# Kubernetes and Google Cloud

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**CERN IT-CM** 

CERN OpenLab Workshop https://indico.cern.ch/event/1009424/





# Summary and Goals

Ongoing collaboration since early 2019

Validate the use and scalability of the Google Cloud

Evaluate its use for future computing models

2019: Cover for spikes with on-demand resources (CPUs)

2020: Access to a larger number of scarce resources (GPUs)

2020: Access to resources not available otherwise (TPUs)

### Recent Achievements

Google Cloud customer story

Deployed Kubernetes based infrastructure to manage scale out use cases

Onboarding use cases into the new system

Done: GitLab Runners and Kubeflow / Machine Learning

Ongoing: JupyterHub, Binder, Dask, ...

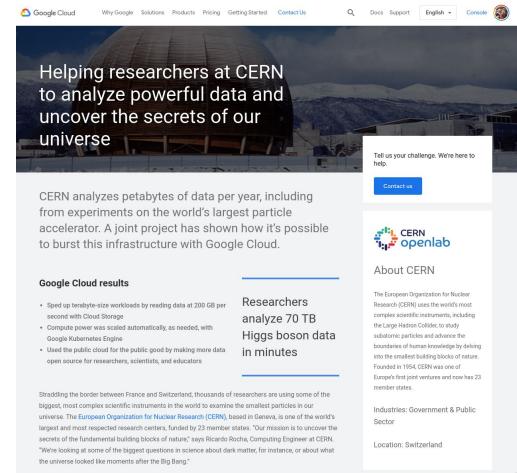
Cost analysis for usage of GPUs, TPUs and GPU vs TPU

Moved to rely on Cloudbank EU / Broker Pilot resources

Focus on the results from 2019

"Reperforming a Nobel Prize Discovery on Kubernetes"

https://www.youtube.com/watch?v=CTfp2woVEkA

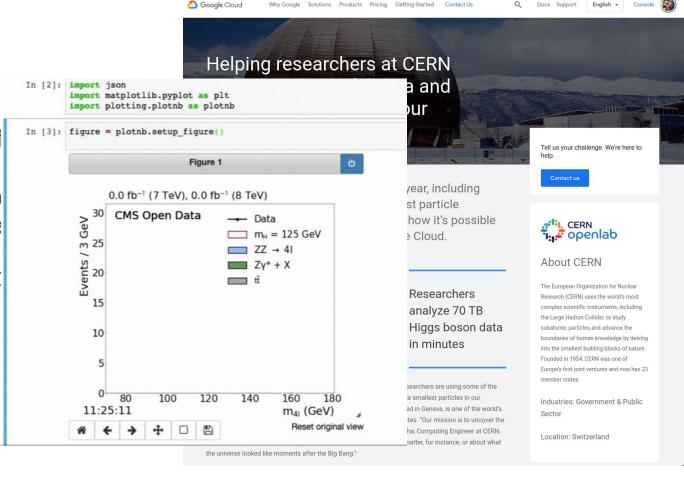


## **Customer Story**

Focus on the results f

"Reperforming a Nobi Discovery on Kuberne

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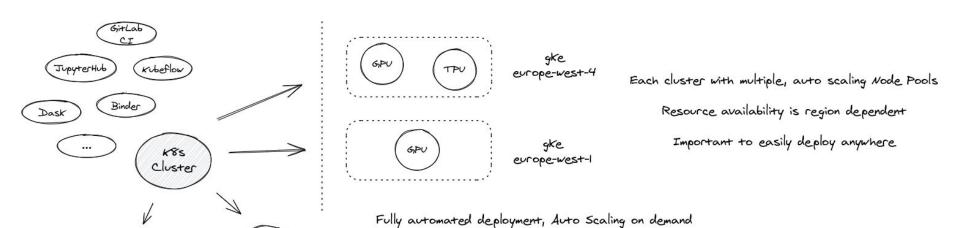


