# Centralized Management of Your Machine Learning Lifecycle Preparation, Training and Model Serving

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### A bit of history...

First kubeflow trials at CERN started ~2.5 years ago

Helping a few users scale out machine learning use cases

From a single GPU to distributed training with 10s GPUs

Gradual expansion to a preview service (ongoing)

Slowly onboarding new users

Exploring the remaining bits of the ML lifecycle

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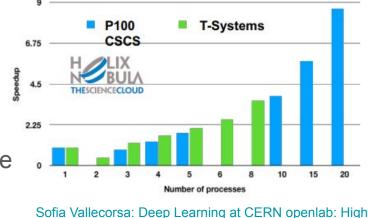
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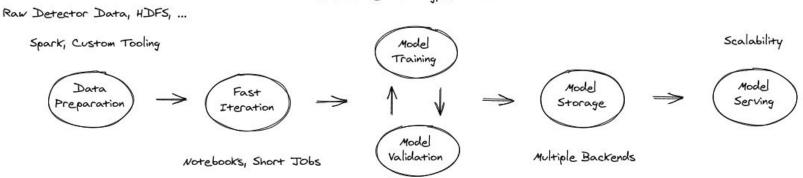
Exploring the remaining bits of the ML lifecycle



Energy Physics and Beyond

#### Motivation

Offer a platform to manage the full machine learning lifecycle



Distributed Training, Automation

#### **Motivation**

Ensure efficient usage of our All node groups auto scaling on demand Node Pay only on actual usage, aggressive downscale on idle CPU Group on premises GPU resources Node TPU V3 Group (Node Group) europe-west4 1 GPU K80 GCP  $\rightarrow$ Node Provide easy access to public cloud accelerators GPU AIOO Node GPU VIDO (GPUs, TPUs, IPUs, FPGAs, ...) europe-west  $\rightarrow$ CERN GCP GPU T4 Group 11 Node AWS ARM Group

> Azure > (Node Group IPU

#### Infrastructure



Based on Kubeflow, the machine learning toolkit for Kubernetes

Open source project started by Google in 2018

https://github.com/kubeflow/kubeflow

Declarative API, Operators, Auto healing, Application and Cluster auto scaling

Support for most common frameworks (TensorFlow, PyTorch, MXNET, ...)

In production at multiple companies

Google, Spotify, Bloomberg, Zillow, Arrikto...

#### Infrastructure

#### On Premises GPUs: Nvidia V100s and T4s

Full GPU card assignment

Distributed training, hyper parameter optimization, model serving

#### On Premises vGPUs (soon)

Time sharing of a GPU, up to 4x

Notebooks, code validation, quick iteration

#### Public Cloud GPUs, TPUs

Available on demand

Not yet fully integrated into the centralized service

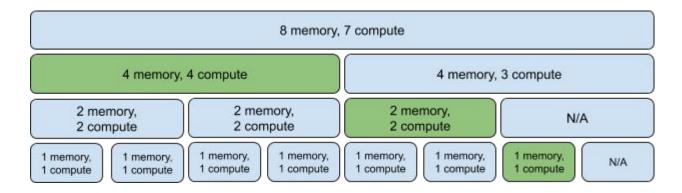
#### Infrastructure

#### Expanding soon: Nvidia A100s

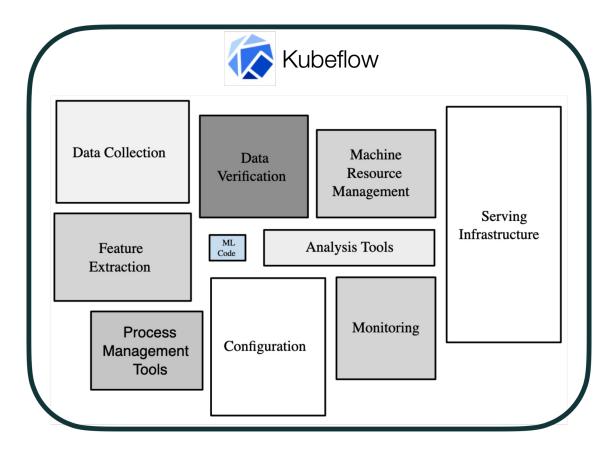
Coming to CERN IT beginning of next year

Physical partition of each card up to 7x - Multi Instance GPU (MIG)

