# Aryl: An Elastic Cluster Scheduler for Deep Learning

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#### **Abstract**

Companies build separate training and inference GPU clusters for deep learning, and use separate schedulers to manage them. This leads to problems for both training and inference: inference clusters have low GPU utilization when the traffic load is low; training jobs often experience long queueing time due to lack of resources. We introduce Aryl, a new cluster scheduler to address these problems. Aryl introduces capacity loaning to loan idle inference GPU servers for training jobs. It further exploits *elastic scaling* that scales a training job's GPU allocation to better utilize loaned resources. Capacity loaning and elastic scaling create new challenges to cluster management. When the loaned servers need to be returned, we need to minimize the number of job preemptions: when more GPUs become available, we need to allocate them to elastic jobs and minimize the job completion time (JCT). Aryl addresses these combinatorial problems using principled heuristics. It introduces the notion of server preemption cost which it greedily reduces during server reclaiming. It further relies on the JCT reduction value defined for each additional worker for an elastic job to solve the scheduling problem as a multiple-choice knapsack problem. Prototype implementation on a 64-GPU testbed and large-scale simulation with 15-day traces of over 50,000 production jobs show that Aryl brings 1.53x and 1.50x reductions in average queuing time and JCT, and improves cluster usage by up to 26.9% over the cluster scheduler without capacity loaning or elastic scaling.

### 1 Introduction

Recently, Deep Neural Networks (DNNs) have seen wild successes in many applications [26]. Hyperscale online service providers have adopted DNN, and build large-scale GPU clusters to accelerate DNN workloads for both training and inference. GPU cluster scheduling is a fundamental and critical task to utilize the expensive GPU clusters efficiently, by optimizing the job resource allocation and task placement.

It is common practice today to separately build and manage two types of GPU clusters, one for training and one for

inference. This is because, for the same model, inference requires less computation and GPU memory than training and is less likely to utilize the numerous cores of training GPU [11,35,39]. Inference clusters usually use weaker GPUs, like Nvidia T4, with a fraction of the resources of the training GPUs, e.g., Nvidia V100 and A100.

This separation creates problems for both sides (§2). Our observations are based on experiences of operating production clusters with  $O(10\mathrm{K})$  GPUs for training and even more for inference. Specifically, inference cluster utilization is usually low (<40%) for an extended period of time due to the diurnal traffic pattern. At the same time, training jobs experience long queuing before they can start, with an average of over 3,000s and 95%ile of almost 10,000s as seen from a 15-day trace with over 50,000 jobs. The long queuing time is due to both the high cluster utilization and the GPU resource fragmentation.

To address the above problems, we propose *capacity loan*ing to allow the inference cluster to loan the idle GPU servers during low-traffic periods to run training jobs, and reclaim them back when inference workloads increase again (§2.1). Capacity loaning mitigates both the utilization problem for inference and queuing problem for training. It is feasible for training jobs which do not have strict requirements on GPU type. For on-loan servers, we need to ensure that they are rapidly utilized by training jobs when they become available. We draw inspiration from *elastic scaling* [1,5,36] for training jobs to better use the on-loan servers (§2.2). Elastic scaling enables a running job to scale out or scale in to better utilize the dynamically changing resource pool. It also helps reduce queueing delay since an elastic job can start with a small number of workers first and increase its workers when more resources become available.

Capacity loading and elastic scaling create new degrees of freedom for cluster scheduling. As we navigate the new design space, we meet several new challenges that must be addressed before we can reap the benefits.

First, though loaning decisions can be solely made by the inference cluster scheduler to ensure inference workloads are not affected, reclaiming is more intricate. When the inference

cluster needs to reclaim some on-loan servers, the training scheduler has to preempt all running jobs on those servers. Given the high overhead and prolonged running time associated with preemption, the scheduler must carefully select the servers in order to minimize the total preemptions.

Second, the job scheduling problem is inherently more complicated with elastic scaling. Resource allocation has to consider a mix of inelastic jobs with fixed demand and elastic jobs with *variable* demand. We show that classical scheduling policies such as shortest job first (SJF) no longer works well with elasticity, and finding the JCT-optimal solution for merely two jobs is difficult. Given the allocation results, the scheduler still needs to determine the worker-server placement to minimize fragmentation, where servers are now heterogeneous with different GPUs because of capacity loaning.

Our key intuition in solving these challenges is to prioritize the minimum resources needed by each job over the elastic demand, and to prioritize the dedicated training servers over the on-loan inference servers. This makes sense because the minimum demand of an elastic job is equivalent to an inelastic job to which not allocating resources is detrimental, but the elastic part can be fulfilled later without stalling the job.

Our solution therefore exhibits a two-phase structure following the above intuition. For reclaiming, we first kill the elastic workers running on on-loan servers since stopping them does not lead to any job-level preemption. When preemption becomes inevitable, we characterize the problem as a knapsack problem with dependent item values [32] and develop an efficient heuristic to solve it (§4).

For resource allocation, we first allocate for both inelastic jobs and elastic jobs' base demand, with the aim of launching as many jobs as possible. We then scale out the scheduled elastic jobs if resources permit. The first phase can be solved using SJF to reduce queuing time and the second phase is formulated as a multiple-choice knapsack problem [47] to minimize running time, which in practice can often be solved using dynamic programming (§5.2). We then tackle the placement problem by placing the inelastic jobs to training servers, and elastic jobs to on-loan servers as much as feasible. Jobs are ordered based on the best-fit-decreasing policy to address the bin packing nature [10] and minimize fragmentation (§5.3).

Putting everything together, we design (§3–§5), implement (§6), and evaluate (§7) Aryl, a new cluster scheduler that realizes capacity loaning with elastic scaling. Aryl has an orchestrator that manages capacity loaning by executing instructions from the inference scheduler on when and how much to loan or reclaim, and by deciding which on-loan servers to return for reclaiming. Then a job scheduler periodically determines allocation and placement, and scales new and existing elastic jobs in response to the resource and job dynamics. To be pragmatic, Aryl considers elastic scaling only for large DNNs whose training throughput scales well in our experiments.

The results of Aryl are promising (§7). We build a high-fidelity simulator, and replay a 15-day job trace collected

from 3,544 training GPUs and 4,160 inference GPUs. We find that compared to a FIFO scheduler, Aryl can reduce the average and 95%ile JCT by up to 1.50x and 1.47x, respectively, and improve GPU usage by 26.9%. In terms of job scheduling, Aryl also outperforms state-of-the-art Pollux by 1.32x and 1.37x in median JCT and 95%ile JCT when elastic jobs occupy 36% training resources.

We summarize our contributions as follows.

- We report problems of separate management of training and inference clusters, i.e. low utilization in the inference cluster and long queuing time in the training cluster, measured from production GPU clusters.
- We propose cluster-level capacity loaning and job-level elastic scaling, two new control knobs for cluster scheduling to address the above problems.
- We study the resulting cluster scheduling problems, develop a key intuition to prioritize the minimum resources needed by each job to address elasticity, and use a principled approach to characterize and solve each problem.
- We design and implement Aryl, a novel cluster scheduler that integrates our solutions. Aryl works with existing resource management frameworks and is ready for deployment. Evaluation using testbed experiments and large-scale simulations validates its superior performance.

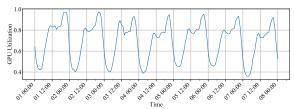
### 2 Motivation

# 2.1 Why Capacity Loaning?

Large GPU clusters are built to accommodate inference and training workloads with distinct requirements. Inference jobs are latency-sensitive since they are customer-facing [11, 39]. Training jobs are much more resource-heavy and run for an extended period of time. Thus they emphasize on job completion times instead. Operators usually deploy separate clusters with different GPU for training and inference, and manage them independently to minimize interference. Our production environment, for example, mainly uses Tesla V100 in the training cluster and T4 in the inference cluster. Job traces show that this practice leads to low utilization of inference resources and sub-optimal performance for training jobs.

**Inefficient inference resource utilization.** Similar to many web services [27], the inference cluster is overprovisioned in order to handle the peak traffic. Inevitably, its resources are often underutilized due to the dynamic inference requests generated by customers.

We plot the GPU utilization in one of our inference clusters with 5-minute intervals for one week's time in Figure 1. Utilization is defined as the fraction of GPUs occupied by at least one inference job. We observe a clear diurnal pattern: peak traffic lasts about four hours at night, and demand trough occurs before dawn. The peak-to-trough ratio is  $\sim$ 2.2 within a day, and the average utilization is  $\sim$ 65%, both implying that there are abundant resources to be exploited in the inference



**Figure 1:** Inference cluster GPU utilization, i.e. fraction of GPUs serving at least one request, in our inference cluster. The measurement spans one week's time from Oct 1 to Oct 7, 2020. The cluster has about 4,000 GPUs. In peak hours GPU utilization approaches 95%.

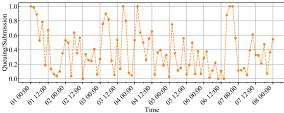


Figure 2: The fraction of queuing jobs among all the newly-submitted jobs in each hour in our training cluster for one week's time. A job suffers queuing time when the scheduler fails to satisfy its resource demand in the first try. If the ratio is high, it means most of the jobs submitted in that hour is queued. The cluster has  $\sim 3.500$  GPUs and the average utilization is 82%.

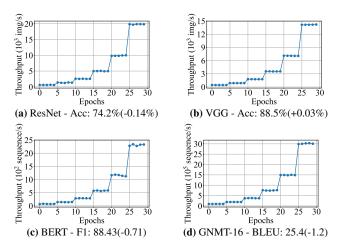
cluster for extended periods of time.

