

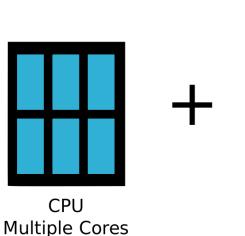
Scaling up distributed deep learning on the SLICES infrastructure

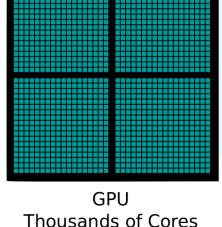
Póra Krisztián



Experiment motivation

- Deep Learning
 - Neural networks with a large number of layers
 - Significant increase in trainable parameters
 - Better suited for solving complex tasks
- Highly resource intensive
 - Large volume of training data
 - Prolonged training time
 - A limiting factor for a long time
- Toolset and methodology
 - GPU cards
 - Distributed training
 - Frameworks





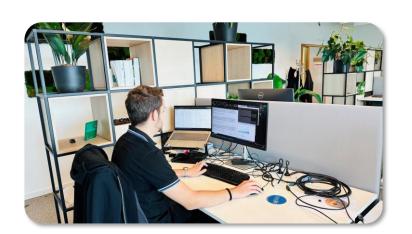
https://www.cherryservers.com/blog/gpu-vs-cpu-what-are-the-key-differences





Transnational access

- Trip to Ghent, Belgium
 - Travel and accommodation
- Work at the IDLab office
- Presentations and tour
- Continuous support









Virtual Wall

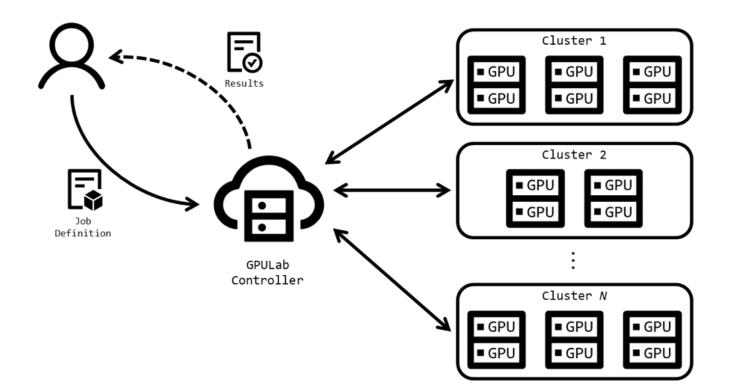
- 550+ bare metal and GPU servers
- Fully configurable (nodes and network configuration)
- Fast context switching
- Remote access
- Networking, cloud, big data and application testing and research





GPULab

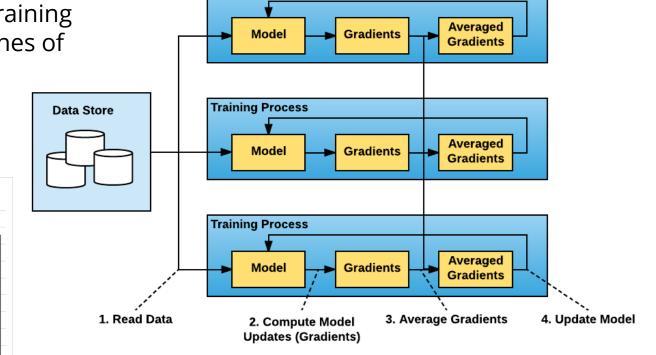
- Heterogenous clusters
- 150+ GPUs
 - 700.000 CUDA cores
 - 3TB GPU RAM
- Job-based GPU processing
- Containerized execution
- JupyterHub access
- Al and data processing research







- Open-source distributed deep learning framework by Uber
- Supports TensorFlow, Keras, PyTorch, Apache MXNet and Spark
- Provide an easy-to-use framework for distributed training
 - Execute on hundreds of GPUs with just a few lines of additional code
- Data parallel execution



