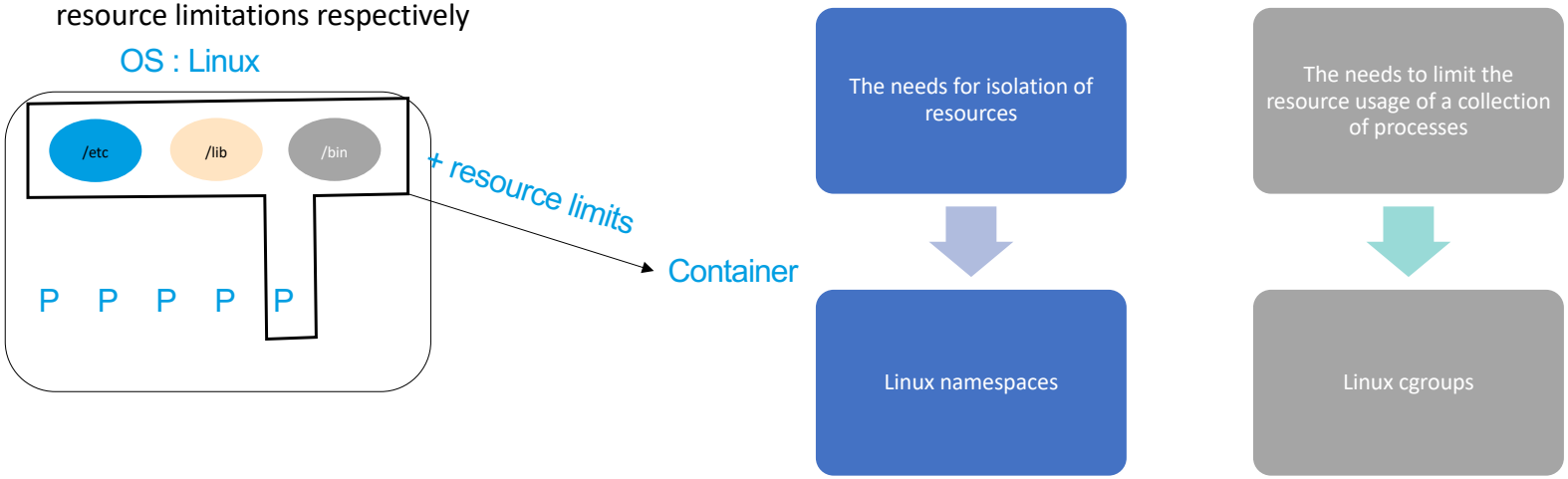
COMS E6998 010

Practical Deep Learning Systems Performance

Lecture 11

What are Containers?

- Containers are an abstraction at the app layer that
  - package code and dependencies together.
  - each running as isolated processes in user space.
  - Multiple containers can run on the same machine and share the OS kernel with other containers,
  - Containers are basically leveraging linux namespaces and cgroups for isolation of processes execution and resource limitations respectively



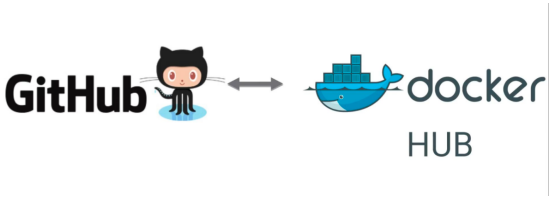
Tutorial: https://www.youtube.com/watch?v=EnJ7qX9fkcU
https://jvns.ca/blog/2016/10/10/what-even-is-a-container/

Docker

- Docker is a tool designed to make it easier to *create*, *deploy*, and *run* applications by using containers.
  - **Docker image**: A Docker image is a file, comprised of multiple layers, used to execute code in a Docker container.
  - **Dockerfile**: The Dockerfile is essentially a set of build instructions to build the image. A Dockerfile is a text document used to indicate to Docker a base image, the Docker settings you need, and a list of commands you would like to have executed to prepare and start your new container.
- Docker can associate a seccomp profile with the container using the **--security-opt** parameter.

Docker image repositories:

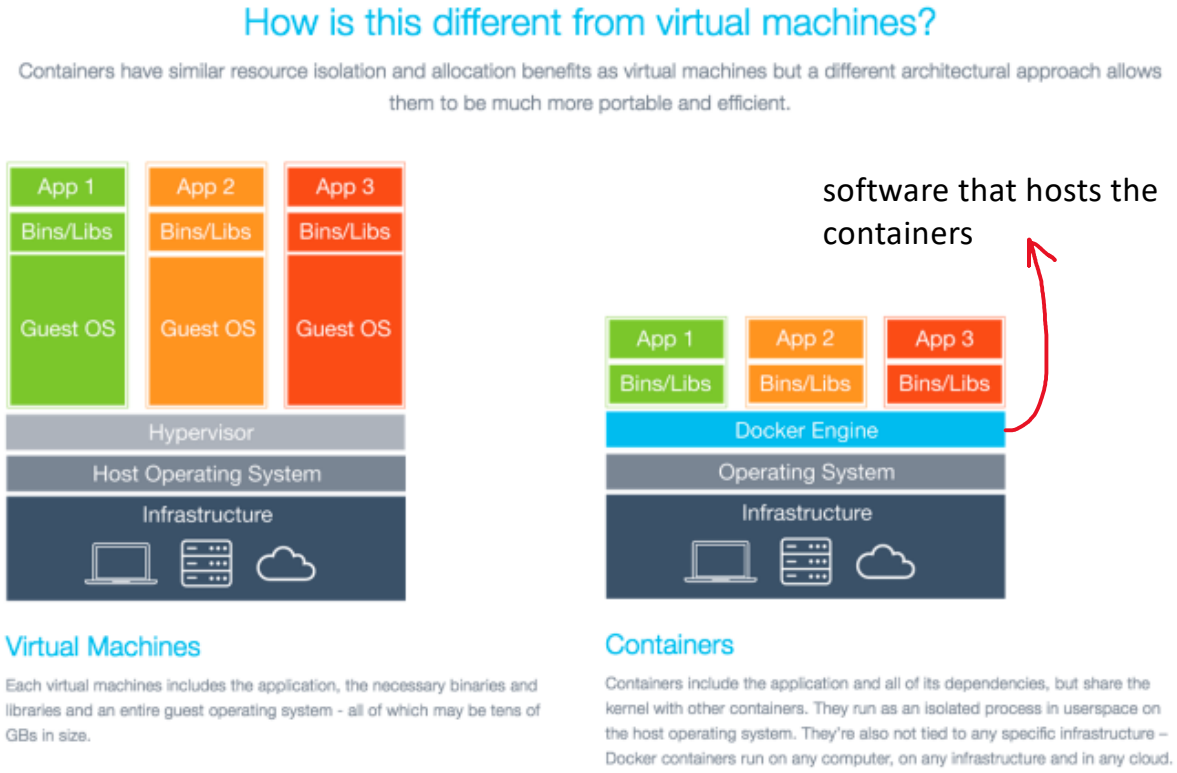
- Private: IBM Kubernetes Registry
- Public: Docker Hub



