



Deploying Machine Learning at Petascale on Secure Large Scale HPC Production Systems with Containers.

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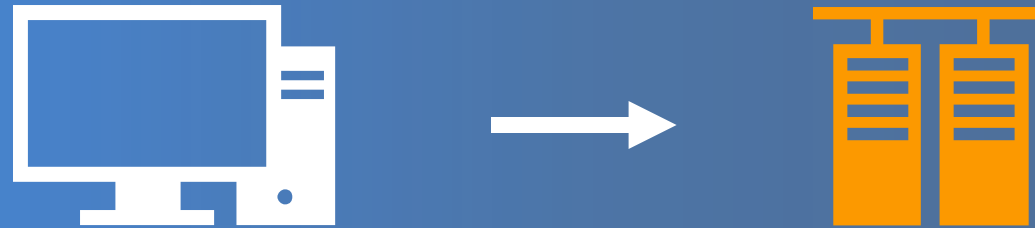
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Transition AI algorithms from the
laptop to supercomputer
with minimal effort



“It just works”

HPAI =

Modeling & Simulation

- Equation based on model
- Computing driven
- Numerically intensive
- Creates simulations
- Monte Carlo
- Larger problems
- Iterative methods
- PDE

+

- Linear algebra
- Matrix operations
- Iterative methods
- Compute intensive
- Data transfer
- Predictive
- Probabilities
- Stencil codes
- Calculus
- Pattern recognition
- Graphs

Analytics

- Finds patterns
- Correlations in data
- Logic driven
- Creates inferences
- Knowledge discovery
- Graphs
- Data-driven science
- Predictions
- CNN
- RNN

Requirements for AI on HPC

Compute intensive hardware



Optimized AI frameworks

TensorFlow,
PyTorch, Caffe

Optimized software
numerical libraries,
Python

HPC specific software

distributed
computing,
workload manager

Method of deploying the AI software

in a simple, straight-forward and flexible way

Need to get to: “It just works”

