Docker for Machine Learning!

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DGTL-BRKPRG-2438





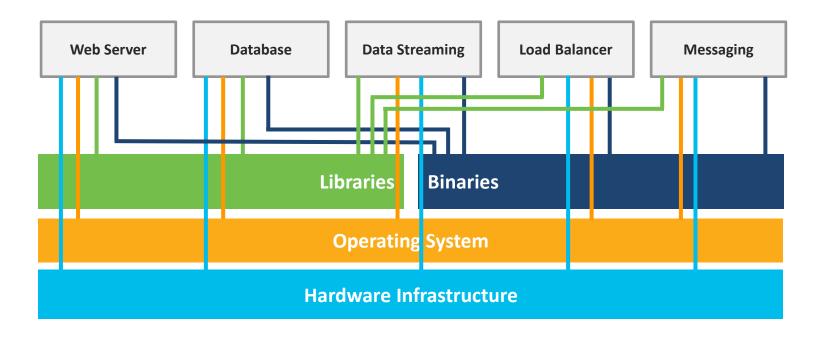
Agenda

- Machine Learning Workflows using Docker Containers
 - Docker basics
 - Networking and storage options in Docker
- Docker during machine learning model development
 - Building Docker image for a simple ML problem
 - Initialize and running container
- Deploy Machine Learning Models at Edge using Docker
- Docker Containers with GPU Support
 - Cisco UCS GPU enabled platforms: C480 ML M5, Cisco UCS C220/C240 M5
 - Setting up the platforms to support Docker environment with GPU support
 - Downloading and running Tensorflow containers
- Cisco Converged Infrastructure Solutions for AI/ML
 - FlexPod and FlashStack AI/ML solutions
 - GPU support in the VMware environments NVIDIA vComputeServer



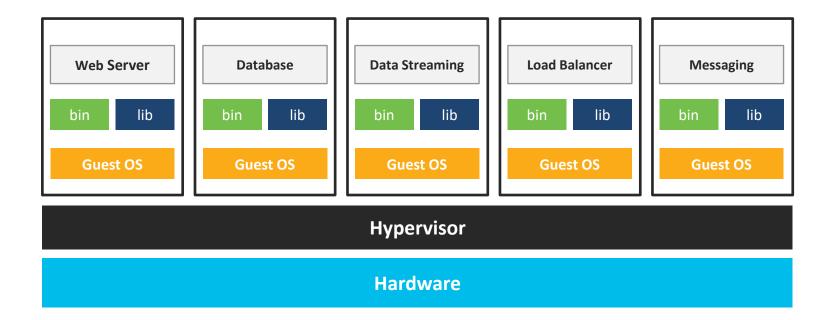


Deployments on Physical Infrastructure



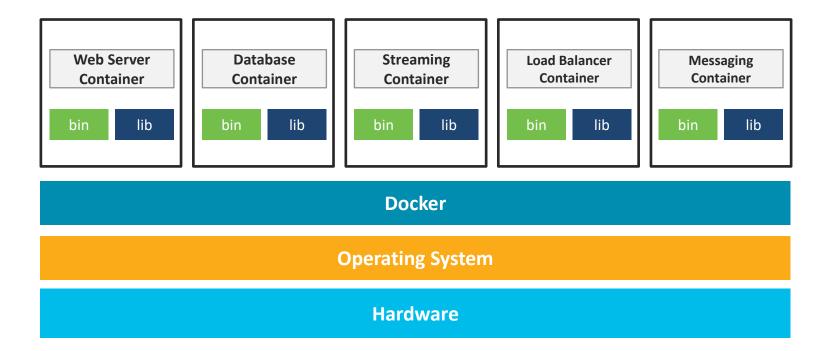


Deployment on Virtual Machine





Application deployment with Container





What is Docker ??