Container vs Virtual Machine

- Virtual machines
  - have a full OS
  - own memory management
  - own device drivers
  - own daemons
  - own binaries, libraries, and applications

- Containers
  - Share the host's OS kernel
  - Share the binaries and libraries i read-only mode.



	CONTAINER BENEFITS	VIRTUAL MACHINE BENEFITS
Consistent Runtime Environment	✓	✓
Application Sandboxing	✓	✓
Small Size on Disk	✓	
Low Overhead	✓	

Benefits of using Container

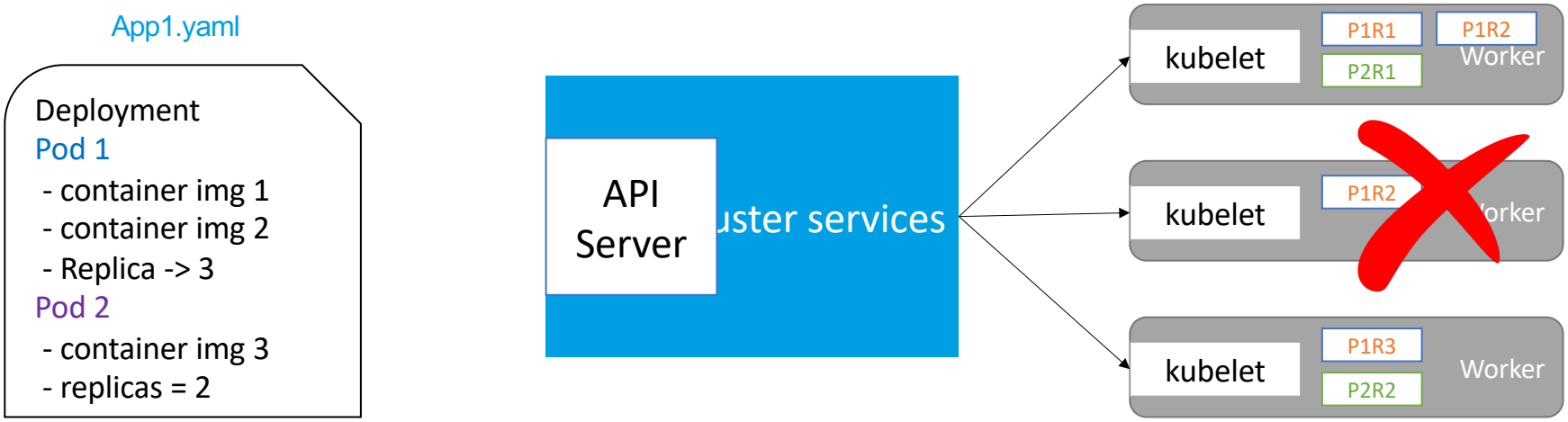
- Containerization allows our development teams to
  - move fast
    - Decoupling from environment
    - Compared to VMs, containers are far more lightweight.
  - deploy software efficiently
    - Consistent environment
    - Run Anywhere
    - Isolation
    - Easy version control
    - Agile development
  - and operate at an unprecedented scale
    - Kubernetes: Production-Grade Container Orchestration

Slide contents from Dr. Chen Wang, IBM Research

What is Kubernetes (K8s)?

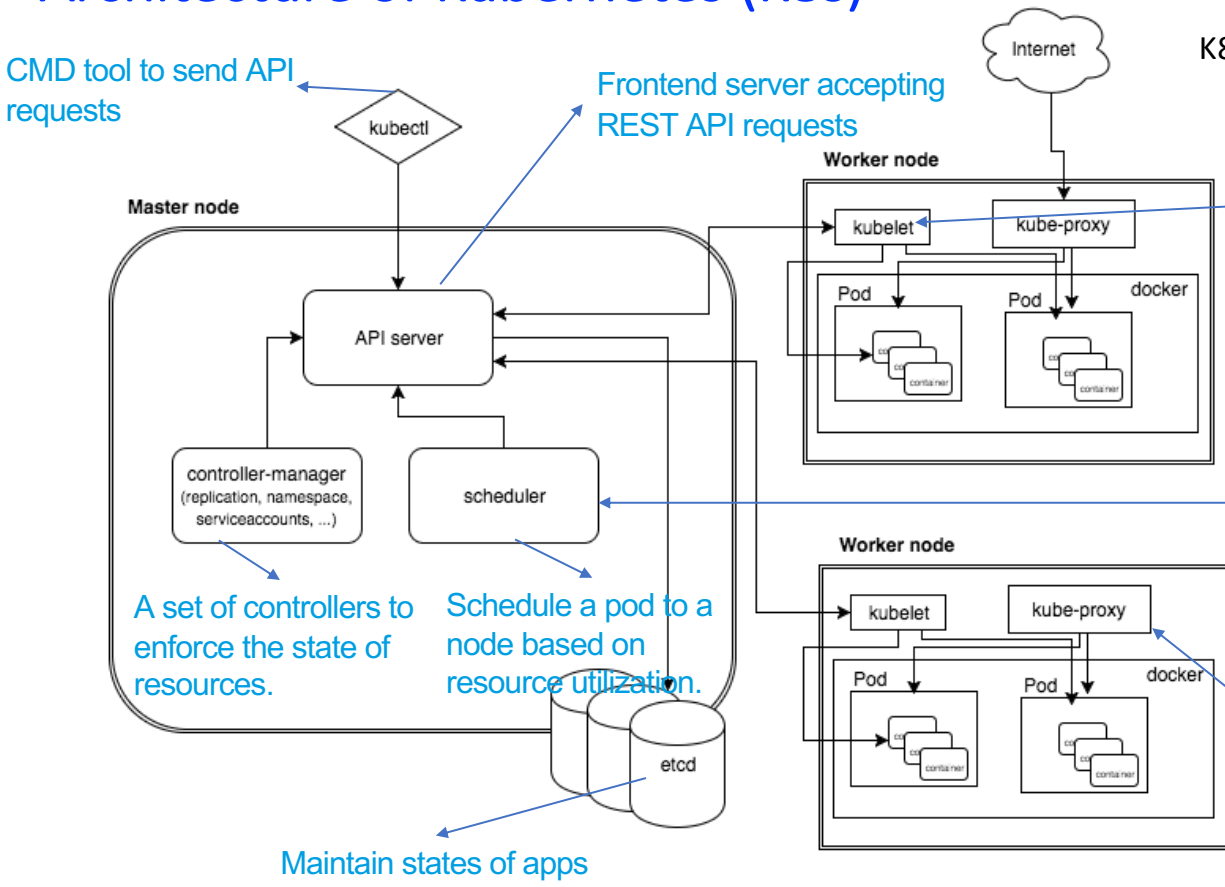
- Kubernetes is an *open source system* for managing containerized applications across *multiple hosts*, providing basic mechanisms for *deployment*, *maintenance*, and *scaling* of applications.

