

MLPerf Training Benchmark

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MLSys 2020



MLPerf

Why MLPerf?

Why MLPerf?

Machine learning (ML) is changing whole industries such as automotive safety, e-commerce, and medicine.

ML hardware is projected to be a ~\$60B industry in 2025.

(Tractica.com \$66.3B, Marketsandmarkets.com: \$59.2B)

Need a standard benchmark to provide the field/industry with clear metrics.

Prior Work

SPEC and TPC, consortium-backed standards but not ML

DeepBench, but only ML primitives

Fathom and TBD, measure throughput for broad ML suite

DAWNBench, measure time-to-train for a few ML tasks

**MLPerf = consortium +
broad suite +
time-to-train +
novel contributions**



Goals

What:

Enable fair comparisons

Encourage innovation

Serve commercial and research communities

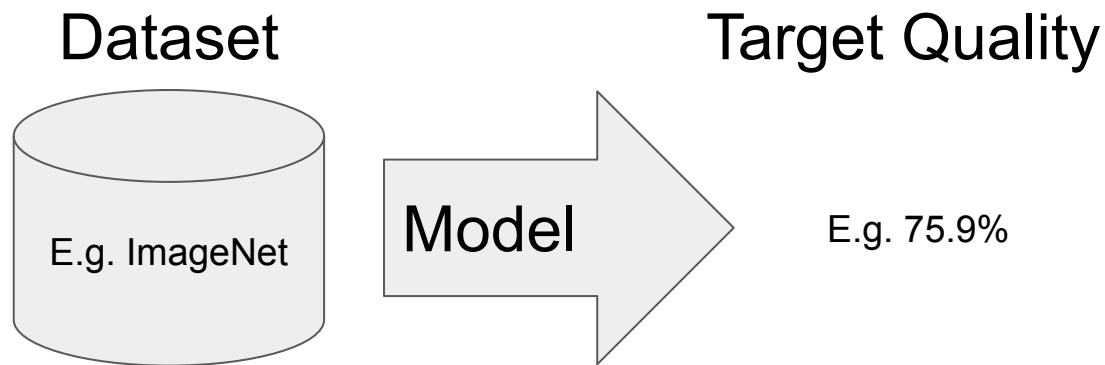
How:

