Differentiate Quality of Experience Scheduling for Deep Learning Applications with Docker Containers in the Cloud

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Abstract—With the prevalence of big-data driven applications, such as face recognition on smartphones and tailored recommendations from Google Ads, we are on road to a lifestyle with significantly more intelligence than ever before. For example, Aipoly Vision [1] is an object and color recognizer that helps the blind, visually impaired, and color blind understand their surroundings. At the back end side of their intelligence, various neural networks powered models are running to enable quick responses to users. Supporting those models requires lots of cloud-based computational resources, e.g. CPUs and GPUs. The cloud providers charge their clients by amount of resources that they occupied. From clients’ perspective, they have to balance the budget and quality of experiences (e.g. response time). The budget leans on individual business owners and the required Quality of Experience (QoE) depends on usage scenarios of different applications, for instance, an autonomous vehicle requires real-time response, but, unlocking your smartphone can tolerate delays. However, cloud providers fail to offer a QoE based option to their clients. In this paper, we propose DQoES, a differentiate quality of experience scheduler for deep learning applications. DQoES accepts client’s specification on targeted QoE, and dynamically adjust resources to approach their targets. Through extensive, cloud-based experiments, DQoES demonstrates that it is able to schedule multiple concurrent jobs with respect to various QoE and achieve up to 8x times more satisfied models when compared to the existing system.

Index Terms—Docker Containers; Resource Management; Cloud Systems; Deep Learning; Quality of Experience;

I. INTRODUCTION

In recent years, a dramatic growth of big data has been witnessed from different sources such as web, cameras, smartphones, and sensors. To utilize the data, many businesses start to powered by big data analytics [2], [3]. For example, Google AdSense [4] recommends clients the advertisements by studying data that they generated through Google applications and Apple FaceID [5] learns from user’s face images with a TrueDepth camera for a secure authentication solution. Consequently, various learning algorithms and models are proposed to facilitate the analytical processes. In this domain, deep learning technologies, such as artificial neural networks (e.g. convolutional neural network [6] and recurrent neural network [7]) are popular solutions to enhance the learning and improve the results. For instance, generative adversarial networks [8] are deep neural net architectures that use two neural networks, pitting one against the other in order to generate new, synthetic instances of data that can pass for real data.

Although deep learning algorithms empower many popular applications, obtaining a well-trained model is not only an intellectual challenge but also time and resource-intensive. In general, a typical training process of a deep learning model involves three major phases, model training, model evaluation and hyperparameter tuning. After collecting the data from producers, it is divided into two parts: training set and evaluation set. When training the model, the algorithm is fed with the training set and randomly assigned parameters, so that it can learn from examples and improve itself iteratively and incrementally by checking every example in the set. In the model evaluation phase, the algorithm is expected to use previously learned experience to make decisions based on the data in the evaluation set. The evaluation phase allows developers to test the model against undeveloped collected data with a predefined loss function, which reveals how the model might perform against data that it has not yet seen. Whenever a round of evaluation is done, it is always common for users to question if the model can be further improved with different parameter settings. Generally, the algorithm processes data iteratively. Given a specific iteration, its objective is to find the best combination of parameters that minimizes the loss function in this iteration (local minimum). As the algorithm keeps running, more iterations are examined for hyperparameter tuning to achieve the global minimum of the predefined loss function.

In reality, not many companies could afford to collect their own datasets and train the models, big players, such as Amazon SageMaker [9], provide pre-trained machine learning services of ready-made intelligence for targeted applications and workflows. A well-trained model could be directly obtained by loading a pre-trained one, however, deploying a model is still a computationally intensive task. The cloud providers, such as Microsoft Azure [10] and Amazon Web Service [11], offer the resources, e.g. CPU and GPU, to host those models. In general, clients are charged by the resource levels that they occupied, for example, an a1.xlarge EC2 instance from Amazon Web Service contains 4 vCPUs and 8GB memory and is priced at $0.1 per hour. A larger instance provides more resources and faster response to the users. From clients’ perspective, they have to balance the budget from its own end and delivered quality of experiences on user’s side (e.g. response time). The financial states of different developers are definitely varied.