Docker allows us to package and run applications in an isolated environment

Develop and share layered applications

Package code + its dependencies to enable application to run in an isolated

Share the same Operating System Kernel

Uses kernel features: namespaces and cgroups

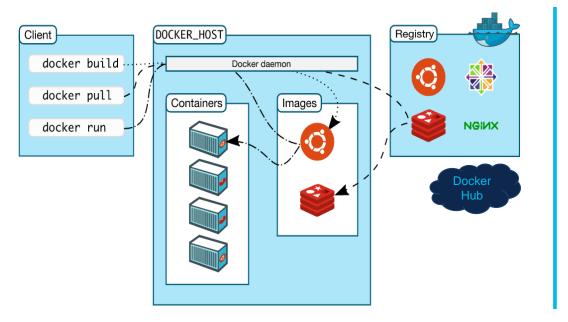


"By 2022, more than 75% of global organizations will be running containerized applications in production, which is a significant increase from fewer than 30% today"

Gartner



Architecture



Docker Daemon

Daemon (dockerd) which interacts with OS and performs all kind of services

Docker Client

CLI tool to interact with Daemon

Image

Is the application package

Container

Running instance of image

Registry

Repository of images Default: Docker Hub

Analogy

Object Oriented paradigm



Why containerize ML workflow?

Reproduce experiments easily!

Solves -- it works on my machine problem!

Reduced Complexity to develop and deploy

Easy sharing - No complex software dependencies.

> Dev -> Test -> Production easier and faster

Easier to clear data in large scale

Speed.... Speed.... Speed....



10

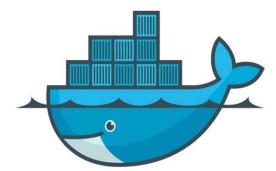


Applications



Cloud











Data Center





Demo -1

Docker during ML Model Development



Machine learning Workflow Summary

Data Infrastructure

Prepare Data

Train a Model

Evaluate the Model

Deploy, Inference & Improve

Data Infrastructure



ML/DL Framework / Infrastructure

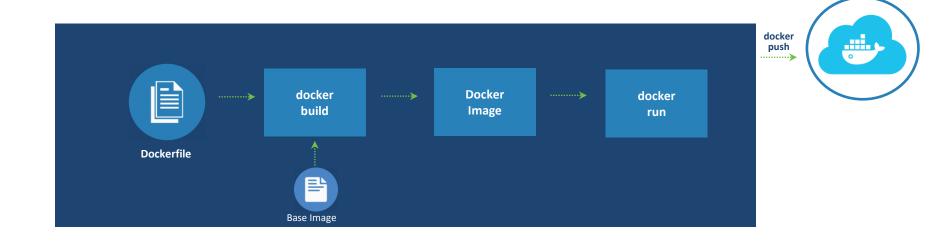


Inferencing & Ingestion End Point





Docker – Build, run and upload process





Dockerfile

```
FROM
         python:latest
        maintainer="Paniraj Koppa <pkoppa@cisco.com>" \
LABEL
        description="Docker for machine learning demonstration Cisco Live!"
RUN
        pip --no-cache-dir install \
           pandas==0.24.2 \
           jupyter \
           seaborn==0.9.0 \
           matplotlib==3.0.3 \
           missingno==0.4.1 \
           numpy==1.16.3 \
           sklearn
WORKDIR /ml_space
EXPOSE 8888
COPY
        titanic.ipynb titanic.csv /ml space
        ["jupyter", "notebook", "--ip='0.0.0.0'", "--port=8888", "--no-browser", "--allow-root"]
CMD
```



Summary of Commands

Format of the command

\$ docker <management_commands> <commands> <option> <image_name>

Samples

- \$ docker container run -d --rm -p 4321:8888 --name my_trial ml_trials
- \$ docker image Is
- \$ docker image inspect ml_trials
- \$ docker container Is
- \$ docker container logs my_trial
- \$ docker container inspect my_trial
- \$ docker container exec -it my_trial bash



Sharing your research

Step 1: You build the image

\$ docker image build -t ml_trials .

Step 2: You "push" it to Docker Hub

- \$ docker login
- \$ docker image tag ml_trials pkoppa/ml_trials
- \$ docker image push pkoppa/ml_trials

Step 3: Others will "pull" from Docker Hub

\$ docker image pull pkoppa/ml_trials

Step 4: Running a container

docker container run -d --rm -p 4321:8888 --name my_trial ml_trials



Demo - 2

ML@edge!

