

The **AlgoPerf**: Training Algorithms Benchmark

Faster neural network training through better training algorithms

Frank Schneider

September 14, 2023

EBERHARD KARLS
UNIVERSITÄT
TÜBINGEN



MAX PLANCK INSTITUTE
FOR INTELLIGENT SYSTEMS



imprs-is

Neural Networks are extremely useful models...

...but!

In practice, neural networks are...

- ▶ ...**slow** to train (training can easily take days or weeks)
- ▶ ...**tedious** (demanding human intervention and fiddling)
- ▶ ...**expensive** (requiring dozens of trial runs)

Neural Networks are extremely useful models...

...but!

In practice, neural networks are...

- ▶ ...**slow** to train (training can easily take days or weeks)
- ▶ ...**tedious** (demanding human intervention and fiddling)
- ▶ ...**expensive** (requiring dozens of trial runs)

We all want neural network training to be faster, more automatic, and more efficient!

The state of deep learning training methods

A confusingly crowded field of methods & hyperparameters

A huge number of training methods...

Name	Ref.	Name	Ref.	Name	Ref.
AccGrad	[14]	CGMAM	[103]	DFE	[114]
ACCip	[110]	GDMA	[111]	DAL	[115]
AdaNet	[112]	Grad Momentum	[113]	PolyAdam	[116]
AdaNet2	[114]	LRp	[117]	PyAda	[118]
AdaNetw/AdaNetw-05	[115]	Curvature	[119]	ProxSGD/ProxSGM	[119]
AdaNetw	[116]	Dolan	[120]	ProxAdaGrad	[120]
AdaPAC	[117]	DropInplace	[121]	ProxS	[121]
AdaPACw	[118]	DropNet	[122]	ProxSGD	[122]
AdaComp	[119]	DRGrad	[123]	QMA/AdaQMA	[123]
AdaCuts	[120]	ESG	[124]	AdaCuts	[124]
AdaCuts2	[121]	EEFC	[125]	Ranger	[125]
AdaIn	[122]	ES	[126]	RangerLars	[126]
AdaInw	[123]	Expograd	[127]	RMSProp	[127]
AdaPTL	[124]	FairAdaBelief	[128]	RMSprop	[128]
Adagrad	[129]	IRGAD	[129]	SRG2	[129]
AdaM/AdaM	[130]	GradGrad	[131]	AdaRM	[130]
AdaM	[130]	IGMAM	[132]	AdaRM-NonGrad	[130]
AdaNew	[131]	Golden	[133]	MAR	[131]
AdaO	[132]	IGPLS	[134]	SMS	[132]
AdaO*	[133]	IGPLS*	[135]	SG-Adagrad/SG-DRPProp	[133]
AdaO-L	[134]	Grad-Any	[136]	SGProp	[134]
AdaOw	[135]	GRADY	[137]	SGD	[135]
AdaOS	[136]	Gradient	[138]	SGD-BE	[136]
AdaOS2	[137]	Grady	[139]	SGD-G2	[137]
AdaPAC	[138]	AdaIn	[140]	SGDM	[138]
AdaPACDF	[139]	HypoAdaIn	[141]	SGEloss	[139]
AdaPAC	[140]	IRP/LS/IRP/LS*	[142]	SGDM	[140]
AdaPAC*	[141]	SGD-CM	[143]	SGDR	[141]
AdaPAC*	[142]	SGC	[144]	SGDRgrad	[142]
AdaM	[143]	MLR/SGRA	[145]	Stochastic	[143-145]
AdaG	[144]	Tikhanov/Adamomom	[146]	SGDRstoch+	[144]
AdaGrad	[145]	LAMB	[147]	SGDR2	[145]
AdaNG2	[146]	LofProp	[148]	SGON/SGQN	[146]
AdaOR	[147]	LARS	[149]	SGD	[147]
AdaOpt	[148]	LIRP*	[150]	SGC	[148]
AdaPAC	[149]	LookAhead	[151]	SGM	[149]
AdaM/AdaMw	[150]	MS-Adam	[152]	SoftAdapt	[150]
AdGD	[151]	MANCGRAD	[153]	SRG2	[151]
AdG-C	[152]	MVA	[154]	step-based SG2	[152]
AdaptiveW	[153]	MEGA	[155]	SGD	[153]
AdMSGrad	[154]	MT-Adam	[156]	SWATS	[154]
AdaptiveGrad	[155]	MYC-LM/RFC2	[157]	Trainers	[155]
AdaptiveL	[156]	Naive	[158]	TREXAC	[156]
AdRL	[157]	NaiveSG/NaiveSG*	[159]	Trainers*	[157]
AdSM	[158]	ND-Adam	[160]	VRSGD	[158]
AdLRK	[159]	Novo	[161]	rSGDw/SGDp/SGOM	[159]
AdGrad	[160]	Novomem	[162]	rSGD-ld	[160]
Adaptive	[161]	NovoAdam/NovoAdAC	[163]	rSGDgrad	[161]
Adaptive	[162]	NovoAdaIn	[164]	SoftAdapt	[162]
AdComp	[163]	Novograd	[165]	Vari	[163]
AdaptiveProp	[164]	NOGD	[166]		
AdGD	[165]	Dolan	[167]		

