Applied Containerization for Machine Learning

A Hands-on Guide to Running ML Workloads in HPC Environments

RCC Workshop Series

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Workshop Overview

- **Duration**: 2 hours (1 hour presentation, 1 hour hands-on)
- **Level**: Intermediate
- **Prerequisites**:
  - Basic programming knowledge
  - Linux CLI familiarity
  - Active RCC/cluster account
- **Repository**: GitHub

1. Introduction to Containerization in HPC

Why Containers for ML in HPC?

- **Dependency Management**:
  - Package complex ML software stacks with all dependencies (Python, CUDA, MPI, etc.).
  - Resolve version conflicts and avoid "dependency hell."
- **Portability**:
  - Run the same containerized environment on any cluster, cloud, or laptop.
  - "Build once, run anywhere" across diverse HPC systems.
- **Security & Isolation**:
  - Restrict software to a controlled environment, reducing risk to the host system.
  - Run untrusted or experimental code safely.
- **Collaboration**:
  - Share containers with colleagues for consistent results.
  - Simplifies onboarding and reproducibility in research teams.

Why Containers for ML in HPC? (Cont.)

- **Reproducibility**:
  - Capture the exact software environment for consistent, repeatable results.
  - Essential for scientific research and peer review.
- **Performance**:
  - Near-native speed with minimal overhead; direct access to GPUs and high-speed interconnects.
  - Optimized images can boost job throughput and resource utilization.
- **Scalability**:
  - Easily scale workloads from a laptop to thousands of nodes.
  - Integrate seamlessly with schedulers like SLURM for large ML jobs.

> [!callout]
> **Summary: Why Containers?**
>
> - Solve dependency and environment headaches
> - Speed up onboarding and collaboration
> - Achieve reproducible, portable, and secure ML workflows
> - Unlock scalable, high-performance computing for modern research

Container Basics: What is a Container?

- An isolated, encapsulated user-space instance.
- Runs on a shared OS kernel but has its own:
    - Filesystem
    - Processes
    - Network interfaces (can be configured)
- Lightweight compared to Virtual Machines (VMs) as they don't require a full guest OS.

Containers vs Virtual Machines (VMs)

Aspect	Virtual Machine (VM)	Container
Isolation	Full (hardware/emulated)	Process/user-space
Guest OS	Full OS per VM	Shares host OS kernel
Startup	Slow (minutes)	Fast (seconds)
Resource Use	Heavy (more RAM/CPU)	Lightweight (minimal overhead)
Portability	Hypervisor-dependent	"Build once, run anywhere"
Use Case	Legacy apps, OS-level isolation	ML, microservices, HPC, CI/CD

Container vs VM

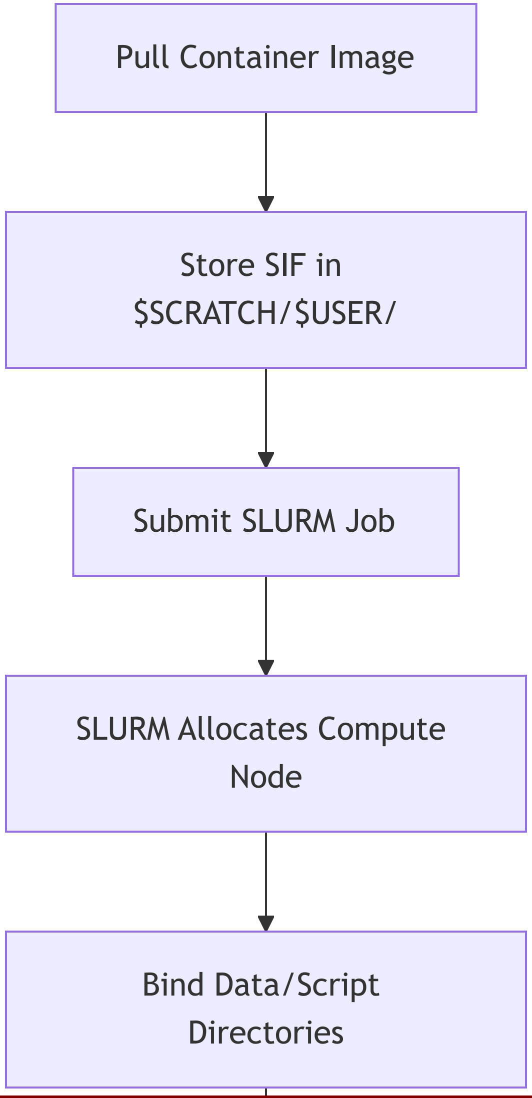
Image source: apptainer.org

Key Takeaways:

Container Basics: Key Components

- **Container Images**:
  - Read-only templates used to create containers.
  - Contain application code, libraries, dependencies, and metadata.
  - Examples: Docker Hub images, SIF files (Apptainer).
- **Runtime Environments**:
  - Software that runs containers (e.g., Apptainer, Docker, Charliecloud).
  - Manages container lifecycle, isolation, and resource allocation.

