# Who Limits the Resource Efficiency of My Datacenter: An Analysis of Alibaba Datacenter Traces

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## ABSTRACT

Cloud platform provides great flexibility and cost-efficiency for end-users and cloud operators. However, low resource utilization in modern datacenters brings huge wastes of hardware resources and infrastructure investment. To improve resource utilization, a straightforward way is co-locating different workloads on the same hardware. To figure out the resource efficiency and understand the key characteristics of workloads in co-located cluster, we analyze an 8-day trace from Alibaba's production trace. We reveal three key findings as follows. First, memory becomes the new bottleneck and limits the resource efficiency in Alibaba's datacenter. Second, in order to protect latency-critical applications, batch-processing applications are treated as second-class citizens and restricted to utilize limited resources. Third, more than 90% of latency-critical applications are written in Java applications. Massive self-contained JVMs further complicate resource management and limit the resource efficiency in datacenters.

## CCS CONCEPTS

• **Computer systems organization → Cloud computing**.

## KEYWORDS

Resource efficiency, cloud computing, datacenter

**ACM Reference Format:**
Jing Guo, Zihao Chang, Sa Wang, Haiyang Ding, Yihui Feng, Liang Mao, and Yungang Bao. 2019. Who Limits the Resource Efficiency of My Datacenter: An Analysis of Alibaba Datacenter Traces. In *IEEE/ACM International Symposium on Quality of Service (IWQoS '19), June 24–25, 2019, Phoenix, AZ, USA.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3326285.3329074

*Work done while interning at Alibaba Inc.


*IWQoS '19, June 24–25, 2019, Phoenix, AZ, USA*

ACM ISBN 978-1-4503-6778-3/19/06…$15.00
https://doi.org/10.1145/3326285.3329074

## 1 INTRODUCTION

The huge cost of investment with low resource utilization has long been a great concern to cloud providers. Early in 2012, [24] revealed that the average CPU and memory utilization in Google's production cluster were only 20% and 40% respectively. Nearly at the same time, the average CPU utilization of Amazon AWS EC2 was only 7% to 17% [17]. Since then, industry and academia have both devoted much effort to improve resource efficiency in datacenters [5, 7, 19].

However, the major obstacle to further improve resource efficiency is the performance interference brought by co-located workloads. The more workloads we co-locate on the same hardware, the more likely each workload suffers performance interference from each other [3, 19, 31]. The uncertainty of performance interference makes things even more complicated and highly reduces the Quality of Service (QoS) provided by cloud providers. How to improve the resource efficiency while guaranteeing the QoS of workloads becomes a great challenge to cloud providers.

To address this issue, some prior works [7, 9] attempt to exploit an efficient *co-location* and *resource allocation* strategy for applications before launching. One of the widely accepted strategies is prioritizing latency-critical (LC) applications and co-locating batch-processing applications to harness stranded CPU cycles [19]. Batch-processing applications could be deferred or evicted when any performance spike happens to the co-located LC applications. Some studies seek to *adjust* resource allocation dynamically during application's execution, such as increasing the cache size of applications [19], or even rescheduling the tasks with lower priority when needed [7]. Resource allocation and dynamic adjustment are orthogonal techniques and can be adopted simultaneously in datacenters for higher resource efficiency.

In this paper, we ask the following question: *after years of endeavor, how is it going in production datacenters now?* How about the resource efficiency of today's datacenters? Fortunately, Alibaba released a new Trace (AT) from their production cluster recently. The AT consists of 4K machines, 9K different services and 4M batch

jobs with static and runtime information over 8 days. Comparing to the Google trace released in 2011, AT exhibits several new characteristics and trends which we believe could shed some lights on the resource management in datacenters, especially those confronting Java workloads. Our key findings are summarized as follow:

**Memory becomes the new bottleneck of datacenters.** In Alibaba's cluster, memory seemingly becomes the new bottleneck that prevents co-locating more workloads on one physical server, whereas there still left considerable spare CPU cycles. The state-of-the-art on improving resource efficiency of datacenters mainly focus on CPU utilization of servers [6, 8]. However, we observe that the average resource utilization of CPU and memory in AT turn out to be 38.2% and 88.2% respectively, and some nodes nearly run out of memory. As we further analyze the breakdown of memory utilization in §4, we discover that Alibaba uses a conservative approach to allocate resource to LC applications instead of fine-grained allocation. LC applications reserve massive CPU and memory resource in case of performance spike happens. Meanwhile, in each physical host, memory is statically partitioned into several regions and applications (LC and batch) are only allowed to request memory in their own regions. Due to the lack of efficient memory reclaim techniques, the memory stranded by LC applications can not reallocate to other jobs. The static memory management and conservative resource allocation greatly affects the resource efficiency of datacenters.

**Batch-processing applications can only conservatively harvest limited amount of resources.** Batch-processing applications are always treated as second-class citizens in prior works [7, 19]. How about their de facto resource utilization in production datacenters? We find out that they are subject to even worse treatments in Alibaba trace. Batch-processing applications mainly follow three principles to make compromise to LC applications. (1) They can only utilize pre-defined limited amount of resource with lower priority. (2) They are the only applications suffering from rescheduling in any case. (3) They are restricted to harvest limited amount of resources in daytime, though there left remarkable spare resource. The majority of batch workloads are launched at midnight, which is of an order of magnitude larger than the amount of workload in daytime. Those three principles directly put batch-processing applications in chains, which overprotects latency-critical applications and hurts the resource efficiency of datacenters.

**Massive self-contained JVMs further complicate resource management in datacenters.** In AT, more than 90% of LC and some batch-processing applications are written in Java. Accordingly, they will launch thousands of Java virtual machines (JVMs) that are separated from each other and manage resource by their own automatically. Co-locating so many self-contained JVMs will cause at least two issues. (1) The unpredictable performance interference caused by the well-known garbage collection (GC) in JVMs will exacerbate. Unfortunately, we can only overprovision enough memory indirectly for each container to lower the frequency of GC. It further reduces the resource efficiency. (2) The potentially reserved but stranded memory resource will scale up, due to the lack of efficient techniques to reclaim and reallocate memory in JVMs to other applications. Since LC applications in Alibaba are encapsulated into containers, dynamically managing memory means holistically coordinating between JVMs, containers and underlying host systems to reclaim and reallocate stranded memory. It further complicates resource management in datacenters.

In a nutshell, this work makes the following contributions:

- We analyze the characteristics of co-located workloads and resource efficiency of Alibaba's cluster from two perspectives, resource allocation and adjustment.
- Based on the observation, we extract three key insights and believe our findings will be applicable to future research.
- We introduces two metrics to quantify the compromise impact of batch-processing applications, Reschedule Time Cost (*RTC*) and Reschedule time cost Over execution Time (*ROT*).
- We propose a periodic GC adaptive mechanism to exploit memory resource stranded by LC applications.

