HAL: Computer System for Scalable Deep Learning

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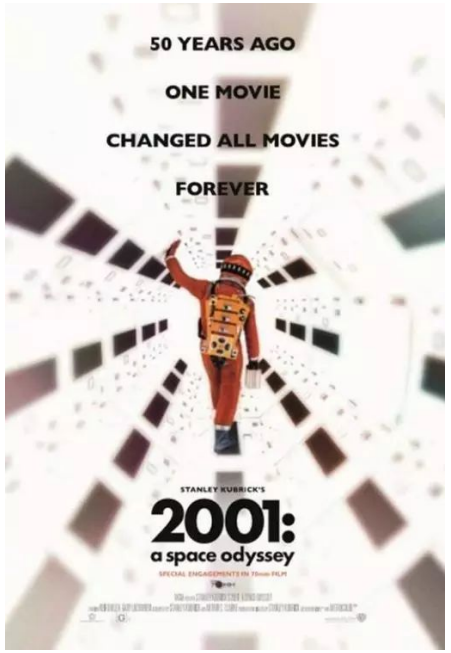
Introduction

- In 2017, NCSA was funded by the NSF's Major Research Instrumentation program.
- The goal is to develop and deploy a computational "instrument" for supporting deep learning applications at scale.
- The machine was named as Hardware Accelerated Learning (HAL) cluster.
- It became operational in March 2019.

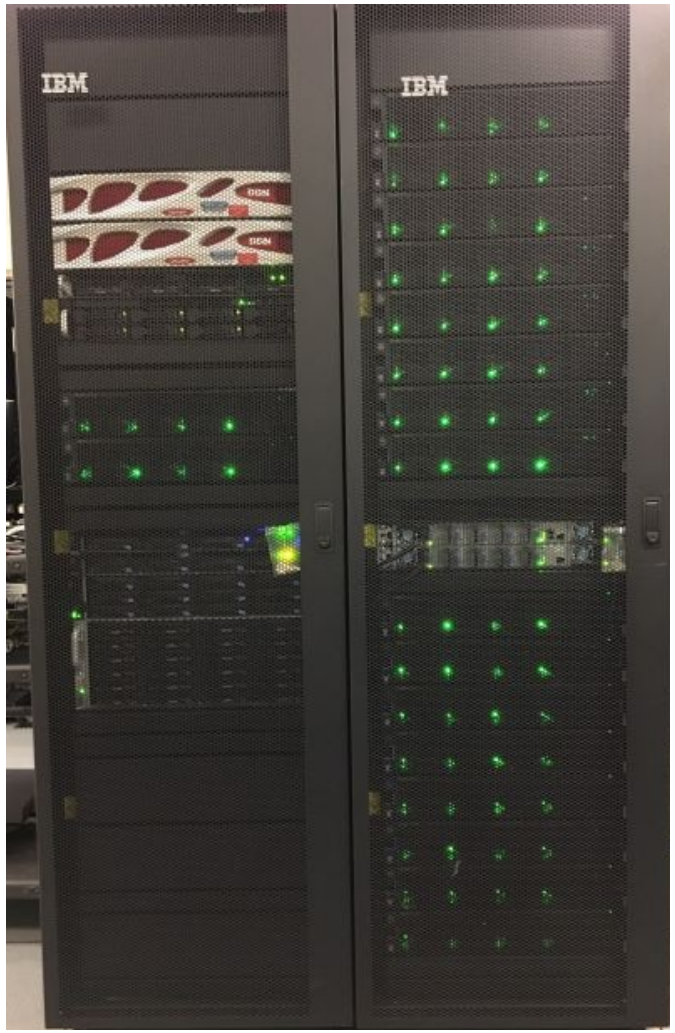


System Requirements

- Performance Requirements
  - Many modern DL frameworks have been optimized for NVIDIA GPUs
  - Fast cross-GPUs bandwidth delivered by NVLink 2.0 interconnection
  - Storage and node interconnects support simultaneous data processing
- Usability Requirements
  - Traditional HPC job submission and resource scheduling which access the system via ssh through the command line interface
  - Interactive apps like Jupyter Notebook through web-based interface.
  - Customizable environments via modules, containers, and isolation of Python environments within the user space.

