MLModelScope: Evaluate and Measure ML Models within AI Pipelines

Abdul Dakkak *1 Cheng Li *1 Abhishek Srivastava 1 Jinjun Xiong 2 Wen-Mei Hwu 3

ABSTRACT

The current landscape of Machine Learning (ML) and Deep Learning (DL) is rife with non-uniform frameworks, models, and system stacks but lacks standard tools to facilitate the evaluation and measurement of model. Due to the absence of such tools, the current practice for evaluating and comparing the benefits of proposed AI innovations (be it hardware or software) on end-to-end AI pipelines is both arduous and error prone — stifling the adoption of the innovations. We propose MLModelScope—a hardware/software agnostic platform to facilitate the evaluation, measurement, and introspection of ML models within AI pipelines. MLModelScope aids application developers in discovering and experimenting with models, data scientists developers in replicating and evaluating for publishing models, and system architects in understanding the performance of AI workloads. We describe the design and implementation of MLModelScope and show how it is able to give users a holistic view into the execution of models within AI pipelines. Using AlexNet as a case study, we demonstrate how MLModelScope aids in identifying deviation in accuracy, helps in pin pointing the source of system bottlenecks, and automates the evaluation and performance aggregation of models across frameworks and systems.

1 INTRODUCTION

The emergence of Machine Learning (ML) as a popular application domain has led to great deal of innovation. Data scientists have developed novel models and techniques to improve performance of existing AI algorithms and have enabled new AI tasks. System developers and architects have developed frameworks, libraries, and hardware to serve and accelerate ML workloads. Application builders have leveraged these models, software, and hardware to develop intricate AI application pipelines. An important reason for the success of ML is the rapid pace of innovations introduced by data scientists and system developers, as well as the adoption of these innovations by the application builders within AI pipelines.

Yet, as with any fledgling field, there are issues that hinder rapid adoption of state-of-the-art methods. For the case of ML algorithms and workloads (jointly referred to as

ML models), adoption is stifled by: the lack of evaluation

Figure 1. Shows the execution of an AI pipeline at different levels of hardware and software abstraction. 1 An application pipeline (which usually spans multiple machines) employs a set of models. 2 Each model defines its own pipeline for input and output processing. 3 A framework executes a model through a network-layer execution pipeline. 4 Layers executed by a framework are pipelines of library calls. 5 The library calls in turn invoke a chain of system runtime functions. All the while the 6 hardware has its own pipeline to execute instructions. Because of the many levels of abstractions, the HW/SW stack must work in unison to maintain accuracy, performance, and efficiency.

Preliminary work. Under review by the Systems and Machine Learning (SysML) Conference. Do not distribute.
and profiling tools that can cope with the diverse and fast paced nature of the ML landscape (AI pipelines, models, frameworks, and HW/SW stacks). The complicated and sometimes non-repeatable procedure to evaluate and measure ML models is identified as a significant pain point for ML researchers and application builders.

There have been concerted community efforts to remedy model reproducibility issues and ease model evaluation. Currently, however, there is no one tool that: ① enables understanding of the proposed models and systems at each abstraction level (or level of the HW/SW stack), ② makes it simple to reproduce, evaluate, debug, compare, and manage reported results, and ③ allows users to measure proposed models and systems within one’s own AI workflow. Having a tool that: defines common techniques to specify and provision workflows with specified HW/SW stack; provides a consistent evaluation and reporting system; and enables profiling of experiments throughout the entire ML pipeline (shown in Figure 1), would facilitate the adoption of state-of-the-art ML innovations.

We propose MLModelScope, an open source, extensible, and customizable platform to facilitate evaluation and measurements of ML models within AI pipelines. More specifically, MLModelScope is a batteries-included platform for evaluating and profiling ML models across datasets, frameworks, and systems. These evaluations can be used to assess model accuracy and performance across different stacks. It is designed to enable: ① data scientists in reproducing and comparing with published models, and designing algorithms with performance and deployment in mind. ② system developers in profiling model execution at all levels of the HW/SW stack to optimize ML frameworks, libraries and hardware for the latest ML workloads. ③ AI application builders in discovering and using frameworks and models that are applicable to a user-input dataset.

To enable ① and ②, MLModelScope provides a specification to define a model inference workflow along with its HW/SW requirements. It has built-in performance tracing capabilities that integrate with user applications, libraries, and hardware and allows users to “zoom-in” to view performance of an AI pipeline at different abstraction levels.

To enable ③, MLModelScope is designed as community effort that encourages publishing of AI artifacts — and currently provides over 180 common ML inference artifacts that leverage popular ML models, datasets, and hardware. We provide an online hub of continuously updated assets, evaluation results, and access to hardware resources — allowing users to test and evaluate models without installing or configuring systems. It is framework and hardware agnostic — with current support for Caffe (Jia et al., 2014), Caffe2 (Jia, 2018),CNTK (Seide & Agarwal, 2016), MXNet (Chen et al., 2015), Tensorflow (Abadi et al., 2016), and TensorRT (TensorRT) running on ARM, PowerPC, and X86 with CPU, GPU, and FPGA. MLModelScope can be used as an application with a web, command line, or API interface or can be compiled into a standalone library.

Through MLModelScope, users can: ④ experiment with custom or public models and evaluate them systematically across systems in terms of accuracy or performance; ⑤ deploy and publish their model artifacts within MLModelScope and expose them to the public users for evaluation and introspection; ⑥ profile the end-to-end system performance at various granularities for model inference to identify system bottle necks in a cloud setting.

This paper is divided as follows: Section 2 motivates MLModelScope and describes current state-of-the-art solutions. Section 3 and 4 describe our design and implementation. In Section 5, we evaluate models using MLModelScope across frameworks and hardware. We conclude in Section 6.

2 Motivation and Related Work

The lack of a standard for publishing ML models, uniform model evaluation and measurement tools, and fast paced nature of ML innovations is a significant pain point for AI consumers. Application builders — who may have limited ML knowledge — struggle to discover and experiment with state-of-the-art models within their application pipelines. Data scientists find it difficult to reproduce, reuse, or gather unbiased comparison between published models. And, finally, system developers often fail to keep up with current trends, and lag behind in measuring and optimizing frameworks, libraries, and hardware.

