Running Deep Learning Applications on HPC System

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Content

Introduction

ML Perf

Create Kernels

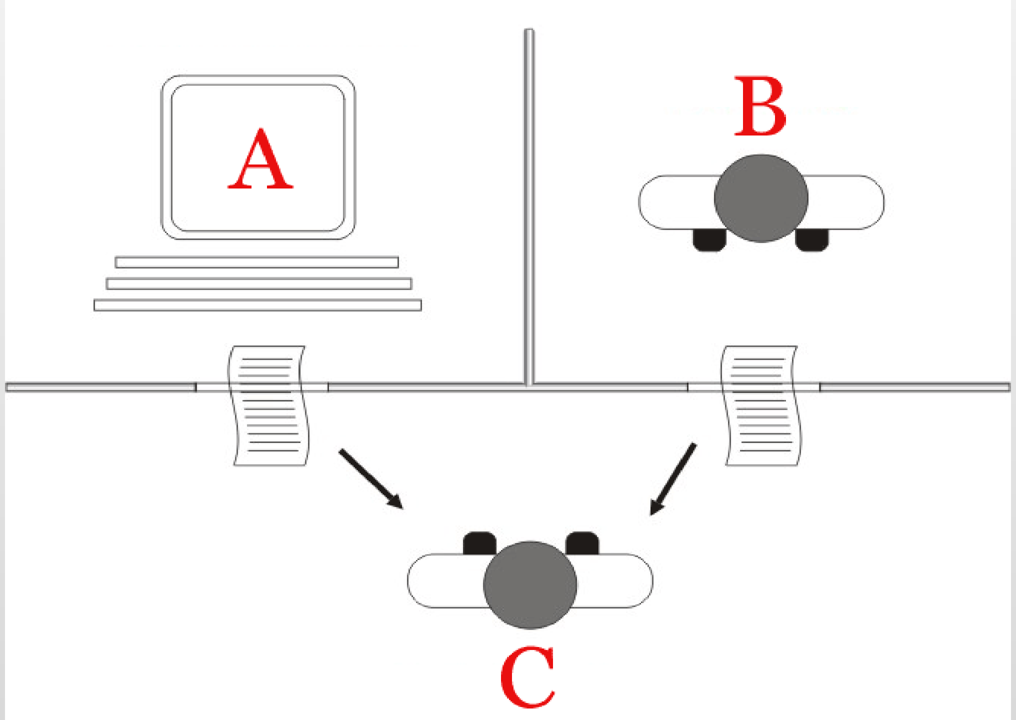
Running DL Models

History of AI

Pre-1950s: Foundations of AI

The formal study of AI began with mathematicians and philosophers like Alan Turing.

In 1950, Alan Turing proposed the famous "Turing Test," a measure of a machine's ability to exhibit human-like intelligence. This concept laid the groundwork for future AI research.



The "standard interpretation" of the Turing test, in which player C, the interrogator, is given the task of trying to determine which player – A or B – is a computer and which is a human. The interrogator is limited to using the responses to written questions to make the determination.

History of AI

1950s and 1960s: Early Research and Symbolic AI

The term "artificial intelligence" was coined in 1956 at the Dartmouth Conference, where the field of AI research was officially established.

During this period, researchers focused on symbolic AI, using rules and logic to mimic human problem-solving processes.

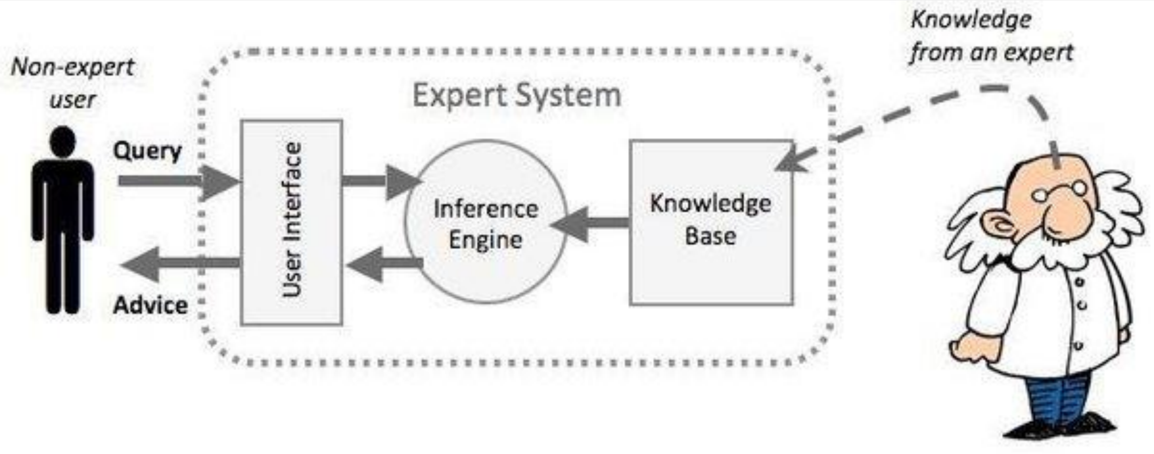
History of AI

1970s and 1980s: Knowledge-Based Systems AI

Research saw a shift towards knowledge-based systems and expert systems.

These systems utilized large knowledge bases to reason and draw conclusions about specific domains.

Though promising, early expert systems faced limitations due to the complexity of representing all human knowledge in a formalized manner.

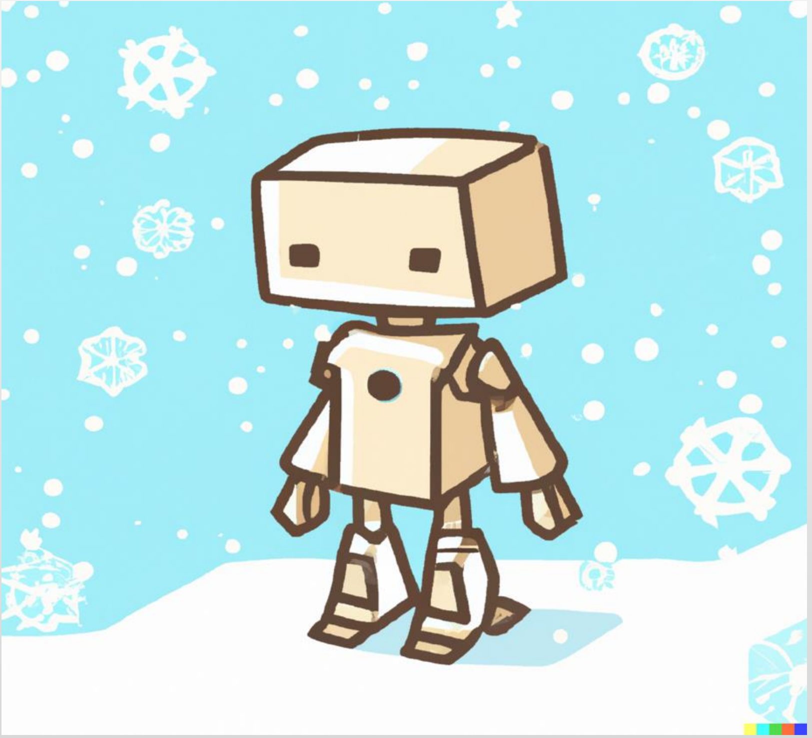


History of AI

1980s and 1990s: AI Winter

During this period, AI faced a decline in interest and funding due to unmet expectations and the inability to deliver on grand promises.