The rest of the paper is organized as follows: Section 2 introduces background and related work. Section 3 presents an overview of Alibaba's new trace, cluster overall usage and workload characteristics. Section 4 and 5 describe the resource efficiency of Alibaba's datacenter from two perspectives, resource allocation and adjustment. Section 6 further discusses two topics about how to further improve resource usage in datacenter.

## 2 BACKGROUND AND RELATED WORK

This section presents the motivation for workload characterization, state-of-the-art cluster management systems and then describes the architecture of Alibaba's cluster management system.

### 2.1 Workload characterization

Co-locating multiple workloads on the same hardware is a straightforward approach to achieve high resource efficiency, but brings severe resource contention [31]. Such contention leads to unpredictable performance variability and highly reduces the QoS of user-facing services [19]. Therefore, co-location makes things more complicated in how to improve the resource efficiency while guaranteeing the QoS of workloads.

To better face this issue, it is necessary to understand the key characteristics of workloads from real production environment. In 2011, Google released a public dataset from their production cluster, presenting a 29-day trace of co-located workloads [25]. Reiss et al. [24] thoroughly characterize the workloads in resource needs, utilization and resource assignment. [1] investigates the resource usage of Google cluster from user behavior. Besides, another line of works characterize the workloads in VM-based datacenters. [5] presents a detailed analysis of VM workloads behaviors from Azure. [2] provides a view from private clouds in application characteristics. These efforts provide a broad perspective and help us better understand the various task shapes in large-scale datacenters.

In 2017, Alibaba, the largest cloud service provider in China, released a publicly accessible dataset. It consists of 1.3K machines that run both LC and batch-processing applications in a 12-hour period [11]. Recent studies have analyzed the characteristics of co-located cluster from multiple perspectives. Lu et al. [20] analyzed the imbalance phenomenon in the cluster. Liu et al. [18] focused on the elasticity and plasticity of their semi-containerized cloud. And [4] provided a unique view about how the co-located workloads interact and interfere with each other.

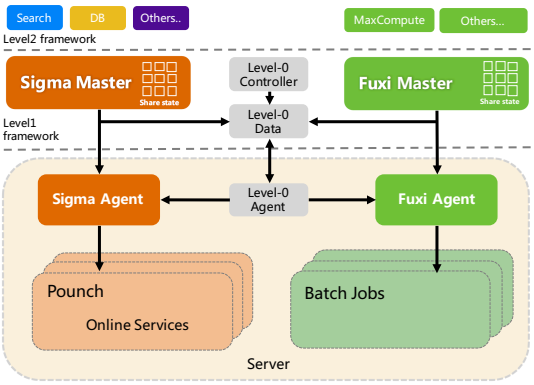



**Figure 1: The architecture of Alibaba cluster management system.**

In this paper, we analyse a new trace [12] released by Alibaba in late 2018 with larger scale and longer period. It's the first publicly available dataset with precise information about the category of LC and batch applications. Based on the new trace, we provide a more comprehensive and microscopic view of the current practice about resource usage and resource allocation. Different from the prior works [4, 18, 20], this work mainly focuses on resource efficiency of Alibaba's production cluster.

## 2.2 Cluster management systems

With the respect of availability and scalability, cluster management systems (CMS) play a key role in co-locating LC applications with batch jobs. A series of state-of-the-art CMSes like Borg [28] and Quasar [7] adopt an elaborate centralized scheduler for resource allocation and job placement. Two-level CMSes such as Mesos [10] uses a thin resource manager layer that allows multiple computing frameworks to share resources. Share state CMSes like Omega [26] allows multiple schedulers have a view of the entire cluster. Distributed CMSes such as Sparrow [23] makes random scheduling decisions for short batch jobs to achieve high throughput.

As for Alibaba, unlike the CMSes we discussed above, they use *a hybrid of two-level and share-state architecture* to manage resource and two different workloads. At the beginning, it's online and batch applications are running separately in different clusters. The batch-workload cluster achieves high CPU utilization that more than 75%, while online-service cluster exhibits only about 10%, on average [13]. To improve resource efficiency, therefore, Alibaba co-located online services with batch jobs. As shown in figure 1, level1 has two schedulers: Sigma [13] and Fuxi [30], each one has its own resource pool. Sigma is responsible for managing user-facing, long-running online services, which are running in containers. Fuxi manages batch jobs, which are directly running on physical hosts. Meanwhile, in order to obtain global view and make better scheduling decisions, Sigma and Fuxi share the state of the entire cluster. This hybrid architecture has been verified to be a successful design by China's biggest Shopping Festival in 2017 and 2018. It is worth noting that the co-located cluster is Alibaba's internal private cloud rather than the public cloud Aliyun.

Because of some historical reasons, they did not redesign a new scheduler. Instead, they used a coordinated way to manage two independent schedulers and unified the resource pool. Level-0 controller is a central scheduler, which is responsible for resource management, data transfer and communication between Sigma and Fuxi. Level2 is on top of level1, consists of multiple business frameworks such as DB, search engine and compute.

# 3 CLUSTER TRACE OVERVIEW

This section describes the Alibaba's new trace, overall cluster usage compared with the resource usage in 2017. And then presents the characteristics of workloads in co-located cluster that observed from the dataset.

## 3.1 Dataset

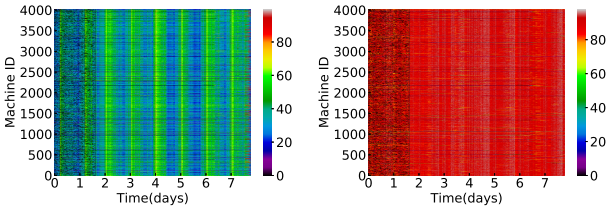
The new released trace [12] contains larger scale of machines and longer period. It consists of 4K machines, 9K online services and 4M batch jobs with static and runtime information over 8 days. The dataset contains three separate traces, i.e., servers, online services and batch jobs. Each trace contains two files, meta file records basic information and usage file stores the runtime data.

**Servers**. The dataset contains 4K machines. The meta file records machine ID, status, specifications and disaster level. Machine has two states, *USING* indicates that the machine is in using and *IMPORT_INSTALLING* means is is being imported (e.g. installing operating system). Unlike the heterogeneity in Google's machines [24], all server's specifications are same in the trace with 96 cores and 1 unit memory normalized. The usage file records the runtime resource usage, including CPU, Memory, Network, IO and MPKI.

**Online services**. As an e-commerce company, Alibaba's online services are mainly user-facing, long-running applications, such as search engine, online shopping and advertising. All of these services are running in containers and scaled across thousands of servers with strict Service Level Objectives (SLO) in tail latency. Each online service has two or more containers, which are scheduled on different hosts. Meanwhile, the containers of different services are co-located with each other on the same physical host. Besides, the majority of online services are written in Java, making up to more than 90% services and containers. It forms a huge Java applications cluster.

