Contents

1. Reviewer 1......2
(1) System Design Description......2
1) DLT job:......2
2) Three stages:......3
3) The design and execution of the three modules......3
(2) System Contribution Description:......4
(3) Refactor the code and add the comments......5
2. Reviewer 2......5
3. Reviewer 3......5
(1) Assumption of resources involved:......5
1) weighted cluster utilization score U and dominant resource utilization U_l......5
(2) Assumption of applications......6
1) Assumption of the iterativeness......6
2) Assumption of the convergence......6
3) Assumption of the ratio between the number of PS and Worker in a DLT job......7
4) Assumption of the decline rate......7
(3) Definition of variables......7
(4) Resource Configuration of the Testbed Clusters......9
(5) Parameter settings......10
1) alpha1 (α_1) and alpha2 (α_2)......10
2) Parameters in the machine learning models GBDT and random forest......11
3) β_l in Eq.(1) and Eq.(16)......11
4) Three threshold of the U: θ_1,θ_2,θ_3......11
5) Submission rate of DLT jobs......11
6) Decline rate range......11
(6) Evaluations to the real clusters......12
(7) Deploying the Qore-DL into prodcution cluster......12
4. Reviewer 4......12
(1) PS framework is not the state-of-the-art......12
(2) Choice Motivation and the heuristic techniques......13
5. Committee Comments......15
(1) Assumptions......15
(2) Parameter Settings......15
1) alpha1 (α_1) and alpha2 (α_2) in the Section V.A (Setup) of paper manuscript......16
2) Parameters in the machine learning models GBDT and random forest......16
3) β_l in Eq.(1) and Eq.(16)......16
4) Three threshold of the U: θ_1,θ_2,θ_3......16
5) Submission rate of DLT jobs......17
6) Decline rate range......17
(3) Details of Experiments Setup......17
(4) real system for realistic training studies......17
Reference......18

First of all, we would like to extend our appreciation to the reviewers for their valuable comments on our paper. We have carefully reviewed all the comments. If I have a chance of the second round modification, we will revisions according to these comments. In this document, I will explain the concerns of the reviews which are summarized as follows.

1. Reviewer 1

> The paper is exceptionally hard to follow. Even though experimental results seem to indicate that the proposed framework outperforms existing state-of-the-art schedulers, I really have a very hard time following the design and making a good sense of the described contribution.

Thank you for the comments of our paper manuscript. I will revision the architecture of the papers and describe the design of the Qore-DL more clearly. Now let me describe the system design and the contribution of Qore-DL generally. More code, data and information can be found at: https://github.com/qore-dl/qore-dl-code .

(1) System Design Description

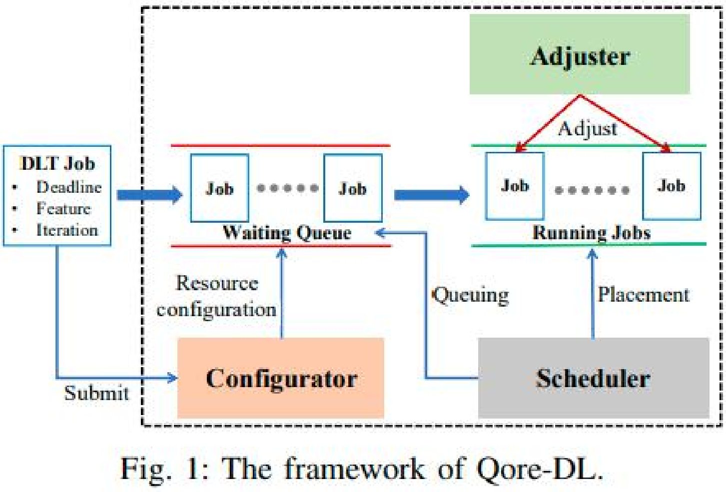


Figure 1:The framework of Qore-DL

Let we review the Figure 1 in the paper. Qore-DL consists of three modules: **configurator, scheduler** and **adjuster.** The design of the three modules aims to jointly optimize the resource configuration of the DLT jobs in the three stages (**submission, queuing** and **running**) of their lifecycles. All the optimizations in Qore-DL is bi-objective: QoS satisfaction and cluster resource efficiency. First of all, let me explain the DLT jobs.

1) DLT job:

DLT job means the deep learning training jobs. Each DLT job consists of multiple instances. For example, a DLT job in the PS-framework have two types of instances: Parameter Server (PS) and the worker. The DLT jobs runs iteratively as shown in Figure 2 in the paper manuscripts.

In our paper, for each iteration, a batch size (e.g., 32) of samples in the dataset are inputed to each worker in the DLT job. Each worker have the same model with millions of trainable parameters. Then Each worker computes the gradient of the trainable parameters with the forward propagation and back propagation which consist of a large number of floating calculation operations. For each iteration, each PS aggregates the gradient of different part of the trainable parameters in the model from all the workers. At the end of the iteration, PSs send the aggregated gradient to the workers for synchronization and workers update the trainable parameters based on the aggregated gradient.

Therefore, we summarize that the training model of each DLT job have three inherent **features**: **batch size, the number of the floating calculation operations and the number of the trainable parameters**. All these three features is extracted by the Qore-DL automatically.

2) Three stages:

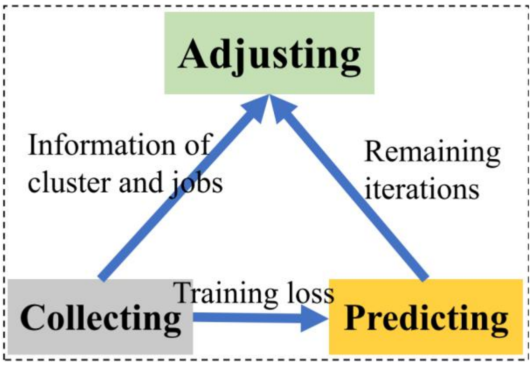
In our paper, we divide the lifecycle of a DLT job into three general stages: **submission, queuing** and **running**. We design three optimization modules corresponding to the three stages respectively. Qore-DL address the QoS-aware optimization of DLT jobs. This means that Qore-DL attempts to complete the DLT jobs before the user-specified deadline to guarantee the deadline satisfaction and consider the resource efficiency of the cluster. Now let me describe the three stages and the modules generally.