Training Process

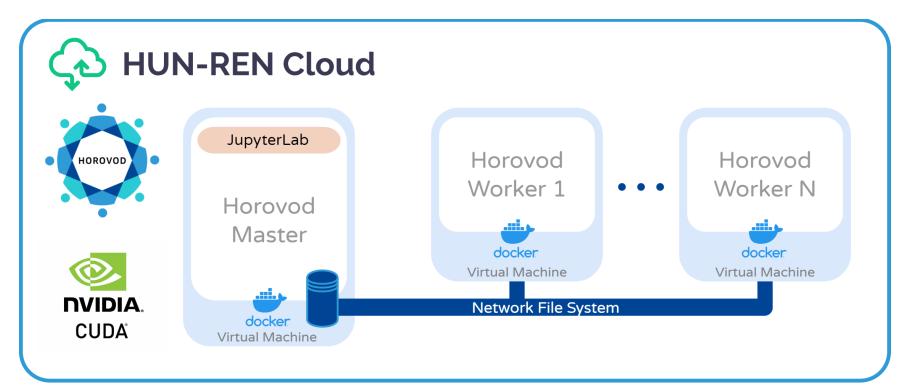
Sergeev, A., & Balso, M.D. (2018). Horovod: fast and easy distributed deep learning in TensorFlow. ArXiv, abs/1802.05799.

Training with synthetic data on NVIDIA[®] Pascal[™] GPUs 18,000.0 16.000.0 14,000.0 12,000.0 10,000.0 8,000.0 6,000.0 4,000.0 2,000.0 0.0 32 128 64 32 64 128 Inception V3 ResNet-101 Number of GPUs and model name Distributed TensorFlow Horovod □Ideal



Horovod Reference Architecture

- Support for distributed deep learning applications
- JupyterLab development environment
- Network based file sharing between nodes
- Utilization of GPU resources





Deployment



Provision infrastructure

- Virtual machines
- Network settings
- Firewall rules
- Execute tasks
- Invoke Ansible



ANSIBLE

- Configure nodes
 - Install packages
 - Start services
 - Run Docker containers



Deployment – Virtual Wall



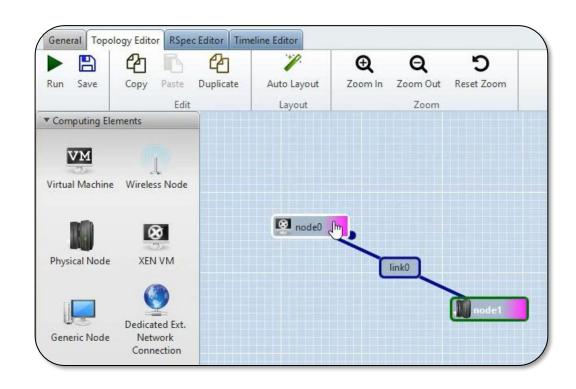
- **Provision infrastructure**
 - Virtual machines
 - Network settings
 - Firewall rules ٠
 - Execute tasks ٠
 - Invoke Ansible •



ANSIBLE

- **Configure nodes** ٠
 - Install packages •
 - Start services •
 - Run Docker containers •







Deployment - GPULab

HashiCorp Terraform **Provision infrastructure** Virtual machines • Network settings **Firewall rules** Execute tasks Invoke Ansible A ANSIBLE Configure nodes Install packages ٠ Start services Run Docker containers •

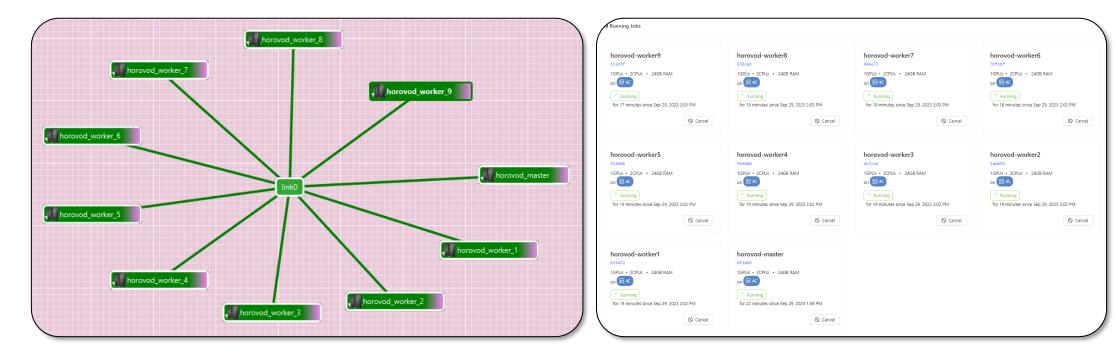
Create a job		Resulting jobDefiniti	
Job Definitio	n 🗄 Load template 🗸	스 Download	Save in Browser
Core info * Name:	🗋 Load saved job 🗸	<pre> { " "jobDefinition" : { "name" : "NVIDIA SMI" "description" : "Writes the output of the command 'nvidia-smi' to the log and exits" "dockerImage" : "gpulab.ilabt.imec.be:5000/sample:n' smi" "command" : "" "command" : "" " </pre>	
	NVIDIA SMI		
Deboliption.	Writes the output of the command 'nvidia-smi' to the		
	Describe what your experiment does (optionally)		
* Cluster ID :	v 1	▼ "resoun "gpus	rces" : { " : 1
	Uncheck this to run this job on any compatible cluster		emMemory" : 2048 ores" : 2
* Docker Image:	gpulab.ilabt.imec.be:5000/sample	"minCudaVersion" : 10 }	



