



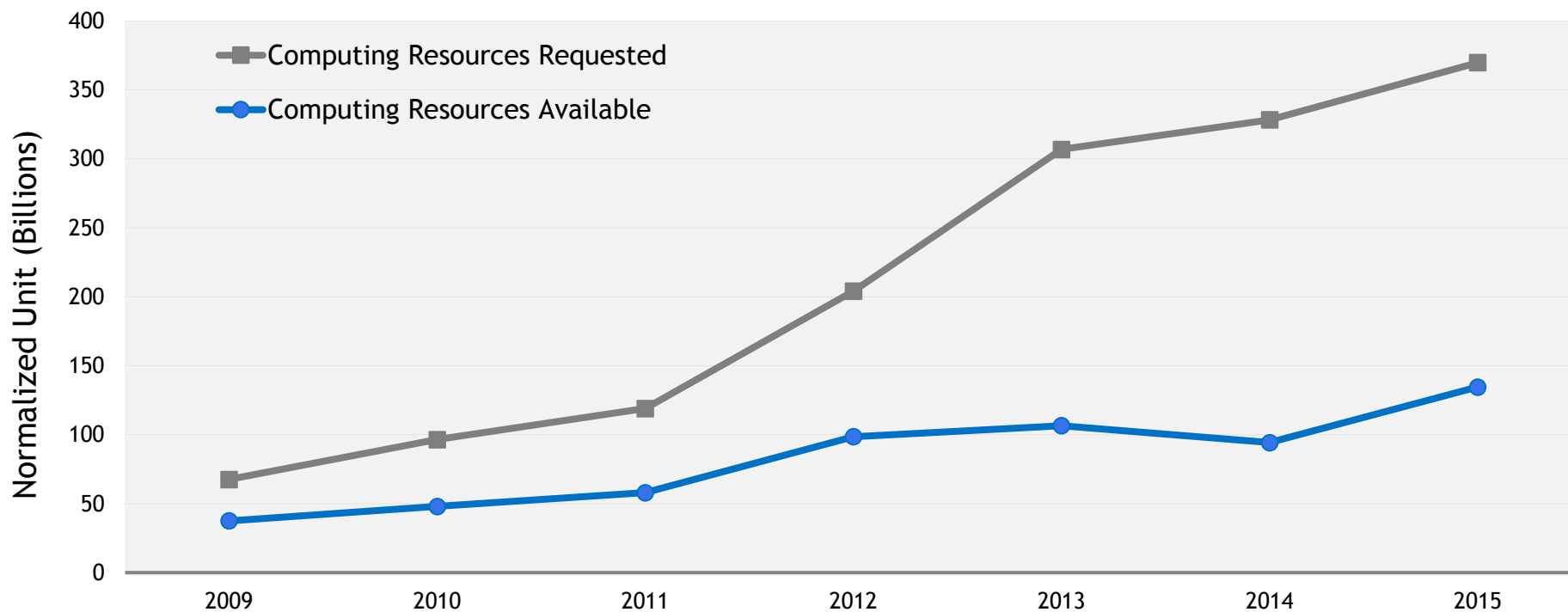
SCALING DEEP LEARNING TO EXASCALE ACM GORDON BELL PRIZE 2018

Pedro Mario Cruz e Silva
Solutions Architect Manager, Latin América | Global Energy Team

200B CORE HOURS OF LOST SCIENCE

Data Center Throughput is the Most Important Thing for HPC

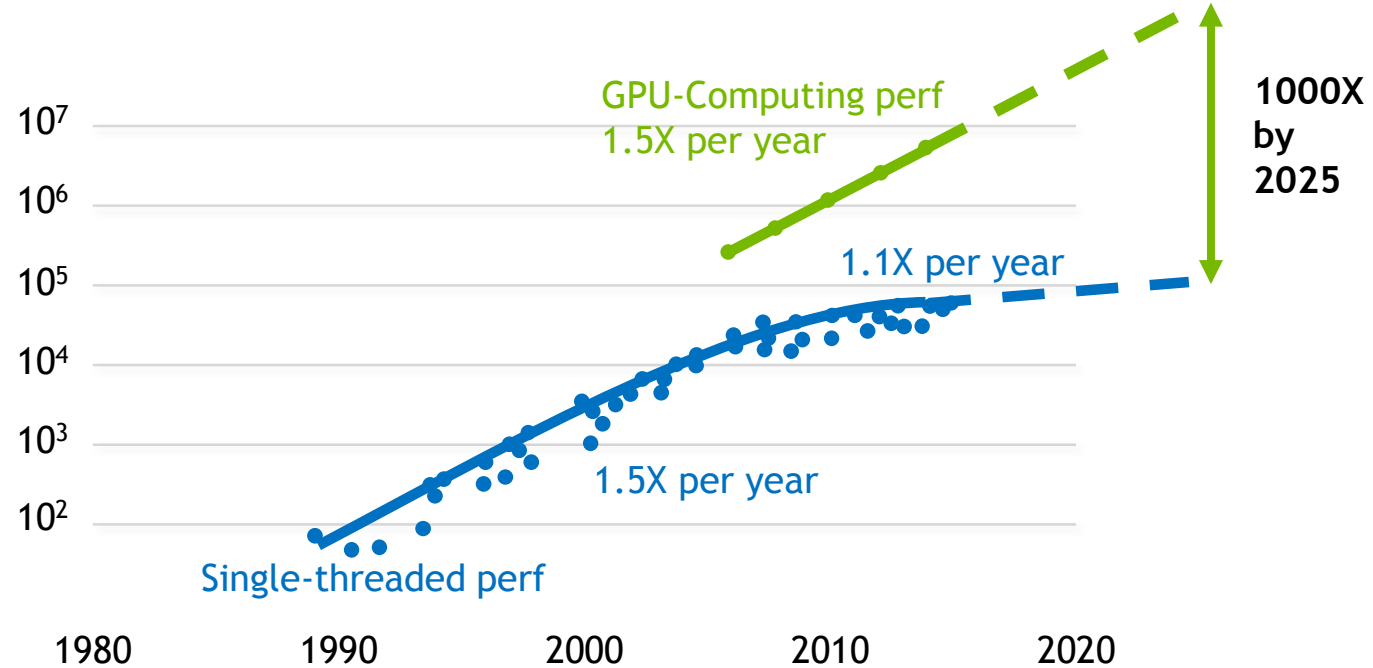
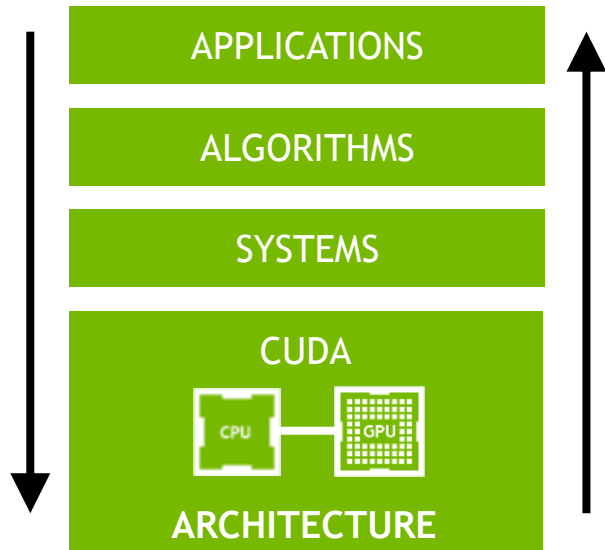
National Science Foundation (NSF XSEDE) Supercomputing Resources



Source: NSF XSEDE Data: <https://portal.xsede.org/#/gallery>

NU = Normalized Computing Units are used to compare compute resources across supercomputers and are based on the result of the High Performance LINPACK benchmark run on each system

RISE OF GPU COMPUTING



Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten New plot and data collected for 2010-2015 by K. Rupp

BEYOND MOORE'S LAW

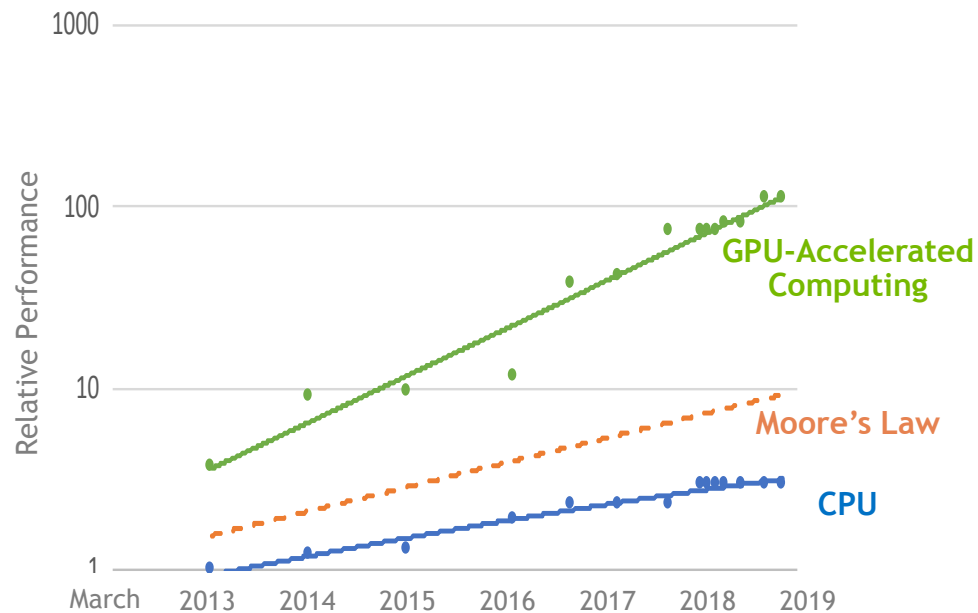
Progress Of Stack In 6 Years

2013

cuBLAS: 5.0
cuFFT: 5.0
cuRAND: 5.0
cuSPARSE: 5.0
NPP: 5.0
Thrust: 1.5.3
CUDA: 5.0
Resource Mgr: r304
Base OS: CentOS 6.2



Accelerated Server
With Fermi



Measured performance of Amber, CHROMA, GTC, LAMMPS, MILC, NAMD, Quantum Espresso, SPECfem3D

2019

cuBLAS: 10.0
cuFFT: 10.0
cuRAND: 10.0
cuSOLVER: 10.0
cuSPARSE: 10.0
NPP: 10.0
Thrust: 1.9.0
CUDA: 10.0
Resource Mgr: r384
Base OS: Ubuntu 16.04