Ensure reliable results

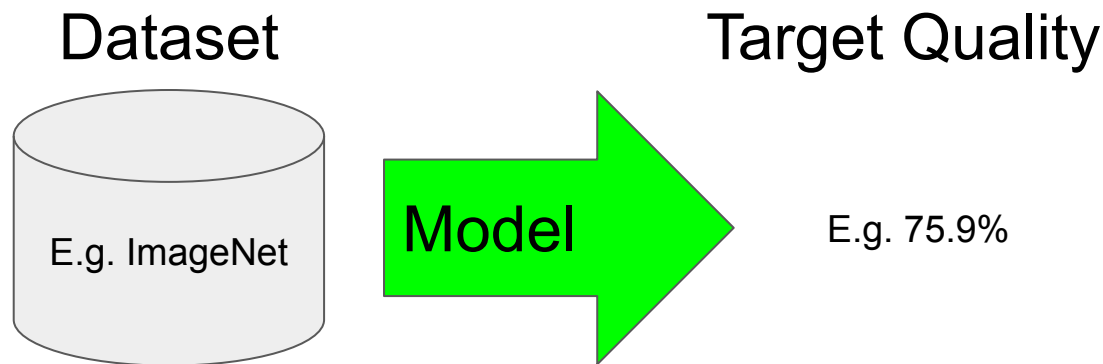
Keep benchmarking easy and affordable

MLPerf Training Benchmark

MLPerf Training benchmark definition



Two divisions with different model restrictions



Closed division: specific model e.g. ResNet v1.5 → direct comparisons

Open division: any model → innovation

Benchmark suite

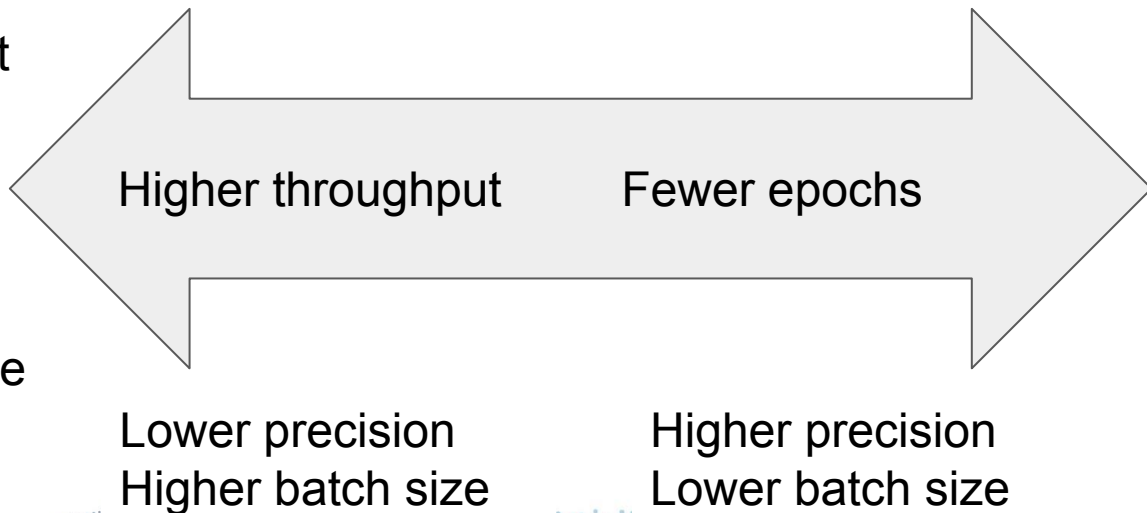
Area	Task	Dataset	Model (closed)	Target Quality (v0.5)
Vision	Image recognition	ImageNet	ResNet	74.9% Top-1
	Object detection	COCO	SSD	21.2 mAP
	Object segmentation	COCO	Mask R CNN	37.7 Box mAp 33.9 Mask minAP
Language	Translation	WMT Eng.-German	NMT	21.8 Sacre Bleu
	Translation	WMT Eng.-German	Transformer	25.0 Bleu
Commerce	Recommendation	Movielens-20M	NCF	0.635 HR @ 10
Research	Go	n/a	Mini go	40.0% move prediction

Metric: time-to-train

Alternative is throughput
Easy / cheap to measure

But can increase throughput at
cost of total time to train!

Time-to-train (end-to-end)
Time to solution!
Computationally expensive
High variance
Least bad choice



Time-to-train excludes

System initialization

Depends on cluster configuration and state

Model initialization

Disproportionate for big systems with small benchmarking datasets

Data reformatting

Mandating format would give advantage to some systems

Challenges and Contributions

ML Training benchmarking challenges

Diverse software stacks and hardware systems

- Can't use the same executable
- Can't use the same *code*

ML Training benchmarking challenges

Diverse software stacks and hardware systems

Different scales and/or numerics require tuning

- E.g.: larger systems → larger SGD mini batches → different optimizer hyperparams
- Hyperparameter tuning is computationally expensive, can be unfair

