Model Scale

- 10 Trillion parameters

Compressed Training

- Boosted efficiency

Speed

- Fast & scalable training

Accelerated inference

- Up to 6x faster & cheaper

Democratize AI

- Bigger & faster for all

Usability

- Few lines of code changes

deepspeed

DL training and inference optimization library towards speed and scale

Samyam Rajbhandari, Jeff Rasley, Olatunji Ruwase, Reza Yazdani Aminabadi, Elton Zheng, Minjia Zhang, Niranjan Uma Naresh, Shaden Smith, Ammar Ahmad Awan, Conglong Li, Cheng Li, Zhewei Yao, Jeffrey Zhu, Yuxiong He

DL System Challenges and Capability

Challenges

- Too slow to train high-quality models on massive data
  - More hardware ≠ higher throughput, bigger model
  - Higher throughput ≠ better accuracy, faster convergence
  - Better techniques ≠ handy to use
- Less data / smaller models, tradeoff accuracy for training time
- Slow and expensive to deploy the models

Desired Capability of DeepSpeed

- **Efficiency:** Efficient use of hardware for high throughput and scalability
- **Effectiveness:** High accuracy and fast convergence, lowering cost
- **Easy to use:** Improve development productivity of model scientists

DL Training and Inference Optimization: DeepSpeed

DL Models

DL Optimizations (DeepSpeed)

DL Framework (e.g., PyTorch, TensorFlow)

DL Infrastructure (e.g., AML, Singularity, ITP, MPI-based platforms)

Hardware (e.g., GPU/CPU clusters)

Bert - Original

```
# Construct distributed model
model = BertMultiTask(...)
model = DistributedDataParallel(model)

...

# Construct FP16 optimizer
optimizer = FusedAdam(model_parameters, ...)
optimizer = FP16_Optimizer(optimizer, ...)
```

```
# Forward pass
loss = model(batch)

# Backward pass
optimizer.backward(loss)

# Parameter update
optimizer.step()
```

Bert – w. DeepSpeed

```
# Construct Bert model
model = BertMultiTask(...)

# Wrap to get distributed model and FP16 optimizer
model, optimizer, _, _ = deepspeed.initialize(
    args=args,
    model=model,
    model_parameters=model_parameters,
    ...
)
```

```
# Forward pass
loss = model(batch)

# Backward pass
model.backward(loss)

# Paramter update
model.step()
```

Minimal code change

↓

Efficiency + Effectiveness

↓

Speed + Scale

DeepSpeed

https://github.com/microsoft/DeepSpeed

Model Scale
- 10 Trillion parameters

Speed
- Fast & scalable training

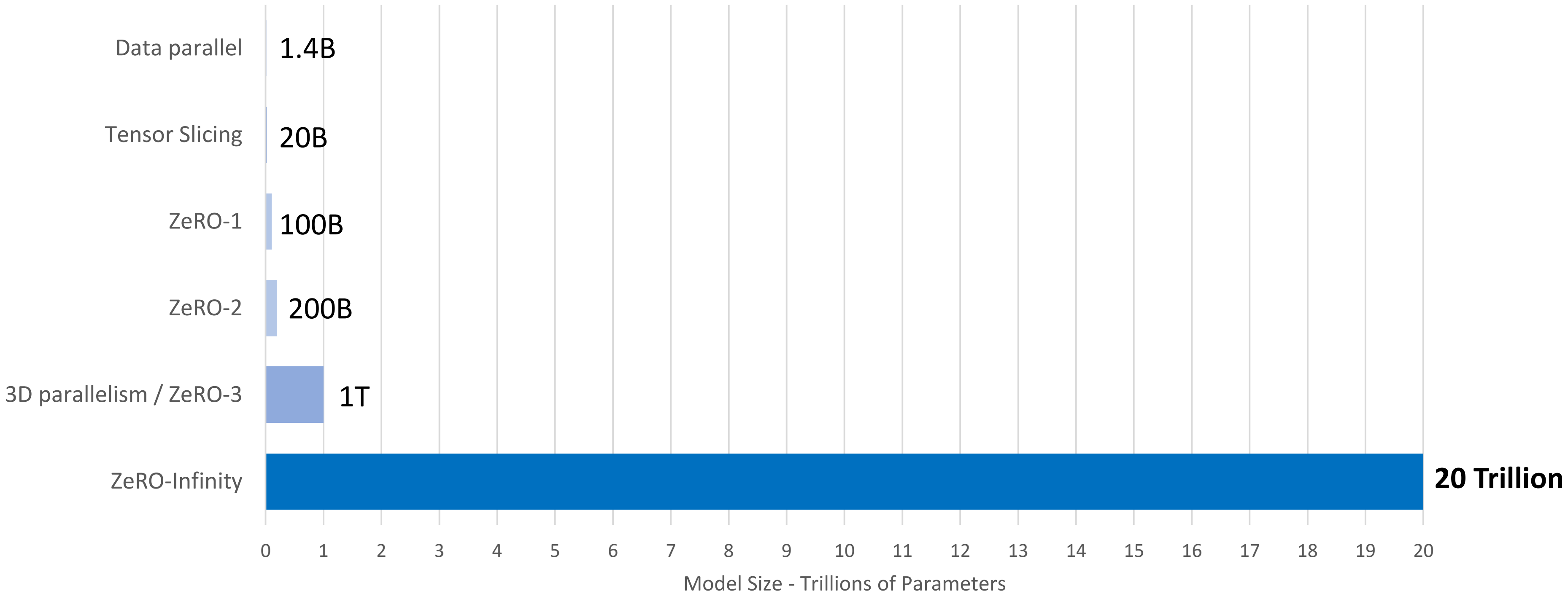
Democratize AI
- Bigger & faster for all