Progress in AI did not match initial optimism, leading to a phase known as the "AI Winter."



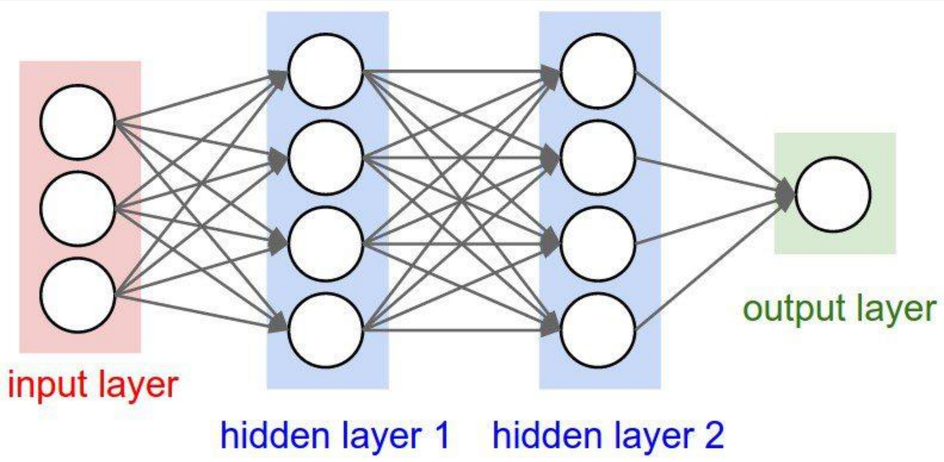
History of AI

Late 1990s and 2000s: Machine Learning and Neural Networks

The resurgence of AI came with the advent of machine learning techniques, particularly neural networks.

Improved computational power and access to vast amounts of data allowed neural networks to excel in tasks like image recognition and language processing.

Support vector machines and other machine learning algorithms also gained popularity.

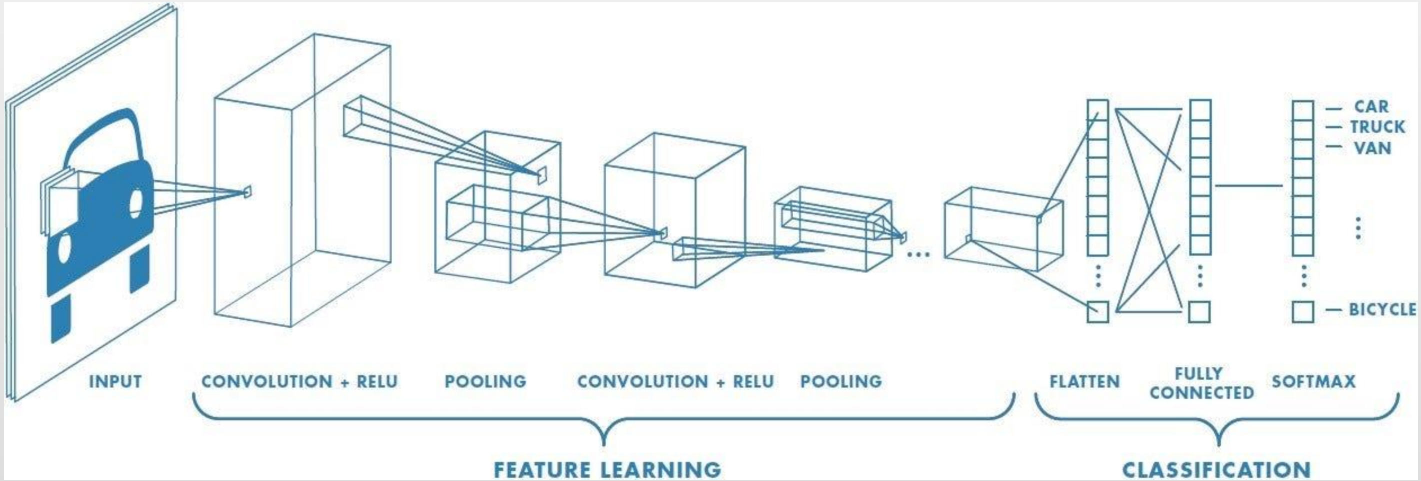


History of AI

2010s: Deep Learning and AI Breakthroughs

Deep learning, a subset of machine learning using artificial neural networks with multiple layers, became the driving force behind many AI breakthroughs.

Applications of AI proliferated in various fields, including natural language processing, computer vision, robotics, and autonomous vehicles.



