Dependability in a Multi-tenant Multi-framework Deep Learning as-a-Service Platform

Scott Boag, Parijat Dube, Kaoutar El Maghraoui, Benjamin Herta, Waldemar Hummer, K. R. Jayaram, Rania Khalaf, Vinod Muthusamy, Michael Kalantar, Archit Verma
IBM Research AI
{scott_boag,pdube,kelmaghr,bherta,whummer,jayaramkr,rkhalaf,vmuthus,mkalantar,archit.verma}@us.ibm.com

Abstract—Deep learning (DL), a form of machine learning, is becoming increasingly popular in several application domains. As a result, cloud-based Deep Learning as a Service (DLaaS) platforms have become an essential infrastructure in many organizations. These systems accept, schedule, manage and execute DL training jobs at scale.

This paper explores dependability in the context of a DLaaS platform used in IBM. We begin by explaining how DL training workloads are different, and what features ensure dependability in this context. We then describe the architecture, design and implementation of a cloud-based orchestration system for DL training. We show how this system has been architectured with dependability in mind while also being horizontally scalable, elastic, flexible and efficient. We also present an initial empirical evaluation of the overheads introduced by our platform, and discuss tradeoffs between efficiency and dependability.

I. MOTIVATION AND INTRODUCTION

The increasing popularity of deep learning can be attributed to the following four factors: (1) Artificial neural networks can often learn features in an unsupervised manner, taking feature engineering out of the picture, (2) Recent improvements in GPU technologies have made large scale matrix computations typical of deep-learning algorithms effective, (3) Advances in interconnection technologies and data center networking technologies like NVLink, Infiniband and 100G Ethernet have enabled distributed DL training algorithms to effectively synchronize by transferring large amounts of training data and models, and (4) widely available open-source deep learning frameworks like Tensorflow, PyTorch, Caffe, Torch, Theano, Horovod and MXNet have reduced the effort required to design, train, and use deep learning models.

While advances in hardware have enabled DL to scale, said hardware remains expensive and should be effectively utilized to obtain good returns on investment. A cloud-based distributed deep learning platform helps organizations (like ours) utilize expensive hardware effectively, and enables developers, applications and customers to share deep learning infrastructure. IBM Deep Learning as a Service (DLaaS) is a distributed cloud-based software platform that handles the scheduling, orchestration, elasticity and resilience of deep learning jobs, and is agnostic to the internals of the deep learning job. DLaaS aims to reduce the barrier to entry even further by enabling developers to focus on training neural nets and choosing hyper-parameters rather than focusing on installation, configuration and fault tolerance.

DLaaS has four main goals – (1) Flexibility to support different deep-learning frameworks. (2) Scalability, i.e., horizontal scalability or the ability to manage increasing numbers of deep learning jobs by increasing the hardware resources available to the platform, (3) Dependability, meaning that the platform should be highly available, reliable and handle faults in a robust manner, secure and maintainable, and (4) Efficiency, meaning that the overheads introduced by the platform to achieve aforementioned goals (especially flexibility and dependability) and the response time of the platform to external requests must be minimal. The goal of this paper is to examine dependability in the context of IBM DLaaS.

II. DEPENDABILITY CHALLENGES IN DEEP LEARNING

DL training jobs have unique characteristics, which introduce dependability challenges in DLaaS:

• DL training jobs are typically run for a few days (1-7) continuously, for hundreds of thousands of iterations over a large data set. So the consequences of failure can be large (potential loss of several days of work).

• DL jobs are GPU-heavy, and are engineered to exploit the massive SIMD parallelization in GPUs and maximize GPU utilization. This increases heat generated by GPU servers in the datacenter, and server machine failures (typically reboots, power downs, etc.) are not uncommon.

• DL jobs impose a heavier load on datacenter networks. DL algorithms make several passes over the data set, which can be tens (or sometimes hundreds) of TB. At these sizes, data cannot be stored locally and typically has to be streamed over the network (either from a cloud-based store or NFS) for each pass.

In addition, operating a flexible multi-framework, multi-tenant deep-learning as a service platform supporting single node and distributed DL jobs requires the following dependability guarantees:

• Deploying a DL job is seldom instantaneous; it is a multi-step process, involving placement on an appropriate cluster node with available GPUs, setting up network (MPI) interconnections, provisioning shared volumes and
credentials to access data, etc. Users require that provisioning of DL jobs be atomic, either the whole job is provisioned with the requisite resources or none.

