HTCondor in Foxconn Hyperscale AI HPC Cloud

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Outline

Foxconn AI HPC Cloud Solution

- Introduction
- AI/HPC Cloud Stack Hardware & Software
- Applications
- HTCondor in Foxconn Cloud
 - Research Case Bayesian Optimization of Deep Learning Hyperparameters

Foxconn HPC Solution

- Collaborate with Microsoft: "TECHNOLOGY OF THE YEAR" award of InfoWorld in 2018
- Solution in multiple scales
 - HGX-1, HGX-2, and workstations: standalone usage.
 - M100 Rack: All-in-one HPC box for on-premise solution
 - M500 Cloud: Ultimate scalable HPC system for public cloud
 - Serving computations of wide variety of scales
 - Massively scalable performance (HPC)
 - Huge number of smaller-scale and independent tasks for many customers (HTC)



Fii Cloud & HPC



Objectives



Foxconn AI HPC Stack

Applications

- 1. High-Resolution (8K) Image/Video Object Detection
- 2. Industrial Application / Surface Defect Detection
- 3. Medical Application / Deep learning / Industrial AI / NGS



Foxconn AI HPC Stack

Machine Learning / Deep Learning Service

- 1. Multi-node multi-GPU cluster environment
- 2. Training and inference workflow
- 3. Deep learning inference application platform
- 4. Performance autotuning (FAUST, SOFA, POTATO)



Foxconn AI HPC Stack

HPC Service

- 1. Optimized job scheduler and virtualization environment according to specified performanceenergy criteria
- 2. Job dispatch in hybrid HPC environment, including on-premise HPC clusters and public cloud data centers



Hybrid Cluster Management (In Progress)

- Coexist HTCondor, Slurm, and K8S cluster under an OpenStack tenant
- Allow Slurm, K8S, and HTCondor batch jobs to share the same cluster hardware resources



HGX-1 Architecture

Modular GPU computing solution

- Reconfigurable scale-up system
- High-density GPU clusters for space saving
- CPU node
 - 32 cores in total



• Single-node with 8 or 16 GPUs





HGX-1 Stingray-HPC64, Local M.2 SSD



CPU: Intel(R) Xeon(R) Gold 6154 CPU @ 3.00GHz Memory: DDR4 2666MHz 32G x 24 GPU: Tesla V100-SXM2-32GB Driver: 410.72 OS: NGC nvcr.io/nvidia/tensorflow:18.09-py3 Cuda: cuda 10 Cudnn: 7.3.0.29-1 Tensorflow: 1.10 Benchmark: 1.9

8 GPU

ResNet50 Real, Hvd	BS=64	BS=128	BS=256	BS=512
fp32	2395	2760	2987	Х
fp16	3959	5129	6029	6464

16 GPU

ResNet50 Real, <u>Hvd</u>	BS=64	BS=128	BS=256	BS=512
fp32	4448	5306	5847	Х
fp16	7140	9459	11244	12362

Next Generation Sequencing

Parabricks NGS

- NGS pipeline speedup: 30 ~ 50X
- Sequencer-generated FASTQ files to variant call files (VCFs) with GPUs



Medical Applications

Mammogram abnormality detection

Real-time instant identification

- Single image upload identification
 - Detection of abnormal position and score



Multiple database image recognition

- Batch detection and anomaly location
- Batch process with 8 GPUs
 - 600,000+ images processed per day

Batch identification processing



Reference:

- 1. Ribli et al., "Detecting and classifying lesions in mammograms with deep learning," Scientific Reports vol. 8, 4165 (2018)
- 2. Digital Mammography DREAM Challenge

HGX-2 Architecture



	HGX-1	<u>HGX-2</u>
GPU # in single node	8 (single box) or 16 (cascaded boxes)	16
Inter-GPU communication	NVLink 'Cube Mesh' + PCIe	NVLink Switch
Inter-GPU performance	1 or 2 hops in 8 GPUs of an expansion box, plus 2 hops across PCIe of different boxes	2 hops between 16 GPUs via non-blocking NVSwitch
Ideal applications	Applications require moderate GPU data exchange, e.g. most DL training models, ResNet, AlexNet, etc.	Applications require heavy GPU data exchange, e.g. Scientific simulation, etc.
TCO per GPU	Low	Higher cost due to extra NVSwitch cost and power consumption
Availability	Now	Q3, 2019

Ref: https://www.nextplatform.com/2018/04/13/building-bigger-faster-gpu-clusters-using-nvswitches/

GPU Infrastructure Consideration

On-premise GPU clusters

- Improved data security and application latency
- Limited computing resource
- High maintenance effort

Off-premise GPU data center

- Virtually unlimited computing resource for bursts of critical demands
- Low maintenance cost