Package Management

Frameworks have conflicting dependencies



The frameworks & their dependencies need to be combined in a single module

Rapid update cycles



Provide a mechanism for users to build their own frameworks

Dynamic Programming Environment

Python dependencies



Each unique framework needs its own Python instance

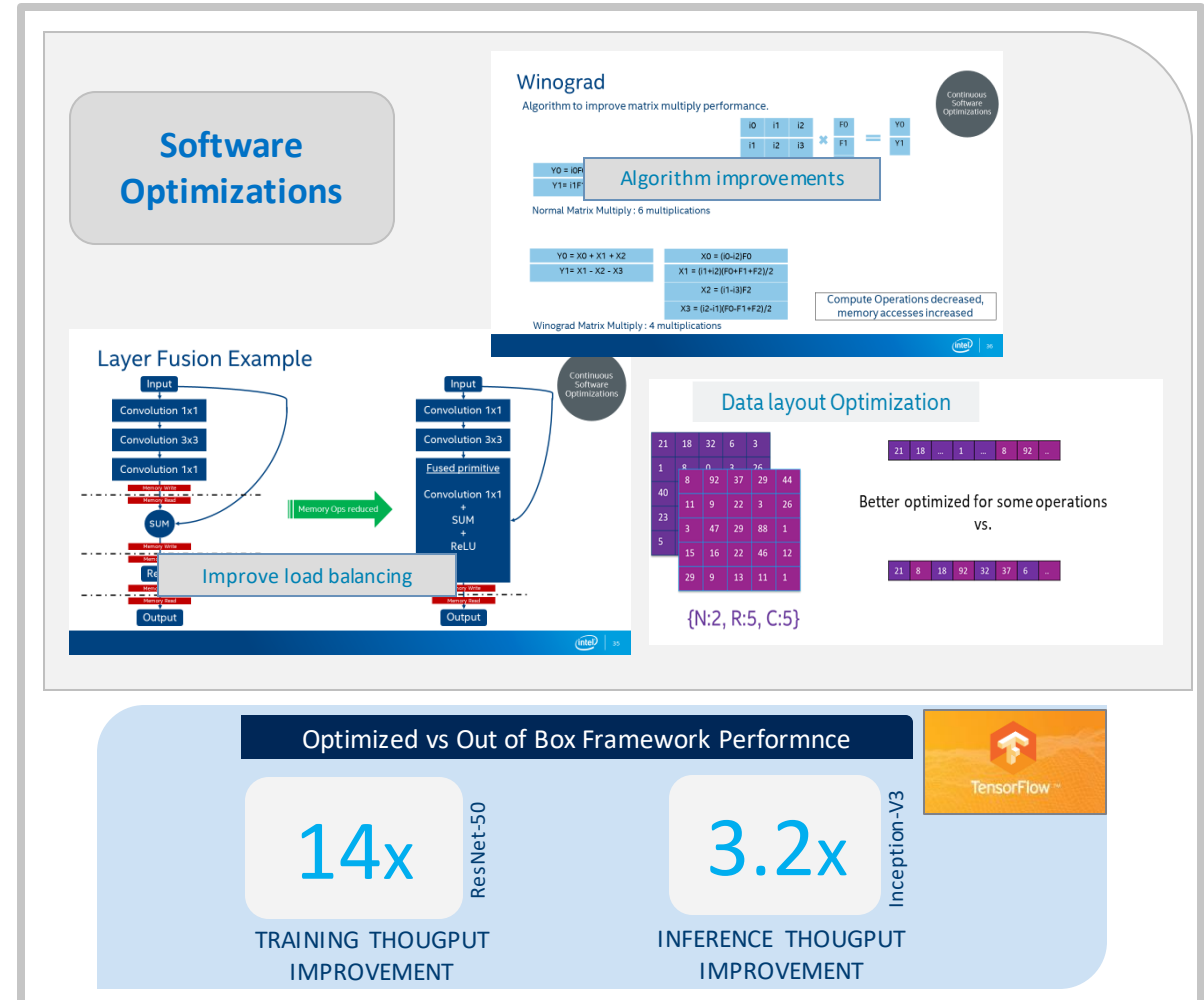
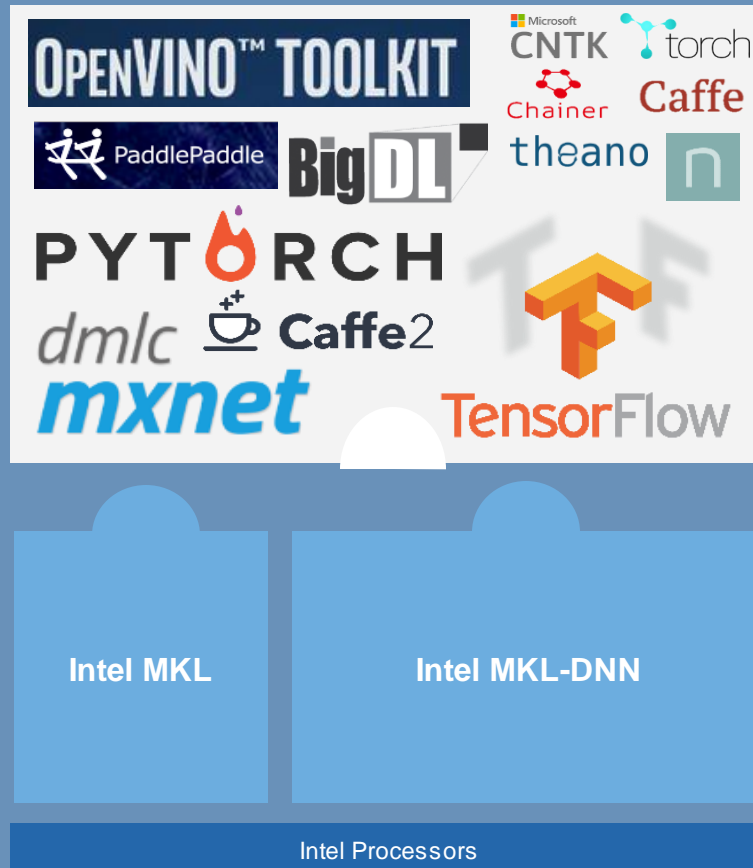
Connecting to external servers