3) The design and execution of the three modules

As shown in Figure 1, after the user submits a DLT job to the cluster, this DLT job proceeds to the submission stage. For users, Qore-DL aims to specify the submitting operations. This means that users only need to specify two user-level configuration item: 1) the **deadline** of the DLT job and 2) the the upper limit of the number of **iterations** of the DLT job, which can be regarded as the expected number of **iterations** when only have 1 worker. In the submission stage, the Qore-DL first extracts the three inherent **features** from the DLT job: batch size, the number of the floating calculation operations and the number of the trainable parameters. Then the **configurator** module will make two configurations: 1) use the GBDT model to predict the resource quota (or limit) of the worker and the PS of the DLT job based on the inherent features; 2) use the random forest model to predict the average iteration time (duration of executing the training iteration) and compute the number of PSs and workers according to the predicted iteration time, deadline and the number of iterations. Then the configured DLT jobs will enter the waiting queue and proceeds to the queuing stage.

The **scheduler** module will schedule the jobs in the queuing stage. The priority of the queuing jobs is computed according to the deadline and the dynamic cluster resource availability as shown in Eq.(8) in the paper manuscripts. This priority computation reflect the dual-optimization of the deadline satisfaction and resource efficiency. Specifically, the queuing job with a urgent deadline will have a high priority. When the cluster has a light workload, the jobs with a large resource requirement may have a higher priority. When the cluster has a heavy workload, the jobs with a small resource requirement may have a higher priority. After the target selection, the greedy scheduling algorithm of the Qore-DL is shown in the Algorithm 1 in the paper manuscripts. After placing the jobs in the cluster, the job proceeds to the running stage.

For **adjuster**, since the cluster is highly dynamic and the resource configuration and scheduling decision is not the globally optimal solution of the NP-hard problem, i.e., the dual optimization of deadline satisfaction and resource efficiency. The running DLT jobs need to be adjusted. The adjuster has to realize three functionalities: 1) collecting the resource and loss trace of the DLT jobs; 2) predicting the remaining iterations using the LSTM model; 3) adjusting the resource. The collecting and predicting provides the information to the adjusting functionality.



In the adjusting process, the adjuster select the target jobs based on the Section 4.D.1) in the manuscript as:

Then, we compute the $S_i = \max\left(S_i^1, S_i^0\right)$ of τ_i as the maximum of the two values corresponding to the two adjustment methods: S_i^1 obtained by increasing or decreasing one worker and S_i^0 obtained by increasing or decreasing $\frac{r_{ij}^w}{N_i^w}$ resources to each worker for $j \in J$.

Finally, Qore-DL selects n jobs in the four cases according to the guidelines and the normalized cluster resource utilization U: 1) existing timeout jobs and $U \leq \theta_2$: selecting the timeout jobs with the highest S_i; 2) existing timeout jobs and $U > \theta_2$: selecting the timeout jobs with the highest S_i to increase resources and selecting the deadline-redundancy jobs ($O_i < 0$) with the lowest S_i to preempt resources; 3) no timeout jobs and $U \leq \theta_1$: selecting the jobs with the highest S_i to increase resources; and 4) no timeout jobs and $U > \theta_3$: selecting the jobs with the lowest S_i to reduce resources for future jobs.

At last, we use the generic algorithm to generate the adjustment solutions with highest fitness defined in Eq.(15) in the manuscripts.

(2) System Contribution Description:

1) Bi-objective optimization: first of all the Qore-DL is QoS-aware, the optimization in the three stages are all QoS-oriented to guarantee the deadline satisfaction. On this basis, Qore-DL the resource efficiency optimization is reflected at: 1) the scheduling priority and algorithm in Section IV.C.1 and IV.C.2; 2) the adjusting scheme in Section IV.D: (i) design 4 cases when job selection: increasing resource quota of the jobs with high efficiency and preempt the resource of jobs with poor efficiency and redundant deadline; 2) generate adjusting solution with high efficiency.

2) Three-stage joint optimization: according to the system design description above, the three modules in the Qore-DL realize the bi-objective optimization in the three stages of the DLT jobs. The scheduler leverage the configuration result of the configurator and the adjuster relieve the limitation of the scheduler and configurator caused by the dynamic property of the clusters.

3) Implementation and the Evaluation: We implement the protype in the real cluster and execute realistic training studies in the real cluster. We are developing the Qore-DL to the production cluster of the cooperation company now.

The referenced github code repository is not helpful either and the code is poorly commented, with many comments written in con-English language, and lengthy sections of the code commented out.

(3) Refactor the code and add the comments

We are developing the Qore-DL for the cooperation company and now we refactor some codes including the frontend, monitor, flask server and backend controllers. As for the experiments codes in the github, we are add the comment to describe the role of the functions. With the project advancement, we will update the detailed document as well. More code, data and information can be found at: https://github.com/qore-dl/qore-dl-code .

2. Reviewer 2

Thank you for the comments of our paper manuscript. Now we are developing the Qore-DL in the production cluster and attempt to support the non-PS framework and Pytorch. We will optimize the parameter settings during the test and deploy in the production cluster. More code, data and information can be found at: https://github.com/qore-dl/qore-dl-code .

3. Reviewer 3

Thank you for the comments of our paper manuscript. I will explain the main concern in this document.

More code, data and information can be found at: https://github.com/qore-dl/qore-dl-code .

> The primary weakness of the current manuscript is clarity in both the approach and the experiments. The paper describes about six pages worth of equations making a number of assumptions about both the resources involved and the applications. The description is hard to follow and unnecessarily complicated. The assumptions are not clearly stated and in numerous places.

We will remove the unnecessary equations in revisions of the paper manuscripts. For example, the Definition 1 and Definition 3 in the Section III of paper manuscript use the equation to define the DLT job and the QoS satisfaction. We will use the text description to define them. For the DLT job, we have summarize the features of a DLT job including: 1) **inherent features**: **batch size, the number of the floating calculation operations and the number of the trainable parameters;** 2) the **deadline** of the DLT job and 3) the the upper limit of the number of **iterations** of the DLT job. For the QoS satisfaction of a DLT job, we define it as that the DLT job complete the **iterations** of training or achieve the congestion before the user-specified **deadline**.

