MLModelCI: An Automatic Cloud Platform for Efficient MLaaS

Huazheng Zhang  
Nanyang Technological University  
huazheng001@e.ntu.edu.sg  

Yuanming Li  
Nanyang Technological University  
yil056@e.ntu.edu.sg  

Yizheng Huang  
Nanyang Technological University  
yizheng.huang@ntu.edu.sg  

Yonggang Wen  
Nanyang Technological University  
ygwenn@ntu.edu.sg  

Jianxiong Yin  
NVIDIA AI Tech Center  
jianxiongy@nvidia.com  

Kyle Guan  
Nokia Bell Labs  
kyle.guan@nokia.com

ABSTRACT
MLModelCI provides multimedia researchers and developers with a one-stop platform for efficient machine learning (ML) services. The system leverages DevOps techniques to optimize, test, and manage models. It also containerizes and deploys these optimized and validated models as cloud services (MLaaS). In its essence, MLModelCI serves as a housekeeper to help users publish models. The models are first automatically converted to optimized formats for production purpose and then profiled under different settings (e.g., batch size and hardware). The profiling information can be used as guidelines for balancing the trade-off between performance and cost of MLaaS. Finally, the system dockerizes the models for ease of deployment to cloud environments. A key feature of MLModelCI is the implementation of a controller, which allows elastic evaluation while only utilizes idle workers while maintaining online service quality. Our system bridges the gap between current ML training and serving systems and thus free developers from manual and tedious work often associated with service deployment. We release the platform as an open-source project on GitHub under Apache 2.0 license, with the aim that it will facilitate and streamline more large-scale ML applications and research projects.

KEYWORDS
Machine Learning, Deployment, Conversion, Profiling, Cloud

1 INTRODUCTION
Machine Learning (ML) techniques, especially Deep Learning (DL), have been widely adopted into multimedia applications, ranging from video analysis to artwork generation. To meet the needs of developing ever sophisticated ML applications, both academia and industrial researches have invested a lot of resources and efforts to build systems for speeding up the process of deploying ML as a service (MLaaS). We refer to those systems as “System for ML” [11], which supports the entire ML lifecycle including large-scale distributed training, model deployment, and online inference serving. While most efforts have been focusing on training and serving systems, there is a growing need for efficient, streamlined, and automated model deployment systems.

The development cycle of deploying a MLaaS is often a long and arduous journey. According to [1], 40% of companies need to spend more than one month deploying a ML model into production while only 14% can finish this in one week or less. First, developers need to take consideration of a variety of factors such as model running environment and learning parameters to ensure the model performance in the production environment. Second, developers need to very fluent with the architecture of web services such as RESTful or gRPC and write much boilerplate code for different services. Third, to maintain a scalable MLaaS, the developer also need to have a full grasp of infrastructure knowledge of the targeted cloud environment. To address these issues, many systems have been developed, as summarized in Table 1. A common thread among these systems is the use of containerization techniques with Docker [10] for simplifying the deployment.

Though these systems are widely used, few of them meet the requirements of the real industrial deployment scenario. First, the trained models with python scripts can not be directly deployed to the production environment due to the performance issue. Usually, engineers need to convert a newly trained model to an optimized and hardware-dependent format such as TensorRT [5] or ONNX [7], to reap the maximal performance benefits of the invested hardware (e.g. graphic processing unit (GPU) and tensor process unit (TPU). Second, the current available systems provide few insights into automatically balancing the trade-off between performance and cost. The performance metrics such as latency and throughput depend on the batch size, the underlying hardware devices, etc. With current solutions, developers still need to go through a manual and time-consuming tuning process.

To address these issues, we develop MLModelCI, a fully open-source platform that provides a one-stop service for optimizing, managing, and deploying MLaaS. The system is informed and motivated by DevOps techniques such as continuous integration (CI) and continuous deployment (CD), which automates software testing and building before they go online. Specifically, MLModelCI allows users to publish their models and provides management for them. Then it automatically converts models to optimized formats, profiles models under different settings (e.g., batch size and devices), and containerizes models as cloud services.
In MLModelCI, multimedia researchers and engineers have a highly automated solution for robust and efficient MLaaS with a well-designed command line (CLI) toolkit and web interface (i.e., RESTful). Our system reduces the development cycle from weeks or days to hours even minutes. It is written in Python and supported by a lot of industry software frameworks and practice such as Docker, MongoDB, etc., making it easy to be deployed in the cloud and adopted into the existing tool-chains of a team. MLModelCI adheres to best practices in distributed computing and cluster management, by providing a controller to utilize idle workers while maintaining online service quality at the same time. It also provides much needed features for collaborative ML research, such as bookkeeping models, building demo applications, evaluating model performance, etc.

MLModelCI has been released at https://github.com/cap-ntu/ML-ModelCI under the license of Apache 2.0. We plan to continuously maintain and upgrade the project to incorporate the rapidly evolving ML techniques. We also build an online discussion community to encourage more researchers and developers to join our effort.