Long queuing time for training jobs. Turning to the training cluster, a salient observation we make is that many training jobs experience long queuing time before they can be dispatched with enough resources. Figure 2 depicts the hourly queuing job ratio in our training cluster for the same week as in Figure 1. A significant fraction of jobs (as high as 100%) still have to wait for resources from time to time. The average queuing time is longer than 3,000 seconds and certainly non-negligible. resolve their queuing delay.

The long queuing time is not only due to lack of resources. In fact, the average GPU utilization across the same period of time is 82%, which means there are often idle GPUs. The dynamic training demand certainly also contributes to the long queuing time. In addition, training demand does not exhibit a clear pattern for prediction.

Capacity loaning. We propose to exploit the unused inference resources in demand trough to run training jobs temporarily, i.e. loaning inference capacity for training. It mitigates both above problems at the same time: The inference cluster is better utilized, and training jobs have more resources to help reduce queuing time. The on-loan capacity can be reclaimed dynamically in case the inference traffic spikes to ensure quality of service.

Though training jobs typically request specific GPUs, we find that up to 21% of jobs in our production traces do not do so and can work with any GPU types. Aryl can launch these jobs on the loaned inference servers rather than waiting for training servers. To ensure feasibility, we may need to adjust the batch size of the training job so that the models and the intermediate data can fit into the smaller inference GPU memory. This is straightforward since we know the GPU memory



**Figure 3:** Throughput of four elastic training jobs using Tesla V100 GPUs. In our testbed, each server hosts 8 GPUs connected by NVLink. Servers use 100G InfiniBand interconnects. Each worker container uses 2 GPUs. The workers are doubled every 5 epochs, starting from 1 worker. We list the performance and the gap with inelastic training in the brackets.

differences; more details can be found in Appendix §E.

Another more aggressive way to exploit the borrowed servers is to run a training job on heterogeneous GPUs, i.e. using both training and inference GPUs (e.g. V100 and T4). Heterogeneous training further improves the scheduling flexibility with more performance gains potentially. However, it requires delicate systems and algorithm support to work well, since the workers have to adopt different hyperparameter settings and inherently make progress at different paces [8, 33, 38, 57]. Given that heterogeneous training remains an active research topic, our production training system only provides experimental support for it at the moment. Aryl's design does not depend on it, and we evaluate the effect of heterogeneous training on Aryl in §7.2 when it is enabled for a small fraction of our jobs with non-ideal performance.

# 2.2 Elastic Scaling for the Full Potential

To better cope with the constantly changing cluster capacity and further exploit the loaned inference resources, Aryl considers *elastic scaling*. Recently, elastic scaling has been introduced into ML frameworks [1, 5, 36] where a job can take a variable number of workers according to resource availability. One can even adjust the number of workers on-the-fly when the job is running.

Elastic scaling can greatly facilitate capacity loaning. With additional resources, training jobs can dynamically scale out to use more workers with more inference GPUs to accelerate training (provided they are running on inference GPUs already). When the cluster experiences high loads, some jobs could scale in to free some servers. In addition, when vacating the inference resources so they can be reclaimed, the scaling-in operation reduces the need of completely preempting the jobs which incurs high overheads with checkpointing, re-launching containers, etc. An acute reader might be won-

dering about the feasibility and benefit of elastic scaling in general. Indeed, besides the scalability issue of distributed training systems [22, 24, 41, 56], when we change the number of workers on-the-fly, the training hyperparameters may have to be updated as well in order to cope with the new setup. This can be fairly complex: for example, simply keeping the local batch size unchanged and linearly increasing the global batch size may impede the convergence of the model [17].

Thus in Aryl, elastic scaling is only adopted for jobs that scale well to changing number of workers without updating the local batch size. Existing studies [9,23,29,30,58] show that certain models like ResNet [21] and BERT [13] satisfy this requirement. We also find that, as shown in Figure 3, ResNet-50 [21], VGG16 [46], BERT [13], and GNMT-16 [53] all enjoy good throughput scalability and are well-suited for elastic scaling. Our traces reveal that these large jobs account for 36% of training cluster resources with an average running time of 14.2 hours, suggesting ample potential gains using Aryl. For these jobs Aryl also restricts itself to *limited elasticity* where the worker number varies within a range, beyond which more complicated hyperparameter tuning becomes necessary and thus out of scope.

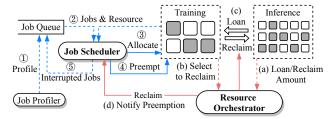
## 2.3 Existing Cluster Schedulers

Much prior work exists on GPU cluster scheduling amid the proliferation of DL workloads. Aryl differs from them mainly in two aspects.

First, capacity loaning represents a new angle to the cluster scheduling problem few have studied. Though shared infrastructure is exploited by recent systems [28, 48, 49, 51, 52, 62], their focus is to schedule multiple types of workloads in a single cluster. Aryl instead focuses on virtually loaning resources between two different clusters. Specifically, it considers the problem of how to reclaim the transient on-loan resources while minimizing its negative impact on training jobs running on them (§4), which has not been considered before. Further, Aryl takes advantage of elasticity of training jobs to better utilize the dynamic cluster resources.

Second, some recent studies also considered scheduling elastic jobs. Gandiva [54] adopts an opportunistic approach to grow or shrink of number of GPUs used by a job without considering cluster-wide efficiency. AFS [22] greedily prioritizes the jobs with the highest throughput per GPU. Pollux [42] co-optimizes both resource allocation and hyperparameter of DNN jobs to achieve high resource efficiency.

Compared to them, Aryl exploits the interplay between elastic scaling and capacity loaning to further improve the performance which has not been explored. In terms of technical approach, Aryl preserves the problem nature of scheduling elastic jobs and treats it as a variant of the knapsack problem, enabling it to make globally good allocation decisions and outperform greedy local heuristics in prior work. Though Aryl does not consider tuning hyperparameters, it can be readily



**Figure 4:** Aryl system architecture. Solid lines indicate control flow and dashed ones data flow. Red lines represent capacity loaning workflow, while blue ones elastic scaling workflow. Each square represents a GPU server; the gray ones are in use.

integrated into Aryl to provide even better performance (§7.4). More details on the differences between Aryl and existing schedulers are presented in Appendix §F for brevity.

# 3 Design Overview

In this section, we describe Aryl's overall architecture and the key design questions we need to address.

**Overall architecture.** Aryl is a GPU cluster scheduler that exploits capacity loaning with elastic job scheduling. It runs on top of a cluster resource manager such as YARN [50] and Kubernetes [3] to execute its decisions.

Figure 4 presents Aryl's architecture. At the cluster level, the *resource orchestrator* obtains instructions from the inference cluster about the number of servers to loan or reclaim (a), determines which servers shall be returned for reclaiming (b), and commands the underlying resource manager to move the selected servers virtually across management boundaries to enforce the decisions (c). When the orchestrator reclaims onloan servers, it may need to preempt the training jobs running on them (d). Job preemption is executed via the job scheduler.

At the job level, jobs are submitted to the job queues. The job profiler estimates the workload ① after jobs are enqueued. The job scheduler ② periodically collects job status and resource usage of the training cluster. Then it ③ computes the resource allocation and placement decisions for each job. Meanwhile, it gets preemption instructions from the orchestrator, interrupts the running jobs ④, and puts them back to the job queues ⑤. Job launching, scaling and interruption actions are again executed by the resource manager. Job scheduler works periodically in a much smaller interval than the orchestrator in order to better handle job dynamics.

Since Aryl mainly deals with the training cluster and does not interfere with inference cluster scheduling, we use "jobs" to simply refer to training jobs hereafter without ambiguity. The basic unit of capacity loaning is a physical server. This is to prevent training jobs from interfering with the inference jobs on the same server [16].

**Key questions.** Aryl's design is centered around two key questions.

• **Server reclaiming.** Which servers should be returned so that the number of preempted jobs is minimized, when some on-loan servers need to be reclaimed?

• **Job scheduling.** How should we determine resource allocation across jobs, and how do we place a job's workers on servers, when some jobs are elastic and some servers are loaned from the inference cluster?

We now present how we address them with Aryl's detailed design in §4 and §5, respectively.

# 4 Loaning and Reclaiming Inference Servers

Aryl moves resources dynamically across inference and training clusters to improve utilization and training performance.

We presume that the inference cluster scheduler dynamically estimates the capacity needed to meet the latency, GPU utilization [4], or other performance targets, based on the predicted inference traffic [11, 20, 44]. Inference workloads are able to grow or shrink their containers along with the incoming traffic. Inference scheduler informs Aryl's resource orchestrator of (1) the amount of resources available for loaning when traffic is low, and (2) the amount of resources to be reclaimed from training in busy hours if any. That is, the inference cluster scheduler completely determines when and which servers to lend, and when and how many servers to ask back, based on its own policy. This way the inference performance is not affected by capacity loaning.

The key question for the training scheduler is the reclaiming mechanism as mentioned in §3, i.e. which on-loan servers should be returned given the number of servers needed by the inference scheduler. This matters because reclaiming a server entails preempting all its running jobs immediately. A job with checkpointing incurs overheads to save and load the checkpoint when resuming training later. If the job does not involve checkpointing [31], its entire progress is lost and training has to restart from the very beginning. To use checkpointing or not is solely controlled by the user. Therefore, the scheduler needs to minimize preemptions by strategically picking the servers to return, especially considering that it is actually common in our environment for jobs to not have checkpointing.

