Parallelizing machine learning application in the cloud with Kubernetes: A case study

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September 2020

2020 embedded VISION summit

Agenda

- ML application end-to-end flow
- Kubernetes: A brief introduction
- Scaling image classification in the cloud using Kubernetes
- Scaling inference from one server node to many
- Load balancing and identifying bottlenecks in the deployment pipeline
- How to choose between CPUs or GPUs for performance
- Conclusion
  - Kubernetes is available at https://github.com/kubernetes/kubernetes and licensed under Apache 2.0

ML application end-to-end flow

- CPUs/GPUs or dedicated
- With right software infrastructure

- Data collection is tedious and quality of data matters
- Need synthetic data generation with tools for augmentation

- Start with simple model, train and update for accuracy
- Need many CPU and GPU cores to run these in a short amount of time

- Efficient data pipeline is required to get optimal throughput
- When the model is given new data, there is a need to evaluate and update the model for accuracy.

Choose Hardware → Data Collection → Build Model → Train → Deploy → Evaluate and Update

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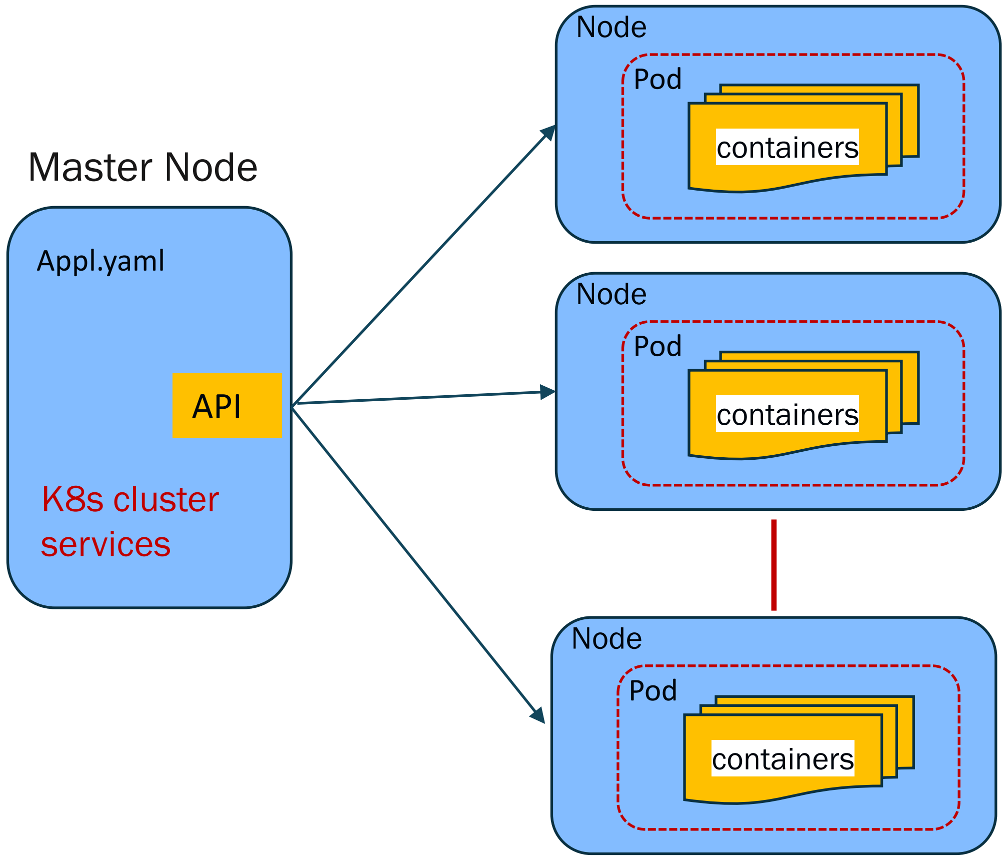
ML Software stack for application deployment

Applications	Vision	NLP	Classification /Detection	Video	
Cluster Deployments	Docker	Kubernetes	Singularity	SLURM	
Frameworks and exchange formats	TensorFlow	PyTorch	Caffe2	ONNX	NNEF
Middleware libs	Blas/Eigen	RNG/FFT	MIOpen	CuDNN	
Programming models	OpenCL	HIP	Cuda	OpenVX	Python
Processors	CPU	GPU	APU	DLA	

Kubernetes®(K8s): A brief introduction

Kubernetes is an open-source system for automatic deployment, scaling and management of containerized applications



- **Node**
  - Runs Kubelets (“node agent” service)
  - Communicates with master
  - Runs Pods
- **Pod**
  - Runs one or more containers
  - Exists on a node
- **Service**
  - Handles requests
  - Load balances
- **Deployment**
  - Defines what you want(cluster services); Kubernetes handles it for you

Need for containerized and scalable deployment

The Task

Develop the application

Create docker container

Launch on Kubernetes

Each deployment is self-contained & can run on any system which has the hardware resources.