https://cloud.google.com/customers/cern

#### Kubernetes, Helm, ArgoCD, Prometheus, Crossplane, ...

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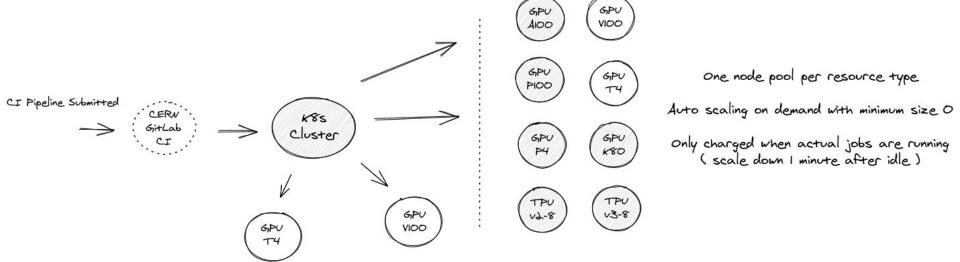
CVMFS, EOS Access, ...

## GitLab CI Runners

Access to a larger pool of resources, including some not accessible on-premises

End users do not realise they are running on public cloud resources

#### https://gitlab.cern.ch/rbritoda/gitlab-runner-public



16 17 18 • 20	Waiting for pod gitlab-runner/runner-ka9reaze-project-108952-concurrent-1dgllp to be running, status is Pending  ContainersNotReady: "containers with unready status: [build helper]"  ContainersNotReady: "containers with unready status: [build helper]"  Running on runner-ka9reaze-project-108952-concurrent-1dgllp via gitlab-runner-gpu-a100-gitlab-runner-854f7d54b7-z9t9f  Getting source from Git repository  Fetching changes with git depth set to 50	00:01
22	22 Initialized empty Git repository in /builds/rbritoda/gitlab-runner-public/.git/	
	23 Created fresh repository.	
	24 Checking out 828259f8 as load	
	25 Skipping Git submodules setup	
	27 Executing "step_script" stage of the job script	00:00
	28 \$ nvidia-smi	
	29 Tue Feb 9 20:55:13 2021	
	30 +	
	31   NVIDIA-SMI 450.51.06 Driver Version: 450.51.06 CUDA Version: 11.0	
	32	
	33   GPU Name Persistence-M  Bus-Id Disp.A   Volatile Uncorr. ECC	
	34   Fan Temp Perf Pwr:Usage/Cap  Memory-Usage   GPU-Util Compute M.	
	35   MIG M.   36  ========	
	37   0 Al00-SXM4-40GB	
	38   N/A 33C P0 42W / 400W   0MiB / 40537MiB   0% Default	
	39   Disabled	
	40 +	
	41	
	42 +	
43	43   Processes:	
44	44   GPU GI CI PID Type Process name GPU Memory	
45	45   ID ID Usage	
	46	
	47   No running processes found	
	48 ++ 50 Cleaning up file based variables	00:00
	52 Job succeeded	

```
62 Waiting for pod gitlab-runner/runner-hdgec7c-project-108952-concurrent-1fbmnv to be running, status is Pending
              ContainersNotReady: "containers with unready status: [build helper]"
              ContainersNotReady: "containers with unready status: [build helper]"
    65 Running on runner-hdgec7c-project-108952-concurrent-1fbmnv via gitlab-runner-tpu-v3-8-gitlab-runner-5d54df77b-wcgq8...

✓ 67 Getting source from Git repository

   68 Fetching changes with git depth set to 50...
   69 Initialized empty Git repository in /builds/rbritoda/gitlab-runner-public/.git/
    70 Created fresh repository.
   71 Checking out 828259f8 as load...
    72 Skipping Git submodules setup
V 74 Executing "step script" stage of the job script
       #!/usr/bin/pvthon3
        import tensorflow as tf
        import os
        from tensorflow.python.profiler import profiler client
        endpoint = os.environ['KUBE GOOGLE CLOUD TPU ENDPOINTS']
        print("Connecting to TPU at %s\n" % endpoint)
    8
        tpu = tf.distribute.cluster resolver.TPUClusterResolver()
        print('Running on TPU ', tpu.cluster spec().as dict()['worker'])
  11
        tf.config.experimental connect to cluster(tpu)
        tf.tpu.experimental.initialize tpu system(tpu)
  14
        print(profiler client.monitor(endpoint.replace('8470', '8466'), 100, 2))
   87 2021-02-09 21:01:12.702455: I tensorflow/core/distributed runtime/rpc/grpc server lib.cc:390] Started server with target: grpc://localhost:30018
   88 Connecting to TPU at grpc://10.116.18.178:8470
        Running on TPU ['10.116.18.178:8470']
         Timestamp: 21:01:22
         TPU type: TPU v3
         Utilization of TPU Matrix Units (higher is better): 0.000%

✓ 94 Cleaning up file based variables

    96 Job succeeded
```