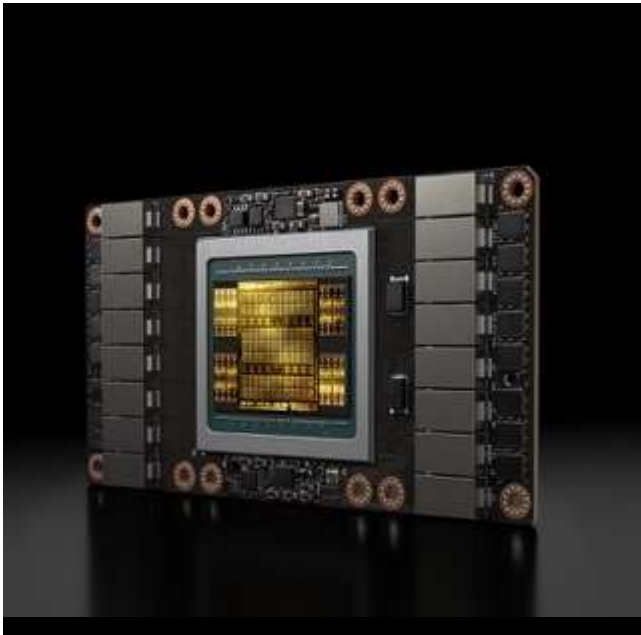


Accelerated Server
with Volta

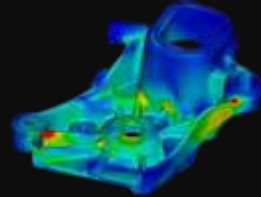


DIGITAL SCIENCE
HPC + AI + DATA

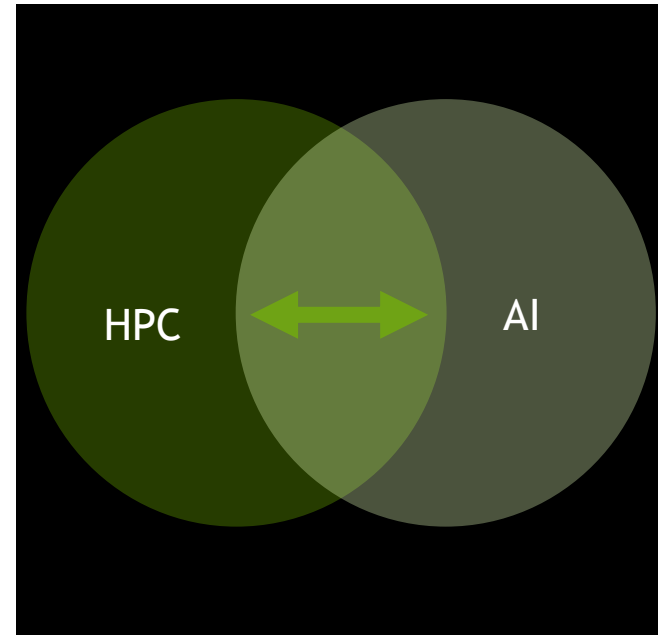
GPU FUSES HPC & AI COMPUTING



HPC (Simulation) - FP64, FP32



AI (Deep Learning) - FP16, INT8



AI - A NEW INSTRUMENT FOR SCIENCE

HPC

- > Algorithms based on first principles theory.
- > Proven models for accurate results

AI

- > Neural Networks that learn patterns from large data sets
- > Improve predictive accuracy and faster response time.

Dramatically Improves Accuracy and Time-to-Solution



Commercially viable fusion energy



Understanding cosmological dark energy and matter



Clinically viable precision medicine



Improvement and validation of the Standard Model of Physics



Climate/weather forecasts with ultra-high fidelity

“ACCELERATING EULERIAN FLUID SIMULATION WITH CONVOLUTIONAL NETWORKS”

Tompson, J., Schlachter, K., Sprechmann, P., & Perlin, K. (2016). Accelerating Eulerian Fluid Simulation With Convolutional Networks. *arXiv preprint arXiv:1607.03597*.



Fig. 1: Smoke simulation using our system - our method is capable of fast and accurate simulation of the Euler Equations for incompressible fluid flow at interactive frame-rates. Videos can be found at: <http://cims.nyu.edu/~schlacht/CNNFluids.htm>.

AI FOR SCIENCE

Transformative Tool To Accelerate The Pace of Scientific Innovation



90% accuracy
Fusion Sustainment
Clean Energy




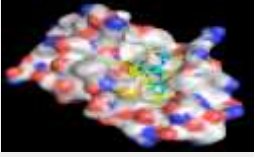
33% Faster
Track Neutrinos
Particle Physics



5,000X Faster
Process LIGO Signal
Understanding Universe



300,000X Faster
Predict Molecular Energetics
Drug Discovery




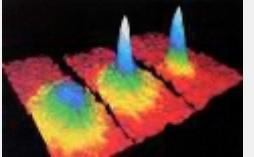
70% accuracy
Score Protein Ligand
Drug Discovery



11% higher accuracy
Monitor Earth's Vital
Climate



Weeks to 10 milliseconds
Analyze Gravitational Lensing
Astrophysics



14X Faster
Generate Bose-Einstein
Condensate (Physics)

Improves Accuracy
Enabling realization of full scientific potential

Accelerates Time to Solution
Unlocking the use of science in exciting new ways

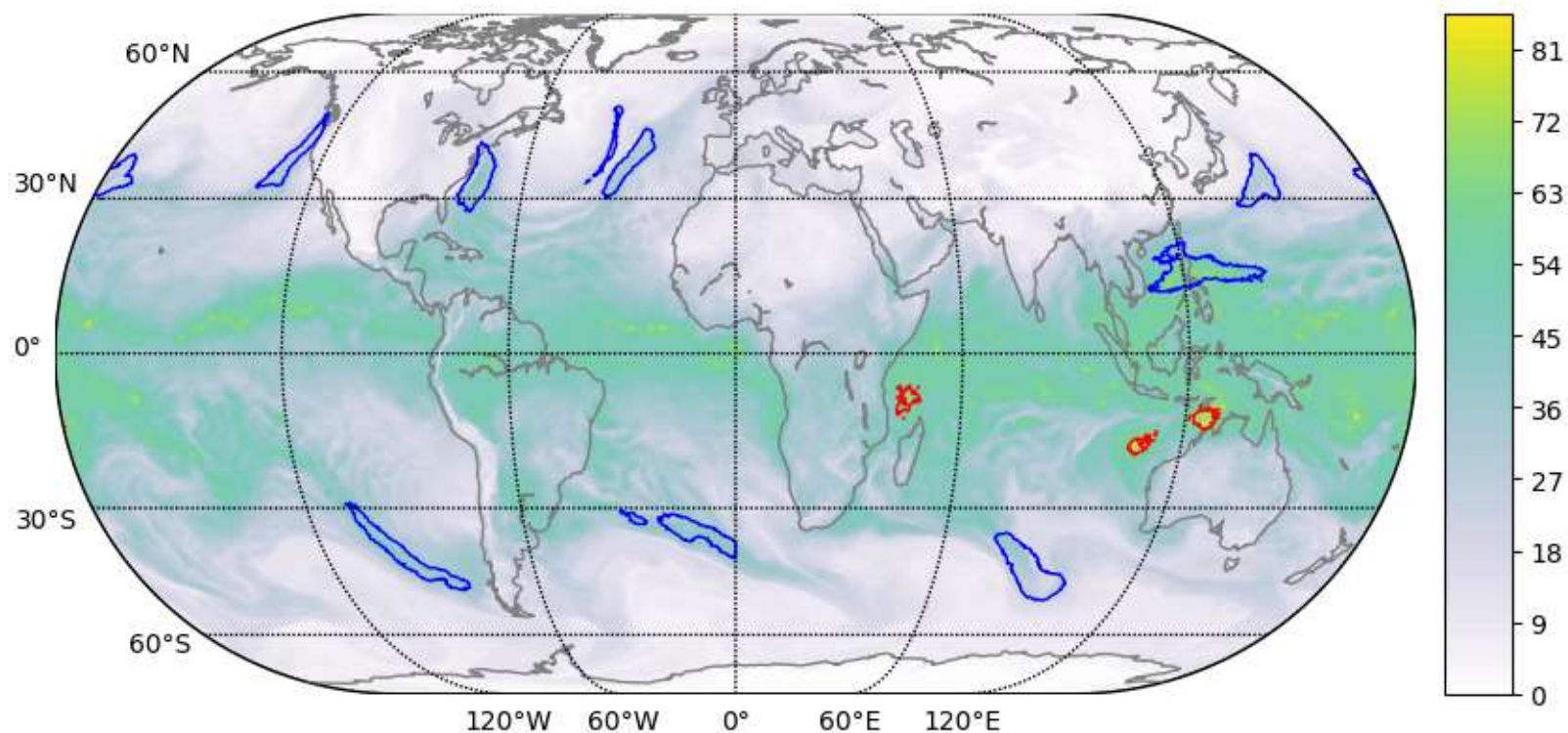


THE PROBLEM

IMAGE SEGMENTATION

Pattern Detection for Characterizing Extreme Weather

Atmospheric rivers (ARs) are labeled in blue, while tropical cyclones (TCs) are labeled in red



CLIMATE DATASET AND GROUND TRUTH LABELS

Climate data used is currently 3.5 TB

- ▶ 0.25-degree Community Atmosphere Model (CAM5) output
- ▶ Climate variables are stored on an 1152x768 spatial grid, with a temporal resolution of 3 hours
- ▶ All available 16 variables (water vapor, wind, precipitation, temperature, pressure, etc).
- ▶ Process climate model output with the Toolkit for Extreme Climate Analysis to identify TCs.
- ▶ A floodfill algorithm is used to create spatial masks of ARs
- ▶ There are about 63K high-resolution samples in total
- ▶ Split into 80% training, 10% test and 10% validation sets
- ▶ The pixel mask labels correspond to 3 classes:
 - 1) Tropical Cyclone (TC)
 - 2) Atmospheric River (AR)
 - 3) Background (BG)



THE TEAM

NERSC & NVIDIA



Exascale Deep Learning for Climate Analytics

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Abstract—We extract pixel-level masks of extreme weather patterns using variants of Tiramisu and DeepLabv3+ neural networks. We describe improvements to the software frameworks, input pipeline, and the network training algorithms necessary to efficiently scale deep learning on the Piz Daint and Summit systems. The Tiramisu network scales to 5300 P100 GPUs with a sustained throughput of 21.0 PF/s and parallel efficiency of 79.0%. DeepLabv3+ scales up to 27360 V100 GPUs with a sustained throughput of 325.8 PF/s and a parallel efficiency of 90.7% in single precision. By taking advantage of the FP16 Tensor Cores, a half-precision version of the DeepLabv3+ network achieves a peak and sustained throughput of 1.13 EF/s and 999.0 PF/s

communities. For instance, the state of California receives over 50% of its rainfall through Atmospheric Rivers (ARs), and Water Resource Management planners are interested in understanding if AR tracks will shift in the future, potentially resulting in a dramatic shortfall in fresh water supply. In the state of Florida, homeowners are interested in understanding if Tropical Cyclones (TCs) or hurricanes will become more intense and start making landfall more often. This has a direct impact on home prices and the insurance industry. TCs have caused the US economy over \$200B worth of damage in 2017,