Many other layouts possible



# **Kubeflow Features**



# **Kubeflow Components and Features**

Jupyter Notebooks

**ML** Pipelines

Katib - Hyperparameter Optimization

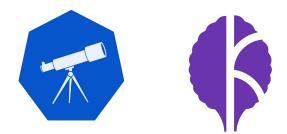
KALE - Notebooks to Pipelines

**Distributed Training** 

Model Serving







## Jupyter Notebooks



github-namespace	notebook-server1
natality-namespace	notebook-server2
mnist-namespace	notebook-server3 nb1 Nb2
Kubeflow deployment	
Kubernetes	

Easiest way to start experimenting with Kubeflow

Integration with other Kubeflow components

Distributed training, inference services, Katib jobs

Ability to customize Python environment

Or use one of prebuilt images (Tensorflow, Pytorch)

Select resources (CPU, MEM, GPU)

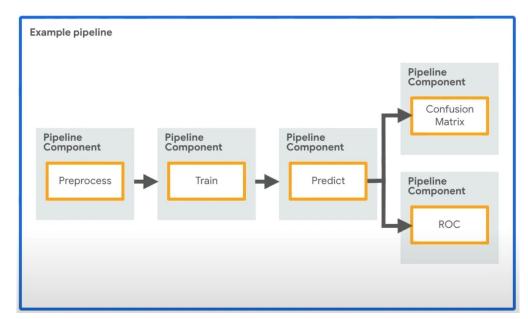
Good for experimentation and prototyping phase

## **Machine Learning Pipelines**



Automated machine learning workflows

Sequence of self-contained and reusable components

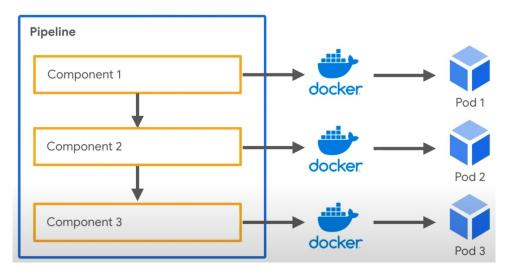


#### **Machine Learning Pipelines**

A user interface (UI) for managing and tracking experiments, jobs, and runs

An engine for scheduling multi-step ML workflows

An **SDK** for defining and compiling pipelines and components



### **Benefits of Machine Learning Pipelines**

Clear isolation between components

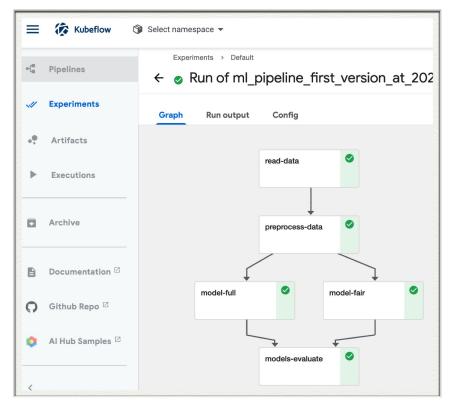
Can be scheduled to run periodically

Can run with different input parameters

Versioning

Parallelisation

Non-blocking GPU access



# Katib - Hyperparameter Optimization

Standardized development process

Create a training script

Build a Docker image

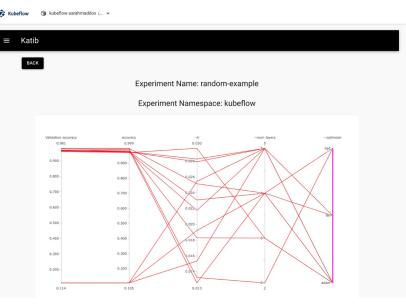
Run with various sets of inputs

Improved hardware efficiency

Run each trial on a separate GPU

Visualization of **results and metrics** 

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### **Distributed Training**

