Using Singularity Containers in Virtual Machines and HPC

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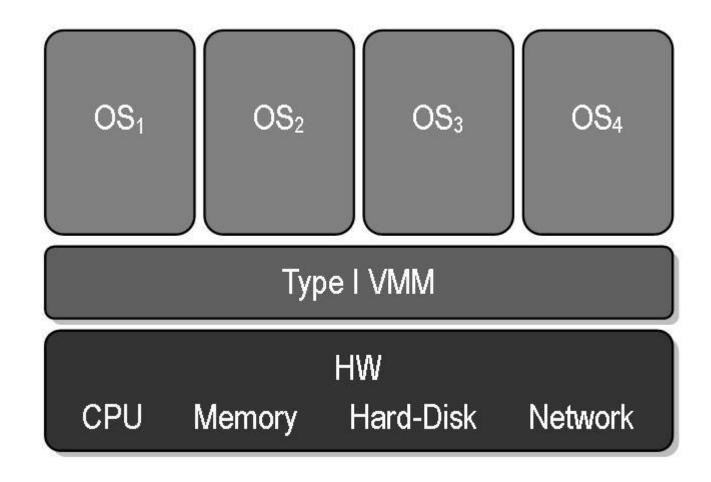
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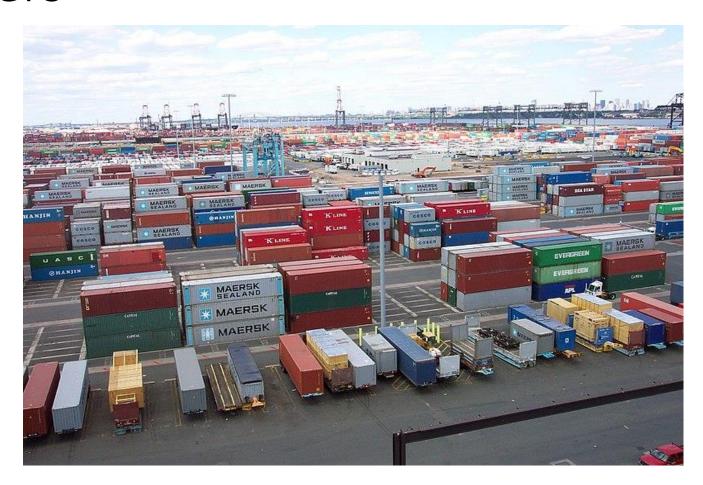


Virtualization





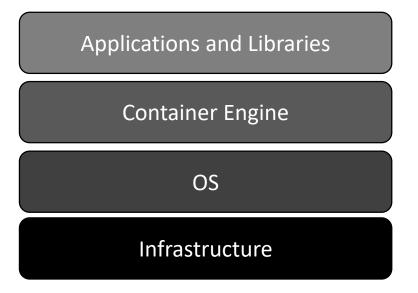








 Containers provide an additional layer of abstraction over virtualization.







 However, containers do not require virtual machines and can happily run on bare-metal.

 Lightweight compared to VMs in terms of memory and storage requirements.

• Increases portability of applications between datacenters, private clouds, and public clouds.





 Can provide a very customized environment specific to research use cases.

• Commercial software that requires old, obsolete libraries or operating system versions.

Bottom line: use containers where it makes sense to your workflow.





Why Use Containers

Reproducibility.

Portability.

• Isolation.

Avoiding complexity aka dependency hell.





Docker

• The advent of Docker resulted in widespread adoption of container technology.

