Robust Scheduling and Elastic Scaling of Deep Learning Workloads

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Motivation[1]

- Popularity of deep learning in several fields
  - Ability to learn features in an unsupervised manner
  - Availability and ability to collect large amounts of data, especially unstructured data
  - Recent improvements to GPU technologies
  - Advances in interconnection technologies (NVLink, Infiniband, 100 GbE, etc.)
  - Easy-to-use open source deep-learning framework
    - Caffe, Caffe2, Torch, Tensorflow, etc.
Need for scalable and robust deep learning platforms

- A large organization with a private data center
  - Multiple teams, frameworks and application domains
  - Goals:
    - Make effective use of expensive hardware
    - Run deep learning workloads in a robust and secure manner
    - Avoid repetitive work, and situations where each team has to set up and maintain its own deep-learning “software stack”
    - Reduce barrier to entry: data scientists should focus on their algorithms, data, hyperparameter optimization, etc. and not on installations, maintenance, failure handling etc.

- A cloud provider
  - Enable small, medium and large businesses to address said goals
This Talk

Robust Scheduling and Elastic Scaling of Deep Learning Workloads

- **Context:** A deep learning platform developed and used at IBM Research
  - **DLaaS:** Deep Learning as a Service
    - Released March 20, 2018
    - Part of IBM Watson Studio, available on IBM Cloud
    - [https://www.ibm.com/cloud/deep-learning](https://www.ibm.com/cloud/deep-learning) (trials are free)
  - **FfDL:** Fabric for Deep Learning
    - Open source release of major portions of DLaaS
    - [https://github.com/IBM/FfDL](https://github.com/IBM/FfDL)

- **Built by composing several open-source technologies**
  - Simple concepts (compared to academic papers)
  - Simplicity → Maintainability
DLaaS : Key Challenges

- Training jobs typically run continuously for 1-7 days
  - Make several passes over a large data set (several TB)
  - Consequence of failure is significant (loss of several days of work)
  - Need (user configurable/directed) reliable checkpointing

- GPU-heavy
  - Designed to maximize GPU utilization
  - Hardware failures (reboots, bad GPUs) in DL clusters are more common than other clusters

- Impose a heavier load on the datacenter network

- Job deployment is not instantaneous

- Users need reliable status updates (e.g., QUEUED, DOWNLOADING, FAILED)

- Reliable streaming of logs during training

- Isolation (multi-tenancy)

- Resilience to node and job crashes (with reliable notifications)
DLaaS : Goals

- Horizontal scalability
- Flexibility -- supports popular DL frameworks; like programming languages data scientists have an affinity towards frameworks
- Dependability -- highly available, robust (timely, handle hardware and software faults), secure and maintainable
- Efficiency -- overheads introduced to achieve (above) goals and response time to external requests should be minimal
- Elasticity -- user driven and system-driven
- Priorities and pre-emption
1. Motivation and Goals of DLaaS/FfDL
2. Architecture
3. Scheduling
4. Elastic Scaling
5. Lessons learned and future research
A Training Job

- Consists of several “training”/”learning” processes, each using GPUs and synchronizing over MPI or by using parameter servers
- DLaaS view: a set of Docker containers instantiated using a manifest file
  - Docker images corresponding to popular DL frameworks
  - DLaaS instantiates docker images with user code to create the training job
  - Each learning process → a DLaaS learner
  - Manifest file: framework to use, #CPUs, #GPUs, RAM, location of training data/checkpoints/results, credentials to access said locations, etc.