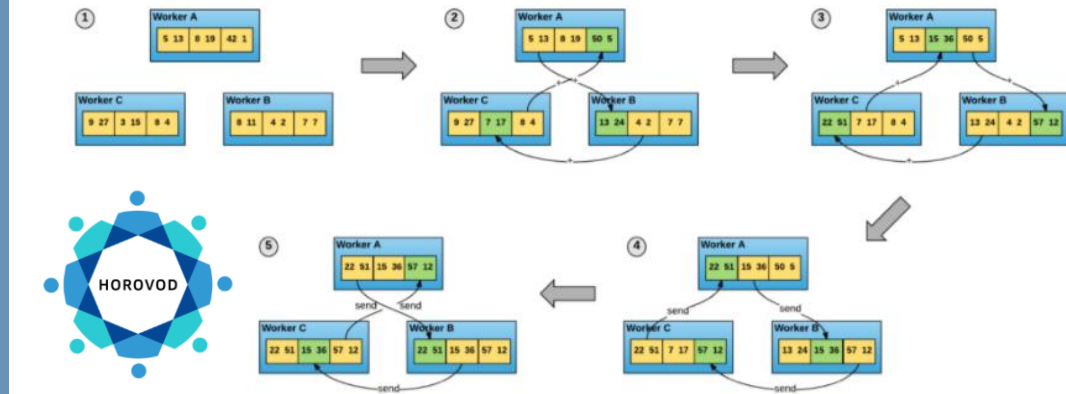
Build frameworks on systems without internet access