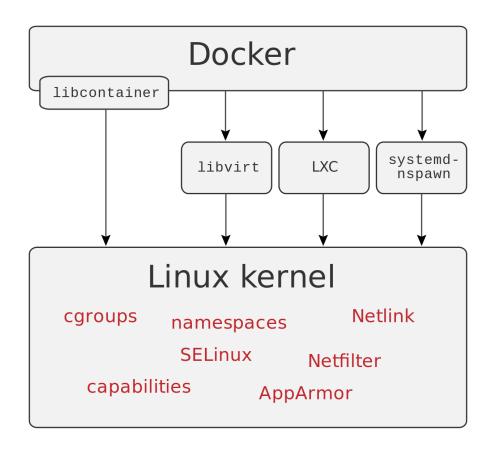
• Uses cgroups, kernel namespaces, OverlayFS (union filesystem) to allow containers to run in a singular Linux instance.

Very mature technology with ~7 million DockerHub users.





Docker







Singularity

 However, Docker is not a perfect fit in the advanced research computing space.

• The Docker daemon needs to run in the background with elevated privileges on every node (in the datacenter, private/public Cloud VM, etc.) that hosts containers.

 This is a security concern which can be mitigated but limits some features.





Singularity

 Docker also does not provide close integration with the standard HPC software stack such as MPI as well as schedulers and resource managers such as Slurm & PBS Pro.

 Container orchestration technologies such as Kubernetes can replicate some of the aforementioned functionality but the existing HPC stack is well entrenched and robust.





Singularity features

Was developed at Lawrence Berkeley National Lab specifically for HPC workloads.

No daemon process required; an executable is provided.

• The user permissions are maintained both in and outside the container; mitigates privilege escalation concerns.





Singularity features

 Support for both NVIDIA and AMD GPUs: pass the --nv or --rocm flag to the singularity command line.

 The host and container must have compatible versions of the GPU drivers and libraries installed.

 Support for MPI via a couple of different models: the hybrid model and the bind model.





Singularity features

- MPI via the Hybrid model:
 - Both the host and the container must have compatible versions of MPI libraries and runtime installed.
 - Simplifies the running of MPI applications (just run the singularity command after mpirun or srun if using Slurm).
- MPI via the Bind model:
 - Mount the MPI implementation of the host in the container.
- https://sylabs.io/guides/3.7/user-guide/mpi.html





What about performance?

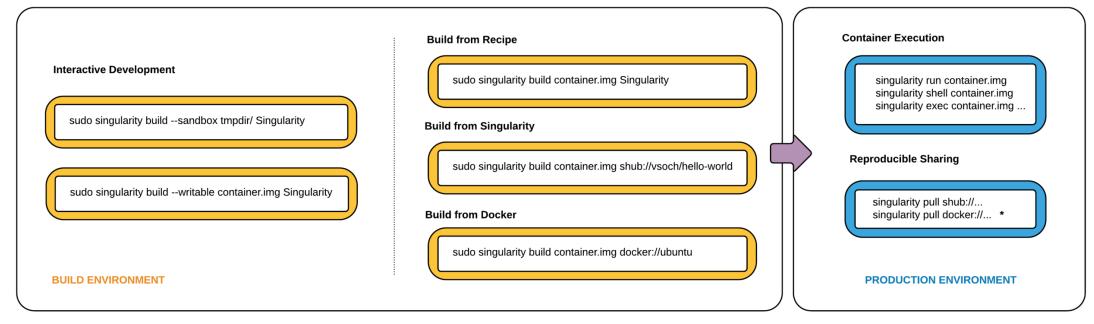
• On bare-metal, there is almost no performance gap between running in a Singularity container vs. directly on the host system.

- Papers benchmarking the performance of Singularity with various applications have found near native performance (within 1-2% performance) on bare-metal HPC systems:
 - https://ieeexplore.ieee.org/abstract/document/8855563
 - https://people.csail.mit.edu/dpaz/img/PDF/a065-LePaz.pdf