ML Training benchmarking challenges

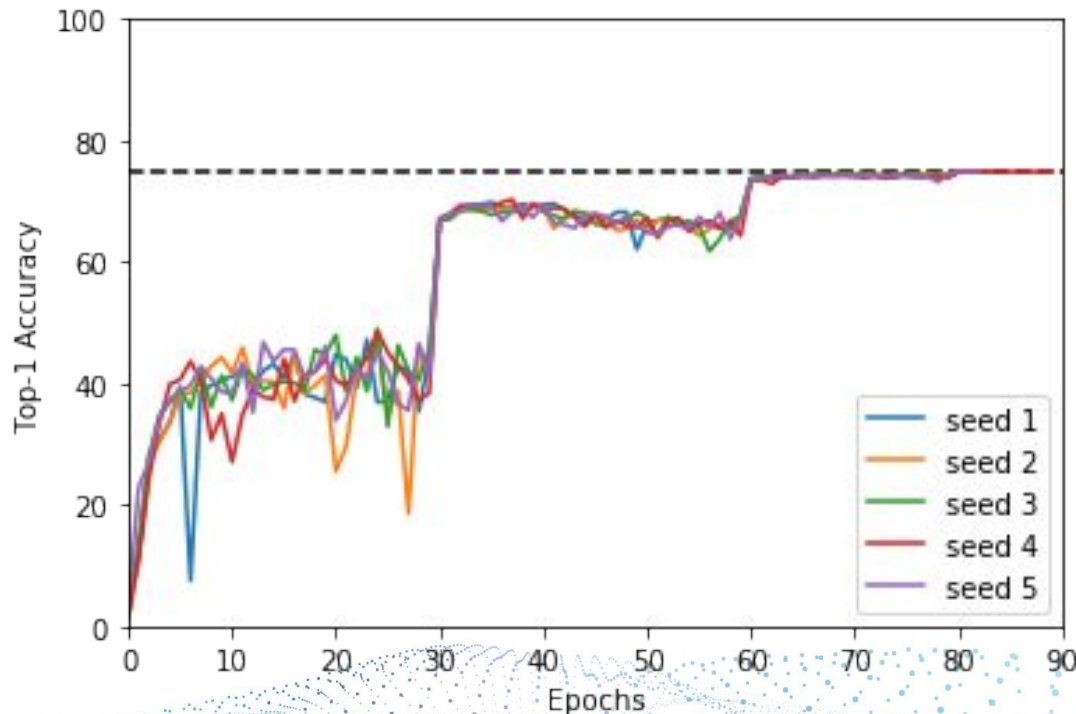
Diverse software stacks and hardware systems

