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Reinforcement Learning Empowered MLaaS Scheduling for Serving Intelligent Internet of Things

Heyang Qin, *Student Member, IEEE,* Syed Zawad, *Student Member, IEEE,* Yanqi Zhou, *Member, IEEE,* Sanjay Padhi, *Member, IEEE,* Lei Yang, *Senior Member, IEEE,* Feng Yan, *Member, IEEE,*

***Abstract*—Machine learning (ML) has been embedded in many IoT applications (e.g., smart home and autonomous driving). Yet it is often infeasible to deploy ML models on IoT devices due to resource limitation. Thus, deploying trained ML models in cloud and providing inference services to IoT devices becomes a plausible solution. To provide low latency ML serving to massive IoT devices, a natural and promising approach is to use parallelism in computation. However, existing ML systems (e.g., Tensorflow) and cloud ML serving platforms (e.g., SageMaker) are Service-Level-Objective (SLO) agnostic and rely on users to manually configure the parallelism at both request and operation levels. To address this challenge, we propose a Region-based Reinforcement Learning (RRL) based scheduling framework for ML serving in IoT applications that can efficiently identify optimal configurations under dynamic workloads. A key observation is that the system performance under similar configurations in a region can be accurately estimated by using the system performance under one of these configurations due to their correlation. We theoretically show that the RRL approach can achieve fast convergence speed at the cost of performance loss. To improve the performance, we propose an adaptive RRL algorithm based on Bayesian optimization to balance the convergence speed and the optimality. The proposed framework is prototyped and evaluated on the Tensorflow serving system. Extensive experimental results show that the proposed approach can outperform state-of-the-art approaches by finding near-optimal solutions over 8 times faster while reducing inference latency up to 88.9% and reducing SLO violation up to 91.6%.**

***Index Terms*—Model inference, internet of things (IoT), machine-learning-as-a-service (MLaaS), parallelism parameter tuning, reinforcement learning, workload scheduling, service-level-objective (SLO)**

I. Introduction

Recent years have witnessed the proliferation of Internet of Things (IoT) in every aspect of people's life, work and entertainment. Meanwhile, artificial intelligence (AI) has recently shown a remarkable success in a wide range of fields, spanning from computer vision [2], speech recognition [3], natural language processing [4] to chess playing (e.g., AlphaGo [5]) and robotics. With the emergence of diverse IoT applications (e.g., smart home, smart city, industrial automation, connected car), it is envisaged that AI could deal with these heterogeneous IoT environments. However, limited by the IoT device capability, it is challenging to deploy machine learning models on IoT devices, which prompts the development of Machine-Learning-as-a-Service (MLaaS) [6] that provides *machine model inference* service in the cloud. Many major cloud service providers including Google, Microsoft and Amazon have offered MLaaS in their cloud environment. Differ from local inference, IoT device will use machine learning as a service and require a timely and highly available machine learning service to function properly. MLaaS frees the IoT device from the burden of providing storage and computation for machine learning models and allows the manufacturer to update the models without having to push the update to all the IoT devices. At the same time, it becomes challenging to provide low latency machine model inference service to massive IoT devices in heterogeneous environments.

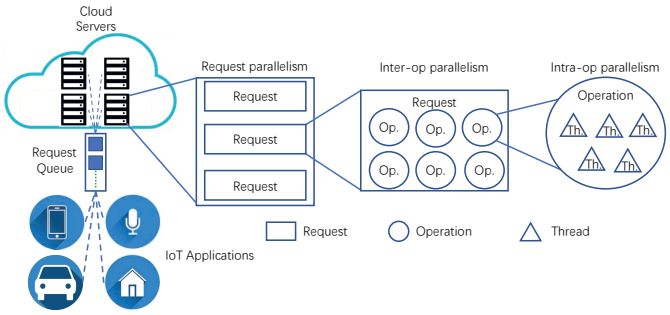

Fig. 1: Flow graph of how requests from IoT applications are handled in MLaaS.

In this paper, we focus on providing low latency *model inference* service (a.k.a. machine learning serving) for IoT devices in heterogeneous environments. Unlike offline machine learning model training, which may take hours or even days, one main requirement of machine learning serving is to achieve consistently low latency to meet the need of interactive and real-time IoT applications like smart home and autonomous driving. However, the challenge lies in the fact that productional machine learning models for many complicated tasks often contain billions of neural connections, and it may take seconds or even minutes to fulfill users' requests [7][1] if executed in a *sequential* manner, leading to unacceptably long latency for IoT applications.

A natural and promising approach to meet the strict latency Service Level Objective (SLO) is to use parallelism in computation [9], [10]. Machine learning is an ideal appli-

Part of this work was presented at the International Conference for High Performance Computing, Networking, Storage and Analysis [1].

H. Qin, S. Zawad, L. Yang and F. Yan are with the Department of Electrical and Computer Engineering, University of Nevada, Reno, NV, 89557 USA (e-mail: heyang_qin@nevada.unr.edu, szawad@nevada.unr.edu, leiy@unr.edu, fyan@unr.edu).

Y. Zhou is with Google Brain, (email: yanqiz@google.com).

S. Padhi is with Amazon Web Services, (email: sanpadhi@amazon.com).

[1]The time for fulfilling users' requests includes the processing time and the queuing time.

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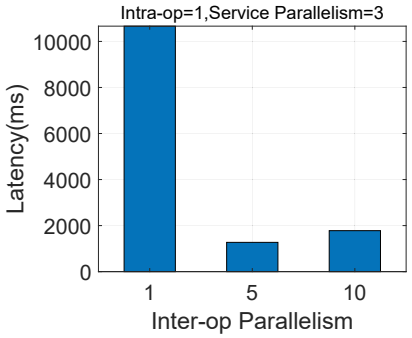

Fig. 2: Tensorflow serving performance under different parallelism configurations for Inception V3 model running on CPU. Appropriate parallelism improves system performance yet excessive parallelism decreases it because of interference. This observation is consistent with previous study [8]. Experimental setup is detailed in Section VI-A.

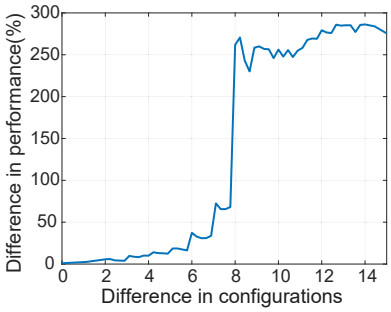

Fig. 3: Difference in performance vs. difference in configuration. The difference in configurations is calculated by their Euclidean distance.

cation of parallelization because most underlying operations in these models are vector-matrix multiplications or matrix-matrix multiplications [11]. Parallelization usually have two levels [7] for modern machine learning systems on CPU based infrastructure. Upon arriving at system, multiple requests can be served in parallel, which is noted as *request parallelism*. Each request can usually be decomposed into many operations. Further parallelization happens at the operation level, including *inter-op parallelism* where multiple operations executing simultaneously and *intra-op parallelism* where multiple threads working on each operation. Fig. 1 illustrates these three parallel implementations. Distinct parallelization mechanism can be found on hardware accelerator based infrastructure. For example, GPU has the built-in parallelism such as thread blocks and scheduling partitions that are controlled by its own hardware schedulers. These low-level parallelisms are difficult to control directly through software-based approaches [12]. Fortunately, even for GPU infrastructure we can still indirectly impact the parallelization by a few user defined parameters. All of the parallel implementations and related configurations become control knobs in machine learning serving system. System performance is significantly determined by parallelism configurations. As indicated in Fig. 2, system performance can be boosted up to 10 times by a well-tuned parallelism configuration compared to sequential execution (e.g., running Inception V3 on CPU infrastructure).