Easily manage resources over multiple servers

The ability to cluster and schedule container processing to scale

Can easily access data across the nodes

Typical deployment YAML file for Kubernetes configuration

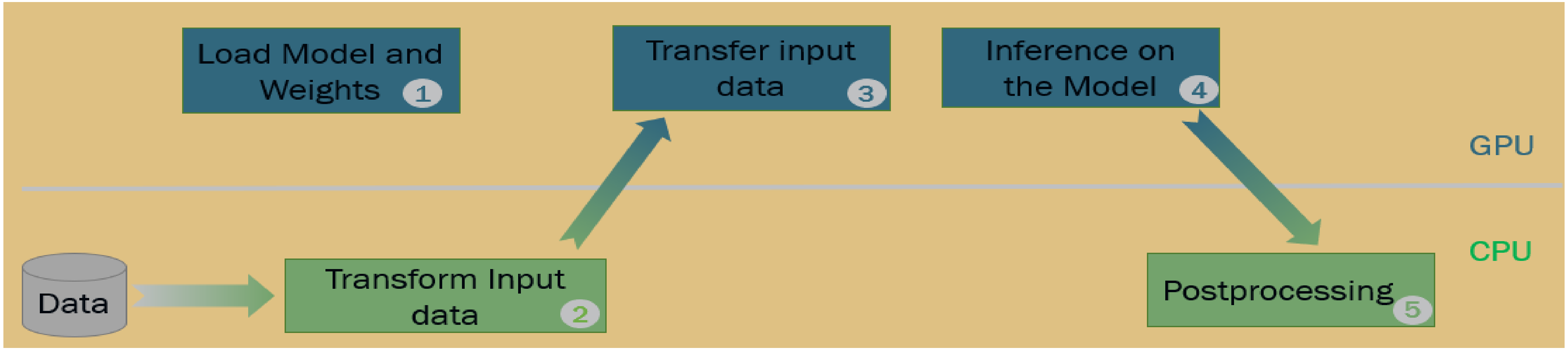
Deployment YAML configuration

```yaml
# deployment yml file
apiVersion: apps/v1
kind: Deployment
metadata:
  name: mivisionx-deployment
  labels:
    app:  mivisionx-server
spec:
  replicas: n #number of replicas
  selector:
    matchLabels:
      app:  mivisionx-server
  template: # define the pods specifications
    metadata:
      labels:
        app:  mivisionx-server
    spec:
     containers:
       - name:  mivisionx-server
         image: mivisionx/ubuntu-18.04:rocm3.3
         ports:
         - containerPort: 28282
         workingDir: /root
         env:
          - name: HIP_VISIBLE_DEVICES
            value: "0" # # 0,1,2,...,n for GPU, -1 for CPU
         command: ["/bin/sh", "-c", "--"]
         resources:
           limits:
             amd.com/gpu: 1 # requesting 1 GPU
```

Service YAML configuration

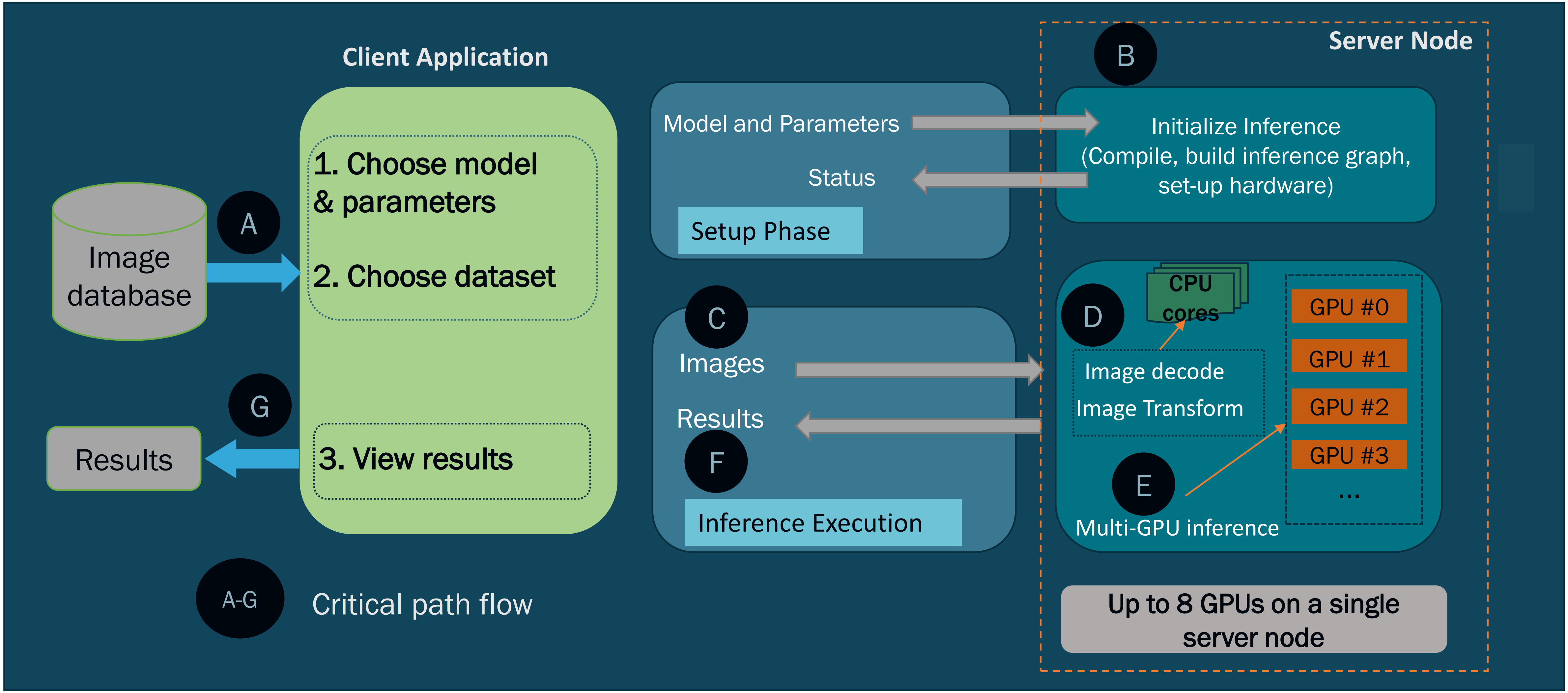
```yaml
---
apiVersion: v1
kind: Service

metadata:
  name: mivisionx-deployment-service
  namespace: default
spec:
  type: NodePort
  selector:
    app:  mivisionx-server
  ports:
    - port: 28282     #port accessible inside the cluster
      targetPort: 28282 #port which sends traffic from service to container
      nodePort: 30001   #port which is accessable outside the cluster
      protocol: TCP
      labels:
        app:  mivisionx-server
```