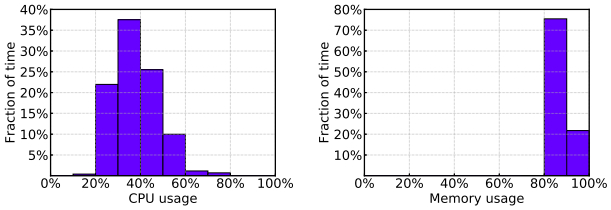
In the dataset, the meta file contains static information of containers such as status, its owner service, resource needs and the host where the container is running on. Container status includes *Allocated*, *Started*, *Stopped* and *Unknown*. *Allocated* indicates the container is in resource allocation stage; *Started* implies container is running; *Stopped* means it's stopped; *Unknown* indicates some unknown errors happened. The usage file stores the runtime resource usage of containers, including CPU, memory, Network, etc.

**Batch Jobs**. Batch jobs such as MapReduce and machine learning are submitted by internal users. They are all non-production jobs, directly running on physical host. Batch jobs can be described by a 'Job-Task-Instance' model. Each submitted job will be split into multiple tasks with different computing logic. There are 12 different types of tasks and some of them can be expressed by a Directed Acyclic Graph (DAG) according to the computation dependency. Therefore, the completion time of a job is determined by all of




(a) CPU usage. (b) Memory usage.

**Figure 2: Moving 15-minutely average of CPU and memory utilization. Black point means missing data.**




(a) Average CPU usage. (b) Average Memory usage.

**Figure 3: Average resource usage of all machines, aggregating every 10 second.**

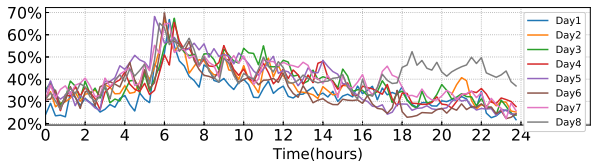
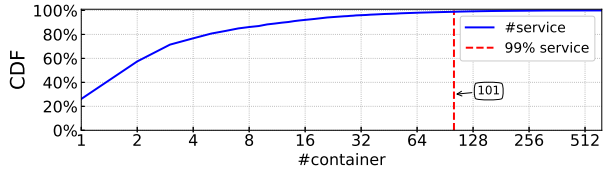


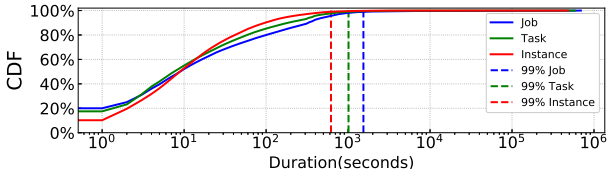

**Figure 4: Machine average CPU usage in 8 days.**

its tasks. Each task contains at least one instance, the smallest scheduling unit in Fuxi. Besides, each instance of the same task has same binary code and resource needs. Similarly, the duration of a task depends on all of its instances. This dataset includes 4 million batch jobs, 14 million tasks and 1.4 billion instances.

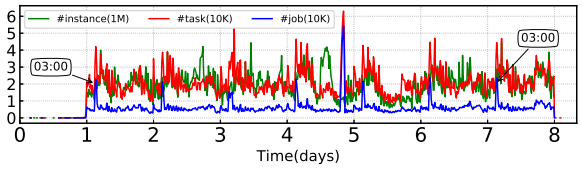
The meta file records basic information such as task type, start and finish time, DAG dependency, the amount of instance and planed resource. Each record in usage file indicates one instance execution information, including resource usage and final state. *Failed* state means the instance dose not run successfully; *Interrupted* implies it's failed without completion; *Ready* indicates the it's failed when ready to run; *Running* means it's failed when running (such as terminated by user), while only *Terminated* state implies the instance is completed. An instance may fail due to various reasons (e.g. resource insufficient or machine failures). However, details are not provided in the dataset.




(a) Number of containers per-service.




(b) Batch job, task and instance durations.




(c) Number of batch job, task and instance arrived by time.

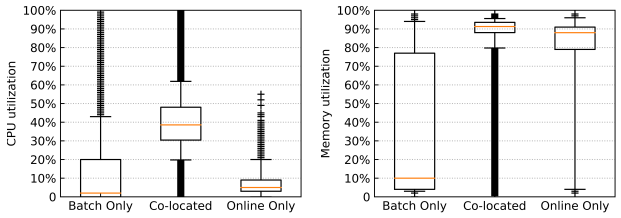
**Figure 5: (a) The number of containers per-service. (b) The CDF of batch job, task, and instance durations. (c) The number of batch job, task and instance arrived by time.**

## 3.2 Overall Usage

We first analyse the overall resource usage of Alibaba cluster. From the dataset, all machines have the same specification of 96 cores and 1 unit memory normalized. Figure 2 shows the heatmap of machine-level resource usage over 8 days trace period. Each horizontal stripe corresponding to one machine, and memory seems achieve more higher resource utilization than CPU. From Figure 3 we can observe that the average CPU utilization of entire cluster is between 20%-50% in majority of the time, while average memory utilization is above 80% all the time and is almost fully utilized. Besides, we can find out the average CPU usage exhibits strong periodicity, which is clearly shown in Figure 4. Everyday it has a peak at 06:00 and then gradually declines, implying the accurate prediction is possible.

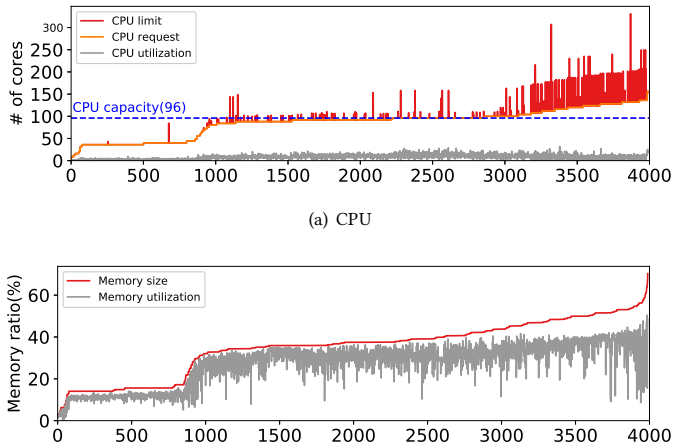
Different from the old trace in 2017, the new trace indicates Alibaba's cluster achieved higher resources efficiency. Surprisingly the improvement of memory usage are much larger than CPU, from 50% [4] to more than 80%. At cluster level, the average utilization of CPU and memory are 38.2% and 88.2%, respectively. The cluster is nearly run out of memory. Besides, a common occurrence in the cluster is that **a large number of batch jobs are queued with sufficient CPU resources, but they cannot be scheduled due to lack of memory**[1]. It seems that memory shortage has became the main obstacle preventing co-locating more workloads on one physical server. And this phenomenon further limits the CPU efficiency of datacenter.

[1]This phenomenon is confirmed by Alibaba engineers.