Containerization Workflow in HPC



Container Basics: Key Components (Cont.)

- **Mount Points for Data (Bind Mounts)**:
    - Mechanism to make host directories/files accessible inside the container.
    - Essential for accessing datasets, scripts, and output directories.
- **Resource Allocation**:
    - Containers share host resources (CPU, memory, GPUs).
    - HPC schedulers (like SLURM) manage resource allocation for containerized jobs.

2. Apptainer (formerly Singularity) Introduction

Apptainer & Singularity: A Quick Note

- **Apptainer** is the direct successor to **Singularity**.
- You might see `singularity` used in older documentation or as the module name on some HPC systems.
- Commands are largely interchangeable (e.g., `singularity pull` vs. `apptainer pull`).
- This workshop uses modern `apptainer` commands.

Hands-on with Apptainer (Introduction)

(This section introduces Apptainer. The actual hands-on will follow in the next hour.)

Apptainer: Getting Started

```
# Load Apptainer module (on HPC systems)
module load apptainer

# Pull a PyTorch container image from Docker Hub
apptainer pull docker://pytorch/pytorch:latest
# This creates a .sif file (e.g., pytorch_latest.sif)
```

- **SIF (Singularity Image Format)**: Apptainer's default, optimized image format.
- **Storage Tip**: For large images, consider pulling/storing them in your scratch directory.
  - On Midway3: `$SCRATCH/$USER/sif_files/` (where `$SCRATCH` is `/scratch/midway3`).
  - Check your system's recommended scratch location.

Apptainer: Basic Commands

- **Interactive Shell**:

```
# Start an interactive shell inside the container
# --nv enables NVIDIA GPU access
apptainer shell --nv pytorch_latest.sif
```

- **Run a Python Script**:

```
# Execute a command (e.g., a Python script) inside the container
apptainer exec --nv pytorch_latest.sif python my_script.py
```

Apptainer: Basic Commands (Cont.)

- **Bind Data Directories**:

```
# Run a container and mount /data on host to /data in container
apptainer run --nv --bind /path/on/host:/path/in/container pytorch_latest.sif

# Example: Mount current working directory ($PWD) to /mnt inside container
apptainer run --nv --bind $PWD:/mnt pytorch_latest.sif
```

  - `apptainer run` executes the default runscript defined in the image (if any).
  - Binding `$PWD` (current working directory) is very useful for accessing your scripts and local data within the container.

Apptainer: Key Features

- **GPU Support**: `--nv` flag for seamless NVIDIA GPU access.
- **Data Binding**: Mount host directories inside the container (`--bind` or `-B`).
  - Crucial for accessing datasets and saving results.
- **Environment Variables**: Pass configuration through the container boundary.
  - Apptainer typically inherits host environment; can be controlled.
- **MPI Support**: Run distributed workloads across nodes.
  - Often requires MPI compatibility between host and container.

3. Charliecloud Overview

Charliecloud vs. Apptainer

Feature	Apptainer (formerly Singularity)	Charliecloud
Security Model	set-UID (optional), rootless execution	Fully unprivileged (user namespaces)
Image Format	SIF (optimized, single file)	Directory trees, SquashFS
Build Process	`.def` files, build from Docker Hub	Direct Dockerfile support
Best Use Case	Complex ML workflows, ease of use	Security-critical environments, Docker familiarity

Charliecloud: Key Benefits

- **Minimal Attack Surface**:
  - Fully unprivileged operation using user namespaces.
  - Reduces security risks on shared HPC systems.
- **Docker Compatibility**:
  - Direct use of Dockerfiles for building images (`ch-convert`).
  - Easier transition for users familiar with Docker.
- **Lightweight & Simple**:
  - Simpler architecture and deployment compared to some other runtimes.
  - Focuses on core containerization features.

4. Practical ML Container Deployment (Examples)

TensorFlow Example with Apptainer

```
# 1. Pull TensorFlow container (GPU version)
apptainer pull docker://tensorflow/tensorflow:latest-gpu

# 2. Run training script
# Assumes train.py and data are accessible via bind mounts
apptainer exec --nv tensorflow_latest-gpu.sif \
  python /path/to/your/train.py --data /path/to/data
```

- `--nv` : Enables NVIDIA GPU access.
- Bind mount your script directory and dataset directory.

