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Machine Learning Using Various GPU Technologies with Kubeflow

Jihye Choi, SAMSUNG SDS

Machine Learning Using Various GPU Technologies with Kubeflow

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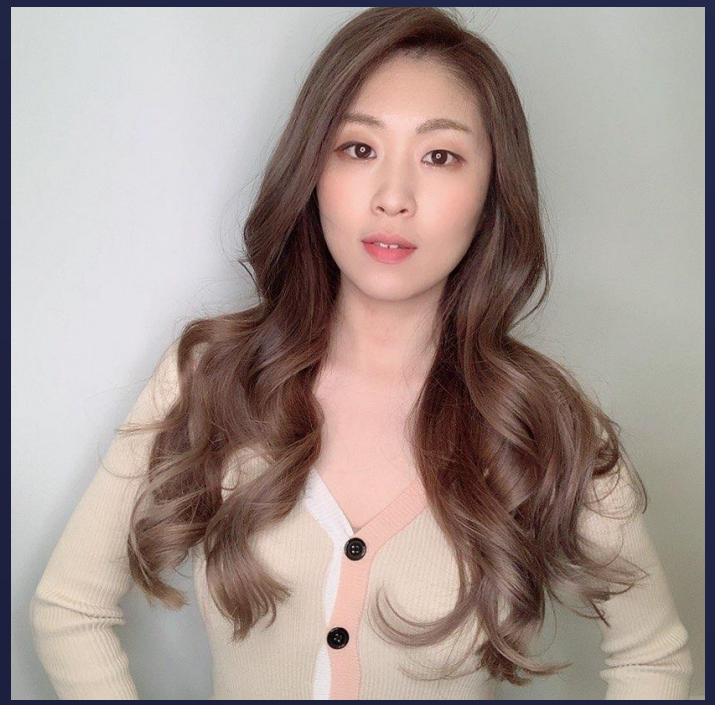


Jihye Choi
Cloud Architect
SAMSUNG SDS

October 24-28, 2022

Samsung Cloud Platform

- Compute
- Storage
- Database
- Container
- Networking
- Security
- Application Service
- DevOps Tools
- Analytics
- AI Service
- Management

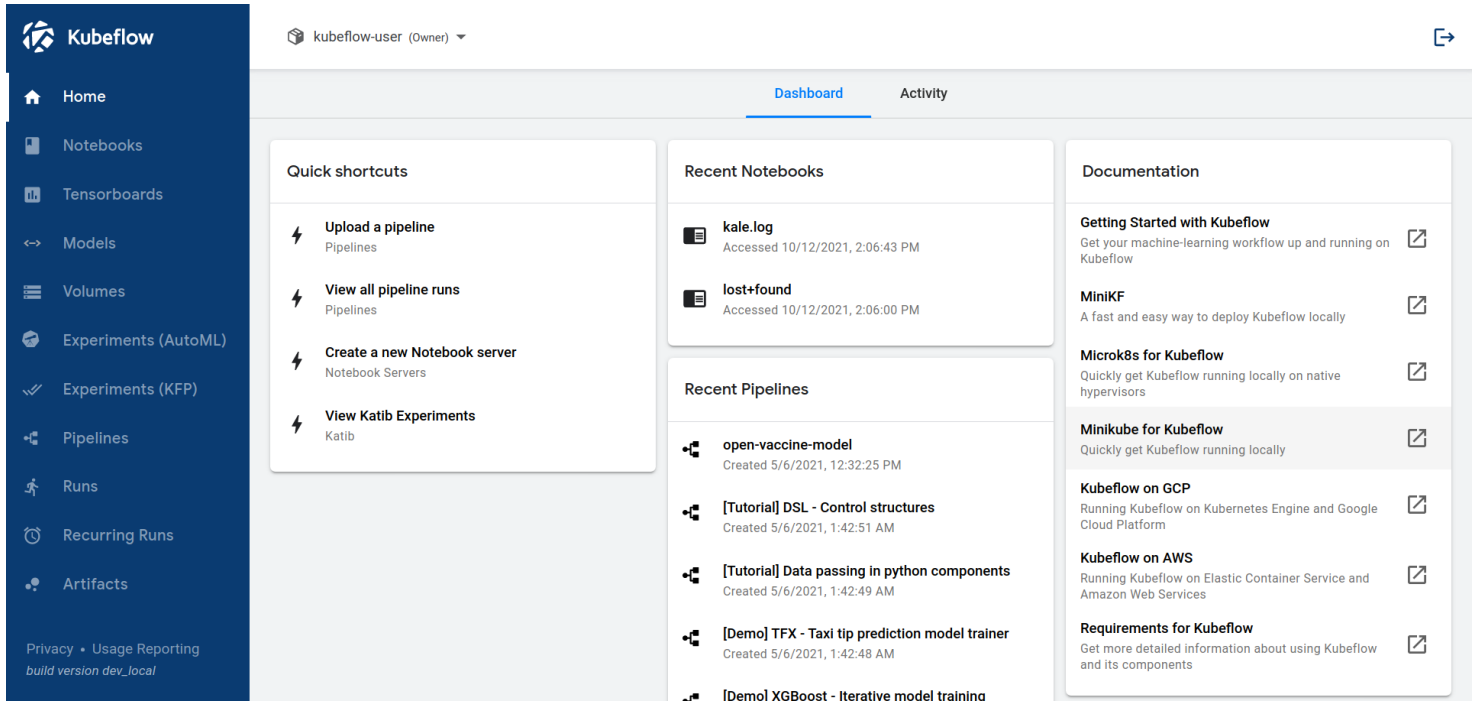
Kubeflow

Kubernetes-based Machine Learning Platform

SAMSUNG SDS

What is Kubeflow?