HARDWARE

NVIDIA POWERS TODAY'S FASTEST SUPERCOMPUTERS

22 of Top 25 Greenest



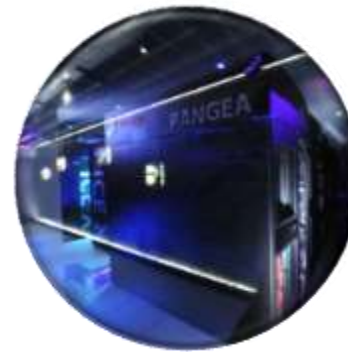
ORNL Summit
World's Fastest
27,648 GPUs | 149 PF



LLNL Sierra
World's 2nd Fastest
17,280 GPUs | 95 PF



Piz Daint
Europe's Fastest
5,704 GPUs | 21 PF



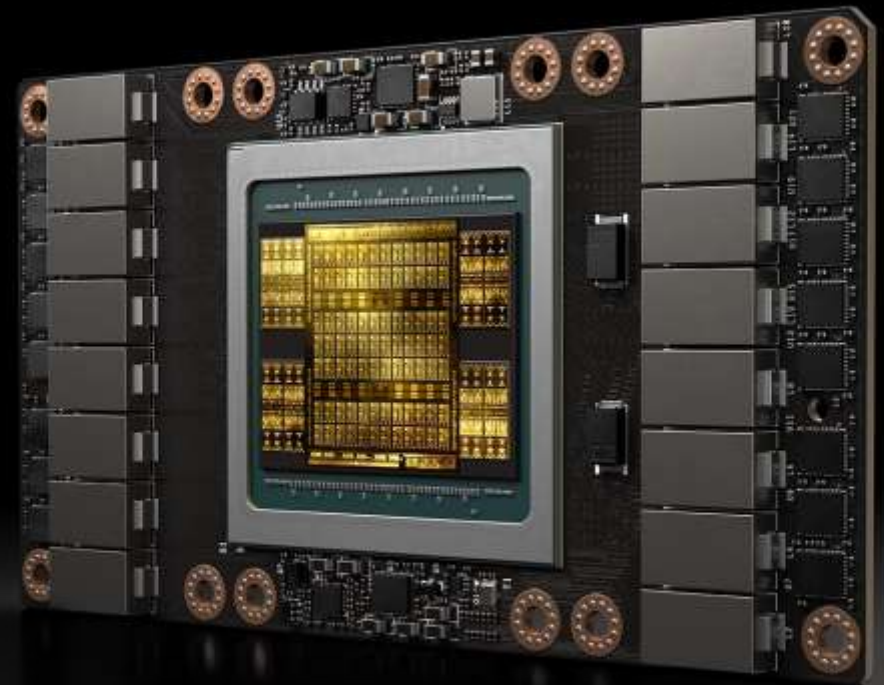
Total Pangea 3
Fastest Industrial
3,348 GPUs | 18 PF



ABCI
Japan's Fastest
4,352 GPUs | 20 PF

NVIDIA POWERS WORLD'S FASTEST SUPERCOMPUTER

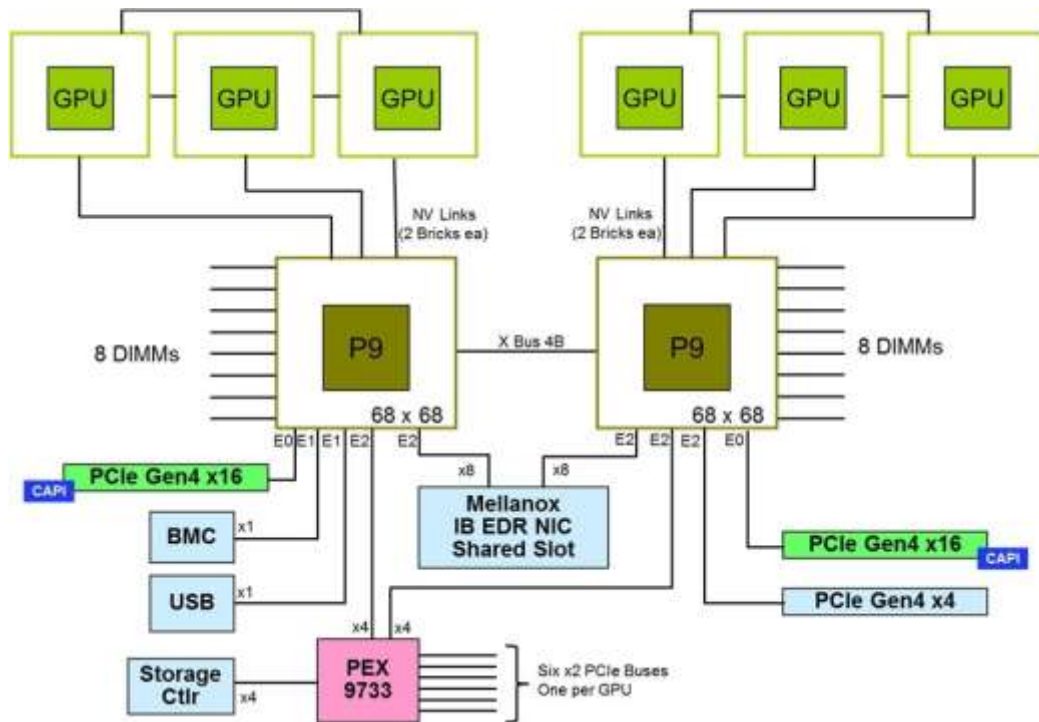
Summit Becomes First System To Scale The 100 Petaflops Milestone



27,648
Volta Tensor Core GPUs

IBM AC922

6xV100 + 2xP9 (Water Cooled)



TESLA V100 TENSOR CORE GPU

World's Most Powerful
Data Center GPU

5,120 CUDA cores

640 NEW Tensor cores

7.8 FP64 TFLOPS | 15.7 FP32 TFLOPS

| 125 Tensor TFLOPS

20MB SM RF | 16MB Cache

32 GB HBM2 @ 900GB/s |

300GB/s NVLink



TENSOR CORE

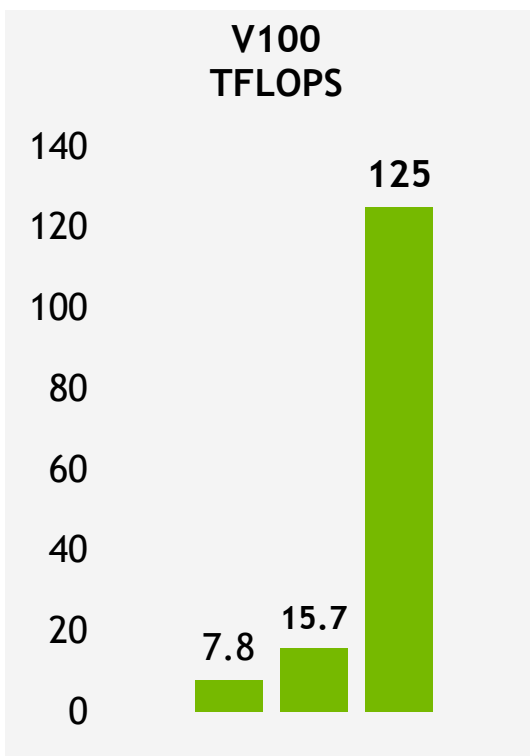
4x4x4 matrix multiply and accumulate

$$\mathbf{D} = \begin{pmatrix} A_{0,0} & A_{0,1} & A_{0,2} & A_{0,3} \\ A_{1,0} & A_{1,1} & A_{1,2} & A_{1,3} \\ A_{2,0} & A_{2,1} & A_{2,2} & A_{2,3} \\ A_{3,0} & A_{3,1} & A_{3,2} & A_{3,3} \end{pmatrix} \begin{pmatrix} B_{0,0} & B_{0,1} & B_{0,2} & B_{0,3} \\ B_{1,0} & B_{1,1} & B_{1,2} & B_{1,3} \\ B_{2,0} & B_{2,1} & B_{2,2} & B_{2,3} \\ B_{3,0} & B_{3,1} & B_{3,2} & B_{3,3} \end{pmatrix} + \begin{pmatrix} C_{0,0} & C_{0,1} & C_{0,2} & C_{0,3} \\ C_{1,0} & C_{1,1} & C_{1,2} & C_{1,3} \\ C_{2,0} & C_{2,1} & C_{2,2} & C_{2,3} \\ C_{3,0} & C_{3,1} & C_{3,2} & C_{3,3} \end{pmatrix}$$

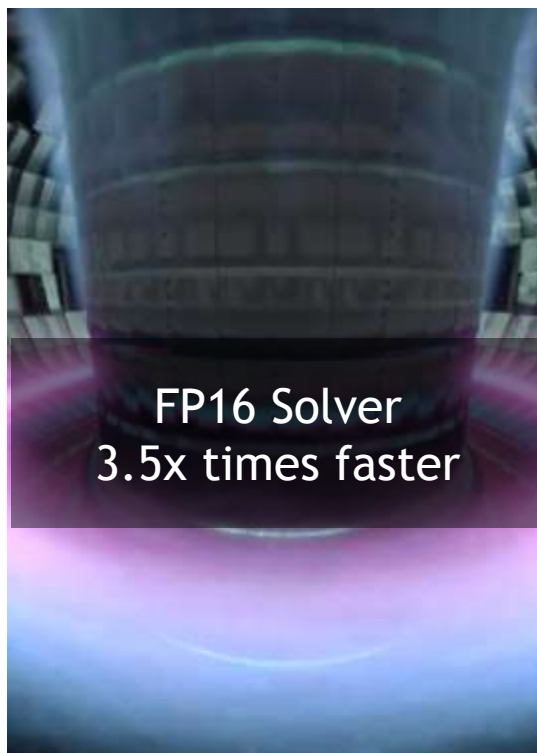
FP16 or FP32 FP16 FP16 FP16 or FP32

TENSOR CORES FOR SCIENCE

Multi-precision computing



FP64+ MULTI-PRECISION




PLASMA FUSION
APPLICATION



AI-POWERED WEATHER
PREDICTION



EARTHQUAKE SIMULATION

The background features a complex network of thin, light green lines connecting various nodes. The nodes are represented by small, glowing circles in shades of green and blue, scattered across the dark blue background. The overall effect is that of a digital or neural network.