Compressed Training
- Boosted efficiency

Accelerated inference
- Up to 6x faster & cheaper

Usability
- Few lines of code changes

System capability to efficiently train models with **20 trillion** parameters



DeepSpeed key technologies:

- ZeRO: Zero Redundancy Optimizer
- 3D parallelism : data parallelism, pipeline, and model parallelism
- ZeRO-Infinity

Model Scale
- 10 Trillion parameters

Speed
- Fast & scalable training

Democratize AI
- Bigger & faster for all

Compressed Training
- Boosted efficiency

Accelerated inference
- Up to 6x faster & cheaper

Usability
- Few lines of code changes

Fastest Transformer Kernels

⇩

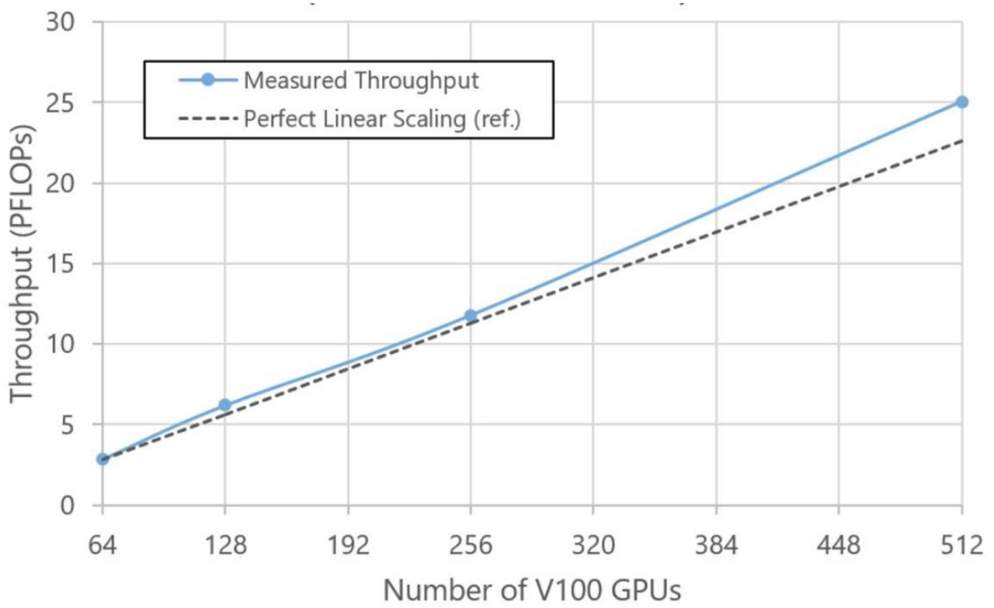
World Fastest BERT Training

#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

Scalable distributed training through ZeRO-powered DP

⇩

Superlinear speedup with increasing #GPUs



DeepSpeed key technologies

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

Model Scale
- 10 Trillion parameters

Speed
- Fast & scalable training

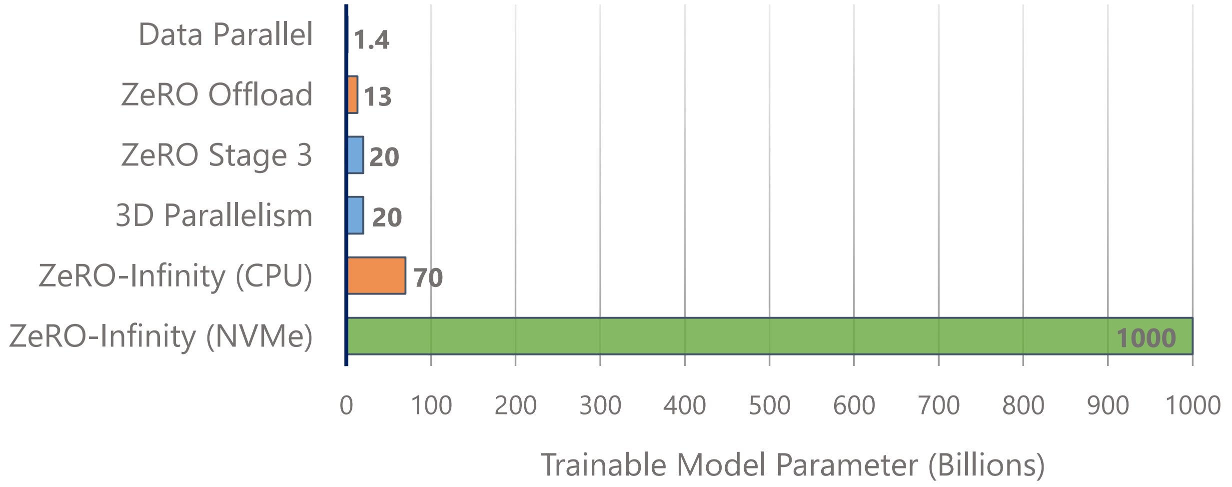
Democratize AI
- Bigger & faster for all