To provide low latency machine learning serving, we propose a swift machine learning serving scheduling framework for IoT applications. The proposed framework is driven by a lightweight region-based reinforcement learning (RRL) [1] approach that can efficiently identify optimal parallelisms configurations under heterogeneous IoT environments. The key insight is that the system performances under different similar configurations in a region can be accurately estimated by using the system performance under one of these configurations, due to their similarity (see Fig. 3). This key finding motivates us to develop RRL that can speed up the learning process by orders of magnitude faster than state-of-the-art deep reinforcement learning methods with very limited training data. Theoretical analysis shows that the speedup increases with the size of the region; however, our initial results [1] show a performance gap between the RRL and the optimal solution due to the estimation error. To reduce such performance gap, we propose an adaptive algorithm namely RRL Plus to adaptively adjust the region size to achieve fast learning speed as well as near-optimal performance.

We prototype the proposed framework on top of the popular Tensorflow Serving [13] machine learning serving system and support both CPU and GPU based hardware infrastructure. We release the source code for public access.[2] Extensive experimental evaluations on both CPU and GPU clusters show that by continuously learning the new traffic patterns and updating the scheduling policies, RRL Plus can quickly adapt to the ever-changing dynamics of IoT workloads and system environments. Compared to state-of-the-art approaches (e.g., DeepRM [14] and CAPES [15]), RRL Plus can reduce the average latency up to 88.9% on CPU-based infrastructure and up to 71.5% on GPU-based infrastructure. In the SLO-aware scenario, RRL Plus can offer SLO guarantee under strict targets and provide up to 89.3% SLO violation reduction compared to CAPES and up to 91.6% compared to DeepRM. In addition, the proposed framework does not make assumptions on workload or machine learning applications and thus is applicable to most modern IoT applications.

II. Challenges and Observations

Machine learning in IoT applications is often interactive and latency sensitive [16] in contrast to model training or other cloud applications which are usually throughput-oriented (i.e., SLO-agnostic). Compared with traditional services (e.g., web service), machine learning service usually involves hundreds to thousands of operations together with complex correlation among them [17], which makes it challenging to model or to breakdown and fine-tune at operation level. How to optimally control these knobs is an important yet challenging problem as the overall performance depends on the performance requirement, workload characteristic, and available computing resources.

Many recent works focus on parallelism configuration tuning [18], [19]. However, existing methods rely on domain specific information and techniques to tune the parallelism configuration (see the detailed discussion in Section VII), which may not be applicable to many machine learning

[2]https://github.com/SC-RRL/RRL

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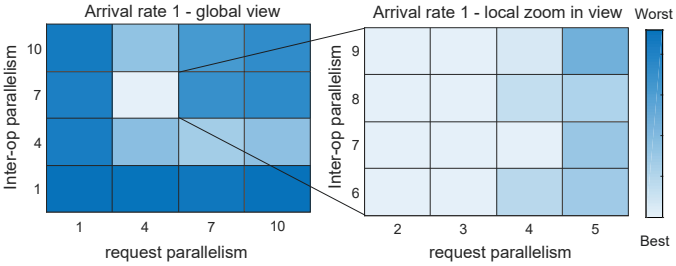

Fig. 4: Latency under the arrival rate of 14 requests per second on CPU with different parallel configurations (intra-op parallelism is set to 10) using Inception V3 deployed in Tensorflow Serving. The lighter the color, the lower the latency. The left plot shows a global performance view of configurations and the right plot is the zoomed in view of the performance in a small region of configurations. The coarse-grained plot shows the latency is quite versatile globally while the zoomed-in fine-grained plot shows the latency is smooth locally (i.e., the neighboring points in the heatmap).

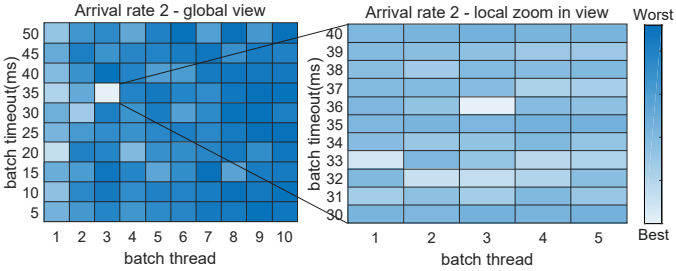

Fig. 5: Latency under the arrival rate of 61 requests per second on GPU with different parallel configurations (batch size is set to 50) using Inception V3 model deployed in Tensorflow Serving. The lighter the color, the lower the latency. Left plot shows a global performance view of configurations and the right plot is the zoomed in view of the performance in a small region of configurations.

applications. Notably, Feng *et al.* proposed SERF in [8], [20] using an analytical queuing model to achieve optimal parallelism configuration for machine learning serving, which works on exponential arrival process and homogeneous request size in certain image classification applications. Unfortunately, the arrival process may not be exponential for many other applications (such as video, speech, and natural language processing) and their request sizes can be heterogeneous. In addition, SERF supports only request level parallelism and CPU-based hardware. Therefore, there is a pressing need for a novel approach that can support two levels of parallelisms and hardware accelerators like GPU to effectively and efficiently tune parallelism configuration for machine learning applications with diverse arrival processes and heterogeneous request sizes.

There are many challenges for tuning parallelism configuration in modern machine learning serving systems. For CPU-based infrastructure, the multi-level parallelism results in a relatively large configuration space. Fig. 4 illustrates request latency under only two parallelism configurations with fixed intra-op parallelism on a machine with only 10 cores. The number of configurations will be magnitude larger with more parallelism parameters or complicated hardware environments, making it challenging for algorithms to locate the ideal one. Fig 5 shows the similar observation on GPU-based infrastructure. As the configuration parameters have wider range on GPU, the search space is even larger (e.g., Batch Timeout alone can have hundreds to thousands possible choices). In addition, the indirect impact of configuration parameters in the GPU case makes it even harder to model or predict the behaviors. Even for the optimal parallelism configuration, it is also very sensitive to the load. When load experiences a slight change, the latency distribution which composes of both service time and queuing waiting time under different parallelism configurations becomes quite different. Such sensitivity significantly increases the search space and prohibits exhaustive search. Among parallel computations, there are also complex interference behavior [8], [20] as a result of the high computation and memory needs of machine learning models, which leads to non-linear performance behavior of different configurations. All these together brings significant challenges for profiling and analytical modeling approaches [21].

Another challenge that could result in the state-of-the-art modeling techniques [8], [20] ineffective is the tens of thousands of operations with complex dependencies among them in modern machine learning models. Moreover, the workload and system environment in many IoT applications are often highly dynamic [22], [23], [24], which requires the scheduling policy with an agile adaptive ability, in order to meet the sensitive latency SLO [25] of IoT applications. In this case, traditional learning-based methods [21], requiring a large training set and a long convergence time, can hardly be applicable. Therefore, it is of paramount importance to provide machine learning serving with swift deployment that can learn the dynamics of the IoT workload and system environment and optimize the performance in an online manner.

III. RRL-based Scheduling Framework

In this section, we present the RRL-based scheduling framework for machine learning service in IoT. The RRL-based scheduling framework is designed to dynamically adjust the parallelism configuration of machine learning serving systems according to dynamic system load, in order to optimize machine learning performance in IoT (e.g., response latency and resource consumption). It is challenging to model the relationship among the system performance, parallelism configurations and system load in a closed form. As illustrated in Fig. 4, system performance varies under different parallelism configurations even for the same load. To tackle this challenge, a learning approach is used in the proposed framework to find the optimal parallelism configuration. Specifically, the proposed framework consists of three main components: 1) profiler, 2) scheduler, and 3) region-based reinforcement learning, as illustrated in Fig. 6. Various system characteristics are collected by the profiler, including the current user traffic load and the corresponding system performance under this load and the present parallelism configuration. The scheduler then adjusts the parallelism configuration for the measured load level based on the current scheduling policy. Meanwhile, the region-based reinforcement learning asynchronously updates the scheduling policy to adapt to the system dynamics based on the measured system load and corresponding performance.