Intel Optimized Machine learning Frameworks

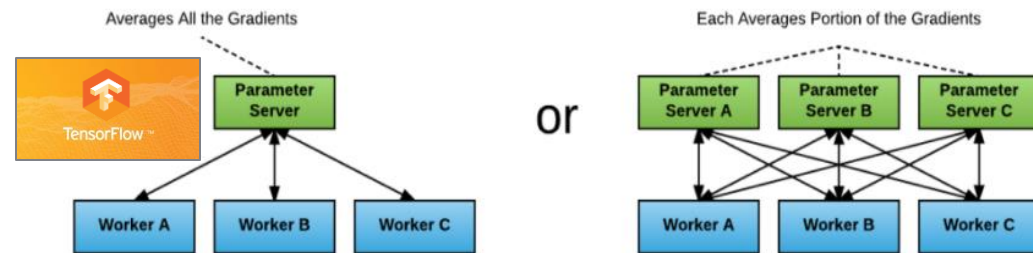
Intel AI Software Stack



Distributed Mechanisms

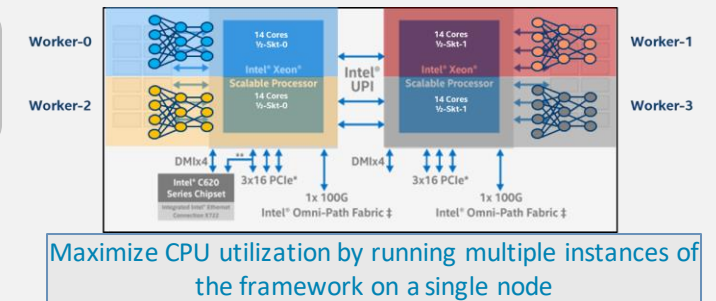


VS



System-level Optimizations

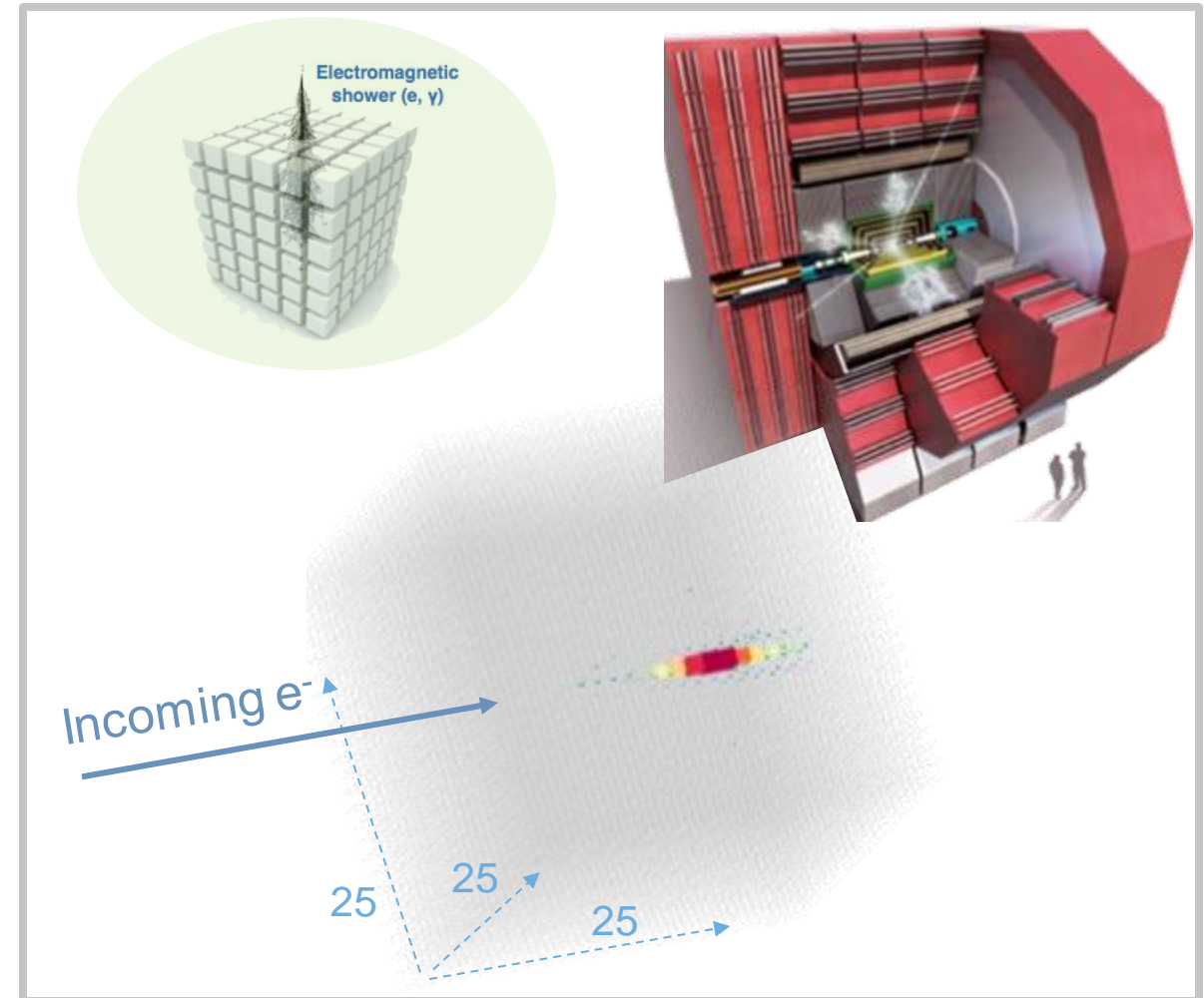
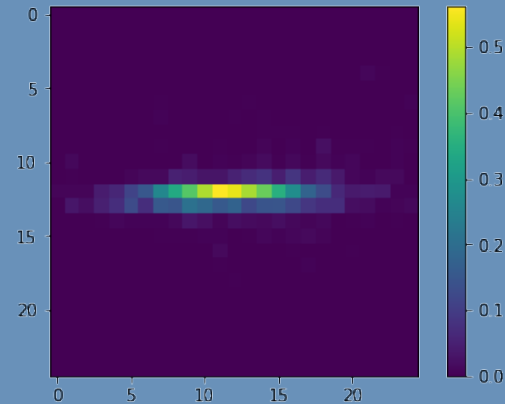
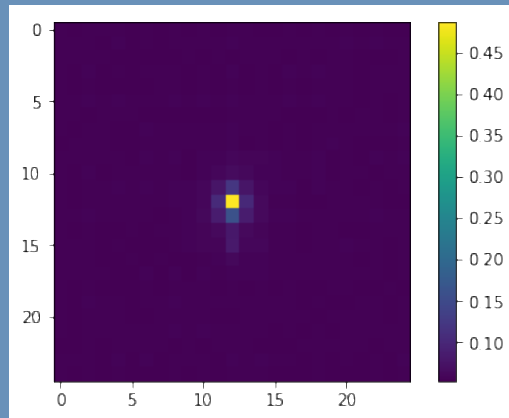
System-level
Optimizations



Interconnect Fabric (OPA or Ethernet)