(a) CPU usage. (b) Memory usage.

**Figure 6: Boxplot of CPU and memory utilization distributions for three regions. The horizontal line in the each boxplot shows the median. The boundaries of the boxplots depict the 25th and 75th percentiles, the whiskers indicate the 5th and 95th percentiles.**




(a) CPU

(b) Memory

**Figure 7: Resource reserved for online services in each machine. X-axis represents the machines which is sorted by the number of CPUs/Memory request. (a) shows CPU request, limit and average utilization. The horizontal dashed line indicates the CPU capacity of one physical host; (b) shows memory reserved and used by containers on each machine.**

## 3.3 Characteristics

**Workload heterogeneity**. The diversity applications are now a nature feature in modern datacenters [8] and it exacerbates the heterogeneity of workloads. We make the following observations: (1) There is a great variety of workloads of online and batch applications. In the dataset, batch jobs are submitted by internal users and the 'Job-Task-Instance' model highly increases the diversity of batch jobs. Moreover, there are 9K different online services, which are all end-user-facing applications. (2) The online services and batch tasks are have various resource requirements, and the containers of the same service may configured with different specifications. The number of containers for each service is clearly shown in Figure 5(a). The thousands of applications make resource allocation an arduous task. (3) The various online services are with diverse SLO in tail latency. Based on the observations, the workload heterogeneity brings great challenge to resource allocation in co-located cluster, while guaranteeing the performance of online services and achieving high resource efficiency.

**Majority of batch jobs are small and short**. Data analytics frameworks such as MapReduce are running many short (seconds to minutes) jobs. In AT, majority of batch jobs are small and short with various resource needs. As shown in Figure 5(b), more than 50% of batch jobs, tasks and instances are finished within 10 seconds, while some are within sub-second. Therefore, Fuxi are designed to support high throughput and low scheduling latency, while ensuring placement quality. Besides, compared to the long-running online services, the high throughput of batch jobs brings high dynamic of cluster, which can further improve resource efficiency.

**Diurnal and nocturnal patterns**. Some studies have found out that user's activity follows diurnal pattern and clusters received more requests and batch jobs at daytime [2]. In the dataset, online services and batch jobs also follow diurnal and nocturnal patterns. Because of user's behavior, user-facing services are more active during the day, while batch jobs are reverse with high arrival rate at midnight. In order to improve resource usage, Fuxi will schedule more batch jobs to co-located cluster at midnight, while lower batch jobs during the day to protect LC application's performance. As shown in Figure 5(c), batch job has a high arrival rate at 03:00 everyday and then gradually declines. Although diurnal and nocturnal patterns can better exploits the available resources in day level, it impacts the load varies of cluster. The uncertainty of user's access and high throughput of batch jobs brings unpredictability in resource interference, which further complicates the resource management in co-located cluster.

# 4 RESOURCE ALLOCATION

As we analyzed in Section 3, memory seemingly becomes the new bottleneck and limits the resource efficiency of datacenter. In this section, we further decompose this phenomenon from the view of resource allocation.

According to the types of workloads running on, we partition the cluster into three regions, i.e., batch jobs only, LC applications only and co-located regions. To explore the impact of co-location on resource usage, we calculate the distribution of resource utilization for these three areas. As shown in Figure 6, we observe that batch only and LC only regions' CPU utilizations are significantly lower than that of co-located region. Batch only region's average memory utilization is lower than others. Co-located area achieves higher resource efficiency. Because LC and batch jobs are all sensitive to resource allocations [3], how to allocate resource to them remains a problem. Conservative allocation will hurt the throughput for batch jobs, while optimistic allocation will cause unpredictable performance variability for LC services [19]. Below, we describe how Sigma and Fuxi allocate resource to LC applications and batch jobs, and static memory partition in detail. And then present how this hybrid allocation method limits the resource efficiency of datacenter.

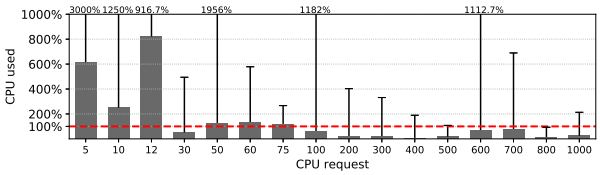
## 4.1 CMS resource allocation

**Conservative allocation**. In order to guarantee the QoS of LC applications, a common approach is reserving ample resources for them [7]. Sigma takes this method to allocate sufficient resources for each container. It is a kind of over-provisioning and we called *conservative allocation*. As shown in Figure 7, we calculate the per-machine's resource requested by online services. Resource of CPU has two values, one is request (requested by container) and another is limit (maximum CPU container can use). We observe that the sum of CPU cores requested by online services is almost equal to total capacity of cluster (94.2% average) and 37% memory resources are reserved by them. However, these applications' CPU usage is very low (9.5% average) with only few moment achieve high efficiency. Containers' memory utilization is higher (80.6% average), because of the feature of JVM. With the respect of resource efficiency, some servers' CPU are oversold to improve usage. As a compressible resource, CPU can be effectively used by other jobs through CPU share or priority-based scheduling. Things are different to memory resource. In Alibaba, the majority of containers' JVM configuration of minimum memory size for pile and heap (xms) and maximum memory size for pile and heap (xmx) are equal. Besides, due to the lack of memory reclaim technology, these memory will be always stranded in container's lifecycle. Although when unpredictable bursty spike occurs, reserving sufficient resources can guarantee online service's QoS, it hurts resource efficiency of cluster.

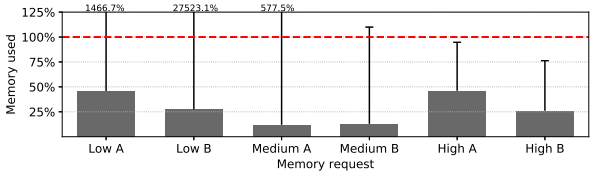
**Optimistic allocation**. Batch jobs can exploit the idle resources on host to improve usage and can use more than they request. They will request resources before scheduling and Fuxi uses an incremental resource allocation approach to meet their request [30]. However, as shown in Figure 8(c), majority batch instances actually use more resources in runtime than they requested, which brings high elasticity in cluster. Figure 8(a,b) depicts instances' average runtime resource used vs. amount of resource they requested. We can find out that instances with low resources request tend to use more resources and most of highest average utilizations in each group are exceed 100% (used more than requested). This phenomena relevants to Fuxi's incremental resource management protocol. It's a kind of over-commitment and we called *optimistic allocation*. In this way, batch jobs can use the resources underutilized when online services are not busy, which is determined by Fuxi. Meanwhile, resources can be reclaimed by their owners when needed.

**Resource mismatch**. As discussed above, Alibaba's CMS uses a *conservative allocation* method to protect online service's QoS, while using a *optimistic allocation* approach for batch jobs to exploit the spare resources. However, behind these allocation, there exist a *resource mismatch of CPU and memory*, and memory first tends to be used up before CPU.