**Minimizing preemptions.** Vacating an on-loan server means its jobs are preempted in a cluster with no elastic jobs. We start with how Aryl minimizes inevitable preemption under this case. and will explain how elastic scaling plays its part in minimizing preemptions in §5.3.

Denote the number of servers that need to be returned at this point as  $N_R$ . Our problem is to pick  $N_R$  on-loan servers—which host inelastic jobs' workers—in order to minimize preemptions. More concretely, we choose to minimize the number of preempted jobs so fewer users are affected. This implies when reclaiming a server, we prefer the one with a big job to the one with a few small ones.

The problem closely resembles the classic knapsack problem (i.e. the 0-1 knapsack problem): The number of servers to reclaim  $N_R$  can be considered as the capacity of the knapsack; each server consumes one unit capacity, and the num-



**Figure 5:** A reclaiming example. Each server has 8 GPUs. GPUs in-use are indicated by the job ID inside each square. GPUs with the same color are hosting the same job.

Server	# running jobs	sum of job's GPU fraction	sum of job's server fraction
1	1	0.5	0.5
2	1	0.5	0.5
3	1	1	1
4	1	0.8	0.5
5	2	0.4	1
6	1	0.8	0.5

**Table 1:** Different definitions of server preemption cost for the reclaiming example in Figure 5.

ber of running jobs is each server's preemption cost (i.e. value). However, the server's preemption cost actually has inter-dependencies that make the problem more difficult.

Consider an example as depicted in Figure 5. Table 1 shows each server's preemption cost as the number of its running jobs (second column). Suppose we need to reclaim two servers. Servers 1 and 2 are obviously the optimal choice with one preemption. Yet the corresponding knapsack problem would select any two 1-cost servers such as 3 and 4 which lead to more preemptions. The issue here is that in our problem the costs of servers are coupled when they host the same job(s), whereas in the 0-1 knapsack problem the cost is independent of each other. Reclaiming server 1 for instance results in an idle server 2 whose cost becomes 0 instead of 1.

Knapsack problem with dependent item values is known to be NP-hard [32]. When  $N_R$  is one server, selecting the one with fewest preemptions is simply by iterating all the on-loan servers. Given an  $N_R$  larger than a single server, we propose to resolve the dependency by treating it as part of the server preemption cost. One possible way is to define server preemption cost as the sum of the GPU fractions of each job on the server. For instance, server 4's cost would be 0.8 as it hosts 80% of job c's GPUs, and server 5's cost is 0.4 (0.2+0.2) as shown in Table 1. One can immediately see that this does not work well as it does not capture the job count. It causes server 5 to be selected with the least cost, which actually leads to two preemptions. Thus we choose to define server preemption cost as the sum of the server fractions of each job as shown also in Table 1. This way server 5's cost is 0.5+0.5=1, i.e. the highest.

Once the preemption cost of each server is computed, the orchestrator selects the servers using the following heuristic: it iteratively picks the server with the lowest preemption cost, preempts its jobs by removing them from all their servers, and updates the cost of these servers correspondingly, until  $N_R$  servers are vacated. Appendix §B summarizes the complete reclaiming design.

Job	w <sup>min</sup>	w <sup>max</sup>	Min. running time
A	2	6	50
В	2	6	20

**Table 2:** Two elastic jobs and their demand information. Jobs completes in min. running time when allocated with  $w^{max}$  workers.

Solution	Initial al	location	JC	Average	
Solution	A	В	A	В	JCT
1	6	2	50	53.33	51.67
2	2	6	63.33	20	41.67
3	4	4	60	30	45

**Table 3:** Possible resource allocation results for the two jobs when they share a cluster that can host 8 workers. Only the initial allocation is shown; once the first job finishes, the other is immediately allocated more resources as much as possible. Three solutions lead to very different JCTs.

# 5 Job Scheduling

Aryl schedules jobs—both inelastic and elastic—to reduce overall JCT by utilizing resources as efficiently as possible. We start by explaining the challenge due to elasticity (§5.1). Then we present the solutions to the two facets of our scheduling problem. The first is *resource allocation* with both elastic and inelastic jobs, i.e. how to determine the number of workers each job gets (§5.2); the second is *placement*, i.e. which servers to place a job's workers on (§5.3). Here we assume that training throughput scales linearly with the number of workers within the scaling range, as discussed in §2.2.

# 5.1 Challenge of Elasticity

Job elasticity presents a unique challenge to resource allocation. Conventional schedulers either deal with jobs with fixed demands, or ones that can arbitrarily scale [22, 42]. However, for jobs with *limited elasticity* [36], the question of how to arbitrate resources so as to minimize average JCT is intricate.

Let us consider a simple example as shown in Table 2. There are two elastic jobs with different minimum running times when allocated their maximum demand. Assume the cluster has eight workers in total. Table 3 shows three common allocation strategies and the corresponding JCT performance. In solution 1, we favor job A by giving it the maximum demand; in solution 2, we favor B instead; and in solution 3 we equally allocate resources to them. All three strategies lead to different JCTs and the difference between the worst and best is 24%, demonstrating that inefficient allocation can lead to poor JCT performance.

Classic algorithms are not optimal. One may be wondering if the classic shortest (or smallest) job first strategies would work here. At least in the example of Table 2, the optimal allocation is indeed to first satisfy job B, which has the shortest running time. Yet, we can construct a counter example as depicted in Table 4 to show that this does not always work. We slightly modify job A to have a maximum demand of 3, and minimum running time of 100; other setup is identical to Table 2. In this case, if we satisfy B first, the average JCT (63.33) is actually worse than satisfying A's demand first (62). Intuitively, shortest job first, or SJF, is designed for fixed

Job	w <sup>min</sup>	w <sup>max</sup>	Min. running time	JCT when favored	Avg. JCT
A	2	3	100	A: 100, B: 24	62
В	2	6	20	A: 106.67, B: 20	63.33

**Table 4:** A counter example with two elastic jobs, where prioritizing A with longer running time is actually better for JCT.

job running times with the intuition that each job should be given the least queuing time, which is the only variable in computing JCT [45]. In our case, job running time itself varies along with the resource allocated, which in turn affects the overall JCT and makes the problem more complex.

More specifically, the above examples reveal two characteristics of elastic job's running time that SJF cannot handle. (1) Elastic scaling complicates the job sorting decision of SJF. Since job running time varies with resource allocated, it is no longer apparent that we simply sort them based on their minimum running time. As shown already, doing so does not lead to the optimal result. (2) The resource efficiency of each job is different. In Table 4, job A has a larger workload (i.e. product of maximum demand and minimum running time) than B, implying that the running time improvement of A is larger than that of B if both are given the same number of workers. Even though the resource allocation difference is merely one when we prioritize different jobs, job A's running time contributes to a 6.67-second JCT reduction while job B's only increases by 4 seconds.

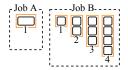
In the simplest two-job case, we can analyze the outcome of different allocation strategies. In Appendix §C, we provide a complete theoretical analysis of this case. Allocation in the general case is undoubtedly more complicated with more elastic jobs plus inelastic jobs, as the optimal strategy requires enumerating the exponentially many possible resource allocations. Our quest in the following is therefore to find a good heuristic for the problem.

## 5.2 Two-Phase Resource Allocation

Intuition: Prioritize inelastic workload. To ease the challenge of elasticity, our insight is that an elastic job has two types of demand: a *base demand* that is inelastic in nature, i.e. the minimum demand, and a *flexible demand* that is elastic. They should be treated separately: The base demand essentially corresponds to an inelastic job whose allocation strategy is binary, and not allocating resources to it incurs more queuing delay to the job. In contrast, the flexible demand can be unfulfilled without serious impact since the job is still making progress with base demand.

Therefore, we treat the *inelastic* workload, including elastic jobs' base demands and inelastic jobs, as the first class citizen. We schedule them first with all available resources to minimize the average JCT. This also avoids starvation. Then in phase two, we consider the flexible demand of elastic jobs to fully utilize the remaining resources from phase one.

**Setup and assumptions.** We focus on solving the offline setting myopically where the set of jobs and resources are given, and cope with the job dynamics and cluster capacity change



Group	Item	Weight	JCT Reduction Value
A	1	2	50
	1	1	20
B	2	2	30
"	3	3	36
1	4	4	40

**Figure 6:** Item weights and JCT reduction values for jobs in Table 4. Here, we assume job A needs 2 GPU per worker and job B 1 GPU per worker.

by periodically performing scheduling in high frequency. This is common in the literature [15,60]. Our scheduling solution is non-preemptive to minimize disruptions to training; preemption only happens during reclaiming when it becomes inevitable as in §4. Thus at a scheduling epoch, the set of available resources refer to idle GPUs and GPUs being used by flexible workers for resizing (including on-loan GPUs), and the set of jobs include those waiting in the queue and running elastic jobs (only flexible workers). The on-loan inference GPUs are normalized relative to training GPUs when calculating the resource capacity.

We rely on job's running time information (min. running time for elastic jobs), which can be predicted with profiling and ML methods [59,61]. Details can be found in §6 and the effect of prediction error will be discussed in §7.5.

**Two-phase heuristic design.** We now elaborate our heuristic. The problem in phase one is how to minimize average JCT for jobs with fixed demands and known running times, for which we adopt the shortest job first (SJF) policy [14] which is a sensible and commonly used solution. As long as there are idle GPUs and pending jobs, we schedule job  $j^*$  with the smallest running time. If demand of  $j^*$  exceeds the remaining capacity, we remove it from the pool and continue.