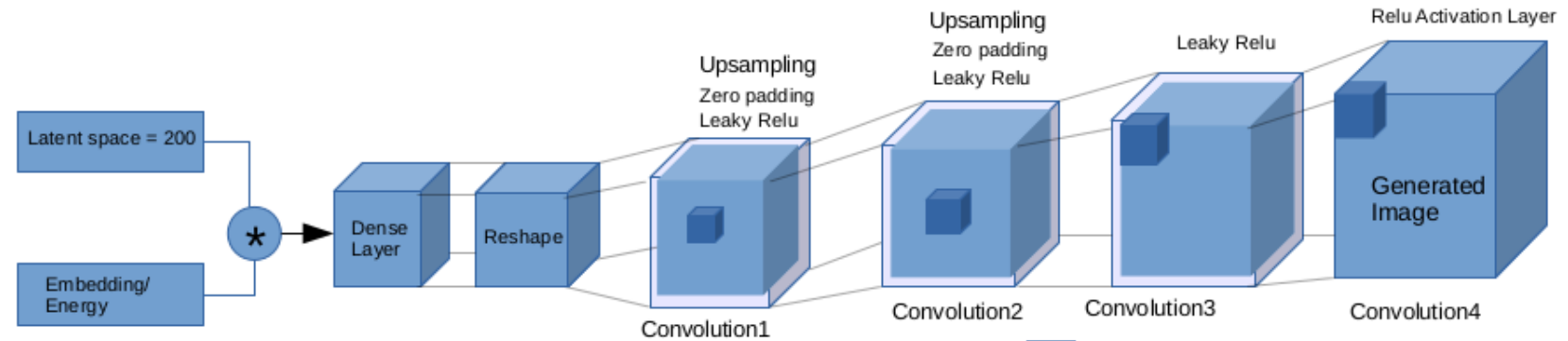


- CLIC Electromagnetic calorimeter
 - Sparse images
 - Highly segmented (pixelized)
 - Large dynamic range
- Segmentation is critical for particle identification and energy determination

