Open Fabric for Deep Learning Models

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Abstract

We will show the advantages of using a fabric of open source AI services and libraries, which have been launched by the AI labs in IBM Research, to train, harden and de-bias deep learning models. The motivation is that model building shouldn’t be monolithic. Algorithms, and operations, to build and refine models should be modularized and reused as needed. The componentry presented meets these requirements and shares a philosophy of being framework and vendor agnostic as well as extensible. To train models in the cloud in a distributed, framework agnostic way, we use the Fabric for Deep Learning (FfDL). To launch adversarial attacks against the model in order to harden it, we use the Adversarial Robustness Toolkit (ART). We detect and remove bias using AI Fairness 360 (AIF360). And we publish to the open source developer community using the Model Asset Exchange (MAX). This will overall demonstrate operations on deep learning models, and a set of developer APIs, that will help open source developers create robust and fair models for their applications, and for open source sharing. We will also call for community collaboration on these projects of open services and libraries, to democratize the open AI ecosystem.

1 Introduction

The AI labs of IBM Research have imagined and launched a series of AI componentry for operations on deep neural network models. The motivation is that model building shouldn’t be monolithic. Algorithms and operations to build and refine models should be modularized and reused as needed. The componentry presented share a philosophy of being framework and vendor agnostic as well as extensible.

The Fabric for Deep Learning (FfDL, pronounced “fiddle”) is a fabric to train deep learning models in the cloud via Kubernetes. It is largely framework agnostic and thus supports Tensorflow, PyTorch, Keras, Caffe2 and others, while making it easy to add new frameworks as well. It is completely open source and can be cloned from Github [1]. The FfDL platform uses a microservices architecture to reduce coupling between components, keep each component simple and as stateless as possible, isolate component failures, and allow each component to be developed, tested, deployed, scaled, and upgraded independently. Leveraging the power of Kubernetes, FfDL provides a scalable, resilient, and fault tolerant deep-learning framework. A resource provisioning layer enables flexible job management on heterogeneous resources, such as GPUs and CPUs on top of Kubernetes.

To launch adversarial attacks against the model in order to harden it, we use the Adversarial Robustness Toolbox (ART [2][3]). ART provides many state-of-the-art techniques for attacking and hardening classifiers out of the box, can be extended with new approaches and together with its capability of composing these building blocks via interfaces it provides a comprehensive foundation of defense mechanisms for real world AI systems, cmp. [4]. Protecting models against adversarial attacks is vital, since otherwise the results can be influenced arbitrarily by adding noise that is imperceptible to humans which can have disastrous effects from autonomous cars which might be tricked...
into misinterpreting traffic signs to insurance claims where evidence photos could be manipulated to yield wrong valuations.

Furthermore, we show how to find and remove bias using the AI Fairness 360 toolkit (AIF360), cmp. [5, 6]. AIF360 is a Python package that uses fairness metrics like statistical parитет difference, equal opportunity difference, average odds difference, disparate impact or the Theil index to detect bias. It can leverage explainers to report its findings in natural language and finally use bias mitigators to remove bias from the dataset which can be verified using the same fairness metrics from the first step. Besides the obvious ethical reason to strive for fairness a company might want to do so to adapt its models to its strategic goals (e.g. to sell to all income groups equally) or to avoid legal traps like deciding based on age which might be considered age discrimination in the country the model is supposed to be used in and thus illegal.

We publish to the open source developer community using the Model Asset Exchange (MAX). MAX can be described as an app store to discover, share and rate models that can be implemented using any of the popular machine learning frameworks and that provides a standardized way to classify, annotate and deploy them, cmp. [7].

Finally, we will give a brief overview of external collaborations. The FfDL project is targeted at training, so it made sense to partner with Seldon [8] as a serving solution. We also integrated Uber’s Horovod [9] as an alternative to parameter servers for distributed training as well as the machine learning and predictive analytics platform H2O [10].

2 Related Work

2.1 Publications

Our team has published on IBM’s Deep Learning as a Service [11], Scalable Multi-Framework Multi-Tenant Lifecycle Management of Deep Learning Training Jobs [12] and Dependability in a Multi-tenant Multi-framework Deep Learning as-a-Service Platform [13], but this will be the first time that we present the open source counterpart and wider ecosystem. These publications and links to the product allow us to not only speak about open source technology, but also real-world challenges regarding multi-tenancy, fault tolerance, scalability and open sourcing itself, since we encountered several complications when moving from code deeply integrated with internal infrastructure to open code everyone can deploy to on-premise or public cloud targets.

With the success of deep learning several cloud and AI companies have released platforms to offer deep learning as a service, e.g. IBM Watson Machine Learning [14], AWS SageMaker [15], Microsoft Azure Machine Learning [16], Google TFX [17], Uber Michelangelo [18] and Facebook FBLearner [19]. The main idea is to isolate infrastructure challenges and hide the complexity of multi-tenancy, metrics collection, fault tolerance and cloud provisioning from data scientists such that they can concentrate on their actual work. Besides these products, there have also been several open source efforts, the most popular of which is Kubeflow [20] followed by FfDL [1] and Microsoft Deep Learning Workspace [21]. While solving the same problem, there are differences between the projects in terms of job scheduling and distribution, framework support, ecosystem and general architecture.

2.2 Open AI Fabric in Media and at Summits

After releasing FfDL at Think earlier this year, we have already published multiple blog posts about it [22, 23, 24, 25, 26] and were also published about by diverse external sources like TechCrunch, IT World and InfoQ, e.g. [27, 28, 29]. Furthermore, we already presented the fabric at several venues like the IEEE Computer Society Silicon Valley [30] and have published additional video presentations, e.g. [31, 32].

3 Structure of Talk

We will first discuss deployment options, since FfDL can be setup both on-premise and in public clouds making it relevant for many industries which are reluctant to compute confidential models on
public infrastructure. This also includes aspects like the storage setup (FfDL currently uses cloud object storage via S3 APIs for data access as well as NFS for logs) and GPU support in Kubernetes.

Once setup, we will demonstrate how to train a model based on a manifest that specifies the framework, data access and requested resources. We will briefly describe the architecture and APIs, how we expose a public REST endpoint for the end user while internally using gRPC to reduce latency as well as how to distribute training with Horovod or parameter servers.

We will also present how to train a fashion MNIST model, launch an adversarial attack against it, and subsequently demonstrate how to protect against it by employing the Adversarial Robustness Toolkit. Moreover, we will show bias detection and how to submit to MAX.

Finally, we can discuss potential collaborative future ideas for open source AI and share some thoughts about the state of AI systems in the open source world.

References