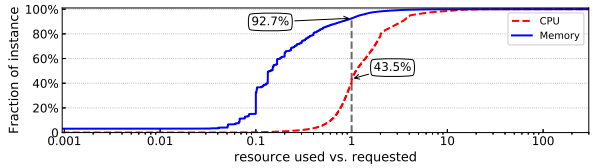
As for diverse online services, they only use a few types of static resource patterns. The resource request for online service includes CPU (request and limit) and Memory. The number of CPU request range from 1 to 32 cores (with 8 values in total), the CPU limit range from 1 to 192 (with 19 values) and the memory range from 0.0 to 25 (with 24 values in total, 25 means 25% memory resource of one physical host). Theoretically, there should be 3648 different resources combinations. However, only 61 patterns of ⟨CPU Request, CPU Limit, Memory⟩ are used observed from 9K services and




(a) CPU usage.




(b) Memory usage.




(c) Used/Requested

**Figure 8: Batch instances' average (a) CPU and (b) memory utilization relative to the resource they request. The top bar represents the highest average utilization in each group. Memory requests are classified into 6 groups: LowA [0.02, 0.1), LowB [0.1, 1), MediumA [1, 5), MediumB [5, 10), HighA [10, 15) and HighB [15, 17.17]. (c) The CDF of instances' maximum used CPU and memory resource in runtime vs. they requested before scheduling.**

70K containers. Besides, ⟨400, 400, 1.56⟩ (400 means 4 CPU core) is most widely used resource pattern, covering 66.8% containers. With diverse online services, each application at most has two different patterns, meanwhile with low utilization. It indicates deprovision excess resource from LC applications and reallocate them to batch jobs is possible. As for batch instances, majority are CPU intensive and they have more flexibility to use spare CPU cycles and idle memory resources in host. However, batch jobs can not use the memory resources stranded by LC applications. In sum, given this hybrid allocation method, memory reaches the roof first. After years of endeavor, *memory seemingly becomes the new bottleneck that prevents co-locating more workloads on one server.*

## 4.2 Static memory partition

In Alibaba's co-located hosts, memory resources are statically partitioned into three regions for LC applications, batch jobs and system. Figure 9 shows the memory model of co-located server. The solid line brackets represent the memory quotas of LC applications, batch jobs and system, the sum represents the total memory of the one server. In general, each machine has different quota ratio. However, LC applications generally would not request all memory in online

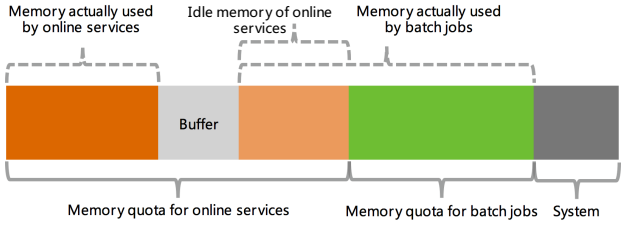
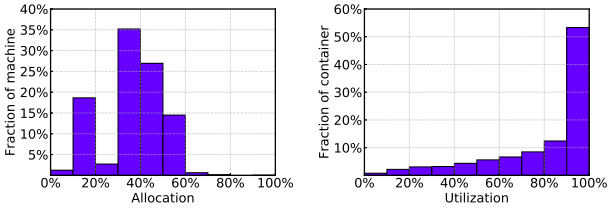



**Figure 9: Static memory allocate model in co-located server. Quota ratios are various for different host.**




(a) Memory occupied by LC applications. (b) Memory utilization.

**Figure 10: Distribution of (a) memory occupied by latency-critical containers per-machine (b) and average memory utilization per-container.**

quota and remains some idle memory. A part of them will be reserved as a buffer in order to prevent the bursty resource needs, and the remaining part can be used by batch jobs. But memory shortage is still a problem in some nodes, thereby infeasible for co-locating more batch workloads to further use idle CPU cycles. Figure 10 represents the distribution of memory requested by LC containers per-machine. 30%-60% of memory resource in majority servers are stranded by online services, while on average 30% of memory are underutilized. Furthermore, as discussed above, majority memory resource will be always stranded by Java applications and can not be reallocated to other jobs. Although static memory partition is temporarily a reasonable approach to assign resource, it wastes massive memory resource.

## 4.3 Implication

Sigma and Fuxi's hybrid resource allocation and static memory partition methods bring high resource efficiency of cluster. However, it causes serious resource mismatch of CPU and memory and it's not sustainable in the long run. Based on these observations, we argue the following. (1) Although conservative allocation can protect LC application's performance, identifying the specific resources requirements of workloads is necessary to further improve resource efficiency. (2) Hardware resource disaggregation such as CPU and memory will bring great benefits. In Alibaba, they have deployed the compute and storage disaggregated infrastructure and achieve high efficiency. Besides, it brings high flexibility because resource allocation is independent from other components [27] and batch jobs can be reschedule to any machine without caring about data migration. (3) Better global perspective and elaborate scheduling

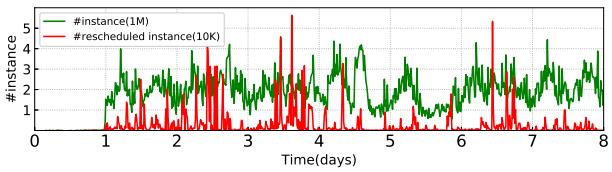



**Figure 11: The number of instance arrived by time and the number of instance reschedule happened in 15 minutes window over 8 days.**

algorithms are needed to improve cluster usage in Alibaba's CMS. For example, there remains some idle machines in the batch only region when the majority of machines are busy.

# 5 RESOURCE ADJUSTMENT

As we discussed above, Sigma and Fuxi use conservative and optimistic allocation approaches for two types of workloads. However, due to the dynamic of cluster, the uncertain contentions on shared resources can significantly affect LC application's performance and highly reduce the QoS provided by cloud providers. Therefore, some dynamic mechanisms are needed, such as feedback controller and dynamic adjustment in co-located cluster. From AT, we find both effective dynamic adjustment (+) and some shortcomings (-).

## 5.1 Batch job eviction and rescheduling-

As second-class citizens, batch jobs are always make compromise to protect LC applications. Due to the unpredictable interference on shared resources, batch jobs could be deferred or evicted when any performance spike happens. In Alibaba's cluster, Fuxi's agent will halt batch instances first when online service's performance is affected, and then reschedule the instances to another host if interference still exists. The uncompleted instances will retry multiple times until being completed successfully. For each retry, instance will be rescheduled to another host, which has sufficient resources, without data migration.[2] In the dataset, batch jobs are only one suffering from rescheduling in any case. According to AT, although the rescheduling ratio (number of rescheduled instances over all instances in 8 days) is only 0.081%, the number of rescheduled-instances (RIS) reaches 1 million and 20% of the RISs have rescheduled more than once. Furthermore, 61% of RIS are rescheduled after running a while, 38% are rescheduled without running and 3% belong to DAG tasks. Figure 11 shows the number of RIS and instance arrived by time over 8 days. We can observe that rescheduling occurs more frequently during the day when online services are more active, while infrequently at midnight when batch jobs have high arrive rate.