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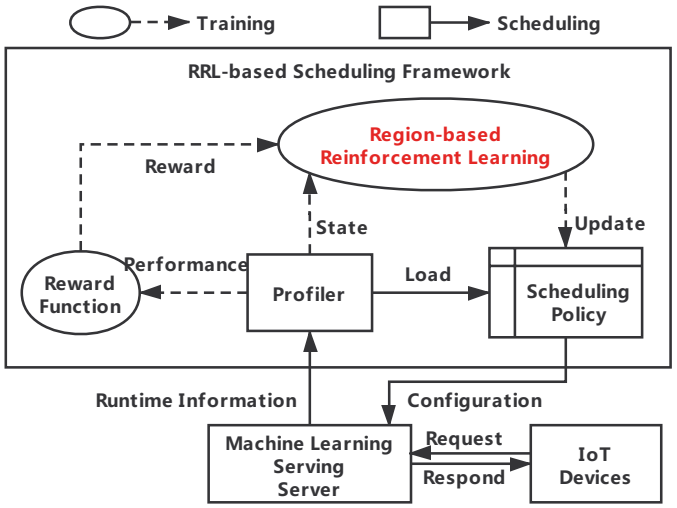

Fig. 6: Overview of RRL-based scheduling framework for IoT applications.

Profiler: The profiler measures system performance including the system load (i.e., request arrival rate) and the latency (a.k.a. response time) of each request. The profiler also collects hardware-related information (e.g., CPU core number, CPU utilization, available GPUs, GPU utilization, and network statistics). All the information can be used in reward functions to optimize the system performance for various scheduling objectives.

Scheduler: The scheduler takes into consideration the current system load, scheduling policies and hardware information such as the availability of resource, and adjusts the parallelism configuration accordingly.

Region-based reinforcement learning: As the core of the proposed framework, the region-based reinforcement learning component aims to find the optimal scheduling policy and quickly adjust the scheduling policy to adapt to the system dynamics. Specifically, the system performance measured by the profiler will be passed to the reward function in Fig. 6 to calculate the value of the system objective function, and then the learning component learns the scheduling policy based on this observed reward. Traditionally, the scheduling policy is incrementally improved in a point-by-point learning manner that makes learning process significantly long. To address this challenge, the proposed region-based reinforcement learning can speedup this learning process by leveraging the key feature of the system as illustrated in Fig. 3 that the system performances under different similar configurations are similar. Based on this feature, the system performance under one configuration can be used to estimate the system performances under other similar configurations, which would significantly reduce the number of samples needed to learn the optimal scheduling policy. For example, if we choose the radius of the configuration region equal to 2, then we can use a single observation to update all configurations in this region and obtain a roughly 10 times faster convergence with limited performance loss due to the estimation error. The detailed design is presented in Section IV.

IV. Region-Based Reinforcement Learning

In this section, we propose a region-based reinforcement learning (RRL) approach, in order to speed up the learning process of the scheduling policy to meet the requirements of IoT applications. Specifically, we first formulate the machine learning serving scheduling as a Markov Decision Process (MDP), and then theoretically show that the RRL approach can achieve a near optimal solution with fast convergence speed.

A. ML Serving Scheduling: A MDP View

The objectives of machine learning serving scheduling in IoT are 1) to minimize response latency using a given amount of resources [8] or 2) to minimize resource consumption while meeting latency SLO [26]. Our scheduling framework supports both objectives. We focus on the first objective of minimizing response latency due to the space limitation.

Define system state as $s \in \mathcal{S}$ where s denote the overall load level and $\mathcal{S}$ denotes the set of possible load levels. System action is defined as the parallelism configuration $c \in \mathcal{C}$ which is a tuple of request parallelism c^{service}, inter-op parallelism c^{inter}, and intra-op parallelism c^{intra}, i.e., $c = (c^{\text{service}}, c^{\text{inter}}, c^{\text{intra}})$, where $\mathcal{C}$ denotes the set of possible parallelism configurations. For machine learning serving in IoT, it is challenging to characterize latency in a closed form as it can vary under different loads (system states) for the same parallelism configuration [8]. Instead we use the average request latency $r(s, c)$ under the system state s and the parallelism configuration c as reward. In this paper, we assume that the scheduler does not have a priori knowledge of system state transitions, except the Markov property (i.e., the state transition depends on only the previous state)[3]. Under this model, the machine learning serving scheduling is cast as a Markov Decision Process, aiming to minimize the expected cumulative discounted latency $\mathbb{E}[\sum_{t=0}^{\infty} \gamma^t r_t(s_t, c_t)]$, where $\gamma \in (0, 1]$ is a discount factor and $r_t(s_t, c_t)$ denotes the latency observed at time t under system state s_t and parallelism configuration c_t.

At each time t, the scheduler chooses a parallelism configuration based on a policy, defined as $\pi : \pi(s, c) \to [0, 1]$, where $\pi(s, c)$ is the probability that configuration c is used in state s. The Q-learning method can be applied to find the optimal policy yet its convergence is slow, especially when the space of state-configuration pairs is large. One key reason for this slow convergence is that it searches the space point by point and incrementally improves the policy. To improve the convergence speed, many approaches [28], [29] have been proposed but they are still *point-based* learning essentially and would not be applicable to our problem with large state-configuration space as shown in our experiments in Section VI.

B. RRL: From Point-based to Region-based Learning

To speed up the learning process, we propose the RRL approach. *The key idea is that when observing the latency*

[3]Markov models are often used to model the workload dynamics, e.g., [27] verifies the Markov property for different applications. In our application, the Markov property is also satisfied. The experiments in Section VI also corroborate the correctness of the Markov model in our application.

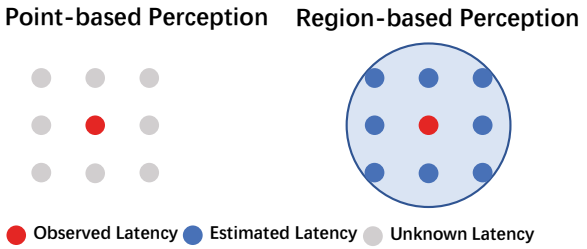

Fig. 7: Point-based vs. region-based learning. The RRL approach can more efficiently learn the latency under different configurations.

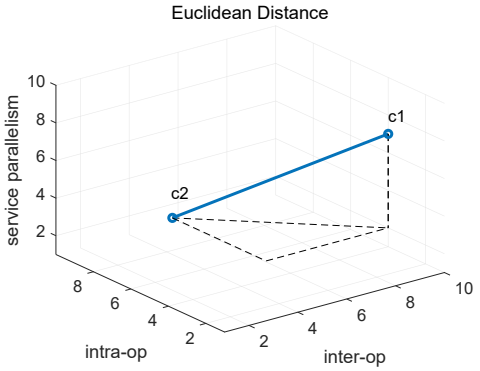

Fig. 8: An example of Euclidean distance between two configurations c_1 and c_2, i.e., $\sqrt{(c_1^{\text{service}} - c_2^{\text{service}})^2 + (c_1^{\text{inter}} - c_2^{\text{inter}})^2 + (c_1^{\text{intra}} - c_2^{\text{intra}})^2}$.

$r(s, c)$, *we will estimate the latency in a region with configurations close to* c *under this state* s*, and then use the estimated latency in this region to learn the policy, as illustrated in Fig. 7.* Intuitively, the learning speed would be significantly improved if this region-based learning approach uses a large region. However, the potential estimation errors of the latency associated with the region may make the converged policy deviate from the optimal one. In other words, the larger the region is, the larger the potential errors might be, which indicates a trade-off between the learning speed and the optimality of the policy depending on the size of the region and the latency estimation scheme. When the region degenerates to a single point, the RRL approach would degenerate to the traditional reinforcement learning approaches. In this paper, Euclidean distance is used to measure the distance between two configurations since both CPU and GPU configurations are numeric, see Fig. 8. Note that other similarity measures can also be applied in RRL.