- Given that DL jobs are long running, users expect periodic and accurate status updates (e.g., whether the job is DEPLOYING, PROCESSING). These status updates should be dependable because users use associated timestamps for job profiling and debugging.
- Reliable streaming of logs from the job, irrespective of the stage it is in, even if it crashes/fails. This is key for users to debug their jobs.
- DL frameworks are so flexible that e.g., a Tensorflow job can be arbitrary customer code. Hence, for multi-tenancy, DL jobs must be isolated from DLaaS system processes, and from each other.
- Support for both user-directed and configurable automatic periodic checkpointing, given the longevity of DL jobs.
- Resilience to node and job crashes. Both failure detection and recovery are important because users expect to be notified when DL jobs are restarted, because “training progress graphs” differ (slightly) between a job that never experienced a failure and a job that did.

III. DEPENDABILITY IN IBM DLAAS

DLaaS is a cloud-native application architected as a set of loosely-coupled microservices communicating with each other using GRPC. Logically, DLaaS has three layers (1) DLaaS Core-Services Layer, consisting of two components/microservices – API and Lifecycle Manager (LCM) (2) DLaaS Platform Layer which consists of the infrastructure that the core-services rely on – Docker, Kubernetes [6], ETCD [1], and MongoDB [10], and (3) DLaaS Helpers – components which are part of the DL job during execution. Helpers perform failure detection, status recording and updates, log collection, data/results transfer, and metrics collection.

a) A DL Training Job: DLaaS supports several popular DL frameworks like Caffe, Torch, Horovod, etc. DLaaS maintains Docker images corresponding to each of these frameworks. In its simplest form, a DL training job consists of a single learning process (“learner”) in a Docker container using a GPU, i.e., a framework docker image instantiated with user code. Typically, DL jobs use several GPUs and/or consist of several learners synchronizing over MPI or using a centralized parameter server. Users submit training jobs and manage them using the DLaaS API (both GRPC and REST are supported). Job parameters, including the source of training data, credentials to access training data, framework, number of learners, location where results and logs should be stored, learning rate, etc., are specified using a manifest file.

b) Cluster Management: DLaaS employs Kubernetes (K8S) [6] for container orchestration and cluster management. A K8S pod is a group of one or more containers (such as Docker containers), with shared storage/network, and a specification for how to run the containers. A pod’s contents are always co-located and co-scheduled, and run in a shared context. All containerized DLaaS core services are executed as K8S deployments, exposed through the K8S service abstraction. DLaaS core services use K8S to deploy containerized DL jobs using appropriate K8S abstractions (Jobs and Stateful Sets).

c) DLaaS Core Services: The DLaaS API microservice handles all the incoming API requests including load balancing, metering, and access management. It exposes both a RESTful API as well as a GRPC API endpoint. The API service instances are dynamically registered into a K8S service registry that provides load balancing and fail-over support for incoming API requests. For the lifetime of a DL job, all its metadata, including its job parameters, are stored in MongoDB [10]. When a job deployment request arrives, the API layer stores all the metadata in MongoDB before acknowledging the request. This ensures that submitted jobs are never lost. The API layer then submits the job to the DLaaS Lifecycle Manager (LCM) microservice. As its name suggests, the LCM is responsible for the job from submission to completion/failure, i.e., the deployment, monitoring, garbage collection, and user-initiated termination of the job.

d) Atomic Job Deployment: The LCM uses a Kubernetes (K8S) abstraction (unfortunately also called a “Job”) for atomic deployment of DL jobs. K8S Jobs are essentially tasks (i.e. Docker containerized code) that K8S guarantees to reliably run to completion exactly once. If a K8S Job crashes for any reason (like a OS, Docker, K8S or machine failure), K8S will automatically restart it and execute it again. To deploy a DL job, the LCM simply instantiates a component called the Guardian with all the metadata of the DL job. The Guardian is a DLaaS component created on the fly as a K8S Job for every DL job. Creation of the Guardian is a very quick (less than 3s in our experiments) single step process. The Guardian then executes the multi-step process of actually deploying the DL job by further interacting with K8S. This involves instantiating Docker containers (corresponding to the DL framework used, like Caffe, Torch, etc.) with training parameters and user code, setting up shared NFS volumes to monitor training progress, K8S policies to restrict network
access from the learner in a multi-tenant environment, etc. If the Guardian crashes in the middle of a job deployment, K8S is guaranteed to restart it. The restarted Guardian will roll back the previous partially deployed DL job and starts a fresh deployment process. In the presence of persistent failures, this process will be repeated for a (configurable) number of times before the Guardian gives up and marks the DL job in MongoDB as FAILED. Once a DL job is successfully deployed, the Guardian is then responsible for monitoring its progress.