**SOFTWARE:
PERFORMANCE &
PRDUCTIVITY**

POWERING THE DEEP LEARNING ECOSYSTEM

NVIDIA SDK Accelerates Every Major Framework

COMPUTER VISION

OBJECT DETECTION



IMAGE CLASSIFICATION



SPEECH & AUDIO

VOICE RECOGNITION



LANGUAGE TRANSLATION



NATURAL LANGUAGE PROCESSING

RECOMMENDATION ENGINES



SENTIMENT ANALYSIS



DEEP LEARNING FRAMEWORKS

Caffe

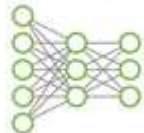


PYTORCH



NVIDIA DEEP LEARNING SDK and CUDA

cuDNN



NCCL



cuBLAS



TensorRT



cuSPARSE



DeepStream SDK



NVIDIA SDK

The Essential Resource for GPU Developers

DEEP LEARNING

Deep Learning SDK

High-performance tools and libraries for deep learning

AUTONOMOUS VEHICLES

NVIDIA DRIVE Platform

Deep learning, HD mapping and supercomputing solutions, from ADAS to fully autonomous

VIRTUAL REALITY

NVIDIA VRWorks™

A comprehensive SDK for VR headsets, games and professional applications

GAME DEVELOPMENT

NVIDIA GameWorks™

Advanced simulation and rendering technology for game development

ACCELERATED COMPUTING

NVIDIA ComputeWorks

Everything scientists and engineers need to build GPU-accelerated applications

DESIGN & VISUALIZATION

NVIDIA DesignWorks™

Tools and technologies to create professional graphics and advanced rendering applications

AUTONOMOUS MACHINES

NVIDIA JetPack™

Powering breakthroughs in autonomous machines, robotics and embedded computing

SMART CITIES

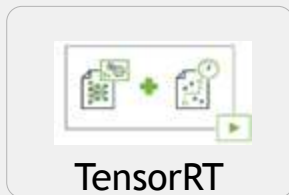
NVIDIA Metropolis

Edge-to-cloud development platform for smart cities

GPU ACCELERATED LIBRARIES

“Drop-in” Acceleration for Your Applications

DEEP LEARNING



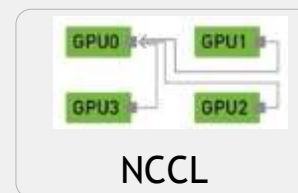
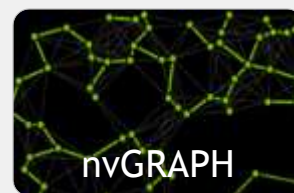
SIGNAL, IMAGE & VIDEO



LINEAR ALGEBRA



PARALLEL ALGORITHMS



NVIDIA DEEP LEARNING SDK

High Performance GPU-acceleration for Deep Learning

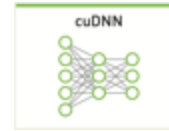
Powerful tools and libraries for designing and deploying GPU-accelerated deep learning applications

High performance building blocks for training and deploying deep neural networks on NVIDIA GPUs

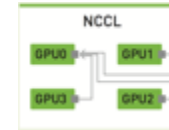
Industry vetted deep learning algorithms and linear algebra subroutines for developing novel deep neural networks

Multi-GPU and multi-node scaling that accelerates training on up to eight GPU

developer.nvidia.com/deep-learning-software



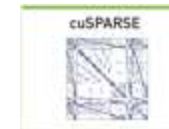
Deep Learning Primitives



Multi-GPU Communication



Linear Algebra



Sparse Matrix Operations



Programmable Inference Accelerator



Deep Learning for Video Analytics

NVIDIA cuDNN

Deep Learning Primitives

High performance building blocks for deep learning frameworks

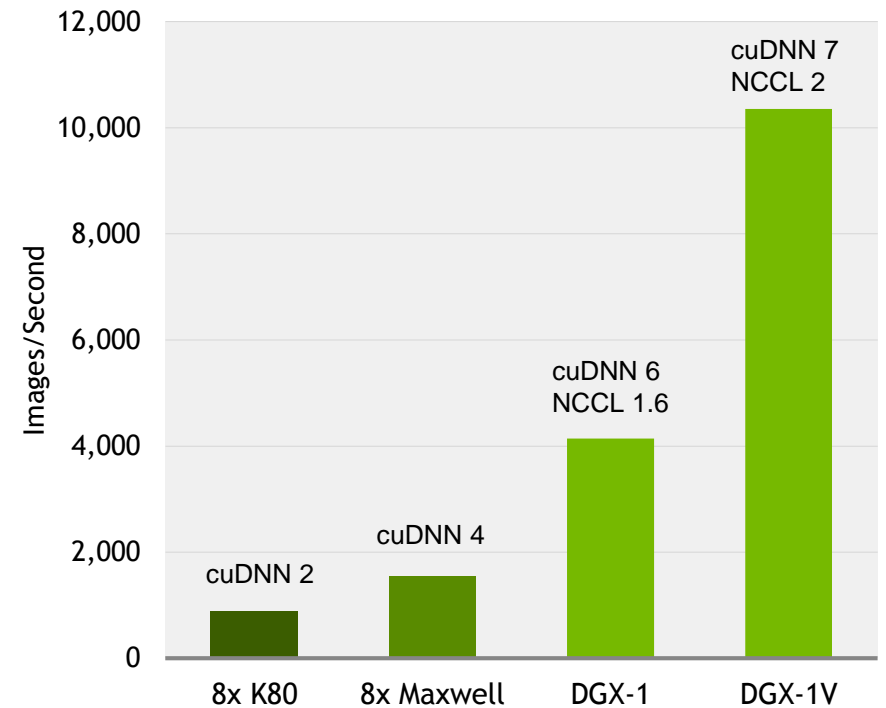
Drop-in acceleration for widely used deep learning frameworks such as Caffe2, Microsoft Cognitive Toolkit, PyTorch, Tensorflow and others

Accelerates industry vetted deep learning algorithms, such as convolutions, LSTM RNNs, fully connected, and pooling layers

Fast deep learning training performance tuned for NVIDIA GPUs

developer.nvidia.com/cudnn

Deep Learning Training Performance



“ NVIDIA has improved the speed of cuDNN with each release while extending the interface to more operations and devices at the same time.”

— Evan Shelhamer, Lead Caffe Developer, UC Berkeley

NVIDIA COLLECTIVE COMMUNICATIONS LIBRARY (NCCL)

Multi-GPU and Multi-node Collective Communication Primitives

Open-source High-performance multi-GPU and multi-node collective communication primitives optimized for NVIDIA GPUs

Fast routines for multi-GPU multi-node acceleration that maximizes inter-GPU bandwidth utilization

Easy to integrate and MPI compatible. Uses automatic topology detection to scale HPC and deep learning applications over PCIe and NVLink

Accelerates leading deep learning frameworks such as Caffe2, Microsoft Cognitive Toolkit, MXNet, PyTorch and more

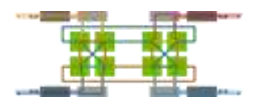
developer.nvidia.com/nccl



Multi-GPU:
NVLink, PCIe

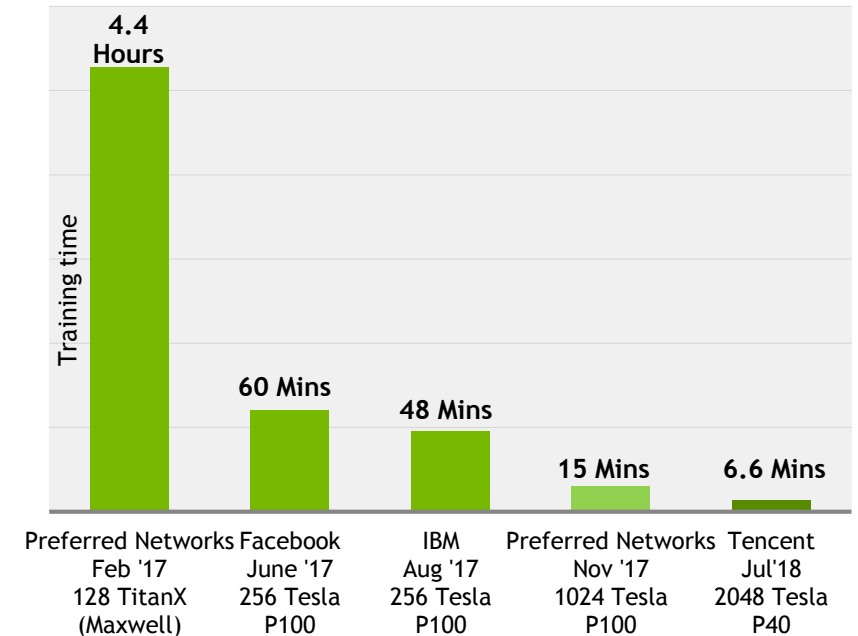


Multi-Node:
InfiniBand verbs,
IP Sockets



Automatic
Topology
Detection

Scaling training to 2048 GPUs



ResNet-50 | Dataset: Imagenet | Trained for 90 Epochs

HOROVOD (UBER)

Horovod: fast and easy distributed deep learning in TensorFlow

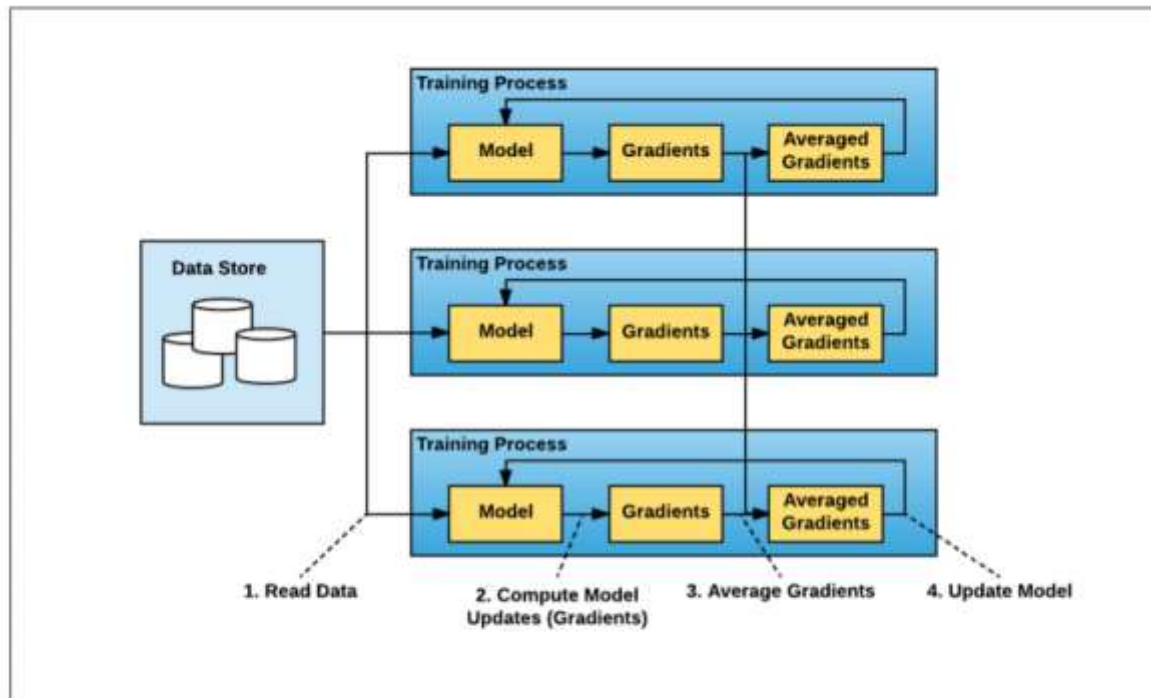


Figure 2: The “data parallel” approach to distributed training involves splitting up the data and training on multiple nodes in parallel. In synchronous cases, the gradients for different batches of data are calculated separately on each node but averaged across nodes to apply consistent updates to the model copy in each node.