I think the assumptions of the resource and applications in the paper manuscript can be summarized as follow:

(1) Assumption of resources involved:

1) weighted cluster utilization score U and dominant resource utilization of host $\mathrm{H_l}$, U_l:

These variables are defined in the Eq.(1) in the manuscript. Actually, U is not the resource utilization but is a metric or score to quantify the pressure of cluster workload, so we compute it in a weighted way and give a larger weight to hosts(machines) having lighter workloads. This is because that when scheduling and adjusting the DLT jobs, the host (machine) with a lighter workload will have a larger resource capacity to place the containers. Actually, our scheduler and adjuster tends to leverage the resource of the machines which have lighter workload. Meanwhile, the weights of $\mathrm{H_l}$ is in the range of (0,1) and the sum of the weights is 1, which guarantee that the weighted cluster utilization score U is positive related to the actual arithmetic mean value of the machine resource utilization in the cluster.

As for the U_l, i.e., the dominant resource utilization of host H_l in the cluster. Firstly, we explain the dominant resource. In the manuscript, we took the idea of Dominant Resource Fairness (DRF) [1] scheduling strategy. In DRF, the dominant resource type of a job is defined as the resource type whose quota of the job has the largest percentage of total cluster resource. For example, for a job A, CPU quota has the 10% of the CPU capacity of the cluster and Memory quota has the 5% of the Memory capacity of the cluster, then CPU is the dominant resource type of the job A. In our manuscript, the dominant resource in Eq.(1) is a formalized description since is in the Section III, the problem definition section. It means the resource type whose quota or consumption has the largest percentage of the cluster resource when running DLT jobs, compared to other resource types. For example,when running DLT jobs in our testbed, we can regard CPU and GPU are the dominant resource types in the CPU and GPU clusters respectively.

(2) Assumption of applications

1) Assumption of the iterativeness

We ran 2,000+ DLT jobs, including VGG, ResNet, DenseNet, Xception and etc in the Kuberentes cluster and collect the data of resource consumption and iteration time(duration) of these jobs. Then we find the iterativeness of the DLT jobs: 1) the resource consumption of the instance in the DLT job has a iterative property, and a almost constant peak of resource consumption appears in each iteration; 2) without the adjusting, the iteration time of a DLT job is similar (or the average iteration time is almost constant). This insight is shown in th Figure 2 in the paper manuscript. Moreover, we can find the similar insight in some references, such as Gandiva (OSDI'2018)[2]. In addition, we have present the iterative process of the running DLT job in the answer of Review 1 (Page 1). The iterative execution of DLT jobs is the reason of the iterativeness of the DLT job. And the resource consumption and the average iteration time should be affected by the inherent features: batch size, the number of the floating calculation operations and the number of the trainable parameters. Meanwhile, the cluster workload also affect the iteration time according to the [2].

Therefore, we propose a GBDT model to predict the resource peak of the DLT jobs. Since the PS and workers have the different execution process as mentioned in the part of this document: Review1.(1).1), we train two GBDT models for PSs and Workers respectively. As for the average time, we use the random forest model to predict it based on the inherent features, weighted cluster utilization score and the resource utilization of the host placing the job.

Furthermore, we need to build the models for the CPU cluster and GPU cluster respectively. As for the performance of the GBDT models, the R^2 value of the CPU, RAM and GPU estimations reaches 86.9%, 96.9% and 97.57%, respectively. As for the RF model, the R2 value of the iteration time estimation is 97.9%. The mean squared error of the iteration time estimation is 21.79 and 0.0556 for the CPU and GPU cluster, respectively. The performance of models seems to be kind of unsatisfied. But this is because that the Kubernetes can support a more fine-grained CPU resource unit (1/1000 CPU cores) but only support the GPU resource unit as 1 GPU card. In addition, iteration time may be up to tens of seconds in the CPU cluster.

2) Assumption of the convergence

Since the inherent of the training process in DLT jobs is to update the parameters with gradient, a large number of the deep learning models will be convergent to a locally optimal solution of parameters [3]. As for the data collected from our submitted DLT jobs we can observe the convergence as well. Then we can leverage this convergence property when predicting the remaining iterations.

3) Assumption of the ratio between the number of PS and Worker in a DLT job.

Since I can not find the theoretical reference of the set of this ratio when I design the Qore-DL according to the collected data of our submitted DLT jobs. Specifically, we give the range of the ratio mainly based on the influence of the average execution time and iteration time shown in the Figure 3 of the manuscript. We will collect data from the DLT jobs training more models, such as conformer and transformer models in the production cluster and analysis the open source data such as [4] to quantify this ratio more reasonably.

4) Assumption of the decline rate

We define the decline rate in the Eq.10 in the Section IV.D.1) of the paper manuscript and use this metric to predict the convergence of the DLT jobs. In our collected data, the decline rate can reflect the convergence property of the DLT job and we present a threshold range of the decline rate in the Section V.A.3) (the workload generation section in the Setup of the Evaluation). The prediction of the convergence is also utilized in some prior work, such as Optimus[5], SLAQ[6] and Klein, Aaron, et al's prediction[7]. However, these researches tends to assume that the value of training or validation loss has a inversely proportional or inversely-square proportional relationship with the number of the executed iterations. In Qore-DL, we use the LSTM model to learn the relationship to avoid the arbitrary assumption. As for the decline rate, a similar metric is defined in SLAQ[6], i.e., the reduction of the normalized loss value between iterations.

the connection of a variable or statement are not justified by references or relation to what is happening on the system.