Because of the lack of an ML model evaluation and deployment standard, models published through public repositories — where the authors may have information on the HW/SW stack requirements and ad-hoc scripts to run the experiments — are hard to reproduce. A typical workflow of reproducing a model involves: instantiating the required hardware, installing ML software packages and their dependencies; obtaining the model parameters and related dataset; configuring the system, software, and models (while ensuring compatibility across the software stack); and, finally, collecting, analyzing, measuring, and correlating the evaluation results with what the model authors reported.

The current practice is however not sustainable, error prone, and places the burden of evaluation and profiling models solely on the ML users. This section describes the concerted effort by the ML stakeholders to remedy this — as shown in Table 1.
2.1 Evaluation and Reproducibility

Frameworks maintain a repository of models — or “model-zoos” — aimed at developers to test and evaluate the framework. These “model-zoos” tend to lack state-of-the-art models and are framework specific. There has also been work to maintain curated repository containing development environments, execution scripts, and evaluation results for published work (Fursin, Grigori and Lokhmotov, Anton and Savenko, Dmitry and Upton, Eben, 2018; Fursin et al., 2018; Vandewalle et al., 2009; Jimenez et al., 2015; Tatman and Savenko, Dmitry and Upton, Eben, 2018; Fursin et al., 2016; Zhang et al., 2018; Vartak et al., 2016; Baylor et al., 2017; Miao et al., 2017; Crankshaw et al., 2017; Hazelwood et al., 2018; Michelangelo; Chan et al., 2013). However, the software environments are hard to create — taking weeks (Moreau et al., 2018) — and integrate within existing AI pipelines.

2.2 Model Serving Platforms

MLModelScope’s functionality overlaps with model serving platforms (Oracle, 2018; Olston et al., 2017; Boehm et al., 2016; Zhang et al., 2018; Vartak et al., 2016; Baylor et al., 2017; Miao et al., 2017; Crankshaw et al., 2017; Hazelwood et al., 2018; Michelangelo; Chan et al., 2013). These platforms are designed to serve models as black boxes, optimize for efficient use of the underlying hardware (through batching) and/or decrease latency of requests (through model caching). Although MLModelScope’s components can be used to serve models, this is not its primary use case for the purposes of this paper — instead we focus on MLModelScope’s evaluation and measurement capabilities.

2.3 Measuring and Profiling

Current practice of measuring and profiling models within AI pipelines, involves the use a concoction of tools aimed at capturing information at different levels of the HW/SW stack. For example, in Figure 1, for developers to profile the application or model abstract levels they must manually log (Sigelman et al., 2010; Kaldor et al., 2017) the time taken by important steps within their application. When evaluating models running within frameworks, developers need to explicitly enable the built-in, or community contributed, framework profiler — which usually outputs the results to a file. To understand the performance at layer level, users either use tools to intercept and log library calls (such as strace or DTrace), or use hardware vendor profilers (such as NVIDIA’s nvprof or Intel’s VTune). Finally, to capture hardware and OS levels, developers use a different set of tools (such as PAPI (Browne et al., 2000) and Perf). Currently, users — wanting to understand AI application performance — have to run the application using the aforementioned tools and manually weave all outputs into a single time line.

Framework Profilers — Framework provide tools that measure the performance of each layer and track the execution of a model. These tools are typically bundled with the framework and offer a high level view of the model execution. They are aimed at helping users understand the framework’s layer performance and execution pipeline, and, thus, lack the ability to capture lower level system information.

System and Hardware Profilers — For systems developers, the results of the framework profilers are too coarse-grained to provide valuable insights. They instead use system- and hardware-level profilers (such as Intel’s VTune and/or NVIDIA’s nvprof) to capture low level information (such as library calls, hardware utilization, and memory movement information), which are then manually correlated

| Platforms | Profilers | Benchmark Suites |
|-----------|-----------|------------------|
| MLModelScope | Artifact Evaluation | System Profiler |
| Hardware | Model | Reference Benchmarks |
| | Dataset | Model Benchmarks |
| | Evaluation | Layer Benchmarks |

Table 1. MLModelScope provides a holistic environment for artifact reproducibility, profiling, and model evaluation. It is software, hardware, framework, and model neutral and allows one to evaluate and measure components at different granularities within AI pipelines.
with the results of the framework profiler.

2.4 Benchmark Suites

To compare HW/SW stacks, both research and industry have developed coarse-grained (model-level) and fine-grained (layer-level) benchmark suites. The benchmarks are designed to be manually run offline, but benchmark authors encourage their users to submit their evaluation results. The evaluation results are curated to provide a semi-“live” scoreboard of model performance across systems.

Reference Workloads — There have been efforts to codify a set of ML applications (Adolf et al., 2016; MLPerf; DLP) that are representative of modern AI workloads — to enable comparisons between hardware stacks. These workloads are aimed at serving a purpose similar to that of SPEC benchmarks (Henning, 2006; Juckeland et al., 2014) for CPUs and GPUs.

Model Benchmark Suites — There has been work to replicate and measure the performance of published ML models (Coleman et al., 2017; 2018; Hanhirova et al., 2018; Dong & Kaeli, 2017; Zhu et al., 2018; Shams et al., 2017; Kim et al., 2017; Bahrampour et al., 2015; AliBaba; Shi et al., 2016; Cheng et al., 2018). These benchmark suites provide scripts to run frameworks and models to capture the end-to-end time of model execution time and evaluate their accuracy. Unlike MLModelScope, they are primarily designed to perform the evaluation offline — whereas we advocate for an online experimentation platform.

Layer Benchmark Suites — At the other end of the spectrum, system and framework developers have developed sets of fine-grained benchmarks that profile specific layers (Braun, 2018; Chintala, 2018; Baidu, 2018). These tend to be convolutional or RNN layers. The targets users of these benchmarks are algorithm developers (to develop better algorithms and strategies), compiler writers (to propose new transformations and analysis for loop structures found within ML kernels), and system researchers (to propose new hardware to accelerate ML workloads).