2 SYSTEM HIGHLIGHT
MLModelCI provides a complete platform for managing, converting, profiling, and deploying models as cloud services, with well-documented tutorials for all of the related tasks. As such, it serves as a good starting point for researchers to address the gap between models and services and to familiarize themselves with the widely deployed cloud infrastructure. By design, MLModelCI intends to keep the entry barrier as low as possible, so as to make the integration into existing toolchains as efficient and seamless as possible. In this section, we first highlight the key features and advantages of MLModelCI and then compare them with those of other related platforms.

2.1 Highlights

Modularity. Our platform is designed to be as modular as possible from the get go, allowing a seamless extension to new functions, model formats, and serving systems. We have implemented many features to support model conversion, serving, etc., and provide a lot of examples to show how they can be employed to build efficient MLaaS for various multimedia tasks.

Automation. Upon receiving users’ model registration, MLModelCI automates the rest of the tasks. Specifically, it supports a variety of model auto-convertion. It automatically profiles models on available devices. It automates the model binding to existing serving systems and containerization for further deployment.

Elastic. MLModelCI efficiently uses the available hardware resources by harnessing the idle workers in a server cluster to complete the profiling. Our platform monitors the hardware status and running models. Once it finds the available hardware resources, it will invoke the profiler to complete the model analysis.

2.2 Comparison to Related Platforms
We provide a survey of related platforms in Table 1. MLModelCI differs from these platforms in two important aspects:

(1) We focus on supporting online serving rather than recording training experiments. While most of the ModelDB related work focuses on assisting users to log experiments for hyper-parameter searching and can be integrated into training systems, our system focuses on the scenario where the models have been trained successfully and waited to be deployed for online serving.

(2) Our system not only containerizes models as services but also optimizes and tests them before they go online. By automatically converting and profiling models, MLModelCI ensures a robust and efficient MLaaS and thus saves users’ effort and resources.

3 SYSTEM ARCHITECTURE
In this section, we present the MLModelCI architecture, as illustrated in Figure 1. We first summarize the system workflow and then give a detailed description of the functionalities of the core modules.

Table 1: Comparison of several model deployment frameworks.

| Project       | Open Source | Model Management | Multi Framework | Conversion | Profiling | Dockerization | Multi Serving | Monitoring |
|---------------|-------------|------------------|-----------------|------------|------------|---------------|---------------|------------|
| DLHub [8]     | ✓           | ✓                | ✓               | ✓          | ✓          | ✓             | ✓             | ✓          |
| ModelDB [6]   | ✓           | ✓                | ✓               | ✓          | ✓          | ✓             | ✓             | ✓          |
| ModelHub.AI [2] | ✓       | ✓                | ✓               | ✓          | ✓          | ✓             | ✓             | ✓          |
| Cortex [3]    | ✓           | ✓                | ✓               | ✓          | ✓          | ✓             | ✓             | ✓          |
| MLModelCI     | ✓           | ✓                | ✓               | ✓          | ✓          | ✓             | ✓             | ✓          |

Figure 1: MLModelCI architecture.

Workflow. Figure 2 shows a typical workflow of building a MLaaS with MLModelCI. First, a model weight file associated with the conversion function to optimize the model, and the profiling
The module focuses on automatically converting research models to
Two parameters, conversion, and profiling, can be set to trigger au-
The housekeeper of MLModelCI is the essence of the model man-
The dynamic profiling information refers to the runtime perfor-
serialized and optimized models from Python code rather than car-
our modelhub.
the stored model information. (4)
accepts a
The former, built on top of the HTTP, is very useful for applications
MLModelCI supports building two kinds of web service, RESTful and gRPC.
 MLModelCI runs models on the underlying devices in the clusters,
and collects, aggregates, and processes running model performance. We use
cAdvisor as the backend and get container status from it periodically. The information includes resource usage (e.g.,
and invokes the dispatcher to deploy a MLaaS. It then sends test
data from the client to the service with a variety of batch sizes and
serving systems on different devices. Users can have hundreds of
combinations available, which is very useful for setting parameters
for online services.

3.4 Profiler
MLModelCI runs models on the underlying devices in the clusters,
and collects, aggregates, and processes running model performance. Specifically, there are six indicators that will be acquired, peak
throughput, P50-latency, P95-latency, P99-latency, GPU memory
usage, and GPU computation utilization.
To get real model performance in practice, the profiler simulates
the real service behavior by invoking a gRPC client and a model
service. In particular, the profiler contains many build-in clients and
upon it receives a profiling signal, it starts the corresponding client
and invokes the dispatcher to deploy a MLaaS. It then sends test
data to the client to the service with a variety of batch sizes and
serving systems on different devices. Users can have hundreds of
combinations available, which is very useful for setting parameters
for online services.

3.5 Dispatcher
The dispatcher launches a serving system (e.g. Tensorflow-Serving)
to load a model in a containerized manner and dispatches the MLaaS
to a device. We have dockerized many widely used serving systems
as shown in Figure 1 to support different model formats. MLModel-
CI supports building two kinds of web service, RESTful and gRPC.
The former, built on top of the HTTP, is very useful for applications
that only need one model. In comparison, gRPC is designed for low
latency and high throughput communication, and supports to build
a service with multiple models well.