Phase two is more interesting. We must determine the number of additional GPUs elastic jobs get to maximize the JCT reduction. Note elastic jobs here include those already running. It turns out this problem can be transformed into *multiple-choice knapsack problem* [47]: The knapsack's capacity is the number of remaining GPUs. An elastic job j is a group with  $w_j^{max} - w_j^{min}$  items, each representing a possible allocation result for j's flexible demand. An item's weight is the number of GPUs required for this allocation, and its value is the JCT reduction it brings over the job's maximum running time. Figure 6 illustrates this transformation with the two-job example in Table 4. The problem is to pack the items into the knapsack so that the total value is maximized, with the constraint of taking exactly one or zero item from each group.

The multiple-choice knapsack problem, similar to the classical knapsack, is NP-hard and often solved by dynamic programming which runs in pseudo-polynomial time [47]. With a moderate number of GPUs and jobs, dynamic programming can usually solve the instance efficiently. Appendix §D shows the complete algorithm.

#### **5.3** Worker Placement

Given the allocation results, i.e. number of workers each job gets, we need to determine the placement of each worker.

Our fundamental strategy is bin packing with best-fit decreasing heuristic [37]. Elastic jobs are preferably placed on the inference servers to maximize the potential for scaling in during reclaiming and reduce job preemptions while inelastic jobs are placed on training servers whenever possible. §7.2 presents how this placement strategy helps reduce the job preemptions in reclaiming the on-loan servers when there are elastic jobs.

Given the allocation results, i.e. number of workers each job gets, we still need to determine the placement of each worker to complete scheduling. Our goal is to reduce fragmentation. The primary concern is the mix of inelastic and elastic jobs as well as the transient on-loan servers with different GPUs.

Our fundamental strategy is bin packing with best-fit decreasing (BFD) heuristic [37]. Jobs are sorted in decreasing order of their per-worker GPU demand as GPU is most likely the bottleneck resource for training. Starting from the largest job, we place each worker of the job into a non-empty server that best fits its demand; if none has sufficient remaining resources, we place it on a new server. If the job is elastic, we prefer to place it on inference servers in order to maximize the potential for scaling in during reclaiming and reduce job preemptions. If it is inelastic, we prefer to placing it on training servers. When placing elastic jobs, we also place their base and flexible demands on separate groups of inference servers so that during reclaiming (§4), Aryl can release the server group for flexible demands first without any preemption to see if this alone is sufficient.

### **6** Implementation

We have implemented a prototype of Aryl with about 3500 lines of Python. The prototype works with our existing YARN and Kubernetes deployment to move servers across clusters virtually, manage worker containers for training, and monitor the status of servers and workers. The reclaiming and scheduling algorithms are implemented following Algorithms 1 and 2 in Appendices §B and §D.

We highlight key details of the implementation as follows. **Interface for capacity loaning.** We create a *whitelist* API to facilitate capacity loaning operations. Both Aryl's scheduler and the inference scheduler maintain their own whitelist of servers under their control. Aryl's orchestrator adds onloan servers to job scheduler's whitelist during loaning and removes the selected servers during reclaiming after its scheduler confirms they no longer have running workers.

**Data locality and resource isolation.** Aryl performs capacity loaning only between clusters in the same datacenter to ensure the network bandwidth across servers is consistently high. Also, the basic unit of loaning is a physical server so co-location of inference and training jobs is not possible, and no additional isolation mechanisms are needed.

**Enable elastic scaling.** We enable elastic training with a few modifications to the ML frameworks. We embed a controller

process to each elastic job that coordinates the worker join and departure. Base demand guarantees the gang scheduling of minimum requests and the flexible demand shortens the running time whenever possible while preserving loss convergence. Some recent work [36,55] developed more complete scaling solutions that our implementation could also utilize.

**Job running time estimation.** Aryl's job scheduler relies on the running time estimated by the job profiler. We implement a simple profiler based on the properties of the training jobs. For the planned routine jobs, the profiler estimates based on the history runs of the same job. For those ad-hoc exploratory jobs, we adopt the prediction model in [59] for estimation.

**Heterogeneous GPU training.** As discussed in §2, some training jobs can run on heterogeneous GPUs experimentally. When this feature is turned on, Aryl's job scheduler places them lastly on the remaining resources. The actual scheduling logic for these jobs remains the same, except that if they are elastic, their base demands are placed on training servers, and flexible demands on inference servers whenever possible.

#### 7 Evaluation

We evaluate Aryl using both large-scale simulations and testbed experiments with traces from our production clusters. The highlights of our findings are:

- In large-scale simulations, Aryl's benefit is more salient with 1.53x and 1.50x reductions on average queuing time and JCT, respectively. Capacity loaning has a factor of 1.39 and 1.33 reductions in average queuing time and JCT. Elastic scaling leads to reductions of 1.35x and 1.38x in average queuing time and JCT.
- Compared to state-of-the-art scheduler Pollux [42], Aryl's scheduling algorithm brings 1.35x average queuing time and 1.42x average JCT reductions when both consider tuning the training hyperparameters. Aryl's reclaiming algorithm performs comparably against the optimal solution with only 1–3ms running time.
- In testbed, Aryl improves average job queuing time by 1.38x and average JCT by 1.22x over the baseline without loaning or scaling. Preemption only happens to ∼9% of the jobs in reclaiming with an average 63-second overhead.

These benefits are achieved with only  $\sim$ 5% of the jobs being elastic as discussed in §2.2.

### **7.1 Setup**

**Traces.** We rely on a 15-day job trace from one of our production training clusters with 3,544 GPUs (443 8-GPU servers). There are 50,390 training jobs, and job running time range from minutes to days. We also use a GPU utilization trace from the inference cluster for the same time period. Part of the traces have been shown in Figures 1 and 2 already.

**Simulator.** We built a discrete-event simulator for evaluating Aryl at scale using job traces from production. It simulates the cluster scale, hardware configuration, and all job events including arrival, completion, scaling, and preemption. Job's running time in the simulator is derived from actual training time in the traces. For elastic jobs, we compute its actual training time based on the traces which is inversely proportional to its resource allocation as discussed in §5. We also evaluate Aryl when jobs have imperfect scalability in §7.2.

**Testbed.** Our testbed consists of four 8-GPU training servers and four 8-GPU inference servers. Each training server uses Nvidia V100 GPUs with 32GB GPU memory and has 92 vCPU with 350 GB memory. Each inference server uses Nvidia T4 GPUs with 16GB GPU memory and has 92 vCPU with 210 GB memory. The resource management framework is YARN, and training data is stored in HDFS.

**Scenarios.** We consider various scenarios with different degrees of support for elastic scaling and heterogeneous training, both of which are not widely used today.

- *Basic*: Only large jobs with good scalability as discussed in §2.2 (~5% of all jobs) support elastic scaling within a given range. No heterogeneous training. This corresponds to the status quo in our environment and is the default scenario.
- Advanced: On top of Basic, 10% jobs can run on heterogeneous GPU with non-ideal performance. Specifically, heterogeneous training jobs only achieve at most 70% of the ideal results. We present an empirical analysis of heterogeneous training performance in Appendix §A.
- *Ideal*: All jobs support scaling and heterogeneous training with ideal performance.

**Schemes compared.** We compare Aryl to the following schemes that represent the state-of-the-art and/or the most common solutions to each sub-problem of Aryl. We consider two basic strategies for server reclaiming:

- Random: On-loan servers are randomly selected.
- Smallest (Job) Count First (SCF): The top-k servers that host the smallest number of jobs are chosen.

We consider several solutions to elastic scheduling. Some are slightly modified to conform with our setup for elastic jobs.

- Gandiva [54]: Elastic scaling is also mentioned in Gandiva. It exploits elasticity by scaling out jobs to utilize the remaining resources on servers whenever they are under-utilized. We consider under-utilization to be the period when there are available resources but no pending jobs.
- AFS [22]: It allocates one GPU to each job first and iteratively gives one more GPU to the job with the largest marginal throughput gain. We implement AFS by allocating base demand to each job first and allocating one more worker to the job with the largest throughput gain per GPU.
- Pollux [42]: Pollux computes the goodput of training jobs and applies genetic algorithms to find the resource

#	Scenario	Solution	Qı	euing Tim	e (s)		JCT (s)		GPU Usage		Preemption
"	Scenaro	Bolation	Mean	Median	95%ile	Mean	Median	95%ile	Training	Overall <sup>1</sup>	Ratio <sup>2</sup>
1	Baseline	_	3072	55	8357	16610	791	82933	0.72	0.52	0
2	Basic		2008	25	3356	11089	567	56477	0.86	0.66	10.20%
3	Advanced	Aryl	1833	23	3238	10402	523	56553	0.87	0.69	7.05%
4	Ideal		1157	22	3197	8874	417	41146	0.92	0.72	5.57%
5		Random	2843	23	5471	14657	703	62912	0.76	0.64	20.89%
6	Capacity Loaning	SCF	2791	24	4991	14965	692	62451	0.76	0.66	18.74%
7		Aryl	2204	23	3418	12414	655	57982	0.76	0.66	12.34%
8		Gandiva	3035	49	6632	15912	755	80567	0.79	NA	NA
9	Elastic Scaling	AFS	2284	47	3488	15045	686	60883	0.95	NA	NA
10	(Basic)	Pollux	2791	58	5883	14534	721	72123	0.93	NA	NA
11		Aryl	2275	47	3475	12048	602	57597	0.92	NA	NA
12		Aryl+TunedJobs	2054	43	2749	10229	564	52458	0.91	NA	NA

<sup>(1)</sup> Overall GPU usage denotes the GPU utilization in both training and inference cluster. It is applied when the training cluster size is changing in capacity loaning. (2) Preemption ratio is the ratio between total number of preemptions and the total number of job submissions.