3 MLModelScope Design

MLModelScope is designed as a tool to evaluate and measure ML models within AI pipelines across the HW/SW stack. Since real world AI pipelines leverage models that are deployed in the cloud, MLModelScope employs a distributed system design. MLModelScope deploys, evaluates, and measures models across systems to mirror the behavior of real-world AI pipelines. This design decision has the byproduct of allowing users to perform parallel evaluation and measurement of models across systems. It is designed to automate the aggregation, summarization, and comparison of evaluations and measurements across runs. This section describes the keys components of MLModelScope (shown in Figure 2) which can be extended or composed to instantiate customized versions of the platform.

3.1 User Interface and API

MLModelScope can be used as an application or as a library. Users interact with MLModelScope application through its website, command line, or its API interface. The website and command line interface allow users to evaluate and profile models without familiarity with the underlying frameworks or profiling tools. Users who wish to integrate MLModelScope within their existing tools or pipelines can use the REST or RPC APIs. They can also compile MLModelScope as a standalone shared library and use it within their C/C++, Python, or Java projects.

3.2 ML Artifacts

Replication of model accuracy and performance results is dependent on: the usage of specific HW/SW stack; the training dataset; and the pre/post-processing steps on the inputs and outputs. MLModelScope specifies these requirements via a model manifest file. The manifest tells MLModelScope the HW/SW stack to instantiate and how to evaluate the model. A model manifest is defined in YAML (Ben-Kiki & Evans, 2018) format and contains all the information needed to reproduce a model’s evaluation results. An example model manifests is shown in Listing 1. The model manifest describes the model metadata (Lines 1–2), framework name and version (Lines 5–7), docker containers to use for evaluation (Lines 8–14), model inputs and common pre-processing...
MLModelScope: Evaluate and Measure ML Models

Listings 1. AlexNet’s model manifest contains all information needed to run the model using MXNet on CPUs or GPUs.

```
1 name: AlexNet # model name
2 version: 1.0 # semantic version of model
3 description: ...
4 element_type: float32 # datatype used for compute
5 framework: # framework information
6 name: MXNet
7 version: 1.0.0 # framework version constraint
8 container: # available containers
9 amd64:
10 - cpu: mlmodelscope/mxnet:1-4-0_amd64-cpu
11 - gpu: mlmodelscope/mxnet:1-4-0_amd64-gpu
12 ppc64le:
13 - cpu: mlmodelscope/mxnet:1-4-0_ppc64le-cpu
14 - gpu: mlmodelscope/mxnet:1-4-0_ppc64le-gpu
15 inputs: # model inputs
16 - type: image # first input modality
17 parameters: # type parameters
18 dimensions: [3, 227, 227]
19 mean: [0, 0, 0]
20 color_mode: RGB
21 layout: NCHW
22 outputs: # model outputs
23 - type: feature # first output modality
24 parameters: ...
25 url: https://.../synset.txt
26 preprocessor: 
27 postprocessor: 
28 model: # model resources
29 graph_path: repo://mxnet/alexnet.json
30 weights_path: repo://mxnet/alexnet.params
31 attributes: # extra model attributes
32 training_dataset: # dataset used for training
33 - name: ImageNet
34 version: 1.0.0
```

steps (Lines 15–21), model outputs and common post-processing steps (Lines 22–25), custom pre/post-processing operations (Lines 26–27), model resources (Lines 28–30), and attributes (Lines 31–34).

Asset Versioning — Models, frameworks, and datasets are versioned using a semantic versioning (Preston-Werner, 2018) scheme. The MLModelScope middleware layer uses this information for asset management and discovery. To request a model, for example, users specify model, framework, and dataset constraints. MLModelScope solves the constraint and returns the predictors (systems where the model is deployed) that satisfy the constraint. The model evaluation can then be run on one of (or, at the user request, all) the predictors.

Docker Containers — To maintain the SW stack and to guarantee isolation, evaluation occurs within docker containers. To facilitate user introspection of the SW stack, MLModelScope integrates with existing docker tools that allows querying images’ SW environment and metadata, and performing diffs between container images.

Pre/Post-Processing Operations — MLModelScope provides the ability to perform common operations such as resizing, normalization, and scaling without writing code. By supporting the ability to specify code snippets for pre/post-processing in the manifest file, MLModelScope is able to support a wide variety of models for different input modalities.

Evaluation History — MLModelScope uses the manifest information as keys to store the evaluation results in a database. Users can view historical evaluations through the website or command line using query constraints similar to the ones mentioned above. MLModelScope summarizes and generates plots to aid in comparing the performance across experiment.

3.3 Framework and Model Predictors

A predictor is a thin abstraction layer that exposes a framework through a common API. A predictor is responsible for evaluating models (using the manifest file) and capturing the framework’s profile information. A predictor publishes its HW/SW stack information to MLModelScope’s registry at startup, can have multiple instantiations across the system, and is managed by MLModelScope’s middleware.

3.4 Middleware

The middleware layer is composed of services and utilities for orchestrating, provisioning, aggregating, and monitoring the execution of predictors — acting as a conduit between the user-facing APIs and the internals of the system.

Manifest and Predictor Registry — MLModelScope uses a distributed key-value database to store the registered model manifests and running predictors. MLModelScope leverages the registry to facilitate discovery of models, load balancing across predictors, and to solve user constraint for selecting the predictor (using HW/SW stack information registered). The registry is dynamic — both model manifests and predictors can be added or deleted at runtime throughout the lifetime of the application.

Data Manager — MLModelScope data manager is responsible for downloading the assets (dataset and models) required by the model’s manifest file. Assets can be hosted within MLModelScope’s assets repository, or hosted externally. For example, in Listing 1 (Lines 28–30) the manifest uses a model that’s stored within the MLModelScope repository, the data manager downloads this model on demand during evaluation.

Within MLModelScope’s repository, datasets are stored in an efficient data format and are placed near compute on demand. The dataset manager exposes a consistent API to get values and iterate through the dataset.

