

Do More with Less: Large Model Training and Inference with DeepSpeed

https://github.com/microsoft/DeepSpeed

LLMs in Production Part II | June 2023

MLOps Community

Samyam Rajbhandari Co-founder and Architect for DeepSpeed Microsoft Model Scale

10+ Trillion parameters

SpeedFast & scalable training

Democratize AI

• Bigger & faster for all

Compressed TrainingBoosted efficiency

Accelerated inference

• Up to 12x faster & cheaper

Usability

DeepSpeed: Reshaping the Large Model Training Landscape

DeepSpeed Powered Massive Models:

- METRO-LM (5.4B)
- Microsoft-Turing NLG (17B)
- GPT Neo-X (**20B**)
- o AlexaTM (20B) a
- YaLM (100B) Yandex
- o GLM (130B) 🐵
- BLOOM: Big Science (176B)
- Jurrasic-1 (**178B) Al21 labs**

0 ...

Key training technologies:

- □ Zero Redundancy Optimizer (ZeRO)
- □ ZeRO-Infinity
- 3D parallelism
- Memory and compute efficient MoE training
- Optimized CUDA/ROCm/CPU kernels
- Gradient compression 1-bit Adam/LAMB, 0/1 Adam
- □ Sparse Attention
- Mixture of quantization
- Progressive layer dropping
- Curriculum learning



System capability to efficiently train models with trillions of parameters

Model Scale

• 10+ Trillion parameters

Speed

• Fast & scalable training

Democratize Al

• Bigger & faster for all

Compressed Training

Boosted efficiency

Accelerated inference

• Up to 12x faster & cheaper

Usability

Fastest Transformer Kernels

#Devices	Source	Training Time
256 V100 GPUs	Nvidia	236 mins
256 V100 GPUs	DeepSpeed	144 mins
1024 TPU3 chips	Google	76 mins
1024 V100 GPUs	Nvidia	67 mins
1024 V100 GPUs	DeepSpeed	44 mins

Throughput Scaling on 1024 A100 Azure Cluster



Azure empowers easy-to-use, high-performance, and hyperscale model training using DeepSpeed - DeepSpeed

- Efficiency: ZeRO, ultra-fast GPU kernels, IO/compute/communication overlapping
- Effectiveness: Advance HP tuning, large-batch scaling

Model Scale10+ Trillion parameters

SpeedFast & scalable training

Democratize Al

Bigger & faster for all

Compressed Training

Boosted efficiency

Accelerated inference

• Up to 12x faster & cheaper

Usability

ZeRO-Infinity: 1 Trillion model on a single GPU, 700x bigger



1-bit Adam: 5x less communication, 3.5x faster training



Model Scale10+ Trillion parameters

SpeedFast & scalable training

Democratize Al

• Bigger & faster for all

Compressed Training

Boosted efficiency

Accelerated inference

• Up to 12x faster & cheaper

Usability

DeepSpeed Journey

Let's Train Bert Large! Early 2019, Microsoft

- Distributed Data Parallel Training •
 - NVIDIA Apex
- Compute:
 - 64x V100 16GB
- Network: •
 - 4 Gbps Ethernet
 - For comparision DGX-2 SuperPod: 1600 Gbps
 - 400x slower
- Max Batch Size: 4 per GPU limited by memory ٠
- **DeepScale:** •
 - Smart Gradient Accumulation
 - Global Batch Size: 4K
 - Micro Batch: 4, Gradient Accumulation: 16
 - Bert in 8-days

NVIDIA Apex for i in range(iterations):

```
for j in range(gas):
```

```
loss = model.forward( get batch() )
local gradients = backward gradients(loss/gas)
average gradients += distributed.reduce(local gradients/gpus)
```

optimizer.step(average gradients)

DeepScale

```
for i in range(iterations):
```

```
for j in range(gas):
```

```
loss = model.forward( get_batch() )
local gradients += backward gradients(loss/gas)
```

```
average gradients = distributed.reduce(local_gradients/gpus)
optimizer.step(average_gradients)
```