History of AI

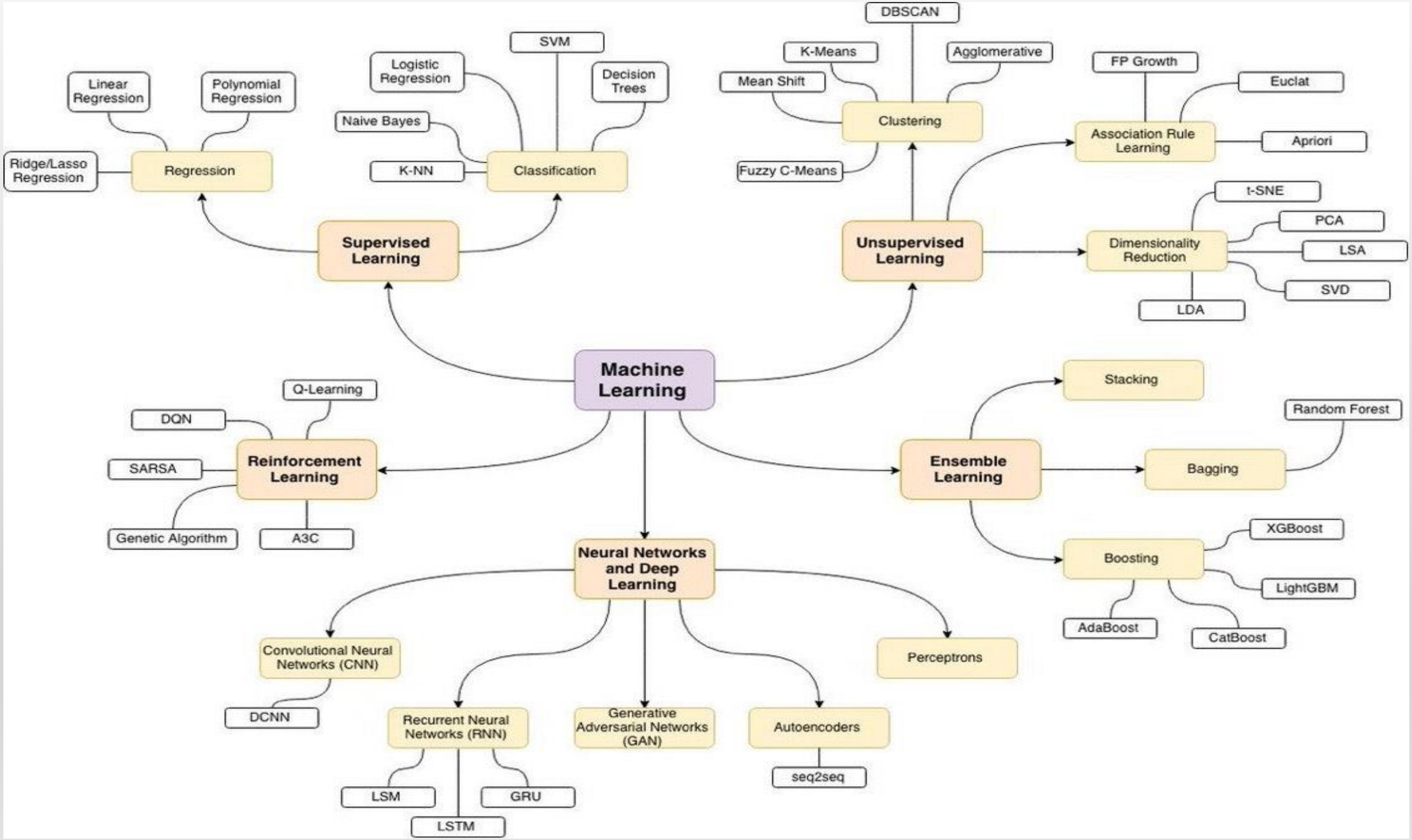
Present and Beyond

AI continues to evolve rapidly, with ongoing research in areas like reinforcement learning, explainable AI, Large Language Model and AI ethics.

Integration of AI in everyday life through virtual assistants, smart devices, and recommendation systems is becoming increasingly common.

However, concerns about AI's societal impact, privacy, and ethical implications persist.

Introduction of Machine Learning



ML Perf Benchmark

ML Perf: A broad ML benchmark suite for measuring the performance of ML software frameworks, ML hardware accelerators, and ML cloud and edge platforms

Alibaba	AMD	Arm	Baidu	Cadence	Cerebras	Cisco
Cray	Dividiti	Enflame Tech	Esperanto	Google	Groq	Huawei
Intel	MediaTek	Mentor Graphics	Mythic	NetApp	NVIDIA	One Convergence
Rpa2ai	Sambanova	Samsung S.LSI	Sigopt	Synopsys	Tensyr	Wave Computing

Harvard University	Stanford University	University of Arkansas, Littlerock	University of California, Berkeley	University of Minnesota	University of Texas, Austin	University of Toronto

MLPerf

ML Perf Benchmark

Area	Benchmark	Dataset	Quality Target	Reference Implementation Model	Latest Version Available
Vision	Image classification	ImageNet	75.90% classification	ResNet-50 v1.5	v3.1
Vision	Image segmentation (medical)	KiTS19	0.908 Mean DICE score	3D U-Net	v3.1
Vision	Object detection (light weight)	Open Images	34.0% mAP	RetinaNet	v3.1
Vision	Object detection (heavy weight)	COCO	0.377 Box min AP and 0.339 Mask min AP	Mask R-CNN	v3.1
Language	Speech recognition	LibriSpeech	0.058 Word Error Rate	RNN-T	v3.1
Language	NLP	Wikipedia 2020/01/01	0.72 Mask-LM accuracy	BERT-large	v3.1
Language	LLM	C4	2.69 log perplexity	GPT3	v3.1
Commerce	Recommendation	Criteo 4TB multi-hot	0.8032 AUC	DLRM-dcnv2	v3.1
Marketing, Art, Gaming	Image Generation	LAION-400M-filtered	FID<=90 and CLIP>=0.15	Stable Diffusionv2	v3.1
Commerce	Recommendation	1TB Click Logs	0.8025 AUC	DLRM	v2.1
Research	Reinforcement learning	Go	50% win rate vs. checkpoint	Mini Go (based on Alpha Go paper)	v2.1
Vision	Object detection (light weight)	COCO	23.0% mAP	SSD	v1.1
Language	Translation (recurrent)	WMT English-German	24.0 Sacre BLEU	NMT	v0.7
Language	Translation (non-recurrent)	WMT English-German	25.00 BLEU	Transformer	v0.7

ML Perf Benchmark

ML Perf Training

The MLPerf Training benchmark measures how fast systems can train models to a target quality metric.

- MLPerf Training
- MLPerf Training: HPC

ML Perf Inference

The MLPerf inference benchmark suite measures how fast systems can process inputs and produce results using a trained model

- MLPerf Inference: Datacenter
- MLPerf Inference: Edge
- MLPerf Inference: Mobile
- MLPerf Inference: Tiny

ML Perf Storage

The MLPerf Storage benchmark suite measures how fast storage systems can supply training data when a model is being trained.