HAL System Design

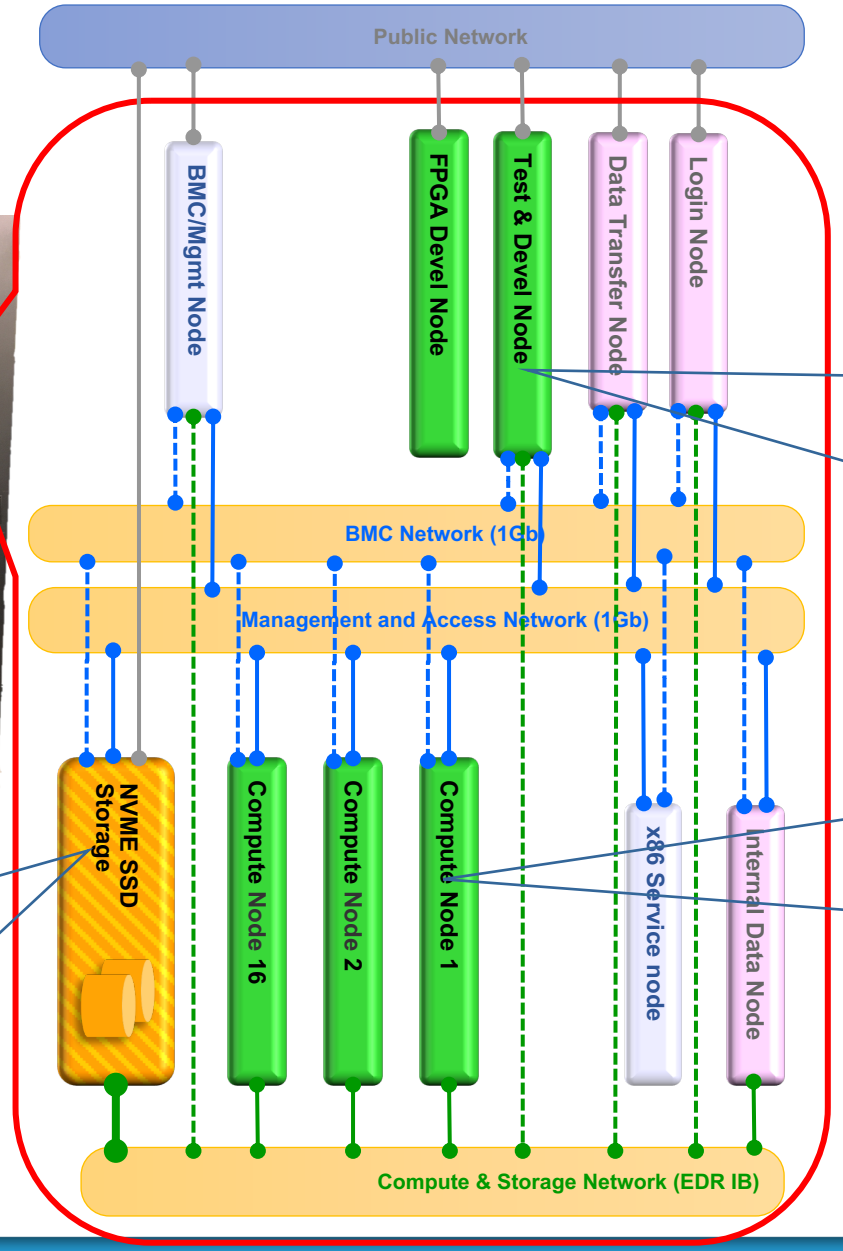
- Hardware Selection
  - Login Node
    - IBM LC921 server
  - Storage Node
    - IBM LC922 server (initial)
    - DDN GS400NVE flash arrays server (final)
  - Compute Node
    - IBM POWER9 AC922 server with NVLink 2.0 interconnected V100 GPUs (compute node)
  - Network
    - Mellanox EDR InfiniBand



HAL cluster

Hardware Accelerated Learning

- CentOS 7.7
- CUDA 10.2, cuDNN 7.6.5, NCCL 2.5.6
- IBM XLC 16.1.1, IBM XLFORTRAN 16.1.1
- Advance toolchain for Linux on Power 12.0
- IBM Watson Machine Learning Community Edition 1.7.0 (TensorFlow, PyTorch, RAPIDS cuML and cuDF)
- SLURM & Open OnDemand