Load balancing a deployment pipeline with CPU and GPU



- Model Initialization is done only once as part of initialization
- Preprocessing involves decoding and applying many transformations
- CPUs are best suited for preprocessing and postprocessing
- Data-parallel processors are efficient for running inference on a batch of images
- Postprocessing is needed to produce useful result

Inference deployment client server application case study



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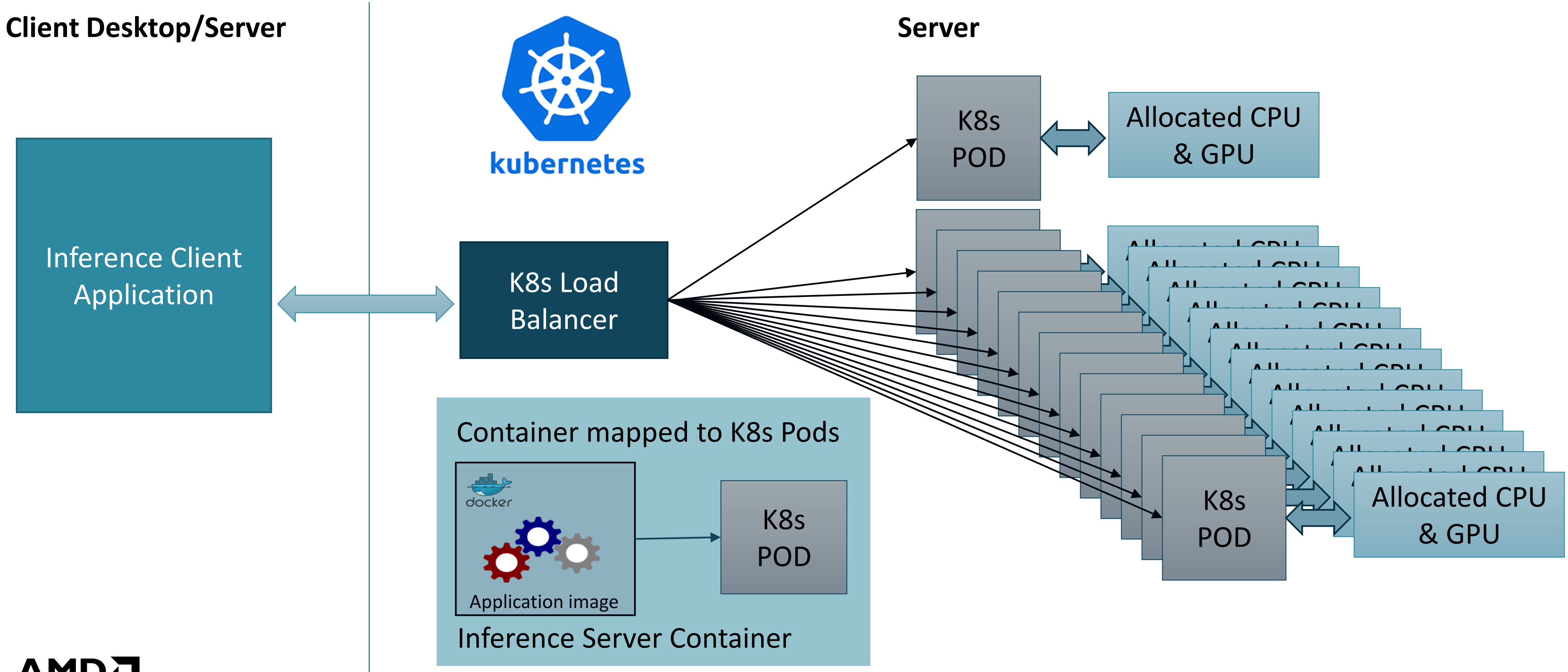
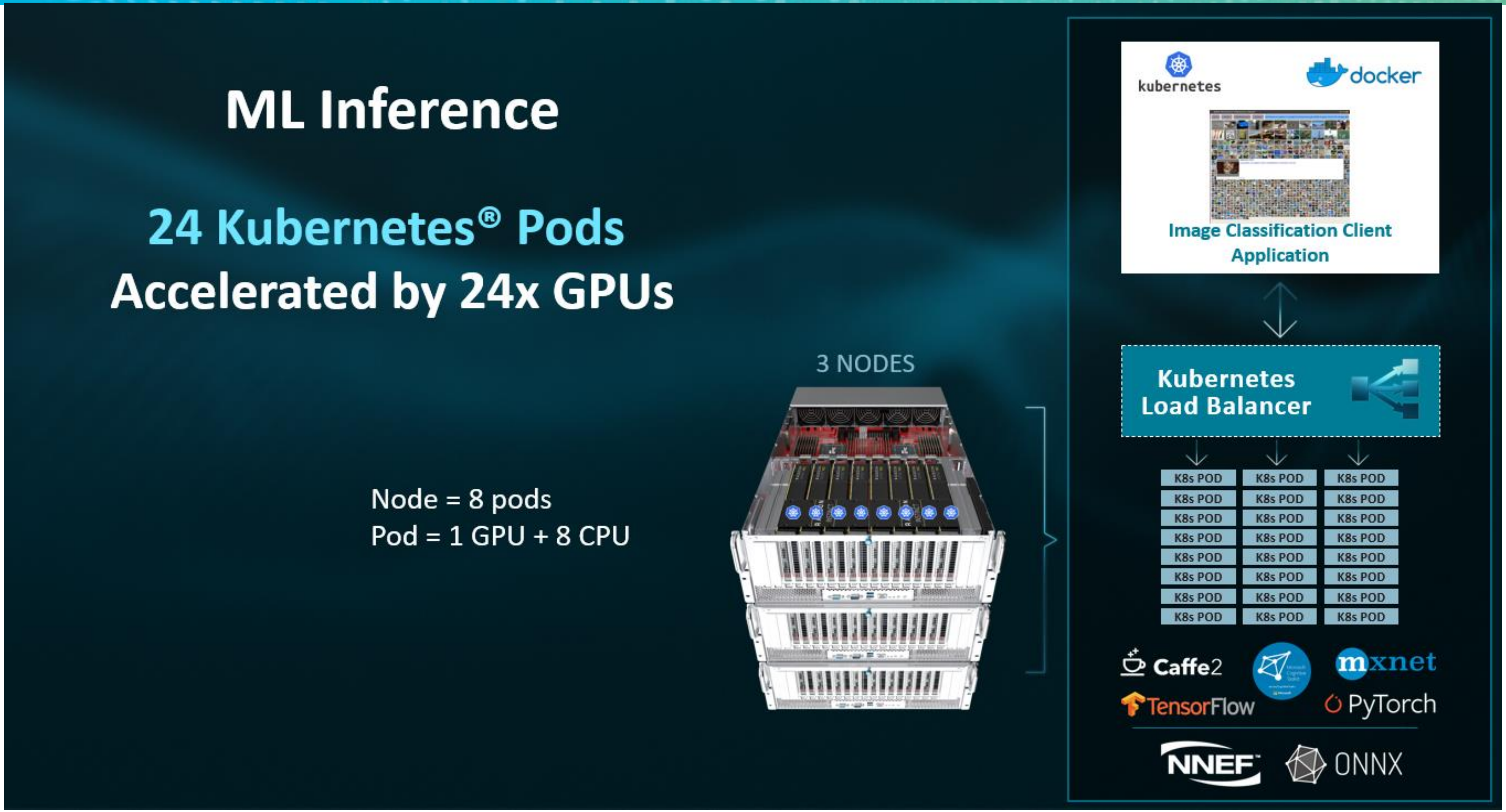
Inference Deployment Using Kubernetes