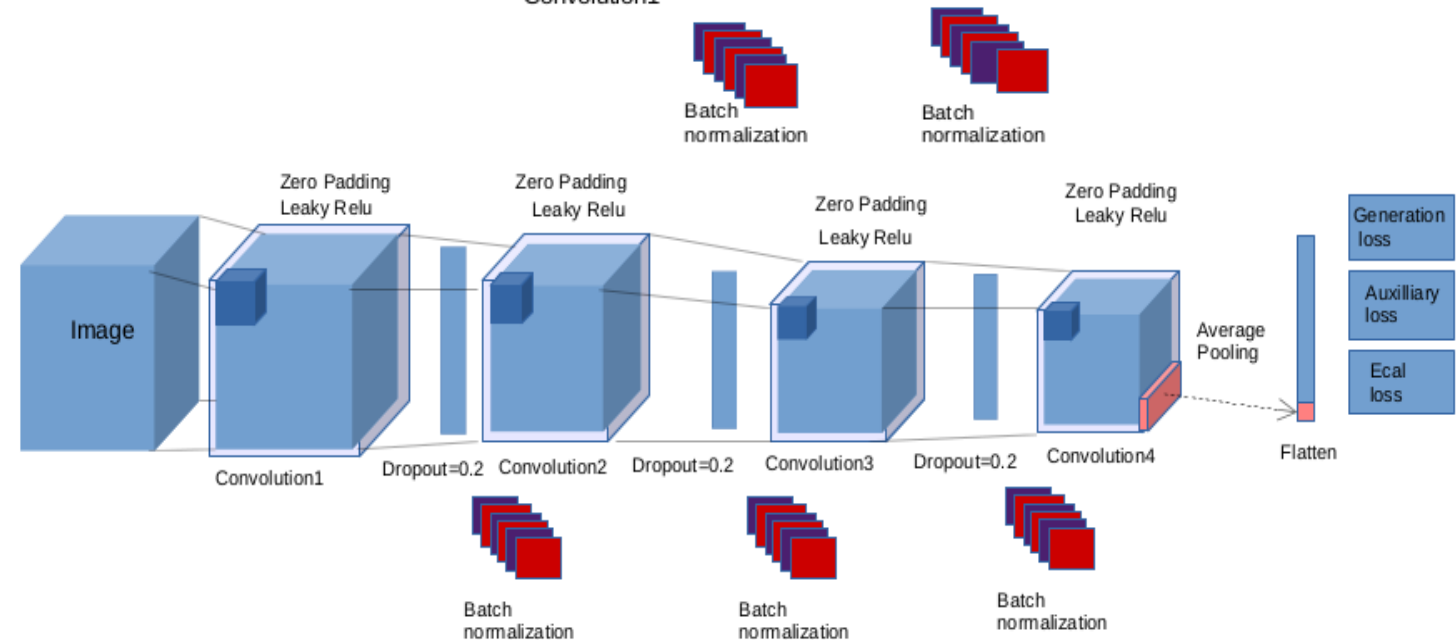


Future 3D Convolutional GAN

Generator



Discriminator



~1M parameters

Total model Size: 3.8MB

Charliecloud Containers in HPC



- Easy to install
- Charliecloud was developed to be run on highly secure HPC systems at US government labs
- Charliecloud runs entirely under the User ID
- Ability to run legacy design flows in containers
- Low overhead and ~ 800 lines of code
- LRZ deploys Charliecloud via Spack
- Charliecloud is available in the module system at LRZ



Mechanism for deploying AI at LRZ

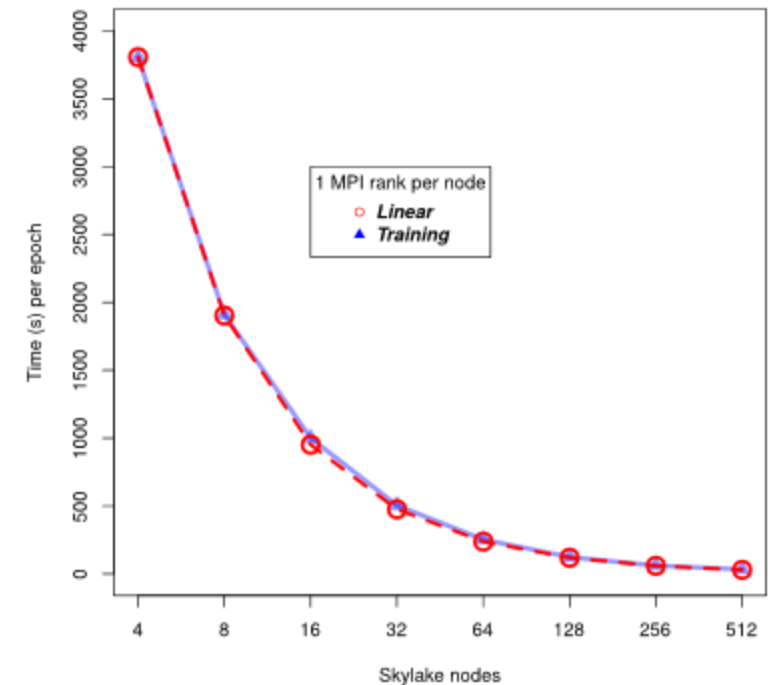
- Download the Intel optimized TensorFlow Docker Image (intelaipg Dockerhub)
- Modify the Linux Docker image for HPC
- Modify Python to enable distributed TensorFlow execution
- Copy the training data and execution scripts to the modified Docker image
- Convert to a Charliecloud UDSS and copy the file to the HPC system
- Load the Charlicloud module
- Execute on SuperMUC-NG via Slurm

Distributed TensorFlow Results LRZ SNG 1 MPI Rank per Node

1 MPI rank & 48 OpenMP threads per node

Intel Skylake Platinum Xeon 8174

Nodes	Training Time(S) per Epoch	Linear Time(S) per Epoch	Scaling Efficiency
4	3806	3806	-
8	1910	1903	99.6%
16	1001	951.5	95.1%
32	504	475.75	94.4%
64	253	237.87	94%
128	124	118.93	95.9%
256	61	59.46	97.5%
512	33	29.73	90.1%



Throughput Overheads

Benchmark	Free System Memory with Charliecloud (GB)	Free System Memory without Charliecloud (GB)
AlexNet with cifar	331.29	331.33
ResNet50 with imagenet	324.47	324.89

Memory Overheads

Benchmark	Free System Memory with Charliecloud (GB)	Free System Memory without Charliecloud (GB)
AlexNet with cifar	331.29	331.33
ResNet50 with imagenet	324.47	324.89

3DGAN Execution on SNG with ≥ 2 MPI Ranks per Node

Hyperthreading, 48 OpenMP threads per MPI task & 2 MPI ranks per node Intel Skylake Platinum Xeon 8174, Standard horovod + MPI

Nodes	Training Time(S) per Epoch	Linear Time(S) per Epoch	Scaling Efficiency
4	2302	2302	-
8	1238	1151	93%
16	638	575.5	90.2%
32	323	287.75	89.1%
64	164	143.87	87.7%
128	88	79.93	81.8%
256	47	35.96	76.6%
512	25	17.98	71.9%