3.6 Monitor & Node Exporter
Our monitor collects and aggregates running model container per-
formance. We use cAdvisor as the backend and get container status
from it periodically. The information includes resource usage (e.g.,
GPU memory, CPU usage, etc.), and network statistics.
The node exporter collects hardware status and exposes them to
our system. The node exporter is based on two software, prometheus
dcgm exporter. The former can aggregate the CPU and network
utilization, and the later can collect the GPU metrics.

3.7 Controller
The controller receives data from the monitor and node exporter,
and controls the whole workflow of our system. First, it guides
the profiler to evaluate models when devices are idle periodically.
Users choose the threshold of device utilization that constitutes
a system being considered as idle. For instance, users can set this
threshold as 40%. If the utilization of a GPU is higher than this

function to evaluate model performance on different devices. The
information is recorded to guide users to choose the proper batch
size, devices, etc., during deployment. At the same time, the model
is bound to a serving system and containerized as a service. Finally,
users can dispatch the service to a specific device with the help of
the deploy API.
Controller, accepting both hardware and running model status,
is designed to manage the whole workflow and utilize the idle
resources. Non-experts can rely on its automation directly; while
experts can customize it for more fine-grained control.

3.1 ModelHub
MLModelCI stores models in the modelhub where a model is ab-
stracted into three parts - basic information, dynamic profiling
information and a model weight file. Specifically, the basic informa-
tion includes the model name, the training dataset, accuracy, etc.
The dynamic profiling information refers to the runtime perform-
ance (e.g., throughput and latency) which is coupled with many
aspects (e.g. devices) and is acquired during the profiling process.
In practice, this information is more important for guiding online
deployment since many papers have mentioned that static informa-
tion such as FLOPs is often inconsistent with the real speed.
To persist the information related to a trained model, we adopt
MongoDB, a document-based and ease-to-use database, as the stor-
age backend. Meanwhile, its built-in GridFS, a distributed file ser-
vice, supports large-capacity storage, which is very useful for stor-
ing large model weight files. Since the data structure is highly
abstracted, users can choose their existing database schema and
architecture and applied it to our system with ease.

3.2 Housekeeper
The housekeeper of MLModelCI is the essence of the model man-
agement - a team may produce hundreds of models a day. The housekeeper has four key responsibilities for the management and they are encapsulated into four APIs. (1) register accepts a YMAL
file contains model basic information and a model file from users.
Two parameters, conversion, and profiling, can be set to trigger au-
tomation processing. (2) retrieve takes the inputs and search for
related models to list their information. (3) update is for revising
the stored model information. (4) delete is to delete a model from
our modelhub.

3.3 Converter
The module focuses on automatically converting research models to
serialized and optimized models from Python code rather than carry-
ning out conversion between frameworks (as discussed in MMdnn
[4]). The output models from our converter are independent of

Figure 2: Workflow for a MLaaS deployment task
threshold, the model cannot be profiled on it now. Second, it helps to automatically set up a MLaaS to available devices.

4 DEMONSTRATION

This section illustrates the MLaaS deployment supported by MLModelCI. We use widely deployed models for multimedia analysis as examples and relevant source code is released on GitHub1.

![Figure 4: Web interface and a demo application.](image)

4.1 Model Publishing & Conversion

To deploy a MLaaS, the first step is to publish a model to our system. We use a widely deployed image classification model - ResNet50 - as an example. A registration YAML file associated with a model file is prepared. After uploading them to MLModelCI, users can manage the model as shown in Figure 4a. More detailed evaluation results are presented after the conversion and profiling. As shown in Figure 4a, there is a successful converted model and a TensorflowSaved model served by Tensorflow-Serving. The model runtime performance is also presented, indicating that profiling has finished.

4.2 Service Profiling

We now use a real-world example to illustrate the necessity of the model (service) profiling2. MLModelCI manages to obtain as much information as possible and generates a comparison report. As shown in Figure 3, the model runtime performance is determined by many as aspects (from left to right, batch size, devices and serving platforms), and their resource usage such as the GPU utilization varies. MLModelCI provides all of the information to users to help build a more cost-effective solution.

4.3 MLaaS Deployment

We deploy another widely used model in the multimedia application: Mask R-CNN [9], as shown in Figure 4b. By following the official deployment code from TensorFlow-Serving, developers need to write more than 500 lines of code (LoC) to complete the Mask R-CNN MLaaS building, not including any conversion and profiling. The whole deployment works may take days or weeks depending on developers’ familiarity with TensorFlow-Serving’s deployment. In contrast, with the help of MLModelCI, users only need to write about 20 LoC to complete the deployment.

5 CONCLUSION

In this paper, we described MLModelCI, an automated and easy-to-use platform for building efficient and robust MLaaS in cloud. It is designed to free researchers and developer from the tedious and error-prone model deployment works. We develop and automate many much needed functions/features, thus bridging the gap between existing training and serving systems. We demonstrate the usability of the system with representative case studies. We plan to continually maintain the system for further improving both the speed and the efficiency of ML model delivery and deployment.

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