Split training jobs across multiple GPUs

TensorFlow and Pytorch support distributed training

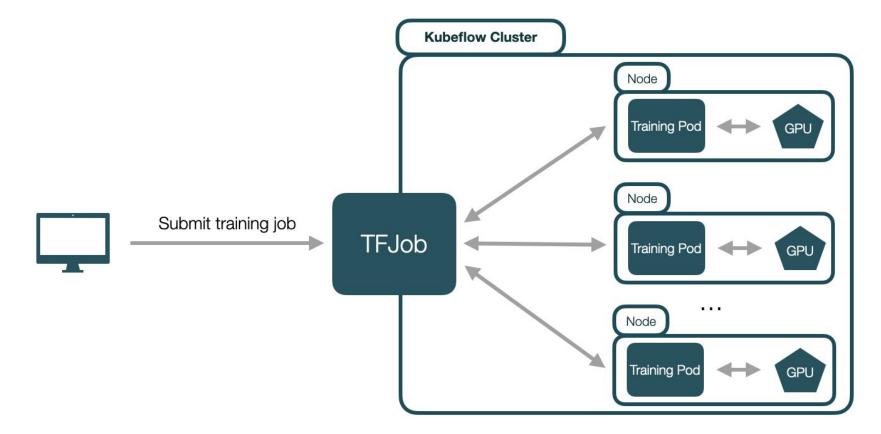
Jobs are split across multiple local GPUs

TFJob, PytorchJob - Kubernetes custom resources for distributed training

Jobs are split across multiple **cluster GPUs** 

Operators for Tensorflow and Pytorch to support containerised distribution

#### **Distributed GPU Training**



### **TFJob Example**

apiVersion: kubeflow.org/v1 kind: TElob metadata: generateName: tfjob namespace: your-user-namespace spec: tfReplicaSpecs: PS: replicas: 1 restartPolicy: OnFailure template: metadata: annotations: sidecar.istio.io/inject: "false" spec: containers: - name: tensorflow image: gcr.io/your-project/your-image command: - python - -m - trainer.task - --batch size=32 - --training\_steps=1000

Worker: replicas: 3 restartPolicy: OnFailure template: metadata: annotations: sidecar.istio.io/inject: "false" spec: containers: - name: tensorflow image: gcr.io/your-project/your-image command: – python - -m - trainer.task - --batch size=32 - --training\_steps=1000



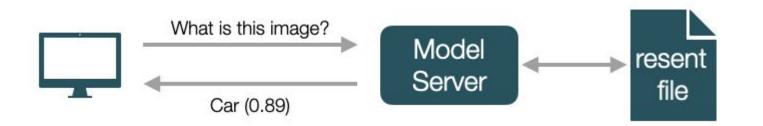
#### Deploy a server to run inference via http requests

curl -v -H "Host: host" "http://host\_ip/v1/models/mnist:predict" -d @./input.json