from "Descending through a Crowded Valley"
(Schmidt, Schneider, Hennig; 2021)

The state of deep learning training methods

A confusingly crowded field of methods & hyperparameters

A huge number of training methods...

Name	Ref.	Name	Ref.	Name	Ref.
AccGrad	[11]	CGMAM	[10]	EDGE	[14]
ACCip	[10]	GADA	[14]	DAL	[14]
AdaNet	[17]	Grad Momentum	[11]	PolyAdam	[10]
AdaNet2	[17]	LRp	[14]	Prp	[14]
AdaNet3	[17]	Curvature	[14]	ProxSGD/ProxSGM	[14]
AdaNet4	[17]	Dadan	[14]	ProxSGD/ProxSGM	[14]
AdaNet5	[17]	DeepHistory	[14]	ProxLS	[14]
AdaNet6	[17]	LRp2	[14]	ProxSG	[14]
AdaNet7	[17]	DMGrad	[17]	QPLAdapt/QPLM	[10]
AdaNet8	[17]	EGM	[14]	Radar	[10]
AdaNet9	[17]	EEFC	[14]	Range	[10]
AdaNet10	[17]	low	[14]	RangeAdapt	[10]
AdaNet11	[17]	Populated	[14]	RMSProp	[10]
AdaNet12	[17]	FastAdaBelief	[14]	RMSprop	[10]
AdaNet13	[17]	TRGD	[14]	S-GD	[14]
AdaNet14	[17]	Gr-AdaBelief	[14]	Adapt	[10]
AdaNet15	[17]	GDMM	[10]	Adapt-SAMSGrad	[10]
AdaNet16	[17]	GDmm	[10]	MAE	[10]
AdaNet17	[17]	GDPL	[10]	SAM	[10]
AdaNet18	[17]	GDPL2	[10]	SG-Adapt/SG-AdaptProp	[10]
AdaNet19	[17]	Grad-Arg	[10]	SGProp	[10]
AdaNet20	[17]	GRADY	[10]	SGR	[10]
AdaNet21	[17]	Gradient	[10]	SGDR	[10]
AdaNet22	[17]	Grady	[10]	SGDR2	[10]
AdaNet23	[17]	GRAD	[10]	SGDM	[10]
AdaNet24	[17]	HypoAdapt	[10]	SGDRm	[10]
AdaNet25	[17]	IMPLICIT/SGDR	[10]	SGDM	[10]
AdaNet26	[17]	SGDR/SGDM	[10]	SGDR	[10]
AdaNet27	[17]	SGDR	[10]	SGDRm	[10]
AdaNet28	[17]	SGDR	[10]	SGDRm	[10]
AdaNet29	[17]	SGDR	[10]	SGDRm	[10]
AdaNet30	[17]	SGDR	[10]	SGDRm	[10]
AdaNet31	[17]	SGDR	[10]	SGDRm	[10]
AdaNet32	[17]	SGDR	[10]	SGDRm	[10]
AdaNet33	[17]	SGDR	[10]	SGDRm	[10]
AdaNet34	[17]	SGDR	[10]	SGDRm	[10]
AdaNet35	[17]	SGDR	[10]	SGDRm	[10]
AdaNet36	[17]	SGDR	[10]	SGDRm	[10]
AdaNet37	[17]	SGDR	[10]	SGDRm	[10]
AdaNet38	[17]	SGDR	[10]	SGDRm	[10]
AdaNet39	[17]	SGDR	[10]	SGDRm	[10]
AdaNet40	[17]	SGDR	[10]	SGDRm	[10]
AdaNet41	[17]	SGDR	[10]	SGDRm	[10]
AdaNet42	[17]	SGDR	[10]	SGDRm	[10]
AdaNet43	[17]	SGDR	[10]	SGDRm	[10]
AdaNet44	[17]	SGDR	[10]	SGDRm	[10]
AdaNet45	[17]	SGDR	[10]	SGDRm	[10]
AdaNet46	[17]	SGDR	[10]	SGDRm	[10]
AdaNet47	[17]	SGDR	[10]	SGDRm	[10]
AdaNet48	[17]	SGDR	[10]	SGDRm	[10]
AdaNet49	[17]	SGDR	[10]	SGDRm	[10]
AdaNet50	[17]	SGDR	[10]	SGDRm	[10]

