TACC: A Full-stack Cloud Computing Infrastructure for Machine Learning Tasks

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Abstract
In Machine Learning (ML) system research, efficient resource scheduling and utilization have always been an important topic given the compute-intensive nature of ML applications.

In this paper, we introduce the design of TACC, a full-stack cloud infrastructure that efficiently manages and executes large-scale machine learning applications in compute clusters. TACC implements a 4-layer application workflow abstraction through which system optimization techniques can be dynamically combined and applied to various types of ML applications. TACC also tailors to the lifecycle of ML applications with an efficient process of managing, deploying, and scaling ML tasks.

TACC’s design simplifies the process of integrating the latest ML system research work into cloud infrastructures, which we hope will benefit more ML researchers and promote ML system researches.

1 Introduction

Turing AI Computing Cloud (TACC) [16] is a cloud platform for research and education in Machine Learning (ML) with open access to the research community. Developed by HKUST and initially opened for beta-testing in 2020, TACC powers experiments and applications in a wide range of ML researches with its high-performance and scalable infrastructure on both software- and hardware levels.

TACC combines the design goals of two different types of infrastructure. The first type is specialized ML systems (e.g., Ray [14], Pollux [18]) which employ strategies and algorithms that accelerate the execution of a specific type of ML task. The other type is general-purpose cloud platforms (e.g., Amazon AWS [1], Microsoft Azure [13]), whose goal is to efficiently allocate available hardware resources based on on-demand resources requests from users.

Being a full-stack cloud infrastructure for ML tasks, TACC differs from the above two types of infrastructures primarily in the following two perspectives:

- **Task Execution**: TACC abstracts the program execution workflow into 4 programmable layers: schema, compiling, scheduling and execution. ML optimization techniques can be implemented in applicable layers, and dynamically combined and applied to various types of ML applications.

- **Task Management**: TACC tailors to the lifecycle of ML applications, providing its users with a more efficient process of managing, deploying, and scaling compute-intensive ML applications in a large cluster. TACC can also guarantee reproducible task execution.

As a result, TACC users can benefit system-level optimization techniques from research areas including distributed DNN training [7–9, 15, 17, 22, 23], datacenter networking [2, 3, 5, 6, 27] and specialized hardware [4, 11, 12, 24, 25] to accelerate and scale their ML applications with zero or minimum code modifications.

This paper makes a contribution to the ML community by proposing a pathway to an ML cloud infrastructure that can continuously evolve by incorporating the latest ML system research findings with less system operating or engineering efforts. We hope it will not only benefits more ML researchers but also promote ML system researches.

2 Background

We begin by considering the two basic steps of a typical ML task execution workflow, provisioning and executing, and explain the key requirements for a full-stack ML infrastructure.

**Provisioning.** The provisioning step prepares the runtime environment for the ML task to be executed, which typically includes creating a working directory for the user’s code, fetching dependencies, and ensuring the interconnection between nodes for distributed computation. In this regard, previous work [10, 21] usually behaves like a cluster manager which utilizes general-purpose cloud platforms [1, 13] for efficient resource allocation. They do not directly optimize for the ML training procedure.

**Executing.** This step trains or infers Neural Networks (NN) on input datasets, typically executed on hardware accelerators such as GPU. In the distributed training, allreduce aggregation or a parameter server is used for NN parameter synchronization. Previous work [9, 17, 18] builds one-off specialized ML systems which employ strategies and algorithms that optimize for computation and communication in a specific type of ML tasks.

We envision a new infrastructure that efficiently supports both provisioning and executing ML tasks is needed to bridge the gap between these two research directions. In particular,
such an infrastructure should satisfy the following requirements:

- **Online task processing.** The infrastructure is multi-tenant and responds to users’ on-demand task submissions.
- **Fine-grained resource allocation.** ML tasks require heterogeneous hardware resources and the duration of computation also varies.
- **Adaptive optimization.** Current system optimization techniques apply to unique aspects of the execution process and are suitable for different types of tasks.

We make one final comment that a full-stack ML infrastructure is not intended for implementing an ML system or a hardware abstraction layer from scratch. Instead, it should seamlessly integrate current system optimizations, apply them to suitable tasks and introduce little overhead.

3 Task Execution on TACC

TACC proposes an ML application workflow abstraction that consists of 4 layers. Every task submitted to TACC should follow the task schema defined in the first layer, then the task is processed and scheduled by the middle two layers, and finally executed in the bottom layer.

This abstraction decouples system-level optimizations from the typical monolithic program execution workflow, creating a new design space where different optimization techniques can be dynamically combined and applied to tasks from a live growing queue.

3.1 Definition of Abstraction Layers

We describe the definition of each layer as follows while referring to Figure 1.

**Task Schema Layer.** This layer defines all aspects of a task’s specification. All tasks submitted to TACC should be described with this self-contained, unified task schema, which guarantees consistent and reproducible task execution.