Compressed Training
- Boosted efficiency

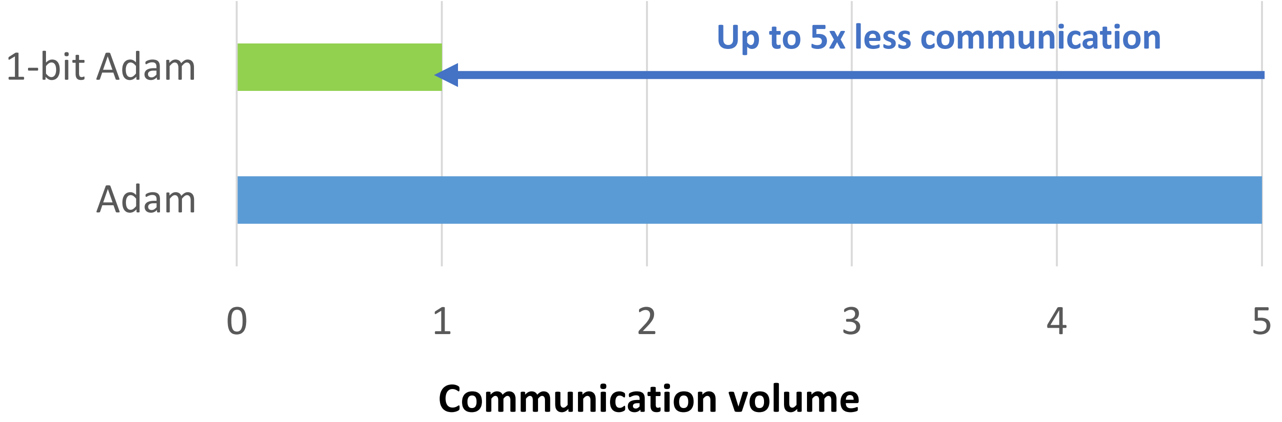
Accelerated inference
- Up to 6x faster & cheaper

Usability
- Few lines of code changes

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



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



Model Scale
- 10 Trillion parameters

Speed
- Fast & scalable training

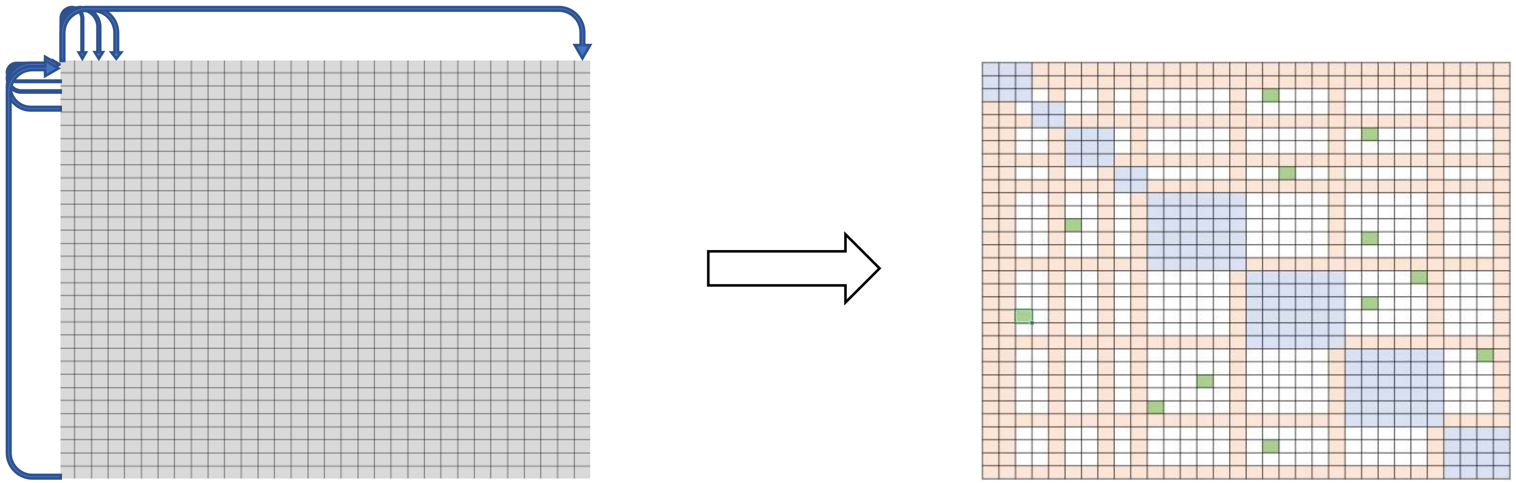
Democratize AI
- Bigger & faster for all