 Table 5: Simulation results using different solutions.

Scenario	Avg. Queuing Time	Avg. JCT	Preemption Ratio
Basic	2231	13864	12.56%
Advanced	1950	12237	10.28%
Ideal	1257	9751	11.89%

**Table 6:** Performance without special placement of elastic jobs. Aryl naively places jobs based on the BFD heuristics.

allocation. It also adjusts batch size to maximize goodput and learning rate based on Adascale [25]. We adopt the model distribution listed by Pollux to capture the model goodput.

We notice that Pollux's idea of tuning the hyperparameters according to allocated resources is orthogonal to job scheduling. To compare with Pollux fairly, we integrate this idea into Aryl in §7.4:

 Aryl+TunedJobs: Use Aryl's job scheduler and adapt Pollux's job agent for job-level hyperparameter-tuning within the scaling range. Job agent adjusts model batch size and learning rate whenever job resource allocation changes.

We consider *Baseline* to be a FIFO cluster scheduler with no capacity loaning or elastic scaling.

### 7.2 Overall Performance in Simulation

We evaluate Aryl thoroughly with large-scale simulation. We first provide overall performance of Aryl. Analyses of its individual components are presented in §7.3 and §7.4.

**Simulator fidelity.** To first establish its fidelity, we evaluate our simulator against the prototype system in testbed with the small trace. We add 63-second overhead whenever a job is preempted in simulation. The simulation results are similar to testbed results, with a difference of 6.2% and 3.4% in average and 95%ile JCT, and 3.5% and 4.4% in average and 95%ile queuing time. The small difference mainly stems from the overhead of placing workers and moving resources between clusters which the simulator does not capture.

**Cluster scale and workload.** We use the full 15-day trace and the same cluster configuration as our production clusters. **Queuing time, JCT, and cluster usage.** Table 5 records the

performance of Aryl in different scenarios. Overall, queuing time and JCT are improved by 1.53x and 1.50x when comparing to Baseline in the Basic scenario (row 2). The overall cluster usage is improved by 26.9%. In the Advanced case with non-ideal heterogeneous training, queuing time and JCT are reduced by 1.68x and 1.60x over Baseline and by 1.10x and 1.07x over Aryl itself in the Basic scenario. In the Ideal case which represents the performance upper bound, the average combined usage of the inference and training clusters is improved by 38.5% (to 72%) in Baseline. Compared with the Basic case, average queuing time and JCT in the Ideal case show additional 1.12x and 37% improvements by virtue of complete job flexibility and perfect performance scalability.

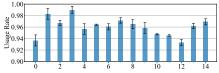
Since the training cluster resource is dynamically changing, we depict the hourly combined cluster usage for 48 hours in Figure 9. The Baseline usage curve shows a clear diurnal pattern mostly attributable to the inference cluster. When capacity loaning is enabled, Aryl improves the usage and flattens the curve; the most significant improvement is a 14% usage increase between Basic and Baseline. The combined usage does not reach 100% as the inference cluster needs some headroom to gracefully handle the latency SLA.

Gain from capacity loaning. We disable elastic scaling in Aryl and evaluate its gain over Baseline to understand the benefit of capacity loaning. Table 5 (row 7) shows that loaning alone reduces average queuing time and JCT by 1.39x and 1.34x over Baseline. Loaning also improves the combined cluster usage from 52% to 66%. We observe that the JCT improvement is not as significant as elastic scaling (row 11). This is mainly because (1) loaning depends on idle inference resources and its gain is less stable, and (2) compared to scaling, loaning itself does not affect job running time.

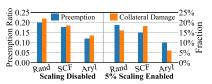
How scaling helps capacity loaning? We now seek to understand how our two key ideas interact and complement each. Scaling helps capacity loaning, especially in reducing preemptions in reclaiming the on-loan servers. With elastic scaling disabled, Table 5 shows that preemption as percentage of running jobs increases from 10.20% (row 2) to 12.34%

	Qι	euing Tim	e (s)	JCT (s)			
	Mean	Median	95%ile	Mean	Median	95%ile	
Baseline	4573	1283	23351	11547	2122	60170	
Aryl	1029	272	7249	6832	1256	35604	

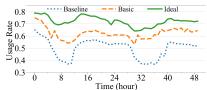
**Table 7:** Queuing time and JCT of jobs running on on-loan servers.



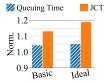
**Figure 7:** The daily average resource usage of onloan servers (monitored every 5 minutes).



**Figure 8:** Preemption ratio and average collateral damage comparison in simulator.



**Figure 9:** Overall resource usage rate in different scenarios.



**Figure 10:** Queuing time and JCT degradation in imperfect scaling.

(row 7). We also observe that on average the flexible server group (hosting flexible workers only) alone satisfies 52.6% of reclaiming demand each time. With more aggressive flexibility (row 4), preemption is reduced to 5.57% and satisfy 82.4% of reclaiming demand each time.

In §5.3, we discussed how Aryl places elastic and inelastic jobs with on-loan servers in the cluster. In Table 6, we compare the placement performance in different scenarios without special treatment to elastic jobs, i.e. instead of grouping their flexible demand and placing to on-loan servers as much as possible, the scheduler places them to training servers first just like inelastic jobs. The most significant difference is in preemption ratio. Without grouping the flexible demand, preemption ratio increases by up to 113% in Ideal (compared to Table 5 row 4). Preemptions also incur degradation to job runtime; for example average queuing time and JCT in the Basic case increase by up to 10% and 20%.

Impact of imperfect scaling Thus far we have assumed linear scalability of elastic jobs based on our empirical analysis in §2.2. Here we also evaluate Aryl's performance where elastic jobs scale imperfectly with throughput loss. Specifically, whenever a job scales beyond the midpoint of its scaling range, its throughput suffers additional 10% loss from the ideal performance each time it scales one step further. Figure 10 presents the queuing time and JCT degradation compared with linear scalability in Basic and Ideal scenarios. In Basic, average queuing time and JCT are 4% and 12% higher than those with linear scalability (Table 5 row 2). Since Aryl prioritizes base demand, queuing time does not degrade much even in the Ideal case. Yet average JCT is inflated by 19% to 10,564 seconds (compared to Table 5 row 4).

# 7.3 Deep-Dive: Capacity Loaning

We first focus on capacity loaning, aiming to understand its sources of gain and how our knapsack-based reclaiming heuristic (Algorithm 1) compares to other schemes. The results here are obtained without elastic scaling.

Sources of gain. The JCT improvement mainly comes from

reduction in queuing time as jobs now can run on the loaned resources instead of waiting in the queue. Table 7 shows the statistics of queuing time and JCT for jobs running on the on-loan servers. The median and 95%ile queuing time is improved by 4.72x and 3.22x, respectively, compared to Baseline. The resource usage rate of on-loan servers throughout the experiment is consistently above 93% as depicted in Figure 7, which proves the effectiveness of resource loaning. **Reclaiming heuristic.** We compare our reclaiming heuristic to Random and SCF. We consider two metrics, percentage of preempted jobs among running jobs, and collateral damage as the fraction of GPUs vacated in excess of the reclaiming demand. It is clear from Figure 8 Aryl outperforms other solutions with and without elastic scaling. Without scaling, Aryl's knapsack-based heuristic reduces preemption and collateral damage by 1.5x, 1.67x and 1.37x, 1.59x over SCF and Random, respectively. With scaling, Aryl scales elastic jobs on the flexible server group first which further widens the gap. From Table 5, it is clear that reducing preemptions is beneficial: Arvl reduces the average queuing time and JCT by 1.26x, 1.28x and 1.20x and 1.18x over SCF and Random.

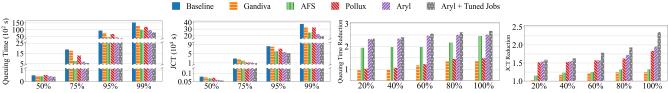
We also run an exhaustive search to find the optimal reclaiming solution as the upper bound. Aryl results in the same number of preemptions as optimal when reclaiming fewer than 60 servers, and incurs 19% more preemptions otherwise. Aryl's reclaiming decision shows an average 84% resemblance as the optimal solution. The average running time of the optimal solution, however, is 420k times that of Aryl.

#### 7.4 Deep-Dive: Job Scheduling

We evaluate job scheduling in more details here. The results are obtained without capacity loaning in Basic scenario.

Sources of gain. Figures 11–12 plot the distribution of queuing time and JCT for all schemes. Our key insight in solving the scheduling problem is to prioritize the inelastic workload (§5.2). Gandiva does not improve Baseline much due to its opportunistic nature: it only scales jobs in low-utilization periods. Both Aryl and AFS allocate the minimum demand to each job initially. From Figure 11, they have similar median queuing time. Though Pollux considers job's minimum demand and favors those with large goodput, it does not explicitly launch as many jobs as possible, thus incurring longer queuing time. Aryl outperforms Pollux by 1.23x and 1.69x in median and 95%ile queuing time.

Turning to JCT, we find from Figure 12 that Pollux tends to prolong the large-and-long jobs by shrinking their resources



**Figure 11:** 50%ile, 75%ile, 95%ile and **Figure 12:** 50%ile, 75%ile, 95%ile and **Figure 13:** Queuing time reduction of **Figure 14:** JCT reduction of Baseline 99%ile of queuing time (Basic).