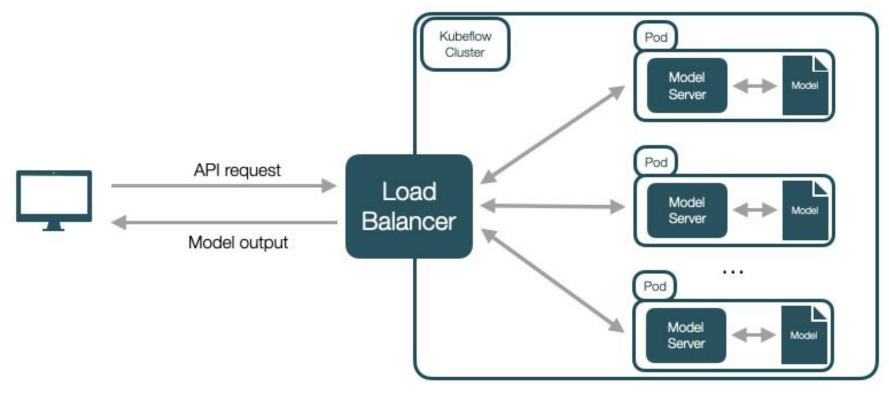
#### Serverless architecture

Automatic scaling per number of requests

Provided via KServe component



### Model Serving



# Demo

### **Current Limitations I**

#### Pipelines and pipeline artifacts isolation

Experiments and runs are isolated, but pipelines are not

The fix is coming up, ~3 months

#### Katib jobs logging

Not there yet, Katib jobs can be monitored using `kubectl`

Automatic credential renewal - coming up in ~1 month

Accessing cookies for model serving, currently done manually

### **Current Limitations II**

Running a Tensorboard server

Notebook culling not in place yet

Remove unused notebooks periodically

GPU / vGPU availability numbers for notebook creation

No built-in support yet for model versioning, model catalog

# Early Adopters Experiences

## **Early Adopters**

OpenLab 3DGAN

UNOSAT

ATLAS Spanet

**CMS** ParticleNet

ADMON - anomaly detection

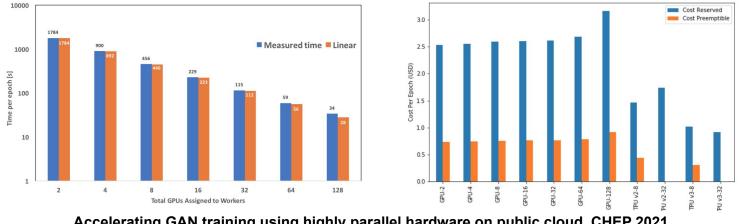
#### **3DGAN OpenLab**

Run distributed training with **TFJob** on a **local cluster** and on a **public cloud** 

Using up to 128 preemptible Google Cloud GPUs and TPUs

Resources from the Cloudbank EU project

Particularly well behaved, performance improvement close to linear



Accelerating GAN training using highly parallel hardware on public cloud, CHEP 2021 https://doi.org/10.1051/epiconf/202125102073

# My experience with Kubeflow | Jona Bossio (CERN)

#### Context:

- ML project within an ATLAS SUSY search
- Goal: assign (uniquely) every resonance particle to a set of jets while preserving symmetries and handling a variable-size set of input jets
- Plan: Use SPANet (Symmetry Preserving Attention Networks) to resolve such assignment problem

#### How I used ml.cern.ch so far?

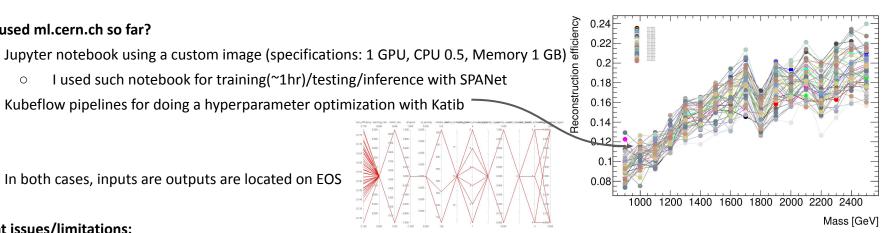
- - I used such notebook for training(~1hr)/testing/inference with SPANet Ο
- Kubeflow pipelines for doing a hyperparameter optimization with Katib

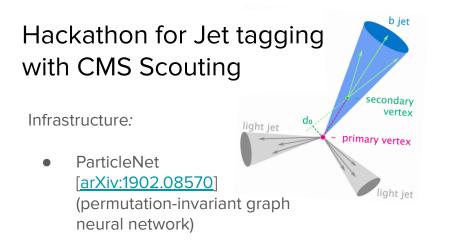
#### Notes:

In both cases, inputs are outputs are located on EOS

#### **Current issues/limitations:**

- Not enough available machines with a GPU (limiting possible # of simultaneous trials, sometimes no GPU is available)
- Not possible to run over 24hs (limiting the size of the scan in the hyperparameter space) [kerberos token expires after 24hs]





Goal:

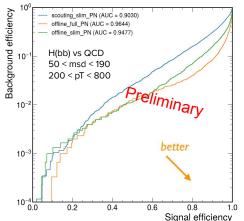
• Study the effects of the CMS Run3 Scouting reconstruction on the jet tagger performance

Team:

- Some experienced and some new to ML/K8s
- Everybody excited to have access to GPU

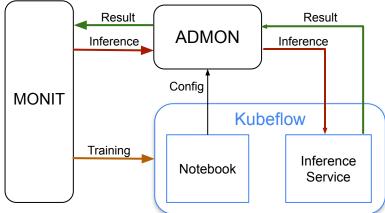
Our initial experience of Kubeflow:

- Very helpful team
  - Daniel Holmberg provided custom
     Docker image and example
  - Tutorial by Dejan Golubovic
- Limited to max 24h training (Krb5 authentication)
- Some cases more RAM needed
- Would be helpful to have access to Tensorboard for real-time monitoring
   Would be helpful to have access to tensorboard for monitoring
- We will continue to use Kubeflow to complete project