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More importantly, different application usage scenarios lead to various quality of experiences (QoEs) requirements. For instance, in an autonomous vehicle (e.g. Waymo [12]), the system has to, immediately, react an object that suddenly appears in the front. Milliseconds delay may result in life loss; however, when unlocking the smartphones, users can tolerate a short delay, up to 1 second [13]. Without any constraints, the system should react users as soon as possible. When taking both budget and required QoSs into consideration, however, cloud providers fail to enable a QoSs option to be specified by their clients. In this project, we propose DQoES, a scheduler that supports client-specified Quality of Experiences. When launching a back-end service, a value can be given to DQoES as a targeted QoE to an application. In a cluster, DQoES keeps monitoring running models as well as their associated QoE targets and tries to approach their targets through efficient resource management. The main contributions of this paper are summarized as follows.

- We introduce differentiate quality of experience to the deployment of various deep learning applications. With the respect to varied budget limitations and usage scenarios, our system is able to react differently.
- Without modifying the existing cloud system, we propose DQoES with a suite of algorithms that accepts targeted QoE specifications from clients and dynamically adjust resources to approach their individual targets to achieve satisfied performance at user’s end.
- DQoES is implemented into Docker Swarm [14], a popular container management toolkit in industry. Based on extensive cloud-executed experiments, DQoES demonstrates its capability to react to different workload and achieves up to 8x times more satisfied models when compared to the existing system.

The rest of this paper is organized as follows. In Section II we report the related work. In Section III we introduce our DQoES system design. We present the proposed DQoES algorithms in Section IV. We carry out extensive cloud-based evaluation of DQoES in Section V and conclude this paper in Section VI.

II. RELATED WORK

Learning from massive datasets to drive businesses is drastically reshaping our economy. Lots of projects have been done to improve the performance of the learning models from various perspectives. For example, based on ImageNet, a large visual database designed for use in visual object recognition research, many innovative learning algorithms have been proposed as a tournament to improve the accuracy of the classification. Among the solutions [15], NoisyStudent [16], which currently ranks on the top of the list, shows that it is able to use unlabeled images to significantly advance both accuracy and robustness of the learning model. Focusing on the transfer learning, authors in [17] revisit classical transfer learning and propose BiT that uses a clean training and fine-tuning setup, with a small number of carefully selected components, to balance complexity and performance.

Although promoting the accuracy of a learning model is important, from service providers’ perspectives, obtaining a well-trained model is still a both time and resource consuming process. Many on-going research projects have been proposed to improve it [18]–[25]. For example, Terngrad [21] is proposed to quantize gradients to ternary levels to reduce the overhead of gradient synchronization, which results in overall communication reduction. Focusing on mobile devices, DeepRebirth [22] is proposed to accelerate the execution deep neural network in a resource constraint environment. Moreover, Deepsec [23] is developed to measure the vulnerability of deep learning models as well as to conduct comparative studies on attacks/defenses in a comprehensive and informative manner. Considering a cloud system, FlowCon [24] is designed to schedule the resources with the respect to growth efficiency of the loss function. On the other hand, ProCon [25] and Draps [26] optimize the system by efficient container placement schemes.

As an application, various learning techniques have been applied, from clients’ points of view, to assure the quality of experience at end users. Authors in [29] present the first attempt to predict video quality of experience based on information directly extracted from the network packets, which can detect anomalies at the current time instant and predict them at the next immediate instant. Utilizing a novel deep neural network, [30] is able to learn the relationships between the network parameters and the subjective scores that indicate quality of experience when a user is viewing videos transmitted over the mobile internet in a practical environment. Additionally, CVART [31] studies application response times by using image recognition to capture visible changes in the display of the device running the application to compute the application response time of an operation that triggers these visual changes. However, CVART is a toolkit and fails to improve response time.

Despite the efforts have been devoted from different perspectives, limited works focus on differentiate quality of experiences for various deep learning backed application. For instance, both unlocking screen and editing photo applications may use deep learning services, but users’ expectations and tolerance, such as response delay and detection rate, are definitely different. TRADL [32] tries to differentiate the applications by taking advantage of a user specified target, however, it only focuses on training process, which is the service provider’s side. Considering the end user, we propose DQoES, which supports a deliverable quality of experience target, such as reaction time, from developers. Given a multititenacy cloud system, DQoES is able to approach specific targets through dynamic resource distribution.

III. DQoES System Design

This section presents the system architecture of DQoES in detail, including its framework, design logics and functionalities of key modules.