e) Detecting Failure/Completion of Learner Processes: The Guardian uses the K8S abstraction called Stateful Set to deploy a DL Job. This enables DLaaS to create replicated learners (for distributed training) and is well suited for DL frameworks like Horovod and distributed Tensorflow. For each DL job, the Guardian also creates a separate helper K8S pod using the K8S Deployment abstraction, which contains a number of “helper” containers – load-data, log collector, store-results, and controller. The helper pod remains isolated from the learner pods, but both share a common NFS filesystem, mounted by the Guardian using a K8S persistent volume claim. The shared NFS volume enables the controller container running separately in the helper pod to monitor the execution and exit status of the learner processes and detect both learner process completion and failures by reading their output (e.g., exit status redirected to a file).

f) Reliable Status Updates: In addition to detecting completion and failure, the controller can read the status/output of the load-data and store-results containers because all the helper and learner containers share a common file system. To reduce coupling between DLaaS components and ensure reliable status updates, we employ the ETCD key-value store [1] to co-ordinate between the controller and LCM/Guardian. ETCD itself is replicated (3-way), and uses the Raft consensus protocol to ensure consistency. The controller records the current status of each learner in ETCD, where it is read by the Guardian. The Guardian aggregates the statuses of each learner to record the overall status of the job in MongoDB, from where the user can read it through a REST/GRPC API call to DLaaS. Using ETCD makes status updates resilient to crashes of both the controller/helper pod and crashes of the Guardian. Using NFS makes status updates resilient to controller crashes; K8S will restart the controller which can read current status redirected from NFS.

g) Checkpointing: Given the long running nature of DL training jobs, checkpointing is vital. DLaaS enables users to configure checkpointing intervals; and checkpoints are stored in a cloud-hosted object store. The checkpointing interval depends on the tolerance level of the user to failures, i.e., how many hours of work the user is willing to lose in the event of a failure. Typically, users execute training jobs on a local laptop/server on a small subset of the input to profile the training job and identify good checkpointing intervals; and specify these intervals as parameters while submitting the DL job.

h) Node/Container Crashes: Orderly learner failures, i.e., by writing an appropriate exit code to NFS, can be detected by the controller. However, DL job crashes due to node/container crashes are handled by K8S. Crashed learners will be restarted automatically by K8S, because learners are deployed as stateful sets. A recovered learner can continue training either (1) from the latest checkpoint (2) in the case of distributed DL jobs, by rejoining other learners and getting the latest neural net parameters from a parameter server (if the DL framework supports this). The amount of work lost due to a crash is determined by the checkpointing interval.

IV. EVALUATION

In this section, we demonstrate empirically that the dependability features of DLaaS and execution in a containerized environment have minimal impact on performance of DL training jobs. We illustrate this by using several DL benchmarks [13] (VGG-16 [22], Resnet-50 [15] and InceptionV3 [23]), two different PCIe-based GPU types (K80 [19] and P100 [20]), and two different DL frameworks (Caffe v1.0 [12] and TensorFlow v1.5 [8]).

| Benchmark | Framework | # PCIe K80 GPUs | Difference in Performance |
|-----------|-----------|-----------------|--------------------------|
| VGG-16    | Caffe     | 1               | 3.29%                    |
| VGG-16    | Caffe     | 2               | 0.34%                    |
| VGG-16    | Caffe     | 3               | 5.88%                    |
| VGG-16    | Caffe     | 4               | 5.2%                     |
| InceptionV3 | TensorFlow | 1             | 0.32%                    |
| InceptionV3 | TensorFlow | 2             | 4.86%                    |
| InceptionV3 | TensorFlow | 3             | 5.15%                    |
| InceptionV3 | TensorFlow | 4             | 1.54%                    |

Fig. 2. Performance overhead of DLaaS vs. IBM Cloud Bare Metal Servers on popular Image Processing Benchmarks. Performance is quantified as images processed/sec for training. Caffe v1.0 and TensorFlow v1.5 were used.