Tracer — The MLModelScope tracer is middleware that captures the stages of the model evaluation, leverages the predictor’s framework profiling capability, and interacts with hardware and system level profiling libraries to capture fine grained metrics. The profiles do no need to reflect the wall clock time, for example, users may integrate a system simulator and publish the simulated time rather than wall-clock time.
MLModelScope publishes the tracing results asynchronously to a distributed server (Sigelman et al., 2010; Kaldor et al., 2017) — allowing users to view a single end-to-end time line containing the pipeline traces. Users can view the entire end-to-end time line and can “zoom” into specific component (shown in Figure 1) and traverse the profile at different abstraction levels. To reduce trace overhead, users control the granularity (AI component, framework, library, or hardware) of the traces captured.

MLModelScope leverages standard tools to enable whole AI pipeline tracing (OpenTracing). To enable the AI pipeline tracing, users inject a reference to their tracer as part the model inference API request to MLModelScope. MLModelScope then propagates its profiles to the injected application tracer instead of the MLModelScope tracer — placing them within the application time line. This allows MLModelScope to integrate with existing application time lines and allows traces to span API requests.

4 MLModelScope Implementation

We implemented the MLModelScope design presented in Section 3 with support for common frameworks and software/hardware stacks, and populated it with over 180 vision models and the corresponding datasets. We verified MLModelScope’s results by evaluating the built-in artifacts across a set of representative systems using system profiling tools. Since we use the framework and system profiling libraries, we incur the same overheads introduced by the framework and system profiling tools. We similarly verified our accuracy and performance results to those publicly reported. We maintain a running version of MLModelScope on a representative set of systems along with the evaluation results of the built-in artifacts. This section describes the implementation, existing capabilities, and how to extend and customize it.

MLModelScope is developed using a statically compiled programming language. To minimize overhead due to scripting languages, MLModelScope directly binds to the frameworks’ C-level API. MLModelScope uses Protocol Buffers (ProtoBuf) and gRPC (gRPC) for data exchange. The analysis and aggregation of profile data is performed on different systems to avoid interference with the program being measured.

4.1 Existing Capabilities

MLModelScope supports popular frameworks, has profiling coverage across AI pipelines and HW/SW stacks, and works across hardware platforms.

Frameworks — At time of writing, MLModelScope has built-in support for Caffe, Caffe2, CNTK, MXNet, TensorFlow, and TensorRT. MLModelScope uses “vanilla” unmodified versions of the frameworks and uses facilities within the framework to enable layer-level profiling — this allows MLModelScope to work with binary versions of the frameworks (version distributed through Python’s pip, for example) and support customized or different versions of the framework with no code modifications. To avoid overhead introduced by scripting languages, MLModelScope’s supported frameworks use the frameworks’ C-level API directly — consequently the evaluation profile is as close to the hardware as possible.

Library and System Profilers — MLModelScope can be used to inject observers to capture and measure library calls, such as cuDNN and CUBLAS, and report their execution time to the tracer. MLModelScope can integrate with system and hardware profilers to capture GPU profiles, system traces, and hardware performance counters. The metrics are stored along with the trace information, can span multiple machines, and are viewable within the same time line as the evaluation trace. To capture CUDA events, MLModelScope uses the CUPTI (CUPTI) library — the same library used by nvprof. Users can control which CUDA runtime functions to capture, along with whether to capture low level details such as GPU occupancy and branch divergence.

Hardware Architectures — MLModelScope has been tested on X86, PowerPC, and ARM CPUs as well as NVIDIA’s Kepler, Maxwell, Pascal, and Volta GPUs. It can leverage NVIDIA Volta’s TensorCores, and can also perform inference with models deployed on FPGAs. During evaluation, users can select hardware constraints such as: whether to run on CPU or GPU, type of architecture, type of interconnect, and minimum memory requirements — which MLModelScope considers when selecting a system.

4.2 Execution Pipeline

Figure 3 shows the execution pipeline of a user request to evaluate GoogleNet on any machine running MXNet v1.3. We show the distributed evaluation pipeline, but each agent in MLModelScope can be invoked locally or compiled to a shared library and used within any software that is able to call C libraries. At system start, each agent registers itself with the registry. When the user submits a task, the registry is queried and the predictors that satisfied the framework, model, and hardware constraints specified are selected. The registry returns an IP address which is used to perform an RPC dial to the predictor. Load balancing logic is in place when there are multiple agents that satisfy the constraints.

On the predictor, the data I/O manager downloads the assets

\(^1\)Currently Caffe2 is the inference engine used by PyTorch.
required to perform inference and 5 invokes the inference process. The predictor also 6 activates the profiling specified by the user. Concurrently — as the inference is processed — the profilers measure user-defined events within the program and asynchronously publish their results to a distributed tracing server. Once inference is complete, the profilers are deregistered and both the evaluation and profiling results are collected and 7 published to the database and 8 sent to the user.

4.3 Extensibility and Customization

As shown in Section 3, MLModelScope is built from a set of modular components and is designed to be an extensible and customizable platform — this allows users to use MLModelScope within their application pipeline and customize it to develop new tools. Users can extend MLModelScope by adding models, frameworks, or system metrics.

Adding Models — MLModelScope requires no coding to publish models, models are defined through the manifest file which can be published through MLModelScope’s website, command line, or API interfaces. Through the manifest file, permissions can be set on the model to control who is able to use or view it.

Adding Frameworks — Adding new versions or customizing a built-in framework requires no code modifications. Instead, the users need to provide a Dockerfile of the framework. Multiple versions of frameworks can run in parallel.

Users that need to integrate a new type of framework within MLModelScope need to define 3 functions — one to open a model, another to perform the inference, and finally one to close the model. These functions can be implemented in any popular language and communicate with the rest of the system through gRPC.

Adding System Metrics — MLModelScope is configured to capture hardware performance counters (such as power draw, L1 cache misses, and RAM utilization) using PAPI, Intels power counters, and NVML. Users can add extra system metrics as meta information to tracing events.