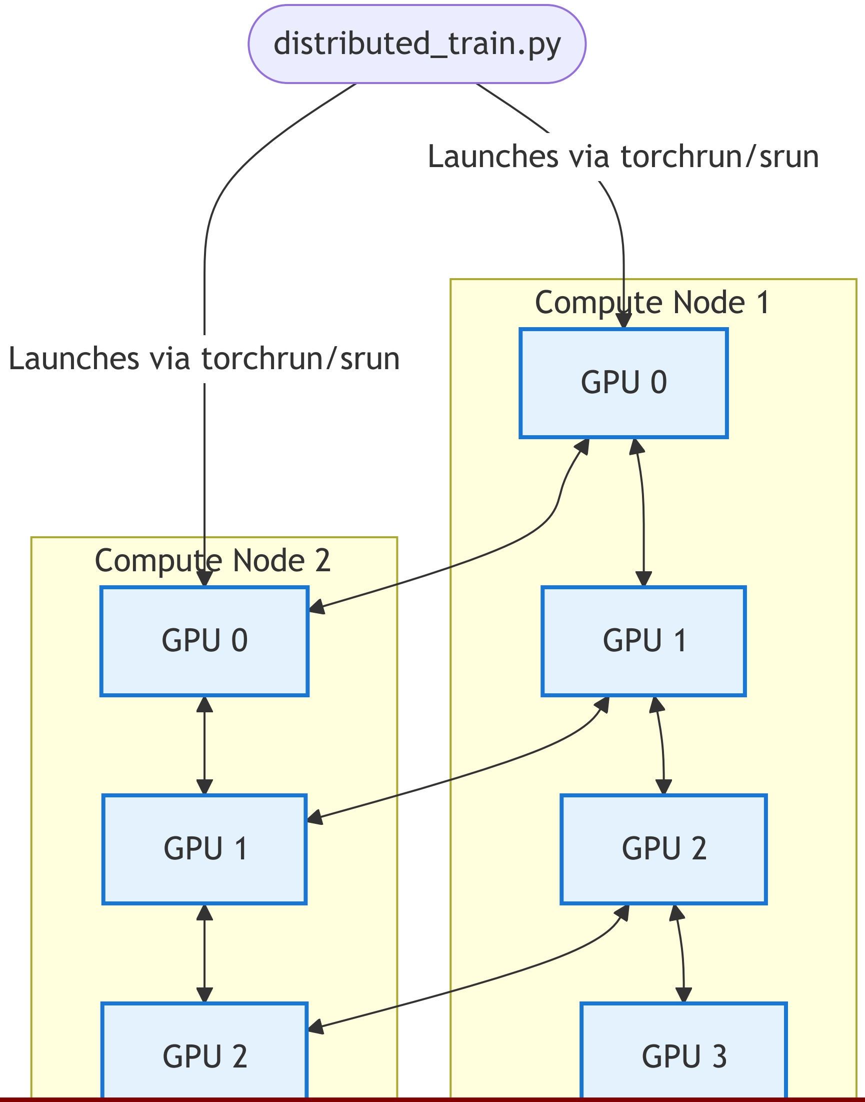
PyTorch Example with Apptainer (Multi-GPU)

```
# Pull PyTorch container (if not already done)
# apptainer pull docker://pytorch/pytorch:latest

# Multi-GPU training using torchrun (formerly torch.distributed.launch)
apptainer exec --nv pytorch_latest.sif \
  torchrun --nproc_per_node=4 /path/to/your/distributed_train.py
```

- Assumes `distributed_train.py` is set up for PyTorch DDP.
- `--nproc_per_node` should match available GPUs.

Distributed Training Topology (Multi-Node/Multi-GPU)



5. SLURM Integration (Brief Overview)

SLURM Job Lifecycle

Kroki

Convert **plain text** diagrams
to **images** !

SLURM: Single-Node Job Example

```
#!/bin/bash
#SBATCH --job-name=ml-training
#SBATCH --gres=gpu:1          # Request 1 GPU
#SBATCH --partition=gpu       # Specify GPU partition
#SBATCH --cpus-per-task=4     # Request 4 CPUs
#SBATCH --mem=16G             # Request 16GB RAM

# Load Apptainer module
module load apptainer

# Define paths (replace with your actual paths)
CONTAINER_IMAGE=/path/to/pytorch_latest.sif
SCRIPT_DIR=/path/to/your/scripts
DATA_DIR=/path/to/your/data
OUTPUT_DIR=/path/to/your/output

# Ensure output directory exists
mkdir -p $OUTPUT_DIR

# Run the containerized job
apptainer run --nv \
  --bind $SCRIPT_DIR:/scripts \
  --bind $DATA_DIR:/data \
  --bind $OUTPUT_DIR:/output \
  $CONTAINER_IMAGE python /scripts/train.py --data_dir /data --output_dir /output
```