Specifically, the RRL approach consists of two main components: 1) latency estimation based perception and 2) policy update.

1) Latency estimation based perception: Let $Q_t(s_t, c_t)$ denote the perception of the expected cumulative discounted latency under state s_t and configuration c_t. Define the region around c_t as $\mathcal{C}(c_t) = \{c | ||c - c_t|| \leq \delta, \forall c \in \mathcal{C}\}$, where $\delta \geq 0$ denotes the size of the region. Using the observed latency $r_t(s_t, c_t)$, the latency under other configurations in $\mathcal{C}(c_t)$ can be estimated as

$$\hat{r}_t(s_t, c) = f(c, r_t(s_t, c_t)), \forall c \in \mathcal{C}(c_t), \tag{1}$$

where $f : \mathcal{C} \times \mathbb{R}^+ \to \mathbb{R}^+$ is the latency estimation function and $f(c_t, r_t(s_t, c_t)) = r_t(s_t, c_t)$. Based on (1), we update the perception of the expected cumulative discounted latency in the region by

$$\forall c \in \mathcal{C}(c_t),\ Q_{t+1}(s_t, c) = \begin{array}{l}(1 - \alpha_t) Q_t(s_t, c) + \alpha_t (\hat{r}_t(s_t, c) \\ +\gamma \min_{\tilde{c} \in \mathcal{C}} Q_t(s_{t+1}, \tilde{c})),\end{array} \tag{2}$$

where $\alpha_t \in [0, 1]$ is the learning rate. As is standard, the learning rate is assumed to satisfy $\sum_{t=1}^{\infty} \alpha_t = \infty$ and $\sum_{t=1}^{\infty} \alpha_t^2 < \infty$. The perceptions of other configurations ($c \notin \mathcal{C}(c_t)$) will remain the same, i.e., $Q_{t+1}(s_t, c) = Q_t(s_t, c), \forall c \notin \mathcal{C}(c_t)$.

2) Policy update: Based on the perceptions, we can use the Boltzmann distribution [30] to update the policy for state s_t

$$\pi_t(s_t, c) = \frac{\exp(-\beta Q_t(s_t, c))}{\sum_{\hat{c} \in \mathcal{C}} \exp(-\beta Q_t(s_t, \hat{c}))}, \forall c \in \mathcal{C}, \tag{3}$$

where $\beta \geq 0$ controls the exploration-exploitation trade-off. When β is very small, the scheduler would explore the space randomly; when β is large, the scheduler would tend to exploit the configuration with the lowest perceived latency.

It is worth noting that the accuracy of the latency estimation (1) directly impacts the performance of the RRL approach. Due to the stochastic nature of the state and the latency, it is challenging to characterize f in a closed form in practice. To tackle this challenge, we use neural network to implement this estimation function as discussed in Section V. The detailed description of the RRL approach is given in Algorithm 1.

Algorithm 1 Region-based reinforcement learning

Initialization: Choose β, δ, and γ. Set $t = 0$ and $Q_0(s, c) = 1/|\mathcal{C}|,\ \forall c \in \mathcal{C}, s \in \mathcal{S}$.
For each time slot t
1) Choose a configuration based on the current policy π_t.
2) Update the perception based on Eq. (2).
3) Update the policy for the current state s_t using Eq. (3).

C. Performance Analysis of RRL

In this section, we will analyze the convergence rate and optimality performance of the RRL approach. To facilitate the analysis, we assume that the estimation error of the latency estimation (1) is upper bounded by $\Delta \geq 0$ for all state-configuration pairs in the space, i.e.,

$$|\hat{r}_t(s_t, c) - r_t(s_t, c)| \leq \Delta, \forall c \in \mathcal{C}(c_t),\ s_t \in \mathcal{S}, \tag{4}$$

where $r_t(s_t, c)$ denotes the real latency that can be observed if the configuration c is chosen. In (4), Δ is intimately related to the size of the region δ. In general, Δ increases with δ, and Δ becomes zero when δ is zero.[4] The main results are summarized in the following theorem.

Theorem 1. *The RRL approach can asymptotically converge to a near optimal solution with probability one as* t *goes to infinity. The performance gap is upper bounded by*

[4]Note that Δ also highly depends on the accuracy of the estimation function. In this paper, a neural network based estimation function is implemented, and the error bound is shown to be small in our experiments.

$\frac{\Delta}{1-\gamma}$. *The asymptotic convergence rate is* $O(1/(n_\delta t)^{R(1-\gamma)})$ *if* $R(1-\gamma) < 1/2$ *and* $O(\sqrt{\log\log(n_\delta t)/(n_\delta t)})$ *otherwise, where* n_δ *denotes the number of state-configuration pairs in the region with size* δ *and* R *denotes the ratio of the minimum and maximum state-configuration selection probabilities.*

Proof. Proof can be found in Reference [1]. □

Remarks: Theorem 1 confirms our intuition that the RRL approach can accelerate the convergence speed of the reinforcement learning such that the larger n_δ (i.e., the larger δ), the faster the RRL converges. However, the fast convergence speed is at the cost of performance loss, i.e., there would be a gap $\frac{\Delta}{1-\gamma}$ between the RRL and the optimal solution. When $\delta = 0$, we have $n_\delta = 1$ and $\Delta = 0$, and the results of Theorem 1 degenerates to the results for the traditional point-based reinforcement learning [31]. *Thanks to the unique structure of our problem (see Fig. 3), we use Bayesian Optimization to choose a suitable size of the region with fast learning speed as well as near-optimal performance (see Section IV-D).*

D. Adaptive RRL

From the analysis of RRL, it is shown that excessive region size can lead to large performance gap, whereas small region size leads to low convergence rate. In order to find a suitable region size, we propose a Bayesian based optimization approach to automatically adjust region size to achieve fast learning speed as well as near-optimal performance.

Specifically, we introduce an acquisition function to characterize the expected latency improvement under a give region size as our optimization target,

$$\alpha(\delta) = \mathbb{E}[(\overline{r}(\delta^*) - r(\delta))^+], \tag{5}$$

where $\overline{r}(\delta^*)$ is the best observed average latency and δ^* is the corresponding region size. $r(\delta)$ denotes the latency random variable following Gaussian distribution $\mathcal{G} \sim \mathcal{N}(m(\delta), \sigma(\delta, \delta'))$ with mean $m(\delta)$ and covariance $\sigma(\delta, \delta')$. In each iteration, we choose the region size δ that maximizes the acquisition function α and use this δ for RRL perception. Then, the observed average latency $\overline{r}(\delta)$ will be added into the sample set, and the mean $m(\delta)$ and covariance $\sigma(\delta, \delta')$ of $\mathcal{G}$ will be updated based on Bayesian optimization [32]. The idea is to model the unknown function between the region size and the latency as a multivariate Gaussian distribution, and then use a computational cheap acquisition function to guide the search for the optimal point. Thus, we can reduce the latency by adaptively adjusting region size. The details are given in Algorithm 2.

V. Implementation

In this section, we discuss the implementation of the proposed approach. Specifically, we focus on the neural network based estimation function design as the Tensorflow Serving integration of the proposed framework has been described in our previous work [1].

Algorithm 2 RRL Plus

Initialization: Initialize sample set D.
For each time slot t
1) Calculate the region size δ by maximizing α, i.e., $\delta = \underset{\delta}{argmax}\ \alpha(\delta)$.
2) Update the perception with region size δ using Eq. (2).
3) Update the policy for the current state s_t using Eq. (3).
4) Get the current average latency $\overline{r}_t(\delta)$, and update the sample set $D = \{D, (\delta, \overline{r}_t(\delta))\}$ and the parameters $m(\delta)$ and $\sigma(\delta, \delta')$ using D.