5 Evaluation

We present some of MLModelScope’s capabilities with a case study. We choose GoogleNet (Szegedy et al., 2015) as it exhibits accuracy anomalies across frameworks on the same machine. And, to simplify presentation of the performance profiling, we choose AlexNet (Krizhevsky et al., 2012) — MLModelScope is more necessary for intricate models where independent layers can run in parallel and a time line cannot be easily correlated between executions. Both models’ weights were converted from their original Caffe format using MMdnn (Microsoft, 2018). All evaluations are performed with float32 precision on GPUs using the ILSVRC2012 (Deng et al., 2009) validation dataset.

Table 2. Evaluations were performed using 6 systems that cover current GPU cloud offerings and GPU architectures.

| Name | CPU | GPU |
|------|-----|-----|
| AWS G3 | Intel Xeon E5 2686 v4 | Tesla M60 |
| AWS P2 | Intel Xeon E5 2686 v4 | Tesla K80 |
| X86-P110 | Intel Core i9-7900X | TITAN Xp P110 |
| AWS P3 | Intel Xeon E5-2698 v4 | Tesla V100-PCIE |
| IBM P8 | IBM S822LC Power8 | Tesla P100-SXM2 |
| Jetson TX2 | ARM Cortex-A57 | 256-core Pascal |

Evaluations were performed on the systems listed in Table 2 using the latest release versions of the frameworks — Caffe 0.8, Caffe2 1.0, CNTK 2.6, MXNet 1.3, Tensorflow 1.10, and TensorRT 4. With the exception of CNTK, which uses CUDA 9.0, all the frameworks and systems use NVIDIA Driver 410.48, CUDA 9.2.148, and cuDNN 7.2.1.

5.1 Model Accuracy

The Top 1 and Top 5 accuracy — and full probabilities — of models across frameworks and systems can be computed through MLModelScope using a single command. The accuracy are placed in a database and a report summarizing the accuracy information of models across frameworks and machines on the selected datasets can be generated.

Table 3. The Top-1 and Top-5 accuracy of AlexNet and GoogleNet on Pascal GPUs (X86-P110 and IBM P8) across frameworks using the ILSVRC2012 validation dataset.

| Model | Accuracy | Caffe2 | Others |
|-------|----------|-------|--------|
| AlexNet |          |       |        |
| Top 1 | 55.58%   | 55.58%|        |
| Top 5 | 79.09%   | 79.09%|        |
| GoogleNet |       |       |        |
| Top 1 | 68.08%   |        | 67.75% |
| Top 5 | 88.48%   |        | 88.29% |
While system researchers are aware that different hardware architectures can result in variance in accuracy — because different architectures leverage different ML libraries and kernels. It might be less known that the interaction between frameworks and libraries may also result in a difference.

Table 3 shows Top 1 and Top 5 accuracy of AlexNet and GoogleNet using systems with Pascal GPUs as we vary the frameworks. We note that there is an accuracy discrepancy between Caffe2 and other frameworks for GoogleNet. We did not expect this when using the same version cuDNN across frameworks, since cuDNN guarantees bit-wise reproducibility for inference (cuDNN) for the same architecture, cuDNN version, and the number of SMs. Using MLModelScope’s sub-layer tracer, we find that Caffe2 does not dispatch to cuDNN for all its layers. For convolution, we find that Caffe2 uses an explicit GEMM computation (FWD_ALGO_GEMM) for its cuDNN calls whereas the other frameworks use an implicit GEMM (FWD_ALGO_IMPLICIT_GEMM) algorithm.

5.2 Model Latency across Frameworks
MLModelScope can be used to measure the latency of a model on a system using a user-defined dataset. Figure 4 shows the inference performance of AlexNet across different frameworks and batch sizes on the AWS P3 machine. We omit the input/output processing time — since all frameworks share common code — and assume the model weights to be persistent on the GPU.

As expected, the per-batch latency increases as the batch size increases — this is due to the larger convolution filters that needs to be performed. In general we find that Caffe incurs the largest latency for small batch sizes, but is on par with Caffe2 and CNTK for larger batch sizes.

Across the batch sizes, TensorRT (which is primarily designed for inference) performs the best. Since all the frameworks leverage the same CUDA runtime, CUBLAS library, and cuDNN library, performance difference between frameworks is solely due to the framework’s execution pipeline overhead (for example: overheads as a result of the CPU code, CUDA kernel launch, GPU synchronization, memory copies, and omitting the use of CUDA streams) or choice of cuDNN algorithms. The model-level granularity of profiling, however, does not give us a window into the framework’s execution pipeline.

TensorFlow has the largest latency due to: 1⃝ The conversion tool used not performing tensor layout transformation (from NHWC to NCHW), this causes many calls to transpose the tensor. 2⃝ TensorFlow is optimized for training and not inference and advises users to use TensorFlow XLA (Leary & Wang, 2017), TensorFlow Lite (TensorflowLite), or the TensorRT backend for inference.

5.3 Sub-Model and Sub-Layer Latency Analysis
We can use MLModelScope as a window — by leveraging its sub-model and sub-layer latency analysis — to understand the choice of cuDNN function and algorithm made by the framework along with the overheads the framework introduces. Figure 5 shows the per-layer latency for each framework where the batch size is 64 — we omit CNTK since it does not currently support CUDA 9.2. As can be seen from the timeline, there are a few differences between frameworks. Some frameworks, such as TensorRT and MXNet perform analysis on the graph to facilitate both horizontal and vertical fusion of layers — enabling better occupancy and avoiding excessive kernel launches. When comparing Caffe and Caffe2, we find that their performance is comparable, with Caffe2 edging on Caffe because of its lower constant overhead.