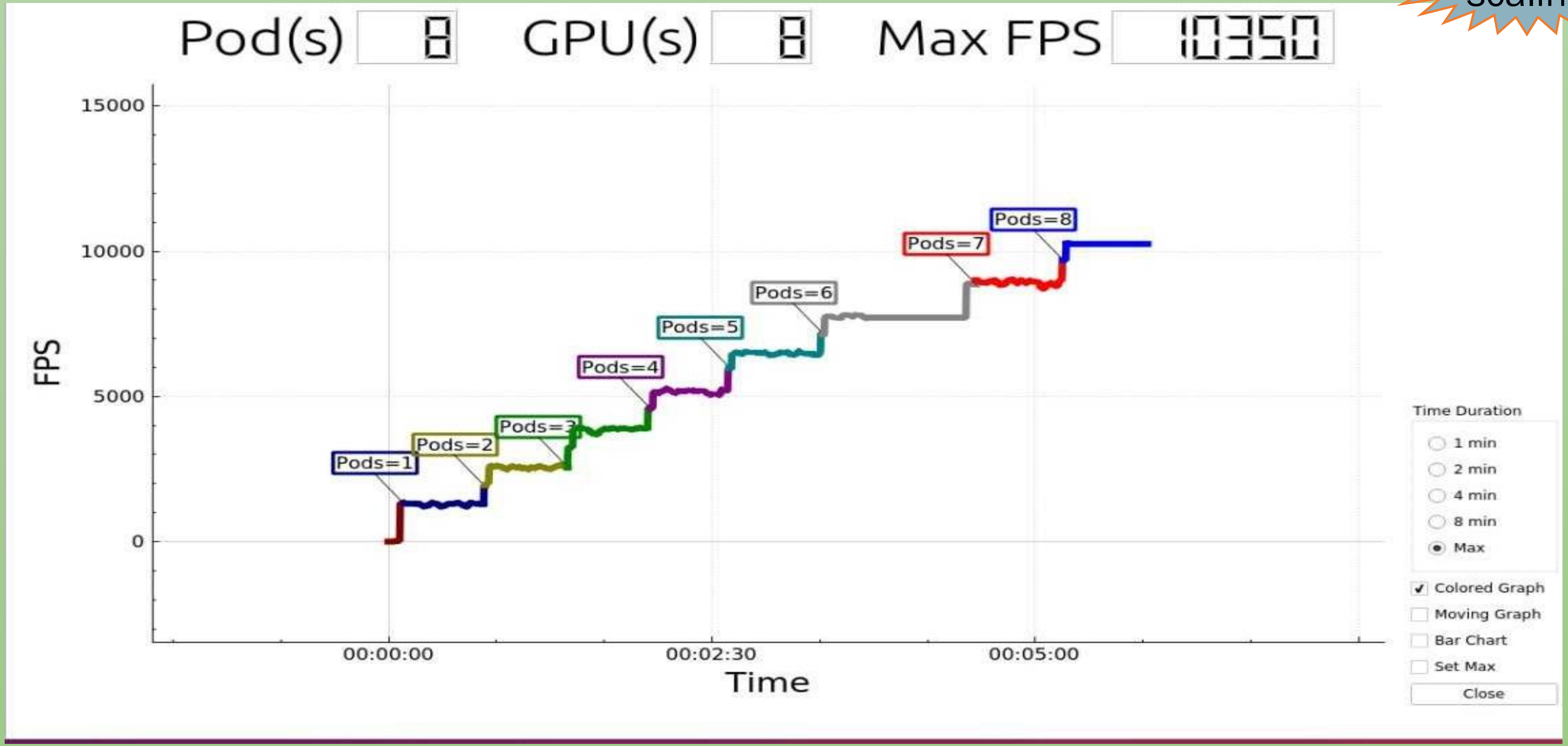


Scaling ML Inference with Kubernetes®



Performance Graph with multiple GPUs and CPUs

98% scaling



Steps for achieving linear scaling

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- Remove bottlenecks in the inference server critical path.
- Allocate hardware resources for each deployment pod. In this case we choose 1 GPU and 8 CPU cores
- The application needs to maintain separate queues (as shown in the next slide) for each instance of application so multiple instances won’t block each other.
- The model is pre-launched and initialized for each nod separately
- The data loading bottleneck is avoided by preloading input images for each nod in advance
- Finally, use a multi-threaded client application that feeds and sends requests for each of the K8s pod with minimal latency.