- MLPerf Storage

Edge: Lenovo SE450 Edge Server

Mobile: Xiaomi note12 turbo

Tiny: Cora Z7 for ARM/FPGA SoC Development

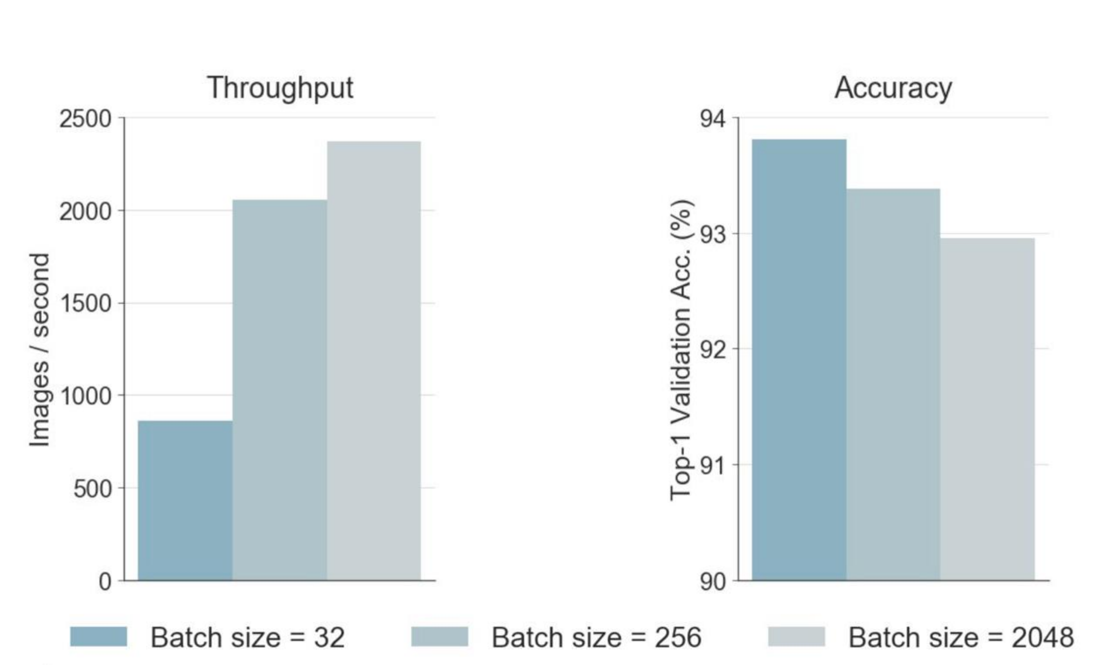
ML Perf Training Benchmark

Performance

How fast is a model for training, inference?

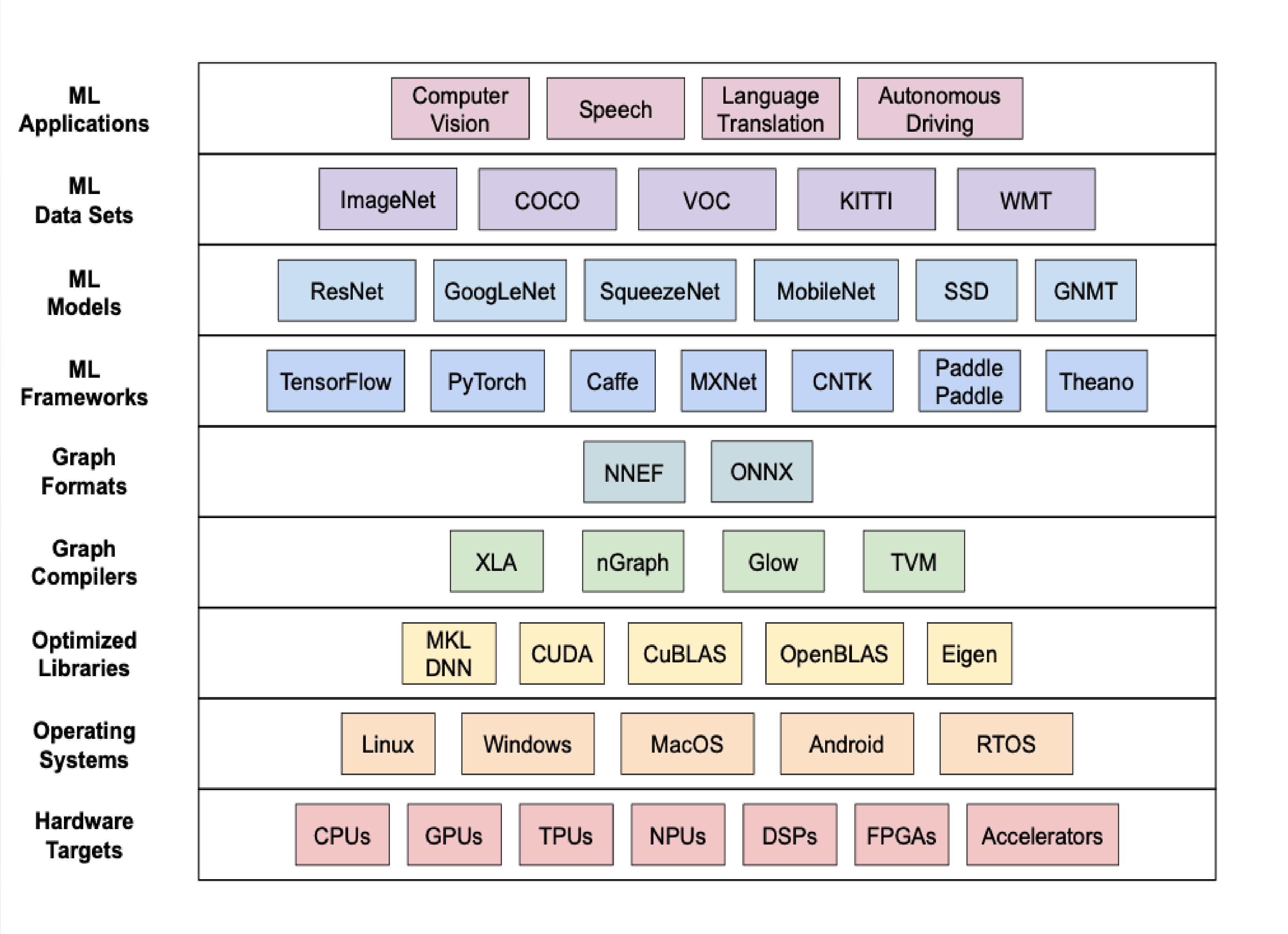
Quality

How good are a model's predictions?



- End to end training of a Resnet56 CIFAR10 model
- Nvdia P100 with 512GB of memory and 28 CPU cores
- TensorFlow 1.2 compiled from source with CUDA 8.0 and CuDNN 5.1