Different scales and/or numerics require tuning

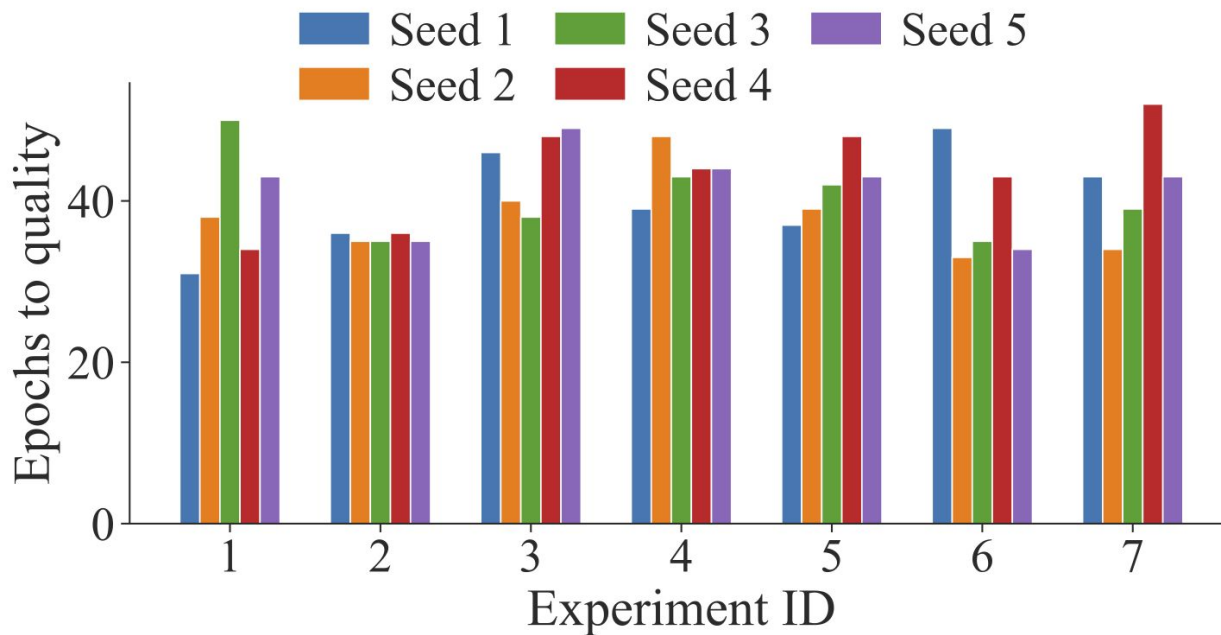
Convergence is stochastic

- Random weight initialization
- Non-deterministic floating point effects

Convergence variance: ResNet



Convergence variance: MiniGo



MLPerf contributions

Diverse software stacks and hardware systems	Reference implementations Rules for reimplementation
Different scales and/or numerics require tuning	
Convergence is stochastic	

MLPerf contributions

Diverse software stacks and hardware systems	Reference implementations Rules for reimplementation
Different scales and/or numerics require tuning	Limited tunable hyperparameters; limited values
Convergence is stochastic	

List of tunable hyperparameters

Benchmark	Tunable hyperparameters
All that use SGD	Mini batch size, Learning-rate schedule parameters
ResNet-50 v1.5	--
SSD-ResNet-34	Maximum samples per training patch
Mask R-CNN	Number of image candidates
GNMT	Learning-rate decay function, Learning rate, Decay start, Decay interval, Warmup function, Warmup steps
Transformer	Optimizer: Adam or Lazy Adam, Learning rate, Warmup steps
NCF	Optimizer: Adam or Lazy Adam, Learning rate, β_1 , β_2
MiniGo	--

MLPerf contributions

Diverse software stacks and hardware systems	Reference implementations Rules for reimplementation
Different scales and/or numerics require tuning	Limited tunable hyperparameters; limited values
Convergence is stochastic	Require multiple runs Drop low and high, average

Submission Process

Pre-submit

Download **reference implementation**, read rules,
join submitters working group



Reimplement benchmark for system under test (SUT)



Tune hyperparameters (allowed by list, to allowed values)



Run benchmark required number of times



Submit logs from all runs, code, metadata in Github by deadline



Post-submit

↓

All submitters **peer review** all submissions, raise issues

↓

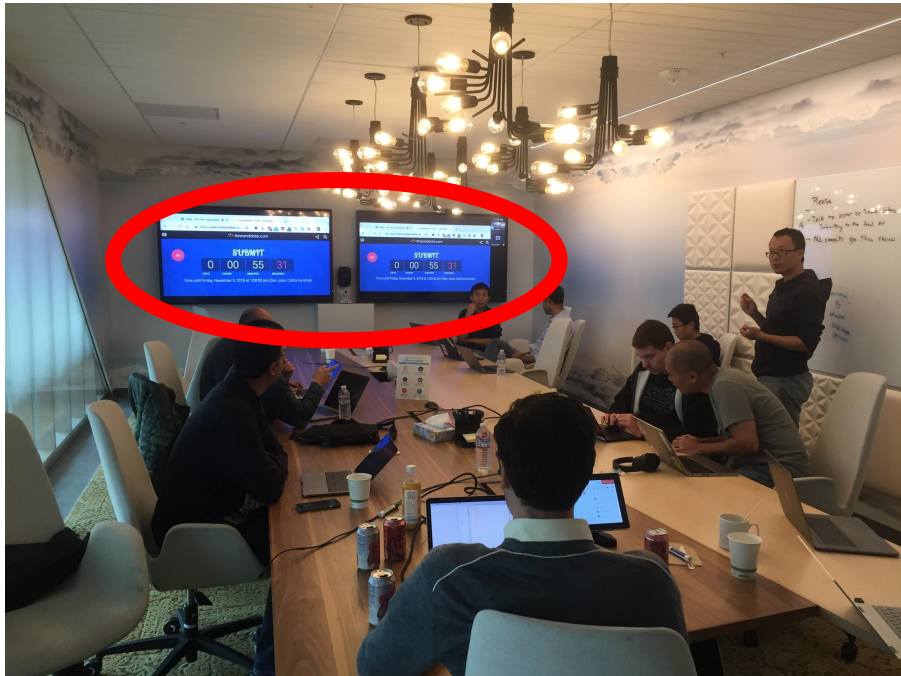
Borrow hyperparameters from other submissions and resubmit if desired

↓

MLPerf posts all results and makes logs, metadata, and code public under Apache-2

↓

Celebrate!!!