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Inference server critical path

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CLIENT: READ HDD	CLIENT: XMIT	SERVER: JPEG DECODE	COPY: PCIE TO GPU	GPU: INFERENCE	SERVER: SEND RESULTS	CLIENT: DISPLAY RESULTS
A	B	C	D	E	F	G
Drive Speed NVMe = ~3.5GB/sec (~5000fps)	Network bandwidth ~100 Gbps	JPEG decode, resize and convert to tensor multi-threaded ~200 MB/sec *128 threads (~100000 fps)	PCIe™ bandwidth 32GB/s for x16 (~50000 FPS)	Execute batched deep learning inference on the model 1200 fps (fp16 on MI50)	Collect inference results (PCIe™ from GPU to CPU) and xmit back to client ~32 GB/s for x16	Check and show results Update performance specs

Limiting factor or tasks

A-G Critical path flow

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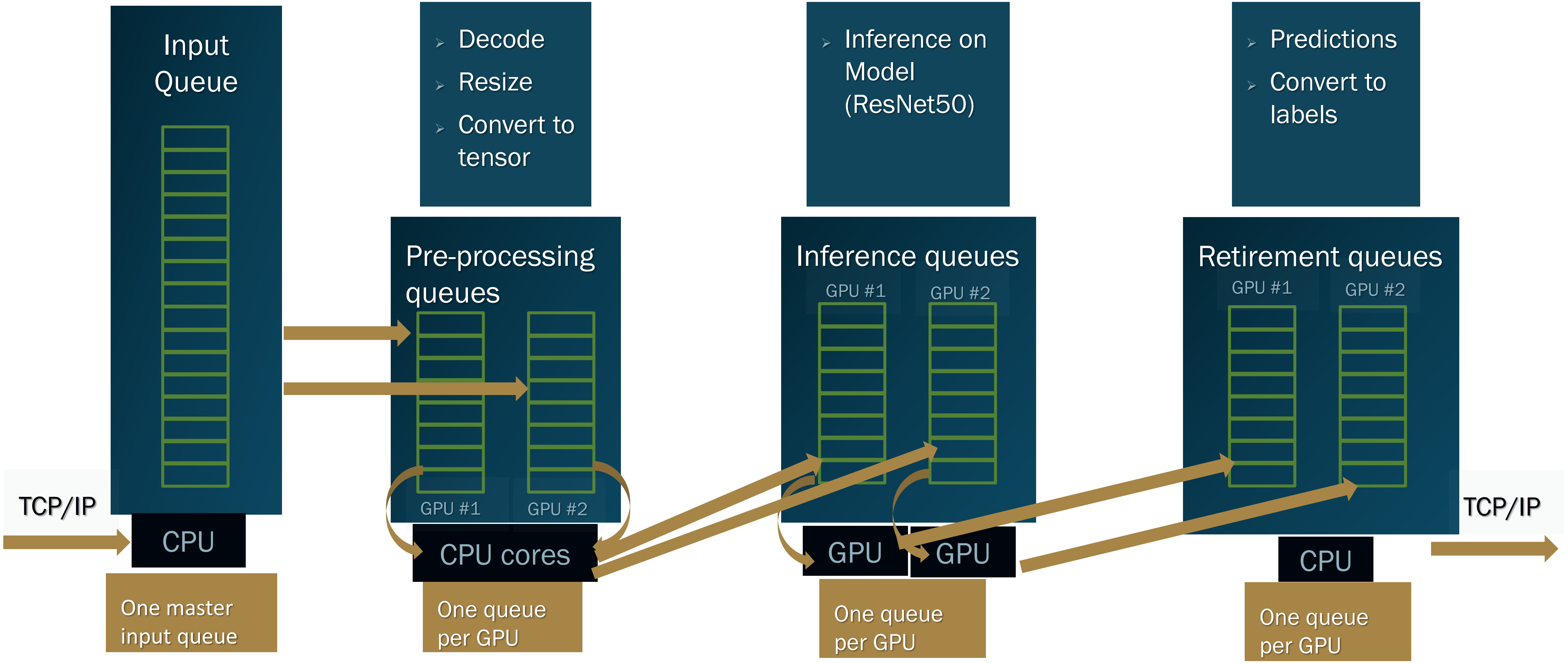
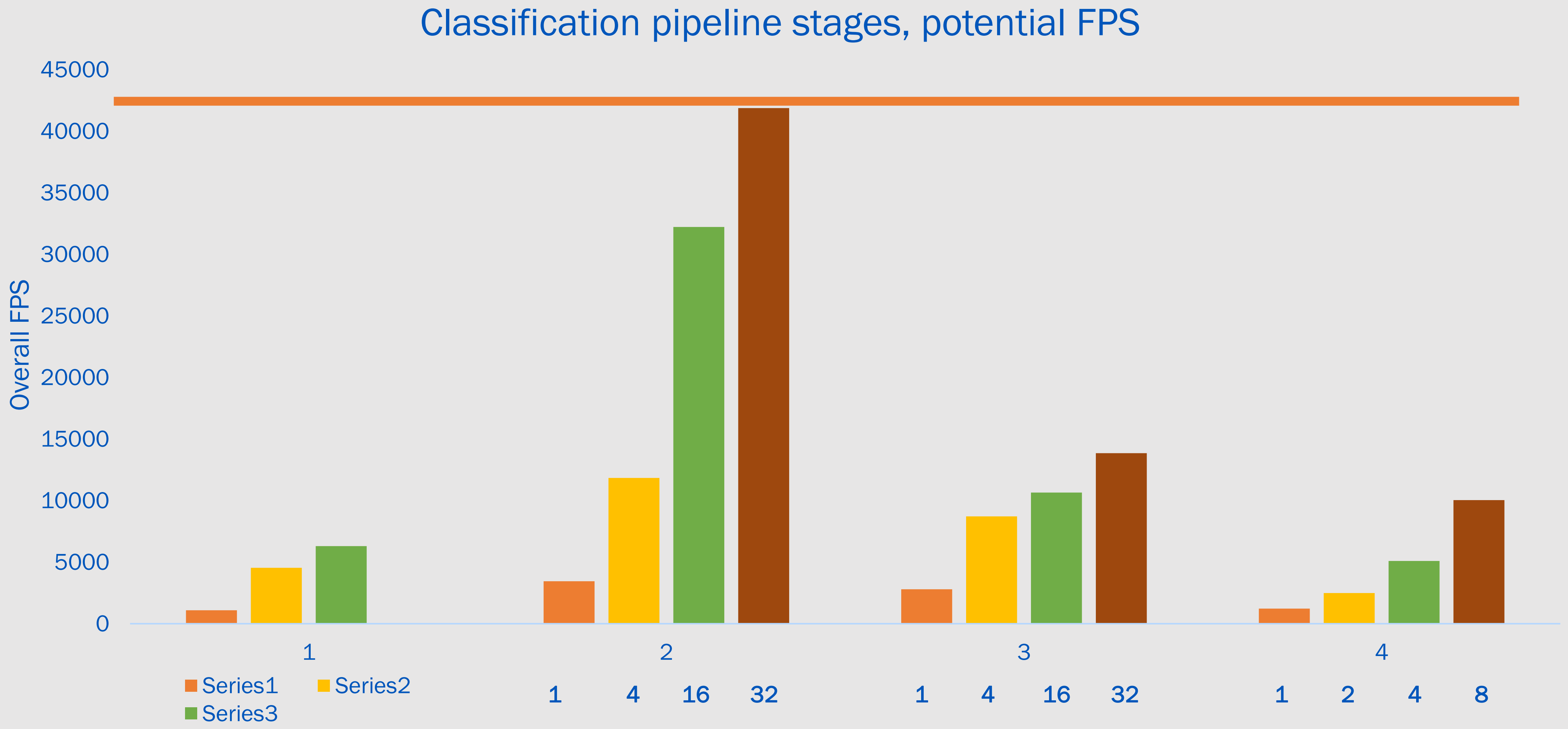
Server processing queues