When instances are rescheduled to a new machine, they need to run from scratch. To quantify the impact of rescheduling on instance's execution, here we define Reschedule Time Cost (*RTC*) and Reschedule time cost Over execution Time (*ROT*) as follows:

$$RTC = ST^i_{LST} - ST^i_{FST} \quad (1)$$

[2]Because of the compute and storage disaggregated infrastructure in Alibaba, datas are stored in other cluster.

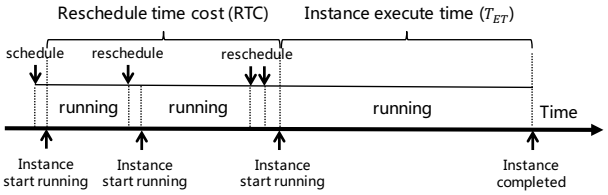



**Figure 12: Defination of reschedule time cost and reschedule time cost over execution time.**

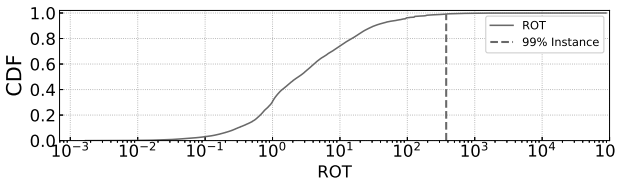



**Figure 13: The CDF of ROT about all rescheduled instances.**

$$ROT = RTC/T_{ET} \quad (2)$$

where $ST^i_{LST}$ refers the start time of instance i in final completed running, $ST^i_{FST}$ represents the start time in first schedule running and $T_{ET}$ indicates the execution time of the instance, as shown in Figure 12. RTC means the overhead of one instance because of rescheduling, the smaller the better. ROT indicates the percent of RTC in instance's execution time, the smaller the better.

Taking a specific instance (ins_63835109 in the dataset) as an example, it was firstly scheduled on server m_1718 at timestamp 373421 and then ran 609 seconds without completion. After that it was rescheduled to server m_177 and began running at timestamp 374031 with execution time of 1196 seconds. We call 610 (374031-373421) seconds as RTC and 0.51 (610/1196) as ROT. This instance was delayed by 10 minutes due to rescheduling.

Figure 13 represents the CDF of ROT about all rescheduled instances, we observe that about 69.2% of RIS's RTC are larger than their execution time and majority RISs suffer from severe delay. With the feature of all-or-nothing, if the instance be halted and rescheduled, it would severely hurts instance's execution time. Although this dynamic mechanism protect LC job's performance, it sacrifices batch job's performance and limits resource efficiency indirectly.

## 5.2 Nocturnal pattern+

In order to guarantee the QoS of online services, Fuxi and level0 strictly limit the resource utilization of batch jobs. Recall that Figure 5(c) shows batch jobs have obvious nocturnal pattern. At midnight, when the online services are inactive, Fuxi will schedule more batch jobs to the co-location cluster to improve resource usage[3]. In this way, it can leverage the underutilized resource at night. Figure 14 depicts the fluctuations of CPU, memory and disk I/O utilizations

[3]In Alibaba, besides co-location cluster, it still has batch-only and online-only cluster. Only part of batch jobs can be scheduled to co-location cluster and others are in batch-only cluster.

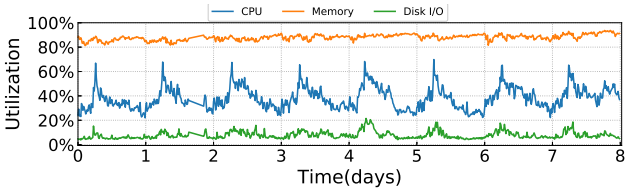



**Figure 14: Overall resource utilization of the co-located cluster within 8 days.**

within 8 days. We observe obvious periodicity of diurnal variation. Every day, batch jobs have a high arrival rate at 03:00, and then CPU utilization increases dramatically and reaches the peak at 06:00, since there are many resource-consuming tasks running at that time. The nocturnal pattern greatly improve the resource efficiency at midnight. However, Fuxi schedules less batch jobs to the co-location cluster during the day to protect LC services, whereas there are ample resource.

## 5.3 Memory stranding-

Alibaba has a large number of online services to provide real-time services. In the dataset, more than 90% of online services are Java applications. Due to the characteristics of Java Virtual Machine (JVM) in memory usage [22] and conservative allocation, online services reserve a large amount of resources at the beginning and strand them in their lifecycle[4]. Figure 10 shows the distribution of memory stranded by containers per-machine and memory utilization. In each server, the memory allocated to the containers is typically between 40% and 60%, and most containers' memory utilization are more than 90%, consuming over 40% of cluster memory resources.

By analyzing the memory stranded by LC applications we find that most of memory are consumed by JVM heap. JVM heap memory consists of two parts: Young Generation and Old Generation. Young Generation is the place where all the new objects are created. When young generation is filled, Minor garbage collection (Minor GC) will be performed. The frequency of Minor GC reflects the real memory requirements of JVM as well as the online workloads. Figure 15 reveals container's Minor GC interval. The online containers have a longer interval of Minor GC from midnight to early morning, which means they require very little memory at that time. When the memory demand of JVM is declined, the JVM heap memory size remains constant, causing plenty of memory are stranded. But during this period, batch jobs need more memory to support the execution of millions of tasks. Therefore, self-contained JVM and lack of reclaim technique further limit the resource efficiency of datacenter.

## 5.4 Implication

Dynamic adjustment and nocturnal pattern are both effective approaches to better leverage idle resources in cluster. Although Alibaba has made great endeavor, it still has some deficiencies. Based on these observations, we argue the following. (1) Memory reclaim

[4]Sigma not fully support real-time resource adjustment, container migration and reshedule.

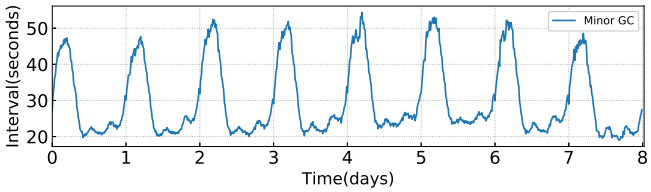



**Figure 15: Overall Minor garbage collection interval within 8 days. Lower interval indicates containers consume memory more frequently.**

technique is needed to improve resource usage. A large amounts of memory can be reclaimed from online services at midnight and reallocated to batch-processing jobs. (2) Targeted optimization is necessary for such a large-scale JVM cluster, such as dynamic management of JVM heap memory. (3) Capacity planning can be better optimized according to the diurnal pattern of online services and prediction information.