# Anomaly Detection for MONIT data | ADMON

- Infrastructure for continuous AD analysis of data stored in MONIT (IT Monitoring Service) [under development] - full details @ <u>ASDF 9th Dec 2021</u>
- Kubeflow role in ADMON:
  - Provides complete platform for building and deploying models
  - *KServe* brings important inference service features:
    - Supports HTTP endpoint
    - Request based auto-scaling on CPU/GPU
    - Integrates Transformer for pre/post-processing
- Very positive initial Kubeflow experience:
  - All components are well integrated
  - K8S cluster available under the hood
  - Deployed InferenceService running both Transformer and Predictor
  - Very grateful to Dejan and Ricardo for the collaboration !
- Looking forward to some extra features:
  - Spark support in the Notebook Server
  - e-groups for shared namespace ACLs



Nikolay Tsvetkov on behalf of the ADMON Team

# **Best Practices for Scalable ML**

#### Code and Datasets Storage

Containers are **ephemeral**, notebook servers can crash

Keep code and datasets on **persistent storage** that can be easily accessed

Code - Github or GitLab, commit regularly

Datasets - EOS or S3 object storage



# Model Training

Develop models with scalability in mind

Develop model training to be **distributed** across multiple GPUs

Only prototype using a single GPU

TF Distributed - TFJob

Pytorch Distributed - PyTorchJob

### **Tensorflow Distributed Example**

```
strategy = tf.distribute.MultiWorkerMirroredStrategy()
with strategy.scope():
  model = tf.keras.Sequential([
    tf.keras.layers.Dense(2, input_shape=(5,)),
  1)
  optimizer = tf.keras.optimizers.SGD(learning_rate=0.1)
def dataset_fn(ctx):
  x = np.random.random((2, 5)).astype(np.float32)
  y = np.random.randint(2, size=(2, 1))
  dataset = tf.data.Dataset.from_tensor_slices((x, y))
  return dataset.repeat().batch(1, drop_remainder=True)
dist_dataset = strategy.distribute_datasets_from_function(dataset_fn)
model.compile()
model.fit(dist_dataset)
```

## **Containerised Workloads**

Build Docker images for your ML workloads

Allows for **reproducibility** 

Mobility - can run anywhere

Fast deployment

Integration with multiple Kubeflow components

Pipelines

**Distributed training** 

Hyperparameter optimization



### **Building Docker Images**

Automate builds with **Gitlab Cl** 

Trigger image build with every push

Store images on CERN registries

https://gitlab.cern.ch/ci-tools/docker-image-builder

https://clouddocs.web.cern.ch/containers/registry/gitlab.html

### **Building Docker Images**

20d764f3 ta	Kerberos' into 'master' •••• Holmberg authored 1 week ago		
	D configuration	README	
Last update	Last commit	Name	
1 week ago	Image naming and pip cache	a notebook	
1 week ago	Include kerberos for eos authentication	🖿 torchjob	
1 week ago	.gitlab-ci.yml Image naming and pip cache		
2 weeks ago	Initial commit	README.md     Initial commit	

master v particlenet-images / notebook	/ + - Lock History Find	master v particlenet-i	nages / torchjob / + - Lock History Fit	nd file Web IDE 🛃 🗸 🗸 Clone 🗸	
Image naming and pip cache Daniel Rickard Holmberg authored 1 week ago		Include kerberos for eos authentication 6f5a8c80 1			
Name Last comm	nit	Name	Last commit	Last update	
✤ Dockerfile Image name	ning and pip cache	👉 Dockerfile	Include kerberos for eos authentication	1 week ago	
E requirements.txt Create ima	iges	krb5.conf	Include kerberos for eos authentication	1 week ago	
		i requirements.txt	Create images	1 week ago	

# **Conclusion and Next Steps**

### Where we are today

Already offering a lot of what users ask for

Code validation on notebooks / small jobs

Distributed Training, Hyper Parameter Optimization

Model Serving

Direct kubernetes access still required in some cases

Launching distributed training jobs, checking katib logs

Plus the limitations described earlier

# **Coming Soon**

**VSCode** development environments

Multi model serving on a single GPU (Nvidia Triton)

Additional dashboard integrations

Tensorboards

Katib jobs (Auto ML)

Model / inference servers

# **Coming Next**

**Enforced Quotas** 

Shared profiles based on Idap / egroups

Improved integration with other services - continuous integration, notebooks/swan, etc

#### Security improvements

Prevent vulnerable workloads, runtime verification, etc

(ASDF) https://indico.cern.ch/event/1054454/

Artifact navigation

Experiment with a dataset catalog and automated feature discovery



- Notebooks
- III Tensorboards
- <→ Models
- Volumes
- Experiments (AutoML)
- ✓ Experiments (KFP)
- Pipelines
- 🖈 Runs
- Recurring Runs
- Artifacts