## ML and Kubeflow



https://www.kubeflow.org/

#### Scaling out a ML workload can be hard

Access to often scarce resources

Adapting the code, managing the deployment / infrastructure

Kubeflow is the machine learning toolkit for Kubernetes

Manages the full ML lifecycle: from data preparation to serving

Built-in constructs (operators) for distributing workloads

Support for all popular frameworks: TensorFlow, Pytorch, MXNet, MPI, ...

Hiding all the infra details so end users focus on their code

## ML and Kubeflow: 3D GANs

With Renato Cardoso, Sofia Vallecorsa, Dejan Golubovic

Fast simulation with 3DGANs (see Renato's talk earlier)

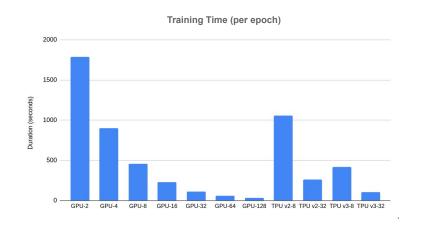
TF based, already adapted to use tf.distributed.Strategy

#### Can we scale this out to a large number of GPUs? And TPUs?

#### Steps

- 1. Wrap it in a TFJob
- 2. Evaluate optimal GPU layout (cards per node, number nodes), minimize contention
- 3. Evaluate optimal batch size
- 4. Train with a large number of resources, evaluate efficiency

## ML and Kubeflow: 3D GANs



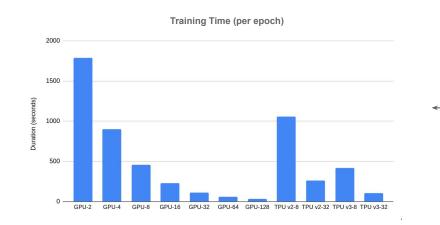
Settled on nodes with 8 GPUs each, total 128 GPUs

Training time reduced from 1780 secs to 34 secs

Close to linear scaling almost all the way 52x improvement with 128 GPUs vs 2 GPUs

TPU-v3 with slighter better results vs equivalent GPUs

## ML and Kubeflow: 3D GANs



Close to flat cost when scaling out the number of GPUs

Preemptibles a major cost saving option when possible

TPUs offer 2.5x savings compared to equivalent GPU setup

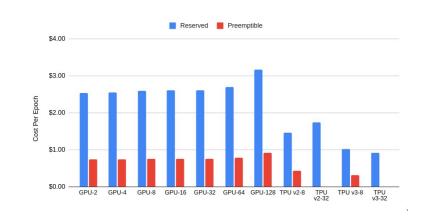
Preemptible TPUs only available with 8 cores

Settled on nodes with 8 GPUs each, total 128 GPUs

Training time reduced from 1780 secs to 34 secs

Close to linear scaling almost all the way 52x improvement with 128 GPUs vs 2 GPUs

TPU-v3 with slighter better results vs equivalent GPUs



# Summary

Running a multi-cloud Kubernetes based infrastructure

Auto scaling based on demand - grow and pay only when needed

Transparent to end users, multiple service entrypoints

Achieved linear scaling of single workload up to 128 GPUs

52x times faster than 2 GPUs, with similar overall cost

Demonstrated the public cloud can scale and be cost effective

With potential benefits in compute time for end users

Preemptible GPUs (as for CPUs) offer a huge gain in cost

(Preemptible up to 8) **TPUs** even better if / when workloads can make use of them

# **Next Steps**

Continue onboarding new use cases ( do reach out - ricardo.rocha@cern.ch )

Continue pushing scale out workloads

Ongoing test with up to 1024 GPUs for a single workload

Similar test with much larger TPUs, up to v3-512 cores

Evolve usage accounting and billing

Prototype deployed for (external) billing estimation - Prometheus based

Explore options to link single cluster usage to multiple billing accounts