DeepScale was the precursor to DeepSpeed

ZeRO and DeepSpeed

- Multi-billion parameter models in 2019
 - 1.5B GPT-2, 8.3B Megatron
- Data Parallel replicates model states
 - Limited by Single GPU memory
- Model Parallel incurs high communication
 - Limited within a single Node
- Zero Redundancy Optimizer (ZeRO)
 - Data Parallel without Replication
 - Partitions Optimizer States, Gradients, and Parameters
- Microsoft Turing-NLG 17B
 - Largest LLM at the time
 - ZeRO + MP
- DeepScale → DeepSpeed
 - And it's a Palindrome

Usability Max Parameter (in Max Compute (Model Rewrite) billions) Parallelism Efficiency Data Parallel (DP) Approx. 1.2 >1000 Very Good Great Model Parallel (MP) Approx. 20 Approx. 16 Needs Model Rewrite Good Needs Model Rewrite Approx. 20 Good MP + DP > 1000 ZeRO > 1000 > 1000 Verv Good Great



ZeRO was open-sourced and released with the DeepSpeed Library, 2020

Models Trained: TNLG-17B, Bloom-176B, GPT-NeoX, MPT, Alexa-TM, Metro-LM, etc

A Trillion Parameters!

- June 2020: Open-AI GPT-3 175B ٠
- What would it take to get to a trillion parameters? •
- Two possible approaches •
 - ZeRO-3
 - **3D** Parallelism ٠

3D Parallelism •

- Pipeline, Model and ZeRO Parallelism ٠
- Extremely good Compute Efficiency ٠
- Megatron-Turing 530B ٠
 - 2months+ and 2K A100 GPUs ٠
 - 270B tokens ٠
 - Microsoft NVIDIA collaboration

Bloom-176B ٠

- 3.5 months and 384 GPUs ٠
- 350B Tokens ٠
- Collaborations across dozens of organizations ٠





Pipeline Parallel

	Max Parameter (in billions)	Max Parallelism	Compute Efficiency	Usability (Model Rewrite)
Data Parallel (DP)	Approx. 1.2	>1000	Very Good	Great
Model Parallel (MP)	Approx. 20	Approx. 16	Good	Needs Model Rewrite
MP + PP + DP	> 1000	> 1000	Excellent	Needs Significant Model Rewrite
ZeRO	> 1000	> 1000	Very Good	Great

End of dense scaling?

- Megatron-Turing 530B
 - Over 2 months on 2K A100 GPUs
 - < 300B Tokens
 - Under-trained
- Training tokens on recent models
 - LAMMA 65B \rightarrow 1.2 Trillion Tokens
 - MPT 7B → 1T Trillion Tokens
- 500B-1T model on a trillion tokens
 - 6 months 1 year on 2K GPUs
 - 10T \rightarrow 10 years
- Scale with Sparsity
 - Mixture of Experts
 - 5x reduction in training cost



Training Throughput on 128 A100

	Training samples per sec	Throughput gain/ Cost Reduction
6.7B dense	70	1x
1.3B+MoE-128 (52B Total)	372	5x

DeepSpeed-MoE for training multi-trillion parameter MoE models with excellent efficiency



Democratization of LLMs

- Accessibility to large model training
 - 256 V100 GPUs to fine-tune GPT-3 175B model
 - Limited access to such resources
- Can we leverage GPU/CPU/NVMe memory
 - 32T params on 32 nodes
 - 1T params on a single node
- Bandwidth: PCIe < NVME < CPU << GPU
 - PCle \rightarrow 16GB/s 1x
 - NVMe \rightarrow 30 GB/s 2x
 - CPU → 200 GB/s 12x
 - GPU → 2TB /s 120x



ZeRO-Infinity

- Partition each parameter across GPUs
- Send from NVMe to GPU in parallel

GPU 0

NVME

PCle

Layer 0 Layer 1 Layer 2

• Bandwidth Increases linearly with devices

GPU Interconnect

GPU 1

NVME

GPU 2

NVME

- 8 Node Cluster: $30 \rightarrow 240$ GB/s
- Finetune 100B+ parameter models on a single GPU
- Eliminate barrier to entry

Memory available on a Single DGX-2 Node





Do More with Less: Large Model Training and Inference with DeepSpeed

https://github.com/microsoft/DeepSpeed

LLMs in Production Part II | June 2023

Samyam Rajbhandari Co-founder and Architect for DeepSpeed Microsoft **Model Scale** • 10+ Trillion parameters Speed Fast & scalable training **Democratize Al** Bigger & faster for all **Compressed Training Boosted efficiency Accelerated inference** • Up to 12x faster & cheaper