If one “zooms-in” to the sub-layer level, one notices a more detailed timeline which explains some of the performance differences. For Caffe, Caffe2, and MXNet, the convolution layer is implemented using multiple CUDA kernel calls. Both Caffe and Caffe2 use cuDNN’s FWD_ALGO_IMPLICIT_GEMM, whereas MXNet uses both the FWD_ALGO_IMPLICIT_GEMM...
Figure 5. We compare the per-layer performance of AlexNet across Caffe, Caffe2, MXNet, and TensorRT with batch size 64 on the AWS P3 system. We “zoom-into” the second convolution and the following relu layer and show the CUDA calls being performed. The axis on top (0–35) is the duration to evaluate each layer within the model, while the axis at the bottom (0–3) is the duration to evaluate the kernels within the second convolution and relu layers. For TensorRT, conv2+relu is shown as a single block, since fuses both layers. The color coding of layers and runtime functions signify that they have the same kernel implementation, but does not imply that the parameters are the same. For example, the reason volta_scudnn_128x128_relu_small has higher latency than trt_volta_scudnn_128x128_relu_small is due its larger grid launch dimension.

Figure 6. The MLModelScope evaluation on a “cold-start” AlexNet network with batch size 64 running Caffe 0.8 on AWS P3 and IBM P8. The color coding of layers and runtime functions signify that they have the same kernel implementation, but does not imply that the parameters are the same. We “zoom-into” the longest running layer (fc6) and show the model inference choke point. We find that most of the time is spent performing copies for the (fc6) layer weights. Caffe performs weight copies lazily, resulting in a 144MB copy for the fc6 layer on first inference. Even though the V100 performs better for SGEMM computation, the the IBM P8 system (through the NVLink interconnect’s) achieves higher memory bandwidth and thus achieves a 2x speedup for fc6 layer.
and \texttt{FWD\_ALGO\_WINODRAD\_NONFUSED} convolution algorithms. MXNet, by default, performs auto-tuning at startup to determine the ideal convolution algorithm to use for the host system.

Both TensorRT and MXNet perform symbolic analysis on the DL network in an attempt to optimize and fuse the convolution and relu layers, but as we can see in the sub-layer level trace only TensorRT was successful. Furthermore, Caffe, Caffe2, and MXNet perform multiple kernel calls to implement the \texttt{conv+relu} layers using the sequence \texttt{conv} → \texttt{add_conv_bias} → \texttt{activation}. For MXNet, the MXNet profiler reports the convolution within the same layer as the activation, which initially we assumed to mean that the layers were fused, but looking at the sub-layer profile we see this is not the case.

### 5.4 Non-Persistent Model Latency

To show why a consistent evaluation metric is important, and how MLModelScope can facilitate understanding (the otherwise opaque) sub-layer level latency, we examine Caffe’s first fully connected (\texttt{fc6}) layer. Currently, there is a discrepancy in how research reports evaluation for this layer, in (Kang et al., 2017) the authors report \texttt{fc6} as the major contributor to the overall inference latency, whereas according to Figure 5 it is not. This is due to how one measures an inference: does one measure the first inference after loading a model (“cold-start”), or have a warm up period and then average the execute time of multiple inferences.

Usually model weights persist between user requests (Chung et al., 2018; Crankshaw et al., 2017; Baylor et al., 2017), but in some cases, such as low memory systems, this is not possible. Figure 6 shows the per-layer timing of AlexNet using Caffe in a “cold-start” setting on the AWS P3 and IBM P8 systems using a batch size of 64.

On the AWS P3 (with Volta GPU) system the \texttt{fc6} layer takes 39.44\textit{ms} whereas it takes 32.4\textit{ms} on the IBM P8 (with Pascal GPU) system. This is due to the IBM P8 system having an NVLink interconnect which has a theoretical CPU to GPU bandwidth of 40 GB/s (33 GB/s measured) while the AWS P3 system performs the copy over PCIe-3 which has a maximum theoretical bandwidth of 16 GB/s (12 GB/s measured). Therefore, despite AWS P3’s lower compute latency, we observe a lower overall layer and model latency for the IBM P8 system due to the \texttt{fc6} layer being memory bound.

Using MLModelScope’s sub-layer profiling, it is clear that the memory copy is the bottle neck for the “cold-start” inference. To verify this observation, we examined the Caffe source code. Caffe performs lazy memory copies for layer weights just before execution. This causes compute to stall while the weights are being copied — since the weights of the FC layer are the biggest. A better strategy — used by Caffe2, MXNet, Tensorflow, and TensorRT — is to eagerly copy data asynchronously and utilize CUDA streams to overlap compute with memory copies.

### 5.5 Model Latency across Systems

MLModelScope can be used as a tool to enable the evaluation of frameworks and models across hardware. The process is simple in MLModelScope, since multiple predictors can be launched across systems and profiled in parallel. Figure 7 compares the normalized latency of TensorRT across the systems in Table 2. as we vary the batch size. The latency is normalized to the latency of the X86-P110 system. As one can see, with the exception of the Jetson TX2 — which is designed for embedded SoC — TensorRT is faster on successive generations of GPUs.

![Figure 7. AlexNet using TensorRT across the systems shown in Table 2. Results are normalized to X86-P110’s latency.](image)

### 6 Conclusion and Future Work

ML systems are in their infancy, with algorithm performance and end-to-end system design considered an art rather than a science. A big hurdle in developing systems to optimize ML workflows is understanding the current usage and bottlenecks. MLModelScope offers a unified and holistic way to evaluate and measure ML models within AI pipelines, and gain insights to understand sources of accuracy and inefficiency.

The techniques described also apply to model training, although training poses a few challenges, in terms of resource allocation, transfer of large datasets, and long running time. Future work would leverage the model manifest specification, distributed tracing, asset versioning, and middleware to enable performance analysis on training workloads.

We are currently working on using the data captured from MLModelScope to give users suggestions on the model to use for a dataset, perform intelligent scheduling and hardware selection, and manage the models to optimize the inference pipeline. We are currently adding predictors that work within cycle accurate simulators (Aamodt et al., 2012; Binkert et al., 2011; Shao et al., 2014). We believe
this would lower the barrier for hardware architects when designing their own custom inference architectures. We are also adding support for specialized ASICs inference hardware, and expanding the number of models supported through our FPGA interface.