ML Perf Benchmark



ML Perf Benchmark

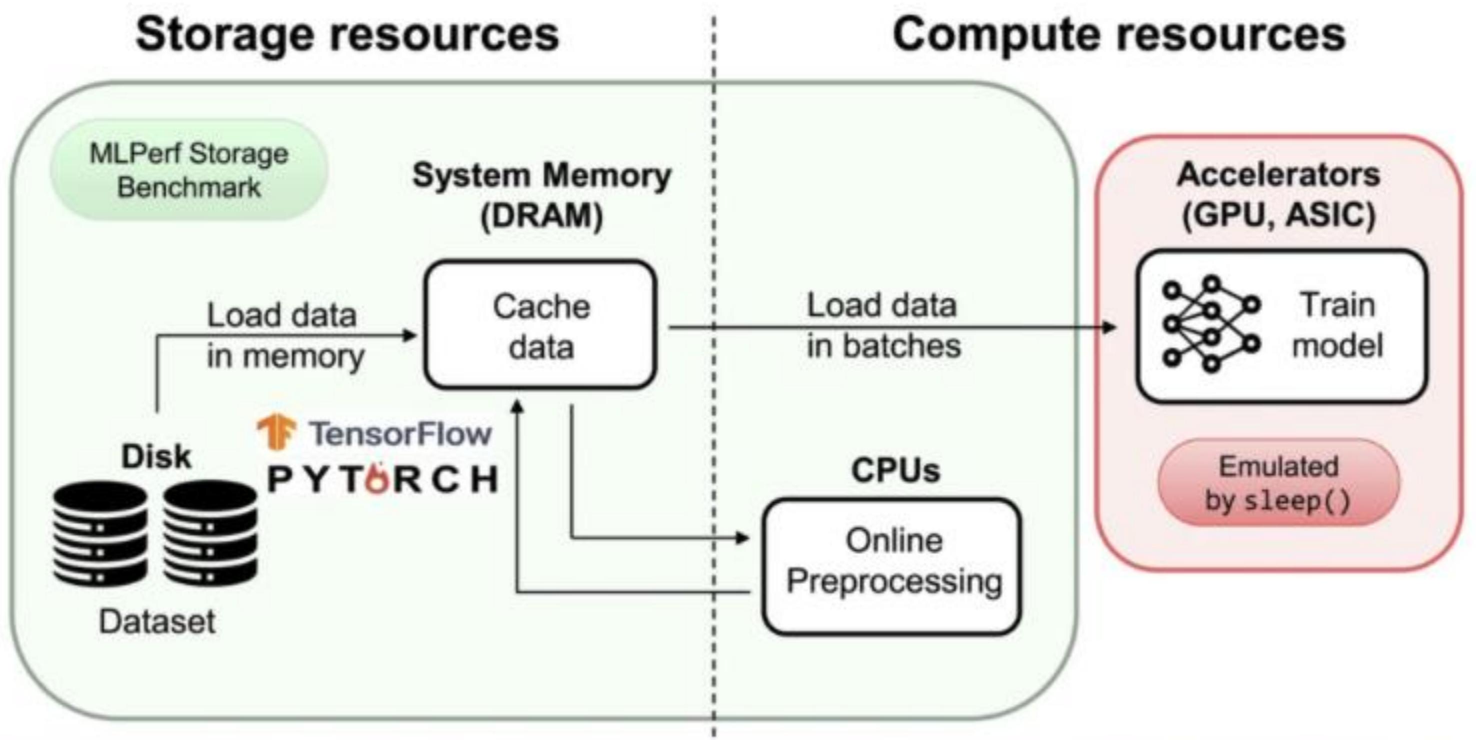
Training v1.1

Closed | Open

ID	Submitter	System	Processor	#	Accelerator	#	Software	Benchmark results (minutes): Image classification — ImageNet — ResNet	Image segmentation (medical) — KiTS19 — 3D U-Net	Object detection, light-weight — COCO — SSD	Object detection, heavy-weight — COCO — Mask R-CNN	Speech recognition — LibriSpeech — RNN-T	NLP — Wikipedia — BERT [1]	Recom-mendation — 1TB Clickthrough — DLRM	Reinforce-ment Learning — Go — Minigo	Details	Code
Available cloud																	
1.1-2000	Azure	nd96amsr_a100_v4_ngc21.09_merlin_hugectr	AMD EPYC 7V12	2	NVIDIA A100-SXM4-80GB (400W)	8	Merlin HugeCTR with NVIDIA DL Frameworks Release 21.09							1.875		details	code
1.1-2001	Azure	nd96amsr_a100_v4_ngc21.09_mxnet	AMD EPYC 7V12	2	NVIDIA A100-SXM4-80GB (400W)	8	MXNet NVIDIA Release 21.09	29.720	25.400	8.309						details	code
1.1-2002	Azure	nd96amsr_a100_v4_ngc21.09_pytorch	AMD EPYC 7V12	2	NVIDIA A100-SXM4-80GB (400W)	8	PyTorch NVIDIA Release 21.09				47.064	37.550	21.213			details	code
1.1-2003	Azure	nd96amsr_a100_v4_ngc21.09_tensorflow	AMD EPYC 7V12	2	NVIDIA A100-SXM4-80GB (400W)	8	TensorFlow NVIDIA Release 21.09								319.410	details	code
1.1-2004	Azure	nd96amsr_a100_v4_n4_ngc21.09_pytorch	AMD EPYC 7V12	8	NVIDIA A100-SXM4-80GB (400W)	32	PyTorch NVIDIA Release 21.09				14.912					details	code
1.1-2005	Azure	nd96amsr_a100_v4_n8_ngc21.09_mxnet	AMD EPYC 7V12	16	NVIDIA A100-SXM4-80GB (400W)	64	MXNet NVIDIA Release 21.09	4.587		1.517						details	code
1.1-2006	Azure	nd96amsr_a100_v4_n8_ngc21.09_pytorch	AMD EPYC 7V12	16	NVIDIA A100-SXM4-80GB (400W)	64	PyTorch NVIDIA Release 21.09						3.111			details	code
1.1-2007	Azure	nd96amsr_a100_v4_n9_ngc21.09_mxnet	AMD EPYC 7V12	18	NVIDIA A100-SXM4-80GB (400W)	72	MXNet NVIDIA Release 21.09		3.800							details	code
1.1-2008	Azure	nd96amsr_a100_v4_n16_ngc21.09_pytorch	AMD EPYC 7V12	32	NVIDIA A100-SXM4-80GB (400W)	128	PyTorch NVIDIA Release 21.09					4.533				details	code
1.1-2009	Azure	nd96amsr_a100_v4_n32_ngc21.09_tensorflow	AMD EPYC 7V12	64	NVIDIA A100-SXM4-80GB (400W)	256	TensorFlow NVIDIA Release 21.09								30.714	details	code
1.1-2010	Azure	nd96amsr_a100_v4_n34_ngc21.09_pytorch	AMD EPYC 7V12	68	NVIDIA A100-SXM4-80GB (400W)	272	PyTorch NVIDIA Release 21.09				3.908					details	code
1.1-2011	Azure	nd96amsr_a100_v4_n48_ngc21.09_tensorflow	AMD EPYC 7V12	96	NVIDIA A100-SXM4-80GB (400W)	384	TensorFlow NVIDIA Release 21.09								24.802	details	code
1.1-2012	Azure	nd96amsr_a100_v4_n96_ngc21.09_mxnet	AMD EPYC 7V12	192	NVIDIA A100-SXM4-80GB (400W)	768	MXNet NVIDIA Release 21.09		1.262							details	code
1.1-2013	Azure	nd96amsr_a100_v4_n128_ngc21.09_mxnet	AMD EPYC 7V12	256	NVIDIA A100-SXM4-80GB (400W)	1024	MXNet NVIDIA Release 21.09	0.583		0.455						details	code
1.1-2014	Azure	nd96amsr_a100_v4_n128_ngc21.09_pytorch	AMD EPYC 7V12	256	NVIDIA A100-SXM4-80GB (400W)	1024	PyTorch NVIDIA Release 21.09						0.656			details	code
1.1-2015	Azure	nd96amsr_a100_v4_n192_ngc21.09_pytorch	AMD EPYC 7V12	384	NVIDIA A100-SXM4-80GB (400W)	1536	PyTorch NVIDIA Release 21.09					3.205				details	code
1.1-2016	Azure	nd96amsr_a100_v4_n224_ngc21.09_tensorflow	AMD EPYC 7V12	448	NVIDIA A100-SXM4-80GB (400W)	1792	TensorFlow NVIDIA Release 21.09								17.439	details	code
1.1-2017	Azure	nd96amsr_a100_v4_n256_ngc21.09_mxnet	AMD EPYC 7V12	512	NVIDIA A100-SXM4-80GB (400W)	2048	MXNet NVIDIA Release 21.09	0.438								details	code
1.1-2018	Azure	nd96amsr_a100_v4_n256_ngc21.09_pytorch	AMD EPYC 7V12	512	NVIDIA A100-SXM4-80GB (400W)	2048	PyTorch NVIDIA Release 21.09						0.422			details	code
Available on-premise																	