A. DQoES framework

A typical management system for a cluster of containers, such as Docker Swarm [14] and CNCF Kubernetes [33],
involves managers and workers. It works in a distributed manner, in which managers, on the one hand, interact with the users, analyze their requests as well as manage the workers that associated with this cluster and workers, on the other hand, are the workhorses that provide the computing resources, such as CPU, GPU and memory, to execute the tasks, store the data as well as report their status to managers.

DQoES employs the manager-worker architecture. In DQoES, the manager collects QoE targets from clients, pass them the workers and maintains an overall performance assessment table to keep monitoring the real-time performance of all the active workloads in the system. The workers, who host the deep learning applications, track the performance of each individual model and its real-time resource usages. According to the QoE targets, the worker dynamically adjust resource limits for each container to achieve best overall performance among all models that resident in it.

Figure 1: DQoES System Architecture

B. DQoES Modules

As demonstrated in Figure 1, DQoES consists of four major modules, an Application Monitor, a Worker Monitor and an Executor on the worker side. A QoE Analyst on the manager side. Each module runs independently and exchanges information about models inside the containers as well as the worker status. Their functionality is detailed below.

**Application Monitor:** it maintains performance metrics for each deep learning model runs this worker. For example, when users queries the model, the response time would be recorded along with the resource usage that associated with the time cost. Comparing with the QoE targets, The DQoES executes an algorithm to adjust resource assignments for active containers and approaches the targeted values iteratively.

**Worker Monitor:** it measures the active container pool. When a new model is assigned by a manager, the worker monitor adds it to the pool and keep tracking performance difference in each iteration by using an adaptive listener. The listener hosts an algorithm that regulates the frequency of updating the resource assignment.

**Executor:** it is a key module that, accepts the workload and collects data on the worker. Based on data, it calculates the parameters that required by the algorithms (described in Section IV) in Application and Worker Monitor. Upon receiving a new plan for resource configuration for each container, the Executor will interrupt the current limits and update containers with newly calculated values.

**QoE Analyst:** it resides on the manager side. A QoE analyst interacts with clients and collects the QoE targets for each of the deep learning application. The targeted values are sent to workers through the System Scheduler. When the status reports arrive from workers, it utilizes a Performance Evaluator to preserve data and monitor the overall system performance.

C. System Optimization Problem

In DQoES, we consider deep learning applications host on the cloud with a cluster of containers and each learning model resides in a container. DQoES aims to provide users the service with a predefined QoE target.

In the system, we denote $c_i \in C$ to be a container that serves one deep learning application. For each $c_i$, we have $r_i \in R$ is the resource usage of $c_i$ that can be monitored through the system APIs, such as docker stats, where function $R(c_i, t) = r_i$ is defined to retrieve the resource usages in real-time.

For the model that runs in each container, we keep tracking its performance $P(c_i, t) = p_i$, which is a value to represent a predefined quality metric, e.g. response time, of a particular service. Additionally, there is an pre-defined QoE targeted value for each model, $o_i \in O$. Then, the quality of a given container $c_i$ (a learning model runs inside) is $q_i = o_i - p_i$. Therefore, the system performance on a specific worker node $W_i$ is,

$$Q_{W_i} = \sum_{c_i \in W_i} q_i$$  \hspace{1cm} (1)

DQoES anticipates a system that minimizes the performance difference between the predefined QoE target and current container outputs. Considering the real-time container outputs, DQoES classifies running models into three different categories.

- **Class G:** The models in this category perform better than the preset QoE value, e.g. response faster than the target.
- **Class S:** The models in this category achieve the predefined QoE targets and they are satisfied containers.
- **Class B:** The model in this category is underperformed due to lacking of resources or unrealistic targets.

Assume that there are $n$ containers, each runs one learning model in the system. Then, our performance optimization problem, $P$, can be formalized as

$$P : \text{Min} \sum_{c_i \in B \text{ OR } c_i \in G} q_i$$  \hspace{1cm} (2)

$$\text{s.t. } \sum_{c_i \in W_i} r_i \leq T_R$$

The following table summarizes the parameters that utilize in DQoES.