Compressed Training
- Boosted efficiency

Accelerated inference
- Up to 6x faster & cheaper

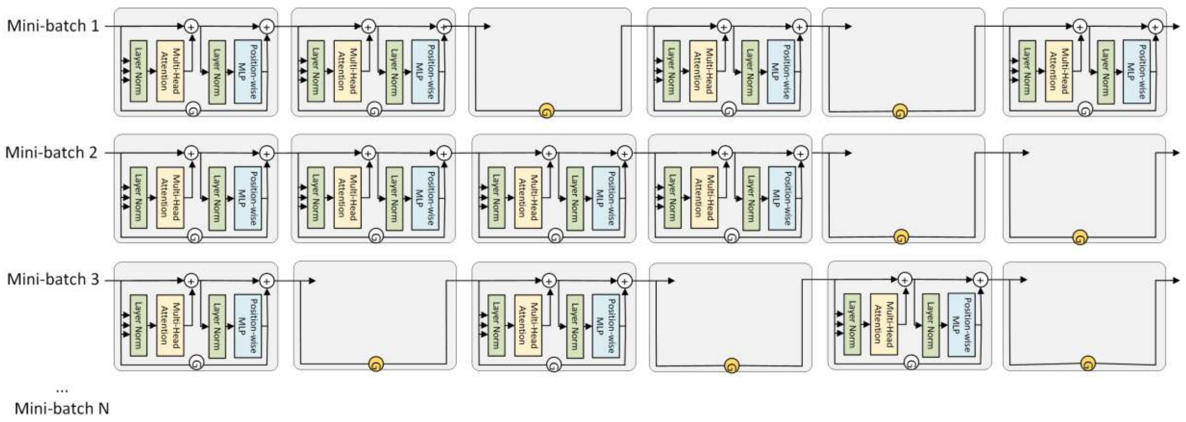
Usability
- Few lines of code changes

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



- **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



Model Scale
- 10 Trillion parameters

Speed
- Fast & scalable training

Democratize AI
- Bigger & faster for all

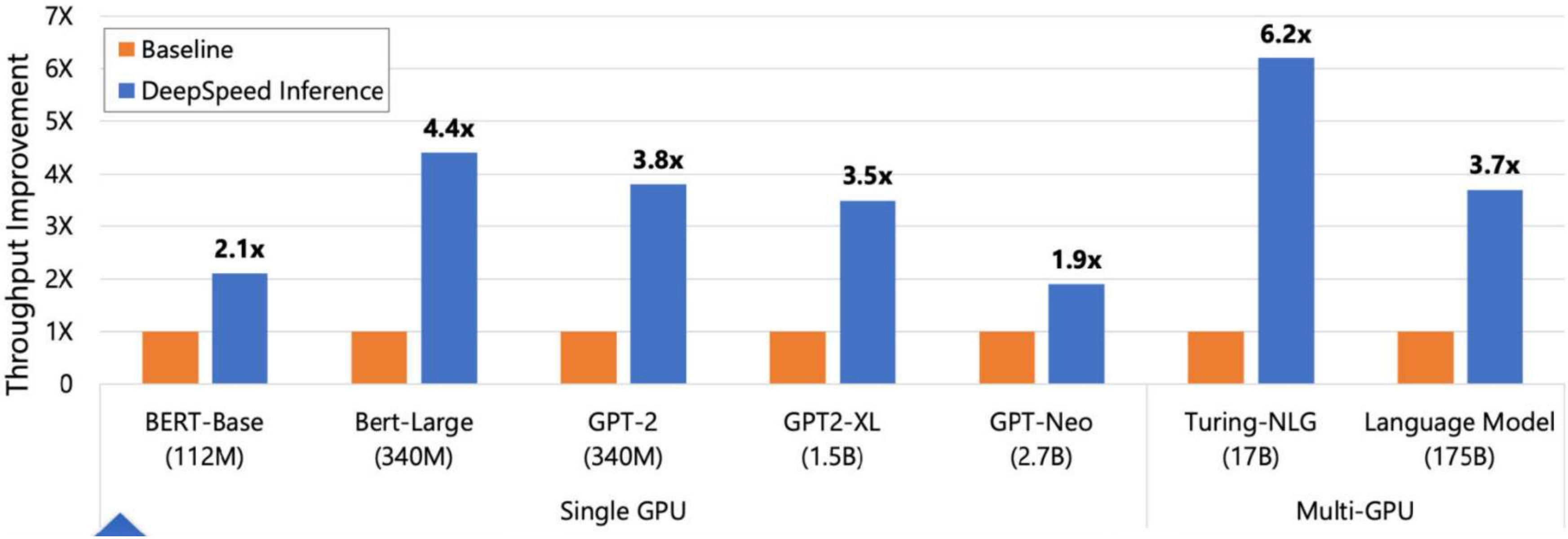
Compressed Training
- Boosted efficiency

Accelerated inference
- Up to 6x faster & cheaper

Usability
- Few lines of code changes

Accelerated inference for large-scale transformer models

Up to 6x faster and cheaper



DeepSpeed key inference technologies:

- Inference-adapted parallelism
- Inference optimized CUDA kernels
- Effective quantize-aware training and efficient quantized kernels

Model Scale
- 10 Trillion parameters

Speed
- Fast & scalable training

Democratize AI
- Bigger & faster for all

Compressed Training
- Boosted efficiency

Accelerated inference
- Up to 6x faster & cheaper

Usability
- Few lines of code changes

Model Scale
- 10 Trillion parameters

Speed
- Fast & scalable training

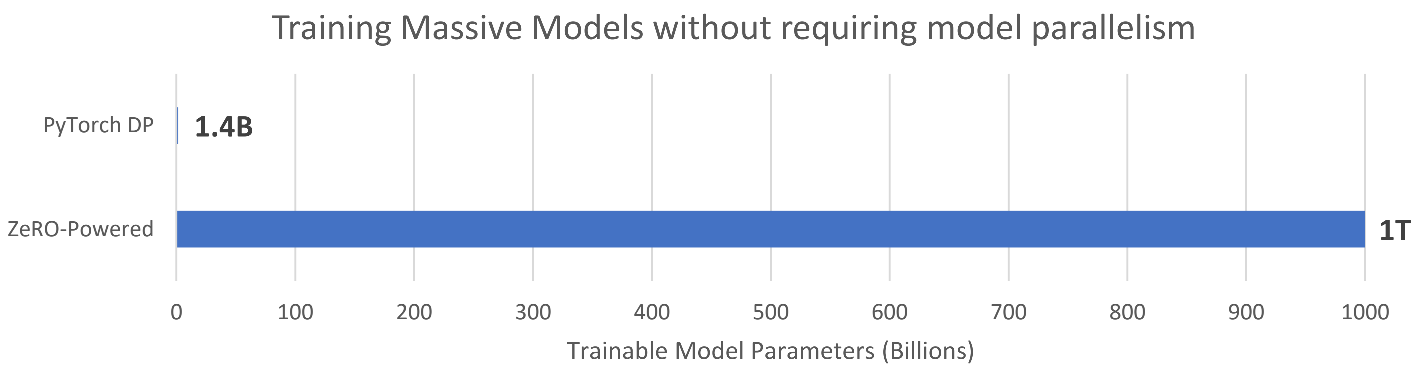
Democratize AI
- Bigger & faster for all