## 6 DISCUSSION

Aiming at achieving high resource efficiency of cluster, Alibaba co-locates batch-processing jobs with online services to leverage idle resource. However, hybrid resource allocation and adjustment further complicate resource management in datacenters. Recent research works reveal that the ratio of computing-to-memory-capacity is becoming more imbalanced [14, 15]. The utilization of CPU and memory from AT also confirms this observation (Figure 14). [16] has pointed out that the increasing imbalance between computation and memory may cause memory capacity per-core dropping by 30% every two years. Therefore, the performance of future systems will be limited because of inadequate memory capacity and new memory wall will emerge in co-located cluster. Below, we will discuss from two perspectives, JVM optimization and hardware resource disaggregation, to address this imbalance.

### 6.1 Periodic GC adaptive adjustment

As discussed in section 5.3, a large amount of memory resources are stranded by LC applications due to the conservative allocation and the feature of JVM. Since the performance of garbage-collected applications is highly sensitive to heap size[29], applications with larger heap size will have low frequency of garbage collections (GC). However, it limits resource efficiency in datacenter and will cause thrashing[21]. Based on this observation, we propose a mechanism of Periodic GC adaptive adjustment in JVM. It is an effective solution to maintain an appropriate heap size and it will set a fixed GC frequency for JVM. If a Java application is inactive with few GC, it will actively perform GC operation to reclaim stranded memory, and we will be able to reallocate such memory resource to batch jobs at specific times (e.g. 03:00-06:00). This mechanism can increase the throughput of batch tasks and overall resource usage of cluster.

To quantify the benefit of this mechanism, firstly we design a formula to represent the relationship among workload's CPU utilization, Young Generation Size (*YGS*) and Minor GC Interval (*MGCI*) as follows:

$$CPU = k \cdot \frac{MinorGCInterval(MGCI)}{YoungGenerationSize(YGS)} \quad (3)$$

Where CPU indicates the CPU utilization, MinorGCInterval and YoungGenerationSize are values corresponding to CPU, and k is a constant. According to the formula, the fine-grained control can provide **3.43%** of memory for each physical machine.

Several assumptions need to be made before going into detail:

(1) Under the same workload (CPU utilization), the interval of JVM's Minor GC is linearly related to young generation size.

$$YGS = k \cdot \frac{MGCI}{CPU} + b$$

(2) Theoretically, when the size of the young generation size approaches zero, the interval of Minor GC will also approach zero, thus b = 0.

$$CPU = k \cdot \frac{MGCI}{YGS}$$

(3) 15 seconds is a empirical value for periodic GC adaptive adjustment.

$$\frac{MGCI_a}{YGS_a} = \frac{MGCI_{15s}}{YGS_{15s}}$$

According to the online services' JVM trace[5], the memory size of young generation accounts for 5.49% of one physical host memory and the minimum GC interval (Min) is lager than 40 seconds from 03:00 to 06:00. Assuming that the Minor GC interval is compressed from 40s to 15s, the young generation size can be compressed to 2.06% according to the formula above. This indicates that 3.43% memory resource in one host can be reallocate to other jobs. Taking a cluster with 4,000 machines (256G memory each) as an example, about 34.3T memory can be provided in the certain time, which is equivalent to a capacity of 137 servers.

### 6.2 Hardware resource disaggregation

As discussed in section 4, hybrid resource allocation method causes severe resource mismatch of CPU and memory. Machine, as the natural boundary of hardware resource, has become the bottleneck to achieve higher resource utilization in datacenters. For example, a container can only use CPU and memory resource in the same physical host. With the increasing heterogeneity of applications, the traditional monolithic server [27] is reaching its limits. Separating the monolithic server into several independent hardware components like computation, storage and networking will greatly improve resource utilization and elasticity. Each component has its own resource controller and resource packing will become more efficient, since resource will not be restricted to the same machine. Thanks to the advances network technologies, it becomes common to break the storage components from traditional computer architecture with more cost-effectively and it has been used in Alibaba's co-located cluster. Batch instances can be scheduled on any servers with sufficient resources without caring about data migration.

Since the resource mismatch of CPU and memory heavily limits the resource efficiency in Alibaba's cluster, the hardware resource disaggregation in CPU and memory will bring following the benefits

[5]This part of traces are not open source in Alibaba's dataset.

to their cluster. (1) Due to the disaggregation, memory and CPU resource requests can go beyond the boundary of a physical host. In fact, they can be satisfied by the entire cluster and can make resource packing more efficiency. (2) Memory fragment will be rarely seen and resource usage will become more effective.

## 7 CONCLUSION AND FUTURE WORK

This work has made a thorough analysis of newly released dataset from Alibaba's production cluster. To better understand the resource efficiency and characteristics of workloads in their datacenter, we breakdown into two perspectives, resource allocation and resource adjustment. The result shows several findings as follows. a) Resource mismatch between CPU and memory is acute in their cluster and memory becomes the new bottleneck. b) Batch-processing jobs are treated as second-class citizens and always make compromise to protect latency-critical applications' performance. c) Hybrid of conservative and optimistic allocation method and massive self-contained Java application further complicate resource management. Overall, we believe our findings will be applicable to system designers and provide broad visibility for future research.

## 8 ACKNOWLEDGEMENT

We would like to thank anonymous reviewers for their valuable feedbacks and suggestions. We thank Alibaba's engineers Guoyao Xu, Cheng Wang, Jie Chen, Shun Lv, Xiaoyu Zhang, Yinghao Yu for their feedback on the paper.

This work was supported in part by National Key R&D Program of China (2016YFB1000201), and the National Natural Science Foundation of China (Grant No. 61420106013 and 61702480), and Youth Innovation Promotion Association of Chinese Academy of Sciences (2013073) and Alibaba Group through Alibaba Innovative Research (AIR) Program.

## REFERENCES

[1] Omar Arif Abdul-Rahman and Kento Aida. 2014. Towards understanding the usage behavior of Google cloud users: the mice and elephants phenomenon. In *2014 IEEE 6th International Conference on Cloud Computing Technology and Science (CloudCom)*. IEEE, 272–277.

[2] George Amvrosiadis, Jun Woo Park, Gregory R Ganger, Garth A Gibson, Elisabeth Baseman, and Nathan DeBardeleben. 2018. On the diversity of cluster workloads and its impact on research results. In *2018 {USENIX} Annual Technical Conference ({USENIX}{ATC} 18)*. 533–546.

[3] Shuang Chen, Christina Delimitrou, and Jose F. Martinez. 2019. PARTIES: QoS-Aware Resource Partitioning for Multiple Interactive Services. In *Proceedings of the Twenty Fourth International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS)*.