### IV. DQoES Solution Design

In this section, we present the detailed design of the performance management algorithms in DQoES, which can adjust resource assignment for containers at run time. In addition, we discuss the algorithm of an adaptive listener to reduce the overhead of DQoES.
Table I: Notation Table

| $W_i$ | Worker $i$ |
|-------|------------|
| $c_i \in C$ | The container $i$ in the set $C$ |
| $G$ | Set $G$ contains the $c_i$ with a better performance than $o_i$ |
| $S$ | Set $S$ contains the $c_i$ with targeted performance $o_i$ |
| $B$ | Set $B$ contains the $c_i$ with a worse performance than $o_i$ |
| $o_i \in G$ | Objective value $o_i$ for $c_i$ in the set $G$ |
| $r_i \in R$ | Resource usage $r_i$ for $c_i$ in the set $R$ |
| $R(c_i, t)$ | The function that uses to calculate $r_i$ at time $t$ |
| $p_i$ | The performance indicator of $c_i$ |
| $P(c_i, t)$ | The performance function that calculate $p_i$ at time $t$ |
| $L_i$ | The total resource usage of containers in set $i$ |
| $R(c_i, t)$ | The resource usage of containers in set $G$, $S$, $B$ |
| $Q(c_i, t)$ | The sum of qualities for containers in set $G$, $S$, and $B$ |
| $L(c_i, t)$ | The limit of the resource usage for container $c_i$ at time $t$ |

Algorithm 1: Performance Management on $W_i$

1: Initialization: $W_i$, $c_i \in C$, $o_i \in O$, $p_i \in P$,

2: for $c_i \in W_i$ do
3: \hspace{1em} $R(c_i, t) = r_i$
4: \hspace{1em} $P(c_i, t) = p_i$
5: \hspace{1em} $q_i = o_i - p_i$
6: \hspace{1em} if $q_i > \alpha \times o_i$ then
7: \hspace{2em} $G$.insert($c_i$)
8: \hspace{2em} $Q_G = q_i + Q_G$
9: \hspace{2em} $R_G = r_i + R_G$
10: \hspace{1em} else if $q_i < -\alpha \times o_i$ then
11: \hspace{2em} $B$.insert($c_i$)
12: \hspace{2em} $Q_B = q_i + Q_B$
13: \hspace{2em} $R_B = r_i + R_B$
14: \hspace{1em} else
15: \hspace{2em} $S$.insert($c_i$)
16: \hspace{1em} for $c_i \in W_i$ do
17: \hspace{2em} if $c_i \in G$ then
18: \hspace{3em} $L(c_i, t + 1) = L(c_i, t) \times (1 - \frac{q_i}{Q_G} \times R_G \times \beta)$
19: \hspace{3em} if $L(c_i, t + 1) < \frac{1}{2^{2^t}}$ then
20: \hspace{4em} $L(c_i, t + 1) = \frac{1}{2^t}$
21: \hspace{2em} else if $c_i \in B$ then
22: \hspace{3em} $L(c_i, t + 1) = L(c_i, t) \times (1 + \frac{q_i}{Q_B} \times R_G \times \beta)$
23: \hspace{3em} if $L(c_i, t + 1) > T_R$ then
24: \hspace{4em} $L(c_i, t + 1) = T_R$

A. DQoES Performance Management

DQoES manages the QoE of learning models through updating the resource distribution for their host containers. The administrators of a container management system, such as Docker Swarm, are able to configure a “soft limit” for a running container. The limit specifies an upper bound of the resources that a container can be assigned. For example, the command `docker update --cpus=\4.5
" Container-ID` can set the container is guaranteed at most one and a half of the CPUs assuming the host has at least 2 CPUs.

DQoES utilizes Algorithm 1 to manage the performance, in terms of QoE targets, of each deep learning application. Firstly, it initializes the parameters that required by the algorithm (Line 1). For every active container, it fetches the runtime resource usage, $r_i$, the current performance value, $p_i$, and, together with the predefined target, it calculates the quality of the container, $q_i$, at this moment (Line 2-5).

DQoES , then, classifies all learning models into three different categories, $G$, $B$, and $S$. Based on the current quality of $c_i$, if it is larger than $\alpha \times o_i$, which means the quality level is higher than the target, $c_i$ is marked as $G$. The $\alpha$ is a percentage value that used to represent developer’s tolerance of the target; on the other hand, if $q_i$ is smaller than $-\alpha \times o_i$, then $c_i$ is marked as $B$. Finally, in the case of $q_i$ falls within the interval $[-\alpha \times o_i, \alpha \times o_i]$, it suggests that the service provided by $c_i$ satisfies the predefined QoE target and $c_i$ joins $S$. When classifying the containers, DQoES calculates a total quality value of learning models in $G$ and $B$ as well as the sum of resource usages, respectively (Line 6-15).