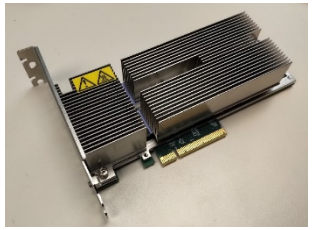


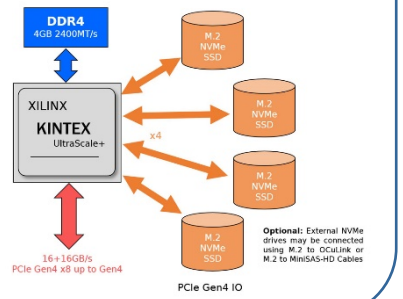
DDN GS400NVE Flash Array

- 244 TB usable
- NVME SSD-based storage
- Spectrum Scale File System

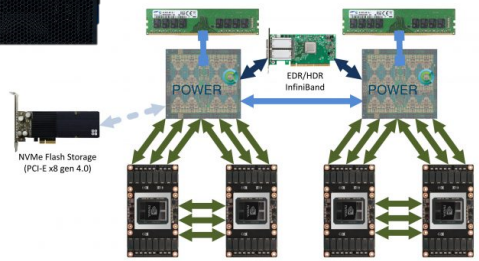
- 16 IBM AC922 nodes
  - IBM 8335-GTH AC922 server
    - 2x 20-core POWER9 CPU @ 2.4GHz
    - 256 GB DDR4
    - 4x NVIDIA V100 GPUs
      - 5120 cores
    - 16 GB HBM 2
  - 2-Port EDR 100 GB IB ConnectX-5 Adapter

Nallatech 250S+ CAPI FPGA board





IBM Power9 AC922



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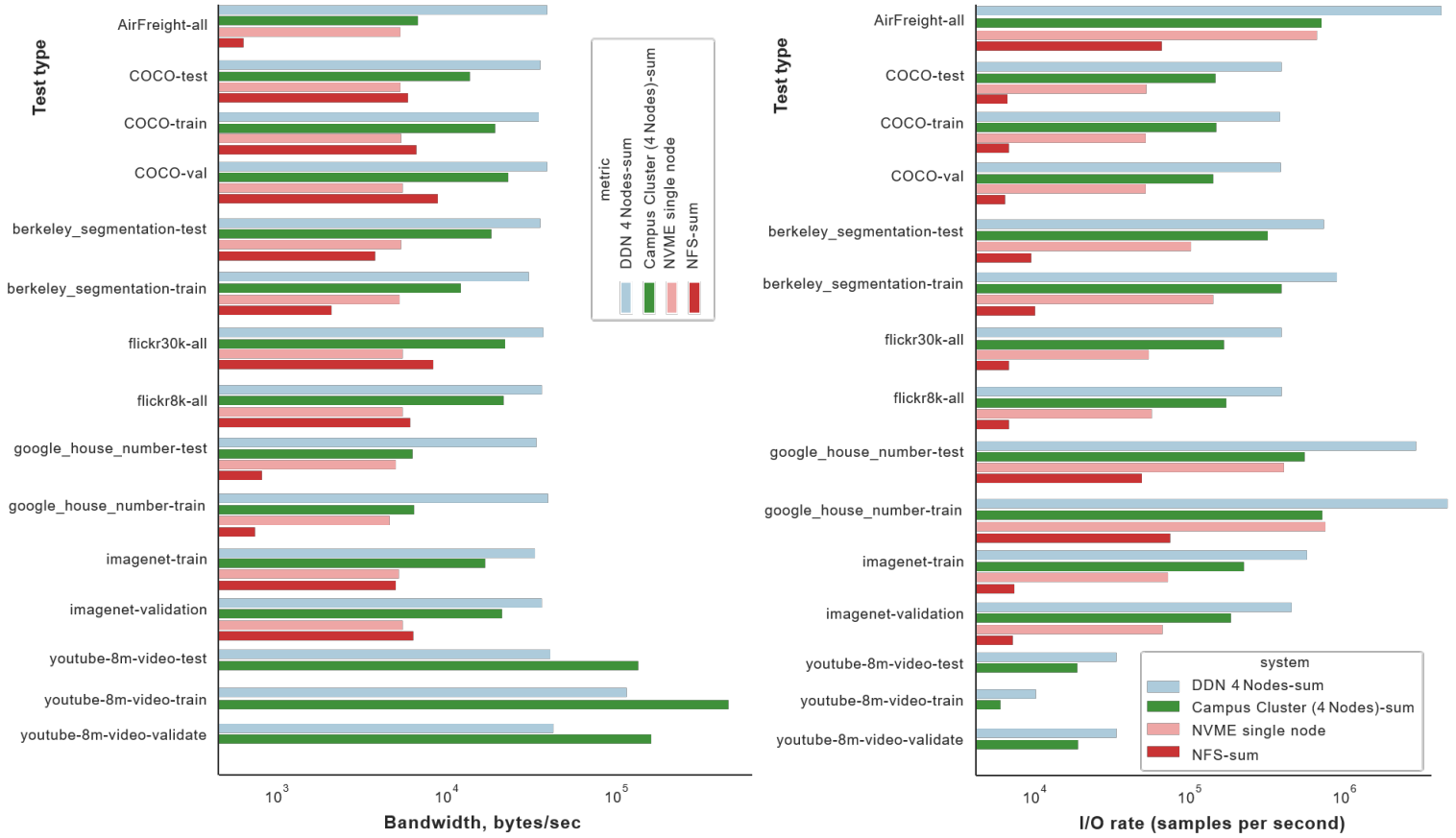
HAL System Design