A. Neural Network based Estimation Function

It is challenging to characterize the estimation function in a closed form as discussed in Section IV. Since Neural network based approaches have shown great potentials in many applications [33], we propose a neural network based estimation function in this paper. To support swift machine learning serving scheduling, one key challenge is how to find a suitable neural network structure for the estimation function (1). Simple network structure may not effectively capture the structure of the underlying state-configuration space, which may lead to high estimation error [34]; complicated network structure may take a long training time, which is not suitable for online serving systems.

As indicated in previous study [34], we need to strike a balance between complexity and efficiency. Our network design contains two hidden layers (one with 256 neurons and the other with 64 neurons) using ReLu [35] as activation function and one output layer with linear activation, after experimenting different network structures. Follow-the-regularized-Leader (FTRL) [36] optimizer is used to optimize network parameters instead of the Adam method or other popular optimizers. This is because the number of training samples in our problem is far less than the number of state-configuration pairs in the space during online tuning, and thus FTRL performs well here. Moreover, FTRL is insensitive to model parameters. Our experiments in Tensorflow Serving show that FTRL performs well even where there is limited training data (see Section VI).

B. Tensorflow Serving Integration

The proposed scheduling framework is integrated into Tensorflow Serving [13], a popular production-ready machine learning serving system. While we do a case study with Tensorflow Serving, we do not rely on any Tensorflow specific features and nothing prevents the proposed work being integrated into other machine learning serving systems. All the implementation details can be found in [1].

VI. Experimental Evaluation

In this section, we conduct extensive experimental evaluation simulating heterogeneous IoT environments and workloads to corroborate the effectiveness and robustness of the proposed RRL-based scheduling framework using a rich selection of state-of-the-art machine learning applications on

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both CPU and GPU based infrastructure. We first evaluate the sensitivity of RRL in convergence speed by adjusting the region size, and compare RRL Plus and RRL in terms of convergence process. Then we compare RRL Plus with the latest reinforcement learning approaches for the following four key features in IoT applications: (i) minimizing latency for image classification; (ii) minimizing latency for speech recognition; (iii) satisfying strict SLO guarantee; (iv) effectiveness of meeting SLO while minimizing resource usage.

A. Experimental Setup

Machine Learning Serving System: We prototype RRL based scheduling framework and integrate it in Tensorflow Serving, refer to [1] for more details.

Service Workloads: We use three machine learning models commonly used in IoT applications for evaluation: image classification models Inception V3 [37], Inception ResNet V2 [38], and speech recognition model Deep Speech V2 [39]. They cover popular machine learning tasks in IoT applications such as smart home, smart city and autonomous driving.

Arrival Process: We use two non-exponential arrival processes simulating IoT workloads for evaluation:

- WiKi: an arrival process based on traces of user traffic visiting Wikipedia website [40] with unpredictable load spikes to simulate the request patterns in IoT applications.
- Dynamic: a synthetic dynamic arrival process composed of periods of Poison process with randomly changing average, which has pronounced changes from one period to the next.

Hardware: We use a cluster of 10 identical servers. Each of them is equipped with dual-sockets Intel(R) Xeon(R) CPU E5-2630 v4 @ 2.20GHz with hyper-threading disabled and four NVIDIA GeForce GTX 1080 Ti GPUs, 64 GB of memory, and connected through Infiniband.

Baseline Approaches: Since there is no alternative intelligent scheduling framework for a direct comparison, we opt to implement the state-of-the-art reinforcement learning approaches for tuning parallelism configuration in our scheduling framework: CAPES [15] and DeepRM [14], as they are the closest approaches for online ML-serving scheduling. DeepRM is a job scheduling algorithm designed to work under limited resources and CAPES is a general-purpose parameter tuning algorithm.

SLO Setting: As our testbed is not production-level, we set relatively loose SLOs in our evaluation, i.e., a range between 400ms and 2500ms to emulate different latency requirements for ML serving in production, which is consistent with previous studies [25], [8], [20].

B. Convergence Speed Analysis of RRL and RRL Plus

The key tuning parameter in RRL is the region size as it controls the trade-off between convergence speed and optimality. We validate the theoretical results in Theorem 1 by sensitivity analysis of RRL using Inception, as illustrated in Fig. 9. The results show the convergence time measured in iteration (left y-axis) and distance from optimal Q-learning function (right y-axis) as a function of the region size. It is clear that convergence time drops very quickly when the region size increases while the prediction error increases in a much slower speed. For example, when the region size is one, RRL converges five times faster than Q-learning, which verifies the potential of the region based methodology. When region size is zero, RRL degenerates to point-based learning, which has the same accuracy and the longest convergence time as Q learning. We use RRL Plus to controls the balance of performance and convergence time.

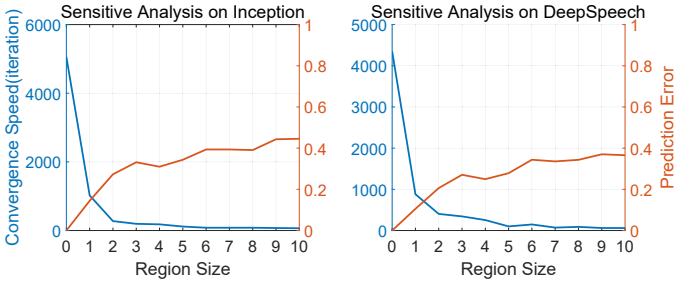

Fig. 9: Sensitivity analysis of RRL in terms of the convergence time in iteration (left y-axis) and the prediction error (right y-axis) as a function of region size using Inception and DeepSpeech.

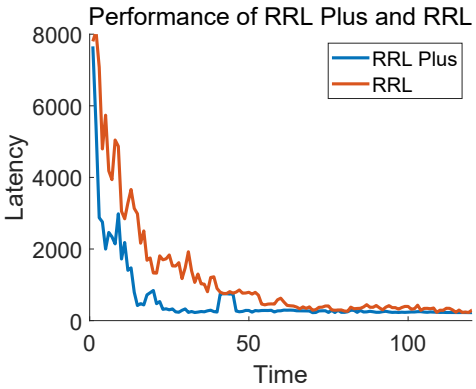

Fig. 10: Performance comparisons of RRL Plus with adaptive region size and RRL with fixed region size on Inception. RRL Plus has shorter learning process and lower latency.

We evaluate the effectiveness of our adaptive algorithm RRL Plus by comparing it to the RRL with fix region size. Fig. 10 shows the convergence process between RRL Plus and RRL. It can be inferred that during the converging process, RRL Plus performs better and has shorter learning process. On average, RRL Plus has 17.54% less converge time and 15.31% less latency.

C. Minimizing Serving Latency for Image Classification

In this section, we evaluate the famous image classification model Inception on RRL Plus and the two baseline Deep Reinforcement Learning approaches: DeepRM[14] and CAPES[15] to compare their effectiveness of minimizing serving latency on both CPU and GPU based infrastructure under WiKi and Dynamic arrival processes. This evaluation aims to test the algorithms' ability to keep low response latency under perturbation which are common in IoT applications.

WiKi arrival process. We show latency results of Inception running on CPU cluster in Fig. 11(b) using WiKi trace to

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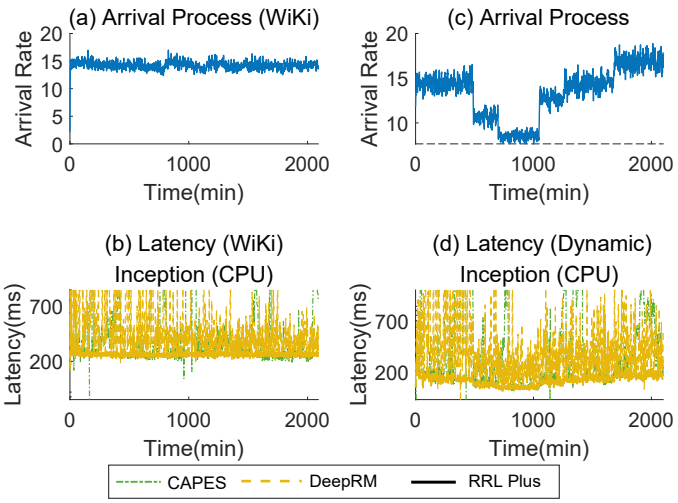

Fig. 11: Comparisons of RRL Plus with CAPES and DeepRM under different arrival processes and service workloads. The first column (a)(b) shows the first scheduling objective of minimizing latency using WiKi as arrival process for Inception; the second column (c)(d) also shows the scheduling objective of minimizing latency but under dynamic arrival process for Inception on CPU.