Model Servers + NEW MODEL SERV								
Status	Name	Age	Predictor	Runtime	Protocol	Storage URI		
0	flowers	4 minutes ago	Tensorflow	1.14.0		gs://kfserving-samples/models/tensorflow/flo	Ē	
κ.	pmml-demo	4 minutes ago	PMML	v0.5.1		https://raw.githubusercontent.com/openscorin		
	sklearn-iris	4 minutes ago	SKLearn	0.2.1	v2	gs://seldon-models/sklearn/iris	Ē	
	torchserve	4 minutes ago	PyTorch	0.3.0	v1	gs://kfserving-examples/models/torchserve/i	Ē	
	xgboost-iris	4 minutes ago	XGBoost	0.2.1	v2	gs://kfserving-samples/models/xgboost/iris	Ē	

# Community

**Community** effort to improve machine learning infrastructure

Kubeflow still not fully complete

CERN users can influence future developments

High interest in our feedback

Anyone can contribute to open source - https://github.com/kubeflow

Everyone is invited to **provide feedback**!

#### **Previous Talks**

KubeCon North America 2021, October 12 2021

A Better and More Efficient ML Experience for CERN Users

KubeCon Europe 2021, May 6 2021

Building and Managing a Centralized ML Platform with Kubeflow at CERN

25th International Conference on Computing in High-Energy and Nuclear Physics, May 20 2021

Training and Serving ML workloads with Kubeflow at CERN

Fast Machine Learning for Science Workshop, Dec 01 2020

Making ML Easier with Kubeflow

#### Important Links

https://ml.cern.ch - the service landing page

ml.docs.cern.ch - documentation pages

https://gitlab.cern.ch/ai-ml/examples - examples repository

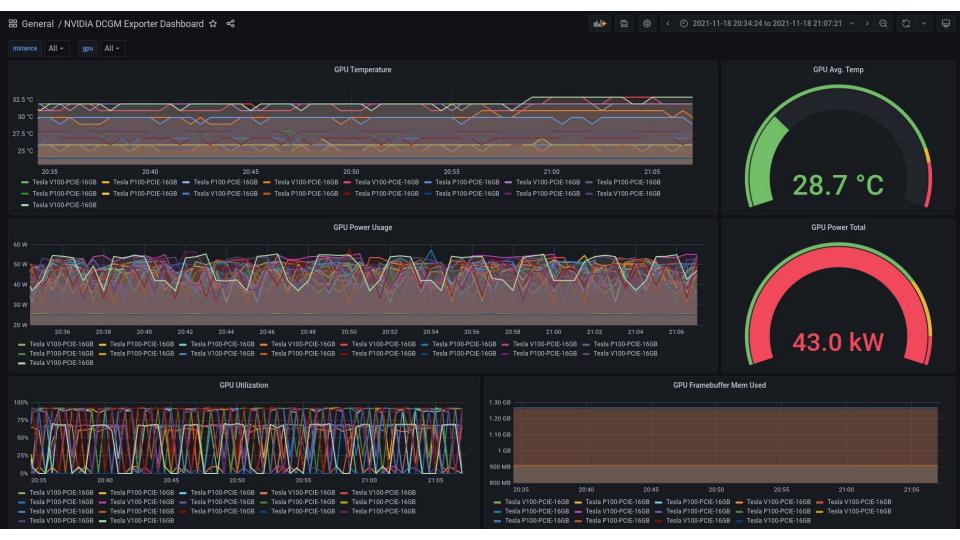
https://mattermost.web.cern.ch/it-dep/channels/ml - Mattermost channel

For any questions, please write here

Others may benefit from your questions!

# Q&A

# **Backup Slides**



### Hyperparameter Jobs

Make sure the script runs on a single GPU in a notebook server

Make sure it uses a GPU + it completes

Make sure the script runs on a single GPU as a Katib job with 1 trial

Then carefully expand to 2, 4, 10, 20 trials, and monitor closely

Once sure it works, run a complete search

Be aware that some combinations of HP might crash the script

Prepare the script for these edge cases (exception handling etc)

Store metrics in a preferred format in two places

In the container storage to be accessed by the UI

On EOS or S3 for persistent storage