from "Descending through a Crowded Valley"
(Schmidt, Schneider, Hennig; 2021)

...and training tricks

- ▶ OneCycle scheduler, gradient checkpointing
- ▶ Genetic Algorithm for Hyperparameters
- ▶ Avoid batches that lead to NaN/inf losses
- ▶ One cycle, low fidelity training, SGD with restarts
- ▶ Proximal optimization for regularizers
- ▶ Line searches for the maximum learning rate
- ▶ Normalized updates
- ▶ Distributed Shampoo, Normformer, GLU
- ▶ Weight averaging
- ▶ FreezeOut
- ▶ A different epsilon value!
- ▶ Check hyperparameter performance over multiple seeds
- ▶ Lowering the learning rate!
- ▶ Normalizing data works better than batch or layer norm
- ▶ Mixed precision training
- ▶ Train with a small subset
- ▶ Cyclic and one cycle LR
- ▶ Label smoothing
- ▶ ...

from the NeurIPS "HITY Workshop"
(Schneider et al.; 2022)

We desperately need new benchmarks for neural network training algorithms.

The state of "benchmarking" in current deep learning optimizer papers

No standardized procedure to follow

- ▶ Each paper "invents" their own evaluation protocol.
- ▶ Unreasonably hard to perform a convincing, informative, and practically relevant comparison with strong baselines.
- ▶ Lot's of subtle pitfalls with tuning, problem-specification, etc.



Example of pitfalls when comparing training algorithms

Which algorithm trains the fastest depends on what it means for training to be complete

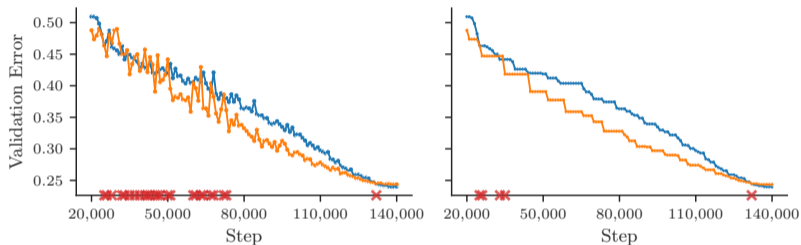


Figure 1: *Left*: Validation error for two different runs (—, —) of ADAM on RESNET-50 on IMAGENET. *Right*: The *best* validation error obtained so far. The runs intersect multiple times (✕).