Compressed Training
- Boosted efficiency

Accelerated inference
- Up to 6x faster & cheaper

Usability
- Few lines of code changes

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



- Infrastructure agnostic, supporting AzureML, Azure VMs, local-nodes
- [HuggingFace]() and [PyTorch Lightning]() integrate DeepSpeed as a performance-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 \
```

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

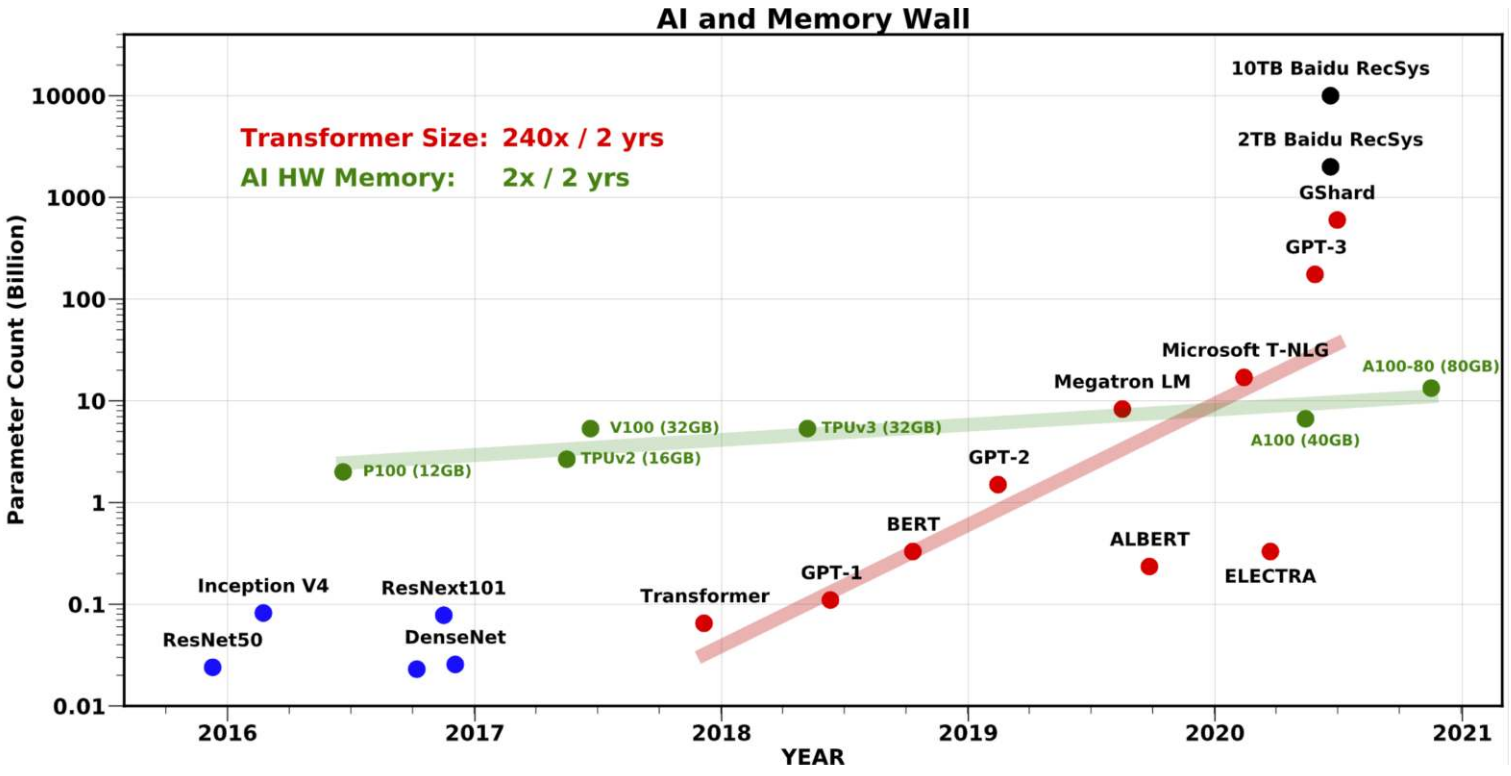
deepspeed.py hosted with ❤ by GitHub view raw

ZeRO-Infinity

Breaking GPU Memory Wall for DL Training

Large model training landscape today

- GPU Memory Wall
  - 1T (10T) params: 800 (8K) V100 GPUs
  - How do we support the growth in model size?