Kubernetes cluster services → "Desired State Management"



https://kubernetes.io/

Architecture of Kubernetes (K8s)



K8s follows a client-server architecture

- Ensure pods heathy and running
- Reports to the master to report the health of the host.

Scheduler assigns a node to the pod by

(1) filtering the nodes that satisfy the pod resource requirements and other predicate constraints,

(2) ranking the candidate nodes based on priority functions, and

(3) selecting the node with the highest rank.

- Deal with individual host subnetting
- Expose services to the external world.
- Request forwarding across isolated networks in a cluster.

Cloud Services running in Container Cloud

- Internal Customers of IBM Cloud Kubernetes Service: *Launched on May 23, 2017*
  - IBM Watson (Conversation, NLC, sentiment analysis, etc.)
  - IBM Deep Learning as a Service (DLaaS)
- Google: *Launched in 2015*
  - Almost everything from YouTube to Gmail.
  - Google Kubernetes Engine: https://cloud.google.com/kubernetes-engine/
- Alibaba:
  - 90% of their main business, especially e-commerce like Taobao and Tmall
  - Alibaba Cloud Container Service for Kubernetes: https://www.alibabacloud.com/product/kubernetes
- AWS: *Nov. 29, 2017*
  - Amazon Elastic Container Service for Kubernetes: https://aws.amazon.com/eks/
- Azure: *Oct. 27, 2017*
  - Azure Kubernetes service: https://azure.microsoft.com/en-us/services/kubernetes-service/

Slide contents from Dr. Chen Wang, IBM Research

Cloud Storage

- File, Block, Object Storage
- Medium article: https://medium.com/ai-platforms-research/fundamentals-of-ibm-cloud-storage-solutions-8739f36f024e

Platform specialized for DL training workloads

- “Why do we need a platform specialized for DL training workloads”?
- Can I build my own platform over K8s ?
- You need to understand low level details of K8s
- You need to keep track of job life-cycle including deployment, monitoring, termination of associated pods using K8s APIs.

Is K8s Enough for Data scientists and ML Developers ?

- Too “low-level” for use by data scientists
  - Training job vs pods, deployment, replica sets …
- DL training workloads need specialized scheduling algorithms for better performance, not natively supported by K8s
- Cannot track DL specific job status: DOWNLOADING, PROCESSING, STORING, HALTED, RESUMED

Distributed DL Platform Requirements

- Ease of Use
  - Users do not need to worry about job life-cycle, security, and failure recovery
- Flexibility
  - Support of different frameworks
- Dependability
  - Highly available, reliable, and fault tolerant
- Efficiency
  - Negligible platform overhead; End-to-end job performance should be close to bare metal
- Scalability
  - End-to-end job performance should not degrade significantly with increasing load on the cluster

IBM FfDL (Fabric for Deep Learning)

- Cloud-based distributed DL platform
- Design Goals: a distributed DL platform should be easy to use, flexible, dependable, scalable, and efficient.
- Open source: https://github.com/IBM/FfDL

FfDL Design

- Cloud-native platform architected as a set of loosely-coupled microservices communicating with each other using gRPC https://grpc.io

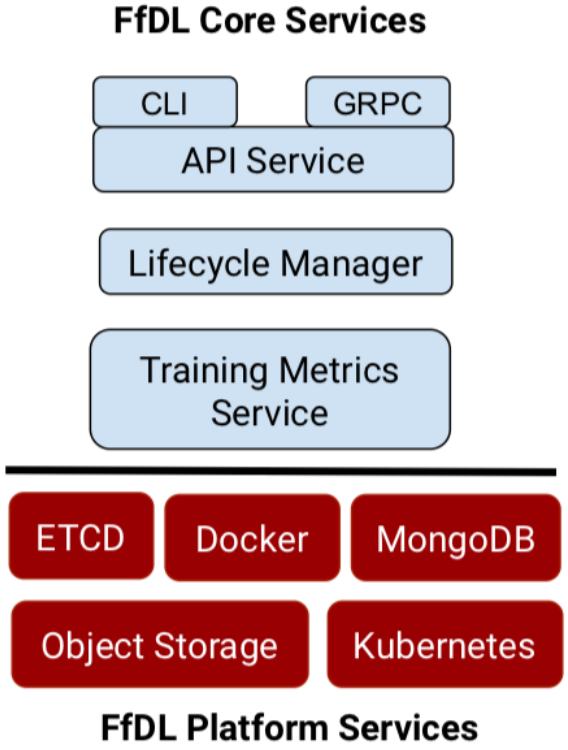
"Cloud native is a term used to describe container-based environments. Cloud-native technologies are used to develop applications built with services packaged in containers, deployed as microservices and managed on elastic infrastructure through agile DevOps processes and continuous delivery workflows."