Results and Lessons Learned

Impact of good benchmarks

Benchmarks

- Defined set of problems
- Clear metrics

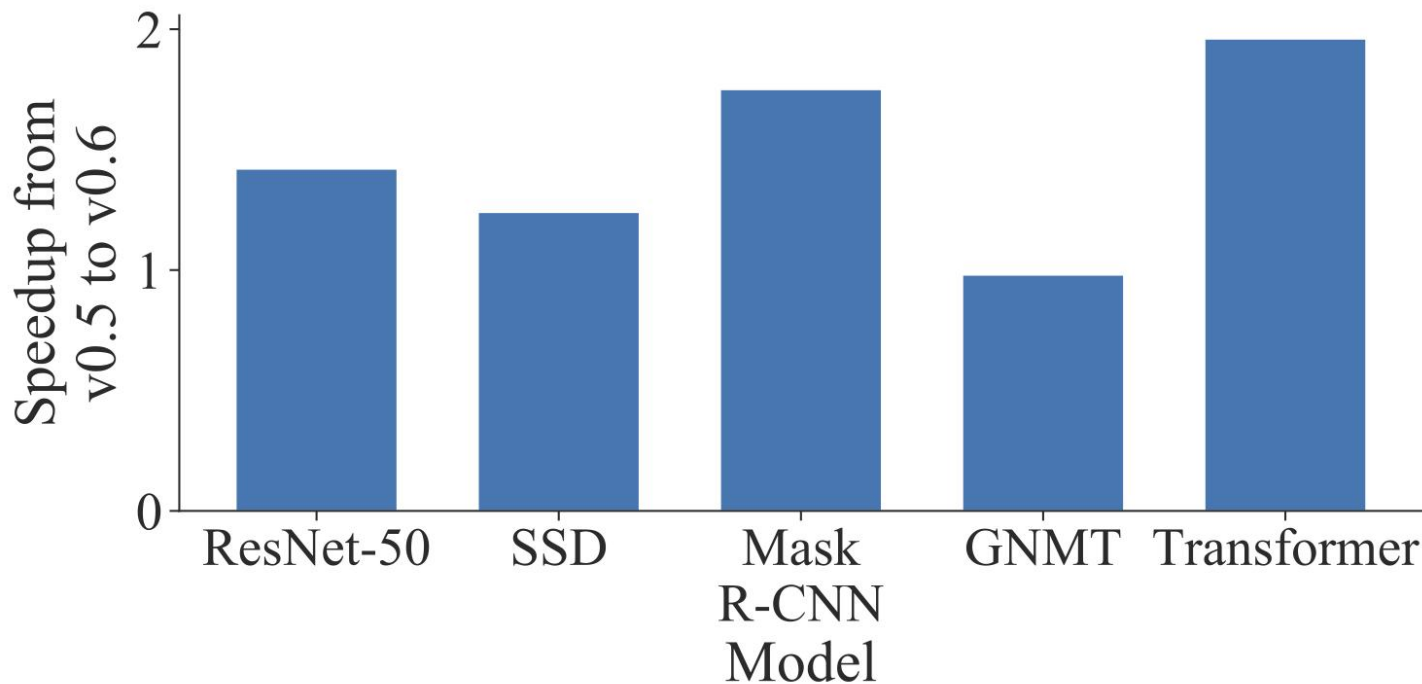
Competition

- Competing engineering teams try different approaches
- Results show what works best