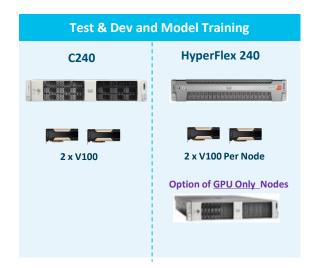


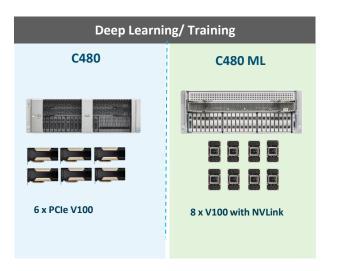
GitHub Repo:
https://github.com/pkoppa/docker_for_ml





Cisco AI/ML Compute Portfolio – Addressing All Aspect







Unified Management







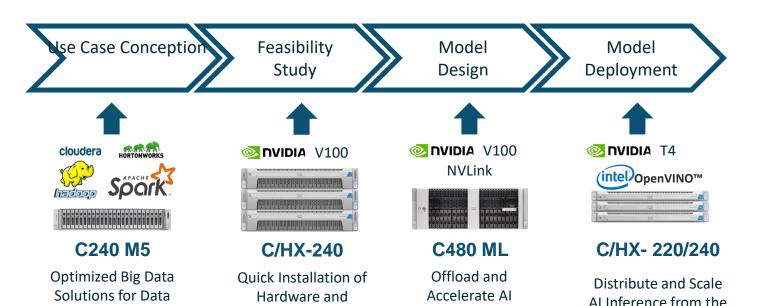




Simplified Management, Customer Choice, Cisco Validated Design



Cisco Portfolio Alignment With Deployment Lifecycle



Software for AL

Exploration and

Experimentation



Collection and

Preparation

Training at Scale with

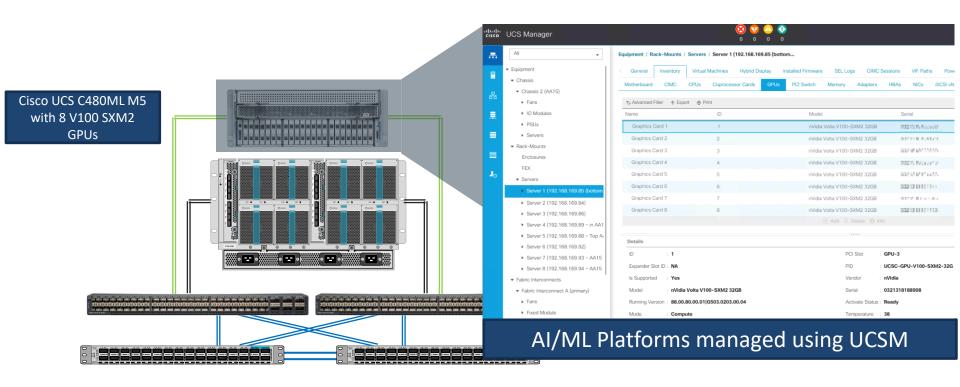
Performance

Optimized Systems

Data Center to the

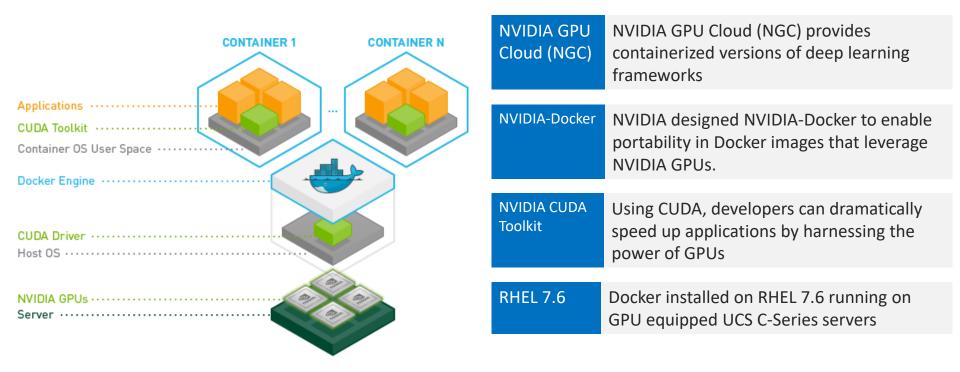
Edge

Unified Management for Cisco UCS Platforms





AI/ML – Software and Workload





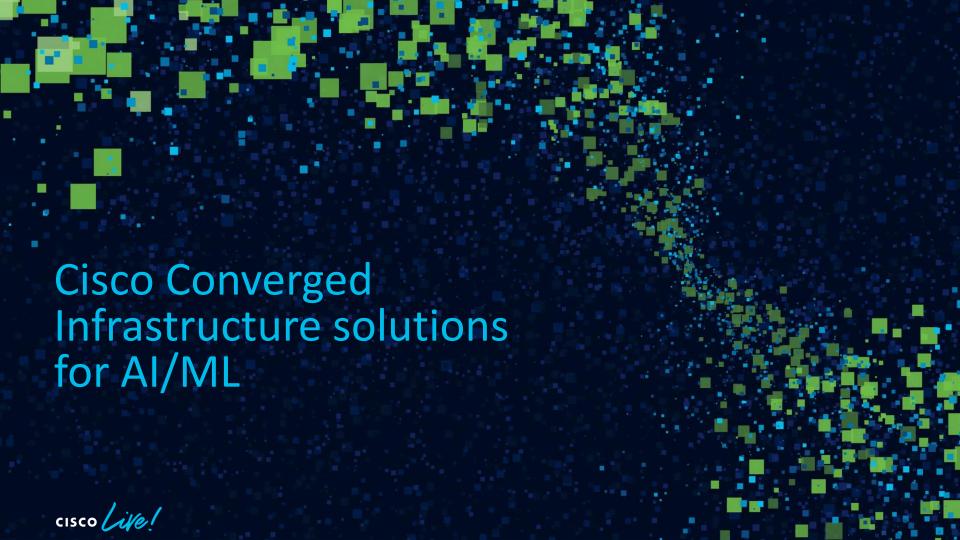
NGC Containers for AI/ML

- Eliminate time consuming complex builds and simply pull and run the NVIDIA GPU enabled AI/ML frameworks
- Support multi-GPU and multi-Node systems for scale up and scale out environments
- Support both Bare-Metal (BM) deployment and vSphere environments
- Flexible customer deployment options:
 - For maximum performance, deploy BM servers
 - For flexible GPU configuration, such as fractional GPUs, deploy in VMware environment





Demo 4 Running Tensorflow Container on NVIDIA Docker cisco like!



Cisco Converged Infrastructure for Al

Fast, efficient, easy and scalable