Kubeflow



kubernetes

jupyter

PyTorch

Istio

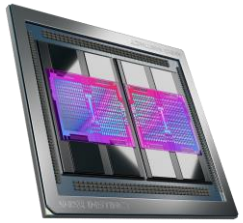
TensorFlow

mxnet

TensorRT

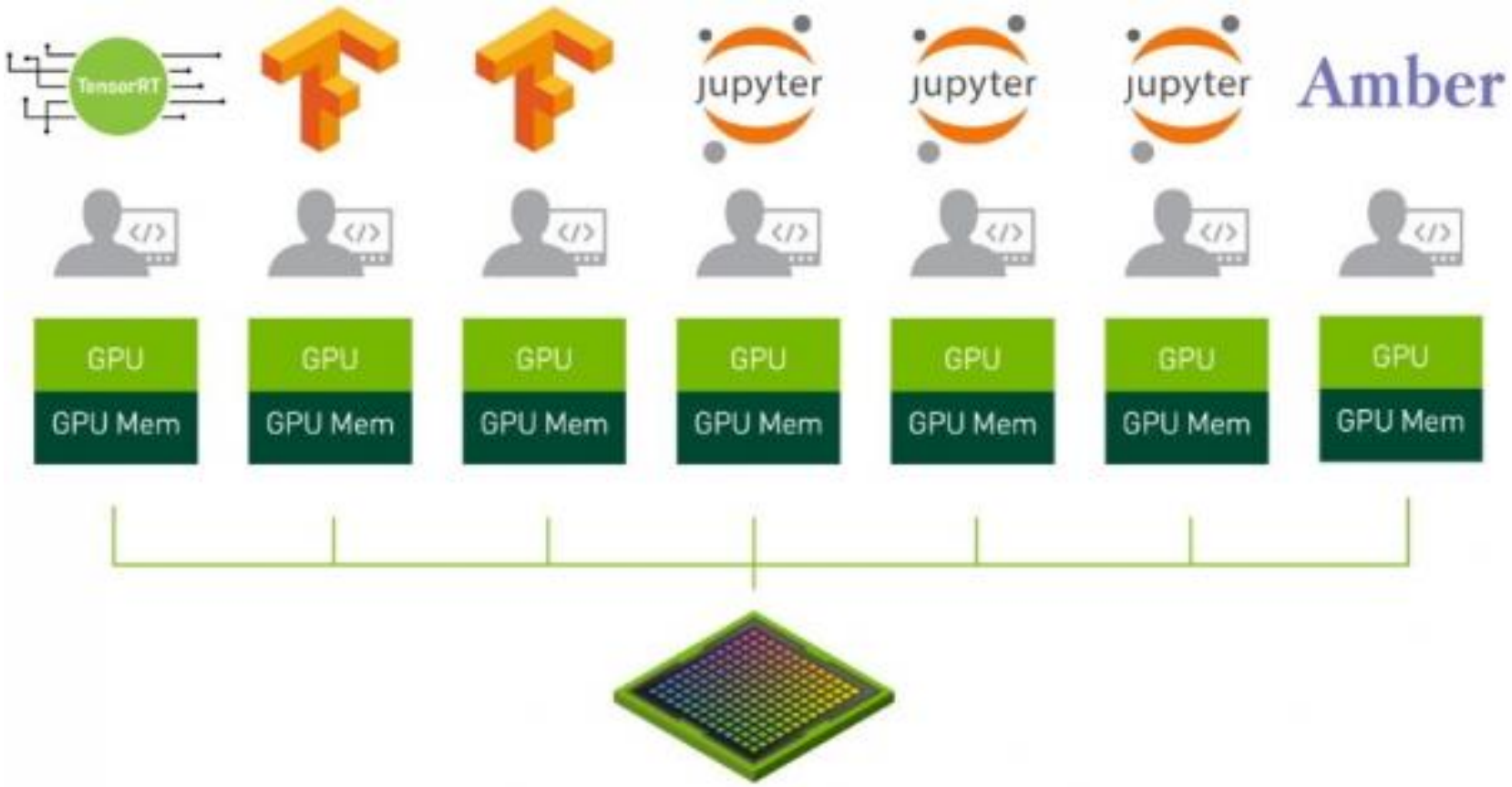
Case Study 1 : Multi-Instance GPU

GPUs in **Data Center** VS **Professional Desktop**

	NVIDIA H100	NVIDIA A100	AMD MI250	NVIDIA RTX
				
GPU Memory	80GB	80GB	128GB	4GB - 48GB
Memory Bandwidth	2.0TB/s	1,935 GB/s	3,276 GB/s	80 GB/s – 768 GB/s
Interconnect	PCIe Gen5	PCIe Gen4	PCIe Gen4	PCIe Gen3 PCIe Gen4
	GPUs in Data Center			**GPUs in Professional Desktop**

Case Study 1 : Multi-Instance GPU

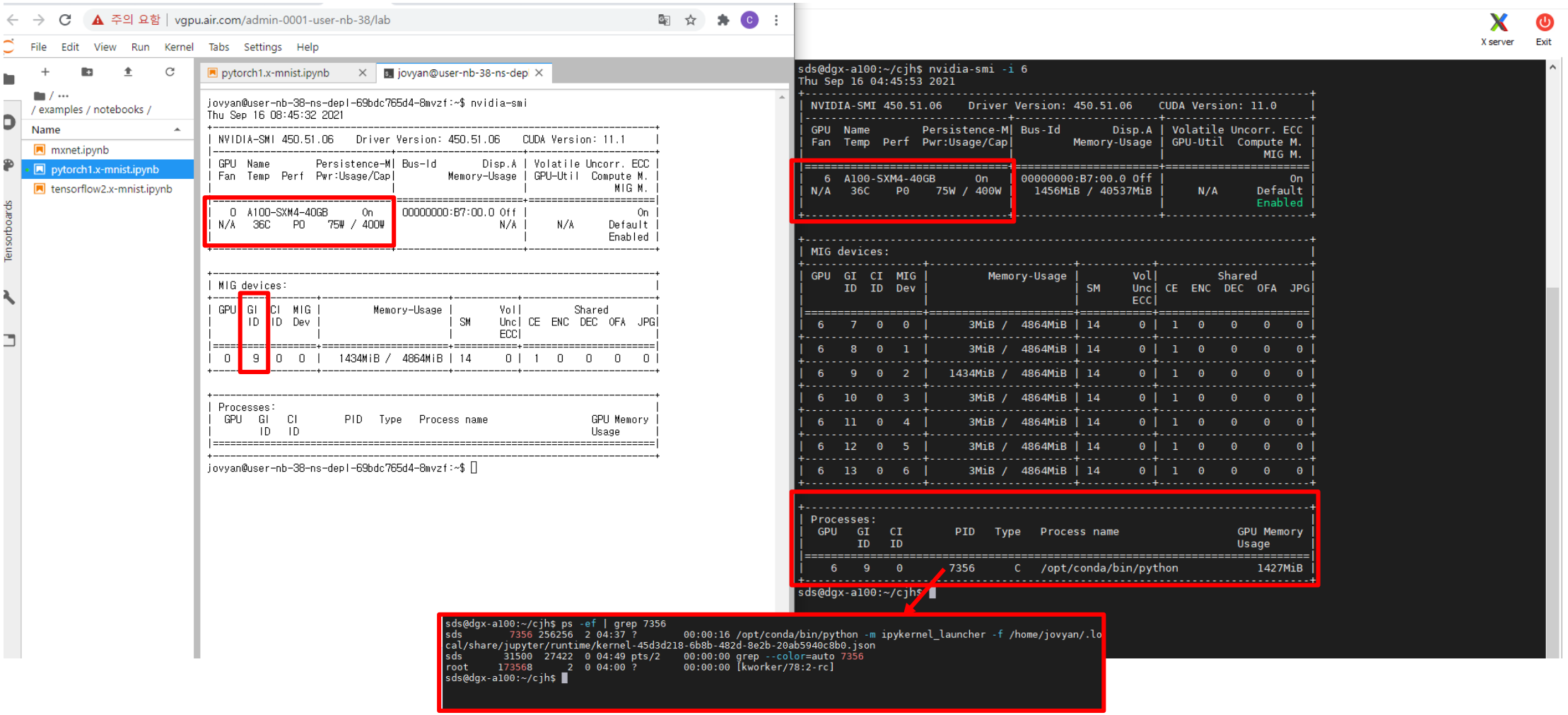
What is Multi-Instance GPU (MIG)?