Overall balance of different stages of pipeline



Kubernetes Pros and Cons

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PROS

- Deep integration into cloud native ecosystem
- Broad support for containers and runtimes
- Automatic scaling and load balancing
- Efficient resource management
- Multiple workloads and deployment options
- Built-in security
- Integration with major cloud providers

CONS

- Steep learning curve
- Challenging to install and configure manually
- Not suited for simple applications and can reduce productivity adopting it
- Need expensive talent to adopt it

Next Steps: Collecting metrics and evaluating the results

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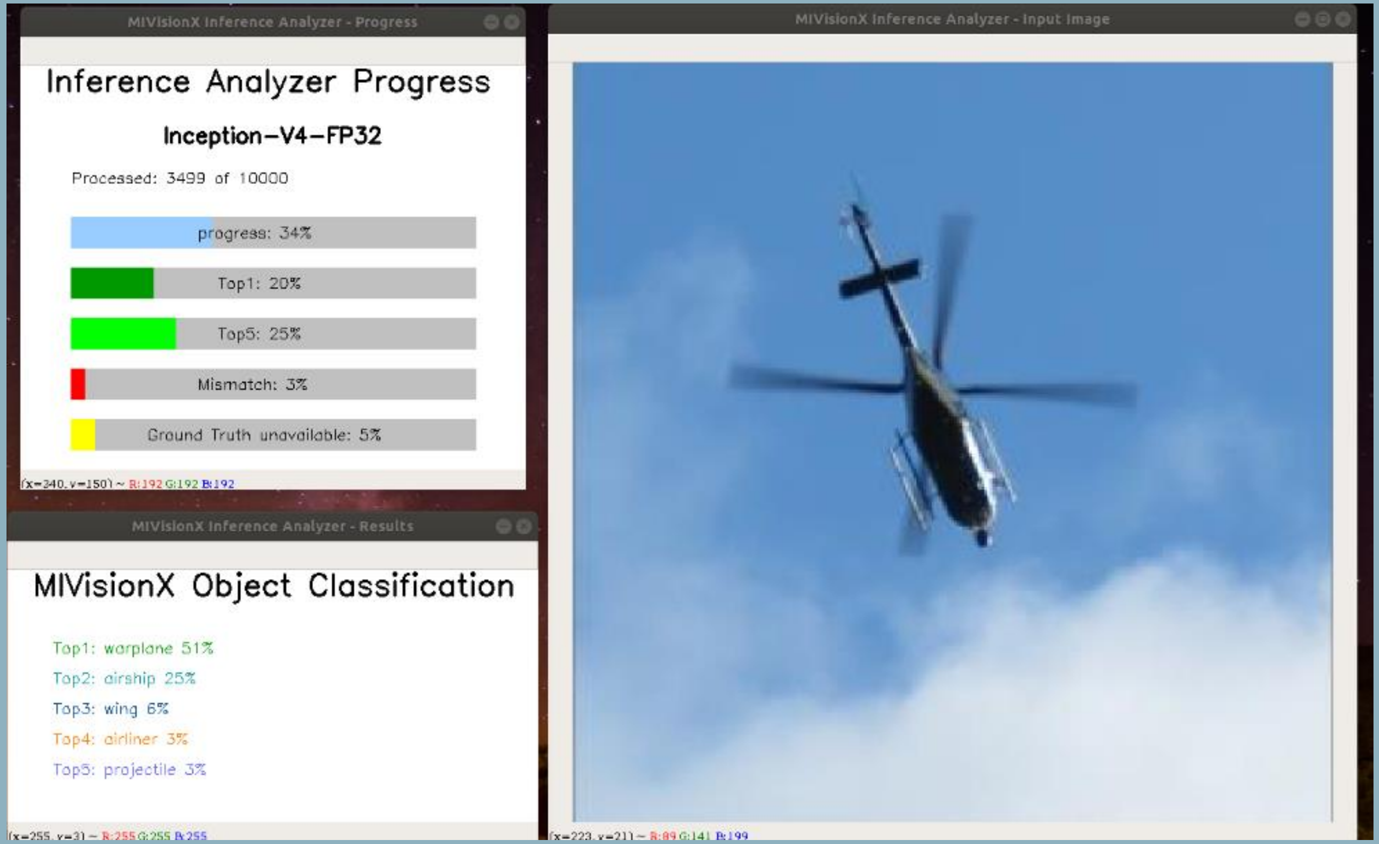
- Each K8s container can collect metrics asynchronously.
- Evaluating the neural network model guarantees the model will perform well given new data
- Various tools can be used to evaluate model for a given dataset
- E.g., inference analyzer to validate different models on one or more dataset



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Final Thoughts

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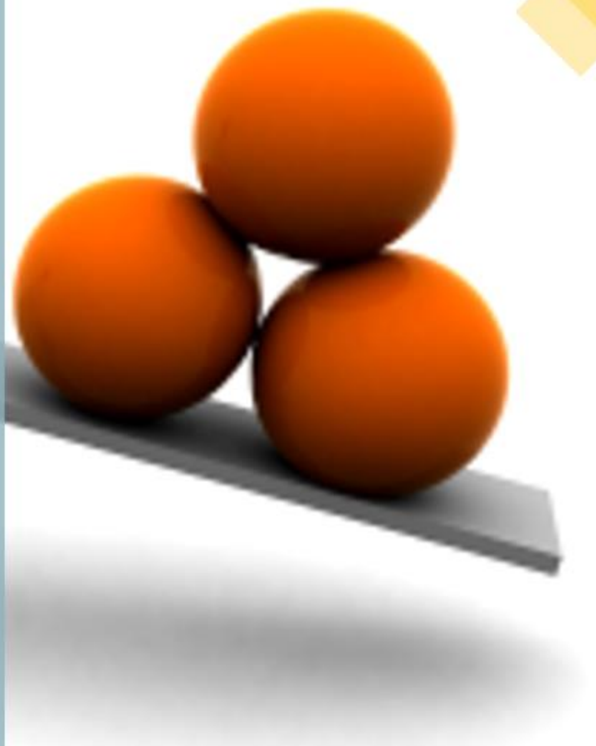
- Intelligent load balancing between CPU and GPU can increase the overall throughput
- By carefully analyzing the input pipeline and identifying parts that affect the gross performance, the latency can be minimized
- Different image sizes and complex models tip the workload to weigh on CPU/GPU or data-parallel processors
- Maintaining data queues at various stages is essential to reduce data-transfer bottlenecks
- Smaller batch sizes lower latency but doesn't give the best performance
- Finally, having the right tools to visually analyze the results is key to understand the whole picture



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Conclusion

As ML takes over many parts of our lives from protecting people to autonomous driving, we need simple automated ways to deploy and scale those applications

Data scientists need to analyze and iterate data-sets, algorithms and without slowing them down or placing heavy burden on company resources

By carefully developing your application for cloud-native environment with containers and micro-services, scientist can greatly scale those for portability and performance

References

MIVisionX

https://github.com/GPUOpen-ProfessionalCompute-Libraries/MIVisionX

Kubernetes

https://kubernetes.io/docs/home/

ResNet

https://github.com/onnx/models/tree/master/vision/classification/resnet

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