- Isolation and Confidentiality
  - Using Docker containers
  - Policies on network traffic to/from training jobs
  - End-to-end encryption of data transferred to the training job and model parameters during synchronization
DLaaS/FfDL Architecture
DLaaS Architecture

- Middleware
  - Above cluster manager (Kubernetes)
- Loosely coupled microservices
- GRPC
- Kubernetes for cluster management
  - Docker containers for training jobs encapsulated using stateful sets
  - Ordered start, guaranteed restarts
- ETCD for coordination
DLaaS Job Deployment and Management

Diagram:
- DL Job
- Trainer
- MongoDB
- LCM
- ETCD
  - Status updates
  - Status updates
  - Atomic deploy
- Shared NFS Volume
  - Learner
  - Learner
  - ... Learner
  - Helper
- IBM Cloud Object Store
  - Training Data
  - Checkpoints, Logs
  - Logs
  - Checkpoints

Flow:
- DL Job
- Deploy DL Job
- Metadata
- Deploy
- Status updates
- Atomic deploy

Components:
- LCM (Load balancer)
- ETCD (Event协同数据存储)
- Shared NFS Volume
- IBM Cloud Object Store
Lifecycle Manager (LCM)

- Responsible for Creating, Deleting and Halting a Job
- Creating a training Job by interacting with Kubernetes
  - Job Monitor to babysit the job
  - Learners
  - Helper pod -- controller, log collector, download-data, store-results
  - Persistent volume claims
- Controller
  - Direct monitoring of learners through shared NFS
  - Updates status to ETCD (DOWNLOADING, PROCESSING, STORING, COMPLETED, FAILED)
  - Monitors exit state of learning process (Caffe, etc.)
Job Monitor

● 1 Job Monitor per Job
● Monitors the status of the learner pods by talking to Kubernetes
  ○ Image pull errors
  ○ Volume mount errors
  ○ Insufficient resources
  ○ Pods stuck in Container Creating/Terminating
● Monitors the status updates from Controller in ETCD
  ○ Reads status from each learner, aggregates status and updates status in Mongo through a Trainer API call
● Responsible for initiating garbage collection
Job Deployment in DLaaS

- Not instantaneous
  1. Create Network policies
  2. Create Secrets for data access
  3. Create learners as stateful sets
     - Ordered deployment of learners
     - N learners: learner-0...learner-n-1
     - Guaranteed restart upon crash failure
- LCM is 3 way replicated
- Q: What happens if a replica crashes in the middle of the steps outlined above?
DLaaS Job Deployment and Management

- DL Job
- Metadata
- MongoDB
- LCM
- Deploy DL Job
- Deploy Monitor
- ETCD
- Status updates
- Atomic deploy
- Helper
- Shared NFS Volume
- Learner
- IBM Cloud Object Store
- Training Data
- Checkpoints, Logs
- Logs
- Status updates
<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Framework</th>
<th>#PCIe GPUs</th>
<th>GPU type</th>
<th>Decrease in Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>VGG-16</td>
<td>Caffe</td>
<td>1</td>
<td>K80</td>
<td>3.29%</td>
</tr>
<tr>
<td>VGG-16</td>
<td>Caffe</td>
<td>2</td>
<td>K80</td>
<td>0.34%</td>
</tr>
<tr>
<td>VGG-16</td>
<td>Caffe</td>
<td>3</td>
<td>K80</td>
<td>5.88%</td>
</tr>
<tr>
<td>VGG-16</td>
<td>Caffe</td>
<td>4</td>
<td>K80</td>
<td>5.2%</td>
</tr>
<tr>
<td>InceptionV3</td>
<td>Tensorflow</td>
<td>1</td>
<td>K80</td>
<td>0.32%</td>
</tr>
<tr>
<td>InceptionV3</td>
<td>Tensorflow</td>
<td>2</td>
<td>K80</td>
<td>4.86%</td>
</tr>
<tr>
<td>InceptionV3</td>
<td>Tensorflow</td>
<td>3</td>
<td>K80</td>
<td>5.15%</td>
</tr>
<tr>
<td>InceptionV3</td>
<td>Tensorflow</td>
<td>4</td>
<td>K80</td>
<td>1.54%</td>
</tr>
</tbody>
</table>
### Overhead (vs. NVIDIA DGX-1)

