactional mechanism [183]. Dejavu identifies a few workload classes and reuses previous resource allocations for each class, to minimize reallocation overheads [207]. Cloud-Scale [190], PRESS [96], AGILE [160] and the work by Gmach et al. [95] predict future resource needs online, often without a priori workload knowledge. Finally, auto-scaling systems, such as Rightscale, automatically scale the number of physical or virtual instances used by web-serving workloads, to accommodate changes in user load.

A second line of work tries to identify the specific resources that are appropriate for incoming tasks [63, 149, 156, 226]. Paragon uses classification techniques to determine the impact of platform heterogeneity and workload interference on an unknown, incoming workload [63]. It then uses this information to schedule each workload in a way that enables high performance for the job and high utilization for the cluster. Paragon, assumes that the cluster manager has full control over all resources, which is often not the case in public clouds. Nathuji et al. developed a feedback-based scheme that tunes resource assignments to mitigate interference effects [157]. Yang et al. developed an online scheme that detects memory pressure and finds colocations that avoid interference on latency-sensitive workloads [226]. Similarly, DeepDive detects and manages interference between co-scheduled workloads in a VM environment [161]. Finally, CPI2 [235] throttles low-priority workloads that induce interference to important services. In terms of managing platform heterogeneity, Nathuji et al. [156] and Mars et al. [147] quantified its impact on conventional benchmarks and Google
services, and designed schemes to predict the most appropriate server type for each workload.

**Hybrid clouds:** Hybrid clouds consist of both privately-owned and publicly-rented machines and have gained increased attention over the past few years for several reasons, including cost-efficiency, as well as security and privacy concerns [34]. Breiter et al. [34] describe a framework that allows service integration in hybrid cloud environments, including actions such as overflowing in on-demand resources during periods of high load. The provisioning strategies discussed here are also applicable to hybrid clouds.

**Cloud economics:** The resource pricing of cloud providers has been extensively analyzed. Ben-Yehuda et al. [28] contest whether the pricing strategy of spot instances on EC2 is indeed market-driven, and discuss alternative pricing strategies. Deelman et al. [58] discuss provisioning strategies for a single astronomy application on a cloud provider. Li et al. [137] compare the resource pricing of several cloud providers to assist users provision their applications. Finally, Guevara et al. [103] and Zahed et al. [230] incorporate the economics of heterogeneous resources in market-driven and game-theoretic strategies for resource allocation in shared environments.

### 8.7 Conclusions

We have discussed the different provisioning strategies available on cloud providers today and showed their advantages and pitfalls with respect to cost, performance predictability and initialization overheads. We have also designed two new hybrid provisioning strategies, that use both reserved and on-demand resources, and leverage the information on resource preferences of incoming jobs and the quality of previously-obtained on-demand instances, to map jobs to reserved versus on-demand resources. We showed that hybrid provisioning strategies can provide the best of both worlds in terms of performance and cost-efficiency; they preserve QoS for the majority of jobs, improve performance by 2.1x compared to fully on-demand resources, and reduce cost by 46% compared to fully reserved resources.
Chapter 9

Conclusions and Future Work

This dissertation has presented scheduling and resource management techniques that enable resource-efficient and performance-aware datacenters. In particular we have made the following contributions.

- **Big Data in System Management:** We have designed two systems that leverage data mining techniques to quickly extract the resource preferences of previously-unknown applications. First, Paragon (Chapter 3) uses a recommender system based on collaborative filtering to determine the most suitable hardware platforms for a new workload, and the sensitivity it experiences to interference in shared resources (Chapter 5). Subsequently, Quasar (Chapter 4) generalizes this framework to tackle the more general problem of cluster management in datacenters, addressing both resource assignment (type of resources), and resource allocation (amount of resources). Leveraging data mining not only improves application performance and cluster-wise utilization by 2-3x, but enables practical management solutions at the scale of thousands of machines.

- **High-Level Declarative Interfaces:** We have highlighted the performance and efficiency pitfalls of reservation-based interfaces in datacenters. In Quasar (Chapter 4), we have proposed a high-level, declarative interface that centers around performance. Users specify the performance (QoS) target a new application must meet and the system translates it to resources using the data mining approach.
detailed above. The declarative interface simplifies the responsibility of the user, while allowing flexibility to the cluster manager to better allocate resources.

- **Scalable Scheduling Techniques:** We have developed two systems that enable scalable scheduling in the presence of heterogeneous resources. First, we presented Tarcil (Chapter 7), a scheduler that bridges the gap between centralized systems that optimize decision quality, and distributed schedulers that optimize decision latency. Tarcil relies on a simple analytical framework, that provides statistical guarantees on the quality of allocated resources. Second, we designed HCloud (Chapter 8) which enables efficient resource provisioning in public clouds. Both systems enable millisecond-level scheduling decisions at high cluster load, while guaranteeing per-application performance constraints.

We believe that these contributions open several interesting directions for future work. Our work on applying data mining principles to datacenter management places an emphasis on the importance on finding practical solutions for large-scale system challenges. We have shown that contrary to the traditional trial-and-error approach, mining the knowledge systems accumulate through data collection in a mindful fashion can provide invaluable insight on application requirements, which translates to both performance and efficiency benefits. We hope that architects and system designers will apply this approach to other large-scale problems, including managing dependencies across multi-tier services, performance debugging for distributed applications, and design of heterogeneous and reconfigurable systems. Additionally, while we have so far focused on improving resource efficiency at the cluster management level, efficiency is sacrificed in lieu of performance across the system stack. Designing hardware and software schemes that guarantee strict isolation between applications sharing system resources can further improve resource efficiency. Finally, a lot of performance unpredictability comes from the many levels of indirection in the software stack. Providing feedback to application designers on application-level inefficiencies can bridge the programmability-performance gap and improve predictability in large-scale systems. We leave these endeavors to future work.
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