FULLY CONVOLUTIONAL NETWORKS (FCN)

“Fully Convolutional Networks for Semantic Segmentation”,
Shellhammer et al, 2015

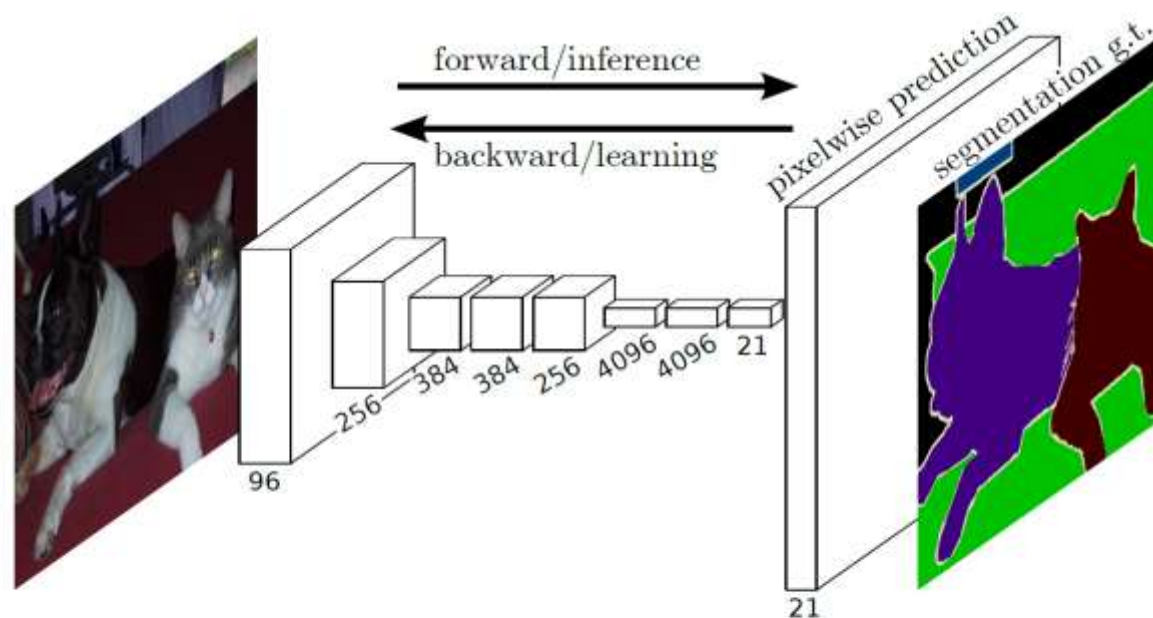
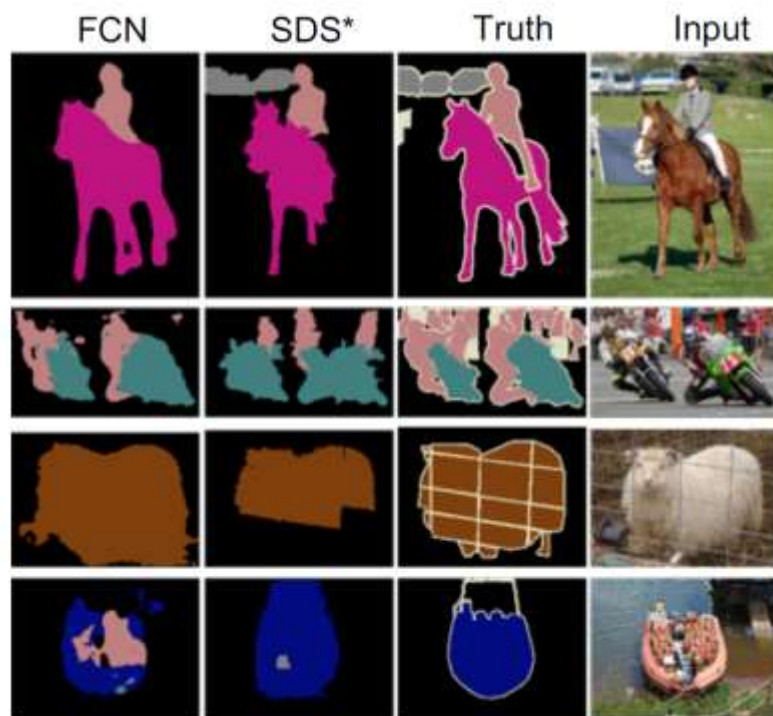


Figure 1. Fully convolutional networks can efficiently learn to make dense predictions for per-pixel tasks like semantic segmentation.

SEMANTIC SEGMENTATION

FCN vs SDS



Slide credit: Jonathan Long

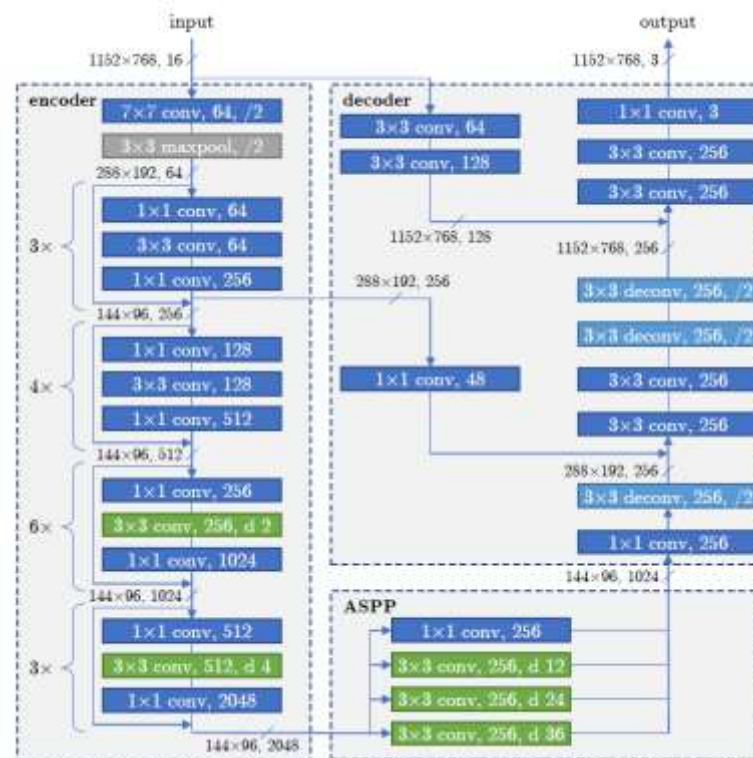
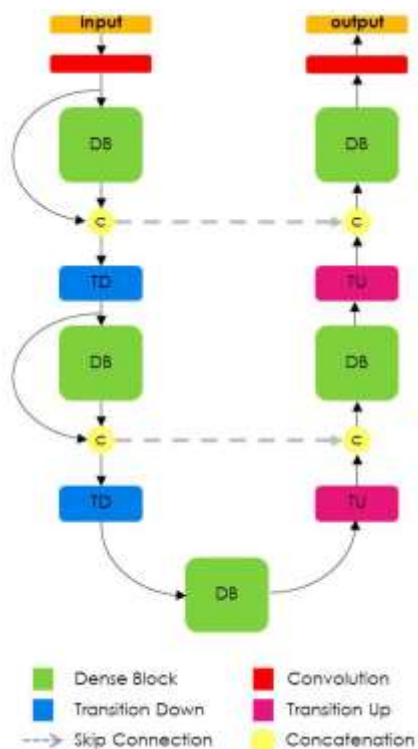
Relative to prior state-of-the-art SDS:

- 20% relative improvement for mean IoU
- 286× faster

*Simultaneous Detection and Segmentation
Hariharan et al. ECCV14 25

DEEP NEURAL NETWORKS

Tiramisu (left) and DeepLabv3+ (right)



INNOVATIONS (1)

Deep Learning Innovations

- Weighted loss
- Layer-wise adaptive rate control (LARC)
- Multi-channel segmentation
- Gradient lag
- Modifications to the neural network architectures

INNOVATIONS (2)

System Innovations

- High speed parallel data staging
- Optimized data ingestion pipeline
- Hierarchical all-reduce

INNOVATIONS (2)

System Innovations

- High speed parallel data staging
 - Read 1500 images per node (250 per GPU)
 - 800GB of high-speed SSD storage on each node
 - Distributed data staging system that first divides the data set into disjoint pieces, read to some nodes, than copy to other nodes

INNOVATIONS (2)

System Innovations

- Optimized data ingestion pipeline
 - TensorFlow input pipeline that reads the input files and converts them into the tensors that are fed through the network (read and convert to TFRecords)
 - Eliminate serialization by enabling the prefetching option of TensorFlow datasets
 - HDF5 Library serializes calls
 - By using the Python multiprocessing module, transform these parallel worker threads into parallel worker processes, each using its own instance of the HDF5 library

INNOVATIONS (2)

System Innovations

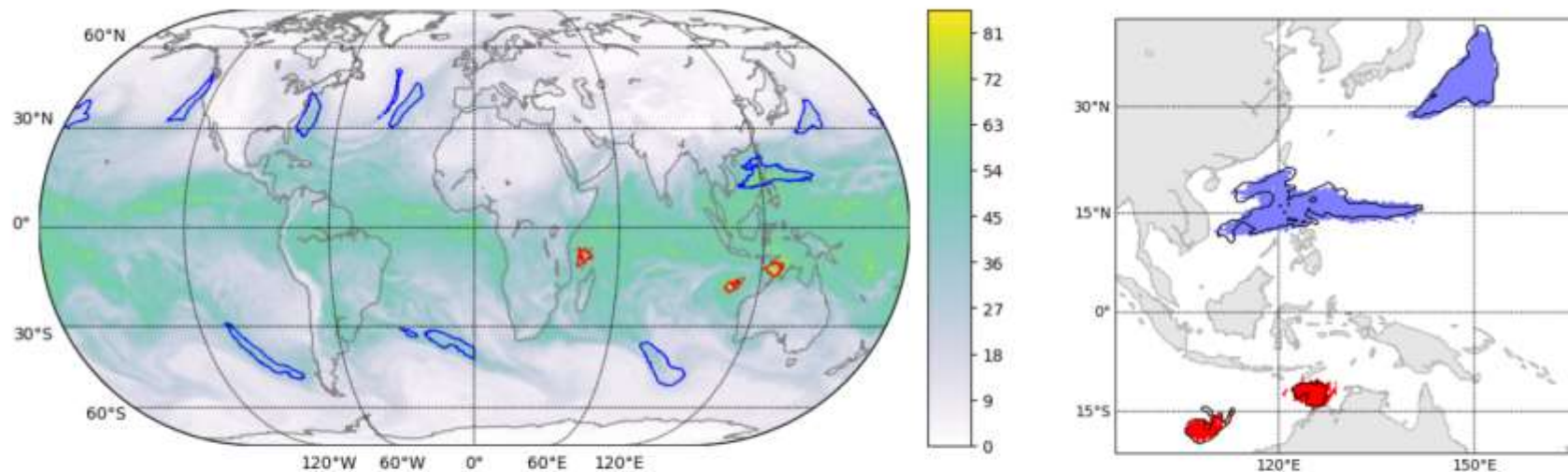
- Hierarchical all-reduce
 - Horovod is a Python module that uses MPI to transform a single-process TensorFlow application into a data-parallel implementation
 - Each MPI rank creates its own identical copy of the TensorFlow operation graph.
 - The first issue was a bottleneck on the first rank, which acts as a centralized scheduler for Horovod operations. Solution: organize in a communication tree.
 - The existing Horovod implementation is able to reduce data residing on GPUs in two different ways, either by a standard MPI_Allreduce or by using the NVIDIA Collective Communications Library (NCCL)
 - NCCL is better for intra-node (exploits NVLINK) and Standard MPI is better for inter-node