- Storage Selection
  - Multiple Vendors
  - Multiple Benchmarks
    - IOR
    - mdtest
    - DIOT
  - Cost per Usable TB
- Storage Tuning
  - balance between bandwidth and IOPs



HAL System Design

- Software Stack
  - OS
    - CentOS 7.7 LE ALT for POWER9
  - Environment Module
    - Lmod
  - ML/DL Tools
    - IBM Watson Machine Learning Community Edition, which includes Caffe, Tensorflow and Pytorch.
    - Both python 2.7 and 3.6/3.7 versions of WMLCE.
  - Other Software Components
    - NVIDIA CUDA tools
    - PGI compiler
    - IBM Advance toolchain
    - Jupyter Notebook and Jupyter Lab
    - Tensorboard
    - H2O AI

HAL System Design

- Software Stack
  - Slurm Wrapper Suite
    - Designed to simplify the use of the Slurm resource allocation and job submission utility.

```
srun –partition=gpu –time=24:00:00 –nodes=1 –ntasks-per-node=160 \
     –sockets-per-node=2 –cores-per-socket=20 –threads-per-core=4 \
     –mem-per-cpu=1200 –wait=0 –export=ALL –gres=gpu:v100:4 –pty /bin/bash
```

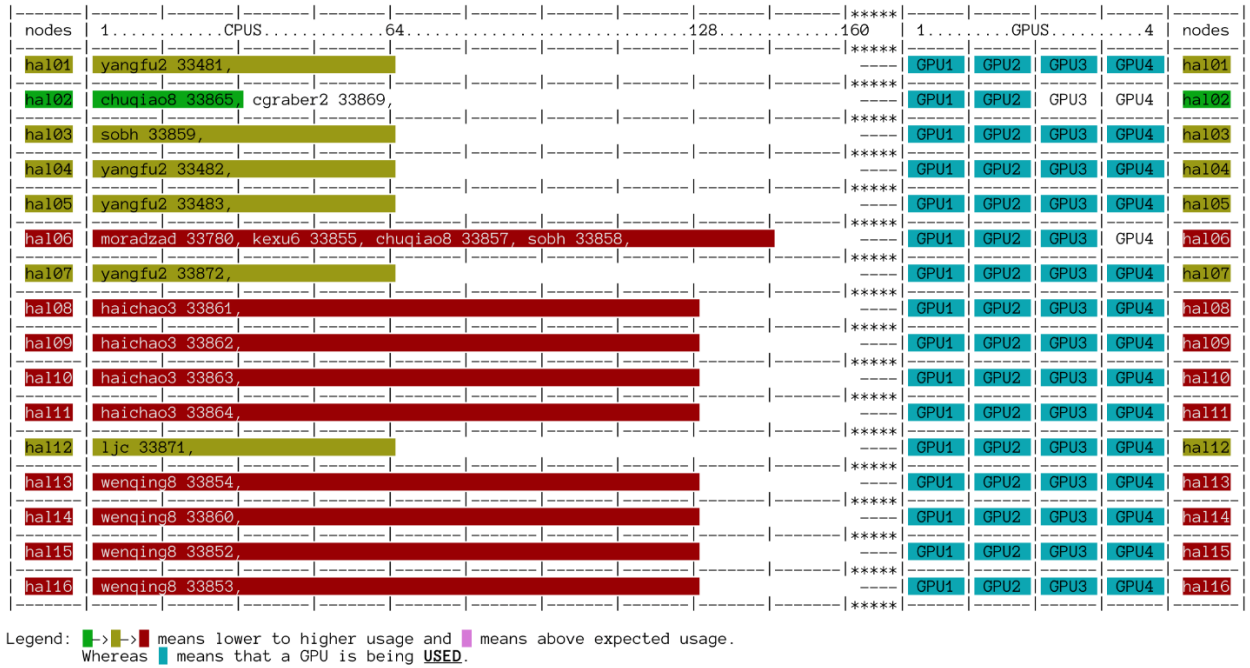
```
swrun -p gpux4 -c 40 -t 24
```

```
#!/bin/bash
#SBATCH --partition=gpu
#SBATCH --time=4:00:00
#SBATCH --nodes=1
#SBATCH --ntasks-per-node=16
#SBATCH --sockets-per-node=1
#SBATCH --cores-per-socket=4
#SBATCH --threads-per-core=4
#SBATCH --mem-per-cpu=1200
#SBATCH --export=ALL
#SBATCH --gres=gpu:v100:1

python3 mnist_train_pytorch.py
```