- Simplified Management: Extend your existing designs to seamlessly support AI/ML. Manage the AI/ML platforms like any other UCS Server
- Consistent operation and support model
- Repeatable building blocks to increase the scale of the environment, including GPUs, allowing you to start small and grow non-disruptively
- Easily deploy AI Frameworks with GPU support
- Close partnership with leading storage vendors to develop Cisco validated designs and solutions







theano









Cisco UCS Platforms for AI - Integration

Cisco UCS C220 M5 with 2 T4 GPUs

Cisco UCS C240 M5 with 2 V100 PCIE or 6 T4 GPUs

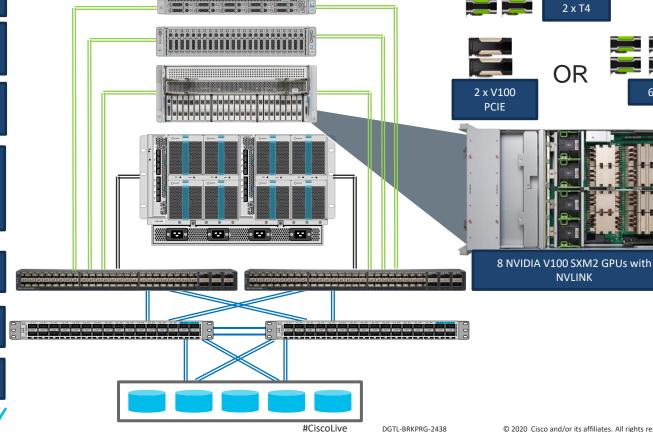
Cisco UCS C480ML M5 with 8 V100 SXM2 **GPUs**

Cisco UCS 5108 Chassis with IOM 2208XP for **VMware Environment**

Cisco UCS 6454 FI

Cisco Nexus 9336C-FX2

Storage System



6 x T4

NVIDIA GPUs for vComputeServer

NVIDIA recommends **T4** and **V100** GPUs for vComputeServer deployments

Fractional GPU: assign more than 1 VM to a GPU

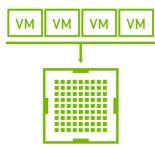
- Optimize GPU utilization
- Upto 8 VMs to a single GPU
- Minimum profile size of 4GB
- Maximum profile size of 32 GB

Aggregate GPUs: assign more than 1 GPU to a VM

- Scaling for higher performance
- Upto 4 vGPU to a VM (ESXi 6.7 U3)









Demo 5NVIDIA vComputeServer
Fractional GPU support









#CiscoLive