RESULTS

CLIMATE RESULTS

Atmospheric Rivers (AR) in Blue and Tropical Cyclones (TC) in Red

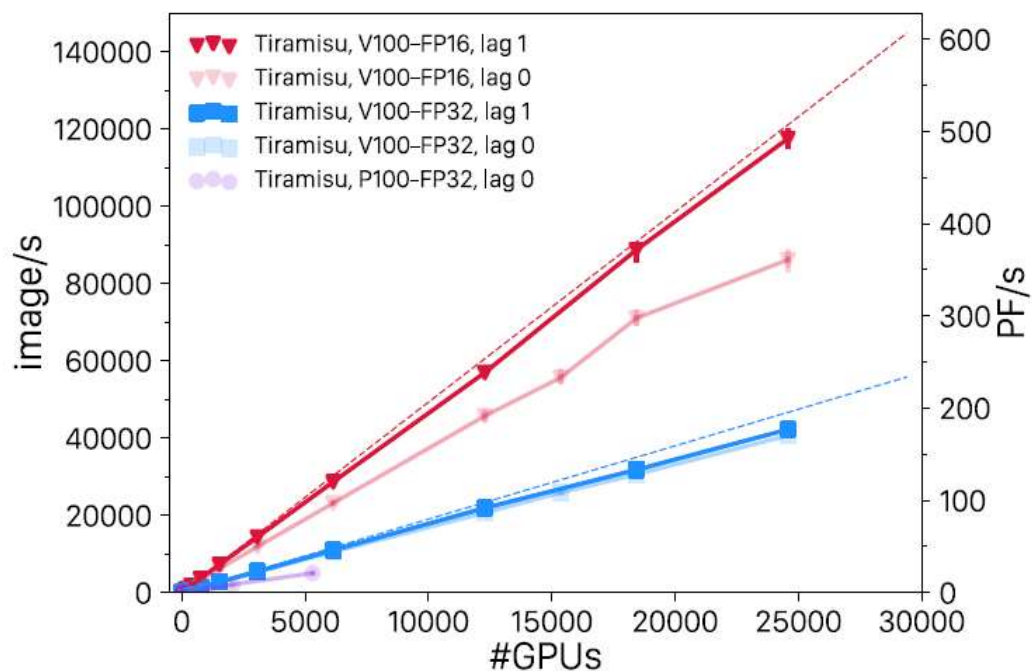


(a) Segmentation masks overlaid on a globe. Colors (white->yellow) indicate IWV (integrated water vapor, kg/m^2), one of the 16 input channels used by the network.

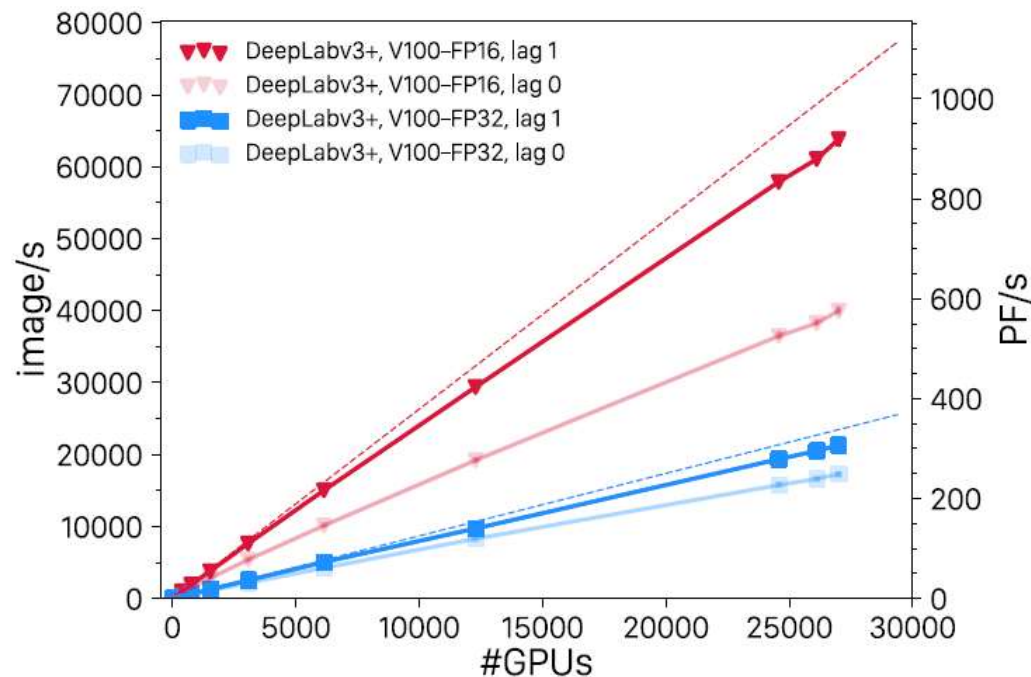
(b) Detailed inset showing predictions (red and blue) vs. labels used in training (black).

Fig. 7: Segmentation results from modified DeepLabv3+ network. Atmospheric rivers (ARs) are labeled in blue, while tropical cyclones (TCs) are labeled in red.

SCALING RESULTS



(a) Tiramisu



(b) DeepLabv3+

Fig. 4: Weak scaling results in terms of images/sec and sustained performance in PF/s on Summit (FP16 and FP32, Tiramisu and DeepLabv3+) and Piz Daint (FP32, Tiramisu). The dashed lines represent the ideal scaling lines for the different architectures and precisions.

OVERALL RESULTS

Tiramisu (PizDaint) and DeepLabv3 (Summit)

	#GPUs	GPU Arch	Peak (PFLOPS)	Sustained (PFLOPS)	Efficiency
Tiramisu (FP32)	5300	P100 (CUDA)	26.6	21	79.0%
DeepLabv3+ (FP32)	27360	V100 (CUDA)	359.2	325.8	90.7%
DeepLabv3+ (FP16)	27360	V100 (Tensor Cores)	1130.0	999	88.4%



**PUSHING AI
COMPUTING LIMITS**

NVIDIA® DGX-1™



NVSWITCH

World's Highest Bandwidth On-node Switch

7.2 Terabits/sec or 900 GB/sec
18 NVLINK ports | 50GB/s per
port bi-directional
Fully-connected crossbar
2 billion transistors |
47.5mm x 47.5mm package



NVIDIA DGX-2

THE LARGEST GPU EVER CREATED



2 PFLOPS | 512GB HBM2 | 10 kW | 350 lbs

A network diagram with green nodes and lines on a dark background. The nodes are represented by small, glowing green circles of varying sizes, and they are interconnected by thin, light green lines. The overall appearance is that of a complex, interconnected network or data structure. The background is dark, with some faint, larger green circles scattered throughout, possibly representing data points or nodes in a different context.

**MORE SCIENTIFIC
EXAMPLES**

GALAXY CLASSIFICATION

Merging vs Not-Merging

Astronomy & Astrophysics manuscript no. Paper-Real-Sim-Mergers
May 13, 2019

©ESO 2019

Identifying Galaxy Mergers in Observations and Simulations with Deep Learning

W. J. Pearson^{1,2}, L. Wang^{1,2}, J. W. Trayford³, C. E. Petrillo², F. F. S. van der Tak^{1,2}

¹ SRON Netherlands Institute for Space Research, Landleven 12, 9747 AD, Groningen, The Netherlands
e-mail: w.j.pearson@sron.nl

² Kapteyn Astronomical Institute, University of Groningen, Postbus 800, 9700 AV Groningen, The Netherlands

³ Leiden Observatory, Leiden University, P.O. Box 9513, 2300 RA Leiden, The Netherlands

Received DD Month YYYY / Accepted DD Month YYYY

GALAXY CLASSIFICATION

Merging vs Not-Merging

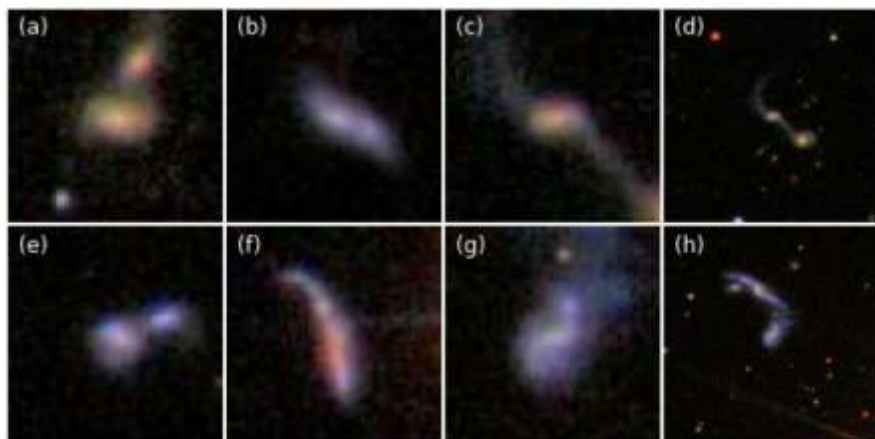


Fig. 20. Examples of SDSS FN galaxies from the simulation network for (a) a galaxy with a clear merging counterpart, (b) a clearly disturbed system, (c) a galaxy whose merger companion is outside of the 64×64 pixel image and (d) the larger 256×256 pixel image showing the merger companion outside of panel (c). Panels (e) to (h) show TP galaxies that are visually similar to those shown in (a) to (d).

Table 3. Confusion matrix for SDSS images classified by the observation network.