(3) Definition of variables

We list all the variables in the Table I in the Section III.B of the paper manuscript as follow:

TABLE I: Symbols used in Qore-DL

Symbol		Description
Job request	d_i	Deadline
	I_i	Maximum number of iterations
	γ_i	Threshold of loss decline rate
(L hosts) Cluster	U_l	Weighted resource utilization of host H_l defined in Eq. (17)
	U	Weighted resource utilization of the cluster defined in Eq. (1)
	α_j	Weight of resource type $j \in J$, $\sum_{j \in J} \alpha_j = 1$
	β_l	The probability of placing a task on host H_l defined in Eq. (16)
	$\theta_1 < \theta_2 < \theta_3$	Thresholds of U for cluster status
Configurator	N_i^w, N_i^p	Number of workers and PSs
	r_{ij}^p, r_{ij}^w	Peak requirement of resource $j \in J$ of PS and worker
	ρ	The ratio between N_i^p and N_i^w in Eq. (5)
Scheduler	T_i^A	Available time before deadline defined in Eq. (9)
	R_i^p	Normalized resource requirements of PSs defined in Eq. (7)
	R_i^w	Normalized resource requirement of workers defined in Eq. (7)
	R_i	Normalized overall resource requirement defined in Eq. (6)
	p_i	Priority of τ_i when scheduling defined in Eq. (8)
	N^C	The number of the candidate hosts in Algorithm 1
Adjuster	I_i^r	Predicted necessary remaining iterations
	T_i^I	Average iteration time
	T_i^E	Remaining execution time defined in Eq. (11)
	dr	Decline rate defined in Eq. (10)
	O_i	Time-out degree defined in Eq. (12)
	S_i	Resource sensitivity defined in Eq. (13)
	f_{iu}	Fitness of adjustment solution u in GA defined in Eq. (15)

We will add the reference of the variables when using it if we have the equation to define it or if this variable definition takes the idea of the prior work in our revision. We divide the variables in Qore-DL into five groups.

1) "Job request" variable set: it means the users need to specified for the DLT jobs, including **deadline**, maximum number of **iterations** as presented in part Review1.(1).2) in this document. And we explain the assumption and threshold of loss decline rate in the part: Review3.(1).4) of this document. This threshold of loss decline rate is used to predict the convergence and the necessary remaining iterations of running DLT jobs. If the decline rate of the loss value remains below the threshold in enough number of continuous iterations, we can judge that the DLT job is convergent. If the jobs complete the maximum number of iterations or become convergent, we think the job is completed. The similar completion judgement of deep-learning training is applied in the Tensorflow, Pytorch and scikit-learn library, which are widely used in the real systems.

As for the user-specified deadline, Qore-DL is QoS-aware to guarantee the deadline satisfaction and allow the users to specify the deadline of the DLT jobs. in production, a DLT job is often time-consuming and execute for hours or even days as shown in the paper manuscript. Client concerns the time cost of the jobs in production as presented in [4]. A series of prior research, such as Optimus[5], SLAQ[6] attempts to reduce the completion time of the DLT jobs, however, these frameworks are not QoS-aware, they tend to give more computing resource to the jobs with high resource efficiency or high convergence speed, but users can not control the jobs to complete before the user-expected deadlines.

2) "Cluster" variable set: Since the DLT jobs need to run in the real clusters. The variable in this set attempt to describe the cluster behavior in the real system. We explain the definition of U and U_l in the part: Review 3.(1).1) of this document. We use the weighted cluster utilization score U to quantify the pressure of the cluster workload and this metric can be computed in the real cluster of system. We will validate this metric in the production cluster. If in Eq.(1) of paper, we set the weight $\beta_l = \frac{1}{L}$ for each host in the cluster, U is equivalent to thearithmetic mean value of the cluster resource utilization. As for the dominant resource utilization of host H_l, U_l, we think this metric reflect the resource consumption of the concerned resource type in the real cluster. For example, in our testbed or the Alibaba cluster shown in [4], the resource type: CPU, GPU and Memory are considered.

3) "Configurator" variable set: As we have mentioned in part Reviewer1.(1) of this document, a DLT job running the real clusters have multiple instances. The configurator needs to quantify the number of instances, i.e., the number of PSs and workers for PS framework. As the assumption of iterativeness presented in the part Reviewer3.(2).1) of this document, the instance of the DLT job has a peak resource consumption in each iteration for each resource type, we can use this peak as the resource quota of the instance.

4) "Scheduler" subset: As we have mentioned in part Reviewer1.(1) of this document, the scheduler of the Qore-DL considers the deadline and the resource workload of the cluster. This means that we need to compute the priority of the queuing jobs. Meanwhile, the normalized resource requirement defined in Eq.(7) of the paper manuscript and the available time before deadline defined in Eq.(9) of the paper manuscript are computed for the scheduling priority quantification. As for the candidate host N^C in Algorithm 1, when placing a DLT job into a real cluster, traversing each machine in the large cluster is not feasible, Qore-DL first selects some

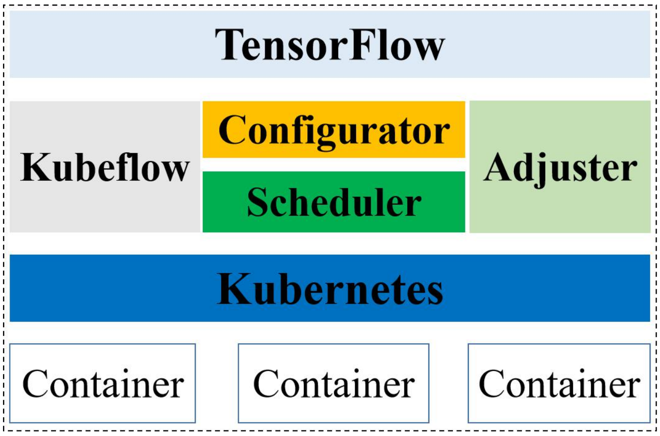
machines as the candidate host to place the scheduling job. This scheme is designed to simplify the placing process.

5) "Adjuster": According to the DLT job running process and the iterativeness and convergence explained in the part Review3.(2) of this document, we can estimated the average iteration time T^{I} and the remaining necessary iterations before convergence, I^{r} to estimate the remaining running time T^{E} of a DLT job. If we know the remaining time, we can judge if the DLT jobs face the QoS violation risk, and can make the adjusting decision in the real system. The time-out degree O_i and the resource sensitivity S_i are the metrics, which represent the deadline satisfaction and the resource efficiency of DLT jobs in the adjusting methodology respectively.

> The Experiments are simply indecipherable. It appears the authors are using containers running on "testbeds" that are running on "7-host" systems. I have no idea what this means. Is this 7 containers? 7-nodes? 7 CPUs or GPUs? vCPUs?