1.1-2019	Baidu	1_node_8_A100_NGC21.05_MXNet	Intel(R) Xeon(R) Platinum 8350C	2	NVIDIA A100-SXM4-80GB (400W)	8	MXNet NVIDIA Release 21.05	28.605								details	code
1.1-2020	Baidu	1_node_8_A100_PaddlePaddle	Intel(R) Xeon(R) Platinum 8350C	2	NVIDIA A100-SXM4-80GB (400W)	8	PaddlePaddle (branch: develop, commitID: 605e7f0)	28.613								details	code
1.1-2021	Dell	DSS8440x8A100-PCIE-40GB	Intel(R) Xeon(R) Gold 6248R CPU @ 3.00GHz	2	NVIDIA A100-PCIE-40GB (250W)	8	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	38.871		11.193	61.505		66.631		393.431	details	code
1.1-2022	Dell	DSS8440x8A100-PCIE-40GB-NVBridge	Intel(R) Xeon(R) Gold 6248R CPU @ 3.00GHz	2	NVIDIA A100-PCIE-40GB (250W)	8	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	37.083		10.899	58.571				405.424	details	code
1.1-2023	Dell	R750xax4A100-PCIE-80GB	Intel(R) Xeon(R) Gold 6338 CPU @ 2.00GHz	2	NVIDIA A100-PCIE-80GB (300W)	4	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	62.949	60.586	18.321	93.134	84.025	56.260		590.009	details	code
1.1-2024	Dell	R750xax4A100-PCIE-80GB-8368	Intel(R) Xeon(R) Platinum 8368 CPU @ 2.40GHz	2	NVIDIA A100-PCIE-80GB (300W)	4	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	64.131		18.390	91.562		56.131			details	code
1.1-2025	Dell	2xR750xax4A100-PCIE-80GB	Intel(R) Xeon(R) Gold 6338 CPU @ 2.00GHz	4	NVIDIA A100-PCIE-80GB (300W)	8	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	32.087								details	code
1.1-2026	Dell	DSS8440x8A100-PCIE-80GB	Intel(R) Xeon(R) Gold 6248R CPU @ 3.00GHz	2	NVIDIA A100-PCIE-80GB (300W)	8	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	33.553	28.543	9.835	55.033	60.763	41.269			details	code
1.1-2027	Dell	DSS8440x10A100-PCIE-80GB	Intel(R) Xeon(R) Gold 6248R CPU @ 3.00GHz	2	NVIDIA A100-PCIE-80GB (300W)	10	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	28.187		8.223	46.948		36.859			details	code
1.1-2028	Dell	4xR750xax4A100-PCIE-80GB	Intel(R) Xeon(R) Gold 6338 CPU @ 2.00GHz	8	NVIDIA A100-PCIE-80GB (300W)	16	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	17.336								details	code
1.1-2029	Dell	8xR750xax4A100-PCIE-80GB	Intel(R) Xeon(R) Gold 6338 CPU @ 2.00GHz	16	NVIDIA A100-PCIE-80GB (300W)	32	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	10.586		3.477						details	code
1.1-2030	Dell	XE8545x4A100-SXM-40GB	AMD EPYC 7763 64-Core Processor	2	NVIDIA A100-SXM4-40GB (400W)	4	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	61.820		16.998	95.157	79.563				details	code
1.1-2031	Dell	XE8545x4A100-SXM-80GB	AMD EPYC 7713 64-Core Processor	2	NVIDIA A100-SXM4-80GB (500W)	4	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	56.326	55.999	16.244	83.774	106.542	38.855	9.522	451.293	details	code
1.1-2032	Dell	2xXE8545x4A100-SXM-80GB	AMD EPYC 7713 64-Core Processor	4	NVIDIA A100-SXM4-80GB (500W)	8	NGC MXNet 21.09 , NGC PyTorch 21.09 , NGC TensorFlow 21.09-tf1	30.123		8.735	48.788	35.068	26.547			details	code
1.1-2033	Fujitsu	PRIMERGY-GX2460M1-mxnet	AMD EPYC 7502 32-Core Processor	2	NVIDIA A100-PCIe-40GB (250W)	4	MXNet NGC21.09	70.294	49.946	20.916						details	code
1.1-2034	Fujitsu	PRIMERGY-GX2460M1-pytorch	AMD EPYC 7502 32-Core Processor	2	NVIDIA A100-PCIe-40GB (250W)	4	Pytorch NGC21.09					109.216	127.843			details	code

ML Perf Storage Benchmark

The MLPerf Storage benchmark suite measures how fast storage systems can supply training data when a model is being trained.



MLPerf Storage overview: Data loading and on-line pre-processing are performed using the ML frameworks, while model training is emulated.

ML Perf Storage Benchmark

Workloads: Each workload supported by MLPerf Storage is defined by a corresponding MLPerf Training benchmark.