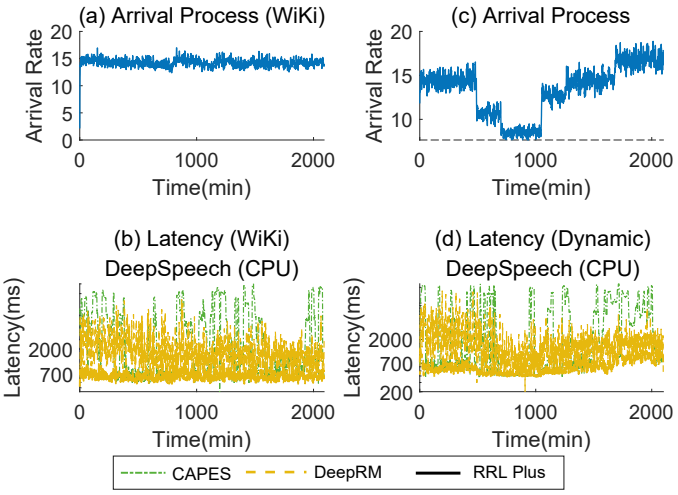

Fig. 12: Comparisons of RRL Plus with CAPES and DeepRM under different arrival processes and service workloads. The first column (a)(b) shows the first scheduling objective of minimizing latency using WiKi as arrival process for Inception on CPU; the second column (c)(d) also shows the scheduling objective of minimizing latency but under dynamic arrival process for Inception on CPU.

drive the arrival process, which is demonstrated in Fig. 11(a). The results verify that RRL Plus converges much faster than the baseline approaches, i.e., RRL Plus converges to a near optimal performance in about 150 minutes, while DeepRM roughly converges around 1400 minutes with variance and CAPES could not converge even after 2000 minutes. The results also show that RRL Plus is able to achieve better latency performance compared to deep reinforcement learning based approaches, thanks to the swift learning capabilities. More specifically, the average latency of RRL Plus improves from CAPES and DeepRM by 70.1% and 75.2% respectively for Inception.

Dynamic arrival process. Workload can change dynamically over time in practice. In this section, we evaluate the robustness of the proposed scheduling framework in terms of the ability to quickly adapt to the workload change. We use a synthetic dynamic arrival process for evaluation, as shown in Fig. 11(c), the arrival change is more pronounced than the WiKi arrival process, which emulates the change of user traffic patterns over time.

The latency results are shown in Fig. 11(d). The results suggest that RRL Plus can adapt to the user traffic change quickly with limited number of samples thanks to the region-based learning approach, which leads to a much shorter adapting time and more stable latency performance compared to CAPES and DeepRM. In contrast, DeepRM takes a much longer time to update scheduling polices and CAPES shows significant variation due to its slow learning process. On average, RRL Plus reduces the latency of Inception by 71.0% and 59.9% compared to CAPES and DeepRM respectively.

D. Minimizing Serving Latency for Speech Recognition

One key feature of speech recognition application is that its requests are heterogeneous since the user can say a long sentence as well as just a few words, which is challenging to scheduling system as the system has no a priori knowledge of the computation cost of requests. Thus it requires the scheduling system the ability to handle requests with various lengths. The application we use is DeepSpeech V2, a reputable speech recognition model.

Wiki arrival process. The latency results on CPU cluster for DeepSpeech are shown in Fig. 12(b). Similar to previous evaluation, RRL Plus reaches a near optimal configuration within shorter adapting time compared to CAPES and DeepRM. RRL Plus has better performance than CAPES by 88.9% and DeepRM by 80.7% on average.

Dynamic arrival process. As it shown in Fig. 12(d), even under ever changing arrival process and heterogeneous request, RRL Plus is still able to keep a stable and low response latency whereas DeepRM has slower converge rate and CAPES shows significant variation. On average, RRL Plus reduces the latency of DeepSpeech by 86.0% and 63.3% compared to CAPES and DeepRM respectively.

E. Minimizing Serving Latency on GPU Infrastructure

As explained in earlier sections, the parallelism on GPU is controlled by the hardware scheduler and difficult to be adjusted through software approaches. Here we control the parallelism using an indirect approach by tuning the batching parameters (parallel batch threads, batch size, and batch timeout). Similar as CPU case, we use scaled WiKi workload and CAPES and DeepRM as baselines and report the results in Fig. 13. Compared with CPU results, the variance in latency is higher on GPU which is caused by the indirect control mechanism. In spite of the challenge of high variance, RRL Plus still converges quickly and outperforms CAPES and DeepRM in latency. Specifically, RRL Plus performs 56.5% better than DeepRM and 68.1% than CAPES.

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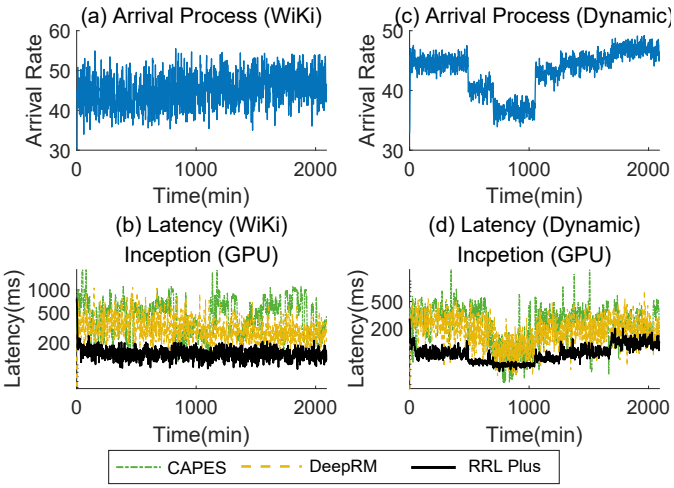

Fig. 13: Comparisons of RRL Plus with CAPES and DeepRM under different arrival processes and service workloads. The first column (a)(b) shows the first scheduling objective of minimizing latency using WiKi as arrival process for Inception on GPU; the second column (c)(d) also shows the scheduling objective of minimizing latency but under dynamic arrival process for Inception on GPU.

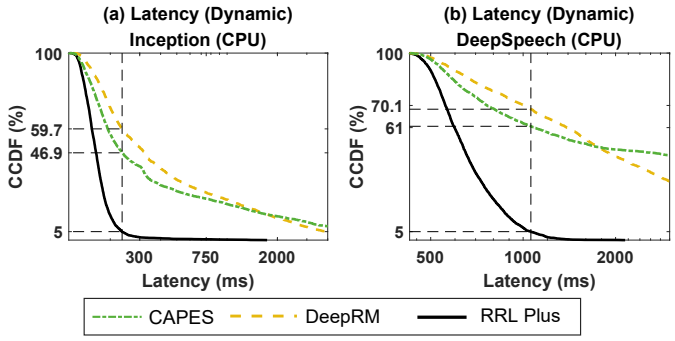

Fig. 14: Comparisons of RRL Plus with CAPES and DeepRM under strict SLO (95th percentile latency of 235ms for Inception and 1060ms for Deepspeech).