- Employs Kubernetes (K8S) for container orchestration and cluster management
- Flexibility through Containerization
  - Maintains docker images of different frameworks
  - Communication and synchronization methods internal to different frameworks are preserved
  - FfDL takes user code, and automatically instantiates Docker containers (from stored Docker images) containing all necessary packages to run the training job

Training job specification

- YAML file
- https://dataplatform.cloud.ibm.com/docs/content/wsj/analyze-data/ml_dlaas_e2e_example.html

FfDL Components



- Each FfDL microservice is also (Docker) containerized and executed using a K8S abstraction called replica set, with their APIs exposed using the K8S service abstraction.
  - K8S service is a way to expose an application running on a set of Pods as a network service.
- API Service
  - gRPC and REST end points
  - FfDL CLI interacts with API service
- Lifecycle Manager
  - Responsible for job lifecycle from submission to completion/failure
- Training Metrics Service
  - Collects metrics about both training jobs and FfDL microservices like memory and network usage, number of times microservices fail and recover
- MongoDB
  - Stores job metadata as well as job history (for a specific user or client organization) including job status
  - Data is long-lived and spans several jobs
- Etcd:
  - Store status updates and messages
  - Data is short lived (a DL job's data is erased after it terminates)
  - Use for FfDL microservices coordination

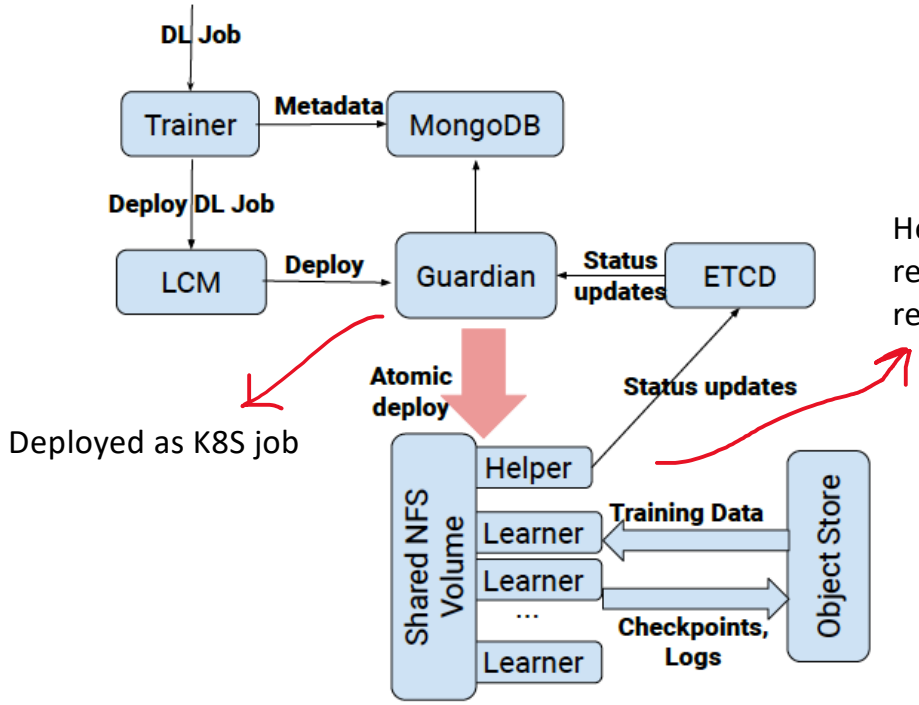
Life Cycle Manager (LCM)

- Responsible for the job from submission to completion or failure.
- Takes care of deployment, monitoring, garbage collection, and user-initiated job termination
- LCM performs some of these functions directly, but creates delegates for others
  - Scalability reasons
  - Delegates avoid LCM becoming a single point of failure
- Atomic provisioning of DL jobs
  - Either the whole job is provisioned with the requisite resources or none

Guardian: LCM delegate for a job's lifecycle

- Guardian is an LCM launched delegate for atomic deployment and further monitoring of each DL job.
- LCM instantiates Guardian with all the metadata of the DL job.
- Guardian executes the multi-step process of actually deploying the DL job by interacting with K8S.
  - Instantiating learner pods
  - Setting up shared NFS volumes to monitor training progress
  - Applying network access policies to the learners
- Guardian monitors the progress of successfully deployed jobs
- Unsuccessful job deployment are marked as FAILED by Guardian in MongoDB

FfDL Job Deployment Flow



Helpers perform failure detection, status recording and updates, log collection, data and results transfer, and metrics collection.

Scalability and Elasticity

- Each microservice is replicated
  - Number of replicas chosen based on the size of the cluster as well as the expected number of concurrent training jobs
- Replicated microservices are K8S deployments or replica sets
  - gRPC requests are automatically load balanced by K8S among the available replicas
- Replica set for each microservice can be elastically scaled as physical machines are added to or removed from the cluster.
- Guardian for job deployment ensures that FfDL can handle thousands of deployment requests concurrently.
- Guardians consume only a fraction of a CPU and need little RAM.

T-shirt size of learners

Goal is to dimension the CPU threads per learner to achieve close to 100% utilization of the GPUs

CPU-threads	thpt-1P100	thpt-1V100
2	65.96	106.46
4	66.14	106.5
8	65.67	107.24
16		107.45
28		107.47

Table 4. Throughput (images/sec) scaling of VGG-16/Caffe with CPU threads for learners with 1 P100 and 1 V100 and batch size 75.

CPU-threads	InceptionV3	Resnet-50	VGG-16
16	217.8 (86.8%)	345.3 (93.3%)	216.2 (98.7%)
28	223.6 (90.5%)	345.8 (92.7%)	216.2 (97.3%)

Table 6. Throughput (images/sec) scaling of TensorFlow with CPU threads for learners with 1 V100 and batch size 128. Also shown in parentheses is the GPU utilization.

GPU-type	CPU	memory (GB)
1-K80	4	24
2-K80	8	48
4-K80	16	96
1-P100	8	24
2-P100	16	48
1-V100	26	24
2-V100	42	48

Table 5. T-shirt size recommendation for FfDL jobs.