HTCondor

- High throughput for massive number of tasks
- Configurable hardware demand for each application
- Docker universe
 - Swift deployment of complex application container
- On-demand GPU computing
 - HTCondor Annex
 - VM instance management in cloud
- Federation of clusters
- DAGMan
 - Easy orchestration of tasks



Data Apps Libraries Services **OS Cloud Burst Request** w/ Container Management Platform

Public Cloud

On-premise HPC Rack

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 Research Case – Bayesian Optimization of Deep Learning Hyperparameters

Task dispatch for hyperparameter optimization

Application

- Optimization of AI model or many scientific problems
- Optimization scheme
 - Grid search (parallel)
 - Random search (parallel)
 - Bayesian optimization (serial in general)

HTCondor Features

- GPU computing
- Docker universe
 - Default runtime set to "nvidia"
- Partitionable slots
- HTCondor-Python

Major Tools

- Scikit-optimize (Bayesian optimization)
- Image: nvcr.io/nvidia/tensorflow:18.12-py3 (Keras)



Task dispatch for hyperparameter optimization Environments and Setting

- Single-node with 8 Tesla P100 in Foxconn/DCT data center in Kaohsiung
- Mini-HTCondor
 - Single worker with partitionable resources
- Submitter
 - Python environment with HTCondor API and scikit-optimize
 - Eight observation tasks submitted in each round of optimization
 - One GPU and 4 CPU slots for each task



Task dispatch for hyperparameter optimization

Test script

- Keras example: cifar10_cnn.py
 - 50 epochs
- 8 optimization rounds
- Generally underfitting
 - Baseline setting
 - Learning rate: 1.0e-4
 - Layer size: 512
 - Validation accuracy: 77.74%
 - Tuning range
 - Learning rate: [1.0e-6, 1.0]
 - Layer size: [128, 1024]

Summary

- Best accuracy in the 5th round
- Suggested learning rate: [0.00005, 0.00015]
- Suggested layer size: [512, 1024]

Extension

- Scale-out for more observations in one round
- Good results could be obtained with less rounds

Score	0.779900	for	parameter	set	[1024, 8.049824704019605e-05]
Score	0.773200	for	parameter	set	[577, 8.505281624321753e-05]
Score	0.770400	for	parameter	set	[1018, 9.877286181054077e-05]
Score	0.767200	for	parameter	set	[1024, 6.368165079811596e-05]
Score	0.764600	for	parameter	set	[1022, 9.790266862705711e-05]
Score	0.763900	for	parameter	set	[1024, 6.749912931702168e-05]
Score	0.761900	for	parameter	set	[1024, 6.594575565833666e-05]
Score	0.757700	for	parameter	set	[636, 0.00012910071728580158]
Score	0.754500	for	parameter	set	[1024, 5.395416679452777e-05]
Score	0.753900	for	parameter	set	[1019, 9.833030469970878e-05]
Score	0.753800	for	parameter	set	[975, 0.00012207698981520957]
Score	0.751900	for	parameter	set	[1024, 6.789389450271147e-05]
Score	0.748900	for	parameter	set	[617, 6.775072733733407e-05]
Score	0.748400	for	parameter	set	[1024, 5.228268927494645e-05]
Score	0.747400	for	parameter	set	[465, 5.028506626893611e-05]
Score	0.746500	for	parameter	set	[968, 6.174024931710192e-05]
Score	0.746200	for	parameter	set	[511, 6.273130395796479e-05]
Score	0.746200	for	parameter	set	[1024, 5.30120813707728e-05]
Score	0.744500	for	parameter	set	[1024, 6.026359849627899e-05]
Score	0.744000	for	parameter	set	[1024, 5.151728265597643e-05]
Score	0.739500	for	parameter	set	[1018, 4.9762599359445486e-05]
Score	0.738800	for	parameter	set	[1024, 7.081208890468328e-05]
Score	0.734600	for	parameter	set	[405, 7.719624788188919e-05]
Score	0.734300	for	parameter	set	[128, 6.685671725193425e-05]
Score	0.733200	for	parameter	set	[213, 5.144708557740793e-05]
Score	0.732500	for	parameter	set	[1024, 5.264280995142357e-05]



Task dispatch for hyperparameter optimization Discussion & Further Investigation

- Network bandwidth
 - Training data upload for multiple tasks
 - ImageNet: over 100 GB of data
 - Potential solutions
 - Lustre share storage
 - Proxy
 - Docker volume mount
 - Prepare data before optimization tasks start
 - Mount volume of prepared data
 - Pro: data sharing of multiple tasks in the same node
 - Caveat: data nodes v.s. worker nodes specified by central manager
- Data Security
 - Primary concern in commercial applications
 - Potential solution
 - Encrypted filesystem

Thank You!