SLURM: Multi-Node Distributed Training Example

```
#!/bin/bash
#SBATCH --job-name=dist-ml-train
#SBATCH --nodes=2                # Request 2 nodes
#SBATCH --ntasks-per-node=4      # 4 tasks (processes) per node
#SBATCH --gres=gpu:4             # 4 GPUs per node (total 8 GPUs)
#SBATCH --cpus-per-task=2        # 2 CPUs per task
#SBATCH --partition=gpu-multi    # Example partition for multi-node GPU jobs

module load apptainer

CONTAINER_IMAGE=/path/to/your/ml_container.sif
# Script should handle distributed setup (e.g., using torchrun environment variables)

# srun will launch 'ntasks-per-node' copies of this command on each node
srun apptainer run --nv \
  --bind /path/to/data:/data \
  $CONTAINER_IMAGE \
  torchrun --nnodes=$SLURM_NNODES \
           --nproc_per_node=$SLURM_NTASKS_PER_NODE \
           --rdzv_id=$SLURM_JOB_ID \
           --rdzv_backend=c10d \
           --rdzv_endpoint=$SLURM_STEP_NODELIST:29500 \
           /path/to/your/distributed_train.py
```

6. Best Practices

Best Practices: Container Management

- **Version Control & Tagging**:
  - Tag containers with specific versions (e.g., `myimage:1.0.0`, `myimage:latest-cuda11.8`).
  - Store definition files (`.def`, Dockerfiles) in version control (Git).
- **Data Management**:
  - Use bind mounts for large datasets to avoid including them in images.
  - Keep images small and focused on software environment.
- **Resource Allocation**:
  - Match container resource needs to SLURM (or other scheduler) requests.
  - Avoid over-subscribing resources.

Best Practices: Performance Optimization

- **GPU Access**: Always use `--nv` (Apptainer) or equivalent for GPU workloads.
- **I/O Optimization**:
    - Bind fast storage for temporary files. On Midway3, compute nodes often have a high-throughput SSD directory at `$TEMP` (e.g., `/scratch/local/$USER/`) ideal for this.
    - For frequently accessed small files or datasets, consider staging them to such temporary storage.
    - Be mindful of I/O patterns within the container.
- **MPI Configuration**:
    - For multi-node MPI jobs, ensure compatibility between container MPI and host MPI (Hybrid model or Bind model).
    - Consult HPC center documentation for recommended MPI practices with containers.

Best Practices: Security Considerations

- **Unprivileged Execution**:
  - Run containers without root access whenever possible.
  - Apptainer runs as user by default. Charliecloud is designed for unprivileged execution.
- **Data Protection**:
  - Use appropriate bind mounts; be specific about what host paths are exposed.
  - Avoid overly broad mounts (e.g., binding `/`).
- **Resource Limits**:
  - Rely on the HPC scheduler (SLURM) to enforce resource limits (CPU, memory, GPU).
  - Containers operate within the cgroups/namespaces set by the scheduler.

7. Additional Resources

Resources: Documentation

- **Apptainer Official Documentation:**
  https://apptainer.org/docs/

Apptainer Logo

- **Charliecloud User Guide:**
  https://hpc.github.io/charliecloud/

Charliecloud Logo

- **Workshop Repository:**
  (Contains this presentation, examples, and hands-on materials)

Resources: Example Repositories & Further Learning

- **ML Framework Containers (Official Hubs):**
  - Docker Hub: https://hub.docker.com/

    (e.g., `pytorch/pytorch`, `tensorflow/tensorflow`)
  - NVIDIA NGC: https://ngc.nvidia.com/

    NVIDIA Logo
- **SLURM Integration Scripts:** Check your HPC center's documentation for specific examples.
- **Further Learning Topics:**
  - Advanced container building (multi-stage builds, custom base images)
  - Creating custom ML environments from scratch
  - Advanced distributed training patterns (e.g., with Horovod, DeepSpeed)

Key Takeaway

> **Containerization enables reproducible, portable, and efficient ML workflows in HPC environments.**

- Choose between **Apptainer** and **Charliecloud** based on your specific needs for:
  - Security model
  - Ease of use
  - Image format preferences
  - Integration requirements with existing Docker workflows

Q&A and Thank You!

Next: Hands-on Session!

References & Further Reading

- Apptainer Documentation
- Charliecloud User Guide
- Singularity/Apptainer on RCC
- Docker Documentation
- NVIDIA NGC Containers
- PyTorch Containers
- TensorFlow Containers
- SLURM Documentation
- HPC Best Practices
- Research Computing Center, UChicago

For more info, see the workshop repo: github.com/rcc-uchicago/hpc-ml-containers-workshop