Scale Testing of FfDL Cluster

GPU-type-batch#	jobs-LL	jobs-HL	start time
K80-batch1	30	300	first 1 min
K80-batch2	24	240	after 15 min
P100-batch3	11	110	after 30 min
V100-batch4	5	50	after 32 min

Table 7. Light-load (LL) and heavy-load (HL) job mix

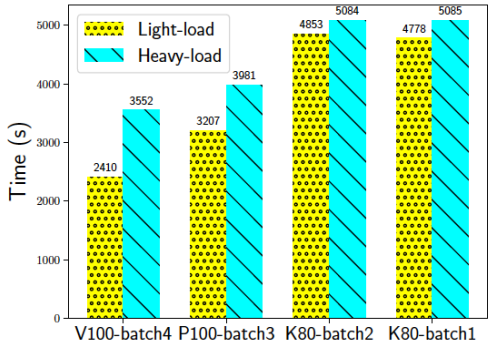


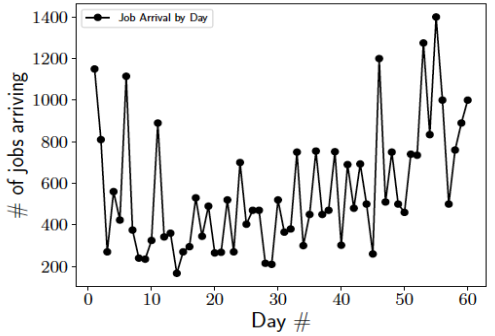
Figure 5. E2E job runtime by GPU-type for light-load and heavy-load scenarios

- Cluster under test has about 680 GPUs
- Each job is a Resnet-50/TensorFlow-1.5 training job using Imagenet1K dataset
- With 700 concurrent jobs the cluster achieved on average aggregate throughput of ~837 iterations/sec or 54K images processed/sec.

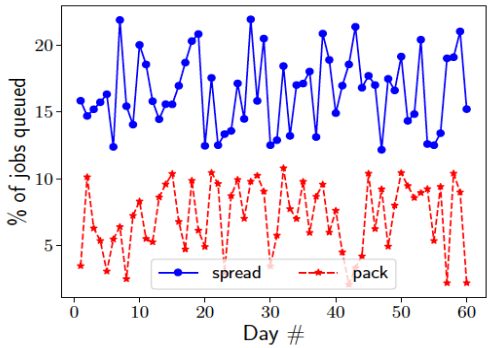
K80 jobs have the lowest performance degradation (6-8%) at heavy- load compared to low-load, followed by P100 (24%) and then V100 (51%). This is due to the staggered start of jobs; by the time V100 jobs are running, the load is at its peak, and hence the shared resources (network and cloud object storage band- width) start impacting performance.

Job Scheduling in FfDL

- Spread
  - Default placement policy of K8S pods
  - Spread distributes pods over the cluster, and avoids placing two pods belonging to the same job on the same physical machine
  - Problems:
    - Increased communication costs
    - Increased fragmentation
- Pack
  - Pods from a DL job are packed into as few physical machines as possible
  - Implemented as an extension to K8S scheduler



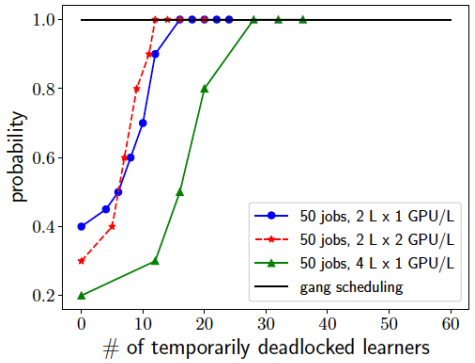
(a) Arrival of jobs by day over a 60 day period at a production cluster



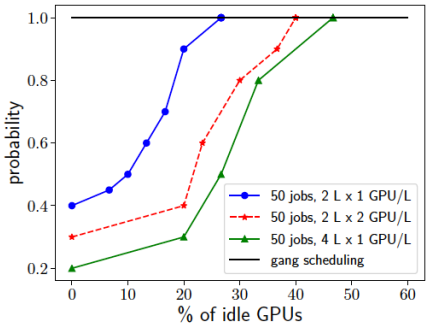
(b) Percentage of arriving jobs that would be queued for over 15 mins, in SPREAD vs. PACK

Gang Scheduling

- Ideally a job should either be fully scheduled or fully queued
- DL job can have multiple pods
- K8S scheduler doesn't consider one whole job while scheduling, it considers each of the learner pods individually
- Scheduling pods of a job individually can cause temporary deadlocks; learners are waiting and holding hardware resources while waiting for other pods (learners) of the job to get deployed
  - GPU held by the learner is idle because training has not started
- Gang scheduler schedules all pods that belong to a DL job holistically, as a group/gang

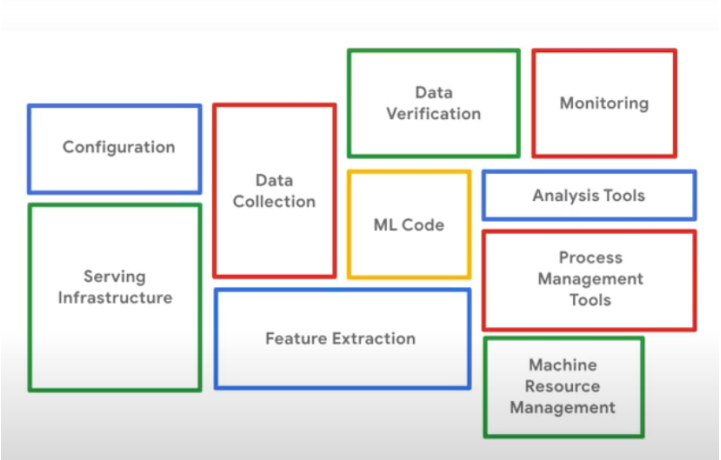


(a) CDF of the probability of temporarily deadlocked learners with and without gang scheduling