Source : https://blogs.nvidia.com/blog/2020/05/14/multi-instance-gpus/

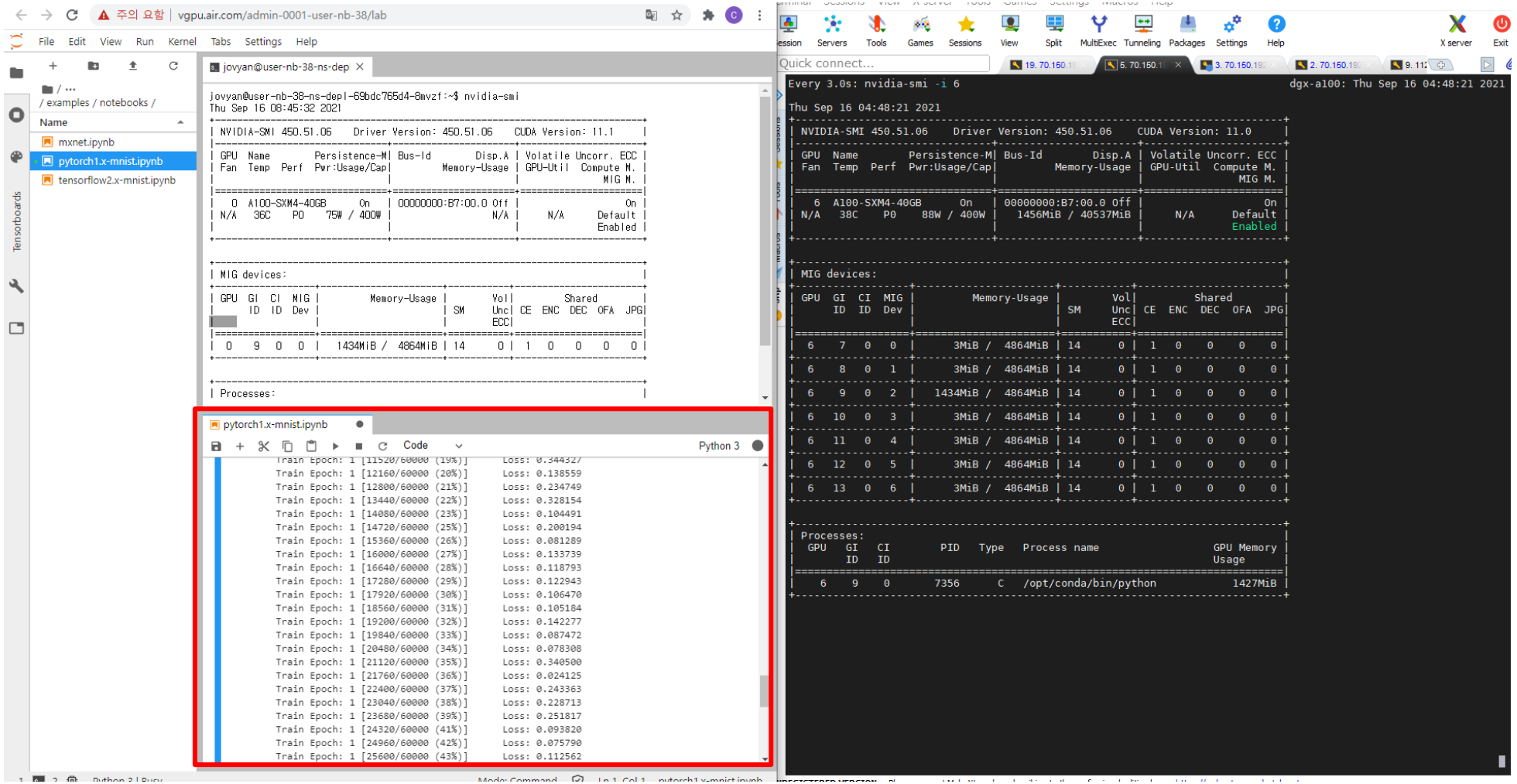
Case Study 1 : Multi-Instance GPU

1. Does it work well on Kubeflow?



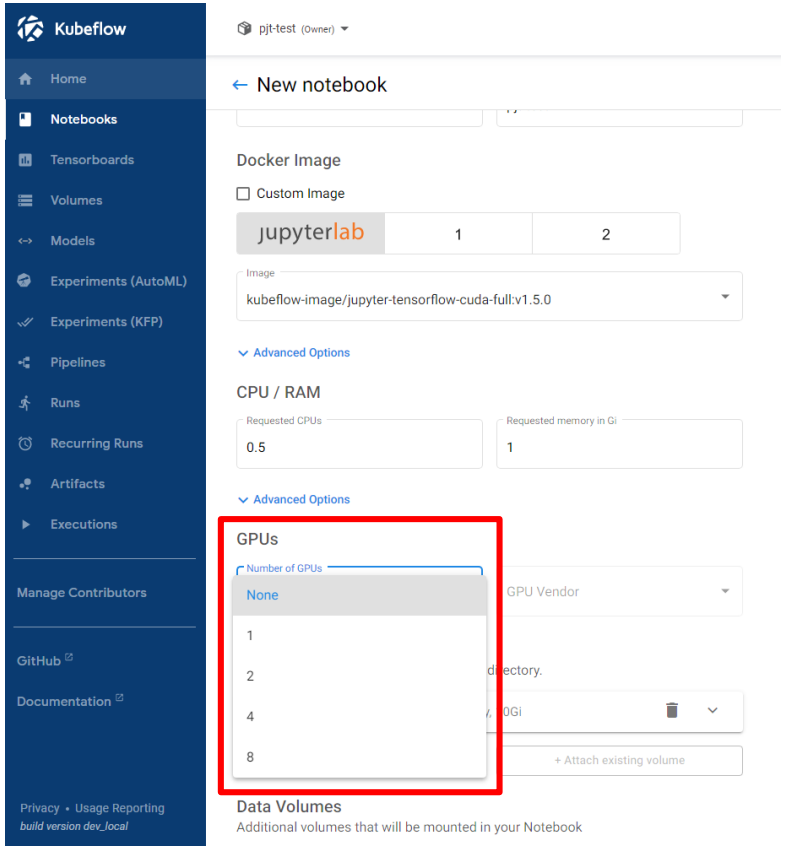
Case Study 1 : Multi-Instance GPU

1. Does it work well on Kubeflow?