Better Software / HW

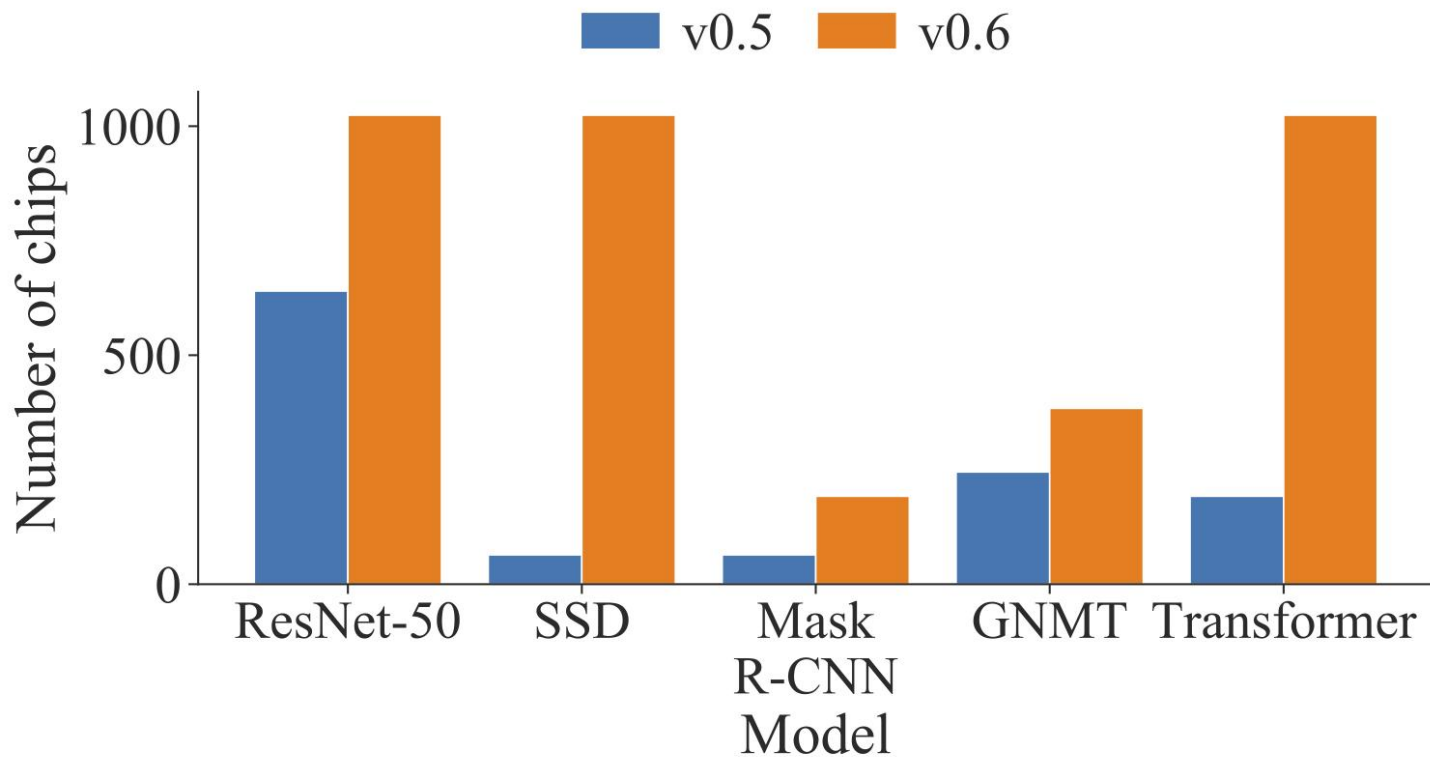
- Improved understanding of performance
- Faster, more scalable software stacks
- Future hardware designs driven by best-of-breed ideas

MLPerf Training: 16-chip speedup v0.5 to v0.6*



* Benchmark quality targets, and hence workload, increased in v0.6 for ResNet, SSD, GNMT, and Transformer. MLPerf