Baseline as elastic jobs increases.

as elastic jobs increases.

towards the end of training to yield for newly-started jobs that make rapid progress with the same resources. Moreover, Pollux's performance heavily hinges upon the problem scale and the number of iterations allowed for its genetic algorithm. In a large cluster of over 3,500 GPUs with heavy workload, the preset 100 iterations are not sufficient to get an efficient allocation result. To keep the scheduling overhead acceptable, we set the number of iteration to 250 and Aryl still has 1.20x and 1.25x improvements in median and 95%ile JCT. AFS assumes unbounded elasticity and shows a higher resource usage. However, unlimited elasticity and greedy allocation implicitly favor jobs with better throughput at the cost of others. Its average JCT is 1.2x that of Aryl which balances the resources each job gets by making global allocation and considering limited elasticity.

Sensitivity analysis: Proportion of elastic jobs. We wish to analyze whether Aryl is sensitive to the proportion of elastic jobs in the mix. Figure 13 shows the performance comparison when elastic jobs grow from 20% to 100% of the population. All schemes show improvements as a result. Aryl delivers the largest gains in both queuing time and JCT compared to other schemes with more elastic jobs, demonstrating that its scheduler most efficiently exploits job elasticity. AFS also has good gains in queuing time as it initially allocates minimum demand to each job. Its JCT gains, however, are much lower due to the greedy heuristic in ordering the jobs for allocation. Pollux's queuing time performance is poor as queuing time is not considered in its design. Its JCTs are much better because it auto-tunes the hyperparameters for best performance.

Using hyperparameter tuning. We study Aryl+TunedJobs now which adapts Pollux's job agent to tune jobs' hyperparameters as explained in §7.1. In the Basic scenario, Aryl+TunedJobs (row 12 in Table 5) contributes an additional 18% and 13% improvements over Baseline in 95%ile JCT and 99%ile JCT. The improvement is more significant when all the jobs are elastic as seen in Figures 13–14.

More importantly, Aryl+TunedJobs allows for a fair comparison of job scheduling against Pollux as both have hyperparameter tuning now. It outperforms Pollux by 1.32x and 1.37x in median and 95%ile JCT in Basic scenario (Figure 12). Aryl's gain over Pollux is larger here which shows that Aryl's scheduling policy performs better in JCT. The main reason is that Aryl specifically optimizes JCT while Pollux optimizes goodput in order to improve resource efficiency. Thus JCT for some jobs is affected especially near the end of training when the marginal gain of resources becomes smaller (i.e. goodput

is lower) and resource allocation is decreased. Another side-effect of goodput-based scheduling is back-and-forth scaling as goodput varies as soon as hyperparameter or allocation changes. We find the total scaling times of Pollux is 1.76x that of Aryl+TunedJobs in the Ideal scenario, and many are scaling-out followed immediately by scaling-in in the next interval. This may also degrade JCT.

#### 7.5 Testbed Results

Here we use our prototype in testbed experiments to schedule jobs and YARN to run, scale, and preempt them on servers. **Workload.** We use a scaled-down version of the traces with 180 training jobs with 10 elastic ones (similar to the Basic scenario); jobs with (maximum) demand larger than 16 GPUs (50% cluster) are excluded. Job submission in the trace lasts for 8 hours and training time varies from 2 minutes to 2 hours. The inference trace is also scaled down according to the testbed capacity.

JCT and queuing time. Table 8 shows the statistics of queuing time and JCT. Aryl improves average and 95%ile queuing time by 1.38x and 1.36x over Baseline (row group 1). In terms of JCT, Aryl improves the median and 95%ile by 19.9% and 11.7% over Baseline. The gains come from both capacity loaning and elastic scaling: the orchestrator performed 6 loaning and 8 reclaiming operations involving a total of 10 servers, and the scheduler issued 73 scaling operations. In capacity loaning, Aryl outperforms Random and SCF by 19% and 15% in average queuing time. In elastic scaling, Aryl's tail queuing time is 10% shorter than AFS. Its JCT gain is 1.19x over Baseline compared to 1.14x and 1.15x for AFS and Pollux.

The results here show that Aryl is highly effective in reducing queuing time. The JCT improvements are relatively small due to the inference cluster's limited resources compared to job demand. We observe the inference cluster loaned at most three servers which is equivalent to one training server in computational capability, while it is common for a job to demand an entire training server in our trace.

**Preemption.** Aryl reduces preemption significantly by over 1.3x compared to Random and SCF reclaiming schemes (row group 2). We also measure the preemption overhead, including the time to save a checkpoint to the disk, terminate containers, launch new containers on different servers, and load the checkpoint before training starts. The average overhead is 63 seconds, which is adopted in our large-scale simulation.

Sensitivity analysis: Error in running time estimation.

Scenario	Solution	Qu	Queuing Time (s)			JCT (s)			
Secilario		Mean	Median	95%ile	Mean	Median	95%ile	Ratio	
Basic	Baseline Aryl	1532 1109	772 503	1003 738	4078 3335	2183 1747	3096 2731	0 18%	
Capacity Loaning	Random SCF Aryl	1527 1473 1230	658 614 594	993 864 823	3893 3857 3748	2046 1994 1946	3015 3001 2864	34% 30% 22%	
Elastic Scaling	Gandiva AFS Pollux Aryl	1443 1338 1405 1318	645 534 576 546	1002 882 937 798	3882 3521 3552 3413	2015 1836 1934 1791	2893 2803 3004 2794	NA NA NA NA	

Table 8: Testbed results using different solutions.

60-		-					-100%	)
č		Preer	nption	Col	lateral D	amage		
.ॗ 45-							-75%	<u> </u>
Ē 30−		-			-		-50%	cţi
§ 15-		_	_		_	_	-25%	Fre
⊸ 0-				╙.			-0%	
	Rand	SCF	Aryl	Rand	SCF	Aryl	0,0	
	Scal	ing Dis	abled	5% Sca	ling En	abled		

Figure 15: The number of job preemptions and average collateral damage comparison in testbed.

Our second sensitivity analysis concerns the running time prediction which Aryl's scheduler relies on. Table 9 shows the performance under different estimation accuracy. Aryl improves queuing delay by 1.76x over Baseline even when there are 60% wrong predictions (each with at most 25% error). Its gain is consistent with less than 60% wrong predictions.

#### 8 Discussion

Fine-grained resource sharing. Aryl uses bare-metal machine as the basic unit of loaning and reclaiming. Our intention is to avoid interference between training and inference. This concern can be alleviated by improvements from the infrastructure (e.g. better isolation mechanisms). Then one may consider fine-grained sharing on the GPU level, which allows more sharing opportunities but also demands a more careful scheduling design because of the larger problem scale.

**Performance under scaling.** We assume the elastic job's training throughput is linear in the amount of allocated resources within the scaling range. In practice training throughput is likely to scale sub-linearly due to factors such as network communication and synchronization overhead. An improved approach may be to empirically profile the throughput and running time of the workloads as a non-linear function of resources. Aryl's scheduling algorithm still works with non-linear scaling which does not change the combinatorial nature of the problem; we provided simulation results in §7.2.

Heterogeneous GPU training. Training with heterogeneous GPUs is still an active area of research and the current mechanisms are primitive [8]. We observe that though adjusting the batch size can roughly synchronize the workers, it may prolong the convergence of the model in some cases. More effort is needed to improve training efficiency with heterogeneous GPUs and to automate hyperparameter adjustment [7, 34].

% wrong prediction	Queuing time gain	JCT gain
0%	2.37	1.57
20%	2.21	1.52
40%	2.17	1.49
60%	1.76	1.38

**Table 9:** Queuing delay and JCT gain with incorrect running time estimation. The fraction of incorrect estimation varies from 0% to 60%. We assume each incorrect prediction is within an error margin of 25%.

#### 9 Related Work

We now discuss related work not mentioned in §2.

GPU cluster schedulers. There are some schedulers tailored for GPU training clusters. We have discussed Pollux, AFS, and Gandiva extensively in §2.3 and §7.2. Tiresias [19] applies least-attained-service to minimize average JCT. It does not consider elastic scaling. Optimus [40] schedules jobs with a online fitting model, which predicts training model's running time. PAI [52] introduces a scheduler which reserves high-end GPUs for high-GPU tasks and packs low-GPU tasks on less advanced GPUs. These works all schedule jobs in a cluster with fixed capacity. In Appendix §F, we further elaborate the differences between Aryl and existing DNN schedulers.

Systems support for elastic scaling. There is emerging interest in exploiting resource elasticity in distributed training. Systems such as [1,2,5] extend various ML frameworks to support elasticity. [36] proposes an auto-scaling policy by considering cost and scaling efficiency and proves that the scaling overhead is only 4% of checkpointing overhead. AntMan [55] provides a scaling mechanism to micromanage computation and GPU memory during training, and a job scheduler for performance guarantees. They are complementary to Aryl as they provide practical solutions for scaling DNN jobs.

**Dynamic resource allocation.** Graphene [18] and PriorityMeister [62] dynamically adjust resource allocation to fit job's time-varying demand and utilize resources more efficiently. In Aryl, we consider scaling for jobs that can work with a range of resources, which are taken as constraints to the scheduling problem. Aryl schedules jobs with an extra dimension of how much resource should a job get and its impact on cluster performance.

#### 10 Conclusion

We have presented Aryl, an elastic GPU cluster scheduler for deep learning. The key idea is to exploit cluster-level elasticity by loaning idle inferences servers for training, and job-level elasticity by scaling jobs to better utilize the dynamic resource pool. In designing and evaluating Aryl, we have addressed new challenges in cluster management, by introducing heuristics to reduce job preemption cost due to loan-reclaiming, and to minimize job completion time when elastic jobs are presented. We plan to extend Aryl to support training over

heterogeneous GPUs, and to investigate information-agnostic scheduling without knowing jobs' running time a priori.