- Accessibility to large model training
  - 256 GPUs to fine-tune GPT-3
  - Limited access to such resources
- Model code refactoring
  - Re-writing the model using 3D parallelism (tensor-slicing + pipeline parallelism)
  - Painful and error prone



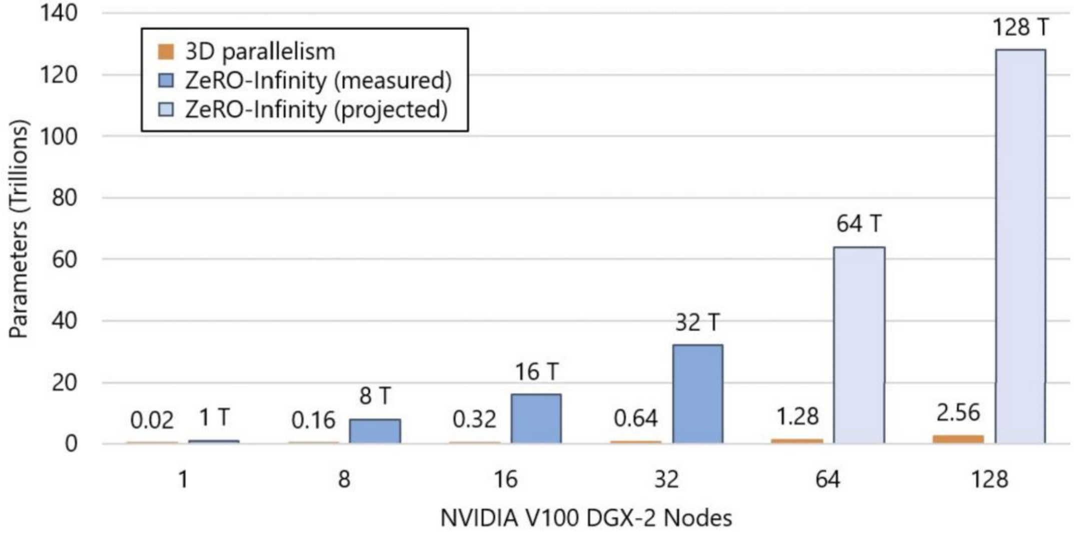
*[AI and Memory Wall. (This blogpost has been written in… | by Amir Gholami | riselab | Medium]

Redefining the landscape with ZeRO-Infinity

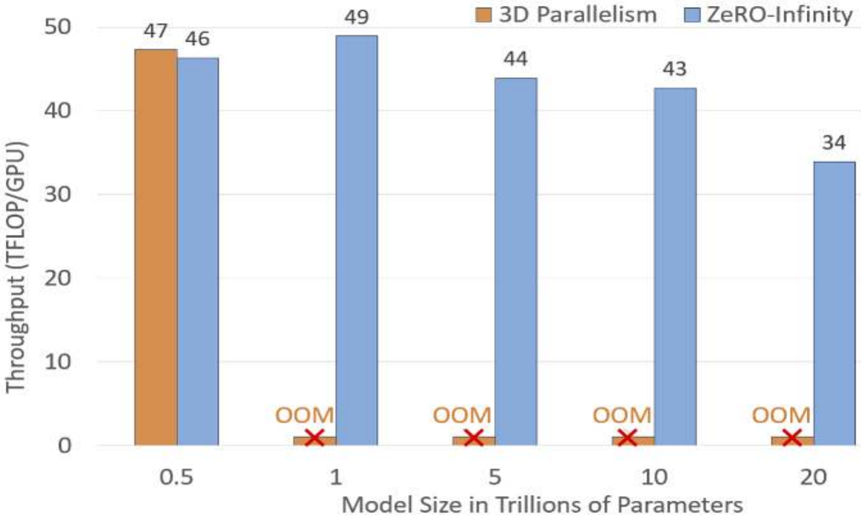
- Beyond GPU Memory
  - 50x larger models
  - 32T params on 512 GPUs (instead of 25K)
- Broader access to large model training
  - GPT-3 sized fine-tuning on a single node/GPU (instead of 16 nodes)
- Excellent Throughput and Scalability
  - Comparable to 3D-parallelism