12 OpenMP threads per MPI task & 4 MPI ranks per node Intel Skylake Platinum Xeon 8174, Standard horovod + MPI

Nodes	Training Time(S) per Epoch	Linear Time(S) per Epoch	Scaling Efficiency
4	959	959	-
8	507	479.5	94.6%
16	264	239.75	90.8%
32	137	119.87	87.5%
64	72	59.93	83.3%
128	39	29.96	76.8%
256	21	14.98	71.4%
512	12	7.49	62.5%

3DGAN Execution on SNG using Intel MPI from the System

Mounted the LRZ file system into the container and used the system version of Intel MPI.

```
ch-run -b /lrz/sys/./lrz/sys/ -w container_name – python /location/in/container/training_script.py
```

Nodes	Training Time(S) per Epoch	Linear Time(S) per Epoch	Scaling Efficiency
4	907.26	907.26	-
8	479.52	453.63	94.6%
16	244.42	226.82	92.8%
32	124.22	113.41	91.3%
64	62.24	56.70	91.1%
128	31.22	28.35	90.8%
256	15.63	14.18	90.7%
512	7.84	7.09	90.4%
768	3.94	3.54	89.9%

Nodes	Measured Performance petaflops	Percentage of Theoretical Peak
4	0.01099	66.17%
8	0.02199	66.21%
16	0.04450	67.01%
32	0.08386	63.14%
64	0.17313	65.17%
128	0.31878	67.60%
256	0.70547	66.39%
512	1.39412	65.60%
768	2.08143	65.29%

Beyond 768 nodes the constant set up costs become the dominant factor.

2020



General HPC Docker image

Verified recipes to enable the deployment of AI on HPC systems using secure containers

Current Users

DLR German Aerospace Center, PyTorch, inferencing of high resolution satellite images on SuperMUC-NG

New Users & Infrastructure

More users; cloud providers; additional ML, AI & data analytics software; different operational modes.

- **High Performance AI (HPAI)**
- Github repository <https://github.com/DavidBrayford/HPAI>
- **Online Documentation**
- <https://docs.docker.com/>
- <https://hpc.github.io/charliecloud/tutorial.html>
- **Contacts**
- brayford@lrz.de (via LinkedIn)



Demonstration: Using Charliecloud to Deploy a Containerized TensorFlow Workflow on a HPC System in the Cloud with the OpenHPC Software Stack.

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- **Acknowledgements**

- Adrian Reber (RedHat)
- Chris Downing (Amazon)
- Sarosh Quraishi (Intel)
- OpenHPC (<https://openhpc.community/>)



- Install Docker on your local system.
- Download Docker images from DockerHub:
 - `sudo docker pull image`
- Build your own Docker image:
 - `sudo docker build -t my_image ./Dockerfile`
- View images:
 - `sudo docker images`
- Run a docker image:
 - `sudo docker run -itd my_image`



- List all active Docker images:
 - `sudo docker ps -a`
- Start a bash shell in the Docker container:
 - `sudo docker exec -it <container_ID> /bin/bash`
- Install software in the container:
 - `apt-get install`
 - `pip install`
 - `make`
- Exit out of the container:
 - `exit`



- List all active Docker images:
 - `sudo docker ps -a`
- Save the modified images:
 - `sudo docker commit <CONTAINER_ID> new_container_name`





- Build Docker image using Charliecloud:
 - `ch-build -t hello .`
- Build the Charliecloud compressed flat file:
 - `sudo ch-builder2tar <Docker_file_name> /dir/to/store/`
- Copy the tar.gz file to the HPC system:
- Unpack the Charliecloud tar.gz image:
 - `ch-tar2dir Docker_file_name.tar.gz /foo/bar/`



- Load the Charliecloud module:
- Execute the Charliecloud containerized command:
 - `ch-run -w <container_name> -- bash`
 - `ch-run -w <container_name> -- python /model/train.py`
 - `ch-run -b /lrz/sys/./lrz/sys/ -w <container_name> -- bash`
- Distributed execution line in a Slurm script:
 - `mpiexec -n $SLURM_NTASKS -ppn $SLURM_NTASKS_PER_NODE ch-run -b /lrz/sys/./lrz/sys/ -w ./container_name -- python /model/train.py`