Typical workflow

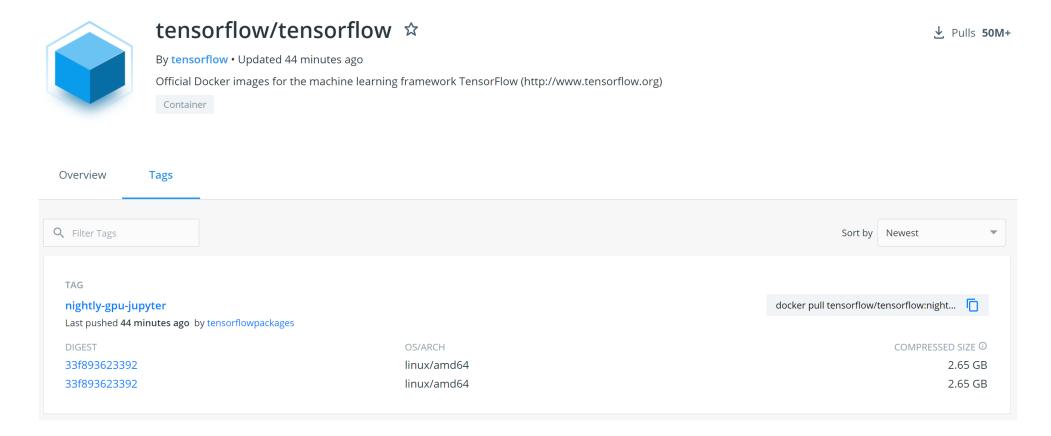


^{*} Docker construction from layers not guaranteed to replicate between pulls





DockerHub







Virtual Machines and HPC

 There is always going to be a performance impact of virtualization vs bare-metal.

 However, running containers on virtual machines and whole HPC clusters on VMs and Clouds is gaining popularity.

• Performance impacts can be mitigated by tuning VMs and underlying hardware (e.g. AWS Elastic Network/Fabric Adapter).





Deep Learning with Horovod

 Horovod is a distributed deep learning training framework for TensorFlow, Keras, PyTorch, and Apache MXNet.

https://github.com/horovod/horovod/

 The stated goal is to take single-GPU training and scale it across many GPUs in parallel.





Distributed training example

• Build singularity container using DockerHub:

singularity pull horovod.sif docker://horovod/horovod:sha-40cbc9b

Run on a single GPU:

singularity exec --nv horovod.sif horovodrun -np 1 -H localhost:1 python ~/pytorch_imagenet_resnet50.py --train-dir ~/tiny-imagenet-200/train --val-dir ~/tiny-imagenet-200/val





Distributed training example

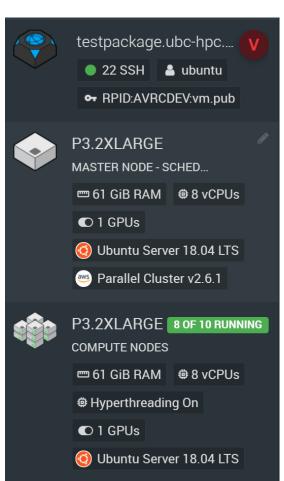
• Will run the example on a virtual HPC on AWS Parallel Cluster.

• 8 GPU nodes with V100 running on AWS EC2 P3 instances.

Slurm scheduler with Open MPI.