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Framework</th>
<th>#PCIe GPUs</th>
<th>GPU type</th>
<th>Decrease in Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>InceptionV3</td>
<td>Tensorflow</td>
<td>1</td>
<td>P100</td>
<td>3.30%</td>
</tr>
<tr>
<td>Resnet-50</td>
<td>Tensorflow</td>
<td>1</td>
<td>P100</td>
<td>7.07%</td>
</tr>
<tr>
<td>Resnet-152</td>
<td>Tensorflow</td>
<td>1</td>
<td>P100</td>
<td>8.13%</td>
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<tr>
<td>VGG-16</td>
<td>Tensorflow</td>
<td>1</td>
<td>P100</td>
<td>7.84%</td>
</tr>
<tr>
<td>InceptionV3</td>
<td>Tensorflow</td>
<td>2</td>
<td>P100</td>
<td>10.06%</td>
</tr>
<tr>
<td>Resnet-50</td>
<td>Tensorflow</td>
<td>2</td>
<td>P100</td>
<td>10.53%</td>
</tr>
<tr>
<td>Resnet-152</td>
<td>Tensorflow</td>
<td>2</td>
<td>P100</td>
<td>12.29%</td>
</tr>
<tr>
<td>VGG-16</td>
<td>Tensorflow</td>
<td>2</td>
<td>P100</td>
<td>13.69%</td>
</tr>
</tbody>
</table>
## Recovery Times

<table>
<thead>
<tr>
<th>Component</th>
<th>Recovery Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>API</td>
<td>3-5s</td>
</tr>
<tr>
<td>LCM</td>
<td>4-6s</td>
</tr>
<tr>
<td>Guardian</td>
<td>1-2s</td>
</tr>
<tr>
<td>Helper</td>
<td>3-4s</td>
</tr>
<tr>
<td>Learner</td>
<td>10-20s</td>
</tr>
</tbody>
</table>
Scheduling Deep Learning Jobs

- Kubernetes default scheduler
  - Scheduling at the pod level
  - FCFS
- PACK
  - Pack components of deep learning jobs (i.e. kubernetes pods) into as few physical servers as possible
  - 4 machines (4 GPUs each), a job with 2 learners (2 GPUs/learner) → 1 machine is used
- SPREAD
  - Opposite of PACK, ideal for replicated services
  - 4 machines (4 GPUs each), a job with 2 learners (2 GPUs/learner) → 2 machines are used
- Locality awareness
  - Try not to place across racks
  - Try not to place across network “areas”
  - Kubernetes labels
PACK vs. SPREAD

- 100 machines, 32 CPU cores, 4 K80 GPUs, 128GB RAM per machine
- 4000 Jobs
  - 1-4 GPUs/learner, avg 2.5
  - 4-16 CPUs/learner, avg 5
  - 1-8 learners/job, avg 4.5
PACK vs. SPREAD

- 100 machines, 32 CPU cores, 4 K80 GPUs, 128GB RAM per machine
- 4000 Jobs
  - 1-4 GPUs/learner, avg 2.5
  - 4-16 CPUs/learner, avg 5
  - 1-8 learners/job, avg 4.5
Gang Scheduling

- Enhancement to Kubernetes default scheduler
- Scenario: Cluster has 8 GPUs, 4 jobs arrive, with 4 learners and 1 GPU/learner
  - Desired outcome: 2 jobs running, 2 jobs “pending”
  - Kubernetes default scheduler
    - 4 jobs with 2 learners/job running, 2 learners/job queued. Deadlock!
    - 4 jobs, 1st job 1 learner running, 2nd job 2 learners running, 3rd job 3 learners running, 4th job 2 learners running. Deadlock!
- Gang scheduling needed
  - A distributed deep learning job is a “gang” of learners
  - Either the whole gang should be scheduled or none at all
- Gang scheduling is different from atomic job deployment
- Atomic job deployment – all artifacts of a job, implemented above cluster manager
- Gang scheduling – learners only, implemented inside the cluster manager
Elasticity in Deep Learning

- Ability to dynamically scale-up or scale-down training resources (GPUs, CPUs)

Need for elasticity:
  - User: Ability to complete the job faster by increasing the batch-size (using more resources) in the middle of training
  - System: maintain desired utilization levels, support job priorities, spot pricing
Most deep learning models yield poor accuracy when using a very large batch size.