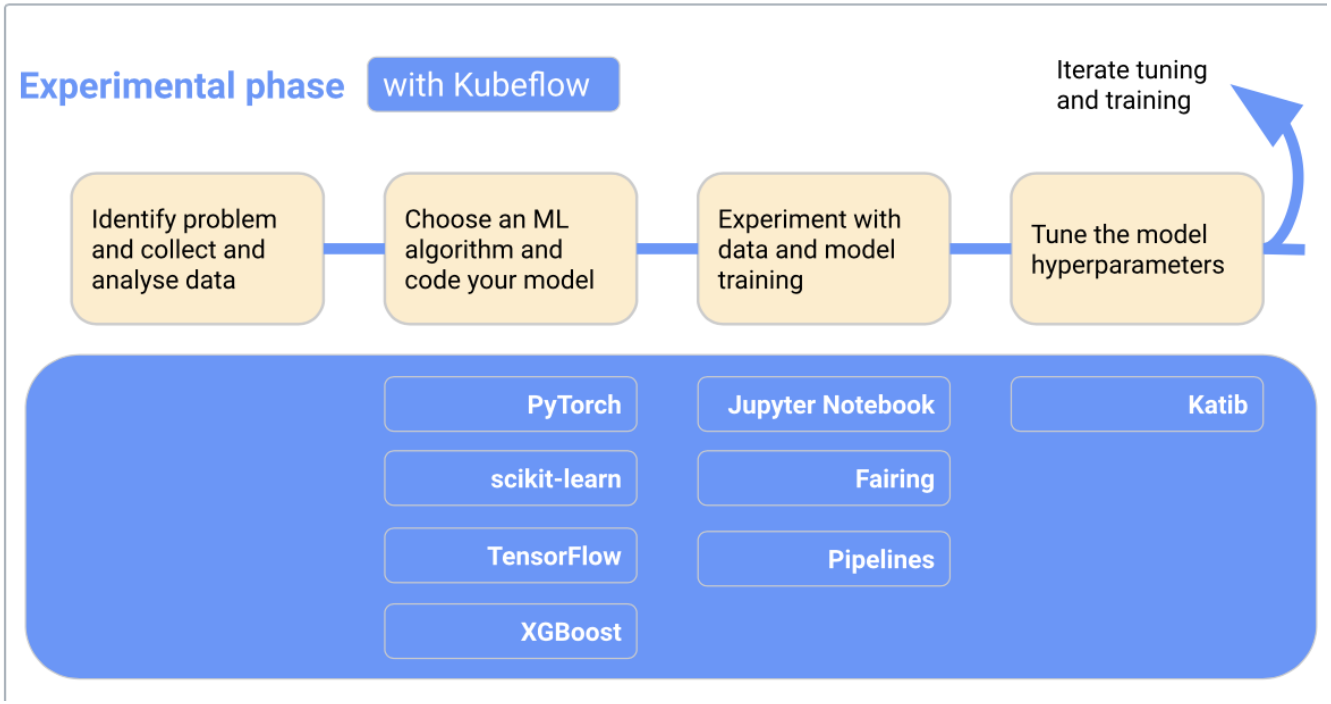
(b) CDF of the probability of idle GPUs with and without gang scheduling

Kubeflow

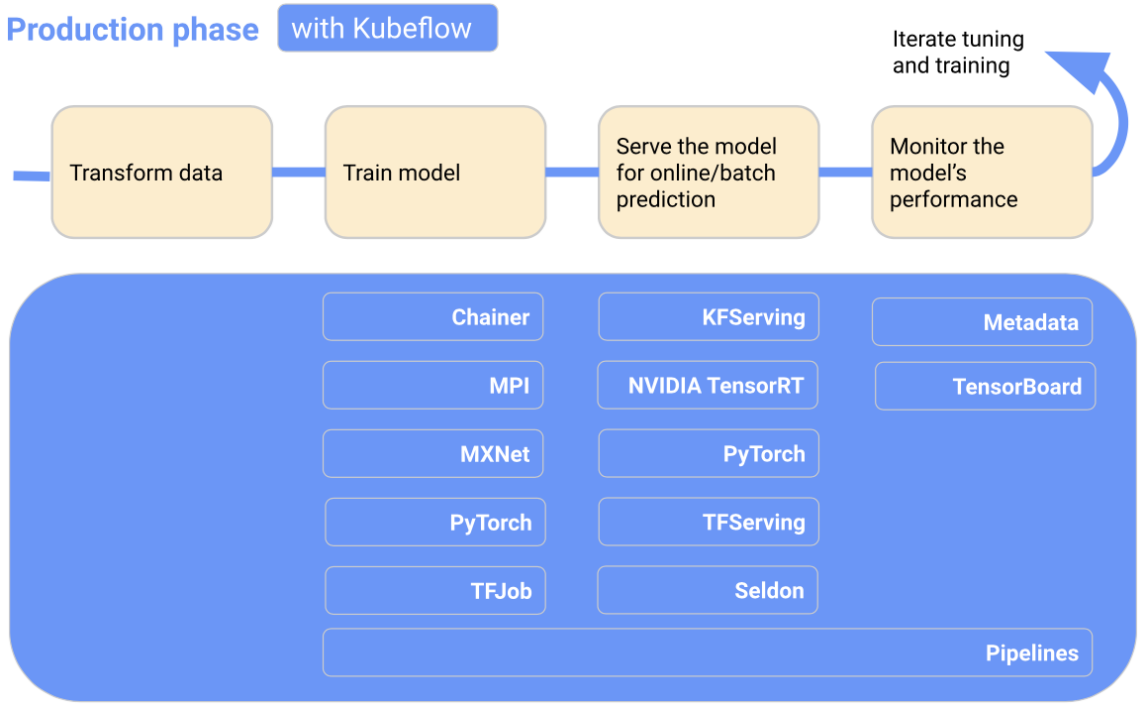


- https://www.kubeflow.org/docs/about/kubeflow/
- Kubeflow is an effort to standardize deployment of ML apps and managing the entire lifecycle from development to production
- Kubeflow provides a *machine learning toolkit for Kubernetes*
- Goal: To making deployments of machine learning (ML) workflows on Kubernetes simple, portable and scalable
- Multi-architecture, multi-cloud framework for running entire machine learning pipelines
- Open source; built on top of K8S