# 11 Acknowledgment

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# **Heterogeneous GPU Training**

In §2.1, we consider heterogeneous training as a special approach to utilize different types of GPUs. We also evaluate Aryl in a scenario where 10% of jobs can run on heterogeneous GPU with non-ideal performance in §7.2. We now provide some details regarding the implementation of heterogeneous GPU training and empirical analysis of the training performance. Distributed data-parallel training with bulk synchronous parallel for communication is adopted as they are the most widely used techniques in distributed training. The key to efficient training is to balance the training time among workers and avoid stragglers. We adopt a similar approach as [8] to tune the batch size of each work in an online manner. Initially, we set the local batch size of each worker based on their computation capacity and GPU memory constraints. Specifically, the batch size of T4 workers is one-fourth of the batch size of V100 workers. During training, we adjust the local batch size and ensure a similar training time for each iteration. We initialize the window size to be 10 and the step size is set to 1. At each observation window, local batch size of leader workers will increase and that of straggler workers will decrease in step size.

Table 10 shows the throughput and running time of different DNN jobs running on V100 and T4. By comparing the experimental results with the theoretical throughput, we find naively tuning batch size without additional optimization techniques leads to an average degradation of 27%. To achieve the same validation metric, the running time is also lengthened by up to 34% compared with homogeneous training with V100. Therefore, we quantify the non-ideal performance of heterogeneous training to be 70% of the theoretical results in §7.2.

## **Reclaiming Heuristics**

Algorithm 1 shows the pseudo code of how to select servers during reclaiming operation.

# **Analysis of Scheduling Elastic Jobs**

In §5.1, we design a simplified example to show the challenges of finding optimal resource allocation to elastic jobs. Here we provide a formal analysis on which factors affect the optimal allocation in a two-job scenario.

**Setup.** In a cluster with C available GPUs, two pending elastic jobs p and q are waiting for resource allocation. Both jobs have specified their minimum and maximum resource demand. Table 11 lists the notations to be used in the following analysis.

**Objective.** The objective is to determine the resource allocation  $g_p$  and  $g_q$  of the two elastic jobs p and q so that the average JCT is minimized.

#### **Algorithm 1** Server selection for reclaiming.

**Input:**  $\mathcal{I}$ : set of jobs on on-loan severs, where each job j has info of  $S_i$ , the set of servers it is hosted; OnLoanList: set of on-loan severs, where each server s has info of  $\mathcal{I}_s$ , the set of jobs running on it;  $N_R$ : reclaim demand.

```
Output: ReclaimList, set of servers to reclaim
 1: procedure INITPREEMPTIONCOST(J, OnLoanList)
         Q \leftarrow Queue()
 2:
         for server s \in OnLoanList do
 3:
 4:
              Q.\operatorname{push}(\langle s,0\rangle)

    initialize preemption cost

         for job j \in \mathcal{I} do
 5:
             for s \in S_i do
 6:
                  Q.add\_preemption\_cost(s, 1/|S_i|) \triangleright add job
 7:
     cost to s
 8:
         SortByCostIncreasing(Q)
         return Q
 9:
10: procedure UPDATECOST(Q, s')
11:
         for job j \in \mathcal{I}_{s'} do
              for s \in S_i and s \notin s' do
12:
                  \mathcal{I}_s.remove_job( j )
                                                      \triangleright preempt job j
13:
                  Q.subtract\_preemption\_cost(s, 1/|S_i|)
14:
15:
         SortByCostIncreasing(Q)
         return Q
16:
    procedure SELECTSERVERS(\mathcal{I}, OnLoanList, N_R)
         if N_R = 1 then
18:
              s \leftarrow \text{FindBestServer}(OnLoanList})
19:
              return ReclaimList(s)
20:
         Q \leftarrow InitPreemptionCost(\mathcal{I}, OnLoanList)
21:
         ReclaimList \leftarrow []
22:
         while N_R > 0 do
23:
              \langle s, cost \rangle \leftarrow Q.top()
24:
              ReclaimList.append(s)
25:
              Q.pop()
                                              ⊳ remove from the top
26:
              N_R \leftarrow N_R - 1
27:
              UpdateCost(Q, s)
28:
         return ReclaimList
```

**Definitions and constraints.** To facilitate understanding, we still assume linear scalability of elastic jobs. In specific, we define the workload L to be the GPU hours of a job. For elastic scaling jobs, the total workload is constant. Its running time can be computed from L and its resource allocation.

$$rt(L, g_{min}) = \frac{L}{g_{min}} \tag{1}$$

We also make assumptions on the cluster capacity. We omit some of the scenarios as they have straightforward results, including (1) the available resources can merely fulfill the minimum demand of one job (2) there are abundant available resources to host the maximum demand of both jobs. The most intricate case is considered by adding the following

29:

Models & Dataset & Metric	Allo	cation	Batc	h Size	Thro	ughput	Running Time (m)
Wodels & Dataset & Wethe	V100	T4	V100	T4	Theoretical	Experimental	Kulling Time (III)
	16	0	256	-	-	18883	127
ResNet-50 [21] & ImageNet [12]	12	4	248	85	15342	14383	162
& Top 1 Accuracy: 75%	8	8	250	84	11801	9823	155
	4	12	237	82	8261	7297	161
	16	0	128	-	-	791771	35
GNMT [53] & WMT'16 [6]	12	4	128	66	643313	484684	46
& BLEU: 25.5	8	8	123	67	494856	436631	47
	4	12	124	66	346399	312033	44
	32	0	10	-	-	1572	46
BERT [13] & SQuaD v1.1 [43]	24	8	10	4	1277	923	61
& F1: 86	16	16	9	5	982	874	61
	8	24	9	5	687	655	57

<sup>(1)</sup> Theoretical throughput is computed based on the computation capacity difference with homogeneous training using V100 GPU. Here, we consider T4 to be one fourth of V100.

Table 10: Performance of DNN jobs adopting heterogeneous training. Local batch size is measured when it is stabled.

Term	Description
C	Number of GPUs in the cluster
$L_j$	Workload of job j
$g_{min}(j)$	Minimum (base) demand GPU of job j
$g_{max}(j)$	Maximum demand GPU of job j
$g_j$	Allocation of job j
$rt(L_j,g_j)$	Running time of job $j$ in $g_j$ allocation when the
	remaining workload is $L_j$

Table 11: Notations and their descriptions.

constraints:

$$g_{max}(p) \le g_{max}(q) < C$$
  

$$g_{min}(p) + g_{min}(q) < C < g_{max}(p) + g_{max}(q)$$
(2)

where *C* denotes the cluster capacity and it is constrained by the minimum demand and maximum demand of pending jobs, implying that the cluster has sufficient capacity to host two jobs simultaneously, but not enough to host at their maximum demand.

**Problem formulation.** Since in Equation 2 we already narrow down the value of cluster capacity, it can be inferred that neither of the jobs will experience any queuing time. We can then formulate the average JCT by solely considering their running time. From Equation 1, the job running time can be derived from its resource allocation. The average JCT can be represented as:

$$\min_{g_p, g_q} \quad f(g_p, g_q) \tag{3}$$

$$g_{min}(p) \le g_p \le g_{max}(p)$$
 (3b)

$$g_{min}(q) \le g_a \le g_{max}(q) \tag{3c}$$

To minimize the average JCT, it is reasonable to let the jobs reserve as many GPUs as possible (Equation 3a). Meanwhile, the resource allocation should conform with the scaling constraints of the jobs (Equation 3b, 3c).

Under the initial allocation, the average JCT could be represented as:

$$f(g_p, g_q) = \frac{1}{2} \times \sum_{i \in \{p, q\}} \frac{L_i}{g_i}$$
 (4)

It is certain that either (1) two jobs complete at the same time or (2) one of the jobs completes before the other. In terms of the latter case, the uncompleted elastic job can use the vacated resources and scale up to its maximum demand to shorten its running time. For example, job p completes first before job q. The JCT can be computed as:

$$JCT_p = rt(L_p, g_p)$$
  

$$JCT_q = JCT_p + rt(L_q - JCT_p \times g_q, g_{max}(q))$$

where the running time of job q consists of two parts: (1) the time trained in  $g_q$  GPUs, which is the same as the running time of job p and (2) the time to train the remaining workload in its maximum demand. We could also derive the JCT if job q completes first in the same approach.

We refine the formulation case by case with details of the prerequisites.

**Case I:** Job *p* completes first. By substituting  $g_q$  with  $C - g_p$ , the average JCT can be further transformed as:

$$\min_{g_p} \quad \frac{1}{2} \times \left(\frac{L_p}{g_p} + \frac{L_p}{g_p} + \frac{L_q - \frac{L_p}{g_p} \times (C - g_p)}{g_{max}(q)}\right) \tag{5}$$

s.t 
$$\frac{L_p}{g_p} < \frac{L_q}{C - g_p}$$
, (5a)

$$g_{min}(p) \le g_p \le g_{max}(p),\tag{5b}$$

$$C - g_{max}(q) \le g_p \le C - g_{min}(q) \tag{5c}$$

where Equation 5a guarantees job p completes first in the initial allocation (or at the same time as job q). Equation 5b and 5c constrain the resources allocated to each job.