(4) Resource Configuration of the Testbed Clusters

The testbed are the Kubernetes clusters consists of machines. We mentioned run "containers" on the testbeds. This is means that the prototype of the modules of Qore-DL and the realistic training DLT jobs are run as containers in the cluster as the figure follow:



In our evaluation, we write the code of the deep learning model using the Tensorflow library and then we add the codes to the docker images which package the Tnesorflow and CUDA environment. When We submit a job, Qore-DL uses the tf-operator of the Kubeflow to execute the DLT job as the containers running in the Kubernetes cluster. Each instance (PS or worker) in the DLT job are running as a container, which execute the program packaged in the docker image. The containers of a DLT jobs are communicated in a PS framework.

The prototype of the Qore-DL are based on the Kubernetes and some operators of Kubeflow and run as the containers in the Kuberentes cluster.

For details of the testbeds, we will modify the invalid description in the revision. In Section V (EXPERIMENTS) of the paper manuscript, "7-host CPU", "24-host CPU" means the CPU clusters consist of 7 and 24 cloud hosts (machines) respectively. The "5-host GPU" means a GPU clusters consists of 5 cloud hosts (machines). The detail of the resource capacity of the testbed clusters are presented as the follow table:

TABLE II: Resource configuration of the three clusters

CPU cluster consists of 7 hosts						CPU cluster consists of 24 host						GPU cluster consists of 5 hosts		
vCPUs \ Memory(GB)	48	96	128	192	256	vCPUs \ Memory(GB)	64	96	128	192	256	vCPUs \ GPUs	4	1
8						8						8		×2
16			×1			16	×16		×1			16		
24	×1	×3				24		×4		×1		24		
32			×1		×1	32			×1			32	×3	
64						64					×1	64		

The CPU cluster consisting of 7 cloud hosts has a total of 160 vCPUs and 908GB Memory. The CPU cluster consisting of 24 cloud hosts, has 488 vCPUs and 2TB Memory. The GPU cluster consisting of 5 cloud hosts, has 14 V100 GPU cards, each with 16GB GPU memory. For each cluster, we use NFS to share a 3TB SSD storage space, and bandwidth of the LAN is 10Gbps.

> Later, the CPUs and GPUs are described in terms of weighted coefficients alpha1 = .7 and alpha2 = .3 seemingly because "DLT jobs are always compute intensive". Several things wrong here: what do these numbers mean? how are they being used? In the paper this leads to some concept called "dominant resource utilization" of a host?

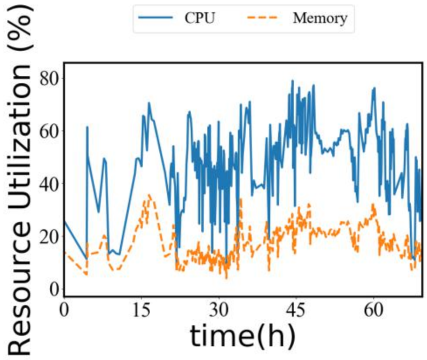
(5) Parameter settings

The parameter settings is based on four aspects: 1) the inherent training process of the DLT jobs; 2) the collected resource and training trace of the realistic training DLT jobs in our testbeds; 3) the designed approach of Qore-DL; 4) some open-source dataset of the large-scale production clusters such as Alibaba dataset. The paraemter settings below is for our evaluation The paraemter settings below is for our evaluation. Since these parameters are general for the real clusters and real DLT jobs, they can be tuned when running on the production cluster to satisfy the user requirement in real production. However, some profile of the production clusters may be needed.

1) alpha1 (α_1) and alpha2 (α_2)

I am sorry that I do not explain the parameter alpha1 and alpha2 clearly in Section V.A.2) (Parameter Setting) of the paper manuscript. Actually, we consider the resource type: CPU, GPU and Memory in the evaluation. In order to consider the multiple resource type in a metric, in our evaluation, we compute the dominant resource utilization of host H_l, U_l in the Eq.(17) in the paper manuscript. alpha1 is the wight of normalized utilization of CPU / GPU in the CPU / GPU cluster respectively and alpha2 is the weight of the normalized utilization of Memory in the cluster. alpha1 and alpha2 are used in the Eq.(17) and Eq.(7) in the paper manuscript to compute the normalized utilization of the dominant resource of hosts and the normalized resource requirement of DLT jobs.

As for the value of alpha1 and alpha2, we set it as 0.7 and 0.3 in our evaluations. It can be attributed to three reason: 1) we ran the 2,000+ DLT jobs in the cluster consists of 24 hosts using Kubeflow scheduler and find that the average cluster CPU utilization fraction and Memory utilization fraction is about 46.62% and 16.73% respectively, which reflect that the CPU resource is more dominant in our evaluations according to the DRF algorithm[1]; 2) since we have present the training process in the part Review1.(1).1) in this document, we can find that the DLT jobs are often compute intensive for the gradient computation; 3) CPU/GPU is often more costly in the production. For instance, the figure bellow presents an example of running DLT jobs in our cluster for 70 hours using the Kubeflow scheduler:



2) Parameters in the machine learning models GBDT and random forest.

The number of the trees in the GBDT models and random forest models are tuned when we training the models. In our experiments, more trees for these models do not bring the valuable accuracy improvement and we do not need to complicate the models with more regression trees to waste the computing resources.

3) β_l in Eq.(1) and Eq.(16)

We define the weight of the U_l as the β_l when computing the weighted cluster utilization score U. The value of β_l is in the range of (0,1) and the sum of the β_l is 1. In our scheduling algorithm, Qore-DL tends to leverage the resource in the hosts (machines) having lighter workload to optimize the cluster efficiency in a balance way. Therefore, we use β_l as the probability of placing the DLT-job container on the host H_l. and the computation of β_l in Eq.(16) of the paper manuscript means that, in our evaluation, the probability of placing the jobs on the first third of hosts with lightest workload is about 95%. And the weight β_l gives larger weight to these first third of hosts can reflect the available resource for scheduling and adjusting more fitting to our approaches. However, we will conduct more evaluations to validate the affect of the β_l.