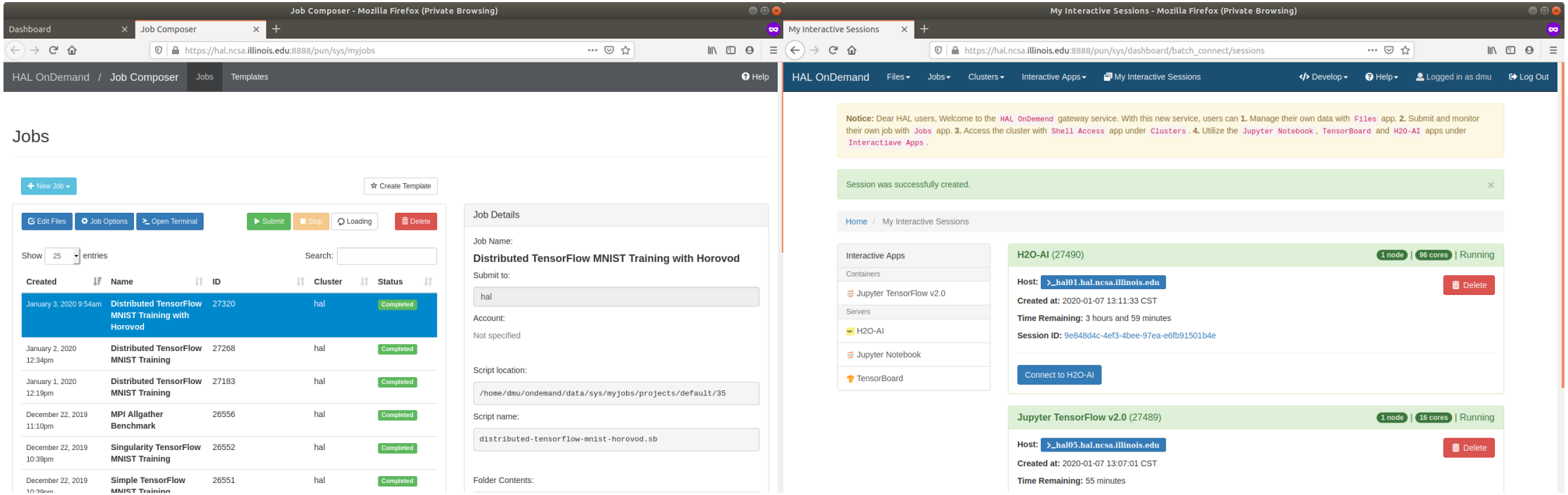
```
#!/bin/bash
#SBATCH --partition=gpux1

python3 mnist_train_pytorch.py
```