Distributed training example

```
2021-05-26 14:16:22.116100: I tensorflow/stream_executor/platform/default/dso_loader.cc:53] Successfully opened dynamic library libcudart.so.11.0
Train Epoch
               #7:
                     1%|
                                   3/391 [00:02<04:36, 1.40it/s, loss=3.4, accuracy=22.9]
Train Epoch
               #7:
                     2%||
                                  6/391 [00:03<02:58, 2.16it/s, loss=3.5, accuracy=21.4]
                    2%||
Train Epoch
               #7:
                                   9/391 [00:05<02:30, 2.53it/s, loss=3.46, accuracy=22]
Train Epoch
                    3%|
                                   12/391 [00:06<02:20, 2.69it/s, loss=3.46, accuracy=23.1]
               #7:
                    4%
                                   16/391 [00:07<02:15, 2.76it/s, loss=3.45, accuracy=23.1]
Train Epoch
               #7:
                    5%|
                                  | 19/391 [00:08<02:17, 2.71it/s, loss=3.45, accuracy=23.4]
Train Epoch
               #7:
                    6%|
                                   22/391 [00:09<02:18, 2.66it/s, loss=3.43, accuracy=23.7]
Train Epoch
                    6%
Train Epoch
                                  25/391 [00:11<02:16, 2.68it/s, loss=3.43, accuracy=23.6]
               #7: 7%||
Train Epoch
                                   28/391 [00:12<02:17, 2.64it/s, loss=3.44, accuracy=23.4]
                    8%
Train Epoch
                                    31/391 [00:13<02:14, 2.67it/s, loss=3.44, accuracy=23.6]
               #7:
                    9%
Train Epoch
               #7:
                                    35/391 [00:14<02:10, 2.74it/s, loss=3.43, accuracy=23.7]
               #7: 10%
                                    38/391 [00:15<02:10, 2.71it/s, loss=3.41, accuracy=24.1]
Train Epoch
Train Epoch
               #7: 10%
                                   41/391 [00:16<02:14, 2.60it/s, loss=3.4, accuracy=24.2]
Train Epoch
               #7: 11%||
                                    44/391 [00:18<02:21, 2.45it/s, loss=3.4, accuracy=24.3]
Train Epoch
               #7: 12%
                                    47/391 [00:19<02:12, 2.59it/s, loss=3.41, accuracy=24.2]
               #7: 13%
Train Epoch
                                    50/391 [00:20<02:17, 2.48it/s, loss=3.41, accuracy=24.2]
                                    54/391 [00:21<02:08, 2.62it/s, loss=3.4, accuracy=24.3]
               #7: 14%
Train Epoch
Train Epoch
               #7: 15%
                                    57/391 [00:23<02:10, 2.56it/s, loss=3.41, accuracy=24.2]
               #7: 15%
Train Epoch
                                   60/391 [00:24<02:09, 2.56it/s, loss=3.41, accuracy=24.3]
Train Epoch
               #7: 16%
                                   63/391 [00:25<02:08, 2.55it/s, loss=3.41, accuracy=24.2]
Train Epoch
               #7: 17%
                                    66/391 [00:26<02:04, 2.60it/s, loss=3.41, accuracy=24.2]
               #7: 18%
                                    69/391 [00:28<02:03, 2.60it/s, loss=3.41, accuracy=24.3]
Train Epoch
Train Epoch
               #7: 18%
                                    72/391 [00:29<01:57, 2.72it/s, loss=3.4, accuracy=24.3]
Train Epoch
               #7: 19%
                                    75/391 [00:30<01:53, 2.78it/s, loss=3.4, accuracy=24.4]
Train Epoch
               #7: 20%
                                   78/391 [00:31<01:46, 2.95it/s, loss=3.39, accuracy=24.3]
Train Epoch
               #7: 21%
                                   82/391 [00:32<01:50, 2.81it/s, loss=3.4, accuracy=24.3]
:51, 2.78it/s, loss=3.4, accuracy=24.3]
ubuntu@ip-10-255-2-228:~$
```





TTK Demo on HPC







References

 Singularity on Compute Canada HPC: https://docs.computecanada.ca/wiki/Singularity

• Sylabs.io Singularity Official User Guide: https://sylabs.io/guides/3.7/user-guide/

 Westgrid YouTube channel: https://www.youtube.com/channel/UCfgds4Qf7VFOv4ORRvFFmhw





Attributions

- https://en.wikipedia.org/wiki/Intermodal container#/media/File:Line3174 Shipping Containers at the terminal at Port Elizabeth, New Jersey NOAA.jpg
- https://commons.wikimedia.org/wiki/File:VMM-Type1.JPG
- https://en.wikipedia.org/wiki/Docker (software)#/media/File:Docker-linux-interfaces.svg
- http://singularity.lbl.gov/assets/img/diagram/singularity-2.4-flow.png