REFERENCES

Aamodt, T. M., Fung, W. W., Singh, I., El-Shafey, A., Kwa, J., Hetherington, T., Gubran, A., Boktor, A., Rogers, T., Bakhoda, A., et al. Gppu-sim 3. x manual, 2012.

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., et al. Tensorflow: a system for large-scale machine learning. In OSDI, volume 16, pp. 265–283, 2016.

Adolf, R., Rama, S., Reagen, B., Wei, G.-Y., and Brooks, D. Fathom: Reference workloads for modern deep learning methods. In Workload Characterization (IISWC), 2016 IEEE International Symposium on, pp. 1–10. IEEE, 2016.

AliBaba. AI Matrix. https://aimatrix.ai. Accessed: 2018-09-04.

Baidu. Deepbench. https://github.com/baidu-research/DeepBench. Accessed: 2018-09-04.

 Coleman, C., Narayanan, D., Kang, D., Zhao, T., Zhang, J., Nardi, L., Bailis, P., Olukotun, K., Ré, C., and Zaharia, M. Dawnbench: An end-to-end deep learning benchmark and competition. Training, 100(101):102, 2017.

Coleman, C., Kang, D., Narayanan, D., Nardi, L., Zhao, T., Zhang, J., Bailis, P., Olukotun, K., Ré, C., and Zaharia, M. Analysis of dawnbench, a time-to-accuracy machine learning performance benchmark. arXiv preprint arXiv:1806.01427, 2018.

Crankshaw, D., Wang, X., Zhou, G., Franklin, M. J., Gonzalez, J. E., and Stoica, I. Clipper: A low-latency online prediction serving system. In NSDI, pp. 613–627, 2017.

cuDNN. cuDNN: Reproducibility (determinism). https://docs.nvidia.com/deeplearning/sdk/cudnn-developer-guide/index.html#reproducibility. Accessed: 2018-08-04.

CUPTI. The CUDA Profiling Tools Interface. https://developer.nvidia.com/cuda-profiling-tools-interface. Accessed: 2018-08-04.

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., and Fei-Fei, L. Imagenet: A large-scale hierarchical image database.
In *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*, pp. 248–255. IEEE, 2009.

Di Tommaso, P., Palumbo, E., Chatzou, M., Prieto, P., Heuer, M. L., and Notredame, C. The impact of docker containers on the performance of genomic pipelines. *PeerJ*, 3: e1273, 2015.

DLP. HPE Deep Learning Performance Guide. [https://dlpg.labs.hpe.com](https://dlpg.labs.hpe.com), 2018. Accessed: 2018-09-04.

Dong, S. and Kaeli, D. DNNMark: A deep neural network benchmark suite for gpus. In *Proceedings of the General Purpose GPUs, GPGPU-10*, pp. 63–72, New York, NY, USA, 2017. ACM. ISBN 978-1-4503-4915-4. doi: 10.1145/3038228.3038239. URL [http://doi.acm.org/10.1145/3038228.3038239](http://doi.acm.org/10.1145/3038228.3038239).

Fursin, G., Moreau, T., Hunter, H., Chen, Y., Qi, C., and Dong, S. and Kaeli, D. DNNMark: A deep neural network benchmark suite for gpus. In *Proceedings of the 1st on Reproducible Quality-Efficient Systems Tournament on Co-designing Pareto-efficient Deep Learning, ReQuEST@ASPLOS 2018*, Williamsburg, VA, USA, March 24, 2018, pp. 7. ACM, 2018. doi: 10.1145/3229762.3233976. URL [http://doi.acm.org/10.1145/3229762.3233976](http://doi.acm.org/10.1145/3229762.3233976).

Fursin, Grigori and Lokhmotov, Anton and Savenko, Dmitry and Upton, Eben. A Collective Knowledge workflow for collaborative research into multiobjective autotuning and machine learning techniques. January 2018. URL [http://cknowledge.org/repo/web.php?wcid=report:rpi3-crowd-tuning-2017-interactive](http://cknowledge.org/repo/web.php?wcid=report:rpi3-crowd-tuning-2017-interactive).

Gent, I. P. The recomputation manifesto. *arXiv preprint arXiv:1304.3674*, 2013.

gRPC. gRPC. [https://www.grpc.io](https://www.grpc.io), 2018. Accessed: 2018-09-04.

Hanhiriiva, J., Kämäräinen, T., Seppälä, S., Siekkinen, M., Hirvisalo, V., and Ylä-Jääski, A. Latency and throughput characterization of convolutional neural networks for mobile computer vision. *arXiv preprint arXiv:1803.09492*, 2018.

Hazelwood, K., Bird, S., Brooks, D., Chintala, S., Diril, U., Dzhulgakov, D., Fawzy, M., Jia, B., Jia, Y., Kalro, A., et al. Applied machine learning at facebook: A data-center infrastructure perspective. In *High Performance Computer Architecture (HPCA), 2018 IEEE International Symposium on*, pp. 620–629. IEEE, 2018.

Henning, J. L. Spec cpu2006 benchmark descriptions. *ACM SIGARCH Computer Architecture News*, 34(4):1–17, 2006.

Jia, Y. Caffe2. [https://www.caffe2.ai](https://www.caffe2.ai), 2018.

Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., Guadarrama, S., and Darrell, T. Caffe: Convolutional architecture for fast feature embedding. In *Proceedings of the 22nd ACM international conference on Multimedia*, pp. 675–678. ACM, 2014.

Jimenez, I., Maltzahn, C., Moody, A., Mohror, K., Loftstead, J., Arpaci-Dusseau, R., and Arpaci-Dusseau, A. The role of container technology in reproducible computer systems research. In *Cloud Engineering (IC2E), 2015 IEEE International Conference on*, pp. 379–385. IEEE, 2015.

Juckeland, G., Brantley, W., Chandrasekaran, S., Chapman, B., Che, S., Colgrove, M., Feng, H., Grund, A., Henschel, R., Hwu, W.-M. W., et al. Spec accel: A standard application suite for measuring hardware accelerator performance. In *International Workshop on Performance Modeling, Benchmarking and Simulation of High Performance Computer Systems*, pp. 46–67. Springer, 2014.