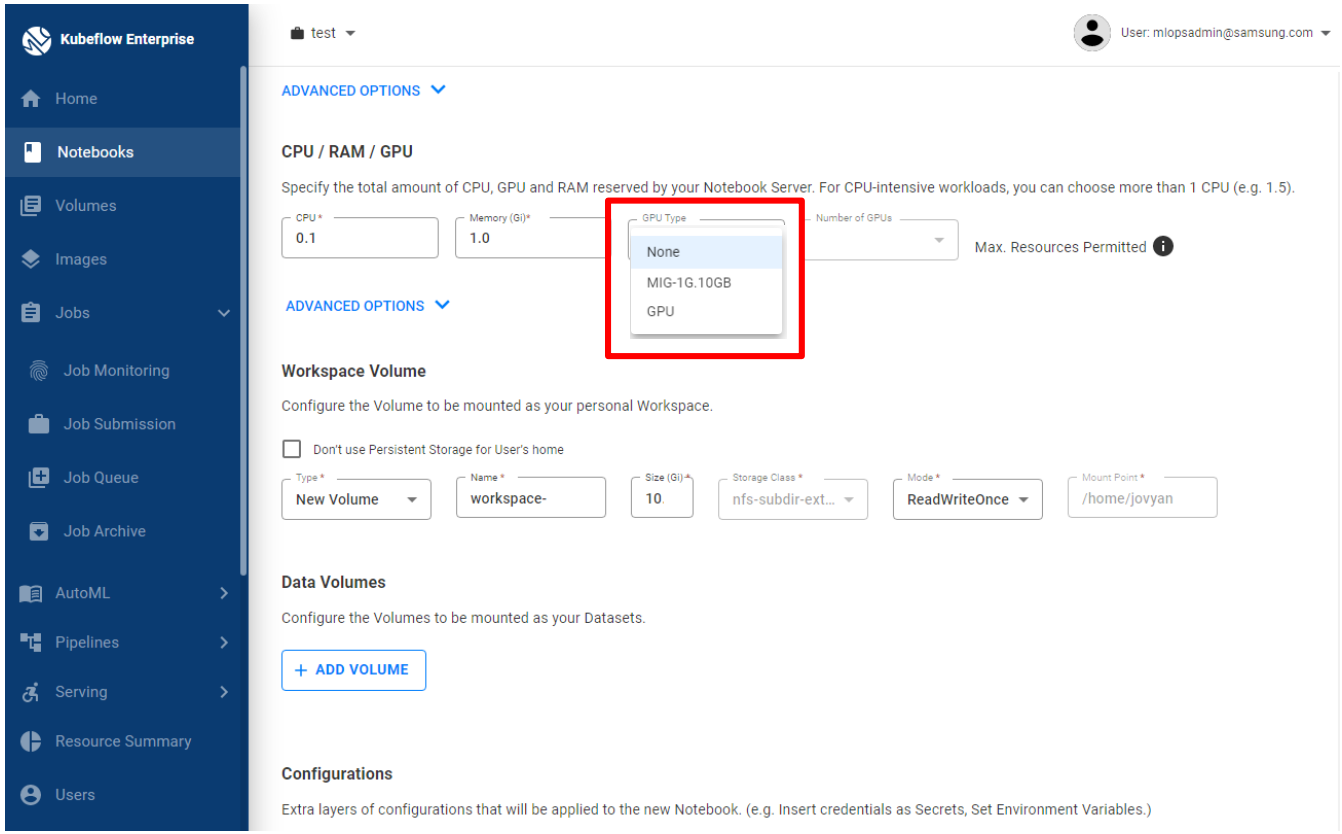


Case Study 1 : Multi-Instance GPU

1. Does it work well on Kubeflow?



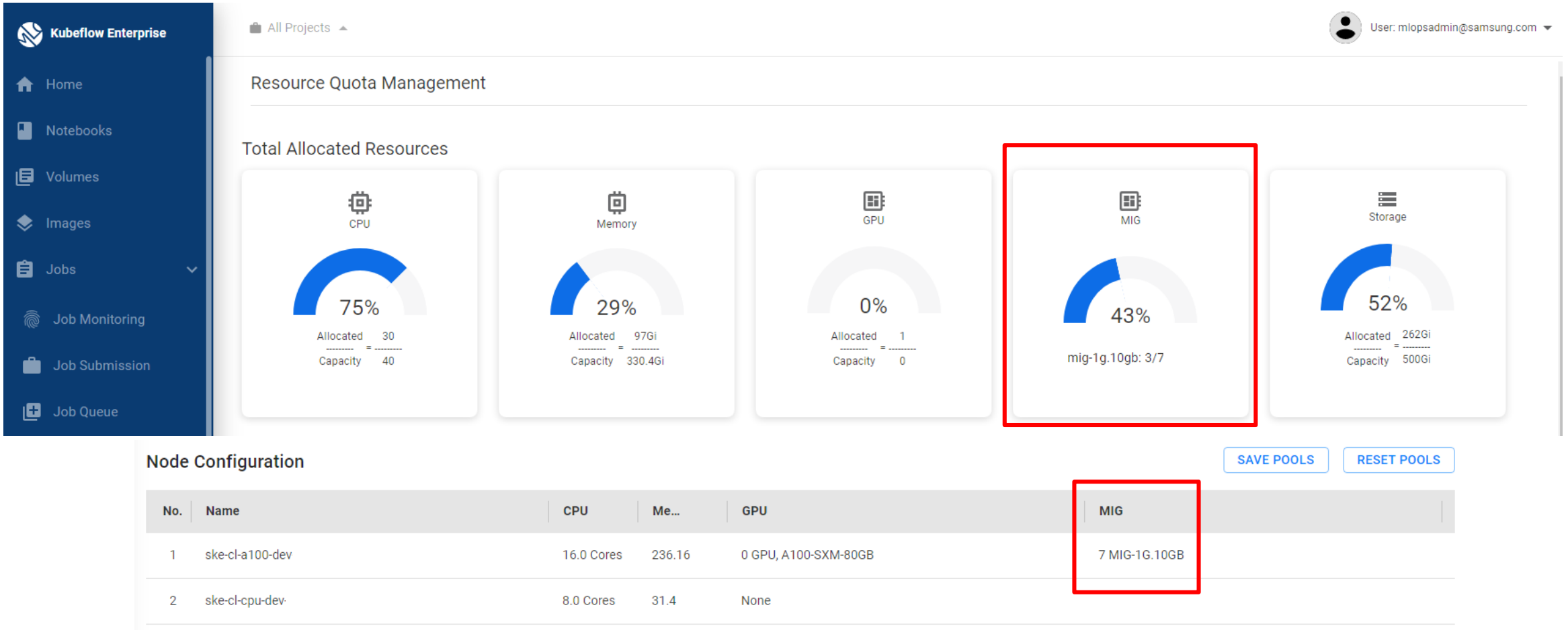
Open Source Kubeflow



SCP Kubeflow Service

Case Study 1 : Multi-Instance GPU

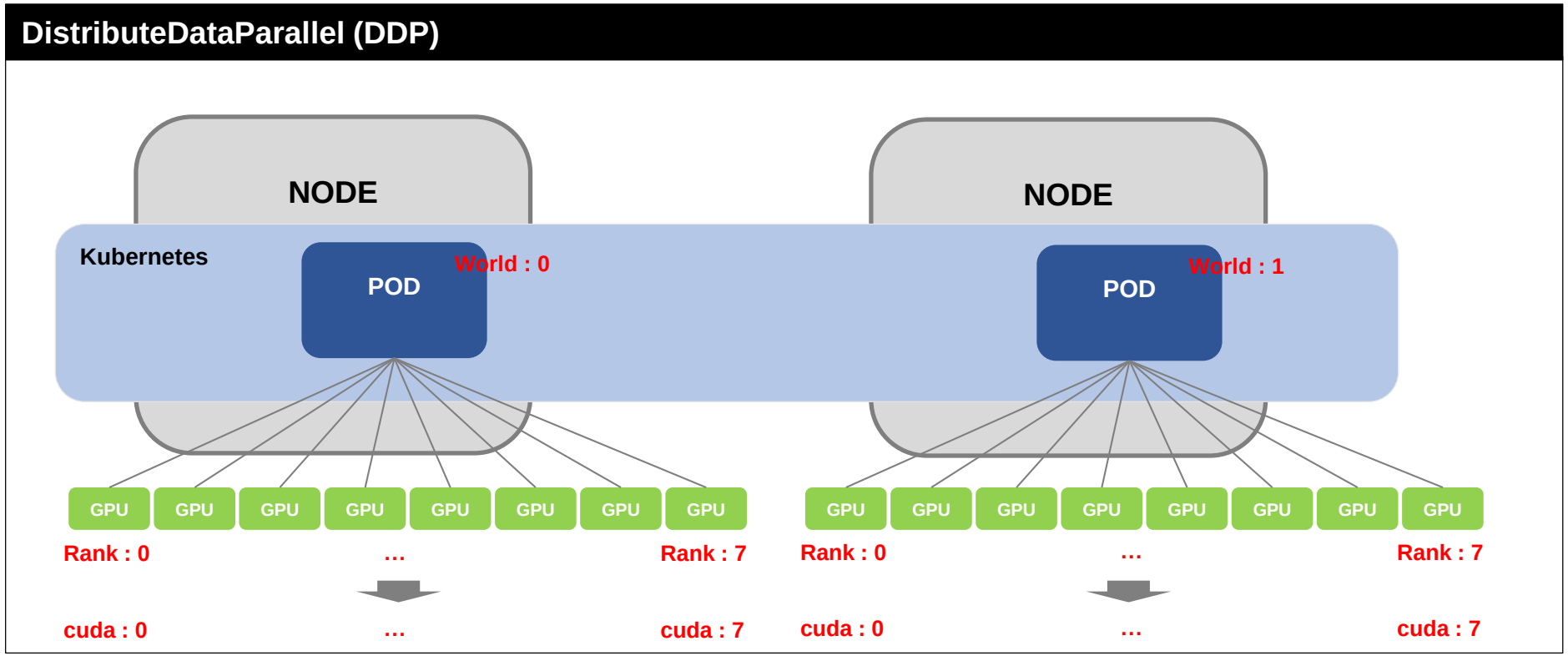
1. Does it work well on Kubeflow?