MLPerf Training, system scale increase v0.5 to v0.6







































































Lessons learned

- Benchmarking with reimplementations is possible
- Realistic dataset size is critical to ML performance benchmarking
- Hyperparameters are surprisingly portable at similar scales; borrowing works
- Low ratio of (standard deviation of epochs to train) : (mean epochs to train) is key to acceptable variance
- Variance in time to train increases at high batch sizes
- Frameworks had differences in optimizers that impact convergence

Support and Adoption

MLPerf Support: Companies

													
AI Labs.tw	Alibaba	AMD	Andes Technology	Aon Devices	Arm	Baidu	Lenovo	MediaTek	Mentor Graphics	Microsoft	Myrtle	Mythic	NetApp
													
Cadence	Calypso AI	Centaur Technology	Cerebras	Ceva	Cirrus	Cisco	NVIDIA	One Convergence	Oppo	PathPartner Technology	Pure Storage	Qualcomm	Rpa2ai
													
Code Reef	Cray	CTuning Foundation	Dell	Dividiti	DDN Storage	Edgify	Sambanova	Samsung S.LSI	Sigopt	SiMa AI	Skymizer	Supermicro	Synopsys
													
Enflame Tech	Esperanto	Facebook	FuriosaAI	Google	Groq	Habana	Tencent	Tensyr	Teradyne	Transpire Ventures	VerifiAI	VMind	VMware
													
Hewlett Packard Enterprise	Hop Labs	Horizon Robotics	Iluvatar	Inspur	Intel	In-Q-Tel	Volley	Wave Computing	Wiwynn	WekaIO	Xilinx		

MLPerf Support: Researchers



Harvard
University



Stanford
University



University of
Arkansas,
Littlerock



University of
California,
Berkeley



University of
Illinois, Urbana
Champaign



University of
Minnesota



University of
Texas, Austin



University of
Toronto

MLPerf Adoption: Press

The Curious Case Of MLPerf Inferencing Benchmark Results

Forbes • Last month



MLPerf Releases First Inference Benchmark Results; Nvidia Touts its Showing

HPCwire • Last month



Centaur Releases In-Depth Analysis from The Linley Group for World's First x86 Processor with AI Coprocessor Technology

StreetInsider.com • 2 days ago

MLPerf Expands Toolset; Launches Inferencing Suite

HPCwire • Jun 24



Is Intel Considering Another AI Acquisition?

EE Times • 6 days ago



Benchmark Scores Reveal Who's Winning the AI Inference Race - EETimes

EE Times • Last month



Google, Nvidia tout advances in AI training with MLPerf benchmark results

ZDNet • Jul 10



MLPerf – Will New Machine Learning Benchmark Help Propel AI Forward?

HPCwire



NVIDIA Turing GPUs and NVIDIA Xavier Achieve Fastest Results on MLPerf Benchmarks Measuring Data Center and Edge AI Inference Performance

EE Journal • Last month

myrtle.ai to Develop a Speech Recognition Benchmark for MLPerf

HPCwire

It Is About Latency

HPCwire • 9 days ago



Reading Between the MLPerf Lines

The Next Platform



NVIDIA Gets Tiny With Jetson Xavier NX

Forbes • Last month



Nvidia Crushes Self to Take AI Benchmark Crown

ExtremeTech



NVIDIA Xavier wins critical AI performance benchmarks

Automotive World • Last month

Why Are Baidu, Google, Harvard And Stanford Collaborating For This ML Benchmark?

Analytics India Magazine • Jul 15



AI Accelerators: TOPS is Not the Whole Story - EETimes

EE Times • 2 days ago



Intel unveils next-gen Movidius VPU, codenamed Keem Bay

ZDNet • Last month



Centaur Unveils an x86 SoC with Integrated AI Coprocessor

CNX Software • Last month



The MLPerf Consortium, with Members like ARM & Google, have introduced Tech Industry's First Standard ML Benchmark Suit

Patently Apple • Jun 26



MLPerf benchmark results showcase Nvidia's top AI training times

ZDNet



Google Cloud and Nvidia Tesla set new AI training records with MLPerf benchmark results

Packt Hub • Jul 15



Who's Winning the AI Inference Race?