Kaldor, J., Mace, J., Bejda, M., Gao, E., Kuropatwa, W., O’Neill, J., Ong, K. W., Schaller, B., Shan, P., Viscomi, B., et al. Canopy: an end-to-end performance tracing and analysis system. In *Proceedings of the 26th Symposium on Operating Systems Principles*, pp. 34–50. ACM, 2017.

Kang, Y., Hauswald, J., Gao, C., Rovinski, A., Mudge, T., Mars, J., and Tang, L. Neurosurgeon: Collaborative intelligence between the cloud and mobile edge. *SIGARCH Comput. Archit. News*, 45(1):615–629, April 2017. ISSN 0163-5964. doi: 10.1145/3093337.3037698. URL [http://doi.acm.org/10.1145/3093337.3037698](http://doi.acm.org/10.1145/3093337.3037698).

Kim, H., Nam, H., Jung, W., and Lee, J. Performance analysis of cnn frameworks for gpus. *Performance Analysis of Systems and Software (ISPASS)*, 2017.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pp. 1097–1105, 2012.

Leary, C. and Wang, T. Xla: Tensorflow, compiled. *TensorFlow Dev Summit*, 2017.

Miao, H., Li, A., Davis, L. S., and Deshpande, A. Towards unified data and lifecycle management for deep learning. In *2017 IEEE 33rd International Conference on Data Engineering(ICDE)*, volume 00, pp. 571–582, April 2017. doi: 10.1109/ICDE.2017.112. URL [doi.ieeecomputersociety.org/10.1109/ICDE.2017.112](doi.ieeecomputersociety.org/10.1109/ICDE.2017.112).
Michelangelo. Meet Michelangelo: Ubers Machine Learning Platform. https://eng.uber.com/michelangelo, 2018. Accessed: 2018-09-04.

Microsoft. Mmdnn. https://github.com/Microsoft/Mmdnn, 2018.

MLPerf. MLPerf. https://mlperf.org, 2018. Accessed: 2018-09-04.

Moreau, T., Lokhmotov, A., and Fursin, G. Introducing ReQuEST: an Open Platform for Reproducible and Quality-Efficient Systems-ML Tournaments. January 2018.

Olston, C., Fiedel, N., Gorovoy, K., Harmsen, J., Lao, L., Li, F., Rajashekar, V., Ramesh, S., and Soyke, J. Tensorflow-serving: Flexible, high-performance ml serving. arXiv preprint arXiv:1712.06139, 2017.

OpenTracing. OpenTracing: Cloud native computing foundation. http://opentracing.io, 2018. Accessed: 2018-09-04.

Oracle. GraphPipe. https://oracle.github.io/graphpipe, 2018.

Preston-Werner, T. Semantic versioning 2.0.0. https://www.semver.org, 2018.

ProtoBuf. Protocol buffers. https://developers.google.com/protocol-buffers/, 2018. Accessed: 2018-09-04.

Seide, F. and Agarwal, A. Cntk: Microsoft’s open-source deep-learning toolkit. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 2135–2135. ACM, 2016.

Shams, S., Platania, R., Lee, K., and Park, S.-J. Evaluation of deep learning frameworks over different hpc architectures. In Distributed Computing Systems (ICDCS), 2017 IEEE 37th International Conference on, pp. 1389–1396. IEEE, 2017.

Shao, Y. S., Reagen, B., Wei, G.-Y., and Brooks, D. Aladdin: A pre-rtl, power-performance accelerator simulator enabling large design space exploration of customized architectures. In Computer Architecture (ISCA), 2014 ACM/IEEE 41st International Symposium on, pp. 97–108. IEEE, 2014.

Shi, S., Wang, Q., Xu, P., and Chu, X. Benchmarking state-of-the-art deep learning software tools. In 2016 7th International Conference on Cloud Computing and Big Data (CCBD), pp. 99–104, Nov 2016. doi: 10.1109/CCBD.2016.029.

Sigelman, B. H., Barroso, L. A., Burrows, M., Stephenson, P., Plakal, M., Beaver, D., Jaspan, S., and Shanbhag, C. Dapper, a large-scale distributed systems tracing infrastructure. Technical report, Technical report, Google, Inc, 2010.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., and Rabinovich, A. Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 1–9, 2015.

Tatman, R., VanderPlas, J., and Dane, S. A practical taxonomy of reproducibility for machine learning research, 2018.

TensorflowLite. Tensorflow lite is for mobile and embedded devices. https://www.tensorflow.org/lite/, 2018. Accessed: 2018-09-04.

TensorRT. NVIDIA TensorRT. https://developer.nvidia.com/tensorrt, 2018. Accessed: 2018-09-04.

Vandewalle, P., Kovacevic, J., and Vetterli, M. Reproducible research in signal processing. IEEE Signal Processing Magazine, 26(3), 2009.

Vartak, M., Subramanyam, H., Lee, W.-E., Viswanathan, S., Husnoo, S., Madden, S., and Zaharia, M. Modeldb: A system for machine learning model management. In Proceedings of the Workshop on Human-In-the-Loop Data Analytics, HILDA ’16, pp. 14:1–14:3, New York, NY, USA, 2016. ACM. ISBN 978-1-4503-4207-0. doi: 10.1145/2939502.2939516. URL http://doi.acm.org/10.1145/2939502.2939516.

Zhang, M., Rajbhandari, S., Wang, W., and He, Y. Deepcpu: Serving rnn-based deep learning models 10x faster. In 2018 USENIX Annual Technical Conference (USENIX ATC 18), pp. 951–965, Boston, MA, 2018. USENIX Association. ISBN 978-1-931971-44-7. URL https://www.usenix.org/conference/atc18/presentation/zhang-minjia.

Zhu, H., Akrout, M., Zheng, B., Pelegris, A., Phanishayee, A., Schroeder, B., and Pekhimenko, G. TBD: benchmarking and analyzing deep neural network training. CoRR, abs/1803.06905, 2018. URL http://arxiv.org/abs/1803.06905.