For the containers in $G$, which perform better than their QoE targets, Algorithm 1 cuts their resource usages to reduce the performance and approach their targets. For underperformed containers in $B$, DQoES tries to increase their resource allocation to help them move toward the QoE targets. Specifically, the following two branches are executed.

- For $c_i \in G$, the total resource limits are reduce from the previous values by $R_G \times \beta$, where $\beta$ is a parameter that system administrator can configure to gradually update the containers. The degree of the reduction depends on the how far away a $c_i$ is from its QoE target. For example, when a learning model is performing slightly better than the targeted value, the value of $\frac{Q_G}{Q_B}$ is very small and the resource reduction is limited (Line 16-18). When updating the limits, DQoES set $\frac{1}{2^t}$ to be the lower bound of the model to prevent abnormal behaviors due to lacking of resources (Line 19-20).

- For containers in $B$, the saved resources from $G$ will be reallocated to them. Similar to $G$, the degree of increase depends on how bad a container performs when comparing to its QoE target. For example, if a given container, $c_i$, is underperforming a lot, which results in a large value of $\frac{Q_B}{Q_G}$ and leads to a hike on the resource limit (Line 21-22). However, there is an upper limit (e.g. hardware limits) of the resource allocation, $T_R$, to each of the container (Line 23-24).

B. Adaptive Listener on DQoES

The Algorithm 1 aims to dynamically update the resource allocation for active containers in order to make the learning models approach their predefined QoE targets iteratively. To achieve the goal, DQoES has to keep measuring performance of each container and their resource usages, which create overhead to the system. In addition, with a fixed number of active containers and untouched QoE targets, DQoES, after several iterations, converges to the state with a stable resource distribution. Therefore, it is unnecessary to frequently collect information and execute Algorithm 1.

In DQoES, it implements an adaptive listener with an exponential back-off scheme to control the frequency. Algorithm 2
Algorithm 2 Adaptive Listener on $W_i$

1: Initialization: $W_i, c_i \in W_i, o_i \in O, p_i \in P, q_i, G, S, B$

2: for $c_i \in W_i$ do
3:     if $c_i \in G$ then
4:         $Q_G = Q_G + q_i$
5:         $Q_G(t) = Q_G$
6:     else if $c_i \in B$ then
7:         $Q_B = Q_B + q_i$
8:         $Q_B(t) = Q_B$
9:     else if $c_i \in S$ then
10:        $Q_S = |S|$
11:        $Q_S(t) = Q_S$
12:    if $|Q_G(t + 1) < Q_G(t)| \& |Q_B(t + 1) > Q_B(t)|$ then
13:        $i + +$
14:        if $i \geq 2$ then
15:           $IV = IV \times 2$
16:        $i = 0$
17:    else if $Q_S(t + 1) < Q_S(t)$ then
18:        $IV = IV \div 2$
19:        $i = 0$
20:    Execute Algorithm 1
21: else
22:    $IV = IV$
23: $i = 0$

presents the details in the listener. At the very beginning, it initializes the parameters, such as the sets $G, S, B$, that require for execution (Line 1). Then, the sum of qualities, $Q_G, Q_B, Q_S$ for each of the container set is calculated. Please note that, for $c_i \in S$, the learning models have satisfied their QoE targets. Thus, their $q_i = 0$ and we use the number of containers in $S$ to represent $Q_S$. While $Q_G, Q_B, Q_S$ are per iteration values, $DQoES$ uses $Q_G(t), Q_B(t), Q_S(t)$ to record the time serial of these values (Line 2-11).

Then, $DQoES$ compares the most recent two values of $Q_G$ and $Q_B$. If both $Q_G$ and $Q_B$ are approaching to 0, which indicates by $Q_G(t + 1) < Q_G(t)$ and $Q_B(t + 1) > Q_B(t)$, it means they are all converging to $S$. When the trend maintains for 3 consecutive iterations, Algorithm 2 doubles the interval, which reduce the frequency of updating the resource allocation (Line 12-16). However, when $Q_S(t)$ reduces, it suggests the stable state is broken. It could be abnormal usages of one particular container or a new one joins the system. In this case, $DQoES$ halves the interval and execute Algorithm 1 immediately (Line 17-20). When the system performance is still bouncing, $DQoES$ maintains the original interval (Line 21-23).