		Network Classification		Total
		Merger	Non-merger	
Catalogue Classification	Merger	276 TP	24 FN	300
	Non-merger	27 FP	273 TN	300
Total		303	297	

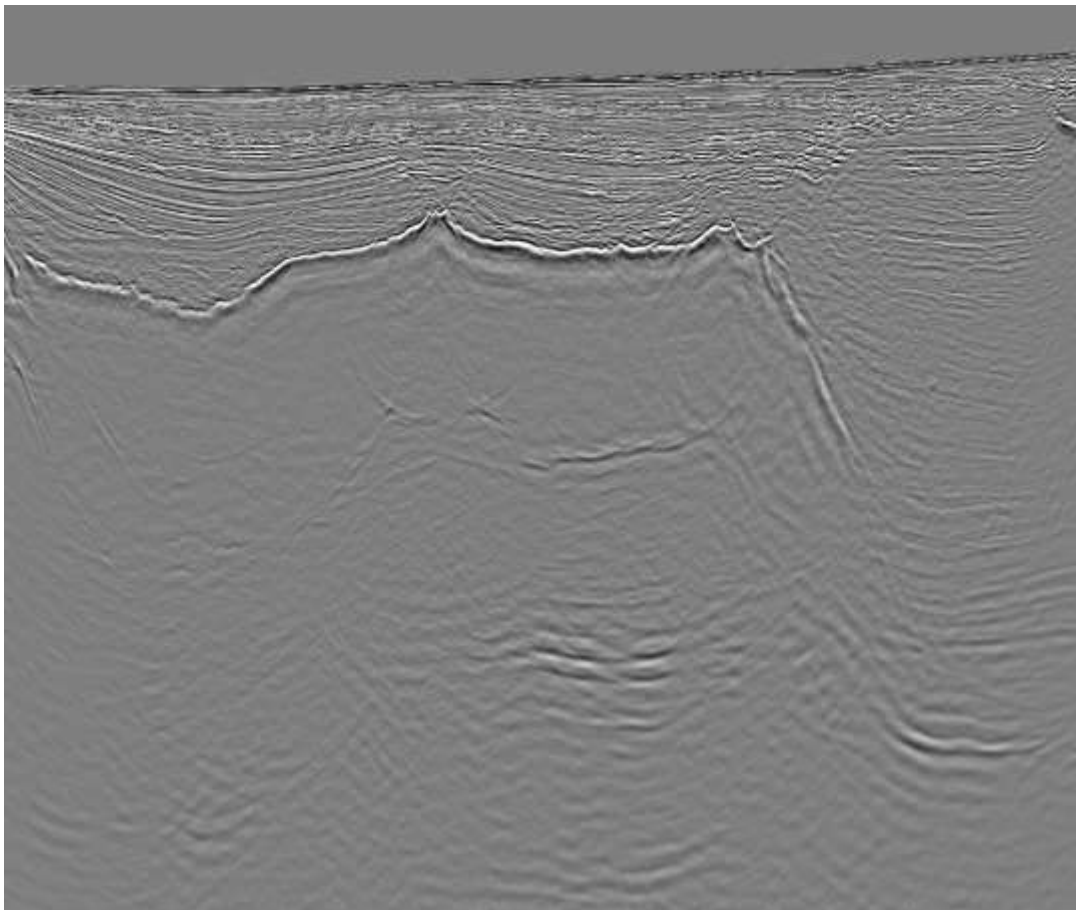
1° LATIN AMERICA SUPER-COMPUTER: PETROBRAS FENIX

Fenix is at the 142nd position in the Top500
List.
576x V100 = 288x Nodes w/ 2xGPU/node

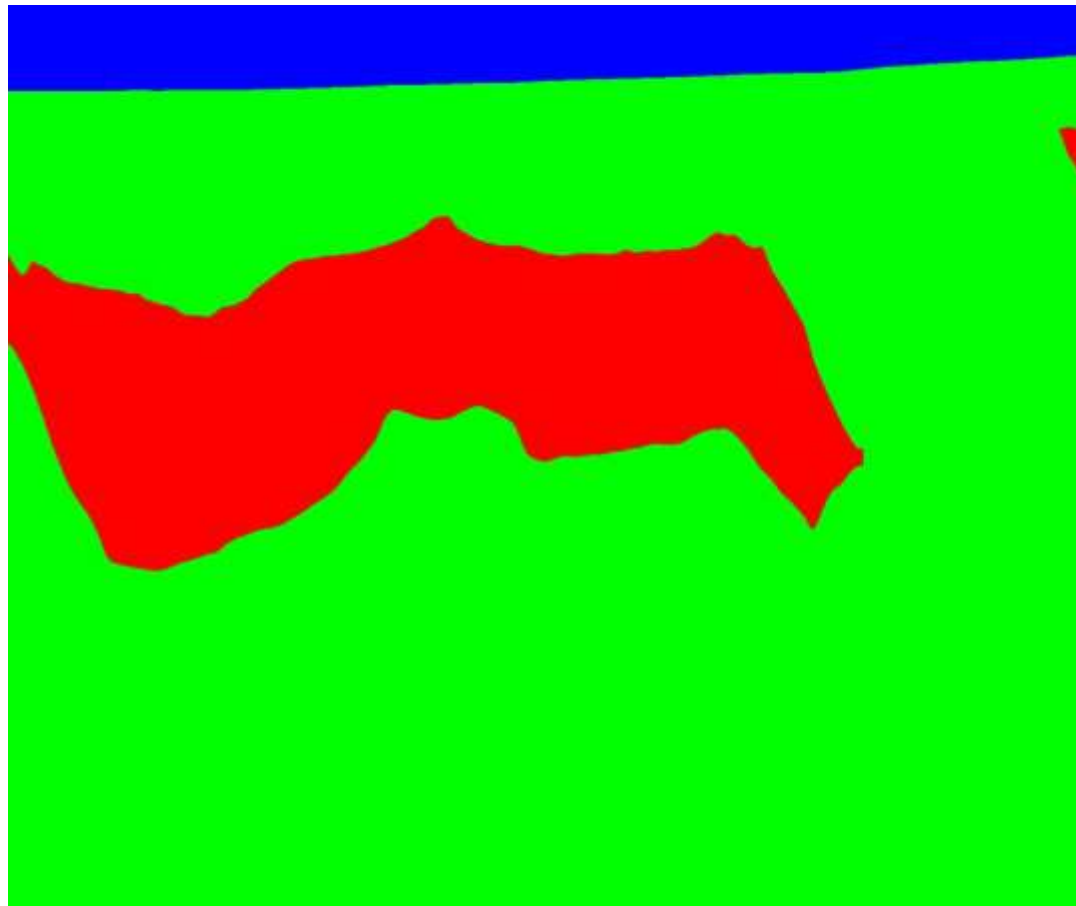
Source: Top500.org.



TRAINING SET



Features (Seismic)

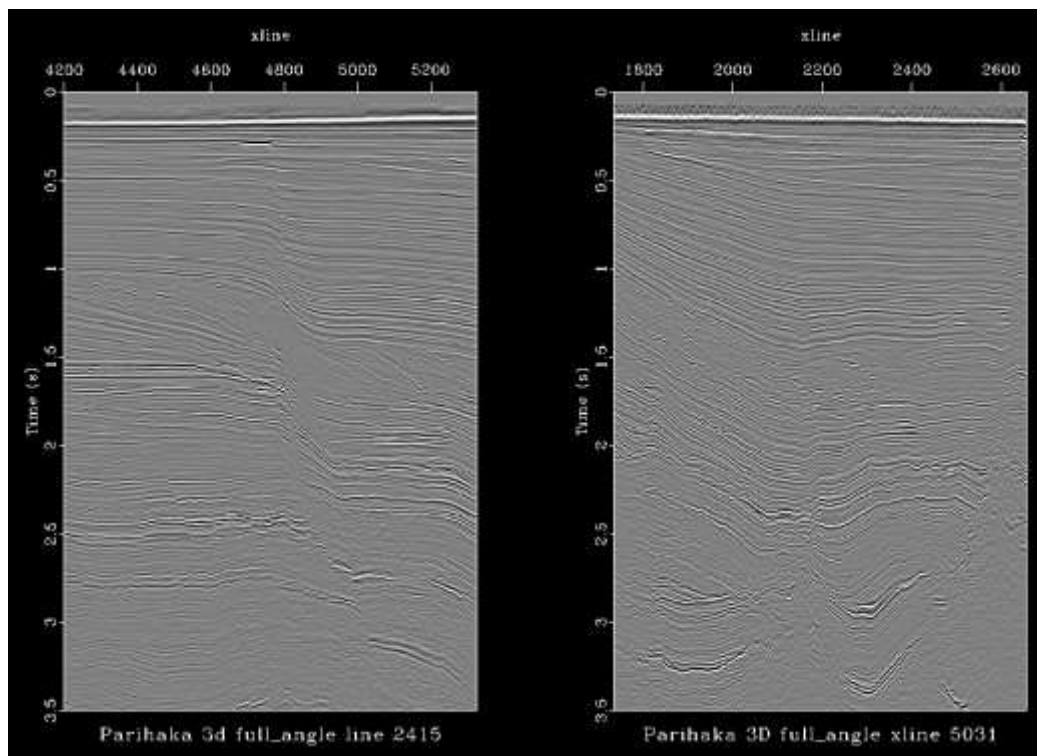
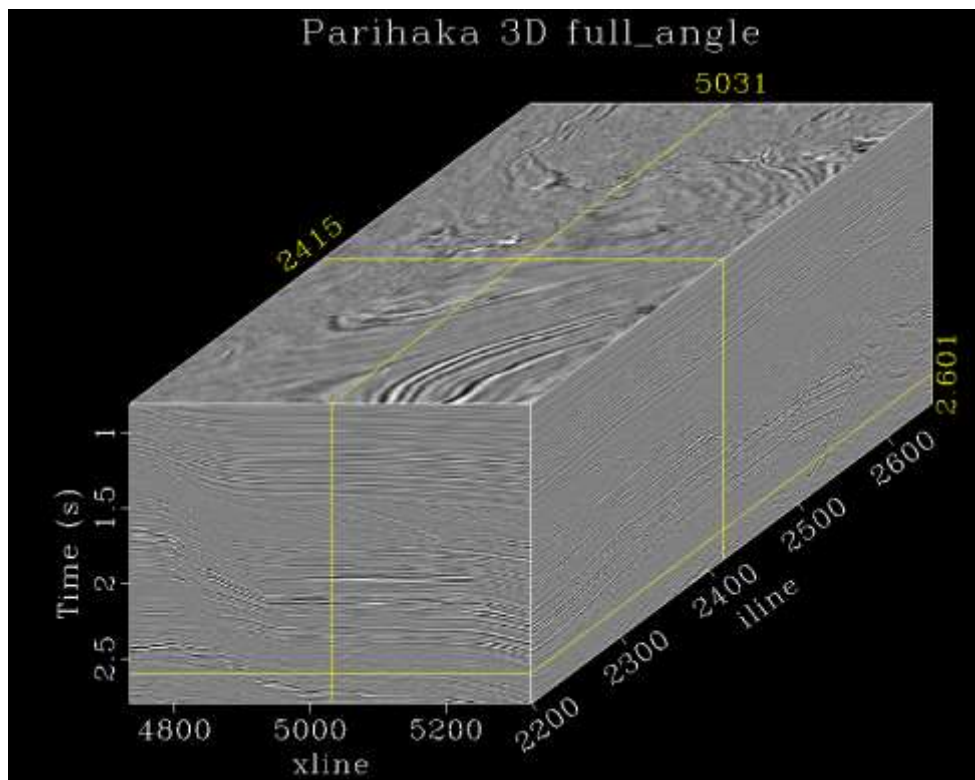