[4] Yue Cheng, Zheng Chai, and Ali Anwar. 2018. Characterizing Co-located Datacenter Workloads: An Alibaba Case Study. In *Proceedings of the 9th Asia-Pacific Workshop on Systems (APSys '18)*. ACM, New York, NY, USA, Article 12, 3 pages. https://doi.org/10.1145/3265723.3265742

[5] Eli Cortez, Anand Bonde, Alexandre Muzio, Mark Russinovich, Marcus Fontoura, and Ricardo Bianchini. 2017. Resource central: Understanding and predicting workloads for improved resource management in large cloud platforms. In *Proceedings of the 26th Symposium on Operating Systems Principles*. ACM, 153–167.

[6] Christina Delimitrou and Christos Kozyrakis. 2013. Paragon: QoS-Aware Scheduling for Heterogeneous Datacenters. In *Proceedings of the Eighteenth International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS)*.

[7] Christina Delimitrou and Christos Kozyrakis. 2014. Quasar: resource-efficient and QoS-aware cluster management. *ACM SIGPLAN Notices* 49, 4 (2014), 127–144.

[8] Christina Delimitrou, Daniel Sanchez, and Christos Kozyrakis. 2015. Tarcil: reconciling scheduling speed and quality in large shared clusters. In *Proceedings of the Sixth ACM Symposium on Cloud Computing*. ACM, 97–110.

[9] Nosayba El-Sayed, Anurag Mukkara, Po-An Tsai, Harshad Kasture, Xiaosong Ma, and Daniel Sanchez. 2018. KPart: A hybrid cache partitioning-sharing technique for commodity multicores. In *2018 IEEE International Symposium on High Performance Computer Architecture (HPCA)*. IEEE, 104–117.

[10] Benjamin Hindman, Andy Konwinski, Matei Zaharia, Ali Ghodsi, Anthony D Joseph, Randy H Katz, Scott Shenker, and Ion Stoica. 2011. Mesos: A platform for fine-grained resource sharing in the data center.. In *NSDI*, Vol. 11. 22–22.

[11] Alibaba Inc. 2017. Alibaba production cluster data v2017. Website. https://github.com/alibaba/clusterdata.

[12] Alibaba Inc. 2018. Alibaba production cluster data v2018. Website. https://github.com/alibaba/clusterdata/tree/v2018.

[13] Alibaba Inc. 2018. Evolution of Alibaba Large-Scale Colocation Technology. Website. https://www.alibabacloud.com/blog/evolution-of-alibaba-large-scale-colocation-technology_594172.

[14] Sudarsun Kannan, Ada Gavrilovska, Vishal Gupta, and Karsten Schwan. 2017. HeteroOS: OS Design for Heterogeneous Memory Management in Datacenter. In *Proceedings of the 44th Annual International Symposium on Computer Architecture, ISCA 2017, Toronto, ON, Canada, June 24-28, 2017*. 521–534. https://dl.acm.org/citation.cfm?id=3080245

[15] James R. Larus. 2008. Spending Moore's Dividend. 19. https://www.microsoft.com/en-us/research/publication/spending-moores-dividend/

[16] Kevin Lim, Jichuan Chang, Trevor Mudge, Parthasarathy Ranganathan, Steven K Reinhardt, and Thomas F Wenisch. 2009. Disaggregated memory for expansion and sharing in blade servers. In *ACM SIGARCH computer architecture news*, Vol. 37. ACM, 267–278.

[17] Huan Liu. 2011. A measurement study of server utilization in public clouds. In *2011 IEEE Ninth International Conference on Dependable, Autonomic and Secure Computing*. IEEE, 435–442.

[18] Qixiao Liu and Zhibin Yu. 2018. The Elasticity and Plasticity in Semi-Containerized Co-locating Cloud Workload: a View from Alibaba Trace. In *Proceedings of ACM Symposium on Cloud Computing (SOCC)*.

[19] David Lo, Liqun Cheng, Rama Govindaraju, Parthasarathy Ranganathan, and Christos Kozyrakis. 2015. Heracles: Improving resource efficiency at scale. In *ACM SIGARCH Computer Architecture News*, Vol. 43. ACM, 450–462.

[20] Chengzhi Lu, Kejiang Ye, Guoyao Xu, Cheng-Zhong Xu, and Tongxin Bai. 2017. Imbalance in the cloud: an analysis on Alibaba cluster trace. In *Big Data (Big Data), 2017 IEEE International Conference on*. IEEE, 2884–2892.

[21] Martin Maas, Tim Harris, Krste Asanović, and John Kubiatowicz. 2015. Trash day: Coordinating garbage collection in distributed systems. In *15th Workshop on Hot Topics in Operating Systems (HotOS {XV})*.

[22] Jeremy Manson, William Pugh, and Sarita V Adve. 2005. *The Java memory model*. Vol. 40. ACM.

[23] Kay Ousterhout, Patrick Wendell, Matei Zaharia, and Ion Stoica. 2013. Sparrow: distributed, low latency scheduling. In *Proceedings of the Twenty-Fourth ACM Symposium on Operating Systems Principles*. ACM, 69–84.

[24] Charles Reiss, Alexey Tumanov, Gregory R Ganger, Randy H Katz, and Michael A Kozuch. 2012. Heterogeneity and dynamicity of clouds at scale: Google trace analysis. In *Proceedings of the Third ACM Symposium on Cloud Computing*. ACM, 7.

[25] Charles Reiss, John Wilkes, and Joseph L. Hellerstein. 2011. *Google cluster-usage traces: format + schema*. Technical Report. Google Inc., Mountain View, CA, USA. Revised 2014-11-17 for version 2.1. Posted at https://github.com/google/cluster-data.

[26] Malte Schwarzkopf, Andy Konwinski, Michael Abd-El-Malek, and John Wilkes. 2013. Omega: flexible, scalable schedulers for large compute clusters. In *Proceedings of the 8th ACM European Conference on Computer Systems*. ACM, 351–364.

[27] Yizhou Shan, Yutong Huang, Yilun Chen, and Yiying Zhang. 2018. LegoOS: A Disseminated, Distributed {OS} for Hardware Resource Disaggregation. In *13th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 18)*. 69–87.

[28] Abhishek Verma, Luis Pedrosa, Madhukar Korupolu, David Oppenheimer, Eric Tune, and John Wilkes. 2015. Large-scale cluster management at Google with Borg. In *Proceedings of the Tenth European Conference on Computer Systems*. ACM, 18.

[29] Ting Yang, Emery D Berger, Scott F Kaplan, and J Eliot B Moss. 2006. CRAMM: Virtual memory support for garbage-collected applications. In *Proceedings of the 7th symposium on Operating systems design and implementation*. USENIX Association, 103–116.

[30] Zhuo Zhang, Chao Li, Yangyu Tao, Renyu Yang, Hong Tang, and Jie Xu. 2014. Fuxi: a fault-tolerant resource management and job scheduling system at internet scale. *Proceedings of the VLDB Endowment* 7, 13 (2014), 1393–1404.

[31] Sergey Zhuravlev, Sergey Blagodurov, and Alexandra Fedorova. 2010. Addressing shared resource contention in multicore processors via scheduling. In *ACM Sigplan Notices*, Vol. 45. ACM, 129–142.