V. PERFORMANCE EVALUATION

In this section, we evaluate the effectiveness and efficiency of $DQoES$ through intensive, cloud-executed experiments.

A. Experimental Framework and Evaluation Metrics

$DQoES$ utilizes Docker Engine [34] 19.03 and is implemented as a plugin module that runs on both local and cluster versions. We build a testbed on NSF Cloudlab [35], which is hosted by the Downtown Data Center - University of Utah. Specifically, the testbed uses the M510 physical node, which contains Intel Xeon D-1548 and 64GB ECC Memory.

$DQoES$ is evaluated with various deep learning models using both the Pytorch and Tensorflow platforms. When conducting experiments, pretrained parameters from the platforms are loaded with the built-in workloads. The time for each image recognition task is far less than 1 second. However, the cost for real-time reconfiguration in $DQoES$ fails to take action in seconds level since the more frequent it updates the system, the more overhead it introduces. Therefore, $DQoES$ utilizes a batch processing of the images and define 100 images as a batch. Table II lists the models used in the experiments.

There are two system parameters in $DQoES$, (1) $\alpha$, the threshold for classifying each job into different set $G$ (outperform), $B$ (underperform) and $S$ (satisfied); (2) $\beta$, the value that controls the amplitude of resource adjustments at each round. Due to the page limit, we omit the discussion of these parameters. In the evaluation, we set $\alpha = 0.1\%$. Note that these values can be easily update by the system administrator.

The key metric that we consider in $DQoES$ is the number of jobs in $S, G$ and $B$. If all the containers are in $S$, it means that the system has achieved the user-specified objectives on each individual jobs and delivered the best quality of experience according the clients. Thus, the difference between objectives and experiences is 0, $Q_S = 0$. It is possible that user inputs an unrealistic objective, e.g exceed theoretical boundaries. In this scenario, $DQoES$ attempts to achieve the best possible experience to approach the objective. Therefore, metrics that we used to assess $DQoES$ is the gap between predefined objective and real delivered experience that is presented by $Q_S, Q_G, Q_B$, the sum qualities for containers in set $G, S$ and $B$.

We evaluate $DQoES$ on individual severs and a cluster with 4 nodes. In addition, $DQoES$ is tested with the following job submission schedules.

- Burst schedule: it simulates a server with simultaneously workloads, which is challenge for $DQoES$ to adjust resources according to each individual objective.
- Fixed schedule: the time to launch a job is controlled by the administrator. When a new job joins the system, $DQoES$ will have to redistribute the resources to accommodate it.
- Random schedule: the launch times are randomized to simulate random submissions of jobs by users in a real cluster. $DQoES$ has to frequently adjust resources to achieve the best overall experience.
B. Single Model

We conduct a set of experiments with a single model. Each job is providing services inside a container with a specific objective. Our single model experiments use Resnet-50 as the source image.

1) Identical Objectives: Firstly, we launch 10 models simultaneously to simulate the burst traffic. The objectives of all them are set to 20, which means making decisions for a batch of tasks, 100 images, take 20 seconds. Fig. 2 presents the QoE from the user’s side. As we can see from the figure, all of the containers are classified in set B, which means that they are all underperformed. This is due to the fact that, given the resources, the objective of 20 seconds per batch is unachievable. The system evenly distribute all the available resources, but average value of their QoEs is still underperformed. for example, at time 350s, the average delivered QoEs is 31.61s with a 0.35 standard deviation. Fig. 3 illustrates the CPU distribution among 10 models. Given an identical, unachievable objective, the best DQoES could do is to approach the targets by evenly distribute all the resources.