Fig.13(d) shows the evaluation on GPU-based infrastructure under dynamic workload. The indirectly controlled parallelism on GPU leads to a slower adapt speed than CPU case. However, even in this challenging scenario, RRL Plus still consistently outperforms CAPES and DeepRM by 71.5% and 55.7% on average respectively.

F. Meeting SLO With Minimum Resources

We evaluate our approach under the scenario of meeting strict SLO target, i.e., 95th percentile latency SLO of 235ms for Inception and 1060ms for Deepspeech.[5] Fig. 14 (note that x-axis is logscale) demonstrates the CCDF of RRL Plus latency on CPU cluster and GPU cluster compared with the baselines. The tail comparison indicates that RRL Plus has shorter tail latency and can provide strict SLO guarantee. Compared with CAPES and DeepRM, RRL Plus achieves up to 89.3% and 91.6% SLO violation reduction respectively, thanks to its SLO-aware design.

Our scheduling framework also supports another common scheduling objective in IoT applications which is meeting relatively loose SLO while minimizing the resource usage (e.g., cloud environment or shared cluster). The evaluations on CPU and GPU infrastructure of this scheduling objective using DeepSpeech, ResNet, and Inception under dynamic workload are shown in Fig. 15.

CPU Cluster. Fig. 15(b) shows the latency of DeepSpeech running on CPU cluster over the time using different scheduling methods, where both CAPES and DeepRM perform poorly on achieving the SLO target. DeepRM spent around 500 minutes before finding a scheduling policy that can achieve the SLO but at the expense of high CPU utilization whereas CAPES violates the SLO when the workload increases. RRL Plus in contrast always guarantees the SLO, even during abrupt workload changes. Another comparison is on resource utilization, which is critical for consolidating resources and achieve cost efficient serving. We report the CPU utilization at Fig. 15(c), where RRL Plus consistently consumes much less CPU resource than both CAPES and DeepRM, which is especially important for commercial IoT applications with a rather large number of requests from all end devices. Similar observations hold for the ResNet results in Figs. 15(e)(f), where all three methods achieve SLO in a short time, but RRL Plus uses only one third CPU resources compared to the deep reinforcement learning based methods. On average, compare with CAPES and DeepRM, RRL Plus uses 32.0% and 35.0% less CPU resources respectively for DeepSpeech. For ResNet, the resource saving is even more significant: RRL Plus on average saved 61.8% compared to CAPES and 68.9% compared to DeepRM.

GPU Cluster. We show the GPU results in Figs. 15(h)(i), where RRL Plus keeps a stable latency right under SLO and only uses half GPU resources compared with DeepRM. On average, RRL Plus saved 43.7% GPU resources compared with DeepRM. Compared with CAPES, RRL Plus uses same level of GPU resources and achieves 38.8% latency reduction and 98.6% SLO violation reduction.

G. Discussion

Evaluation results show that RRL Plus outperforms RRL and other standard deep reinforcement learning methods in both speed and accuracy. RRL Plus uses the unique characteristics of ML-serving to accelerate the learning process: when parallelism changes, the latency is quite versatile globally while smooth locally. Other methods do not have such insights. Compared with RRL, PPL Plus automatically sets the region size during optimization, which leads to less convergence time. When environment/workload changes, RRL Plus may have already converged to a near optimal solution, whereas other methods may be still far away. Therefore, in online systems, RRL Plus outperforms the standard deep reinforcement learning methods in both speed and accuracy.

[5]It is worth to emphasize again that the relative high latency is because our testbed is not enterprise scale nor equipped with latest hardware, so both the processing time and the queuing waiting time is relatively high.

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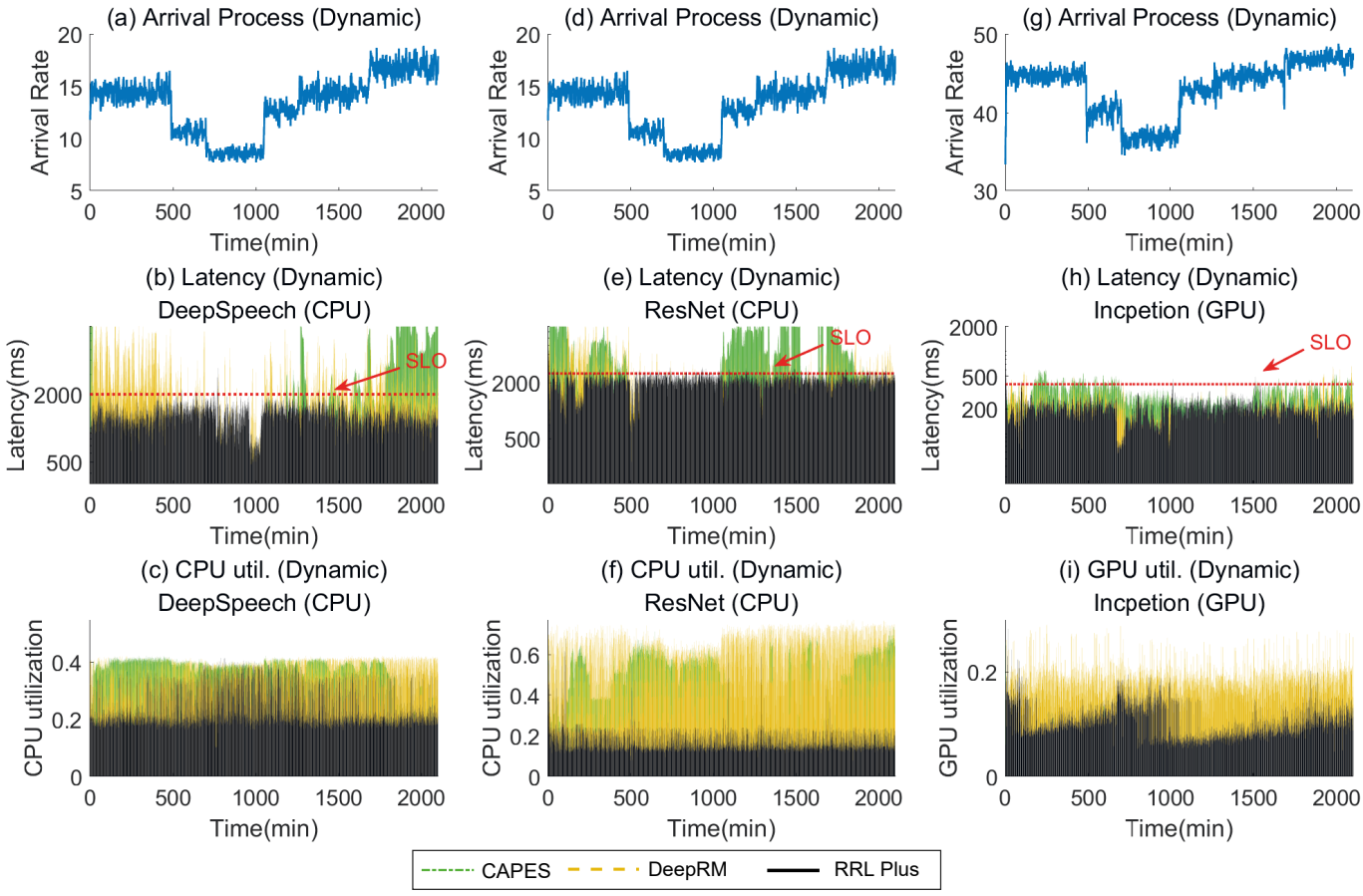

Fig. 15: Comparisons of RRL Plus with CAPES and DeepRM when achieving SLO while optimizing resource usage (i.e., CPU and GPU utilization) under dynamic arrival processes and service workloads. (a)-(f) shows the scheduling objective of minimizing CPU utilization with respect to given SLOs for model DeepSpeech and ResNet under dynamic workloads. (g)(h)(i) shows the second scheduling objective of achieving SLO while minimizing GPU usage with Inception under dynamic arrival process. The SLOs for DeepSpeech, ResNet and Inception are 2000ms, 2500ms, and 400ms, respectively.