Usability

• Sparse attention: 10x longer seq, up to 6x faster



Model Scale10+ Trillion parameters

SpeedFast & scalable trainir

Democratize Al

Bigger & faster for all

Compressed Training

• Boosted efficiency

Accelerated inference

• Up to 12x faster & cheaper

Usability

- Progressive Layer Drop: Compressed robust training
- 24% faster when training the same number of samples
- 2.5X faster to get similar accuracy on downstream tasks



DeepSpeed Accelerated inference for large-scale transformer models

A systematic composition of diverse set of optimizations

- Many-GPU Dense transformer optimizations powering large and very large models like Megatron-Turing 530B
- □ Massive Scale Sparse Model Inference-*a trillion parameter MoE model inference under 25ms*
- □ ZeRO-Inference -> 40x bigger model inference on single-GPU device



Speed

Fast & scalable training

Democratize A

Bigger & faster for all

Compressed Training

Boosted efficiency

Accelerated inference

Up to 12x faster & cheaper

Usability

• Few lines of code changes

DeepSpeed Inference: SoTA latency and throughput across the large model inference landscape



DeepSpeed-MII powered by DeepSpeed-Inference









Train 15X Faster and Scale to 5x Bigger Models than SOTA RLHFs



Easy-Breezy Training	High Performance System	Accessible Large Model Support	A Universal Acceleration Backend for RLHF
A complete end-to-end RLHF training experience with a single click	Hybrid Engine achieves 15X training speedup over SOTA RLHF systems with unprecedented cost reduction at all scales	Training ChatGPT-Style models with tens to hundreds of billions parameters on a single or multi-GPUs through ZeRO and LoRA	Support InstructGPT pipeline and large-model finetuning for various models and scenarios

- Only few lines of code changes to enable DeepSpeed on PyTorch models
- Scalable and convenient data parallelism



Model Scale • 10+ Trillion parameters

Speed

Compressed Training

Accelerated inference

• Up to 10x faster & cheaper

• Few lines of code changes

Usability

HuggingFace and PyTorch Lightning integrate DeepSpeed as a performance-٠ optimized backend



deepspeed examples/pytorch/translation/run translation.py \ -- deepspeed tests/ deepspeed /ds_config_zero3.json \ --model_name_or_path t5-small --per_device_train_batch_size 1 --output dir output dir --overwrite output dir --fp16 \

trainer = Trainer(gpus=4, plugins='deepspeed', precision=16)

deepspeed.py hosted with 💙 by GitHub

view raw

Infrastructure agnostic, supporting AzureML, Azure VMs, local-nodes ۲

DeepSpeed/ZeRO Usability

•••

construct torch.nn.Module
model = MyModel()

wrap w. DeepSpeed engine
engine, *_ = deepspeed.initialize(
 model=model,
 config=ds_config

training-loop w.r.t. engine
for batch in data_loader:
 loss = engine(batch)
 engine.backward(loss)
 engine.step()

•••

```
ds_config = {
  "optimizer": {
    "type": "Adam",
    "params": {"lr": 0.001}
  },
  "zero": {
    "stage": 3,
    "offload_optimizer": {
        "device": "[cpu|nvme]"
    },
    "offload_param": {
        "device": "[cpu|nvme]"
```

DeepSpeed OSS Community

- 4 Million+ installs since release in 2020
- 200 unique contributors
- 1000 public packages have hard dependencies on DeepSpeed
 - Open-source frameworks
 - Hugging Face, PyTorch-Lightning, EleutherAI, MosaicML, etc.
 - External companies
 - Meta AI (FAIR), AstraZeneca, Fidelity, Salesforce, Intel, Bloomberg, Tencent, SAP, etc.
 - National Labs
 - Oak Ridge, Argonne, Lawrence Livermore, etc.



Thank You!



We welcome contributions! Make your first pull request ⁽²⁾ Please star our repo if you enjoyed this talk!

https://github.com/microsoft/DeepSpeed

www.deepspeed.ai

Follow us on twitter: @MSFTDeepSpeed

ZeRO-Infinity in Action