The Task Schema Layer decouples user programs from the runtime environment, making the tasks easily reproducible across different TACC implementations/instances or when shared with fellow researchers.

Some examples of specification in TACC’s task schema:

- Computing, network resource, and QoS requirements
- Application code, dependencies and input dataset
- Runtime environment and provisioning configurations

**Compiler Layer.** This layer parses the aforementioned task description file, prepares a runtime environment for the task, and submits the job to the scheduling layer for queueing. This layer generates an execution-ready task instruction for the Execution Layer.

The output task instruction is self-contained with application code, dependency libraries, input data, and other files needed to make an application run independently. Depending on the task’s characteristics and the choice of the Execution layer, the output of this compiler layer could be as simple as a few lines of shell commands, or as complicated as a Docker image.

In the cases of large input datasets or third-party dependencies which result in large task instructions with duplicate files across multiple task submissions, TACC uses a caching mechanism that only updates the delta of the instruction and retains the unchanged parts.

**Scheduling Layer.** This layer manages the tasks queue and decides when and where a task should be executed. It also handles preemptions when needed.

We currently use Slurm[19] as the backbone of our scheduling layer. Slurm supports various scheduling strategies such as fair-share scheduling, gang scheduling (time-slicing
Table 1. Examples of factors that affects the choice of underlying runtime system in the Execution Layer

| Layer       | Example Factors                          |
|-------------|------------------------------------------|
| Task Schema | user-indicated preference                |
| Compiler    | static characteristic: language, task size |
| Scheduling  | runtime characteristic: expected duration |
| Execution   | fail-safe switching                      |

In the most recent ML system researches, ML tasks can be scheduled with learning-based methods in real-time\cite{18, 20}, with dynamic factors such as task queue length, task age, size, and QoS, and runtime factors such as task scalability. Task placement that is optimized for the current network topology\cite{9} is also explored.

Execution Layer. This layer connects to the underlying runtime system and provisions the user program. TACC currently employs the following hardware to accelerate computing and communication in distributed ML applications:

- High-performance with RDMA interconnections
- Reliable networked file system for shared big data storage
- In-network computation with smart NICs and switches

Note that there can be more than one underlying system running at the same time for the execution of different types of tasks, and the choice of running on which system could be either indicated in the user’s task description or dynamically determined by the other layers. Table 1 shows some examples of the factors that affects the choice of the underlying runtime system in the Execution Layer.

3.2 Comparing to Specialized ML Systems

The 4-layer workflow abstraction enables TACC to integrate different optimization techniques into its full-stack infrastructure, and dynamically combine and apply them to incoming ML tasks.

This design differentiates TACC from related machine learning systems such as Ray or Pollux, which only target a specific type of applications (i.e., reinforcement learning) or a specific optimization goal (i.e., global training throughput), and does not allow online task submission (i.e., all tasks are pre-defined before the system starts).

4 Task Management on TACC

TACC users use tcloud, a local Command Line Interface (CLI) tool that communicates with TACC clusters to submit, monitor, and manage tasks. tcloud has the following main advantages:

Serverless Experience. The user experience of TACC is similar to serverless architectures: users submit ML tasks to the TACC cluster with tcloud from their personal computers or servers without the need to maintain experiment environments.

Distributed Monitoring. When an ML task runs in a distributed manner, tcloud can aggregate program status and output log files from all running nodes and transmit to the local terminal, making it easier for TACC users to debug distributed applications. When applicable, tcloud can also retrieve files and kill running processes simultaneously on multiple nodes.

Cross-platform Portability. tcloud has minimal local system dependencies except for an SSH protocol implementation, making tcloud easily portable on all kinds of operating systems. Combining with the serverless experience and distributed debugging features, TACC users can write, test, and submit their ML tasks virtually anywhere with internet access.

Moreover, tcloud provides another layer of abstraction where a user can submit their tasks to different cluster instances of TACC by simply changing a line of configuration.

5 Related Work

Components of TACC have similar design goals with the following types of cloud infrastructures or distributed systems.

ML Systems. Flexflow \cite{8} uses guided randomized search to find a fast parallelization strategy for a specific parallel machine learning task.

Pollux \cite{18} is a DL cluster scheduler that adaptively allocates resources, while at the same time tuning each training job to best utilize those resources.

Cloud Platforms. Beldi \cite{26} runs on existing cloud service providers and supports stateful serverless applications with fault tolerance and transactional semantics.

DCM \cite{21} builds cluster managers which encode the cluster state synthesized from high-level specifications, then compute decisions by solving an optimization problem.

6 Conclusion

In this paper, we have introduced the design of TACC, a full-stack cloud infrastructure that efficiently manages and executes large-scale machine learning applications in compute clusters. TACC’s design simplifies the process of integrating the latest ML system research work into ML task executions. Therefore, TACC users can easily utilize optimization techniques such as communication scheduling, network transport design, and specialized hardware, to accelerate and scale their ML applications.

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