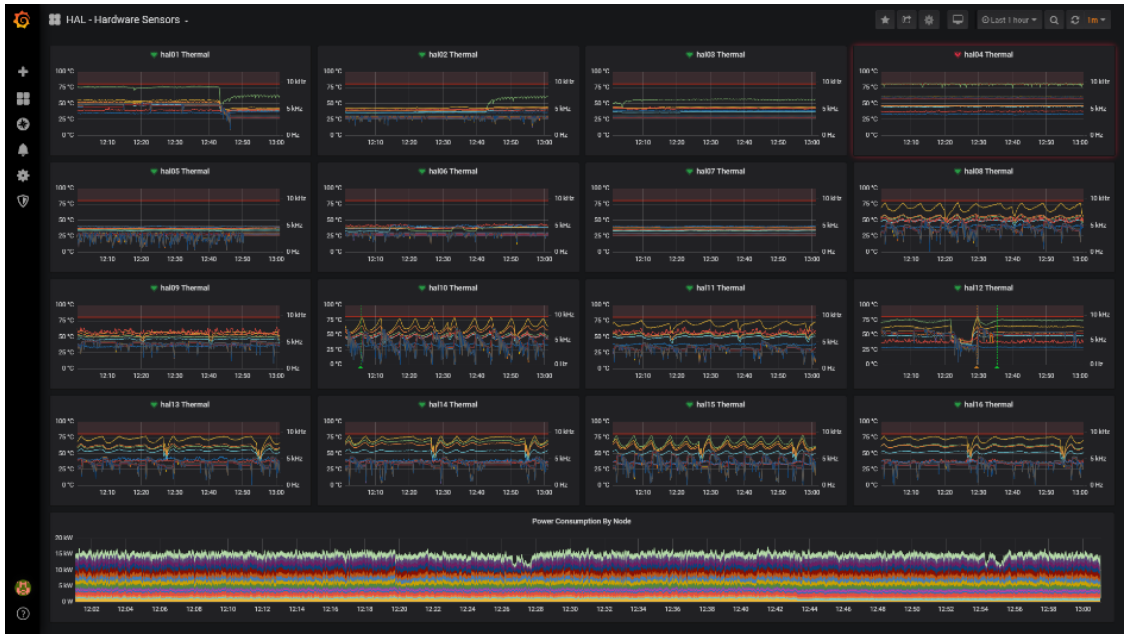
HAL System Design

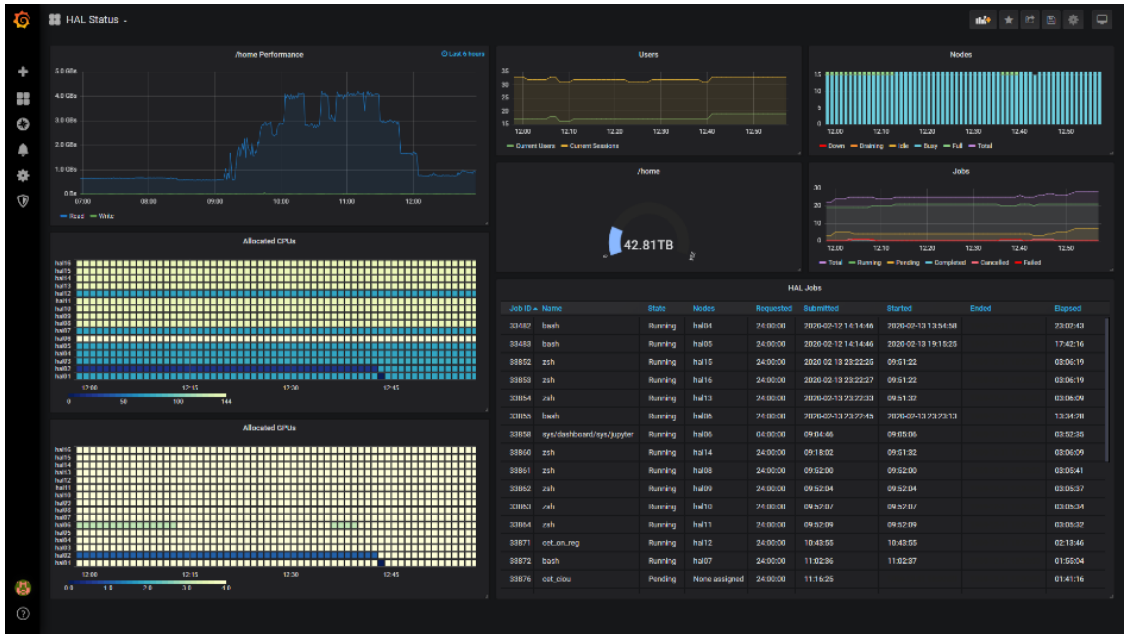
- Software Stack
  - HAL OnDemand is based on Open OnDemand Project, which provide web-based access to our HPC resources



HAL System Design

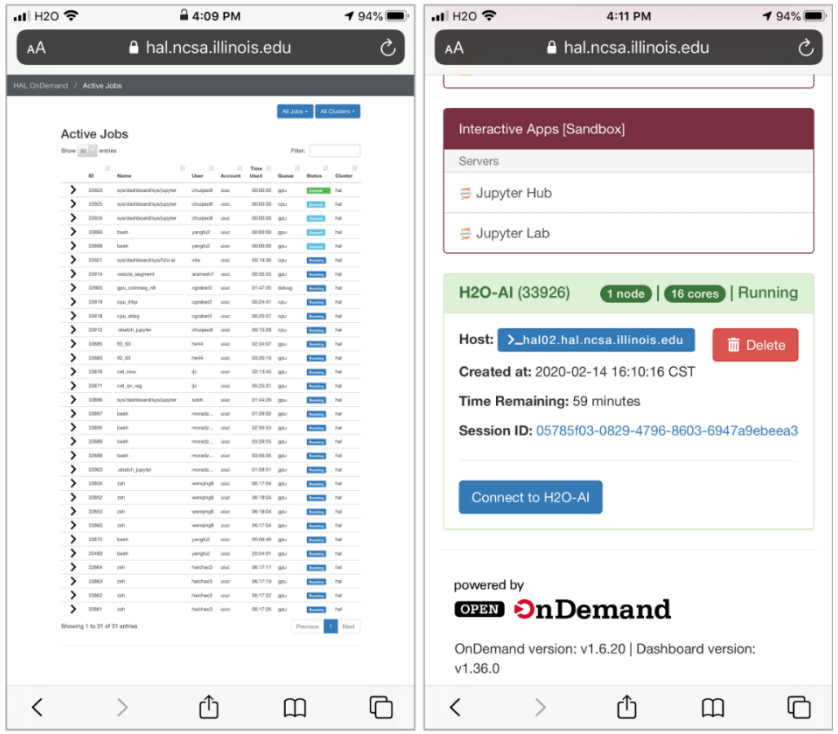
- Software Stack
  - Monitoring Stack
    - Telegraf collects metric
    - InfluxDB stores dataset
    - Grafana provides visualization