ML workflow using Kubelfow – experimental phase



ML workflow with Kubeflow – production phase



Kubeflow Logical Components

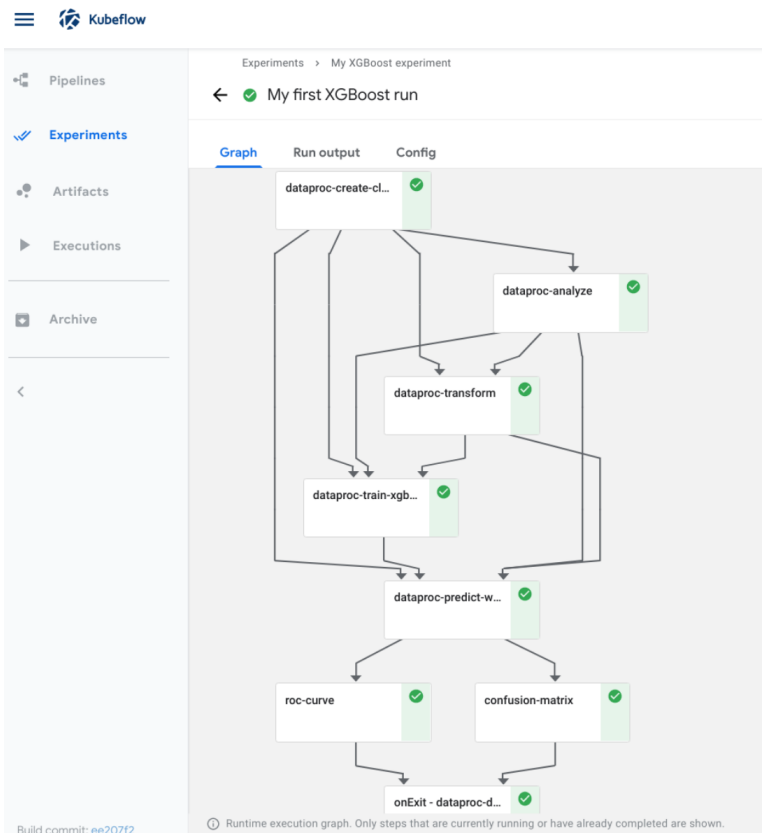
- **Jupyter Notebooks**
- **Hyperparameter Tuning**
- **Pipelines**
- **Serving**
- **Training**

Kubeflow Pipelines

- A platform for building, deploying, and managing multi-step ML workflows based on Docker containers.
- The Kubeflow Pipelines platform consists of:
  - A user interface (UI) for managing and tracking experiments and runs.
  - An engine for scheduling multi-step ML workflows.
  - An SDK for defining and manipulating pipelines and components.
  - Notebooks for interacting with the system using the SDK.
- https://www.kubeflow.org/docs/pipelines/pipelines-quickstart/

Pipeline

- Description of ML workflow
- Pipeline is formed using pipeline components
- Pipeline includes
  - Components and their inputs and outputs
  - Definition of the inputs (parameters) required to run the pipeline
- https://www.kubeflow.org/docs/pipelines/overview/pipelines-overview/



Pipeline Components

- https://www.kubeflow.org/docs/pipelines/overview/concepts/component/
- A *pipeline component* is a self-contained set of user code, packaged as a Docker image, that performs one step in the pipeline.
- A component for data preprocessing, data transformation, model training, data visualization…
- A component is analogous to a function, in that it has a name, parameters, return values, and a body.
- Each component in a pipeline executes independently.
- The components do not run in the same process and cannot directly share in-memory data.

Component Specification

Example of a component specification

A component specification takes the form of a YAML file, `component.yaml`. Below is an example:

```
name: xgboost4j - Train classifier
description: Trains a boosted tree ensemble classifier using xgboost4j

inputs:
- {name: Training data}
- {name: Rounds, type: Integer, default: '30', help: Number of training rounds

outputs:
- {name: Trained model, type: XGBoost model, help: Trained XGBoost model}

implementation:
  container:
    image: gcr.io/ml-pipeline/xgboost-classifier-train@sha256:b3a64d57
    command: [
      /ml/train.py,
      --train-set, {inputPath: Training data},
      --rounds,    {inputValue: Rounds},
      --out-model, {outputPath: Trained model},
    ]
```

https://www.kubeflow.org/docs/pipelines/reference/component-spec/

Metadata (name, description), input and output interfaces, implementation (docker image url)

Real world component specifications
Link here

Example Pipeline

- https://www.kubeflow.org/docs/pipelines/overview/pipelines-overview/
- https://github.com/kubeflow/pipelines/tree/master/samples/core/xgboost_training_cm

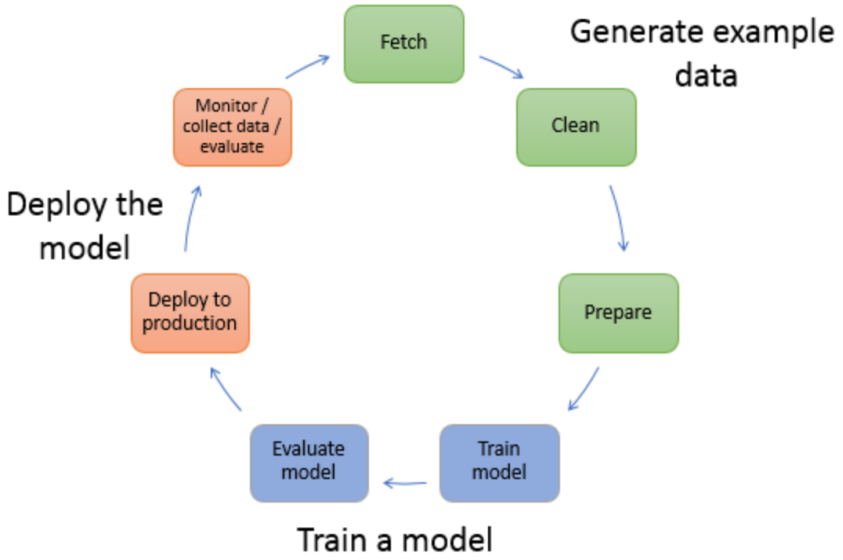
Kubeflow Tutorials Using GCP

- https://codelabs.developers.google.com/codelabs/kubeflow-introduction/index.html#0