- Ease of Use
  - No model refactoring necessary

Paper: [ZeRO-Infinity: Breaking the GPU Memory Wall for Extreme Scale Deep Learning (arxiv.org)]

Trainable Model Size



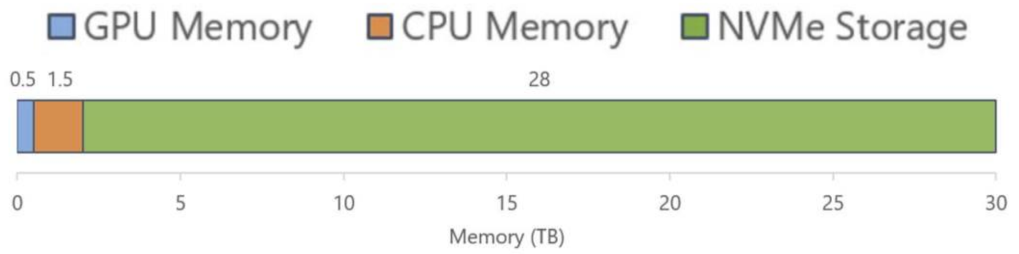
Training Throughput on 512 V100 GPUs



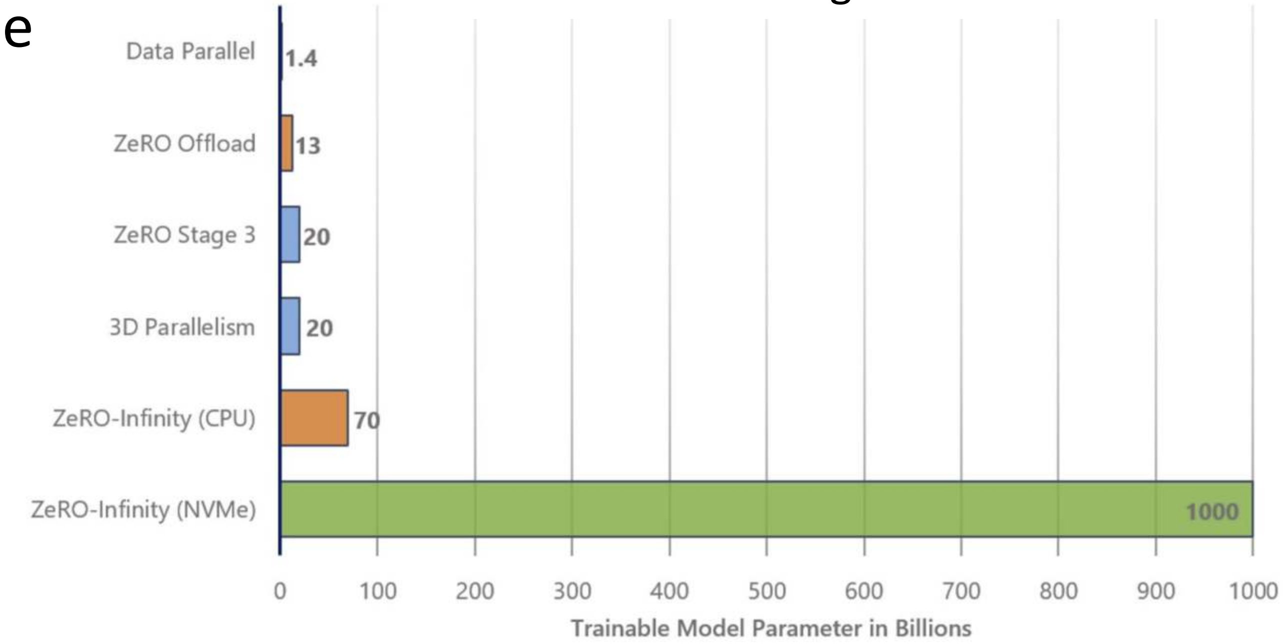
Beyond the GPU Memory

- Modern clusters have heterogeneous memory systems.
- GPU memory comprises a small fraction
- ZeRO-Infinity leverages GPU/CPU/NVMe memory
  - 32T params on 32 nodes
  - 1T params on a single node
- GPT-3 can be fine-tuned on a single node

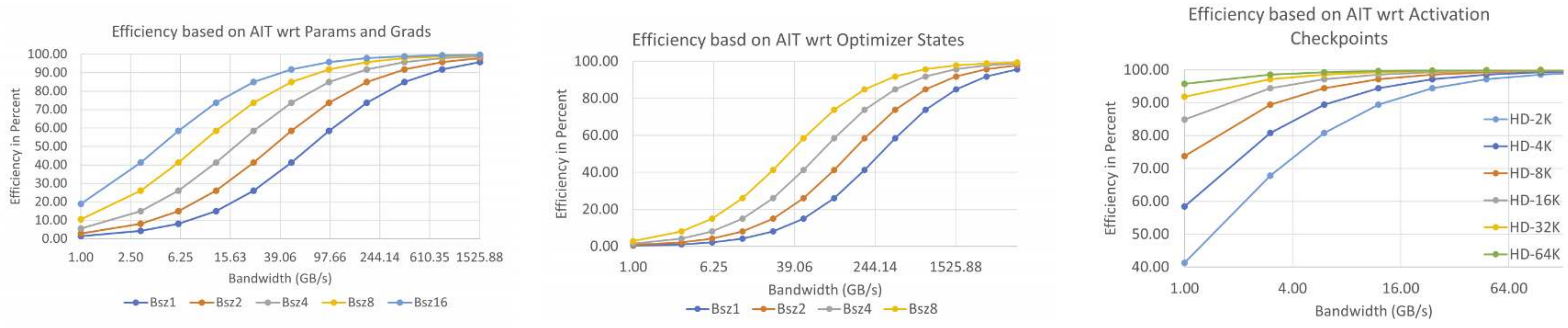
Memory available on a Single DGX-2 Node



Model Size on a Single DGX-2 Node



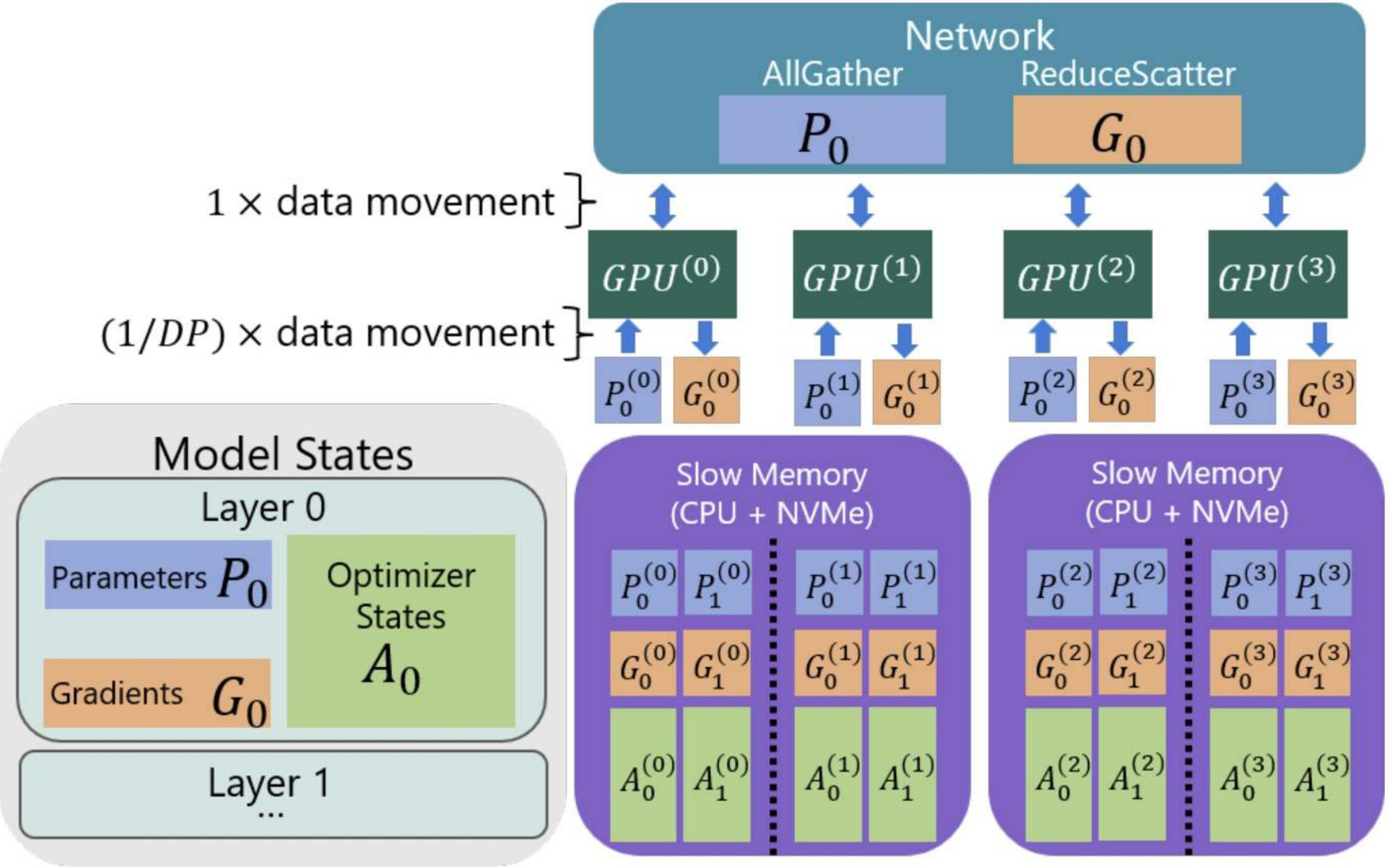