HAL System Design

- Software Stack
  - HAL System on Mobile Platforms



(a) (b)

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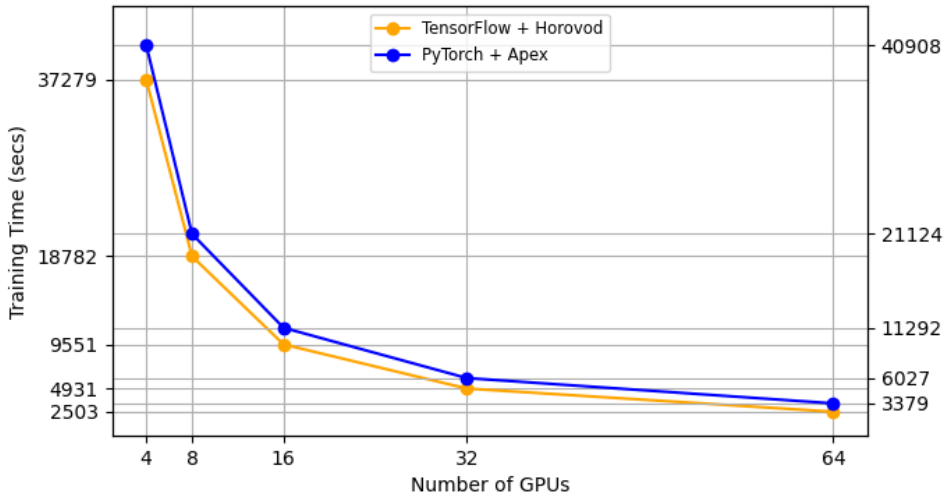
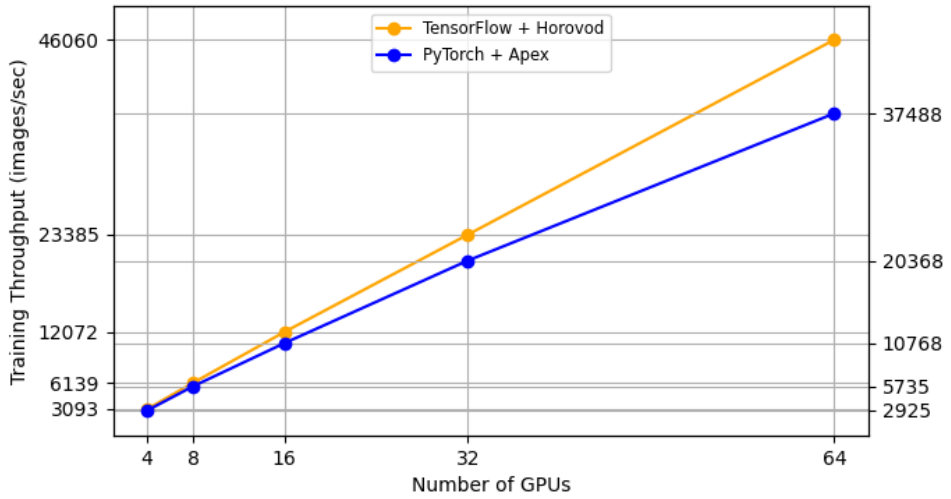
ImageNet Distributed Training Benchmark

- Implementation Details
  - Scaling ResNet-50 (TensorFlow and PyTorch) trained on ImageNet across multiple GPUs and multiple compute nodes
  - Official implementations of ResNet-50 for both frameworks
  - The optimizer utilized standard momentum with m of 0.9 and a weight decay λ of 0.0001
  - All models were trained for 90 epochs
  - Per-GPU batch size of 256 images
  - NVIDIA NCCL as communication backend
  - cnn_tf_v1.14_compatible branch and horovod for TensorFlow
  - Automatic Mixed Precision (Amp) and Distributed Data Parallel (DDP) from NVIDIA Apex for mixed-precision and distributed training for PyTorch