**Case II:** Job q completes first. Similar as Case (I), the average JCT is:

$$\min_{g_p} \quad \frac{1}{2} \times \left( \frac{L_q}{C - g_p} + \frac{L_q}{C - g_p} + \frac{L_p - \frac{L_q}{C - g_p} \times g_p}{g_{max}(p)} \right) \tag{6}$$

s.t 
$$\frac{L_q}{C - g_p} < \frac{L_p}{g_p}$$
, (6a)

$$g_{min}(p) \le g_p \le g_{max}(p),\tag{6b}$$

$$C - g_{max}(q) \le g_p \le C - g_{min}(q) \tag{6c}$$

where the remaining workload of p is completed by  $g_{max}(p)$  GPUs.

Equation 5 and 6 intersect when two jobs completes at the same time (i.e.  $\frac{L_p}{g_p} = \frac{L_q}{g_q}$ ). With further simplification, the average JCT can be represented as:

$$f(g_p) = \begin{cases} \frac{L_p + L_q}{2 \times g_{max}(q)} + \frac{L_p}{g_p} \times (1 - \frac{C}{2 \times g_{max}(q)}) & \text{(I)} \\ \frac{L_p + L_q}{2 \times g_{max}(p)} + \frac{L_q}{C - g_p} \times (1 - \frac{C}{2 \times g_{max}(p)}) & \text{(II)} \end{cases}$$
(7)

By integrating the constraints of both cases with the problem setup (Equation 2), we find the cluster capacity C is the deciding factor as it changes the sign of the coefficient of  $g_p$  (i.e.  $1 - \frac{C}{2 \times g_{max}(q)}$ ).

When the cluster capacity is within the following range:

$$2 \times g_{max}(p) \le C < g_{max}(p) + g_{max}(q) \tag{8}$$

which makes the value of Equation 7 monotonically decrease with  $g_p$ . The minimum average JCT occurs when  $g_p$  is maximum (i.e. fulfulling job p's maximum demand).

However, when the cluster capacity is smaller as:

$$g_{min}(p) + g_{min}(q) \le C < 2 \times g_{max}(p) \tag{9}$$

the value of Equation 7 increases first and then decreases, implying the minimum average JCT are at the end points of  $g_p$ 's interval. Specifically, the optimal allocation is when job p receives its maximum demand or job q receives its maximum demand, depending on the job workload.

We summarize the optimal allocation as follows.

- When the cluster capacity  $C \in [2 \times g_{max}(p), g_{max}(p) + g_{max}(q)]$ , fulfilling the maximum demand of job p (i.e. the job with a smaller  $g_{max}$ ) will bring best average JCT.
- When the cluster capacity  $C \in [g_{min}(p) + g_{min}(q), 2 \times g_{max}(p)]$ , the best average JCT is when the job with a smaller workload L receives its maximum demand.

**Conclusion.** From the result, we find that the optimal resource allocation is affected by multiple factors, including cluster capacity C, the job workload L and the scaling range  $g_{min}, g_{max}$ . Given the complexity of scheduling two elastic jobs, generalizing a consistent solution of optimal resource allocation when there are additional constraints (e.g. inelastic jobs, dynamic cluster, GPU demand per worker) is hard. Therefore, we propose a two-phase heuristic that prioritizes base demand to reduce queuing time and resorts to Knapsack packing to shorten the running time of elastic jobs.

# **D** Job Scheduling Heuristics

Algorithm 2 shows the detailed steps of how we schedule and allocated resources to the queuing jobs.

# Algorithm 2 Two-phase heuristic for resource allocation

```
Input: \mathcal{I}^q: set of queuing jobs, \mathcal{I}^r_e: set of running elastic jobs,
       C^a: available resources
  1: procedure SORTJOBS(\mathcal{J})
             \mathcal{I}' \leftarrow []
 3:
             for job j \in \mathcal{I} do
 4:
                   if j is elastic then
                          \mathcal{I}'.append(\langle j, T_i^{max} \rangle)
                                                                   ⊳ max. running time
 5:
 6:
                          \mathcal{I}'.append(\langle j, T_i \rangle)
 7:
             \mathcal{I}' \leftarrow SortByRunTimeIncrease(\mathcal{I}')
 8:
 9.
             return I'
10: procedure ALLOCATEELASTIC(\mathcal{I}, C)
             groups \leftarrow []
                                                       11:
12:
             for job j \in \mathcal{I} do
                   g \leftarrow \text{NewGroup}()
13:
                   groups.append(g)
14:
                  for w = 1; w \le w_j^{max} - w_j^{min}; w + + \mathbf{do}

m \leftarrow \text{NewItem}()

m.weight \leftarrow (w + w_j^{min})D_j \triangleright D_j: per-worker
15:
16:
       GPU demand
                         m.value \leftarrow T_j^{max} \times w/(w+w_j^{min})

groups.append(m)
18:
19:
             S \leftarrow \text{MaxValueDP}(groups, C) \Rightarrow \text{allocation result}
20:
             return S
21:
22: procedure ALLOCATION(\mathcal{J}^q, \mathcal{J}^r_{\rho}, \mathcal{C}^a)
23:
             \mathcal{I} \leftarrow \text{SortJobs}(\mathcal{I}^q)
             \mathcal{I}^*, C^* \leftarrow \text{AllocateInelastic}(\mathcal{I}, C^a) \triangleright \text{SJF for inelastic}
       demand
             if C^* > 0 then
25:
26:
                   \mathcal{I}_{e}^{r}.add(\mathcal{I}^{*}.get_elastic_jobs())
                   \mathcal{J}_{\varrho}^* \leftarrow \text{AllocateElastic}(\mathcal{J}_{\varrho}^r, C^*)
                                                                               ⊳ allocate for
27:
       flexible demand
                   return \mathcal{I}^*, \mathcal{I}_{\scriptscriptstyle o}^*
28:
```

#### E Jobs on Inference Servers

In §2.1, we note that up to 21% of jobs in our production trace do not request specific GPUs. As long as the models and intermediate data fit into the GPU memory, it can be trained on either training GPU or inference GPU. Since inference GPUs have smaller memory of 16GB, some of these jobs need adjustment of the batch size. When Aryl schedules these jobs on inference servers, it cut down the batch size to half based on the theoretical GPU memory difference between V100 and T4 to ensure feasibility, if necessary.

# F Existing Job Schedulers

Apart from the discussion in §2.3, we compare the Aryl's job scheduler with other existing schedulers in an algorithmic perspective. Table 13 provides a summary.

#	Solution	Queuing Time			JCT			Preemption
"		Mean	Median	95%ile	Mean	Median	95%ile	Ratio
1	Static	3649	41	4993	18747	734	66524	36.75%
2	SSF	2354	26	3657	14953	688	62293	14.34%
3	LSF	2993	28	4774	12953	674	61005	28.58%
4	Aryl	2204	23	3418	12414	655	57982	12.34%

Table 12: Simulation results using different reclaiming heuristics

	Dynamic capacity	Limited elasticity	Avoid starvation	Worker-unit scaling
Tiresias [19]	Х	Х	1	Х
Optimus [40]	X	Δ	X	✓
Gandiva [54]	X	Δ	X	×
AFS [22]	X	X	/	×
Pollux [42]	Δ	Δ	X	×
Aryl	✓	✓	✓	✓

**Table 13:** Comparison with existing job schedulers.  $\Delta$  indicates that it is handled implicitly.

**Dynamic capacity.** Aryl takes cluster capacity as a changing variable in both resource allocation and job placement. During resource allocation, existing schedulers greedily allocate resources job-by-job based on certain metrics regardless of the cluster capacity. Specifically, Tiresias adopts the least attained service to rank jobs; Optimus uses the largest marginal gains; AFS computes the largest throughput improvement. In designing the scheduling policy, these works ignore the outstanding question of whether there are remaining resources to host them. Though Pollux implicitly considers the cluster capacity during scheduling, the random crossover in its genetic algorithm could easily violate the capacity constraints, and repairing operation is randomly conducted. Aryl considers all possible allocations of each job and the cluster capacity and groups the flexible workers during placement when the cluster resource is dynamic. Though Gandiva supports flexible system primitives to handle dynamic capacity, it adopts an opportunistic approach to schedule jobs.

Limited elasticity. Aryl's job scheduler takes every elastic job demand into account during allocation and effectively avoid excessive scaling. Tiresias allocates resources based on the fixed job requirement. Gandiva scales up the job when the cluster is underutilized and the hosting servers have available resources. Though it avoids excessive scaling, it neglects the scalability of the jobs. AFS unlimitedly scales up jobs as long as they have a good throughput gain. Pollux's scheduling policy states that a job can only be allocated with twice of the maximum resources it has been allocated previously. Eventually, it could still cause unlimited scaling. Optimus has no specific boundaries for jobs but heavily relies on an accurate prediction of loss convergence to adjust job resources.

**Avoid starvation.** Aryl allocates base demand of all queuing jobs in phase one to minimize starvation, as well as for AFS. Tiresias is a preemptive scheduler where starvation is handled properly with priority promotion. Optimus, Gandiva and Pollux do not launch as many jobs as possible initially, incurring starvation for jobs at the end of the queue.

**Worker-unit scaling.** Aryl allocates resources in worker demand instead of GPUs. It frees DL frameworks from adjusting the job's distributed architecture and preserves the balance

of pace each worker trains. Only Optimus considers the parameter server architecture of distributed jobs and adjust the workers of each job. AFS naively allocates 1 GPU at a time; Pollux only cares about how many GPUs should be allocated to each job. They are built on an assumption that a running job could either switch between different training modes or balance the training pace with negligible effort. Both are still operations requiring delicate adjustments.