Eetasia.com • Last month



AI Gets Inference Benchmarks

EE Times • Jun 24

Intel, GraphCore And Groq: Let The AI Cambrian Explosion Begin

Forbes • Last month

Centaur announces new SoC featuring an 8-core server-class x86 CPU with AVX512 support and an integrated 20 TOPS AI co-processor

Notebookcheck.net • Last month

MLPerf Releases Five Benchmarks

EE Times India • Jun 26

NVIDIA Corp (NVDA) Q3 2019 Earnings Call Transcript

The Motley Fool • Last month

Twitter wants help with deepfakes, and Microsoft Azure will rent out new AI chips for its cloud users, and more

The Register • Last month

Embedded Benchmark Calls for Support

EE Times • Jun 12

Startup Runs AI in Novel SRAM

EE Times • Jul 22



MLPerf Releases v0.6 Training Results

HPCwire • Jul 10



MLPerf To Provide Much Needed Clarity In The Field Of Machine Learning

Forbes • Jun 25



Digging into MLPerf Benchmark Suite to Inform AI Infrastructure Decisions

HPCwire • Apr 9



MLPerf Is Changing the AI Hardware Performance Conversation. Here's how

Data Center Knowledge • Aug 1



GPUs Continue to Dominate the AI Accelerator Market for Now

InformationWeek • Last month



Nvidia tops AI inference benchmarks, also announces 'world's smallest supercomputer' chip for AI tasks

Firstpost • Last month



Why I joined MLPerf

EE Times • Mar 20



Work in Progress / Future Work

Future work

Expand and update benchmark suite

Improve rules: hyperparameter tables, out-of-the box division

More efficiency information: power, cloud cost

New suites:

- Inference (launched in 2019)

- Mobile (launching in 2020)

- HPC (in progress)

- TinyML (in progress)

The next frontier: accuracy?

Shameless Plugs

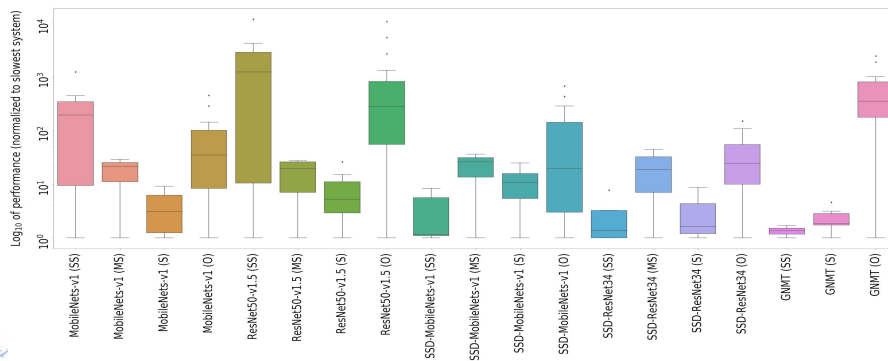
“Benchmarking Machine Learning Workloads” Workshop Tomorrow

Keynote:

MLPerf Inference

Vijay Janapa Reddi, Harvard

9:10 AM



MLPerf Training: Open Division needs you!

Want to Showcase faster models, compilers,
pruners, data-set optimizers

Only need to use Dataset and Target to
submit

Low overhead, low-risk exposure



Some assembly required

Plan for impact

Think big: conceive of your work as 10% of a larger whole

Great idea + coalition >> great idea alone

Build different skills sets

Make the world better

Summary

Summary

Introduced MLPerf training

Broad suite of tasks + time-to-train metric + consortium

Solved ML benchmarking challenges: diverse systems, scaling, variance

Results show MLPerf helps drive performance improvements

Achieved broad support/adoption: industry, academia, press

More to do! Join us: mlperf.org/get-involved or info@mlperf.org.