![Figure 2: Delivered QoE: 10 jobs with the same unachievable objectives (Burst schedule)](image)

Next, we utilize the same setting, but update the identical objective values to 40, which makes it achievable by the system. Fig. 5 presents a more diverse result. With a dynamic resource configuration, running containers are classified into different sets. For example, at the very beginning, all of the 10 models are in set G, which means that they all perform better than the predefined objective and thus, occupy more resources than necessary. Consequently, DQoES starts reducing their resource limits to approach the target, 40s. At time 94.06s, running models in Container-1, 3, 6, 7, 8, 9, and 10, produce a deliverable experience, which falls within $1 \pm \alpha \times \text{objective}$ ($\alpha = 10\%$ and $\alpha_i = 40$). Therefore, they are classified to set S, which indicates they satisfied the objective. Whenever, there is, at least, one container in S, the Qs with QoE = 0 shows on the figure. DQoES continues updates the resource allocation to improve QoEs of the other three models. However, at time 144.05s, container-7, 9 and 10 become underperformed with a batch cost at 47.57s, 50.91s, 47.93s. The reason is that DQoES adjust the resource adaptively and in the previous round of adjustment, it cuts too much resources from them. As the system goes, DQoES algorithms converge and all models achieve their targeted objectives. The small picture in Fig. 4 illustrates the number of containers in set S. We can clearly see the value goes up and down due to the adaptive adjustment, and stabled at 10 for the best performance. Fig. 5 presents the real-time resource distribution among all the models. In general, they obtain the same shares between each other due to the identical objective settings. In difference between Fig. 3 and Fig. 5 is that when the system stabilized, the experiments with achievable objectives have resources to accommodate for more workloads.

![Figure 4: CPU distribution: 10 jobs with the same achievable objectives (Burst schedule)](image)

2) Varied Objectives: Next, we conduct a set of experiments with varied objectives. The values of objectives are randomly selected and consists of both achievable and unachievable targets, which generates more challenges for DQoES.

Fig. 6 and Fig. 7 plot the results from a burst schedule experiment. It clearly indicates that DQoES is able to redistribute resources to approach their objectives individually. At the meanwhile, DQoES achieves best overall QoE. For example, the objective values in this experiments are 75, 53, 61, 44, 31, 95, 82, 5, 13, 25 for container 1-10, respectively. Obviously, target value 5 from container-8 is unachievable. DQoES attempts to approach this objective by allocating more resource to it than the others (Fig. 7). On Fig. 6, the number
of containers in set $S$ is stabilize 7 instead of 8 is because DQoES tries to minimize overall QoE system-wide.

Due to the submission gap of 50 seconds, DQoES has to update the resource distribution continually. Whenever, a new container joins the system, DQoES adjusts the allocation to adapt new workload and its objective. Since the submission happens from 0 to 450 seconds, DQoES begin convergence after 450 seconds. At time 769.69s, the number of containers in set $G$ becomes 0, which suggests that all the outperformed models have released resources to promote underperformed containers. As the system goes, the number of containers in $S$ raises to 8 such that only the container-1 and 2 with unachievable targets are still in the underperformed set $B$. Fig.9 verified the results from the resource allocation aspect that container-1 and 2 receive a larger amount of resources than others.

C. Multiple Models

In this subsection, we conduct experiments with multiple models. It creates even more challenges for DQoES since different models have various resource usage patterns and diverse achievable targets. When running the experiments, we first randomly select a model image from Table II and assign an arbitrary number as its objective value. Then, each container randomly picks up a submission time from a given interval.
1) **Single Node Environment:** We conduct the experiment in a single node setting, which hosts 10 running models and submission interval is set to [0, 300s]. A similar trend is discovered on Fig. 10 such that QoE of the system keeps getting worse from 0 to 300s. Due to a random submission schedule, it lacks of time for DQoES to adjust resource allocation at very beginning. However, given limited room, DQoES dynamically configures resources with respect to their individual objectives. For example, at time 257.07s, container-6’s performance is 36.12s and its objective is 35. Therefore, it is classified to set $S$, which means it satisfied the predefined target. After 300s, the overall QoE keep approaching to 0 and the number of containers in $S$ is increasing. With a stable workload, DQoES is able to quickly react and adjust the resources to improve the QoE. Fig. 11 clearly indicates that the resource is not evenly distributed and, during the submission interval, it is keep updating to adopt the dynamic workloads. At the end, it converges to a stable allocation.