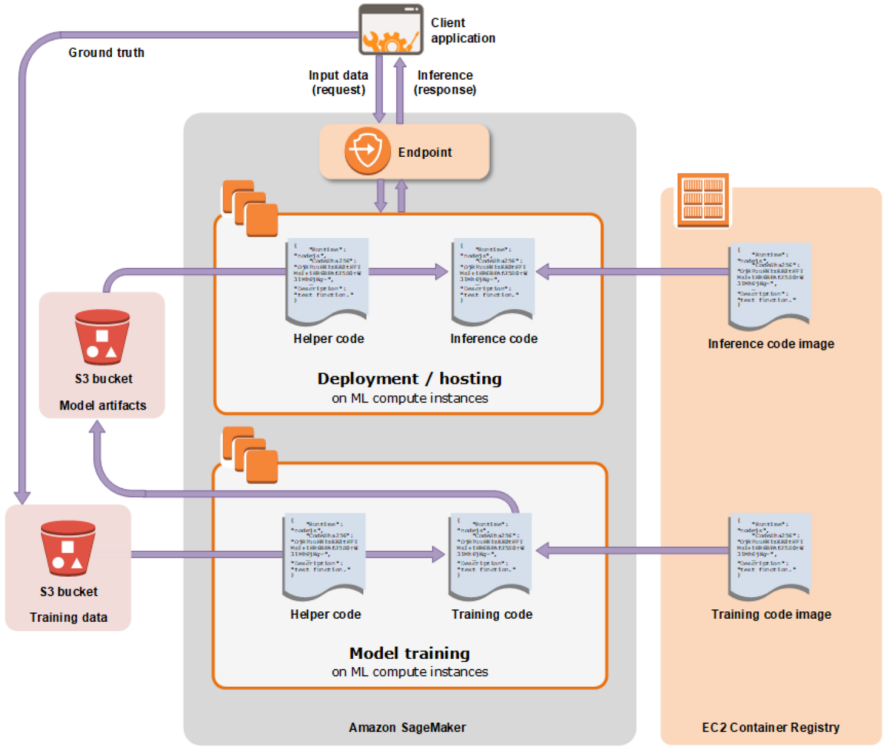
Amazon Sagemaker

- Fully managed machine learning service by Amazon
- Supports:
  - Quick and easy building and training of ML models
  - Model deployment in production-ready hosted environment

Typical ML Workflow



Train with Amazon Sagemaker



Training algorithm options

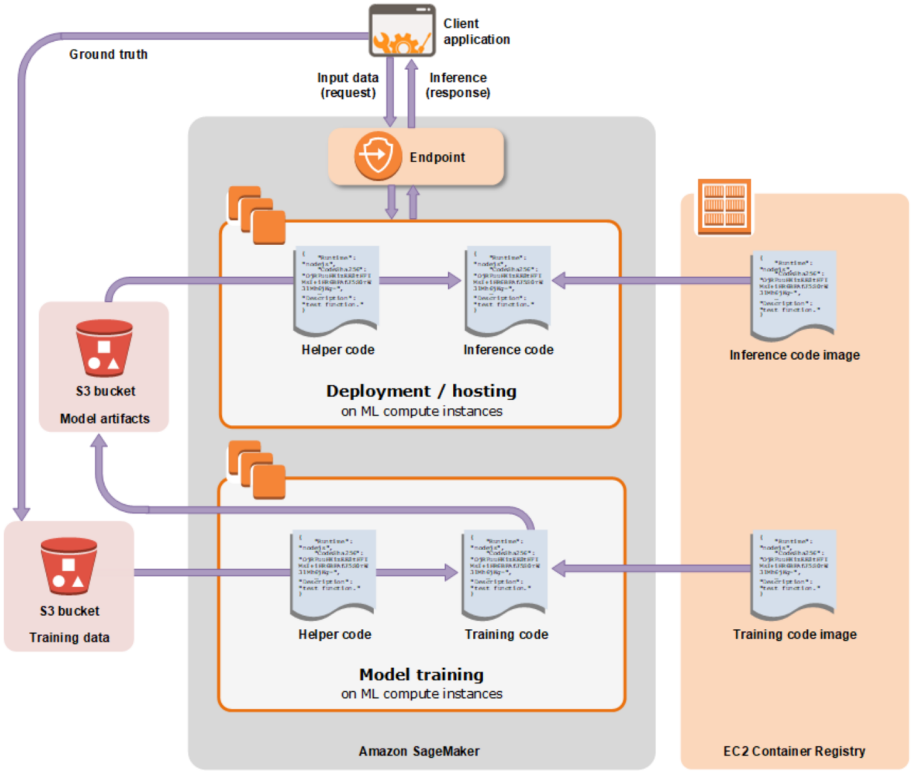
- Use an out-of-the-box algorithm provided by Amazon
  - Pre-built docker images
- Use Apache Spark MLLib with Amazon Sagemaker
- Custom python code to train with DL frameworks
  - Tensorflow and Apache MXNet
- Use your own custom algorithm in any programming language and framework
  - Package as a docker image and register it
- Use an algorithm from AWS Marketplace

https://docs.aws.amazon.com/sagemaker/latest/dg/how-it-works-training.html

CreateTrainingJob API

- https://docs.aws.amazon.com/sagemaker/latest/dg/API_CreateTrainingJob.html

Deploy on Amazon Sagemaker Hosting Services



https://docs.aws.amazon.com/sagemaker/latest/dg/how-it-works-hosting.html

Other ML Platforms

- **Azure ML**
- **Google Cloud ML Engine**
- **Amazon Sagemaker RL**

Reference Papers

- Jayaram et al. FfDL: A Flexible Multi-tenant Deep Learning Platform. Middleware 2019.
- Bhattacharjee et al. IBM Deep Learning Service. IBM Journal of Research and Development. 2017.

Blogs, Videos, Code Links

- Janakiram. 10 KEY ATTRIBUTES OF CLOUD-NATIVE APPLICATIONS
- AWS Documentation. How Amazon Sagemaker Works
- James Quigley. Microservices, Docker, and Kubernetes
- Ben Corrie. What is a container?. Video
- Microsoft Azure. Kubernetes Learning Path. A hands-on course.
- Kubeflow. Getting Started with Kubeflow