ImageNet Distributed Training Benchmark

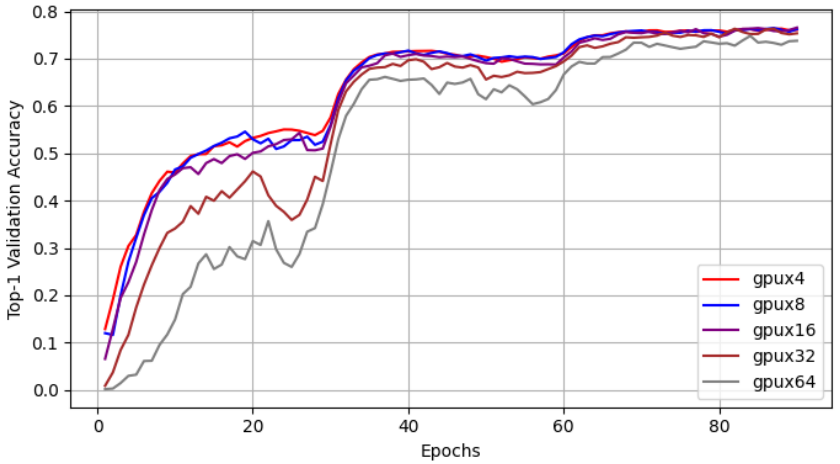
- Analysis of Results
  - With 64 GPUs across 16 compute nodes, we can train ResNet-50 in 41 mins, 43 secs with TensorFlow and 56 min, 18 sec with PyTorch, while maintaining comparable top-1 and top-5 accuracy
  - The global throughput shows that we were able to achieve near linear performance scaling in both frameworks

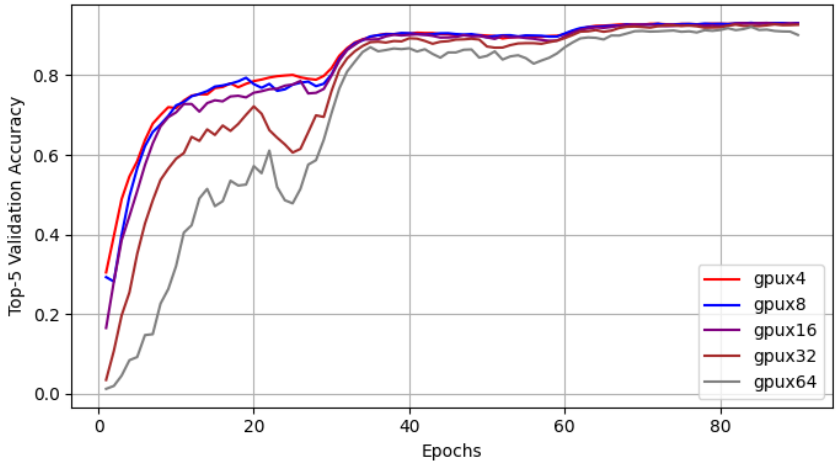


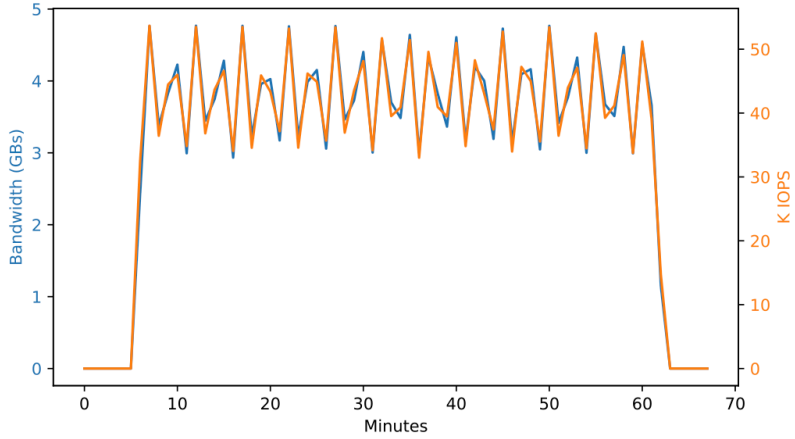


ImageNet Distributed Training Benchmark

- Analysis of Results
  - We achieve distributed training speed-up without the loss of accuracy.
  - Most experiments reached a top-1 validation accuracy of 76% in the PyTorch benchmark.
  - The Accuracy all peak at comparable accuracy near the end of training during the TensorFlow benchmark.
  - Average bandwidth is 3.84 GB/s and average IOPS is 42.95K.







Discussion and Lessons Learned

- Issued over 300 user accounts, supported over 70 faculty research groups from over 20 departments
- Over 30 publications along with 4+ Students Thesis
- Using AWS (p3.2xlarge instance) cost as a reference, HAL provides over $141,000.00 in value every month.
- Provide regular training sessions for new users
- Organize hackathons where students can work on various problems that require building and training DNN models.

Acknowledgments

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