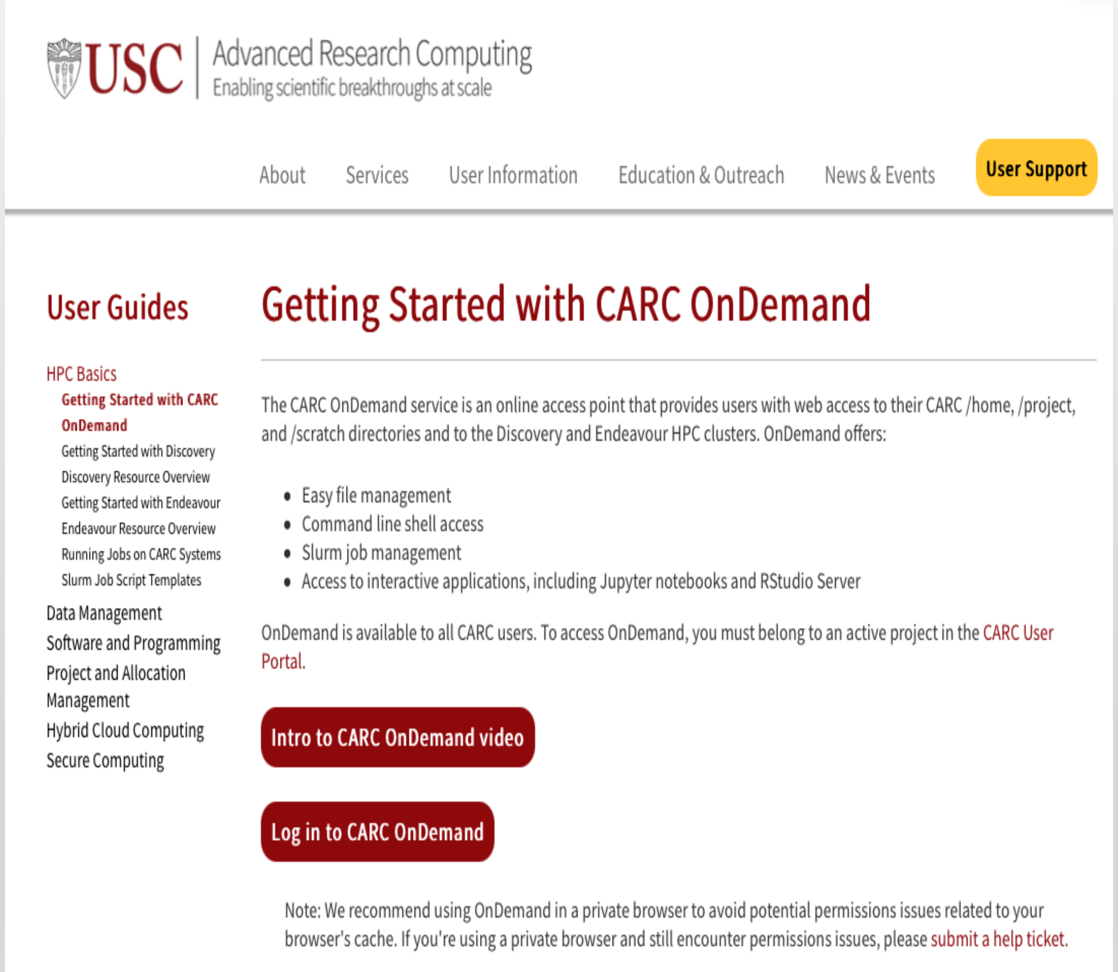
Area	Task	Model	Nominal Dataset (see below)	Latest Version Available
Vision	Medical image segmentation	3D UNET	KITS 2019 (602x512x512)	v0.5
Language	Language processing	BERT-large	Wikipedia (2.5KB/sample)	v0.5

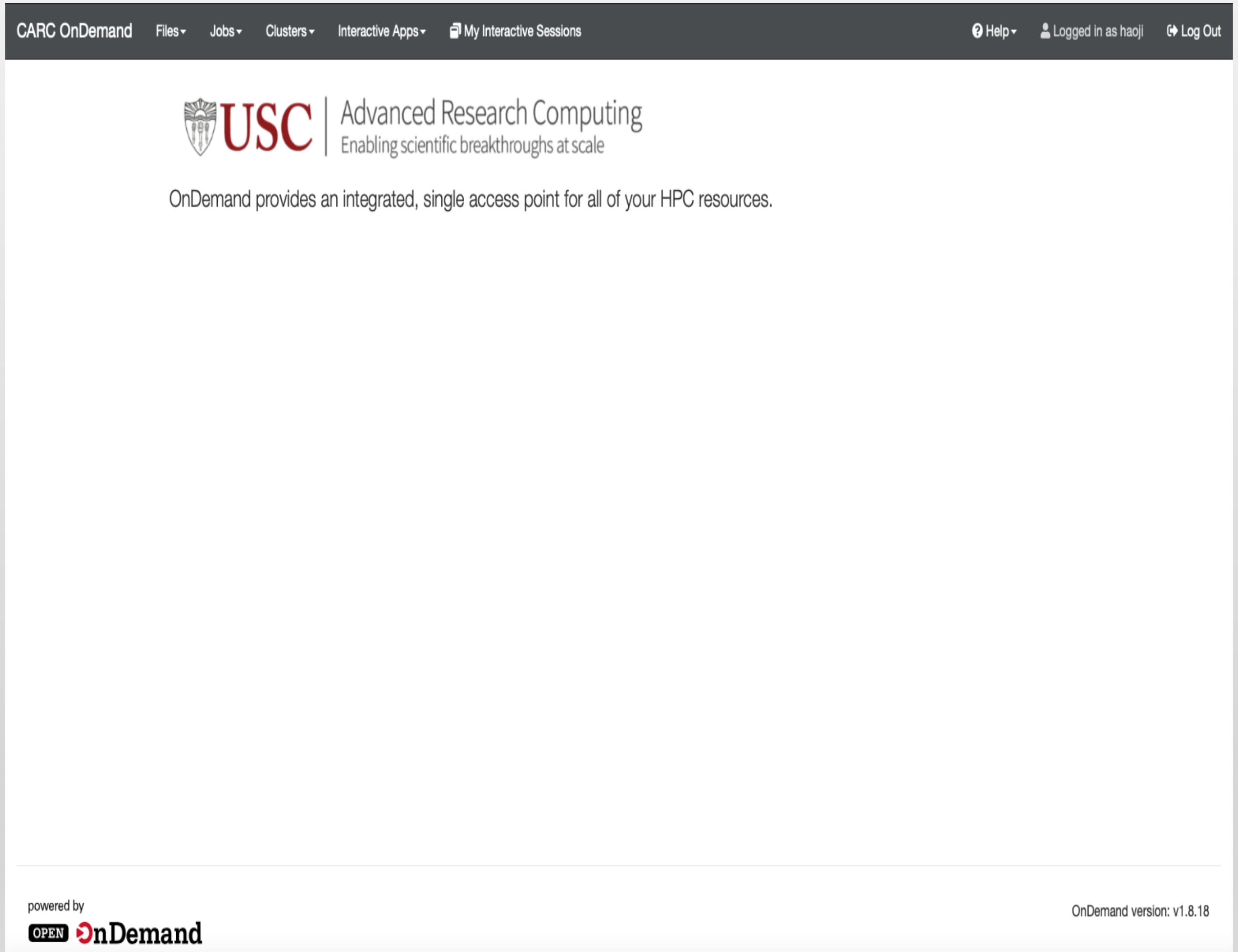
The dataset is referred to as a “nominal dataset” above because the MLPerf Storage benchmark simulates the above named real datasets using synthetically generated populations of files where the distribution of the size of the files matches the distribution in the real dataset.