4) Three threshold of the U: θ_1,θ_2,θ_3

We set three threshold of the weighted utilization score U. These three threshold $\theta_1 < \theta_2 < \theta_3$ are used to describe the pressure of the cluster workload. In different pressure level (status) of the workload, we use different scheduling and adjusting approach to retain the cluster resource efficiency. In order to get closer to the large-scale clusters in production, we analysis the Alibaba datasets (4000+ hosts) and compute the weighted utilization score U as the definition in paper. Then we get the result shows in the Figure 5 and Figure 6 in the paper manuscript and set the $\theta_1 = 0.35$, $\theta_2 = 0.55$, $\theta_3 = 0.7$ in our evaluations. The threshold can be tuned when using different scenarios or production clusters according to the behaviors of the real systems.

5) Submission rate of DLT jobs.

We analysis the submission rate of machine learning jobs for the production cluster in Alibaba. And use a more frequent submission in our testbed to guarantee the workload behaviors are more closer to the real production.

6) Decline rate range.

In our collected data from 2,200+ DLT jobs training different models, the decline rate can reflect the convergence property of the DLT job and we present a threshold range of the decline rate. In the future, we will validate our metric in two ways: using the larger open source dataset of the training loss of benchmark models to calculate the more robust decline rate range and collect data from more deep learning models, such as conformer and transformer with deploying Qore-DL into larger production clusters to validate and update the decline rate range.

> Again, I have no way to decipher what this means in the context of a real system and there are numerous examples of this lack of clarity throughout the paper. The results are presented as if they are measurements of a job scheduler running workloads on a real system though I think this is basically an unvalidated simulation using AliBaba traces running in containers.

(6) Evaluations to the real clusters

In our evaluations, we built three clusters as the testbed as we shown above. All the DLT-job workloads are the realistic training DLT jobs. Specifically, we train the widely used deep learning models: VGG, ResNet, DenseNet and Xception as the benchmarks. By varying the architecture of the models (e.g., number of layers, number of neural units, size of convolution kernel, activation functions, batch size), we can get thousands of different models to train. In our evaluations, DLT jobs train these models on the cifar10 and imagenet dataset for CPU cluster and GPU cluster respectively. In order to run the DLT jobs as containers, we build the docker image: qoredl/cifar and qoredl/imagenet, which are available at dockerhub. These workload submit to the real cluster and the instance of the real DLT jobs runs as a container. Some data are available at:

https://github.com/qore-dl/qore-dl-code

(7) Deploying the Qore-DL into prodcution cluster

Now we are developing the Qore-DL to the production cluster of the cooperation company. We have build a origin version in our private GPU cluster and have schedule tens of DLT jobs for the real production. Some code are available at:

https://github.com/qore-dl/qore-dl-code/tree/main/qoredl_project

In addition, the Qore-DL in the production cluster can support the DLT jobs in non-PS framework and we also build the docker image: qoredl/wenet-k8s-torch to support to run the DLT jobs in non-PS framework and coding with Pytorch.

4. Reviewer 4

Thank you for the comments of our paper manuscript. I will explain the main concern in this document.

> The description of the state of the art could be improved. Are PSs still the best architecture for DL training? The focus on that architecture should be better explained and compared to other architectures not using PSs. Also, more recent GPU schedulers like Gavel or Themis are not mentioned.

(1) PS framework is not the state-of-the-art

Tensorflow and Pytroch are phasing in non-PS frameworks, e.g., ring-all-reduce framework. However, in the non-PS framework, we still need to configure, schedule and adjust worker resources. We think Qore-DL can be a general framework for the DLT jobs and can be applied to the non-PS framework. This is because that the key of the Qore-DL is: 1) the QoS-aware resource optimization scheme for the DLT jobs; 2) achieve the bi-objetctive optimization of DLT-job QoS satisfaction and cluster resource efficiency, which are concerned by the users and cluster providers respectively; 3) realize the joint optimization for the three stages of the DLT jobs. These optimizations are not depended on the framework of the DLT job but are general for the DLT jobs in the clusters.

We will apply the Qore-DL to the non-PS framework and add the completion with the popular non-PS framework and the recent GPU schedulers in our future work. In our revision, we think we will investigate the state-of-the-art framework and explain the PS framework and non-PS framework more clearly.

Actually, we have submitted non-PS DLT jobs in the cooperation-company's cluster where we are deploying the Qore-DL. We made the public docker images: qoredl/wenet-k8s-torch to support the DLT jobs in non-ps framework and We will support the non-PS framework better with the project advancement.

Some choices are not motivated. In particular, heuristic techniques and models are not discussed.

(2) Choice Motivation and the heuristic techniques

I will add more description about the choice in our revisions. I think I need to explain the motivation of this work more and I need to explain why I choose the methodology.

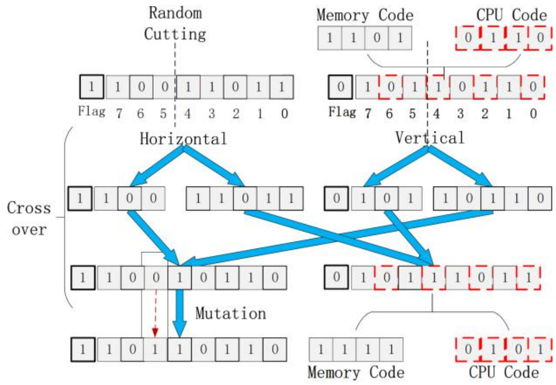
As for the motivation of this work, we think there are three limitations of the DLT jobs in cluster: 1) the users often have to made manual resource configuration for DLT jobs, which is casued by the lack of the automatic resource configuration; 2) QoS-aware optimization is still the challenge of the DLT jobs; 3) prior research often focus on the single stage of DLT jobs, which is kind of insufficient for the dynamic clusters. These limitations cause the DLT jobs running in the cluster with low resource efficiency and the high risk of the QoS violations. For example, Weng, Qizhen, et al[3] propose that: in Alibaba production cluster (6,000+ GPUs), the utilization of the user-requested resource for DLT jobs is only about 50% and about 63% of the execution duration of the DLT jobs are wasted due to the in-efficiency scheduling and adjusting.

As for the choice of the methodology, we use the data-driven machine learning when configuring the resource. These methodologies is choosed because: 1) we can extract the general and inherent features of DLT jobs from their behaviors; 2) we can collect plenty data of DLT jobs traces, which applies to the data-driven approach. In addition, as presented in [3], 65% of the DLT jobs are repeatedly executed for more than 5 times in production, which makes the data-driven approach is feasible.