![Figure 10: Delivered QoE: 10 jobs with varied objectives (Random schedule)](image)

2) **Cluster Environment:** Finally, we evaluate DQoES in a cluster environment with 4 worker nodes. In these experiments, we launch 40 randomly selected models along with various objective values. Fig. 12 illustrates the delivered QoE of DQoES. A similar trend of results are found across all workers. The QoE keeps improving as the algorithms execute iteratively. However, depending on individual objectives that are randomly generated, the number of containers, which satisfied predefined values varies. For example, there are 8, 5, 7, 6 for Worker-1, 2, 3, 4 respectively. In addition, when the first model appears in set $S$ is also difference from each other. For instance, on Worker-4, container-32 satisfies the objective at 20.25s, where the batch cost 65.24s and the predefined target is 65. While on Worker-2, the first model that satisfies its objective is found at time 238.88s such that container-26 meet the requirement (68.01 vs. 70). When more models with unachievable objectives, e.g. Worker-3, the number of containers in $S$ is bouncing since DQoES tries to make the overall QoE approach to 0 and the distribution is keep updating within underperformed models.

The same experiment is conducted on the original Docker Swarm platform, where default resource management algorithms are in charge for scheduling decisions. Fig. 13 plots the results on each worker in the cluster. Clearly, due to missing mechanism to react on the associated objective values, whether a model can satisfy the target is purely depending on the value itself and how many concurrent running models on the same worker. As we can see that there are 1 container in set $S$ on Worker-1, 3, and 4. On Worker-2, none of the models could meet theirs target. While not a fair comparison, DQoES is able to promote as much as 8x more models to satisfy their predefined objective values.

Fig. 14 and Fig. 15 present the CPU distribution of the two experiments. Comparing them, the improvement is achieved by dynamically adjust resource allocation at runtime with respects each objective values. When there is an unachievable one, DQoES attempts to fully utilize the released resources from the models with an achievable objective. With default system, however, the resource can only be evenly distributed, where each individual container gets its equal share of resource.

![Figure 11: CPU distribution: 10 jobs with varied objectives (Random schedule)](image)

**VI. Conclusion**

In this work, we present DQoES a differentiate quality of experience based scheduler for containerized deep learning applications. It enables user-specified objectives to the cloud system and attempts to meet multiple clients’ specifications in the same cluster. When deploying a learning model in the cloud, DQoES accepts a targeted QoE value from each client. This value is analyzed by DQoES, which would increase or decrease its resource limit in order to achieve the target. When multiple models reside in a cluster, DQoES is able to respect to their individual QoE objectives and approach user-specified QoEs through dynamical adjustment on the resource allocation at runtime. DQoES is implemented as a plugin to Docker Swarm. Based on extensive, cloud executed experiments, it demonstrates its capability to react to different workload patterns and achieves up to 8x times more satisfied models as compared to the existing system.

To further improve DQoES in a cluster environment, we will design a workload distribution strategy with respects to the states of each worker node. Currently, Docker Swarm places container base on the number of container on each
worker and assuming each container allocates an equal share of resources. However, when there is a underperformed job on a worker that is in a stable state, the system should avoid putting more workload on this worker, which may result in an increased number of underperformed jobs. We plan to enhance DQoES with a novel container placement algorithm to balance workload according to clients’ specifications.

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5.2 Worker-4’s QoE

5.3 Worker-5’s QoE

5.4 Worker-6’s QoE

5.5 Worker-7’s QoE

5.6 Worker-8’s QoE

5.7 Worker-9’s QoE

5.8 Worker-10’s QoE

5.9 Worker-11’s QoE

5.10 Worker-12’s QoE

5.11 Worker-13’s QoE

5.12 Worker-14’s QoE

5.13 Worker-15’s QoE

5.14 Worker-16’s QoE

5.15 Worker-17’s QoE

5.16 Worker-18’s QoE

5.17 Worker-19’s QoE

5.18 Worker-20’s QoE

5.19 Worker-21’s QoE

5.20 Worker-22’s QoE

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5.33 Worker-35’s QoE

5.34 Worker-36’s QoE

5.35 Worker-37’s QoE

5.36 Worker-38’s QoE

5.37 Worker-39’s QoE

5.38 Worker-40’s QoE

Figure 12: Delivered QoE in the cluster with 40 models and varied objective with DQoES

Figure 13: Delivered QoE in the cluster with default resource management algorithms

Figure 14: CPU distribution in the cluster with 40 models and varied objective with DQoES

Figure 15: CPU distribution in the cluster with default resource management algorithms
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