SCP Kubeflow Service

Case Study 1 : Multi-Instance GPU

2. Is Distributed Training Feasible? (only one MIG device can be assigned per POD)




```
device = torch.device("cuda:{}".format(rank))
```

- World Size: Total Number of Process
- Rank : Name of Process

Case Study 1 : Multi-Instance GPU

2. Is Distributed Training feasible? (only one MIG device can be assigned per POD)

```yaml
kind: PyTorchJob
metadata:
  name: pytorch-albert-4gpu
spec:
  pytorchReplicaSpecs:
    Master:
      replicas: 1
      template:
        spec:
          containers:
            image:
            name: pytorch
            resources:
              limits:
                nvidia.com/gpu: 4
    Worker:
      replicas: 1
      restartPolicy: OnFailure
      template:
        metadata:
          annotations:
            sidecar.istio.io/inject: "false"
        spec:
          containers:
            image:
            name: pytorch
            resources:
              limits:
                nvidia.com/gpu: 4
```

Total 8 GPUs

<4 GPUs per POD, Total 2 PODs>

```
Every 2.0s: nvidia-smi

Wed Oct 20 09:58:54 2021
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 470.57.02    Driver Version: 470.57.02    CUDA Version: 11.4     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  NVIDIA A100-SXM...  Off  | 00000000:07:00.0 Off |                    0 |
| N/A   30C    P0    63W / 400W |   1012MiB / 81251MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   1  NVIDIA A100-SXM...  Off  | 00000000:0B:00.0 Off |                    0 |
| N/A   30C    P0    65W / 400W |   1012MiB / 81251MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   2  NVIDIA A100-SXM...  Off  | 00000000:48:00.0 Off |                    0 |
| N/A   30C    P0    66W / 400W |   1012MiB / 81251MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   3  NVIDIA A100-SXM...  Off  | 00000000:4C:00.0 Off |                    0 |
| N/A   31C    P0    69W / 400W |   1012MiB / 81251MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   4  NVIDIA A100-SXM...  Off  | 00000000:88:00.0 Off |                    0 |
| N/A   29C    P0    66W / 400W |   1012MiB / 81251MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   5  NVIDIA A100-SXM...  Off  | 00000000:8B:00.0 Off |                    0 |
| N/A   30C    P0    67W / 400W |   1012MiB / 81251MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   6  NVIDIA A100-SXM...  Off  | 00000000:C8:00.0 Off |                    0 |
| N/A   30C    P0    68W / 400W |   1012MiB / 81251MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+
|   7  NVIDIA A100-SXM...  Off  | 00000000:CB:00.0 Off |                    0 |
| N/A   30C    P0    66W / 400W |   1012MiB / 81251MiB |      0%      Default |
|                               |                      |             Disabled |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|    0   N/A  N/A   4044499      C   /opt/conda/bin/python            1009MiB |
|    1   N/A  N/A   4044500      C   /opt/conda/bin/python            1009MiB |
|    2   N/A  N/A   4044501      C   /opt/conda/bin/python            1009MiB |
|    3   N/A  N/A   4044502      C   /opt/conda/bin/python            1009MiB |
|    4   N/A  N/A   4041834      C   /opt/conda/bin/python            1009MiB |
|    5   N/A  N/A   4041840      C   /opt/conda/bin/python            1009MiB |
|    6   N/A  N/A   4041842      C   /opt/conda/bin/python            1009MiB |
|    7   N/A  N/A   4041843      C   /opt/conda/bin/python            1009MiB |
+-----------------------------------------------------------------------------+
```

Case Study 1 : Multi-Instance GPU

2. Is Distributed Training feasible? (only one MIG device can be assigned per POD)

Case Study 1 : Multi-Instance GPU

2. Is Distributed Training feasible? (only one MIG device can be assigned per POD)

```yaml
kind: PyTorchJob
metadata:
  name: pytorch-albert-mig2
spec:
  pytorchReplicaSpecs:
    Master:
      replicas: 1
      template:
        spec:
          containers:
            image:
            name: pytorch
            resources:
              limits:
                nvidia.com/mig-1g.10gb: 2
    Worker:
      replicas: 1
      restartPolicy: OnFailure
      template:
        metadata:
          annotations:
            sidecar.istio.io/inject: "false"
        spec:
          containers:
            image:
            name: pytorch
            resources:
              limits:
                nvidia.com/mig-1g.10gb: 2
```

Total 4 MIGs

<2 MIGs per POD, Total 2 PODs>

```
root@ac-a100-10:~/cjh# kubectl logs -f pytorch-albert-mig2-master-0
World Size: : 2
Number of Gpus : 2
Node Rank : 0
Master Addr : localhost
Master Port : 23456
Params :  --do_train --fp16 --train_batch_size 1 --gradient_accumulation_steps 1 --num_train
b_disable 1 --nccl_ib_gdr_level 0
*****************************************
Setting OMP_NUM_THREADS environment variable for each process to be 1 in default, to avoid y
 for optimal performance in your application as needed.
*****************************************
============================================================
Train Batch Size:              1
Gradient Acculumation Steps:   1
NCCL Debug:           INFO
NCCL_DEBUG_SUBSYS:    INIT
NCCL_IB_DISABLE:      1
NCCL_IB_GDR_LEVEL:    0
Model Name:           albert
Config File:          /workspace/src/bert/albert_config_large_with_dropout.json
============================================================
Traceback (most recent call last):
  File "/workspace/src/bert/benchmark.py", line 2250, in <module>
    main()
  File "/workspace/src/bert/benchmark.py", line 2207, in main
    torch.cuda.set_device(args.local_rank)
  File "/opt/conda/lib/python3.6/site-packages/torch/cuda/__init__.py", line 263, in set_dev
    torch._C._cuda_setDevice(device)
RuntimeError: CUDA error: invalid device ordinal
============================================================
```

Error!

Case Study 1 : Multi-Instance GPU

2. Is Distributed Training feasible? (only one MIG device can be assigned per POD)

```yaml
kind: PyTorchJob
metadata:
  name: pytorch-albert-mig2
spec:
  pytorchReplicaSpecs:
    Master:
      replicas: 1
      template:
        spec:
          containers:
            image:
            name: pytorch
            resources:
              limits:
                nvidia.com/mig-1g.10gb: 1
    Worker:
      replicas: 1
      restartPolicy: OnFailure
      template:
        metadata:
          annotations:
            sidecar.istio.io/inject: "false"
        spec:
          containers:
            image:
            name: pytorch
            resources:
              limits:
                nvidia.com/mig-1g.10gb: 1
```

Total 2 MIGs

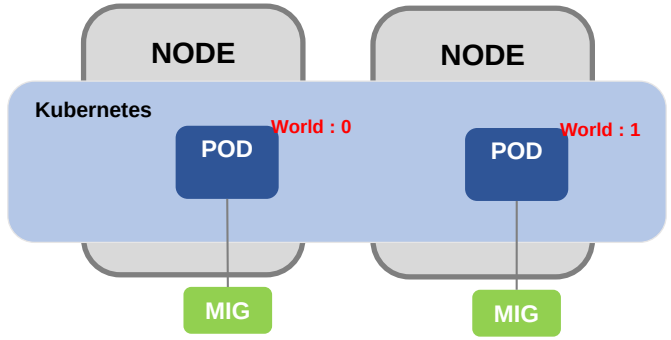
<1 MIGs per POD, Total 2 PODs>

```
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|    0    8    0    3595546      C   /opt/conda/bin/python             585MiB |
|    5   13    0    3594150      C   /opt/conda/bin/python             585MiB |
```

```
Init Process
[__main__] device: cuda:0 n_gpu: 1, distributed training: True, 16-bits training: True
Train Start
WARNING: Output directory /workspace/shared-dir/bert/results/squad ... 281181_2e-05
korquard_config.pt', 'albert_korquard_model_final.pt']
LOADING CHECKPOINT
LOADED CHECKPOINT
to device
Selected optimization level O2:  FP16 training with FP32 batchnorm and FP32 master weights.
```

Running!