Bandwidth Requirements



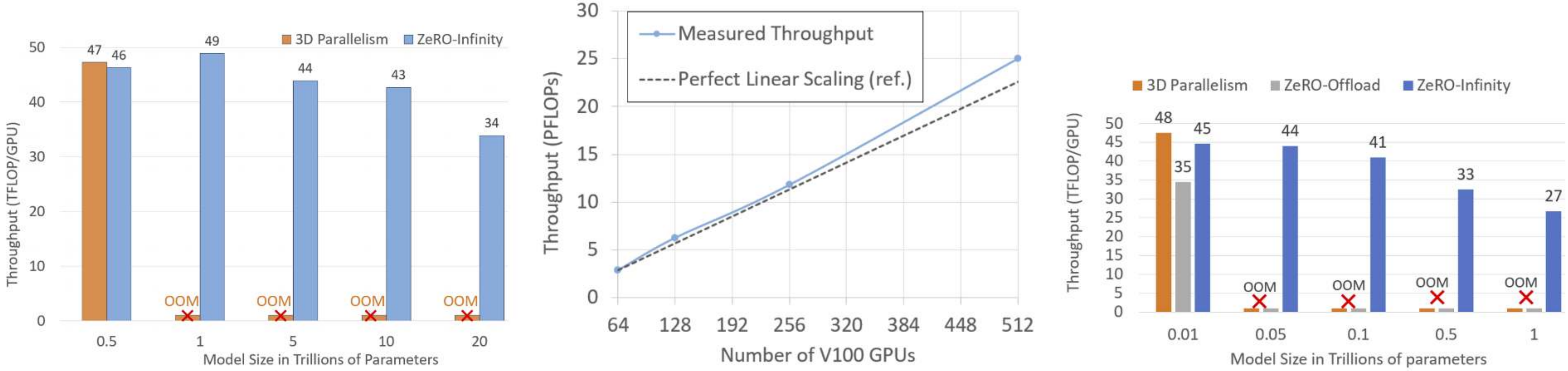
(a) Parameter and Gradient Bandwidth **(b) Optimizer States bandwidth** **(c) Activation Checkpoint Bandwidth**

Figure 3: Impact of bandwidth on efficiency assuming an accelerator with 70 TFlops of single GPU peak achievable throughput.

ZeRO-Infinity Architecture



Evaluation



(a) ZeRO-Infinity efficiently trains 40x larger models than 3D parallelism on 512 GPUs.

(b) ZeRO-Infinity exceeds linear scaling from 64 to 512 GPUs for a 1T parameter model.

(c) ZeRO-Infinity can train up to 1T model on a DGX-2 node without model parallelism.

Figure 5: Efficiency and scalability of ZeRO-Infinity for training multi-trillion parameter models.

ZeRO-Infinity in a nutshell