- Similar accuracy till 8K batch size
- Accuracy drops at 16K BS

Max Accuracy: **BS4K** (70 epochs) - 75.09%, **BS8K** - 75.26%, **BS16K** - 70.8%
Larger batch sizes can be used after initial phase of training

- Run with 8K till 30 epochs, change/simulate to 16K after that.
- LR doubles as per 16K BS after 30 epochs

**Observation:**
- Doubling the BS at 31\textsuperscript{st} epoch provides same accuracy.
- Accuracy drops when doubling after 7 epochs.

Reference: Smith et al. paper, Don't Decay the Learning Rate, Increase the Batch Size, ICLR 2016 (https://openreview.net/forum?id=B1Yy1BxCZ)
User-driven Elasticity

• Static/Pre-defined
  – Larger batch size can be used (hence more resources can be employed) after certain # of epochs
  – Scenario: epochs 1-30 with \(<x \text{ GPUs, config1}>,\) 30 to 60 with \(<y \text{ GPUs, config2}>\)

• Dynamic
  – User decides when to scale elastically through a UI/CLI command
  – Scenario: User analyzes logs and decides to change hyper-parameters on the fly

```python
Resume from last checkpoint
Setup hyper-parameters
For every epoch
  train batches for this epoch
  If (epoch == 30)
    module.call_as_restart(4 /*GPUs*/)
```
System-driven Elasticity -- Scenarios

- **Optimal cluster utilization**
  - Cluster does not have spare capacity but maintenance needs to be performed → Elastically scale down jobs instead of terminating them
  - Automatically scale-up jobs when cluster is under-utilized

- **Supporting priorities**
  - Scale-down a lower priority job if a higher priority job arrives and resources aren’t available
  - Currently, higher priority users may not be entertained if lower priority jobs are occupying the system

- **Support some spot pricing models**
  - When cluster is under-utilized, offer GPUs at a cheaper price if the user is willing to scale-down the job later on

- **Increase flexibility while starting jobs**
  - Start a job with smaller number of available GPUs and later scale as more GPUs become available
User-driven Elastic Scaling

Dynamic

Static/Predefined
System-driven Elastic Scaling

Optimize cluster utilization
• Scale jobs up when cluster under-utilized (and vice-versa)
• min,max GPUs specified by user

Better handle planned maintenance and outages
• Avoid terminating jobs on nodes going down
• Scale jobs down instead

Handle priorities better [Ongoing work]
• Scale down jobs to admit higher priority jobs
• Choose jobs to scale-up based on priorities
• Interact with BSA scheduler and kube arbitrator
Impact on Users

• Requires (minimal) code changes from the user
  – Regular Checkpointing (which the users mostly use and are already familiar with)
  – For static/predefined scenario, user invokes simple functions by importing modules that hide details

• User specifies range of acceptable resources
  – Currently the user specifies number of GPUs; now the user will specify range of GPUs (min and max) per learner
  – System can schedule job with any number of GPUs between min and max
  – User code (Learner), upon startup queries number of resources allocated and sets up hyper-parameters accordingly

• Non-intrusive
  – Works without modifying any framework – can work with all DLaaS frameworks
Lessons Learned

- Cluster managers alone are insufficient to run DL workloads effectively
- DL workloads are similar in many ways but are also different in important ways to regular datacenter workloads (gang, no overcommitment, etc.)
- Users hate jobs being queued with no estimate of how long the job will remain in the queue
- Non-distributed DL workloads are not rare; distributed DL workloads are not large scale (< 10 learners)
- Futile to try and predict job arrival trends
- Simplicity is key to scalability, fault tolerance and maintainability of DL platforms
- Popular open source technologies (ETCD, Kubernetes, Docker, GoLang) can be helpful, but need to be augmented where necessary
Avenues for further research

- Priority and pre-emption while scheduling deep learning jobs
- Dynamic priority (based on number of jobs submitted)
- Priority + elasticity
- Runtime estimation and estimating the amount of time jobs remain in the queue
- “Smarter” scheduling and load prediction for user-driven static elasticity scenario