DistributeDataParallel (DDP)



Case Study 1 : Multi-Instance GPU

3. Performance

□ Model

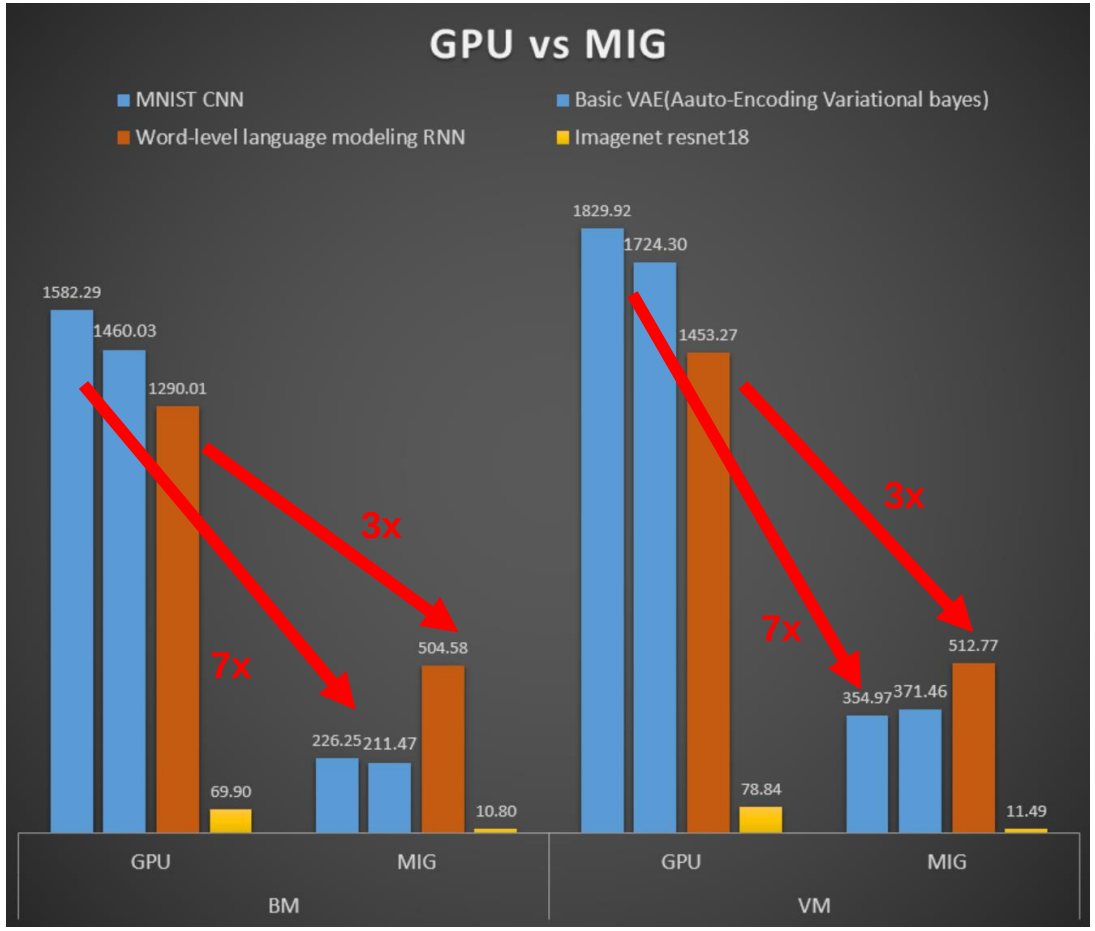
Dataset	MNIST	Basic VAE	ImageNet	World-Level Languge
ML Models	CNN		Resnet18	RNN
ML Frameworks	PyTorch			

□ How to Test

- GPU : Sequentially 7 times on 1 GPU
- MIG : Parallelly 1 time on 7 MIGs (1g.10gb)

□ Result

- Comparing **Total Execution Time**
  . CNN : 500-700%
  . Resnet18 : 700%
  . RNN : 300%