Deployed cluster

Virtual Wall





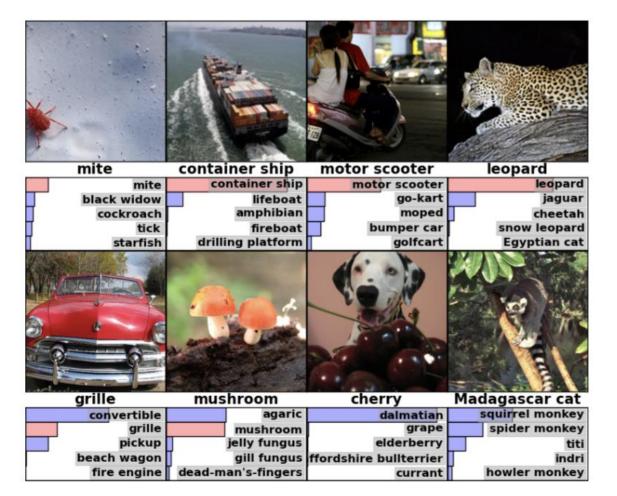
Benchmark parameters



- Training dataset
 - ImageNet
- Batch size
 - 32, 64, 96
- Number of nodes (1-10)
- Measured parameters
 - Processing performance
 - Scaling efficiency

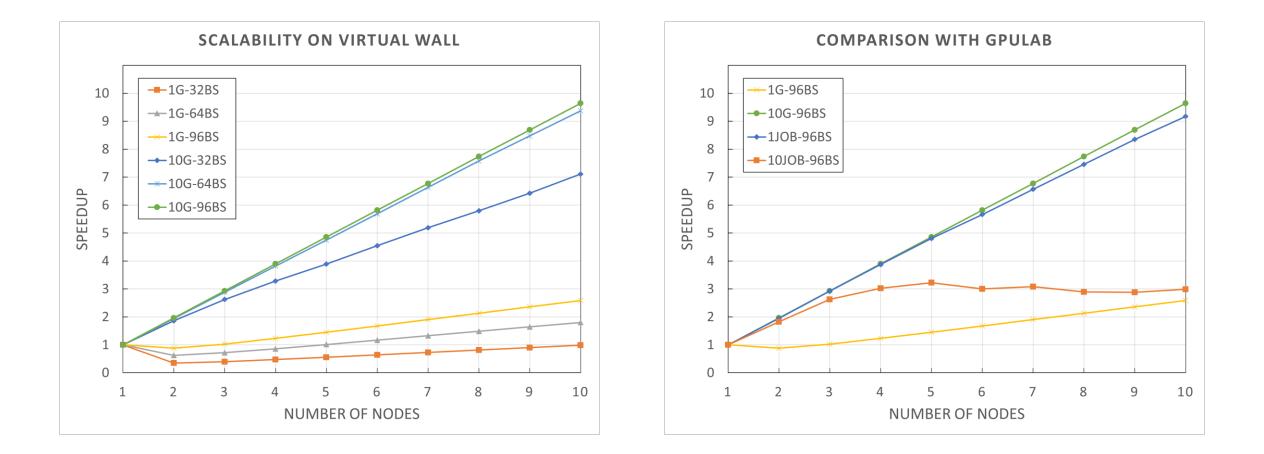
• Environment

- Virtual Wall 1 Gbit/s
- Virtual Wall 10 Gbit/s
- GPULab 1 job with 10 GPUs
- GPULab 10 jobs with 1 GPU each





Benchmark results





Thank you for your attention!