Example of pitfalls when comparing training algorithms

Which algorithm trains the fastest depends on what it means for training to be complete

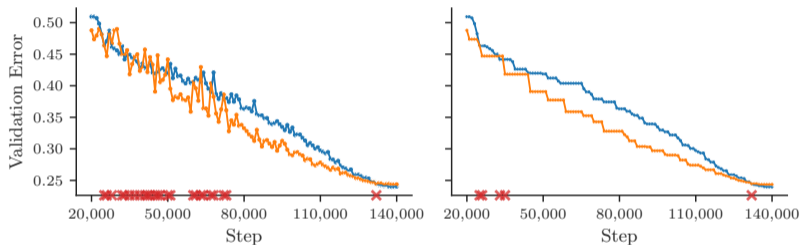


Figure 1: *Left*: Validation error for two different runs (—, —) of ADAM on RESNET-50 on IMAGENET. *Right*: The *best* validation error obtained so far. The runs intersect multiple times (✕).

- ▶ Directly comparing training curves is ill-posed.
- ▶ Without defining the target in advance, we can champion any method (moving the goal post after the experiment).
- ▶ Tuning goals must align.

MLCommons introduces the **AlgoPerf**: Training Algorithm Benchmark

An unprecedented effort to find faster deep learning training algorithms



AlgoPerf: Training Algorithm Benchmark

A standardized benchmark competition to measure neural network training speedups due to algorithmic changes.

An open large-scale effort by 25+ researchers from Google, University of Tübingen, University of Toronto, Meta AI, etc.

Chaired by



George Dahl

Google



Frank Schneider

University of Tübingen

The key features of AlgoPerf

A standardized competitive time-to-results benchmark

- ▶ **A competitive time-to-results benchmark.**
→ Everyone's submissions are everyone's **strong baselines**.

The key features of AlgoPerf

A standardized competitive time-to-results benchmark

- ▶ **A competitive time-to-results benchmark.**
→ Everyone's submissions are everyone's **strong baselines**.
- ▶ **Fixed hardware, workloads, and process.**
→ Submissions need to provide **training algorithm improvements**.

The key features of AlgoPerf

A standardized competitive time-to-results benchmark

- ▶ **A competitive time-to-results benchmark.**
→ Everyone's submissions are everyone's **strong baselines**.
- ▶ **Fixed hardware, workloads, and process.**
→ Submissions need to provide **training algorithm improvements**.
- ▶ **Aggregate across a variety of realistic workloads using performance profiles.**
→ No specialized solutions but **general-purpose methods**.

The key features of AlgoPerf

A standardized competitive time-to-results benchmark

- ▶ **A competitive time-to-results benchmark.**
→ Everyone's submissions are everyone's **strong baselines**.
- ▶ **Fixed hardware, workloads, and process.**
→ Submissions need to provide **training algorithm improvements**.
- ▶ **Aggregate across a variety of realistic workloads using performance profiles.**
→ No specialized solutions but **general-purpose methods**.
- ▶ **Explicitly accounts for hyperparameter tuning by providing search spaces.**
→ **Runnable training algorithms**, not algorithm templates.

The AlgoPerf Training Algorithms Benchmark

We need you!

Read the Rules

github.com/mlcommons/algorithmic-efficiency/blob/main/RULES.md

Read the Paper

arxiv.org/abs/2306.07179

Submit!

Call for Submission coming soon

- ▶ **Benchmark experts** Join the effort and tell us how to improve!
- ▶ **ML community** Help us spread the word!
- ▶ **Algorithm researchers** Submit! AlgoPerf is the easiest way to convincingly demonstrate the capabilities of your training algorithm.