Case Study 1 : Multi-Instance GPU

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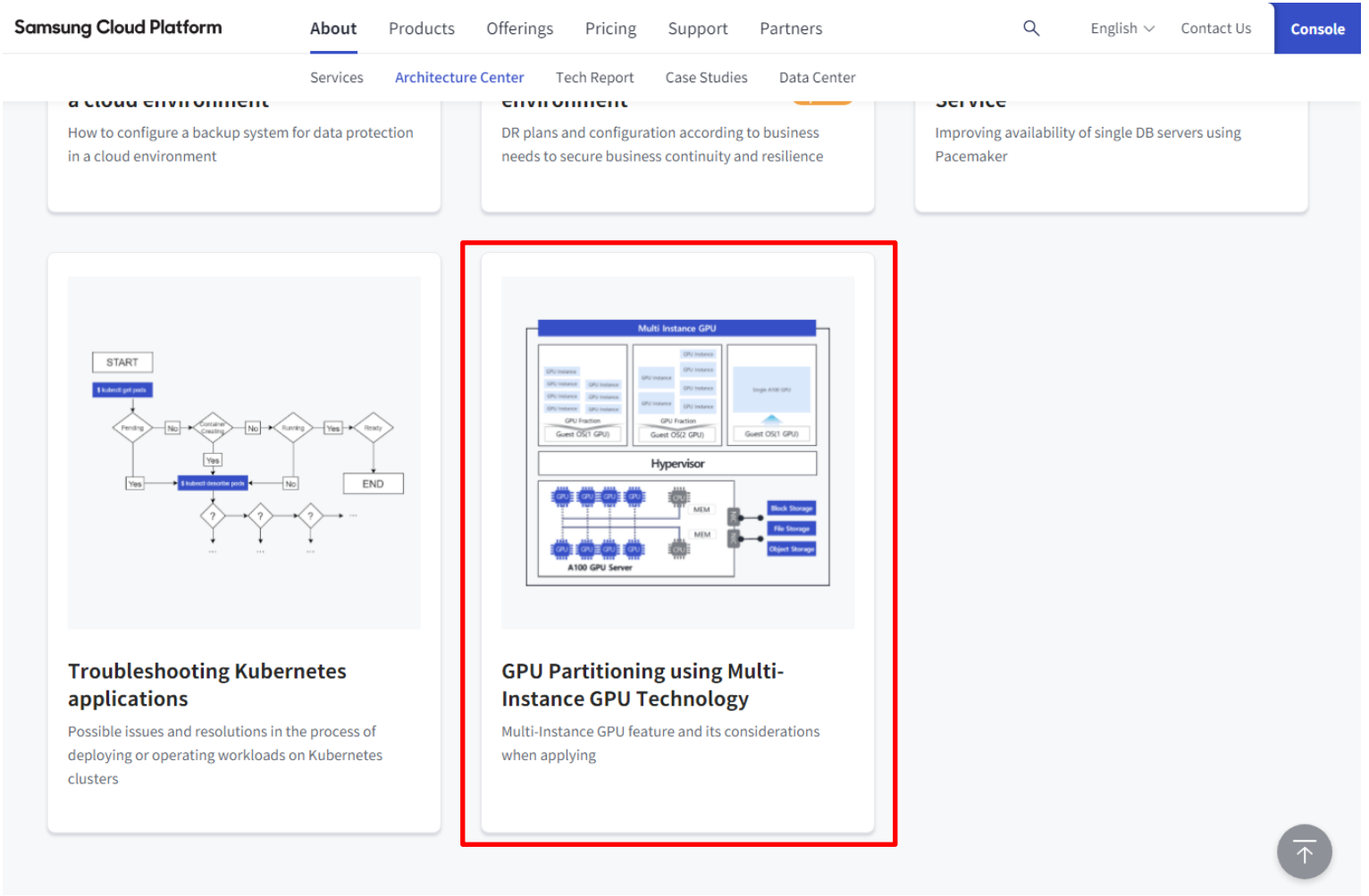
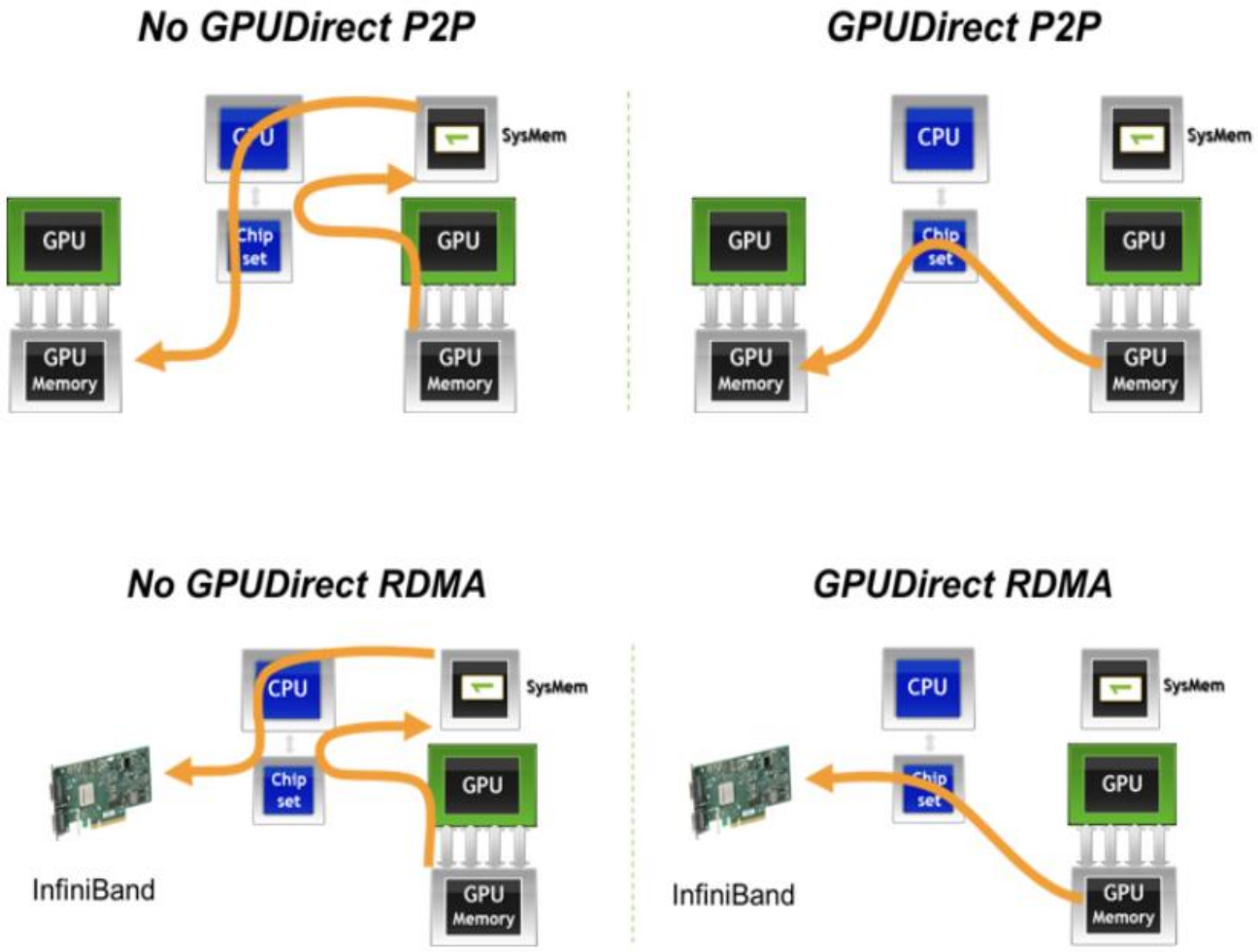
https://cloud.samsungsds.com/

Architecture Center > Technical Guides



Case Study 2 : GPUDirect RDMA

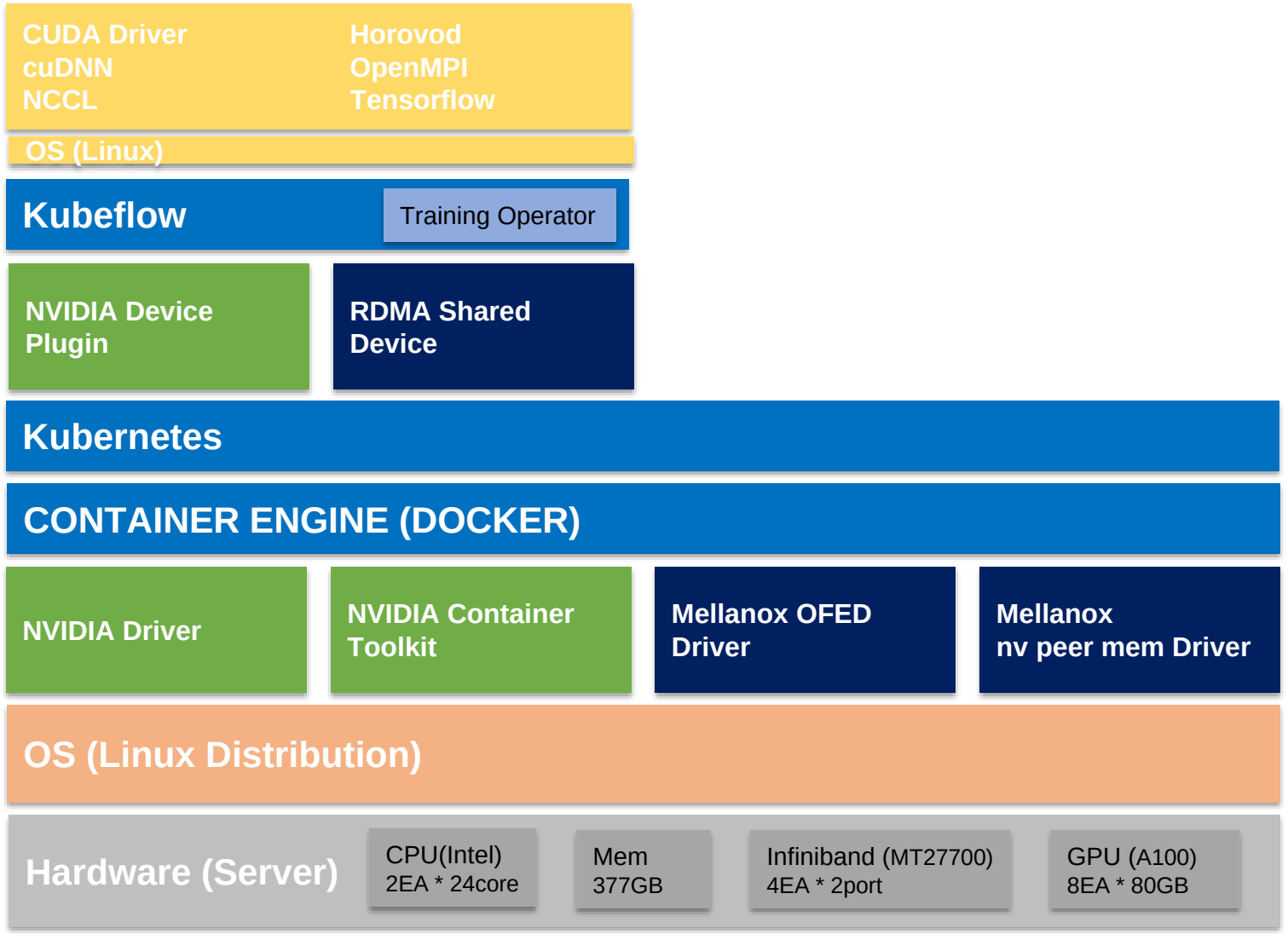
What is GPUDirect RDMA(Remote Direct Memory Access)?