For the heuristic techniques, they are mainly used in the adjuster. This is because that the bi-objective optimization problem in our work is NP-hard according to [8]. Meanwhile, the solution of the adjusting is equivalent to the selection of target jobs and the quantification of the adjustment size of the resource. In this situation, heuristic techniques, such as genetic algorithm adapt to searching the local optimal solution well.

In the adjuster, We use the genetic-algorithm heuristic model in the adjusting. We code the adjusting way (horizontal as 1 and vertical as 0) and the adjusting size of the resource in a binary format and use the crossover-mutation methodology to search the solution with better fitness.

In particular, We use a 9-bit binary code to encode candidate solutions. The highest digit of the code represents the two adjustment methods. The lower 8 bits are constructed by the sub-codes of each resource type alternately. For example, The following figure shows the genotype code when considering resource type, CPU and memory:



We maintain a set of candidate solutions for each target job τ_i, and update the set iteratively based on the fitness of solutions. We define the fitness of candidate solution u to τ_i according to the four cases, as shown in Eq.(15) in section IV.D.2) the paper manuscript.

In addition, all the selected approaches in Qore-DL are light-weight and made trade-off between the performance and the resource consumption.

> The contribution made by this work is relevant. Its positioning could be improved.

In our revision, we will summarize more state-of-the-art research and add the description of our work compared to these works.

As for the positioning of our work, we will summarize the innovations of the Qore-DL. DLT-job users and cluster provider expect to complete the DLT job within the required makespan and precision in a high resource efficiency in production [2,4,5,6]. However, there are some long-standing limitations: 1) automatic and reasonable resource configuration of DLT jobs is kind of absent in practice; 2) QoS-aware optimization of the DLT jobs is often insufficient but is user-concerned; 3) the prior researches often focus on the single stage of the DLT jobs but lack the joint optimization in the lifecycle of DLT jobs. The Qore-DL address these limitations and consider the bi-objective optimization of resource efficiency and QoS satisfaction to realize the joint optimization of DLT jobs in clusters.

5. Committee Comments

The paper seems to over rely on equations and assumption.

(1) Assumptions

We made some assumption when define and solve the problem. These assumption about both the resources involved and the applications. However, most of these assumptions are the formalized description of running realistic DLT jobs in the real system.

We explained these assumptions in the part: Reviewer 3. (1) and Reviewer 3. (2). The assumption about resource is mainly the weight cluster utilization score U and dominant resource utilization of a host. The weight cluster utilization score U is the metric to quantify the pressure of the DLT-job workload but not the real average utilization of the cluster. We give a larger weight to the machines with lighter workload. This is because that we tends to utilize the resource from the machines with lighter workload. Therefore, this metric can reflect the resource availability in Qore-DL better. As for the dominant resource utilization of a host, we refer the idea of the DRF[1] algorithm. The dominant resource means the resource type whose quota or consumption has the largest percentage of the real cluster resource when running DLT jobs. For example, CPU/GPU resource can be regarded as the dominant resource of the CPU/GPU cluster when running DLT jobs.

As for the assumption of applications, such as iterativeness, convergence, effective ratio between the number of PSs and workers and decline rate. These assumptions is proposed from:

1) theory: we analysis the inherent features and training process of the realistic DLT jobs in part Review 1.(1).1) in this document. Since the execution process of DLT jobs is the repeated iterations of computing gradient and update parameters, the iterativeness, convergence are the inherent feature of the DLT jobs. Some prior research, such as Gandiva [2] and convergence theory [3] can support our definitions of iterativeness and convergence respectively.

2) Insights: we ran 2,000+ realistic training DLT jobs in the real clusters. And then we can summarize the insight as shown in the Figure 2,3,4 in the Section IV of the paper manuscripts.

Therefore, most of our assumptions of the resource and application are based on the behaviors of real DLT jobs or are the formalization of the real clusters which deploys Qore-DL. We will revise our paper and present the behaviors of DLT jobs in the real clusters firstly and summarize the features of the DLT jobs before the system design. Meanwhile, we will try to use more clear text description to present the system design and remove the unnecessary equations.

better to explain how to make parameter choice and apply them in real system/simulations. Some weighting parameter in the equations seems to be chose based on unrealistic assumption

(2) Parameter Settings

The parameter settings in our evaluation is based on four aspects: 1) the inherent training process of the DLT jobs; 2) the collected resource and loss value trace of the realistic training DLT jobs in our testbeds; 3) the designed approach of Qore-DL; 4) some open-source dataset of the large-scale production clusters such as Alibaba dataset. The paraemter settings below is for our evaluation. Since these parameters are general for the real clusters and real DLT jobs, and they can be tuned when running on the production cluster to satisfy the user requirement in real production. However, some profile of the production clusters may be needed.

1) alpha1 (α_1) and alpha2 (α_2) in the Section V.A (Setup) of paper manuscript

I think the weighted parameters which are chose based on unrealistic assumption means these two parameters.I am sorry that I do not explain the parameter alpha1 and alpha2 clearly in Section V.A.2) (Parameter Setting) of the paper manuscript.

Actually, we consider the resource type: CPU, GPU and Memory in the evaluation. In order to consider the multiple resource type in an aggregated metric, in our evaluation, we compute the dominant resource utilization of host $\mathrm{H_l}$, $\mathrm{U_l}$ in the Eq.(17) in the paper manuscript. alpha1 is the wight of normalized utilization of CPU / GPU in the CPU / GPU cluster respectively and alpha2 is the weight of the normalized utilization of Memory in the cluster. alpha1 and alpha2 are used in the Eq.(17) and Eq.(7) in the paper manuscript to compute the normalized utilization of the dominant resource of hosts and the normalized resource requirement of DLT jobs.

As for the value of alpha1 and alpha2, we set it as 0.7 and 0.3 in our evaluations. It can be attributed to three reason: 1) we ran the 2,000+ DLT jobs in the cluster consists of 24 hosts using Kubeflow scheduler and find that the average cluster CPU utilization fraction and Memory utilization fraction is about 46.62% and 16.73% respectively, which reflect that the CPU resource is more dominant in our evaluations according to the DRF algorithm[1]; 2) since we have present the training process in the part Review1.(1).1) in this document, we can find that the DLT jobs are often compute intensive for the gradient computation; 3) CPU/GPU is often more costly in the production.