The size of the dataset used in each benchmark submission is automatically scaled to a size that prevents significant caching of the dataset in the systems actually running the benchmark code.

CARC OnDemand

Web Address: https://carc-ondemand.usc.edu





Using Conda on CARC

Anaconda: package and environment manager primarily used for open-source data science packages for the Python and R programming languages.

Building a Customized Conda Environment

Last updated July 05, 2023

Anaconda is a package and environment manager primarily used for open-source data science packages for the Python and R programming languages. The Conda module is available on CARC, users do not need to install it themselves.

1. Request an interactive session

The login node is meant for login purposes only and has process limits.

It is a good practice to request an interactive session for package installation. The following example code requests one GPU, 8 CPU cores, and 32GB memory in the gpu partition with a time limit of 1 hour.

```
[user@discovery1 ~]$ salloc --partition=gpu --gres=gpu:1 --cpus-per-task=8 --mem=32GB --time=1:00:
salloc: Pending job allocation 15731446
salloc: job 15731446 queued and waiting for resources
salloc: job 15731446 has been allocated resources
salloc: Granted job allocation 15731446
salloc: Waiting for resource configuration
salloc: Nodes a02-15 are ready for job
[user@a02-15 ~]$
```

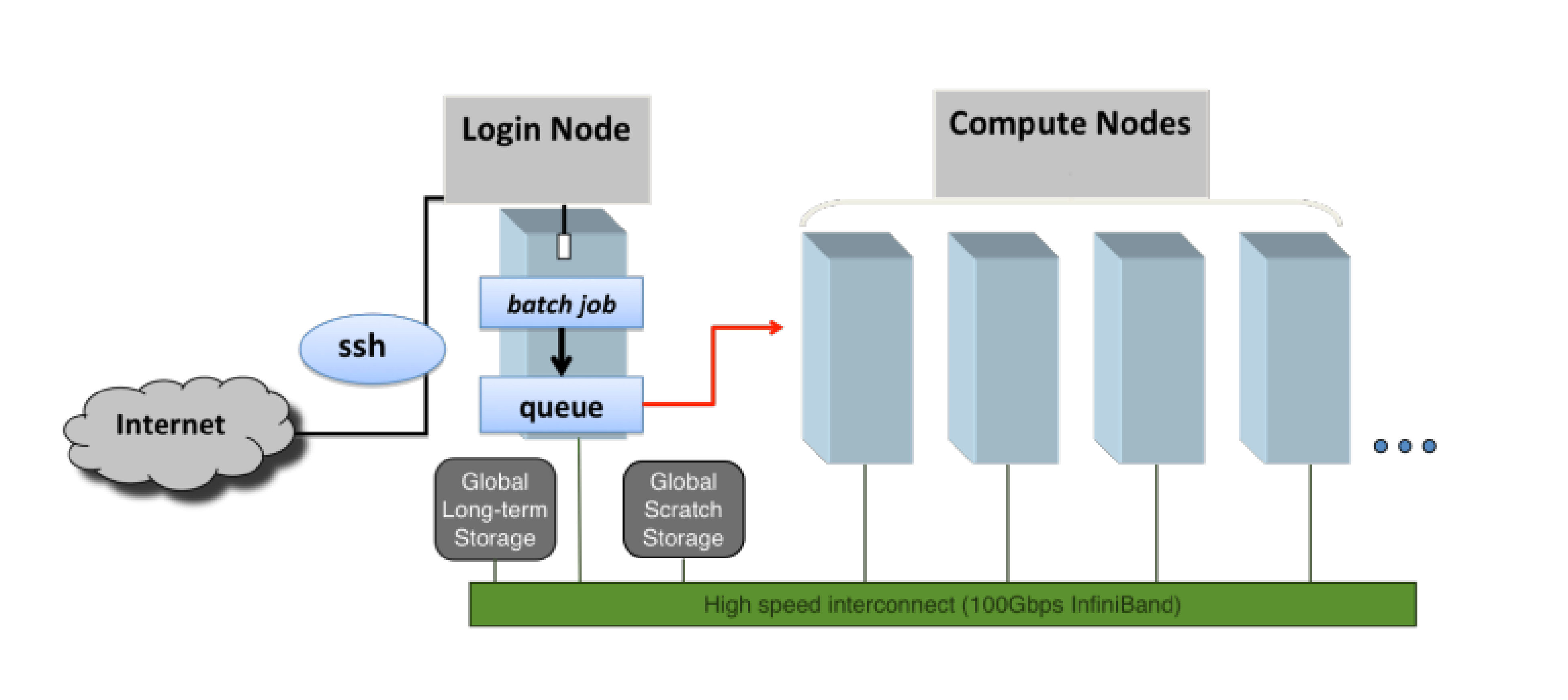
Table of Contents

https://www.carc.usc.edu/user-guides/data-science/building-conda-environment

An example of Training

The problem we're going to solve today is to train a model to classify MNIST datasets. The MNIST database of handwritten digits has a training set of 60,000 examples, and a test set of 10,000 examples.

CARC Cluster



Slurm script for job submission

```
git clone https://github.com/uschpc/Running-DL-Applications.git
```

Common types of GPU

Partition	CPU model	CPU frequency	CPUs/node	GPU model	GPUs/node	Memory/node	Nodes
gpu	xeon-6130	2.10 GHz	32	V100	2	184 GB	29
gpu	xeon-2640v4	2.40 GHz	20	P100	2	123 GB	38
gpu	epyc-7282	2.80 GHz	32	A40	2	248 GB	12
gpu	epyc-7513	2.60 GHz	64	A100	2	248 GB	12

Common types of GPU

GPU specifications in the GPU partition

There are four kinds of GPUs in the GPU partition: A100, A40, V100, P100. The following is a summary table for the GPU specifications:

GPU model	Architecture	Memory	Memory Bandwidth	Base Clock Speed	Cuda Cores	Tensor Cores	Single Precision Performance (FP32)	Double Precision Performance (FP64)
A100	ampere	40GB	1.6TB/s	765MHz	6912	432	19.5TFLOPS	9.7TFLOPS
A40	ampere	48GB	696GB/s	1305MHz	10752	336	37.4TFLOPS	584.6GFLOPS
V100	volta	32GB	900GB/s	1230MHz	5120	640	14TFLOPS	7TFLOPS
P100	pascal	16GB	732GB/s	1189MHz	3584	n/a	9.3TFLOPS	4.7TFLOPS