For our first set of measurements, we compare DLaaS deployed on IBM Cloud with directly executing the benchmarks (non containerized) on bare metal machines manually on IBM Cloud datacenters. 1GbE interconnect was used in both cases. Training data was stored in IBM Cloud Object Store. Results are illustrated in Figure 2. From Figure 2, we observe that performance overhead induced by DLaaS is minimal (when compared to dependability and ease of use)

For the second set of measurements, we compare DLaaS to NVidia’s specialized hardware – DGX-1 [11], which incurs \( \approx 2-3 \times \) in additional costs compared to off-the-shelf hardware (such as IBM Cloud [5]). DGX-1 has advanced hardware (NVLink and High Bandwidth Memory), and is expected to have higher performance than DLaaS. However, we observe from Figure 3, that degradation in performance, though non-trivial is only modest (up to \( \approx 15\% \)).

Finally, our cloud-native design and implementation has ensured that DLaaS remains loosely coupled and each component can fail independently of the other. Within a DL training
| Benchmark  | Framework      | # PCIe GPUs | GPU Type | Difference in Performance |
|------------|----------------|-------------|----------|---------------------------|
| InceptionV3 | TensorFlow     | 1           | P100     | 3.30%                     |
| Resnet-50  | TensorFlow     | 1           | P100     | 7.07%                     |
| VGG-16     | TensorFlow     | 1           | P100     | 7.84%                     |
| InceptionV3 | TensorFlow     | 2           | P100     | 10.06%                    |
| Resnet-50  | TensorFlow     | 2           | P100     | 10.53%                    |
| VGG-16     | TensorFlow     | 2           | P100     | 13.69%                    |

Fig. 3. Performance overhead of DLaaS vs. NVIDIA DGX-1 bare metal server on TensorFlow HPM benchmarks [9]. Performance is quantified as images processed/sec for training.

| Component | Time to recover from crash failure |
|-----------|-----------------------------------|
| API       | 3-5s                              |
| LCM       | 4-6s                              |
| Guardian  | 1-2s                              |
| Helper    | 3-4s                              |
| Learner   | 10-20s                            |

Fig. 4. Time taken to recover from crash failures, by component.

job, a learner can crash and be restarted by K8S independently of the helper. Guardians can crash/restart independently of the LCM and API, and so on. Time taken for each component to restart is minimal and illustrated in Figure 4. These times were calculated by manually crashing various components (using the kubectl tool of K8S [3]) and measuring time taken for the component to restart. Learners take longest to restart because binding to cloud object store and persistent NFS volumes takes longer, and Caffe/Tensorflow pods take longer to restart when compared to DLaaS microservice pods (written in GoLang).

V. RELATED WORK

Efforts to develop machine learning (ML) systems have appeared in industry and academia. Representatives of the former include IBM Watson Machine Learning [2], Amazon SageMaker [21], Google Cloud Machine Learning [7], and Microsoft Azure [18]. These offerings differ in their capabilities, but none address the complete AI lifecycle and dependability issues of the underlying platform. Li et al. [16] discuss challenges associated with building a scalable ML service, including feature computation over global data. Their focus is mainly on real-time serving of large number of models, without considering the integration lifecycle. ModelHub [17] and ModelDB [24] are lifecycle management systems for ML models supporting efficient storing, querying, and sharing of artifacts. These systems are focused on the model lifecycle, and do not consider the co-evolution of the applications or platform optimizations. While there has been a lot of focus on securing multi-tenant services [14], there has been little attention paid to DL workloads in such an environment.

VI. CONCLUSIONS

This paper provides a brief overview of how dependability is addressed in the context of IBM DLaaS – a publicly available, multi-tenant, multi-framework, deep-learning as a service platform. It provides an initial evaluation of the efficacy of our approach, by measuring performance overhead. We have open-sourced major portions of this platform at [4], and hope it can be a foundation for further research in this area.

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