Labels

TRAINING IMAGES

Parihaka dataset (SEG Y)

<https://wiki.seg.org/wiki/Parihaka-3D>



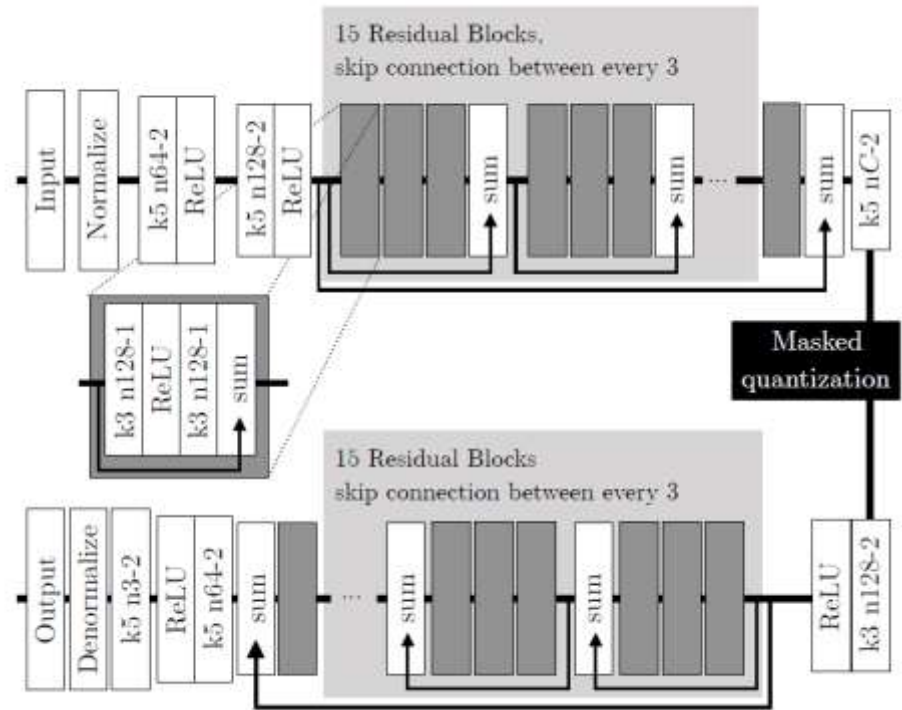
METHOD

Conditional Probabilistic Deep Auto-Encoder

Based on the state-of-art on image compression work (CVPR-18):

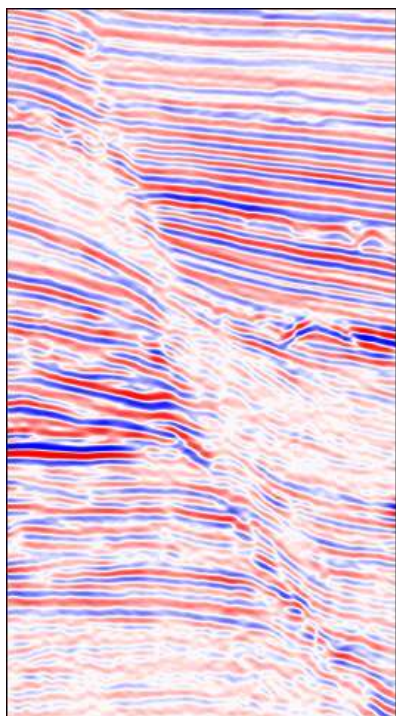
“Conditional Probability Models for Deep Image Compression” - Mentzer et. al.

Original work operates on 8-bits depth images. Changes for 32-bits and specific training protocols were performed for 3D post-stacked seismic data.

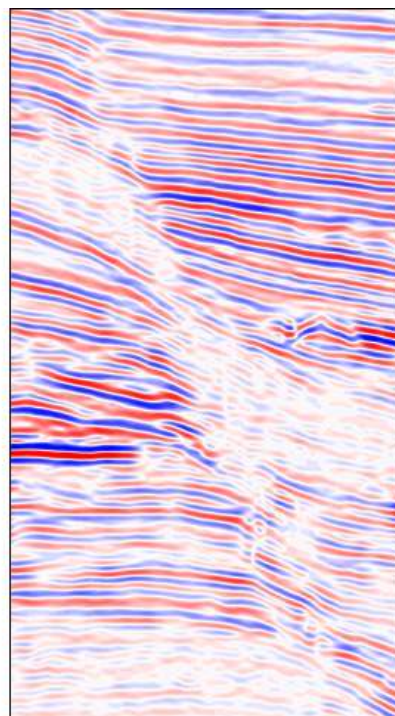


EXPERIMENTS

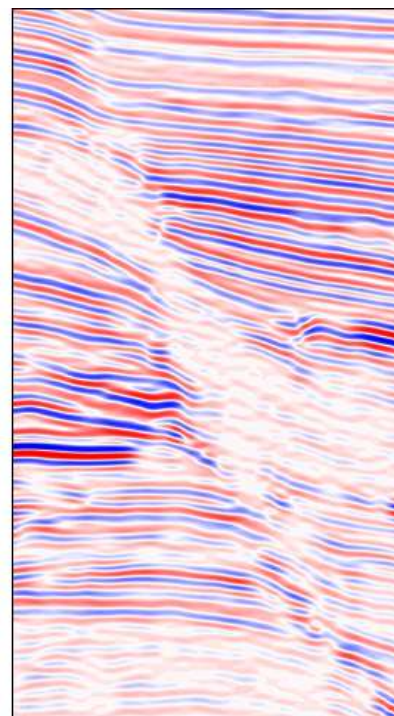
Visual Comparison



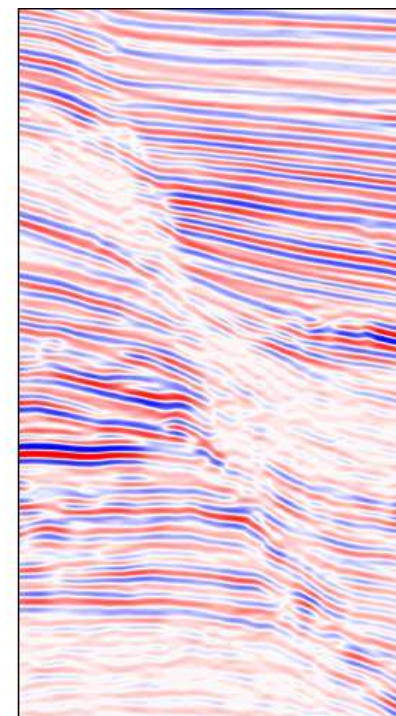
Original



40.08db | 3.58bpv



39.9db | 1.56bpv



37.87db | 0.74bpv

Figure 2 Visual comparison of different trained models for Parihaka-3D dataset. The results (crossline 4791) refer to training models targeting different compression rates. PSNR and bpv are below the decompressed slices. As we move to lower compression rates (rightmost panel), the reconstruction error increases but most representative seismic features are still preserved.

NEW SUPERCOMPUTERS IN BRAZIL

LNCC (Rio de Janeiro)

376x V100 = 96x Nodes w/ 4xGPU/node

SENAI-SIMATEC (Salvador)


312x V100 = 78x Nodes w/ 4xGPU/node

SDUMONT 2.0




CONFIGURATION (SEQUANA)

- ▶ + ~4.0 PFlops computing capability
- ▶ 376 nodes with 3 configurations: X1120 CascadeLake 384 & 768 Gb, X1125 Volta V100 (4 pn)
- ▶ + ~1 Pb Lustre storage; Infiniband interconnection (EDR)



- X1120 CL 384G
- X1120 CL 768G
- X1125 CL+V100



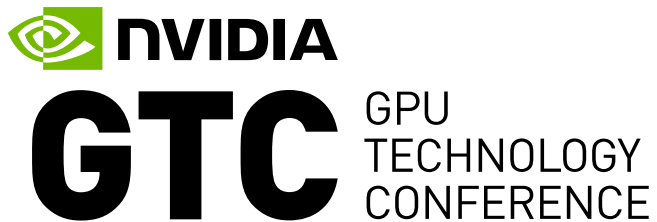
Repsol Sinopec Brasil e SENAI CIMATEC convidam para o lançamento do supercomputador

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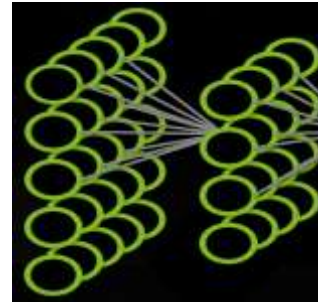
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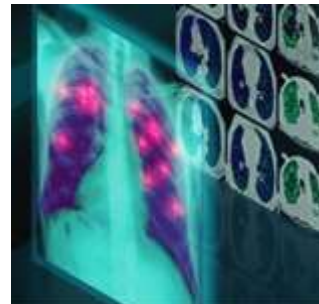
Download the course catalog, view upcoming workshops, and learn about the University Ambassador Program: www.nvidia.com/dli



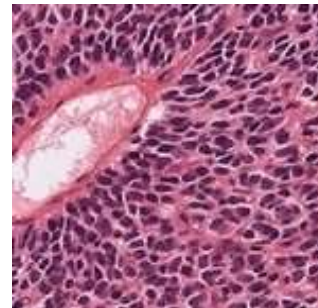
Deep Learning Fundamentals



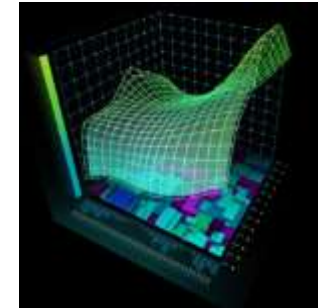
Autonomous Vehicles



Medical Image Analysis



Genomics



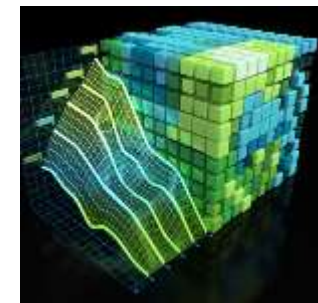
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Intelligent Video Analytics



Game Development & Digital Content



Accelerated Computing Fundamentals

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- HPC
- Deep Learning

Quadro P6000



- Scientific Visualization
- Virtual Reality

Jetson TX2
(Dev Kit)



- Robotics
- Autonomous Machines

https://developer.nvidia.com/academic_gpu_seeding

Obrigado
Gracias
Thank you

pcruzesilva@nvidia.com