2) Parameters in the machine learning models GBDT and random forest.

The number of the trees in the GBDT models and random forest models are tuned when we training the models. In our experiments, more trees for these models do not bring the valuable accuracy improvement and we do not need to complicate the models with more regression trees to waste the computing resources.

3) β_l in Eq.(1) and Eq.(16)

We define the weight of the $\mathrm{U_l}$ as the β_l when computing the weighted cluster utilization score U. The value of β_l is in the range of (0,1) and the sum of the β_l is 1. In our scheduling algorithm, Qore-DL tends to leverage the resource in the hosts (machines) having lighter workload to optimize the cluster efficiency in a balance way. Therefore, we use β_l as the probability of placing the DLT-job container on the host H_l. and the computation of β_l in Eq.(16) of the paper manuscript means that, in our evaluation, the probability of placing the jobs on the first third of hosts with lightest workload is about 95%. And the weight β_l gives larger weight to these first third of hosts can reflect the available resource for scheduling and adjusting more fitting to our approaches. However, we will conduct more evaluations to validate the affect of the β_l.

4) Three threshold of the U: θ_1,θ_2,θ_3

We set three threshold of the weighted utilization score U. These three threshold $\theta_1 < \theta_2 < \theta_3$ are used to describe the pressure of the cluster workload. In different pressure level (status) of the workload, we use different scheduling and adjusting approach to retain the cluster resource efficiency. In order to get closer to the large-scale clusters in production, we analysis the Alibaba datasets (4000+ hosts) and compute the weighted utilization score U as the definition in paper. Then we get the result shows in the Figure 5 and Figure 6 in the paper manuscript and set the $\theta_1 = 0.35$, $\theta_2 = 0.55$, $\theta_3 = 0.7$ in our evaluations. The threshold can be tuned when using different scenarios or production clusters according to the behaviors of the real systems.

5) Submission rate of DLT jobs.

We analysis the submission rate of machine learning jobs for the production cluster in Alibaba. And use a more frequent submission in our testbed to guarantee the workload behaviors are more closer to the real production.

6) Decline rate range.

In our collected data from 2,200+ DLT jobs training different models, the decline rate can reflect the convergence property of the DLT job and we present a threshold range of the decline rate. In the future, we will validate our metric in two ways: using the larger open source dataset of the training loss of benchmark models to calculate the more robust decline rate range and collect data from more deep learning models, such as conformer and transformer with deploying Qore-DL into larger production clusters to validate and update the decline rate range.

Need more details on the testbed system and experiments setup. Was the evaluation done on a real system for realistic training studies or on some simulated system using traces running in containers?

(3) Details of Experiments Setup

For details of the testbeds, we will modify the invalid description in the revision. In Section V (EXPERIMENTS) of the paper manuscript, "7-host CPU", "24-host CPU" means the CPU clusters consist of 7 and 24 cloud hosts (machines) respectively. The "5-host GPU" means a GPU clusters consists of 5 cloud hosts (machines). The detail of the resource capacity of the testbed clusters are presented as the follow table.

TABLE II: Resource configuration of the three clusters

CPU cluster consists of 7 hosts						CPU cluster consists of 24 host						GPU cluster consists of 5 hosts		
Memory(GB) / vCPUs	48	96	128	192	256	Memory(GB) / vCPUs	64	96	128	192	256	GPUs / vCPUs	4	1
8						8						8		×2
16			×1			16	×16		×1			16		
24	×1	×3				24		×4		×1		24		
32			×1		×1	32			×1			32	×3	
64						64					×1	64		

The CPU cluster consisting of 7 cloud hosts has a total of 160 vCPUs and 908GB Memory. The CPU cluster consisting of 24 cloud hosts, has 488 vCPUs and 2TB Memory. The GPU cluster consisting of 5 cloud hosts, has 14 V100 GPU cards, each with 16GB GPU memory. For each cluster, we use NFS to share a 3TB SSD storage space, and bandwidth of the LAN is 10Gbps.

(4) real system for realistic training studies

In our evaluations, we built three clusters as the testbed as we shown above. All the DLT-job workloads are the realistic training DLT jobs. Specifically, we train the widely used deep learning models: VGG, ResNet, DenseNet and Xception as the benchmarks. By varying the architecture of the models (e.g., number of layers, number of neural units, size of convolution kernel, activation functions, batch size), we can get thousands of different models to train. In our evaluations, DLT jobs train these models on the cifar10 and imagenet dataset for CPU cluster and GPU cluster respectively. In order to run the DLT jobs as containers, we build the docker image: qoredl/cifar and qoredl/imagenet, which are available at dockerhub. These workload submit to the real cluster and the instance of the real DLT jobs runs as a container. Some data are available at:

https://github.com/qore-dl/qore-dl-code

Reference

[1] Ghodsi, Ali, et al. "Dominant Resource Fairness: Fair Allocation of Multiple Resource Types," in Nsdi. Vol.11, 2011, pp. 24-24.

[2] Xiao, Wencong, et al. "Gandiva: Introspective cluster scheduling for deep learning," in Conf. OSDI, 2018, pp. 595-610.

[3] ALLEN-ZHU, Zeyuan; LI, Yuanzhi; SONG, Zhao. A convergence theory for deep learning via over-parameterization. In: International Conference on Machine Learning. PMLR, 2019. p. 242-252.

[4] Weng, Qizhen, et al. "MLaaS in the Wild: Workload Analysis and Scheduling in Large-Scale Heterogeneous GPU Clusters" in Conf. NSDI, 2022.

[5] Peng, Yanghua, et al. "Optimus: an efficient dynamic resource scheduler for deep learning clusters," in Conf. EuroSys, 2018, pp. 1-14.

[6] Zhang, Haoyu et al. "Slaq: quality-driven scheduling for distributed machine learning," in Conf. SoCC, 2017, pp.390-404.

[7] Klein, Aaron, et al. "Learning curve prediction with Bayesian neural networks." (2016).

[8] Ullman, Jeffrey D. "NP-complete scheduling problems," Journal of Computer and System sciences, vol.10, 1975, pp. 384-393.