VII. Related Work

A. Machine Learning in IoT Applications

IoT applications have brought the number of end devices and the information they collected to a magnitude higher [41], [42]. To manage, process and utilize such large amount of data, machine learning has been applied to many IoT scenarios.

Mohammadi *et al.* [43] apply a semisupervised reinforcement learning algorithm to smart city scenario that improves the accuracy of indoor localization. Cao *et al.* [44] combines SVM with belief network to optimize wireless network capacity. Chen *et al.* [45] use extreme learning machine to recognize human activity from data collected by smart health sensors. Liang *et al.* [46] detects soil moisture by applying neural network to sensor data.

However, a key challenge of combining machine learning with IoT applications is that IoT devices are usually low-energy and embedded whereas machine learning models need considerable memory and computational power to run. Reagen *et al.* [47] propose a design of hardware accelerator to accommodate DNN in IoT devices. Dhurandhar *et al.* [48] develop a method to compress RNN models to reduce resource usage. Even with the aid of these approaches, it is often infeasible to deploy machine learning to end devices, thus using machine learning as cloud service is a popular choice for many IoT applications.

B. Machine Learning Serving

How to efficiently deploy trained machine learning models in serving (or sometimes called inference) mode to provide low latency services has drawn great attention in both academia and industry [49], [8], [20] . Several machine learning serving systems have been open-sourced recently [13], [49], [50]. Hardware acceleration [51] has been used to accelerate the computation in machine learning serving. Software techniques using model compression and simplification [52], compiler techniques [53] and acceleration library [54] have also successfully reduced model computation time.

Another promising technique for reducing the latency of machine learning serving is parallelism [11]. *Request parallelism*, *inter-op parallelism*, and *intra-op parallelism* are the typical ways to parallel computation on CPU in today's machine learning serving systems. On GPU, computation is parallelized through SMs and scheduling partitions which can be indirectly adjusted through batching parameters such as

batch size, *batch threads*, and *batch timeout*. As discussed in the introduction, existing methods [19], [18], [8], [20] either require domain specific information to tune the parallelism configuration or are applicable for special arrival process with homogeneous request size in certain applications. To achieve a more general solution, we design a scheduling framework that can work with general user traffic patterns and system environments on both CPUs and GPUs based infrastructure.

C. Parameter Tuning using Reinforcement Learning

During 1940s, reinforcement learning [55] was first proposed and has been widely used in different applications. Here we focus on the works that apply reinforcement learning to system parameter tuning. Mao *et al.* propose reinforcement learning based resource management method for multi-resource cluster scheduling problem [14]. Li *et al.* develop a reinforcement learning based parameter tuning system for storage systems [15]. Both works use traditional point-based reinforcement learning and suffer from slow convergence and adaptivity. Mirhoseini *et al.* propose to optimize Tensorflow operation placement between CPU and GPU using long short-term memory (LSTM), which is applicable for only CPU-GPU co-design architecture [56]. In our previous work [1], we present initial results of performance tuning using the RRL approach. However, the region size is hand-tuned and fixed throughout the optimization process, which leads to a performance gap between the RRL solution and the optimal one. In this paper, we develop an enhanced region-based reinforcement learning based framework using Bayesian Optimization to dynamically update the region size, in order to improve the convergence speed and the agility in dynamic environment.

VIII. Conclusion

In this paper, we proposed a RRL-based scheduling framework for machine learning serving in IoT applications that can efficiently identify optimal configurations under dynamic workloads. A key observation is that the system performance under similar configurations in a region can be accurately estimated by using the system performance under one of these configurations due to their correlation. We theoretically showed that the RRL approach can achieve fast convergence speed at the cost of performance loss. To reduce the performance loss, we proposed an adaptive RRL algorithm, namely RRL Plus, to balance the convergence speed and the optimality. The proposed framework was prototyped and evaluated on Tensorflow Serving system. Convergence analysis indicates that RRL Plus can shorten the average convergence time by 17.54% and reduce the average latency by 15.31%, compared to RRL. Extensive experimental evaluation on both CPU cluster and GPU cluster show that the RRL Plus can quickly adapt to the dynamics of workloads and system environments. The proposed scheduling framework can reduce the average latency by up to 88.9% on CPU cluster and 71.5% on GPU cluster, compared to the state-of-the-art Deep Reinforcement Learning based methods (DeepRM and CAPES). In the SLO-aware scenario, the RRL Plus can reduce up to 91.6% SLO violation under strict SLO requirements, while reducing the resource usage by up to 68.9% on CPU and 43.7% on GPU under loose SLO requirements. In addition, the proposed solution does not have assumptions on workload or underlying systems and thus can be used for most modern machine learning systems and applications.

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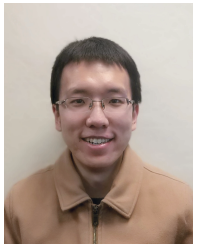

Heyang Qin is a PhD student in the Department of Computer Science and Engineering at University of Nevada, Reno, where he works as a teaching assistant and research assistant. He conducts research in areas of Deep Learning and Reinforcement Learning under the supervision of Dr. Feng Yan and Dr. Lei Yang. He got his bachelor's degree in University of Electronic Science and Technology of China in 2017.

Syed Zawad is a PhD student in the Department of Computer Science and Engineering at the University of Nevada, Reno. His research area of interest is in High Performance Computing, Deep Learning, Federated Learning, and Neural Architecture Search. He completed his B.Sc in Computer Science and Engineering from BRAC University (Bangladesh) and has interned as a researcher in Baidu USA. He also has 3 years of work experience as a Software Engineer for Web applications.

Yanqi Zhou is a research scientist at Google Brain. Her research interest lies in computer systems and machine learning. She obtained her Ph.D. degree from Princeton University and her bachelor degree from the University of Michigan, Ann Arbor.

Sanjay Padhi leads Research Initiatives at Amazon Web Services. He is also an Adjunct Professor of Physics at Brown University. Before AWS, Dr. Padhi worked as a physicist for about 15 years and had vast experience in predictive analytics, machine learning, algorithm developments including analytics with streaming data. He led various groups with hundreds of members at CERN in Physics, Simulations as well as Distributed Computing. Created and operated worldwide late-binding based resource management systems, currently used by the CMS Collaboration for all its computing activities across 140 institutions worldwide. Dr. Padhi's obtained his Ph.D from McGill University in High Energy Physics.

Lei Yang (M'13, SM'19) received the B.S. and M.S. degrees in electrical engineering from Southeast University, Nanjing, China, in 2005 and 2008, respectively, and the Ph.D. degree from the School of Electrical Computer and Energy Engineering, Arizona State University, Tempe, AZ, USA, in 2012. He was a Postdoctoral Scholar with Princeton University, Princeton, NJ, USA, and an Assistant Research Professor with the School of Electrical Computer and Energy Engineering, Arizona State University. He is currently an Assistant Professor with the Department of Computer Science and Engineering, University of Nevada, Reno, NV, USA. His research interests include big data analytics, edge computing and its applications in IoT and 5G, stochastic optimization and modeling in smart cities and cyber-physical systems, data privacy and security in crowdsensing, and optimization and control in mobile social networks. He was a recipient of the Best Paper Award Runner-up at the IEEE INFOCOM 2014. He is currently associate editor for IEEE Access.

Feng Yan is an Assistant Professor in the Department of Computer Science and Engineering at the University of Nevada, Reno. He has a broad interest in big data and system areas. His current research focus includes machine learning, cloud/edge/fog computing, high performance computing, storage, and cross-disciplinary topics among them and others. He obtained both M.S. (2011) degree and Ph.D. (2016) degree in Computer Science from the College of William and Mary, and worked at Microsoft Research (2014-2015) and HP Labs (2013-2014).