Source :https://developer.nvidia.com/blog/introduction-cuda-aware-mpi/

Case Study 2 : GPUDirect RDMA

Software Architecture



Case Study 2 : GPUDirect RDMA

Examples

```yaml
apiVersion: "kubeflow.org/v1"
kind: "PyTorchJob"
metadata:
  name: "pytorch-flower-rdma"
spec:
  pytorchReplicaSpecs:
    Master:
      replicas: 1
      restartPolicy: OnFailure
      template:
        metadata:
          annotations:
            sidecar.istio.io/inject: "false"
        spec:
          containers:
            - name: pytorch
              image:
              command: ["python","/workspace/jovyan/src/launch.py","--dist","2“, "--nccl_ib_disable","0","--nccl_ib_gdr_level","1"]
              # Comment out the below resources to use the CPU.
              resources:
                limits:
                  nvidia.com/gpu: 8
                  rdma/hca_shared_devices_a: "1"
              securityContext:
                capabilities:
                  add: [ "IPC_LOCK" ]
```

OS ENV

Kubernetes Resource
& SecurityContext

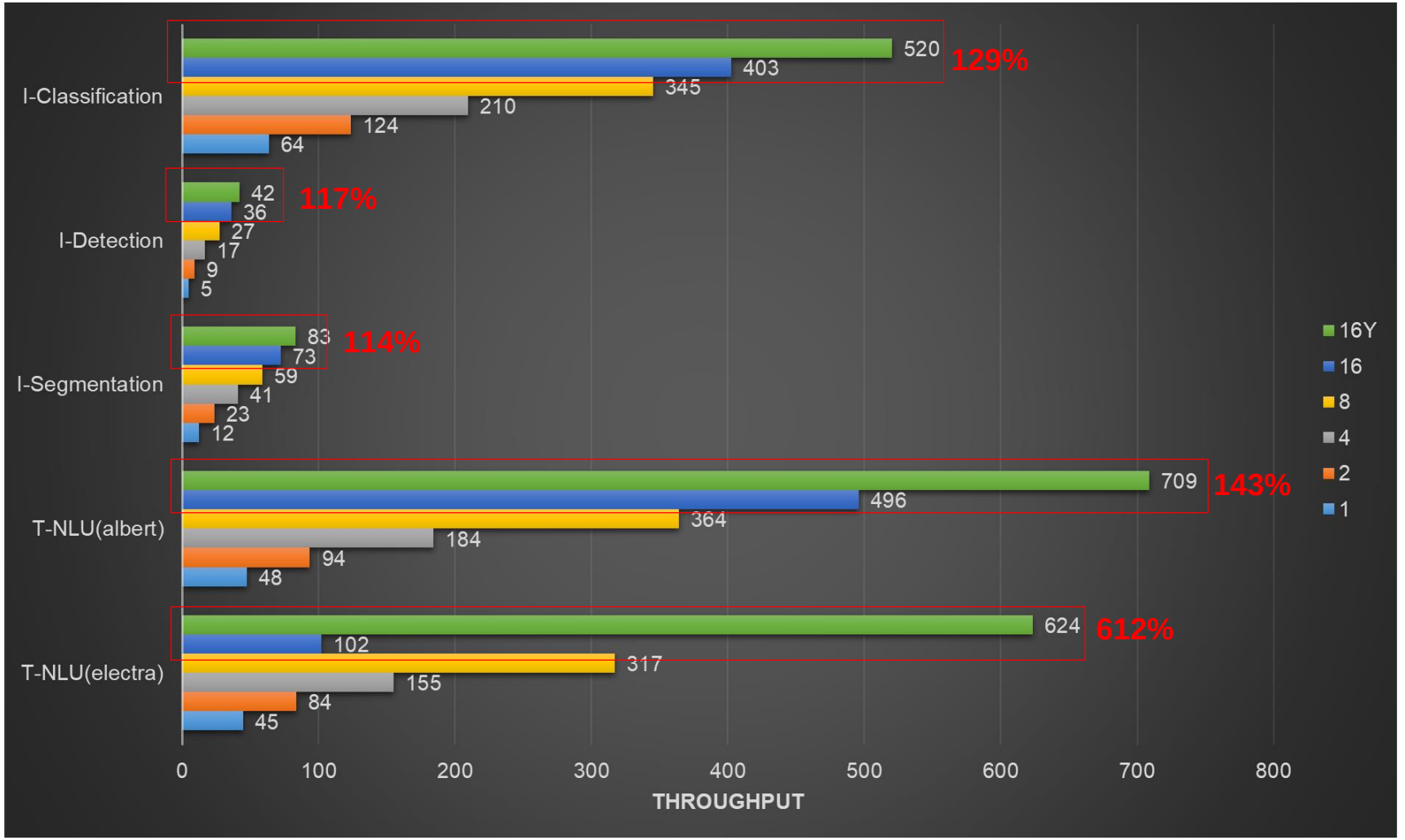
Case Study 2 : GPUDirect RDMA

Examples

```
World Size:          2
Number of Gpus:      8
Dist World Size:     16 (World Size x Number of Gpus)
Node Rank:           0
NCCL_IB_DISABLE:     0
NCCL_IB_GDR_LEVEL:   1
(중략)
INFO: =============   start   =============
INFO: ## model_type             : segmentation
INFO: ## model_name             : unet
INFO: ## model_input    : [512,512,3]
INFO: ## gpu_name               : A100 Graphics Device
INFO: ## gpus                   : 16
INFO: ## epochs                 : 5
INFO: ## batch_size             : 128
pytorch-flower-rdma-master-0:149:149 [0] NCCL INFO Bootstrap : Using [0]eth0:40.244.64.19<0>
pytorch-flower-rdma-master-0:149:149 [0] NCCL INFO NET/Plugin : No plugin found (libnccl-net.so), using internal implementation
pytorch-flower-rdma-master-0:149:149 [0] NCCL INFO NCCL_IB_DISABLE set by environment to 0.
pytorch-flower-rdma-master-0:149:149 [0] NCCL INFO NET/IB : Using [0]mlx5_0:1/IB [1]mlx5_2:1/IB [2]mlx5_5:1/RoCE [3]mlx5_7:1/IB ; OOB
eth0:40.244.64.19<0>
pytorch-flower-rdma-master-0:149:149 [0] NCCL INFO Using network IB
NCCL version 2.7.8+cuda11.1
(중략)
pytorch-flower-rdma-master-0:154:299 [5] NCCL INFO GPU Direct RDMA Enabled for GPU 8b000 / HCA 3 (distance 3 <= 3), read 0
pytorch-flower-rdma-master-0:153:300 [4] NCCL INFO Channel 01 : 4[88000] -> 3[4c000] via P2P/IPC/read
pytorch-flower-rdma-master-0:156:296 [7] NCCL INFO GPU Direct RDMA Enabled for GPU cb000 / HCA 1 (distance 3 <= 3), read 1
pytorch-flower-rdma-master-0:154:299 [5] NCCL INFO Channel 01 : 10[48000] -> 5[8b000] [receive] via NET/IB/3/GDRDMA
pytorch-flower-rdma-master-0:156:296 [7] NCCL INFO Channel 02 : 7[cb000] -> 12[88000] [send] via NET/IB/1/GDRDMA
(중략)
INFO: =============   end   =============
```

Case Study 2 : GPUDirect RDMA

Performance



※ throughput = total_examples / exec_time

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